Recurrent autoencoder with sequence-aware encoding

Robert Susik
rsusik@kis.p.lodz.pl
Institute of Applied Computer Science,
Łódź University of Technology, Poland
2020

Abstract

Recurrent Neural Networks (RNN) received a vast amount of attention last decade. Recently, the architectures of Recurrent AutoEncoders (RAE) found many applications in practice. RAE can extract the semantically valuable information, called context that represents a latent space useful for further processing. Nevertheless, recurrent autoencoders are hard to train, and the training process takes much time. In this paper, we propose an autoencoder architecture with sequence-aware encoding, which employs 1D convolutional layer to improve its performance in terms of model training time. We prove that the recurrent autoencoder with sequence-aware encoding outperforms a standard RAE in terms of training speed in most cases. The preliminary results show that the proposed solution dominates over the standard RAE, and the training process is order of magnitude faster.

1 Introduction

Recurrent Neural Networks (RNN) \cite{21, 29} received a vast amount of attention last decade and found a wide range of applications such as language modelling \cite{18, 23}, signal processing \cite{8, 22}, anomaly detection \cite{19, 24},

The RNN is (in short) a feedforward neural network adapted to sequences of data that have the ability to map sequences to sequences achieving excellent performance on time series. Multiple layers of RNN can be stacked to process efficiently long input sequences \cite{12, 20}. The training process of deep recurrent neural network (DRNN) is difficult because the gradients (in backpropagation through time \cite{29}) either vanish or explode \cite{3, 9}. It means that despite the RNN can learn long dependencies the training process may take a much time or even fail. The problem was resolved by application of Long Short-Term Memory (LSTM) \cite{13} or much newer and simpler Gated Recurrent Units (GRU) \cite{6}. Nevertheless, it is not easy to parallelise calculations in recurrent neural networks what impact the training time.

A different and efficient approach was proposed by Aäron et al. \cite{26} who proved that stacked 1D convolutional layers can process efficiently long sequences handling tens of thousands of times steps. The CNNs have also been widely applied to autoencoder architecture as a solution for problems such as outlier and anomaly detection \cite{10, 14, 1}, noise reduction \cite{5}, and more.

Autoencoders \cite{4} are unsupervised algorithms trained to attempt to copy its input to its output. The desirable side effect of this approach is a latent representation (called context or code) of the input data. The context is usually smaller than input data to extract only the semantically valuable information. Encoder-Decoder (Sequence-to-Sequence) \cite{7, 25} architecture looks very much like autoencoder and consists of two blocks: encoder, and decoder, both containing a couple of RNN layers. The encoder takes the input data and generates the code (a semantic summary) used to represent the input. Later, the decoder processes the code and generates the final output. The encoder-decoder approach allows having variable-length input and output sequences in contrast to classic RNN solutions. There are several related attempts, including an interesting approach introduced by Graves \cite{12} that have been later successfully applied in practice in \cite{2, 17}. The authors proposed a novel differentiable attention mechanism that allows the decoder to focus on appropriate words at each time
step. This technique improved state of the art in neural machine translation (NMT) and was later applied even without any recurrent or convolutional layers [28]. Besides the machine translation, there are multiple variants and applications of the Recurrent AutoEncoders (RAE). In [10], the proposed generative model of variational recurrent autoencoder (VRAE) learns the latent vector representation of data and use it to generate samples. Another variational autoencoder was introduced in [27, 11] where authors apply convolutional layers and WaveNet for audio sequence. Interesting approach, the Feedback Recurrent AutoEncoder (FRAE) was presented in [30]. In short, the idea is to add a connection that provides feedback from decoder to encoder. This design allows efficiently compressing the sequences of speech spectrograms.

In this paper, we present an autoencoder architecture, which employs 1D convolutional layer in order to improve its performance in terms of training time and model accuracy. We also propose a different interpretation of the context (the final hidden state of the encoder). We transform the context into the sequence that is passed to the decoder. This technical trick, even without changing other elements of architecture, improves the performance of recurrent autoencoder.

We demonstrate the power of the proposed architecture for time series reconstruction. We perform a wide range of experiments on a dataset of generated signals, and the preliminary results are promising.

Following contributions of this work can be enumerated: (i) We propose a recurrent autoencoder with sequence-aware encoding that trains much faster than standard RAE. (ii) We suggest an extension to proposed solution which employs the 1D convolutional layer to make the solution more flexible. (iii) We show that this architecture performs very well on univariate and multivariate time series reconstruction.

2 The model

In this section, we describe our approach and its variants. We also discuss the advantages and disadvantages of the proposed architecture and suggest possible solutions to its limitation.

The recurrent autoencoder generates an output sequence \( Y = (y^{(0)}, y^{(1)}, \ldots, y^{(n_Y - 1)}) \) for given an input sequence \( X = (x^{(0)}, x^{(1)}, \ldots, x^{(n_X - 1)}) \), where \( n_Y \) and \( n_X \) are the sizes of output and input sequences respectively (both can be of the same or different size). Usually, \( X = Y \) to force autoencoder learning the semantic meaning of data. First, the input sequence is encoded by the RNN encoder, and then the given fixed-size context variable \( C \) is decoded by the decoder (usually also RNN), see Figure 1.

2.1 Recurrent AutoEncoder with Sequential context (RAES)

We propose a recurrent autoencoder architecture (Figure 2 where the context \( C \) (the output of the final hidden state of the encoder) is interpreted as the sequence \( C' \), of \( m_{C'} = \lambda \) features producing the output sequence \( Y \). The \( C = (c_i)_{i=0}^{n_C-1} \) is transformed to

\[
C' = ((c_{i\lambda + j})^{\lambda - 1}_{j=0})_{i=0}^{n_C/\lambda - 1}
\]  

where \( \lambda = n_C/n_X \) (\( \lambda \in \mathbb{N} \)).

Once the context is transformed \( (C' = (c'^{(0)}, c'^{(1)}, \ldots, c'^{(n_X - 1)})) \), the decoder starts to decode the sequence \( C' \) of \( m_{C'} = \lambda \) features. This technical trick in the data structure speeds...
up the training process (Section 3). Additionally, this way, we put some sequential meaning to the context. The one easily solvable disadvantage of this solution is the fact that the size of context must be multiple of input sequence length $n_C = \lambda n_X$, where $n_C$ is the size of context $C$.

### 2.2 RAES with 1D Convolutional layer (RAESC)

In order to solve the limitation mentioned in the previous section (Section 2.1), we propose to add 1D convolutional layer (and max-pooling layer) to the architecture right before the decoder (Figure 3). This approach gives the ability to control the number of output channels (also denoted as feature detectors or filters), defined as follows:

$$C''(i) = \sum_k \sum_l C'(i + k, l) w(k, l)$$  \hspace{1cm} (2)

In this case, the $n_C$ does not have to be multiple of $n_X$, thus to have the desired output sequence of $n_Y$ length, the number of filters should be equal to $n_Y$. Moreover, the output of the 1D convolution layer $C'' = \text{conv1D}(C')$ should be transposed, hence each channel becomes an element of the sequence as shown in Figure 3. Finally, the desired number of features on output $Y$ can be configured with hidden state size of the decoder.

A different and simpler approach to solve the mentioned limitation is stretching the $C$ to the size of decoder input and filling in the gaps with averages.

The described variant is very simplified and is only an outline of proposed recurrent autoencoder architecture (the middle part of it, to be more precise) which can be extended by adding pooling and recurrent layers or using different convolution parameters (such as stride, or dilation values). Furthermore, in our view, this approach could be easily applied to other RAE architectures (such as [30, 11]).

### 3 Experiments

In order to evaluate the proposed approach, we run a few experiments, using a generated dataset of signals. We tested the following algorithms:

- Standard Recurrent AutoEncoder (RAE) [7, 25].
- RAES with Sequence-aware encoding (RAES).
- RAES with Convolutional and max-pooling layer (RAESC).

The structure of decoder and encoder is the
same in all algorithms. Both, decoder and encoder are single GRU layer, with additional time distributed fully connected layer in the output of decoder. The algorithms were implemented in Python 3.7.4 with TensorFlow 2.3.0. The experiments were run on a desktop PC with an Intel i5-3570 CPU clocked at 3.4 GHz with 256 KB L1, 1 MB L2 and 6 MB L3 cache and GTX 1070 graphic card. The test machine was equipped with 16 GB of 1333 MHz DDR3 RAM and running Fedora 28 64-bit OS. The dataset contains 5000 sequences of size 200 with \{1, 2, 4, 8\} features. The dataset was shuffled and split to training and validation sets in proportions of 80:20, respectively. We trained the models with Adam optimizer \[15\] in batches of size 100 and Mean Squared Error (MSE) loss function.

In the first set of analyses we investigated the impact of context size and the number of features on performance. We noticed that there is a considerable difference in training speed (number of epochs needed to achieve plateau) between the classic approach and ours. To prove whether our approach has an advantage over the standard RAE, we performed tests with different size of the context \(n_C\) and a different number of input features \(m_X\). We set the \(n_C\) size proportionally to the size of the input and we denote it as:

\[ \sigma = \frac{n_C}{m_X n_X} \]  

Figure 4 proves that the training of standard RAE takes much more time (epochs) than RAESC. In chart a) the size of context is set to \(\sigma = 25\%\) and in b) it is set to \(\sigma = 100\%\) of the input size. For \(\sigma = 25\%\) the RASEC achieves plateau after 20 epochs while standard RAE does not at all (it starts decreasing after nearly 100 epochs). There is no RAES result presented in this plot because of the limitation mentioned in Section 2.1 (size of code was too small to fit the output sequence length). For the \(\sigma = 100\%\) both RASEC and RAES achieve the plateau in less than five epochs while the standard RAE after 50 epochs (order of magnitude faster).

Figure 5 shows the loss in function of the number of epochs for 8 features. This figure is interesting in several ways if compared to the previous ones (Figures 4, 5). The chart a) shows that, for much larger number of features and relatively small size of the context, the training time of RAES variant is much longer. The similar observation may be noticed for RAESC, where the loss drops much faster than the standard RAE at the begining of the training, but achieves the plateau at almost the same step. On the other hand, chart b) shows that for larger size of context, the proposed solution dominates. The most striking fact to emerge from these results is that the RAE does not drop in the whole period.

We compared also the algorithms’ perfor-
Figure 5: Loss as function of epoch number for two features ($m_X = 2$) and $\sigma = \{25\%, 100\\%\}$.

Figure 6: Loss as function of epoch number for $m_X = 8$ and $\sigma = \{25\%, 100\\%\}$.

Figure 7: Loss as function of time [s] for $m_X = 4$ and $\sigma = \{25\%, 100\%\}$.

4 Conclusions and future work

In this work, we proposed an autoencoder with sequence-aware encoding. We proved that this solution outperforms a standard RAE in terms of training speed (for the same size of context)
Table 1: Epoch time [s] (median) for different number of features \((m_X)\) and context size \((\sigma)\).

| features \((m_X)\) | algorithm | \(25\%\) | \(50\%\) | \(100\%\) |
|----------------------|-----------|-----------|-----------|-----------|
| 1                    | RAE       | 1.05      | 1.00      | 1.41      |
|                      | RAES      | -         | -         | 1.23      |
|                      | RAESC     | 0.97      | 0.98      | 1.64      |
| 2                    | RAE       | 1.00      | 1.47      | 3.69      |
|                      | RAES      | -         | 1.29      | 3.10      |
|                      | RAESC     | 0.97      | 1.63      | 3.99      |
| 4                    | RAE       | 1.47      | 3.66      | 10.60     |
|                      | RAES      | 1.31      | 3.08      | 8.24      |
|                      | RAESC     | 1.60      | 3.97      | 10.95     |
| 8                    | RAE       | 3.65      | 10.51     | 35.01     |
|                      | RAES      | 3.14      | 8.28      | 26.28     |
|                      | RAESC     | 3.89      | 10.80     | 35.68     |

in most cases.

The experiments confirmed that the training of proposed architecture is much faster than the standard RAE. The context size and a number of features in the input sequence have a high impact on training performance. Only for relatively large number of features and small size of the context the proposed solution achieves comparable results to standard RAE. In other cases our solution dominates and the training time is order of magnitude shorter.

In our view these results constitute a good initial step toward further research. The proposed architecture was much simplified and the use of different layers or hyperparameter tuning seems to offer great opportunities. We believe that the proposed solution has a wide range of practical applications and it is worth confirming.

References

[1] J. An and S. Cho. Variational autoencoder based anomaly detection using reconstruction probability. *Special Lecture on IE*, 2(1):1–18, 2015.

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

[3] Y. Bengio, P. Simard, and P. Frasconi. Learning long-term dependencies with gradient descent is difficult. *IEEE transactions on neural networks*, 5(2):157–166, 1994.

[4] H. Bourlard and Y. Kamp. Auto-association by multilayer perceptrons and singular value decomposition. *Biological cybernetics*, 59(4-5):291–294, 1988.

[5] H.-T. Chiang, Y.-Y. Hsieh, S.-W. Fu, K.-H. Hung, Y. Tsao, and S.-Y. Chien. Noise reduction in ecg signals using fully convolutional denoising autoencoders. *IEEE Access*, 7:60806–60813, 2019.

[6] K. Cho, B. van Merrienboer, D. Bahdanau, and Y. Bengio. On the properties of neural machine translation: Encoder-decoder approaches. *CoRR*, abs/1409.1259, 2014.

[7] K. Cho, B. Van Merriënboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio. Learning phrase representations using rnn encoder-decoder for statistical machine translation. *arXiv preprint arXiv:1406.1078*, 2014.

[8] J. Ding and Y. Wang. Wifi csi-based human activity recognition using deep recurrent neural network. *IEEE Access*, 7:174257–174269, 2019.

[9] K. Doya. Bifurcations of recurrent neural networks in gradient descent learning. *IEEE Transactions on neural networks*, 1(75):218, 1993.

[10] O. Fabius and J. R. van Amersfoort. Variational recurrent auto-encoders. *arXiv preprint arXiv:1412.6581*, 2014.

[11] C. Gârbacea, A. van den Oord, Y. Li, F. S. Lim, A. Luebs, O. Vinyals, and T. C. Walters. Low bit-rate speech coding with vq-vae and a wavenet decoder. In *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 735–739. IEEE, 2019.
[12] A. Graves. Generating sequences with recurrent neural networks. arXiv preprint arXiv:1308.0850, 2013.
[13] S. Hochreiter and J. Schmidhuber. Long short-term memory. Neural computation, 9(8):1735–1780, 1997.
[14] T. Kieu, B. Yang, C. Guo, and C. S. Jensen. Outlier detection for time series with recurrent autoencoder ensembles. In IJCAI, pages 2725–2732, 2019.
[15] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014.
[16] W. Liao, Y. Guo, X. Chen, and P. Li. A unified unsupervised gaussian mixture variational autoencoder for high dimensional outlier detection. In 2018 IEEE International Conference on Big Data (Big Data), pages 1208–1217. IEEE, 2018.
[17] M.-T. Luong, H. Pham, and C. D. Manning. Effective approaches to attention-based neural machine translation. arXiv preprint arXiv:1508.04025, 2015.
[18] T. Mikolov, S. Kombrink, L. Burget, J. Černocký, and S. Khudanpur. Extensions of recurrent neural network language model. In 2011 IEEE international conference on acoustics, speech and signal processing (ICASSP), pages 5528–5531. IEEE, 2011.
[19] A. Nanduri and L. Sherry. Anomaly detection in aircraft data using recurrent neural networks (rnn). In 2016 Integrated Communications Navigation and Surveillance (ICNS), pages 5C2–1. Ieee, 2016.
[20] R. Pascanu, C. Gulcehre, K. Cho, and Y. Bengio. How to construct deep recurrent neural networks. In Proceedings of the Second International Conference on Learning Representations (ICLR 2014), 2014.
[21] D. E. Rumelhart, G. E. Hinton, and R. J. Williams. Learning representations by backpropagating errors. nature, 323(6088):533–536, 1986.
[22] S. Shahtalebi, S. F. Atashzar, R. V. Patel, and A. Mohammadi. Training of deep bidirectional rns for hand motion filtering via multimodal data fusion. In GlobalSIP, pages 1–5, 2019.
[23] Y. Shi, M.-Y. Hwang, X. Lei, and H. Sheng. Knowledge distillation for recurrent neural network language modeling with trust regularization. In ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 7230–7234. IEEE, 2019.
[24] Y. Su, Y. Zhao, C. Niu, R. Liu, W. Sun, and D. Pei. Robust anomaly detection for multivariate time series through stochastic recurrent neural network. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pages 2828–2837, 2019.
[25] I. Sutskever, O. Vinyals, and Q. V. Le. Sequence to sequence learning with neural networks. In Advances in neural information processing systems, pages 3104–3112, 2014.
[26] A. van den Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. Senior, and K. Kavukcuoglu. Wavenet: A generative model for raw audio. In Arxiv, 2016.
[27] A. Van Den Oord, O. Vinyals, et al. Neural discrete representation learning. In Advances in Neural Information Processing Systems, pages 6306–6315, 2017.
[28] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin. Attention is all you need. In Advances in neural information processing systems, pages 5998–6008, 2017.
[29] P. J. Werbos. Backpropagation through time: what it does and how to do it. Proceedings of the IEEE, 78(10):1550–1560, 1990.
[30] Y. Yang, G. Sautière, J. J. Ryu, and T. S. Cohen. Feedback recurrent autoencoder. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 3347–3351. IEEE, 2020.