Encoder-Decoder Models

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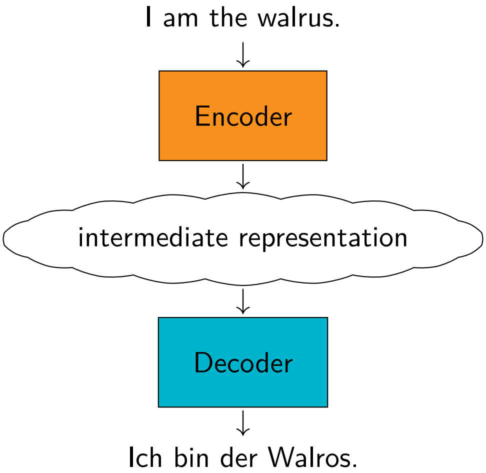
Model Concept

Conceptual Scheme of the Model



Neural model with a sequence of discrete symbols as an input that generates another sequence of discrete symbols as an output.

- pre-process source sentence (tokenize, split into smaller units)
- convert input into vocabulary indices
- run the encoder to get an intermediate representation (vector/matrix)
- run the decoder
- postprocess the output (detokenize)

Language Models and Decoders

What is a Language Model

LM = an estimator of a sentence probability given a language

- From now on: sentence = sequence of words $w_1, \dots, w_n$
- Factorize the probability by word
  i.e., no grammar, no hierarchical structure

$$\begin{aligned}\mathsf{Pr}\left(w_1, \dots, w_n\right) &= \mathsf{Pr}(w_1) \cdot \mathsf{Pr}(w_2 | w_1) \cdot \mathsf{Pr}(w_3 | w_2, w_1) \cdot \cdots \\ &= \prod_{i}^{n} \mathsf{Pr}\left(w_i | w_{i-1}, \dots, w_1\right)\end{aligned}$$

What is it good for?

- Substitute for grammar: tells what is a good sentence in a language
- Used in ASR, and statistical MT to select more probable outputs
- Being able to predict next word = proxy for knowing the language
  - language modeling is training objective for word2vec
  - BERT is a masked language model

- **Neural decoder is a conditional language model.**

n-gram vs. Neural LMs

n-gram
cool from 1990 to 2013

- Limited history = Markov assumption
- Transparent: estimated from n-gram counts in a corpus

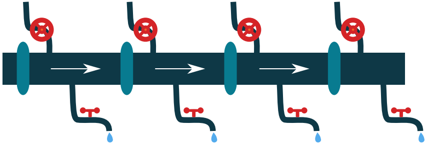
$$\mathsf{P}(w_i|w_{i-1}, w_{i-2}, \dots, w_{i-n}) \approx \sum_{j=0}^{n} \lambda_j \frac{c(w_i|w_{i-1}, \dots, w_{i-j})}{c(w_i|w_{i-1}, \dots, w_{i-j+1})}$$

Neural
cool since 2013

- Conditioned on RNN state which gather potentially unlimited history
- Trained by back-propagation to maximize probability of the training data
- Opaque, but works better (as usual with deep learning)

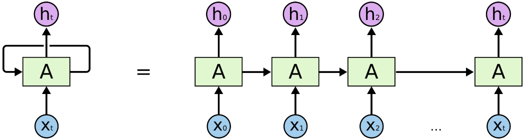
Reminder: Recurrent Neural Networks

RNN = pipeline for information



In every step some information goes in and some information goes out.

Technically: A "`for`" loop applying the same function A on input vectors x_i



At training time unrolled in time: technically just a very deep network

Image on the right: Chris Olah. Understanding LSTM Networks. A blog post: `http://colah.github.io/posts/2015-08-Understanding-LSTMs`

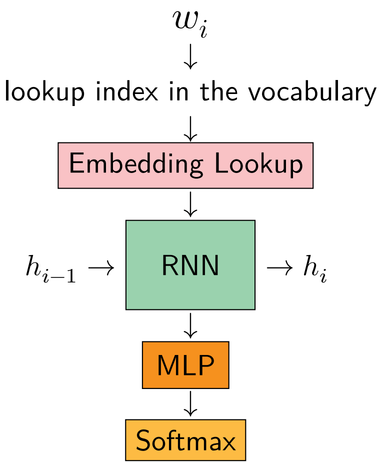
Sequence Labeling

- Assign a label to each word in a sentence.
- Tasks formulated as sequence labeling:
    - Part-of-Speech Tagging
    - Named Entity Recognition
    - Filling missing punctuation

MLP = Multilayer perceptron
  $n\times$ layer: $\sigma\left(Wx+b\right)$

Softmax for K classes with logits $\mathbf{z}=(z_1,\dots,z_K)$:

$$\frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$



Detour: Why is softmax a good choice

Output layer with softmax (with parameters W, b) — gets categorical distribution:

$$P_y = \mathrm{softmax}(\mathbf{x}) = \Pr(y \mid \mathbf{x}) = \frac{\exp\{\mathbf{x}^\top W\} + b}{\sum \exp\{\mathbf{x}^\top W\} + b}$$

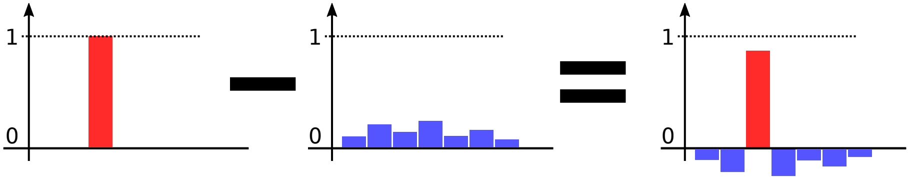
Network error $=$ cross-entropy between estimated distribution and one-hot ground-truth distribution $T = \mathbf{1}(y^*) = (0, 0, \ldots, 1, 0, \ldots, 0)$:

$$\begin{aligned} L(P_y, y^*) = H(P, T) &= -\mathbb{E}_{i\sim T} \log P(i) \\ &= -\sum_i T(i) \log P(i) \\ &= -\log P(y^*) \end{aligned}$$

Derivative of Cross-Entropy

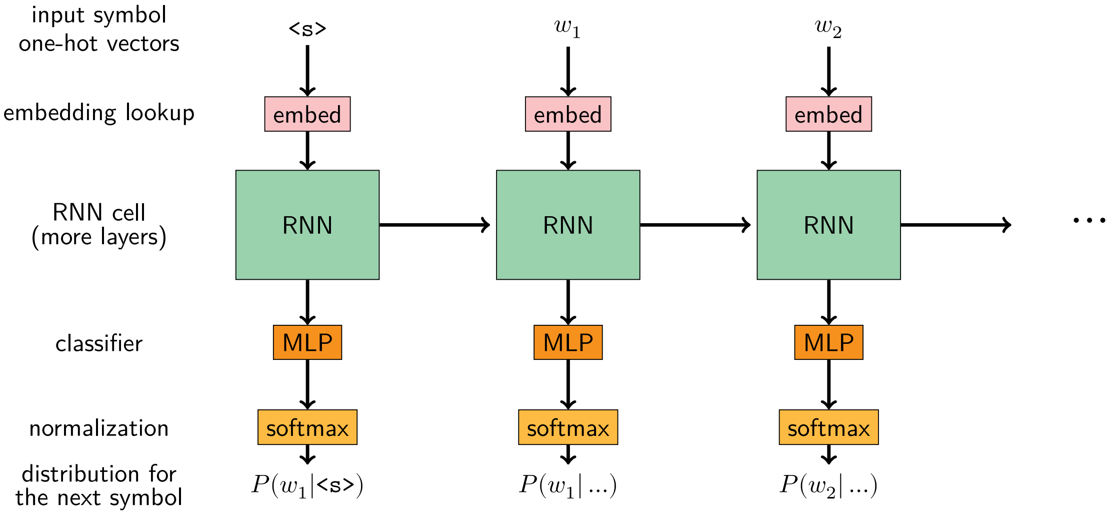
Let $l = \mathbf{x}^\top W + b$, l_{y^*} corresponds to the correct one.

$$
\begin{aligned}
\frac{\partial L(P_y, y^*)}{\partial l} &= -\frac{\partial}{\partial l} \log \frac{\exp l_{y^*}}{\sum_j \exp l_j} = -\frac{\partial}{\partial l} \left(l_{y^*} - \log \sum \exp l \right) \\
&= \mathbf{1}_{y^*} + \frac{\partial}{\partial l} - \log \sum \exp l = \mathbf{1}_{y^*} - \frac{\sum \mathbf{1}_{y^*} \exp l}{\sum \exp l} = \\
&= \mathbf{1}_{y^*} - P_y(y^*)
\end{aligned}
$$

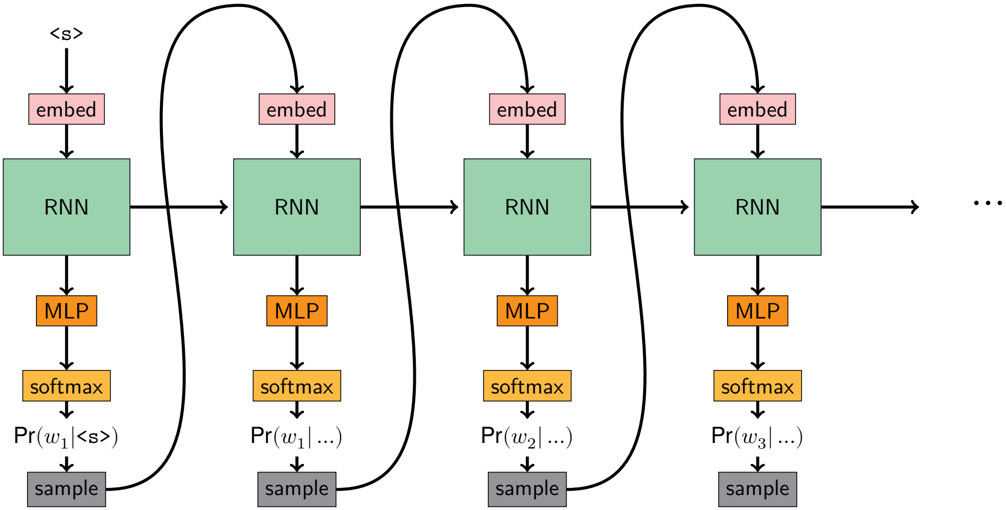


Interpretation: Reinforce the correct logit, suppress the rest.

Language Model as Sequence Labeling



Sampling from a Language Model



Sampling from a Language Model: Pseudocode

```
last_w = "<s>"
state = initial_state
while last_w != "</s>":
    last_w_embeding = target_embeddings[last_w]
    state = rnn(state, last_w_embeding)
    logits = output_projection(state)
    last_w = vocabulary[np.random.multimial(1, logits)]
    yield last_w
```

Training

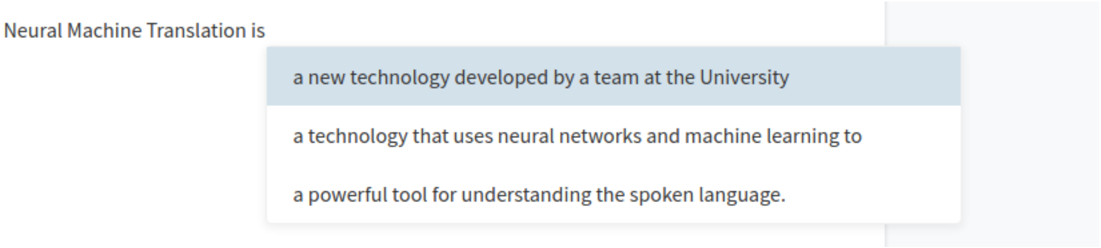
Training objective: negative-log likelihood:

$$\mathsf{NLL} = -\sum_{i}^{n} \log \mathsf{Pr}\left(w_i | w_{i-1}, \dots, w_1\right)$$

I.e., maximize probability of the correct word.

- Cross-entropy between the predicted distribution and one-hot “true” distribution
- Error from word is backpropagated into the rest of network unrolled in time
- Prone to exposure bias: during trainining only well-behaved sequences, it can break when we sample something weird at inference time

Generating from a Language Model



(Example from GPT-2, a Tranformer-based English language model, screenshot from `https://transformer.huggingface.co/doc/gpt2-large`)

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. *OpenAI Blog*., 2019

Cool, but where is the source language?

Conditioning the Language Model & Attention

Conditional Language Model

Formally it is simple, condition distribution of

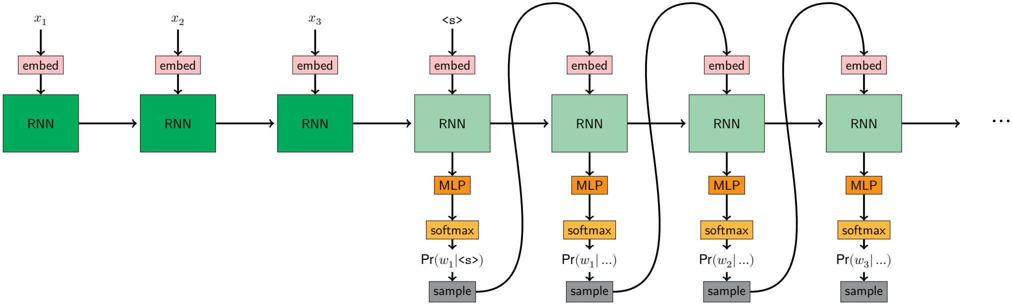
- target sequence $\mathbf{y} = (y_1, \dots, y_{T_y})$ on
- source sequence $\mathbf{x} = (x_1, \dots, x_{T_x})$

$$\Pr(y_1, \dots, y_n | \mathbf{x}) = \prod_i^n \Pr(y_i | y_{i-1}, \dots, y_1, \mathbf{x})$$

We need an *encoder* to get a representation of $\mathbf{x}$!

What about just continuing an RNN…

Sequence-to-Sequence Model



- The interface between encoder and decoder is a single vector regardless the sentence length.

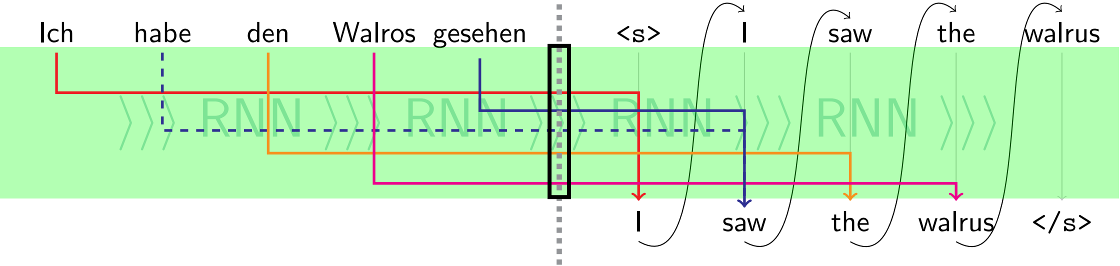
Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In *Advances in Neural Information Processing Systems 27*, pages 3104–3112, Montreal, Canada, December 2014

Seq2Seq: Pseudocode

```
state = np.zeros(rnn_size)
for w in input_words:
    input_embedding = source_embeddings[w]
    state = enc_cell(encoder_state, input_embedding)

last_w = "<s>"
while last_w != "</s>":
    last_w_embeding = target_embeddings[last_w]
    state = dec_cell(state, last_w_embeding)
    logits = output_projection(state)
    last_w = vocabulary[np.argmax(logits)]
    yield last_w
```

Vanila Seq2Seq: Information Bottleneck



Bottleneck all information needs to run through.
A single vector must represent the entire source sentence.

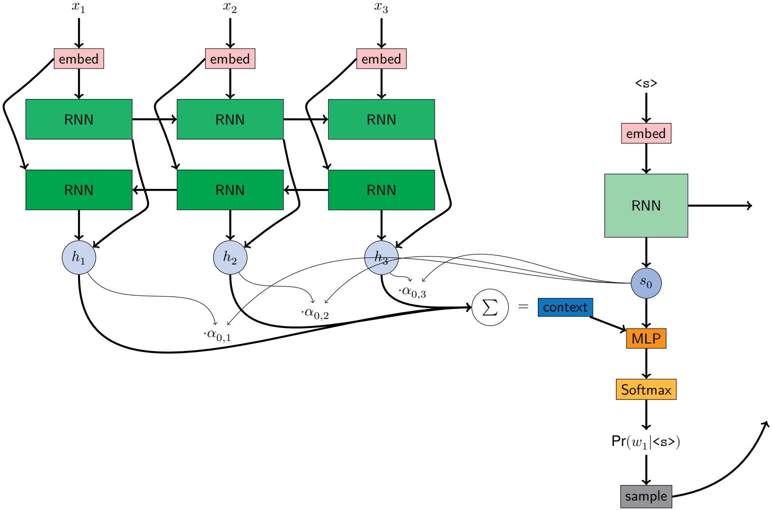
Main weakness and the reason for introducing the attention.

- Motivation: It would be nice to have variable length input representation
- RNN returns one state per word ...
- ...what if we were able to get only information from words we need to generate a word.

> **Attention** = probabilistic retrieval of encoder states for estimating probability of target words.

Query = hidden states of the decoder
Values = encoder hidden states

Sequence-to-Sequence Model With Attention



- Encoder = bidirectional RNN states h_i ≈ retrieved values
- Decoder step starts as usual state s_0 ≈ retrieval query
- Decoder state s_0 used to compute distribution the over encoder states
- Weighted average of encoder states = context vector
- Decoder state & context concatenated MLP + Softmax predicts next word

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. In Yoshua Bengio and Yann LeCun, editors, *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*, 2015

Attention Model in Equations (1)

Inputs:

decoder state s_i

encoder states $h_j = \left[\overrightarrow{h_j}; \overleftarrow{h_j}\right] \quad \forall i = 1 \ldots T_x$

Attention energies:

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

Attention distribution:

$$\alpha_{ij} = \frac{\exp\left(e_{ij}\right)}{\sum_{k=1}^{T_x} \exp\left(e_{ik}\right)}$$

Context vector:

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

Attention Model in Equations (2)

Output projection:

$$t_i = \mathsf{MLP}\left(s_{i-1} \oplus v_{y_{i-1}} \oplus c_i\right)$$

...attention is mixed with the hidden state
(different in diffent models)

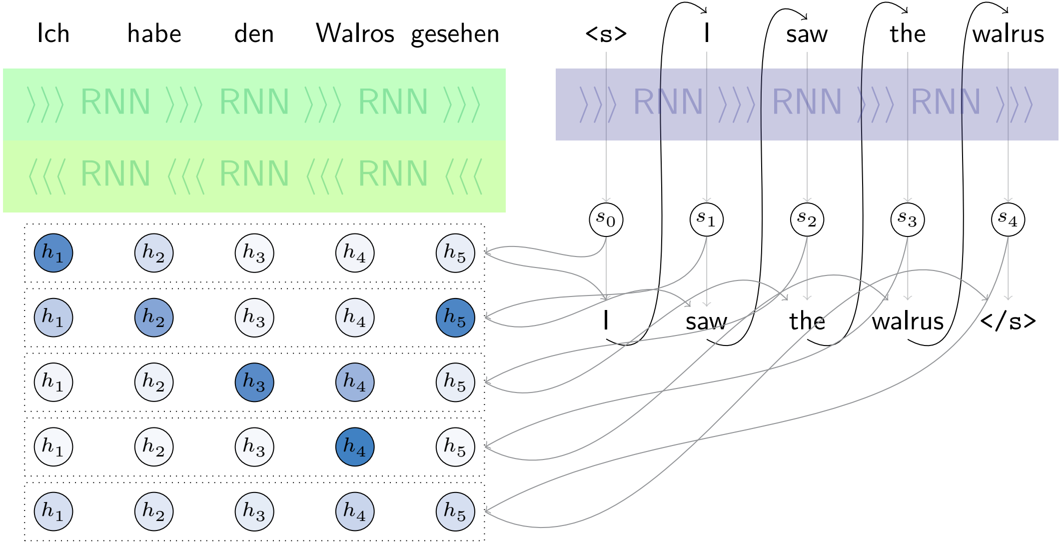
Output distribution:

$$p\left(y_i = k | s_i, y_{i-1}, c_i\right) \propto \exp\left(W_o t_i + b_k\right)_k$$

(usual trick: use transposed embeddings as W_o)

- Different version of attentive decoders exist
- Alternative: keep the context vector as input for the next step
- Multilayer RNNs: attention between/after layers

Workings of the Attentive Seq2Seq model



Seq2Seq with attention: Pseudocode (1)

```
state = np.zeros(emb_size)
fw_states = []
for w in input_words:
    input_embedding = source_embeddings[w]
    state, _ = fw_enc_cell(encoder_state, input_embedding)
    fw_states.append(state)

bw_states = []
state = np.zeros(emb_size)
for w in reversed(input_words):
    input_embedding = source_embeddings[w]
    state, _ = bw_enc_cell(encoder_state, input_embedding)
    bw_states.append(state)

enc_states = [np.concatenate(fw, bw) for fw, bw in zip(fw_states,
    reversed(bw_states))]
```

Seq2Seq with attention: Pseudocode (2)

```
last_w = "<s>"
while last_w != "</s>":
    last_w_embeding = target_embeddings[last_w]
    state = dec_cell(state, last_w_embeding)
    alphas = attention(state, enc_states)
    context = sum(a * state for a, state in zip(alphas, enc_states))
    logits = output_projection(np.concatenate(state, context, last_w_embeding))
    last_w = np.argmax(logits)
    yield last_w
```

Attention Visualization (1)

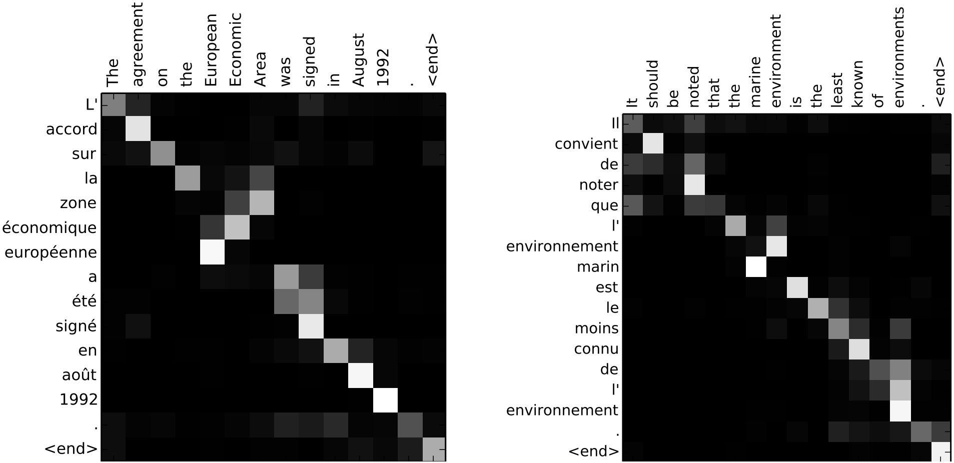


Image source: Bahdanau et al. (2015), Fig. 3

Attention Visualization (2)

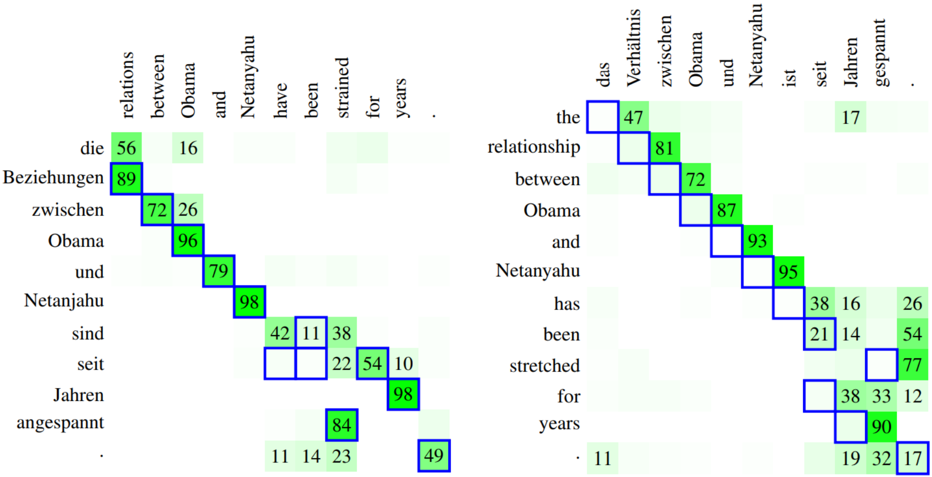


Image source: Koehn and Knowles (2017), Fig. 8

Attention vs. Alignment

Differences between attention model and word alignment used for phrase table generation:

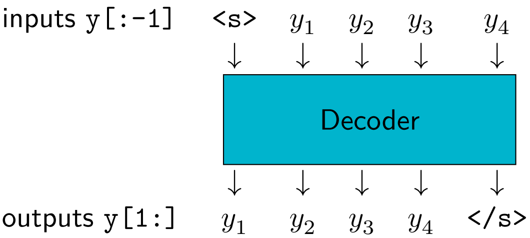
attention (NMT)	**alignment (SMT)**
probabilistic	discrete
declarative	imperative
LM generates	LM discriminates

Training Seq2Seq Model

Optimize negative log-likelihood of parallel data, backpropagation does the rest.

If you choose a right optimizer, learning rate, model hyper-parameters, prepare data, do back-translation, monolingual pre-training ...

Confusion: decoder inputs vs. output



Inference

Getting output

- Encoder-decoder is a conditional language model
- For a pair $\mathbf{x}$ and $\mathbf{y}$, we can compute:

$$\Pr(\mathbf{y}|\mathbf{x}) = \prod_{i=1}^{T_y} \Pr(y_i|\mathbf{y}_{:i}, \mathbf{x})$$

- When decoding we want to get

$$\mathbf{y}^* = \underset{\mathbf{y}'}{\operatorname{argmax}} \Pr(\mathbf{y}'|x)$$

☠ **Enumerating all $\mathbf{y}'$s is computationally intractable** ☠

Greedy Decoding

In each step, take the maximum probable word.

$$y_i^* = \operatorname*{argmax}_{y_i} \Pr\left(y_i | y_{i-1}^*, \ldots, \text{<s>}\right)$$

```
last_w = "<s>"
state = initial_state
while last_w != "</s>":
    last_w_embeding = target_embeddings[last_w]
    state = dec_cell(state, last_w_embeding)
    logits = output_projection(state)
    last_w = vocabulary[np.argmax(logits)]
    yield last_w
```

What if...

This is a

platypus random end . </s>

25%

30% each

rather good sentence . </s>

24%

60% each

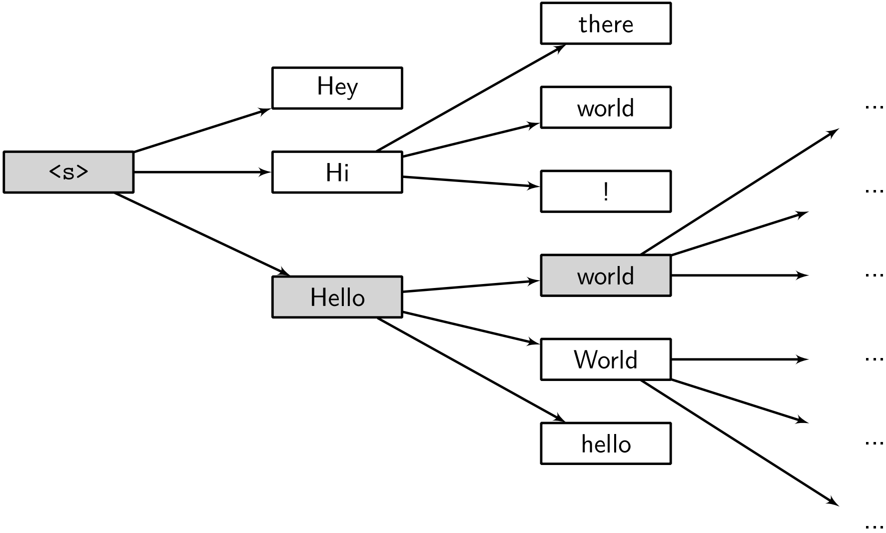
⚠ Greedy decoding can easily miss the best option. ⚠

Beam Search

Keep a small k of hypothesis (typically 4–20).

1. Begin with a single empty hypothesis in the beam.
2. In each time step:
    2.1 Extend all hypotheses in the beam by all (or the most probable) from the output distribution (we call these *candidate hypotheses*)
    2.2 Score the candidate hypotheses
    2.3 Keep only k best of them.
3. Finish if all k-best hypotheses end with `</s>`
4. Sort the hypotheses by their score and output the best one.

Beam Search: Example



Beam Search: Pseudocode

```
beam = [(["<s>"], initial_state, 1.0)]
while any(hyp[-1] != "</s>" for hyp, _, _ in beam):
    candidates = []

    for hyp, state, score in beam:
    distribution, new_state = decoder_step(hyp[-1], state, encoder_states)
        for i, prob in enumerate(distribution):
            candidates.append(hyp + [vocabulary[i]], new_state, score * prob)

    beam = take_best(k, candidates)
```

Implementation issues

- Multiplying of too many small numbers $\rightarrow$ float underflow
  need to compute in log domain and add logarithms
- Sentences can have different lengths

This	is	a	good	long	sentence	.	</s>	
0.7	$\times$ 0.6	$\times$ 0.9	$\times$ 0.1	$\times$ 0.4	$\times$ 0.4	$\times$ 0.8	$\times$ 0.9	**= 0.004**

This	</s>	
0.7	$\times$ 0.01	**= 0.007**

$\Rightarrow$ use the geometric mean instead of probabilities directly

- Sorting candidates is expensive, assomptotically $|V| \log |V|$:
  k-best can be found in linear time, $|V| \sim 10^4 - 10^5$

Final Remarks

Brief history of the architectures

- **2013** First encoder-decoder model (Kalchbrenner and Blunsom, 2013)
- **2014** First really usable encoder-decoder model (Sutskever et al., 2014)
- **2014/2015** Added attention (crucial innovation in NLP) (Bahdanau et al., 2015)
- **2016/2017** WMT winners used RNN-based neural systems (Sennrich et al., 2016)
- **2017** Transformers invented (outperformed RNN) (Vaswani et al., 2017)

The development of achitectures still goes on...

Document context, non-autoregressive models, multilingual models, ...

Summary

- Encoder-decoder architecture = major paradigm in MT
- Encoder-decoder architecture = conditional language model
- Attention = way of conditioning the decoder on the encoder
- Attention = probabilistic vector retrieval
- We model probability, but need heuristics to get a good sentence from the model

http://ufal.mff.cuni.cz/courses/npfl116

References I

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. In Yoshua Bengio and Yann LeCun, editors, *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*, 2015.

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Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems 30*, pages 6000–6010, Long Beach, CA, USA, December 2017. Curran Associates, Inc.