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Dissertation Proposal

Topic
Systemic Risk Simulation Using Graph Neural Networks

Approach

Financial systemic risk refers to the threat that instability at one institution or market can cascade through interconnections and jeopardize the entire financial system. The 2008 crisis exemplified how interbank exposures and common asset holdings transmit shocks widely. Ensuring financial stability requires models that capture these contagion dynamics. Traditional econometric or simulation approaches often treat banks in isolation or make simplifying assumptions about network structure, limiting their ability to predict knock-on failures. Graph Neural Networks (GNNs) offer a novel solution by directly learning from the graph of financial relationships, thus leveraging information on how institutions are linked. GNNs can incorporate both node features (e.g. balance sheet ratios) and the web of interbank connections, which is crucial since network topology critically amplifies or dampens systemic shocks. Recent studies have applied GNNs to rank banks by systemic importance, finding significant predictive gains over non-network machine learning models.

This proposal will build on the literature of systemic risk propagation in financial networks – e.g. contagion models by Battiston *et al.* (2012) and others that introduced metrics like DebtRank to quantify cascades – and harness GraphSAGE, an advanced GNN architecture, to simulate contagion and evaluate stability policies. In doing so, it aims to bridge financial network theory (e.g. network fragility analyses) with modern deep learning, developing a data-driven yet theoretically grounded tool for systemic risk analysis.

Research Objectives

1. **GraphSAGE Framework for Risk:** Develop a Graph Neural Network model (using the GraphSAGE architecture) to capture direct and indirect contagion channels in the financial system. This GNN will learn from network structure and institution features to model systemic risk propagation.
2. **Contagion Simulation & SIFI Identification:** Simulate financial contagion scenarios by introducing exogenous shocks (e.g. a bank default) and observe propagation through the network. The model will identify high-risk institutions (potential *systemically important financial institutions*, SIFIs) that contribute most to cascade effects.

3. **Macroprudential Policy Evaluation:** Test the impact of various macroprudential interventions – such as higher capital buffers, emergency liquidity injections, and interbank lending caps – within the simulation framework. The goal is to quantify how these policies mitigate systemic fallout (e.g. reducing default cascades or loss magnitudes).

<u>Methodology</u>

- **Data Sources:** We will construct an interbank network from real-world data on bilateral exposures (e.g. Bank for International Settlements reports or regulatory stress test data). Nodes represent banks or financial institutions, and weighted edges represent **interbank lending exposures** or common asset portfolio overlaps, forming a directed weighted graph of the financial system. If actual exposure data are unavailable (often confidential), we will use network reconstruction techniques (e.g. maximum entropy method) to infer plausible interbank links from aggregate balance sheet data.
- **Network Modelling:** Each node will be annotated with features such as size, leverage, liquidity ratio, etc., and each edge with exposure amount. The GraphSAGE GNN will be configured to perform message-passing on this graph: at each layer, a bank node aggregates feature information from its neighbors (creditors/debtors) to update its own risk representation. We choose GraphSAGE for its inductive capability to generalize to new nodes and scalability to large graphs, as demonstrated by Hamilton *et al.* (2017). This is advantageous over, say, a classical Graph Convolutional Network, because new or evolving institutions can be evaluated without retraining the entire model.
- **Contagion Simulation:** Using the learned GNN, we will simulate shock propagation by initially "failing" one or more institutions (setting their shock state to 1) and letting the model predict the resulting stress on others in successive rounds. This process mirrors Monte Carlo network simulations in prior literature: an initial default causes losses to counterparties who then may default in a second round, and so on. The GNN will effectively learn the non-linear dynamics of these contagion paths. We will compare the GNN-driven simulation to a traditional threshold model (e.g. DebtRank or Eisenberg-Noe cascade) to ensure consistency in capturing default cascades.
- **Systemic Risk Metrics:** Several quantitative risk measures will be extracted. *DebtRank* will be computed to quantify the impact of a node's default on total system capital, following Battiston *et al.*. We will also record the aggregate cascade size (fraction of network defaulted) and total loss in each scenario as a network fragility index. "Shock absorption" capacity can be defined as the minimum capital buffer that prevents a cascade – this can be evaluated by varying banks' capital and seeing when the GNN-predicted cascade halts. These metrics allow benchmarking the severity of contagion under different conditions and interventions.

Experimental Design

- **Stress Test Scenarios:** We will design multiple stress scenarios, such as an idiosyncratic failure of a major bank, a sector-wide asset write-down (affecting many banks' portfolios simultaneously), and liquidity freezes. In each scenario, the baseline outcome (with current network and no policy action) will be simulated using the GNN model and classical stress test methods for comparison.
- **Baseline vs. GNN Predictions:** We will compare the GNN's risk forecasts to those from standard models. For example, we may compare against a logistic regression or random forest that uses only aggregate bank features (ignoring network structure). Prior work suggests GNNs significantly outperform such models in identifying systemically important nodes. We will evaluate metrics like prediction accuracy of whether each bank becomes distressed, and goodness-of-fit to historical crisis events if applicable.
- **Policy Intervention Analysis:** For each scenario, we will simulate the effect of macroprudential policies. For instance, we will increase capital ratios of banks (to emulate stricter capital buffers) and run the contagion simulation again to see if fewer banks fail. We will simulate liquidity infusions by the central bank as an external resource that absorbs some losses, and interbank exposure caps by truncating or removing the largest interbank loans in the network. By comparing outcomes (e.g. total default count or DebtRank) with and without these interventions, we can quantify their effectiveness. We expect, in line with literature, that higher capital buffers dramatically reduce cascade size, while capping interbank links might localize losses at the cost of reduced diversification.

Expected Contributions

- **Improved Systemic Risk Prediction:** The GNN approach is expected to yield more accurate and granular predictions of systemic risk than traditional models. By learning complex non-linear interactions, it can serve as an early warning system to identify vulnerable institutions or network structures before crises.
- **Policy Insight and Tool for Regulators:** By simulating "what-if" scenarios, the framework will inform macroprudential policy decisions. For example, regulators can virtually test how much raising capital requirements or altering network connectivity would reduce systemic fragility, providing quantitative evidence for policy design. This helps move beyond static stress tests toward simulation-based evidence of intervention efficacy.
- **Interdisciplinary Innovation:** The project will demonstrate a novel integration of financial network theory and deep learning. It translates concepts like interbank contagion and shock propagation into a data-driven GNN model, thus bridging the gap between theoretical models of contagion and modern AI techniques. The outcome is a framework that continuously learns from financial data and network topology, contributing to the academic literature on systemic risk modeling and offering a dynamic tool that can adapt as the financial system evolves.

Bibliography

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