Stockbot

Stock Price Prediction with Historical and Sentiment data

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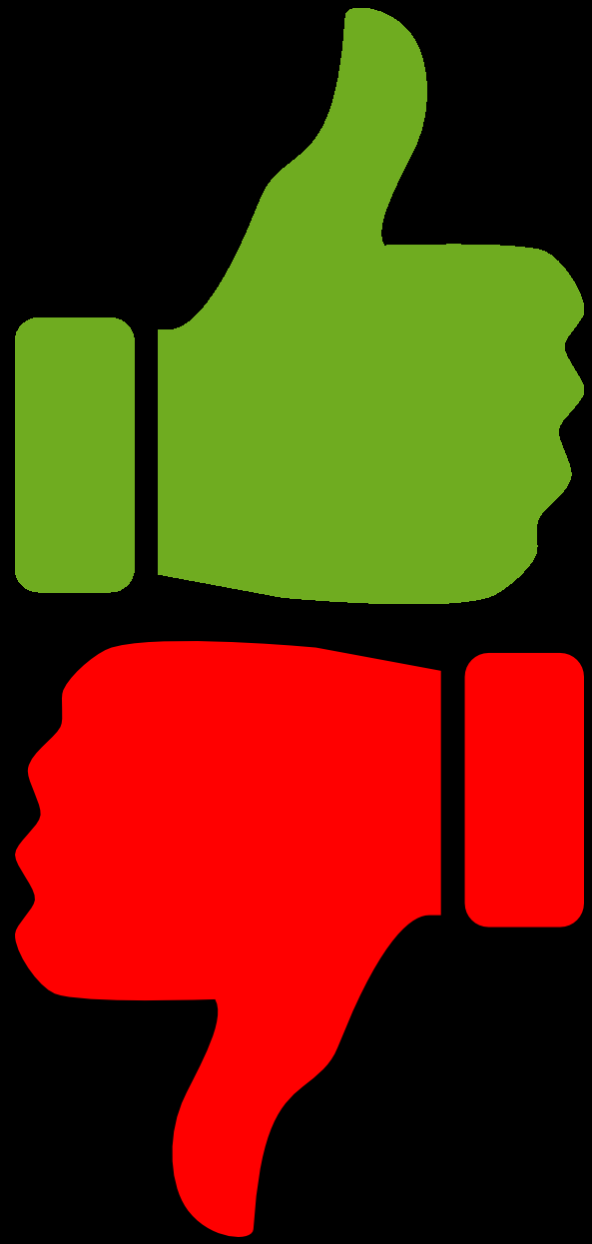
Motivation

The Stock Market

- Efficient Market Hypothesis
  - "… asset prices reflect all available information." – Wikipedia
  - What counts as available information?
- Stock prices fluctuate
  - "Buy low, sell high"
- How can we model stock prices?

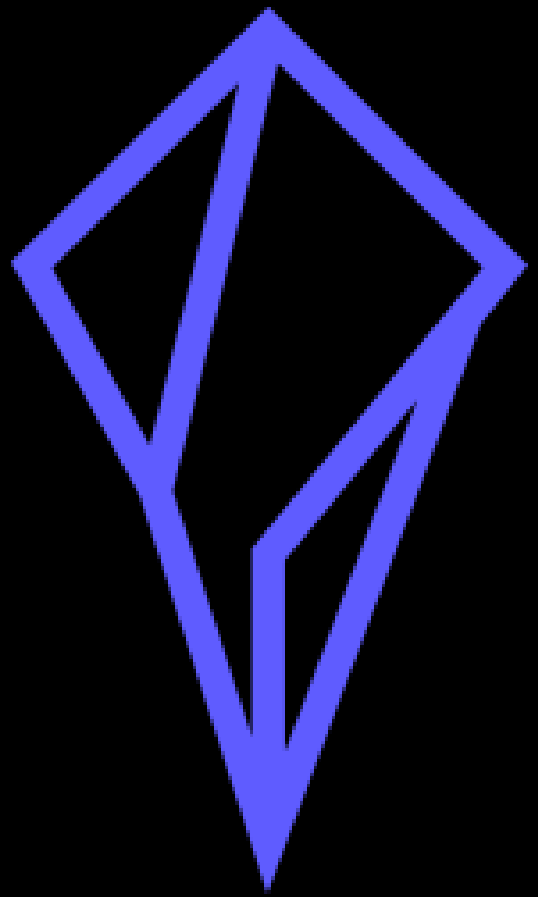
Sentiment

- Reflects perceptions and captures reactions in text
  - Public perceptions may reflect general trust/belief
- General positivity or negativity of text
- Can we capture sentiment associated with companies?



Data Collection

Financial Data



Obtained from Polygon

- Start date: January 1st, 2010
- End date: December 31st, 2019
- 15 companies
- Data
  - Open price
  - Closing price
  - High
  - Low
  - Volume

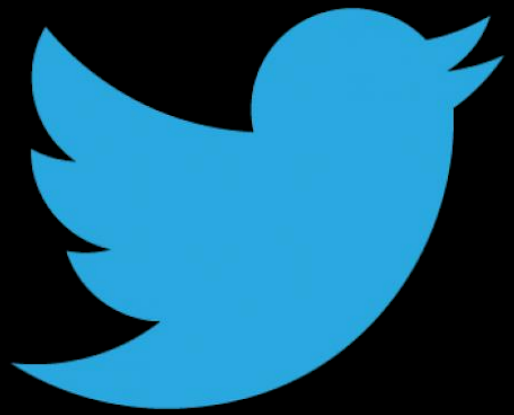
Sentiment Data

Sentiment140 dataset on Kaggle

- 1,600,000 tweets
- Labels
  - Negative: 0 → 0
  - Neutral: 2 → 0.5
  - Positive: 4 → 1

Scraping Tweets

- Scraped hashtag(#) and cashtag($) tweets associated with companies by stock ticker*
  - E.g. for Apple, #AAPL and $AAPL
  - ~2.5 million # tweets
  - ~1.7 million $ tweets
- Built with python
  - Using Selenium and BeautifulSoup4

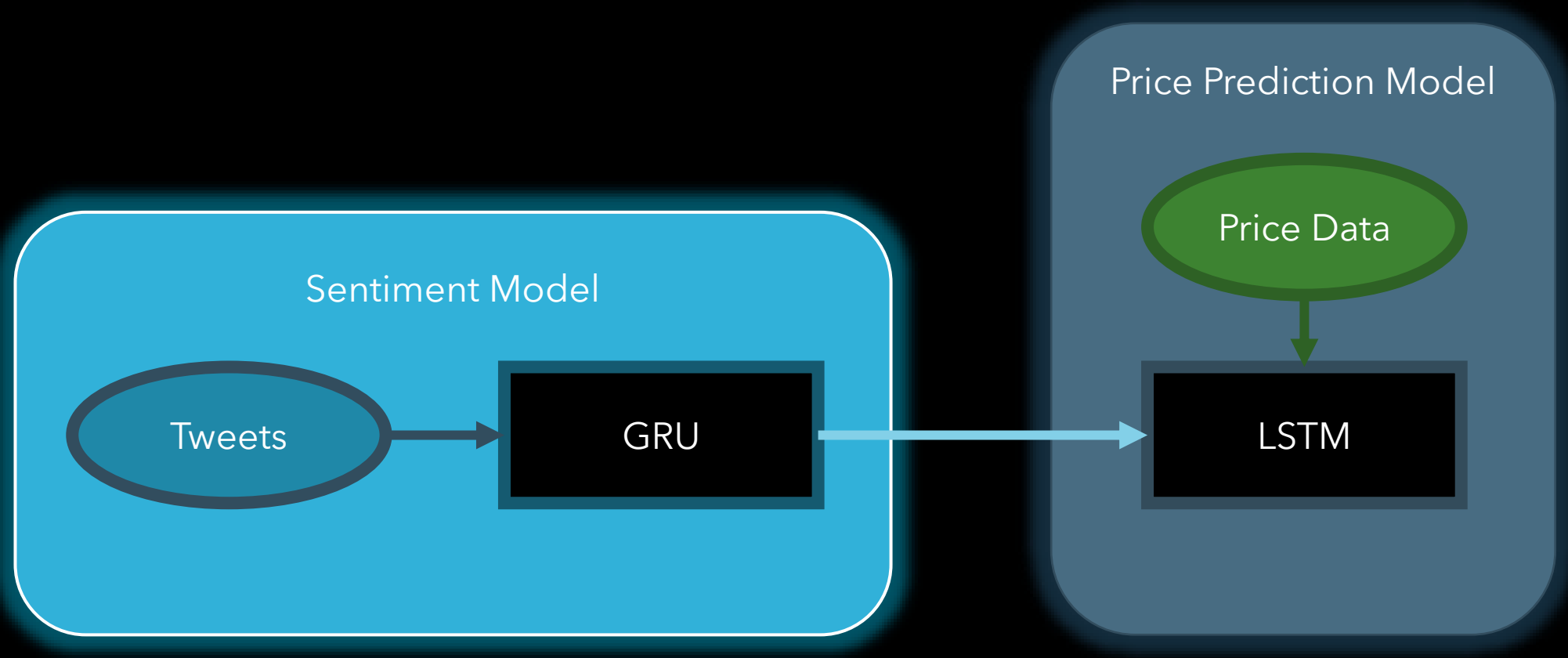


* - avoiding usage collisions, e.g. KO is the stock ticker for CocaCola, but also the term for knocked out, so we looked up #CocaCola

Companies Tracked

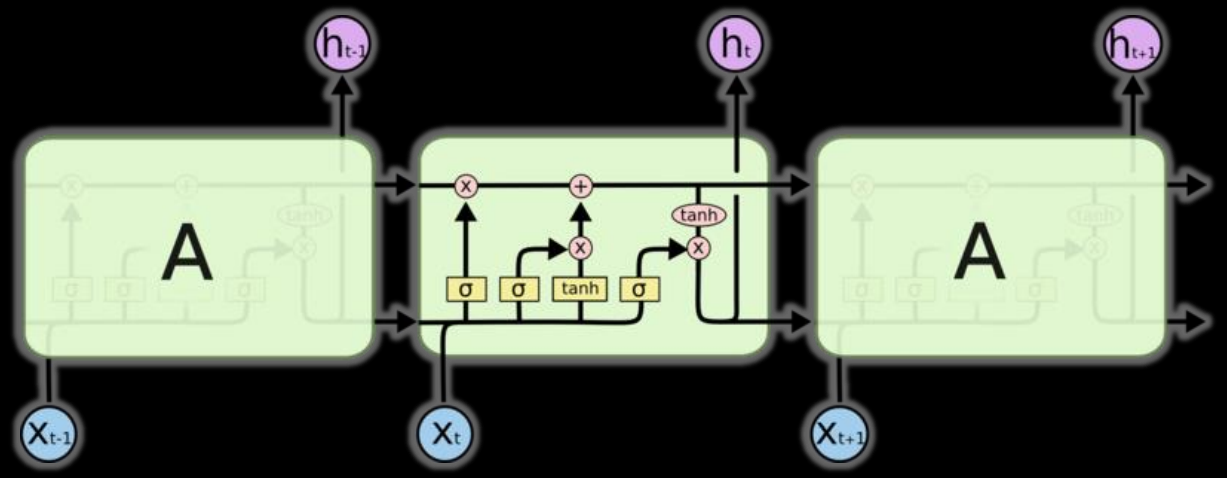
Methods

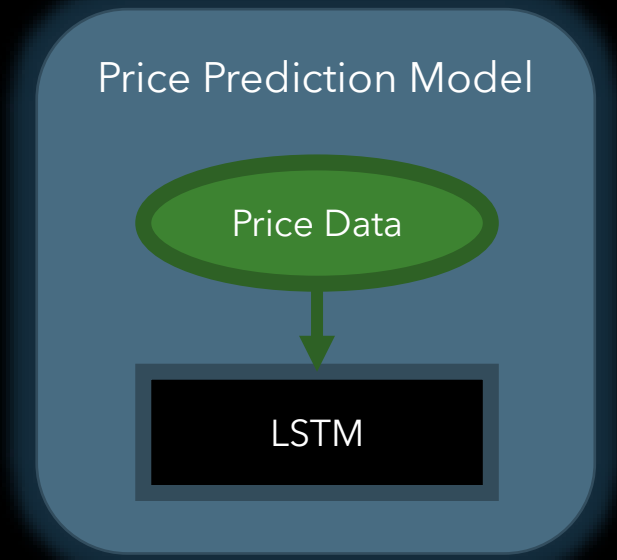
Architecture



Price Prediction Model

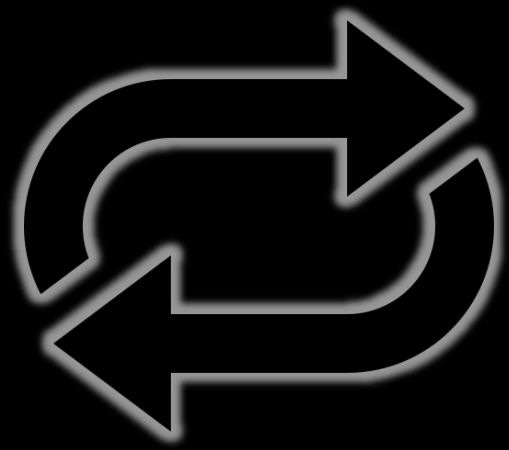
- Leverages financial data
- LSTMs
  - input dim = 5
    - open, high, low, closing price, volume
  - hidden dim = 32
  - number of layers = 2
  - output dim = 1
    - Price estimate for next date
- One model per company
- Uses previous 30 days to make a prediction

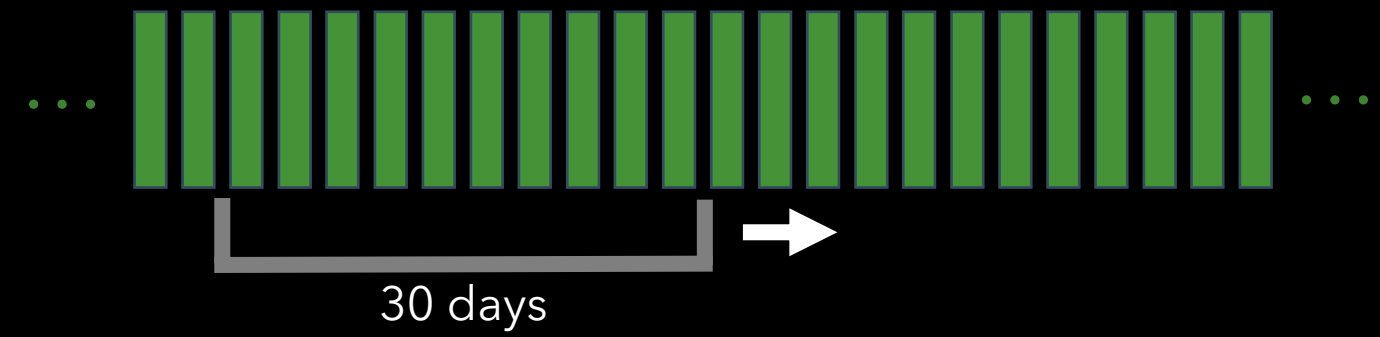




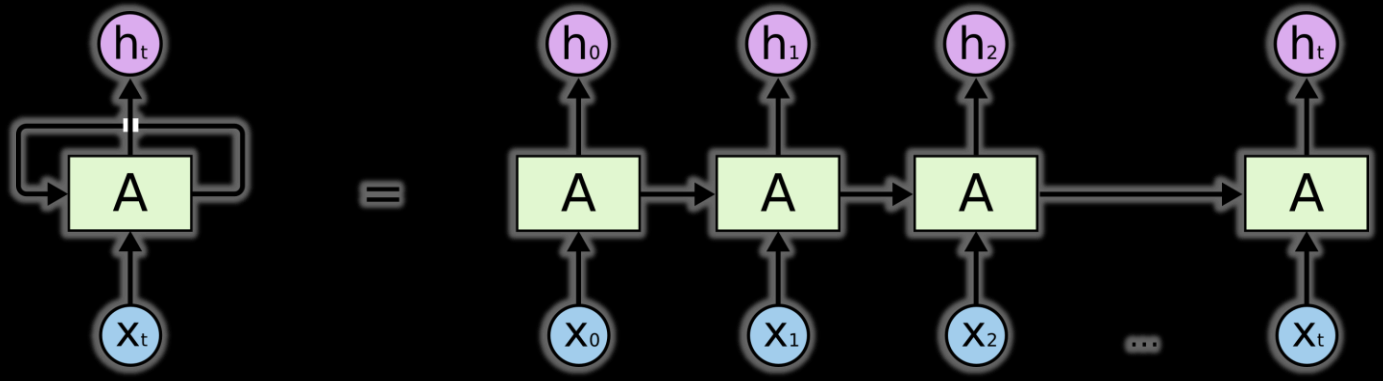
Iterative Training

Once a prediction is made, include the actual test data point and retrain, then predict again

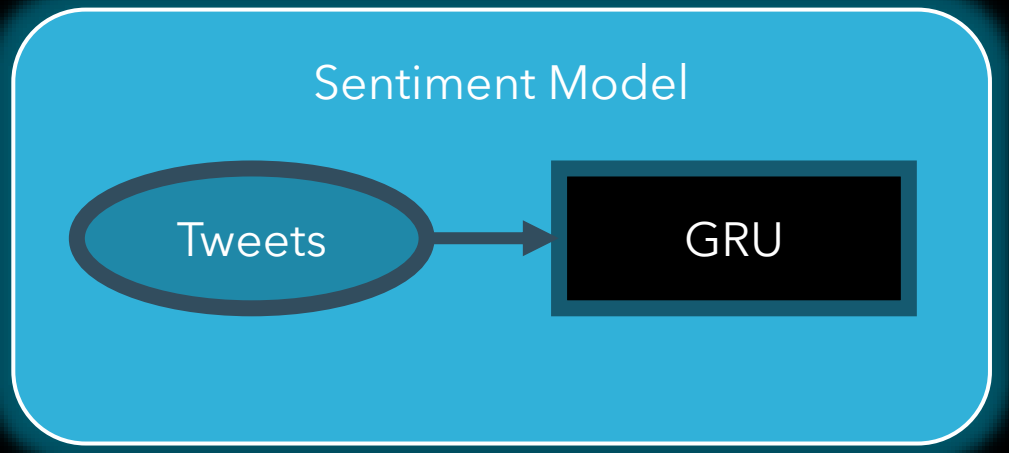




Sentiment Model

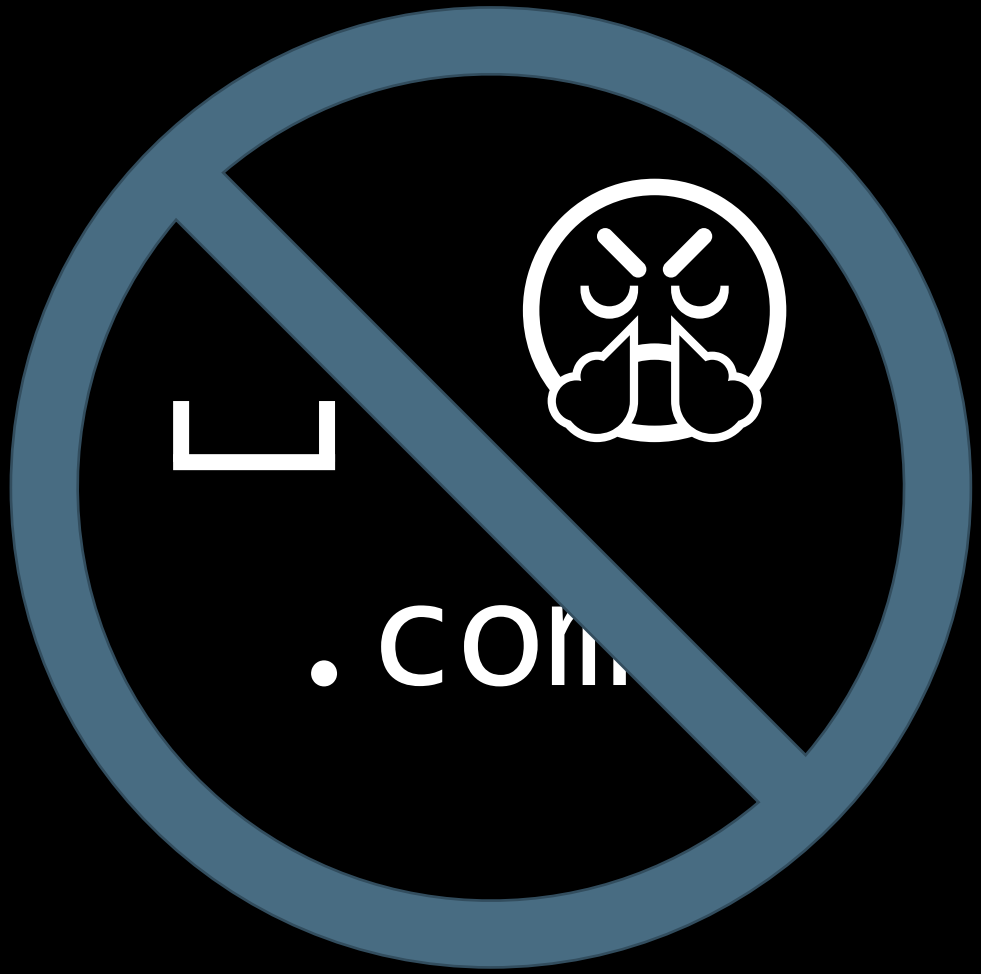


- Trained and tested on Sentiment140 dataset
- Used scraped Tweets
- GRU
  - embedding dim = 350
  - hidden dim = 350
  - number of layers = 2
  - output dim = 1
  - dropout = 0.025
  - batch size = 200



Data Processing

- Removes:
  - Strips whitespace
  - Emojis
  - Links
- Performs UNK-ing
  - UNK probability = 0.6



Price Change Labeling

- Labeling tweets using price changes
  - Labels need to be validated somehow
- Is there a correlation between tweet sentiment on a day and the price of the next day?

Results

Baseline

Simple Moving Average

- Smooths volatility
- Relatively effective in general
- Averages over 10 days, so $n = 10$

$$\frac{1}{n}\sum_{i=k}^{k+n} A_i$$

Trend Prediction

When the price goes up or down, how often does our model predict an increase or decrease respectively?

- Roughly correct 50% of the time, but the error isn't too bad

Subset of graphs generated

Apple Inc. (AAPL)

Microsoft Corporation (MSFT)

Bank of America Corp (BAC)

RMSE table

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{\left(\text{prediction}(i) - \text{actual}(i)\right)^2}{n}}$$

Ticker	AAPL	BAC	CMG	DAL	FB	GOOG	JPM	KO	LUV	MCD	MSFT	PEP	UAL	V	WFC
No Iter (Test)	11.36	0.52	13.43	0.96	3.49	18.64	2.07	0.96	1.02	7.45	16.46	2.31	1.99	13.80	0.70
SMA	**3.80**	**0.63**	**17.70**	**1.34**	**4.20**	**24.41**	**1.88**	**0.69**	**1.29**	**2.22**	**1.52**	**1.54**	**2.24**	**1.78**	**1.14**
Iter (Test)	4.60	0.47	11.76	0.87	3.45	18.29	1.68	0.52	0.91	2.37	2.28	1.36	1.41	2.73	0.69

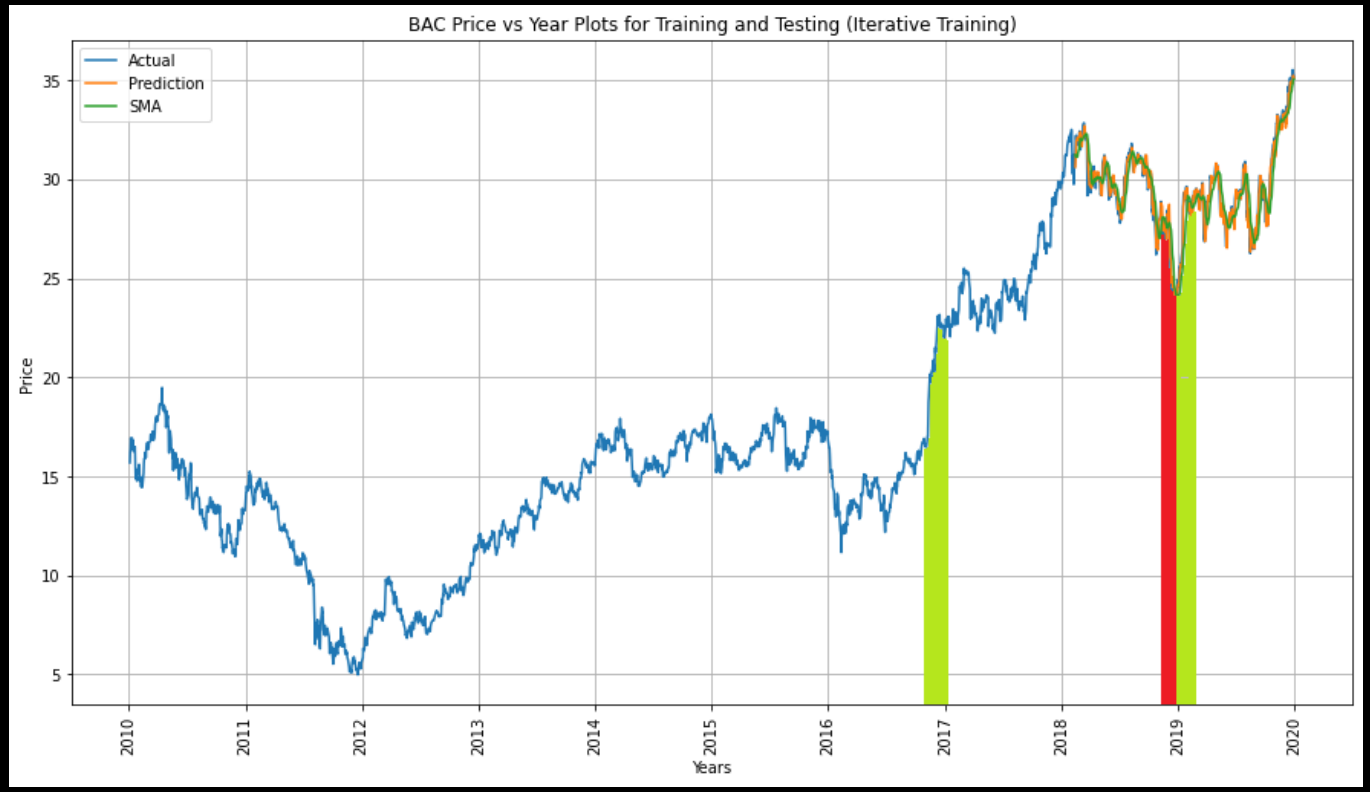
■ = Lower RMSE ■ = Higher RMSE

Sentiment results

- Trained on Sentiment140
  - Train accuracy: 89%
  - Test accuracy: 88%
- We predicted the sentiment of scraped tweets
  - Give neutral rating if no tweets on the day
  - Otherwise give average sentiment score for that day

Sanity check

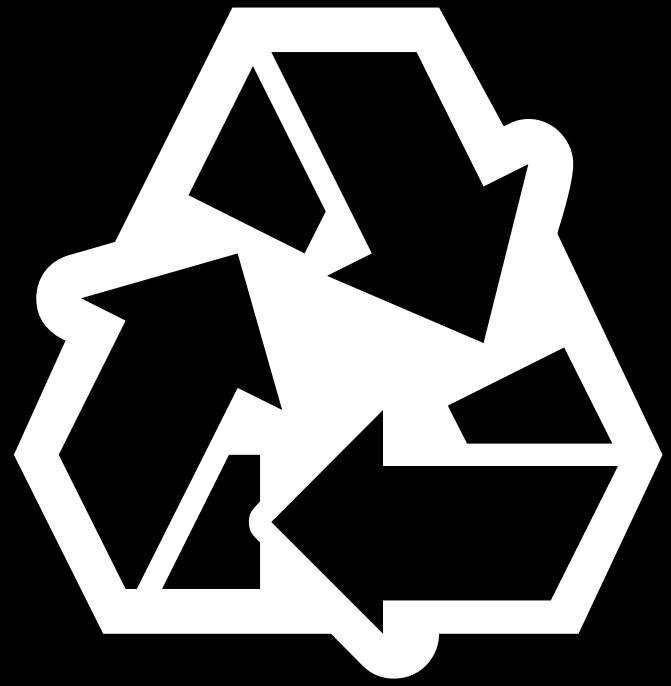
- We found that the predictions performed worse when we included them
- To sanity-check our model, we checked regions of increase and decrease for sentiment for BAC and found that they were all generally ~0.54, i.e. slightly positive



Discussion

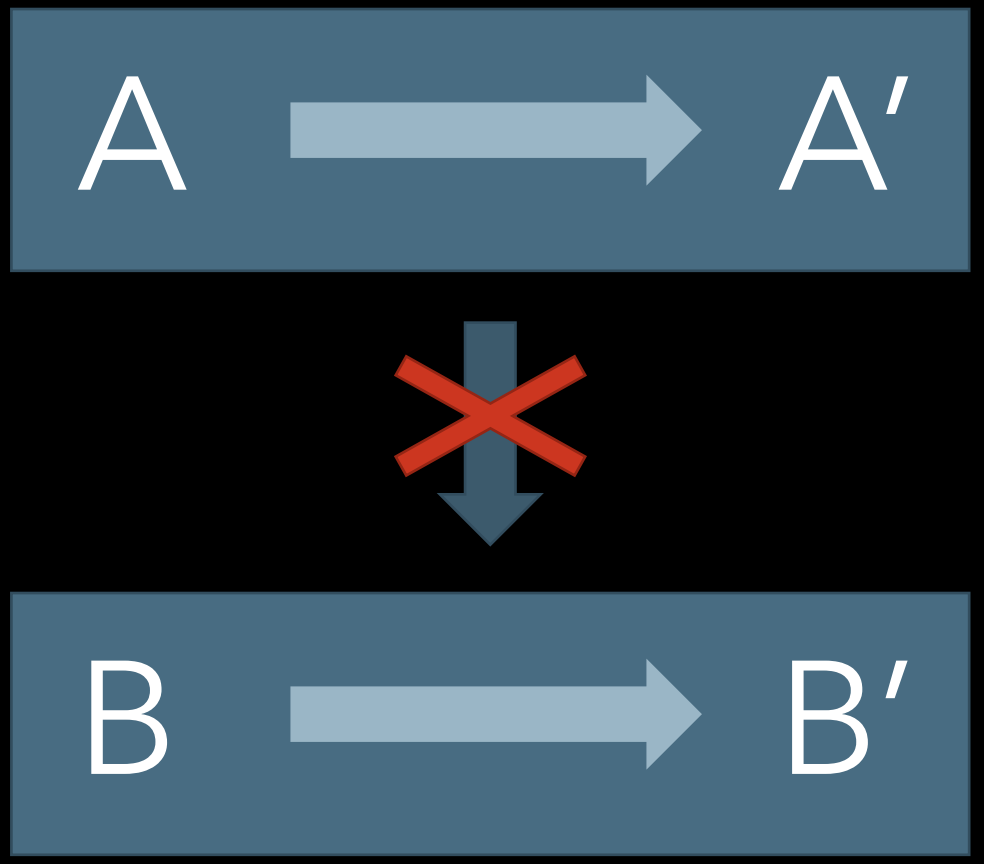
Iterative Training

- Does it make sense?
  - Data is limited
  - Can’t generate new data for the past
- Not aiming for generalization



Sentiment Generalization

- Didn't generalize very well
- Trained setting differs from applied setting
- Will likely perform better if we have more relevant training data



Future Work

Labeling the collected tweets

Training new sentiment model on labeled tweets

Predicting up-to-date stock prices

Test out the predictions with our own money

Conclusion

Contributions

- Price Prediction model
  - Iterative training
- Sentiment model
- Scraped tweets for 15 companies stock tickers
  - January 1st, 2010 → December 31st, 2019