

MASTER: Market-Guided Stock Transformer for Stock Price Forecasting



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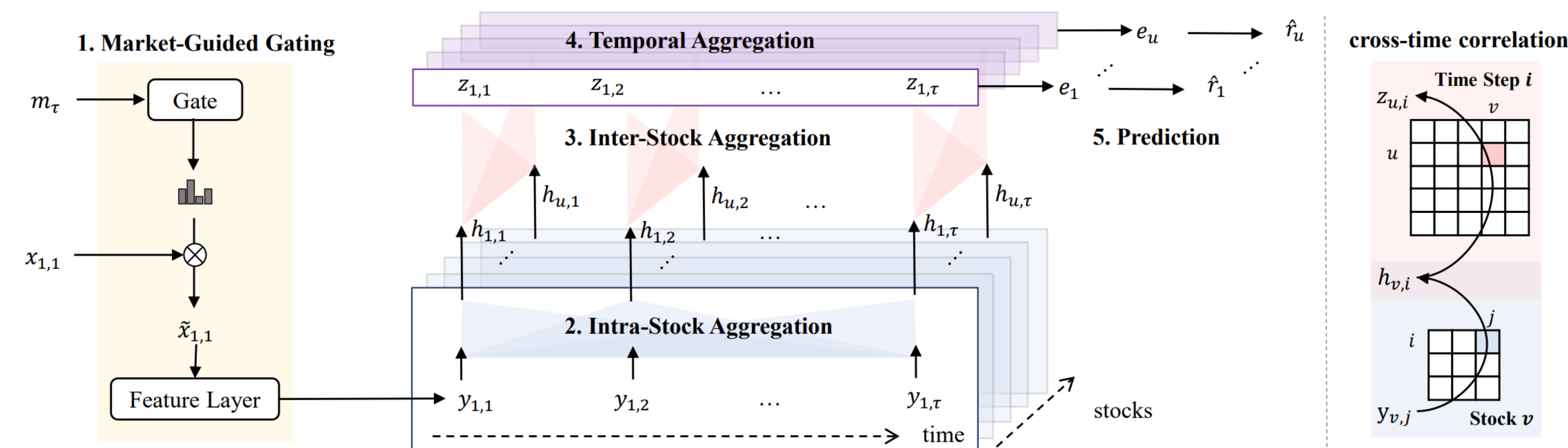
1. Background

- 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 \neq 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**.
 - Momentary:** The dominating factors of stock prices constantly change.
 - 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:**
 - 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.
 - 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 $\alpha(m_\tau) = F \cdot \text{softmax}_\beta(W_\alpha m_\tau + b_\alpha)$, 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: $Y_u = ||_{t \in [1, \tau]} \text{LayerNorm}(f(\tilde{x}_{u,t}) + p_t)$, $f(\cdot)$ 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 . $H_u^1 = ||_{t \in [1, \tau]} h_{u,t} = \text{FFN}^1(\text{MHA}^1(Q_u^1, K_u^1, V_u^1) + Y_u)$.
 - At time t , transform $H_t^2 = ||_{u \in S} h_{u,t}$ into Q_t^2, K_t^2, V_t^2 . $Z_t = ||_{u \in S} z_{u,t} = \text{FFN}^2(\text{MHA}^2(Q_t^2, K_t^2, V_t^2) + H_t^2)$.
- 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.
 - $L = \sum_{u \in S} \text{MSE}(r_u, \hat{r}_u)$. r_u is the normalized return ratio in d days, encoded with ranking information.

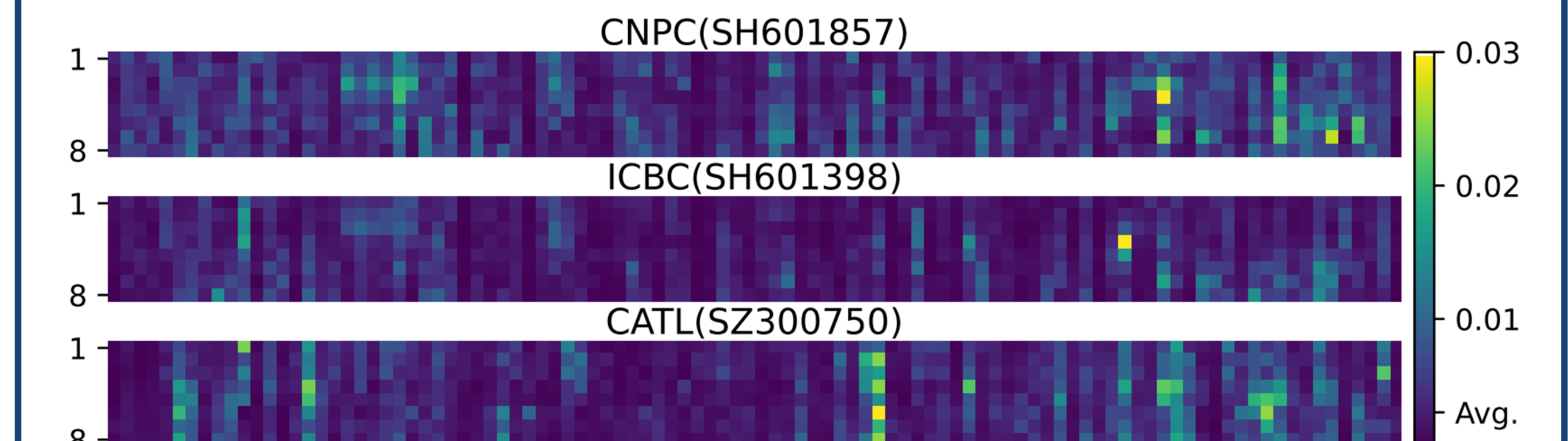
4. Experiments

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

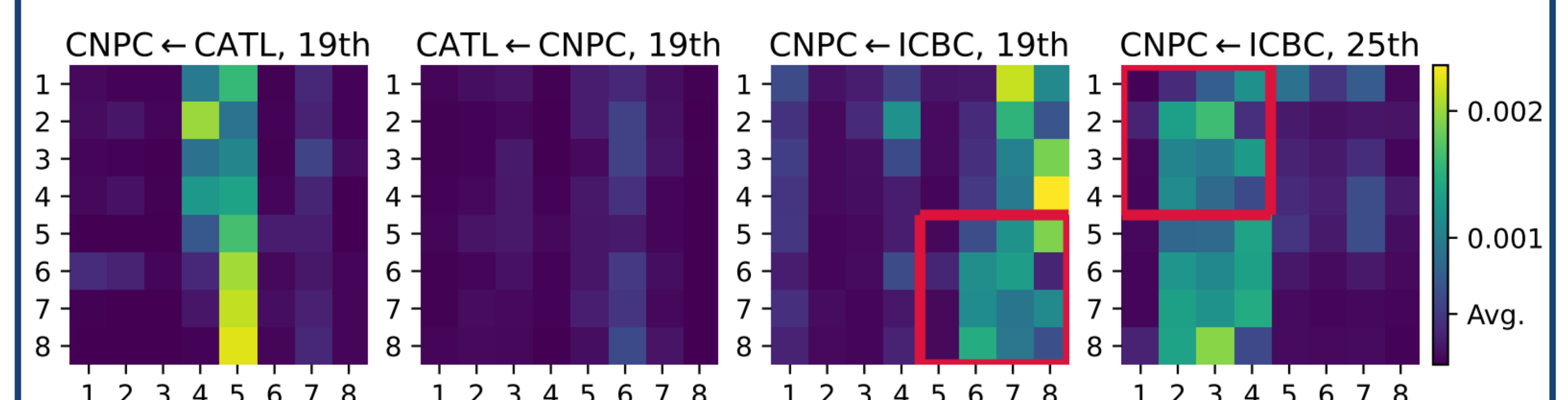
Dataset	Model	IC	ICIR	RankIC	RankICIR	AR	IR
CSI300	XGBoost	0.051 \pm 0.001	0.37 \pm 0.01	0.050 \pm 0.001	0.36 \pm 0.01	0.23 \pm 0.03	1.9 \pm 0.3
	LSTM	0.049 \pm 0.001	0.41 \pm 0.01	0.051 \pm 0.002	0.41 \pm 0.03	0.20 \pm 0.04	2.0 \pm 0.4
	GRU	0.052 \pm 0.004	0.35 \pm 0.04	0.052 \pm 0.005	0.34 \pm 0.04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