Following Hillary Clinton and Donald Trump: A dissection of their tweets in the 2016 U.S. presidential election
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Abstract
In this work, the tweets of Donald Trump and Hillary Clinton in the 2016 U.S. presidential campaign are studied and analyzed from a language-based perspective. The tweets are divided into two batches. The first is from the earliest announcement of candidacy until the last announcement of nomination of candidates. The second is between the end of the first interval and the inauguration of Trump. Readability statistics of tweets are computed and the Scholastic Aptitude Test (SAT) words — subject of much cramming by test takers — in the tweets are analyzed, as well as Ogden’s Simple English words. Some of the readability indexes exhibit minor differences, implying that Clinton’s tweets are more readable whereas the other readability indexes are proximate for the candidates. Clinton’s use of unique SAT words is found to be denser than Trump’s, indicating that employing such words less might be wiser for political campaigns. Simple English analysis does not tell of a noticeable difference. Syntactic Dependency Distance of tweets and Integrative Complexity of tweets were also analyzed but no significant difference for the two candidates was discerned.

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1. Introduction

According to Merriam-Webster (n.d.), the word politico comes from Italian politico or Spanish politico, and originally from Latin politicus. It means “politician.” The dictionary is quick to give an amusing example: “a politico who will do anything to win an election.”

In the 2016 U.S. presidential campaign, Twitter was used by all candidates (politics par excellence) on an impressive scale for the first time. In this paper, an analysis (primarily, from a language perspective) is offered to see how they penne their tweets to achieve their political aim — winning the election — and to what extent they were persuasive in this regard.
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Answering this question would necessarily involve studying individual tweets for content, truth (accuracy), sentiment, style, frequency, repetitiveness, feedback (i.e., likes, retweets, and comments from followers or non-followers), authenticity, accompaniments (e.g., audiovisuals embedded in a tweet), nature and number of followers, and so on and so forth. This is undoubtedly a humongous and labor-intensive undertaking (AI technology is not sufficiently mature at this point to execute all these tasks reliably) but we trust that certain computational machinery designed for language analysis may be used to address portions of the overall endeavor.

As indicated in the title of the paper, our coverage is immediately narrowed down to the analysis of the tweets of Donald Trump, the candidate of the Republican Party, and Hillary Clinton, the candidate of Democratic Party. The rationale for this decision became even clearer in the last six years or so: they are, arguably, still the most popular social media personalities (along with Barack Obama) in the present-day American political arena.

Clinton and Trump’s tweets are analyzed from a computational linguistics point of view to detect any meaningful correlations with previous (NLP-based) work. However, “Does Twitter oversimplify the entire campaign discourse?” remains a question to ponder. In other words, is it feasible or even desirable for a voter to estimate the policy preferences of a candidate from his or her compressed — in the past 140, now 280 characters long — word bites? We remain noncommittal regarding the right answer, if any, to this question.

It is worth mentioning that especially the most bizarre, foolish, ridiculous, quirky (the list goes on) tweets sent by a candidate (generalizing, a politico or a celebrity) are deliberately repeated in the ‘press’ — a portmanteau word we employ to denote the totality of TV, newspapers, YouTube, Facebook, Instagram, TikTok, etc. — with additional comments, or explications de texte, if you will. These proliferations provide more visibility and impact to such tweets; their sway is no longer limited to the realm of Twitterverse. Surely P.T. Barnum was dead-on when he (reportedly) said: “There’s no such thing as bad publicity.”

2. Related work

The use of Twitter in politics has stimulated the interest of social media researchers. They have investigated the role of Twitter in elections, the use of language in tweets by candidates, the features that Twitter provides as a political medium, and the role of followers on campaign ‘trails.’ A wide-ranging recap of the political uses and effects of Twitter in a global (world elections) context is available in Davis, et al. (2016).

A good synopsis of Twitter’s role in the 2016 U.S. presidential election is provided by Galdieri, et al. (2018). While considerable attention has been paid to Trump’s idiosyncratic use of Twitter — especially as a venue to distract attention from weightier matters — this book is an analysis of the influence Twitter exerted on the actual election itself. In a similar vein, Schill, et al. (2017) is an account of how electronic political media played, according to the authors, an overbearing and disintegrating role in the democratic process, again with emphasis on the 2016 presidential election.

Case studies of competitive House contests and high-profile U.S. Senate campaigns were given by Foreman and Godwin (2018), with an assessment of the effects of the 2016 presidential race.

Using Twitter for political campaigns generally results in positive consequences. Certainly this medium makes it easier for candidates to disclose elements of their private persona (Kruikemeier, 2014). Another study on 2012 U.S. and French elections (Nooralahzadeh, et al., 2013) conducted sentiment analysis of tweets and laid emphasis on the use of social media in soliciting feedback from voters.

Social media platforms as a toolbox started to receive more attention in the 2010s, after the triumphant 2008 Obama campaign (Yaqub, et al., 2017). As a natural extension of this, in the 2016 U.S. presidential campaign Twitter was used by all candidates (and before the nominations, by all presidential hopefuls) on an impressive scale. Halpern (2017) provided the following numbers, originally reported by TwitterAudit (n.d.):

- Donald Trump had 11,972,303 followers (nearly 40 percent of these were bots).
- Hillary Clinton had 10,696,761 followers (about 5 percent bots).
Swain (2016) provided some interesting work on the 2016 U.S. election and Twitter. He created, using graph theory, a conversation map representing the communication between voters and their communities.

Enli (2017) described three focus areas on research for social campaigns and elections: historical development of digital campaigns, level of interaction between voters and candidates, and level of professionalization of campaigns. She singled out two strategies used in the 2016 U.S. election: professionalization (routinely heeded by Clinton) and amateurism (oftentimes heeded by Trump). She argued that amateurism, widely seen as a counterforce to professionalization, indeed had a clumsy and imperfect look (optics!) but may be praised by crowds as pure, creditable, and authentic.

Ott (2017) remarked that Twitter’s communication medium set ground for negative connotations and insults, regularly cropping up in Trump’s tweets. He argued that ‘meritorious’ tweeting demands simplicity, promotes impulsivity, and fosters incivility.

Lee, et al. (2018) related the ‘agenda setting’ and the ‘issue ownership’ theories in mass communication to the use of Twitter in the campaigns of the 2016 elections. They defined so-called attack tweets as “criticism of unfavorable qualities, policies, behaviors, or any flaws of the other candidates.” It turns out that these constituted half of the tweets during the final three months of the campaign. The authors reported that attack tweets were an effective way to attract voter reaction because they spawned retweets. Trump’s retweet counts, on the average, were found to be three times as many as Clinton’s. Lee and coworkers thought that Twitter users were more prone “to support and disseminate attack messages than others,” given that animosity toward Clinton was significant in Trump’s campaign. (Clinton did not ordinarily follow such a strategy.)

In Parmelee and Bichard (2012), nine facets were itemized for a political tweet likely to be seen and acted upon:

- clarity,
- a call to action,
- personal relevance,
- professional usefulness,
- helpful links and hashtags,
- a political counterpoint,
- humor,
- interactivity, and
- outrageousness.

In the same work, some interesting results were derived. Women were more likely “to retweet information” and “to be opinion leaders, at least in the online sphere.” The authors also pointed out that individuals with less education were more likely to indulge in retweets. They notice two types of communication on political Twitter: one-way and two-way. They observed that

“[i]n terms of one-way communication, participants find value in receiving political information and in transmitting their views to their followers. In addition, participants enjoy two-way communication in the form of engaging in discourse with politicians, political activists, journalists, and fellow political junkies.”

The tweets of candidates for the 2016 U.S. elections were mainly re-broadcasted by followers, as opposed to followers creating novel content. Parmelee and Bichard’s (2012) analysis was done on tweets posted over a period of three weeks, before and after the elections (held on 8 November 2016). A sentiment analysis of the tweets demonstrated that Trump’s tweets had more positive words than Clinton’s. Yet, the authors’ hypothesis — the impact of sentiment of messages on sentiment of the overall political discourse — did not materialize. To wit, a positive sentiment in tweets had negligible effect on the overall sentiment of the campaigns, taking retweets into account (Yaqub, et al., 2017).

A gripping work on the use of Twitter in the 2016 US election scene described a rumor detection algorithm (Jin,
et al., 2017). Another study (Conway III, et al., 2012) illustrated that complexity of communication was not directly related to content but resided in the background and had an effect of votes. The authors also stated that simplicity, rather than complexity, was what people ultimately chose.

Linguistic Inquiry and Word Count (LIWC) is a text analysis tool (Tausczik and Pennebaker, 2010) that calculates the percentage of words in a given text that fall into nearly 100 categories comprising a variety of social, cognitive, and affective processes. LIWC can be used to determine the degree in which a text uses positive or negative emotions, self-references, or causal words. It was reported by Ahmadian, et al. (2017) that LIWC informality correlated with success in electoral results. (Informality was defined as making more frequent use of non-standard and low-complexity words.)

3. Dataset

Tweets published on the official accounts of Hillary Clinton and Donald Trump during the 2016 U.S. elections were collected. Important dates were identified in order to have a consistent time interval for data. Here is a list of landmarks for the candidacy of Clinton:

- Sunday, 12 April 2015. Former Secretary of State Hillary Clinton formally announces her candidacy for the presidential nomination of the Democratic Party.
- Monday, 6 June 2016. Clinton passed 2,383 pledged delegates, the minimum required to secure the Democratic presidential nomination.
- Thursday, 9 June 2016. President Barack Obama officially endorses Clinton.
- Friday, 22 July 2016. Democratic presumptive nominee Clinton announces that U.S. senator and former Virginia governor Tim Kaine will be her vice presidential running mate.
- Thursday, 28 July 2016. Hillary Clinton accepts the nomination from the Democratic Party, becoming the first female presidential nominee of a major party in U.S. history.

A chronology of similar occasions for Trump consists of the following:

- Tuesday, 1 June 2015. Business magnate Donald Trump officially declares his candidacy for the presidential nomination of the Republican Party.
- Tuesday, 3 May 2016. Ted Cruz formally withdraws his candidacy for the Republican presidential nomination.
- Thursday, 26 May 2016. Trump passed 1,237 pledged delegates, the minimum required to secure the Republican presidential nomination.
- Friday, 15 July, 2016. Republican presumptive nominee Trump announces that Indiana governor Mike Pence will be his vice presidential running mate.
- Thursday, 21 July 2016. Donald Trump formally accepts the Republican nomination.

Election day in the U.S. was Thursday, 8 November 2016; inauguration of Trump occurred on Friday, 20 January 2017. Reflecting upon these dates, we decided to set two time intervals for the analysis of tweets:

- The first interval (Epoch 1, in the sequel) was between Sunday, 12 April 2015 and Thursday, 28 July 2016, viz., it started from the earliest announcement of candidacy (Clinton) and extended until the last announcement of nomination (Clinton).
- The second interval (Epoch 2, in the sequel) was between Thursday, 28 July 2016 and Friday, 20 January 2017, viz., it started with the last announcement of nomination (Clinton) and extended until the inauguration of Trump.

We framed the intervals in this way in order to be rigorous and consistent while analyzing the tweets. When the candidates first declared their candidacy, they were opponents not only to each other but also to other candidates from their parties. Since the Clinton- Trump rivalry started even in this early phase, we decided to analyze Epoch 1. Epoch 2 stretches out to the inauguration of Trump even though he was the projected winner on the night of the election day. We chose to extend it because tweets during that time were, in our view, also worthy of
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Just to be clear, we did not expect to find differences between two epochs. The epochs served another purpose, that of conceptual clarity. In any case, the epochs’ split may seem somewhat arbitrary. We understand this concern. After all, it became clear earlier (circa April 2016) who the two party nominees would be. Better still, Clinton and Trump began directing their arrows more against each other than against their primary opponents again as early as spring 2016.

The Twitter API was used to collect tweets from Twitter accounts with user names (Twitter handles) @HillaryClinton and @realdonaldtrump. Our dataset is freely available to any interested party.

For Epoch 1, a total of 5,224 and 7,964 tweets of Clinton and Trump were collected, respectively. For Epoch 2, a total of 2,244 and 1,525 tweets of Clinton and Trump were collected, respectively. We did not take into account deleted tweets. We also ignored contributions of images and audio to tweets, despite the fact that audiovisuals figured to some extent in tweets from these candidates.

4. Methods

There have been certain attempts so far to analyze the tweets. Some of them were inconclusive whereas some reported consistent results.

4.1. Readability statistics

Readability statistics are studied with the help of the Python library “textacy” (DeWilde, 2021). The library provides readability statistics for the following (brief explanations delegated to the Appendix):

- Automated Readability Index
- Coleman-Liau Index
- Flesch-Kincaid Grade Level
- Flesch Reading Ease
- Gunning Fog Index
- SMOG Index

The library also provides simple morphological analysis of words and sentences. It gives the number of

- sentences,
- long words (e.g., those with seven or more letters),
- polysyllabic words,
- syllables,
- words,
- unique words,
- characters, and
- monosyllabic words.

Before analyzing the raw tweets, we preprocessed them by removing links related to any media, including only tweets written in English. During the preprocessing stage, emojis/emoticons were also removed even though they were few. We also changed the mentions that were written with an at-sign in front of a Twitter user’s name with their full name. We wanted to enforce content integrity this way and also ease analysis.

4.2. Word complexity

The next method measured sentence complexity with a criterion of word complexity. We looked for words that are considered to be sophisticated and used less in daily contexts but more in formal (especially academic) contexts. Thus, we used a vocabulary learning Web site (https://satvocabulary.us) aimed at young test takers.
studying for the Scholastic Aptitude Test (SAT). Contrary to popular belief, the revised SAT still tests vocabulary, now predominantly in the context of excerpts in its reading and writing sections.

There are six different word lists in the SAT Vocabulary site, dubbed

- Most Comprehensive SAT Word List on the Web,
- SAT Basic I Word List,
- SAT Basic II Word List,
- SAT Challenging I Word List,
- SAT Challenging II Word List, and
- SAT Most Important Word List.

with sizes 6,000, 287, 313, 291, 109, and 500 words, respectively. Some representative words from these lists are antediluvian, atrophy, castigate, and ostensible. We took every word in the tweets to see whether it appeared in any of the SAT word lists and if so, we kept a count for each such word.

Since we were making a word analysis, punctuation marks, digits, and special characters were all removed. In addition, the word don was removed from the SAT 6,000 Word List because it was mingled with don’t when punctuation was removed.

After exercising this method with SAT words, we reapplied it using a different set of words. We consulted Ogden’s Simple English Word List which consists of 850 words, selected by Charles K. Ogden in his renowned quest to create a simplified English language (Basic-English Institute, 2012). The list consists of casual words that learners of English are presumed to know for basic communication.

4.3. Syntactic dependency distance

In the third method, we applied the syntactic dependency distance technique, described by Oya (2011) as a proposed measurement method for sentence complexity. The measurement is done by first parsing a sentence with the words’ dependencies to each other taken into account. Then, a dependency distance is computed by summing the difference of the positional distance of words in the sentence and dividing it by the number of dependencies.

Figure 1 is a directed acyclic graph (DAG) representation of Clinton’s tweet “We need more love and kindness in this country,” showing the dependencies between words. The direction of an arrow reveals the dependency. Thus, “We” is dependent on “need,” “more” is dependent on “love,” “country” is dependent on “in,” and so on. The difference of their positional distance is 1 for “We” and “need,” 2 for “country” and “in,” 4 for “need” and “kindness,” etc. From these values, average dependency distance (ADD) is calculated as $\frac{17}{8} = 2.125$. Because Oya observed that sentences with 10 words and over and less than 20 words were statistically different, we only used tweets within this word length interval. The Stanford Parser was used as a server for Python clients to process the data (de Marneffe, et al., 2006). The links and hash tag symbols (along with their labels) were removed from the tweets before inputting the sentences to the parser. Replacing the mentions with the corresponding names was also done. Punctuation marks were not removed to make sure that the given sentence was meaningful and that possible ambiguities were reduced. Yet, when calculating the ADD, the dependency distances for the punctuation marks were disregarded.
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**Figure 1:** Directed acyclic representation of “We need more love and kindness in this country,” a tweet by Clinton. (Here, we take liberties in relating *more* only to *love*.)

### 4.4. Integrative complexity

The last method we used was measuring the complexity level by the integrative complexity of the tweets, in order to see how different dimensions of an issue or occasion were addressed by the candidates. Here, we used the Automated Integrative Complexity (AIC) tool of Conway III, *et al.* (2014). Measurements were on a scale between 1 and 7 such that

- scores of 1 conceptually represent a total lack of differentiation or integration,
- scores from 2 to 3 represent levels of differentiation, and
- scores from 4 to 7 represent differentiation plus integration.

Even though the tool does not claim to be an approximate equivalent of human scoring, it has a high correlation with human-scored values compared to other methods.

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### 5. Results

#### 5.1. Readability statistics

The results of the first method, which was based on readability scores to measure complexity, are given in Tables 1 and 2. Overall, small differences in readability statistics for Epoch 1 were observed between the candidates. However, appreciable differences in the values existed for Epoch 2. Table 2 is given but does not offer a direct measurement of readability; rather, the values were used for the computation of tests in Table 1. Nevertheless, we provided relative values per 100 tweets (instead of absolute values) in order to make Table 2 more comprehensible.
Table 1: Readability statistics.

<table>
<thead>
<tr>
<th>Readability Types</th>
<th>Clinton Epoch 2</th>
<th>Trump Epoch 2</th>
<th>Clinton Epoch 1</th>
<th>Trump Epoch 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Automated Readability</td>
<td>5</td>
<td>7</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Coleman-Liau</td>
<td>7.64</td>
<td>9.08</td>
<td>7.91</td>
<td>8.63</td>
</tr>
<tr>
<td>Flesch Kincaid</td>
<td>4.72</td>
<td>5.48</td>
<td>4.75</td>
<td>4.80</td>
</tr>
<tr>
<td>Gunning Fog</td>
<td>8.00</td>
<td>8.17</td>
<td>8.00</td>
<td>7.65</td>
</tr>
<tr>
<td>SMOG</td>
<td>8.83</td>
<td>9.20</td>
<td>8.84</td>
<td>8.59</td>
</tr>
</tbody>
</table>
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Table 2: Morphological analysis.

<table>
<thead>
<tr>
<th>MA Parameters</th>
<th>Clinton Epoch 2</th>
<th>Trump Epoch 2</th>
<th>Clinton Epoch 1</th>
<th>Trump Epoch 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Characters</td>
<td>7,939</td>
<td>7,635</td>
<td>7,289</td>
<td>8,129</td>
</tr>
<tr>
<td>#Long words</td>
<td>354</td>
<td>382</td>
<td>340</td>
<td>349</td>
</tr>
<tr>
<td>#Monosyllabic words</td>
<td>1,332</td>
<td>1,157</td>
<td>1,190</td>
<td>1,260</td>
</tr>
<tr>
<td>#Polysyllabic words</td>
<td>165</td>
<td>165</td>
<td>156</td>
<td>159</td>
</tr>
<tr>
<td>#Sentences</td>
<td>165</td>
<td>146</td>
<td>156</td>
<td>175</td>
</tr>
<tr>
<td>#Syllables</td>
<td>2,435</td>
<td>2,311</td>
<td>2,231</td>
<td>2,438</td>
</tr>
<tr>
<td>#Unique words</td>
<td>198</td>
<td>288</td>
<td>139</td>
<td>235</td>
</tr>
<tr>
<td>#Words</td>
<td>1,782</td>
<td>1,630</td>
<td>1,612</td>
<td>1,744</td>
</tr>
</tbody>
</table>

5.2. Word complexity

The results for the SAT-words analysis are given in Table 3. It can be seen that proportion of number of unique SAT words used to total number of unique words in tweets was larger for both Epochs 1 and 2 in Clinton’s tweets, whereas proportion of total number of SAT words used to total number of words used in tweets was the same for candidates in Epoch 2 but larger for Clinton in Epoch 1. It is also worth pointing out that the number of unique words is different from the results in Table 2 due to the fact that additional filtering was used (e.g., to remove punctuation and special characters).
<table>
<thead>
<tr>
<th>Measurements</th>
<th>Clinton (Epoch 2)</th>
<th>Trump (Epoch 2)</th>
<th>Clinton (Epoch 1)</th>
<th>Trump (Epoch 1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Unique words (A)</td>
<td>3,974</td>
<td>3,654</td>
<td>6,102</td>
<td>11,248</td>
</tr>
<tr>
<td>#SAT words (B)</td>
<td>349</td>
<td>211</td>
<td>763</td>
<td>900</td>
</tr>
<tr>
<td>#Unique SAT words (C)</td>
<td>135</td>
<td>82</td>
<td>208</td>
<td>272</td>
</tr>
<tr>
<td>B ÷ #Words</td>
<td>0.0089</td>
<td>0.0085</td>
<td>0.0092</td>
<td>0.0069</td>
</tr>
<tr>
<td>C ÷ A</td>
<td>0.0340</td>
<td>0.0224</td>
<td>0.0340</td>
<td>0.0242</td>
</tr>
</tbody>
</table>

Table 3: SAT words (analysis).

The same method applied to Ogden’s Simple English words gives the results summarized in Table 4. The proportion values were found to be the closest to each other for Epoch 2. Total number of words figures were also close to each other for Epoch 1 but the proportion with the number of unique words was larger for Clinton.
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Table 4: Ogden’s Simple English words (analysis).

<table>
<thead>
<tr>
<th>Measurements</th>
<th>Clinton Epoch 2</th>
<th>Trump Epoch 2</th>
<th>Clinton Epoch 1</th>
<th>Trump Epoch 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Unique words (A)</td>
<td>3,794</td>
<td>3,654</td>
<td>6,102</td>
<td>11,248</td>
</tr>
<tr>
<td>#Simple words (B)</td>
<td>9,722</td>
<td>6,021</td>
<td>20,966</td>
<td>29,722</td>
</tr>
<tr>
<td>#Unique simple words (C)</td>
<td>227</td>
<td>214</td>
<td>283</td>
<td>312</td>
</tr>
<tr>
<td>B ÷ #Words</td>
<td>0.2473</td>
<td>0.2433</td>
<td>0.2529</td>
<td>0.2275</td>
</tr>
<tr>
<td>C ÷ A</td>
<td>0.0571</td>
<td>0.0585</td>
<td>0.0464</td>
<td>0.0277</td>
</tr>
</tbody>
</table>

5.3. Syntactic dependency distance

The ADD measurements involved 1,498 and 183 tweets of Clinton in Epochs 2 and 1, respectively. On the other hand, the number of tweets of Trump were 301 and 5,287 for Epochs 2 and 1, respectively. Interestingly, the number of tweets with the number of words over 10 and less than 20 was considerably larger for Clinton in Epoch 2 and larger for Trump in Epoch 1.

The ADDs were found to be 2.979, 2.985, 3.000, 2.836 for Clinton Epoch 2, Trump Epoch 2, Clinton Epoch 1, and Trump Epoch 1, respectively. Overall, the ADD values and variance were close to each other for both candidates in both epochs.

5.4. Integrative complexity

Results of the AIC analysis were similar to the ADD results. This analysis involved 441 and 80 tweets of Clinton in Epochs 2 and 1, respectively. On the other hand, Trump had 256 and 3,265 tweets for Epochs 2 and 1, respectively. The average AIC measurements was found to be 1.191, 1.212, 1.234, 1.152 for Clinton Epoch 2, Trump Epoch 2, Clinton Epoch 1, and Trump Epoch 1, respectively.

6. Discussion

6.1. Readability statistics

The results of the readability statistics were not always consistent with each other. For example, the values were close to each other for SMOG and Gunning Fog Index for Epoch 2 in Clinton’s and Trump’s tweets yet there were considerable differences for Automated Readability and Coleman-Liau Indexes and smaller differences for
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Flesch Kincaid Grade Level and Flesch Reading Ease. The pattern was similar for Epoch 1 but the differences were smaller than Epoch 2. Overall, readability statistics favored Clinton’s tweets: they were more readable. This result coincides with the professionalization that Clinton followed during the period (Enli, 2017); her tweets were well worked on before being posted. On the other hand, the spontaneity of Trump’s tweets might be the reason for their low readability statistics.

6.2. Word complexity

SAT Words analysis provided a salient result that the proportion of number of unique SAT words to total number of unique words in tweets was consistent for both candidates and the proportion of these values of candidates yielded \(0.0340 \div 0.0224 = 1.52\) and \(0.0340 \div 0.0242 = 1.40\) using the entries of Tables 3 and 4. This means that Clinton’s employment of unique SAT words in her tweets was 1.46 (average of 1.52 and 1.40) times denser than Trump’s overall. SAT words are considered to be not casual words but rather contextual words. They are expected to appear in, among others, scholarly articles. It is reasonable to posit that using fewer such contextual words in a casual (even relaxed) environment like Twitter is better for a political campaign (Halpern, 2016). However, more analysis using similar election data is required in order to strengthen this ‘heuristic’ (or perhaps, question its validity).

Ogden’s Simple English words analysis did not give any distinct results for the candidates’ tweets. We can say that such daily and basic words were of similar quantity in their tweets. One interesting case was for the difference of \(C \div A\) values in Table 4 for Epoch 1. Accordingly, it is the case that the number of such basic words does not increase linearly by the total number of unique words in a text. The total number of unique words in the tweets of Trump was nearly twice that of Clinton’s, whereas the numbers of unique words from Ogden’s Simple English words were close to each other.

6.3. Syntactic dependency distance and integrative complexity

ADD and AIC analysis did not produce any noticeable difference. Yet, a disengaged implication from the obtained results was that Trump’s tweets were overall longer in Epoch 1 but shorter in Epoch 2 (and vice versa for Clinton’s tweets), assuming that tweets with more words than 20 were few compared to all tweets of the candidates.

7. Conclusion

Future U.S. presidential aspirants — and politicos elsewhere — are to be expected to learn from Trump’s and Clinton’s impressive performances on Twitter in the 2016 campaign. While the use of Twitter (when the first stage of its novelty passed) by Obama and Mitt Romney in the 2012 election was highly notable (Enli and Naper, 2015), the 2016 race was simply an all-out event.

Many other methods (such as n-gram analysis, sentiment analysis, and analysis of punctuation marks) have been used to study tweets of political campaigns (Bruin, 2019; Tunguz, 2018). Enli (2017) argued that exclamation marks and capital letters used by Trump gave his tweets a sense of authenticity. She also argued that Hillary uses her voice less, as one can see from her tweets when she used her first initial “--H,” but mostly quoted others.

In this work, tweets of two candidates who loomed large in the 2016 U.S. presidential campaign were studied. Readability statistics gave results uncorrelated with each other, yet for some of the readability indexes Clinton’s tweets were found to be more easily readable. Clinton’s tweets were found to use denser unique SAT words than Trump’s. The same method applied with Ogden’s Simple English words did not give distinctive results. AAD and AIC analyses did not produce considerable differences either. Similar work could be done with other political election campaign data to test for correlations or incongruities.

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Appendix: Readability indices

In the formulas in the sequel, the sharp-sign denotes “number of.”

Automated readability (Smith and Senter, 1967)

The Automated readability index was designed for real-time monitoring of readability on electric typewriters. Higher scores are indicative of higher grade levels (e.g., 1 being kindergarten and 14 being college). The formula is:

\[
4.71 \frac{\text{total \#characters}}{\text{total \#words}} + 0.5 \frac{\text{total \#words}}{\text{total \#sentences}} - 21.43
\]
Coleman-Liau (Coleman and Liau, 1975)

This method is based on the number of characters rather than syllables per word. A larger value of the index corresponds to a higher grade level and thus, low readability. The formula is:

\[ 0.0588L - 0.296S - 15.8 \]

where \( L \) is the average number of letters per 100 words and \( S \) is the average number of sentences per 100 words.

Flesch-Kincaid Grade Level and Flesch Reading Ease (Kincaid, et al., 1975)

Both tests use word length and sentence length as the main source of measurements but with differing weight factors. The Flesch Reading Ease Score (FRES) is computed as:

\[ 206.835 - 1.015 \frac{\text{total #words}}{\text{total #sentences}} + 84.6 \frac{\text{total #syllables}}{\text{total #words}} \]

FRES gives a score on a scale \([0,100]\), where a high score means high readability. On the other hand, the Flesch-Kincaid Grade Level is designed to give the U.S. grade level, meaning, a lower index indicates high readability. The formula is:

\[ .39 \frac{\text{total #words}}{\text{total #sentences}} + 11.8 \frac{\text{total #syllables}}{\text{total #words}} - 15.59 \]

Gunning Fog (Gunning, 1969)

Similar to the Flesch-Kincaid Grade Level, this index (sometimes simply called FOG) estimates the years of formal education that a person needs to have in order to understand a text on first reading. A high index value indicates less readability. The formula is:

\[ 0.4 \left[ \frac{\text{total #words}}{\text{total #sentences}} + 100 \frac{\text{total #complex words}}{\text{total #words}} \right] \]
where complex words are those consisting of three or more syllables.

**SMOG (McLaughlin, 1969)**

The SMOG (“Simple Measure of Gobbledygook”) Index is frequently used in evaluating consumer-oriented healthcare materials. It estimates the years of education needed to understand a given text. A high index value means less readability. The formula is:

\[
1.043 \sqrt{\frac{\text{total syllables}}{\text{total sentences}}} + \frac{30}{\text{total sentences}} + 3.1291
\]

*N.b.*, for texts of fewer than 30 sentences this formula is statistically invalid, for it was normed on 30-sentence samples.

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