

Graph Theory Applications in Investment Analysis and Risk Modeling

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Introduction



Complex Markets

Financial markets are increasingly intricate.



Advanced Tools

New modelling tools are crucial.



Graph Theory's Role Role

Graph theory offers unique insights.

The evolving complexity of global finance demands sophisticated analytical approaches. Graph theory provides a powerful framework for navigating this complexity, offering visual and analytical advantages over traditional methods. In this work, we explore how graph-based methods can support investors in identifying risk and optimizing the timing of investment decisions. We implement Python-based tools that use stock price correlations to generate adjacency matrices and construct diversified portfolios. Graph algorithms also assist in minimizing risk, particularly in currency investments.



Fundamentals of Graph Theory

1 Key Concepts

Nodes, edges, and adjacency matrices are core.

2 Graph Types

Graphs can be directed, undirected, or weighted.

3 Visual Representation

They visualise complex data networks clearly.

At its heart, graph theory involves understanding relationships. Nodes represent entities, edges represent connections. The adjacency matrix quantifies these links, forming the basis for network analysis.

Graph Theory in Financial Systems

Financial Mapping

Banks, stocks, and instruments are nodes.

Loans and correlations are edges.

Network Approach

It helps model market complexity.

Visualising interconnectedness is key.

Graph theory offers a powerful lens to view financial ecosystems. By mapping financial entities as nodes and their interactions as edges, we can uncover hidden structures and dependencies, crucial for robust analysis.

Portfolio Construction and Diversification

Stock Correlations
Graphs reveal asset clusters.



Diversification
Opportunities are easily identified.

Stock Clustering
Group stocks by sector or behaviour.

Constructing optimal portfolios benefits significantly from graph analysis. By visualising stock correlations, investors can identify truly diversified asset clusters, reducing risk and improving returns.

Graph Theory in Systematic Investing

1

Graph theory is applied in many areas of investing: portfolio building, stock selection, risk management, and currency trading.

2

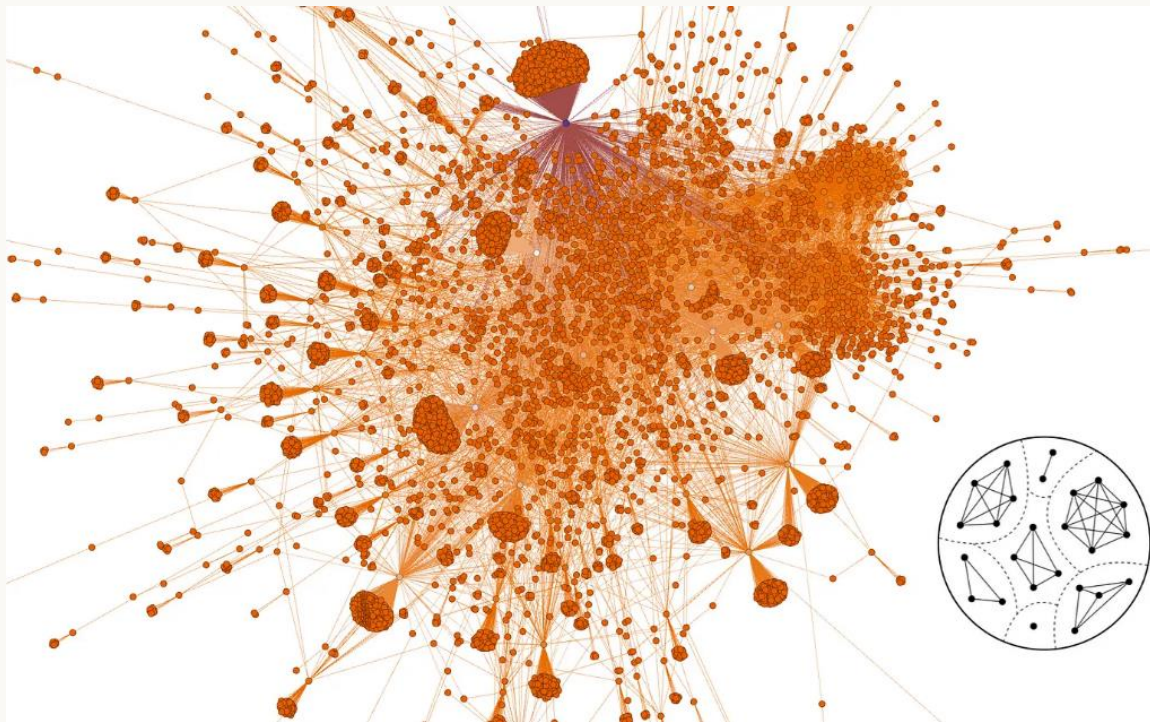
Systematic investing uses mathematical models to adjust portfolio allocations in response to market changes, aiming to maximize returns with minimal risk.

3

Core graph concepts improve portfolio design when applied to real-world financial data.



Key Concepts in Systematic Portfolio Construction



Data Enrichment

Symmetry: Declaring a competitor implies a two-way edge in the competition graph.

Transitivity: Infers new relations between companies of similar size via graph paths.

Standardization

Uses **cluster graphs** to represent granular industry classifications.

Helps identify tightly connected sectors or groups without overlap.

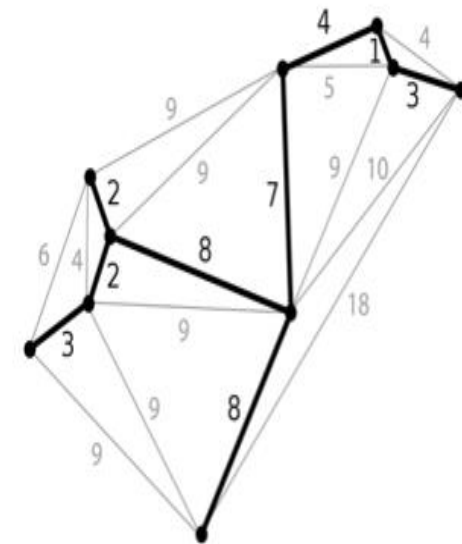
Neutralization – Key Drivers of Market Return

The **Minimum Spanning Tree (MST)** algorithm identifies a subset of graph edges that keeps all nodes connected while minimizing the total edge weights.

By assigning the return correlation between two stocks as the weight of each edge, we convert the competitor graph into a weighted graph.

Multiplying all weights by -1 and applying the MST algorithm reveals the **key drivers of market or sector returns**.

This technique provides valuable insights for **neutralization strategies and risk modeling**.



Investing in Stocks – Key Concepts

When analyzing stock data, analysts work with various price types, including opening, closing, high, low, volume, and **adjusted closing prices** — the latter is used in our analysis.

Key stock investment terms:

Stock Split: A company increases the number of shares by dividing each existing share into multiple ones, lowering their price but keeping the investor's total value unchanged.

Dividend: A payout of company profits to shareholders, which reduces the stock's price accordingly.

Diversification: A risk management strategy where stocks from different sectors are selected to reduce overall portfolio risk.

Diversified Portfolio: Weak correlations between stocks (closer to 0).

Non-Diversified Portfolio: Strong correlations (closer to +1 or -1).

Correlation and Adjacency Matrix Construction

In this paper, we calculate the **correlation between each pair of stocks** in a given dataset and generate a **correlation matrix**.

We then apply a **threshold** to transform the values into 1s or 0s, depending on whether they are above or below the threshold.

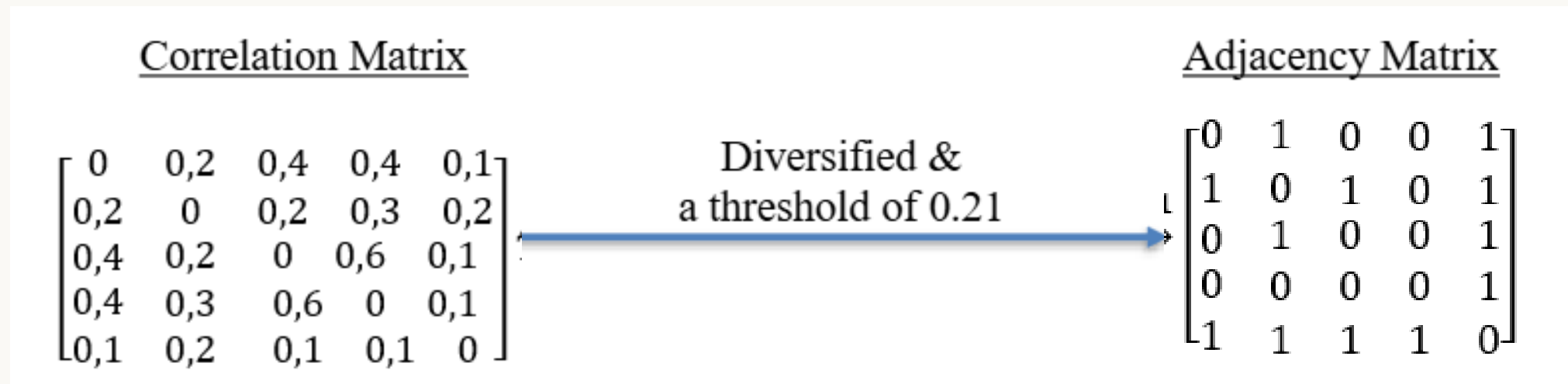
The resulting **adjacency matrix** represents a graph where:

Nodes = individual stocks

Edges = strongest or weakest correlations between them

Correlation and Adjacency Matrix Construction

If we transform the given correlation matrix using diversification and a threshold of 0.21, we obtain the following adjacency matrix.



When analyzing correlations among dozens of stock pairs, it becomes difficult to define an effective threshold and interpret the graph accurately.

To simplify the process, **statistical analysis** is applied using **mean, median, and standard deviation**.

By adjusting the threshold using ± 1 standard deviation from the mean, we can isolate the **top 16% most correlated** or **bottom 16% least correlated** stock pairs, allowing for a well-structured and meaningful graph.

Portfolio Selection in Investing

Diversified or Non-Diversified Portfolio?

To determine whether diversified portfolios are more effective than non-diversified ones, we use a Python-based program.

The program constructs a **graph of selected stocks** based on the **correlations between them**, helping to analyze the structure and performance of each type of portfolio.

The resulting matrix will be properly formatted to create a graph with nodes and edges, but the correlation values must be adjusted.

The next part of the program **compares each correlation value to a chosen threshold and** changes the value to **1 if an edge exists** or **0 if it doesn't**.

In this way, the **correlation matrix is transformed into an adjacency matrix** suitable for graph-based analysis.



Complete Subgraphs and Portfolio Optimization

Finding the largest complete subgraphs is computationally difficult, so we use the **NetworkX** library in Python, which has a built-in function to identify and visualize all complete subgraphs within a graph. The program converts a **correlation matrix into an adjacency matrix**, allowing us to identify either **diversified portfolios** (with low correlations) or **non-diversified portfolios** (with high correlations). Results show that diversified portfolios **consistently outperform the index during stable economic periods**, while non-diversified ones have **unpredictable outcomes**.

Conclusion

Graph theory provides a powerful framework for analyzing financial data and building investment strategies.

By transforming stock correlation data into adjacency matrices, we can model relationships as graphs and identify meaningful structures such as complete subgraphs and diversified portfolios.

Using Python and statistical thresholds, we constructed tools for portfolio selection based on correlation strength.

The results suggest that **diversified portfolios**, built from weakly correlated stocks, **tend to be more stable and perform better** during economically stable periods, while **non-diversified portfolios** carry higher risk and less predictable outcomes.

This approach demonstrates the practical value of graph theory in modern investment analysis and risk modeling.

Thank you for your attention.

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