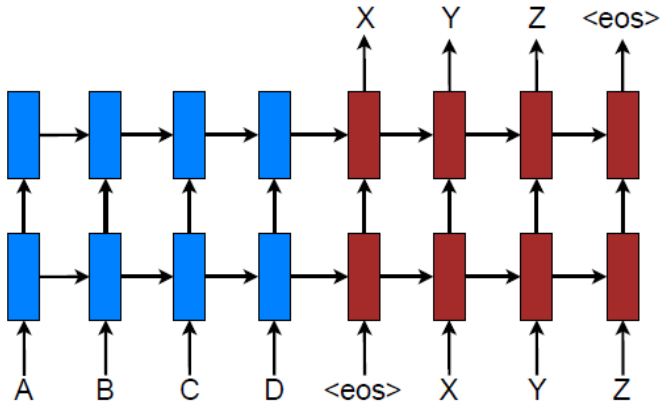


Seq2Seq Learning with Neural Networks

집현전 초급반 심형민
hyungmin.b.shim@gmail.com

1 Introduction

Deep Neural Networks (DNNs) are extremely powerful machine learning models that achieve excellent performance on difficult problems such as speech recognition [13, 7] and visual object recognition [19, 6, 21, 20]. DNNs are powerful because they can perform arbitrary parallel computation for a modest number of steps. A surprising example of the power of DNNs is their ability to sort N N-bit numbers using only 2 hidden layers of quadratic size [27]. So, while neural networks are related to conventional statistical models, they learn an intricate computation. Furthermore, large DNNs can be trained with supervised backpropagation whenever the labeled training set has enough information to specify the network's parameters. Thus, if there exists a parameter setting of a large DNN that achieves good results (for example, because humans can solve the task very rapidly), supervised backpropagation will find these parameters and solve the problem.

Despite their flexibility and power, DNNs can only be applied to problems whose inputs and targets can be sensibly encoded with vectors of fixed dimensionality. It is a significant limitation, since many important problems are best expressed with sequences whose lengths are not known a-priori. For example, speech recognition and machine translation are sequential problems. Likewise, question answering can also be seen as mapping a sequence of words representing the question to a sequence of words representing the answer. It is therefore clear that a domain-independent method that learns to map sequences to sequences would be useful.

Introduction (2 / 3)

Sequences pose a challenge for DNNs because they require that the dimensionality of the inputs and outputs is known and fixed. In this paper, we show that a straightforward application of the Long Short-Term Memory (LSTM) architecture [16] can solve general sequence to sequence problems. The idea is to use one LSTM to read the input sequence, one timestep at a time, to obtain large fixed-dimensional vector representation, and then to use another LSTM to extract the output sequence from that vector (fig. 1). The second LSTM is essentially a recurrent neural network language model [28, 23, 30] except that it is conditioned on the input sequence. The LSTM's ability to successfully learn on data with long range temporal dependencies makes it a natural choice for this application due to the considerable time lag between the inputs and their corresponding outputs (fig. 1).

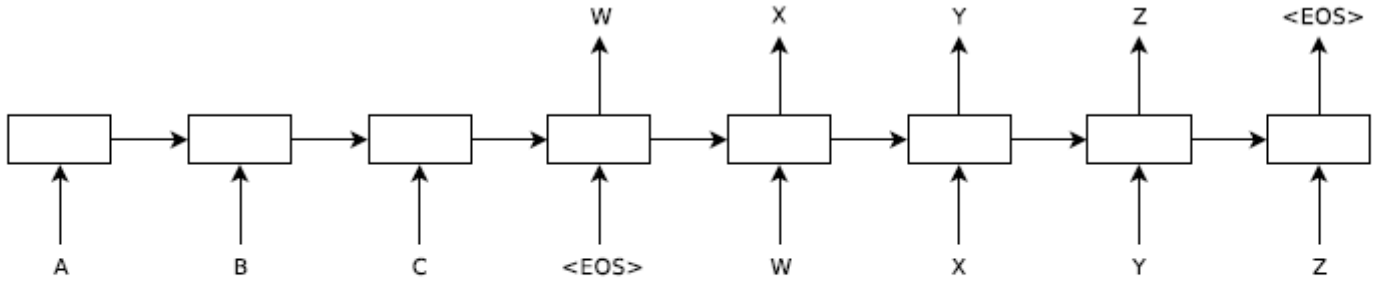


Figure 1: Our model reads an input sentence "ABC" and produces "WXYZ" as the output sentence. The model stops making predictions after outputting the end-of-sentence token. Note that the LSTM reads the input sentence in reverse, because doing so introduces many short term dependencies in the data that make the optimization problem much easier.

Introduction (3 / 3)

The main result of this work is the following. On the WMT'14 English to French translation task, we obtained a BLEU score of **34.81** by directly extracting translations from an ensemble of 5 deep LSTMs (with 380M parameters each) using a simple left-to-right beam-search decoder. This is by far the best result achieved by direct translation with large neural networks. For comparison, the BLEU score of a SMT baseline on this dataset is 33.30 [29]. The 34.81 BLEU score was achieved by an LSTM with a vocabulary of 80k words, so the score was penalized whenever the reference translation contained a word not covered by these 80k. This result shows that a relatively unoptimized neural network architecture which has much room for improvement outperforms a mature phrase-based SMT system.

Finally, we used the LSTM to rescore the publicly available 1000-best lists of the SMT baseline on the same task [29]. By doing so, we obtained a BLEU score of 36.5, which improves the baseline by 3.2 BLEU points and is close to the previous state-of-the-art (which is 37.0 [9]).

Surprisingly, the LSTM did not suffer on very long sentences, despite the recent experience of other researchers with related architectures [26]. We were able to do well on long sentences because we reversed the order of words in the source sentence but not the target sentences in the training and test set. By doing so, we introduced many short term dependencies that made the optimization problem much simpler (see sec. 2 and 3.3). As a result, SGD could learn LSTMs that had no trouble with long sentences. The simple trick of reversing the words in the source sentence is one of the key technical contributions of this work.

A useful property of the LSTM is that it learns to map an input sentence of variable length into a fixed-dimensional vector representation. Given that translations tend to be paraphrases of the source sentences, the translation objective encourages the LSTM to find sentence representations that capture their meaning, as sentences with similar meanings are close to each other while different sentences meanings will be far. A qualitative evaluation supports this claim, showing that our model is aware of word order and is fairly invariant to the active and passive voice.

2 The model

The Recurrent Neural Network (RNN) [31, 28] is a natural generalization of feedforward neural networks to sequences. Given a sequence of inputs $(x_1, \ldots, x_T)$, a standard RNN computes a sequence of outputs $(y_1, \ldots, y_T)$ by iterating the following equation:

$$\begin{aligned} h_t &= \text{sigm}\left(W^{\text{hx}} x_t + W^{\text{hh}} h_{t-1}\right) \\ y_t &= W^{\text{yh}} h_t \end{aligned}$$

The RNN can easily map sequences to sequences whenever the alignment between the inputs the outputs is known ahead of time. However, it is not clear how to apply an RNN to problems whose input and the output sequences have different lengths with complicated and non-monotonic relationships.

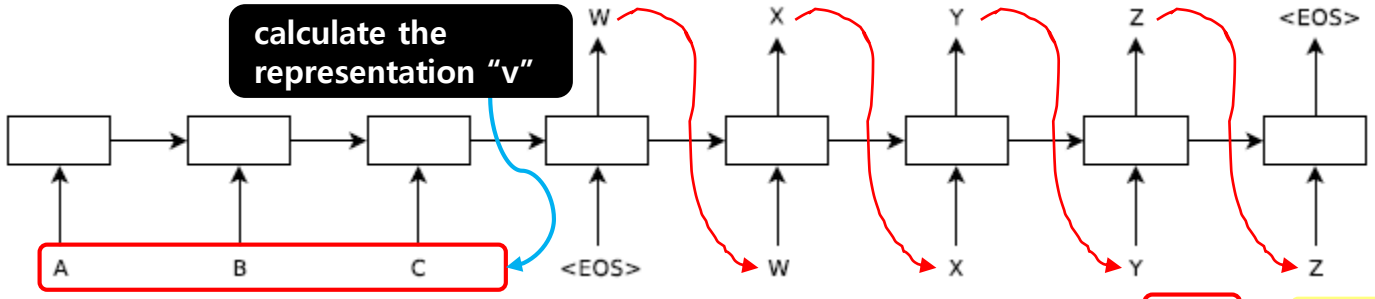
A simple strategy for general sequence learning is to map the input sequence to a fixed-sized vector using one RNN, and then to map the vector to the target sequence with another RNN (this approach has also been taken by Cho et al. [5]). While it could work in principle since the RNN is provided with all the relevant information, it would be difficult to train the RNNs due to the resulting long term dependencies [14, 4] (figure 1) [16, 15]. However, the Long Short-Term Memory (LSTM) [16] is known to learn problems with long range temporal dependencies, so an LSTM may succeed in this setting.

The model (2 / 2)

The goal of the LSTM is to estimate the conditional probability $p(y_1, \ldots, y_{T'}|x_1, \ldots, x_T)$ where $(x_1, \ldots, x_T)$ is an input sequence and $y_1, \ldots, y_{T'}$ is its corresponding output sequence whose length T' may differ from T. The LSTM computes this conditional probability by first obtaining the fixed-dimensional representation v of the input sequence $(x_1, \ldots, x_T)$ given by the last hidden state of the LSTM, and then computing the probability of $y_1, \ldots, y_{T'}$ with a standard LSTM-LM formulation whose initial hidden state is set to the representation v of $x_1, \ldots, x_T$:

$$p(y_1, \ldots, y_{T'}|x_1, \ldots, x_T) = \prod_{t=1}^{T'} p(y_t|v, y_1, \ldots, y_{t-1}) \quad (1)$$

In this equation, each $p(y_t|v, y_1, \ldots, y_{t-1})$ distribution is represented with a softmax over all the words in the vocabulary. We use the LSTM formulation from Graves [10]. Note that we require that each sentence ends with a special end-of-sentence symbol "<EOS>", which enables the model to define a distribution over sequences of all possible lengths. The overall scheme is outlined in figure 1, where the shown LSTM computes the representation of "A", "B", "C", "<EOS>" and then uses this representation to compute the probability of "W", "X", "Y", "Z", "<EOS>".



Our actual models differ from the above description in three important ways. First, we used two different LSTMs: one for the input sequence and another for the output sequence, because doing so increases the number model parameters at negligible computational cost and makes it natural to train the LSTM on multiple language pairs simultaneously [18]. Second, we found that deep LSTMs significantly outperformed shallow LSTMs, so we chose an LSTM with four layers. Third, we found it extremely valuable to reverse the order of the words of the input sentence. So for example, instead of mapping the sentence a, b, c to the sentence α, β, γ, the LSTM is asked to map c, b, a to α, β, γ, where α, β, γ is the translation of a, b, c. This way, a is in close proximity to α, b is fairly close to β, and so on, a fact that makes it easy for SGD to "establish communication" between the input and the output. We found this simple data transformation to greatly boost the performance of the LSTM.

Experiments (1 / 7)

dataset details

3 Experiments

We applied our method to the WMT'14 English to French MT task in two ways. We used it to directly translate the input sentence without using a reference SMT system and we it to rescore the n-best lists of an SMT baseline. We report the accuracy of these translation methods, present sample translations, and visualize the resulting sentence representation.

3.1 Dataset details

We used the WMT'14 English to French dataset. We trained our models on a subset of 12M sentences consisting of 348M French words and 304M English words, which is a clean "selected" subset from [29]. We chose this translation task and this specific training set subset because of the public availability of a tokenized training and test set together with 1000-best lists from the baseline SMT [29].

As typical neural language models rely on a vector representation for each word, we used a fixed vocabulary for both languages. We used 160,000 of the most frequent words for the source language and 80,000 of the most frequent words for the target language. Every out-of-vocabulary word was replaced with a special "UNK" token.

Experiments (2 / 7)

decoding and rescoring

3.2 Decoding and Rescoring

The core of our experiments involved training a large deep LSTM on many sentence pairs. We trained it by maximizing the log probability of a correct translation T given the source sentence S, so the training objective is

$$1/|\mathcal{S}| \sum_{(T,S)\in\mathcal{S}} \log p(T|S)$$

where $\mathcal{S}$ is the training set. Once training is complete, we produce translations by finding the most likely translation according to the LSTM:

$$\hat{T} = \arg\max_{T} p(T|S) \tag{2}$$

We search for the most likely translation using a simple left-to-right beam search decoder which maintains a small number B of partial hypotheses, where a partial hypothesis is a prefix of some translation. At each timestep we extend each partial hypothesis in the beam with every possible word in the vocabulary. This greatly increases the number of the hypotheses so we discard all but the B most likely hypotheses according to the model's log probability. As soon as the "<EOS>" symbol is appended to a hypothesis, it is removed from the beam and is added to the set of complete hypotheses. While this decoder is approximate, it is simple to implement. Interestingly, our system performs well even with a beam size of 1, and a beam of size 2 provides most of the benefits of beam search (Table 1).

We also used the LSTM to rescore the 1000-best lists produced by the baseline system [29]. To rescore an n-best list, we computed the log probability of every hypothesis with our LSTM and took an even average with their score and the LSTM's score.

Experiments (3 / 7)

reversing the source sentences

3.3 Reversing the Source Sentences

While the LSTM is capable of solving problems with long term dependencies, we discovered that the LSTM learns much better when the source sentences are reversed (the target sentences are not reversed). By doing so, the LSTM's test perplexity dropped from 5.8 to 4.7, and the test BLEU scores of its decoded translations increased from 25.9 to 30.6.

While we do not have a complete explanation to this phenomenon, we believe that it is caused by the introduction of many short term dependencies to the dataset. Normally, when we concatenate a source sentence with a target sentence, each word in the source sentence is far from its corresponding word in the target sentence. As a result, the problem has a large "minimal time lag" [17]. By reversing the words in the source sentence, the average distance between corresponding words in the source and target language is unchanged. However, the first few words in the source language are now very close to the first few words in the target language, so the problem's minimal time lag is greatly reduced. Thus, backpropagation has an easier time "establishing communication" between the source sentence and the target sentence, which in turn results in substantially improved overall performance.

Initially, we believed that reversing the input sentences would only lead to more confident predictions in the early parts of the target sentence and to less confident predictions in the later parts. However, LSTMs trained on reversed source sentences did much better on long sentences than LSTMs trained on the raw source sentences (see sec. 3.7), which suggests that reversing the input sentences results in LSTMs with better memory utilization.

Experiments (4 / 7)

training details

3.4 Training details

We found that the LSTM models are fairly easy to train. We used deep LSTMs with 4 layers, with 1000 cells at each layer and 1000 dimensional word embeddings, with an input vocabulary of 160,000 and an output vocabulary of 80,000. We found deep LSTMs to significantly outperform shallow LSTMs, where each additional layer reduced perplexity by nearly 10%, possibly due to their much larger hidden state. We used a naive softmax over 80,000 words at each output. The resulting LSTM has 380M parameters of which 64M are pure recurrent connections (32M for the "encoder" LSTM and 32M for the "decoder" LSTM). The complete training details are given below:

- We initialized all of the LSTM's parameters with the uniform distribution between -0.08 and 0.08
- We used stochastic gradient descent without momentum, with a fixed learning rate of 0.7. After 5 epochs, we begun halving the learning rate every half epoch. We trained our models for a total of 7.5 epochs.
- We used batches of 128 sequences for the gradient and divided it the size of the batch (namely, 128).
- Although LSTMs tend to not suffer from the vanishing gradient problem, they can have exploding gradients. Thus we enforced a hard constraint on the norm of the gradient [10, 25] by scaling it when its norm exceeded a threshold. For each training batch, we compute $s = \|g\|_2$, where g is the gradient divided by 128. If $s > 5$, we set $g = \frac{5g}{s}$.
- Different sentences have different lengths. Most sentences are short (e.g., length 20-30) but some sentences are long (e.g., length > 100), so a minibatch of 128 randomly chosen training sentences will have many short sentences and few long sentences, and as a result, much of the computation in the minibatch is wasted. To address this problem, we made sure that all sentences within a minibatch were roughly of the same length, which a 2x speedup.

Experiments (5 / 7)

experimental results

3.6 Experimental Results

We used the cased BLEU score [24] to evaluate the quality of our translations. We computed our BLEU scores using `multi-bleu.pl`[1] on the *tokenized* predictions and ground truth. This way of evaluating the BELU score is consistent with [5] and [2], and reproduces the 33.3 score of [29]. However, if we evaluate the state of the art system of [9] (whose predictions can be downloaded from `statmt.org\matrix`) in this manner, we get 37.0, which is greater than the 35.8 reported by `statmt.org\matrix`.

The results are presented in tables 1 and 2. Our best results are obtained with an ensemble of LSTMs that differ in their random initializations and in the random order of minibatches. While the decoded translations of the LSTM ensemble do not beat the state of the art, it is the first time that a pure neural translation system outperforms a phrase-based SMT baseline on a large MT task by a sizeable margin, despite its inability to handle out-of-vocabulary words. The LSTM is within 0.5 BLEU points of the previous state of the art by rescoring the 1000-best list of the baseline system.

Method	test BLEU score (ntst14)
Bahdanau et al. [2]	28.45
Baseline System [29]	33.30
Single forward LSTM, beam size 12	26.17
Single reversed LSTM, beam size 12	30.59
Ensemble of 5 reversed LSTMs, beam size 1	33.00
Ensemble of 2 reversed LSTMs, beam size 12	33.27
Ensemble of 5 reversed LSTMs, beam size 2	34.50
Ensemble of 5 reversed LSTMs, beam size 12	34.81

Table 1: The performance of the LSTM on WMT'14 English to French test set (ntst14). Note that an ensemble of 5 LSTMs with a beam of size 2 is cheaper than of a single LSTM with a beam of size 12.

Method	test BLEU score (ntst14)
Baseline System [29]	33.30
Cho et al. [5]	34.54
State of the art [9]	**37.0**
Rescoring the baseline 1000-best with a single forward LSTM	35.61
Rescoring the baseline 1000-best with a single reversed LSTM	35.85
Rescoring the baseline 1000-best with an ensemble of 5 reversed LSTMs	**36.5**
Oracle Rescoring of the Baseline 1000-best lists	~45

Table 2: Methods that use neural networks together with an SMT system on the WMT'14 English to French test set (ntst14).

Experiments (6 / 7)

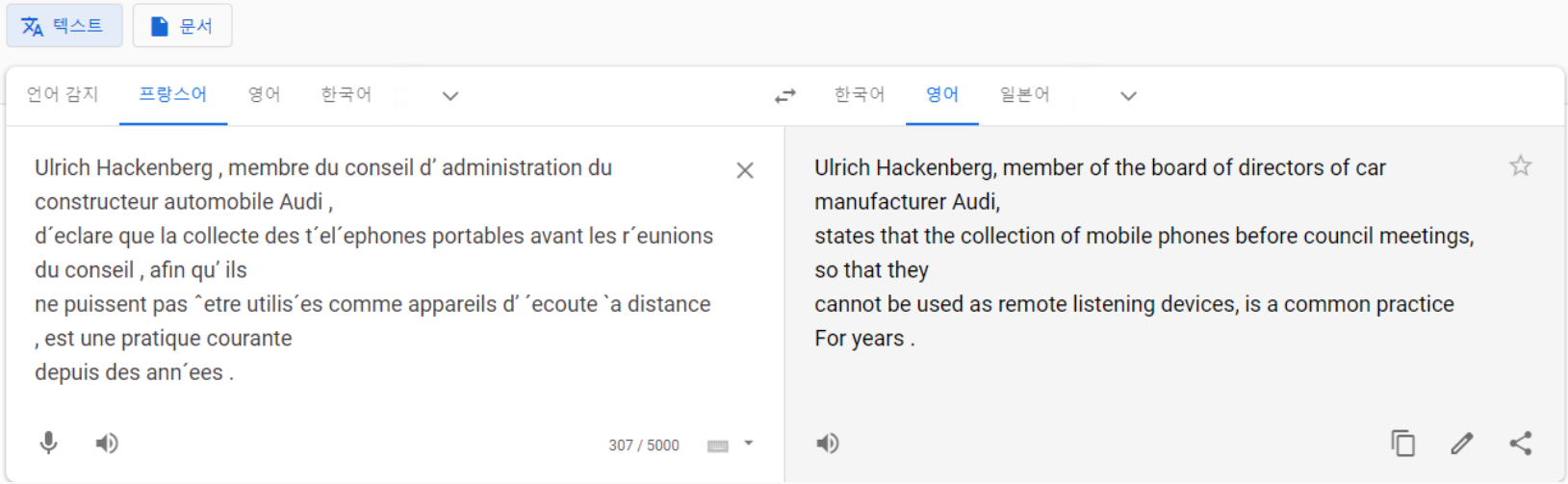
performance on long sentences

Type	Sentence
Our model	Ulrich UNK , membre du conseil d' administration du constructeur automobile Audi , affirme qu' il s' agit d' une pratique courante depuis des années pour que les téléphones portables puissent être collectés avant les réunions du conseil d' administration afin qu' ils ne soient pas utilisés comme appareils d' écoute à distance .
Truth	Ulrich Hackenberg , membre du conseil d' administration du constructeur automobile Audi , déclare que la collecte des téléphones portables avant les réunions du conseil , afin qu' ils ne puissent pas être utilisés comme appareils d' écoute à distance , est une pratique courante depuis des années .
Our model	" Les téléphones cellulaires , qui sont vraiment une question , non seulement parce qu' ils pourraient potentiellement causer des interférences avec les appareils de navigation , mais nous savons , selon la FCC , qu' ils pourraient interférer avec les tours de téléphone cellulaire lorsqu' ils sont dans l' air " , dit UNK .
Truth	" Les téléphones portables sont véritablement un problème , non seulement parce qu' ils pourraient éventuellement créer des interférences avec les instruments de navigation , mais parce que nous savons , d' après la FCC , qu' ils pourraient perturber les antennes-relais de téléphonie mobile s' ils sont utilisés à bord " , a déclaré Rosenker .
Our model	Avec la crémation , il y a un " sentiment de violence contre le corps d' un être cher " , qui sera " réduit à une pile de cendres " en très peu de temps au lieu d' un processus de décomposition " qui accompagnera les étapes du deuil " .
Truth	Il y a , avec la crémation , " une violence faite au corps aimé " , qui va être " réduit à un tas de cendres " en très peu de temps , et non après un processus de décomposition , qui " accompagnerait les phases du deuil " .

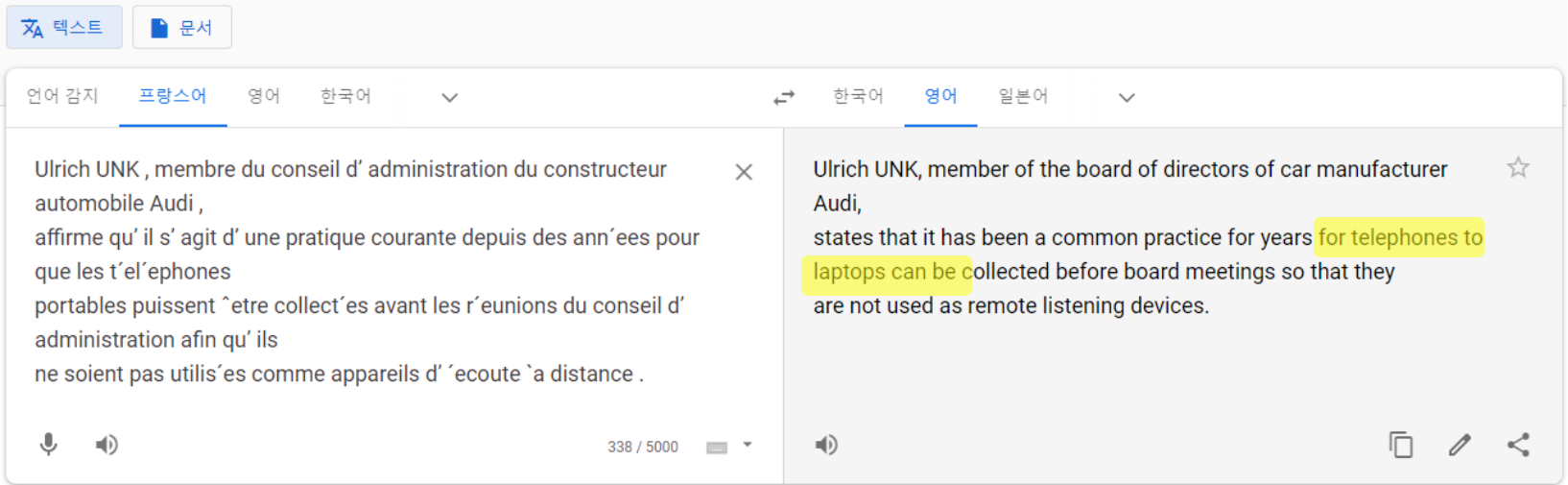
Table 3: A few examples of long translations produced by the LSTM alongside the ground truth translations. The reader can verify that the translations are sensible using Google translate.

Type	Sentence
Our model	Ulrich UNK , membre du conseil d' administration du constructeur automobile Audi , affirme qu' il s' agit d' une pratique courante depuis des années pour que les téléphones portables puissent être collectés avant les réunions du conseil d' administration afin qu' ils ne soient pas utilisés comme appareils d' écoute à distance .
Truth	Ulrich Hackenberg , membre du conseil d' administration du constructeur automobile Audi , déclare que la collecte des téléphones portables avant les réunions du conseil , afin qu' ils ne puissent pas être utilisés comme appareils d' écoute à distance , est une pratique courante depuis des années .

Truth



Model



Experiments (7 / 7)

performance on long sentences

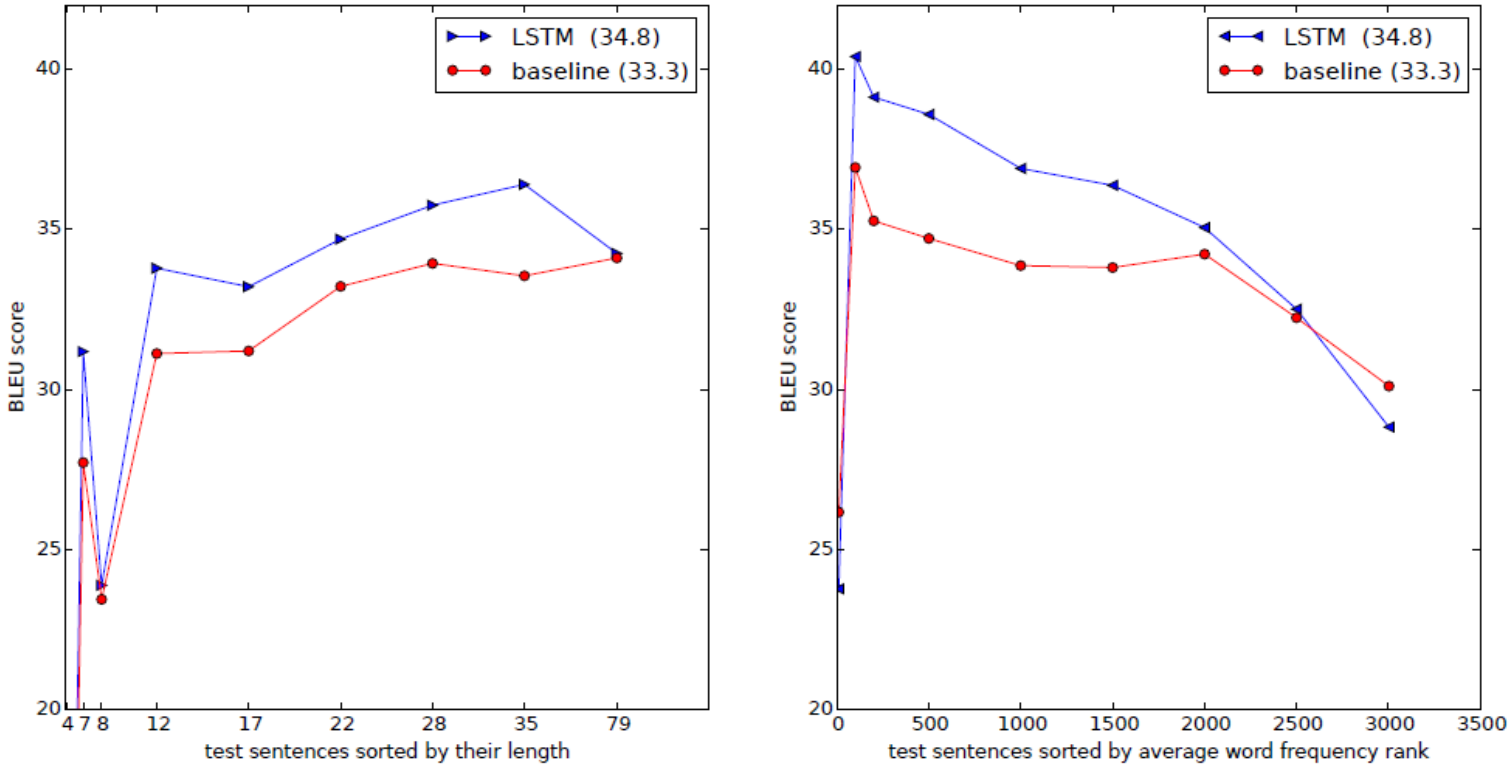


Figure 3: The left plot shows the performance of our system as a function of sentence length, where the x-axis corresponds to the test sentences sorted by their length and is marked by the actual sequence lengths. There is no degradation on sentences with less than 35 words, there is only a minor degradation on the longest sentences. The right plot shows the LSTM's performance on sentences with progressively more rare words, where the x-axis corresponds to the test sentences sorted by their "average word frequency rank".

Conclusion

5 Conclusion

In this work, we showed that a large deep LSTM with a limited vocabulary can outperform a standard SMT-based system whose vocabulary is unlimited on a large-scale MT task. The success of our simple LSTM-based approach on MT suggests that it should do well on many other sequence learning problems, provided they have enough training data.

We were surprised by the extent of the improvement obtained by reversing the words in the source sentences. We conclude that it is important to find a problem encoding that has the greatest number of short term dependencies, as they make the learning problem much simpler. In particular, while we were unable to train a standard RNN on the non-reversed translation problem (shown in fig. 1), we believe that a standard RNN should be easily trainable when the source sentences are reversed (although we did not verify it experimentally).

We were also surprised by the ability of the LSTM to correctly translate very long sentences. We were initially convinced that the LSTM would fail on long sentences due to its limited memory, and other researchers reported poor performance on long sentences with a model similar to ours [5, 2, 26]. And yet, LSTMs trained on the reversed dataset had little difficulty translating long sentences.

Most importantly, we demonstrated that a simple, straightforward and a relatively unoptimized approach can outperform a mature SMT system, so further work will likely lead to even greater translation accuracies. These results suggest that our approach will likely do well on other challenging sequence to sequence problems.

Thank you for listening !

Experiments

parallelization

3.5 Parallelization

A C++ implementation of deep LSTM with the configuration from the previous section on a single GPU processes a speed of approximately 1,700 words per second. This was too slow for our purposes, so we parallelized our model using an 8-GPU machine. Each layer of the LSTM was executed on a different GPU and communicated its activations to the next GPU (or layer) as soon as they were computed. Our models have 4 layers of LSTMs, each of which resides on a separate GPU. The remaining 4 GPUs were used to parallelize the softmax, so each GPU was responsible for multiplying by a 1000×20000 matrix. The resulting implementation achieved a speed of 6,300 (both English and French) words per second with a minibatch size of 128. Training took about a ten days with this implementation.

A year later …

Attention-based Neural Machine Translation !

Attention-based Neural Machine Translation

Intro

Neural Machine Translation

그동안 NMT 모델들
2013
2014
2015
동안 Plain RNN / Stacked LSTM / GRU 등 다양한 RNN layer 활용한 모델들 있었음 ~

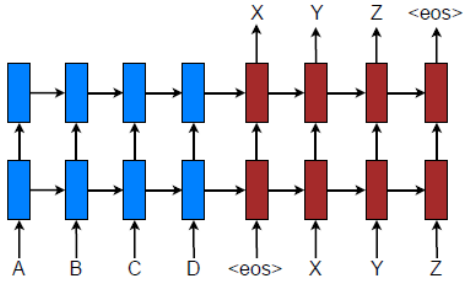


Figure 1: **Neural machine translation** – a stacking recurrent architecture for translating a source sequence A B C D into a target sequence X Y Z. Here, <eos> marks the end of a sentence.

In (Kalchbrenner and Blunsom, 2013; Sutskever et al., 2014; Cho et al., 2014; Luong et al., 2015), the source representation s is only used once to initialize thedecoder hidden state

In (Bahdanau et al., 2015; Jean et al., 2015) and this work, s, in fact, implies a set of source hidden states which are consulted throughout the entire course of the translation process

Such an approach is referred to as an attention mechanism ~ 그리고 우리는 following (Sutskever et al., 2014; Luong et al., 2015) 을 따라서 stacking LSTM 모델을 쓸 거야 ~ figure 1

Attention-based Models

attention 에는 global / local 있는데, 우리는 local 을 사용할거야 ~
Global 과 local 의 가장 큰 차이만 설명하고, local attention 만 디테일하게 설명할게 ~

Local Attention

Input-feeding Approach

Experiments

Training Details

English-German Results

-> BLEU Score 얘기가 나오는데, BLEU 가 정확히 어떻게 계산되는지 내용 추가 ?

German-English Results

Analysis

- Learning Curves
- Effects of Translating Long Sentences
- Choices of attentional architectures
- Alignment Quality
- Sample Translation

Conclusion

Beam Search Decoding

- Core idea: On each step of decoder, keep track of the k most probable partial translations (which we call *hypotheses*)
  - k is the beam size (in practice around 5 to 10)

- A hypothesis $y_1, \ldots, y_t$ has a score which is its log probability:

$$\text{score}(y_1, \ldots, y_t) = \log P_{\text{LM}}(y_1, \ldots, y_t | x) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$$

  - Scores are all negative, and higher score is better
  - We search for high-scoring hypotheses, tracking top *k* on each step

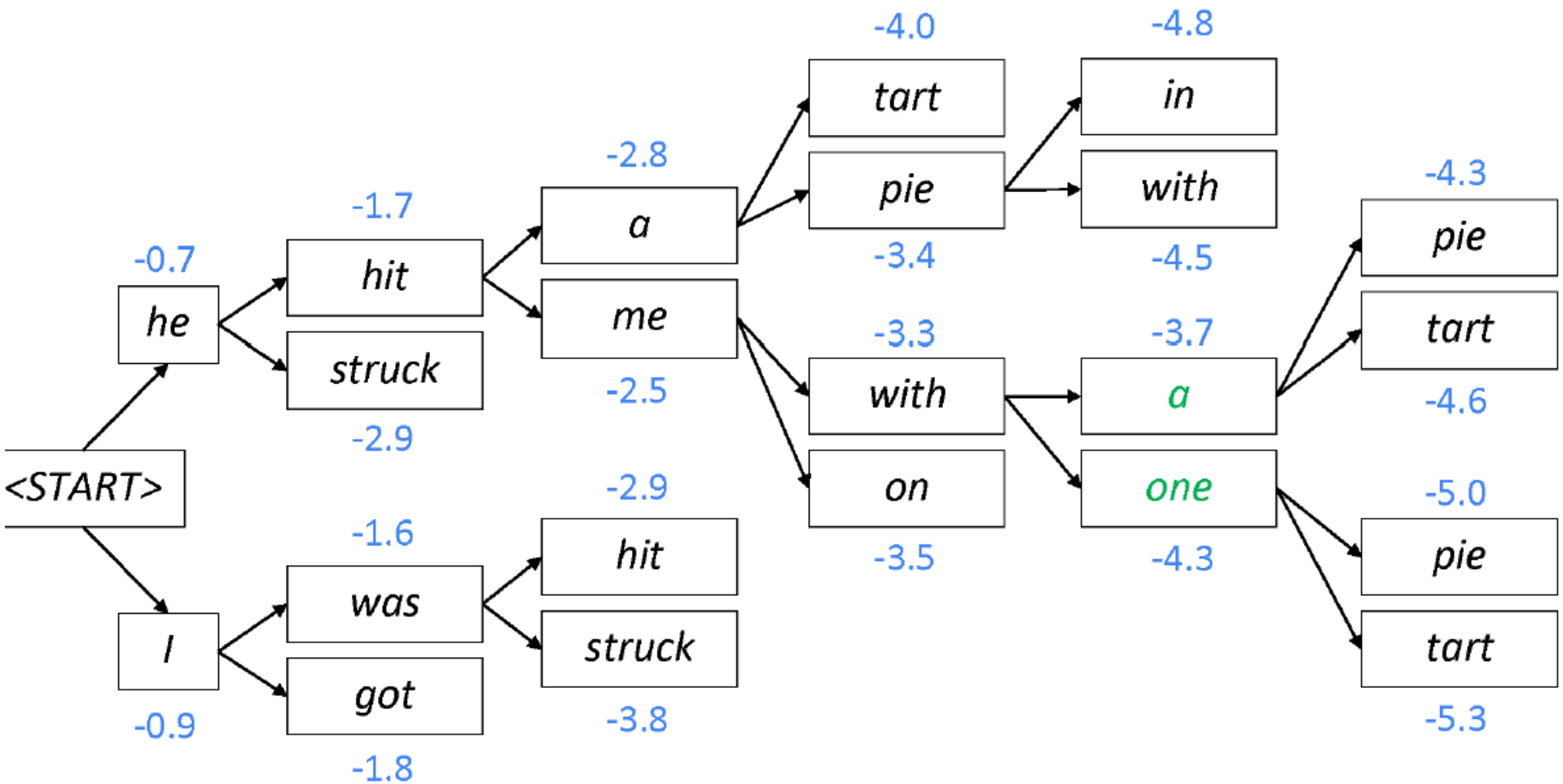
Beam Search Decoding

- Beam search is not guaranteed to find optimal solution
- But much more efficient than exhaustive search!

Let's look at an example...

Beam search decoding: example

Beam size = k = 2. Blue numbers = $\text{score}(y_1, \ldots, y_t) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$



For each of the *k* hypotheses, find top *k* next words and calculate scores

Beam Search Decoding: stopping criterion

- In greedy decoding, usually we decode until the model produces a <END> token
  - For example: <START> he hit me with a ball <END>

- In beam search decoding, different hypotheses may produce <END> tokens on different timesteps
  - When a hypothesis produces <END>, that hypothesis is complete
  - Place it aside and continue exploring other hypotheses via beam search

Beam Search Decoding: stopping criterion

- Usually we continue beam search until:
  - We reach timestep T (where T is some pre-defined cutoff), or
  - We have at least n completed hypotheses (where n is pre-defined cutoff)

Beam Search Decoding: finishing up

- We have our list of completed hypotheses.
- How to select top one with highest score?

- Each hypothesis $y_1, \ldots, y_t$ on our list has a score

$$\text{score}(y_1, \ldots, y_t) = \log P_{\text{LM}}(y_1, \ldots, y_t | x) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$$

Beam Search Decoding: finishing up

- Problem with this: longer hypotheses have lower scores
  - *0 < prob < 1*

- Fix: Normalize by length. Use this to select top one instead:

$$\frac{1}{t}\sum_{i=1}^{t}\log P_{\mathrm{LM}}(y_i|y_1,\ldots,y_{i-1},x)$$