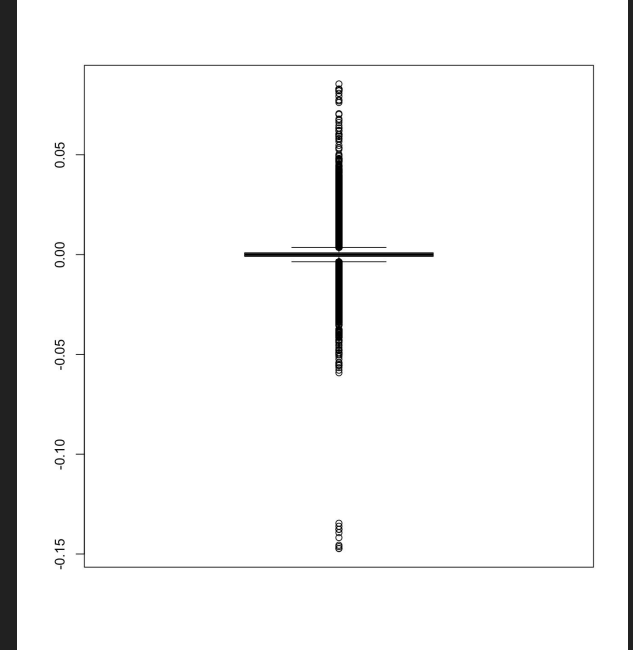
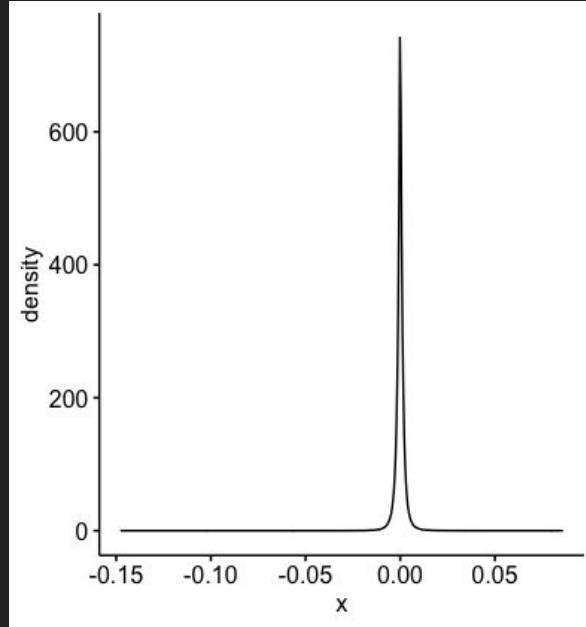


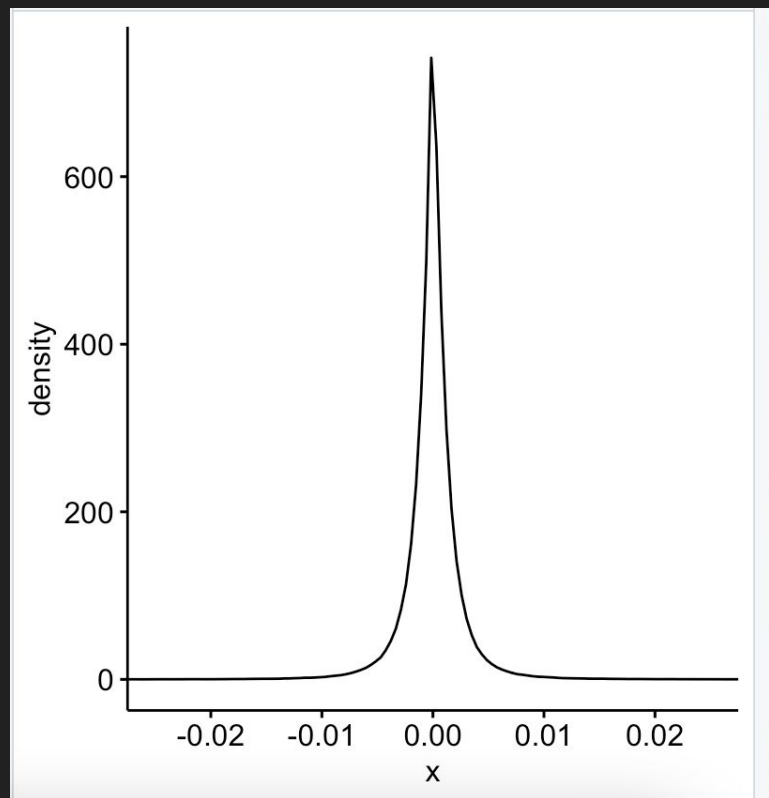
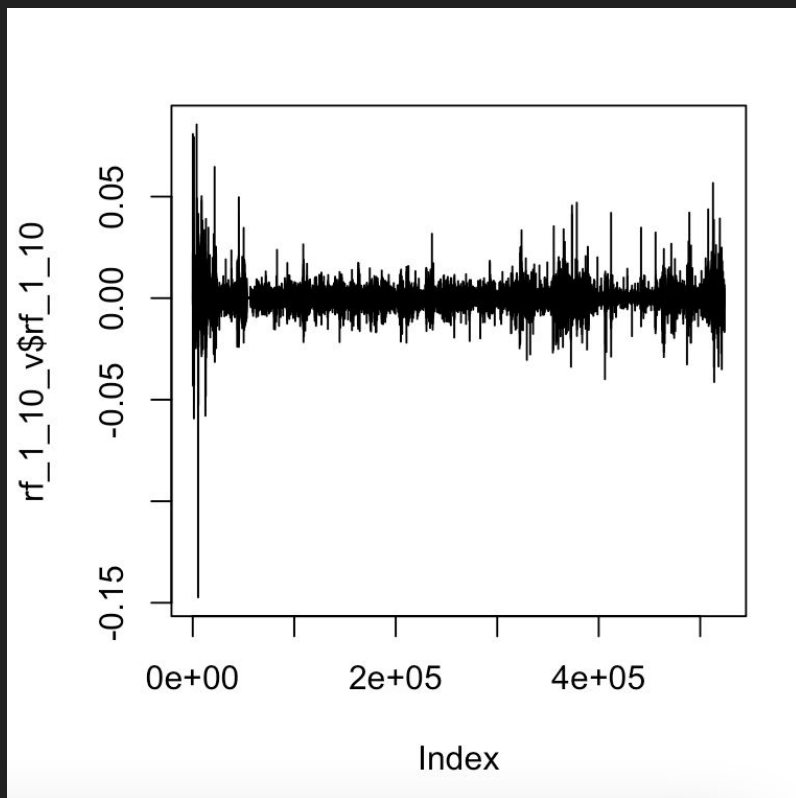
# 415 Final Project Advanced

Yanyijie Zhou, Haijian Wu, Rui Qiu

# What we found about the given price dataset

- Real Dataset
- Outliers
- Noise





# Features we tried and used in the end

- Features we tried
  - Backward Return
  - Forward Return
  - Asset Price
  - ARIMA features
  - Moving average & weighted moving average
  - Stock Price Indicators: (Abandoned due to computational complexity)
    - Relative Strength Index (comparison of losses and recent gains / overbought/ oversold )
    - Accumulation/Distribution Oscillator (indicator of momentum, using Highest - Lowest)
    - Average True Range (Measuring bull and bear price trends)
- Features we used in the end
  - Backward returns of asset 1-3 (chosen by AIC)

# Model training & evaluation

1. Tried lots of different models
  - a. OLS
  - b. KNN
  - c. ARIMA (Popular model in stock price prediction)
  - d. Simplified Auto Regression
  - e. Random Forest
  - f. SVR (regression version of SVM)
  - g. Gradient Boosting
2. Notice that these models perform worse on OJ -- overfitting or other issues?
3. Not applicable on OJ / Perform too slow
  - a. ARIMA / KNN & Random Forest & SVR
4. Look through dataset -- outliers & noise

# Model training & evaluation

## 1. Data Cleaning

- a. Remove the approximate values
- b. Remove the extreme values

## 2. Model Training

- a. Different models
- b. `trunc(0.8 * nrow(data)) & nrow(data)`

## 3. Model Selecting (based on AIC)

- a. AIC -- useful in time series prediction
- b. BIC -- confident that variables we use include the “real” variables
- c. `adjr2` -- for training data (observations)

# Model training & evaluation

## 1. Local Test

```
corr <- cor(pred, real)
print(corr)

# RECORDs 1000 times
# OLS (lasso): -0.150
# OLS (RB+RF): -0.071
# OLS (SVM): -0.105
# OLS (RB + 1440): -0.047
# OLS (RB + 1440+asset): -0.043
# OLS (clean + aic + RB(1440)): 0.073
# Boost: 0.14 -> 0.098 -> 0.0689 -> 0.139 -> 0.110(aic)
# ols aic: -0.061
```

```
rm(list=ls())
source("prediction.R")

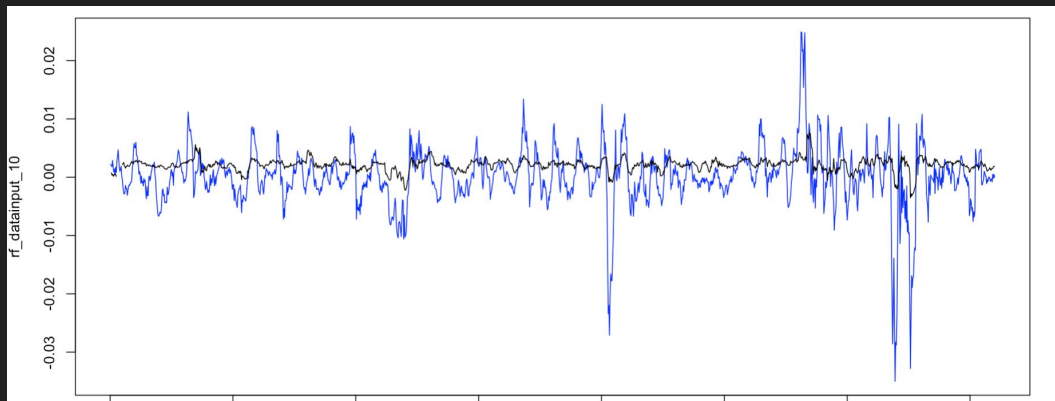
originDATA <- read.csv("final_project_data.csv")
real_rf_10 <- read.csv("rf_10.csv")
originDATA <- originDATA[, c(2,3,4)]

h = 10
window = 1440
trytimes <- 1000
pred = rep(0, trytimes)
real = real_rf_10[(nrow(originDATA) - h - trytimes + 1):(nrow(originDATA) - h), 1]
real_check = rep(0, trytimes)

for(i in (nrow(originDATA) - window - h + 1 - trytimes + 1):(nrow(originDATA) - window - h + 1)){
  index = i - (nrow(originDATA) - window - h + 1 - trytimes + 1) + 1;
  datainput <- originDATA[i:(i+window - 1),]
  pred[index] <- prediction(datainput)
  # real_check[index] <- real_rf_10[(i+window - 1), 1]
}

corr <- cor(pred, real)
print(corr)
```

## 2. Visualizing



# Accelerating Our Code

## 1. Model Fitting & Local Testing

- a. **Model Selecting:** Abandoned most non-parameter models (KNN & Random forest & SNR).
- b. **Predictors Selecting:** Abandoned all computational demanding features
- c. **Local Testing:** Perform parallel computing.
- d. **Overfitting Problem:** Remove unnecessary features from our model
- e. Using Python or Using Rccp to include C code in R may be helpful

## 2. Prediction

- a. Optimize the process of getting input / output value
  - i. **Input:** Deleted all for-loops -  $O(N)$  v.s.  $O(Nn)$
  - ii. **Output:** OLS predicted value = predictor vector `%*%` coefficient vector

## 3. Prettified Codes & Detailed Comments



# What we can do to improve

## 1. Trying more features & models

- a. The final version of our model was decided one day before the submission deadline.  
Some possible predictors & models were abandoned due to limited submission times.

## 2. More organized version control

- a. Forgot to record every submission & error feedback  
Spent too much time on debugging

# Thank you

Reference:

- <https://www.sciencedirect.com/science/article/pii/S2405918818300060>
- <https://towardsdatascience.com/an-introduction-to-support-vector-regression-svr-a3ebc1672c2>
- <https://otexts.com/fpp2/>