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Towards Better Diagnosis Prediction Using Bidirectional Recurrent Neural Networks

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Abstract

Bidirectional recurrent neural networks (RNN) improved performance of various natural language processing tasks and recently have been used for diagnosis prediction. Advantages of general bidirectional RNN, however, are not readily applied to diagnosis prediction task. In this study, we present a simple way to efficiently apply bidirectional RNN for diagnosis prediction without using any additional networks or parameters.

Keywords:

Deep Learning, Neural Networks, Data Science

Introduction

Bidirectional recurrent neural networks (RNN)[7] achieved remarkable improvements in various natural language processing tasks. Unlike unidirectional RNN that learns by seeing input sequences in a single direction, bidirectional RNN can leverage more information by seeing input sequences in forward (i.e., left-to-right) and backward (i.e., right-to-left) directions. This advantage of bidirectional RNN over unidirectional RNN leads to efficient learning by carrying more information for each prediction, which improves the model's performance on downstream tasks. For instance, a variety of natural language processing tasks such as language modeling and speech recognition have achieved performance gains by using bidirectional RNN[1; 2; 5; 6]. Along with this successful application in the natural language processing domain, bidirectional RNN have recently been adopted for medical prediction tasks.

Diagnosis prediction is a task that aims to predict a person's future diagnoses based on the person's historical medical records and has been considered one of the important research challenges in preventive medicine. For diagnosis prediction, however, general bidirectional RNN framework lose the benefit of using the backward RNN layer since the backward RNN only sees a single input sequence of the last timestamp. To tackle this problem, a few studies have proposed ways to apply bidirectional RNN to diagnosis prediction by using attention[4] or adding another layer of RNN[8].

In this study, we present a simple way to apply bidirectional RNN for diagnosis prediction without using any additional networks or parameters. We also evaluated the proposed model against existing bidirectional RNN models developed for the diagnosis prediction task using electronic health record datasets obtained from two real-world data sources: New York Presbyterian Hospital/Columbia University Irving Medical Center database; and MIMIC-III database[3].

Methods

Our proposed model allows each directional RNN in a bidirectional RNN to learn by utilizing all input sequences, which leads to efficient learning without using additional parameters. **Figure 1** depicts the architecture of the proposed model. The forward RNN learns to predict future diagnoses by seeing visits chronologically (i.e., moving from past visits to future visits), and the backward RNN learns to predict future diagnoses by seeing visits reverse-chronologically (i.e., moving from future visits to past visits). The hidden state of each directional RNN is updated as follows:

$$\overrightarrow{h}_t = \overrightarrow{RNN}(x_{t-1}, x_t)$$
$$\overleftarrow{h}_t = \overleftarrow{RNN}(x_{t+1}, x_t)$$

where $\overrightarrow{RNN}$ and $\overleftarrow{RNN}$ are the forward and backward RNN cell, respectively; $\overrightarrow{h}_t$ and $\overleftarrow{h}_t$ are the hidden state at timestamp *t* (i.e., *t*-th visit) from the forward RNN and backward RNN, respectively. The output representation, o, is a concatenation of the hidden state of the last sequence of each directional RNN (i.e., the hidden state of the (*T*-1)-th visit of the forward RNN and the hidden state of the first visit of the backward RNN).

Since the output representation is a concatenation of the hidden state of the last sequence of each directional RNN, each directional RNN is able to learn by propagating the information through all input sequences in each direction. We denote the proposed model as bidirectional RNN-LS (bidirectional RNN-Last Sequence) throughout the paper because the model utilizes the hidden state of the last sequence at each directional RNN.

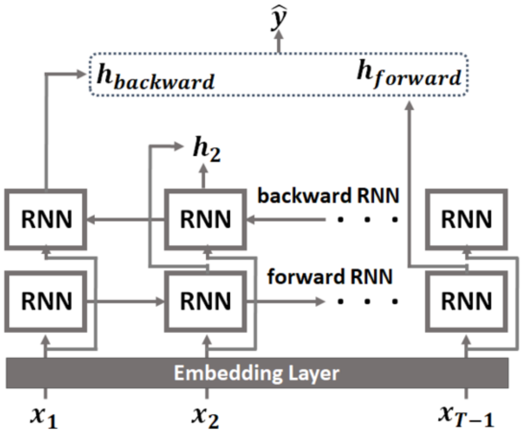

Figure 1. Bidirectional RNN-LS model.

Results

Experimental setup

The diagnosis prediction task for evaluation was defiend as follows. We set aside the last visit of each patient and the rest of the visits were fed into the models as input. Prediction was made for the last visit once per patient. Recall@k was used as an evaluation metric and is defined as Eq(1):

$$Recall@k = \frac{\#\ of\ TP\ in\ top\ k\ predictions}{\#\ of\ TP\ in\ the\ last\ visit} \quad Eq(1)$$

where TP indicates true positive medical concepts. Recall@k was averaged on all patients to evaluate each model's performance. We set k=30 for evaluation of the models based on both NYP/CUIMC EHR dataset and MIMIC-III EHR dataset.

Diagnosis prediction performance

Table 1 shows the diagnosis prediction performance (Recall@30) of all models using two EHR datasets. Bidirectional RNN-LS model outperformed other models in the evaluation based on MIMIC-III dataset. In the evaluation based on NYP/CUIMC dataset, bidirectional RNN with attention model showed the best performance followed by bidirectional RNN-LS model.

Table 1. *Diagnosis prediction performance (Recall@30) of all models using two EHR datasets. The best performing model is highlighted in **bold**.*

Model	NYP/CUIMC EHR dataset	MIMIC-III EHR dataset
1-layered Unidirectional RNN	0.6135	0.5740
2-layered Unidirectional RNN	0.5835	0.5476
Bidirectional RNN with attention (Dipole)	**0.6211**	0.5748
Entangled RNN (E-RNN)	0.5760	0.5419
Bidirectional RNN-LS	0.6168	**0.5803**

Conclusions

In this study, we proposed a simple way to efficiently apply bidirectional recurrent neural network for diagnosis prediction. We empirically evaluated the proposed model with several baselines including existing bidirectional RNN models and showed the proposed model has better or comparable performance on diagnosis prediction task. Future works include developing a novel model using bidirectional RNN with the state-of-the-art methods and investigation of the diagnosis prediction performance in using deeper architectures of unidirectional and bidirectional RNN models. The full length paper and source codes to implement all models are available at https://github.com/Jayaos/birnn_exploration.

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References

[1] E. Arisoy, A. Sethy, B. Ramabhadran, and S. Chen, Bidirectional recurrent neural network language models for automatic speech recognition, in: *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, IEEE, 2015, pp. 5421-5425.

[2] A. Graves and J. Schmidhuber, Framewise phoneme classification with bidirectional LSTM and other neural network architectures, *Neural networks* **18** (2005), 602-610.

[3] A.E. Johnson, T.J. Pollard, L. Shen, H.L. Li-Wei, M. Feng, M. Ghassemi, B. Moody, P. Szolovits, L.A. Celi, and R.G. Mark, MIMIC-III, a freely accessible critical care database, *Scientific data* **3** (2016), 1-9.

[4] F. Ma, R. Chitta, J. Zhou, Q. You, T. Sun, and J. Gao, Dipole: Diagnosis prediction in healthcare via attention-based bidirectional recurrent neural networks, in: *Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining*, 2017, pp. 1903-1911.

[5] M.E. Peters, W. Ammar, C. Bhagavatula, and R. Power, Semi-supervised sequence tagging with bidirectional language models, *arXiv preprint arXiv:1705.00108* (2017).

[6] M.E. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer, Deep contextualized word representations, *arXiv preprint arXiv:1802.05365* (2018).

[7] M. Schuster and K.K. Paliwal, Bidirectional recurrent neural networks, *IEEE transactions on Signal Processing* **45** (1997), 2673-2681.

[8] J. Yoon and M. van der Schaar, E-RNN: Entangled recurrent neural networks for causal prediction, in: *Proc. ICML Workshop Principled Approaches Deep Learn.*, 2017, pp. 1-5.

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