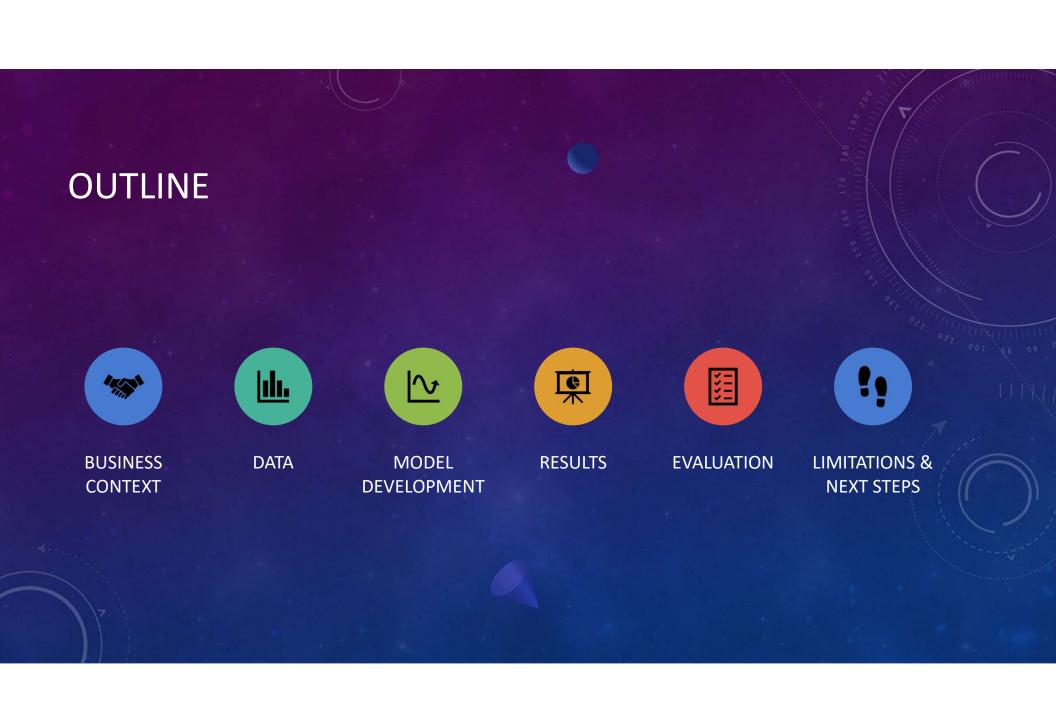
Sentiment Analysis A Modern Approach to Political Polling

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BUSINESS CONTEXT

- Gallup, a global analytics and advice firm, wants to expand their polling capabilities
- Company currently relies primarily on telephone interviews to conduct polls
- Gallup has decided to begin exploring the viability of using sentiment data from Twitter to conduct polls
 - provides a far more efficient means of gathering data
 - larger sample of the population can be polled
 - makes polling data more robust overall
- The board at Gallup requests a demonstration that shows polling via sentiment data is a viable option
 - should feature a model that can accurately predict the sentiment of a tweet
 - the model needs to deliver estimates of Joe Biden's approval ratings with respect to the nation and each one of the 50 stated

DATA

Training Data

- consists of \sim 1,600,000 tweets
- relevant variables include:
 - o text
 - o sentiment label

Test Data

- consists of \sim 100,000 tweets relating to president Joe Biden
- scraped from Twitter (07/12/2022 07/19/2022)
- relevant variables include:
 - o text
 - o like count
 - user location
 - o sentiment label

DATA

❖ All sentiment labels were created using *VADER*:

- utilizes a set of rules + dictionary that maps lexical features (i.e. word/phrase/emoji) to sentiment scores
- provides a convenient, yet accurate, means of labeling data
- tweets categorized as one of the following:
 - o POSITIVE
 - o NEUTRAL
 - o NEGATIVE

Why don't we just use VADER to classify sentiment?

- VADER cannot adapt as language changes
- Cannot be applied to other languages
- Does not perform well on text containing specialized terms
- Misspelling & grammatical mistakes cause performance to suffer
- Cannot detect more subtle nuances in language

MODELING

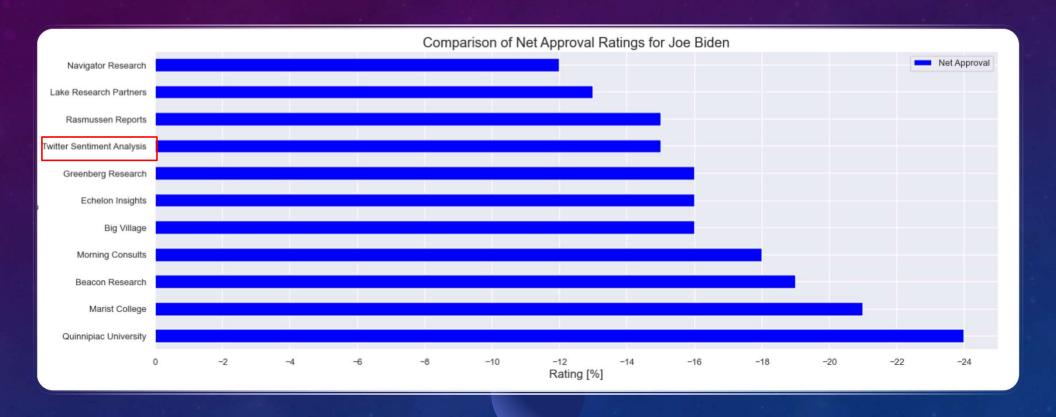
- ❖ The following models were trained:
 - Naive Bayes
 - Logistic Regression
 - Random Forest
 - Recurrent Neural Network
- ❖ After training, models were fed a portion of the Training Set they had not seen before
- ❖ Model with best performance was chosen -- Recurrent Neural Network
- **RNN** was then fed the Test Data, and these predictions were compared to:
 - test labels (from VADER)
 - real polling data
- ❖ The sentiment labels predicted by the RNN were converted into approval ratings:
 - NEUTRAL tweets were discarded
 - **Approval Rating** → percentage of tweets that were POSITIVE
 - \circ **Disapproval Rating** \rightarrow percentage of tweets that were NEGATIVE
 - **Net Approval Rating** → Approval Rating Disapproval Rating

RESULTS

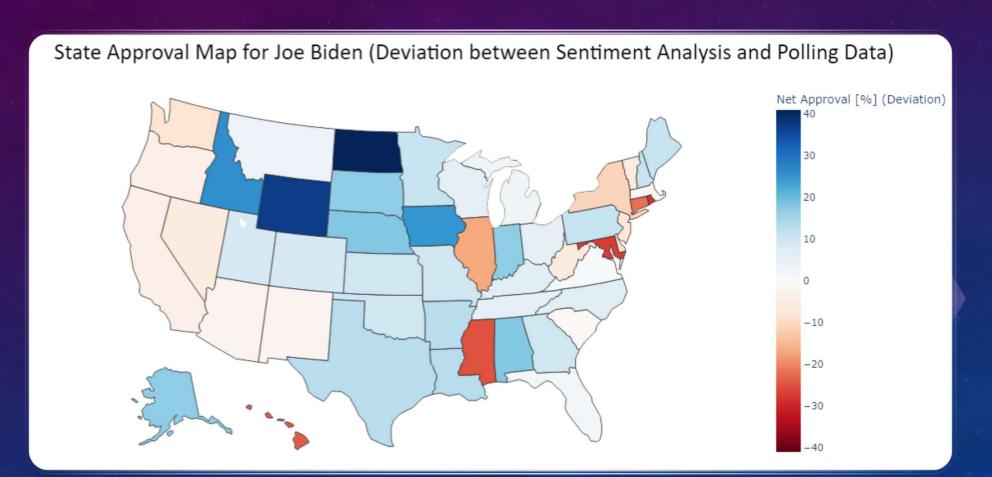
- The overall approval and disapproval rating predicted by the RNN model was compared to sets of real polling data
 - all 10 polls were conducted on, or near, the week all tweets in the Test Set were posted



The net approval rating predicted by the RNN model was also compared to the same 10 sets of polling data



- The difference in net approval between the RNN model and traditional polling data was calculated for each state
 - predicted net approval for each state was compared to a single poll from that state



EVALUATION

- The model shows a great deal of promise
- Performed very well when compared to overall polling data
- Although not as accurate, the RNN predicted statewide net approval ratings surprisingly well
 - there was, on average, only around 435 labeled tweets per state
 - predictions from the RNN deviated from polling data by
 - o ≤10% in 27 states
 - \circ ≤ 15% in 37 states.
- The RNN model chosen had a relatively simple architecture
 - implies there is a great deal of potential if we choose to develop more complex networks

LIMITATIONS & NEXT STEPS

- * Rate limits imposed by Twitter API
- Issues pertaining to location data
- Fine-grained sentiment analysis
- Identifying topic of tweets
- Utilizing emoticon data
- Utilizing other social media platforms to collect sentiment data

THANK YOU

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