A Short Survey on Graph Neural Networks Based Stock Market Prediction Models

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- Lei Zhou completed his master's degree in Computer and Information Science at the Auckland University of Technology, New Zealand, in 2017. He is now pursuing a Doctor of Philosophy degree, further advancing his academic and professional journey in the field of computer science.

- Lei's research primarily focuses on the application of Graph Neural Networks (GNNs) for stock market prediction. This innovative approach involves leveraging the power of GNNs to model and analyze complex relationships and interactions within financial markets.

Why GNN for stock prediction?

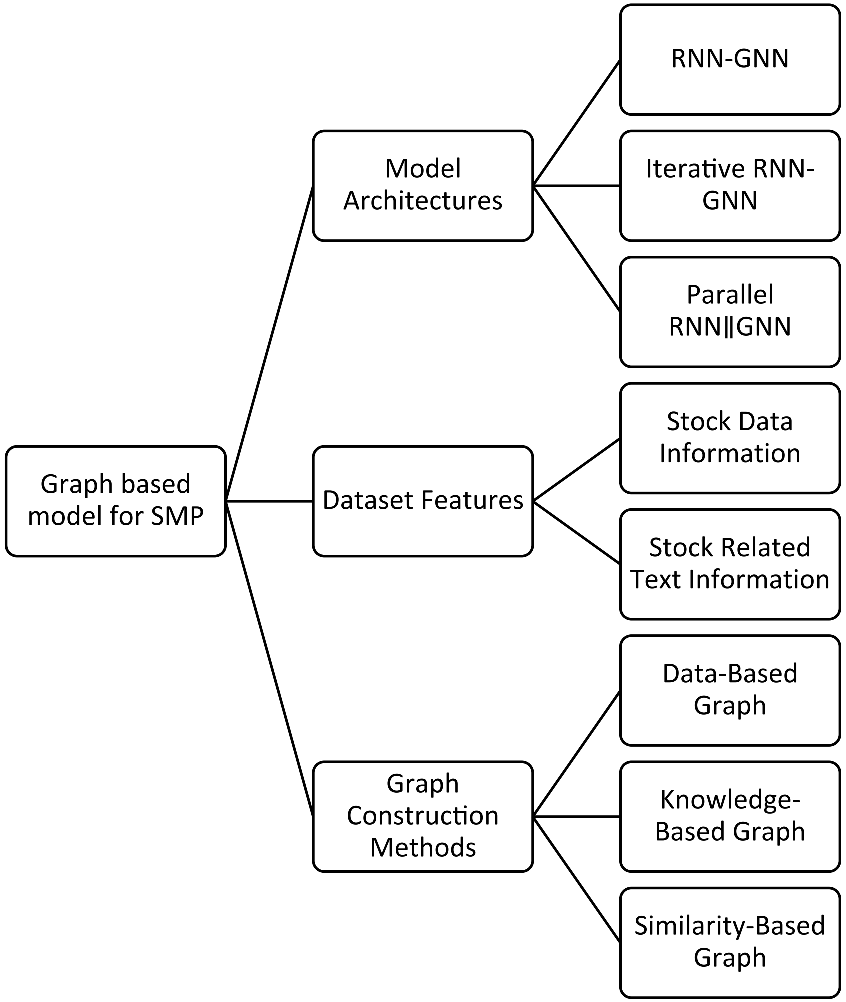
- Traditional forecasting models like ARIMA[1] and GARCH[2] face limitations due to the market's nonlinear evolution.
- Deep learning, especially GNN[6], surpasses these methods by handling diverse data types and capturing complex, non-linear relationships between stocks.
- GNN enables relational reasoning, improving performance by incorporating stock relationships into prediction models.

Contributions of our paper

- A comprehensive review of current literature on stock market predictions using various approaches, with a focus on GNN based stock prediction approaches.
- Proposal of a novel classification framework and taxonomy for GNN-based stock market prediction methods.
- Identification of potential research gaps and future directions in the field.

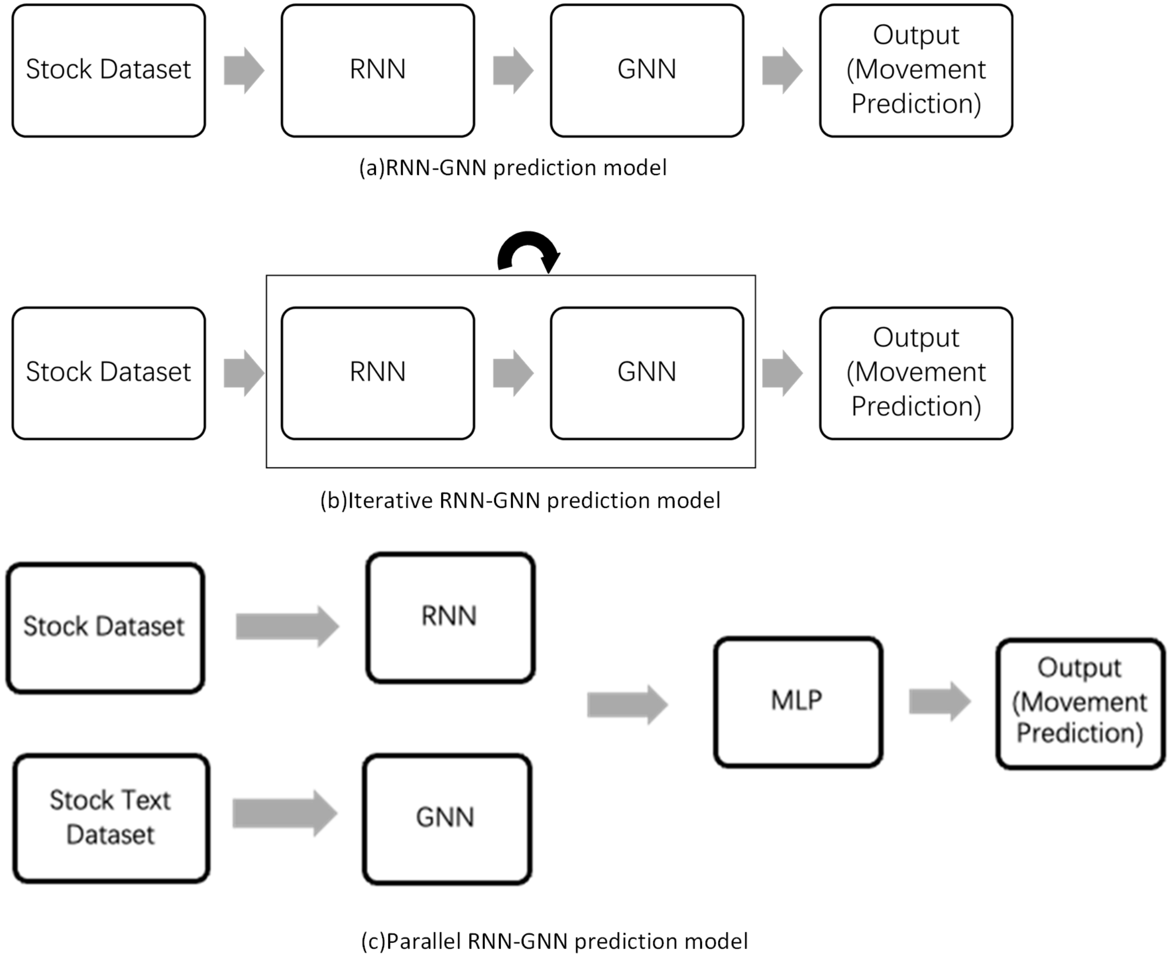
Classification Framework

- Introduction of a novel classification framework analyzing approaches from three aspects: Model Architecture, Dataset Features, and Graph Construction Method.
- The framework facilitates categorization and deeper analysis of existing works, promoting a structured approach to reviewing GNN applications in stock prediction.



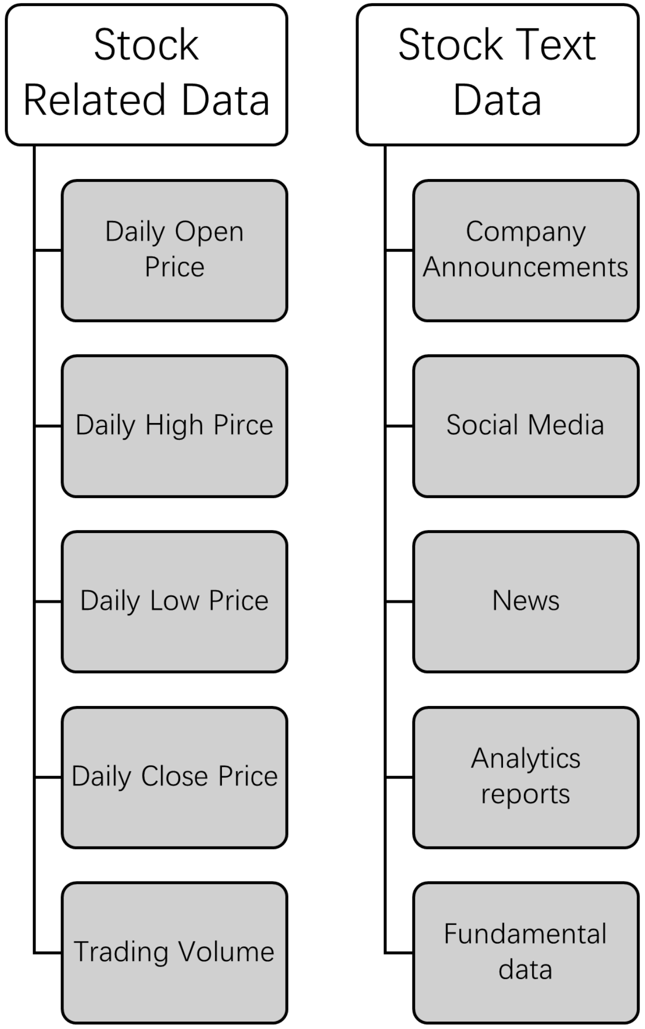
Model Architecture

- Identification of three main types of model architecture:
- RNN-GNN
- Iterative RNN-GNN
- Parallel RNN || GNN



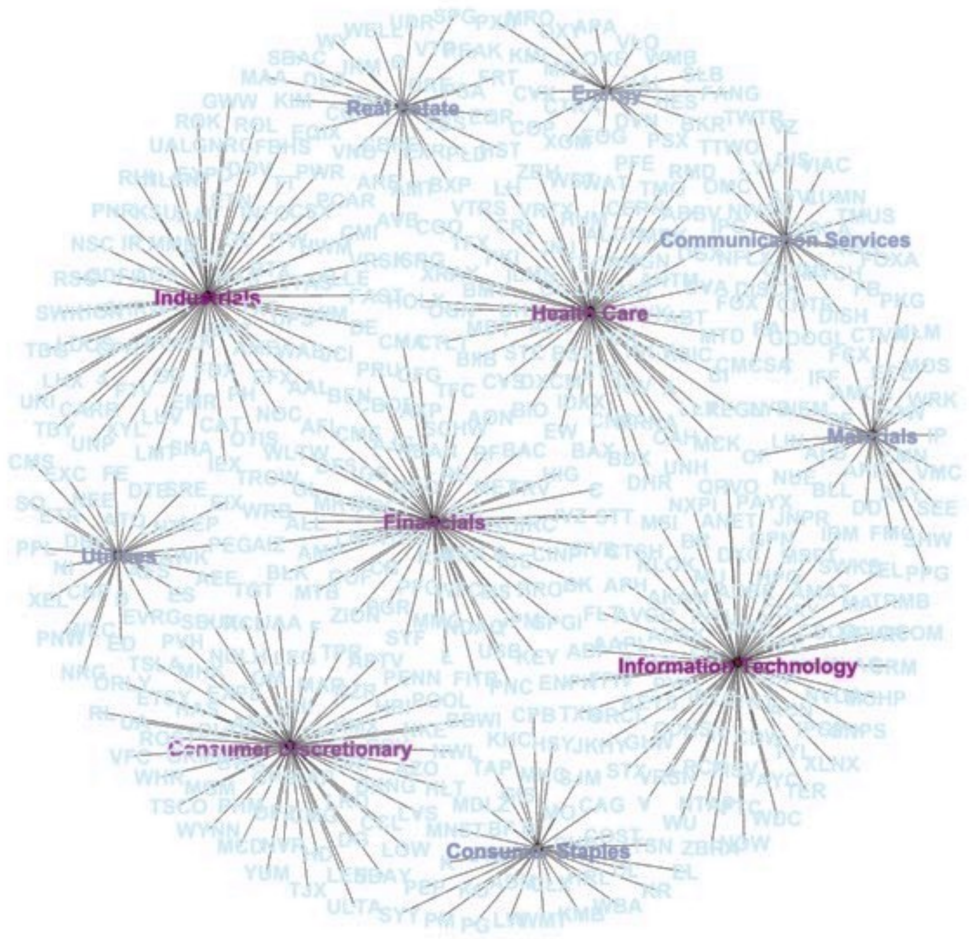
Datasets Features

- Examination of the types of data used in GNN models for stock prediction, including numeric and text data.
- Numeric Data: Includes historical prices, volumes, and other quantitative metrics from stock markets.
- Datasets: CSI300, S&P500, and others, providing foundational data for models to analyze past trends and forecast future stock movements.
- Text Data: Incorporates unstructured data like news articles, financial reports, and social media sentiment, requiring NLP techniques for analysis.
- Example: The integration of financial news and social media data in models such as MAN-SF[25] demonstrates the value of text data in capturing market sentiments and external factors affecting stock prices.



Graph Construction Method

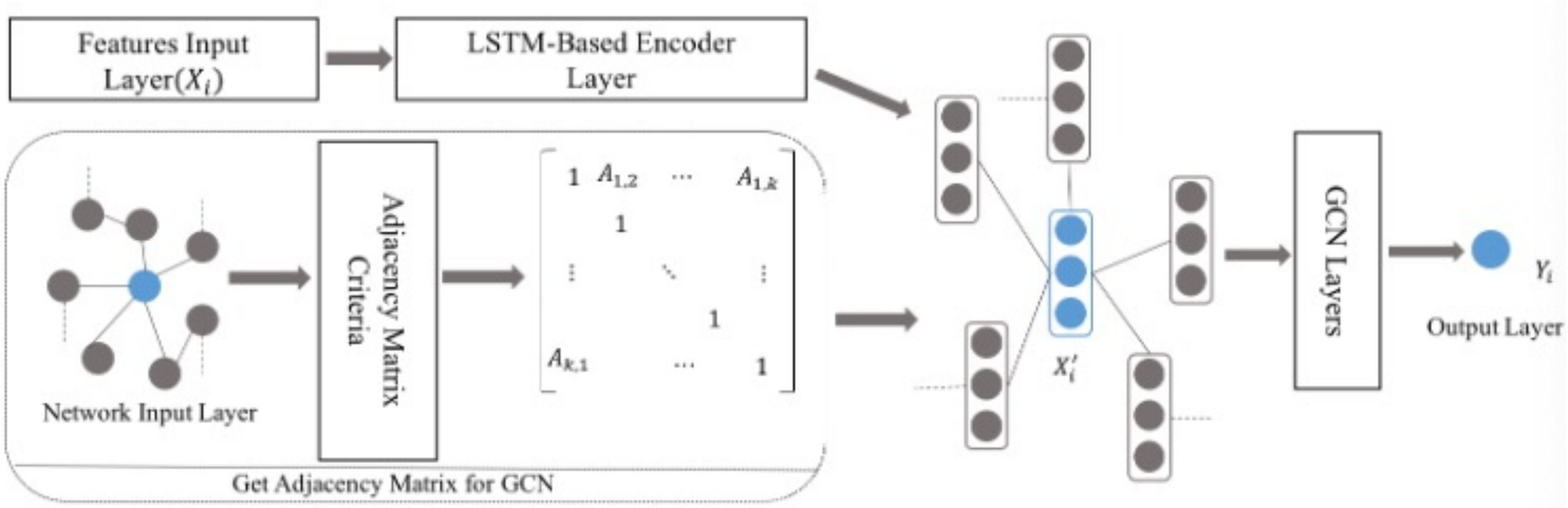
- Overview of three primary methods for graph construction:
  - Correlation-based graph
  - Knowledge-based graph
  - Similarity-based graph



Graph Construction Method

- Correlation-based: Builds graphs based on the statistical relationships between stocks, using metrics like price correlations to connect nodes.
  - Chen et al.[7] used in models to understand direct stock-to-stock influences, facilitating the prediction of market movements based on historical price data correlations.
- Knowledge-based: Leverages domain knowledge or external information sources, such as industry sectors or company fundamentals, to construct the graph.
  - HATs[26] model uses Wikidata to construct a heterogeneous graph, analyzing complex entity relationships beyond mere statistical correlations.
- Similarity-based: Constructs graphs by identifying similarities among stocks, often using measures like cosine similarity or Euclidean distance, to map implicit stock relationships.
  - LSTM-RGCN[24] model employs similarity scores to build graphs, enabling the detection of nuanced patterns and dependencies among stocks not directly related through common metrics.

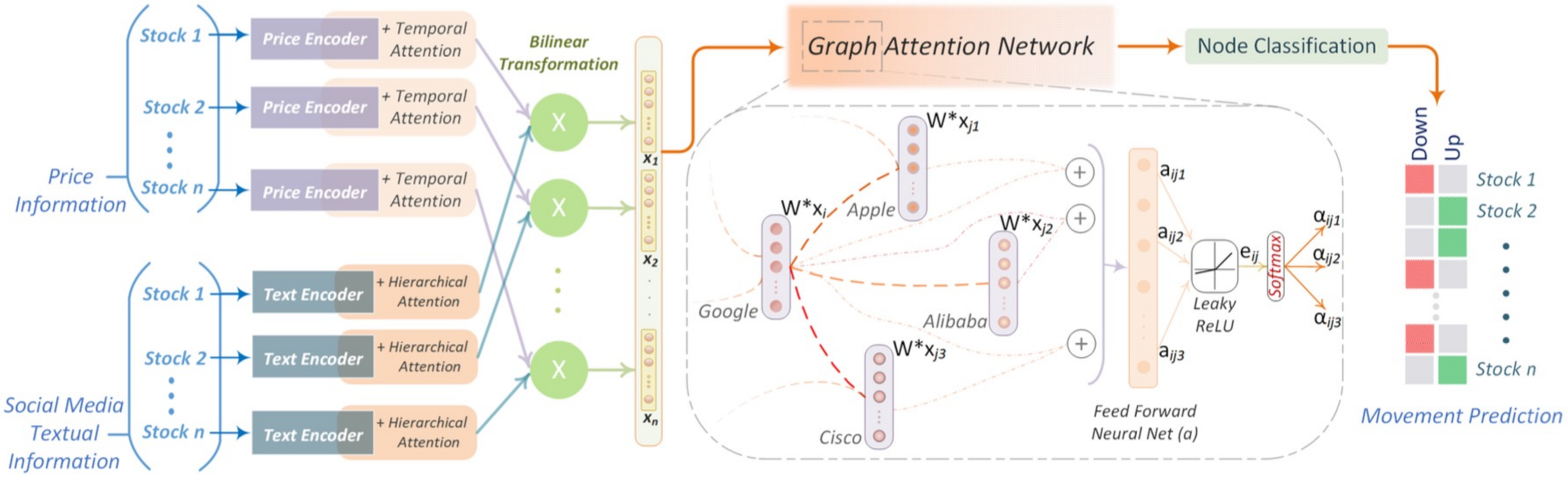
Approaches - Model Architecture



$$Y = \text{softmax}\left(\hat{A}ReLU\left(\hat{A}ReLU\left(\hat{A}X'W\right)W\right)W\right)$$

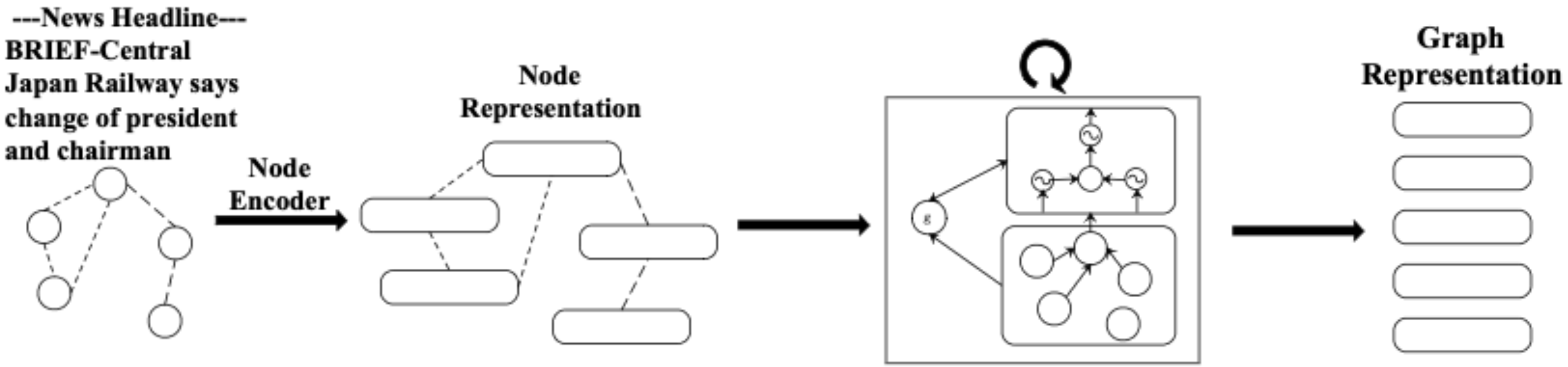
- **RNN-GNN Architecture**
- Models combining Recurrent Neural Networks (RNN) with Graph Neural Networks (GNN) to encode both time series data for capturing temporal sequences and graph-based data for understanding stock interrelations.
- Chen et al.[7] proposed a model integrating LSTM for time series analysis and GCN for node classification, highlighting how combining these architectures leverages both temporal and relational data for stock prediction.

Approaches - Model Architecture



- **RNN-GNN Architecture**
- Sawhney et al.[25]propose a Multipronged Attention Network for Stock Movement Prediction (MAN-SF)by learning from historical prices, social media, and inter-stock relations. It is made up of a hierarchical attention network and a graph attention network.
- GRU is used as a Price Encoder (PE) that takes the prices of a stock over a period of time and uses that to produce a price feature. The temporal attention mechanism is a way of aggregating information from different time steps into an overall representation. This is done by assigning learned weights to each time step, which allows the most important information to be aggregated together.

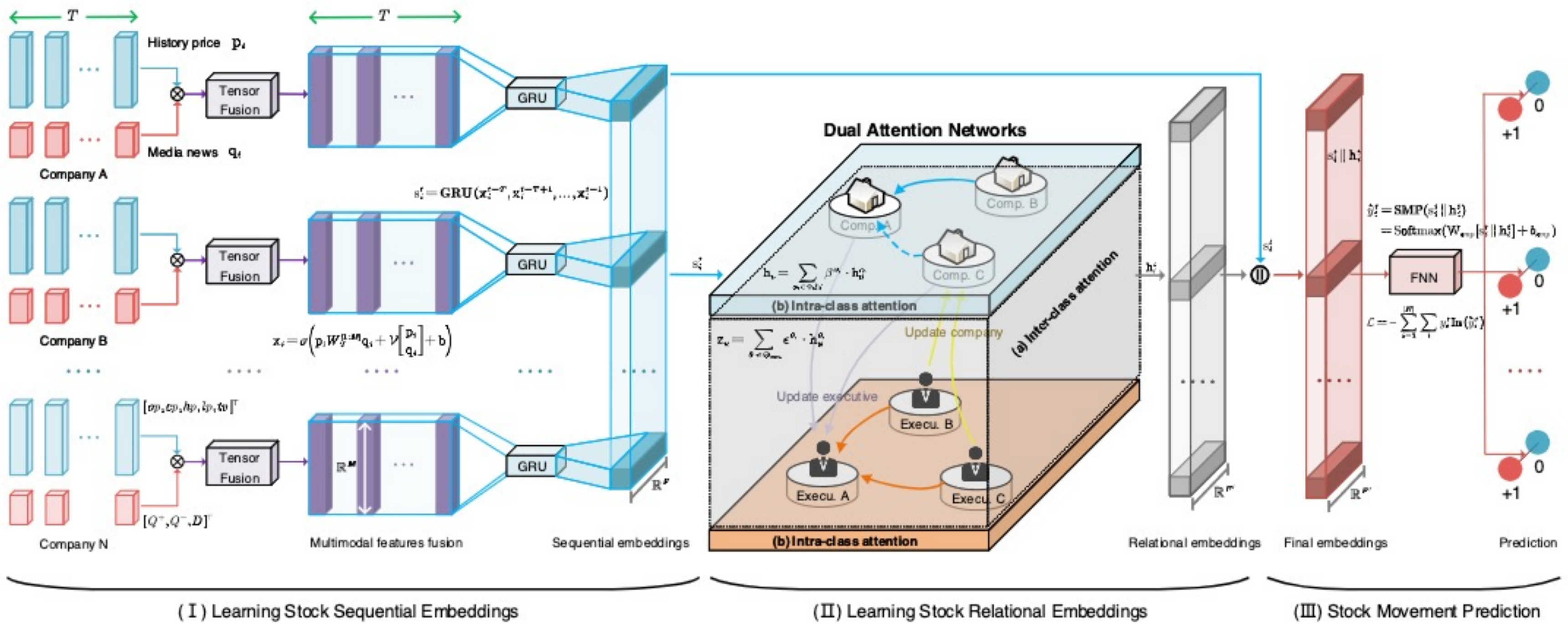
Approaches - Model Architecture



$$N^{l+1} = \sigma\left(\sum_r D_r^{-\frac{1}{2}} A_r D_r^{-\frac{1}{2}} H^l W_r^l + W_h H^l\right)$$

- **Iterative RNN-GNN Architecture**
- This architecture involves deeper integration between RNN and GNN components, allowing for iterative information exchange and enhancing the model's ability to capture complex relationships between temporal and relational data.
- Li et al.'s[24] LSTM-RGCN model predicts stock movements by first encoding news data into vectors with LSTM and then using RGCN to encode the graph structure, demonstrating the power of iterative architecture in leveraging news-related stock correlations.

Approaches - Model Architecture



- **Parallel RNN-GNN Architecture**
- Features parallel processing of RNN and GNN components to capture both temporal and relational information simultaneously, offering a comprehensive approach to stock market prediction.
- Zhao et al.'s[23] Dual Attention Networks (DANSMP) leverage a market knowledge graph and dual attention mechanisms to understand stock momentum spillover, showcasing the effectiveness of parallel architectures in analyzing complex market dynamics.

Approaches – Comparison

TABLE I: Comparison model & metrics between articles

Framework	Model	Dataset	Graph relationships	AUX DATA
ICR-GCN	LSTM-GCN	CSI300	Stock-Stock	Financial investment fact from WIND
HATS	RNN-GAT	S&P500	Stock-Stock Stock-Owner	Wikidata
TGC	LSTM-TGC	NASDAQ NYSE	Stock-Stock	Wikidata
MAN-SF	GRU-GAT	S&P500	Stock-Stock Stock-Owner	Wikidata
RGCN	LSTM-RGCN	TPX500 TPX100	Stock-Stock	News
DANSMP	GRU-DAN	CSI100E CSI300E	Stock-Stock Stock-Owner Owner-Owner	News

Conclusion and future work

- GNNs show significant potential in overcoming the limitations of traditional stock market prediction models by leveraging complex stock relationships.

- The survey lays the foundation for future research in GNN-based stock prediction, highlighting the need for further exploration of dynamic graphs and integration with other deep learning techniques.

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