MASTER:Market-Guided Stock Transformer for Stock Price Forecasting[1]

Tong Li, Zhaoyang Liu, Yanyan Shen, Xue Wang, Haokun Chen, Sen Huang

AAAI-24

Presented by Group 7

110705009 陳重光、313551047 陳以瑄、313554043 戴明貴

Outline

- Introduction & Main Purpose
- Related Work - Yoo et al., KDD 2021
- Method
- Experienment & Ablation Study
- Conclusion

Intro - Dynamic Stock Correlation Modeling

Why Correlation Matters

In stock prediction, not only individual histories matter, but also:

1. Cross-stock correlation
2. Market-stock correlation

Types of Correlation Modeling

1. Static correlation modeling
   Predefined rules, cannot capture real-time changes
2. Dynamic correlation modeling
   Transformer architecture, learns time-varying correlations

Main Purpose

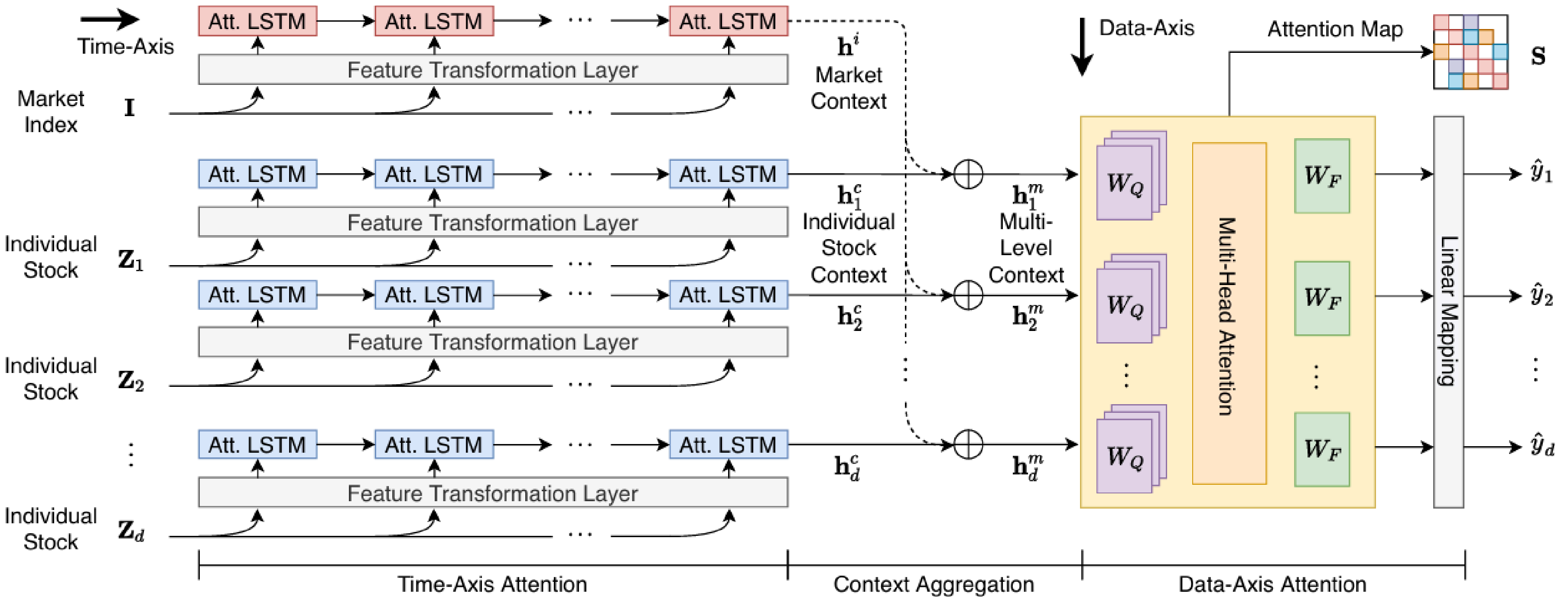
This study aims to model two phenomena:

1. Market status influence on feature relevance
2. Momentary and cross-time stock correlations

Both issues are limitations identified in Yoo et al. (KDD 2021).[2]

Related Work – Yoo et al., KDD 2021

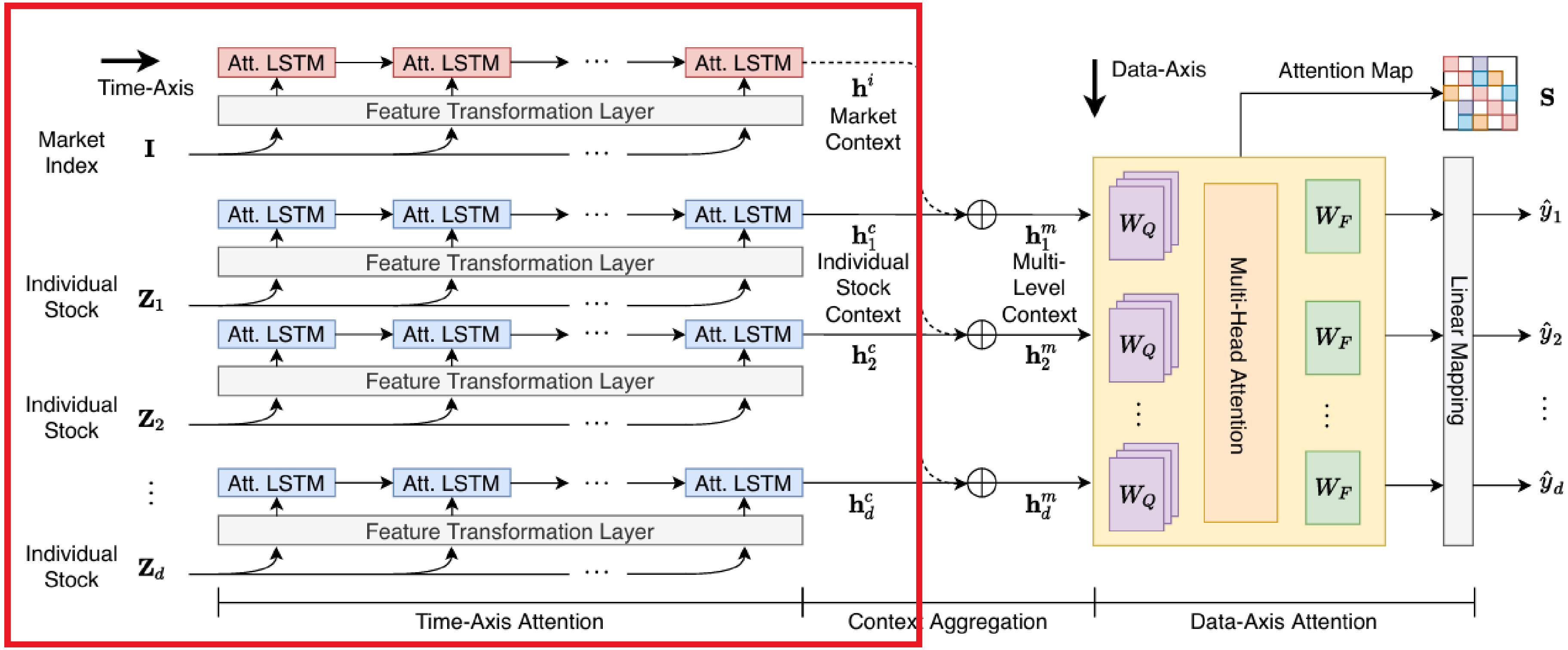
Accurate Multivariate Stock Movement Prediction via Data-Axis Transformer with Multi-Level Contexts



Related Work (Cont.)

Part 1: Time Axis Attention

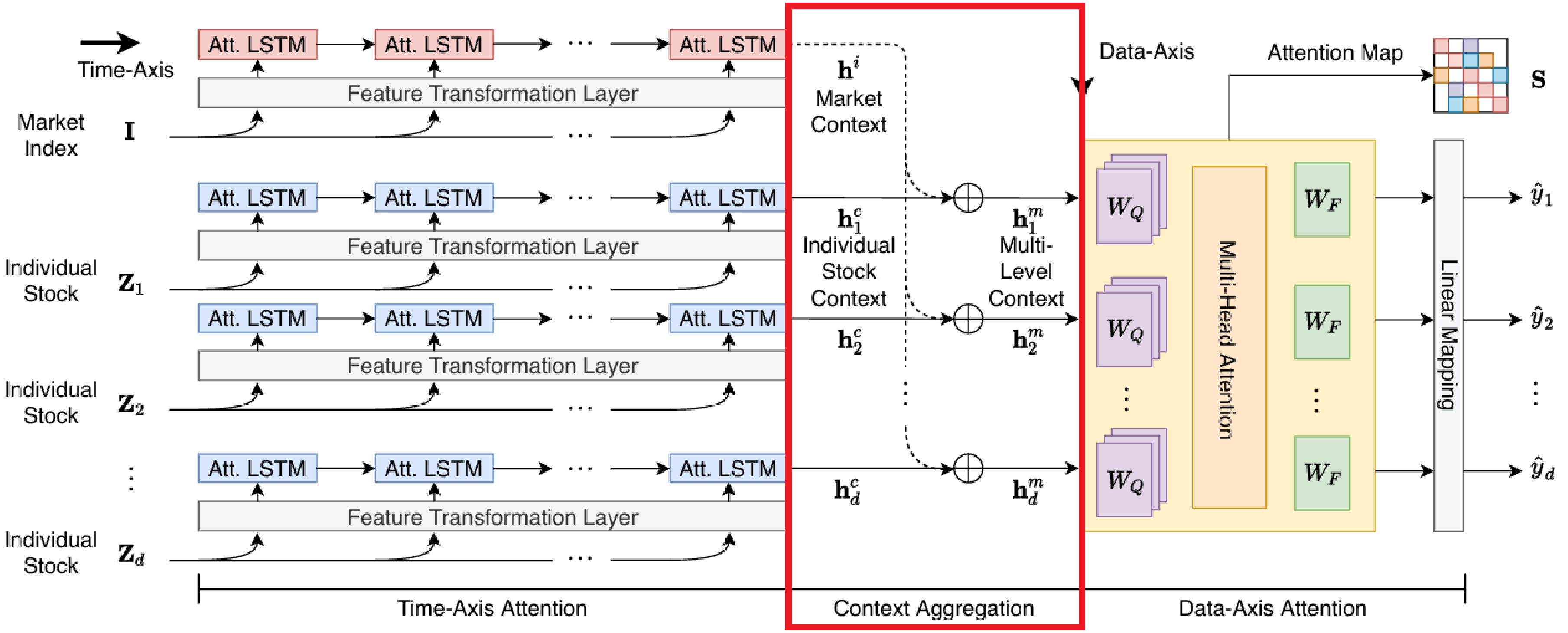
Single stock time series → Attention LSTM → Summarized embedding



Related Work (Cont.)

Part 2: Content Aggregation

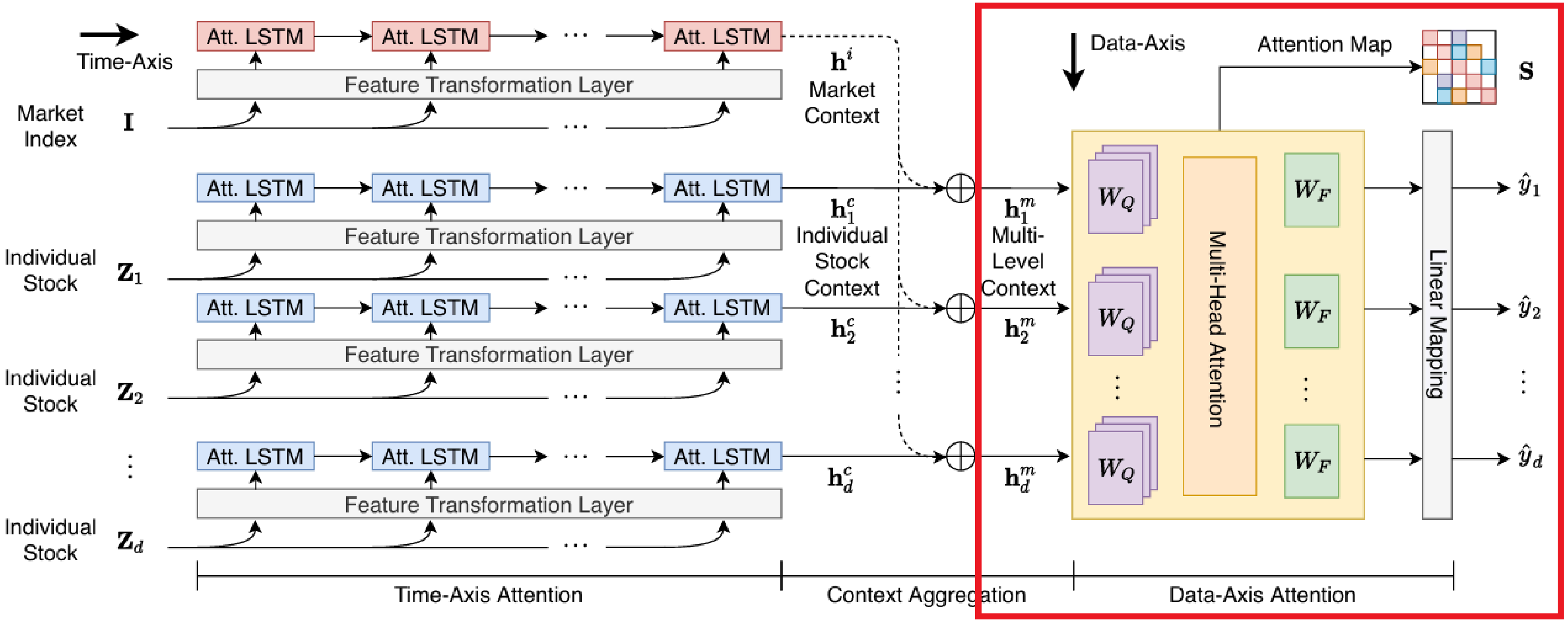
Incorporates market and stock representations: $h_u^m = h_u^c + \beta h^i$



Related Work (Cont.)

Part 3: Data Axis Attention

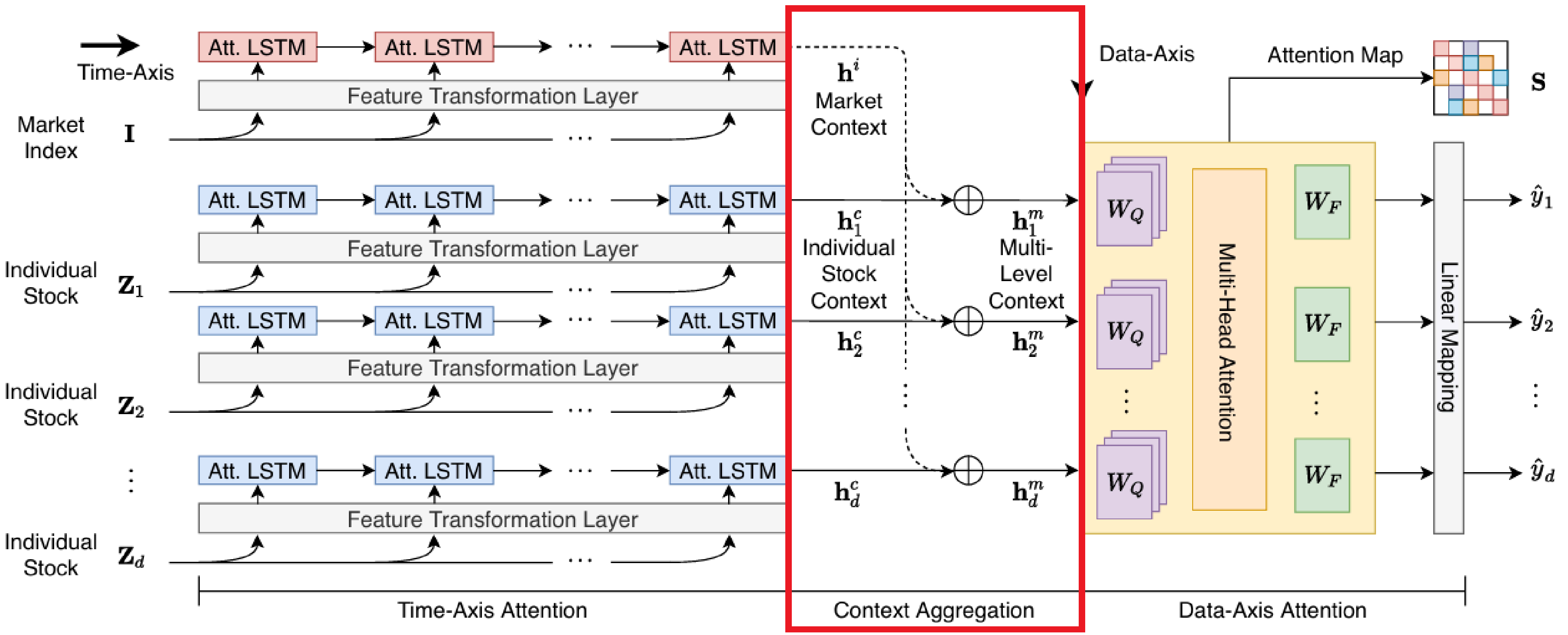
Uses Multihead attention to learn inter-stock correlation.



Limitation 1 - Market Status and Feature Selection

Problem in Prior Work (Step 2):

Integrates market information directly into stock representations.



Limitation 1 - Market Status and Feature Selection

What Is Missed:

Market status influences which features are useful for prediction.

Example: Momentum

$\text{Momentum} = P - P_x$, where P_x is the price *x* days ago.

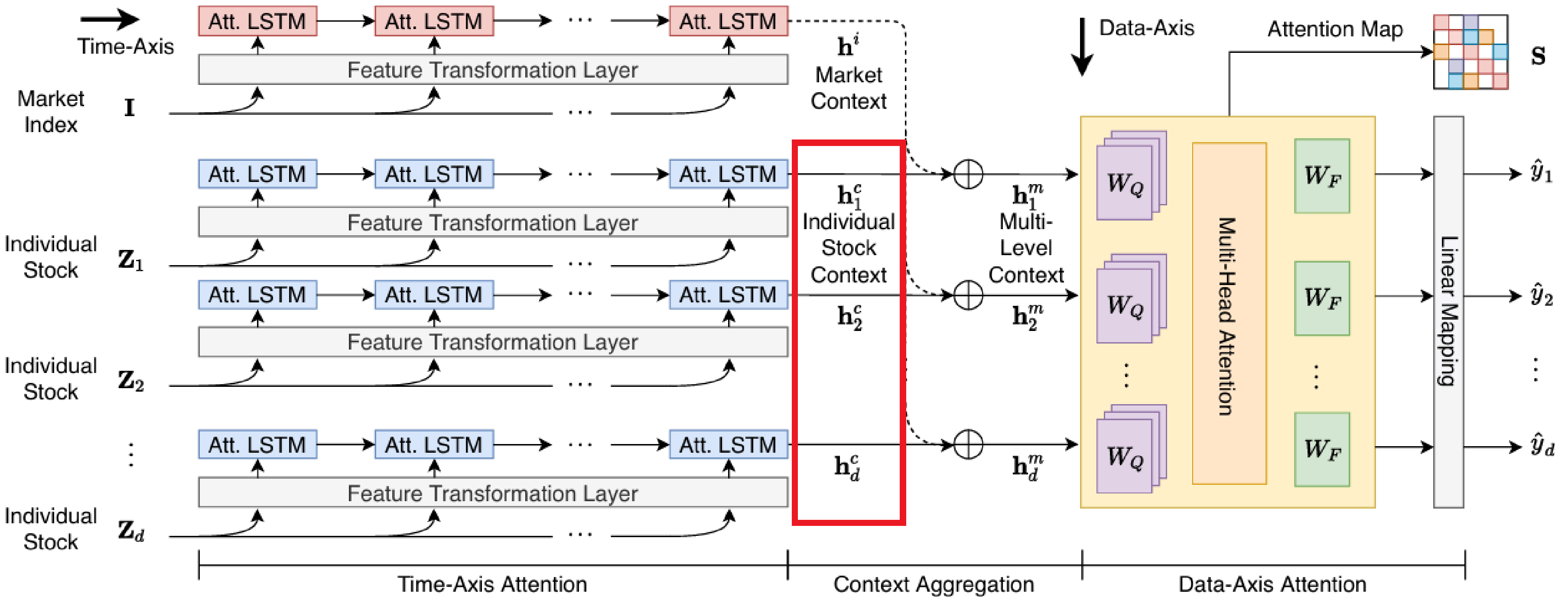
→ Shows how fast a stock's price is rising or falling.

Market Status	Sentiment	Investor Behavior	Effect on Momentum
Bull Market	Optimism	Chase strong performers	Past winners keep winning
Bear Market	Pessimism	Sell profitable stocks to cut risk	Past winners may reverse

Limitation 2 - Cross-time Stock Correlation

Problem in Prior Work (Step 1 & 3):

Uses overall stock representation to learn cross-stock correlation.

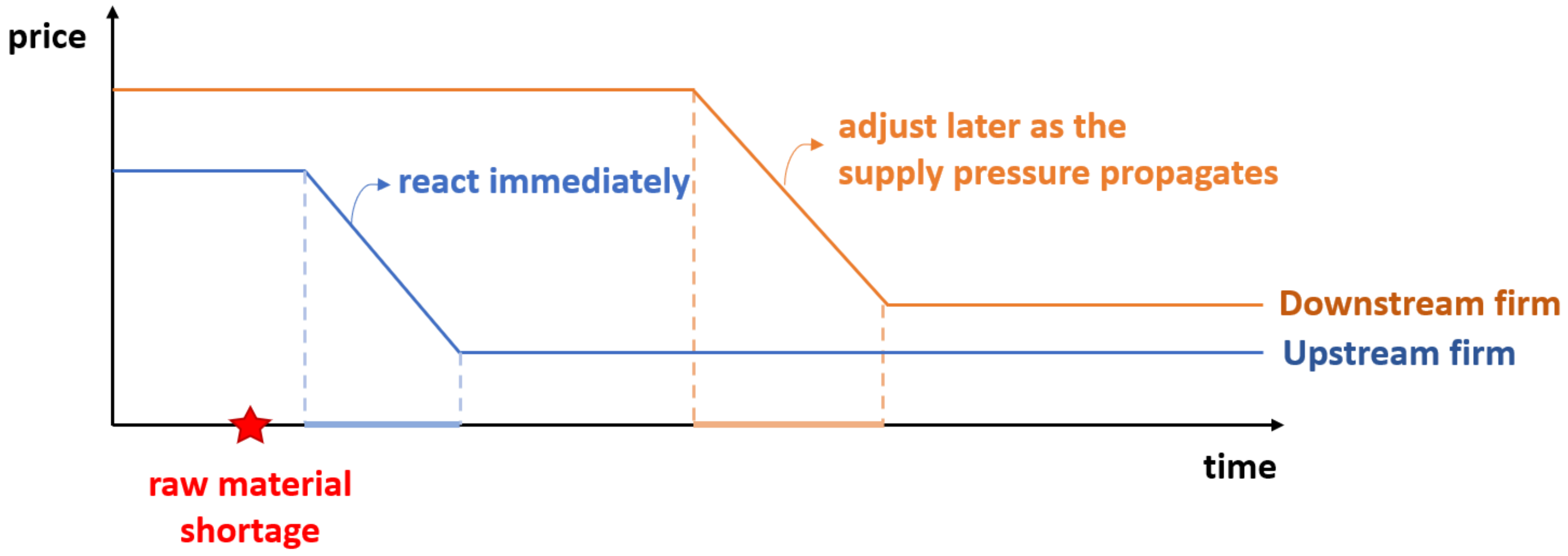


Limitation 2 - Cross-time Stock Correlation

What Is Missed:

Stocks often respond to the same external factors at different times.
→ Correlation is not aligned in time but occurs across time steps.

Example: Raw Material Shortage



Method-Framework

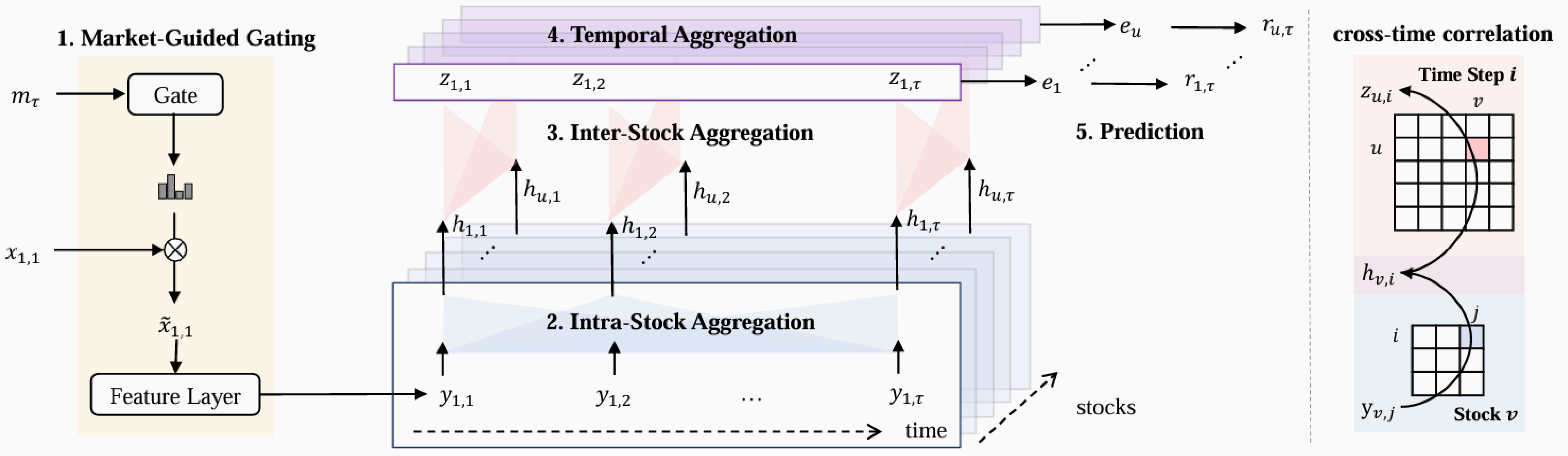
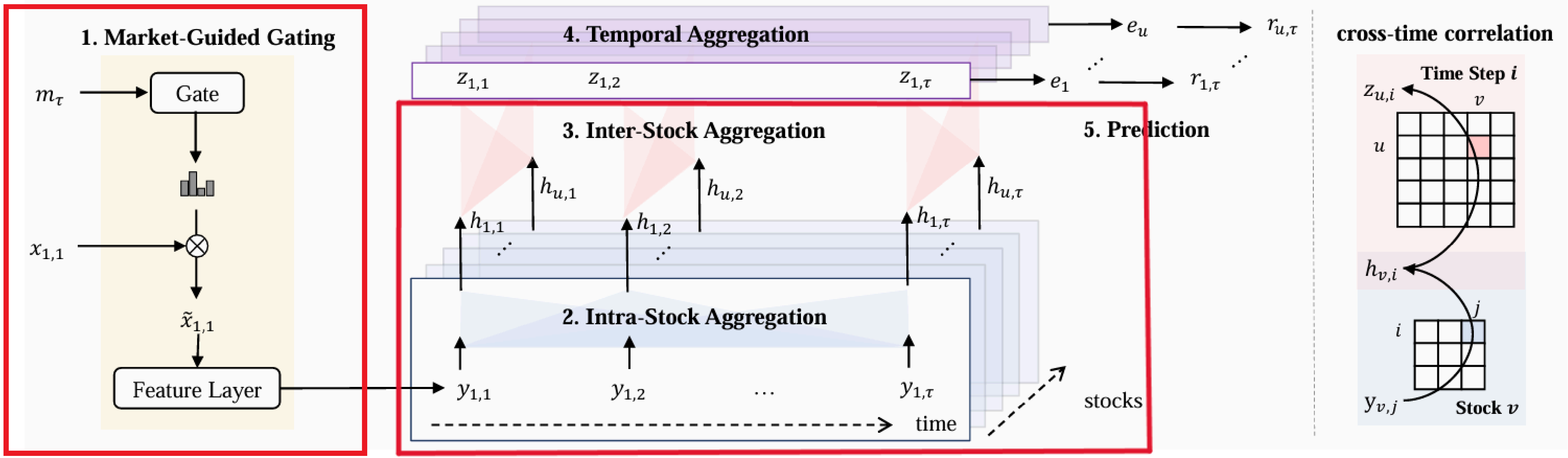


Figure 2: Overview of the MASTER framework.

Method-Framework (Cont.)



Limitation 1

Figure 2: Overview of the MASTER framework.

Limitation 2

Step1: Market-Guided Gating

Idea: adaptively select and scale features based on market conditions

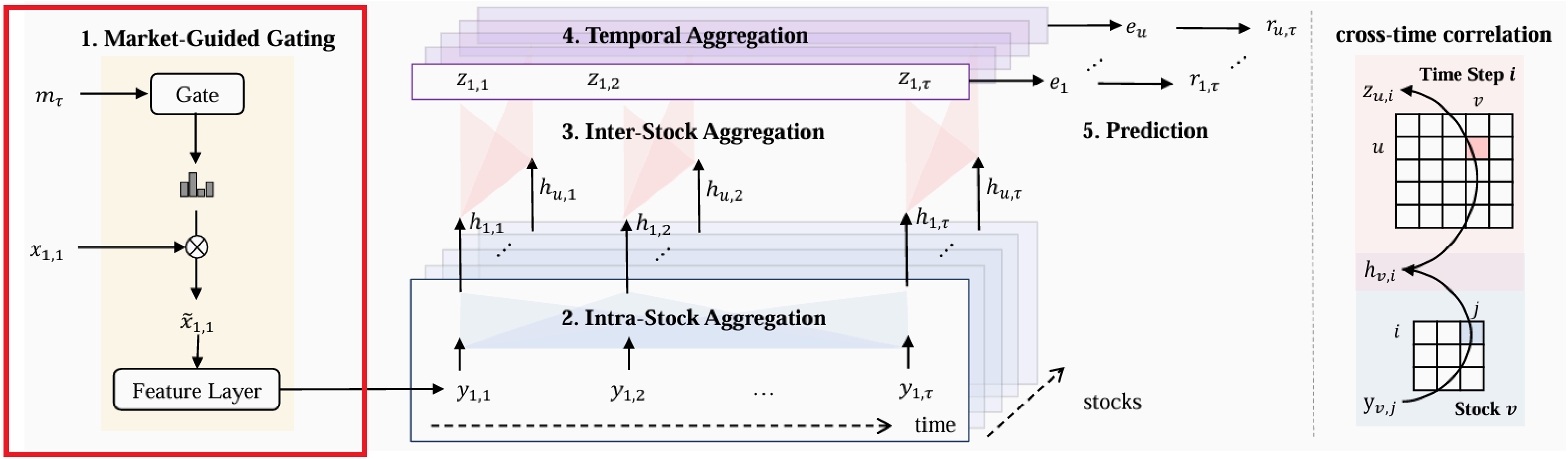


Figure 2: Overview of the MASTER framework.

Market-Guided Gating

Guiding Feature: Market status vector m_τ

- $|m_\tau| = F'$
- Market index price (current value, historical mean, std dev)
- Market index trading volume

Guided Feature: Stock Features $x_{u,t}$

- $|x_{u,t}| = F$
- Raw input features for stock u at time t

Market-Guided Gating

Gating Mechanism

1. Learn the scale factor: $\alpha(m_\tau) = F \cdot \mathrm{softmax}_\beta(W_\alpha m_\tau + b_\alpha)$
    - α: shared across all stocks $x_{u,t}$
    - β: smaller β → stronger filtering
2. Rescale each stock features: $\tilde{x}_{u,t} = \alpha(m_\tau) \circ x_{u,t}$

Addresses limitation 1:

Captures how market status influences the usefulness of features.

Step2: Intra-Stock Aggregation

Idea: Single stock behavior is continuous → a simpler distribution

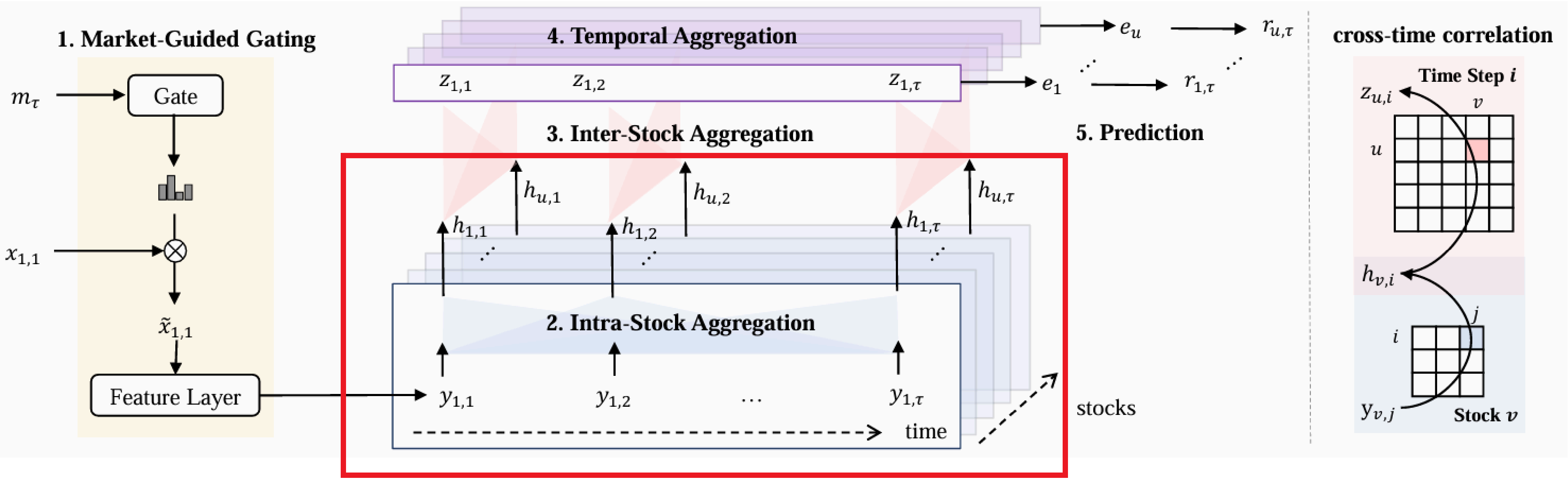


Figure 2: Overview of the MASTER framework.

Intra-Stock Aggregation

Multi-Head Attention

- Input: Rescaled features $\tilde{x}_{u,t}$
- Embedding: $y_{u,t} = f(\tilde{x}_{u,t}), |y_{u,t}| = D$
- Positional Encoding: Add sinusoidal p_t to retain temporal order
- Sequence: $Y_u = \|_{t \in [1,\tau]} \mathrm{LN}(f(\tilde{x}_{u,t}) + p_t)$

Intra-Stock Aggregation

Multi-Head Attention

- Sequence: $Y_u = \Vert_{t\in[1,\tau]} \mathrm{LN}(f(\tilde{x}_{u,t}) + p_t)$
- Attention

  $Q_u^1 = W_Q^1 Y_u, K_u^1 = W_K^1 Y_u, V_u^1 = W_V^1 Y_u$

  $H_u^1 = \mathrm{FFN}^1(\mathrm{MHA}^1(Q_u^1, K_u^1, V_u^1) + Y_u)$
- Output: Time-aware feature embeddings $h_{u,t}$ for each time step

Step3: Inter-Stock Aggregation

Idea: Capture the momentary stock correlation at each time step.

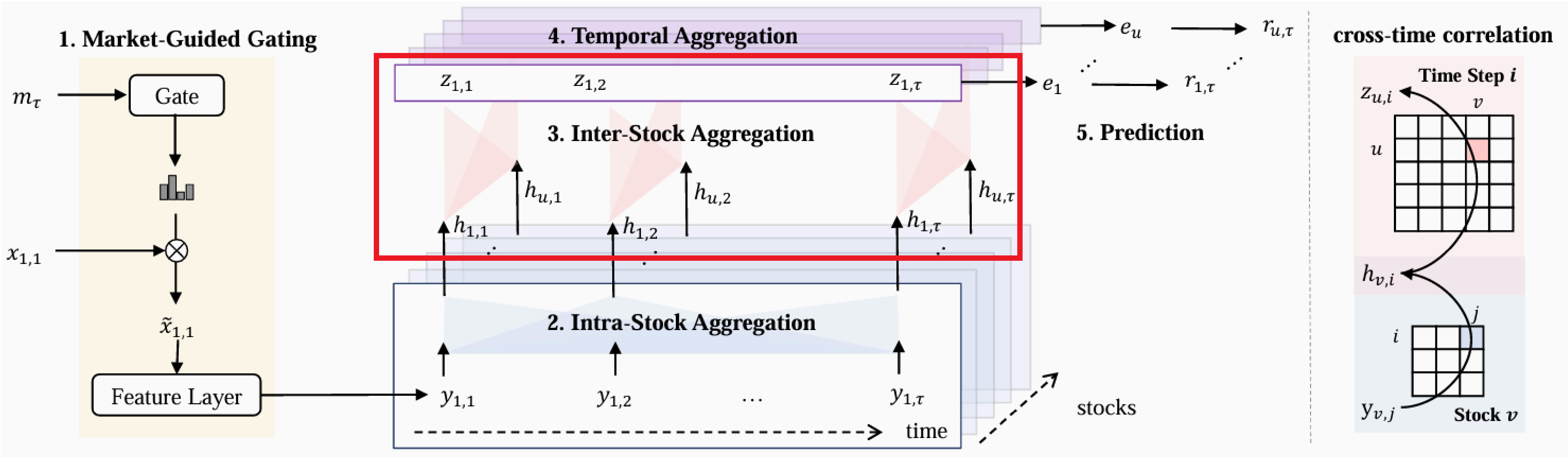


Figure 2: Overview of the MASTER framework.

Inter-Stock Aggregation

Multi-Head Attention

- Input: Gather intra-stock embeddings: $H_t^2 = \|_{u\in S} h_{u,t}$
- Attention:

$$Q_t^2 = W_Q^2 H_t^2, K_t^2 = W_K^2 H_t^2, V_t^2 = W_V^2 H_t^2$$

$$Z_t = \|_{u\in S} z_{u,t} = \mathrm{FFN}^2\left(\mathrm{MHA}^2(Q_t^2, K_t^2, V_t^2) + H_t^2\right)$$

- Output: Temporal embedding $z_{u,t}$ for each stock

Step 2+3: Inter-Stock & Intra-Stock Aggregations

Addresses Limitation 2:

Capture dynamic cross-stock correlations across time steps.

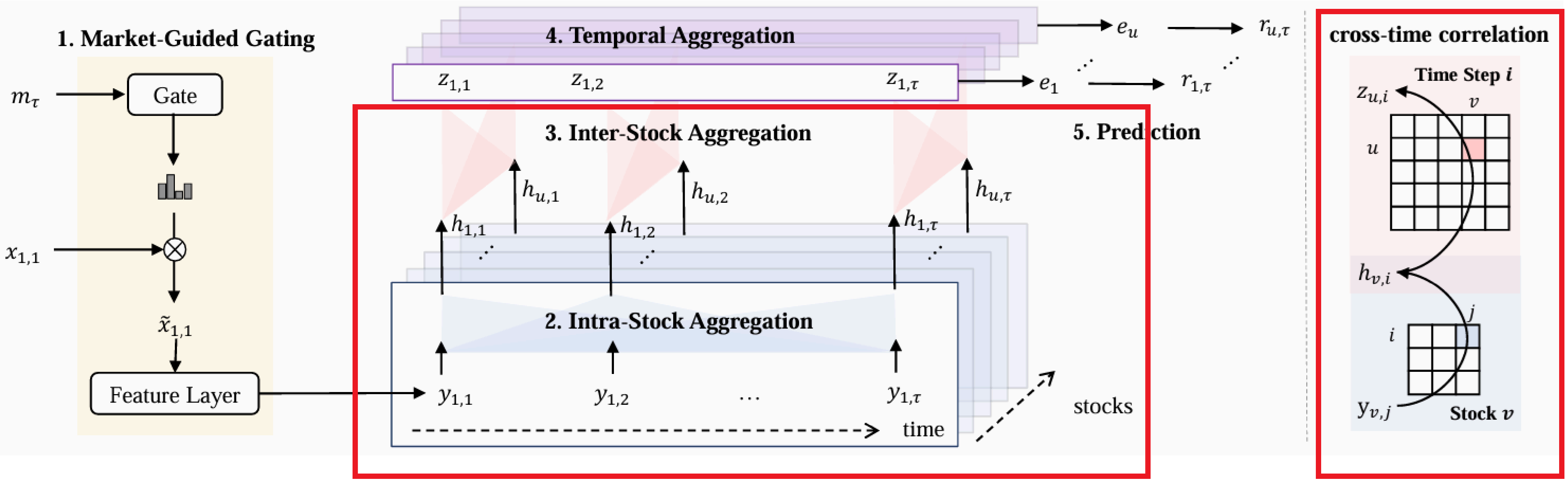


Figure 2: Overview of the MASTER framework.

Step 4: Temporal Aggregation

Idea: Summarize the obtained temporal embeddings.

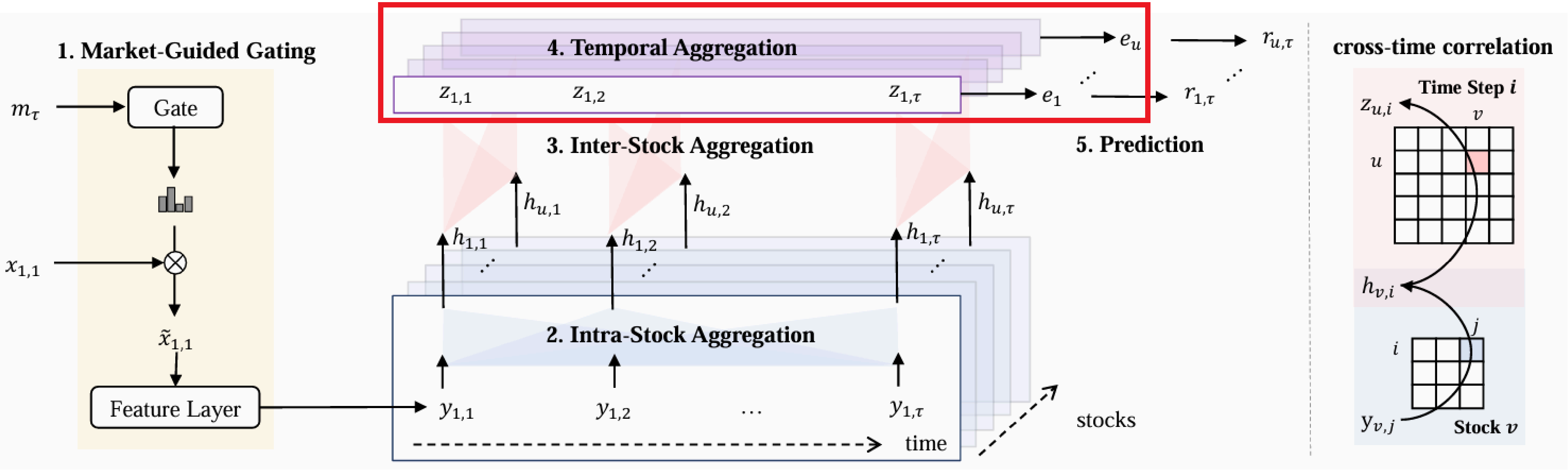


Figure 2: Overview of the MASTER framework.

Temporal Aggregation

- Input: Temporal embedding $z_{u,t}$
- Temporal attention layer:
  - Use the latest temporal embedding $z_{u,\tau}$ as the query vector
  - Compute attention scores: $\lambda_{u,t} = \frac{\exp(z_{u,t}^T W_\lambda z_{u,\tau})}{\sum_{i\in[1,\tau]} \exp(z_{u,i}^T W_\lambda z_{u,\tau})}$
- Aggregate embeddings: $e_u = \sum_{t\in[1,\tau]} \lambda_{u,t} z_{u,t}$

Step 5: Prediction

Idea: Use the stock embedding to predict the stock return.

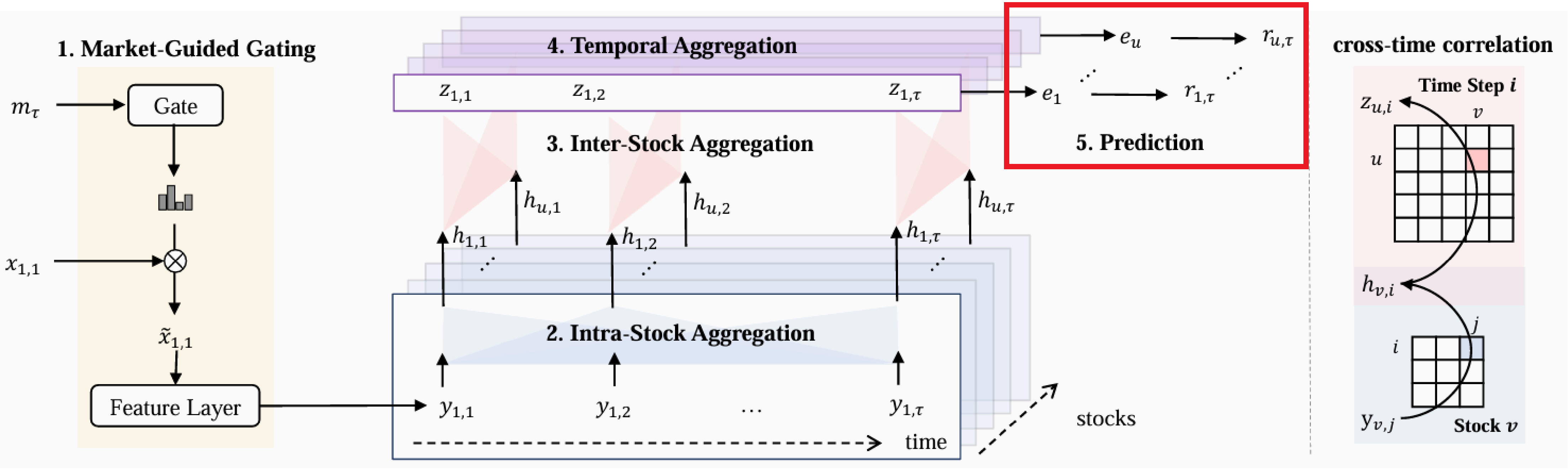


Figure 2: Overview of the MASTER framework.

Prediction

- Predicted return:
  $\hat{r}_u = g(e_u), g(.)$ is a linear layer for regression.
- Ground truth return:
  r_u is the normalized return ratio
- Loss Function: $L = \sum_{u \in S} MSE(r_u, \hat{r}_u)$

Experiments - Dataset

- **Stock sets:** Chinese stock market CSI300 and CSI800
- **Time:** 2008 to 2022

	Time
Training	Q1 2008 to Q1 2020
Validation	Q2 2020
Testing	Q3 2020 to Q4 2022

- **Feature:**
  Individual stock feature: Alpha158 indicators
  Shared market feature: CSI300, CSI500 and CSI800 index

Evaluation Metrics

Metric	Type	Description
IC	Ranking-based	Pearson correlation btw predictions and actual returns.
RankIC	Ranking-based	Spearman rank correlation btw predictions and actual returns.
ICIR	Ranking-based	Normalized IC (divided by std dev.)
RankICIR	Ranking-based	Normalized RankIC
AR	Portfolio-based	Annualized excess return from investing in top-ranked stocks
IR	Portfolio-based	Normalized AR

For all metrics, higher values indicate better performance.

Experiments - Result

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	0.23 ± 0.03	1.9 ± 0.3
	LSTM	0.049 ± 0.001	0.41 ± 0.01	0.051 ± 0.002	0.41 ± 0.03	0.20 ± 0.04	2.0 ± 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	0.42 ± 0.04	0.22 ± 0.06	2.0 ± 0.4
	GAT	0.054 ± 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	0.052 ± 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	0.043 ± 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	0.053 ± 0.008	0.37 ± 0.06	0.16 ± 0.03	1.3 ± 0.2
	MASTER	$\mathbf{0.052^{*} \pm 0.006}$	0.40 ± 0.06	$\mathbf{0.066 \pm 0.007}$	0.48 ± 0.06	$\mathbf{0.28^{*} \pm 0.02}$	$\mathbf{2.3^{*} \pm 0.3}$

Ablation Study - Beta

Temperature β

- A hyperparameter in the gating mechanism.
- Small β → stronger gating effect → filter more features.

Result: X-axis: β; Y-axis: Performance Metric

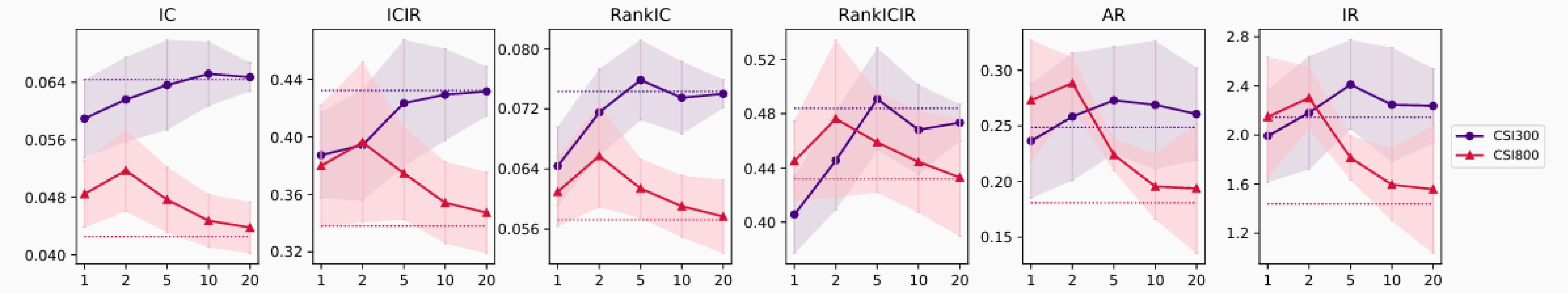


Figure 4: MASTER performance with varying β. The horizontal dash lines are performance without market-guided gating.

Ablation Study - Beta (Cont.)

Result: X-axis: β; Y-axis: Performance Metric

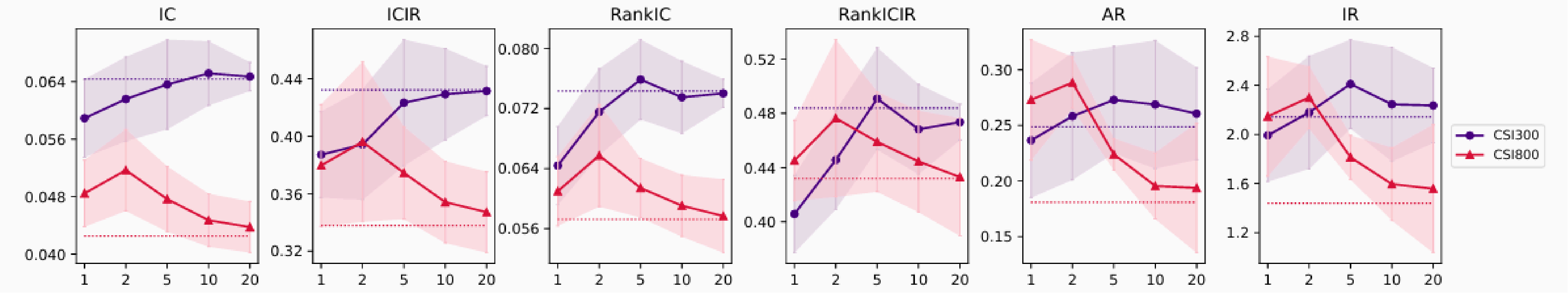
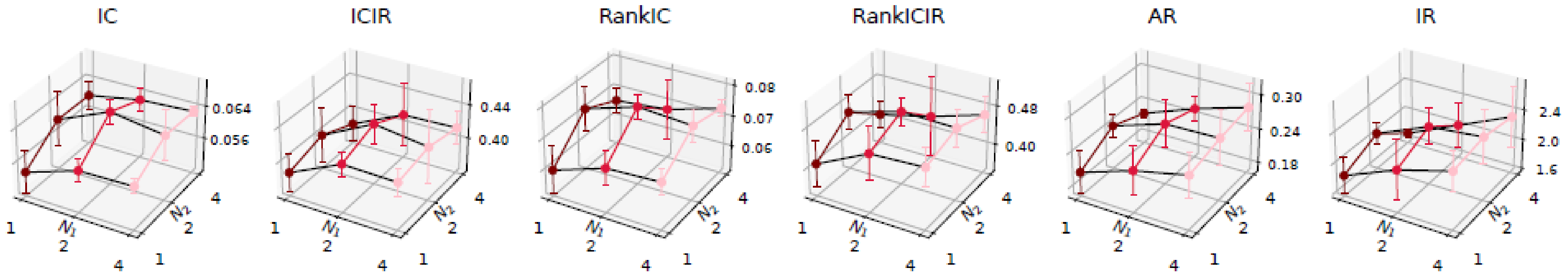


Figure 4: MASTER performance with varying β. The horizontal dash lines are performance without market-guided gating.

- CSI300: easier dataset → most features are effective → larger β
- CSI800: complex dataset → need feature selection → smaller β

Ablation Study - (N1, N2)

(N1, N2): The number of multi-heads in the attention mechanism.



Findings:

- Differences between head combinations are not significant.
- Most settings outperform the baseline → robustness

Conclusion

MASTER Key Features:

1. Models realistic stock correlations.
2. Guides feature selection with market information.

Experiments Result on the CSI300 and CSI800

- improves 13% on ranking metrics
- improves 47% on portfolio-based metrics

References

[1] Li, T., Liu, Z., Shen, Y., Wang, X., Chen, H., and Huang, S. (2024). MASTER: Market-Guided Stock Transformer for Stock Price Forecasting. In Proceedings of the AAAI Conference on Artificial Intelligence, 38(1), 162-170.

[2]Yoo, J., Soun, Y., Park, Y.-c., and Kang, U. (2021). Accurate multivariate stock movement prediction via data-axis transformer with multi-level contexts. In Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining, 2037–2045.

Thank you for listening.