Stock Trend Prediction with News Data using Deep Learning

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LYU2004

Motivation

Buy today Sell tomorrow (BSTS) trading

- Buy a stock and sell it within several days
- Profit from frequent transactions

Advantage: Easier to manage risk

Disadvantage: High transaction cost

Can machine learning help us to find which stock will rise on the next day?

Project Context & Objective

Simplify the situation

1. Focus on one large cap stock, Apple Inc (AAPL)
2. Not considering the transaction cost

Objective

To classify whether AAPL will rise on the next day
To evaluate the influence of news to the stock trend

Overview

Overview of the model

Introduce the components of the model

Data acquisition & dataset

Explain how we obtain the data
Characteristic of each dataset

Experiment

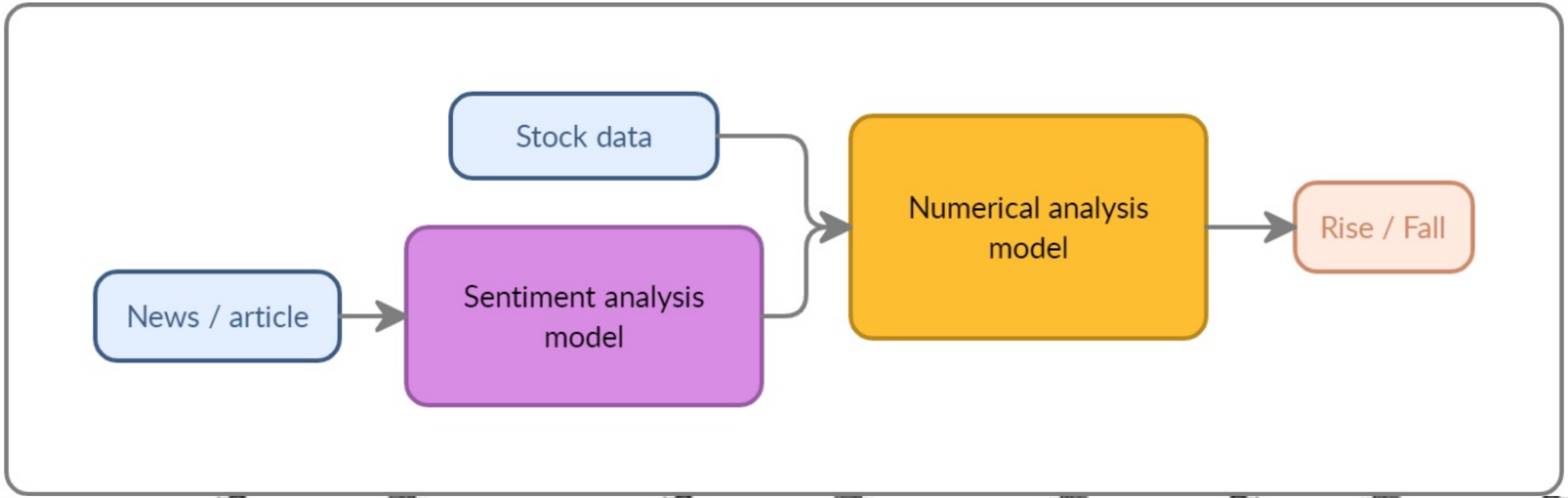
Experiment result
Discuss and evaluate the experiment result

Conclusion & future development

Q&A

Model overview:
Stock trend prediction model

- Two components
  - Numerical analysis
  - Sentiment analysis



Data acquisition & Dataset

Stock Dataset

Yahoo Finance
- Pandas DataReader
- AAPL, ^GSPC, ^IXIC
- 2010 – 2019 (2729 days)
- High, low, open, close, adj Close, volume

News Dataset 1

Sentiment analysis for financial news
- Kaggle
- Labelled (positive, neutral, negative)
- Financial news, not related to Apple
- Training set (sentiment)
- 4837 records

DATA

News Dataset 2

News selected by MarketWatch
- Web crawler
- Crawl the data once per day
- Financial news, highly related to Apple
- Training & test set (merge model)
- 379 news (until Nov 23)

News Dataset 3

New York Time
- Web crawler & API
- General news, some related to Apple
- Training & test set (merge model)
- 29084 news

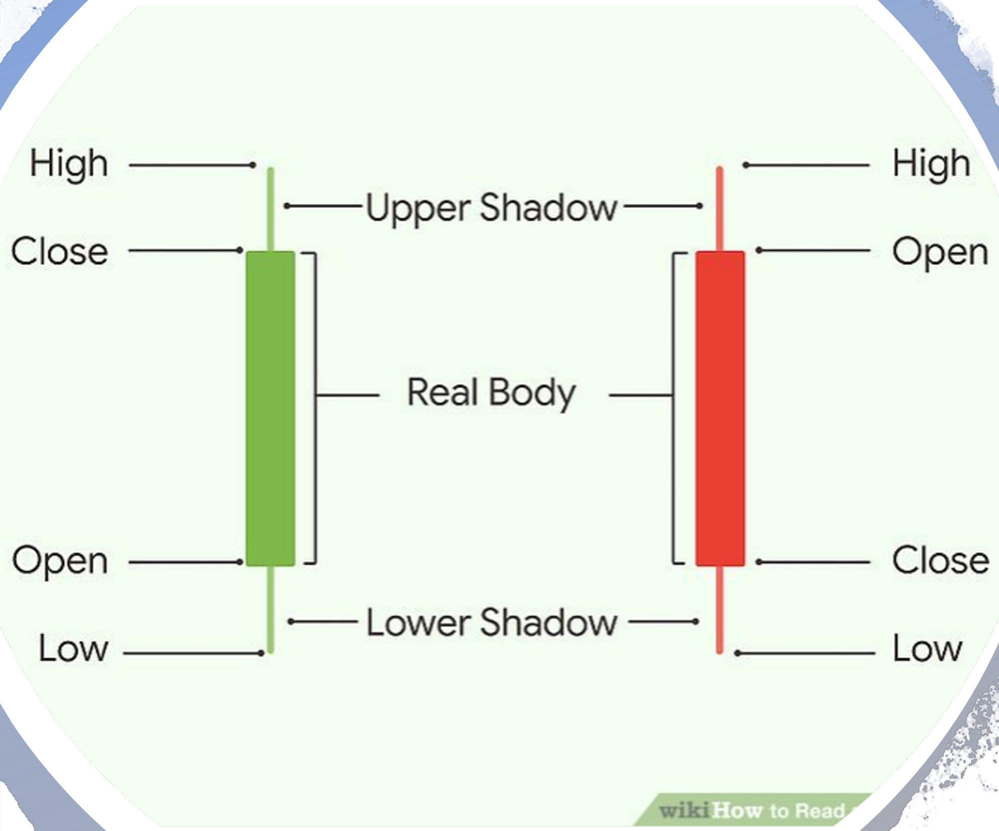
Experiment

01 Visualization

02 Numerical Analysis

03 Sentiment Analysis

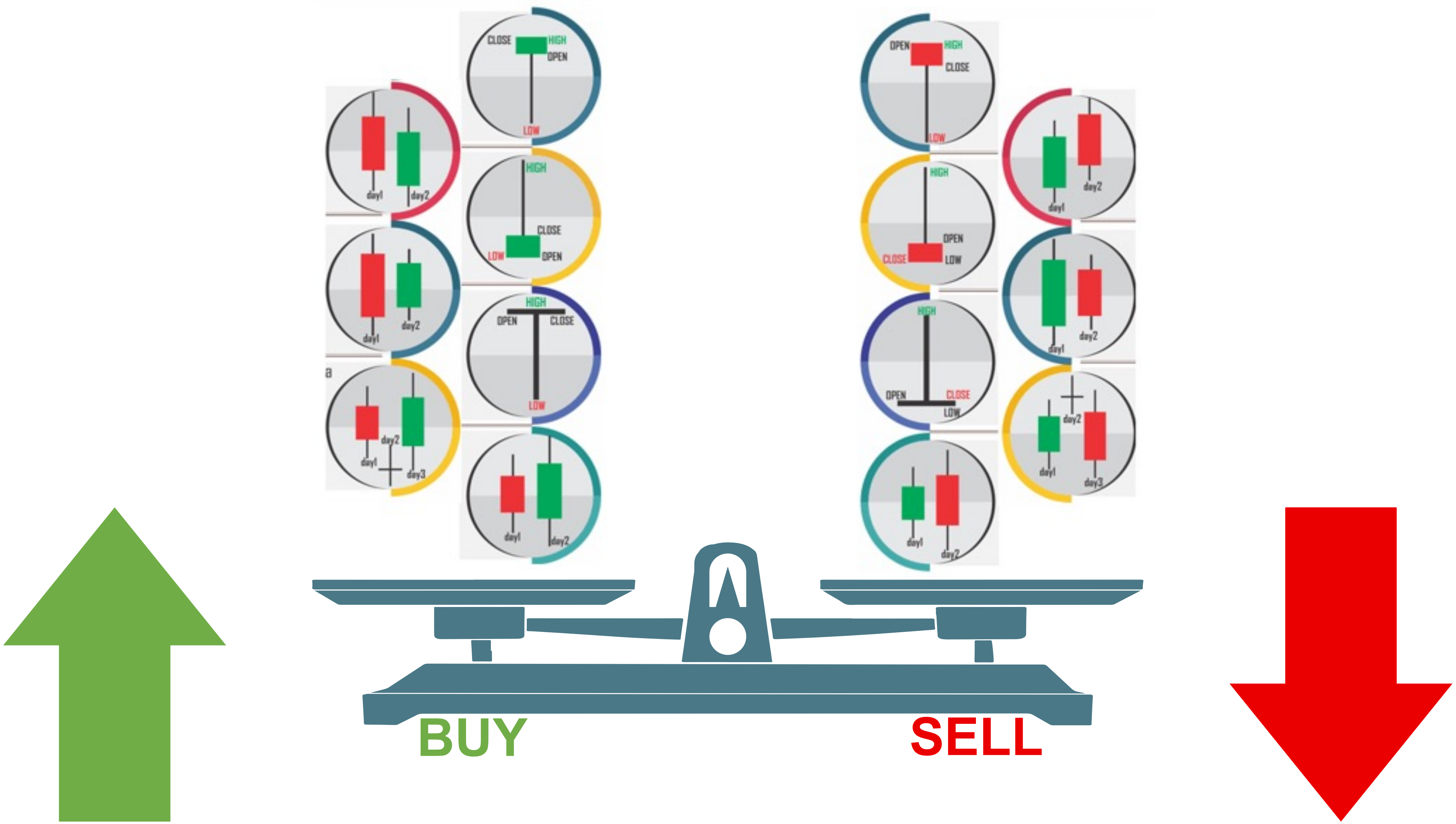
04 Model Merging



Candlestick chart

- Investors study the chart to deduce the stock trend
- A candlestick
  - High, Low, Open, Close
  - Upper, Lower shadow, and Real body

Candlestick chart pattern

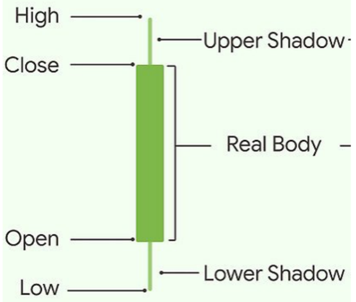


01 Visualization

Visualization

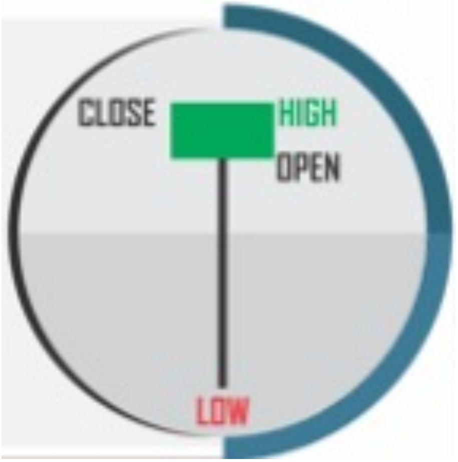
Preprocessing

- NSL = USL – LSL
- BL = Close - Open
- Labeling
  - Rise / Fall on the next day
  - E.g. label day t is rise if close of day t+1 > close of day t



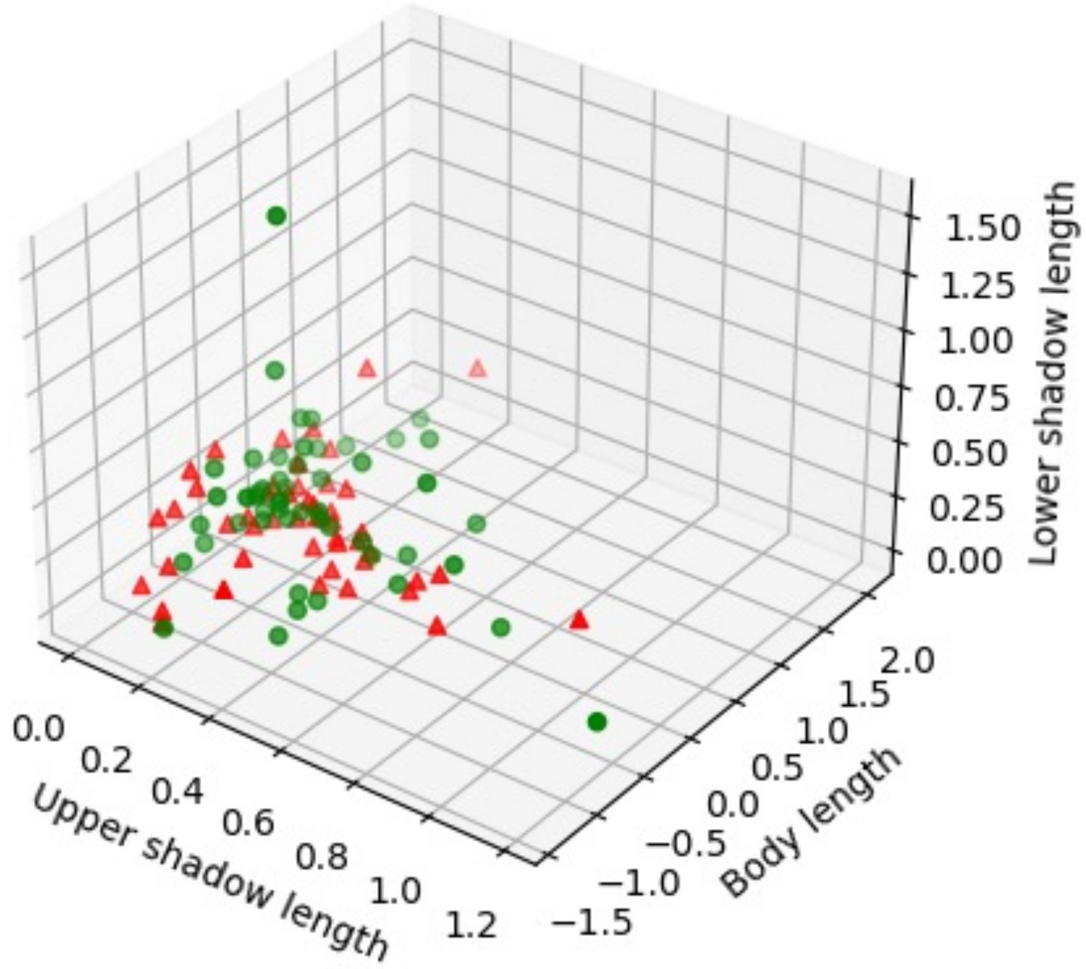
Expectation

- Hammer
  - Short & positive BL
  - Long & negative NSL

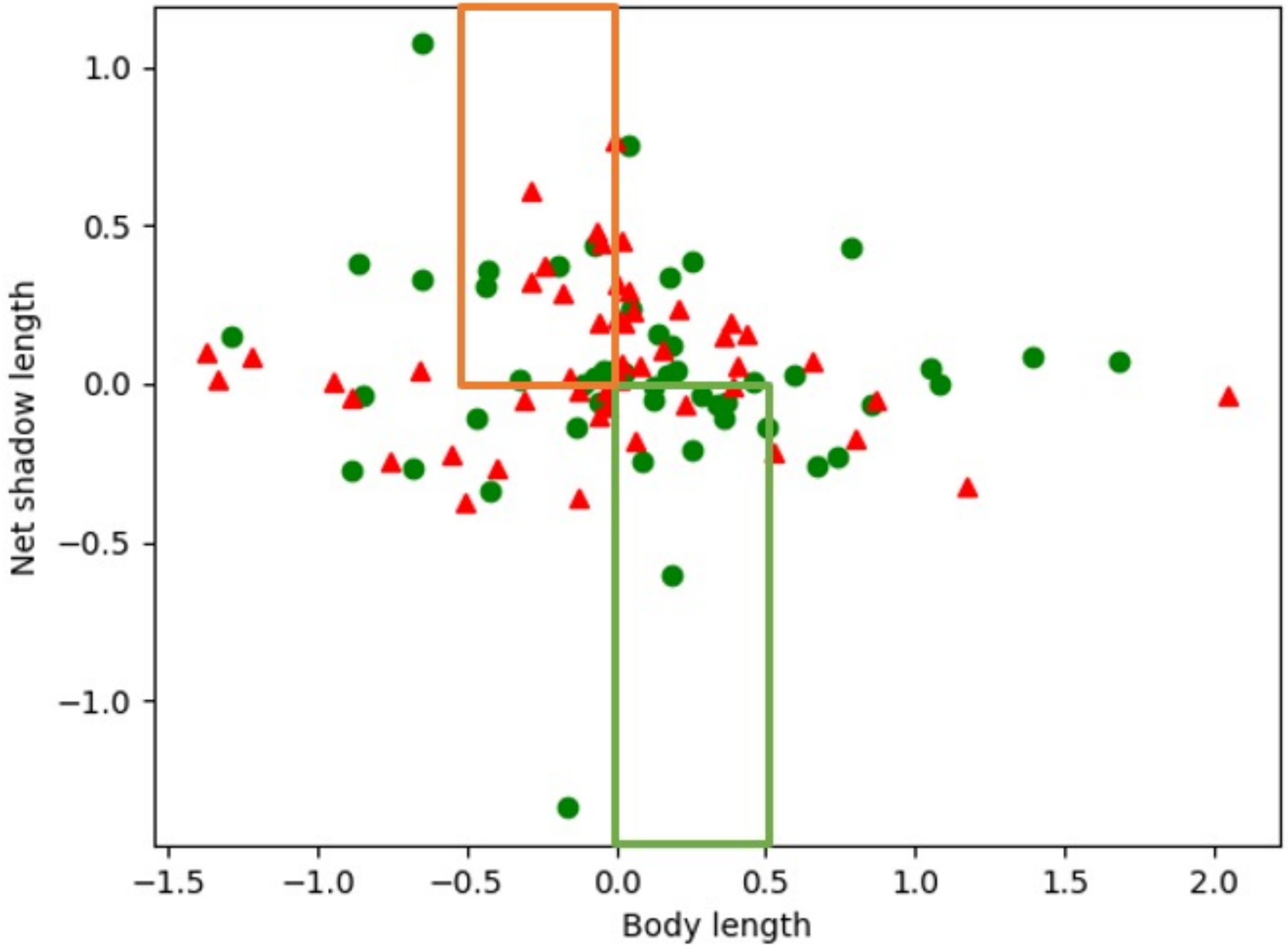


- Shooting Start
  - Short & negative BL
  - Long & positive NSL

Result



1.50
1.25
1.00
0.75
0.50
0.25
0.00
Lower shadow length
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Upper shadow length
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
Body length



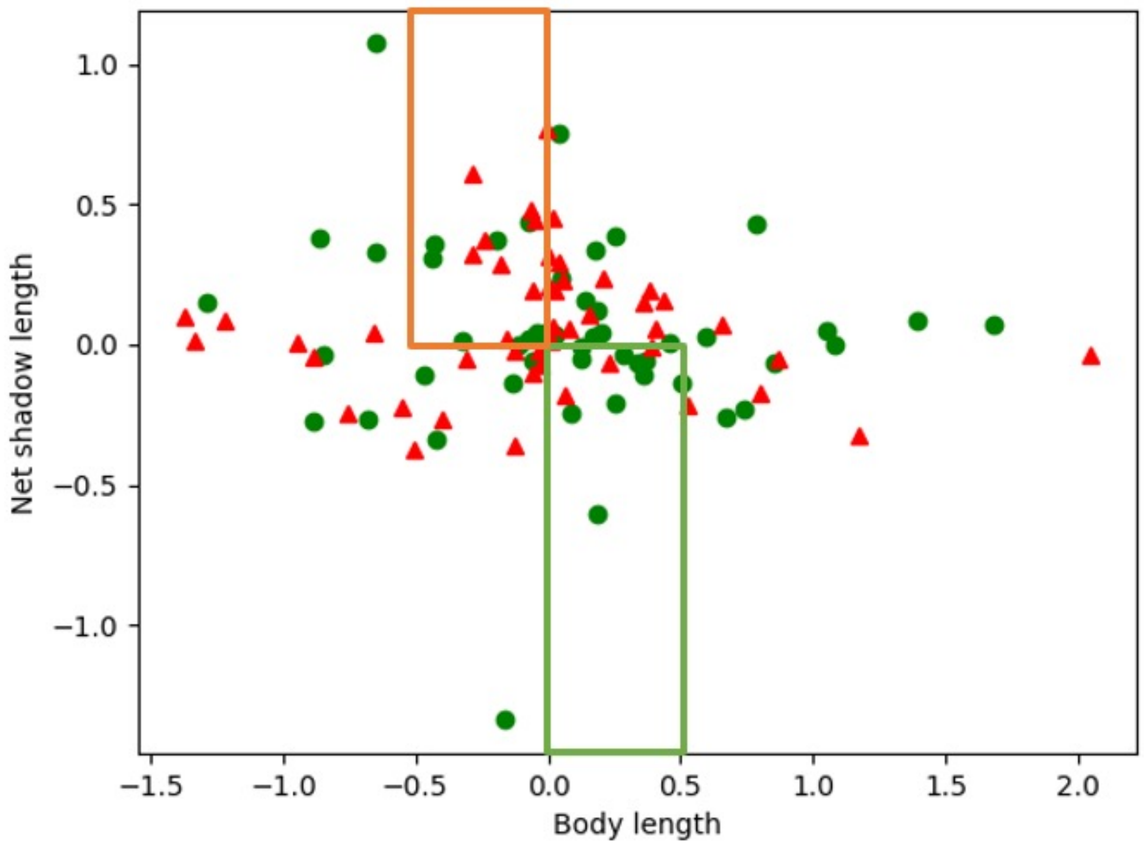
1.0
0.5
0.0
−0.5
−1.0
Net shadow length
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
Body length

Result

- Green box: 9 green and 3red
- Red box: 8 green and 8 red

- “Accuracy” about 58.6%
  - Not a rigorous approach

- Statistical model may not be a good starting point
  - Other paper about 70% accuracy

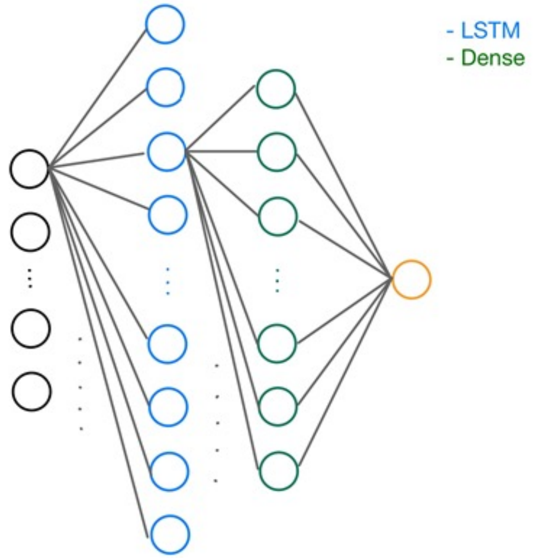


02 Numerical analysis

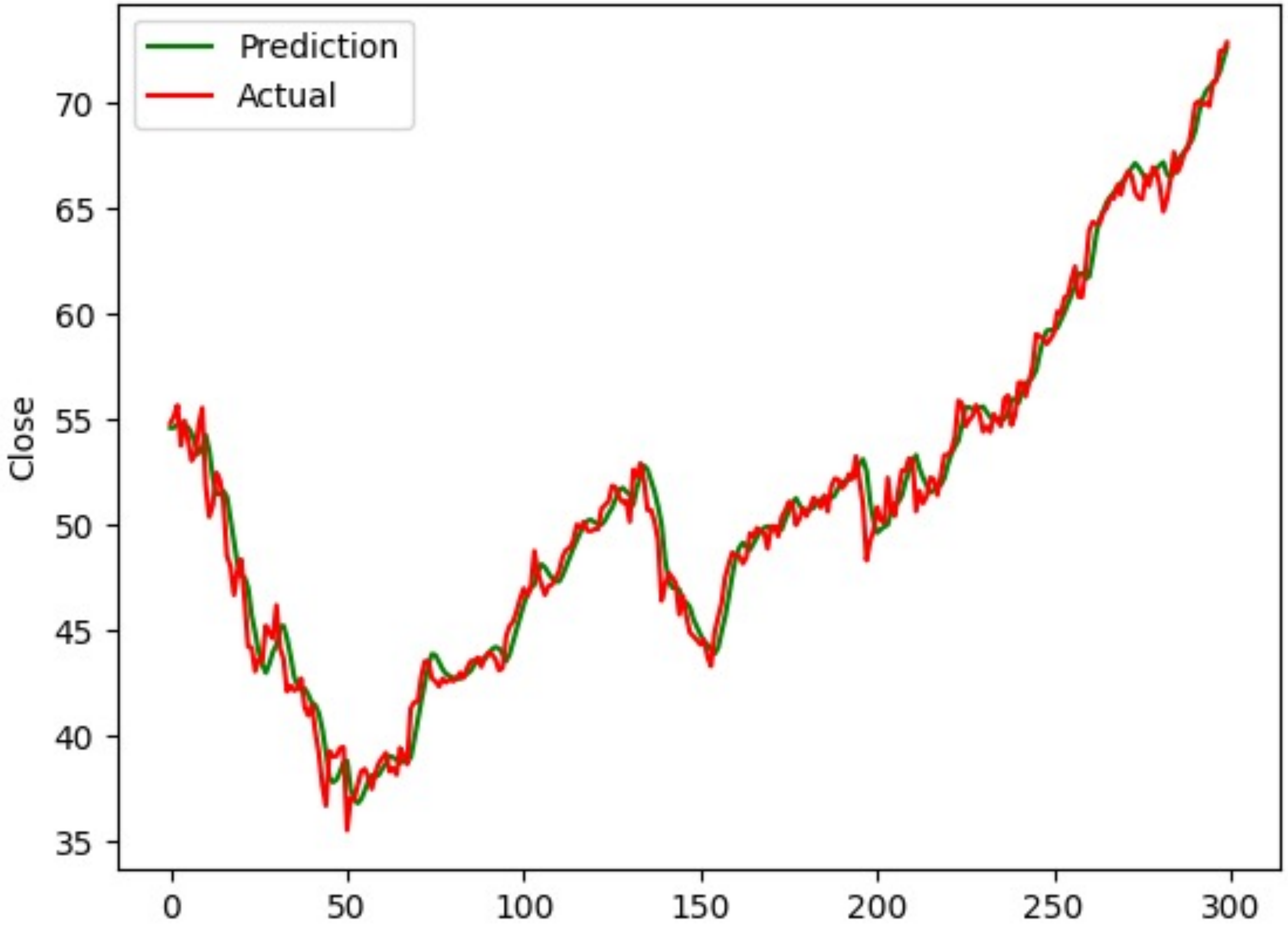
LSTM
GRU
KNN
Prophet

LSTM

- Stock data is a typical time series data
- Input feature: (six basic values)High, low, open, close, adj close, volume
- Sequence length: 10 days
- Output: The predicted close price of the next day
- Architecture:
  - 1 input layer
  - 1 LSTM layer
  - 1 dense layer
  - 1 output later

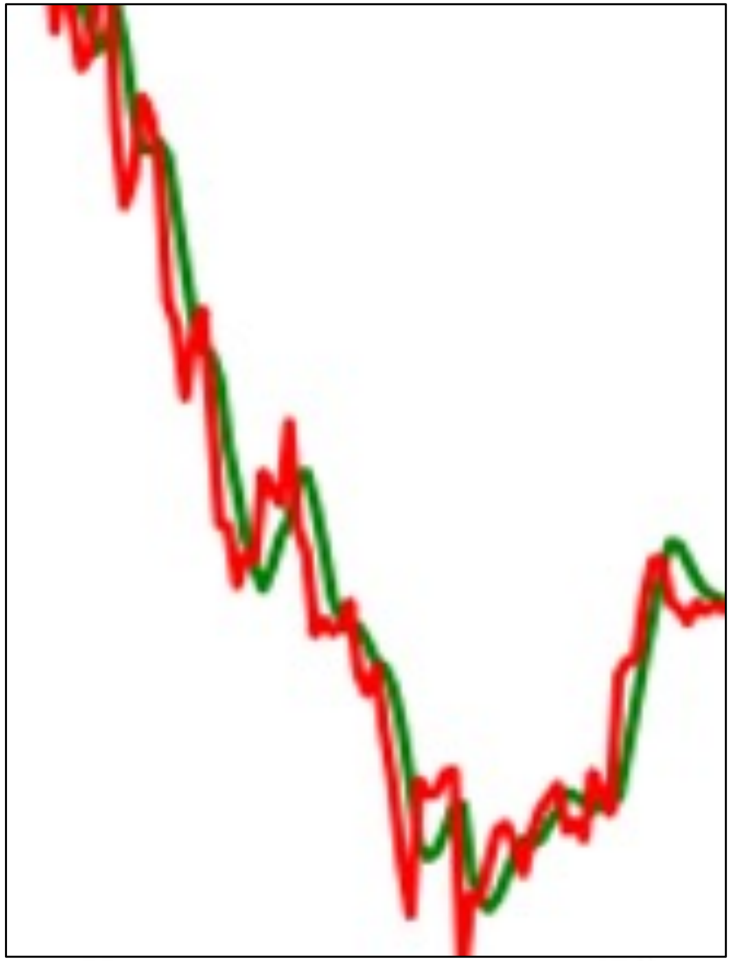


LSTM – Experiment result



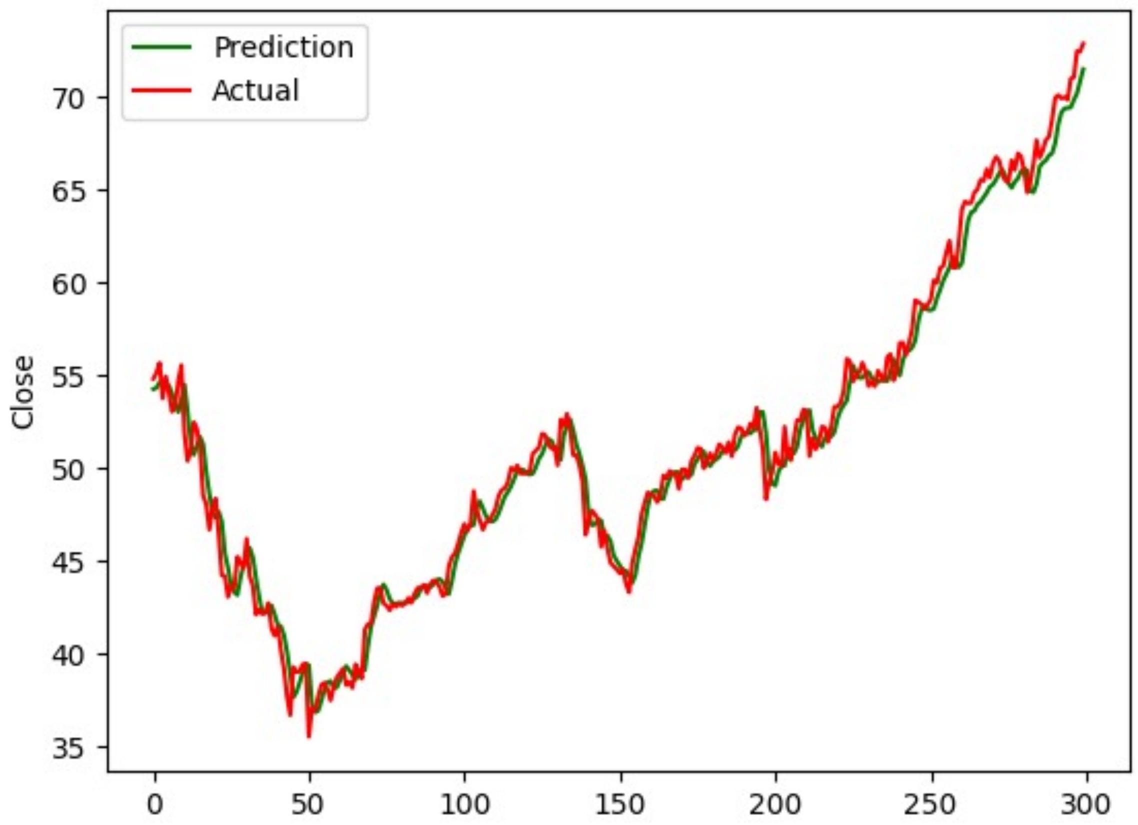
- MSE: 1.083
- The prediction is quite close the ground truth

LSTM – Experiment result



- Not a good prediction
- Not sensitive to short-term volatility
- Delayed real trend, shifted to right
- Using today’s closing price as tomorrow’s closing price

GRU – Experiment result



- Replace LSTM cells by GRUs
- MSE: 1.174
- Still base on the current trend to give the prediction
- Similar problems with LSTM

Problems in LSTM & GRU

- As they use a sequence of days to predict the coming close price
- The models will follow the trend of the input sequence to make prediction
- It give the same trend of the input sequence
- Not able to predict a turning point

A better model should be

- Not always follow the trend of recent stock price
- Try to predict the turning points

KNN Regression

- The average value of nearest points

Key differences:

- Nearest points are not necessary to be the recent stock data
- Less likely to follow the trend of recent data

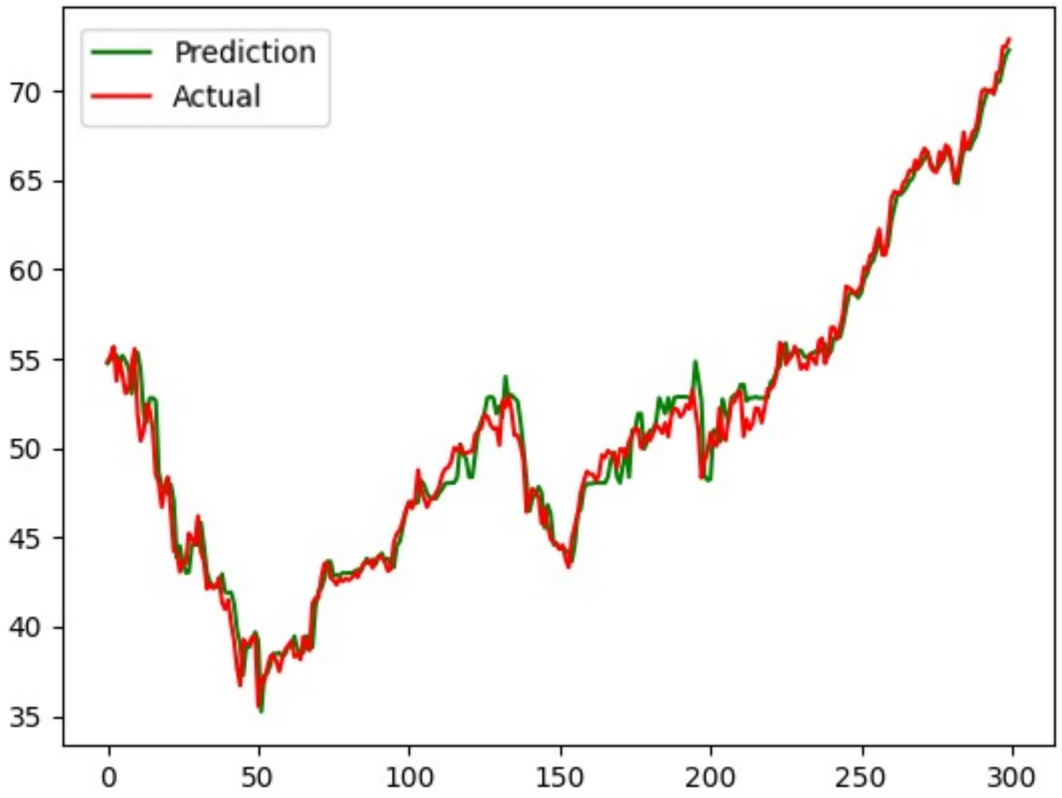
KKNR – Experiment result

- Input: Six basic values of day t
- Output: Closing price of day t+1
- Training set: 2010 – 2018 (~2250)
- Test set: 2019 – 2020 (~300)

- Best MSE is 1.162 when K is 13

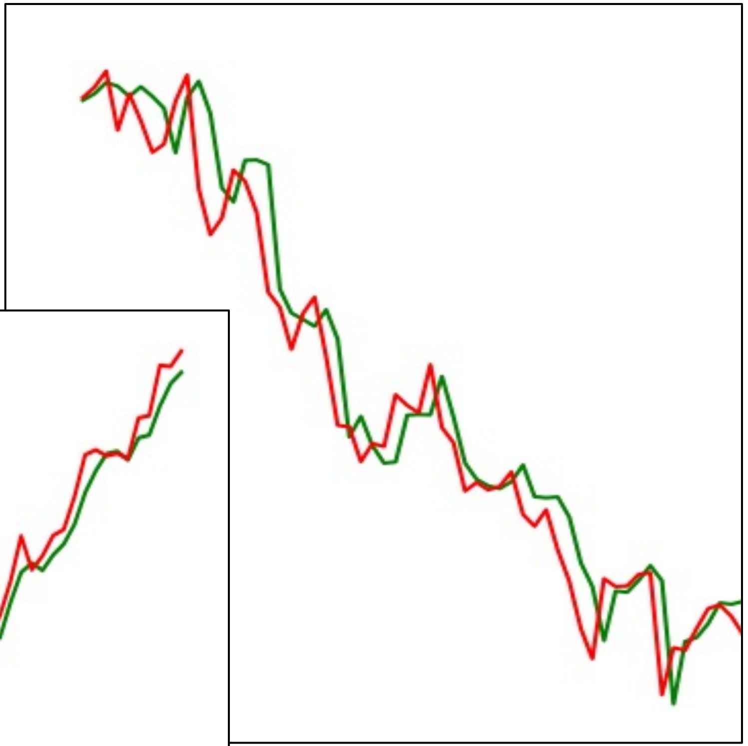
K	7	10	12	13	14	15
MSE	1.191	1.180	1.163	1.162	1.186	1.169
RMSE	1.091	1.086	1.078	1.078	1.089	1.081

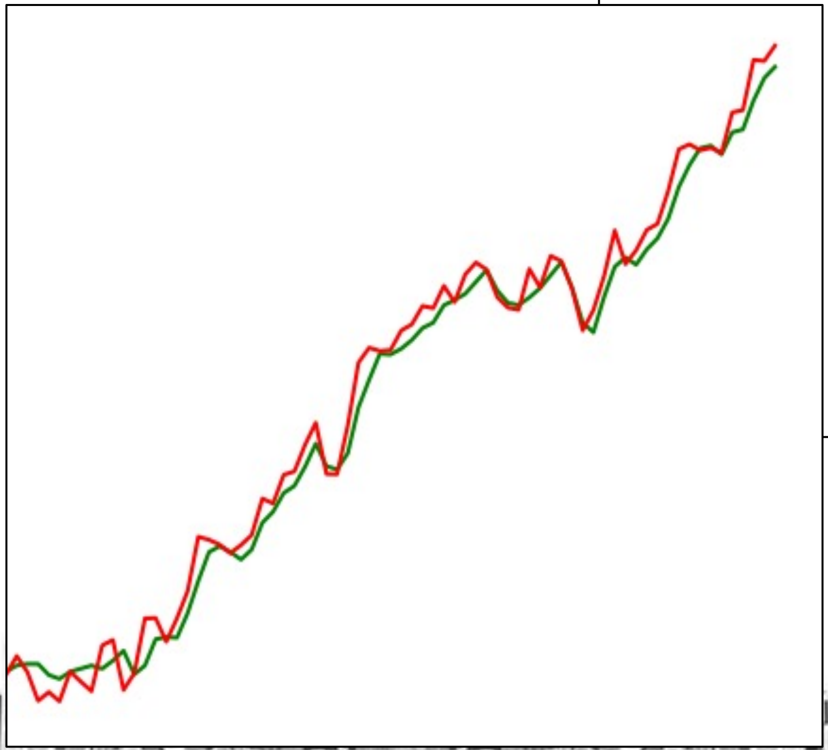
KKNR – Experiment result



- KNN is a better prediction model
- “Delay” still exist but improved
- Try to predict turning points

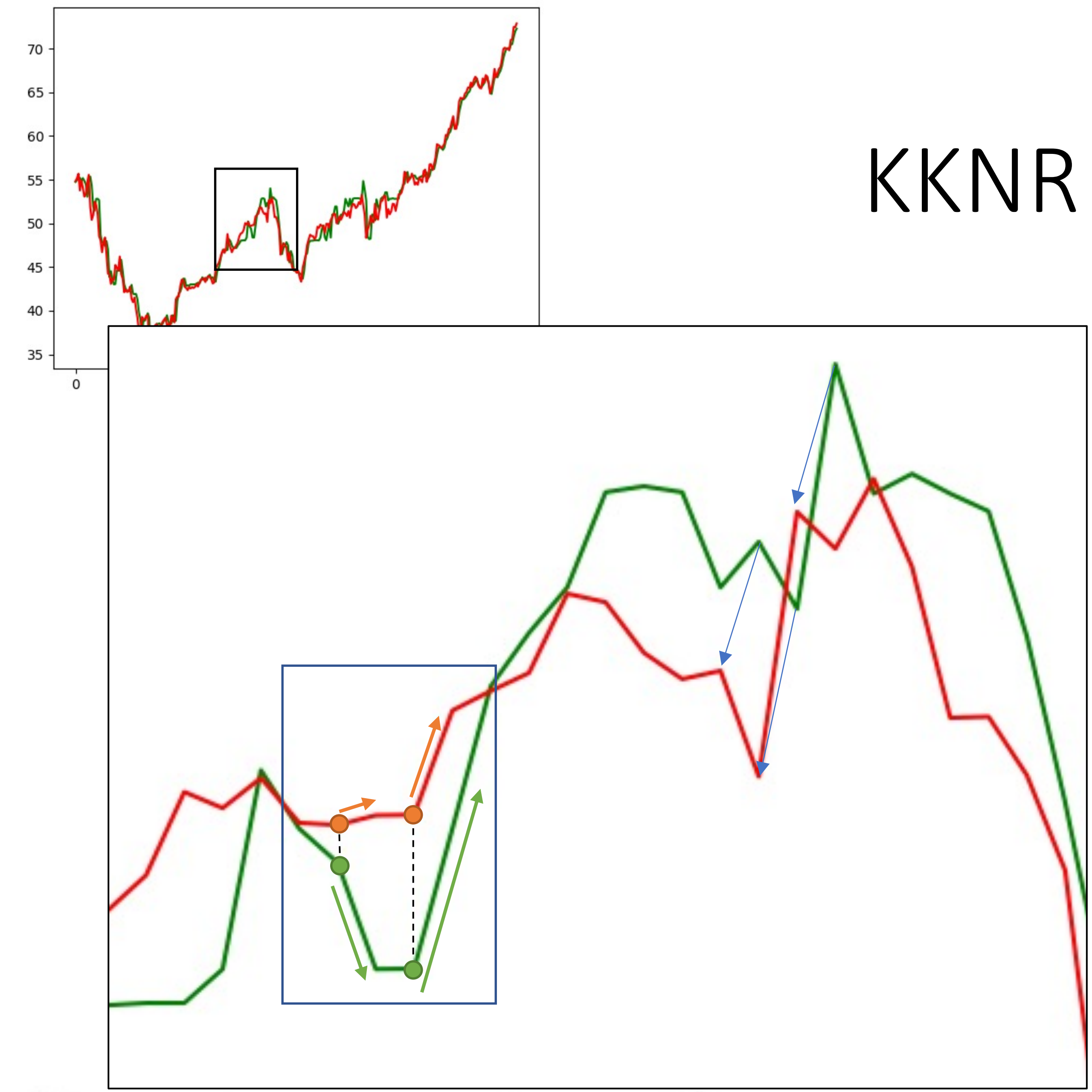
KKNR – Experiment result





- “Delay” **mainly** occurs when there is an obvious rising or falling trend
- If the trend is relatively steady, KNNR can give us interesting prediction

KKNR – Experiment result



- We can see KNNR is trying to predict the turning point
- There are two “on time” turning point predictions made in the box
  - One correct prediction
  - One wrong prediction

KNN Classification

- KNN Classification
  - Given the stock data of day t
  - To predict whether the closing price of day t+1 is higher or lower than the closing price of day t

- Preprocess
  - Label each day by comparing it closing price with the closing price of the next day

KNNC – Experiment result

- Input: Features of day t
- Output: Closing price of day t+1
- Training set: 2010 – 2018 (~2250)
- Test set: 2019 – 2020 (~300)

- Best accuracy 0.557 when K is 5

K	3	4	5	6	7	8
Accuracy	0.530	0.498	0.566	0.518	0.530	0.470

KNNR: As a classifier

- As KNNR can make turning point prediction
- This characteristic helps predict whether the stock will rise or fall
- Performance measure
  - $Close_t$: Actual close price of day t (today)
  - $Close_{t+1}$: Actual close price of day t+1 (tomorrow)
  - $\widehat{Close}_{t+1}$: Predicted close price of day t+1 (tomorrow)

$$Correct\ if\ \left(\widehat{Close}_{t+1} > Close_t\ and\ \ Close_{t+1} > Close_t\right)$$
$$or\left(\widehat{Close}_{t+1} \le Close_t\ and\ \ Close_{t+1} \le Close_t\right)$$

$$Wrong\ if\ \left(\widehat{Close}_{t+1} > Close_t\ and\ \ Close_{t+1} \le Close_t\right)$$
$$or\left(\widehat{Close}_{t+1} \le Close_t\ and\ Close_{t+1} > Close_t\right)$$

KNNR: As a classifier – Experiment result

- The best accuracy is 0.583 when K = 11

K	4	5	7	10	11	12	13	15
Accuracy	0.567	0.550	0.553	0.573	0.583	0.580	0.567	0.477

- As a comparison, accuracy of previous KNNC is 0.557

K	3	4	5	6	7	8
Accuracy	0.530	0.498	0.566	0.518	0.530	0.470

Prophet

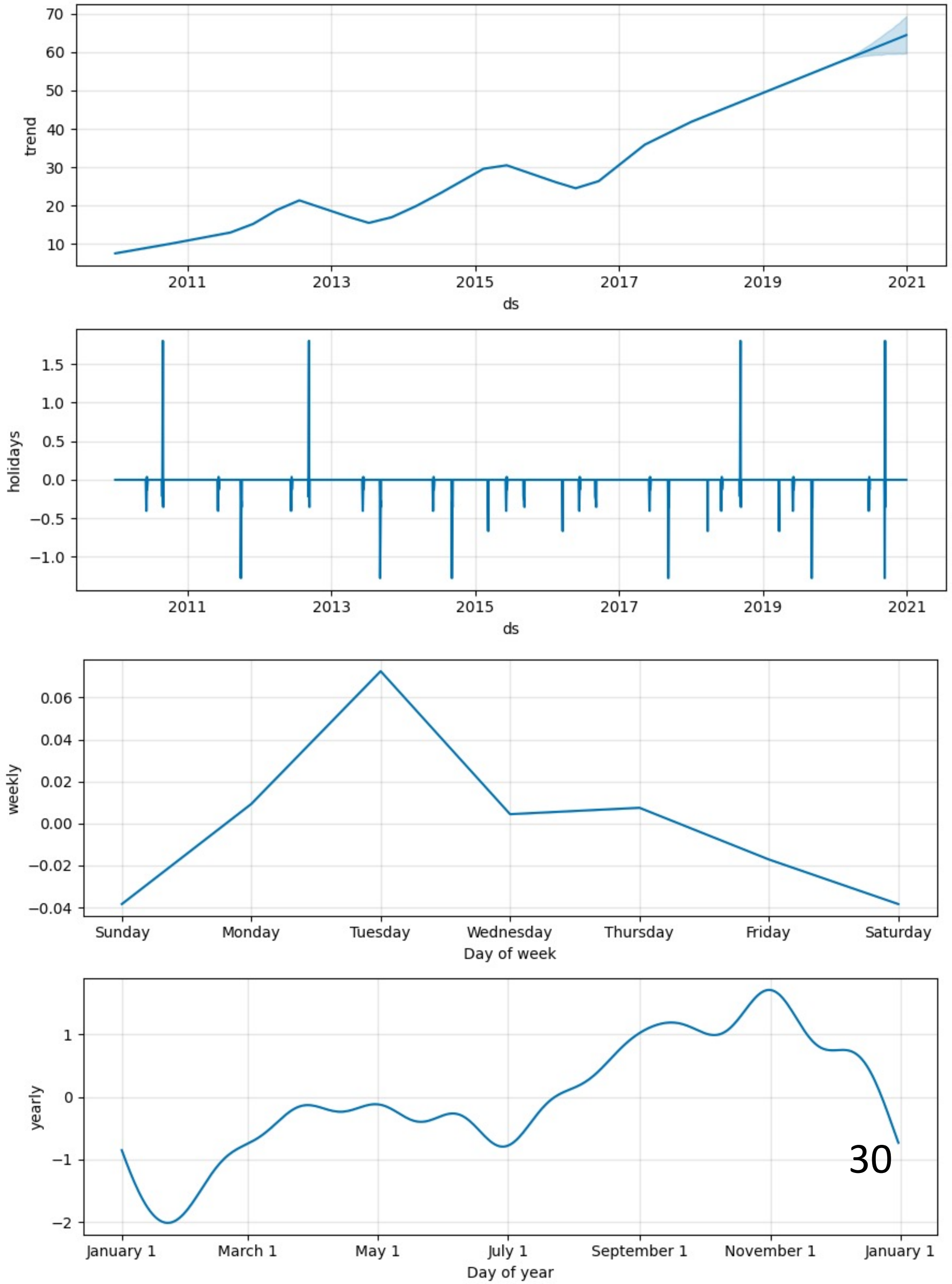
- A time series forecast model proposed by Facebook in 2017
- Three main components
  - g(t) measures the non-periodic change
  - s(t) measures the periodic change
  - h(t) measures the holiday effect

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t$$

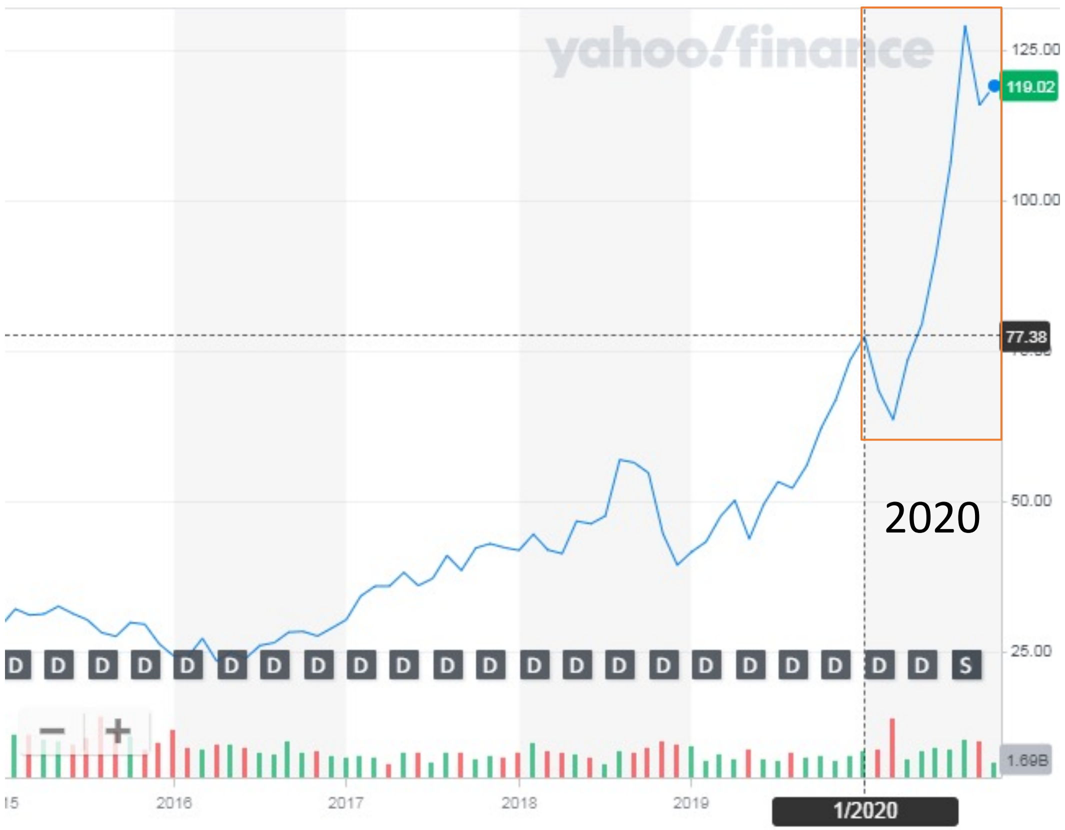
- Apple has 3 events in each year
  - Spring, autumn conferences, and WWDC
  - Define those days for h(t)

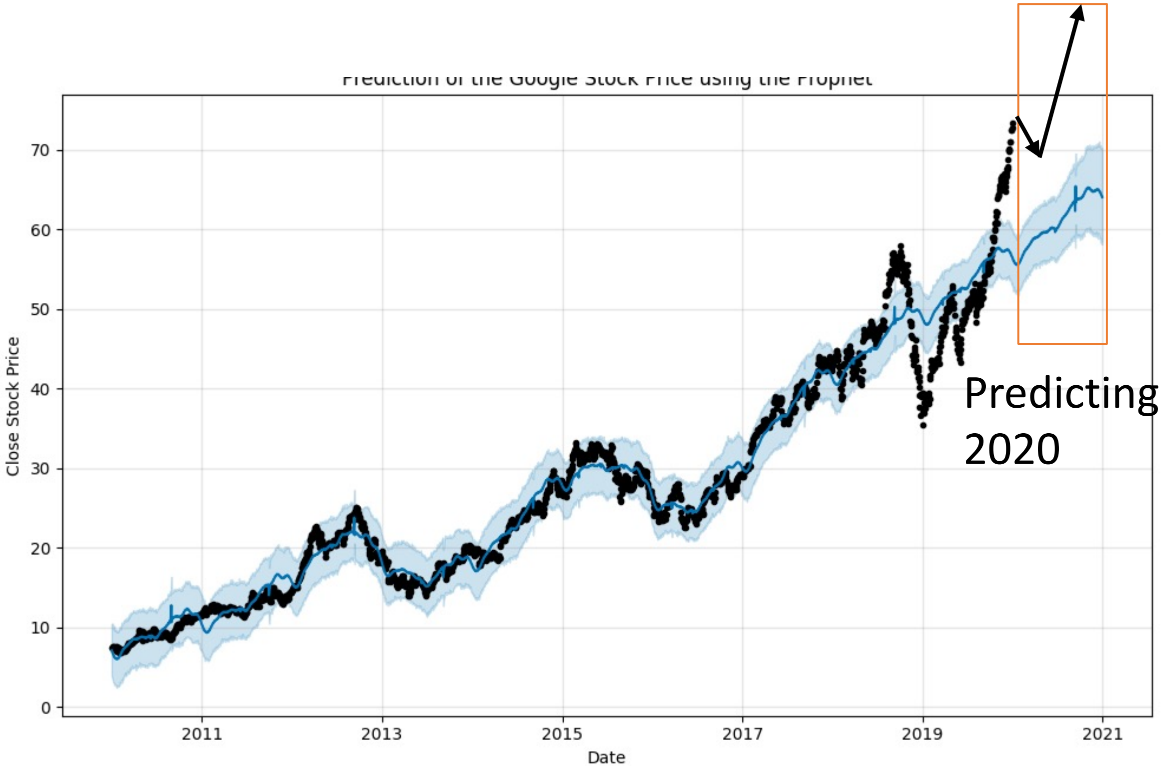
Prophet – Experiment result

- The graph show the trend learned
  - Overall trend
  - Holiday effect
  - Weekly trend
  - Yearly trend



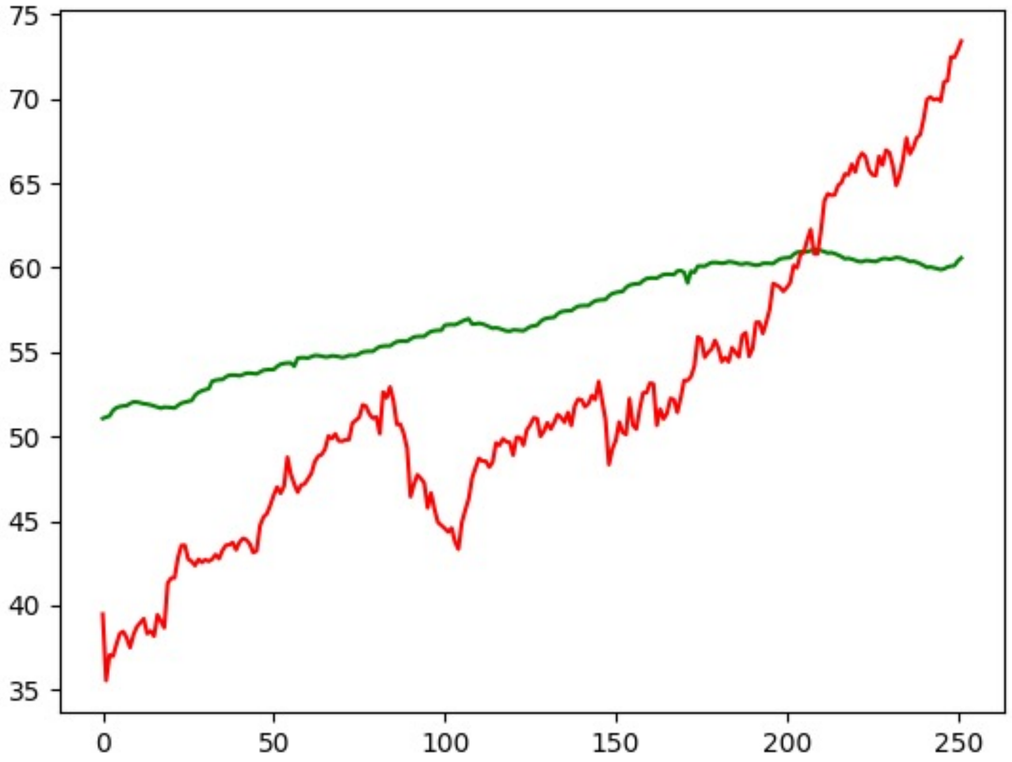
Prophet – Experiment result





Prophet – Experiment result

Prediction of 2019



- MSE: 150
- Not a good prediction model for stock
- It gives an overall trend

03 Sentiment analysis

TextBlob
VADAR Sentiment
ANN
BERT

TextBlob

- Python library for processing textual data
- Input sentence -> output polarity score
- Test on pre-labelled dataset
- 49% accuracy

```
      Sentiment                                          Headlines  tb_hl_polarity
0             0  According to Gran , the company has no plans t...               0
1             0  Technopolis plans to develop in stages an area...               1
2            -1  The international electronic industry company ...               0
3             1  With the new production plant the company woul...              -1
4             1  According to the company 's updated strategy f...               0
...         ...                                                ...             ...
4841         -1  LONDON MarketWatch -- Share prices ended lower...              -1
4842          0  Rinkuskiai 's beer sales fell by 6.5 per cent ...               0
4843         -1  Operating profit fell to EUR 35.4 mn from EUR ...               0
4844         -1  Net sales of the Paper segment decreased to EU...               1
4845         -1  Sales in Finland decreased by 10.5 % in Januar...              -1

[4846 rows x 3 columns]

accurancy: 49.113
```

VADAR Sentiment

- A lexicon and rule-based sentiment analysis tool
  - specifically attuned to sentiments expressed in social media
- Test on pre-labelled dataset
- 54% accuracy

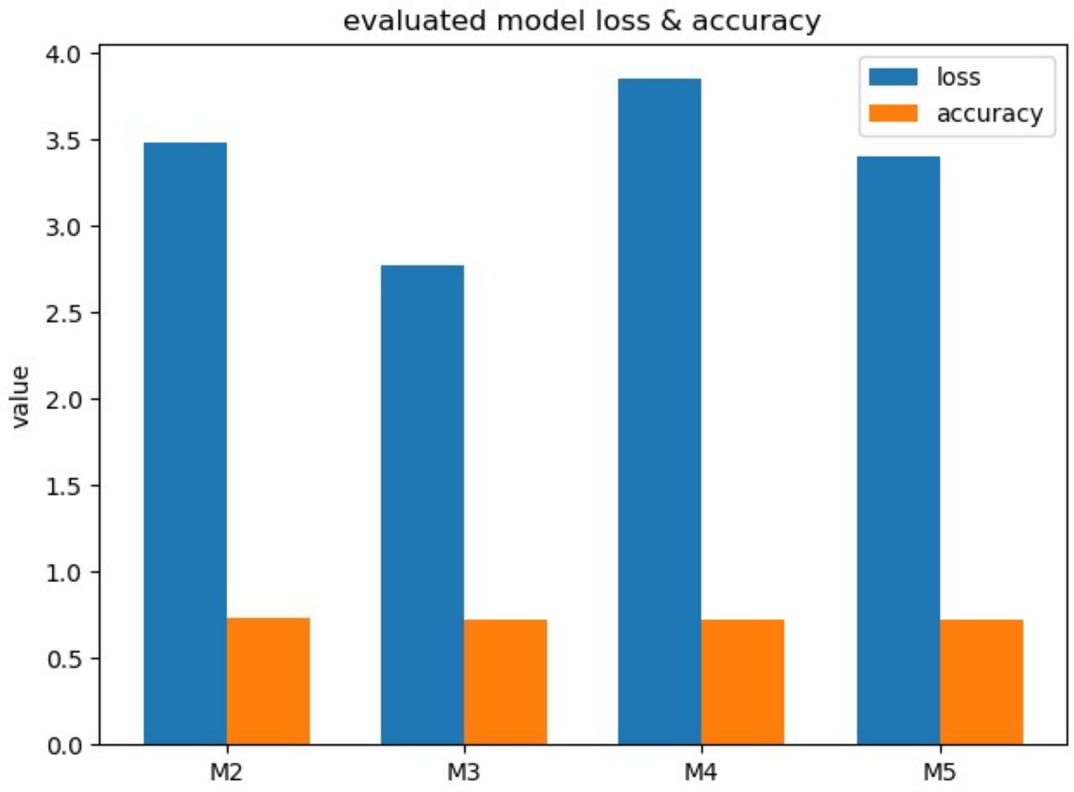
```
      Sentiment                                          Headlines  vadar_polarity
0             0  According to Gran , the company has no plans t...              -1
1             0  Technopolis plans to develop in stages an area...              -1
2            -1  The international electronic industry company ...               0
3             1  With the new production plant the company woul...               1
4             1  According to the company 's updated strategy f...               1
...         ...                                                ...             ...
4841         -1  LONDON MarketWatch -- Share prices ended lower...              -1
4842          0  Rinkuskiai 's beer sales fell by 6.5 per cent ...               0
4843         -1  Operating profit fell to EUR 35.4 mn from EUR ...               1
4844         -1  Net sales of the Paper segment decreased to EU...               1
4845         -1  Sales in Finland decreased by 10.5 % in Januar...               0

[4846 rows x 3 columns]

accurancy: 54.354
```

ANN

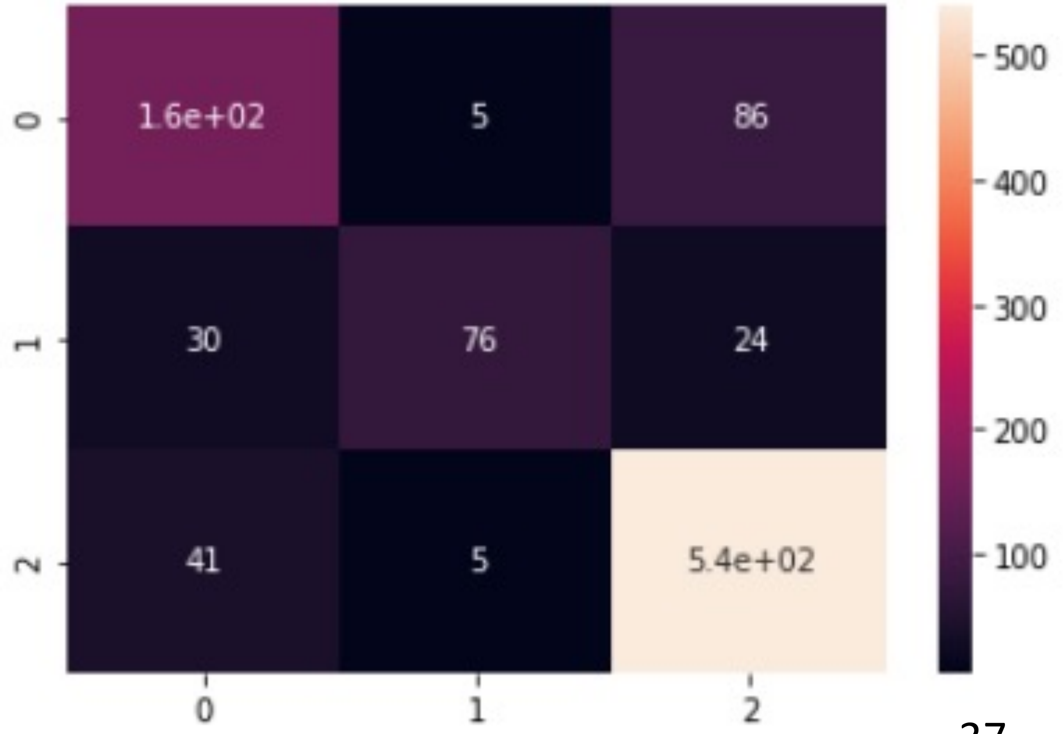
- Input feature: sentence / word count vector
- Output: sentiment score (-1, 0, 1)
- Test on pre-labelled dataset
- Accuracy 72.78%



BERT – Experiment result

- Classify the sentiment of a given sentence
  - Positive, neutral, and negative

- Training set: sentiment for financial news
- Test set: sentiment for financial news
- Accuracy: 81.6%
- Balanced accuracy: 80.3%

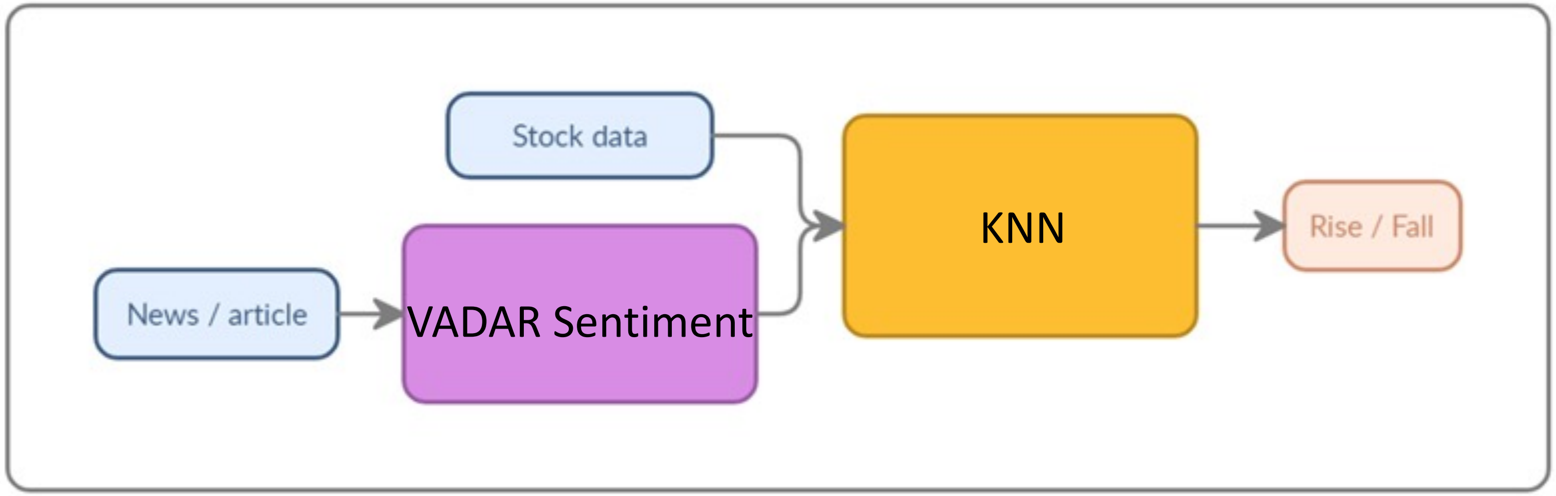


04 Model Merging

KNN + VADAR
LSTM + BERT

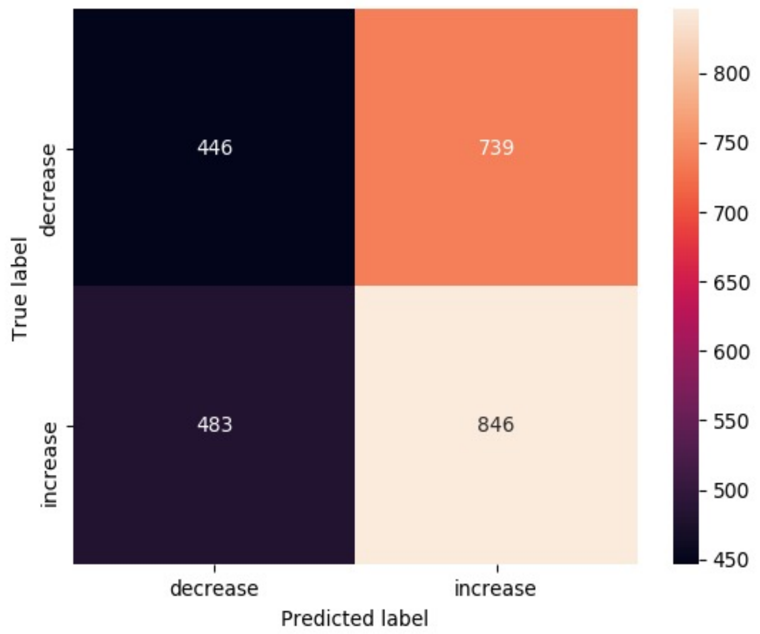
Final model 1: KNN + VADAR Sentiment

- Input:
  - Average sentiment score of today's news
  - Close price of today
- Output:
  - Rise (1) / Fall (0) of tomorrow's close price

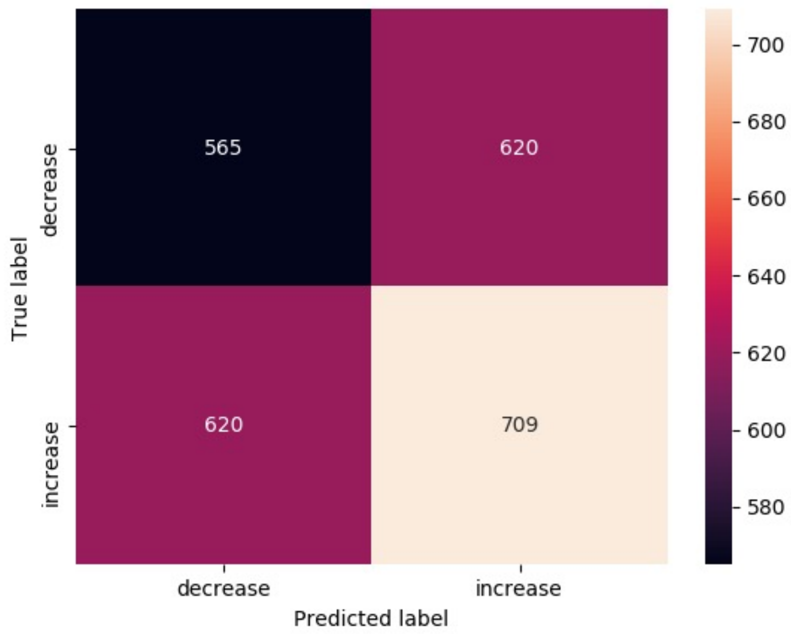


Final model 1 – Experiment result

- With sentiment
- Accuracy 51.39%



- Without sentiment
- Accuracy 50.68%



Final model 1 – Experiment result

- Overall performance

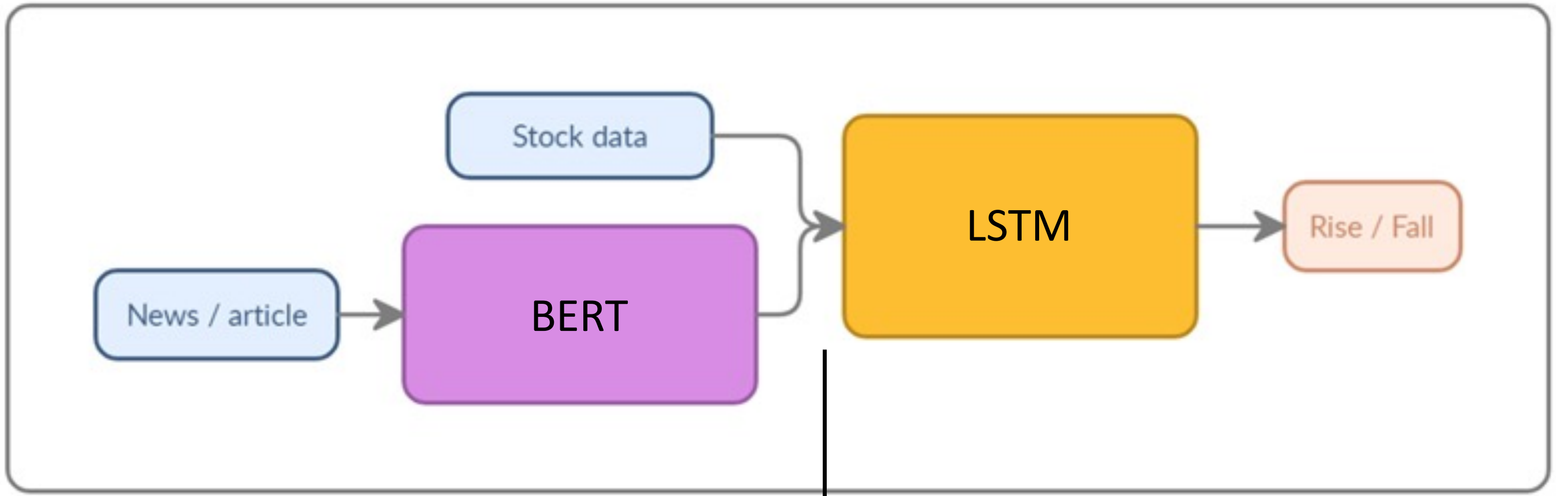
	w/ sentiment	w/o sentiment	changes
accuracy	51.39%	50.68%	0.72%
balanced accuracy	50.65%	50.51%	0.13%

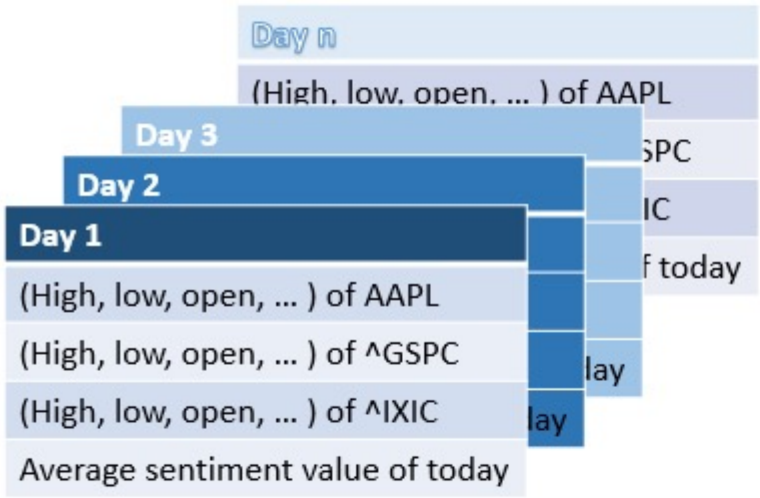
Final model 2: LSTM + BERT

- Output of Bert
  - Sentiment value of **each news** (New York Time)

- Preprocess
  - As there are multiple news on one day
  - Find the average sentiment values for **each day**

- LSTM
  - Input features: Stock data of AAPL, ^GSPC, ^IXIC, and sentiment
  - Output: Rise / fall


Stock data
News / article
BERT
LSTM
Rise / Fall


Day n
(High, low, open, ...) of AAPL
Day 3
Day 2
Day 1
(High, low, open, ...) of AAPL
(High, low, open, ...) of ^GSPC
(High, low, open, ...) of ^IXIC
Average sentiment value of today

Final model 2 – Experiment result

- Without sentiment
  - No sentiment value (all set to 0)
  - Accuracy: 50.83%
  - Balance accuracy: 50.92%

- With sentiment
  - Accuracy: 52.08%
  - Balance accuracy: 52.14%

- Comparison

	No sentiment	With sentiment	Changes
Accuracy	50.83%	52.08%	+1.25%
Balanced accuracy	50.92%	52.14%	+1.22%

Final model 2 – Experiment result

- Examples

	High	Low	Open	Close	Volume	Adj Close	Sentiment	Prediction	Ground truth
Without sentiment	44.80	44.17	44.49	44.58	8.49E+07	43.97	N/A (0)	Rise (FP)	Fall
With sentiment							-0.613	Fall (TN)	
Without sentiment	44.48	42.57	43.9	43.325	1.62E+08	42.74	N/A (0)	Fall (FN)	Rise
With sentiment							0.359	Rise (TP)	

Conclusion

Numerical analysis

- Initially we though statistical approach may not give us a good prediction.
- Based on the inspiration of LSTM/GRU experiment, we inferred what a good model should be capable of.
- In the KNN experiment, we saw it is trying to predict the turning points

Sentiment analysis

- News datasets availability affected the performance of our model
- General news are used to test the model which is trained with financial news

Model merging

- Adding sentiment values improves the accuracy
- Loss between the sentiment analysis model and the numerical analysis model. It will be a bottleneck of the whole model.

Timeline Style

01 Pattern learning
Analysis more stocks, to identify the pattern that may imply a rising trend.

02 Public emotion
To further understand the public emotion, we will study the data from social media.

03 Decision making
Train the modules to make decision, finding the opportunity for entering the market and delisting.

04 Assemble into a tool
Integrate everything into a tool which help user to build their own portfolio

January **February** **March** **April**

Thank You

Thank you for your listening

Q&A