# Fake News and Propaganda: Trump's Democratic America and Hitler's National Socialist (Nazi) Germany ⋆

EI2019-17

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**Abstract**

This paper features an analysis of President Trump's two State of the Union addresses, which are analysed by means of various data mining techniques including sentiment analysis. The intention is to explore the contents and sentiments of the messages contained, the degree to which they differ, and their potential implications for the national mood and state of the economy. In order to provide a contrast and some parallel context, analyses are also undertaken of President Obama's last State of the Union address and Hitler's 1933 Berlin Proclamation. The structure of these four political addresses is remarkably similar. The three US Presidential speeches are more positive emotionally than Hitler's relatively shorter address, which is characterized by a prevalence of negative emotions. However, it should be said that the economic circumstances in contemporary America and Germany in the 1930s are vastly different.

*Keywords:* Text Mining, Sentiment Analysis, Word Cloud, Emotional Valence
JEL: C19, C65, D79.

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⋆The analysis in the paper was undertaken with a number of R packages, including "textmining", "tm", "wordcloud" and "syuzhet" packages.

**Acknowledgements:** For financial support, the first author acknowledges the Australian Research Council, and the second author is most grateful to the Australian Research Council, Ministry of Science and Technology (MOST), Taiwan, and the Japan Society for the Promotion of Science.

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*March 19, 2019*

### 1. Introduction

President Trump continues to attract controversy in the media and in political commentary, partly because of his attitude to 'fake news', combined with his own lavish use of his Twitter account and lack of attention to the verification of some of his more extreme pronouncements. In 2018 the President used Twitter to announce the “winners” of his 'fake news' awards, most frequently naming the New York Times and CNN for a series of perceived transgressions which varied from minor errors by journalists on social media to news reports that later invited corrections.

Given his predilection for criticising the media, the authors have previously analysed his prouncements on climate change, Allen and McAleer (2018a), on nuclear weapons and Kim Jong Il, Allen and McAleer (2018b), and contrasted his first State of the Union Address (SOU) with the previous one by President Obama (see Allen, McAleer and Reid (2018).

Given the recent controversy about the timing and delivery of his most recent SOU address, the authors thought it might be of interest to subject both of his SOU addresses to textual analysis using data mining techniques.

We decided to analyse both his 2018 State of the Union Address (SOU1), and his recent 2019 address (SOU2) to assess whether there had been any change in the structure and emotional tenor of his two addresses, in response to changing political and economic circumstances, at the end of the second year of his term in office. To provide a contrast, one contemporary and another more historically extreme, we also analyse President Obama's last SOU and Hitler's 1933 Berlin Proclamation.

The contents of these are analysed using a variety of R packages including several in data mining: 'tm' a text mining package, created by Feinerer and Hornik (2018). We also used 'syuzhet', a sentiment extraction tool, originally developed in the NLP group at Stanford University, and then incorporated into an R package by Jockers (2015), and 'wordcloud' by Fellows (2018).

Data mining refers to the process of analysing data sets to reveal patterns, and usually involves methods that are drawn from statistics, machine learning, and database systems. Text data mining similarly involves the analysis of patterns in text data. Sentiment analysis is concerned with the emotional context of a text, and seeks to infer whether a section of text is positive or negative, or the nature of the emotions involved. There is a variety of methods and dictionaries that exist for undertaking sentiment analysis of a piece of text.

Although sentiment is often framed in terms of being a binary distinction (positive versus negative), it can also be analysed in a more nuanced manner. We decided to apply the R package 'syuzhet', which distinguishes between eight different emotions, namely trust, anticipation, fear, joy, anger, sadness, disgust and surprise. There are many different forms of sentiment analysis, but most use the same basic approach. They begin by constructing a list of words or dictionary associated with different emotions, count the number of positive and negative words in a given text, and then analyse the mix of positive and negative words to assess the general emotional tenor of the text.

Clearly, there are considerable limitations to the basic approach adopted in the paper. Pröllochs et al. (2017) discuss the difficulties in processing negations, which invert the meanings of words and sentences. Equally problematic are sarcasm, backhanded compliments, and inflammatory gibberish, such as "Pocohontas" and "Crooked Hillary", in the context of President Trump's tweets. Nevertheless, sentiment analysis can reveal the general emotional direction of a piece of text, and machine-based learning systems are well-established methods for the sifting and interpretation of digital information. This tool has numerous applications in, for example, financial markets.

We can now apply machine learning techniques to news feeds to determine what average opinion is. For example, the Thomson Reuters News Analytics (TRNA) series could be termed news sentiment, and is produced by the application of machine learning techniques to news items. The TRNA system can scan and analyse stories on thousands of companies in real time, and translate the results into a series that can be used to help model and inform quantitative trading strategies. RavenPack is another example of a commercial news analytics product that has applications to financial markets. There is now considerable evidence about the commercial relevance of financial news analysed using machine learning methods.

Allen, McAleer and Singh (2015, 2017) analyse the economic impact of the TRNA sentiment series. The first of these papers examines the influence of the Sentiment measure as a factor in pricing DJIA constituent company stocks in a Capital Asset Pricing Model (CAPM) context. The second uses these real time scores, aggregated into a DJIA market sentiment score, to analyse the relationship between financial news sentiment scores and the DJIA return series, using entropy-based measures. Both studies find that the sentiment scores have a significant information component which, in the former, is priced as a factor in an asset pricing context.

Allen, McAleer and Singh (2018) use the Thomson Reuters News Analytics (TRNA) data set to construct a series of daily sentiment scores for Dow Jones Industrial Average (DJIA) stock index constituents. The authors use these daily DJIA market sentiment scores to study the influence of financial news sentiment scores on the stock returns of these constituents using a multi-factor model. They augment the Fama–French three-factor model with the day's sentiment score along 20 with lagged scores to evaluate the additional effects of financial news sentiment on stock prices in the context of this model. Estimation is based on Ordinary Least Squares (OLS) and Quantile Regression (QR) to analyse the effects around the tails of the returns distribution. The results suggest that even when market factors are taken into account, sentiment scores have a significant effect on Dow Jones constituent returns, and also that lagged daily sentiment scores are often significant.

Other research on this topic argues that news items from different sources influence investor sentiment, which feeds into asset prices, asset price volatility and risk (see, among others, Tetlock (2007), Tetlock, Macskassy and Saar-Tsechansky (2008), Da, Engleberg and Gao, (2011), Barber and Odean (2008), diBartolomeo and Warrick (2005), Mitra, Mitra and diBartolomeo (2009), and

Dzielinski, Rieger and Talpsepp (2011)). The diversification benefits of the information impounded in news sentiment scores provided by RavenPack have been demonstrated in Cahan, Jussa and Luo (2009), and Hafez and Xie (2012), who examined the benefits in the context of popular asset pricing models.

In the current paper, the focus is on the actual content of President Trump's 2018 SOU1, and his subsequent 2019 SOU2 address. The intention is to explore whether there are any systematic differences in the sentiments of these two SOUs, and whether there is any evidence of a tendency by President Trump to generate a 'positive' spin for the benefit of his voter base. A contrast is provided by parallel analyses of President Obama's last SOU and Hitler's 1933 Berlin Proclamation.

Could President Trump's addresses be fairly described as constituting 'propaganda'? This has been defined as being the presentation of information, ideas, opinions, or images, which may only present one part of an argument, and which are broadcast, published, or in some other way spread with the intention of influencing people's opinions. Sentiment analysis will not give a clear answer as to whether content represents propaganda per se, but it will give an indication as to the emotional tenor of a text or speech. It will reveal correlations between the use of words, changes in sentiment, and any patterns revealed through time in the presentation of a speech.

The remainder of the paper is divided into four sections. An explanation of the research method is given in Section 2, Section 3 presents the results, and Section 4 provides some concluding comments.

## 2. Research Method

The analysis features the use of a number of R libraries which facilitate data mining and sentiment analysis, namely word cloud, tm and syuzhet, plus a variety of graphics packages. The R package tm has a focus on extensibility based on generic functions and object-oriented inheritance, and provides a basic infrastructure required to organize, transform, and analyze textual data. The basic document is imported into a 'corpus', which is then transformed into a suitable form for analysis using stemming, stopword removal, and so on. Then we can create a term-document matrix from a corpus which can be used for analysis. Once we have the text in matrix form, a huge amount of R functions (like clustering, classifications, among others) can be applied. We can explore the associations of words, correlations, and so forth, and screen the text for frequently occurring words. The analysis can be used to create a word cloud of the most frequently used words. Feinerer and Hornik (2018) provide an introduction to the package.

The R package wordcloud by Fellows (2018) provides functionality to create word clouds, visualize differences and similarity between documents, and avoid over-plotting in scatter plots with text. We use the R package 'syuzhet' for sentiment analysis. The package comes with four sentiment dictionaries, and provides a method for accessing the robust, but computationally expensive, sentiment extraction tool developed in the NLP group at Stanford University.

We transform the text in character vectors. Once we have the vector, we can select which of the four available sentiment extraction methods available in 'syuzhet' to employ. We used the default syuzet lexicon, which was developed in the Nebraska Literary Lab under the direction of Jockers (2015).

The name 'Syuzhet' comes from the Russian Formalists Shklovsky (1928) and Propp (1917) who divided narrative into two components, the 'fabula' and the 'syuzhet'. 'Syuzhet' refers to the 'device' or technique of a narrative, whereas 'fabula' is the chronological order of events. 'Syuzhet', therefore, is concerned with the manner in which the elements of the story (fabula) are organized (syuzhet). The R syuzhet package attempts to reveal the latent structure of narrative by means of sentiment analysis and we can construct global measures of sentiment into eight constituent emotional categories, namely trust, anticipation, fear, joy, anger, sadness, disgust and surprise.

While these global measures of sentiment can be informative, they tell us very little in terms of how the narrative is structured and how these positive and negative sentiments are activated across the text. In order to explore this, we plot the values in a graph where the x-axis represents the passage of time from the beginning to the end of the text, and the y-axis measures the degrees of positive and negative sentiment.

President Trump's first SOU in 2018 contained 5,169 words and 30,308 characters, while his second SOU in 2019 contained 5,493 words and 32,204 characters. Therefore, the two addresses were of similar size.

The limitations of the analysis should be borne in mind. The context of 'natural language processing', of which sentiment analysis is a component, is important. The use of sarcasm and other types of ironic language are inherently problematic for machines to detect, especially when viewed in isolation.

## 3. Results and Interpretation of the Analysis

Figure 1 presents a word cloud analysis of President Trump's two SOUs. In his first 2018 SOU, depicted in Figure 1A, the most frequently occurring word is 'American' followed by the symbol $a\epsilon\bullet$, which is a generic representation of different dollar amounts mentioned at various stages in his address. Other words emphasized include 'will', 'year', 'one', 'tonight', 'people', 'new', 'year', 'america', 'together', 'great', 'home', 'tax', 'congress', 'families', 'countries', 'proud', 'just', 'job', and 'citizen'.

The second, most recent SOU by President Trump is shown in Figure 1B. The is dominated by the words 'will', 'American', 'years', 'one', 'new', 'thank', 'americans', 'tonight', 'now', 'can', 'must', 'congress' 'border', 'last', 'time', 'also', and 'country'.

In order to provide a further contrast, the authors thought it might be instructive to compare this SOU with President Obama's last SOU. Moreover, to provide an extreme contrast, we undertook an analysis of Hitler's proclamation to the German nation, in Berlin on February 1, 1933. The intention was to see whether a political speech has typical common elements, or whether more extreme National Socialist (Nazi) proclamations have a different structure and emotional tenor. A further caveat is that the analysis is undertaken on an English translation of Hitler's 1933 proclamation, and not on the original German version.

It must be borne in mind that the economic circumstances in Germany in 1933, were markedly different from those in the USA in recent years. The German economy experienced the effects of the Great Depression with unemployment soaring around the Wall Street Crash of 1929. When Adolf Hitler became Chancellor in 1933, he introduced policies aimed at improving the economy, including privatization of state industries. National Socialist (or Nazi) Germany increased its military spending faster than any other state in peacetime, and the military eventually came to represent the majority of the German economy by the 1940s.

Figure 2 presents a word cloud analysis of both President Obama's last SOU plus Hitlers 1933 Berlin proclamation. The word cloud for President Obama's last SOU, shown in Figure 2A, displays that 'will', 'American', and 'year' received the greatest emphases in terms of their frequency of use. These words were closely followed by 'work', 'America', 'now', 'change', 'people', and 'just'. Further prominent words include 'world', 'want', 'job', 'can' and 'need'.

Hitler's 1933 proclamation, as represented by the word cloud depicted in Figure 2B reveals that the most frequently occurring word is 'nation', followed by 'German', 'year', 'will', 'govern', 'people', 'work', 'class', 'must', 'world', 'fourteen', 'life', 'upon', and so on.

Figure 3 provides bar plots of the words used most frequently in President Trump's two SOUs. The bar charts reinforce the word cloud analysis, but provide an indication of the relative frequency of use of the twenty most frequently occurring words. Figure 3A shows that in the first SOU, 'American' occurs over 50 times, followed by various indications of dollar amounts and 'will' occurs more than thirty times, while 'great'. 'last', 'together' and 'tax' occur around twenty times.

In his second SOU, depicted by the bar chart in Figure 3B, 'will' becomes the most frequently occurring word, followed by 'years', 'one' and American', but the top few words are less frequent in President Trump's second SOU than in his first one. 'American' is now the fourth most frequent word rather than the first, as in the pervious SOU. Perhaps surprisingly, given the political battles enveloping the topic, 'border' is the twentieth-most frequently used word.

**Figure 1 Word Cloud representing President Trump's two SOU addresses.**

**Figure 1A: Word Cloud SOU 2018**


**Figure 1B: Word Cloud SOU 2019**


**Note: The â€ is a symbol representing different dollar amounts**

**Figure 2 Word Cloud Analysis of President Obama's last SOU and Hitlers 1933 Berlin Proclamation**

**Figure 2A: President Obama's last SOU**

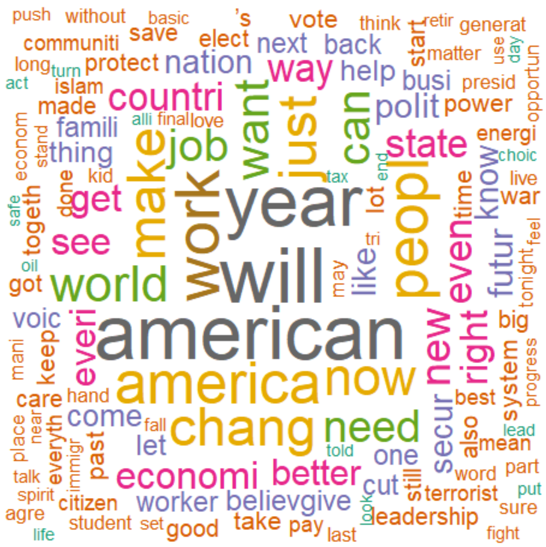



**Figure 2B: Hitler's 1933 Proclamation**

**Figure 3 Bar Plots of words used frequently in President Trump's two SOUs.**

**Figure 3A: President Trump SOU 1**

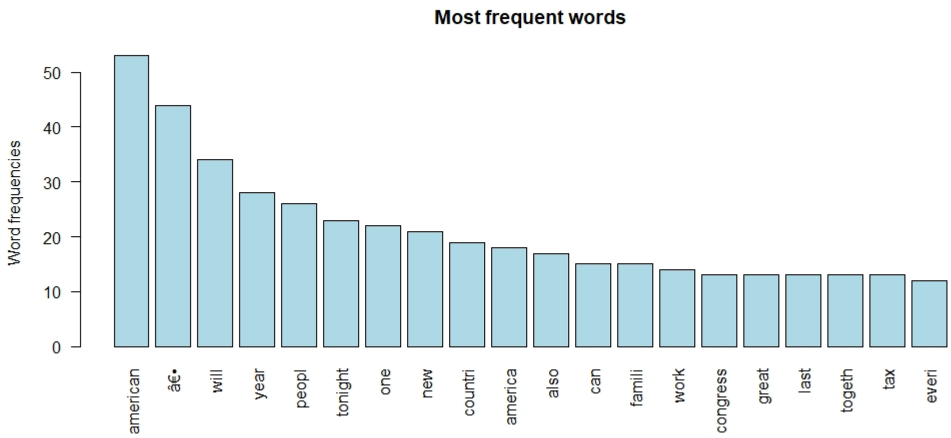



**Figure 3B; President Trump SOU2**

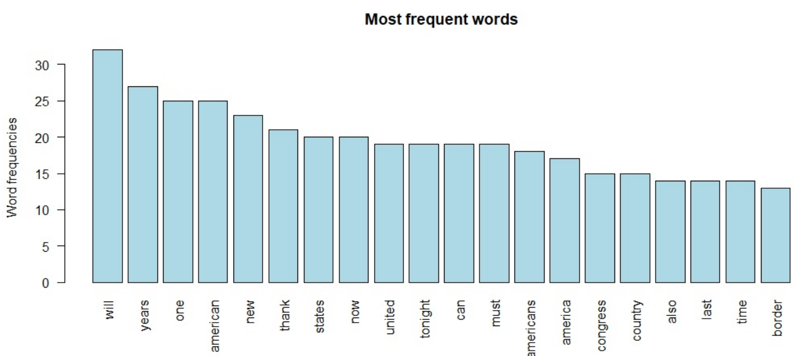


**Figure 4 Bar Plots of most frequently used words in President Obama's last SOU and in Hitler's 1933 Proclamation**

**Figure 4A: President Obama's last SOU**

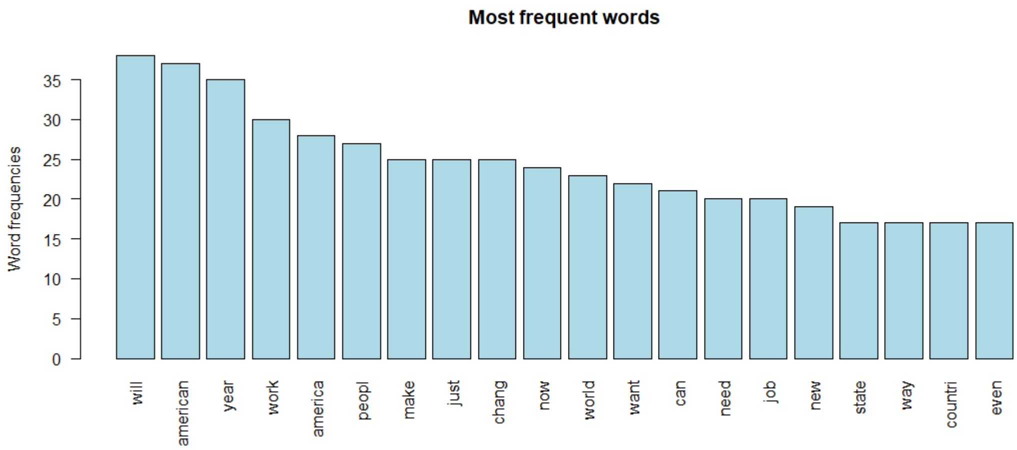



**Figure 4B: Hitler's 1933 Proclamation**

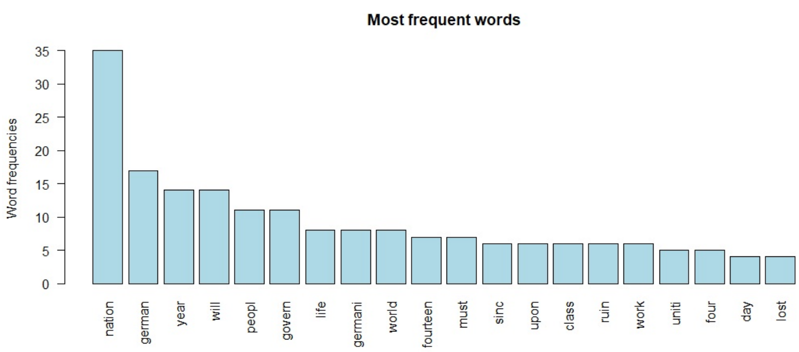


Table 1: Words highly correlated with frequently used words in President Trump's SOUs

| Trump SOU 2018 | | | Trump SOU 2019 | | |
|---|---|---|---|---|---|
| Word | Correlated Words | Correlation | Word | Correlated Words | Correlation |
| American | bridge | 0.34 | Will | never | 0.49 |
| | gleam | 0.34 | | Afghan | 0.41 |
| | grit | 0.34 | | constructive | 0.41 |
| | heritage | 0.34 | | counter terrorism | 0.41 |
| | highway | 0.34 | | focus | 0.41 |
| | railway | 0.34 | | groups | 0.41 |
| | reclaim | 0.34 | | indeed | 0.41 |
| | waterway | 0.34 | | taliban | 0.41 |
| | background | 0.34 | | talks | 0.41 |
| | color | 0.34 | | troop | 0.41 |
| | creed | 0.34 | | agreement | 0.38 |
| | dreamer | 0.34 | | achieve | 0.37 |
| | official | 0.34 | | make | 0.37 |
| | religion | 0.34 | | progress | 0.37 |
| | sacred | 0.34 | | proudly | 0.37 |
| | dream | 0.33 | | dream | 0.37 |
| | hand | 0.33 | | holding | 0.37 |
| | land | 0.31 | | whether | 0.35 |
| | duty | 0.31 | | incredible | 0.32 |
| | right | 0.31 | American | back | 0.51 |
| | arsenal | 0.44 | | soldiers | 0.40 |
| will | deter | 0.44 | | astronauts | 0.37 |
| | magic | 0.44 | | Buzz | 0.37 |
| | part | 0.44 | | space | 0.37 |
| | someday | 0.44 | | intellectual | 0.37 |
| | unfortunate | 0.44 | | property | 0.37 |
| | use | 0.44 | | Dachau | 0.37 |
| | weapon | 0.44 | | second | 0.37 |
| | yet | 0.44 | | | |
| | aggression | 0.40 | | | |
| | moment | 0.32 | | | |
| | modern | 0.32 | | | |

Table 2: Words highly correlated with frequently used words in President Obama's last SOU and Hitler's 1933 Proclamation.

| Obama SOU | | | Hitler 1933 | | |
|---|---|---|---|---|---|
| Word | Correlated Words | Correlation | Word | Correlated Words | Correlation |
| American | various numbers | n.a. | Nation | life | 0.42 |
| will | preserve | 0.44 | | will | 0.40 |
| | status-quo | 0.44 | | govern | 0.37 |
| | planet | 0.30 | | regard | 0.32 |
| America | George Washington Carver | 0.36 | will | health | 0.50 |
| | Katherine Johnson | 0.36 | | lead | 0.40 |
| | Sally Ride | 0.36 | | nation | 0.40 |
| | unit | 0.35 | | back | 0.33 |
| | | | | assist | 0.33 |
| | | | German | work | 0.34 |
| | | | | rescue | 0.32 |
| | | | | support | 0.32 |

Figure 4 provides a similar analysis for President Obama's last SOU and for Hitler's 1933 proclamation. Figure 4A reveals that the most frequently used word in President Obama's last SOU was 'will' which occurred 38 times, closely followed by 'American' 37 times, and 'year' 35 times. 'Work', 'America' and 'people' were the next most frequently occurring words.

Hitler's 1933 proclamation was a much shorter speech than the SOUs we have just considered. However, it was relatively dominated by the word 'nation', which ocurred 35 times, while the next most frequently word used was 'German', mentioned 17 times, 'year' and 'will' occurred 14 times each.

Patriotism and Nationalism appear to be frequently occurring themes in these four very different political addresses. 'American' is the first and fourth most frequently occurring words in President Trump's two SOUs, and it is the second most frequently used word in President Obama's last SOU. The most frequently used word in Hitler's 1933 proclamation was 'Nation', which had double the frequency of any other words mentioned, followed by 'German'. There is clearly a strong nationalistic tone in his 1933 address.

The other recurrent theme in all of these four political speeches is the importance of intention, as captured by the use of the word 'will'. It is the third and first most frequently occurring word used in President Trump's two SOUs respectively. It is the mosty frequent word in President Obama's last SOU and the fourth most frequently occurring word in Hitler's 1933 proclamation.

Table 1 shows the words most highly correlated with President Trump's frequently used words in his two SOUs. 'American' is the most frequently used word in his first SOU. Its use is most highly correlated with: 'bridge', 'gleam', 'grit', 'heritage', 'highway', 'railway', 'reclaim', 'waterway', 'background', 'colour', 'creed', 'dreamer', 'official', 'religion', and 'sacred'.

A second frequently used word is 'will,' which is highly correlated with 'deter', 'magic, 'part', 'someday', 'unfortunate', 'use', 'weapon', and 'yet'. The same two words are reversed in relative frequency of use in the second SOU. 'Will' is most highly correlated with 'never', followed by 'Afghan', 'constructive', 'counter-terrorism', 'focus', 'groups', 'indeed', 'Taliban', 'talks', and 'troop'. 'American is most highly correlated with 'back' and 'soldiers'.

Table 2 provides an analysis of the words most highly correlated with frequently used words in President Obama's last SOU and Hitler's 1933 Proclamation. The analysis of President Obama's last SOU reveals the weaknesses of a statistical analysis of individual words used as components of a particular address. The words most correlated with the word 'American' were individual dollar amounts. 'Will' is highly correlated with 'preserve', 'status-quo', and "planet'. 'America' is highly correlated with individual names, the components of which the program picked up individually, and it was not until the authors analysed the original text that the analysis made sense. In the speech, President Obama stated: "Now, that spirit of discovery is in our DNA. America is Thomas Edison and the Wright Brothers and George Washington Carver. America is Grace Hopper and Katherine Johnson and Sally Ride. America is every immigrant and entrepreneur from Boston to Austin to Silicon Valley racing to shape a better future".

The analysis of Hitler's 1933 Berlin Proclamation was more revealing. 'Nation' the most frequently used word, is highly correlated with 'life', 'will', 'govern', and 'regard'. 'Will' is highly correlated with 'health', 'lead', 'nation', 'back', and 'assist'. Finally, 'German' is highly correlated with 'work', 'rescue', and 'support'. This supports the national rebuilding of the German economy and the promotion of employment that was part of Hitler's agenda in the early 1930s. He adopted the view that the natural unit of mankind was the Volk ("the people"), of which the German people was the greatest. He also believed that the state existed to serve the Volk. This leads to a consideration of 'National Socialism' (or 'Nazism').

Smith (1994, pp. 18-19) has suggested that "... nationalists have a vital role to play in the construction of nations, not as culinary artists or social engineers, but as political archaeologists rediscovering and reinterpreting the communal past in order to regenerate the community. Their task is indeed selective - they forget as well as remember the past - but to succeed in their task they must meet certain criteria. Their interpretations must be consonant not only with the ideological demands of nationalism, but also with the scientific evidence, popular resonance and patterning of particular ethnohistories".

Nationalism holds that each nation should govern itself, free from outside interference (self-determination), and that the nation is the only rightful source of political power (popular sovereignty). It usually involves the maintainance of a single national identity, which would be based on shared social characteristics such as shared history culture, language, religion, and politics. President Trump, with his slogan "MAGA" - make America great again, espouses a form of Nationalism.

President Obama's last SOU is not free of nationalistic sentiment. He stated that: "I told you earlier all the talk of America's economic decline is political hot air. Well, so is all the rhetoric you hear about our enemies getting stronger and America getting weaker. Let me tell you something. The United States of America is the most powerful nation on Earth, period. Period. It is not even close. It is not even close. We spend more on our military than the next eight nations combined.".

However, as the mechanical and statistical form of textmining used in this paper, though revealing, is not suited to teasing out the nuances in meaning of different forms of nationalism, emphasis is placed on a statistical analysis of the text.

We also used the R package 'syuzhet' to examine the the sentiment of each string of words or sentences. We calculated the overall score and the mean or average sentiment score. The results vary slightly, depending on which lexicon or base dictionary is used. Syuzhet incorporates four sentiment lexicons. The default 'syuzhet' lexicon was developed in the University of Nebraska Literary Lab under the direction of Jockers (2015), the creator of the R syuzhet package. This is the default lexicon. We also cross-checked using the nrc lexicon developed by Mohammad, who is a research scientist at the National Research Council Canada (NRC), (see: http://saifmohammad.com). However, the results were quantitatively similar, and hence are not reported in the paper.

The analysis tells us whether the speech has a predominantly positive or negative score in emotional tenor. In the case of President Trumps first SOU, the total score was 113.75 and the mean score was 0.02196. This positive sentiment score is consistent with Allen, McAleer and Reid (2018), who reported similarly positive results for President Trump's first SOU, on the basis of an application of the R package 'sentiment', which used a different lexicography. In the previous analysis, on the basis of a primary binary division into positive and negative sentiments, 60 per cent of the first SOU, in cases where sentiment could be ascribed, was recorded as being positive.

In his second SOU in 2019, the address had a total score of 139.85 and a mean score of 0.02557. His first SOU contained 5190 words and 30,271 characters, while his second SOU was slightly larger at 5,442 words and 32,045 characters. President Obama's last SOU had a total score of 169.8 and a mean score of 0.02712. President Obama's last SOU was quite a large speech, containing 6,233 words and 34,634 characters. In the case of Hitler's 1933 proclamation, the sum is 8.4 and the mean is 0.0053, but Hitler's parsimonious proclamation only contained 1578 words and 9,286 characters.

An interesting feature of these various speeches is the degree to which they contained predominantly positive or negative emotions. These are plotted in Figures 5 and 6. In both of President Trump's SOUs, 'Trust ' is the predominant emotion displayed. In all speeches, apart from President Trump's second SOU, it accounts for more than 25 per cent of the total emotional content. This is also the case in President Obama's last SOU, and in Hitler's 1933 proclamation. In all four speeches, 'Trust' dominates by a large margin in the order of 10 per cent, though it is slightly lower in President Trump's second SOU.

'Fear' is the second dominant emotion in his first SOU, and drops to third in his second SOU. 'Fear' is the third emotion in President Obama's last SOU, accounting for about 14 per cent of the emotional content, but it is more prominent in Hitler's 1933 proclamation, in which it is the second ranked emotion, and accounts for about 18 per cent of the emotional content.

'Anticipation' plays a large role in President Trump's and Obama's addresses, in which it always accounts for around 15 per cent of total emotional content, indeed slightly more than 15 per cent in the case of President Obama. It is much less prominent in Hitler's proclamation, where it is the fifth most frequently occurring emotion accounting for about 12 per cent of the total emotional content. Indeed, a feature of Hitler's address is the predominance of negative emotions, with 'fear', 'sadness' and 'anger' taking precedence after 'trust'.

In contrast, 'anticipation' and 'joy' are much more predominant in the two US President's SOUs, never dropping below 13 per cent in emotional content, and always ranking in the top four emotions. In Hitler's speech, 'anticipation' is the fifth ranked emotion.

**Figure 5: The Emotional tenor of President Trumps two SOUs.**

**Figure 5A: President Trump's First SOU**

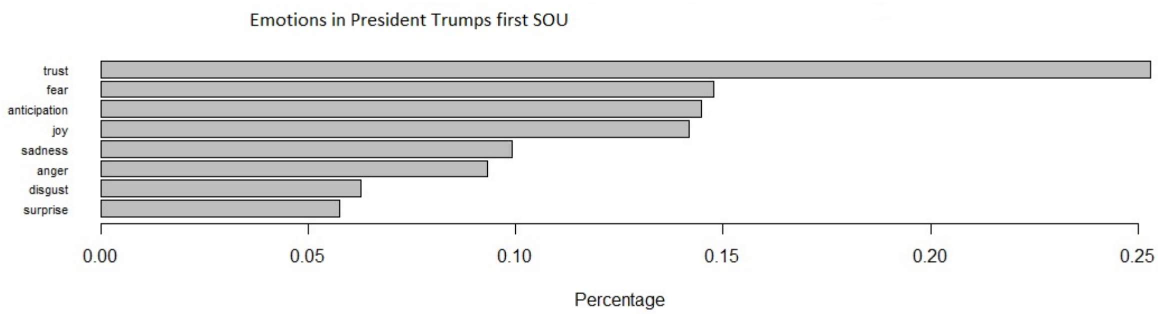



**Figure 5B: President Trump's Second SOU**

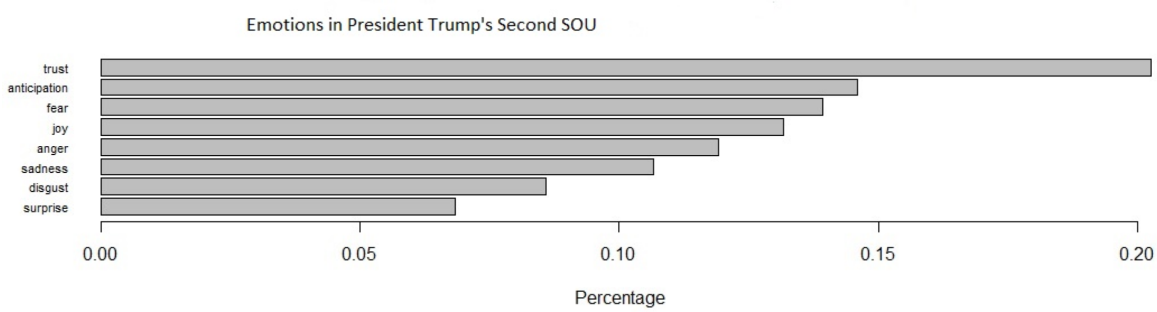


**Figure 6 The Emotional Tenor of President Obama's last SOU and Hitler's 1933 Berlin Proclamation**

**Figure 6A: President Obama's last SOU**

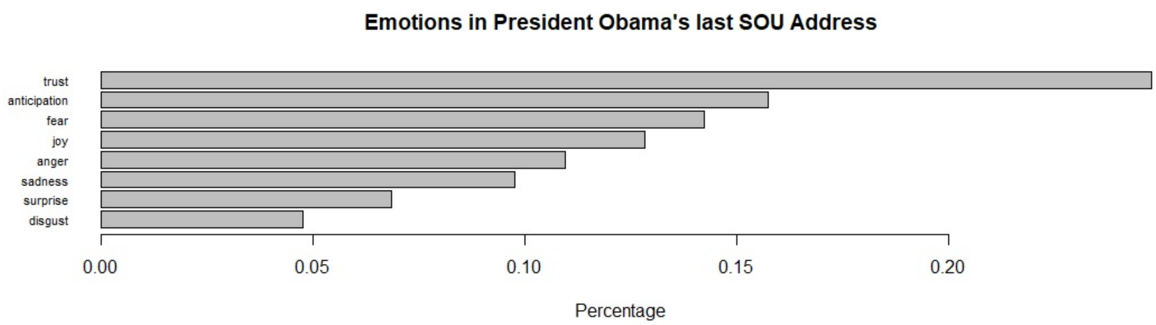



**Figure 6B: Hitler's 1933 Proclamation**

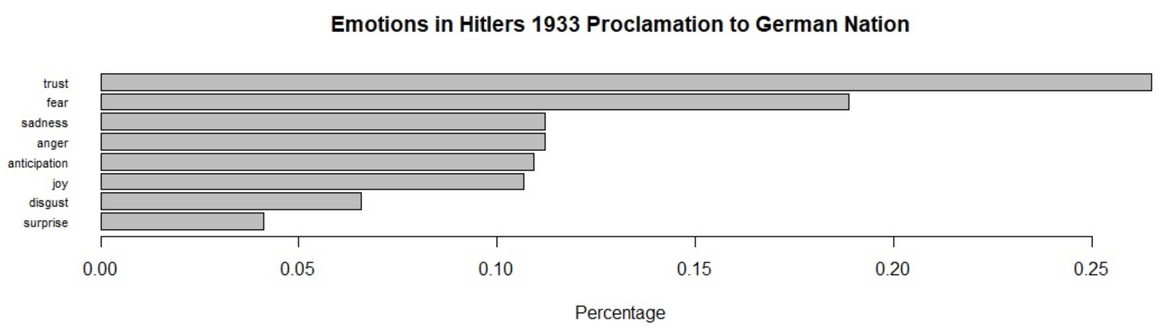


**Figure 7: The Emotional valence of President Trumps two SOUs.**

Figure 7A: President Trump's first SOU

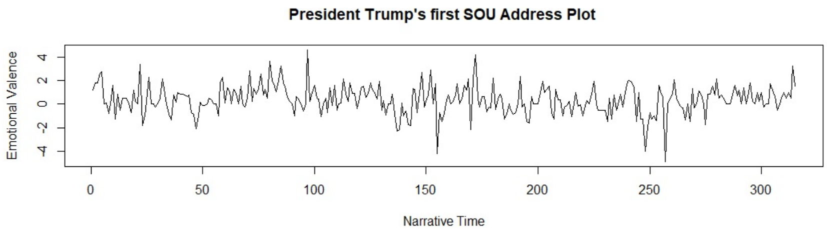



Figure 7B: President Trump's second SOU

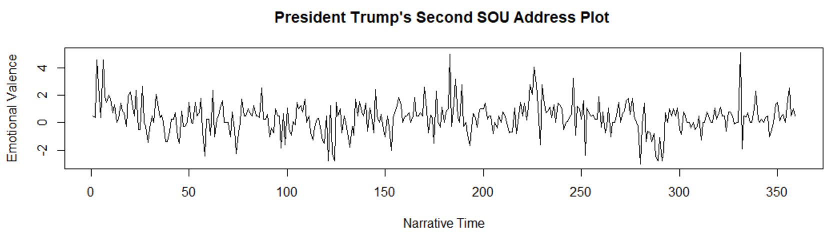



**Figure 8: The Emotional valence of President Obama's last SOU and Hitler's 1933 Berlin Proclamation.**

Figure 8A: President Obama's last SOU

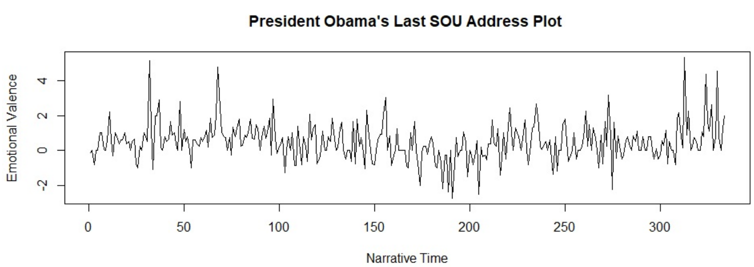
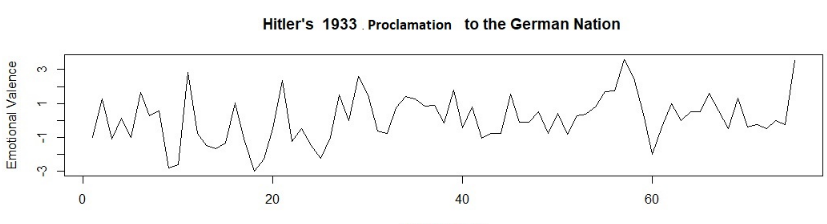



Figure 8B: Hitler's 1933 Berlin Proclamation



Another interesting feature of the four speeches is their 'emotional valence', or the pattern of sequential positive and negative emotions displayed as the speech unfolds through time. Plots of these patterns are shown in Figures 7 and 8. There is a distinct change in pattern in the emotional valence of President Trump's two SOUs, as shown in Figure 7A and 7B. In the first, he commences on a positive emotional tone and is fairly upbeat in the first part of the speech, but then has multiple negative drops in the second half of the speech, before ending on a positive emotional note. In his second SOU, the pattern is roughly reversed, and there are more emotional negative points in the first half of the SOU, whereas the emotional volatility increases in the second half of the speech, with more frequent extreme highs and lows, and a predominantly positive tone at the end of the speech.

Figure 8A reveals that President Obama, in his last SOU, commences on a predominantly positive note, with some pronounced positive spikes, becomes more measured and negative in the middle of the speech, and ends on a predominantly positive note, with multiple positive peaks towards the end of his speech. Figure 8B shows that Hitler's much shorter 1933 Proclamation is quite volatile in the first part of the speech, becomes more measured in the second half, with fewer extreme peaks and troughs, and finishes on a positive note.

## 4. Conclusion

In this paper we have analysed President Trump's two SOUs and contrasted their content with those of the last SOU of President Obama and that of Hitler's 1933 Berlin Proclamation. All four are political speeches, and share a great deal of commonality. They emphasize the nation, America and American, in the case of the two US Presidents, and Nation and German in the case of Hitler. The word 'will' features prominently in all four speeches, and relates to the respective political agendas of the speakers. The emotional tenor of the speeches of the two US Presidents is more positive than those adopted by Hitler in his 1933 Berlin Proclamation. All speakers chose to end their speeches on a positive emotional note, and all four speeches contain Nationalistic elements.

The limitation of the text-mining approach adopted in the analysis of the contents of these four speeches is that it does not feature a verification of the statements made, and cannot pick up nuances in meaning and context. However, the approach does provide a broad indication of the structure and emotional flavour of the content, subject to the limitations of the lexicon applied.

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