A Systematic Literature Review on Graph-Based Models in Credit Risk Assessment

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Overview

Motivation for the Use of Graph-Based Models in Credit Risk Assessment

Current Limitations of Traditional Models:

- Rely on static borrower-specific features (e.g., credit scores, financial ratios).
- Assume independence among borrowers, neglecting interconnectedness.
- Fail to address systemic risks and contagion in financial networks.

Advantages of Graph-Based Models:

- Capture latent relationships (e.g., social, economic, and transactional ties).
- Identify systemic vulnerabilities and propagation of financial distress.
- Enable dynamic analysis of evolving networks (e.g., P2P lending, interbank markets).

Increasing Adoption in Finance:

- Applications in P2P lending, SME credit scoring, and systemic risk management.
- Growing interest due to advancements in Graph Neural Networks (GNNs) and network analytics.

Research Questions

Primary Research Question:

How do different graph-based models compare in enhancing credit risk assessment?

Sub-Questions:

What types of graph-based models (e.g., GNNs, centrality measures, community detection) are most commonly used?

What specific applications (e.g., default prediction, systemic risk analysis) benefit from these models?

What challenges and opportunities exist for future adoption in credit risk assessment?

Broader Objective:

Bridge the gap between traditional risk assessment techniques and network-driven methodologies.

Contributions of the Study

Systematic Literature Review (SLR):

- Comprehensive review of a final selection of 78 scholarly articles from top databases (Scopus, Web of Science).
- Application of structured coding to identify trends, methods, and key insights.

Mapping the Research Landscape:

- Analysis of temporal trends (e.g., significant growth since 2018).
- Insights into journal coverage (e.g., focus on finance, computer science, and economics).
- Keyword analysis to highlight interdisciplinary themes.

Insights into Applications:

- Utility in diverse settings:
  - P2P lending: Improved credit scoring and borrower profiling.
  - SME credit scoring: Integration of transactional and relational data.
  - Systemic risk: Understanding contagion in interbank networks.

Explore Future Directions:

- Identified gaps in hybrid model integration and real-time credit scoring.
- Recommendations for expanding functionality (e.g., predictive modeling in decentralized finance).

Systematic Review Process

Objective: Conduct a comprehensive review of scholarly literature on graph-based models in credit risk assessment.

Framework of Varsha P S et al. (2024):

1. Define review goals by chosen research questions.
2. Develop a detailed review methodology to guide the approach.
3. Conduct an extensive literature search.
4. Apply inclusion and exclusion criteria.
5. Assess study quality and extract/code data.
6. Synthesize and analyze findings.
7. Report results systematically.

Databases Used: Scopus and Web of Science (broad coverage and robust search features).

Search and Inclusion Criteria

Search Query:

- Keywords: "graph," "network models," "credit risk," "P2P lending," etc.
- Boolean Operators: AND/OR to refine results.

Inclusion Criteria:

- Articles in scientific journals, written in English.
- Articles including predefined keywords in the title, abstract, or keywords.

Exclusion Criteria:

- Publications before 1993, or from publishers like MDPI or Hindawi.
- Irrelevant abstracts, titles, or unavailable online.

Outcome:

- From 1,066 retrieved articles, 78 were included after quality and relevance checks.

Coding Framework

Purpose:

Organize and analyze data systematically from reviewed articles.

We applied a double-blind peer review process for the article coding.

Criteria for Coding:

Graph Type: Directed, undirected, weighted, etc.

Application Situation: Credit scoring, systemic risk, etc.

Research Questions: Goals of each study.

Methodology: Types of graph-based models used.

Data Source: P2P platforms, banking data, etc.

Task Type: Classification, prediction, clustering, etc.

Performance Metrics: AUC, F1-score, etc.

Validation: Cross-validation, hold-out tests, etc.

Temporal Distribution of Literature

Key Insights:

First study on graph-based credit risk assessment published in 2012 (Hu et al.).
Significant growth in publications since 2018, with a peak in 2024.

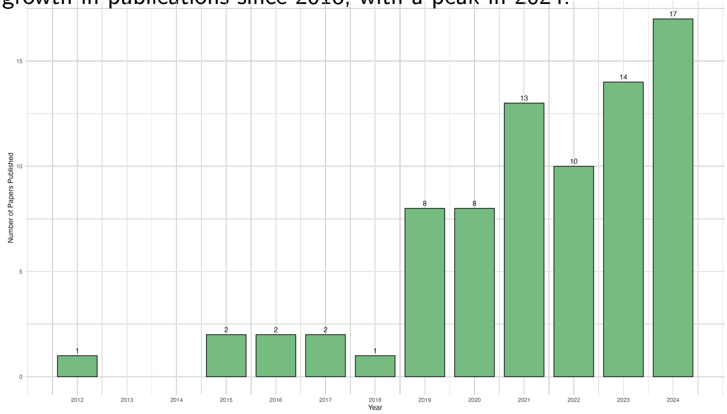

Figure: Temporal Distribution of Literature

Journal and Topic Distribution

Key Insights:

- Top-cited papers are predominantly published in journals covering Business & Economics, Computer Science, and Operations Research.
- Reflects interdisciplinary nature of the field.
- Significant presence in applied journals for practical methodologies.

Visualization:

- Next slide.

Journal and Topic Distribution

Key Insights:

Top Journals:

Journal of Financial Stability, *Expert Systems with Applications*, *MIS Quarterly*.

Top Topics:

Business & Economics (45%), Computer Science (30%), Operations Research (15%), Others (10%).

Journal	**Focus Areas**	**Top-Cited Papers (#)**
Journal of Financial Stability	Business & Economics	2
Expert Systems with Applications	Computer Science; Operations Research	4
MIS Quarterly	Computer Science; Business & Economics	1
Applied Soft Computing	Computer Science	2
Physica A	Physics	1
Others (e.g., Omega, JME, EJOR)	Interdisciplinary	10

Table: Summary of Top Journals and Topics

Keyword Analysis

Key Insights:

Most frequent keywords include "credit risk," "credit scoring," and "peer-to-peer lending."
Emerging topics: "machine learning," "graph neural networks," and "financial stability."

Application of Graph-based Models in P2P Lending and SME Credit Scoring

Key Insights:

- **P2P Lending:**
  - Network-derived variables significantly improve default prediction (Giudici et al., 2019; Ahelegbey et al., 2019b).
  - Studies show the role of borrower connectivity in influencing risk assessments (Liu et al., 2024).
  - Advanced techniques like latent factor models reveal clustering patterns (Ahelegbey et al., 2019a).
- **SME Credit Scoring:**
  - Inter-firm relationships captured through transactional networks (Kou et al., 2021; Vinciotti et al., 2019).
  - Enhanced credit scoring models using graph-based centrality measures (Giudici et al., 2020; Rishehchi Fayyaz et al., 2020).
  - Frameworks like GNNs outperform traditional scoring methods (Lee et al., 2021).

Application of Graph-based Models in Systemic Risk Assessment in Banking

Key Insights:

Study Focus:

- Interbank lending, cross-border credit networks, and systemic contagion (Poledna et al., 2015).
- Quantifying risk propagation across interconnected banking systems (Tonzer, 2015; Cheng et al., 2022).

Techniques Used:

- Multi-layer networks to capture interbank dependencies (Poledna et al., 2015).
- Graphical Gaussian Models (GGMs) to model systemic risks (Cerchiello and Giudici, 2016).
- Dynamic multi-layer networks for real-time risk monitoring (Jin et al., 2024).

Applications:

- Identifying vulnerable nodes and key contagion pathways (Chen et al., 2020).
- Supporting macroprudential policy development for risk containment (Lin et al., 2022).

Emerging Techniques: GNNs and Hypergraphs

Graph Neural Networks (GNNs):

- Combine node features with graph structure for advanced predictions (Liu et al., 2024).
- Applications in credit risk prediction and fraud detection (Shi and Zhao, 2023).
- E.g., hierarchical GNNs capturing borrower-supplier relationships (Song et al., 2024).

Hypergraphs:

- Extend traditional graphs to model higher-order relationships (Shi et al., 2024).
- Useful for capturing complex interactions in SME lending and P2P platforms.
- Show promise in systemic risk modeling with multi-entity transactions (Zhao et al., 2023).

Challenges in Graph-Based Credit Risk Assessment

Key Challenges:

- **Data Availability and Quality:**
  - Limited access to detailed datasets, especially in real-world financial networks (Muñoz-Cancino et al., 2023).
  - Incomplete or noisy data impacts the robustness of graph-based models (Hu et al., 2012).
- **Scalability and Computational Complexity:**
  - High computational resources required for processing large and dynamic networks (Wu et al., 2023; Yıldırım et al., 2021).
  - Difficulty in scaling models for real-time risk monitoring in volatile credit markets.
- **Integration with Traditional Models:**
  - Lack of established frameworks for combining graph-based and statistical methods (Dastile et al., 2020).

Future Directions in Graph-Based Credit Risk Assessment

Real-Time Credit Scoring:

- Leverage graph-based models for dynamic monitoring of financial networks.
- Enhance predictive accuracy of these models in volatile credit markets.

Decentralized Finance (DeFi) Applications:

- Adapt graph models to assess credit risk in blockchain-based lending and DeFi platforms.
- Identify risks in smart contracts and lending pools using network patterns.

Hybrid Frameworks for Risk Assessment:

- Integrate graph-based methods with traditional models to create more robust systems.
- Develop frameworks for seamless adoption in financial institutions.

Conclusion

Summary of Key Findings:

- Graph-based models enhance credit risk assessment by capturing complex interdependencies.
- Significant applications in P2P lending, SME credit scoring, and systemic risk assessment.

Implications for Research and Practice:

- Need for broader adoption of graph-based techniques in dynamic and decentralized contexts.
- Potential to improve financial stability and risk management in evolving markets.

Limitations and Recommendations:

- Challenges in data availability, scalability, and integration with traditional frameworks.
- Future research to focus on hybrid systems, real-time scoring, and applications in DeFi.

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