Sentence Simplification with Memory-Augmented Neural Networks

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Abstract

Sentence simplification aims to simplify the content and structure of complex sentences, and thus make them easier to interpret for human readers, and easier to process for downstream NLP applications. Recent advances in neural machine translation have paved the way for novel approaches to the task. In this paper, we adapt an architecture with augmented memory capacities called Neural Semantic Encoders (Munkhdalai and Yu, 2017) for sentence simplification. Our experiments demonstrate the effectiveness of our approach on different simplification datasets, both in terms of automatic evaluation measures and human judgments.

1 Introduction

The goal of sentence simplification is to compose complex sentences into simpler ones so that they are more comprehensible and accessible, while still retaining the original information content and meaning. Sentence simplification has a number of practical applications. On one hand, it provides reading aids for people with limited language proficiency (Watanabe et al., 2009; Siddharthan, 2003), or for patients with linguistic and cognitive disabilities (Carroll et al., 1999). On the other hand, it can improve the performance of other NLP tasks (Chandrasekar et al., 1996; Knight and Marcu, 2000; Beigman Klebanov et al., 2004).

Prior work has explored monolingual machine translation (MT) approaches, utilizing corpora of simplified texts, e.g., Simple English Wikipedia (SEW), and making use of statistical MT models, such as phrase-based MT (PBMT) (Štajner et al., 2015; Coster and Kauchak, 2011; Wubben et al., 2012), tree-based MT (TBMT) (Zhu et al., 2010; Woodsend and Lapata, 2011), or syntax-based MT (SBMT) (Xu et al., 2016).

Inspired by the success of neural MT (Sutskever et al., 2014; Cho et al., 2014), recent work has started exploring neural simplification with sequence to sequence (Seq2seq) models, also referred to as encoder-decoder models. Nisioi et al. (2017) implemented a standard LSTM-based Seq2seq model and found that they outperform PBMT, SBMT, and unsupervised lexical simplification approaches. Zhang and Lapata (Zhang and Lapata, 2017) viewed the encoder-decoder model as an agent and employed a deep reinforcement learning framework in which the reward has three components capturing key aspects of the target output: simplicity, relevance, and fluency.

The common practice for Seq2seq models is to use recurrent neural networks (RNNs) with Long Short-Term Memory (LSTM, Hochreiter and Schmidhuber, 1997) or Gated Recurrent Unit (GRU, Cho et al., 2014) for the encoder and decoder (Nisioi et al., 2017; Zhang and Lapata, 2017). These architectures were designed to be capable of memorizing long-term dependencies across sequences. Nevertheless, their memory is typically small and might not be enough for the simplification task, where one is confronted with long and complicated sentences.

In this study, we go beyond the conventional LSTM/GRU-based Seq2seq models and propose to use a memory-augmented RNN architecture called Neural Semantic Encoders (NSE). This architecture has been shown to be effective in a wide range of NLP tasks (Munkhdalai and Yu, 2017). The contribution of this paper is twofold:

(1) First, we present a novel simplification model which is, to the best of our knowledge, the first model that uses memory-augmented RNN for the task. We investigate the effectiveness of neural Seq2seq models when different neural architectures for the encoder are considered. Our experiments reveal that the NSE LSTM model that uses an
1). Given a complex source sentence

2.1 Attention-based Encoder-Decoder Model

2.2 Neural Semantic Encoders

An RNN allows us to compute a hidden state \( h_t \) of each word summarizing the preceding words \( x_{1:t} \), but not considering the following words \( x_{t+1:T_x} \) that might also be useful for simplification. An alternative approach is to use a bidirectional-RNN (Schuster and Paliwal, 1997). Here, we propose to use Neural Semantic Encoders (NSE, Munkhdalai and Yu, 2017). During each encoding time step \( t \), we compute a memory matrix \( M_t \in \mathbb{R}^{T_y \times D} \) where \( D \) is the dimensionality of the word vectors. This matrix is initialized with the word vectors and is refined over time through NSE’s functions to gain a better understanding of the input sequence. Concretely, NSE sequentially reads the tokens \( x_{1:T_x} \) with its read function:

\[
r_t = F_{\text{enc}}^{\text{read}}(r_{t-1}, x_t),
\]

where \( F_{\text{enc}}^{\text{read}} \) is an LSTM, \( r_t \in \mathbb{R}^D \) is the hidden state at time \( t \). Then, a compose function is used to compose \( r_t \) with relevant information retrieved from the memory at the previous time step, \( M_{t-1} \):

\[
c_t = F_{\text{enc}}^{\text{compose}}(r_t, m_t),
\]

where \( F_{\text{enc}}^{\text{compose}} \) is a multi-layer perceptron with one hidden layer, \( c_t \in \mathbb{R}^{2D} \) is the output vector, and \( m_t \in \mathbb{R}^D \) is a linear combination of the memory slots of \( M_{t-1} \), weighted by \( \sigma_t \in \mathbb{R} \):

\[
m_t = \sum_{i=1}^{T_y} \sigma_{ti} M_{t-1,i}, \quad \sigma_{ti} = \frac{\exp(r_t \odot M_{t-1,i})}{\sum_{j=1}^{D} \exp(r_t \odot M_{t-1,j})}.
\]

Here, \( M_{t-1,i} \) is the \( i \)-th row of the memory matrix at time \( t-1, M_{t-1} \). Next, a write function is used to map \( c_t \) to the encoder output space:

\[
w_t = F_{\text{enc}}^{\text{write}}(w_{t-1}, c_t),
\]

where \( F_{\text{enc}}^{\text{write}} \) is an LSTM, \( w_t \in \mathbb{R}^D \) is the hidden state at time \( t \). Finally, the memory is updated accordingly. The retrieved memory content pointed by \( \sigma_{ti} \) is erased and the new content is added:

\[
M_{t,i} = (1 - \sigma_{ti}) M_{t-1,i} + \sigma_{ti} w_t.
\]

NSE gives us unrestricted access to the entire source sequence stored in the memory. As such, the encoder may attend to relevant words when encoding each word. The sequence \( w_{1:T_x} \) is then used as the sequence \( h_{1:T_x} \) in Section 2.1.
2.3 Decoding

We differ from the approach of Zhang et al. (2017) in the sense that we implement both a greedy strategy and a beam-search strategy to generate the target sentence. Whereas the greedy decoder always chooses the simplification candidate with the highest log-probability, the beam-search decoder keeps a fixed number (beam) of the highest scoring candidates at each time step. We report the best simplification among the outputs based on automatic evaluation measures.

3 Experimental Setup

3.1 Datasets

Following (Zhang and Lapata, 2017), we experiment on three simplification datasets, namely: (1) Newsela (Xu et al., 2015), a high-quality simplification corpus of news articles composed by Newsela1 professional editors for children at multiple grade levels. We used the split of the data in (Zhang and Lapata, 2017), i.e., 94,208/1,129/1,077 pairs for train/dev/test. (2) WikiSmall (Zhu et al., 2010), which contains aligned complex-simple sentence pairs from English Wikipedia (EW) and SEW. The dataset has 88,837/205/100 pairs for train/dev/test. (3) WikiLarge (Zhang and Lapata, 2017), a larger corpus in which the training set is a mixture of three Wikipedia datasets in (Zhu et al., 2010; Woodsend and Lapata, 2011; Kauchak, 2013), and the development and test sets are complex sentences taken from WikiSmall, each has 8 simplifications written by Amazon Mechanical Turk workers (Xu et al., 2016). The dataset has 296,402/2,000/359 pairs for train/dev/test. Table 1 provides statistics on the training sets.

| Dataset     | vocab size  | #tokens/sent |
|-------------|-------------|--------------|
|             | src         | tgt         |
|             | 41,066      | 30,193      |
| Newsela     | 113,368     | 93,835      |
| WikiSmall   | 201,841     | 168,962     |
| WikiLarge   | 159,030     | 127,856     |

Table 1: Statistics for the training sets: the vocabulary size (vocab size), and the average number of tokens per sentence (#tokens/sent) of the source (src) and target (tgt) language.

3.2 Models and Training Details

We implemented two attention-based Seq2seq models, namely: (1) LSTM-LSTM: the encoder is implemented by two LSTM layers; (2) NSELSTM: the encoder is implemented by NSE. The decoder in both cases is implemented by two LSTM layers. The computations for a single model are run on an NVIDIA Titan-X GPU. For all experiments, our models have 300-dimensional hidden states and 300-dimensional word embeddings. Parameters were initialized from a uniform distribution [-0.1, 0.1]. We used the same hyperparameters across all datasets. Word embeddings were initialized either randomly or with Glove vectors (Pennington et al., 2014) pre-trained on Common Crawl data (840B tokens), and fine-tuned during training. We used a vocabulary size of 20K for Newsela, and 30K for WikiSmall and WikiLarge. Our models were trained with a maximum number of 40 epochs using Adam optimizer (Kingma and Ba, 2015) with step size $\alpha = 0.001$ for LSTM-LSTM, and 0.0003 for NSELSTM, the exponential decay rates $\beta_1 = 0.9, \beta_2 = 0.999$. The batch size is set to 32. We used dropout (Srivastava et al., 2014) for regularization with a dropout rate of 0.3. For beam search, we experimented with beam sizes of 5 and 10. Following (Jean et al., 2015), we replaced each out-of-vocabulary token $\langle unk \rangle$ with the source word $x_k$ with the highest alignment score $\alpha_{ti}$, i.e., $k = \arg\max_i (\alpha_{ti})$.

Our models were tuned on the development sets, either with BLEU (Papineni et al., 2002) that scores the output by counting $n$-gram matches with the reference, or SARI (Xu et al., 2016) that compares the output against both the reference and the input sentence. Both measures are commonly used to automatically evaluate the quality of simplification output. We noticed that SARI should be used with caution when tuning neural Seq2seq simplification models. Since SARI depends on the differences between a system’s output and the input sentence, large differences may yield very good SARI even though the output is ungrammatical. Thus, when tuning with SARI, we ignored epochs in which the BLEU score of the output is too low, using a threshold $\varsigma$. We set $\varsigma$ to 22 on Newsela, 33 on WikiSmall, and 77 on WikiLarge.

3.3 Comparing Systems

We compared our models, either tuned with BLEU (-B) or SARI (-S), against systems reported in (Zhang and Lapata, 2017), namely DRESS, a deep reinforcement learning model, DRESS-LS, a combination of DRESS and a lexical simplifi-
ication model (Zhang and Lapata, 2017), PbMT-R, a PbMT model with dissimilarity-based re-ranking (Wubben et al., 2012), HYBRID, a hybrid semantic-based model that combines a simplification model and a monolingual MT model (Narayan and Gardent, 2014), and SbMT-SARI, a SBMT model with simplification-specific components. (Xu et al., 2016).

3.4 Evaluation

We measured BLEU, and SARI at corpus-level following (Zhang and Lapata, 2017). In addition, we also evaluated system output by eliciting human judgments. Specifically, we randomly selected 40 sentences from each test set, and included human reference simplifications and corresponding simplifications from the systems above. We then asked three volunteers to rate simplifications with respect to Fluency (the extent to which the output is grammatical English), Adequacy (the extent to which the output has the same meaning as the input sentence), and Simplicity (the extent to which the output is simpler than the input sentence) using a five point Likert scale.

4 Results and Discussions

4.1 Automatic Evaluation Measures

The results of the automatic evaluation are displayed in Table 2. We first discuss the results on Newsela that contains high-quality simplifications composed by professional editors. In terms of BLEU, all neural models achieved much higher scores than PbMT-R and HYBRID. NsLSTM-B scored highest with a BLEU score of 26.31. With regard to SARI, NsLSTM-S scored best among neural models (29.58) and came close to the performance of HYBRID (30.00). This indicates that NSE offers an effective means to better encode complex sentences for sentence simplification.

On WikiSmall, HYBRID – the current state-of-the-art – achieved best BLEU (53.94) and SARI (30.46) scores. Among neural models, NsLSTM-B yielded the highest BLEU score (53.42), while NsLSTM-S performed best on SARI (29.75). On WikiLarge, again, NsLSTM-B had the highest

| Model    | Newsela BLEU | WikiSmall BLEU | WikiLarge BLEU |
|----------|--------------|----------------|----------------|
| PbMT-R   | 18.19        | 15.77          | 46.31          |
| HYBRID   | 14.46        | 30.00          | 53.94          |
| SbMT-SARI| NA           | NA             | 30.46          |
| Dress    | 23.21        | 27.37          | 34.53          |
| Dress-Ls | 24.30        | 26.63          | 36.32          |
| LSTM-LSTM-B | 24.38  | 27.66          | 30.33          |
| NsLSTM-B | 26.31        | 27.42          | 53.42          |
| LSTM-LSTM-S | 23.50  | 28.67          | 77.18          |
| NsLSTM-S | 22.69        | 29.58          | 81.11          |

Table 2: Model performance using automatic evaluation measures (BLEU and SARI).

BLEU score of 92.02. SbMT-SARI – that was trained on a huge corpus of 106M sentence pairs and 2B words – scored highest on SARI with 39.96, followed by Dress-Ls (37.27), Dress (37.08), and NsLSTM-S (36.88).

4.2 Human Judgments

The results of human judgments are displayed in Table 3. On Newsela, NsLSTM-B scored highest on Fluency. PbMT-R was significantly better than all other systems on Adequacy while LSTM-LSTM-S performed best on Simplicity. NsLSTM-B did very well on both Adequacy and Simplicity, and was best in terms of Average. Example model outputs on Newsela are provided in Table 4. On WikiSmall, NsLSTM-B performed best on both Fluency and Adequacy. On WikiLarge, LSTM-LSTM-B achieved the highest Fluency score while NsLSTM-B received the highest Adequacy score. In terms of Simplicity and Average, NsLSTM-S outperformed all other systems on both WikiSmall and WikiLarge.

As shown in Table 3, neural models often outperformed traditional systems (PbMT-R, HYBRID, SbMT-SARI) on Fluency. This is not surprising given the recent success of neural Seq2seq models in language modeling and neural machine translation (Zaremba et al., 2014; Jean et al., 2015). On the downside, our manual inspection reveals that neural models learn to perform copying very well in terms of rewrite operations (e.g., copying, deletion, reordering, substitution), often outputting the same or parts of the input sentence. Finally, as can be seen in Table 3, Reference scored lower on Adequacy compared to Fluency and Simplicity on Newsela. On Wikipedia-based datasets, Reference obtained high Adequacy scores but much lower Simplicity scores compared to Newsela. This supports the assertion by previous work (Xu et al., 2015) that SEW has a large proportion of inadequate simplifications.
Table 3: Average human ratings (Fluency (F), Adequacy (A), Simplicity (S), and Average (Avg.)).

| Model       | Newsla | WikiSmall | WikiLarge |
|-------------|--------|-----------|-----------|
|             | F      | A        | S        | Avg.    | F      | A        | S        | Avg.    |
| REFERENCE   | 4.58   | 2.98     | 3.99     | 3.85    | 4.63   | 3.97     | 3.59     | 4.06    | 4.59   | 4.43     | 2.38     | 3.80    |
| PBMT-R      | 3.73   | 3.90     | 1.98     | 3.20    | 4.07   | 4.11     | 2.28     | 3.49    | 4.22   | 4.09     | 2.31     | 3.54    |
| HYBRID      | 2.77   | 2.56     | 2.41     | 2.58    | 3.21   | 3.62     | 2.56     | 3.13    | 2.63   | 2.48     | 2.26     | 2.46    |
| SBMT-SARI   | NA     | NA       | NA       | NA      | 4.35   | 3.33     | 3.49     | 3.72    | 4.56   | 3.66     | 2.63     | 3.62    |
| DRESS       | 3.98   | 2.84     | 2.93     | 3.25    | 4.43   | 3.33     | 3.56     | 3.77    | 4.68   | 3.88     | 2.63     | 3.73    |
| DRESS-LS    | 3.99   | 2.90     | 2.98     | 3.29    | 4.35   | 3.33     | 3.56     | 3.77    | 4.68   | 3.88     | 2.63     | 3.73    |
| LSTM/LSM-B  | 3.95   | 2.93     | 3.14     | 3.34    | 4.42   | 3.88     | 2.65     | 3.65    | 4.80   | 4.47     | 1.89     | 3.72    |
| NSELSTM-B   | 3.42   | 3.13     | 3.39     | 3.59    | 4.74   | 4.22     | 2.49     | 3.82    | 4.73   | 4.58     | 1.94     | 3.75    |
| LSTM/LSM-S  | 3.24   | 3.03     | 3.45     | 3.57    | 4.59   | 3.40     | 3.42     | 3.80    | 4.73   | 4.23     | 2.21     | 3.72    |
| NSELSTM-S   | 3.83   | 2.78     | 3.01     | 3.21    | 4.57   | 3.28     | 3.81     | 3.89    | 4.65   | 3.95     | 2.90     | 3.83    |

Table 4: Example model outputs on Newsla. Substitutions are shown in bold.

4.3 Correlations

Table 5 shows the correlations between the scores assigned by humans and the automatic evaluation measures. There is a positive significant correlation between Fluency and Adequacy (0.69), but a negative significant correlation between Adequacy and Simplicity (-0.64). BLEU correlates well with Fluency (0.63) and Adequacy (0.90) while SARI correlates well with Simplicity (0.73). BLEU and SARI show a negative significant correlation (-0.54). The results reflect the challenge of managing the trade-off between Fluency, Adequacy and Simplicity in sentence simplification.

| Adequacy | Simplicity | BLEU | SARI |
|----------|------------|------|------|
| Fluency  | 0.69***    | -0.03| 0.63**| -0.48**|
| Adequacy | -0.64**    | 0.90* | -0.81**|
| Simplicity | -0.56** | 0.73* |      |
| BLEU     | -0.54**    |      |      |      |

Table 5: Pearson correlation between the scores assigned by humans and the automatic evaluation measures. Scores marked "**" are significant at p < 0.01.

5 Conclusions

In this paper, we explore neural Seq2seq models for sentence simplification. We propose to use an architecture with augmented memory capacities which we believe is suitable for the task, where one is confronted with long and complex sentences. Results of both automatic and human evaluation on different datasets show that our model is capable of significantly reducing the reading difficulty of the input, while performing well in terms of grammaticality and meaning preservation.

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