Visualizing Hillary Clinton's Emails

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1 Introduction

In light of the recent U.S. presidential election race between candidates Donald Trump and Hillary Clinton, there have been large amounts of interest in the controversy involving Hillary's use of personal email accounts on non-government servers during her previous career as Secretary of State. After a number of Freedom of Information lawsuits were filed against the Department of State, the Department of State released on August 31, 2015 nearly 7,000 pages of Clinton's heavily redacted communications in PDF form.

Subsequent to this release, the data science competition website Kaggle released a sanitized version of the extracted content of the emails for public use and analysis. Our group was interested in analyzing and exploring this data given its connection to current events at the time.

2 Objectives

Our main objective with this project was to reduce the immense dimensionality and volume of the data so that the resulting output could be more easily digested by a data analyst or other interested party. We wanted to find patterns in the data that might be of interest, such as communities of receiving or sending parties that shared certain commonalities.

We tried to discover such patterns through the application of three methods: social network analysis, textrank, and cluster analysis.

However, rather than simply report on the results of such analysis, we believed that a more effective way to communicate results and allow for the generation of new insights would be to create an interactive visualization that would empower the user to both view our findings and explore the simplified data at will. This visualization would show the results of

3 Data Source

Some 7,000 pages of Clinton's emails were released by the State Department in PDF format [2]. Kaggle then scraped the text from these PDFs and hosted them as CSVs and SQL databases on the Kaggle Kernels platform. The dataset contains nearly 8,000 emails sent within Clinton's inner circle from December 2010 to September 2012. In CSV format, the dataset weighs in at just under 7 MB.

Unsurprisingly, the email dataset seems to be Hillary-centric. In addition, the histogram of emails received seems to be much more highly dispersed than the histogram of emails sent, which may suggest that many emails are sent to multiple people.

4 Methodology

4.1 An Overview of our Summarization Procedure for one Document

Because our end goal is to create a visual dashboard for our users, we have to be careful about our bookkeeping while we slice and dice our text data. A brief overview of our procedure from end-to-end for one e-mail is as follows:

1. Split the e-mail into sentences
2. Clean each sentence
3. Represent each sentence as a bag-of-words
4. Run TextRank to get a ranking of the bags-of-words
5. Return the top k sentences from the original e-mail associated with the top k ranking bags-of-words

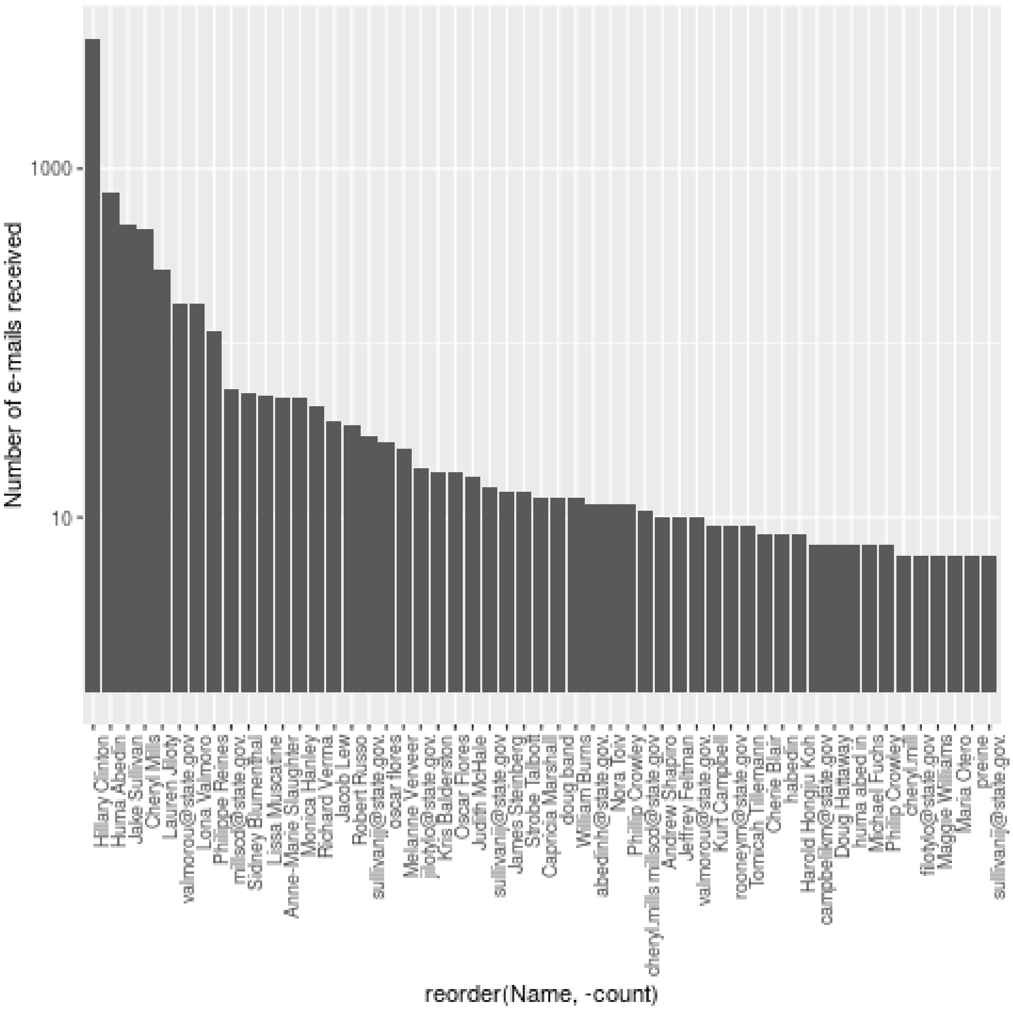

Figure 1: Histogram of how many emails some person has received

Of particular importance to our implementation is keeping track of how the bags-of-words are associated with the original sentences from the e-mail, as the bags-of-words are not nearly as informative to the user.

4.2 The TextRank Algorithm

We treat each e-mail as a self-contained document and attempt to summarize each document using TextRank [4], which is a derivative of PageRank [5] adapted to units of text instead of web pages.

The PageRank algorithm is a way of ranking web pages based on the way that they link to each

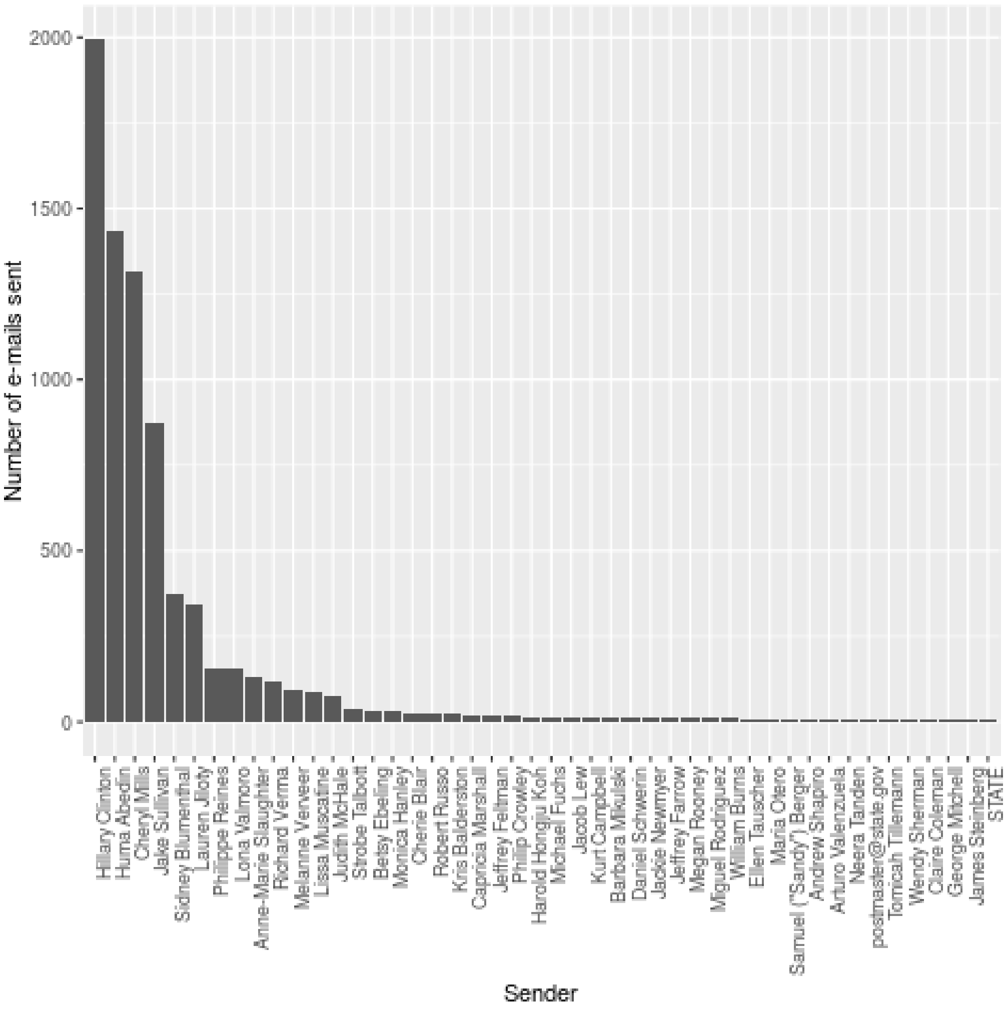

Figure 2: Histogram of how many emails some person has sent

other. The algorithm is based on a random walk model of the typical internet user. We assume the user starts on some arbitrary web page, and then either randomly clicks links on the current page or with some re-seeding probability, d, navigates to another random web page that was not necessarily linked to from the current one. The process of such a user's browsing history is clearly Markovian under this assumption. The addition of the re-seeding probability makes this Markov process irreducible and aperiodic, or equivalently, ergodic [6]. Ergodicity allows us to conclude that there exists a so-called stationary distribution over the set of all web pages. Moreover, this stationary distribution is unique and is the limit of a certain quantity.

The stationary distribution of an ergodic Markov chain has many interpretations. One is that the distribution assigns probability mass to each state, and this mass is equivalent to the probability of the Markov process to be observed in some state after the chain has mixed or lost its dependence on its initial position. The other is the “time-average” interpretation: the average proportion of time-steps a process will spend in some state tends to this state’s mass in the stationary distribution.

Web pages that are assigned a large probability mass are thought to be relatively important in the sense that a random web surfer is more likely to visit it. One can sort the pages by the amount of mass assigned to them by the stationary distribution to get a ranking of pages by this notion of importance.

To turn this idea into something that can summarize text, we need to decide on two things. The first is the notion of an item to rank, or in our case, units of text. The second is the notion of how all items pairwise indicate each other’s importance.

A typical choice of unit of text is either sentences or phrases. We choose to rank sentences for the sake of simplicity.

For text, we might imagine that a sentence that is highly similar to many of the other sentences is important in the sense that it may mix the contents of the most sentences to provide an insightful summary of the entire document. Naturally, we might choose to define the transition matrix of the Markov chain over sentences by the similarity between sentences, which now reduces our problem to figuring out a measure of pairwise similarity between sentences.

A naive view of sentences is to think of them as sets or multisets of words. An easy measure of similarity over sets S_1, S_2 is the Jaccard similarity:

$$J(S_1, S_2) \triangleq \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|}$$

which can easily be extended to multisets [7].

We opt to use the recommendation of the original TextRank paper [4]:

$$\text{Similarity}(S_1, S_2) \triangleq \frac{|\{w_k | w_k \in S_1 \& w_k \in S_2\}|}{\log(|S_1|) + \log(|S_2|)}$$

although there are many other variations that we did not have the chance to evaluate [1].

To actually compute the TextRank of a document represented as a collection of bags-of-words, we perform the following procedure:

1. For each pair of sentences S_i and S_j, compute their similarity $\text{Similarity}(S_i, S_j)$ and store it in a matrix as entry $\tilde{M}_{ij}$.

2. Normalize $\tilde{M}$ to get a transition matrix M, representing a Markov chain over sentences.

3. Starting with an initial guess of the stationary distribution R_0, iteratively compute

$$R_{t+1} = dMR_t + \frac{1-d}{N}\mathbf{1},$$

   where d is the re-seeding probability, N is the number of sentences, and $\mathbf{1}$ is a column vector of ones.

4. After enough iterations, R_t will be close enough to the true stationary distribution of our damped Markov chain, and thus can be regarded as the TextRank of our document.

Running an entirely analogous algorithm on the entirety of the web (a graph consisting of about 322 million edges) took the authors of PageRank approximately 52 iterations for their ranking to converge, and about 45 iterations on a graph half that size [8]. They concluded that the number of iterations to convergence should be approximately logarithmic in the size of the network. Since documents tend to create relatively small and dense similarity graphs, we set our number of iterations to a highly conservative 10 iterations.

4.3 Cleaning the e-mails

Many similarity functions [1] as well as the one we implemented rely on metrics defined on bag-of-words representations of text. While the bag-of-words representation is a popular one, it's well known to have many deficiencies that are exacerbated by carelessly processed text.

One consequence of using a bag-of-words is that words that are not a character-for-character match will not be counted as the same. Much of our text cleaning effort is dedicated to ensuring that words that are indicative of sentence similarity are mapped to the same word, and that words that are not indicative of sentence similarity are removed.

The very first part of cleaning a sentence is simple: we set all of the characters to lowercase, as the capitalization of a word should, in most cases, not change its meaning.

Similarly, we remove any nonalphanumeric symbols from our text, as it seems that the method used to extract the text from the e-mails into a database left many wayward symbols (e.g.`\n`, the newline symbol). Any nonalphanumeric symbols were turned into spaces, and any extraneous whitespace was subsequently deleted.

The next transformation we apply is removing stop words. Stop words are words that almost every valid sentence in the English language contains, such as “the”, “a”, “as”, or “for”. Because stop words are so common, leaving them in the sentences would likely inflate the similarity between many bags-of-words. Leaving stop words in our text would effectively dilute our measure of how important a sentence is.

Our last problem is that different conjugations of words such as “run” and “running” will be counted as different although they ostensibly are referring to the same activity. We can attempt to mitigate this problem by applying a popular text cleaning procedure called stemming [9], which attempts to reduce all words to their roots. For example, “running” would be reduced to “run”, and “run” would stay the same. This allows us to measure text like “I am running for president” and “a run for office” as similar despite the fact that (after removing stopwords) none of the words are a character-for-character match. The `R` implementation we used is from the `tm` package, which implements the standard Porter stemming algorithm.

5 Results

6 Model Validation

6.1 Choice of hyperparameters for TextRank

There are a few parameters to choose for TextRank. For any use of TextRank at all, one must certainly decide on the re-seeding probability, d, as well as some criterion to decide to stop the iterative estimation of the stationary distribution. For the purpose of summarization, one must also choose how much of the original text to return to the user.

To better understand the effects of the re-seeding probability, d, we first decompose our Markov chain into two Markov chains, one of which exclusively uses the re-seeding effect, and one of which never uses the re-seeding effect. Let M be the Markov chain which we eventually compute the stationary distribution of. Then M has the form

$$M = [M_{ij}]_{i,j=1}^{N} = [\mathbb{P}[X_{t+1} = j | X_t = i]]_{i,j=1}^{N}.$$

Denote the event that a random walker is re-seeded $\mathfrak{R}$. A trivial statement of probability is to decompose the above matrix as

$$\begin{aligned} M_{\mathfrak{R}} &= [\mathbb{P}[X_{t+1} = j | X_t = i, \mathfrak{R}]]_{i,j=1}^{N} \\ M_{\mathfrak{R}^C} &= \left[\mathbb{P}\left[X_{t+1} = j \middle| X_t = i, \mathfrak{R}^C\right]\right]_{i,j=1}^{N} \\ M &= M_{\mathfrak{R}}\mathbb{P}[\mathfrak{R}] + M_{\mathfrak{R}^C}\mathbb{P}\left[\mathfrak{R}^C\right] \end{aligned}$$

However, because the decision of a random-walker to be re-seeded is just an independent Bernoulli trial before she takes her next step, we find that $M_{\mathfrak{R}}$ is the matrix where every entry is $1/N$ and $M_{\mathfrak{R}^C}$ is merely the normalized matrix of similarities

By definition, $\mathbb{P}[\mathfrak{R}] = d$ and therefore

$$M = M_{\mathfrak{R}}d + M_{\mathfrak{R}^C}(1 - d).$$

At the extreme where $d = 0$, the ranking is the ranking of just the normalized similarity matrix if such a ranking exists. If $d = 1$, then at every step the random walker is choosing a random state from the entire state space with equal probability. It's easy to intuit in this scenario that the ranking is a tie across the entire state space. A more rigorous explanation of this phenomenon invokes the concept of time reversibility. The eager reader can refer to [6] for a more detailed exposition of this concept.

For $0 < d < 1$, the ranking is both guaranteed to exist, and is typically not a tie across the state

Rank 1:	4	4	4	4	4	4	4	4	4	4	4	4	4
Rank 2:	19	19	19	19	19	19	6	6	6	6	6	6	6
Rank 3:	6	6	6	6	6	6	19	19	19	19	19	19	19

Figure 3: Top 3 ranking sentence (represented by their index) for 10 TextRank iterations for values of $0.1 < d < 0.9$.

space in most applications. Therefore, it suffices for us to investigate how often or how wildly the ranks change for various settings of d. Most articles about the PageRank algorithm or derivatives thereof recommend setting $d = 0.85$. For our application, we find that the overall ranking is not very sensitive to d. The overall ranking is typically quite similar for a wide range of d with a few transpositions of adjacent ranks. One example is included in Figure 3, where the second and third most important sentences exchange ranks around the middle of our range of d.

The question of how quickly our initial guess converges to the correct stationary distribution is one that can be handled in a surprisingly theoretical fashion [3], and the proposition by the authors of PageRank that only logarithmically many iterations are necessary is quite prescient. Indeed, a central result in the theory of mixing times for discrete Markov chains is that for for any initial distribution x and ergodic Markov chain with transition matrix M with eigenvalues $\lambda_1, \lambda_2, ...\lambda_n$ and stationary distribution π,

$$\frac{\|xM^t - \pi\|}{\|x\|} \leq \max\left(|\lambda_2|, |\lambda_n|\right)^t$$

7 Conclusions

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