Crypto Trading Strategies

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Dataset Selection

Data universe

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

500+ cryptocurrency exchanges[2]

30+ public APIs available[3]; 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

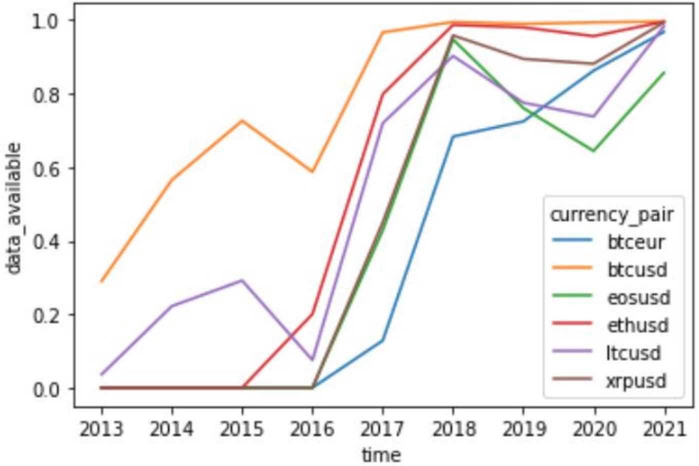
1 https://e-cryptonews.com/how-many-cryptocurrencies-are-there-in-2021/
2 https://www.cryptimi.com/guides/how-many-cryptocurrency-exchanges-are-there
3 https://github.com/public-apis/public-apis#cryptocurrency

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

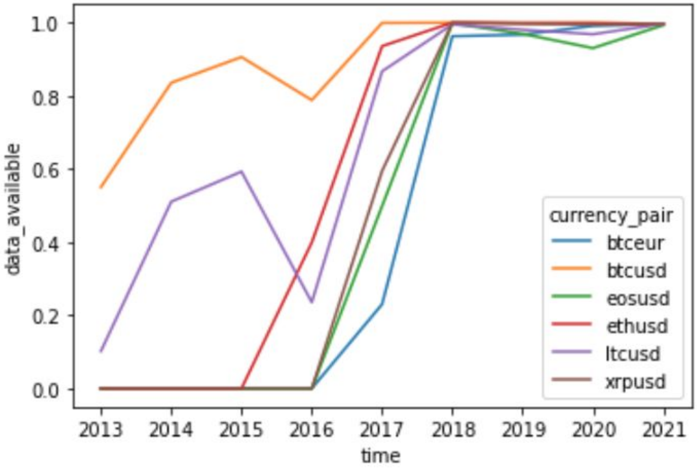
Resolution technique for syncing “close” time stamps (+/- 2 minutes). This yielded much higher data availability percentage than minute-level data, as expected.

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

Exact filtering on on-the-hour timestamps



+/- 2 minute timestamp leniency



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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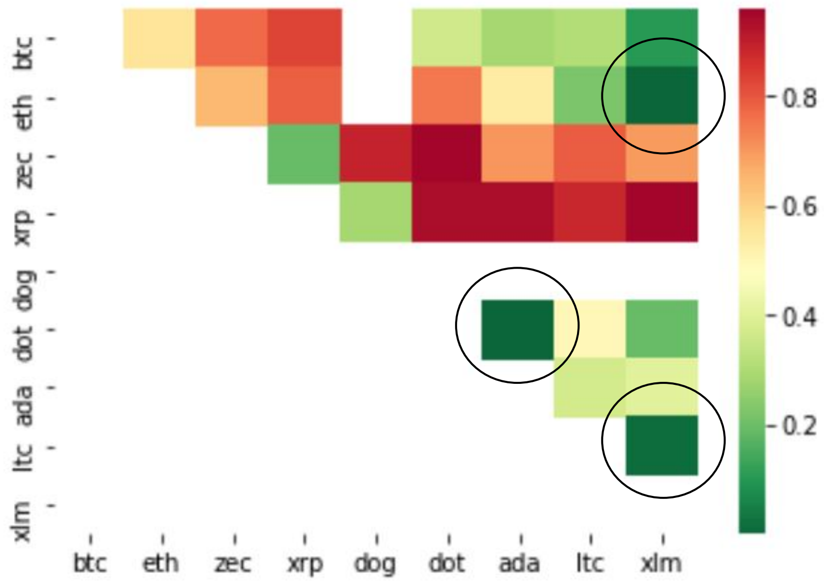
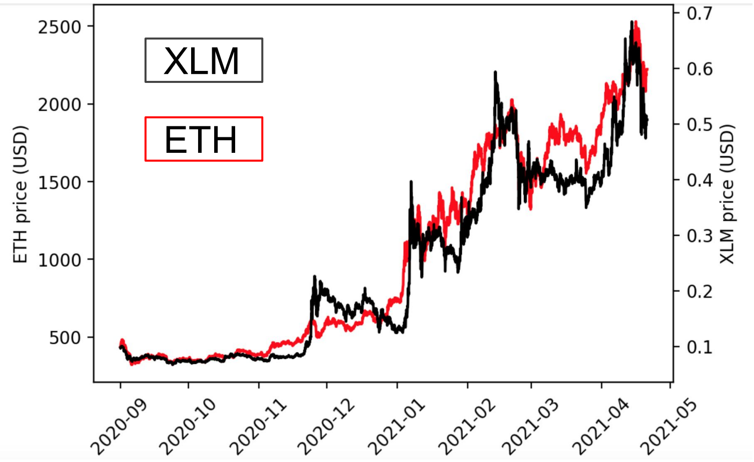
Co-integrated pairs

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

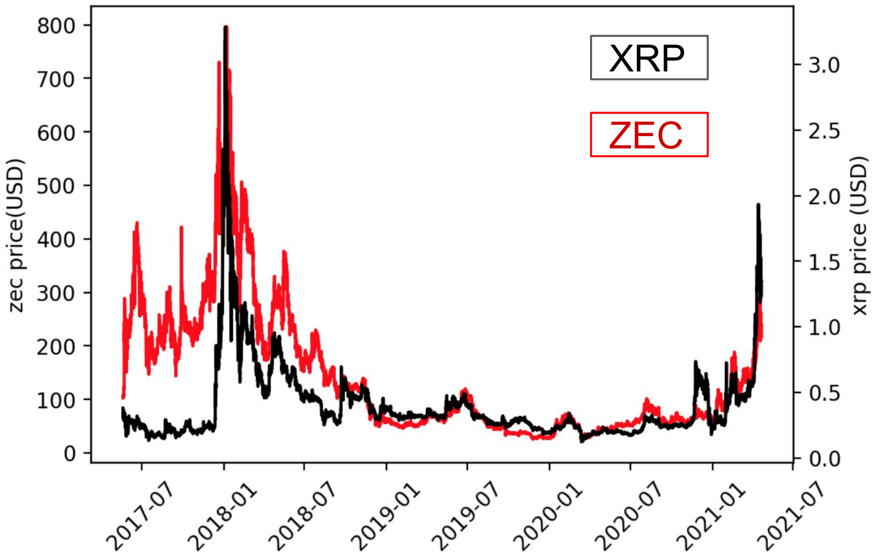


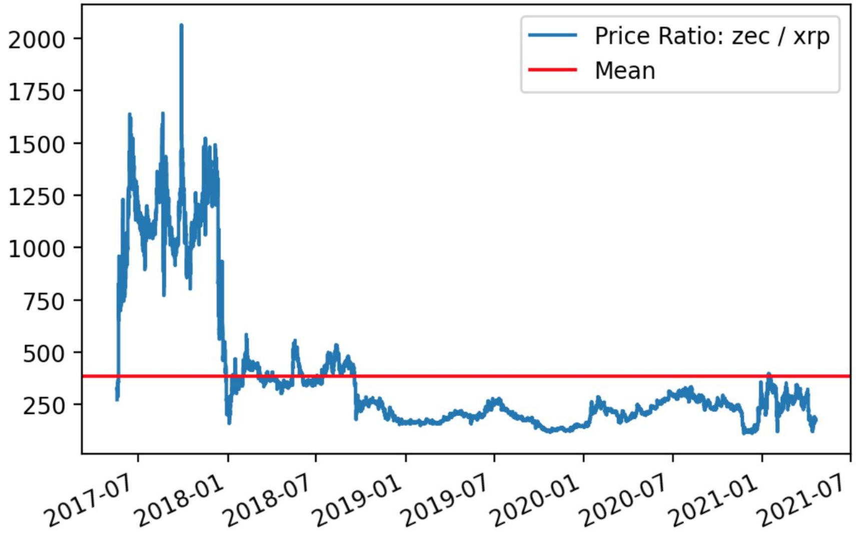
Pairs where p-value is < 0.05:

(ETH, XLM)
(DOT, ADA)
(LTC, XLM)

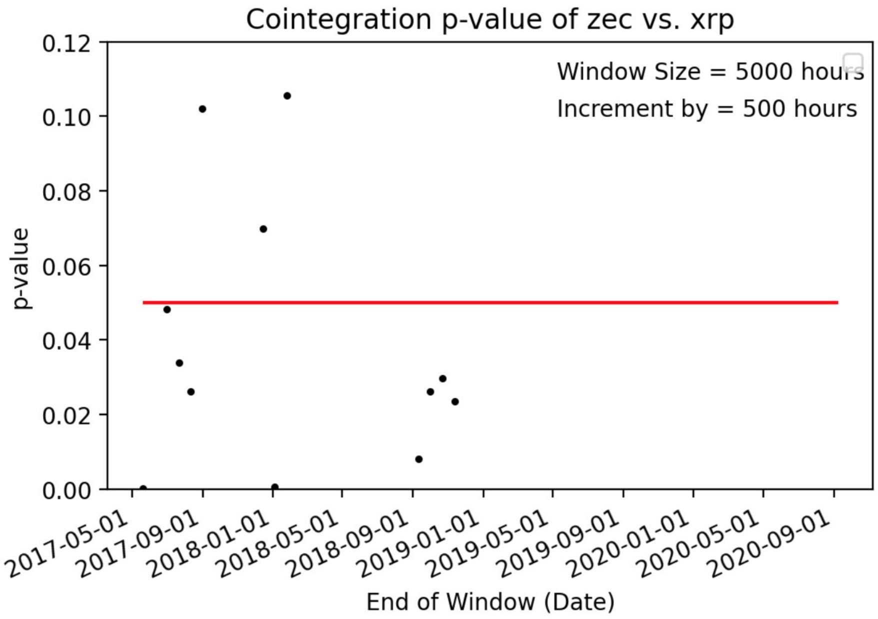


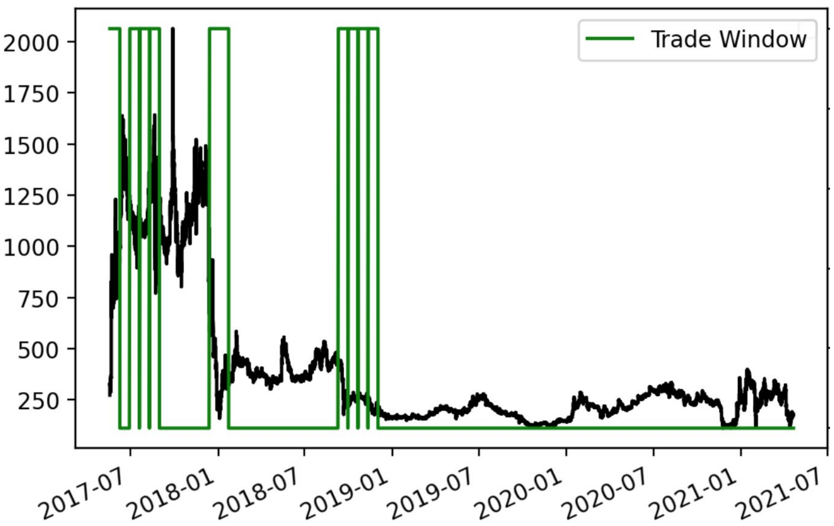
Find Correlated Pairs and Take the Ratio





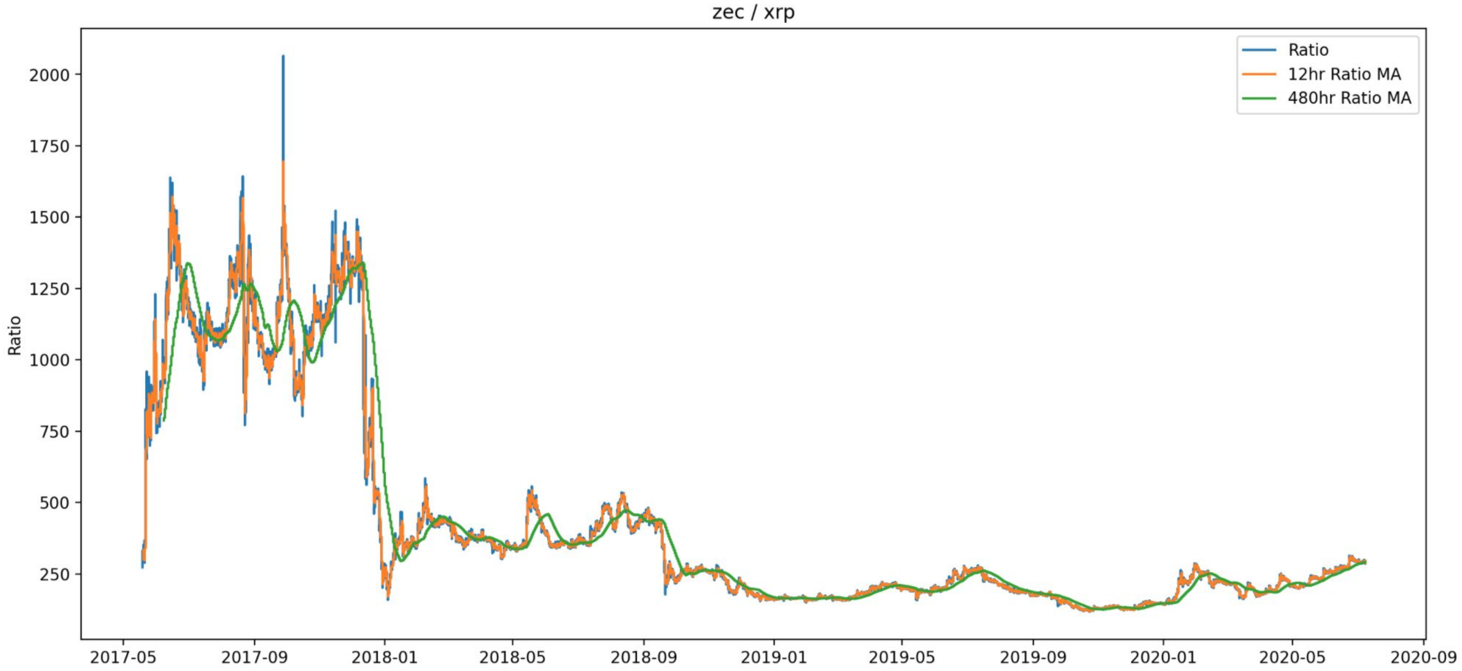
Trading Windows ($p < 0.05$)





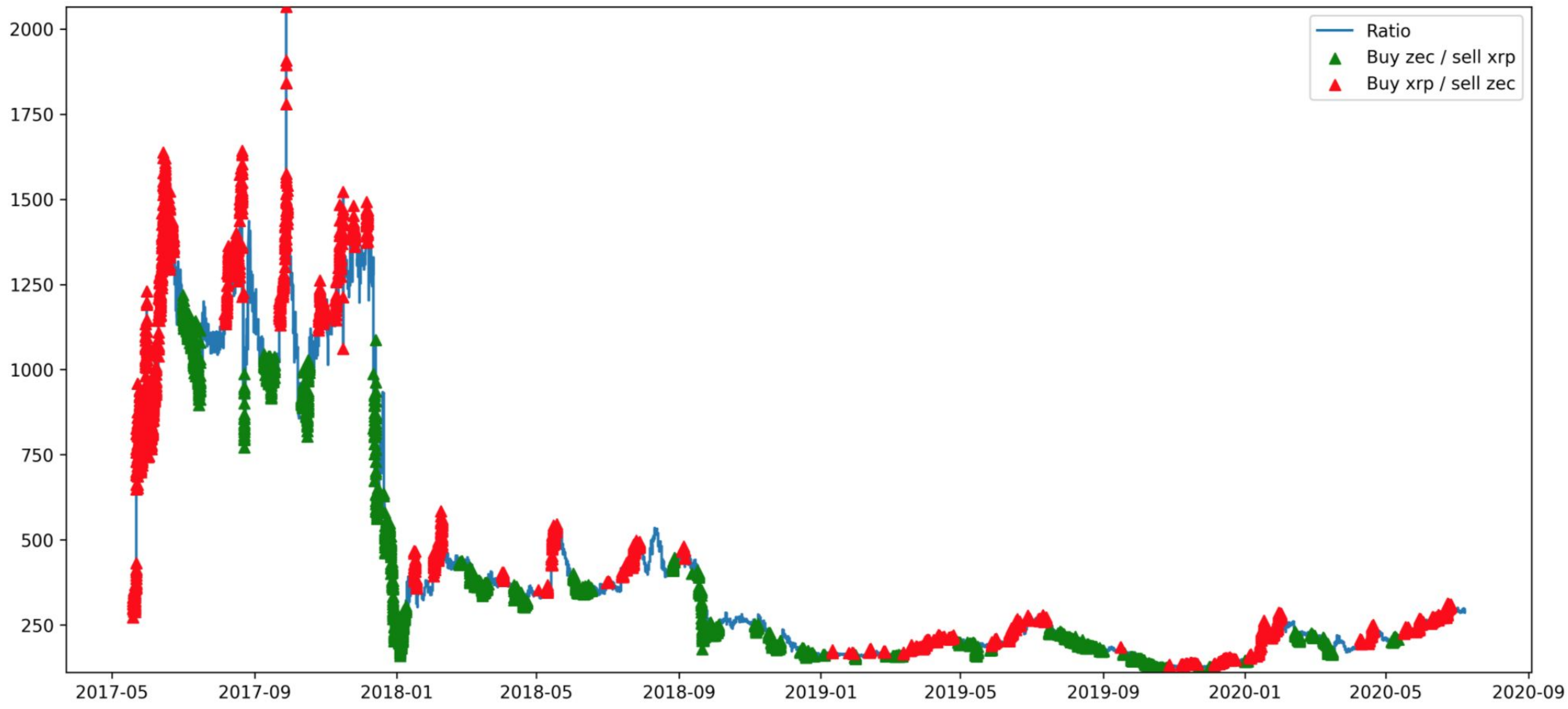
Short Term and Long Term Moving Average

z-score = (ma1 - ma2) / std(ma2)



Taking positions where abs(z-score) > 2

Ratio = zec / xrp



Taking positions during cointegrated phases

Taking positions during non-cointegrated phases

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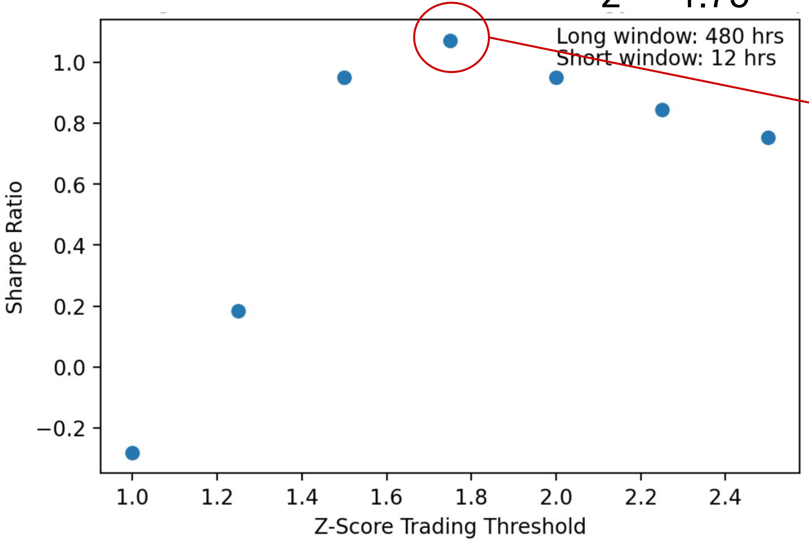
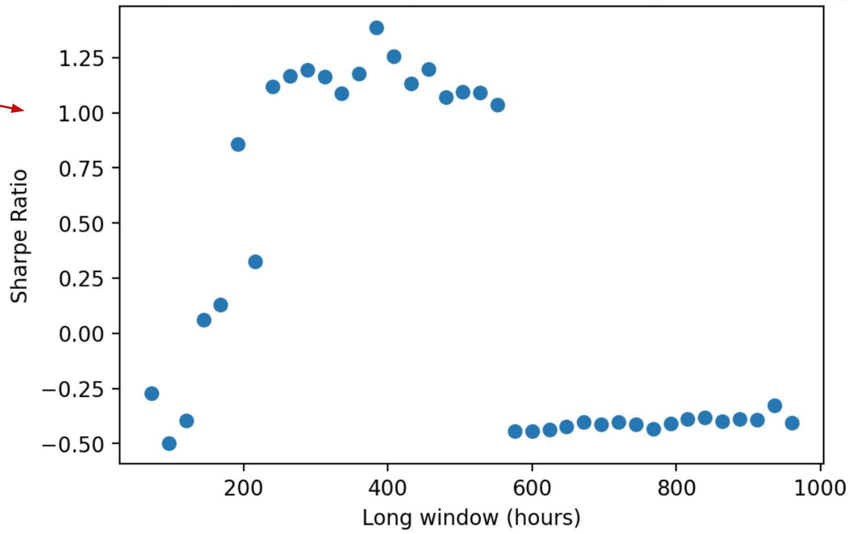
Tuning

Z-Score Threshold

$z^* = 1.75$



Long-Horizon Window Length

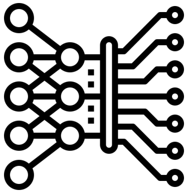


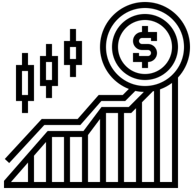
Training:	Testing:
Max return: 2.61%	Return: 1.12%
Sharpe: 1.26	Sharpe: 0.11
LW: 408 hrs	LW: 408 hrs
Zscore threshold: 1.75	Zscore threshold: 1.75

Machine Learning Models

- Data Preparation
- Models
- Trading

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





Data Preparation	**Models**	**Trading**
Regime changes and stationarity Low volatility in predictions Model Setup	Lagged linear models NeuralProphet XGBoost RNN (LSTM)	Execution Approaches

Machine Learning Models

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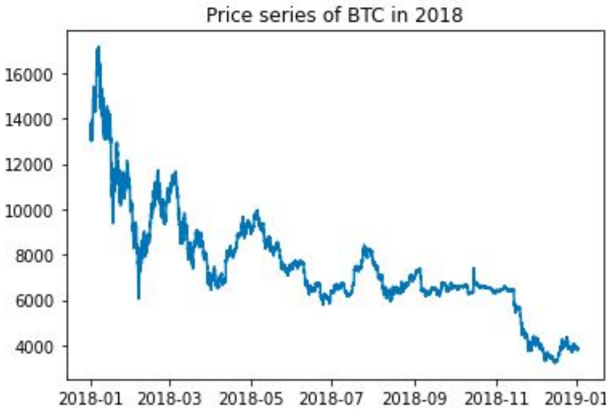
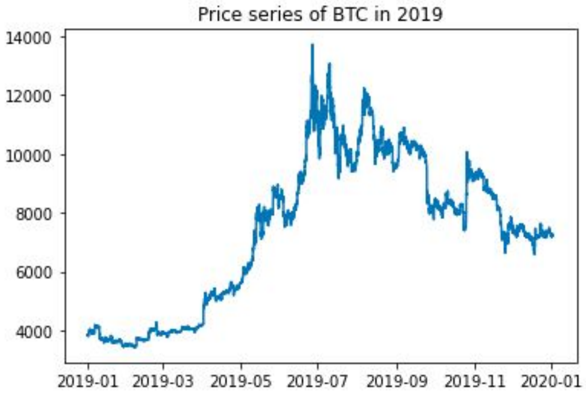
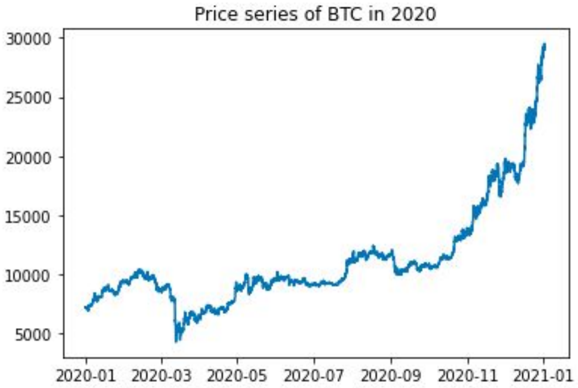
Regime changes and stationarity

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



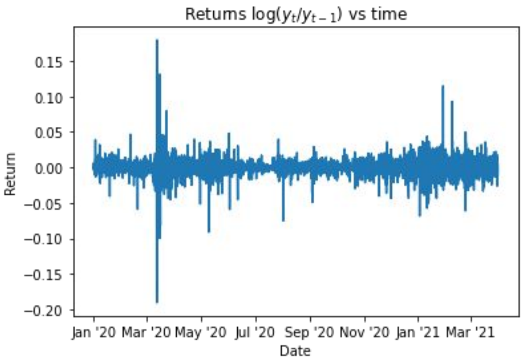


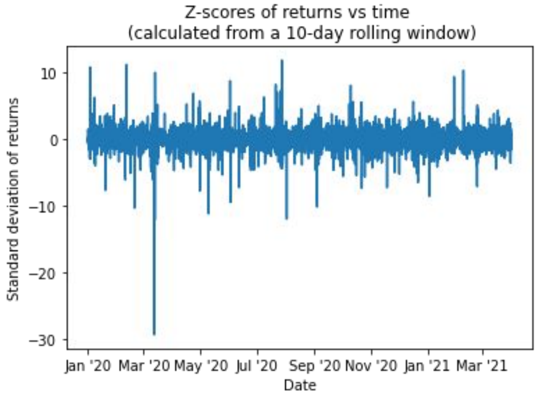


Stationarity

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

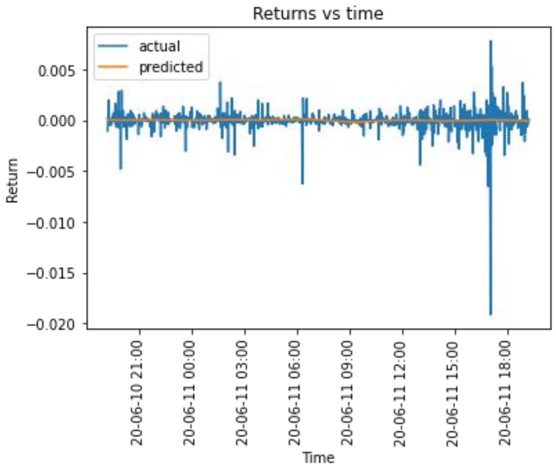
Low volatility in predictions

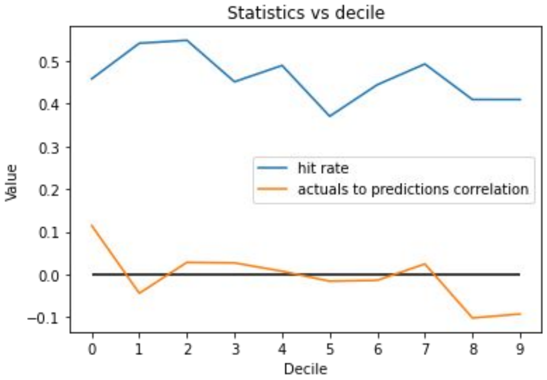
Prediction output was typically of a much lower volatility than the actuals (top graph).

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

Input

19 sequential data points of log returns (as a time series)

Model

Output

21st data point
or
Sum of 21st to 21+xth data points

Featurized Vector of Lagged Inputs

Model

Log return of the proceeding tradeable timestep (timestep t+2 hours)

Machine Learning Models

- Data Preparation
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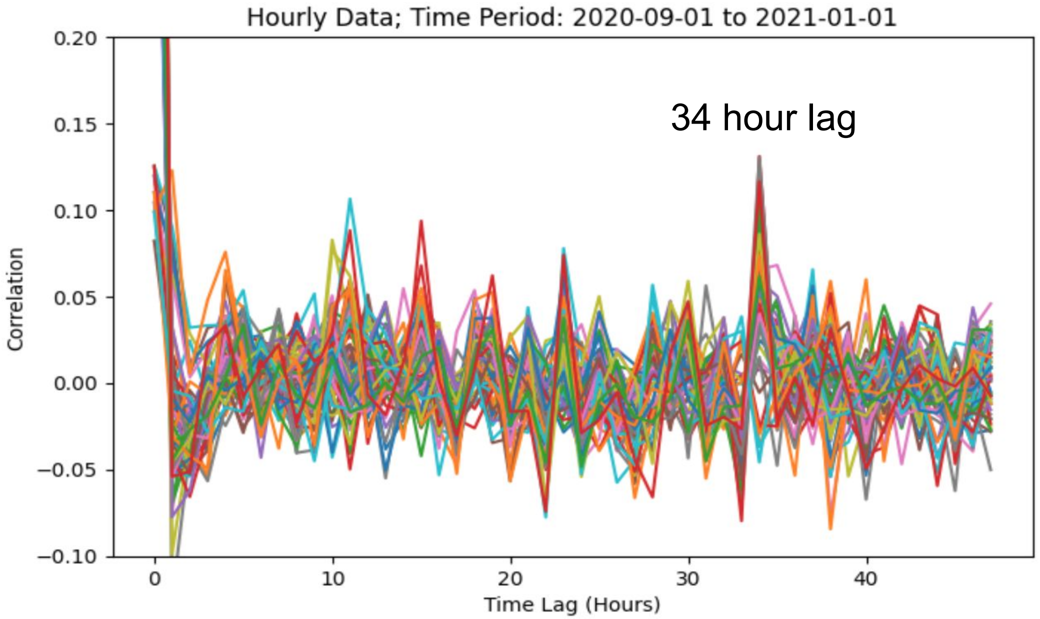
34-hour lagged models

Recall: 34-hr lag corr. spike

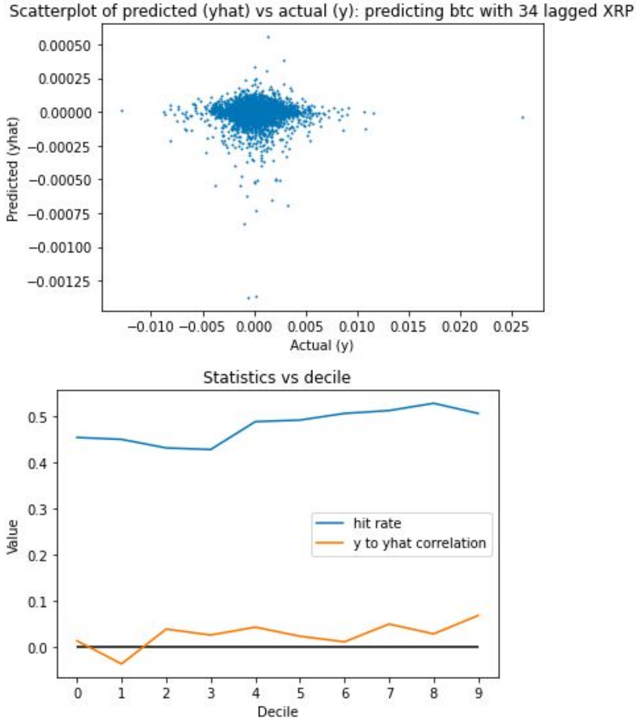


Top 4 Lagged Corrs:

```
(btc, xrp), corr = 0.11
(xrp, xlm), corr = 0.13
(ada, xlm), corr = 0.13
(xlm, xlm), corr = 0.12
```

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.



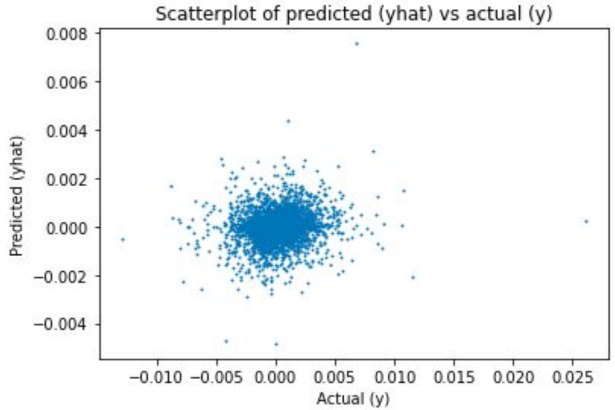
Predicting BTC with Lagged XRP

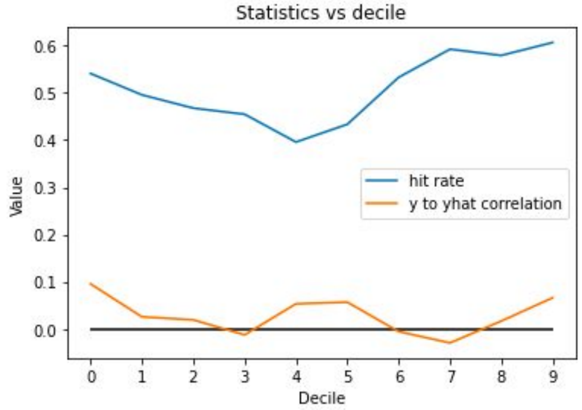
General feature engineering techniques

- 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

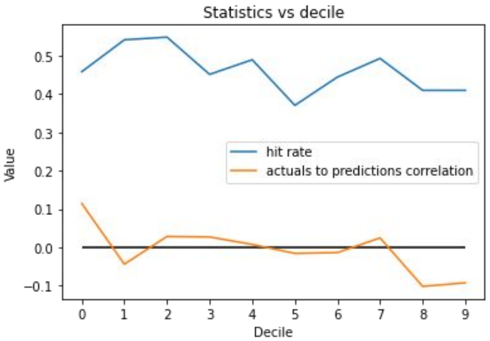
- Target standardization over 24 hour windows (tended to work better for some periods and not as well for others)
- Overfitting tended to be an issue: tried L1 and L2 regularization
- Tried logistic regression models to predict sign of a trade

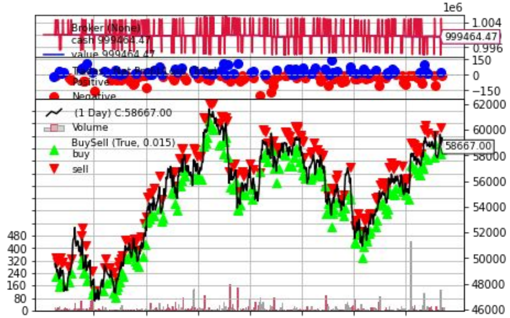




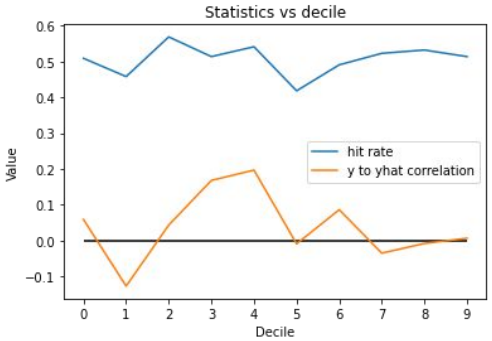
Machine learning and neural models

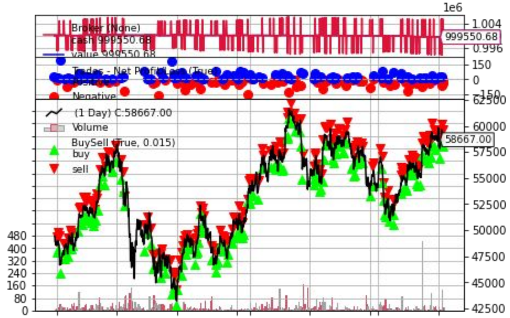
NeuralProphet
(Seasonality & autocorrelation, neural net)
Sharpe ratio: 2.40



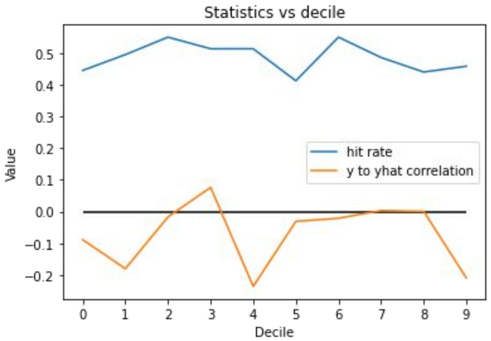


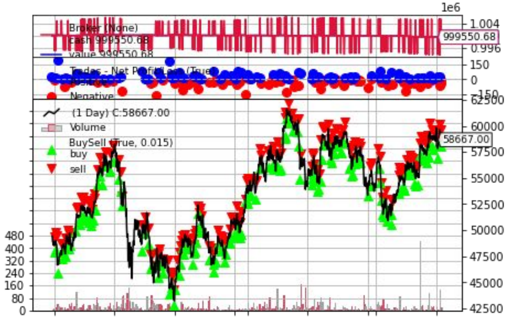
XGBoost
(Optimized gradient boosting library)
Sharpe ratio: 2.54





Recurrent Neural Network
(For series data prediction; uses LSTM*)
Sharpe ratio: 2.69





Machine Learning Models

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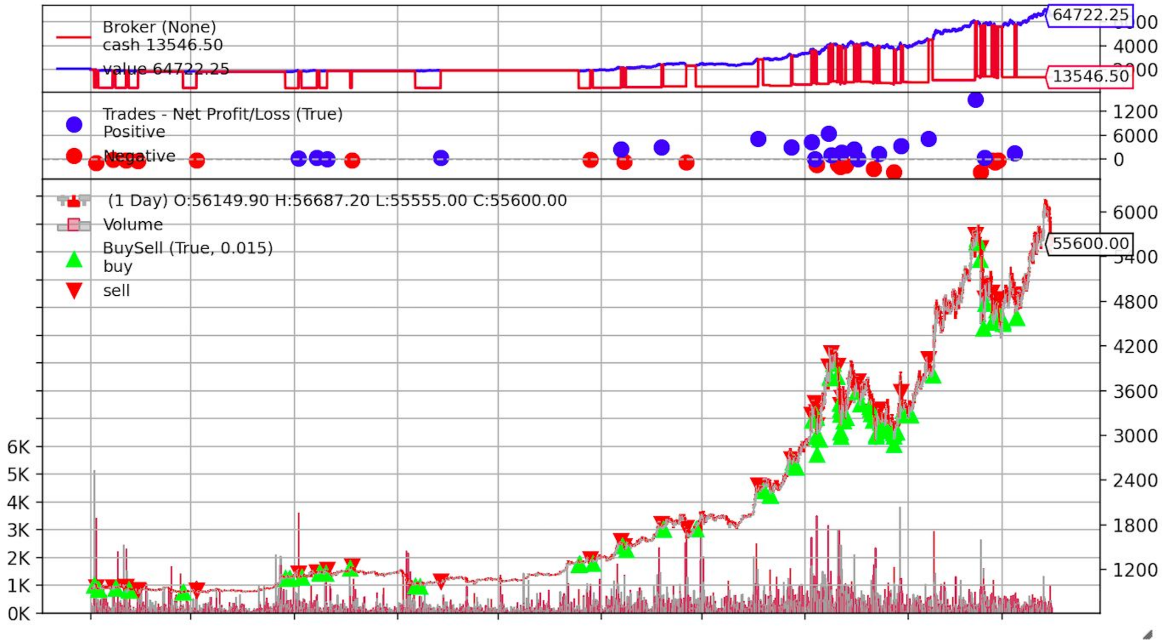
Strategy execution

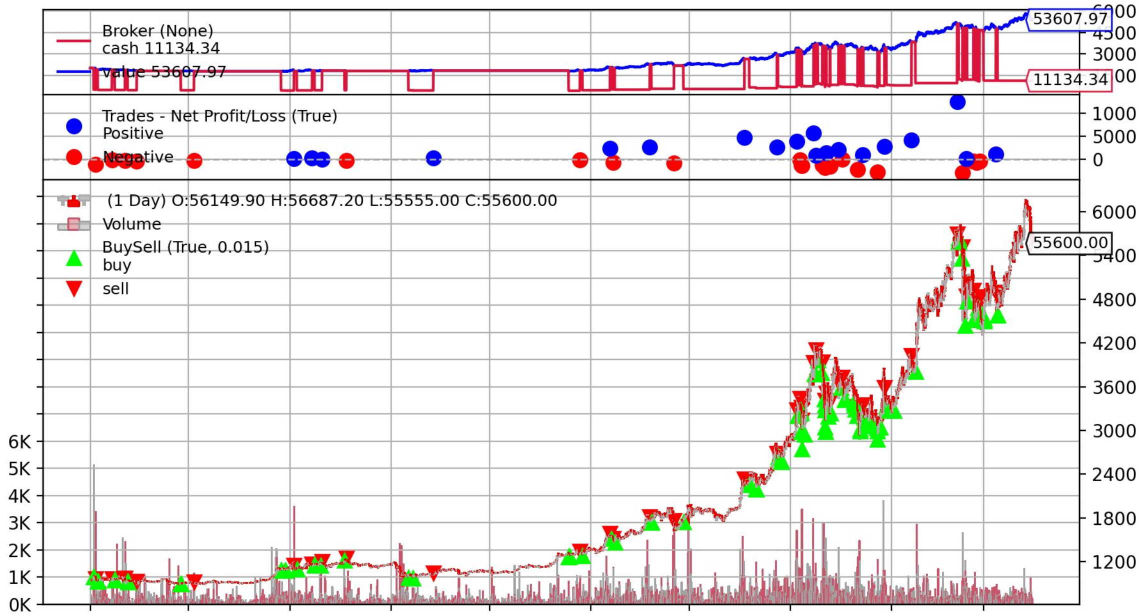
- $20,000 to start
- Add stop-loss bounds (if you lose 10% of initial capital, sell out of position)
- Buy a fraction of a coin up to $1,000 dollars per trade



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