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
Best WMT'14 result [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	$\sim$45

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

task by a sizeable margin, despite its inability to handle out-of-vocabulary words. The LSTM is within 0.5 BLEU points of the best WMT'14 result if it is used to rescore the 1000-best list of the baseline system.

3.7 Performance on long sentences

We were surprised to discover that the LSTM did well on long sentences, which is shown quantitatively in figure 3. Table 3 presents several examples of long sentences and their translations.

3.8 Model Analysis

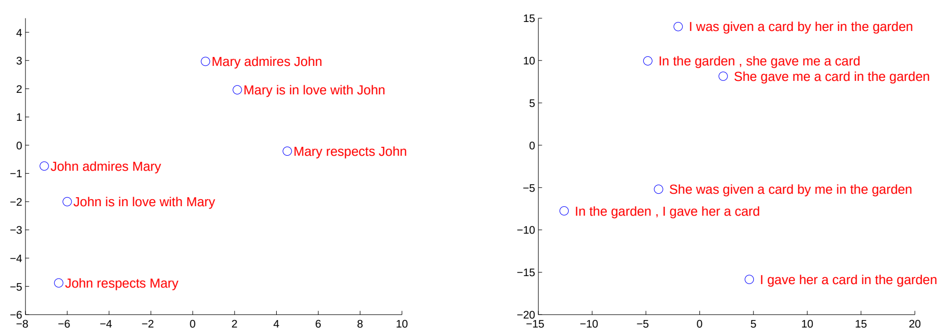

Figure 2: The figure shows a 2-dimensional PCA projection of the LSTM hidden states that are obtained after processing the phrases in the figures. The phrases are clustered by meaning, which in these examples is primarily a function of word order, which would be difficult to capture with a bag-of-words model. Notice that both clusters have similar internal structure.

One of the attractive features of our model is its ability to turn a sequence of words into a vector of fixed dimensionality. Figure 2 visualizes some of the learned representations. The figure clearly shows that the representations are sensitive to the order of words, while being fairly insensitive to the

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.

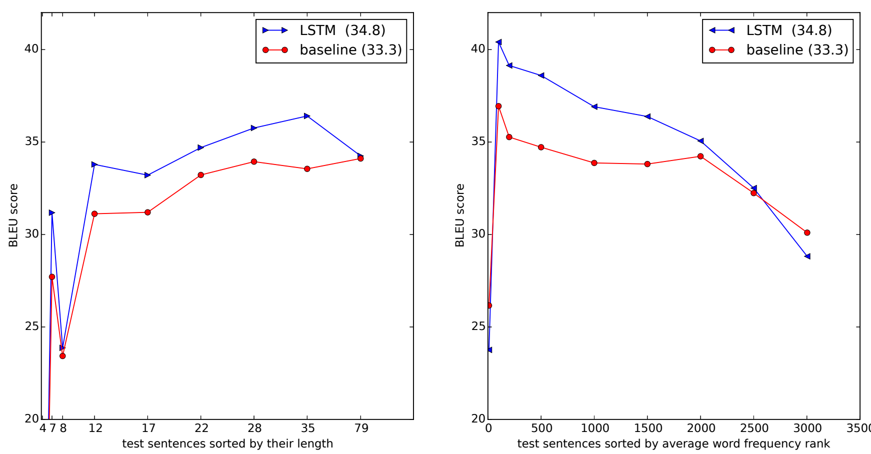

Figure 3: The left plot shows the performance of our system as a function of sentence length, where the x-axis corresponds to the test sentences sorted by their length and is marked by the actual sequence lengths. There is no degradation on sentences with less than 35 words, there is only a minor degradation 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”.

replacement of an active voice with a passive voice. The two-dimensional projections are obtained using PCA.

4 Related work

There is a large body of work on applications of neural networks to machine translation. So far, the simplest and most effective way of applying an RNN-Language Model (RNNLM) [23] or a

Feedforward Neural Network Language Model (NNLM) [3] to an MT task is by rescoring the n-best lists of a strong MT baseline [22], which reliably improves translation quality.

More recently, researchers have begun to look into ways of including information about the source language into the NNLM. Examples of this work include Auli et al. [1], who combine an NNLM with a topic model of the input sentence, which improves rescoring performance. Devlin et al. [8] followed a similar approach, but they incorporated their NNLM into the decoder of an MT system and used the decoder's alignment information to provide the NNLM with the most useful words in the input sentence. Their approach was highly successful and it achieved large improvements over their baseline.

Our work is closely related to Kalchbrenner and Blunsom [18], who were the first to map the input sentence into a vector and then back to a sentence, although they map sentences to vectors using convolutional neural networks, which lose the ordering of the words. Similarly to this work, Cho et al. [5] used an LSTM-like RNN architecture to map sentences into vectors and back, although their primary focus was on integrating their neural network into an SMT system. Bahdanau et al. [2] also attempted direct translations with a neural network that used an attention mechanism to overcome the poor performance on long sentences experienced by Cho et al. [5] and achieved encouraging results. Likewise, Pouget-Abadie et al. [26] attempted to address the memory problem of Cho et al. [5] by translating pieces of the source sentence in way that produces smooth translations, which is similar to a phrase-based approach. We suspect that they could achieve similar improvements by simply training their networks on reversed source sentences.

End-to-end training is also the focus of Hermann et al. [12], whose model represents the inputs and outputs by feedforward networks, and map them to similar points in space. However, their approach cannot generate translations directly: to get a translation, they need to do a look up for closest vector in the pre-computed database of sentences, or to rescore a sentence.

5 Conclusion

In this work, we showed that a large deep LSTM, that has a limited vocabulary and that makes almost no assumption about problem structure 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 an 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.

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