



SPECTRAL CLUSTERING AND CRYPTO CURRENCY NETWORK STRUCTURE

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MSCF ML II Group Project



Paper replication



Spectral Clustering



Applications to Crypto



Further Research

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Paper Replication

Spectral Clustering

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Further Research

Data

Eigenspectra

Dissimilarities

Minimal Spanning Trees

Observations

Analysis of a network structure of the foreign currency exchange market

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Stanisław Drożdż · Andrzej Górski

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Abstract We analyze structure of the world foreign currency exchange (FX) market viewed as a network of interacting currencies. We analyze daily time series of FX data for a set of 63 currencies, including gold, silver and platinum. We group together all the exchange rates with a common base currency and study each group separately. By applying the methods of filtered correlation matrix we identify clusters of closely related currencies. The clusters are formed typically according to the economical and geographical factors. We also study topology of weighted minimal spanning trees for different network representations (i.e., for different base currencies) and find that in a majority of representations the network has a hierarchical scale-free structure. In addition, we analyze the temporal evolution of the network and detect that its structure is not stable over time. A medium-term trend can be identified which affects the USD node by decreasing its centrality. Our analysis shows also an increasing role of euro in the world's currency market.

Keywords Foreign exchange market · Correlation matrix · Networks · Minimal Spanning Tree

- The FX market can be viewed as a **network of interacting exchange rates**.
- Interactions are assumed to be **strongly nonlinear**.
- There can be no **independent frame of reference**.

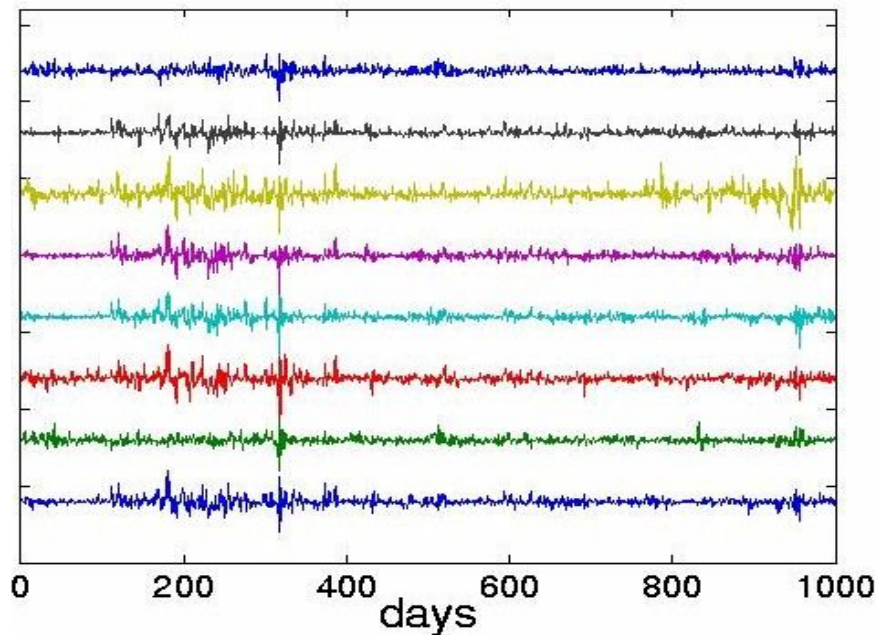
DATA

- 60 most traded currencies
- 3 precious metals (XAG, XAU, PTC)
- From/To: Jan 1999 - Jun 2008 (9.5 yr)
- Daily data: 5 days a week
- 2,394 observations



EXCHANGE RATE EIGENSPECTRA

1) Select base currency. $N \times N$ matrix X



2) Compute correlation matrix.

3) Compute eigenvalues.

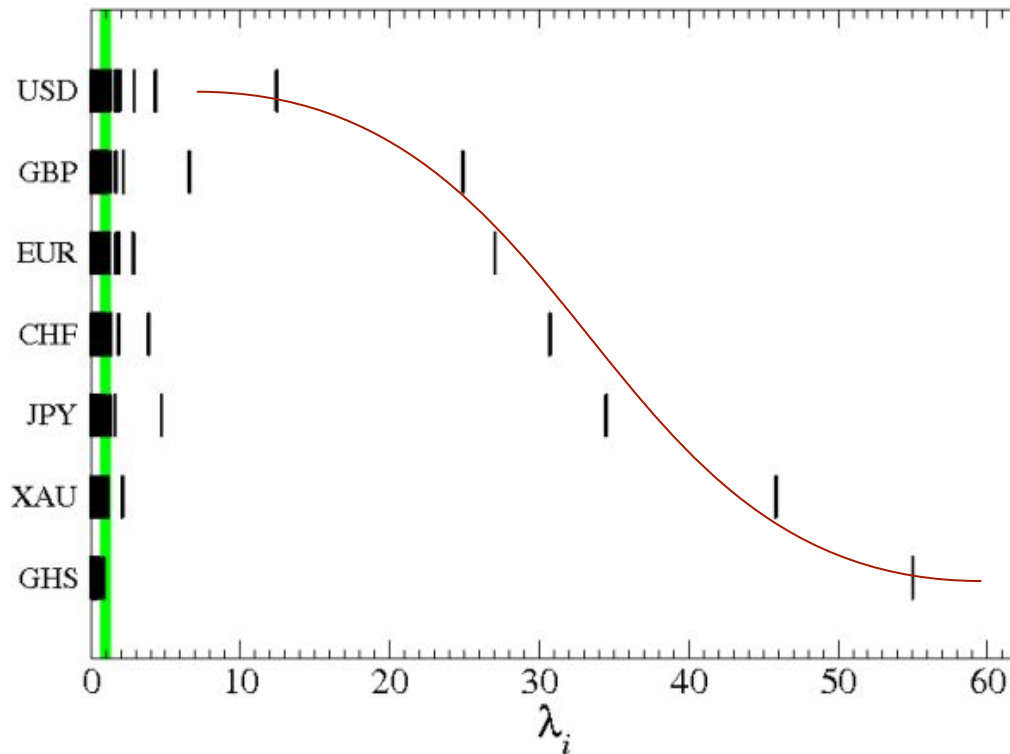
3) Inspect **largest eigenvalue**.

EXCHANGE RATE EIGENSPECTRA

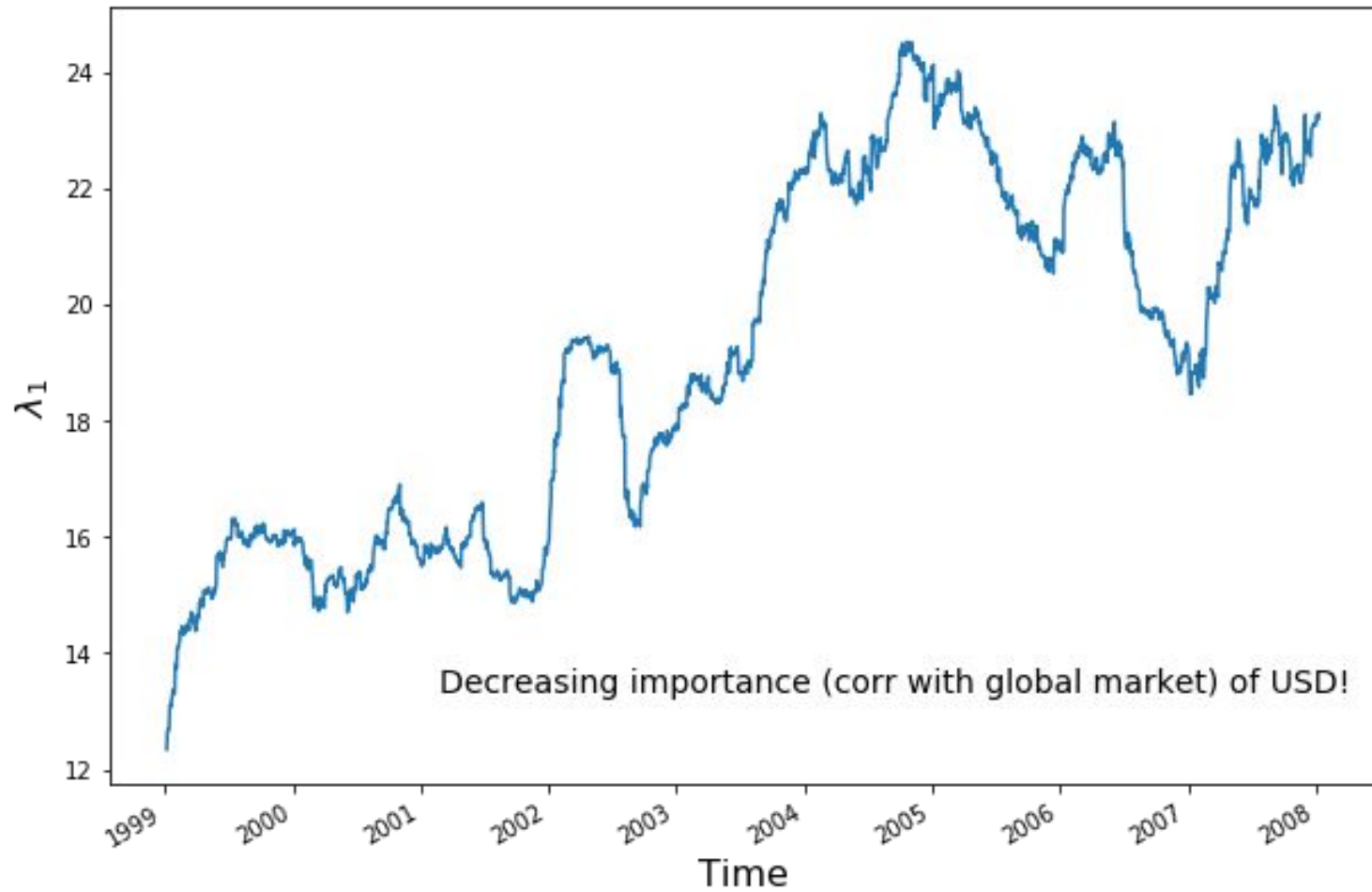
$$0 = \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_N$$



- Small max eigenvalue:
Central currency.
- Large max eigenvalue:
Peripheral currency.

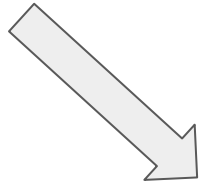


λ_1 over Time

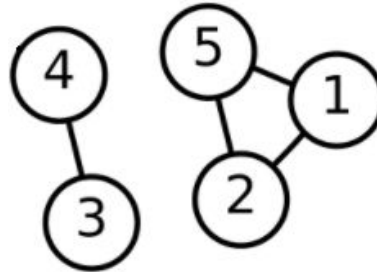
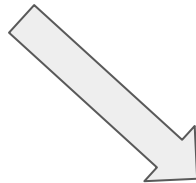


CLUSTER STRUCTURE

$$C = \begin{pmatrix} 1 & 0.6 & 0.2 & 0.2 & 0.8 \\ 0.6 & 1 & 0.3 & 0.1 & 0.6 \\ 0.2 & 0.3 & 1 & 0.7 & 0 \\ 0.2 & 0.1 & 0.7 & 1 & 0.4 \\ 0.8 & 0.6 & 0 & 0.4 & 1 \end{pmatrix}$$



$$T = \begin{pmatrix} 1 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 \end{pmatrix}$$



1) Correlation matrix.



2) Threshold by ρ .

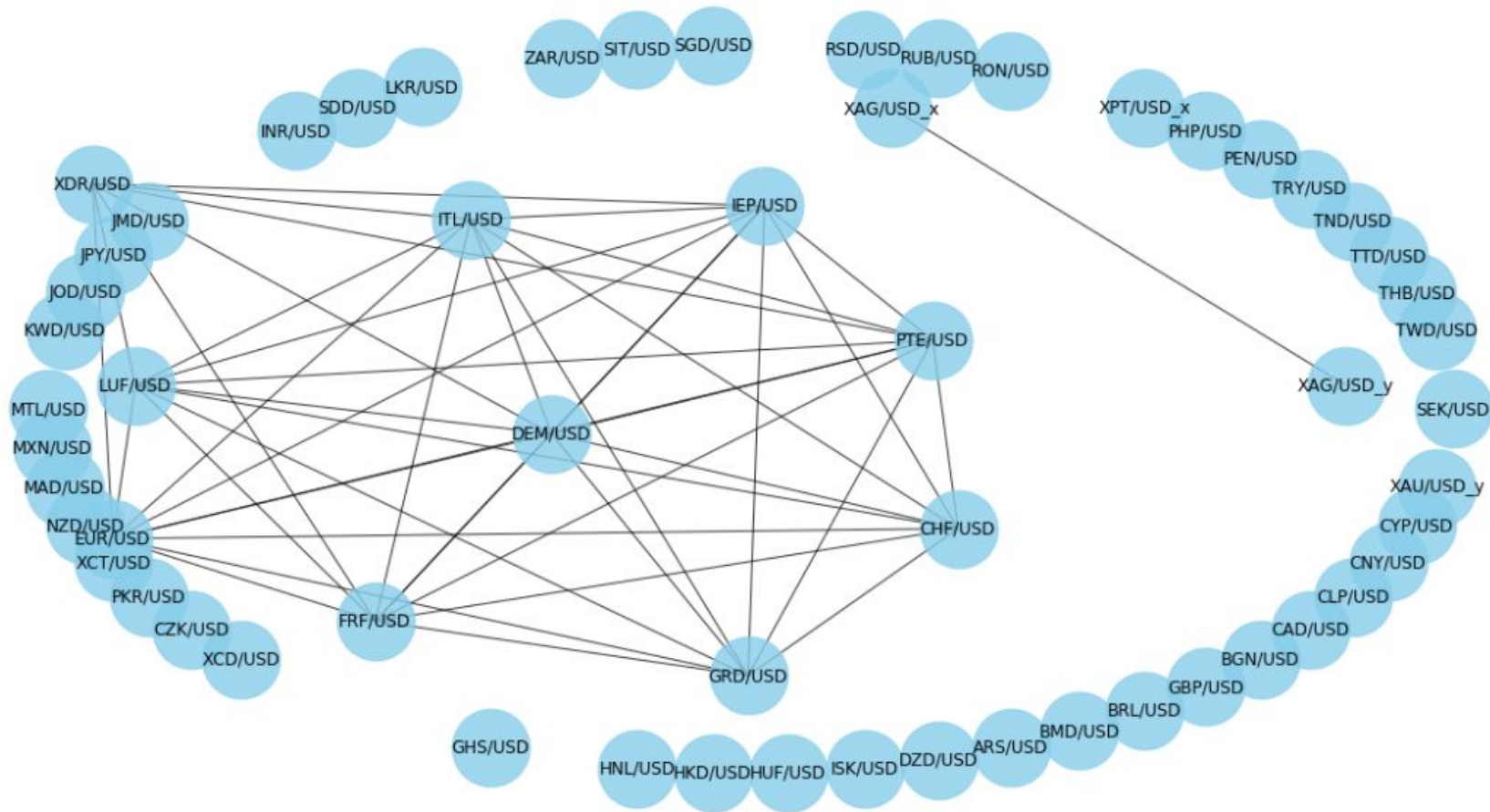


3) Draw links.

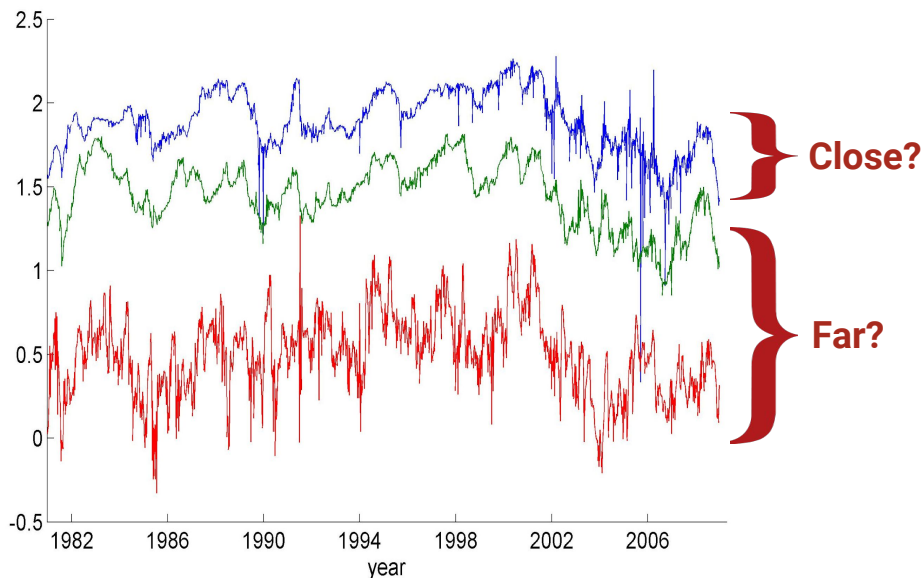


4) Try different bases.

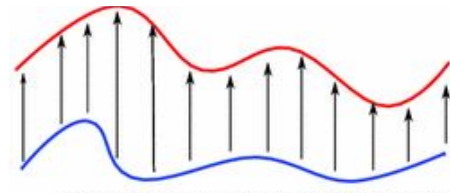
$$p_c = 0.90$$



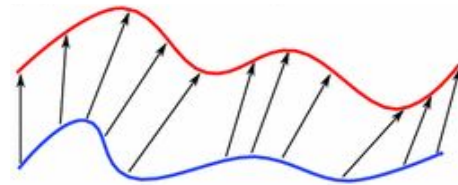
DISSIMILARITY OF EXCHANGE RATES



- Euclidean distance (bad).



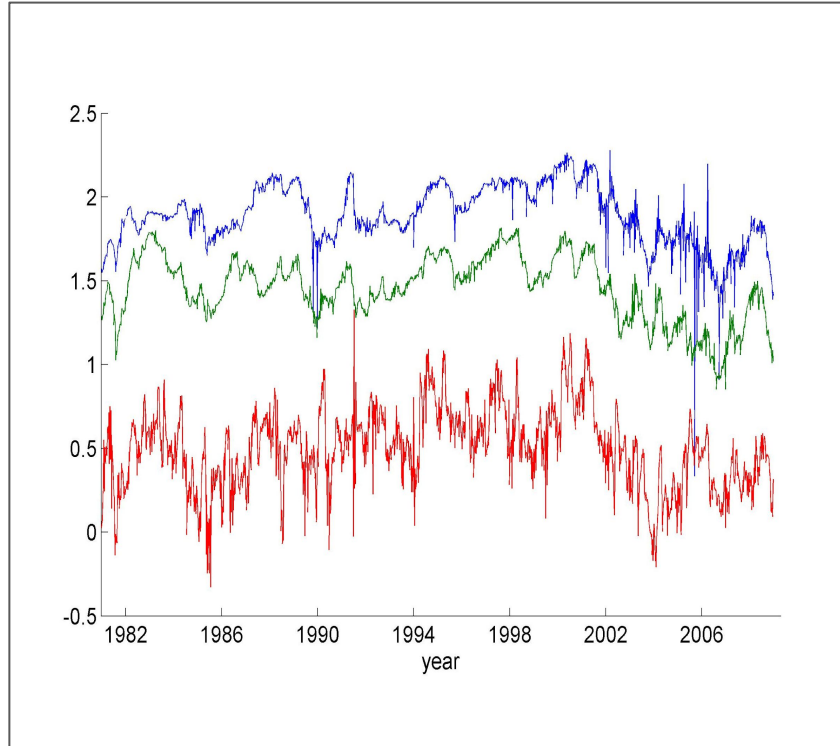
- DTW/MJC (okay).



- Pearson dissimilarity (good).

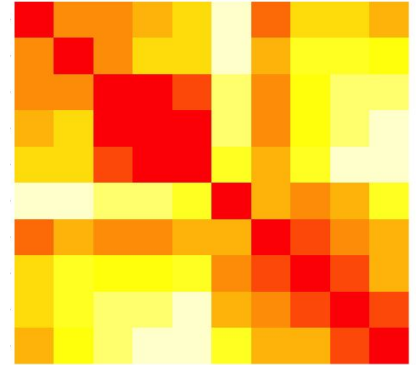
$$d_{X,Y}^B = \sqrt{2(1 - C_{X,Y}^B)}.$$

DISSIMILARITY OF EXCHANGE RATES



$$d_{X,Y}^B = \sqrt{2(1 - C_{X,Y}^B)}.$$

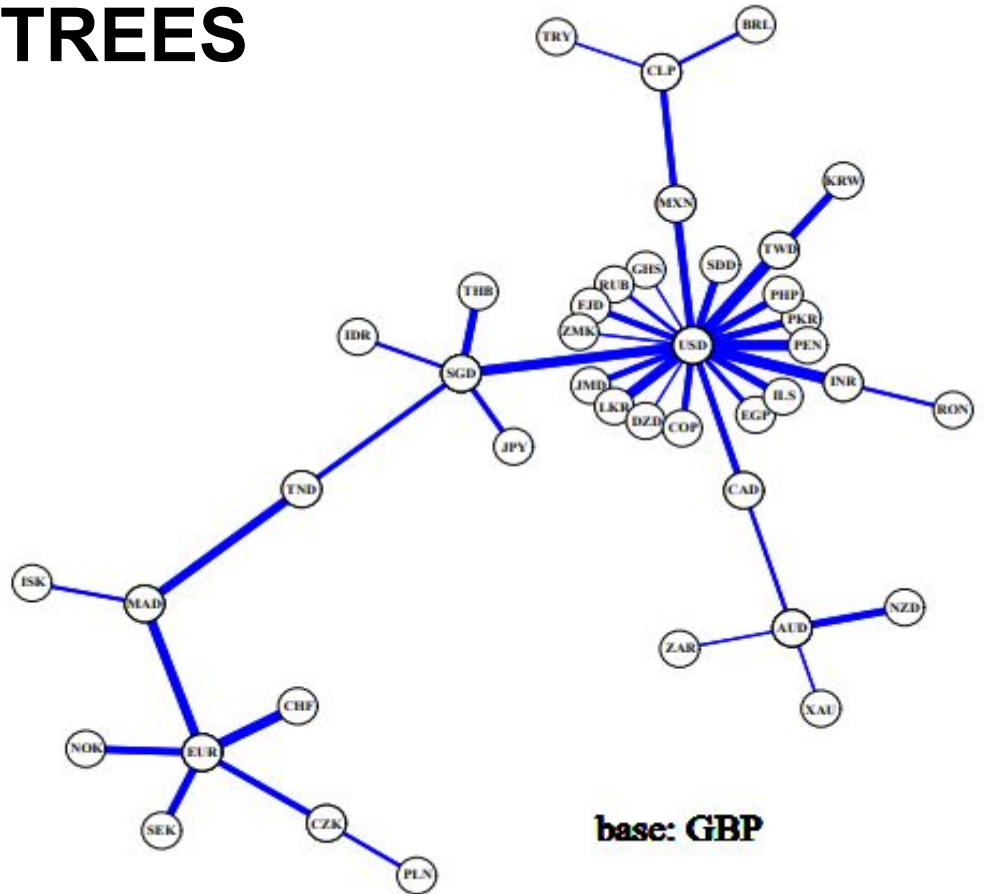
Dissimilarity matrix



MINIMAL SPANNING TREES

$$\begin{bmatrix} 0 \\ d(2,1) & 0 \\ d(3,1) & d(3,2) & 0 \\ \vdots & \vdots & \vdots \\ d(n,1) & d(n,2) & \dots & \dots & 0 \end{bmatrix}$$

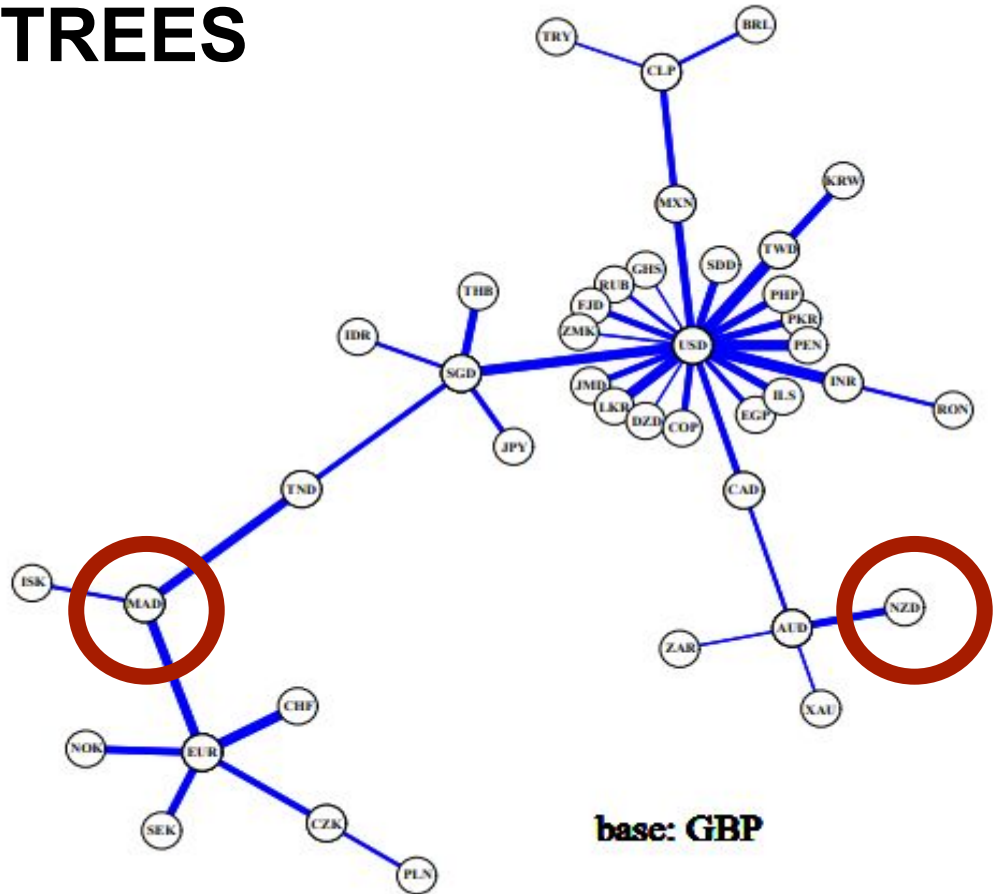
$$\begin{bmatrix} 0 \\ d(2,1) & 0 \\ d(3,1) & d(3,2) & 0 \\ \vdots & \vdots & \vdots \\ d(n,1) & d(n,2) & \dots & \dots & 0 \end{bmatrix}$$



MINIMAL SPANNING TREES

$$\begin{bmatrix} 0 \\ d(2,1) & 0 \\ d(3,1) & d(3,2) & 0 \\ \vdots & \vdots & \vdots \\ d(n,1) & d(n,2) & \dots & \dots & 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 \\ d(2,1) & 0 \\ \text{red} & \text{red} & 0 \\ \text{red} & \text{red} & \vdots \\ d(n,1) & d(n,2) & \text{red} & \dots & 0 \end{bmatrix}$$

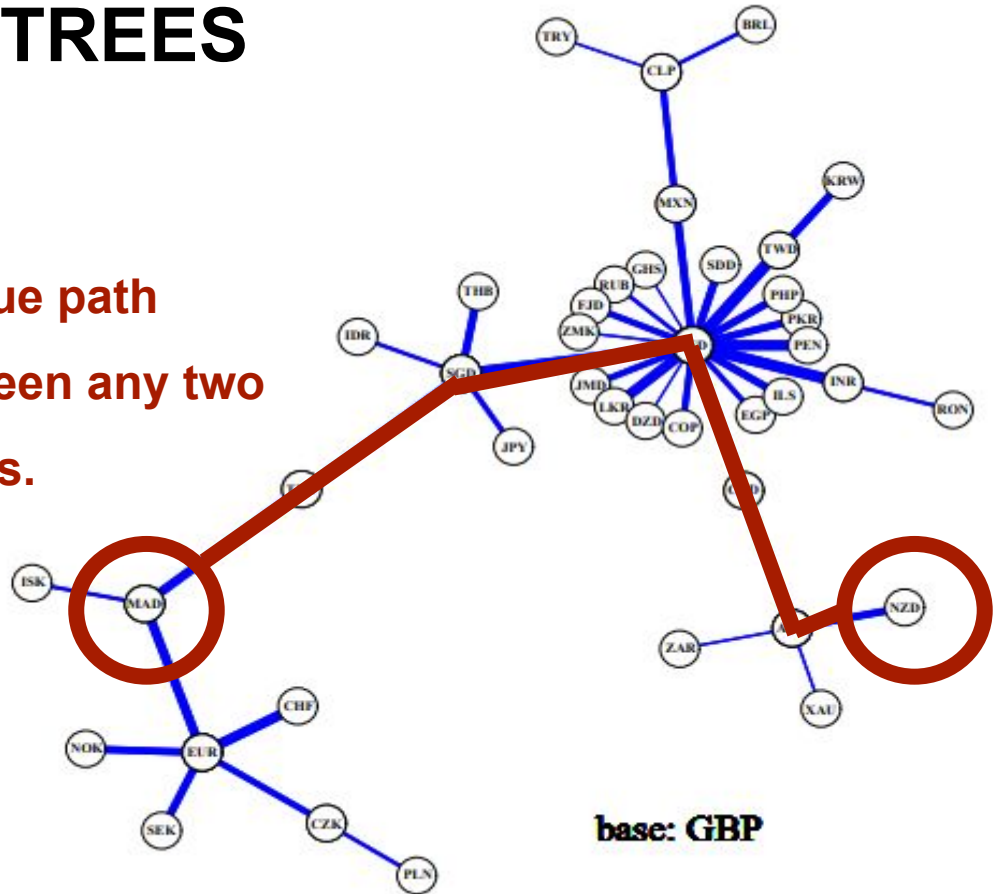


MINIMAL SPANNING TREES

$$\begin{bmatrix} 0 \\ d(2,1) & 0 \\ d(3,1) & d(3,2) & 0 \\ \vdots & \vdots & \vdots \\ d(n,1) & d(n,2) & \dots & \dots & 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 \\ d(2,1) & 0 \\ d(3,1) & d(3,2) & 0 \\ \vdots & \vdots & \vdots \\ d(n,1) & d(n,2) & \dots & \dots & 0 \end{bmatrix}$$

Unique path
between any two
nodes.



OBSERVATIONS

- Thresholding 'C' cluster analysis indicated relationships among:
 - Precious metals
 - European legacy currencies and the Euro
- Spectral clustering indicated relationships among:
 - Jordan Dinar and Kuwaiti Dinar given pegged to USD relationship (2003-2007)
 - Kuwaiti Dinar and a basket of global currencies (2007-Present)





Paper Replication



Spectral Clustering

Introduction

Laplacian

Interpretation



Applications to Crypto



Further Research

INTRO TO SPECTRAL CLUSTERING

- Most traditional clustering methods
 - Perform poorly on non-convex data: “non-blobs”
 - Have difficulty with high dimensional data
- Time series data has both of these qualities
- Spectral clustering fixes these issues!
- Steals from well developed graph theory ideas

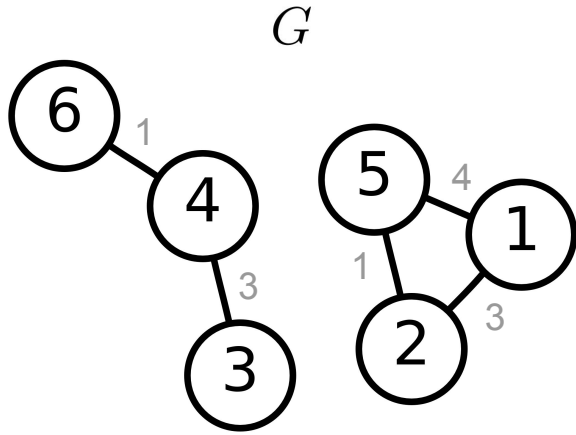


K-means



Mean Shift

BUILDING BLOCKS



$$W = \begin{pmatrix} 0 & 3 & 0 & 0 & 4 & 0 \\ 3 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 3 & 0 & 0 & 0 \\ 4 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

$$D = \begin{pmatrix} 7 & 0 & 0 & 0 & 0 & 0 \\ 0 & 4 & 0 & 0 & 0 & 0 \\ 0 & 0 & 3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 5 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

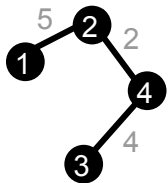
Note: Each subgraph making up G is a so called *connected component*

PROPERTIES OF LAPLACIAN MATRIX

$$L = D - W$$

1. L is symmetric and positive semi-definite
2. Row and columns sum to 0
3. N non-negative eigenvalues $0 = \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_N$
4. $f'Lf = \frac{1}{2} \sum_{i,j=1}^N w_{ij}(f_i - f_j)^2 \quad \forall f \in \mathbb{R}^N$
5. **Multiplicity of eigenvalue 0 equals the number of connected components**

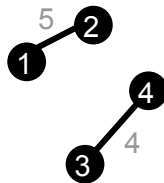
WHY IT WORKS



$$L_f = \begin{pmatrix} 5 & -5 & 0 & 0 \\ -5 & 6 & 0 & -1 \\ 0 & 0 & 4 & -4 \\ 0 & -1 & -4 & 5 \end{pmatrix}$$

$$0 = \lambda_1^f < \lambda_2^f \leq \dots \leq \lambda_N^f$$

$$v_1^f = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$



$$L_d = \begin{pmatrix} 5 & -5 & 0 & 0 \\ -5 & 5 & 0 & 0 \\ 0 & 0 & 4 & -4 \\ 0 & 0 & -4 & 4 \end{pmatrix}$$

$$0 = \lambda_1^d = \lambda_2^d < \lambda_3^d \leq \dots \leq \lambda_N^d$$

$$v_1^d = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

$$v_2^d = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix}$$

ALGORITHM

Algorithm 1 Spectral Clustering

Input: Weighted adjacency matrix $W \in \mathbb{R}^{N \times N}$, number of clusters k

Compute degree matrix D

$L \leftarrow D - W$

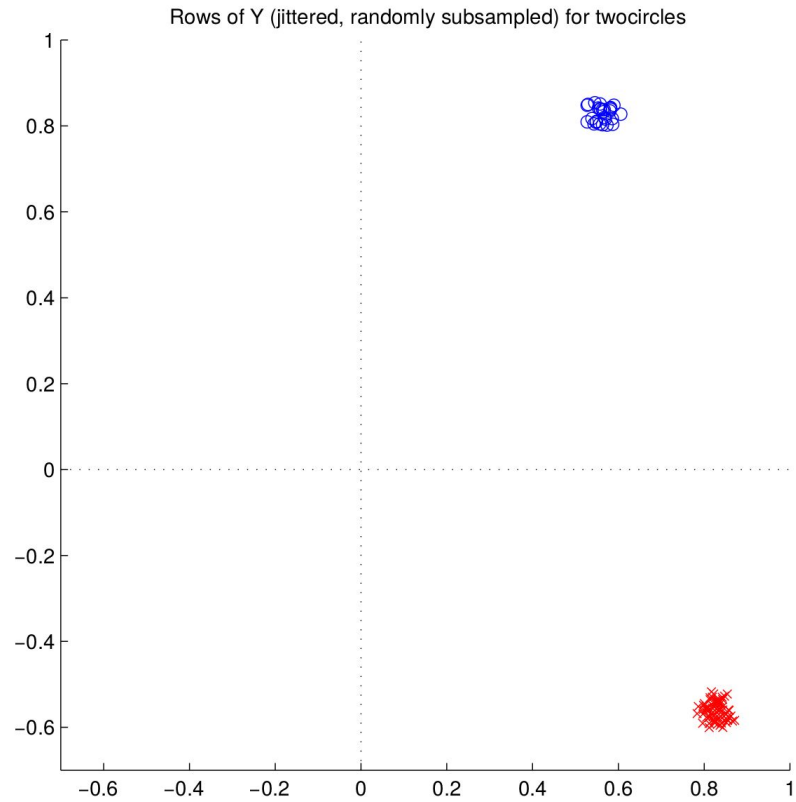
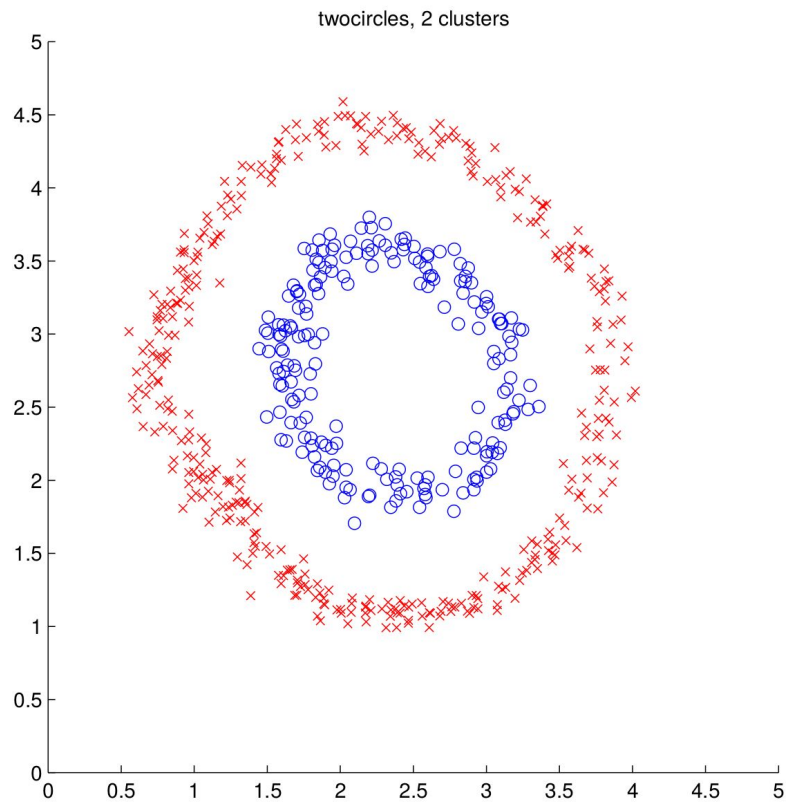
Compute first k eigenvectors v_1, \dots, v_k of L and stack them into $X \in \mathbb{R}^{N \times k}$

$y_i \leftarrow$ normalized i th row of X (note: $y_i \in \mathbb{R}^k$)

Cluster $(y_i)_{i=1, \dots, n}$ into clusters C_1, \dots, C_k using k-means

Output: Clusters A_1, \dots, A_k where $A_i = \{j | y_j \in C_i\}$

HOW IT WORKS





Paper Replication

Spectral Clustering

Applications to Crypto

Further Research

Data

Analysis

Observations

Conclusion

DATA

- 18 crypto currencies
- USD
- One exchange: Poloniex
- From/To: Jul 2017 - Apr 2018 (10 mo.)
- Hourly data 24/7
- 7,167 observations



BITCOIN



DASH



RIPPLE



NEO



OMISEGO



IOTA



ETHEREUM



ZCASH



LITECOIN



DOGECOIN



STRATIS



MONERO



**ETHEREUM
CLASSIC**



NXT



STEEM



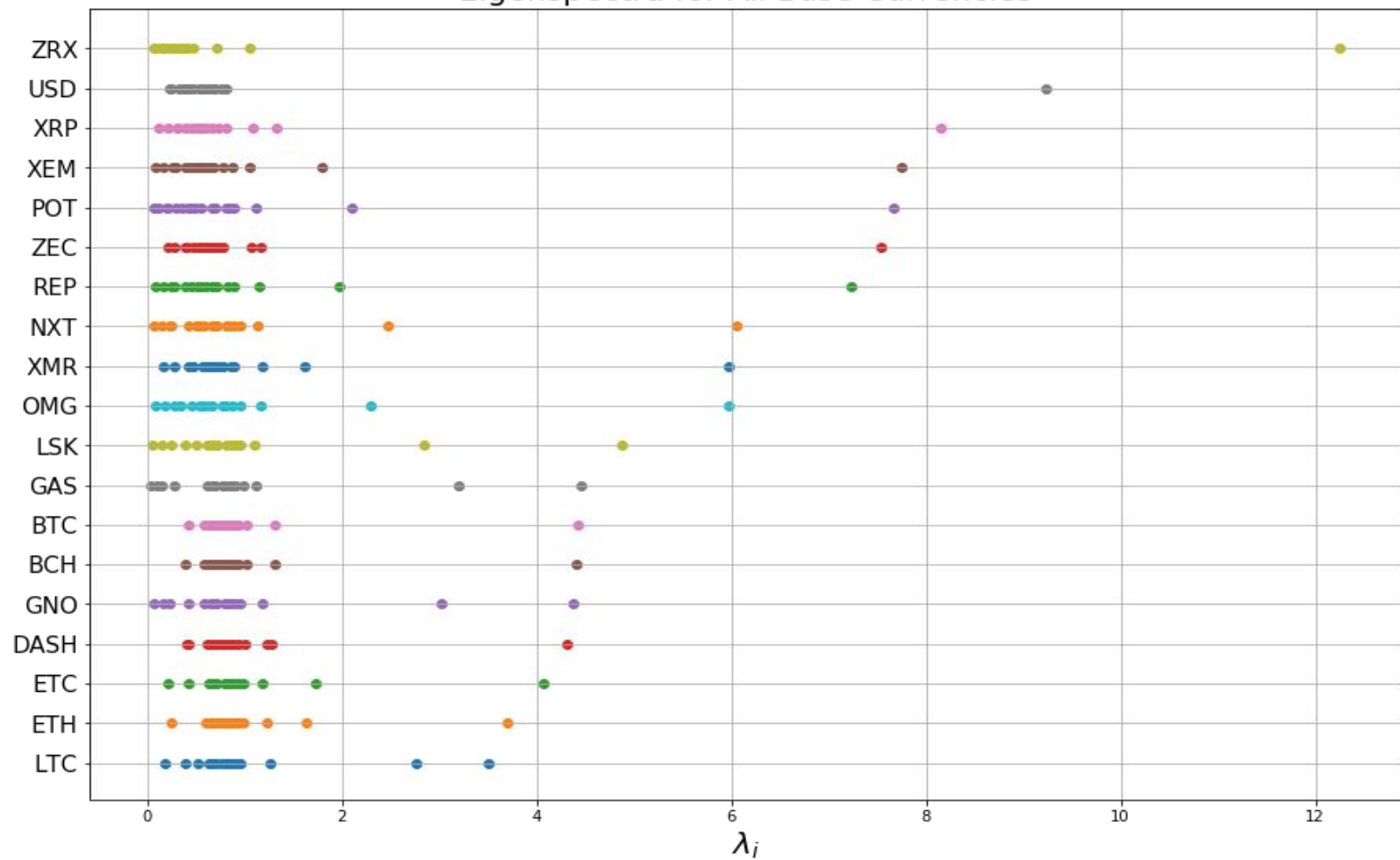
ARK

ANALYSIS & CONCLUSIONS

- Important dynamics shaping crypto markets:
 - “Bridge Currencies” and “Niche Currencies”
 - Differentiated Investment and Speculative Investment
- The eigenspectra analysis highlighted:
 - Relatively large max eigenvalues for USD and XRP
 - Relative small max eigenvalues for Bridge Currencies
 - BTC, LTC, ETH, BCH



Eigenspectra for All Base Currencies

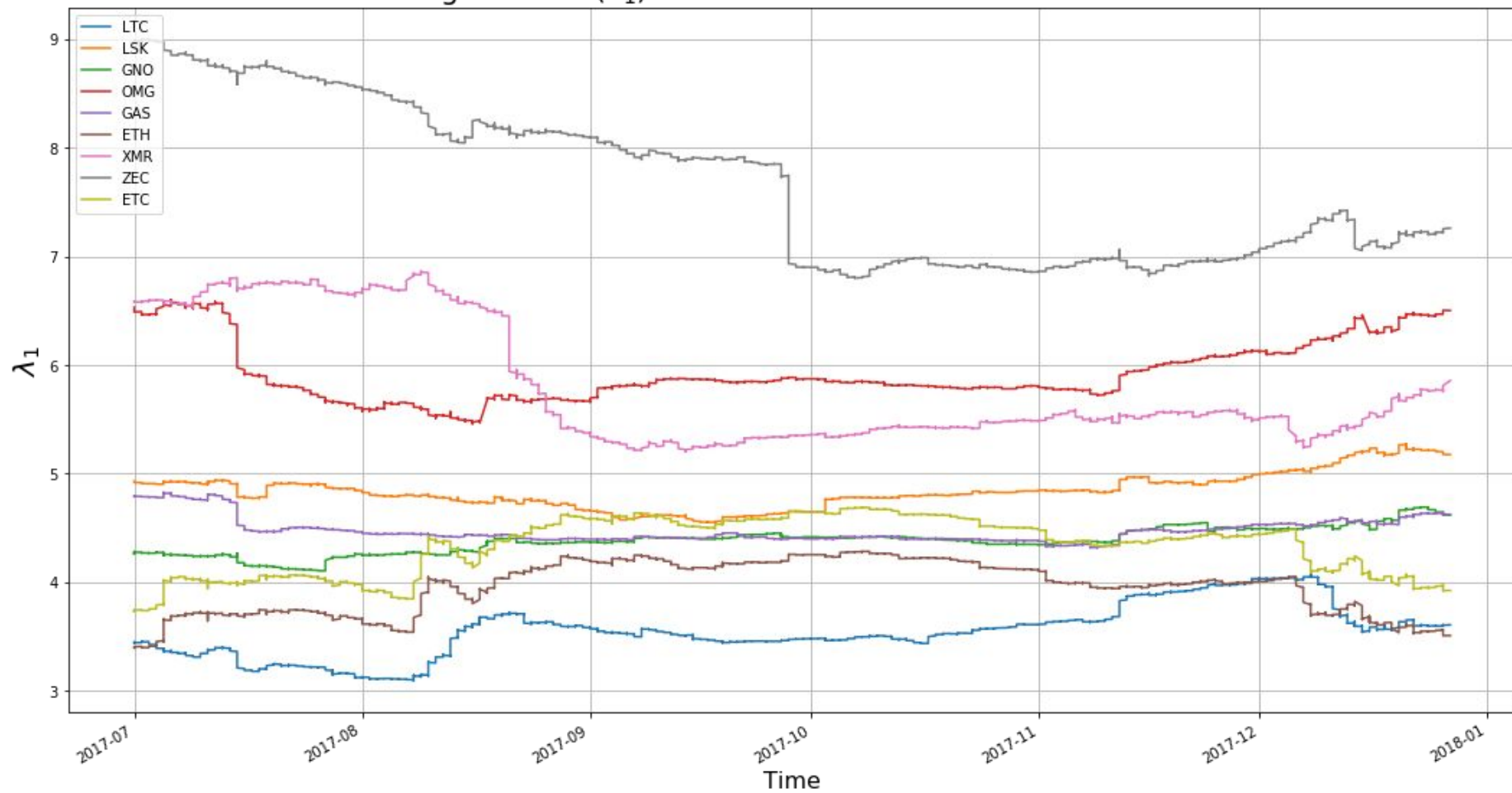


ANALYSIS & CONCLUSIONS

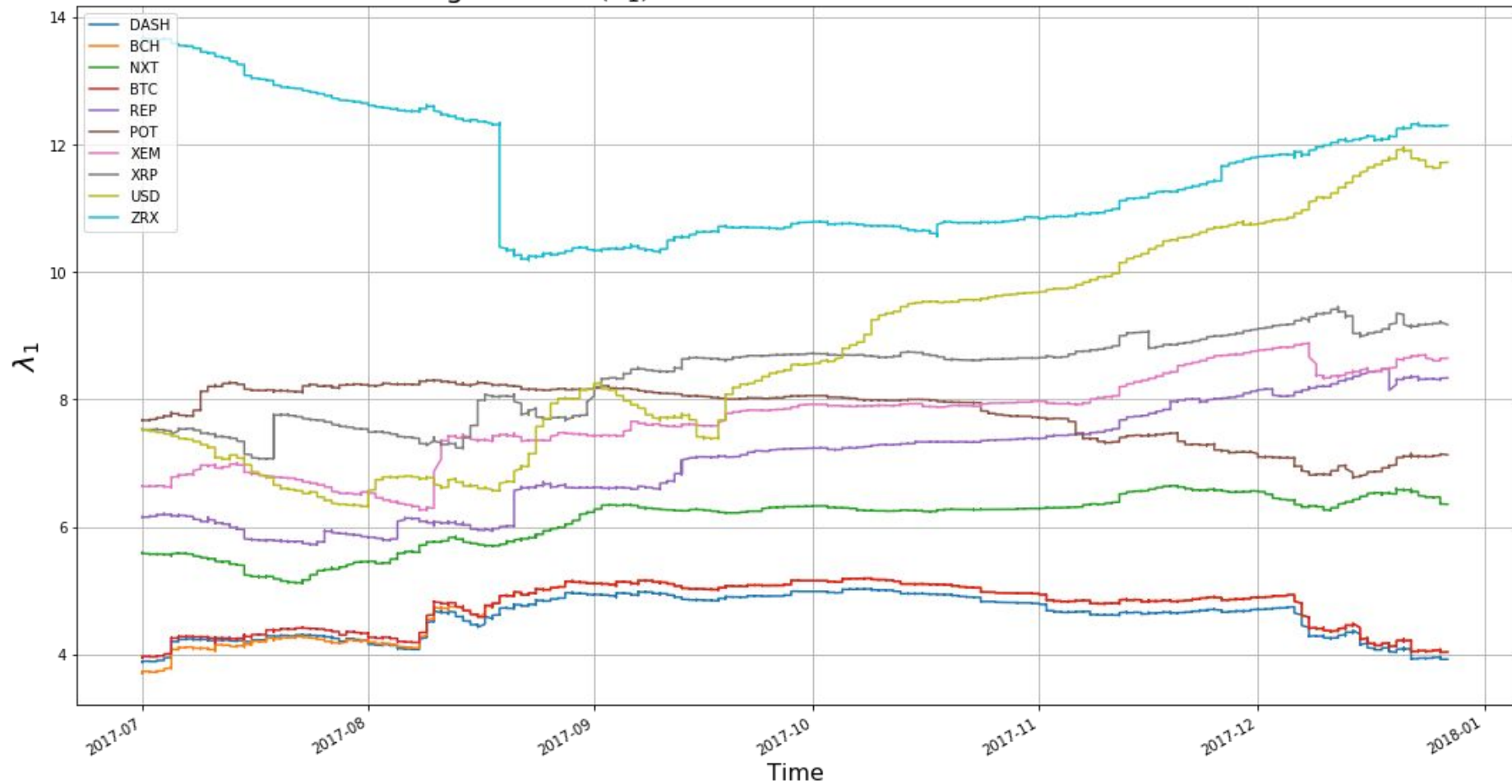
- The eigenspectra converged over time due to the influx of speculative capital
 - Sharp decreases in max eigenvalue associated with shock events in cryptocurrency price
- Spectral clustering and minimal spanning tree analysis indicate:
 - Unique relationships with ETH base
 - Unexpected relationship between BTC and ZEC



Max Eigen Value (λ_1) Over Time for All Bases in Baskets 1 & 2

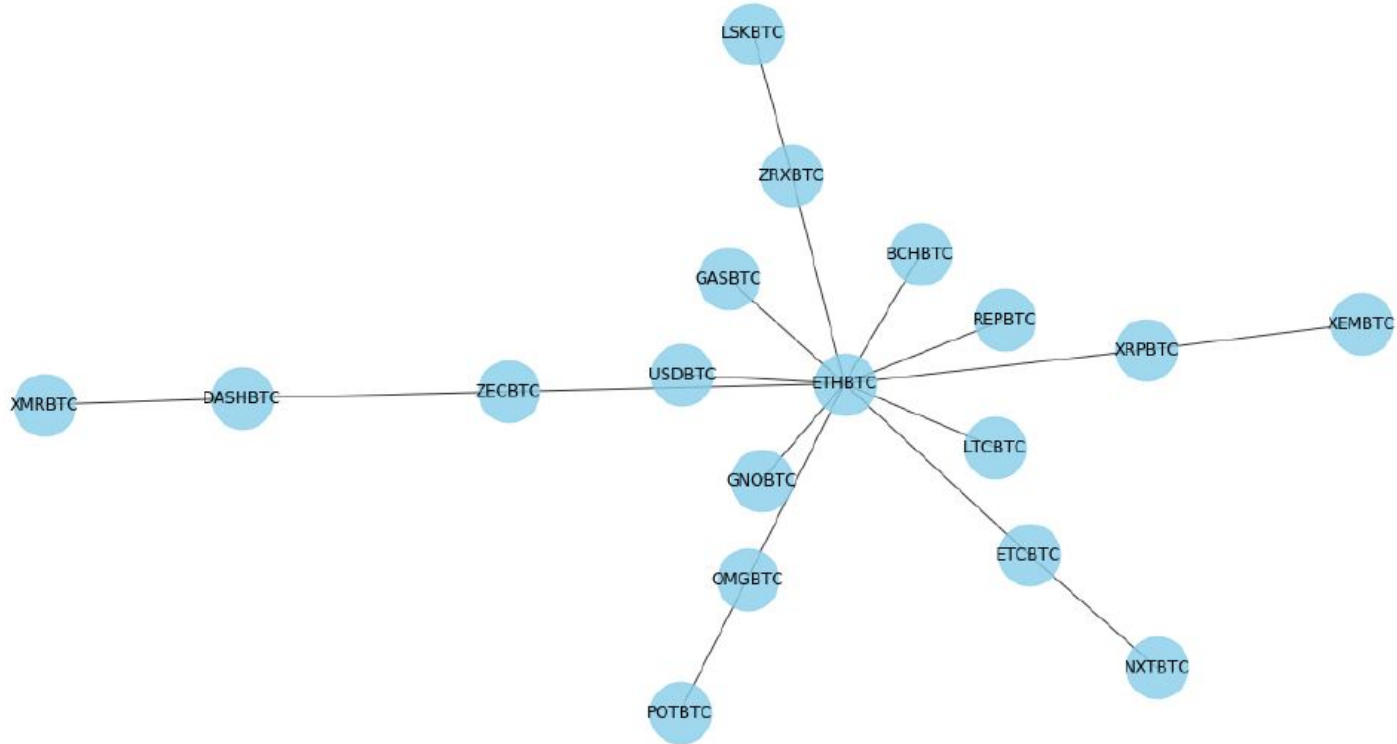


Max Eigen Value (λ_1) Over Time for All Bases in Baskets 2 & 4



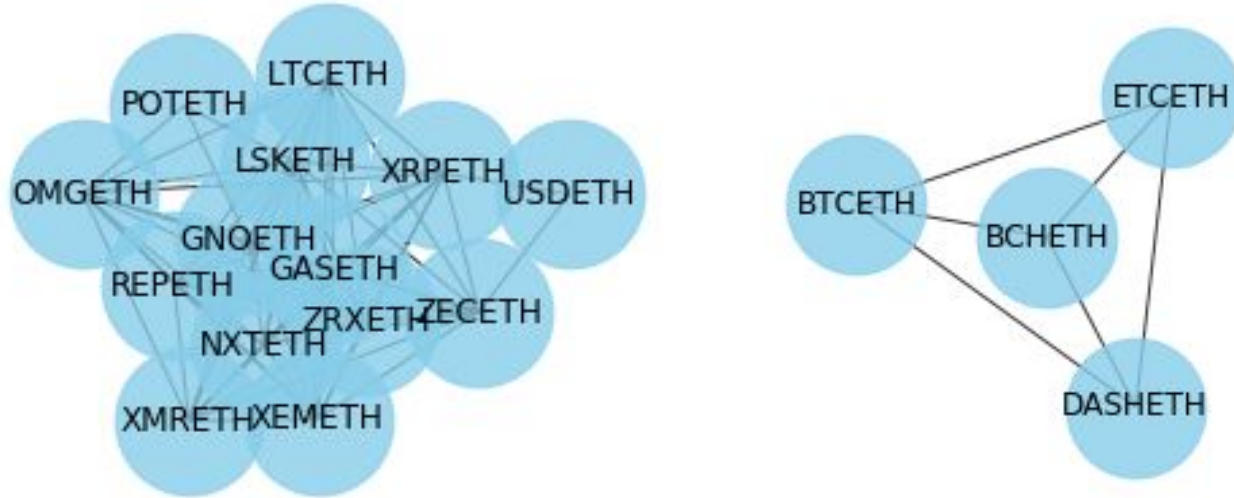
MINIMAL SPANNING TREES

BTC Base:



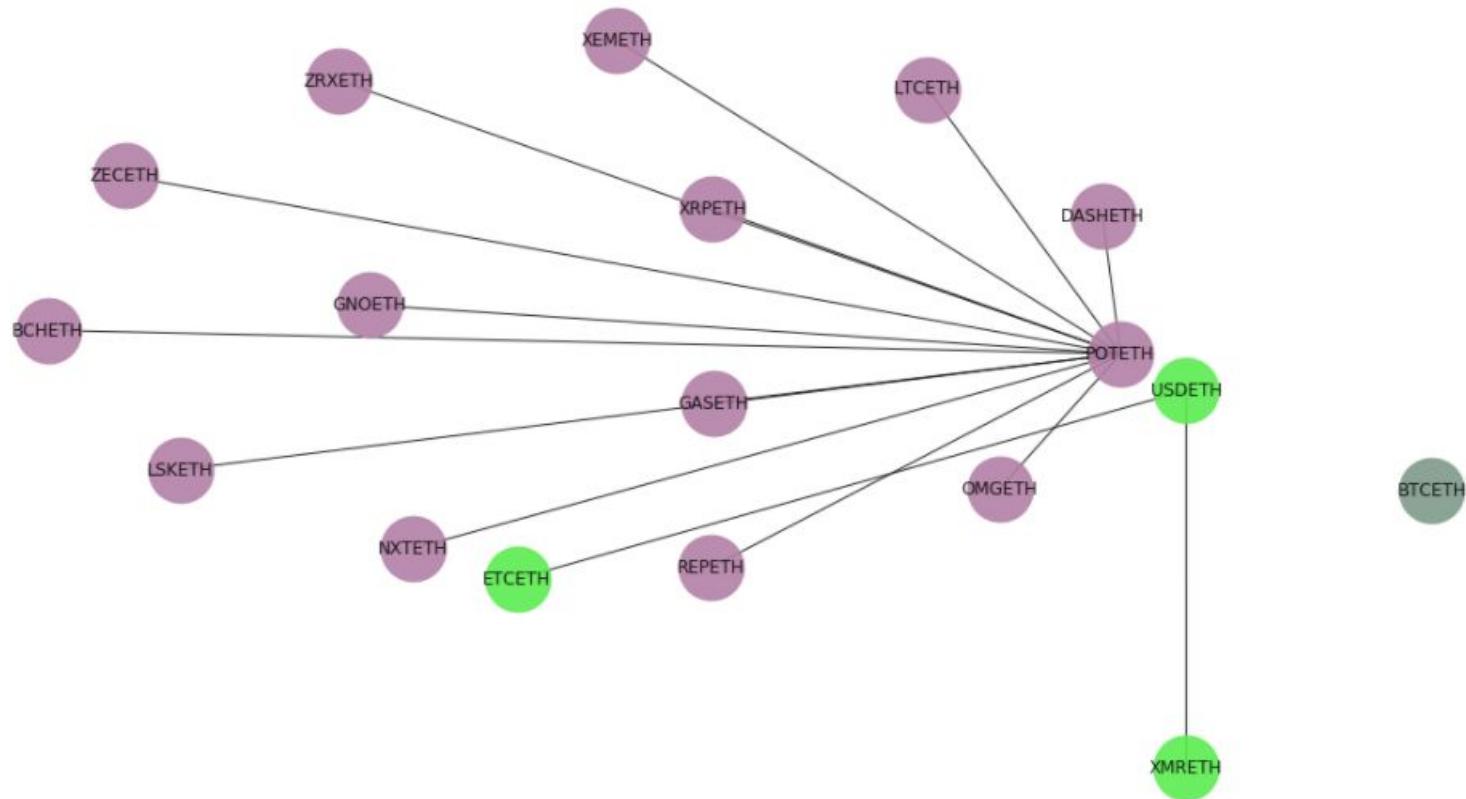
THRESHOLDING C METHOD

ETH as Base: Networks as p_c ranges in [0.10, 0.70]



SPECTRAL CLUSTERING

Base ETH: Spectral Clustering with Connected Components Subgraphs In Different Colors





Paper Replication



Spectral Clustering



Applications to Crypto



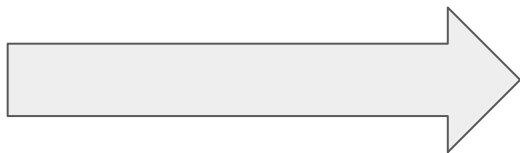
Further Research

Cointegration.

Network Evolution.

Triangular arbitrage.

FURTHER RESEARCH



Methodology



Visualization



**TRIANGULAR
ARBITRAGE**

THANK YOU!

For a copy, please contact:

Justin Skillman,

Andrew Previc,

Nick Eterovic,

Eloy Lanau-Rosello

Spectral Clustering and Network Analysis of the Cryptocurrency Market

Replication of Kwapień et al.[1]

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May 4, 2017

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