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The appeal to political sentiment: An analysis of Donald Trump's and Hillary Clinton's speech themes and discourse strategies in the 2016 US presidential election

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ABSTRACT

This study investigated Hillary Clinton's and Donald Trump's speeches during the 2016 presidential election to identify their sentiments and discourse themes and strategies by using machine-based methods, including computerized sentence-level sentiment analysis, structural topic modeling for themes, and *word2vec* exploration for thematic associations. The machine-based automatic analyses were also complemented by a qualitative examination of the speech data motivated by the top thematic terms identified by the automatic analyses. The results of the study revealed that Trump's speeches were significantly more negative than Clinton's. The results also provided evidence supporting many previous findings regarding Clinton's and Trump's discourse/rhetoric styles and major campaign themes produced by studies using different research methods. The results of this study might also help explain Trump's victory despite the significant more negative sentiment in his discourse.

1. Introduction: Background and rationale

An important line of research on the 2016 US presidential election and its surprising results is the exploration of the language and discourse/rhetoric strategies used by the two main candidates, Donald Trump and Hillary Clinton (e.g., Degani, 2016; Enli, 2017; Lakoff, 2017; Ott, 2017; Quam and Ryshina-Pankova, 2016; Savoy, 2017a, 2017b; Sclafani, 2018; Wang and Liu, 2017). These studies were rich in approaches, perspectives, and foci. While some of them are essentially qualitative in nature (e.g., Enli, 2017; Lakoff, 2017; Sclafani, 2018), the others are more quantitatively-oriented corpus-driven quantitative studies (e.g., Degani, 2016; Savoy, 2017a, 2017b; Wang and Liu, 2017). In terms of research foci, the qualitative studies concentrated on the critical examination of the language and discourse strategies the candidates used whereas the corpus-driven quantitative studies focused mainly on various linguistic and semantic features of the candidates' language and how these features reflected and/or affected the candidates' communication styles and campaign themes. Despite their differences in methodology, these studies have all provided interesting findings on various aspects of the candidates' use of language and discourse during the election. One finding that is of special interest to the present study is Savoy's (2017b) discovery of a higher frequency of negative emotion words by Trump than by Clinton. While some political commentary essays have also addressed the noticeable negativity in Trump's speeches (e.g., Golshan, 2016), Savoy (2017b) appears to have been the only study that touched on this issue, but it did so in passing as the issue was not a main research question of the study. Given this fact, further research focusing on this issue, i.e., discourse sentiment, is therefore warranted because it may help not only test Savoy's (2017b) and other previous research's findings but also explore how and/or why the negativity of Trump's discourse might have helped his election victory. Against this backdrop, the present study aims to render a sentiment, discourse, and thematic examination of Trump's and Clinton's speeches during the 2016 election by using methods different from those used in the existing studies.

1.1. Review of related studies on the two candidates' speeches

1.1.1. Qualitative studies

Of the qualitative studies, Lakoff (2017) rendered a critical analysis aimed at showing how Trump's "idiosyncracies of discourse" and his victory "compromised the culture's notions of 'truth' – via a continuum from 'lie' through 'post-truth,' 'truthiness,' and 'alternative facts' to 'truth'" (p. 595). A point in her analysis

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particularly relevant to the present study is that Trump's idiosyncratic "post truth" discourse relied heavily on "appeals to emotion and personal belief" (Lakoff, 2017, p. 604). Sclafani (2018) provided a book-length sociolinguistic study of Trump's communication style and metadiscourse, focusing particularly on his political identity construction discourse. With ample examples, Sclafani (2018) demonstrated how Trump's discourse centered on creating a negative "other" through "negative stereotypes" (81) and on juxtaposing this negative "other" against a self-righteous "us." In other words, negativity figured prominently in Trump's language.

Enli's (2017) and Ott's (2017) studies focused on the candidates' use of Twitter. Enli (2017) approached it from three perspectives: the "historical development" of the use of social media in political campaigns, the "level of interaction with voters," and the level of "professionalisation" of the campaigns' use of Twitter (p. 51). One key finding of the study is that while Clinton followed the controlled and professionalized communication style, Trump exhibited a spontaneous "amateurish yet authentic style" (p. 50). Unlike Enli (2017), Ott (2017) did a case study of Trump's tweets only. Based on a close investigation of the characteristics of Trump's tweets, Ott (2017) concluded that "Twitter privileges discourse that is simple, impulsive, and uncivil" (p. 59) and that such discourse has resulted in "post truth" or "falsehoods" (66), a point also emphasized by Lakoff (2017) as noted above. It is important to note that similar findings were also reported by Kreis's (2017) study of Trump's tweets after he won the election, for the results of the latter study also show that "Trump uses an informal, direct, and provoking communication style to construct and reinforce the concept of a homogeneous people and a homeland threatened by the dangerous other" (p. 607).

1.1.2. Corpus-driven quantitative studies

The existing related corpus-driven studies have examined two common issues: (i) the level of linguistics complexity and readability of the candidates' speeches and (ii) the candidates' main themes and discourse strategies. Because linguistic complexity of the candidates' speeches is not an issue examined in the present study, it will not be reviewed. The following review thus focuses on the investigation of Clinton's and Trump's speech themes and discourse practices.

Using Systemic Functional Linguistics' (SFL) Engagement framework, Quam and Ryshina-Pankova (2016) analyzed the audience engagement strategies in the state primary election victory speeches of Trump, Clinton, and Bernie Sanders. The results of their quantification of the types of engagement strategies each candidate used show that although the extent of the use of the two main strategy categories of heteroglossic (i.e., statements admitting "the possibility of a competing truth claim") and monoglossic (i.e., statements or "bare assertions" that do not admit such possibility) was similar for the three candidates, Trump "is more prone to long strings of monoglossic statements without the interruption of a heteroglossic assertion" (Quam and Ryshina-Pankova, 2016, p. 147). More importantly, this feature in Trump's speeches "has the effect of presenting a stream of assertions that rarely recognizes or references alternative positions" (Quam and Ryshina-Pankova, 2016, p. 147). The two authors also found that Trump used few different types of engagement moves and more repetitions. However, they argued that "Trump's selection of simplistic, repetitive assertions and denials" might have helped more forcefully convey his messages and appeal to those who shared his views (Quam and Ryshina-Pankova, 2016, p. 154).

Degani (2016) examined both the language complexity levels and the main themes in the Clinton's and Trump's candidacy announcement speeches. For the analysis of the main themes, Degani (2016) first generated a wordlist from each candidate's speeches and then identified the 30 most frequent content words. One key result from the lexical choice analysis was that while a majority of Clinton's most frequent nouns were people-related (*Americans*, *families*, and *women*), those of Trump's were names of adversary countries (*China* and *Mexico*) and business-related words (*money*, *billion*, and *Ford*). Such lexical choice differences, Degani (2016) argues, reveal a stark difference between Clinton's and Trump's speech themes with the former advocating for developing more social/economic equality and the latter calling for a business-oriented solution to America's problems. Furthermore, expressed in much simpler (sometimes crude) language, Trump's business-focused themes formed a "brash and self-aggrandizing" discourse, "promoting an anti-intellectual culture of fear, suspicion and conspiracy (China and Mexico are enemies), and catering to populist anger with extremist proposals (building a wall along the Mexican border)" (Degani, 2016, p. 144).

Savoy's (2017a) study investigated similar lexical and syntactic features and themes of nine candidates' (five Republicans' and four Democrats') debates during the primary election. To determine the thematic concentration of the candidates' speeches, Savoy employed Popescu's (2007, 2009) *h*-point frequency-distribution measure as well as Čech, Garabik, and Altmann's (2015) proportional thematic concentration (PTC) measure. The *h*-point refers to the point in the frequency rank of the word types in a text where the frequency of a given word type is equal to its frequency rank. The words above the *h*-point are usually functional words, but some lexical words in a text may appear above this point and these lexical words are considered "thematic words." Two important relevant findings in this study were that Trump's speeches were marked by "short sentences" and a repetition of "the same arguments with simple words" and that the pronoun *I* was Trump's second most frequently used word behind the article *the* and his "most specific" or prominent thematic term, a fact that reveals a "high intensity of his ego" (Savoy, 2017a, pp. 14-15). Employing essentially the same methodologies, Savoy (2017b) studied Trump's and Clinton's speech style and rhetoric strategies by examining and comparing their informal speeches (interviews and TV debates) and their prepared speeches at meetings/gatherings. One aspect of the study that is particularly relevant to the present study is a "semantic-based analysis" of the two candidates' words and expressions. The author used two computer-based lexical semantic analysis systems developed by Hart (1984) and Tausczik and Pennebaker (2010) respectively to help identify the major themes in the two candidates' speeches. These computer-based analysis systems group words into semantic categories, such as *affect, cognition, exclusive, human, posemo* (positive), and *negemo* (negative). One important finding from the semantic analyses is that Trump used more negative emotion words.

Drawing on Degani's (2016) and Savoy's (2017a, 2017b) studies both methodologically and thematically, Wang and Liu (2017) investigated Trump's speech style against Clinton's and Obama's by looking at their debates and campaign speeches. Besides examining the candidates' linguistic complexity, they also investigated their thematic concentrations using the *h*-point based PTC formula. Their results indicate that "Trump's speeches contain relatively more central themes in his campaign speeches," which might have helped "meet key interests of a large proportion of electorates" (Wang and Liu, 2017, p. 1). However, unlike Savoy (2017b), Wang and Liu (2017) did not conduct a semantic-based analysis and hence no sentiment analysis was conducted. It is thus clear from the above review that while the existing studies have examined various aspects of Trump's and Clinton's speech styles and discourse/rhetoric strategies and produced many important findings, Savoy (2017b) is the only study that touched on sentiment analysis, an issue that is worth more focused studies, especially those that use different research methods.

1.2. Sentiment analysis

Sentiment analysis is the study of emotions, opinions, appraisals, and attitudes regarding "services, products, individuals, organizations, issues, topics, events and their attributes" (D'Andrea et al., 2015, p. 27). Emotions, opinions, appraisals, and attitudes are subjective and often fall into polarities such as positive/negative, good/bad, and pro/con, although being neutral/no opinion can be an option. Thus, sentiment analyses essentially "extract subjectivity and polarity" in language to identify the "semantic orientation" or "the polarity and strength of words, phrases, or texts" (Taboada et al., 2011, p. 268). As a result, sentiment analysis can provide valuable information for various organizations in many different fields, especially in business, regarding products and services, and politics and sociology, concerning issues and policies (Feldman, 2013). In the field of politics, there have been a few sentiment studies using Twitter data in examining the public's sentiments about political candidates, issues, and the predictive values of such sentiments (e.g., Bhattacharya et al., 2015; Murthy, 2015). However, as already noted earlier, there have not been any sentiment study focused on presidential candidates' speeches—the topic of this study.

In terms of methodology for sentiment analysis, there are two main approaches: machine-learning and lexicon-based, though a hybrid method combining these two approaches can also be employed (D'Andrea et al., 2015). The machine-learning approach, a classification-based method, uses training and testing datasets to determine the semantic orientation of a text. In contrast, the lexicon-based approach uses a sentiment lexicon that contains the target sentiment words to help determine the sentiment of a target text. The machine-learning and lexicon-based approaches each have their strengths and weaknesses. On the one hand, the machine-learning approach has "the ability to adapt and create trained models for specific purposes and contexts," but its applicability is low due to a lack of readily available labelled data, especially such data across different domains (e.g., business and politics). On the other hand, the lexicon-based approach provides a "wide term coverage" (D'Andrea et al., 2015, p. 29). Due to the limited applicability of the machine-learning approach across domains, some experts prefer the use of the lexicon-based approach (Taboada et al., 2011). In this sense, "the sentiment lexicon is the most crucial resource for most sentiment analysis algorithms" (Feldman, 2013, p. 86). There are some useful existing sentiment lexicons or tools available that work well across domains, such as Jockers' (2017a), Liu et al. (2005), and Tausczik and Pennebaker's (2010).

Finally, it is also important to note that sentiment analysis may be performed at three different levels: document-level, sentence-level, and aspect-level (D'Andrea et al., 2015; Feldman, 2013). As their names suggest, document-level analysis evaluates the overall sentiment of a document as a whole as it assumes that the document expresses a main opinion about an entity or topic that the document covers. Sentence-level analysis assesses the sentiment of a sentence. Sentence-level analysis thus provides more detailed information than document-level analysis. Aspect-level analysis is used for "entities that have many aspects (attributes)," such as consumer products, because often individuals may "have a different opinion about each of the aspects," i.e., the product's appearance, look, or functionality (Feldman, 2013, p. 85). As such, aspect-level analysis is frequently used for consumer products.

2. Methodology

2.1. Data used

The data used in this study were downloaded from the UC Santa Barbara's (2017) "The American Presidency Project" website. They consist of Trump's and Clinton's written speeches (i.e., not transcripts of interviews or debates) during the 2016 presidential election that began with their candidacy declarations (April 1, 2015 for Clinton and June 16th, 2015 for Trump) and ended with Trump's victory and Clinton's concession speeches on November 9, 2016. Each candidate's data form a corpus. Specifically, the Clinton corpus contains 89 scripts with a total of 286,899 words while the Trump corpus includes 74 scripts with a total of 276,212 words. The two corpora are quite comparable in both number of texts and total number of words as shown in Table 1.

2.2. Sentiment analysis

The two candidates' corpora were submitted to a sentence-level, lexicon-based sentiment analysis using Jockers' (2017a) *syuzhet*, a sentiment analysis program in R (version 1.04). To help make the results more reliable, we ran the analysis twice using two different sentiment lexicons, once with the Jockers' (2017b) sentiment lexicon and once with Liu et al.'s (2005) sentiment lexicon. We chose these two lexicons for the following reasons. First, unlike some other lexicons (e.g., Hart, 1984; Tausczik and Pennebaker, 2010) that are designed for analyzing and identifying a variety of semantic categories, such as "activity," "cognitive," and "process," these two lexicons are designed exclusively for positivity/negativity sentiment analysis for general purposes (i.e., not for analysis of specific fields or registers, such as business). In other words, it better serves the purpose of our study. However, it is important to note a limitation of this sentiment lexicon-based analysis in cases where a negative word, such as "war," is used in a positive context, e.g., "war on poverty" and "anti-war movement." To address this potential weakness, we followed this sentiment analysis with a close examination of the context of all the key words identified by our structural topic modeling analysis to be described immediately below. Second, these two sentiment lexicons are both quite large and comprehensive, with Jockers' boasting 10,748 words and Liu, Hu, and Cheng's consisting of 6789 words. Third, both have been well tested and used in sentiment research in humanities and social sciences. With the two general sentiment lexicons, the *syuzhet* program can determine the sentiment of every sentence in a document in a binary (positive or negative) fashion and in turn provide the proportion of negativity/positivity of a text.

Table 1
Statistical information regarding the two candidates' corpora.

Corpora	# of files	# of sentences	# of tokens	# of word types	Type/token ratio
Clinton	89	16,786	286,899	9682	0.0337
Trump	74	17,805	276,212	7401	0.0268

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2.3. Structural topic-modeling thematic analysis

To help further understand the results of the sentiment analysis, e.g., in what ways one candidate was more negative, we carried out a thematic analysis of the two candidates' speeches by employing a machine learning-based topic-modeling technique called structural topic modeling (*stm*) developed by Roberts and colleagues (Roberts et al., 2014; Roberts et al. 2016). This technique differs from frequency-based methods for identifying key thematic terms used in the aforementioned previous studies on Clinton and Trump. Instead of relying on word frequency information, *stm* uses an algorithm to calculate document-level covariate information to estimate the highest probability that certain words constitute the key topics in the inputted documents of two or more different speakers/writers. *stm* has been widely used for thematic word exploration in social science research (e.g., Mildenberger, and Tingley, 2017; Bail et al., 2017; Farrell, 2016). It is necessary to note that in our analysis, we removed, from the data, all the functional words (1,149 in total), such as prepositions and pronouns, because such words typically do not carry theme-related meanings.

After the important thematic terms were identified, we then employed Mikolov et al' (2013) *word2vec* technique to calculate and extract the words that are most likely to co-occur with the thematic terms, i.e., words that we will hereafter call the most probable or the strongest "companion words" of a given thematic term. Specifically, the *word2vec* technique outputs a vector space of word embeddings that will enable an easy calculation of words that share a common context with, or in close proximity to, a thematic term (Mikolov et al., 2013; Goldberg and Omer, 2014). The *word2vec* analysis was conducted using Schmidt's (2017) *wordVectors* R program with the size of word vectors set as 200.

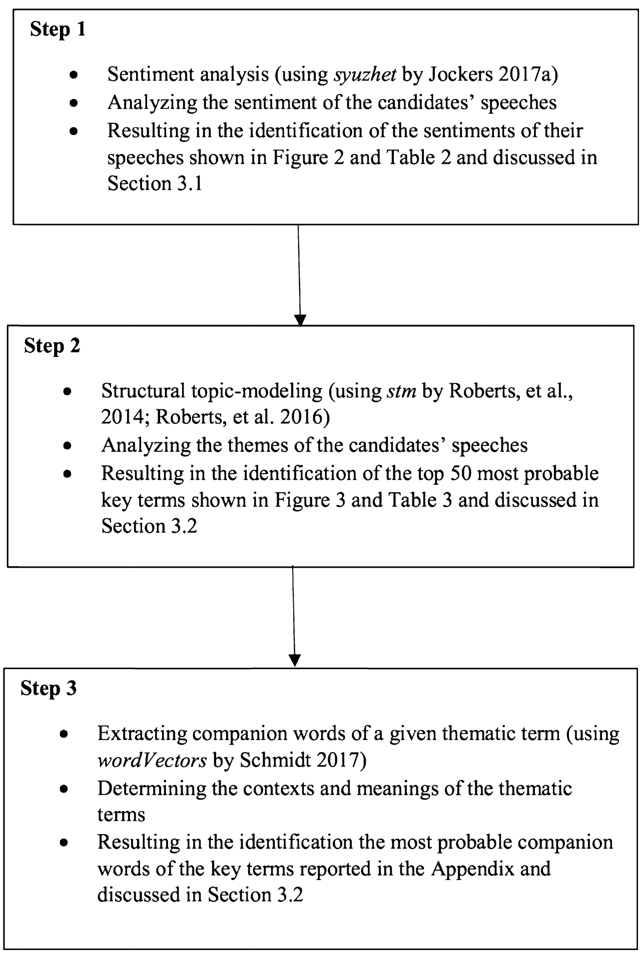

Fig. 1. Flowchart of data analyses and corresponding results.

3. Results and discussion

To make it easier for the reader to follow the discussion of the results, we have provided in Fig. 1 a flowchart showing step-by-step the three types of data analysis we did, their respective results, and the discussions related to these results.

3.1. Results of sentiment analysis

As mentioned above, we ran two sentiment analysis tests, each with a different lexicon. We report the results of both, with those from the analysis using Jockers's (2017b) lexicon being referenced as SA1 (sentiment analysis 1) and those from using Liu et al.'s (2005) as SA2. The sentiment analysis tests calculated sentence-level negativity in each candidate's corpus. Each candidate's total number of sentences, number of negative sentences, and the proportion of negative sentences from the two sentiment tests were reported in Table 2 along with the results of a Chi-square test done to determine whether there was a significant difference between the two candidates' negativity levels. The overall negative sentiment levels of the two candidates' speeches are also visualized in Fig. 2.

As results in Table 2 show, Trump's speeches exhibited a significantly higher negativity level than Clinton's in both sentiment analyses though the difference was larger in SA1 likely due to the larger size of the semantic lexicon used in SA1 than that in SA2. This result supports both Sclafani's (2018) finding that Trump's discourse was noted for its negativity and Savoy's (2017b) finding that Trump used more negative emotion words than Clinton.

To help illustrate what negative sentences look like, we have included below a few excerpts from Trump's September 20th, 2016 campaign speech in South Carolina. The speech was identified as Trump's most negative one in SA1 and second most in SA2 boasting a negative proportion of 48.54% and 40.78% respectively. In other words, nearly a half of the sentences in the speech were negative.

> ... *Over the weekend, there were Islamic terrorist attacks in Minnesota and New York City, and in New Jersey. These attacks were made possible because of our extremely open immigration*

Table 2
Results of both sentiment analyses.

	Total # of sentences	# of negative sentences and its proportion in total (SA1)	# of negative sentences and its proportion in total (SA2)
Clinton	16,794	3134 (18.66%)	2441 (14.53%)
Trump	17,805	5056 (28.40%)	3944 (22.15%)
Chi-square results		X^2 = 280.45, p < .0000	X^2 = 229.58, p < .0000

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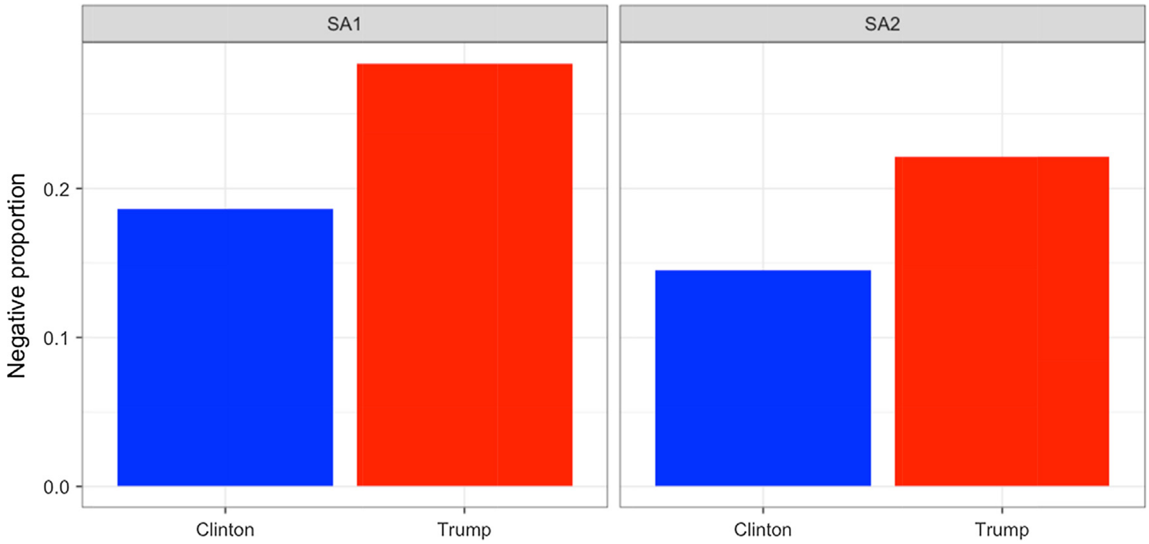

Fig. 2. Comparison of Clinton's and Trump' negativity.

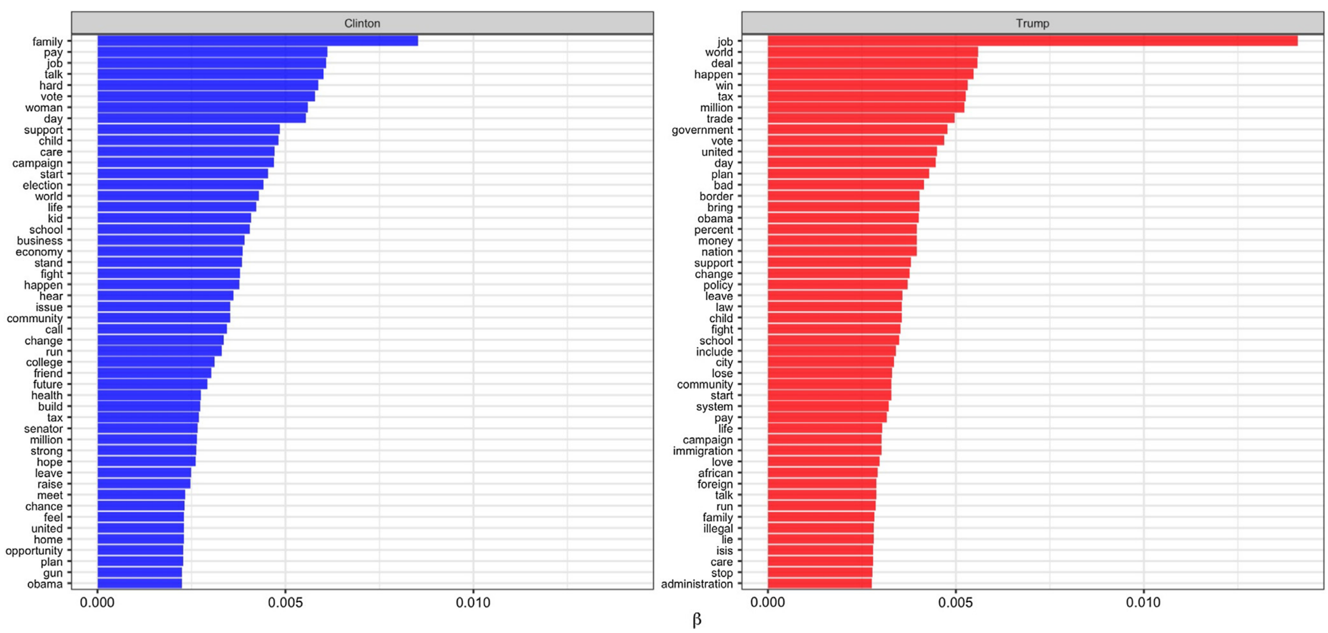

Fig. 3. Top 50 thematic words of highest probability for each candidate.

system, which fails to properly vet and screen the individuals or families coming into our country.

Attack after attack – from 9/11 to San Bernardino to Orlando – we have seen how failures to screen who is entering the United States puts all of our citizens in danger.

So let me state this very clearly: immigration security is national security.

My opponent has the most open borders policy of anyone ever to seek the presidency. As Secretary of State, she allowed thousands of criminal aliens to be released into our communities because their home countries wouldn't take them back.

. . .

Nearly 4 in 10 African-American children live in poverty, including 45% of African-American children under the age of six. 58% of African-American youth are not working.

Violent crime rose in America's fifty largest cities last year. Homicides are up nearly 50% in Washington, D.C. and more than 60% in Baltimore. More than 3000 people have been shot in Chicago since January of this year. The schools are failing, the jobs are leaving, and millions are trapped in poverty.

The above excerpts contain many negative sentences or discourse units, including those about frequent terrorist attacks, continuous influxes of criminal aliens, alarming numbers of minority children living in poverty, disturbing increases of homicides, unprecedented rising of failing schools, and shocking ongoing losses of jobs.

3.2. Results of topic-modeling and word2vec association analysis of thematic words

First, the *stm* topic-modeling thematic analysis identified all the possible important thematic terms in each candidate's corpus. Fig. 3 shows the top 50 most probable thematic terms for each

Table 3
Top 50 thematic/key words of highest probability for each candidate. (Number in parentheses after each term being its probability value).

Rank	Clinton	Trump	Rank	Clinton	Trump
1	family (0.0085)	job (0.0141)	26	community (0.0035)	child (0.0036)
2	pay (0.0061)	world (0.0056)	27	**call** (0.0034)	fight (0.0035)
3	job (0.0061)	**deal** (0.0056)	28	change (0.0033)	school (0.0035)
4	talk (0.006)	happen (0.0055)	29	run (0.0033)	**include** (0.0034)
5	**hard** (0.0059)	**win** (0.0053)	30	**college** (0.0031)	**city** (0.0033)
6	vote (0.0058)	tax (0.0053)	31	**friend** (0.003)	**lose** (0.0033)
7	**woman** (0.0056)	million (0.0052)	32	**future** (0.0029)	community (0.0033)
8	day (0.0055)	**trade** (0.005)	33	**health** (0.0028)	start (0.0033)
9	support (0.0049)	**government** (0.0048)	34	**build** (0.0027)	**system** (0.0032)
10	child (0.0048)	vote (0.0047)	35	tax (0.0027)	pay (0.0032)
11	care (0.0047)	united (0.0045)	36	**senator** (0.0027)	life (0.003)
12	campaign (0.0047)	day (0.0045)	37	million (0.0026)	campaign (0.003)
13	start (0.0045)	plan (0.0043)	38	**strong** (0.0026)	**immigration** (0.003)
14	**election** (0.0044)	**bad** (0.0042)	39	**hope** (0.0026)	**love** (0.003)
15	world (0.0043)	**border** (0.004)	40	leave (0.0025)	**African** (0.0029)
16	life (0.0042)	**bring** (0.004)	41	**raise** (0.0025)	**foreign** (0.0029)
17	**kid** (0.0041)	Obama (0.004)	42	**meet** (0.0023)	talk (0.0029)
18	school (0.0041)	**percent** (0.004)	43	**chance** (0.0023)	run (0.0029)
19	**business** (0.0039)	**money** (0.004)	44	**feel** (0.0023)	family (0.0028)
20	**economy** (0.0039)	**nation** (0.004)	45	united (0.0023)	**illegal** (0.0028)
21	**stand** (0.0038)	support (0.0038)	46	**home** (0.0023)	**lie** (0.0028)
22	fight (0.0038)	change (0.0038)	47	**opportunity** (0.0023)	ISIS (0.0028)
23	happen (0.0038)	**policy** (0.0037)	48	plan (0.0023)	care (0.0028)
24	**hear** (0.0036)	leave (0.0036)	49	**gun** (0.0023)	**stop** (0.0028)
25	**issue** (0.0035)	**law** (0.0036)	50	Obama (0.0022)	**administration** (0.0028)

candidate ranked by their probability values. In simple or lay language, a probability value indicates the likelihood of a word in the two candidates' corpora being a key term (defined as one of the most possible important thematic terms) for each of the two candidates. To avoid using the same word repeatedly, we will alternate "key terms" with "prominent terms" hereafter. Our decision to examine the top 50 key terms rather than more or fewer terms was admittedly arbitrary in a sense, but it was motivated by our belief that 50 was the appropriate number as it was not too small to leave out some truly important terms but not too large to include some unimportant ones. Our *stm* analysis identified from the two corpora a total of 8746 words as possible terms. In average, the probability value or the chance for one of these words to be a key term for a candidate is thus 0.0001143. The higher a term's probability value is for a candidate, the higher the chance the word is a prominent term for the candidate. Table 3 lists the same top 50 topic terms for each candidate in the same order but with those terms that appeared in only one candidate's list marked in bold to help the reader easily differentiate these terms from those that appeared on both candidates' lists, i.e., key thematic terms shared by both candidates. It is of interest to note that *job* boasts an exceptionally high probability value in Trump's speeches, likely the result of Trump's use of repetition of key issues as a main campaign strategy.

Second, as noted earlier, we also performed a *word2vec* analysis on the top 50 key terms of each candidate to identify the most closely associated companion words of each prominent thematic term for the candidate. By "closely associated companion words," we mean the words that occur most frequently with a given key term. The co-occurring probability measure of a closely associated companion word with a key term may range from 0.0 to 1.0. The higher the value a companion word has with a thematic term, the higher its chance of co-occurring with the term is. Limited by space, we have provided only samples of the strongest companion words of the key thematic terms as an Appendix A in a table format, which lists the eight strongest companion words of each key term along with their co-occurring probability values with the key term. The complete list of the strongest companion words of all the key terms is provided as supplementary material online. Finally, as we will show below, the information regarding a key thematic term's strongest companion words along with a reading of the candidates' utterances involving these words can help us better and more accurately understand the candidates' attitudes, feelings, positions, and perspectives on these thematic issues.

3.2.1. Results regarding the prominent thematic terms unique to each candidate

As shown in Table 3, Clinton and Trump each had 25 unshared or unique prominent thematic terms. These terms reveal noticeable differences between the two candidates' discourse foci. For example, Clinton's most prominent thematic words boast *future, build, hope, friend, raise, chance,* and *opportunity* (hereafter all italicized words are key thematic term or their strongest companion words), which carry a positive, unifying, and forward-looking vision; in contrast, Trump's key thematic words include *bad, lose, stop, border, lie,* and *foreign*, which project a more negative, divisive, and inward-looking view. Furthermore, while Clinton's prominent thematic terms showcase many education/family/health-related themes, such as *woman, kid, college, health,* and *home*, Trump's feature many money/trade and law-enforcement-related themes, such as *deal, money, trade,* and *company*. These results, along with the results regarding the two candidates shared prominent thematic terms discussed below, support Degani's (2016) finding that whereas Clinton's discourse focused on the need and effort to achieve more social/economic equality for the minority and underprivileged as a preferable approach to American problems, Trump's discourse, instead, advocated for a largely business-oriented solution. Indeed, based on the strongest companion words of Trump's thematic terms of *deal, trade*, and *stop*, he was mostly speaking about how he would *stop, withdraw,* and *renegotiate trade deals* with other countries and *stop trade deficit* with other countries, particularly *China.* Furthermore, the strongest companion words (e.g., *booming, prosperity, revitalization* of *farm* and *gas* business) for *bring* and *include*, two positive items in Trump's unique key terms, also demonstrate his business-oriented approach. A reading of the strongest companion words of the two verbs in Trump's speeches reveals that Trump's utterances involving *bring* and *include* were mainly about how he would *bring back prosperity* by having *lower tax* and how his plans *include simplification* of tax codes and *revitalization* of the *gas* and *farm* business. In other words, he was not talking about how he would *bring* the country together by *including* all people.

Of course, Clinton's key terms also include *business* and *economy,* but her strongest companion words for the two terms suggests that her focus was *small business* and *businessman* as the *backbone* for *economic growth* rather than tax cut, especially tax cut for corporations and the rich. As for Clinton's focus on economic equality, it is further evidenced by her unique prominent thematic term *raise* and its strongest companion words, such as *minimum wage, income*, and *middle class*. In other words, to *raise* the *minimum wage* and *raise income* for the *middle class* was a key theme for Clinton's campaign. Clinton's unifying and forward-looking themes are clearly evidenced by many of the strongest companion words of her two key thematic terms *build* and *future:* for *build* there were *global coalition, fairness*, and *bridges* and those for *future* we see *optimism, confidence, unifying, destiny,* and *optimistic*. For Trump's main prominent themes, it is important to note that his unique term list also includes *law, immigration, illegal,* and *ISIS.* A look at the strongest companion words of these terms and a reading of them in Trump's speeches reveals that he was mainly discussing how he would *stop/suspend* the *inflow* of *immigration/immigrants* and *amnesty* for *illegal immigrants* and give *law enforcement* the *authority* and the *tool* to *deport illegal immigrants* and *stop illegal drugs and criminals* including *rapists*. He would also *extinguish ISIS* and *stop* the *turmoil unleased* by *ISIS.* Clearly, this latter prominent theme of Trump constitutes evidence for the previous research finding that Trump's discourse concentrated on constructing the negative "other" and on the dangers facing the US and the world (Degani, 2016; Kreis, 2017, Sclafani, 2018).

However, a couple of items among the two candidates' unique thematic terms seem to be themes that on the surface would contradict their respective major discourse thematic patterns noted above. One such term for Clinton, who is clearly not a fan for guns, is *gun* and two such terms for Trump, a renowned tough businessman who approaches everything in purely business terms and who is not known as an advocate for African Americans, are *African* and *love*. Yet a close look at the respective strongest companion words of these terms, along with a reading of the candidates' utterances involving these words, reveals that their uses of the respective terms did not constitute any contradiction to their major themes. Clinton's strongest companion words for *gun* and their uses in her speeches indicate that when she mentioned *gun*, she was primarily criticizing *gun lobby/violence* and calling for *commonsense* and stricter *background* checks for gun purchases, i.e., she was against uncontrolled use of guns. As for Trump's prominent use of *African*, the strongest companion words of the term in his speeches include *poverty, unemployed, African Americans,* and [food] *stamps*. He was thus mainly discussing negative issues and images associated with African Americans, though we should note that he was also talking about how he would change such negative conditions for them. Regarding the term *love,* Trump's strongest companion words for the term include *patriots, expression, hardworking*, and *Chris*. A reading of his utterances involving *love* and the said companion words show that the American *patriots* he said he loved were those his "opponent [Clinton] slandered" as "deplorable and irredeemable," who he called "hardworking American patriots" (Des Moines, Iowa, 9/13, 2016). *Chris* [Chris Christie, former Governor of New Jersey] was a person who he loved because the former endorsed him early and "took a lot of heat" for that (Green Bay, Wisconsin, 8/5, 2016). The word *expression,* a strong companion of Trump's *love,* was "drain the swamp in Washington," which he said he did not like first, but which he had grown to *love* and *repeat*. In short, who/what Trump said he loved during the election were a relatively small number of people and things, rather than American people in general.

3.2.2. Results regarding the two candidates' shared thematic terms

First, as can be seen in Table 3 and Fig. 3, many of the shared key thematic terms ranked very differently in the candidates' lists and showed markedly different probability values (PV) in the two candidates' discourses. For example, *family* ranked 1st on Clinton's list but 44th on Trump's with the PV of the word in Clinton's discourse being three times that in Trump's (0.0085:0.0028). In contrast, *job* ranked first on Trump's list with a 0.0141 PV, but third on Clinton's list with a 0.0061 (less than half of its value in Trump's discourse). Similarly, while both candidates had *tax* as a major theme, the term ranked 6th on Trump's list with a 0.0053 PV, but 35th on Clinton's with a PV of 0.0027 (again only half of its value in Trump's). Besides difference in the ranking of the key terms and the PVs of the strongest companion words in the two candidates' discourses, a more important difference for these shared thematic terms is that their strongest companion words for the shared terms differed enormously. As noted earlier, we reported eight strongest companion words for each of the 25 shared terms in the supplementary table. That means there were 200 companion words in total for the 25 shared terms for each candidate. Of this total, only 30 (15%) appeared on both candidates' list. The rest (85%) were different. In fact, for eight of the 25 shared key terms, there was not a single common strong companion word between the two candidates. This large difference in the companion words for the two candidates' shared thematic terms, as we will show below, helps reveal that even on these shared themes, the two candidates' attitudes, positions, and perspectives were often very different and sometime even entirely opposite. Due to lack of space, we will provide just a few examples to show how the two candidates' attitudes and positions differed on these shared major themes.

First, for the shared prominent term *tax*, the two candidates' positions were essentially opposite as shown by their entirely different strong companion words for the term and their utterances involving these words. Clinton wanted to raise taxes for the *wealthy*, especially *billionaires* but to *cut* taxes or provide tax *relief* for the middle class and the poor. In contrast, Trump planned to *massively* and *substantially lower* taxes and *simplify* the tax *code* for all, including the wealthiest and large corporations. Concerning their shared key thematic term *leave*, while both have *behind* as a strong companion word, Clinton used *leave* primarily as a noun to discuss *sick leave*, *childcare leave*, and the *leave* to take care of one's sick *relatives*. Trump, on the other hand, used *leave* mainly as a verb to discuss how current US policies make *companies leave* or *flee* from the US. Regarding the use of the shared key thematic word *change*, although both candidates advocated for *real* changes, they differed in what types of change to focus on. For Clinton, *climate* change was the most important change she was discussing; as a result, she often discussed how to *tackle/combat* the problems of climate change as well as criticized Trump's *denial* of *climate* change as a *hoax*. On the other hand, Trump focused on how he would *deliver* real *outcome* of *bold* changes and *begin* such change immediately if elected.

As for the overlapping top thematic term *pay*, the two candidates' different strongest companion words for the term show that while Clinton was mainly discussing *equal pay* and the need and cost of paying for *childcare*, Trump focused on *fair pay*. Similarly, concerning the shared key term *school,* whereas Clinton concentrated on education in general but highlighted particularly for those who were in *wheelchair* or *blind,* Trump centered on *charter/-magnet schools* and *school choices.* Finally, regarding the shared term *care*, while both candidates addressed *health* and *medical care*, including *mental* health care, they also had very different foci in terms of what aspects of health care to provide and who were the priority for receiving such care. Whereas Clinton concentrated on *healthcare* and *affordable care*, especially for the *elderly* and *childcare*, Trump emphasized *professional* care, especially for *veterans* evidenced by the fact that *vet* and *veteran* were both among his strongest companion words for the term *care*.

3.3. Further exploration of the results and their implications

The results above have shown that the sentiment and messages of Trump's speeches during the election were significantly more negative than Clinton's and that while the two candidates shared some common themes, they also had many different thematic foci. Furthermore, even on the shared key themes, the two candidates' attitudes and perspectives were very different and sometimes even opposite. One likely reason for these sharp differences appears to be that each candidate was speaking mainly to their supporters and those who shared or sympathized with their views and emotions.

Then, how can we explain Trump's victory considering the stronger negativity? Based on the results of our study and drawing on findings from not only existing research but also discussions and reports in the media, we argue that Trump's negativity and his chosen key themes might have contributed to his victory by simultaneously inciting and appealing to the negative sentiment found among a substantial portion of the American population. Or as Wang and Liu (2017, p. 1) put it, Trump's chosen "central themes" might have helped him "meet key interests of a large proportion of electorates." Trump's negativity and chosen themes might have also worked because they constituted what Lakoff (2017) called a "post-truth" discourse, which is found to be effective in "shaping public opinion" because it relies mainly on "appeals to emotion and personal belief" (Lakoff, 2017, pp. 595, 604).

Furthermore, Trump's negative but also assertive discourse might not only have galvanized his base (those who enthusiastically shared his views and his negativity about the current social and economic state of the country) but also have, as Quam and Ryshina-Pankova (2016, 154) noted, helped him reach "new audiences who express grievances that other politicians would be loath to air..." There were also some discussions and reports in the media that seem to support this point. For example, J.D. Vance, author of new fiction *Hillbilly Elegy*, made the following claim in an interview reported in Dreher (2016): "these people — my people —[poor white people] are really struggling, and there hasn't been a single political candidate [like Trump] who speaks to those struggles in a long time."

Obviously, the fact that *job* was the overwhelming number 1 prominent thematic word in Trump's speeches means that in his speeches he repeatedly emphasized the problem of loss of jobs in America and repeatedly promised to create *millions* of jobs if he was elected. This, plus his constant talks about other countries having taken advantage of America and about terrorist attacks and problems of illegal criminal immigrants, must have appealed very strongly to many Americans, including those who might not share his other views and positions. As Golshan (2016) noted in a *Vox* online article, Trump's speeches successfully aroused in his audience strong resonating sentiments of "fears of joblessness, worries about the United States losing its status as a major world power, concerns about foreign terrorist organizations." Golshan also quoted Kristin Kobes Du Mez, a Calvin College historian, who believed that "Trump validates their [his audience] insecurities and justifies their anger... taps into fear and insecurity, but then enables his audience to express that fear through anger. And anger gives the illusion of empowerment" (Golshan, 2016). Equally importantly, Golshan (2016) also contended that Trumps success could not be attributed completely to his speech style and appeals to emotions because "[I]t certainly has a lot to do with what he is actually saying." In other words, his speech themes helped. The results of this study, especially the results of the topic-modeling analysis, may have provided some support for this theory.

4. Conclusion

Via a machine-based sentiment analysis, a structure topic modeling exploration, and a *word2vec* association examination, this study has revealed a significant difference in sentiment between Clinton's and Trump's discourses and also produced results that support many previous research findings about Clinton's and Trump's rhetoric/discourse strategies and major campaign themes during the 2016 presidential election. For instance, while Clinton used the more established strategy of appealing to reason and inclusiveness, which might not have helped mobilize her base very much, Trump, on the other hand, seized on repetition and appealing to negative sentiments as his main strategies to help quite successfully fire up his base. The findings might help explain Trump's victory despite the significantly more negative sentiment in his discourse. In terms of research methodology, the results of the study have shown that the machine-based research methods and techniques we used are effective for sentiment and theme exploration of politicians' discourses as they allow us to quickly and accurately identify the sentiments and major themes in the two candidates' speeches. Particularly, combining the *stm* and the *word2vec* analyses provided information that enabled us to gain more in-depth understanding of candidates' actual attitudes, opinions, and perspectives on the same issues that their opponents seemed to also champion. The results also reveal that, to gain a clear and accurate understanding of the candidates' themes, machine-based automatic analysis should also be complemented by a close qualitative examination of the data (specifically the reading of the candidates' actual utterances involving key thematic terms and their strongest companion words). Without such close qualitative analysis, machine-based automatic analysis may miss out some very important information.

Our combined methods may be especially useful for analyzing large datasets as the automated sentiment *stm* and *word2vec* analyses can quickly and effectively find the information of interest, something that cannot be done manually. However, the effectiveness of the methods we used will need to be tested in future studies on the sentiment and major themes of political speeches. Possible targets and topics for such future research include Trump and any other election candidates and politicians. For research on Trump, it will be interesting to use the methods for a study on Trump's tweets, a diachronic examination of Trump's speeches during the election and those during his presidency, and a comparison of Trump's speeches with other US presidents'. An even more interesting study will be one that uses the methods to compare the sentiment and themes of the candidates with those of the media and the public expressed in polls.

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Appendix A

Sample strongest companion words of the top thematic terms (results generated by the *word2vec* analysis).

Key term	Speaker	Strongest companion words
For shared key thematic terms		
tax(0)	Clinton	wealthy (0.62), millionaire (0.58), dime (0.56), corporation (0.53), penny (0.51), billionaire (0.5), trillion (0.5), cut (0.49)
	Trump	massively (0.62), decrease (0.62), simplify (0.61), simplification (0.58), substantially (0.56), relief (0.54), code (0.52), lower (0.52)
change(1)	Clinton	climate (0.65), science (0.46), tackle (0.45), hoax (0.45), planet (0.41), <u>real</u> (0.4), combat (0.35), denial (0.34)
	Trump	<u>real</u> (0.51), bold (0.4), reckless (0.39), deliver (0.37), outcome (0.37), conversation (0.37), honesty (0.36), begin (0.32)
leave(1)	Clinton	<u>behind</u> (0.57), sick (0.4), rightly (0.35), childcare (0.34), rush (0.32), badly (0.31), relative (0.3), somewhere (0.3)
	Trump	flee (0.45), quit (0.42), fire (0.41), Indianapolis (0.4), Wisconsin (0.4), entirely (0.39), company (0.37), <u>behind</u> (0.36)
care(2)	Clinton	<u>health</u> (0.5), coverage (0.45), healthcare (0.44), affordable (0.43), relative (0.42), elderly (0.41), <u>mental</u> (0.41), childcare (0.4)
	Trump	<u>health</u> (0.54), <u>mental</u> (0.53), vet (0.5), medical (0.49), veterans (0.46), professional (0.46), deplete (0.45), veteran (0.45)
For Clinton's unique key thematic terms		
future		chart (0.52), grandkid (0.46), optimism (0.44), confidence (0.38), unifying (0.38), destiny (0.37), optimistic (0.37), shape (0.36)
build		resilient (0.44), global (0.39), harness (0.39), electric (0.38), unleash (0.37), fairness (0.37), coalition (0.36), bridge (0.35)
opportunity		skill (0.5), widen (0.48), chart (0.45), circle (0.45), fulfill (0.44), quality (0.42), chance (0.4), strive (0.37)
gun		lobby (0.66), owner (0.6), safety (0.59), violence (0.58), collect (0.58), hunting (0.56), background (0.55), commonsense (0.55)
For Trump's unique key thematic terms		
include		simplification (0.36), revitalization (0.35), search (0.35), dramatically (0.34), farm (0.33), gas (0.33), consumer (0.33), match (0.33)
love		patriot (0.5), expression (0.47), hardworking (0.41), Chris (0.4), truly (0.38), fellow (0.37), room (0.37), talent (0.36)
African		brink (0.65), Los (Angeles) (0.57), Latino (0.57), poverty (0.56), (Los) Angeles (0.54), unemployed (0.52), African-American (0.52), stamps (0.52)
illegal		immigrant (0.65), burglary (0.53), catch-and-release (0.52), gang (0.51), deport (0.49), criminal (0.49), overstay (0.49), rapist (0.48)

Note: 1. The number in parenthesis under a key term in Part 1 is the number of strong companion words shared by both candidates.
2. The number after each companion word is its association probability value with the key term.
3. The underline words in the strongest companion words of the shared key thematic terms are the only ones that appeared in both candidates' lists.

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.dcm.2018.05.001.

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