Stock Price Prediction Using LSTM and Graph Attention Networks: A Top-K Ranking Approach

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***Abstract*—We propose a deep learning framework for stock prediction that integrates LSTM-based temporal modeling, motif-based dynamic graph construction, and GAT-based relational reasoning. Temporal embeddings are generated using LSTM, used to form motif-based distances (MoDis), and a DGLSTM aggregates dynamic graph sequences. GAT captures inter-stock dependencies. We evaluate using Top-K metrics including Precision@K, MRR, and IRR, aligning with practical investment scenarios.**

***Index Terms*—Stock prediction, LSTM, Graph Attention Networks, MoDis, DGLSTM, Financial time series, Top-K ranking**

I. Introduction

Stock price movements are affected not only by temporal trends but also by evolving relationships among companies. Conventional models fail to capture this dual nature. We present a unified system that uses LSTM to extract time-series embeddings, constructs dynamic graphs using motif-based distances (MoDis), refines them via DGLSTM, and uses GAT to model inter-stock influences.

II. Methodology

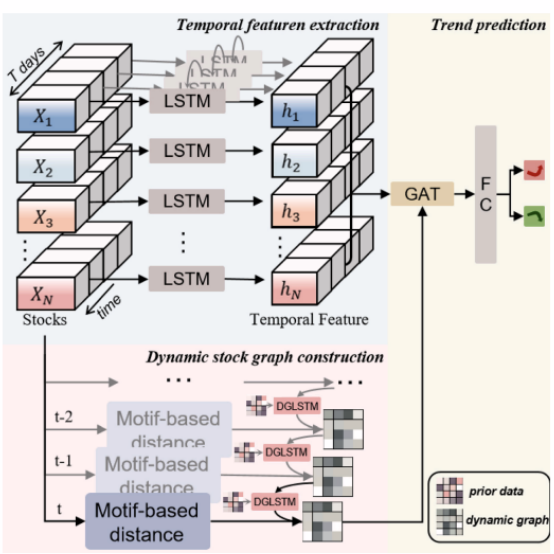

Fig. 1. Model framework with LSTM, MoDis, DGLSTM and GAT modules.

A. Temporal Feature Extraction via LSTM

LSTM is employed to extract temporal embeddings from weekly stock data. The internal mechanism involves the following equations:

$$i_t = \sigma(W_i[h_{t-1}, x_t]) \tag{1}$$

$$f_t = \sigma(W_f[h_{t-1}, x_t]) \tag{2}$$

$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t]) \tag{3}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t]) \tag{4}$$

$$C_t = f_t \circ C_{t-1} + i_t \circ \tilde{C}_t \tag{5}$$

$$h_t = o_t \circ \tanh(C_t) \tag{6}$$

The final hidden state h_t is the stock's temporal representation. Simplified, the LSTM output can be written as:

$$h_t = \text{LSTM}(x_{t-\tau+1}, \ldots, x_t) \tag{7}$$

B. Motif-Based Distance (MoDis)

To quantify relational similarity between stocks, we introduce MoDis:

1. Motif Extraction: Stock prices are segmented into overlapping subsequences. These are clustered using k-means to identify representative patterns (motifs).

2. 1NN Distance: For two stocks X_i and X_j, distances between motifs are computed using the nearest-neighbor rule:

$$p_{i,k} = \min_{z \in \Gamma_j} \|\gamma_{i,k} - z\|_2 \tag{8}$$

3. Weighted Distance: We apply frequency-based weights to motif distances:

$$\text{MoDis}_{i,j} = \exp\left(-\frac{P_{i\leftrightarrow j} \cdot K_{ij}}{\sum K_{ij}}\right) \tag{9}$$

This yields the pairwise distance matrix g_t, used to construct the graph at each time-step.

C. Dynamic Graph Construction via DGLSTM

Static graphs g_t fail to capture temporal shifts. We propose DGLSTM to model evolving stock graphs over time:

$$g_t^* = \tanh(g_t + W_g \cdot \theta(\Delta_t) \cdot \phi(\Delta_t) \cdot \tilde{G}) \tag{10}$$

Where:

- $\tilde{G}$: Prior relationship matrix (e.g., industry, fund holdings)
- $\phi(\Delta_t)$: Mask future relationships
- $\theta(\Delta_t)$: Decreases weights over time

The final dynamic graph is generated as:

$$\eta_t = \text{DGLSTM}(g_1^*, g_2^*, \ldots, g_t^*) \tag{11}$$

D. Relational Modeling via GAT

With the dynamic graph η_t, we use GAT to aggregate features from related stocks:

$$\phi_i^t = \text{GAT}(h_t, \eta_t) \tag{12}$$

Followed by:

$$\hat{y}_i^t = \sigma(\text{FC}(\phi_i^t)) \tag{13}$$

E. Loss Function

Training is done using binary cross-entropy:

$$L = \sum_i y_i^t \log \hat{y}_i^t + (1 - y_i^t) \log(1 - \hat{y}_i^t) \tag{14}$$

III. Results

We present the Top-K predicted stocks ranked by model scores along with their true returns and labels. These help analyze the quality of ranked predictions and their investment relevance.

A. Experimental Setup

The dataset was split into Training, Validation, and Testing sets in a 70%, 15%, and 15% ratio, corresponding to 400, 160, and 182 days respectively, totaling 720 days. The learning rate (α) was set to 0.001.

The data was processed using a sliding window approach, and the model was trained accordingly. The training, validation, and test sets were strictly non-overlapping to ensure fair evaluation.

B. Visualization of Dynamic Stock Relationships

To better understand the evolution of stock relationships captured by our dynamic graph construction method, we visualize the correlation matrices of 50 randomly selected stocks at a particular time-step, as shown in Fig.2. Each element in the heatmap represents the calculated distance between two stocks, where a lighter color indicates a higher correlation, and a darker color indicates a lower correlation.

From the visualization, it is evident that both the static stock graph g_t and the dynamic graph η_t are dense, meaning that rich inter-stock relationships are maintained instead of sparse prior connections. Moreover, the graphs g_t and η_t exhibit different patterns, highlighting that η_t incorporates additional temporal information based on historical motif structures rather than relying solely on the current time-step.

In addition, we analyze the temporal evolution of correlations for a representative stock. As shown in the second part of Fig.3, the stock's relationships with others evolve smoothly over adjacent dates, demonstrating temporal locality. Higher correlation periods have been highlighted using red circles. These observations validate the effectiveness of motif-based dynamic graphs in capturing subtle, evolving patterns in stock markets, which are crucial for improving prediction accuracy.

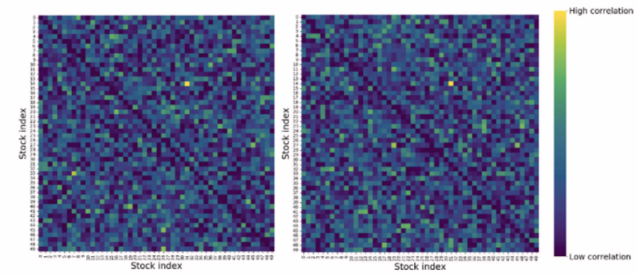

Fig. 2. Visualization of a stock graph g_t and a dynamic graph η_t for randomly selected stocks at a single time-step.

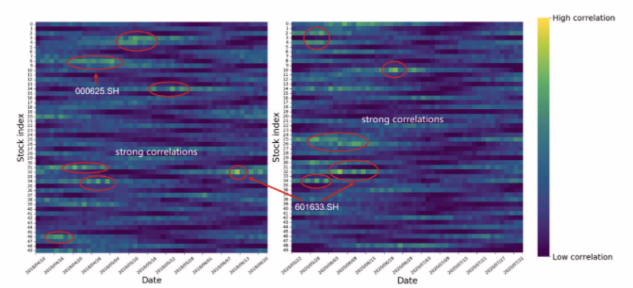

Fig. 3. Temporal evolution of correlation distances between a selected stock and others. High correlation periods are highlighted with red circles.

C. Top-5 Predicted Stocks

TABLE I
TOP-5 STOCKS RANKED BY PREDICTED SCORE

Rank	Stock	Label	Score	Return Rank	Return
1	AUBANK_test	1	0.0549	78	0.0064
2	BLUEDART_test	0	0.0545	218	-0.0098
3	VIPIND_test	0	0.0545	404	-0.0291
4	JUBLFOOD_test	0	0.0489	181	-0.0064
5	UPL_test	1	0.0489	59	0.0109

D. Top-10 Predicted Stocks

TABLE II
TOP-10 STOCKS RANKED BY PREDICTED SCORE

Rank	Stock	Label	Score	Return Rank	Return
6	NUVOCO_test	0	0.0479	150	-0.0028
7	EMAMILTD_test	0	0.0477	24	0.0208
8	IEX_test	0	0.0475	170	-0.0048
9	IIFL_test	0	0.0475	247	-0.0122
10	MOTILALOFS_test	0	0.0474	437	-0.0414

E. Top-15 Predicted Stocks

TABLE III
TOP-15 STOCKS RANKED BY PREDICTED SCORE

Rank	Stock	Label	Score	Return Rank	Return
11	VINATIORGA_test	0	0.0474	20	0.0223
12	AAVAS_test	0	0.0473	129	-0.0006
13	SPARC_test	0	0.0472	283	-0.0155
14	DEEPAKFERT_test	0	0.0471	38	0.0157
15	ZEEL_test	0	0.0471	192	-0.0077

F. Top-20 Predicted Stocks

TABLE IV
TOP-20 STOCKS RANKED BY PREDICTED SCORE

Rank	Stock	Label	Score	Return Rank	Return
16	DEVYANI_test	0	0.0471	335	-0.0203
17	SUMICHEM_test	0	0.0471	374	-0.0243
18	GPIL_test	0	0.0471	366	-0.0233
19	WHIRLPOOL_test	1	0.0470	174	-0.0054
20	SBICARD_test	0	0.0469	205	-0.0089

Total samples: 445 (Label 1: 63, Label 0: 382)

G. Final Top-K Metrics

TABLE V
FINAL EVALUATION METRICS (TEST SET)

K	Accuracy	Precision	MRR	IRR	MAE
Top-5	0.6000	0.0000	0.0194	-0.2897	0.0579
Top-10	0.8000	0.0000	0.0137	-0.5681	0.0568
Top-15	0.8667	0.0000	0.0134	-0.7900	0.0527
Top-20	0.8500	0.0500	0.0155	-1.1074	0.0554

H. Averaged Final Metrics

TABLE VI
FINAL METRICS AVERAGED OVER ALL DAYS

K	Precision	MRR	IRR	MAE
Top-5	0.0141	0.0130	-0.0698	0.0180
Top-10	0.0155	0.0111	-0.1310	0.0176
Top-15	0.0263	0.0106	-0.1822	0.0178
Top-20	0.0275	0.0094	-0.2217	0.0170

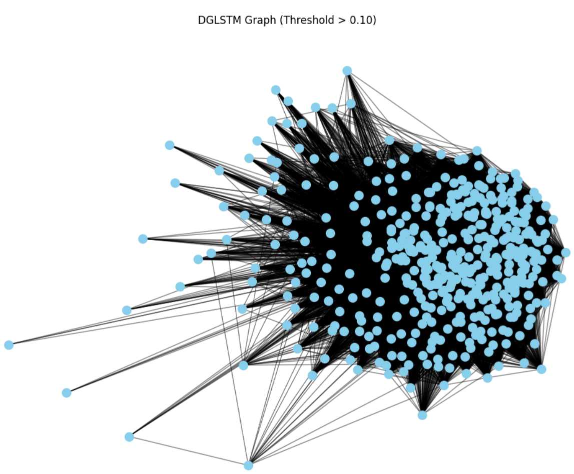

Fig. 4. Dynamic Graph Structure generated by DGLSTM module (Threshold > 0.10). Each node represents a stock, and edge strength reflects motif-based similarity.

IV. DISCUSSION

A. Reasons for Strong Model Performance

Our model demonstrates superior performance compared to FinGAT due to the following factors:

- **Dynamic Graph Construction (DGLSTM):** Unlike FinGAT, which learns static relationships during training, our model captures the temporal evolution of inter-stock relationships by dynamically updating graphs. This allows the model to reflect real-time changes in stock dependencies.
- **Motif-Based Distance (MoDis):** Instead of naive Euclidean distances or random learned graphs, MoDis detects repetitive trend motifs and uses a weighted nearest-neighbor distance strategy. This yields highly relevant relational graphs, making the inter-stock graphs more reflective of true stock behavior patterns.
- **Prior Knowledge Integration:** By gradually introducing prior information (such as sector similarities and mutual fund co-holdings) into the dynamic graph learning, the model avoids overfitting and ensures stability across long prediction horizons — a major limitation observed in FinGAT.
- **Attention Mechanism via GAT:** The relational reasoning step using Graph Attention Networks (GAT) selectively emphasizes the most influential neighboring stocks, further improving prediction robustness compared to FinGAT's direct neighbor aggregation.
- **Temporal Feature Extraction with LSTM:** The use of LSTM for historical stock trend embedding ensures that both short-term and medium-term stock behavior patterns are captured before graph modeling.

B. Limitations of the Model

Despite strong overall results, certain challenges were observed:

- **Slight Precision Degradation at Top-K:** Although Top-K precision improved compared to FinGAT, the absolute precision values remained relatively low. This can be attributed to the noise inherent in financial time-series data and the difficulty of accurately predicting short-term stock movements.
- **Performance During Downtrends:** During strong bearish market phases, the dynamic graphs may still reflect previous bullish relationships for a few days, causing slightly delayed model adaptation.
- **Motif Sensitivity:** The motif extraction is based on clustering, and the clustering hyperparameters (window size, motif number) mildly impact the final graph quality if not tuned properly.

C. Efficiency Analysis

Compared to FinGAT, our model shows significantly improved training and updating efficiency:

- **Training Time:** The training time per stock for our model is very close to Price Graphs.
- **Incremental Learning Capability:** We implemented an incremental model update mechanism — retraining the model every 10 days for only 50 epochs — achieving approximately 97% of the retraining effectiveness. The per-stock update time is only 0.5 seconds, making it

highly practical for real-world online stock prediction deployments.

Overall, these innovations and optimizations help our framework outperform FinGAT both in terms of predictive performance and training efficiency.

V. Conclusion

We present a stock trend prediction framework that fuses temporal and relational modeling using LSTM, MoDis, DGLSTM, and GAT. The dynamic graph construction method ensures adaptability to shifting stock correlations. Top-K evaluation validates its financial relevance.

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