Final Report

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MXB362 – Advanced Visualization and Data Science

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Investigating the Correlation Network in Foreign Currency Exchange Market

Summary

The foreign currency exchange (FOREX) market is the biggest financial market in the world. It exerts an enormous impact on all other markets (Ismaila and Dallah, 2010). It is because the currency presents the price of any asset and its value represents the country's economic status. A foreign exchange rate is a relative price of a region's currency in terms of the currency of another region. It can express the economic balance between two regions (Mizuno et al., 2006). The FOREX market is a typical complex system and can be presented by the correlation networks and minimum spanning tree (MST) maps. The measures of centrality (degree, closeness, eigenvector, and betweenness) are all used to describe the characteristics of the FOREX market (Kazemilari and Djauhari, 2013). They can illustrate the significance of each currency inside the FOREX market network by investigating the components and interrelationships.

The project will study a set of currencies rates during the COVID-19 period from 30 December 2019, until 29 June 2021. The expected audience of visualizations will be investors and companies who want to develop the new investment strategy during the pandemic period. There are many benefits for companies and investors when important currencies are identified. The influential currencies tend to exert an impact on others. The increase or decrease in the foreign exchange rate of influential currencies would lead to a change in the trend of related currencies. Many investors are using key currencies as an indicator to take advantage of market opportunities. Those currencies are monitored carefully. For example, the information about events and policies which could affect the trend of influential currencies will be the priority for the investors to focus on.

The measures of centrality will explore the differences between the behavior of currencies and determine the most influential currencies. The analysis of the Foreign Currency Exchange Network aims to reveal the information about market's structure

and the role of each particular currency. The project centers on quantifying the currencies' importance in the global financial market. To achieve the aim, some currency correlation networks and their minimum spanning tree which contain general currencies information will be constructed.

Aim: Better understand the behavior of currencies and find the most influential currencies.

Project Description

The Data

The daily closing prices of 58 currencies are retrieved from Exchange Rate Service (http://fx.sauder.ubc.ca/). The data includes three attributes: trading date (DateTime), currency symbol (string), and daily closing price (double). The small samples of data are displayed in Figure 18. A table is constructed to display the countries' name and their respective currency symbol [Figure 17]. The project uses US Dollars as the base currency to state the daily exchange rate.

Correlation Heatmap

The heatmap is a conventional method to illustrate the correlations between sectors [Figure 1]. Constructing the heatmap of the correlation matrix is necessary. It helps to validate the results from the correlation calculations and provides a high-level understanding of relationships between currencies.

Currency network

Although heatmap is helpful, it can only present one dimension of data (the correlation between two currencies). As the outlined purpose of the project, even with a heatmap, crucial issues about the most influential currencies and their behavior remain unanswered. The currency network will be utilized to study further based on initial findings achieved from the correlation heatmap [Figure 2]. The visualization of the currency network also provides a more accessible method to convey meaningful messages.

Minimum Spanning Tree

The minimum spanning tree is widely used to visualize the financial networks [Figure 3]. While the number of edges displayed in the currency network can be up to N(N – 1) (with N being the number of currencies), the minimum spanning tree only has (N-1) edges. It contains the edges that link all the nodes together, minimize the sum of edge weights, and do not include any cycles. The project will implement Kruskal's algorithm in building the minimum spanning tree (Kruskal, 1956), which would aid to understand, simplify and summarize the message obtained from the currency network.

Visualization Environments and Tools

For all three visualizations, I expect to explore the capabilities of Python Libraries such as Numpy, Pandas, Networkx, Matplotlib, Seaborn to pre-process data and construct basic visualizations. I also expect to implement network drawing software Gephi in mapping the currency network in geographical layout. The custom color palette, the scale, the size of each element, and the layout of visualization will be studied carefully to display the information most efficiently.

The output obtained from analyzing the visualizations is expected to be particularly helpful in some real-world use cases. For example, the analysis of the correlation between currencies would help investors diversify their portfolios since it helps to identify uncorrelated currencies to invest in. Another example is that by pointing out the most influential currencies, it would be the suggestion for investors to focus more on these currencies.

Results and Outputs

Background research, reading, and investigations carried out

Many studies proposed methods to analyze the correlation network of the world currency exchange rate. Kazemi Lari and Djauhari (2013) examined the network topology of the Forex market from 2009 to 2012 based on centrality measures. Their paper successfully pointed out nine influential currencies during this period and suggested investors and companies should monitor these currencies carefully. Kwapień et al. (2009) provide the analysis of a network structure of the foreign currency exchange market. This paper did identify the clusters of strongly connected currencies and study the network topology of minimum spanning trees constructed by different base currencies such as GPB or USD. The analysis indicates that EUR has played a crucial role in the global Forex market.

There is an interesting reading that discusses visualizing asset price correlation written by Julian West (2019). In this article, the author showed how to visualize the correlation matrix of asset price as an interactive network graph that provides the audience with a high-level overview of the connection between asset classes.

Collected and generated data

A CSV file named 'country-currency-region.csv' contains information about the symbol of currencies and their corresponded country name and region.

Two CSV files 'nodes_network.csv' and 'edges_network.csv' contain node and edge data for network visualization using Gephi software. Those files are generated by MatLab script in the 'data_process.mlx' file.

A CSV file named 'fxdata.csv' contains the daily closing prices of 58 currencies retrieved from the Exchange Rate Service (http://fx.sauder.ubc.ca/).

A CSV file named 'pythonData.csv' contains the cleaned data from 'fxdata.csv'. It is ready to be used and processed as a data frame by Pandas library.

Algorithm and visualization techniques [Figure 19]

Before constructing the heatmap, normalizing data and converting the absolute asset values into log returns are of importance [Figure 6, Figure 7]. This transformation is prevalent in financial time-series data since investors are more concerned with asset returns than their absolute values. Moreover, it is easier to compare the returns of two currencies when the data is normalized. First, we compute the daily returns of the logarithm rate:

$$\boldsymbol{R_i(t) = \ln\left(P_i(t+1)\ /\ P_i(t)\right)}$$

where $\boldsymbol{i = 1, 2, \dots N}$ (number of currencies), $\boldsymbol{R_i(t)}$ is the daily return at time t of currency $\boldsymbol{i}$ and $\boldsymbol{P_i(t)}$ is the closing price of currency $\boldsymbol{i}$ at time $\boldsymbol{t}$.

After the closing prices are converted into log returns, the *corr*() function is used to compute the pairwise correlations between currencies. This function is available in both Python and MatLab, and it will return an NxN correlation matrix. Python provides a data visualization library called Seaborn, which visualizes the correlation matrix as a clustered heatmap via a useful function called *clustermap*(). The clustered heatmap is a conventional approach to illustrate correlations between variables in a dataset, especially if the data is multidimensional because it automatically organizes similar variables into clusters. This improves the structure and readability of the heatmap, making it simpler to notice connections between currencies that act similarly. The result of the visualization is shown in Figure 10.

The Marchenko–Pastur distribution is implemented to detect and remove insignificant eigenvalues and eigenvectors of the matrix, reduce noise and make the matrix display only meaningful messages [Figure 8]. The next step is converting the cleaned correlation matrix into the lists of nodes and edges to visualize it as a network. In MatLab, this step is done by using the OutputNetwork.p function, which takes the correlation matrix and an array of currencies' labels as parameters and returns two CSV files: nodes.csv and edges.csv [Figure 9]. Then, those files are loaded into Gephi to generate network visualization. To improve the visualization, insignificant edges are removed if their correlation value is below a 0.3 threshold value. Gephi uses the Louvain method to compute the modularity and detect community structure in networks. It successfully detects three major communities in the currency network as shown in Figure 11.

To produce the minimum spanning tree (MST), a technique of MST introduced by Mizuno et al. (2006) is implemented. The correlation matrix is transformed to the distance matrix as follows:

$$\boldsymbol{d^t_{\mathrm{ij}} = \sqrt{2(1 - c_{ii})}}$$

The three axioms of Euclidean distance are satisfied: (i) $\boldsymbol{d^t_{\mathrm{ij}} = 0 \; if \; and \; only \; if \; i = j}$, (ii) $\boldsymbol{d^t_{\mathrm{ij}} = d^t_{ji}}$, (iii) $\boldsymbol{d^t_{\mathrm{ij}} \le d^t_{ik} + d^t_{kj}}$, where $\boldsymbol{d^t_{\mathrm{ij}}}$ is the distance between the rate of currency $\boldsymbol{i}$ **and** $\boldsymbol{j}$. Using the distance matrix as a parameter, the OutputNetwork.p function outputs nodes and edges CSV files. Those files are imported to Gephi to generate MST visualization. In Gephi, a plugin called Minimum Spanning Tree implements Kruskal's algorithm to construct the FX network.

Since centrality is one of the most researched topics in network analysis, a variety of measurements have been proposed such as closeness centrality, betweenness centrality, degree centrality, eigenvector centrality, flow betweenness, the rush index, etc. In this project, the network centrality was examined by evaluating four particular node-level centrality metrics that are essential in most network studies (Kazemi Lari and Djauhari, 2013). Degree, closeness, betweenness, and eigenvector centralities are calculated for each node in a network.

- Degree Centrality illustrates the degree of importance of information for each currency (Niemincn, 1974). It is calculated as follows:

$$\boldsymbol{C(v) = \frac{degree(v)}{n-1}}$$

- Betweenness Centrality illustrates the frequency for each currency in the shortest routes between indirectly linked nodes (Freeman, 1977). It is calculated as follows:

$$\boldsymbol{c_{(v)} = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}(N-1)(N-2)}}$$

  Where $\boldsymbol{\sigma_{st}}$ is the total number of shortest paths from $\boldsymbol{s}$ to $\boldsymbol{t}$, and $\boldsymbol{\sigma_{st}(v)}$ is the number of those paths that pass through node $\boldsymbol{v}$.

- Closeness Centrality: measures the time to transfer information between a node $\boldsymbol{v}$ to each other reachable node. The higher the closeness centrality score is, the more important the currency is (Sabidussi, 1966). It is calculated as follows:

$$\boldsymbol{c_{(v)} = \sum_{v \neq t} \frac{n-1}{d_G(v,t)}}$$

  Where $\boldsymbol{n}$ is the size of the connected component that node $\boldsymbol{v}$ can reach

- Eigenvector Centrality identifies which currency is connected to the most connected nodes (Banocicha, 2007). The eigenvector centrality of node $\boldsymbol{i}$ is calculated as follows:

$$\boldsymbol{e_{(i)} = \frac{1}{\lambda_{max}} \sum_{j=1}^{n} (A_{ij} x_j)}$$

Visualization analysis

The clustered heatmap [Figure 10]

- A diverging colorblind-friendly color palette is used to colorize the heatmap. The positive correlations are green, uncorrelated currencies are white and negative correlations are brown. Looking at the clustered heatmap visualization, there are interesting insights the audience could gain.

- Overall, the strongly negative correlations are hardly seen between currencies. The currencies that are close to each other according to geographic regions tend to be grouped in the same cluster. For example, it is shown in the visualization that the list of currencies run from CHF (Switzerland) to PLN (Poland) are mostly European currencies. CAD (Canada), GPB (United Kingdom), SGD (Singapore), AUD (Australia), and NZD (New Zealand) are grouped into a cluster. It could be because they are Commonwealth countries that have political and cultural backgrounds in common. There is also a cluster of non-European regions, which consists of the list of currencies run from IDR (Indonesia) to ZAR (Africa). Most of those currencies come from the Asian region. It is also noticeable that HKD (Hong Kong) and JPY (Japan) are not correlated with Asian currencies; otherwise, they are correlated with European currencies. The event that the CNY (China) and JPY (Japan) joined XDR (the special draw rights) could be the reason for that. SAR (Saudi Arabia), ARS (Argentina), and PKR (Pakistan) are three currencies that are uncorrelated with all others.

The currency network [Figure 11]

- A qualitative color palette is used to colorize the nodes based on the communities detected in the currency network. The network visualization provides the audience with a better picture of the data. By removing insignificant edges with correlation values smaller than 0.3, the graph only displays the meaningful correlations between currencies. The edge thickness is scaled based on the magnitude of correlation. The Louvain method successfully detects which groups of currencies behave similarly. Four clusters can be seen from the graph: orange, green, blue, and grey. It is noticeable that all of the nodes in the orange cluster (except JPY) come from the European region. The European currencies are strongly correlated to each other and have a significant correlation to other currencies. Looking at the green cluster, there are four currencies namely COP, PEN, BRL, and CLP located in the left part of the cluster. All of them are from South/Latin America and they only connect to the currencies within the same cluster. Therefore, it is true to say that there is no correlation in the currency exchange rate between South/Latin America and Europe. It is also noteworthy that even TRY and RUB come from Europe, they do not correlate with European currencies. It might be because of their unique geographic position, both Turkey and Russia are lying partly in Asia and partly in Europe. Regarding the blue cluster, it contains 12 currencies (9 of them are in Europe and 3 of them are in Asia). It is shown that European currencies are grouped into two different clusters. Moreover, even though MYR, PHP, and THB are from South East Asia, they tend to be more correlated with European currencies.

The minimum spanning tree [Figure 12]

- A qualitative color palette is used to colorize the nodes based on their region (i.e., Europe, orange; Asia & Pacific, dark green; South/Latin America, blue; Africa, pink; North America, light green; Middle East, yellow). The minimum spanning tree is a more readable and well-structured version of the previous network graph. There is some knowledge obtained from the minimum spanning tree. The NOK is at the center of the FX network since it connects currencies from four different regions (i.e., Asia, South/Latin America, Middle East, and Europe). The majority of the currencies are grouped based on geographical regions. The currencies of Commonwealth countries are connected such as MYR, CAD, AUD, NZD, and SGD. The currencies of Europe are the most closely linked. EUR has a predominant position in the European monetary system. JPY is connected to European currencies, whereas CNY is more attached to the Asian cluster although both currencies join the special drawing rights.

- Different colors and sizes are utilized to show the rank of importance of each currency to make the Minimum Spanning Tree as clear as possible. For example, the currency with the highest centrality score is the largest dark green node. From the measurement of betweenness, closeness, degree, and eigenvector centrality, the following results are obtained:

- Based on the betweenness centrality measure [Figure 13], EUR (the largest node) has the highest score of the betweenness measure (1155). It indicates that EUR is the closest node among other indirectly linked nodes. The four other nearest nodes with a high betweenness centrality are NOK, ESP, SEK, and AUD.

- According to the closeness centrality measure [Figure 14], it can be seen that EUR is also the most important currency. It has the highest closeness centrality (0.261) to others. After ESP; SEK and NOK are the significant currencies with high closeness measures. In the network, other currencies with low scores of closeness centrality are not particularly essential.

- Based on the degree centrality measure [Figure 15], EUR is the influential node that has the most linkage with the highest degree centrality score (0.19). MXN has 4 linkages whereas SGD, AUD, and IEP have 3 linkages. Other currencies which are at lower levels only have 1 or 2 links.

- In terms of eigenvector centrality measure as shown in Figure 16, EUR again has the highest score (1.000). Meanwhile, IEP (0.458) is the second-highest, which is followed by ESP (0.345), PTE (0.333), and DEM (0.332). The other three high-scoring nodes are NOK (0.314), NLG (0.311), and FRF (0.311).

- From the four centrality measures, we can see that EUR has the most predominant position in the global monetary system, with the highest score achieved from all four measures. Overall, NOK, ESP, SEK, and AUD are four high-scoring currencies based on betweenness centrality measures. ESP, NOK, and SEK are also important currencies in closeness centrality. MXN, SGD, AUD, and IEP are the influential currencies in the degree centrality measure. IEP, ESP, and PTE are strong in eigenvector measures. Even though GBP and CHF are the major global currencies, they exist in the lowest linkage during the examined period.

Interactive visualization

The code for the website can be accessed via my GitHub: https://github.com/hoangqwe159/forex-analysis-covid19. The live demo of the website can be accessed via the link: https://forex-network.herokuapp.com. The website allows the audience to interact with visualization such as hovering for additional information, highlighting the connected nodes, dragging, and zooming the network. However, the interactive version does not successfully visualize the network with the correct graph layout used in Gephi. It is because the D3 library has its interaction and simulation rule to construct the network graph.

Effective visualization issues

A diverging colorblind-friendly color palette is used to colorize the heatmap. A qualitative color palette is used to colorize the cluster in network graphs. The color sets are generated using the Color Brewer tool. There are no issues such as simultaneous contrast and apparent size in the use of color. Title and legend are added as additional contextual cues to help the audience understand the context and interpret data. In the heatmap, lines are used to illustrate the relationship between currency clusters. In the network graphs, lines indicate the orientation between currencies. The visualizations have sensible use of type. The type does not overpower the graph. Minimal type successfully enhances the images. In terms of format and structure, a suitable layout algorithm is implemented to separate the clusters and help the audience distinguish them easily. Labels of the nodes do not collapse each other. The number of clusters is ideal so that it does not increase the complexity of the network graphs. Expanded & minimal background is used to enhance distances. The pure white background for each visualization creates a clean, cohesive, and professional look.

Project Timeline

The Gantt Chart

The list of tasks expected to be accomplished is displayed in the Gantt Chart [Figure 5].

Project Journal

The project journal can be seen in Figure 4.

Conclusion

This project uses the Pearson correlation coefficient to construct and examine currency heatmap and networks. It offers some background knowledge about currency characteristics by analyzing the result obtained from the four measures of centrality, namely: betweenness, closeness, degree, and eigenvector centrality. It identifies the relative importance of currencies within the global FOREX market. Some basic findings of this project seem to be consistent with the result achieved from other past studies. All three visualizations achieve the proposed aim and deliver a meaningful message. The analysis can be a useful resource for companies and investors to take advantage of market opportunities. One problem that can be witnessed is using different environments and tools might cause inconsistency in visualization outputs. The suggestion for future work is to make a comparison between currencies from different periods. So that it could reflect the impact of COVID19 on the FOREX market more clearly.

Reference

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12. Appendix

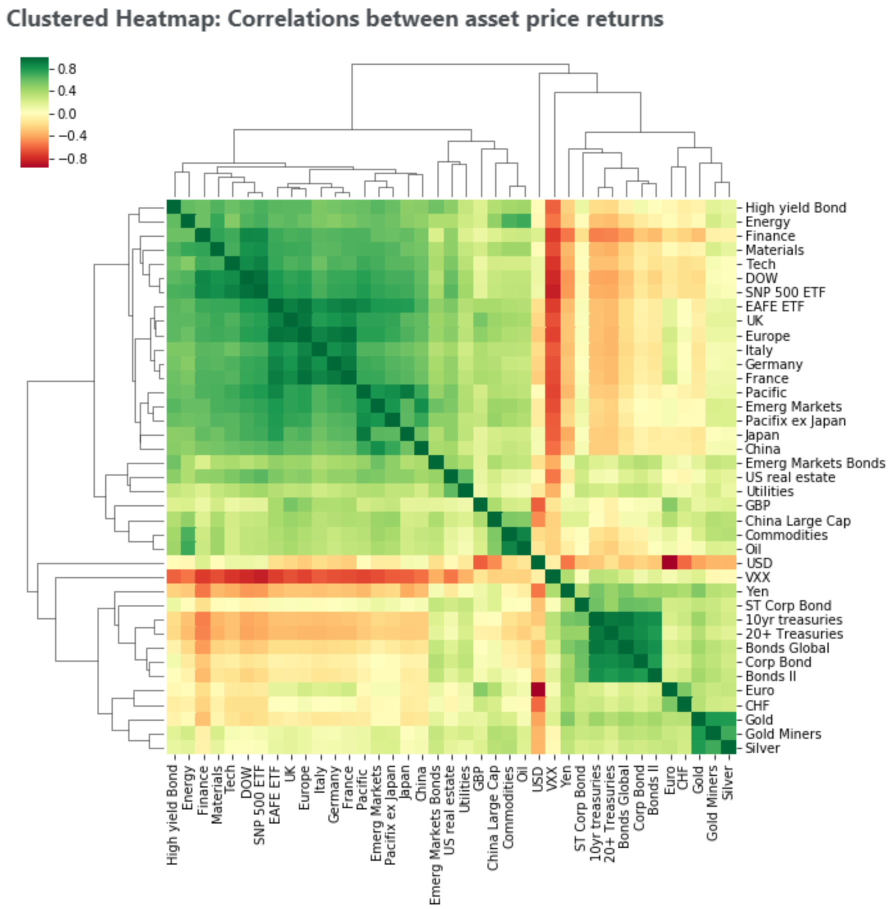

Figure 1: Illustration of the Heatmap Correlation Matrix (Julian, 2019)

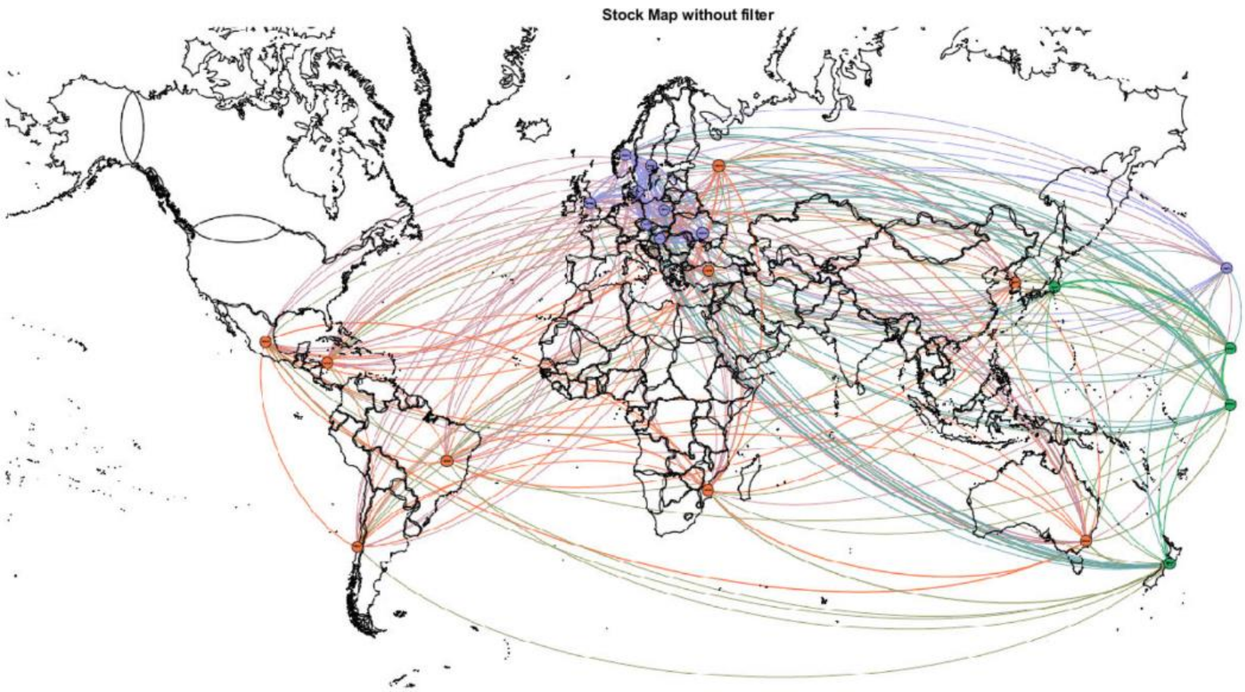

Figure 2: Illustration of the Currency Network using Geographical Layout

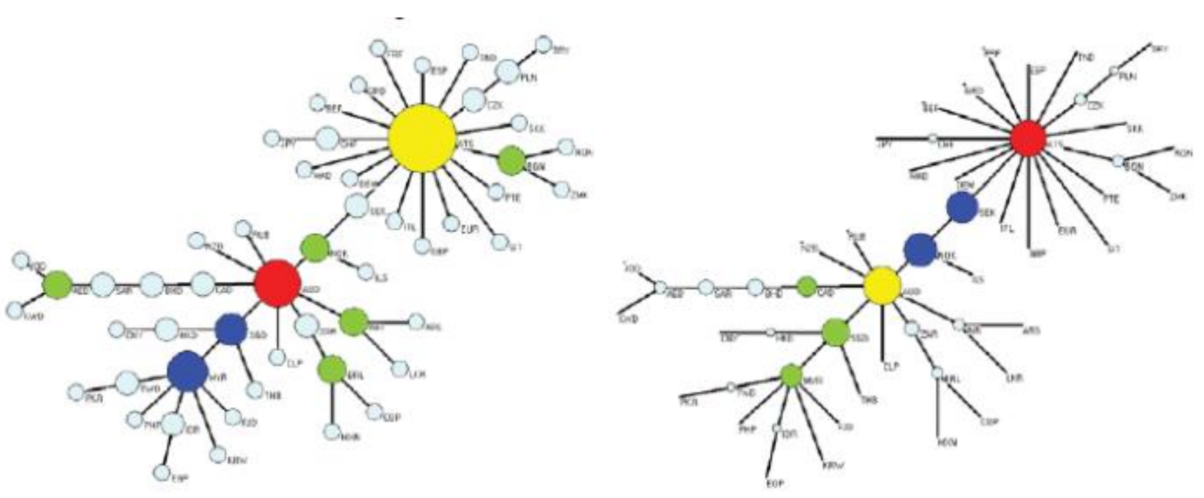

Figure 1. MST based on degree centrality **Figure 2**. MST based on betweenness centrality

Figure 3: Illustration of Minimum Spanning Tree with different bases (Kazemilari and Djauhari, 2013).

Date	Task	Time allocated (hours)
1/08/2021	Reading some research related to analyzing and visualizing the currency network	3
4/08/2021	Study the related term and understand the purpose of different visualizations.	2
7/08/2021	Finalize to determine the expected output.	1
10/08/2021	Study some methods to clean the noise from the correlation matrix.	3
13/08/2021	Study some community detection methods and Kruskal's algorithm.	3
16/08/2021	Loading a small set of data and load it to MATLAB and play around with it. Try to construct a very basic correlation matrix and network currency.	10
24/08/2121	Load data into Python and using some visualization libraries to generate clustered heatmap	5
1/09/2021	Apply studied algorithm and generate node and edge tables from data. Load data into Gephi and visualize the currency network.	6
8/09/2021	Calculate distance matrix from correlation matrix. Output node and edge tables from distance matrix. Add region information into the node table. Load data into Gephi and visualize the MST	6
15/09/2021	Generate different MST visualizations based on four measures of centrality.	4
22/09/2021	Provide analysis for each visualization. Choosing optimal color scale for the visualization.	4
30/09/2021	Build a website displaying interactive visualization.	15
2/10/2021	Gather findings and write the progress report.	6
9/10/2021	Provide deeper analysis of the visualization	2
16/10/2021	Add contextual cues such as legends and titles to help audience understand the data clearly	2
23/10/2021	Finalize the coding for interacting web app and document the code	6
30/20/2021	Gather findings and write the final report.	6
Total Time		**84**

Figure 4: Project Journal to 30/10/2021

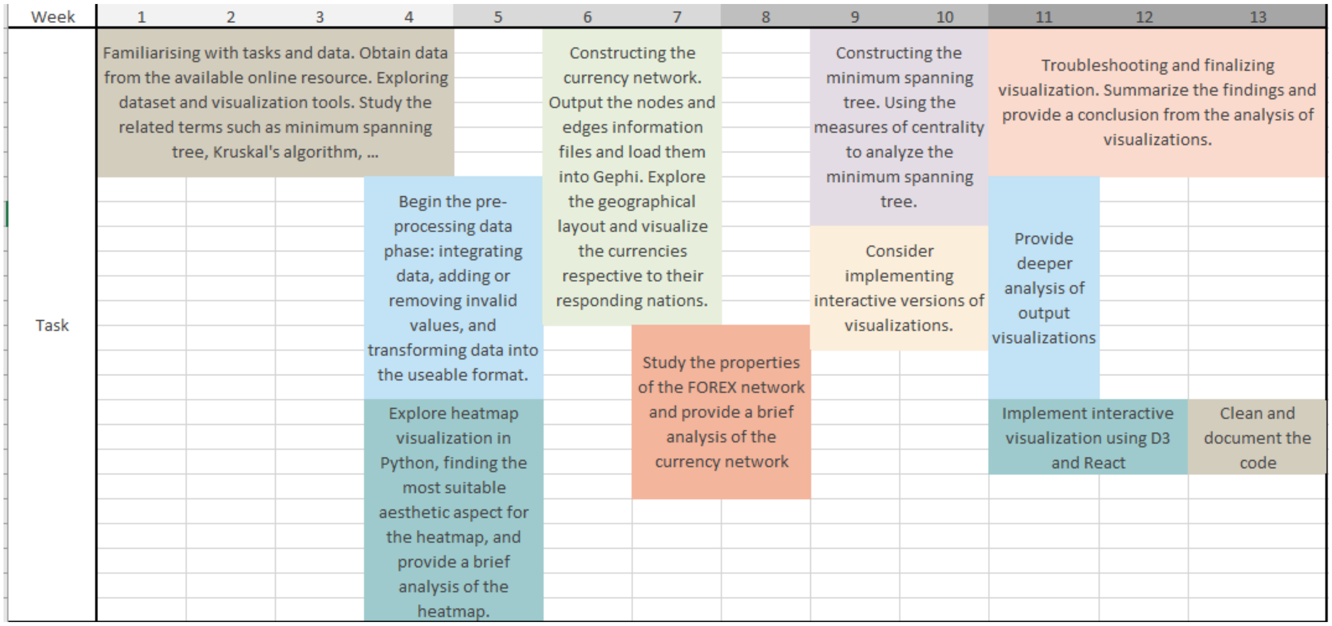

Figure 5: Gantt Chart

```
% Read data from csv file and save to table
T = readtable('fxdata.csv', 'ReadVariableNames',false);

% Transpose the data
X = T;
Xc = table2cell(X);
X_transposed = Xc';
A = X_transposed;

% Extract currency labels and daily return value
tickers = A(1,:);
data = A(2:378,:);

% Fill missing data with previous data
data = cell2mat(data);
data = fillmissing(data, "previous",1);

```

Figure 6: Load and pre-process data

```
% Array to store daily log-returns
size_data = size(data);
log_daily = zeros(size_data(1) - 1, size_data(2));


% Compute the daily log-returns
for j =1:size_data(2)
    for i=1:size_data(1)-1
        log_daily(i,j) = log(data(i+1,j) / data(i,j));
    end
end

% Calculate correlation matrix
correlation = corrcoef(log_daily);
distances = zeros(size_data(2), size_data(2));

% Calculate distance matrix
for j =1:size_data(2)
    for i=1:size_data(2)
        distances(i,j) = sqrt(2 * (1 - correlation(i,j)));
    end
end

% Rename the currency labels
tickers = string(tickers);
for i= 1:length(tickers)
    tickers(i) = erase(tickers(i), '/USD');
end
```

Figure 7: Compute Daily return and Correlation matrix

```
% Apply Marchenko-Pastur distribution
lamda = 58/377;
lamda_plus = (1+sqrt(lamda))^2;
lamda_minus = (1-sqrt(lamda))^2;

%Calculate eigevalue/vectors for the correlation data
correlation(1:1+size(correlation,1):end) = 1;
[V1, D1] = eig(correlation);
D1_abs = abs(D1);

% Set the eigenvalues that are  indistinguishable from noise to 0
D1_filter = (D1_abs >= lamda_plus);
D1_reconstitued = D1 .* D1_filter;

%  A*V = V*D.
correlation_reconstituted = V1 * D1_reconstitued * inv(V1);
correlation_reconstituted = abs(correlation_reconstituted);
```

Figure 8: Reduce noise from Correlation Matrix

```
% Output the nodes and edges data of reconstituted correlation matrix for
% currency network
OutputNetwork(correlation_reconstituted,tickers);

% Open country, region, and node data file
opts = detectImportOptions('country-currency-region.csv');
T_country = readtable('country-currency-region.csv',opts);
country = string(T_country.Country);
region = string(T_country.Region);
node_table = readtable("nodes.csv");

% Add region, country data to node table
node_table.Country = country;
node_table.Region = region;


% Output the node table
writetable(node_table,'nodes.csv','Delimiter',';');
```

Figure 9: Output nodes and edges file for Gephi

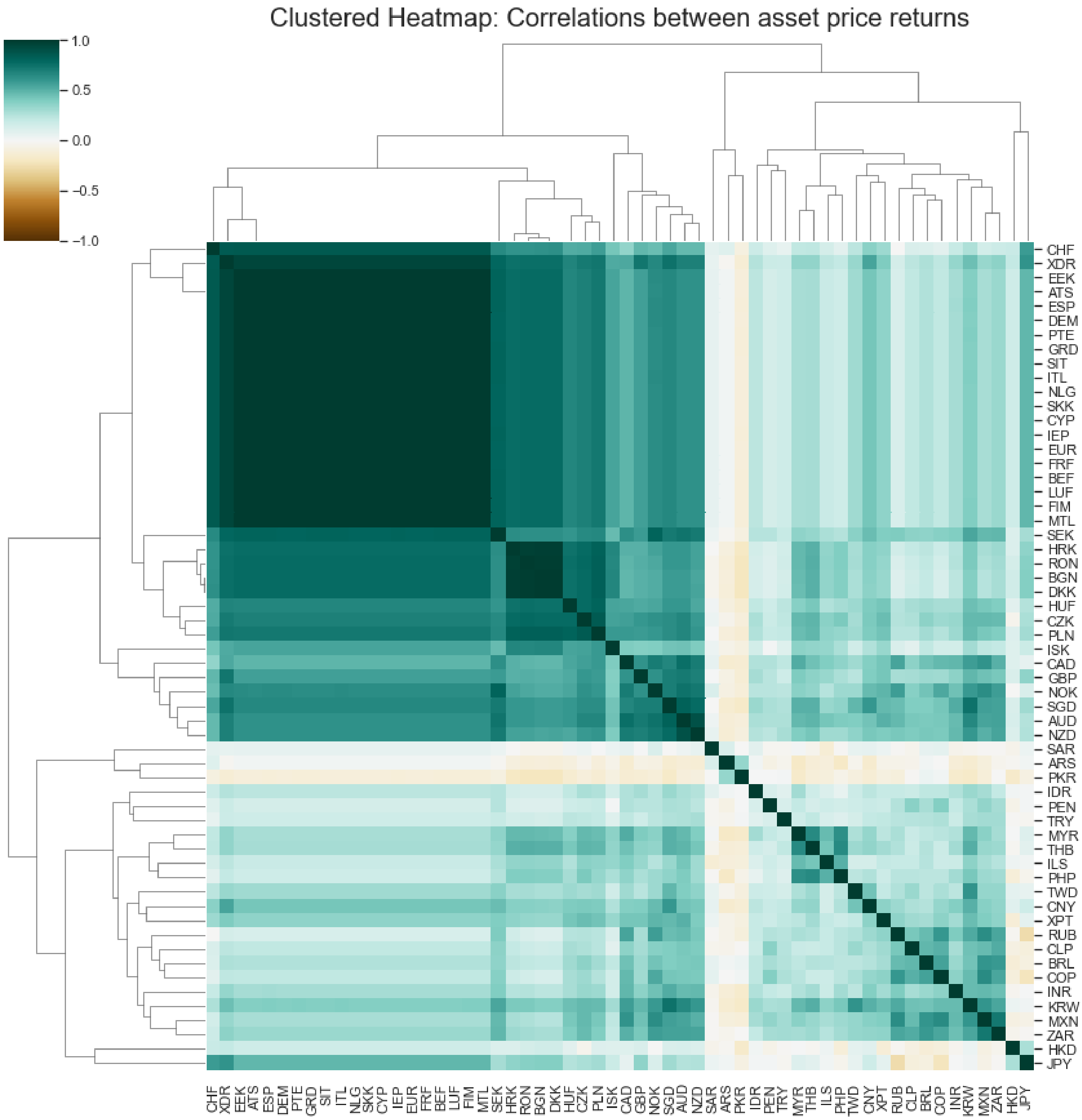

Figure 10: Clustered Heatmap

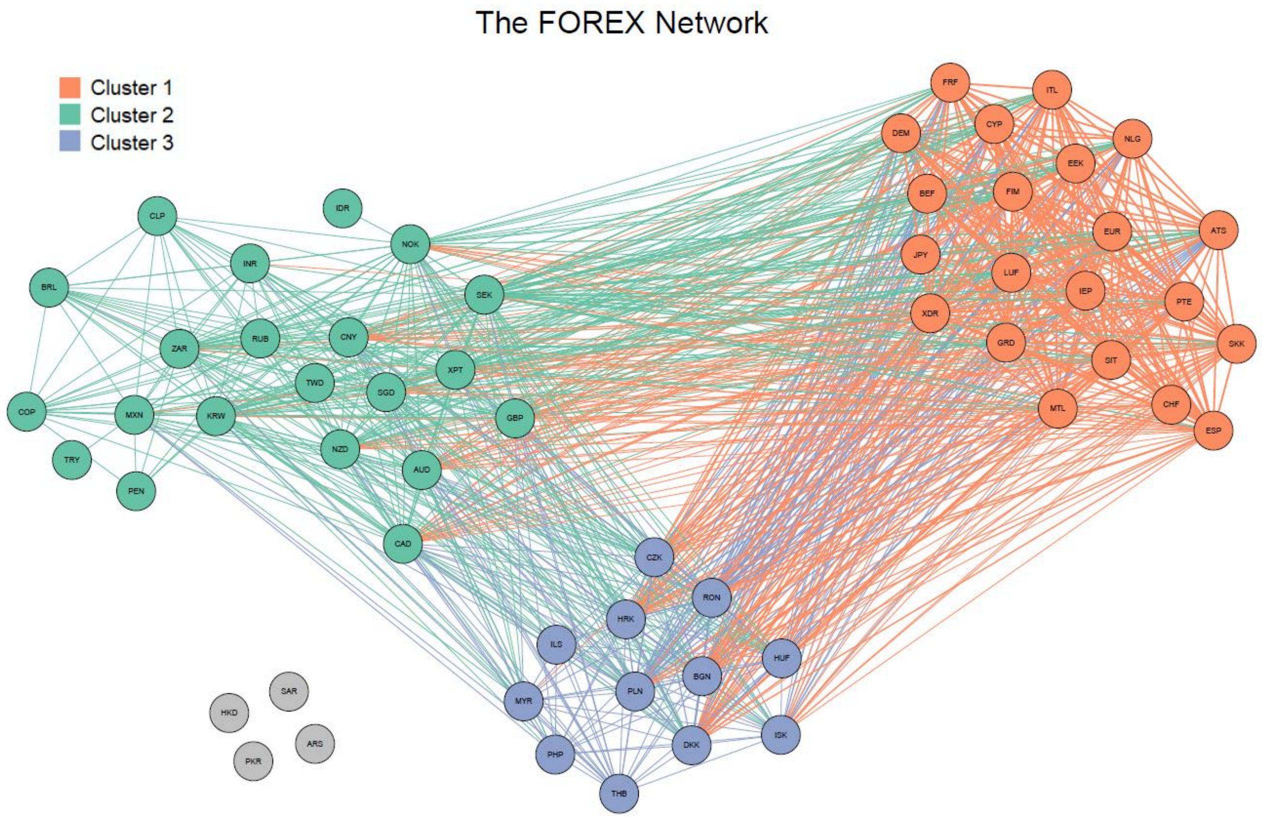

Figure 11: Currency network. The currencies from the same cluster have the same color.

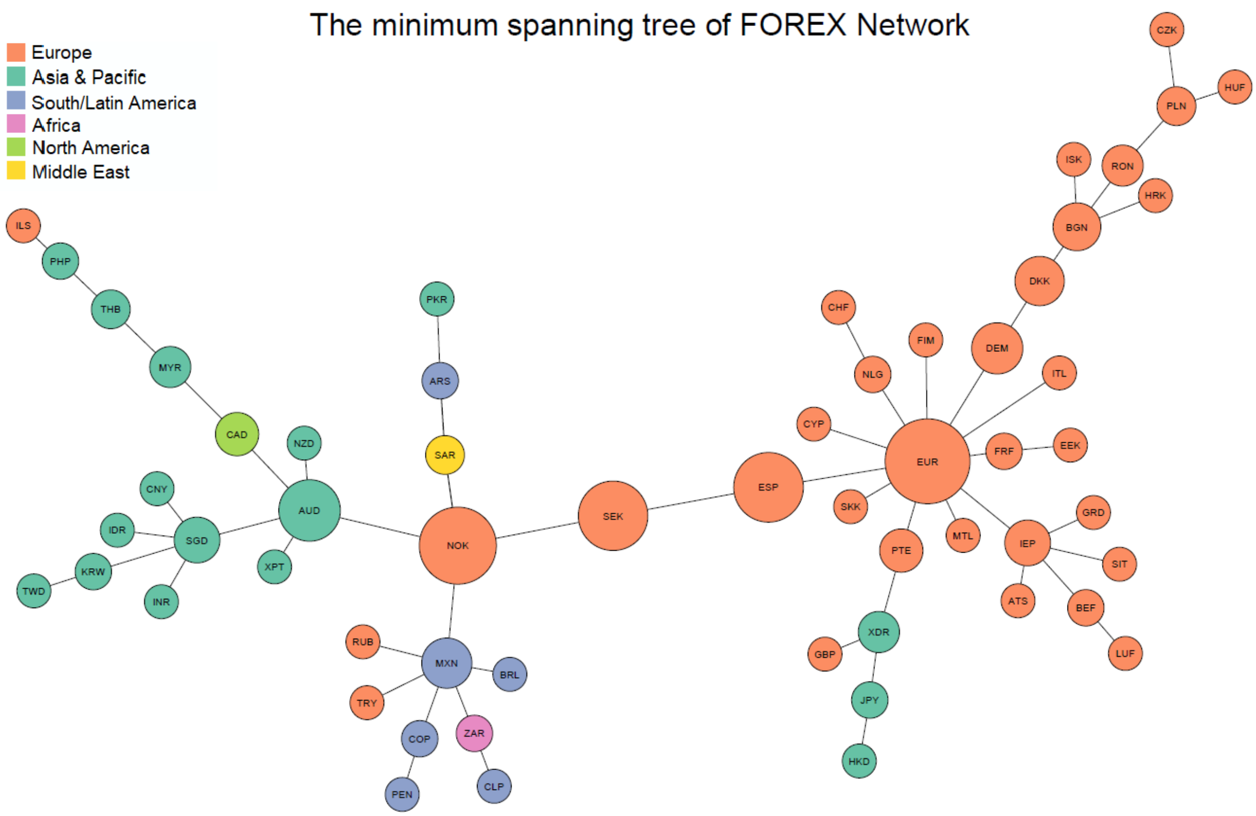

Figure 12: Minimum Spanning Tree. The currencies from the same region have the same color. (i.e., Europe, orange; Asia & Pacific, dark green; South/Latin America, blue; Africa, pink; North America, light green; Middle East, yellow)

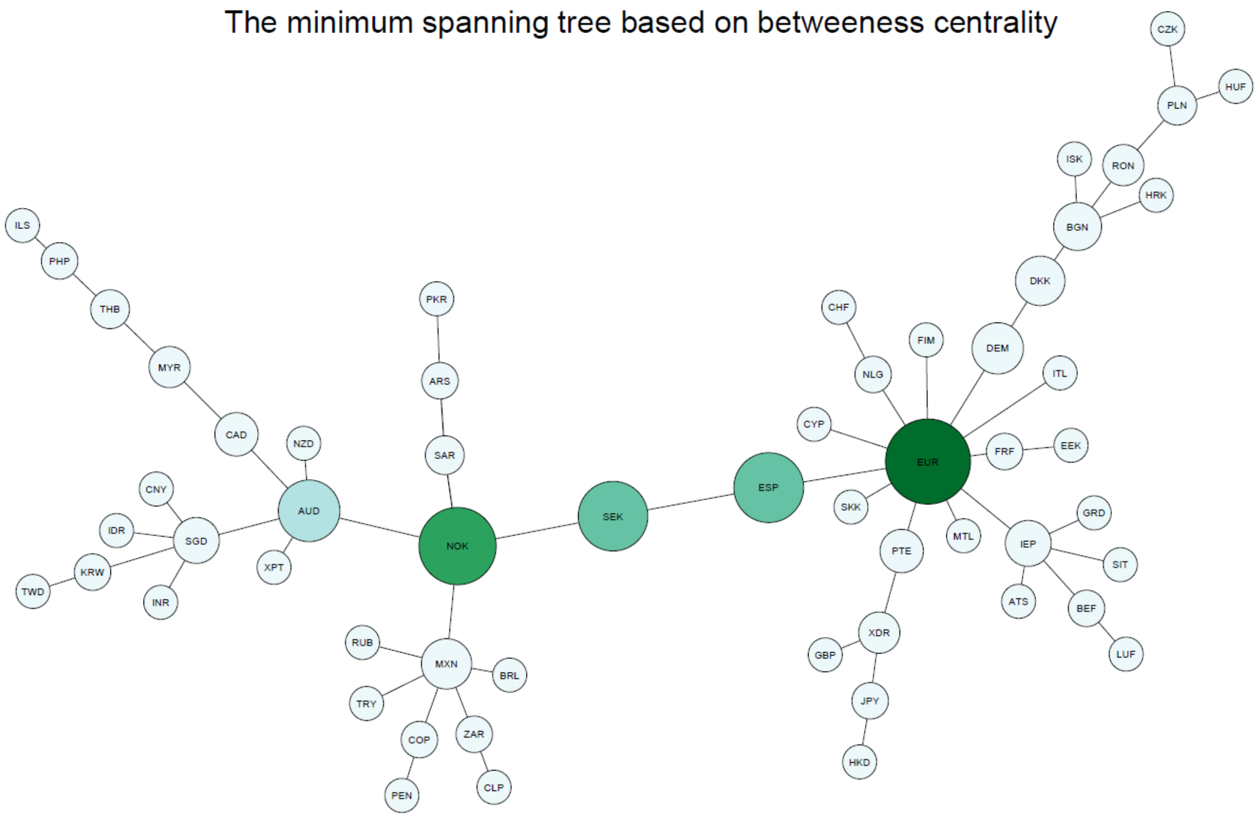

Figure 13: MST based on betweenness centrality

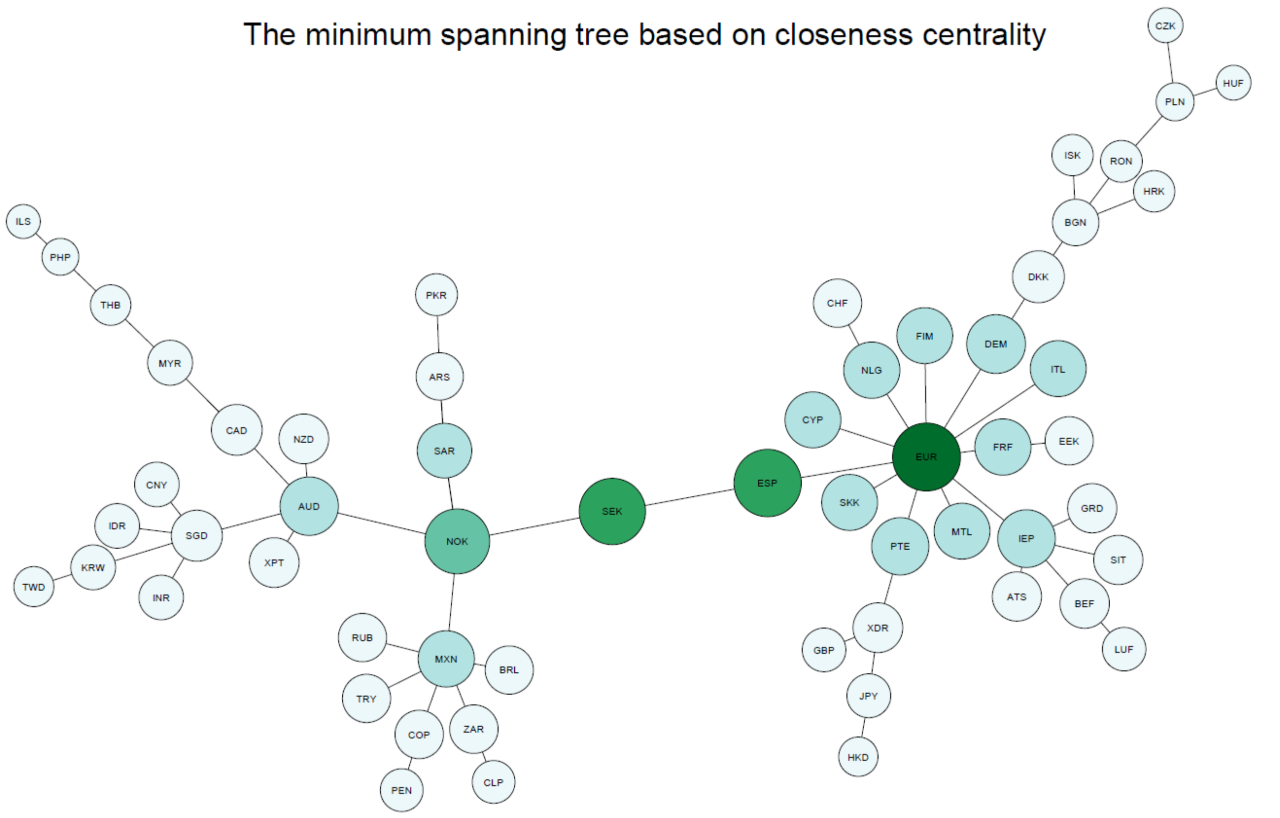

Figure 14: MST based on closeness centrality

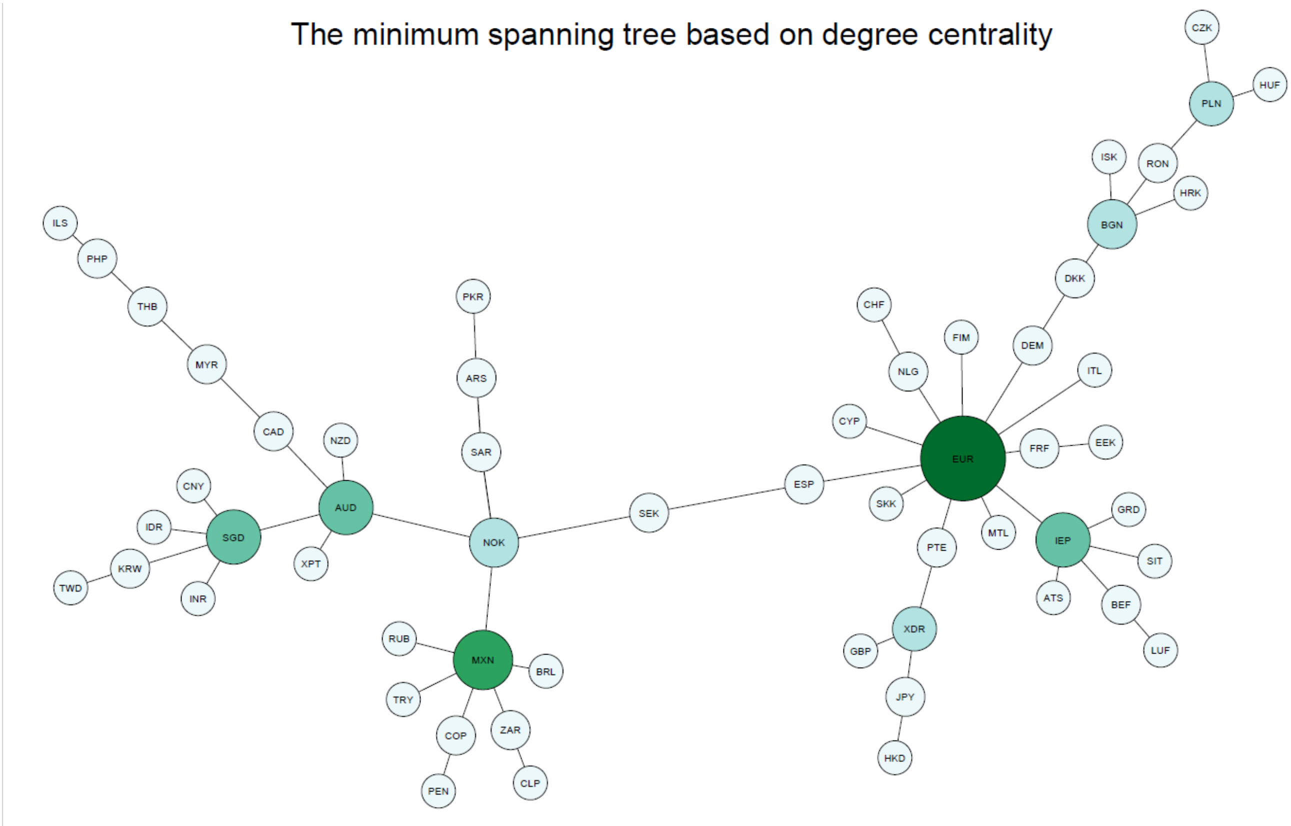

Figure 15: MST based on degree centrality

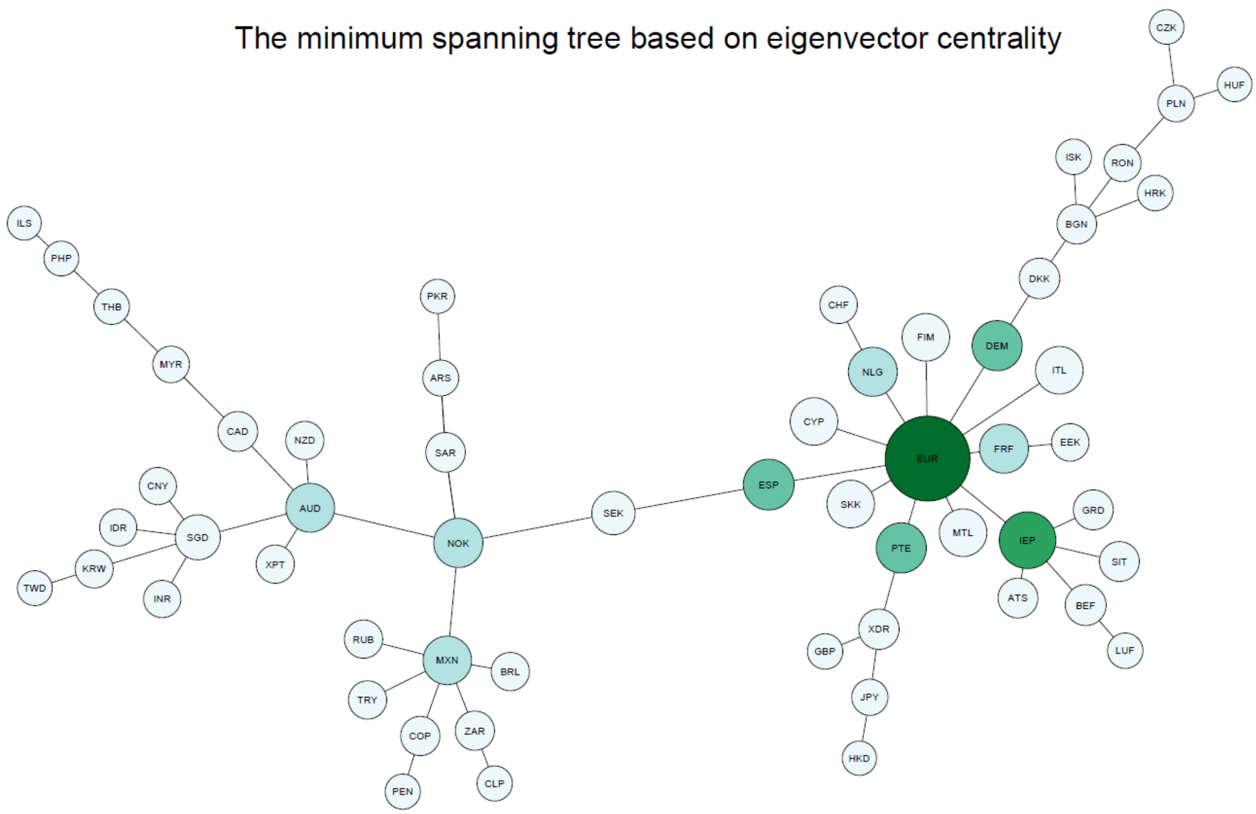

Figure 16: MST based on eigenvector centrality

ID	Label	Country	Region	Closeness	Betweeness	Eigenvector	Degree
1	ARS	Argentina	South/Latin America	0.170	56	0.059	0.034
2	AUD	Australia	Asia & Pacific	0.219	625	0.305	0.086
3	ATS	Austria	Europe	0.178	0	0.135	0.017
4	BEF	Belgium	Europe	0.179	56	0.155	0.034
5	BRL	Brazil	South/Latin America	0.174	0	0.104	0.017
6	GBP	United Kingdom	Europe	0.153	0	0.050	0.017
7	BGN	Bulgaria	Europe	0.166	315	0.129	0.069
8	CAD	Canada	North America	0.185	212	0.133	0.034
9	CLP	Chile	South/Latin America	0.149	0	0.044	0.017
10	CNY	China	Asia & Pacific	0.157	0	0.083	0.017
11	COP	Colombia	South/Latin America	0.175	56	0.122	0.034
12	HRK	Croatia	Europe	0.143	0	0.052	0.017
13	CYP	Cyprus	Europe	0.208	0	0.283	0.017
14	CZK	Czech Republic	Europe	0.114	0	0.033	0.017
15	DKK	Denmark	Europe	0.190	350	0.147	0.034
16	NLG	Netherlands	Europe	0.210	56	0.311	0.034
17	EEK	Estonia	Europe	0.174	0	0.089	0.017
18	EUR	Europe	Europe	0.261	1155	1.000	0.190
19	FIM	Finland	Europe	0.208	0	0.283	0.017
20	FRF	France	Europe	0.210	56	0.311	0.034
21	DEM	Germany	Europe	0.221	392	0.332	0.034
22	GRD	Greece	Europe	0.178	0	0.135	0.017
23	HKD	Hongkong	Asia & Pacific	0.134	0	0.027	0.017
24	HUF	Hungary	Europe	0.114	0	0.033	0.017
25	ISK	Iceland	Europe	0.143	0	0.052	0.017
26	INR	India	Asia & Pacific	0.157	0	0.083	0.017
27	IDR	Indonesia	Asia & Pacific	0.157	0	0.083	0.017
28	IEP	Ireland	Europe	0.216	269	0.458	0.086
29	ILS	Israel	Europe	0.110	0	0.021	0.017
30	ITL	Italy	Europe	0.208	0	0.283	0.017
31	JPY	Japan	Asia & Pacific	0.154	56	0.064	0.034
32	LUF	Luxembourg	Europe	0.152	0	0.050	0.017
33	MYR	Malaysia	Asia & Pacific	0.159	162	0.072	0.034
34	MTL	Malta	Europe	0.208	0	0.283	0.017
35	MXN	Mexico	South/Latin America	0.210	369	0.301	0.103
36	NZD	New Zealand	Asia & Pacific	0.180	0	0.103	0.017
37	NOK	Norway	Europe	0.248	978	0.314	0.069
38	PKR	Pakistan	Asia & Pacific	0.145	0	0.025	0.017
39	PEN	Peru	South/Latin America	0.149	0	0.044	0.017
40	PHP	Philippines	Asia & Pacific	0.123	56	0.037	0.034
41	XPT	Platinum Ounce	Asia & Pacific	0.180	0	0.103	0.017
42	PLN	Poland	Europe	0.128	111	0.069	0.052
43	PTE	Portugal	Europe	0.214	212	0.333	0.034
44	RON	Romania	Europe	0.145	162	0.084	0.034
45	RUB	Russia	Europe	0.174	0	0.104	0.017
46	SAR	Saudi Arabia	Middle east	0.202	110	0.129	0.034
47	SGD	Singapore	Asia & Pacific	0.186	269	0.234	0.086
48	SKK	Slovakia	Europe	0.208	0	0.283	0.017
49	SIT	Slovenia	Europe	0.178	0	0.135	0.017
50	ZAR	South Africa	Africa	0.175	56	0.122	0.034
51	KRW	South Korea	Asia & Pacific	0.158	56	0.100	0.034
52	ESP	Spain	Europe	0.259	810	0.345	0.034
53	XDR	Special drawing rights	Asia & Pacific	0.180	164	0.144	0.052
54	SEK	Sweden	Europe	0.254	806	0.202	0.034
55	CHF	Switzerland	Europe	0.174	0	0.089	0.017
56	TWD	Taiwan	Asia & Pacific	0.137	0	0.038	0.017
57	THB	Thailand	Asia & Pacific	0.139	110	0.051	0.034
58	TRY	Turkey	Europe	0.174	0	0.104	0.017

Figure 17: Countries, respective symbols, and centrality measures

YYYY/MM/DD	30/12/2019	31/12/2019	2/01/2020	3/01/2020	6/01/2020	7/01/2020	8/01/2020	9/01/2020	10/01/2020	13/01/2020
ARS/USD	59.732	59.408	59.797	59.833	59.648	59.801	59.794	59.735	59.78	59.91
AUD/USD	1.4286	1.4238	1.431	1.4375	1.4418	1.4561	1.4566	1.4587	1.4496	1.4477
ATS/USD	12.282	12.255	12.312	12.328	12.296	12.344	12.379	12.39	12.382	12.359
BEF/USD	36.006	35.928	36.095	36.141	36.046	36.187	36.289	36.321	36.299	36.23
BRL/USD	4.0219	4.0198	4.0273	4.0486	4.0582	4.0768	4.0579	4.0795	4.0784	4.1344
GBP/USD	0.76181	0.75626	0.76043	0.76432	0.76008	0.7621	0.76296	0.76597	0.76554	0.76984
BGN/USD	1.7469	1.7401	1.7465	1.7554	1.7464	1.7523	1.7606	1.7635	1.7606	1.7583
CAD/USD	1.3059	1.2988	1.2992	1.2988	1.297	1.3009	1.3026	1.3079	1.3051	1.3048
CLP/USD	746.73	742.67	750.22	757.08	772.36	768.32	759.98	765.81	770.52	774.46

Figure 18: Sample FOREX data

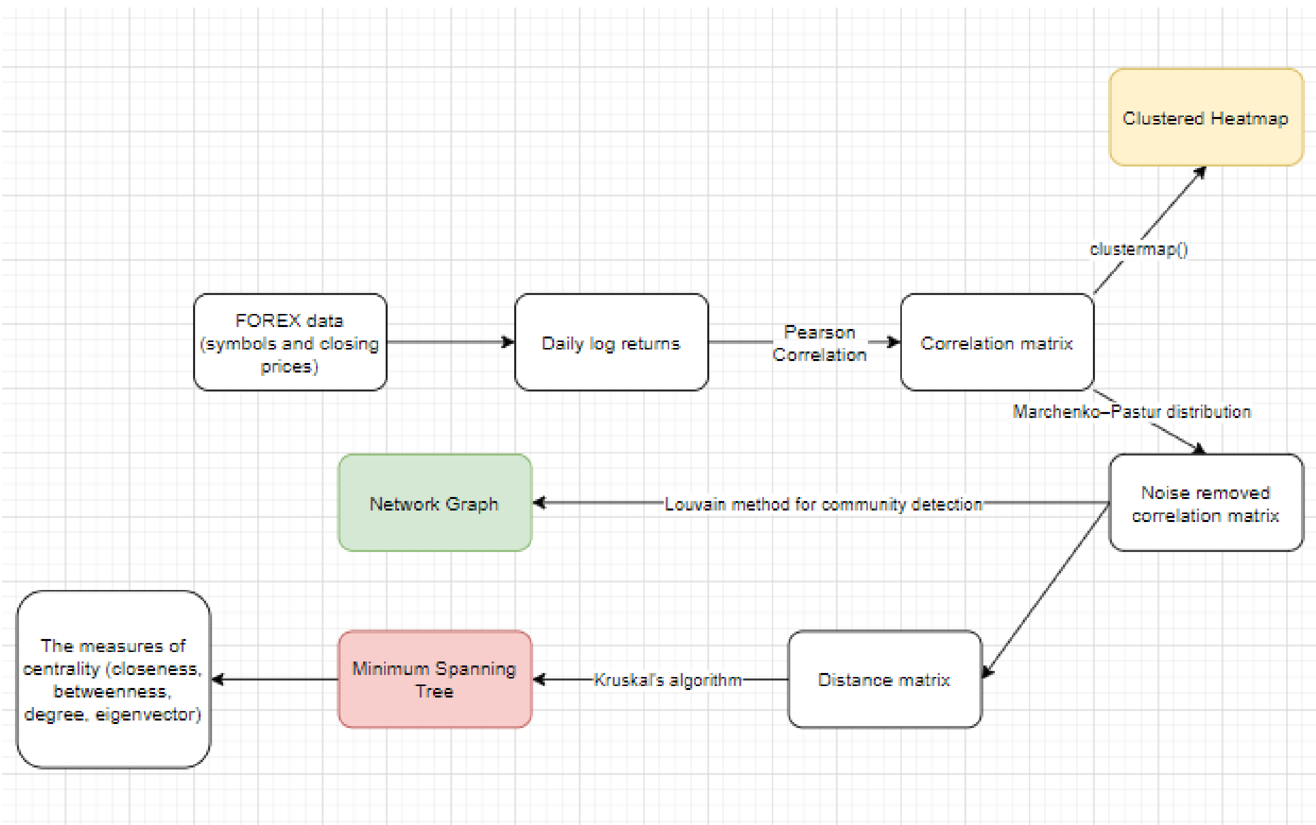

Figure 19: Algorithm pipeline