Multivariate Time Series Forecasting with Parallel Extraction of Long-Term Trends and Short-Term Fluctuations Framework

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Abstract

Multivariate time series (MTS) forecasting is widely used in various fields. Reasonable prediction results can help people make decisions, avoid risks and make a profit. Normally, there are two characteristics of time series, that is, long-term trends and short-term fluctuations. For example, stock prices will rise in the long term, but may fall slightly in the short term. These two characteristics are often relatively independent of each other. However, the existing prediction methods often do not distinguish between them and thus cannot fully extract the characteristics of the time series. In this article, we propose an MTS forecasting method that can capture the long-term trends and short-term fluctuations of time series in parallel. This method uses different modules, which take the original time series and the difference between time stamps as input, to extract the characteristics of both the long-term trends and short-term fluctuations. In the overall optimization goal, the idea of multi-task learning is used for reference, which is to make the prediction results of long-term trends and short-term fluctuations as close to the ground truth as possible. Experiments on three real-world datasets show that the proposed method uses more supervision information and can more accurately capture the changing trends of the time series, thereby improving the forecasting performance.

Introduction

Time series forecasting is a key issue in many disciplines, including finance (Li and Chiang 2012), industry (Blinowska and Malinowski 1991), environment (Shen et al. 2013), etc. For example, in the financial sector, a reasonable prediction of the price trends of the stock market can help investors make a profit. In the industrial field, the prediction result of the sensor signal can indicate the operating status of the system to avoid the occurrence and deterioration of faults. The prediction of weather information in the environmental field can better help people specify environmental protection strategies. Due to the diversity of the real world, one system usually contains multiple variables to be predicted, which makes the research of multivariate time series (MTS) prediction particularly important.

In most cases, time series collected from the real world have the following two characteristics, one is long-term trends, and the other is a short-range fluctuations. As a concrete example, the temperature not only has periodic long-term trends with the change of day and night, but also has fluctuations in the short term due to temporary weather reasons such as rain, snow and other factors. Figure 1 shows the normalized temperature curve of a photovoltaic power plant in ten days, with a sampling period of 15 minutes. It can be seen that the temperature changes periodically with day and night, but the part in the red box has obvious short-
term fluctuations, which is caused by the weather. It is worth noting that day and night changes and sudden weather conditions generally do not interfere with each other. The same situation often occurs in daily life. For example, the traffic flow will show periodic changes from Monday to Sunday, but the occasional heavy rain will reduce the traffic flow in a short period of time. The former represents a kind of long-term trends, while the latter can be seen as a short-term fluctuations. Obviously, these two characteristics are relatively independent with each other, but both contain meaningful information and will contribute to the prediction of the future value of the time series. In this case, the time series forecasting task can be decomposed into two parts, one is to predict its long-term trends, the other part is to predict its short-term fluctuations. The two together constitute a complete forecasting result. Most of the existing time series forecasting methods take the original value of the time series as input to directly predict its future value. This confuses the two independent change rules and may reduce the prediction accuracy and interpretability of the model.

In economics, the value of the original time series is often used to represent the long-term trends, and the difference between time stamps is used as a measure of short-term fluctuations. Inspired by this representation, we design a prediction network framework that can extract long-term trends and short-term fluctuations in parallel. We call it the Parallel Forecasting Network (PFNet). PFNet is composed of three sub-modules, namely long-term trends prediction module (LTPM), short-term fluctuations prediction module (SFPM), and information fusion module (IFM). LTPM and SFPM are two independent prediction sub-networks take the original time series and its difference between time stamps as input, respectively. They predict the value at a certain time point in the future and the difference between it and the value at the next time point. Then the two are input into IFM together and added to obtain the final prediction result (that is, the value at the next time point). In the overall optimization goal, the outputs of the three sub-modules are required to be as close to the corresponding ground truth as possible. Therefore, the proposed PFNet uses three supervised information, including the ground truth to be predicted and its value at the previous moment and its corresponding first-order difference. Compared with direct forecasting, PFNet method uses more supervision information and can more accurately capture the changing trends of the time series, thereby improving the forecasting performance. Our main contributions are summarized as follows:

- We first propose an MTS prediction framework that can predict long-term trends and short-term fluctuations of time series in parallel.
- We construct a triplet loss function and use more supervision information to guide the model to extract key features of the time series for prediction.
- We conduct extensive experiments on MTS benchmark datasets, and the experimental results prove that the performance of the proposed method is better than state-of-the-art models.

The rest of this paper is organized as follows. In section 2 we present related work. Section 3 describe the preliminaries and the proposed PFNet algorithm. Section 4 reports the evaluation results of the proposed model in comparison with baselines on real-world datasets. Finally, in Section 5, the paper is concluded with a discussion on the future research.

**Related Work**

So far, there have been many previous studies on time series forecasting. In this paper, we summarized it into three types of methods, namely linear regression methods, nonlinear regression methods and deep learning methods.

**Linear Regression Method**

One of the most classic linear regression methods is the autoregressive (AR) model. AR establishes the linear relationship between the value to be predicted and the past value, and uses the least square method to obtain the regression coefficient. On this basis, moving average (MA) was proposed, which uses the linear combination of random interference or prediction errors in various past periods to calculate the predicted value. Based on AR and MA, ARIMA (Box, Jenkins, and Reinsel 2011) combines the advantages of AR and MA, thus has the flexibility and adaptability to various types of time series. However, due to the high computational complexity, the above methods is hard to handle multivariate situations. Vector autoregressive (VAR) (Box, Jenkins, and Reinsel 2011) expands the AR to the vector level, so it can handle MTS prediction. In recent years, the research on VAR has made great progress. Many improved versions of the VAR model have been proposed, such as elliptical VAR (Qiu et al. 2015) and structured VAR (Melnyk and Banerjee 2016). However, linear regression methods have a common disadvantage, that is, they can not handle the nonlinear characteristics, which will reduce their forecasting accuracy.

**Nonlinear Regression Method**

Nonlinear Regression Method With the development of machine learning, some nonlinear regression methods have gradually been applied to time series forecasting tasks. Yang et al. use support vector regression (SVR) for time series prediction (Yang et al. 2009), which deals with nonlinearity through kernel technology. Kane et al. introduces random forest to time series forecasting (Kane et al. 2014). This method uses multiple nonlinear decision trees for ensemble learning. In addition, probability methods represented by Gaussian process regression (GPR) are also used for time series forecasting (Roberts et al. 2013). Although many linear or nonlinear regression methods can be directly applied to time series forecasting, these methods have many problems. The number of parameters in these models increases quadrally with the window size and the number of variables (Cheng, Huang, and Zheng 2020). The high computational cost and easily overfitting make it difficult to process high-dimensional multivariate time series.

**Deep Learning Method**

The application of deep learning technology in time series forecasting tasks has been widely studied in recent years.
Many neural network structures for sequence data are designed, which can well extract the key information of the time series and improve the prediction accuracy. In addition, due to the existence of the activation function, deep learning can naturally deal with the nonlinear problem. Many classic neural network structures can be used for feature extraction of time series, such as convolutional neural network (CNN) (LeCun, Bengio et al. 1995), recurrent neural network (RNN) (Elman 1990), long and short-term memory (LSTM) (Hochreiter and Schmidhuber 1997), and gated recurrent unit (GRU) (Chung et al. 2014). In addition, the introduction of the attention mechanism (Vaswani et al. 2017a) also makes the prediction at each time step more flexible and accurate. On the basis of these units, scholars have designed many improved frameworks to make them better adapted to time series forecasting tasks. Lai et al. propose the LSTNet framework (Lai et al. 2018), which uses CNN and RNNskip component to capture the long-term and short-term patterns of MTS, respectively. Cheng et al. (Cheng, Huang, and Zheng 2020) build a MLCNN framework based on LSTM and CNN for fusing near and distant future visions.

The existing regression models and deep learning models have one limitation: just as shown in Figure 1, it is relatively easy to capture the overall trend, but it is challenging for these models to capture the fluctuations in the red box at the same time. And our proposed PFNet can well meet this challenge by predicting both long-term trends and short-term fluctuations.

**Framework**

In this section, we present the proposed PFNet in detail. First, we define the formula expression of the MTS prediction problem. Later, we introduce the vector autoregressive model used to deal with the coexistence of long-term trends and short-term fluctuations in economics, termed the vector error correction model (VECM), which is the source of our ideas. Finally, we introduce the framework structure and optimization objectives of PFNet in detail. The schematic of the model structure is shown in Fig 2.

![Figure 2: The schematic of PFNet. The red line represents the data flow of the long-term trends of the time series, and the blue line represents the short-term fluctuations. We predict both of them in parallel through the LTPM and SFPM. Here we use Highway CNN as the network $\alpha$ and $\beta$, and MLP as the network $\gamma$. In this diagram $\Delta X_t \in \mathbb{R}^{N \times (t-1)}$ and $x_t \in \mathbb{R}^{N \times t}$. $x_t$, $x_{t+h}$, $x_{t+h-1}$, and $\Delta x_{t+h} \in \mathbb{R}^{N \times 1}$. As shown by the red dotted line, part of the long-term trends ($x_t$) is used with $\Delta X_t$ to predict $\Delta x_{t+h}$. Finally, we add the predicted $x_{t+h-1}$ and $\Delta x_{t+h}$ to get the final result $x_{t+h}$.](image-url)

**Problem Formulation**

In this paper, the task of MTS forecasting is focused. Given a matrix containing multiple observed MTS $X = [x_1, x_2, ..., x_t]$, in which the element in the $i$-th row and $j$-th column $x_{ij}$ means the value of the $j$-th variable at the $i$-th time stamp. The main purpose of our forecasting model is to predict $x_{t+h}$ as accurately as possible, where $h$ is the horizon ahead of the current time stamp, which is usually determined according to the application scenario.

In addition, we also define the first-order difference of MTS at the $i$-th time point as $\Delta x_i$, where $\Delta x_i = x_i - x_{i-1}$. Obviously, when $X$ is known, its difference matrix $\Delta X = [\Delta x_2, \Delta x_3, ..., \Delta x_t]$ can be simply obtained by making the difference by time stamp.

**Vector Error Correction Model (VECM)**

As mentioned earlier, VAR is the most commonly used linear MTS prediction method. For the $x_{t+h}$ to be predicted, the method establishes the following expression:

$$x_{t+h} = \sum_{i=1}^{t} A^h_i x_i + \epsilon_t,$$

where $A^h_i (i = 1, 2, ..., t)$ are the regression coefficients when horizon $h$, and $\epsilon_t$ is the white noise vector. VAR is a simple linear model, so the prediction performance for non-stationary time series is poor. To solve this problem, VECM (Mukherjee and Naka 1995) is proposed. Assuming $h = 1$,
the following equations are established:
\[
\begin{cases}
x_{t+1} = x_t + \Delta x_{t+1} \\
x_{t-k} = x_t - \sum_{j=0}^{k-1} \Delta x_{t-j} \quad (k \geq 1)
\end{cases}
\] (2)

Substituting equation (2) into equation (1), the following expression can be obtained:
\[
\Delta x_{t+1} = \Pi x_t + \sum_{k=1}^{t} \Gamma_k \Delta x_{t-k} + \epsilon_t,
\] (3)

where \( \Pi \) and \( \Gamma_k \) are the coefficient matrices of the model, they are calculated as:
\[
\Pi = \sum_{k=1}^{t} A_k^1 - I, \quad \Gamma_k = - \sum_{j=k+1}^{t} A_j^1.
\] (4)

Equation 3 is the expression of VECM, which can be used to predict short-term fluctuations in time series. Similarly, \( \Delta x_{t+h} \) can also be written in a similar form:
\[
\Delta x_{t+h} = \Pi' x_t + \sum_{k=1}^{t} \Gamma_k' \Delta x_{t-k} + \epsilon_t.
\] (5)

The form of \( \Pi' \) and \( \Gamma_k' \) can refer to \( \Pi \) and \( \Gamma_k \) in equation 5, which can be expressed by \( A_1, A_2, ..., A^\nu \). It can be seen that the short-term fluctuations to be predicted is related to two parts, one is the value of MTS at time \( t \), and the other is the short-term fluctuations value on multiple previous time stamps. In the design of the PFNet model, we draw on the expression of VECM, and used these two parts to predict future short-term fluctuations. In our model, we replace the linear transformation in equation 3 with a neural network. It should be noted that here we only use the form of VECM for reference instead of establishing a nonlinear form that is completely equivalent to VECM, so there is no need to follow the assumption of \( h = 1 \) in PFNet.

**Long-Term Trends Prediction Module (LTPM)**

As mentioned earlier, as the first sub-module of PFNet, LTPM predicts long-term trends of MTS. LTPM takes \( X \) as input, but its output is different from common MTS forecasting frameworks. It is used to predict \( \hat{x}_{t+h-1} \) instead of directly predicting \( x_{t+h} \), which facilitates the combination of long-term trends \( (x_{t+h-1}) \) and short-term fluctuations \( (\Delta x_{t+h}) \) to get the final forecasting value \( \hat{x}_{t+h} \).

In this article, we use Highway-CNN (Slimani et al. 2019) to deal with long-term trends prediction. This structure parallels the information highway on the traditional CNN structure, which allows input information to directly traverse the complex multi-layer nonlinear network. The highway structure can avoid vanishing gradient phenomenon, prevent falling into local optimum, and shorten training time.

CNN is a typical network structure for feature extraction of sequence data. Different from the general multi-layer perception, CNN uses multiple convolution filters to process the input time series. Since the data at adjacent time points are accepted by the convolution kernels, it captures the timing characteristics of the time series. For the \( i \)-th CNN filters, given the input time series \( X \), the features vector \( h_i \) are extracted as follows:
\[
h_i = \sigma(W \ast X + b)
\] (6)

where \( \ast \) denotes the convolution operation, \( \sigma \) is a nonlinear activation function, such as \( \text{RELU}(x) = \max(0, x) \), \( W \) represents the CNN kernel and \( b \) is the bias. In this paper, we adopt the multi-layer CNN stacking strategy to extract the deep nonlinear features of MTS.

Denote the nonlinear transformation of the multi-layer CNN as \( H(X, \theta) \), where \( \theta \) represents model parameters. The output of Highway-CNN can be calculated using the following equation:
\[
y = H(X, \theta) \circ T(X, W_T) + W_LX \circ (1 - T(X, W_T)),
\] (7)

where \( \circ \) is dot product and \( W_L \) is a trainable linear mapping. \( W_T \) is a weight matrix and \( T \) and \( (1 - T) \) represent the transform gate and carry gate respectively. Here \( T \) is calculated as:
\[
T(X, W_T) = 1/(1 + e^{-W_TX}).
\] (8)

Through LTPM, the predicted value \( \hat{x}_{t+h-1} \) is obtained.

**Short-Term Fluctuations Prediction Module (SFPM)**

Refer to VECM, SFPM takes \( \Delta X \) and \( x_t \) as inputs to predict \( \Delta x_{t+h} \), thereby characterizing its short-term fluctuations. Similar to LTPM, SFPM uses Highway-CNN to extract the features of \( \Delta X \). In addition, a multilayer perceptron (MLP) structure is used for nonlinear transformation of \( x_t \). Therefore, the expression of the output vector \( \hat{x}_{t+h} \) of SFPM is:
\[
\Delta \hat{x}_{t+h} = \text{highwayCNN}(\Delta X) + \text{MLP}(x_t)
\] (9)

**Information Fusion Module (IFM)**

The final forecasting result is obtained by the superposition of long-term trends and short-term fluctuations. The IFM takes the output of LTPM and SFPM as input, and merges them to obtain the forecasting \( \hat{x}_{t+h} \).
\[
\hat{x}_{t+h} = \hat{x}_{t+h-1} + \Delta \hat{x}_{t+h}
\] (10)

So far, the entire end-to-end prediction process has been completed.

**Objective Function**

General MTS prediction tasks usually require that the final predicted value is the closest to the ground truth, so as to construct an optimization goal. PFNet is improved on this basis. Since the entire network actually has three targets to be predicted, the overall optimization objective function is also composed of three parts, including the forecasting error of \( x_{t+h-1}, x_{t+h} \) (the long-term trends) and \( \Delta x_{t+h} \) (the short-term fluctuations), that is:
\[
\min \epsilon \sum_{t \in \Omega_{\text{train}}} \| \hat{x}_{t+h} - x_{t+h} \| + c_1 \| \hat{x}_{t+h-1} - x_{t+h-1} \| + c_2 \| \Delta \hat{x}_{t+h} - \Delta x_{t+h} \|
\] (11)
where $\| \cdot \|_1$ represents the L1 norm, $\Theta$ denotes all trainable parameters in the PFNet model, $c_1$ as well as $c_2$ are the penalty coefficients for long-term trends and short-term fluctuations. This optimization problem can be solved by stochastic gradient descent (SGD) or its improved versions such as Adam (Kingma and Ba 2014).

The design of PFNet optimized objective function actually embodies the idea of multi-task learning. In addition to the final prediction results $x_{t+h}$, the other two item, $x_{t+h-1}$ and $\Delta x_{t+h}$, can also guide the entire network to better extract the timing characteristics of MTS, thereby improving the accuracy of forecasting.

Algorithm 1 Framework of Parallel Forecasting Network.

**Input:** A matrix of multivariate time series $X = [x_1, x_2, ..., x_t]$; A matrix of its difference between time stamps, $\Delta X = [\Delta x_2, \Delta x_3, ..., \Delta x_t]$; 

**Output:** The forecasting value at time $t + h$ in the future, $x_{t+h}$;

1: LTPM takes $X$ as its input to get the value at time $t + h - 1$ in the future, or $x_{t+h}$;
2: SFPM takes $\Delta X$ as its input to get the difference at time $t + h$ in the future, or $\Delta x_{t+h}$;
3: IFM takes the output of LTPM and SFPM, and merges them to obtain the final forecasting result, $x_{t+h}$;
4: return $x_{t+h}$;

**Experiments**

In this section, we conduct extensive experiments on three benchmark datasets for multivariate time series forecasting tasks, and compare the results of our model (PFNet) with other 7 baselines.

**Datasets**

We use three benchmark datasets which are publicly available:

- **Exchange-Rate**: the exchange rates of eight foreign countries collected from 1990 to 2016, collected per day.
- **Energy** (Candanedo, Feldheim, and Deramaix 2017): measurements of 26 different quantities related to appliances energy consumption in a single house for 4.5 months, collected per 10 minutes.
- **Nasdaq** (Qin et al. 2017): the stock prices are selected as the multivariable time series for 82 corporations, collected per minute.

**Metrics**

We apply three conventional evaluation metrics to evaluate the performance of different models for multivariate time series prediction: Relative Squared Error (RSE), Relative Absolute Error (RAE) and Empirical Correlation Coefficient (CORR):

\[
RSE = \frac{\sum_{i=1}^{n} (p_i - \bar{a}_i)^2}{\sum_{i=1}^{n} (\bar{a} - a_i)^2}
\]

\[
RAE = \frac{\sum_{i=1}^{n} |p_i - a_i|}{\sum_{i=1}^{n} |\bar{a} - a_i|}
\]

\[
CORR = \frac{\sum_{i=1}^{n} (p_i - \bar{p})(a_i - \bar{a})}{\sqrt{\sum_{i=1}^{n} (p_i - \bar{p})^2} \sqrt{\sum_{i=1}^{n} (a_i - \bar{a})^2}}
\]

For RSE and RAE metrics, lower value is better; for CORR metric, higher value is better.

**Methods for Comparison**

The methods in our comparative evaluation are as follows:

- **VAR** (Hamilton 1994) stands for the well-known vector regression model, which has proven to be a useful machine learning method for multivariate time series forecasting.
- **RNN** (Chung et al. 2014) is the Recurrent Neural Network using GRU cell with AR components.
- **MHA** (Vaswani et al. 2017b), or MultiHead Attention, stands for multi-head attention components in the famous Transformer model, where multi-head mechanism runs through the scaled dot-product attention multiple times in parallel.
- **LSTNet** (Lai et al. 2017) is a famous MTS forecasting framework which shows great performance by modeling long-term and short-term temporal patterns of MTS data.
- **MLCNN** (Cheng, Huang, and Zheng 2019) is a novel multi-task deep learning framework which adopts the idea of fusing forecasting information of different future time.
- **MTGNN** (Wu et al. 2020) is a joint framework for modeling multivariate time series data generally from a graph-based perspective with graph neural networks.
- **TEGNN** (Xu et al. 2020) stands for Graph Neural Network with Transfer Entropy, which applies multi-layer CNN and k-GNNs to perform MTS forecasting tasks.
- **PFNet** stands for our proposed Parallel Forecasting Network, which predicts long-term trends and short-term fluctuations of time series in parallel.

**Training Details**

We conduct grid search on tunable hyper-parameters on each method over all datasets. Specifically, the same grid search range of input window size for each method is set from $\{2^0, 2^1, 2^2, ... 2^9\}$ and different hyper-parameters are chosen for each method to achieve their best performance on this task.
For RNN-GRU and LSTNet, the hidden dimension of Recurrent and Convolutional layer is chosen from \{10, 20, ..., 100\}. For LSTNet, the skip-length \(p\) is chosen from \{0, 12, ..., 48\}. For MLCNN, the hidden dimension of recurrent and convolutional layer is chosen from \{10, 25, 50, 100\}. We adopt dropout layer after each layer, and the dropout rate is set from \{0.1, 0.2\}. For TEGNN, we calculate transfer entropy matrix based on train and validation data and set the size of the three convolutional kernels to be \{3, 5, 7\} respectively. For our proposed PFNet, the kernel size of CNN is 3 and the size of highway window of CNN component is chosen from \{4, 8, 16, 32\}. During the training phase, the batch size is 128 and the learning rate is 0.001. The Adam algorithm is used to optimize the parameters of our model.

**Main Results**

Table 1 shows the evaluation results of all the methods on three benchmark datasets with three metrics. Following the test settings of (Lai et al. 2017), we use each model for time series predicting on future moment \(t + 3, t + 6, t + 12, t + 24\), thus we set horizon = \{3, 6, 12, 24\}, which means the horizon is set from 3 to 24 days for forecasting over the Exchange-Rate data, from 30 to 240 minutes over the Energy data, and from 3 to 24 minutes over the Nasdaq data. The best results for each metrics on each dataset are set bold in Table 1. We save the model that has the best performance on validation set based on RSE or RAE metric after training 1000 epochs for each method. Then we use the model to test and record the results.

Overall, the performance of VAR is weaker than other baselines, which also shows that the linear regression method is not conducive to fully extracting the variety of information in the time series. MTGNN or TEGNN achieves the best in some cases (for example, the \(RSE\) indicator of MTGNN in the energy dataset when the horizon is 6, and the \(CORR\) indicator of TEGNN in the energy dataset when the horizon is 24), which shows the superiority of using graph structure to exploit the relationships among different variables in multivariate time series. The results in the Table 1 show that our proposed PFNet outperforms these baselines in most cases. Even in some cases (for example, when the horizon = 12 or 24 in the Energy dataset), it does not exceed all baselines, and the performance of PFNet is also competitive. This indicates the effectiveness of our proposed model on multivariate time series forecasting tasks.

It is worth noting that, as models for predicting the value of multiple time points in the future, PFNet performs better than MLCNN. The reason could be that LTPM and SFPM can better capture the long-term and short-term characteristics of the time series, and a single model may be easier to confuse both. PFNet uses the idea of parallel forecasting to capture the long-term trends and short-term fluctuations of multivariate time series. Thus it can break through the restriction that traditional methods and other deep learning methods cannot use both of them. This is exactly the original intention of our design of PFNet.

**Time Complexity Analysis**

Although the proposed PFNet architecture designs three modules, it does not require much time. Following (Cheng, Huang, and Zheng 2020), we compare the performance of all models as a function of sample size and display the results on the NASDAQ dataset in Figure 3 to prove PFNet’s efficiency. The training and testing time of our PFNet model is about twice as long as that of other simple baselines. This is in line with our expectations. Because we not only forecast the long-term trends but also forecast the short-term fluctuations and the time used for each part is similar to that of an ordinary prediction network. It is worth noting that when processing high-dimensional time series, the time required for training and prediction of MLCNN, which also adopts the idea of multi-task learning, costs 3.6 and 6.5 times compared with our model PFNet. This proves the efficiency of our multi-task learning framework: there is no complicated network structure, and good performance can be achieved by combining this parallel forecasting framework with ordinary prediction networks (like highway-CNN in this paper).

**Ablation Study**

We conduct an ablation study on exchange-rate dataset to validate the effectiveness of key components that contribute to the improved outcomes of our proposed model. We name
Table 1: MTS forecasting results under different horizons measured by RSE/RAE/CORR score over three datasets.

| Dataset | Exchange-Rate | Energy | Nasdaq |
|---------|---------------|--------|--------|
|         | horizon 3     | horizon 6 | horizon 12 | horizon 24 | horizon 3 | horizon 6 | horizon 12 | horizon 24 | horizon 3 | horizon 6 | horizon 12 | horizon 24 |
| Methods | RSE           | RAE    | CORR   | RSE           | RAE    | CORR   | RSE           | RAE    | CORR   | RSE           | RAE    | CORR   | RSE           | RAE    | CORR   | RSE           | RAE    | CORR   | RSE           | RAE    | CORR   |
| VAR     | 0.0186        | 0.0262 | 0.0370 | 0.0505        | 0.1197 | 0.1314 | 0.1498        | 0.1791 | 0.0009 | 0.0151        | 0.0319 | 0.0442 | 0.0587        | 0.0793 | 0.111  | 0.0008        | 0.0131 | 0.0177 | 0.0027 |
| RNN     | 0.0200        | 0.0262 | 0.0366 | 0.0527        | 0.1106 | 0.1162 | 0.1255        | 0.1322 | 0.0012 | 0.0115        | 0.0016 | 0.0114 | 0.0442        | 0.0562 | 0.0680 | 0.0011        | 0.0166 | 0.0105 | 0.0020 |
| MHA     | 0.0194        | 0.0260 | 0.0360 | 0.0485        | 0.1103 | 0.1162 | 0.1260        | 0.1300 | 0.0010 | 0.0122        | 0.0016 | 0.0114 | 0.0410        | 0.0561 | 0.0773 | 0.0009        | 0.0111 | 0.0019 | 0.0020 |
| LSTNET  | 0.0216        | 0.0277 | 0.0359 | 0.0482        | 0.1082 | 0.1160 | 0.1187        | 0.1243 | 0.0013 | 0.0110        | 0.0016 | 0.0119 | 0.0404        | 0.0546 | 0.0688 | 0.0011        | 0.0121 | 0.0019 | 0.0020 |
| MLCNN   | 0.0172        | 0.0447 | 0.0519 | 0.0448        | 0.1113 | 0.1324 | 0.1225        | 0.1331 | 0.0009 | 0.0111        | 0.0015 | 0.0113 | 0.0267        | 0.0378 | 0.0664 | 0.0008        | 0.0101 | 0.0018 | 0.0020 |
| MTGNN   | 0.0194        | 0.0253 | 0.0345 | 0.0447        | 0.1127 | 0.1149 | 0.1203        | 0.1273 | 0.0010 | 0.0112        | 0.0016 | 0.0104 | 0.0267        | 0.0378 | 0.0664 | 0.0008        | 0.0101 | 0.0018 | 0.0020 |
| TEGNN   | 0.0175        | 0.0245 | 0.0362 | 0.0449        | 0.1142 | 0.1181 | 0.1211        | 0.1265 | 0.0010 | 0.0110        | 0.0016 | 0.0121 | 0.0267        | 0.0378 | 0.0664 | 0.0008        | 0.0101 | 0.0018 | 0.0020 |
| PFNet   | 0.0156        | 0.0229 | 0.0332 | 0.0437        | 0.1074 | 0.1159 | 0.1211        | 0.1312 | 0.0007 | 0.0099        | 0.0013 | 0.0018 | 0.0267        | 0.0378 | 0.0714 | 0.0007        | 0.0099 | 0.0013 | 0.0019 |

PFNet without different components as follows:

- **LTPM**: PFNet without short-term fluctuations prediction module. Here we use multi-layer CNN with AR components (CNN-AR (LeCun, Bengio et al. 1995)) to perform MTS forecasting tasks.

- **PFNet-RNN**: PFNet that replaces CNN-AR module with RNN.

- **PFNet-LSTNet**: PFNet that replaces CNN-AR module with LSTNet.

- **PFNet-xt**: PFNet without MLP in short-term fluctuations prediction module. That means we only use \( \Delta X \) to predict \( \Delta \hat{x}_{t+h} \).

Table 2 shows the comparison results. The important conclusions of these results are as follows:

- **PFNet** has the best performance, compared with these variants.

- After removing the short-term fluctuations prediction module, as shown by **LTPM**, the performance will drop, which proves that short-term fluctuations are useful for time series forecasting and PFNet takes advantage of this.

- The relatively poor performance after removing MLP in SFPF (PFNet-xt) also proves the contribution of introducing \( x_t \) in forecasting short-term fluctuations and the necessity for us to design SFPF with reference to the VECM model.

Table 2: Ablation Study.

| Dataset | Exchange-Rate |
|---------|---------------|
|         | horizon 3     | horizon 6 | horizon 12 | horizon 24 |
| Methods | RSE           | RAE    | CORR   |
|---------|---------------|--------|--------|
| LTPM    | 0.0194        | 0.0250 | 0.0342 | 0.0466 |
|         | 0.0150        | 0.0201 | 0.0281 | 0.0392 |
|         | 0.9776        | 0.9694 | 0.9548 | 0.9560 |
| PFNET-XT | 0.0168        | 0.0234 | 0.0336 | 0.0449 |
|         | 0.9744        | 0.9723 | 0.9570 | 0.9374 |
| PFNET-RNN | 0.0159        | 0.0239 | 0.0355 | 0.0557 |
|         | 0.9806        | 0.9719 | 0.9567 | 0.9359 |
| PFNET-LSTNet | 0.0181        | 0.0232 | 0.0390 | 0.0484 |
|         | 0.9797        | 0.9726 | 0.9572 | 0.9348 |
| PFNET   | 0.0156        | 0.0229 | 0.0332 | 0.0437 |
|         | 0.9813        | 0.9732 | 0.9583 | 0.9386 |
• As shown in PFNet-RNN and PFNet-LSTNet, even if the CNN-AR module is replaced by RNN or LSTNet, the result will not be much worse, which proves that the framework of parallel forecasting we provide is robust. Other prediction networks can also be combined with our framework to achieve good performance.

Conclusion

In this paper, we propose a MTS forecasting framework, called parallel forecasting network (PFNet) to capture the long-term trends and short-term fluctuations of time series in parallel. Inspired by the idea of multi-task learning, PFNet uses the original value and its difference between time stamps to optimize MTS forecasting problems from different perspectives at the same time. Experiments on three real-world datasets show that our model outperforms 7 baselines in terms of the three metrics (RAE, RSE and CORR). For future research, different models can be incorporated into our framework to characterize long-term trends and short-term fluctuations, so as to improve prediction accuracy and make PFNet more robust.

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