Trump vs Twitter

Juat Tan

Purpose and Goal

- Trump’s presidency polarizing
  - Large presence on Twitter
- Shifting approval ratings
  - Things he’s said and done
  - Responses by the public on Twitter
- Predict / look at correlation between approval and the public’s sentiment
  - Via public Tweets
  - vs averaged approval ratings through polls

Data

- Tweets
  - 2017-01-20 to 2020-01-20
  - English
  - @realDonaldTrump
  - 1,000 Tweets / day, ~1,000 days of data

```
822594203058405376 2017-01-20 18:58:35 -0400 <mrkford1979> @realDonaldTrump God bless you Mr. President
822594201397379073 2017-01-20 18:58:35 -0400 <shakeraldafeery> @realDonaldTrump We congratulate you on the inauguration of the presidency of the USA.
822594198071373825 2017-01-20 18:58:34 -0400 <Bobbykeysradio> @realDonaldTrump YOU WORK FOR THE PEOPLE NOT HOME SHOPPING NETWORK  OR TWITTER THE PEOPLE  THE HOUSE YOU LIVE IN OURS  WE OWN U NOW
```

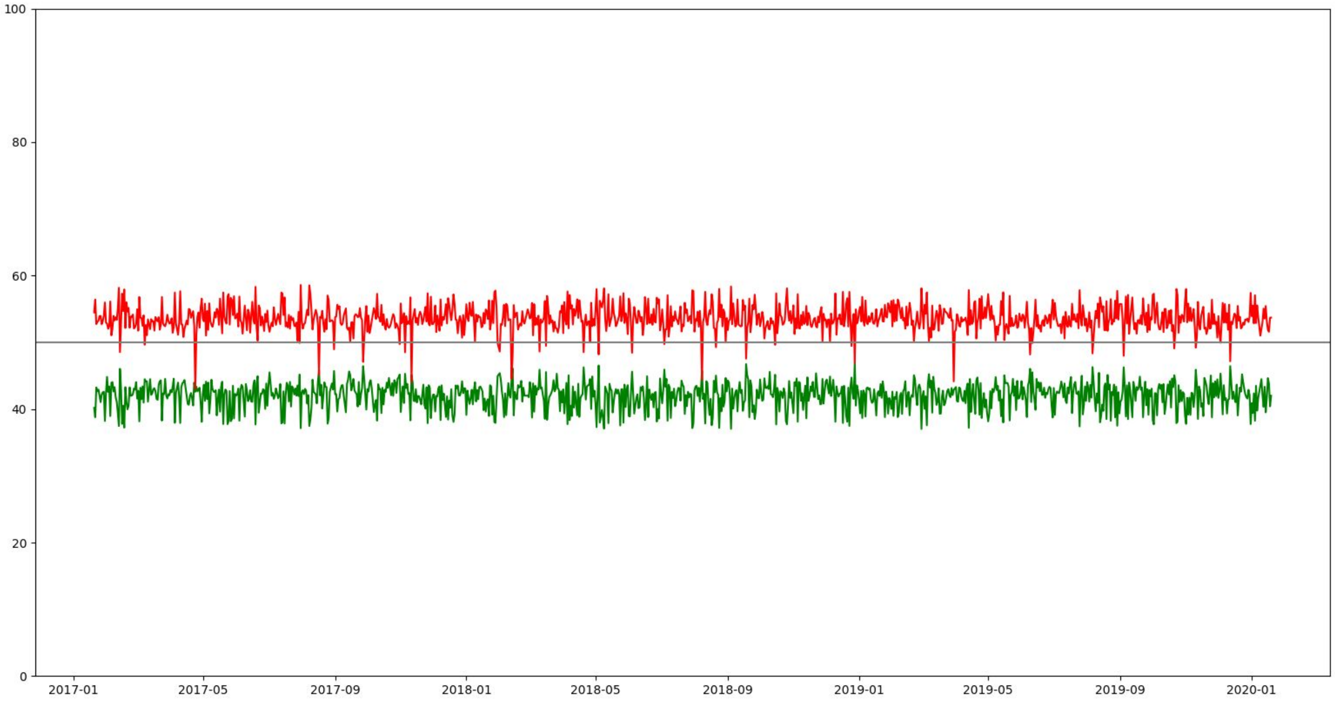
```
1217959335747174401 2020-01-16 18:58:28 -0400 <SpartanMatt8497> @realDonaldTrump Ok Boomer.
1217959335281688582 2020-01-16 18:58:28 -0400 <TruckNuts3435> @JeffreyGuterman @realDonaldTrump You are one real pervert but this one is kinda funny
```

Data

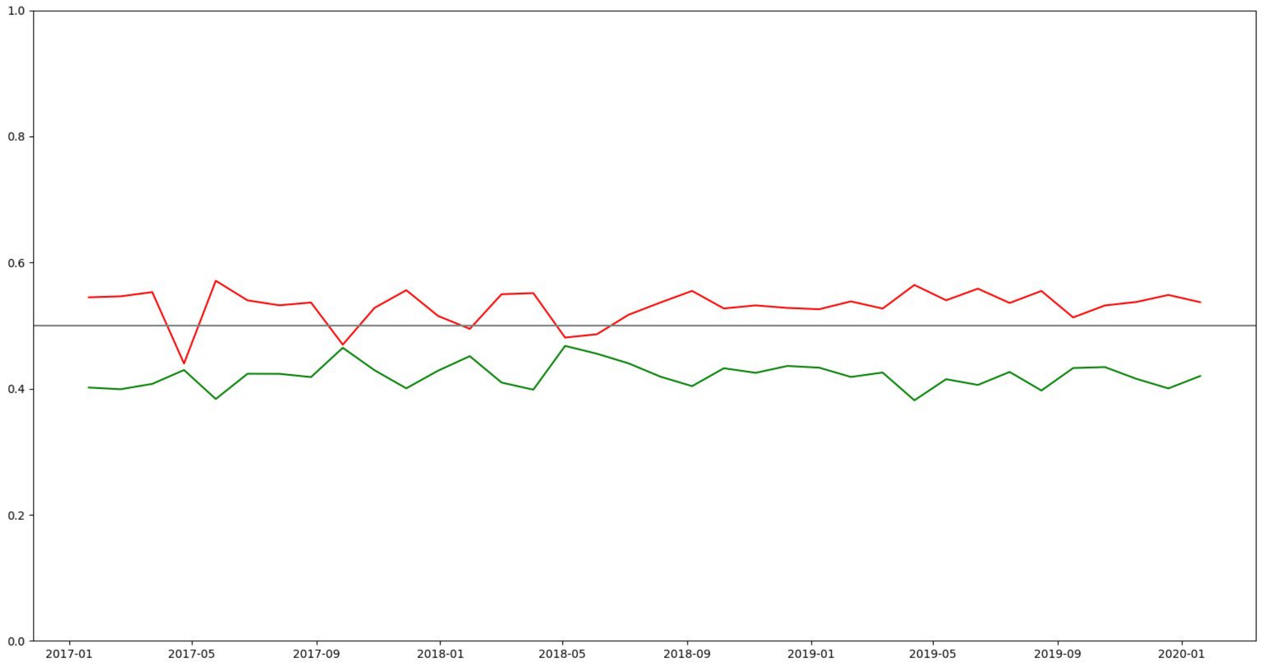
- Polls
  - Span multiple days
  - Average all polls which span each day

```
president,subgroup,modeldate,startdate,enddate,pollster,grade,samplesize,population,weight,influence,approve,disapprove,
Donald Trump,All polls,1/20/2021,1/20/2017,1/22/2017,Morning Consult,B/C,1992,rv,.6800286,0,46,37,45.686784,38.055805,""
```

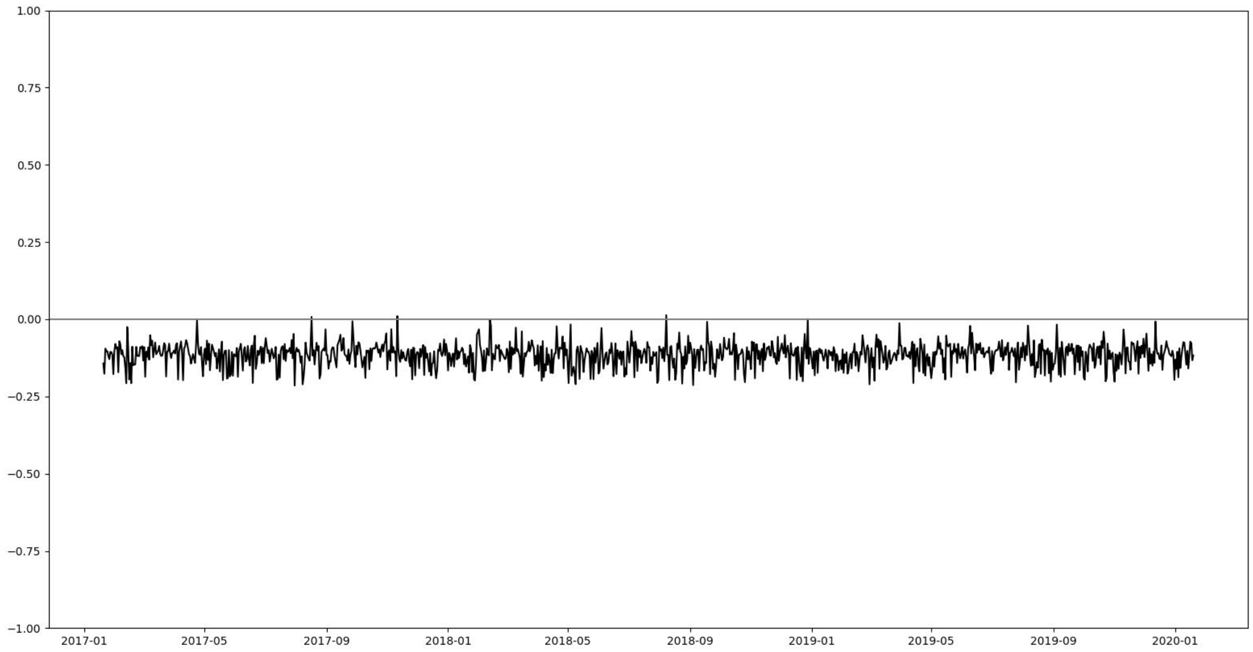
Trump Approval Ratings



Trump Approval (Smoothed Monthly)



Trump Approval Difference (Approve - Disapprove)



Approve

Disapprove

Models

NLTK

- VADER (Valence Aware Dictionary for Sentiment Reasoning)
- Words in a lexicon map to a positive or negative score
- Words not in lexicon have score 0
- Add up all scores to get overall sentiment -> $\frac{x}{\sqrt{x^2 + \alpha}}$
- Alpha = 15, maximum expected value of x

Textblob

- Similar to NLTK's sentiment analysis
- Words also looked up in a lexicon
- Negation multiplied by -0.5x
- Modifier words, like "very" multiply the following word by an *intensity* score
- Range [-1, 1]
- Averages all the scores

Flair

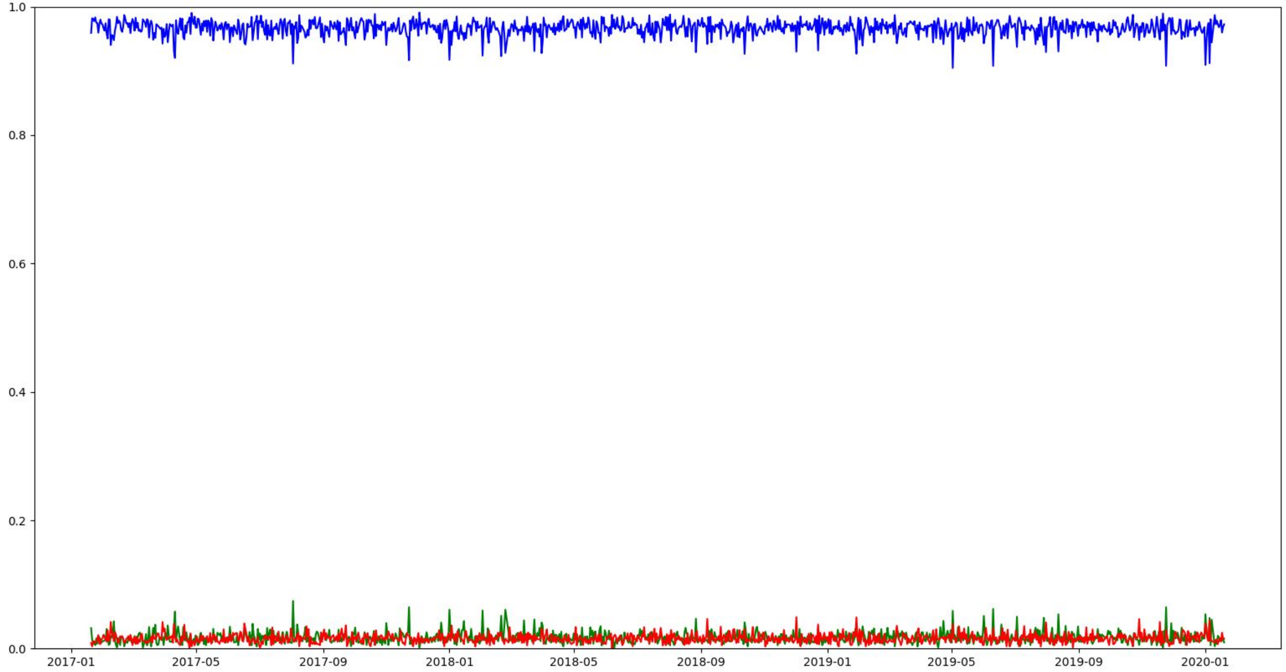
- Character-level LSTM neural network
- Sequences of letters and words taken into account when predicting
- Predict sentiment for OOV words
- The Flair sentiment analysis model is trained on IMDB (Maas et al., 2011) dataset for binary sentiment classification containing 25,000 highly polarized movie reviews for training, and 25,000 for testing.

Twitter Text

- Text
  - Links
  - Emojis
  - Slang
  - Capitalization
  - Too much punctuation

```
1217959518577090561 2020-01-16 18:59:12 -0400 <Chicago1Ray> @realDonaldTrump TRUMP WILL SAVE US FROM THE EVIL LEFT 🇺🇸 https://t.co/GZzSVyES7v
```

NLTK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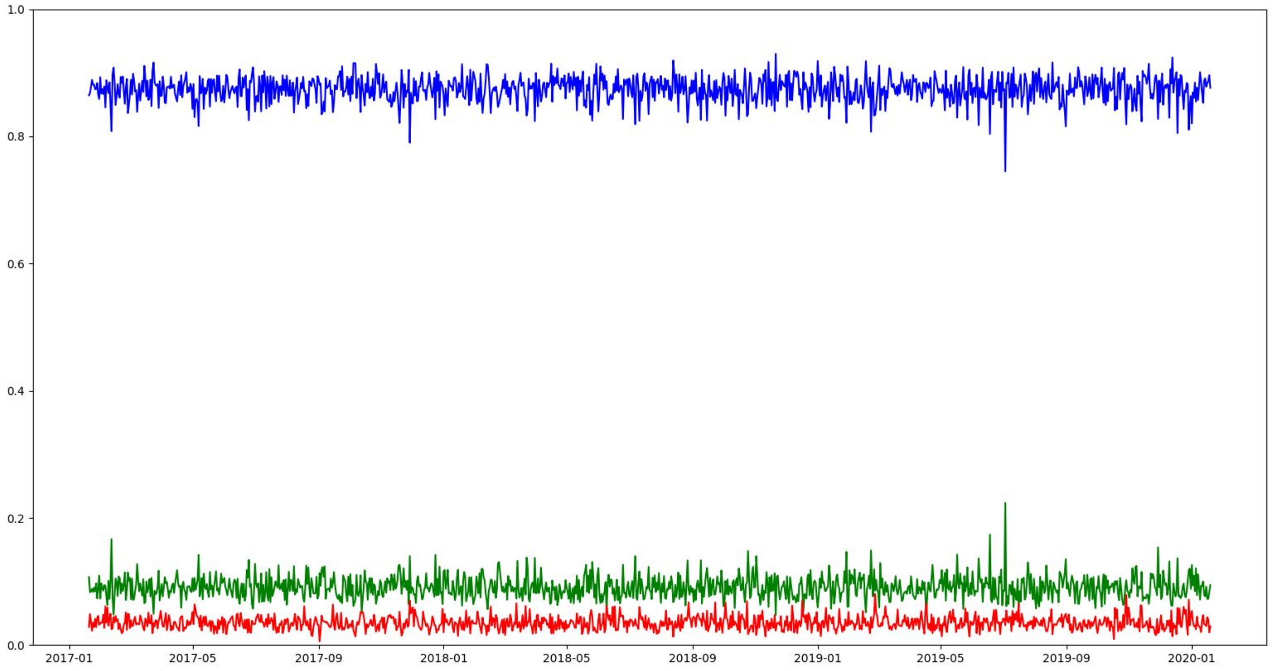
Textblob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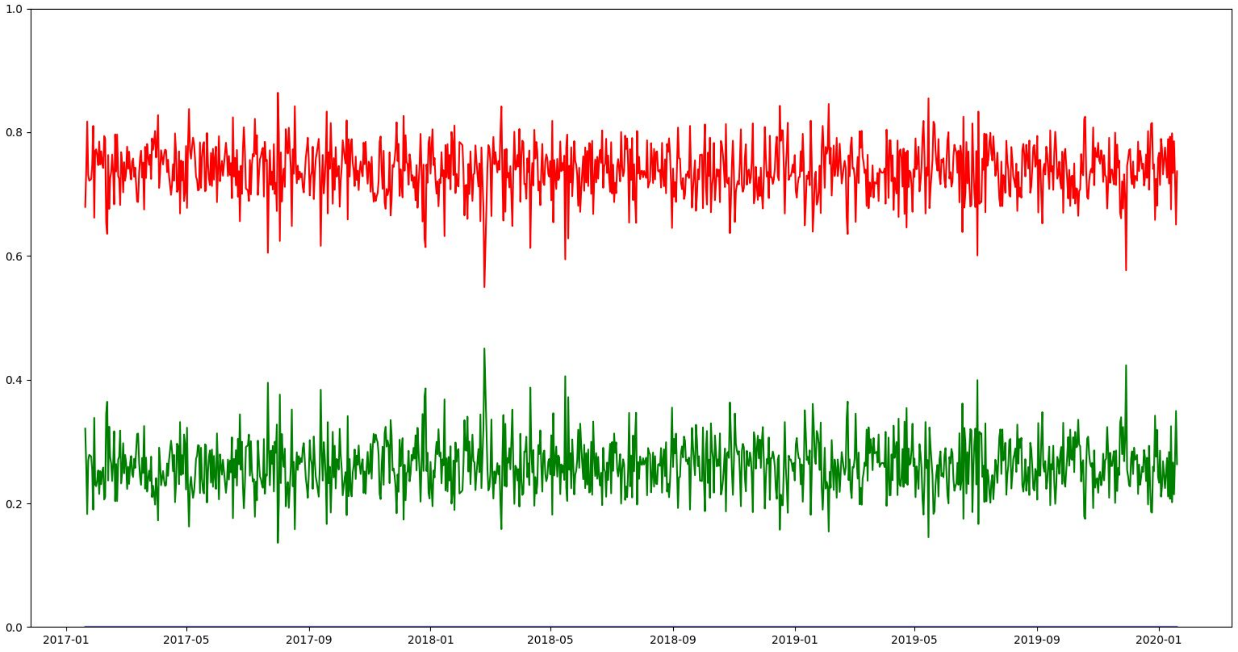
Flair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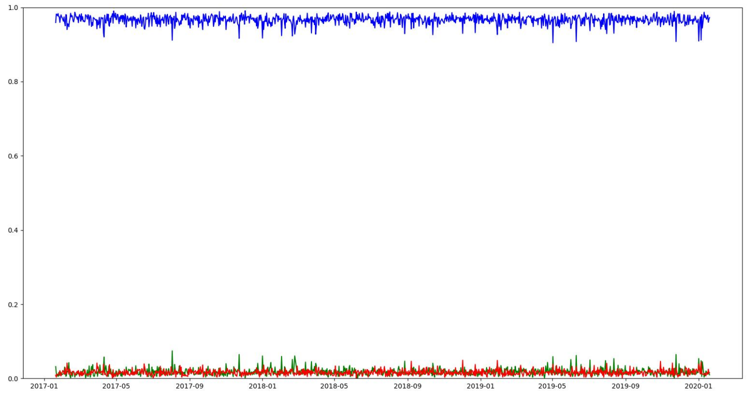
After cleaning

- Remove
    - Emojis
    - Stopwords
    - URLs
    - @mentions
    - Too much punctuation
- Lowercase
- Replace numbers with textual representation

```
come man havent seen anything yet sdny waiting leave office changing residence florida going help trump criminal enterprise remains new york sweating donnie
```

NLTK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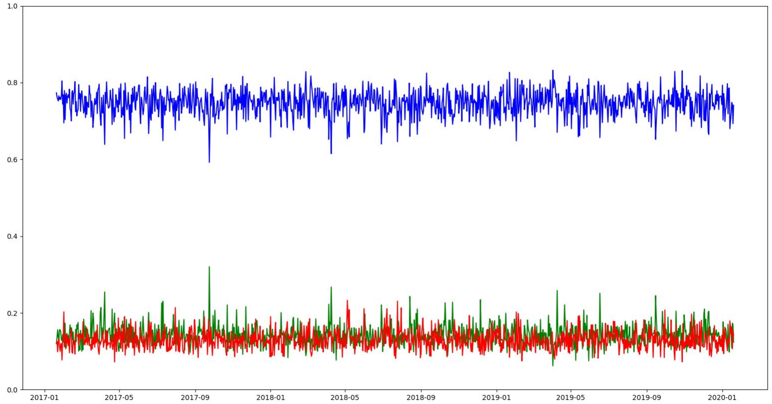
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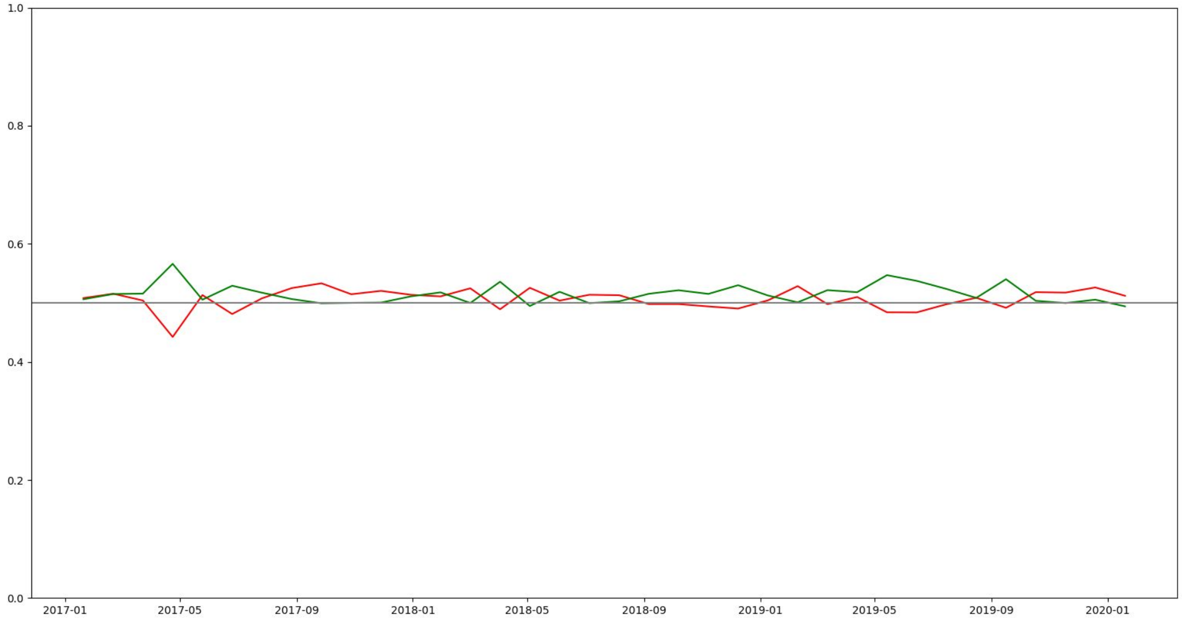
NLTK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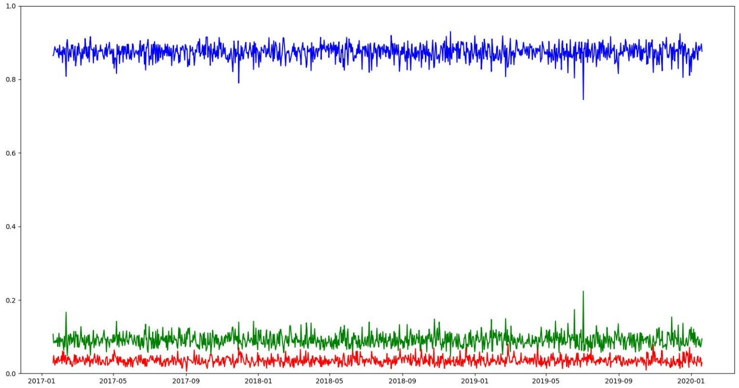
TextBlob



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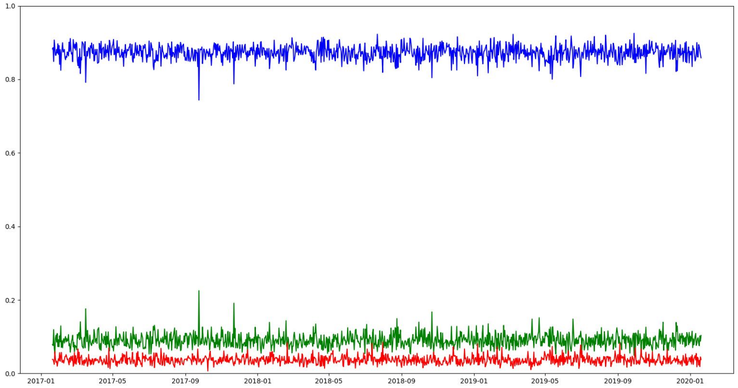

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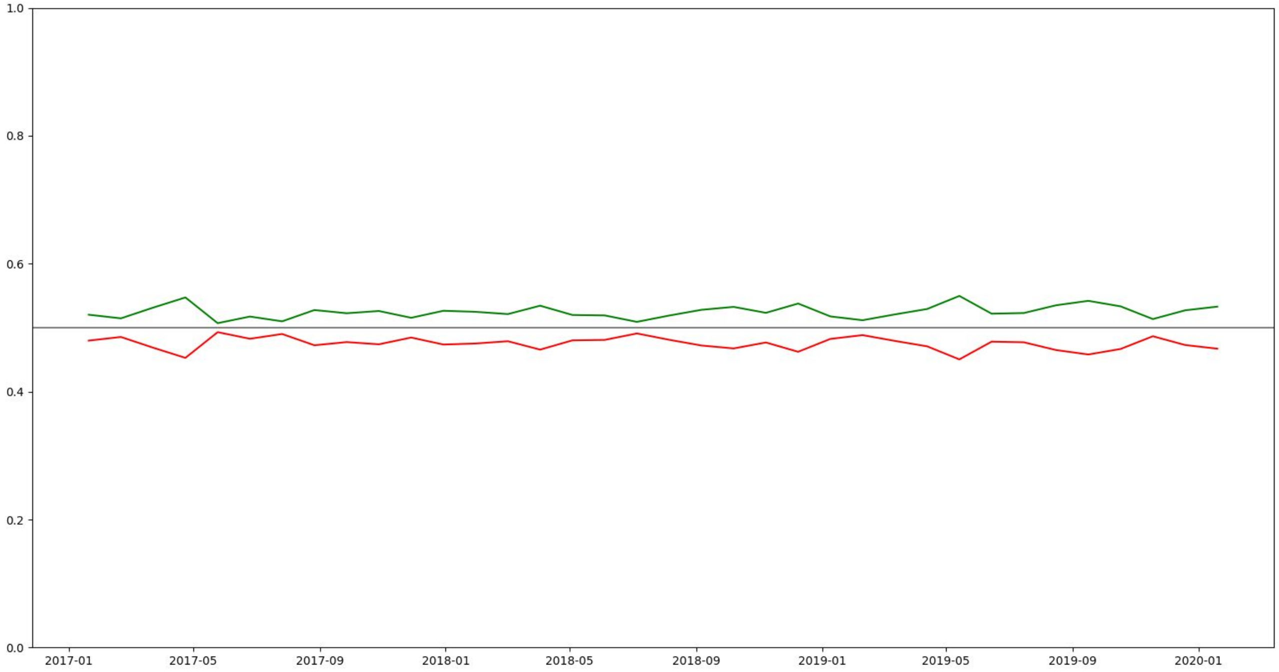

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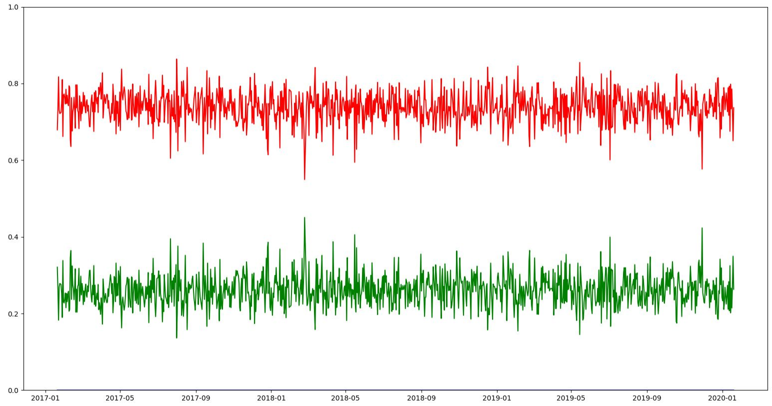
Flair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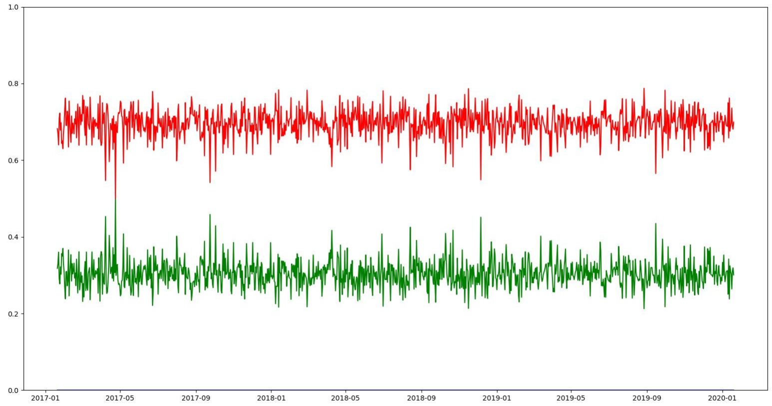
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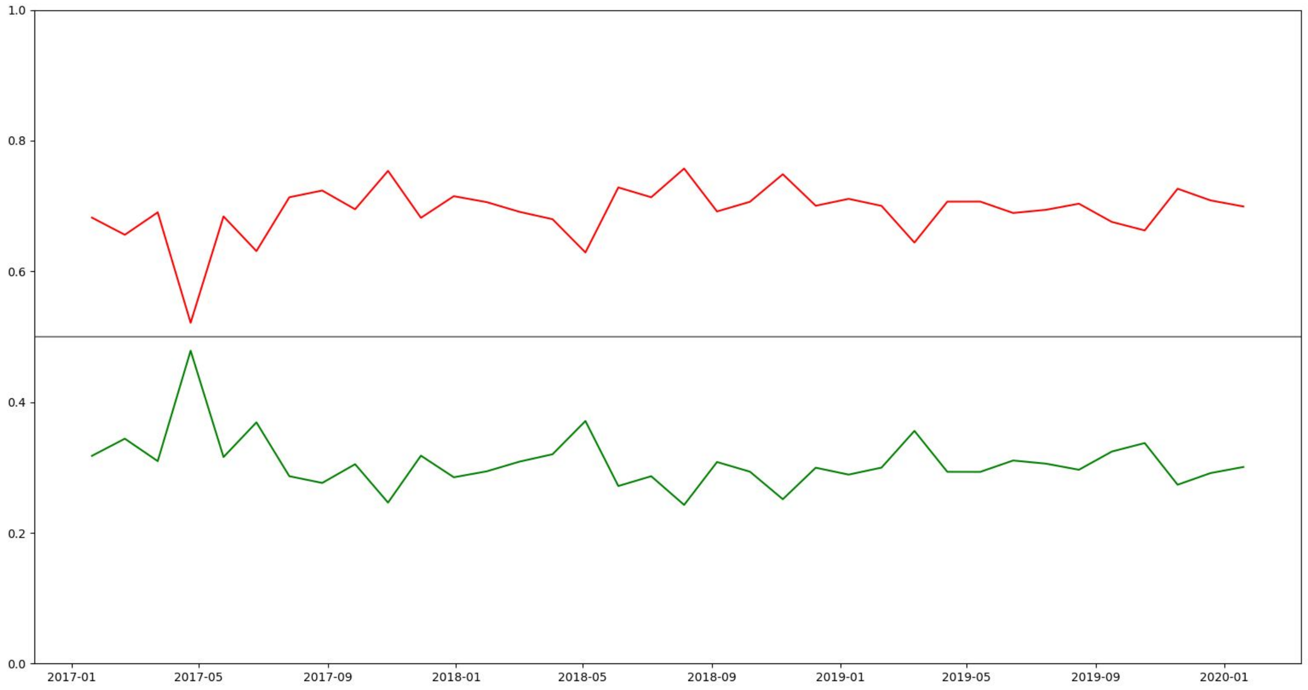
Flair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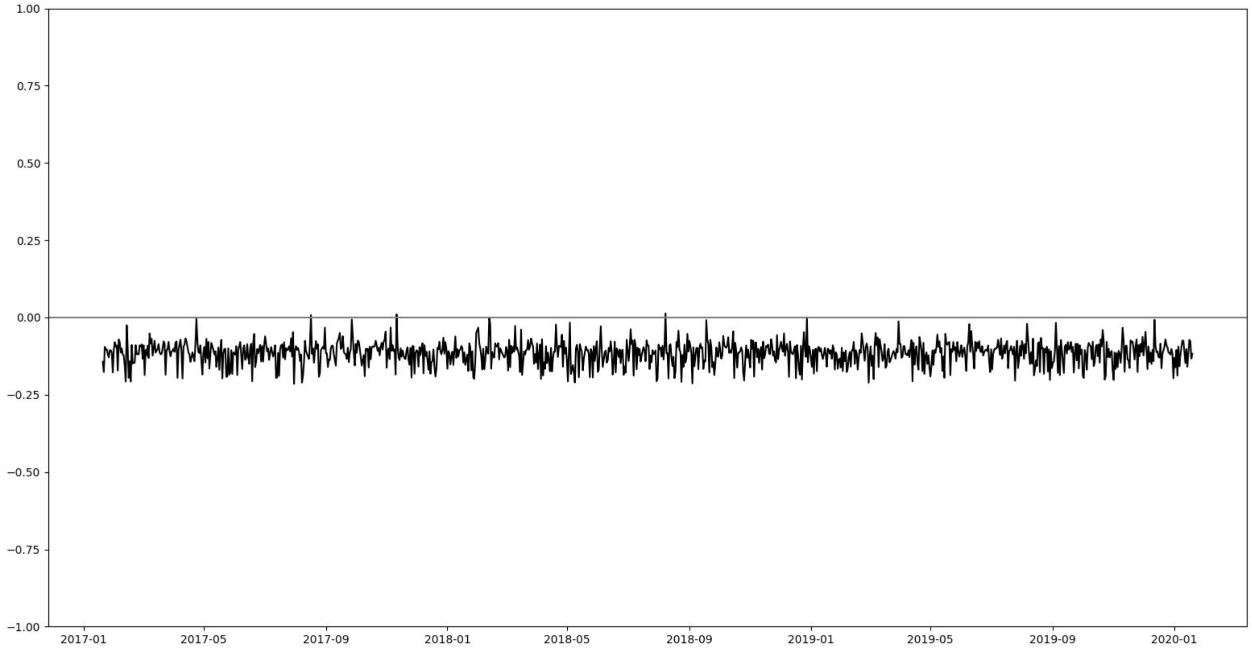
Calculating Differences

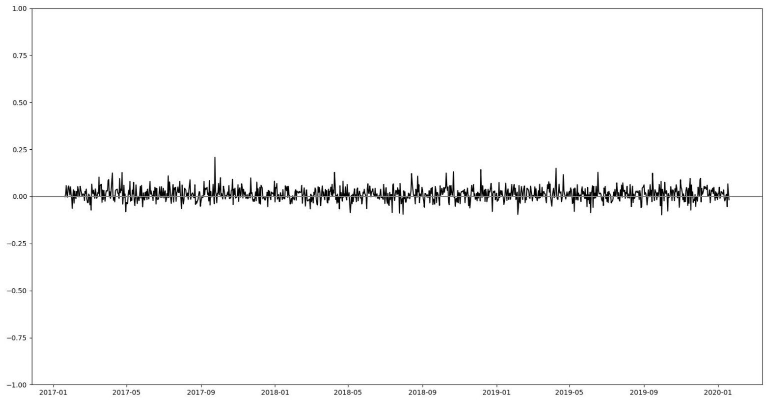
- Shrink 4 sets of data to 2
  - Comparison
    - Polls
    - Twitter
  - Correlation = good

- Proportion approve - proportion disapprove

Trump Approval



NLTK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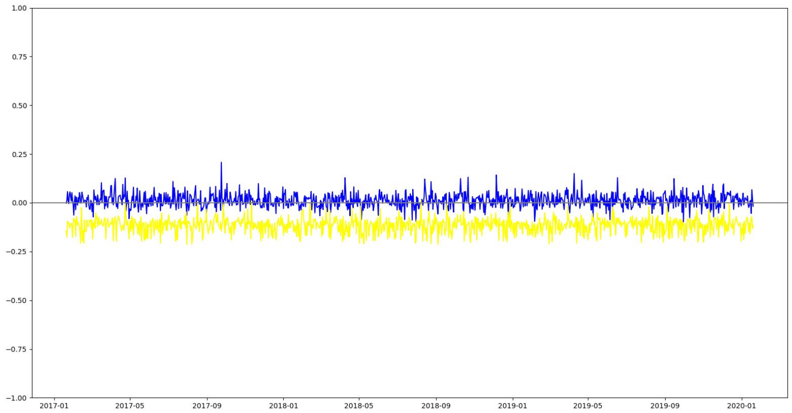
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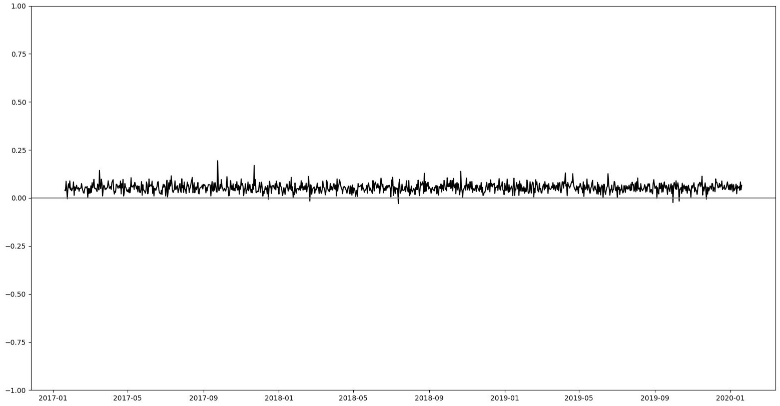
Textblob



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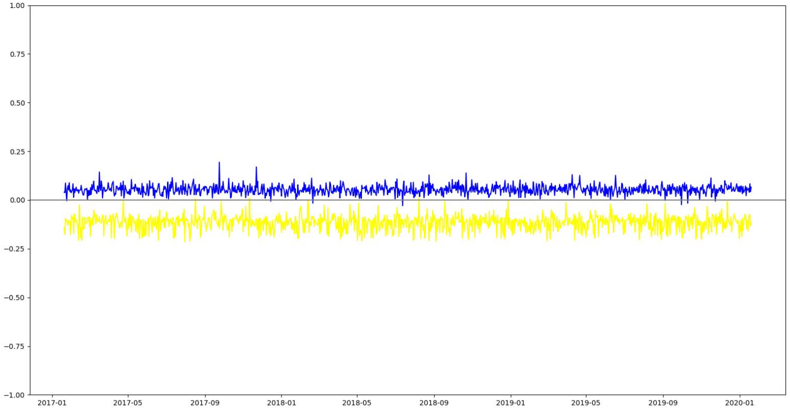

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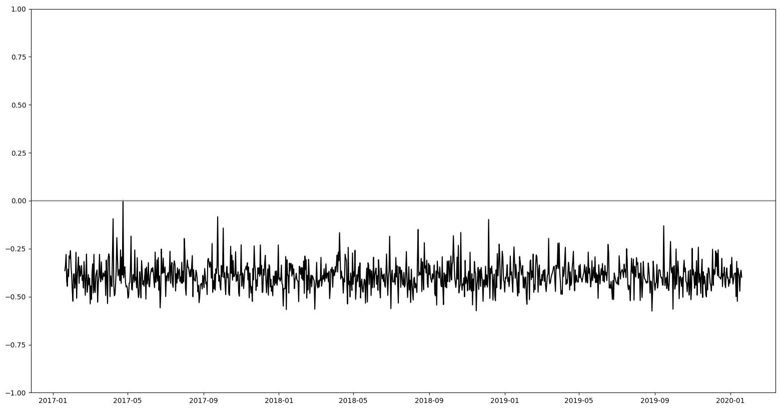
Flair



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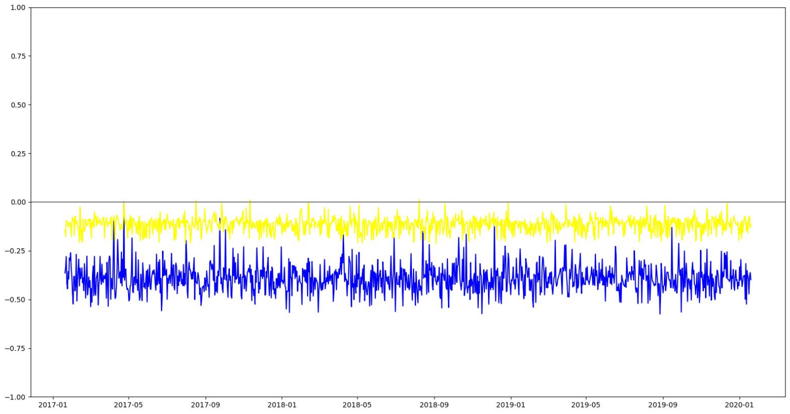

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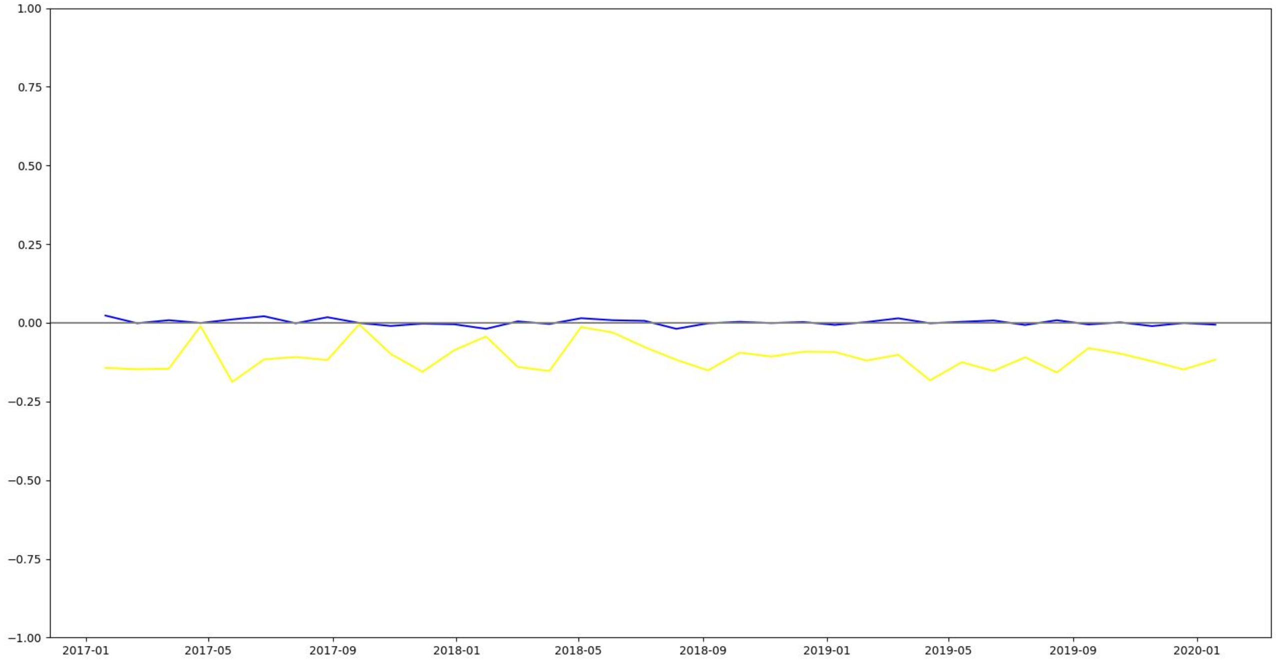
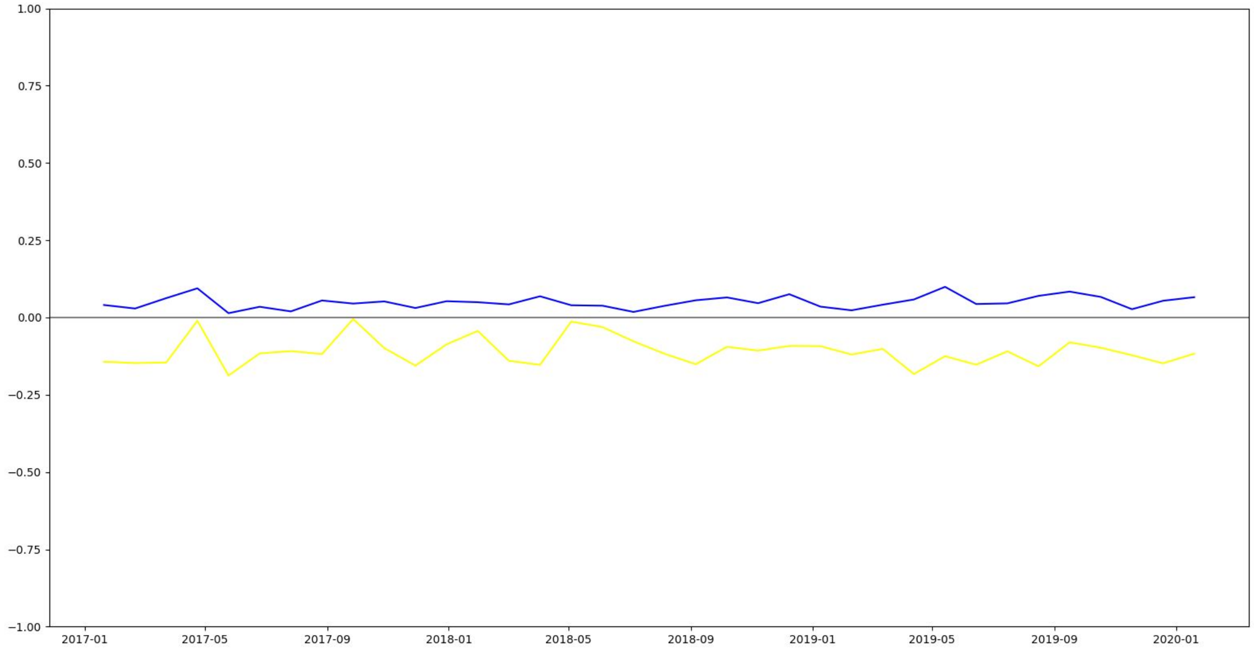
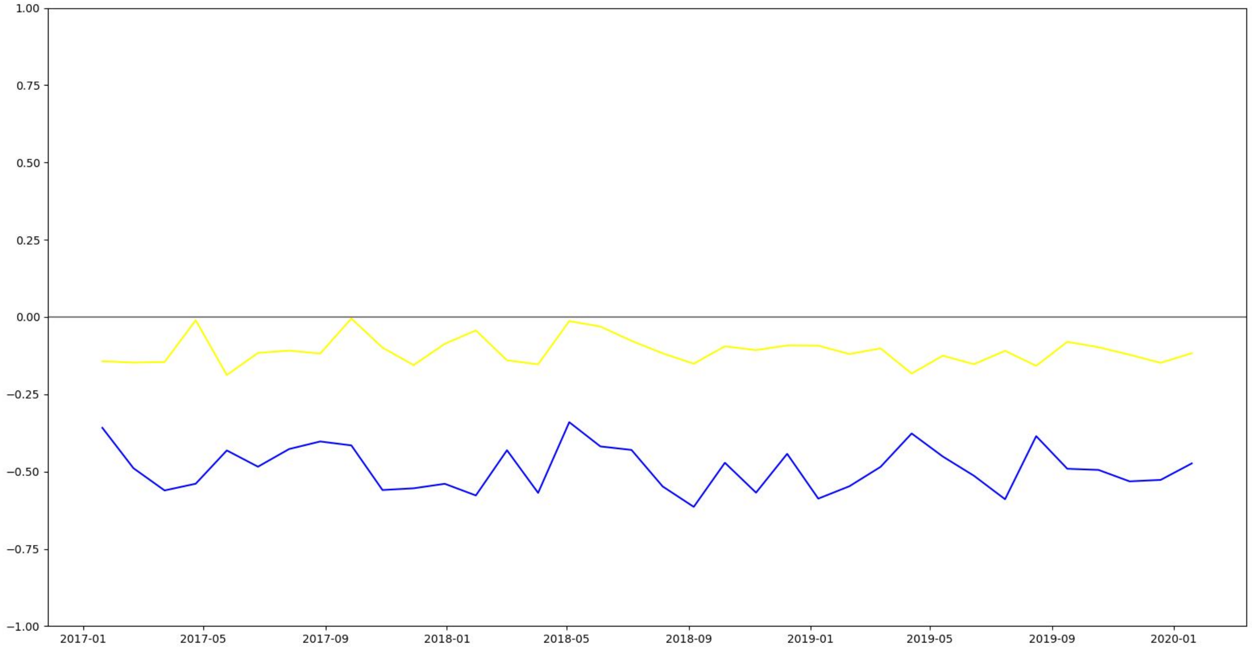
NLTK - 0.04775279 vs **0.11848797**



Textblob - 0.03088764 vs **0.13494615**



Flair - 0.06580662 vs **0.26252651**



Takeaways

- Data is very noisy, hard to interpret
  - Too many data points
  - Visualization
  - Condensing
- Correlation coefficient
  - Single number to compare accuracy between models
- Expected results
  - New slang and dirty data
  - Training models differently will help
  - Neural net performs better, but it’s slow
  - Manually inspect word lists, not very Twitter-like