**Trading Strategy Methodology:**

The trading environment was built allowed agents to buy at lowest ask price and sell at the highest bid price every 15 seconds. 15 seconds was chosen as the aggregation level as it showed the most promising results for level2 trading indicators from our investigation into classification techniques.

All agents are given data from a full day to train upon and trade/test on the following day solely using the previous day’s information. This is realistic**…… JUSTIFICIATION.**

Agents need to predict what the price should be at each time step and a comparison of the prediction, lowest ask price and highest bid price determines the agents action. The actions the agent can take are to buy with 1 volume, sell with 1 volume or hold / do nothing. This is a very simplistic and restricted model **BUT SOMETHING TO DO WITH TIME CONSTRAINTS.** It is clear how the time series forecasting agents fit this format but adjustments were needed to incorporate the classification models for a fair comparison.

The DTC models return outputs in the form of {-1,0,1} but the trading simulation requires a price prediction to run. A related model to the DTC that followed the same architecture is the Decision Tree Regressor (DTR). The DTR should be parasitised in a similar manner to the DTC as the feature space is unchanged. Various DTR agents will be tested using solely level1 data, solely level2 data and a optimised mixture of both level1 and level2 data.

**Trading Strategy Results:**

Table REFERENCE shows a variety of metrics used to the evaluate the performance of the trading agents. A few additional agents are included; mean\_reversion that takes the mean of the previous day and buys below it and sells above it, optimistic that buys when the price has moved up and sells when the price has moved down, MA\_10 that takes a moving average of 10 time steps and uses that as the predicted price and BUY\_AND\_HOLD that gives a few statistics describing the overall movement of the asset.

A screenshot of a computer

Description automatically generated

The MA\_10 is found to be the most profitable strategy, this is expected due to the mean reverting nature of the data explored in the EDA and small aggregation level, 15s, allowing for HFT. The ARIMA follows as next most profitable and it is shown to closely follow the MA\_10 strategy as show in the correlation heatmap below and similar metrics in the table. It is logical to conclude that the ARIMA is near identical to a moving average strategy due to this and the simple parameter choice of (1,0,1). LSTM can also be categorised alongside the MA\_10 strategy with high profits and a large number of trades. An interesting observations is that the LSTM is in the market 3 times more than the ARIMA and MA\_10 yet still yields a 3.80 profit per trade matching ARIMA and MA\_10. This would also explain why the LSTM yields a higher volatility as it holds less in cash.

With these three strategies performing in a similar way it is quite clear that the additional computational cost from using an ARIMA and LSTM does not benefit the agent and a simple moving average is best. **EXPAND AND RELATE**

The mean\_rev agent follows with less than half the profit of the LSTM and is moderately correlated with all agents, this is logical as the mean price of the previous day is likely to be not far from an agent predicting the price at any point of the current day. The profit per trades is on par with the HFT strategies but with a lower number of trades per day, explaining the decrease in profitability.

The three DTR agents follow and share similar values across all metrics aside from profit. When comparing the DTRs, the inclusion of level2 features boosts the profitability by 3x and solely using level2 features by 4x, a promising result. It is even more interesting that the DTR solely using the level2 data outperforms the mixed one as it does not have key information such as the trend in price

**SO THER MUST BE SOMETHING USEFUL HERER RIGHT>>>????**

All DTR agents exhibit a far lower number of trades averaging ~90 a day and the level2 DTRs exhibit 2/3rds the profit per trade as the HFT strategies. With this lower number of trades, this suggests a move away from the simplistic nature of the HFT strategies to hopefully more informed decisions using the level2 features extracted.

The optimistic agent performs terribly but this expected due to the non-trending nature of the data. **EXPLAIN SLIGHTLY MORE?**

A screenshot of a graph

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Knowing that the Level2 DTR outperforms the Level1 DTR it is important to untangle the DTR models for explainability **WAFFLE ABOUT WHAT JP WANTS.**

Averging the feature importance across all 124 trees generate from the dataset, it is found that BETA\_close is the most important feature from these scores, another independent feature AWS\_mean being second most important.

A graph of blue bars with white text

Description automatically generated

Looking across the whole dataset we get these graphs **COMMENTS AND SUPPORT OUR CAUSE**

A graph of different colored dots

Description automatically generated with medium confidence

An exploration into a day where the DTR algorithm doubles it’s money (day 10) shows non-mean-reverting behaviour during the start of the day and profit being made upon and exceeding the price increase in the second half of the day. **Probably needs better explanation.**

A graph of a line graph

Description automatically generated with medium confidence

Exploring the two most important features from day 10 against the prices on this day highlights an interesting structure with similar price levels are clustered together. The AWS was also a key indicator of anomalous behaviour in our literative review paper.

A diagram of a graph

Description automatically generated with medium confidence

***Im tired its bed time, I may start making even less sense***

**Conclusion:**

*Say something like….*

Given the introduction of 60 new features being extracted from the LOB and a wide range of time aggregations to investigate it was simply unfeasibly to produce conclusive results from such a wide investigation. We would hope that this initial investigation into Level2 trading indicators makes a strong enough case for a more succinct investigation into maximising the value from these features. Although each feature largely evaluated individually within our EDA against the y variable, many moments pointed towards greater value being derived from an ensemble of these 60 features. (finding a good ensemble within a feature space with 60 dimensions is a HUGE TASK).

*This is also similar….*

However due to the sheer number of indicators, time constraints etc etc, we have not been able to investigate it enough to the degree that we can make concretely quantitative conclusions on the performance/applicability of these indicators.

*Hone down on….*

Mainly that there is promise and signs that they COULD be good but we lack the resources/knowledge/time to figure this out. That so far the introduction of level2 over level1 has given us a significant boost in profit that is potentially not derived from mean reversion.

**Further Work:**

Better simulations that punish mean reversion

***Cant think no more***