Neural Machine Translation

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1 Neural Machine Translation

Encoder-Decoder Model

Recurrent Neural Network

Encoder

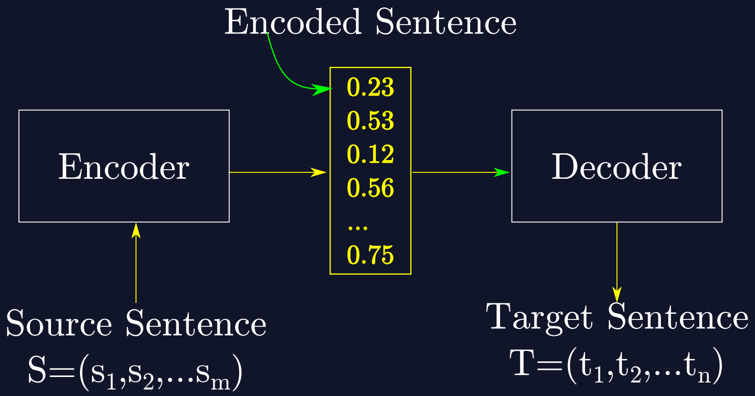
Decoder

Estimating Model Parameters

NEURAL MACHINE TRANSLATION

Neural Machine Translation (NMT) is the mechanism of modeling the Machine translation process using artificial neural network Let F and E be the source and the target sentences in a parallel corpora, respectively.

ENCODER-DECODER MODEL



- All sentences (of varying length) are encoded into fixed sized vector
- Uses fraction of the memory needed by traditional SMT models[1]
- Performance of this model decreases as the length of a source sentence increase

[1] Cho et al, On the Properties of Neural Machine Translation: Encoder-Decoder Approaches, 2014

Neural Machine Translation

RNN-BASED TRANSLATION MODEL

- Uses RNN for both encoding and decoding
- Encoder maps the variable length sentence into a fixed-length vector
- Decoder translates the vector representation back to a variable-length target sequence
- Two networks are trained jointly to maximize the conditional probability of the target sentence, given the source sentence - $P(f|e)$
- This model learns a continuous space representation of a phrase that preserves both the semantic and syntactic structure of the phrase[2].

Neural Machine Translation

RECURRENT NEURAL NETWORK

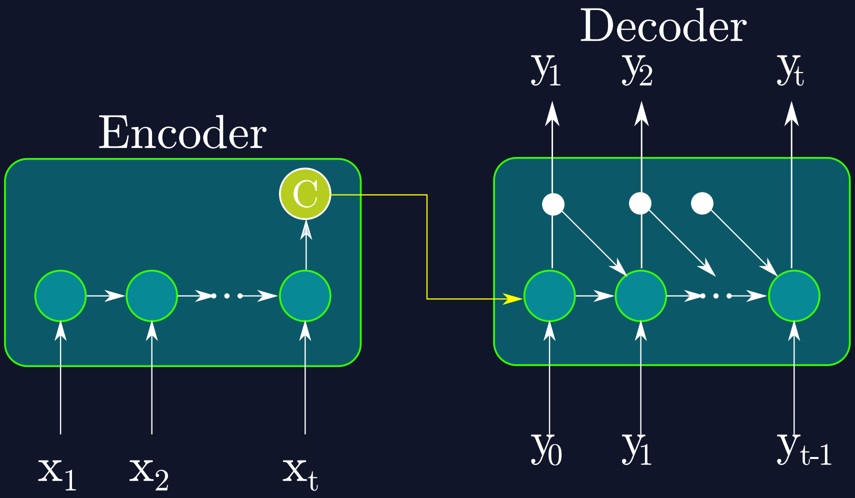
- Input units - variable length source sequence $x = (x_1, x_2, \ldots, x_T)$
- Output units - variable length target sequence $y = (y_1, y_2, \ldots, y_T')$
- Hidden units for each input state,

$$h_t = f(h_{(t-1)}, x) \tag{1}$$

where f is a simple non-linear activation function (sigmoid or $\tanh$) or a complex LSTM/GRU cell

- RNN is trained to predict the next word in the sequence or RNN learns a probability distribution over a sequence
- The output at each time step $t = p(x_t|x_{t-1}, \ldots x_1)$
- The output distribution (Softmax layer) size is equal to the size of the vocabulary V at every unit
- Then, $p(\mathbf{x}) = \prod_{t=1}^{T} p(x_t|x_{t-1}, \ldots x_1)$

RNN-BASED ENCODER-DECODER



RNN-BASED ENCODER

- RNN learns to map an input sentence of variable length into a fixed-dimensional vector representation.
- It learns to decode a fixed length vector representation back into a variable length sequence
- This model learns to predict a sequence given a sequence $p(y_1, y_2, \ldots, y'_T | x_1, x_2, \ldots, x_T)$. T and T' may differ
- Encoder reads every symbol in **x**, sequentially
- Hidden state changes according to Eq.(1)
- C is the summary of the hidden states at time T and has encoded all the symbols in the sequence

Neural Machine Translation

RNN-BASED DECODER

- This is trained to predict the next symbol y_t and generate the output sequence, given the previous state h_t
- y_t and $\mathbf{h}_t$ are conditioned on the summary from the encoder, C and its previous hidden state
- Decoder's hidden state is given by
- Conditional distribution for the next symbol is

$$\mathbf{h}_t = f(\mathbf{h}_{t-1}, y_{t-1}, \mathbf{C}) \tag{2}$$

$$P(y_t | y_{t-1}, y_{t-2} \ldots, y_1, \mathbf{C}) = g(h_{t-1}, y_{t-1}, \mathbf{C}) \tag{3}$$

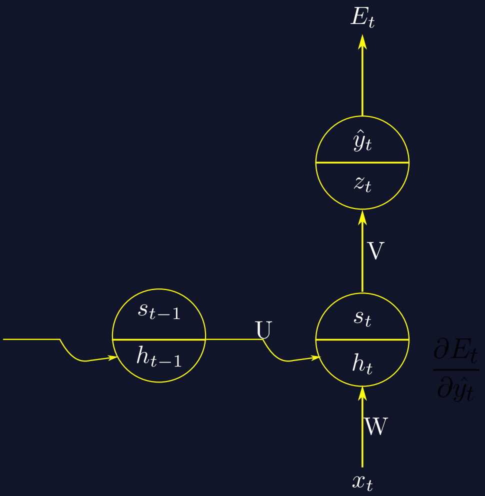
ESTIMATING MODEL PARAMETERS

Both encoder and decoder are jointly trained to maximize the conditional likelihood

$$J(\theta) = \max_{\theta} \frac{1}{N} \log p_{\theta}(\mathbf{y}_n | \mathbf{x}_m) \tag{4}$$

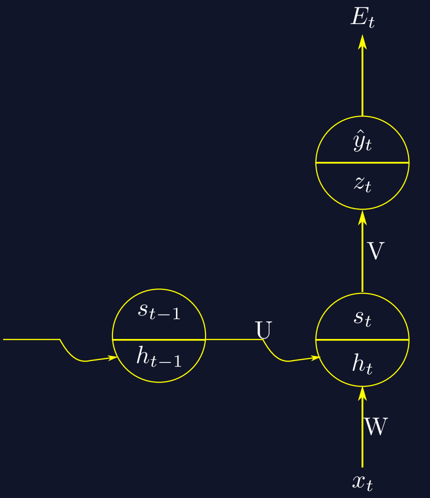
where θ is the set of model parameters that will be learned during the BPTT and $(\mathbf{x}_m, \mathbf{y}_n)$ is the source sentence sequence and target sequence pair

BPTT - DERIVATIVE FOR V



$$h_t = (Wx_t + Uh_{t-1})$$
$$s_t = \mathtt{tanh}(h_t)$$
$$z_t = Vs_t$$
$$\hat{y}_t = \mathtt{softmax}(z_t)$$
$$E_t = -y_t \log(\hat{y}_t)$$
$$\frac{\partial E_t}{\partial V} = \frac{\partial E_t}{\partial \hat{y}_t}\frac{\partial \hat{y}_t}{\partial z_t}\frac{\partial z_t}{\partial V} \tag{5}$$
$$\text{Let } \delta^t_{out} = \frac{\partial E_t}{\partial \hat{y}_t}\frac{\partial \hat{y}}{\partial z_t}$$
$$\frac{\partial E_t}{\partial V} = \delta^t_{out} s_t \tag{6}$$

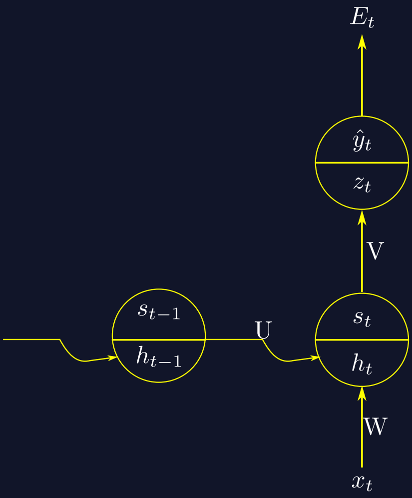
Here δ^t_{out} is the loss for each of the units in the output layer



$$\frac{\partial E_t}{\partial W} = \underbrace{\frac{\partial E_t}{\partial \hat{y}_t} \frac{\partial \hat{y}}{\partial z_t}} \frac{\partial z_t}{\partial s_t} \frac{\partial s_t}{\partial h_t} \frac{\partial h_t}{\partial W} \tag{7}$$

$$= \delta^t_{out} V \sigma^{'}(h_t) x_t \tag{8}$$

Since the hidden layer activation depends on the previous time state, we have another similar term δ_{t-1} that get added to (8)



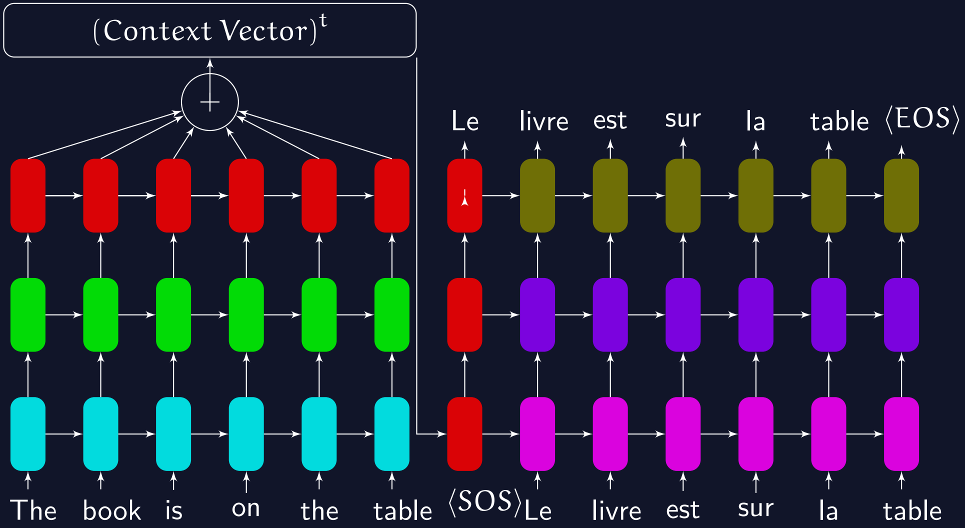
$$\frac{\partial E_t}{\partial U} = \underbrace{\frac{\partial E_t}{\partial \hat{y}_t}\frac{\partial \hat{y}}{\partial z_t}\frac{\partial z_t}{\partial s_t}\frac{\partial s_t}{\partial h_t}}\frac{\partial h_t}{\partial U} \tag{9}$$

$$= \delta^t_{out} V \sigma^{'}(h_t) h_{t-1} \tag{10}$$

Since we are back propagating the error from the current state to the previous state, $\delta_{next} = \sigma(h_t) U \delta^t_{out} V \sigma^{'}(h_t)$ needs to be added

Neural Machine Translation

SEQ2SEQ TRANSLATOR



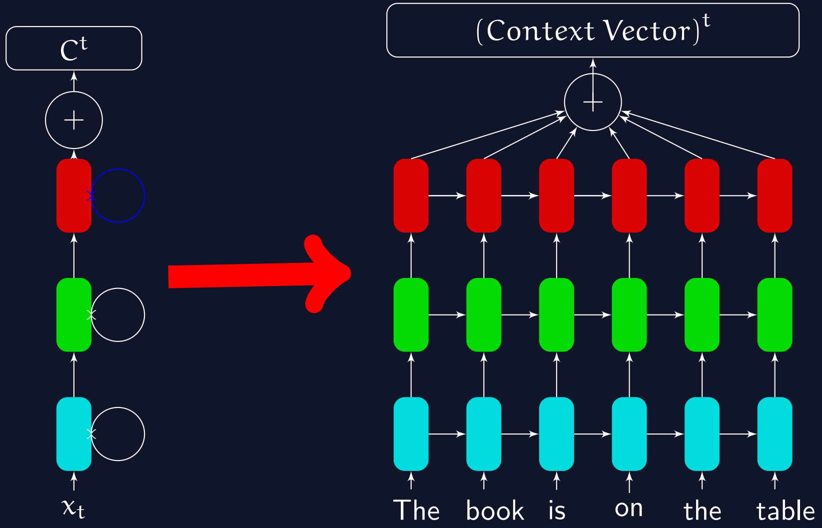
VARIATIONS IN RNN MODELS

Choices vary in picking the Translation Architecture

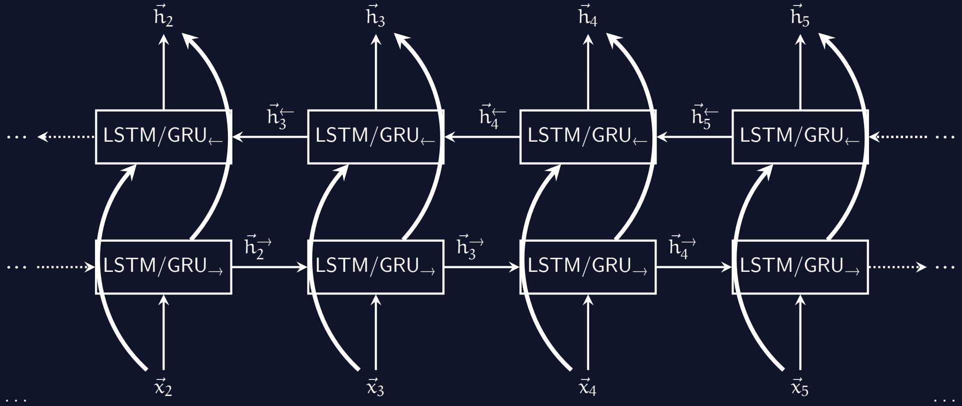
- Directionality - Unidirectional or bidirectional
- number of hidden layers and units
- Plain vanilla RNN
- Long Short-term Memory units
- Gated Recurrent Unit
- Choice of Learning Algorithm

Neural Machine Translation

SEQ2SEQ ENCODER

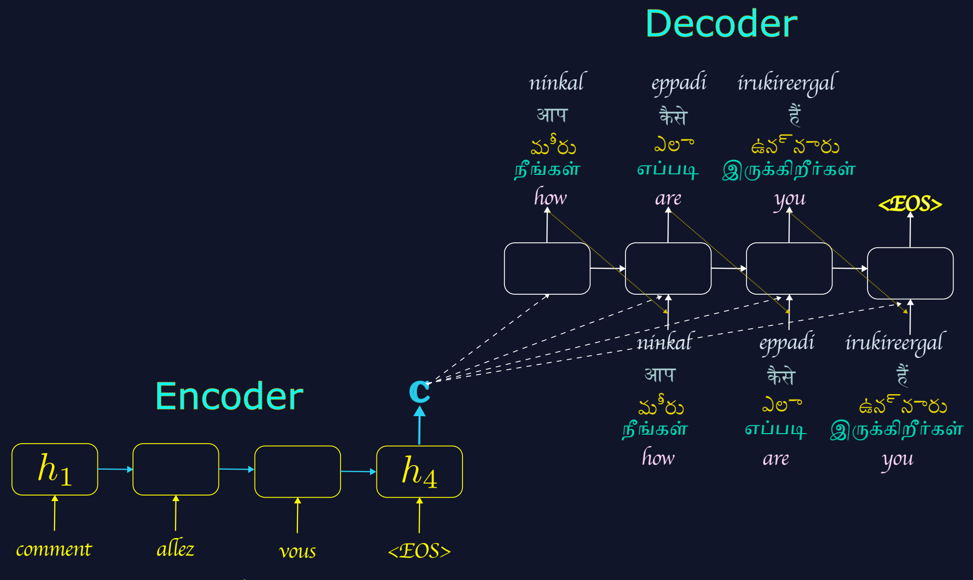


BIDIRECTIONAL RNN

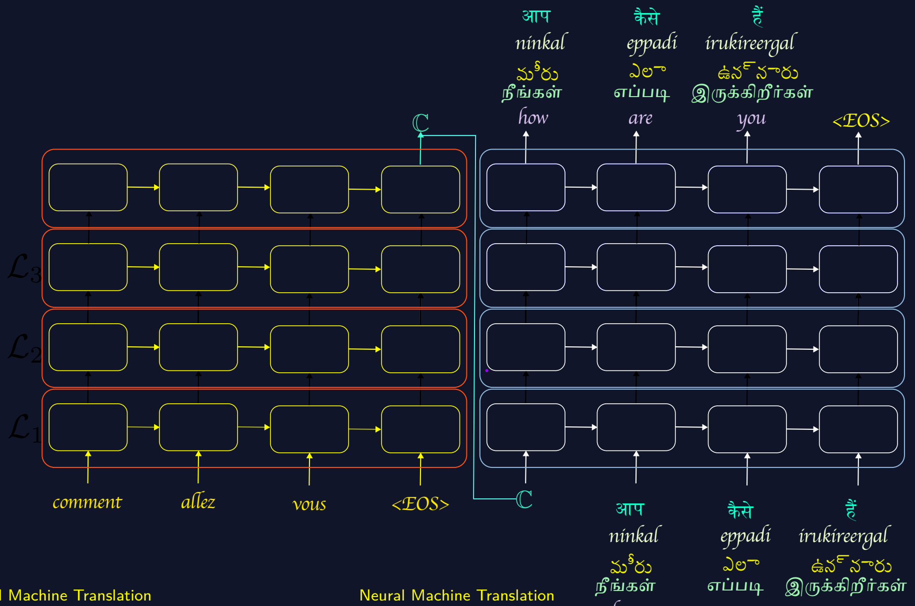


Neural Machine Translation

SEQUENCE TO SEQUENCE TRANSLATION - NMT



SEQUENCE TO SEQUENCE TRANSLATION - DEEP RNN



APPLICATIONS

- Translation
- Dialog
- Code generation!

Neural Machine Translation

RNN WITH ALIGNMENT

- The objective of attention is to capture the information from the passage tokens that is relevant to the contents of the translation
- Different parts of an input have different levels of significance
- Different parts of the output may even consider different parts of the input as "important"
- The purpose of the attention mechanism is to let the decoder *peek* at the relevant information encapsulating the source sentence as it generates the answer
- Attention mechanisms provide the decoder network with the entire input sequence at every decoding step; the decoder can then decide what input words are important at any point in time

- The attention-based model learns to assign significance to different parts of the input for each step of the output.
- In the context of translation, attention can be thought of as "alignment."
- Bahdanau et al [3] argue that the attention scores α_{ij}, at decoding step i, signify the words in the source sentence that align with word j in the target.
- We can use attention scores to build an alignment table. It is a table mapping of words in the source to corresponding words in the target sentence - based on the learned encoder and decoder from our Seq2Seq NMT system.

ENCODER

Let $x(x_1, x_2, \ldots, x_n)$ and $y(y_1, y_2, \ldots, y_m)$ be the source and target sentences

The encoder reads the input sentence x and converts into a context vector c

$$h_t = f(x_t, h_{t-1}) - \text{hidden values calculated at time } t \tag{11}$$

$$c = g(h_1, h_2, \ldots, h_n) - \text{context vectors computed using all } h_t \text{ values} \tag{12}$$

where functions f and g are non-linear functions.

How does c differ from the *context* of an n-gram language model?

DECODER

Decoder is trained to predict the next word using the c computed by the encoder

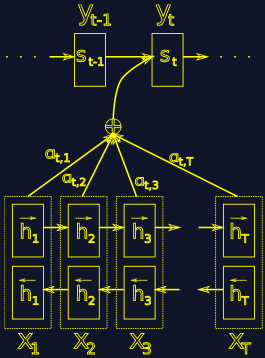
$$p(y) = p(y_t | c, \{y_1, y_2, \ldots, y_{t-1}\}) \tag{13}$$

For the RNN, the probability of the next word $p(y_t)$ is computed using

$$p(y_t) = g(y_{t-1}, s_t, c) \tag{14}$$

The hidden states s of the decoder are computed using a recursive formula of the form $s_i = f(s_{i-1}, y_{i-1}, c_i)$, where s_{i-1} is the previous hidden vector, y_{i-1} is the generated word at the previous step, and

c_i is a context vector that capture the context from the original sentence that is relevant to the time step i of the decoder.



NMT WITH ATTENTION

Conditional probability for each output neuron

$$p(y_i|y_1, y_2, \ldots, x) = g(y_{i-1}, s_i, c_i) \tag{15}$$

where s_i if the RNN hidden neuron at time i and

$$s_i = f(s_{i-1}, y_{i-1}, c_i) \tag{16}$$

The context vector c_i depends on the sequence of annotations $(h_1, h_2, \ldots . h_{T_x})$[1].
Each h_i contains information about every word with a strong focus on context words surrounding the i^{th} word of the input sequence.
The context vector c_i is computed as the weighted sum of these annotations h_i

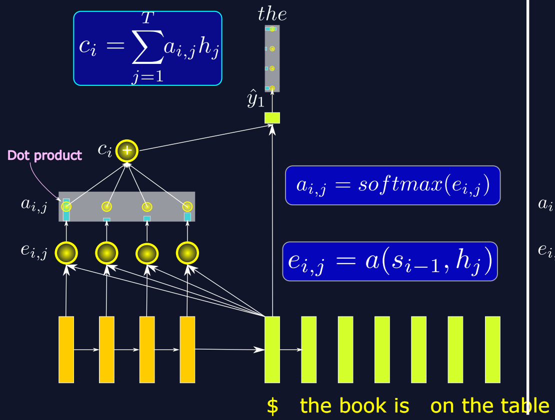
$$c_i = \sum_{j=1}^{T_x} \alpha_{i,j} h_j$$

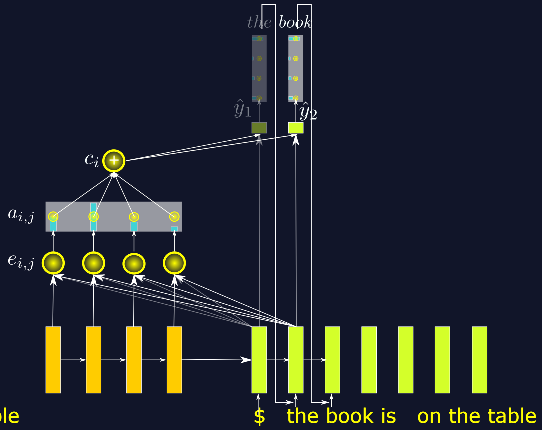
$$\alpha_{i,j} = \frac{\exp(e_{i,j})}{\sum_{k=1}^{t_x} \exp(e_{i,k})}$$

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

α_{ij} of each annotation h_j is computed by is the alignment model. This learns how well the inputs surrounding position j and the output at position i match

- The alignment is explicitly computed and not latent
- This alignment model is also trained along with the translation model
- α_{ij} is the probability that the target word y_i is aligned to the source x_j
- c_i is the expected annotation over all possible annotations α_{ij}
- α_{ij} or e_{ij} reflects the importance of the annotation h_j wrt to the previous hidden state s_{i-1} of the target. This enables the next state s_i to generate y_i
- The decoder decides which part of the input is important to generate a respective translation rather than depending on the encoded vector of the entire sentence
- Decoder has control over the input sequence and selectively learns to align words/phrases automatically



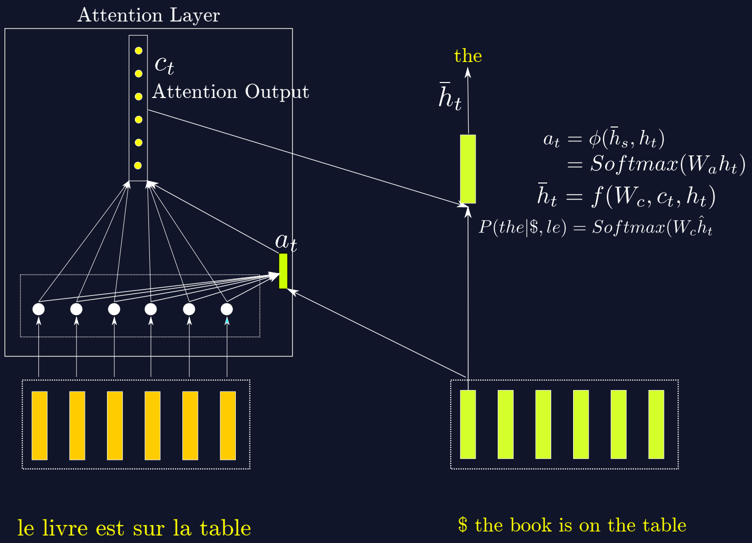


$e_{i,j}$ — attention score

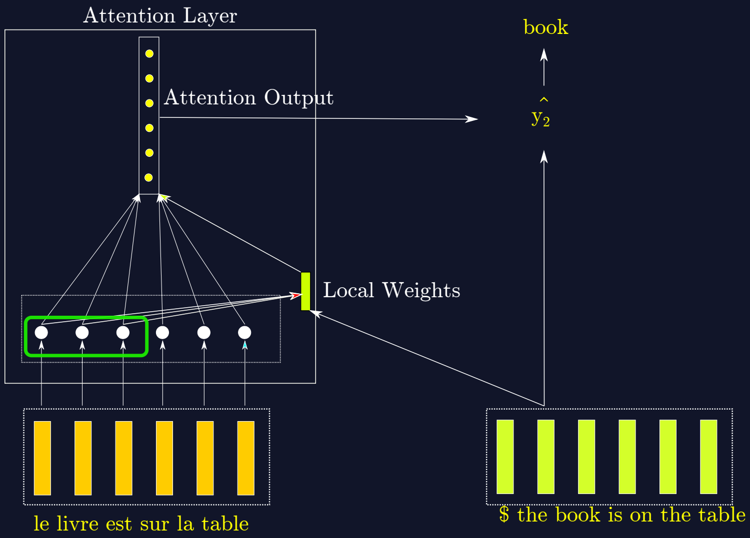
$a_{i,j}$ — attention distribution

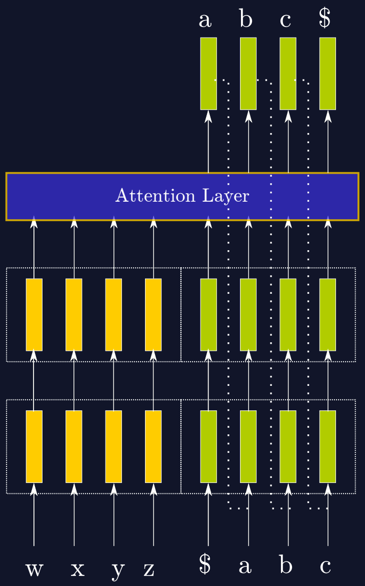
c_i — attention output

TRANSLATION WITH GLOBAL ATTENTION



TRANSLATION WITH LOCAL ATTENTION





Source: Minh-Thang Luong et al, Effective Approaches to AIttention-based Neural Machine Translation

A TYPICAL SETUP

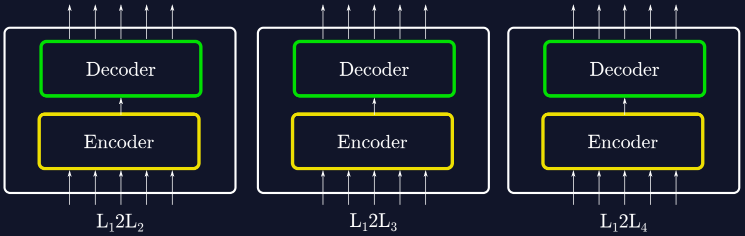
Sentence pairs	3-5M
English words	110M
French words	116M
Vocabulary	≈50K (Source and Target)
Word Embedding size	1000
Hidden layer	1000 LSTM cells
Stacked Hidden Layer	4-8
Learning Rate	Initially as high as 1 and exponential reduction
Training	
Mini batch Gradient Descend size	128
Training Time	1 GPU - about 7-10 days
Evaluation	Bleu - scores ranging from 27-32

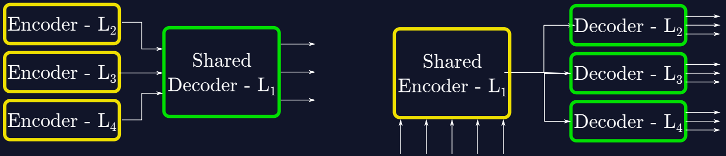
ADVANTAGES OF ATTENTION

- Ability to focus on significant part of the sentence
- Ability to peek into source sentence
- Reduces the problem of vanishing gradient
- Alignments are found automatically during the training process
- Improves NMT performance for alignment

Neural Machine Translation

DIFFERENT TYPE OF NMT



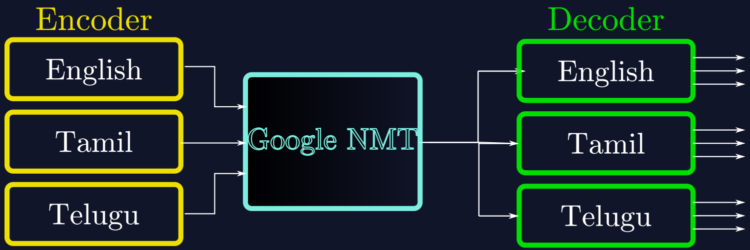


NMT FROM GOOGLE - ZERO-SHOT TRANSLATION

- Moved away from maintaining Seq2Seq model for every pair of languages
- A single system that translates between any two languages even in the absence of the training corpus for these two languages
  - Assume that only examples of Japanese-English and Korean-English translations are available, Google found hat the multilingual NMT system trained on this data could actually generate reasonable Japanese-Korean translations.
  - Is it trained create the Interlingua?
  - Is the system learning a common representation or a translational knowledge?

Ref: Johnson et el. 2016, "Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation"

ZERO-SHOT TRANSLATION



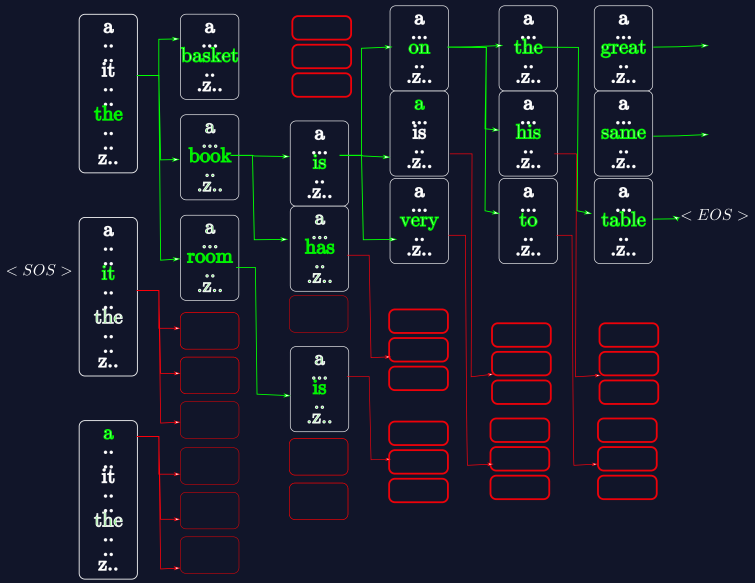
BEAM SEARCH

Beam search is a heuristic search algorithm that selects a few candidate hypothesis from $|V|$. It reduces memory requirement by using only a $M < |V|$ candidates using a score.

- Maintain M candidates/hypothesis at each time step - $C_t = (x_1^1, ..x_t^1)...(x_1^M...x_t^M)$
- Compute C_{t+1} by expanding C_t and keeping the best M candidates
- $\tilde{C} = \bigcup_{i=1}^{M} C_{t-1}^i$

Typical Beam width of size 5-10 used in NMT. The BLEU scores computed using Beam search using B=5-10 are comparable

BEAM SEARCH - BEAM WIDTH = 3



1. Use all possible partial translations - exhaustive search
2. Beam size, $b = 1$ - greedy search - Words are predicted until the $< EOS >$ is found
3. $b > 1$ - several hypotheses
4. Each hypothesis will be produced until the $< EOS >$ is found
5. Each hypothesis will have a translation
6. The length of all hypothesis may not be the same
7. We could use different ***terminate*** conditions
   - Fixed time steps
   - Compute until $< EOS >$ is reached for each hypothesis
8. Use either log probability or product of conditional probability to find the scores for each hypothesis that maximizes
   - $P(y_1, y_2, ...y_m|\mathbf{X}) = \prod_{t=1}^{T} P(y_t| < SOS >, \ldots, y_{t-1}, \mathbf{X})$
   - $P(y_1, y_2, ...y_m|\mathbf{X}) = \sum_{t=1}^{T} \log P(y_t| < SOS >, \ldots, y_{t-1}, \mathbf{X})$

REFERENCES

[1] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. "Neural machine translation by jointly learning to align and translate". In: *Proceedings of the International Conference on Learning Representations (ICLR)*. 2015.

[2] Kyunghyun Cho et al. "Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation". In: *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Doha, Qatar: Association for Computational Linguistics, Oct. 2014, pp. 1724–1734. DOI: 10.3115/v1/D14-1179. URL: https://www.aclweb.org/anthology/D14-1179.

[3] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. "Neural machine translation by jointly learning to align and translate". English (US). In: *arXiv* (2014).