# The prediction of return on stock price——Two approaches

#### Team10

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Classification: SVM using features of stock prices and market conditions from the past

Prediction of stock prices via coding and data analysis

Regression: Using ARMA model

#### First Step: Get information and handle information

#### Get stock information from Yahoo:

```
def get_stock(stock,n):
    column_names=['Date','Open','High','Low','Close','Volume','Adj Close']
    info=pd.read_csv(stock,names=column_names)
    adj_close=info['Adj Close']
    op=info['Open']
```

#### Read local csv file directly:

info=pd. read\_csv('C:/Users/Yawang/Documents/HS300&A50\_data.csv')

#### Calculate the log return of the asset:

```
def get_return(price_data):
    ret=[0]
    for i in range(1, len(price_data)):
        ret. append(math. log(float(price_data[i]))-math. log(float(price_data[i-1])))
    return ret
```

### **SVM Classification Method: Introduction**

#### support vector machines (SVM):

- supervised learning models
- constructs a hyperplane or set of hyperplanes in a high-or infinitedimensional space, which can be used for classification, regression, or other tasks
- a good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class, since in general the larger the margin the lower the generalization error of the classifier

## **SVM Classification Method: Training**

Step 1: building a data frame of the features of training samples

0

```
y, x1, x2, x3=get_stock(stock, n)
                                                      Features
x4, x5, x6=get_market(market, n)
data={'ret1_stock':x1,
                                     Stock return
                                                                  Market return
     'ret2 stock': x2,
     'ret3 stock':x3,
                                      Yesterday
                                                                    Yesterday
     'ret1_market': x4,
                                                           The day before yesterday
                              The day before yesterday
     'ret2 market': x5,
     'ret3 market': x6}
                                    Three days ago
                                                                 Three days ago
X=pd. DataFrame (data)
  for returns in ret:
                                                       Labels
      if returns>=0:
          label. append (1)
                               The stock prices declines
      else:
                                      Otherwise
          label. append (0)
```

## **SVM Classification Method: Training**

• Step 2: Split the data into training data & Train the SVM

```
# split the data into training data and testing data
X_train, X_test, y_train, y_test=train_test_split(X, y, test_size=0.25, random_state=0)

#Using Support Vector Machine to predict whether the stock price will go upwards tomorrow or not
m=svm. SVC()
m. fit(X_train, y_train)
y_pred=m. predict(X_test)
```

Step 3: Check the accuracy of the algorithm

```
print metrics.accuracy_score(y_test, y_pred)
```

### **SVM Classification Method: Run and Result**

- The accuracy rate is only a little more than 50%
- when using 1000 training data, predicting IBM stock and using the return on Dow Jones index as the market return

```
stock='http://real-chart.finance.yahoo.com/table.csv?s=IBM&d=4&e=23&f=2016&g=d&a=0&b=2&c=1962&ignore=.csv' market='http://real-chart.finance.yahoo.com/table.csv?s=%5EIXIC&d=4&e=23&f=2016&g=d&a=1&b=5&c=1971&ignore=.csv' n=1000 main(stock, market, n)
```

0.52

- The prediction is only a little better than flipping a coin
- However, other models (KNN and logistic regression) and other training data (GOOG, APPL and S&P500) also produce no better accuracy.

# The difficulty of stock prediction

 The connection between the past price data and the present price is ambiguous.

• Other factors such as the change of policy, investors' attitudes and the condition of the company can also influence the stock price.

 Besides, if many people predict that the stock price will rise tomorrow, they are likely to buy stock today, causing the price to rise immediately instead of rise tomorrow.(reflexivity)

#### **ARMA** model: Introduction

- Autoregressive-moving-average model
- The notation ARMA(p, q) refers to the model with p autoregressive terms and q moving-average terms. This model contains the AR(p) and MA(q) models,

$$X_t = c + arepsilon_t + \sum_{i=1}^p arphi_i X_{t-i} + \sum_{i=1}^q heta_i arepsilon_{t-i}$$

• ARMA is appropriate when a system is a function of a series of unobserved shocks (the MA part) as well as its own behavior. For example, stock prices may be shocked by fundamental information as well as exhibiting technical trending and mean-reversion effects due to market participants.

# **ARMA** model: Main Purpose

 Ordinary data also have poor result, high frequency data turns out to have nice quality.

Using prices and returns of every minute to predict.

• Build the model based on the difference between H\$300 and A50 to do arbitrage via shorting one asset and long the other.

#### • Step 1: get the data and handle it

```
# a function to calculate the log return of the asset

def get_return(price_data):
    ret=[0]
    for i in range(1, len(price_data)):
        ret. append(math. log(float(price_data[i]))-math. log(float(price_data[i-1])))
    return ret
```

#### The data is downloaded from the Wind Database

# read the high frequency data of HS300 and A50 between 2015/12/1 and 2015/12/25
info=pd.read\_csv('C:/Users/Yawang/Documents/HS300&A50\_data.csv')

#### • Step 1: get the data and handle it

```
# get the price data of HS300 and A50
HS300=info['HS300']
A50=info['A50']
# handle the data at similar size
hs300=np. array (HS300) /HS300[0]*1000
a50=np. array (A50) /A50[0]*1000
# get the return of hs300 and a50
r hs=get return(hs300)
r a=get return(a50)
# calculate the difference between the returns
r_diff=np. array (r_hs) -np. array (r_a)
```

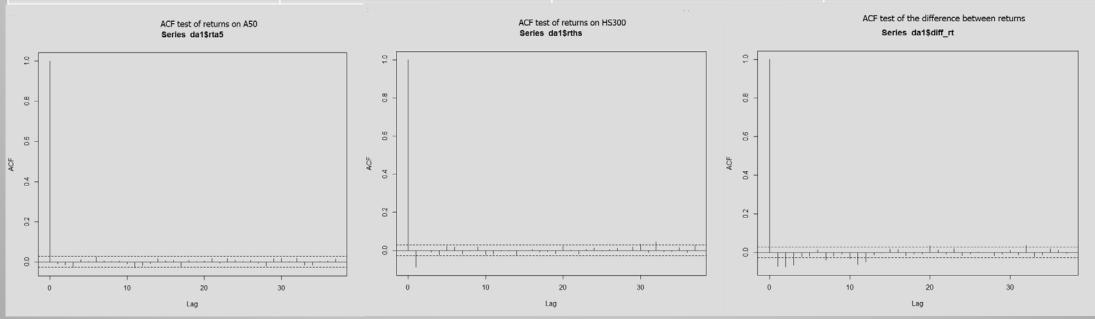
 Basic statistic information for three series – returns on both HS300 and A50 and the difference between returns:

HS300		A50		nobs	5.
nobs	5129	nobs	5129	NAS Minimum	
Minimum	-0.007359	Minimum	-0.015929	Maximum 1. Quartile	
Maximum	0.009338	Maximum	0.009716	3. Quartile	
Mean	0.000021	Mean	0.000017	Mean Median	
Median	0	Median	0	Sum SE Mean	
Variance	0.00001	Variance	0.00001	LCL Mean	
Stdev	0.000999	Stdev	0.000965	UCL Mean Variance	
Skewness	0.219524	Skewness	-0.636954	Stdev	
Kurtosis	5.44164	Kurtosis	23.424518	Skewness Kurtosis	

5129.000000
0.000000
-0.006915
0.009244
-0.000759
0.000762
0.000005
0.000000
0.023491
0.000018
-0.000031
0.000040
0.000002
0.001294
0.125291
2.075146

#### • Step2: Statistic tests for autocorrelation and for unit root stability

	HS300	A50	R_diff
X-squared	44.28	5.9418	83.369
df	5	5	5
p-value	2.032e-08	0.3119	< 2.2e-16



```
Title:
                                                             Title:
Title:
Augmented Dickey-Fuller Test Augmented Dickey-Fuller Test
                                                              Augmented Dickey-Fuller Test
                             Test Results:
Test Results:
                                                             Test Results:
  PARAMETER:
                               PARAMETER:
                                                               PARAMETER:
   Lag Order: 1
                                 Lag Order: 1
                                                                 Lag Order: 1
  STATISTIC:
                               STATISTIC:
                                                               STATISTIC:
    Dickey-Fuller: -53.2138
                                 Dickey-Fuller: -51.595
                                                                 Dickey-Fuller: -56.8594
  P VALUE:
                               P VALUE:
                                                               P VALUE:
   0.01
                                 0.01
                                                                 0.01
```

- Summary of the test results: nice quality of the data
- Precondition: Stationarity & Auto correlation √

• Step 3: building the model according to the data

The parameter p and q are determined by several tests.

```
# build ARMA(p, q)model
arma=tsa.ARMA(r_diff, order =(p, q))
model=arma.fit()
```

Coeff	icients:			
	ar1	ar2	ar3	ma1
	0.6463	0.0640	-0.1461	-0.8634
s.e.	0.0544	0.0424	0.0399	0.0454

# ARMA model: Results and Analysis

model.predict(start, end)

		predict
[1,]	-0.0005323726	-4.458022e-04
[2,]	-0.0008481140	-1.795850e-04
[3,]	-0.0004498944	-2.218592e-04
[4,]	-0.0003581392	-8.975605e-05
[5,]	0.0016422886	-4.597222e-05

Training set error measur	es:					
М	E	RMSE	MAE	MPE	MAPE	MASE
Training set -1.128083e-0	5 0.003	1238978	0.0009569406	NaN	Inf 0	. 6224464

# Summary

- Although the issue is of great complexity and none of the model manages to solve the problem accurately, there are certain circumstances where we can use machine learning and time series analysis to get accurate predictions.
- For example, the second model is extremely powerful, or at least extremely powerful in some circumstances, in the prediction of return series with certain qualities.
- And SVM can be combined with data mining of social network(Twitter and Weibo) to get people's attitudes towards certain stock, which can also be applied to the prediction of stock price