SHANGHAI JIAOTONG UNIVERSITY

Data Mining EE359

Data Mining Final Project

Author:
Yuting JIA

Supervisor: Dr. Yuan Bo

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Abstract

Your abstract.

1 Introduction

Your introduction goes here! Some examples of commonly used commands and features are listed below, to help you get started.

If you have a question, please use the support box in the bottom right of the screen to get in touch.

2 Data Collection

We collected two different types of data. The first one is collected from Wind, a financial data company. This part of data is about the price of stock. And the other one is the data which TA give us, about the trade of some future goods.

2.0.1 Wind Data

Wind Financial Terminal (WFT), an indispensable tool to tap into the Chinese financial market, provides the most complete data and information on the Chinese financial market, covering stocks, bonds, funds, indices, warrants, commodity futures, foreign exchanges, and the macro industry, for securities analysts, fund managers and other financial professionals. This enables you to obtain the most accurate, timely and complete 7x24x365 financial information.

WFT provides users several interface to collect financial data, including EXCEL, MATLAB, R, Python and some other programming language. In this project, we chose the python interface because python is very convenient and stable.

From this interface, we collected the price information in recent three years for **2467** stocks. By this data, easily we can figure the price trend for each stock, and Figure 1 are some examples of the trend of price of some stocks in recent three years.

2.0.2 Future Goods Trade

This dataset is given by TA, including the trade record of several different future goods. According to TA, this dataset is enough for us to predict the price trend of future goods. And almost all exchange bourse are using this kind of data to predict future price and trade automatically.

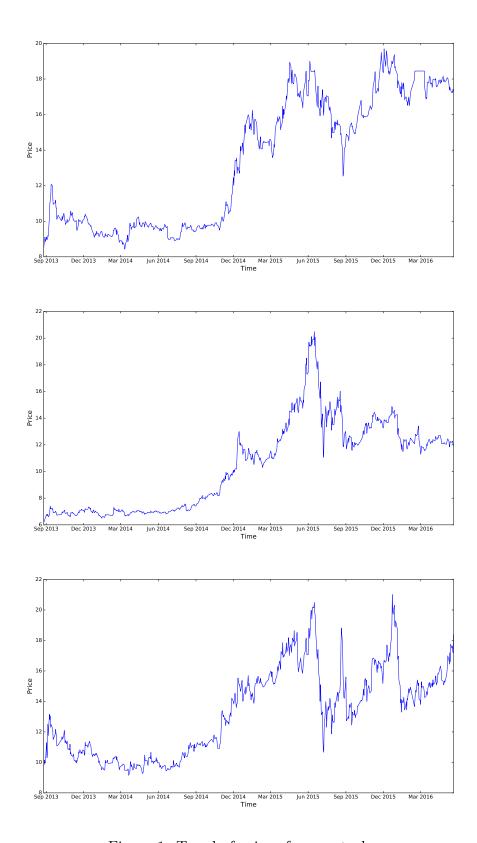


Figure 1: Trend of price of some stocks

2.1 Experiments

2.1.1 Experiment 1

Firstly we use the dataset collected from WFT. This dataset contains the open, close, highest and lowest price for each day. So the easiest and most intuitive thought is to use one day's four price to predict whether this stock rise up or fall down. So for each stock, we convert the four prices of each day to a vector, and use the trend of the second day as label(1 means rise up and -1 means fall down).

We decided to use SVM to learn this feature because it's useful, efficient and easy to realize. For each stock, we randomly chose 70% percents of feature vectors as test set, and the other as test set. What's more, we think that different stock may hold different features, so we learn different SVM model for different stock respectively. Because we has 2467 stocks, so we count and print the cumulated accuracy rate for every 10 stocks. Figure 2 shows the change of accuracy rate with the number of stocks we have learned increase. We can find the the accuracy is about 53%, just a little higher than randomly choose because this is a binary classification problem.

This results is not beyond our expection. Because the method to extract features is so easy that cannot contain much hidden information of this financial market. And following we will try some other complex and meaningful methods to extract some more useful features.

2.1.2 Experiment 2

The data we collected is a timing series data. But in the former one experiment, we only use one day's data to predict the next day's trend. But the result is not very well. So now we come up with another thought that we can use data of several days to predict the following day's price. So now we use the continuous 5 days' price as the feature vector, and the label is just same with the label in the former experiment.

Figure 3 shows the result of this experiment. From this figure we can find that the result is a little better than the former experiment, but the result is neither good enough. We think there are two reasons. The first one is that the time region we selected is not suitable. We chose to use five days' data to predict the following one day. But the region of five days can not express neither the instantaneous vibration nor the long-term trend of financial market. So the accuracy of the prediction is so low. The other one reason is that in this experiment we only use the close price of each day, so finally we also only used 5 number to be a feature vector, so the information in the feature is not enough.

```
1980 stocks, accuracy rate: 0.526708
1990 stocks, accuracy rate: 0.526734
2000 stocks, accuracy rate: 0.526713
2010 stocks, accuracy rate: 0.526633
2020 stocks, accuracy rate: 0.526605
2030 stocks, accuracy rate: 0.526555
2040 stocks, accuracy rate: 0.526459
2050 stocks, accuracy rate: 0.526413
2060 stocks, accuracy rate: 0.526294
2070 stocks, accuracy rate: 0.526172
2080 stocks, accuracy rate: 0.526023
2090 stocks, accuracy rate: 0.525877
2100 stocks, accuracy rate: 0.525820
2110 stocks, accuracy rate: 0.525655
2120 stocks, accuracy rate: 0.525625
2130 stocks, accuracy rate: 0.525615
2140 stocks, accuracy rate: 0.525571
2150 stocks, accuracy rate: 0.525587
2160 stocks, accuracy rate: 0.525575
2170 stocks, accuracy rate: 0.525628
2180 stocks, accuracy rate: 0.525688
2190 stocks, accuracy rate: 0.525720
2200 stocks, accuracy rate: 0.525658
2210 stocks, accuracy rate: 0.525541
2220 stocks, accuracy rate: 0.525501
2230 stocks, accuracy rate: 0.525406
2240 stocks, accuracy rate: 0.525289
2250 stocks, accuracy rate: 0.525225
2260 stocks, accuracy rate: 0.525216
2270 stocks, accuracy rate: 0.525163
2280 stocks, accuracy rate: 0.525199
2290 stocks, accuracy rate: 0.525161
2300 stocks, accuracy rate: 0.525151
2310 stocks, accuracy rate: 0.525216
2320 stocks, accuracy rate: 0.525301
2330 stocks, accuracy rate: 0.525286
2340 stocks, accuracy rate: 0.525312
2350 stocks, accuracy rate: 0.525278
2360 stocks, accuracy rate: 0.525274
2370 stocks, accuracy rate: 0.525267
2380 stocks, accuracy rate: 0.525234
2390 stocks, accuracy rate: 0.525226
2400 stocks, accuracy rate: 0.525197
2410 stocks, accuracy rate: 0.525187
2420 stocks, accuracy rate: 0.525161
2430 stocks, accuracy rate: 0.525161
2440 stocks, accuracy rate: 0.525126
2450 stocks, accuracy rate: 0.525083
2460 stocks, accuracy rate: 0.525106
```

Figure 2: Change of Accuracy

```
590 stocks, accuracy rate: 0.539203
600 stocks, accuracy rate: 0.539210
610 stocks, accuracy rate: 0.539342
620 stocks, accuracy rate: 0.539696
630 stocks, accuracy rate: 0.540056
640 stocks, accuracy rate: 0.540460
650 stocks, accuracy rate: 0.541092
660 stocks, accuracy rate: 0.541109
670 stocks, accuracy rate: 0.541050
680 stocks, accuracy rate: 0.540534
690 stocks, accuracy rate: 0.540390
700 stocks, accuracy rate: 0.540272
710 stocks, accuracy rate: 0.540143
720 stocks, accuracy rate: 0.540228
730 stocks, accuracy rate: 0.540504
740 stocks, accuracy rate: 0.540643
750 stocks, accuracy rate: 0.540603
760 stocks, accuracy rate: 0.540492
770 stocks, accuracy rate: 0.540385
780 stocks, accuracy rate: 0.540628
790 stocks, accuracy rate: 0.540917
800 stocks, accuracy rate: 0.540927
810 stocks, accuracy rate: 0.540419
820 stocks, accuracy rate: 0.540065
830 stocks, accuracy rate: 0.539668
840 stocks, accuracy rate: 0.539353
850 stocks, accuracy rate: 0.539208
860 stocks, accuracy rate: 0.538945
870 stocks, accuracy rate: 0.538852
880 stocks, accuracy rate: 0.538604
890 stocks, accuracy rate: 0.538702
900 stocks, accuracy rate: 0.538458
910 stocks, accuracy rate: 0.538573
920 stocks, accuracy rate: 0.538679
930 stocks, accuracy rate: 0.538509
940 stocks, accuracy rate: 0.538415
950 stocks, accuracy rate: 0.538456
960 stocks, accuracy rate: 0.538652
970 stocks, accuracy rate: 0.538624
980 stocks, accuracy rate: 0.538670
990 stocks, accuracy rate: 0.538780
1000 stocks, accuracy rate: 0.538793
1010 stocks, accuracy rate: 0.538590
1020 stocks, accuracy rate: 0.538468
1030 stocks, accuracy rate: 0.538433
1040 stocks, accuracy rate: 0.538483
1050 stocks, accuracy rate: 0.538455
1060 stocks, accuracy rate: 0.538643
1070 stocks, accuracy rate: 0.538856
```

Figure 3: Change of Accuracy

AskPrice5	AskPrice4	AskPrice3	AskPrice2	AskPrice1	BidPrice1	BidPrice2	BidPrice3	BidPrice4	BidPrice5
6018	6017.8	6015	6014.8	6013.6	6011.2	6010.6	6008.8	6008	6007.8
6018	6017.8	6015	6014.8	6013.6	6011.2	6010.6	6008.8	6008	6007.8
6017.8	6015	6014.8	6013.6	6013.4	6011.2	6010.6	6008.8	6008	6007.8
6017.8	6015	6014.8	6013.6	6013.4	6011.2	6010.6	6008.8	6008	6007.8
6017.8	6015	6014.8	6013.6	6013.4	6010.6	6008.8	6008	6007.8	6007.6

Figure 4: Dataset of Future Goods

2.1.3 Experiment 3

Because the time region of 5 days is not suitable, so we started to predict a long-term trend of the market. We start to combine each 5 days in one week to be one time-stamp and use five weeks of data to predict the trend of the next week. Unfortunately, this time the final accuracy is also about 54%, which equals to the last experiment. This result means that actually we cannot only use price to predict price. What's more, if we think about the real financial market, we can find that the price of one stock in the last some week cannot mean anything. And it's price will only be affected by some other informations like the global financial state or some other news, but not only the price. So now we think that using price to predict price can not success.

2.1.4 Experiment 4

By WFT, we can only get the price data. But only use these informations is not enough, so we start to use the dataset provided by TA. In the dataset provided by TA, there are some record of the price provided by consumers and sellers. So by this information we can know the detailed process of the trade, showed in Figure 4. And we think we can use the process of trade to predict the price of the following trade.

From Figure 4, we can know the trend of the price provided by sellers and consumers respectively. And the change of price in this process can tell us the trend of the price of the future goods. So we count the number of rise up and fall down for each price as features and continue to use whether the price rise up as label. But this time is a little different, because we focus on twice adjacent trades, in which price often stay stable and do not change. So this time we has three labels, 1 means rise up, -1 means fall down and 0 means stay same.

Figure 5 shows the result of this classification problem. We can see that in most occasions, the accuracy is greater than 50%. Please remember that this time the problem is a three-classification problem. So the accuracy of 50% is much greater then 33% and much better than the result we got in the former experiments.

```
TK_IC1604: 0.485084
TK_IC1605:
           0.505591
TK_IC1606:
           0.564014
TK_IC1609:
           0.538723
           0.529590
TK IF1606:
TK_IF1609:
           0.537683
TK_IH1606:
           0.561003
TK_IH1609:
           0.561549
TK_rb1605:
            0.522366
TK_rb1610:
            0.610763
 K rb1701: 0.540456
```

Figure 5: Accuracy of Prediction of Future Goods

Item	Quantity
Widgets	42
Gadgets	13

Table 1: An example table.

2.2 Sections

Use section and subsection commands to organize your document. LATEX handles all the formatting and numbering automatically. Use ref and label commands for cross-references.

2.3 Comments

Comments can be added to the margins of the document using the <u>todo</u> command, as shown in the example on the right. You can also add inline comments too:

This is an inline comment.

Here's a comment in the margin!

2.4 Tables and Figures

Use the table and tabular commands for basic tables — see Table 1, for example. You can upload a figure (JPEG, PNG or PDF) using the files menu. To include it in your document, use the includegraphics command as in the code for Figure 6 below.



Figure 6: This is a figure caption.

2.5 Mathematics

LATEX is great at type setting mathematics. Let X_1, X_2, \ldots, X_n be a sequence of independent and identically distributed random variables with $\mathrm{E}[X_i] = \mu$ and $\mathrm{Var}[X_i] = \sigma^2 < \infty$, and let

$$S_n = \frac{X_1 + X_2 + \dots + X_n}{n} = \frac{1}{n} \sum_{i=1}^{n} X_i$$

denote their mean. Then as n approaches infinity, the random variables $\sqrt{n}(S_n - \mu)$ converge in distribution to a normal $\mathcal{N}(0, \sigma^2)$.

2.6 Lists

You can make lists with automatic numbering ...

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