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Adaptive Stock Price Forecasting Using Temporal and Market-Guided Architectures

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Challenges of Stock Price Forecasting

- Volatility:
  - Stock prices are influenced by numerous unpredictable factors like macroeconomic conditions, geopolitical events, and investor sentiment. This introduces a high level of noise in the data, making predictions difficult.
- Nature of High Frequency:
  - In high- and medium-frequency trading, decisions need to be made in fractions of a second, requiring models to process and predict rapidly.
- Dynamic Market Signaling:
  - Market conditions change constantly, and static models fail to adapt effectively to real-time variations

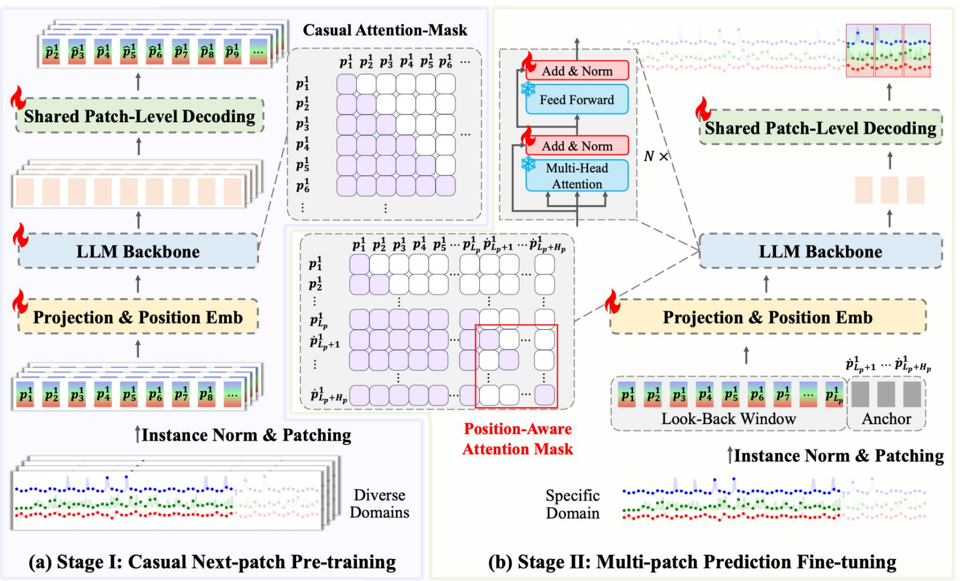
Multi-Patch Prediction: Enhancing Time-Series Representation

The Paper:

- Adapts LLMs for time-series via patch-based segmentation.
- Two-stage training: causal pretraining and multi-patch fine-tuning.
- Introduces a patch-wise decoding layer for better temporal representation.

Our incorporation:

- Inspired our patch-based preprocessing for time-series data.
- Used in our fusion models to capture temporal dependencies.


Casual Attention-Mask
$\hat{p}_2^1$ $\hat{p}_3^1$ $\hat{p}_4^1$ $\hat{p}_5^1$ $\hat{p}_6^1$ $\hat{p}_7^1$ $\hat{p}_8^1$ $\hat{p}_9^1$ ...
Shared Patch-Level Decoding
LLM Backbone
Projection & Position Emb
p_1^1 p_2^1 p_3^1 p_4^1 p_5^1 p_6^1 p_7^1 p_8^1 ...
Instance Norm & Patching
Diverse Domains
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
N ×
p_1^1 p_2^1 p_3^1 p_4^1 p_5^1 ... $p_{L_p}^1$ $\dot{p}_{L_p+1}^1$ ... $\dot{p}_{L_p+H_p}^1$
Position-Aware Attention Mask
Shared Patch-Level Decoding
LLM Backbone
Projection & Position Emb
$\dot{p}_{L_p+1}^1$ ... $\dot{p}_{L_p+H_p}^1$
p_1^1 p_2^1 p_3^1 p_4^1 p_5^1 p_6^1 p_7^1 ... $p_{L_p}^1$
Look-Back Window
Anchor
Instance Norm & Patching
Specific Domain

(a) Stage I: Casual Next-patch Pre-training

(b) Stage II: Multi-patch Prediction Fine-tuning

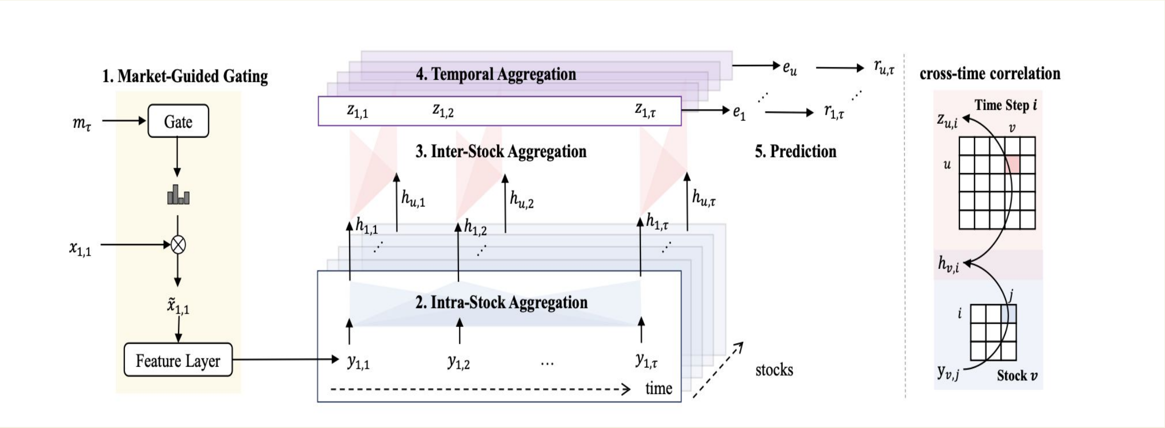
MASTER: Market-Guided Stock Transformer

The Paper:

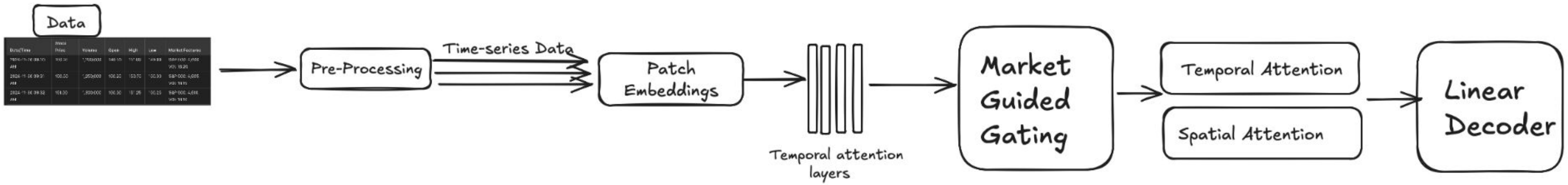
- Transformer-based model for stock price forecasting.
- Combines temporal and spatial attention with a market-guided gating mechanism.
- Adapts features dynamically based on market conditions.

Our incorporation:

- Inspired market-guided gating in our Parallel Fusion model.
- Used temporal and spatial attention layers to model intra- and inter-stock dependencies.



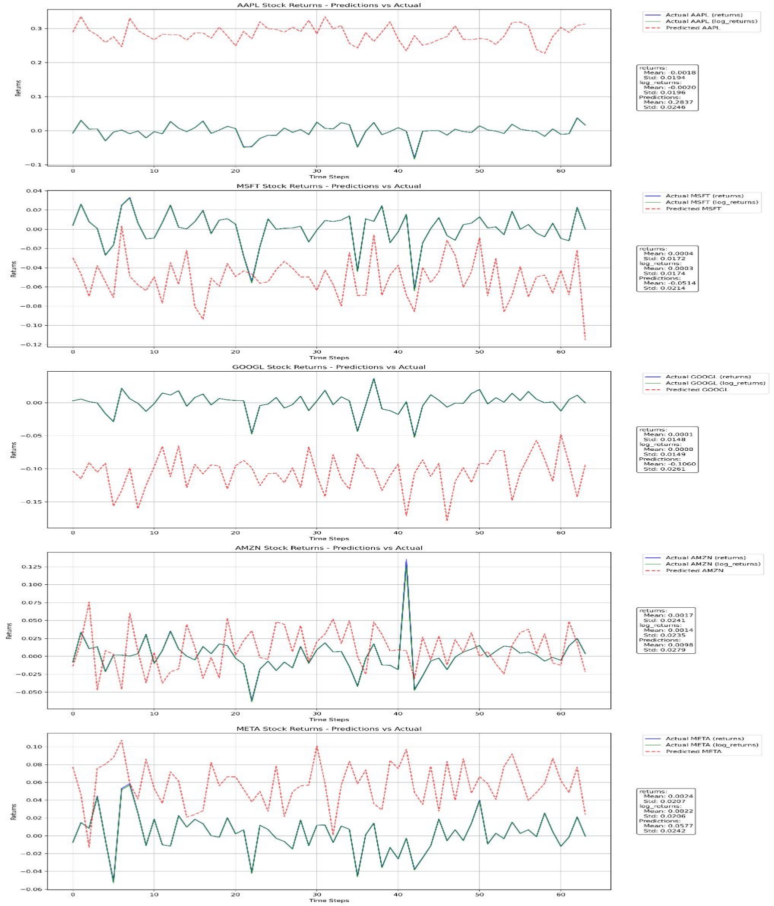
Our Approach

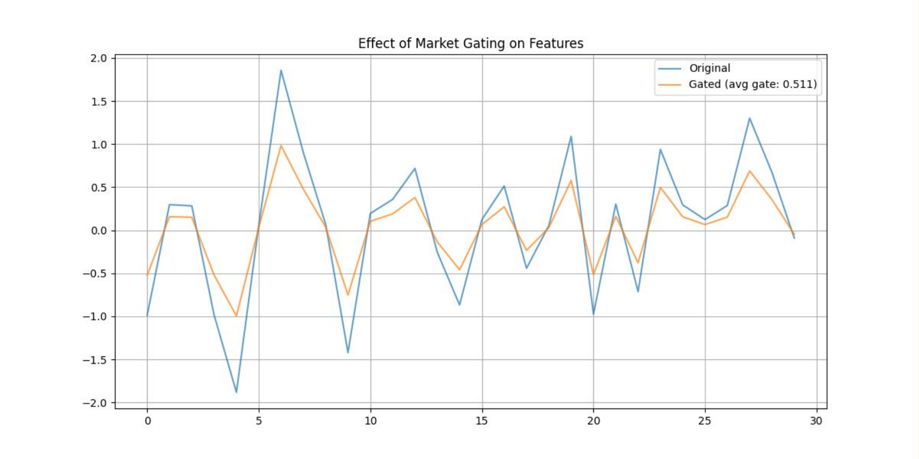


Date/Time	Stock Price	Volume	Open	High	Low	Market Features
2024-11-26 09:30 AM	[illegible]	1,200,000	[illegible]	[illegible]	[illegible]	S&P 500: 4,600 VIX: 15.20
2024-11-26 09:31 AM	100.00	1,250,000	100.20	[illegible]	100.00	S&P 500: 4,605 VIX: 18.15
2024-11-26 09:32 AM	101.00	1,300,000	100.30	101.25	100.25	S&P 500: 4,610 VIX: 18.10

- Integrated patch-based representation from Multi-Patch Prediction.
- Adopted dynamic, market-aware attention from MASTER.
- Created **Parallel Fusion** for simultaneous multi-stock forecasting.

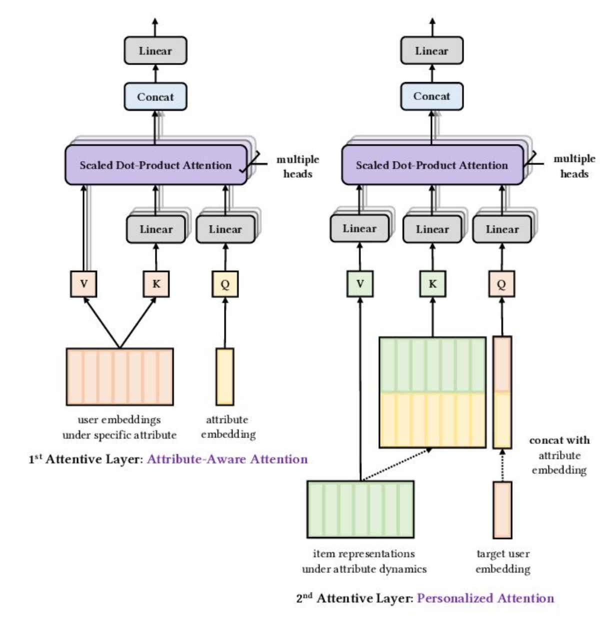
Results


AAPL Stock Returns - Predictions vs Actual
Returns
0.3
0.2
0.1
0.0
−0.1
0
10
20
30
40
50
60
Time Steps
Actual AAPL (returns)
Actual AAPL (log_returns)
Predicted AAPL
returns:
Mean: -0.0018
Std: 0.0194
log_returns:
Mean: -0.0020
Std: 0.0196
Predictions:
Mean: 0.2837
Std: 0.0246
MSFT Stock Returns - Predictions vs Actual
Returns
0.04
0.02
0.00
−0.02
−0.04
−0.06
−0.08
−0.10
−0.12
Time Steps
Actual MSFT (returns)
Actual MSFT (log_returns)
Predicted MSFT
returns:
Mean: 0.0004
Std: 0.0172
log_returns:
Mean: 0.0003
Std: 0.0174
Predictions:
Mean: -0.0514
Std: 0.0214
GOOGL Stock Returns - Predictions vs Actual
Returns
0.00
−0.05
−0.10
−0.15
Time Steps
Actual GOOGL (returns)
Actual GOOGL (log_returns)
Predicted GOOGL
returns:
Mean: 0.0001
Std: 0.0148
log_returns:
Mean: 0.0000
Std: 0.0149
Predictions:
Mean: -0.1060
Std: 0.0261
AMZN Stock Returns - Predictions vs Actual
Returns
0.125
0.100
0.075
0.050
0.025
0.000
−0.025
−0.050
Time Steps
Actual AMZN (returns)
Actual AMZN (log_returns)
Predicted AMZN
returns:
Mean: 0.0017
Std: 0.0241
log_returns:
Mean: 0.0014
Std: 0.0235
Predictions:
Mean: 0.0098
Std: 0.0279
META Stock Returns - Predictions vs Actual
Returns
0.10
0.08
0.06
0.04
0.02
0.00
−0.02
−0.04
−0.06
Time Steps
Actual META (returns)
Actual META (log_returns)
Predicted META
returns:
Mean: 0.0024
Std: 0.0207
log_returns:
Mean: 0.0022
Std: 0.0206
Predictions:
Mean: 0.0577
Std: 0.0242


Effect of Market Gating on Features
Original
Gated (avg gate: 0.511)
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
0
5
10
15
20
25
30

Future Work

- Implementing hierarchical fusion and self-attention mechanisms.
- Compare and contrast both models and attempt to create a fusion and further evaluate performance.


Linear
Concat
Scaled Dot-Product Attention
multiple heads
Linear
Linear
V
K
Q
user embeddings under specific attribute
attribute embedding
1st Attentive Layer: Attribute-Aware Attention
Linear
Concat
Scaled Dot-Product Attention
multiple heads
Linear
Linear
Linear
V
K
Q
concat with attribute embedding
item representations under attribute dynamics
target user embedding
2nd Attentive Layer: Personalized Attention