NATIONAL RESEARCH
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National Research University Higher School of Economics
Faculty of Computer Science
Master’s Programme ‘System and Software Engineering’

Stock Price Trend Forecasting Using News Analysis based on Deep Learning Methods

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INTRODUCTION

- Trading is the process of buying and selling of financial instruments
- Stock market prediction is the act of trying to determine the future value of a company stock or other financial instrument traded on an exchange. The successful prediction of a stock's future price could yield significant profit
- The stock (also capital stock) of a corporation constitutes the equity stake of its owners. It represents the residual assets of the company that would be due to stockholders after discharge of all senior claims such as secured and unsecured debt.
- Stock market one of the most important sources for companies to raise money
- Mittermayer and Knolmayer (2006) note that press releases "have far more impact onstock prices than other news"[3]
- Prediction of stock markets—challenging task.Because, its randomness in nature.
- financial news articles have a strong relationship with stock market fluctuation, therefore analyzing financial news reports can help in predicting the stock market movements [1]
- Numerous researches shows strong correlation between stock price and financial news [2][4]

  Financial news conveys novel information to broad market participants and a fast reaction to the release of new information is an impor-tant component of trading strategies[8]

Motivation

"We try to stick to businesses we believe we understand. That means they must be relatively simple and stable in character. If a business is complex and subject to constant change, we're not smart enough to predict future cash flows." Value Investing: From Graham to Buffett and Beyond

Stock market consists of different parties[5]

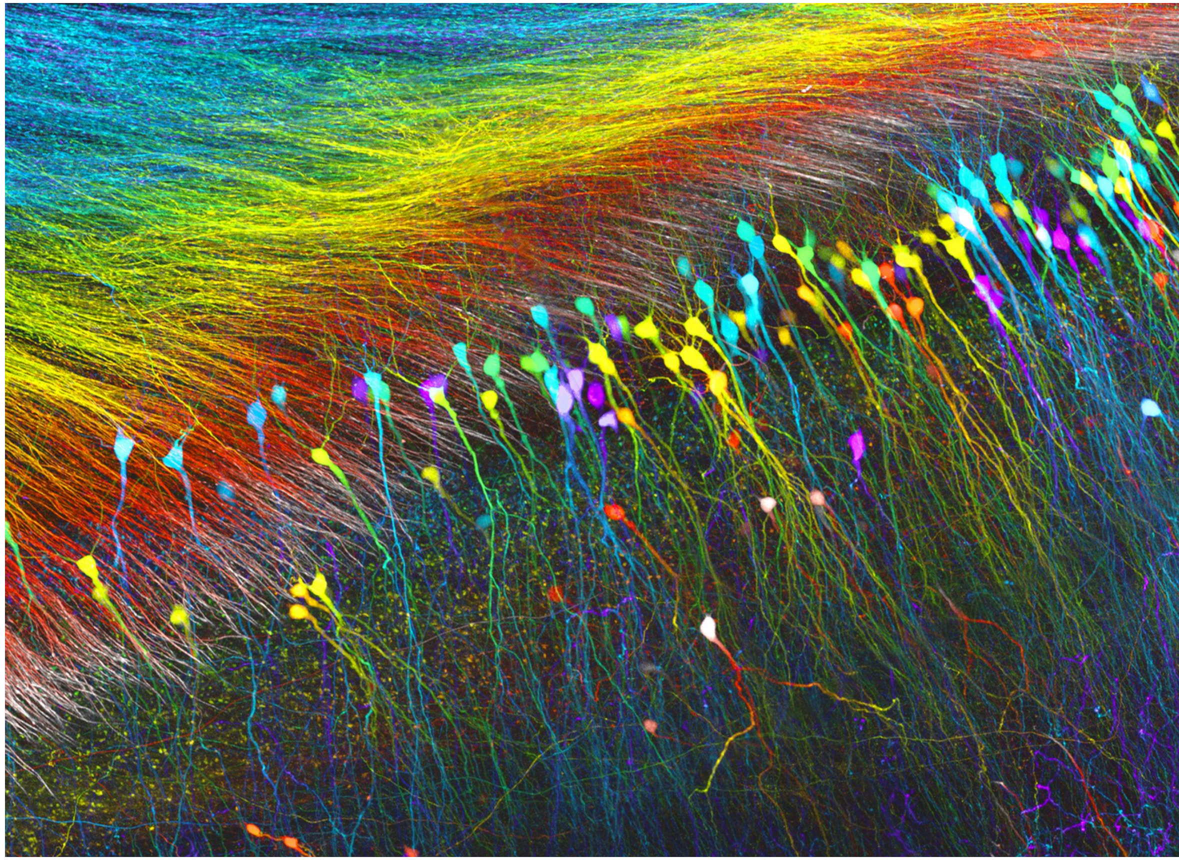
Broker-Dealers **Clearing Agencies** **Credit Rating Agencies**

ECNs/ATSs **Investment Advisers** **Securities Exchanges**

Self-Regulatory Organizations (SROs) **Transfer Agents**

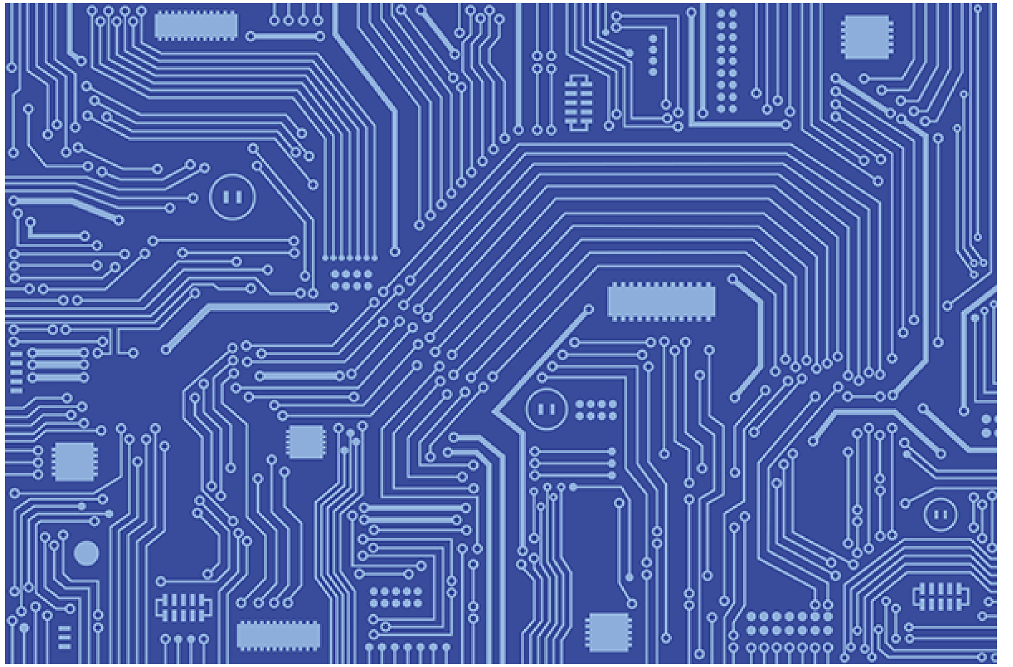
Goals

1. Create several hybrid deep learning models
    - Create baseline models
    - Search for the best parameters for neural network
2. Check the hypothesis:
    - Model using several variables, including sentiment based on news, gives more accurate predictions than a model that does not use only stock price data
    - Check efficient market hypothesis
3. Base predictions not less than 5 different stocks
4. Use at least two different approaches for neural networks
5. Build at least 1 baseline model
6. Use at least 3 metrics for calculating accuracy
7. Get accuracy not less than 90% or MAPE: 10.0



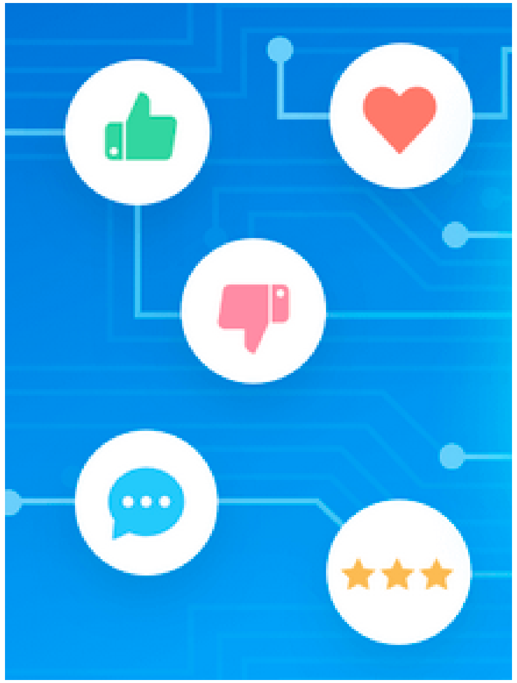
Why deep learning?

- better accuracy[6]
- Handles nonlinear timeseries problems better than econometric models[7]
- ignore a lot of implicit information developing overtime
- Much better at grasping patterns [11-13]
- Can collect and effectively use all previous behavior of specific stock[11-13]
- Novel and promising area of research[9]
- missing values less affect the performance of the models
- Work better with long-term forecasts[16]



Why sentiment analysis?

Sentiment analysis uses text mining, natural language processing, and computational techniques to automatically extract sentiments from a text[10]



- Providing supportive information, such as future markets direction
- Hybrid approach of sentiment analysis + neural networks gives new thoughts and results
- ignore a lot of implicit information developing overtime
- Such models can help traders to make better decisions
- Sorting Data at Scale
- Helps with insights vacuum problem[14]

Limitations of created solutions

- Deep learning techniques is not a holy grail[17]
- Sentiment retrieved on headlines does not count importance of news, which is subjective
- Also it does not classify the news (by default financial news sticked to stock)
- Also there is no "true" semantic analysis
- Market is a living thing
- More factors influence stock price
- "Ideal" formula not exists
- People are irrational

Model choice

Table 1. Models comparison

	RNN	LSTM	GRU	MLP	Attention Mechanism	ARIMA
Strength	1. not significantly affected from missing values 2. Can find complex patterns in the input time series 3. give good results in forecasting more then few-steps 4. can model sequence of data with dependence on previous values	1. Solves vanishing gradient problem 2. Great with sequence data 3. Can handle noise 4. Does not need as much a parameter tuning as other models 5. Good at generalizing 6. Computationally cheaper	1. Computationally cheaper 2. Require less training data 3. Easy to modify	1. Easy to setup and train 2. Can use explicitly statistical approaches 3. Gives easy to interpret results 4. Have fully connected layers	1. good results on long-term data 2. Can give more interpretable results	1. Great on short and medium term forecasts 2. Less sensitive to the underlying assumptions of the nature of the data fluctuations 3. can forecast small ups and downs much better than regression 4.Great with time series problems (handling temporal effects)
Weakness	1. exploding gradient problem 2. unable to take into account several elements of the past 3. computationally expensive	1. require more memory to train 2. easy to overfit 3. sensitive to different random weight initializations	1. Weaker memory, than LSTM 2. slow convergence 3. Low learning efficiency	1. Can lead to dramatical growth of dimensions 2. Computationally expensive 3. Cannot handle missing values 4. Weak at long-term forcasts	1. Adding more parameters 2. Computationally expensive 3. difficult to incorporate as a component 4. Performance degrades with increasing of data	1. Computationally expensive 2. Require more data 3. Can be unstable

MLP, Multi layer perceptron; LSTM, long-short term memory; GRU,gated recurrent units; ARIMA, autoregressive integrated moving average; WE, RNN, recurrent neural network

Relevant studies on time series forecasting, model comparison

Table 2. LSTM and ARIMA relevant studies

Model architecture	Year	Outperforming	Application	Reference
LSTM	1. 2015 2. 2015 3. 2018 4. 2018 5. 2019	1. MLP, NARX, SVM 2. MLP, Autoencoders 3. Linear regression, kNN,RF, MLP 4. Logistic regression,MLP, RF 5. ARIMA, ERNN, GRU	1. raffic speed 2. Traffic flow 3. Electric load 4. S&P 500 index 5. Petroleum production	1. [17] 2. [18] 3. [19] 4. [20] 5. [21]
ARIMA	1. 2014 2. 2017 3. 2020 4. 2019	1. WE, MA, 2. ANN 3. XGboost 4. GRU, LSTM	1. sales volume forecasting 2. sales volume forecasting 3. Cases of human brucellosis 4. Cryptocurrency price	1. [22] 2. [23] 3. [24] 4. [25]

MLP, Multi layer perceptron; CNN, convolutional neural networks; LSTM, long-short term memory; GRU,gated recurrent units; SVM, Support vector machine; RF, random forest; kNN, K-Nearest Neighbour; ARIMA, autoregressive integrated moving average; WE, Winter Exponential; MA, moving average;

Case studies

Table 3. LSTM and ARIMA case studies

Study	LSTM	ARIMA
A Comparison between ARIMA, LSTM, and GRU for Time Series Forecasting[25]	MAPE: 6.80 RMSE: 603.68	MAPE: 2.76 RMSE: 302.53
Study of effectiveness of time series modeling (arima) in forecasting stock prices [26]		MAPE: 9.05
Stock price prediction using DEEP learning algorithm and its comparison with machine learning algorithms [27]	MAE: 0.21035 RMSE: 0.306543	
A comparative study of svm and lstm deep learning algorithms for stock market prediction [28]	MAPE: 1.03 RMSE: 347.46 MAE: 262.42 MSE: 120731.4	
Comparison of ARIMA Time Series Model and LSTM Deep Learning Algorithm for Bitcoin Price Forecasting [29]	MAPE: 1.40 RMSE: 1146.07 MAE: 81.56	MAPE: 11.86 RMSE: 93.27 MAE: 939.58
Forecasting Economics and Financial Time Series: ARIMA vs. LSTM. [30]	RMSE: 32.5745	RMSE: 258.74

LSTM, long-short term memory; ARIMA, autoregressive integrated moving average;

Tools and technologies

Fig. 1. Technologies used in project

Metrics

MAPE (Mean Absolute Percentage Error)

$$MAPE = \frac{1}{n}\sum \frac{|e_t|}{d_t}$$

RMSE (Root Mean Square Error)

$$RMSE = \sqrt{\frac{1}{n}\sum e_t^2}$$

MAE (mean absolute errors)

$$MAE = \frac{1}{n}\sum |e_t|$$

MSE (mean square error)

$$MSE = \frac{1}{n}\sum e_t^2$$

Proposed architecture

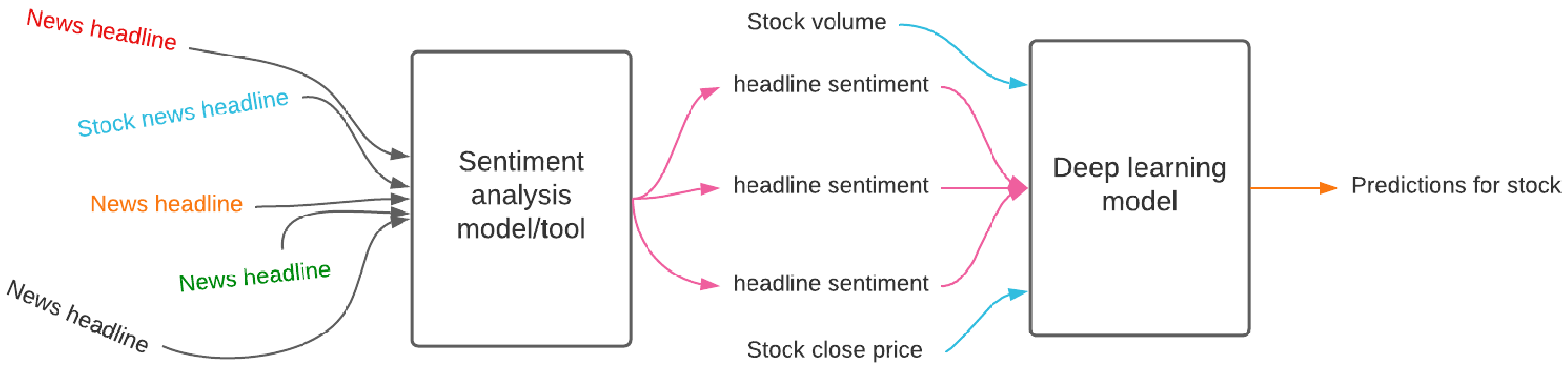


Fig. 2. Proposed architecture data flow

Proposed architecture (2)

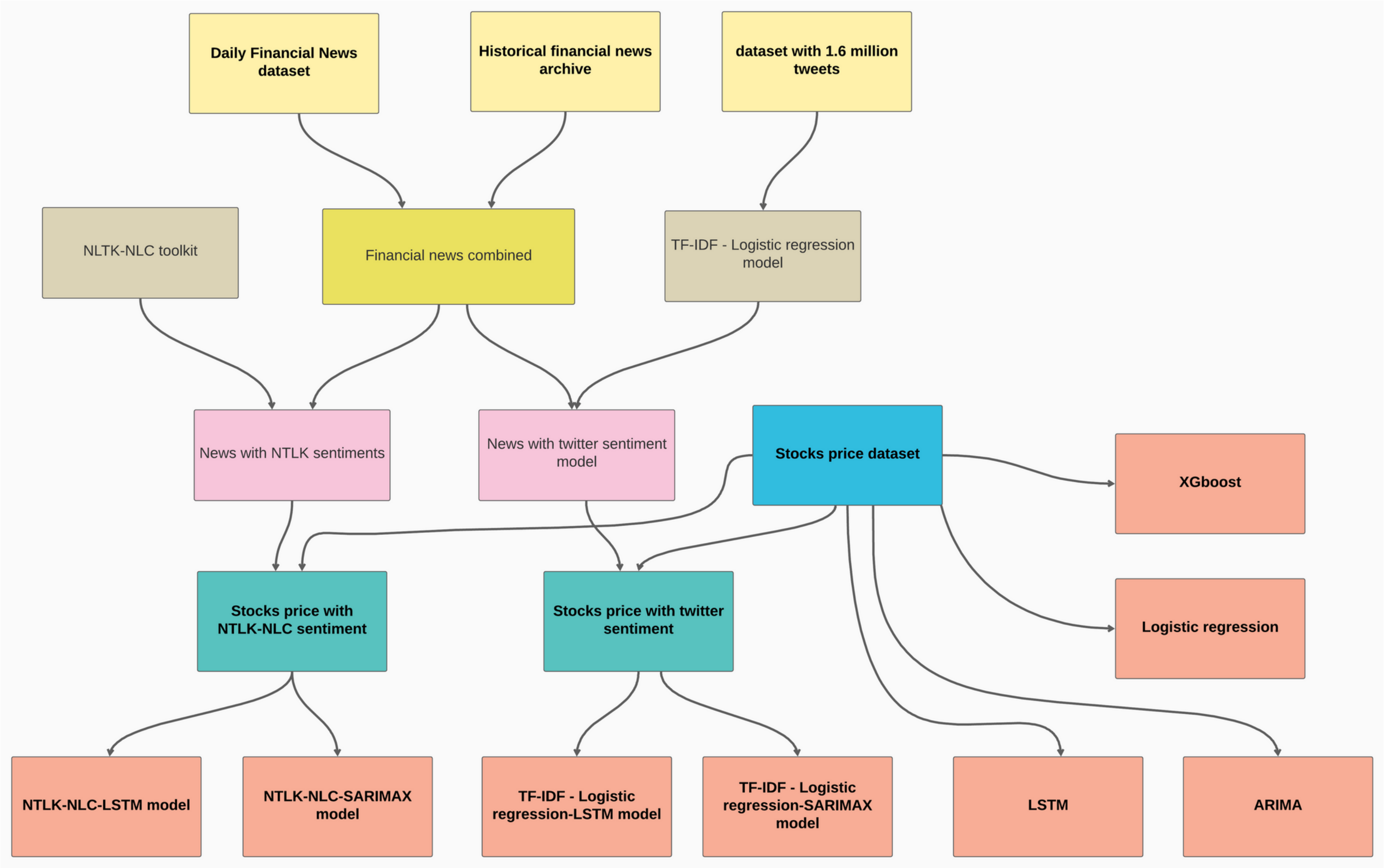


Fig. 3. Proposed architecture datasets and models usage

Proposed architecture (2)

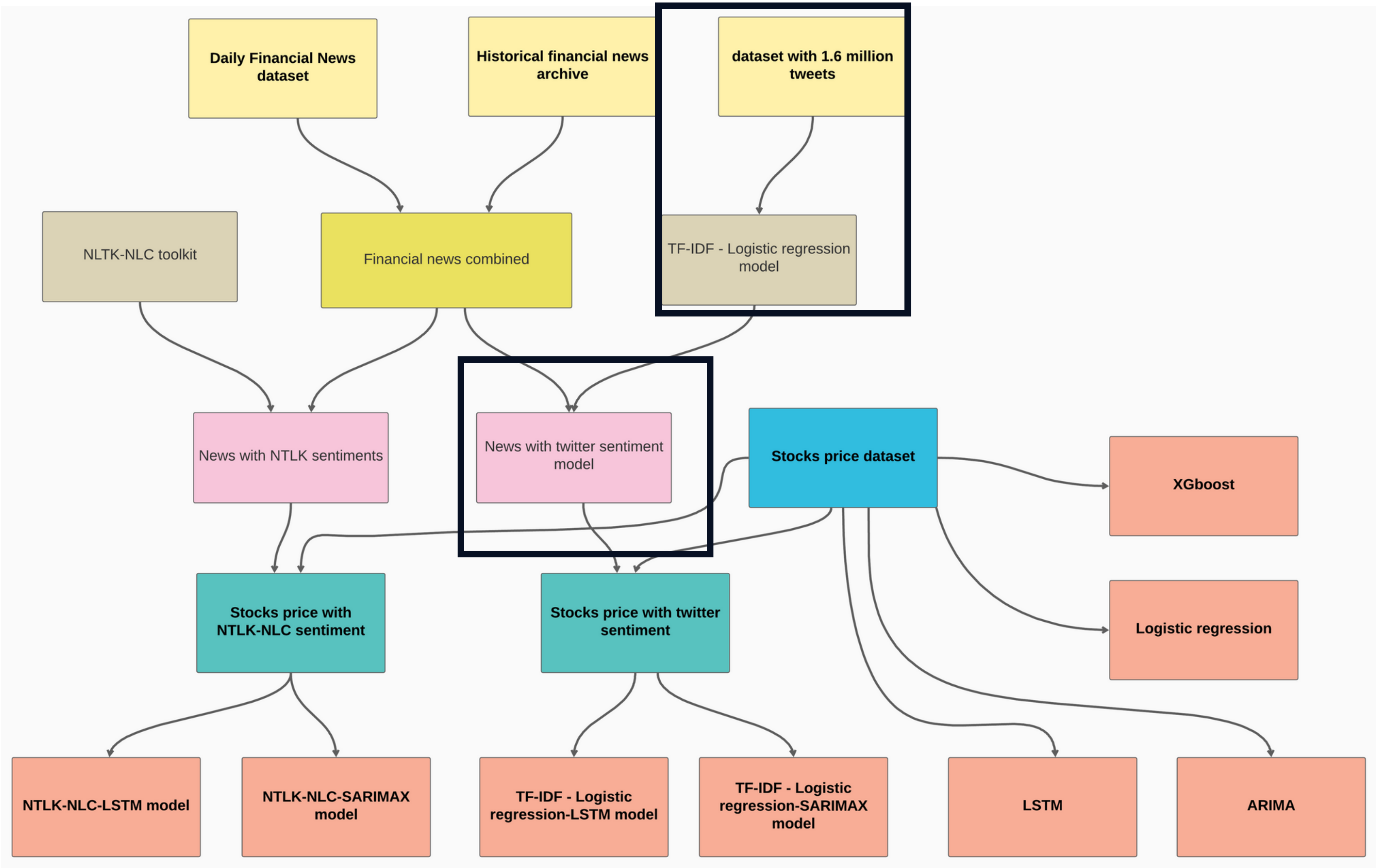


Fig. 3. Proposed architecture datasets and models usage

Twitter sentiment TF-IDF-logistic regression

# 0	# 1467810369	Mon Apr 0...	NO_QUERY	_TheSpeci...	@switchfo...
0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by texting it... and might cry as a result School today ...
0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Managed to save 50% The rest go out of bounds
0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire
0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all. i'm mad. why am i here? because I can't see you all o...

Fig. 5. Twitter sentiment dataset head rows

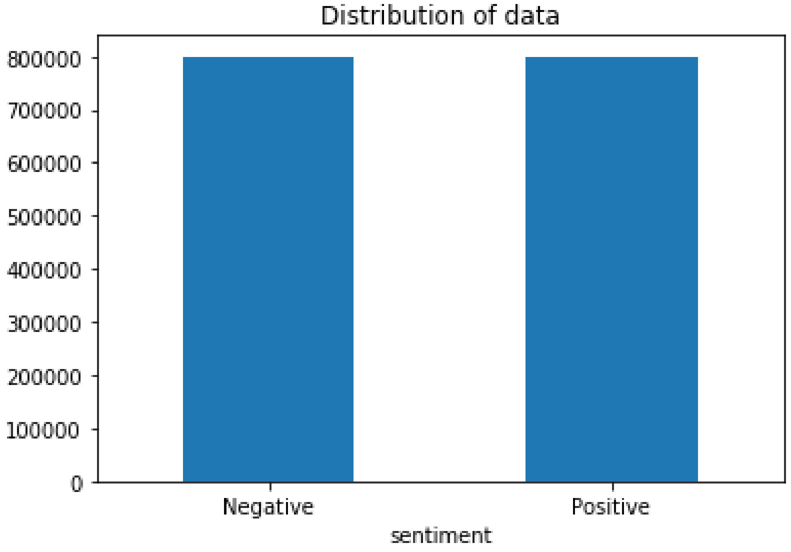


Fig. 4. Twitter sentiment dataset distribution of data

$$tf\,idf\,(t, d, D) = tf\,(t, d)\;.\;idf\,(t, D)$$

TF-IDF(term frequency - inverse document frequency)

Twitter sentiment TF-IDF-logistic regression (2)

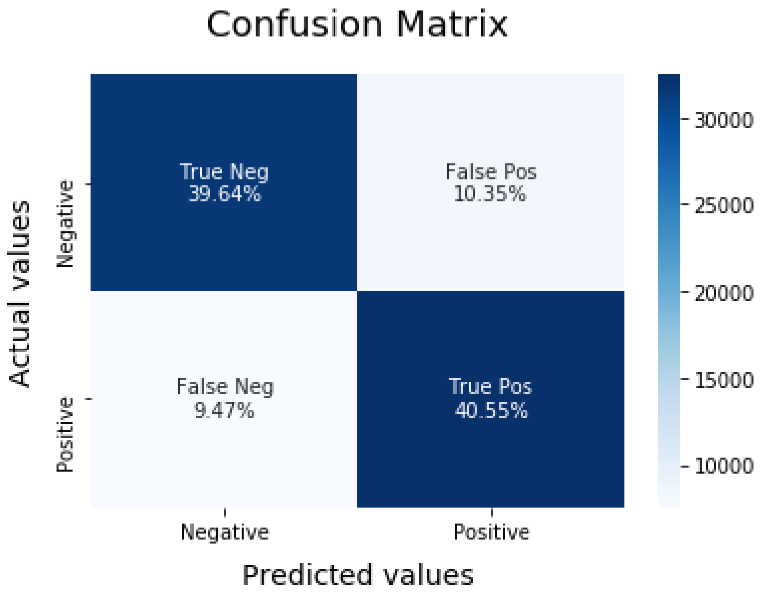


Fig. 6 BernoulliNB confusion matrix

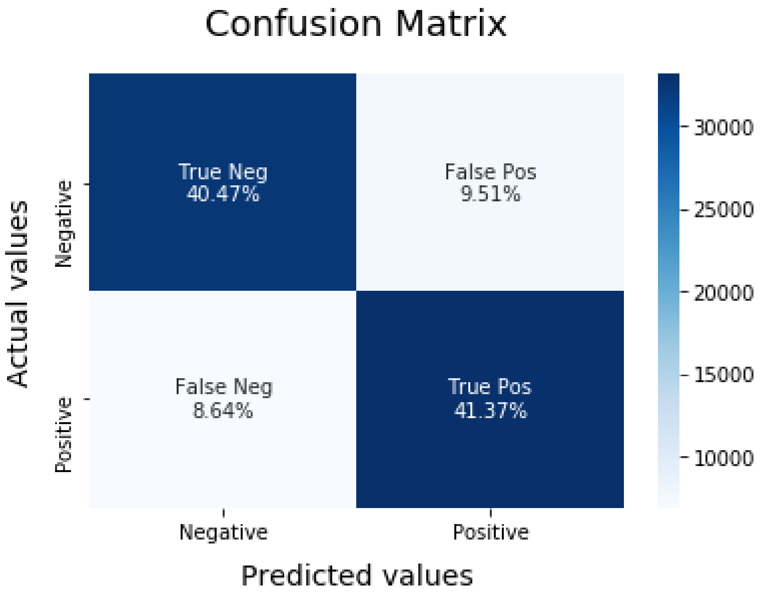


Fig. 7 LinearSVC confusion matrix

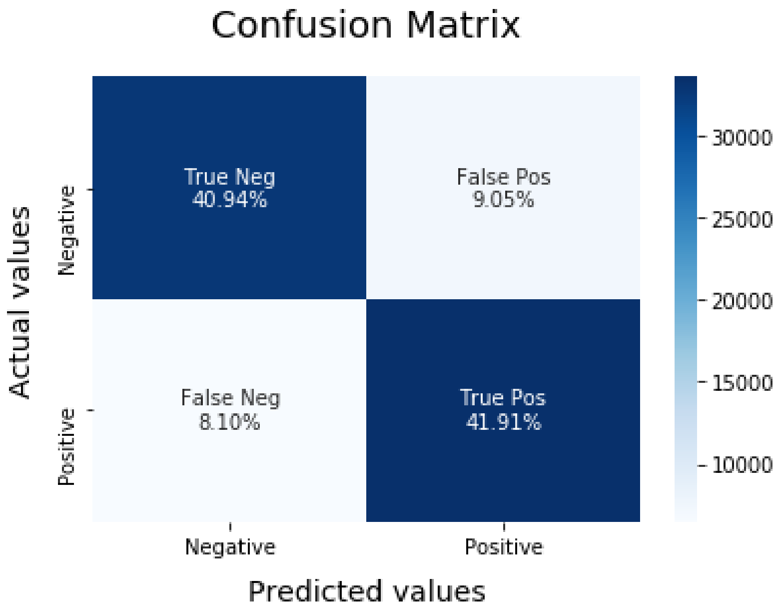


Fig. 8 Logistic Regression confusion matrix

TF-IDF(term frequency - inverse document frequency)

Proposed architecture

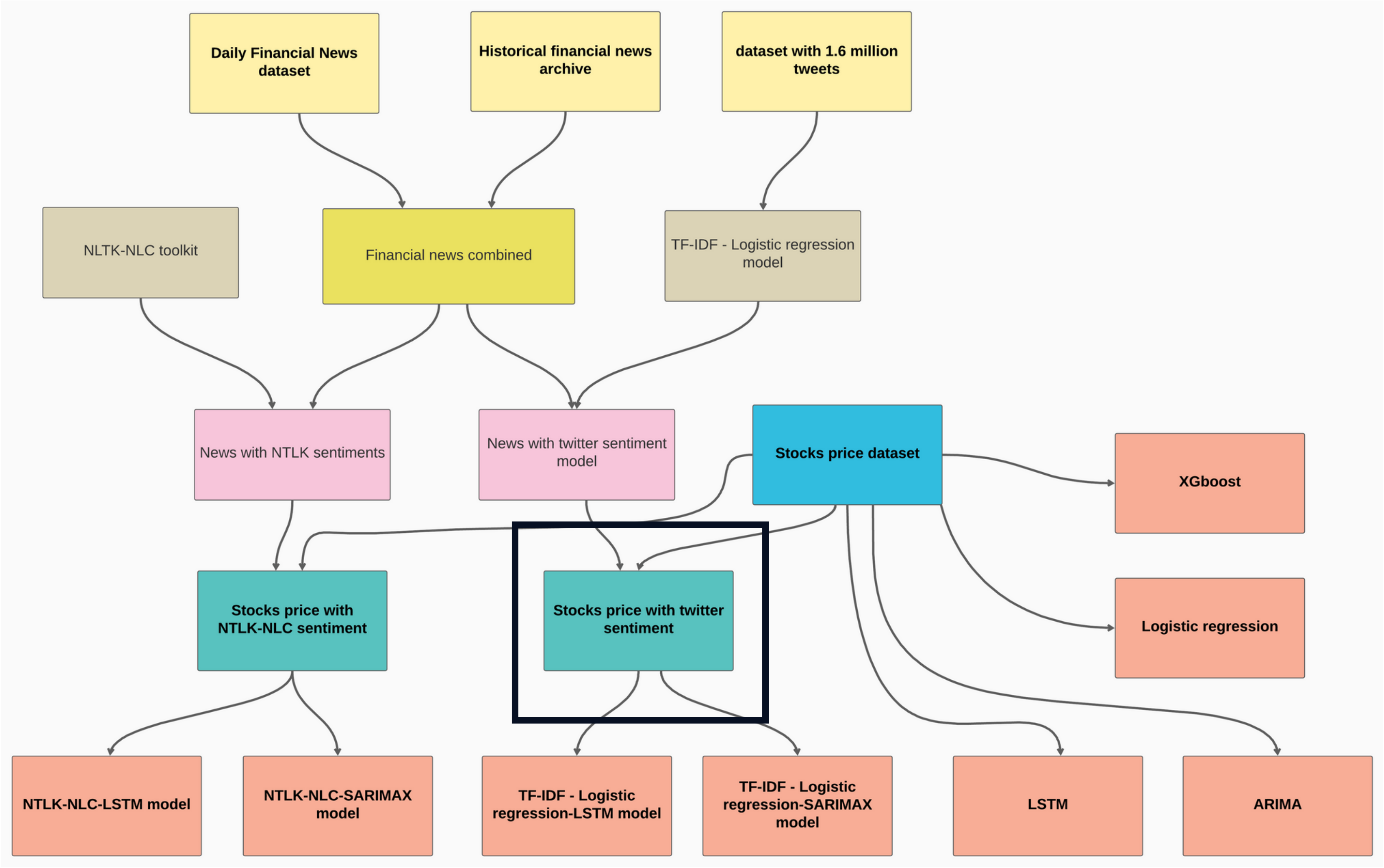


Fig. 3. Proposed architecture datasets and models usage

Stocks price with sentiment

Date	Close	Volume	sentiment
2008-10-29	23.0	111701800.0	0.0
2008-11-03	22.620001	61923500.0	1.0
2008-12-09	20.6	80484900.0	0.0
2009-02-26	16.42	83219500.0	1.0
2009-04-16	19.76	67688700.0	0.0
2009-05-29	20.889999	46134900.0	1.0
2009-06-09	22.08	50887700.0	0.5
2009-06-11	22.83	65124600.0	0.0
2009-06-23	23.34	56752700.0	0.0
2009-06-24	23.469999	54287700.0	0.5

Fig. 9 TF-IDF-logistic regression + stock price dataset (Boeing)

NLTK Vader - NRC sentiment

SentimentIntensityAnalyzer()

```
bo['senti_label'].value_counts()
```

```
neutral     1137
positive     733
negative     306
Name: senti_label, dtype: int64
```

Fig. 10 NLTK classification counts Boeing news

fear, anger, anticipation, trust, surprise, positive, negative, sadness, disgust and joy

date	title	anger	fear	negative	positive	sadness	trust	anticipation	joy	disgust	su
2020-06-11	Shares of several technology companies are tra...	0.0	0.0	0.007937	0.011905	0.003968	0.003968	0.00000	0.00000	0.0	0.
2020-06-11	Amazon Places One-Year Moratorium On Police Us...	0.0	0.0	0.000000	0.000000	0.000000	0.000000	0.00000	0.00000	0.0	0.
2020-06-10	Cloudera Analysts Examine Potential Suitors, T...	0.0	0.0	0.000000	0.000000	0.000000	0.000000	0.00000	0.00000	0.0	0.
2020-06-09	Shares of several technology companies are tra...	0.0	0.0	0.002710	0.005420	0.002710	0.005420	0.00271	0.00271	0.0	0.
2020-06-09	IBM Discontinues Facial Recognition Technology...	0.0	0.0	0.000000	0.000000	0.000000	0.000000	0.00000	0.00000	0.0	0.

Fig. 11 NRC analysis result (Boeing)

NLTK Vader - NRC sentiment

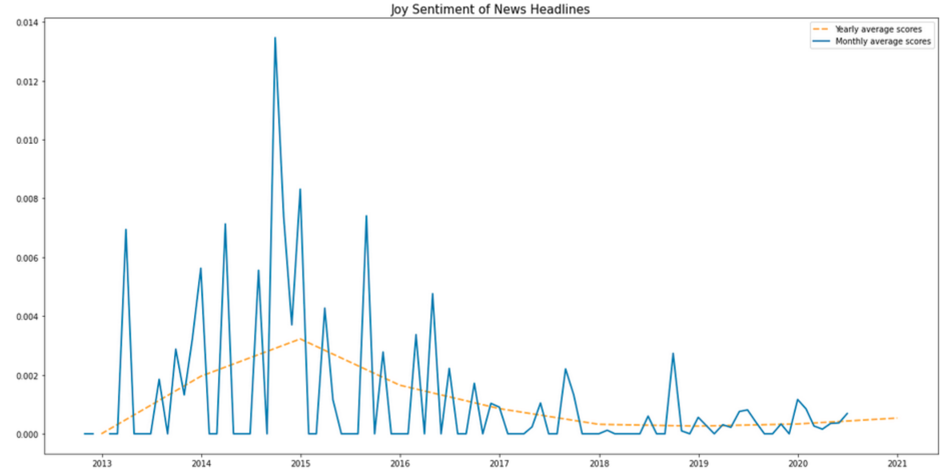


Fig. 11 Sentiments detected by NRC - Joy

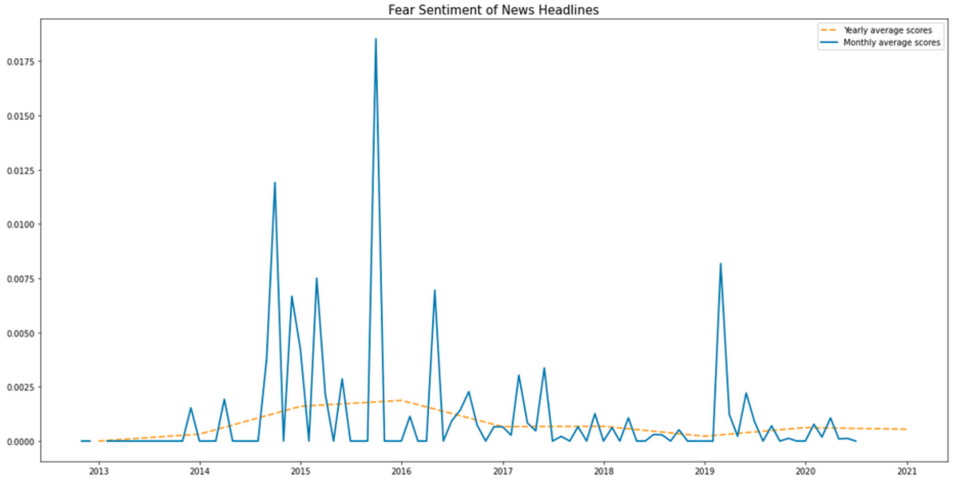


Fig. 12 Sentiments detected by NRC - fear

Yellow line - yearly average scores, blue line - monthly average scores

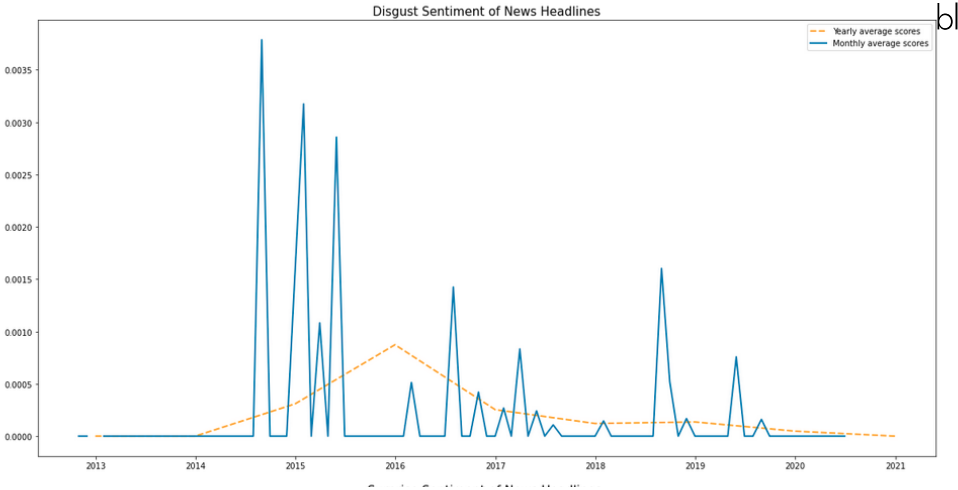


Fig. 13 Sentiments detected by NRC - disgust

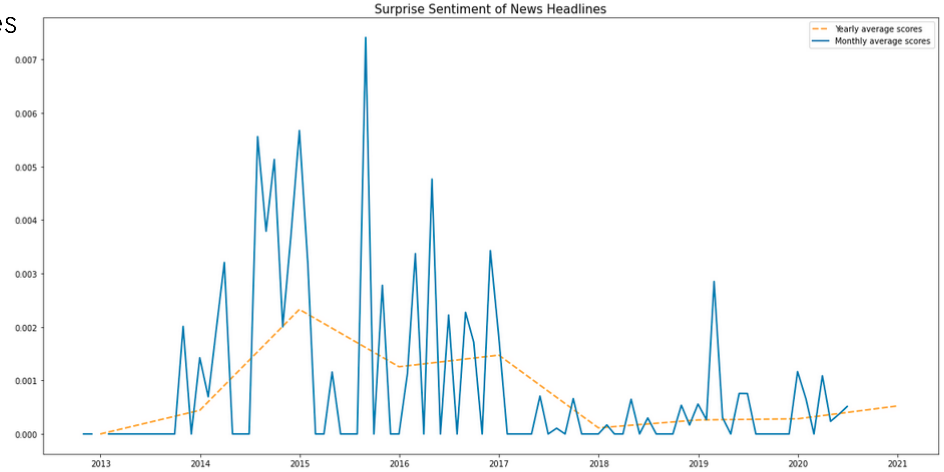


Fig. 14 Sentiments detected by NRC - surprise

Proposed architecture

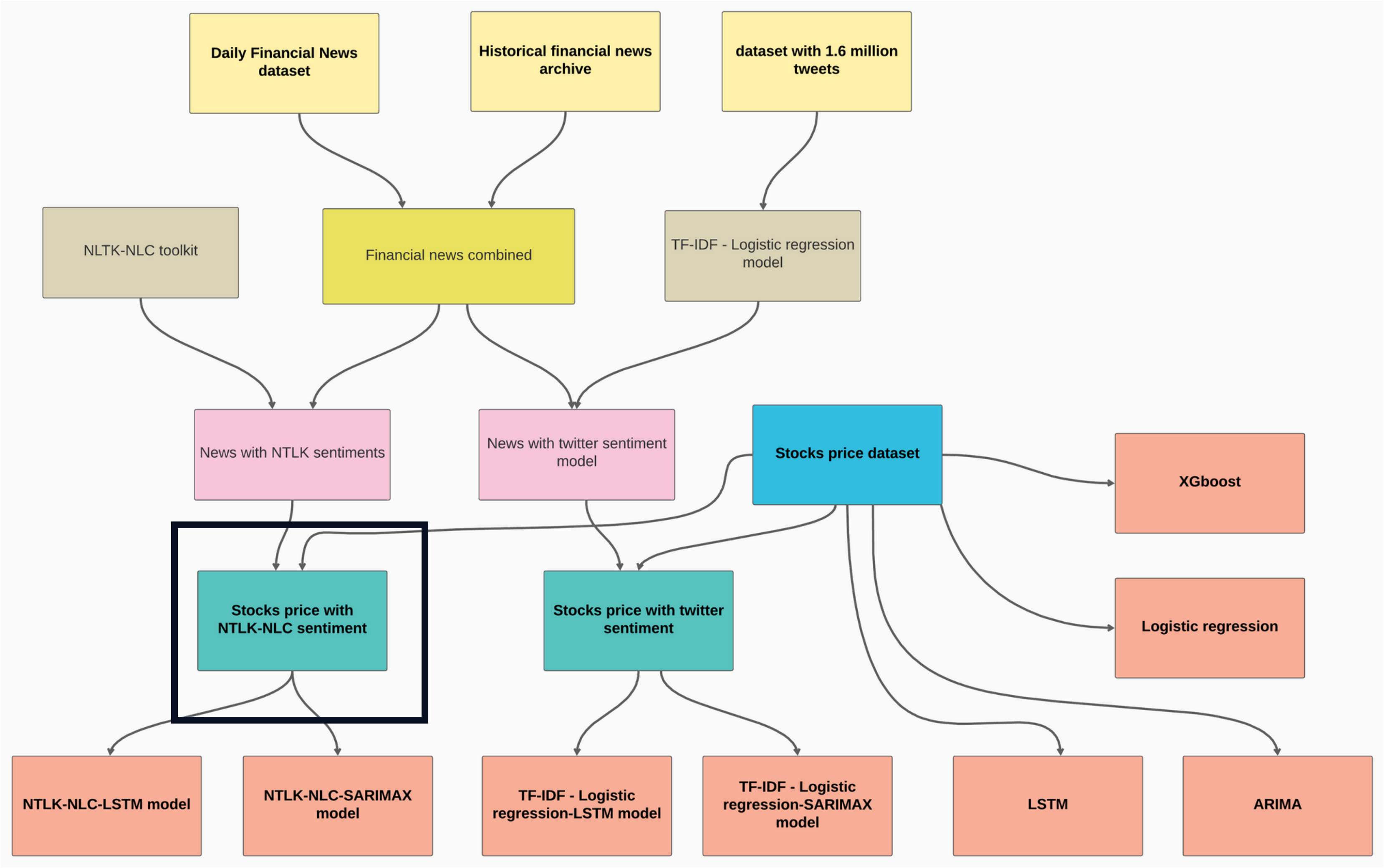


Fig. 3. Proposed architecture datasets and models usage

NLTK Vader - NRC sentiment

Date	Close	Volume	anger	fear	negative	positive	sadness	trust	anticipation	joy	disgust
2012-09-13	30.940001000000002	45047300.0	0.0	0.0	0.02750582750582748	0.011188811188811178	0.00512820512820512 51195	0.0	0.03484848484848484	0.0	0.0
2012-09-17	31.209999	36488500.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2012-09-27	30.16	47129900.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2012-10-01	29.49	54042700.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2012-10-02	29.66	43338900.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2012-10-11	28.950001	41488500.0	0.0	0.0	0.0	0.01041666666666665	0.0	0.01041666666666665	0.01041666666666665	0.0	0.0
2012-10-24	27.9	53320400.0	0.0	0.0	0.011479591836734675	0.02593537414965985	0.00255102040816325	0.0085034013605442	0.00255102040816325	0.00255102040816325	0.0
2012-10-25	27.879999	54084300.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2012-11-06	29.860001	43401500.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2012-11-28	27.360001	53018400.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Fig. 15 NLTK -NRC sentiment final training dataset (Boeing)

Proposed architecture

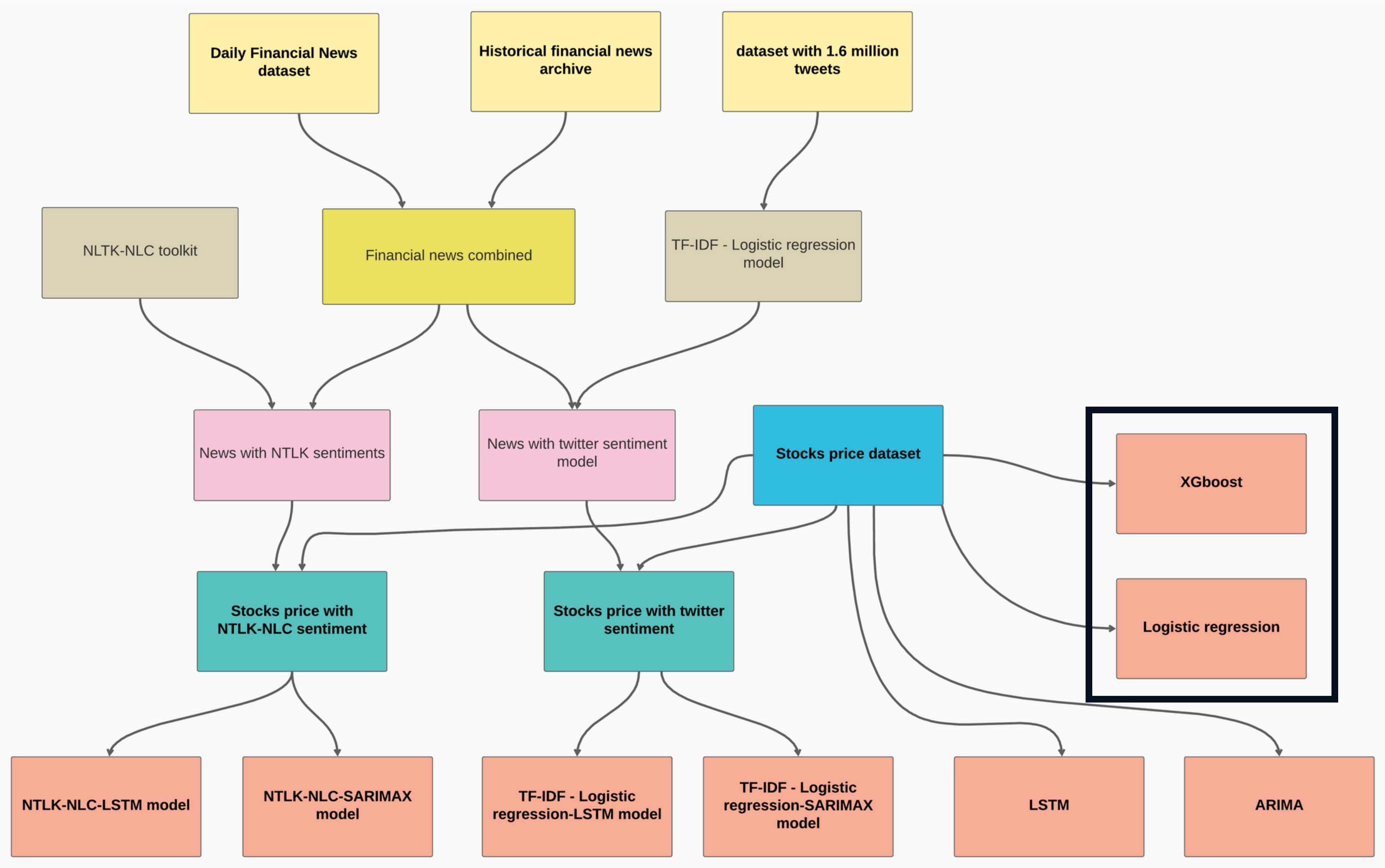


Fig. 3. Proposed architecture datasets and models usage

Baseline models. Linear regression

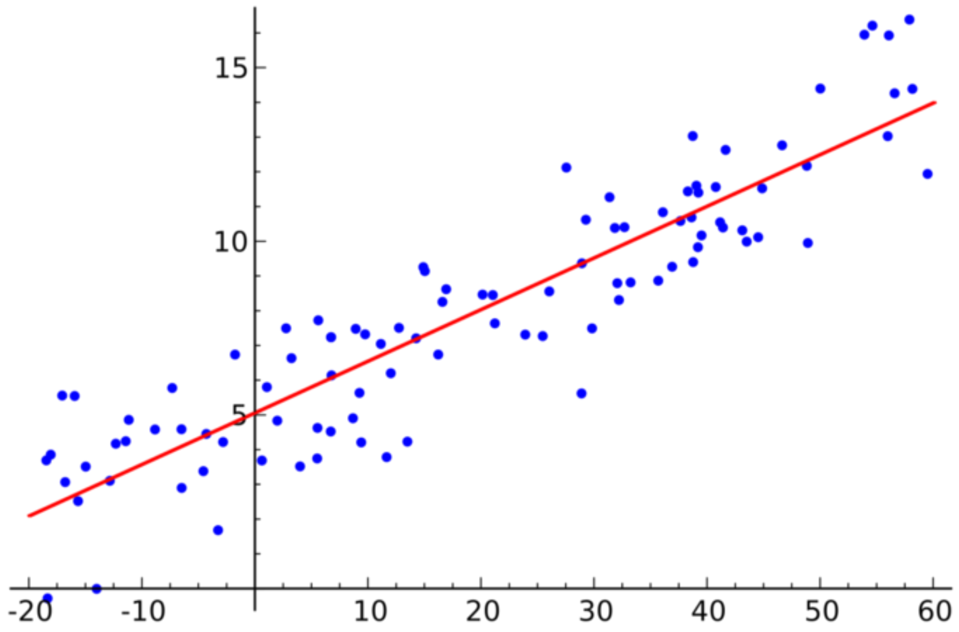


Fig. 16. Linear regression

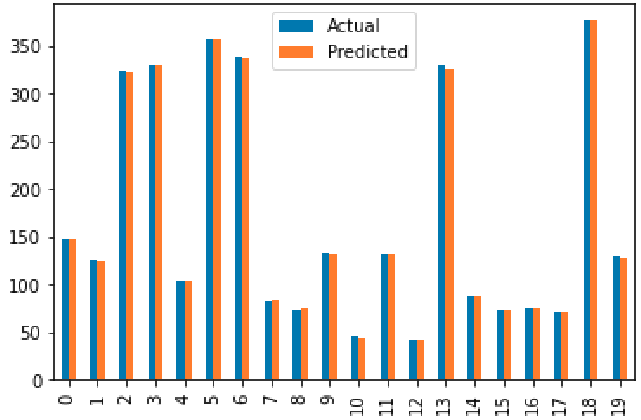


Fig. 17. Linear regression predictions for Boeing (20 days)

Baseline models. XGboost

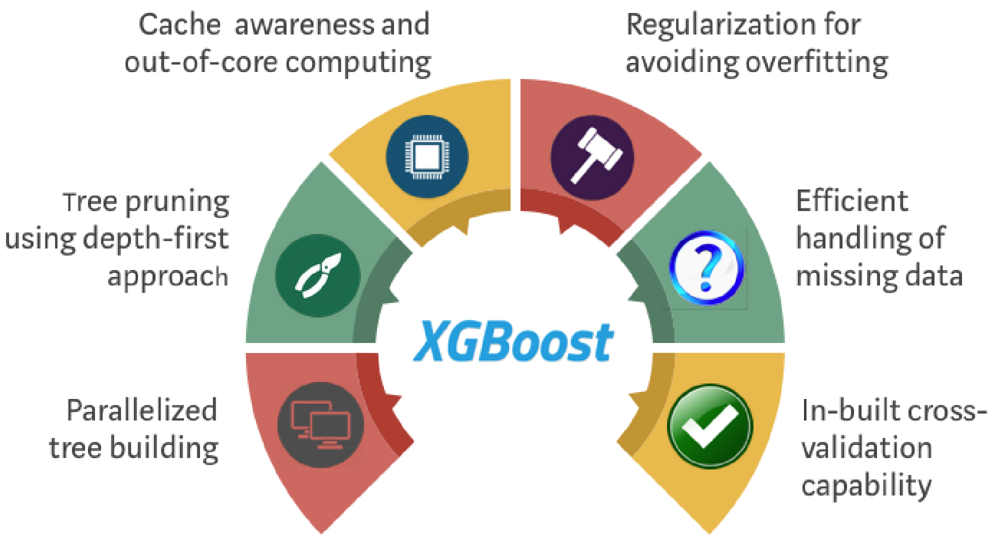


Fig. 18. XGboost features

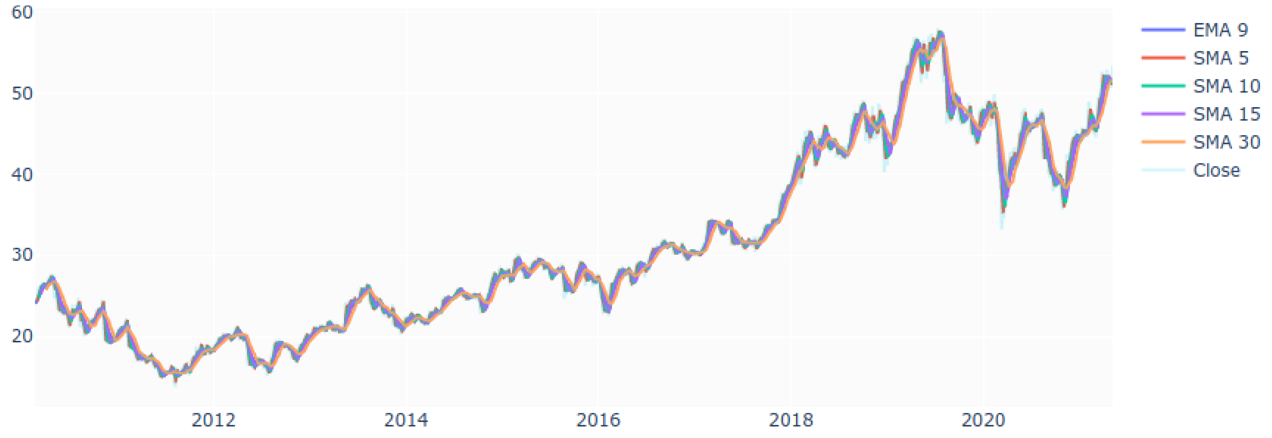


Fig. 19. Technical indicators (Boeing)

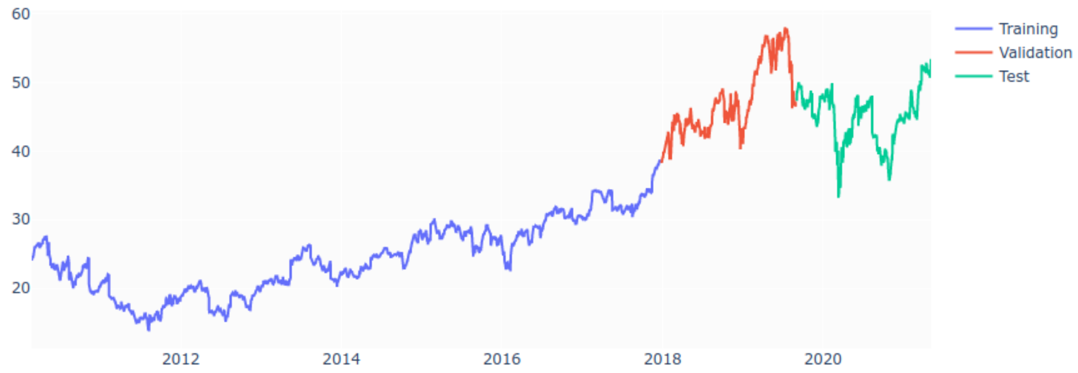


Fig. 20 Trainig, validation, test split

Baseline models. XGboost (2)

Fig. 21. XGboost IBM, VZ, WMT stocks plots

Fig. 21. Baseline models MSE comparison

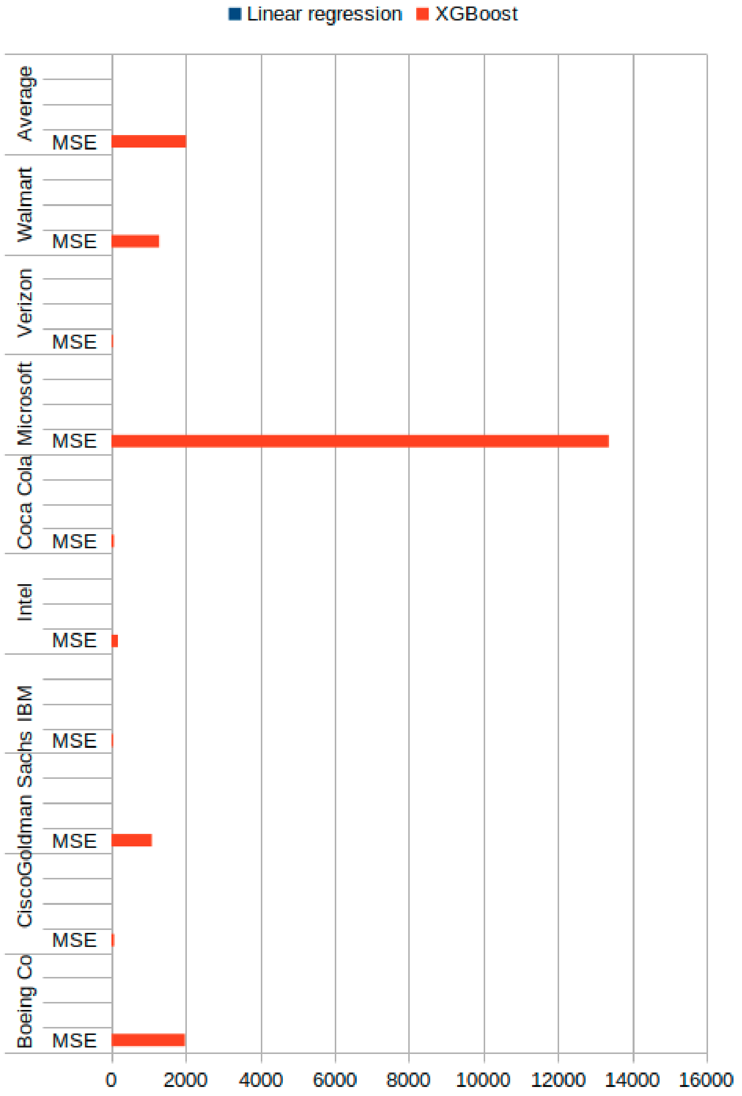


Fig. 22. Baseline models RMSE and MAE comparison

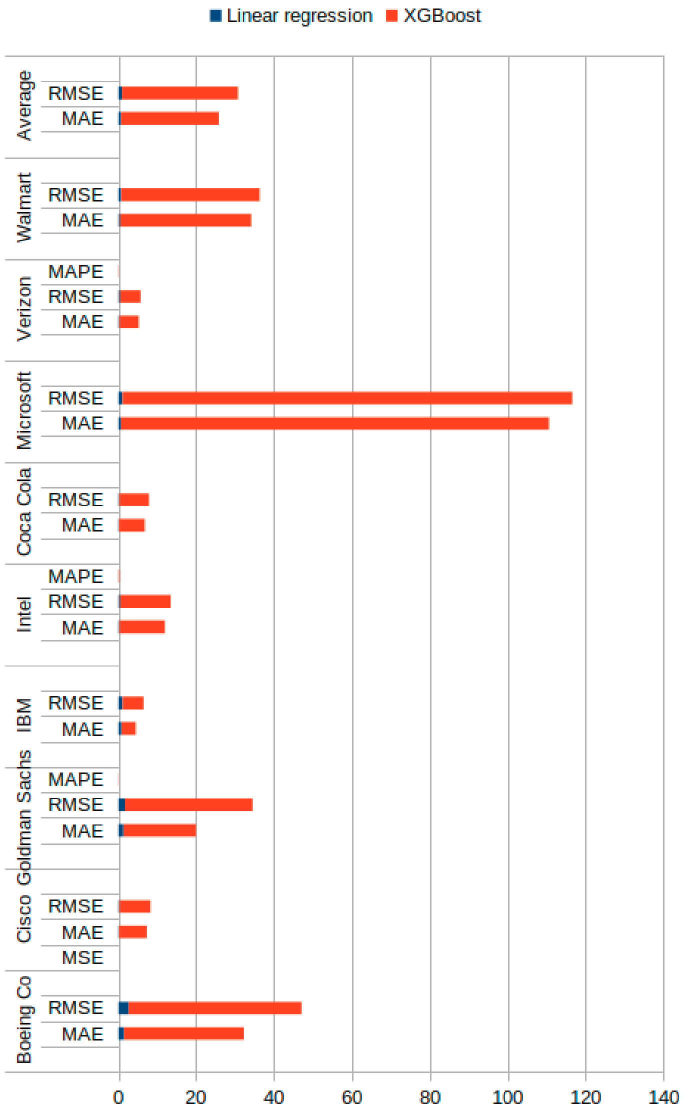
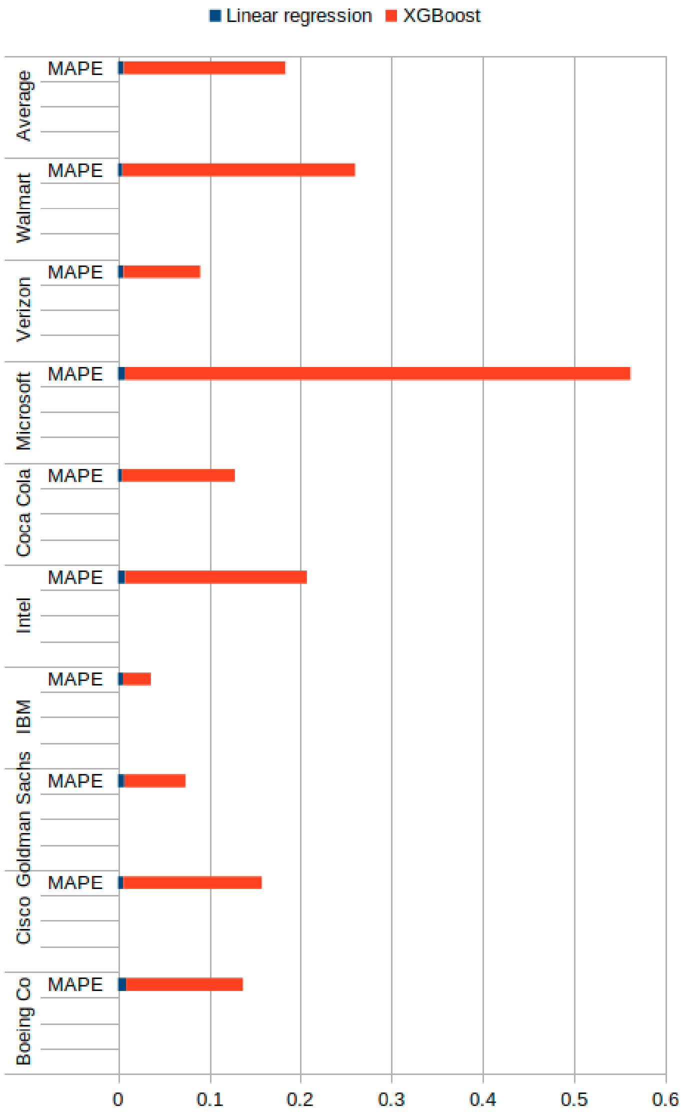


Fig. 23. Baseline models MAPE comparison



Proposed architecture

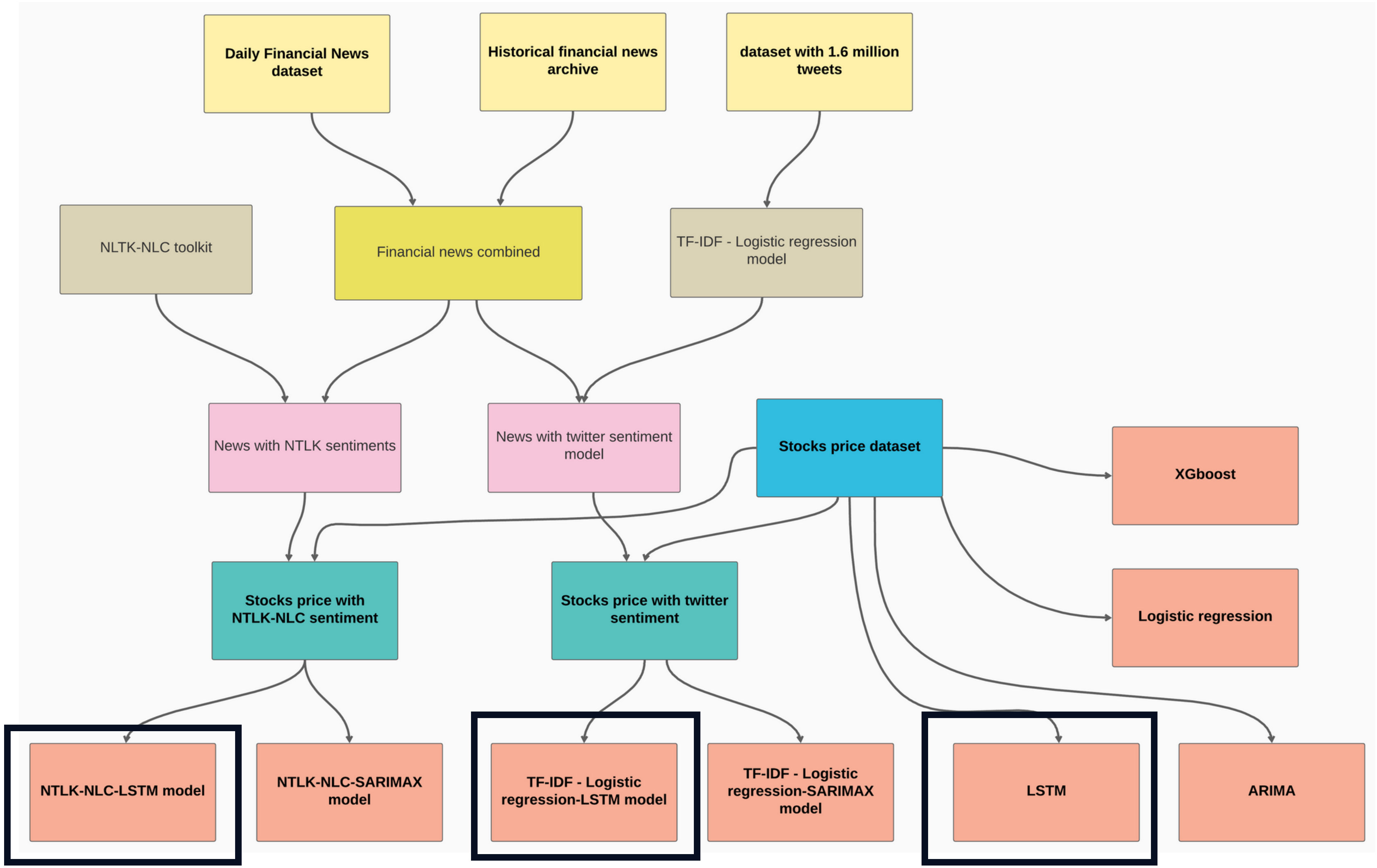


Fig. 3. Proposed architecture datasets and models usage

LSTM models

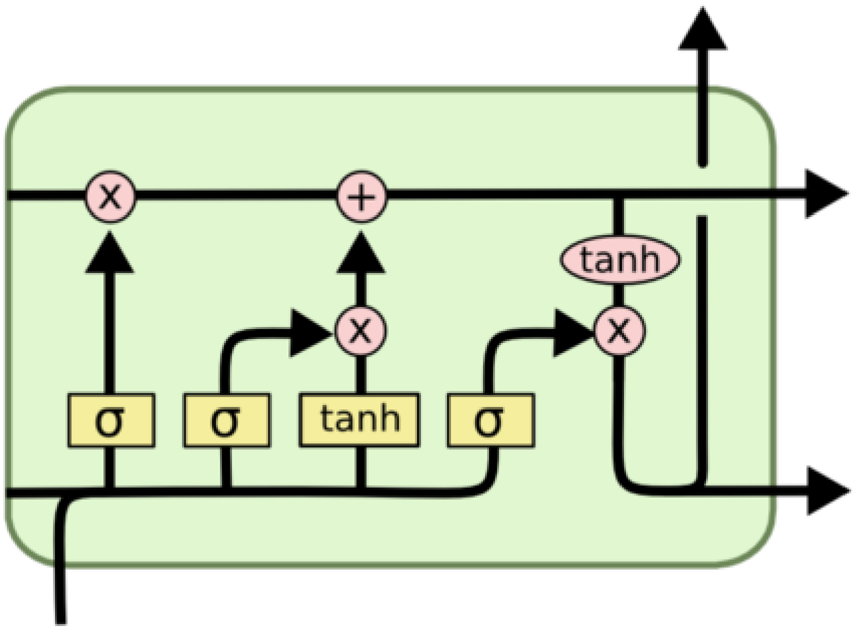


Fig. 24 LSTM architecture

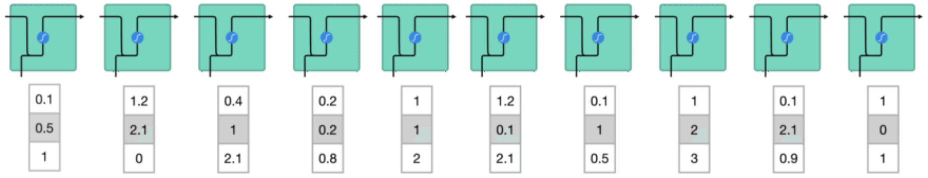
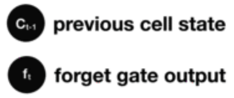


Fig. 25 Processing sequence one by one



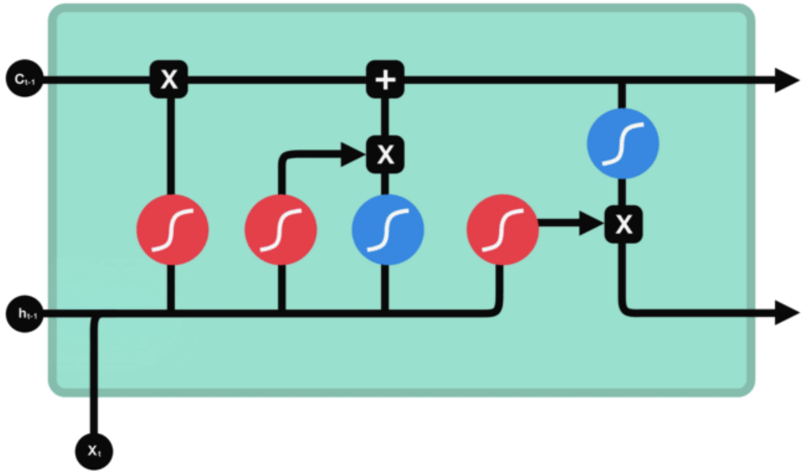


Fig. 26 LSTM forget gate

LSTM models (single layer)

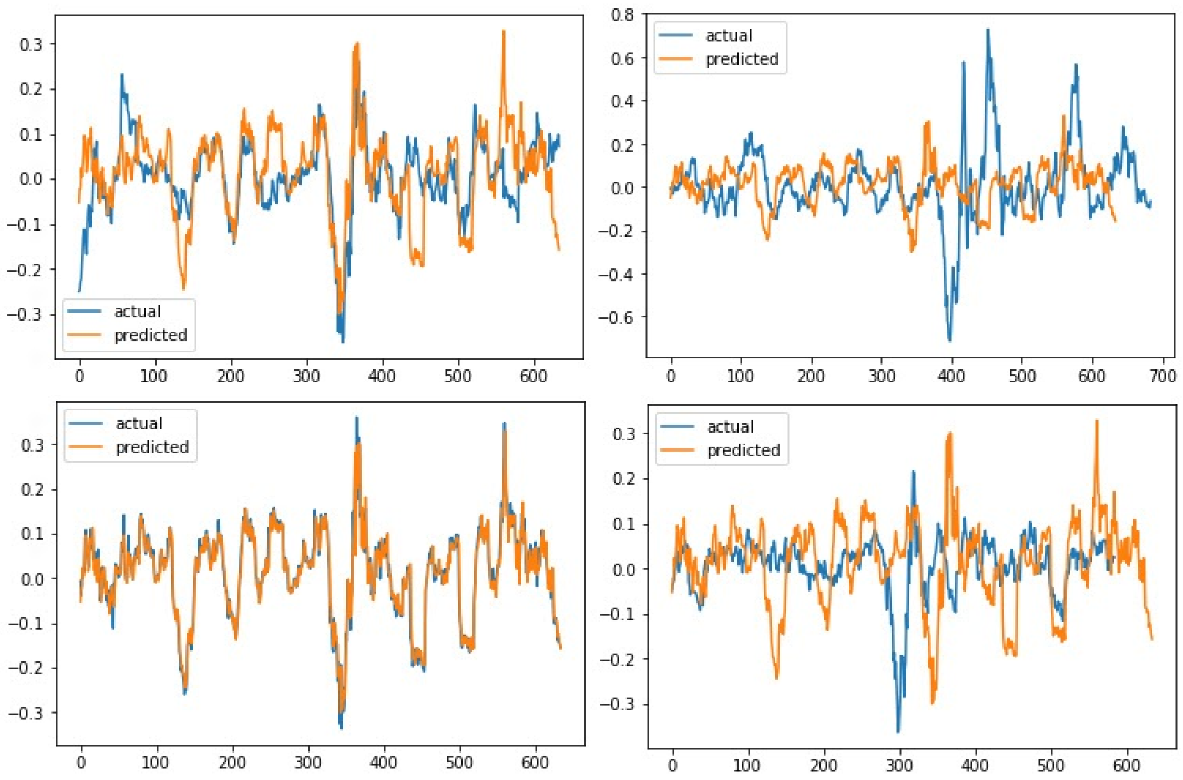


Fig. 27 Predictions of LSTM without sentiment data for Boeing, IBM, Cisco, Intel, Microsoft, Goldman Sachs companies

LSTM models (multiple layers)

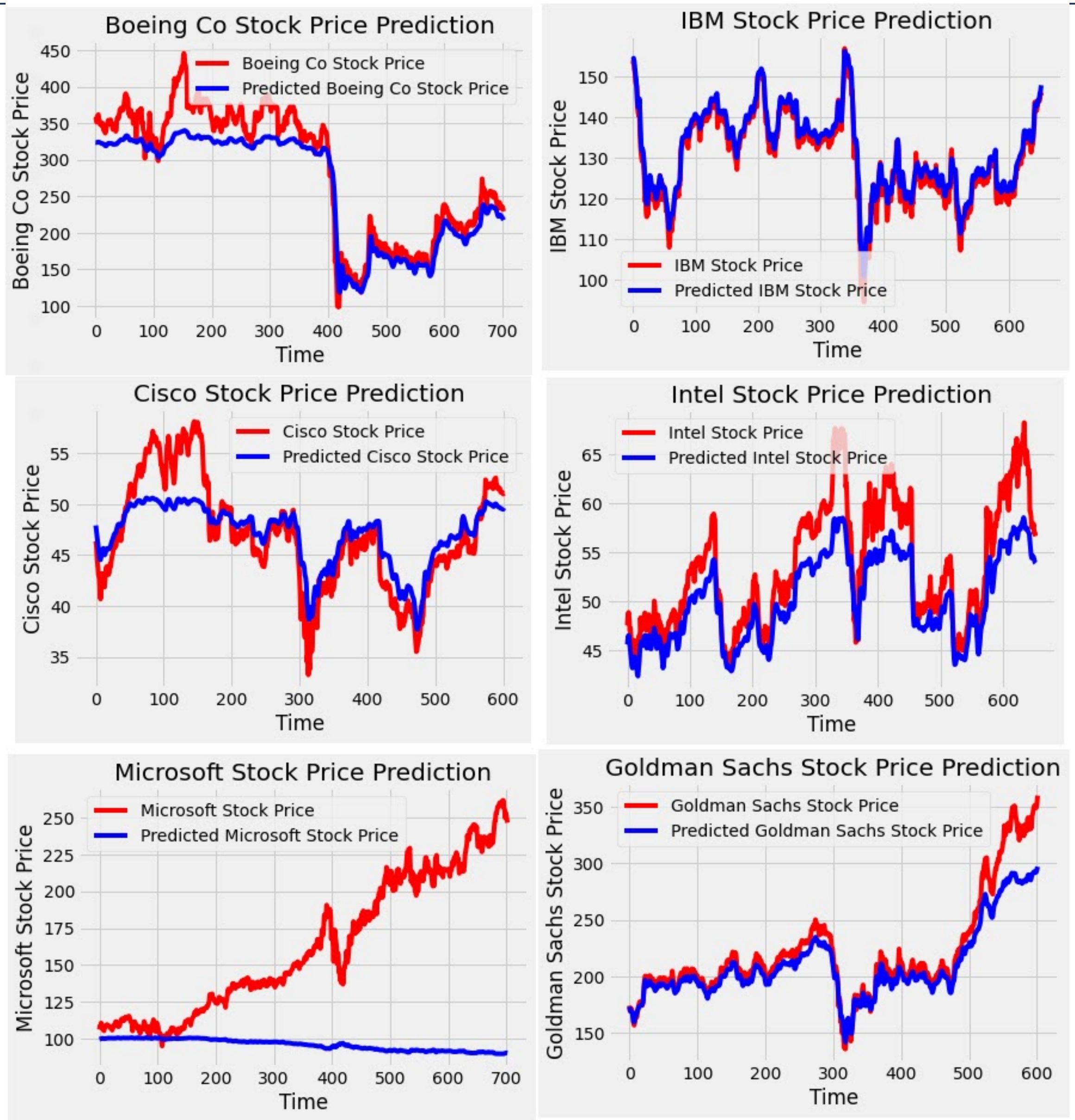


Fig. 28 Predictions of LSTM without sentiment data for Boeing, IBM, Cisco, Intel, Microsoft, Goldman Sachs companies

Multivariate LSTM models (TF-IDF-logistic regression)

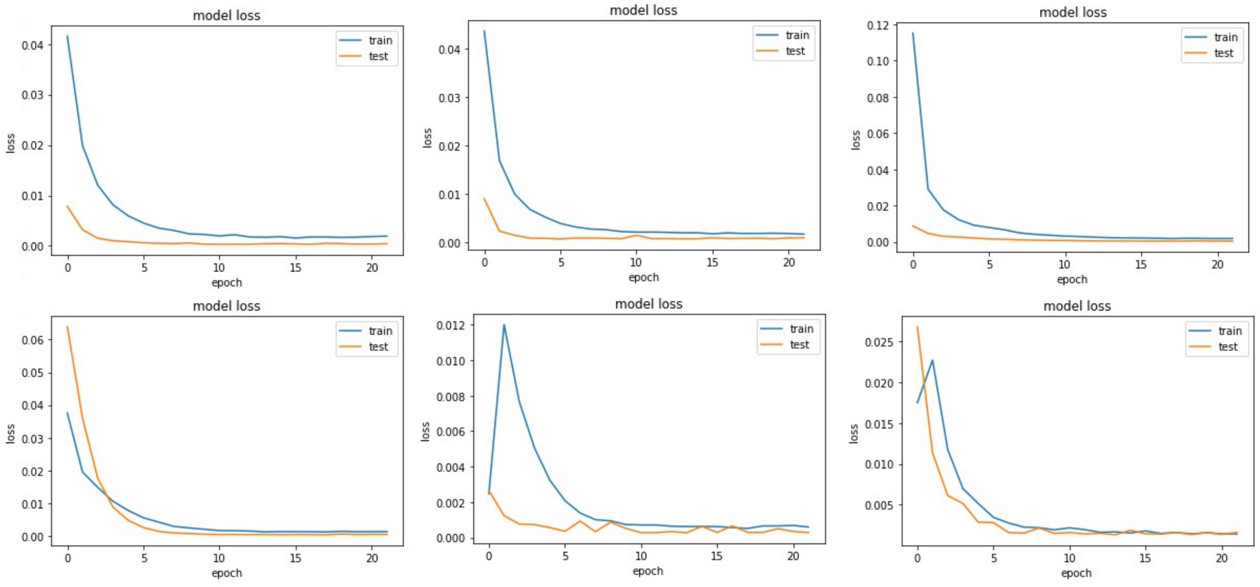


Fig. 29 Log loss plots for stocks: Walmart, Verizon, Microsoft, Coca Cola, IBM, CiscoGenerally

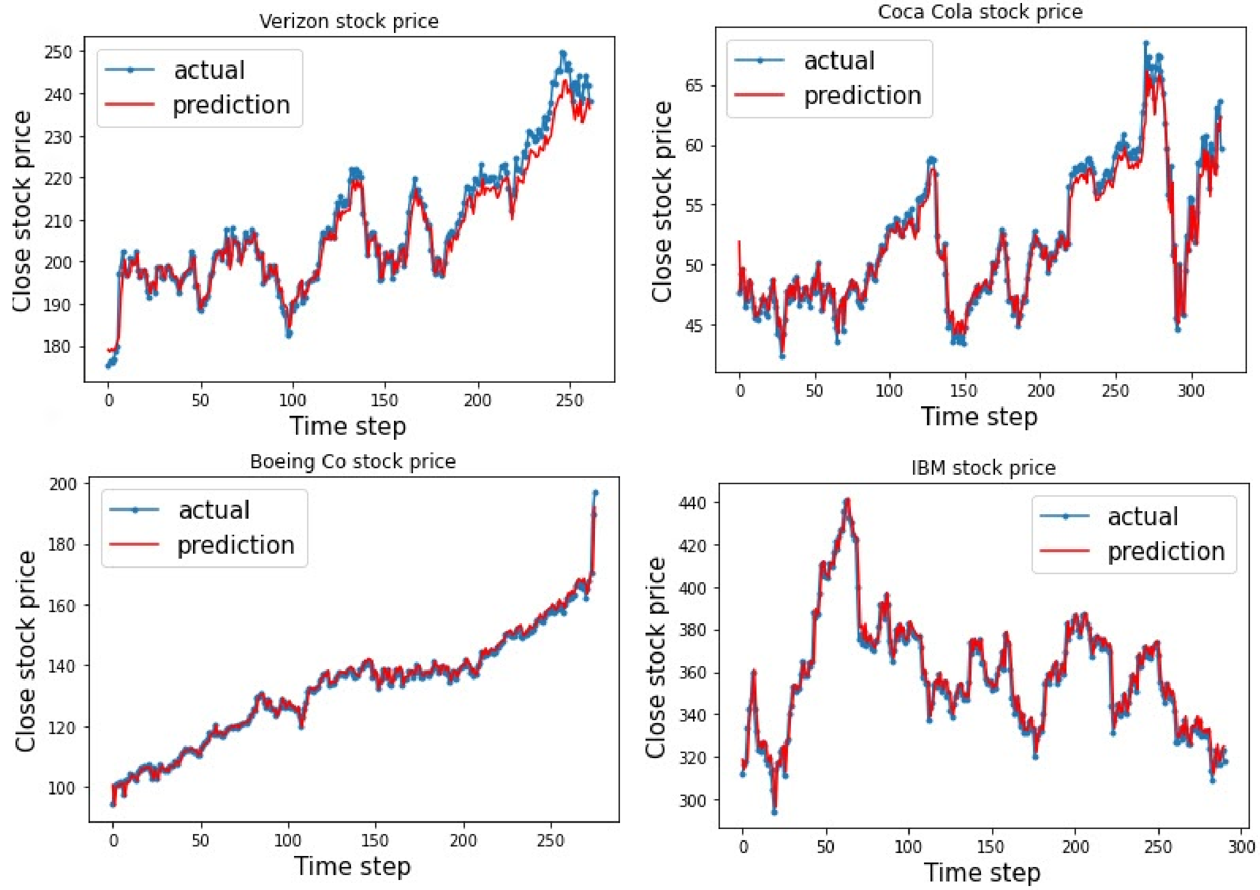


Fig. 30 Prediction results for test set for stocks: Verizon, Coca cola, Boeing, IBM

Multivariate LSTM models (NLTK Vader - NRC)

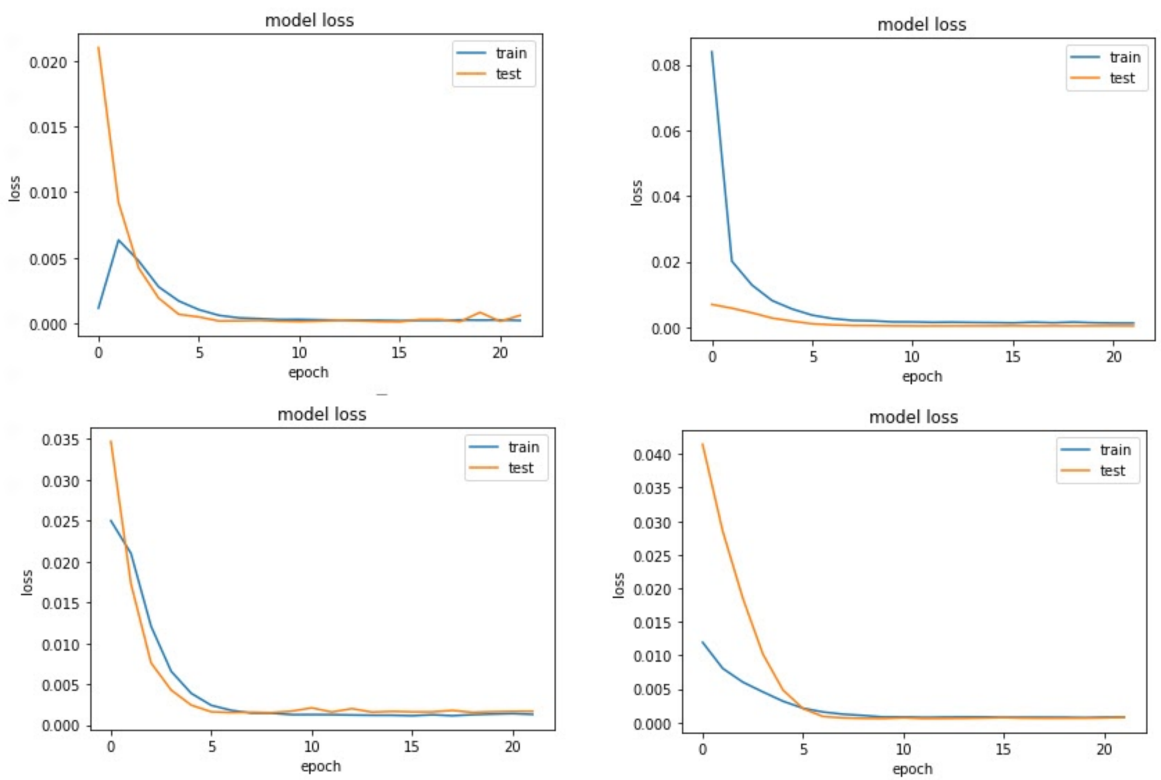


Fig. 31 Log loss plots for stocks: IBM, Coca Cola, Microsoft, Walmart

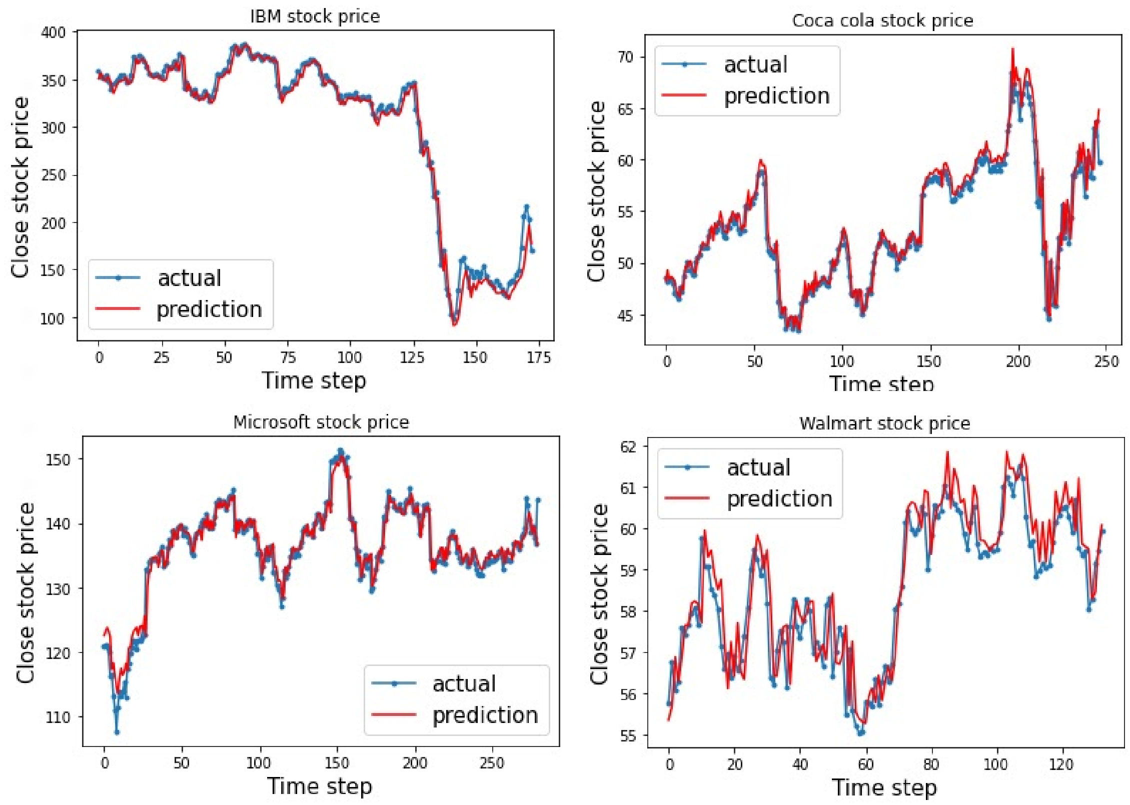


Fig. 32 Prediction results for test set for stocks: IBM, Coca cola, Microsoft, Walmart

LSTM models results

Fig. 33. LSTM models MSE comparison

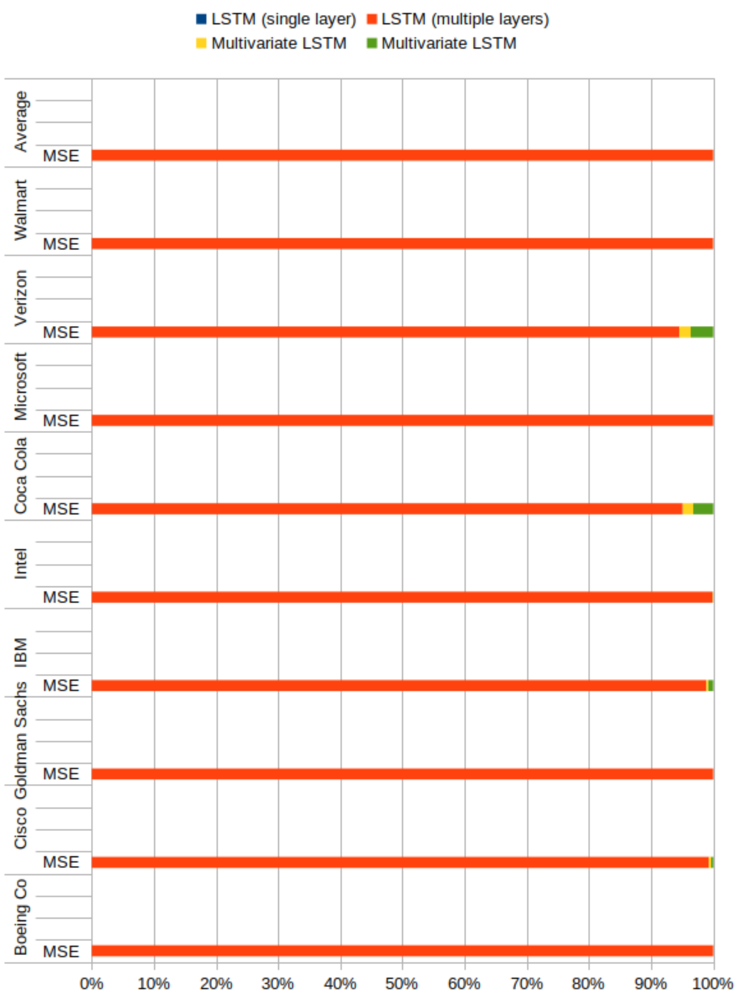


Fig. 34. LSTM models MSE comparison

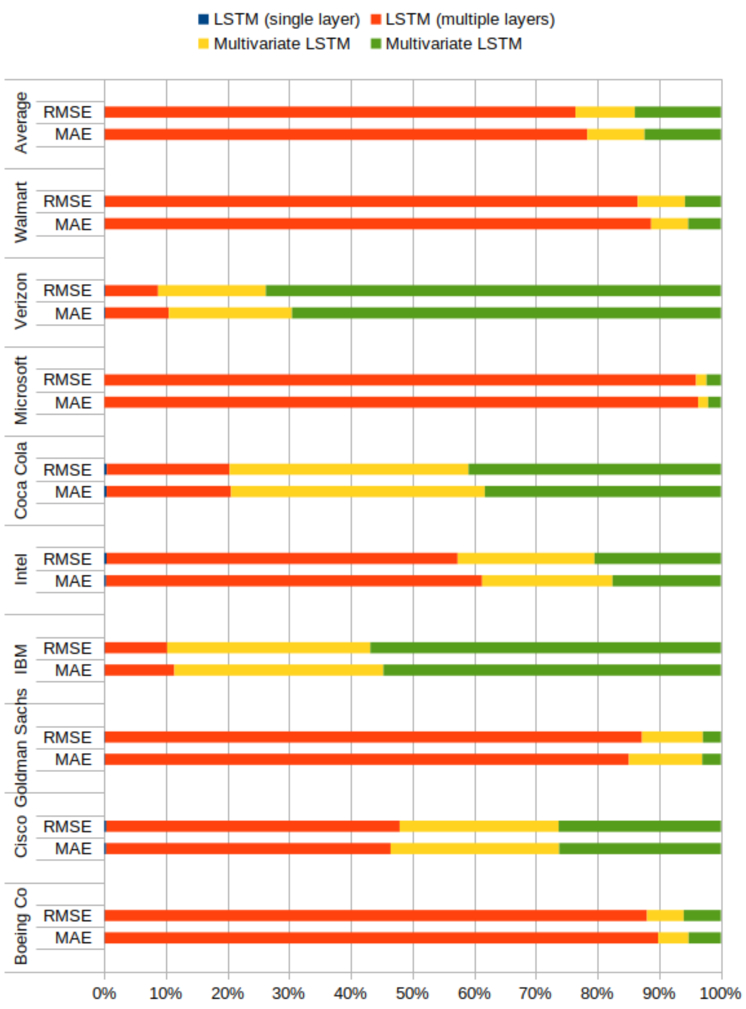
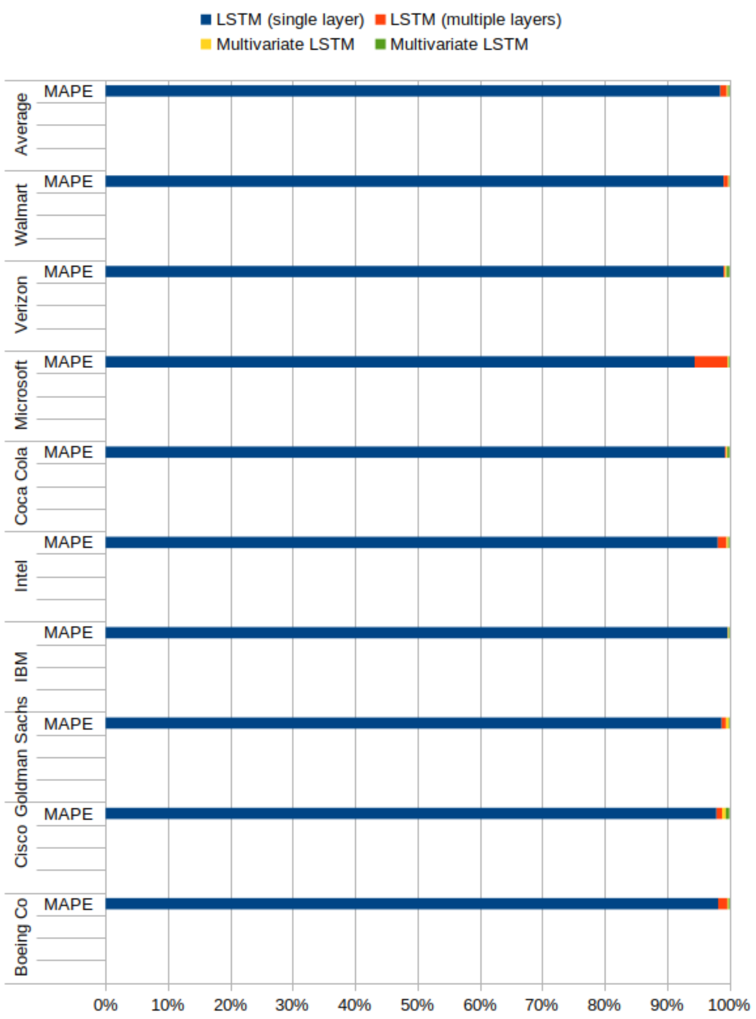


Fig. 35. LSTM models MSE comparison



Proposed architecture

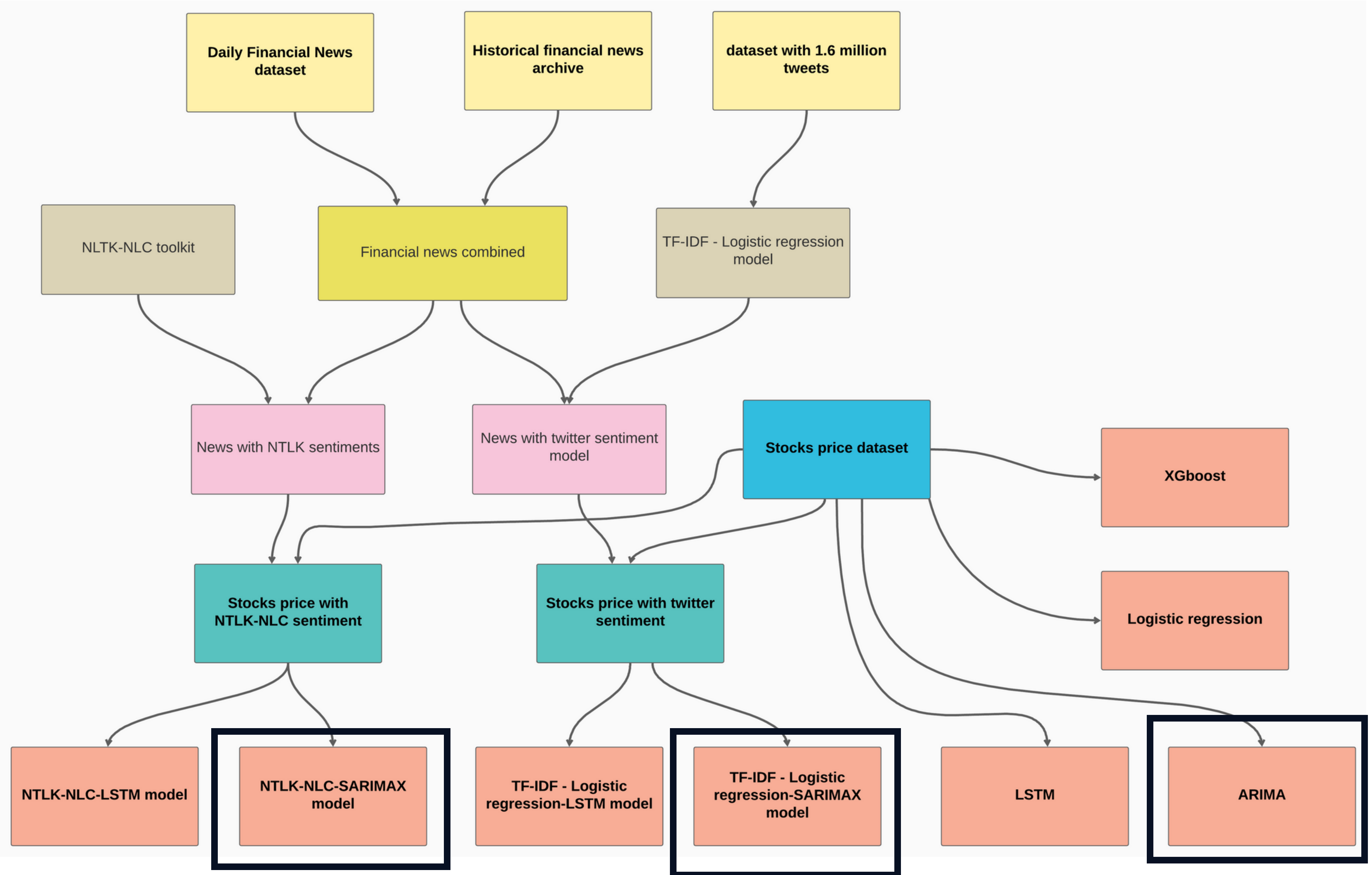


Fig. 3. Proposed architecture datasets and models usage

ARIMA and SARIMAX

AR(x) means **x** lagged error terms are going to be used in the ARIMA model.

Characterized by 3 terms: **p, d, q**

Moving average (**MA**) removes non-determinism or random movements from a time series

SARIMAX is used on data sets that have seasonal cycles + exogenous factors

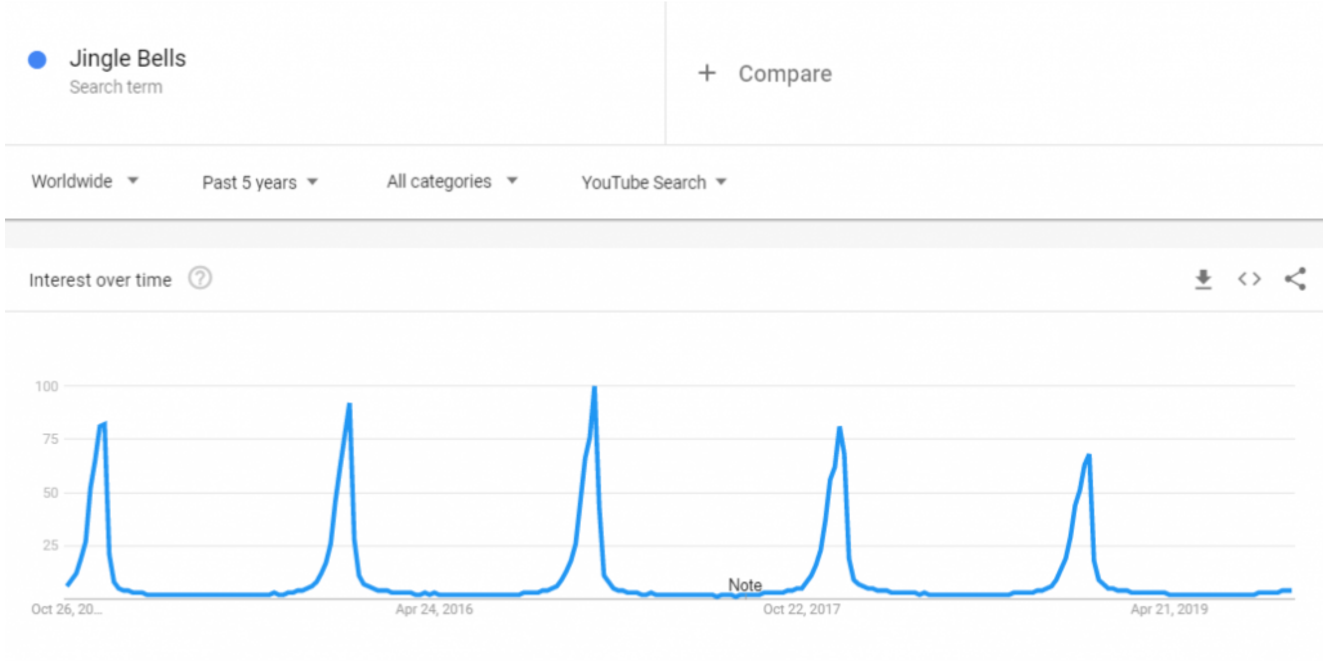


Fig. 36. "Jingle bells" song playings

ARIMA and SARIMAX data preprocessing

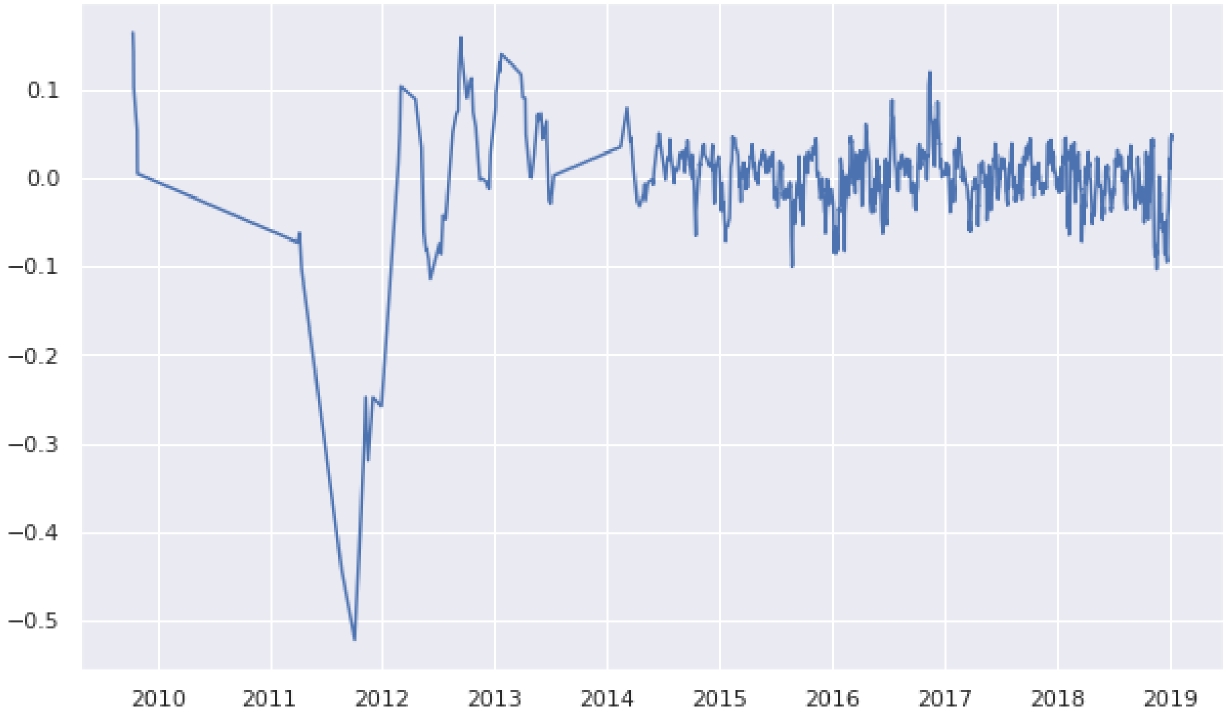


Fig. 37. Logarithmic differentiation of initial values

SARIMAX model

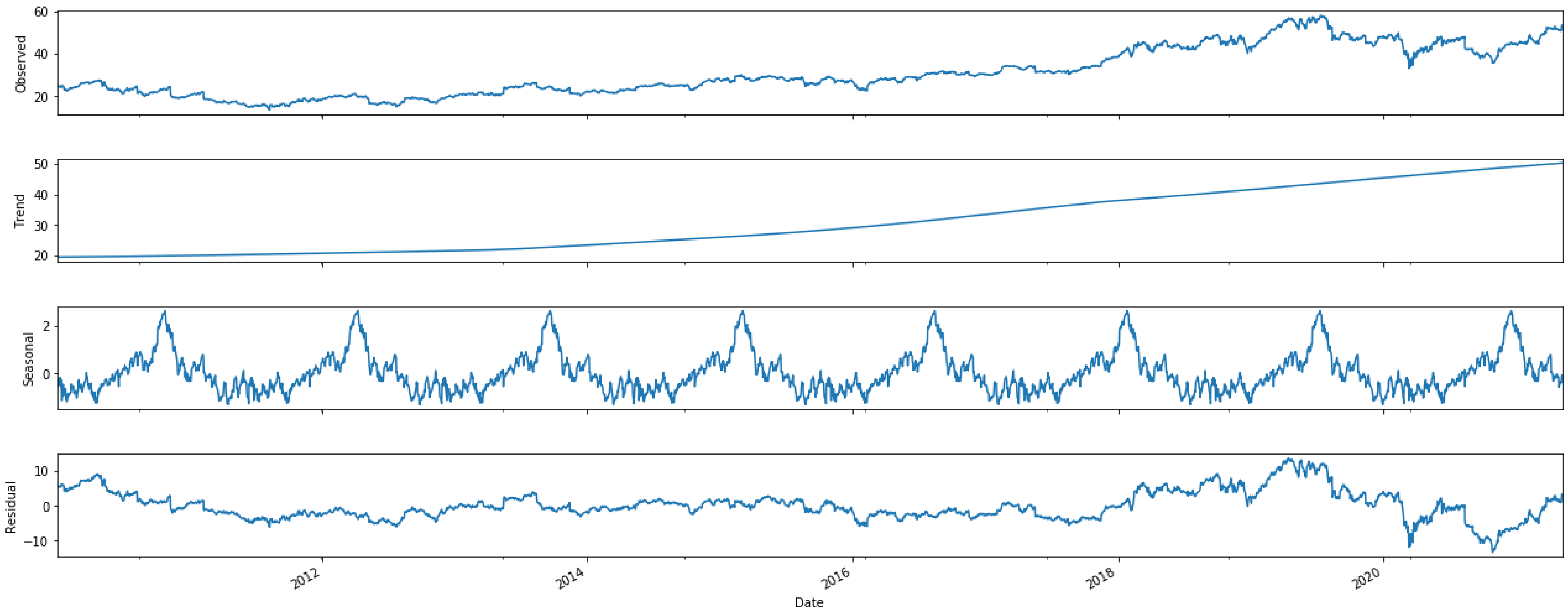


Fig. 38. Boeing Co, Price, trend, seasonality and residuals plots

ARIMA and SARIMAX models results

Fig. 39. ARIMA SARIMAX models MSE comparison

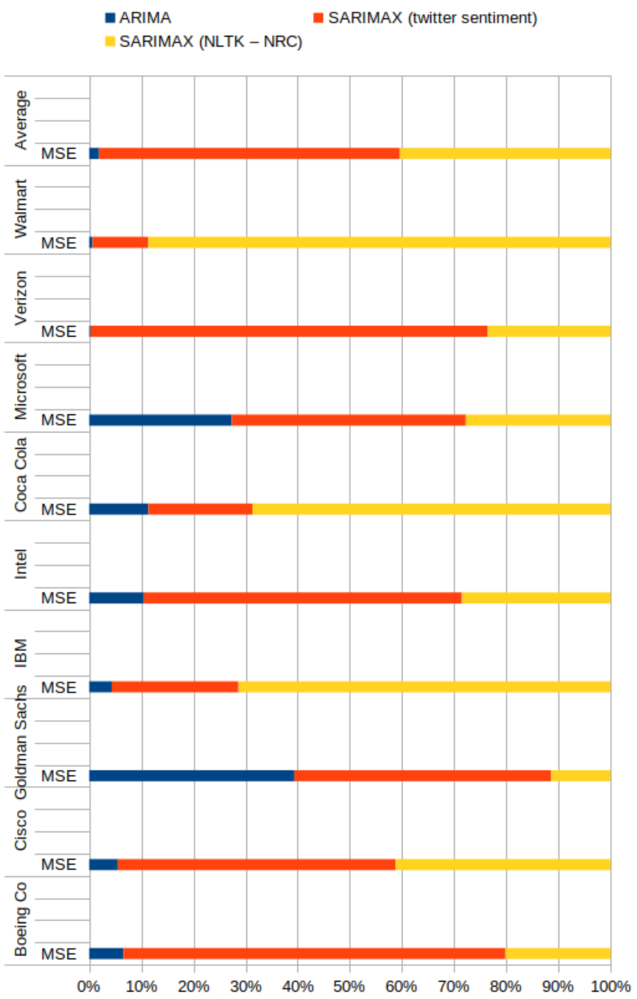


Fig. 40. ARIMA and SARIMAX models MSE

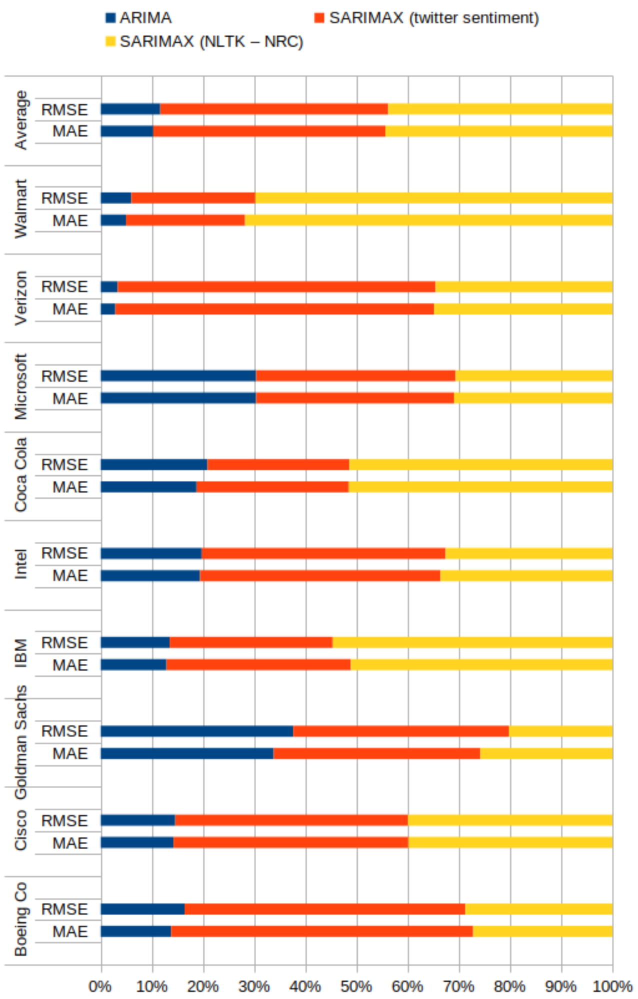
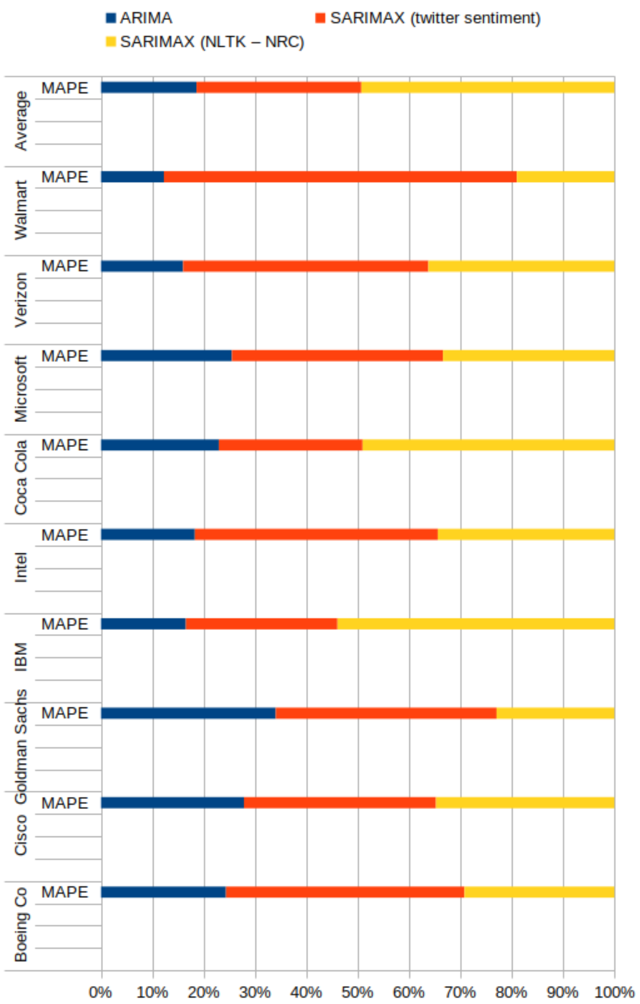


Fig. 41. ARIMA and SARIMAX models MSE comparison



Final comparison

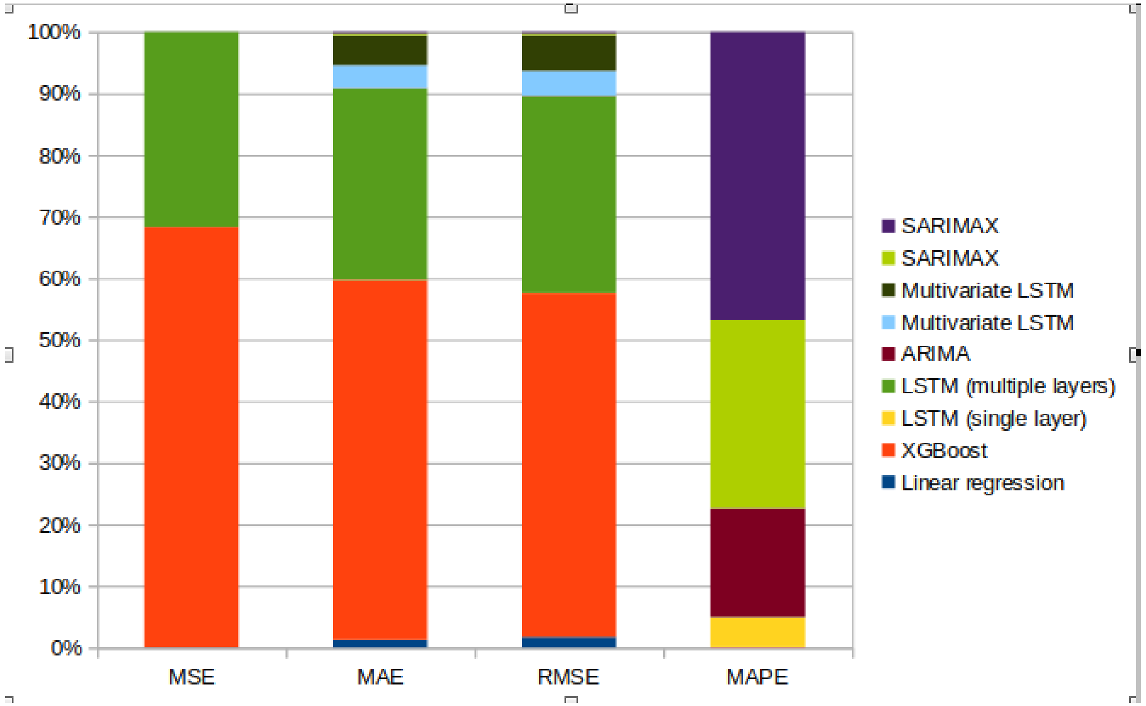


Fig. 42. Final comparison among all models

Final comparison

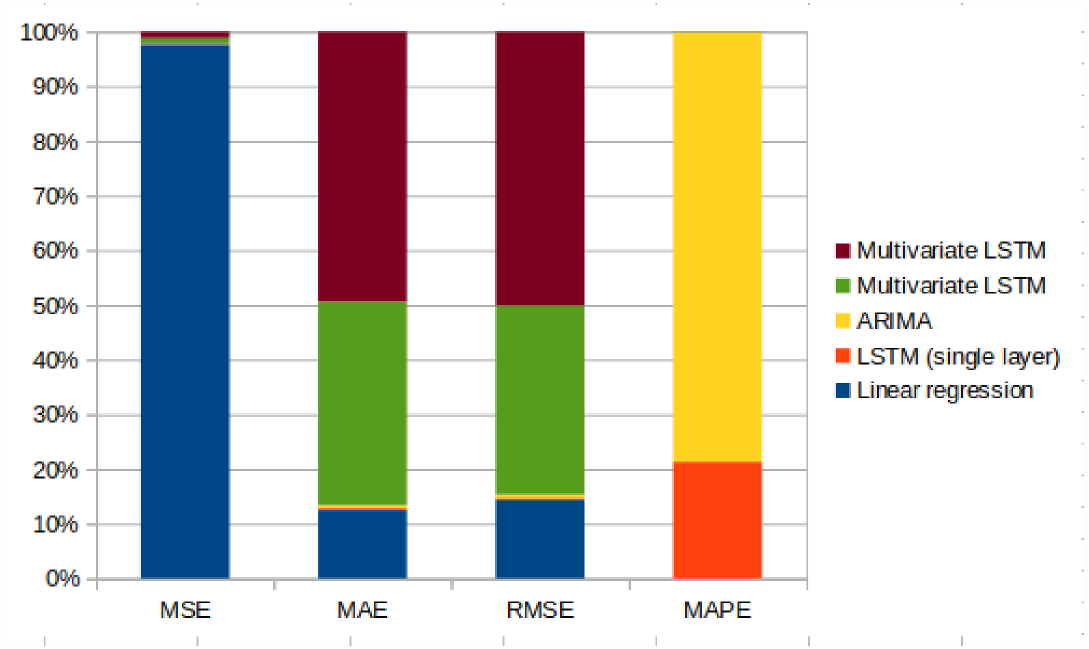


Fig. 43. Final comparison of all models with highest scores

No free lunch theorem

For any given problem, a specific neural network architecture could be effective, while another will not function well, if at all.

Conclusions and findings

Null hypothesis rejected

3 out of 5 models are univariate

9 Models created with relatively high accuracy

Collated best ideas to arrive at this solution

LSTM models bettern than ARIMA

XGboost is weakes, probably technical indicators does not help

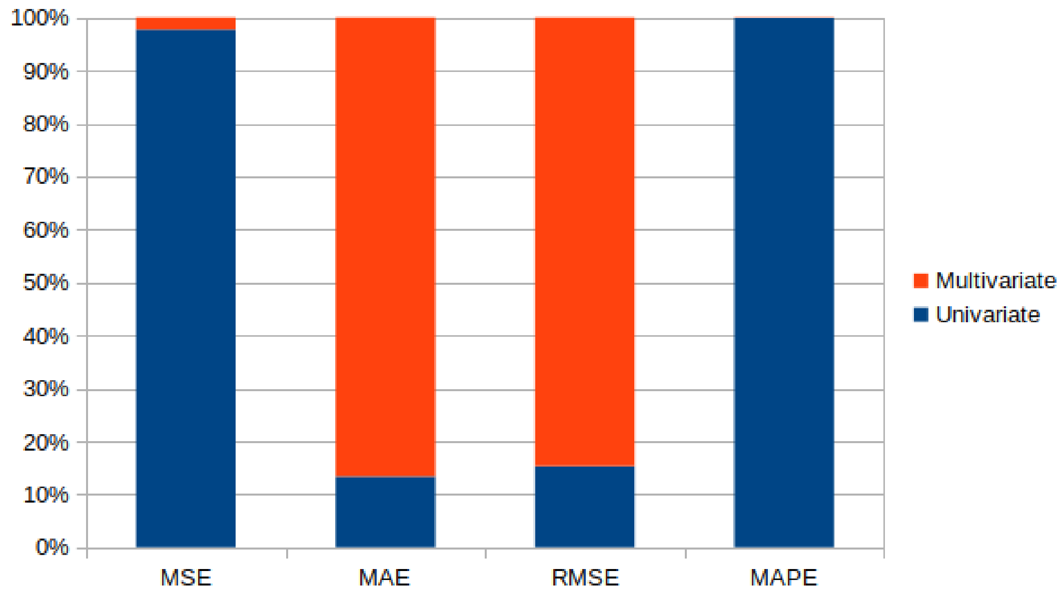


Fig. 44. Best models average scores

Future work

Use of more factors, that can help predict the market price

- Fundamental analysis
- Demography
- Inflation/Deflation
- Incidental transactions
- Liquidity
- Industry economic strength
- Main index dynamics (dow theory)
- Signals and patterns (technical analysis)
- Thematic analysis
- Newstrace analysis

  Classification analysis

  Derivative analysis

Try different approaches and techniques

- Sentimental analysis with R libraries
- Sentimental analysis RNN models
- Sentimental analysis CNN models
- More hybrid models
- Liquidity
- More optimizations of model architectures
- Collecting sentiment data from different sources (social media, news contents)
- Research more about usage of purely technical data
- More analysis on factors related to price changes

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