Predict correct response and analyze the influence of visualization using Recurrent Neural Network with bidirectional neural network technique

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Abstract. Visualization is to create an image and let users easy to obtain information from a large and complex data. Recurrent Neural Network (RNN) is a kind of neural network that connect nodes from directed graph along a temporal sequence, and Bidirectional Neural Networks (BDNN) is a kind of neural networks that allow to use output value during training process. In this report, it designed an RNN model with BDNN technique to solve a classification problem. Accuracy, precision, recall and F1-score is introduced to evaluate its performance. The BDNN technique do not improve the performance of RNN in this experiment. Additionally, this report considered whether the visualizations have influenced on this prediction. Through the experiment, the hierarchical visualization can improve the prediction accuracy and the radial visualization has a bad influence on prediction, which is different result with the experiment of Hossain [9] and previous work [10].

Keywords: Recurrent Neural Network, Bidirectional Neural Network, predict correct response, visualization

1 Introduction

Visualization can be used to help users to exact information from a user defined mapping relationship [1]. A study uses the cartographic mapping relationship that is to visualize a lot of conference abstracts and it indicates that the visualization offered a high interaction between user and knowledge [2]. ThemeRiver visualization is introduced to abstract the theme in a lot of documents and it also shows the different information between the user get by the visualization and the original [3]. The goal of visualization is to create an image from large and complex data without information lost, so that the user can analyze, explore and discover new ideas more easily [4]. It also includes combining data in a diagram and the observer can get the message from it [5].

Radial visualization is the term used to describe a visualization system that uses circular or elliptical layout to display data [6], and it is used to show different information about the structure of multivariate data [7]. Hierarchical visualization is a kind of visualization and it is used to show the diagram with hierarchical structure [8]. An experiment is introduced in order to investigate the differences in two visualizations (radial and hierarchical) from observer's fixations and saccades [9].

In this experiment, each visualization includes 6 questions and all these questions are used different datasets. However, the dataset is quite similar so that the questions have similar quality and it can avoid unnecessary error. Each question is displayed 45 seconds and there is no break before the observer finished. During the experiment, the response time, number of fixation and correct response are recorded, and the average time about fixation duration and saccades duration are also calculated after the experiment. This study uses above data to analyze the difference between two visualization and demonstrated hierarchical visualization is superior to the radial based on their hypothesis. Furthermore, they also proved that the users could get information more quickly on the hierarchical visualization even though the graph included more large and complex data [9].

it is considered that the correct response rate is not used to distinguish the visualization [9]. However, if we want to predict the correct response, it is necessary to consider the visualization. Thus, in this report, it will use the experiment data to predict the correct response and analyse whether the visualization has influenced on this prediction.

In previous work, we use simple two-layer neural network and bidirectional neural network to solve above problem [10]. This report will use Recurrent neural network (RNN) to solve above problem and implement the BDNN technique in RNN. RNN is one kind of neural network that connect nodes from directed graph along a temporal sequence, and it can use internal memory to process a series of inputs even if the input size is larger [11].

In this report, it will analyse the data set first. Secondly, it shows the RNN model with BDNN technique and explains the process to predict correct response including the hyperparameters selection. Then, it will talk about evaluation about the model and the prediction under different visualization. After that, it shows the result and discuss the possible reason. Finally, it will give a conclusion and talk about future work.

2 Method

2.1 Pre-process data

The data set used in this report is offered by Hossian's experiment [9]. In this data set, it includes It includes four parts: the information of the observers, the information of questions, the information about the observers answering the questions and some related statistic data. Considered that the neural networks work internally with numeric data, all non-numeric data need to encode as numeric data. Because ID, major and language belongs to enumerate types of data, it can be encoded as integer regardless of their order. Nevertheless, the data of education respect an observer's education level, Thus, higher education level can be encoded as a larger number and vice versa. Similarly, question and interface in data set are considered as enumerate data and in the data of vision, 1 is normal and 0 is abnormal.

2.2 The RNN model with BDNN technique

In this report, the structure of RNN with BDNN technique is showed as Fig 1. When we instantiate an RNN model, we can use the parameter "bidirectional" to decide what's the type of RNN we create. If we set it as true, our RNN is Bi-RNN, which means our RNN can be trained with two directions. On the other hand, our RNN is basic RNN if we set "bidirectional" as false. It's worth noting that the default value of "bidirectional" is false.

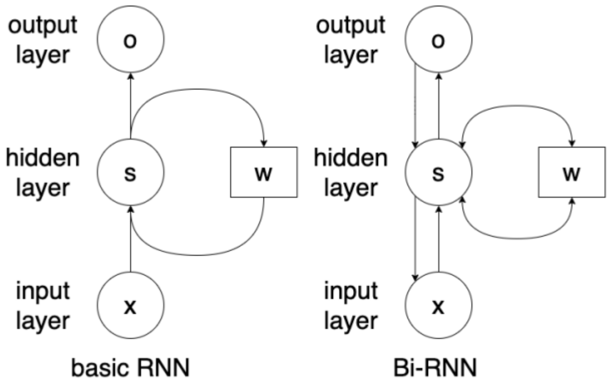

Fig. 1. The model of basic RNN and Bi-RNN

This RNN module is 2 linear layers which operate on an input and hidden state, with a LogSoftmax layer after the output. There are additional two linear layers and a LogSoftmax layer which is used when the RNN is Bi-RNN.

According to a study that implement a BDNN [12], we train it as a basic RNN for the first 50 iterations. Then, it will change its training direction and keep it until the current loss is less than the loss of the pervious direction. When training the reserve direction, we use the last output of the pervious forward direction as the input and get a predicted input. Then, we use the predicted input to train with forward direction and get an output, which is used to calculate the loss. In this way, we can maintain the weigh, which is shared in both directions.

When finding the optimized hyperparameters (iterations, learning rate, number of hidden units), K-fold cross validation is used to evaluate the model. In terms of 288 samples, 5-fold cross validation is suitable for this report. During each training, the original data set is split into 5 parts, one part is considered as test set and other 4 parts are combined as training set. The followed Table 1 shows the average result for different hyperparameter configuration.

Table 1. The average accuracy of simple neural network model with different hyperparameter configuration

model	iterations	learning rate	hidden size	Average accuracy
Basic RNN	50	0.005	128	66.29%
	100	0.005	128	78.87%
	500	0.005	128	79.64%
	1000	0.005	128	80.16%
	500	0.005	64	77.79%
	500	0.005	32	82.58%
	500	0.005	16	81.50%
	500	0.01	32	78.93%
	500	0.001	32	72.86%
Bi-RNN	50	0.005	32	67.83%
	100	0.005	32	75.36%

	500	0.005	32	78.98%
	1000	0.005	32	79.24%
	500	0.005	128	80.29%
	500	0.005	64	78.64%
	500	0.005	16	80.02%
	500	0.01	32	74.44%
	500	0.001	32	70.24%

From the table, we can find that the average accuracy increases with the increasing of iteration. However, when iteration is larger than 100, growth is slowing down whether the model is basic RNN or Bi-RNN. In terms of hidden size, we can find it doesn’t have a significant influence on the prediction accuracy because all the average accuracy is close to 80%. As for learning rate, when it is equal to 0.005, it will get the highest average accuracy. Hence, we will set iterations as 500, learning rate as 0.005 and hidden size as 32 in later experiment and analyzing.

2.3 Evaluation

To evaluate the RNN models with BDNN technique, confusion metrics is used in this paper. In confusion metrics, there are four terms, which are True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). Additionally, accuracy, precision, recall and F1-score are also calculated to evaluate the mode and their definition is list as followed:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$
$$\text{Precision} = TP / (TP + FP)$$
$$\text{Recall} = TP / (TP + FN)$$
$$\text{F1-score} = 2 / (\text{Recall}^{-1} + \text{Precision}^{-1})$$

Accuracy shows the prediction performance in terms of accuracy. Precision reflect the performance of prediction correct while recall means the performance of prediction comprehensiveness.

Additionally, to evaluate how the visualization influence on the correct response, it needs to consider the performance whether the data belongs to radial and hierarchical. Thus, the original data set will be processed before evaluation. We have designed four parts. The first part, we use the original data set and use the data set without “Interface” in second part. As for three and four part, we use the data set only belong to radial and hierarchical respectively.

3 Result and Discussion

In order to make the data more meaningful, we try to train the RNN model with setting bidirectional true or false 50 times respectively and the statistic is showed as followed figure.

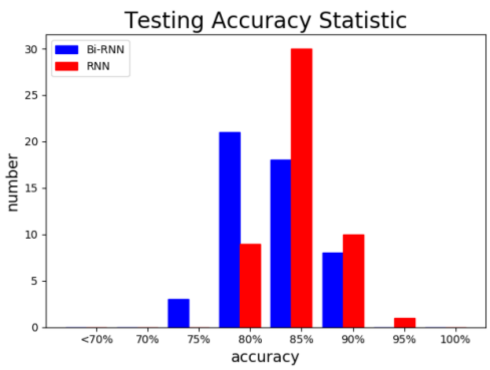

Fig. 2. Testing Accuracy Statistic of Bi-RNN and RNN

From the figure, we can see that the average prediction accuracy of Bi-RNN is slightly less than basic RNN. For a lot of prediction of basic RNN, the accuracy was above 85 percent a lot of prediction while lots of the prediction accuracy is more than 80% in Bi-RNN. It's important to point out that all the accuracy of prediction in RNN is more than 80% and there is no any accuracy of Bi-RNN prediction more than 95%. The RNN prediction accuracy is more than 95% once and the Bi-RNN prediction accuracy is less than 80% three times. From the followed Table 2, we can find the highest accuracy of Bi-RNN and basic RNN are 93.75 % and 96.88 % while the lowest accuracy is 79.69% and 81.25% respectively.

Table 2. The statistic of RNN and Bi-RNN after training 50 times

	RNN	Bi-RNN
The average accuracy	87.97%	85.84
The highest accuracy	96.88%	93.75%
The lowest accuracy	81.25%	79.69%

Overall, the performance of basic RNN is better than Bi-RNN, both at average prediction accuracy and highest prediction accuracy. The reason might be the RNN model we designed. In our model, when training a bidirectional RNN, we will use the pervious output value as input value and get a prediction of input. But, the weights of forward direction and reverse direction are independent. In order to implement the weight is shared between two directions, we use the prediction input again to get a new output value. In this way, the weight of forward direction is influenced by both two directions, and we consider the weight of forward direction as the weight of our model.

The Bi-RNN can be seen as the basic RNN in terms of its forward pass. However, the weight of Bi-RNN is also maintained by reverse direction. Thus, once the direction is changed, there may be two case when calculating the loss. One is better than previous loss and another is less. As a result, the loss of Bi-RNN might change a lot and it is not stable as the loss of RNN. Thus, it might lead to that the performance of Bi-RNN is not as good as RNN.

However, according to previous work, the BDNN technique can improve the performance but it is not very consistent [10]. The most likely reason is that the RNN has a better performance than simple two-layer neural network. In terms of RNN, the BDNN technique is more likely to have bad effects due to its unpredictability when changing training direction. But it will make a better impact for two-layer neural network.

The loss curve of one training session is showed as followed Fig 3. The basic RNN loss curve is decline fast at beginning and slow at the end. By contrast, the loss curve of Bi-RNN is fluctuating decline and a sudden change represents a change in training direction. At the first, the loss of RNN is higher than the loss of Bi-RNN, and the loss of RNN is less than Bi-RNN since around the iteration 220. The loss curve of RNN tends to flatten after iteration 200 and the reason is likely that the training is close to overfit.

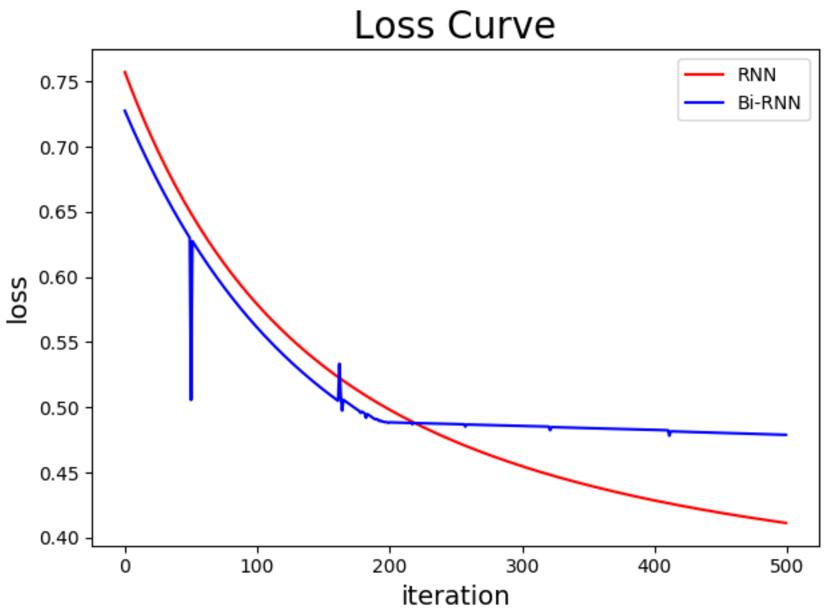

Fig. 3. Loss curve of RNN and Bi-RNN

The followed Table 3 shows the average confusion matrix after training 50 times and the evaluation index. Through calculating accuracy, precision, recall and F1-score, we can find the precision of RNN is much higher than that of Bi-RNN. That means the in the correct response, RNN predicted more correctly. The recall of Bi-RNN is higher than RNN, which means there are more correct response in prediction correct response. The F1-socre between two model is close. Hence, the performance of RNN is slightly better than Bi-RNN.

In a study about BDNN technique [13], there is a 74% accuracy of a trained BDNN to classify student mark patterns. But these are two different experiments and the results are not comparable. There is not any work about predicting correct response in original experiments [9]. Thus, there is no data to compare. Compare with pervious work [10], the accuracy of predicting correct response has increased. However, the BDNN technique has bad influence on the basic model in this report while it improves the performance in previous work.

Table 3. The average confusion matrix and evaluation index of RNN and Bi-RNN

RNN

		prediction	
		True	False
actual	True	53.48	1.52
	False	6.18	2.82
accuracy		0.8797	
precision		0.9724	
recall		0.8964	
F1-score		0.9329	

Bi-RNN

		prediction	
		True	False
actual	True	50.58	4.42
	False	4.64	4.36
accuracy		0.8584	
precision		0.9196	
recall		0.9160	
F1-score		0.9178	

The following Table 4 shows the result of the experiment about comparing two visualizations. In this part, we train each data set 10 times in order to keep the experiment result more sense. In the original data and the data without visualization, the average accuracy of RNN and Bi-RNN is similar. The highest accuracy of RNN and Bi-RNN in original data are higher than data without visualization while the lowest accuracy of RNN and Bi-RNN in original data is less than that in data without visualization. However, all the statistic accuracy in radial data are less than original data and data without visualization, and all the statistic accuracy in hierarchical data are higher than original data and data without visualization except the lowest accuracy of Bi-RNN. We can find there is a significant difference between radial data and hierarchical data. Additionally, we can conclude that the Bi-RNN is not as stable as basic RNN from this table.

Table 4. The result of experiment in different training data about whether includes visualizaions

	Original data	Data without visualization	Radial Data	Hierarchical Data
Average accuracy of RNN	76.61%	75.00%	70.67%	85.55%
Average accuracy of Bi-RNN	75.59%	74.06%	66.67%	76.55%
Highest accuracy of RNN	79.66%	78.12%	73.33%	89.66%
Highest accuracy of Bi-RNN	81.36%	78.12%	73.33%	86.21%
Lowest accuracy of RNN	72.88%	73.44%	66.67%	82.76%
Lowest accuracy of Bi-RNN	69.49%	70.31%	60.00%	65.52%

The potential reason why there is a huge difference between radial data and hierarchical data is that the training set is totally different. For original data and data without visualization, the only difference between them is that the original data include a column value to identify the visualization. The combination of radial data set and hierarchical data set is the original data set. The RNN also consider the time series and the totally different set might led to the significant difference after training. But in radial data set and hierarchical data set, there is one column that only has one value. When normalizing this column, there will be "nan" and all "nan" will bet set as 0. In this way, the radial data set and hierarchical data set both include one column with 0. So, we infer that the difference between the radial data and hierarchical data after training is due to other data. However, the literal descriptive data are same in both two data set, and statistic data is produced under different visualizations. As a result, we can consider that the visualization has influenced on the prediction of correct response.

4 Conclusion and Future Work

In this report, visualization is discussed, and it can create an image so that the user can get information and analyse data more easily. The interaction between users and big data has been enhanced through visualization. Then, an RNN model with BDNN technique has been presented. We use this model to forecast whether the observer has a correct response and whether the visualization has influence on it. The data set is come from a study about investigating differences in two visualizations from observer's fixations and saccades [9]. In this data set, there are some literal descriptive data and numeric data. Before training the model, the data set has been encoded. The main process is to change the literal descriptive data into numeric data and to normalize the training data and test data. In our model, there is a parameter "bidirectional" which control whether use the BDNN technique. If it is "False", our model will be trained as a basic RNN model. If it is "True", additional two connections from output to hidden and output to input are used. When training in reserve direction, the previous forward direction output is mapped to a prediction input by these two connections. Then it uses the prediction input to produce the prediction output which is used to calculate loss. After the training, the model predicted the test set and compared the results, producing the confusion matrix. Accuracy, precision, recall and F1-score are used to evaluate this mode. By comparing these figures, we can find the performance of basic RNN is slightly better than Bi-RNN. As a result, BDNN technique do not improve the performance of RNN. However, previous work proves the BDNN technique can improve the performance of two-layer neural network [10]. We also use k-fold cross validation in order to find the suitable hyperparameters.

Besides that, we design an experiment to evaluate whether the visualization has influence on prediction of correct response. The experiment result indicates the hierarchical visualization is helpful for predicting the correct response and the radial visualization is likely to have a bad influence on the prediction. By contrast, the pervious work shows the visualization has limit influence on the prediction [10]. Moreover, the study demonstrates the correct response do not have any statistically significant differences between two visualizations [9].

Overall, there are two difference results between this report and previous work, and we need more experiment to verify that. On one hand, we need to design another model to implement BDNN technique and focus on whether the BDNN technique improve the performance of RNN. We also need to consider whether the original data set has influence on these two works. On the other hand, RNN is considered to solve problem about time series. The study also provides a data set about that the observer's eye pupil diameters when answering each question with time series [10]. This data set is likely useful in this experiment, but we do not use it in this report. Thus, we can use it at future work. We can also do more analyzing about the original data set and improve our encoding method.

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