Spectral Temporal Graph Neural Network for Multivariate Time-series Forecasting with applications to crypto data

Spectral Temporal Graph Neural Network for Multivariate Time-series Forecasting

Why:

- Graph based methods are now finding their use in finance
- Captures both inter- and intra-series correlations
- Converts multiple-time series to graph data structure through transformer based module
- Versatile framework

Spectral Temporal Graph Neural Network for Multivariate Time-series Forecasting

How it works

- The first step converts matrix X, a multiple time series table of size N × T in graph data structure, in particular, it returns a pair (X,W), where W is the adjacency matrix
- (Advantage) Constructing the adjacency matrix operation takes O(N^2 * d) (usually N is fixed and d is not a very large constant)
- The second step works with the obtained pair and applied so-called StemGNN block (this roughly does some inter and intra-series analysis)

Data

- Kaggle dataset with 400+ cryptocurrency pairs with resolution of 1 minute collected from Bitfinex exchange
- Observations are temporally misaligned
- 95110 observations for each of 12 cryptocurrencies: BTC, ZEC, OMG, UST, LEO, NEO, ETCIOT, EOS, XRP, LTC and ETH.
- We take 80% of the dataset for training, 10% for validation and the 10% for testing

Trading strategy

- Pairs trading statistical arbitrage strategy that aims at exploiting long-run relationships between asset prices X and U
- Need to calculate spread S=X - U, thresholds α_L for buying assets, α_S for selling and α_{exit} for exiting position.
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- Spread S=X-U is calculated and is used to fit the model. This model is used to make a 1 step prediction of spread, which is used to calculate expected spread change.

- If this change is less than the lowest threshold, α_S then we sell all of X and invest all in U If this change is larger than highest threshold α_L, sell all of U and invest in X
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- The portfolio is revalued on each day prior to any trades
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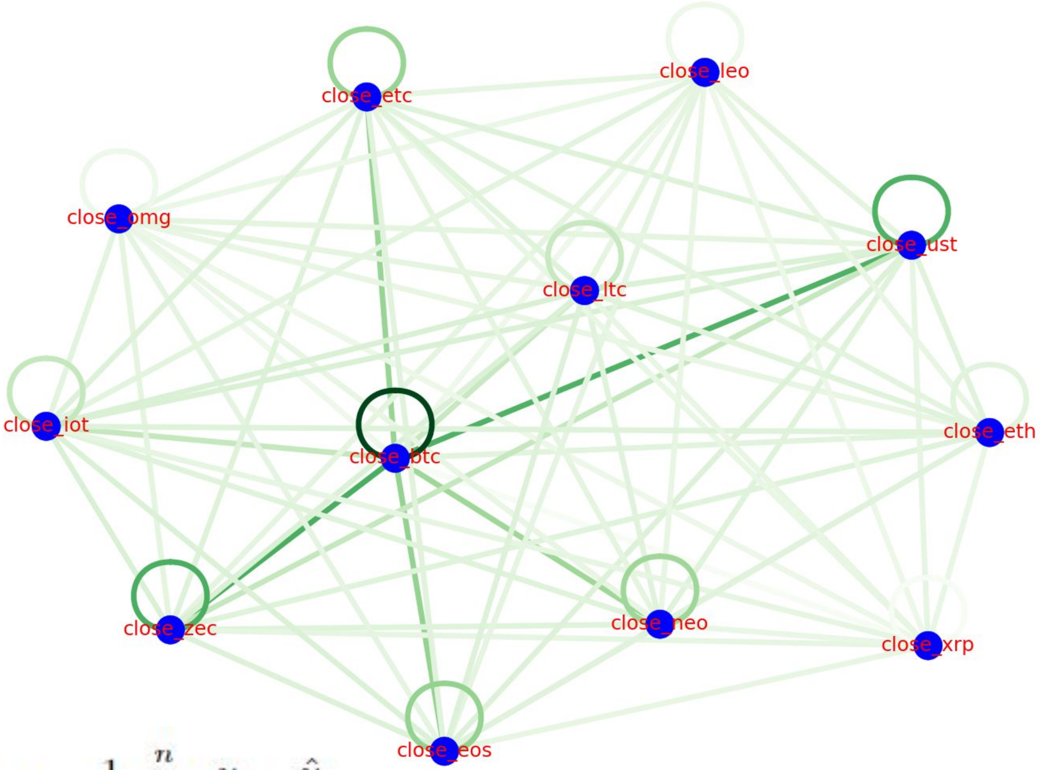
Results

Obtain the following graph (MAE 26.14, MAPE 0.01, RMSE 107.62)

Use minimum spanning tree and disparity filter to obtain backbone

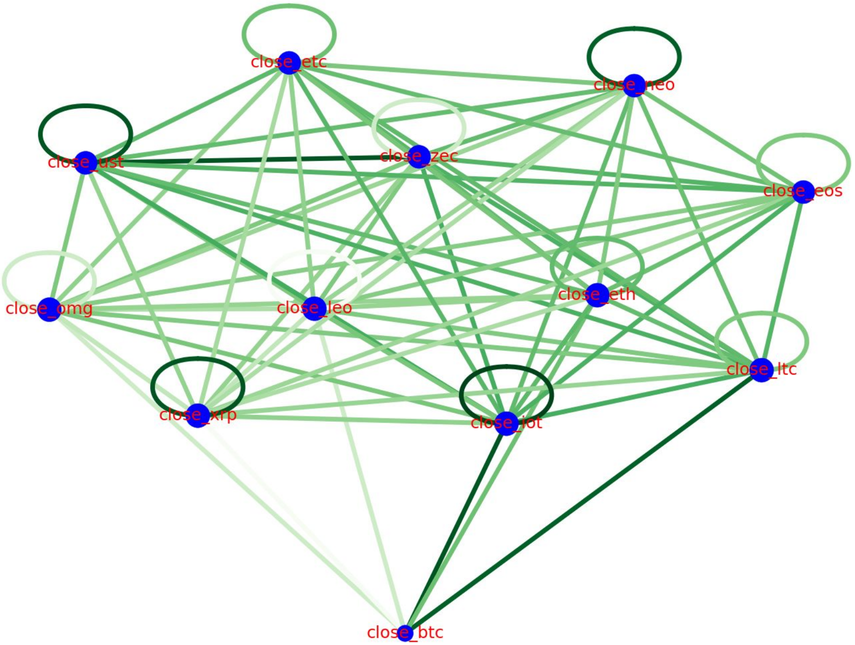
$$MAPE = \frac{1}{n}\sum_{i=1}^{n} |\frac{y_i - \hat{y}_i}{y_i}|$$



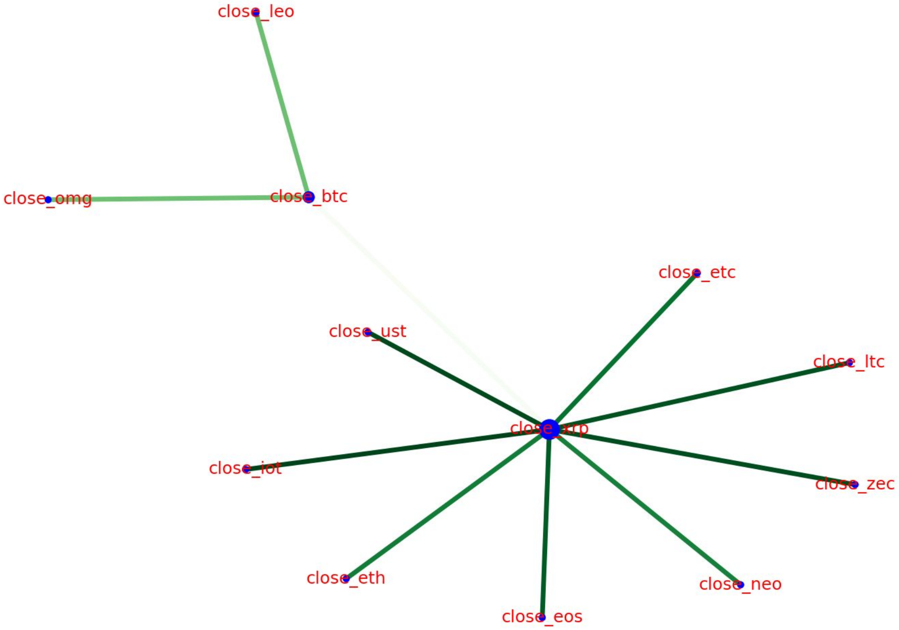
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad MAPE = \frac{1}{n}\sum_{i=1}^{n} |\frac{y_i - \hat{y}_i}{y_i}|$$

Results

Disparity filter



Minimum spanning tree



Results

Based on the graph constructed from adjacency matrix W, we identified the following cryptocurrencies with the highest correlation from which 3 pairs were constructed based on validation dataset: BTC, ZEC and UST

We use ARIMA(1,0,1) as baseline model

$$y_t = a_0 + a_1 y_{t-1} + b_1 e_1$$

StemGNN seems to underperform in comparison with simple ARIMA model, since it does not identify any profitable pairs while ARIMA finds BTC-ZEC and BTC-UST profitable

Pair	StemGNN return (%)	ARIMA return (%)
BTC-ZEC	-1.20	1.00
BTC-UST	-0.10	1.00
ZEC-UST	-0.10	-1.18

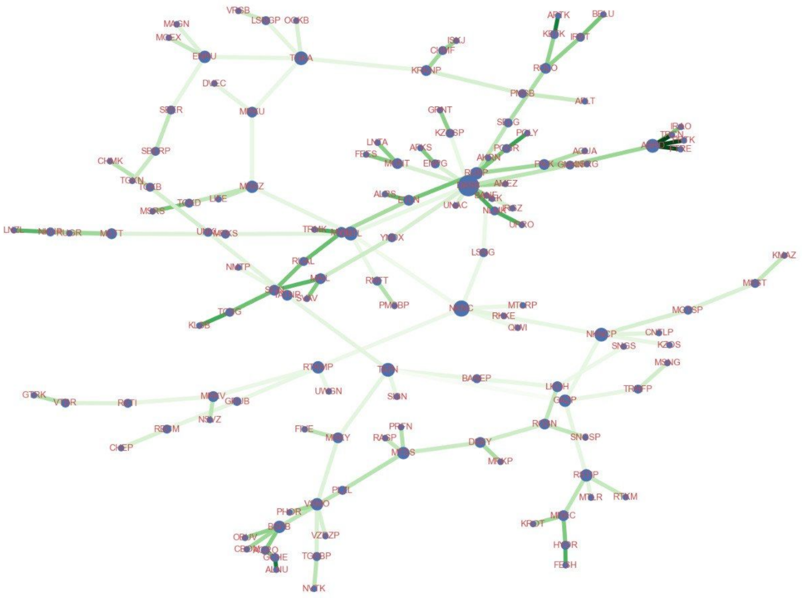
Social Network Analysis for stocks: additional case study

- We study a more classical approach of SNA applied to daily stock data
- Motivation: capture more fundamental properties that are not present in higher frequency
- Data is simpler (and aligned which is perfect). Data was collected for Russian stocks from 2010 to 2020 september on daily basis
- Interesting to combine with other approaches such classical time series analysis and classical machine learning such as boosting

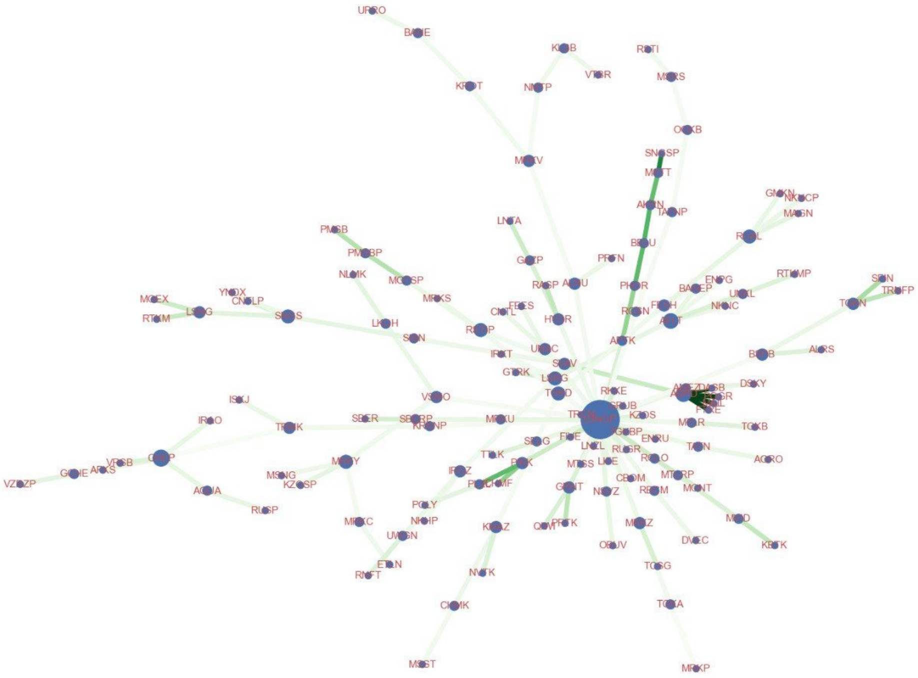
Social Network Analysis for stocks: results

- By using graph-based methods we can analyze stock data in a form of a network
- This gives opportunities to generate statistically significant features and do an interpretable analysis

Social Network Analysis for stocks: results

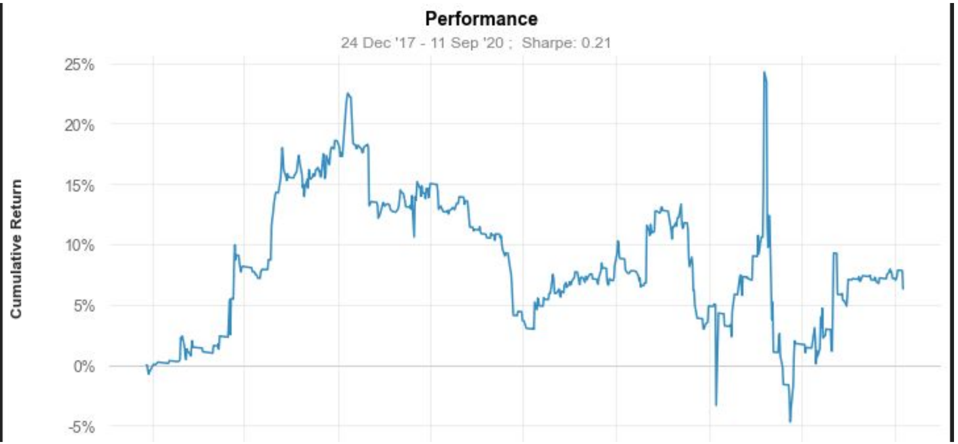


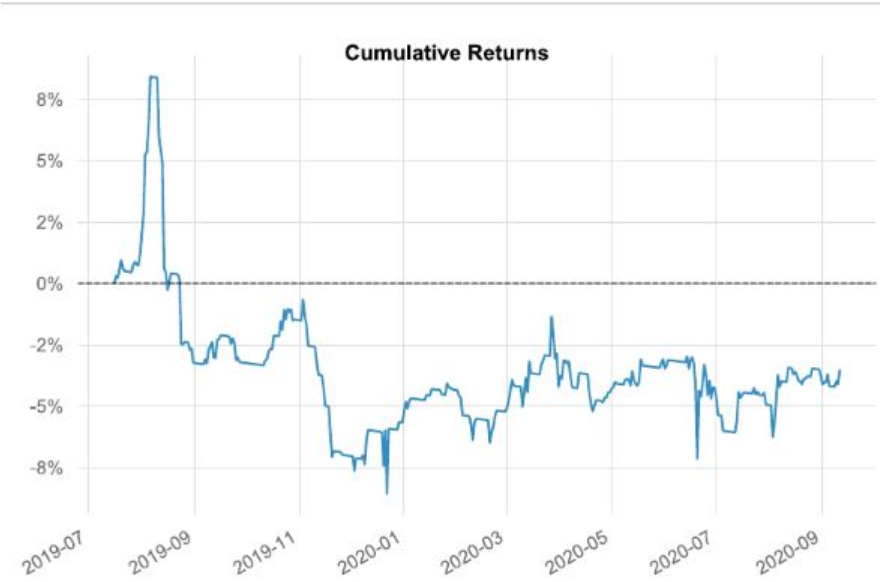
Network of Russian stocks 5 months prior to coronavirus crisis



Network of Russian stocks during the peak of coronavirus crisis in March-April

Social Network Analysis for stocks: results





Performance of dynamic portfolio allocation strategy with network-based features

Performance of dynamic portfolio allocation strategy based on basic time series analysis