MS&E 448 Midterm Presentation
High Frequency Algorithmic Trading

Francis Choi George Preudhomme Nopphon Siranart
Roger Song Daniel Wright

Stanford University

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Overview

Order Book and Message book

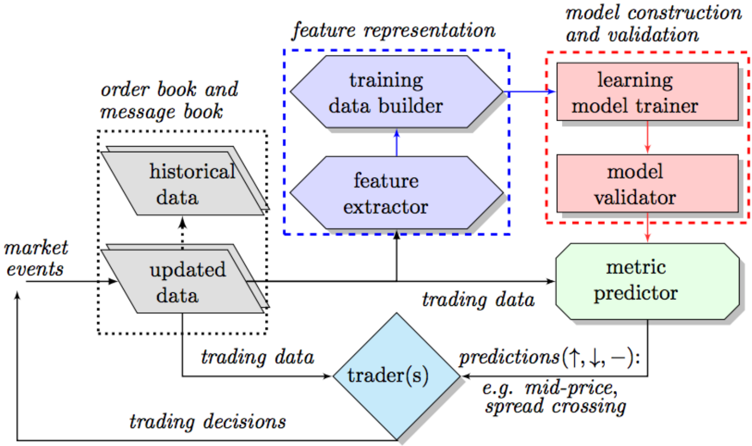
Message book

	Time(sec)	Price($)	Volume	Event Type	Direction
$k-1$	34203.011926972	585.68	18	execution	ask
k	34203.011926973	585.69	16	execution	ask
...	...	...	...	...	...
$k+4$	34203.011988208	585.74	18	cancellation	ask
$k+5$	34203.011990228	585.75	4	cancellation	ask
...	...	...	...	...	...
$k+8$	34203.012050158	585.70	66	execution	bid
$k+9$	34203.012287906	585.45	18	submission	bid
$k+10$	34203.089491920	586.68	18	submission	ask

Order book

	Ask^1		Bid^1		Ask^2		Bid^2		Ask^3		Bid^3		...
	Price	Vol.	Price	Vol.	Price	Vol.	Price	Vol.	Price	Vol.	Price	Vol.	...
$k-1$	585.69	16	585.44	167	585.71	118	585.40	50	585.72	2	585.38	22	...
k	585.71	118	585.44	167	585.72	2	585.40	50	585.74	18	585.38	22	...
...	...	...	...	...	...	...	...	...	...	...	...	...	...
$k+4$	585.71	118	585.70	66	585.72	2	585.44	167	585.75	4	585.40	50	...
$k+5$	585.71	118	585.70	66	585.72	2	585.44	167	585.80	100	585.40	50	...
...	...	...	...	...	...	...	...	...	...	...	...	...	...
$k+8$	585.71	100	585.44	167	585.80	100	585.40	50	585.81	100	585.38	22	...
$k+9$	585.71	100	585.45	18	585.80	100	585.44	167	585.81	100	585.40	50	...
$k+10$	585.68	18	585.45	18	585.71	100	585.44	167	585.80	100	585.40	50	...

Architecture of Our Model Framework



Random Forest

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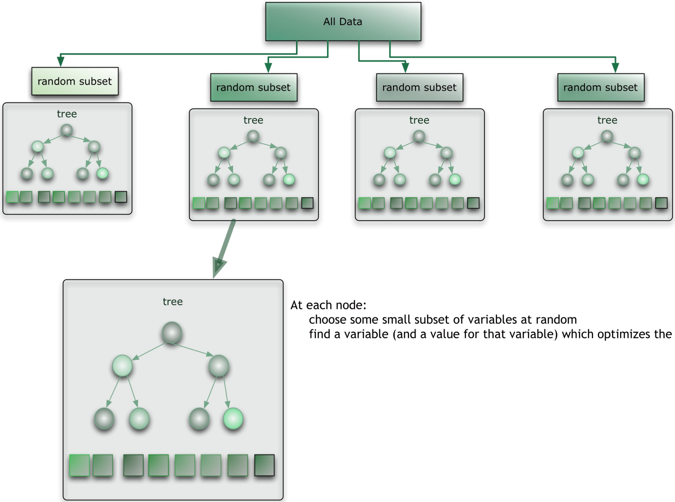


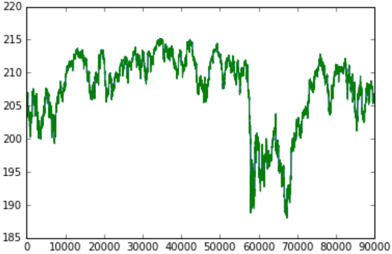
At each node:

choose some small subset of variables at random

find a variable (and a value for that variable) which optimizes the split

Data Summary

- IVV Stock Prices in Year 2015 containing 89,869 datapoints.
- Minute-by-minute (Except beginning/End of trading days)
- We used the first 80% for Training Set and the last 20% for Test Set



Features

Basic Set	Description(i = *level index*)
$v_1 = \{P_i^{ask},\ V_i^{ask},\ P_i^{bid},\ V_i^{bid}\}_{i=1}^n,$	*price and volume(n levels)*

Time-insensitive Set	Description(i = *level index*)
$v_2 = \{(P_i^{ask} - P_i^{bid}), (P_i^{ask} + P_i^{bid})/2\}_{i=1}^n,$	*bid-ask spreads and mid-prices*
$v_3 = \{\max P_i^{ask} - \min P_i^{ask},\ \max P_i^{bid} - \min P_i^{bid}\}_{i=1}^n,$	*max-min price differences*
$v_4 = \{\frac{1}{n}\sum_{i=1}^n P_i^{ask},\ \frac{1}{n}\sum_{i=1}^n P_i^{bid},\ \frac{1}{n}\sum_{i=1}^n V_i^{ask},\ \frac{1}{n}\sum_{i=1}^n V_i^{bid}\},$	*mean prices and volumes*
$v_5 = \{\sum_{i=1}^n (P_i^{ask} - P_i^{bid}),\ \sum_{i=1}^n (V_i^{ask} - V_i^{bid})\},$	*accumulated differences*

Time-sensitive Set	Description(i = *level index*)
$v_6 = \{dP_i^{ask}/dt,\ dP_i^{bid}/dt,\ dV_i^{ask}/dt,\ dV_i^{bid}/dt\}_{i=1}^n,$	*price and volume derivatives*
$v_7 = \{\lambda_{\Delta t}^{la},\ \lambda_{\Delta t}^{lb},\ \lambda_{\Delta t}^{ma},\ \lambda_{\Delta t}^{mb},\ \lambda_{\Delta t}^{ca},\ \lambda_{\Delta t}^{cb}\ \}$	*average intensity of each type*
$v_8 = \{\mathbf{1}_{\{\lambda_{\Delta t}^{la} > \lambda_{\Delta T}^{la}\}},\ \mathbf{1}_{\{\lambda_{\Delta t}^{lb} > \lambda_{\Delta T}^{lb}\}},\ \mathbf{1}_{\{\lambda_{\Delta t}^{ma} > \lambda_{\Delta T}^{ma}\}},\ \mathbf{1}_{\{\lambda_{\Delta t}^{mb} > \lambda_{\Delta T}^{mb}\}}\},$	*relative intensity indicators*
$v_9 = \{d\lambda^{ma}/dt,\ d\lambda^{lb}/dt,\ d\lambda^{mb}/dt,\ d\lambda^{la}/dt\},$	*accelerations(market/limit)*

Label

- Originally, binary classification (mid-price change)
- Changed to three-way classification (spread crossing)

Time	Bid	Ask	Upward	Downward	Label
1	207.29	207.32	-0.07	-0.02	-1
2	207.25	207.27	-0.01	0.02	0
3	207.26	207.27	0.04	0.08	1

Table: Labels using Upward cross and Downward Cross

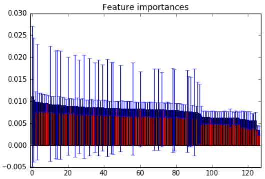
- Our data: 26,105 ups (+1), 37,870 zeros (0), 25,894 downs (-1) - Evenly distributed

Results

Key Observations

- We notice that those features in the lower levels are more important than those higher ones
- Volume and number of orders are the most significant features

Ranking	Features	Score
1	bids size 1	0.010127
2	asks size 2	0.010027
3	asks nord 0	0.010024
4	asks size 1	0.009959
5	bids nord 3	0.009956
6	asks nord 3	0.009895



Results

- Out of 17,973 entries, there are 1,947 ups (+1), 14,715 zeros (0), 1,311 downs (-1) in our predicted labels - biased towards zero
- Below shows the confusion matrix

		Prediction		
		1	0	-1
Truth	1	420	4063	543
	0	503	6579	829
	-1	388	4073	575

Table: Confusion Matrix of the Predictions

- Not good enough !! $\Rightarrow$ Set the threshold

Trading Strategy

- Consider likelihoods that model predicts for each new data point
- If the highest likelihood is -1 or 1 and that likelihood is sufficiently large enough (above our threshold), then trade in that direction
- For example, if the threshold = 0.40, only time 1 and time 2 have the likelihood above the threshold. However, we only open position at time 2 as our predicted label at time 1 is 0

Time	**-1**	**0**	**-1**	**Predicted**	**Threshold**	**Position**
1	0.253	0.479	0.266	0	Yes	No
2	0.301	0.269	0.428	-1	Yes	Sell
3	0.358	0.303	0.337	1	No	No

Table: Likelihood of our random forest model

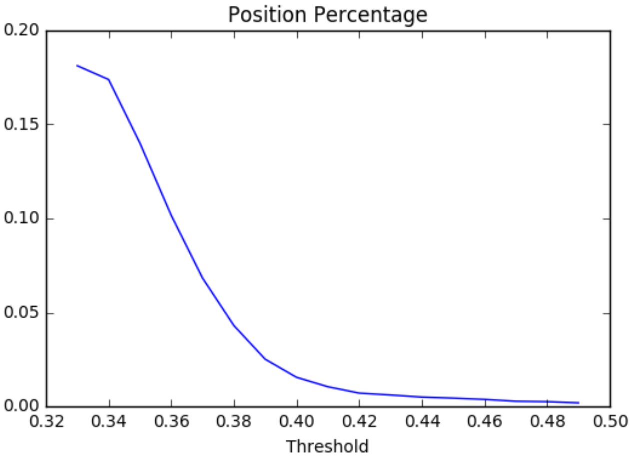
Trading Strategy - Calculating Profit

- Once we open a position, we will close it in the next time step
- For example, total profit of the positions in the following table is $0 + (-0.02) + 0.04 = 0.02$

Time	**Bid**	**Ask**	**Upward**	**Downward**	**Position**	**Profit**
1	207.29	207.32	-0.07	-0.02	0	0
2	207.25	207.27	-0.01	0.02	-1	-0.02
3	207.26	207.27	0.04	0.08	1	0.04

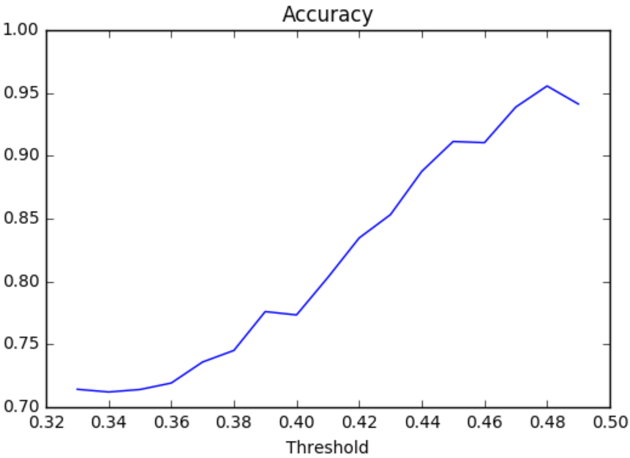
Results

- As the threshold increases, the number of total positions decreases



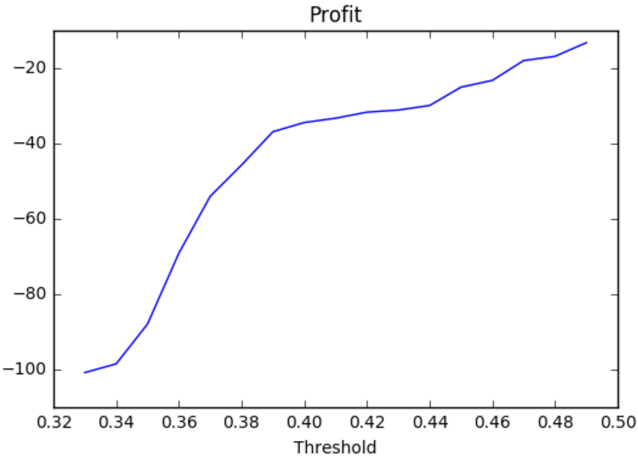
Results

- Accuracy is measured as follows. If we our position is 1, and the true label is either 1 or 0, then we say it is accurate and vice versa for -1.
- As the threshold increases, the accuracy also increases as well



Results

- As the threshold increases, the profit also increases as well



Next Steps

- Tuning Hyperparameters e.g. Max Depth, Number of Trees in Random Forest, Threshold etc.
- Try different prediction models such as SVM, Regression, Time Series
- Running the strategy using the simulator