

‘Speech’ Recognition: Using NLP to Attribute Quotes to Speakers

LING 227 Final Project

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Introduction

History remembers great speakers for their idiosyncracies. From JFK’s authenticity and passion to Donald Trump’s divisive rhetoric, U.S. presidents are particularly identifiable by their speeches. While nearly any citizen can name the presidents who said “Nothing to fear but fear itself” (Franklin Delano Roosevelt), “Ask not what your country can do for you—ask what you can do for your country” (John F. Kennedy), and “Yes We Can!” (Barack Obama), it remains to be seen whether a language model can do the same. Our project aims to build a language model that determines the most likely speaker of a given input quote. Moreover, our project seeks to investigate how the model discernability changes when trained on three types of data: presidential speeches, part of speech tags for presidential speeches, and politicians’ tweets.

Methodology

Data Sources

Speeches from each of the 44 presidents and 2016 Democratic Nominee Hillary Clinton were obtained from an open source online corpus compiled by [The Grammar Lab](#). Tweets from Presidents Donald Trump and Barack Obama and various Senators were collected from [data made public by FiveThirtyEight](#).

Data Cleaning

Tweets were parsed and tokenized before using the model. All words were lowercased so that various capitalization wouldn’t affect the results. All punctuation (including commas) was removed from tweets and was replaced with beginning and end of sentence speech tags (<s> and </s>). Given that tweets can be quoted (in the form of a hyperlink to said tweet), everything after (and including) the text pattern “http” was removed when such a pattern appeared in a tweet. Additionally, Twitter offers users the option to share or “Retweet” posts that other users have made. Since retweets, indicated in our corpus by RT, aren’t necessarily direct words from a given user, all retweets were removed from the training corpus. When all is said and done, this tweet



Donald J. Trump ✓

@realDonaldTrump

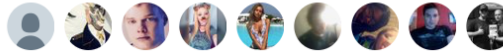
Follow



.@NFL: Too much talk, not enough action.
Stand for the National Anthem.

4:42 PM - 18 Oct 2017

22,985 Retweets 98,496 Likes



40K 23K 98K

is represented as follows:

[‘<s>’, u’@nfl’, u’:’, u’too’, u’much’, u’talk’, u’not’, u’enough’, u’action’, ‘</s>’, ‘<s>’, u’sand’, u’for’, u’the’, u’national’, u’anthem’, ‘</s>’]

Presidential speeches were cleaned in a manner that matched the output of the tweet parser. That is, all punctuation marks were removed and sentences were marked with appropriate tags. The first two lines of each document was removed as it provided the name and date of each speech. A few speeches were transcripts of interviews, and thus had reporter questions that were not presidential text. Given that these interjections were infrequent and could not be easily removed with regular expressions, we decided to leave them in with the assumption that they would not change any bi-gram or tri-gram probabilities in a significant way.

Fitting the Model

The model we choose to implement is an n -gram model with $n = 2$. To deal with the issue of unseen counts, we use Good-Turing Smoothing, explained in more detail below. Bigram and Trigram counts are computed from the various training corpuses. We will use three different types of data to train the model in order to see if any type of data works best. They are as follows:

1. Text from presidential speech corpus.
2. Part of speech tags from presidential speech corpus.
3. Tweet text from Obama, Trump and several U.S. senators.

Since the corpus of presidential speeches does not come with POS tags, we use a Hidden Markov Model to compute the most likely tag sequence for each sentence. The HMM is trained on data from the Brown Corpus built into Python’s Natural Language Toolkit library.

Good Turing Smoothing

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Testing the Model

For each of the three types of training files, we have compiled a list of 10 quotes, each from a different speaker. The 10 possible speakers are then used as training files for the model. The probability of each quote for a given speaker is calculated as follows, using addition of logarithms to account for small probabilities.

$$\mathbb{P}(Q) = \prod_{i=1}^n \mathbb{P}(w_i|w_{i-1}) = 2^{\sum_{i=1}^n \log_2(\mathbb{P}(w_i|w_{i-1}))}$$

After computing the probability of each sentence for all possible speakers, we attribute to each quote the speaker that yields the highest probability for the given quote. That is, our model predicts the speaker S of a quote Q as follows:

$$\hat{S} = \underset{s \in \text{Possible Speakers}}{\arg \max} \mathbb{P}(Q|s)$$

Results

Presidential Speech Corpus

The probabilities of each of the following presidential quotes were computed using the relevant speakers' speeches as training files for the bigram model.

- Quote 1: <s> yes we can </s> - Barack Obama
- Quote 2: <s> and so my fellow Americans ask not what your country can do for you ask what you can do for your country </s> - JFK
- Quote 3: <s> when the president does it that means that it is not illegal </s> - Richard Nixon
- Quote 4: <s> the only thing we have to fear is fear itself </s> - FDR
- Quote 5: <s> liberty when it begins to take root is a plant of rapid growth </s> - George Washington
- Quote 6: <s> the care of human life and happiness and not their destruction is the first and only object of good government </s> - Thomas Jefferson
- Quote 7: <s> make america great again </s> - Donald Trump
- Quote 8: <s> a house divided against itself cannot stand </s> - Abraham Lincoln
- Quote 9: <s> we must teach our children to resolve their conflicts with words not weapons </s> - Bill Clinton
- Quote 10: <s> i would rather belong to a poor nation that was free than to a rich nation that had ceased to be in love with liberty </s> - Woodrow Wilson

Part of Speech Tags

Tweet Data

The probabilities of each of the following tweets were computed using the relevant speakers' twitter history as training files for the bigram model.

- Quote 1: <s> yes we can </s> - Barack Obama
- Quote 2: <s> make america great again </s> - Donald Trump
- Quote 3: <s> stark reminder of the threat radical islamic terror still poses to our homeland </s> - Ted Cruz

- Quote 4: <s> it's not by giving massive tax breaks to your billionaire friends </s> - Bernie Sanders
- Quote 5: <s> tax bill equals swamp creature </s> - Tim Kaine
- Quote 6: <s> @SenBernieSanders & I are talking about things democrats are fighting for in this spending bill that would make a big difference to working families </s> - Elizabeth Warren
- Quote 7: <s> whether you are in the media politics or anywhere else abuse of power is unacceptable & shouldn't be tolerated at any place at any level </s> - Lisa Murkowski
- Quote 8: <s> in a foreign relations committee hearing today i discussed how u.S. nuclear forces protect our nation and allies in the 21st century </s> - Marco Rubio
- Quote 9: <s> president trump did the people of utah a great favor today by rolling back harmful land use restrictions in southern utah #utpol </s> - Mike Lee
- Quote 10: <s> better #GetCovered it's the last weekend to sign up for 2018 health coverage before the 12/15 deadline </s> - Chuck Schumer

Probability outputs for each speaker on each of the ten quotes are shown below in Figure 3. Overall, the model correctly identified 5/10 (50%) of the people who said these tweets. The most likely tweet-speaker pair was Donald Trump “Make America Great Again”. Interestingly, this combination was over 10,000,000,000 times more likely any other combination! While some of this discrepancy can be explained by the fact that it is a shorter tweet, it also speaks to the unprecedented manner in which President Trump uses Twitter compared to other politicians.

speaker	quote_1	quote_2	quote_3	quote_4	quote_5	quote_6	quote_7	quote_8	quote_9	quote_10
Barack Obama	1.66E-32	1.58E-33	3.30E-106	8.80E-108	1.00E-60	7.47E-161	9.53E-230	1.02E-169	3.80E-219	1.20E-130
Donald Trump	1.19E-25	5.56E-05	1.08E-97	9.22E-93	3.23E-64	7.89E-171	5.72E-231	4.72E-164	3.31E-184	1.93E-134
Ted Cruz	1.13E-33	1.03E-43	6.65E-88	1.09E-107	1.03E-63	3.52E-214	3.40E-240	1.07E-178	3.94E-207	2.56E-185
Bernie Sanders	1.98E-16	3.34E-48	4.15E-117	2.19E-73	6.27E-54	3.37E-172	5.39E-226	2.95E-182	2.19E-196	1.13E-154
Tim Kaine	1.12E-27	5.72E-27	1.38E-127	1.56E-98	5.42E-64	7.88E-162	8.07E-247	7.67E-167	1.37E-206	7.70E-147
Elizabeth Warren	6.18E-36	2.93E-34	1.10E-126	2.31E-108	1.00E-60	5.75E-178	1.08E-235	3.98E-156	3.93E-200	7.82E-139
Lisa Murkowski	1.27E-23	3.06E-44	8.16E-126	4.75E-113	6.12E-64	6.30E-168	7.97E-222	1.79E-163	5.74E-229	1.22E-140
Marco Rubio	4.39E-33	1.04E-44	9.96E-107	2.84E-118	1.00E-60	8.55E-249	1.29E-239	4.61E-118	1.60E-198	5.11E-167
Mike Lee	1.37E-27	6.20E-35	1.30E-124	2.12E-94	5.58E-54	1.84E-179	1.32E-203	2.19E-158	2.80E-183	3.76E-151
Chuck Schumer	9.07E-27	3.62E-37	1.53E-117	3.13E-101	7.82E-54	2.19E-176	8.03E-238	2.23E-184	9.58E-190	8.92E-163

Key Probabilities in each column are sorted from largest (green) to smallest (red)

Correctly Identified

Incorrectly Identified

Figure 1: Tweet Results

Discussion