

Crypto Trading Strategies

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Dataset Selection





Data universe

7,800+ cryptocurrencies (as of Jan 2021)¹

500+ cryptocurrency exchanges²

30+ public APIs available³; we looked into Kraken and Bitfinex as they had downloadable data without needing an API

BTCUSD is the most traded pair

Data availability: many new currencies have only been in existence for < 3 years

Data is mostly already clean, but missing when exchange is down or trade volume is zero

¹ <https://e-cryptonews.com/how-many-cryptocurrencies-are-there-in-2021/>

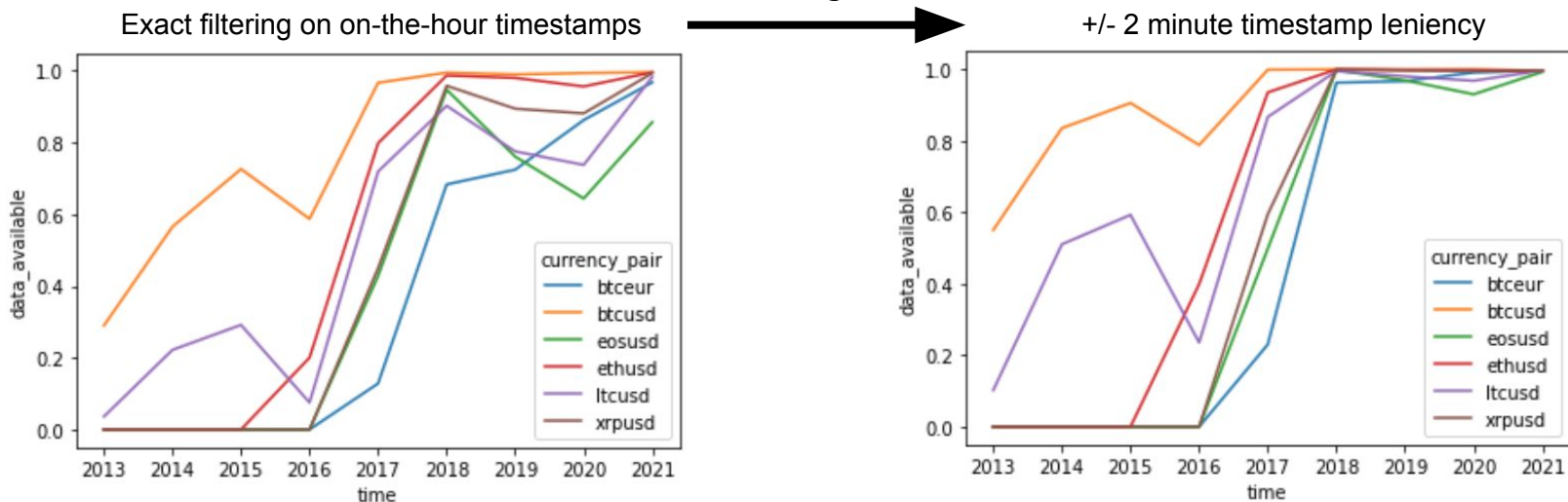
² <https://www.cryptimi.com/guides/how-many-cryptocurrency-exchanges-are-there>

³ <https://github.com/public-apis/public-apis#cryptocurrency>

Hourly-level data cleaning and availability was done by syncing 'close' timestamps

Resolution technique for syncing “close” time stamps (± 2 minutes). This yielded much higher data availability percentage than minute-level data, as expected.

Data availability (percentage non-missing) at the hour level
calculated using two methods



Pairs Trading Strategy



Pairs Trading Strategy

- Overview
- Identifying Pairs and Trading
- Tuning Strategy



Pairs trading

Pairs trading

- Market neutral strategy that enables profits in any market conditions

Steps involved

- Identify two highly correlated stocks
- Entering positions during times of temporarily weaker correlation
- Short an outperforming stock and long an underperforming one
- Clear positions when the spread between the stocks converges

Identifying the right pair?

- Cointegration: a statistical test to determine whether two (nonstationary) time series are correlated in the long term

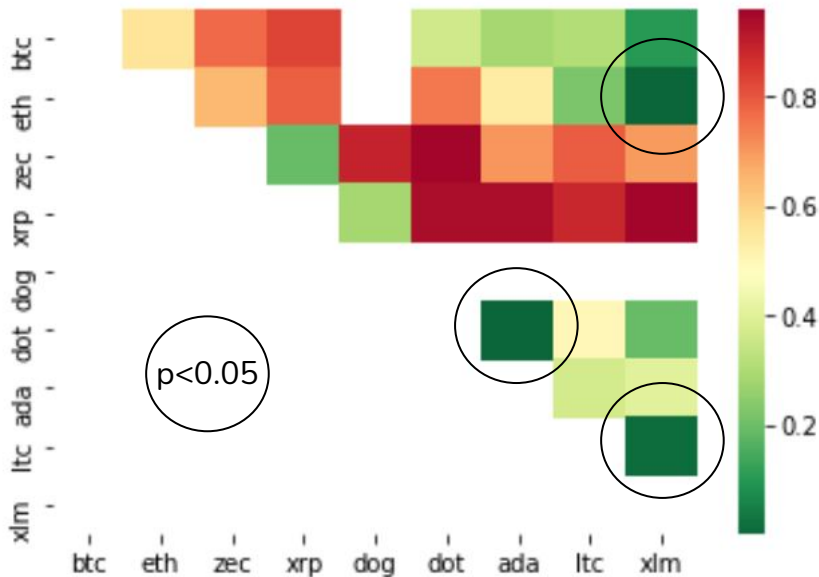
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Co-integrated pairs

Co-integration p-values (plotting $p < 0.98$)



Pairs where p-value is < 0.05 :

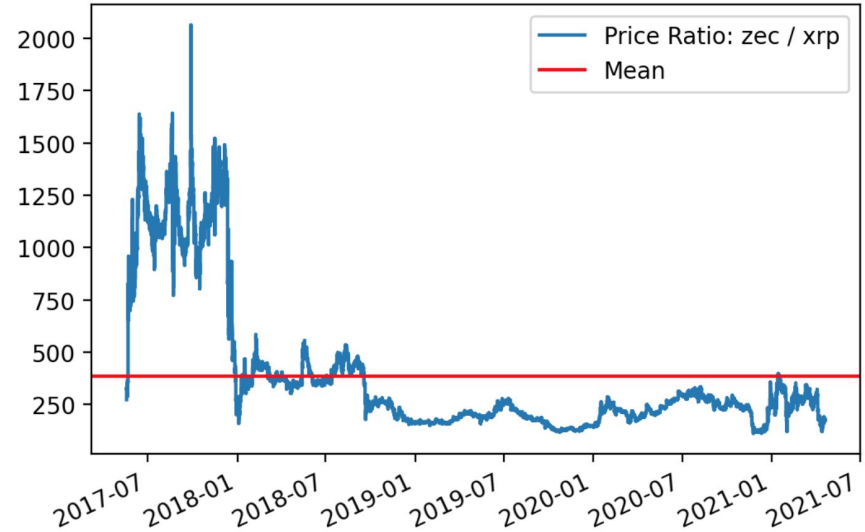
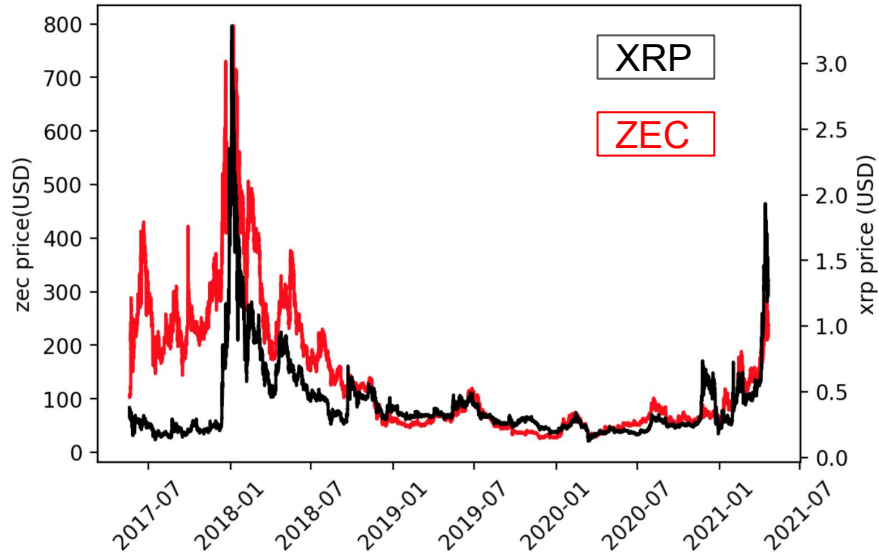
(ETH, XLM)

(DOT, ADA)

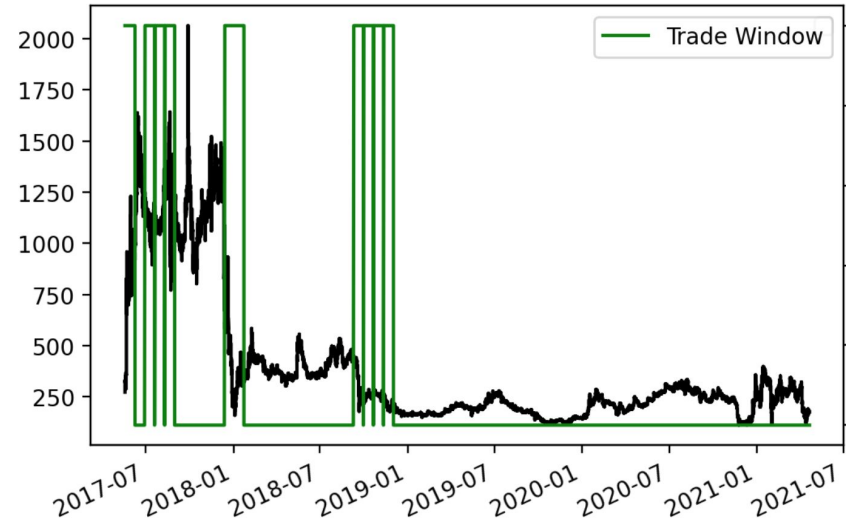
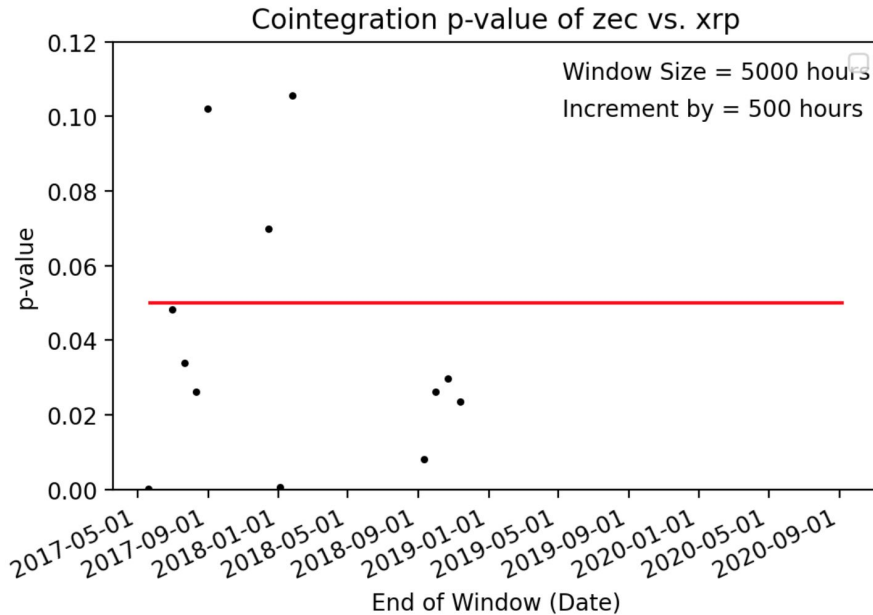
(LTC, XLM)



Find Correlated Pairs and Take the Ratio

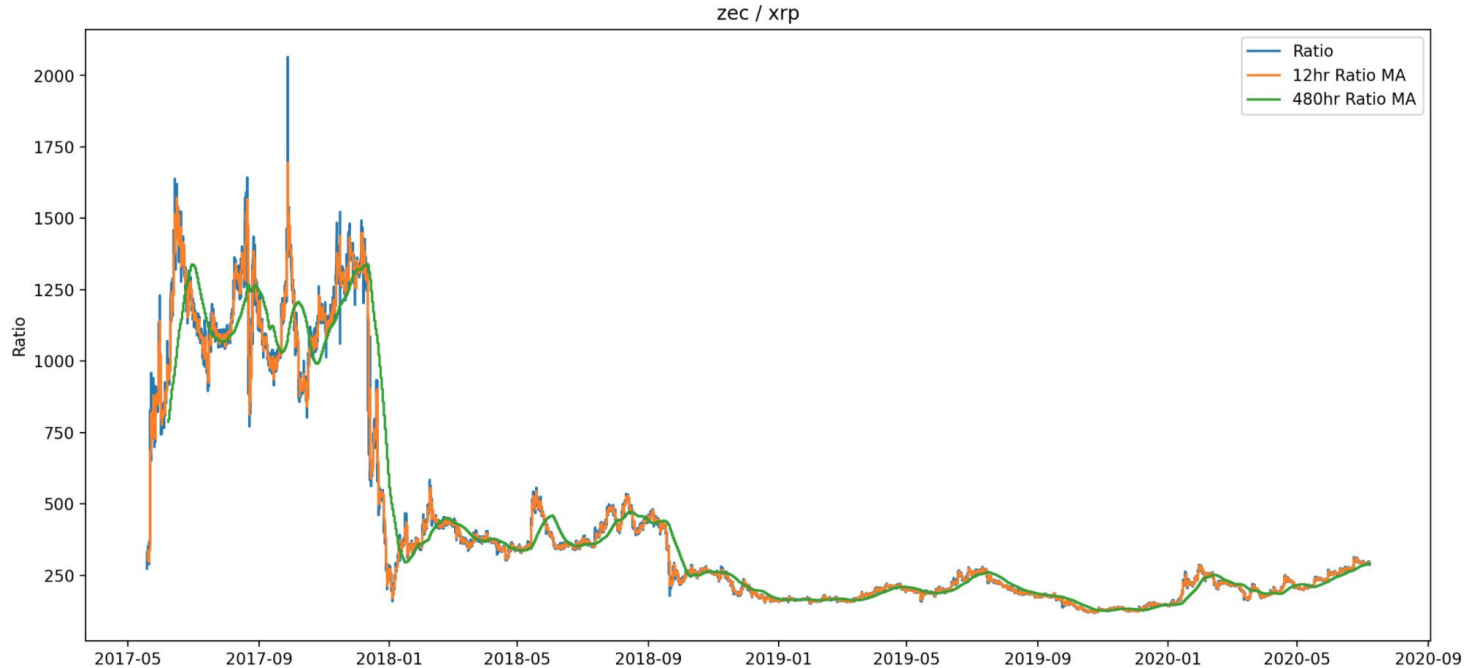


Trading Windows ($p < 0.05$)



Short Term and Long Term Moving Average

$$\text{z-score} = (\text{ma1} - \text{ma2}) / \text{std}(\text{ma2})$$

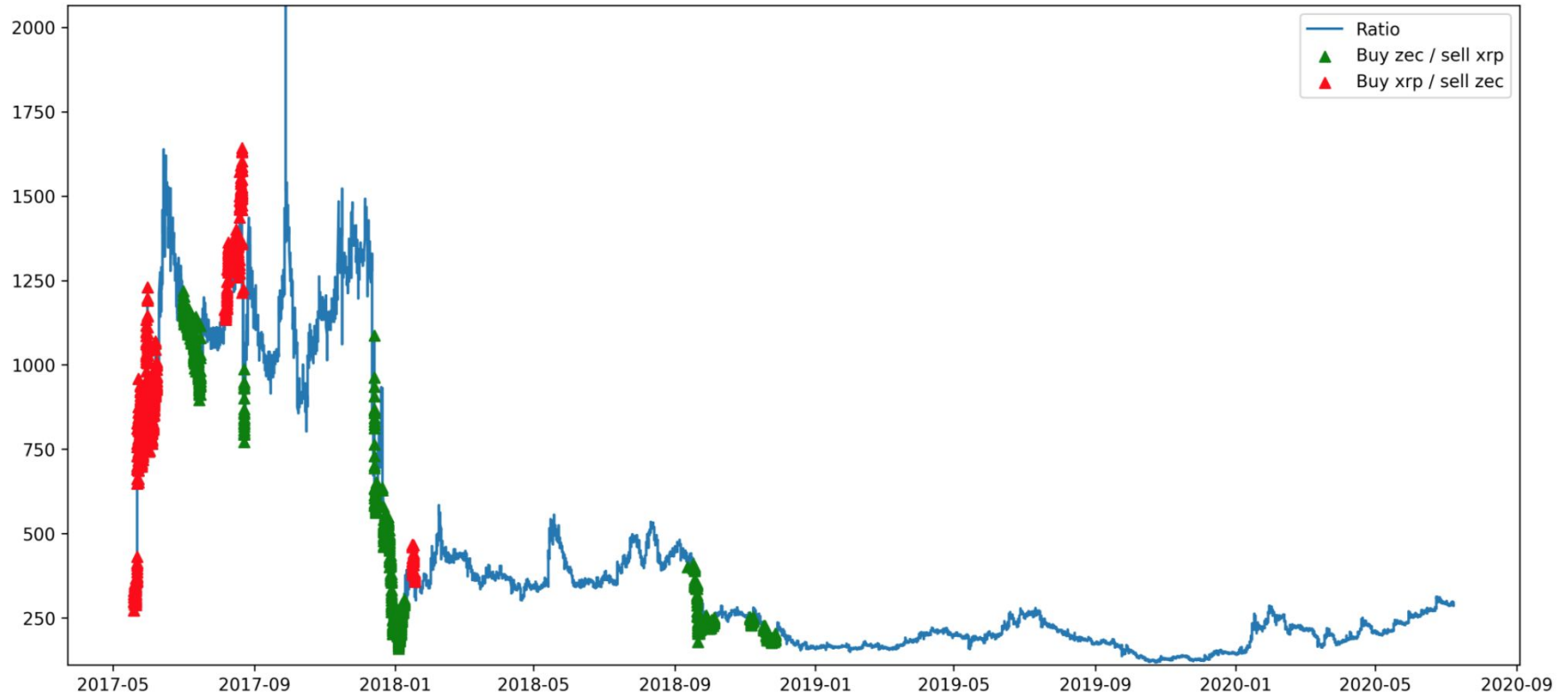


Taking positions where $\text{abs}(\text{z-score}) > 2$

Ratio = zec / xrp



Taking positions during cointegrated phases



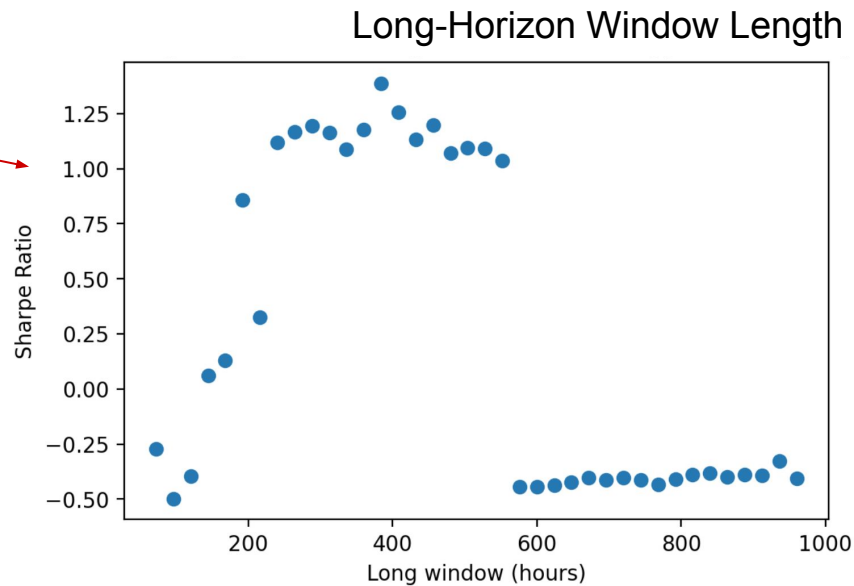
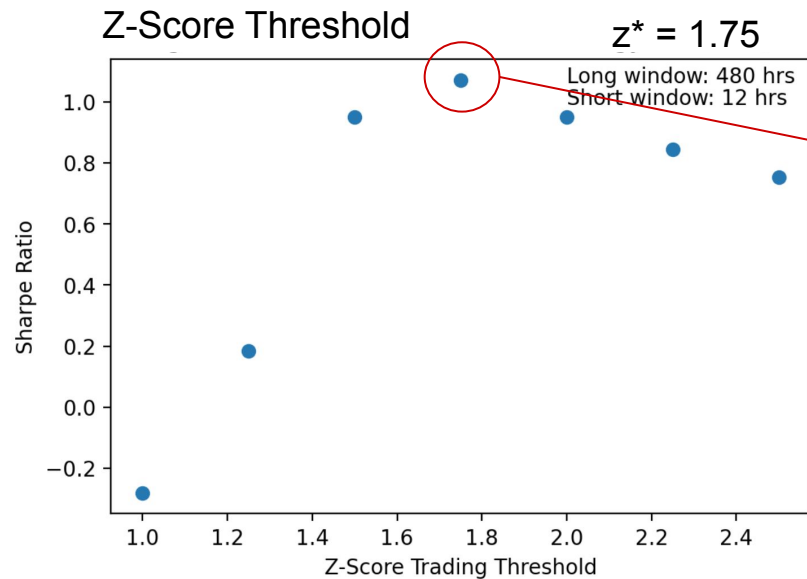
Taking positions during non-cointegrated phases



Pairs Trading Strategy

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Tuning



Training:

Max return: 2.61%

Sharpe: 1.26

LW: 408 hrs

Zscore threshold: 1.75

Testing:

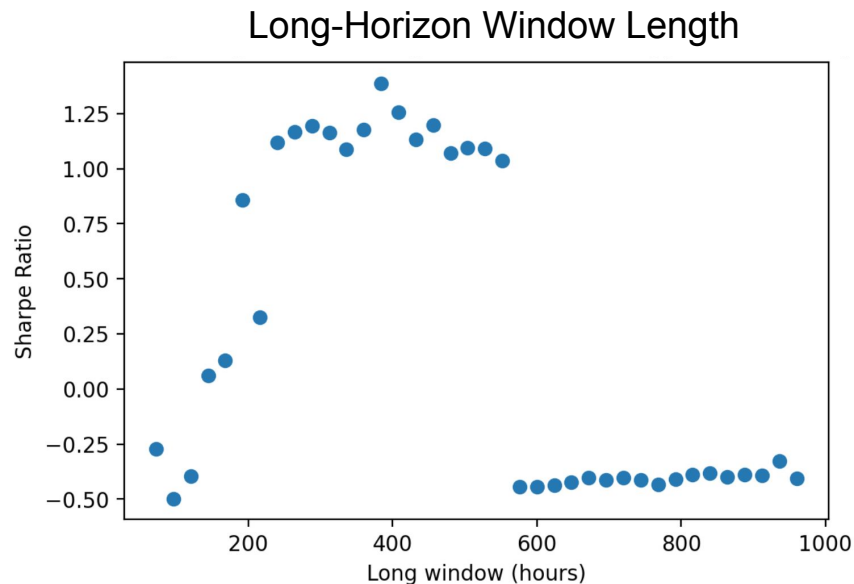
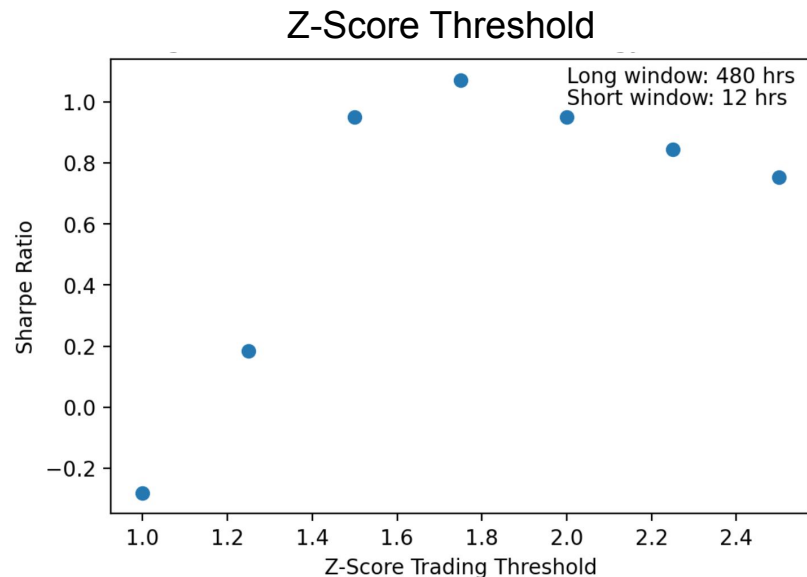
Return: 1.12%

Sharpe: 0.11

LW: 408 hrs

Zscore threshold: 1.75

Tuning



Training:

Max return: 2.61%

Sharpe: 1.26

LW: 408 hrs

Zscore threshold: 1.75

Testing:

Return: 1.12%

Sharpe: 0.11

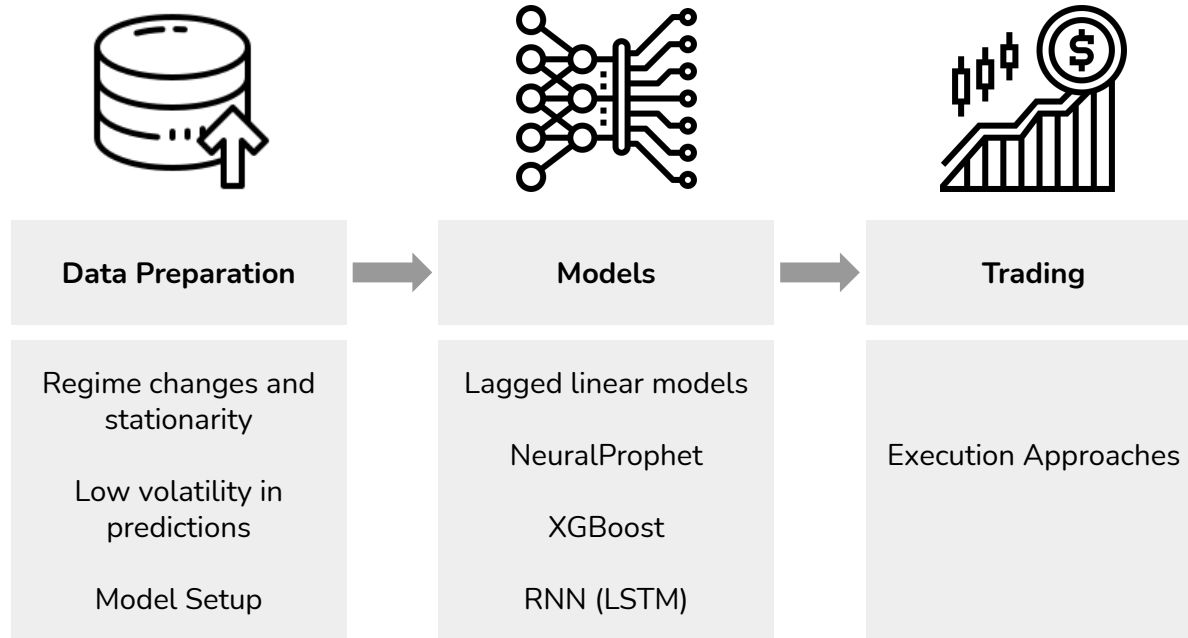
LW: 408 hrs

Zscore threshold: 1.75

Machine Learning Models

- Data Preparation
- Models
- Trading

Goal: use time series techniques in machine learning to trade at high frequency on technical signals only



Machine Learning Models

- **Data Preparation**
- **Models**
- **Trading**

Regime changes and stationarity

- Very speculative pricing on Crypto assets
- Regime changes in both the short and long term
- Massive changes in trends between 2018, 2019 and 2020

Price series of BTC in 2018



Price series of BTC in 2019



Price series of BTC in 2020



Stationarity

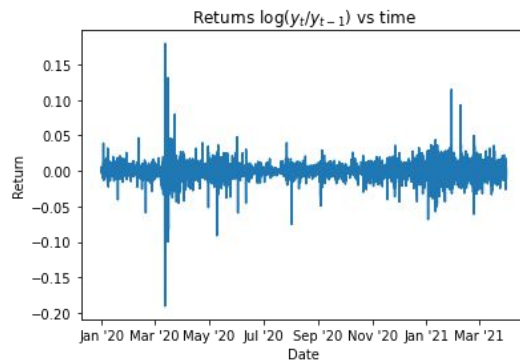
The nature of cryptocurrency is that it is very **volatile** - e.g., BTC suddenly rallied from \$10k to \$60k from Oct '20 to March '21. We addressed this in three ways - by:

- Increasing the stationarity of the time series to predict
- Restricting the time frame of it, to avoid overfitting
- Adding short-term and long-term volatility features to help indicate regime changes

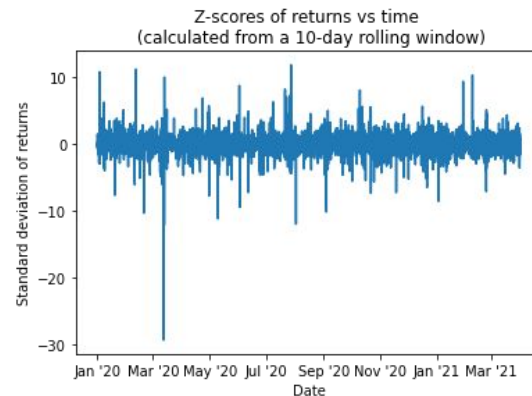


Oct
'20

Mar
'21



Returns series is more stationary
than prices



Z-score (with 10-day rolling window as
time horizon) are even more stationary

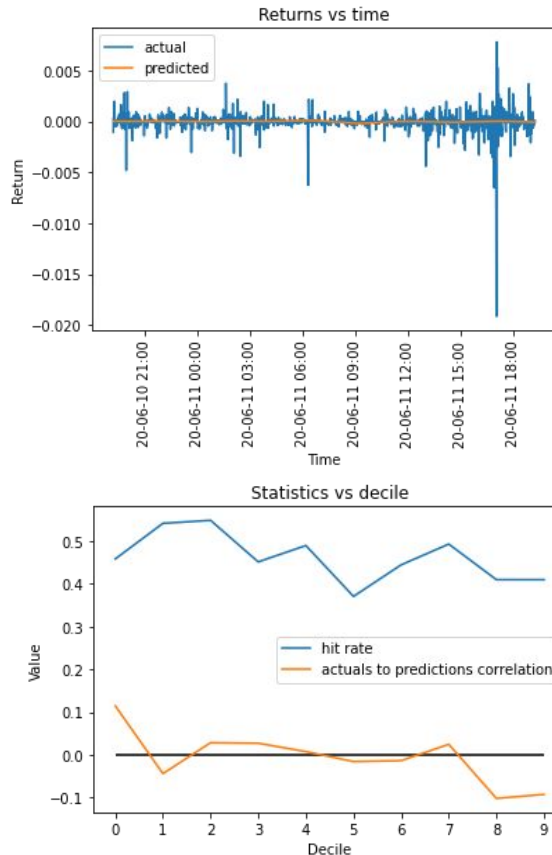
Low volatility in predictions

Prediction output was typically of a much lower volatility than the actuals (top graph).

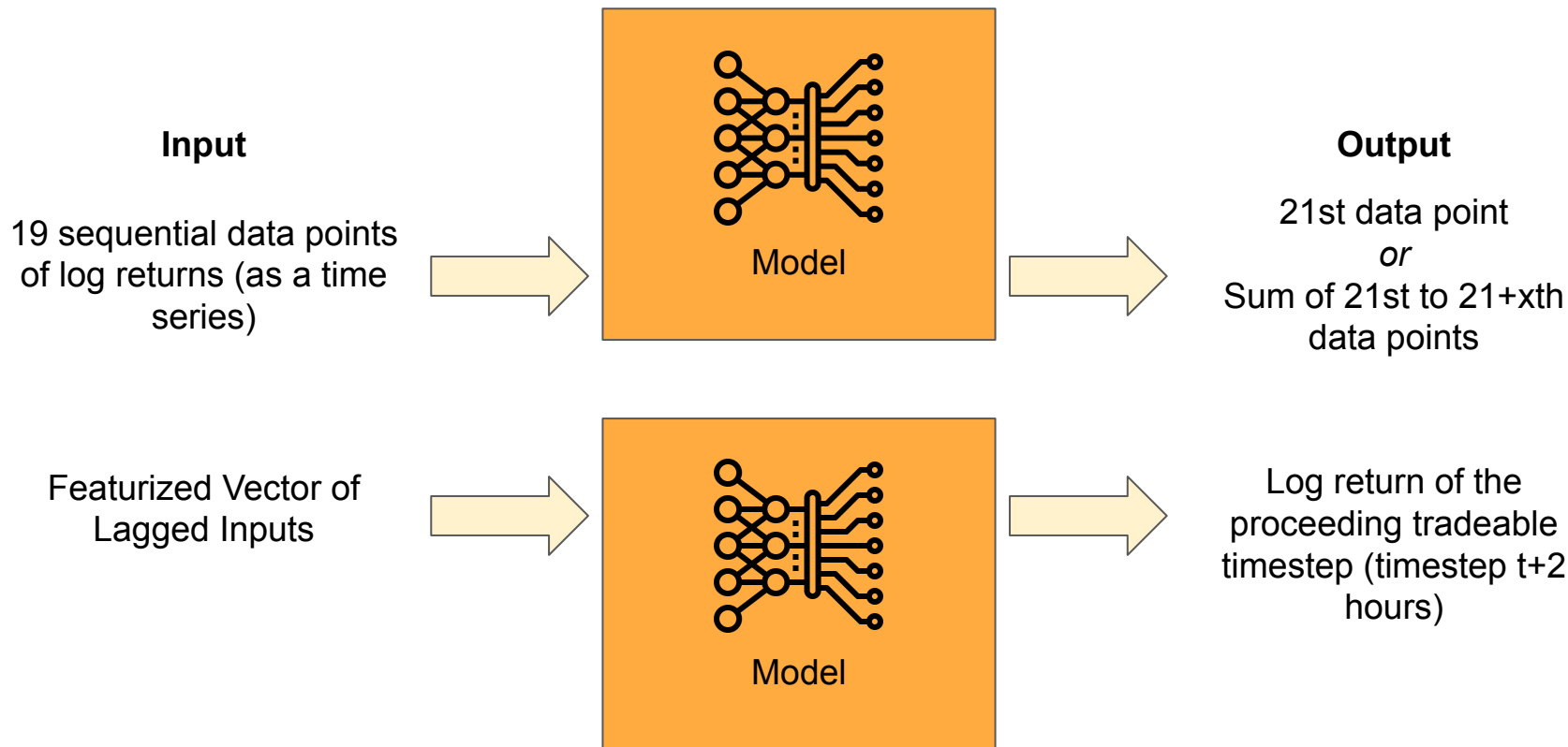
To find signals in this, we divided the value of the predictions into ten deciles and plotted (bottom graph):

- The correlation between actual and predicted values
- Hit rate, or % samples where the sign of the actual and predicted values matched

We could then use these measures as signals to trade - correlation for the magnitude of our trade and hit rate for the sign of our trade.



Model Setup

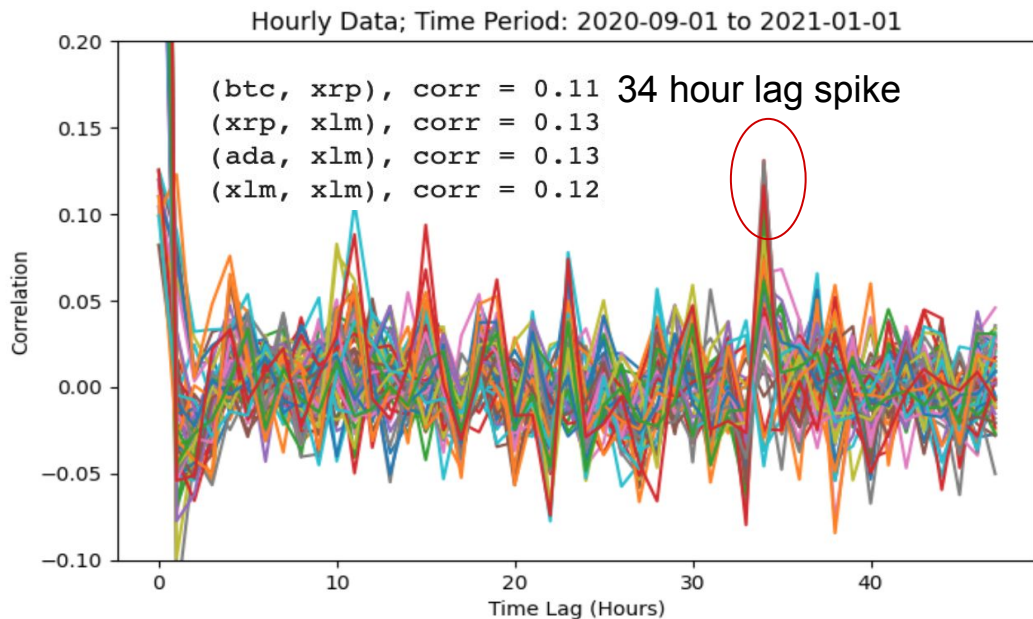


Machine Learning Models

- Data Preparation
- Models
- Trading

34-hour lagged models

Recall: 34-hr lag corr. spike



Top 4 Lagged Corrs:

(xrp, xlm): 0.13

(ada, xlm): 0.13

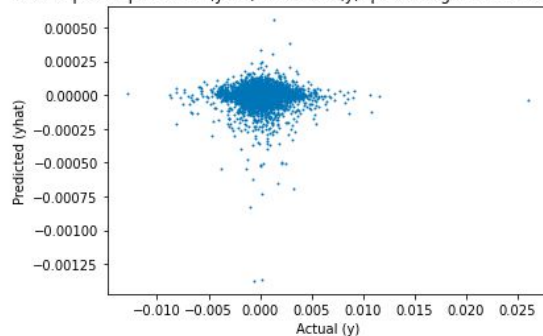
(xlm, xlm): 0.12

(btc, xrp): 0.11

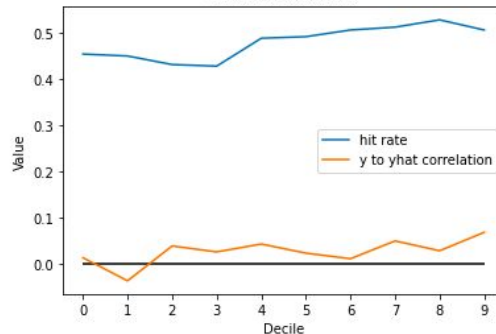
34-hour lagged linear model performances

- Correlations were fleeting and so did not generalize well overall
- Technical indicators are highly non-stationary, meaning it is tricky to trade on purely lagged features.

Scatterplot of predicted (yhat) vs actual (y): predicting btc with 34 lagged XRP



Statistics vs decile



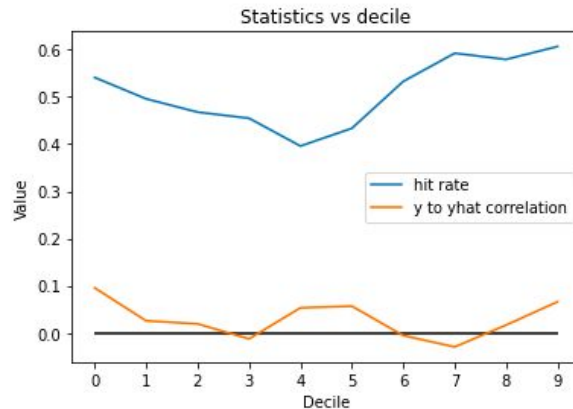
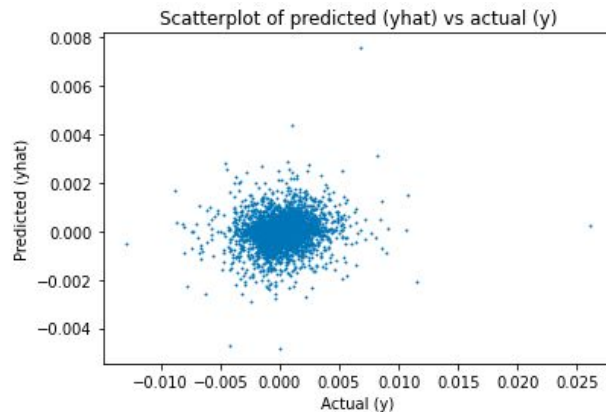
Predicting BTC with Lagged XRP

General feature engineering techniques

- Time-based features
 - Hour of the day, day of the week, month
 - Important to avoid spurious time features such as the year (never comes again)
- Moving averages
 - Moving averages can encode trends in a series and are useful in stationarity analyses
 - Like in pairs trading, looking at short-term vs long-term moving averages could be useful features.
 - Variants of these such as exponential moving averages can also be significant.
- Standardization
 - Features have different scales and may be non-stationary
 - Standardize them into z-score like numbers over a fixed window can help more clearly represent relative changes.

Linear models takeaways and performance

- Target standardization over 24 hour windows (tended to work better for some periods and not as well for others)
- Overfitting tended to be an issue: tried L1 and L2 regularization
- Tried logistic regression models to predict sign of a trade

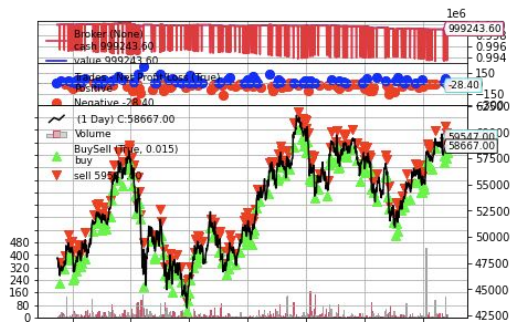
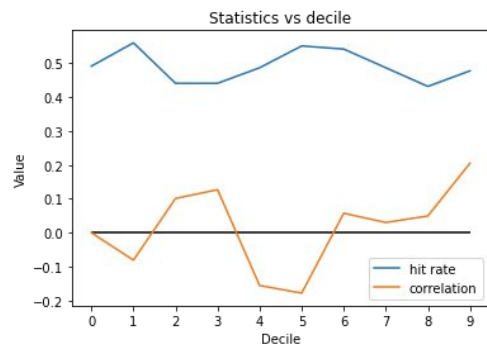


Machine learning and neural models

NeuralProphet

(Seasonality & autocorrelation, neural net)

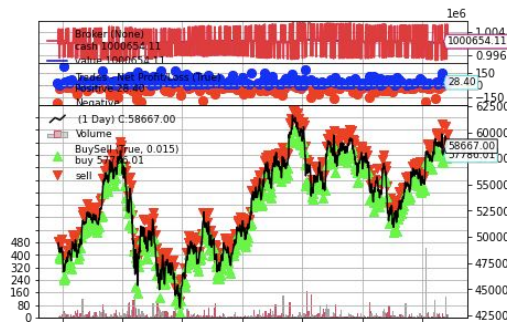
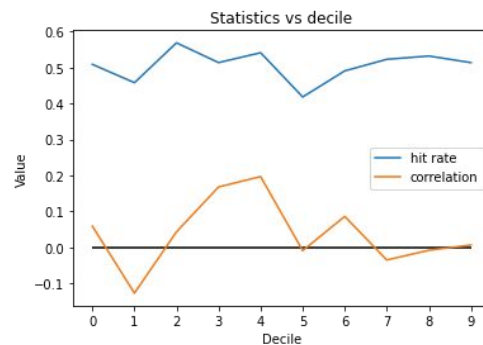
Sharpe ratio: -2.75



XGBoost

(Optimized gradient boosting library)

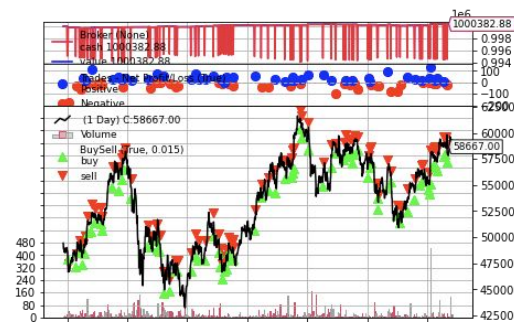
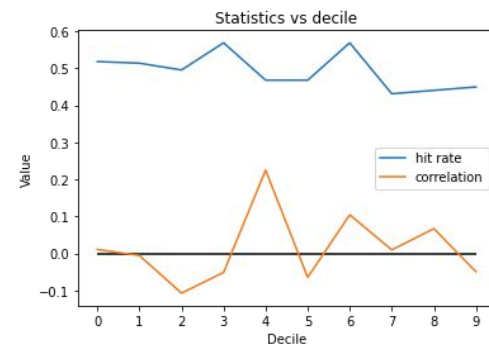
Sharpe ratio: 1.54



Recurrent Neural Network

(For series data prediction; uses LSTM*)

Sharpe ratio: 2.64

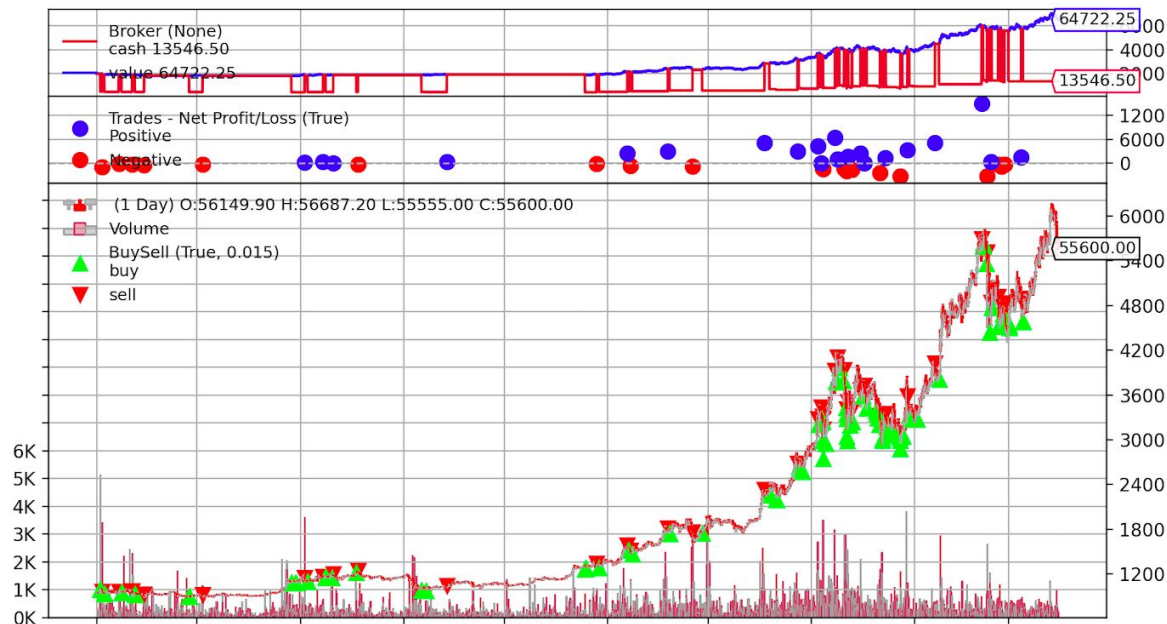


Machine Learning Models

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Strategy execution

- \$20,000 to start
- Add stop-loss bounds (if you lose 10% of initial capital, sell out of position)
- Buy a fraction of a coin up to \$1,000 dollars per trade



Sharpe ratio: 3.34

Top features: 5, 10, 20, 50, 100 hour moving averages and standard deviations, time features

Additional considerations for strategy execution

- Add transaction costs to get a more realistic backtest (0.3% of transaction)
- If two trades cancel out in some window, don't trade
- If your model performs better on specific deciles, trade only when you believe you are in those deciles.



Sharpe ratio: 2.83 (Down from 3.34)

Top features: 5, 10, 20, 50, 100 hour moving averages and standard deviations, time features

Conclusions + Retrospective Discussion

Conclusions

- Modeling crypto assets using only technical signals is hard due to its speculative and volatile nature
- Not very many cointegrated assets for pairs trading
- They are extremely volatile and seem to be valued mostly by speculation
- It is important to be able to handle regime changes in order to build strong alpha models over many time periods

Where to go from here

- More nuanced execution needed: consider shorting/trading on margin and other techniques
- Handle regime changes with external features: use news and network data in order to reason about speculation surrounding crypto assets
- Consider positions in specific coins together, to make a multi-asset portfolio
- Apply risk management and portfolio optimization techniques to this