A Dual-Stage Attention-Based Recurrent Neural Network for Time Series Prediction

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Abstract

The Nonlinear autoregressive exogenous (NARX) model, which predicts the current value of a time series based upon its previous values as well as the current and past values of multiple driving (exogenous) series, has been studied for decades. Despite the fact that various NARX models have been developed, few of them can capture the long-term temporal dependencies appropriately and select the relevant driving series to make predictions. In this paper, we propose a dual-stage attention based recurrent neural network (DA-RNN) to address these two issues. In the first stage, we introduce an input attention mechanism to adaptively extract relevant driving series (a.k.a., input features) at each timestamp by referring to the previous encoder hidden state. In the second stage, we use a temporal attention mechanism to select relevant encoder hidden states across all the timestamps. With this dual-stage attention scheme, our model can not only make prediction effectively, but can also be easily interpreted. Thorough empirical studies based upon the SML 2010 dataset and the NASDAQ 100 Stock dataset demonstrate that DA-RNN can outperform state-of-the-art methods for time series prediction.

1 Introduction

Time series prediction algorithms have been widely applied in many areas, e.g., financial market prediction [Wu et al., 2013], weather forecasting [Chakraborty et al., 2012], and complex dynamical system analysis [Liu and Hauskrecht, 2015]. Although the well-known autoregressive moving average (ARMA) model [Whittle, 1951] and its variants [Thiesson et al., 2004] [Brockwell and Davis, 2009] have shown their effectiveness for various real world applications, they cannot model nonlinear relationships and do not differentiate among the exogenous (driving) input terms. To address this issue, various nonlinear autoregressive exogenous (NARX) models [Lin et al., 1996] [Siegelmann et al., 1997] [Gao and Er, 2005] [Diaconescu, 2008] [Yan et al., 2013] have been developed. Typically, given the previous values of the target series, \(i.e., (y_1, y_2, \ldots, y_{T-1})\) with \(y_t \in \mathbb{R}\) where \(T\) is the length of the sequence, as well as the current and past values of \(n\) driving (exogenous) series, \(i.e., (x_1, x_2, \ldots, x_{T'})\) with \(x_t \in \mathbb{R}^n\), the NARX model aims to learn a nonlinear mapping to the current value of target series \(y_T\), \(i.e., \hat{y}_T = F(y_1, y_2, \ldots, y_{T-1}, x_1, x_2, \ldots, x_{T'})\), where \(F(\cdot)\) is the mapping function to learn.

Despite the fact that a substantial effort has been made for time series prediction via kernel methods [Chen et al., 2008], ensemble methods [Bouchachia and Bouchachia, 2008], and Gaussian processes [Frigola and Rasmussen, 2014], the drawback is that most of these approaches employ a predefined nonlinear form and may not be able to capture the true underlying nonlinear relationship appropriately. Recurrent neural networks (RNNs) [Rumelhart et al., 1986] [Werbos, 1990] [Elman, 1991], a type of deep neural network specially designed for sequence modeling, have received a great amount of attention due to their flexibility in capturing nonlinear relationships. In particular, RNNs have shown their success in NARX time series forecasting in recent years [Gao and Er, 2005] [Diaconescu, 2008]. Traditional RNNs, however, suffer from the problem of vanishing gradients [Bengio et al., 1994] and thus have difficulty capturing long-term dependencies.

Recently, long short-term memory units (LSTM) [Hochreiter and Schmidhuber, 1997] and the gated recurrent unit (GRU) [Cho et al., 2014b] have overcome this limitation and achieved great success in various applications, e.g., neural machine translation [Bahdanau et al., 2014], speech recognition [Graves et al., 2013], and image processing [Karpathy and Li, 2015]. Therefore, it is natural to consider state-of-the-art RNN methods, e.g., encoder-decoder networks [Cho et al., 2014b] [Sutskever et al., 2014] and attention based encoder-decoder networks [Bahdanau et al., 2014], to perform NARX modeling for time series prediction.

Based upon LSTM or GRU units, encoder-decoder networks [Kalchbrenner and Blunsom, 2013] [Cho et al., 2014a] [Cho et al., 2014b] [Sutskever et al., 2014] have become popular due to their success in machine translation. The key idea is to encode the source sentence as a fixed-length vector and use the decoder to generate a translation. One problem with encoder-decoder networks is that their performance will deteriorate rapidly as the length of input sequence increases [Cho et al., 2014a]. In time series analysis, this could be a concern since we usually expect to make predictions based upon a relatively long segment of the target
series as well as driving series. To resolve this issue, the attention-based encoder-decoder network [Bahdanau et al., 2014] employs an attention mechanism to select parts of hidden states across all the timestamps. Recently, a hierarchical attention network [Yang et al., 2016], which uses two layers of attention mechanism to select relevant encoder hidden states across all the timestamps, was also developed. Although attention-based encoder-decoder networks and hierarchical attention networks have shown their efficacy for machine translation, image captioning [Xu et al., 2015], and document classification, they may not be suitable for time series prediction. This is because when multiple driving (exogenous) series are available, the network cannot explicitly select relevant driving series to make predictions. In addition, they have mainly been used for classification, rather than time series prediction.

To address these aforementioned issues, and inspired by some theories of human attention [Hübner et al., 2010] that human behavior is well-modeled by a two-stage attention mechanism, we propose a novel dual-stage attention-based recurrent neural network (DA-RNN) to perform time series prediction. In the first stage, we develop a new attention mechanism to adaptively extract the relevant driving series at each timestamp by referring to the previous encoder hidden state. In the second stage, a temporal attention mechanism is used to select relevant encoder hidden states across all timestamps. These two attention models are well integrated within an LSTM-based recurrent neural network (RNN) and can be jointly trained using standard back propagation. In this way, the DA-RNN can adaptively select the most relevant input features as well as capture the long-term temporal dependencies of a time series appropriately. To justify the effectiveness of the DA-RNN, we compare it with state-of-the-art approaches using the SML 2010 dataset and the NASDAQ 100 Stock dataset with a large number of driving series. Extensive experiments not only demonstrate the effectiveness of the proposed approach, but also show that the DA-RNN is easy to interpret, and robust to noisy input.

2 Dual-Stage Attention based RNN

In this section, we first introduce the notation we use in this work and the problem we aim to study. Then, we present the motivation and details of the DA-RNN for time series prediction.

2.1 Notation and Problem Statement

Given \( n \) driving (exogenous) series of length \( T \), i.e., \( X = (x^1, x^2, \ldots, x^n) \in \mathbb{R}^{n \times T} \), we use \( x^k = (x^k_1, x^k_2, \ldots, x^k_T) \in \mathbb{R}^T \) to represent a driving series of length \( T \) and employ \( x_t = (x^1_t, x^2_t, \ldots, x^n_t) \in \mathbb{R}^n \) to denote a vector of \( n \) exogenous (driving) input series at time \( t \).

Typically, given the previous values of the target series, i.e., \((y_1, y_2, \cdots, y_{T-1})\) with \( y_t \in \mathbb{R} \), as well as the current and past values of \( n \) driving (exogenous) series, i.e., \((x^1_t, x^2_t, \cdots, x^n_t)\) with \( x^k_t \in \mathbb{R}^n \), the NARX model aims to learn a nonlinear mapping to the current value of the target series \( y_T \), given a sliding window of length \( T \):

\[
\hat{y}_T = F(y_1, \ldots, y_{T-1}, x^1_t, \ldots, x^n_t),
\]

where \( F(\cdot) \) is a nonlinear mapping function we aim to learn.

2.2 Model

Some theories of human attention [Hübner et al., 2010] argue that behavioral results are best modeled by a two-stage attention mechanism. The first stage selects the elementary stimulus features while the second stage uses categorical information to decode the stimulus. Inspired by these theories, we propose a novel dual-stage attention-based recurrent neural network (DA-RNN) to perform NARX modeling for time series prediction. In the encoder, we introduce a novel input attention mechanism that can adaptively select the relevant driving series (a.k.a., input features). In the decoder, a temporal attention mechanism is used to automatically select relevant encoder hidden states across all timestamps. For the objective, a square loss is used. With these two attention mechanisms, the DA-RNN can adaptively select the most relevant input features and capture the long-term temporal dependencies of a time series. A graphical illustration of the proposed model is shown in Figure 1.

Encoder with Input Attention

The encoder is essentially an RNN that encodes the input sequences into a feature representation in machine translation [Cho et al., 2014b] or gated recurrent unit (GRU) [Cho et al., 2014b]. For time series prediction, given the input sequence \( X = \langle x_1, x_2, \cdots, x_T \rangle \) with \( x_t \in \mathbb{R}^n \), where \( n \) is the number of driving (exogenous) series, the encoder can be applied to learn a mapping from \( x_t \) to \( h_t \) (at time step \( t \)) with

\[
h_t = f_1(x_t, h_{t-1}),
\]

where \( h_t \in \mathbb{R}^m \) is the hidden state of the encoder at time \( t \), \( m \) is the size of hidden state, and \( f_1 \) is a non-linear activation function that could be an LSTM [Hochreiter and Schmidhuber, 1997] or gated recurrent unit (GRU) [Cho et al., 2014b].

Inspired by the theory that the human attention system can select elementary stimulus features in the early stages of processing [Hübner et al., 2010], we propose an input attention-based encoder that can adaptively select the relevant driving series, which is of practical meaning in time series prediction.

Given the \( k \)-th input driving series \( x^k = (x^k_1, x^k_2, \cdots, x^k_T) \in \mathbb{R}^T \), we can construct an input attention mechanism via a deterministic attention model, i.e., a multilayer perceptron, by referring to the previous hidden state \( h_{t-1} \) in the encoder with

\[
e^k_t = v^k_t \tanh(W v h_{t-1} + U x^k_t)
\]

and

\[
\alpha^k_t = \frac{\exp(e^k_t)}{\sum_{i=1}^n \exp(e^i_t)}
\]

where \( v^k_t \in \mathbb{R}^T, W^k_t \in \mathbb{R}^{T \times m} \) and \( U_x \in \mathbb{R}^{T \times T} \) are parameters to learn. \( \alpha^k_t \) is the attention weight measuring the importance of the \( k \)-th input features (driving series) at time \( t \). A softmax function is applied to \( e^k_t \) to ensure the sum of \( \alpha^k_t \) equals to 1. The input attention mechanism is a feed forward network that can be jointly trained with other components of the RNN. With these attention weights, we can adaptively extract the driving series with

\[
\tilde{x}_t = (\alpha^1_t x^1_t, \alpha^2_t x^2_t, \cdots, \alpha^n_t x^n_t) \in \mathbb{R}^n.
\]
Then the hidden state at time $t$ can be updated as

$$h_t = f_1(\tilde{x}_t; h_{t-1}),$$  \hspace{1cm} (6)

where we choose the nonlinear function $f_1$ as an LSTM unit [Sutskever et al., 2014], which have been widely used in modeling long-term dependencies. With the proposed input attention mechanism, the encoder can selectively focus on certain driving series rather than treating all the input driving series equally.

**Decoder with Temporal Attention**

To predict the output $\hat{y}_T$, we use another recurrent neural network to decode the encoded input information. However, as suggested by Cho et al. (2014a), the performance of encoder-decoder network can deteriorate rapidly as the length of input sequence increases. Therefore, following the encoder with input attention, a temporal attention mechanism is used in the decoder to adaptively select relevant encoder hidden states across all the timestamps. Specifically, the attention weight of each encoder hidden state at time $t$ is calculated based upon the previous decoder hidden state $d_{t-1}$ with

$$l_i^t = v_d^T \tanh(W_d d_{t-1} + U_d h_i), \quad 1 \leq i \leq T,$$  \hspace{1cm} (7)

and

$$\beta_i^t = \frac{\exp(l_i^t)}{\sum_{j=1}^{T} \exp(l_j^t)},$$  \hspace{1cm} (8)

where $v_d \in \mathbb{R}^p$, $W_d \in \mathbb{R}^{p \times p}$ and $U_d \in \mathbb{R}^{p \times m}$ are parameters to learn. The attention weight $\beta_i^t$ represents the importance of $i$-th encoder hidden state for the prediction at time $t$. Since each encoder hidden state $h_i$ is mapped to a temporal component of the input, the attention mechanism computes the context vector $c_t$ as a weighted sum of all the encoder hidden states $\{h_1, h_2, \cdots, h_T\}$,

$$c_t = \sum_{i=1}^{T} \beta_i^t h_i.$$  \hspace{1cm} (9)

Note that the context vector $c_t$ is distinct at each timestamp.

Once we get the weighted summed context vector, the decoder hidden state can be computed with

$$d_t = f_2(d_{t-1}, y_{T-1}, c_t),$$  \hspace{1cm} (10)

where $f_2$ denotes a LSTM unit.

For NARX modeling, we aim to use the DA-RNN to approximate the function $F$ so as to obtain an estimate of the current output $\hat{y}_T$ with the observation of all inputs as well as previous outputs. Specifically, $\hat{y}_T$ can be obtained with

$$\hat{y}_T = F(y_1, \cdots, y_{T-1}, x_1, \cdots, x_T) = v_c^T (W_c [d_T; c_T] + b_w) + b_v,$$  \hspace{1cm} (11)

where $[d_T; c_T] \in \mathbb{R}^{p+m}$ is a concatenation of the decoder hidden state and the context vector. The parameters $W_c \in \mathbb{R}^{p \times (p+m)}$ and $b_w \in \mathbb{R}^p$ maps the concatenation to the size of the decoder hidden states. The linear function with weights $v_c \in \mathbb{R}^p$ and bias $b_v \in \mathbb{R}$ produces the final prediction result.

**Training Procedure**

We use minibatch stochastic gradient descent (SGD) together with the Adam optimizer [Kingma and Ba, 2014] to train the model. The size of the minibatch is 128. The learning rate starts from 0.001 and is reduced by 10% after each 10000 iterations. The proposed DA-RNN is smooth and differentiable, so the parameters can be learned by standard back propagation with the objective function as mean squared error:

<table>
<thead>
<tr>
<th>Dataset</th>
<th>driving series</th>
<th>size</th>
</tr>
</thead>
<tbody>
<tr>
<td>SML 2010</td>
<td>16</td>
<td>3,200, 400, 537</td>
</tr>
<tr>
<td>NASDAQ 100 Stock</td>
<td>81</td>
<td>35,100, 2,730, 2,730</td>
</tr>
</tbody>
</table>
Table 2: Time series prediction results over the SML 2010 Dataset (best performance displayed in boldface). The size of encoder hidden states \( m \) and the size of decoder hidden states \( p \) are set as \( m = p = 64 \) and 128.

<table>
<thead>
<tr>
<th>Models</th>
<th>SML 2010 Dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAE ((10^{-2}))</td>
</tr>
<tr>
<td>ARIMA [2011]</td>
<td>1.95</td>
</tr>
<tr>
<td>NARX RNN [2008]</td>
<td>1.79±0.07</td>
</tr>
<tr>
<td>Enc-Dec (64) [2014b]</td>
<td>2.59±0.07</td>
</tr>
<tr>
<td>Enc-Dec (128) [2014b]</td>
<td>1.91±0.02</td>
</tr>
<tr>
<td>Attention RNN (64) [2014]</td>
<td>1.78±0.03</td>
</tr>
<tr>
<td>Attention RNN (128) [2014]</td>
<td>1.77±0.02</td>
</tr>
<tr>
<td>Input-Attn-RNN (64)</td>
<td>1.88±0.04</td>
</tr>
<tr>
<td>Input-Attn-RNN (128)</td>
<td>1.70±0.03</td>
</tr>
<tr>
<td>DA-RNN (64)</td>
<td>1.53±0.01</td>
</tr>
<tr>
<td>DA-RNN (128)</td>
<td><strong>1.50±0.01</strong></td>
</tr>
</tbody>
</table>

\[
\mathcal{O}(y_T, \hat{y}_T) = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i^T - y_T^i)^2, \quad (12)
\]

where \( N \) is the number of training samples.

We implemented the DA-RNN in the Tensorflow framework [Abadi et al., 2015] and the source code will be made publicly available.

3 Experiments

In this section, we first describe two datasets for empirical studies. Then, we introduce the parameter settings of DA-RNN and the evaluation metrics. Finally, we compare the proposed DA-RNN against four different baseline methods, interpret the input attention as well as the temporal attention of DA-RNN, and study its the parameter sensitivity.

3.1 Datasets and Setup

To test the performance of different methods for time series prediction, we use two different datasets as shown in Table 1.

SML 2010 dataset is a public dataset used for indoor temperature forecasting. This dataset is collected from a monitor system mounted in a domestic house. We use room temperature as the target series and select 16 relevant driving series which contains approximately 40 days of monitoring data. The data was sampled every minute and was smoothed with 15 minute means. In our experiment, we use the first 3200 data points as the training set, the following 400 data points as the validation set, and the last 537 data points as the test set.

In NASDAQ 100 Stock dataset, we collect the stock prices of 81 major corporations under NASDAQ 100, which are used as the driving time series. The index value of NASDAQ 100 is used as the target series. The frequency of the data collection is one-minute. This data covers the period from July 26, 2016 to December 26, 2016, in total 104 days. Each day contains 390 data points from the opening to closing of the market. In our experiments, we use the first 90 days as the training set and the following seven days as the validation set. The data in the last seven days is used as the test set. This dataset will be publicly available and will be continuously enlarged to aid the research in this direction.

3.2 Parameter Settings and Evaluation Metrics

There are three parameters in the DA-RNN, \( i.e., \) the length of timestamps \( T \), the size of hidden states for encoder \( m \), and the size of hidden states for decoder \( p \). To determine the length of timestamps \( T \), we conduct grid search over \( T \in \{3, 5, 10, 15, 25\} \). The one \((T = 10)\) that achieves the best performance over validation set is used for test. For the
Table 3: Time series prediction results over the NASDAQ 100 Stock Dataset (best performance displayed in **boldface**). The size of encoder hidden states \( m \) and the size of decoder hidden states \( p \) are set as \( m = p = 64 \) and 128.

<table>
<thead>
<tr>
<th>Models</th>
<th>MAE</th>
<th>MAPE ( \times 10^{-2}% )</th>
<th>RMSE</th>
<th># of Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA [2011]</td>
<td>0.91</td>
<td>1.84</td>
<td>1.45</td>
<td>38</td>
</tr>
<tr>
<td>NARX RNN [2008]</td>
<td>0.75±0.09</td>
<td>1.51±0.17</td>
<td>0.98±0.10</td>
<td>12,929</td>
</tr>
<tr>
<td>Enc-Dec (64) [2014b]</td>
<td>0.97±0.06</td>
<td>1.96±0.12</td>
<td>1.27±0.05</td>
<td>38,721</td>
</tr>
<tr>
<td>Enc-Dec (128) [2014b]</td>
<td>0.72±0.03</td>
<td>1.46±0.06</td>
<td>1.00±0.03</td>
<td>110,209</td>
</tr>
<tr>
<td>Attention RNN (64) [2014]</td>
<td>0.76±0.08</td>
<td>1.54±0.02</td>
<td>1.00±0.09</td>
<td>46,977</td>
</tr>
<tr>
<td>Attention RNN (128) [2014]</td>
<td>0.71±0.05</td>
<td>1.43±0.09</td>
<td>0.96±0.05</td>
<td>143,105</td>
</tr>
<tr>
<td>Input-Attn-RNN (64)</td>
<td>0.28±0.02</td>
<td>0.57±0.04</td>
<td>0.41±0.03</td>
<td>39,471</td>
</tr>
<tr>
<td>Input-Attn-RNN (128)</td>
<td>0.26±0.02</td>
<td>0.53±0.03</td>
<td>0.39±0.03</td>
<td>115,599</td>
</tr>
<tr>
<td>DA-RNN (64)</td>
<td>0.21±0.002</td>
<td>0.43±0.005</td>
<td>0.31±0.003</td>
<td>47,727</td>
</tr>
<tr>
<td>DA-RNN (128)</td>
<td>0.22±0.002</td>
<td>0.45±0.005</td>
<td>0.33±0.003</td>
<td>144,495</td>
</tr>
</tbody>
</table>

The time series prediction results of DA-RNN and baseline methods over the two datasets are shown in Table 2 and Table 3. Note that although we employ three different evaluation metrics to quantify the effectiveness of different methods, they all use mean squared error as the objective to learn model parameters. Therefore, RMSE is directly related to model performance, while the other two measures are provided for reference.

In Table 2 and Table 3 we observe that the RMSE of ARIMA is generally worse than RNN based approaches. This is because ARIMA only considers the target series \( \{y_1, \ldots, y_t\} \) and ignores the driving series \( \{x_1, \ldots, x_t\} \). For RNN based approaches, the performance of NARX RNN and Encoder-Decoder are comparable. Attention RNN generally outperforms Encoder-Decoder since it is capable to select relevant hidden states across all the timestamps in the encoder. Within DA-RNN, the input attention RNN (Input-Attn-RNN (128)) consistently outperforms Encoder-Decoder as well as Attention RNN. This suggests that adaptively extracting driving series can provide more reliable input features to make accurate predictions. Also, it should be noted that the number of parameters in the input attention mechanism is relatively small compared to the number of parameters.

3.3 Results-I: Time Series Prediction

To demonstrate the effectiveness of the DA-RNN, we compare it against 4 baseline methods. Among them, the autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model [Asteriou and Hall, 2014]. NARX recurrent neural network (NARX RNN) is a classic method to address NARX problem [Diaconescu, 2008]. We also modify the encoder-decoder network (Encoder-Decoder) [Cho et al., 2014b] and attention-based encoder-decoder network (Attention RNN) [Bahdanau et al., 2014] such that they can be used for time series prediction. Furthermore, we show the effectiveness of DA-RNN via step-by-step justification. Specifically, we compare dual-stage attention based recurrent neural network (DA-RNN) against the setting that only employs its input attention mechanism (Input-Attn-RNN).

The first 81 weights are on 81 original driving series and the last 81 weights are on 81 noisy driving series. (a) Input attention weights on NASDAQ100 training set. (b) Input attention weights on NASDAQ100 test set.

Figure 3: Plot of the input attention weights for DA-RNN. The first 81 weights are on 81 original driving series and the last 81 weights are on 81 noisy driving series. (a) Input attention weights on NASDAQ100 training set. (b) Input attention weights on NASDAQ100 test set.
ners in the LSTM units. With integration of the input attention mechanism as well as temporal attention mechanism, our DA-RNN achieves the best MAE, MAPE, and RMSE across two datasets since it not only uses an input attention mechanism to extract relevant driving series, but also employs a temporal attention mechanism to select relevant hidden features across all timestamps.

For visual comparison, we show the prediction result of Encoder-Decoder \((m = p = 128)\), Attention RNN \((m = p = 128)\) and DA-RNN \((m = p = 64)\) over the NASDAQ 100 Stock dataset in Figure 4. We observe that DA-RNN generally fits the ground truth much better than Encoder-Decoder and Attention RNN.

3.4 Results-II: Interpretation

To study the effectiveness of the input attention mechanism within DA-RNN, we test it with noisy driving (exogenous) series as the input. Specifically, within NASDAQ 100 Stock dataset, we random generate 81 additional noisy driving series by random permuting the original 81 driving series. Then, we put these 81 noisy driving series together with the 81 original driving series as the input and test the effectiveness of DA-RNN. When the length of timestamps \(T\) is 10 and the size of hidden states is \(m = p = 128\), DA-RNN achieves MAE \(0.28 \pm 0.007\), MAPE \((0.56 \pm 0.01) \times 10^{-2}\) and RMSE \(0.42 \pm 0.009\), which are comparable to its performance in Table 3. This indicates that DA-RNN is robust to noisy input.

To further investigate the input attention mechanism, we plot the input attention weights of DA-RNN for the 162 input driving series (the first 81 are original and the last 81 are noisy) in Figure 3. We observe that the input attention mechanism can automatically put larger weights to the 81 original driving series and put smaller weights to the 81 noisy driving series. This demonstrates that input attention mechanism can aid DA-RNN to select relevant input driving series and suppress noisy input driving series.

To investigate the effectiveness of the temporal attention mechanism within DA-RNN, we compare DA-RNN to input attention based RNN (Input-Attn-RNN) when the length of timestamps \(T\) varies from 3, 5, 10, 15, to 25. The detailed results over two datasets are shown in Figure 4. We observe that when \(T\) is relatively large, DA-RNN can significantly outperform input attention based RNN (Input-Attn-RNN). This suggests that temporal attention mechanism can capture long-term dependencies by selecting relevant encoder hidden states across all the timestamps.

3.5 Results-III: Parameter Sensitivity

We study the sensitivity of DA-RNN with respect to its parameters, i.e., the length of timestamps \(T\) and the size of hidden states for encoder \(m\) (decoder \(p\)). When we vary \(T\) or \(m\) (\(p\)), we keep the other fixed. By setting \(m = p = 128\), we plot the RMSE versus different lengths of timestamps \(T\) in Figure 4. It is easily observed that the performance of DA-RNN and input attention RNN (Input-Attn-RNN) will be worse when the length of timestamps is too short or too long while DA-RNN is relatively more robust to input attention RNN. By setting \(T = 10\), we also plot the RMSE versus different sizes of hidden states for encoder and decoder \((m = p \in \{16, 32, 64, 128, 256\})\) in Figure 5. We notice that DA-RNN usually achieves the best performance when \(m = p = 64\) or 128. Moreover, we can also conclude that DA-RNN is more robust to parameters than input attention RNN (Input-Attn-RNN).

4 Conclusion

In this paper, we proposed a novel dual-stage attention based recurrent neural network (DA-RNN), which consists of an encoder with an input attention mechanism and a decoder with a temporal attention mechanism. The newly introduced input attention mechanism can adaptively select the relevant driving series. The temporal attention mechanism can naturally capture the long-range temporal information of the encoded inputs. Based upon these two attention mechanisms, the DA-RNN can not only adaptively select the most relevant input features, but can also capture the long-term temporal dependencies of a time series appropriately. Extensive experiments on the SML 2010 dataset and the NASDAQ 100 Stock dataset demonstrated that our proposed DA-RNN can outperform state-of-the-art methods for time series prediction.

The proposed dual-stage attention based recurrent neural network (DA-RNN) not only can be utilized for time series prediction, but also has the potential to serve as a general feature learning tool for time series analysis. This is because the final hidden state in the decoder of DA-RNN is actually a good summarization of the whole input driving series. With this representation, we can perform various application tasks, e.g., time series retrieval, anomaly detection, etc.