Machine Translation
Attention Mechanism

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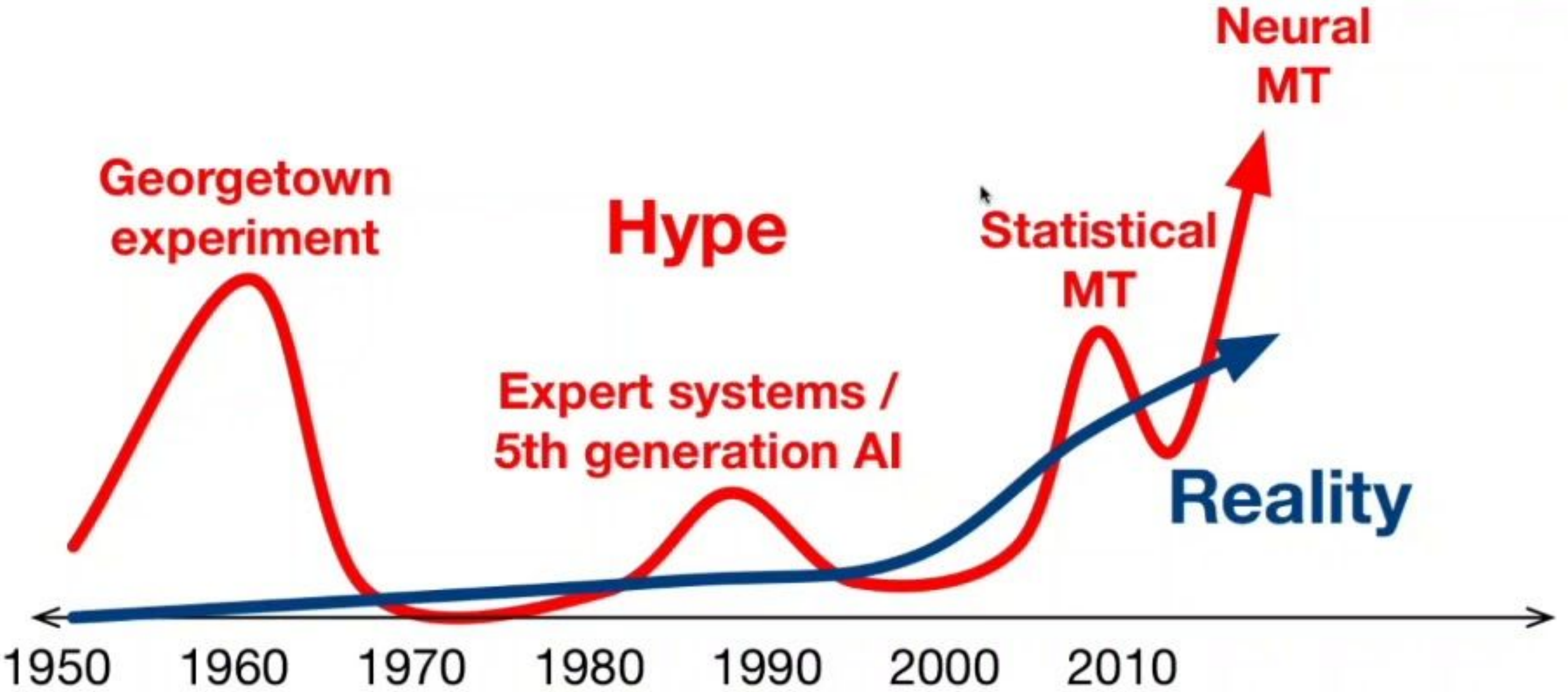
Outline

- Machine Translation historical overview
  - Statistical Machine Translation
  - Word alignments
- Neural Machine Translation (NMT)
  - Seq2Seq
  - Beam Search
- Attention mechanism

Inspired by: http://web.stanford.edu/class/cs224n/slides/cs224n-2019-lecture08-nmt.pdf

Historical overview



Before Deep Learning

1950s: first Machine Translation

- Georgetown experiment (7 Jan 1954)
  - Automatic Russian-English translation of 60 sentences
  - 250 vocabulary articles
  - 6 grammar rules
  - Calculated on Mainframe IBM 701
- The same experiment in the USSR (1954 too)
  - Rule-based translation
  - Calculated on BESM

MT Training Data

- Parallel corpora
    - Pairs <source, translation>
    - Typically sentence-level (although sometimes can be paragraph- or doc-level)
    - Can be manually curated by translators, crawled from web or synthetic

Source	角柱を過ぎる粘性流体の乱流をラージエディシミュレーションし，フィルタ幅と数値粘性の影響を調べた。
Reference	The large eddy simulation of a turbulent flow of a viscous fluid passing through a square column was conducted, and the effects of the filter width and numerical viscosity were examined.

1990-2010: Statistical Machine Translation

Want to find best English sentence y, given French sentence x

Let's use Bayes Rule to break this down into two components:

$$
\begin{aligned}
&\operatorname{argmax}_y P(y|x) \\
&= \operatorname{argmax}_y \underbrace{P(x|y)}\,\underbrace{P(y)}
\end{aligned}
$$

Translation Model

Models how words and phrases should be translated (*fidelity*). Learnt from parallel data.

Language Model

Models how to write good English (*fluency*). Learnt from monolingual data.

Source: http://web.stanford.edu/class/cs224n/slides/cs224n-2019-lecture08-nmt.pdf

1990-2010: Statistical Machine Translation

How to learn translation model from the parallel corpus?

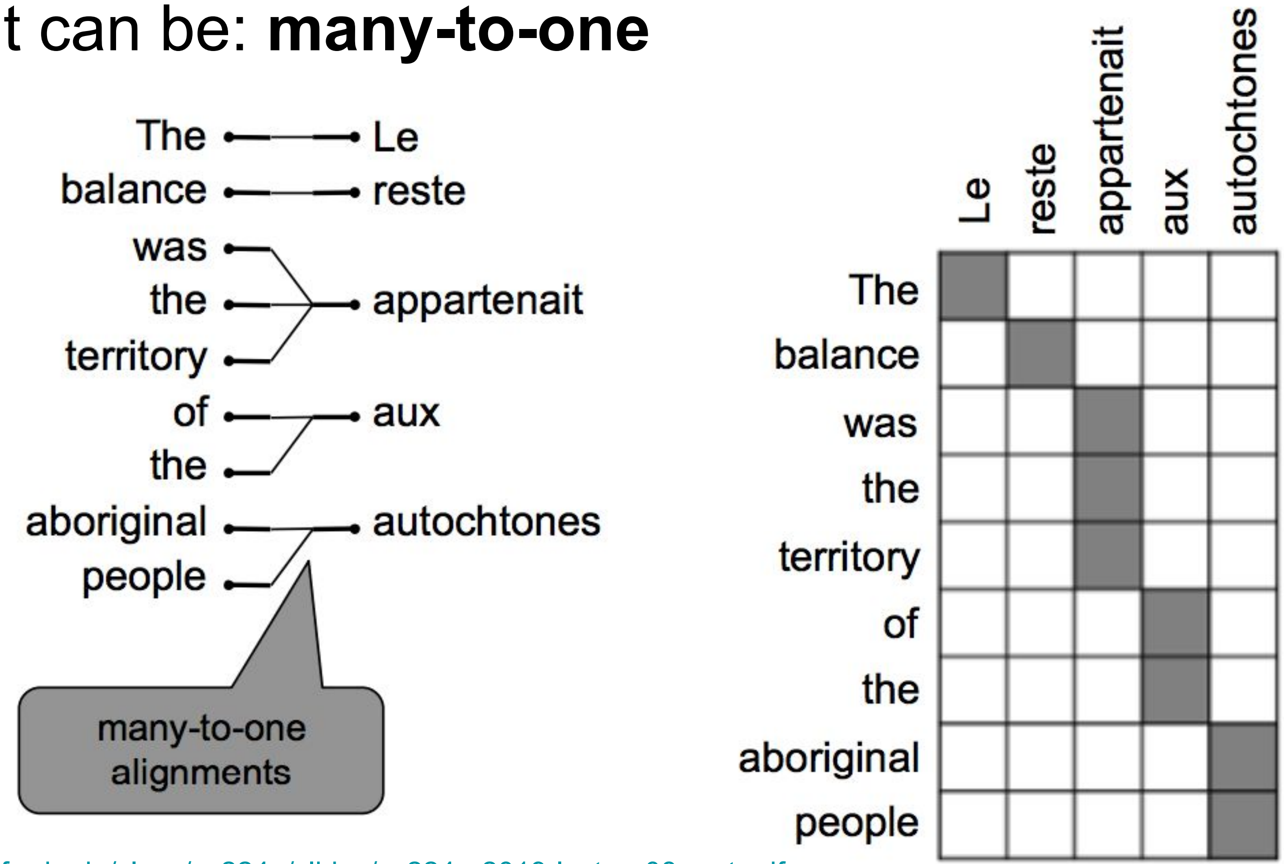
Let's calculate

$$P(x, a|y)$$

Where **a** is an **alignment** (word-level correspondence between French sentence x and English sentence y)

1990-2010: Statistical Machine Translation

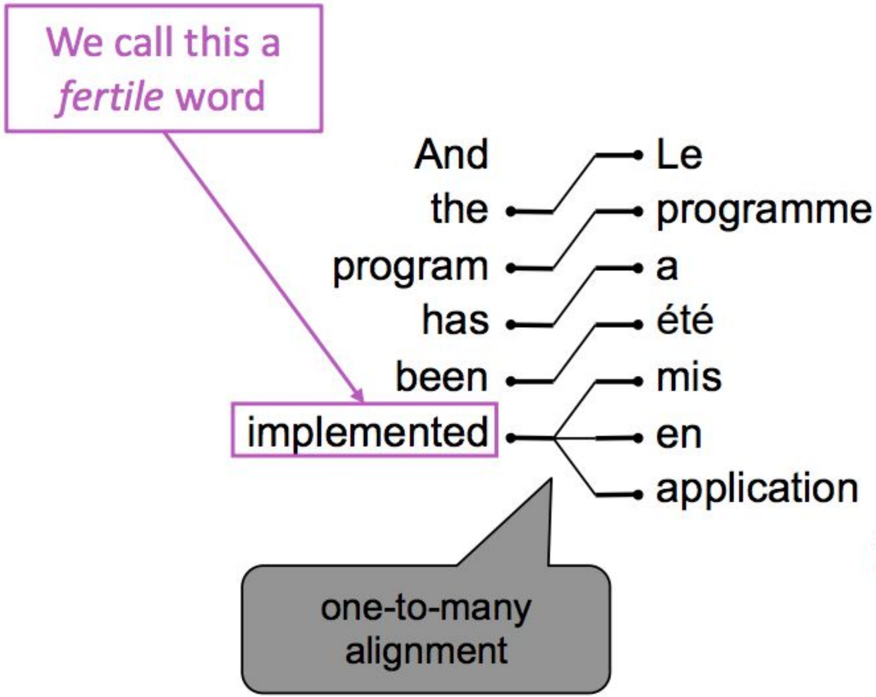
Alignment can be: **many-to-one**

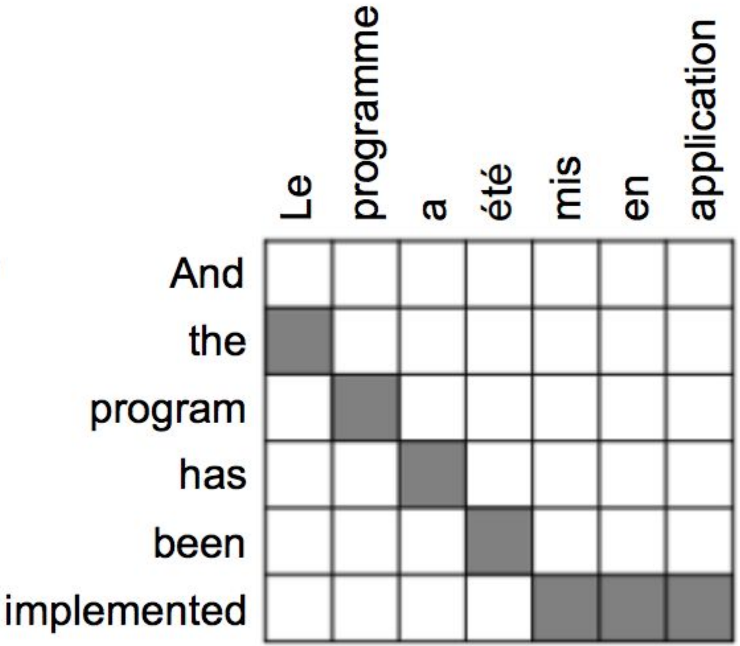


Source: http://web.stanford.edu/class/cs224n/slides/cs224n-2019-lecture08-nmt.pdf

1990-2010: Statistical Machine Translation

Alignment can be: **one-to-many**





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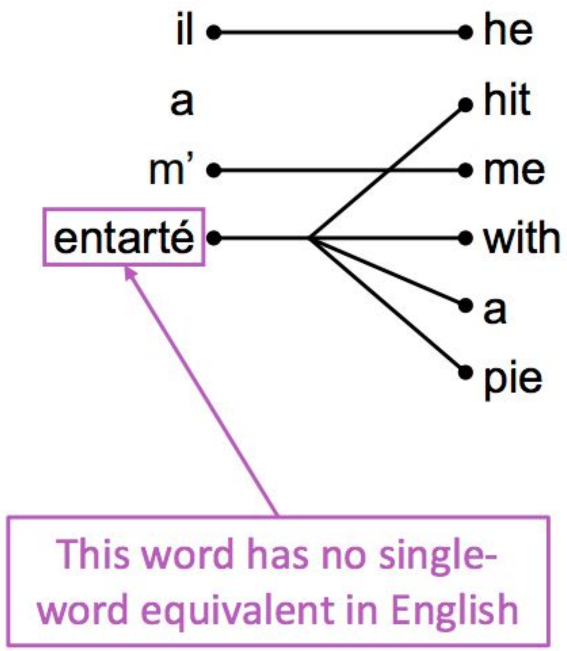
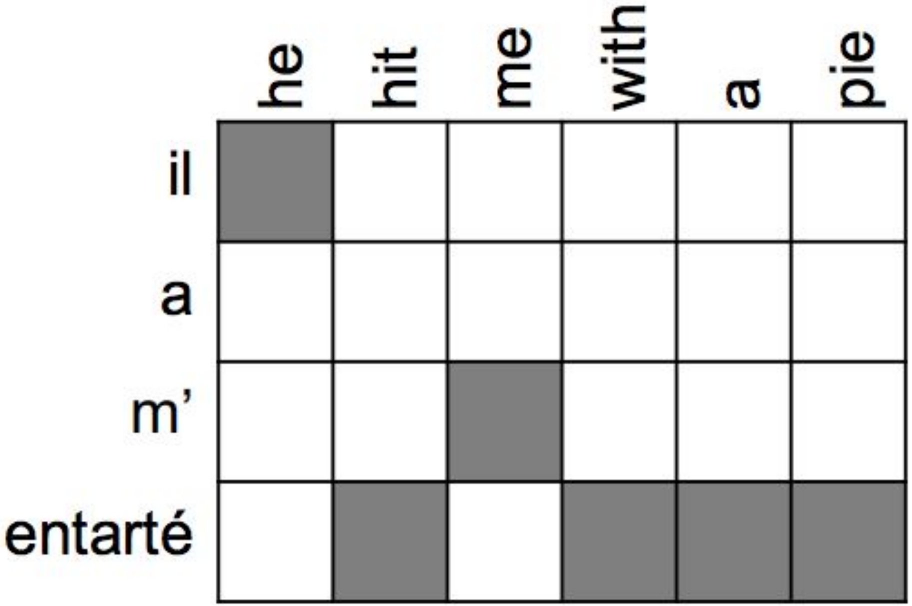
1990-2010: Statistical Machine Translation

Some words are very fertile!





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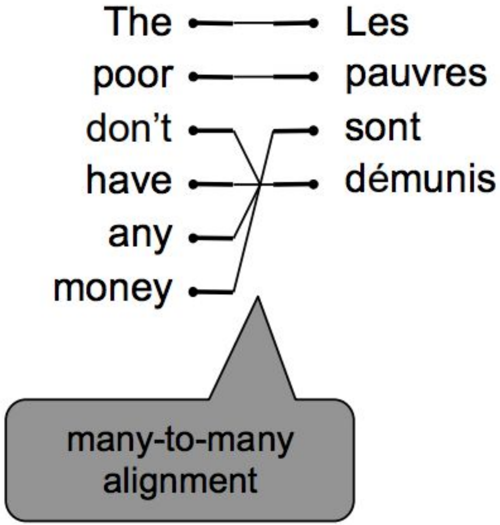
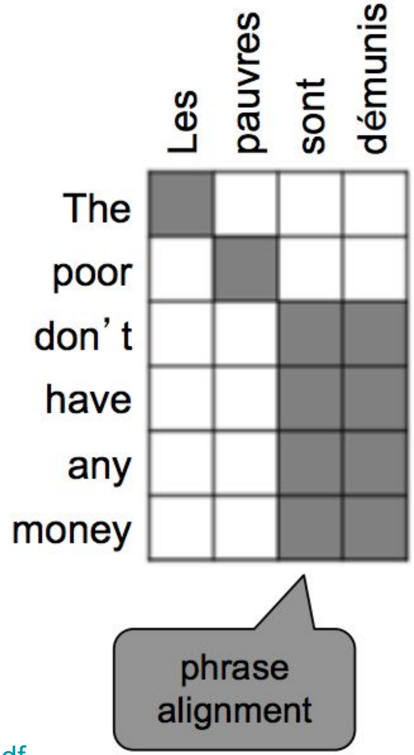
1990-2010: Statistical Machine Translation

Alignment can be: **many-to-many**





Source: http://web.stanford.edu/class/cs224n/slides/cs224n-2019-lecture08-nmt.pdf

1990-2010: Statistical Machine Translation

$$\underbrace{\operatorname{argmax}_y}\underbrace{P(x|y)}_{\text{Translation Model}}\underbrace{P(y)}_{\text{Language Model}}$$

Question:
How to compute this argmax?

Enumerate every possible y and calculate the probability? No!

Use a heuristic search algorithm to search for the best translation, discarding hypotheses that are too low-probability

Source: http://web.stanford.edu/class/cs224n/slides/cs224n-2019-lecture08-nmt.pdf

PBMT

- PBMT: phrase-based machine translation
  - N-Gram phrase table
  - N-Gram language model

Phase tables

Source language
N-Gram
I saw a cat

Target language N-Gram
set // -logP

Я видел кошку // 4.5
Я увидел кошку // 9.8
Я видел кошечку // 8.2

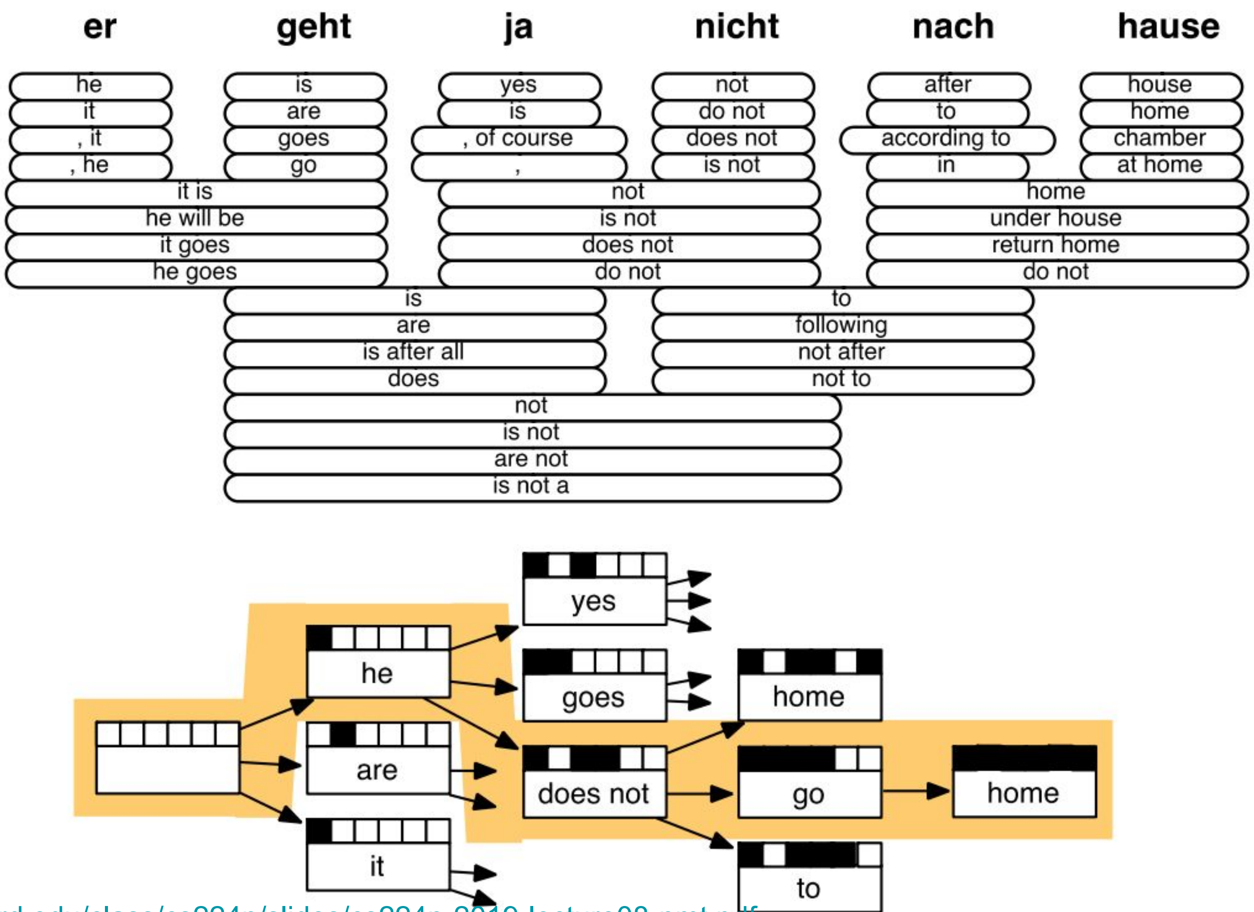
PBMT

- PBMT: phrase-based machine translation
  - N-Gram phrase table
  - N-Gram language model

NGram LM’s

Source language N-Gram // -logP (next | prefix) *I saw a cat* *I saw a dog* *I saw a bicycle*

PBMT



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1990-2010: Statistical Machine Translation

- Systems had many separately-designed subcomponents
- Lots of feature engineering
- Need to design features to capture particular language phenomena
- Require compiling and maintaining extra resources (tables of equivalent phrases)
- Lots of human effort to maintain
- Repeated effort for each language pair!

Neural Machine Translation

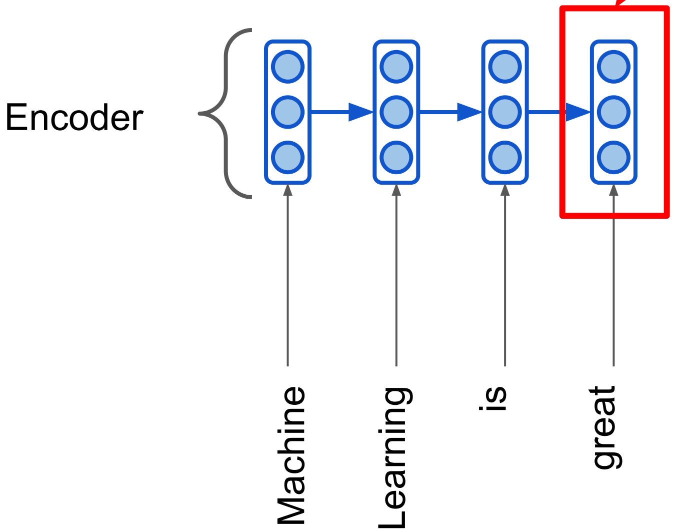
What is Neural Machine Translation?

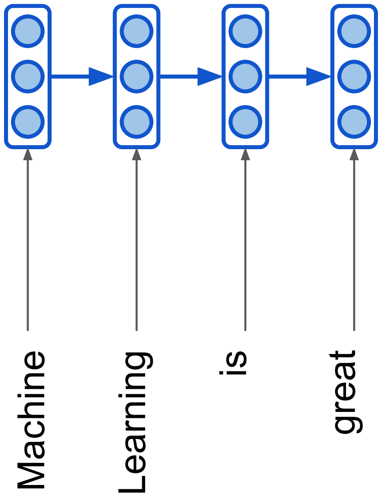
- Neural Machine Translation (NMT) is a way to do Machine Translation with a single neural network

- The neural network architecture is called sequence-to-sequence (aka **seq2seq**), it involves two **RNNs**

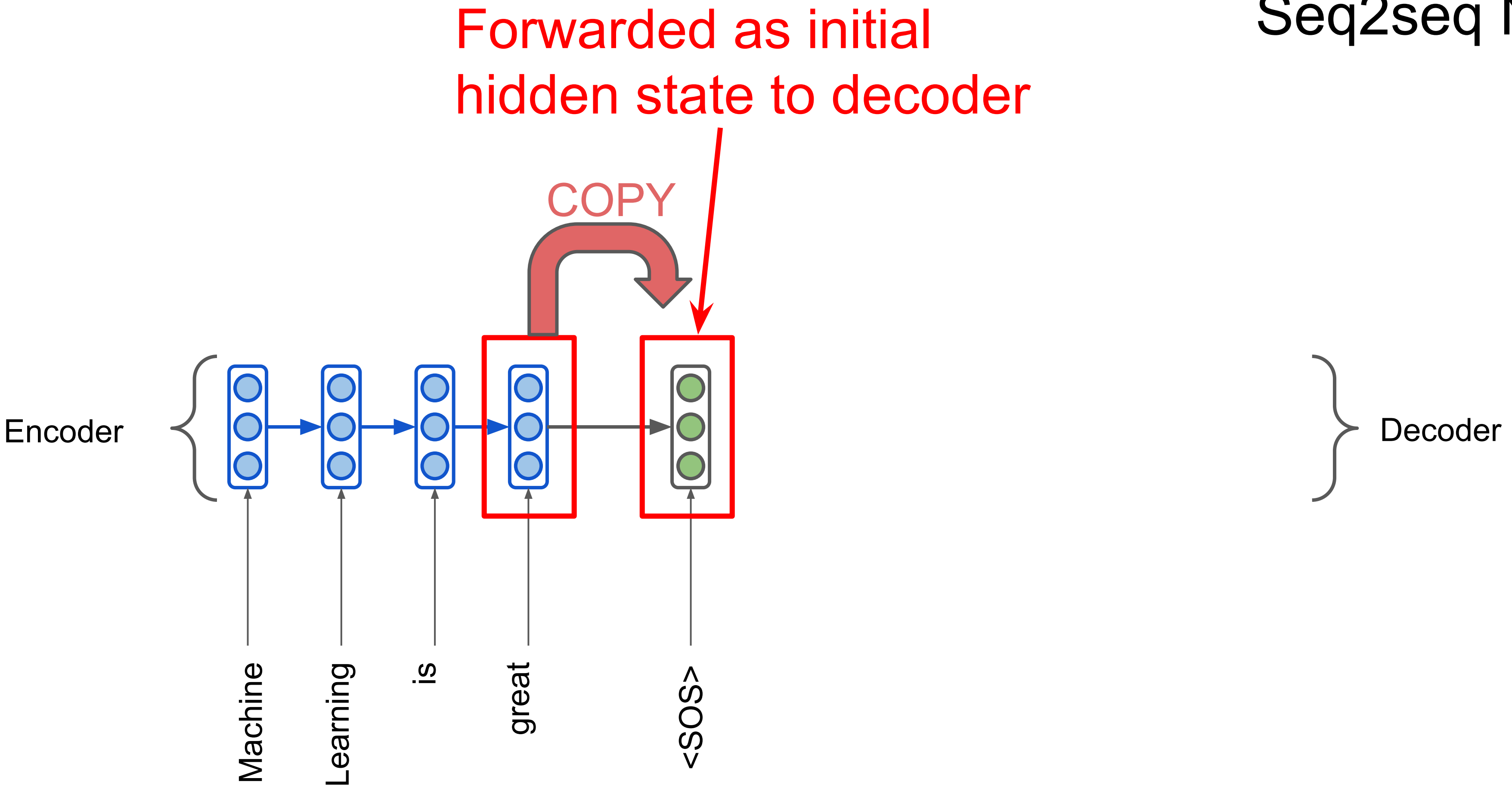
Seq2seq NMT

This state encodes
the whole sentence




Machine
Learning
is
great

Seq2seq NMT


Forwarded as initial
hidden state to decoder
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Encoder
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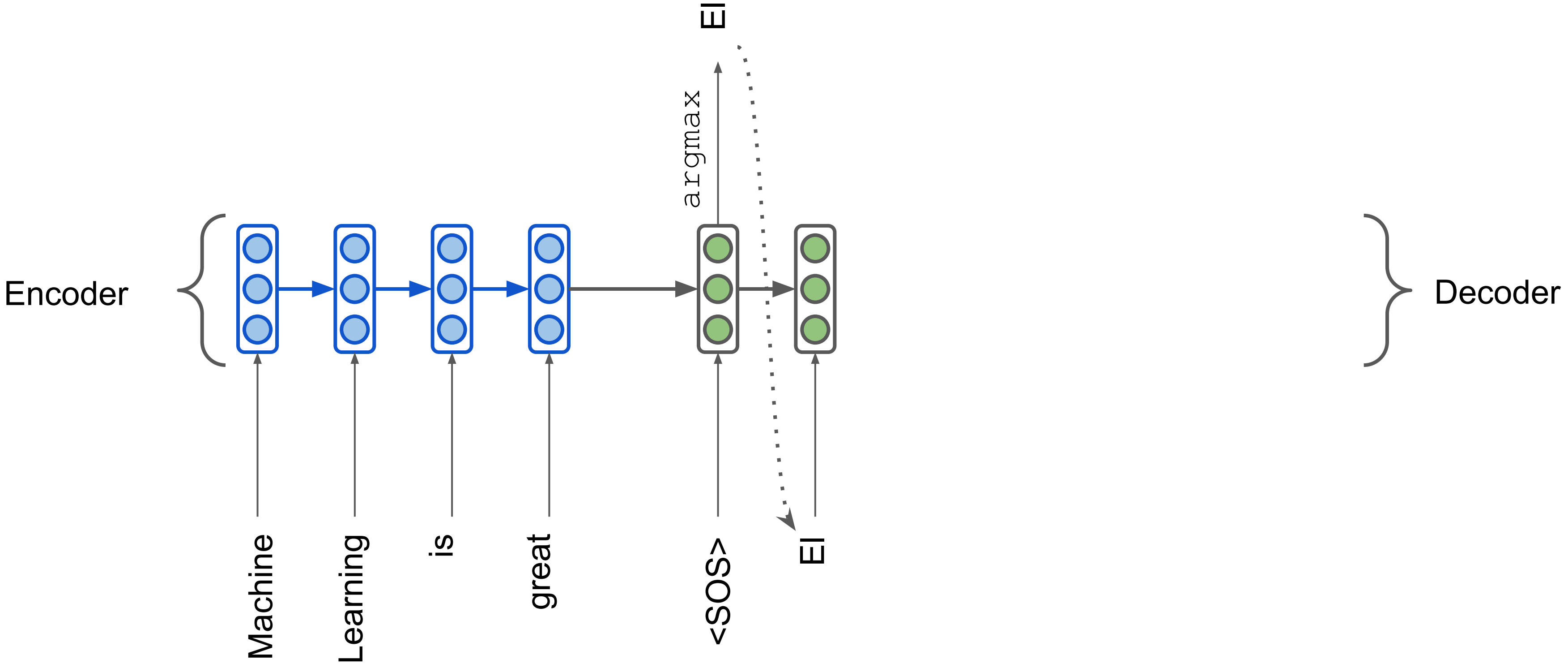
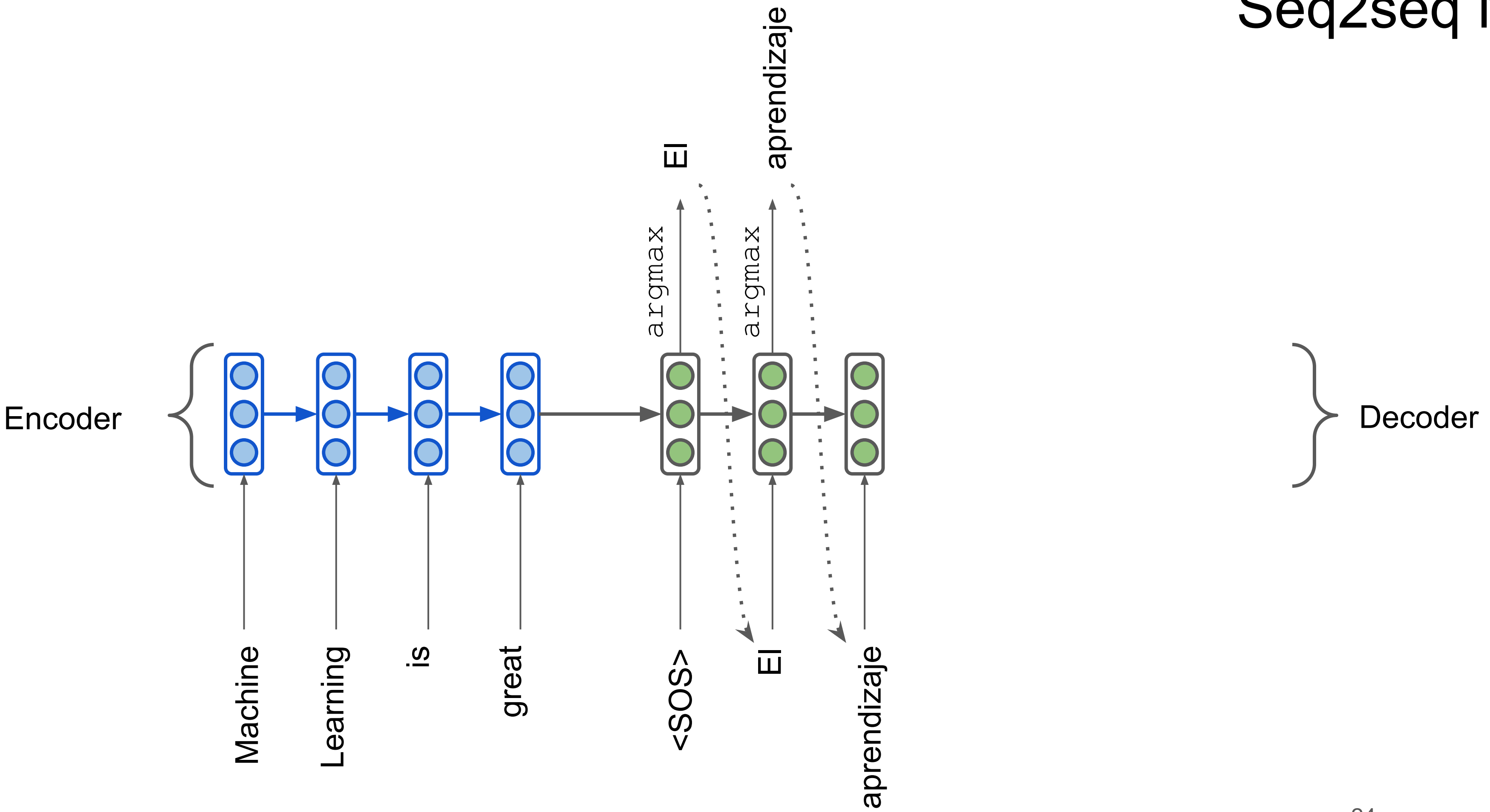
Seq2seq NMT



Seq2seq NMT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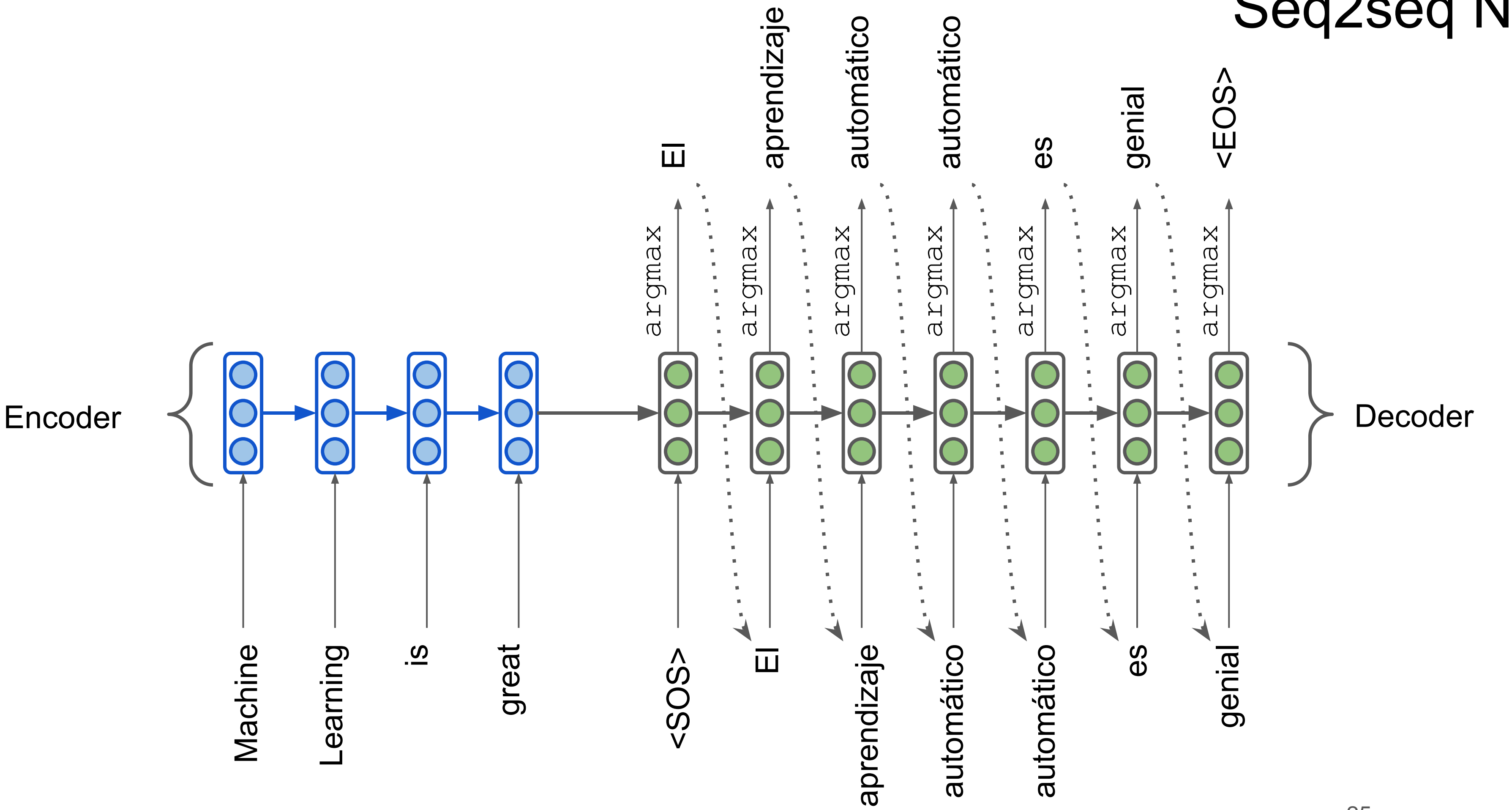
Seq2seq NMT



Encoder
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El
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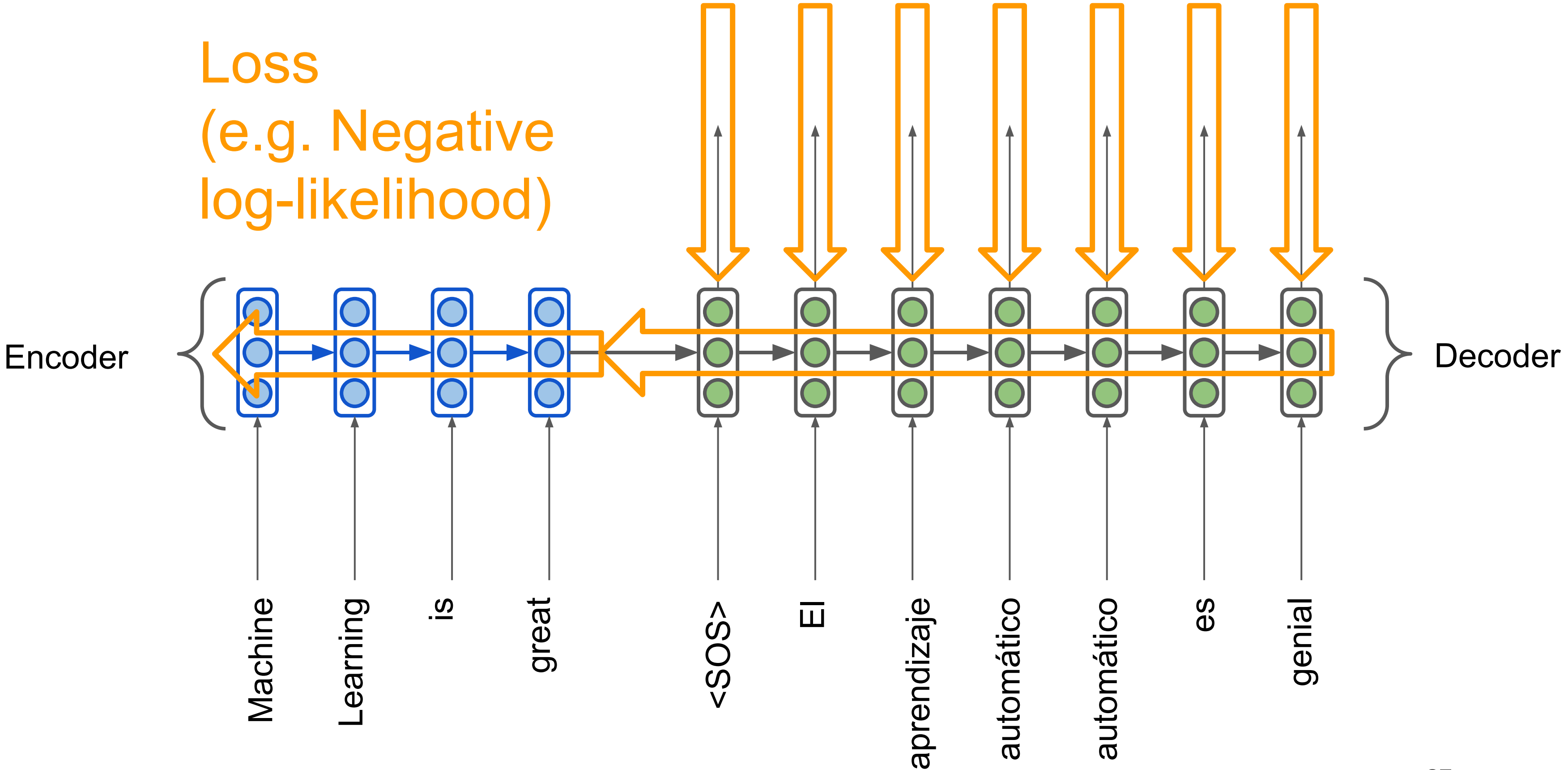
NMT: how does it work?

- NMT directly calculates P(y|x)
  - y – target sentence, x – source sentence

$$P(y|x) = P(y_2|y_1, x)P(y_3|y_1, y_2, x)\dots\underbrace{P(y_T|y_1, y_2, \dots, x)}_{\text{Probability of next word in target language}}$$

- To train it we need a huge parallel corpus.

Seq2seq is trained end-to-end

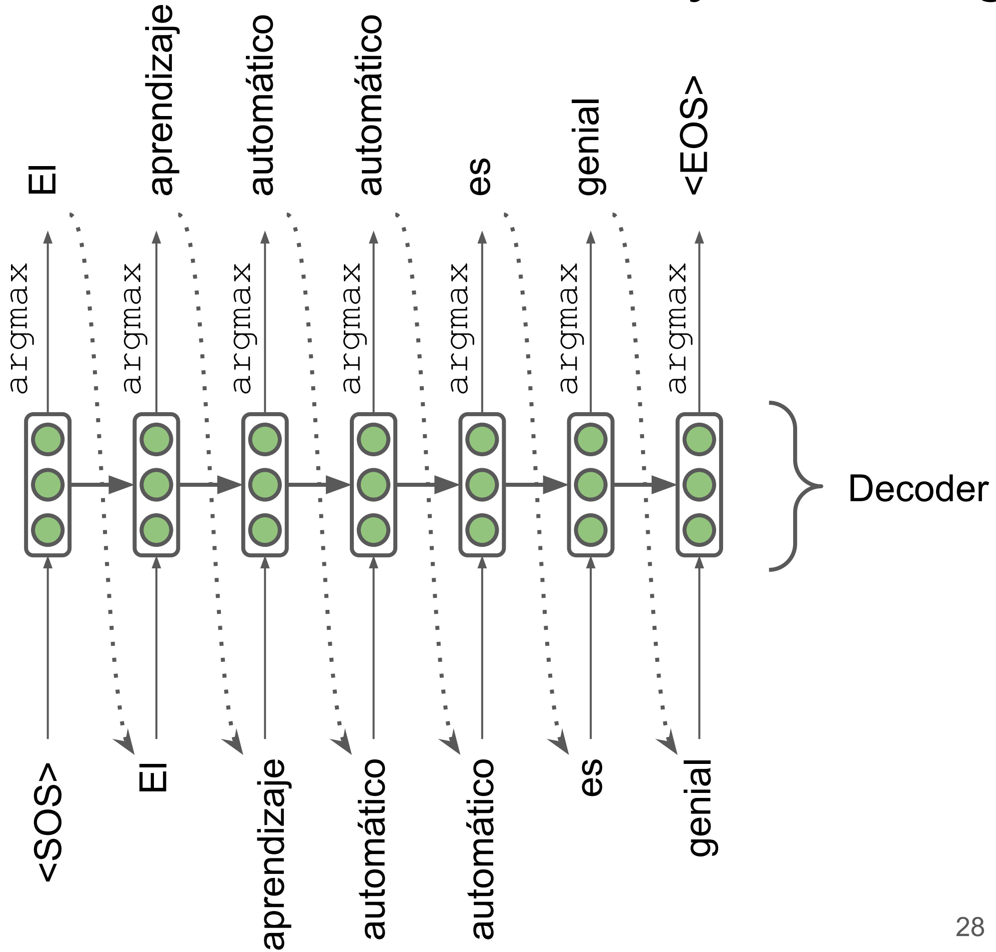


Greedy decoding

- Decoder predicts the most probable token (argmax) on each step
- The approach is **greedy**

Any problems with it?

Any mistake is treated as input on the next step!



Exhaustive search

- We want the translation that maximizes the likelihood:

$$P(y|x) = P(y_1|x) \prod_{t=2}^{T} P(y_t|y_1, \ldots\, y_{t-1}, x)$$

- We cannot compute all the possible sequences (exponential complexity)

Beam search

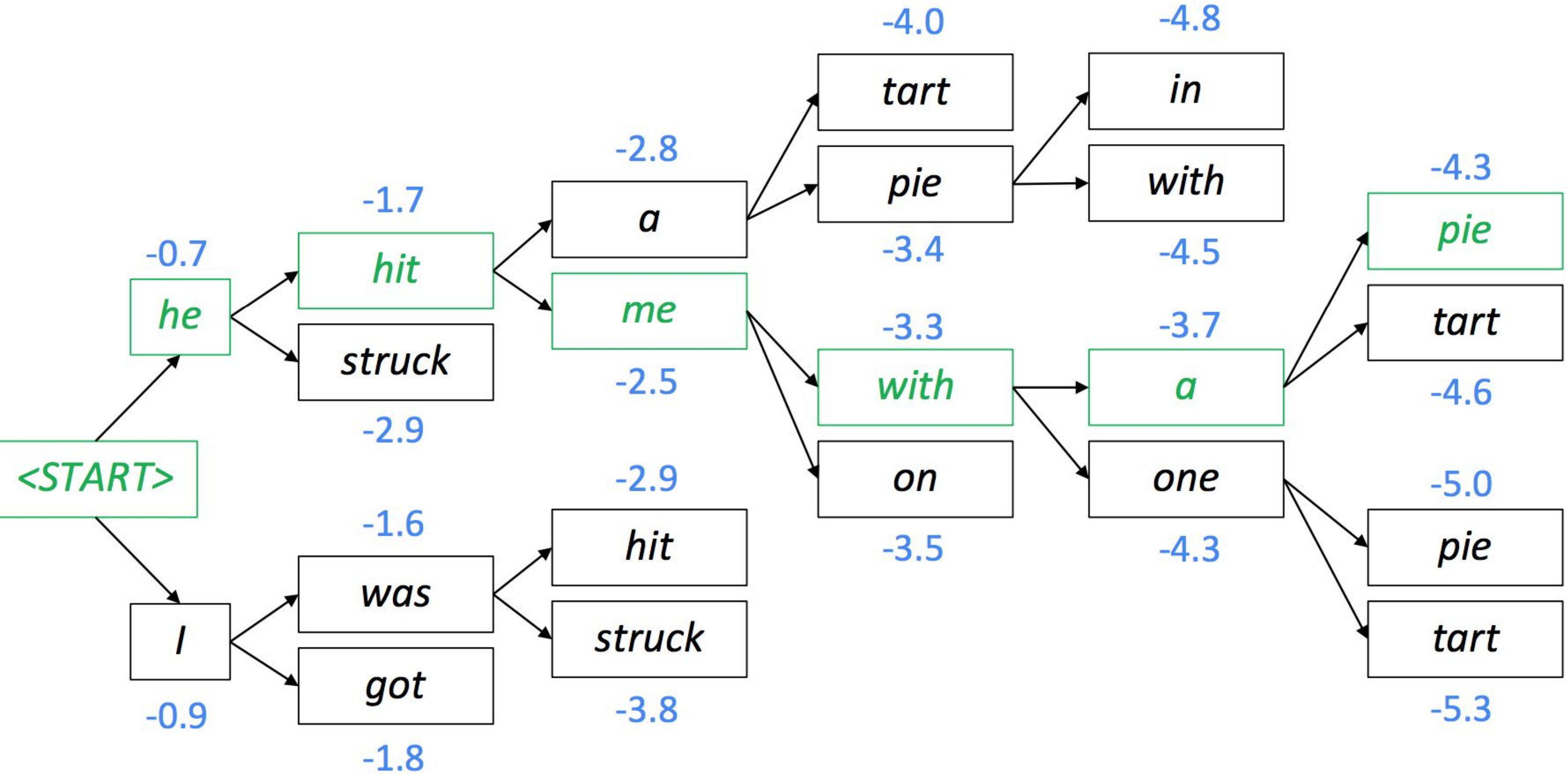
- On each step of decoder, keep track of the k most probable partial translations (which we call hypotheses)
- k is the beam size (in practice around 5 to 10)
- A hypothesis has a score which is its log probability:

$$\text{score}(y_1, \ldots, y_t) = \log P_{\text{LM}}(y_1, \ldots, y_t|x) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i|y_1, \ldots, y_{i-1}, x)$$

- We search for high-scoring hypotheses, tracking top k on each step
- Beam search does not guarantee finding optimal solution

Beam search decoding: example

Beam size = k = 2. Blue numbers = $\text{score}(y_1, \ldots, y_t) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$



Source: http://web.stanford.edu/class/cs224n/slides/cs224n-2019-lecture08-nmt.pdf

Beam search decoding: stopping criterion

- In **greedy decoding**, usually we decode until the model produces <EOS> token
- In **beam search decoding**, different hypotheses may produce <EOS> tokens on different timesteps
  - When a hypothesis produces <EOS>, that hypothesis is complete.
  - Place it aside and continue exploring other hypotheses via beam search.
- Usually we continue beam search until:
  - We reach pre-defined timestep T
  - We have at least n completed hypotheses

Beam search decoding: finishing up

- How to select top one with highest score?
- Each hypothesis on our list has a score:

$$\text{score}(y_1,\ldots,y_t) = \log P_{\text{LM}}(y_1,\ldots,y_t|x) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i|y_1,\ldots,y_{i-1},x)$$

- **Problems?**

  Longer hypotheses have lower scores

- **Fix:** Normalize by length. Use this to select top one instead:

$$\frac{1}{t}\sum_{i=1}^{t} \log P_{\text{LM}}(y_i|y_1,\ldots,y_{i-1},x)$$

NMT: Quality Evaluation

BLEU

BLEU (Bilingual Evaluation Understudy) compares the machine-written translation to human-written translation, and computes a similarity score based on:

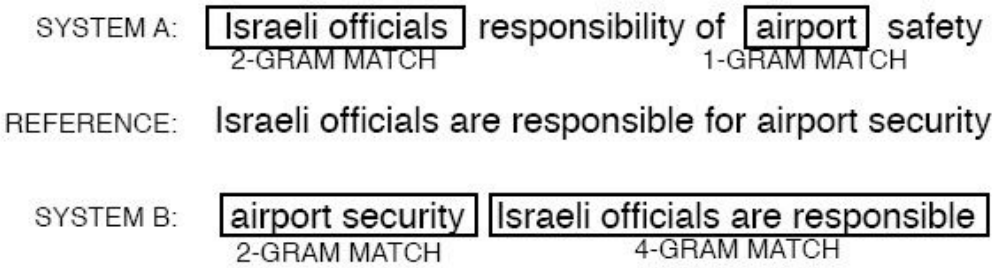
- n-gram precision
- penalty for too-short system translations (brevity penalty)

$$BLEU = \text{brevity penalty} \cdot \left(\prod_{i=1}^{n} \text{precision}_i \right)^{1/n} \cdot 100\%$$

$$\text{brevity penalty} = min\left(1, \frac{\text{output length}}{\text{reference length}}\right)$$

BLEU (Bilingual Evaluation Understudy) compares the machine-written translation to human-written translation, and computes a similarity score based on:

- n-gram precision
- brevity penalty



Metric	System A	System B
precision (1gram)	3/6	6/6
precision (2gram)	1/5	4/5
precision (3gram)	0/4	2/4
precision (4gram)	0/3	1/3
brevity penalty	6/7	6/7
BLEU	0%	52%

$$BLEU = \text{brevity penalty} \cdot \left(\prod_{i=1}^{n} \text{precision}_i \right)^{1/n} \cdot 100\%$$

BLEU is imperfect:

- There are many valid ways to translate a sentence
- So a good translation may get a poor BLEU score just because of low n-gram overlap with the human translation

- **ROUGE** (Recall-Oriented Understudy for Gisting Evaluation)
- **METEOR** (Metric for Evaluation of Translation with Explicit ORdering)
  - Uses synonyms from WordNet

Quality metrics for MT

- **Human evaluation**

Side-by-side (SbS HE)

Q: Pick the best translaiton

Src: Beam search decoding
System1: декодирование с поиском лучадекодирование поиска луча
System2: декодирование поиска луча

Direct Assessment (DA)

Q: Rate this translation of 5-point scale
Src: Beam search decoding
Translation: декодирование поиска луча

Quality metrics for MT

Human eval is expensive

Solution: ML models trained to approximate HE

1. BLEURT (Google) - BERT finetuned on DA ratings
2. XCOMET (Unbabel) - XLM finetuned on DA + MQM ratings
3. LLM-based estimators - prompt LLM to estimate MT quality

NMT: advantages

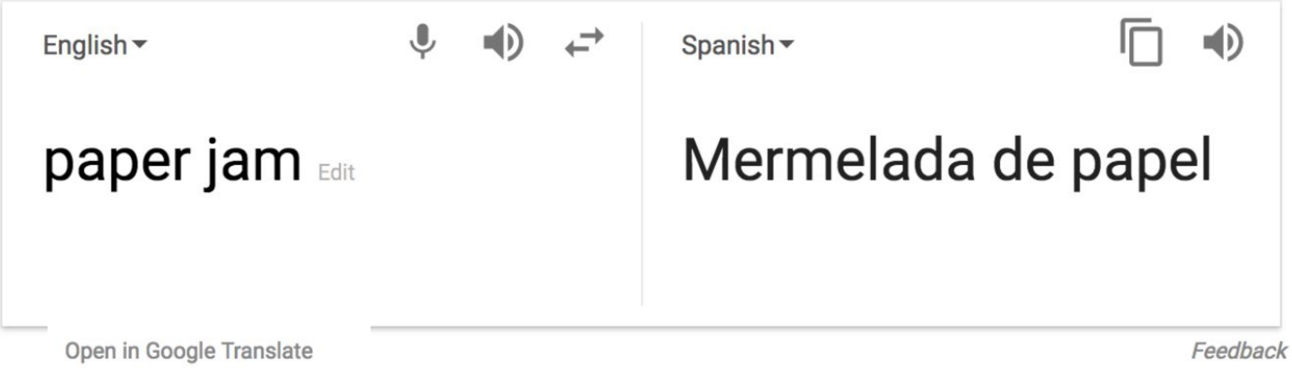
- Better performance
  - More fluent
  - Better use of context
  - Better use of phrase similarities
- A single neural network to be optimized end-to-end
  - No subcomponents to be individually optimized
- Requires much less human engineering effort
  - No feature engineering
  - Same method for all language pairs

NMT: disadvantages

- NMT is less interpretable
  - Hard to debug

- NMT is difficult to control
  - For example, can’t easily specify rules or guidelines for translation
  - Safety concerns!

NMT: disadvantages



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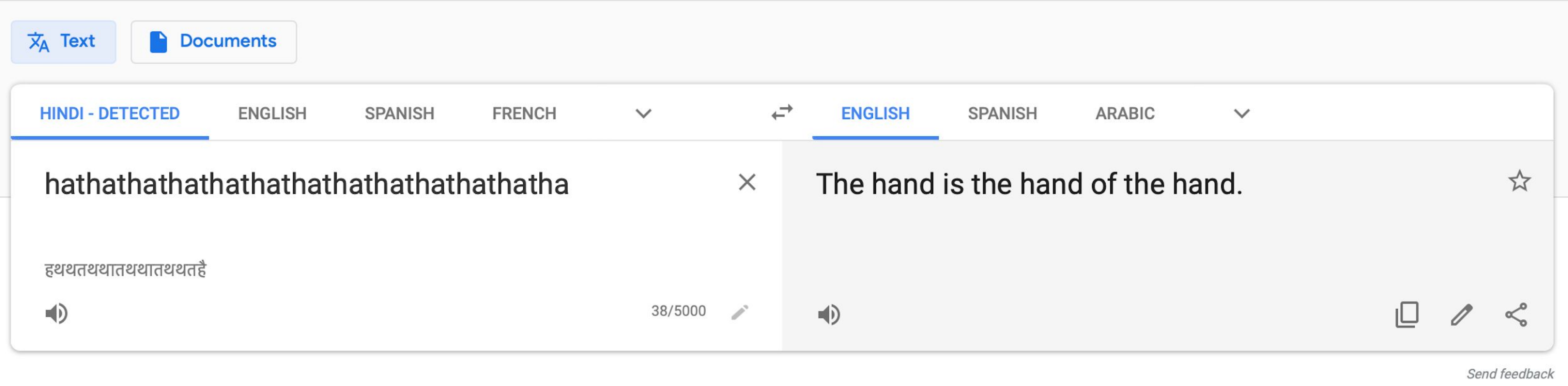
NMT: disadvantages

NMT: disadvantages



Is Machine Translation solved?

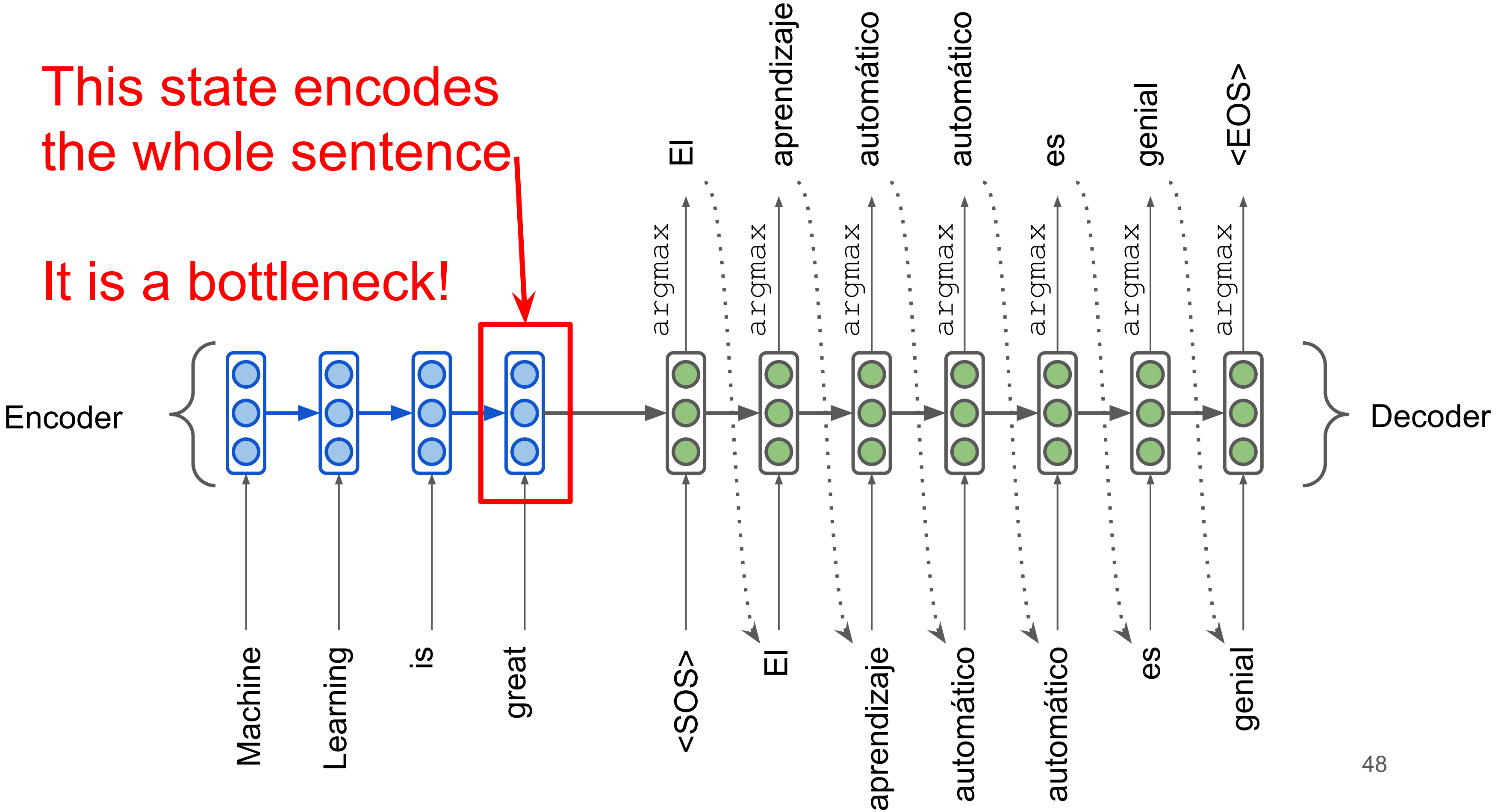
- Challenges yet to be resolved
  - Use of large context in translation
  - Low-resource language pairs (no big parallel corpora)
  - Slang and narrow domains
  - Robustness to errors and typos

Attention

Seq2seq NMT

This state encodes the whole sentence

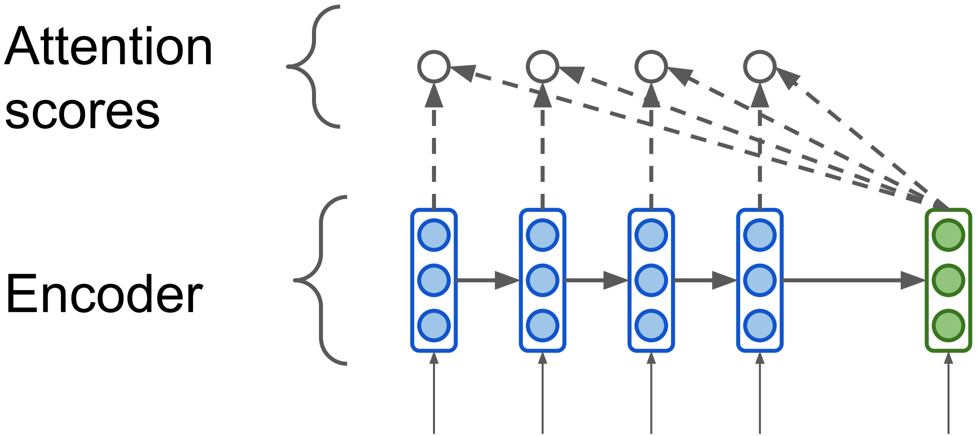
It is a bottleneck!



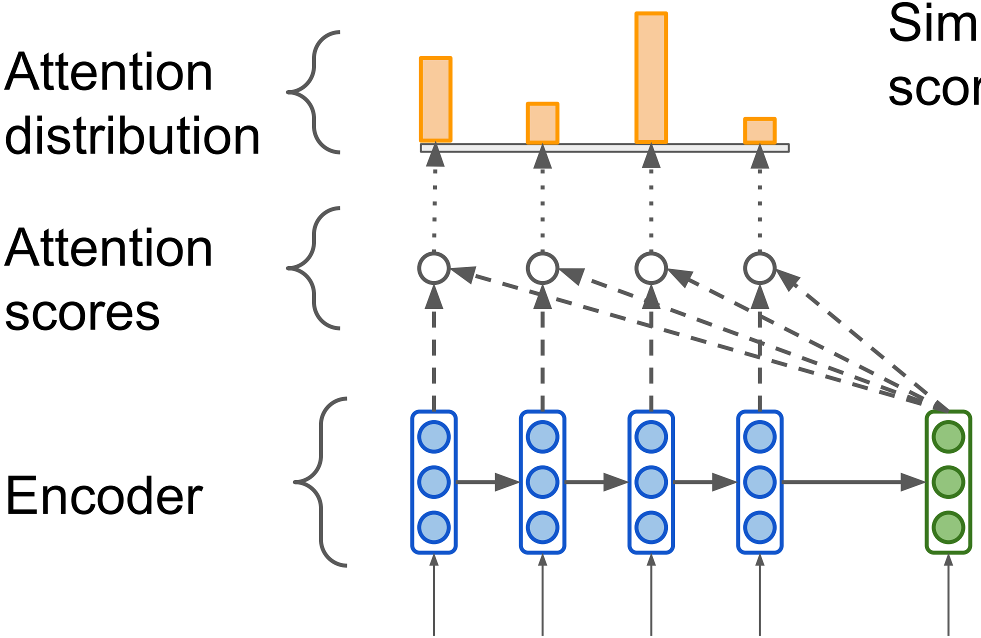
Main idea:

on each step of the **decoder**, use **direct connection to the encoder** to focus on a particular part of the source sequence

Seq2seq with attention

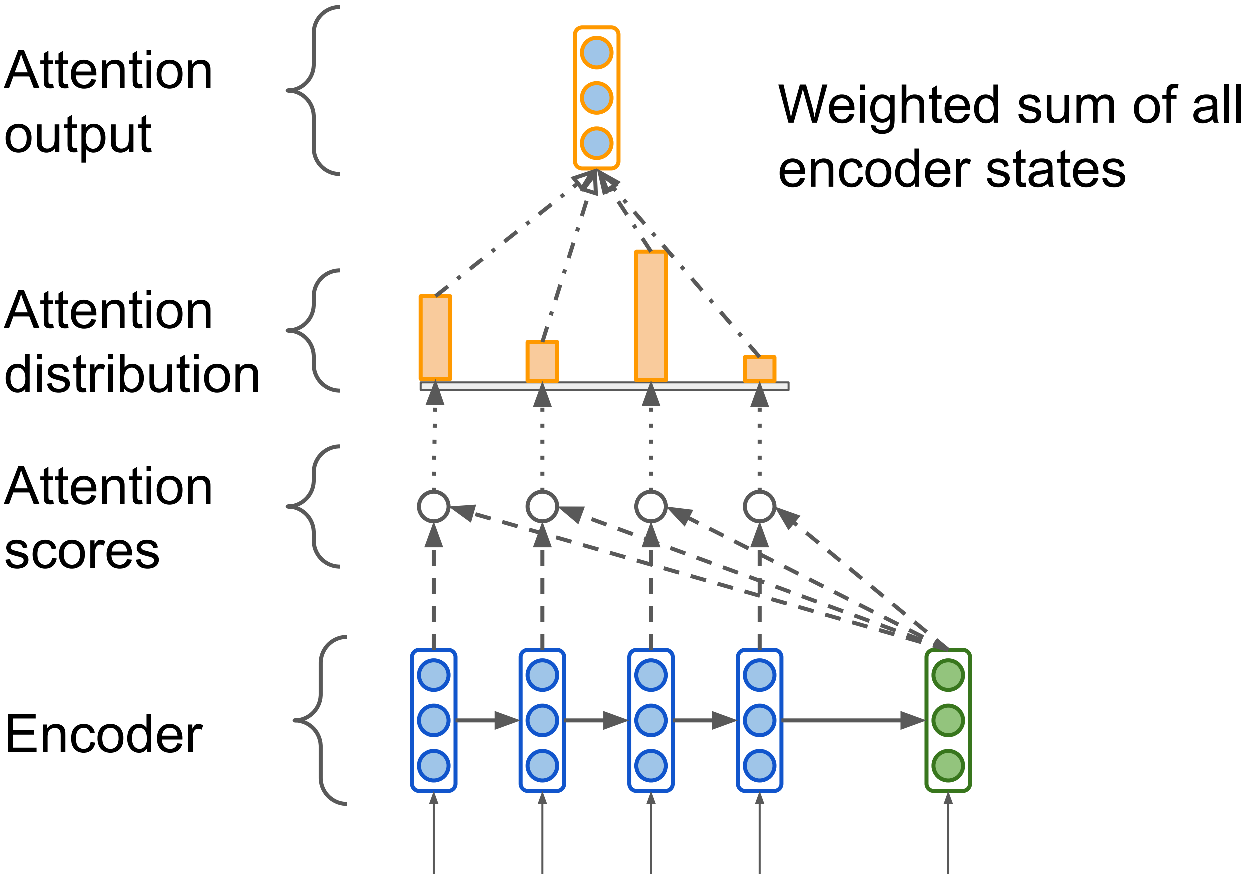


Seq2seq with attention

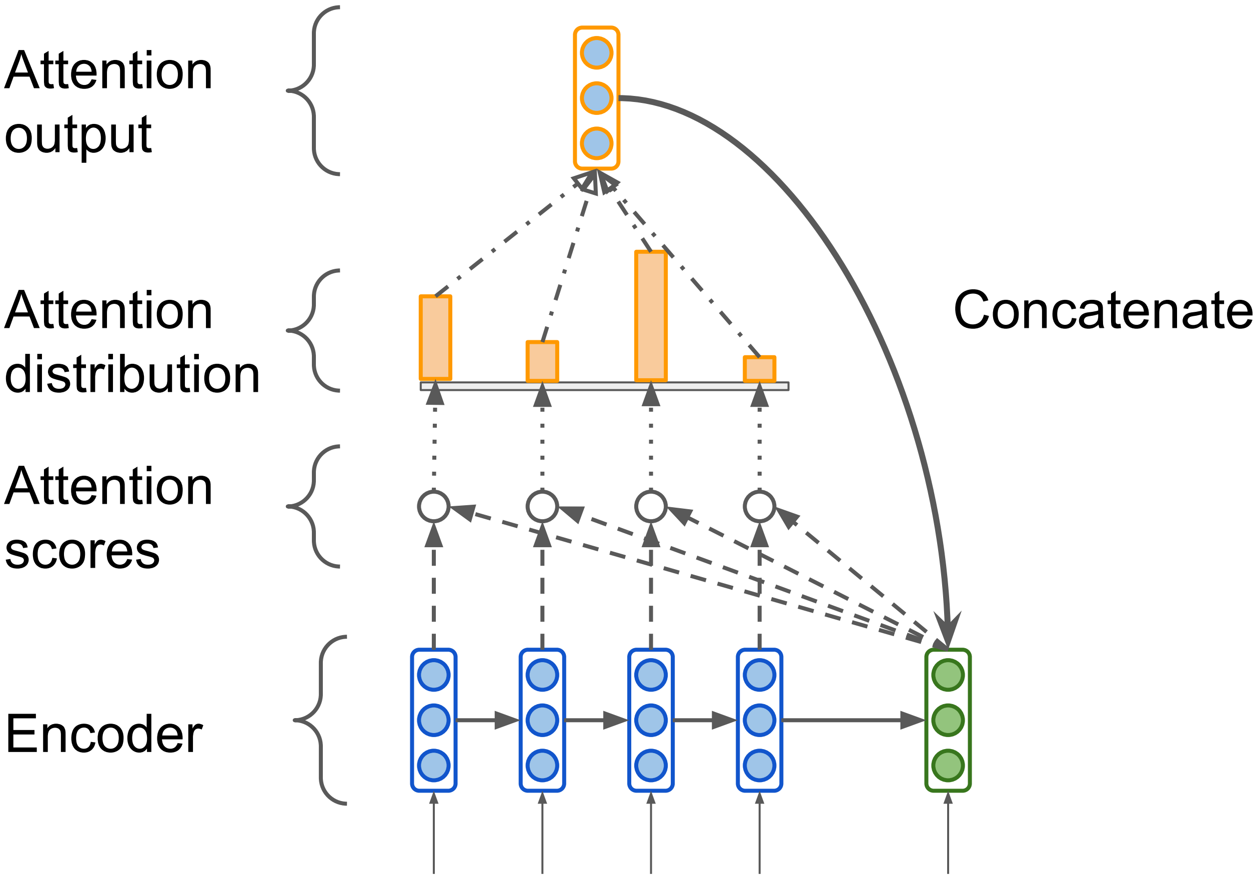


Simply apply softmax to scores

Seq2seq with attention



Seq2seq with attention



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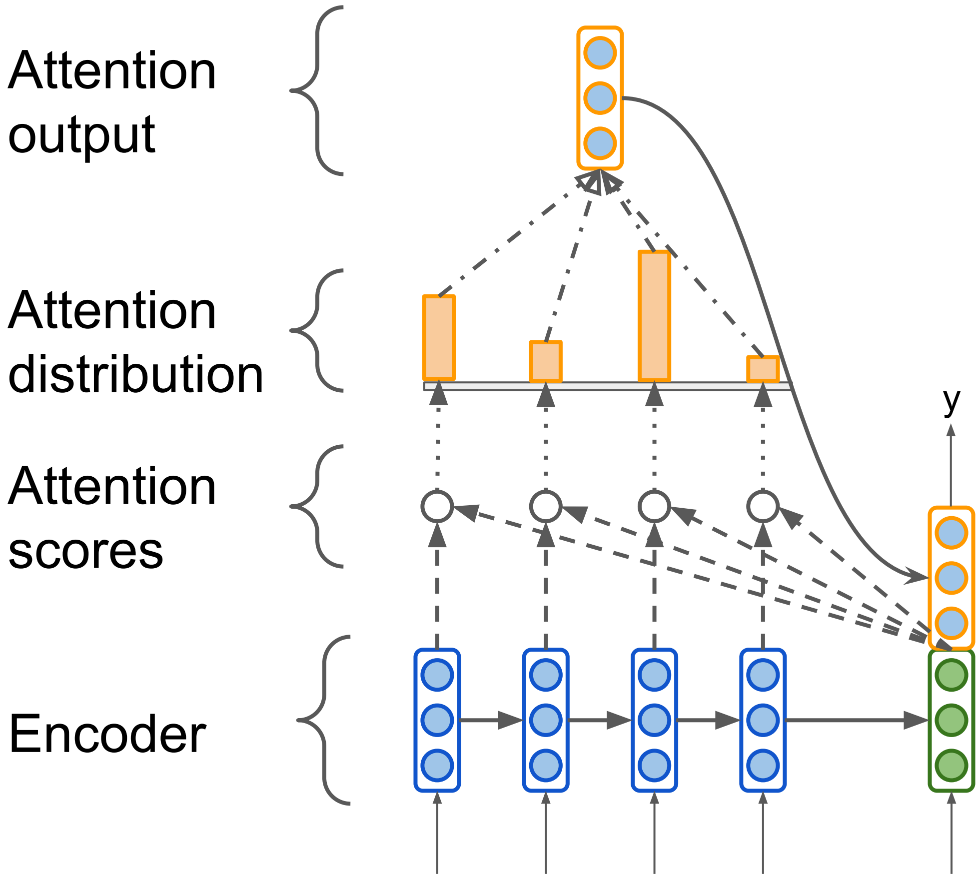

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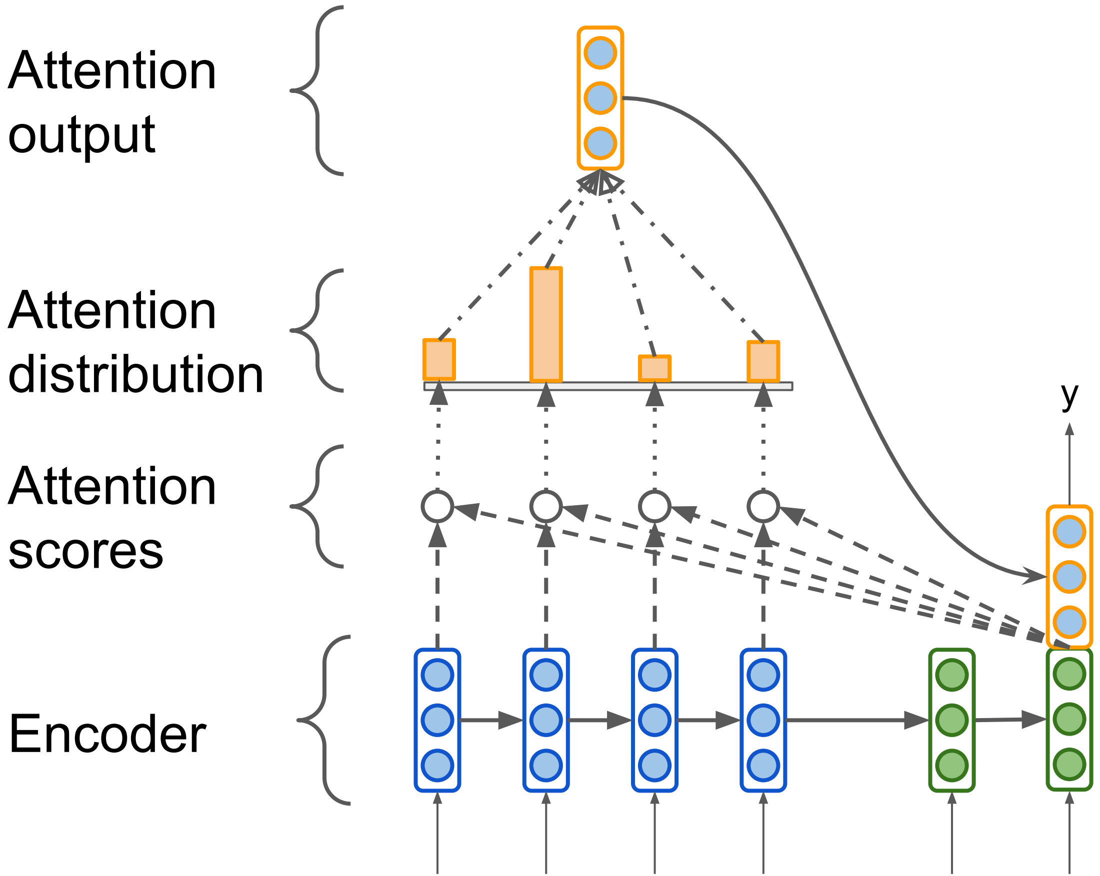
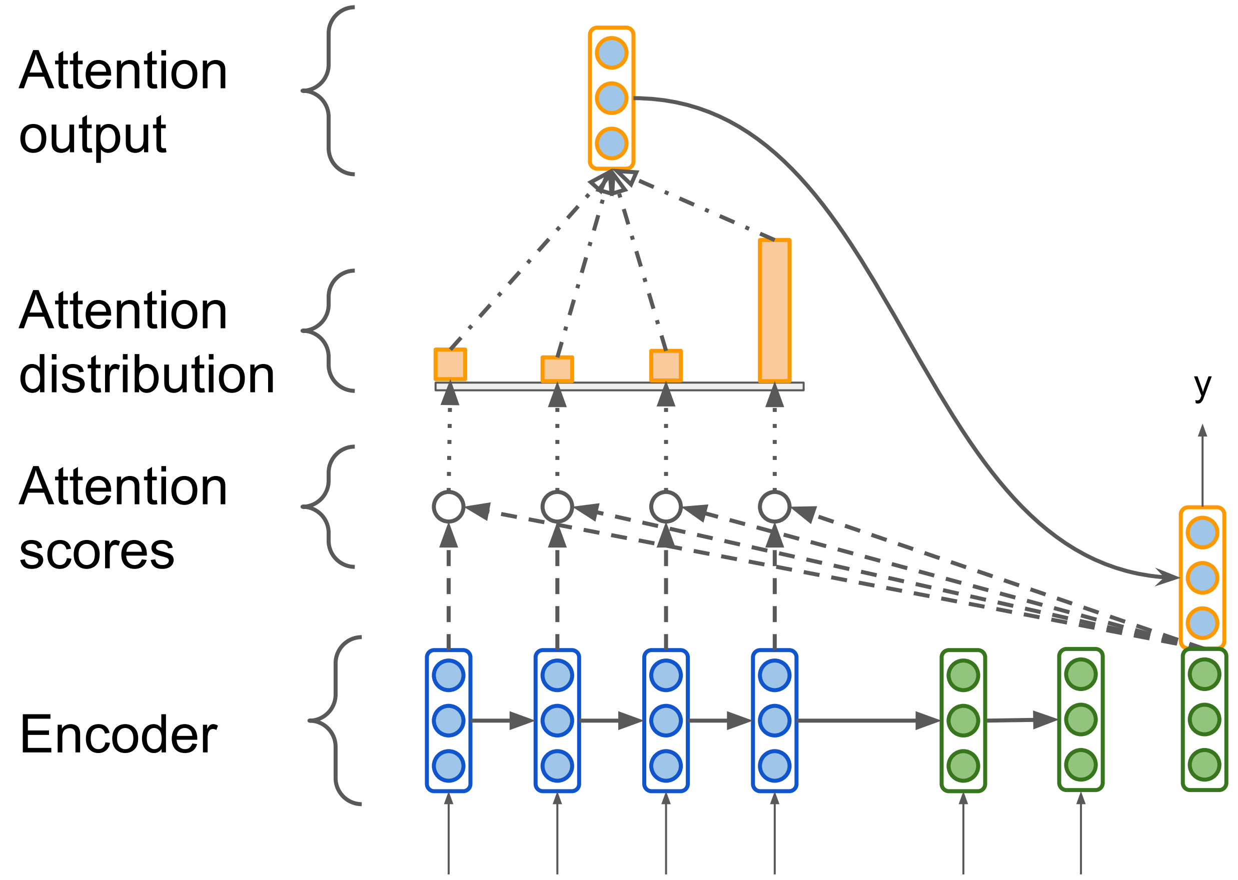


Seq2seq with attention



Attention in equations

Denote encoder hidden states $\mathbf{h}_1, \ldots, \mathbf{h}_N \in \mathbb{R}^k$

and decoder hidden state at time step t $\mathbf{s}_t \in \mathbb{R}^k$

The attention scores $\mathbf{e}^t$ can be computed as dot product

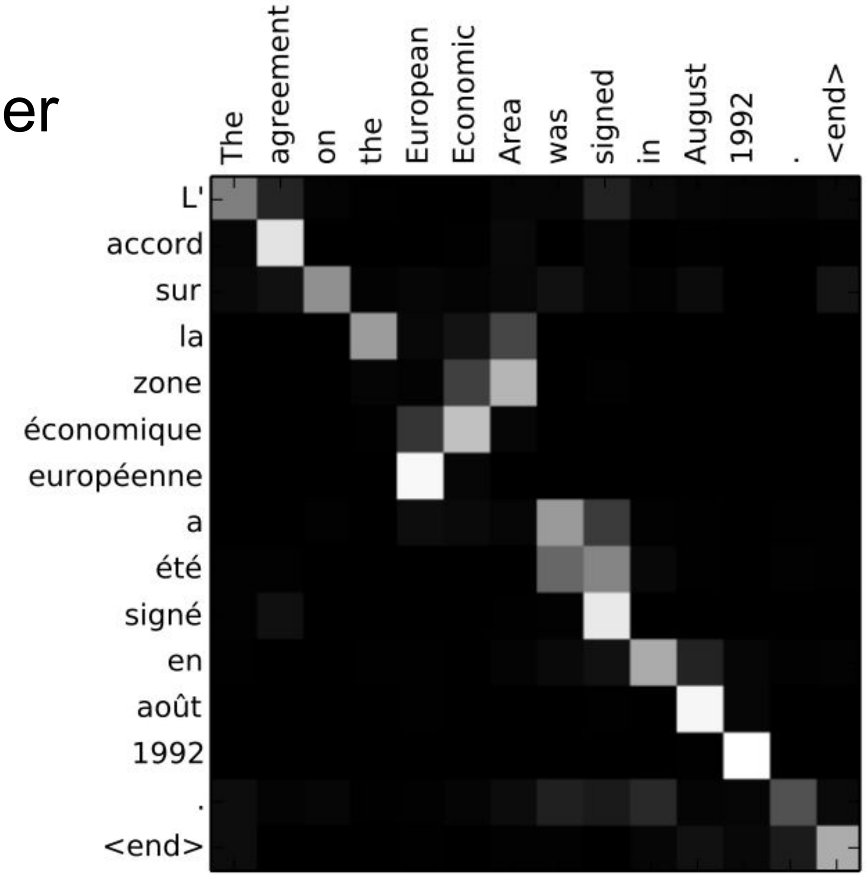
$$\mathbf{e}^t = [\mathbf{s}^T \mathbf{h}_1, \ldots, \mathbf{s}^T \mathbf{h}_N]$$

Then the attention vector is a linear combination of encoder states

$$\mathbf{a}_t = \sum_{i=1}^{N} \boldsymbol{\alpha}_i^t \mathbf{h}_i \in \mathbb{R}^k$$, where $$\boldsymbol{\alpha}_t = \mathrm{softmax}(\mathbf{e}_t)$$

Attention provides interpretability

- We may see what the decoder was focusing on
- We get word alignment for free!

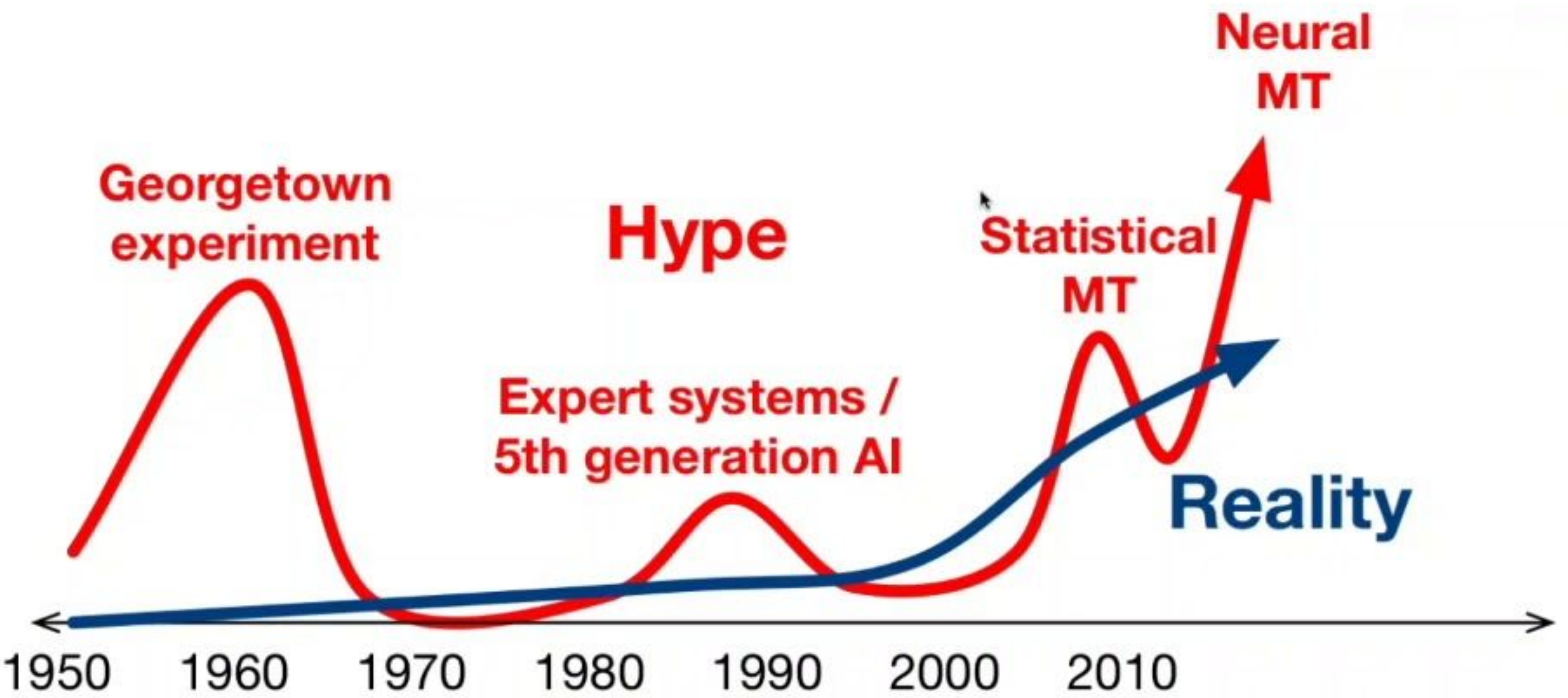


Bahdanau et al. "Neural Machine Translation by Jointly Learning to Align and Translate", 2014

Attention variants

- Basic dot-product (the one discussed before): $\boldsymbol{e}_i = \boldsymbol{s}^T \boldsymbol{h}_i \in \mathbb{R}$
- Multiplicative attention: $\boldsymbol{e}_i = \boldsymbol{s}^T \boldsymbol{W} \boldsymbol{h}_i \in \mathbb{R}$
  - $\boldsymbol{W} \in \mathbb{R}^{d_2 \times d_1}$ - weight matrix
- Additive attention: $\boldsymbol{e}_i = \boldsymbol{v}^T \tanh(\boldsymbol{W}_1 \boldsymbol{h}_i + \boldsymbol{W}_2 \boldsymbol{s}) \in \mathbb{R}$
  - $\boldsymbol{W}_1 \in \mathbb{R}^{d_3 \times d_1}, \boldsymbol{W}_2 \in \mathbb{R}^{d_3 \times d_2}$ - weight matrices
  - $\boldsymbol{v} \in \mathbb{R}^{d_3}$ - weight vector

Summary



Neural
MT
Georgetown
experiment
Hype
Statistical
MT
Expert systems /
5th generation AI
Reality
1950
1960
1970
1980
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2000
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