MASTER: Market-Guided Stock Transformer for Stock Price Prediction

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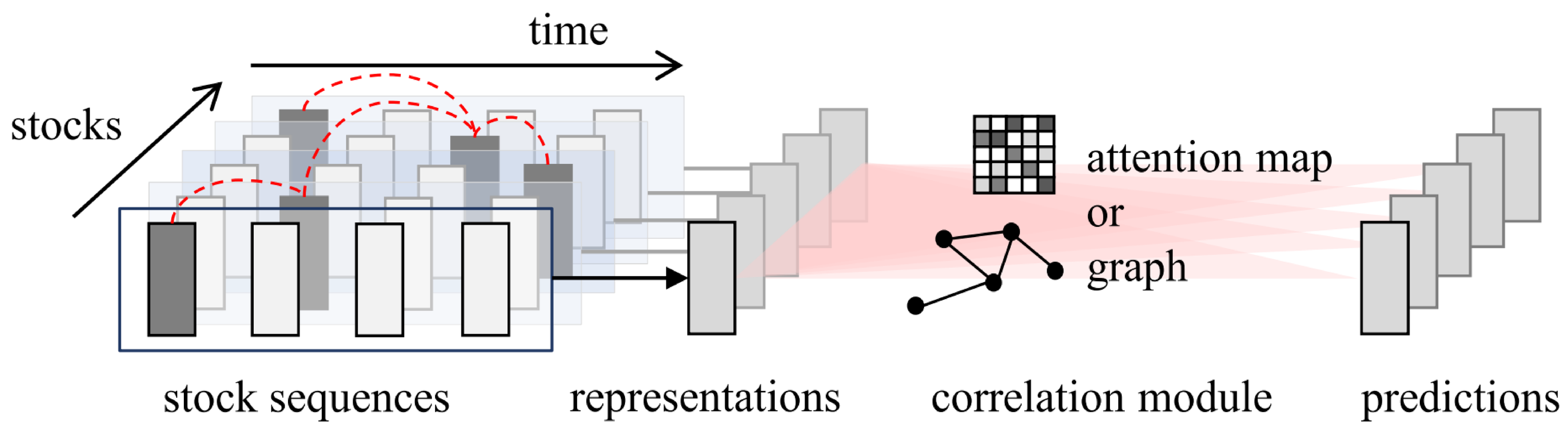
1. Background

- Stock price forecasting uses the historical data of stocks to predict their future trends, which is vital in profitable stock investment.
- Multiple factors, such as macroeconomic factors, capital flows and investor sentiments, interweave the stocks as a **correlated** network.
- Previous works model stock correlation
  - **Static:** Predefined relationships, concepts or rules. (e.g. industry graph). (1) relationship ≠ real-time correlation (2) Not generalizable when events such as company listing, delisting or change in main business happen.
  - **Dynamic:** Leverage attention mechanism to mine the latent correlation. (1) Data-driven, (2) More flexible.

2. Motivation

- **Issue:** Existing works share a framework which fails to model the **realistic stock correlation.**

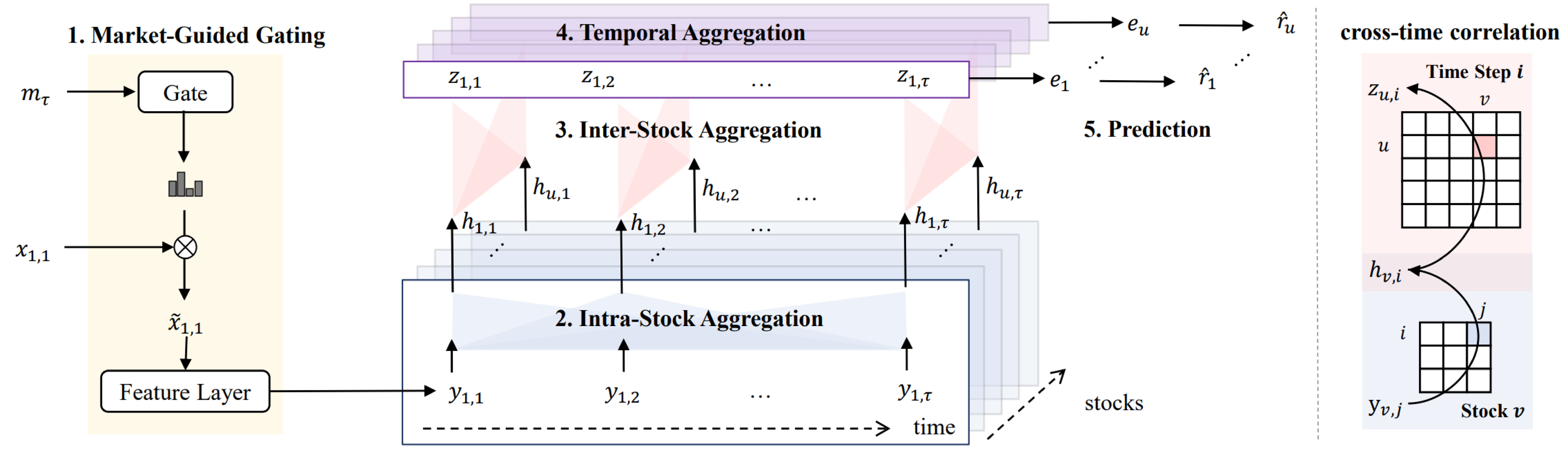


1. **Momentary**: The dominating factors of stock prices constantly change.
2. **Cross-time**: Different stocks may react to the same factor with different delays. (e.g. Upstream companies' stock prices may react faster to a shortage of raw materials than those of downstream companies.)

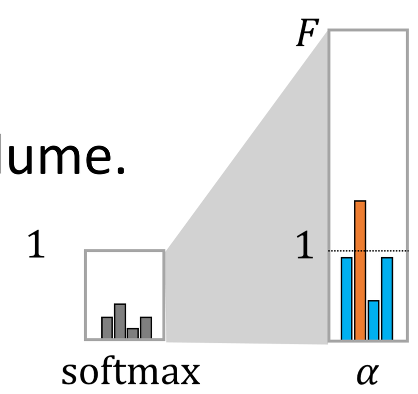
- **Challenges:**

1. The **large and complex attention field** is challenging in learning in stock domain.
   - **Our solution:** Aggregate information from different time steps and other stocks alternatively.
2. The stock correlation is different under **varying market status.** (e.g. in a bull market, the correlation are more significant due to investors' optimism.)
   - **Our solution**: Incorporate the market information to perform automatic feature selection.

3. Method



- **Market-Guided Gating** generates one scaling coefficient for each feature.
  - Feature vector $x_{u,t}$ is the indicators of stock $u \in S$ at time step $t \in [1,\tau]$, $F = |x_{u,t}|$.
  - Market status vector m_τ contains (1) market index price, (2) market index trading volume.
  - Coefficient $\alpha(m_\tau) = F \cdot \mathrm{softmax}_\beta(W_\alpha m_\tau + b_\alpha)$, β is the temperature, $|\alpha(\cdot)| = F$.
  - Enlarge or shrink the magnitude of each feature by $\tilde{x}_{u,t} = \alpha(m_\tau) \circ x_{u,t}$.
  - Feature layer: $Y_u = ||_{t\in[1,\tau]} \mathrm{LayerNorm}(f(\tilde{x}_{u,t}) + p_t)$, $f(\cdot)$ is a linear layer and p is positional code.



- **Intra-stock** and **inter-stock aggregation** to model cross-time stock correlation.
  - For stock u, transform Y_u into Q_u^1, K_u^1, V_u^1. $H_u^1 = ||_{t\in[1,\tau]} h_{u,t} = \mathrm{FFN}^1(\mathrm{MHA}^1(Q_u^1, K_u^1, V_u^1) + Y_u)$.
  - At time t, transform $H_t^2 = ||_{u\in S} h_{u,t}$ into Q_t^2, K_t^2, V_t^2. $Z_t = ||_{u\in S} z_{u,t} = \mathrm{FFN}^2(\mathrm{MHA}^2(Q_t^2, K_t^2, V_t^2) + H_u^2)$.
- **Temporal aggregation** summarizes temporal embeddings to gain one stock embedding.
  - $e_u = \sum_{t\in[1,\tau]} \lambda_{u,t} z_{u,t}$. The last embedding queries from others for weights $\lambda_{u,t} = \frac{\exp(z_{u,t}^T W_\lambda z_{u,\tau})}{\sum_{i\in[1,\tau]} \exp(z_{u,i}^T W_\lambda z_{u,\tau})}$.
- **Prediction**
  - $\hat{r}_u = g(e_u)$, $g(\cdot)$ is a linear layer for regression.
  - $L = \sum_{u\in S} \mathrm{MSE}(r_u, \hat{r}_u)$. r_u is the normalized return ratio in d days, encoded with ranking information.

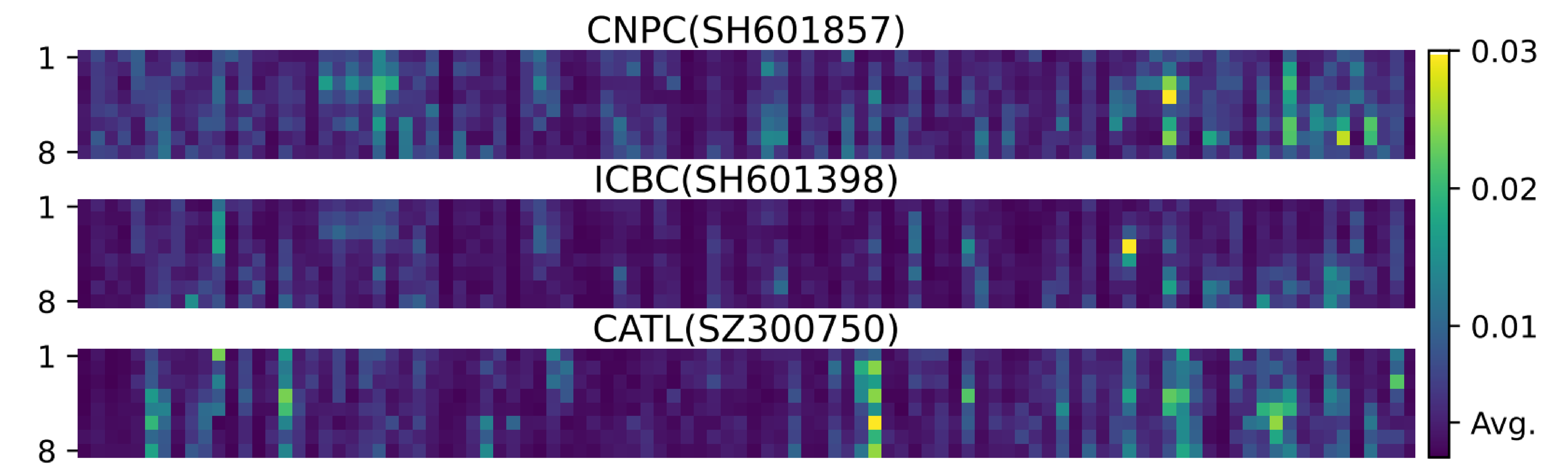
4. Experiments

- **Performance**. MASTER outperforms the second-best by **13%** on ranking metrics, and **47%** on portfolio-based metrics.

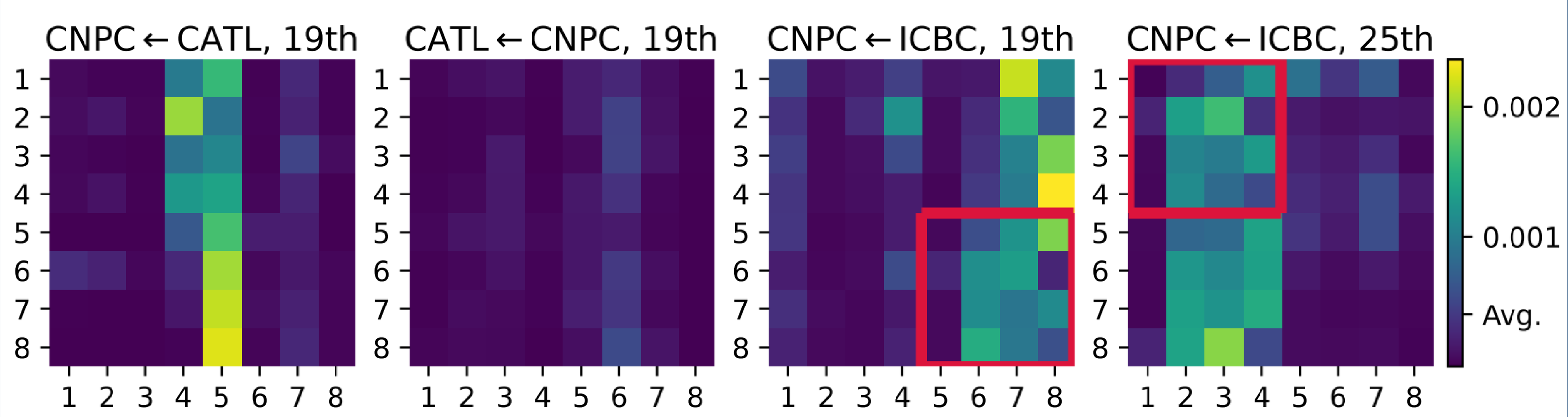
Dataset	Model	IC	ICIR	RankIC	RankICIR	AR	IR
CSI300	XGBoost	0.051 ± 0.001	0.37 ± 0.01	0.050 ± 0.001	0.36 ± 0.01	$\underline{0.23 \pm 0.03}$	1.9 ± 0.3
	LSTM	0.049 ± 0.001	$\underline{0.41 \pm 0.01}$	0.051 ± 0.002	0.41 ± 0.03	0.20 ± 0.04	$\underline{2.0 \pm 0.4}$
	GRU	0.052 ± 0.004	0.35 ± 0.04	0.052 ± 0.005	0.34 ± 0.04	0.19 ± 0.04	1.5 ± 0.3
	TCN	0.050 ± 0.002	0.33 ± 0.04	0.049 ± 0.002	0.31 ± 0.04	0.18 ± 0.05	1.4 ± 0.5
	Transformer	0.047 ± 0.007	0.39 ± 0.04	0.051 ± 0.002	$\underline{0.42 \pm 0.04}$	0.22 ± 0.06	2.0 ± 0.4
	GAT	$\underline{0.054 \pm 0.002}$	0.36 ± 0.02	0.041 ± 0.002	0.25 ± 0.02	0.19 ± 0.03	1.3 ± 0.3
	DTML	0.049 ± 0.006	0.33 ± 0.04	$\underline{0.052 \pm 0.005}$	0.33 ± 0.04	0.21 ± 0.03	1.7 ± 0.3
	MASTER	$\mathbf{0.064^* \pm 0.006}$	$\mathbf{0.42 \pm 0.04}$	$\mathbf{0.076^* \pm 0.005}$	$\mathbf{0.49 \pm 0.04}$	$\mathbf{0.27 \pm 0.05}$	$\mathbf{2.4 \pm 0.4}$
CSI800	XGBoost	0.040 ± 0.000	0.37 ± 0.01	0.047 ± 0.000	0.42 ± 0.01	0.08 ± 0.02	0.6 ± 0.2
	LSTM	0.028 ± 0.002	0.32 ± 0.02	0.039 ± 0.002	0.41 ± 0.03	0.09 ± 0.02	0.9 ± 0.2
	GRU	0.039 ± 0.002	0.36 ± 0.05	0.044 ± 0.003	0.39 ± 0.07	0.07 ± 0.04	0.6 ± 0.3
	TCN	0.038 ± 0.002	0.33 ± 0.04	0.045 ± 0.002	0.38 ± 0.05	0.05 ± 0.04	0.4 ± 0.3
	Transformer	0.040 ± 0.003	$\mathbf{0.43 \pm 0.03}$	0.048 ± 0.003	$\mathbf{0.51 \pm 0.05}$	0.13 ± 0.04	1.1 ± 0.3
	GAT	$\underline{0.043 \pm 0.002}$	0.39 ± 0.02	0.042 ± 0.002	0.35 ± 0.02	0.10 ± 0.04	0.7 ± 0.3
	DTML	0.039 ± 0.004	0.29 ± 0.03	$\underline{0.053 \pm 0.008}$	0.37 ± 0.06	$\underline{0.16 \pm 0.03}$	$\underline{1.3 \pm 0.2}$
	MASTER	$\mathbf{0.052^* \pm 0.006}$	$\underline{0.40 \pm 0.06}$	$\mathbf{0.066 \pm 0.007}$	$\underline{0.48 \pm 0.06}$	$\mathbf{0.28^* \pm 0.02}$	$\mathbf{2.3^* \pm 0.3}$

- **Visualization**. The stock correlation captured by MASTER is **momentary**, **cross-time**, **asymmetric** and **evolve in time**.

a. Correlation towards specific stock. (y: time step, x: source stocks)



b. Cross-time correlation between stock pairs. (y: target, x: source)



More Information

- **Data & Code**: github.com/SJTU-Quant/MASTER
- **Contact us**: 2017lt@sjtu.edu.cn