

# Neural Machine Translation with Recurrent Networks\*

## Extended Abstract<sup>†</sup>

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### ABSTRACT

In recent years, neural machine translation (NMT) has been a wide and open area to study Natural Language Processing. With increasing work, there is still much to do. NMT is an approach to machine translation that uses a large neural network. It departs from phrases-based statistical approaches that use separately engineered subcomponents. Neural machine translation (NMT) is not a drastic step beyond what has been traditionally done in statistical machine translation (SMT).

### CCS CONCEPTS

• **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability;

### KEYWORDS

ACM proceedings, L<sup>A</sup>T<sub>E</sub>X, text tagging

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## 1 INTRODUCTION

This means the model does not have to explicitly store gigantic phrase tables and language models as in the case of standard MT; hence, NMT has a small memory footprint. Lastly, implementing NMT decoders is easy unlike the highly intricate decoders in standard MT.

## 2 NEURAL MACHINE TRANSLATIONS

NMT is an approach to machine translation that uses a large neural network. It departs from phrases-based statistical approaches that

use separately engineered subcomponents. Neural machine translation (NMT) is not a drastic step beyond what has been traditionally done in statistical machine translation (SMT). NMT starts emitting one target word at a time as illustrated in. NMT is often a large neural network that is trained in an end-to-end fashion and has the ability to generalize well to very long word sequences.

### 2.1 Encoder and decoder architecture

A neural machine translation system is a neural network that directly models the conditional probability  $p(y|x)$  of translating a source sentence  $x_1, \dots, x_n$  to a target sentence  $y_1, \dots, y_n$ . A basic form of NMT consists of two components: (a) an encoder which computes representations for each source sentence and (b) a decoder which generates one target word at a time and hence decomposes the conditional probability as:

$$\log p(y|x) = \sum_{j=1}^m \log p(y_j | y_{<j}, s)$$

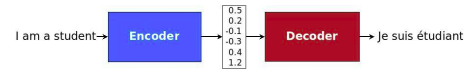


Figure 1. Encoder-decoder architecture

### 2.2 Long short term memory

We consider as examples a deep multi-layer RNN which is unidirectional and uses LSTM as a recurrent unit. We show an example of such a model in Figure 2. In this example, we build a model to translate a source sentence "I am a student" into a target sentence "Je suis Étudiant". At a high level, the NMT model consists of two recurrent neural networks: the encoder RNN simply consumes the input source words without making any prediction; the decoder, on the other hand, processes the target sentence while predicting the next words.

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

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

$$C_t = \tanh(W_c[h_{t-1}, x_t] + b_c)$$

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<sup>†</sup>The full version of the author's guide is available as `acmart.pdf` document

<sup>‡</sup>Dr. Trovato insisted his name be first.

<sup>§</sup>The secretary disavows any knowledge of this author's actions.

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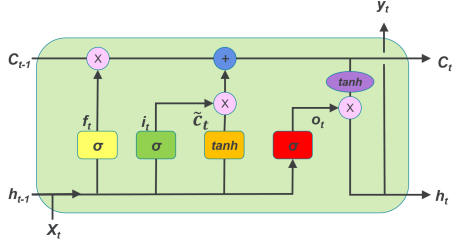


Figura 2. Long short-term memory

### 3 ATTENTION BASED MODELS

Our various attention-based models are classified into two broad categories, global and local. These classes differ in terms of whether the attention is placed on all source positions or on only a few source positions.

Common to these two types of models is the fact that at each time step  $t$  in the decoding phase, both approaches first take as input the hidden state  $h_t$  at the top layer of a stacking LSTM. The goal is then to derive a context vector  $c_t$  that captures relevant source-side information to help predict the current target word  $y_t$ . While these models differ in how the context vector  $c_t$  is derived, they share the same subsequent steps.

Specifically, given the target hidden state  $h_t$  and the source-side context vector  $c_t$ , we employ a simple concatenation layer to combine the information from both vectors to produce an attentional hidden state as follows:

$$\tilde{h}_t = \tanh(W_c[c_t, h_t])$$

The attentional vector  $h_t$  is then fed through the softmax layer to produce the predictive distribution formulated as:

$$p(y_t|y_{<t}, x) = \text{softmax}(W_s \tilde{h}_t)$$

#### 3.1 Global attention

The idea of a global attentional model is to consider all the hidden states of the encoder when deriving the context vector  $c_t$ . In this model type, a variable-length alignment vector  $a_t$ , whose size equals the number of time steps on the source side, is derived by comparing the current target hidden state  $h_t$  with each source hidden state  $h_s$ .

$$a_t(s) = \text{align}(h_t, \tilde{h}_s) = \frac{\exp(\text{score}(h_t, \tilde{h}_s))}{\sum_{s_p} \exp(\text{score}(h_t, \tilde{h}_{s_p}))}$$

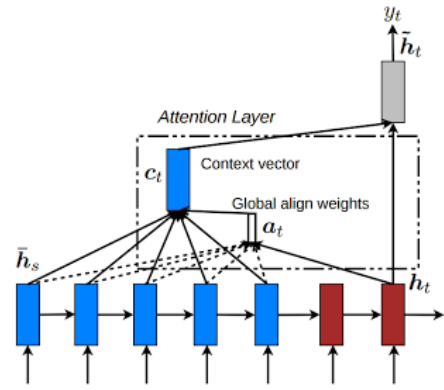


Figura 3. Global attentional model - at each time step  $t$ , the models infer a variable-length alignment weight vector  $a_t$  based on the current target state  $h_t$  and all source states  $\tilde{h}_s$ . A global context vector  $c_t$  is then computed as the weighted average, according to  $a_t$ , over all the source states.

Here, score is referred to as a *content-based* function for which we consider three different alternatives:

$$\begin{aligned} \text{score}(h_t, \tilde{h}_s) &= \tilde{h}_t^T \tilde{h}_s \\ \text{score}(h_t, \tilde{h}_s) &= \tilde{h}_t^T W_a \tilde{h}_s \\ \text{score}(h_t, \tilde{h}_s) &= \tilde{v}_t^T \tanh(W_a[h_t : \tilde{h}_s]) \end{aligned}$$

Besides alignment vector as weights, the context vector  $c_t$  is computed as the weight average over all the source hidden states.

#### 3.2 Local attention

The global attention has a drawback that it has to attend to all words on the source side for each target word, which is expensive and can potentially render it impractical to translate longer sequences, e.g., paragraphs or documents. To address this deficiency, we propose a local attentional mechanism that chooses to focus only on a small subset of the source positions per target word.

This model takes inspiration from the tradeoff between the soft and hard attentional models proposed by Xu et al.(2015) to tackle the image caption generation task. In their work, soft attention refers to the global attention approach in which weights are placed "softly" over all patches in the source image. The hard attention, on the other hand, selects on patch of the image to attend to a time.

#### 3.3 Input-feeding Approach

In our proposed global and local approaches, the attentional decisions are made independently, which is suboptimal. Whereas, in standard MT, a coverage set is often maintained during the translation process to keep track of which source words have been translated. Likewise, in attentional NMTs, alignment decisions should be made jointly taking into account past alignment information. To address that, we propose an input-feeding approach in which attentional vectors  $\tilde{h}_t$  are concatenated with inputs at the next time. The effects of having such connections are two-fold: (a) we hope to make the model fully aware of previous alignment



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