On the Properties of Neural Machine Translation: Encoder–Decoder Approaches

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Abstract

Neural machine translation is a relatively new approach to statistical machine translation based purely on neural networks. The neural machine translation models often consist of an encoder and a decoder. The encoder extracts a fixed-length representation from a variable-length input sentence, and the decoder generates a correct translation from this representation. In this paper, we focus on analyzing the properties of the neural machine translation using two models; RNN Encoder–Decoder and a newly proposed gated recursive convolutional neural network. We show that the neural machine translation performs relatively well on short sentences without unknown words, but its performance degrades rapidly as the length of the sentence and the number of unknown words increase. Furthermore, we find that the proposed gated recursive convolutional network learns a grammatical structure of a sentence automatically.

1 Introduction

A new approach for statistical machine translation based purely on neural networks has recently been proposed (Kalchbrenner and Blunsom, 2013; Sutskever et al., 2014). This new approach, which we refer to as *neural machine translation*, is inspired by the recent trend of deep representational learning. All the neural network models used in (Sutskever et al., 2014; Cho et al., 2014) consist of an encoder and a decoder. The encoder extracts a fixed-length vector representation from a variable-length input sentence, and from this representation the decoder generates a correct, variable-length target translation.

The emergence of the neural machine translation is highly significant, both practically and theoretically. Neural machine translation models require only a fraction of the memory needed by traditional statistical machine translation (SMT) models. The models we trained for this paper require only 500MB of memory in total. This stands in stark contrast with existing SMT systems, which often require tens of gigabytes of memory. This makes the neural machine translation appealing in practice. Furthermore, unlike conventional translation systems, each and every component of the neural translation model is trained jointly to maximize the translation performance.

As this approach is relatively new, there has not been much work on analyzing the properties and behavior of these models. For instance: What are the properties of sentences on which this approach performs better? How does the choice of source/target vocabulary affect the performance? In which cases does the neural machine translation fail?

It is crucial to understand the properties and behavior of this new neural machine translation approach in order to determine future research directions. Also, understanding the weaknesses and strengths of neural machine translation might lead to better ways of integrating SMT and neural machine translation systems.

In this paper, we analyze two neural machine translation models. One of them is the RNN Encoder–Decoder that was proposed recently in (Cho et al., 2014). The other model replaces the encoder in the RNN Encoder–Decoder model with a novel neural network, which we call a *gated recursive convolutional neural network* (grConv). We evaluate these two models on the task of translation from French to English.

Our analysis shows that the performance of the neural machine translation model degrades

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Proceedings of SSST-8, Eighth Workshop on Syntax, Semantics and Structure in Statistical Translation, pages 103–111,
October 25, 2014, Doha, Qatar. ©2014 Association for Computational Linguistics

quickly as the length of a source sentence increases. Furthermore, we find that the vocabulary size has a high impact on the translation performance. Nonetheless, qualitatively we find that the both models are able to generate correct translations most of the time. Furthermore, the newly proposed grConv model is able to learn, without supervision, a kind of syntactic structure over the source language.

2 Neural Networks for Variable-Length Sequences

In this section, we describe two types of neural networks that are able to process variable-length sequences. These are the recurrent neural network and the proposed gated recursive convolutional neural network.

2.1 Recurrent Neural Network with Gated Hidden Neurons

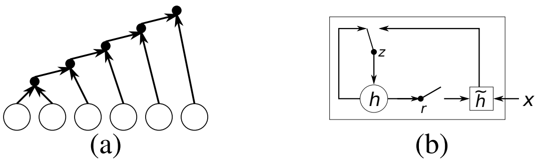


Figure 1: The graphical illustration of (a) the recurrent neural network and (b) the hidden unit that adaptively forgets and remembers.

A recurrent neural network (RNN, Fig. 1 (a)) works on a variable-length sequence $x = (\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_T)$ by maintaining a hidden state $\mathbf{h}$ over time. At each timestep t, the hidden state $\mathbf{h}^{(t)}$ is updated by

$$\mathbf{h}^{(t)} = f\left(\mathbf{h}^{(t-1)}, \mathbf{x}_t\right),$$

where f is an activation function. Often f is as simple as performing a linear transformation on the input vectors, summing them, and applying an element-wise logistic sigmoid function.

An RNN can be used effectively to learn a distribution over a variable-length sequence by learning the distribution over the next input $p(\mathbf{x}_{t+1} \mid \mathbf{x}_t, \cdots, \mathbf{x}_1)$. For instance, in the case of a sequence of 1-of-K vectors, the distribution can be learned by an RNN which has as an output

$$p(x_{t,j} = 1 \mid \mathbf{x}_{t-1}, \ldots, \mathbf{x}_1) = \frac{\exp\left(\mathbf{w}_j \mathbf{h}_{\langle t \rangle}\right)}{\sum_{j'=1}^{K} \exp\left(\mathbf{w}_{j'} \mathbf{h}_{\langle t \rangle}\right)},$$

for all possible symbols $j = 1, \ldots, K$, where $\mathbf{w}_j$ are the rows of a weight matrix $\mathbf{W}$. This results in the joint distribution

$$p(x) = \prod_{t=1}^{T} p(x_t \mid x_{t-1}, \ldots, x_1).$$

Recently, in (Cho et al., 2014) a new activation function for RNNs was proposed. The new activation function augments the usual logistic sigmoid activation function with two gating units called reset, $\mathbf{r}$, and update, $\mathbf{z}$, gates. Each gate depends on the previous hidden state $\mathbf{h}^{(t-1)}$, and the current input $\mathbf{x}_t$ controls the flow of information. This is reminiscent of long short-term memory (LSTM) units (Hochreiter and Schmidhuber, 1997). For details about this unit, we refer the reader to (Cho et al., 2014) and Fig. 1 (b). For the remainder of this paper, we always use this new activation function.

2.2 Gated Recursive Convolutional Neural Network

Besides RNNs, another natural approach to dealing with variable-length sequences is to use a recursive convolutional neural network where the parameters at each level are shared through the whole network (see Fig. 2 (a)). In this section, we introduce a binary convolutional neural network whose weights are recursively applied to the input sequence until it outputs a single fixed-length vector. In addition to a usual convolutional architecture, we propose to use the previously mentioned gating mechanism, which allows the recursive network to learn the structure of the source sentences on the fly.

Let $x = (\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_T)$ be an input sequence, where $\mathbf{x}_t \in \mathbb{R}^d$. The proposed gated recursive convolutional neural network (grConv) consists of four weight matrices $\mathbf{W}^l$, $\mathbf{W}^r$, $\mathbf{G}^l$ and $\mathbf{G}^r$. At each recursion level $t \in [1, T-1]$, the activation of the j-th hidden unit $h_j^{(t)}$ is computed by

$$h_j^{(t)} = \omega_c \tilde{h}_j^{(t)} + \omega_l h_{j-1}^{(t-1)} + \omega_r h_j^{(t-1)}, \quad (1)$$

where ω_c, ω_l and ω_r are the values of a gater that sum to 1. The hidden unit is initialized as

$$h_j^{(0)} = \mathbf{U}\mathbf{x}_j,$$

where $\mathbf{U}$ projects the input into a hidden space.

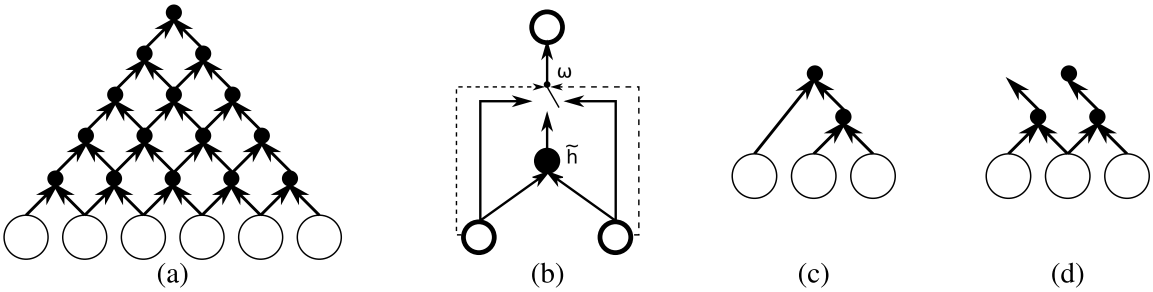


Figure 2: The graphical illustration of (a) the recursive convolutional neural network and (b) the proposed gated unit for the recursive convolutional neural network. (c–d) The example structures that may be learned with the proposed gated unit.

The new activation $\tilde{h}_j^{(t)}$ is computed as usual:

$$\tilde{h}_j^{(t)} = \phi\left(\mathbf{W}^l h_{j-1}^{(t)} + \mathbf{W}^r h_j^{(t)}\right),$$

where ϕ is an element-wise nonlinearity.

The gating coefficients ω's are computed by

$$\begin{bmatrix} \omega_c \\ \omega_l \\ \omega_r \end{bmatrix} = \frac{1}{Z} \exp\left(\mathbf{G}^l h_{j-1}^{(t)} + \mathbf{G}^r h_j^{(t)}\right),$$

where $\mathbf{G}^l, \mathbf{G}^r \in \mathbb{R}^{3 \times d}$ and

$$Z = \sum_{k=1}^{3} \left[\exp\left(\mathbf{G}^l h_{j-1}^{(t)} + \mathbf{G}^r h_j^{(t)}\right)\right]_k.$$

According to this activation, one can think of the activation of a single node at recursion level t as a choice between either a new activation computed from both left and right children, the activation from the left child, or the activation from the right child. This choice allows the overall structure of the recursive convolution to change adaptively with respect to an input sample. See Fig. 2 (b) for an illustration.

In this respect, we may even consider the proposed grConv as doing a kind of unsupervised parsing. If we consider the case where the gating unit makes a hard decision, i.e., ω follows an 1-of-K coding, it is easy to see that the network adapts to the input and forms a tree-like structure (See Fig. 2 (c–d)). However, we leave the further investigation of the structure learned by this model for future research.

3 Purely Neural Machine Translation

3.1 Encoder–Decoder Approach

The task of translation can be understood from the perspective of machine learning as learning the conditional distribution $p(f \mid e)$ of a target sentence (translation) f given a source sentence e. Once the conditional distribution is learned by a model, one can use the model to directly sample a target sentence given a source sentence, either by actual sampling or by using a (approximate) search algorithm to find the maximum of the distribution.

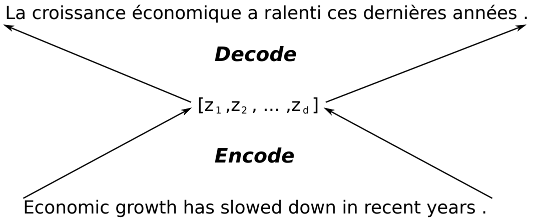

La croissance économique a ralenti ces dernières années .
Decode
[z₁ ,z₂ , ... ,z_d]
Encode
Economic growth has slowed down in recent years .

Figure 3: The encoder–decoder architecture

A number of recent papers have proposed to use neural networks to directly learn the conditional distribution from a bilingual, parallel corpus (Kalchbrenner and Blunsom, 2013; Cho et al., 2014; Sutskever et al., 2014). For instance, the authors of (Kalchbrenner and Blunsom, 2013) proposed an approach involving a convolutional n-gram model to extract a vector of a source sentence which is decoded with an inverse convolutional n-gram model augmented with an RNN. In (Sutskever et al., 2014), an RNN with LSTM units was used to encode a source sentence and starting from the last hidden state, to decode a target sentence. Similarly, the authors of (Cho et al., 2014) proposed to use an RNN to encode and decode a pair of source and target phrases.

At the core of all these recent works lies an encoder–decoder architecture (see Fig. 3). The encoder processes a variable-length input (source sentence) and builds a fixed-length vector representation (denoted as $\mathbf{z}$ in Fig. 3). Conditioned on the encoded representation, the decoder generates a variable-length sequence (target sentence).

Before (Sutskever et al., 2014) this encoder–decoder approach was used mainly as a part of the existing statistical machine translation (SMT) system. This approach was used to re-rank the n-best list generated by the SMT system in (Kalchbrenner and Blunsom, 2013), and the authors of (Cho et al., 2014) used this approach to provide an additional score for the existing phrase table.

In this paper, we concentrate on analyzing the direct translation performance, as in (Sutskever et al., 2014), with two model configurations. In both models, we use an RNN with the gated hidden unit (Cho et al., 2014), as this is one of the only options that does not require a non-trivial way to determine the target length. The first model will use the same RNN with the gated hidden unit as an encoder, as in (Cho et al., 2014), and the second one will use the proposed gated recursive convolutional neural network (grConv). We aim to understand the inductive bias of the encoder–decoder approach on the translation performance measured by BLEU.

4 Experiment Settings

4.1 Dataset

We evaluate the encoder–decoder models on the task of English-to-French translation. We use the bilingual, parallel corpus which is a set of 348M selected by the method in (Axelrod et al., 2011) from a combination of Europarl (61M words), news commentary (5.5M), UN (421M) and two crawled corpora of 90M and 780M words respectively.[1] We did not use separate monolingual data. The performance of the neural machien translation models was measured on the news-test2012, news-test2013 and news-test2014 sets (3000 lines each). When comparing to the SMT system, we use news-test2012 and news-test2013 as our development set for tuning the SMT system, and news-test2014 as our test set.

Among all the sentence pairs in the prepared parallel corpus, for reasons of computational efficiency we only use the pairs where both English and French sentences are at most 30 words long to train neural networks. Furthermore, we use only the 30,000 most frequent words for both English and French. All the other rare words are considered unknown and are mapped to a special token ([UNK]).

4.2 Models

We train two models: The RNN Encoder–Decoder (RNNenc)(Cho et al., 2014) and the newly proposed gated recursive convolutional neural network (grConv). Note that both models use an RNN with gated hidden units as a decoder (see Sec. 2.1).

We use minibatch stochastic gradient descent with AdaDelta (Zeiler, 2012) to train our two models. We initialize the square weight matrix (transition matrix) as an orthogonal matrix with its spectral radius set to 1 in the case of the RNNenc and 0.4 in the case of the grConv. $\tanh$ and a rectifier ($\max(0, x)$) are used as the element-wise nonlinear functions for the RNNenc and grConv respectively.

The grConv has 2000 hidden neurons, whereas the RNNenc has 1000 hidden neurons. The word embeddings are 620-dimensional in both cases.[2] Both models were trained for approximately 110 hours, which is equivalent to 296,144 updates and 846,322 updates for the grConv and RNNenc, respectively.

4.2.1 Translation using Beam-Search

We use a basic form of beam-search to find a translation that maximizes the conditional probability given by a specific model (in this case, either the RNNenc or the grConv). At each time step of the decoder, we keep the s translation candidates with the highest log-probability, where $s = 10$ is the beam-width. During the beam-search, we exclude any hypothesis that includes an unknown word. For each end-of-sequence symbol that is selected among the highest scoring candidates the beam-width is reduced by one, until the beam-width reaches zero.

The beam-search to (approximately) find a sequence of maximum log-probability under RNN was proposed and used successfully in (Graves, 2012) and (Boulanger-Lewandowski et al., 2013). Recently, the authors of (Sutskever et al., 2014) found this approach to be effective in purely neural machine translation based on LSTM units.

[1] All the data can be downloaded from http://www-lium.univ-lemans.fr/~schwenk/cslm_joint_paper/.

[2] In all cases, we train the whole network including the word embedding matrix. The embedding dimensionality was chosen to be quite large, as the preliminary experiments with 155-dimensional embeddings showed rather poor performance.

	Model	Development	Test
All	RNNenc	13.15	13.92
	grConv	9.97	9.97
	Moses	30.64	33.30
	Moses+RNNenc*	31.48	34.64
	Moses+LSTM$^\circ$	32	35.65
No UNK	RNNenc	21.01	23.45
	grConv	17.19	18.22
	Moses	32.77	35.63

(a) All Lengths

	Model	Development	Test
All	RNNenc	19.12	20.99
	grConv	16.60	17.50
	Moses	28.92	32.00
No UNK	RNNenc	24.73	27.03
	grConv	21.74	22.94
	Moses	32.20	35.40

(b) 10–20 Words

Table 1: BLEU scores computed on the development and test sets. The top three rows show the scores on all the sentences, and the bottom three rows on the sentences having no unknown words. ($\star$) The result reported in (Cho et al., 2014) where the RNNenc was used to score phrase pairs in the phrase table. ($\circ$) The result reported in (Sutskever et al., 2014) where an encoder–decoder with LSTM units was used to re-rank the n-best list generated by Moses.

When we use the beam-search to find the k best translations, we do not use a usual log-probability but one normalized with respect to the length of the translation. This prevents the RNN decoder from favoring shorter translations, behavior which was observed earlier in, e.g., (Graves, 2013).

5 Results and Analysis

5.1 Quantitative Analysis

In this paper, we are interested in the properties of the neural machine translation models. Specifically, the translation quality with respect to the length of source and/or target sentences and with respect to the number of words unknown to the model in each source/target sentence.

First, we look at how the BLEU score, reflecting the translation performance, changes with respect to the length of the sentences (see Fig. 4 (a)–(b)). Clearly, both models perform relatively well on short sentences, but suffer significantly as the length of the sentences increases.

We observe a similar trend with the number of unknown words, in Fig. 4 (c). As expected, the performance degrades rapidly as the number of unknown words increases. This suggests that it will be an important challenge to increase the size of vocabularies used by the neural machine translation system in the future. Although we only present the result with the RNNenc, we observed similar behavior for the grConv as well.

In Table 1 (a), we present the translation performances obtained using the two models along with the baseline phrase-based SMT system.[3] Clearly the phrase-based SMT system still shows the superior performance over the proposed purely neural machine translation system, but we can see that under certain conditions (no unknown words in both source and reference sentences), the difference diminishes quite significantly. Furthermore, if we consider only short sentences (10–20 words per sentence), the difference further decreases (see Table 1 (b).

Furthermore, it is possible to use the neural machine translation models together with the existing phrase-based system, which was found recently in (Cho et al., 2014; Sutskever et al., 2014) to improve the overall translation performance (see Table 1 (a)).

This analysis suggests that that the current neural translation approach has its weakness in handling long sentences. The most obvious explanatory hypothesis is that the fixed-length vector representation does not have enough capacity to encode a long sentence with complicated structure and meaning. In order to encode a variable-length sequence, a neural network may “sacrifice” some of the important topics in the input sentence in order to remember others.

This is in stark contrast to the conventional phrase-based machine translation system (Koehn et al., 2003). As we can see from Fig. 5, the conventional system trained on the same dataset (with additional monolingual data for the language model) tends to get a higher BLEU score on longer

[3] We used Moses as a baseline, trained with additional monolingual data for a 4-gram language model.

Source	She explained her new position of foreign affairs and security policy representative as a reply to a question: ”Who is the European Union? Which phone number should I call?”; i.e. as an important step to unification and better clarity of Union’s policy towards countries such as China or India.
Reference	Elle a expliqué le nouveau poste de la Haute représentante pour les affaires étrangères et la politique de défense dans le cadre d’une réponse à la question: ”Qui est qui à l’Union européenne?” ”A quel numéro de téléphone dois-je appeler?”, donc comme un pas important vers l’unicité et une plus grande lisibilité de la politique de l’Union face aux états, comme est la Chine ou bien l’Inde.
RNNEnc	Elle a décrit sa position en matière de politique étrangère et de sécurité ainsi que la politique de l’Union européenne en matière de gouvernance et de démocratie .
grConv	Elle a expliqué sa nouvelle politique étrangère et de sécurité en réponse à un certain nombre de questions : ”Qu’est-ce que l’Union européenne ? ” .
Moses	Elle a expliqué son nouveau poste des affaires étrangères et la politique de sécurité représentant en réponse à une question: ”Qui est l’Union européenne? Quel numéro de téléphone dois-je appeler?”; c’est comme une étape importante de l’unification et une meilleure lisibilité de la politique de l’Union à des pays comme la Chine ou l’Inde .

Source	The investigation should be complete by the end of the year when the findings will be presented to Deutsche Bank’s board of managing directors - with recommendations for action.
Reference	L’examen doit être terminé d’ici la fin de l’année, ensuite les résultats du conseil d’administration de la Deutsche Bank doivent être présentés - avec recommandation, d’ habitude.
RNNEnc	L’étude devrait être terminée à la fin de l’ année, lorsque les conclusions seront présentées au conseil d’administration de la Deutsche Bank, conseil d’association avec des mesures.
grConv	L’enquête devrait être terminée à la fin de l’année où les conclusions seront présentées par le conseil d’administration de la BCE à la direction des recommandations.
Moses	L’enquête devrait être terminé d’ici la fin de l’année lorsque les résultats seront présentés à la Deutsche Bank conseil des directeurs généraux - avec des recommandations .

Source	And there are thorny mechanical questions that must be resolved during that time, like how to balance the state’s mandate of ”adequate access” to licensed marijuana with its prohibitions on cannabis businesses within 1,000 feet of a school, park, playground or child care center.
Reference	Pendant ce temps, des questions pratiques restent en suspens: comment équilibrer le mandat de l’état qui garantit un accès approprié à la marijuana agréée et interdit l’installation de commerces de vente de cannabis dans un rayon de 30 km autour d’une école, d’un parc, d’un terrain de jeu ou d’une crèche.
RNNEnc	Il y a des questions préventives qui se posent quant à l’équilibre des droits de l’enfant dans les limites d’une entreprise de collecte de sang.
grConv	De façon générale, il y a des raisons de sécurité pour que les entreprises aient accès à des milliers de centres de pêche, d’eau ou de recherche.
Moses	Et il y a des problèmes mécaniques complexes qui doivent être résolues au cours de cette période, comme la manière d’équilibrer le mandat de ”l’accès adéquat” permis de marijuana avec l’interdiction du cannabis aux entreprises de 1000 pieds d’une école de jeu ou de parc, le service de garde.

(a) Long Sentences

Source	There is still no agreement as to which election rules to follow.
Reference	Toutefois il n’existe toujours pas d’accord selon quel règlement de vote il faut procéder.
RNNEnc	Il n’y a pas encore d’accord sur les règles électorales.
grConv	Il n’y a pas encore d’accord sur la question des élections à suivre.
Moses	Il y a toujours pas d’accord sur l’élection des règles à suivre.

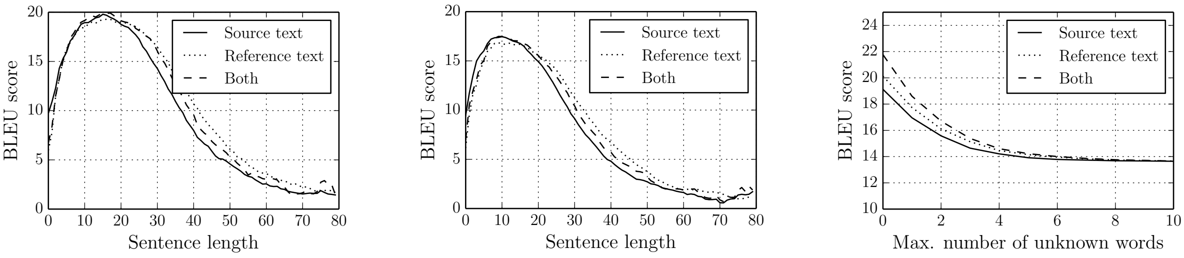
Source	Many of these ideas may have been creative, but they didn’t necessarily work.
Reference	Beaucoup de ces idées étaient créatives mais elles n’ont pas forcément fonctionné.
RNNEnc	Bon nombre de ces idées ont peut-être été créatrices, mais elles ne s’appliquaient pas nécessairement.
grConv	Beaucoup de ces idées peuvent être créatives, mais elles n’ont pas fonctionné.
Moses	Beaucoup de ces idées ont pu être créatif, mais ils n’ont pas nécessairement.

Source	There is a lot of consensus between the Left and the Right on this subject.
Reference	C’est qu’il y a sur ce sujet un assez large consensus entre gauche et droite.
RNNEnc	Il existe beaucoup de consensus entre la gauche et le droit à la question.
grConv	Il y a un consensus entre la gauche et le droit sur cette question.
Moses	Il y a beaucoup de consensus entre la gauche et la droite sur ce sujet.

Source	According to them, one can find any weapon at a low price right now.
Reference	Selon eux, on peut trouver aujourd’hui à Moscou n’importe quelle arme pour un prix raisonnable.
RNNEnc	Selon eux, on peut se trouver de l’arme à un prix trop bas.
grConv	En tout cas, ils peuvent trouver une arme à un prix très bas à la fois.
Moses	Selon eux, on trouve une arme à bas prix pour l’instant.

(b) Short Sentences

Table 2: The sample translations along with the source sentences and the reference translations.



(a) RNNenc (b) grConv (c) RNNenc

Figure 4: The BLEU scores achieved by (a) the RNNenc and (b) the grConv for sentences of a given length. The plot is smoothed by taking a window of size 10. (c) The BLEU scores achieved by the RNN model for sentences with less than a given number of unknown words.

sentences.

In fact, if we limit the lengths of both the source sentence and the reference translation to be between 10 and 20 words and use only the sentences with no unknown words, the BLEU scores on the test set are 27.81 and 33.08 for the RNNenc and Moses, respectively.

Note that we observed a similar trend even when we used sentences of up to 50 words to train these models.

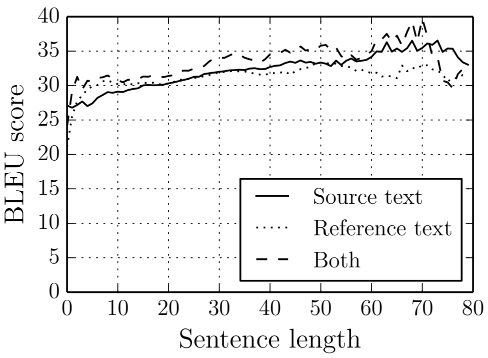


Figure 5: The BLEU scores achieved by an SMT system for sentences of a given length. The plot is smoothed by taking a window of size 10. We use the solid, dotted and dashed lines to show the effect of different lengths of source, reference or both of them, respectively.

5.2 Qualitative Analysis

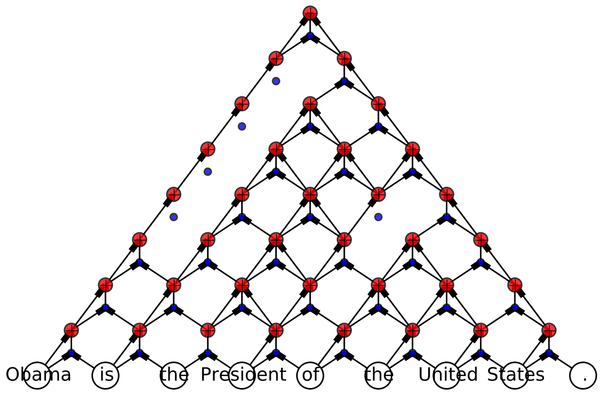
Although BLEU score is used as a de-facto standard metric for evaluating the performance of a machine translation system, it is not the perfect metric (see, e.g., (Song et al., 2013; Liu et al., 2011)). Hence, here we present some of the actual translations generated from the two models, RNNenc and grConv.

In Table. 2 (a)–(b), we show the translations of some randomly selected sentences from the development and test sets. We chose the ones that have no unknown words. (a) lists long sentences (longer than 30 words), and (b) short sentences (shorter than 10 words). We can see that, despite the difference in the BLEU scores, all three models (RNNenc, grConv and Moses) do a decent job at translating, especially, short sentences. When the source sentences are long, however, we notice the performance degradation of the neural machine translation models.

Additionally, we present here what type of structure the proposed gated recursive convolutional network learns to represent. With a sample sentence *"Obama is the President of the United States"*, we present the parsing structure learned by the grConv encoder and the generated translations, in Fig. 6. The figure suggests that the grConv extracts the vector representation of the sentence by first merging *"of the United States"* together with *"is the President of"* and finally combining this with *"Obama is"* and *"."*, which is well correlated with our intuition. Note, however, that the structure learned by the grConv is different from existing parsing approaches in the sense that it returns *soft* parsing.

Despite the lower performance the grConv showed compared to the RNN Encoder–Decoder,[4] we find this property of the grConv learning a grammar structure automatically interesting and believe further investigation is needed.

[4] However, it should be noted that the number of gradient updates used to train the grConv was a third of that used to train the RNNenc. Longer training may change the result, but for a fair comparison we chose to compare models which were trained for an equal amount of time. Neither model was trained to convergence.



(a)

Translations
Obama est le Président des États-Unis . (2.06)
Obama est le président des États-Unis . (2.09)
Obama est le président des Etats-Unis . (2.61)
Obama est le Président des Etats-Unis . (3.33)
Barack Obama est le président des États-Unis . (4.41)
Barack Obama est le Président des États-Unis . (4.48)
Barack Obama est le président des Etats-Unis . (4.54)
L'Obama est le Président des États-Unis . (4.59)
L'Obama est le président des États-Unis . (4.67)
Obama est président du Congrès des États-Unis .(5.09)

(b)

Figure 6: (a) The visualization of the grConv structure when the input is *"Obama is the President of the United States."*. Only edges with gating coefficient ω higher than 0.1 are shown. (b) The top-10 translations generated by the grConv. The numbers in parentheses are the negative log-probability.

6 Conclusion and Discussion

In this paper, we have investigated the property of a recently introduced family of machine translation system based purely on neural networks. We focused on evaluating an encoder–decoder approach, proposed recently in (Kalchbrenner and Blunsom, 2013; Cho et al., 2014; Sutskever et al., 2014), on the task of sentence-to-sentence translation. Among many possible encoder–decoder models we specifically chose two models that differ in the choice of the encoder; (1) RNN with gated hidden units and (2) the newly proposed gated recursive convolutional neural network.

After training those two models on pairs of English and French sentences, we analyzed their performance using BLEU scores with respect to the lengths of sentences and the existence of unknown/rare words in sentences. Our analysis revealed that the performance of the neural machine translation suffers significantly from the length of sentences. However, qualitatively, we found that the both models are able to generate correct translations very well.

These analyses suggest a number of future research directions in machine translation purely based on neural networks.

Firstly, it is important to find a way to scale up training a neural network both in terms of computation and memory so that much larger vocabularies for both source and target languages can be used. Especially, when it comes to languages with rich morphology, we may be required to come up with a radically different approach in dealing with words.

Secondly, more research is needed to prevent the neural machine translation system from underperforming with long sentences. Lastly, we need to explore different neural architectures, especially for the decoder. Despite the radical difference in the architecture between RNN and grConv which were used as an encoder, both models suffer from *the curse of sentence length*. This suggests that it may be due to the lack of representational power in the decoder. Further investigation and research are required.

In addition to the property of a general neural machine translation system, we observed one interesting property of the proposed gated recursive convolutional neural network (grConv). The grConv was found to mimic the grammatical structure of an input sentence without any supervision on syntactic structure of language. We believe this property makes it appropriate for natural language processing applications other than machine translation.

Acknowledgments

The authors would like to acknowledge the support of the following agencies for research funding and computing support: NSERC, Calcul Québec, Compute Canada, the Canada Research Chairs and CIFAR.

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