GROUP 9
FINAL REPORT

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Introduction

From literature review, we have learnt that ML trading strategies can utilize either Price Prediction (using regression) or Direction Prediction (using classification). Our objective was to implement both forms of prediction and incorporate both results into a robust risk management strategy to eventually place a trade. By doing so, we hope that our model would not only stand to achieve greater returns, but we would also gain greater insights into the financial prediction task and equip ourselves with more industry and practical knowledge.

Asset Selection

Our primary criteria for selecting a currency pair were high liquidity (to avoid slippage) and the absence of significant event-driven swings to avoid unexpected movements in the currencies that would not be captured by our algorithm. Hence, we avoided currencies of countries that were struggling financially such as the Turkish lira which crashed in August 2018 (Eliott, 2018), and instead focused on the 8 major currencies[1] that tend to be relatively more stable. Our secondary criterion was being able to correlate the currency pair with another currency pair for added information such as lagging indicators. We decided to trade using AUD/USD currency pair as it ticked off our criteria and chose the inputs to our model based on that currency pair, as we will elaborate in the next section.

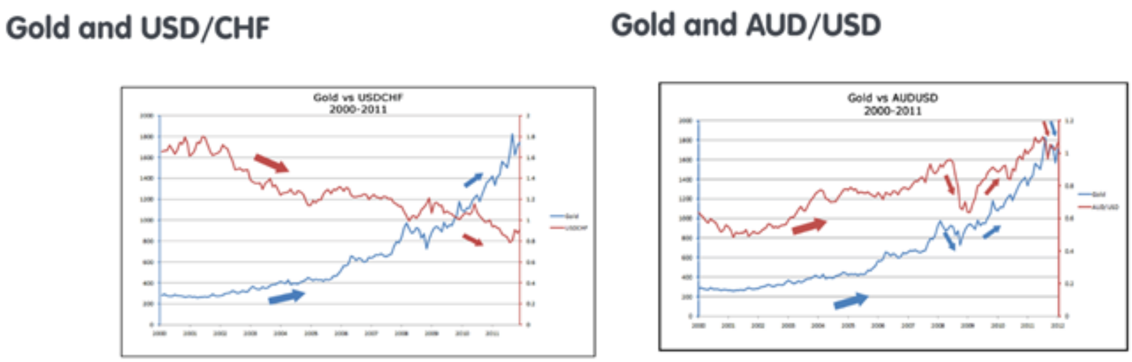
Feature Selection

Due to the complexity of the machine learning task, we sought to select features that incorporate numerous aspects of the task (Gerlein et al., 2016). Hence, we chose to include price indicators such as opening and closing prices, prices of correlated assets, as well as technical indicators that represented characteristics about stock price movements. (Refer to Appendix for the specific metrics used.)

Correlated Assets

We decided to include information about correlated currency pairs in order to train our models. Research revealed that the USD/CHF pair is inversely correlated with the AUD/USD, because Australia exports Gold (a safe-haven asset)[2], and the Swiss Franc is a safe-haven asset class[3], which makes it correlated with Gold.

[1] https://www.investopedia.com/trading/most-tradable-currencies/
[2] https://atlas.media.mit.edu/en/profile/country/aus/
[3] https://www.investopedia.com/articles/forex/031715/swiss-franc-safe-haven.asp



[4]

Fig 1. Gold Correlation

Technical Indicators

Due to the complexity of the markets, we chose these 4 technical indicators as they each represent unique dimensions of data:

1) Moving Average – Trend[5]

2) Bollinger Bands – Volatility[6]

3) Relative Strength Index – Volume, Momentum[7]

4) MACD – Trend[8]

By choosing these four different technical indicators, we sought to incorporate various attributes and characteristics of the currency pair to enhance the classification and regression capabilities. In addition, the merits of including price related features were discussed in a research paper that we read, and we decided to include them as part of our features (Gerlein et al., 2016).

<u>Explanation of the trading model, why you selected them, and what relationship, if any, you found?</u>

In selecting the models, we kept in mind that for stock price prediction, we have to avoid overfitting and creating models that depend on irrelevant, noisy features which would lead to good backtesting results but poor live performance (Bailey et al., 2015). We sought to make our final model and prediction more robust by not only choosing models that are appropriate for our use case, but also stacking them and creating a majority voting system to reduce bias and variance (Bramer, 2016).

[4] https://www.babypips.com/learn/forex/as-gold-as-it-gets
[5] https://www.investopedia.com/terms/m/movingaverage.asp
[6] https://www.investopedia.com/terms/b/bollingerbands.asp
[7] https://www.investopedia.com/terms/r/rsi.asp
[8] https://www.investopedia.com/terms/m/macd.asp

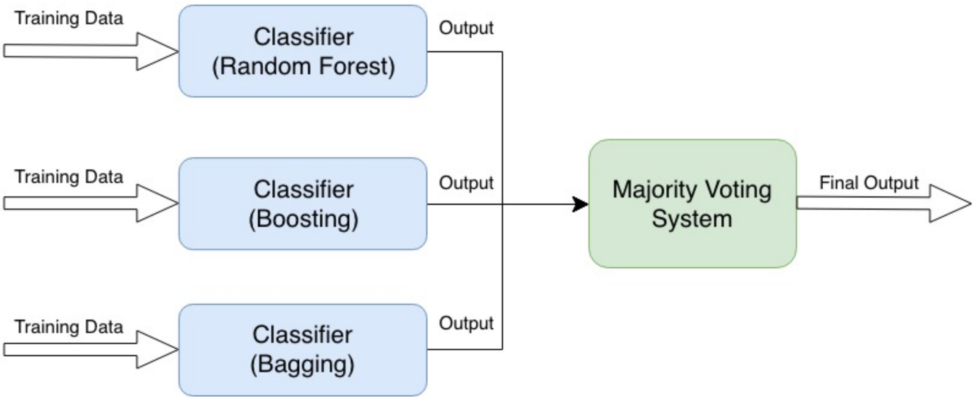


Fig 2. Stacking

The models used are Long Short-Term Memory for price prediction (regression), and we stacked Bagging, Boosting and Random Forest using majority voting for direction prediction (classification). We then combined the two different algorithms to decide on trades; if both algorithms agreed, we would then execute the trade which results in a more robust risk management strategy.

Long Short Term Memory (LSTM)

LSTM is a special kind of Recurrent Neural Network that is capable of learning long-term dependencies and is also reinforcement learning (Colah, 2015).

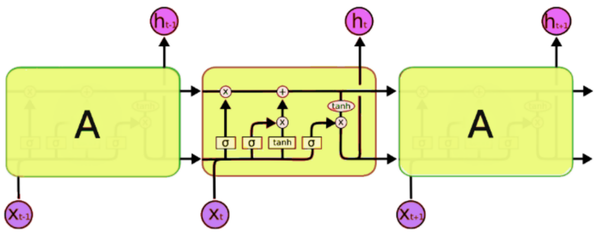
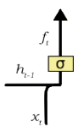
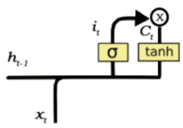


Fig 3. LSTM Network Cell





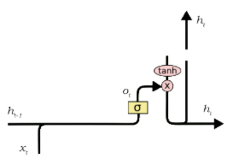


Fig 4. Forget Gate Fig 5. Input Gate Fig 6.Output Gate [9]

Our LSTM model trained will use the previous data to predict the next day's closing price. LSTM uses a forget gate, input gate and output gate to learn optimal features. We used LSTM

[9] http://colah.github.io/posts/2015-08-Understanding-LSTMs/

because of its ability to select the optimal features for the use-case using its activation functions and discarding insignificant information through using the forget gate (Colah, 2015). To account for overfitting, we used a regularization technique, dropout, to drop components of the neural network and reduce co-dependency amongst neurons.[10]

Random Forest

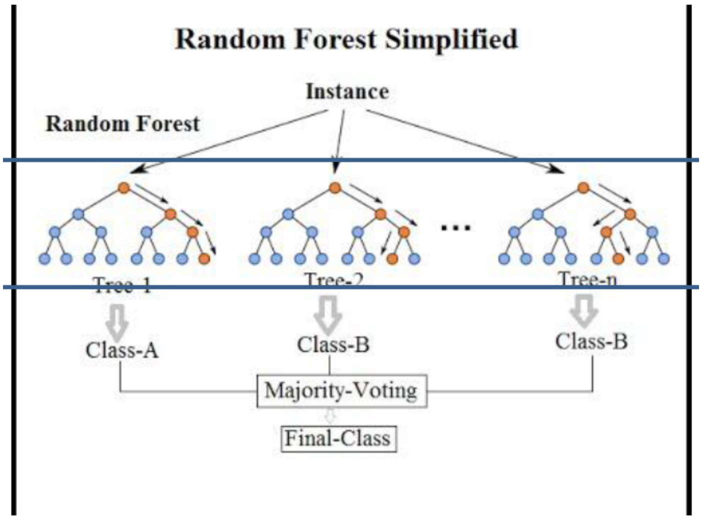


Fig 7. Random Forest Structure

We decided to include the random forest model in our prediction because of its advantages such as reducing variance and increasing accuracy by decorrelating the trees (Carter, 2018). Due to the nature of its feature selection of randomly choosing subsets of all features present to construct trees and using a majority voting system, the algorithm would learn of the optimal set of features to use (Bramer, 2016).

Adaboosting

Boosting is a machine learning ensemble algorithm that reduces bias and variance (Carter, 2018). Adaboosting iteratively learns weak classifiers, and adds them to a strong classifier with weights related to the weak learner's accuracy. In addition, it is also robust to overfitting (Buja et al., 2008).

Bagging

Bagging has the effect of generating multiple different but related training sets from a single set to train different models. This has the effect of reducing variance and overfitting as we build separate prediction models using different training sets and averaging the resulting prediction. We obtain different training sets by sampling with replacement and using each individual training set, calculate the average parameter estimators and average standard errors of parameter estimators (Carter, 2018). Predictions from the bagged trees will be highly correlated if there is a strong predictor in the data set (Carter, 2018). By stacking

[10] https://www.commonlounge.com/discussion/694fd08c36994186a48d122e511f29d5

Bagging along with other methods, we allow the strong predictors a "vote" in decision making while reducing overfit as we take into account the other models as well.

Process for updating your model and selecting the security

To account for ever changing market sentiments, we first tried retraining the model on every datapoint so that the models would be updated. However, this slowed down the back-tests and did not improve the accuracy much. We soon realised the reason why. Our initial training was on the past 200 datapoints; 1 additional datapoint would not make much difference and unnecessarily take up computational power. Hence, we decided to remove the retraining and simply kept the model that was built upon initialization. Our retraining strategy would have been appropriate had the stipulated trading period been longer than a month, in which case retraining every month would have been a viable option and could have produced incrementally better models. We therefore did not update our models throughout the trading period.

Strengths and weaknesses

The strengths of the model include being able to avoid overfitting, decreasing variance and co-dependency amongst results. In addition, emotions and speculations will be out of the picture as the models execute trade based on logic and analysis. Our model predictions were robust as supported with 80% win-rate and a sharpe ratio of 1.53 (Refer to Appendix). However, we would also like to test it on a longer time period as our model does not trade on short term fluctuations but rather on long term performance. We would then have a better sense of its true potential and performance when testing live.

One inherent weakness for the models that we have chosen is the loss of interpretability. This is because of the nature of LSTM with its many neurons and the ensemble methods of bagging, adaboost and random forest with the multitude of trees trained. Perhaps our risk management strategy might have been a bit too stringent, and that is why our model did not liquidate any holdings during the trading period, but we found this as necessary to maximize returns while minimizing drawdown. This may have been a result of the extra layer of conditions we wanted the model to satisfy before making trades. Another weakness of the model is being based on technical factors and not being able to incorporate fundamental factors into the price prediction of AUD/USD, as will be elaborate in the next section.

Improvements

If we had more time to both acquire more knowledge and conduct research, we would have liked to incorporate event-based information into our models. The usage of technical indicators serves to detect patterns and predict stock prices, but it may not be able to react to news releases that are indicative of fundamental changes and could have a greater effect on AUD/USD price movements. By capturing the sentiments of news, we could then back up the model prediction with fundamentals which could have resulted in a more robust model. For example,

Fig 8. AUD/USD Chart[11]

1. Sentiment analysis on news about politics such as trump tweets, or uncertainty caused by the midterm elections causing depreciation in USD[12]
2. Tweet/news analysis - Jerome Powell's Dovish statements on 16th November (Notice the sharp depreciation on 16th November in the chart)[13]
3. Economic data
    a. Unemployment rate that was released on 16th November for USA (flat)[14] and 15th November for Australia (unemployment decreased)[15], linked to inflation
    b. Inflation hit and misses which would guide for interest rates affecting point 3[16]
4. Faster/slower than expected rate hikes which would pump/depreciate either types of dollar[17], (9th November Fed Rates were released)[18]
5. Economic policies (theme for this year being tight monetary policy and loose fiscal policy causing a rally in USD, hawkish stance priced in?)[19]
6. Other correlated assets for such as US treasury yields[20]
7. Dumping of USD denominated debt by sovereign wealth funds potentially dethroning USD as reserve currency[21]
8. Both weakening USA and Australian housing markets that could favour a dovish view (USA Housing Index released 19th November)[22]

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[11] https://www.xe.com/currencycharts/?from=USD&to=AUD&view=1M
[12] https://www.cnbc.com/2018/11/07/forex-markets-dollar-us-midterm-elections-in-focus.html
[13] https://www.bloomberg.com/news/articles/2018-11-16/fed-rate-pause-possible-in-2019-as-powell-highlights-headwinds
[14] https://www.bls.gov/news.release/pdf/empsit.pdf
[15] http://abs.gov.au/ausstats/abs@.nsf/latestProducts/6202.0Media%20Release1October%202018
[16] https://www.investopedia.com/ask/answers/111314/what-methods-can-government-use-control-inflation.asp
[17] https://www.cnbc.com/2018/06/12/forex-dollar-in-focus-investors-look-for-clues-on-fed-rate-projection.html
[18] https://www.ft.com/content/8989b08c-e387-11e8-8e70-5e22a430c1ad
[19] https://seekingalpha.com/article/4224010-outlook-u-s-dollar
[20] https://www.marketwatch.com/story/dollar-climbs-as-treasury-yields-resume-rise-2018-02-20
[21] https://www.rt.com/business/436193-japan-china-us-debt-dumping/
[22] https://www.fxstreet.com/news/us-housing-indicators-turning-around-danske-bank-201811200750

Backtesting Versus Live, Decisions and Rationale

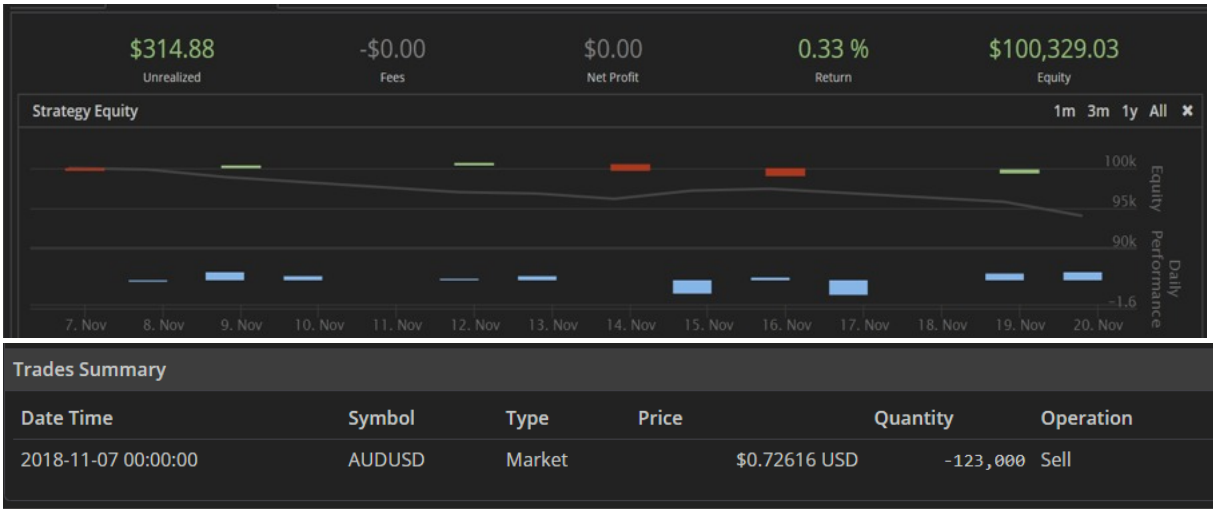

Fig 9. Backtest

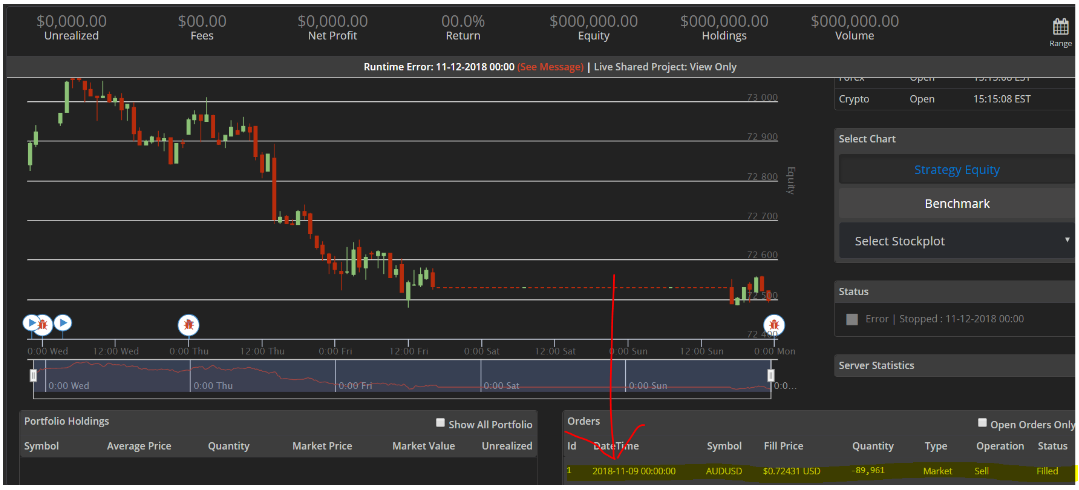

Fig 10. Live Trading, start from 7th November

Neither backtesting nor live trading liquidated and realized the gains or losses. In all trades made during this time frame, only shorts were made and these short were not covered to take profit or for stop loss.

When	Trade	Performance if liquidated
Live Trade	Short 9th November, Short 17th November	-
Backtesting	Short 7th November	+0.33%

We are unable to specifically pinpoint the rationale behind the short as made by the models trained. The nature of the neural networks and ensemble methods makes interpretability of the rationale poor. However, we can provide a fundamentally driven approach to justify this trade.

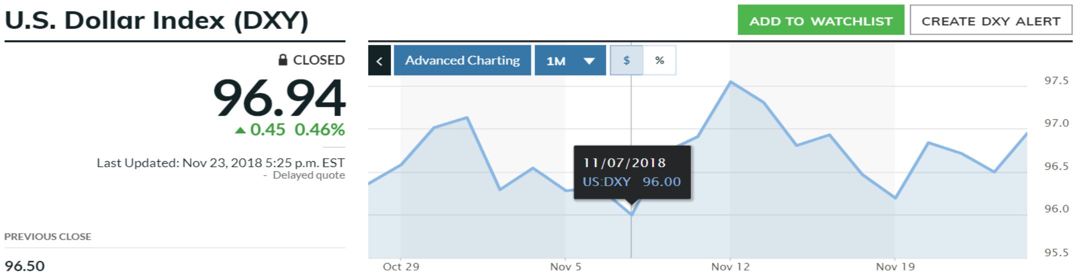

Fig 10. Dollar Index

We have shown the Dollar Index (against a basket of currencies) that has the effect of isolating movements in USD. There was uncertainty in the markets due to the USA midterm elections which had caused a selloff in USD in the last week of October going into November up till 7th November, the results of the elections.[23] This resulted in an oversell in USD. Past the elections, there were expectations that the fed was to remain on track to raise interest rates which supported the dollar, on the expectations that employment rate would rise as well.[24]

Fig 11. AUD Index

We can also see that the AUD was relatively flat from 7th November onwards. For the short to be profitable, the rate of increase in USD has to be greater than the rate of change (no matter which direction) in AUD and we can see the trade working. This was probably due to mixed economic data. While employment rate was expected to increase hawkish sentiments, we also saw a depression in the housing market[25] which could make the RBA more dovish. This had the cumulative effect in causing the AUD to be flat. Coupled with the rise in USD, this caused the trade to be shorted and we saw an unrealised return of +0.33% in the backtesting model.

There were technical faults in the QuantConnect system, and our live testing was not able to be run during 7th November to short the AUD/USD as shown in the backtest.

[23] https://www.cnbc.com/2018/11/07/forex-markets-dollar-us-midterm-elections-in-focus.html
[24] https://www.ft.com/content/8989b08c-e387-11e8-8e70-5e22a430c1ad
[25] https://www.businessinsider.com.au/australia-property-market-turnover-stamp-duty-2018-11

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Appendix

A: Features

Price Prediction Model Features		Direction Prediction Model Features	
Feature	**Remark**	**Feature**	**Remark**
Open_ytd	Open prices of the past 7 days	Close_diff_ytd	Difference in consecutive Close prices of the past 7 days
Open_shifted_by_1		Close_diff_shifted_by_1	
Open_shifted_by_2		Close_diff_shifted_by_2	
Open_shifted_by_3		Close_diff_shifted_by_3	
Open_shifted_by_4		Close_diff_shifted_by_4	
Open_shifted_by_5		Close_diff_shifted_by_5	
Open_shifted_by_6		Close_diff_shifted_by_6	
Close_ytd	Close prices of the past 7 days	correl_close_diff_ytd	Difference in consecutive Close prices of the past 5 days, for the correlated asset class
Close_shifted_by_1		correl_close_diff_shifted_by_1	
Close_shifted_by_2		correl_close_diff_shifted_by_2	
Close_shifted_by_3		correl_close_diff_shifted_by_3	
Close_shifted_by_4		correl_close_diff_shifted_by_4	
Close_shifted_by_5		BB_Upper_diff	Upper Bollinger Band – Actual Price
Close_shifted_by_6		BB_lower_diff	Actual Price – Lower Bollinger Band
High_ytd	High Prices of the past 7 days	RSI	Relative Strength Index
High_shifted_by_1		MACD_diff	High MA – Low MA
High_shifted_by_2		StDev	Standard Deviation
High_shifted_by_3		Moving_Average_diff	Absolute difference between actual price and exponential moving average:

<table>
<tr><td></td><td></td><td></td><td>| Actual Price – EMA |</td></tr>
<tr><td>High_shifted_by_4</td><td></td><td></td><td></td></tr>
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<tr><td>High_shifted_by_6</td><td></td><td></td><td></td></tr>
<tr><td>Low_ytd</td><td rowspan="7">Low prices of the past 7 days</td><td></td><td></td></tr>
<tr><td>Low_shifted_by_1</td><td></td><td></td></tr>
<tr><td>Low_shifted_by_2</td><td></td><td></td></tr>
<tr><td>Low_shifted_by_3</td><td></td><td></td></tr>
<tr><td>Low_shifted_by_4</td><td></td><td></td></tr>
<tr><td>Low_shifted_by_5</td><td></td><td></td></tr>
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<tr><td>BB_lower</td><td>Lower Bollinger Band</td><td></td><td></td></tr>
<tr><td>BB_upper</td><td>Upper Bollinger Band</td><td></td><td></td></tr>
<tr><td>MACD</td><td>Moving Average Convergence-Divergence</td><td></td><td></td></tr>
<tr><td>RSI</td><td>Relative Strength Index</td><td></td><td></td></tr>
<tr><td>StDev</td><td>Standard Deviation</td><td></td><td></td></tr>
<tr><td>EMA</td><td>Exponential Moving Average</td><td></td><td></td></tr>
<tr><th>Label</th><th>Remark</th><th>Label</th><th>Remark</th></tr>
<tr><td>Price</td><td>Predicts next close price</td><td>Direction</td><td>1 (up) or 0 (down)</td></tr>
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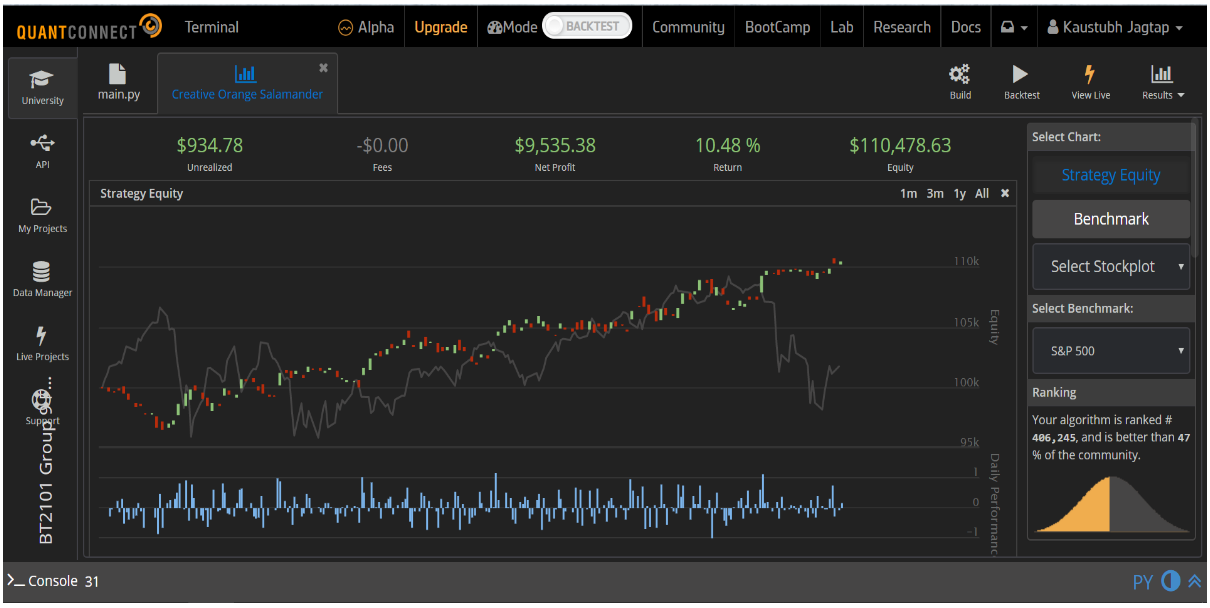
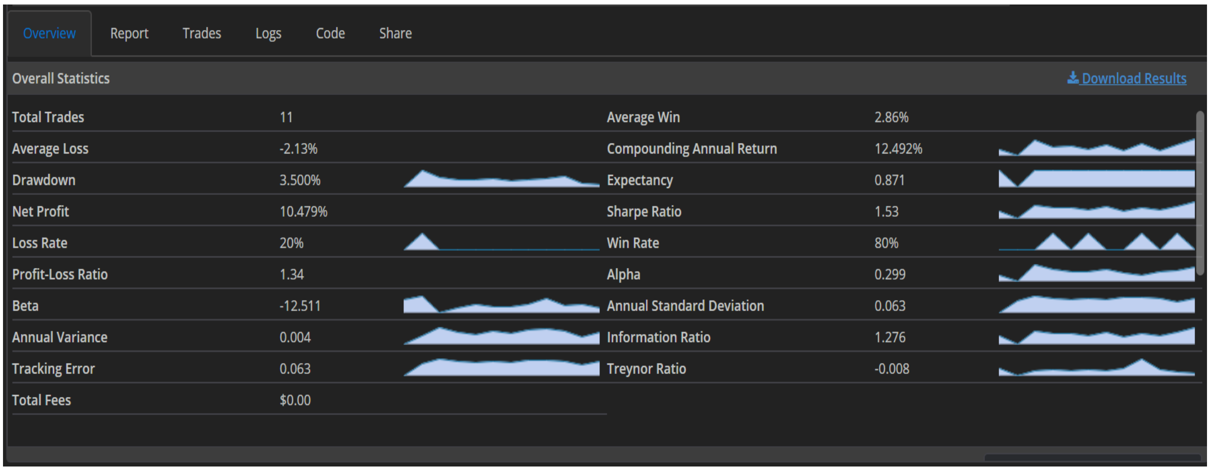
B: Model Results (Backtesting)





Overview | Report | Trades | Logs | Code | Share

Overall Statistics — Download Results

Total Trades	11	Average Win	2.86%
Average Loss	-2.13%	Compounding Annual Return	12.492%
Drawdown	3.500%	Expectancy	0.871
Net Profit	10.479%	Sharpe Ratio	1.53
Loss Rate	20%	Win Rate	80%
Profit-Loss Ratio	1.34	Alpha	0.299
Beta	-12.511	Annual Standard Deviation	0.063
Annual Variance	0.004	Information Ratio	1.276
Tracking Error	0.063	Treynor Ratio	-0.008
Total Fees	$0.00		