Series Saliency: Temporal Interpretation for Multivariate Time Series Forecasting

Qingyi Pan, Wenbo Hu, Jun Zhu
Tsinghua University,
pqy19@mails.tsinghua.edu.cn, i@wbhu.net, dcszj@tsinghua.edu.cn

Abstract
Time series forecasting is an important yet challenging task. Though deep learning methods have recently been developed to give superior forecasting results, it is crucial to improve the interpretability of time series models. Previous interpretation methods, including the methods for general neural networks and attention-based methods, mainly consider the interpretation in the feature dimension while ignoring the crucial temporal dimension. In this paper, we present the series saliency framework for temporal interpretation for multivariate time series forecasting, which considers the forecasting interpretation in both feature and temporal dimensions. By extracting the “series images” from the sliding windows of the time series, we apply the saliency map segmentation following the smallest destroying region principle. The series saliency framework can be employed to any well-defined deep learning models and works as a data augmentation to get more accurate forecasts. Experimental results on several real datasets demonstrate that our framework generates temporal interpretations for the time series forecasting task while produces accurate time series forecast.

Introduction
Time series is the data configured with a sequential order (Hamilton 1994), which is widely used in various applications with representative tasks as classification, forecast, imputation, etc (Keogh and Kasetty 2003). Traditional time series forecasting methods are often formulated as parametric models with a shallow architecture, such as the Box–Jenkins methods (Box and Jenkins 1976) and the structural time series models (Harvey 1990). Such methods adopt some explicit model assumptions that are easy-to-interpret, while their strict assumptions typically restrict the predictive capabilities and wide applications.

More recently, deep learning methods have become increasingly effective and popular for time series forecasting. The representative deep models for time series forecasting (Gamboa 2017) include recurrent neural networks (RNN), long-short term memory (LSTM) (Hochreiter and Schmidhuber 1997), gated recurrent unit (GRU) (Chung et al. 2014) and neural attention methods. Although effective, deep learning methods are typically treated as a black-box and difficult to interpret the outputs (Castelvecchi 2016), which stands as a crucial bottleneck of the further applications of such models. In particular for the time series forecasting task, the model interpretations should explain not only the single-point output but also the temporal trends and changes.

A straightforward solution is to use the interpretation methods for general neural networks, such as LIME (Ribeiro, Singh, and Guestrin 2016), DeepLift (Shrikumar, Greenside, and Kundaje 2017), and Shap (Lundberg and Lee 2017). These methods use gradient information to extract feature information for single-time forecasts after the back-propagation training. However, these methods do not consider the temporal information for forecasting interpretation, which leads to single-point explanations for temporal sequential forecasts. Another line of research on time series forecast interpretations is to migrate the attention methods from the sequence-based language or speech representation methods (Bahdanau, Cho, and Bengio 2014; Vaswani et al. 2017). The attention mechanism...
uses sequence align functions for sequence recurrent neural networks and is found effective for sequence predictions tasks, such as language modeling and machine translation. However, the attention values for explaining RNNs are calculated via the related importance of the different time steps and there are doubts that they are based on the intermediate feature importance instead of model interpretations (Serrano and Smith [2019], Jain and Wallace [2019]).

In this work, we jointly consider both the feature and temporal information and propose the series saliency interpretable framework, which is a temporal interpretable multivariate time series forecast model with saliency maps. As shown in Figure 1, we consider the temporal multivariate time series as a window × feature “series image” and use the series saliency framework to segment the most meaningful and useful part for the time series forecast task. Following the smallest destroying region (SDR) principle (Dabkowski and Gal [2017], Chang et al. [2017]), we use the masking technique to get heatmaps of feature importance for one input series image. With the masking techniques, the added Gaussian noise or blur can also improve the robustness and overall forecasting performance, as shown in (DeVries and Taylor [2017]). We present both quantitative and qualitative results on several typical time series datasets, which show that our method provides temporal interpretations for the time series forecasts and meanwhile achieves better or comparable forecast results.

**Preliminaries**

In this section, we introduce the useful preliminaries, including: 1) the time series forecasting task and interpretations and 2) the saliency map method used in computer vision and the effective smallest destroying region principle.

**Time Series Forecasting and Interpretations**

We consider interpreting multivariate time series forecasting results. Formally, we use $X$ to denote a series of observed time series signals, where every single signal $x_t$ is a real vector with dimension $D$:

$$X = [x_1, x_2, \ldots, x_t, \cdots]^T, \quad x_t \in \mathbb{R}^D. \quad (1)$$

For every time step $t$, we aim to predict the future time value after a given horizon $\tau$: $x_{t+\tau}$. In most of the cases, the horizon of the forecasting task is chosen according to the task settings. For example, for the traffic usage, the horizon $\tau$ of interest ranges from an hour to a day; for the stock market data, even second or minute ahead forecast can be meaningful for generating returns.

After getting the forecasting results, we are interested in the question of the forecasting interpretation: what features most and least contribute to the final forecast predictions? The traditional statistical methods, such as Box-Jenkins methods (Box and Jenkins [1976]) and structural methods (Harvey [1990]), are easy to interpret because they adopt the explicit model assumptions that can extract interpretations directly from the learned model parameters. Though deep learning methods have superior prediction capabilities (Heaton [2018]), they are hard to interpret since the deep model assumptions are stacked with multiple non-linear activations or blocks. Some works tried to use the explainability methods for general neural networks to obtain the time series forecasting feature importance, such as LIME (Ribeiro, Singh, and Guestrin [2016]), DeepLift (Ribeiro, Singh, and Guestrin [2016]) and Shap (Lundberg and Lee [2017]). However, these methods do not capture the temporal information for forecasting. Attention mechanism calculates the related importance values among different time steps, so it is hard to capture the interdependence among features well at the same time (Serrano and Smith [2019], Jain and Wallace [2019]). As for interpreting the time series forecasts, feature importance aligns through the temporal dimension, which is the key challenge in our paper. Our method jointly consider the feature and temporal information via the saliency map method and can produce more global and applicative forecasting interpretations.

**Saliency Map and Masks for Smallest Destroying Region**

Saliency map (Kadir and Brady [2001]) is a widely-used method in computer vision, which segments the parts of inputs that are important for a model’s outputs. One popular principle to learn saliency maps is the smallest destroying region (SDR) (Dabkowski and Gal [2017]), which learns the smallest informative removing region of the input that preserves a confident output.

We denote an input image as $X$ with a corresponding class $c$. By adding noise (e.g., Gaussian blur) to the input image, we get the reference image $\tilde{X}$. Following the SDR principle, we aim to learn a mask $M$ and part of an image will be wiped out by applying the mask to it. The mask $M$ is assigned to each pixel $x_i$ from an image and the value of the mask will be between 0 and 1: $m(x_i) \in [0, 1]$. Here $m(x_i) = 0$ means that the original pixel is used and $m(x_i) = 1$ means that the reference region added some noise is used. Through the definition of the mask, we can introduce a local perturbation to the image as:

$$\tilde{X} = M \odot X + (1 - M) \odot \tilde{X}, \quad (2)$$

where $\odot$ is the element wise dot product. The SDR saliency map prevents the confident classification with the smallest destroying region (Dabkowski and Gal [2017]):

$$\min_M P_g(c|M \odot X + (1 - M) \odot \tilde{X}) + \lambda \mathbb{I}(M), \quad (3)$$

where $P_g(c|X)$ is the output probability of the class $c$, $g(\cdot)$ is the classification model, $\lambda$ is the regularization parameter and $\mathbb{I}(M)$ is a complexity regularization function of the mask $M$. The obtained mask represents the feature importance of the input.

Dabkowski and Gal (Dabkowski and Gal [2017]) amortizes the cost of computes saliency map by auxiliary neural networks. Fong (Fong and Vedaldi [2017], Fong, Patrick, and Vedaldi [2019]) solves for input feature saliency map as the parameters of the mask that optimize the SDR objective. In this paper, we formulate the time series as “series images”, as shown in Figure 1 and propose the series saliency method to interpret the temporal multivariate time series forecast.
We introduce the series saliency method: the windows of time series is formulated as "series images", then the saliency method is proposed to interpret the time series forecasting task and finally result is presented as interpretation of Mask, i.e., \( L(M) \) in Equation \( 8 \). The size of mask should be as small as possible and 2) the masks shapes should be smooth.

We denote \( \ell_p = \phi(x_{t+i, f}(X, M)) \) as the multivariate time series forecasting prediction part. We design \( \phi(.) \) to measure model performance, where \( \phi(.) \) represents the mean squared error of \( (x_{t+i, f} f_c(X, M)) \), or other metrics. The penalty function for the mask size is defined as \( \ell_m \):

\[
\ell_m = \| M \|_{p_0},
\]

where the matrix norm \( \| M \|_{p_0} \) is set as 2-norm or 3-norm. Another penalty function for the mask smoothness is defined as \( \ell_r \):

\[
\ell_r = \sum_{(t,i)} (m_{t,i} - m_{t,i+1})^2 + \sum_{(t,i)} (m_{t,i} - m_{t+1,i})^2.
\]

In training procedure, noise injection or blur on masks region is actually a data-augmentation method (Wen et al. 2020). Our model can learn most salient data characteristics by data augmentation and achieve better performance. The strategies can help network focuses on the most salient data characteristics (Tsipras et al. 2018, Cubuk et al. 2019, 2018).

Overall, the training minimizing objective \( L_1 \) can be:

\[
L_1 = \ell_p + \lambda_1 \ell_m + \lambda_2 \ell_r,
\]
where $\lambda_1$ and $\lambda_2$ are two regularization parameters. We use gradient descent to optimize the objective function $L_1$. In each step of training iterations, we sample mini-batch of $n$ samples series image $X^{(b)}$, reference series images $\tilde{X}^{(b)}$, mask $M$ (in previous definition). Firstly, we use Equation 2 to generate perturbations $\tilde{X}^{(b)}$ for original series image. The $\tilde{X}^{(b)}$ is feed into deep learning module and linear auto-regressive module separately. $y^{g}$ obtained by deep learning module and $y^{r}$ obtained by the auto-regressive module is integrated together to get $\hat{y}$. Then the final prediction part $\ell_p$, and regularization term ($\ell_m, \ell_r$) are calculated simultaneously to get objective function $L_1$. Then the parameters of deep learning module, linear module and mask are updated simultaneously by the back-propagation.

**Forecast Interpretation**

After training the forecasting model by optimizing $L_1$, we use a subsequent procedure to learn forecast interpretations through the smallest destroying region (SDR) principle [Dabkowski and Gall 2017], as defined in Equation 3. Given an “series image” $x_0$, this interpretation procedure is to summarize compactly the effect of deleting feature regions, either setting values to zeros or Gaussian noise, in order to explain the behaviour of the deep neural net forecasters. The SDR principle is finding the higher salient feature regions by identifying the highly representative mask. The SDR interpretation procedure considers a deletion game and the goal is to find the smallest deletion mask $m$ for input X that regression have the worst performance, i.e.,to maximize the forecast error $\ell_p$. The loss function of the interpretation procedure is:

$$L_2 = -\ell_p + \lambda_1 \ell_m + \lambda_2 \ell_r,$$  

where $\ell_m$ and $\ell_r$ are also used to limit the complexity of the masks. In this procedure, we fix the learned model parameters of the forecasting modules including the deep learning model and the AR model. By the above definition, we sample a series image $X^{(s)}$ in the test set, mask $M$ and reference series image $\tilde{X}^{(s)}$. $\tilde{X}^{(s)}$ is feed into series for forecasting to obtain $L_2$ loss. Then only the parameter of mask can be updated by back-propagation in interpretable process.

The overall training and interpretation process is outline in Algorithm 2. In algorithm, the number of training steps of mask component $k_g$ is the hyperparameter. The mask parameter is $\theta_k$.

**Feature exchangeability**

As shown in Figure 1, after the series saliency, we can obtain the series saliency map in the interpretable procedure, where each row corresponds to the dynamic changes of feature importance in time series. Due to the mask smoothness penalty $\sum_{(i,j)}(m_{t,i}-m_{t+1, i})^2$ between features in Equation 8, it assumes that there exists some unknown correlation between features.

For some multivariate time series datasets, like the electricity dataset used in the paper, the feature dimension means the powerplant position and nearby features correspond to the nearby stations. Thus the order of feature and time dimension of “series image” is both fixed. In this case, one can use our series saliency framework to obtain interpretations directly. While for other series data contains exchangeable features (like the air quality or the industry stock indices), we may modify our algorithm slightly. In interpretation procedure, we remove the $\sum_{(i,j)}(m_{t,i}-m_{t+1, i})^2$ term in smoothness penalty, and use $\ell_i$ instead,

$$\ell_i = \sum_{(i,j)}(m_{t,i}-m_{t+1, i})^2$$

which means $\ell_i$ only consider the correlation through the time line. After the interpretation procedure, the temporal feature importance of each feature is calculated. We use simulated annealing to search the permutation. It makes sure that the nearby feature have the correlative importance to the forecasting results.

Given an “series image” $X^{(s)}$, we can obtain the dynamic feature importance in $M^{(s)}$ during the interpretation procedure. We could formulate it as travelling salesman problem. Label the features with the numbers $\{f_1,...f_D\}$ and define:

$$x_{i,j} = \begin{cases} 
1 & i \rightarrow j \\
0 & \text{other}
\end{cases}$$

For $i = \{1...n\}$, take $d_{i,j}$ to the similarity between dynamic importance of feature $a$ and feature $b$ on permutation of mask $M$.

$$d(f_a, f_b) = \sqrt{\sum_{i=1}^{T} |f_{(a,i)} - f_{(b,j)}|^2}$$

Then the objective function can be written as the following problem:

$$g(.) = \min \sum_{i=1}^{D} \sum_{j \neq i, j=1}^{D} (d(f_i, f_j)x_{i,j})$$

**Algorithm 1 Minibatch stochastic gradient descent training of series saliency.**

1: for number of training iterations do  
2: Sample mini-batch of $n$ samples series image $x^{(b)}$ and correspond horizon of $x^{(b)}_{t+\tau}$ from training dataset; $M$ represents the mask.  
3: Update the series saliency parameter including mask component by descending its stochastic gradient:  
4: $\nabla_{\theta} \frac{1}{n} \sum_{i=1}^{n} \left( (x^{(b)}_{i,t+\tau}, f_0(x, M)) + \lambda_1 \|1-M\|_1 + \lambda_2 \ell_r \right)$;  
5: end for  
6: Get accuracy on test set, and select one unseen samples $(x^{(s)}, y^{(s)})$ in test set.  
7: for $k_2$ steps do  
8: Only update mask parameters $\theta_k$ to obtain series saliency map by descending its stochastic gradient:  
9: $\nabla_{\theta_k} (-\ell_p + \lambda_1 \ell_m + \lambda_2 \ell_r)$;  
10: end for
where \( x_{i,j} \in \{0, 1\} \). We use simulated annealing algorithm to solve the permutation. The simulated annealing consists of the following operators: initialization, neighbor selection, evaluation and output, where \( \psi \) represents the temperature, \( s \) is the current permutation of features, \( v \) is the candidate solution, \( g(\cdot) \) is the objective value of current state \( v \), \( h(s) \) is to swap the order of two features in permutation.

**Algorithm 2 Simulated Annealing for feature permutation**

1: Create the initial permutation of feature \( s = \{f_1, f_2...f_D\} \)
2: Input distance matrix \( dis(s) \in \mathbb{R}^{D \times D} \) calculated by \( d(f_a, f_b) = \sqrt{\sum_{i=1}^{T} |f_{a,i} - f_{b,i}|^2} \)
3: Set the initial temperature \( \psi \)
4: while \( \psi > \psi_0 \) do
5: Perturbing the current state \( s \) to generate \( v = h(s) \)
6: Evaluate the new state \( g(v) \) by Equation\([14]\)
7: if \( g(v) \) satisfies the probabilistic acceptance criterion then
8: Update current state \( s = v \)
9: end if
10: Update \( \psi \) according to the annealing schedule.
11: end while
12: Output current permutation \( s \)

**Experiment and analysis**

For the empirical experiments, firstly we compare the performance of four widely-used deep learning models with and without the proposed series saliency method on three representative multivariate time series forecasting datasets. We also give an ablation study on the mask and AR model components. Then we show extensive qualitative results of how saliency heatmaps interpret the forecasts.

**Experimental Setting**

We test different methods on three representative time series forecasting dataset: electricity, air-quality and industry data. In Appendix, we summarize the statistics of experiment datasets. More details about the datasets is given in Appendix. For time series forecasting performance we use two evaluation metrics, relative squared error (RSE) and empirical correlation coefficient (CORR), which are defined in Appendix. For RSE, lower values are better. For CORR, higher values are better. Other experimental setups are given in Appendix.

**Deep Learning Modules**

We use four state-of-art deep learning methods for comparison(CNN, GRU+Attention, LSTNet and Self Attention encoder), more details are given in Appendix. These four deep learning models achieve superior forecasting performances and in the following results they are used as a deep learning module to get interpreted by the proposed series saliency method.

**Forecasting Results**

In Table 1, we summarize the forecasting results of the four methods on the three datasets in two metrics. We compare the four deep learning methods with and without the series saliency method. We set horizons as 3, 6, 12, respectively. For example, the horizons was set from 3 to 12 hours for the electricity forecasting. The best result for each (data, metric) pair is highlighted in bold font. By comparing the upper and lower groups of results in the table, for most settings with the same model and dataset, adding the series saliency would bring better forecasting results, i.e., lower RSE or larger CORR. This is because that the added series saliency masks work as a data augmentation method and strengthen the generalization for the testing data. The performance improvements from the incorporated series saliency module are found more obvious on datasets with higher dimensions (the electricity with 321 dimensions VS air quality with 12 dimensions). For all eight comparing methods, the self-attention encoder with the series saliency obtains most of the best forecasting result and this is due to the powerful representation capability of the transformer encoder model.

Figure 3 gives an example of forecasting results of the self-attention encoder with the series saliency on the electricity dataset. As can be seen, our method gives accurate forecasts that predicts multiple peaks and trends. The forecasting results on more datasets are deferred to Appendix.

**Ablation study**

In order to test that the effectiveness of all model modules, we conduct an ablation study: delete every mask component and compare the forecasting results through the two metrics, RSE and CORR. We name the different tested model with the four deep learning methods with and without the series saliency, including mask and AR components as follows:

- **With series saliency** Four different deep learning models with series saliency
- **Series saliency w/o mask** The series saliency model without mask component
- **Series saliency w/o AR** The series saliency model without auto-regressive component.
### Table 1: Results summary (in RSE, and CORR) of implemented methods on three multivariate time series datasets. Each row has the results of a specific method in a particular metric. Each column compares the results of all methods on a particular dataset with a specific horizon value. Bold face indicates the best result of each column in a particular metric.

| Dataset | Industry | Air Quality | Electricity |
|---------|----------|-------------|--------------|
|         | Horizon  | Horizon     | Horizon      |
| Methods | Metrics  | 3 | 6 | 12 | 3 | 6 | 12 | 3 | 6 | 12 |
| CNN     | RSE      | 0.1622 | 0.1682 | 0.1983 | 0.3088 | 0.3620 | 0.4048 | 0.1004 | 0.1049 | 0.1066 |
|         | CORR     | 0.8968 | 0.9196 | 0.8107 | 0.7749 | 0.7009 | 0.6361 | 0.8829 | 0.8715 | 0.8661 |
| GRU     | RSE      | 0.2115 | 0.1913 | 0.2219 | 0.3121 | 0.3574 | 0.4048 | 0.1192 | 0.1249 | 0.1316 |
|         | CORR     | 0.9531 | 0.9359 | 0.9056 | 0.8037 | 0.7120 | 0.6366 | 0.8789 | 0.8774 | 0.8671 |
| LSTNet  | RSE      | 0.1806 | 0.1901 | 0.2284 | 0.3268 | 0.3600 | 0.4072 | 0.1004 | 0.1049 | 0.1066 |
|         | CORR     | 0.9501 | 0.9335 | 0.8645 | 0.7771 | 0.6775 | 0.6237 | 0.9264 | 0.9157 | 0.9095 |
| Self-Attention | RSE    | 0.1474 | 0.1518 | 0.1857 | 0.3007 | 0.3526 | 0.3871 | 0.0882 | 0.0921 | 0.1005 |
|         | CORR     | 0.9501 | 0.9335 | 0.8645 | 0.7771 | 0.6775 | 0.6237 | 0.9264 | 0.9157 | 0.9095 |
| CNN     | RSE      | 0.1531 | 0.1762 | 0.1951 | 0.3071 | 0.3507 | 0.4022 | 0.0991 | 0.0993 | 0.1003 |
|         | CORR     | 0.9612 | 0.9418 | 0.9048 | 0.8129 | 0.7223 | 0.6966 | 0.9193 | 0.9065 | 0.9097 |
| GRU     | RSE      | 0.1771 | 0.1974 | 0.1996 | 0.2901 | 0.3228 | 0.3418 | 0.1077 | 0.1116 | 0.1121 |
|         | CORR     | 0.9551 | 0.9255 | 0.9117 | 0.8085 | 0.7125 | 0.6492 | 0.9803 | 0.8875 | 0.8774 |
| LSTNet  | RSE      | 0.1777 | 0.1791 | 0.2261 | 0.2993 | 0.3495 | 0.3869 | 0.0881 | 0.0942 | 0.0936 |
|         | CORR     | 0.9504 | 0.9343 | 0.9011 | 0.7935 | 0.7293 | 0.6501 | 0.9284 | 0.9173 | 0.9057 |
| Self-Attention | RSE    | 0.1195 | 0.1304 | 0.1735 | 0.2879 | 0.3505 | 0.3859 | 0.0877 | 0.0908 | 0.0985 |
|         | CORR     | 0.9553 | 0.9591 | 0.9165 | 0.8119 | 0.7093 | 0.6379 | 0.9293 | 0.9125 | 0.9106 |

**Qualitative Study on Interpretation Features by Series Saliency**

We give a qualitative study on the interpretation features of the series saliency method by analyzing the learned saliency mask heatmaps.

**Visualization of Saliency Heatmap** We apply the series saliency methods with the self-attention encoder module on the air quality dataset. In Figure 5 we visualize the learned mask component when forecasting the randomly-selected future value after the horizon \( \tau = 6 \). As can be seen from the saliency mask heatmap, the features in the time from 20 to 30 have the largest saliency and this corresponds to the extreme low value in dimension 1 which means the concentration of CO. Afterwards in the time from 30 to 50, the relatively low saliency corresponds to the more stationary concentration of CO. More saliency results on other datasets can be found in Appendix.

**Correspondence between Saliency and Frequency** In this experiment, we analyze the correspondence between saliency map region in the mask, the original time series data and the data frequencies. We run the self attention encoder method with series saliency method on the electricity dataset and show the results in Figure 7. As can be seen from the results, the data of the channel 250 has the high value of the saliency mask and reflects a periodic structure (top left corner figure). To the contrary, the data of the channel 36 has the low value of the saliency mask and reflects a relatively acyclic structure (top right corner figure). In order to prove the periodicity of our selected channels, we map the corresponding feature to frequency domain by fast Fourier transform (FFT) (Nussbaumer 1981) and show the the frequency result below the data of the two channels.

**Series Saliency for AR Method, A Validation** In order to validate the effective information learnt by mask, we de-
We delete the deep learning module and only reserve 50-order autoregressive model to forecast for electricity on horizon=6. The experiment results is shown in Figure 6. The learned saliency maps within the time order is distinctly different from the maps beyond the time order. However when beyond the time order, i.e., the time between 0 and 250, the saliency mask has a saliency uniformity which reflects that AR(50) has no feature saliency beyond the time order.

Figure 6: Series saliency for AR(50) on the electricity dataset with the horizon as 5. As can be seen, within the time order 50, AR(50) have distinct feature saliency while beyond the time order 50, AR(50) has no feature saliency. The figure is best viewed in color.

Related Works and Discussions

In this section, we give related works and give discussions.

Deep Learning for Time Series Forecast

Deep learning model have been successfully used for time series forecasting, like(CNN, RNN, or Transformer etc). To adapt convolutional neural network to time series datasets, multiple layers of convolutions filters were used to to capture past information for forecasting (Borovykh et al., 2017, Oord et al., 2016). Also, LSTM or GRU (Hochreiter and Schmidhuber, 1997) were developed to model long-range dependencies. Lai et al. (2018) proposed LSTNet, which is a model using a combination of CNN for short-term information and RNN for long-term information. Recently, Transformer is used as a new architecture which leverages the self-attention mechanism to process a sequence of data (Parikh et al. 2016; Vaswani et al. 2017; Li et al., 2019) tackles time series forecasting using transformer. It enhances the locality by using casual convolutions for each cell in each layer. Lim et al. (2019) introduces the Temporal Fusion Transformer(TFT)-a novel attention-based architecture which combines the high-performance multihorizon forecasting with considering temporal dynamic.

Saliency Map for Computer Vision

Saliency map shows which parts of an image feature are important for network’s output, which is generally used in the computer vision applications. Examples include visualizing the middle layer of neural network (Simonyan, Vedaldi, and Zisserman 2013), mapping a specified class to a region in an image (Zeiler and Fergus 2014) and simulating learning procedure (Mahendran and Vedaldi 2015) and so on. Specifically, masks (Dabkowski and Gal 2017) propose two principles for learning saliency maps: 1) smallest destroying region: Fong and Vedaldi (2017) proposes mask to “deleting” different regions of input feature for reinterpret network saliency map, which leading to more meaningful perturbation and hence explanations; and 2) smallest sufficient region: Fong, Patrick, and Vedaldi (2019) proposes to constrain the area of mask to a fixed value that maximize the model’s output, and use mask to interpret saliency map.

Recently, there are several works on the saliency map method for analyzing time series. (Wang et al., 2018) proposed mWDN for time series classification to decomposed
sub-series in different frequencies as input. mWDN exhibits the importance spectrum in saliency map and varying importance of all the features. But it does not capture the map between series data and importance spectrum. Compared with mWDN, our proposed method can generate saliency maps that give interpretations for time series forecasts and this type of interpretation gives both temporal and feature dimension information.

(Ren et al. 2019) combines the spectral residual (SR) and the convolution neural network in time-series anomaly detection. They use SR model from visual saliency map to detect anomaly, and use CNN to improve performance.

Feature Exchangeability in Series Saliency

As shown in Figure 7, the series image in the feature dimension is sensitive to the feature exchangeability due to the mask smoothness penalty in Equation 8. Thus, a pre-defined feature ordering is recommended for our series saliency method. Also for some multivariate time series datasets, like the electricity dataset used in this paper, the feature dimension means the powerplant position and nearby features correspond to the nearby stations. In this case, one can use series saliency to obtain forecast interpretations directly. Otherwise, a clustering preprocess is recommended to make sure nearby feature have the correlative importance to the forecasting results.

Conclusion

In the paper, we presented a novel temporal interpretation framework (Series Saliency) for multivariate time series forecasting. By jointly consider both the feature and temporal information, we model temporal feature importance successfully for the final predictions. Also the series saliency method can be employed to any deep learning models and works as data augmentation to improve performance. With in-depth analysis and series saliency visualization, we shows that our series saliency framework can do improve multivariate time series forecasting, while produces some meaningful interpretation by series heatmap.

For future work, there are several promising directions in extending the work. The deep learning model likes a neural basis in frequency domain. How to model the basis of deep learning model is an challenging model.

References

Bahdanau, D.; Cho, K.; and Bengio, Y. 2014. Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473.

Borovykh, A.; Bohte, S.; and Oosterlee, C. W. 2017. Conditional time series forecasting with convolutional neural networks. arXiv preprint arXiv:1703.04691.

Box, G. E.; and Jenkins, G. M. 1976. Time series analysis. Forecasting and control. Holden-Day.

Castelvecchi, D. 2016. Can we open the black box of AI? Nature News 538(7623): 20.

Chang, C.-H.; Creager, E.; Goldenberg, A.; and Duvenaud, D. 2017. Interpreting neural network classifications with variational dropout saliency maps. In Proc. NIPS, volume 6.

Chung, J.; Gulcehre, C.; Cho, K.; and Bengio, Y. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555.

Cubuk, E. D.; Zoph, B.; Mane, D.; Vasudevan, V.; and Le, Q. V. 2018. Autoaugment: Learning augmentation policies from data. arXiv preprint arXiv:1805.09501.

Cubuk, E. D.; Zoph, B.; Shlens, J.; and Le, Q. V. 2019. Randaugment: Practical data augmentation with no separate search. arXiv preprint arXiv:1909.13719 (2(4): 7.

Dabkowski, P.; and Gal, Y. 2017. Real time image saliency for black box classifiers. In Advances in Neural Information Processing Systems, 6967–6976.

DeVries, T.; and Taylor, G. W. 2017. Improved regularization of convolutional neural networks with cutout. arXiv preprint arXiv:1708.04552.

Elman, J. L. 1990. Finding structure in time. Cognitive science 14(2): 179–211.
Fong, R.; Patrick, M.; and Vedaldi, A. 2019. Understanding deep networks via extremal perturbations and smooth masks. In Proceedings of the IEEE International Conference on Computer Vision, 2950–2958.

Fong, R. C.; and Vedaldi, A. 2017. Interpretable explanations of black boxes by meaningful perturbation. In Proceedings of the IEEE International Conference on Computer Vision, 3429–3437.

Gamboa, J. C. B. 2017. Deep learning for time-series analysis. arXiv preprint arXiv:1701.01887.

Hamilton, J. D. 1994. Time series analysis, volume 2. Princeton New Jersey.

Harvey, A. C. 1990. Forecasting, structural time series models and the Kalman filter. Cambridge university press.

Heaton, J. 2018. Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning.

Hochreiter, S.; and Schmidhuber, J. 1997. Long short-term memory. Neural computation 9(8): 1735–1780.

Ioffe, S.; and Szegedy, C. 2015. Batch normalization: Accelerating deep network training by reducing internal covariate shift. arXiv preprint arXiv:1502.03167.

Jain, S.; and Wallace, B. C. 2019. Attention is not Explanation. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 3543–3556.

Kadir, T.; and Brady, M. 2001. Saliency, scale and image description. International Journal of Computer Vision 45(2): 83–105.

Keogh, E.; and Kasety, S. 2003. On the need for time series data mining benchmarks: a survey and empirical demonstration. Data Mining and knowledge discovery 7(4): 349–371.

Kingma, D. P.; and Ba, J. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Lai, G.; Chang, W.-C.; Yang, Y.; and Liu, H. 2018. Modeling long-and short-term temporal patterns with deep neural networks. In The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, 95–104.

LeCun, Y.; et al. 1989. Generalization and network design strategies. Connectionism in perspective 19: 143–155.

Li, S.; Jin, X.; Xuan, Y.; Zhou, X.; Chen, W.; Wang, Y.-X.; and Yan, X. 2019. Enhancing the locality and breaking the memory bottleneck of transformer on time series forecasting. In Advances in Neural Information Processing Systems, 5243–5253.

Lim, B.; Arik, S. O.; Loeff, N.; and Pfister, T. 2019. Temporal fusion transformers for interpretable multi-horizon time series forecasting. arXiv preprint arXiv:1912.09363.

Lundberg, S. M.; and Lee, S.-I. 2017. A unified approach to interpreting model predictions. In Advances in neural information processing systems, 4765–4774.

Mahendran, A.; and Vedaldi, A. 2015. Understanding deep image representations by inverting them. In Proceedings of the IEEE conference on computer vision and pattern recognition, 5188–5196.

Nussbaumer, H. J. 1981. The fast Fourier transform. In Fast Fourier Transform and Convolution Algorithms, 80–111. Springer.

Oord, A. v. d.; Dieleman, S.; Zen, H.; Simonyan, K.; Vinyals, O.; Graves, A.; Kalchbrenner, N.; Senior, A.; and Kavukcuoglu, K. 2016. Wavenet: A generative model for raw audio. arXiv preprint arXiv:1609.03499.

Parikh, A. P.; Täckström, O.; Das, D.; and Uszkoreit, J. 2016. A decomposable attention model for natural language inference. arXiv preprint arXiv:1606.01933.

Ren, H.; Xu, B.; Wang, Y.; Yi, C.; Huang, C.; Kou, X.; Xing, T.; Yang, M.; Tong, J.; and Zhang, Q. 2019. Time-Series Anomaly Detection Service at Microsoft. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 3009–3017.

Ribeiro, M. T.; Singh, S.; and Guestrin, C. 2016. “Why should I trust you?” Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining, 1135–1144.

Serrano, S.; and Smith, N. A. 2019. Is Attention Interpretable? In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, 2931–2951.

Shrikumar, A.; Greenside, P.; and Kundaje, A. 2017. Learning important features through propagating activation differences. arXiv preprint arXiv:1704.02685.

Simonyan, K.; Vedaldi, A.; and Zisserman, A. 2013. Deep inside convolutional networks: Visualising image classification models and saliency maps. arXiv preprint arXiv:1312.6034.

Tsipras, D.; Santurkar, S.; Engstrom, L.; Turner, A.; and Madry, A. 2018. There is no free lunch in adversarial robustness (but there are unexpected benefits). arXiv preprint arXiv:1805.12152 2(3).

UCI. 2006. Air quality multivariate time series data. URL https://archive.ics.uci.edu/ml/datasets/Air+Quality

UCI. 2011-2014. UCI electricity multivariate time series data. URL https://archive.ics.uci.edu/ml/datasets/ElectricityLoadDiagrams20112014

Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, L.; and Polosukhin, I. 2017. Attention is all you need. In Advances in neural information processing systems, 5998–6008.

Wang, J.; Wang, Z.; Li, J.; and Wu, J. 2018. Multilevel wavelet decomposition network for interpretable time series analysis. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2437–2446.

Wen, Q.; Sun, L.; Song, X.; Gao, J.; Wang, X.; and Xu, H. 2020. Time Series Data Augmentation for Deep Learning: A Survey. arXiv preprint arXiv:2002.12478.
Zeiler, M. D.; and Fergus, R. 2014. Visualizing and understanding convolutional networks. In *European conference on computer vision*, 818–833. Springer.
**Dataset Details**

**Electricity**  The UCI electricity (UCI 2011–2014) load diagrams data set contains 370 customer power consumption per unit time. There is no missing value in this data set, recording the power consumption per 15 minutes (KWH) from 2011 to 2014. Each column of data represents a customer (370 columns in total), each row represents a quarter (140256 rows in total), and all time labels are subject to Portuguese time.

**Air-Quality**  The dataset (UCI 2006) contains 9358 instances of hourly averaged responses from an array of 5 metal chemical sensors embedded in Air quality Device. Data was recorded from March 2004 to February 2005 (one year). The device was located on the field in a significantly polluted area.

**Industry data**  The data of Hangseng Stock Composite Index (HSCI) and another eleven industry stock indices are obtained from Wind platform. Eleven industry stock indices include consumer good manufacturing, consumer service, energy, finance, industry, information technology, integrated industry, raw material, real estate, utilities. The dataset covers time period from September 2006 up to September 2019.

| Datasets                      | T    | D  | L       |
|-------------------------------|------|----|---------|
| Electricity                   | 26304| 321| 1 hour  |
| Air-Quality                   | 9358 | 12 | 1 hour  |
| Industry Stock Composite Index| 3205 | 12 | 1 day   |

Table 2: Dataset statistics, where $T$ is length of time series or data size, $D$ is the number of variables, $L$ is the sample rate.

**Metric Description**

On typical multivariate time series datasets, we followed the evaluate metrics **RSE** and **CORR** to measure the accuracy of models’ forecasting ability. The first metric is the root relative squared error (**RSE**). The **RSE** are the scaled version of the widely used Root Mean Square Error (**RMSE**), which is designed to make more readable evaluation, regardless the data scale.

$$RSE = \frac{\sqrt{\sum_{t=t_0}^{t_1} \sum_{i=1}^{n} (y_{t,i} - \hat{y}_{t,i})^2}}{\sqrt{\sum_{t=t_0}^{t_1} \sum_{i=1}^{n} (\hat{y}_{t,i} - \hat{y}_{t_0:t_1,i})^2}}$$ (15)

The second metric is the empirical correlation coefficient (**CORR**).

$$CORR = \frac{1}{n} \sum_{i=1}^{n} \frac{(y_{t,i} - \overline{y})(\hat{y}_{t,i} - \overline{\hat{y}})}{\sqrt{\sum_{t=t_0}^{t_1} (y_{t,i} - \overline{y})^2} \sqrt{\sum_{t=t_0}^{t_1} (\hat{y}_{t,i} - \overline{\hat{y}})^2}}$$ (16)

where $y$ and $\hat{y}$ is the ground truth and the predicted value. $\overline{y}$ denotes the mean of set $y$. For **RSE**, the lower the better, whereas for **CORR**, the higher the better.

**Detailed Experimental Settings**

**Base module**

The four state-of-art deep learning methods for comparison (CNN, GRU, LSTNet and Self Attention encoder). We introduce more details of models.

- **CNN**: Convolutional nerual network (Heaton 2018) designed to ensure only past information for forecasting. We use 7-layer CNN to do time series forecasting.
- **GRU + Attention**: GRU (Chung et al. 2014) had been used in time series forecasting and combined with attention to improve interpretability.
- **LSTNet**: LSTNet (Lai et al. 2018) is a model using CNN and RNN for multivariate time series forecasting. The architecture use convolutional network and the Recurrent Neural Network (RNN) to extract short-term local dependency patterns among variables and to discover long-term patterns for time series trends.
- **Self Attention encoder**: Transformer-based (Li et al. 2019) architecture has been modified for forecasting. We design a variant of Transformer with encoder-only structure which consists of $L$ blocks of multi-head self-attention layers and position-wise feed forward layers.
Hyperparameters

Since the model structure is universal for all methods, we adjust the same optimal hyperparameters on the training data. Firstly, we use the Adam (Kingma and Ba 2014) algorithm for the optimization with learning rate $10^{-4}$ and weight decay $10^{-3}$. For data preprocessing, we scale the data into the range $[0, 1]$ by batch normalization (Ioffe and Szegedy 2015) to avoid extreme values and improve the computation stability. The matrix norm of mask is set $p_0 = 2, 3$. Also, we set the $\lambda_1 = 10^{-3}$ and $\lambda_2 = 10^{-3}$ in $L_1$ and $L_2$. We select the batch size correspond the size of dataset.

Forecasting Visualization and Interpretation Features on More Datasets

Because the self attention encoder obtains most of the best performance result, we evaluate the forecasting results of self attention encoder visually in series saliency on total three datasets. As shown in Figure 8, our method gives accurate forecasts. Proposed model clearly yields better forecasts around the flat line after the peak and in the valley.

![Horizon=3](image1.png)

![Horizon=6](image2.png)

![Horizon=12](image3.png)

Figure 8: Prediction results for self-attention encoder in series saliency on air quality with horizon=3, 6, 12 and window size=64. The feature is the true hourly averaged concentration CO in $mg/m^3$.

Because the self attention encoder obtains most of the best performance result, we visualize the series saliency on the other datasets, including the air quality and industry stock composite index, for horizon=6. As shown in Figure 11 and Figure 12, we could analyze the series saliency and obtain global feature importance.
Figure 9: Prediction results for self-attention encoder in series saliency on electricity with horizon=3, 6, 12 and window size=168. The feature is power consumption of No.7 powerplant. The model learned the periodicity of electricity data.

Figure 10: Prediction results for self-attention encoder in series saliency on industry stock indices with horizon=3, 6, 12 and window size=64. The feature is No.1 stock indices of Hangseng Stock Composite Index.
Figure 11: Series saliency for self-attention encoder on industry stock indices with horizon=6 and window size=64. As shown in the Figure, the highlighted area corresponds to the dramatic change in the industry stock indices. The phenomenon shows that the stock indices influences the forecasting greatly.

Figure 12: Series saliency for self-attention encoder on air quality with horizon=6 and window size=64. The highlighted area corresponds that benzene increases sharply in air quality. As you known, benzene is harmful, which impacts air quality greatly.