# Encoder-Decoder Models

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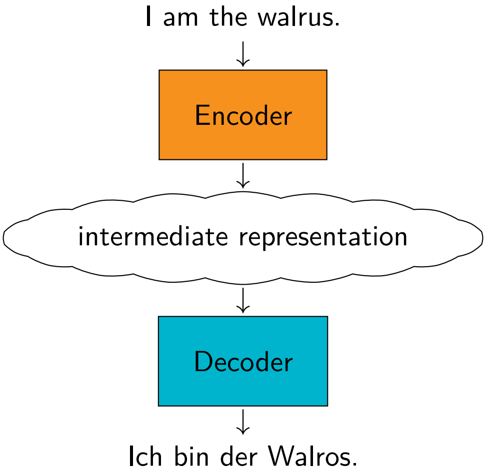
# Model Concept

# 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 $w_1, \ldots, w_n$
- Factorize the probability by word
  i.e., no grammar, no hierarchical structure

$$\begin{aligned}\Pr(w_1, \ldots, w_n) &= \Pr(w_1) \cdot \Pr(w_2|w_1) \cdot \Pr(w_3|w_2, w_1) \cdot \cdots \\ &= \prod_i^n \Pr(w_i|w_{i-1}, \ldots, w_1)\end{aligned}$$

# 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

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

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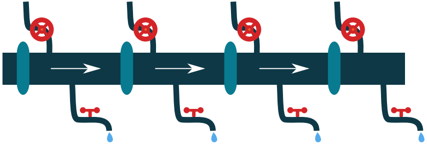
**Neural**
cool since 2013

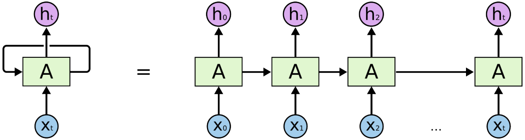
- Conditioned on RNN state which gather potentially unlimited history
- Trained by back-propagation to maximize probability of the training data
- Opaque, but works better (as usual with deep learning)

**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 $x_i$

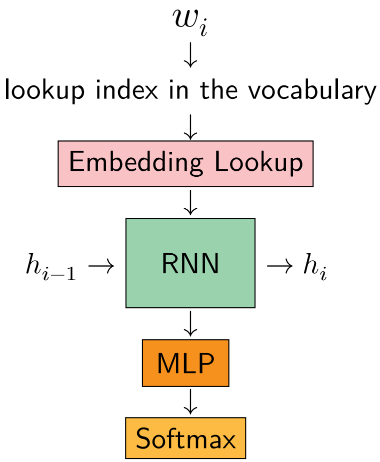



At training time unrolled in time: technically just a very deep network

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

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

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

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

# Detour: Why is softmax a good choice

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

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

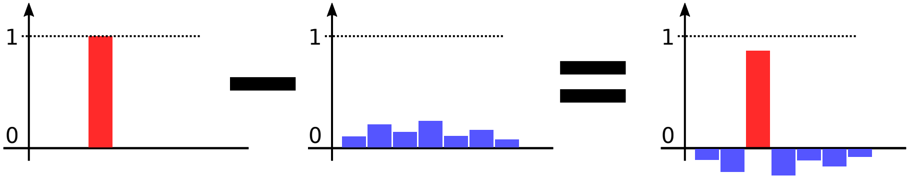
Network error = cross-entropy between estimated distribution and one-hot ground-truth distribution $T = \mathbf{1}(y^*) = (0, 0, \dots, 1, 0, \dots, 0)$:

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

# Derivative of Cross-Entropy

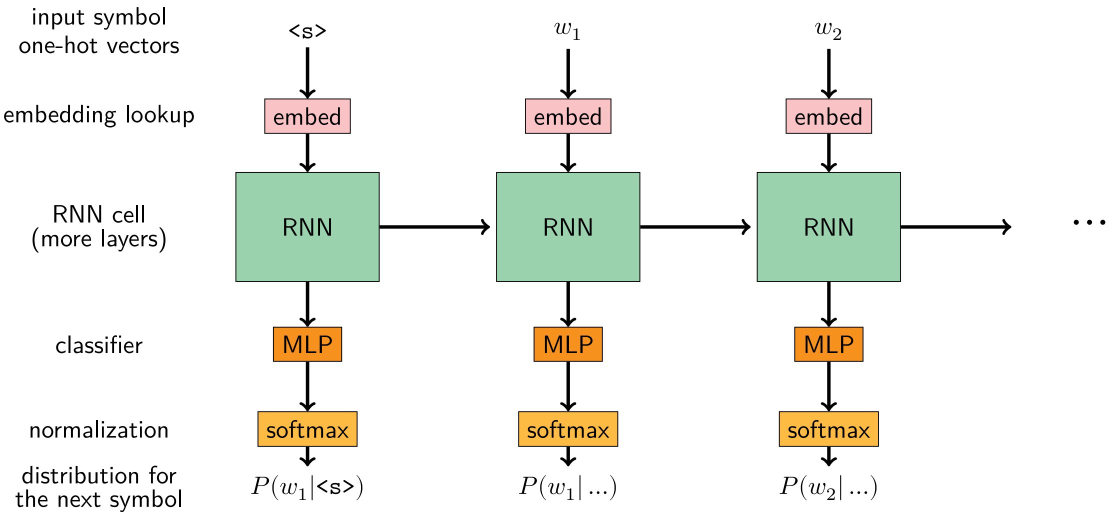
Let $l = \mathbf{x}^\top W + b$, $l_{y^*}$ corresponds to the correct one.

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

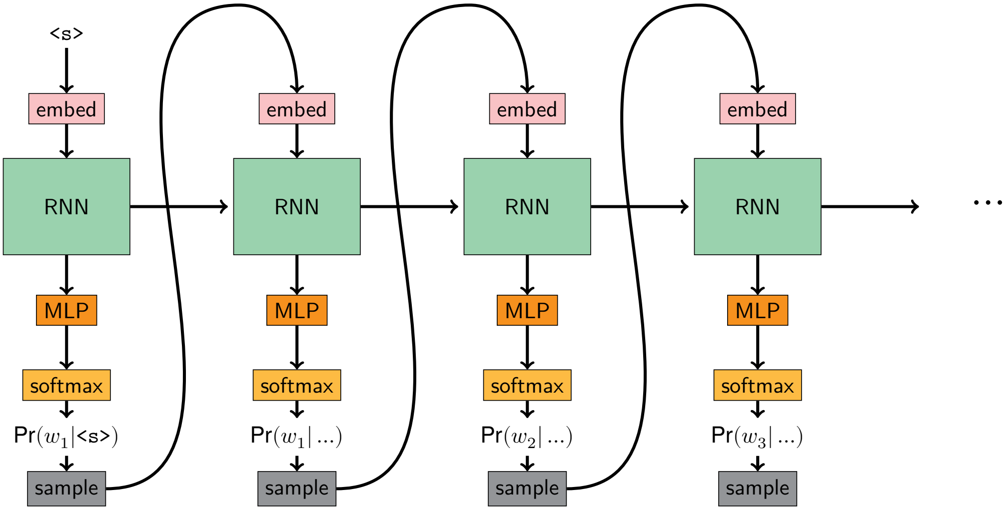



Interpretation: Reinforce the correct logit, suppress the rest.

# 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:

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

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

Neural Machine Translation is

a new technology developed by a team at the University

a technology that uses neural networks and machine learning to

a powerful tool for understanding the spoken language.

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

**Cool, but where is the source language?**

# Conditioning the Language Model & Attention

# Conditional Language Model

Formally it is simple, condition distribution of

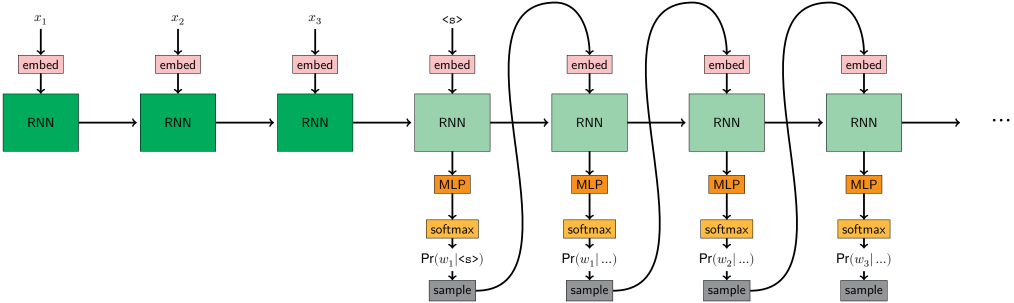
- target sequence $\mathbf{y} = (y_1, \ldots, y_{T_y})$ on
- source sequence $\mathbf{x} = (x_1, \ldots, x_{T_x})$

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

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

**What about just continuing an RNN…**

# Sequence-to-Sequence Model



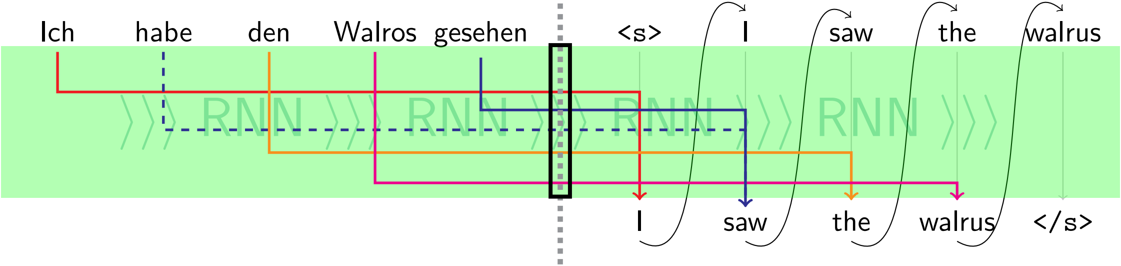

- The interface between encoder and decoder is a single vector regardless the sentence length.

# 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.**

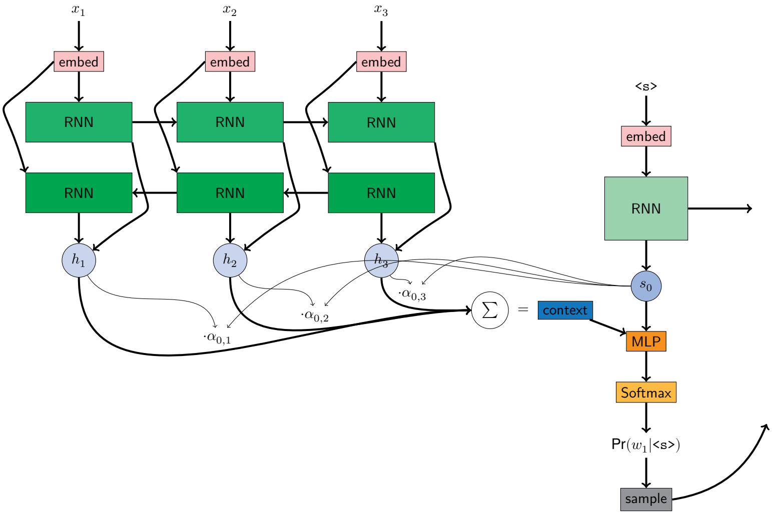
# The Attention Model

- 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

**Inputs:**

decoder state $s_i$

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

**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 differnt models)

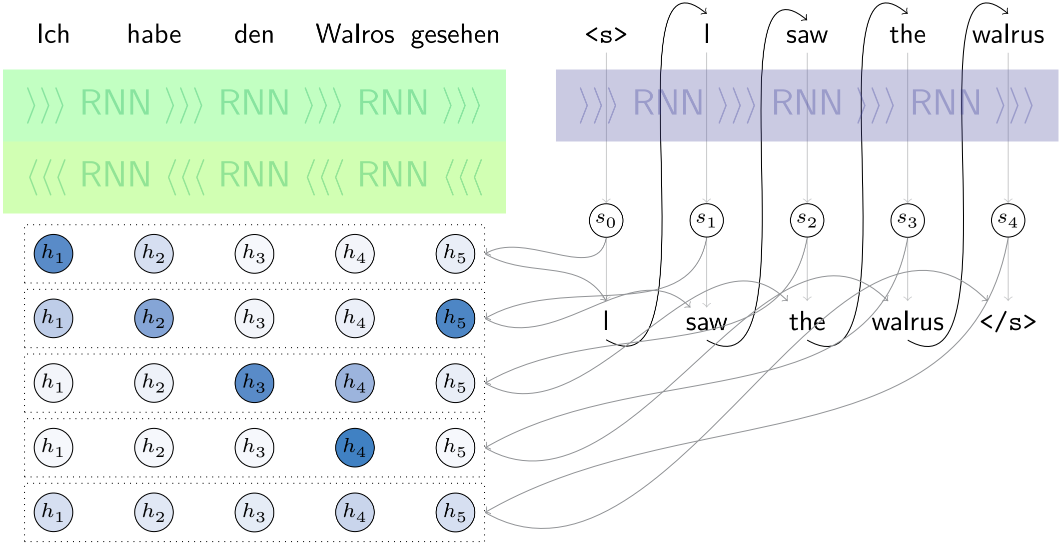
**Output distribution:**

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

(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: **?**, Fig. 3

# Attention Visualization (2)

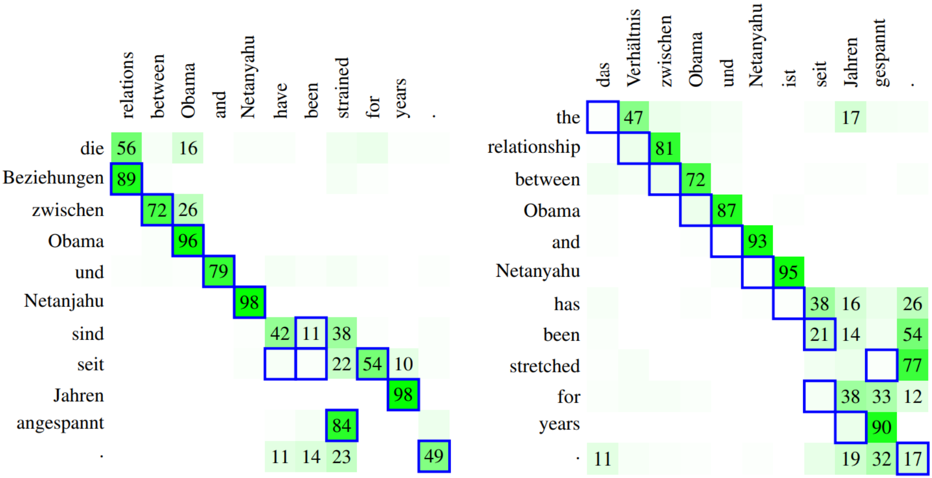



Image source: ?, Fig. 8

# Attention vs. Alignment

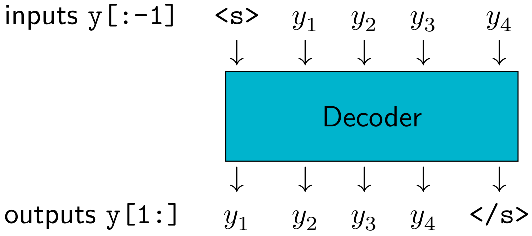
Differences between attention model and word alignment used for phrase table generation:

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

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 **x** and **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

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

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

# Greedy Decoding

In each step, take the maximum probable word.

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

```
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

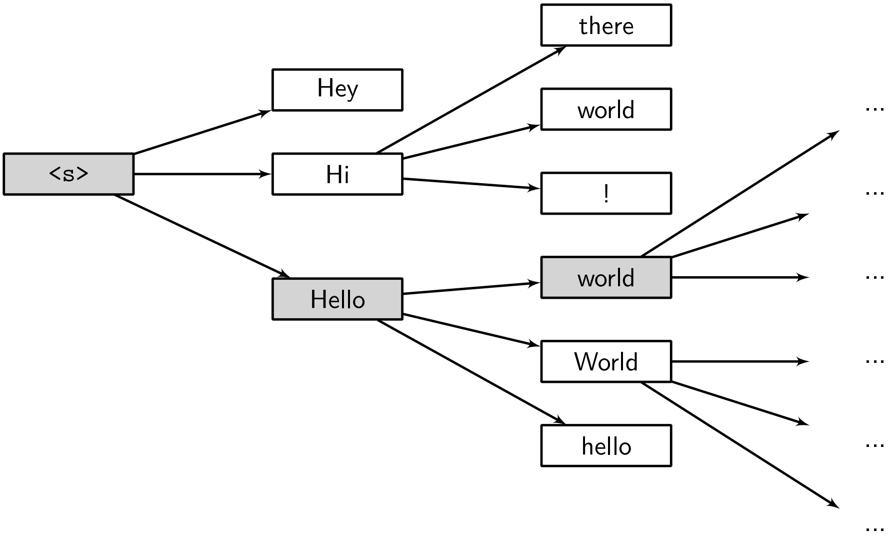
⚠ Greedy decoding can easily miss the best option. ⚠

# 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 (?)
- **2014** First really usable encoder-decoder model (?)
- **2014/2015** Added attention (crucial innovation in NLP) (?)
- **2016/2017** WMT winners used RNN-based neural systems (?)
- **2017** Transformers invented (outperformed RNN) (?)

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

# References I