Graph Neural Networks for Multi-Modal Stock Trading with Reinforcement Learning Agent

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1 Problem Motivation

Financial markets exhibit complex dependencies—sectoral, fundamental, and behavioral—yet traditional models often treat stocks independently. This project introduces a graph-based, multi-modal framework that:

- Models heterogeneous inter-stock relations (sector, correlation, supply chain, sentiment);
- Learns interpretable, role-aware embeddings of stocks;
- Integrates reinforcement learning (RL) for sequential portfolio optimization.

The approach enhances predictive accuracy, interpretability, and portfolio performance.

2 Overview

We propose a **role-aware multi-modal graph learning framework** combining predictive modeling, graph representation, and RL-based decision-making.

Nodes: stocks. **Edges:** sector/industry, correlation, fundamental similarity, supply chain, competitor, and sentiment. **Node features:** technical indicators, fundamentals, sentiment, macro signals. **Model:** Graph Transformer + PEARL positional embeddings. **RL agent:** uses embeddings to select Buy/Sell/Hold actions.

3 Graph Construction

Static edges: sector, supply chain, and competitor relations (stable backbone). **Dynamic edges:** rolling correlation and fundamental similarity (updated periodically). Each edge type encodes complementary dependency structures:

- Sector/Industry — shared sector membership.
- Rolling correlation — 30-day return correlation ($|\rho_{ij}| > 0.6$).
- Fundamental similarity — cosine similarity of normalized ratios (> 0.8).
- Supply chain / Competitor — binary dependencies.
- Sentiment — optional, weighted by news polarity.

This hybrid graph captures both stable and evolving market structures.

4 Node Features

Technical: returns, MA20/50, volatility, RSI, MACD, volume. **Fundamental:** market cap, P/E, P/B, ROE, EPS growth, debt/equity. **Sentiment:** news polarity, social signals. **Macro:** sector index, VIX, interest rate.

5 Model and RL Integration

Graph Transformer (Ying et al., 2021) handles heterogeneous edges via attention-based aggregation. **PEARL embeddings (You et al., 2023)** encode structural roles (hubs, bridges, twins). **RL Agent:**

- *State:* portfolio + graph embeddings;
- *Action:* Buy/Sell/Hold;
- *Reward:* risk-adjusted portfolio return.

6 Prediction and Evaluation

Node-level task: predict 5-day-ahead return sign $\hat{y}_{i,t+5} = P(y_{i,t+5} = 1)$. RL task: optimize sequential portfolio decisions.

Metrics: accuracy, F1, IC, Precision@Top-K, and backtested Sharpe ratio. **Ablations:** edge types, embedding choices, correlation thresholds. **Visualization:** t-SNE/UMAP for interpretable role patterns.

7 Pipeline

1. Data collection and feature engineering;
2. Graph construction with static + dynamic edges;
3. Baseline GCN/SAGE training;

4. Graph Transformer + PEARL joint training;
5. RL agent fine-tuning with trading simulation;
6. Evaluation via predictive and portfolio metrics.

8 Milestones / MVP

MVP	Description
1	Static graph + GCN baseline (next-day prediction).
2	Multi-modal features + heterogeneous edges (Graph Transformer).
3	PEARL role-aware embeddings.
4	RL agent for sequential portfolio optimization.
5	Optional: dynamic edge updates and multi-agent RL.

9 Expected Contributions

- A dynamic, heterogeneous financial graph dataset (2015–2025).
- Role-aware Graph Transformer integrated with RL.
- Empirical insights into stock "roles" and evolving dependencies.
- Improved interpretability and performance vs. time-series or static GNN baselines.

References

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