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STORM: A Spatio-Temporal Factor Model Based on Dual Vector Quantized Variational Autoencoders for Financial Trading

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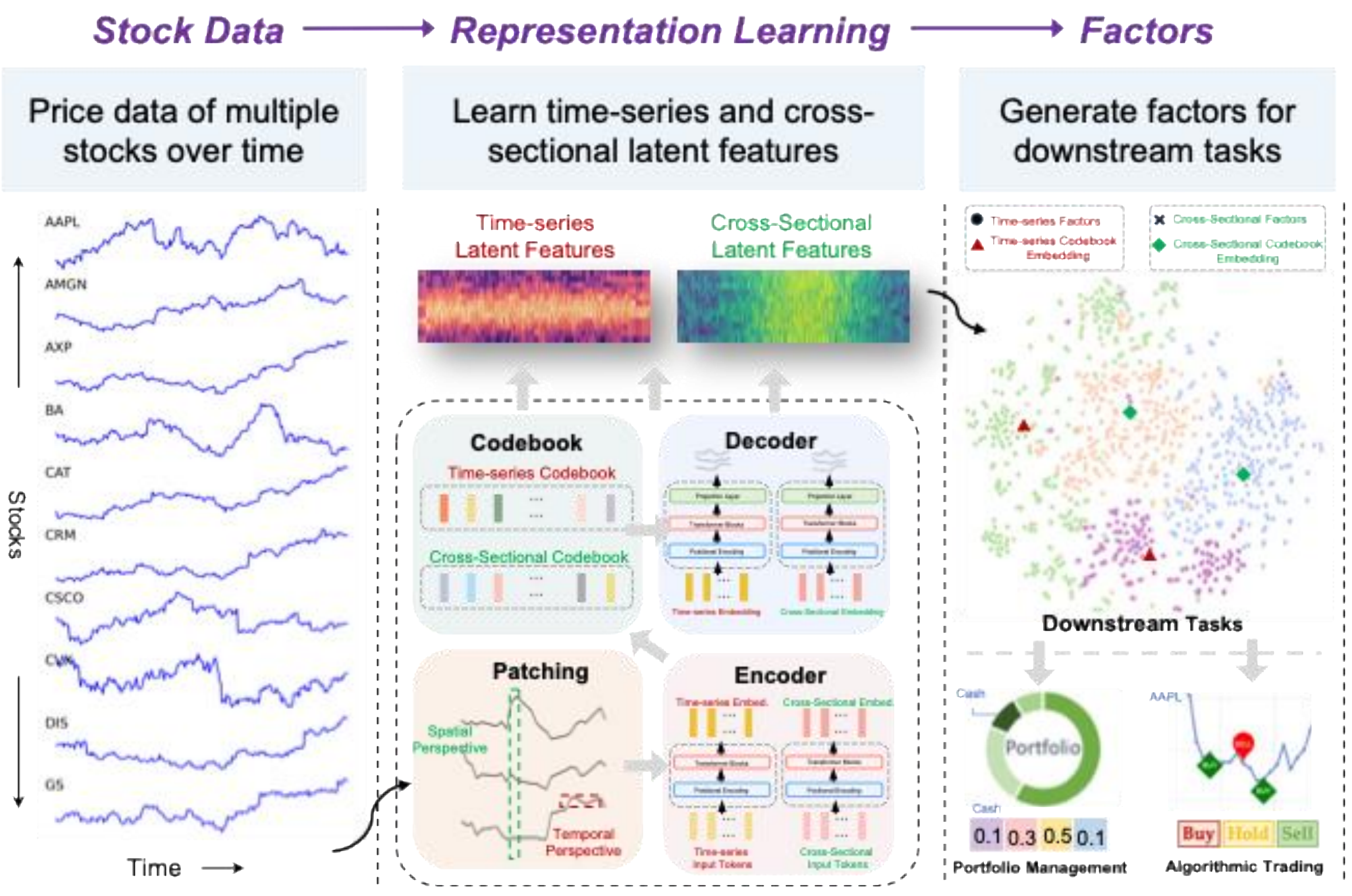
Problem Formulation

- **Latent Factor Models:** This research targets a spatio-temporal framework that captures both cross-sectional asset variations and individual temporal evolutions to model the underlying drivers of stock returns.
- **Portfolio Management:** The efficacy of generated factors is assessed by converting predictive signals into optimal capital allocation weights to achieve maximized risk-adjusted returns.
- **Algorithmic Trading:** This task aims to optimize trade execution for individual assets by determining discrete actions—buy, hold, sell—to balance transaction returns against market risks.



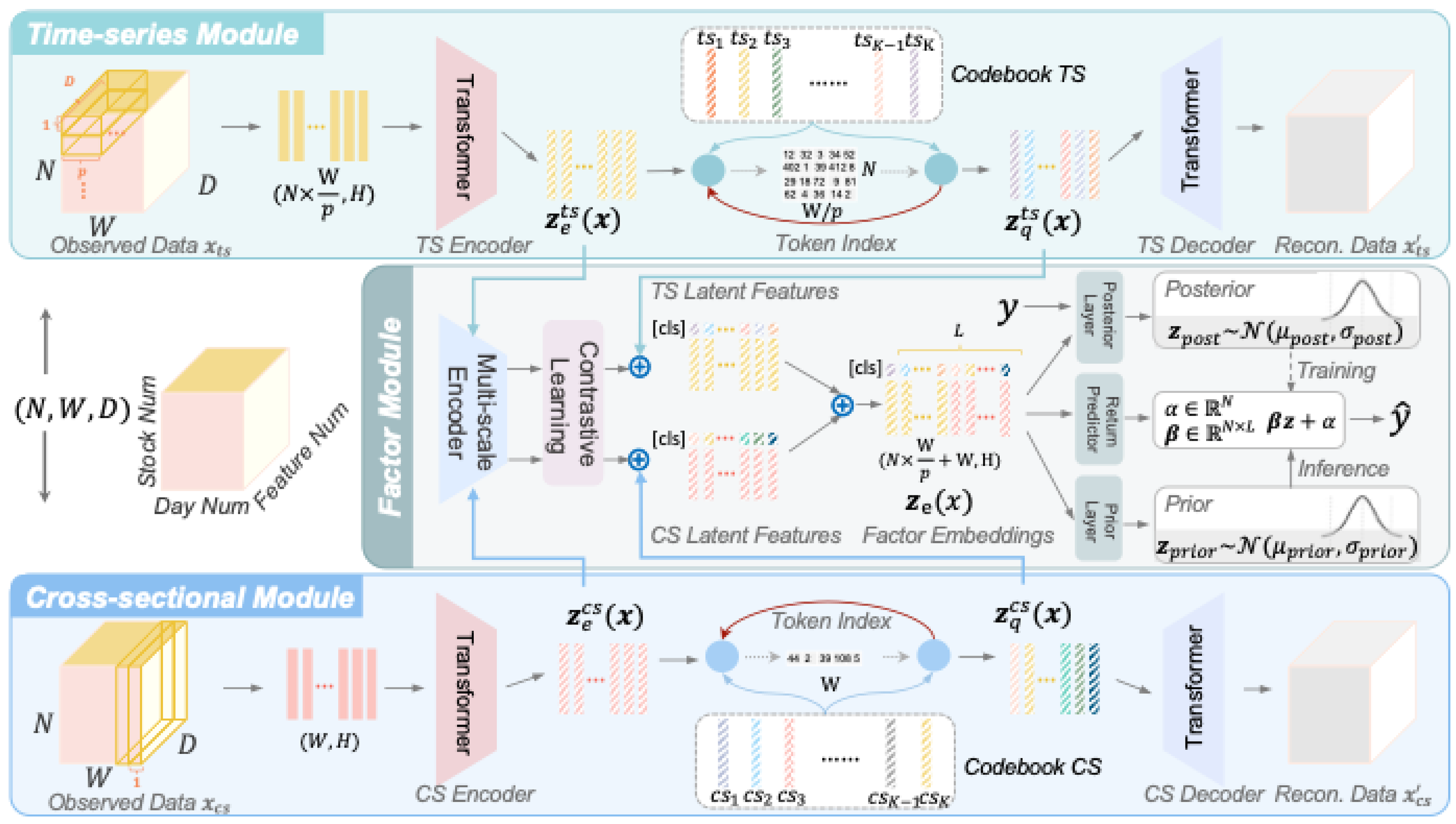
Challenges

- **Limited Reflection of Market Complexity.** Single-value factor representations struggle to capture the non-linear nature of financial data, leading to reduced predictive stability.
- **Factor Inefficiency.** VAE-based factors often ignore temporal dynamics, succumb to latent space noise, and suffer from multicollinearity due to a lack of factor independence.
- **Lack of Factor Selection.** Existing models prioritize factor generation over evaluation, failing to implement selection mechanisms necessary to identify and utilize the most impactful signals.

Motivations & Designs

- **High-Dimensional Vector Representation**: Captures intricate market complexity and non-linearity through high-dimensional latent vectors, overcoming the inherent constraints of traditional scalar-valued factors.
- **Dual VQ-VAE Spatio-Temporal Architecture**: Integrates cross-sectional and time-series features using a dual VQ-VAE structure with diversity and orthogonality loss constraints to ensure factor efficacy and independence.
- **Codebook-Based Categorization & Selection**: Employs discrete codebook embeddings as cluster centers to categorize and differentiate factors, providing a transparent mechanism for impactful factor selection.

Architecture of STORM



Time-series and Cross-sectional Modules

Patching and Encoding: In TS module, observed data is divided along the stock number dimension. In CS module, it's divided along the time axis. Then we use Transformer as encoders and decoders to capture complex patterns.

Codebook Construction and Optimization:

Diversity loss helps enhance representational capacity.

Orthogonality loss forces factor orthogonality.

$$\mathcal{L}_{\text{div}} = \frac{1}{GK}\sum_{g=1}^{G}\sum_{k=1}^{K}\bar{p}_{g,k}\log\bar{p}_{g,k},\quad \mathcal{L}_{\text{ortho}} = \frac{1}{K^2}\left\|\ell_2(\mathbf{e})^{\top}\ell_2(\mathbf{e}) - I_K\right\|_F^2$$

Decoding and Reconstruction

$$\begin{aligned}\mathcal{L}_1 = &\lambda_{\text{ortho}}\mathcal{L}_{\text{ortho}} + \lambda_{\text{div}}\mathcal{L}_{\text{div}} + \|\mathbf{x}-\mathbf{x}'_{ts}\|_2^2 + \|\mathbf{x}-\mathbf{x}'_{cs}\|_2^2\\ &+\left\|sg[z_e^{ts}(\mathbf{x})] - z_q^{ts}(\mathbf{x})\right\|_2^2 + \left\|sg[z_q^{ts}(\mathbf{x})] - z_e^{ts}(\mathbf{x})\right\|_2^2\\ &+\left\|sg[z_e^{cs}(\mathbf{x})] - z_q^{cs}(\mathbf{x})\right\|_2^2 + \left\|sg[z_q^{cs}(\mathbf{x})] - z_e^{cs}(\mathbf{x})\right\|_2^2\end{aligned}$$

Factor Module

Feature Fusion and Alignment: We use multiscale encoder and contrastive learning layer to fuse and align TS and CS features at fine-grained and semantic levels.

Prior - Posterior Learning: Concatenate two latent features, which are used to predict the future returns. The factors are then be used in portfolio and trading downstream tasks.

Experimental Results

Models	AAPL APY↑	AAPL CW↑	AAPL CR↑	JPM APY↑	JPM CW↑	JPM CR↑	IBM APY↑	IBM CW↑	IBM CR↑	INTC APY↑	INTC CW↑	INTC CR↑	MSFT APY↑	MSFT CW↑	MSFT CR↑
Buy&Hold	0.120	1.404	0.383	0.096	1.316	0.236	0.145	1.499	0.727	-0.117	0.690	-0.184	0.214	1.784	0.569
LightGBM	0.135	1.390	0.487	0.116	1.335	0.333	0.227	1.654	1.091	-0.042	0.880	0.038	0.267	2.068	0.637
LSTM	0.053 ± 0.015	1.152 ± 0.042	0.283 ± 0.101	0.079 ± 0.019	1.290 ± 0.053	0.266 ± 0.023	0.134 ± 0.141	1.386 ± 0.406	0.754 ± 0.69	0.060 ± 0.119	1.262 ± 0.429	0.381 ± 0.62	0.178 ± 0.122	1.513 ± 0.352	0.893 ± 0.822
Transformer	0.083 ± 0.099	1.240 ± 0.284	0.512 ± 0.864	0.133 ± 0.07	1.384 ± 0.201	0.614 ± 0.509	0.131 ± 0.072	1.377 ± 0.207	0.782 ± 0.541	0.079 ± 0.174	1.290 ± 0.68	0.458 ± 0.824	0.138 ± 0.118	1.397 ± 0.338	0.726 ± 0.643
DQN	0.135 ± 0.075	1.374 ± 0.226	0.510 ± 0.239	0.105 ± 0.132	1.305 ± 0.383	0.607 ± 0.673	0.139 ± 0.055	1.400 ± 0.158	0.802 ± 0.270	0.061 ± 0.106	1.185 ± 0.305	0.442 ± 0.436	0.166 ± 0.035	1.475 ± 0.100	0.534 ± 0.107
SAC	0.147 ± 0.021	1.509 ± 0.060	0.528 ± 0.052	0.131 ± 0.038	1.383 ± 0.111	0.400 ± 0.198	0.207 ± 0.057	1.598 ± 0.163	1.170 ± 0.335	0.056 ± 0.210	1.165 ± 0.6	0.353 ± 0.994	0.229 ± 0.114	1.656 ± 0.331	0.929 ± 0.585
PPO	0.137 ± 0.073	1.379 ± 0.209	0.496 ± 0.213	0.128 ± 0.026	1.372 ± 0.071	0.356 ± 0.059	0.146 ± 0.047	1.422 ± 0.136	0.779 ± 0.205	-0.019 ± 0.177	0.954 ± 0.514	0.040 ± 0.418	0.216 ± 0.081	1.620 ± 0.232	0.569 ± 0.105
STORM	**0.229** ± 0.033	**1.857** ± 0.154	0.750 ± 0.066	**0.174** ± 0.032	**1.621** ± 0.133	0.559 ± 0.081	**0.236** ± 0.039	**1.893** ± 0.184	**1.470** ± 0.445	**0.173** ± 0.067	**1.625** ± 0.284	**0.773** ± 0.293	**0.290** ± 0.052	**2.154** ± 0.262	**1.216** ± 0.597
STORM-w/o-TS	0.199 ± 0.059	1.730 ± 0.260	**0.766** ± 0.274	0.127 ± 0.058	1.437 ± 0.214	**0.627** ± 0.187	0.154 ± 0.023	1.536 ± 0.089	1.294 ± 1.012	0.106 ± 0.120	1.212 ± 0.145	0.267 ± 0.135	0.254 ± 0.060	1.979 ± 0.093	0.964 ± 0.503
STORM-w/o-CS	0.148 ± 0.069	1.521 ± 0.283	0.641 ± 0.184	0.103 ± 0.043	1.347 ± 0.154	0.350 ± 0.106	0.152 ± 0.054	1.534 ± 0.219	0.814 ± 0.352	0.136 ± 0.082	1.474 ± 0.300	0.541 ± 0.328	0.181 ± 0.051	1.650 ± 0.221	0.648 ± 0.361
Improvement(%)	55.782	23.062	45.076	30.827	17.124	2.117	3.965	14.4501	20.408	118.987	26.969	66.594	8.614	4.159	30.893

Models	AAPL ASR↑	AAPL MDD↓	AAPL AVO↓	JPM ASR↑	JPM MDD↓	JPM AVO↓	IBM ASR↑	IBM MDD↓	IBM AVO↓	INTC ASR↑	INTC MDD↓	INTC AVO↓	MSFT ASR↑	MSFT MDD↓	MSFT AVO↓
Buy&Hold	0.447	0.313	0.269	0.405	0.406	0.237	0.679	0.199	0.213	-0.324	0.635	0.359	0.777	0.376	0.275
LightGBM	0.950	0.309	0.017	0.921	0.386	0.015	1.822	0.175	0.011	0.098	0.553	0.023	1.456	0.370	0.017
LSTM	0.623 ± 0.163	0.244 ± 0.072	0.012 ± 0.003	0.801 ± 0.185	0.335 ± 0.061	0.012 ± 0.002	1.268 ± 0.924	0.163 ± 0.017	0.010 ± 0.001	0.287 ± 1.02	0.149 ± 0.101	0.010 ± 0.007	1.345 ± 0.842	0.246 ± 0.124	0.014 ± 0.003
Transformer	0.972 ± 0.748	0.239 ± 0.187	0.010 ± 0.006	1.332 ± 0.607	0.226 ± 0.100	0.010 ± 0.003	1.336 ± 0.688	0.182 ± 0.100	0.010 ± 0.003	0.604 ± 0.789	0.257 ± 0.194	0.014 ± 0.006	1.206 ± 0.754	0.182 ± 0.134	0.011 ± 0.006
DQN	0.974 ± 0.472	0.288 ± 0.159	0.016 ± 0.007	1.085 ± 1.270	0.212 ± 0.118	0.010 ± 0.003	1.415 ± 0.403	0.161 ± 0.049	0.009 ± 0.004	0.609 ± 0.584	0.243 ± 0.310	0.014 ± 0.009	1.194 ± 0.148	0.309 ± 0.079	0.015 ± 0.004
SAC	1.054 ± 0.223	0.292 ± 0.022	0.016 ± 0.002	1.044 ± 0.276	0.350 ± 0.085	0.014 ± 0.001	1.794 ± 0.458	0.157 ± 0.068	0.011 ± 0.005	0.527 ± 1.061	0.359 ± 0.191	0.017 ± 0.004	1.638 ± 0.736	0.229 ± 0.215	0.013 ± 0.005
PPO	0.974 ± 0.412	0.300 ± 0.030	0.016 ± 0.001	1.000 ± 0.189	0.381 ± 0.018	0.015 ± 0.001	1.386 ± 0.231	0.177 ± 0.027	0.011 ± 0.003	-0.044 ± 1.689	0.511 ± 0.115	0.019 ± 0.007	1.276 ± 0.299	0.353 ± 0.036	0.017 ± 0.001
STORM	**1.346** ± 0.162	0.282 ± 0.000	0.016 ± 0.001	1.245 ± 0.106	0.299 ± 0.016	0.014 ± 0.001	**2.107** ± 0.302	0.137 ± 0.033	0.009 ± 0.001	**1.189** ± 0.386	**0.227** ± 0.055	**0.015** ± 0.002	**1.672** ± 0.201	**0.210** ± 0.067	**0.015** ± 0.002
STORM-w/o-TS	1.199 ± 0.300	0.262 ± 0.052	0.017 ± 0.001	**1.587** ± 0.296	**0.194** ± 0.038	**0.011** ± 0.001	1.868 ± 0.956	**0.131** ± 0.077	**0.008** ± 0.003	0.580 ± 0.229	0.344 ± 0.061	0.017 ± 0.000	1.553 ± 0.187	0.244 ± 0.093	**0.015** ± 0.004
STORM-w/o-CS	1.027 ± 0.326	**0.229** ± 0.030	**0.015** ± 0.001	0.858 ± 0.236	0.327 ± 0.064	0.013 ± 0.001	1.397 ± 0.405	0.177 ± 0.028	0.010 ± 0.001	0.914 ± 0.397	0.312 ± 0.136	0.018 ± 0.004	1.401 ± 0.224	0.295 ± 0.090	0.016 ± 0.002
Improvement(%)	27.704	4.184	-	19.144	8.491	-	15.642	16.561	11.111	95.238	-	-	2.076	-	-

← *Results on Algorithmic Trading*

↓ *Results on Factor evaluation*

Models	SP500 RankIC↑	SP500 RankICIR↑	DJ30 RankIC↑	DJ30 RankICIR↑
Future Return Prediction in Portfolio Management Task				
LightGBM	0.027 ± 0.006	0.274 ± 0.084	0.031 ± 0.005	0.272 ± 0.049
LSTM	0.034 ± 0.006	0.333 ± 0.042	0.031 ± 0.004	0.329 ± 0.056
Transformer	0.035 ± 0.007	0.340 ± 0.078	0.033 ± 0.005	0.343 ± 0.045
CAFactor	0.037 ± 0.005	0.356 ± 0.084	0.040 ± 0.003	0.380 ± 0.043
FactorVAE	0.052 ± 0.010	0.543 ± 0.122	0.056 ± 0.012	0.520 ± 0.081
HireVAE	0.057 ± 0.006	0.558 ± 0.058	0.058 ± 0.006	0.563 ± 0.053
STORM	**0.062** ± 0.018	**0.673** ± 0.155	**0.065** ± 0.038	**0.668** ± 0.287
STORM-w/o-TS	0.053 ± 0.017	0.513 ± 0.145	0.055 ± 0.015	0.563 ± 0.127
STORM-w/o-CS	0.054 ± 0.014	0.522 ± 0.118	0.053 ± 0.016	0.559 ± 0.156
Improvement(%)[1]	8.772	20.609	12.069	18.650

Experiments on 7 datasets from two U.S. stock markets, covering the stock future return prediction task (DJ30 and SP500), portfolio management (DJ30 and SP500), and algorithmic trading (five stocks), show that STORM outperforms all baselines across two prediction metrics and six standard financial metrics.