Simplified Hierarchical Recurrent Encoder-Decoder for Building End-To-End Dialogue Systems

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Abstract
As a generative model for building end-to-end dialogue systems, Hierarchical Recurrent Encoder-Decoder (HRED) consists of three layers of Gated Recurrent Unit (GRU), which from bottom to top are separately used as the word-level encoder, the sentence-level encoder, and the decoder. Despite performing well on dialogue corpora, HRED is computationally expensive to train due to its complexity. To improve the training efficiency of HRED, we propose a new model, which is named as Simplified HRED (SHRED), by making each layer of HRED except the top one simpler than its upper layer. On the one hand, we propose Scalar Gated Unit (SGU), which is a simplified variant of GRU, and use it as the sentence-level encoder. On the other hand, we use Fixed-size Ordinally-Forgetting Encoding (FOFE), which has no trainable parameter at all, as the word-level encoder. The experimental results show that compared with HRED under the same word embedding size and the same hidden state size for each layer, SHRED reduces the number of trainable parameters by 25%–35%, and the training time by more than 50%, but still achieves slightly better performance.

1 Introduction
Dialogue systems are designed to naturally and meaningfully converse with humans. Many dialogue systems are developed using retrieval-based models, which hold a repository of predefined responses and pick an appropriate response from it given a dialogue context. Retrieval-based models can avoid grammatical mistakes since all their responses are predefined, but cannot deal with situations where no appropriate response exists in the repository. Another way to develop dialogue systems is to use generative models, which have no predefined response at all but to generate each response from scratch. Compared with retrieval-based models, generative models need more training data, and often make grammatical mistakes. However, responses from generative models tend to be more diverse, which makes generative models increasingly attractive.

A typical example of generative models is Hierarchical Recurrent Encoder-Decoder (HRED), which was initially proposed to generate query suggestions (Sordoni et al., 2015) and later applied to building end-to-end dialogue systems (Serban et al., 2016). HRED is both hierarchical and recurrent because it consists of three layers, each of which is a recurrent structure. Since a dialogue can be seen as a sequence of sentences, each sentence in turn is a sequence of words, HRED models this hierarchy using its bottom layer, the word-level encoder, and its middle layer, the sentence-level encoder. Specifically, the word-level encoder summarizes the words in each sentence, and the sentence-level encoder summarizes the sentences appearing so far in the dialogue. Based on a dialogue context representation obtained from the two encoder layers, HRED generates a response using its top layer, the decoder.

According to Sordoni et al. (2015), each layer of HRED was originally implemented as a Gated Recurrent Unit (GRU), which leads to a highly complicated model. For this reason, despite performing well on dialogue corpora (Serban et al., 2016; Lowe et al., 2017), HRED is computationally expensive to train. We believe there is a great potential for improving the training efficiency of HRED. Therefore in this paper, we analyze the causes to the poor training efficiency of HRED, and solve them by proposing a new model, which is based on but much simpler than HRED. We name the new model as Simplified HRED (SHRED), and by experiments we compare it with HRED in both training efficiency and performance.
2 Related Works

2.1 HRED for Building End-To-End Dialogue Systems

HRED encodes a dialogue context using two layers of encoder GRU, which work respectively at the word level and the sentence level. Based on the resulting dialogue context representation, HRED generates a response using another layer of decoder GRU. As shown in Figure 1, within each sentence, the word-level encoder GRU at the bottom layer iteratively takes the word embeddings to update its hidden state, thus its final hidden state is a fixed-size representation of the sentence. Similarly, within the dialogue, the sentence-level encoder GRU at the middle layer iteratively takes the sentence representations to update its hidden state, thus its hidden state at each time-step is a fixed-size representation of the current dialogue context. The decoder GRU at the top layer takes each such dialogue context representation to initialize its hidden state, and thereby predicts a response word by word, which is quite similar to a language model. By the way, HRED has a variant named as VHRED (Serban et al., 2017), which is almost the same as HRED except that the decoder GRU is augmented with a latent variable.

2.2 GRU and its Simplified Variants

GRU (Cho et al., 2014) uses a gating mechanism to learn long-term dependencies:

\[
\begin{align*}
\text{Update Gate: } & z_t = \sigma(W_z[h_{t-1}, x_t]) \\
\text{Reset Gate: } & r_t = \sigma(W_r[h_{t-1}, x_t]) \\
\text{New Memory: } & \hat{h}_t = \tanh(W_h[r_t \odot h_{t-1}, x_t]) \\
\text{Hidden State: } & h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \hat{h}_t
\end{align*}
\]

Empirical studies (Chung et al., 2014; Jozefowicz et al., 2015) showed that GRU achieves comparable performance with Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997), which also relies on gates but is more complicated than GRU. To explore better recurrent structures, many simplified variants of GRU have been proposed, such as Minimal Gated Unit (MGU) (Zhou et al., 2016), which merges the update gate and the reset gate into a single forget gate:

\[
\begin{align*}
\text{Forget Gate: } & f_t = \sigma(W_f[h_{t-1}, x_t]) \\
\text{New Memory: } & \hat{h}_t = \tanh(W_h[f_t \odot h_{t-1}, x_t]) \\
\text{Hidden State: } & h_t = (1 - f_t) \odot h_{t-1} + z_t \odot \hat{h}_t
\end{align*}
\]

According to Zhou et al. (2016), compared with GRU, MGU has fewer operations and trainable parameters, consumes less training time, but still achieves similar performance.

2.3 Fixed-size Ordinally-Forgetting Encoding

Fixed-size Ordinally-Forgetting Encoding (FOFE) (Zhang et al., 2015) is used for mapping a sequence of words to a fixed-size representation:

\[
h_t = \begin{cases} 
0, & \text{if } t = 0 \\
\alpha \ast h_{t-1} + x_t, & \text{otherwise}
\end{cases}
\]

where \(h_t\) is the hidden state at time step \(t\), \(x_t\) is the embedding of the \(t\)-th word, and \(\alpha\) (0 < \(\alpha\) < 1) is the forgetting factor used for decaying the previous hidden state. Given a sentence containing \(N\) words, the final hidden state \(h_N\) is returned as a fixed-size representation of the sentence.

Although formulated as a recurrent structure, actually FOFE can be implemented simply by matrix multiplication. On top of that, the forgetting factor \(\alpha\) is designed as a hyper-parameter so that FOFE has no trainable parameter at all. Therefore it is obvious that FOFE is simpler than other recurrent structures, such as LSTM and GRU. However, in terms of performance, according to Zhang et al. (2015), a language model consisting of a FOFE followed by several dense layers outperforms both LSTM and GRU language models.

3 Simplified HRED

3.1 Motivations

We have observed that the training of HRED on dialogue corpora consumes a lot of time and memory. This is due to the fact that HRED is a three-layer hierarchical model, where each layer is a GRU. Although the gating mechanism of GRU is helpful in learning long-term dependencies, it also introduces a large number of operations and trainable parameters. As a result, the cascaded GRUs in HRED greatly complicate the forward propagation and the backward propagation, which makes the training computationally expensive.

It is easy to see that in the training of neural networks, the backward propagation consumes much more resource than the forward propagation. Furthermore, considering the chain rule in the backward propagation, the complexity of computing gradients in a hierarchical model increases exponentially from the top layer to the bottom. Faced
with this, one strategy to improve the training efficiency is to make each layer except the top one simpler than its upper layer, which can accelerate the backward propagation. Take HRED for example, if the sentence-level encoder was simpler than the decoder, and the word-level encoder was even simpler than the sentence-level encoder, then the backward propagation would be faster, so that the training would be more efficient.

3.2 Our Model

To improve the training efficiency of HRED, we propose a new model, where we first propose a simplified variant of GRU named as Scalar Gated Unit (SGU), and use it as the sentence-level encoder. Many simplified variants of GRU have been proposed by others, such as MGU mentioned earlier, but SGU is even simpler than them:

Scalar Update Gate: \( z_t = \sigma(w_z[h_{t-1}, x_t]) \)
Scalar Reset Gate: \( r_t = \sigma(w_r[h_{t-1}, x_t]) \)
New Memory: \( \hat{h}_t = \tanh(W_h[r_t * h_{t-1}, x_t]) \)
Hidden State: \( h_t = (1 - z_t) * h_{t-1} + z_t * \hat{h}_t \)

By comparing the formulation of SGU with that of GRU, it is easy to find that both the update gate \( z_t \) and the reset gate \( r_t \) change from the vectors in GRU to the scalars in SGU. Accordingly, the weights for computing the gates change from the matrices \( W_z \) and \( W_r \) in GRU to the vectors \( w_z \) and \( w_r \) in SGU. Moreover, the gating operation also changes from the element-wise multiplication (\( \odot \)) in GRU to the scalar multiplication (\( * \)) in SGU. These changes guarantee that SGU is the simplest among all variants of GRU.

In the new model, to further improve the training efficiency, we use Fixed-size Ordinally-Forgetting Encoding (FOFE) as the word-level encoder, because FOFE is simpler than both GRU and SGU according to the earlier description. However, due to the fact that the forgetting factor \( \alpha < 1 \), the information contained in the beginning of a long sentence could vanish in the final hidden state of FOFE. Therefore, for each sentence we run FOFE in both forward and backward directions, and then concatenate the two final hidden states to obtain the sentence representation.

In conclusion, based on HRED, we construct the new model by replacing the GRU at the middle layer with an SGU, and the bi-directional GRU at the bottom layer with a bi-directional FOFE. Our modifications to HRED make the new model much simpler than HRED, therefore we name it as Simplified HRED (SHRED).

4 Experiments

4.1 Dialogue Corpora

We compare SHRED with HRED on two dialogue corpora, one of which is the MovieTriples corpus provided by Serban et al. (2016), and the other is the Ubuntu corpus provided by Lowe et al. (2017). The MovieTriples corpus contains 240 thousand dialogues collected from movie scripts, with each dialogue having 3 sentences. The Ubuntu corpus contains 490 thousand dialogues collected from
Table 1: Experimental results on MovieTriples (each model is trained using a single GTX 1070 GPU)

| Model | Word Embedding | Hidden States (bottom-up) | Trainable Parameters | Training Time (secs * epochs) | Performance (ppl, err rate) |
|-------|----------------|---------------------------|----------------------|-------------------------------|-----------------------------|
| SHRED | 200            | 200-1200-200              | 6,456,605            | 2,030 * 35                    | 35.14, 66.46%              |
|       | 400            | 400-1200-400              | 12,019,605           | 2,210 * 30                    | 34.01, 66.05%              |
|       | 600            | 600-1200-600              | 18,142,605           | 2,590 * 29                    | 33.79, 65.89%              |
| HRED  | 200            | 200-1200-200              | 10,777,003           | 4,100 * 33                    | 35.72, 66.62%              |
|       | 400            | 400-1200-400              | 18,740,403           | 4,660 * 29                    | 34.35, 66.13%              |
|       | 600            | 600-1200-600              | 28,223,803           | 5,700 * 29                    | 34.11, 65.95%              |

Table 2: Experimental results on Ubuntu (each model is trained using a single GTX 1070 GPU)

| Model | Word Embedding | Hidden States (bottom-up) | Trainable Parameters | Training Time (secs * epochs) | Performance (ppl, err rate) |
|-------|----------------|---------------------------|----------------------|-------------------------------|-----------------------------|
| SHRED | 600            | 600-1200-600              | 30,150,203           | 21,690 * 33                   | 45.55, 68.55%              |
| HRED  | 600            | 600-1200-600              | 40,231,401           | 51,770 * 33                   | 46.29, 68.76%              |

4.2 Implementation Details

We implement both SHRED and HRED using TensorFlow (Abadi et al., 2016). For the word embedding size, we try out 200, 400, and 600 on the MovieTriples corpus, and set it to 600 on the Ubuntu corpus. For the forgetting factor \( \alpha \) of FOFE, we set it to 0.9 on both corpora. For the hidden state size of the word-level encoder GRU, we try out 200, 400, and 600 on the MovieTriples corpus, and set it to 600 on the Ubuntu corpus. For the hidden state size of both the SGU and the GRU used as the sentence-level encoder, we set it to 1200 on both corpora. For the hidden state size of the decoder GRU, we try out 200, 400, and 600 on the MovieTriples corpus, and set it to 600 on the Ubuntu corpus. For the mini-batch size, we set it to 10 on the MovieTriples corpus and 1 on the Ubuntu corpus. For the evaluation, we use perplexity and error rate as our metrics, which were also adopted by Serban et al. (2016). In the training, we initialize all trainable parameters, including the word embeddings, using a Gaussian distribution with a mean of 0 and a standard deviation of 0.01, and then iteratively minimize the average cross-entropy loss on each mini-batch using an Adam optimizer (Kingma and Ba, 2014) with an initial learning rate of 0.0001. After each epoch, we calculate the perplexity on the validation set. If an epoch yields a lower perplexity than its previous epoch, we save the trainable parameters, otherwise we restore them to the last saved version. After each two failed epochs, we decay the learning rate by 50%, and the training is terminated after the 10th decay.

4.3 Experimental Results

The experimental results on both corpora are separately given in Table 1 and Table 2. From the results we observe that compared with HRED under the same word embedding size and the same hidden state size for each layer, SHRED reduces the number of trainable parameters by 25%–35%, and the training time by more than 50%, but still achieves slightly better performance. Besides, Table 1 also shows that a proper increase in model scale brings better performance, but also consumes more resource, which means that when time or memory is limited, SHRED can achieve better performance than HRED. Finally, it can be found that the advantage of SHRED over HRED is more obvious on the Ubuntu corpus than on the MovieTriples corpus, which implies that SHRED can be well applied to processing long dialogues that are common in the real world.

5 Conclusion

In this paper, we propose SHRED, a new generative model for building end-to-end dialogue systems, the significance of which lies not only in that we improve the training efficiency of HRED, but also in that we find a method to reduce the unnecessary complexity in neural network models. We will apply this method to more corpora and tasks.
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