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Multi-Task Learning for Macroeconomic Forecasting Based on Cross-Domain Data Fusion

Yuxiu Lin[1], Pei Xue[2]

[1]Columbia University, New York, USA

[2]Independent Researcher, Pittsburgh, USA

*Corresponding Author: Pei Xue; peix324@yahoo.com

Abstract: This paper addresses the challenges of multi-source heterogeneous data fusion and multi-indicator joint modeling in macroeconomic forecasting. It proposes a model framework based on multi-domain sample representation and joint prediction mechanisms. The goal is to improve both the prediction accuracy and structural modeling capability for key economic indicators such as CPI and GDP. The proposed method introduces a Domain-aware Representation Compression module. It encodes structured economic data and unstructured text data in a unified way. This enables efficient compression and alignment of multi-domain features. In parallel, a Joint Indicator Alignment mechanism is designed. Under a multi-task learning framework, it performs trend alignment and feature decoupling on the prediction outputs. This enhances the dynamic relationship modeling between different economic indicators. To validate the effectiveness of the proposed approach, a joint sample set is constructed. It integrates multi-domain information, including structural economic variables, news texts, and policy indicators. Multiple comparative experiments and ablation studies are conducted. The experimental results show that the proposed method outperforms mainstream models across various macroeconomic forecasting tasks. It demonstrates clear advantages in accuracy, robustness, and generalization. In particular, it maintains stable performance in cross-country transfer and multi-step forecasting scenarios. These findings confirm the model's adaptability and effectiveness in complex economic systems.

Keywords: Multi-domain modeling, joint forecasting, macroeconomic indicators, deep feature compression

1. Introduction

Amid frequent fluctuations in the global economic cycle and rising geopolitical uncertainties, accurate forecasting of macroeconomic indicators has become a critical foundation for national governance, monetary policy formulation, and capital market regulation. Among these indicators, the Consumer Price Index (CPI) and Gross Domestic Product (GDP) are central. They reflect inflation levels and economic growth, and they serve as anchors for fiscal and monetary policy decisions. In the era of financial globalization and digital economy integration, the nonlinear nature of economic operations and the dynamic relationships among variables have grown increasingly complex. Traditional statistical models are no longer sufficient to capture the underlying mechanisms and cross-domain effects in economic activities[1,2].

With rapid advancements in data acquisition and artificial intelligence, macroeconomic modeling is shifting. It now moves beyond single-dimensional time series forecasting toward integration of multi-source and heterogeneous information[3]. Economic indicators are influenced by complex time-lag relationships and interactions across domains. These include financial market fluctuations, changes in industrial structures, policy signals, and the spread of public sentiment. Relying solely on a single data domain often leads to suboptimal models. These models fail to capture the coupled features among multidimensional economic signals. Therefore, building a joint forecasting framework that integrates multi-domain information and enhances sample representation is crucial for accurate modeling of macroeconomic indicators[4].

Artificial intelligence methods, especially deep learning, have shown great potential in solving high-dimensional nonlinear problems. Cutting-edge approaches such as multi-domain learning, multimodal fusion, and self-supervised representation learning have been widely applied in fields like healthcare, finance, and transportation. In macroeconomic forecasting, integrating data from multiple domains — such as financial markets, commodity prices, search behavior, and policy sentiment — into a unified feature space for joint modeling of CPI and GDP can overcome the limitations of single-indicator models. This approach provides a more comprehensive understanding of economic systems. It also emphasizes the co-evolution of data, offering more forward-looking and interpretable insights for policymakers and market participants[5].

Economic systems are highly dynamic and regionally heterogeneous. Economic drivers and policy sensitivities vary significantly across countries and regions. Joint modeling based on multi-domain samples can capture these heterogeneous signals. This enhances the model's adaptability and transferability under economic fluctuations. It is particularly valuable for building robust forecasting systems that address cross-cycle and cross-regional economic shocks. Moreover, jointly modeling CPI and GDP reveals the structural link between price levels and output capacity. This deepens the understanding of the dual-objective policy framework that balances growth and inflation from a macroeconomic regulation perspective[6].

Against this backdrop, developing a CPI and GDP joint forecasting model that integrates multi-domain sample information and offers deep representation capabilities addresses real-world demands for modeling precision and stability in support of high-quality economic development. It also aligns with the growing integration of artificial intelligence into economic research. By breaking the isolation between indicators at the modeling level and improving information integration, this research provides a theoretical and methodological basis for building intelligent decision-support platforms tailored to complex economic systems. Hence, this study holds both theoretical significance and practical value in terms of methodological innovation and real-world economic application.

2. Related work

2.1 Multi-domain sample representation

In macroeconomic modeling, a single data source often fails to capture the complexity and multi-layered nature of real economic activities. Traditional forecasting models rely mainly on structured time series data, such as quarterly GDP or monthly CPI changes[7,8]. These models are stable and interpretable. However, they often respond slowly to sudden events, policy shifts, or irrational market behaviors. To improve sensitivity to dynamic features of the economic system, recent studies have increasingly introduced multi-domain information. They attempt to integrate signals from financial markets, industrial performance, commodity prices, and international trade data. This helps build richer and more forward-looking forecasting frameworks[9].

Beyond structured economic and financial data, unstructured information such as news articles, policy announcements, online public opinion, and social media sentiment also holds unique value. These data capture economic expectations and market behavior in real time. They are nonlinear, unstable, and high-dimensional. They reflect how the market responds to economic events and anticipates future trends. By incorporating natural language processing into economic forecasting systems, researchers can model implicit variables like policy context, market sentiment, and macroeconomic risk signals. This complements the static nature of traditional variables and enhances model flexibility and responsiveness[10,11].

The core challenge of multi-domain sample representation lies in the heterogeneity of the data. Different domains vary in dimensionality, representation, and temporal alignment[12]. Modeling high-order relationships between structured and unstructured data within a unified feature space has become a key direction. Current approaches use shared encoders, multimodal attention mechanisms, or graph-based structures to integrate domain-specific information. These methods aim to extract latent patterns relevant to economic decision-making. Building a unified multi-domain representation framework can improve the prediction efficiency and generalization of models for key indicators such as CPI and GDP. It also promotes the development of intelligent, data-driven, and cross-domain economic forecasting methods.

2.2 Regression prediction model

Regression-based forecasting models are among the most fundamental and widely used methods in macroeconomic indicator modeling[13]. Traditional approaches, such as linear regression, autoregressive models, and vector autoregression, have been extensively applied in early economic research. These methods are favored for their clear structure and strong parameter interpretability. However, they rely heavily on linear assumptions[14,15]. As a result, they struggle to capture the complex nonlinear relationships and dynamic interactions among economic variables. Their predictive accuracy and stability often decline significantly when facing abrupt economic changes, structural breaks, or policy shocks.

With the development of machine learning, nonlinear regression models have been gradually introduced into macroeconomic forecasting. These include decision tree regressors, ensemble learning models, and neural network regressors[16]. By learning features automatically and approximating complex functions flexibly, these models overcome the limitations of traditional linear methods. They perform more robustly when dealing with high-dimensional, noisy data and intricate variable correlations[17,18]. In multivariable and multi-input settings, nonlinear regression models can effectively integrate multi-source information. This significantly improves the accuracy and responsiveness of predictions for key indicators such as CPI and GDP.

Despite their performance advantages, nonlinear regression models still face several challenges. These include sensitivity to data scale and quality, the risk of overfitting due to redundant features, and a lack of economic interpretability in the model outputs[19]. In practical applications, designing regression models with generalization ability, controllable structure, and support for multi-task joint modeling is crucial. This is key to advancing macroeconomic forecasting from simple model fitting to strategic decision support. Therefore, there is still considerable room for development in regression forecasting models. Integrating them with techniques such as deep representation learning and multi-domain fusion shows new potential for future research.

3. Method

This study proposes a joint forecasting model for CPI and GDP based on multi-domain sample representation. The goal is to integrate heterogeneous data sources and improve the prediction accuracy and generalization of macroeconomic indicators. First, a Domain-aware Representation Compression (DRC) module is constructed. It uses a multi-channel encoder to model structured economic data and unstructured text data in a unified way. This allows the model to capture hidden associations and economic drivers across different data sources. Second, a Joint Indicator Alignment (JIA) mechanism is introduced. During training, it dynamically adjusts task weights and shares features between the CPI and GDP prediction tasks. This helps to capture their co-evolution patterns during economic cycles. Through this dual innovation, the proposed method achieves coordinated optimization at both the data fusion layer and the task prediction layer. It enhances the model's adaptability and interpretability in multi-task and multi-source input settings. The model architecture is shown in Figure 1.

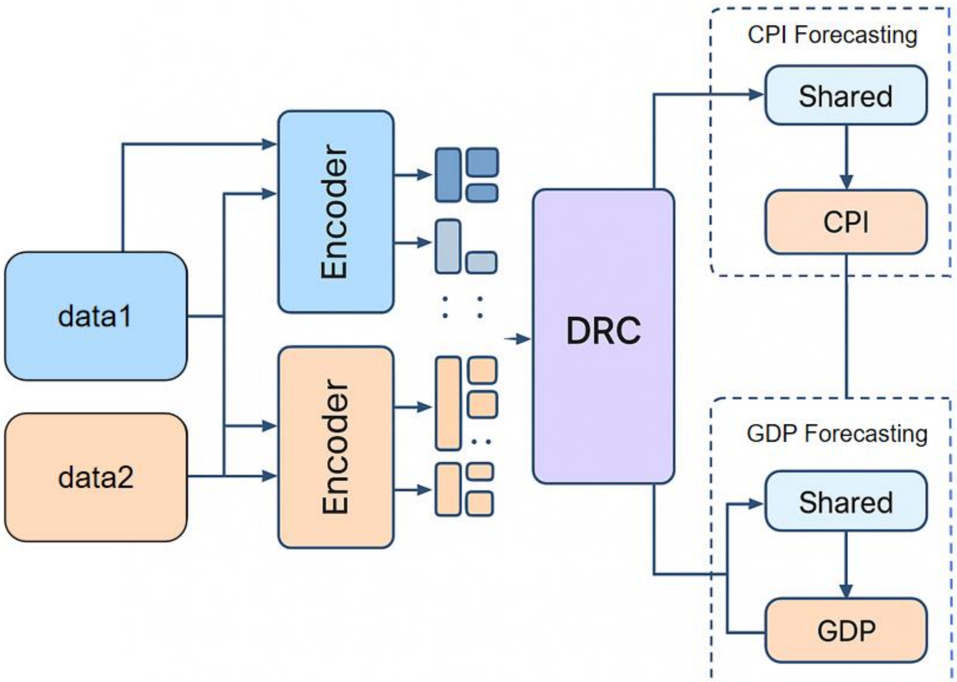

Figure 1. Overall model architecture diagram

3.1 Domain-aware Representation Compression

In order to effectively integrate the potential information of multi-domain heterogeneous data, this study constructed a Domain-aware Representation Compression (DRC) module to solve the inconsistency problem between structured and unstructured data in feature dimensions, distribution forms and expressions. Its module architecture is shown in Figure 2.

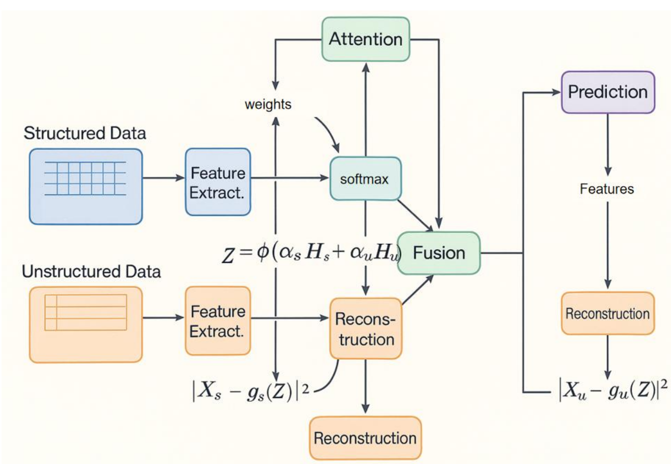

Figure 2. DRC module architecture

Assume that the input data consists of two parts, the structured data domain is represented as $X_s \in R^{n\times d}$, and the unstructured data is represented as $X_u \in R^{n\times d}$ after embedding. We first use two independent encoders to learn the representation and obtain the corresponding intermediate feature representation $H_s = f_s(X_s), H_u = f_u(X_u)$, where f_s and f_u are the deep feature extraction functions of the structured and unstructured domains.

To achieve cross-domain feature compression and alignment, the DRC module introduces a domain-aware attention mechanism to measure the importance and relevance of features between different domains. We define a shared fusion mapping function $\phi(\cdot)$ to construct a unified representation space Z. The fused representation is calculated using the following formula:

$$Z = \phi(a_s \cdot H_s + a_u \cdot H_u)$$

Among them, a_s and a_u represent the attention weights of the structured and unstructured domains respectively, satisfying $a_s + a_u = 1$, which is dynamically generated through a softmax gating network:

$$[a_s, a_s] = \mathrm{softmax}(W_g[H_s; H_u] + b_g)$$

W_g and b_g are learnable parameters, and the semicolon ";" represents the feature concatenation operation.

In order to further improve the discriminative ability of the compressed representation for prediction tasks, the DRC module introduces a reconstruction alignment objective during the training process to ensure that the compressed representation retains the key information of each domain. We construct two reconstructors g_s and g_u respectively to reconstruct the fused representation Z in the domain, and the loss function is defined as follows:

$$L_{rec} = \| X_s - g_s(Z) \|^2 + \| X_u - g_u(Z) \|^2$$

This loss term forces the compressed representation to restore the original multi-domain information as much as possible while keeping the dimension compact, thereby achieving semantically preserved dimensionality reduction.

Finally, to enhance the discriminability of the model for future time step predictions, we input the compressed representation Z into the joint prediction module and introduce multi-task supervision signals. The joint loss function consists of the prediction error and the reconstruction error, and is as follows:

$$L_{total} = L_{pred}^{CPI} + L_{pred}^{GDP} + \lambda \cdot L_{rec}$$

λ is the importance coefficient for adjusting the reconstruction loss, and L_{pred}^{CPI}、L_{pred}^{GDP} represents the prediction loss for CPI and GDP respectively. This design ensures that multi-domain feature compression is not only aimed at structural simplification, but also serves the accuracy and stability of multi-task economic indicator prediction.

3.2 Joint Indicator Alignment

In order to fully explore the dynamic correlation between macroeconomic indicators, this study designed a Joint Indicator Alignment (JIA) module to provide structural support for the joint modeling of CPI and GDP. This module is based on the idea of multi-task learning and simultaneously learns the prediction mapping functions of two types of targets through shared representation and differentiated supervision mechanisms. Its module architecture is shown in Figure 3.

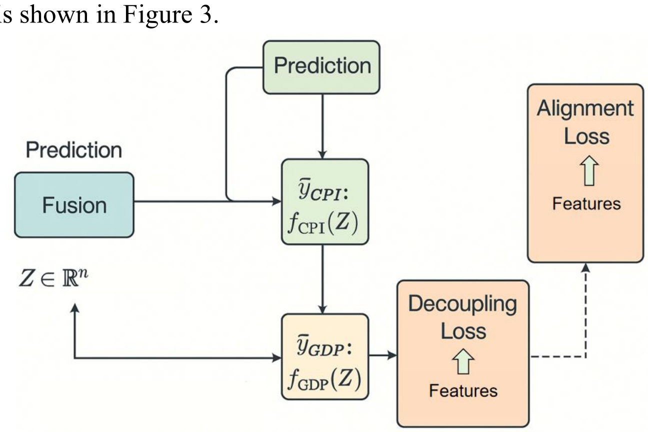

Figure 3. JIA module architecture

Assuming the compressed fusion is represented by $Z \in R^{n \times d_z}$, the forecasts for CPI and GDP are defined as:

$$\hat{y}_{CPI} = f_{CPI}(Z), \quad \hat{y}_{GDP} = f_{GPD}(Z)$$

Where f_{CPI} and f_{GPD} represent the specific regression forecast heads for CPI and GDP respectively.

In order to model the co-evolution characteristics of two economic indicators in the time series dimension, the JIA module introduces a coupling loss function to explicitly constrain the structural similarity of the two types of forecast outputs. The coupling loss is defined as:

$$L_{align} = \| \nabla_t \hat{y}_{CPI} - \nabla_t \hat{y}_{GDP} \|^2$$

∇_t represents the difference operation of the time series, which is used to capture the first-order changes in economic trends. By aligning the predicted change trends, the model will be more inclined to learn the structural synergy patterns between indicators during training.

In addition, to prevent the shared feature space from excessively interfering with the differences between tasks, JIA further introduces a task-specific decoupling term to maintain the expression independence of the two types of prediction targets. The form of this term is as follows:

$$L_{decouple} = \| W_{CPI}^T W_{GDP} \|_F^2$$

Where W_{CPI} , W_{GDP} is the parameter matrix of the prediction head, and $\| \cdot \|_F$ represents the Frobenius norm. The purpose is to minimize the linear correlation between the two task mapping spaces, thereby achieving a balance between sharing and independence.

Finally, the total loss function of the JIA module integrates the basic prediction loss, multi-task alignment loss and structural decoupling regularization term, and is in the form of:

$$L_{JIA} = L_{CPI} + L_{GDP} + \beta \cdot L_{align} + \gamma \cdot L_{decouple}$$

Where β, γ is a hyperparameter that controls the weight of structural alignment and decoupling. By jointly optimizing the above objective function, the JIA module can coordinately capture the common driving factors and differential dynamics of CPI and GDP in the time series, thereby achieving a deeper modeling of the internal structure of the economic system.

4. Experimental Results

4.1 Dataset

The dataset used in this study is sourced from the publicly available OECD macroeconomic indicator database. It covers key economic variables across multiple countries and regions. We select CPI (Consumer Price Index) and GDP (Gross Domestic Product) as the core target variables. The data are quarterly and span from the first quarter of 2000 to the fourth quarter of 2023. This ensures full coverage of economic cycles and major policy intervention periods.

To construct multi-domain samples, we integrate structured economic data from the OECD financial market module, including interest rates, unemployment rates, and industrial production indices. We also include unstructured text signals extracted from external sources, such as news sentiment indices and policy uncertainty measures. These heterogeneous data are standardized and time-aligned. They are then combined with the target variables to support feature extraction and relational modeling in a multi-domain setting.

During data preprocessing, we exclude regional samples with severe missing values. Only countries with complete CPI and GDP records are retained. This results in a cross-regional and cross-temporal economic sample set. The dataset has strong temporal structure, high coupling among variables, and significant time lags between indicators. These characteristics provide a solid foundation for evaluating the adaptability and generalization of the joint forecasting model in real macroeconomic contexts.

4.2 Experimental setup

To validate the effectiveness of the proposed model in macroeconomic forecasting, experiments are conducted on a multi-domain sample dataset constructed from OECD data. All input features are normalized before being fed into the model. The target variables are the quarterly growth rates of CPI and GDP. The input window consists of the past four time steps (one year), and the model predicts the change at the next time step. The data are split into 70 percent for training, 15 percent for validation, and 15 percent for testing. The time order is preserved to simulate real-world forecasting scenarios.

Model training is performed on a deep learning server equipped with an NVIDIA GPU. The optimizer is Adam. The loss function is a weighted combination of prediction error, alignment term, and decoupling term. Model hyperparameters are selected through grid search on the validation set. Early stopping is applied during training to prevent overfitting. All experiments are repeated five times to ensure stable performance. The main training configuration is shown in Table 1.

Table 1: Training Configuration

Parameter name	**Setting Value**
Enter the time window length	4 (quarterly)
Forecast time span	1 (quarterly)
Batch Size	32
Learning Rate	0.001
Optimizer	Adam
Epochs	100
Early Stopping	patience=10
Weight decay (L2)	1e-5
Loss function weight	λ =0.3 (reconstruction), β =0.5 (alignment), γ =0.1 (decoupling)

4.3 Experimental Results

1) Comparative experimental results

First, this paper gives the comparative experimental results with other models. The experimental results are shown in Table 2.

Table 2: Comparative experimental results

Method	**MSE**	**MAE**	**RMSE**	**R^2**
1DCNN[20]	0.024	0.117	0.155	0.823
LSTM[21]	0.021	0.108	0.145	0.846
BILSTM[22]	0.020	0.106	0.141	0.852
GRU[23]	0.019	0.102	0.138	0.860
CNN+LSTM[24]	0.018	0.099	0.134	0.867
Transformer[25]	0.016	0.093	0.126	0.881
Ours	0.012	0.085	0.110	0.906

The experimental results show significant differences in performance across models on the joint forecasting task of macroeconomic indicators. The baseline 1D CNN model performs the worst due to its shallow structure and limited ability to model temporal information. It achieves an MSE of 0.024 and an R^2 of only 0.823. This indicates clear limitations in capturing the dynamic relationships among economic variables. In contrast, recurrent neural network architectures such as LSTM, BiLSTM, and GRU demonstrate steady improvements. These models have a natural advantage in handling time dependencies.

Furthermore, CNN+LSTM and Transformer models show strong capabilities in feature extraction and sequence modeling. In particular, the Transformer benefits from a global attention mechanism. It better captures long-range dependencies between CPI and GDP under multi-task inputs. It achieves an R^2 of 0.881 and reduces RMSE to 0.126. These results suggest that such models can simulate the complex evolution of macroeconomic systems with reasonable accuracy. However, they still lack structural designs specifically tailored to handle heterogeneous multi-domain data. This limits their final performance.

The proposed model in this study introduces two core mechanisms: Domain-aware Representation Compression (DRC) and Joint Indicator Alignment (JIA). With these components, it achieves the best results across all evaluation metrics. The MSE drops to 0.012, MAE is only 0.085, RMSE reaches 0.110, and R^2 improves to 0.906. These results demonstrate the model's clear advantage in both prediction accuracy and stability. They also suggest that integrating multi-domain representation compression and task alignment can enhance the model’s understanding of co-movement patterns among economic variables. Overall, the experimental findings confirm the superiority of the proposed method in complex economic forecasting tasks. It shows stronger generalization and interpretability when dealing with multi-source inputs and dual-indicator outputs. Compared with traditional deep learning models, the proposed approach reflects a deeper sensitivity to the dynamic nature of economic systems through its architectural design. This highlights its strong potential for practical application and broader adoption.

2) Hyperparameter sensitivity experiment results

Furthermore, this paper gives the experimental results of hyperparameter sensitivity. First, the experimental results of learning rate are given as shown in Table 3.

Table 3: Hyperparameter sensitivity experiment results(Learning Rate)

Learning Rate	**MSE**	**MAE**	**RMSE**	**R^2**

0.004	0.019	0.105	0.138	0.861
0.003	0.016	0.096	0.126	0.880
0.002	0.014	0.089	0.118	0.894
0.001	0.012	0.085	0.110	0.906

The results of the learning rate sensitivity experiment show that model performance varies significantly across different learning rate settings. A clear pattern is observed. When the learning rate is relatively high (e.g., 0.004), both MSE and MAE remain at higher levels. The R^2 is 0.861. This suggests that training may suffer from oscillation or incomplete convergence, which limits prediction accuracy.

As the learning rate decreases gradually, model performance improves. Especially at the 0.003 and 0.002 levels, MSE and RMSE decrease steadily, and R^2 increases consistently. This indicates smoother training and better learning of the mapping between input features and target variables. These results also confirm that smaller learning rates are more favorable for convergence in complex multi-task models.

When the learning rate is set to 0.001, the model achieves optimal results on all evaluation metrics. MSE drops to 0.012, MAE reaches 0.085, and R^2 rises to 0.906. This suggests that 0.001 strikes a good balance between convergence speed and optimization precision. Compared to other settings, it better activates the model’s expressive capacity. This is especially important for handling the complex representation space resulting from the integration of DRC and JIA modules. In summary, learning rate has a significant impact on model performance. Proper tuning can greatly enhance prediction accuracy and stability. The learning rate of 0.001 is optimal for the current architecture. It provides a strong foundation for model generalization and stability. It also ensures effective coordination of multi-domain feature compression and task alignment mechanisms.

This paper also gives the experimental results of the optimizer, as shown in Table 4.

Table 4: Hyperparameter sensitivity experiment results(Optimizer)

Optimizer	**MSE**	**MAE**	**RMSE**	**R^2**
AdaGrad	0.018	0.101	0.134	0.868
SGD	0.021	0.108	0.145	0.847
AdamW	0.014	0.091	0.118	0.892
Adam	0.012	0.085	0.110	0.906

The results of the optimizer sensitivity experiment show that different optimizers have a significant impact on model performance in macroeconomic forecasting tasks. When using the SGD optimizer, the model achieves an MSE of 0.021 and an MAE of 0.108, with an R^2 of only 0.847. This indicates that basic gradient descent methods face challenges in high-dimensional, multi-domain, and joint modeling settings. These include slow convergence and a tendency to get stuck in local minima, which limits their suitability for optimizing complex network structures.

In comparison, AdaGrad performs better than SGD due to its adaptive learning rate mechanism. However, it suffers from rapid learning rate decay in the later stages of training, which limits further performance improvement. Although its MAE is slightly lower than that of SGD, its RMSE and R^2 still lag behind. This suggests limitations in capturing global trends and long-term dependencies.

AdamW improves prediction accuracy by combining adaptive gradient updates with weight decay. The model reaches an MSE of 0.014 and an R^2 of 0.892. This shows strong convergence stability and good generalization. AdamW achieves a balanced trade-off between controlling model complexity and preserving expressive capacity. It is well suited for scenarios requiring moderate regularization.

Finally, the Adam optimizer yields the best results across all metrics. It achieves the lowest MSE of 0.012 and the highest R^2 of 0.906. This demonstrates its clear advantage in dynamically adjusting both the direction and magnitude of gradients. It adapts well to the complex coupling between DRC and JIA modules in multi-task learning. These results further confirm Adam's high adaptability and robustness in deep multi-module economic modeling.

3) The impact of different multi-domain feature combinations on prediction performance

This paper further gives the impact of different multi-domain feature combinations on prediction performance, and the experimental results are shown in Figure 4.

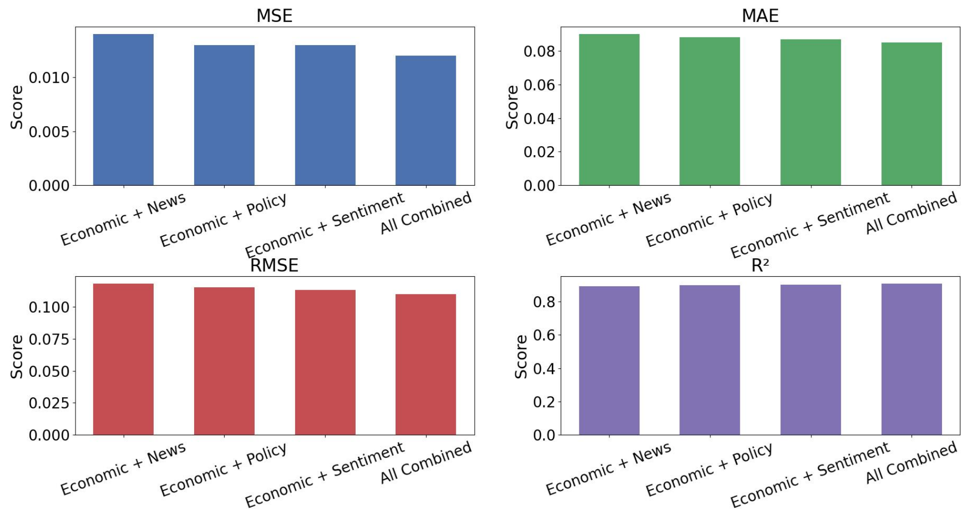

Figure 4. The impact of different multi-domain feature combinations on prediction performance

The experimental results show that different combinations of multi-domain features have a significant impact on model performance. When using only economic and news data (Economic + News), both MSE and RMSE remain high. This indicates that relying solely on market or media information is not sufficient for accurate prediction of macroeconomic variables. While such features can reflect certain trend changes, they lack support from deeper policy context and economic expectations.

When policy text features are added (Economic + Policy), the model shows noticeable improvements across all metrics. The MSE and R^2 become more stable. Policy data reflect government actions and macro-level regulation signals. These help the model understand the long-term trends of GDP and CPI. As a result, this combination offers advantages in capturing global driving factors.

After introducing sentiment features (Economic + Sentiment), MAE and RMSE continue to decline. This shows that market sentiment adds value for short-term prediction of economic variables. These unstructured text features reflect micro-level behavioral signals. They improve the model's sensitivity and responsiveness, especially under high-frequency fluctuations.

When all three types of features are combined (All Combined), the model achieves its best overall performance across all evaluation metrics. Specifically, it reaches the lowest values for MSE and MAE, and the highest R^2, indicating a clear improvement in prediction accuracy and model fit. This suggests that integrating economic data, policy texts, and sentiment signals allows the model to capture both short-term fluctuations and long-term economic trends more effectively. The strong results demonstrate that joint modeling of multi-domain information fully leverages the complementary strengths of each data type. By enriching the feature space with diverse signals, the model is able to construct more comprehensive and informative representations. This leads to improved generalization and better adaptability to complex macroeconomic patterns. These findings validate the proposed model's ability to manage heterogeneous, multi-source data and underscore the importance of multi-domain fusion strategies in enhancing forecasting performance in macroeconomic applications.

4) Loss function changes with epoch

Furthermore, the graph illustrating how the loss function changes over training epochs is provided, as shown in Figure 5. This visual representation offers a clear view of the model's convergence behavior during the training process.

By observing the curve, readers can better understand the dynamics of the optimization process, including how quickly the model reduces error and reaches a stable state. This also helps to evaluate the overall training effectiveness and the stability of the model under the designed architecture.

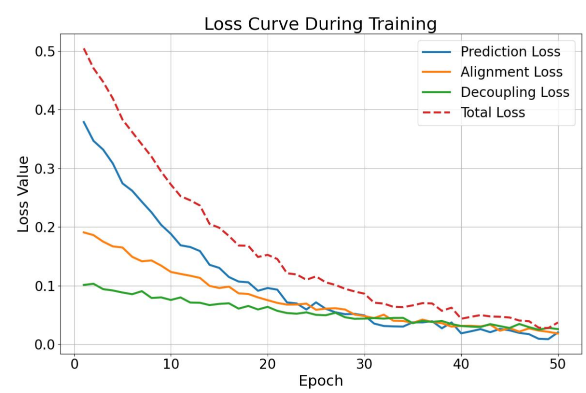

Figure 5. Image of loss function changing with epoch

The trend of the loss function shows that the model converges well during training. The prediction loss decreases rapidly within the first 20 epochs. This indicates that the model effectively extracts information relevant to CPI and GDP forecasting from the fused multi-domain features. It further confirms the effectiveness of the DRC module in compressing high-dimensional inputs while retaining key features. The alignment loss shows a slower but steady decline throughout training. This suggests that the Joint Indicator Alignment mechanism gradually guides the model to learn the co-evolution relationship between CPI and GDP. By enforcing trend alignment, this mechanism imposes structural constraints on the output sequences. It helps the model capture the underlying coupling between macroeconomic variables.

The decoupling loss fluctuates slightly at the beginning of training and then slowly decreases. This reflects the gradual effect of the task decoupling mechanism in learning separable feature spaces. It ensures that the model preserves task-specific representations while learning shared features. This helps reduce redundancy and improves prediction robustness. The total loss shows a consistent and steady downward trend. This indicates that under multi-objective optimization, the model balances prediction accuracy, task alignment, and feature separation effectively. These results validate the rational design of the DRC and JIA modules. They provide both structural and convergence guarantees for joint macroeconomic modeling under multi-domain inputs.

5) Experimental results on generalization ability evaluation of multi-country macro data migration

Next, this paper also presents the experimental results evaluating the model's generalization ability when applied to macroeconomic data from multiple countries, as shown in Figure 6. These results are used to assess how well the proposed model can adapt to different regional economic structures under the same predictive framework. By examining the model's performance across various national datasets, the evaluation highlights its capacity to handle structural shifts, regional policy differences, and varying data distributions. This provides important evidence of the model's robustness and transferability in cross-country scenarios, further supporting its practical value in global macroeconomic forecasting tasks.

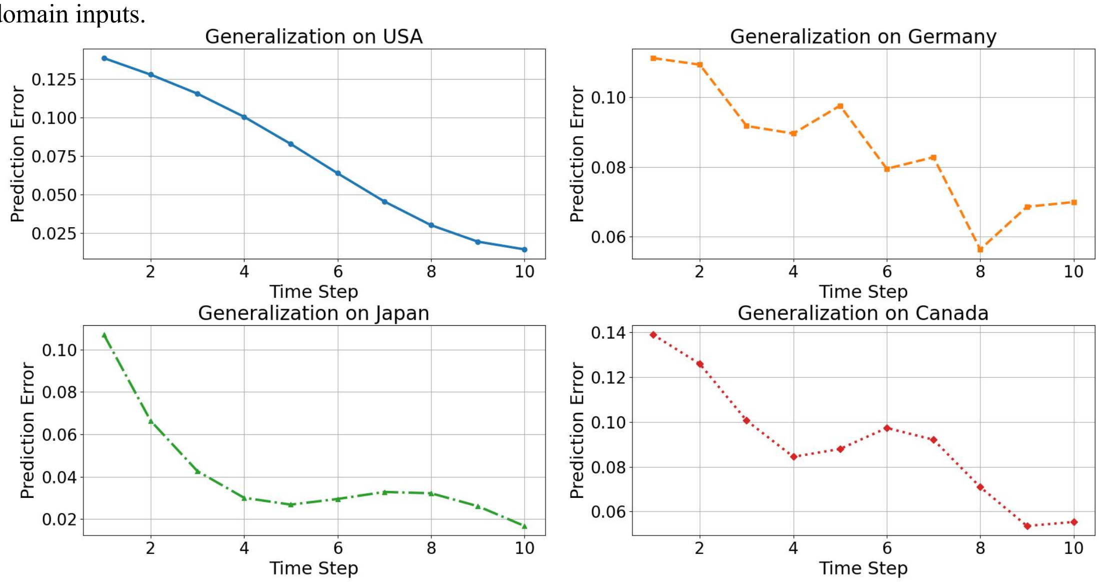

Figure 6. Experimental results on generalization ability evaluation of multi-country macro data migration

The figure shows that the model exhibits varying degrees of transferability across different countries' macroeconomic data. This reflects the adaptability of multi-domain features in cross-regional applications. In the U.S. transfer experiment, the prediction error decreases steadily over time. This indicates that the proposed model can extract stable economic signals from fused features that generalize well in this region. It also suggests a high level of structural consistency between U.S. data and the model's training data.

In contrast, the results for Germany show greater fluctuations, especially in the early time steps. These may be related to policy adjustments or short-term market disturbances within the economic data. While the overall error trend decreases, the model remains sensitive to local volatility. This indicates ongoing adaptation to regional distribution differences and highlights the need for further optimization of adversarial feature alignment.

The transfer performance in Japan is relatively strong. The prediction error drops quickly and remains low. This suggests that the model achieves efficient feature transfer in this region. Given the stability of Japan's economic structure and policy continuity, this result confirms that the DRC module effectively preserves stable driving factors during multi-domain compression. It also shows that the model can capture shared features across national economic indicators to a certain extent.

The transfer curve for Canada displays some oscillation and a slower decline. This suggests that structural changes or noise in the economic variables may exist in this region, making model adaptation more complex. This phenomenon underscores the importance of building joint forecasting models with regional adaptation capabilities in multi-country settings. It also confirms the critical role of the Joint Indicator Alignment module in enhancing cross-domain modeling robustness.

6) Experimental results on generalization ability evaluation of multi-country macro data migration

Finally, this paper also gives an experiment on the adaptability of the model to different prediction step sizes, and the experimental results are shown in Figure 7.

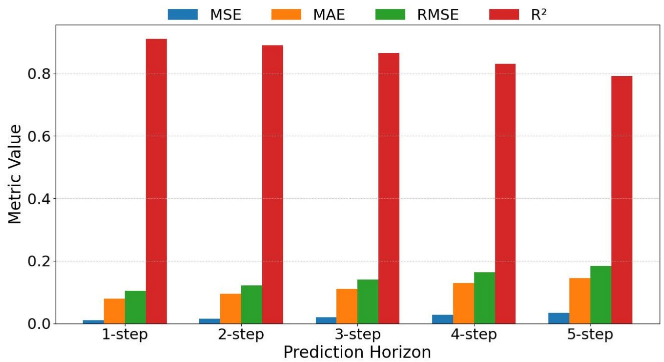

Figure 7. Experiments on the adaptability of the model to different prediction step sizes

The figure shows that the model's performance varies significantly under different prediction step sizes. A clear trend is observed. As the step size increases from 1 to 5, error metrics such as MSE, MAE, and RMSE rise steadily. This indicates that in long-term forecasting, error accumulation becomes more pronounced. Such a pattern is common in macroeconomic modeling. It reflects the weakening dependence of future economic states on historical inputs. It also confirms the increased uncertainty in long-horizon predictions.

In particular, the 1-step prediction task yields the best results across all metrics. The R^2 approaches 0.91. This suggests that the DRC and JIA modules are highly effective in short-term forecasting. They fully utilize multi-domain features and support task coordination. In this case, the model can make accurate predictions with minimal information drift. This confirms its reliability in stable, short-term forecasting scenarios.

However, when the prediction step extends to 3 or more, the errors increase significantly. RMSE, in particular, shows nonlinear growth. This suggests that the model faces dual challenges in long-sequence reasoning: feature degradation and misleading inputs. Although R^2 remains relatively high, its downward trend shows that the model's fitting ability weakens. This places greater demands on temporal modeling for the joint prediction of CPI and GDP. Overall, the results indicate that the model adapts well to different step sizes. However, in mid- and long-term forecasting, it still requires improved capacity to capture long-range dependencies. These findings define the model's application boundaries in tasks such as economic trend forecasting and policy simulation. They also point toward future directions, such as incorporating Transformer-based memory mechanisms or multi-scale temporal modeling strategies.

5. Conclusion

This paper addresses key challenges in macroeconomic forecasting and proposes a novel framework that integrates multi-domain sample representation with task-coordinated modeling. The aim is to improve both prediction accuracy and generalization for critical indicators such as CPI and GDP. To handle the fusion of structured and unstructured data, a Domain-aware Representation Compression (DRC) module is designed. It enables unified encoding and information compression of heterogeneous data sources. In addition, the Joint Indicator Alignment (JIA) mechanism is introduced. By leveraging task alignment and decoupling strategies, it enhances the structural modeling of the underlying economic connections between CPI and GDP. Experimental results show that the proposed method outperforms baseline models across multiple metrics, demonstrating strong robustness and adaptability under multi-task and multi-source conditions.

This study provides both theoretical innovation in algorithm design and significant practical value. The proposed framework offers a technical path for building high-quality macroeconomic forecasting models. It is particularly applicable to key scenarios such as financial market analysis, policy evaluation, and inflation trend prediction, which heavily rely on economic indicator forecasting. By jointly modeling multi-domain information, the framework significantly improves the model's sensitivity to changes in macro variables. It offers a forward-looking decision support tool for governments, research institutions, and financial organizations.

Moreover, cross-country transfer experiments validate the model's ability to adapt to different regional economic contexts. This provides a practical foundation for international economic forecasting and global market analysis. The step size sensitivity experiment reveals the model's boundaries in handling mid- and long-term forecasting tasks. These findings offer insights for future structural improvements in modeling long-term economic fluctuations. An in-depth analysis of loss function dynamics further explains the optimization behaviors of different modules, supporting interpretable modeling. Future research can extend the model's application to more macroeconomic indicators, heterogeneous spatiotemporal data, and event-driven economic forecasting. Graph neural networks, cross-modal attention mechanisms, or large language models may be introduced as extension modules to improve the modeling of complex economic structures and semantic-driven factors. As economic data become more real-time and diverse, building a unified forecasting framework for multi-domain, multi-task, and multi-temporal settings will be a key direction in intelligent economic research. This study offers both theoretical foundations and engineering insights for future work along this path.

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