Portfolio Management Using SVM

- Abhishek Kumar [2010MT50582]
- Raghav Goyal [2010MT50612]

INTRODUCTION

- We aim to create a portfolio optimization technique using SVM and Universal Portfolio model.
- We assign labels (+1/-1) to trading data points using SVM
- In order to create our portfolio we choose all the equities with label +1 and apply portfolio optimization technique, universal portfolio to assign weights to each asset.

DATASET

- Dataset of 52 stocks downloaded from yahoo finance.
- Each dataset contains 2015 points(8 years data).
- We iteratively train our SVM model on 100 day data points (~4 months) and predicted labels for the next 25 day data points(~1 month).
- It contains Open, High, Low, Close, Volume for each stock.

FEATURE EXTRACTION

- % change in open = $\frac{\text{open(t)} - \text{open(t-1)}}{\text{open(t-1)}}$ [Feature 1]
- % change in high = $\frac{\text{high(t-1)} - \text{high(t−2)}}{\text{high(t−2)}}$ [Feature 2]
- % change in low = $\frac{\text{low(t−1)} - \text{low(t−2)}}{\text{low(t−2)}}$ [Feature 3]
- % change in close = $\frac{\text{close(t−1)} - \text{close(t−2)}}{\text{close(t−2)}}$ [Feature 4]
- % change in volume = $\frac{\text{volume(t−1)} - \text{volume(t−2)}}{\text{volume(t−2)}}$ [Feature 5]

FEATURE EXTRACTION - Contd..

- We took $l = 5$ for the following calculations.
- l day high open = max(open(t-i)), i=1,2,3,4,5
- l day low open= min(open(t-i)), i=1,2,3,4,5
- l day high volume= max(volume(t-i)), i=1,2,3,4,5
- l day high volume= max(volume(t-i)), i=1,2,3,4,5

- fractional change in open = $\frac{\text{open(t)} - \text{open(t}-1)}{l\ day\ high\ open - l\ day\ low\ open}$ [Feature 6]
- fractional change in volume = $\frac{\text{volume(t-1)} - \text{volume(t}-2)}{l\ day\ high\ volume - l\ day\ low\ volume}$ [Feature 7]

DATA LABELLING

- We considered 2 classes, +1 and -1.
- +1 indicates to buy the stock
- -1 represents not to buy the stock (short selling is not allowed).
- We labelled the data +1 for positive returns after deduction the transaction costs if traded, otherwise -1.
- $\frac{\text{close(t) - open(t) - } 0.002 * \text{open(t)}}{\text{open(t)}} > 1,$ then +1, else -1

PREDICTION USING SVM

- We iteratively train our SVM model on 100 day data points (~4 months) and predicted labels for the next 25 day data points(~1 month).
- For training on 100 days we do the following procedures:
- Feature selection
  - We select features for each stock using forward search cross validation technique. Initially feature set for the stock was set null. Select first feature which gives maximum 5 –fold cross validation accuracy.
  - Next, include features which gives maximum improvement in accuracy
  - Terminate feature selection procedure, if accuracy doesn’t improves.
- Training
  - Trained our model using RBF Kernel and selected features for each stock independently.
- Prediction
  - Predict labels for next 25 day data points using above model.

UNIVERSAL PORTFOLIO

- Given a set of ‘m’ stocks universal portfolio gives us a better way to select portfolio. One key feature is that we don’t allow short selling in this portfolio and the wealth has to be completely invested on each day.
- In order to perform comparably with best stock we need to revise our portfolio as frequently as possible, in our case we are doing it daily.
- At any day we should invest more fraction in the equity which has given higher returns on previous trading days.
- We created a window of size 5 past trading days. Choose the best portfolio for each day and take average as current portfolio.

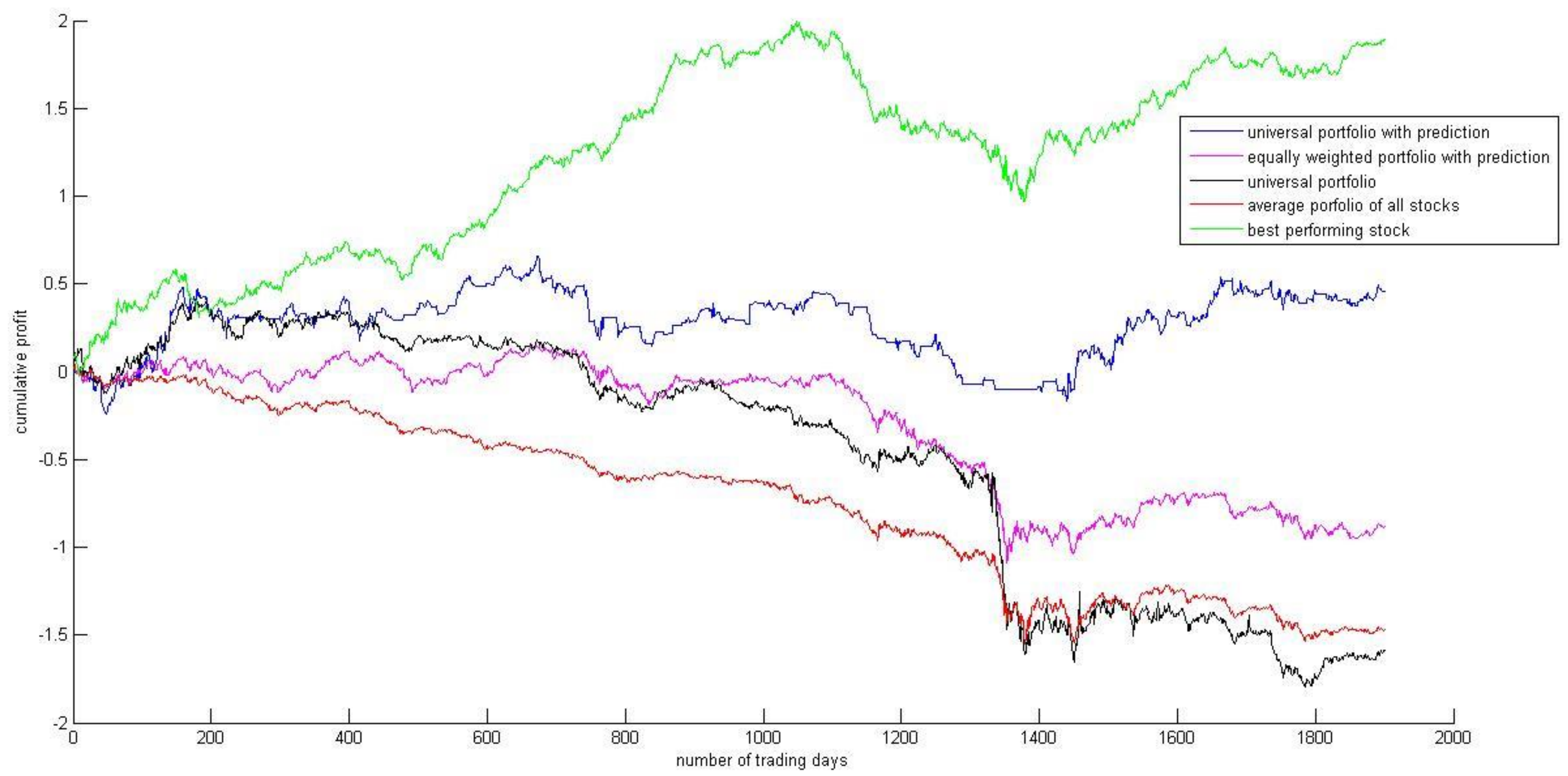
OUR APPROACH

- Approach 1
  - For any trading day, select stocks with predicted label +1
  - For these selected stocks, make equally weighted portfolio with total investment of 1.
- Approach 2
  - For any trading day, select stocks with predicted label +1
  - For these stocks, create Universal Portfolio.

BENCHMARK MODELS

1. Equally weighted portfolio of all the 52 stocks.
2. Best performing stock.
3. Universal Portfolio on 52 stocks.

RESULT



cumulative profit
number of trading days
universal portfolio with prediction
equally weighted portfolio with prediction
universal portfolio
average porfolio of all stocks
best performing stock
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
0
200
400
600
800
1000
1200
1400
1600
1800
2000

REFERENCE

- [1] Universal Porfolios, Thomas M. Cover, Stanford University, October 23, 1996
- [2] CS229 Project Report, Automated Stock Trading Using Machine Learning Algorithms by Tianxin Dai, Arpan Shah, Hongxia Zhong.

THANK YOU