Hyper Attention Recurrent Neural Network: Tackling Temporal Covariate Shift in Time Series Analysis

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Abstract

Analyzing long time series with RNNs often suffers from infeasible training. Segmentation is therefore commonly used in data pre-processing. However, in non-stationary time series, there exists often distribution shift among different segments. RNN is easily swamped in the dilemma of fitting bias in these segments due to the lack of global information, leading to poor generalization, known as Temporal Covariate Shift (TCS) problem, which is only addressed by a recently proposed RNN-based model. One of the assumptions in TCS is that the distribution of all divided intervals under the same segment are identical. This assumption, however, may not be true on high-frequency time series, such as traffic flow, that also have large stochasticity. Besides, macro information across long periods isn’t adequately considered in latest RNN-based methods. To address the above issues, we propose Hyper Attention Recurrent Neural Network (HARNN) for the modeling of temporal patterns containing both micro and macro information. An HARNN consists of a meta layer for parameter generation and an attention-enabled main layer for inference. High-frequency segments are transformed into low-frequency segments and fed into the meta layers, while the first main layer consumes the same time series segments as conventional methods. In this way, each low-frequency segment in the meta inputs generates a unique main layer, enabling the integration of both macro information and micro information for inference. This forces all main layers to predict the same target which fully harnesses the common knowledge in varied distributions when capturing temporal patterns. Evaluations on multiple benchmarks demonstrated that our model outperforms a couple of RNN-based methods on a federation of key metrics.

1 Introduction

Modern time series data collected in domains such as air quality monitoring [Zhang et al., 2017] and renewable energy production [Lee and Kim, 2019] often contain large amount of information spanning over long periods. The length of these time series often presents challenges for the training of modern RNN-based model, as the gradient back-propagation chain can get extremely long. Therefore, segmentation is commonly used as a necessary pre-processing step in order to reduce the length of the time series processed by RNNs during training.

However, simple segmentation of long time series may impose other problems, one of which is known as the distribution shift problem. As the statistical properties of a time series can vary with time, there exists often distribution shift among different segments. [Du et al., 2021] formulated this problem as the Temporal Covariate Shift (TCS) problem and proposed a novel RNN-based solution. One of the assumptions in TCS is that the distribution of all divided intervals under the same segment are identical. This assumption, however, may not be true on high-frequency time series, such as traffic flow, that also have large stochasticity.

Another problem is the lack of “big picture”: during training, a neural network almost never gets the chance to learn over the whole time span. Thus the large-scale macro information across long periods of time is often ignored, albeit RNN architectures like the LSTM possesses the potential to have “long-term memory”. This strongly limits the ability of RNN-based methods to capture the macro information, which can be very helpful in cases like air-quality prediction.

In order to tackle the above mentioned issues during time series analysis, we propose in this paper Hyper Attention Recurrent Neural Network (HARNN). An HARNN consists of a meta layer for parameter generation and an attention-enabled main layer for inference. High-frequency segments are transformed into low-frequency segments and fed into the meta layers, while the first main layer consumes the same time series segments as conventional methods. In this way, each low-frequency segment in the meta inputs generates an unique main layer processing a corresponding high-frequency segment, enabling the integration of both macro information and micro information for inference. This forces all main layers to predict the same target which fully harnesses the common knowledge in varied distributions when capturing temporal patterns. Evaluations on multiple benchmarks demonstrated that our model outperforms a couple of RNN-based methods on a federation of key metrics.
to predict the same target which fully harnesses the common knowledge in varied distributions across time.

Our main contributions and results are as follows.

- Without the requirement of the assumptions in TCS [Du \textit{et al.}, 2021] that the distribution of all divided intervals under the same segment are identical, HARNN is able to solve the distribution shift problem in a more practical scenario where high-frequency time series with large stochasticity requires a fine-grained processing approach. Combined with the ability of learning macro information over long time spans, HARNN provides state-of-the-art performance on time-series inference tasks.
- Evaluations on five real world datasets show that HARNN outperforms the state-of-the-art baselines on all datasets. Particularly, our model achieves a high performance on exceeding the latest model by 3.82% on air quality prediction.

2 Related Work

2.1 Deep Learning for Time Series Analysis

Due to the sequence learning power of Recurrent Neural Networks (RNNs)[Connor \textit{et al.}, 1992], Gated Recurrent Unit (GRU) and Long Short Term Memory (LSTM) have been popular for time series analysis. These rnn-based models model time series by combining CNNs, leveraging attention and seq2seq models[Lee and Kim, 2019; Lai \textit{et al.}, 2019; Yao \textit{et al.}, 2019; Le Guen and Thome, 2020; Salinas \textit{et al.}, 2020; Le Guen and Thome, 2019]. Another trend is to use transformer to model time series, \textit{e.g.}, informer[Zhou \textit{et al.}, 2021], which aims to model long sequence. More recently, the TCS is first defined in [Du \textit{et al.}, 2021], which is a more practical and challenging setting to model time series, and a novel ADARNN is proposed to tackle TCS problem. Unlike ADARNN, our model reduce TCS without the requirement of the assumption in ADARNN.

2.2 Hyper Networks

Hyper Networks were first introduced in [Ha \textit{et al.}, 2017], are networks that generate the weights for another network that computes specific tasks. Hyper Networks are often used in few-shot[Bertinetto \textit{et al.}, 2016] and continual learning tasks, and it is also introduced to efficient parameter fine-tuning of NLP tasks[Duan \textit{et al.}, 2021]. Dynamic neural networks, such as gating, attention, and hyper networks, were shown to extend standard DNNs[Galanti and Wolf, 2020]. However, to the best of our knowledge, no prior work studies general framework for time series via hyper networks from TCS problem perspective.

3 Our Method

In this section, Hyper Attention RNN (HARNN) is presented, it mainly consists of two modules:

- \textit{Meta layer}: a RNN unit for modeling macro information.
- \textit{Main layer}: another RNN unit with an attention layer for modeling micro information. The attention layer takes the state of the main layer at the current timestep and outputs of meta layer as inputs, outputs the next timestep parameters of the main layer.

HARNN is agnostic to the type of RNN, any recurrent networks can be used to construct it. Technically, the meta layer and main layer are the same type of RNN.

3.1 Inputs

Given a raw sequence $X = \{x_t\}_{t=1}^T$ and a sliding window with size $k$, \textit{step} = 1. We have the corresponding segments set $D = \{D_t\}_{t=k+1}^{T}$ by using the sliding window, where $D_t = \{x_t\}_{1}^{k+1}$. Then, We transform $D$ to $\overline{D}$ by:

$$
\overline{D}_t = \left\{ \frac{\sum_{i=0}^{N-1} x_{t+i} \cdot x_t}{N} \right\}_{t=1}^{T-k+1}
$$

where $(T - k + 1) \mod N = 0$. Let $x_i = \{x_{t+i}\}_{t=1}^l$ be a main input of length $l$. $D_{t-1}$ is the corresponding meta inputs since the main input $x_i$ should not see the future.

Obviously, the frequency of $D_{t-1}$ is lower than that of $x_i$. This allows HARNN to model temporal patterns from multi temporal view, the meta layer is expected to learn temporal pattern from macro view where the main layer can learn temporal pattern from micro view. Through our model, the two views are integrated via hyper networks.

3.2 Meta Layer

We first apply a bidirectional RNN as the meta layer. For each $D_t \in D$, it is fed into the meta layer to get the state sequence $h_t$, so we have a set of state sequences:

$$
H = \{h_t\}
$$

$$
h_t = \{h_{t, (i)}\}_{i=1}^{T} = \text{BiRNN}(\overline{D}_t)
$$

Each $h_t \in H$ can generate a set of weights for the main layer.
Meta Layer

Since the parameters of this RNN is dependent on the main layer output, we can obtain the corresponding meta inputs set $\overline{D}_{1:t-1}$. First, each $D_t \in \overline{D}_{1:t-1}$ is fed into the meta layer to generate the parameters of the main layer. So we have $|\overline{D}_{1:t-1}|$ number of main layers for prediction. Let $\hat{y}_t$ be the prediction of one main layer dependent on $\overline{D}_t$. Then, we can use an objective function (e.g., L2 loss function) to compute the corresponding loss $s_j$. Finally, we minimize the sum of these losses to optimize HARNN.

3.3 Main Layer

The main layer is another RNN unit with an attention layer. Since the parameters of this RNN is dependent on $D_t$, it is denoted as $\text{RNN}_{t}$, which takes the $x_t$ as input:

$$s_j^t = \text{RNN}_t(s_{j-1}^t, x_{t,(j)})$$

where $x_{t,(j)}$ is the value of the main input $x_t$ at timestep $j$, $s_j$ is the hidden state of RNN at timestep $j$. Specifically, the last hidden state $h_{t,(\overline{D}_t)}$ of $h_t$ is applied to compute the initialization state $s_0$ of RNN by following formula:

$$s_0 = W_{init}h_{t,(\overline{D}_t)} + b_{init}$$

We adopt attention mechanism to get the weighted representation of each time interval of the meta input $h_t$ and calculate the main-aware meta representation $z_j^t$ at timestep $j$. So for one meta input $D_t$, we have a set of representation $\{z_j^t\}_{j=1}^{|\overline{D}_t|}$. Formally, the representation $z_j^t$ is defined as:

$$z_j^t = W_c c_j$$

$$c_j^t = \sum_{i=1}^{l} \alpha_{ji} h_{t,(i)}$$

where $\alpha_{ji}$ is a score function, similar to Luong attention[Luong et al., 2015], the score function is given by:

$$\alpha_{ji} = \frac{\exp \text{score}(s_{j-1}^t, h_{t,(i)})}{\sum_{i=1}^{l} \exp \text{score}(s_{j-1}^t, h_{t,(i)})}$$

where $\text{score}(\cdot, \cdot)$ is a score function, similar to Luong attention[Luong et al., 2015], the score function is given by:

$$\text{score}(s_{j-1}^t, h_{t,(i)}) = V^T \tanh(W_s s_{j-1}^t + W_h h_{t,(i)} + b_s)$$

where $V$, $W_s$, $W_h$, and $b_s$ are learnable parameters. Then the weights of the main layer at timestep $j$ is controlled by $z_j^t$.

$$W_{1h} = W_{hz} z_j^t$$
$$W_{lx} = W_{xz} z_j^t$$
$$W_{lb} = W_{zb} z_j^t$$

We make following notes on the main layer:

1. Since the weights of the main layer are dependent on $z_j^t$, the macro information $h_t$ of meta layer is explicitly modeled and conveyed for prediction.

2. The historical sequential information $s_{j-1}^t$ generated by the main layer and $h_t$ jointly generates $z_j^t$. Thus, the main layer can dynamically adjust its parameters at each timestamp. Dynamic networks are effective in improving the representation of neural networks in various applications[Han et al., 2021].

Next, we will elaborate on how to generate the weights and the assignment of these weights for main layer. LSTM and GRU are the most popular variants of RNN in practice. Due to page limit, only the form of GRU-based main layer is given. The standard formulation of a GRU is given by:

$$r_t = \sigma(W_{rr} x_t + W_{hr} h_{t-1} + b_r)$$
$$z_t = \sigma(W_{rz} x_t + W_{hz} h_{t-1} + b_z)$$
$$n_t = \tanh(W_{rn} x_t + r_t \circ (W_{hn} h_{t-1} + b_n))$$
$$h_t = (1 - z_t) \circ n_t + z_t \circ h_{t-1}$$

As mentioned above, all the parameters of the Main Layer are generated by $W_{1h}$, $W_{lx}$, and $W_{lb}$:

$$(W_{ir}, W_{iz}, W_{in}) = \text{Chunk}(W_{1h})$$
$$(W_{hr}, W_{hz}, W_{hn}) = \text{Chunk}(W_{lx})$$
$$(b_r, b_z, b_n) = \text{Chunk}(W_{lb})$$
Chunk(·) is the operation to split a tensor into a specific number of equal-sized chunks.

### 3.4 Training

From Sec. 3.2 and Sec. 3.3, the output $h_t$ of the meta layer and the historical state $s_{i-1}^j$ jointly generate the main-aware meta representation $z_j^t$ at current timestep $j$, which generates the parameters for the main layer that takes $x_j$ as input. We implement the above HARNN via RNN units, i.e.,

$$s_j^t = \text{RNN}_4(x_{(i,j)}; z_j^t)$$ (10)

where $s_j^t$ is the fused representation of meta input $\hat{D}_k$ and the $j$-th element $x_{(i,j)}$ of main input $x_i$ for forecasting. As mentioned in Sec. 3.2, each meta input $\hat{D}_k \in \hat{D}$ has its corresponding main layer. So, we have:

$$L_{\text{pred}}(\theta) = \frac{1}{T-k+1} \sum_{t=k}^{T} \frac{1}{N} \sum_{j=1}^{l} \ell(y_{j}, \hat{y}_{j})$$ (11)

where $\phi$ is a predictor, e.g., a softmax layer for classification or a tanh function for regression. $\ell(\cdot, \cdot)$ is an objective function, and $\theta$ denotes the learnable parameters of our model.

### 4 Experiments

In this section, we evaluate our model on datasets detailed in Table 1, among which UCI smartphone activity, Air-quality and Electric power datasets are general time series, while NYC-Taxi[NYC, 2017a] and NYC-Bike[NYC, 2017b] belong to spatio-temporal data, a special kind of time series that needs take spatial dependency into account. Correspondingly, experiments on general time series and spatio-temporal data are implemented separately with different settings.

#### 4.1 General Time Series

The performance between GRU-based HARNN and LSTM-based RNN is very close, but GRU-based HARNN has fewer parameters and is mainly used in this subsection.

### Baselines

- LightGBM[Ke et al., 2017]: a lighter and more efficient Gradient Boosting Decision Tree.
- MMD-RNN: an MMD-based[Wang et al., 2018; Li et al., 2018] RNN implemented in [Du et al., 2021].
- DANN-RNN: a popular domain adversarial training method[Yu et al., 2019] implemented in RNN by [Du et al., 2021].
- LSTNet[Lai et al., 2018]: a method combining CNN and LSTM to learn long- and short-term temporal patterns.
- STRIPE[Le Guen and Thome, 2020]: an encoder-decoder model with a diversification mechanism relying on a specific determinantal point processes.
- ADARNN[Du et al., 2021]: an adaptive model first introduced for TCS problem.
convert traffic flow value to about 10 km

NYC is split into gridded regions and each region contains trip records, as detailed follows. New York City (NYC) is split into regular gridded regions. New York City Taxi and NYC-Bike are popular datasets for analysis of spatio-temporal data to further verify effectiveness of HARNN.

In this subsection, we conduct experiments on spatio-temporal datasets, they are not applicable to this dataset. It’s obvious that HARNN achieves the best performance on all evaluation metrics. Compared with ADARNN, HARNN outperforms with 1.32% increase on ACC and 1.04% increase on F1 score.

4.2 Traffic prediction

In this subsection, we conduct experiments on spatio-temporal data to further verify effectiveness of HARNN.

Datasets

NYC-Taxi and NYC-Bike are popular datasets for analysis of spatio-temporal data in regular gridded regions. New York City (NYC) is split into gridded regions and each region contains trip records, as detailed follows.

• NYC-Taxi: NYC-Taxi contains 22,349,490 taxi trip records of NYC from 01/01/2015 to 03/01/2015. The first 40 days are used as training set.

• NYC-Bike: NYC-Bike contains 2,605,648 bike trip records of NYC from 07/01/2016 to 08/29/2016. The first 40 days are used as training set.

Settings

NYC is split into 10 × 20 regions, the size of each region is about 1km × 1km. The Min-Max normalization is used to convert traffic flow value to [0, 1] scale. The time interval is set as half-hour. We set \( k = 1344 \) (four weeks), \( N = 48 \) (one day) for meta inputs, and \( l = 7 \) for main input.

Baselines

Analysis of spatio-temporal data requires consideration of space patterns and temporal patterns. However, HARNN is an RNN-based method which focuses on learning temporal patterns. Thus, we compare HARNN with models that use RNN to model time patterns. Since HARNN has no spatial component, we adapt HARNN to spatio-temporal dataset analysis by replacing the temporal component of baselines with HARNN.

• ConvLSTM: an extension of LSTM uses convolution operators to build cell. To compare with ConvLSTM, we use two ConvLSTM units to construct HARNN.

• DMVST-Net [Yao et al., 2018]: it takes the advantage of CNN and LSTM in a joint model that captures the complex relations from both spatial and temporal perspectives. To compare with DMVST-Net, We use LSTM-Based HARNN to replace the LSTM unit in it.

• STDN [Yao et al., 2019]: it designs a periodically shifted attention mechanism to capture long-term dependency and applied LSTM to learn short-term dependency. To compare with STDN, We use LSTM-based HARNN to replace its temporal component.

Results

Table 4 summarizes the pickup and pickoff RMSE and MAPE of different models without and with HARNN. For the same competing methods, the pickup RMSE reduces by 3.49% to 6.27% on NYC-Taxi and by 5.54% to 8.13% on NYC-Bike, and the pickoff RMSE reduces by 2.73% to 6.73% on NYC-Taxi and by 6.23% to 6.50% on NYC-Bike. For all the two datasets, the highest performance is achieved when the temporal component of baselines is replaced with HARNN. These demonstrates the effectiveness of modeling temporal patterns with hyper networks.

5 Analysis

5.1 Effect of Meta Input Length

The length of meta input (determined by \( k \)) is an important hyper-parameter, we investigate the effect of varying the length in HARNN on NYC-Taxi and NYC-Bike. We see that when \( |D_k| < 6 \), the performance is increasing with the increment of \( |D_k| \), but degraded when \( |D_k| > 160 \). One potential

| Method      | ACC  | P    | R    | F1   |
|-------------|------|------|------|------|
| LightGBM    | 84.11| 83.73| 83.63| 84.91|
| GRU         | 85.68| 85.62| 85.51| 85.46|
| MMD-RNN     | 86.39| 86.80| 86.26| 86.38|
| DANN-RNN    | 85.88| 85.59| 85.62| 85.56|
| ADARNN      | 88.44| 88.71| 88.59| 88.63|
| HARNN(ours) | 89.61| 89.64| 89.45| 89.43|

Table 3: Performance of UCI smartphone activity classification

Table 2: Performance of Air-quality and Electric Power.

| Method      | (RMSE/MAE) | (RMSE/MAE) | (RMSE/MAE) | (RMSE/MAE) | Electric Power |
|-------------|------------|------------|------------|------------|---------------|
| LSTNet      | 0.0544/0.0651 | 0.0519/0.0651 | 0.0548/0.0696 | 0.0599/0.0705 | 0.080 |
| MMD-RNN     | 0.0360/0.0267 | 0.0183/0.0133 | 0.0267/0.0197 | 0.0288/0.0168 | 0.082 |
| DANN-RNN    | 0.0356/0.0255 | 0.0214/0.0157 | 0.0274/0.0203 | 0.0291/0.0211 | 0.080 |
| STRIPE      | 0.0365/0.0216 | 0.0204/0.0148 | 0.0248/0.0154 | 0.0304/0.0139 | 0.086 |
| ADARNN      | 0.0295/0.0185 | 0.0164/0.0122 | 0.0196/0.0122 | 0.0233/0.0150 | 0.077 |
| HARNN(ours) | 0.0285/0.0182 | 0.0156/0.0111 | 0.0184/0.0119 | 0.0229/0.0138 | 0.075 |

Table 2: Performance of Air-quality and Electric Power.
Table 4: HARNN adapted for spatio-temporal data.

| Dataset | Method   | pickup RMSE | MAPE | pickoff RMSE | MAPE |
|---------|----------|-------------|------|--------------|------|
| NYC-Taxi | ConvLSTM | 28.13/20.50 |      | 23.67/20.70  |      |
|         | DMVST-Net| 25.74/17.38 |      | 20.51/17.14  |      |
|         | STDN     | 24.10/16.30 |      | 19.05/16.25  |      |
|         | w/HARNN  | 26.45/19.41 |      | 22.15/29.64  |      |
|         | w/HARNN  | 24.22/16.59 |      | 19.13/16.53  |      |
|         | w/HARNN  | 23.26/15.74 |      | 18.53/16.26  |      |

| NYC-Bike | ConvLSTM | 10.40/25.10 |      | 9.22/23.20   |      |
|          | DMVST-Net| 9.14/22.20  |      | 8.50/21.56   |      |
|          | STDN     | 8.85/21.84  |      | 8.15/20.87   |      |
|          | w/HARNN  | 9.73/25.10  |      | 8.64/21.82   |      |
|          | w/HARNN  | 8.66/23.91  |      | 7.97/20.45   |      |
|          | w/HARNN  | 8.13/21.23  |      | 7.62/19.97   |      |

Figure 3: Effect of varying meta input length on model performance.

reason is that the distribution of a very short segment is unavailable for learning temporal patterns and the length is too long to optimize when $|D_t| > 160$. By varying the length from 6 to 160, the variance range of RMSE on both datasets is rather small, indicating a richer temporal information of meta segments doesn’t always bring gain to model performance. This might be explained by the training manner of our model. HARNN enforces all segments of meta inputs to generate parameters for one main input prediction. Thus, regardless of the meta input length, HARNN can always use macro information across time to make predictions, due to the common knowledge sharing ability of hyper networks [Galanti and Wolf, 2020; Le Guen and Thome, 2019]. This results also show the robustness of HARNN since it is insensitive to meta input length.

5.2 Visual Analysis

We conduct visual analysis on air quality prediction since this dataset contains four station, providing rich information. For each station, a mini-batch with 128 segments from meta input and one instance from main inputs are sampled. Let $|D_t|$ be the original embedding of a segment and $\{z_j\}_{j=1}^{|D_t|}$ be the corresponding learned embedding for the specific main input, which is calculated as in (5). We visualize the distribution of all mini-batch by t-SNE [Laurens and Hinton, 2008]. From Figure 4, we observe that the original distributions of embeddings are random while the learned distributions on all four stations can be approximately fitted by a linear model, indicating that common knowledge among all meta inputs has been learned by HARNN. From an other perspective, similar to batchnorm that tackles the internal covariate shift problem [Ioffe and Szegedy, 2015], HARNN can be regarded as a normalization which reduces TCS.

Figure 4: The left parts (a, c, e, g) present the original distribution visualization of four stations, and the right parts (b, d, f, h) present the learned distribution visualization of four stations, one scatter represents a segment in meta inputs.

6 Conclusion

This paper proposed HARNN, a general framework for time series to tackle TCS. HARNN enable the integration of both macro information and micro information for inference via hyper networks. It also forces all main layers to predict the same target which fully harnesses the common knowledge in varied distributions across time, reducing TCS. Extensive experiments show its effectiveness in five datasets. One future direction of our work is to explore extension of HARNN to TCN and Transformer, proving that HARNN is agnostic to network structures.
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