PREDICTING REALIZED VOLATILITY IN STOCK PRICES

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WHAT IS REALIZED VOLATILITY & WHY PREDICT IT?

- Volatility captures the amount of fluctuation in bid/ask prices of a stock
- It is an important input for pricing options
- Optiver is a leading global electronic market maker firm
- It wants to further evolve its industry leading pricing algorithm

Realized Volatility computation:

$$RV = \sqrt{\sum_{t} r_{t-1,t}^{2}}$$

$$WAP = \frac{bid\_price * ask\_size + ask\_price * bid\_size}{ask\_size + bid\_size}$$

r is the log return of *WAP (Weighted Average Price)*

PROBLEM STATEMENT: PREDICT REALIZED VOLATILITY FOR THE FUTURE 10-MINUTE PERIOD

Context : Optiver has book and trade data for current 10-min period, using which it wants to predict realized volatility for future 10-min period. Accurately predicting future volatility is critical input for pricing stock options that Optiver trades in.

Criteria for Success : A model that can minimize RMSPE (*Root Mean Squared Percentage Error*) between predicted and true values of future volatility.

Scope : **112 stocks traded by Optiver**

Constraints:

- Non-availability of data beyond 10-minute period
- Non-availability of external factors influencing a particular stock or the market as a whole

Stakeholders to provide Key Insight :

1) Ben Bell – Springboard Mentor

Data Sources : Book & Trade data for 112 stocks for approx. 3800 ten-minute time periods.

https://www.kaggle.com/code/jiashenliu/introduction-to-financial-concepts-and-data/data?scriptVersionId=67183666

DATA INSPECTION

Prices are normalized, Time_id's have no sequential logic

Book File: Contains Top 2 bid/ask prices and sizes

	time_id	seconds_in_bucket	bid_price1	ask_price1	bid_price2	ask_price2	bid_size1	ask_size1	bid_size2	ask_size2
0	5	0	1.001422	1.002301	1.00137	1.002353	3	226	2	100
1	5	1	1.001422	1.002301	1.00137	1.002353	3	100	2	100
2	5	5	1.001422	1.002301	1.00137	1.002405	3	100	2	100
3	5	6	1.001422	1.002301	1.00137	1.002405	3	126	2	100

- Missing 'seconds_in_bucket' : means no change in bid/ask prices or sizes for those seconds.
- Each time_id **is 10-min,** has upto 600 seconds of data
- WAP is derived from bid1 / ask1 data

Trade File: Data on trade prices, sizes

	time_id	seconds_in_bucket	price	size	order_count
0	5	21	1.002301	326	12
1	5	46	1.002778	128	4
2	5	50	1.002818	55	1

- Missing 'seconds_in_bucket' : no trades for those seconds
- This file is sparse compared to Book file

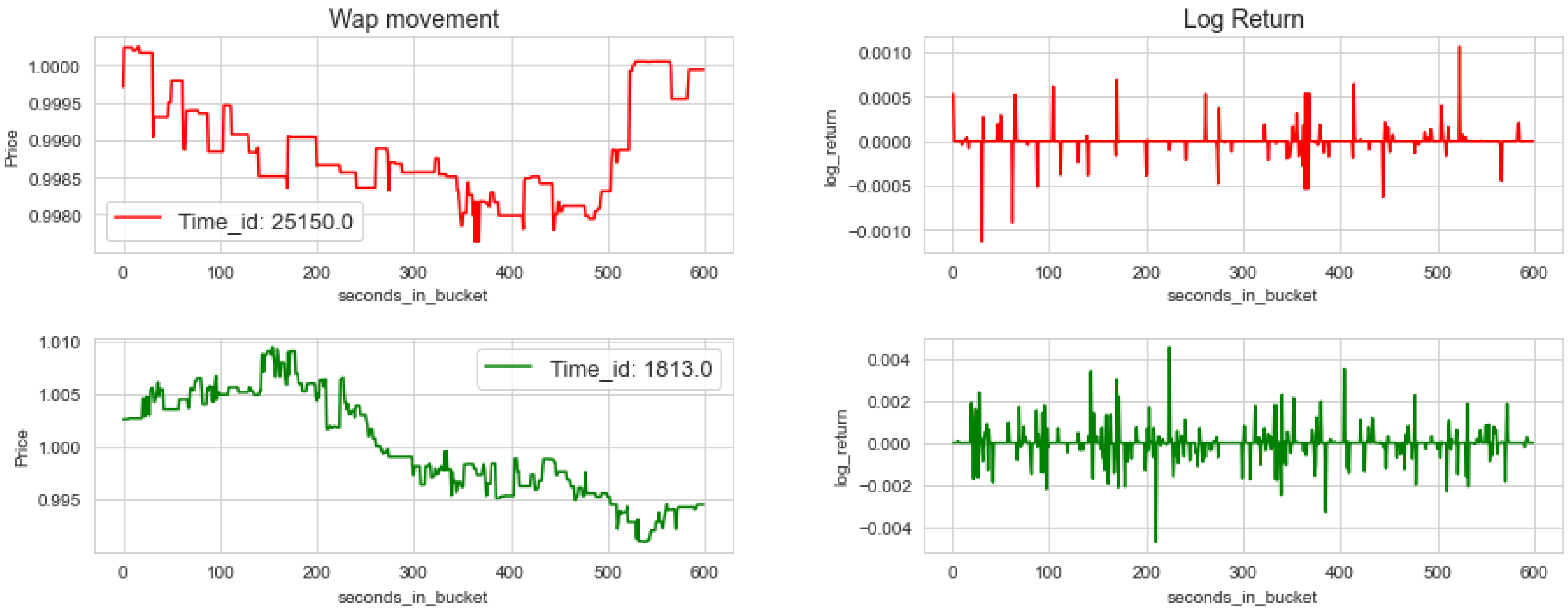
Training File: Contains target

	stock_id	time_id	target
0	0	5	0.004136
1	0	11	0.001445
2	0	16	0.002168

- 'target' : realized volatility in 10-min following time_id 5 /11/16
- To be predicted using book & trade data for respective time_id

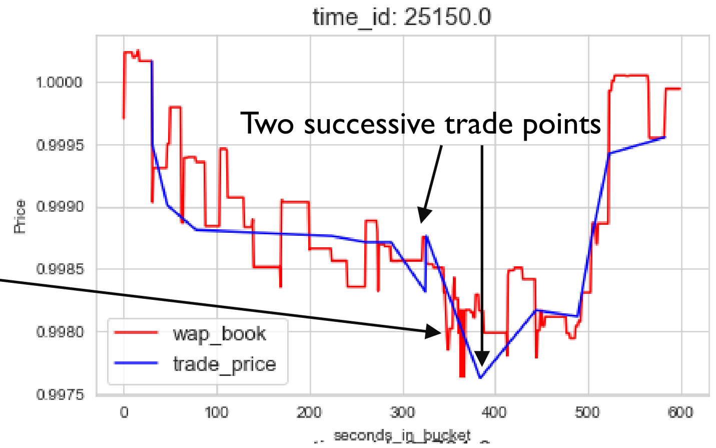
EXPLORATORY DATA ANALYSIS

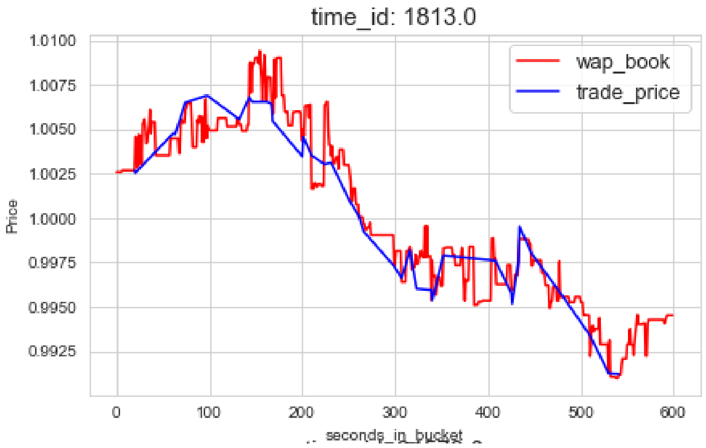
WAP is a random walk, Log returns are stationary



WAP & Trade Price closely track one another

WAP moves a lot between 2 trade points



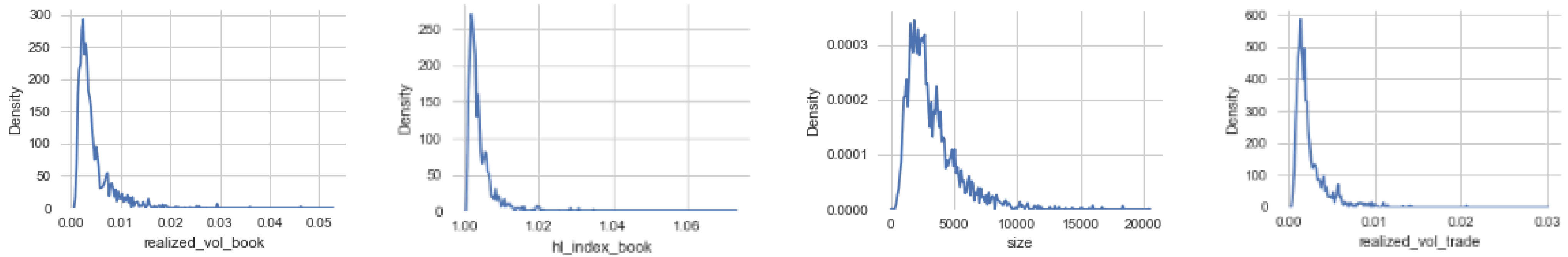


Difficult to say which one (WAP or Trade Price) drives the other.

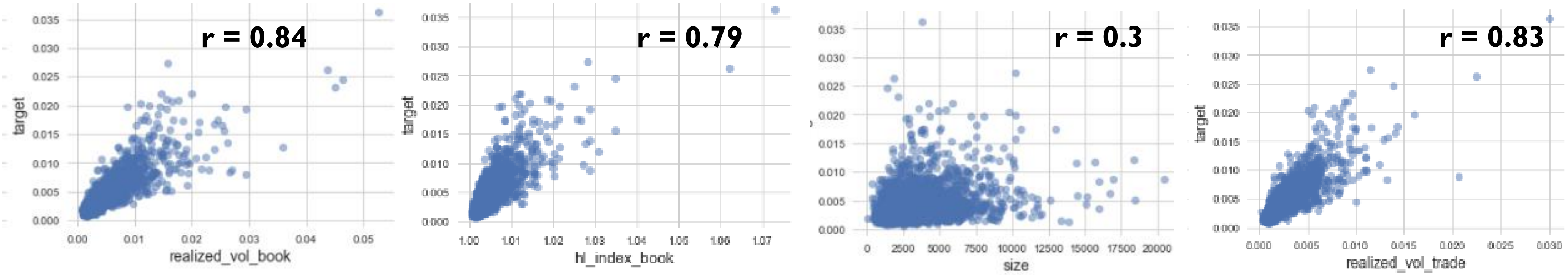
EXPLORATORY DATA ANALYSIS

Features are not normally distributed

Kolmogorov Smirnov test returns p-value of **0.00** for all features



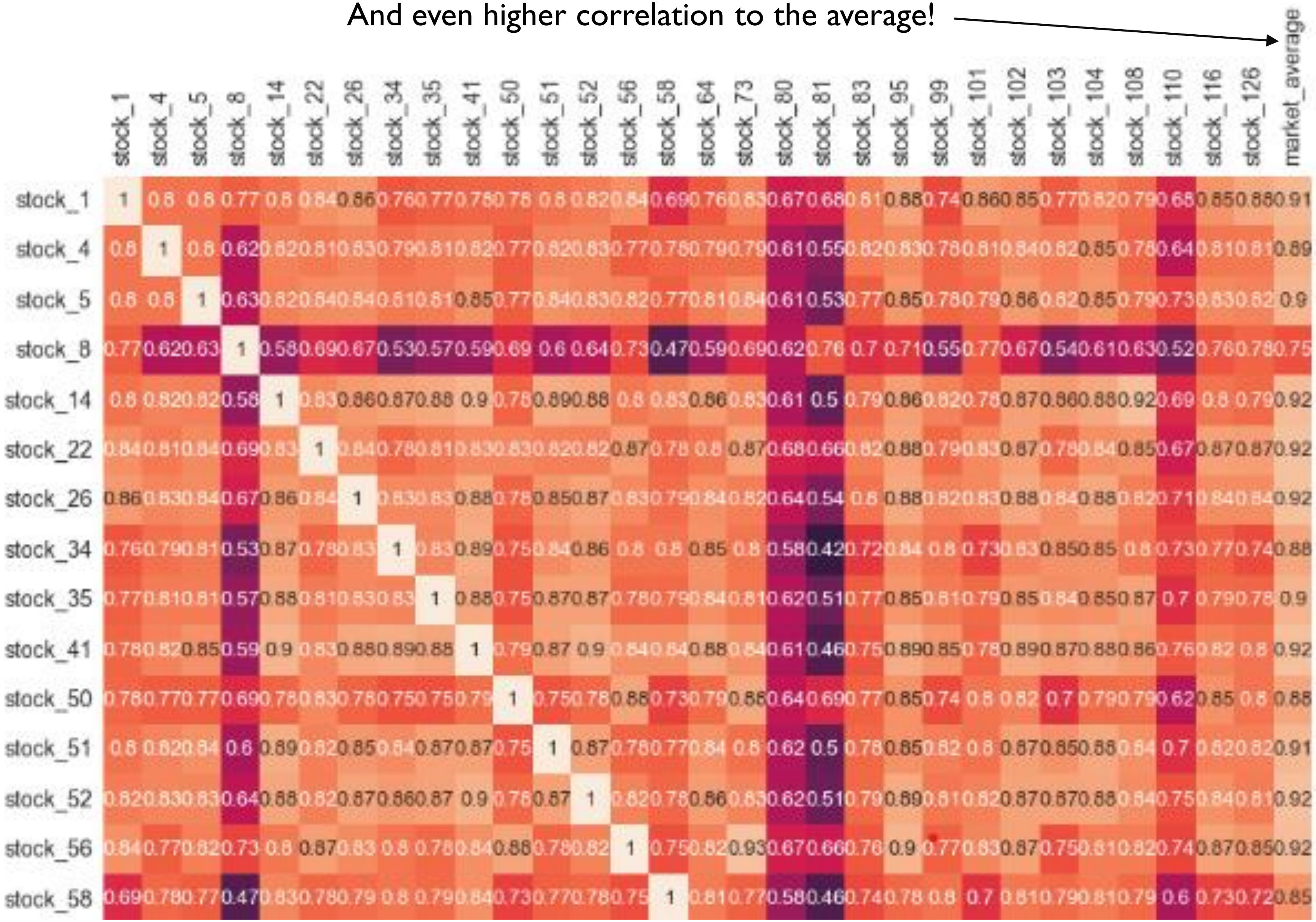
‘realized_vol_book’, ‘hl_index_book’, ‘realized_vol_trade’ have high correlation with ‘target’



Many stocks have strong correlation in realized volatility

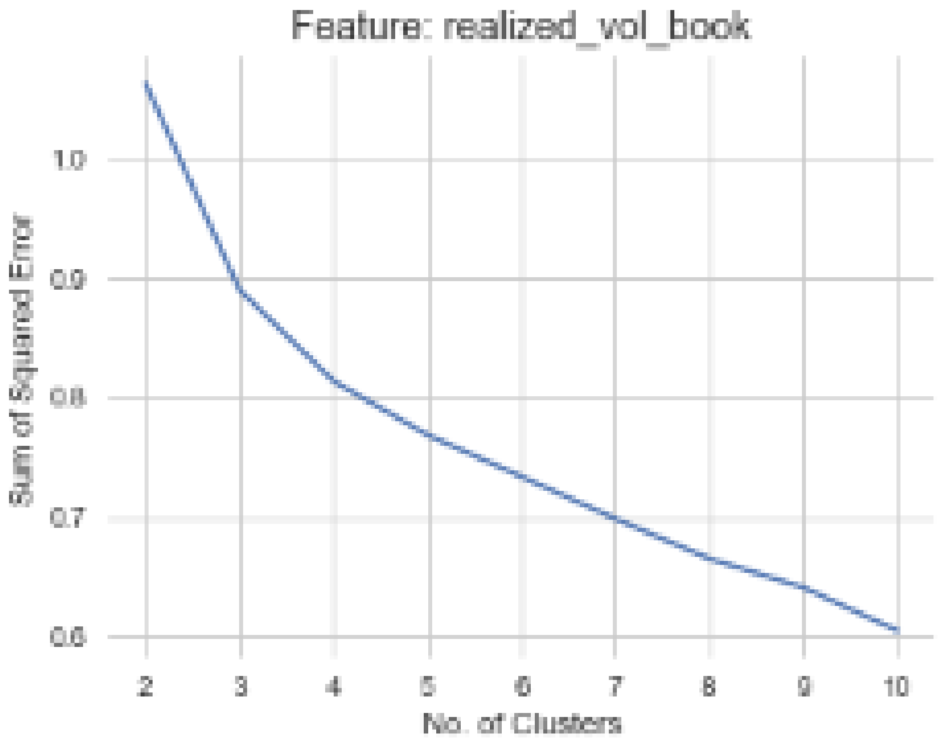
And even higher correlation to the average!

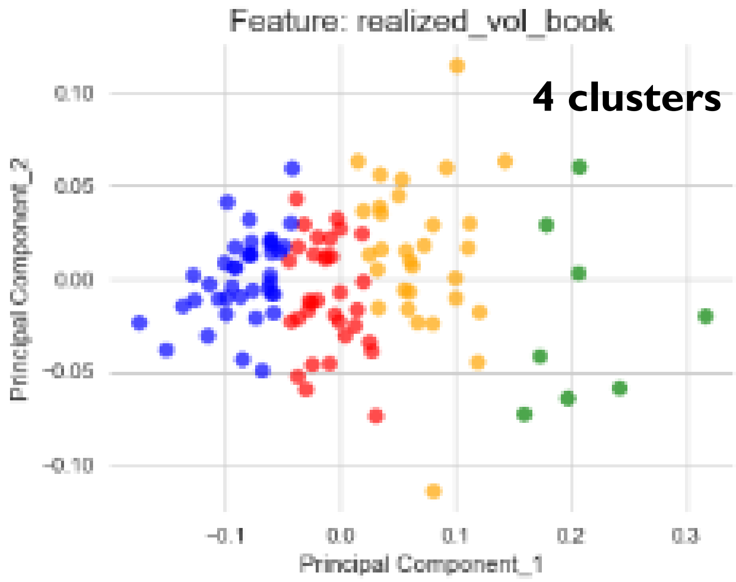
(Average of 30 stocks)

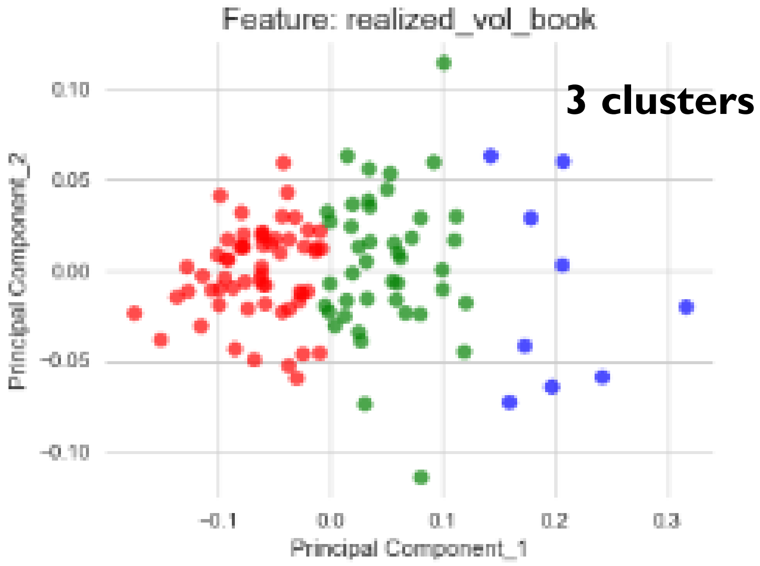


EXPLORATORY DATA ANALYSIS

The 112 stocks show 3–4 clusters







EDA: KEY LEARNINGS

- WAP is a random walk, it's log returns are stationary
- WAP & Trade Price closely track one another, but difficult to say which one drives the other
- Features are not normally distributed
- 'target' is strongly correlated to
    - 'realized_volatility_book'
    - 'hl_index_book'
    - 'realized_volatility_trade'
- The 112 stocks can be clustered into 3-4 groups based on realized volatility feature

FEATURE ENGINEERING

Generated 170+ features based on technical analysis, concepts of motion, stocks clusters & time-bands

1. Basic Features : simple features from book & trade files
   - wap1, wap2, spread, price_premium, realized volatility, turnover
2. Based on concepts of motion : Capture movement dynamics of price
   - speed, acceleration
3. On technical analysis : Capture magnitude & inertia of price activity
   - high-low index, momentum (size * speed) , force (size * acceleration)
4. Cluster Features :
   - Cluster (categorical feature), avg/std of realized volatility of a cluster
5. Some of above features across time-bands : Divided the 10-minutes into
   - Two 5-min halves (H1 & H2)
   - Four 2.5-min quarters (Q1 – Q4)

MODELLING

Naïve (baseline) Model: Setting the benchmark

- This model simply assumes that future 10-min volatility is the same as current 10-min volatility
- It delivers an RMSPE score of 0.341 across all 112 stocks for the training dataset
- The performance of the naive model is not amazing, but it helps to establish a benchmark

MODELLING

Linear Model: Understanding feature importance

- Removed colinear features and multicollinear features
- This filtered out 140+ features, leaving around 25 features
- Model had a RMSPE score of 0.2833 on validation set
- More importantly, it helped understand feature importances
- Top 10 features in this model were:

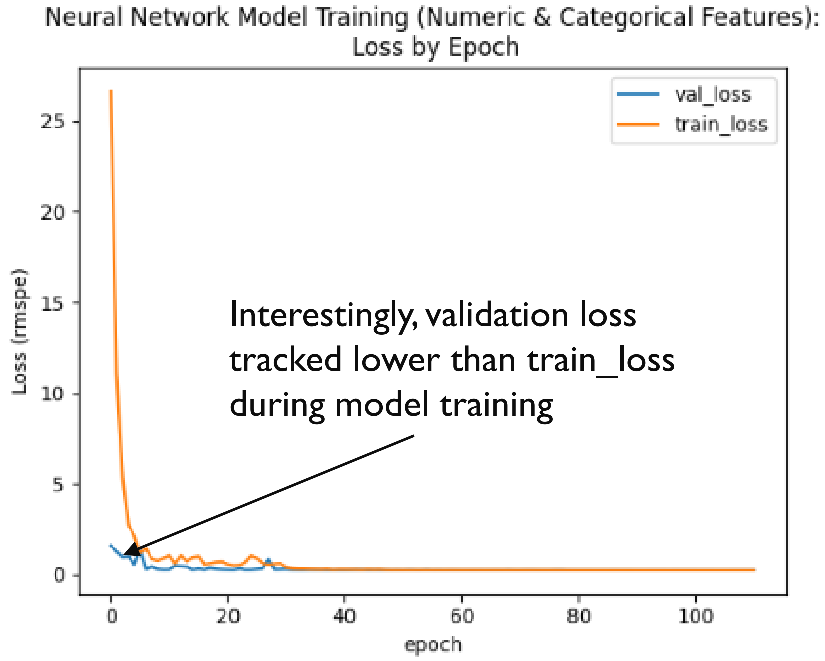
1. realized_volatility_wap1
2. realized_volatility_wap1_cluster_mean
3. realized_volatility_wap1_H2
4. price_premium_1
5. realized_volatility_trade_price
6. acceleration_trade_price_mean
7. momentum_trade_mean
8. wap1_hl_index
9. momentum_book_sum
10. value_premium_1_sum

- The top features confirmed that most of the concepts used for feature engineering were useful for the model

MODELLING

Deep Learning Model: Significant jump in performance

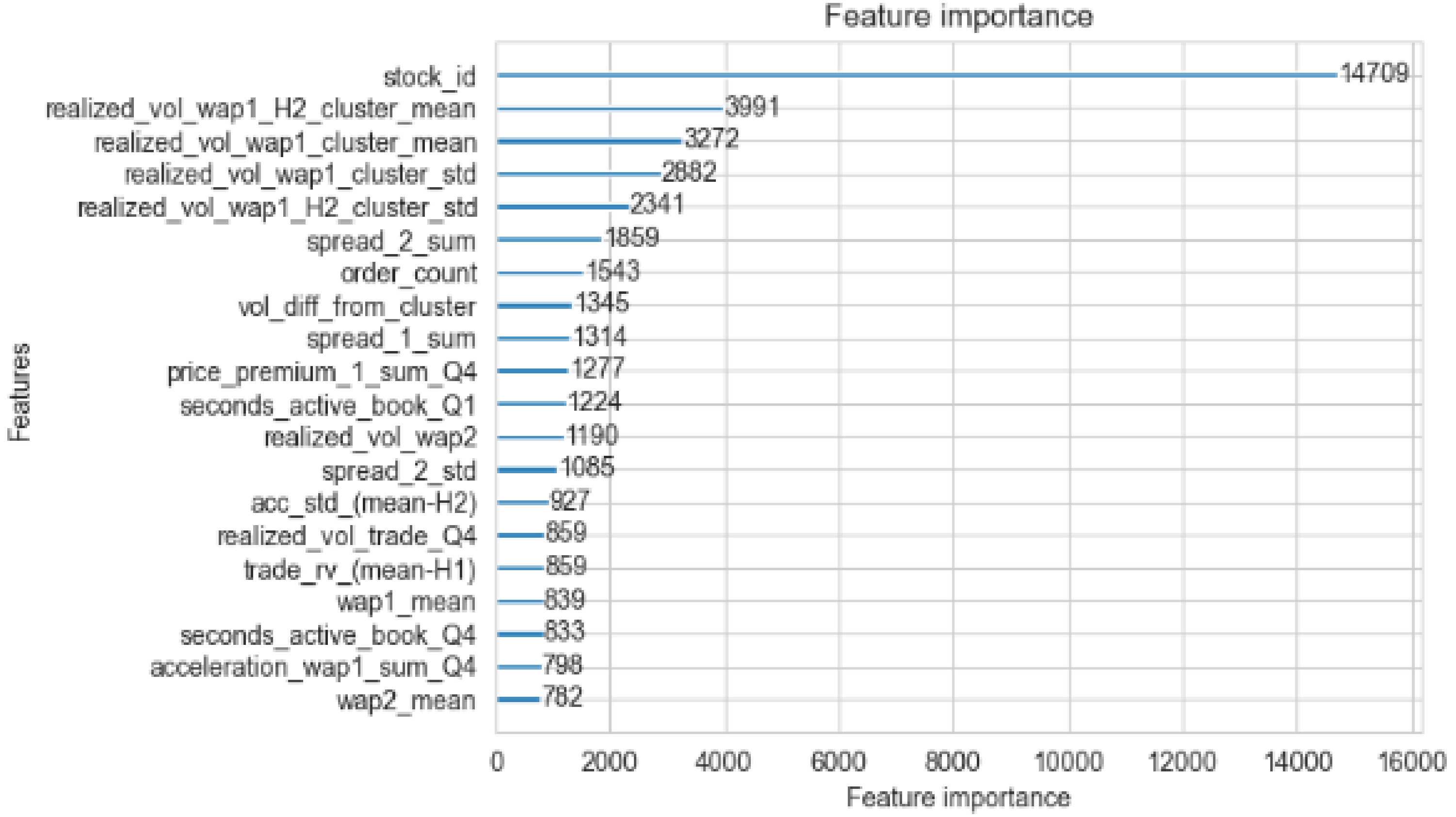
- Developed 2 deep learning models:
  - Model 1 : Based on only numeric features
  - Model 2 : Based on numeric features and categorical features (cluster ids)
- Tuned hyperparameters such as no. of layers, no. of neurons, activation function, learning rate & batch size
- RMSPE scores on validation set
  - Model 1 : 0.2125
  - Model 2 : 0.2104
- RMSPE score of Model 2 on test set was 0.215365.
- This score was among Top 30 scores present on the Kaggle contest leaderboard
- Model 2 has 1 embedding layer and 3 hidden layers



MODELLING

Light GBM Model: Understanding feature importance

- As with linear model, the Light GBM model helped understand feature importance
- Tuned hyperparameters such as learning rate, feature_fraction, max_depth, min_data_in_leaf
- Model had a RMSPE score of 0.2335 on validation set
- Top 20 features in this model were:



- '**stock_id**' had an outsized importance in this model
- realized_vol of the cluster was more important than that of the stock!

KEY FINDINGS

- Features based on technical analysis, price motion dynamics, clustering and time-bands are useful for modelling future 10-min volatility
- Features based on both book and trade data are important
- A deep learning model based on numeric and categorical features delivers a strong performance with an RMSPE score of 0.215365 on the test set
- 2 categorical features were used in addition to approx. 170 numeric features

BUSINESS APPLICATIONS

- The deep learning model is quite simple & delivers good computational performance
- It took an average of just 0.018 seconds per time_id to make predictions for all 112 stocks
- As such, it suited for real time applications like stock options trading and can be tested by electronic market maker firms such as Optiver

IDEAS FOR FURTHER DEVELOPMENT

- The model trained on data for ~3000 time_ids. More data could help train the model better

- Gathering more domain knowledge to further understand factors that have a bearing on short term volatility