Jane Street Market Prediction : Kaggle Project

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Problem Statement

Day (0-500)

Weight and Returns

130 Masked Features

Trade or Not Trade
(Target Variable)

	date	ts_id	weight	resp	feature_1	feature_2	feature_128	feature_129
0	0	0	0.000000	0.006270	-1.872746	-2.191242	2.301488	11.445807
1	0	1	16.673515	-0.009792	-1.349537	-1.704709	-1.304614	1.898684
2	0	2	0.000000	0.023970	0.812780	-0.256156	6.638248	9.427299
3	0	3	0.000000	-0.003200	1.174378	0.344640	3.856384	1.013469
4	0	4	0.138531	-0.002604	-3.172026	-3.093182	0.362636	3.926633

Predict Action

action
1
0
1
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Timestamp
of trades

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Timestamp
of trades

Not Available
In test data

Not Given In
Train Data

Objective function

Daily Returns : $p_i = \sum_j (weight_{ij} * resp_{ij} * action_{ij}),$

Sharpe Ratio : $t = \frac{\sum p_i}{\sqrt{\sum p_i^2}} * \sqrt{\frac{250}{|i|}},$

Utility Score : $min(max(t, 0), 6) \sum p_i.$

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	Scenario 1	Scenario 2
Day1 : P1	1	5
Day2 : P2	9	5
Sharpe	12.3 (Lower)	15.8 (Higher)

Methodology

1) Exploratory Data Analysis

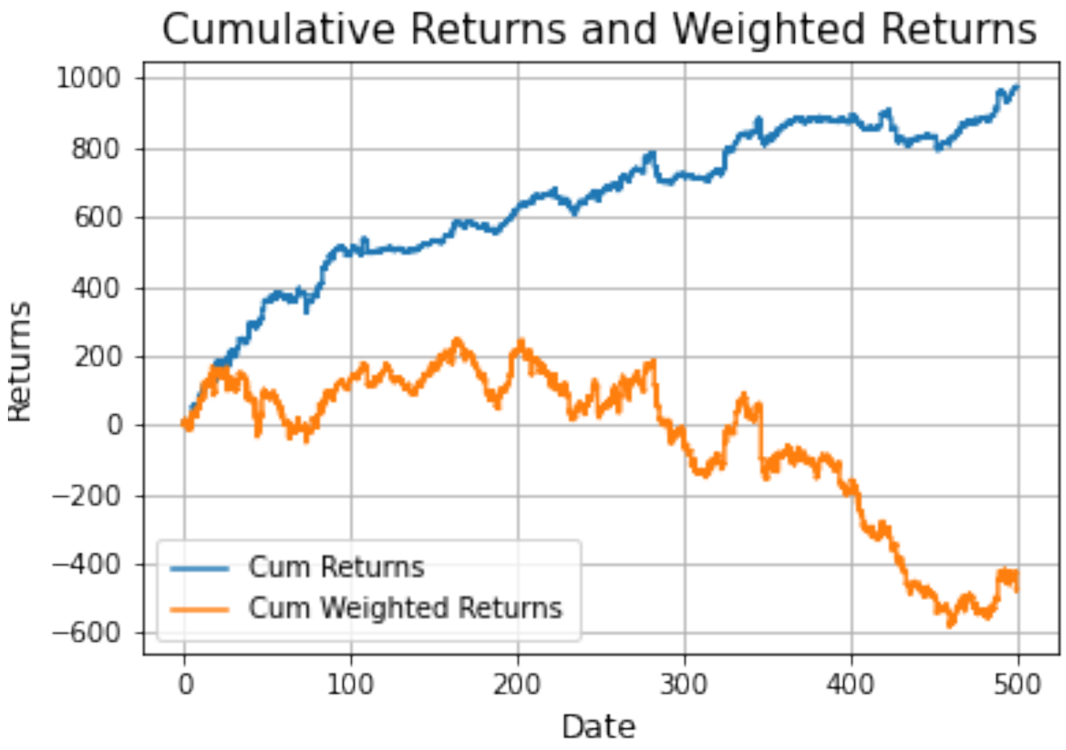
2) Train, Test and Validation Data Split

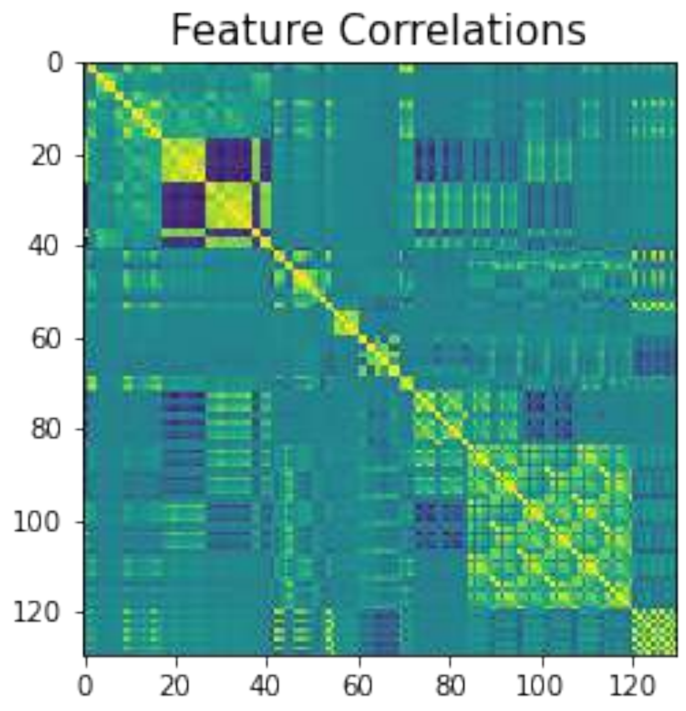
4) Building the Model

- Model 1 : Benchmark XBG Classifier
- Model 2 : Adjusting for weights distribution
- Model 3 : Ensemble model

5) Results

6) Future work

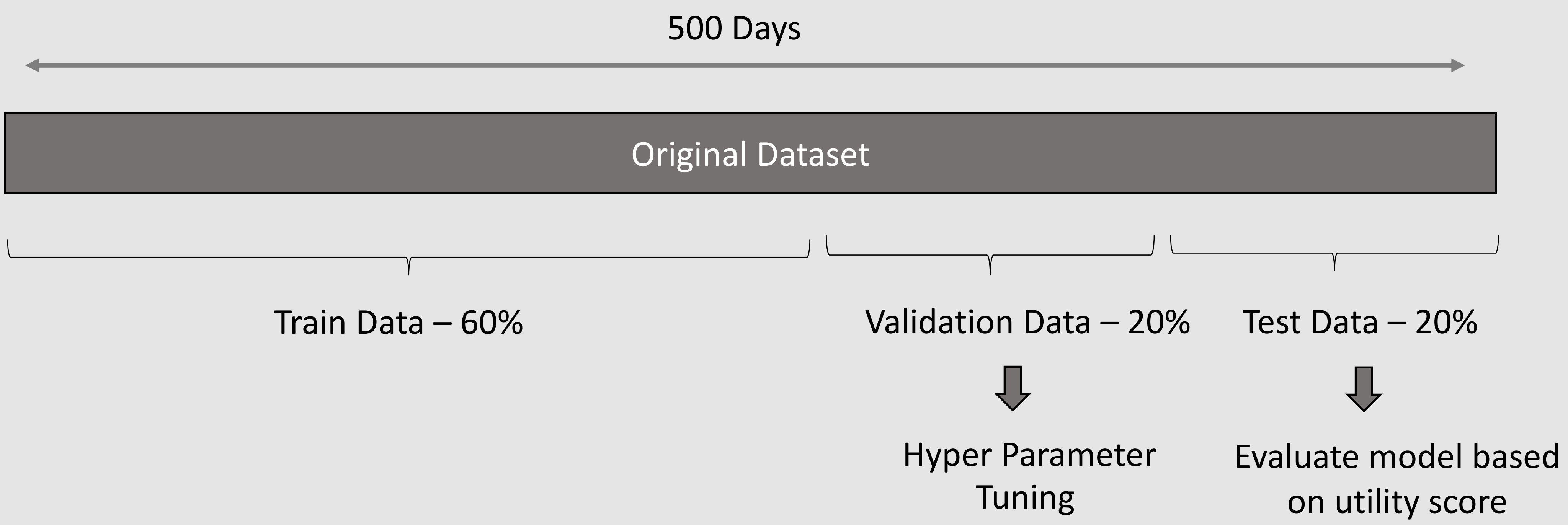




Exploratory Data Analysis

- The Cumulative Resp shows an upwards trend
- The cumulative weighted resp stays stable till 300 days and then falls
- The features are highly correlated and can be clustered

Train, Test and Validation Data Split



Benchmark XGB Classifier

1) Classification Problem : Predict Action as (1 ,0)

2) Created Action column in the training data :

Action = 1 if resp > 0

Action = 0 if resp < 0

3) Trained the XGB Classifier

4) Tuned the probability threshold based on the Validation data

Action = 1 if Prob > Threshold

Action = 0 if Prob < Threshold

5) Evaluation : **Score = 1220.64 for Th = 0.527**

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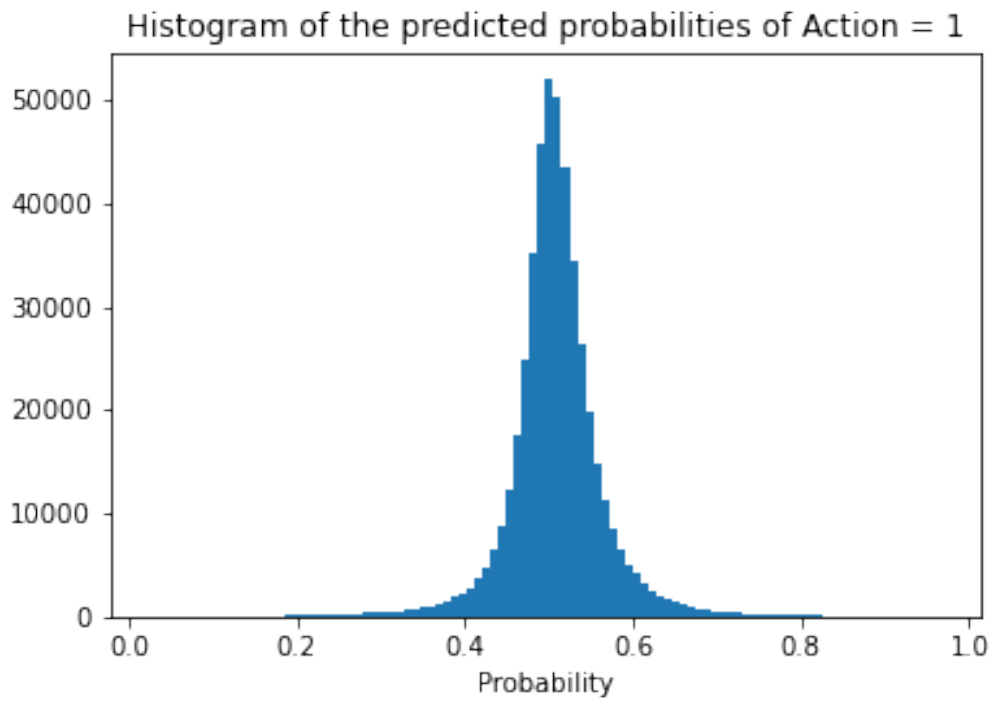
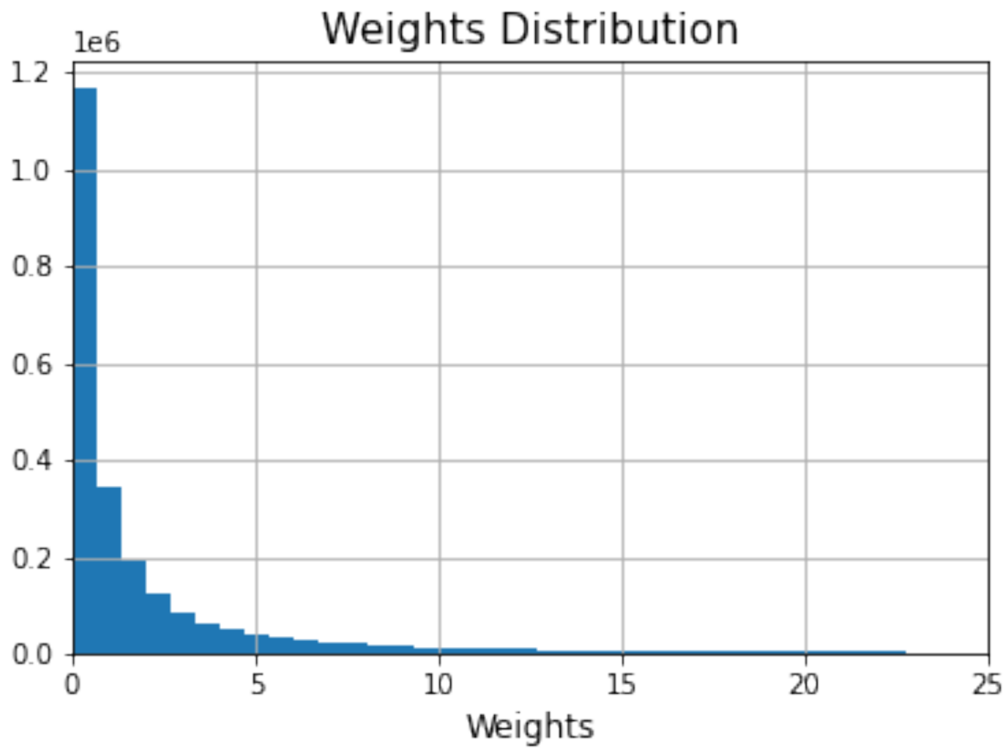
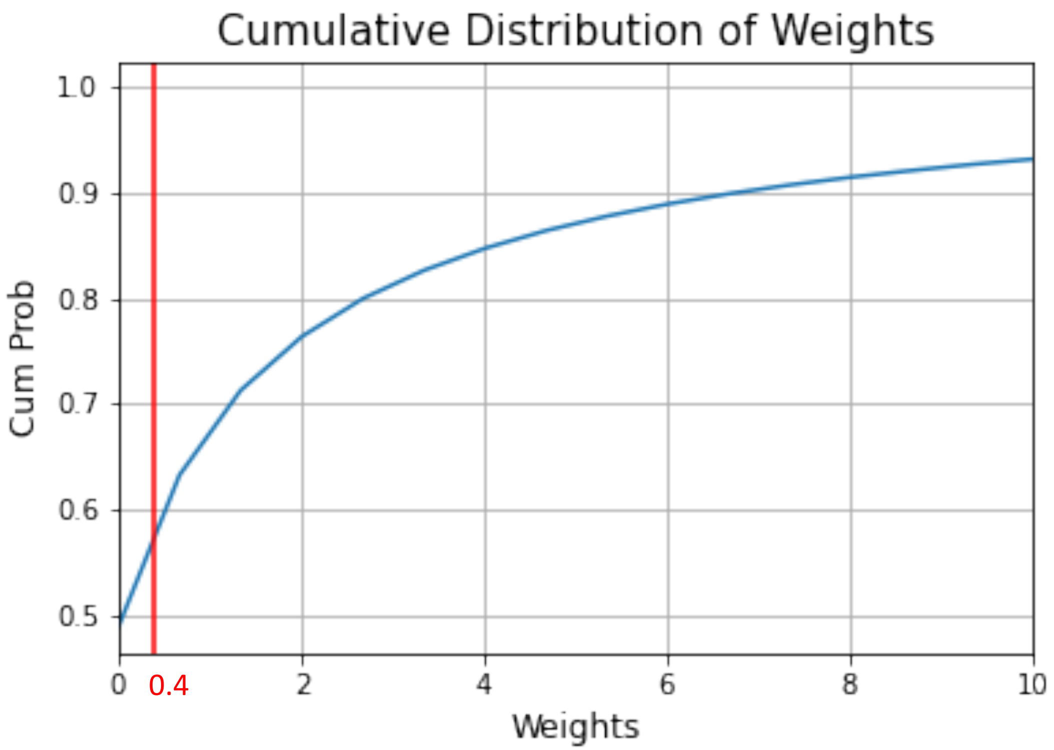




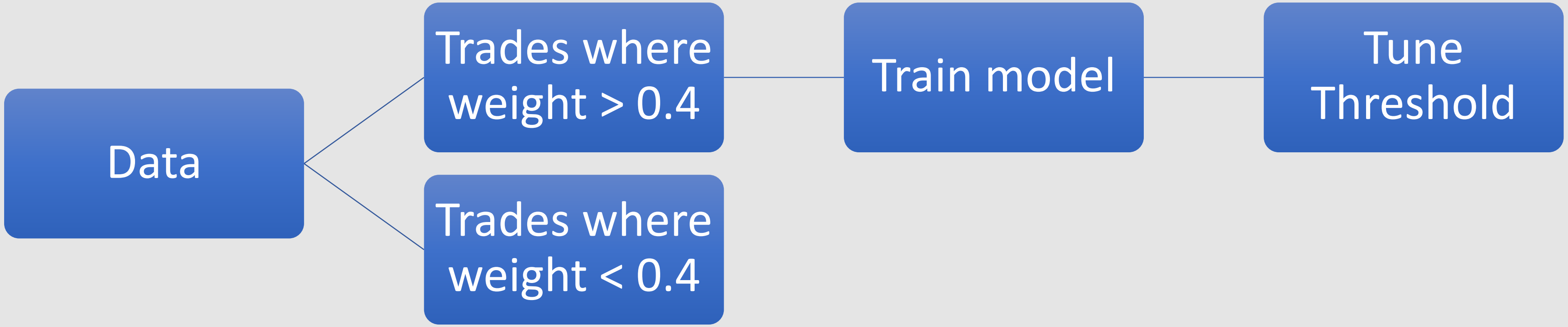


Contribution of weights to Utility Score

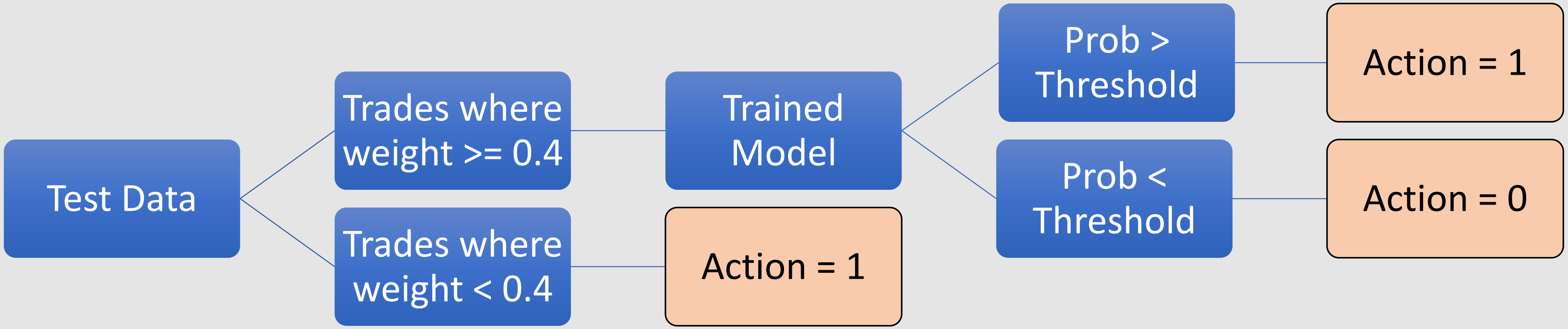
60% of the trades have weights less than 0.4

These 60% contribute to just 3% of utility score

Model 2: Weights Division

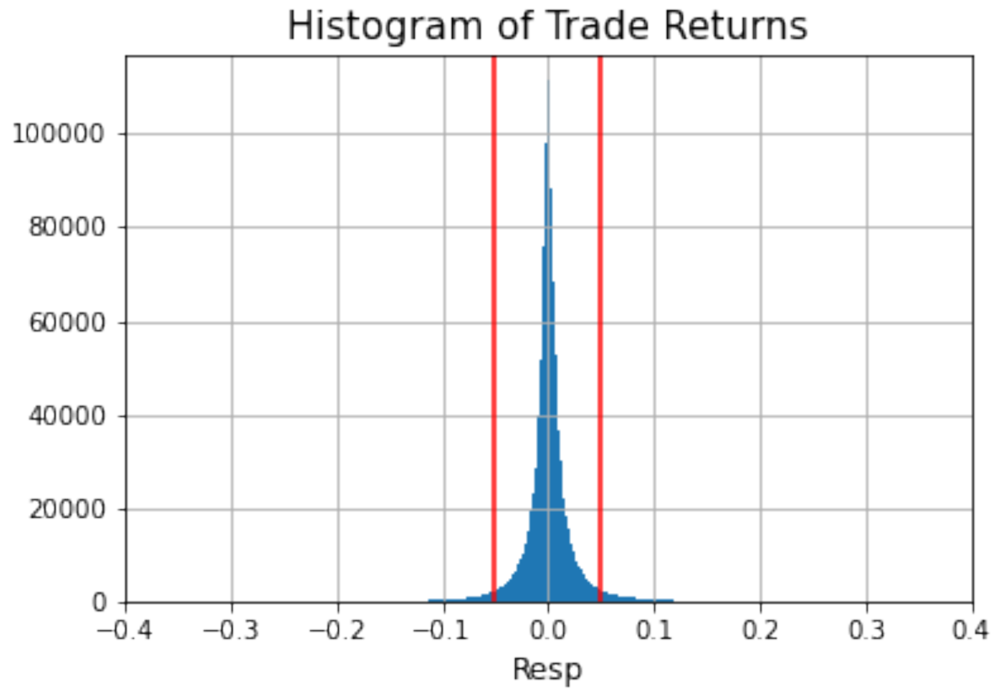


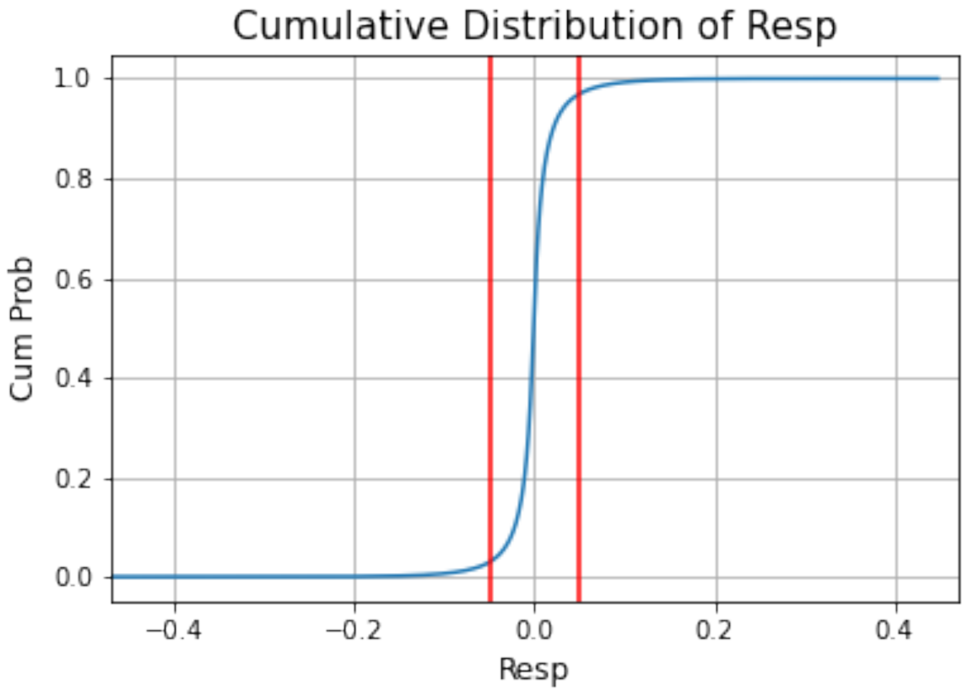
Model 2: Prediction



Evaluation :
Model Score = 1412.66 for threshold = 0.52
Improvement over Model 1 : 15%

Volatility of Returns





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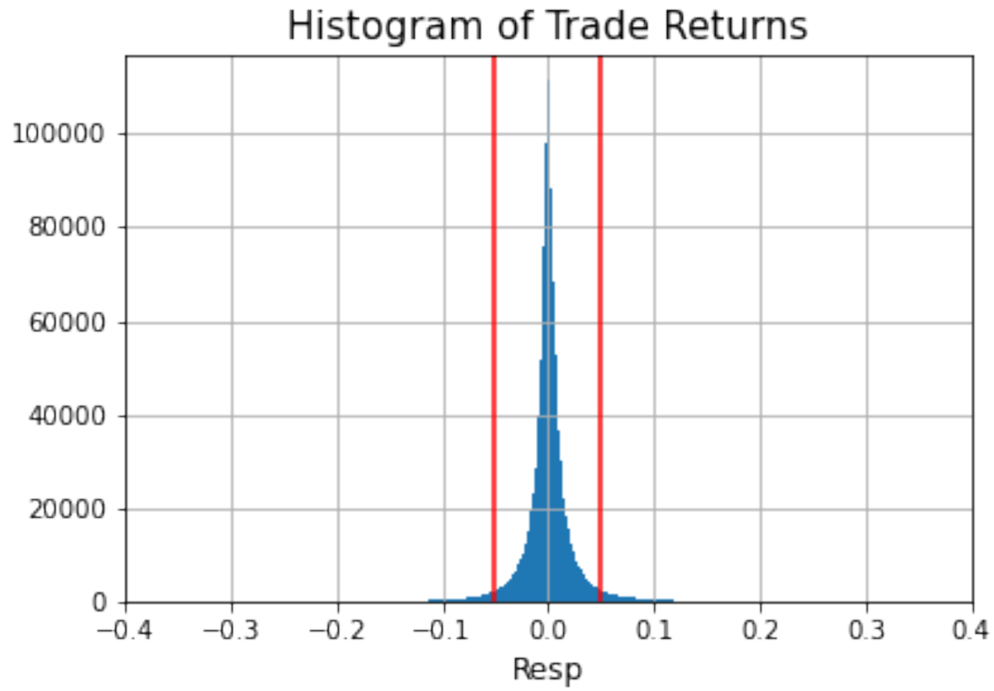

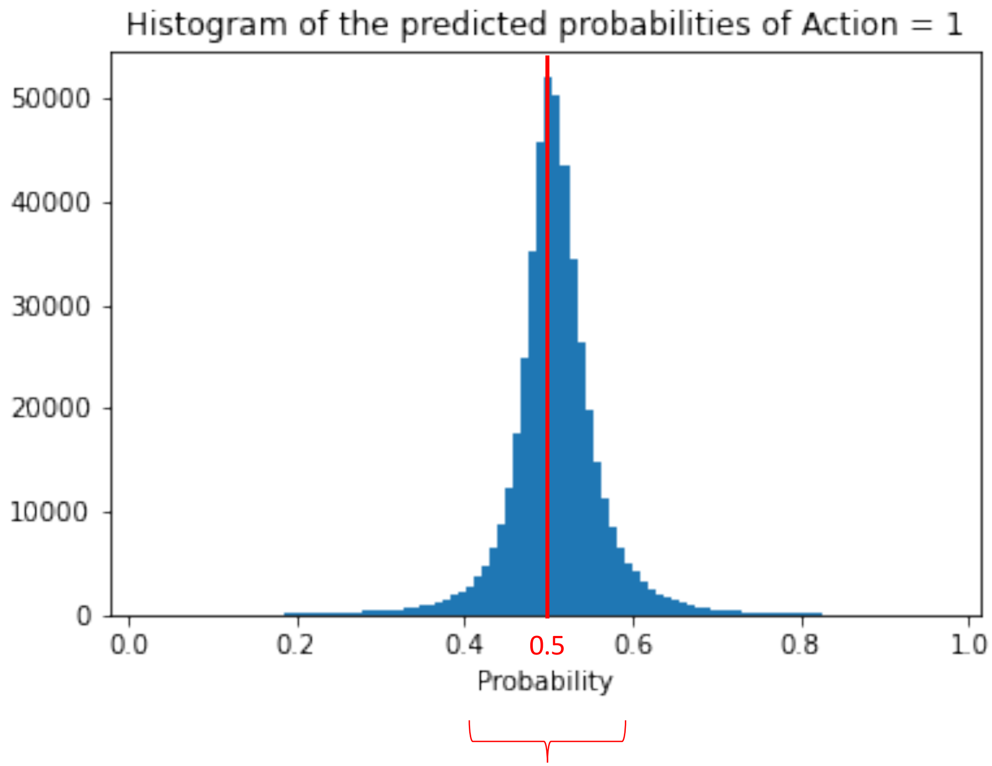

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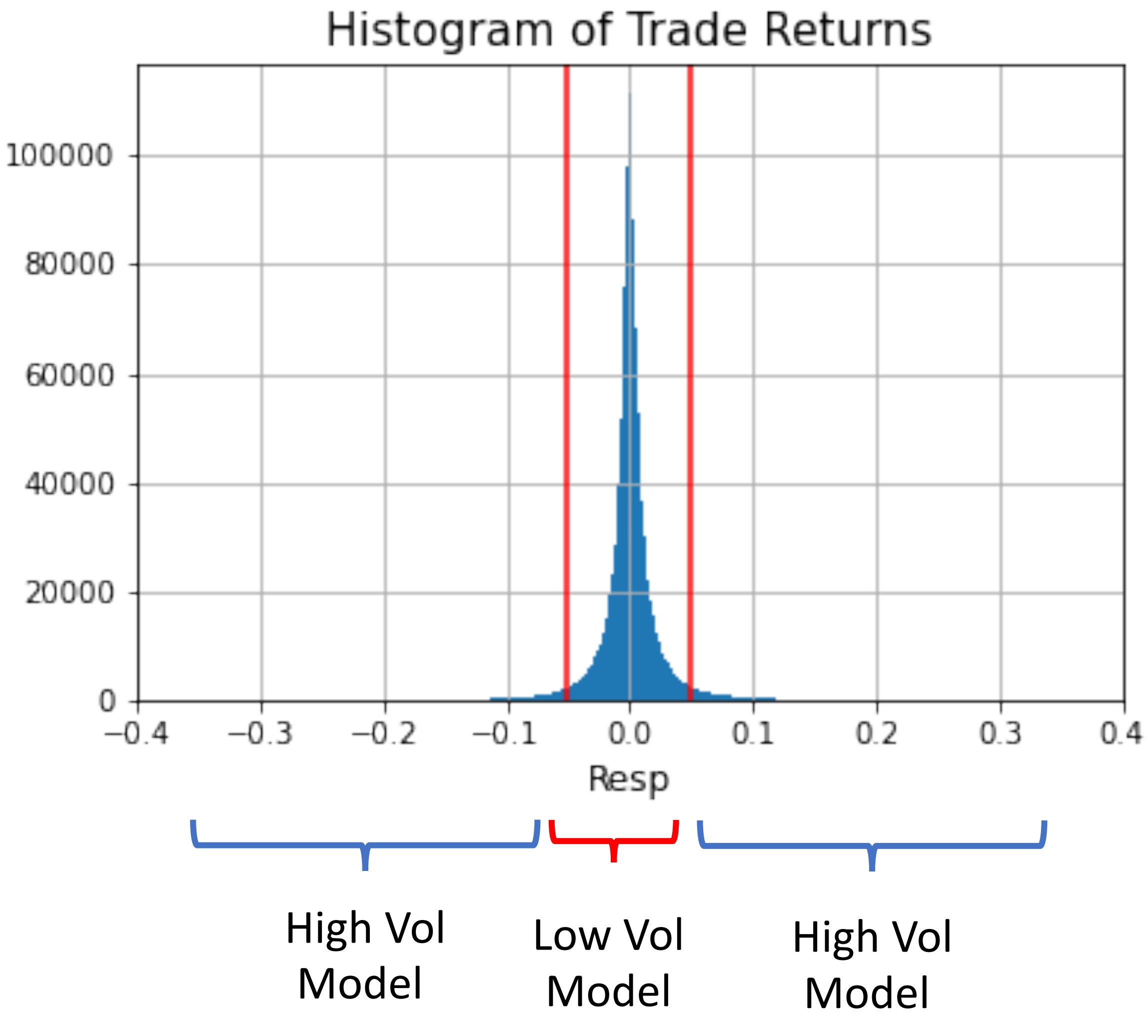
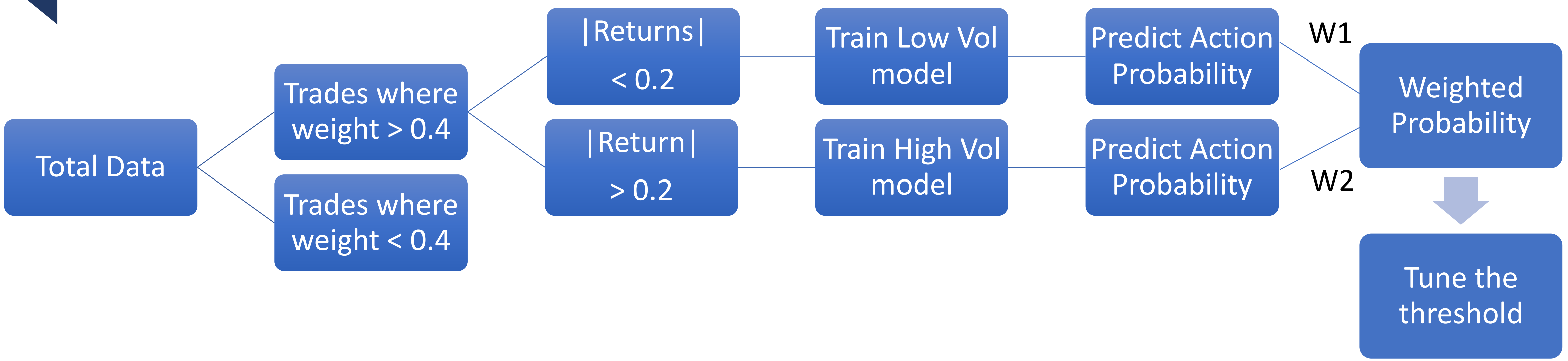
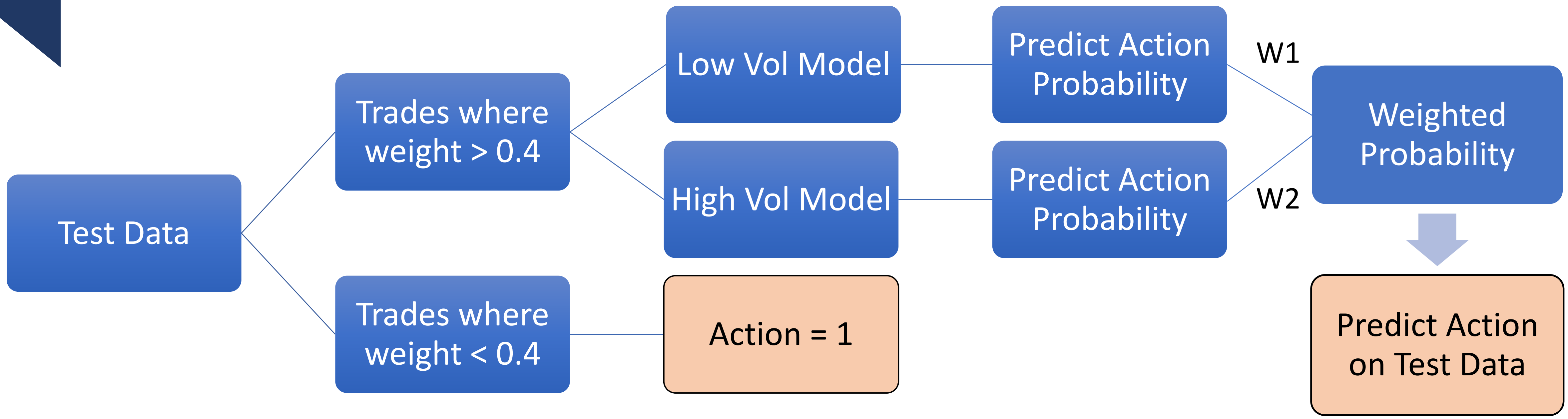


Model 3 : Ensemble Model Architecture



Model 3 : Prediction



Model Score = 1989.42 for threshold = 0.525

Improvement over Model 2 : 40%

Model Summary

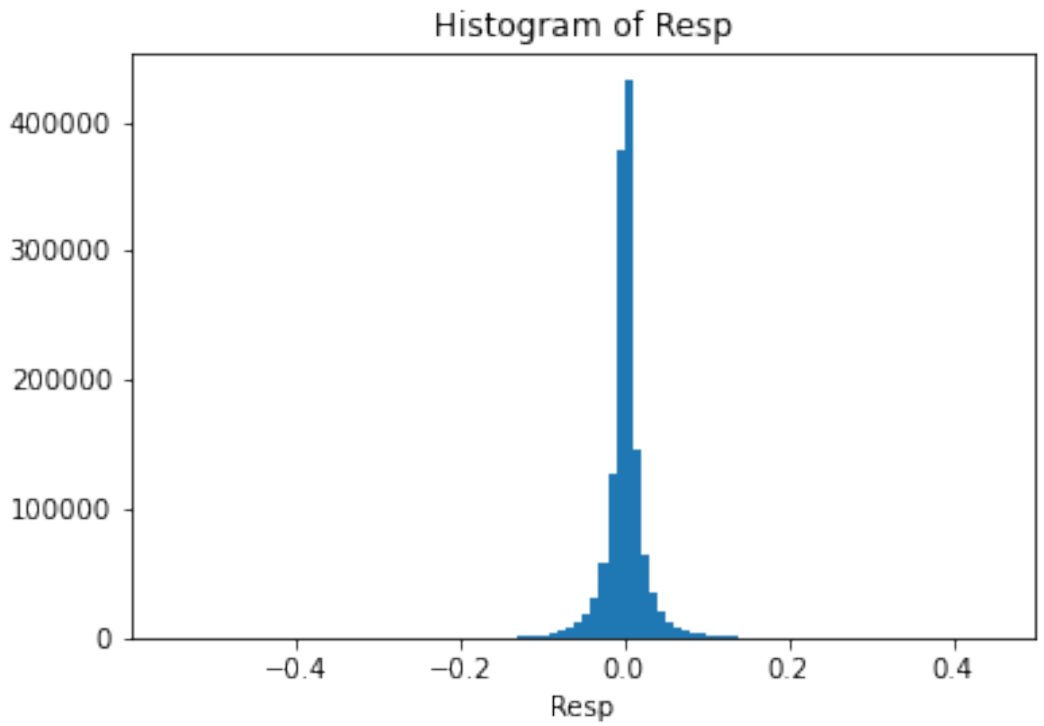
	Utility	Sharpe	Threshold	Precision	Accuracy	Recall	F1 score
Model 1	1220.641	4.120	0.527	0.383	0.473	0.261	0.351
Model 2	1412.661 (15% Boost)	4.730	0.520	0.520	0.511	0.152	0.354
Model 3	1989.423 (40% Boost)	5.210	0.525	0.528	0.515	0.315	0.460

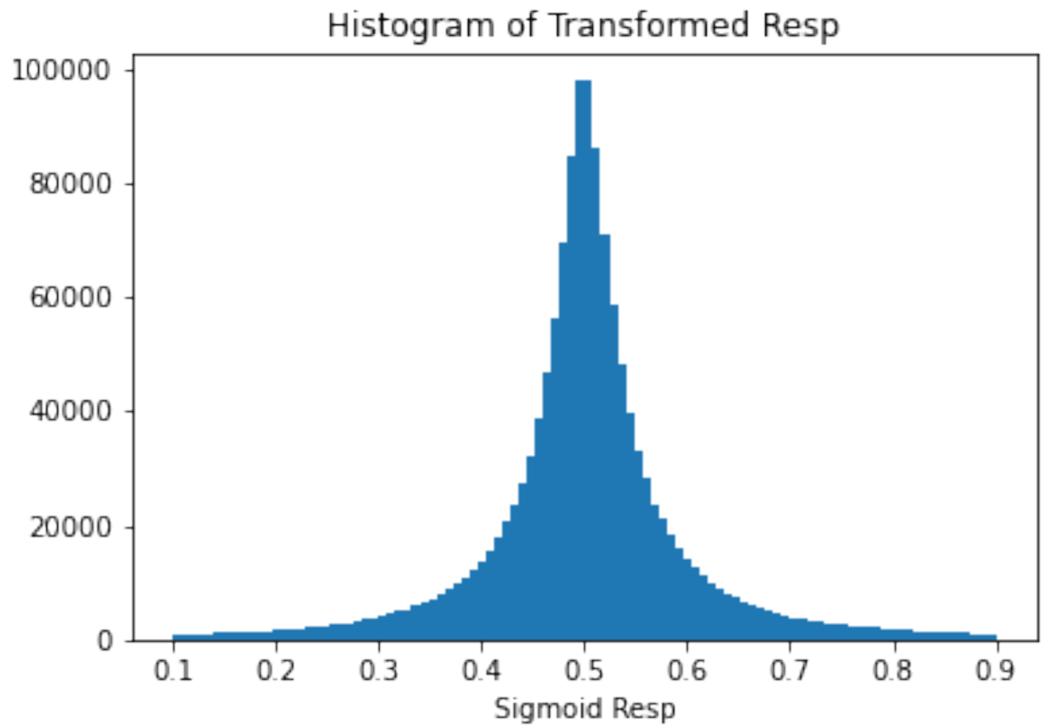
Future Work

Precision Issue

The models have low precision. The Ensemble model slightly improves the scores but its still not great.

Possible Solution : Sigmoid Transformation of Resp





Future Work

Data Clustering

Trades can correspond to different asset classes and return distributions.

Possible Solution :

We can cluster the data and build individual models for each cluster.

THANK YOU FOR YOUR TIME!