A Bibliometric and Network Analysis of the Field of Computational Linguistics

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The ACL Anthology is a large collection of research papers in computational linguistics. Citation data were obtained using text extraction from a collection of PDF files with significant manual postprocessing performed to clean up the results. Manual annotation of the references was then performed to complete the citation network. We analyzed the networks of paper citations, author citations, and author collaborations in an attempt to identify the most central papers and authors. The analysis includes general network statistics, PageRank, metrics across publication years and venues, the impact factor and h-index, as well as other measures.

Introduction

A typical outcome of a research project is a publication in a journal, conference, or other venue. Scientific papers cite each other and thus the ensemble of papers in a given field of research forms a directed network.

Analyzing the network of citations, we may be able to find interesting correlations that give us a new perspective on the importance of certain papers, their authors, the ideas presented in them, and the papers to which these important papers are connected.

In this paper we investigate the corpus of papers published by the Association for Computational Linguistics (ACL) by creating citation and collaboration networks and analyzing them using a variety of statistical measures.

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With the help of these networks, we have been able to identify the most central papers and the most central authors according to different measures. We also disclose the identity of the Kevin Bacon of the AAN (ACL Anthology Network), that is, the most central author in the collaboration network (Fass, Ginelli, & Turtle, 1996; Tjaden, 1999). We also analyze the correlation between the different ranking measures to identify if there is any single aspect that all the ranking measures value highly. We were also able to analyze and observe patterns about the overall impact of different venues in the field of computational linguistics over time. We also studied the effect of self citations, that is, an author citing his previous work, on the ranking of authors based on different measures.

In the next section we review previous research on citation and collaboration networks. Then, we describe the ACL Anthology, and following that describe the measures used in the analysis. In Paper Networks and Author Networks, we present the networks created and the findings of our analysis. Finally, we discuss our conclusions and future work to be performed.

Related Work

Recently, there have been many papers (Albert & Barabasi, 2002; da F. Costa, Rodrigues, Travieso, & Villas Boas, 2007; Dorogovtsev & Mendes, 2002; Newman, 2003) on analysis of real-world networks. With the ability to accumulate large amounts of information automatically, analysis of large-scale networks has become much easier than in the past. Some of the networks that have been studied are the World Wide Web (WWW), the Internet, citation networks, movie actor collaboration network, the web of human sexual contacts, as well as power and neural networks. Newman (2003) showed that real-world networks are very different from random graphs (Erdös & Rényi, 1961), using an empirical analysis of the network properties. Network properties like average shortest path length, clustering coefficients, degree distribution, and spectral properties clearly help distinguish between a random network and a real-world network. Based on these analyses, different models of evolution of the citation networks have been proposed.

Numerous papers have been published regarding collaboration networks in scientific journals, resulting in a number of important conclusions. In Elmacioglu and Lee (2005), it was shown that the Digital Bibliographic Library Browser (DBLP) network resembles a small-world network due to the presence of a high number of clusters with a small average distance between any two authors. This average distance is compared to Milgram's (1967) "six degrees of separation" experiments, resulting in the DBLP measure of average distance between two authors stabilizing at approximately six. Similarly, in Nascimento, Sander, and Pound (2003), the current (as of 2002) largest connected component of the SIGMOD network is identified as a small-world network, with a clustering coefficient of 0.69 and an average path length of 5.65.

Citation networks have also been the focus of recent research, with added concentration on the proceedings of major international conferences, and not just on leading journals in the scientific fields. In Rahm and Thor (2005), the contents over 10 years of the SIGMOD and VLDB proceedings along with the TODS, VLDB Journal, and SIGMOD Record were combined and analyzed. Statistics were provided for total and average number of citations per year. Although there are concerns as to its validity (*Nature* Editorial, 2005), the impact factor was also considered for the journal publications. Lastly, the most-cited papers, authors, author institutions, and their countries were found. In the end, they determined that the conference proceedings achieved a higher impact factor than journal articles, thus legitimizing their importance.

Citation networks other than paper citation networks, for example, the citation networks of legal court cases or patents, have been studied. Patents cite other patents for a variety of reasons, mostly to establish their novelty over previous work. In legal citation networks, legal opinions cite other cases to establish precedent. One such network, the network of opinions of the United States Supreme Court, was analyzed extensively in Leicht, Clarkson, Shedden, and Newman (2007). Leicht et al. proposed a mixture model of citation patterns to discover community structure in citation networks. The hypothesis they put forth is that there exists a community structure in citation networks, each distinctly identifiable by its citation pattern. They use the expectation-maximization algorithm (EM) to fit the mixture model they developed to the observed citation data. Also, they apply Kleinberg's eigenvector centrality measure (Kleinberg, 1999) to the citation network to observe the top authority scores over time and reveal interesting facts about the evolution of the network. In particular, the plot of the average age of the top k authorities over time shows that the average age increases with time but with sudden drops. This shows that the top authorities remain the same for a substantial period of time but are swiftly replaced by younger leaders.

Another interesting aspect of citation networks and information diffusion was addressed in Shi, Tseng, and Adamic (2009). They addressed the question of what features are predictive of the popularity a paper would obtain in the citation graph. They found that papers which cite other recent papers in the same community garner a lot of citations over time, whereas the most influential papers are papers that are interdisciplinary and come out of ideas fused across communities. They also observed that the citation structure in computer science depends on the area of research and the time period.

Interesting work has also been done regarding the availability of articles and the number of citations those articles receive (Lawrence, 2001), although this paper does not explore that correlation.

The ACL Anthology

The ACL is an international professional society dedicated to the advancement in natural language processing (NLP) and Computational linguistics research. The ACL Anthology is a collection of papers from a journal published by the ACL—*Computational Linguistics*—as well as all proceedings from ACL-sponsored conferences and workshops (www.aclweb.org/anthology-new) (Bird et al., 2008). It is from these papers that the AAN was constructed (Joseph & Radev, 2007) from the ACL anthology.

Table 1 includes a listing of the different conferences and the meeting years analyzed in Phase 1 of this work, as well as the years for the ACL journal, *Computational Linguistics*. This represents the contents and standing of the ACL Anthology in February, 2007. Since then, the proceedings of SIGDAT (special interest group for linguistic data and corpus-based approaches to NLP) of the ACL have been extracted from the workshop heading and categorized separately.

Individual workshop listings have not been included in Table 1 due to space constraints. The assigned prefixes intended to represent each forum of publication are also included. These will be referenced in numerous tables within the paper and should make it easier to find the original conference or paper. For example, the proceedings of the European Chapter of the Association for Computational Linguistics conference have been assigned "E" as a prefix. So the ACL ID E02-1005 is a paper presented in 2002 at the EACL conference and assigned number 1005. It must be noted that not every year has been completed, as articles from HLT-02 are still absent.

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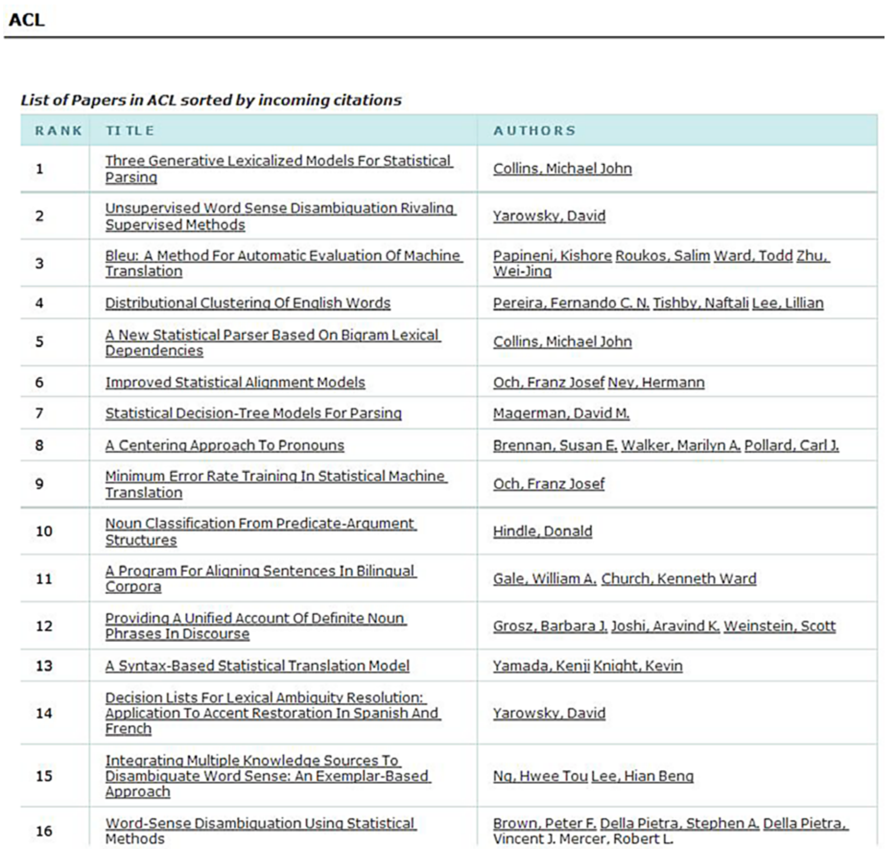
TABLE 1. ACL Conference Proceedings. This includes the years for which analysis was performed.

Name	Prefix	Meeting years
ACL	P	79–83, 84 w/COLING, 85–96, 97 w/EACL, 98 w/COLING, 99–05, 06 w/COLING
COLING	C	65, 67, 69, 73, 80, 82, 84 w/ACL, 86, 88, 90, 92, 94, 96, 98 w/ACL, 00, 02, 04, 06 w/ACL, 07
EACL	E	83, 85, 87, 89, 91, 93, 95, 97 w/ACL, 99, 03, 06
NAACL	N	00 w/ANLP, 01, 03 w/HLT, 04 w/HLT, 06 w/HLT, 07
ANLP	A	83, 88, 92, 94, 97, 00 w/NAACL
SIGDAT (EMNLP & VLC)	D	93, 95–00, 02–04, 05 w/HLT, 06
TINLAP	T	75, 78, 87
Tipster	X	93, 96, 98
HLT	H	86, 89–94, 01, 03 w/NAACL, 04 w/NAACL, 05 w/EMNLP, 06 w/NAACL
MUC	M	91–93, 95
IJCNLP	I	05
Workshops	W	90–91, 93–07
Computational Linguistics	J	74–05

In total, the ACL Anthology contains 11,749 unique papers from these various sources. Certain texts that did not include citations were not included, such as the Table of Contents, Front Matter, Author Index, Book Review, etc.

The AAN website (http://clair.eecs.umich.edu/aan/index.php) displays all the statistics computed in this paper, the different rankings, and also includes features to select papers by conference, as shown in Figure 1, and search by author name, paper ID, paper title, etc. A snapshot of the search feature is shown in Figure 2.

Each of the papers was processed using an optical character recognition (OCR) text extraction tool (http://pdfbox.apache.org/) and the references from each paper were parsed and extracted. The OCR text extraction outputs all the references as a single block and we had to manually insert line breaks between references. These references were then manually matched to other papers in the ACL Anthology using an "n-best" (with $n = 5$) matching algorithm built into a CGI interface. A snapshot of this interface is shown in Figure 3. The matched references were then compiled to produce a citation network. References to papers outside of the ACL were recorded but not included in the network. The statistics of the anthology citation network in comparison to the total number of references in the 11,749 papers can be seen in Table 2.


ACL

List of Papers in ACL sorted by incoming citations

RANK	TITLE	AUTHORS
1	Three Generative Lexicalized Models For Statistical Parsing	Collins, Michael John
2	Unsupervised Word Sense Disambiguation Rivaling Supervised Methods	Yarowsky, David
3	Bleu: A Method For Automatic Evaluation Of Machine Translation	Papineni, Kishore Roukos, Salim Ward, Todd Zhu, Wei-Jing
4	Distributional Clustering Of English Words	Pereira, Fernando C. N. Tishby, Naftali Lee, Lillian
5	A New Statistical Parser Based On Bigram Lexical Dependencies	Collins, Michael John
6	Improved Statistical Alignment Models	Och, Franz Josef Ney, Hermann
7	Statistical Decision-Tree Models For Parsing	Magerman, David M.
8	A Centering Approach To Pronouns	Brennan, Susan E. Walker, Marilyn A. Pollard, Carl J.
9	Minimum Error Rate Training In Statistical Machine Translation	Och, Franz Josef
10	Noun Classification From Predicate-Argument Structures	Hindle, Donald
11	A Program For Aligning Sentences In Bilingual Corpora	Gale, William A. Church, Kenneth Ward
12	Providing A Unified Account Of Definite Noun Phrases In Discourse	Grosz, Barbara J. Joshi, Aravind K. Weinstein, Scott
13	A Syntax-Based Statistical Translation Model	Yamada, Kenji Knight, Kevin
14	Decision Lists For Lexical Ambiguity Resolution: Application To Accent Restoration In Spanish And French	Yarowsky, David
15	Integrating Multiple Knowledge Sources To Disambiguate Word Sense: An Exemplar-Based Approach	Ng, Hwee Tou Lee, Hian Beng
16	Word-Sense Disambiguation Using Statistical Methods	Brown, Peter F. Della Pietra, Stephen A. Della Pietra, Vincent J. Mercer, Robert L.

FIG. 1. Papers selected by a conference (ACL). [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

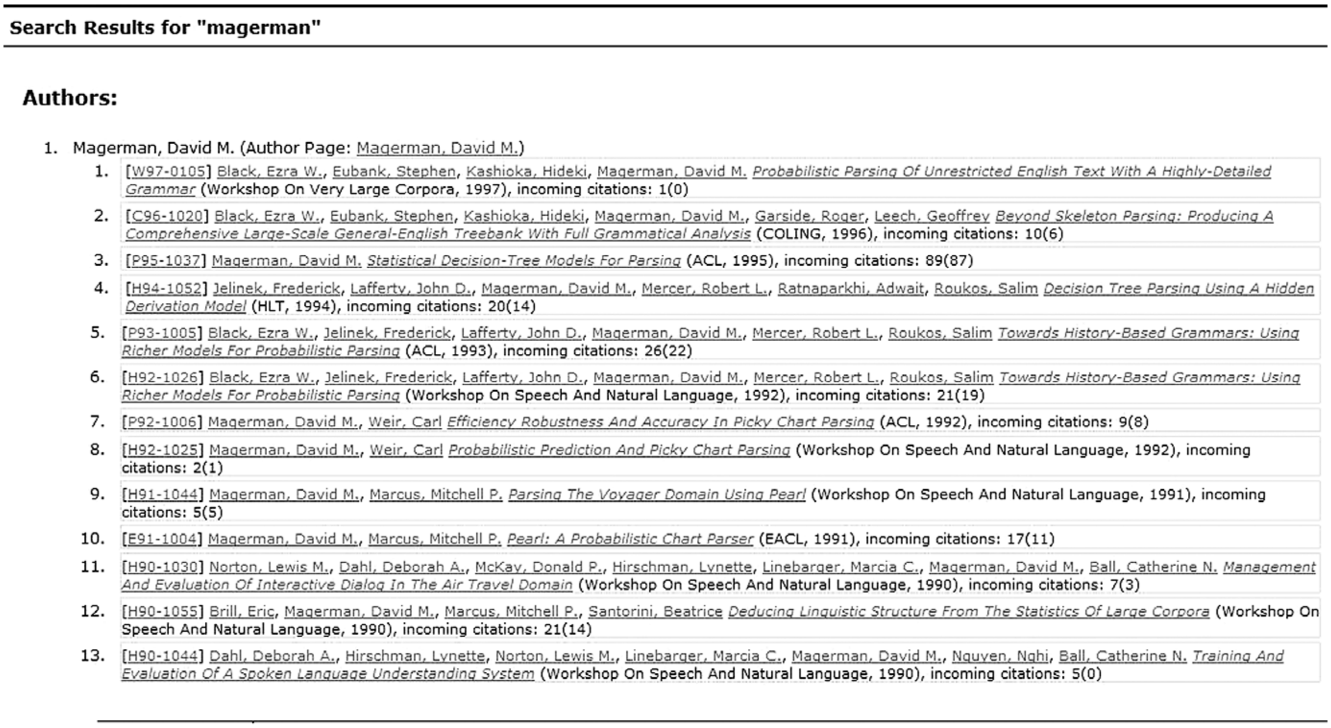


FIG. 2. Search results for "Magerman."

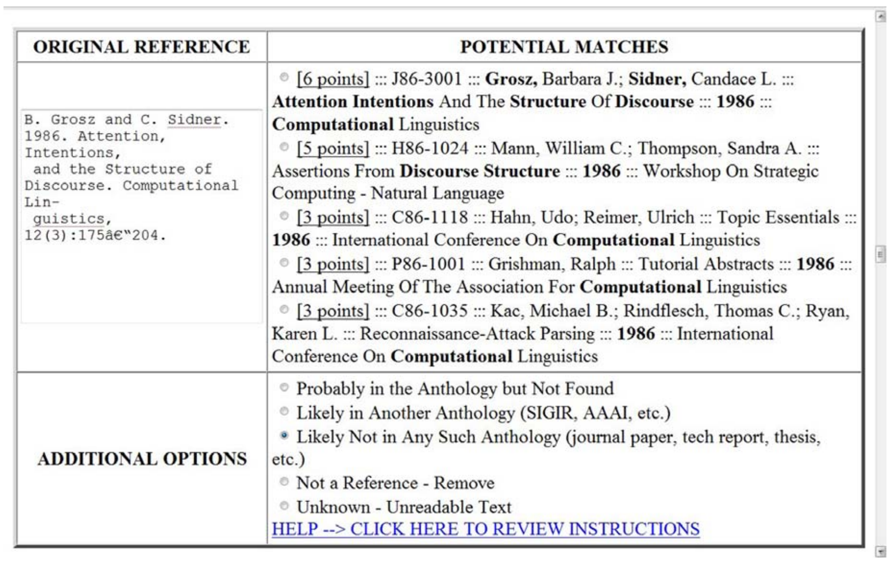


FIG. 3. Snapshot of the CGI interface used for matching references of new papers to existing papers. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

This process was very time-consuming due to the sheer amount of data available and all the data inconsistencies that were encountered. An estimated 1,100 hours were spent on the extraction of the citations alone. Around 60% of the time was spent on matching the reference text to the correct papers using the CGI interface, 30% of time on formatting the text version of the papers so that we can extract the

TABLE 2. General statistics. A citation is considered to be inside the anthology if it points to another paper in the ACL Anthology Network.

Total papers processed	11,749
Total citations	167,165
Citations inside anthology	44,138, or approx. 26.4%
Citations outside anthology	123,023, or approx. 73.6%

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references individually, 8% of time in cleaning up the data and correcting the citation data, and 2% of the time in getting the different files in the right format and setting up the whole system.

In addition to the paper citation network, an author citation network and an author collaboration network were also created. The creation of these networks is described in detail in the section Author Networks. In attempting to build these author networks it was essential that we identified the correct authors for each paper. Aside from the casual misspelling of an author name, author names were sometimes missing from the publications. Often, a comma was lost or missing to indicate the appropriate order of the first and last name, resulting in *Klein Dan* (instead of *Dan Klein*). Also, authors have a tendency to use different versions of their name over the course of their publishing career (for instance, *Martha Stone* and *Martha Palmer*). An attempt to correct all such inconsistencies was made. The number of these issues was small in comparison to the vast number which were correct.

In the following section we quickly go through the network analysis methods that will be used extensively in the later sections. Using these methods we analyze the connectedness, power law distributions in the paper citation network, and the author networks. In the Paper Network section we analyze the paper citation network in an attempt to identify the papers with the most impact using different measures of centrality. In the Author Networks section we analyze the author citation network and the author collaboration network. We look at different evaluation measures for ranking authors according to their impact by analyzing the author citation network. Also, we look at the correlation between the centrality in the citation network and the collaboration network.

Before we begin looking at the analysis of the network, we describe some of the measures used in this analysis.

Network Analysis Methods

The citation network was analyzed using Clairlib.[1]

Diameter and Average Shortest Path

In a network, the average smallest number of steps along edges between any two nodes is called the average shortest path.

We computed two versions of average shortest path. The first is the sum of the length of shortest paths of all reachable node pairs divided by the number of reachable pairs.

$$d_1 = \frac{\sum_{i=1}^{n}\left(\sum_{j=1}^{n} L_{ij}\right)}{N_{rp}} \tag{1}$$

[1]Clairlib is a Perl library designed by the University of Michigan Computational Linguistics And Information Retrieval (CLAIR) group (http://www.Clairlib.org) (Radev et al., 2007).

where L_{ij} is the length of the shortest path from node i to node j, and N_{rp} is the number of reachable pairs of nodes. We refer to the average shortest path calculated using only reachable pairs of nodes as the Clairlib average shortest path. The second comes from Ferrer i Cancho and Solé (2001), and is calculated as:

$$d_2 = \frac{\sum_{i=1}^{n}\left(\frac{\sum_{j=1}^{n} L_{ij}}{n_i}\right)}{N} \tag{2}$$

where L_{ij} is the length of the shortest path from node i to node j, n_i is the number of neighbors of node i, and N is the number of nodes in the network.

Additionally, we calculated the harmonic mean geodesic distance as defined in Newman (2003). This measure gives an average of the distances between nodes, with lower values having a larger impact than higher outliers. In a network that does not allow self-loops, as is the case for the networks studied here, it is calculated as:

$$H = \frac{n(n-1)/2}{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\frac{1}{L_{ij}}} \tag{3}$$

Another common measure is the network diameter. The diameter of a graph is defined as the length of the longest shortest path between any two vertices.

For calculating the network diameter and distance, only the largest connected component of the network was used.

Power Law

The degree of a node is the number of nodes adjacent to the node. The degree distribution of a graph refers to the probability distribution of degrees of nodes in the graph. The degree distribution $P(k)$ of a graph is then defined to be the fraction of nodes in the network with degree k. Thus, if there are N_k nodes with a degree of k and a total of N nodes, then the degree distribution can be mathematically written as:

$$P(k) = \frac{N_k}{N} \tag{4}$$

The degree distribution helps us understand the underlying generative characteristics of the graph. For example, the Bernoulli random graph, in which each possible edge is included in the graph with a probability of p, has a binomial distribution of degrees. Many real-world networks, like the WWW and social networks, are found to have degree distributions that follow a power law:

$$P(k) = ck^{-\gamma} \tag{5}$$

where c and γ are constants. Such networks are called scale-free networks with γ typically in the range of $2 < \gamma < 3$ (Clauset, Shalizi, & Newman, 2009).

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One of the ways to identify the characteristics of a power law network's degree distribution is to calculate its power law exponent (α). We use two methods to calculate power law exponents. The first (α_{LS}) is a measure of the slope of the cumulative log-log degree distribution using the fitting of least squares (York, 1966). The power law exponent a is calculated as:

$$\alpha = \frac{n\sum(x*y)-\left(\sum x*\sum y\right)}{\left(n*\sum x^2\right)-\left(\sum x\right)^2} \tag{6}$$

The r^2 statistic tells how well the linear regression line fits the data. The higher the value of r^2, the less variability in the fit of the data to the linear regression line. It is calculated as:

$$r^2 = \frac{s_{xy}}{\sqrt{(s_{xx} * s_{yy})}} \tag{7}$$

where x is the independent variable, y the dependent variable, n the number or observations, and

$$s_{xy} = \frac{\left(\sum(x*y)\right)-\left(\sum x*\sum y\right)}{n}, \tag{8}$$

$$s_{xx} = \frac{\sum x^2-\left(\sum x\right)^2}{n}, \tag{9}$$

$$s_{yy} = \frac{\sum y^2-\left(\sum y\right)^2}{n} \tag{10}$$

The second calculation of the power law exponent (α_N) is modeled after Newman's (2005) fifth formula, which is sensitive to a cutoff parameter that determines how much of the "tail" to measure. Newman's power law exponent α is calculated as

$$\alpha_N = 1+n\left[\sum_{i=1}^{n}\ln\frac{x_i}{x_{min}}\right]^{-1} \tag{11}$$

where n is the number of nodes in the network, x_i for $i = 1 \ldots n$ are the measured values of x, and x_{min} is the minimum value of x.

Newman's error is an estimate of the expected statistical error, and is calculated as:

$$\sigma = \frac{\alpha-1}{\sqrt{n}} \tag{12}$$

For example, Newman's power law exponent for a network where $\alpha = 2.500$ and $\sigma = 0.002$ would estimate to $\alpha = 2.500 \pm 0.002$.

Clustering Coefficient

Finally, clustering coefficients are used to determine whether a network can be labeled as a small-world network. Two calculations were used.

The first, the Watts-Strogatz clustering coefficient (C_{WD}) (Watts & Strogatz, 1998), is computed as:

$$C_{WD} = \frac{\sum_i C_i}{n} \tag{13}$$

where n is the number of nodes and

$$C_i = \frac{T_i}{R_i} \tag{14}$$

with T_i defined as the number of triangles, or completely connected triples, connected to node i and R_i defined as the number of triples, both completely and partially connected, centered on node i.

The second, the Newman clustering coefficient (C_N) (Newman, 2003), is computed as:

$$C = \frac{3*\text{number of triangles in the network}}{\text{number of connected triples of vertices}} \tag{15}$$

For instance, if paper A cites paper B and paper B cites paper C, this is a connected triple. If paper A also cites paper C, or C cites A, then this is a triangle. Determining the number of triangles relative to the number of connected triples gives a measure of a network's transitivity. A real-world network will generally have a much higher clustering coefficient than a random network of the same size.

Paper Network

The paper citation network includes all connections between ACL Anthology papers. It is a directed network with each node representing a paper labeled with an ACL ID number and the edges representing a citation within that paper to another paper represented by an ACL ID. The ACL ID number for each paper consists of a single letter denoting the venue and the year of publication.

Paper Network—General Statistics

The network consists of 11,749 nodes, each representing a unique ACL ID number, and 44,138 directed edges. Of these nodes, 1,945 are completely disconnected with a degree of 0, leaving 9,764 connected nodes. The distribution of the in-degree, which is the number of citations a publication receives, is shown in Figure 4. The size of the largest connected component is 9,594 with an average degree of 9.04, a diameter of 20, a Clairlib average directed shortest path of 5.82, a Ferrer average directed shortest path of 5.11, and a harmonic mean geodesic distance is 90.65. The paper citation network network contains 2,085 connected components. For this network $C_{WS} = 0.1879$ and $C_N = 0.0804$. A random network of the same size composed using the Erdos-Renyi model gives $C_{WS} = 0.0009$, which is much lower than that of the AAN paper citation network, confirming that the AAN paper citation network is a small-world network.

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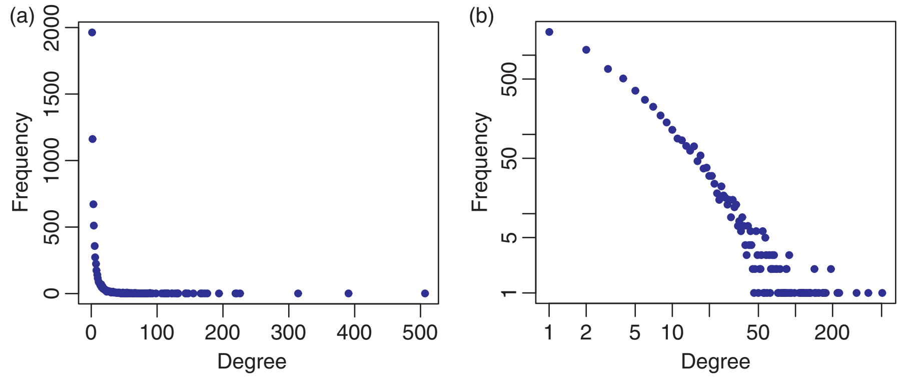

FIG. 4. Degree distribution of the paper citation network. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

TABLE 3. Paper citation network power law measures.

Type	α_{LS}	r^2	α_N	σ
In-degree	2.52	0.97	2.03	0.02
Out-degree	3.67	0.87	2.15	0.01
Total degree	2.75	0.97	1.82	0.01

One of the most convincing and widely accepted mechanism for generating power law distributions in a graph is the Yule process or preferential attachment process (Albert & Barabasi, 2002). In this process, new nodes are added to the network one at a time. Each new node is connected to m existing nodes with a probability that is proportional to the number of links that the existing nodes already have. Formally, the probability p_i that the new node is connected to node i is:

$$p_i = \frac{k_i}{\sum_j k_j} \tag{16}$$

where k_i is the degree of node i. Thus, the new nodes have a preference to connect to existing high-degree nodes. The power law values of the network are shown in Table 3. The value of α_N approaches 2, indicating a preference for edge attachment to a small number of high degree nodes.

Measures of Impact

In this section, we explore three measures of impact for publications and venues. All the measures are based on the paper citation network and derived networks (Venue citation network). We would like to emphasize that all measures of impact are based on the citation network of the publications in the ACL anthology. Hence, all resulting conclusions are valid only within the ACL anthology.

Incoming citations. In an effort to analyze the impact of individual papers on the network, we looked at the total number of citations for each paper. The 20 most-cited papers within the anthology are listed in Table 4.

Figure 5 shows the incoming citations by year from each year in the anthology, regardless of venues. Recent years show a stronger occurence of reference than much older proceedings. This could be explained by the presence of higher numbers of papers in more recent years. The dominance of 1993 as a resource for citation does not fit well into the overall scheme until you consider that the two most-cited papers in the anthology: *Building a Large Annotated Corpus of English: The Penn Treebank* by Mitchell P. Marcus, Mary Ann Marcinkiewicz, and Beatrice Santorini (cited 507 times) and *The Mathematics Of Statistical Machine Translation: Parameter Estimation* by Peter F. Brown, vincent J. Della Pietra, Stephen A. Della Pietra, and Robert L. Mercer (cited 391 times) were both published in *Computational Linguistics* in 1993.

Impact factor. One popular measure of a venue's quality is its impact factor, one of the standard measures created by the Institute for Scientific Information (ISI, now Thomson Reuters). The impact factor is calculated as follows:

$$\frac{\text{Citations to Articles Published in Previous } k \text{ Years}}{\text{No. of Articles Published in Previous } k \text{ Years}} \tag{17}$$

For example, the impact factor over a 2-year period for a 2005 journal is equivalent to the number of citations included in that paper to publications in 2003 and 2004 divided by the total number of articles published in those 2 previous years (Amin & Mabe, 2000). This method may skew results in favor of popularity and not necessarily importance. Modifications and additional metrics have been proposed to account for this (Bollen, Rodriguez, & Van de Sompel, 2006), such as instead using a weighted PageRank or a combination of the two.

The impact factor was calculated for the ACL Anthology network based on a 2-year period using $k = 2$ in Equation (17). Note that impact factor and all other citation-based metrics are calculated based on the citation network which only includes citations within the ACL anthology. Therefore, all metrics that are calculated in this paper, like the impact factor, PageRank, and all resulting conclusions, are valid

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TABLE 4. 20 most-cited papers in the anthology.

ACL ID	Title	Authors	Number of times cited
J93-2004	*Building A Large Annotated Corpus Of English: The Penn Treebank*	Marcus, Mitchell P.; Marcinkiewicz, Mary Ann; Santorini, Beatrice	507
J93-2003	*The Mathematics Of Statistical Machine Translation: Parameter Estimation*	Brown, Peter F.; Della Pietra, Vincent J.; Della Pietra, Stephen A.; Mercer, Robert L.	391
J86-3001	*Attention Intentions And The Structure Of Discourse*	Grosz, Barbara J.; Sidner, Candace L.	314
A88-1019	*A Stochastic Parts Program And Noun Phrase Parser For Unrestricted Text*	Church, Kenneth Ward	226
A00-2018	*A Maximum-Entropy-Inspired Parser*	Charniak, Eugene	221
J96-1002	*A Maximum Entropy Approach To Natural Language Processing*	Berger, Adam L.; Della Pietra, Vincent J.; Della Pietra, Stephen A.	219
P02-1040	*Bleu: A Method For Automatic Evaluation Of Machine Translation*	Papineni, Kishore; Roukos, Salim; Ward, Todd; Zhu, Wei-Jing	194
P97-1003	*Three Generative Lexicalized Models For Statistical Parsing*	Collins, Michael John	194
W96-0213	*A Maximum Entropy Model For Part-Of-Speech Tagging*	Ratnaparkhi, Adwait	176
J95-4004	*Transformation-Based-Error-Driven Learning And Natural Language Processing: A Case Study In Part-Of-Speech Tagging*	Brill, Eric	172
P95-1026	*Unsupervised Word Sense Disambiguation Rivaling Supervised Methods*	Och, Franz Josef; Ney, Hermann	166
J03-1002	*A Systematic Comparison Of Various Statistical Alignment Models*	Och, Franz Josef; Ney, Hermann	166
J02-3001	*Automatic Labeling Of Semantic Roles*	Gildea, Daniel; Jurafsky, Daniel	155
J90-2002	*A Statistical Approach To Machine Translation*	Brown, Peter F.; Cocke, John; Della Pietra, Stephen A.; Della Pietra, Vincent J.; Jelinek, Frederick; Lafferty, John D.; Mercer, Robert L.; Roossin, Paul S.	147
P03-1021	*Minimum Error Rate Training In Statistical Machine Translation*	Och, Franz Josef	143
J93-1003	*Accurate Methods For The Statistics Of Surprise And Coincidence*	Dunning, Ted E.	143
N03-1017	*Statistical Phrase-Based Translation*	Koehn, Philipp; Och, Franz Josef; Marcu, Daniel	143
J92-4003	*Class-Based N-Gram Models Of Natural Language*	Brown, Peter F.; DeSouza, Peter V.; Mercer, Robert L.; Watson, Thomas J.; Della Pietra, Vincent J.; Lai, Jennifer C.	132
J90-1003	*Word Association Norms Mutual Information And Lexicography*	Church, Kenneth Ward; Hanks, Patrick	131
J96-2004	*Assessing Agreement On Classification Tasks: The Kappa Statistic*	Carletta, Jean	130

within the context of ACL Anthology. For example, a high impact factor for a journal implies that the journal is impactful only within the ACL Anthology. The overall impact of these venues cannot be necessarily and sufficiently substantiated with metrics computed from the ACL Anthology citation networks alone. Figure 6 shows the results for each year where there are data in the AAN. In most of the years with lower impact (1989, 1995, 1999, 2001) there were fewer papers published than in neighboring years. Although 1985 had the same number of publications as the neighboring years, the number of citations from the publications published in 1985 to the previous 2 years' publications was less than average.

We also studied the impact of conferences and journals separately based on the number of citations they receive.

Table 5 shows the number of citations from papers in one type of publication to others, shown by year. (W = WS, J = CLJ, A = ANLP, N = NAACL, E = EACL, H = HLT, I = IJCNLP). For example, all ACL 2005 papers together included a total of 849 citations to other Anthology papers. Of these, 515 were to other conference papers, 191 were to workshop papers, and 143 were to (CL) journal papers.

This table shows that 75% of all citations in the journal to other Anthology papers go to conference and workshop papers and that 85% of all citations in ACL proceedings go to conference and workshop papers. In other words, on average a paper in the ACL or *Computational Linguistics* cites four to five times as many conference or workshop papers than journal papers.

Also, the percentage of citations from conference and workshop papers grows from year to year. In ACL 2007, 88% of its citations are from conference and workshop papers, compared with 78% in 2004. Note that the total number of citations from ACL Anthology papers to ACL 2007 papers has almost doubled from the number of ACL Anthology citations to ACL 2004 papers. This is due to increase in the overall number of publications. However, conferences and workshop publications account for a bigger portion of the total number of ACL Anthology citations. This shows that

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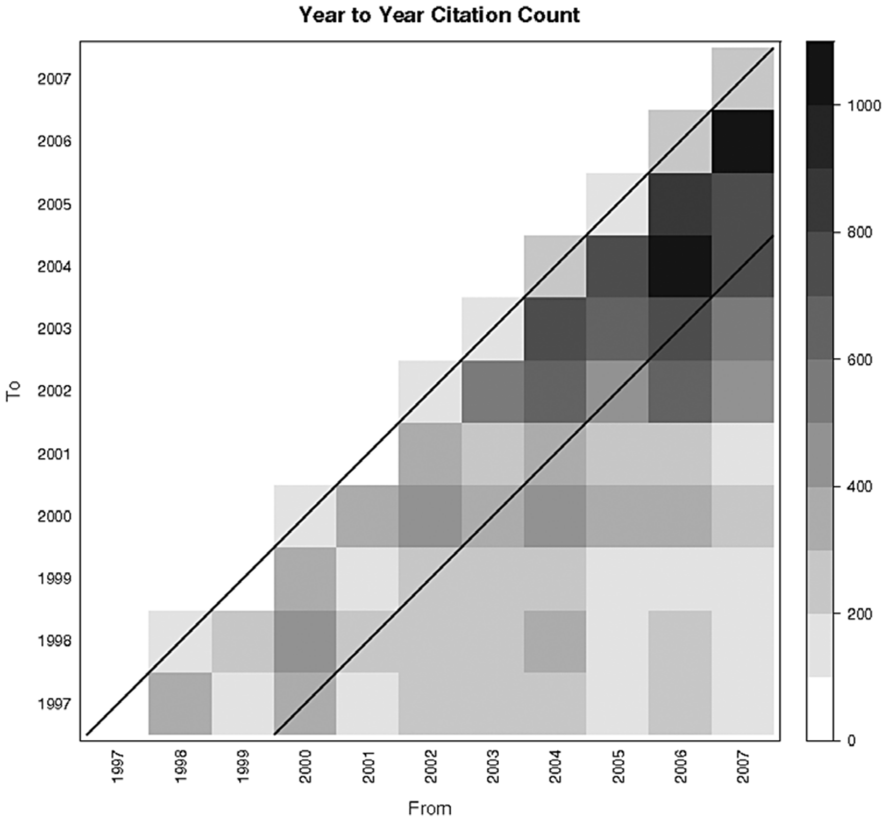

FIG. 5. Citation counts from one year to another (1997–2007). The area between the lines is a range of citations to the previous 2 years. Most papers cite recent papers.

conference and workshop papers are advancing in the field and they are having more and more significant impact.

PageRank. The Clairlib library includes code to analyze the centrality of a network using the PageRank algorithm described in Page, Brin, Motwani, and Winograd (1998). In calculating the ACL Anthology network centrality using PageRank, we find a general bias towards older papers. Older papers have had longer to accumulate new citations over time. It is not surprising, then, that the papers with the highest PageRank scores are slightly older. Table 6 includes a listing of the 20 papers with the highest PageRank—rounded to the nearest ten-thousandth.

To address the fact that older papers have had a longer time period to accumulate direct and indirect incoming citations and hence are more likely to have higher PageRank values, we also calculated the PageRank per year for all of the papers in the ACL Anthology. To calculate this, we simply took the PageRank for each paper and divided by the number of years that had passed since that paper's publication. So, if a paper had been published in 2000, the PageRank would be divided by eight (2008 minus 2000). Although this is not a widely studied statistic, we felt if may offer some further insight into the structure of the network. As one can see from the results in Table 7, this measure seems to favor the newer papers.

Author Networks

Using the paper network, and the metadata associated with each paper, we also created a network of author citations and a network of author collaborations. The following two sections describe in greater detail these two networks, as well as provide statistics and comparisons to other research.

Citation Network

The author citation network is derived from the paper network described previously, where each node is a unique author and each edge is an occurrence of one author citing another author. For each paper, each author of that paper occurs as a node in the network. If one paper cites another paper, then all authors of the first paper cite all authors of the second paper. For example: if Andrea Setzer cites an earlier paper by James D. Pustejovsky, then the link "Setzer, Andrea → Pustejovsky, James D." would occur in the network. Self-citations are treated the same way. We have created two versions of the author citation network, one that includes self-citations and one that does not. Statistics from the network devoid of self-citations are shown in parentheses. Note that disconnected nodes are removed from the network. This explains the difference in the number of nodes between the two networks.

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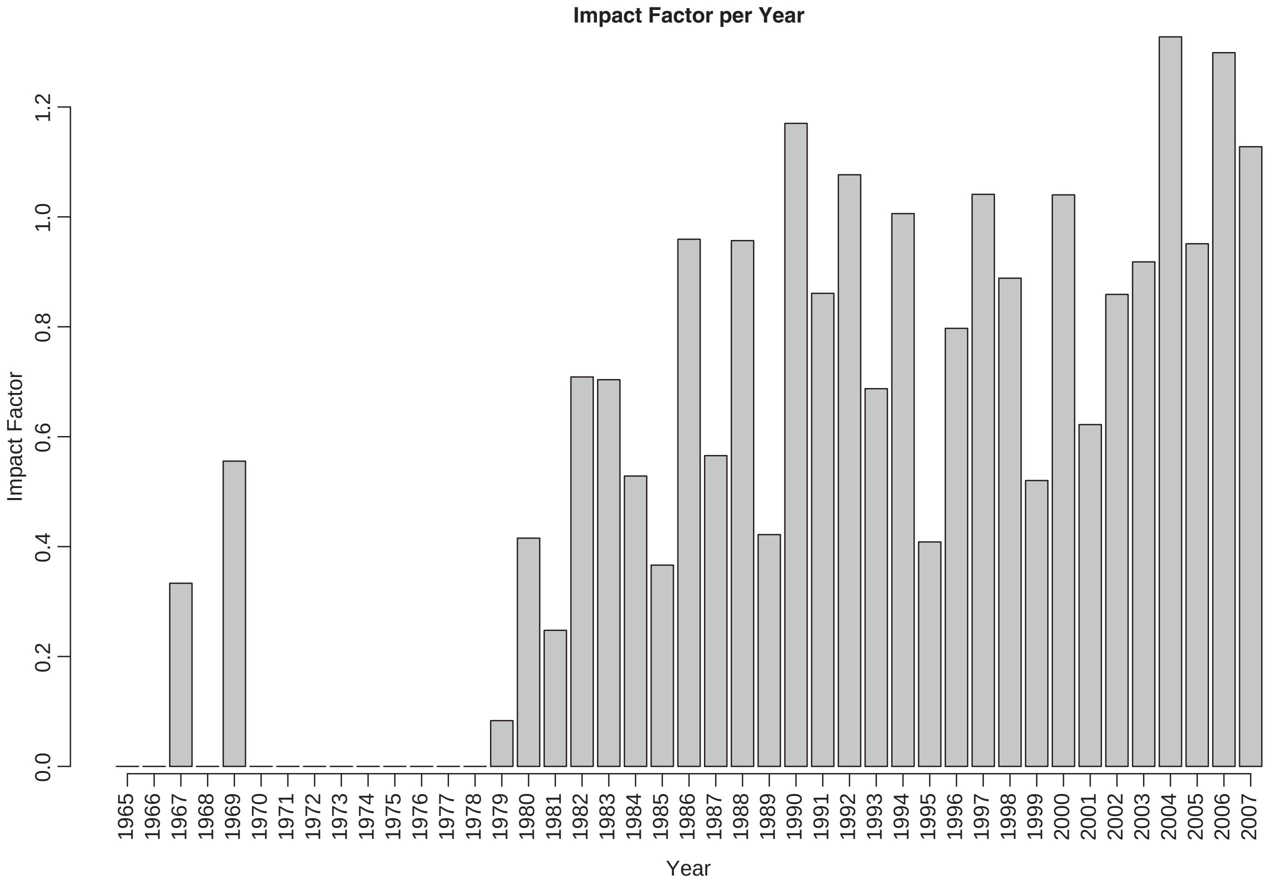

FIG. 6. Impact factor per year from 1965 to 2007.

Citation network—general statistics. The author citation network consists of 9,421 (8,504) nodes and 158,497 (134,903) directed edges. The degree distribution can be seen in Figure 7. The size of the largest connected component is 7,672 (7,672) with a diameter of 10 (10), a Clairlib avg. directed shortest path of 3.34 (3.34), and a Ferrer avg. directed shortest path of 3.3 (3.3). The harmonic mean geodesic distance is 7.88 (7.88). Power law measures are given in Table 8. The power law measure given by the least squares method indicates a strong preference for new edges to attach to high degree nodes, while the Newman method gives a value showing a weaker preference.

The clustering measures of this network are $C_{WS} = 0.4687$ (0.4584) and $C_N = 0.1474$ (0.1374). In a random network of the same size, both C_{WS} and C_N would be 0.0017. The actual network values are significantly higher, indicating a small-world network.

Citation network—degree statistics. In Table 9, we show the top 20 authors in both incoming and outgoing citations. Outgoing citations refer to the number of times an author cites other authors within the ACL Anthology. Incoming citations refer to the most-cited authors within the ACL Anthology. It should be noted that the out-degree measure is expected to be proportional to the number of papers written by a specific author. In Table 10, the top 30 weighted edges are listed from the citation network. The weight represents the number of citations from one author to another. So, for instance, as one can see from the chart, Hermann Ney cites different works by Franz Josef Och 103 times. Individual papers may have multiple references to papers by the same author. It is common to cite your own research, which can be seen by the fact that 21 of the top 30 strongest edges in the graph are self-citations. This shows not only the prevalence of self-citation in research, but also points to a potential problem in networks of this type. The decision to include self-citations in a citation network will obviously skew the data in favor of authors who have written more papers and who use many self-citations.

An additional experiment performed was to calculate the log base 10 of the number of incoming citations for each paper for an author and to then sum these logs. This greatly reduced the skew of those authors with very large numbers of citations. The top 20 authors by this value are shown in Table 11.

Citation network—h-index. In 2005, a new metric to calculate author prestige was proposed (Hirsch, 2005, p. 1) called the h-index. "A scientist has index h if h of their N papers have at least h citations each, and the other $(N-h)$

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TABLE 5. Interconference citation.

	W07	W06	W05	W04	W03	ACL07	ACL06	ACL05	ACL04	ACL03	N07	N06	N04	N03
A	51	77	58	97	79	31	70	45	26	33	15	20	18	29
C	106	208	112	179	144	93	222	69	54	71	36	45	29	29
E	70	77	28	40	29	49	55	16	16	12	25	11	6	6
H	74	118	13	47	35	61	119	11	15	9	47	51	15	15
J	225	330	241	414	180	163	287	143	144	104	90	103	71	73
M	6	10	1	8	20	5	4	2	4	7	2	1	4	3
ACL	566	760	318	540	337	456	663	281	220	162	293	219	152	117
W	660	772	407	560	319	313	465	191	135	117	165	162	104	75
X	0	1	0	0	0	0	1	1	0	0	0	0	0	0
N	158	188	111	125	37	134	147	90	50	13	98	89	48	13
Total	1,916	2,541	1,289	2,010	1,180	1,305	2,033	849	664	528	771	701	447	360
CONF	1,031	1,439	641	1,036	681	829	1,281	515	385	307	516	436	272	212
WS	660	772	407	560	319	313	465	191	135	117	165	162	104	75
JRNL	225	330	241	414	180	163	287	143	144	104	90	103	71	73
CONF (%)	0.54	0.57	0.5	0.52	0.58	0.64	0.63	0.61	0.58	0.58	0.67	0.62	0.61	0.59
WS (%)	0.34	0.3	0.32	0.28	0.27	0.24	0.23	0.22	0.2	0.22	0.21	0.23	0.23	0.21
JRNL (%)	0.12	0.13	0.19	0.21	0.15	0.12	0.14	0.17	0.22	0.2	0.12	0.15	0.16	0.2

	J05	J04	J03	I05	H05	E06	E03	C04	C02	A00
A	14	9	18	17	26	12	33	54	56	63
C	26	22	32	72	72	41	57	134	129	43
E	7	3	7	6	12	18	20	34	15	7
H	9	6	15	5	31	20	6	22	24	13
J	55	70	59	67	143	75	73	201	146	88
M	4	0	0	3	12	1	3	4	13	14
ACL	89	76	77	115	297	129	123	313	249	179
W	53	39	48	162	234	101	85	250	155	62
X	0	0	0	0	0	0	0	0	0	2
N	14	5	4	30	93	24	2	66	16	0
Total	271	230	260	477	920	421	402	1,078	803	471
CONF	163	121	153	248	543	245	244	627	502	321
WS	53	39	48	162	234	101	85	250	155	62
JRNL	55	70	59	67	143	75	73	201	146	88
CONF (%)	0.6	0.53	0.59	0.52	0.59	0.58	0.61	0.58	0.63	0.68
WS (%)	0.2	0.17	0.18	0.34	0.25	0.24	0.21	0.23	0.19	0.13
JRNL (%)	0.2	0.3	0.23	0.14	0.16	0.18	0.18	0.19	0.18	0.19

Note. W = WS; J = CLJ; A = ANLP; N = NAACL; E = EACL; H = HLT; I = IJCNLP.

papers have no more than h citations each." It is designed to highlight an author's overall productivity, penalizing those authors who have only a few highly cited papers or many papers with fewer citations. There is some disagreement as to the relevance of this metric, as it appears to penalize younger authors and authors with fewer papers (Lehmann, Jackson, & Lautrup, 2006). Modifications to the calculation have been attempted to fix this deficiency (Sidiropoulos, Katsaros, & Manolopoulos, 2006). Here, we continue to use the original method of computation as it continues to produce interesting results that match intuition (Hirsch, 2007).

One of the drawbacks of the h-index is that it can vary widely between different scientific disciplines, as well as between a broader discipline and one of its subdisciplines. Using the author citation network, we attempt to look at how the h-index for a group of specialty publications, the ACL, compares to the h-index of those same researchers when calculated against their full publication history, approximated by their citations recorded in Google Scholar (GS).

We calculated the h-index for all authors in the AAN (h_{AAN}), but, due to time constraints, chose to only compare authors with an h-index of 9 or above, which amounted to 51 authors, against their GS h-index (h_{GS}). To find the h-index from GS, we used the Publish or Perish tool (Harzing, 2008). This tool queries GS to retrieve all publication data for each author entered. We queried the author names within all categories (science, humanities, etc.) due to the fact that many of the authors publishing in ACL venues also publish in venues devoted to other subjects (e.g., linguistics, information retrieval, databases, bioinformatics, cognitive science). Since Google Scholar is particularly noisy with respect to citation data, only articles and books were considered publications and care was taken to remove publications retrieved by name collisions or name misspellings, as well as records returned pertaining to patent submissions. The h_{GS} values were all recorded at the end of April, 2008 and reflect the current values at that time.

The resulting data can be found in Table 12. The average h_{AAN} for our sample is 10.63, with a high of 16 and a low of 9.

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TABLE 6. Papers with the highest PageRanks.

ACL ID	PageRank	Authors	Title
J93-2004	0.0062	Marcus, Mitchell P.; Marcinkiewicz, Mary Ann; Santorini, Beatrice	*Building A Large Annotated Corpus Of English: The Penn Treebank*
J93-2003	0.0050	Brown, Peter F.; Della Pietra, Vincent J.; Della Pietra, Stephen A.; Mercer, Robert L.	*The Mathematics Of Statistical Machine Translation: Parameter Estimation*
J86-3001	0.0070	Grosz, Barbara J.; Sidner, Candace L.	*Attention Intentions And The Structure Of Discourse*
J96-1002	0.0012	Berger, Adam L., Della Pietra, Vincent J., Della Pietra, Stephen A.,	*A Maximum Entropy Approach To Natural Language Processing*
A00-2018	0.0012	Charniak, Eugene	*A Maximum-Entropy-Inspired Parser*
P97-1003	0.0010	Collins, Michael John	*Three Generative Lexicalized Models For Statistical Parsing*
P02-1040	0.0010	Papineni, Kishore, Roukos, Salim, Ward, Todd, Zhu, Wei-Jing	*Bleu: A Method For Automatic Evaluation Of Machine Translation*
J95-4004	0.0009	Brill, Eric	*Transformation-Based-Error-Driven Learning And Natural Language Processing: A Case Study In Part-Of-Speech Tagging*
P95-1026	0.0009	Yarowsky, David	*Unsupervised Word Sense Disambiguation Rivaling Supervised Methods*
W96-0213	0.0008	Ratnaparkhi, Adwait	*A Maximum Entropy Model For Part-Of-Speech Tagging*
J03-1002	0.0008	Och, Franz Josef; Ney, Hermann	*A Systematic Comparison Of Various Statistical Alignment Models*
J02-3001	0.0008	Gildea, Daniel; Jurafsky, Daniel	*Automatic Labeling Of Semantic Roles*
J93-1003	0.0007	Dunning, Ted E.	*Accurate Methods For The Statistics Of Surprise And Coincidence*
J90-2002	0.0007	Brown, Peter F., Cocke, John, Della Pietra, Stephen A., Della Pietra, Vincent J., Jelinek, Frederick, Lafferty, John D., Mercer, Robert L., Roossin, Paul S.	*A Statistical Approach To Machine Translation*
J92-4003	0.0007	Brown, Peter F., DeSouza, Peter V., Mercer, Robert L., Watson, Thomas J., Della Pietra, Vincent J., Lai, Jennifer C.	*Class-Based N-Gram Models Of Natural Language*
N03-1017	0.0007	Koehn, Philipp, Och, Franz Josef, Marcu, Daniel	*Statistical Phrase-Based Translation*
P03-1021	0.0007	Och, Franz Josef	*Minimum Error Rate Training In Statistical Machine Translation*
J90-1003	0.0007	Church, Kenneth Ward, Hanks, Patrick	*Word Association Norms Mutual Information And Lexicography*

The corresponding average for these authors for all h_{GS} is 27.08, with a high of 45 and a low of 11. The high values in GS are much higher than in the AAN, again due to the AAN being just a subset of the authors' full publication history.

The Pearson correlation of the h_{GS} to the h_{AAN} is 0.51 for those authors with an h_{AAN} of 9 or above. The fairly low correlation shows that a high h_{GS} does not necessarily mean a high h_{AAN}. This is most likely due to the fact that some authors produce most of their highly cited work within the field covered by the ACL, while others produce most of their highly cited work outside of this field. For instance, Hermann Ney has published much in the speech community, leading to a much higher h_{GS} than h_{AAN}. The same is true of Fernando Pereira, publishing many papers in the machine learning community. To test the theory that authors with a much higher h_{GS} than h_{AAN} publish a significant amount outside of the AAN, we did a regression of the AAN versus GS h-index scores, shown in Figure 8. Author's more than 2 σ away from this line have an abnormal AAN-to-GS h-index ratio. The two authors who fall $\geq 2\ \sigma$ above the line, Marti A. Hearst and Eduard H. Hovy, have many more highly cited papers outside of AAN than within AAN. Their h_{AAN}, using a subset of their papers, was significantly lower than their overall h-index. The author who falls below 2 σ, Stephen Clark, has published all of his papers within the AAN. The AAN index here is representative of the total h-index for the author. Another correlation tested was that of h_{AAN} against the author's incoming citation count within the AAN, again for authors with an AAN h-index of 9 or above. The Pearson correlation here was also low, at 0.52. Figure 9 shows the calculated regression. All the authors above the line of regression have a small number of very highly cited papers. This is one argument against the h-index, that authors who might be considered central due to the importance of one or two of their papers are penalized. Therefore, neither the total number of citations nor the h-index can be used alone to rank authors since the metrics measure very different quantities and, depending on the use case, the right metric should be chosen. For example, if longevity of research career or consistency of citations to publications is important, then the h-index is a better measure than the total number of citations. The last correlation we investigated was between an author's h_{AAN} and their PageRank in the author citation network. This is the weighted PageRank, where each citation from one

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TABLE 7. Papers with the highest PageRank per Year (PPY).

ACL ID	PPY	Authors	Title
J93-2004	0.00019	Marcus, Mitchell P.; Marcinkiewicz, Mary Ann; Santorini, Beatrice	*Building A Large Annotated Corpus Of English: The Penn Treebank*
J03-1002	0.00017	Och, Franz Josef; Ney, Hermann	*A Systematic Comparison Of Various Statistical Alignment Models*
P02-1040	0.00016	Papineni, Kishore; Roukos, Salim; Ward, Todd; Zhu, Wei-Jing	*Bleu: A Method For Automatic Evaluation Of Machine Translation*
N03-1017	0.00015	Koehn, Philipp, Och, Franz Josef, Marcu, Daniel	*Statistical Phrase-Based Translation*
A00-2018	0.00015	Charniak, Eugene	*A Maximum-Entropy-Inspired Parser*
P03-1021	0.00014	Och, Franz Josef	*Minimum Error Rate Training In Statistical Machine Translation*
J93-2003	0.00014	Brown, Peter F.; Della Pietra, Vincent J.; Della Pietra, Stephen A.; Mercer, Robert L.	*The Mathematics Of Statistical Machine Translation: Parameter Estimation*
J02-3001	0.00013	Gildea, Daniel; Jurafsky, Daniel	*Automatic Labeling Of Semantic Roles*
P05-1033	0.00012	Chiang, David	*A Hierarchical Phrase-Based Model For Statistical Machine Translation*
P05-1022	0.00011	Charniak, Eugene; Johnson, Mark	*Coarse-To-Fine N-Best Parsing And MaxEnt Discriminative Reranking*
D07-1096	0.00010	Nivre, Joakim; Hall, Johan; Kubler, Sandra; McDonald, Ryan; Nilsson, Jens; Riedel, Sebastian; Yuret, Deniz	*The CoNLL 2007 Shared Task on Dependency Parsing*
J96-1002	0.00010	Berger, Adam L., Della Pietra, Vincent J., Della Pietra, Stephen A.,	*A Maximum Entropy Approach To Natural Language Processing*
P97-1003	0.00009	Collins, Michael John	*Three Generative Lexicalized Models For Statistical Parsing*
P03-1054	0.00009	Klein, Dan; Manning, Christopher D.	*Accurate Unlexicalized Parsing*
P00-1056	0.00008	Och, Franz Josef; Ney, Hermann	*Improved Statistical Alignment Models*
W06-2920	0.00008	Buchholz, Sabine; Marsi, Erwin	*CoNLL-X Shared Task On Multilingual Dependency Parsing*
J04-4002	0.00008	Och, Franz Josef; Ney, Hermann	*The Alignment Template Approach To Statistical Machine Translation*
W05-0620	0.00008	Carreras, Xavier; Marquez, Lluis	*Introduction To The CoNLL-2005 Shared Task: Semantic Role Labeling*
P05-1012	0.00007	McDonald, Ryan; Crammer, Koby; Pereira, Fernando C. N.	*Online Large-Margin Training Of Dependency Parsers*
P02-1038	0.00007	Och, Franz Josef, Ney, Hermann	*Discriminative Training And Maximum Entropy Models For Statistical Machine Translation*

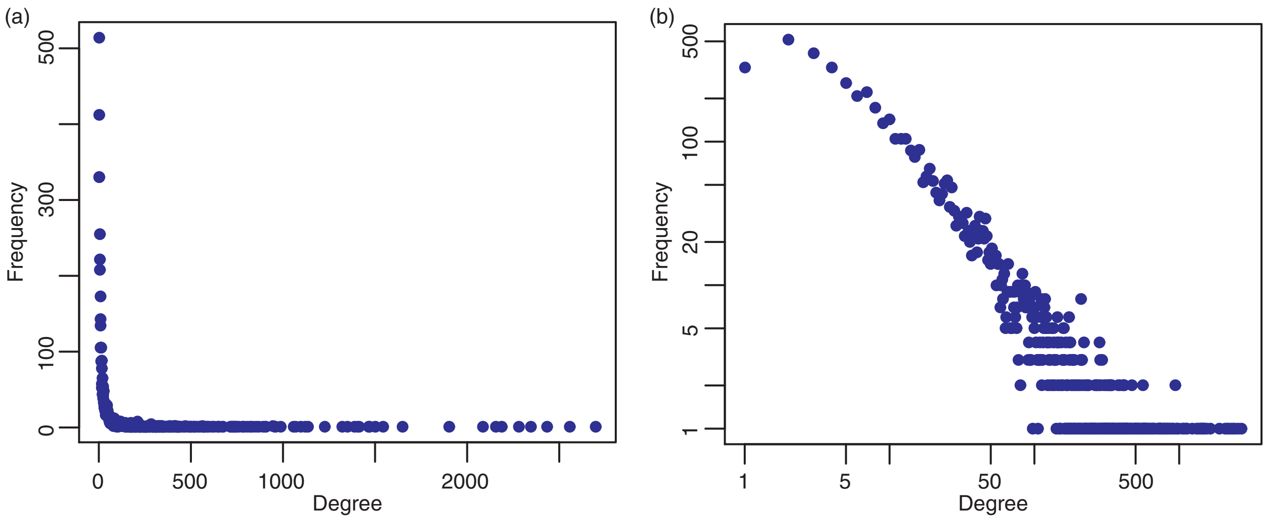

FIG. 7. Degree distribution of the author citation network. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

author to another is counted as a weight between those authors. Again, we used the same list of 51 top authors by h-index. The results can be seen in Figure 10. The correlation here is not very strong at all, with a Pearson correlation coefficient of 0.33. All of the authors who appear as outliers are early pioneers who wrote very influential papers early on. Their papers have gained important links disproportionate to other authors in the list. In order to investigate where authors may be publishing papers outside of the AAN, we chose to look at one author and determine the venue of all of the papers

TABLE 8. Author citation network power law measures. Refer to Network Analysis Methods section for an explanation of these measures.

Type	α_{LS}	r^2	α_N	σ
In-degree	2.21 (2.21)	0.91 (0.91)	1.57 (1.57)	0.01 (0.01)
Out-degree	2.57 (2.57)	0.85 (0.85)	1.55 (1.55)	0.00 (0.00)
Total degree	2.28 (2.28)	0.89 (0.89)	1.46 (1.46)	0.00 (0.00)

TABLE 9. Author citation network highest in- and out-degrees.

Out-degree (Prolificness)		In-degree (Popularity)	
1,367	Ney, Hermann	2,699	Och, Franz Josef
1,223	Tsujii, Jun'ichi	2,557	Della Pietra, Vincent J.
1,023	Marcu, Daniel	2,433	Ney, Hermann
988	McKeown, Kathleen R.	2,347	Mercer, Robert L.
848	Matsumoto, Yuji	2,281	Della Pietra, Stephen A.
816	Hovy, Eduard H.	2,187	Marcus, Mitchell P.
798	Collins, Michael John	2,155	Church, Kenneth Ward
794	Grishman, Ralph	2,086	Brown, Peter F.
760	Joshi, Aravind K.	1,902	Collins, Michael John
758	Lapata, Mirella	1,649	Yarowsky, David
723	Palmer, Martha Stone	1,543	Charniak, Eugene
702	Koehn, Philipp	1,502	Pereira, Fernando C. N.
657	Knight, Kevin	1,469	Marcinkiewicz, Mary Ann
644	Miyao, Yusuke	1,467	Grishman, Ralph
631	Carroll, John A.	1,466	Santorini, Beatrice
625	Curran, James R.	1,415	Joshi, Aravind K.
619	Ng, Hwee Tou	1,408	Knight, Kevin
614	Wiebe, Janyce M.	1,388	Brill, Eric
599	Johnson, Mark	1,349	Marcu, Daniel
598	Och, Franz Josef	1,323	Roukos, Salim

that appear in a GS search for that author that contributes to their h-index score. We chose the author "Yarowsky, D" due to the rare spelling, making the search easier. The results are shown in Table 13. Out of 29 publications, only 15 are included in both AAN and GS, dramatically reducing the papers available for h_{AAN} as compared with h_{GS}.

Citation network—PageRank. We computed the PageRank centrality of the author citation network. For this measure, in order to avoid bias due to repeated citations, we analyzed two different networks, both an unweighted and a weighted citation network. The weighted network weights each edge with the number of repeated citations, whereas the unweighted network treats all incidences of a citation from one author to another as a single occurrence.

The top-weighted and unweighted PageRank results can be seen in Table 14. Values have been rounded to the nearest hundred-thousandth. Both weighted and unweighted networks still generally share the same central authors in the ACL Citation Network—17 out of 20 authors show up in both lists.

Citation network—correlations between different measures of impact. We performed several experiments in comparing the different measures of impact. Currently, there are various measures of impact proposed for citation networks. We computed various measures of impact in the author citation network such as h-index, total number of incoming citations, and PageRank.

We computed the Pearson's rank correlation coefficient for each pair of the measures of the impact. We chose the top

TABLE 10. Author citation network highest edge weights. Bold values are self-citations.

(168)	**Ney, Hermann → Ney, Hermann**
(122)	Ney, Hermann → Och, Franz Josef
(85)	**Tsujii, Jun'ichi → Tsujii, Jun'ichi**
(84)	**Grishman, Ralph → Grishman, Ralph**
(80)	**Joshi, Aravind K. → Joshi, Aravind K.**
(72)	Ney, Hermann → Della Pietra, Vincent J.
(71)	Ney, Hermann → Della Pietra, Stephen A.
(70)	Och, Franz Josef → Ney, Hermann
(69)	**Seneff, Stephanie → Seneff, Stephanie**
(68)	Ney, Hermann → Tillmann, Christoph
(64)	**Litman, Diane J. → Litman, Diane J.**
(64)	**Knight, Kevin → Knight, Kevin**
(62)	Ney, Hermann → Mercer, Robert L.
(62)	Ney, Hermann → Brown, Peter F.
(60)	Zens, Richard → Ney, Hermann
(60)	**Weischedel, Ralph M. → Weischedel, Ralph M.**
(60)	**Curran, James R. → Curran, James R.**
(59)	**Och, Franz Josef → Och, Franz Josef**
(59)	**Palmer, Martha Stone → Palmer, Martha Stone**
(57)	Zens, Richard → Och, Franz Josef
(57)	**Rambow, Owen → Rambow, Owen**
(57)	**McKeown, Kathleen R. → McKeown, Kathleen R.**
(56)	Curran, James R. → Clark, Stephen
(56)	**Johnson, Mark → Johnson, Mark**
(53)	**Clark, Stephen → Clark, Stephen**
(51)	**Schabes, Yves → Schabes, Yves**
(51)	**Wu, Dekai → Wu, Dekai**
(51)	**Bangalore, Srinivas → Bangalore, Srinivas**
(51)	**Marcu, Daniel → Marcu, Daniel**
(49)	**Hovy, Eduard H. → Hovy, Eduard H.**

TABLE 11. Author citation network—incoming citations log sums. Value is the sum of logs base 10 of incoming citations for each paper authored.

Log sum	Author
34.63	Grishman, Ralph
33.42	Pereira, Fernando C. N.
31.43	Ney, Hermann
31.15	Church, Kenneth Ward
30.59	Joshi, Aravind K.
28.71	Johnson, Mark
28.44	Knight, Kevin
26.69	Hovy, Eduard H.
26.65	Manning, Christopher D.
26.60	McKeown, Kathleen R.
26.18	Och, Franz Josef
26.08	Marcu, Daniel
26.06	Yarowsky, David
25.80	Collins, Michael John
24.84	Charniak, Eugene
23.22	Brill, Eric
22.29	Mercer, Robert L.
21.97	Schabes, Yves
21.56	Moore, Robert C.
21.28	Palmer, Martha Stone

TABLE 12. Author citation h-index—AAN versus Google Scholar for AAN h-index ≥9.

Author	AAN h-index	GS h-index
Church, Kenneth Ward	16	38
Knight, Kevin	15	32
Grishman, Ralph	14	30
Joshi, Aravind K.	14	33
Ney, Hermann	14	45
Pereira, Fernando C. N.	14	45
Yarowsky, David	13	30
Collins, Michael John	12	24
Manning, Christopher D.	12	32
Marcu, Daniel	12	32
McKeown, Kathleen R.	12	39
Mercer, Robert L.	12	35
Och, Franz Josef	12	25
Schabes, Yves	12	25
Shieber, Stuart M.	12	34
Brill, Eric	11	23
Charniak, Eugene	11	37
Dagan, Ido	11	24
Johnson, Mark	11	20
Resnik, Philip	11	30
Carroll, John A.	10	28
Daelemans, Walter	10	30
Gale, William A.	10	27
Hirschman, Lynette	10	30
Hovy, Eduard H.	10	36
Jelinek, Frederick	10	34
Jurafsky, Daniel	10	33
Klein, Dan	10	18
Moore, Robert C.	10	22
Palmer, Martha Stone	10	25
Roukos, Salim	10	30
Weischedel, Ralph M.	10	25
Alshawi, Hiyan	9	19
Bangalore, Srinivas	9	16
Briscoe, Ted	9	29
Brown, Peter F.	9	22
Clark, Stephen	9	11
Della Pietra, Vincent J.	9	15
Gildea, Daniel	9	15
Hearst, Marti A.	9	39
Lee, Lillian	9	18
Marcus, Mitchell P.	9	20
Melamed, I. Dan	9	17
Mihalcea, Rada	9	25
Moens, Marc	9	22
Ng, Hwee Tou	9	17
Rambow, Owen	9	21
Riloff, Ellen	9	27
Tillmann, Christoph	9	15
Walker, Marilyn A.	9	32
Webber, Bonnie Lynn	9	30

200 authors alone for computation of the correlation coefficient. This is because we are more interested in finding out how the different metrics perform in ranking the authors at the top than those at the bottom. These correlation values are shown in Table 15. The metric along the rows is the metric according to which we sorted the authors. Since we chose only the top 200 authors, the matrix is asymmetric, although the Pearson's rank correlation coefficient is symmetric. The correlation curves are shown in Figure 11.

For computing correlations, we had to decide if we should use the measures of impact including self-citations or excluding self-citations. To help us decide, we computed the correlation between the different measures of impact including self-citations and excluding self-citations. The Pearson correlation coefficient values were around 0.99 for the top 200 authors and 0.999 when we use all the authors. From these correlation coefficient values it is clear that it does not matter whether we include self-citations or not for computing the correlations between the measures of impact.

The most interesting fact from these correlation curves is that, when we sort the authors according to their h-index and then compute the correlation between h-index and Total Incoming Citations, we get a much higher correlation than when we sort the authors according to Total Incoming Citations and then compute the correlation. In the former method of computing correlation, the hypothesis we are testing is, does a high h-index imply a high number of Total Incoming Citations? Similarly, in the latter method, the hypothesis being tested is does a high number of Total Incoming Citations imply a high h-index. From the curves, it is clear that a high h-index implies a high number of Total Incoming Citations, whereas the corollary is not true.

Collaboration Network

The author collaboration network is based on the metadata of the ACL Anthology. Whenever one author coauthors (or collaborates on) a paper with another author, an edge between the two is recorded. For instance, the paper *Balancing Data-Driven and Rule-Based Approaches in the Context of a Multimodal Conversational System* was authored by Srinivas Bangalore and Michael Johnston. This collaboration exists as the edge "Bangalore, Srinivas ↔ Johnston, Michael" in the network. Because of the way collaborations are inferred from authorship lists, it should be noted that this network is undirected.

Collaboration network—general statistics. The collaboration consisted of 9,421 nodes and 22,941 undirected edges. The degree distribution can be seen in Figure 12. The largest connected component is 7,672, with a diameter of 20, a Clairlib avg. directed shortest path of 5.86, a Ferrer avg. directed shortest path of 4.63, and a harmonic mean geodesic distance of 9.57. Power law exponent results can be found in Table 16. Note that because this network is undirected, only the total degree power law measure has been computed.

The power law values indicate that the network likely demonstrates characteristics of a power law relationship.

For this network, $C_{WS} = 0.6380$ and $C_N = 0.3799$ are much higher than in a random network of the same size, where $C_{WS} = C_N = 0.00025$. The author collaboration network should be considered a small-world network.

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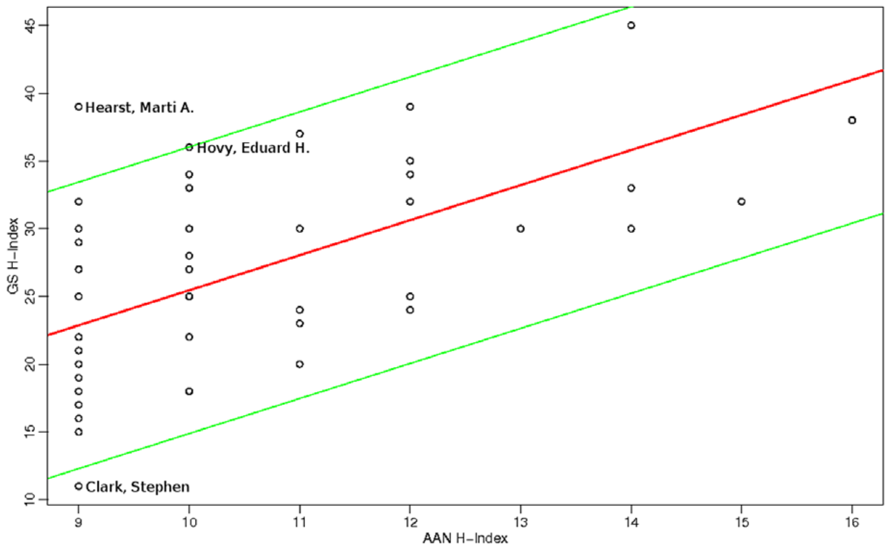

FIG. 8. AAN versus GS h-index regression. The thicker line represents the regression while the two thinner lines represent 2 σ from the regression. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

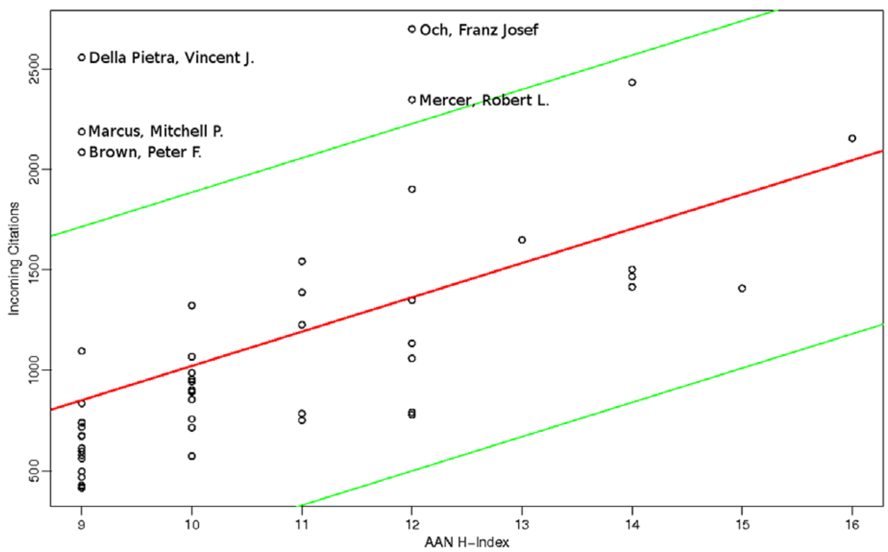

FIG. 9. AAN h-index versus incoming citations. The thicker line represents the regression while the two thinner lines represent 2 σ from the regression. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

The results of other research are included in comparison to our findings for the ACL Anthology Network in Table 17. The power law values are similar, showing a similar propensity for papers with high numbers of citations to gain new citations. The clustering coefficient, however, is different, with the DBLP appearing to be a much more well-connected network.

Collaboration network—degree statistics. In Table 18, we show the 20 authors with the most collaborations in the ACL Anthology Network and the number of collaboration they have been party to, where a collaboration is an event of one author publishing a paper with another author. This equals the degree of the author's node in the collaboration network. In Table 19, the top 34 weighted edges are listed from the collaboration network. The edge weight *n* represents the number of times the two authors have collaborated together.

Collaboration network—shortest paths. We also analyzed the shortest paths in the collaboration network. Since the network is unweighted and undirected, a simple breadth-first search (BFS) was used to compute the shortest paths. The shortest path distance distribution is shown in Table 20. A value of –1 indicates that there is no path between a pair of authors. The distribution is plotted in both standard and loglog scale in Figure 13. It can clearly be seen that the shortest path distances follow a power law in the tail of the distribution. The Newman's power law exponent is shown in Table 21.

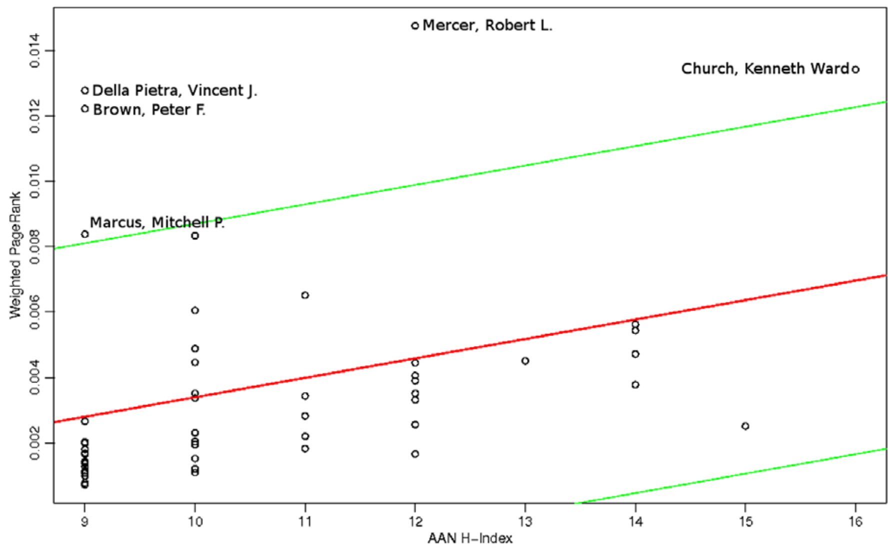

FIG. 10. AAN h-index versus PageRank with regression. The thicker line represents the regression while the two thinner lines represent 2 σ from the regression. PageRank is from the author citation network. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

TABLE 13. Author citation h-index—Google Scholar results venues for Yarowsky, D.

In AAN?	Venue type	Venue	Year	Title
Y	Conference	CoNLL	2003	*Unsupervised personal name disambiguation*
N	Journal	Natural Language Engineering	2003	*Combining Classifiers for word sense disambiguation*
Y	Conference	EMNLP	2002	*Modeling consensus: classifier combination for word sense disambiguation*
N	Report	Progress in Speech Synthesis	2002	*Evaluating sense disambiguation across diverse parameter spaces*
Y	Conference	HLT	2001	*Inducing multilingual text analysis tools via robust projection across aligned corpora*
N	Workshop	SENSEVAL2	2001	*The Johns Hopkins SENSEVAL2 system descriptions*
Y	Conference	NAACL	2001	*Inducing multilingual POS taggers and NP bracketers via robust projection across aligned corpora*
Y	Conference	NAACL	2001	*Multipath translation lexicon induction via bridge languages*
Y	Conference	ACL	2000	*Minimally supervised morphological analysis by multimodal alignment*
Y	Conference	ACL	2000	*Rule writing or annotation: cost-efficient resource usage for base noun phrase chunking*
N	Journal	Computers and the Humanities	2000	*Hierarchical decision lists for word sense disambiguation*
N	Journal	Natural Language Engineering	2000	*Distinguishing systems and distinguishing senses: new evaluation methods for word sense disambiguation*
Y	Conference	ACL	1999	*Dynamic nonlocal language modeling via hierarchical topic-based adaptation*
N	Workshop	JHU Summer WS	1999	*Statistical machine translation*
Y	Conference	SIGDAT	1999	*Language independent named entity recognition combining morphological and contextual evidence*
N	Workshop	ACL SIGLEX	1997	*A perspective on word sense disambiguation methods and their evaluation*
N	Journal	Natural Language Engineering	1997	*Homograph disambiguation in text-to-speech synthesis*
Y	Conference	ACL	1995	*Unsupervised word sense disambiguation rivaling supervised methods*
N	Journal	Annals of Operations Research	1995	*Discrimination decisions for 100,000-dimensional spaces*
Y	Conference	ACL	1994	*Decision lists for lexical ambiguity resolution: application to accent restoration in Spanish and French*
N	Book	Natural Language Processing Using Very Large Corpora	1994	*A comparison of corpus-based techniques for restoring accents in spanish and french text*
Y	Conference	HLT	1993	*One sense per collocation*
N	Conference	AAAI	1992	*Work on statistical methods for word sense disambiguation*
Y	Conference	ACL	1992	*Estimating upper and lower bounds on the performance of word-sense disambiguation programs*
Y	Conference	COLING	1992	*Word-sense disambiguation using statistical models of Rogets categories trained on large corpora*
N	Journal	Computers and the Humanities	1992	*A method for disambiguating word senses in a large corpus*
N	Conference	ICSLP	1992	*A corpus-based synthesizer*
N	Conference	MT	1992	*Using bilingual materials to develop word sense disambiguation methods*
Y	Workshop	WS on Speech and Natural Language	1992	*One sense per discourse*

TABLE 14. Author citation network PageRank. Weighted includes multiple citation from author A to author B, while unweighted removes multiple citations.

Weighted		Unweighted	
Author	PageRank	Author	PageRank
Sampson, Geoffrey	0.01566	Church, Kenneth Ward	0.00606
Mercer, Robert L.	0.01333	Marcus, Mitchell P.	0.00595
Church, Kenneth Ward	0.01284	Della Pietra, Vincent J.	0.00582
Della Pietra, Vincent J.	0.01183	Mercer, Robert L.	0.00542
Brown, Peter F.	0.01147	Della Pietra, Stephen A.	0.00541
Della Pietra, Stephen A.	0.01084	Santorini, Beatrice	0.00519
Marcus, Mitchell P.	0.00774	Roukos, Salim	0.00508
Jelinek, Frederick	0.00714	Brown, Peter F.	0.00500
Brill, Eric	0.00616	Brill, Eric	0.00490
Weischedel, Ralph M.	0.00553	Collins, Michael John	0.00486
Grosz, Barbara J.	0.00547	Marcinkiewicz, Mary Ann	0.00477
Joshi, Aravind K.	0.00522	Grishman, Ralph	0.00476
Pereira, Fernando C. N.	0.00521	Pereira, Fernando C. N.	0.00465
Santorini, Beatrice	0.00492	Jelinek, Frederick	0.00464
Hindle, Donald	0.00481	Hindle, Donald	0.00441
Lafferty, John D.	0.00478	Weischedel, Ralph M.	0.00412
Grishman, Ralph	0.00447	Yarowsky, David	0.00409
Yarowsky, David	0.00446	Ratnaparkhi, Adwait	0.00391
Gale, William A.	0.00422	Ramshaw, Lance A.	0.00388
Schwartz, Richard M.	0.00414	Schwartz, Richard M.	0.00378

TABLE 15. Author citation network—correlations between measures of impact.

	h-index	Total citations	PageRank
h-index	1.0	0.79	0.24
Total citations	0.27	1.0	0.14
PageRank	0.30	0.32	1.0

TABLE 16. Author collaboration network power law measures. Refer to section 4 for an explanation of these measures.

Type	α_{LS}	r^2	α_N	σ
Total degree	3.15	0.90	1.80	0.01

TABLE 17. Author collaboration networks comparison.

Archive	α_{LS}	C_N
DBLP (Elmacioglu & Lee, 2005)	3.68	0.63
ACL Anthology (this paper)	3.15	0.38

The large number of disconnected author pairs is caused by the large number of connected components in the network. This is because there are a lot of components in the graph, with very few authors. But the sizes of the components are such that there is one giant connected component and all the other components are much smaller in size. The sizes of the components are listed in Table 22. The number of connected pairs of authors with a shortest path length of at most six contribute to 69% of the total number of connected pairs. Also, the power law in the tail of the distribution means that the components themselves are very tightly clustered, with the diameter of the network being just 20. This is a good sign, in that findings in the AAN research community will travel quickly through the community.

TABLE 18. Author collaboration network—most collaborations.

(181)	Tsujii, Jun'ichi	(114)	Wilks, Yorick
(167)	Hirschman, Lynette	(112)	Ingria, Robert J. P.
(165)	Weischedel, Ralph M.	(108)	McKeown, Kathleen R.
(163)	Schwartz, Richard M.	(105)	Hovy, Eduard H.
(158)	Isahara, Hitoshi	(105)	Matsumoto, Yuji
(137)	Grishman, Ralph	(103)	Waibel, Alex
(129)	Joshi, Aravind K.	(102)	Lavie, Alon
(124)	Ney, Hermann	(101)	Roukos, Salim
(123)	Rayner, Manny	(99)	Seneff, Stephanie
(116)	Palmer, Martha Stone	(92)	Zue, Victor W.

Collaboration network—PageRank. The PageRank centrality (Page et al., 1998) of the author collaboration network was computed. Both the weighted and unweighted network were analyzed and the results can be seen in Table 23. Values are rounded to the nearest hundred-thousandth.

Both the weighted and the unweighted versions of the networks share generally the same central authors, with 18 authors appearing in both lists.

Collaboration network—citation network centrality correlation. In order to analyze the similaries between the author collaboration and citation networks, we calculated

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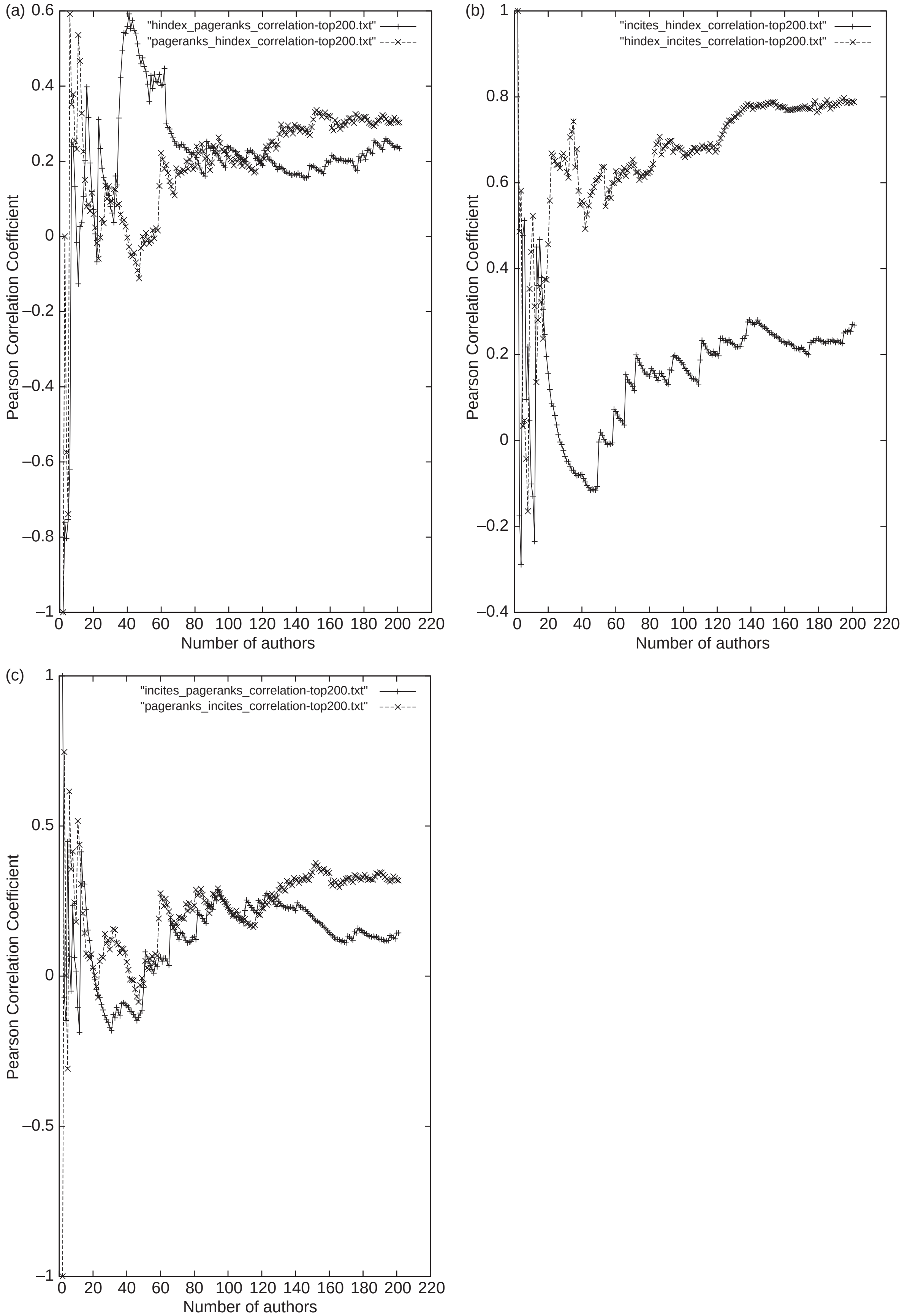

FIG. 11. Correlations between measures of impact in the author citation network.

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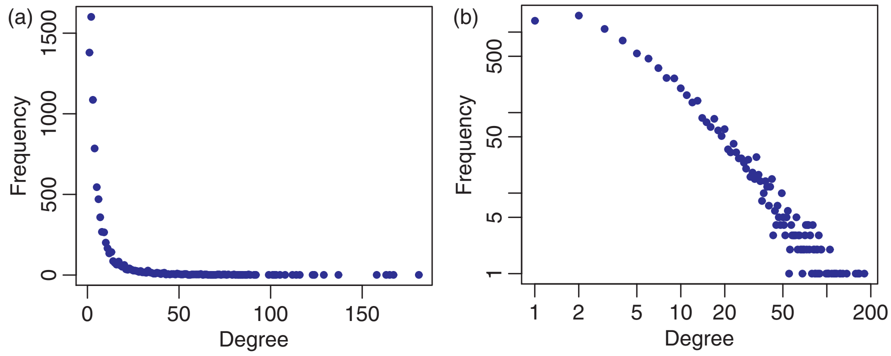

FIG. 12. Degree distribution of the author collaboration network. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

TABLE 19. Author collaboration network highest edge weights.

Degree	Collaboration
(23)	Tsujii, Jun'ichi ↔ Miyao, Yusuke
(21)	Makhoul, John ↔ Schwartz, Richard M.
(19)	Uchimoto, Kiyotaka ↔ Isahara, Hitoshi
(18)	Zens, Richard ↔ Ney, Hermann
(17)	Murata, Masaki ↔ Isahara, Hitoshi
(17)	Joshi, Aravind K. ↔ Webber, Bonnie Lynn
(16)	Isahara, Hitoshi ↔ Ma, Qing
(15)	Rayner, Manny ↔ Hockey, Beth Ann
(15)	Zue, Victor W. ↔ Seneff, Stephanie
(15)	Och, Franz Josef ↔ Ney, Hermann
(14)	Pazienza, Maria Teresa ↔ Basili, Roberto
(14)	Bear, John ↔ Appelt, Douglas E.
(14)	Su, Jian ↔ Zhou, GuoDong
(14)	Curran, James R. ↔ Clark, Stephen
(14)	Lin, Chin Yew ↔ Hovy, Eduard H.
(14)	Grishman, Ralph ↔ Sterling, John
(13)	Wu, Dekai ↔ Carpuat, Marine
(13)	Phillips, Michael ↔ Zue, Victor W.
(13)	Weischedel, Ralph M. ↔ Ayuso, Damaris M.
(13)	Manning, Christopher D. ↔ Klein, Dan
(13)	Rohlicek, J. Robin ↔ Ostendorf, Mari
(13)	Linebarger, Marcia C. ↔ Dahl, Deborah A.
(13)	Li, Wei ↔ Srihari, Rohini K.
(13)	Tanaka, Hozumi ↔ Tokunaga, Takenobu
(13)	Della Pietra, Stephen A. ↔ Della Pietra, Vincent J.
(13)	Seneff, Stephanie ↔ Polifroni, Joseph H.
(12)	Srihari, Rohini K. ↔ Niu, Cheng
(12)	Bobrow, Robert J. ↔ Ingria, Robert J. P.
(12)	Weischedel, Ralph M. ↔ Ramshaw, Lance A.
(12)	Niu, Cheng ↔ Li, Wei
(12)	Glass, James R. ↔ Phillips, Michael
(12)	Zue, Victor W. ↔ Polifroni, Joseph H.
(12)	Mercer, Robert L. ↔ Brown, Peter F.
(12)	Mercer, Robert L. ↔ Della Pietra, Vincent J.
(12)	Nagao, Makoto ↔ Tsujii, Jun'ichi
(12)	Zue, Victor W. ↔ Glass, James R.
(12)	Gale, William A. ↔ Church, Kenneth Ward
(12)	Grishman, Ralph ↔ Macleod, Catherine
(12)	Dahl, Deborah A. ↔ Norton, Lewis M.
(12)	Phillips, Michael ↔ Seneff, Stephanie

TABLE 20. Shortest path distance distribution in the author collaboration.

Shortest path distance	Frequency
−1	47,783,106
0	9,421
1	45,878
2	278,636
3	1,499,786
4	5,310,534
5	10,256,634
6	110,110,580
7	226,446
8	3,341,302
9	1,275,478
10	453,042
11	161,740
12	61,094
13	25,944
14	10,794
15	3,480
16	1,038
17	250
18	42
19	12
20	4

TABLE 21. Power law measures for the shortest path distances in the author collaboration network.

α_{LS}	$r2$	α_N	σ
3.11	0.86	2.61	0.0003

the correlation between the degree centrality values of authors in the collaboration network with those authors' scores in the citation network. Only authors that appeared in both networks were used for analysis.

We found that when all data points (9,421 authors) are included in the calculation, the Pearson correlation coefficient is 0.68, a somewhat significant correlation. As the

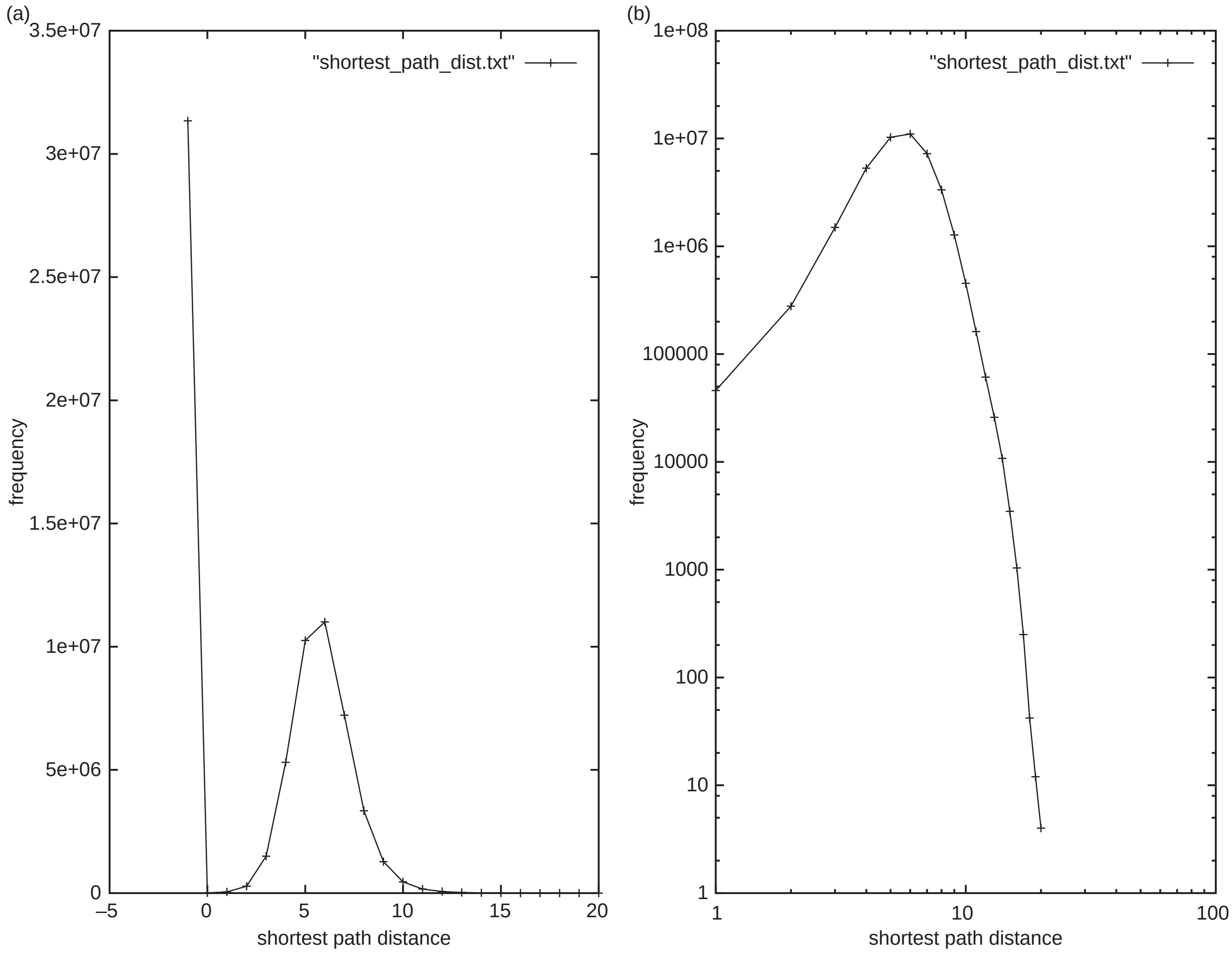

FIG. 13. Shortest path distance distribution of the author collaboration network.

TABLE 22. Sizes of the components in the author collaboration network.

Component size	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	19	38	6400
Number of components	917	313	143	75	44	15	17	4	5	1	3	1	1	2	2	2	1	1	1	1

number of authors is reduced, the correlation decreases dramatically. For instance, for the 200 authors with the highest collaboration degree centrality scores the correlation is reduced to 0.34. This seems to suggest that the most central authors in the collaboration network are not the same authors who are central to the citation network, yet there are a large number of authors who have low scores in both networks, which is to be expected. The results for the correlation coefficient for the top n authors can be seen in Table 24.

Conclusions

In this paper we statistically analyzed three networks composed from the citations between papers found in the ACL Anthology. These statistics were clustering coefficients, power law exponents, PageRank, and degree statistics.

All three networks display similar characteristics. Each one displays power law characteristics indicating a preference for edge attachment to a small number of high-degree nodes, although the author collaboration shows a somewhat smaller number. This shows that in each network there is a small number of papers or authors that are attracting the majority of citations or collaborations.

Additionally, all of the networks display small-world characteristics. This means that all of the networks are very well connected. This points to papers with many citations in the citation networks and a very active community of collaboration in the collaboration network.

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TABLE 23. Author collaboration network PageRanks.

Weighted		Unweighted	
Author	PageRank	Author	PageRank
Weischedel, Ralph M.	0.00447	Tsujii, Jun'ichi	0.00091
Zhu, Muhua	0.00326	Grishman, Ralph	0.00087
Wilson, Theresa	0.00317	McKeown, Kathleen R.	0.00087
Wilks, Yorick	0.00306	Hirschman, Lynette	0.00086
Yeh, Alexander S.	0.00303	Palmer, Martha Stone	0.00085
Zhou, Qiang	0.00275	Joshi, Aravind K.	0.00080
Zhou, Ming	0.00275	Wilks, Yorick	0.00079
Zens, Richard	0.00251	Choi, Key-Sun	0.00078
Tsujii, Jun'ichi	0.00251	Rambow, Owen	0.00077
Zhang, Yuqi	0.00235	Radev, Dragomir R.	0.00076
Yarowsky, David	0.00217	Weischedel, Ralph M.	0.00076
Webber, Bonnie Lynn	0.00212	Matsumoto, Yuji	0.00074
Yoshida, Kazuhiro	0.00212	Waibel, Alex	0.00073
Waibel, Alex	0.00087	Dagan, Ido	0.00072
Zanzotto, Fabio Massimo	0.00193	Hovy, Eduard H.	0.00072
Zimak, Dav	0.00192	Huang, Chu-Ren	0.00071
Zamanian, Alex	0.00191	Zhou, Ming	0.00069
Wiebe, Janyce M.	0.00190	Isahara, Hitoshi	0.00068
Xu, Jinxi	0.00183	Marcu, Daniel	0.00066
Zhang, Jing	0.00180	Moore, Johanna D.	0.00065

TABLE 24. Correlation coefficients between degree centrality in the collaboration network and citation network.

# of authors	Correlation coefficient
50	0.03
100	0.28
200	0.34
500	0.49
1,000	0.57
2,000	0.62
5,000	0.67
all (9,421)	0.68

We also observed that the author collaboration network is very tightly clustered and the existence of a power law in the tail of the shortest path lengths' distribution. This is good in the sense that new findings and ideas will propagate very quickly through the AAN research community.

All of the networks described show a strong tendency for certain authors and papers to play very strong roles in the overall structure of the network. The same authors do not inhabit the same central positions in all of the networks, although there are several authors who consistently appear high in ranked lists.

In addition to finding the most central papers and authors, we also analyzed the impact factor of the journals, conferences, and workshops. On analysis, it was observed that the impact factor of venues had been increasing consistently over the past 4 decades. We also observed that conferences and workshops had shown a higher rate of growth in impact factor as compared to journals.

The maximum weighted edges in the author citation network are self-citation edges, although on further analysis it is clear that the phenomenon of self-citation is not frequent enough in the AAN to alter the rankings according to different measures of impact even slightly.

In our analysis, the h-index does not appear to be strongly correlated with number of incoming citations or PageRank. This is interesting, as the authors who have a high h-index also appear to have high incoming citations and PageRank. It is also clear that the h-index of an author in their subfield will differ, sometimes dramatically, from their overall h-index.

Future Work

We are currently pursuing the completion of a full textual statistical analysis of the papers composing the ACL Anthology Network. In particular, we are looking into correlating lexical centrality and network centrality.

One factor we will investigate is LexRank. Recent research (Erkan & Radev, 2004) applied centrality measures to assist text summarization. The system, LexRank, was successfully applied in the Document Understanding Conferences (DUC) 2004 evaluation, and was one of the top-ranked systems in all four of the DUC 2004 Summarization tasks—achieving the best score in two of them. LexRank uses a cosine similarity adjacency matrix to identify predominant sentences of a text and then ranks these sentences according to centrality and salience. These groups of predominant sentences of individual papers could then be used to create another adjacency matrix between papers.

Additional factors we plan to investigate are the idea of *most cited* papers (Dervos & Kalkanis, 2005), self-citation (Fowler & Aksnes, 2007), and the conference/venue specific impact factor.

In the future, we also hope to expand our work by performing a similar analysis for the PMCOA corpus and the SIGDA corpus.

The PMCOA, or PubMed Central Open Access, database is a free digital archive of journal articles in the biomedical and life sciences fields. It is maintained by the U.S. National Institutes of Health (NIH), and the papers in the Open Access list are mostly distributed under a Creative Commons license. More information can be found at their website (http://www.pubmedcentral.nih.gov/about/openftlist.html).

The SIGDA corpus is a collection of papers from the ACM Special Interest Group on Design Automation. It is a digital collection of papers dating back to 1989 from a number of different symposia, conferences, and journals—most notably, the ACM Transactions on Design Automation of Electronic Systems. More information can be found at their website (http://www.sigda.org/publications.html).

Also, we are in the process of annotating the gender of all the authors. This annotated list will help us in further experiments on finding the correlation between gender and colloboration patterns.

In addition, we plan to rank venues based on the number of high-quality publications that they have hosted. Instead of using all the publications with high incoming citations, we plan to use only publications that have been useful for increasing the h-index of an author.

Lastly, we plan to attempt to use network clustering techniques to categorize and label papers based on subject or topic, automatically. We expect that this categorization will help to highlight papers that might otherwise be missed in certain searches.

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Availability of Data

The networks and associated metadata used in the analysis are available and can be downloaded from: http://clair.eecs.umich.edu/aan/download.php

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