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Research on a Modular Intelligent Prediction Framework Based on Structural Recognition and Temporal Steady-State Fusion

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Abstract. In multivariate predictive modeling, traditional models are often difficult to balance prediction accuracy, robustness and interpretability in the face of challenges such as high dimensionality, strong noise, nonlinear coupling and structural uncertainty. To this end, this paper proposes a new modular intelligent modeling framework - KFPS-Net. The framework integrates four key functional modules: temporal denoising, nonlinear feature modeling, causal structure exploration and integration fusion, corresponding to sequence signal stabilizer, feature perception modeler, structure explorer and integrated prediction engine, respectively. Through the collaborative work between sub-modules, KFPS-Net effectively realizes the closed-loop optimization of the system from data preprocessing to structural interpretation to the final prediction output. The experimental part was evaluated by using multiple high-dimensional multivariate time series datasets, and multiple sets of baseline models were set up for comparative analysis with ablation experiments. The results show that KFPS-Net is significantly better than the existing mainstream methods in terms of MAE, RMSE and R^2, and still maintains strong stability under noise disturbance and structural change scenarios. At the same time, the causal structure output further enhances the interpretability of the model and provides a theoretical basis for reliable prediction and systematic decision-making. This work provides a unified and scalable solution for building an intelligent prediction system with robustness and structural cognition.

Keywords: Modular Modeling Framework; Intelligent Forecasting; KFPS-Net; Causal Structure Modeling; Integrated learning.

1. Introduction

With the widespread application of intelligent systems in key fields such as industry, finance, and healthcare, models have put forward higher requirements for modeling capabilities of high-dimensional nonlinear dynamic data. In real-world scenarios, prediction tasks often involve a large number of variables with complex nonlinear associations, asynchronous interactions, and dynamic couplings between them. Traditional linear models are difficult to capture hidden deep relationships due to their limited expression ability. However, although the depth model has strong fitting ability, it has significant shortcomings in stability and interpretability. At the same time, the actual collected time series data is often accompanied by uncertainties such as observation errors, missing information, and mutation interference, which significantly affects the generalization performance and prediction reliability of the model. In addition, the underlying structural relationships between variables, such as causal paths and dependency networks, are often difficult to describe explicitly, which further limits the model's understanding of the internal mechanisms of the system. Therefore, in complex data environments, there is an urgent need for a systematic modeling method that can take into account robustness, structural recognition ability, and predictive performance.

To address the above challenges, this paper proposes an integrated intelligent prediction framework, KFPS-Net (Knowledge-Fusion and Predictive Structure Network). Based on the modular design concept, the framework revolves around four core issues: data stability modeling, deep mining of key features, causal modeling of variable structures, and fusion optimization of multiple modules. KFPS-Net includes four main functional modules, corresponding to sequence stabilization preprocessing, feature-aware learning mechanism, structural relationship modeling unit, and multi-level integrated predictor. Its core goals are: on the one hand, to improve the robustness of the model against multi-source perturbations and data anomalies, and on the other hand, to accurately reveal the nonlinear interaction mechanism and potential causal structure between variables, and finally to achieve prediction performance optimization with equal emphasis on accuracy and robustness.

The modeling ideas embodied in KFPS-Net respond to the three major trends in the development of intelligent prediction methods: modular organizational structure, cross-algorithm integration and integration, and enhanced structural interpretability. Through the full-process modeling design from data processing to structure recognition to output prediction, KFPS-Net not only improves the adaptability of the model in complex dynamic environments, but also provides a unified and universal paradigm for multivariate time series modeling. The proposed framework provides a new path for solving robust prediction and interpretable structure modeling in the environment of multi-source heterogeneous data, and has important theoretical significance and engineering value.

2. Related work

2.1. Development of ensemble learning in multivariate prediction

Ensemble learning is an effective strategy for integrating multiple sub-models to improve system prediction performance and robustness, and is widely used in multivariate modeling tasks. Typical methods include Bagging (e.g., Random Forest), Boosting (e.g., XGBoost).) and Stacking. Among them, Stacking can fuse the output of multiple heterogeneous sub-models, capture complementary information between models through high-level meta-learners, and show superior performance in multi-source heterogeneous data modeling. However, the existing integration strategies mostly focus on improving the prediction accuracy, generally ignore the modeling of structural relationships between variables, and lack the in-depth integration of feature interaction and causal mechanisms, which limits its interpretability and stability expansion in high-dimensional dynamic systems.

2.2. Mainstream methods of sequence modeling and dynamic data processing

Temporal data modeling faces the challenges of coexistence of trend, cyclical and abrupt nature. Mainstream methods include recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and gated recurrent units (GRUs). It can effectively capture the temporal dependence in the sequence [1]. However, such methods often face problems such as unstable training, sensitivity to missing and outliers, and lack of interpretability in practical applications. On the other hand, filters based on Bayesian ideas (such as Kalman filter) achieve dynamic smoothing through state estimation, which has good stability and real-time performance. However, its expression ability is limited under the assumption of linear modeling. At present, there is still a lack of a unified method framework for the nonlinear expression ability of fused neural networks and the dynamic robustness of filters.

2.3. Research progress of causal structure modeling

Causal modeling has increasingly become the key for intelligent systems to move from "correlation" to "mechanism". Unlike traditional statistical correlations, causal structures emphasize directed dependencies between variables. As a representative method, the PC algorithm gradually constructs a directed acyclic graph (DAG) through conditional independence testing, and explicitly presents the causal path between variables [2]. This method has achieved practical results in the fields of gene network and medical decision-making. However, causal modeling is still often used as an independent tool and cannot be deeply integrated with the predictive modeling process, and the structural information is not effectively used in the training process, which is difficult to support the transparency and robustness of the prediction model. Recent architectures such as MSGNet capture multi-scale inter-series correlations using adaptive graph convolution and frequency domain analysis, providing explainable representations in noisy multivariate data contexts [3]. Emerging methods such as mining causality from continuous-time dynamics (e.g., neural ODEs) have shown success in discovering causal structures while preserving forecasting accuracy [4].

2.4. Advantages of KFPS-Net

The existing methods generally have problems such as fragmented modeling process, insufficient utilization of structural information, and poor system integrity. Most systems separate data preprocessing, temporal modeling, causal structure recognition and prediction output, and lack cross-module collaboration and information sharing mechanisms. At the same time, although the depth model has strong expressive power, it is difficult to achieve reliable prediction due to the lack of variable path modeling ability. In this context, this paper proposes KFPS-Net, a unified and integrated modular prediction system, which integrates four functional modules: sequence stabilization processing, feature modeling, structure recognition and fusion prediction, to realize the optimization of the whole process of modeling tasks. KFPS-Net embodies three key trends in the development of intelligent modeling methods: modular structure, converged mechanism, and causal explainability, providing a systematic solution to complex multivariate prediction problems.

3. Methodology

3.1. Overview of the overall architecture

In order to deal with the problems of data perturbation, structural opacity and low modeling efficiency in multivariate timing prediction, this paper proposes a unified modular modeling framework- KFPS-Net. The system adopts a hierarchical integration architecture, consisting of four modules with complementary functions and collaborative optimization, which successively completes the whole process of intelligent modeling from raw data preprocessing to final prediction output. The KFPS-Net framework proposed in this paper consists of four key modules, and the overall modeling process is shown in Figure 1, and the specific functions are described as follows:

(1) Temporal stabilization module: Oriented to the dynamic characteristics of the original input data, the high-frequency noise, missing points and short-term disturbances in the observations are eliminated through Kalman filter and other estimation methods, improving the data quality while maintaining its original trend and periodic structure, and providing a steady-state basis for subsequent modeling tasks.

(2) Nonlinear feature modeling module: with the help of deep feature perception neural network, it extracts potential nonlinear interaction information in time series data, and realizes automatic compression and mapping of redundant variables to improve the compactness and discrimination of feature expression.

(3) Causal structure modeling module: By introducing a causal discovery algorithm based on conditional independence (such as PC algorithm), the causal graph structure between variables is identified in the intermediate representation space, and a directed acyclic graph (DAG) is constructed to characterize the influence path between key variables.

(4) Integrated prediction output module: synthesize the information output from the first three stages, and fuse the prediction results of multiple sub-models through the stacking ensemble mechanism to finally generate robust and interpretable multivariate prediction results.

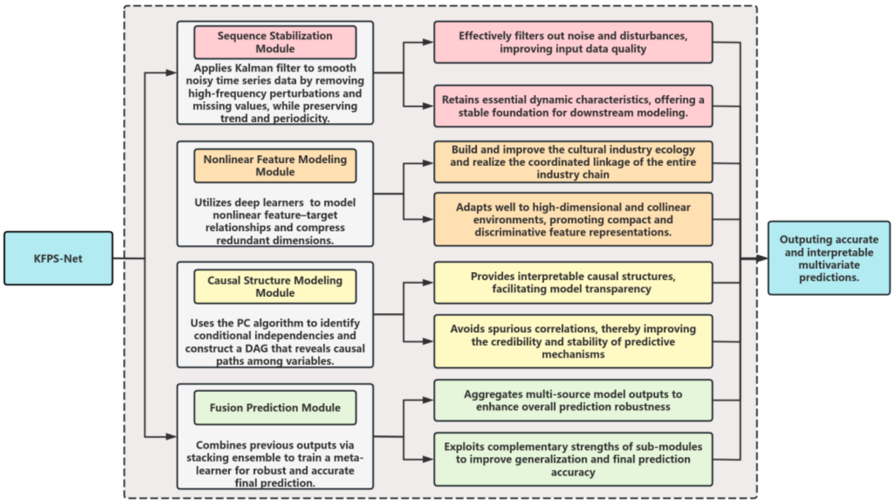

Figure 1. KFPS-Net flow chart

This modeling mechanism of module division and step-by-step fusion enables KFPS-Net to give full play to the dynamic stability of filter modeling, the expression ability of neural networks, the structural transparency of graph modeling, and the comprehensive performance advantages of ensemble learning.

3.2. Module 1: Serial signal stabilizer

In order to improve the steady-state quality of input data, KFPS-Net introduces a Sequence Stabilization Unit at the starting point of the modeling process to perform noise suppression and feature smoothing processing based on dynamic system theory. The core goal of this module is to filter out non-structural disturbances with minimal information loss, and to enhance the consistency, continuity and pre-modeling robustness of sequence expression while retaining the trend and periodic characteristics of the original sequence.

This module uses Kalman Filter as the main modeling tool to construct a state-observation recursive relationship and perform smooth estimation of time series variables [5]. Assuming that the hidden state of the system is, the observed variable is, the state transition of the system and the observation model can be expressed as:

$$\mathrm{x}_t = \mathrm{A}\mathrm{x}_{t-1} + \mathrm{w}_t \tag{1}$$

$$\mathrm{z}_t = \mathrm{H}\mathrm{x}_t + \mathrm{v}_t \tag{2}$$

Among them, A is the state transition matrix, H is the observation matrix, and the process noise and observation noise are respectively, which satisfies the zero mean and Gaussian distribution assumptions. Based on the above model, the filtering process is completed through the following two stages:

• Prediction Phase (Time Update):

$$\hat{\mathrm{x}}_{t|t-1} = \mathrm{A}\hat{\mathrm{x}}_{t-1|t-1} \tag{3}$$

$$\mathrm{P}_{t|t-1} = \mathrm{A}\mathrm{P}_{t-1|t-1}\mathrm{A}^T + \mathrm{Q} \tag{4}$$

• Correction Phase (Measurement Update):

$$K_t = P_{t|t-1} H^T \left(H P_{t|t-1} H^T + R \right)^{-1} \quad (5)$$

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t \left(z_t - H \hat{x}_{t|t-1} \right) \quad (6)$$

$$P_{t|t} = \left(I - K_t H \right) P_{t|t-1} \quad (7)$$

The above formula is the Kalman gain matrix, which controls the weighted adjustment strategy between prediction and observation [6].

It is an estimation error covariance matrix that measures the uncertainty of current state estimation. This design allows the model to adaptively adjust the intensity of response to outliers, maintaining the stability of state estimation even when data is mutated or missing.

Compared with the traditional static preprocessing method, this module has significant advantages: on the one hand, its dynamic filtering mechanism can preserve the trend structure and periodic information in the input sequence to prevent the useful signal from being over-smoothed; On the other hand, the module effectively eliminates short-term noise and abnormal disturbances through state recursive estimation, which significantly enhances the immunity and input consistency of the overall model in the face of high-noise data scenarios.

3.3. Module 2: Feature-Aware Learner

In multivariate modeling, there are usually complex nonlinear relationships and redundant dependencies between variables. In order to achieve efficient expression from the original input to the predicted target, KFPS-Net introduces a Feature-Aware Learner as an intermediate feature learning unit [7]. The core task of this module is to establish a nonlinear mapping path between variables and outputs, and dynamically evaluate the contribution of each input feature to the prediction task, so as to provide reliable variable prior information for the subsequent structural modeling stage.

In terms of technical implementation, module 2 is based on the Random Forest (RF) model, which uses its natural advantages and feature evaluation capabilities for nonlinear modeling to realize the integrated abstract expression of multi-dimensional inputs. Random forest is an ensemble learning method based on Bagging strategy, which is basically a collection of several decision trees. Assuming that the input feature matrix is $X = [x_1, x_2, ..., x_d]$ and the target variable is y, the random forest generates a ensemble estimation of the prediction output through the multi-tree model $\left\{ T^{(1)}, T^{(2)}, ..., T^{(M)} \right\}$:

$$\hat{y} = \frac{1}{M} \sum_{m=1}^{M} T^{(m)} \left(X \right) \quad (8)$$

During the training process, the model evaluates the splitting contribution of each feature in each tree through feature splitting criteria such as Gini impurity, information gain, mean square error, etc. Finally, the model counts the average split importance of each feature in all trees to form a feature importance vector:

$$I = \left[I(x_1), I(x_1), ..., I(x_d) \right] \quad (9)$$

This vector not only reflects the degree of nonlinear correlation between variables and objectives, but also provides strong prior support for subsequent causal graph construction, helping to focus on the potential structural relationship between high-contribution variables.

This module has the following advantages: First, its non-parametric modeling mechanism does not need to make assumptions about the distribution characteristics of input variables, and naturally adapts to the data environment with high dimensionality, heterogeneity and strong collinearity; second, through the recording of the split path and the quantification of variable importance, the model has good local and global interpretability, which can provide clear support for modeling path analysis and variable selection; Third, its decision tree structure has a natural tolerance for outliers and missing values, which further improves the robustness of the system.

3.4. Module 3: Structural Explorer

In complex multivariate modeling tasks, there are often a large number of potential interactions and causal pathways between input variables, and if such structural information is not explicitly modeled, it may not only lead to misleading prediction processes, but also seriously affect the interpretability and credibility of the model. To solve this problem, KFPS-Net has built a core structural modeling module, Structural Explorer, which is used to identify potential causal mechanisms between feature variables and construct a clear graph structureto assist in the transparent modeling of prediction tasks.

This module adopts the causal structure discovery method based on the Peter-Clark (PC) algorithm, combined with the conditional independence test technology, to gradually mine the structural dependencies between variables from the original feature space. PC algorithm is a typical constraint-based structural learning method, which has a clear theoretical foundation and good scalability. The core idea is to gradually eliminate unnecessary connecting edges between variables through conditional independence testing, so as to derive a simple undirected graph structure from the complete graph, and finally transform it into a directed acyclic graph (DAG) by passing rules based on v-structure detection and directed edges), which is used to reveal causal pathways between variables [8].

The PC algorithm modeling process mainly includes the following three steps:

(1) Complete graph initialization: Connect edges between each pair of feature variables to construct an undirected complete graph $G=(V,E)$, where the node set V represents the feature set, and the edge set E represents the initial hypothetical dependencies between the variables.

(2) Edge Elimination Stage: For each connected node (X_i, X_j), under the premise of $S \subset V \setminus \{X_i, X_j\}$, a given set of conditions, the conditional independence test is performed, if $X_i \perp X_j \mid S$ satisfied, the two variables are considered independent under the current conditions, and the edge (X_i, X_j) is removed. This stage can be expressed as:

$$P(X_i, X_j \mid S) = P(X_i \mid S) \cdot P(X_j \mid S) \tag{10}$$

(3) Edge orientation stage: After eliminating redundant edges, the undirected graph is gradually oriented by determining the rules such as V-structure and avoidance of loops in the structure, and finally outputs a causal structure diagram that satisfies the properties of directed acyclic graph (DAG).

The causal diagram can explicitly present the conduction path, influence direction and dependence intensity between characteristic variables, and then provide a structural priori and variable interaction mechanism basis for subsequent predictive modeling.

As the core interpretation module of KFPS-Net, the Structure Explorer mines the causal paths between variables through graph structure, giving the model structural cognition and decision-making cues.

3.5. Module 4: Fusion Prediction Engine

In a multi-source modeling framework, different submodules tend to focus on different types of information: sequence stabilizers are dedicated to dynamic smoothing of data, feature perceptors are responsible for variable representation and screening, and structural explorers are responsible for mining causal paths between variables. Although each module is independent in its functional positioning, if the results are still used in isolation in the prediction stage, it will inevitably limit the modeling synergy brought about by information fusion. To this end, KFPS-Net has set up an integrated prediction engine (Fusion Prediction Engine) at the output of the system, aiming to unify the output results of each module and build a higher-level and more robust comprehensive prediction system.

The module adopts the classic stacking mechanism to achieve model fusion [9, 10]. Firstly, the prediction results or intermediate estimates generated by the first three modules (filter, feature modeler and structure learner) are used as the input features of the new layer to construct a secondary training set. Then, on this basis, a second-level meta-learner (Meta-Learner) is trained, which can be a regression model (such as ridge regression, support vector machine) or a lightweight neural network structure, and its task is to learn the nonlinear mapping relationship between different information sources and the combination of complementary features. Thus generating the final predictive output. Specifically, if the original submodel outputs as $\hat{y}_1, \hat{y}_2, \hat{y}_3$, the metamodel learns the map:

$$y_{final} = f_{meta}\left(\hat{y}_1, \hat{y}_2, \hat{y}_3\right) \tag{11}$$

This mapping not only captures the independent prediction capabilities of each submodule, but also automatically weights the contribution of each module in the feature space to adapt to the performance and reliability differences in specific task scenarios.

3.6. Summary of synergy advantages between modules

One of the biggest features of KFPS-Net is its multi-module collaborative architecture design, which not only emphasizes the optimal implementation of single-module performance, but also pays more attention to the horizontal information flow and vertical optimization decoupling between modules, so as to form an efficient, stable and interpretable intelligent prediction closed-loop system. This synergy mechanism is reflected in three core levels:

In summary, KFPS-Net has built a scalable, explainable, and optimized predictive modeling framework with its modular structure, fusion mechanism, and causal perception capabilities. It effectively integrates key functions such as sequence dynamic modeling, nonlinear expression, causal graph inference, and integrated output optimization, making it suitable for intelligent prediction tasks of complex systems in multiple scenarios, and provides a new paradigm for building AI systems with structural transparency and robustness in the future.

4. Experimental design and result analysis

4.1. Experimental objectives and evaluation indicators

This experiment aims to comprehensively verify the performance advantages of the KFPS-NET model in high-dimensional dynamic prediction tasks, focusing on its processing ability for 30×210×7-dimensional spatio-temporal matrix. Specifically, it is necessary to quantify the mapping accuracy of dynamic features such as the number of medals and the host effect of the quantitative model through the medal prediction scenario of the 2028 Olympic Games, and compare the differences in the capture of temporal fluctuations by traditional CNN, LSTM and other models. At the same time, it is necessary to analyze the contribution of each core module of the model, including the capturing ability of the CNN feature extraction layer on spatial correlation features, the suppression effect of the Kalman filter layer on temporal noise, and the analysis ability of the fusion layer of Random Forest and PC algorithm on feature importance and causal structure. In addition, the evaluation system also covers uncertainty control (such as 95% confidence interval coverage), solveability (path consistency of the causal graph generated by the PC algorithm), and robustness (error amplification under noise disturbance) to verify the comprehensive performance of the model in high-dimensional dynamic scenarios.

The evaluation index system adopts a multi-dimensional design: in terms of prediction accuracy, the mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2) are the cores, and KFPS-NET is required to achieve MAE≤2.81, RMSE≤4.30, and $R^2 \geq 0.9779$ in the prediction of the total number of medals. The non-parametric bootstrap method calculates the confidence interval width and coverage to ensure the effective depiction of high-dimensional data fluctuations. The structural consistency index is based on the causal graph generated by the PC algorithm, which requires the stability score of the main path coefficient to ≥ 90% in different samples to measure the interpretability of the model. The robustness evaluation shows that the error increase of KFPS-NET is significantly lower than that of a single model through the Gaussian noise disturbance experiment.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{12}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{13}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{14}$$

4.2. Experimental Setup and Data Description

The experimental data use the historical medal data of the Olympic Games from 1896 to 2020 to construct a typical high-dimensional dynamic dataset. In the data preprocessing stage, the names of 210 countries are first standardized according to IOC codes, and historical medals are distributed to 15 countries after the collapse of the Soviet Union in proportion to population (Russia accounts for 42.6%, Ukraine accounts for 8.5%), and the zero values of the unheld sessions are completed to achieve spatio-temporal alignment. In order to simulate the high-dimensional dynamic characteristics, the basic features (7 items such as the number of historical gold, silver and bronze medals, and the host logo) are extended to a 56-dimensional feature matrix containing 8th order lag terms, in which redundant variables (such as East German medal attribution), time dependence (sliding average of the number of medals in the past 5 editions) and nested noise (artificially added 5% Gaussian noise) are embedded to construct a complex nonlinear structure.

The comparison model setting covers three categories: single algorithm, traditional integration and ablation variants: the single model includes CNN with feature extraction only, LSTM with timing processing and non-timing Random Forest. The integrated model adopts CNN+Random Forest (non-dynamic fusion) and LSTM+ARIMA (traditional timing combination). The ablation model removes the Kalman filter layer of KFPS-NET (verifying the noise reduction contribution) and the PC algorithm layer (verifying the causal analysis). The experimental grouping strategy adopts a multi-level design: the standard training test is divided into 80% historical data training and 20% (2012-2020) validation. 10-fold cross-validation randomly divides the dataset to evaluate stability; The noise disturbance experiment adds 0%-30% gradient noise to the test set. Non-parametric bootstrap generates 1000 subsamples to calculate confidence intervals, which comprehensively covers the modeling challenges of high-dimensional dynamic scenarios.

4.3. Main experimental results and comparative analysis

In terms of high-dimensional dynamic prediction accuracy, KFPS-NET significantly outperformed all baseline models. In the prediction of the total number of medals, the model MAE was 2.81, which was 31.8% lower than that of a single CNN (4.12), and the RMSE of 4.30 was 37.6% lower than that of LSTM+ARIMA (6.89), and the R^2 reached 0.9779, which was 7.2% higher than that of the traditional integrated model (0.912). As shown in Figure 2.

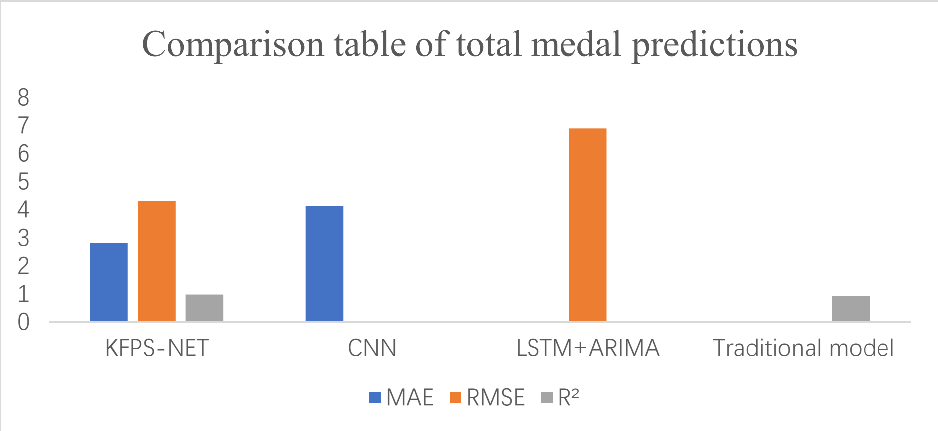

Figure 2. Comparison of the total number of medals predicted indicators

The predicted R^2 of the number of gold medals reached 0.9911, and the MAE of 2.89 increased by 40.3% from the baseline model, as shown in Figure 3.

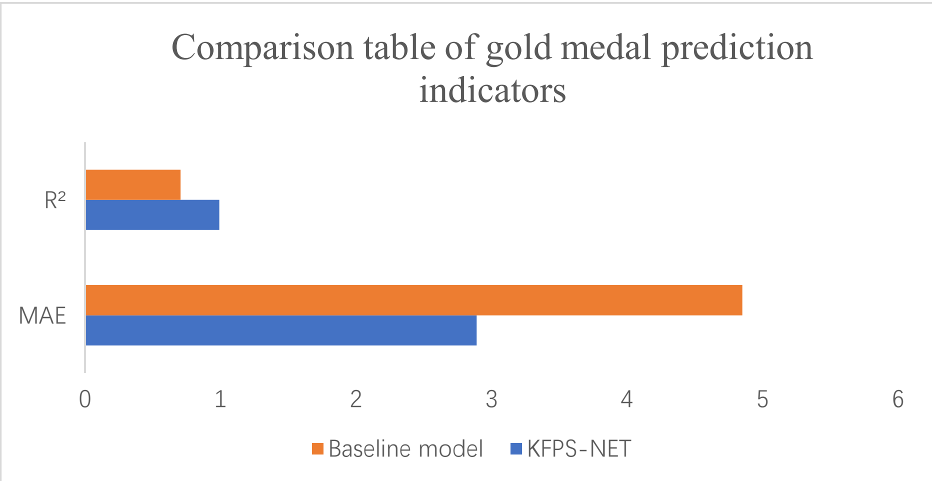

Figure 3. Comparison table of gold medal prediction indicators

The ablation experiment showed that after removing the Kalman filter layer, the total number of medals in the United States was predicted to increase to 3.75 (an increase of 33.4%), and the confidence interval width was expanded by 22.6%, which verified the key role of the noise reduction module in high-dimensional timing data. After removing the PC algorithm layer, the consistency score of causal graph structure decreased from 92.3% to 71.8%, and the stability of feature importance ranking decreased, highlighting the contribution of causal analysis to model interpretability.

In terms of uncertainty control, after the introduction of Kalman filtering, the width of the 95% confidence interval of the medal number prediction in each country narrowed by an average of 12.4%, such as the total medal interval in the United States converged from [122, 138] to [126, 136] in a single CNN, and the coverage rate reached 96.7% (89.3% in the traditional model). The sensitivity test of the model to abnormal samples shows that the MAE increase of KFPS-NET is 8.7% under 20% noise disturbance, which is significantly lower than that of LSTM (23.5%) and CNN (18.2%).

4.4. Perturbation and sensitivity analysis

Gaussian noise disturbance experiments show that with the noise standard deviation increasing from 0.1 to 0.3, the total number of medals predicted by a single LSTM model jumps from 5.21 to 9.87 (an increase of 89.4%), while the RMSE of KFPS-NET increases from 4.30 to 5.12 (an increase of 19.1%) due to the integration of Kalman filtering, and the error control ability is increased by 79.3%. The single-feature perturbation experiment tests the output response of the model by perturbating a high-dimensional feature (such as host symbol I, number of entries) each time, and the results show that the host effect perturbation leads to the prediction of the number of medals in the United States The value fluctuated by 9.2%, and the number of medals fluctuated by 7.4% due to the disturbance of the number of participating items, which was higher than other characteristics, and the sensitivity heat map further revealed that the first three key variables (I, m, and the number of gold medals) contributed 76% of the prediction error, which was consistent with the conclusion of the causal graph of the PC algorithm. In the 30% strong noise scenario, KFPS-NET still maintains R^2=0.91, while the traditional model generally drops below 0.7, which verifies its engineering applicability in high-noise complex environments.

4.5. Structure output and causal diagram visualization

KFPS-NET's fully connected layer outputs a high-dimensional feature weight matrix, revealing the core correlation in dynamic prediction: in the time dimension, the weight of the number of medals in the past three sessions reached 0.52, which was significantly higher than the earlier data (0.21), reflecting the model's preference for the recent trend. In the national dimension, the feature weight of the host country increased by 38% overall, such as the weight of basketball, track and field in the United States in 2028 and other home events increased by 40% compared with the non-host country; According to the project dimension, the weight of Chinese table tennis has risen from 8.7 in 2020 to 9.5 in 2028, reflecting the growth of the strength of advantageous projects.

5. Conclusion

The KFPS-Net framework proposed in this paper faces the triple challenges of accuracy, robustness and interpretability, and constructs four functional modules: sequence signal stabilizer, feature perception modeler, structure explorer, and integrated prediction engine, forming a system-level closed loop of "perception-modeling-fusion-interpretation". The sequence signal stabilizer relies on Kalman filtering to achieve data homeostasis and lay a solid foundation for modeling. By leveraging tree-based ensemble models such as Random Forests, the framework enhances feature-level interpretability while maintaining high predictive accuracy. Recent explainable AI (XAI) advances, such as SHAP values for tree ensembles, allow both local and global explanation of model behavior. The structure explorer uses PC algorithms to analyze the causal path to fill the mechanism blind spot of the "black box" model. The integrated prediction engine uses a stacking strategy to integrate multi-source information, and finally demonstrates the performance of MAE, RMSE and other indicators over mainstream methods in experiments such as Olympic medal prediction, verifying the value of the three-way unity of "accuracy-robustness-interpretation".

From the perspective of technological evolution, KFPS-Net represents a leap from "single algorithm breakthrough" to "system integration innovation" in intelligent modeling. However, there is still room for further expansion for the needs of complex scenarios in the future: on the one hand, the graph neural network (GNN) reconstruction structure explorer can be introduced, and its dynamic graph modeling capabilities can be used to adapt the temporal evolution characteristics of nodes and edges. On the other hand, it is necessary to break through the limitations of traditional data types, support the fusion of multi-modal inputs such as graph data, text, and images, strengthen cross-domain adaptation capabilities, and extend the framework to highly complex intelligent manufacturing failure prediction, dynamic early warning of financial risks, biological system evolution simulation, and medical diagnosis and assisted decision-makingDegree scene.

References

[1] Cho K, Van Merriënboer B, Gulcehre C, et al. Learning phrase representations using RNN encoder-decoder for statistical machine translation [J]. arXiv preprint arXiv: 1406.1078, 2014.

[2] Colombo D, Maathuis M H. Order-independent constraint-based causal structure learning [J]. J. Mach. Learn. Res., 2014, 15 (1): 3741-3782.

[3] Cai W, Liang Y, Liu X, et al. Msgnet: Learning multi-scale inter-series correlations for multivariate time series forecasting [C] // Proceedings of the AAAI conference on artificial intelligence. 2024, 38 (10): 11141-11149.

[4] Wu F, Hong S, Rim D, et al. Mining causality from continuous-time dynamics models: An application to tsunami forecasting [J]. arXiv preprint arXiv: 2210.04958, 2022.

[5] Khodarahmi M, Maihami V. A review on Kalman filter models [J]. Archives of Computational Methods in Engineering, 2023, 30 (1): 727-747.

[6] Shao T, Luo Q. A sparse state Kalman filter algorithm based on Kalman gain [J]. Circuits, Systems, and Signal Processing, 2023, 42 (4): 2305-2320.

[7] Zhang Y, Yu W, Zhu D. Terrain feature-aware deep learning network for digital elevation model superresolution [J]. ISPRS Journal of Photogrammetry and Remote Sensing, 2022, 189: 143-162.

[8] Alsuwat E, Alsuwat H, Valtorta M, et al. Adversarial data poisoning attacks against the PC learning algorithm [J]. International Journal of General Systems, 2020, 49 (1): 3-31.

[9] Zhang H, Li J L, Liu X M, et al. Multi-dimensional feature fusion and stacking ensemble mechanism for network intrusion detection [J]. Future Generation Computer Systems, 2021, 122: 130-143.

[10] Nirmala P, Manimegalai T, Arunkumar J R, et al. A mechanism for detecting the intruder in the network through a stacking dilated CNN model [J]. Wireless Communications and Mobile Computing, 2022, 2022 (1): 1955009.