Momentum Trading
and
VWAP Execution

-Refined Strategies Based On Machine Learning Models

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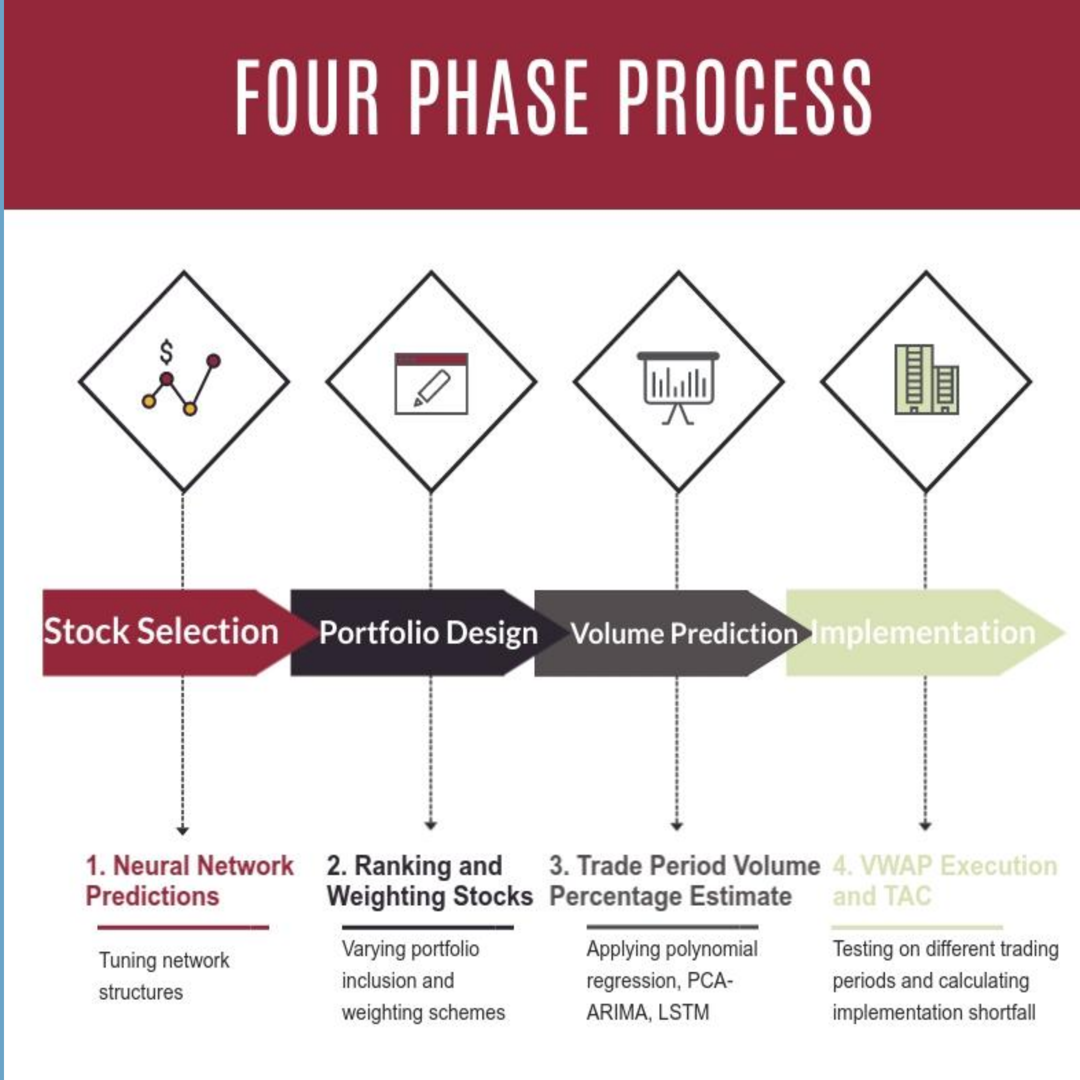
Outline

1. Stock Selection
2. Portfolio Construction
3. Test for Zero Market Drift
4. VWAP Execution Strategies
5. Results and Comparisons
6. Future Perspectives



1

Stock Selection

- Future Returns Prediction Based on Neural Network Models

1

Stock Selection (NN Models)

- Our pool of assets contains 600 stocks with data provided during the fourth quarter of 2018.
- We divide our trading horizon into six semi-monthly rebalance periods.
- We aim to select a subset of these stocks that are expected to perform well on the next period given performance in the past period.
- Our dataset contains Open, Close, High, Low, and Volume for each stock on a minute level basis, which we combine into daily level information.
- The number of stocks to be selected is a customized parameter.

Momentum Trading

- A Naive MACD Baseline

- Momentum trading is a technique in which traders buy and sell according to the strength of recent price trends.
- At first glance we are motivated to use the past period performance as an indicator of the stock’s momentum; this is our baseline model.
- To avoid over-aggressiveness we select the stocks that ranked 30-60 in terms of past returns and picked out those having positive returns and positive MACD values to long. We invest equal weights of capital into each stock.

Observation Period	10.01-10.15	10.16-10.31	11.01-11.15	11.16-11.31	12.03-12.14
Test Period	10.16-10.31	11.01-11.15	11.16-11.31	12.03-12.14	12.17-12.31

Results of the Naive Baseline Portfolio

Compare against a basic benchmark portfolio that invests equally in all 600 stocks (serves as an index portfolio)

We conclude that the naive momentum portfolio has only a slight advantage over the index portfolio.

Testing Period	Index	Naive Momentum
10.16-10.31	-0.02377	0.00842
11.01-11.15	0.00958	0.00989
11.16-11.30	0.00882	0.00867
12.03-12.14	-0.08420	-0.07902
12.17-12.31	-0.04260	-0.03328

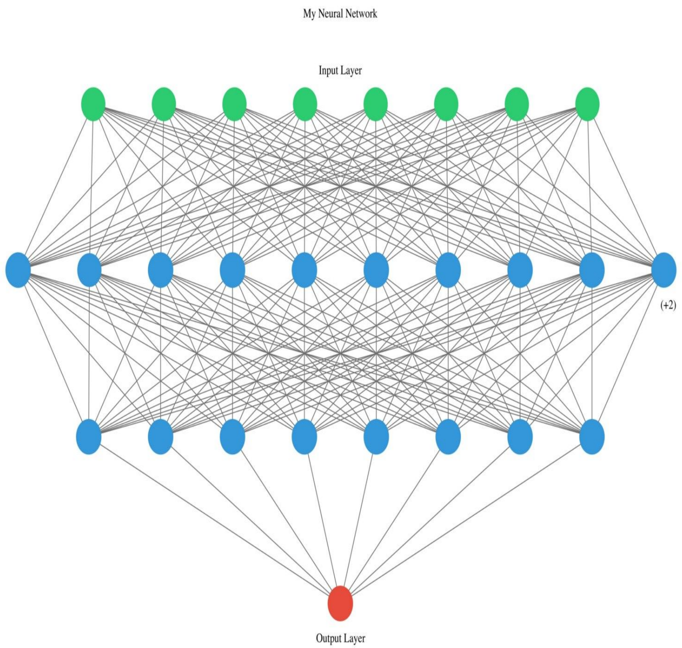
Neural Network Models

We aim to predict the following period's total return given price information in the past period.

For **input features** we included historic sequences (ten-day window) of various technical indicators for a given stock (elaborated in the next slide) and its close price sequence.

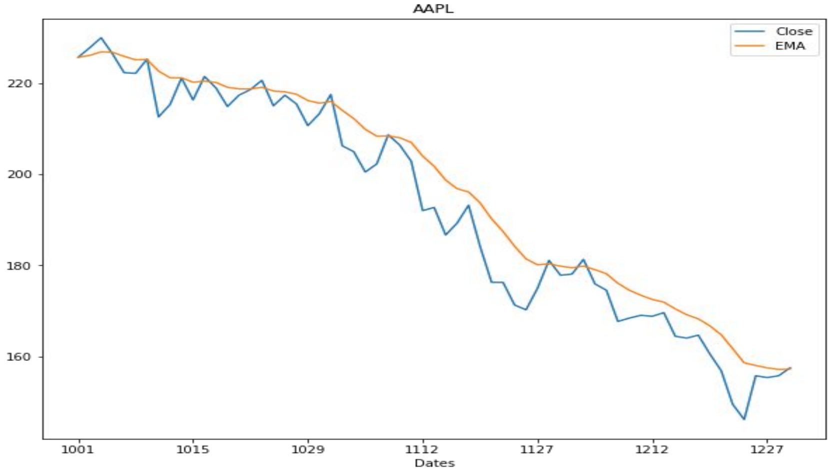
The **output variable** is the total return in the next period (ten days into the future).

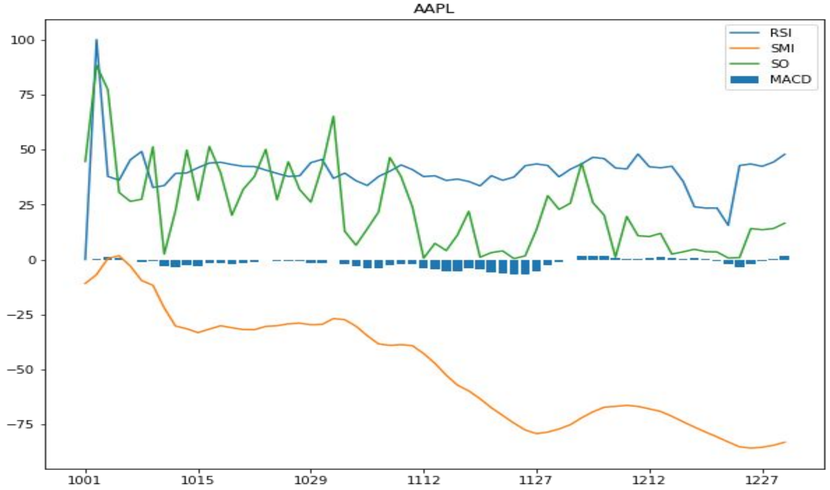
We train a fully-connected network on data aggregated from all stocks using a sliding window approach to generate samples.



Technical Indicators

- **EMA(10)**: Ten day **exponential moving average**
- **MACD(12,26)**: **Moving Average Convergence Divergence** is a trend-following momentum indicator
- **RSI**: The **relative strength index** is a momentum indicator that measures the magnitude of recent price changes
- **SO**: **Stochastic Oscillator** is a momentum indicator comparing a particular closing price to a range of prices over a certain period of time
- **SMI**: **Stochastic Momentum Index** is an enhanced version of SO where a closing price is compared to the high-low midpoint





Neural Network Models

Model 1:

- 1st layer: **100** neurons, 2nd layer: **20** neurons, activation: **sigmoid**
- Test MSE: 0.0059

Model 2:

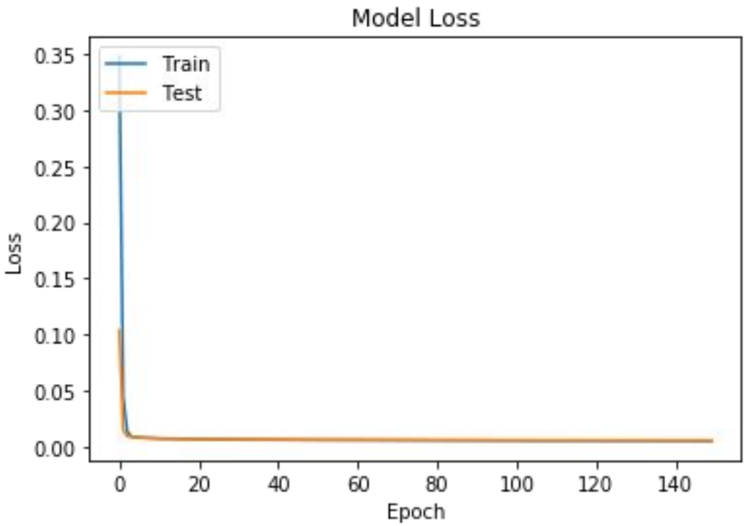
- Adding in a middle layer with **60** neurons and **ReLu** activation
- Test MSE: 0.0054

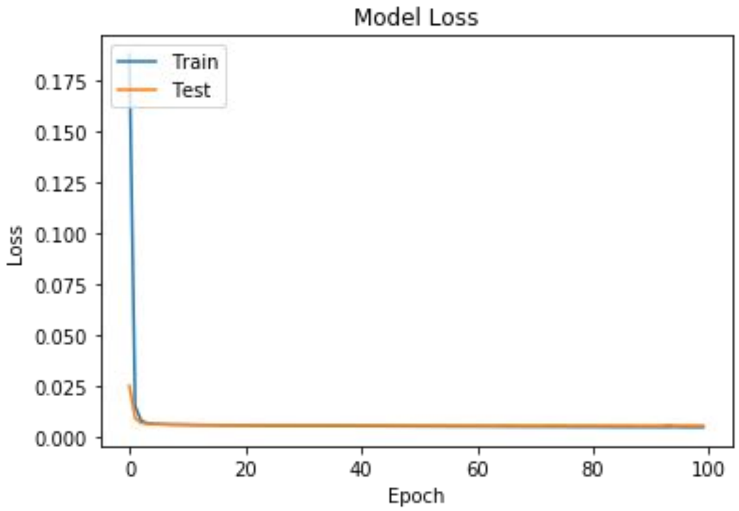
Input Size: **60**

Training sample size: **~20000**

Testing sample size: **~5000**

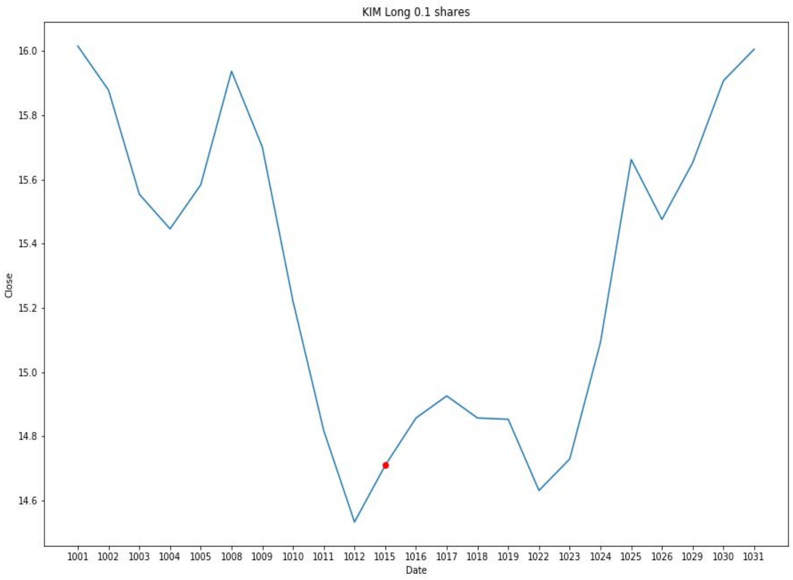
Epochs: **150/100** Batch Size: **1000**





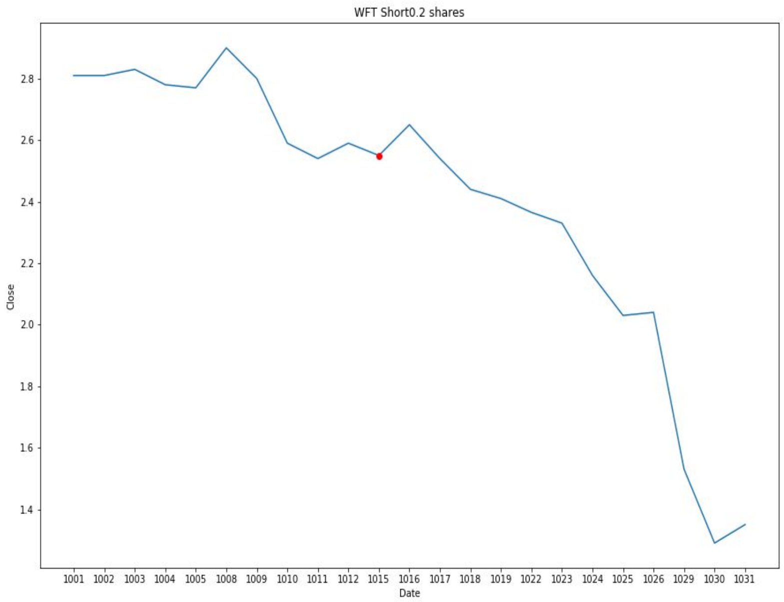
In-sample Stocks Selected by Neural Network Models

Here both good positive return predictions and good negative return predictions are considered valuable. We look at some in sample results from the rebalancing period **10.16-10.31.**



Kimco Realty Corp was identified as a good long opportunity (**top predicted positive returns by both models**) based on the information provided during 10.01-10.15. We can look at its performance during 10.16-10.31 and see that this is indeed a good trade.

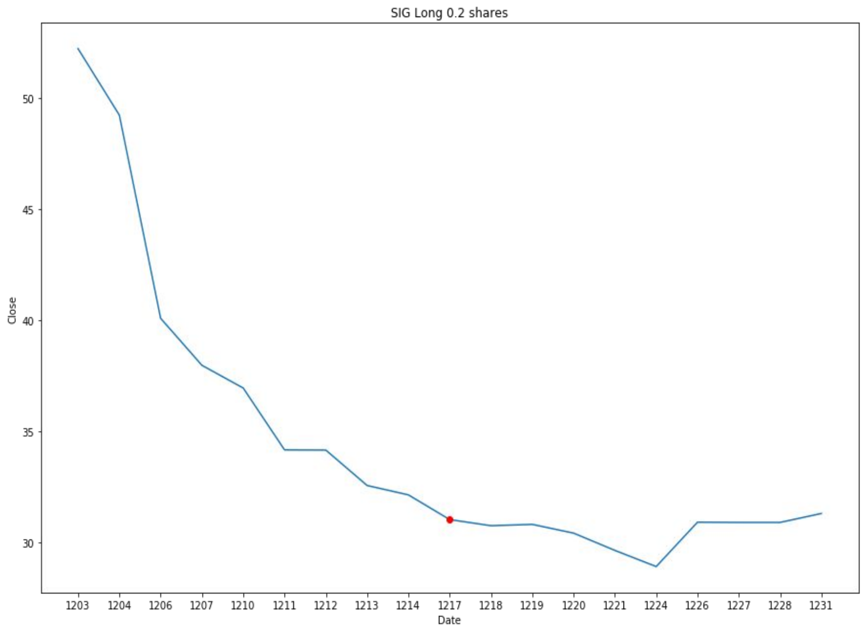
In-sample Stocks (Continued)



Weatherford International was predicted by **both models** to have a large **negative return** during the coming period of 10.16-10.31 based on the performance in 10.01-10.15. We can see that this is indeed a very good prediction and we can generate much profit by shorting.

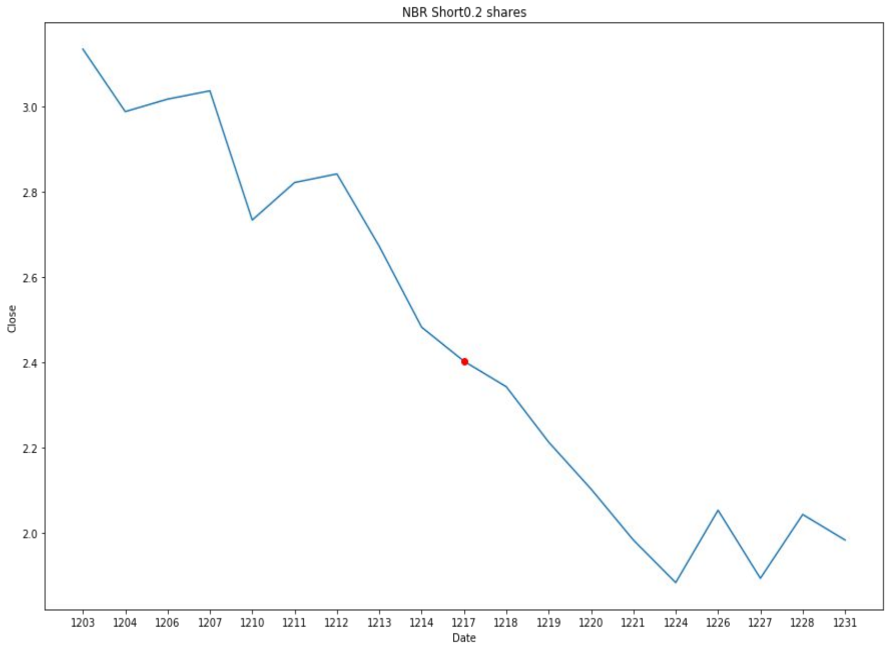
Out-of-sample Stocks Selected by Neural Network Models

In our training-testing setup, **12.17-12.31** was left out as a testing rebalance phase, so we can look at the stocks selected by the two models in this period as a validation.



The month of December saw a large drop in the market overall. Given the market performance, this identified stock **Signet Jewelers Ltd** performed relatively well during the testing period and bounced back from an initial drop.

Out-of-sample Stocks (Continued)



Neighbors Industries Ltd was identified as a good shorting opportunity (**top predicted negative returns by both models**) during 12.17-12.31. The out-of-sample results validate our neural network based stock selection scheme.

2

Portfolio Construction

- Balanced Weight Portfolio
- Aggressive Weight Portfolio
- Balanced Weight Long-Short Portfolio
- Portfolio Size Tuning

2

Description of Different Types of Portfolios

(with N highest ranked stocks included)

Balanced Weight Portfolio:

- Given top-N stocks in a long-only portfolio, each one is weighted 1/N in terms of capital invested.

Aggressive Weight Portfolio:

- Given 2N stocks with projected returns $r_1,\ldots,r_N$ (assuming all positive for a long-only portfolio), the weights are given by $w_i=r_i/(r_1+..+r_N)$ so that stocks predicted to perform better will be weighted more and vice versa.

Long-Short Portfolio:

- Both top-N positive return stocks and top-N negative return stocks are included in a balanced weight fashion.

Which model & portfolio to choose?

- Comparing performance of predicted returns from the same neural network model against different number of top-ranked stocks included in the portfolio
- Comparing performance of different neural networks

Test Period	Index	LS model 1 N=20	LS model 1 N=10	LS model 2 N=20	LS model 2 N=10
20181016-20181031	-0.02377	0.08231	0.12742	0.08719	0.09569
20181101-20181115	0.00958	0.05510	0.10177	0.04631	0.07594
20181116-20181130	0.00882	0.04455	0.06198	0.05408	0.07178
20181203-20181214	-0.08420	0.06537	0.07327	0.06528	0.06479
20181217-20181231	-0.04260	0.03078	0.01812	0.02590	0.05007

- **We can conclude that choosing N=10 results in a better portfolio.**

Portfolio Result Comparison (NN model 1, N=10)

Test Period	Index	Balanced	Aggressive	Long&Short
20181016-20181031	-0.02377	0.04054	0.05091	0.12742
20181101-20181115	0.00958	0.04923	0.04989	0.10177
20181116-20181130	0.00882	0.00578	0.00597	0.06198
20181203-20181214	-0.08420	-0.03879	-0.04873	0.07327
20181217-20181231	-0.04260	-0.04587	-0.04510	0.01812

- **Out results from this section show that balanced portfolio tends to perform better during bad times while aggressive portfolio could generate higher returns during good times while the difference is usually not significant. (This result generalizes well into all the other model cases)**

A Refined Portfolio Based on NN Model Ensembling

- Since we observed that the two NN models have their own strength and weakness, a refined portfolio is constructed by combining the top-5 ranked stocks by each network to form a balanced portfolio. Duplicated selections will be given twice the weight.

Test Period	Index	Balanced	Long&Short
20181016-20181031	-0.02377	0.08361	0.18719
20181101-20181115	0.00958	0.06154	0.11280
20181116-20181130	0.00882	0.03226	0.10018
20181203-20181214	-0.08420	-0.05400	0.07120
20181217-20181231	-0.04260	-0.03783	0.05637

- Clearly, we can generate higher returns by taking into account the opinions of both models.

3

Implementation Shortfall Optimization via Order-Splitting Models

- A look at the dynamic optimization solution
- Test of zero market drift assumption

3

Implementation Shortfall Definition

$$Implementation\ Shortfall = (SP_E - SP_D) - [(SP_E - \sum_{i=1}^{N} s_i P_i) - EC]$$
$$= \sum_{i=1}^{N} s_i P_i - SP_D + EC$$

Our strategy makes **only a limited number of trades** during the entire testing horizon. Therefore, we can confidently **neglect the commission fees** which typically costs around 0.02%-0.1%.

- We assume that after our test period is over, we rebalance at the next opening period, particularly, the 30 minutes period between 9:30 am-10:00 am .
- We wish to liquidate all our shares held and buy in the next period's target stocks on a minute level frequency.
- Our goal is to minimize the weighted execution prices' difference from our decision price, which is taken as the opening price of that day.

Classical Results by Bertsimas and Lo, 1998

A dynamic optimization solution to the order-splitting and timing model

$$m_t = m_{t-1} + \mu + \lambda s_t + \varepsilon_t$$
$$p_t = m_t + \gamma s_t$$

We consider both **market drift** and **permanent impact** in this model where **m_t** is the bid-ask midpoint for time period t, **p_t** is the period t price, and **s_t** is the volume traded during period t.

$$s_t^* = \bar{s}\left(\frac{1}{T} + \frac{(T+1)-2t}{2(2\gamma+\lambda)}\mu\right)$$

The static solution has the above formula when drift is nonzero. When drift term is zero, we invest equally in all T time periods.

Zero Drift Test on Target Market Data

The static solution results in unreasonable trade suggestions when the **permanent effect and the temporary effect parameters are small** which is the case we observed from our test data.

We aim to test if the drift parameter is zero, The portfolio we are interested in is given by the neural networks models and we combine data into larger bins and run a regression test for the drift coefficient and permanent effect coefficient. Here are examples of the millisecond trade and quote data on 11.01 and 12.17 (from WRDS).

	date	time	bid	bidsiz	ask	asksiz	ticker	hour	minute	second
0	20181101	9:30:00.040067730	43.34	39	43.95	2	AIG	9	30	0
1	20181101	9:30:00.040194880	41.98	1	45.27	1	AIG	9	30	0
2	20181101	9:30:00.040199213	41.98	1	45.27	2	AIG	9	30	0
3	20181101	9:30:00.040463802	40.13	1	45.36	1	AIG	9	30	0
4	20181101	9:30:00.040938866	41.28	1	45.27	1	AIG	9	30	0

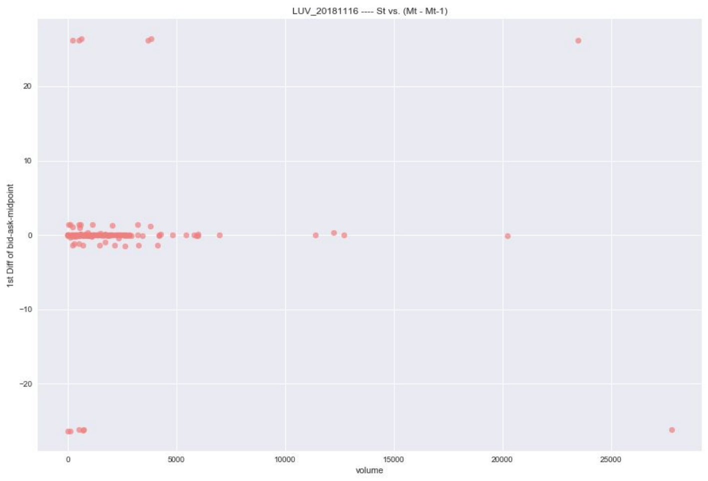
	DATE	TIME_M	EX	SYM_ROOT	SYM_SUFFIX	TR_SCOND	SIZE	PRICE
0	20181217	9:30:01.005852000	N	A	NaN	O	19875	69.11
1	20181217	9:30:01.011290000	N	A	NaN	NaN	100	69.11
2	20181217	9:30:01.019645000	D	A	NaN	NaN	100	69.06
3	20181217	9:30:03.195176000	P	A	NaN	NaN	100	69.05
4	20181217	9:30:03.195210000	P	A	NaN	Q	100	69.05

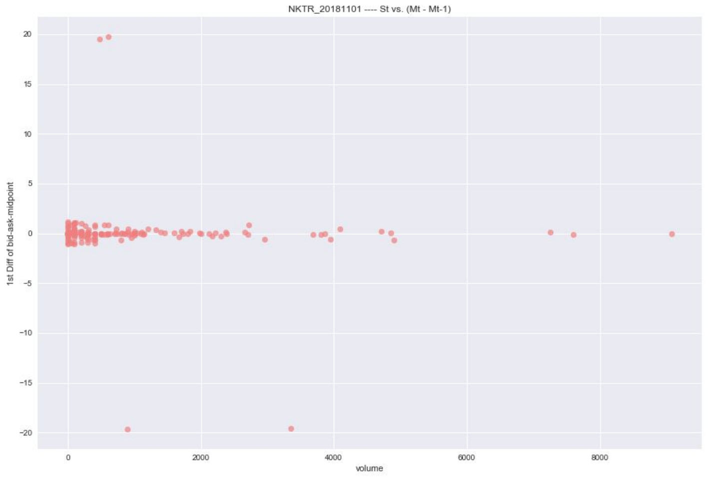
Regression Results

After performing various regressions on targeted stocks and trading periods, we observe results that are consistent with our hypothesis. For example, in the regression table below the constant term has no significance according to a p-value test. The scatter plots on the right demonstrate the zero drift behavior.

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0650	0.590	-0.110	0.912	-1.230	1.100
x1	3.167e-05	0.000	0.214	0.831	-0.000	0.000

Omnibus:	48.008	Durbin-Watson:	2.832
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1037.893
Skew:	-0.042	Prob(JB):	4.21e-226
Kurtosis:	14.796	Cond. No.	4.60e+03





Formulating a Baseline Strategy and moving on to VWAP Targeting Strategies

- The previous results suggest that a baseline strategy can be implemented by averaging target amount of trades over the 30 minute trading horizon.

- We next move on to several strategies targeting the VWAP benchmark by predicting minute level volume percentages and implementing a strategy based on such predictions. We compare the empirical VWAP results and resulting implementation shortfall with that generated by the baseline naive averaging strategy.

4

VWAP Execution Strategies

- Various Volume Prediction Methods
- Transaction Cost Analysis

4

VWAP Execution

$$VWAP = \frac{\sum Price \times Volume\ at\ Price}{\sum Total\ Volume}$$

Four volume percentage determination Strategies:

1) Past period (semi-month) binwise mean
2) Polynomial Fitting
3) PCA-ARIMA
4) LSTM

Baseline Strategy:

5) Average Split

Execution Logic (tested with long-only portfolio)

- We define the total capital in dollar value to be $100,000 per stock.
- Execution time frame is the first 30 minutes of a rebalancing day, trading once per minute.
- We fix a decision price and calculate the number of shares we want to trade for a particular stock.
- Given a predicted volume percentage vector for the entire 30 periods using any of the strategies, we formulate projected number of shares to trade at each minute level.
- We try to execute orders following the real market trade data. If a period's target trade was not completed, the remainder will be carried over to the next period. The last period will try to execute all remaining goals, given the scale of our capital, it is usually not hard to exhaust all our orders according to our planned percentages.
- A realized VWAP is calculated based on this trade sequence and implementation shortfall is calculated against the decision price, which is often the opening price.
- We add the return percentage shortfalls from both the buying and selling periods of that testing phase for each stock that we hold a long position in.

Historic Mean Volume Estimate

➔ Look back at past ten days' per minute volume data in the target trading interval

➔ Perform a minute level binwise historic mean

➔ Determine minute level trade amount based on a normalized percentage sequence

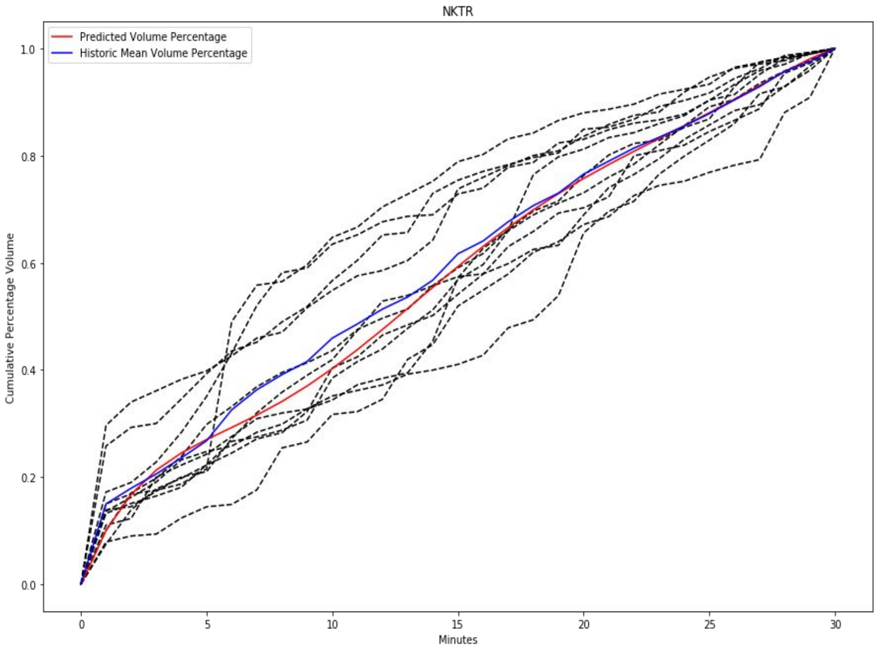
Polynomial Regression Volume Estimate

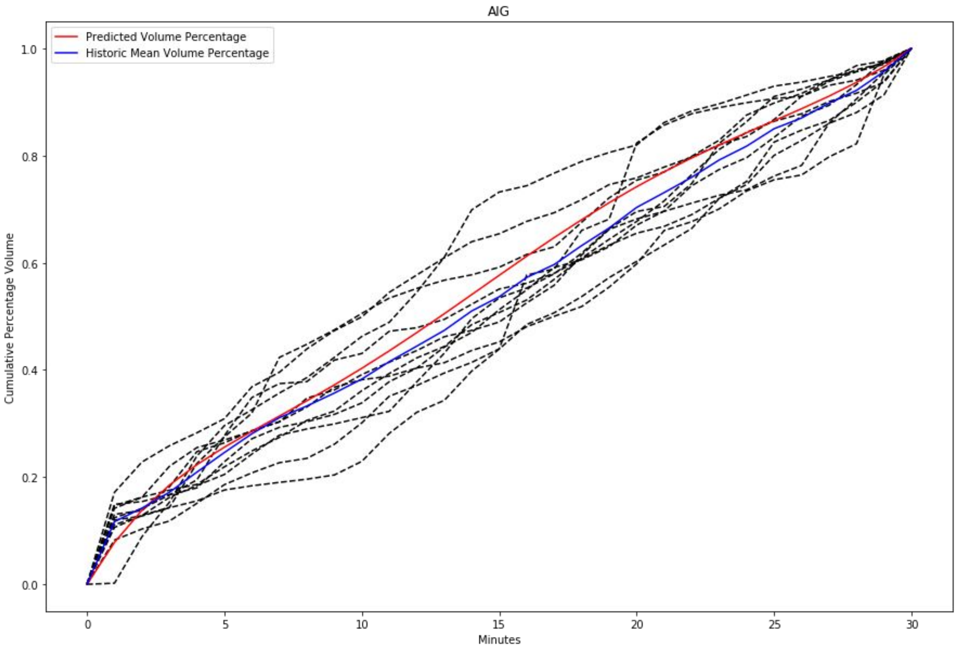
➔ Regress the first 30 minute volume data against the indexed time steps

➔ Regressors include powers of the time steps from one to five ($v_t \sim t+t^2+t^3+t^4+t^5$)

➔ Construct a volume percentage vector for the first 30 minutes of a typical trading day based on predicted volumes

Polynomial Fitting(Red) V.S. Binwise Mean(Blue)





Test Results on 12.17-12.31 Rebalance Phase

- Portfolio consists of stocks selected via refined NN model combination (long only, N=10):
- `fti (double weighted) tex tif sig (double weighted) hpq tjx sanm a pc`
- **Period Theoretical Return:-0.037161334639139516**
- **Fitted mean Shortfall:0.00025178430141614347**
- **Historic mean Shortfall:0.0005278179360995771**

```
TIF
2018.12.17 (Buy)Decision Price:81.4469 Executed VWAP(historic mean):80.509 Executed VWAP(fitted mean):80.481 Benchmark VWAP:80.513
2018.12.31 (Sell)Decision Price:81.34 Executed VWAP(historic mean):79.768 Executed VWAP(fitted mean):79.737 Benchmark VWAP:79.866
IS1:0.007784900229596071 IS2:0.007817060961703285
TJX
2018.12.17 (Buy)Decision Price:45.7799 Executed VWAP(historic mean):44.508 Executed VWAP(fitted mean):44.506 Benchmark VWAP:44.545
2018.12.31 (Sell)Decision Price:44.6543 Executed VWAP(historic mean):44.234 Executed VWAP(fitted mean):44.263 Benchmark VWAP:44.238
IS1:-0.01859503525776433 IS2:-0.01928036285336761
SANM
2018.12.17 (Buy)Decision Price:24.28 Executed VWAP(historic mean):24.193 Executed VWAP(fitted mean):24.17 Benchmark VWAP:24.191
2018.12.31 (Sell)Decision Price:23.92 Executed VWAP(historic mean):23.915 Executed VWAP(fitted mean):23.871 Benchmark VWAP:23.878
IS1:-0.003373117280797818 IS2:-0.0025098461857246237
SIG
2018.12.17 (Buy)Decision Price:32.1531 Executed VWAP(historic mean):31.851 Executed VWAP(fitted mean):31.85 Benchmark VWAP:31.774
2018.12.31 (Sell)Decision Price:30.991 Executed VWAP(historic mean):31.314 Executed VWAP(fitted mean):31.307 Benchmark VWAP:31.217
IS1:-0.019434388932911214 IS2:-0.019246537929517724
```

Test Results on 10.16-11.01 Rebalance Phase

- Portfolio consists of stocks selected via refined NN model combination (long only, N=10):
- `mac symc pch vtr kim ivz ctb(double weighted) dre anf`
- **Period Theoretical Return:0.0836137916348646**
- $\boxed{\textbf{Fitted mean Shortfall:0.000608331288436810}}$
- **Historic mean Shortfall:0.000919029510131526**

```
VTR
2018.10.16 (Buy)Decision Price:52.805 Executed VWAP(historic mean):53.946 Executed VWAP(fitted mean):53.945 Benchmark VWAP:53.953
2018.11.01 (Sell)Decision Price:57.3238 Executed VWAP(historic mean):58.05 Executed VWAP(fitted mean):58.066 Benchmark VWAP:58.115
IS1:0.007843358689424354 IS2:0.007527072883382412
PCH
2018.10.16 (Buy)Decision Price:34.6437 Executed VWAP(historic mean):35.324 Executed VWAP(fitted mean):35.307 Benchmark VWAP:35.271
2018.11.01 (Sell)Decision Price:35.5523 Executed VWAP(historic mean):36.503 Executed VWAP(fitted mean):36.504 Benchmark VWAP:36.456
IS1:-0.00782716627219415 IS2:-0.008306627942734412
CTB
2018.10.16 (Buy)Decision Price:23.6592 Executed VWAP(historic mean):24.469 Executed VWAP(fitted mean):24.453 Benchmark VWAP:24.526
2018.11.01 (Sell)Decision Price:30.9725 Executed VWAP(historic mean):31.199 Executed VWAP(fitted mean):31.207 Benchmark VWAP:31.236
IS1:0.024645449102754725 IS2:0.023670012476797578
KIM
2018.10.16 (Buy)Decision Price:14.9653 Executed VWAP(historic mean):14.915 Executed VWAP(fitted mean):14.911 Benchmark VWAP:14.928
2018.11.01 (Sell)Decision Price:15.7897 Executed VWAP(historic mean):16.136 Executed VWAP(fitted mean):16.136 Benchmark VWAP:16.136
IS1:-0.026534211257365218 IS2:-0.026755330169273214
```

PCA-ARIMA Volume Prediction

Execution
Test results on 12.17-12.31 and 10.16-11.01

ARIMA model
In-sample and out-of-sample prediction

Specific Component—deviation term
The stock specific volume pattern

Market Component—average term
Volume changes due to market evolutions

PCA
Decomposition of portfolio volume

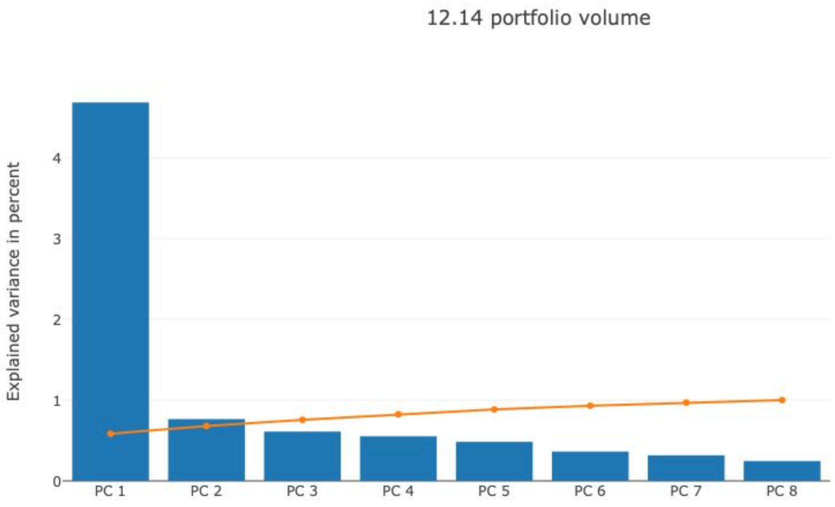
PCA-ARIMA

PCA

- ➔ First term is the average term
- ➔ Second one is the deviation term (residual)

$$x_{it} = c_{i,t} + y_{i,t},$$

$$\begin{aligned} c_{i,t} &= \overline{x}_i + \frac{1}{\lambda_1} Cov(x_{it}, C_t^1) C_t^1, \\ y_{i,t} &= \sum_{k>1} \frac{1}{\lambda_k} Cov(x_{it}, C_t^k) C_t^k. \end{aligned}$$



PCA Explained Variance Plot

PCA-ARIMA

ARIMA

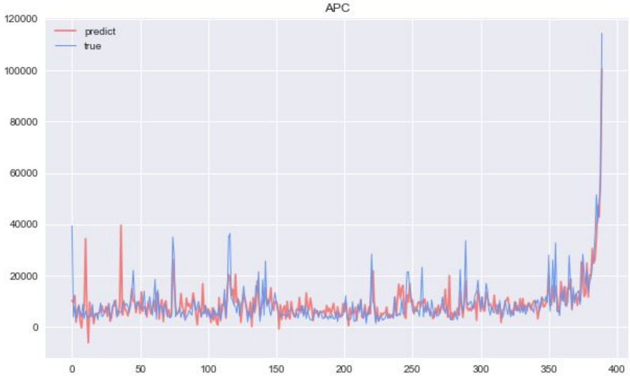
Using ARIMA model to predict specific volume pattern of stock

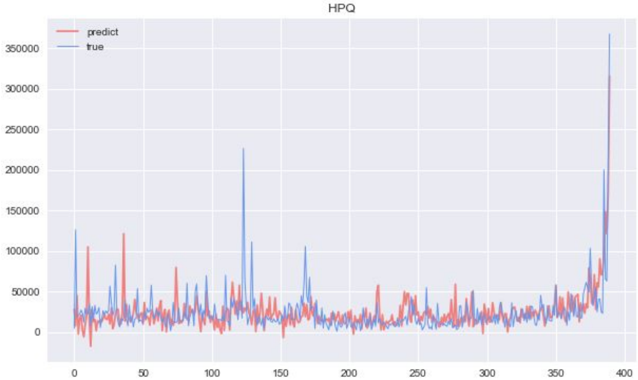
- ➔ Test stationarity of the residuals to determine the integrated times
- ➔ ARIMA(2, diff, 1) to fit data
- ➔ Data: one day before the rebalance date
- ➔ First part is the in-sample prediction
- ➔ Second part is the out-of-sample prediction

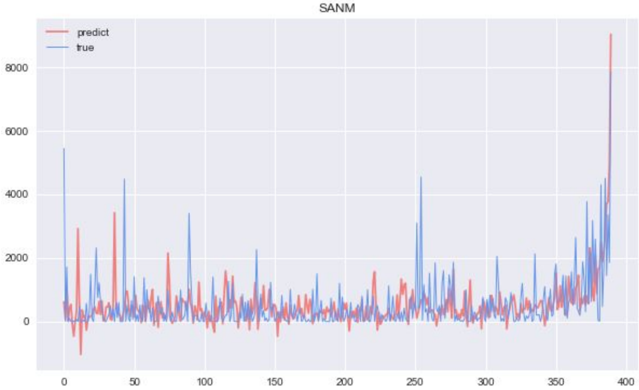
ARIMA model fitted to a residual series after PCA decomposition

PCA-ARIMA

In- sample prediction (volume traded on 12.14, refined NN model portfolio)





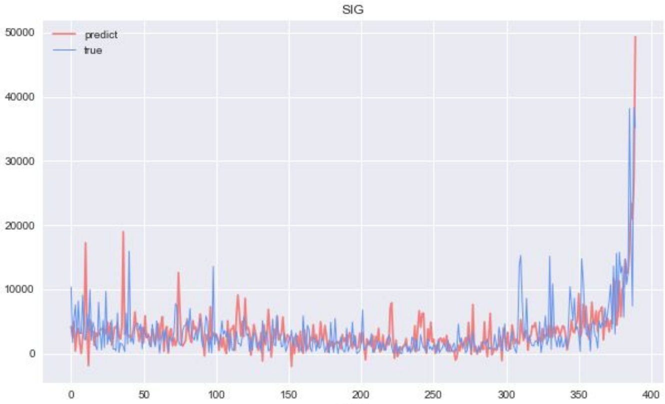


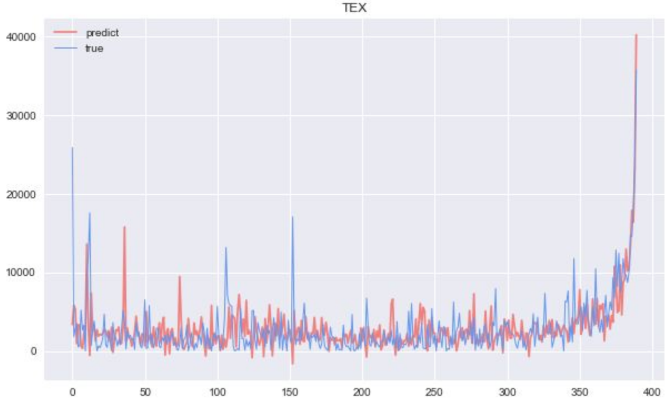
Comparing real volume and predict volume, the trend is similar.

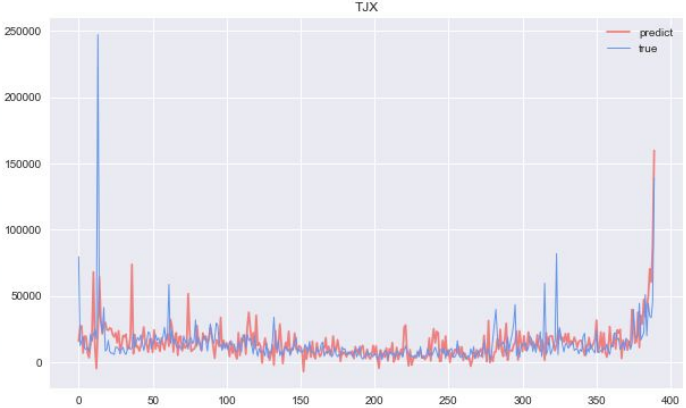
Instead, because of ARIMA model, the trend will delay a little and some peak value cannot be reached.

PCA-ARIMA

In- sample prediction (volume traded on 12.14, refined NN model portfolio)







Measuring Percentage Volume Predictions Error Absolute Deviation

$$\text{Error} = \frac{1}{N}\Sigma_{i=1}^{N}\left|\text{Predicted\_Percentage}_i - \text{Actual\_Percentage}\right.$$

APC: 0.10076%

FTI: 0.16774%

HPQ: 0.14074%

SANM: 0.24621%

SIG: 0.17477%

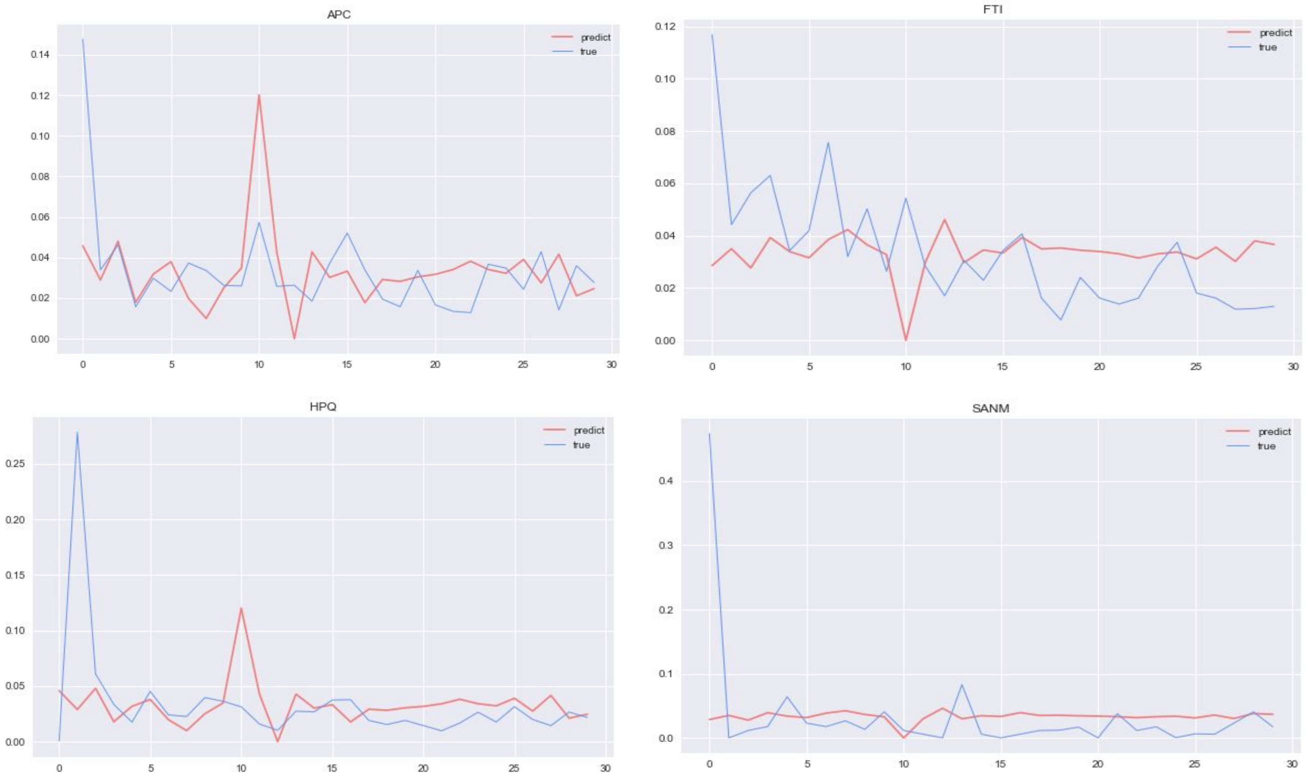
TEX: 0.17323%

TIF: 0.07773%

TJX: 0.13277%

PCA-ARIMA

Out-of- sample prediction (the volume percentage at 9:30am-10:00am on 12.17)



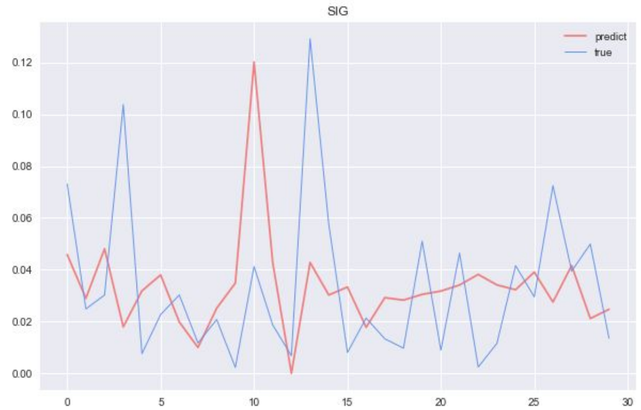
Trading Horizon Forecast

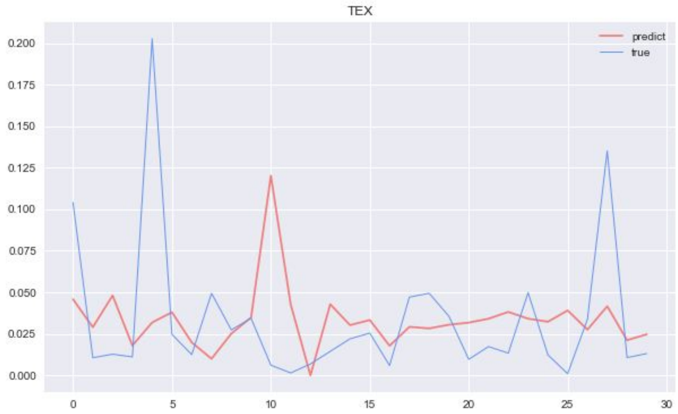
Real volume percentage **vs** predicted volume percentage

At the beginning of each trading day, there will be **extreme points** of the volume.

PCA-ARIMA

Out-of- sample prediction (the volume percentage at 9:30am-10:00am on 12.17)





Error

$$= \frac{1}{N}\Sigma_{i=1}^{N}\left|\text{Predicted\_Percentage}_i - \text{Actual\_Percentage}\right.$$

APC: 1.72524%

FTI: 1.81819%

HPQ: 2.38774%

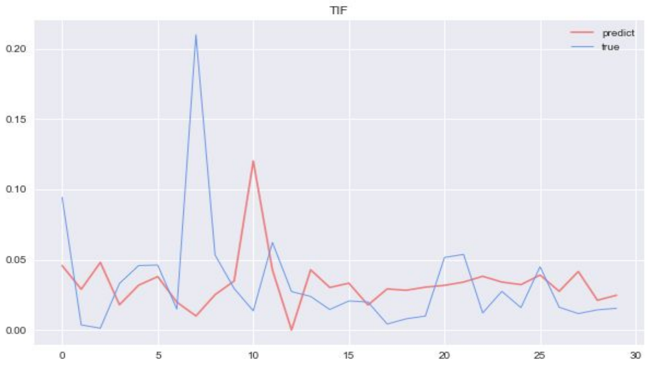
SANM: 3.70149%

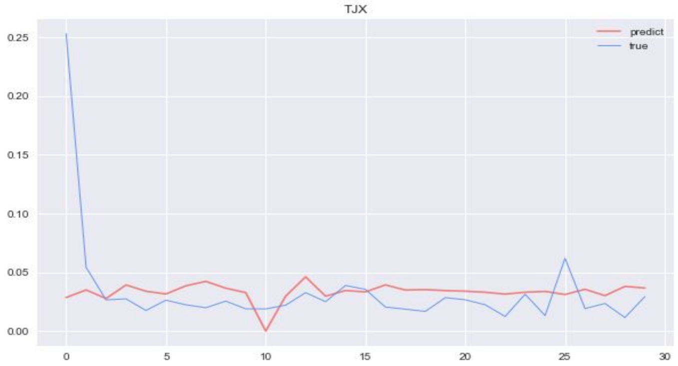
SIG: 2.43435%

TEX: 2.91472%

TIF: 2.72341%

TJX: 1.99972%





Test Results on 12.17-12.31 Rebalance Phase

The portfolio is selected via the refined NN model combination (long only, N=10). Stocks:

- fti (double weighted) tex tif sig (double weighted) hpq tjx sanm apc
- **Period Theoretical Return:-0.037161334639139516**
- **PCA-ARIMA Shortfall:0.00015790107738559642**
- **Average model Shortfall: 0.0008976228396290024**

```
TEX
2018.12.17 (Buy)Decision Price:28.0689 Executed VWAP(volume prediction):28.202 Executed VWAP(average volume):28.213 B
enchmark VWAP:28.221
2018.12.31 (Sell)Decision Price:27.3512 Executed VWAP(volume prediction):27.366 Executed VWAP(average volume):27.362
Benchmark VWAP:27.402
IS1:0.004193656020548309 IS2:0.00474465868825093
HPQ
2018.12.17 (Buy)Decision Price:21.7159 Executed VWAP(volume prediction):21.929 Executed VWAP(average volume):21.93 Be
nchmark VWAP:21.944
2018.12.31 (Sell)Decision Price:20.6053 Executed VWAP(volume prediction):20.524 Executed VWAP(average volume):20.528
Benchmark VWAP:20.521
IS1:0.0135599664027509 IS2:0.013414828266666795
FTI
2018.12.17 (Buy)Decision Price:19.96 Executed VWAP(volume prediction):19.933 Executed VWAP(average volume):19.932 Ben
chmark VWAP:19.909
2018.12.31 (Sell)Decision Price:20.04 Executed VWAP(volume prediction):19.619 Executed VWAP(average volume):19.6 Benc
hmark VWAP:19.617
IS1:0.019746651023928054 IS2:0.020664536425867113
```

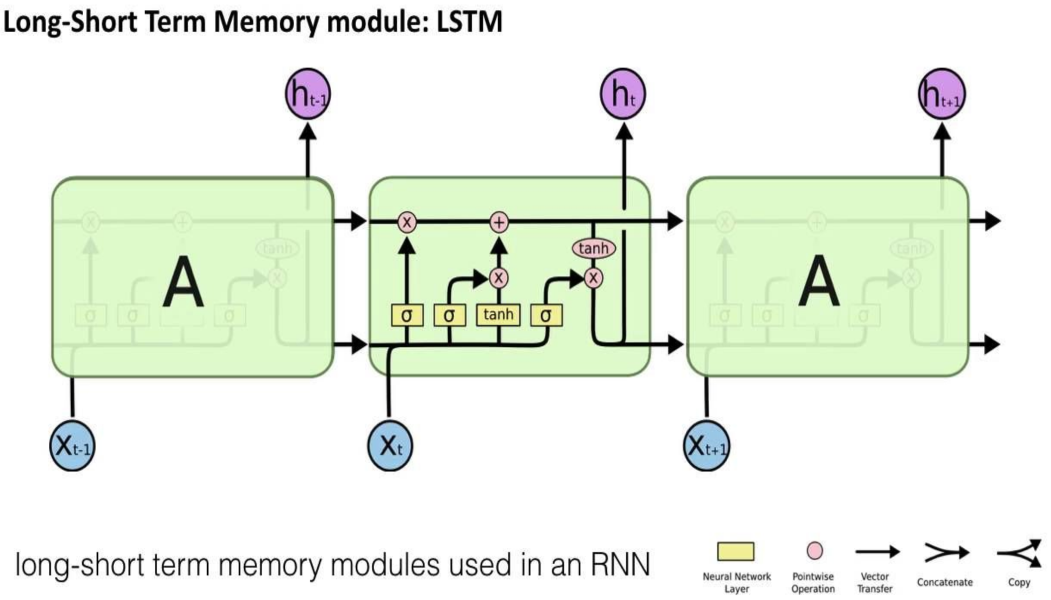
Test Results on 10.16-11.01 Rebalance Phase

The portfolio is selected using the refined NN model combination (long only, N=10). Stocks:

- mac symc pch vtr kim ivz ctb(double weighted) dre anf
- **Period Theoretical Return:0.0836137916348646**
- **PCA-ARIMA Shortfall:-0.00035452314747174015**
- **Average model Shortfall:-0.0003028095372954062**

```
DRE
2018.12.17 (Buy)Decision Price:26.5241 Executed VWAP(PCA-ARIMA):26.807 Executed VWAP(A-C model):26.808 Benchmark VWA
P:26.823
2018.12.31 (Sell)Decision Price:27.3123 Executed VWAP(PCA-ARIMA):27.695 Executed VWAP(A-C model):27.703 Benchmark VWA
P:27.692
IS1:-0.003786210341376668 IS2:-0.004020202333332798
KIM
2018.12.17 (Buy)Decision Price:14.9653 Executed VWAP(PCA-ARIMA):14.897 Executed VWAP(A-C model):14.899 Benchmark VWA
P:14.928
2018.12.31 (Sell)Decision Price:15.7897 Executed VWAP(PCA-ARIMA):16.133 Executed VWAP(A-C model):16.139 Benchmark VWA
P:16.136
IS1:-0.02749490912452146 IS2:-0.02779422446666617
MAC
2018.12.17 (Buy)Decision Price:48.7101 Executed VWAP(PCA-ARIMA):50.033 Executed VWAP(A-C model):50.038 Benchmark VWA
P:50.055
2018.12.31 (Sell)Decision Price:50.3764 Executed VWAP(PCA-ARIMA):52.942 Executed VWAP(A-C model):52.929 Benchmark VWA
P:52.877
IS1:-0.025499654634242055 IS2:-0.025124824800000004
```

LSTM Based Volume Percentage Prediction



LSTM Model Building (Keras)

Layers: **3 LSTMs & 1 Dense**

Input shape :
(time_steps = 30, data_dim = 1)

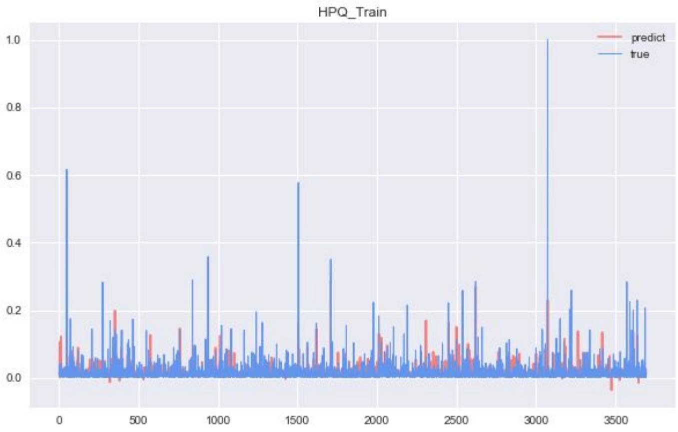
Output dim: **1 (return sequence=True)**

Output Layer Activation: **None**

Batch/Epochs: **Around 300**

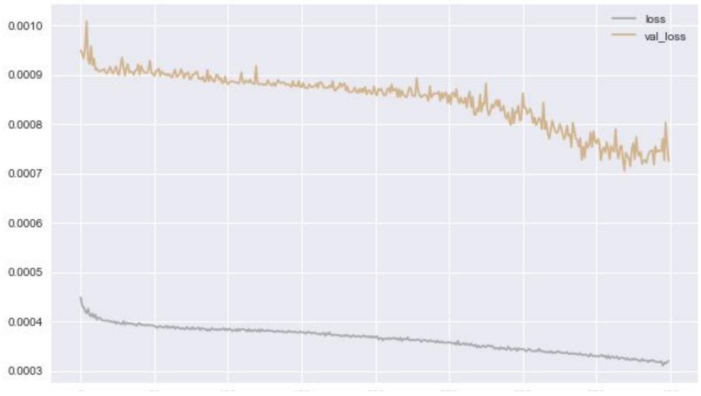
Loss function: **'logcosh'** (log(cosh(x)) is approximately equal to (x ** 2) / 2 for small x and to abs(x) - log(2) for large x.)

LSTM Volume Prediction Sample Results



← Training (HPQ)

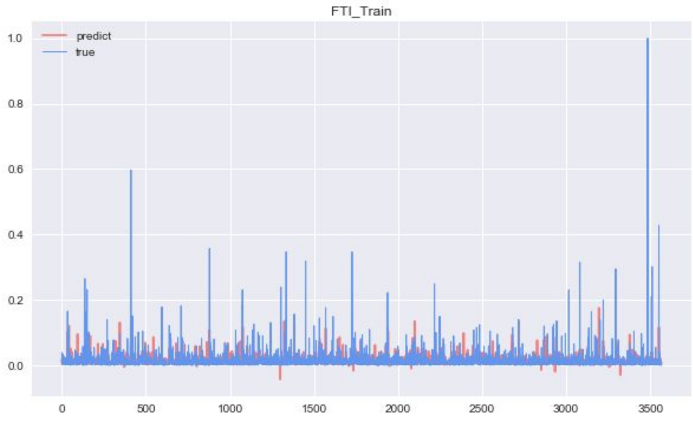
Loss History →



← Testing 12.17

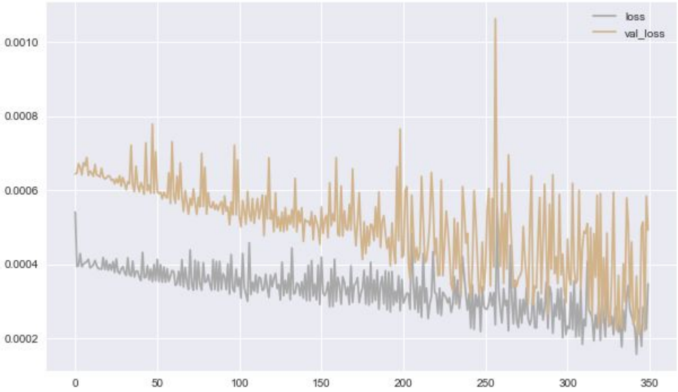
Testing 12.31→

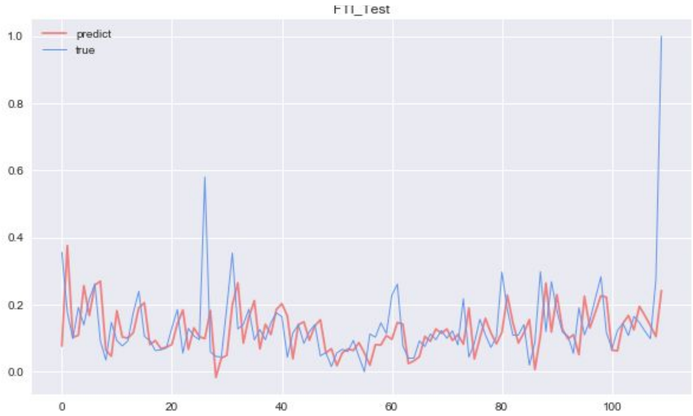
LSTM Volume Prediction Sample Results



← Training (FTI)

Loss History →





← Testing 12.17

Testing 12.31→

Test Results on 12.17-12.31 Rebalance Phase

The portfolio is selected using the refined NN model combination (long only, N=10). Stocks:

- fti (double weighted) tex tif sig (double weighted) hpq tjx sanm apc
- **Period Theoretical Return:-0.03716133463913951 6**
- **LSTM Shortfall: 0.00004559337873964470**
- **Average model Shortfall: 0.00089762283962900 24**

```
TIF
2018.12.17 (Buy)Decision Price:81.4469 Executed VWAP:80.303 Benchmark VWAP:80.513
2018.12.31 (Sell)Decision Price:81.34 Executed VWAP:79.663 Benchmark VWAP:79.866
IS1:0.006537004990051568
APC
2018.12.17 (Buy)Decision Price:50.062 Executed VWAP:50.405 Benchmark VWAP:50.43
2018.12.31 (Sell)Decision Price:43.6963 Executed VWAP:43.745 Benchmark VWAP:43.764
IS1:0.005877740331082862
SIG
2018.12.17 (Buy)Decision Price:32.1531 Executed VWAP:31.721 Benchmark VWAP:31.774
2018.12.31 (Sell)Decision Price:30.991 Executed VWAP:31.266 Benchmark VWAP:31.217
IS1:-0.02199228619368496
```

5

Results and Conclusions

5

Results

- In previous parts, we've shown a rough version of our portfolio performance. In this part, we construct P&L curves associated with our prediction models and portfolios through detailed trade executions and bookkeeping.

- We also summarize and compare the performances of different VWAP targeting execution strategies based on volume predictions.

Backtesting Procedure

Portfolio	Trade	Position	P&L (single stock)	P&L (portfolio)

```
{'ANF': 100000.0,
 'CTB': 200000.0,
 'DRE': 100000.0,
 'IVZ': 100000.0,
 'KIM': 100000.0,
 'MAC': 100000.0,
 'PCH': 100000.0,
 'SYMC': 100000.0,
 'VTR': 100000.0}
```

- Example trade horizon: 10.16-11.01
- Total Capital : $1000000.0

Backtesting Procedure

Portfolio	Trade	Position	P&L (single stock)	P&L (portfolio)


```
{'decision_price': 17.9553,
 'decision_time': Timestamp('2018-10-16 09:30:00'),
 'symbol': 'ANF',
 'trade_price': 17.9553,
 'trade_time': Timestamp('2018-10-16 09:30:00'),
 'volume': 5569}
```

Backtesting Procedure

Portfolio | Trade | **Position** | P&L (single stock) | P&L (portfolio)

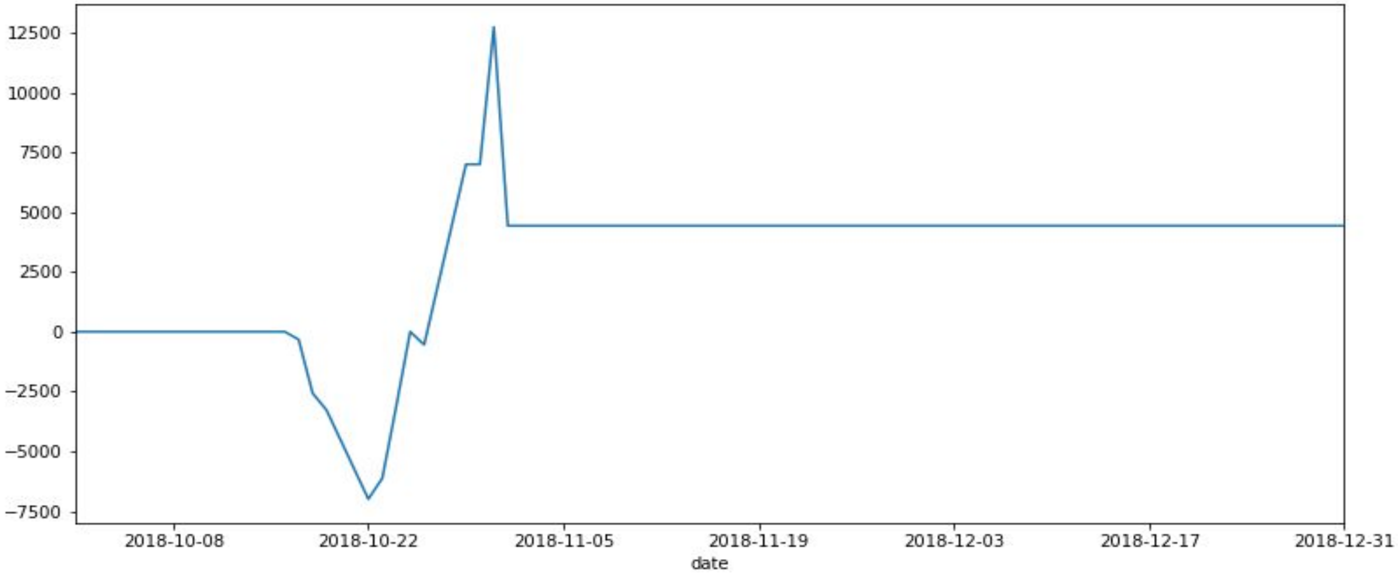
```
{'cash': 0,
 'datetime': datetime.datetime(2018, 10, 1, 9, 30),
 'pos': 0,
 'symbol': 'ANF'}
```

```
{'cash': -99993.0657,
 'datetime': Timestamp('2018-10-16 09:30:00'),
 'pos': 5569}
```

```
{'cash': 4428.468799999988,
 'datetime': Timestamp('2018-11-01 09:30:00'),
 'pos': 0}
```

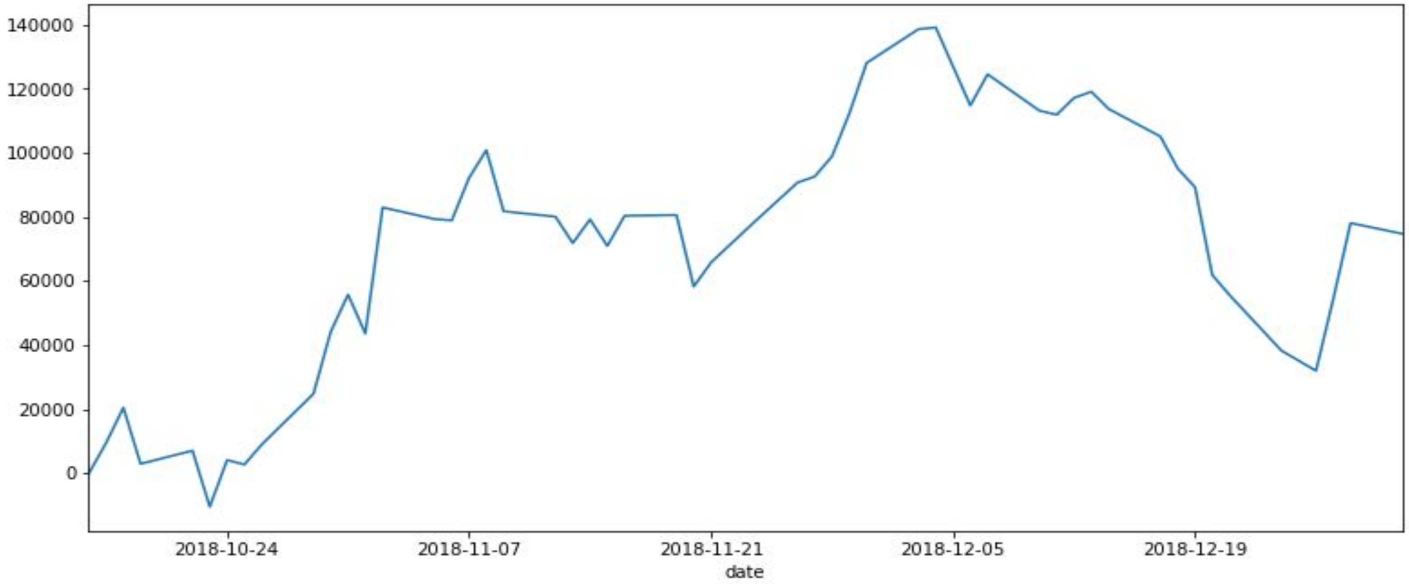
Backtesting Procedure

Portfolio | Trade | Position | P&L (single stock) | P&L (portfolio)

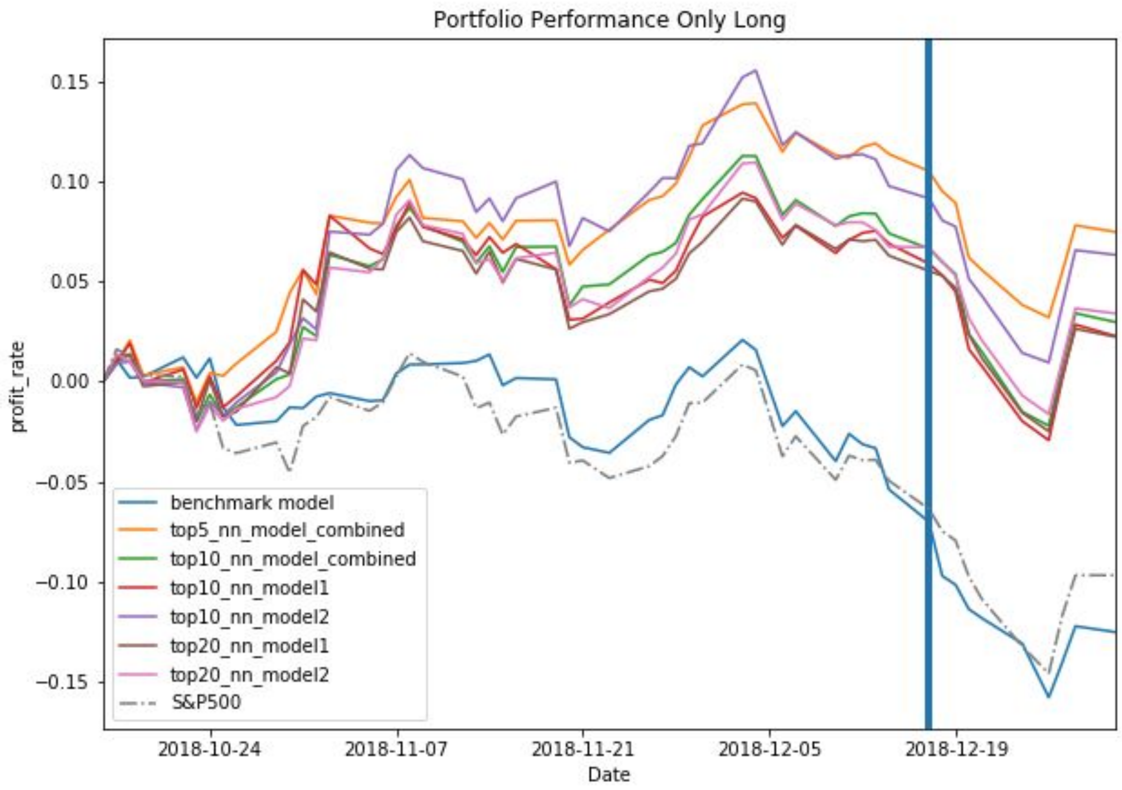


Backtesting Procedure

Portfolio	Trade	Position	P&L (single stock)	P&L (portfolio)



Performance of Long-only Portfolios



The ensemble model with top 5 stocks (orange line) gave us the best portfolio.

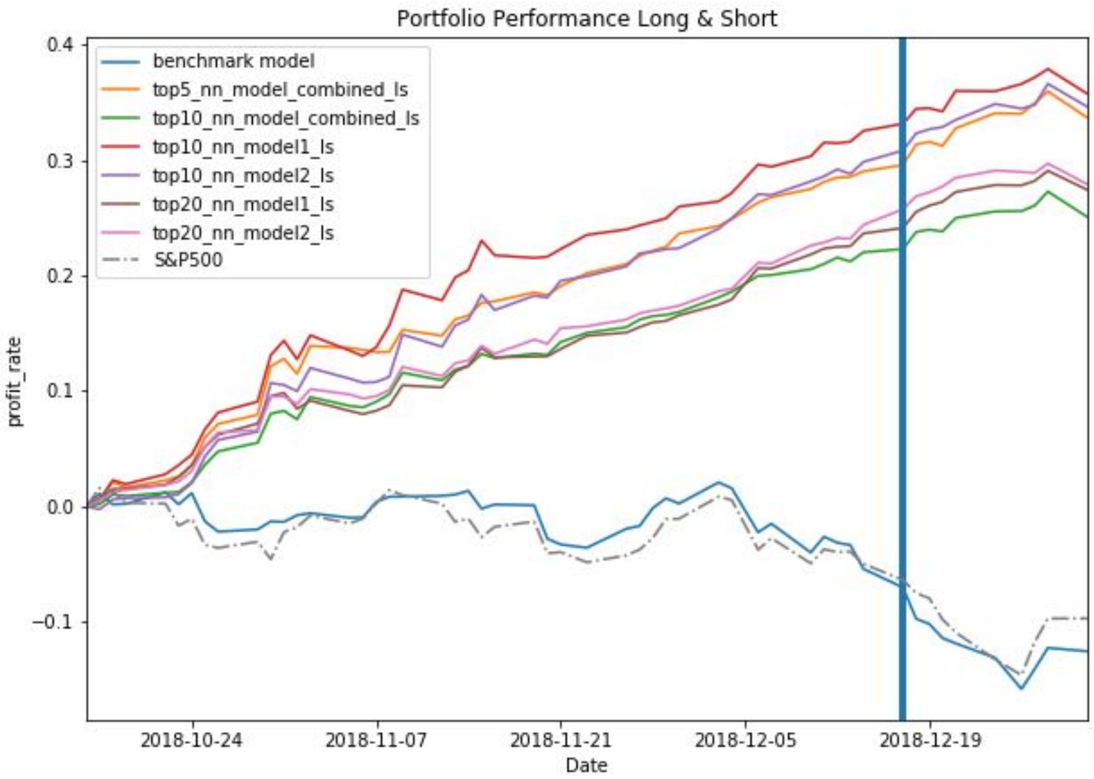
Backtesting Results (long only, all-period)

model	Profit	Sharpe ratio	Max drawdown
Naive MACD	-12.53%	-2.96	17.88%
Combined Top 5	7.48%	1.74	10.71%
Combined Top 10	2.97%	0.62	13.50%
NN1 Top 10	2.27%	0.47	12.38%
NN2 Top 10	6.33%	1.20	14.61%
NN1 Top 20	2.23%	0.47	11.64%
NN2 Top 20	3.40%	0.74	12.59%

Backtesting Results (long only, out-of-sample)

model	Profit	Max drawdown
Naive MACD	-5.52%	8.78%
Combined Top 5	-3.03%	7.31%
Combined Top 10	-3.67%	8.86%
NN1 Top 10	-3.62%	8.83%
NN2 Top 10	-2.82%	8.21%
NN1 Top 20	-3.30%	8.03%
NN2 Top 20	-3.31%	8.35%

Performance of Long & Short Portfolios

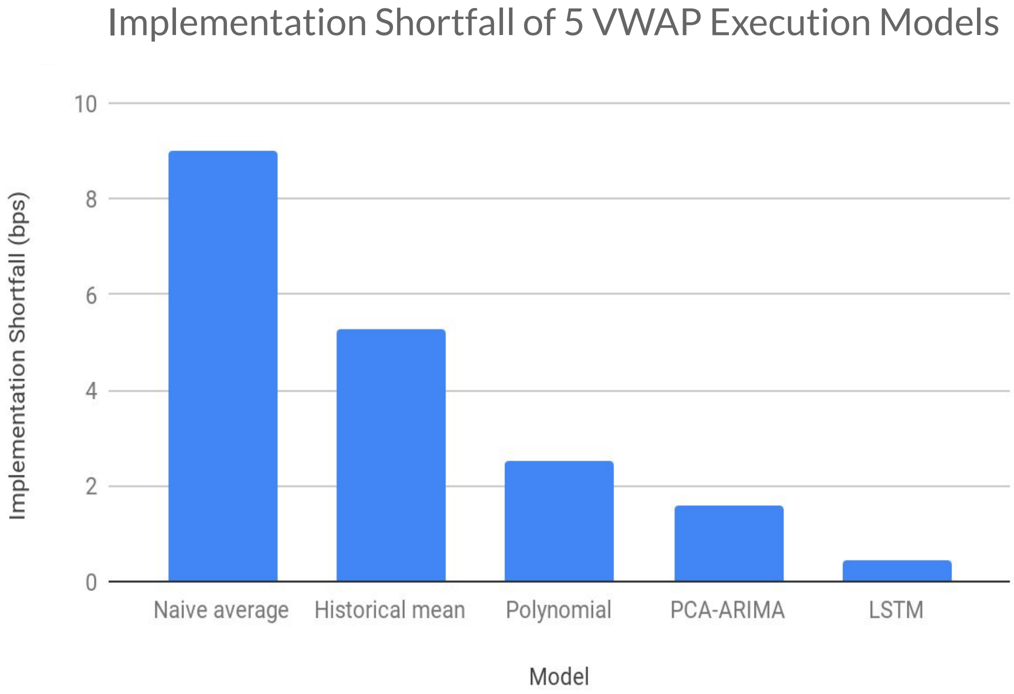


If short selling is allowed, both the in-sample and out-of-sample performance of our NN-based models can beat the market by a significant deficit.

VWAP Execution Comparison (12.17-12.31 period)

- **Based on the refined long-only NN model portfolio**

Model	Implementation shortfall (bps)
Baseline model	8.98
Historical mean	5.28
Polynomial	2.52
PCA-ARIMA	1.58
LSTM	0.46



Highlights of Our Project

- Training and tuning Neural Networks to generate profitable stock selections and construct portfolios that consistently beat the market benchmark.

- Applying various volume prediction strategies to beat the naive average order splitting baseline strategy in terms of realized implementation shortfall as a measure of primary transaction costs associated with our trading strategy.

6

Future Perspectives

- Increase our data sample size to conduct more rebalance tests and improve the performance of neural network models.
- Test the execution performance on diversified trading horizons.
- Vary the length of our position holding period to generate more returns.
- Include exogenous variables in the prediction of volume traded such as price and information extracted from the bid-ask data.
- Conduct Mean-Variance type portfolio optimization analysis to hedge our portfolio risks.
- Introduce factors extracted from company news and market sector information.

References

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- Adaptive Portfolio Asset Allocation Optimization with Deep Learning, Obeidat, Shapiro, and Lemay, 2018.
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- VWAP Execution as an Optimal Strategy, Kato, 2014.
- Improving VWAP Strategies: A Dynamic Volume Approach, Bialkowski, Darolles, and Le Fol, 2006.
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Thank You!