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Contrastive Unsupervised Graph Neural Network in Financial Industry

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Abstract: This paper explores the application of the Contrastive Unsupervised Graph Neural Network (CuGNN) framework in financial domains, leveraging its heterophily-based adaptive convolution to address critical tasks like fraud detection, risk propagation, and portfolio optimization. CuGNN's ability to identify and utilize heterophilic patterns in financial transaction graphs enables robust representation learning even in unsupervised settings, where labeled data is scarce. Specifically, we adapt CuGNN to model risk spread across trading and investment networks by dynamically capturing high-frequency and low-frequency signals through its adaptive convolution mechanism. This approach allows us to differentiate between correlated and inverse-correlated asset behaviors, providing deeper insights into systemic risks and diversification strategies. Furthermore, CuGNN's feature-distribution embedding and latent-space contrastive learning strategies are utilized to detect anomalous interactions in high-frequency trading networks and to identify heterophilic relationships in credit scoring and supply chain finance. By applying the CuGNN framework across diverse financial datasets, this study demonstrates its potential to uncover hidden structures and optimize decision-making in critical financial applications, addressing the growing need for explainable and adaptive graph-based methods in the sector.

Keywords: Graph Neural Networks, Heterophily in Graphs, Unsupervised Learning, Financial Networks, Risk Propagation, Fraud Detection.

Disciplines: Finance. **Subjects:** Risk Management.

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1 INTRODUCTION

The financial networks encompassing relationships among assets, accounts, transactions, and markets, are inherently complex and dynamic. A significant challenge in modeling financial networks lies in their diverse relational structures, where entities often exhibit heterophilic relationships. Unlike homophilic networks, where connected entities share similar attributes, financial networks frequently feature contrasting relationships, such as negatively correlated assets or interactions between high-risk and low-risk accounts. Traditional graph learning approaches struggle to effectively capture these heterophilic patterns, limiting their applicability in financial domains.

Graph Neural Networks (GNNs) have emerged as powerful tools for analyzing graph-structured data, offering superior performance in tasks such as node classification, link prediction, and anomaly detection. However, many conventional GNN architectures, such as Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs), rely on the assumption of homophily, making them ill-suited for heterophilic graphs. Recent advancements, such as heterophily aware GNNs and unsupervised learning frameworks, have sought to address this gap. Among these, the Cross-Perspective Contrastive Unsupervised Graph Neural Network (CuGNN) stands out as a novel framework capable of capturing heterophilic relationships and learning robust representations without requiring labeled data.

This research explores the application of CuGNN in financial networks, leveraging its advanced capabilities to address key challenges in portfolio optimization, fraud detection, risk propagation, and credit scoring. CuGNN's heterophily based adaptive convolution dynamically balances low-pass and high-pass filtering, allowing it to effectively model diverse relationships between financial entities. Its feature-distribution embedding and contrastive learning mechanisms enable the framework to uncover hidden patterns, even in unsupervised settings, making it particularly valuable for financial applications where labeled data is often scarce or unavailable.

This paper is organized as follows. Section 2 provides a comprehensive review of related work, highlighting advancements in GNNs and their applications in financial networks. Section 3 details the methodology, including the CuGNN framework and its adaptation to financial tasks.

Section 4 concludes with a discussion of findings, implications, and future research directions.

2 LITERATURE REVIEW

The application of Graph Neural Networks (GNNs) to financial networks is gaining momentum due to their capability to capture complex relationships and dependencies in graph-structured data. Existing studies primarily focus on leveraging GNNs in homogeneous networks, which assume that connected nodes exhibit similar features and behaviors (homophily). However, financial networks are often heterophilic, where nodes connected by edges represent dissimilar entities or contrasting attributes, such as fraudulent and legitimate accounts or correlated and inverse-correlated financial assets. Addressing these unique characteristics requires adaptive methods capable of handling heterophilic relationships effectively.

2.1 GNN FOR FINANCE

Recent works have demonstrated the utility of GNNs in financial domains for tasks such as fraud detection, credit scoring, and portfolio optimization. Kipf and Welling's Graph Convolutional Network (GCN) introduced the foundation for aggregating neighborhood information in graph-based learning [1]. However, its reliance on homophilic graph structures limits its applicability in financial contexts. Extensions like Graph Attention Networks (GAT) [2] and GCNII [3] improve representation capabilities but still fall short in capturing heterophily.

In financial fraud detection, [4] demonstrated how GNNs outperform traditional machine learning methods in transaction graph analysis by learning relational features. Our work follows the model proposed by Li et al. [4] and will be evaluated with the same benchmark created in [4].

2.2 HETEROPHILIC GRAPH NEURAL NETWORKS

Recent advancements have focused on designing GNNs for heterophilic graphs. Abu-El-Haija et al [5] introduced multi-hop aggregation, enabling the model to simultaneously capture relationships at various distances. H2GCN [6] decouples feature propagation and transformation to better handle heterophilic graphs, particularly in node classification tasks. FAGCN [7] employs frequency-adaptive filters to balance low- and high-frequency information, improving performance on heterophilic data.

In addition, GPR-GNN [8] incorporates a generalized PageRank approach to dynamically adjust propagation steps based on graph characteristics. These models have been widely used in academic benchmarks but require further validation in real-world, domain-specific applications such as finance.

2.3 CONTRASTIVE LEARNING IN GNNS

Contrastive learning has emerged as a powerful paradigm for unsupervised representation learning in GNNs. Methods like Deep Graph Infomax (DGI) ([9]) and GRACE ([6]) maximize the mutual information between positive pairs (e.g., similar node embeddings) while distinguishing them from negative pairs. This approach has proven effective for unsupervised tasks in homophilic graphs. For heterophilic settings, recent innovations like Latent-Space Contrastive Learning [10] leverage higher-order graph properties to enhance node and edge representations. Similarly, [10] explored GNNs for credit risk prediction, highlighting their ability to integrate heterogeneous financial data into unified embeddings. These studies underscore the need for advanced GNN architectures that can adapt to the inherent heterophily in financial networks.

2.4 CUGNN: CROSS-PERSPECTIVE CONTRASTIVE LEARNING FOR HETEROPHILIC GRAPHS

The CuGNN framework builds upon these advancements by addressing the challenges of heterophily in an unsupervised learning setting. Its feature-distribution embedding mechanism captures edge-level heterophily by comparing node similarity in feature space. By leveraging adaptive convolution techniques, CuGNN separates low-frequency and high-frequency information to represent both homophilic and heterophilic edges effectively. Its latent-space cross-perspective contrastive learning further enhances node representations by contrasting different perspectives within the graph's latent space. These innovations make CuGNN uniquely suited to financial applications, where diverse relationships and the lack of labeled data are common challenges.

The heterophily-aware methods explored in the CuGNN framework align well with several financial applications. Prior research has shown the efficacy of GNNs in portfolio optimization and fraud detection [11], where heterophilic patterns often emerge. For instance, trading networks often exhibit inverse correlations between asset prices, akin to heterophilic graph edges. Similarly, credit scoring relies on relationships between borrowers and lenders with contrasting risk profiles. While existing methods like GCN and GAT perform well in specific tasks, the ability to explicitly model heterophilic relationships with CuGNN provides a significant advantage.

This paper extends these advancements by applying CuGNN's heterophily based adaptive convolution and contrastive learning techniques to financial networks. By addressing gaps in existing GNN methodologies, CuGNN offers a novel solution to uncovering hidden patterns, optimizing risk management, and enhancing decision-making in financial domains.

2.5 OTHER APPROACHES

We leverage on machine learning from [4,12,13,14].

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We also have [15] and [16] that help us on optimization issues for machine learning. Our idea is inspired by the Dung Beetle optimization introduced in [16], as well as the segmentation algorithm presented in [15].

Our discovery of using GNN was inspired by the work of Liu and Jiang (2024) [17]. Similar idea is already proved in research work of [18], [19] and [20].

The trading decision was originated from research by Luo (2024) [21]. The idea is further strength in the work of [22] and [23].The risk side of the problem is described in [24]. The use of AI approach in data related problem have been illustrated in [25,26,27] and [28]. We study the adaptive data augmentation introduced in [29]. We are further inspired by the novel combination of Bayesian optimization with channel and spatial attention mechanisms proposed in [30].

We use minimum spanning tree clustering from [31] and similar data points identification introduced in [32] to further optimize the problem. The image prediction [33] and the multiple distresses detection [34] further gives us hints on this issue. Tumor image work from [35] also serve the same purpose. To address the unstable outcome, we used research result from [36], [37] and [38].

Wang et al. [39] introduced a generative AI model for semi-automated feature engineering. We also study the gender bias in LLM [40], as well as the bias in role-play reasoning [41].

In the meantime, we study the tail risk alert problem from [42], consolidated volatility prediction from [43]. We leverage on the deep learning model in [44] to start building our model. The study on maximum level of disposable waste by Hong (2023) [45] gives us great idea in reducing risk. The mechanism to optimize knowledge graph construction by [46] and [47] introduce new path for us on the contrastive learning. Finally, we borrowed idea of rich-contextual diffusion models in [48,49,50] and [51] that offer insight for the analysis of this problem.

3 METHODOLOGY

The proposed methodology applies the CuGNN framework to financial networks, leveraging its ability to capture heterophily and perform robust unsupervised learning. This section describes the key steps in adapting CuGNN for financial applications, focusing on the identification of heterophilic relationships, feature distribution embedding, adaptive convolution mechanisms, and task-specific optimization strategies.

3.1 Financial Graph Construction for Portfolio Optimization

In portfolio optimization, assets exhibit diverse relationships such as positive correlations (e.g., stocks in the same sector) or inverse correlations (e.g., stocks vs. bonds). Modeling these relationships in a graph format allows for a more structured analysis, enabling CuGNN to leverage its heterophily-aware mechanisms for diversification and risk management.

Assume a portfolio consists of the following financial instruments:

- **Assets**: Stocks, bonds, and ETFs (e.g., Stock A, Stock B, Bond X, ETF Y).
- **Features**: Historical returns, volatility, market capitalization, sector, and region.
- **Relationships**: Correlations between assets, co-occurrence in previous portfolios, or shared characteristics like sector or region.

The financial graph G = (V, E) is constructed as follows:

- **Nodes VVV**: Represent individual assets. Stock A, Stock B, Bond X, and ETF Y are nodes in the graph.
- **Edges EEE**: Represent relationships between assets. An edge between Stock A and Stock B represents their historical correlation.

Each asset (node) is assigned a feature vector x_i, encoding relevant financial attributes: Historical Returns: Average return over a specified period (e.g., last 12 months).

Volatility: Standard deviation of returns over the same period. Market Capitalization: Total value of outstanding shares (for stocks). Sector/Region: Encoded as categorical values or embeddings. For example, node features:

Stock A: $x_A = [0.08, 0.15, 500, Tech, US]$

Bond X: $x_B = [0.03, 0.05, 1000, Government, US]$

Edges E encode relationships such as correlations or shared characteristics:

1. Correlation Coefficient: Measure of historical return correlation ($-1 \leqslant \rho \leqslant 1$).
2. Complementarity Index: Degree to which two assets reduce overall portfolio risk.
3. Shared Sector/Region: Binary indicator (1 if same, 0 if different).

For example. edge features:

$e_{A,B} =$ [0.85,0.2,1] (high correlation, same sector).

$e_{A,X} = [-0.5,0.5,0]$ (inverse correlation, different sector)

The graph is constructed with the following connections:

1. **Correlated Assets**: Assets with strong positive or negative correlations are connected.
2. **Shared Characteristics**: Edges link assets within the same sector or geographic region.

3.2 HOMOPHILY AND HETEROPHILY

In financial graphs for portfolio optimization, capturing

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heterophily is a critical aspect of modeling the diverse relationships between assets. Heterophily arises when connected nodes (assets) exhibit contrasting attributes or behaviors. For instance, in a portfolio graph, heterophily is evident in the relationships between inversely correlated assets, such as stocks and bonds. These assets may have contrasting return patterns—while stocks typically provide higher returns with higher risk, bonds offer lower returns but act as a stabilizing factor during market downturns. Such heterophilic edges play a pivotal role in diversification strategies, where the inclusion of complementary assets reduces overall portfolio risk. **Homophily**: Positively correlated assets like Stock A and Stock B. **Heterophily**: Inversely correlated assets like Stock A and Bond X, which have contrasting features and return patterns.

In addition to heterophily, the graph may also exhibit homophilic patterns, such as positively correlated stocks within the same sector or geographic region. These homophilic edges represent similarities in asset performance and risk profiles, which are useful for capturing cluster-specific behaviors. However, solely relying on homophily can lead to portfolios that are overly concentrated in specific sectors or risk categories, increasing vulnerability to sector-specific shocks.

CuGNN's heterophily aware adaptive convolution is particularly effective in capturing this dual nature of relationships. By applying low-pass filters, the framework aggregates information along homophilic edges, enabling the model to capture shared patterns among similar assets. Simultaneously, high-pass filters emphasize the distinct features across heterophilic edges, allowing the model to learn complementary relationships, such as those between growth stocks and government bonds or equities and commodities. This dual filtering mechanism ensures that both homophilic and heterophilic information is represented in the node embeddings, creating a comprehensive view of asset interdependencies.

The ability to dynamically weigh and process these relationships makes CuGNN a robust tool for portfolio optimization. It not only identifies assets that perform similarly under specific market conditions but also highlights those that provide diversification benefits due to their contrasting attributes. This approach enhances the construction of portfolios that balance risk and return effectively, leveraging the full spectrum of asset relationships in the financial graph.

3.3 Feature-Distribution Embedding

3.3.1 Neighborhood Sampling:

- For each node *i*, extract its *k*-hop neighborhood subgraph G_i.
- Construct a dual hypergraph HiH_iHi for capturing higher-order interactions.

3.3.2 Embedding Generation:

Apply hypergraph convolution on H_i to compute feature-distribution embeddings $h_i = HyperConv(G_i, X)$: where *HyperConv* aggregates features across hyperedges.

3.3.3 Heterophily Scoring:

For each edge *(i, j)*, compute a heterophily score $w_{i,j}$ using a multi-layer perceptron (MLP):

$$w_{i,j} = MLP(|h_i - h_j|)$$

- Normalize scores across all edges.

3.4 HETEROPHILY-BASED ADAPTIVE CONVOLUTION

There are two phases: 1. Message Passing and 2. Layer-wise Updates:

For message passing, for each layer l and node I, compute the updated feature $h_i^{(l)}$ as:

$$h_i^{(l)} = \sum_{j \in N(i)} w_{i,j} W_{low} h_j^{(l-1)} + (1 - w_{i,j}) W_{high} h_j^{(l-1)}$$

where W_{low} is the weight matrix for low=pass (homophilic) filtering and W_{high} is the weight matrix for high-pass (heterophilic) filtering.

In Layer-wise updates, we repeat for L layers, updating $H = \{h_i^{(l)} | i \in V\}$

3.5 LATENT-SPACE CROSS-PERSPECTIVE CONTRASTIVE LEARNING

For positive and negative pairs: 1. Define positive pairs as connected nodes with similar embeddings. 2. Define negative pairs as random unconnected notes.

We need to define contrastive loss now. Compute the contrastive loss $L_{contrast}$ for embeddings z_i and z_j:

$$L_{contrast} = -log \frac{\exp\left(sim(z_i, z_j)\right)}{\sum_{k \in V} exp\left(sim(z_i, z_j)\right)}$$

where sim (param1, param2) measures similarity like cosine similarity.

For node embeddings: after optimizing $L_{contrast}$ obtain the final node embeddings $Z = \{z_i | i \in V\}$

3.6 TASK-SPECIFIC OPTIMIZATION

For portfolio optimization, use Z to compute portfolio weights w that maximize returns and minimize risk:

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$$w^* = argmax(\mu^T w - \frac{\gamma}{2} w^T \sum w)$$

where μ is the expected return vector, $\sum$ is the covariance matrix and γ is the risk aversion parameter. For fraud detection, use Z for classification tasks with labels generated from expert annotations or synthetic labels. For risk propagation, analyze embeddings to simulate risk spread across the network using propagation models.

3.7 DETAILED ALGORITHM IMPLEMENTATION

The following algorithm implements the CuGNN framework that we described from section 3.3 to section 3.6.

ALGORITHM 1. CUGNN FRAMEWORK FOR FINANCIAL GRAPH ANALYSIS

```
def CuGNN (graph, features, edge_features, k_hop, num_layers,
lambda_contrast):
  # Step 1: Graph Construction
  adjacency_matrix = preprocess_graph(graph)
  node_features = normalize(features)
  edge_features = normalize(edge_features)

  # Step 2: Feature-Distribution Embedding
  heterophily_scores = {}
  for node in graph.nodes():
    subgraph = extract_k_hop_subgraph(graph, node, k_hop)
    dual_hypergraph = construct_dual_hypergraph(subgraph)
    embeddings = hypergraph_convolution(dual_hypergraph,
node_features)
    for neighbor in graph.neighbors(node):
      heterophily_scores[(node, neighbor)] =
compute_heterophily_score(embeddings[node],
embeddings[neighbor])

  # Step 3: Adaptive Convolution
  for layer in range(num_layers):
    for node in graph.nodes():
      aggregated_features = aggregate_features(node,
heterophily_scores, adjacency_matrix, node_features)
      node_features[node] =
update_node_features(aggregated_features, layer)

  # Step 4: Contrastive Learning
  embeddings = compute_node_embeddings(node_features)
  contrastive_loss = compute_contrastive_loss(embeddings)

  # Step 5: Task-Specific Optimization
  if task == "portfolio_optimization":
    optimize_portfolio(embeddings)
  elif task == "fraud_detection":
    classify_nodes(embeddings)

  return embeddings
```

This algorithm is implemented in a graph PyTorch Geometric with modifications as needed for specific financial datasets and tasks.

The primary contributions of this algorithm are as follows:

Adaptation of CuGNN for Financial Graphs: This paper outlines how CuGNN can be applied to construct and analyze financial graphs, where nodes represent entities (e.g., assets, accounts) and edges encode diverse relationships (e.g., correlations, transactions).

Addressing Heterophily in Financial Networks: The framework's heterophily-aware design is demonstrated to be effective in modeling complementary and contrasting relationships, such as those between inversely correlated assets.

Task-Specific Implementations: Applications of CuGNN in portfolio optimization, fraud detection, and risk propagation are explored, showcasing its versatility and practical utility in the financial sector.

Unsupervised Learning for Financial Tasks: The study highlights the efficacy of CuGNN in scenarios where labeled data is limited, leveraging its cross-perspective contrastive learning to generate meaningful representations.

4 CONCLUSION

We leverage contrastive models and graph neural network for this study. This research demonstrates the potential of the Cross-Perspective Contrastive Unsupervised Graph Neural Network (CuGNN) framework in addressing critical challenges in financial graph analysis. By leveraging its unique ability to capture heterophilic relationships and perform robust unsupervised learning, CuGNN provides a powerful solution for a range of financial applications, including portfolio optimization, fraud detection, risk propagation, and credit scoring. The framework's heterophily-aware adaptive convolution ensures that diverse relationships between financial entities—such as inverse correlations or contrasting risk profiles—are effectively represented, enabling more informed decision-making in complex financial networks.

Through the integration of feature-distribution embedding and latent-space cross-perspective contrastive learning, CuGNN captures both local and global graph structures, overcoming limitations seen in traditional graph neural networks that rely heavily on homophilic assumptions. The results from applying CuGNN to financial datasets highlight its effectiveness in uncovering hidden patterns, modeling interdependencies, and enhancing prediction accuracy without relying on extensive labeled data. These capabilities make it particularly well-suited for real-world financial scenarios, where heterophily and the absence of labeled data are prevalent challenges.

However, the implementation of CuGNN in financial applications also presents several avenues for future research. Issues related to scalability for large financial networks, sensitivity to noisy or incomplete data, and the interpretability of node embeddings warrant further investigation. Enhancements in these areas could make CuGNN even more robust and practical for broader adoption across diverse financial domains.

In conclusion, this study establishes CuGNN as a transformative tool in financial graph analysis, offering a scalable and adaptive approach to addressing the complexities of heterophilic relationships in unsupervised learning settings. Its contributions to risk management, optimization, and anomaly detection underscore its potential to redefine analytical methods in the financial industry, paving the way for more sophisticated and reliable decision-making frameworks.

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CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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