A Convolutional Encoder Model for Neural Machine Translation

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Neural Machine Translation

End to end deep learning based machine translation model.

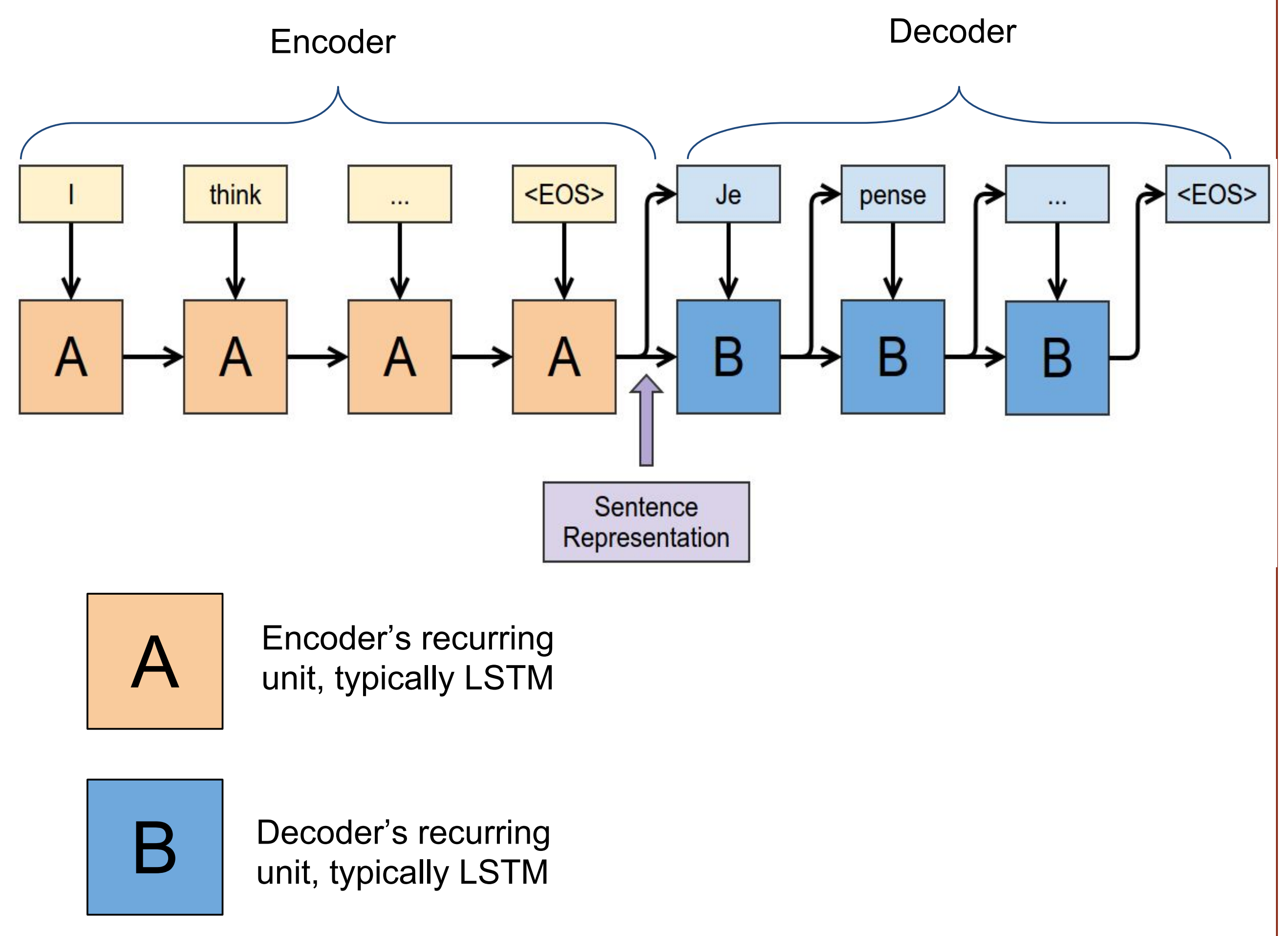
Current State of the Art uses an encoder-decoder model.

Encoder: Creates a hidden representation (encoding) of the input sentence.

Decoder: Converts the hidden representation (decoding) into a sentence in target language.

Encoder and Decoder are generally Recurrent Neural Networks. Current state of the art models use separate Bi-LSTMs for the encoder and decoder components

Drawback: Slow, since recurrent nets are not easily parallelizable.


Encoder
Decoder
I
think
...
<EOS>
Je
pense
...
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A
A
A
A
B
B
B
Sentence Representation
A
Encoder's recurring unit, typically LSTM
B
Decoder's recurring unit, typically LSTM

Image source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Convolutional Encoder

Convolution operations are fast and easy parallelizable.

Challenges:

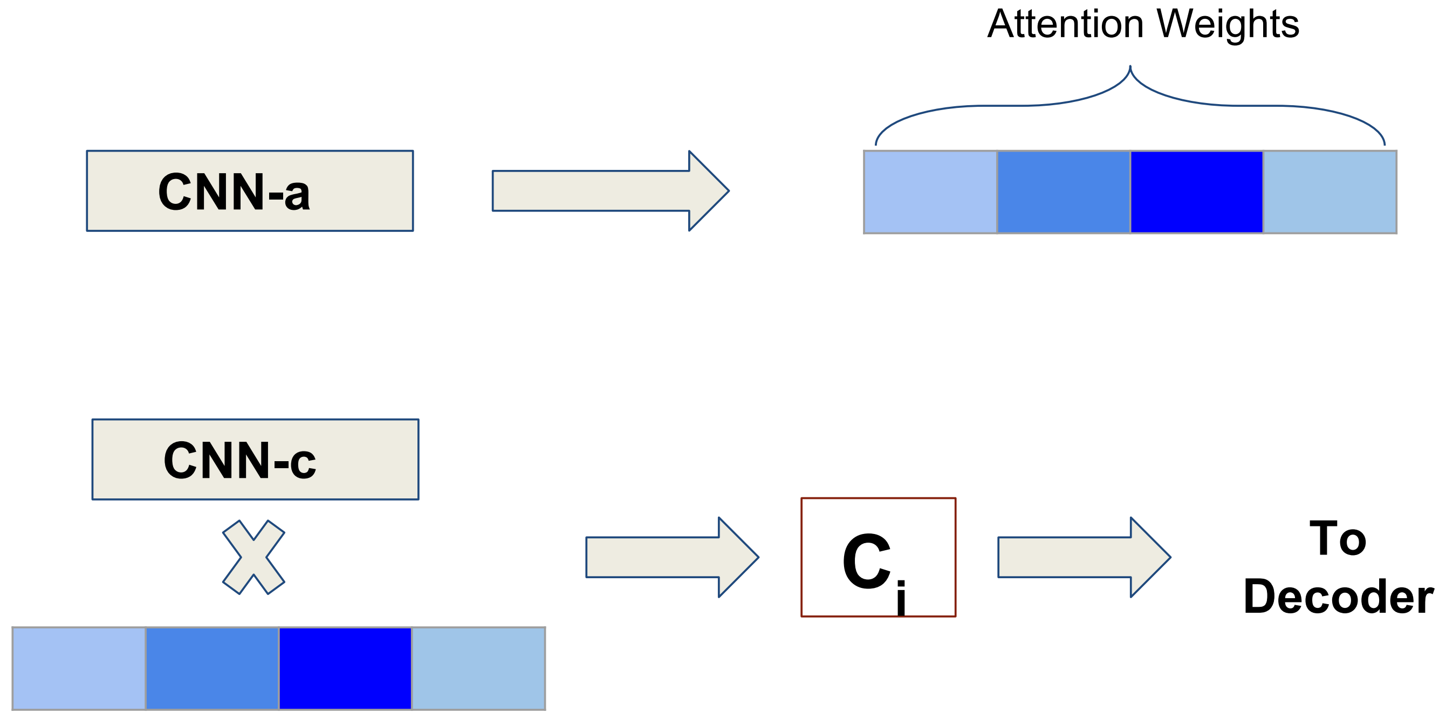
- Convolution does not fit naturally into sequence modeling task due to their spatial nature.
- Word ordering is lost(which is implicitly captured by RNN)

Solution:

- Include position embedding - Append to word representation the embedding of the index of the word in the sequence.

Encoder Architecture

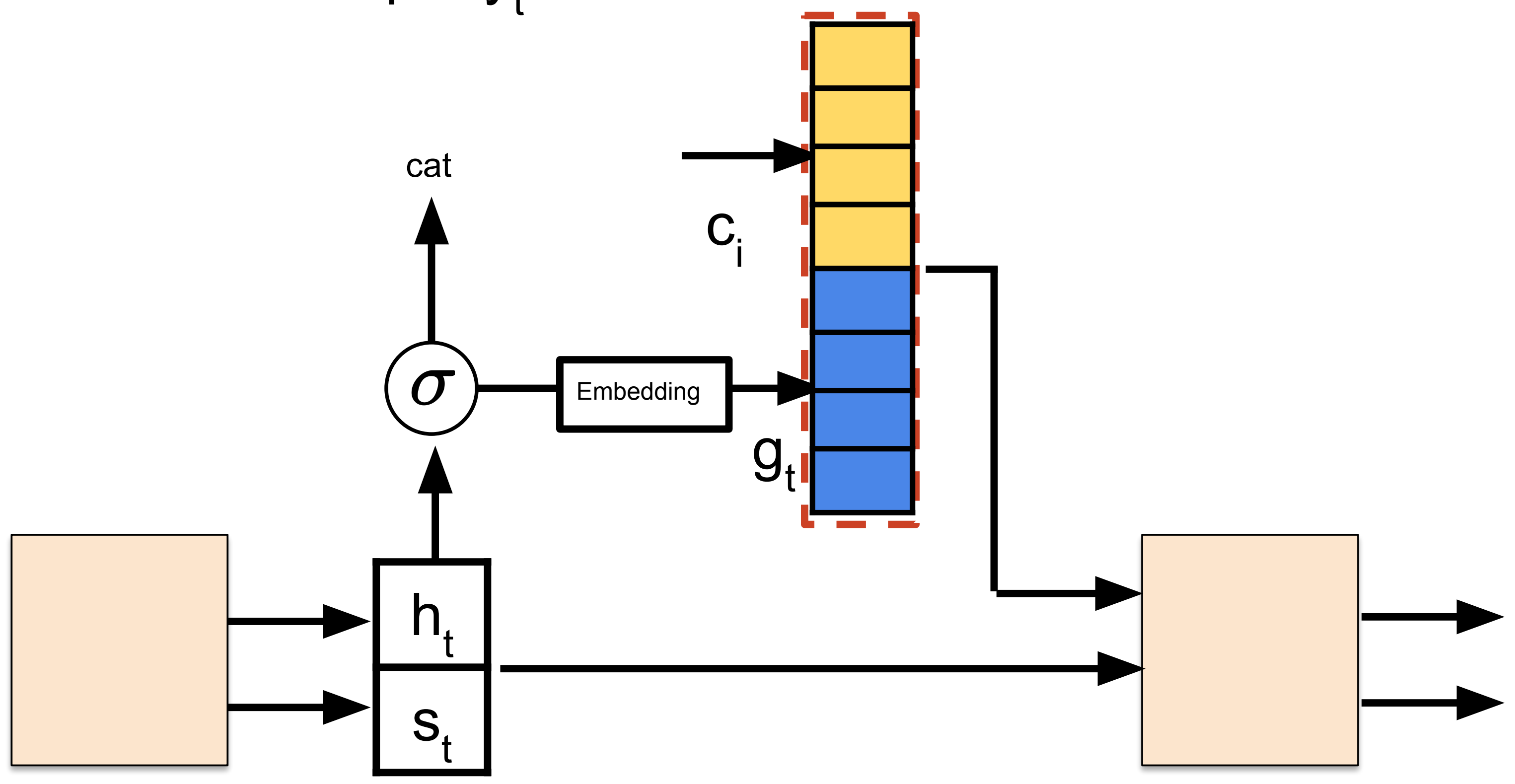
- Two Set of Convolution Layers :
  - CNN-a - Responsible for encoding the sentence and is used to generate attention weights that are applied to CNN-c.
  - cnn-c - Responsible for generating the conditional input c_i to the decoder.
  - Attention weights, having values between 0 and 1, allow the decoder to *focus* on certain aspects of c_i which are useful for generation of the current word in the output sentence



- Both CNN-a/CNN-c have:
  - Input Representation as Word Embeddings + Position Embeddings
  - Fixed Kernel width and fixed number of convolution layers (which are different for CNN-a and CNN-c)
  - Contains Residual connections bypassing convolution layers to ease learning for deep networks.

Decoder Architecture

- Recurrent Neural Network (GRU/LSTM/RNN etc)
- Generates attention weights using CNN-a and current hidden state h_t.
- Applies the attention weights over CNN-c to get input context c_i
- Input to the next step of the recurrent network is concatenation of input step c_i and embedding g_t of the current output y_t



The Complete Architecture

Tying the encoder and decoder together, the whole model looks like this:

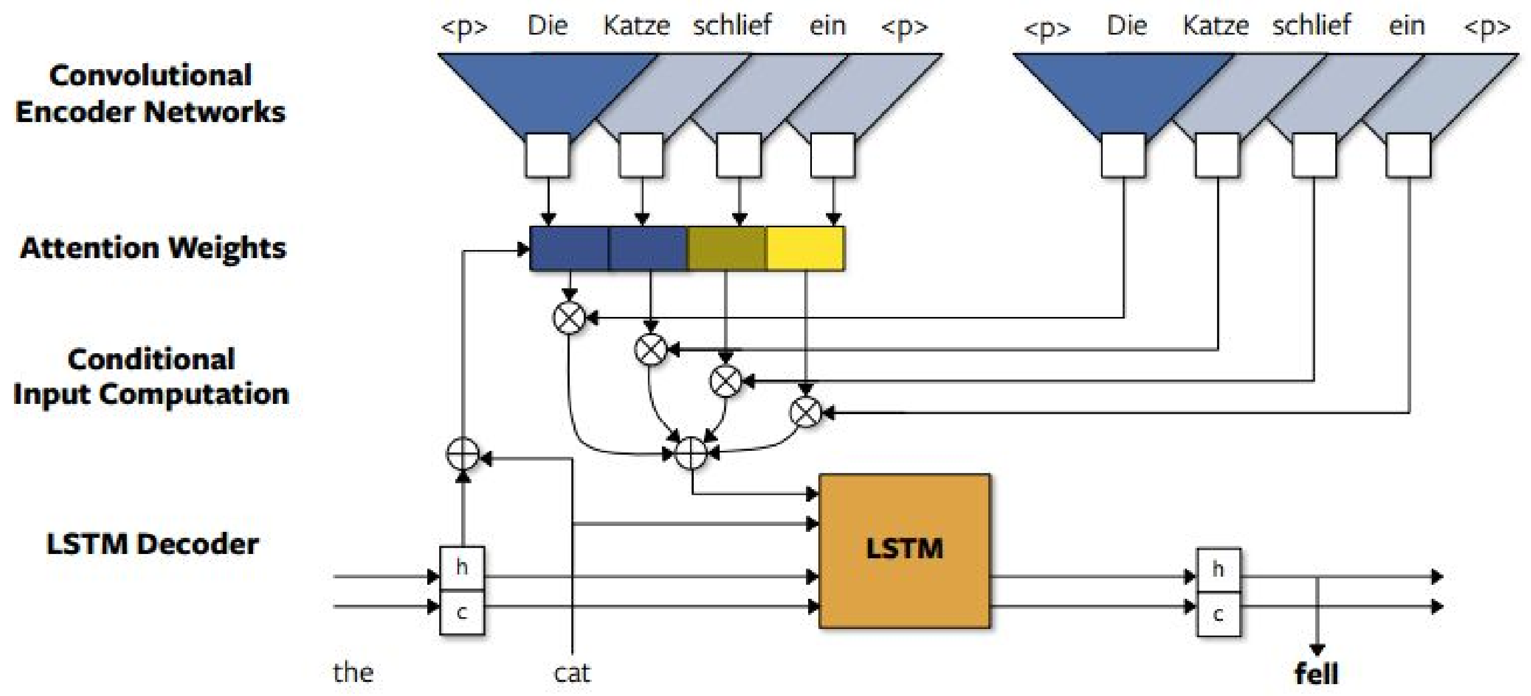


Image source: https://arxiv.org/pdf/1611.02344.pdf

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