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Full Length Article **IJCRAR/FL/83**

"A BFS-DFS Approach" Semi-Stock-Temporal Graph Traversals for Market Influence

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Abstract

In this study each stock is particularized vertex in Temporal Graph model, and directional co-movements based create an edge on trading days $G_t=(V, E_t)$. The discrete time layers are fluctuating the market structure, in imbalance to static graph. Based on Breadth-First Search (BFS) and Depth First Search (DFS), To create a temporal traversal framework to investigate this dynamic market network. Whereas temporal DFS discovers vertical sequence of effect across consecutive days, temporal BFS discovers vertical sequence of effect across Consecutive days, temporal BFS grows level by level across time, capturing the horizontal dispersion of links between equities on each trading day. The Semi-Temporal graph's reachability patterns, linked temporal components, and leading- lagging chains of vertices are all visible through these traversals. This graph-theoretic viewpoint lays the groundwork for developing multigraph structures, constructing temporal routes, and incorporating classical methods into financial network research without depending on statistical models.

Keywords: Semi Temporal Graph (STG), Temporal BFS tree, Temporal DFS path, Temporal Traversal (TT), Temporal Connectivity (TC), Equity Network, Leading- Lagging Sequence, Graph Clustering

Introduction

The use of graph theory to financial markets dates back to Rosario N. Mantegna's (1998) pioneering work, which established the use of a Minimum Spanning Tree (MST) to describe the hierarchical structure of stock correlations. In his model, each stock was represented by a vertex,

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and the correlation between pairs of stock was converted into a weighted edge, from which a spanning tree was built. This graph-theoretical depiction opened up new perspectives on stock clustering and market sectoral structure. However, Mantegna's approach was basically static, providing merely a snapshot the temporal evolution of market dynamics.

Building on this foundation, this study proposes a temporal graph method to stock market analysis. Unlike static MST, our approach includes time into the spanning tree structure. By using Breadth-First search (BFS) and Depth-First search (DFS) traversals across temporal layers of the market graph, we can see how influence spreads between stocks over time. BFS exposes quick, short-term impacts that spread extensively over the market, whereas DFS reveals deeper, sequential relationships that grow over longer time periods.

This combination of temporal spanning trees with BFS/DFS traversal differs from previous static techniques and gives a more comprehensive insight of financial market dynamics. It allows for the detection of lead-lag interactions, the finding of time-varying market clusters, and the simulation of dynamic stock hierarchies. Such a framework is not only theoretically noteworthy, but also practical in terms of portfolio management, risk monitoring, and predictive modelling in current financial systems.

To summarize, our study bridges the gap between graph theory and financial market analysis by expanding the static MST notion to a dynamic temporal model. By incorporating BFS and DFS algorithms into the temporal spanning tree, we develop a unique technique that represents the changing nature of market interactions while also providing fresh insights into the temporal structure of stock market network.

Literature Review

Introduces grouping of stock returns over time, utilizing a graph visualization to show how clusters grow, which aids portfolio methods.[1]

Models the stock market as a temporal network, leveraging temporal centrality to enhance portfolio selection.[2]

Stock market prediction of graph-based approaches in survey application[3]

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Cross-border relationship of forecasting modelling in inter-intra graph neural networks for stock price novel.[4]
STP method on Directed graph for stock trading Network in Simple paths and Cycles.[5]
Analysis of Equity Markets of a graph theory approach.[6], [7]

Preliminaries:

Definition:2.1 Given at temporal graph $\mathcal{G} = (\tilde{\upsilon}, €)$ and a starting time t_{ς}, a DFS in $\mathcal{G}$ starting time at $₮_{\c{s}}$, named as DFS- $\tilde{\upsilon}$1, is defined as follows:

1. Initialize $\sigma(\c{s}) = \infty$ for all $v\epsilon\tilde{\upsilon}$, and select a source vertex ş.
2. Visit s and $\sigma(\c{s}) = ₮_{\c{s}}$ and go to step 2(ɓ)
    a) **After visiting vertex u**: Let E_u be the set of temporal edges outgoing from u, where each edge$(u, v, ₮) \in €_{ų}$, has not been traversed before and $\sigma(u) \leq t$.

If $€_{ų} \neq \emptyset$, we choose the edge $e = (u, v, ₮) \in €_{ų}$, where $t = max\ \{₮' : (u, v', ₮') \in €_{ų}\}$,and traverse e and go to step 2(b).

Else $\left(i.e.,_u €_{ų} \neq \emptyset\right)$, we backtrack to $u's$ predecessor $u'\left(i.e., we\ have\ just\ visied\ u\ via\ the\ temporal\ edge\ (u', u, t')\right)$ and repeat step 2(a); or if u is the source vertex, then terminate the DFS.

b) **After traversing a temporal edge** $(u, v, ₮)$: If $\sigma(v) > ₮$, we visit v and set $\sigma(v) = ₮$, And go to step 2(a). Else, repeat v and set $\sigma(v) = ₮$, and go to Step 2(a). Else, repeat step 2(a).[8]

Definition:2.2 (Time constraint on n-day traversal). Let $G = (V, E_{₮})$ here temporal graph is called as a n-day trading day and form of the edge $(stock\ A,\ stockB,\ time₮,\ w\ )$.
A sequence of temporal traversal is a sequence of an intraday edge:
$\pi = \left[(s_1, s_2, ₮_1,, w_1), \left((s_1, s_2, ₮_2, w_2)\right) \ldots\ldots \left((s_1, s_2, ₮_k, w_k)\right)\right]$

1. Stock Connectivity: Each stock edge end where the next stock edge is started.
2. Ordering of time: The n day order is considering 1-n in-between time is traversal $₮_1, ₮_2 \ldots. ₮_k$. Trading sequence day.

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3. Relation retaining: each edge carries a weight is considered predecessor, successor, neutral

If the time condition is a strict temporal path, then it's $(Ŧ_{i+1} > Ŧ_i)$,
If small overlaps are allowed $(Ŧ_{i+1} \geq Ŧ_i - \delta)$, it becomes a semi-stock-temporal traversal.

Methodology

1. Data Collection
   Gather daily closing prices for certain stocks from a CSV file dataset.
   Eg: 100 data points (10 stocks and 20 days).
2. Data Processing
   Put stock prices in an organized manner. Determine everyday transitions with:
   $\Delta P = P_t - P_{t-1}$
   If $\Delta P > 0 \rightarrow state = '+'$
   If $\Delta P < 0 \rightarrow state = '-'$
   If $\Delta P = 0 \rightarrow state = '0'$
3. Graph construction
   Use Network-X comparable packages to create a semi-temporal graph. The closing price of a stock on a given day is represented by each node. Days are connected by directed edges.
4. Graph Traversal
   Compare stock patterns on the same day using the Breadth-First Search (BFS) method. Depth-First Search follow each stock's whole historical price trajectory.
5. Visualization- Clear, Clustered, Summarized visualization.

Algorithm:

Semi-Temporal Analysis of stock Prices Using Graphs.

Input:

$S = \{S_1, S_2, S_3, \ldots\ldots\ldots, S_m\}$ *Set of m stocks*

$D = \{d_1, d_2, d_3, \ldots\ldots\ldots, d_n\}$ *Set of trading days*

$P_{s,d} \rightarrow$ *Closing price of stock s on day d*

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Output

Semi- temporal graph $G = (V, E)$

BFS traversal results

DFS traversal result

Price Change Calculation

For each stock $s \in S$ and each day $d \in D$ where $d \geq 2$:

$$\Delta P_{s,d} = P_{s,d-1}$$

$$S_{s,d} = \begin{cases} + \ if \ \Delta P_{s,d} > 0 \\ - \ if \ \Delta P_{s,d} < 0 \\ 0 \ if \ \Delta P_{s,d} = 0 \end{cases} \text{ where } +1(I), -(D), 0(N)$$

Graph Construction

Define a directed semi-temporal graph:

$G = (V, E)$

$V = \{v_{s,d} / s \in S, d \in D\} \longrightarrow Each\ node\ represents\ stock\ day\ d$

$E = \{(v_{s,d} \to v_{s,d+1}) / s \in S, 1 \leq d < n\} \to Directed\ edges\ represent\ between\ consecutive\ days.$

BFS Traversal

$$\text{BFS}(v_{s,1}) = \begin{cases} \quad Visit\ nodes\ level\ by\ level \\ S_{s,d} Compare\ states\ across\ all\ stocks\ for\ each\ day \end{cases}$$

BFS is used to identify similar price behaviours among different stocks on the same day.

DFS Traversal

$$\text{DFS}(v_{s,1}) = \begin{cases} \quad Respectively\ visit\ (v_{s,d} \to v_{s,d+1}) \\ Trace\ complete\ price\ path\ from\ 1\ to\ Day\ n \end{cases}$$

DFS is used for Stocks long term price transitions analyse

$$Color(V_{s,d}) = \begin{cases} GREEN \ \ if\ S_{s,d} = + \\ RED \quad\ \ if\ S_{s,d} = - \\ GRAY \quad if\ S_{s,d} = 0 \end{cases}$$

Time constraint on n-day traversal

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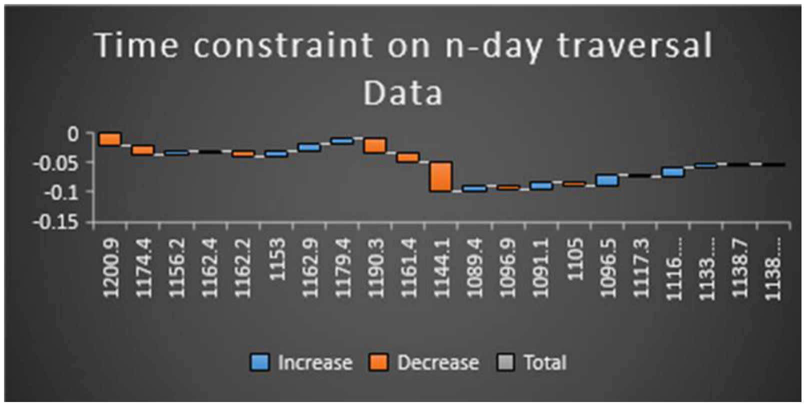

Figure:2.2 Trend line for 10 stock and 20 closing prices

The Semi-temporal graph created using the closing prices of many equities is displayed in Figure 2.2. The stock price on a given day is represented by each node, and the transitions between days are represented by directed edges. Prices rises are represented by green nodes, price reductions by red nodes, no change is represented by blue nodes. Larger datasets like 10 stocks and 200 days) yield more complicated structures that require cluster-wise representation for better comprehension, whereas smaller datasets like 5 stocks and 5 days generate a simple and straightforward graph.

Graph-Based Semi-Temporal Stock Price Analysis Using BFS and DFS Traversal

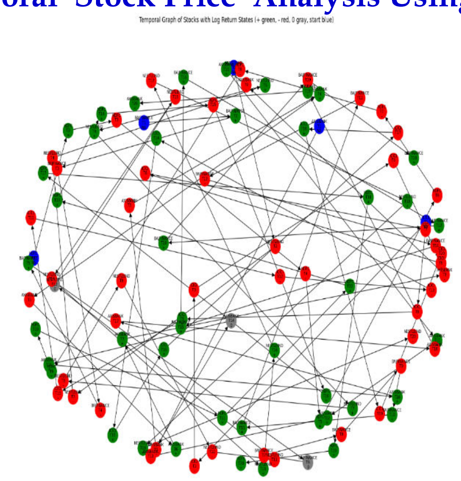

Figure 2.3 Semi-Temporal graph using BFS and DFS large data

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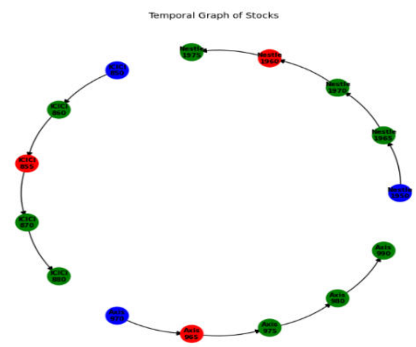

Figure 2.4 Semi- Temporal graph using small data

Conclusion

In this study, we analysed the n-day closing price of taking ten stocks and twenty closing for different sector using Semi-Temporal graph. Each day's price change was represented as +(increase), -(decrease), or 0(no change). Using this approach, we were able to clearly visualize stock price movements and trends.

We applied BFS to compare stock behaviours day by day and DFS to trace the complete price path of each stock. This method makes it easier to understand stock patterns and provides a simple way to study price transitions.

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