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A Transformer-Based Framework for Precious Metal Price Prediction With Explicit Cross-Metal Dependency Modeling

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Abstract. Precious metals serve as critical investment assets and industrial commodities in global financial markets. Accurate price forecasting is challenged by their strong nonlinearity, long-range temporal dependencies, and complex inter-metal linkages. Traditional econometric models and existing deep learning approaches often overlook explicit cross-metal interactions, leading to suboptimal multi-metal prediction performance. This paper proposes an improved Transformer architecture for multi-precious metal price forecasting, which jointly models individual temporal dynamics and cross-metal correlations in a unified framework. The method integrates metal-specific embedding, hybrid multi-head attention for temporal and cross-metal modeling, a cross-attention mechanism for leader–follower relationship capture, and an Informer-based sparse attention for long-sequence efficiency. A hybrid loss function combining Huber regression and inter-metal correlation constraints is designed to preserve realistic market co-movements. Experiments on daily futures data of eight precious metals from 2005 to 2025 show that the proposed method outperforms baseline models including linear regression, gradient boosting, SVR, LSTM, GRU, and CNN across multiple prediction horizons. The results validate that explicit cross-metal dependency modeling significantly enhances forecasting accuracy in interconnected precious metal markets.

Keywords: Precious metal price forecasting, Transformer, cross-metal dependency, multi-head attention, time series, Informer, financial market prediction.

1. Introduction

Precious metals such as gold, silver, platinum, and palladium play a dual role as investment instruments and industrial raw materials, making them indispensable in global financial systems. Their price fluctuations are closely driven by macroeconomic indicators, monetary policies, geopolitical risks, and market sentiment, resulting in high nonlinearity and volatility. Reliable price forecasting supports investors in decision-making, helps policymakers stabilize markets, and enables risk managers to mitigate potential losses.

Over recent decades, extensive methods have been developed for precious metal price forecasting. Traditional econometric models including ARIMA and GARCH variants are widely used to model price dynamics and volatility clustering. However, these models rely on linear assumptions and predefined functional forms, which limit their ability to capture complex nonlinear patterns in real-world markets.

With the advancement of machine learning, data-driven models such as support vector regression (SVR), random forests, and gradient boosting have been adopted to model nonlinear relationships between historical prices and external covariates. These methods improve prediction accuracy but require heavy feature engineering and typically treat each metal as an independent target, ignoring market interdependencies.

Deep learning models, especially recurrent neural networks (RNNs), long short-term memory (LSTM), gated recurrent units (GRUs), and attention-based networks, have shown strong capability in modeling long-term temporal dependencies in financial time series. Transformer-based architectures have also been explored for commodity and precious metal forecasting due to their advantage in long-range dependency capture. Nevertheless, most existing studies concatenate multi-metal data as multivariate inputs without explicitly modeling dynamic cross-metal interactions, which are essential for multi-metal joint forecasting.

In practice, precious metal markets are highly interconnected. Prices exhibit strong co-movement, spillover effects, and leader–follower relationships driven by shared macroeconomic fundamentals and synchronized investment behavior. Ignoring such linkages reduces model generalization and prediction reliability. To address this gap, this paper proposes a Transformer-based forecasting framework that explicitly models both temporal dynamics and cross-metal dependencies.

The main contributions are summarized as follows:

1. A unified Transformer framework that integrates metal-specific embedding and joint representation to explicitly distinguish and model individual precious metals while enabling cross-metal interaction learning.

2. A hybrid multi-head attention mechanism decomposed into temporal-specific heads and cross-metal interaction heads to separately capture intra-metal temporal patterns and inter-metal spillover effects.

3. A cross-attention module to explicitly model leader–follower relationships between core metals (e.g., gold) and subordinate metals.

4. Informer-based sparse attention to reduce computational complexity for long-sequence inputs.

5. A hybrid loss function combining Huber loss and inter-metal correlation constraint loss to improve prediction accuracy while preserving realistic market correlations.

2. Related Work

2.1. Traditional Econometric Methods

Early forecasting research relies on statistical models such as ARIMA, GARCH, and vector autoregressive (VAR) models. These methods provide interpretability and capture short-term linear dependencies but fail to model complex nonlinear behaviors in volatile markets. [1]

2.2. Machine Learning Methods

Tree-based ensembles, SVR, and gradient boosting models are applied to precious metal forecasting to model nonlinear relationships. These approaches outperform traditional models but depend on manual feature engineering and treat each metal independently, neglecting cross-metal linkages. [2]

2.3. Deep Learning for Time Series Forecasting

LSTM, GRU, and CNN-LSTM hybrid models are widely used for gold and silver price prediction. Transformers and its variants (e.g., Informer) are introduced for long-sequence financial time series due to their strong long-range dependency modeling and parallel computing efficiency. [3] However, most deep learning models treat multi-metal data as simple multivariate sequences without explicit cross-metal dependency modeling.

2.4. Cross-Metal Market Linkages

Recent studies reveal significant spillovers and connectedness among precious metals. Despite this evidence, few forecasting frameworks explicitly model these interactions in an end-to-end deep learning architecture. [4] [5] This work fills the gap by designing a Transformer model that explicitly learns and enforces cross-metal relationships.

3. Methodology

3.1. Problem Definition and Data Preprocessing

3.1.1. Problem Formulation

Let K denote the number of precious metals. Given historical multi-feature sequences $X = \{x_1, x_2, ..., x_T\}$, where $x_t \in R^{(K\times D)}$ includes price features and external covariates at time step t, the goal is to predict future prices $\hat{Y} = \{\hat{y}_{T+1}, ..., \hat{y}_{T+H}\}$, where H is the prediction horizon.

3.1.2. Feature Engineering and Standardization

Core features include closing price, logarithmic return, and daily volatility. [6] Logarithmic returns are used to stabilize variance and eliminate scale effects. [3] All features are standardized via Z-score normalization:

$$x' = (x - \mu) / \sigma \quad (1)$$

Where μ and σ are the mean and standard deviation of the training set.

3.1.3. Metal-Specific Embedding and Positional Encoding

Each metal is mapped to a latent space via an independent linear layer. A learnable metal embedding (asset embedding) and positional embedding are added to preserve metal identity and temporal order:

$$e_{k,t} = \mathrm{Linear}(f_{k,t}) + A_k + P_t \quad (2)$$

Where $f_{k,t}$ is the feature vector of metal k at time t, A_k is the asset embedding, and P_t is the positional encoding.

3.1.4. Sliding Window Sampling

A sliding window strategy constructs training samples with fixed lookback length L and forecast horizon H.

3.2. Improved Transformer Architecture

3.2.1. Hybrid Multi-Head Attention

Multi-head attention is split into two functional parts:

1. Temporal-specific heads (60%): Model intra-metal temporal dependencies under masking constraints.

2. Cross-metal interaction heads (40%): Capture inter-metal lead–lag relationships and spillover effects without metal restrictions.

Outputs are concatenated and projected:

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head}_1, \ldots, \mathrm{head}_h)W^O \quad (3)$$

3.2.2. Leader–Follower Cross-Attention

The encoder processes the core metal (e.g., gold) to extract global trends. The decoder uses cross-attention to align subordinate metals with the core metal:

$$\mathrm{CrossAttn}(Q, K, V) = \mathrm{Softmax}(QK^T / \sqrt{d_k})V \quad (4)$$

3.2.3. Informer-Based Sparse Attention

To reduce the $O(N^2)$ complexity of vanilla Transformer, the probabilistic sparse attention from Informer is adopted, lowering complexity to O (N log N) while preserving long-sequence modeling capability.

3.3. Hybrid Loss Function

3.3.1. Huber Regression Loss

$$L\_Huber = (1/2)(y - \hat{y})^2, \quad |y - \hat{y}| \leq \delta \tag{5}$$

$$\delta(|y - \hat{y}| - \delta/2), \quad \text{otherwise} \tag{6}$$

Where $\delta = 1.0$ balances robustness and gradient stability.

3.3.2. Inter-Metal Correlation Constraint Loss

To preserve realistic co-movement:

$$L\_corr = ||Corr(\hat{Y}) - Corr(Y)||\_F \tag{7}$$

Where Corr (·) denotes the Pearson correlation matrix and $||\cdot||\_F$ is the Frobenius norm.

3.3.3. Total Loss

$$L\_total = L\_Huber + \lambda L\_corr \tag{8}$$

Where $\lambda = 0.05$ balances the two terms.

4. Experiments and Results

4.1. Experimental Setup

- Dataset: Daily futures prices of 8 precious metals from January 7, 2005, to January 6, 2025. [7]
- Lookback window: 10 days; forecast horizons: 3, 5, 7, 9, 11 days.
- Baselines: LinearRegression, GradientBoosting, SVR, DecisionTree, Ridge, Lasso, RNN, LSTM, GRU, CNN.
- Metrics: MAE, RMSE, R^2.

4.2. Results and Analysis

Tables 1–5 show that the proposed method achieves the lowest MAE and RMSE and the highest R^2 across all forecast horizons. The explicit modeling of cross-metal dependencies consistently improves performance over independent or implicitly coupled modeling approaches.

Table 1: Performance (Lookback=10, Forecast=3).

Method	MAE	RMSE	R^2
Proposed	180.6754	400.1958	0.9552
LinearRegression	239.9166	483.8438	0.9321
GradientBoosting	209.6730	411.3627	0.9431
SVR	217.1057	441.9531	0.9336
DecisionTree	238.9341	518.1629	0.9052
Ridge	239.0349	483.0102	0.9324

Lasso	272.9201	506.7997	0.9240
RNN	217.3665	434.9407	0.9295
LSTM	191.3664	420.1596	0.9349
GRU	193.9365	431.9816	0.9327
CNN	204.6537	433.0076	0.9325

Table 2: Performance (Lookback=10, Forecast=5)

Method	MAE	RMSE	R^2
Proposed	186.2706	339.4368	0.9529
LinearRegression	257.2493	483.7322	0.9256
GradientBoosting	233.6564	415.8098	0.9402
SVR	231.8670	451.9981	0.9333
DecisionTree	236.4029	505.8879	0.9169
Ridge	256.3392	482.8784	0.9259
Lasso	294.3312	510.9582	0.9147
RNN	221.3453	422.9074	0.9394
LSTM	197.7023	361.0141	0.9524
GRU	192.1174	388.5381	0.9461
CNN	211.0652	400.7193	0.9441

Table 3: Performance (Lookback=10, Forecast=7)

Method	MAE	RMSE	R^2
Proposed	211.6112	379.1005	0.9435
LinearRegression	268.3494	486.4153	0.9198
GradientBoosting	229.9072	388.1146	0.9388
SVR	220.7682	425.8229	0.9312
DecisionTree	252.8020	586.9497	0.8959
Ridge	267.5557	485.6425	0.9201
Lasso	302.2376	518.5577	0.9089
RNN	228.9313	453.4605	0.9310
LSTM	232.5620	404.0388	0.9449
GRU	229.5991	406.6357	0.9429
CNN	215.4314	428.6102	0.9368

Table 4: Performance (Lookback=10, Forecast=9)

Method	MAE	RMSE	R^2
Proposed	216.8812	412.2552	0.9428
LinearRegression	286.5159	520.4886	0.9147
GradientBoosting	239.4798	412.0746	0.9374
SVR	222.2567	408.0299	0.9387
DecisionTree	256.3290	533.0706	0.9040
Ridge	285.3692	518.5596	0.9154
Lasso	310.8624	526.5575	0.9060
RNN	227.4673	431.1943	0.9409
LSTM	226.2116	425.6694	0.9413
GRU	193.1882	379.8175	0.9507
CNN	203.5189	400.5222	0.9460

Table 5: Performance (Lookback=10, Forecast=11)

Method	MAE	RMSE	R^2
Proposed	191.6623	303.9162	0.9548
LinearRegression	315.1412	527.8870	0.8976
GradientBoosting	270.3101	438.1289	0.9237
SVR	223.5328	403.6894	0.9305
DecisionTree	254.2628	508.1425	0.8979
Ridge	314.3750	526.9461	0.8980
Lasso	338.3670	538.9741	0.8908
RNN	239.6132	451.8142	0.9405
LSTM	196.4691	384.8901	0.9540
GRU	207.2062	398.8011	0.9500
CNN	214.0380	420.8730	0.9459

5. Conclusion

This paper presents a Transformer-based framework for multi-precious metal price forecasting that explicitly models cross-metal dependencies. [8] The proposed architecture combines metal-specific embedding, hybrid multi-head attention, leader–follower cross-attention, and Informer-style sparse attention to efficiently capture temporal dynamics and inter-metal linkages. A hybrid loss function ensures accurate prediction while preserving realistic market correlations. [9][10] Experimental results on 20 years of daily data demonstrate superior performance over statistical, machine learning, and deep learning baselines.

Future work will incorporate macroeconomic variables, news sentiment, and high-frequency data. Ablation studies and generalization tests on other commodity markets will further validate the framework's effectiveness.

References

[1] G. Cohen, "Algorithmic strategies for precious metals price forecasting," Mathematics, vol. 10, no. 7, p. 1134, 2022.

[2] C. Pierdzioch and M. Risse, "Forecasting precious metal returns with multivariate random forests," Empirical Economics, vol. 58, pp. 1167–1184, 2020.

[3] P. Foroutan and S. Lahmiri, "Deep learning systems for forecasting the prices of crude oil and precious metals," Financial Innovation, vol. 10, p. 111, 2024.

[4] P. Sadorsky, "Predicting gold and silver price direction using tree-based classifiers," J. Risk Financial Manag., vol. 14, no. 5, p. 198, 2021.

[5] D. N. Gono, H. Napitupulu, and Firdaniza, "Silver price forecasting using extreme gradient boosting (XGBoost) method," Mathematics, vol. 11, no. 18, p. 3813, 2023.

[6] S. B. Jabeur, S. Mefteh-Wali, and J.-L. Viviani, "Forecasting gold price with the XGBoost algorithm and SHAP interaction values," Ann. Oper. Res., vol. 334, pp. 679–699, 2024.

[7] A. Amini and R. Kalantari, "Gold price prediction by a CNN-Bi-LSTM model along with automatic parameter tuning," PLOS ONE, vol. 19, no. 3, p. e0298426, 2024.

[8] Y. Yang, "TCN-QV: An attention-based deep learning method for long sequence time-series forecasting of gold prices," PLOS ONE, vol. 20, no. 5, p. e0319776, 2025.

[9] A. A. Salisu, R. Gupta, E. Bouri, and Q. Ji, "The role of global economic conditions in forecasting gold market volatility: Evidence from a GARCH-MIDAS approach," Res. Int. Bus. Finance, vol. 54, p. 101308, 2021.

[10] W. Mensi, A. Aslan, X. V. Vo, and S. H. Kang, "Time-frequency spillovers and connectedness between precious metals, oil futures and financial markets: Hedge and safe haven implications," Int. Rev. Econ. Finance, vol. 83, pp. 219–232, 2023.