



PROJECT I:

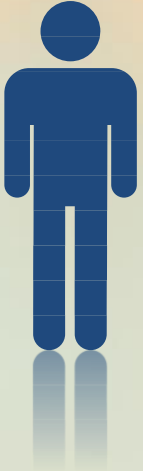
AN ANALYSIS OF
5 NASDAQ STOCKS
AND MEDIA SENTIMENT

TEAM CALABAR
APRIL 10, 2018

OUR TEAM

CALABAR PYTHON

**KETTYL
AMOAKON**



**ALEXA
CAVENAS**



**AURA
JOHNSON**



**ROBIN
VASUDEVAN**



**BETH
YODER**



GUIDING QUESTIONS

1

IS IT POSSIBLE TO PREDICT STOCK MARKET BEHAVIOR?

2

WHAT FACTORS INFLUENCE SHARE COST FLUCTUATIONS?

3

DOES NEWS MEDIA COVERAGE INFLUENCE TRADING?

4

HOW CAN WE MEASURE NEWS MEDIA SENTIMENT?

HYPOTHESIS

A RELATIONSHIP EXISTS
BETWEEN STOCK PRICES
AND MEDIA COVERAGE OF THAT STOCK

OUR INITIAL RESEARCH FOCUSES ON ONLY
5 NASDAQ STOCK EXCHANGE COMPANIES
(CHOSEN ANECDOTALLY BASED ON POPULARITY)
AND 4 VARIABLES. DUE TO TIME CONSTRAINTS



PROGRESSION OF PROJECT

SATURDAY

TUESDAY

THURSDAY

SATURDAY



BEGAN TO
RESEARCH
FIRST
HYPOTHESIS
USING
INSTAGRAM
AND
GEOLOCATION

REALIZED
INSTAGRAM
API END
POINTS WERE
NOT
SUFFICIENT

NEW
HYPOTHESIS

DECIDED TO
USE TWEETPY
FOR
SENTIMENT
ANALYSIS

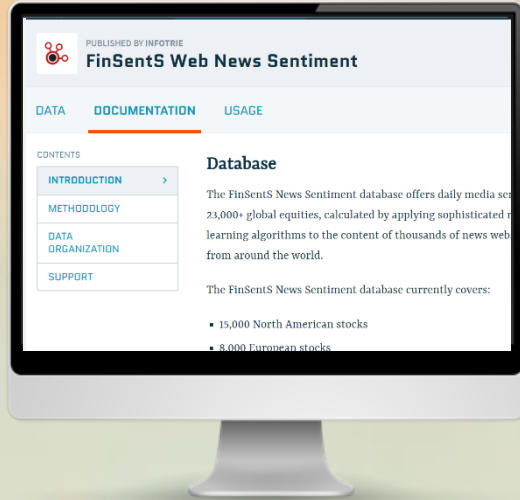
DISSATISFIED
WITH RESULTS
OF TWEETPY

RESEARCHED
NEW DATA
SOURCES

OBTAINED
INSTITUTIONAL
LICENSE FOR
DATA SETS

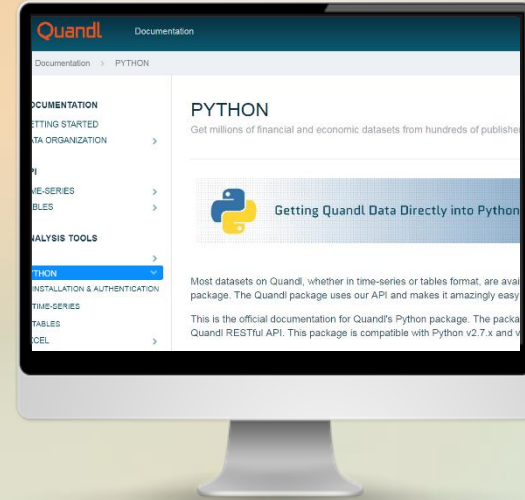
DECIDED TO
USE FIRST
QUARTER
2018 DATA

DATA SOURCES



FINSENTS

FINANCIAL DATA COMPANY



QUANDL API (PYTHON MODULE)

SOURCE OF FINANCIAL DATA

VARIABLES

01

CLOSING PRICE:
ADJUSTED CLOSING PRICE ACCOUNTS FOR
EFFECTS OF STOCK PRICE (END OF DAY)
THAT ARE CAUSED BY CORPORATE ACTIONS

QUANDL MODULE (QUANDL API FOR PYTHON)
COMPILES THIS DATA DAILY

RELIABLE REAL-TIME DATA SOURCE FOR ANALYSIS
OF STOCK PRICES

VARIABLES

02

SENTIMENT SCORE:

A MEASURE OF THE BULLISHNESS / BEARISHNESS
OF THE LANGUAGE USED IN MEDIA COVERAGE
OF A GIVEN STOCK ON A GIVEN DAY

RANGES FROM -5 (EXTREMELY NEGATIVE COVERA
GE) TO +5 (EXTREMELY POSITIVE COVERAGE):
A SCORE OF 0 INDICATES AN ABSENCE OF
ARTICLES FOR THAT DAY

FINSENTS ALGORITHM DETERMINES THIS NUMBER

BULL VS. BEAR MARKET

BEAR MARKET LANGUAGE IS RELATED TO FALLING PRICE TRENDS, PESSIMISM, AND OVERALL NEGATIVE INDICATORS (STOCK MARKETS, UNEMPLOYMENT, ETC) WHILE BULLISH SENTIMENT RATINGS WOULD MEAN THAT LANGUAGE USED IMPLIED UPWARD PRICE TRENDS, OPTIMISM, AND GROWTH



VARIABLES

03

NEWS VOLUME:

THE NUMBER OF NEWS ARTICLES *ABOUT THIS*
STOCK PUBLISHED ON A GIVEN DAY

COMPANY NEWS EXCLUDED

FINSENTS METRIC

VARIABLES

04

NEWS BUZZ:

A MEASURE OF THE RATE OF CHANGE IN
NEWS COVERAGE OF A GIVEN STOCK
ON A GIVEN DAY

NORMALIZED ON A SCALE OF 1 TO 10

MEASURES THE CHANGE IN THE STANDARD
DEVIATION OF PERIODIC NEWS VOLUME

CALCULATED BY FINSENTS

SERVES AS A 'RISK ALERT' INDICATOR

JUPYTER NOTEBOOK I

Jupyter Tuesday_newest_stock_data Last Checkpoint: a few seconds ago (unsaved changes)

File Edit View Insert Cell Kernel Widgets Help

Trusted



In [1]:

```
1 # Import dependencies
2 import pandas as pd
3 from scipy.misc import imread
4 import arrow
5 import numpy as np
6 import seaborn as sns
7 import matplotlib.pyplot as plt
8 from datetime import datetime
9 import quandl
10 quandl.ApiConfig.api_key = '*****'
```

DATA ORGANIZATION

```
1 # Make calls to the Quandl API to get the stock data for our five chosen stocks, for only the variable
2 all_stock = quandl.get_table('WIKI/PRICES', ticker=["AAPL", "AMZN", "FB", "SBUX", "TWTR"],
3                             qopts={"columns":["date", "ticker", "adj_open", "adj_close", "adj_volume"]})
4                             date = {'gte': '2018-01-01', 'lte': '2018-03-31'}, paginate=True)
```

```
5 # Rename date column to make useful for future merges
6 all_stock = all_stock.rename(columns={'date': 'Date'})
7 all_stock.head()
```

	Date	ticker	adj_open	adj_close	adj_volume
None					
0	2018-01-02	AAPL	170.16	172.26	25048048.0
1	2018-01-03	AAPL	172.53	172.23	28819653.0
2	2018-01-04	AAPL	172.54	173.03	22211345.0
3	2018-01-05	AAPL	173.44	175.00	23016177.0
4	2018-01-08	AAPL	174.35	174.35	20134092.0

```
1 # Make calls using the FinSents API wrapper (through Quandl) for our 5 chosen companies on the NASDAQ and put into sent
2 all_sent = quandl.get(['NS1/AAPL_US', 'NS1/AMZN_US', 'NS1/FB_US', 'NS1/SBUX_US', 'NS1/TWTR_US'], start_date='2018-01-0
3
4 # Reset index to make the date column usable for later merges
5 all_sent = all_sent.reset_index()
6 all_sent.head()
```

	Date	NS1/AAPL_US - Sentiment	NS1/AAPL_US - Sentiment High	NS1/AAPL_US - Sentiment Low	NS1/AAPL_US - News Volume	NS1/AAPL_US - News Buzz	NS1/AMZN_US - Sentiment	NS1/AMZN_US - Sentiment High	NS1/AMZN_US - Sentiment Low	NS1/AMZN_US - News Volume	...
0	2018-01-01	4.0	5.0	4.0	19.0	2.0	0.0	0.0	0.0	0.0	...
1	2018-01-02	4.0	5.0	3.0	49.0	3.0	0.0	0.0	0.0	0.0	...
2	2018-01-03	4.0	5.0	4.0	41.0	3.0	0.0	0.0	0.0	0.0	...
3	2018-01-04	4.0	5.0	4.0	21.0	2.0	0.0	0.0	0.0	0.0	...
4	2018-01-05	4.0	5.0	4.0	64.0	9.0	0.0	0.0	0.0	0.0	...

```
In [6]: 1 # Rename columns for readability
2 all_sent_rename = all_sent.rename(index=str, columns={"NS1/AAPL_US - Sentiment": "AAPL Sentiment",
3              "NS1/AAPL_US - News Volume": "AAPL News Volume",
4              "NS1/AAPL_US - News Buzz": "AAPL News Buzz",
5              "NS1/AMZN_US - Sentiment": "AMZN Sentiment",
6              "NS1/AMZN_US - News Volume": "AMZN News Volume",
7              "NS1/AMZN_US - News Buzz": "AMZN News Buzz",
8              "NS1/FB_US - Sentiment": "FB Sentiment",
9              "NS1/FB_US - News Volume": "FB News Volume",
10             "NS1/FB_US - News Buzz": "FB News Buzz",
11             "NS1/SBUX_US - Sentiment": "SBUX Sentiment",
12             "NS1/SBUX_US - News Volume": "SBUX News Volume",
13             "NS1/SBUX_US - News Buzz": "SBUX News Buzz",
14             "NS1/TWTR_US - Sentiment": "TWTR Sentiment",
15             "NS1/TWTR_US - News Volume": "TWTR News Volume",
16             "NS1/TWTR_US - News Buzz": "TWTR News Buzz"})
17 all_sent_rename.head()
```

Out[6]:

	Date	AAPL Sentiment	AAPL News Volume	AAPL News Buzz	AMZN Sentiment	AMZN News Volume	AMZN News Buzz	FB Sentiment	FB News Volume	FB News Buzz	SBUX Sentiment	SBUX News Volume	SBUX News Buzz	TWTR Sentiment	TWTR News Volume
0	2018-01-01	4.0	19.0	2.0	0.0	0.0	0.0	4.0	3.0	4.0	3.0	6.0	5.0	4.0	156.0
1	2018-01-02	4.0	49.0	3.0	0.0	0.0	0.0	4.0	24.0	7.0	4.0	3.0	1.0	4.0	151.0

INITIAL DATAFRAMES WERE
CREATED FROM CALLS TO
EACH API/MODULE

DATA WAS ORGANIZED AND
CLEANED

DATA ANALYSIS

```
1 #Run Additional Stats on Apple
```

```
2 model = LinearRegression().fit(Apple_merged[['AAPL_Sentiment']], Apple_merged[['adj_close']])
```

```
3 m = model.coef_[0]
```

```
4 b = model.intercept_
```

```
5 #equation of the line
```

```
6 print("Equation of the line: Y =
```

```
7 result = sm.ols(formula="adj_clc
```

```
8 print(result.params)
```

```
9 print(result.summary())
```

```
Intercept      157.245575
AAPL_Sentiment   3.644333
dtype: float64
```

OLS Regression Results

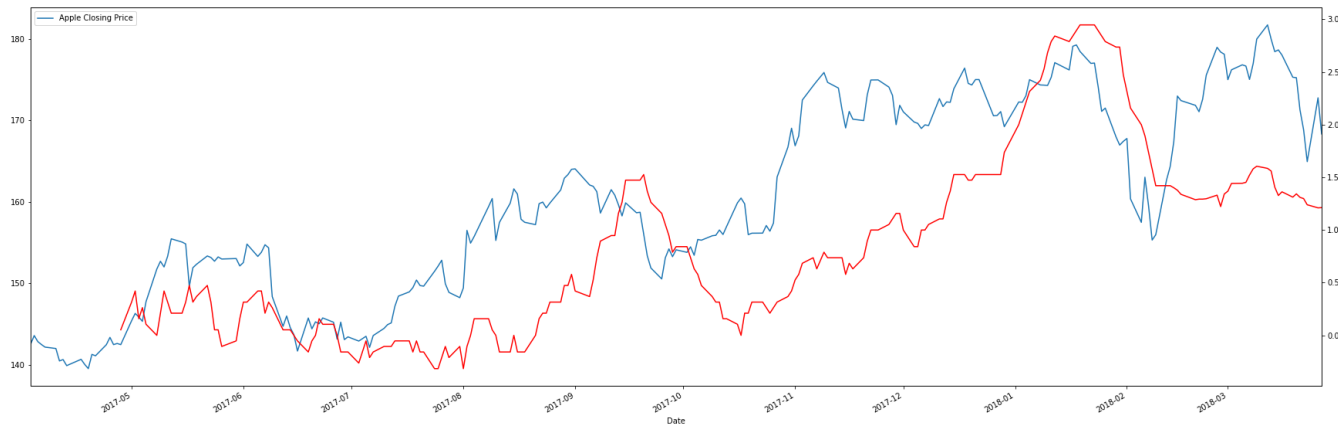
```
=====
Dep. Variable:      adj_close      R-squared:            0.228
Model:              OLS           Adj. R-squared:         0.225
Method:             Least Squares   F-statistic:         72.22
Date:               Tue, 10 Apr 2018 Prob (F-statistic):    1.93e-15
Time:               02:48:55       Log-Likelihood:      -923.17
No. Observations:   246           AIC:                  1850.
Df Residuals:       244           BIC:                  1857.
Df Model:            1
Covariance Type:    nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	157.2456	0.742	212.017	0.000	155.785	158.706
AAPL_Sentiment	3.6443	0.429	8.498	0.000	2.800	4.489

```
=====
Omnibus:            4.652      Durbin-Watson:           0.378
Prob(Omnibus):      0.098      Jarque-Bera (JB):       3.483
Skew:               -0.161     Prob(JB):               0.175
Kurtosis:           2.514      Cond. No.               2.12
=====
```

DATA ANALYSIS II

```
1 # Apple Sentiment analysis
2 fig, ax = plt.subplots()
3 ax2 = ax.twinx()
4 plt.hold(False)
5 Apple_merged["adj_close"].plot(ax=ax,kind="line",figsize=(20,10), label='Apple Closing Price')
6 Apple_merged["Rolling_mean_19"].plot(ax=ax2, style='r-', secondary_y=True, figsize=(30,10), label='Sentiment Index')
7 ax.legend(loc='best')
8 # Save the figure as png image
9 plt.savefig("apple_sent_vs.")
10 plt.show()
```



VISUALIZATION I



50

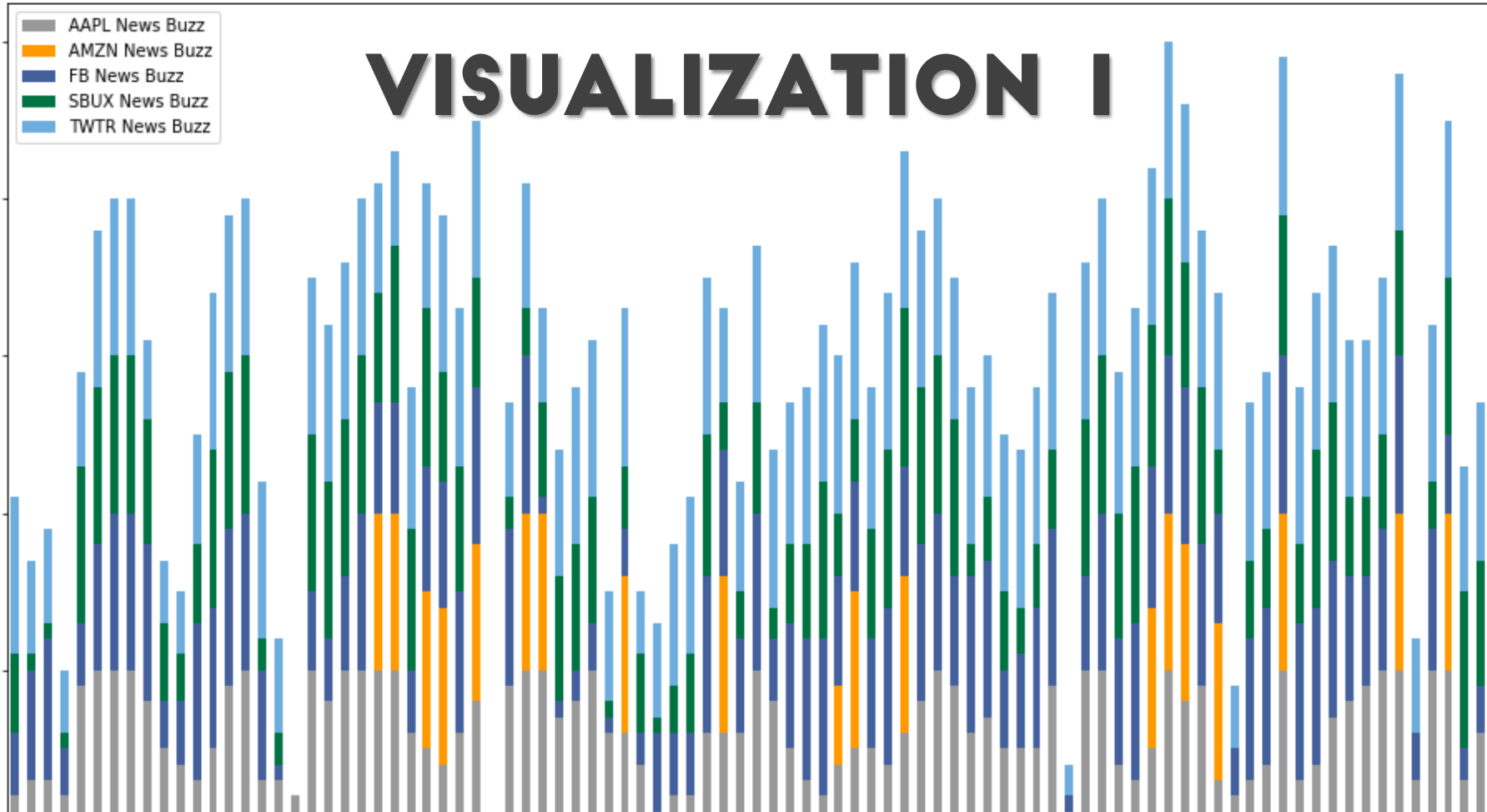
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30

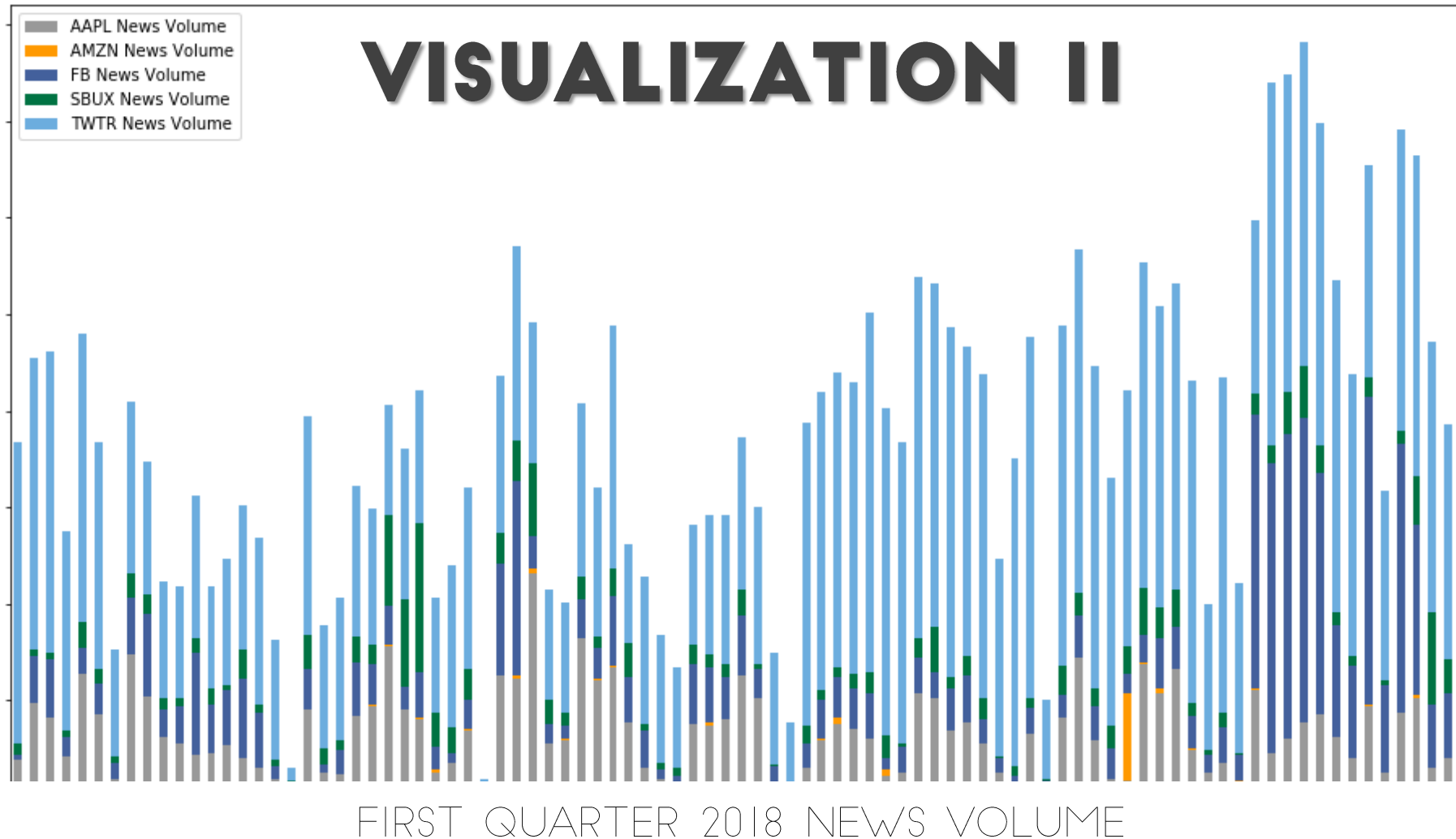
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10

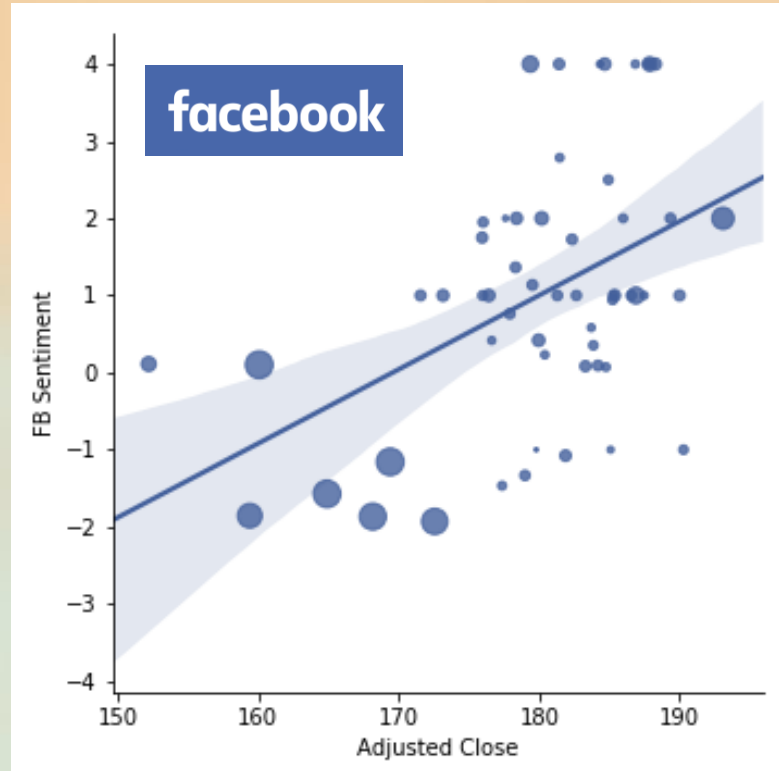
FIRST QUARTER 2018 NEWS BUZZ



VISUALIZATION II

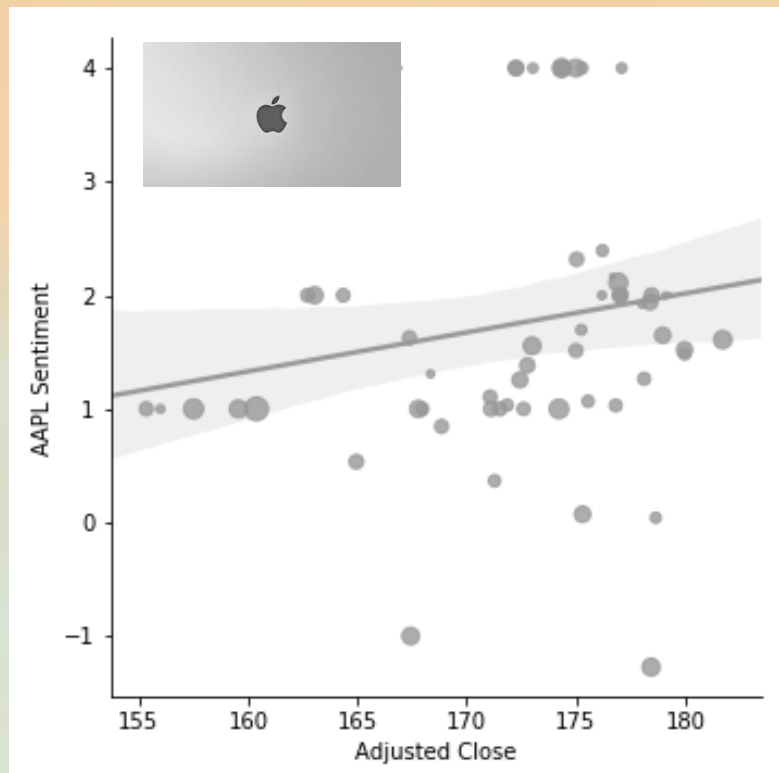


VISUALIZATIONS



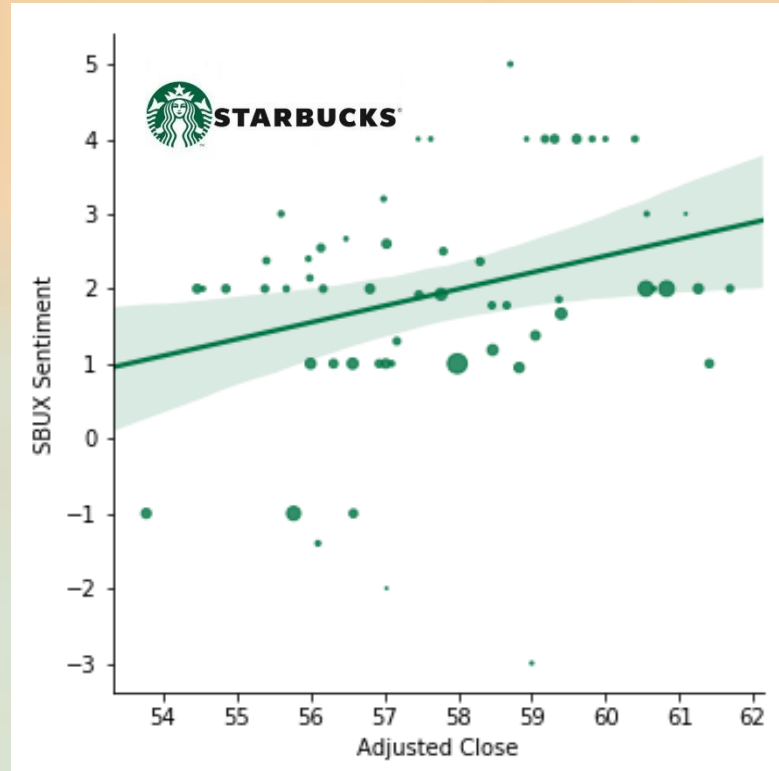
FIRST QUARTER 2018: FACEBOOK CLOSING PRICE VS STOCK SENTIMENT. AS A FUNCTION OF NEWS VOLUME

VISUALIZATIONS CONTINUED



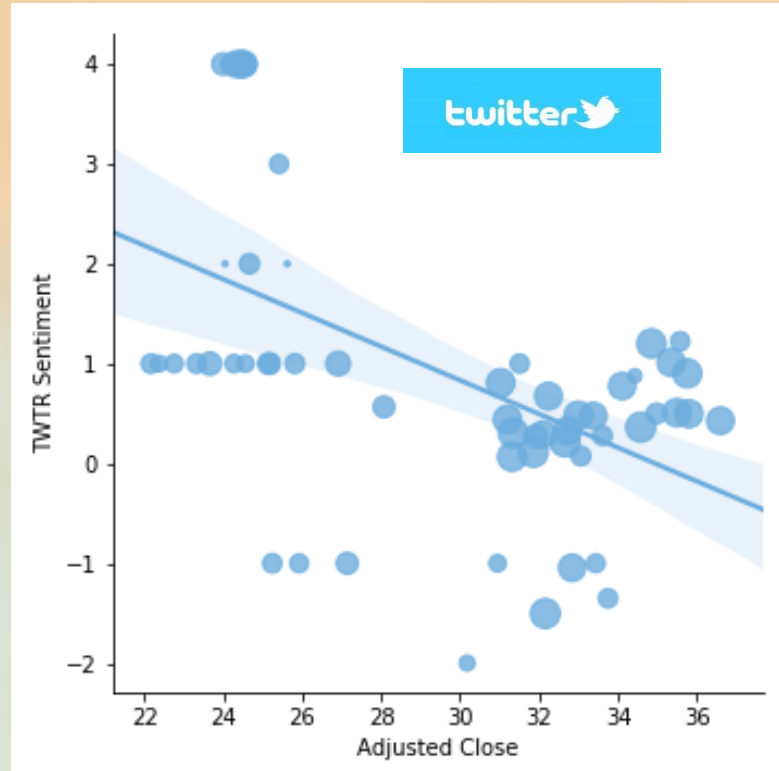
FIRST QUARTER 2018: APPLE CLOSING PRICE VS STOCK SENTIMENT.
AS A FUNCTION OF NEWS VOLUME

VISUALIZATIONS CONTINUED



FIRST QUARTER 2018: STARBUCKS CLOSING PRICE VS STOCK SENTIMENT. AS A FUNCTION OF NEWS VOLUME

VISUALIZATIONS CONTINUED



FIRST QUARTER 2018: TWITTER CLOSING PRICE VS STOCK SENTIMENT. AS A FUNCTION OF NEWS VOLUME

RESULTS

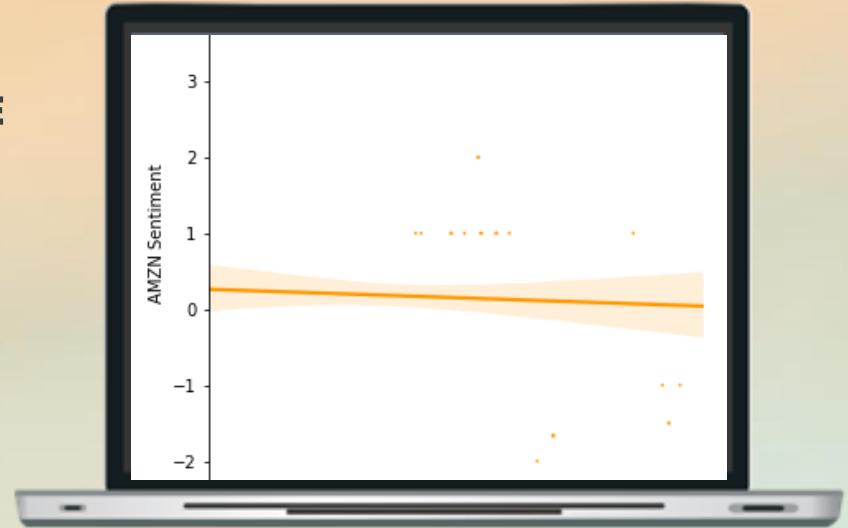
APPLE HAD THE HIGHEST R SQUARE VALUE (.23). INDICATING THE HIGHEST PREDICTIVE RELATIONSHIP BETWEEN ADJUSTED CLOSING PRICE AND MEDIA SENTIMENT

HOWEVER. OUR HYPOTHESIS IS NOT CONFIRMED BECAUSE NEWS SENTIMENT IS NOT THE BEST INDICATOR OF PRICE FLUCTUATIONS

NEWS VOLUME IN CONJUNCTION WITH SENTIMENT IS A BETTER INDICATOR. BUT MOST FLUCTUATIONS ARE DUE TO FACTORS OTHER THAN OUR CHOSEN VARIABLES

LIMITATIONS

- **TIME: OVERALL PROJECT TIME TOO SHORT**
- **SCOPE CREEP: PROJECT GREW BEFORE FINAL FOCUS WAS AGREED UPON**
- **GROUP WORK: DIFFICULT TO DIVIDE WORK EFFICIENTLY: SOME WORK DUPLICATED NEEDLESSLY**
- **SAMPLE DATA: SET TOO SMALL. DATA MISSING FOR AMAZON**
- **STATISTICS: UNDERSTANDING WAS INSUFFICIENT TO CONFIDENTLY USE STATISTICAL TOOLS**



SUGGESTIONS FOR FUTURE RESEARCH

RUN THE SAME ANALYSIS ON ADDITIONAL STOCKS. LIKE THE NASDAQ 100

LOOK INTO HOW TO COMPARE THE PREVIOUS DAY'S SENTIMENT (OR RECENT PAST SENTIMENT) WITH PRICE. AS THERE WOULD BE SOME INTRA-DAY TRADING BASED ON NEWS. BUT SAME DAY CLOSING PRICE MIGHT NOT BE THE BEST INDICATOR

RESEARCH SPECIFIC HIGH VOLUME NEWS DAYS TO EXTRACT MEANING

REFERENCES

[HTTP://FINSENTS.COM/NEWSHOME/HELP](http://finsents.com/newshome/help)

[HTTPS://DOCS.QUANDL.COM/DOCS/PYTHON](https://docs.quandl.com/docs/python)

[HTTPS://WWW.INVESTOPEDIA.COM/TERMS/M/MARKETSENTIMENT.ASP](https://www.investopedia.com/terms/m/market_sentiment.asp)

[HTTP://BLOGS.LSE.AC.UK/USAPBLOG/2017/10/14/CAN-TWITTER-SENTIMENT-PREDICT-STOCK-MARKET-BEHAVIOUR/](http://blogs.lse.ac.uk/usappblog/2017/10/14/can-twitter-sentiment-predict-stock-market-behaviour/)

QUESTIONS?

HI DZMITRY

