Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation

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March 12, 2018

Outline

Recap: Recurrent Neural Networks

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iteratively sample a symbol at each time step.

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decodes the **fixed length** representation into another variable length seq. of symbols

The encoder and decoder are trained **jointly**.

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from probabilistic perspective the model computes,

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general method to learn the **conditional distribution** over a **variable-length** sequence conditioned on yet another **variable-length** sequence

I/0 Structure

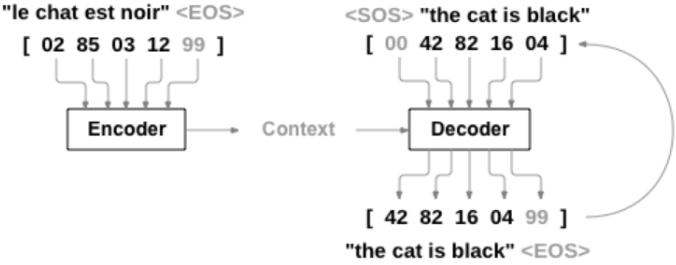

Figure: $< EOS >$ & $< SOS >$ additional tags are added with sentences.

RNN-Encoder

- The encoder reads each symbol of an input sequence x sequentially.
- After reading $< EOS >$, the hidden state of the RNN is a summary c of the whole input sequence.
- This c is used as a context vector for Decoder

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RNN-Decoder

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- $$h_{<t>} = f(h_{<t-1>}, y_{t-1}, c)$$
  $h_{<t>}$ is conditioned on y_{t-1} and contex vector c.
- the **conditional distribution** of the next symbol is,

$$p(y_t | y_{t-1}, y_{t-2}, ..., y_1, c) = g(h_{<t-1>}, y_{t-1}, c)$$

Diagram

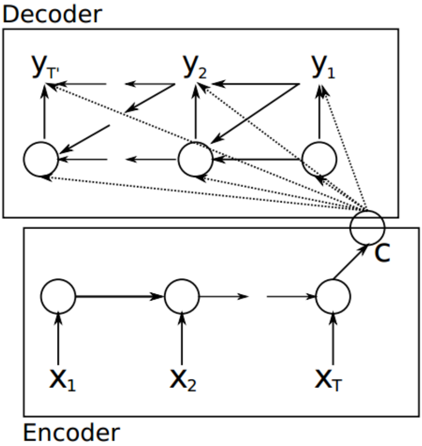

Figure: An illustration of the proposed RNN Encoder-Decoder

Loss Function

Encoder Decoder is trained **jointly** to maximize the **conditional log-likelihood**.

$$max_\theta \frac{1}{N}\sum_{i=1}^{N}\log p_\theta(y_n|\mathbf{x}_n)$$

where,

- θ is model parameter
- x_n is input sequence
- y_n is output sequence

Decoder

Slightly changed decoder structure,

$$h'^{\langle t\rangle}_j = z'_j h'^{\langle t-1\rangle}_j + (1 - z'_j)\tilde{h}'^{\langle t\rangle}_j,$$

$$\begin{aligned}
\tilde{h}'^{\langle t\rangle}_j =& \tanh\left(\left[\mathbf{W}' e(\mathbf{y}_{t-1})\right]_j + r'_j\left[\mathbf{U}'\mathbf{h}'_{\langle t-1\rangle} + \mathbf{C}\mathbf{c}\right]\right),\\
z'_j =& \sigma\left(\left[\mathbf{W}'_z e(\mathbf{y}_{t-1})\right]_j + \left[\mathbf{U}'_z\mathbf{h}'_{\langle t-1\rangle}\right]_j + \left[\mathbf{C}_z\mathbf{c}\right]_j\right),\\
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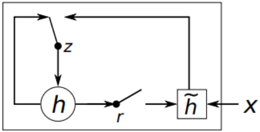
\end{aligned}$$

Cell type

- Model uses GRU Cell.
- The update gate z selects whether the hidden state is to be updated with a new hidden state $\tilde{h}$.
- The reset/forget gate r decides whether the previous hidden state is ignored.

$$
\begin{aligned}
r_j &= \sigma([W_r x]_j + [U h_{<t-1>}]_j) \\
z_j &= \sigma([W_z \mathbf{x}]_j + [U_z h_{<t-1>}]_j) \\
h^{<t>} &= z_j h_j^{<t-1>} + (1 - z_j)\tilde{h}_j^{<t-1>} \\
\tilde{h}_j &= \phi([W x]_j + [U(r \odot h_{<t-1>})]_j)
\end{aligned}
$$



Usages

- Model can be used in two ways.
  - generate a target sequence
  - to score a given pair of input and output seq. $p_\theta(y|\mathbf{x})$

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- $p(\mathbf{f})$ is **language model**

Statistical Machine Translation

$$p(\mathbf{f}|\mathbf{e}) \propto p(\mathbf{e}|\mathbf{f})p(\mathbf{f})$$

In practice, however, most SMT systems model $p(\mathbf{f}|\mathbf{e})$ as a *log* linear model with additional features and corresponding weights

$$\log p(\mathbf{f}|\mathbf{e}) = \sum_{i=1}^{N} w_n f_n(\mathbf{f}, \mathbf{e}) + \log Z(\mathbf{e})$$

where,

- f_n and w_n are the n-th feature and weight
- $Z(e)$ is a normalization constant that
- The weights are often optimized to maximize the BLEU score on a dev. set.

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Objective of the model is to capture **linguistic information** rather than **statistical information**.

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- Activation function : $tanh$
- 384M words, 3 days training time

Quantitative Analysis

Models	BLEU	
	dev	test
Baseline	30.64	33.30
RNN	31.20	33.87
CSLM + RNN	31.48	34.64
CSLM + RNN + WP	31.50	34.54

Figure: BLEU scores computed on the development and test sets using different combinations of approaches.)

*CSLM-Continuous Space Language Model (Schwenk, 2007)

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WP - Word Penalty. (penalizing the number of words that are unknown to the neural networks)

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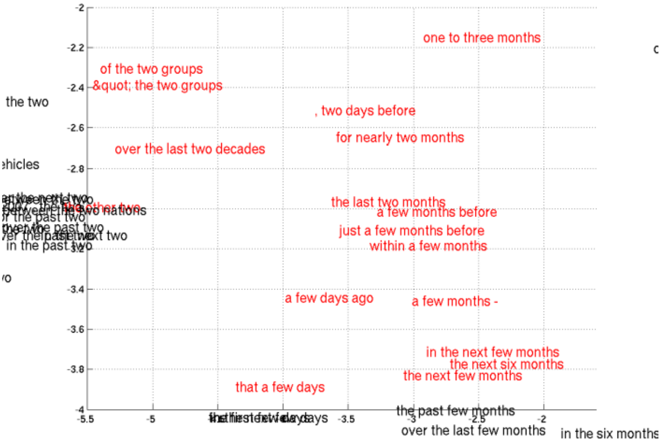

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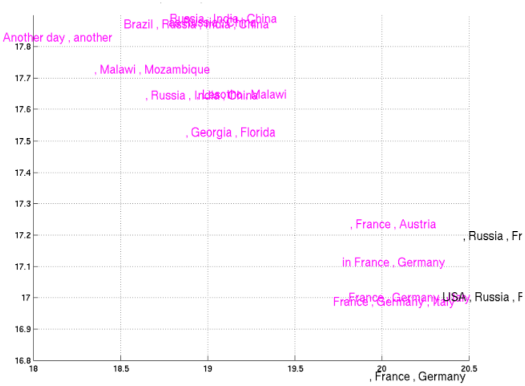

Figure: 2D embedding of the learned phrase representation

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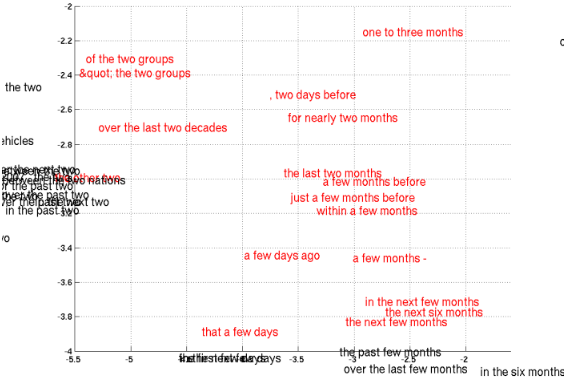

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RNN EncoderDecoder model captures linguistic features.

RNN Encoder-Decoder learns a continuous space representation for phrases that preserves both the semantic and syntactic structure.

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Final words

sentence level encoding vector which can be decoded

Implementation Details

- Paper (After Acknowledgments)
- Code (library implementation)
- A Simple NMT model (Without Attention)