Machine Translation

04: Neural Machine Translation

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Overview

last lecture

- how do we represent language in neural networks?
- how do we treat language probabilistically (with neural networks)?

today's lecture

- how do we model translation with a neural network?
- how do we generate text from a probabilistic translation model?

Modelling Translation

- Suppose that we have:
  - a source sentence S of length m $(x_1, \dots, x_m)$
  - a target sentence T of length n $(y_1, \dots, y_n)$
- We can express translation as a probabilistic model

$$T^* = \arg\max_T p(T|S)$$

- Expanding using the chain rule gives

$$\begin{aligned} p(T|S) &= p(y_1, \dots, y_n | x_1, \dots, x_m) \\ &= \prod_{i=1}^{n} p(y_i | y_1, \dots, y_{i-1}, x_1, \dots, x_m) \end{aligned}$$

Differences Between Translation and Language Model

- Target-side language model:

$$p(T) = \prod_{i=1}^{n} p(y_i | y_1, \dots, y_{i-1})$$

- Translation model:

$$p(T|S) = \prod_{i=1}^{n} p(y_i | y_1, \dots, y_{i-1}, x_1, \dots, x_m)$$

- We could just treat sentence pair as one long sequence, but:
  - We do not care about $p(S)$
  - We may want different vocabulary, network architecture for source text

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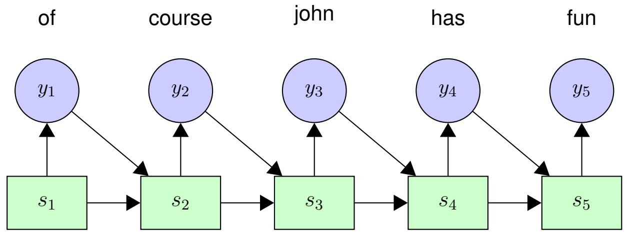
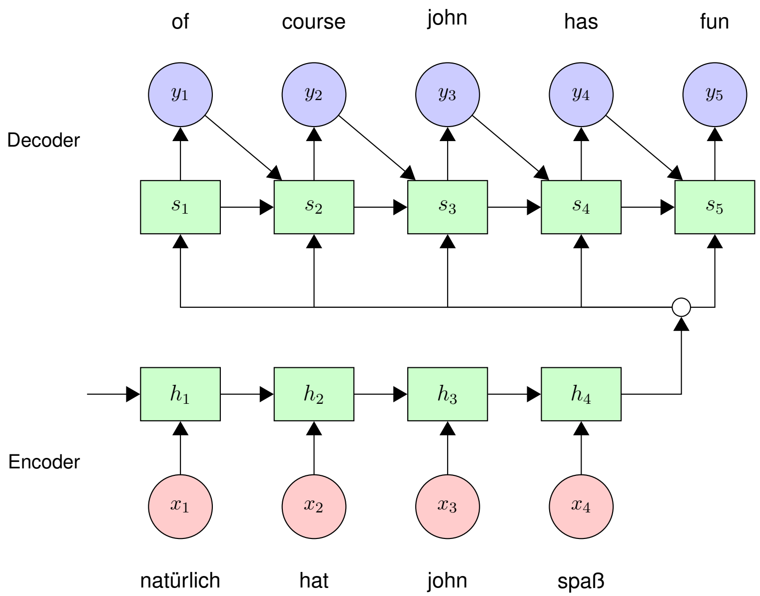
→ Use separate RNNs for source and target.

Encoder-Decoder for Translation

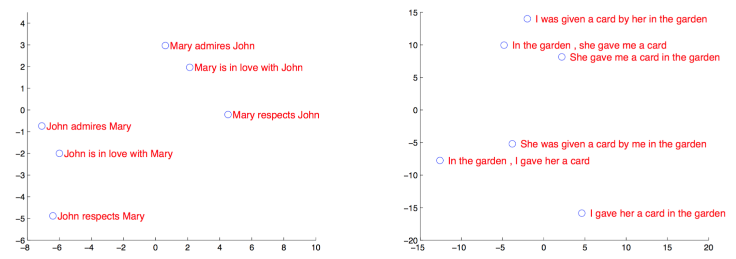


Encoder-Decoder for Translation



Summary vector

- Last encoder hidden-state “summarises” source sentence
- With multilingual training, we can potentially learn language-independent meaning representation

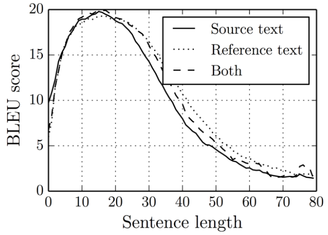


[Sutskever et al., 2014]

Summary vector as information bottleneck

Problem: Sentence Length

- Fixed sized representation degrades as sentence length increases
- Reversing source brings some improvement [Sutskever et al., 2014]



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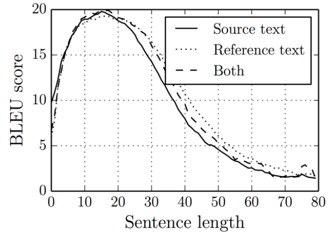
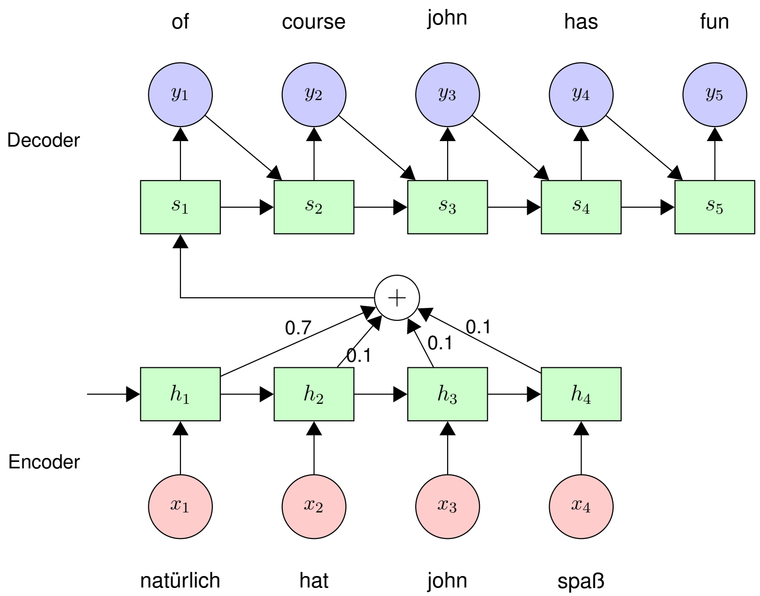


[Cho et al., 2014]

Solution: Attention

- Compute *context vector* as weighted average of source hidden states
- Weights computed by feed-forward network with softmax activation

Encoder-Decoder with Attention



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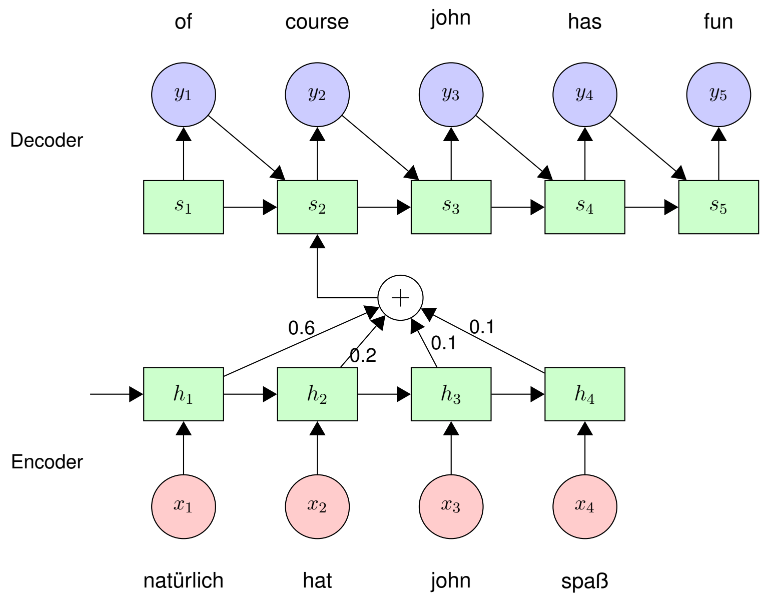

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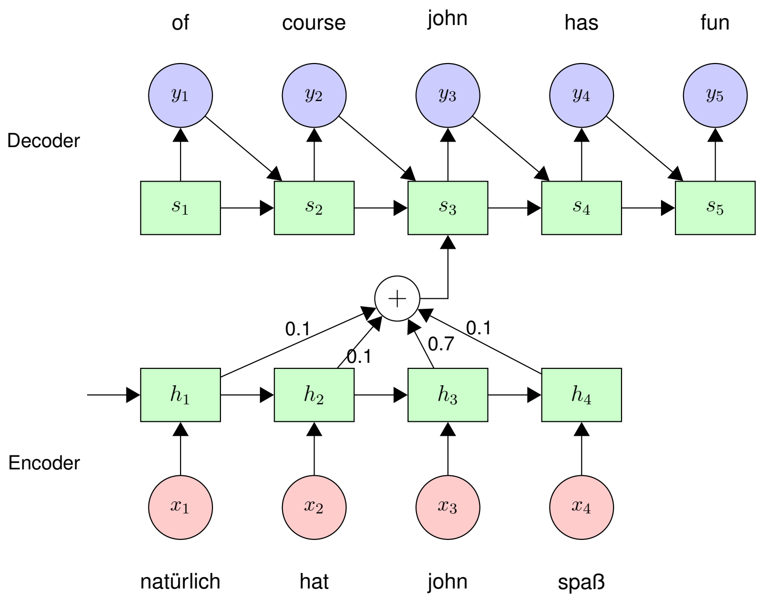

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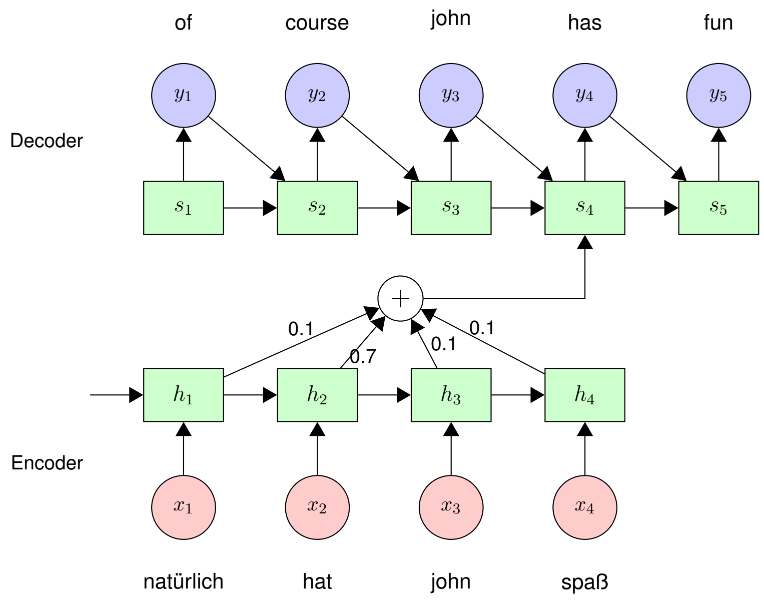

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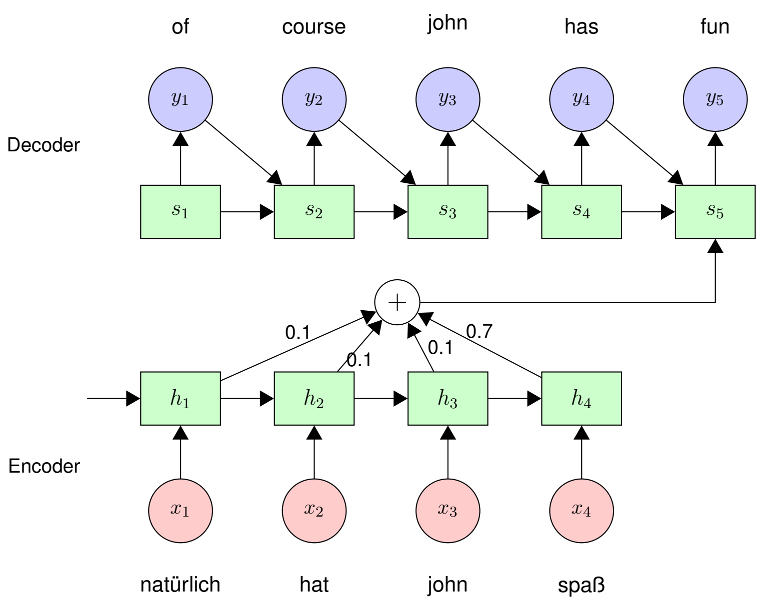


Attentional encoder-decoder: Maths

simplifications of model by [Bahdanau et al., 2015] (for illustration)

- plain RNN instead of GRU
- simpler output layer
- we do not show bias terms
- decoder follows *Look, Update, Generate* strategy [Sennrich et al., 2017]
- Details in `https://github.com/amunmt/amunmt/blob/master/contrib/notebooks/dl4mt.ipynb`

notation

- W, U, E, C, V are weight matrices (of different dimensionality)
  - E one-hot to embedding (e.g. $50000 \cdot 512$)
  - W embedding to hidden (e.g. $512 \cdot 1024$)
  - U hidden to hidden (e.g. $1024 \cdot 1024$)
  - C context (2x hidden) to hidden (e.g. $2048 \cdot 1024$)
  - V_o hidden to one-hot (e.g. $1024 \cdot 50000$)
- separate weight matrices for encoder and decoder (e.g. E_x and E_y)
- input X of length T_x; output Y of length T_y

Attentional encoder-decoder: Maths

encoder

$$\overrightarrow{h}_j = \begin{cases} 0, & \text{, if } j = 0 \\ \tanh(\overrightarrow{W}_x E_x x_j + \overrightarrow{U}_x h_{j-1}) & \text{, if } j > 0 \end{cases}$$

$$\overleftarrow{h}_j = \begin{cases} 0, & \text{, if } j = T_x + 1 \\ \tanh(\overleftarrow{W}_x E_x x_j + \overleftarrow{U}_x h_{j+1}) & \text{, if } j \le T_x \end{cases}$$

$$h_j = (\overrightarrow{h}_j, \overleftarrow{h}_j)$$

Attentional encoder-decoder: Maths

decoder

$$s_i = \begin{cases} \tanh(W_s \overleftarrow{h}_i), & \text{, if } i = 0 \\ \tanh(W_y E_y y_{i-1} + U_y s_{i-1} + C c_i) & \text{, if } i > 0 \end{cases}$$

$$t_i = \tanh(U_o s_i + W_o E_y y_{i-1} + C_o c_i)$$

$$y_i = \text{softmax}(V_o t_i)$$

attention model

$$e_{ij} = v_a^\top \tanh(W_a s_{i-1} + U_a h_j)$$

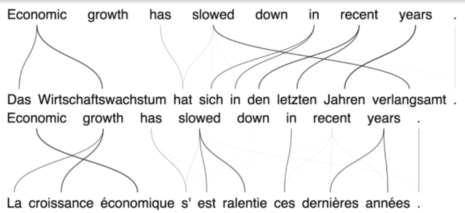
$$\alpha_{ij} = \text{softmax}(e_{ij})$$

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

Attention model

attention model

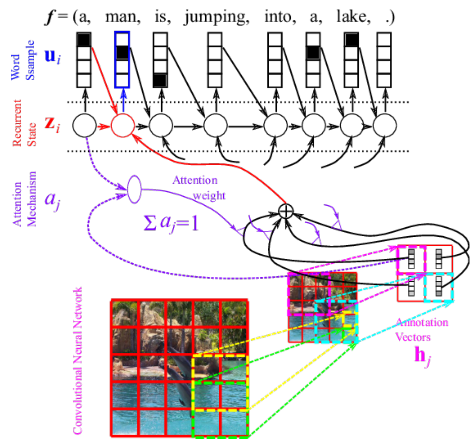
- side effect: we obtain alignment between source and target sentence
- information can also flow along recurrent connections, so there is no guarantee that attention corresponds to alignment
- applications:
  - visualisation
  - replace unknown words with back-off dictionary [Jean et al., 2015]
  - ...



Kyunghyun Cho
http://devblogs.nvidia.com/parallelforall/introduction-neural-machine-translation-gpus-part-3/

Attention model

attention model also works with images:



[Cho et al., 2015]

Attention model

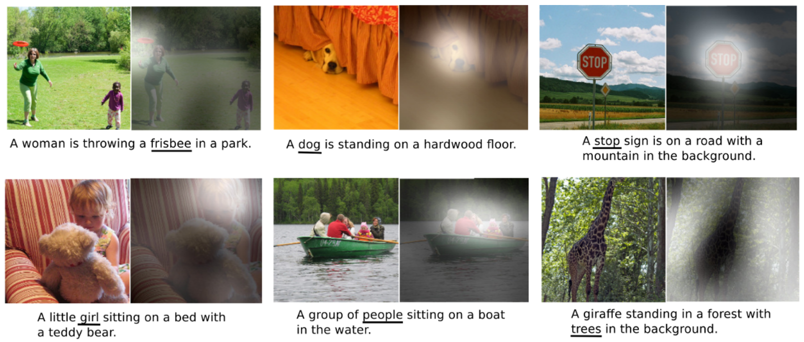


Fig. 5. Examples of the attention-based model attending to the correct object (*white* indicates the attended regions, *underlines* indicated the corresponding word) [22]

[Cho et al., 2015]

Application of Encoder-Decoder Model

Scoring (a translation)

p(La, croissance, économique, s'est, ralentie, ces, dernières, années, . | Economic, growth, has, slowed, down, in, recent, year, .) = ?

Decoding (a source sentence)

Generate the most probable translation of a source sentence

$$y^* = \text{argmax}_y\, p(y|\text{Economic, growth, has, slowed, down, in, recent, year, .})$$

Decoding

exact search

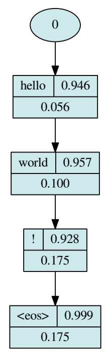
- generate every possible sentence T in target language
- compute score $p(T|S)$ for each
- pick best one

- intractable: $|\text{vocab}|^N$ translations for output length N
  $\rightarrow$ we need approximative search strategy

Decoding

approximative search/1: greedy search

- at each time step, compute probability distribution $P(y_i|S, y_{<i})$
- select y_i according to some heuristic:
  - sampling: sample from $P(y_i|S, y_{<i})$
  - greedy search: pick $\text{argmax}_y\, p(y_i|S, y_{<i})$
- continue until we generate *<eos>*



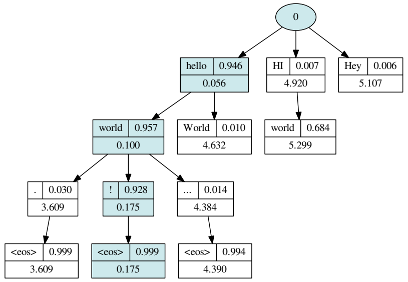
- efficient, but suboptimal

Decoding

approximative search/2: **beam search**

- maintain list of K hypotheses (beam)
- at each time step, expand each hypothesis k: $p(y_i^k|S, y_{<i}^k)$
- select K hypotheses with highest total probability:

$$\prod_i p(y_i^k|S, y_{<i}^k)$$



$K = 3$

- relatively efficient . . . beam expansion parallelisable
- currently default search strategy in neural machine translation
- small beam ($K \approx 10$) offers good speed-quality trade-off

Ensembles

- combine decision of multiple classifiers by voting
- ensemble will reduce error if these conditions are met:
  - base classifiers are accurate
  - base classifiers are diverse (make different errors)

Ensembles in NMT

- vote at each time step to explore same search space (better than decoding with one, reranking n-best list with others)
- voting mechanism: typically average (log-)probability

$$\log P(y_i|S, y_{<i}) = \frac{\sum_{m=1}^{M} \log P_m(y_i|S, y_{<i})}{M}$$

- requirements for voting at each time step:
  - same output vocabulary
  - same factorization of Y
  - but: internal network architecture may be different
- we still use reranking in some situations
  example: combine left-to-right decoding and right-to-left decoding

Further Reading

Required Reading

- Koehn, 13.5

Optional Reading

- Sequence to Sequence Learning with Neural Networks. (Sutskever, Vinyals, Le) : `https://papers.nips.cc/paper/5346-sequence-to-sequence-learning-with-neural-networks.pdf`
- Neural Machine Translation by Jointly Learning to Align and Translate. (Bahdanau, Cho, Bengio) : `https://arxiv.org/pdf/1409.0473.pdf`

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