Neural Machine Translation

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Abstract

Machine translation (MT) is the task of automatically translating a text from one natural language into another. Ever since the invention of modern computers, MT has been one of the applications that envisioned to be automated. In the recent years,the progress in MT has been tremendous. In today's mobile phone era, the need for MT systems is only growing and the demand has grown beyond just text translation. Live translation on video conferences is possible with the current MT systems. In this article, we discuss the latest improvements in the MT research and highlight the most important breakthroughs.

1 Deep Learning

In the recent years, Deep learning has been making a big impact in various fields of computer science. This impact is profound in the perceptual learning task in the fields like computer vision, natural language processing, etc [18]. Though the idea of training a multi layered neural network to perform function approximation is known to the research community for at least a couple of decades[24], due to the nature of training problem requiring large computational resources, the multi layered neural network remained less practical. With the advent of general purpose graphical processing units(GPGPUs) and the availability of training data, the neural networks are now a practical solution for many perceptual tasks. One of the early success of deep learning was in the field of image classification. In the annual ImageNet classification challenge [6], AlexNet [17] showed a remarkable improvement in the state-of- the-art accuracy. Within a few years, more sophisticated architectures like Google Inception Network [26], Deep Residual Network [10], etc., have improved the accuracy to be comparable with a human in that task. The generality of the neural network made it easily possible to be used for a wide variety of tasks. With more people working on deep learning and the ideas arising in solving the problems being easily transferable, the deep learning is the state-of-the-art for many learning tasks. In the following section, we will briefly summarize the basics of deep learning.

The basic building block of a Multilayer network, or in more technical term Multilayer perceptron (MLP) is a perceptron. The preceptron shown in Fig.1 closely resembles a neuron in a human brain. A preceptron takes a set of input values, computes a weighted sum of the inputs, and outputs a scalar value of

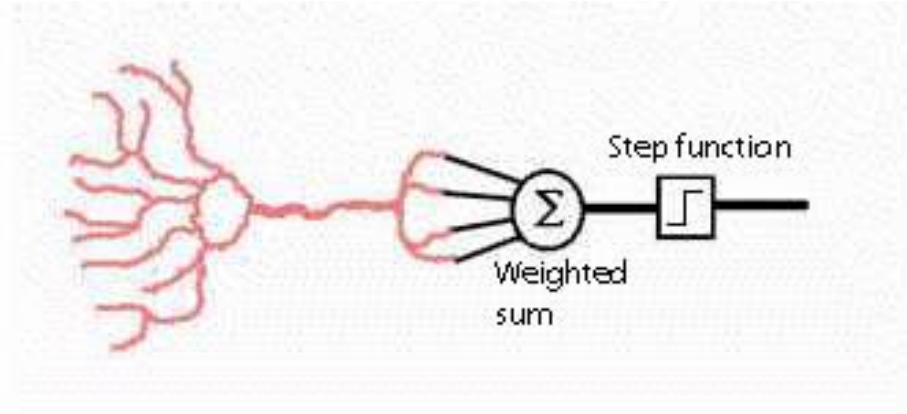


Figure 1: An artificial neuron (perceptron)

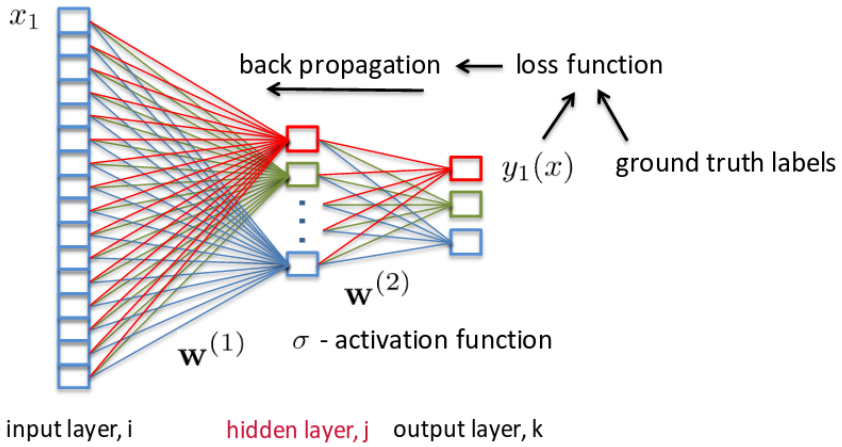


Figure 2: Layered representation in a MLP

a after applying an activation function (mostly non-linear). The weights for computing the weighted sum and the threshold in the activation function are initially set to random values and are learned from the training data. Mathematically, a perceptron with the weight matrix A and the threshold T for an step activation function, for the input vector x, outputs the following,

$$f(x) = \begin{cases} 1, & \text{if } Ax > c \\ 0, & \text{otherwise} \end{cases}$$

A layer has many number of neurons and many layers are stacked one on top of the other to form a MLP. An MLP with many layers is called as Deep Neural Network(DNN). In the following section we will discuss the properties of DNNs and how they are useful in the context of supervised machine learning.

1.1 Supervised learning

Supervised learning is the problem of predicting a new output y' for a new input x', and set of training data that contains a set of input and output $\{x \mapsto y\}$. Most of the supervised learning problems can be formulated as either a classification or regression problem. Classification is the problem of predicting the label for a given x' among a set of given labels $\{Y\}$, while regression is predicting a continuous valued output for a given input. The usual way of doing supervised learning is to extract features from the given data and train a model to perform classification or regression.

$$x \xrightarrow[\text{Feature extraction}]{\mathbb{D}(x)} x'_{intermediate} \xrightarrow[\text{classifier/regressor}]{\mathbb{F}(x'|\theta)} y$$

The power of the DNNs lies in the fact that the models learns the features directly from the given training data and avoids hand engineered features.

$$x \xrightarrow[\text{hierarchical}]{\mathbb{M}(x|\Theta)} y$$

The DNNs with neurons in one layers being connected to all the neurons in the next layer are called Feed Forward Networks. The feed forward networks are harder to train since they have lots of parameters. To make a the DNNs learn useful representation for performing supervised learning, we need special types of connections between the neurons. Two of the most commonly used DNN architectures are Convolutional Neural Networks(CNN) and Recurrent Neural Networks(RNN). In the following section we will discuss these architectures in detail.

1.1.1 Convolutional Neural Networks

Convolutional Neural netowrks are a class of feed-forward networks in which hidden layers are either convolutional, pooling for fully-connected. A convolutional layer applies a convolution operation to the input, and passes the result to the next layer. A pooling layer combines the outputs of a number of neurons from previous layer into a single value. The most commont pooling operations are max-pooling which selects the maximum value from its receptive field and average-pooling which calculates the average of values from its receptive field. A fully-connected layer connects every neuron in one layer to every neuron to another layer, in a similar way as perceptrons. Fig.3 depicts a CNN.

1.1.2 Recurrent Neural Networks

The neurons in the RNNs have recurrent self connections. i.e. the output of the neurons are connected back to the inputs. Thus the output at time step t_1 is computed with taking output at time step t_0 as input. The recurrent connections are shown Fig.4. This enables the RNNs to have an internal memory. RNNs are trained with the a modified version of back propagation called **Back Propagation Through Time(BPTT)** [27].

RNNs in general are harder to train and this is particularity evident when the BPTT is done over a larger number of time steps. This is because the gradients simply converges to zero after a few time steps. This problem known as **vanishing gradients problem** is a well studied phenomenon [3].

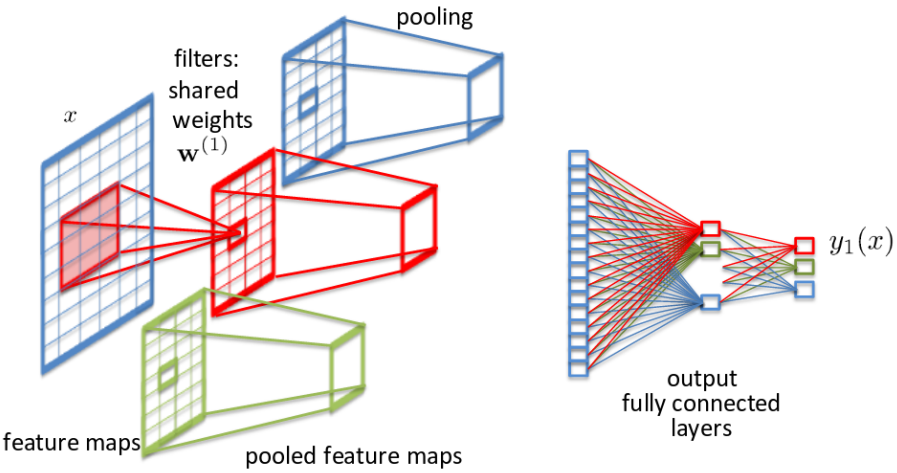


Figure 3: A CNN with a fully connected neurons in the last layer.

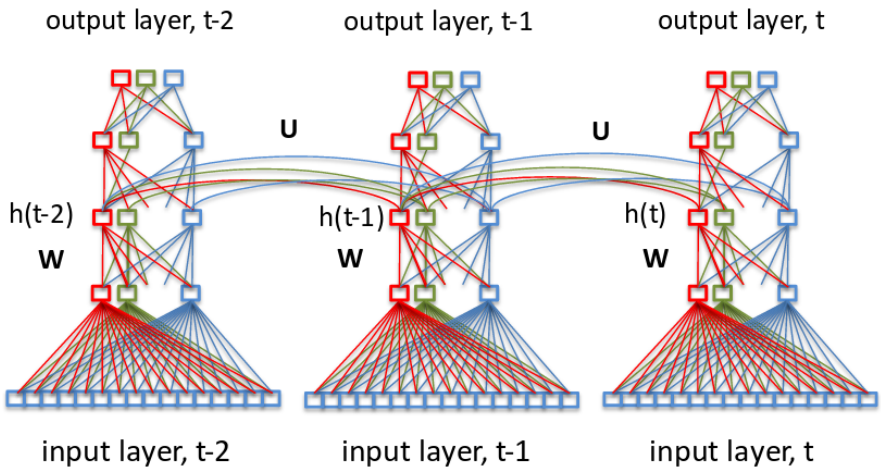
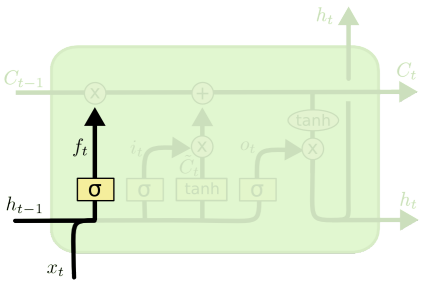
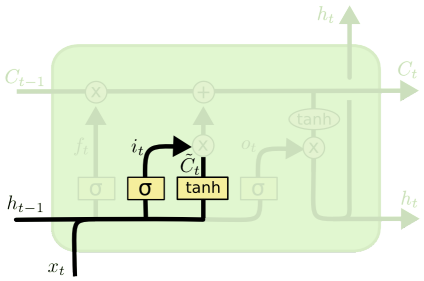


Figure 4: Recurrent connections in a RNN



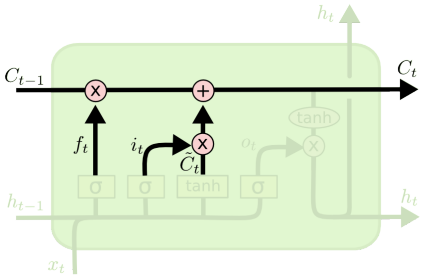
$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

Figure 5: Forget gate in LSTM



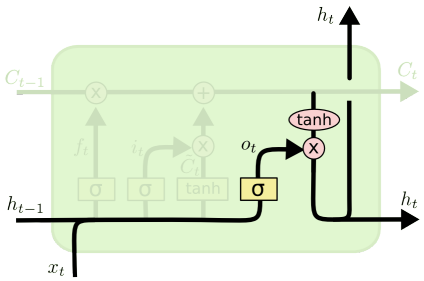
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

Figure 6: Add gate computing parts to be to modified in LSTM



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Figure 7: Add gate computing data to be added to cell state in LSTM



$$o_t = \sigma\left(W_o \; [h_{t-1}, x_t] \; + \; b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$

Figure 8: Add gate computing output in LSTM

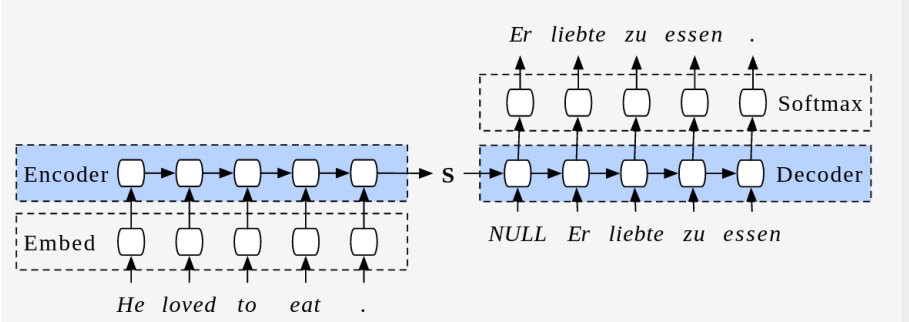


Figure 9: Simple Encoder-Decoder architecture for machine translation

To alleviate the vanishing gradients problem, a special architecture called **Long Short Term Memory(LSTM)** [12] is used.

LSTM cells has separate internal memory vector and has three gates–forget gate, add gate, and output gate. To understand the Mathematical intuition behind these gates, let us consider a LSTM cell in a hidden state h and internal cell memory vector c_{t-1}. At time t, the cell takes input x_t, previous output h_{t-1} and update the cell memory to c_t, produces the output h_t. The forget computes a vector size c between 0 and 1. This vector determines what information should be preserved and what should be forgotten based on the current input x_t as shown in Fig.5. This vector is later multiplied with the cell memory. If the vector is all zeros, multiplying makes all cell state to forget everything while all ones preserve everything. Then the add gate computes which parts in the cell states to be updates as shown in Fig.6 and the new data to be updated as shown in Fig.7. Finally the output gate generates the output h_t and does not modify the cell state as shown in Fig.8.

2 Traditional Machine Translation

2.1 Evaluation score

Translation is a hard task to define an evaluation score for measuring how well a model is performing due to inherent complexity of the task. The most widely used evaluation metric is called Bilingual Evaluation Understudy(BLEU) [23]. It depends on modified n-gram precision (or co- occurrence) and needs lots of target sentences for better results. Despite being the most widely used metric, many researchers have expressed concern about the effectiveness of the metric [30], [4], [1]. To understand how BLEU score works, consider the following translation candidates

- Candidate 1: It is a guide to action which ensures that the military always obey the commands the party.
- Candidate 2: It is toinsure the troops forever hearing the activity guide-book that party direct.

to be evaluated against the set of three reference translations.

- Reference 1: It is a guide to action that ensures that the military will forever heed Party commands.
- Reference 2: It is the guiding principle which guarantees the military forces always being under the command of the Party.
- Reference 3: It is the practical guide for the army always to heed directions of the party.

The BLUEs core idea is to use count the number of N-gram matches. The match could be position-independent. Reference could be matched multiple times. These steps are linguistically-motivated.

Candidate 1: It is a guide to action which ensures that the military always obey the commands of the party.

Reference 1: It is a guide to action that ensures that the military will forever heed Party commands.
Reference 2: It is the guiding principle which guarantees the military forces always being under the command of the Party.
Reference 3: It is the practical guide for the army always to heed directions of the party.
N-gram Precision: 17

Candidate 2: It is to insure the troops forever hearing the activity guidebook that party direct.
Reference 1: It is a guide to action that ensures that the military will forever heed Party commands.
Reference 2: It is the guiding principle which guarantees the military forces always being under the command of the Party.
Reference 3: It is the practical guide for the army always to heed directions of the party.
N-gram Precision: 8

Thus candidate 1 is better.

Issues with N-gram precision:

Candidate: the the the the the the the.
Reference 1: The cat is on the mat.
Reference 2: There is a cat on the mat.

N-gram Precision: 7 and BLEU: 1

This result is very misleading. Thus the following modified BLEU score is often used.

Algorithm	**Example**
Count the max number of times a word occurs in any single reference	Ref 1: The cat is on the mat. Ref 2: There is a cat on the mat. "the" has max count 2
Clip the total count of each candidate word	Unigram count = 7 Clipped unigram count = 2 Total no. of counts = 7
Modified N-gram Precision equal to Clipped count/ Total no. of candidate word	Modified-ngram precision: Clipped count = 2 Total no. of counts =7 Modified-ngram precision = 2/7

Table 1: Translation evalution scores

N-grams with different Ns are used but 4 is most common metric.

2.2 Phrase based Machine Translation (PBMT)

Traditionally there exists two types of machine translation systems:

- **The Rule-based Approach** The source language text is analyzed using parsers and/or morphological tools and transformed into intermediary representation. This representation is used to generate target sentence. The rules are written by human experts. As a large number of rules is

required to capture the phenomena of natural language, this is a time consuming process. As the set of rules grows over time, it gets more and more complicated to extend it and ensure consistency.

- **The Data-driven Approach** In the data-driven approach, bilingual and monolingual corpora are used as main knowledge source. In the statistical approach, MT is treated as a decision problem: given the source language sentence, we have to decide for the target language sentence that is the best translation. Then, Bayes rule and statistical decision theory are used to address this decision problem.

For a given sentence in source language $f^I = f_1 \dots f_i \dots f_I$, we need to find the sentence $e^I = e_1 \dots e_i \dots e_I$ in target sentence by applying Bayes rule to find the sentence that minimizes the expected loss

$$e^I = \arg\min_{I,e^I} \left\{ \sum_{I'} Pr(e'^{i'}|f^J) \cdot L(e^I, e'^{i'}) \right\}$$

Here $L(e^I, e'^{i'})$ denotes loss function under construction. It measures the loss (or errors) of a candidate translation e^I assuming the correct translation is $e'^{i'}$. If the loss function is assumed to be 0-1 loss meaning zero if wrong and 1 if correct, then the Bayes rule can be simplified to,

$$e^I = \arg\max_{I,e^I} \left\{ Pr(e'^{i'}|f^J) \right\}$$

PBMT were the widely scalable models in the beginning of the millennium [16]. The model works at the level of phrases instead of words and had a lot of individual components but the core idea is learning statistical patterns in training data.

Some of the major components used in the PBMT were

- Sentence alignment: Gale and Church Algorithm based on Dynamic programming [19].
- Word alignment: Expectation Maximization.
- Phrases generation: Heuristic based complex algorithms.
- Phrase lookup: Statistical matching.
- Beam search: For generating target sentence. Beam search is a generic algorithm that is used even in the latest NMT systems.

Beam search in general is a heuristic search algorithm that explores a graph by expanding the most promising node in a limited set. In machine translation, beam search is used to generate a set of most likely sentence given a input sentence by retaining only the most promising translations. Number of sentence is kept constant.

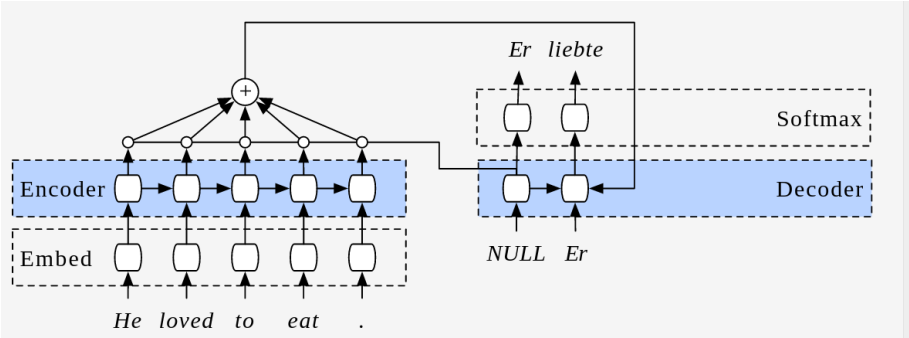


Figure 10: Context for machine translation

3 Neural Machine Translation (NMT)

Though usage of neural networks did not yield promising results in the early years, the recurrent neural networks started to achieve performance comparable to PBMT as in [15] and [11]. Most of the early architectures were simple encoder-decoder architectures. An simple working of encoder-decoder architecture for machine translation is shown in Fig.9. The architecture has an encoder that takes a sentence in source language and encodes it into a vector S of fixed length. The decoder takes the embedding S as input and generates the sentence in the target language. Some of the major drawbacks with the simple architecture is that

1. The encoder has to encode all the information in the source sentence into fixed size embedding S.
2. The decoder never sees the actual input sentence and has to rely completely on S for generating target sentence.
3. Having fixed size embedding vector makes the architecture less flexible. Smaller size means less information where as using larger vector means for smaller sentences we need zero padding and more computation time.

3.1 Jointly learning to align and translate

The paper [2] address this issue of having a fixed size embedding by introducing the idea of context as shown in Fig.10. The main proposal was

1. Encoder outputs a hidden representation for each word in the source sentence F_s.
2. One context vector C in the size of the input sentence that has values between 0 and 1.
3. Each element of the embedding F_s is multiplied with one element in C.

The whole embedding is made available to the decoder and C describes which part of the embedding should be focused to generate the current word based on the previous word.

Encoder RNN at each input step t, generates hidden state, $h_t = f(x_t, h_{t-1})$. Unlike in the previous models where only the last hidden state is made available to the decoder, this paper provided all the hidden state and also a context vector that has a weight for each of the hidden vector. The context vector helps the decoder to focus on a part of the sentence. $c = q(\{h_1, \cdots, h_{T_x}\})$.

The decoder is trained to predict the next work y_t given the context vector c and all previously predicted words $\{y_1, \cdots, y_{t-1}\}$

$$p(y) = \prod_{t=1}^{T} p(y_t | \{y_1, \cdots, y_{t-1}\}, c)$$

With RNN, each conditional probability is modeled as,

$$p(y_t | \{y_1, \cdots, y_{t-1}\}, c) = g(y_{t-1}, s_t, c)$$

where s_t is the hidden state of the RNN. The context vector for a input sentence i, is computed as a weighted sum of hidden states of the encoder (also known as **annotations**)

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j$$

$$\alpha_{ij} = \frac{exp(e_{ij})}{\sum_{k=1}^{T_x} exp(e_{ik})}$$

where,

$$e_{ij} = a(s_{i-1}, h_j)$$

is the alignment model that scores how well the inputs around the j and the output at the position i match.

A feedforward neural network is used as the alignment model and is **jointly trained** with all the NMT system as a whole.

The functionality of the context vector is visualized in the Fig. 11. For example, the French language has the words "European Economic Area"exists in the reverse order as "zone économique européenne". The context learns to focus on the correct order for the decoder.

The idea of context used in the paper was adapted by the MT research community with the name of attention. Several attention mechanism were proposed [21], [5], [9]. The context proposed in section 3.1 to align hidden state h_t with each source hidden state $\bar{h_s}$ can be formulated a,

$$\begin{aligned} a_t(s) &= align(h_t, \bar{h_s}) \\ &= \frac{exp(score(h_t, \bar{h_s}))}{\sum_{s'} exp(score(h_t, \bar{h'_s}))} \end{aligned} \tag{1}$$

The new attention mechanisms proposed are,

$$align(h_t, \bar{h_s}) = \begin{cases} h_t^T \bar{h_s} & \text{dot} \\ h_t^T W_a \bar{h_s} & \text{general} \\ v_a^T tanh(W_a[h_t; \bar{h'_s}]) & \text{concat} \end{cases}$$

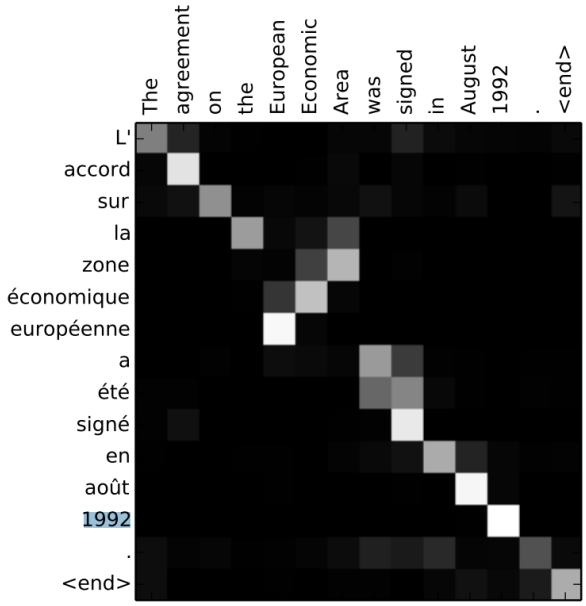


Figure 11: Visualization of the context in action

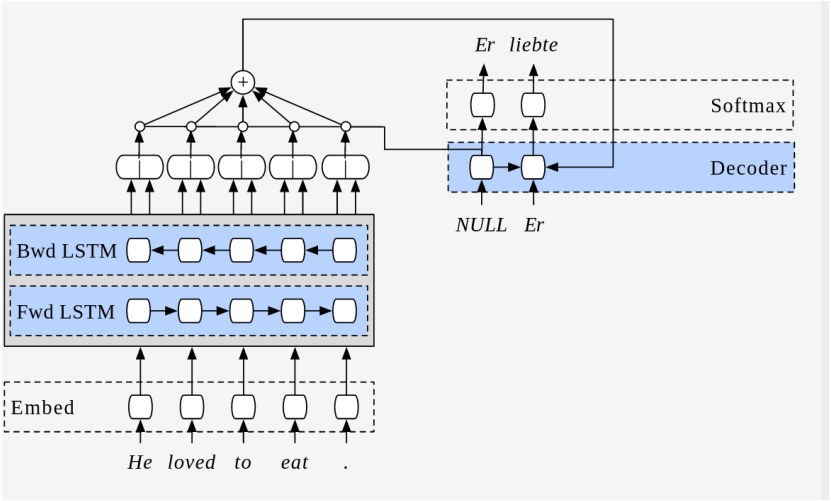


Figure 12: Bi-directional Encoder

These mechanisms are shown do perform better in certain scenarios but none of them is shown to be the best.

This paper also made use of the bi-directional LSTM in the layers of the Encoder. Just like an LSTM that has an internal memory to comprehend the past states, the LSTM also comprehends the words that comes next in the sentence. It has two internal state—one for past states and one for the future state. A bi- directional LSTM is shown in Fig.12.

The whole model is trained with standard maximum-likelihood error minimization $\mathbb{O}_{ML}(\Theta) = \sum_{i=1}^{N} logP_{\Theta}(Y^{*(i)}|X^{(i)})$ with stochastic gradient descent(SGD) on a mini-batch of 80 sentences. For the first time, the BLEU score was comparable to phrase based machine translation system. But the fact that there are no individual pieces in the model was a great benefit and the research community started to consider neural systems as an viable alternative phrase based machine translation system.

3.2 Sequence to Sequence models

With in an year, more deep and powerful models were computationally possible. Taking the availability of the computational power to advantage a new framework for learning sequence to sequence learing was proposed. A sequence to sequence model formulated as

$$p(y_1, \cdots, y_T|x_1, \cdots, x_T) = \prod_{t=1}^{T} p(y_t|v, y_1, \cdots, y_{t-1})$$

where v is the internal memory of the RNNs. With more powerful RNNs, this model can be used to learn a variety of tasks like speech recognition, handwritten digits recognition, machine translation, etc as shown in the paper [25]

A simple sequence to sequence model is shown in Fig.13. Just by making the model more deeper, without any special treatment for machine translation, the paper achieved state-of-the art results. The model is trained on WMT English to French dataset with 12M sentences consisting of 348M French words and 304M English words using 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. The network has 4 LSTM layers with 1000 LSTM cells in each layer. The paper used 1000 dimensional word embedding to represent the words as vector following the word2vec paper [22]. word2vec formulated the problem of learning word embedding as an energy maximization problem using a simple neural network with just one hidden layer. The energy maximized is called Negative sampling. The resulting vector embedding is empirically shown to have arithmetic properties. i.e. France - Paris + Germany is roughly equal to Berlin as shown in Fig.15. The paper an impressive BLEU score of 33.3 even without doing anything specific for machine translation.

3.3 Google Neural Machine System

Most likely Google runs the worlds biggest machine translation service supporting 103 languages(at the time of writing this article) serving about a billion query every day. Google translate team published a detailed paper describing

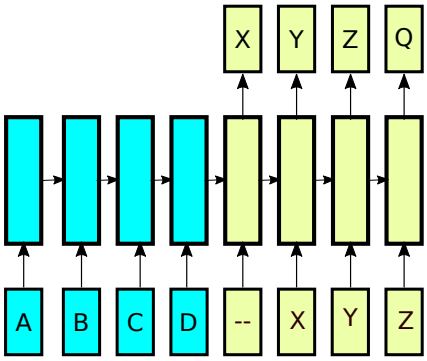


Figure 13: Seq2Seq model

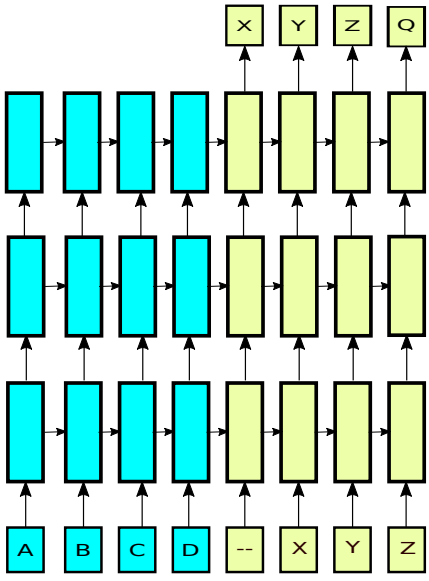


Figure 14: A more powerfuls Seq2Seq model

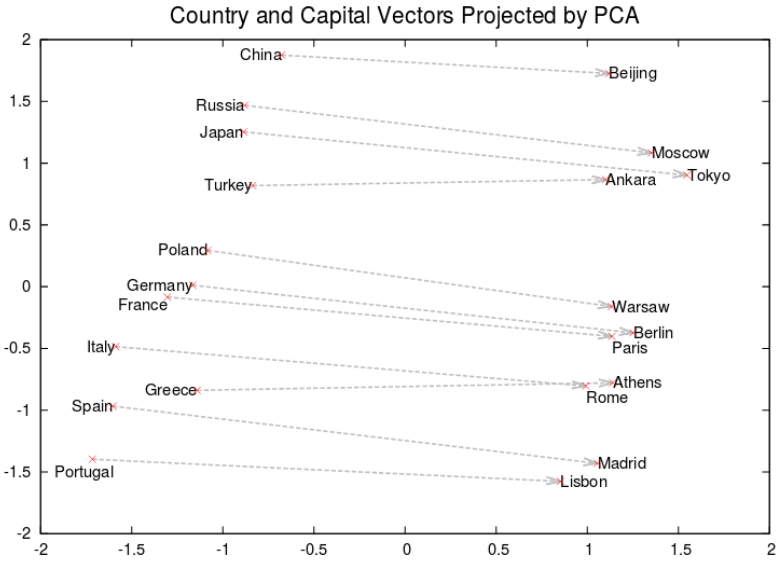


Figure 15: Two-dimensional PCA projection of the 1000-dimensional word embedding.

their neural machine translation system [29]. In the following section we will discuss the key ideas described in the paper. This paper is very unique in the sense that it is much more than an academic paper. The paper explains most of the components of the system including a lot of engineering details and also has a lot of components that are inspired from other recent breakthroughs in machine translation and deep learning research in general. The basic architecture is heavily inspired by the jointly learning to align and translate 3.1 and 3.2. The core architecture is shown in Fig.16. It combines the idea of context with the a deeper sequence to sequence encoder- decoder model with bi-directional LSTM in the initial layers of the encoder. Both the encoder and decoder contains eight layer. It also made use of the Residual connections introduced in [10]. Residual connection are helpful in alleviating the vanishing gradients problem in an interesting manner as shown in Fig.17. In a DNN each layer can be interpreted as transforming the input x to a new manifold by learning $F(x)$ but in a residual network only learn the change to be applied to the input $(x + F(x))$. There is always an identity skip connection between layers helping in the constant gradient flow which otherwise might vanish. The residual learning enables training very deep networks as shown in Fig.18.

The author also tried to use a enhanced cost function. The usual cost function maximized by the training process is the maximum likelihood

$$\mathbb{O}_{ML}(\Theta) = \sum_{i=1}^{N} logP_{\Theta}(Y^{*(i)}|X^{(i)})$$

but this does not directly correspond to the BLEU score. To improve the BLEU

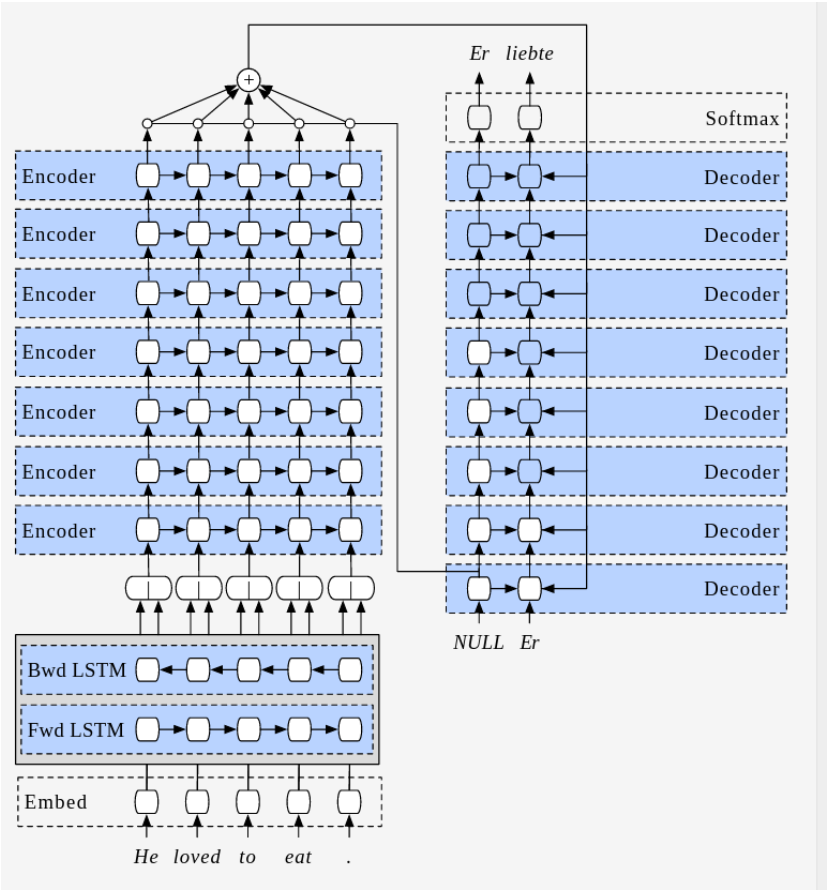


Figure 16: The core architecture of GNMT

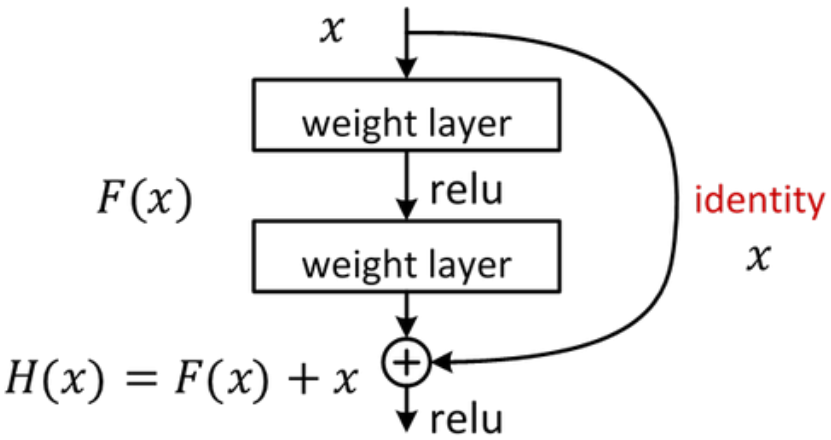


Figure 17: Residual connections

Figure 18: GNMT with residual connections

the authors proposed the following cost function.

$$\mathbb{O}_{ML}(\Theta) = \sum_{i=1}^{N} \sum_{Y=\mathbb{Y}}^{N} logP_{\Theta}(Y^{*(i)}|X^{(i)})r(Y, Y^{*(i)})$$

where $r(\cdot)$ is per-sentence score computed as an expectation over all Y up to certain-length.

In terms of the training process, just one encoder and one decoder is used for all language pairs. The authors reported several nice properties of the joint language training. One highlight is that this enables zero-shot learning. The system is able to translate between the language pairs it never saw in the training data. Also the languages for which huge training data does not exists benefited from the joint training. The zero shot learning property is discussed in detail the paper [13]. To enable a single decoder to generate target sentence for all the languages, the input text is suffixed with additional tokes like $< \_\_EN\_\_ >$ $, < \_\_FR\_\_ >, < \_\_DE\_\_ >, < \_\_ES\_\_ >$ indicating the target language to be generated.

A simple sequence to sequence model is shown in Fig. 13. Just by making the model more deeper as in Fig. 14, without any special treatment for machine translation, the paper achieved state-of-the art results. The model as trained on WMT English to French dataset with 12M sentences consisting of 348M French words and 304M English words using 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. The network has 4 LSTM layers with 1000 LSTM cells in each layer. The paper used 1000 dimensional word embedding to represent the words as vector following the word2vec paper [22]. Word2vec formulated the problem of learning word embedding as an energy maximization problem using a simple neural network with just one hidden layer. The energy maximized is called Negative sampling. The resulting vector embedding is empirically shown to have arithmetic properties. i.e. France - Paris + Germany is roughly equal to Berlin as shown in Fig. 15. The paper an impressive BLEU score of 33.3 even without doing anything specific for machine translation.

One another interesting aspect of the GNMT is the use of Quantizable Model and Quantized Inference. Since GNMT has to serve a huge volume of users in the production, the service is very computationally intensive making hard for low latency translation difficult. Quantized Inference is the process of using low precession arithmetic operations during the inference. The idea of using low precession arithmetic got inference has been tried since the early days of neural networks. In the recent years, the authors in [28] successfully demonstrated that a CNN training can be sped up by a factor of 4-6 with minimal loss of accuracy in the classification task. More interestingly [20] showed that weights of the neural networks can be quantized to just three states, -1,0,1. But most of these success were restricted to CNNs. In the paper GNMT team did the same of RNNs. To achieve this, the model were constrained during training time. The nature of LSTMs remembering state across multiple time steps posts additional challenges in quantizing RNNs. he forward computation of an LSTM stack with residual connections is modified to the following:

$$
\begin{aligned}
c_t^{'i}, m_t^i &= LSTM_i(c_{t-1}^i, m_{t-1}^i, x_t^{i-1}; W^i) \\
c_t^i &= max(-\delta, min(\delta, c_t^{'i})) \\
x_t^{'i} &= m_t^i + x_t^{i-1} \\
x_t^i &= max(-\delta, min(\delta, x_t^{'i})) \\
c_t^{'i}, m_t^i &= LSTM_{i+1}(c_{t-1}^{i+1}, m_{t-1}^{i+1}, x_t^i; W^{i+1}) \\
c_t^{i+1} &= max(-\delta, min(\delta, c_t^{'i+1}))
\end{aligned}
\tag{2}
$$

and for keeping notation simple we drop the superscript i and expand further as,

$$
\begin{aligned}
W &= [W_1, W_2 .... W_8] \\
i_t &= sigmoid(W_1 x_t + W_2 m_t) \\
i'_t &= tanh(W_3 x_t + W_4 m_t) \\
f_t &= sigmoid(W_5 x_t + W_6 m_t) \\
o_t &= sigmoid(W_7 x_t + W_8 m_t) \\
c_t &= c_{t-1} \odot f_t + i_t^{'} \odot i_t \\
m_t &= c_t \odot o_t
\end{aligned}
\tag{3}
$$

All the operations in the above equations are performed only with fixed point 8 bit or 16 bit integer multiplications.

3.4 A Convolutional Encoder Model for NMT

Despite all the success that recurrent neural netowrks have achieved in neural machine translation, they have some shortcomings which makes them less appealing for such a task. Recurrent neural networks have an inherently serial structure, meaning that their camputations cannot be fully parallelized. This contrasts with other types of networks, specifically covolutioanl neural networks, which operate over a fixed-size input sequence enabling simultaneous computation of all the features. Furthermore recurrent neural networks need to traverse the full distance of the serial path between two features to reach from one to another. This characteristics leads to higher difficulty of training these models. Once again this is not the case for some other models such as convolutional neural networks in which a succession of convolutional layers provide shroter path between features. [7] Such desired characteristics of convolutional neural networks have resulted in the recent trend to exploit their power in neural machine translations. In this and next sections we review a number of propsed techniques.

Gehring et al. [7] proposes an encoder-decoder model similar to that of [2] in which the encoder is replaced by a convolutional neural network. In this model, as in [2], the decoder is a long short-term memory recurrent neural network, and the encoder consists of two one-dimensional convolutional networks: One network (CNN-a) generates a sequence containing the encoded information about fixed- sized contexts (of kernel size), and the other (CNN-c) computes

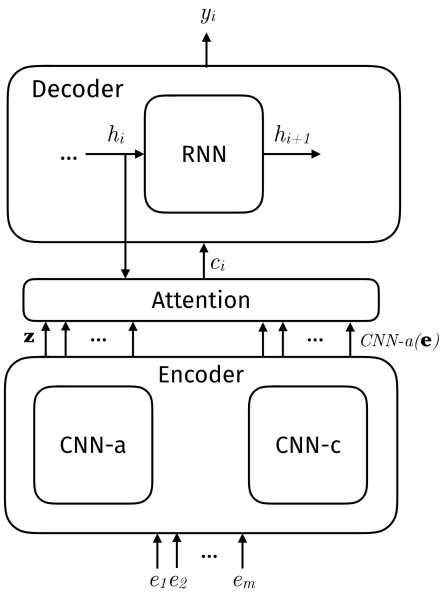


Figure 19: The architecture of convolutional encoder model

the conditional input for the soft-attention mechanism connecting the encoder and the decoder. Fig. 19 schematically illustrates this architecture.

The convolutional networks in the encoder only contain convolutional layers without any pooling layer. This allows the full input sequence length to the encoder to be retained. Moreover stacking multiple convolutional layers on top of each other can increase the context width for each input token of the input sequence.

As convolutional layers do all their calculations in parallel and therefore cannot distinguish position of the input tockens, it is necessary to somehow encode the positional information in the input sequence before feeding it to the encoder. To this end, Gehring et al. [7] proposes to feed a sequence $e_1, e_2, ..., e_m$ to the ecoder in which,

$$e_i = w_i + l_i$$

where w_i is a word embedding on the vocabulary of the source language and l_i is a positional embedding of the words of the source sentence.

The decoder aims to capture a distribution over the possible target vocabulary by transforming its LSTM hidden state h_i via a linear layer with weights W_o and bias b_o,

$$p(y_{i+1}|y_1, ..., y_i, \mathbf{x}) = \text{softmax}(W_o h_{i+1} + b_o)$$

The conditional input c_i to the LSTM is computed via a simple dot-product soft-attention mechanism, i.e. a dot-product between the set of calculated attention weights and the sequence coming form CNN-c. In order to calculate the attention scores, first the hidden state h_i is transformed by a linear transformation with weights W_d and bias b_d to match the size of an embedding of

Encoder	WMT'16 en-ro	WMT'15 en-de	WMT'14 en-fr
BiLSTM	27.4	23.2	34.6
Convolutional	27.8	24.3	35.7

Table 2: Performance comparison of convolutional encoder model with a bi-directional neural network in terms of BLEU score

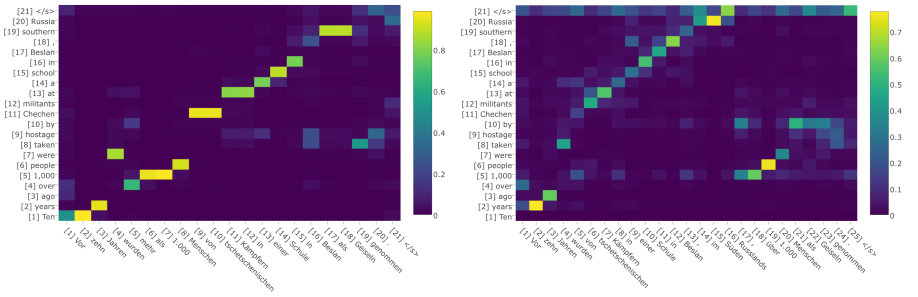


Figure 20: Attention scores for a BiLSTM (top) and a convolutional encoder (bottom)

the previous target word g_i and then it is summed with that embedding. Then this vector is used to calculate the each attention score via a softmax over the product of all these neworks and the sequence comming from CNN-a:

$$
\begin{aligned}
d_i &= W_d h_i + b_d + g_i \\
z_i &= \text{CNN-a}(e_i) \\
c_i &= \sum_{j=1}^{T} a_{ij} \text{CNN-c}(e_j) \\
a_{ij} &= \frac{exp(d_i^T z_j)}{\sum_{t=1}^{m} exp(d_i^T z_t)}
\end{aligned}
$$

The experimental results show that this architecture's performance is comparable to that of bi-directional recurrent neural networks while achieving two times speed up in generation of target translation. Table 2 lists the BLEU score achieved by this model for a few datesets.

Another interesting observation is that in recurrent neural networks the learned attention scores are sharp but do not necessarily represent a correct alignment, while for convolutional encoders the scores are less focused but still indicate an approximate source location. Fig. 20 illustrates the learned attention scores for a sentence from WMT'15 English-German translation using a 2-layer BiLSTM and a convolutional encoder with 15-layer CNN-a and 5-layer CNN-c.

3.5 Convolutional Sequence to Sequence Learning

Based on [7], Gehring et al. [8] further developed the idea of convolutional encoders and introduced a fully convolutional encoder-decoder architecture. In

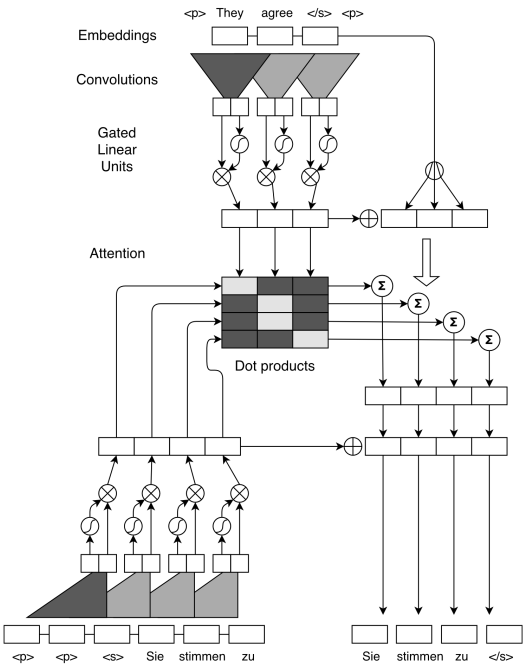


Figure 21: Architecture of convolutional sequence to sequence learning.

this model both encoder and decoder networks share a simple convolution block structure that computes intermediate states based on a fixed number of input elements. Each block consists of a one-dimensional convolution followed by a non-linearity. Once again the relationship between distant words in the input sequence is captured by stacking multiple such blocks on top of one another, and non-linearities in the blocks allow the network to exploit this full input field, or to focus on fewer elements if needed. Gehring et al. [8] proposes the use of gated linear units (GLU) as non-linearity.

Each convolution kernel of size k is parameterized as $W \in \mathbb{R}^{2d \times kd}$, $b_w \in \mathbb{R}^{2d}$ and takes as input $X \in \mathbb{R}^{k \times d}$ which is a concatenation of k input elements embedded in d dimensions and maps them to a single element $Y = [AB] \in \mathbb{R}^{2d}$. Then applying a gated linear unit non- linearity $v([AB]) = A \otimes \sigma(B)$ where $A, B \in \mathbb{R}^d$ and $\otimes$ is point-wise multiplicaiton, results in a single output element of size d. Subsequent layers operate in the same manner over k such elements from previous layer. Fig. 21 illustrates the architecture of the model.

Another introduced improvement over previous model is multi-step attention in which a set of different conditional inputs are calculated for each layer of the decoder. To compute the attention, the current hidden state h_i^l of l-th layer of decoder is combined with an embedding of the previous target element g_i. Once the conditional input c_i^l has been computed, it is simply added to the output of the corresponding layer h_i^l.

Model	WMT'16 en-ro	WMT'15 en-de	WMT'14 en-fr
GNMT	-	24.61	39.92
ConvS2S	29.88	25.16	40.46

Table 3: Performance comparison of convolutional sequence to sequence model with GNMT in terms of BLEU score

$$c_i^l = \sum_{j=1}^{m} a_{ij}^l (z_j^u + e_j)$$

$$a_{ij}^l = \frac{exp(d_i^l \cdot z_j^u)}{\sum_{t=1}^{m} exp(d_i^l \cdot z_t^u)}$$

$$d_i^l = W_d^l h_i^l + b_d^l + g_i$$

$$y_i^l = h_i^l + c_i^l$$

Experimental results show that this translation model achieves similar or higher BLEU scores as that of GNMT while bringing almost an order of magnitude seep up in translation generation. Table 3 lists the BLEU score achieved by this model for a few datesets.

3.6 Depthwise Separable Convolutions for NMT

Another convolution-based translation model is due to Kaiser et al. [14]. Even though convolutions unlike recurrent neural networks can provide an efficient non-local referencing across time, they still suffer from computational complexity and large parameter count. [14] Addresses this issue by introducing a model based upon so-called depthwise separable convolutions. Depthwise Separable Convolution consists of a depthwise convolution, i.e an operator which performs a spatial convolution independently over each channel of the input, followed by a pointwise convolution, i.e. a regular 1×1 convolution.

The rationale behind this definition is the expermentally-verified assumption that the 2D and 3D inputs that convolutions operate on will feature both fairly independent channels and highly correlated spatial locations [14]. As a result one can simplify regular convolution's feature learning over a joint "space-cross-channels realm" into two simpler steps, i.e. a spatial feature learning step, and a channel combination step, while reducing the number of parameters. More formally depthwise separable convolution can be written as follows:

Convolution	Number of parameters
Conv	$k \cdot c^2$
SepConv	$k \cdot c + c^2$

Table 4: Number of parameters in convolution operations

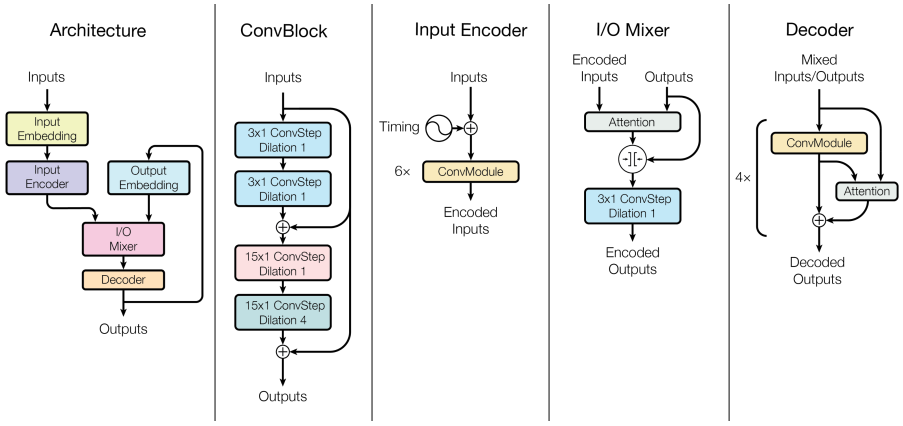


Figure 22: The architecture of SliceNet

$$Conv(W, y)_{i,j} = \sum_{k,l,m}^{K,L,M} W_{k,l,m} \cdot y_{i+k,j+l,m}$$

$$PointwiseConv(W, y)_{i,j} = \sum_{m}^{M} W_m \cdot y_{i,j,m}$$

$$DepthwiseConv(W, y)_{i,j} = \sum_{k,l}^{K,L} W_{k,l} \cdot y_{i+k,j+l}$$

$$SepConv(W_p, W_d, y)_{i,j} = PointwiseConv_{i,j}(W_p, DepthwiseConv_{i,j}(W_d, y))$$

Table 4 lists the number fo parameters for a regular convolution as well as a depthwise separable convolution with c channels and filters and one-dimensional kernel of size k. As it can be seen for larger kernel sizes the number of parameters in depthwise separable convolution is significantly less than regular convolutions.

The SliceNet model introduced in [14], has a similar structure to other encoder-decoder models. It first embeds the inputs and outputs by two independent networks and concatenates them and the feeds the result into a decoder. At each step, the decoder produces a new output prediction given the encoded inputs and the encoding of the previously produces outputs. Fig. 22 illustrates the architecture of SliceNet model.

The convolution modules in SliceNet use rectified linear units (ReLU) as non-linearities. Besides the ReLU activations are followed by a normalization layer. Therefore a complete convolution module is defined as,

Model	newstest 14
GNMT	24.6
ConvS2S	25.1
SliceNet	26.1

Table 5: Performance comparison of SliceNet with other models in terms of BLEU score

$$ConvStep_{d,s}(W, x) = LN(SepConv_{d,s}(W, ReLU(x)))$$
$$LN(x) = \frac{G}{\sigma(x)}(x - \mu(x)) + B$$

In order to encode the positional information, SliceNet add a so-called timing signal to the input sequence. This signal is defined as follows,

$$timing(t, 2d) = sin(t/1000^{2d/depth})$$
$$timing(t, 2d + 1) = cos(t/1000^{2d/depth})$$

For given source of shape $[m, depth]$ and target of shape $[n, depth]$ the attention mechanism used in SliceNet computes the feature vector similarities at each position and re-scales according to the depth,

$$attention(source, target) = Attend(source, ConvStep_{4,1}((W_a 1^{5\times 1}, attention1(target))))$$

$$attention1(x) = ConvStep_{1,1}(W_a 1^{5\times 1} \cdot x + timing)$$
$$Attend(source, target) = \frac{1}{\sqrt{depth}} \cdot softmax(target \cdot source^T) \cdot source$$

The experimental results presented in [14] shows that SliceNet improves the BLEU score in comparison to both GNMT and convolutional sequence to sequence models. Table 5 lists the BLEU scores for one dateset.

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