MENTAL LEXICON OF NOUNS AND VERBS IN ADULT SPEAKERS OF KANNADA

Doctoral Thesis

<u>Submitted to the University of Mysore</u>

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DECLARATION

I declare that this thesis titled **'Mental Lexicon of Nouns and Verbs in Adult Speakers of Kannada'**, being submitted herewith for the award of the degree of Doctor of Philosophy (Speech-Language Pathology) to the University of Mysore, Mysore, is the result of work carried out by me at the All India Institute of Speech and Hearing, Mysore, under the guidance of Dr. K. S. Prema, Professor of Language Pathology, All India Institute of Speech and Hearing, Mysore. I further declare that the results of this work have not been previously submitted for the award of any degree.

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CERTIFICATE

This is to certify that the thesis titled **'Mental Lexicon of Nouns and Verbs in Adult Speakers of Kannada'** submitted by Ms. Prarthana. S. for the degree of Doctor of Philosophy (Speech-Language Pathology) to the University of Mysore was carried out at All India Institute of Speech and Hearing, Mysore under my guidance. I further declare that the results of this work have not been previously submitted for any degree.

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DECLARATION

This is to state that the thesis titled **'Mental lexicon of Nouns and Verbs in Adult Speakers of Kannada'** has been revised, incorporating the suggestions provided by the two examiners.

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Abstract

Background: The processes involved in language production and language comprehension are greatly dependent on the meanings that the words correspond to. These words are assumed to be stored along with their meaning representation in the mental lexicon. Study of words for their semantic features, which are chunks of information about each word, has been the focus of research as they provide valuable insights about its organization and meaning representation. Hence semantic features have been collected in various languages such as English, Dutch, German, Italian etc. In Indian languages, the semantic features have been studied for developing assessment tools and therapy techniques for rehabilitation of persons with communication disorders. However there is no research study that directly focuses on semantic features itself and its contribution to lexical semantic representation in the mental lexicon. Hence the present research was designed to study semantic features of Kannada nouns and verbs in order to describe semantic representation and organization of the mental lexicon.

Method & Materials: The study involved collecting semantic features for Kannada nouns and verbs. 200 nouns belonging to ten semantic categories and 100 verbs belonging to seven semantic categories formed the stimuli. Written semantic features were obtained for these words from 300 native Kannada speaking adults. In order to study lexical semantic representation the semantic features generated for these words were analyzed for distribution of featural properties namely number of features, featural weight, feature types, distinctive features, shared features and feature correlation for the domain of noun and verb and their semantic categories.

Results & Discussion: The distribution of semantic feature properties varied significantly across the domains of nouns and verbs. With respect to semantic categories of nouns and verbs, differences in the distribution of semantic feature properties were more prominently observed for noun categories than verb categories. The results thus reveal that there is substantial difference in the semantic representation of words belonging to domains of nouns and verbs. The differences noted in the semantic feature properties across each category of nouns and verbs further indicate the difference in the organization of words into categories in the two domains. With the goal of understanding organization and categorization of words in the mental lexicon of Kannada a framework for a model was proposed based on the semantic similarity among words based on their featural properties. The model was able to group together words into categories that closely resembled the semantic categories intuitively assigned in the present study. The semantic similarity measures obtained for words in the present study were compared to their translational equivalents in English in order to study the influence of language on semantic representation and organization of mental lexicon. The results revealed a statistically significant difference between the two languages despite the words being translational equivalents representing same concepts emphasizing the influence of linguistic and cultural differences.

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Chapter 1: Introduction

Language is the most effective medium for communication as it can be effortlessly employed to understand and express a wide range of thoughts and feelings. It is used to disseminate information to each other, to describe what we see around us, to reflect on our thoughts about ourselves, about each other and to share them with others. Using language for communication involves complex and intricate mental processes and an immense amount of knowledge about the meanings of words that carry the core information to be passed on. Each language user has a personal vocabulary store or the *mental lexicon*, from which they select the words for use and to which they refer the words they encounter in the utterances of others. The term mental lexicon refers to a language user's mental or cognitive representation of words that allows inferring the referents of a word, the semantic categories to which a word belongs and/or the similarities in word meaning. This information stacked in the mental lexicon is an integral component of knowledge about the world present in the brain alternately referred to as *concepts*. Language is also instrumental in developing these concepts as it is relied upon to obtain insights about the world around us.

The mental lexicon, which is a part of conceptual knowledge, is assumed to consist of a large set of lexical entries for each word. Lexical entries refer to the information stored about a word that is essential to recognize, understand and differentiate that word from similar words. This information about the meaning of the words can be described in terms of semantic features. Semantic features are individual components of meaning which, when added together gives the complete meaning of the word. For example the word apple can be described using semantic features such as <fruit>, <red>, <juicy>, <sweet>, <grows on trees> etc. These features provide insight into the representation of the respective word, the concept corresponding to the word and categorization of concepts. Hence a variety of theories and models proposed to understand the semantic representation[1] and semantic organization[2] of language in the brain (e.g. Shallice, 1993; Jackendoff, 1990; Smith &

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[1] Semantic representation in the present study is viewed as studying the mapping of words in the mental lexicon to their respective concepts

[2] Semantic organization,in the present study is viewed as studying how words in the mental lexicon are grouped together into respective categories(eg: category of animals)

Medin, 1981; Rosch & Mervis, 1975; Norman & Rumelhart, 1975; Minsky, 1975; Smith, Shoben, & Rips, 1974; Collins & Quillian, 1969) have considered the semantic representation in terms of semantic features. The semantic features are typically generated for a given set of concepts by asking the participants to list semantic features that they think are salient in describing respective concepts (E.g.: <animal>, <has four legs>, <barks> etc., for the target word 'dog'). Even though the feature generation task uses words as stimuli, the semantic features nonetheless provide a window into conceptual representation as the word and conceptual knowledge are closely related. The stimuli that are used for generation of semantic feature can be nouns representing concrete concepts, abstract concepts to some extent, verbs representing actions and also adjectives. Factors such as familiarity and imageability of concepts and also frequency of occurrences of these concepts in a language play crucial role in generation of semantic feature.

Acknowledging the relevance of semantic features for understanding semantic representation in the mental lexicon and in formulating theories and models, it is true that collecting semantic feature production norms can provide a strong basis for research in Linguistics and Language sciences. Considering the importance of semantic features, extensive normative databases have been collected for English language (Garrard, Lambon Ralph, Hodges, & Patterson (2001) for 64 nouns; Randall, Moss, Rodd, Greer& Tyler (2004) for 193 nouns; McRae, Cree, Seidenberg & McNorgan (2005) for 725 nouns; Vinson & Vigliocco (2008) for 240 nouns and 216 verbs; Buchanan, Holmes, Teasley & Hutchison(2013) for 1,808 nouns, verbs, adjectives and other parts of speech; Devereux, Tyler, Geertzen & Randall (2013) for 866 nouns). Semantic features have also been collected in Dutch (Ruts, De Deyne, Ameel, Vanpaemel, Verbeemen & Storms (2004) for 338 nouns; De Deyne, Verheyen, Ameel, Vanpaemel, Dry, Voorspoels & Storms (2008) for 425 nouns) and in Italian languages (Kremer & Baroni (2011) for 50 nouns; Montefinese, Ambrosini, Fairfield & Mammarella (2012) for 120 nouns) and also from congenitally blind Italian participants (Lenci, Baroni, Cazzolli & Marotta (2013) for 50 nouns and 20 verbs).

In Indian languages, norms have been established for limited aspects of semantic components, restricted to the purpose of the particular study under consideration. Such norms have been established in Kannada (Karanth, 1984), Hindi

(Sharma, 1995), Malayalam (Asha, 1997), Telugu (Suhasini, 1997) for Linguistic Profile Test developed to assess language comprehension and expression. Ranganatha (1982) has established norms for relative frequency of phonemes and morphemes in Kannada. However, lexical semantic representation in adult speakers of Kannada, with particular reference to the semantic features has not been studied till date.

The collected semantic features are studied for regularities and patterns in the distribution of features as they contribute to a great extent to the understanding of semantic representation in the mental lexicon. The number of features generated by the participants for each target word is the most basic distributional analysis that is carried out. Featural weight is another variable that is found to be very useful which signifies the importance of each feature for a word based on participant's discretion. The features generated are also classified into various types based on the information they carry such as visual, tactile or functional property of the word and are analyzed. The semantic features are then analyzed for distribution of each of these feature types as it is highly informative in explaining neural representation of concepts. The semantic features are also studied for featural correlation, which estimates the occurrence of one feature with respect to others. The distinctive features which help to distinguish between similar words and shared features that are relevant for many words are also studied. These featural properties may vary depending on the categories of target words, concreteness or abstractness of the words and frequency of occurrence of the word in a language.

The featural properties shed light on important aspects of nature of semantic representation in the mental lexicon as these statistical regularities form the organizational principles of various proposed semantic theories and models of meaning representation. The semantic features are also used to carry out accurate and quantitative testing of the claims about the structure of mental lexicon as proposed by these theories and models. Hence many theories of semantic representation such as prototype theory (Rosch & Mervis, 1975) and exemplar theories (Smith & Medin, 1981) are based on semantic features. Semantic features also form the basic ingredients of different kinds of models namely hierarchical network model of semantic memory and language processing (Collins & Loftus, 1975), Semantic Feature Comparison model (Smith, Shoben & Rips, 1974), Featural and Unitary Semantic Space (FUSS) model (Vigliocco, Vinson, Lewis &Garrett, 2004),vector models of memory (Hintzman, 1986; Murdock, 1982), models of semantic computation(McRae, de Sa, & Seidenberg, 1997; McRae, Cree, Westmacott, & de Sa, 1999), object recognition (Plaut, 2002), word recognition (Harm & Seidenberg, 2004), and semantic memory (Hinton & Shallice, 1991; Plaut & Shallice, 1993).

The semantic features are also part of several semantic models which aims to demonstrate how particular patterns of semantic deficits is seen as a consequence of loss of different features caused by brain damage (Farah &McClelland, 1991; McRae et al., 1997; Devlin, Gonnerman, Andersen, & Seidenberg, 1998). This involves training artificial neural networks with input data obtained from the distribution analysis of feature properties that are predicted to be crucial. For instance, a model for words representing living and nonliving concepts constructed by Farah and McClelland (1991) is based on the evidence from the semantic features that the visual-perceptual features are predominant for living things whereas the functional features for nonliving things. In order to demonstrate the behavioural trends seen in patients with semantic deficits, the model was selectively lesioned by impairing either visual-perceptual or functional features. Models have been proposed based on featural correlation and distinctive features of living things and nonliving things to elucidate the progression of semantic deficits caused by Alzheimer's dementia (Devlin, Gonnerman, Andersen &Seidenberg, 1998).Thus the major purpose of collecting semantic features is to construct empirically derived conceptual representations that can be used to test theories of semantic representation and computation (McRae, Cree, Seidenberg & McNorgan, 2005).Semantic features also form the basis of many treatment strategies designed to treat comprehension deficits and anomia in persons with aphasia such as Semantic Feature Analysis (SFA) (Boyle & Coelho, 1995).Semantic feature based therapy techniques are also been evidenced to be effective in Bilingual persons with aphasia (Kiran& Roberts(2010)for Spanish-English bilinguals and French-English bilinguals; Rangamani & Prema, (personal communication) for Kannada-English bilinguals).

Studies involving semantic concepts and representation have been extensively researched in languages such as English, Dutch and Italian to name a few but there is a sparsity of research in Indian languages in the areas comprising of meaning representation, organization of words, models of semantics particularly in Kannada which differs in linguistic properties compared to English. Hence the present study was conceptualized to understand the structure of mental lexicon in Kannada.

The present research was designed to study lexical semantic representation and organization for a set of nouns and verbs in Kannada, by collecting semantic features generated for nouns and verbs from adult native speakers of Kannada. The semantic features obtained were subjected to analysis in order to assess the nature of distribution of different semantic featural properties. Specifically the analysis focused on evaluating the differences and similarities if any, in the distribution of featural properties across the domains of nouns and verbs. Further, the responses were analyzed for distribution of featural properties across different semantic categories to which the target words may belong. The study also attempts to develop a framework for a model of mental lexicon in Kannada based on the semantic featural properties obtained from the present study. Analysis will also be conducted in order to investigate differences and similarities if any in the distribution of featural properties between Kannada and English languages. The next chapter in this thesis presents a detailed review of literature summarizing the past research relevant to the current topic of study. Chapter 3 describes the methodology used for semantic feature collection, tabulation and construction of computer database of the generated semantic features. Chapter 4 reports the results of the analysis of featural properties carried out and description of the model generated followed by discussion of the same. A brief summary and conclusions derived from the study is also presented.

Chapter 2: Review of Literature

Exploration of any human language demonstrates that language is an extremely complex, highly abstract and infinitely productive system (Falk, 1978). From a linguistic point of view, it is considered to be a mental phenomenon, involving knowledge about meanings, syntax and sounds. It has been in the interest of researchers to study what kind of knowledge underlies use of language and what enables individuals to interpret speaker's speech as the expression of meaning. Word meanings or lexical semantics is considered fundamental part of this knowledge, which facilitates comprehension and production of speech. Thus producing and comprehending verbal language involves selection of most appropriate words from the word store in the brain that best matches to the *meaning* of the thought that is intended to be spoken or heard (Levelt, 1989). This storage of words that are assumed to be in the brain and accessible during comprehension and production of language is termed as '*mental lexicon'*.

The mental lexicon cannot be considered as a mere collection of words, as it also concerns with the representation of meanings of the stored words, the activation, processing and access during language tasks. It also concerns with knowledge about objects and events that are formed through various sensory and motoric exposures in the environment of individuals. This knowledge is termed as *'concepts'*. The mental lexicon along with conceptual knowledge is assumed to be stored in semantic memory. Semantic memory is a type of long-term memory that is a highly structured network of concepts, words and images and is capable of making inferences and comprehending language (Collins & Quillian, 1969). Two lines of research have been conducted with respect to conceptual knowledge and mental lexicon. One is directed at the study of retrieval processes of words and their corresponding meaning from the mental lexicon while the other focuses on elucidation of the structure and semantic representation of words and concepts in the mental lexicon.

2.1 Conceptual Knowledge

Study of concepts and its categorization in the mental lexicon provides an invaluable insight with respect to its structure as the latter is assumed to be storing verbal information about the attributes that define concepts. Concepts are considered as the bodies of knowledge that are stored in the semantic memory and are used by our cognitive processes when we categorize, make inductions, understand languages and draw analogies (Machery, 2007). Concepts form the mental representations of the objects and events surrounding our environment. They bind our past experiences with the present situations of the world and enable us to infer the meaning out of each situation we come across in our daily living. For instance, a concept of *dog* is a body of knowledge about dogs that is used by default when we categorize entities as dogs, when we understand sentences that contain ‘dog’ and so on (Machery, 2007). Concepts thus are viewed as embodiment of our knowledge about the world helping us understand what each object is and what traits it consists of.

Categorization, on the other hand, is a process of determining whether or not some entity is a member of a category. Categorization thus allows understanding of new entities and to modify and update the existing concepts. Thus a category refers to a set of entities that are grouped together and they are characterized by members that share many features (E.g.: category of animals). Categories thus result from internal representations that capture the structure in the world. It is grouping of vocabulary within a language, organizing words that are interrelated and define each other in various ways. Categories, therefore consists of groups of concepts aggregated together because of the similarities and resemblances that is shared with each other.

There are at least three distinct levels of hierarchies in categories namely:

i) Superordinate
ii) Basic
iii) Subordinate

Superordinate categories are considered to be abstract ones. Members of this category share few similarities with other members (E.g. category Vehicle). Basic level categories store maximum information about the member of the category and share a great amount of similarity with its members (E.g. category Car). The subordinate categories contain more additional specific information about the members compared to the basic level category (E.g. category Sports car).

Thus the basic level has more attributes in common among its members in comparison to higher-level categories (superordinate category). In comparison with the lower level categories (subordinate category) the basic level contains fewer attributes in common with it. The basic level categories are also of special interest to researchers as they are the fundamental level at which abstractions are made upon the world. Thus there are several levels of conceptual categories of which basic level yields most of the knowledge about the concept.

2.2 Concepts and Mental Lexicon

Concepts, more specifically basic level concepts are studied to describe and understand mapping of conceptual knowledge into lexical semantic knowledge termed as semantic representation. Thus word meaning or Lexical Semantics are assumed to be psychologically represented by mapping words onto conceptual structures (Murphy, 2002). This mapping facilitates easy access of conceptual knowledge through verbal language in the mental lexicon and this knowledge provides the critical information for our interactions with objects and our participation in events. This critical information forms the basis of understanding and producing language for communication. Literature survey proclaims the use of terms ‘word’ and ‘concept’ interchangeable by the researchers owing to considerable similarities between word meanings (lexical semantics) and concepts. Thus a word gets its significance by being connected to a concept or a coherent structure in our conceptual representation of the world. Hence a strong link can be assumed between concepts and word meanings. It can also be observed in the research relating to conceptual knowledge that the results obtained using words as stimuli are interpreted to be true for concepts as well. This is because word meanings and concepts are closely associated such that activation of semantic representations of words in turn activates corresponding conceptual knowledge (Vigliocco & Vinson, 2005). Various empirical evidences as discussed below also support this conceptual basis of word meaning.

The various properties of concepts used to explain structure of conceptual organization such as category membership effects and typicality effects provide a quantum of evidence for conceptual basis of word meaning. Category membership effect refers to the phenomenon wherein members belonging to the same category are more related to one another than the members in different categories. Typicality effect refers to the phenomenon in which experimental participants responds quickly when typical members of a concept are presented (e.g., *robin* for the concept bird) as against atypical members (e.g., *penguin*). Studies have demonstrated these effects, which are well established for concepts, even in pure linguistic experiments such as semantic priming where words are used as stimuli (e.g., Federmeier & Kutas, 1999; Kelly, Bock & Keil, 1986). Hence it is assumed that concept and words are closely associated.

In contrast to this view, there are other factors that provide evidence that word meaning and concepts may not have a straightforward relation. Even though conceptual structure and word meanings have direct influence on each other they do not always share one to one mapping. This is evident in case of synonyms and ambiguous words where in the two words should be mapped onto a single concept in the former case and in latter case a single word should be mapped onto two different concepts. Also it is true that a language user has far more concepts stored in his brain which has no word associated with it. Hence it can be concluded that mapping of words onto concepts is incomplete and there is a distinction between concepts and word at least to a small degree. This is also supported by studies in neuropsychological literature where in semantic deficits have been documented as restricted to linguistic tasks alone (e.g., naming) and not observed for non-verbal tasks (e.g., using tools) (Cappa, Frugoni, Pasquali, Perani & Zorat, 1998; Hart & Gordon, 1992) which suggests only some aspects of concept is represented on a one to one basis with words. Nevertheless the empirical evidences obtained in these studies do not rule out close connections between concepts and word meaning. It is also true that conceptual properties exert great influence in linguistic tasks just as much as they do in nonlinguistic tasks. Hence any theory of one will serve to a large extent as a theory of the other (Murphy, 2002).

Consequently many researchers have studied mental lexicon and concepts by proposing numerous theories and models to describe the same. The structure and organization of concepts along with its corresponding words in the mental lexicon is particularly interesting as it is hypothesized to be a highly structured system and is organized based on robust organizational principles. The following evidences support this hypothesis.

It is undisputable that the mental lexicon stores huge collection of words because any adult native speaker of a language with basic education has an approximate vocabulary of around 150,000 words, 90 percent of which are likely to be accessed during conversation (Seashore & Eckerson, 1940, in Aitchinson, 1994). Evidences derived through psycholinguistic studies of language involving words recognition, retrieval and speech shadowing task demonstrate that the process of recognition and retrieval of words for speech production and comprehension occurs within milliseconds of exposure to stimuli even before all syllables of the word being heard (Marslen-Wilson & Tyler, 1980, Marslen-Wilson & Tyler& Le Page, 1981 in Aitchinson, 1994). This speed and accuracy are also evidenced in tasks of lexical decision involving non-words suggesting the short duration of time required to thoroughly scan the mental lexicon. To facilitate such quick and efficient mechanism involving large number of words requires systematic organization of words. Hence there is evidence to say that there is an orderly pattern of storage of words in the mental lexicon based on certain principles. It also true that the use of mental lexicon and conceptual knowledge in our daily activities almost goes unnoticed as this process occurs so effortlessly and efficiently that its complexity is experienced only when it is attempted to understand the underlying phenomena, organizational principles and the processes involved.

One of the aspects of conceptual knowledge and mental lexicon that is of interest is its acquisition and learning of categorization of concepts and words into its relevant categories, which formed the initial focus of early research. The initial experimental research on acquisition and categorization of concepts was carried out in the beginning of twentieth century, which has contributed substantial insights into the same. Concepts were initially assumed in the earlier studies (e.g., Hull, 1920; Smoke, 1932) to be represented as *'definitions'* in the semantic memory. Therefore defining a concept in terms of its characteristic traits formed the key component in meaning representation and categorization of concepts. Hence the acquisition and categorization of concept was viewed as conscious grasping of the specific attributes of an individual item and grouping the ones with same attributes together. Experimental studies demonstrated this learning of concepts and its categorization using sets of artificial categories such as deformed Chinese letters (Hull, 1920) or meaningless visual stimuli (Smoke, 1932) as experimental stimulus. Learning of these artificial categories for regularities in properties that were useful in defining a concept was quantitatively analyzed for accuracy of categorization to predict the extent to which a category was learnt.

Thus earlier studies presumed concept to be consisting of *definition,* which is a set of necessary and jointly sufficient conditions of membership. This view of concepts based on definition was later termed as 'Classical view of concepts'. The representation of concepts, according to this view is a summary description of an *entire class*, rather than a set of descriptions of various exemplars of that class (Smith & Medin, 1981). However, research mainly in 1960's and 70's refuted this classical view of concepts as these theories failed to explain general properties and phenomena such as category membership effects and typicality effects evidenced in behavioral studies involving concepts. Therefore studies involving alternate ways to describe concepts and meaning representation in mental lexicon were witnessed. Despite the attempt of these later proposed theories to describe semantic representation using word as stimuli their findings more directly applies to structure of conceptual knowledge assuming words and concepts to be closely related such that activation of semantic representations of words in turn activates conceptual knowledge mapped to the word.

2.3 Theories and Models of Semantic Representation

The theories proposed to explain the principles of organization of concepts and word meaning can be broadly divided into two types based on their assumption of how word meaning is represented. One set of theories termed as 'Holistic theories' assume that word meaning are holistic and non-decomposable in nature. To understand organization, holistic theories stress the importance of types of relations among meanings of concepts. Another type of theories called as 'Featural theories' assume word meaning to be decomposable into features or attributes and organization of meaning is explained with respect to featural properties, featural overlap with other concepts (the models of semantic representation are also described in Prarthana & Prema, 2012)

2.3.1 Holistic theories and models.

2.3.1.1 The Hierarchical Network Model. The Hierarchical Network Model was developed by Collins and Quillian in 1969. This model is based on holistic view of meaning representation and is the first model describing in detail the semantic representation and retrieval of words from the mental lexicon. The model was developed employing Artificial Intelligence[3] program written by Quillian in 1968 as an attempt to explain two fundamental factors of the mental lexicon namely its efficient storage of semantic and conceptual knowledge and access of relevant information from this knowledge based on inferential reasoning.

In order to explain the structure of mental lexicon, the model assumes that the concepts in the mental lexicon are arranged in the form of a network as depicted in *Figure 1*. Every node in this network represents a concept and these nodes are hierarchically organized. The concepts representing most generic ones are at the highest nodes and more specific concepts at the lower nodes of the network. The attributes distinguishing one concept from another at the same level and also from the concepts at higher and lower levels are reported at each node. The connections among concepts in this network is said to be governed by two logical relations namely ***category membership relation*** and ***property relation***. Meaning of a concept is computed based on the total configuration of category membership relation and property relation each concept shares with other concepts.

[3]Artificial intelligence is a technology and branch of computer science that studies, designs and develops intelligent machines and softwares using mathematical optimization, logic, methods based on probability and economics. These tools help to develop reasoning, knowledge, planning, learning, communication, and perception.

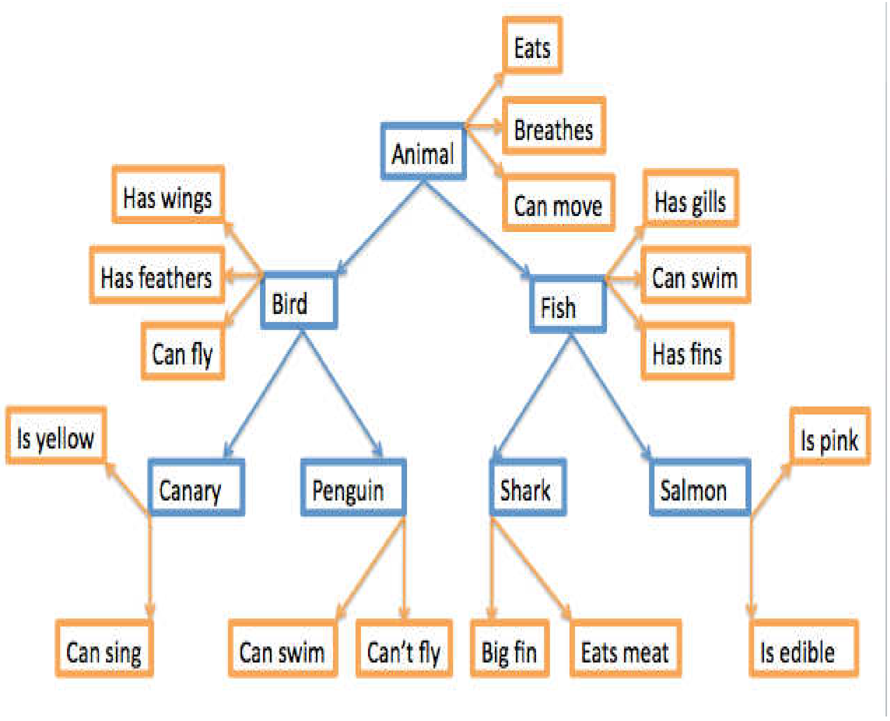

Figure 1. Hierarchical Model (source: Collin's and Quillian, 1969)

The model also proposes that one of the important organizational principles of mental lexicon is its property named 'Cognitive Economy'. Cognitive Economy ensures that the attributes of a concept are represented at only one level of hierarchy in the network. The attributes common to several concepts of the category are represented only at the highest node of the category. For e.g.: the attribute 'breathes' is stored only at the highest node in the network namely 'animal' and not at the lower levels of hierarchy like 'fish'. This property of cognitive economy is based on the logical relation that all animals breathe and 'fish' belonging to the category animals it breathes too. Hence, the attribute 'breathes' is stored at highest level only. Thus the cognitive economy determines the amount of information represented at every node in the network that explains the tremendous storage abilities of the mental lexicon. Also attributes which are applicable to one particular member of the category are stored separately as one of their properties, for instance penguin cannot fly but still belongs to the category 'bird'. This property unique to the member penguin is stored only at this level.

The assumptions and predictions of this model were subjected to testing using behavioural experiments such as sentence verification and reaction time studies. However the results of the behavioural experiments could not account for the principle of cognitive economy. The experimental data on the other hand concluded that the attributes are associated with each node in the hierarchy rather than just at the highest node. For example in a sentence verification task involving two sample sentences such as ‘an animal eats’ and ‘a bird eats’ the model based on the cognitive economy predicts that the first sentence takes less time to be verified than the second sentence. The results of such experiments however revealed that the time taken for verification of both the sentences is equal and hence refuted one of the important assumptions on which the model is built. It is also argued that the time required for verification is not dependent on the hierarchy or the levels of the concepts but is dependent on the amount of association present between the concept and its attribute (Conrad, 1972).

The model is also unable to justify the phenomenon of typicality effect seen for members of a category who are good exemplars of the category than others belonging to the same category. For instance, in a sentence verification study (Rips, Shoben & Smith, 1973) participants took less time to verify that ‘a robin is a bird’ than they took to verify that ‘a penguin is a bird’. ‘Robin’ being more typical member of the category ‘bird’ it was verified quickly than penguin, which is not so typical. The model also failed to justify why familiar concepts are verified faster than unfamiliar ones regardless of their level in the hierarchy as reported by studies (Smith, Shoben, & Rips, 1974) where it takes longer time to verify that ‘dog is a mammal’ (lower level) than to verify that it is an ‘animal’ (higher level). Thus, although the hierarchical network model provided detailed description of the structure and retrieval of concepts there were few drawbacks as the model failed to explain many behavioural phenomena associated with mental lexicon. The model nonetheless provided a strong framework for the future models of mental lexicon developed.

2.3.1.2 Spreading activation model. As described in the previous section the Hierarchical network model had shortcomings and was unable to account for the experimental evidences of behavioural studies. In an attempt to overcome these drawbacks, Collins and Loftus in 1975 developed the Spreading activation model by adding several other assumptions with respect to the structure and working of the Hierarchical network model. One of the major revisions made to the model was elimination of the strict hierarchy. Hence the spreading activation model assumes that direct connections are possible among any two concepts or attributes. The interconnected units of information are called as nodes (*Figure 2*) similar to their previous model. The nodes are connected through links that are formed on the basis of association of each concept or attribute with another. The organization of concepts into close associations is proportional to the thickness and the length of the link. Unlike the previous, this model also assumes that the connections between concepts are not always based on logical relations but personal experiences despite being not logical can lead to the formation of links.

The processing and retrieval of information is initiated by spreading of a pulse of activation among the nodes of the network through their links. Thus, when a node is activated, there is spread of this pulse of activation to the nodes that are linked to it. These nodes further spread the activation to other nodes along their connections. The length of the link determines the strength of the activation. Longer the link between two nodes weaker is the activation reaching the other node. Activation is also weak as it passes over the farther nodes until it completely dissipates. This assumption of the model can explain the basis of semantic and associative priming in the lexicon and the model can also account for various phenomena namely familiarity effect, typicality effect, and concept- attribute associations.

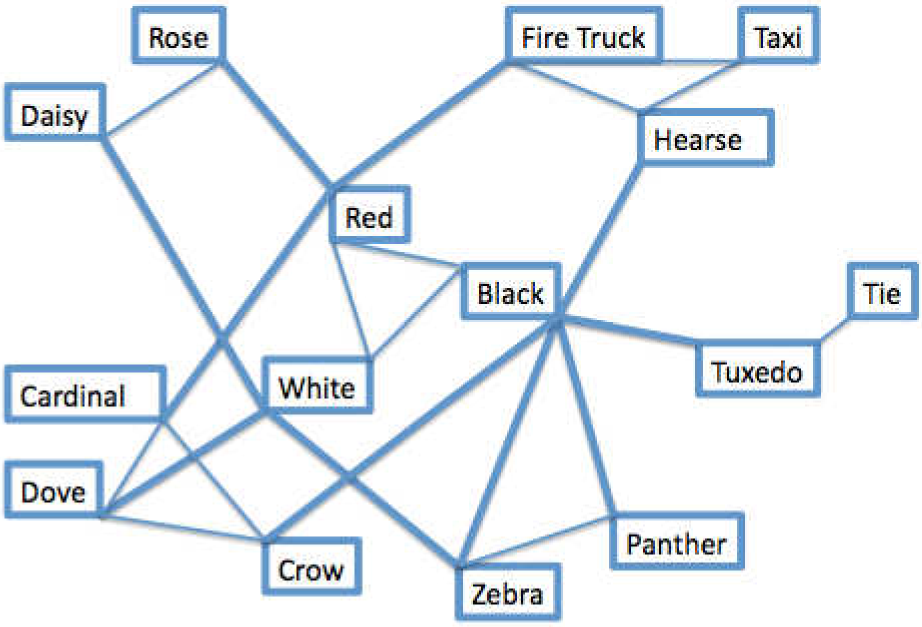

Figure 2. Spreading Activation Model (source: Collins and Loftus (1975)

However the model was questioned for its assumption that personal experiences influence the connections in the mental lexicon. If this assumption were true then the organization of mental lexicon will be entirely idiosyncratic varying from one individual to another which is not practical. The model is also unable to account for the influence of phonology, syntax and morphological aspects of lexical items, which also play a vital role in the language processing. In order to account for these linguistic factors the revised spreading activation model was proposed by Bock and Levelt (1994) the structure of which is depicted in *Figure 3*.

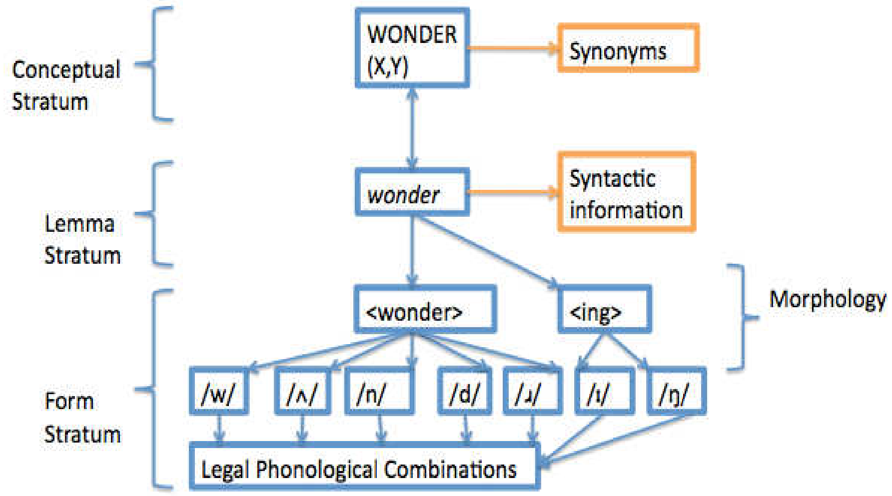

*Figure 3.*Revised Spreading Activation Model (source: Bock and Levelt 1994)

2.3.1.3 The Adaptive Character of Thought (ACT) model. The ACT model was developed by Anderson (1976; 1983) as a general framework to describe the organization of knowledge in the brain. It is a computational[4] model comprising of a production system that is responsible for carrying out higher-level cognitive operations utilizing declarative, procedural and working memory. This framework has been employed to understand organization of linguistic information in the mental lexicon. One of the assumptions of this model is that there are separate representations for concepts and their corresponding words in the brain as opposed to previous models discussed so far. This assumption is based on the argument that there can be concepts in the brain which cannot be lexicalized into words but there are no words which do not have a concept mapped to it (Fellbaum, 1998). Hence there may not be direct one to one mapping of concepts and words in the brain.

The model proposes that the information about a concept and its possible connections with other concepts is highly influenced by the contexts and environment in which the concept most frequently occurs. Hence this model is unique because unlike previous models, it is not dependent entirely on just the meaning and connections among words but it emphasizes that the organization is also dependent on the function and context of words. Therefore, according to this model the words are

[4]A computational model is a mathematical model in computational science that requires extensive computational resources to study the behavior of a complex system by computer simulation

organized based on the real- world, practical relationships among words along with their meanings (Anderson, 1996).

2.3.1.4 WordNet model. Another important model proposed based on holistic theories of meaning representation is the WordNet model. The WordNet comprises of an electronic lexical database[5] developed by Miller in 1995. This database consists of words that are arranged into group of synonyms called *synsets*. The synsets are further hierarchically organized to form a network as in Collins and Quillian's model (1969). Since it is not possible to have exact synonyms for all the words the model proposes terms called hyponymy and hypernymy for such words with non-exact synonyms. For example in the word pair dog and animal, dog is the hyponymy and animal is its hypernymy. The main drawback of this model is that it does not consider context of occurrences of words and hence fails to adequately address concepts that are functionally related. Similar to the one developed for English language, a lexical database called 'indowordnet' (http://www.cfilt.iitb.ac.in/indowordnet/) has been developed for 18 Indian languages by Indian Institute of Technology, Bombay.

2.3.1.5 Computational and Statistical models. These sets of models were developed to describe organization and connections of words by employing various computational and statistical procedures which facilitates discovery of the relations words may possess. These models do not have any prior assumptions about the organizational principles. The most influential models based on this approach are Latent Semantic Analysis (LSA, Landauer & Dumais, 1997) and Hyperspace Analogue to Language (HAL, Burgess & Lund, 1997). These models compute word meanings based on the linguistic context and frequency of co-occurrence of words, which is determined employing large corpora of texts. The main drawback of these models are that they do not take into account real world experiences as they are focused on only certain limited aspects of relations among words.

The holistic theories proposed thus tried to explain the structure and organization of concepts assuming each concept to be non-decomposable units of information. The connections between these units played vital role in processing and storage of information. Every theory had its own set of assumptions and rules based

[5]The access to WordNet lexical data base can be obtained through this address https://wordnet.princeton.edu/wordnet

on which it was built. The holistic theories was quite successful in addressing the issues of organization, however most of them failed to accommodate the behavioural evidences obtained during testing of the predictions of their theories which was received as a severe drawback. For instance, the Hierarchical model was based on the assumption of cognitive economy which was unable to receive support using behavioural studies. The typicality effect seen for concepts also could not be explained based on the organization of hierarchical model. The spreading activation model was proposed assuming no strict hierarchies among concepts however they emphasized on the role of personal experience in the formation of links and networks among concepts which received criticism as it leads to idiosyncratic representation for each individual. Some of the theories such as LSA & HAL proposed were criticized for not taking into account the real world experiences. The holistic theories nonetheless provided an initial groundwork for studying mental lexicon. Featural theories propose to overcome the drawbacks of holistic theories. These theories were based on the assumption that word meanings are decomposable and are represented as sets of features/attributes that may be unique and/or shared by concepts.

2.3.2 Featural theories and models

2.3.2.1 Semantic Feature Comparison model. The models based on holistic theories described in the previous section were less capable as they were producing inconsistent and erroneous predictions for most of the behavioural phenomenon associated with the meaning representation in the mental lexicon. Hence with the aim of studying organization from a featural perspective Semantic feature comparison model was developed by Smith, Shoben and Rips in 1974. The model assumes that the concepts in the mental lexicon are represented as set of attributes/properties termed as semantic features (a detailed description of semantic features is presented in section 2.5 of this chapter). These semantic features add together to form the meaning of the concept (Smith et al., 1974). For instance, consider the concept ‘apple’ for which features such as red in colour, fruit, sweet, grows on trees can be present in the mental lexicon.

The model also assumes that these semantic features are of two types namely ‘Defining features’ and ‘Characteristic features’. Features that are very crucial to define a concept are termed as Defining features. Characteristic features on the other hand are features strongly linked with a concept but which are not very crucial to the concept's definition. The defining features are often relevant and present for all the members of the category, the characteristic features however are specific to only few members of the category. Example for *defining features* according to this model for 'bird' are has wings, lays eggs, and has feathers and the *characteristic feature* is 'can fly' because this feature may not be present for all birds (E.g., Ostrich) (*Figure 4*). Another assumption of this model is that the superordinate members of a category have less number of defining features compared to subordinate members.

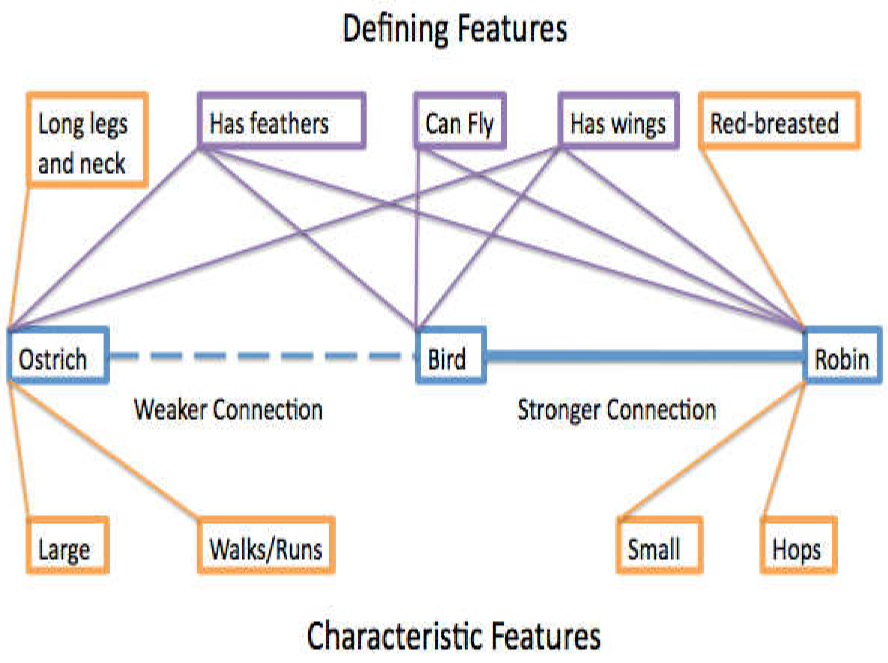

Figure 4. Semantic Feature Comparison model (source: Smith et al., 1974)

The predictions of this model were subjected to testing by employing behavioural measures such as sentence verification tasks. The tests involved analysis of time taken by the participants to verify whether a sentence such as 'robin is a bird' Vs. 'ostrich is a bird' is true or false. If the predictions of the model are correct, the statement 'robin is a bird' should be verified faster as it has higher featural similarity between its subject (robin) and predicate (bird) than with the sentence 'ostrich is a bird'. The results of these experiments were in congruence with the predictions made by the model. The model's predictions were also grounded to principles of meaning similarity and relationship between the subject and predicate. Hence this model has been highly successful in accounting all the main findings in the research of behavioural experiments. However, the model nonetheless had few shortcomings in its predictions (Holyoak & Glass, 1975; McCloskey & Glucksberg, 1979).

In spite of its effectiveness in predicting behavioural phenomenon, this model received criticism that the assumption of semantic representation involving two types of features (defining and characteristic) may not be always true as defining features cannot be identified for all of the concepts present in the mental lexicon (Fodor, Fodor & Garrett 1975; Fodor, Garrett, Walker& Parkes, 1980). Researchers also argued that if word meanings are decomposed the speakers always substitute superordinate category names for subordinate ones (animal for dog) (Roelofs, 1997; Levelt, Roelofs, & Meyer 1999). To overcome this pitfall a computational model was proposed by Bowers in 1999. This revised model had lateral inhibitory connections between two lexical items that facilitates accurate production of both subordinate and super-ordinate category members.

Another model based on same principle assumptions as semantic feature comparison model was proposed by McCloskey and Glucksberg (1979). This model is similar to semantic feature comparison model as it also considers semantic relatedness as a principle of organization and tests the predictions of model based on semantic similarity and relatedness. However, the difference between the two models is that, unlike feature comparison model, one of the assumptions of this model is that there is no distinction between defining and characteristic features and both the feature types are considered to lie in the extreme ends of a continuum. This overcomes one of the drawbacks of semantic feature comparison model as researchers have argued that it is not always possible to know exactly how to distinguish between the two feature types. The second difference is related to that of processing of information wherein the latter model assumes only one comparison stage for all features of the sentences that is used in prediction experiments as opposed to previous model where comparison was assumed to occur at two levels. First level for all features of both subject and predicate and second level for defining features only to generate a similarity index. The third difference is at the level of output, unlike previous model which uses similarity index generated, the latter model uses a

Bayesian decision[6] mechanism to make rational decisions about the test sentences based on the output evidences from comparison process. This model has been quite successful in accounting for the predictions of verification experiments.

2.3.2.2 Prototype theory. One of the most influential theories which provided strong evidence against classical view was proposed by Rosch and Mervis in 1975 termed as Prototype theories. Refuting classical view, the theory proposes that most of the concepts are *not* organized in terms of necessary and sufficient conditions that would lead to a conjunctive definition of a category. Instead they are dependent on properties that are generally true for most of the members of the category but not true for every category member. The semantic knowledge about these properties of a concept is assumed to be stored in a set of '*Prototypes'* for each category. These prototypes of a category thus specify properties that are most likely to be present in the category member.

Prototype theory also proposes that members of a category have a 'family resemblance' structure. The category membership of an exemplar depends basically whether the exemplar has enough characteristic properties to belong to the category (Smith & Medin 1981). According to this theory, not all category members are equally 'good' examples of a concept. The membership is based on characteristic properties and some members have more of these properties than others, so the ones with more properties better exemplify the category (Rips & Medin 1981). For instance 'Robin' but not 'Penguin' has most of the characteristic properties of category 'Bird'. So 'Robin' would be typical exemplar for the category than 'Penguin', which is an atypical exemplar. Exemplars considered to be typical members are found to have many properties in common with other category members and few distinguishing properties, whereas the exemplars considered being atypical members have fewer properties in common and hence more properties unique to it.

The theory was tested using various behavioral experiments to verify prototypicality of category members and family resemblances. The results showed that family resemblance within categories and lack of overlap of elements with contrasting categories were correlated with ease of learning, reaction time in

[6] Bayesian Decision Theory is a fundamental statistical approach that defines how new information should be combined with prior beliefs and how information from several modalities should be integrated to make optimal decisions (Kording & Wolpert, 2006)

identifying an item after learning, and rating of prototypicality of an item (Rosch & Mervis, 1975). The idea of family resemblances thus had greater implications in understanding conceptual categorization according to which natural clustering of members of a category occurs due to sharing of many characteristic features. This phenomenon is also known as co-relational structure of features. These theories thus played a vital role and were responsible to come up with the notion of categorization of concepts based on similarity in meaning.

Despite of the criticism against the assumptions of defining features in the feature comparison model (Fodor, Fodor, & Garrett 1975; Fodor et al., 1980), still various alternative types of featural approaches to study conceptual knowledge have been witnessed in the literature (E.g., Farah & McClelland, 1991; Devlin, Gonnerman, Andersen, & Seidenberg, 1998; Hinton & Shallice, 1991; McRae, et al., 1997; Vigliocco, Vinson, Lewis, & Garrett, 2004). These approaches assume that semantic features are the building blocks of semantic representation which are acquired by concrete interactions with the environment and that these conceptual features are grounded in perception and action (Vigliocco & Vinson 2007). Therefore these featural theories stress the importance of sensory (perceptual) and motor (action) information in conceptual organization.

2.4 Role of Sensory and Motor Information in Semantic Representation

A majority of theories of semantic representation assume that the sensory and motor information about a concept stored in the brain play a vital role in semantic representation. The sensory and motor information is accumulated in the brain during the process of learning these concepts through experience from the environment. The theories proposed to study semantic representation can also be differentiated on the basis of their assumptions with respect to the contribution of sensory and motor information in computing and representing meaning.

A set of theories proposed to study cognitive representation called the embodied theories of cognition adhere to the assumption that semantic representation and retrieval is entirely dependent on simulations in the brain (Barsalou 1999, Jeannerod, 2001; Hesslow, 2002; Gallese & Lakoff, 2005 in Meteyard & Vigliocco, 2008). In other words, these theories say that meaning representation for words is based on simulation involving activation of sensory motor systems in the brain areas that are involved during real life experience of these linguistic units. In other words, semantic content of a word form is assumed to be realized by recreating in weaker version, the sensory and motor activation generated during actual experience of the referents of the word (Meteyard & Vigliocco, 2008). According to these theories semantic representation occurs as a result of embodied content through Hebbain learning[7] where the sensory activation and motor activation together forms the representation of word/ linguistic unit leading to multimodal conceptual representation. Such theories that believe that the sensory motor modalities are directly and should necessarily be engaged to represent and retrieve meaning of words are referred to as stronger versions of embodiment. By direct engagement these theories rule out the mediation of other cognitive processes that helps the semantic system to access sensory motor modalities.

Weaker versions of embodiment theories (E.g.: Vigliocco et al., 2004; Jackendoff,2002; Farah & McClelland, 1991; Tyler & Moss, 2001) believe that the semantic representation comprises of information from sensory and motor modalities however direct activation of these modalities are not always required. These modalities exert influence on semantic processing of linguistic units as they are strongly associated with both, the experience of those events and their semantic representation. Also, the activation of sensory motor system is mediated by cognitive processes such as attention or perceptual learning (Meteyard & Vigliocco, 2008) but this activation is not to the extent of simulation. Most of the featural theories of conceptual organization implicitly believe in weaker versions of embodiment. Featural theories thus assume that the semantic representation is mediated by a supra-modal representation that binds together modality related conceptual features (Vigliocco et al., 2004).Third set of theories propose an amodal semantic system which is independent of sensory motor systems (E.g.:Collins & Loftus, 1975; Levelt, 1989; Landauer & Dumais, 1997). The interactions with sensory motor sytems is explained in these amodal theories to occur through indirect mechanisms outside the semantic system.

[7]Hebbain learning is a neural phenomenon based on Hebb's law, introduced by Donald Hebb, which states that when an axon of cell A is near enough to excite cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency as one of the cells firing B, is increased

Various studies have been conducted in the field of behavioural sciences (E.g.:Tucker & Ellis, 1998; Richardson, Spivey & Cheung, 2001; Myung, Blumstein, & Sedivy, 2006; Meteyard, Bahrami, & Vigliocco, 2007; Siakaluk, Pexman, Aguilera, Owen, & Sears, 2008), neuropsychology (E.g., Neininger & Pulvermüller, 2001; Spatt, Bak, Bozeat, Patterson, & Hodges, 2002; Bak, Yancopoulou, Nestor, Xuereb, Spillantini, Pulvermüller, & Hodges, 2006; Boulenger, Mechtouff, Thobois, Broussolle, Jeannerod, & Nazir, 2008; Mahon & Caramazza, 2008) and neurosciences (Damasio, 1990; Damasio & Damasio, 1994; Pulvermüller, 1999, 2001; Tettamanti, Buccino, Saccuman, Gallese, Danna, Scifo, et al., 2005; Aziz-Zadeh, Wilson, Rizzolatti, & Iacoboni, 2006; Vigliocco,Warren, Arcuili, Siri, Scott, & Wise, 2006; Grabowski, Damasio, & Damasio, 1998; Chao & Martin, 2000; Gerlach, Law, & Paulson, 2002) to provide evidence for these three sets of theories. The summary of evidences from these studies point out clearly the importance of sensory and motor information in the semantic representation.These studies does not rule out strong connections between areas invovled in experiencing sensory and motor information and representation of these information in linguistic forms, however the absolute necessity of simulation is still questionable which leads to believe in weaker embodiment as well. However the theories supporting amodal independent semantic systems received a severe drawback owing to lack of evidence to support the same. Therefore the theories proposing both strong and weak embodiment have equal evidences and call for more detailed and complex investigations to refute any one of them. Thus featural theories and models of conceptual organization proposed on the basis of semantic features which are based on weak embodiment received supporting evidence.

2.5 Semantic Features

The featural models of semantic representation as emphasized earlier are based on semantic features and the study of nature and properties of speaker generated semantic features provide valuable information about the semantic representation and organization. Semantic features form the basic component of various theories proposed to account for meaning representation of words in a language. Semantic features refer to sets of attributes related to a concept wherein each attribute/semantic feature has a part of information about the concept which is stored in the mental lexicon and these semantic features when added together represent the meaning of their associated concept. Semantic features are evidenced to provide clearer and in depth understanding of the organizational principles of mental lexicon along with behavioural phenomena observed in the mental lexicon. Hence semantic features are collected for large sets of words and studied for their properties, which reflect crucial aspects of semantic representation and conceptual categorization.

The semantic features are typically collected from participant as lists of features for a concept/word, which the participant considers to be most salient. For instance, consider the concept ‘apple’, the semantic features that can be generated for this concept include, <fruit>, <red>, <sweet>, <grows on trees> etc. Semantic features are also collected in constrained conditions where in the participants have to fill in the set of simple sentences instead of freely listing the features. For example *a dog is a* ____; *a dog has* ___where in the examiner dictates the type of feature that is to be generated. The task of semantic feature collection thus depends on the nature of study. Features are collected for various categories of concrete nouns and verbs referring to numerous concepts that are present in the mental lexicon. These concepts are selected based on the familiarity and their usage in previous behavioral research so that they provide common ground for comparison.

Semantic features are considered to provide valid information not because they yield a literal record of semantic representations in the brain but rather because such representations are used systematically by participants when generating features (Barsalou, 2003). Thus when participants list semantic features, they directly exploit representations that have developed through repeated multisensory exposure to, and interactions with exemplars of target category (McRae, Cree, Seidenberg, & McNorgan, 2005). Hence during the process of feature generation for a particular target concept, participant refers to a mental imagery of the concepts, which includes the essential features in describing the target concepts and also those which help to distinguish the target concept from rest of the similar concepts. This mental imagery is assumed to be created online for the task of feature generation by the participants. Apart from the features listed during feature generation, there are certainly other aspects about the concepts that are stored in the lexicon which may not be easy to verbalize. For instance, the visuo- spatial relations associated with movement of an animal that is encoded in the brain in order to differentiate between similar ones may be missing in the featural makeup generated verbally. Despite this drawback, the semantic features nonetheless provide an opportunity to understand important aspects of word meaning and its representation.

Apart from its implementation in developing models, semantic features norms have also been useful in conducting various behavioural tasks such as feature verification experiment, typicality studies, semantic priming studies and concreteness decision experiments. The behavioural experiments based on these tasks are conducted in order to support the predictions and assumptions of theories and models using empirical evidences obtained from these experiments. These experiments in turn explain various aspects of semantic processing and representation in the mental lexicon.

Acknowledging the importance and usefulness of semantic feature norms in understanding lexico-semantic representation, a look into the literature reveals that researchers have tried to establish these norms in languages such as English, Dutch, Italian and few others. To list a few, Rosch and Mervis (1975) collected semantic feature norms for 20 basic-level concepts from each of six superordinate categories and used them to explore typicality gradients. Ashcraft (1978b) collected norms for 140 living and nonliving things to use them for constructing feature verification experiments.

Hampton (1979) collected features for eight superordinate categories and used them to test Smith, Shoben, and Rips's (1974) model of category verification and to predict verification latencies. Wu and Barsalou (2009) used feature norms to compare predictions derived from theories based on perceptual symbol systems versus amodal semantics. Devlin, Gonnerman, Andersen, and Seidenberg (1998 for 60 living and nonliving things) and Moss, Tyler, and Devlin (2002 for 93 living and nonliving things), Garrard, Ralph, Hodges, & Patterson (2001), used their norms to investigate accounts of category-specific semantic deficits.

McRae, Cree, Seidenberg, and McNorgan (2005) collected semantic feature norms from 725 participants for 541 living and nonliving basic-level concepts and have made them publicly accessible for use in research. Ruts, De Deyne, Ameel, Vanpaemel, Verbeemen, & Storms (2004) made an extensive set of semantic feature norm, gathered in the Dutch-speaking community for 13 superordinate categories, encompassing a total of 338 target words. Vinson and Vigliocco (2008) have also provided a set of semantic features collected from 280 participants for 456 words (169 nouns referring to objects, 71 nouns referring to events and 216 verbs referring to events). They have further used these norms in research addressing questions concerning semantic representation of objects and events, the interface between semantics and syntax and influence of grammatical class in organization of mental lexicon.

Further, normative data for 15 semantic categories in Dutch language has been established by De Deyne et al. (2008). For all exemplars of the 15 semantic categories, typicality ratings, goodness ratings, goodness rank order, generation frequency, exemplar associative strength, category associative strength, estimated age of acquisition, word frequency, familiarity ratings, imageability ratings, and pair wise similarity ratings were also described. In Italian languages Kremer and Baroni (2011) have collected semantic features for 50 nouns and Montefinese, Ambrosini, Fairfield and Mammarella (2012) for 120 nouns and also from congenitally blind Italian participants by Lenci, Baroni, Cazzolli, & Marotta (2013) for 50 nouns and 20 verbs.

2.5.1 Semantic feature properties. The collected semantic feature norms are studied for the regularities of distribution of semantic feature properties using different statistical measures in order to understand semantic representation and organization of concepts based on semantic features.

2.5.1.1 Number of features and Featural weight. The semantic feature properties such as distribution of number of features across each concept, each category and domains have been studied (Vinson, 2009). The measure of *number of features* generated for a concept is associated with semantic richness in the representation of that concept. Presence of more number of features for a concept indicates greater semantic richness and vice versa. Another important property that has high significance in elucidating the featural makeup of a concept is featural weights. Featural weights are obtained by calculating the total number of participants in the semantic feature data who have generated a particular feature for a particular concept. Hence by investigating about this featural property, it is possible to know how much weightage each semantic feature holds in describing and representing a concept. The significance of this analysis of featural weight is immense as it is based on the participant's discretion on how salient a feature is for a concept.

2.5.1.2 Types of semantic features. The semantic features are studied by classifying the features into different types of features based on the information that they carry. The importance of studying types of features in the norms and the basis of this classification is the modality specific processing of information in the brain. According to embodiment theories discussed earlier, the knowledge about a concept is distributed as patterns of activation across modality specific processing areas of brain. This modality specific representation has been widely accepted as it has substantial empirical evidence over amodal, abstract way of semantic representation. Thus according to modality specific semantic representation, a concept's representation is the sum of the activation across primary sensory-processing channels, motor/action areas, higher order abstract-knowledge areas, and mediating association areas (Cree & McRae, 2003). Whenever a participant attempts to generate features for a concept, he consults a summary of representation of the concept that is formed in the brain as a result of repeated activation through these sensory and motor modalities. This summary representation is also sometimes referred to as mental imagery. Participants extract features from this summary representation that are important to describe that particular concept and also features which help to differentiate the concept from similar ones. Hence based on summary representation across different types of modalities such as vision, touch and motoric areas various proportions of feature types may result in the semantic feature norm. Thus the study of feature types helps in elucidating representation and organization of conceptual knowledge and words in the mental lexicon as well as in understanding patterns of semantic impairment in persons with semantic deficits.

Initially the study of feature types in persons with semantic deficits on various semantic tasks were focused upon as they provide evidence to understanding of category-specific semantic deficits and in turn organization of concepts in healthy individuals. Category-specific semantic deficit refers to the phenomenon wherein patients exhibit differential levels of impairment across different semantic categories and domains (Warrington & Shallice 1984). The first report on such phenomena was given by Warrington and Shallice in 1984, who described four persons recovering from herpes simplex encephalitis who were disproportionately impaired in producing and comprehending the names of living things as opposed to nonliving things. The opposite pattern wherein nonliving things are better comprehended and produced than living things have also been reported in literature. The distribution of different types of sensory and non-sensory features (functional and/or motoric features) has been studied as an important factor that may underlie such category specific deficits. This formed the basis which led to the study of classification of different types of features.

The features are generally classified into sensory and non- sensory/functional features. Accordingly, many theories of category-specific deficits have been proposed based on this classification namely Sensory /Functional theory (Warrington & Shallice 1984), and Sensory/Motor theory (Martin, Ungerleider, & Haxby, 2000). According to these theories, the living things tend to possess greater proportion of sensory features (e.g., dog, {has four legs}) and non-living have more prominent functional features (e.g., Scissors, {used for cutting}). Consequently, if brain damage disrupts sensory feature knowledge then features related to living things tend to be more affected and if there is disruption in the non-sensory feature knowledge then the features related to nonliving things are more affected. Deficits may reflect differential weighting of information from various sensorimotor channels in the representations of living and nonliving things and hence, the category deficits may not be living/nonliving category in nature, but rather, it would be sensory/functional (McRae & Cree, 2002) in nature.

However this dichotomous classification was criticized has having very limited scope to account for the pattern of deficits as it has only two degrees of freedom with only two types of features. It also does not consider substantial amount of information that is stored in other types of features. The demerits of this classification were overcome by detailed classification of semantic feature types given by Wu and Barsalou in 2009. According to this classification each feature is considered to reflect a type of knowledge that is stored in the semantic representation of the concept. Therefore, feature types are referred to as knowledge-type and this classification of features is termed ‘knowledge type taxonomy’. The following factors are accounted for in the development of knowledge-type taxonomy (as described in McRae and Cree, 2002)

1) The set of feature types is designed to cover the tremendous variety of features that subjects generate when describing conceptual content.
2) It is designed to capture the wide variety of information found in ontological kinds (i.e. higher level categories e.g., Keil, 1989), and in event frames and verb arguments (e.g., Barsalou, 1992; Schank Abelson, 1977; Fillmore, 1968).
3) It is designed to correspond systematically to the modality-specific regions of the brain (e.g., motor, somatosensory, and visual cortices).
4) The feature types for entities reflect well-established channels of sensory information in perception (e.g., shape, surface, occlusion, movement).
5) The feature types reflect aspects of introspective experience, as well as aspects of sensory-motor experience.

Based on the above factors, semantic features are classified into 4 major classes namely Entity, Situation, Introspective and Taxonomic. Each of these classes is again subdivided leading to a total of 28 feature types. This classification of features is also adopted by researchers (McRae et al., 1999; McRae & Cree 2002) with suitable modifications (used 21/28 feature types) and additions of feature types (1 feature type) to understand their semantic feature norms generated. It is used to develop stimuli for experiments and to study category-specific semantic deficits. The feature type analysis is also very useful to understand the contribution of semantic feature in categorization of concepts based on salience of each feature type (McRae et al., 1999).

The classification given by Wu and Barsalou is very detailed and useful but it is basically developed as a part of studying perceptual simulation and not semantic feature norms. It is also not clear how all of these feature types can correspond to brain regions. Classification of feature types that helps to map features onto specific areas of processing in the brain can provide more valid information for researchers who are studying differentially damaged mental lexicon and conceptual knowledge. With this view, Cree and McRae in 2003 have developed a knowledge type taxonomy linking featural information to processing regions of the brain. Their semantic feature classification consisted of nine knowledge types. The three of the feature types corresponded to visual information, four to other perceptual modalities, one corresponding to functional/motor information describing the interactions and uses of the entities and the last type corresponding to all other knowledge types. Therefore the nine different feature types are labeled as follows:

1) Visual– colour
2) Visual–parts and surface properties
3) Visual–motion
4) Smell
5) Sound
6) Tactile
7) Taste
8) Function
9) Encyclopaedic

This classification is based on the assumption that semantic knowledge corresponding to each sensory/motor aspects of concept is represented in the vicinity of the primary sensory/motor processing areas in the brain (Cree & McRae, 2003; Allport, 1985; Damasio, Everitt, & Bishop, 1996; Martin & Chao, 2001; Warrington & McCarthy, 1987). This assumption has also been supported by neurophysiological studies, positron emission tomography, fMRI, and event-related potential (ERP) studies that the brain areas close to, but not identical to, the sensory information processing areas were activated in tasks that tests semantic knowledge related to sensory modalities. Cree and McRae conducted a hierarchical cluster analysis of their feature classification and interpreted the results in terms of the category-specific semantic impairments. They reported that the results were remarkably similar to the cluster analysis conducted using Wu and Barsalou taxonomy despite the substantial differences between the two classifications.

The semantic features are also classified into five similar categories to study distribution of semantic information in the sensory and motor modalities using semantic feature norms for object nouns, action nouns and action verbs (Vinson, 2009). The five categories are:

1) Perceptual features- visual features
2) Perceptual features- others
3) Functional
4) Motoric

5) Other features

The first category is termed ‘Perceptual features’, as described by Vinson (2009) which includes features that describe information gained through sensory modality, including body state and proprioception. Perceptual features are further divided into two types namely ‘Visual Features’ and ‘Other Perceptual Features’. The visual features include features that describe information gained through visual modality and ‘Other Perceptual Features’ included features that describe information gained through any other sensory modalities Third category of features are classified as ‘Functional’ which refers to features addressing the purpose of a thing, "what it is used for", or the purpose or goal of an action. Fourth category is ‘Motoric’ which include features describing "how a thing is used, or how it moves", or any feature describing the motor component of an action and the fifth, the ‘Other Features’ include those features meeting none of the previous classifications. Some of the features classified as ‘Other Features’ are encyclopedic (e.g., [comes from] <Africa>); while others refer to relationships among meaning components, (e.g., ISA <animal>; PART OF <face>).

Based on the distribution of the types of features researchers have gained insight about importance of each type of feature in the representation of meaning. Disruption with respect to each feature type and its impact on the resulting impairments are also studied by developing computational models using feature types as basis of conceptual organization. One such model was constructed by Farah and McClelland (1991) for words belonging to both living and nonliving entities. The semantic feature distribution is found to vary in these entities with living things possessing more visual-perceptual features and nonliving things having more of functional features. This difference in featural distribution were derived from an experiment where in participants were asked to rate individual elements of meaning in terms of sensory/perceptual or functional content. The model was lesioned targeting visual-perceptual and/or functional features to demonstrate different types of category-specific semantic deficits. Hence classification of features generated during norming task into different types has been considered a significant issue for investigation.

2.5.1.3 Distinctive features and shared features. Semantic features can be also studied by classifying the features into distinctive and shared features. Distinctive features are those features that occur in only one or two concepts of a category and therefore, are unique to a small set of concepts. Shared features are those that are present across many concepts. While distinctive features are crucial in discriminating among similar concepts, the shared features are presumed to provide stronger correlation as they are present across many concepts and thus are crucial for formation of categories.

Distinctive features are very essential in providing cues to identify their corresponding concept and are vital in describing patterns of errors in persons with semantic deficits as well as organization of concepts in healthy individuals. Studying distinctive features has thus been given much importance and studied extensively under different terms namely cue validity (Bourne & Restle, 1959), distinguishingness (Cree & McRae, 2003), distinctiveness (Garrard, Lambon Ralph, Hodges, & Patterson, 2001) and informativeness (Devlin, Gonnerman, Andersen, & Seidenberg, 1998). Distinctive features have also been viewed as a continuum in which truly distinctive features lie at one end and highly shared features at the other (Cree, McNorgan, & McRae 2006).

Distinctive features, in terms of cue validity, is measured as the probability of a feature appearing in a concept divided by the probability of that feature appearing in all relevant concepts (Bourne & Restle, 1959). Distinctive features, according to this definition are supposed to be possessing higher value in cue validity measure compared to shared features as it occurs in only one or two concepts (Rosch & Mervis, 1975). Shared features on the other hand, tend to appear in many concepts hence possesses very low value in cue validity measures. The cue validity measures are considered critical in categorization of concepts in the mental lexicon. The category membership is described in terms of cue validity as those items with features most distributed among members of a category and least distributed among members of contrasting categories. These form the most valid cues to membership in the category (Rosch & Mervis 1975). Distinctive features are also described as informativeness that each feature may provide to identify a particular concept as some of the features of a concept are more relevant and informative than others to categorize it (Devlin et al., 1998).

Further, distinctive features are considered critical in unfolding the differences in nature of representation between living and nonliving concepts in the mental lexicon (Garrad, Lambon, Ralph, Hodges, & Patterson, 2001). Distribution of distinctiveness, which is a measure equal to the proportion of concepts, for which a feature is present, is reported to vary for living and nonliving domains. The domain of nonliving things has more distinctive features than non-distinct for feature types sensory, functional and encyclopedic. On the other hand, for living things only the encyclopedic features have more distinctive features compared to sensory and functional features (Garrad et al., 2001). With respect to categories of animals (living things) and tools (nonliving things) distinctive features are reported to be more significantly correlated for animals than those for tools (Vinson, 2009) in concord with the findings by Garrad et al. (2001). Similar trend is also reported in Kannada (Prarthana & Prema, 2013) where nonliving things tend to possess more number of distinctive features compared to living things. Thus distinctive feature distribution varies with respect to domains and hence, is vital in explaining categorization of concepts into domains.

Distinctive features are also employed in developing models of semantic representation. One of the influential models based on distinctive features was the Conceptual Structure Account (Tyler & Moss, 2001) which supports distributed connectionist[8] system for semantic representation. According to distributed system, each concept is composed of several units corresponding to the concept with no explicit category boundaries between the concepts. Each concept is assumed to activate overlapping patterns across units representing that concept. The semantic features vary in the degree to which they are distinctive for a particular concept or shared with other concepts and the frequency with which they co-occur with other features. This gives rise to the internal structure of the semantic system. Shared features thus are important in indicating category membership whereas distinctive features are critical for identification of concept. The model also claims that in the domain of living things presence of a distinctive feature does not strongly predict the occurrence of other properties. In other words living things have less correlation

[8]Connectionist models is type of neural network made up of interconnected simple processing devices which include a set of processing units, a set of modifiable connections between units and a learning procedure which is suitable to model mental/behavioural phenomenon.

among distinctive features but high form function correlation (e.g., wings (form) - used for flying (function)) compared to nonliving things.

The predictions of conceptual structure account were tested to support the model with empirical evidences by conducting series of behavioural experiments (e.g., Randall, et al., 2004) using speeded feature verification tasks. The conceptual structure account as described by Randall, et al. predicted that the distinctive features of living things tend to be activated more slowly in the normal system based on the assumption that these features are weakly correlated relative to shared features of living things and both distinctive and shared properties of nonliving things. The experiments support the prediction where in for living things, the more distinctive a feature is, the slower the reaction time in speeded feature verification task and no such effect was seen for nonliving things (Randall et al., 2004).

The speeded feature verification latency however is greatly influenced by the production frequency of the distinctive and shared features studied (Cree, McNorgan, & McRae, 2006; Lamb, 2012). Also, the length of feature names and frequency of occurrence of feature names have significant effect on verification latency. Experiments with these variables controlled and aiming at testing the role of distinctive features in semantic representation were conducted. Contrast to the previous findings (Randall, 2004), it was demonstrated that distinctive features strongly activate their corresponding concepts than shared features.

The distinctive features also aid in interpreting the various trends of semantic deficits seen in patients with category-specific semantic deficits. Inaccessibility to these distinctive features that are informative in distinguishing between two concepts is contemplated to be one of the reasons leading to errors of naming. Computational model have been developed (e.g., Devlin, 1998) based on the distinctive features' informativeness in order to simulate category specific semantic impairments resulting from varying degrees of focal and diffuse brain damage. The model generated to simulate focal and diffuse brain damage was highly influenced by this informativeness (distinctive features) property of semantic representation. Therefore distinctive feature loss was predicted to produce severe behavioural consequences than the loss of shared features. The analysis of distribution of distinctive features for each concept can indeed predict the likeliness of impairment of that particular concept, in case of brain damage (Cree & McRae, 2003). With respect to percentage of distinctive features, the domain of living things consists of a low percentage of distinctive features than the domain of nonliving things which provides evidence for the pattern of deficits where living things are more likely to be impaired than nonliving things.

Distinctive features therefore occupy a special status in semantic representation as they form indispensable part of concept organization in the mental lexicon. Categorization of concepts into different semantic fields, into domains of living and nonliving things has been influenced by distribution of distinctive features. Various models explaining semantic organization are also based on distinctive features. The distinctive features even contribute as a significant factor in the explanation for semantic deficit patterns recorded in persons with semantic impairments. Therefore, study of distinctive features is considered imperative in understanding semantic representation.

Shared features on the other hand are defined, contrasting distinctive features, as those features which occur in the featural makeup of two or more concepts. They provide valuable information about the relationship among concepts. They also influence performance in various behavioural experiments such as semantic priming. They play crucial role similar to distinctive features, in many theories (E.g., Rosch & Mervis, 1975; Tyler & Moss, 2001; Smith, Shoben, & Rips, 1974) proposed to explain semantic organization and category specific semantic deficits. Concepts sharing many features in common with other concepts are considered to be semantically similar to each other. The concept similarity in terms of featural overlap is a primary organizational principle of mental lexicon and hence, it is said that the featural similarity is one dimension along which the semantic network is organized (McRae & Boisvert, 1998; Collins & Loftus 1973). It is also true that concepts with many shared features have a large number of strong associative links through them (McRae & Boisvert, 1998).

Analysis of distribution of shared features in the semantic feature norms, similar to distinctive features facilitates understanding of semantic representation in the mental lexicon. The distribution of shared features across different semantic fields with respect to concrete objects (Cree & McRae 2003; Vinson 2009) and actions

(Vinson 2009) has been studied. The occurrence of shared features may vary with respect to specific semantic categories. But, the proportion of shared features when categories are not considered, tend to be less in nouns compared to verbs representing actions. Since shared features occur in greater proportions in the semantic structure of numerous concepts adding to their semantic similarity, they are very crucial in categorization of concepts. Few researchers have viewed distinctive features and shared features on a continuum using a single metric of measurement called distinctiveness (Cree & McRae, 2003) and have classified features present in many concepts as shared features that possess low distinctiveness value.

The effects of shared features in behavioural experiments aimed at studying properties of concept organization are also very informative. Recent findings have suggested that shared features play crucial part in semantic processing. Presence of greater number of shared features in target concepts was seen to produce faster lexical decisions. This effect was even more enhanced for concreteness decision tasks (wherein the participant is asked to decide whether a target concept is concrete in nature or not) that depend largely on semantic properties of target concepts (Grondin, Lupker, & McRae, 2009). Hence both shared features and distinctive features are differentially important depending on the task under consideration.

2.5.1.4 Feature correlation. Another property of semantic features that is considered valuable is featural correlation. Correlation is defined as the extent of co-occurrence of features in the environment and the probability of one feature predicting the presence of another (e.g. things that have beaks usually also have wings and can fly) (Tyler & Moss, 2001). Featural correlation similar to shared features and distinctive features has been studied for its contribution in representation and computation of word meanings.

The patterns of feature correlation in the domains of living and nonliving things have also been assessed using connectionist models and behavioural experiments. The domain of living things has been reported to have shared functional and perceptual features that are highly intercorrelated compared to distinctive features. For the domain of nonliving things, the stronger correlation is present for distinctive perceptual and functional features compared to shared features (Tyler & Moss, 2001). However, a contrasting trend has also been witnessed in which, for living things the proportion of significant intercorrelation was greater for distinctive than shared features. Also for non-living things it was the reverse pattern observed wherein the overall proportion of significant feature correlation was very small and distinctive feature of living things were more correlated than any of the features of the nonliving concepts (Garrad et al., 2001).

Featural correlation have been focused in order to interpret the way in which they might be learnt using connectionist models and their role in word recognition using behavioural experiments (McRae, de Sa, & Seidenberg, 1997). Behavioural experiments involving on-line semantic processing such as semantic priming tasks are highly influenced by featural correlation. This effect is more prominently seen for living things than nonliving things when the degrees of featural correlation among the semantic features of prime and target were varied. Featural correlations have also been considered as an important variable in lexically based semantic task such as feature verification (McRae, Cree, & Westmacott, 1999). It is also demonstrated that, using the connectionist models featural correlation is learnt through experience from the environment (McRae, Cree, & Westmacott, 1999).

Featural correlation has been studied in persons with semantic breakdown occurring as a result of progressive neurological conditions by simulating connectionist models. The progressive deterioration of semantic knowledge has been predicted by the nature of intercorrelation of features within their semantic representations (E.g.: Gonnerman, Anderson, Devlin, Kempler, & Seidenberg, 1997). Also, predicted patterns of semantic impairments have been simulated using connectionist model by incorporating intercorrelation among form and function properties of concepts (E.g.: Tyler, Durrant-Peatfield, Levy, Voice, & Moss, 1996). It has also been reported by Tyler and Moss (2001) that the features that co-occur frequently during training of connectionist model mutually activate each other and thus are more resilient to damage compared to weakly correlating features.

To obtain deeper insights into the conceptual knowledge using speaker generated features norms, researchers have employed properties of semantic feature norms such as featural weight, featural correlation and featural similarity to develop models of mental lexicon. The models developed using speaker generated norms are far more ideal in representing conceptual knowledge as the featural characteristics that are assumed to influence the formation of models have been decided directly by the norms generated by participants eliminating investigator’s biases. Models based on the two basic assumptions namely componential nature of word meaning and similarity or overlap of semantic features have been accepted to be far more suitable for models of semantic representation as they have provided plausible explanations to the behavioural phenomena seen in psycholinguistic studies of healthy individuals and are also capable of elucidating the trends of semantic deficit patterns reported in persons with semantic deficits (Devlin, Gonnerman, Anderson, & Seidenberg, 1998). Hence quite a number of contemporary models rely upon the componential nature and similarity to explain internal structure of mental lexicon. Thus study of relation of one word with respect to another based on their semantic featural properties provides valuable tool for modeling the structure of mental lexicon.

A model directly based on componential nature and similarity of semantic features without making any assumptions about properties of features beforehand was proposed for object nouns by McRae, et al. in 1997 and McRae, et al. in 1999. It is a connectionist model which examines the role of featural correlation in computing word meaning. It utilizes an attractor network based on correlational learning algorithm that aids the model to investigate the influence of correlated features in processing of word meaning. According to this model each concept is represented as distributed patterns of activation over sets of units. Each unit here corresponds to the features generated by the participants. The model was then made to learn the pattern of correlation among features for a set of concepts using correlational learning algorithm. The model learnt the patterns of featural correlation for a concept through multiple processing cycles before a pattern of activation gets stabilized for the concept. This model was utilized to study various aspects of semantic representation and issues related to category-specific semantic impairment.

Another model for representing words referring to object (object nouns) and words referring to events (action nouns and verbs) called “Featural and Unitary Semantic Space” (FUSS) model was developed by Vigliocco, Vinson, Lewis and Garrett in 2004. This model is based on the assumption that the word meanings are directly linked to conceptual knowledge, which in turn is made up of semantic feature like representation that is organized according to modality. Second assumption is that the semantic featural representations are present in a separate level of lexico-semantic representation this level creates the interface between the conceptual knowledge and other linguistic information such as syntax, morphology and phonology. The model is based on semantic feature norms generated by participants and these features help the model to better predict the representation as it is grounded to the real world experiences of the participants. This model implements a computational technique called self-organizing maps on the semantic feature norms. These maps are trained to be sensitive to various semantic featural properties namely number of features, featural weights and feature correlation unlike McRae's et al. model, which is based only on featural correlation. The self-organizing map thus captures the different influences of each of the semantic feature property in organization of concepts, based on the characteristics of the semantic field for which it is generated. The maps obtained depict the categorization of different concepts into their corresponding semantic field along with clear boundaries separating these concepts from others belonging to different semantic fields. The maps of object nouns tend to possess smooth boundaries indicating well-defined semantic field boundaries (*Figure 5*). However for words representing events no such clear boundaries among different fields is generated (*Figure 5*). Thus, based on the semantic distances among the concepts obtained from feature norms, maps are generated that model the organization and representation of conceptual knowledge. Results of the behavioural studies based on the model provide further evidence that this model predicts semantic effects seen in behavioral experiments.

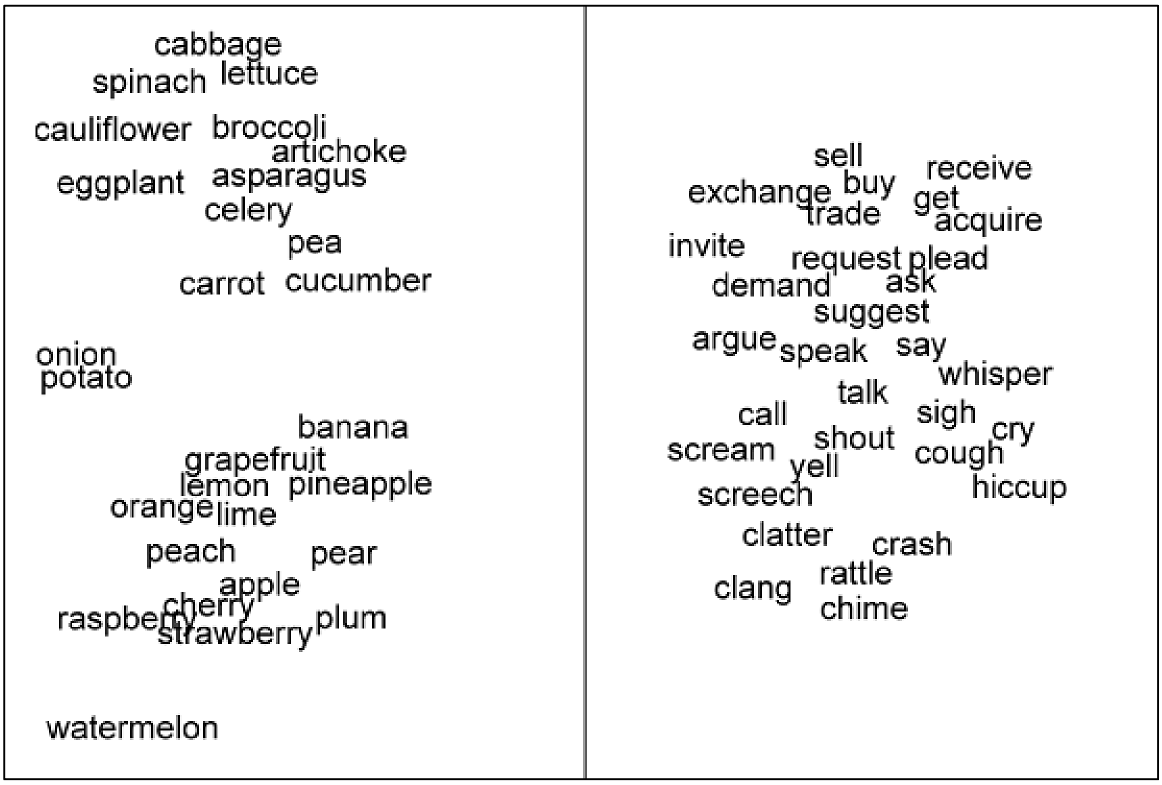

*Figure 5.*Two-dimensional representation of semantic proximity in FUSS (Vinson & Vigliocco, 2002; Vigliocco, et al., 2004 in Vigliocco & Vinson 2007).

It is evident from the literature that the semantic features and its properties have been an integral part of studies carried out in understanding mental lexicon and conceptual knowledge. Theories and models proposed, based directly on semantic feature norms have been successful in capturing the principles of representation and categorization of words in the mental lexicon. This is because the basis of these models comes from analyzing data directly obtained from participants, which capture the saliencies of the real world experiences to a great extent. The models have also accounted for the fundamental phenomenon such as semantic relatedness, typicality effect, concreteness effect, semantic priming in lexical decision seen in behavioural experiments. Thus semantic feature norms invariably provide immense contribution to the knowledge of mental lexicon.

2.6 Semantic Features of Nouns and Verbs

Nouns and verbs form major part of vocabulary of any language. Researchers focusing on meaning representation in mental lexicon have almost always studied various categories of concrete nouns. Even though verbs are also a significant part of mental lexicon, they have received much less attention in research. Although nouns and verbs can be grouped into category of content words, there are significant differences between the two entities. The main difference is that the meaning of objects is static in nature and is comprehendible even when the concept names are produced in isolation whereas the meanings associated with verbs are not static but relational as they are highly dependent on linguistic context and environment in which they can occur, consisting of dynamic entities that unfold in time (Vinson & Vigliocco 2008).

Verbs of a language differ from nouns, as summarized by Vinson (2009), in terms of the semantic featural make up and properties. Nouns, which represent objects possess more number of features referring to narrow semantic fields. Verbs representing action, on the other hand possess more features that broadly apply across wide range of semantic categories. Semantic features are very strongly correlated to the semantic category with respect to nouns than that of verbs. In case of nouns, distinguishing between different levels such as superordinate, basic and subordinate is relatively simple and they can be easily organized into hierarchies with many shared correlated properties. On the other hand, it is very difficult to create comparable sets of hierarchies for verbs as they form matrix -like structure where many semantic properties are orthogonally related rather than correlated (Huttenlocher & Lui, 1979; Graesser, Hopkinson, & Schmid, 1987; as in Tyler et al., 2001). Also the hierarchy that exists for verbs possess fewer levels with very less distinctions at the superordinate levels (Keil, 1989). However, verb taxonomies do show a basic level structure but a less sharply defined and less stable structure than in noun taxonomies (Morris & Murphy, 1990). It is also true that distinction between close semantic neighbours differ across the domains of nouns and verbs. It is noticeable that for many categories of basic level concrete objects, close neighbours offer true distinctions while this is not true in many verbs that seem to overlap to a great extent (Vinson 2009).

The processing of verbs is also considered more complex than nouns even though they may have similar organization (Krishnan, Tiwari, & Bellur, 2009) Verbs play an important role in sentence processing. They contain grammatical information contributing to the structure of the sentence such as the thematic roles of agent, patient, the arguments of the verb and semantic information contributing to its core meaning. Thus the syntactic information embedded in verbs are often richer compared to nouns. Investigators have used data from normal individuals, persons with semantic dementia as well as from aphasia to understand how verbs are stored but it still remains unclear how they may be organized in the mental lexicon.

2.7 Neuroimaging Studies of Mental Lexicon

Apart from theories and models proposed to explain organization and storage of concepts in the mental lexicon, a great amount of knowledge has been imparted through neuroimaging studies. With advent of new technology, increasing number of functional brain imaging studies of concept and category representation in normal as well as persons with semantic deficits has been witnessed. Neuroimaging and electrophysiological studies have provided evidence that language related processing seem to be widely distributed in the brain regions than previously assumed. Word meaning is not confined to just specific brain regions but is distributed in a systematic way throughout the entire brain (Martin, 2007)

Substantial research evidences have implicated that the posterior region of the left temporal lobe (left fusiform gyrus) is critical site in representation of concrete objects and has a significant role in conceptual organization and processing (Mummery, Patterson, Wise, Vandenberghe, Price, & Hodges, 1999; Sharp, Scott &Wise, 2004; Wig, Grafton, Demos, & Kelley, 2005). Studies have been carried out which provide information about representational content of brain areas in terms of features of the objects that might be stored in a particular brain area. The ventral temporal cortex is evidenced to be storing information about object colour (Wiggs, Weisberg, & Martin, 1999; Chao & Martin 1999) and studies report activity in the sensory or motor processing areas of the brain for tasks involving access of corresponding sensory or motor features (Goldberg, Perfetti, & Schneider, 2006). For verbs depicting actions, activation in the posterior middle temporal gyrus was prominent during task of action naming (Tranel, Martin, Damasio, Grabowski, &

Hichwa, 2005b). Also, in a task involving reading of specific action verbs related to specific body parts such as lick (tongue); pick (finger); kick (leg) activated premotor cortical regions in the brain that are also activated from actual movements of these parts (Hauk, Johnsrude, & Pulvermuller, 2004).

Neural representation of semantic categories has also been studied using tasks involving categorization of target stimuli. It has been noted that the regions associated with representing object properties are differentially engaged as a function of object category membership (Martin, 2007). The occipito- temporal cortex has been identified as a structure that plays a major role in object categorization. Distinct category related patterns of activation have been consistently recorded that discriminate between relatively large numbers of object categories and these patterns are reported to be stable both within and between subjects (Cox & Savoy, 2003; Haxby, Gobbini, Furey, Ishai, Schouten, & Pietrini, 2001; Spiridon & Kanwisher, 2002). For the category of animals an increased activation is observed in lateral regions of fusiform gyrus, bilaterally whereas for the category of tools, heightened activation was seen bilaterally in the medial region of fusiform gyrus. Thus the evidences provided by neuroimaging studies, similar to insights obtained from semantic feature norms support that specific sensory and motor-based information of objects are stored in regions adjacent to sensory and motor areas. Therefore, the neuroimaging studies augment our knowledge about semantic representation and also provide strong supporting evidences for the claims made using semantic feature norms for the distribution of knowledge in different sensory and motor modalities.

2.8 Category- Specific Semantic Deficits

Word meanings represented in the mental lexicon, as witnessed in the earlier sections, allows comprehension and expression of our knowledge about objects and actions taking place around us. Impairments of semantic representations are extremely debilitating which may be as a result of several types of neuropathology such as Alzheimer’s disease leading to dementia, herpes simplex encephalitis and cerebrovascular accidents such as stroke-induced aphasia. Research involving semantic deficits also enables better understanding of normal semantic representation. With the objective of testing the efficacy of models and theories developed to understand semantic representation, they are damaged systematically based on the patterns of impairment to simulate such conditions. The behaviour of models under such simulations resembling semantic impairments provides further insight into the nature of processes in specific brain areas, damage to which may lead to deficits. Studying semantic impairment patterns in these conditions are essential to improve therapeutic approaches for better management and prognosis.

It is intriguing that the semantic deficits documented in literature shows a set of specific patterns in which the impairment manifests itself. The pattern shows prevalent regularities in the group of concepts that may be affected by the brain damage over rest of concepts. This phenomenon is termed as category- specific semantic deficits. The most common pattern of impairment seen is differential semantic abilities for the domain of creatures, fruits/vegetables and nonliving things. It has been noted that persons with semantic deficits may experience difficulties of naming items from one domain for instance, creatures while exhibiting no such difficulties in naming items from other domains such as fruits or nonliving things or vice versa. In the literature it is very evident that despite numerous differences in the methodology of studies of category-specific semantic deficits, it is possible to witness these consistent trends in the sets of categories that are susceptible to be impaired/ spared together (Cree & McRae, 2003). There are seven prominent trends in the deficit pattern seen in the persons with semantic deficits as reported by Cree and McRae (2003) that are listed below:

1) The categories of creature cluster together and this cluster can be disrupted separately.
2) The categories of nonliving things cluster together and can be disrupted separately. These exclude musical instruments and foods.
3) The category fruits/vegetables group together and can be separately affected.
4) Fruits/vegetables can cluster with either the creature or the nonliving things.
5) Nonliving foods can be disrupted together with living things.
6) Musical instruments can be impaired together with living things.
7) Impairments of living things are more frequent than nonliving things.

Various theories have been proposed to explain these trends (Tyler & Moss, 2001; Devlin, Gonnerman, Anderson, & Seidenberg, 1998; Gonnerman, Anderson, Devlin, Kempler, & Seidenberg, 1997; Caramazza & Shelton, 1998; Humphreys &

Forde, 2001; Caramazza, Hillis, Rapp, & Romani, 1990; Dixon, Bub, & Arguin, 1997, 1998; Gaffan & Heywood, 1993; Warrington & Shallice, 1984; Martin, Ungerleider, & Haxby, 2000) and one method that has been very effective in providing relevant evidence is study of semantic feature norms. Distributional statistics carried out on the various properties of semantic feature norms such as featural similarity, distinctiveness, shared features, feature types and featural correlation have been successful in addressing most of the trends of category specific impairment patterns documented as these factors influence the representation and computation of concepts (Cree & McRae, 2003). Thus semantic feature norms as discussed previously are very useful for understanding category specific semantic deficits and in formulating treatment strategies based on the factors influencing such patterns can be highly beneficial.

2.8.1 Semantic impairment in aphasia. Brain damage as a result of cerebrovascular accidents may lead to loss of language skills termed as aphasia. Comprehension impairments are more commonly observed along with other language impairments of Aphasia. The impairment is usually associated with lesions in the temporo-parietal and prefrontal regions in the left hemisphere. On the other hand in persons with semantic dementia damage usually occurs in the anterior temporal lobes, bilaterally. This region is rarely damaged due to stroke in persons with Aphasia as they are supplied by two major arteries besides which bilateral lesions in these regions due to stroke are extremely rare.

Patient profiles of persons with Transcortical Sensory Aphasia (TSA), which is associated with fluent speech and good repetition skills, appears superficially similar to the deficits associated with semantic dementia. Studies have reported Aphasia similar to semantic dementia that can lead to multimodal semantic deficits even though the anterior temporal lobes remain intact. Many a times, persons with aphasia experience problems with the relationship between objects and their names. This naming deficit has been attributed to their inability to retrieve the correct word from the mental lexicon and match the target object that is labeled as retrieval deficits (Goodglass & Geshwind, 1976; Weigel- Crump & Koenigsnecht, 1973). However, there has also been an alternative hypothesis proposed to explain their deficits in comprehension and expression which is attributed to the disruptions in the semantic representations contained in the mental lexicon labeled as semantic deficits (Caramazza & Berndt, 1978).

There have been several evidences (Grober, Perecman, Kellar, & Brown, 1980; Grossman, 1978; Lhermitte, Derouesne, & Lecours, 1971; Zurif, Caramazza, Myerson, & Galvin, 1974) to support the latter hypothesis that there is a semantic deficit associated with Aphasia. It is common phenomenon that persons with anomic aphasia often produce semantic paraphasias in spontaneous speech (Geschwind, 1967). The production of semantic paraphasias provides evidence that there is an underlying impairment of the semantic organization in the mental lexicon. Also, the semantic paraphasias that is produced will necessarily violate some of the semantic aspects of the word that is intended (Caramazza, Berndt, & Brownell 1982). Semantic based errors were also noted during object selection task using semantically similar distracters (Gainotti, 1976).Further support to this hypothesis has been obtained from person with Wernicke's Aphasia tested for semantic relatedness and categorization. Evidence of semantic deficits in terms of broadening of semantic field boundaries have been noted during categorization as they inappropriately group words of clearly different meanings (Lhermitte, Derouesne, & Lecours, 1971). Similar results have been reported by Grossman (1978) who found that persons with Wernicke's Aphasia had difficulty correctly naming category members for superordinate categories (E.g.: 'furniture'). Difficulties have also been reported during naming of atypical category members compared to typical members (Grossman, 1978; Grober, Perecmen, Kellar, & Brown, 1980; Buhr, 1980). Thus it is evident that lesions in the brain can result in selective disruption of the semantic organization of the mental lexicon in persons with aphasia that can manifest as naming deficits.

Analysis of semantic features, therefore, has significant clinical implications in developing treatment techniques for semantic deficits prevalent in persons with semantic dementia and aphasia. As evidenced in the review, the disruption of semantic knowledge in the mental lexicon is predicted to result in comprehension and naming deficits in persons with aphasia. Hence several treatment strategies used to treat anomia and other semantic deficits focus on strengthening the semantic feature knowledge. One such treatment technique that is widely employed is the Semantic Feature Analysis (SFA). This technique emphasizes on enhancing the retrieval abilities of semantic knowledge through accessing semantic networks (Boyle & Coelho, 1995). This is achieved by asking the individuals to produce list of words that are semantically related to a target word. Semantic relations may be in terms of their category, use, action, properties, location and association. This treatment technique has been proven to be highly efficient in treating semantic deficits prevalent in persons with aphasia (Boyle & Coelho, 1995; Coelho, McHugh, & Boyle, 2000; Conley & Coelho, 2003; Boyle, 2004; Rangamani & Prema, personal communication). The cumulative results of these experimental studies have thus provided empirical evidences for efficacy of semantic feature based treatments. However one drawback these approaches face is the limited generalization of learnt skills for untreated words and to connected speech (Boyle & Coelho, 1995; Coelho, McHugh, & Boyle, 2000).

Use of distinctive features obtained from semantic feature norms however is proven to overcome the problems of generalization of naming skills. The semantic feature analysis (SFA) technique uses shared features and semantic relatedness to enhance the semantic knowledge. Semantic deficits can be addressed more effectively with techniques facilitating enhancement of distinctive feature knowledge in individuals. This is because it has been evidenced that distinctive features play vital role in naming skills. For instance, during the task of picture naming or identification of named picture from a set of pictures, the individual has to identify the feature that distinguishes the target picture from rest of the similar ones that requires usage of distinctive feature knowledge. It also true that loss of distinctive feature knowledge has severe behavioural consequences than loss of shared features. Thus treating persons with semantic deficits for distinctive feature knowledge enhances the chances of improvement in the naming skills. Evidence supporting use of distinctive feature in therapy has also been provided by researchers (Mason-Baughman, 2009; Kiran & Thompson, 2003) who have found better prognosis in naming skills of treated items along with better generalization to untreated items and to connected speech. Hence it is evident that knowledge of semantic feature norms and their properties can enhance our skills in the management of persons with aphasia and semantic dementia.

To summarize, there has been immense amount of research carried out in the recent years invovling the mental lexicon. The study of semantic feature norms has been very useful in providing a window to understand rather complex organization and meaning representation in the mental lexicon. Semantic feature norms are also building blocks of many theories and models discussed in the literature. Various models have been developed using newer computational techniques and artificial neural networks such as attractor networks, self organizing maps etc. These models have been tested for its predictions of brain mechanisms using behavioural studies which in turn provides empirical evidences for the models. Advancement in Neuroimaging techniques have further enahnced our knowledge to correlate predictions of models, behavioural evidences and evidences from patient data with actual brain regions using more sophosticated functional imaging studies. The norms as such are very useful to track down the statistical regularties such as distribution of different feature types, shared features, distinctive features, featural correlation across semantic categories that play crucial role in organization of mental lexicon. Semantic feature norms also help to understand semantic deficits in persons with dementia and aphasia and in developing treatment techniques for the same. Thus semantic fetaures contribute immensely to our knowledge about mental lexicon.

2.9 Need for the Study

During the past three decades, as witnessed in the literature, research related to semantics and mental lexicon has been extensively carried out in English and other non-Indian languages. In Indian languages, with respect to semantics, norms have been established for limited aspects of semantic components, restricted to the purpose of particular study under consideration. Such norms have been established in Kannada (Karanth, 1984), Hindi (Monika Sharma, 1995), Malayalam (Asha, 1997) and Telugu (Suhasini, 1997) for Linguistic Profile Test developed to assess language comprehension and expression. Ranganatha (1982) has established norms for relative frequency of phonemes and morphemes in Kannada. However, lexical semantic representation in adult speakers of Kannada, with particular reference to the semantic features has not been studied till date. There is an immense need for studies focusing semantic modeling based on the empirically derived semantic feature data that enhance our knowledge in terms of semantic representation and organization in Indian languages. It is also true that studies of mental lexicon in non-Indian languages cannot be directly generalized to Indian languages such as Kannada (language spoken in Karnataka, South India) as it varies to a great extent in terms of origin, structure and linguistic properties.

English is a Germanic language belonging to Indo-European language family whereas Kannada is one of the four major Dravidian languages. The Indo-European languages originated mainly from a common language spoken in southeastern Europe whereas Dravidian languages originated from Brahmi and is mainly spoken in the southern parts of India. Although both English and Kannada share a few borrowed words from Sanskrit language, the linguistic structure and word order is different between the two languages. One important linguistic property of Kannada is its agglutinative nature i.e. words are formed by adding suffixes to the root word in a series leading to several morphophonemic changes. The word order is relatively free in Kannada with verb final order (SOV) being the most prevalent one contrasting English, which has fixed word order containing subject verb and object (SVO). Kannada is also highly inflected language wherein the root word is affixed with several morphemes to generate thousands of word forms. As a result of highly agglutinative nature, it is very difficult to mark word boundaries, more so in the case of verbs. It is evident that the structure and these linguistic properties of a language exert control on the meaning representation in the mental lexicon.

It also true that there is pervasive diversity in mapping of word meanings across languages as there are differences across languages in terms of their word meaning inventories. The diversities noted in the mapping of word meaning in different languages can be attributed to the fact that each language is highly selective and arbitrary in choosing elements of experience they encode in the form of words leading to many possible ways to map between the words and corresponding concepts (Wolff & Malt, 2010). The words of a language have significant impact in molding the conceptual knowledge, as acquisition of conceptual knowledge is heavily reliant on language of the individual. It is also true that the mapping of conceptual features into linguistic features can vary across languages. Languages also differ markedly in how they partition by name many domains including colour, space, body parts, motion, emotion, mental states, causality and ordinary household containers (Wolff & Malt, 2010). For instance, there is difference in mapping of concepts onto words between languages such as English and Italian to that of Japanese. There are two different words for the concept 'foot' and 'leg' in English and Italian but there is only one word 'ashi' in Japanese which refers to both 'foot' and 'leg' (Vigliocco & Vinson, 2005). Similar variations are also noticed for English and Hebrew languages as they have numerous words representing different manners of jumping as against Italian and Spanish languages (Slobin, 1996b). This variability in mapping of concepts to words across languages can be assumed to have important implications in conceptual knowledge representation. Thus, the disparities in the semantic structures of a language have consequences on the structuring of concepts too. Hence studying semantic representations in different languages is imperative as it enhances our knowledge about influence of linguistic variability on organization of mental lexicon.

Language is also greatly influenced by the socio cultural factors of the language user. As the acquisition of words in the mental lexicon depends greatly on the physical and cultural environments of a language community, languages tend to vary in how many distinctions within a domain are encoded in words (Wolff & Malt, 2010). India is a multicultural and multilingual nation. The ethno cultural aspects have great influence on the linguistic environment of an individual in molding his/her language composition. With regards to Indian linguistic scenario it is not uncommon to find coexistence of two or three languages in a person's linguistic environment almost throughout the country. Exposure to many languages by an individual can be predicted to influence the meaning representation and organization of the mental lexicon.

Kannada is a Dravidian language spoken in South India predominantly in the state of Karnataka by around 70 million people. Despite the fact that it is one of the 40 most commonly spoken languages in the world, literature review reveals that studies related to representation and organization of mental lexicon of this language, is still in its infancy. Also there is lack of comprehensive database enumerating characteristics of words and concepts in terms of their semantic features. It is also true that each language is assumed to be formed as a means to meet the cultural and social demands of the community. Exposure to multilingual and multicultural environment may influence the representation of languages in the mental lexicon as culture and language have been influencing each other's structure from times immemorial. In depth understanding of these aspects of semantic representation and organization in the mental lexicon can be obtained by studying properties associated with semantic features. Thus, there is an indisputable need to establish such data in Kannada. Literature survey sheds light on the numerous ways in which semantic feature norms can be used as a means to understand semantic representation of nouns and verbs in normal individuals as well as in person’s with semantic dementia and aphasia. This can in turn help us to formulate more efficient therapy techniques to treat these individuals. The models developed to simulate representation of nouns and verbs also utilize semantic featural weights and other properties obtained from norms. Hence study of semantic features is found to be very useful. Therefore, there is an immense need to develop such semantic feature data in Indian languages including Kannada, in order to gain insights about the mental lexicon in these languages.

2.10 Aims and Objectives of the study

The aim of the present research was to explore the lexical semantic representation and organization in Kannada for a set of nouns and verbs by studying semantic features generated by native speakers of Kannada

1. The primary objective of the present research was to describe semantic features of nouns and verbs in Kannada.

2. The secondary objective was to develop a framework for a model of lexical semantic representation and organization in Kannada.

3. The tertiary objective of the study was to compare the lexical semantic representation and organization of nouns and verbs in Kannada and English.

2.11 Research questions of the study

1. Are there any differences in the distribution of semantic feature properties across the domains of nouns and verbs in Kannada mental lexicon?
2. Are there any differences in the distribution of semantic feature properties across the semantic categories in Kannada mental lexicon?
3. Are there any differences in the distribution of semantic feature properties between Kannada and English language?

2.12 Hypotheses of the study

The following hypotheses have been proposed to answer the research questions by analyzing semantic features obtained from the study.

1. There is no statistically significant difference in the distribution of semantic feature properties between nouns and verbs under study.

2. There is no statistically significant difference in the distribution of semantic feature properties across the semantic categories under study.

3. There is no statistically significant difference in the distribution of semantic feature properties between Kannada and English language

Chapter 3: Method

The present study aimed to examine lexical semantic representation and organization of nouns and verbs in mental lexicon in native speakers of Kannada employing a qualitative descriptive research design. Since semantic features are known to reflect important aspects of lexical semantic representation and organization, the study aimed to collect semantic features generated by adult native speakers of Kannada for a set of nouns and verbs selected from lexical corpus of Kannada.

3.1 Participants

For the selection of target population, ten graduate and post-graduate colleges (offering B.A., B.Sc., B.B.M, L.L.B, B.A.M.S., & B.Ed., courses) were chosen in urban areas of Mysore city. The participants were restricted to urban areas to rule out influence of differences in the cultural and socio economic factors. The upper age limit of participants was restricted to 30 years to rule out possible age related cognitive declination and cortical changes (Sowell et al., 2003). A total of 300 students who met the inclusionary criteria mentioned below participated in the present study. There were 168 females with the mean age 22.3(*SD*= 6.3) years and 132 males with the mean age 23.9 (*SD*= 5.1) years.

- Native speakers of Kannada.
- Age range of 18 -30 years.
- Minimum of 10 years of experience in reading and writing in Kannada.
- No reported history of any speech and language disorder.
- No reported history of any psychological / neurological disorder.

3.1.1 Ethical consideration

The data collection was carried out only after obtaining a written consent from the participants for their willingness to take part in the research. The participants thus signed a consent form agreeing to be part of the study. Permission was also obtained from the respective Heads of the Institutions to include their students for the study. The participants were familiarized with the aims, objectives, procedure of the study and their role in it. They were provided information about the approximate duration for the completion of task and were assured that there was no risk involved. They were also informed that there were only research benefits involved and personally cannot receive any benefits. They were assured that confidentially will be maintained regarding the personal information of the participants. An approval from Ethical Committee, All India Institute of Speech and Hearing was obtained to carry out the research.

3.2 Stimuli

The stimuli considered were set of words denoting nouns and verbs in Kannada. As suggested in the literature, word selection for the stimuli was broadly based to capture the general properties of semantic representation of most of the semantic categories and therefore stimuli selected belonged to a variety of semantic categories. Also the words were chosen to include the ones that are most frequently used in behavioural studies of priming, studies involving assessment and treatment of naming skills and also the translational equivalents of those used in previous studies (Vinson, 2009; McRae et al., 1997) of semantic representation in English so as to enable easy comparison.

Words are usually classified depending on their semantic, syntactic and morphological roles in a language. This classification of words into grammatical categories is termed as ‘parts of speech’ that is common among most of the languages. Similar to other languages the grammatical categories/ parts of speech of Kannada include nouns, verbs, adjectives, adverbs, pronouns, prepositions, conjunctions and interjections. Adjectives in a language are words that describe or modify a person or a thing in a sentence. They carry information about the properties of nouns that occur along with them in the sentence. Semantically, the role of adjectives is between that of most typical nouns and most typical verbs. Nouns in a language are used to suggest a large number of properties (for example, the word ‘dog’ represents properties such as <is an animal>, <has four legs>, <barks> etc) whereas adjectives can be differentiated from nouns in terms of meaning as they describe only a single property (Wierzbicka, 1988). For example, the adjective ‘ferocious’ for the noun ‘dog’ denotes only one quality/ property of the ‘dog’. Similarly adverb in a language is a word that is used to describe or change the meaning of a verb. The nouns, verbs, adjectives and to some extent adverbs in Kannada can be categorized as content words. These content words form the basic building blocks of sentences. The prepositions, conjunctions and pronouns along with grammatical articles form a group called as function words. The function words relate content words with others in a sentence to obtain a grammatically correct sentence, emphasizing the grammatical relationships with other words in the sentence. Hence they have no definitive lexical meaning unlike content words.

Content words were considered in the present study as they carry most of the semantic information. Whereas, function words such as pronouns, prepositions and conjunctions as stated earlier, do not have clear meaning at lexical level but have pivotal role in syntactic structure and sentential semantics. Hence function words usually carry less semantic information. Therefore on encountering a content word, a listener not only has to find a match in the phonological store but also has to access the meaning of the word whereas on encountering a function word, listener only needs to match the words to a phonological sequence stored (Field, 2004). Most of the adjectives and adverbs in Kannada are derived from nouns and verbs. Study of adjectives and adverbs undoubtedly sheds light on the intricacies of the semantic representation. However the focus of the study is on nouns and verbs that provide insight into the semantic aspects of language.

Nouns in Kannada, similar to English are fairly simple compared to verbs and can stand alone. Nouns included in the present study belonged to the type of nouns in Kannada known as 'common nouns'. The common nouns are used to describe concrete entities such as /na:yi/'do g'; /me:dzu/ 'table'. Hence such simple noun stems [E.g., /bekku/ 'cat'] denoting concrete concepts were used as stimuli without any morphological inflections attached to it. On the other hand, verbs in Kannada are more complex than in English as they are highly inflected due to agglutinative nature of Kannada. Verbs in Kannada usually occur in two forms namely finite and non-finite forms. The finite verbs in contrast to non- finite can stand alone without any morphological inflections following them and they are usually found at the end of the sentence (SOV). For the purpose of present study, simple verb stems of finite forms (imperatives) consisting of verb stem + i or + u [E.g., /kudi/ 'drink', /nungu/ 'swallow'] and verb stems with minimum amount of morphological inflections were selected as they can stand alone.

An initial set of 450 words (common nouns and finite verbs) was collected from Kannada dictionaries, web references (http://www.cfilt.iitb.ac.in/commonwords/2000-kan.aci) and from two native speakers of Kannada. The two native speakers had post-graduate education and belonged to urban areas of Mysore. They were instructed to provide a list of common nouns and finite verbs frequently used in Kannada. The 450 words thus collected were subjected to familiarity rating by 3 experienced professionals (Speech language pathologist, Special Educator, and a Linguist). The three experts rated the words using a 3-point rating scale where 2 indicates very familiar, 1indicates familiar and 0 indicates less familiar. Words rated as very familiar and familiar (relatively unambiguous words or words with dominant meaning) by at least two of the raters were included in the study. A total of 300 words, ‘200’ nouns belonging to 10 semantic categories and ‘100’ verbs belonging to 7 semantic categories were selected (the categorization of verbs was adopted from Levin, 1993 as in Vinson, 2009). The words in IPA included in the present study along with their English translation, semantic category and the domain to which they belong are presented in the Appendix A. The semantic categories to which the nouns and verbs belong were verified by three judges who were native speakers of Kannada. The semantic categories to which the nouns and verbs belong have been listed in Table 1. Twenty-eight out of 200 nouns (see Appendix A) were words from English which were included as they are generally used in day to day life by native speakers of Kannada and are an indispensable part of Kannada vocabulary and lexical corpus of spoken language (Mahalakshmi Prasad, personal communication, 2012). Since these borrowed words were rated more familiar than their translational equivalents in Kannada, they were included.

Table 1. *Semantic categories of nouns and verbs (number of words in parenthesis)*

Nouns	Verbs
Animals (30)	Body action (48)
Body parts (12)	Body sense (7)
Clothing (14)	Construction/ destruction (9)
Food (20)	Cooking (4)
Fruits/vegetables (29)	Motion change (9)
Nature (22)	Noises (9)
Common objects (37)	State change (14)
Profession/sports (10)	
Tools (13)	
Vehicles (13)	

A pilot study was conducted on 10 participants to check for the feasibility of task and comprehensibility of instructions provided. Participants were native Kannada speakers undergoing graduate and postgraduate education (Mean age = 23.4 years, *SD*= 4.5). Participants reported that the task was simple and instructions were comprehensible. Following this, for the main study the test items were assigned on a pseudorandom basis into ten word lists each containing 20 nouns and 10 verbs that were distributed across the data sheets on a random basis. Pseudorandom assignment of words into lists was employed to ensure as far as possible even distribution of words belonging to all semantic categories in the lists. In each word list, the words were arranged in approximately five pages, thus distributing six words in each page of that word list. Further, ample space was provided beneath each word for writing down its semantic features. Each word was marked to indicate whether it was a noun or verb. Thus 10 sets of data sheets were prepared containing 30 words each for the main study.

3.3 Procedure

The participants were provided with 30 words and asked to write in the 10 blank spaces the semantic features that they think best describes each word. Semantic features were defined to them as words or phrases when taken alone provide single piece of information about the meaning of the test item given above. For instance, the semantic feature <has legs> for the target item ‘dog’ gives a single piece of information about the word ‘dog’. All the features listed, taken together should be sufficient to define and describe that test item. The participants were instructed to list features that describe the test item instead of giving assumed associations without semantic relatedness. For example, for the word ‘cat’, the generally assumed relationship by the TV viewers is ‘Tom’ and for the word ‘rat’ it would be ‘Jerry’. Such associations are not acceptable as valid responses as they will not help explain what that word actually stands for. They were also provided with written copy of instructions and four examples (2 nouns and 2 verbs) with features generated for their reference, along with the lists. The four examples provided were the features generated by participants in the pilot study.

3.3.1 Instruction

The participants were provided with the following instructions:

“In this study, you will be given lists of 30 words to describe in Kannada using features (described below). For each word you have to write down all the features that describe the given word. For example the features ‘fruit, red, round, sweet, healthy, etc.’ may indicate ‘Apple’. Each feature should contain as fewer words as possible. The features you list when combined should be able to describe the meaning of the word. List all the features that will help to clearly identify the word from among similar words. Key features may be indicated in words and not in sentences. The words have also been marked whether they are nouns or verbs. Please define all words in the order provided and try to complete each word before moving on to the next. There are 4 examples of listed features provided below for your reference. Thank you”.

The data collection targeted at obtaining written semantic feature data from a total 300 participants for 10 lists (30 participants per list). The 10 lists of words prepared were initially distributed among 500 participants in order to compensate for data attrition. The data was collected in their classrooms as a group and participants were requested not to discuss the responses with others. All participants were asked to take as much time as necessary to complete the task and most of them completed it within 90-120 minutes. 28% of the participants failed to return the data sheets back (142 out of 500). 16% of the data sheets returned were either incomplete or the participants failed to understand the task. Such data sheets were discarded (16% i.e. 58 out of 358) and not included in the study. The remaining 300 data sheets collected from 300 participants formed the final data that was utilized for further analysis. The data obtained consisted of lists of semantic features written in Kannada by participants that helps to describe the target word. In the data, each of the ten word lists containing 30 target words were filled by 30 participants, hence each word had 30 participants who had generated semantic features.

3.4 Analysis and tabulation of data

The final data of written semantic features for nouns and verbs in Kannada was compiled for 300 words. The total features generated were about 48,170 features. Considering the large number of responses to be recorded and analyzed, a computer database was necessary as it was not practical to analyze it manually, which would have made it error prone. Hence custom software was developed with the help of a software consultant for this purpose. The custom software was developed using Microsoft Access 2007. It allows easy data entry and various kinds of analysis over the stored semantic feature data. All the responses were entered into the database using an interface designed with Microsoft Visual basic.

The custom software designed had four specific relational tables labeled as follows:

1. *Word*
2. *Volunteer*
3. *Feature*
4. *Response*

The 300 target words along with the semantic category to which they belong and the domain to which the word belonged (a noun or verb) was entered into the first relational table named ‘Word’ (*Figure 6*). For example, as depicted below the target word /a:ne/ (elephant) was entered into the database under the domain of ‘nouns' and under the semantic category of animals. The 300 target words are listed in Appendix A.

feature | response | volunteer | word

word_name	is_noun	semantic_field
aane	☑	animals
alilu	☑	animals
baathu koli	☑	animals
bekku	☑	animals
chirathe	☑	animals
chitte	☑	animals
gini	☑	animals
goobe	☑	animals
haddu	☑	animals
halli	☑	animals
hasu	☑	animals
huli	☑	animals
ili	☑	animals
jinke	☑	animals
kaage	☑	animals
kappe	☑	animals
karadi	☑	animals
katthe	☑	animals
kogile	☑	animals
koli	☑	animals
kothi	☑	animals
kudure	☑	animals
kuri	☑	animals
meenu	☑	animals
mola	☑	animals
naayi	☑	animals
navilu	☑	animals

Record: 1 of 300 No Filter Search

*Figure 6.*Relational table 'word'.

The second table named 'Volunteer' (*Figure 7*) had columns to enter demographic data of participants and it generated volunteer ID code for each participant entered.

volunteer

vol_name	vol_id	affiliation
RV	302	MFGC COLLEGE
AT	303	MFGC COLLEGE
PS	304	SV COLLEGE
BSV	305	XYZ COLLEGE
MS	306	XYZ COLLEGE
	(New)	

Figure 7. Relational table 'volunteer'

The next table constructed was called the 'Feature' (*Figure 8*) table wherein all the unique features generated by participants were entered and was stored.

Information about the type to which the feature belonged (see section 4.2.3 for details of type of features) was also entered in this table.

feature

feature_name	category
bejaru	Affect emotion
gaurava	affect emotion
hudugiyarige priya	Affect emotion
kirikiri	affect emotion
makkalige ishta	affect emotion
manasigge muda	Affect emotion
icecream maduthare	asoociation
aane	association
agasa	association
athe sose	association
baachanige	association
baayi	association
bag	association
balapa balasuthare	association
banale	association
banduka	association
bench	association
benki	association
besige	association
bhava geethe	association
bisilu	Association
chalkpiece	association
chamacha	association
chathri	association
cricket aaduthare	association
devara vigraha	association
dhoolu iddare seenuthare	association

Record: 1 of 4150 No Filter Search

Figure 8. Relational table ‘feature’

The fourth relational table named ‘Response’ (*Figure 9*) had four columns namely volunteer ID code, word name, feature name and rank. Typically a row in the ‘Response’ table captured the response given by a participant for a particular word. Additionally rank of the feature was also captured. If the participant has generated a feature first then it holds the rank ‘1’, feature generated second holds the rank ‘2’ and so on.

response

volunteer_id	word_name	feature_name	rank
1	aane	ambari horuthade	7
1	aane	balishta	3
1	aane	dasara meravanige	6
1	aane	doddadu	2
1	aane	eardu danta ide	4
1	aane	kappu banna	5
1	aane	prani	1
1	beet root	aarogyage olleyadu	3
1	beet root	gaada kempu banna	2
1	beet root	khaara thinusu madabahudu	5
1	beet root	protein iruthade	4
1	beet root	sihi thinusu madabahudu	6
1	beet root	tharakaari	1
1	bende kaayi	chapaathi jothe thinnuthare	4
1	bende kaayi	hasiru banna	5
1	bende kaayi	jnapaka shakthi hechhuthade	2
1	bende kaayi	palya maduthare	3
1	bende kaayi	tharakaari	1
1	bucket	belli inda maduthare	4
1	bucket	hithale inda maduthare	5
1	bucket	kabbinadinda maduthare	3

Record: 1 of 48190 No Filter Search

Figure 9. Relation table ‘response’

In order to enter the responses into the database, a visual basic interface was constructed. This interface was called ‘Add Response form’. It had dropdown comboboxes for volunteer ID, word, feature and rank (*Figure 10*) where in the semantic features generated by a participant for that particular word along with the volunteer ID of the participant was entered. This page had provision to enter the rank of the feature generated by the participant. The page also included text box and a command button to add new semantic features along with the information about the type of feature. With this infrastructure, the total responses of 48,170 features were manually added to the database.

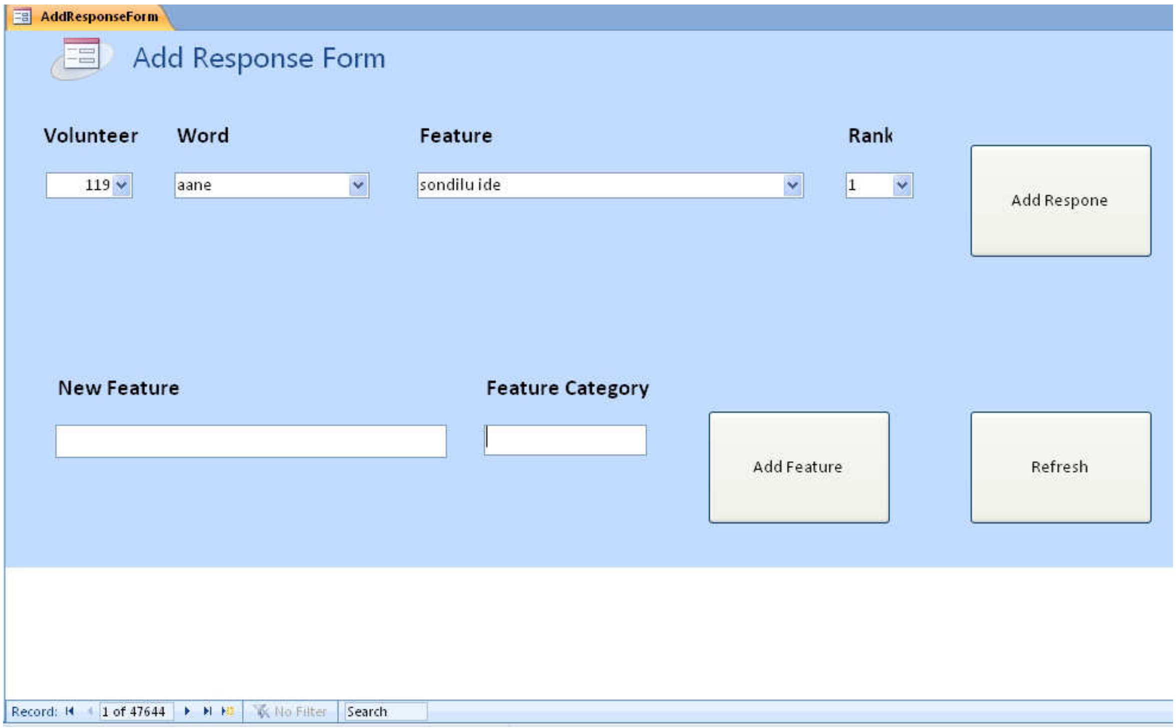

Figure 10. Visual basic interface 'Add Response'

During this process of data tabulation, instances where participants had generated synonymous feature names [for E.g., /hakki/ and /pakshi/ meaning bird for the word 'ka:ge' (crow)], one of the names that were frequently listed (/hakki/) was selected and replaced for all the synonyms so that there is uniformity in representing same piece of information. It was also noted that some of the features generated consisted of conjoint features wherein few of the participants had provided two pieces of information together. For example, the feature <has four legs> was generated for the word 'dog'. This feature has two bits of information namely <has legs> and <it is four in number> such compound features were considered as two different features. Thus all the features generated by participants were stored in the relational table named 'feature'. This 'feature' table was constantly updated, if a participant had generated a new feature during the process of entering responses into the database. On encountering a feature that was already present in the 'feature' table, it was simply selected from the table. Thus the total number of unique features generated by the participants was 4,150 in number. To check for the reliability of the procedure for data tabulation, 10% of the data were randomly selected and were separately tabulated by a Speech-Language Pathologist who is also native speaker of Kannada. The judge was initially familiarized with the steps involved in the procedure used for data tabulation. Percentage of agreement for the two tabulated data resulted in 96.4 % agreement calculated using the following formula:

Number of agreements / total number x 100

Thus, the entire set of written responses were tabulated into the database which contained features generated for words, along with the type to which the feature belonged to. Further, the database thus obtained consisting of semantic features was processed using multiple computer programs. These programs were written using the programming language called ‘Python’. To refine and remove spurious idiosyncratic features each feature listed by fewer than five participants were eliminated from the data. Hence a python program was written in order to discard the features that were generated by less than five participants. This resulted in 1,889 unique features generated five or more times in the entire database. These features were considered for further statistical analysis. Thus, the semantic feature data in the form of computer database which is manageable and productive for future studies of semantic organization and representation were obtained for Kannada nouns and verbs. Following this, the database was subjected to statistical analyses that are reported in the next chapter 4.

Chapter 4: Results and Discussion

The present research aimed to describe the organization of nouns and verbs in the mental lexicon based on semantic feature distribution. Hence collecting semantic features formed the first objective of the study. The first step towards this objective was to select stimuli that included 200 familiar nouns and 100 verbs in Kannada. The next step was to collect semantic features for the same from the native speakers of Kannada. The semantic features were extracted from the responses listed by the participants (as described in the previous section). Semantic features were studied to understand the lexical semantic representation and organization in the mental lexicon. Hence to address the research questions of the present study, the collected semantic features were analyzed using appropriate statistical tools for distribution of the following semantic feature properties.

1) Number of features
2) Featural weights
3) Feature types
4) Distinctive features
5) Shared features
6) Featural correlation

The above semantic feature properties help to understand the nature of semantic representation. Hence they were analyzed with respect to the domains of nouns and verbs. In order to understand role of these semantic featural properties in categorization of words into their respective semantic categories, distribution of the features were analyzed for each of the 17 semantic categories. With respect to the tertiary objective of developing a framework for a model of semantic representation using semantic features, the obtained data was processed for cosine similarity and the structure of mental lexicon was visually modeled using JavaScript based on the semantic distances of words. The extended objective of the present study was to compare featural properties of nouns and verbs in Kannada with nouns and verbs of English Language. In order to understand the nature of the data obtained and its contribution to semantic representation in Kannada, statistical analyses were carried out employing Independent t-test, Mann-Whitney U test, Pearson's product moment correlation and Wilcoxon signed- rank test with Bonferroni correction. The next section (4.1) describes the processing of the raw semantic feature data to facilitate analysis.

4.1 Weight Matrix

The Weight Matrix is fundamental to all the analysis carried out in the present study. The weight matrix is a Word X Feature matrix[9] where every cell in the matrix holds the cumulative count of the number times a feature has been reported for a word. For Example, consider Table 2 that holds nine rows from the response table described in *Figure 9*.

Table 2
Example Response Table

Volunteer	Word	Feature	Rank
1	aane	DoddaDu	1
1	aane	kappu	2
1	mola	cikkaDu	1
1	mola	biLi	2
2	aane	kappu	1
2	aane	DoddaDu	2
2	mola	cikkaDu	1
2	mola	biLi	2
3	aane	kappu	1

This response table has four unique features {*DoddaDu, kappu, cikkaDu, biLi*} generated for two words {*aane, mola*}. The resulting Weight Matrix is a 2X4 matrix with two rows for the words and four columns for the features. The summation of all the cells in the weight matrix is nine, which is the number of responses. The Weight Matrix is depicted in Table 3. In the table for instance, the matrix entry for (*aane, Kappu*) is three because *Kappu* has been reported three times for *aane* in the response table.

[9]The terms Weight matrix and Word x Feature matrix are used interchangeably in this thesis.

Table 3
Example Weight Matrix

	DoddaDu	kappu	cikkaDu	biLi
aane	**2**	**3**	**0**	**0**
mola	**0**	**0**	**2**	**2**

The Weight Matrix was thus generated from the complete response table, which was of order 300 X 1889. A python program took as input the response table and generated as output the weight matrix. In the matrix, examining row vectors allows us to study properties of words, while examining column vectors allows us to study properties of features.

4.1.1 Weight Matrix with Decaying Weights. A volunteer's response consists of multiple features per word. The order in which the volunteer listed the features has to be accounted. A volunteer may have listed features that he strongly associates with the word first. The order in which the volunteer listed the features had been recorded in the database as a field called "Rank" as shown in Table 2. In order to provide emphasis for the ranks of the features produced, the features were assigned decaying weightages of the order of 5 based on their ranks. For instance, the feature with rank 1 was assigned a weightage of 5, the feature with rank 2 a weightage of 4 in decreasing order, similarly feature with rank 3 received a weightage of 3 and fourth rank 2. The remaining features from rank 5 onwards received weightage of 1. For example, Table 4 shows the weight assignments with a maximum weight of 5.

Table 4
Example Decaying Weight Assignment

Rank	1	2	3	4	5	6	7	8	9
Weight	5	4	3	2	1	1	1	1	1

This strategy of decaying weights emphasizes the features that were produced first, denoted by their ranks as these features that are produced first by the participants can have higher relevance in describing that particular concept.

4.2 Analysis of Semantic Feature Properties

4.2.1.Number of features. The semantic features obtained were initially analyzed for distribution of *number of features* across the domains of nouns and verbs. For this purpose, the total number of semantic features generated for each word was calculated. A word is characterized by its corresponding row in the weight matrix. The *number of non-zero entries in the row vector* is the number of features reported for a word by all the participants. For example, Table 6 depicts a weight matrix with 3 words and 6 features; the number of non-zero entries for Word1 is 3, which is the number of features reported for that word.

Table 6
Number of Features from Weight Matrix

	Feature1	Feature2	Feature3	Feature4	Feature5	Feature6	**Number of Features**
Word1	0	0	3	5	0	2	**3**
Word2	2	0	4	0	0	0	**2**
Word3	0	2	1	3	2	0	**4**

The total number of features generated for 200 words in the domain of nouns was 7,474 and for 100 words in the domain of verbs were 3,029. The average number of features produced for each word in nouns (*M* = 37.37, *SD* = 8.8) was greater than that of verbs (*M* = 30.29, *SD* = 9.3). In order to compare whether the differences in the mean number of features between the two domains was statistically significant, two tailed Independent t-test was conducted. The test revealed a statistically significant difference (t (298) = 7.15, p< 0.001) in the mean number of features between nouns and verbs.

Number of features was also studied with respect to semantic categories for which the features were generated in both the domains of nouns and verbs. In the domain of nouns, out of the 10 semantic categories, highest average number of features was generated for the semantic category ‘vehicles’ (*M* = 45.16, *SD* = 6.2) and the least for semantic category ‘profession/ sports’ (*M* = 27.6, *SD* = 7.6). The average number of features generated for each of the semantic category of noun along with the standard deviation is shown in Table 7.

Table 8. *Average Number of Features - Noun semantic categories*

Semantic categories		Mean	SD
<u>Nouns</u>	<u>N</u>		
Vehicles	13	45.16	6.2
Nature	22	40.37	10.5
Animals	30	39.44	7.5
Fruits/vegetables	29	38.38	7.1
Food	20	37.9	7.1
Clothing	14	37.86	6.3
Common objects	37	37.84	6.8
Body parts	12	33.67	8.8
Tools	13	32.7	6.3
Profession/ sports	10	27.6	7.6

In the domain of verbs highest mean number of features was generated for the semantic category ‘cooking’ (*M* = 35.75, *SD* = 11.7) and the least mean number of features for ‘motion change’ (*M* = 24.89, *SD* = 8.9). Table 9 shows the average number of features generated for verbs along with the standard deviation.

Table 9
Average Number of Features -Verb semantic categories

Semantic categories		Mean	SD
Verbs	N		
Cooking	4	35.75	11.7
Construction/ destruction	9	34.34	7.6
Body sense	7	33.15	8.3
Noises	9	31.89	9
Body action	48	30.8	9.4
State change	14	27.22	9.7
Motion change	9	24.89	8.9

To check for differences, if any, in the number of features generated with respect to the semantic categories, parametric test namely, Independent t–test was administered for data with normal distribution and non-parametric test namely Mann-Whitney U test was administered for data with non-normal distribution. The semantic categories were analyzed with each other separately in the two domains of nouns and verbs for the distribution of number of features. In the domain of nouns there were 10 semantic categories and 7 for verbs. The total number of combinations of semantic categories to be compared was calculated according to the following formula

$$nC_2 = n\ (n-1)/2$$

where, C= Combination and n = number of semantic categories

The above formula permitted 45 combinations for the 10 semantic categories of nouns and 21 for 7 semantic categories of verbs. Independent t-tests (for normally distributed data) or Mann-Whitney U test (for non-normal distribution) were administered on these semantic category pairs. The results of the test revealed statistically significant difference in distribution of number of features for a total of 20 semantic category pairs out of 45 analyzed for the domain of nouns. It is evident from the results that in the category of nouns, 'vehicles' was found to be having significantly higher number of features compared to all the remaining 9 semantic categories analyzed namely 'body parts'[t (23) = 4.09, p < 0.001], 'animals'[t (41) = 4.098, p = 0.01], 'fruits/vegetables' [t (40) = 3.11, p = 0.003],'common objects'[t (48) = 3.54, p = 0.001], 'food' [U (30) = 47.00, p = 0.001], 'clothing' [t (25) = 3.23, p = 0.003], 'tools' [t (24) = 5.43, p < 0.001], 'profession/ sports'[t (21) = 6.63, p < 0.001], and nature [t (33) = 2.14, p = 0.03]. The semantic categories of 'animals' had significantly higher number of features compared to the semantic categories namely 'profession/ sports' [t (38) = 4.57, p < 0.001], 'tools' [t (41) = 2.96, p = 0.005] and 'body parts' [t (40) = 2.258, p = 0.029]. Similarly, the semantic categories of 'fruits/ vegetables' had significantly higher number of features compared to the semantic categories 'tools' [t (40) = 2.59, p = 0.013], and 'profession/ sports' [t (37) = 4.31, p < 0.001]. The semantic category of 'food' also resulted in significantly greater number of features compared to 'tools' [U (31) = 73.00, p = 0.018], and 'profession/ sports' [U (28) = 28.50, p = 0.001]. The remaining categories such as clothing and common objects also resulted in significantly higher number of semantic features than profession/ sports and tools (clothing Vs. profession/ sports [t (22) = 3.914, p = 0.001], clothing Vs. tools [t (25) = 2.272, p = 0.031]; common objects Vs. profession/

sports [t (45) = 4.344, p < 0.001], common objects Vs. tools [t (48) = 2.486, p = 0.016])

However for the domain of verbs statistically significant difference was seen only for the semantic category 'Motion Change' against three semantic categories namely 'Construction/ destruction' [t (16) = -2.68, p = 0.015], 'Cooking' [U (11) = 6.00, p = 0.03] and 'Body sense' [U (14) = 11.00, p = 0.01]. There was no statistically significant difference in the number of features generated for the remaining 18 semantic category pairs analyzed.

4.2.1.1 Discussion. The semantic feature data were initially analyzed for distribution of the feature property called the 'Number of features' generated for target words. Number of features was considered as it is the basic and informative measure that can be used for comparison across the semantic feature data. This feature property is also important as it is a measure of semantic richness. More the number of features generated higher the semantic richness of that concept. It is also important to evaluate this feature property because most of the theories of mental lexicon (E.g., Conceptual Structure Account by Tyler et al., 2000) claim that some concepts tend to have more number of features compared to others. The number of features was studied for its distribution broadly across the domains of nouns and verbs. From the results it is evident that the mean number of features generated for nouns (M = 37.37, SD = 8.8) were greater than that for verbs (M = 30.29, SD = 9.3) reaching statistical significance (t (298) = 6.37, p < 0.05). The results obtained can be considered to reflect the nature of organization and representation of nouns and verbs in the mental lexicon. The participants were able to generate more number of features for nouns than verbs. The difference in the distribution of number of features across the domains of nouns and verbs noted in the present study can be attributed to concreteness and imageability of a concept. In order to generate semantic features, participants refer to a mental imagery created online for the task, which includes the essential features that describe the target concepts. This mental imagery has been developed through repeated multisensory exposure to and interactions with the concepts represented by the target words (McRae, Cree, Seidenberg, & McNorgan, 2005) and hence concreteness of a concept plays an important role in the formation of mental imagery. Since concrete concepts are more easily processed and understood through sensory modalities, it is plausible that concreteness of a concept enhances the number of semantic features that can be associated with a concept and participants can readily access these features that are represented strongly through multisensory exposure.

The nouns of Kannada used in the present study include mainly words representing concrete concepts. While it is true that verbs in a language represent more abstract concepts compared to nouns representing concrete concepts, verbs tend to possess lower proportion of sensory features (Vinson, 2009) compared to concrete nouns and hence it may be difficult to produce online semantic feature like information in their mental imagery. This abstract nature of verbs may have contributed to generation of less number of features compared to concrete nouns in the present study. Another factor contributing to this difference in distribution could be the difference in the nature of verbs and nouns itself. Even though nouns and verbs of a language are classified as category of content words, there are significant differences between the two domains. To understand verbs and describe them, context plays a vital role. The action represented by the verb is a continuous relational process, taking place with respect to a referent whereas concrete concepts represented by nouns can be understood in isolation (Vinson & Vigliocco, 2008). Representation of verbs that involve dynamic entities that unfold in time may have resulted in the difference in the semantic featural makeup of the two domains. Similar differences in the distribution of number of features for the domains of nouns and verbs were also reported by Vinson (2009) for English language.

The results of the study indicate that distribution of number of features across semantic categories of nouns is more prominent than that of verbs. Further analysis of number of features was carried out to obtain mean number of features for each of the 10 semantic categories of nouns (Table 8) and 7 semantic categories of verbs (Table 9). This detailed analysis revealed that among the semantic categories of nouns, the participants were able to generate highest number of features for the category ‘vehicles’ compared to all others (Table 8). The number of features produced by participants for semantic categories, in the descending order were as follows: ‘animals’, ‘fruits/vegetables’, ‘food’, ‘clothing’, ‘common objects’, ‘nature’, ‘body parts’, ‘tools’ and ‘profession/ sports’ (Table 8). This trend in distribution of number of features across semantic categories can be attributed to the ease with which the participants can consult their mental images to generate features. The higher the perceptual and or imageable (concrete) features of a concept, larger are the number of features generated by the participants. For instance, the number of features generated for 'animals' (M = 39.44, SD = 7.5) is higher compared to 'profession/sports' (M = 27.6, SD = 7.6).

The mean number of features calculated for the semantic categories was analyzed for statistically significant differences, if any, across the semantic categories. The results showed that the semantic categories of nouns had more number of statistically significant differences (20 out of 45 semantic category pairs) compared to semantic categories of verbs (3 out of 21 semantic category pairs). This result is in concordance with the nature of noun and verb categorization stated in literature (Vinson, 2009). The semantic categorization of verbs of a language differs from nouns, as also reported by Vinson (2009), in terms of the semantic featural make up and properties. The prominent differences seen in the features of noun categories can be because the nouns tend to possess more number of features referring to narrow semantic fields. Hence the featural makeup may vary significantly from one semantic category to another, which has been replicated in the present study. Verbs on the other hand possess more features that broadly apply across wide range of semantic categories, which has resulted in reduced difference in distribution across their semantic categories. It is also true that semantic features are very strongly correlated with the semantic category and hence are applicable to only few semantic categories with respect to nouns than that of verbs.

The feature property with regard to number of features is useful to understand the differences in the nature of representation of nouns and verbs. The number of features generated provides insight into the content and structure of mental representations of nouns and verbs. The difference in the representation of nouns and verbs of a language is also highlighted from the analysis. However, it may not be a very good measure to provide complete picture of representation of mental lexicon as it only considers features generated by participants without considering how important that feature is in describing the concept. In order to obtain further in depth understanding of semantic feature make up of nouns and verbs the analysis of semantic feature data for featural weights was carried out in the present study. Feature weight considers the number of participants generating features, which is a more valid featural property (Vinson, 2009) that can be studied.

4.2.2. Featural weights. Featural weights indicate the total number of participants who have generated a particular feature for a given word. This property was studied as they provide more in depth information about semantic featural make up than number of features. They are also considered to be more reliable measure of semantic composition and a precise reflection of the underlying meaning representation of words (Vinson 2009) as it captures the importance of each feature in defining a concept based on participant's response. Feature weight values were calculated for each feature of a word, by calculating the number of participants who generated that feature for that word as described in the section 4.1. For example, (as shown in Table 10) 29 participants produced the feature </prani/> (animal) for '/a:ne/' (Elephant), so the feature </pra:ni/> gets a weight value of 29 for '/a:ne/' (Elephant). Similarly featural weight matrix was obtained for 1,889 unique features listed for 300 words. Thus the matrix obtained in the present study is of the order 300 x 1889 where 300 rows represent the target words and 1,889 columns represent the total number of unique features generated (A list of the six features with maximum feature weights for each word generated in the present study has been uploaded and is available for viewing at http://tinyurl.com/lexicalstudy). Following this, the featural weight obtained in the word x feature matrix for each word (values in each row of the matrix as in Table 10) was added together across 1889 features to obtain summated featural weights with respect to each word. Thus the summed featural weight was obtained by combining the featural weights across all the features generated for a given word in the set, which was calculated for 300 words across the data. The summed featural weights were further analyzed for their pattern of distribution across the data.

Table 10
Illustration of Word X Feature matrix

Words	Feature 1 /pra:ni/	Feature 2 /DodaDu/	Feature 3 /cikkaDu/	Feature 4 /Dodda kivi/	Feature 5 /kappu/	Feature 6 /biLi/	Summed Featural weight
/aane/	29	28	0	14	29	0	100
/mola/	28	0	18	21	0	28	95

Distribution of summed featural weights across domains of nouns and verbs was also analyzed. The mean featural weight generated for the domain of nouns is $M = 165.33$, $SD = 37.4$ and for the domain of verbs is $M = 101.68$, $SD = 27.0$. The mean featural weight generated for nouns was greater than that of verbs. In order to compare whether the differences in the distribution of mean featural weight between nouns and verbs was statistically significant, two tailed independent *t* test was conducted. The results showed statistically significant difference (t (298) = 16.92, $p < 0.001$) in the distribution of featural weight.

Featural weight was also studied with respect to semantic categories for which the features were generated in both the domains of nouns and verbs. The average featural weights generated for each semantic category of nouns and verbs are listed in Table 11 and Table 12 respectively. While the highest featural weight among nouns categories was generated for ‘animal’ ($M = 193.00$, $SD = 53.2$) and the lowest featural weight for ‘profession/ sports’ ($M = 137.00$, $SD = 44.3$), that for verbs, the highest featural weight was generated for the category ‘Cooking’ ($M = 117.00$, $SD = 43.4$) and the lowest featural weight for the category ‘motion change’ ($M = 80.00$, $SD = 45.4$).

Table 11
Average Featural weight -Noun semantic categories

Semantic categories	Mean & SD	
Nouns		
Animals	193	53.2
Fruits/vegetables	189.21	50.3
Vehicles	183.16	49.6
Food	170.25	50.9
Body parts	158.34	44.9
Nature	157.23	39.8
Common objects	151.79	45.6
Clothing	150.43	44.0
Tools	150	43.4
Profession/ sports	137.3	44.3

Table 12
Average Featural weight - Verb semantic categories

Semantic categories	Mean & SD	
Verbs		
Cooking	117	43.4
Body sense	107.72	44.4
Noises	107.34	44.8
Body action	105.63	29.6
Construction/ destruction	100.78	45.5
State change	91.65	44.7
Motion change	80	45.4

Following this, similar to number of features, the distribution of featural weights across different semantic categories was compared for statistical significance. Independent t-test (for normal distribution) or Mann-Whitney U test (for non-normal distribution) was administered for 45 combinations of noun semantic categories and 21 combinations of verb semantic categories. The results revealed statistically significant difference in distribution of featural weight in the 24 semantic category pairs of nouns out of 45 analyzed. It is evident from the results that the semantic category 'animals' was significantly different as it had more featural weights compared to 'common objects' [t (65) = 6.203, p < 0.001], 'food' [t (48) = 2.644, p = 0.011], 'clothing' [t (42) = 4.233, p < 0.001], 'body parts' [t (40) = 3.15, p = 0.003], 'nature' [t (50) = 4.467, p < 0.001], 'tools' [t (41) = 4.059, p < 0.001] and 'profession/ sports' [t (38) = 4.799, p = 0.015]. The semantic category of 'fruits/vegetables' was found to have significantly higher featural weights compared to the semantic categories namely 'common objects' [t (64) = 6.642, p < 0.001], 'food' [t (47) = 2.65, p = 0.011], 'clothing' [t (41) = 4.672, p < 0.001], 'body parts' [t (39) = 3.37, p = 0.002], 'nature' [t (49) = 4.439, p < 0.001] 'tools' [t (40) = 4.446, p < 0.001] and 'profession/ sports' [t (37) = 5.459, p < 0.001]. The semantic category 'vehicles' had significantly higher featural weights compared to the semantic categories namely 'clothing' [t (25) = 3.214, p = 0.003], 'body parts' [t (23) = 2.179, p = 0.039], 'nature' [t (33) = 2.803, p = 0.008], 'tools' [t (24) = 3.028, p = 0.005] and 'profession/ sports' [t (21) = 3.957, p = 0.001]. The semantic category 'food' was found to be significantly higher in distribution of featural weights compared to semantic categories namely ‘common objects’ [t (55) = 3.128, p = 0.003], ‘clothing’ [t (32) = 2.339, p = 0.025], ‘nature’ [t (40) = 2.423, p = 0.02], ‘tools’ [t (31) = 2.227, p = 0.033] and ‘profession/ sports’ [t (28) = 3.418, p = 0.002].

For the semantic categories of verbs statistically significant difference was seen for five of the category pairs against the semantic category of ‘motion change’ compared to ‘noises’ [U (16) = 15.00, p = 0.01], ‘cooking ’ [U (11) = 3.00, p = 0.01], ‘body sense’ [U (14) = 7.00, p = 0.006], ‘body action’ [U (55) = 99.50, p = 0.006] and ‘Construction/destruction [U (11) = 17.50, p = 0.02]

4.2.2.1. Discussion. The semantic features were analyzed for featural weight as it considers along with features generated for a word, the exact number of participants who agree that a feature describes that word. Featural weight can be a very useful semantic feature property than number of features to understand meaning representation in the mental lexicon. This in turn provides valuable information on how relevant a feature is in describing the concept. Higher the featural weight greater the relevance of the feature as it indicates that more number of participants have agreed upon it as a feature that describes a concept. Hence featural weight was studied for their distribution across the obtained semantic feature data.

In order to understand featural weight distribution, the featural weights were calculated for all the unique features generated based on the number of participants who had generated the feature for that word. Next, the number of participants was added together to generate summated featural weight for each feature (Table 10). Following this the summated featural weights were analyzed to see for the gross distinctions if any, across the domains of nouns and verbs. The results revealed that the featural weight distribution was significantly different in the two domains. The domain of nouns had significantly more featural weight (M = 165.33, SD = 37.4) compared to domain of verbs (M = 101.68, SD = 27.0). Even though the difference between nouns and verbs was also evident for the number of features analyzed in the previous section, the difference noticed in case of featural weight distribution was more consistent and robust suggesting the ease for generation of common features for nouns compared to verbs across participants. The featural makeup of nouns can be considered almost uniform across participants. The greater uniformity of featural makeup can be because concrete nouns in general may not have much contextual information associated with it as the context in which these nouns occur are almost always same. The uniformity in context of occurrence might have resulted in generation of rather uniform mental image for these concrete concepts. This receives support from the data where more number of participants generated same features for the concepts resulting in higher featural weight values. Verbs, on the other hand, compared to nouns are dependent heavily on context and relational attributes. Each verb in a language usually occurs in many contexts which also contributes to a great extent to the realization of their meaning. Therefore verbs might be at a disadvantage when the task is to describe them in isolated word condition using features. This dependency of verbs on context and relation that can be highly subjective in nature may have led to less uniformity in generation of common semantic features across participants. Hence there was significantly less featural weight distribution for verbs compared to nouns. Similar findings where verbs in English language had significantly less feature weight in comparison to nouns are reported by Vinson in 2009. The results also provide evidence that the nouns and verbs in the mental lexicon may differ in organization as a result of dependency of their meaning on context which may result in a more complex representation for verbs involving context and sentential semantic (or syntactic) information. This trend is further supported by the results reported in the previous section for number of features where nouns had significantly more number of features generated than verbs.

Following this, the featural weights were analyzed for each of the semantic category of nouns and verbs similar to number of feature. The semantic category 'animals' had the highest mean featural weight (*M* = 193.00, *SD* = 53.2) and category 'profession/ sports' (*M* = 137.30, *SD* = 44.3) had the lowest compared to all other categories of nouns (Table 11). This can be attributed to the reason that the mental images of features representing words in the semantic category of 'animals' may not have drastic discrepancies in terms of knowledge and has little scope to vary from one participant to another. The category of 'animals' has well-defined and unambiguous features that help to describe them and distinguish from one another. This might have resulted in generating more common features across participants with higher featural weight. Category such as 'profession/ sports' on the other hand has less specific descriptions with wide variations among the participants probably based on their encyclopedic knowledge. Despite the above, the featural weight (*M* = 137.00, *SD* =

44.3) for this noun category was considerably higher than the highest featural weight of the verb category ('Cooking' *M* = 117.00, *SD* = 43.4). For the semantic category of verbs the highest featural weight was generated for the semantic category 'cooking ' (*M* = 117.00, *SD* = 43.4) and lowest for the category 'motion change' (*M* = 80.00, *SD* = 45.4).This difference may be at because description of the concepts in the semantic category of verbs using verbal language can be a challenging task for participants as some of the categories especially 'motion change'(*M* = 80.00, *SD* = 45.4) relies heavily on the spatial relational aspects (McRae, de Sa, & Seidenberg, 1997) and contexts encoded in the mental image which is difficult to verbalize. This might have resulted in lesser agreement among participants to select uniform features and hence produced fewer and varied semantic features contributing to less featural weights.

The mean featural weights obtained for semantic categories were subjected to independent t-tests, results of which revealed that there were more significant differences across semantic categories of nouns and verbs than reported for the measure 'number of features'. A total of 24 out of 45 semantic category pairs differed from each other with respect to featural weight for nouns whereas for the semantic category pairs of verbs it was only 5 out of 21 combinations. As stated for number of features, the difference in the distribution of featural weights across semantic categories of nouns and verbs provides further evidence that noun categories tend to have specific features that are relevant to only limited number of semantic categories. This specificity in distribution of features is reflected in the results of t - tests revealing more semantic categories of nouns to vary significantly from one another than verbs, which tend to have more features that are widely applicable across many semantic categories. The concepts representing verbs may have varying representation, which may result from unique contexts in which they occur, and thus no hardcore features common across participants. This property of features generated for verbs have resulted in reduced difference and hence almost uniform in distribution of featural weights across their semantic categories. Similar results have been reported in literature with respect to English language for feature weight analysis across semantic categories of nouns (Vinson, 2009; Cree & McRae, 2007) and verbs (Vinson, 2009). Thus the study of difference in the distribution across semantic categories can be considered imperative as the featural weight might be a contributing factor for categorization of words into a category. The featural weight also helps to understand the relevance of respective features for the words in the semantic categories.

4.2.3. Feature types. With the aim of understanding the featural composition better, the type and nature of each feature generated was studied along with its featural weights. Analysis of the types of semantic features generated by the participants provides a clear picture of semantic featural makeup and importance of each type of feature in representing meaning of words. Understanding featural makeup hence provides insight about the possible neural regions involved in the semantic representation of words in the mental lexicon. The meaning representation of words in the brain involves indirect activation of the sensory and motor modalities of the brain. Classification of features into types that correlates with the sensory/ motor processing areas of brain is very useful in understanding conceptual knowledge representation as it provides neural basis of representation. Thus each feature can be considered to reflect a type of knowledge that is stored in the semantic representation of the concept. Study of feature type distribution can also be helpful in correlating the variations in semantic deficits resulting from differential brain damage. The semantic features obtained from the present study were classified into 17 feature types. This classification was based on the feature classification called brain region knowledge type taxonomy proposed by Cree and McRae (2003) and knowledge type taxonomy by Wu and Barsalou (2009) to study perceptual simulation. Hence the features obtained in the present data were classified into 17 feature types as follows:

1) *Visual– colour*: includes features describing the information related to colour of the target concepts obtained through visual modality (E.g., <red in colour> for ‘apple’)
2) *Visual–parts and surface properties*: includes features describing the information related to parts and surface properties of the target concepts obtained through visual modality (E.g., <has tusk> for ‘elephant’).
3) *Visual–motion*: includes features describing the information related to motion properties (e.g., how a thing moves) of the target concepts obtained through visual modality (E.g., <runs fast> for ‘cheetah’).
4) *Smell:* includes features describing the information of the target concepts obtained through olfactory sensation (E.g., <smells good> for ‘jasmine’).

5) *Sound:* includes features describing the information about the auditory properties of the target concepts obtained through auditory sensation (E.g., <barks> for ‘dog’).
6) *Tactile:* includes features describing the information about the tactile properties of the target concepts obtained through tactile sensation (E.g., <sharp> for ‘knife’).
7) *Taste:* includes features describing the information about the taste related properties of the target concepts obtained through gustatory sensation (E.g., <sour> for ‘lemon’).
8) *Function:* includes features describing the information about how we use an object (E.g., <used to cut clothes> for ‘scissors’).
9) *Location:* includes features that describe the place where an object is usually present (E.g., < lives in forest> for ‘lion’).
10) *Systemic property:* includes features that describe internal properties of the objects (E.g., <is carnivores> for ‘lion’).
11) *Context:* includes features generated mainly for words representing verbs which describe the linguistic and/or social context in which the verb is used (E.g., <fill water> for verb ‘fill’).
12) *Association:* includes features that depend on the association of target word with others. (E.g., <comes with chair> for ‘table’).
13) *Evaluation:* includes features that describe evaluation of an object by the participant. (E.g., <is dangerous> for ‘lion’).
14) *Contingency:* includes features that describe causation. (E.g., <causes tiredness> for ‘sun light /bisilu/’).
15) *Affect emotion:* includes features that describe the emotional attributes generated by participants for the target words (E.g., <sad> for verb ‘cry’).
16) *Taxonomic:* includes features such as synonyms, antonyms, superordinate and subordinate generated for the target word. (E.g., <animal> for ‘dog’)
17) *Encyclopedic*: includes features describing general knowledge and which cannot be classified into any of the feature types above.

In order to study the distribution of feature types, the word x feature matrix that was initially of the order 300 x 1889 was reduced to the order 300 x 17, by classifying the 1,889 features into the 17 types described above. To check for the reliability of this classification of the feature into 17 types, 10% of the semantic features were randomly selected and were classified separately by a speech language pathologist who is also native speaker of Kannada. The judge was initially familiarized with the definition of each feature type. Amount of agreement for the feature type classification was 97%.

The featural weight values of features classified into same type were added together to obtain featural weights for each type of feature corresponding to each word. For example in case of word 'apple' the features 'round' and 'smooth' were both classified into feature type *visual form and surface properties*. Therefore the featural weights of both 'round' and 'smooth' were added together. The data thus obtained was further analyzed to account for proportion of each type of feature. For this purpose the percentage ratio of each type of feature to that of total features was calculated for 300 words as described below.

In the Weight Matrix, row vector of every word was examined to see the distribution of features across feature types. For example, in Table 13, the 6 features {*F1*,*F2*,*F3*,*F4*,*F5*,*F6*} belong to one of the 3 distinct feature types {*T1*,*T2*,*T3*} To calculate the percentage ratio of a feature type, the cumulative weights of all the features in the type is divided by the summed featural weight. For example, the percentage weight of type T2 for word W1 is calculated as (3+5)/10 * 100 = 80%

Table 13
Feature Type from Weight Matrix

	F1 (T1)	F2 (T1)	F3 (T2)	F4 (T2)	F5 (T3)	F6 (T3)	**Summed Featural Weights**	**P1**	**P2**	**P3**
W1	0	0	3	5	0	2	**10**	**0%**	**80%**	**20%**
W2	2	0	4	0	0	0	**6**	**33%**	**67%**	**0%**
W3	0	2	1	3	2	0	**8**	**25%**	**50%**	**25%**

F- Feature, W- Word & P- Percentage ratio

The distribution of feature types were studied under two conditions namely 'unit weight' where all the features irrespective of their rank received the weight of the order 1 and 'decaying weight' were the features received decaying weight of the order 5 based on their ranks (as described in section 4.1.1). Following this, the distribution of each type of feature was analyzed with respect to domains of nouns, verbs and across different semantic categories in these two conditions.

The results of feature type distribution revealed a lot of variability in the data as reflected by the standard deviation (Table 14). This can be because, each domain/ semantic category may have only few feature types out of 17 which were predominantly present in their featural makeup and the rest of feature types were of very small proportions. Hence it was noted that the standard deviations varied more drastically for feature types that formed a smaller proportion in the featural makeup of a domain and/or category. Therefore in the present section, the feature types whose standard deviation values are below the mean are reported and discussed.

The semantic feature type distribution, similar to number of features and featural weights was studied with respect to the broad domains of nouns and verbs. The results for unit weight, across nouns revealed that the domain of nouns was dependent on features belonging to the feature type *Visual form and surface properties* (*M* = 24.39, *SD* = 11.75). The *Function* or use of objects were the next prominent feature type generated (*M* = 23.50, *SD* = 15.01). With decaying weights the mean percentage of *Function* features (*M* = 23.12, *SD* = 16.37), *Visual form and surface properties* (*M* = 22.19, *SD* = 11.68) and *Taxonomic* features (*M* = 18.43, *SD* = 10.19) formed major proportion of features types. The mean percentage ratios of each feature type to that of total feature types obtained for the domain of Nouns have been listed inTable 14.

In the domain of verbs, the highest mean percentage ratio under unit weight condition was obtained for the feature type *Taxonomic* (*M* = 22.41, *SD* = 13.34) followed by *Context* (*M* = 21.77, *SD* = 19.15) and *Function* (*M* = 17.91, *SD* = 14.49). Similar trend was obtained for decaying weights where in *Taxonomic* (*M* = 25.35, *SD* = 14.79) features were more in number compared to all other feature types followed by *Context* (*M* = 21.92, *SD* = 20.00) and *Function (M* = 17.72, *SD* = 15.67). It was also evident that, in decaying weight condition compared to unit weight, the *Taxonomic* features had greater mean percentage (Table 15) indicating these features had higher ranks in the database. The mean percentage ratio of each feature type to that of total feature types for the domain of verbs have been listed in Table 15.

Table 14
Mean percentage of feature types – Nouns

	Unit weight		Decaying weight	
Nouns	Mean	SD	Mean	SD
Visual form and surface properties	24.39	11.75	22.19	11.68
Function	23.50	15.01	23.12	16.37
Taxonomic	12.58	7.14	18.43	10.19
Encyclopedic	8.43	8.62	7.25	8.90
Visual color	7.33	8.03	7.75	9.50
Location	5.77	5.78	5.53	6.92
Systemic property	3.95	5.84	3.26	5.05
Evaluation	2.73	3.64	2.37	3.74
Visual motion	2.22	4.98	2.14	5.35
Taste	2.18	5.11	2.12	5.49
Context	1.56	3.28	1.40	3.50
Association	1.54	3.29	1.26	3.11
Tactile	0.93	2.77	0.90	3.44
Contingency	0.73	2.73	0.61	2.56
Sound	0.72	2.54	0.63	2.62
Affect emotion	0.63	2.08	0.65	2.52
Smell	0.17	1.11	0.16	1.38

Table 15.
Mean percentage of feature types – Verbs

	Unit weight		Decaying weights	
Verbs	Mean	SD	Mean	SD
Taxonomic	22.41	13.34	25.35	14.79
Context	21.77	19.15	21.92	20.00
Function	17.91	14.49	17.72	15.67
Encyclopedic	6.83	8.89	6.23	8.79
Visual form and surface properties	4.94	5.89	4.66	6.43
Association	4.82	5.43	4.53	5.61
Contingency	4.45	7.49	4.19	7.96
Visual motion	3.12	6.21	3.17	6.75
Systemic property	2.82	4.26	2.63	4.71
Sound	2.22	5.84	2.30	6.31
Tactile	1.82	3.87	1.78	4.21
Evaluation	1.82	3.13	1.60	3.34
Location	1.68	3.37	1.50	3.11
Affect emotion	1.14	2.58	1.07	2.61
Taste	0.74	4.96	0.62	4.68
Smell	0.30	2.98	0.29	2.88
Visual color	0.15	0.51	0.11	0.51

In order to obtain deeper insights with respect to semantic categories, the distribution of the type of features was analyzed for each semantic category under study. This analysis is likely to shed light on the aspects of representation such as the brain regions and sensory modalities that can possibly be involved in the representation of words of each semantic category. The mean (SD) percentage of 17 feature types in each semantic category of nouns under unit weight and decaying weight conditions are shown in Table 16 and the mean percentage of feature types for verb categories in Table 17.

Table 16

Mean percentage and SD of feature types- Noun semantic categories

		Animals		Body parts		Clothing		Common Objects		Cooking	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Visual Surface Properties	UW	28.64	7.90	32.95	8.99	31.02	8.59	26.49	12.03	18.15	10.95
	DW	25.25	7.74	29.52	10.04	25.27	7.62	22.75	11.26	16.37	9.94
Encyclopedic	UW	6.01	3.77	6.06	5.85	5.23	4.82	3.31	3.39	15.97	13.06
	DW	4.9	4.02	6.1	7.04	4.27	4.63	2.68	3.29	15.14	15.23
Function	UW	5.21	7.89	19.87	13.35	35.15	8.45	35.66	10.78	23.25	14.58
	DW	4.18	6.61	17.3	13.36	39.04	9.10	38.44	12.19	22.56	13.44
Taxonomic	UW	15.2	3.27	19.66	9.71	11.31	5.45	10.53	9.09	11.55	7.45
	DW	26.14	4.32	26.83	12.37	16.31	7.32	13.4	10.62	16.64	10.62
Taste	UW	0.59	1.69	0	0.00	0	0.00	0	0.00	9.22	9.26
	DW	0.52	1.58	0	0.00	0	0.00	0	0.00	9.55	10.81
Context	UW	0.93	2.02	0.95	1.33	0.57	1.12	1.78	2.96	0.82	1.46
	DW	0.77	1.72	0.59	1.01	0.32	0.62	2.03	4.15	0.44	0.81
Visual Motion	UW	5.77	5.99	4.16	8.05	0.24	0.71	0.78	2.01	0	0.00
	DW	5	6.22	3.64	7.48	0.27	0.92	0.69	1.92	0	0.00
Evaluation	UW	2.86	3.79	0.74	0.84	3.23	1.93	3.67	4.96	2.86	3.37
	DW	2.38	3.43	0.59	0.93	2.26	1.45	3.78	5.99	2.09	2.71
Sound	UW	3.31	4.93	0.74	2.79	1.09	3.69	0.04	0.16	0	0.00
	DW	2.91	5.45	0.81	2.81	1.06	3.74	0.03	0.13	0	0.00
Association	UW	1.19	2.10	1.63	3.15	1.14	1.46	1.8	3.73	1.65	3.30
	DW	0.8	1.75	1.03	2.16	0.68	0.96	1.59	3.60	1.58	3.68
Systemic Property	UW	14.3	7.12	3.74	3.92	0.43	0.60	1.98	3.08	1.36	2.03
	DW	10.85	6.55	3.39	4.39	0.19	0.28	1.82	3.15	1.08	1.92
Location	UW	7.51	6.38	2.85	5.86	3.33	5.26	7.57	7.01	4.24	3.24
	DW	7.68	7.77	3.9	7.78	3.69	6.55	7.27	8.09	2.93	3.13

Contingency	UW	0.26	0.76	1.16	2.62	0.14	0.75	0.37	0.94	0.38	0.94
	DW	0.15	0.50	0.79	2.16	0.2	0.95	0.31	0.92	0.37	0.84
Tactile	UW	0.16	0.46	0.47	1.00	0.24	0.76	0.43	1.08	1.59	3.08
	DW	0.06	0.17	0.36	0.66	0.34	0.97	0.19	0.48	1.78	4.38
Visual Color	UW	7.74	6.31	4.69	10.14	5.65	3.35	4.92	6.20	6.42	4.62
	DW	8.2	8.17	4.97	10.99	4.77	3.30	4.28	5.92	6.81	5.77
Affect Emotion	UW	0.33	0.67	0.05	0.20	1.24	1.78	0.62	2.79	2.33	4.25
	DW	0.2	0.45	0.02	0.07	1.31	2.17	0.7	3.64	2.51	5.14
Smell	UW	0	0.00	0.26	0.59	0	0.00	0.05	0.45	0.21	0.56
	DW	0	0.00	0.16	0.36	0	0.00	0.06	0.41	0.17	0.44

		Fruits		**Nature**		**Profession**		**Tools**		**Vehicles**	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Visual Surface Properties	UW	19.15	5.61	18.94	12.16	9.54	9.94	30.75	11.59	36.6	8.75
	DW	17.11	6.77	19.19	13.30	7.48	8.63	28.14	11.86	36.95	11.72
Encyclopedic	UW	11.18	6.04	12.28	11.10	13.18	13.77	7.19	9.44	8.53	4.36
	DW	8.72	6.01	11.90	11.56	10.83	12.53	6.84	10.48	5.38	2.96
Function	UW	20.8	9.80	20.67	12.99	24.91	19.29	32.44	12.40	23.36	10.01
	DW	16.46	9.57	17.30	12.53	26.08	21.10	34.49	12.91	21.72	10.79
Taxonomic	UW	12.2	4.58	7.71	6.12	18.65	8.05	14.32	6.01	12.02	3.44
	DW	21.00	7.70	8.58	7.68	25.17	11.63	18.78	8.24	18.78	5.60
Taste	UW	8.14	5.55	0.03	0.19	0	0.00	0	0.00	0	0.00
	DW	7.35	6.48	0.03	0.13	0	0.00	0	0.00	0	0.00
Context	UW	0.16	0.50	4.54	5.86	5.17	6.83	1.54	2.12	0.88	1.40
	DW	0.10	0.30	4.24	6.60	4.26	6.26	1.16	1.74	0.63	1.09
Visual Motion	UW	0	0.00	3.17	6.61	0.87	2.60	0.05	0.13	8.53	7.07
	DW	0	0.00	3.54	7.90	0.93	2.86	0.04	0.11	8.99	9.33

Evaluation	UW	0.53	0.69	3.84	4.44	3.57	4.88	1.39	1.65	3.78	2.36
	DW	0.37	0.62	4.08	4.24	3.15	4.36	1.03	1.57	2.66	2.24
Sound	UW	0	0.00	0.54	1.34	0	0.00	0.05	0.22	0.42	0.63
	DW	0	0.00	0.37	0.95	0	0.00	0.07	0.30	0.28	0.48
Association	UW	0.24	0.50	2.82	3.62	4.22	7.63	2.1	3.62	0.25	0.60
	DW	0.17	0.37	2.08	3.63	3.71	7.12	1.77	3.38	0.26	0.65
Systemic Property	UW	1.61	3.09	3.04	2.88	6.05	6.13	2.77	3.39	1.22	1.67
	DW	1.50	2.80	2.67	3.00	6.14	7.00	2.32	2.80	0.81	1.38
Location	UW	5.74	2.83	6.30	7.48	6.77	6.38	5.08	4.55	1.18	1.19
	DW	4.34	2.91	7.94	9.92	6.91	8.00	3.86	3.62	1.06	1.36
Contingency	UW	0.16	0.62	2.85	6.91	0.73	3.23	0.82	1.46	0.04	0.12
	DW	0.08	0.34	3.03	6.77	0.59	2.45	0.57	1.13	0.02	0.05
Tactile	UW	0.77	1.48	3.81	6.43	0.07	0.22	0.87	2.35	0.13	0.37
	DW	0.57	1.18	4.76	8.43	0.03	0.08	0.4	1.15	0.08	0.27
Visual Color	UW	18.88	7.27	7.45	8.40	5.54	7.97	0.62	0.92	2.77	2.54
	DW	21.81	8.71	8.28	11.18	4.2	6.03	0.53	0.84	2.13	2.37
Affect Emotion	UW	0.22	0.74	0.93	1.99	0.73	1.29	0	0.00	0.29	0.65
	DW	0.28	1.22	0.74	1.84	0.52	1.19	0	0.00	0.25	0.57
Smell	UW	0.22	0.85	1.09	3.07	0	0.00	0	0.00	0	0.00
	DW	0.14	0.51	0.98	4.03	0	0.00	0	0.00	0	0.00

Note: UW- Unit weight, DW- Decaying weight

Table 17
Mean percentage & SD of feature type- verb semantic categories

		Motion change		Noises		State change		Body action		Body sense		Construction/ destruction		Cooking action	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Visual Surface Properties	UW	3.35	3.56	4.16	3.87	2.81	4.45	5.12	5.97	7.57	9.75	8.57	6.81	7.05	5.08
	DW	3.02	3.57	3.35	3.68	2.13	3.69	4.87	6.55	8.47	12.6	7.7	6.47	6.76	5.42
Encyclopedic	UW	3.91	7.76	12.68	15.03	8.68	9.62	7.42	8.45	7.84	7.41	3.79	3.34	5.34	4.38
	DW	3.93	8.67	11.14	15.22	8.58	10.79	6.19	7.76	6.93	6.61	3.64	4.13	3.45	3.19
Function	UW	8.24	7.01	8.84	6.55	18.06	15.03	20.78	13.53	20.32	12.04	23.61	13.5	35.47	31.11
	DW	7.41	7.58	7.43	5.98	16.72	15.68	20.51	15.21	21	13.06	22.65	15.52	34.86	31.95
Taxonomic	UW	20.25	8.65	12.27	10.46	27.76	17.31	22.84	13.1	16.6	12.84	23.16	11.03	20.73	9.56
	DW	21.98	9.46	13.18	12	31.05	18.65	26.71	14.83	18.26	11.95	26.04	11.34	23.92	11.3
Taste	UW	0	0	0	0	0.47	1.45	0.36	0.9	6.91	18.54	0.11	0.23	1.07	1.57
	DW	0	0	0	0	0.47	1.49	0.18	0.46	6.59	17.59	0.04	0.08	0.41	0.67
Context	UW	34.78	23.05	17.57	16.67	29.09	23.05	18.68	16.68	12.62	17.83	13.7	13.58	15.17	24.39
	DW	36.01	23.51	18.76	18.76	28.9	23.73	18.98	17.48	12.79	17.86	13.2	14.71	16.82	27.28
Visual Motion	UW	13.13	11.87	1.14	1.84	0.78	0.97	3.62	5.83	1.46	2.18	1.22	2.39	0	0
	DW	14.2	13.13	1.12	2.35	0.78	1	3.39	6.26	1.2	1.99	1.3	2.4	0	0
Evaluation	UW	0.14	0.51	3.64	3.12	1.95	2.21	1.8	3.32	3.45	5.41	2.23	2.56	0.43	0.55
	DW	0.04	0.14	3.12	3.26	1.8	2.32	1.62	3.74	2.69	5.45	1.68	2.41	0.14	0.17
Sound	UW	0.56	1.5	17.15	9.28	0.23	0.57	0.92	2.7	0.93	2.54	0.45	1.1	0	0
	DW	0.33	0.97	18.63	10.46	0.14	0.44	0.97	3	0.86	2.2	0.56	1.26	0	0
Association	UW	2.37	2.43	6.86	4.71	2.58	4.1	4.68	4.82	5.18	5.95	10.24	7.94	8.12	8.05
	DW	1.99	2.39	6.47	4.7	2.6	4.22	4.13	4.53	4.58	5.91	10.43	8.57	8.99	10.85

Systemic Property	UW	1.82	1.96	2.08	2.2	1.33	1.74	3.5	4.72	3.59	6.64	4.57	5.57	1.07	0.17
	DW	1.32	1.49	2	2.46	1.04	1.56	3.13	5	4.49	8.99	4.76	5.83	0.54	0.17
Location	UW	2.23	3.4	3.22	3.07	0.63	1.66	2.36	4.19	0.53	0.87	0.45	0.89	0	0
	DW	2.03	3.76	2.69	1.94	0.61	2.05	1.98	3.83	0.38	0.73	0.42	0.74	0	0
Contingency	UW	6.98	9.13	7.28	13.46	2.81	4.14	3.88	5.93	8.76	12.72	3.12	3.46	0.21	0.53
	DW	6.46	8.04	8.84	16.62	2.44	3.54	3.48	6.23	8	12.24	2.8	2.96	0.07	0.16
Tactile	UW	1.12	1.63	0.73	1.09	1.8	3.04	1.74	3.89	2.92	3.22	4.57	7.15	5.13	3.47
	DW	0.66	1.18	0.56	0.87	1.8	3.18	1.71	4.33	2.87	3.81	4.59	7.97	3.99	2.75
Visual Color	UW	0	0	0	0	0.16	0.35	0.16	0.57	0.53	0.99	0.11	0.23	0.21	0.53
	DW	0	0	0	0	0.05	0.11	0.15	0.66	0.43	0.83	0.07	0.16	0.07	0.16
Affect Emotion	UW	1.12	1.72	2.39	3.86	0.86	1.57	1.42	3.08	0.8	1.13	0.11	0.42	0	0
	DW	0.62	1.04	2.69	4.91	0.9	1.76	1.28	2.87	0.47	0.65	0.14	0.5	0	0
Smell	UW	0	0	0	0	0	0	0.74	4.31	0	0	0	0	0	0
	DW	0	0	0	0	0	0	0.72	4.16	0	0	0	0	0	0

Note: UW- unit weight, DW- decaying weight

4.2.1.1 Discussion. The classification and study of feature type distribution along with its featural weight analyzed in the previous section helps to understand better the featural makeup of concepts. The features were classified based on the information they carry that corresponds to the brain regions where it might be processed. Hence in the present study, eight of the feature types were based on the brain regions that correspond to sensory processing areas and motor/ action areas. Remaining nine of the features was based on abstract knowledge stored in the memory and the introspective experiences of individuals with the concepts. Dependency of concepts on the type of feature in describing them was main focus of the analysis. The data was analyzed with respect to the domains of nouns and verbs and also with respect to individual semantic categories of nouns and verbs. Also as described earlier in this section, the features were subjected to decaying weights of the order 5 to emphasize on their ranks.

The results of feature type distribution for the domains of nouns and verbs revealed that the concepts under the domain of nouns were highly dependent on visual features (Table 14). The *function* features also formed major portion of features generated and formed higher percentage than visual features when decaying weights were considered. But the difference however is very small.

In the domain of nouns, specifically for living things such as animals, fruits and vegetables, the representation may mainly involve activation of perceptual modalities hence higher percentage of visual features such as *visual form and surface properties* have emerged in the data. This trend has also been reported in the literature where words representing living things tend to possess more perceptual or sensory features (Vinson, 2009; Cree & McRae, 2003; Warrington & Shallice, 1984; Sensory- functional theory by Farah & McClleland, 1991). The domain of nouns in the present study also includes semantic categories of nonliving things such as common objects, tools and vehicles. These semantic categories may have contributed to the percentage of function features generated for the domain. It is plausible to assume that the function features generated for these semantic categories had major role in their representation than their visual appearances. Thus they were more dependent on function features than any other feature types. The present results are in concordance with previous studies in English (Vinson, 2009; Cree & McRae, 2003) who also claim that visual features (for living things) and function features (for nonliving things) are the most salient feature types generated for nouns.

In the domain of verbs, results revealed that *Taxonomic* followed by *Context* and *Function* (Table 15) were the most salient feature types generated. The most significant feature type generated to describe the verbs was *taxonomic* features where the participants had generated mostly synonyms, superordinate and grammatical category (E.g.: <it is a verb>) to which the word belonged. This can be a result of increased difficulty in generating features for verbs as they are more complex and dynamic in nature. It is also noteworthy that the semantic features generated for verbs in the present study were substantially low compared to nouns. The feature type *context* was included in the classification as it was noted that in the features generated, mostly for verbs, the participants had described the semantic context as well as grammatical context in which the verb was most likely to occur. Hence the feature type *context* was included which resulted in significant contribution to the feature type generated for verbs. The words in the domain of verbs were also dependent on the feature type *function* that mainly consists of features that describe the use of the actions symbolized by the words. Similar results have also been reported by Vinson (2009) for ‘action words’ who claims that few of the categories of action words such as change of state, communication and cooking were highly dependent on *function* feature types. Thus, the differences in the domains of nouns and verbs reported in the previous sections for properties number of features and featural weights is also evident in the distribution of feature type across the domains.

The feature type distribution was also studied with respect to individual semantic categories of nouns and verbs. The semantic category of animals was highly dependent on the feature type *visual form and surface properties* (Table 16). In order to recognize and categorize members of animal category visual features such as its body parts, limbs, fur etc play important role. Hence most of the living things especially the category of animals is dominated by *visual form and surface properties* feature type. Unlike semantic categories such as tools or common objects the functional use of animals is rather limited hence very less percentage of function features have been resulted in the data for this category. The result is in concordance with literature where researchers have also reported greater proportion of visual features in the semantic feature make up of creatures (Cree & McRae, 2003; Vinson, 2009). The *taxonomic* feature type also accounted for a significant percentage for semantic category of animals. The participants had generated superordinate categories as features for the target items given such as <is an animal> for target word lion, which has resulted in increased percentage of taxonomic features. The feature type which was also salient for the category of animals was *systemic properties* such as <it is carnivores>. The semantic category animals when analyzed under unit weight condition, was also found to be moderately dependent on feature types *'Visual Colour'* a sensory property which contributes greatly in recognizing the members of the category, *'Location'* where the participants had generated features describing places where the animals are usually found (E.g.: < lives in forest>) and *'Encyclopedic'* features which describe general knowledge about the respective animals (E.g.: <is our national animal > for the target word *tiger*).

The semantic category of body parts was found to be most dependent on '*Visual Form and Surface Properties'* and '*Function'* (Table 16). The participants may have generated features describing perceptual properties acquired through sensory modalities and also listed features describing the functional tasks carried out by most of the body parts that led to the following results. Thus the category of body parts is also dependent on function features. The results obtained differ marginally to results reported in literature (Vinson, 2009) where in the semantic category of body parts is said to be highly reliant on function features and moderately reliant on visual features. Also, they differ from the semantic category of animals, which possess a major proportion of visual features similar to body parts but lack function features. The semantic category of body parts was also seen to be moderately dependent on '*Taxonomic'* features. The features generated for this type mainly included superordinate category names and synonyms that contributed to the increased percentage of *Taxonomic* feature type.

The semantic category of clothing consisted mainly of feature type *'Function'* (Table 16). Thus the semantic category of clothing similar to other nonliving things followed the same trend where functional use of category members formed the major portion of semantic featural makeup. The present result is thus comparable to researcher's claim from previous studies (Vinson, 2009; Cree & McRae, 2003; Warrington & Shallice, 1984) who state that the representation of nonliving things are greatly dependent on the function features which describe their use. Another feature type that also contributed significantly to the featural makeup of this semantic category was '*Visual Form and Surface Properties*' and '*Visual colour*' which consisted of features describing the perceptual attributes of the target items. These perceptual attributes also help to distinguish one target item from another. The category was also found to be moderately dependent on feature types such as '*Taxonomic*' features and '*Encyclopedic*' for unit weight condition that included information mainly about superordinate category names and synonyms.

The semantic category of food included food items and words related to food commonly used in daily living. Analysis of the semantic featural makeup of this category for percentage of each type of feature revealed (Table 16) that the feature type '*Function*' describing the use of food items < is eaten> and '*Visual Form and Surface Properties*' consisting of features describing visual properties formed the highest proportion of features generated. This semantic category is thus partially reliant on 'function' features similar to nonliving things and moderately dependent on visual features similar to living things as also reported by Cree and McRae (2003). It was found that the category was also dependent to certain extent on '*Encyclopedic*' features where in the information about how a food item is prepared and its basic ingredients has been listed as features which were classified as '*Encyclopedic*'. The '*Taxonomic*' features generated were mainly superordinate category names (E.g.: <a type of food item>). Apart from the above feature types, the category, unlike any other semantic category analyzed so far showed dependency on perceptual feature type '*Taste*', which is noteworthy as it has significant role in describing features of food items (Cree & McRae, 2003). The sensory feature type '*Visual colour*' also resulted to be salient for the semantic category food.

The feature type analysis of the semantic category of 'fruits/ vegetables' revealed that the results are comparable to that of the semantic category 'food'. Similar to the category of food, this category was also was dominated by feature types '*Function'* (Table 16). It was also noted that the category was dependent on *'Visual colour'* and '*Visual Form and Surface Properties'*. Similar to the category of food, there was moderate dependency on the sensory feature type '*Taste'*. Identical semantic feature makeup for this category with high visual colour, taste and function features has also been reported by Cree & McRae (2003). Feature type that also formed a major percentage was 'Taxonomic' feature where participants had mostly generated superordinate category names as features (E.g., <is a fruit> for apple). The '*Encyclopedic'* features such as <good for health>, and feature type '*Location'* where features such as <grows on trees> were also generated.

The semantic featural makeup of the category nature was found to be made up of mostly '*Visual Form and Surface Properties'* and '*Function*' features. The category included many concrete concepts (E.g.: /ka:du/ forest, /betta/ mountain, /ele/ leaf etc) accessibly through sensory modality which might have resulted in participants relying heavily upon visual features in describing the words of the category. Participants may have considered function features to be highly salient in describing some of the words such as /bisilu/ (sun light), /benki/ (fire) and /male/ (rain) which might have led to the following results. The study of distribution of feature types in the semantic category of 'common objects' revealed that the most reliant feature type for the category was '*Function'* (Table 16). The semantic representation of the objects used in our daily living thus is highly dependent on how it is used in the daily routine. As reported in literature (Vinson, 2009; Cree & McRae, 2003; Warrington & Shallice, 1984), common objects being non-living in nature is highly dependent on its functional use for their representation. Feature type '*Visual Form and Surface Properties'* is also integral part of the semantic feature makeup of the category as these features are crucial in recognizing and differentiating one object from another. Feature type that also formed a major percentage of features generated was '*Taxonomic'* features and '*Location'* where participants had generated features describing the places where the objects would generally be found.

The feature type distribution in the semantic category of ‘profession/sports’ showed that the category was most dependent on features generated by participants describing the service each profession is assigned to deliver, for instance semantic feature <teaches in schools> for the target word *teacher*, which accounted for feature type ‘*Function’* (Table 16). The category was also dependent on ‘*Taxonomic’* feature types where in the participants had generated superordinate category names and synonyms as features. The ‘*Encyclopedic’* features were also generated which included information about basic knowledge about the target items (e.g.: <2 teams of 11 members> for *cricket).* It is noteworthy that this semantic category had negligible proportion of feature types describing basic perceptual and motoric features as items in the category required to a greater extent the worldly knowledge and thinking higher than mere sensory representation than any other semantic categories discussed above.

The feature type analysis of the semantic category of ‘tools’ (Table 16) revealed that the category was predominantly dependent on feature type ‘*Function’* as it formed the highest percentage of feature type generated for the category. Hence it is evident that the representation of the semantic category of tools is based on the functional use of items in the category similar to any other non-living things. This dependency of tools and other non-living things on the features accounting their function have also been reported by previous researchers (Tyler & Moss; Vinson, 2009; Cree & McRae, 2003; Warrington & Shallice, 1984). The feature type ‘*Visual Form and Surface Properties’* was also found to be highly relevant to this category where participants have generated features ascribed to the appearances of the tools. The features attributed to function and physical appearances for nonliving things such as tools have been reported to have higher probability of co-occurrence in the feature data as these two feature types have been reported to be highly correlated (Cree & McRae, 2003). Hence these two feature types have formed a major percentage of features compared to all other feature types. Feature type that also was found to be reliant on were ‘*Taxonomic’* features and ‘*Encyclopedic’* features.

The semantic category of ‘vehicles’ (Table 16) was highly dependent on feature types ‘*Visual Form and Surface Properties’* and ‘*Function’*. It was also moderately dependent on '*Visual motion'* feature type. However this result slightly varies from the previous study (Vinson, 2009) which reports that the category of vehicles is most reliant on visual motion features and moderately reliant on visual and function features. Although the present analysis is identical to previous study, as it has resulted in dominance of same three feature types, there is minor variation in the mean percentage of each feature type.

The distribution of semantic feature type was analyzed with respect to each of the semantic categories of verbs similar to semantic categories of nouns. It was noticed that the unlike semantic categories of nouns, distinctions in the semantic feature type distribution among the verbs categories was minimal. The prominent feature types listed across most of the categories belonged mainly to feature types '*Taxonomic'* '*Function'* and '*Context'*. The semantic categories in which this pattern was seen were that of body action, body sense, cooking construction/destruction and state change. The remaining categories were nonetheless dependent on these three feature types and also on other features specific to their respective semantic categories. Thus analysis of the semantic category of 'body action' (Table 17) revealed that feature types 'Taxonomic', 'Function' and 'Context' dominated it. In the semantic category of 'body-sense' the feature types which formed highest mean percentage of feature type (Table 17) were again '*Function'* and '*Taxonomic'*. Similar trend was seen for the semantic category of 'cooking' (Table 17) as it was also found to have higher mean percentage of '*Function'* and '*Taxonomic'* features. Following the same pattern, the semantic category construction/destruction (Table 17) was found to have feature types '*Function'*, '*Taxonomic'* features followed by '*Context'*. The semantic category of 'state-change' also followed the same trend (Table 17) as feature types 'context' 'Taxonomic' and 'Function' dominated it. Apart from the three prominent feature types the semantic categories of 'Motion-change' was found to be reliant on sensory feature '*Visual motion'*. Similarly the category 'noises' were found to be dependent on sensory feature '*Sound'*.

Under the taxonomic features listed for these semantic categories, the participants had mostly classified the target word into superordinate domain that it is an action that can be performed. It is also remarkable that the taxonomic features generated for verbs were superordinate domain names (< it is a verb>) and not superordinate category names (<animal> for tiger) that was frequently observed for semantic categories of nouns. The differences noted can be attributed to the difference in the nature of noun and verb categorization. In case of nouns, distinguishing between different levels such as superordinate, basic and subordinate is relatively simple and they can be easily organized into hierarchies with many shared correlated properties. On the other hand, it is very difficult to create comparable sets of hierarchies for verbs as they form matrix -like structure where many semantic properties are orthogonally related rather than correlated (Huttenlocher & Lui, 1979; Graesser, 1987; as in Tyler & Moss, 2001). Also, the hierarchy that exists for verbs possess fewer levels with very less distinctions at the superordinate levels (Keil, 1989). However, verb taxonomies do show a basic level structure but a less sharply defined and less stable structure than in noun taxonomies (Morris & Murphy, 1990).

As reported earlier, the semantic categories discussed above were most dependent on features describing the function the target action would help to achieve. The feature type '*Context'* also formed major portion of the featural makeup, which included features that described the contextual information of the action word where it is frequently used (<neerannu tumbu> for target word <tumbu>). Higher reliance on contextual features may be because the action represented by the verb is a continuous relational process, taking place with respect to a referent (Vinson & Vigliocco, 2008). Unlike concrete nouns it is difficult to describe an action in isolation, which therefore caused the participants to list greater number of context features. It is also evident from the results that the percentage of perceptual/ sensory features listed has been negligible compared to semantic categories of nouns as the action symbolized by the target words are far more abstract in nature than the concrete concepts represented by nouns. Verbs representing action thus tend to possess more features that broadly apply across wide range of semantic categories. This trend can also be a result of difference in the distinction between close semantic neighbours across the domains of nouns and verbs. For the semantic categories of nouns representing basic level concrete concepts the semantic features of close neighbours offer true distinctions while this is not true in many verbs which seem to overlap to a great extent (Vinson 2009). Thus the distinctions reported in the previous sections for properties such as number of features, featural weights for semantic categories of nouns compared to that of verbs has been again observed for the feature type distribution across these categories.

It is also interesting to note that the semantic featural makeup did show variation to some extent when decaying weights were imposed based on their feature ranks. In the semantic categories of clothing and common objects the feature type distribution had differences of about 5% for visual form and surface properties and function features. The feature types taxonomic and encyclopedic had differences up to 10% between the unit weight and decaying weight conditions. Exceptions were also seen however where for rest of the categories difference between the unit weight and decaying weight conditions did not exceed 3% for the feature types. The decaying weights nonetheless provided clear picture of the feature types listed for each category with more emphasis on features generated at the beginning of each word and use of decaying weights are highly informative in understanding the importance of each feature in represented concepts as they are dependent on participant's internal judgment of saliency of feature in describing concepts. Hence the features analyzed with decaying weights have immense significance in semantic representation and to provide semantic feature data.

The analysis of feature type distribution thus assists in understanding the role of different feature types in representation of concepts in the mental lexicon. Most of the feature types classified corresponded to primary sensory-processing channels in the brain and functional/motor information of usage of concepts that provides valuable insights about possible neural representation of conceptual knowledge for each semantic category. It also provides supporting evidence and replication of results for category-specific semantic deficits seen for living vs. nonliving things as the results show differential semantic featural makeup for living things compared to non-living things which is reported as possible explanation for such deficits.

4.2.4. Distinctive features. Another property that augments the findings of previous sections reported in the present study and which provides further detailed insights about nature of semantic feature composition is the study of distinctive features. Distinctive features are those, which are present in only two or three concepts of a category and therefore, are occur in a small group of concepts. The distribution of distinctive features has been studied extensively in English language as it is considered imperative in differentiating similar concepts from one another. Distinctive features are also very essential in providing cues to identify their corresponding concept and are vital in describing patterns of errors in persons with semantic deficits as well as organization of concepts in healthy individuals. Hence the semantic features obtained in the present study were analyzed for distribution of distinctive features. To begin with, the ratio of distinctive features to the total number of features generated for 300 words were calculated as described below.

A feature is characterized by its corresponding column in the weight matrix. A feature that is shared by no more than three words was termed as *Distinctive Feature*. Thus a distinctive feature has no more than three non-zero entries in its column vector. Features that were not distinctive were termed as *Shared Features.* For example, in the weight matrix depicted in Table 18 the summation of non-zero entries along a column gives the number of words for which the features has been generated. For instance, Feature F1 has been generated twice for words W2 and W5. Since this count is less than 3, the feature F1 is deemed distinctive. Similarly feature F3 has been reported for 5 words and hence it is deemed shared.

Table 18
Distinctive and Shared Features from Weight Matrix

	F1	F2	F3	F4	F5	F6
W1	0	0	3	5	0	2
W2	2	0	4	0	0	0
W3	0	2	1	3	2	0
W4	0	2	1	1	2	0
W5	2	1	1	1	0	2
Number of Words	**2**	**3**	**5**	**4**	**2**	**2**
Distinctive Feature	**YES**	**YES**	**NO**	**NO**	**YES**	**YES**

Note: F- Feature, W- Word.

The results revealed that the mean ratio of distinctive features produced for nouns was M = 0.13, SD= 0.08 and M = 0.22, SD = 0.15 for verbs. In order to compare whether the differences in the distribution of distinctive features across the two domains was statistically significant, two tailed Independent t- test was conducted. The test revealed a statistically significant difference (t (298) = -6.49, p < 0.001) between two domains. Hence the distinctive features generated for the domains of nouns were significantly less compared to verbs.

Distinctive features were also studied with respect to semantic categories for which the features were generated in both the domains of nouns and verbs. In the domain of nouns, out of the 10 semantic categories, highest ratio of distinctive features were present for the semantic categories ‘profession/sports’ (M= 0.28, SD= 0.09) and the least for semantic categories ‘fruits/ vegetables’ (M=0.05, SD= 0.04). The average ratio of distinctive features generated for each of the semantic category of nouns along with the standard deviation is shown in Table 19.

Table 19.
Average ratio of distinctive features –Nouns

Semantic categories	Mean	*SD*
Nouns		
Profession/sports	0.28	0.09
Nature	0.2	0.09
Body parts	0.17	0.06
Tools	0.14	0.08
Common objects	0.13	0.06
Animals	0.12	0.04
Food	0.1	0.06
Clothing	0.1	0.04
Vehicles	0.08	0.04
Fruits/vegetables	0.05	0.04

In the domain of verbs maximum ratio of distinctive features was generated for the semantic categories ‘Motion change’ (*M* = 0.33, *SD*= 0.15) and ‘state change’ (*M*= 0.32, *SD* = 0.19). The least ratio of distinctive features were produced for ‘Body sense’ (*M*= 0.16, *SD*= 0.11) and ‘Noises’ (*M*= 0.17, *SD*= 0.11).

Table 20 shows the average ratio of distinctive features to the total number of features generated for verbs along with the standard deviation.

Table 20.
Average ratio of distinctive features - Verbs

Semantic categories	Mean	SD
Verbs		
Motion change	0.33	0.15
State change	0.32	0.19
Body action	0.20	0.15
Construction/ destruction	0.19	0.10
Cooking	0.19	0.08
Noises	0.17	0.11
Body sense	0.16	0.11

With the aim of studying the distribution of distinctive features for statistically significant differences if any, with respect to semantic categories Independent t- test (for normally distributed data) or Mann-Whitney U test (for non-normally distributed data) were administered. Semantic categories of nouns and verbs included in the present study were compared against each other for distribution of distinctive features. The results of the tests revealed statistically significant difference in distribution of distinctive features for a total of 30 semantic category pairs out of 45 analyzed for the domain of nouns. It is evident from the results that the semantic category 'profession/ sports' was found to be significantly high in distribution of distinctive features compared to the semantic categories namely 'fruits/vegetables' [U (37) = 4.00, p < 0.001], 'clothing' [t (22) = 2.916, p = 0.008] 'animals' [t (38) = 2.414, p = 0.02], 'common objects' [t (45) = 2.018, p = 0.049], 'nature' [U (30) = 57.00, p = 0.01], 'food' [t (28) = 3.041, p = 0.005], 'tools' [t (21) = 3.55, p = 0.02],'body parts' [t (20) = 3.12, p = 0.005] and 'vehicles' [t (21) = 2.48, p = 0.021]. The semantic category 'nature' was significantly higher in terms of distinctive features as against the semantic categories namely 'vehicles' [U (33) = 27.00, p <0.001], 'fruits/vegetables' [U (49) = 34.50, p <0.001], 'common objects' [U (57) = 221.5, p = 0.02],'tools' [U (33) = 86.5, p = 0.02], 'food' [U (40) = 87.50, p <0.001], 'animals' [U (50) = 131.50, p <0.001] and 'clothing' [U (34) = 41.50, p <0.001]. The semantic category of 'body parts' had significantly higher distinctive feature ratio compared to semantic categories namely 'clothing' [t (24) = 3.34, p = 0.003] 'animals' [t

(40) = 3.09, p = 0.004], 'food' [t (30) = 2.94, p = 0.006],'fruits/vegetables' [U (39) = 21.50, p <0.001] and 'vehicles' [t (23) = 4.00, p = 0.001].

The semantic category 'tools', 'common objects' and 'animals' showed same trend and had significantly higher distinctive feature ratio compared to semantic categories 'fruits/vegetables' and 'vehicles' ('tools' Vs. 'fruits/vegetables' [U (40) = 58.50, p <0.001], 'tools' Vs. 'vehicles' [t (24) = 2.30, p = 0.003], 'common objects' Vs. 'fruits/vegetables' [U (64) = 149.00, p < 0.001] 'common objects' Vs. 'vehicles'[t (48)=2.74, p = 0.008] 'animals' Vs. 'fruits/vegetables' [U (57) = 117.50, p <0.001] 'animals' Vs. 'vehicles' [t (41) = 2.47, p = 0.01]).It was also noticed that the semantic categories of 'food', 'clothing' and 'vehicles' had higher distinctive feature ratio than the category 'fruits/vegetables' ('food' Vs. 'fruits/vegetables' [U (47) = 163.50, p =0.005], 'clothing' Vs. 'fruits/vegetables' [U (41) = 91.00, p = 0.002] and 'vehicles' Vs. 'fruits/vegetables' [U (40) = 122.50, p = 0.03]).

However for the domain of verbs statistically significant difference in the distribution of number of distinctive features was seen for seven semantic category pairs namely Body sense' Vs. 'state change' [U (19) = 22.00, p = 0.002] 'Body sense' Vs. 'Motion change' [U (14) = 11.50, p = 0.01], 'Body action' Vs. 'Motion change' [U (55) = 104.50, p = 0.008], 'Body action' Vs. 'state change' [U (60) = 200.50, p = 0.01], 'Motion change' Vs. 'construction/destruction' [U (16) = 16.50, p = 0.01], 'construction/destruction' Vs. state change' [U (21) = 34.00, p = 0.003] and 'Noises' Vs. 'state change' [t (21) = -2.15, p = 0.04] There was no statistically significant difference in the distinctive features generated for the remaining semantic category pairs analyzed.

4.2.4.1 Discussion. The distribution of distinctive features similar to other featural properties studied in previous sections, reveal that for the domain of nouns there were significantly less features generated as opposed to the domain of verbs. In the domain of verbs, most of the semantic features generated were unique to each word as it was relatively difficult for participants to generate features describing action depicted by the verb. This might have led to the increase in the ratio of features that are generated for only few verb concepts resulting in higher distinctive features than for the domain of nouns. However results contradicting to this finding have been reported in previous studies (Vinson, 2009) where verbs had significantly less distinctive features compared to nouns. The difference in the distribution of distinctive features noticed in the present study compared to previous studies may be explained as resulting from the influence of differences in the linguistic structures between English and Kannada. The verbs in Kannada are more abstract and relational with many morphological forms due to agglutinating structure of Kannada as opposed to verbs in English (Schiffman, 1979). This might have resulted in increased idiosyncratic features adding up to the ratio of distinctive features of verbs compared to nouns.

The distribution of distinctive feature ratio was also studied with respect to each semantic category of nouns and verbs. The results for the semantic category of nouns reveal that the category of profession/sports and nature had significantly more number of distinctive features (Table 19) compared to others. These categories have highest distinctive features because their items may not be very similar to each other and participants have generated different set of features to describe them. Thus they share very less features from the rest of the items within the category. The semantic categories of tools and common objects were found to have greater distinctive feature ratio compared to fruits and vegetables, clothing, vehicles, food and animals. This pattern has been previously reported in literature (Cree & McRae, 2003) where the concepts belonging to the domain of nonliving things such as items from the category tools and common objects are found to possess greater number of distinctive features compared to living things such as animals and fruits and vegetables. The semantic category of animals was found to possess more number of distinctive features than fruits/vegetables. However Cree and McRae (2003) report that the category of fruits/ vegetables tend to group between living things and nonliving things possessing distinctive features significantly more than living things but less than nonliving things.

The pattern of results obtained in the present study thus provides evidence for difference in the nature of representation of in terms of distinctive features between living things and nonliving things. These differences manifested in the present study provide further evidence for the possible explanation of category specific semantic deficits. The semantic category of living things such as animals tend to have less number of distinctive features in their featural makeup making them more susceptible to damage than nonliving things (such as tools and common objects). The distinctive features being very crucial in identifying and distinguishing the target concept from a set of similar ones (Gonnerman et al., 1997), brain damage leading to loss of these distinctive features may thus present as severe semantic deficits in case of living things which already have less distinctive features than nonliving things. This may explain the pattern of category specific deficits where living things are more affected than nonliving things.

The semantic categories of verbs did not differ from each other much in terms of distinctive feature distribution. There were significant differences seen for seven semantic category pairs as opposed to semantic categories of nouns where 30 category pairs showed significant difference. In spite of the fact that the domain of verbs resulted in more number of distinctive features than nouns in the present study, the difference in distribution at the category level for verbs was not significant for more than seven pairs out of 21 pairs analyzed. The results thus follow the tendency seen for categorization of verbs were in they lack clear distinctions among semantic categories with respect to semantic feature distribution which is so prominently present for semantic categories of nouns (Vinson, 2009). Thus study of distinctive features contributes to the understanding of unique features involved in the semantic featural makeup of individual words. Further insights about features that are present in two or more concepts help to better comprehend the nature of sharing of semantic features among similar words. Hence the analysis of shared features among words was carried out in the next section.

4.2.5 Shared features. Following distinctive feature analysis, the data was subjected to analysis of shared features that helps to understand the nature of relation of features generated. Since shared features are present in the featural make up of two or more concepts, analysis of these features shed light on the relationship among the concepts. It also plays crucial role in conceptual organization, as concept similarity in terms of featural overlap is a primary organizational principle of semantic memory (McRae & Boisvert, 1998). In the present study, the distribution of shared features was analyzed by initially calculating the total number of features that were present in three or more concepts as described in the section on distinctive features in Table 18. Next step involved calculating the ratio of shared features to that of total number of features generated for each word across the domains of nouns and verbs. The average ratio of shared features produced to that of total number of features for nouns was *M*= 0.87, *SD*= 0.08 and *M*= 0.77, *SD*= 0.15 for verbs respectively. In order to compare whether the differences in the distribution of shared features across two domains was statistically significant, two-tailed Independent t- test was administered. The test revealed a statistically significant difference (t (298) = 6.49, $p < 0.001$) between two domains. Hence there was a significant difference in the distribution of shared features for the domains of nouns and verbs.

The distribution of shared features was also studied with respect to semantic categories for which the features were generated in both the domains of nouns and verbs. In the domain of nouns, out of the 10 semantic categories, maximum shared features were generated for the semantic categories ‘Fruits/vegetables’ (*M* = 0.94, *SD* = 0.05) and the least number of features for semantic categories ‘profession/sports’ (*M* = 0.72, *SD* = 0.09). The average ratio of shared features generated for each of the semantic category of noun along with the standard deviation is shown in Table 19.

Table 21
Average ratio of shared Features - Nouns

Semantic categories Nouns	Mean	SD
Fruits/vegetables	0.94	0.05
Vehicles	0.91	0.05
Clothing	0.90	0.05
Food	0.89	0.06
Animals	0.88	0.04
Common objects	0.86	0.06
Tools	0.85	0.09
Body parts	0.82	0.06
Nature	0.80	0.09
Profession/sports	0.72	0.09

In the domain of verbs highest ratio of shared features was generated for the semantic categories ‘Body sense’ (*M* = 0.84, *SD* = 0.11) and ‘Noises’ (*M* = 0.83, *SD* = 0.11) and the least for ‘motion change’ (*M* = 0.68, *SD* = 0.19) and ‘state change’ (*M* = 0.68, *SD* = 0.15). Table 22 shows the average ratio of features generated for verbs along with the standard deviation.

Table 22.
Average ratio of shared Features for Verbs

Semantic categories	Mean	SD
Verbs		
Body sense	0.84	0.11
Noises	0.83	0.11
Cooking	0.81	0.08
Construction/ destruction	0.81	0.10
Body action	0.80	0.15
State change	0.68	0.19
Motion change	0.68	0.15

With the aim of studying the distribution of shared features for statistically significant differences if any with respect to semantic categories Independent t- test or Mann-Whitney U test was administered. Semantic categories of nouns and verbs included in the present study were compared against each other for the distribution of shared features.

The results of the tests revealed statistically significant difference in distribution of shared features for a total of 30 semantic category pairs out of 45 analyzed for the domain of nouns. It is evident from the results that the semantic category ‘fruits/vegetables’ was found to be significantly more in distribution of shared features compared to all the semantic categories namely ‘profession/ sports’ [*U* (37) = 4.00, $p<0.001$], ‘tools’ [*U* (40) = 58.50, *p* <0.001], ‘animals’ [*U* (57) = 117.5, $p<0.001$], ‘clothing’ [*U* (41) = 91.00, $p=0.02$], ‘food’ [*U* (47) = 163.50, $p=0.005$], ‘common objects’ [*U* (64) = 149.00, $p<0.001$], ‘vehicles’ [*U* (40) = 122.5, $p= 0.03$], ‘nature’ [*U*

(37) = 34.5, $p<0.001$] and ‘body parts’[U (39) = 21.50, p <0.001]. The semantic category of ‘vehicles’ also showed similar trend with significantly more shared features compared to same categories namely ‘profession/ sports’ [t (21) = 3.966, p = 0.001], ‘tools’ [t (24) = 2.738, p = 0.011], ‘common objects’ [t (48) = 2.74, p =0.008], ‘animals’ [t (41) = 2.47, p =0.01], ‘nature’ [U (37) = 27.00, p <0.001] and ‘body parts’ [t (23) = 2.38, p = 0.025]. Similarly, the semantic category of ‘clothing’ had more number of shared feature compared to the semantic category of ‘profession/ sports’ [t (22) = 2.994, p = 0.006], ‘nature’ [U (34) = 41.50, p <0.001] and ‘body parts’ [t (24) = 3.34, p = 0.003]. The semantic category of ‘food’ had more number of shared feature compared to the semantic category of ‘profession/ sports’ [t (28) = 3.405, p = 0.002], ‘body parts’ [t (30) = 2.94, p = 0.006] and ‘nature’ [U (40) = 87.50, p < 0.001]. The semantic categories of ‘animals’ was also found to be significantly more in distribution of shared features compared to the semantic categories namely ‘profession/ sports’ [t (38) = 4.243, p < 0.001], ‘nature’ [U (50) = 131.50, p <0.001] and ‘body parts’ [t (40) = 2.086, p = 0.043]. The semantic category of ‘common objects’ also had significantly more number of shared features compared to ‘profession/ sports’ [t (45) = 4.182, p < 0.001] and ‘nature’ [U (57) = 221.50, p= 0.002], as also ‘tools’ Vs. ‘profession/ sports’ [t (21) = 3.55, p = 0.002],‘tools’ Vs. ‘nature’ [U (33) 86.50, p = 0.02], ‘body parts’ Vs. ‘profession/ sports’ [t (32) = 3.11, p = 0.005] and ‘nature’ Vs. ‘profession/ sports’ [U (20) = 57.00, p = 0.001].

However for the domain of verbs statistically significant difference was seen for seven semantic category pairs. The semantic category ‘Motion Change’ had significantly less shared feature ratio as against the semantic category ‘Body action’ [U (55) = 104.50, p = 0.008], ‘construction/destruction’ [U (16) = 16.50, p = 0.01], ‘Body sense’ [U (14) = 11.50, p = 0.001] and ‘Noises’ [t (16) = 2.49, p = 0.02]. Similarly the semantic category ‘state change’ had significantly less shared feature ratio as against the semantic category ‘Body action’ [U (60) = 200.50, p = 0.01], ‘construction/destruction’ [U (21) = 34.00, p = 0.03] and ‘Body sense’ [U (19) = 22.00, p = 0.02]. There was no significant difference in the shared features generated for the remaining semantic category pairs analyzed.

4.2.5.1 Discussion. Along with the featural properties studied so far, the study of shared features is also essential as they provide valuable information about the similarity among concepts that plays crucial role in organization and categorization of concepts. In the present study, the distribution of shared features was initially analyzed across the obtained semantic features with respect to domains of nouns and verbs without considering the semantic categories for which the concepts belonged. The results revealed that the domain of nouns had significantly higher ratio of shared features compared to the domain of verbs. Unlike the results reported in previous studies (Vinson, 2009) where verbs representing action tend to have higher number of shared features, the present study showed opposite pattern. This trend is similar to the results obtained for distinctive features, which is a complementary set to shared features. In the present study, as explained for distinctive features, the increased level of difficulty for generation of features describing verbs than nouns may have caused less uniformity and hence less common features among words describing verbs.

The semantic feature data were also analyzed for distribution of shared features with respect to each semantic category. The results show that the semantic category of fruits/vegetables and vehicles shared a higher number of semantic features within their semantic categories whereas categories such as nature and profession/sports had very few semantic features in common with other categories. This can be attributed to the nature of semantic categories, for instance most of features generated to describe the words in the category profession/sports were based on the description of the job or the rules of a sport. Hence these features are unique to each word resulting in few shared features. On the other hand the semantic categories such as vehicles, fruits and vegetables may have inconsequential variability in the features describing their function or visual forms which has resulted in increased number of common features. Congruent findings have been reported for the semantic categories vehicles, fruits and vegetables by Vinson (2009). The mean number of shared features for the categories of animals, clothing, food, tools, common objects and body parts were found to range between the mean values reported for fruits/vegetables and profession/sports in the present study, contrasting the previous findings (Vinson, 2009) which reports the mean number of shared features is smallest for the category of animals, body parts and common objects.

The semantic categories of verbs shared the maximum number of features within the category body sense, noises and minimum number of features with state change and motion change. The ratio of shared features for the semantic categories of verbs were found to be less, ranging from 0.68 to 0.84 compared to semantic categories of nouns ranging from 0.72 to 0.94. The results of the tests for the semantic categories of verbs however agree with previous findings revealing less significant differences among verb categories compared to that of nouns. The 30 semantic category pairs out of 45 were statistically significant across the domain of nouns whereas for the domain of verbs statistically significant difference was seen for seven semantic category pairs out of 21 analyzed. This trend may be again because the semantic categories of nouns tend to be organized into separable categories whereas semantic categories of verbs more often tend to have less variability among features (Vinson, 2009). Thus shared features also contribute to the understanding of categorization in the domain of nouns and verbs as they tend to follow similar pattern as the other featural properties studied in the previous sections.

4.2.6. Featural correlation. It is interesting to study further, whether the features generated for the concepts analyzed so far in the present study, are independent pieces of information or do they share any relations to one another with respect to the concepts for which they are listed. Previous studies (Malt & Smith, 1984) done in English claim that the semantic features listed for any item of any category are not independent to one another rather they occur in systematic relation to one another and this featural correlation is one of the organizational principles of the mental lexicon. The features obtained from the present study, were thus subjected to analysis in order to understand the occurrence and relation of one feature if any with respect to another. For this purpose, the features were analyzed for correlation with respect to one another by evaluating their corresponding feature weights. In order to avoid idiosyncratic responses and spurious correlation, a feature was considered for correlational analysis only if it appeared five or more times in the response of participants. The selection criteria resulted in a total of 1,226 features in the domain of nouns and 643 features in the domain of verbs. The possible feature pairs that can be paired and analyzed against each other were 1,226 x 1,226 which resulted in 7,50,925 feature pairs for nouns and 643 x 643 which resulted in 2,19, 453 feature pairs for verbs. In order to carry out analysis on such large number of pairs, which is manually impossible, and highly error prone, a python script was written which automates the analysis to a great extent and provides accurate errorless results. These feature pairs were thus subjected to statistical analysis using Pearson's product moment correlation. The results revealed that out of 7,50,925 feature pairs 8,153 pairs had statistically significant positive correlation in the domain of nouns with the correlation coefficient (r) ranging from 0.13 - 0.99 ($p < 0.05$). Out of 8,153 pairs 280 pairs had high positive correlation with correlation coefficient value ranging from 0.75- 0.99 ($p < 0.05$). For the domain of verbs 1514 out of 2,19,453 feature pairs had significant positive correlation with the correlation coefficient (r) ranging from 0.19 - 0.99 ($p < 0.05$). Out of 1514 feature pairs, 148 pairs had high positive correlation with correlation coefficient value ranging from 0.75- 0.99 ($p < 0.05$).

In order to study correlation of semantic features for specific semantic categories, the features listed at least five times for the respective categories were considered in order to avoid spurious correlations. Correlational analysis of the feature pairs for each semantic category of nouns and verbs are shown in Table 23. The table also depicts number of significantly correlating feature pairs and number of feature pairs with high positive correlations along with Pearson's product moment correlation coefficient (r) value range.

Table 23.

Number of correlated feature pairs (range of r value in parenthesis with p<0.05).

Semantic categories	Correlated Feature pairs	Highly correlated feature pairs
Common objects	429	57
	(0.32-0.97)	(0.75-0.97)
Animals	419	47
	(0.36-0.98)	0.76-0.98)
Nature	261	65
	(0.42-0.99)	(0.75-0.99)
Fruits/vegetables	245	12
	(0.36-0.88)	(0.75-0.88)
Food	267	74
	(0.40-0.98)	(0.75-0.98)
Clothing	119	28
	(0.53-0.99)	(0.75-0.99)
Vehicles	85	24
	(0.55- 0.96)	(0.76-0.96)
Body parts	30	18
	(0.57-0.96)	(0.76-0.96)
Tools	26	5
	(0.55-0.93)	(0.79-0.93)
Profession/ sports	3	2
	(0.71-0.91)	(0.75-0.91)
Body action	242	40
	(0.28-0.98)	(0.75-0.98)
Sounds	11	8
	(0.66-0.97)	(0.75-0.97)
Body sense	1	
	(0.65)	
Construction/destruction	1	
	(0.73)	

4.2.6.1 Discussion. The present analysis was carried out in order to identify possible feature relations in the mental lexicon for Kannada for nouns and verbs and their semantic categories. The results of the analysis reveal that many features tend to occur in systematic relation to each other. This has also been reported in several studies of semantic memory (McRae, Cree, & Westmacott, 1999; McRae, De Sa, Seidenberg, 1997; Malt & Smith, 1984) and category specific semantic deficits (Cree & McRae, 2003; Devlin et al., 1998; Gonnerman et al., 1997). Similar to above studies, the present study also revealed many features correlating with each other which cannot be just attributed to chance ascertaining that there could be contribution of feature correlations to the semantic organization and structure of mental lexicon (Malt & Smith, 1984; Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976). It is also evident in the results of featural correlation some relations among the members of a category are readily noticed as they are more apparent and there is a coherent theory why they co-occur. While these relations are explicit, some of the feature co-occurrence do not have logical explanations besides being subtle and therefore are considered essentially arbitrary for the casual observer (Malt & Smith, 1984). Such relations are implicit and statistically based and considerable amount of correlated feature knowledge may be of implicit nature (Holyoak & Spellman, 1993) which appears as co-variation in the environment and people learn these without intention or awareness (McRae, de Sa, Seidenberg, 1997). It is also evident from the results that the correlations are not uniformly distributed across all the domains and semantic categories. The number of feature pairs with significant correlation varies with respect to domains of nouns and verbs with nouns possessing around 8,153 feature pairs as opposed to 1,514 feature pairs in verbs. This difference can be because the relation between the featural properties may be stronger and more consistent in cases of nouns than the verbs as nouns have clear semantic category boundaries with members within the category sharing many features with the other members. This nature of noun categories leads to more number of features to correlate with one another in order to form tighter category structure. It can also be attributed to the fact that participants had generated significantly lesser number of features for the verbs than for the nouns. Thus having less number of features generated in the data because of the relational and context dependent nature of verbs, there were fewer pairs available for comparison which might have also led to the present results The semantic categories of nouns and verbs were analyzed to see whether feature correlations differed across these categories. Substantial variability was seen as there were huge differences across categories even within the domain of nouns, for instance the number of feature pairs with significant correlation ranged from 429 pairs for common objects to just 3 pairs for profession/sports (Table 23). Nonetheless semantic categories of nouns had greater number of feature pairs with significant correlation than verb categories. The semantic category of common objects had highest number of correlating feature pairs (429 pairs) followed by semantic category of animals, which also had substantial number of correlating features (419 feature pairs). The greater number of correlating features may indicate that the semantic features generated form coherent sets that are greatly similar and shared among most of the members of the category. The results also reveal that there was more number of features correlating in case of living things (664 feature pairs for the categories animals and fruits/ vegetables combined) than in the domain of nonliving things (540 feature pairs for common objects, tools and vehicles combined). Similar trend for living and nonliving things have been reported in number of studies (McRae et al., 1997; Keil, 1989; Gelman, 1988) which state that overall feature correlations are stronger and denser within living things and has greater influence in representation of living things. This quantitative variation in distribution of feature correlation among living and nonliving things have also been hypothesized to be leading to category specific semantic deficits (McRae & Cree, 2002) with differential severity of impairment in living vs. nonliving semantic categories.

For the semantic categories of verbs, the feature correlation was very sparse compared to that of noun categories (Table 23). The category body action was the only one observed to have significant correlation for 242 feature pairs and 11 pairs were significant for the semantic category noises. The reason for the sparse correlation of features noted in the semantic categories of verbs can be because verbs being more abstract and contextually dependent may have posed difficulty for the participants in extracting featural relations and producing a coherent set of features that may co-occur across the category. These results may also be reflection of the nature of verb categorization trends where strict category boundaries are absent and hence less features among categories correlating with one another. Thus feature correlations have important consequences for categorization of concepts, in representation of word meanings in the mental lexicon.

4.3 Model of Mental Lexicon

Objective 2: To develop a framework for a model of lexical semantic representation and organization in Kannada using semantic features.

The mental lexicon as stated earlier is considered a huge collection of words referring to concepts of a language assumed to be structured based on certain organizational principles. The framework for the proposed model of mental lexicon in Kannada using the semantic feature data obtained from the present study is based on the two assumptions namely componentiality and similarity of semantic features. By assuming componentiality the meanings of the words are considered to be stored as smaller units of information or semantic features. Similarity resulting from the extent of overlap of semantic features has been hypothesized in this current model to result in the clustering of the words into specific semantic categories that forms the second assumption. In the present study, as described earlier in section 4.1, a word x feature matrix was generated using the feature weights where each cell represents the feature weight of the feature corresponding to the word. Feature weight was considered as it accounts for the salience of each feature in describing the meaning of the word for which it is generated. Thus if more participants have generated a feature higher will be its feature weight value. The word x feature matrix of the order 300 x 1889 was obtained which formed the input to the model. Therefore every word had a vector of length 1,889 associated with it. In order to generate the model based on the principle of similarity of semantic features, the 300 word pairs were compared against each other with respect to their feature weights across 1,889 features.

4.3.1 Modeling of similarity. In order to visually represent the possible organization of words in the mental lexicon, the cosine between vectors associated with each pair of words was employed as a measure of similarity. Apart from cosine similarity other tools have also been considered in literature to calculate the semantic distances and similarity. The selection of appropriate metrics largely depends on the objectives of the individual study. For instance, self-organizing maps (SOMs) have been used as a means to obtain semantic distances (Vinson, 2009) which facilitates comparison of the resulting semantic distances and representation with neuroimaging studies as SOM's are suitable for dimensionality reduction and 2D planar representation similar to the results of neuroimaging studies. However the concern about the use of SOM's is that the reduction of a higher dimensionality into lower ones may lead to coincidental proximity among the words as the distances on the spatial map may not correspond to distances in the prototype space of the model (Vinson, 2009).

4.3.1.1 Cosine Similarity. The cosine similarity measure was considered suitable for the present data as it calculates the similarity for each word by capturing the cumulative influence of the feature vectors of both the words in predicting the similarity. It is based on the dot product of the feature vectors and does not involve dimensionality reduction. The cosine distances were calculated using the following formula:

$$\text{similarity} = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} (A_i)^2} \times \sqrt{\sum_{i=1}^{n} (B_i)^2}}$$

For example, in the weight matrix below, both words have vectors of dimension 4 associated with them. Calculation for cosine similarity is done as shown

	F1	F2	F3	F4
Word 1	**3**	2	0	**2**
Word 2	**4**	0	4	**3**

$$cos(\theta) = \frac{3*4+2*0+0*4+2*3}{\sqrt{3^2+2^2+0^2+2^2}*\sqrt{4^2+0^2+4^2+3^2}}$$

$$cos(\theta) = \frac{18}{\sqrt{17}*\sqrt{41}} = \frac{18}{4.12*6.40} = \frac{18}{26.37} = 0.68$$

As can be seen above, only those entries that are *non-zero in both* word vectors increase the value of the numerator and hence the similarity value. This property of cosine similarity is advantageous because *we want higher similarity score between words that have features common between them*. In contrast, a measure such as Euclidean distance is meant to measure the *dissimilarity* between two vectors. While it is possible to use a dissimilarity measure 'D' to arrive at a similarity measure 'S' using the formula $S = 1/(D+1)$, measures such as Euclidean distance can produce false positives for vectors with high dimensionality. For these reasons, Cosine Similarity was preferred over Euclidean Distance and other measures.

4.3.1.2 Discussion. The total number of similarity calculations was carried out on 44,850 word pairs. For each of these word pairs the cosine distances had to be computed across the vector of length 1,889. This resulted in a total number of computations equivalent to 44,850 x 1889 x 2 = 16,94,43,300. A python program was written to automate the task of computation of cosine similarity and to produce output of the result in an excel file (A list of six most similar words along with their similarity value for the 300 words has been uploaded and is available for viewing at http://tinyurl.com/lexicalstudy). The data in the excel sheet was exported to JSON format (JavaScript object notation) and the results visualized using a JavaScript framework. The following graphs were generated to visualize the cosine distances depicting similarities of words with respect to each other. The visualizations have been uploaded and are available for viewing at http://tinyurl.com/lexicalstudy-model. Therefore the graph depicts the connections each word may have with its most similar words based on their similarity measure. Following are the graphs obtained for each semantic category of nouns and verbs analyzed in the current study.

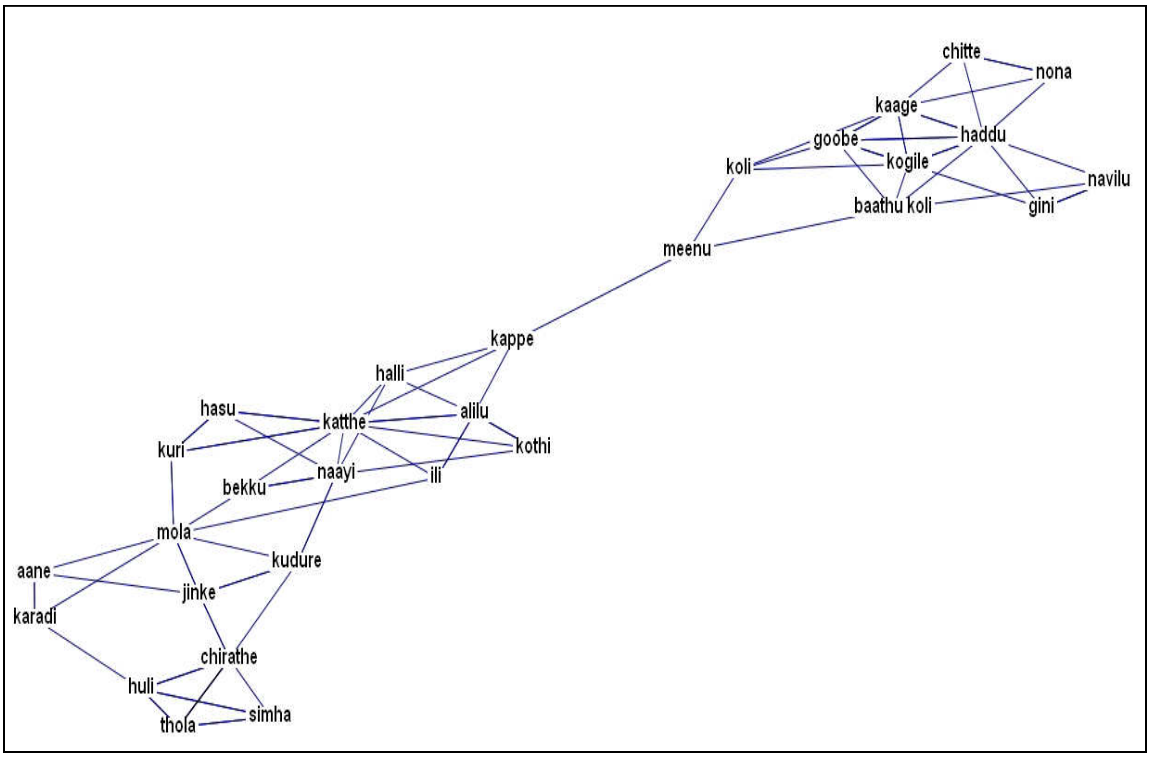

Figure 11.Cosine distances of semantic category- animals

Figure 11, obtained for the words belonging to category of animals depict that the words referring to birds form a separate group from words referring to domestic and wild animals. Also interesting is the connection between ‘frog' '/kappe/ and fish /mi:nu/ which is at the intersection of these two groups. Intuitively it is natural that even within the category of animals the birds will be grouped together and ‘fish’ and ‘frog’ being aquatic and amphibians are grouped separately. The connections in *Figure 11* are thus consistent with the intuitive judgment of similarity.

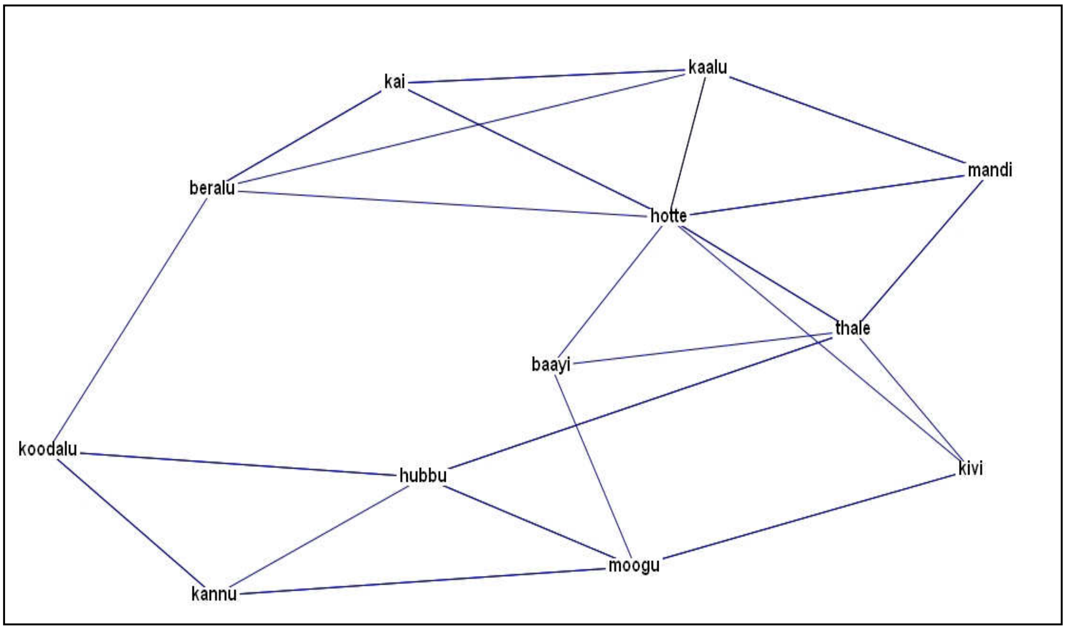

Figure 12.Cosine distances of semantic category- body parts

Figure 12 depicts the interconnections of words belonging to semantic category of body parts. The words have been connected on the basis of their semantic similarities obtained through sharing of features.

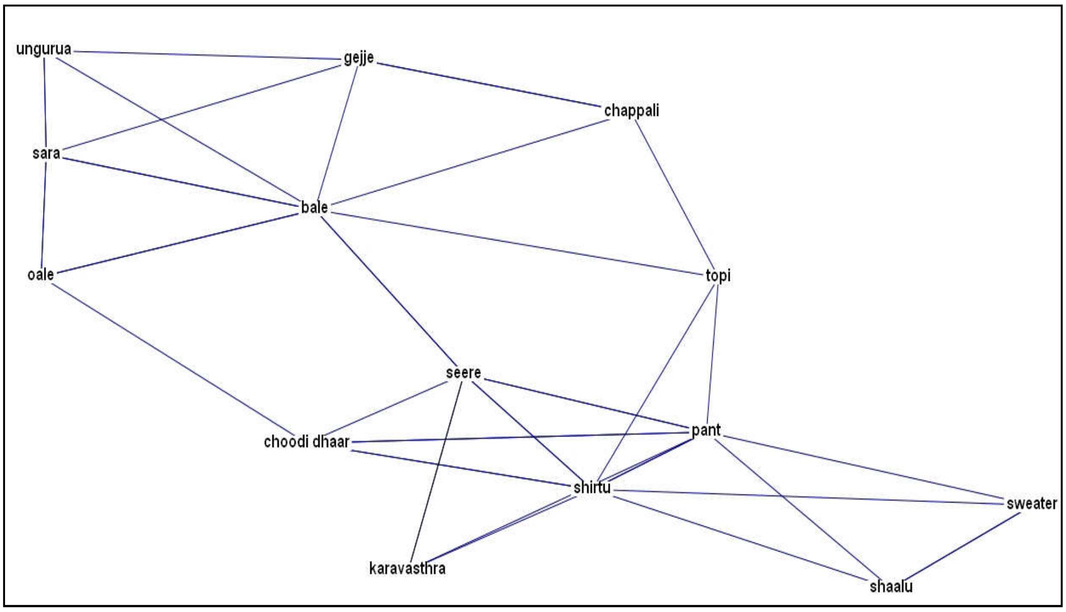

Figure 13.Cosine distances of semantic category- clothing

Figure 13 shows that in the category of clothing, the words referring to typical clothing items such as shirt, pant etc. are grouped together and are away from the words which are not so typical clothing items such as bracelet (/bale/), ring (/ungura/). Hence it is comparable to the intuitive similarity and effect of typicality among these words.

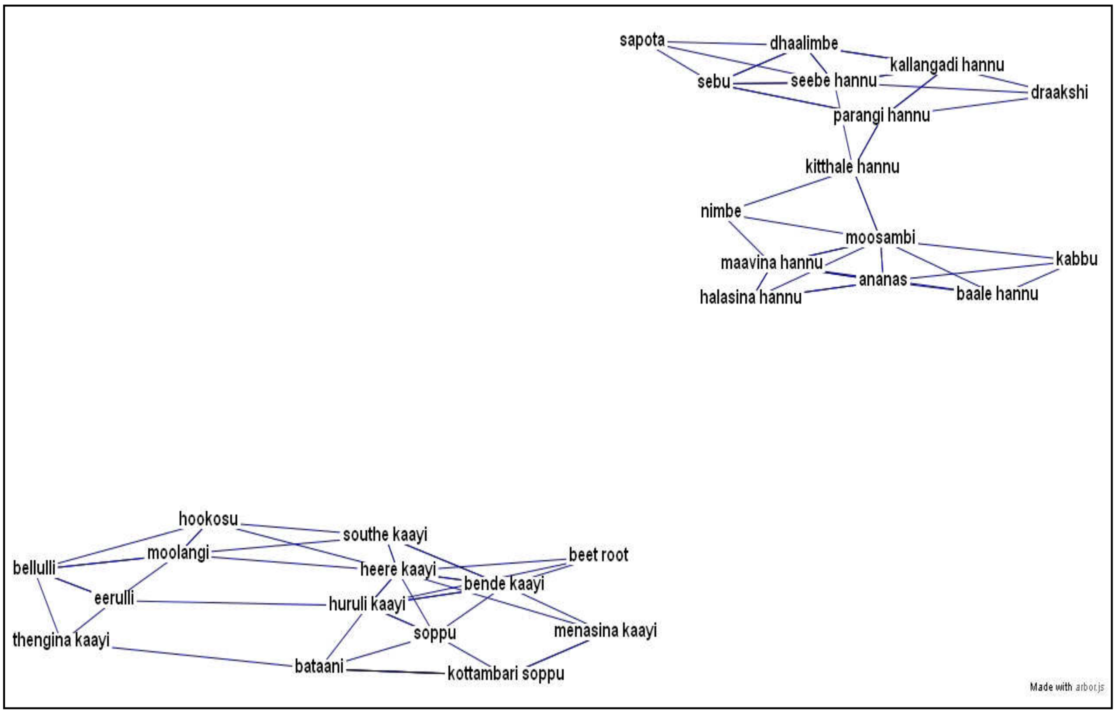

*Figure 14.*Cosine distances of semantic category- fruits/vegetables

Similarly the *Figure 14* reveals the interconnections among the words referring to fruits and vegetables. It is clear from the graph that the words referring to fruits have formed a separate group as they tend to be more similar than words referring to vegetables. This segregation is coherent with the intuitive categorization of these words into fruits and vegetables. Hence the data quantitatively supports the notion of categories of fruits and vegetables.

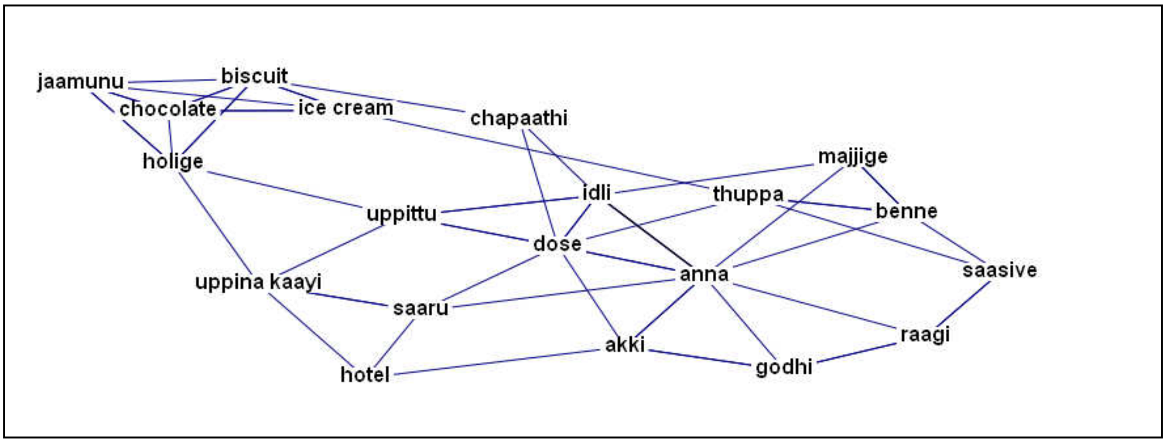

*Figure 15.*Cosine distances of semantic category - Food

The interconnections of words belonging to the semantic category of food are depicted in the above Figure 15. As it can be seen all the words grouped into this category form close connections and are in congruence with the intuitive categorization.

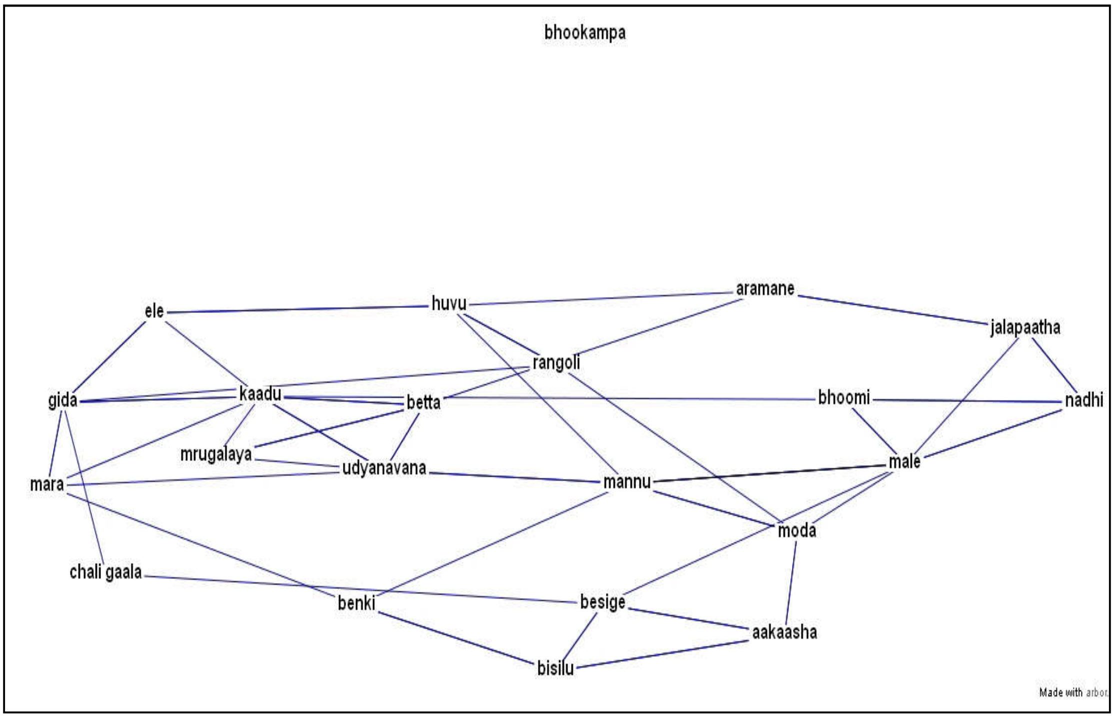

*Figure 16.*Cosine distances of semantic category- nature

The semantic category of nature has been depicted in the *Figure 16.* The interconnections of words with relation to each other can be observed. It is also seen that the word /bho:kampa/ which was grouped intuitively into this category did not show any noteworthy similarity with other words in the category and hence did not result in any connection with other members of the category.

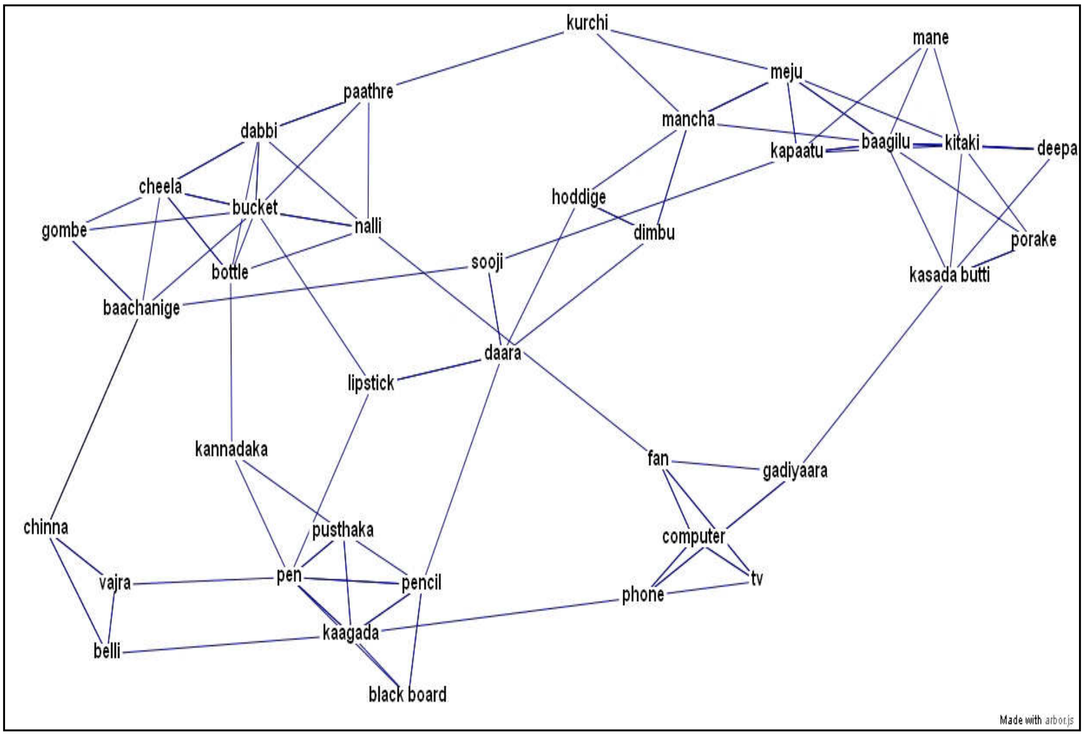

*Figure 17.*Cosine distances of semantic category- common objects

The *Figure 17* shows the interconnections of words referring to common objects. The graph depicts that these common objects have again formed small groups among themselves forming subordinate categories, for instance, the words referring to TV, computer, phone and fan have formed a group and are close together even though they are connected to other members of the category. Similarly the words /chinna/ (gold), /vajra/ (diamond) and /belli/ (silver) have formed a group and so are typical household items.

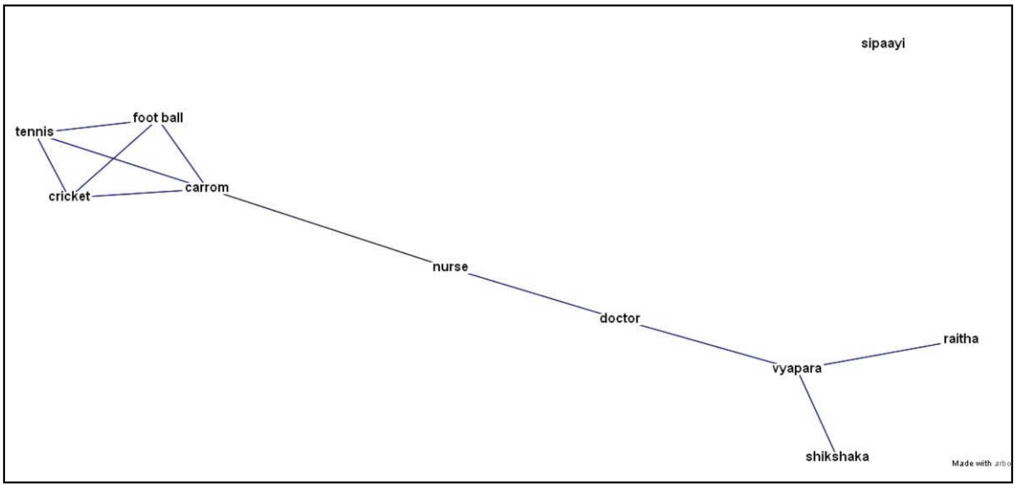

*Figure 18.*Cosine distances of semantic category- profession/ sports

The cosine distances for the words in the semantic category profession/sports and sports have been depicted in the above *Figure 18*. As in the graph the words referring to sports formed a separate group away from words referring to profession. However the word /sipa:yi/ (soldier) tends to show no connections or similarity with any other typical members of the category.

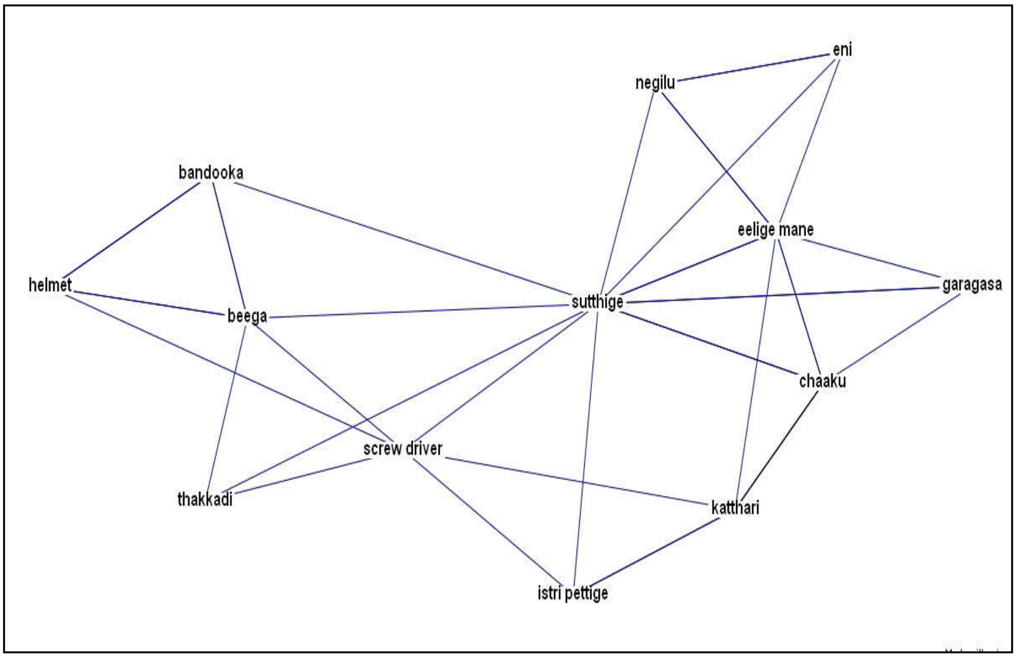

*Figure 19.*Cosine distances of semantic category- tools

The *Figure 19* shows the interconnections of words referring to tools have with each other. The figure reveals that the members intuitively chosen as a category indeed share similarity with other members of the category and have closely related connections with other members of the category.

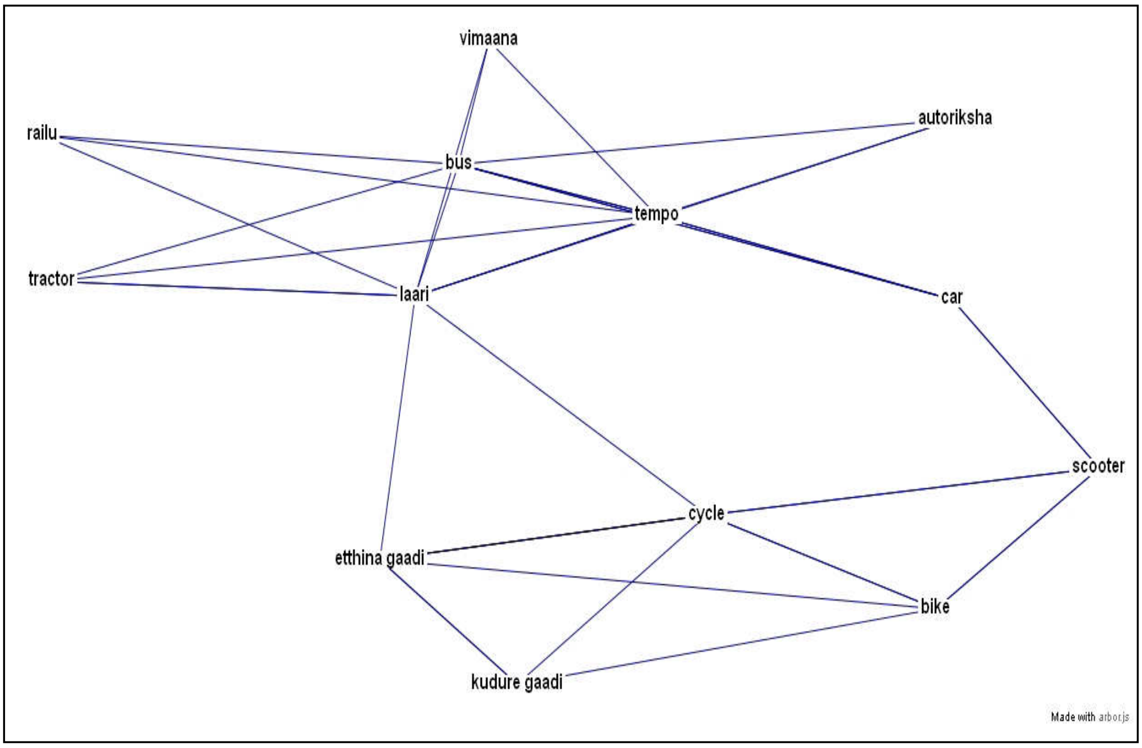

*Figure 20.*Cosine distances of semantic category- vehicles

The semantic category of vehicles as been depicted in the *Figure 20* with the cosine distances the words share with each other. Similar to the category of tools, all the members of the category form a closely related group without any outliers.

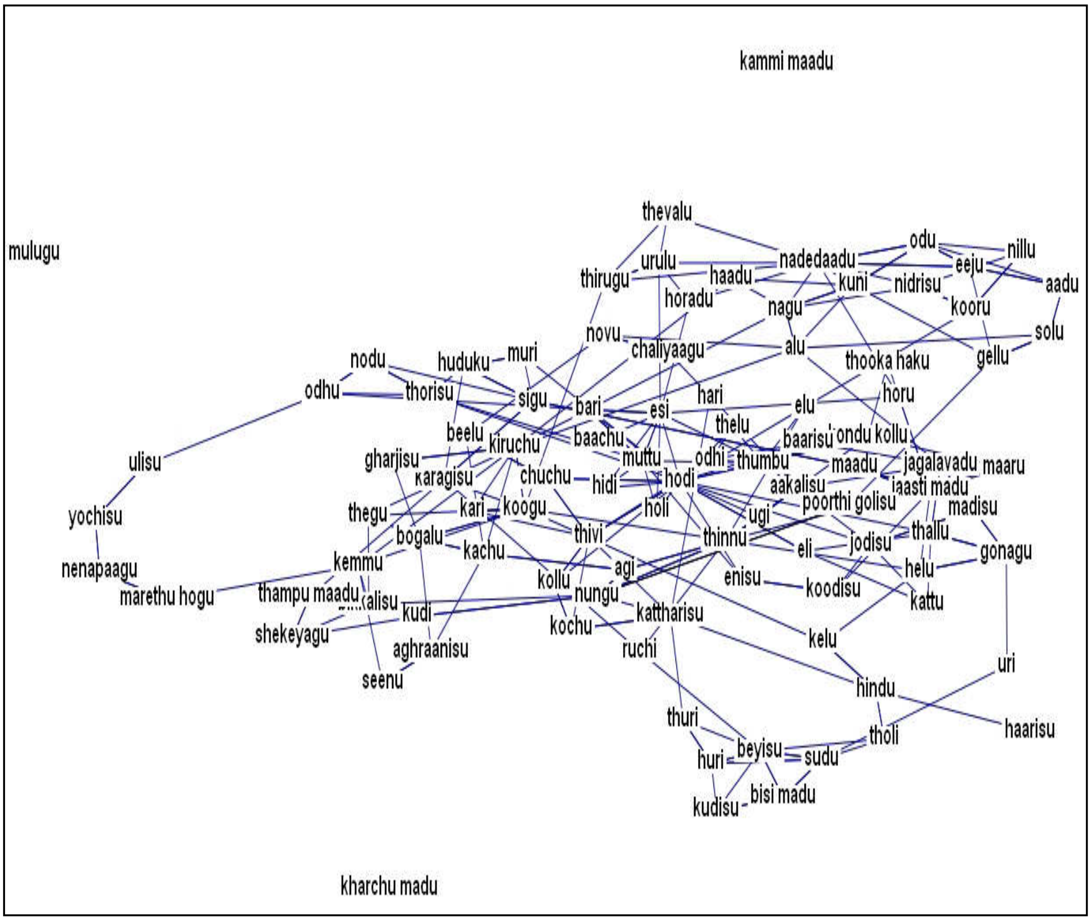

Figure 21.Cosine distances of verbs

The above *Figure 21* depicts the cosine distances of all the verbs together. It is evident from the graph that congruent to intuitive categorization, words belonging to categories such as cooking, body action and noises have clustered together. It is also true that the some of the words did not maintain strict categorization and occurred together even though they were intuitively not classified as belonging to same category. This trend may have resulted because verbs, unlike nouns tend to lack clear boundaries across semantic categories. Few of the words did not show any possible similarities with other words hence were segregated from the clusters (E.g., /mulugu/). Such differences are highly imperative in understanding the differences between people's intuition for categorizing a member to that of actual principles of categorization that work in the mental lexicon.

Hence in the present model, the interconnections among words belonging to the domain of nouns and verbs were visually represented based on their semantic similarity extracted by their semantic feature properties. The model provides the clustering patterns of the words built on their semantic similarities, into respective semantic categories, thus providing an insight into organization of mental lexicon on the principle of semantic similarity i.e. relation of one word with respect to other.

4.3.2. Cosine distances within and across semantic categories. The cosine distances obtained were further studied in order to see whether similar words are depicted closer in the model than dissimilar ones based on their semantic categories. Hence each target word was compared for the cosine distances it might have with words belonging to the same semantic category as the target word and with the words belonging to the rest of the semantic categories. Thus within-category mean cosine distances and across-category mean distances were calculated for 10 noun categories and 7 verb categories. The results show that the mean distances for words within the semantic categories are significantly ($p< 0.05$) less for all semantic categories of nouns and verbs than the mean distances across-category. The across-category and within-category mean cosine distances and their differences for all the semantic categories of nouns and verbs have been depicted in Table 24 and Table 25 respectively

Table 24.
Mean and SD of cosine distances- noun semantic categories

	Mean cosine distances		
Semantic category	Across category	Within category	Difference
Animals	977.53 (11.24)	719.86 (75.41)	257.67 (80.42)
Body parts	982.02 (16.62)	801.39 (30.17)	180.63 (39.37)
Clothing	966.09 (10.25)	735.88 (51.68)	230.21 (45.41)
Common objects	969.47 (12.07)	881.30 (30.94)	88.17 (24.72)
Food	961.81 (11.47)	795.92 (53.07)	165.89 (50.35)
Fruits/vegetables	966.67 (9.08)	627.63 (67.26)	339.04 (65.59)
Nature	975.85 (17.73)	902.77 (26.02)	73.08 (26.63)
Profession/ sports	984.20 (10.83)	837.94 (40.03)	146.26 (37.46)
Tools	971.47 (6.76)	780.79 (50.80)	190.67 (49.84)
Vehicles	980.71 (5.26)	552.19 (57.57)	428.52 (58.21)

Table 25.
Mean cosine distances- verb semantic categories

	Mean cosine distances					
Semantic category	Across category		Within category		Difference	
Body action	963.09	(17.77)	924.99	(28.69)	38.10	(15.52)
Body sense	978.23	(15.07)	835.27	(14.54)	142.96	(22.00)
Construction/ destruction	961.65	(14.76)	827.95	(34.10)	133.70	(25.86)
Cooking	969.24	(6.90)	573.25	(62.97)	395.99	(64.40)
Motion change	965.82	(17.49)	842.84	(21.21)	122.98	(8.18)
Noises	969.53	(13.57)	771.60	(56.85)	197.93	(47.32)
State change	970.52	(19.73)	904.42	(13.70)	66.10	(12.10)

The differences in the mean cosine distances across and within semantic categories in the domain of nouns (Table 24) show that the semantic category of vehicles (*M* = 428.52; *SD*= 58.21) have highest difference followed by fruits/vegetables (*M* = 339.04; *SD*= 65.59), animals (*M* = 257.67; *SD*= 80.42) and clothing (*M* = 230.21; *SD*=

45.41). The least difference is seen for the category nature (*M* = 73.08; *SD*= 26.63). In the semantic categories of verbs, the differences in mean distances (Table 25) are smaller compared to noun semantic categories. The highest mean difference was present for the category cooking (*M* = 395.99; *SD*= 64.40). The least mean difference was seen for body action (*M* = 38.10; *SD*= 15.52). The greater difference indicates that the words belonging to same category are closer to each other and form a tighter cluster. In the present study this tendency was seen more often in the noun categories. The semantic categories of verbs had relatively less differences indicating there were no clear category boundaries. Thus the cosine distances obtained in the present study clearly illustrates the differences in the categorization patterns across nouns and verbs in the mental lexicon. This pattern of differences in categorization is also reported for number of features, distinctive features, shared features, featural weight and feature types in the present study, which augments the present findings in this section.

The structure of mental lexicon and conceptual knowledge is also influenced by higher linguistic and cognitive abilities such as inferential knowledge, reasoning, judgement, visual-spatial knowledge and context. The present model is however based on written semantic features that are dependent on verbal language skills and the verbal language might be unable to capture few aspects of visual-spatial knowledge an individual may possess in the representation of the concept. The linguistic factors such as syntax and morphology also play substantial role in meaning representation however the study of which is outside the realm of current model. The model proposed in this study nonetheless explains the structure at the level of mental lexicon -a level where words referring to various concepts have been stored in a structured manner.

4.4 Comparison of Semantic Features between Kannada and English

Objective 3: To compare lexical semantic representation and organization with respect to semantic features of Kannada with English language.

Research question 3: Are there any differences in the distribution of semantic feature properties between Kannada and English language?

The conceptual knowledge and its structures have been reported to be relatively constant across cultures and any variations arising are attributed to differences at the linguistic levels rather than the conceptual knowledge per se (Vigliocco & Vinson, 2007). There might be variations in the manner in which different languages may map the knowledge from the conceptual level into lexical-semantic level present in the mental lexicon. Hence the linguistic and cultural environment of the language user can influence the semantic representations in the mental lexicon. Kannada studied in the present research belong to an entirely different language family compared to English and is used by people who are culturally very different. In order to see whether the semantic features generated in the present study were sensitive to these differences the semantic features generated for English was compared to the features generated for Kannada. The most extensive and widely used gold standard semantic feature data for English language were collected by McRae et al., (2005). This data consists of semantic features generated for 541 concrete concepts along with distributional statistics that are made publicly accessible. With the aim of comparing the semantic features generated from the present study to that of English data (McRae et al., 2005), the target words common in both the data sets were selected which resulted in 98 words representing the same concepts in both languages. These words were either translational equivalents (e.g., cat for /bekku/) or borrowed Kannada words (e.g., /bassu/ for bus) from English language.

The semantic similarity was analyzed between the two sets by comparing the cosine distances (similarity values) of the words in both the sets. Thus the pair wise similarity values of both the sets were compared using Wilcoxon signed- rank test with Bonferroni correction. The results revealed statistically significant differences (t = 204.5, p<0.001) with set of Kannada words having significantly higher cosine distances than English words. Thus there was substantial variability in the two data sets in terms of semantic similarity.

4.4.1. Discussion. The results thus reveal that there were differences in the semantic features generated and hence the differences in the similarity measures across the words belonging to Kannada and English. The differences cannot be just attributed to methodological differences as the procedure employed for data collection and tabulation were identical for both the sets of data. The incongruity between two languages reported in the results, if not entirely, may be attributed to the influence of linguistic environment and cultural differences among speakers of the two languages. The semantic features are parts of accessible information about objects and actions that individuals acquire from infancy. They acquire this knowledge by watching them, using them, observing others using them and talking and reading about them which develop into internal representations people possess (Cree & McRae, 2003). Thus the environment plays crucial role in formation of this knowledge.

The participants in our study were basically from the urban areas of Mysore, Karnataka which has entirely different cultural and linguistic scenario compared to participants in the McRae et al. (2005) data who were native English speakers from Canada and USA. The influence of culture and language was very evident while comparing the two data sets for common words. It was noted that there were many words in Kannada that lacked translational equivalents in English. For instance, in English language there was a single word /rice/ for both /akki/ and /anna/ (meaning cooked rice) and two different words /mouse/ and /rat/ whereas in Kannada both are labeled using single word /ili/. Similar discrepancies were noted for most of the words in the semantic category food that included food items. Most of the food items frequently consumed in southern parts of India including Mysore were hardly part of the data generated for English language due to the cultural, geographical variations. Differences were also noticed in the category of fruits and vegetables, the frequency of usage of which again largely depends on the geographical location. Such cross-linguistic variations have also been reported for Japanese where they have a single word /ashi/ for the concepts foot and leg and across English and Dutch, where English has two terms describing spatial relations (“on” and “in”), Dutch has three (“aan”, “in” and “op”) (Vigliocco & Vinson, 2007).

Although the words compared in the two data sets in the current study represented same concepts, the results show statistically significant differences in the degree of similarity among them. This indicated that there is variability in the semantic features generated and the salience of each feature for that particular word across two languages.

This can be again influenced by the environmental factors, cultural and linguistic factors that are involved in semantic featural makeup of the concept the word represents. It is also true that even though the participants in the present study were native Kannada speakers, exposure to English language was very common among them. This influence of bilingualism might have had an impact in the semantic organization compared to typical monolinguals studied by McRae et al. (2003). Thus the study provides evidence that the semantic representation of words may be influenced by the linguistic and cultural differences and semantic features are sensitive enough to capture these differences. The results also emphasize the need of establishing semantic feature data in different languages having different origins and cultural diversity.

4.5 General Discussion

The present doctoral research was proposed to study the lexical semantic representation and organization of words representing nouns and verbs of Kannada mental lexicon based on their semantic features. The study of semantic features provides comprehensive knowledge to the understanding of these aspects of mental lexicon. Hence in the present study, the semantic features for a set of Kannada nouns and verbs were collected from native speakers. These features were further studied to address the objectives and research questions posed in the study.

To describe lexical semantic representation in the mental lexicon of native Kannada speakers the distribution of semantic features for the words in the mental lexicon was studied. For this purpose a set of semantic features for 300 familiar nouns and verbs selected from Kannada lexicon. Participants in the study were instructed to write down the semantic features for lists of words provided to them. Each word had 30 participant's responses that were converted into a computer database using custom made software. The database consists of 48,170 responses obtained from 300 participants with 4,150 unique semantic features as responses. Out of 4,150 semantic features, the responses generated by less than five participants for a particular word were eliminated in order to filter out idiosyncratic responses. The final database consisted of 1,889 semantic features that were subjected to statistical analysis to answer the research questions taken up in the study.

The first research question of the present study was ‘are there any differences in the distribution of semantic feature properties across the domains of nouns and verbs in Kannada mental lexicon?’ The research question was formulated to address the first objective of the study. The analysis of semantic features for their properties and their distribution resulted in many significant findings with regard to this question. The distribution of semantic feature properties across domains of nouns and verbs showed significant differences leading to the rejection of the first hypothesis stating that there is no statistically significant difference in the distribution of semantic features between nouns and verbs under study. The semantic features of nouns and verbs in the present study were analyzed for different featural properties namely number of features generated for each word, featural weights, types of features generated, distinctive features, shared features and feature correlation. The results revealed that the distribution of all of these featural properties differs across the domains of nouns and verbs.

The results indicate that there is considerable amount of variations in the representation of nouns Vs. verbs with respect to their semantic featural makeup in the mental lexicon. The number of semantic features participants had generated for the domain of nouns and verbs differed from each other with nouns (M = 37.37, SD = 8.8) having greater number of features than verbs (M = 30.29, SD = 9.3). Nouns used in the present study have richer semantic representations in the mental lexicon as reflected by the greater number of semantic features generated by the participants. These features are also easily accessible from their mental images consulted during the process of semantic feature generation by the participants. Similar trend have also been noted in previous studies (Vinson, 2009) were concrete concepts had higher number of features. Similar results were also obtained using picture naming tasks in persons with Aphasia as well as in their healthy counterparts (Matzig, Druks, Masterson, & Vigliocco, 2009). It was noted that pictures depicting nouns were named far more quickly and had less errors than pictures depicting verbs even in normal healthy individuals, which indicates easy accessibility of information for nouns. The property, featural weights obtained for the words belonging to the domain of nouns (M = 165.33, SD = 37.4) were also significantly higher than the domain of verbs (M = 101.68, SD = 27.0), which indicates that the semantic features generated for nouns are far more uniform across participants. This reflects that there is greater amount of agreement among participants in describing a concept using a feature in the domain of nouns compared to verbs. This tendency of noun is indicative that the words belonging to nouns have consistent patterns of semantic featural makeup across participants.

There were differences in the feature type distribution across nouns and verbs. The words belonging to nouns are mainly represented, owing to their concreteness, through sensory features (Table 14) such as *visual form and surface properties* and features describing *function*. The verbs on the other hand are mostly represented using feature type *context*, *function* and *taxonomic features* (Table 15). The feature type *context* is used to label features generated by participants, which provide information about the situations where the target word is frequently used. The context features also consists of grammatical context which were frequently generated by participants in describing the verbs. Thus features generated for verbs were more complex and could not be attributed to only sensory modalities. The distribution of distinctive features and shared features varied with respect to the domains of nouns and verbs. Participants had generated more number of distinctive features and less shared features for the domain of verbs, as opposed to nouns. The study done in English (Vinson, 2009) however reports the opposite trend wherein the nouns representing objects have more distinctive features and less shared features compared to verbs depicting actions owing to the difference in the nature of categorization among nouns and verbs. The contradicting results obtained in the present study can be attributed to nature of verbs in Kannada being highly morphologically inflected, presents with greater difficulty in generating features to describe them in isolation without syntactic context. This intrinsic difficulty of the task may have lead participants to generate idiosyncratic responses thus decreasing similarity among features generated. The present study nonetheless reports differences in distribution of distinctive and shared features between the two domains. The feature correlation also revealed significant differences with nouns having greater number of feature pairs (280 pairs) highly correlating with each other than the features produced for verbs (148 pairs) (Table 23). This trend is again indicative that words belonging to nouns are represented by many semantic features that are shared among their category members whereas verbs have rather less predictable patterns of features. The higher number of feature correlations may also be a result of the tendency of nouns unlike verbs to have a discreet category boundary and clear hierarchies among the members and the categories where correlating features may contribute to the binding of the members together into a category. The results of differences in featural properties of nouns and verbs noticed in the present study are congruent with previous research findings (Vinson, 2009).

The differences noticed in the semantic featural properties among nouns and verbs may also be considered as the implications of the differences in the nature of nouns and verbs themselves. It has also been reported that acquisition of verbs occurs later compared to nouns (Bassano, 2000; Bates et al., 1994; Caselli et al., 1995; Dromi, 1987; Fenson et al., 1994; Gentner, 1981, 1982; Masterson, Druks, & Gallienne, 2008; Nelson, 1973; Stern, 1924) as the representation and usage of verbs are considered more complex than noun concepts. Nouns and verbs belong to two different kinds of content words with nouns mainly representing concrete and abstract entities referring to objects, animals etc. and verbs represent simple and complex actions. Nouns studied in present research were root word with minimum morphological inflections and easily imageable ones. Verbs in Kannada on the other hand often get attached to various morphological markers that can take different forms to convey different meanings. These aspects of nouns and verbs and their relatively different levels of abstractness may have had implications in their meaning representation, which may have resulted in the variations of their semantic featural makeup noticed in the present study.

The differences in the semantic features and their semantic representation between words representing nouns and words representing verbs may also be due to the different grammatical classes to which they belong. The nouns and verbs of a language have different syntactic roles to play in formation of meaningful and grammatically correct utterances. The grammatical properties of words are considered to be one of the organizational principles of lexical knowledge in the brain (Hillis & Caramazza, 1995; Silveri & Di Betta, 1997). This grammatical class is a lexical property honored by cortical organization (Vinson & Vigliocco 2002). The dissociations seen in naming abilities of persons with Aphasia for the domains of nouns and verbs provides evidence that nouns and verbs may be represented at different cortical regions and hence can be differentially affected by cortical lesions. The neuroimaging studies have provided evidence for the difference in cortical organization of nouns and verbs and claim that the left temporal lobe lesions are commonly seen in persons with noun deficits and left frontal/ parietal lobe lesions in case of verb deficits (Matzig, Druks, Masterson, & Vigliocco, 2009). Hence their grammatical class and syntactic roles may influence the representation of nouns and verbs. The differences in the semantic featural properties across the domains of nouns and verbs reported in the present study thus support the claim that semantic features are capable of capturing these semantic distinctions in the representations of nouns and verbs thereby contributing to the aspects of organization of words in the mental lexicon.

The second research question of the present research was ‘are there any differences in the distribution of semantic feature properties across the semantic categories in Kannada mental lexicon?’ which was also formulated to address the first objective of the study which was to understand the lexical semantic representations of the mental lexicon. The analysis of semantic feature properties with respect to the semantic categories helps to understand the representation and organization of words into categories in the mental lexicon. The semantic featural properties were studied with respect to 10 semantic categories of nouns and 7 categories of verbs. The distribution of semantic features among these categories were again studied for the properties namely number of features, featural weights, types of features, number of distinctive features, number of shared features and feature correlation. The results reveal that there were many statistically significant differences in the distribution of the semantic featural properties across these semantic categories.

To facilitate comparison across semantic categories, 45 possible combinations of semantic category pairs were calculated for the 10 categories of nouns and 21 possible semantic category pairs for 7 verb categories. With respect to the feature property number of features there were more number of semantic category pairs (20 pairs) varying significantly for nouns compared to semantic category pairs (3 pairs) of verbs. The results indicate that the number of features participants generated for words belonging to different semantic categories of nouns varied depending on their categories. For instance, words belonging to the categories of vehicles and animals had more number of features generated compared to the semantic categories of tools, body parts and profession/ sports (Table 8). However for the semantic category of verbs the number of features generated was almost uniform and did not show much variation across categories (Table 9). The semantic feature analysis for featural weights also revealed similar patterns as seen for number of features. The results based on featural weights can be considered more robust as they are based on participant's judgement of how salient a feature is in describing the concept. The words belonging to the semantic categories of animals, fruits/ vegetables and vehicles had greater featural weights whereas the semantic categories of tools and profession/ sports had least featural weights (Table 11). The property featural weight also showed similar trend as seen for number of features with semantic categories of nouns (24 pairs) exhibiting greater differences across categories than verb categories (4 pairs). This trend noticed for number of features and featural weight emphasizes the nature of categorization in the mental lexicon for words belonging to nouns which tend to possess tighter binding of words belonging to same category and clear distinctions for words belonging to other categories as opposed to verbs which tend to possess less category related distinctions.

With the aim of understanding the possible brain regions that might be involved in representation of words of the mental lexicon, the semantic features listed by the participants for words were classified into 17 feature types and distribution of these features were studied across categories. The knowledge about a concept, according to semantic feature based theories, is assumed to be distributed as patterns of activation across different sensory and/or motor information processing areas of brain. This assumption has also received evidence from neuroimaging studies reporting activation of different brain areas during tasks involving access of semantic information from various types of object knowledge (Martin & Chao, 2001; Martin, Wiggs, Ungerleider, & Haxby, 1996). Hence in the present study, some of the feature types were classified into sensory, motor and function information while others corresponded to higher abstract knowledge. The feature type distribution patterns obtained from the semantic features listed by participants are a convincing measure of representation of concepts in the mental lexicon. It is based on the assumption that during generation of semantic features for target words, participants instantiate a multisensory image of the target word and pick out the important information that are essential in describing and differentiating them from similar ones. Thus the features listed by participants referring to this image reflect the relative proportion of each type of information accessible from the representation of the concepts that differentially activates the sensory, motor/action areas, higher order abstract-knowledge areas, and mediating association areas (Cree & McRae, 2003). The featural makeup with respect to the feature types listed for each category in the present study was found to be diverse in noun semantic categories compared to the categories of verbs. Each of the semantic categories of nouns was comprised of different feature types (Table 16). For instance, the category of animals dominated with *visual form and surface property* features and features describing *systemic properties*. The category tools, on the other hand were dominated by features describing the *function* that can be accomplished using the tools. Thus, there were differences in the feature types each category was most reliant on for representation in case of semantic categories of nouns. However such differences were absent across the verb categories that were mostly reliant on feature type *context* and to some extent *function* features (Table 17). The patterns of distribution of feature type across semantic categories obtained in the present study are congruent with the results seen in previous similar studies (Vinson, 2009; Cree & McRae, 2003). The patterns of feature type associated with each category thus, is very crucial as it provides a window into the representation of these concepts.

In the present study, the feature type distribution was also analyzed using decaying weights based on the ranks of the features as explained previously. The decaying weights are highly valid and imperative as they provide emphasis on features produced first by the participants for a concept than the ones produced later. This helps to gain insights into the importance and hierarchy of semantic features for each concept which is empirically derived from participant’s responses. Hence based on these ranked features, a clearer picture of semantic feature composition can be obtained.

The distribution of distinctive features and shared features were also analyzed with respect to each of the semantic categories of nouns and verbs. As the distinctive features are very crucial in identifying a concept from similar ones, study of distribution of these features across semantic categories helps to understand semantic representation of words in their specific categories. The distribution of shared features on the other hand, sheds light on categorization of words into respective categories as they estimate the similarities of featural makeup among words. Similar to the findings for other featural properties and previous studies (Cree & McRae, 2003;Vinson, 2009), the distinctive features and shared features also had significantly more semantic category pairs varying with respect to each other in the domain of nouns (Table 19) compared to that of verbs (Table 20). The results again provide evidence for the differences in the categorization of words belonging to nouns and verbs.

Feature correlation was also studied across semantic categories as it is an important featural property revealing the presence of relations the features may have among each other. This property has influence in the semantic organization of words into categories in the mental lexicon (Malt & Smith, 1984; Rosch, 1978; Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976). The feature correlation predicts the occurrence of one feature in the presence of another thus indicating their co-occurrences. The semantic features listed by participants in the present research were subjected to further correlational analysis to understand category wise distribution. The results revealed that a number of feature pairs showed significant correlation with each other (Table 23). However there were a lot of variations seen even across noun semantic categories as some categories had as high as 429 feature pairs correlating while others had as low as 3 feature pairs correlating with each other. There was thus no obvious trend noticed in the features in terms of their correlations. The semantic categories of verbs however had fewer correlations compared to semantic categories of nouns. Cree and McRae reported similar results in 2003, who studied feature correlation in concepts representing objects (noun) concluded that the analysis of feature correlations is essential for testing knowledge at the featural level, but not a valuable tool for understanding categorization of knowledge.

The present study thus enhances our current knowledge about the lexical semantic representation and organization of words in the mental lexicon of Kannada. As evidenced in the present study, there is a clear distinction in the organization of words referring to nouns from that of verbs in the mental lexicon, which is reflected as the variations in the distribution of semantic features. Each semantic category has different types of features contributing to their representation in the mental lexicon. The study also demonstrates that the words representing semantic categories of nouns have clear boundaries across categories as they presented with significant differences in the distribution of featural properties. The semantic categories of verbs on the other hand, did not show much category wise variation in distribution of featural properties.

The second objective of the study was to develop a framework for a model of lexical semantic representation and organization in Kannada on the basis of the data on semantic features derived from 300 participants who are native speakers of Kannada. The semantic feature distribution plays central role in semantic organization in the mental lexicon. The words in the mental lexicon with overlapping semantic features tend to cluster together to form semantic categories. Thus establishing similarity measures of the words with respect to each other based on their semantic feature weights is one way to understand and visualize the structure of mental lexicon. In the present study, the similarity between words was established by calculating their cosine distances. The cosine distances were calculated based on the feature weights of overlapping features between the word pairs as discussed earlier. The results were graphically visualized to model the organization of words in the mental lexicon on the basis of semantic similarity. Graphical representations were obtained for nouns, verbs and also for semantic categories of nouns. The graphs depict the semantic similarity relations the words share with other words in the mental lexicon. The cosine distances obtained for the words were analyzed to see if in the model the words belonging to same category are closer to each other than to the words belonging to other categories. The results revealed that for all the semantic categories, the within-category mean distances were smaller compared to across-category mean distances for both nouns (Table 24) and verbs (Table 25). The results also revealed that the differences in mean distances in verb semantic categories were smaller compared to noun semantic categories. The greater differences for semantic categories of nouns in the present model are significant as they show that noun categories have clear category boundaries whereas verbs do not show distinct categorization.

The third research question posed in the study was ‘Are there any differences in the distribution of semantic feature properties between Kannada and English language? This research question aimed at addressing the fourth objective of the study, which was to compare the organization of words based on the semantic feature properties in English and Kannada. The semantic features have been extensively studied for English language and most frequently used semantic feature data for semantic memory research are the ones developed by McRae et al. (2005). For the purpose of comparison the words common in the stimuli of the present study and the English data was considered. The common words in both the data sets consisted of English translational equivalents for Kannada words and English borrowed words frequently used in Kannada. The semantic similarity was measured for both the sets by comparing the cosine distances based on their featural weights. The results revealed that the two data sets varied significantly in terms of similarity measures. The cosine distances were smaller for English words compared to Kannada words. Although same words were compared across two languages there were differences in the featural properties such as featural weights across languages as evidenced in the result. The feature weights indicate what features are considered salient by participants in describing a concept.

The differences in the featural properties may be attributed to the differences in the two languages as semantic feature generation is an explicit verbal task greatly dependent on language to describe the features. The difference in the similarity measures of two languages may or may not indicate that there are differences at the conceptual level as the conceptual knowledge is considered universal across all languages (Vigliocco & Vinson, 2007). The difference may be at the lower level, the lexico-semantic level where there is mapping of conceptual knowledge for language use. Variations in the linguistic structures influence what information of conceptual knowledge is mapped onto to lexical semantic level. For instance, it was noticed that in English language there was a single word /rice/ for both /akki/ and /anna/ (meaning cooked rice). This does not mean that English speakers cannot distinguish between the two but it simply means they do not have a separate name for it. Hence the variations resulting in the study may be attributed to influence of language at lexical semantic level rather than at the conceptual level. Language is also highly influenced by the culture and geographical location. The multilingual background in India opens up with a far greater challenge to understand the semantic representation of each language in the mental lexicon as these factors play a crucial role in shaping the language to accommodate the requirements of language users. Thus the results of the study emphasize the differences in semantic representation that may be present across the languages that differ with respect to origin, structure and linguistic properties.

Chapter 5: Summary and Conclusion

The organization of words in the mental lexicon and the nature of representation of the meanings of the words have been central themes of research in psycholinguistic and neurolinguistic studies. The study of semantic features provides comprehensive knowledge to the understanding of these aspects of mental lexicon. They form the basis of numerous models and theories developed to describe mental lexicon. Studying these features helps in better understanding of neural representation of words in the brain of healthy individuals as it can augment the research findings from the neuroimaging studies. Knowledge of meaning representation and organization of words in the mental lexicon plays an extremely crucial role in rehabilitation of persons who have been affected by semantic deficits caused by neurological, brain damaging conditions such as aphasia and dementia. The semantic feature properties are also very helpful in designing stimuli for various behavioural and linguistic experiments used in research of lexical semantics. Even though semantic features have been employed in Indian languages for Aphasia therapy (Rangamani & Prema, personal communication), the features themselves have not been studied for their properties and for their contribution to organization of the mental lexicon. Hence the present research was designed to study the semantic features for organization and representation of nouns and verbs in Kannada mental lexicon. The next section summarizes the results of the analysis done with respect to the aims and objectives and research questions of the study.

With the primary aim of studying the semantic features of nouns and verbs, initially a list of 300 words were selected from the Kannada lexicon comprising of 200 nouns and 100 verbs. These words were pseudo-randomly distributed into 10 lists each consisting of 30 words (20 nouns & 10 verbs). These word lists were distributed among 300 native Kannada speaking adults (18-30 years) and were instructed to list down the semantic features that they think describes the target words. Each participant thus listed features for 30 words. The obtained responses for words were tabulated into custom software to develop a semantic feature database. This database of semantic features was subjected to further analysis in order to address the primary objective by answering the following two research questions.

Research question 1: Are there any differences in the distribution of semantic feature properties across the domains of nouns and verbs in Kannada mental lexicon?

Findings: The semantic feature properties varied significantly across the domains of nouns and verbs. The semantic features of nouns and verbs generated in the present study were analyzed for different featural properties namely number of features generated for each word, featural weights, types of features generated, distinctive features, shared features and feature correlation. The results revealed that the distribution of all of these featural properties differs across the domains of nouns and verbs.

Research question 2: Are there any differences in the distribution of semantic features properties across the semantic categories in Kannada mental lexicon?

Findings: The distribution of semantic features among the 10 semantic categories of nouns and 7 categories of verbs were studied for the properties namely number of features, featural weights, types of features, distinctive features, shared features and feature correlation. The results reveal that there were statistically significant differences in the distribution of the semantic featural properties across the semantic categories of nouns. The differences in distribution of feature properties were comparatively less for the semantic categories of verbs. This was seen for all the semantic feature properties considered for the study.

The results thus emphasize the differences in the organization of words representing nouns from that of verbs in the mental lexicon. The words representing nouns in the present study being concrete concepts have richer semantic representation and readily accessible semantic features than the verbs as revealed by greater number of features listed for nouns. The semantic featural make up of nouns have consistent patterns as opposed to verbs and greater agreement among participants as revealed by higher featural weights. The study also provides insight into the composition of featural information involved in semantic representation of nouns and verbs and their semantic categories that correlates with the information processing areas in the brain thus providing a neural basis for semantic representation. The distinctive feature distribution emphasizes what features are unique to represent a concept and shared features and feature correlations on the other hand illustrate what features are present in more than one concept and thus facilitate clustering of words representing similar concepts together. The present research thus elucidates the organization and semantic representation of words in the mental lexicon.

Based on the semantic feature obtained from the present study, an attempt was made to model the possible structure of words and their interconnections in the mental lexicon that formed the second objective of the study. As semantic similarity is an important organizational principle of the mental lexicon, the semantic similarity measures were obtained for the every word by obtaining cosine distances of each word with another. The cosine distances were calculated based on the featural weights generated for semantic features of respective words. Hence the model utilizes empirical evidence obtained from the present study. The interconnections words may have were graphically depicted. The structure and interconnections of words in the model is in agreement with the intuitive categorization of words into semantic categories. The within-category cosine distances for words were significantly smaller than across-category distances providing evidence that the model is sensitive to the categorization principles of mental lexicon. Noun categories had greater differences than verb categories thus indicating that the model demonstrates the differences in categorization between the domains of nouns and verbs. Hence in the present research the Kannada mental lexicon was modeled based on semantic feature properties. The tertiary objective of the study was to compare the lexical semantic representation and organization in Kannada and English, which was addressed in the following research question.

Research question 3: Are there any differences in the distribution of semantic feature properties between Kannada and English language?

Findings: The semantic similarity measures of words belonging to English and Kannada obtained from their semantic feature properties showed significant difference. Although the words represented same concepts in both the languages there were differences observed in this measure.

The result thus indicates that it is not uncommon to find differences in the semantic featural makeup for words in two languages as generation of semantic features is based on verbal language in both the data sets. It may be true that conceptual knowledge may be universal and may not be affected by language but there might be differences at the lexical level where conceptual knowledge is mapped using linguistic symbols for language production and comprehension. At this lexical semantic level in the mental lexicon, the semantic representation is highly influenced by the linguistic, cultural and geographical background of language user. Shaping of conceptual knowledge into linguistic output to accommodate the varying requirements of language users could have led to the above differences leading to differences in organization and representation of words in the mental lexicon of the two languages.

5.1 Limitations of the study

The present study provides valuable insights into the lexical semantic organization of words in the mental lexicon using empirically derived semantic features. Few aspects nonetheless limited the study. One of which can be the nature of descriptions provided by participants in the semantic feature generation task. It is not usually very easy to describe the visuo-spatial information about the concepts (E.g., feature describing size of an object) using written or verbal language and hence such cues may not be adequately present in written semantic feature data. The participants also tend to list more features that help discriminating one concept from another rather than listing all the features, which might result in poor description of each concept, as they are likely to ignore very obvious features. Another concern about semantic features, especially those generated for verbs is that it is generated for isolated words. Features produced for isolated words may not account for the influence of syntactic relations and context for which the word meanings are highly susceptible. This can be more pronounced for agglutinative languages such as Kannada. Despite these drawbacks, there is substantial evidence that the semantic features nonetheless aid in understanding representation in the mental lexicon.

5.2 Conclusion

The present doctoral research provides empirically derived sets of semantic features for nouns and verbs of Kannada. The obtained semantic features were further studied for their featural properties and implications of these properties in the organization and representation of words in the mental lexicon. An attempt was also made to develop a framework to model the structure and organization of words in the mental lexicon based on the degrees of semantic feature similarity. The influence of language on the semantic features and representation of words in the mental lexicon was also analyzed by comparing the semantic similarity measures for words in English to the Kannada translational equivalent words in present study.

5.2.1 Implications and Future directions

The present study provides semantic feature data for 300 words in Kannada along with their distributional statistical measures. The study also provides six features having the highest featural weights for each word along with their featural weights, five most similar words for each word along with their cosine distances and the highly correlating semantic features along with their correlation coefficient values. This data can be employed to conduct various behavioural studies to understand language processing such as semantic priming. The empirically derived semantic similarity measures obtained from the study can be employed to develop stimuli for such behavioural studies thus increasing the objectivity and reliability of the studies.

The semantic feature data for words along with their featural weight measures can be utilized in the selection of stimuli for research studies, rehabilitation of individuals with semantic deficits. Selection of stimuli for therapy techniques used to treat semantic deficits such as Semantic Feature Analysis (SFA) can be based on the featural weight measures of the study that is derived empirically. The semantic features can also be employed in formulating treatment strategies to improve vocabulary in children with language impairments.

The custom software developed in the present study is flexible and language independent and can be easily employed to develop semantic feature database in other languages. The current semantic feature database for Kannada words can also be further developed by adding more number of words along with their semantic features. Further the semantic features can be studied for abstract concepts and other parts of speech such as adjectives, adverbs, idioms and metaphors to understand their representation in the mental lexicon.

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APPENDIX

A) Word list

Sl No	IPA	English Translation	Domain	Semantic category
1	/a:ne/	Elephant	Noun	Animals
2	/aɭilu/	Squirrel	Noun	Animals
3	/ba:θu koɭi/	Duck	Noun	Animals
4	/bekku/	Cat	Noun	Animals
5	/tʃiraθe/	Cheetah	Noun	Animals
6	/tʃite/	Butterfly	Noun	Animals
7	/giɳi/	Parrot	Noun	Animals
8	/go:be/	Owl	Noun	Animals
9	/haððu/	Eagle	Noun	Animals
10	/halli/	Lizard	Noun	Animals
11	/hasu/	Cow	Noun	Animals
12	/huli/	Tiger	Noun	Animals
13	/ili/	Rat	Noun	Animals
14	/jiɳke/	Deer	Noun	Animals
15	/ka:ge/	Crow	Noun	Animals
16	/kappe/	Frog	Noun	Animals
17	/karaɖi/	Bear	Noun	Animals
18	/kaθθe/	Donkey	Noun	Animals
19	/ko:gile/	Cuckoo	Noun	Animals
20	/ko:ɭi/	Hen	Noun	Animals
21	/ko:θi/	Monkey	Noun	Animals
22	/kudure/	Horse	Noun	Animals
23	/kuri/	Sheep	Noun	Animals
24	/me:nu/	Fish	Noun	Animals
25	/mola/	Rabbit	Noun	Animals
26	/na:yi/	Dog	Noun	Animals
27	/navilu/	Peacock	Noun	Animals
28	/noɳa/	Housefly	Noun	Animals
29	/simha/	Lion	Noun	Animals
30	/θoɭa/	Wolf	Noun	Animals
31	/ba:ji/	Mouth	Noun	Body Parts
32	/beraɭu/	Finger	Noun	Body Parts
33	/hɔtte/	Stomach	Noun	Body Parts
34	/hubbu/	Eyebrow	Noun	Body Parts
35	/ka:lu/	Leg	Noun	Body Parts
36	/kai/	Hand	Noun	Body Parts
37	/kaɳɳu/	Eye	Noun	Body Parts
38	/kivi/	Ear	Noun	Body Parts
39	/ko:dalu/	Hair	Noun	Body Parts
40	/mandi/	Knee	Noun	Body Parts

41	/mo:gu/	Nose	Noun	Body Parts
42	/θale/	Head	Noun	Body Parts
43	/baɭe/	Bracelet	Noun	Clothing
44	/tʃappali/	Footwear	Noun	Clothing
45	/cho:di ða:ra/	-	Noun	Clothing
46	/gejje/	Anklet	Noun	Clothing
47	/karavasθra/	Handkerchief	Noun	Clothing
48	/oale/	Earring	Noun	Clothing
49	/pant/*	Pant	Noun	Clothing
50	/sara/	Necklace	Noun	Clothing
51	/se:re/	Saree	Noun	Clothing
52	/ʃa:lu/	Shawl	Noun	Clothing
53	/ʃartu/*	Shirt	Noun	Clothing
54	/sweater/*	Sweater	Noun	Clothing
55	/to:pi/	Cap	Noun	Clothing
56	/uɳgura/	Ring	Noun	Clothing
57	/akki/	Rice	Noun	Food
58	/anna/	Rice	Noun	Food
59	/beɳɳe/	Butter	Noun	Food
60	/bisket/*	Biscuit	Noun	Food
61	/tʃapa:θi/	-	Noun	Food
62	/tʃɔkɔlet/*	Chocolate	Noun	Food
63	/ðo:se/	-	Noun	Food
64	/go:ði/	Wheat	Noun	Food
65	/hɔɭige/	-	Noun	Food
66	/hɔtel/*	Hotel	Noun	Food
67	/ais kri:m/*	Icecream	Noun	Food
68	/idli/	-	Noun	Food
69	/dza:munu/	-	Noun	Food
70	/madzdzige/	Buttermilk	Noun	Food
71	/ra:gi/	Raagi	Noun	Food
72	/sa:ru/	Soup	Noun	Food
73	/sa:sive/	Mustard	Noun	Food
74	/θuppa/	Ghee	Noun	Food
75	/uppina ka:ji/	Pickle	Noun	Food
76	/uppittu/	-	Noun	Food
77	/ananas/	Pineapple	Noun	Fruits
78	/ba:ɭe haɳɳu/	Banana	Noun	Fruits
79	/bata:ɳi/	Peas	Noun	Fruits
80	/be:t ro:t/*	Beetroot	Noun	Fruits
81	/beɭɭuɭɭi/	Garlic	Noun	Fruits
82	/bende ka:ji/	Lady’s Finger	Noun	Fruits
83	/ða:ɭimbe/	Pomogrenate	Noun	Fruits
84	/ðra:kʃi/	Grapes	Noun	Fruits
85	/e:ruɭɭi/	Onion	Noun	Fruits
86	/halasina haɳɳu/	Jackfruit	Noun	Fruits
87	/he:re ka:ji/	Ridge Gourd	Noun	Fruits

88	/ho:kɔ:su/	Cauliflower	Noun	Fruits
89	/huruḷi ka:ji/	Beans	Noun	Fruits
90	/kabbu/	Sugarcane	Noun	Fruits
91	/kallaɳgadi haɳɳu/	Water Melon	Noun	Fruits
92	/kiθθaḷe haɳɳu/	Orange	Noun	Fruits
93	/koθambari soppu/	Coriander	Noun	Fruits
94	/ma:vina haɳɳu/	Mango	Noun	Fruits
95	/meɳasina ka:ji/	Chilli	Noun	Fruits
96	/mo:laɳgi/	Raddish	Noun	Fruits
97	/mo:sambi/	Sweet Lime	Noun	Fruits
98	/nimbe/	Lemon	Noun	Fruits
99	/parangi haɳɳu/	Papaya	Noun	Fruits
100	/sapota/	Cheeku	Noun	Fruits
101	/se:bu/	Apple	Noun	Fruits
102	/si:be haɳɳu/	Guava	Noun	Fruits
103	/soppu/	Leafy Vegetables	Noun	Fruits
104	/souθe ka:ji/	Cucumber	Noun	Fruits
105	/θeɳgina ka:ji/	Coconut	Noun	Fruits
106	/a:ka:ʃa/	Sky	Noun	Nature
107	/aramane/	Palace	Noun	Nature
108	/benki/	Fire	Noun	Nature
109	/besige/	Summer	Noun	Nature
110	/betta/	Mountain	Noun	Nature
111	/bho:kampa/	Earthquake	Noun	Nature
112	/bho:mi/	Earth	Noun	Nature
113	/bisilu/	Sunlight	Noun	Nature
114	/tʃaḷi ga:la/	Winter	Noun	Nature
115	/ele/	Leaf	Noun	Nature
116	/gida/	Plant	Noun	Nature
117	/hu:vu/	Flower	Noun	Nature
118	/dzalapa:θa/	Waterfall	Noun	Nature
119	/ka:du/	Forest	Noun	Nature
120	/maḷe/	Rain	Noun	Nature
121	/maɳɳu/	Soil	Noun	Nature
122	/mara/	Tree	Noun	Nature
123	/moda/	Cloud	Noun	Nature
124	/mrugalaja/	Zoo	Noun	Nature
125	/naði/	River	Noun	Nature
126	/raɳgoli/	-	Noun	Nature
127	/udjanavana/	Park	Noun	Nature
128	/ba:chaɳige/	Comb	Noun	Common objects
129	/ba:gilu/	Door	Noun	Common objects
130	/beḷḷi/	Silver	Noun	Common objects
131	/bla:k board/	Black Board	Noun	Common objects
132	/bottle/	Bottle	Noun	Common objects
133	/baket/	Bucket	Noun	Common objects
134	/tʃe:la/	Bag	Noun	Common objects

135	/tʃinna/	Gold	Noun	Common objects
136	/kamputer/*	Computer	Noun	Common objects
137	/ða:ra/	Thread	Noun	Common objects
138	/dabbi/	Box	Noun	Common objects
139	/di:pa/	Lamp	Noun	Common objects
140	/dimbu/	Pillow	Noun	Common objects
141	/fan/*	Fan	Noun	Common objects
142	/gadija:ra/	Clock	Noun	Common objects
143	/gombe/	Doll	Noun	Common objects
144	/hoððige/	Blanket	Noun	Common objects
145	/ka:gada/	Paper	Noun	Common objects
146	/kannadaka/	Spectacles	Noun	Common objects
147	/kapa:tu/	Cupboard	Noun	Common objects
148	/kasada butti/	Dustbin	Noun	Common objects
149	/kitaki/	Window	Noun	Common objects
150	/kurtʃi/	Chair	Noun	Common objects
151	/lipstick/*	Lipstick	Noun	Common objects
152	/mantʃa/	Cot	Noun	Common objects
153	/mane/	House	Noun	Common objects
154	/me:dzu/	Table	Noun	Common objects
155	/nalli/	Tap	Noun	Common objects
156	/pa:θre/	Bowl	Noun	Common objects
157	/pen/*	Pen	Noun	Common objects
158	/pensil/*	Pencil	Noun	Common objects
159	/fo:n/*	Phone	Noun	Common objects
160	/porake/	Broom	Noun	Common objects
161	/pusðaka/	Book	Noun	Common objects
162	/su:dzi/	Needle	Noun	Common objects
163	/ti:vi:/*	Tv	Noun	Common objects
164	/wadzra/	Diamond	Noun	Common objects
165	/kerrm/ *	Carom	Noun	Profession/sports
166	/kriket/*	Cricket	Noun	Profession/sports
167	/doctor/*	Doctor	Noun	Profession/sports
168	/fut ba:l/*	Foot Ball	Noun	Profession/sports
169	/nurs/ *	Nurse	Noun	Profession/sports
170	/raiða/	Farmer	Noun	Profession/sports
171	/tʃiktʃaka/	Teacher	Noun	Profession/sports
172	/sipa:ji/	Solider	Noun	Profession/sports
173	/tennis/ *	Tennis	Noun	Profession/sports
174	/wjapa:ra/	Business	Noun	Profession/sports
175	/bando:ka/	Rifle	Noun	Tools
176	/be:ga/	Lock	Noun	Tools
177	/tʃa:ku/	Knife	Noun	Tools
178	/e:ɭige maɳe/	-	Noun	Tools
179	/e:ɳi/	Ladder	Noun	Tools
180	/garagasa/	Saw	Noun	Tools
181	/helmet/ *	Helmet	Noun	Tools
182	/isθri pettige/	Iron Box	Noun	Tools

183	/kaθθari/	Scissors	Noun	Tools
184	/negilu/	Plough	Noun	Tools
185	/skru: driwer/ *	Screw Driver	Noun	Tools
186	/suθθige/	Hammer	Noun	Tools
187	/θakkadi/	Weighing machine	Noun	Tools
188	/aɔtoriktʃa/ *	-	Noun	Vehicles
189	/bike/ *	Bike	Noun	Vehicles
190	/bassu/ *	Bus	Noun	Vehicles
191	/ka:ru/	Car	Noun	Vehicles
192	/saikal/ *	Cycle	Noun	Vehicles
193	/yeθθina ga:di/	Bullock Cart	Noun	Vehicles
194	/kudure ga:di/	Tonga	Noun	Vehicles
195	/la:ri/	Lorry	Noun	Vehicles
196	/railu/	Rail	Noun	Vehicles
197	/sku:tar/ *	Scooter	Noun	Vehicles
198	/tempo/ *	Tempo	Noun	Vehicles
199	/tra:ktar/ *	Tractor	Noun	Vehicles
200	/vima:na/	Airplane	Noun	Vehicles
201	/a:ðu/	Play	Verb	Body Action
202	/a:kaɭisu/	Yawn	Verb	Body Action
203	/a:gra:ɳisu/	Smell	Verb	Body Action
204	/agi/	Chew	Verb	Body Action
205	/aɭu/	Cry	Verb	Body Action
206	/ba:tʃu/	Comb	Verb	Body Action
207	/ba:risu/	Beat	Verb	Body Action
208	/bari/	Write	Verb	Body Action
209	/be:ɭu/	Fall	Verb	Body Action
210	/bikkaɭisu/	Hiccup	Verb	Body Action
211	/tʃutʃtʃu/	Pierce	Verb	Body Action
212	/e:dzu/	Swim	Verb	Body Action
213	/eɳisu/	Count	Verb	Body Action
214	/esi/	Throw	Verb	Body Action
215	/ha:risu/	Fly	Verb	Body Action
216	/hari/	Tear	Verb	Body Action
217	/heɭu/	Tell	Verb	Body Action
218	/hidi/	Hold	Verb	Body Action
219	/hindu/	Squeeze	Verb	Body Action
220	/hodi/	Hit	Verb	Body Action
221	/hɔli/	Stitch	Verb	Body Action
222	/hɔru/	Carry	Verb	Body Action
223	/huduku/	Search	Verb	Body Action
224	/tʃagaɭawa:du/	Quarrel	Verb	Body Action
225	/katʃtʃu/	Bite	Verb	Body Action
226	/kari/	Call	Verb	Body Action
227	/ku:ru/	Sit	Verb	Body Action
228	/kudi/	Drink	Verb	Body Action
229	/kuɳi/	Dance	Verb	Body Action

230	/ma:du/	Do	Verb	Body Action
231	/madisu/	Fold	Verb	Body Action
232	/muttu/	Touch	Verb	Body Action
233	/nadeda:du/	Walk	Verb	Body Action
234	/nagu/	Laugh	Verb	Body Action
235	/nenapa:gu/	Remember	Verb	Body Action
236	/niðrisu/	Sleep	Verb	Body Action
237	/nillu/	Stand	Verb	Body Action
238	/nungu/	Swallow	Verb	Body Action
239	/oði/	Kick	Verb	Body Action
240	/o:ðu/	Read	Verb	Body Action
241	/o:du/	Run	Verb	Body Action
242	/sigu/	Reach	Verb	Body Action
243	/θinnu/	Eat	Verb	Body Action
244	/θoɭi/	Wash	Verb	Body Action
245	/θuka ha:ku/	Weigh	Verb	Body Action
246	/θorisu/	Show	Verb	Body Action
247	/ugi/	Spit	Verb	Body Action
248	/jotʃisu/	Think	Verb	Body Action
249	/tʃaɭija:gu/	Cold	Verb	Body Sense
250	/ke:ɭu/	Ask	Verb	Body Sense
251	/no:du/	See	Verb	Body Sense
252	/no:wu/	Pain	Verb	Body Sense
253	/rutʃi/	Taste	Verb	Body Sense
254	/ʃekejagu/	Hot	Verb	Body Sense
255	/uri/	Burn	Verb	Body Sense
256	/dzodisu/	Arrange	Verb	Construction
257	/kaθθarisu/	Cut	Verb	Construction
258	/kattu/	Bind	Verb	Construction
259	/kotʃtʃu/	Chop	Verb	Construction
260	/kollu/	Kill	Verb	Construction
261	/ku:disu/	Join	Verb	Construction
262	/muri/	Break	Verb	Construction
263	/sudu/	Burn	Verb	Construction
264	/θiwi/	Poke	Verb	Construction
265	/bejisu/	Cook	Verb	Cooking
266	/huri/	Fry	Verb	Cooking
267	/kuðisu/	Boil	Verb	Cooking
268	/θuri/	Grate	Verb	Cooking
269	/eɭi/	Pull	Verb	Motion Change
270	/e:ɭu/	Get Up	Verb	Motion Change
271	/horadu/	Start	Verb	Motion Change
272	/muɭugu/	Drown	Verb	Motion Change
273	/θaɭɭu/	Push	Verb	Motion Change
274	/θe:lu/	Float	Verb	Motion Change
275	/θewaɭu/	Crawl	Verb	Motion Change
276	/θirugu/	Spin	Verb	Motion Change

277	/uruɭu/	Roll	Verb	Motion Change
278	/bogaɭu/	Bark	Verb	Noises
279	/ghardzisu/	Roar	Verb	Noises
280	/goɳagu/	Whisper	Verb	Noises
281	/ha:du/	Sing	Verb	Noises
282	/kemmu/	Cough	Verb	Noises
283	/kirutʃu/	Shout	Verb	Noises
284	/ku:gu/	Call	Verb	Noises
285	/si:nu/	Sneeze	Verb	Noises
286	/θegu/	Burp	Verb	Noises
287	/bisi ma:du/	Heat	Verb	State Change
288	/gellu/	Win	Verb	State Change
289	/dza:sθi ma:du/	Increase	Verb	State Change
290	/kammi ma:du/	Decrease	Verb	State Change
291	/karagisu/	Melt	Verb	State Change
292	/kartʃu ma:du/	Spend	Verb	State Change
293	/kondu koɭɭu/	Buy	Verb	State Change
294	/ma:ru/	Sell	Verb	State Change
295	/mareθu ho:gu/	Forget	Verb	State Change
296	/pu:rθi goɭisu/	Complete	Verb	State Change
297	/so:lu/	Lose	Verb	State Change
298	/θampu ma:du/	Cool	Verb	State Change
299	/θumbu/	Fill	Verb	State Change
300	/uɭisu/	Save	Verb	State Change

***** Borrowed words

- A list of the six features with maximum feature weights for 300 words generated in the present study has been uploaded and is available for viewing at http://tinyurl.com/lexicalstudy

- A list of six most similar words along with their similarity value for the 300 words has been uploaded and is available for viewing at http://tinyurl.com/lexicalstudy

Publications Related to the Thesis

Prarthana.S. & K.S.Prema. (2013).Concrete nouns in Kannada: How Distinct are their Semantic Features. *Language in India. Volume 13*. ISSN No: 1930-2940. (front page attached in the thesis)

Prarthana.S., Mekhala.V.G., & K.S.Prema. (2013).Lexicalization of Idioms and Noun Phrases in Kannada: A reaction time study in Adults. *.Journal of Advanced Linguistics Studies. Volume 2*,1-2, 129-136.(complete paper attached)

Prarthana.S. & K.S.Prema. (2012).Role of Semantics in the Organization of Mental Lexicon. *Language in India. Volume 12.* ISSN No: 1930-2940. (front page attached in the thesis)