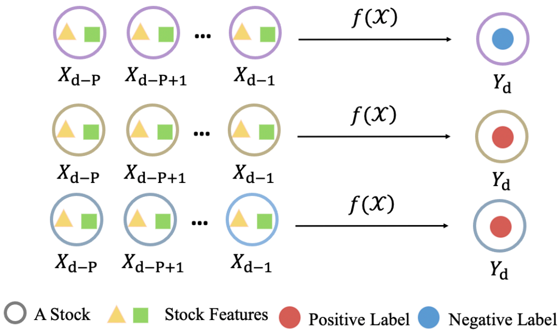
# Multi-Graph Convolutional Network for Relationship-Driven Stock Movement Prediction

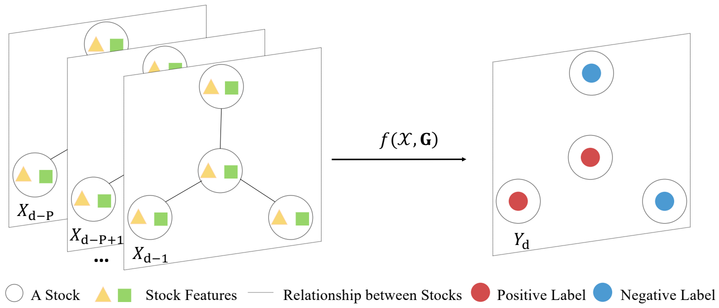
*Jiexia Ye, Juanjuan Zhao, Kejiang Ye, Chengzhong Xu*
Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences
State Key Lab of IOTSC, University of Macau

## 1 Background

### Previous Work

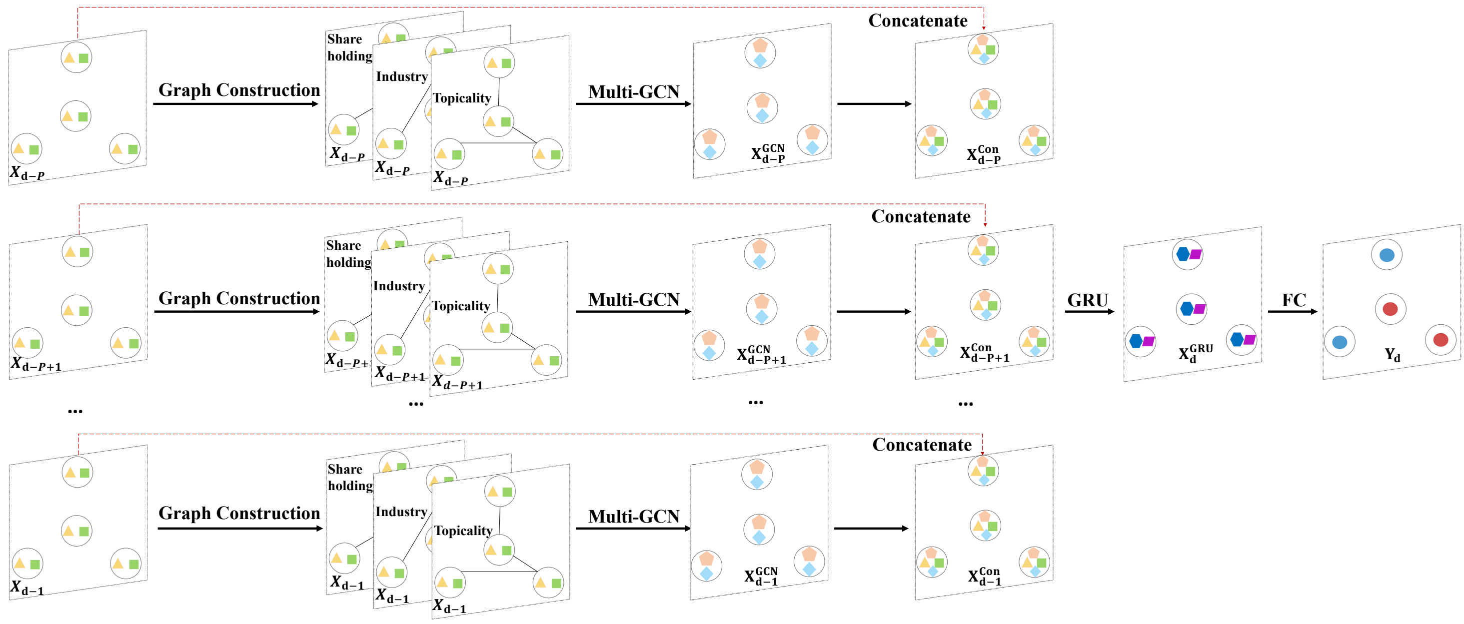



### Our Design

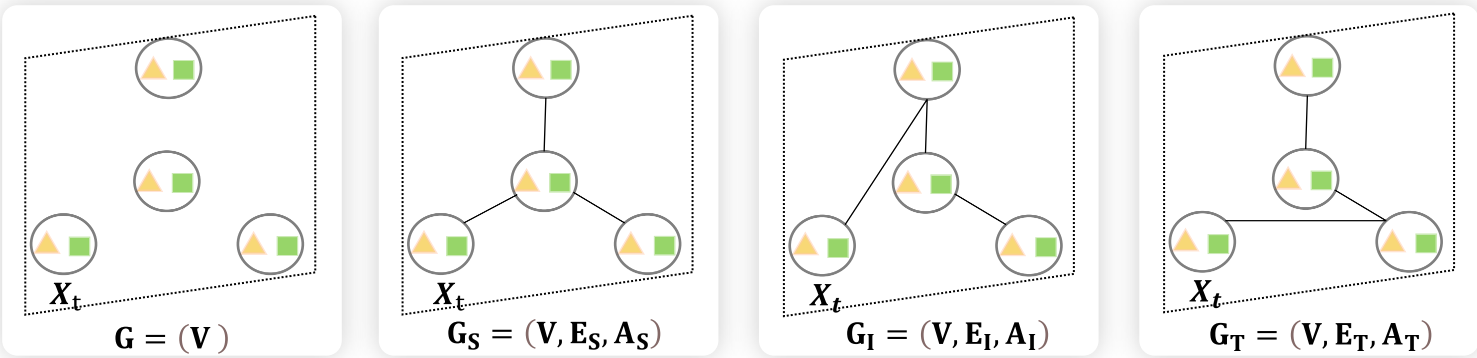



## 2 Model

### Multi-GCGRU

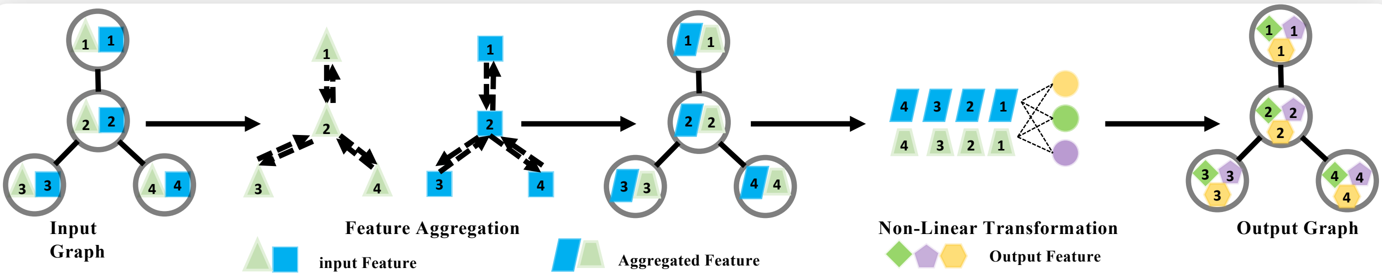



### Stock Graphs




**Stock Collection** **Shareholding Graph** **Industry Graph** **Topicality Graph**

## Multi-GCN




**Graph Convolutional Layer :** $$H^{(l+1)} = \rho\left(\left(\sum_{k=0}^{K-1} \theta_k L^k\right) H^{(l)} W^{(l)}\right)$$

**Multi-Graph Convolutional Layer :** $$H^{(l+1)} = \rho\left(\left(\sum_{k=0}^{K-1} \theta_k \left(\theta_S L_S^k + \theta_I L_I^k + \theta_T L_T^k\right)\right) H^{(l)} W^{(l)}\right)$$

**Dynamic Graph Convolutional Layer :** $$H^{(l+1)} = \rho(\hat{L} H^{(l)} W^{(l)})$$

## GRU

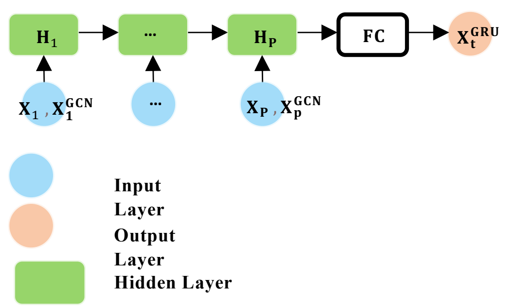



Figure 1 The architecture of our GRU

$$r_t = \boldsymbol{\sigma}([H_{t-1}, X_t, X_t^{\mathbf{GCN}}] \cdot W_r + b_r)$$
$$u_t = \boldsymbol{\sigma}([H_{t-1}, X_t, X_t^{\mathbf{GCN}}] \cdot W_u + b_u)$$
$$\hat{H}_t = \boldsymbol{tanh}([r_t \odot H_{t-1}, X_t, X_t^{\mathbf{GCN}}] \cdot W_h + b_h)$$
$$H_t = u_t \odot H_{t-1} + (1 - u_t) \odot \hat{H}_t$$

## 3 Experiments Results

TABLE II
THE EXPERIMENTAL RESULTS

| Input Feature | Models | CSI300 Accuracy | CSI300 Precision | CSI300 Recall | CSI300 F1 | CSI300 MCC | CSI500 Accuracy | CSI500 Precision | CSI500 Recall | CSI500 F1 | CSI500 MCC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Historical Records | LR | 0.5145 | 0.9746 | 0.5133 | 0.6724 | 0.0228 | 0.5149 | 0.9723 | 0.5148 | 0.6732 | 0.0117 |
| | SVM | 0.5197 | 0.9498 | 0.5165 | 0.6691 | 0.0412 | 0.5253 | 0.9662 | 0.5202 | 0.6763 | 0.0636 |
| | RF | 0.5375 | 0.9298 | 0.5271 | 0.6728 | 0.0957 | 0.5433 | 0.9900 | 0.5294 | 0.6899 | 0.1587 |
| | ANN | 0.5191 | 0.9724 | 0.5158 | 0.6740 | 0.0463 | 0.5202 | 0.9900 | 0.5170 | 0.6792 | 0.0576 |
| | LSTM | **0.5435** | 0.9756 | 0.5291 | 0.6861 | 0.1443 | **0.5461** | 0.9662 | 0.5318 | 0.6860 | 0.1384 |
| Historical Records & Corporation Relationships | GCN-S | 0.5472 | 0.9609 | 0.5317 | 0.6845 | 0.1421 | 0.5463 | 0.9675 | 0.5423 | 0.6950 | 0.0717 |
| | GCGRU-S | 0.5505 | 0.9321 | 0.5346 | 0.6795 | 0.1338 | 0.5521 | 0.9635 | 0.5458 | 0.6969 | 0.0938 |
| | GCGRU-I | 0.5598 | 0.9561 | 0.5392 | 0.6895 | 0.1739 | 0.5678 | 0.9814 | 0.5540 | 0.7082 | 0.1655 |
| | GCGRU-T | 0.5628 | 0.9512 | 0.5412 | 0.6899 | 0.1782 | 0.5751 | 0.9837 | 0.5581 | 0.7122 | 0.1916 |
| | GCGRU-D | 0.5602 | 0.9442 | 0.5402 | 0.6871 | 0.1667 | 0.5697 | 0.9844 | 0.5549 | 0.7097 | 0.1756 |
| | Multi-GCGRU | **0.5754** | 0.9603 | 0.5484 | 0.6981 | 0.2171 | **0.5885** | 0.9894 | 0.5658 | 0.7199 | 0.2377 |

## 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-GCGRU is flexible to consider more valuable pre-defined relationships.