Multi-Graph Convolutional Network for Relationship-Driven Stock Movement Prediction

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1 Background

Previous Work

\[ f(X) \]

Our Design

\[ f(X, G) \]

2 Model

Multi-GCGRU

\[ \mathbf{X} \rightarrow \mathbf{G} \mathbf{S} = \mathbf{V}, \mathbf{E}_S, \mathbf{A}_S \]

\[ \mathbf{X}_t \rightarrow \mathbf{G}_I = \mathbf{V}, \mathbf{E}_I, \mathbf{A}_I \]

\[ \mathbf{X}_t \rightarrow \mathbf{G}_T = \mathbf{V}, \mathbf{E}_T, \mathbf{A}_T \]

Stock Graphs
3 Experiments Results

![Graph Convolutional Layer](image)

**Graph Convolutional Layer:**

\[ H^{(l+1)} = \rho \left( \sum_{k=0}^{K-1} \theta_k L_k^k \right) H^{(l)} W^{(l)} \]

**Multi-Graph Convolutional Layer:**

\[ H^{(l+1)} = \rho \left( \sum_{k=0}^{K-1} \theta_k \left( \theta_S t^k_S + \theta_I t^k_I \right) \right) H^{(l)} W^{(l)} \]

**Dynamic Graph Convolutional Layer:**

\[ H^{(l+1)} = \rho \left( \tilde{L} H^{(l)} W^{(l)} \right) \]

![GRU](image)

**GRU**

\[ r_t = \sigma \left( [H_{t-1}, X_t, X_t^{GCN}] \cdot W_r + b_r \right) \]

\[ u_t = \sigma \left( [H_{t-1}, X_t, X_t^{GCN}] \cdot W_u + b_u \right) \]

\[ \tilde{H}_t = \tanh \left( [r_t \odot H_{t-1}, X_t, X_t^{GCN}] \cdot W_h + b_h \right) \]

\[ H_t = u_t \odot H_{t-1} + \left( 1 - u_t \right) \odot \tilde{H}_t \]

**TABLE II**

**The Experimental Results**

<table>
<thead>
<tr>
<th>Input Feature</th>
<th>Models</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>MCC</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>MCC</th>
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<tbody>
<tr>
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</table>

4 Conclusion

1. We take cross-effect among stocks into consideration, instead of historical observations of only single stock.
2. We novelly design industry/topicality graph to represent cross-effect and also explore a data-driven matrix to get rid of expert knowledge.
3. We utilize graph convolution network to capture cross-effect and GRU to capture temporal dependency in stock price.
4. Our Multi-GCGCRU is flexible to consider more valuable pre-defined relationships.