

PREDICTING STOCK PRICE CHANGES OF HEALTHCARE COMPANIES BASED ON NEWS HEADLINES

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DSI-23 | An NLP project





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Focus on Healthcare
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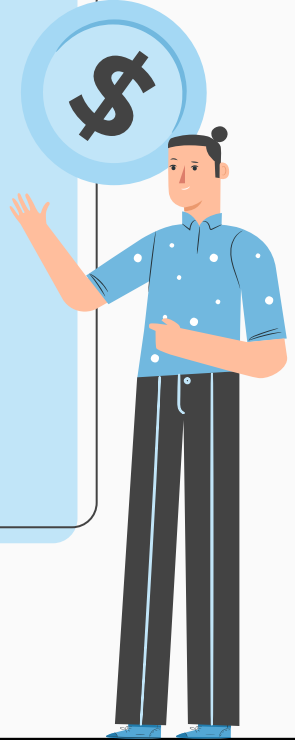
PREDICTING STOCK PRICES IS HARD...

- Technical versus fundamental analysis
- Evidence of post-news drift
- "Buy the rumor, sell the news"

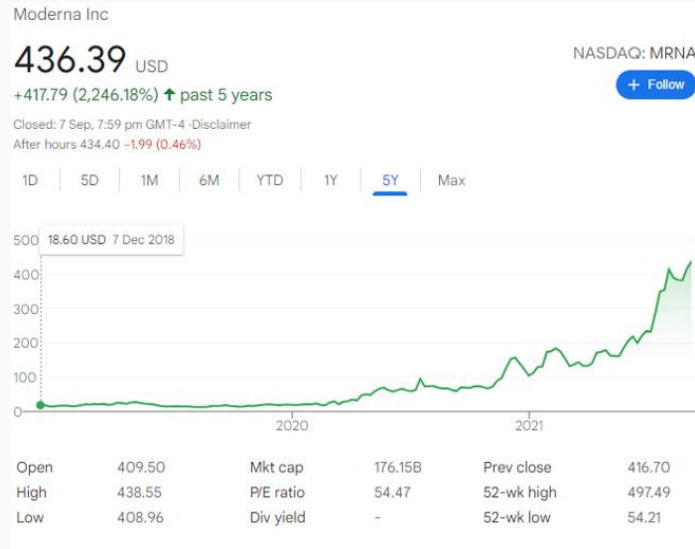


KEY QUESTIONS

1. Can news headlines be relied on to predict stock price movements?
2. Does the release of positive/negative news result in a respective increase/decrease in stock price?



FOCUS ON HEALTHCARE COMPANIES

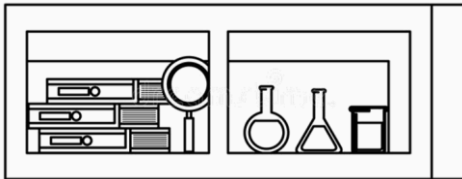


Tremendous Growth & Potential

- Development of vaccines and therapeutics highly valued by society (Moderna stock increased by > 2,000% in the last 5 years)
- Outperforming S&P500 in some instances

Knowledge Gap

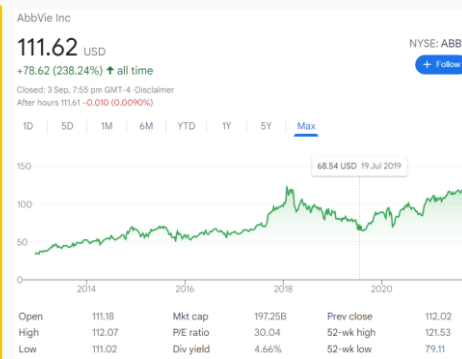
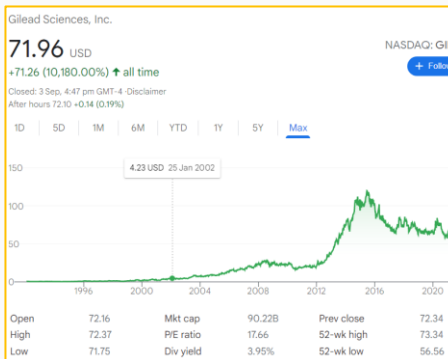
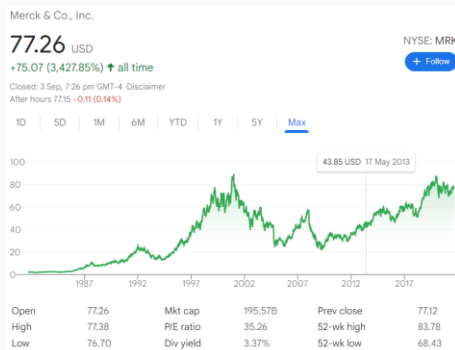
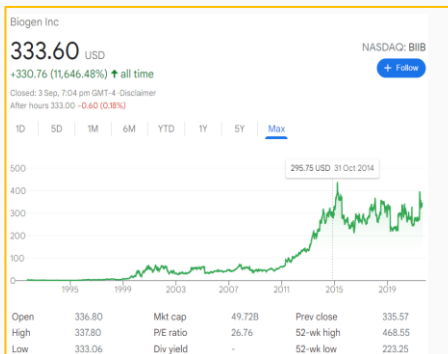
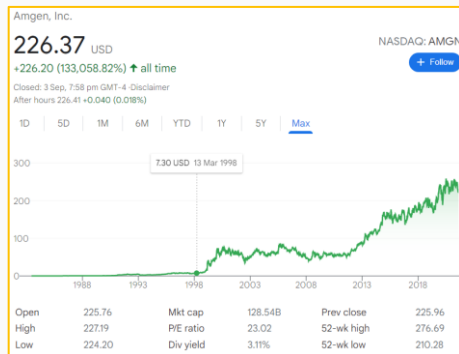
- Finance knowledge is not enough
- Understanding of drug development process, commercial implications of scientific technologies and regulatory frameworks needed





FOCUS ON HEALTHCARE COMPANIES

6 out of 8 companies in list outperformed S&P 500 (~3,616% all time increase)



PROJECT FOCUS

Using NLP/Data Science to help layperson or amateur investors learn about healthcare investing

1. NLP Project to Predict Stock Price Jumps given News Headlines

1. Use past data for prediction	ROC AUC
2. Accurate identification of price jumps on news	Accuracy
3. Precise prediction of price jumps	Precision

2. Deep dive into the headlines that are indicative of price jumps

Study feature importances

DATA



- **Date**
- News headlines



- **Date**
- Adjusted Closing Price (Dividends, Stock Splits, S&P500)
- Trading Volume

Feature	Description
Date	Date during which the stock and news information was pulled.
adjusted_abs	Absolute percentage change for the adjusted closing price of the stock with respect to the previous trading day.
adj_direction	Denote the directionality of the stock price changes.
cleaned	Daily news headlines from Reuters pertaining to the particular ticker concatenated into one single string.
headline_word	Word count of news headlines
dict_score	Score to denote the news sentiment for healthcare domain. Negative values are assigned to bad news (e.g. failed trial) and positive values are assigned to good news (e.g. fda approval).
target_var	Classification label: 1 denotes when stock prices changed by more than 1.31% (P75), 0 for otherwise.

WORKFLOW

Data Cleaning

- Removal of outliers
- Text cleaning – define new stopwords, removal of stopwords, lemmatization

Feature Engg & EDA

- Word Count for News Headlines
- Polarity Scores
- Vectorization – Count & Tf-idf

Choice of Model

- Using PyCaret to compare models
- Choose model based on precision, accuracy & AUC ROC scores

Model Tuning & Evaluation

- GridSearchCV
- Confusion Matrix, AUC ROC Curve



TEXT CLEANING - AMENDING THE LIST OF STOPWORDS

#add words that aren't in the NLTK stopwords list

```
new_stopwords = ['reuters', 'country', 'population', 'government', 'united', 'states', 'company', 'economy',  
                 "said", 'say', 'inc', 'data', 'business', 'one', 'two', 'three', 'four', 'five',  
                 'january', 'february', 'march', 'april', 'may', 'june', 'july', 'august', 'nyse',  
                 'september', 'october', 'november', 'december', 'weekly', 'monthly', 'quarter', 'year',  
                 'abbvie', 'pfizer', 'gilead', 'merck', 'eli', 'lilly', 'amgen', 'biogen', 'regeneron',  
                 'bristol', 'myers', 'squibb', 'nasdaq', 'new', 'york', 'exchange', 'earning', 'price',  
                 'medicine', 'healthcare', 'dow', 'jones', 'index', 'dji', 'investor', 'percent', 'market',  
                 'drug', 'share', 'health', 'biotech', 'per', 'cent', 'co', 'sp']
```

```
new_stopwords_list = stop_words.union(new_stopwords)
```

#remove words that are in NLTK stopwords list

```
not_stopwords = {'no', 'not', 'up', 'further', 'above', 'down', 'under', 'over', 'through', 'off', 'below'}  
final_stop_words = set([word for word in new_stopwords_list if word not in not_stopwords])
```

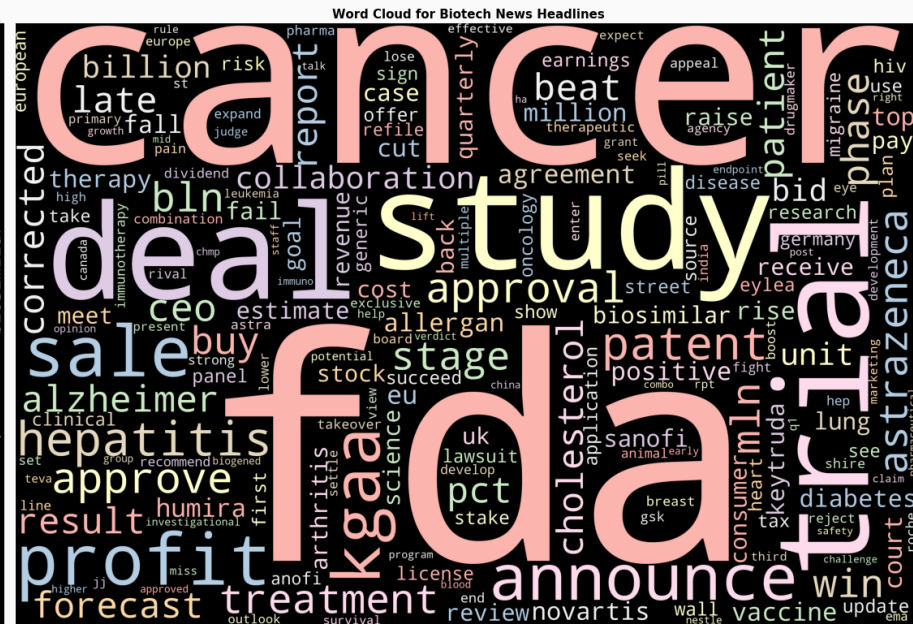
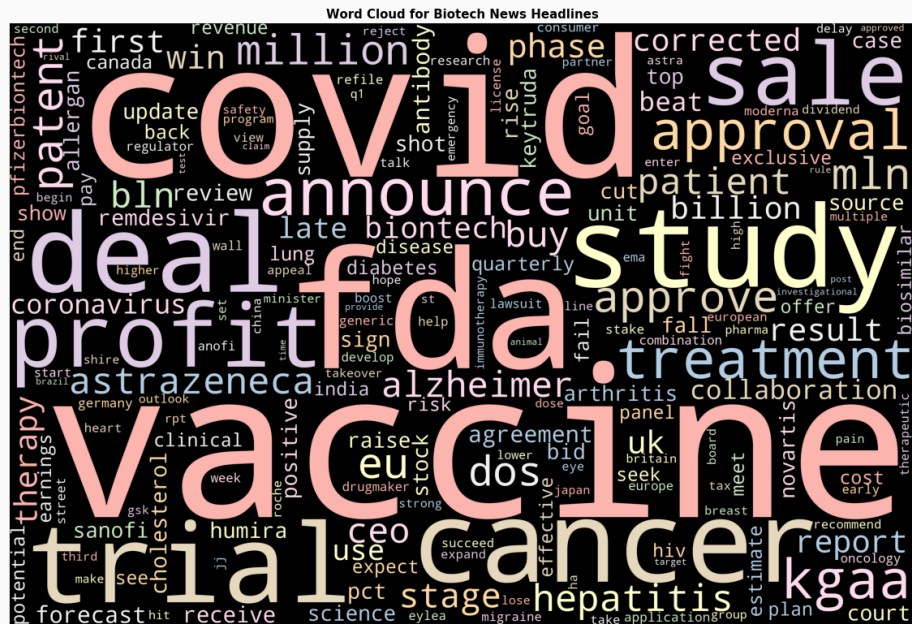
REMOVAL OF OUTLIERS BY YEAR (COVID ADJUSTMENT)

BEFORE: 2012 to 2021

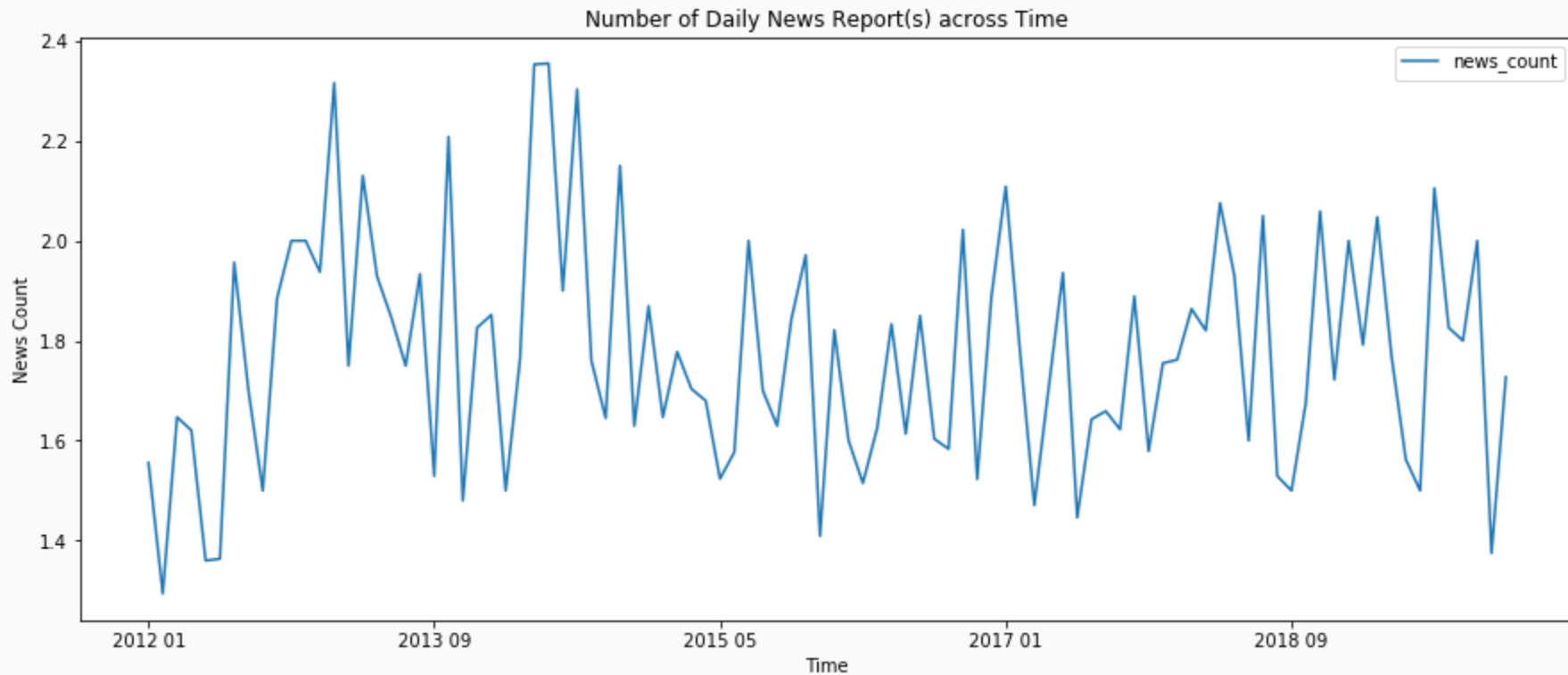
About a decade's worth of news heavily biased
due to high frequency reporting on recent
COVID-19 developments

BEFORE: 2012 to 2019

Remove news headlines dated to 2020 and 2021 to avoid having too much noise regarding COVID/vaccination situation



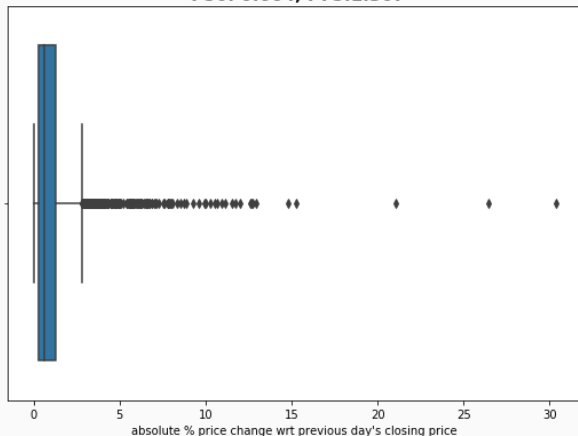
REMOVAL OF OUTLIERS - NUMBER OF NEWS > P99*



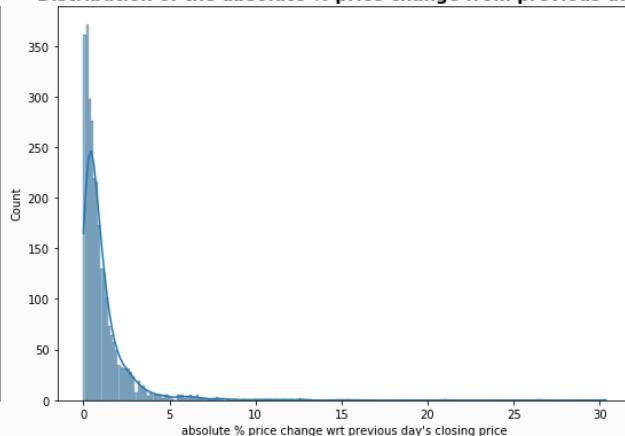
* Days with number of news report > P99 (i.e. 7) for a particular company are also removed

DISTRIBUTION OF WORD COUNT AND PRICE CHANGE VARIABLES

IQR of the absolute % price change from previous day;
P50: 0.664, P75:1.307



Distribution of the absolute % price change from previous days



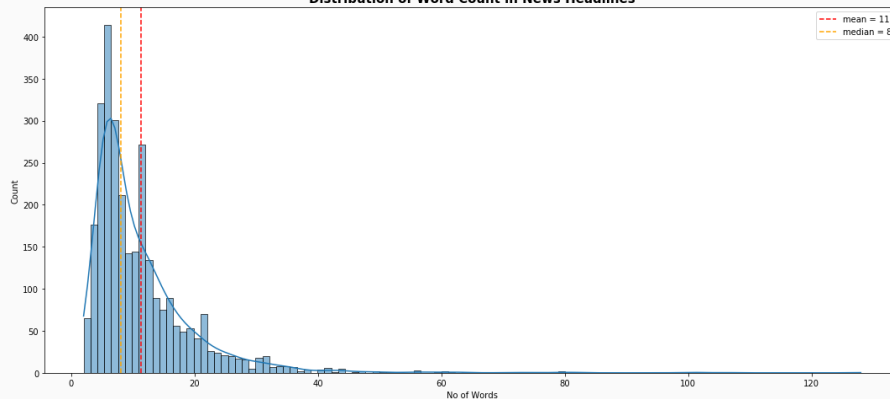
% Price Change

- Right skewed distribution with a long tail
- **P75** to be referenced as **threshold** of 'price jump' for target variable

Word Count

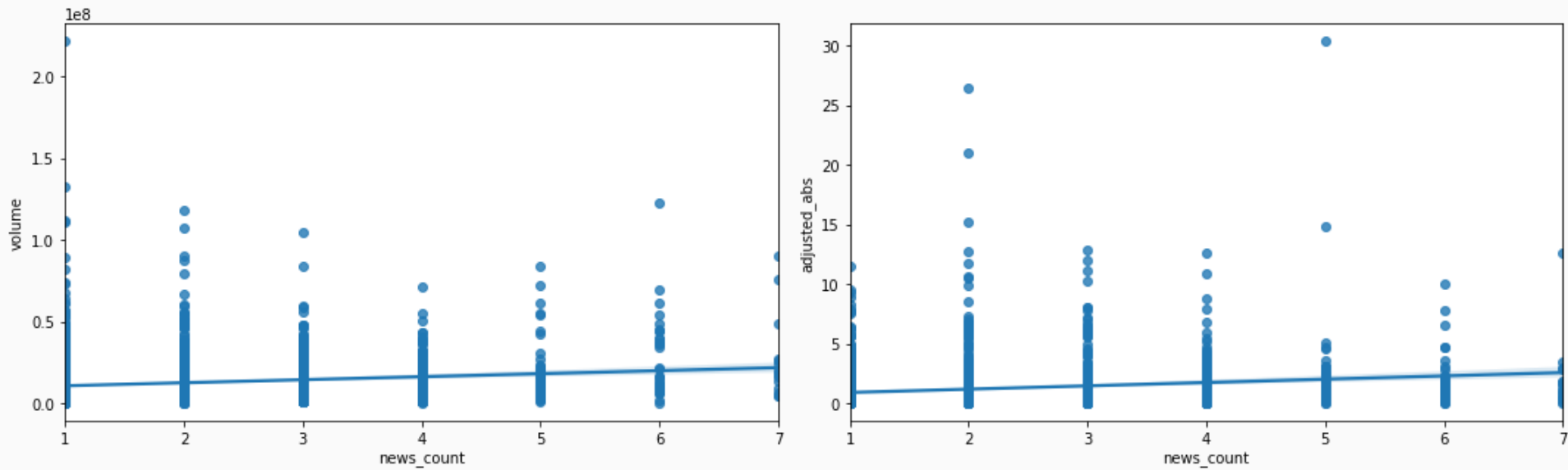
- Right skewed distribution with a long tail
- Mean = 11, median = 8 words; question of sufficiency of text info for NLP analysis

Distribution of Word Count in News Headlines



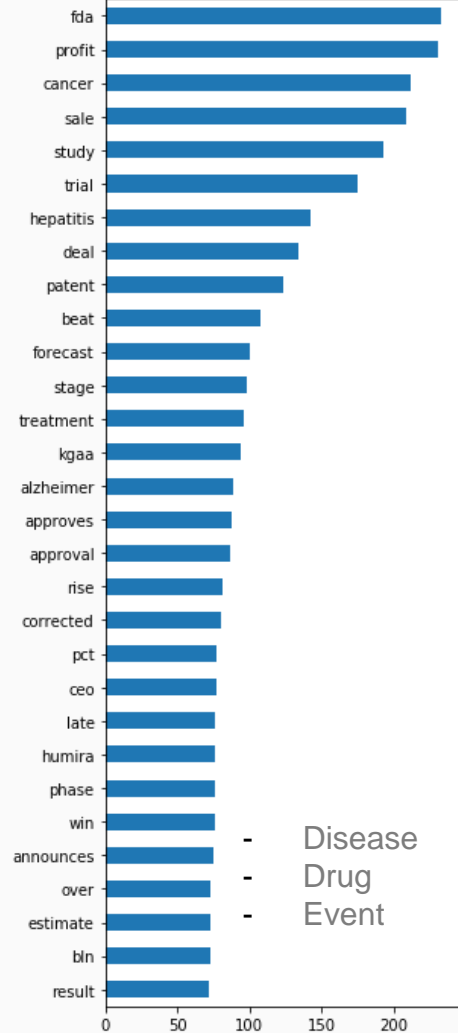
MORE NEWS REPORT SEEM MILDLY ASSOCIATED WITH HIGHER TRADING VOLUME AND STOCK PRICE CHANGES

Plots showing how News Count correlates with Trading Volume and Stock Price Changes

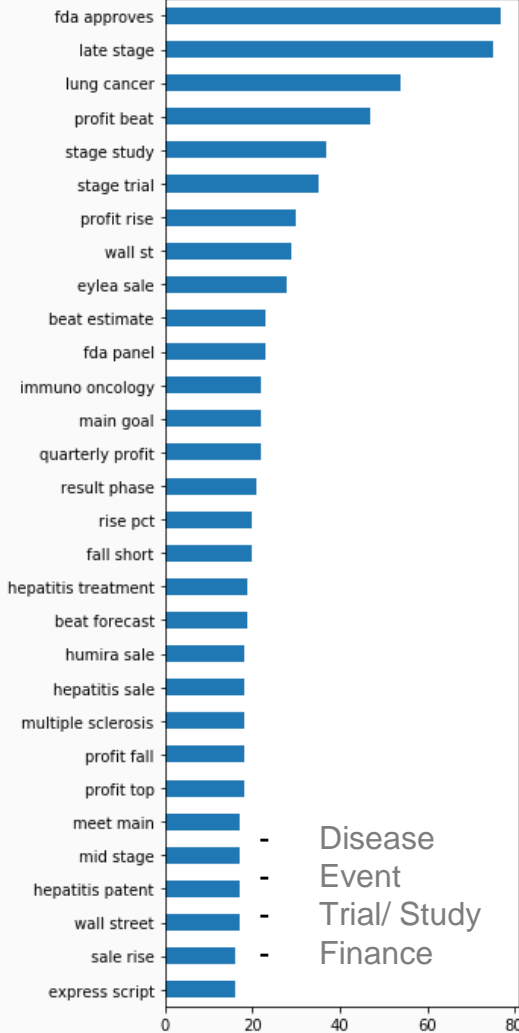


ALL HEADLINES

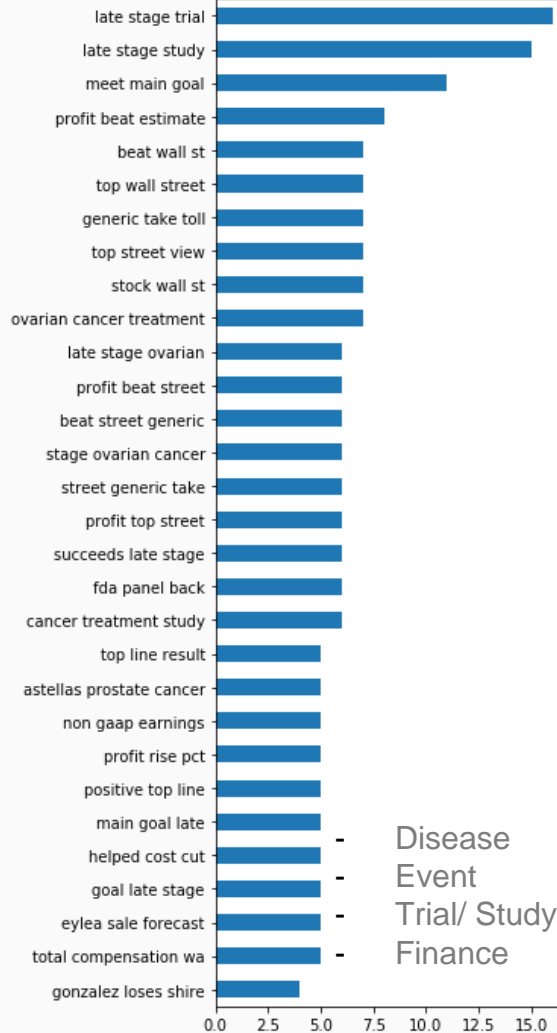
Most Common Words in News Reported



Most Common Words in News Reported

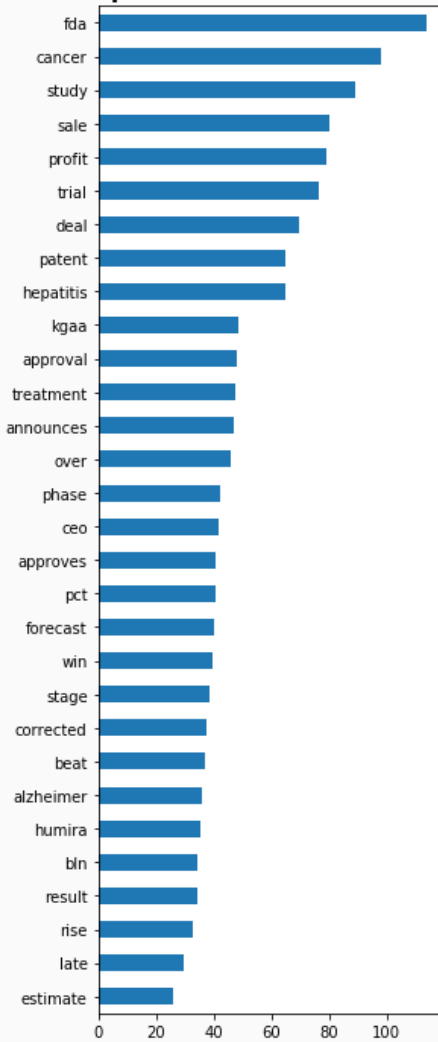


Most Common Words in News Reported

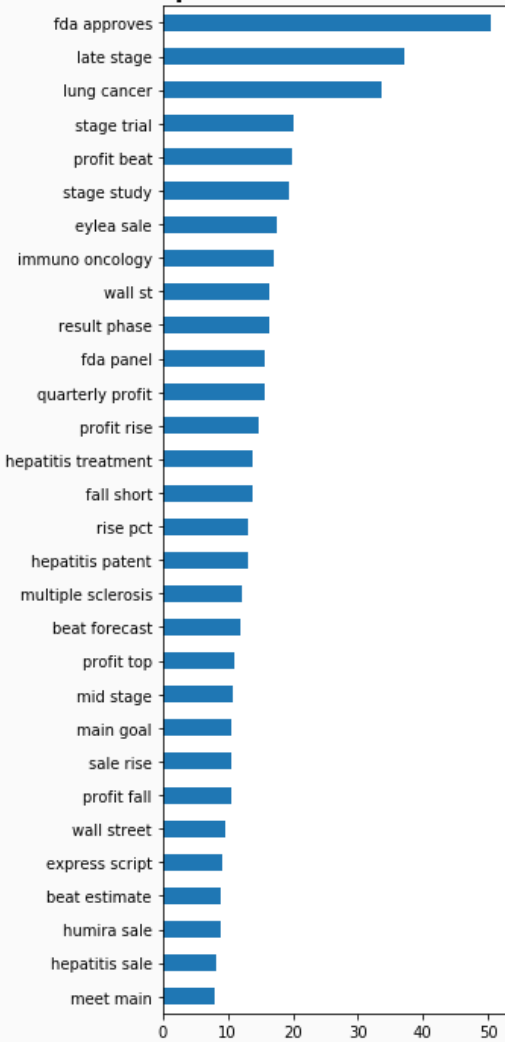


ALL HEADLINES

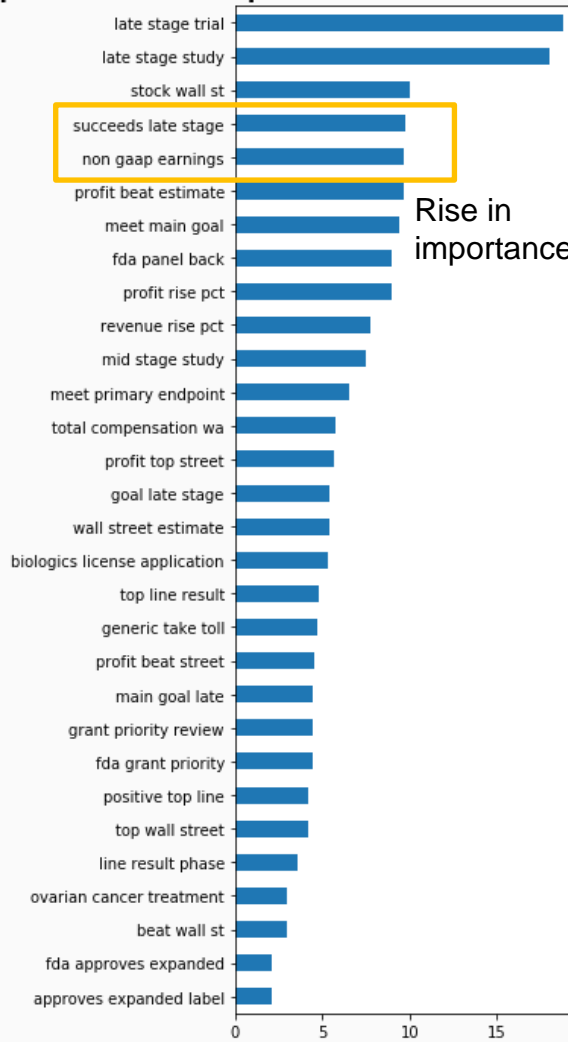
Most Important Words in News Reported



Most Important Words in News Reported

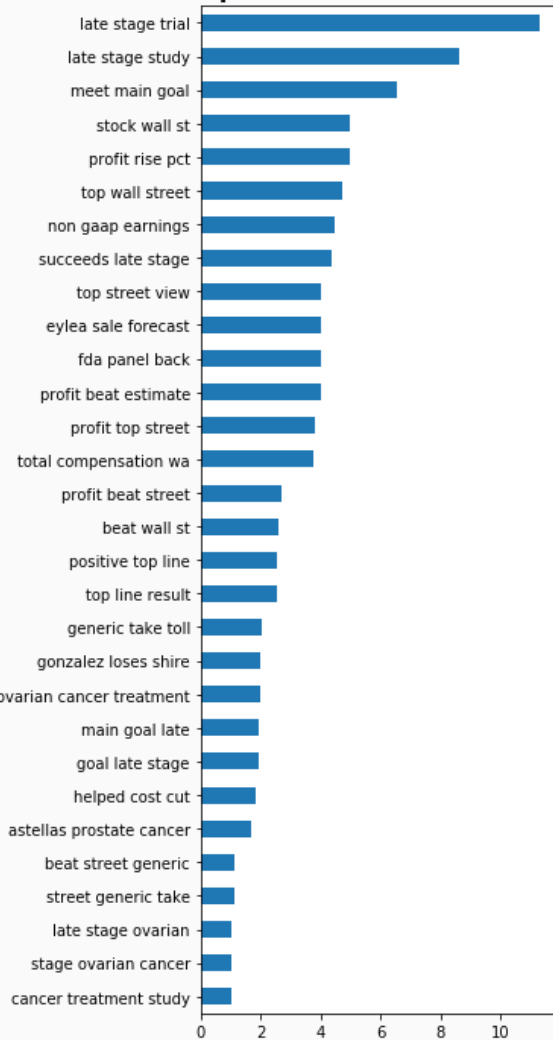


Most Important Words in News Reported



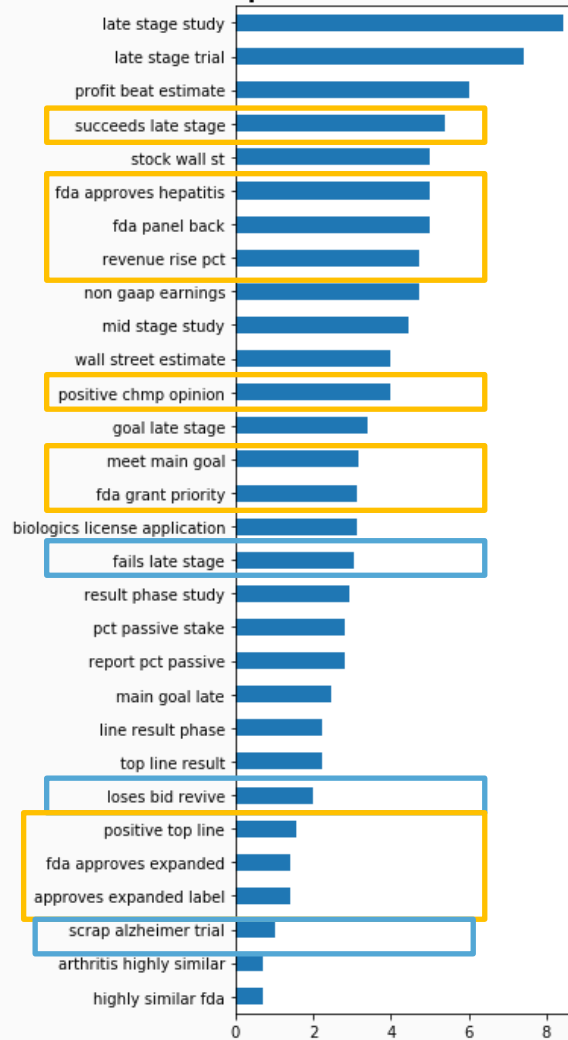
HEADLINES ASSOCIATED WITH PRICE INCREASE

Most Important Words in News Reported



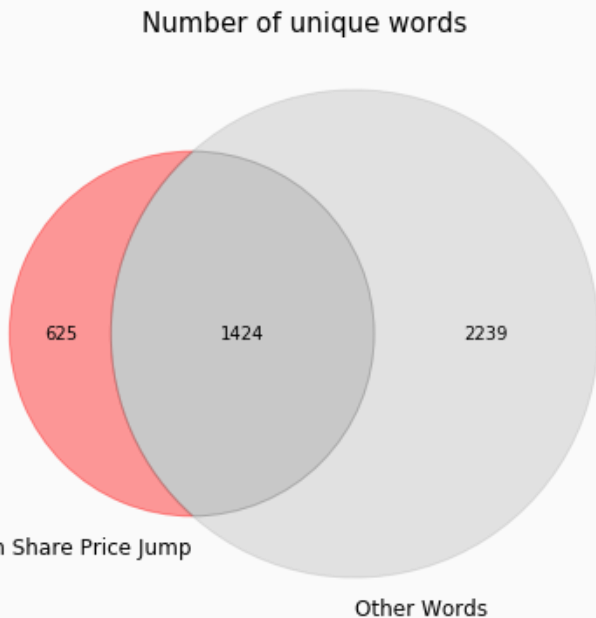
HEADLINES ASSOCIATED WITH PRICE DECREASE

Most Important Words in News Reported



Headlines associated with stock price decrease are a **mixed bag** of positive and negative events

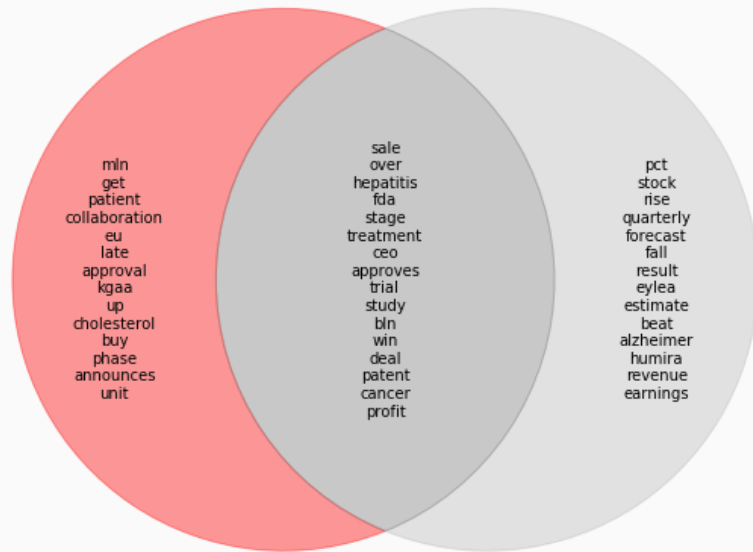
FEWER UNIQUE WORDS ARE ASSOCIATED WITH SHARE PRICE JUMP, BUT THERE ARE NO DISCERNABLE PATTERNS OR WORDS THAT SEEM INDICATIVE OF SHARE PRICE JUMP



Words Associated with Share Price Jump

Other Words

Top 30 words

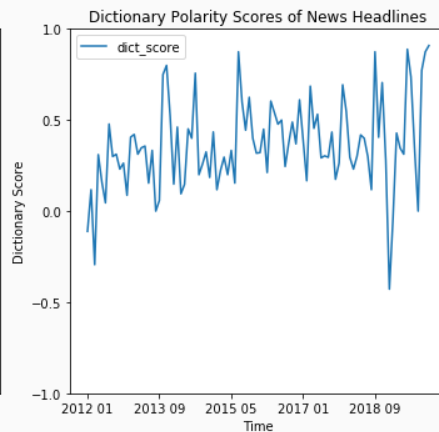
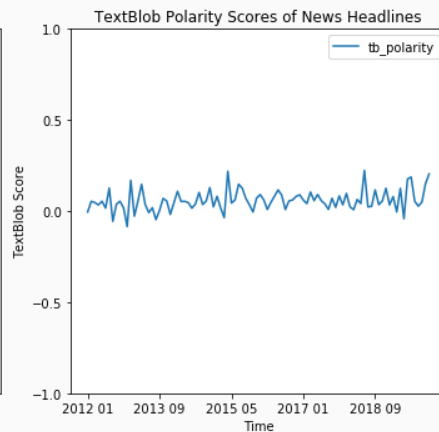
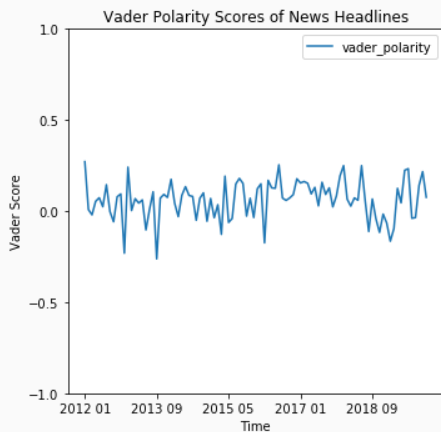
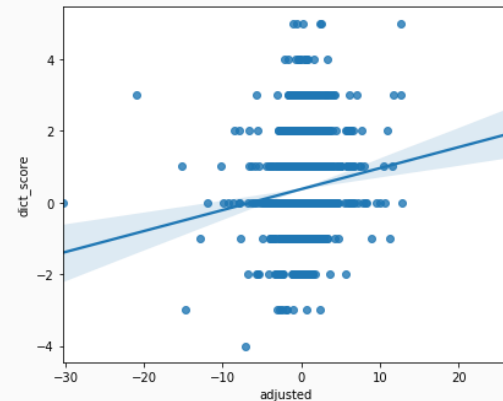
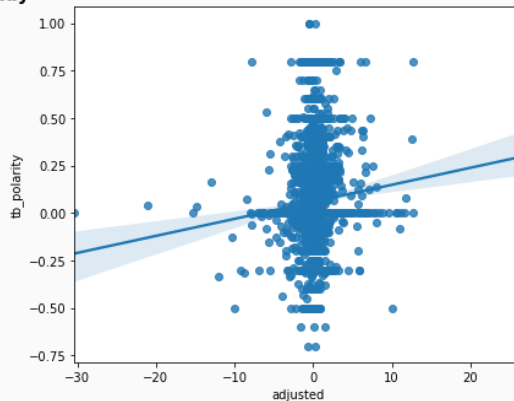
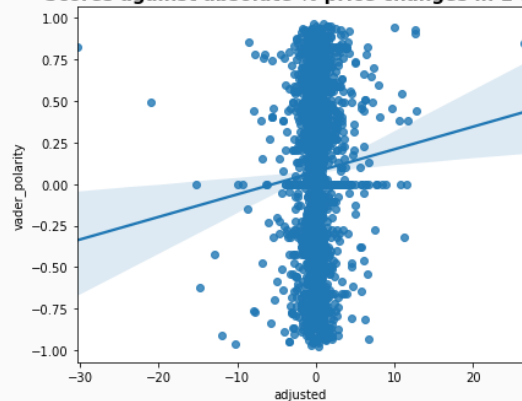


Words Associated with Share Price Shock

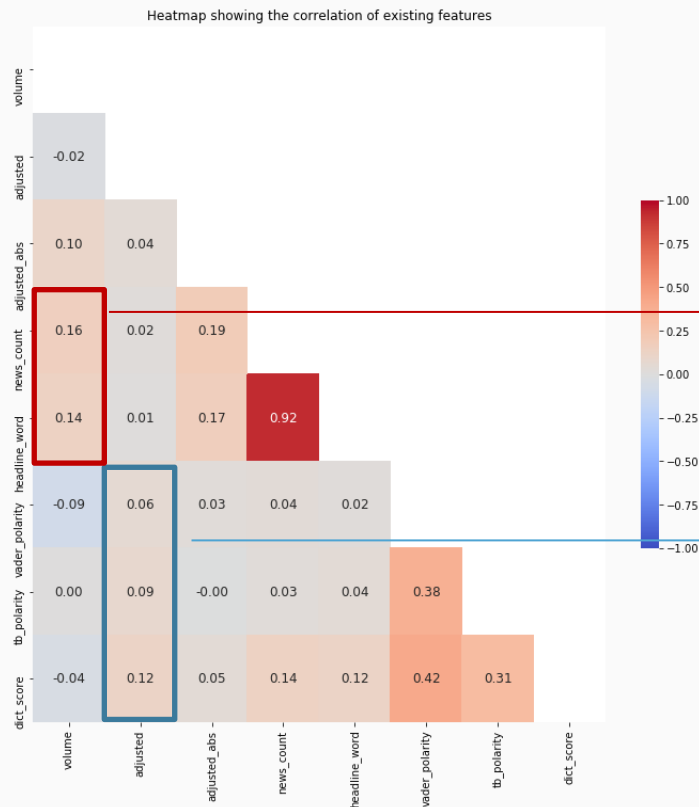
Other Words

SCATTER PLOT OF SENTIMENT SCORES SUGGEST EXISTING LIBRARIES/FUNCTIONS (E.G. VADER & TEXTBLOB) ARE NOT EFFECTIVE AT DIFFERENTIATING NEWS HEADLINES

Scores against absolute % price changes in 1 day



WEAK POSITIVE CORRELATION BETWEEN NEWS AND TRADING VOLUME, AND DICTIONARY SCORE AND ADJUSTED STOCK PRICE CHANGES IN %



Higher news count weakly & positively correlated with higher trading volumes

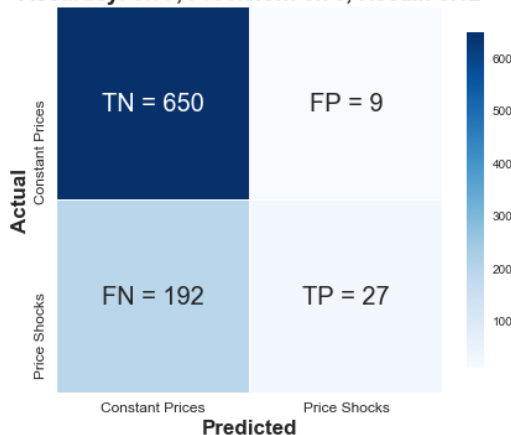
The manually determined dictionary score shows a higher correlation with the percentage change in stock prices than the vader and TextBlob polarity scores

MODEL SELECTION BASED ON RESULTS ARISING FROM PYCARET'S MODEL COMPARISON FUNCTION

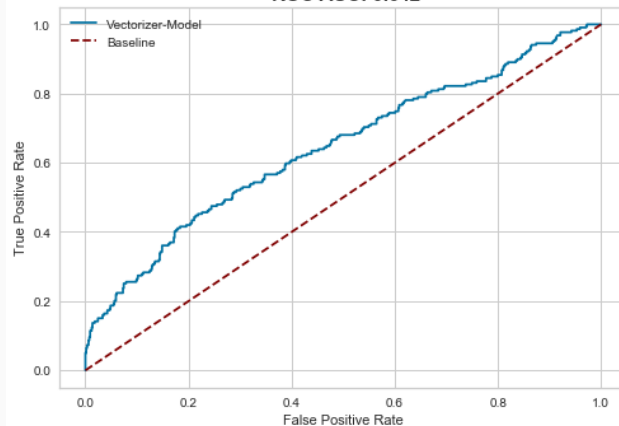
S/N	Model	Vectorizer	N-Gram	Accuracy	AUC	Recall	Precision	F1
1	Light Gradient Boosting Machine	Count	1-gram	0.764	0.625	0.248	0.549	0.339
2	Logistic Regression	Count	1-gram	0.764	0.651	0.307	0.529	0.386
3	Gradient Boosting Classifier	Count	2-gram	0.747	0.560	0.068	0.663	0.120
4	Logistic Regression	Count	2-gram	0.745	0.594	0.165	0.516	0.247
5	Gradient Boosting Classifier	Count	3-gram	0.749	0.522	0.046	0.496	0.084
6	Logistic Regression	Count	3-gram	0.747	0.538	0.060	0.493	0.106
7	Logistic Regression	Tf-idf	1-gram	0.758	0.654	0.117	0.672	0.199
8	K Neighbors Classifier	Tf-idf	1-gram	0.748	0.568	0.114	0.577	0.187
9	Logistic Regression	Tf-idf	2-gram	0.766	0.600	0.043	0.636	0.079
10	Gradient Boosting Classifier	Tf-idf	2-gram	0.764	0.600	0.080	0.524	0.135
11	Logistic Regression	Tf-idf	3-gram	0.748	0.570	0.006	0.150	0.011
12	Ada Boosting Classifier	Tf-idf	3-gram	0.748	0.533	0.066	0.511	0.116

RESULTS OF A ONE-GRAM TD-IDF LOGISTIC REGRESSION

Confusion Matrix for Logistic Regression Model (TF-IDF)
Accuracy: 0.77, Precision: 0.75, Recall: 0.12



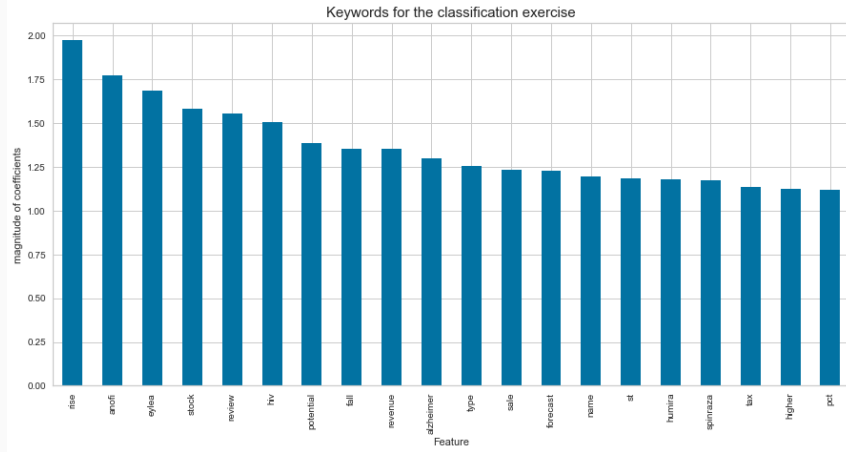
Receiver Operating Characteristic Curve of
Tfidf Vectorizer-Logistic Regression
ROC AUC: 0.642



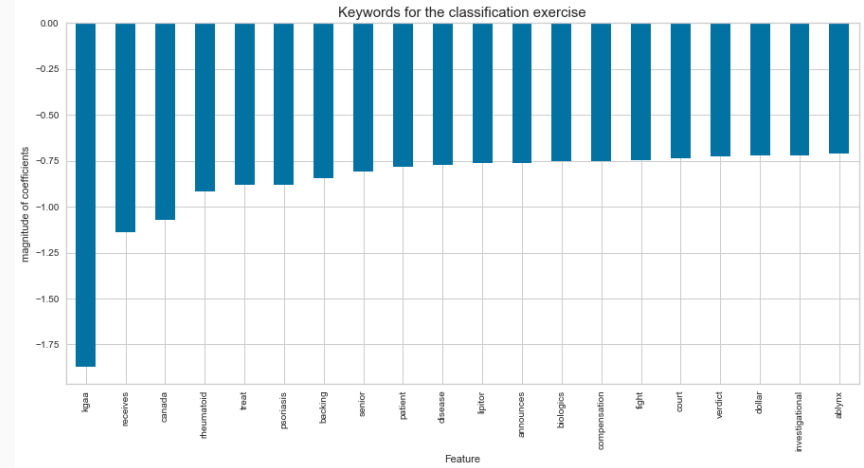
The model has an accuracy score of 0.77, a ROC AUC score of 0.642 and a 0.75 precision score. While the precision score is high, it is obtained at the expense of a lower recall score of 0.12. The **model will be relatively good at predicting when a news headline would likely be a price jumper. However, the model may misclassify other news which are 'price jumper' as 'non-price jumper'.** This may lead to traders missing out on a significant news events that would affect stock prices significantly.

FEATURE IMPORTANCES – SINGLE WORD

Words, e.g. **'rise'**, **'stock'**, **'hiv'**, **'potential'**, **'fall'**, are predictive of stock price jumps

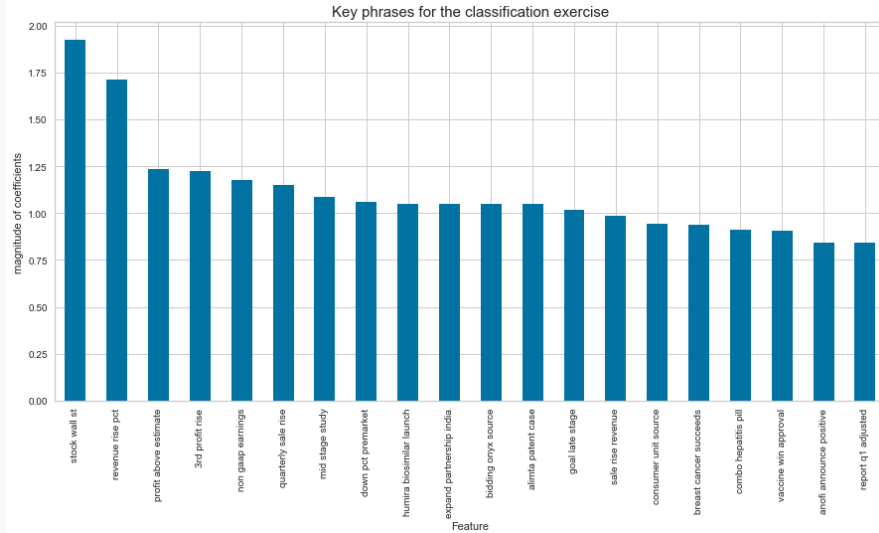


Words, e.g. **'kgaa'**, **'receives'**, **'canada'**, **'rheumatoid'**, are associated with constant stock prices

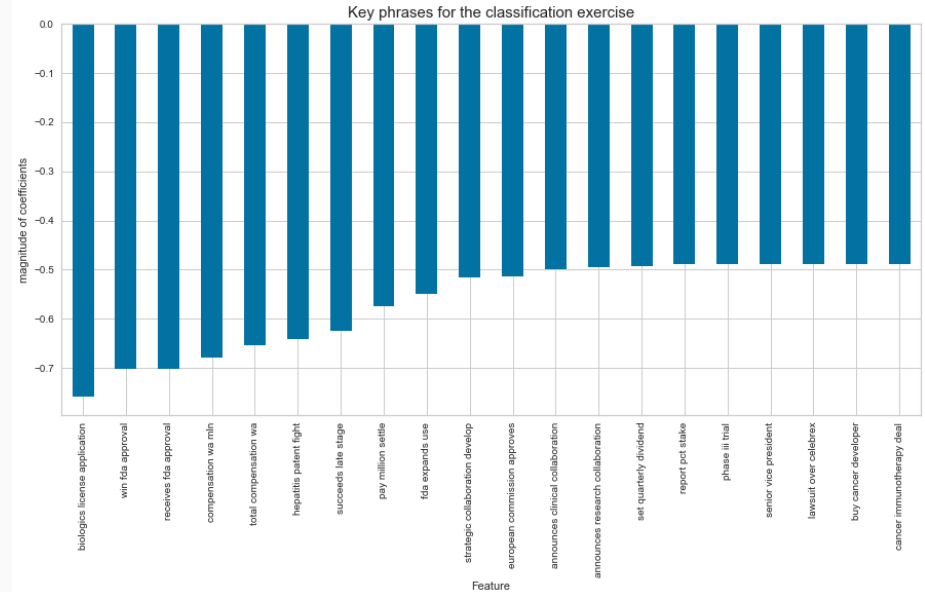


FEATURE IMPORTANCES – THREE-WORD PHRASES

Phrases, e.g. ‘**revenue rise pct**’, ‘**profit above estimate**’, ‘**quarterly sale rise**’, ‘**mid stage study**’, are predictive of stock price jumps

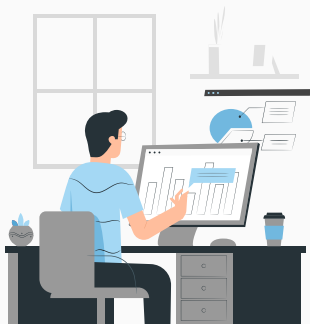


Phrases, e.g. ‘**win fda approval**’, ‘**receives fda approval**’, ‘**succeed late stage**’, are associated with constant stock prices



CONCLUSION & RECOMMENDATIONS

1. **News headlines can be used to predict changes to stock prices.** The tf-idf logistic regression model is able to achieve $> 70\%$ accuracy and precision scores, and $> 60\%$ AUC ROC scores.
2. **The release of positive/ negative news may not necessarily lead to a jump in stock prices.** From this modelling experience, we learn that the announcement of significant milestones (such as FDA approval) may not lead to significant stock price changes.



Considerations for Future Project(s):

- a. Aggregate news headlines from more sources (e.g. Financial Times, Seeking Alpha) for analysis
- b. Study how the long-form news articles affect stock prices
- c. Aggregate news headlines for more healthcare, pharmaceutical or biotech companies for analysis

THANK YOU

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