Attention in Machine Translation

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What is Machine Translation?

- Machine Translation (MT): translate a sentence in one language to a sentence in another language.
  - Special case of sequence transduction

***Source language*:** ru

x: Мороз и солнце - день чудесный!

***Target language*:** en

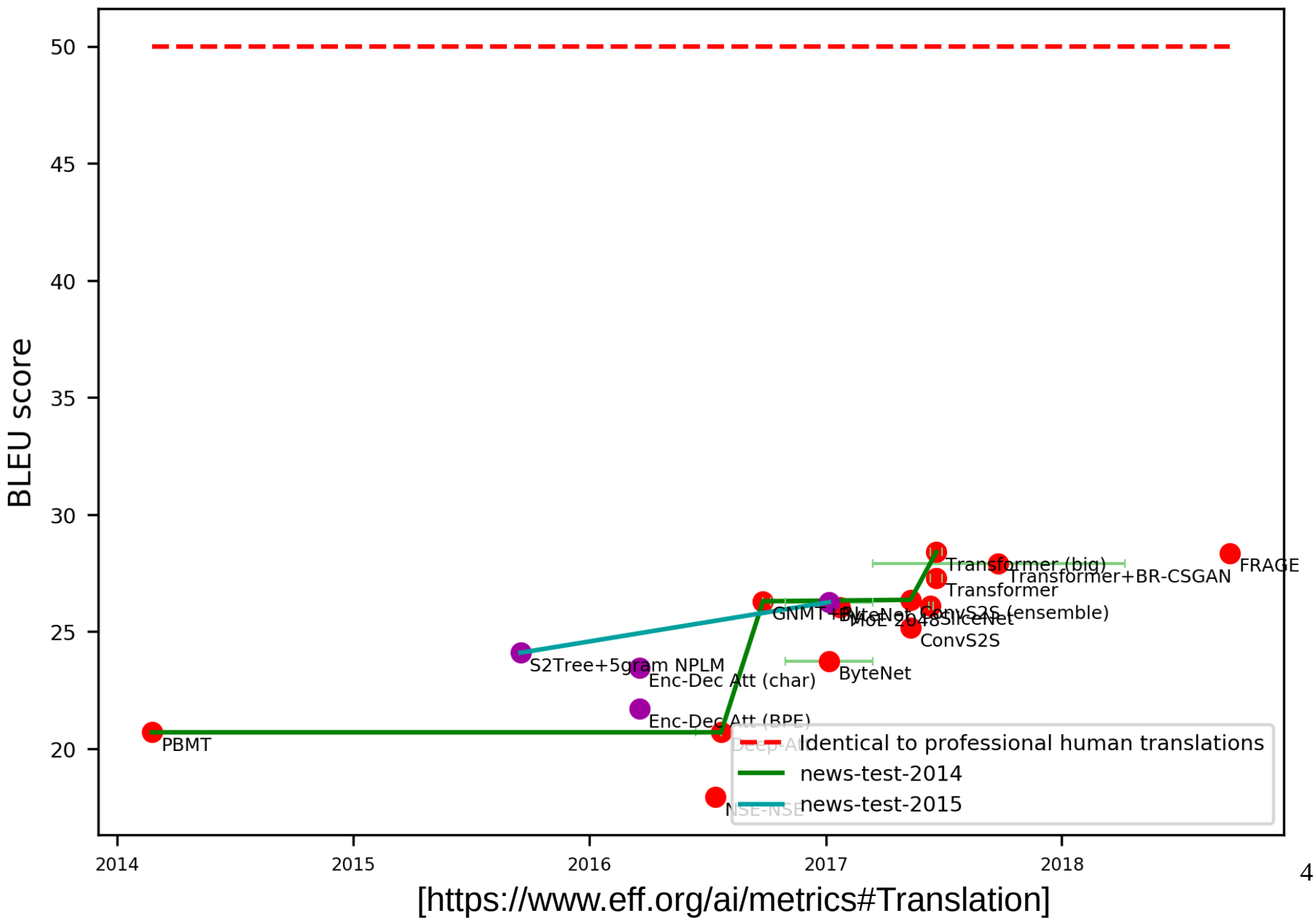
y: Frost and the sun - a wonderful day!

Approaches

- 1950s: Russian→English MT (Cold War)
  - Rule-based systems using bilingual dictionaries
- 1990s-2010s: **Statistical** MT (SMT)
  - Mainly **Phrase-Based** MT (PBMT)
  - Learns from (large) **sentence-aligned** bilingual corpora
    - Millions of sentence pairs
  - Consists of separate very complex components, learnt separately
  - developed by large groups for decades, doesn't generalize to new language pairs
- Since 2014: **Neural** MT (NMT)
  - Single NN learnt **end-to-end**
  - Learns from (large) **sentence-aligned** bilingual corpora
  - A few (good) student / month to implement
  - better quality of translation than SMT systems developed for decades

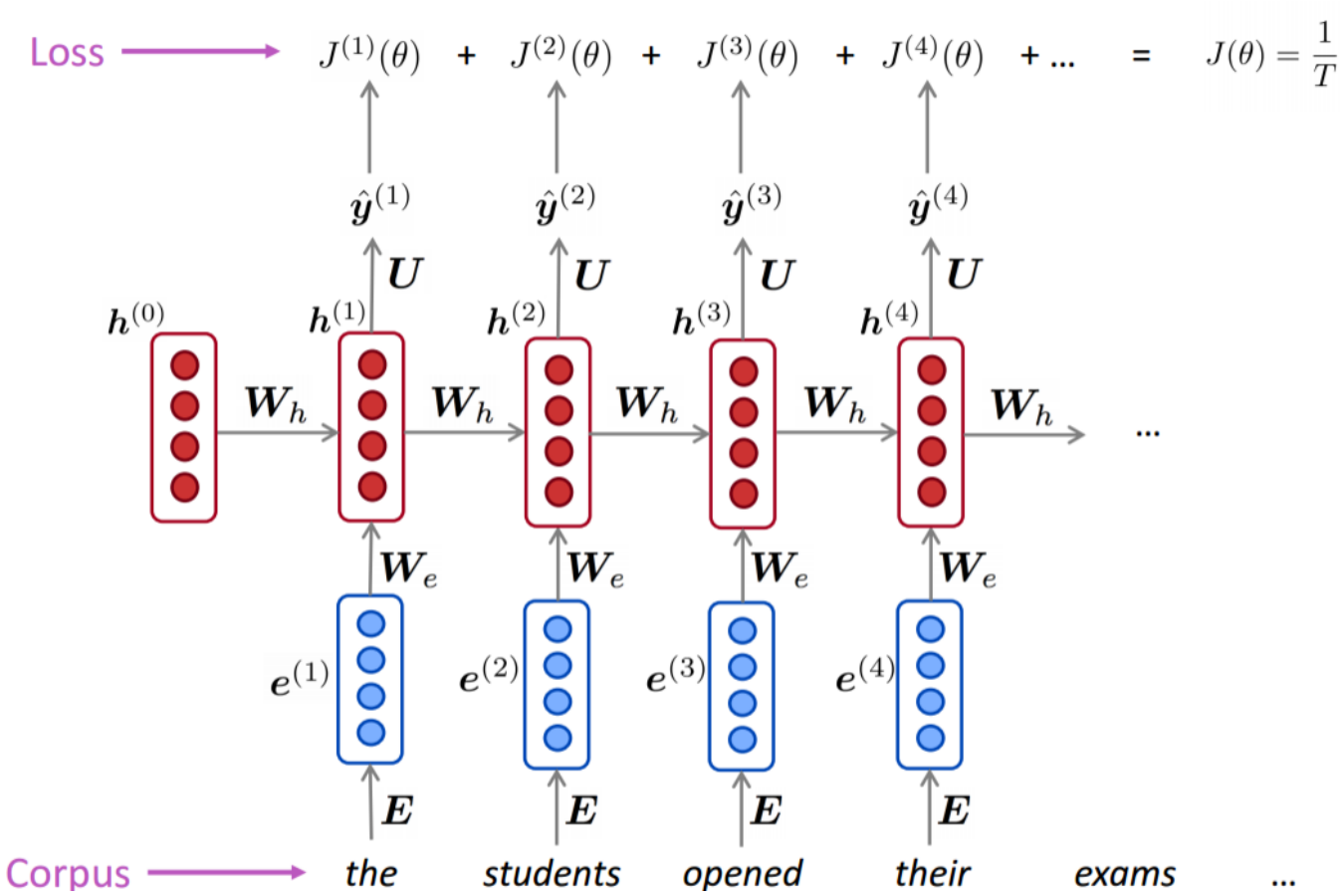
Google Translate: NMT, Yandex Translate: NMT+PBMT

MT vs. Human translation



[https://www.eff.org/ai/metrics#Translation]

RNN LM reminder



output distribution

$$\hat{y}^{(t)} = \text{softmax}\left(Uh^{(t)} + b_2\right) \in \mathbb{R}^{|V|}$$

hidden states

$$h^{(t)} = \sigma\left(W_h h^{(t-1)} + W_e e^{(t)} + b_1\right)$$

$h^{(0)}$ is the initial hidden state

word embeddings

$$e^{(t)} = Ex^{(t)}$$

words / one-hot vectors

$$x^{(t)} \in \mathbb{R}^{|V|}$$

Abigail See. Cs224n, lecture 8

RNN/LSTM LM reminder

$$P(y) = P(y_1)P(y_2|y_1)P(y_3|y_1, y_2)...P(y_T|y_1, ..., y_{T-1})$$

- estimate P(y)
- or generate new y:

  y_1 = random word / <START>

  for i from 2 to T:

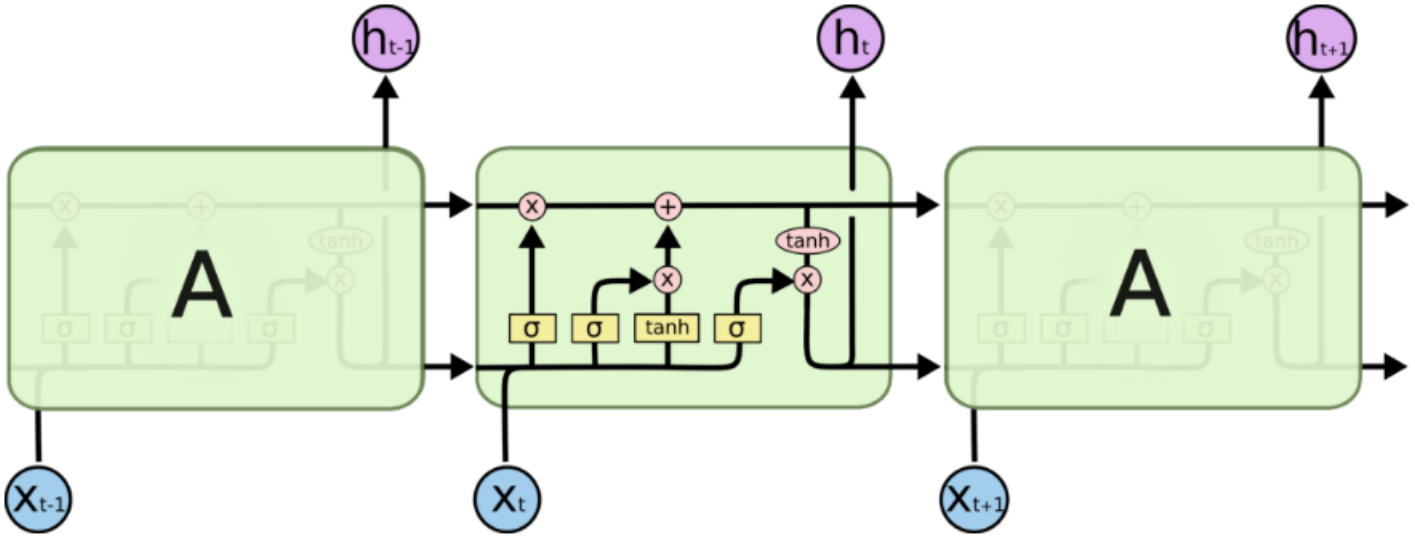
    y_i = argmax_y P(y|$y_{1 ... i-1}$) / sample from P(y|$y_{1 ... i-1}$)

LSTM Reminder

- Solves (partially) vanishing gradient problem of vanilla RNNs

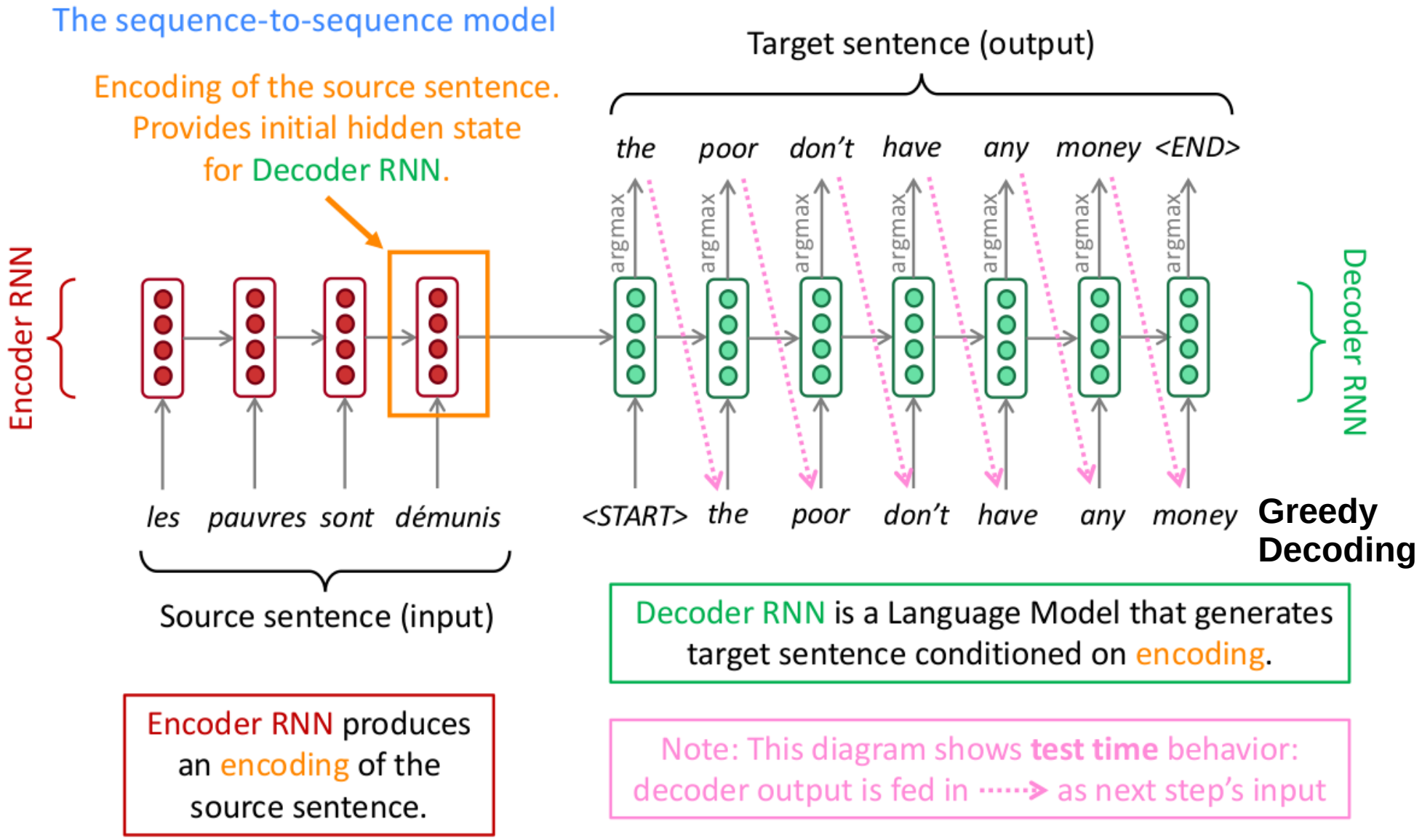
  => better models long range dependencies

$$i_t = \sigma\left(W^{(i)}x_t + U^{(i)}h_{t-1}\right)$$
$$f_t = \sigma\left(W^{(f)}x_t + U^{(f)}h_{t-1}\right)$$
$$o_t = \sigma\left(W^{(o)}x_t + U^{(o)}h_{t-1}\right)$$
$$\tilde{c}_t = \tanh\left(W^{(c)}x_t + U^{(c)}h_{t-1}\right)$$
$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t$$
$$h_t = o_t \circ \tanh(c_t)$$



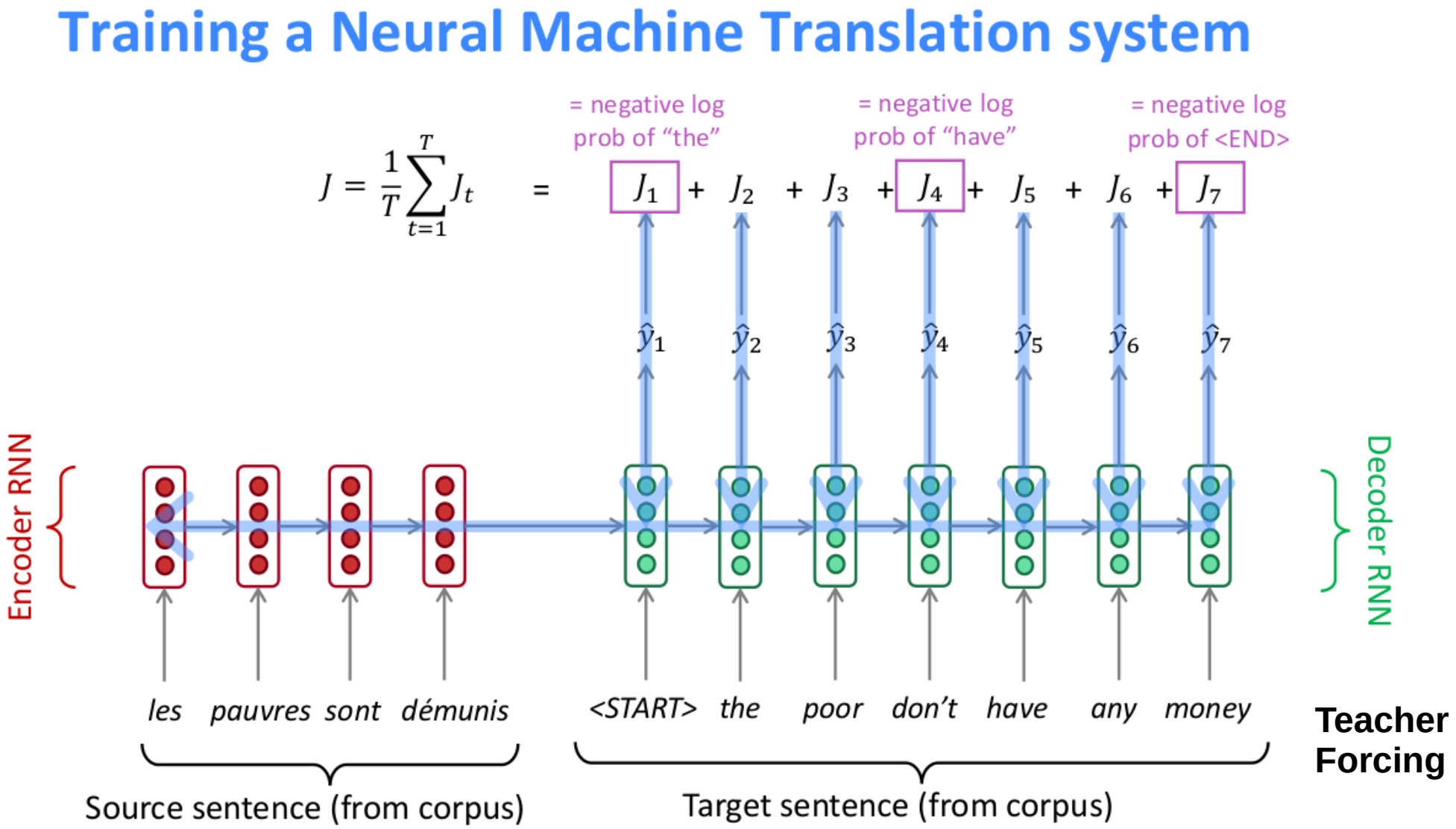
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

NMT: seq2seq



Socher, Manning. Cs224n, 2017

NMT: seq2seq loss



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Conditional LM

- Decoder - conditional language model:

$$P(y|x) = P(y_1|x)P(y_2|y_1, x)...P(y_T|y_1, ..., y_{T-1}, x)$$

  - Machine translation
  - Image captioning
  - Speech recognition

- The whole system (encoder + decoder) is trained "**end-to-end**"
  - Calculate gradients of loss w.r.t. parameters of both encoder and decoder & do SGD

Sutskever 2014. Tricks

Sutskever, Vinyals, Le. Sequence to sequence learning with neural networks, 2014

- **reversed input**: shorter path btw. y_1 and x_1
- **stacked LSTMs: 4 layers**, 1000 cells per layer
- different LSTMs for encoder and decoder (different weights)
- **beam-search decoder**
- 1000 dim embeddings

Sutskever 2014. Training

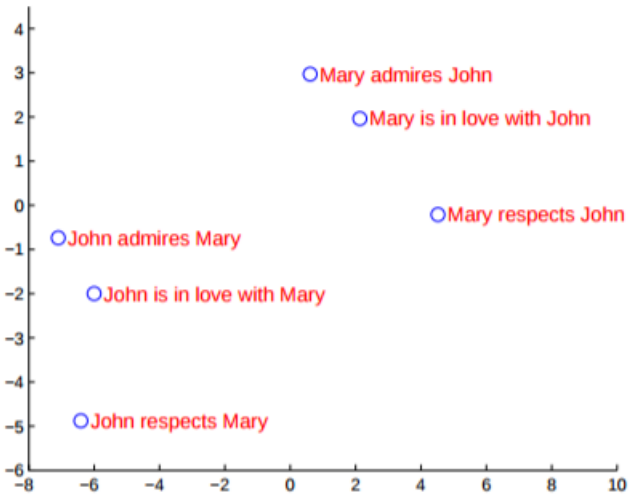
Sutskever, Vinyals, Le. Sequence to sequence learning with neural networks, 2014

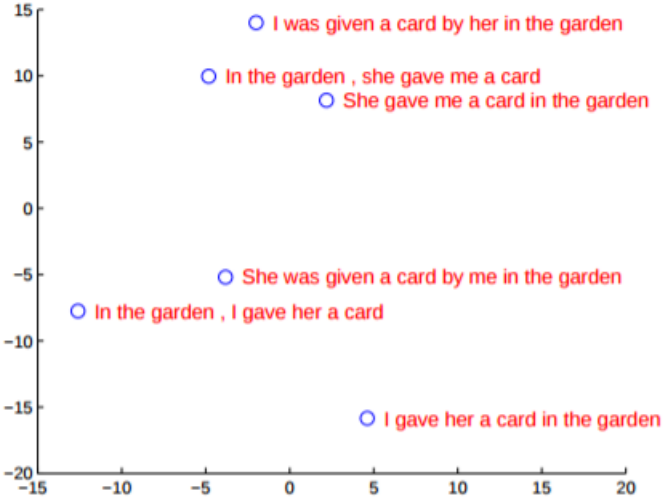
- SGD without momentum, lr=0.7, train for 7.5 epochs, after 5 epochs halve lr every 0.5 epoch
- Bs=128, balanced by length => 2x speedup!
- Gradient clipping: g:=5*g/||g||
- parallel En→Fr corpora: 12M sentence pairs
  - vocabulary: 160K/80K most frequent words + UNK
- Custom C++ impl on 8 GPUs – **<u>10 days</u>**
  - 1GPU per LTSM layer + 4GPUs for softmax

Sutskever 2014. Results

Sutskever, Vinyals, Le. Sequence to sequence learning with neural networks, 2014

- Little worse than SOTA SMT system, but much much simpler and easier to develop
- LSTM hidden state represents “thought”?
  - PCA of LSTM hidden states:

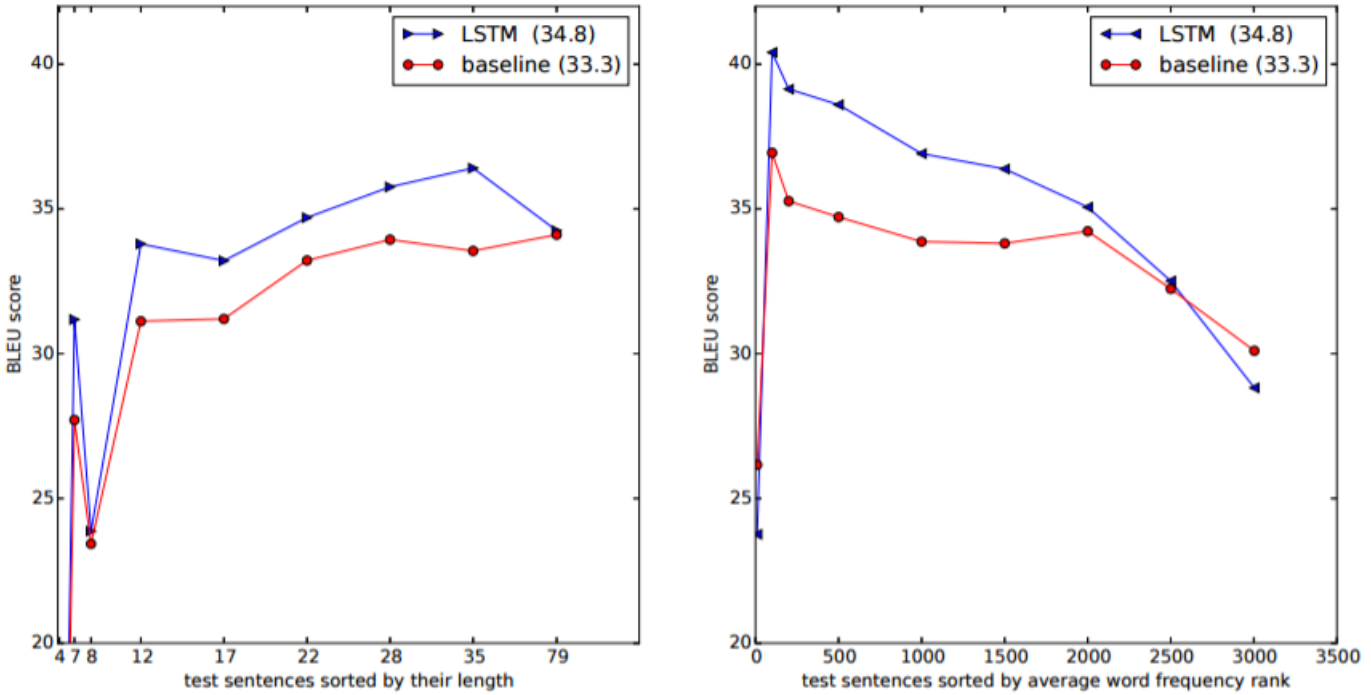




Results

Sutskever, Vinyals, Le. Sequence to sequence learning with neural networks, 2014

- no problems with long sentences (!)
- but problems with rare words



Decoding

- Decoding task: search for sequence y such as

$$y_1 y_2 \ldots y_T = argmax_y P(y|x) = argmax_y P(y_1|x) P(y_2|y_1, x) \ldots P(y_T|y_1, \ldots, y_{T-1}, x)$$

- Cannot enumerate all possible y (do full search)
  - V ^ T, where V=100K-1M, T=10-100
- Use heuristic search (approximate argmax):
  - Ancestral / forward sampling: $y_i \sim P(y \mid y_1, \ldots, y_{i-1})$
  - Greedy search: $y_i = \text{argmax}_y P(y \mid y_1, \ldots, y_{i-1})$
  - Beam search ← most common for MT

Greedy Decoding

- Greedy decoding has no way to undo decisions!
  - *les pauvres sont démunis (the poor don't have any money)*
  - → *the* ____
  - → *the poor* ____
  - → *the poor are* ____

- Better option: use beam search (a search algorithm) to explore *several* hypotheses and select the best one

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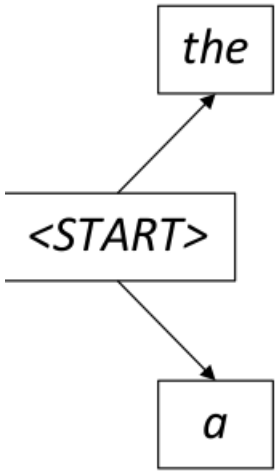
Beam search

Beam size = 2



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Beam search

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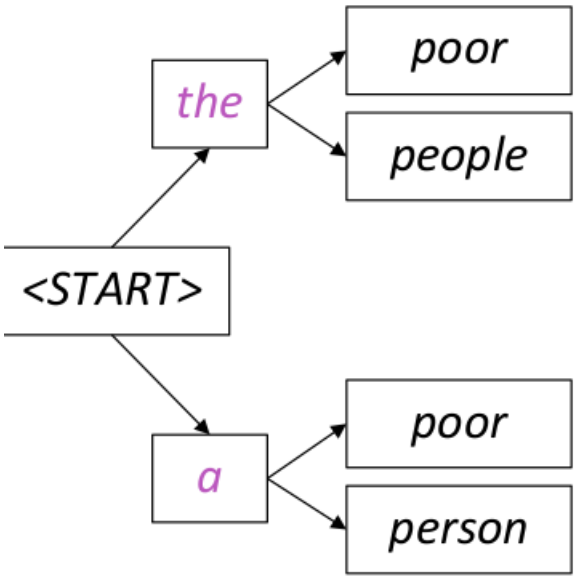

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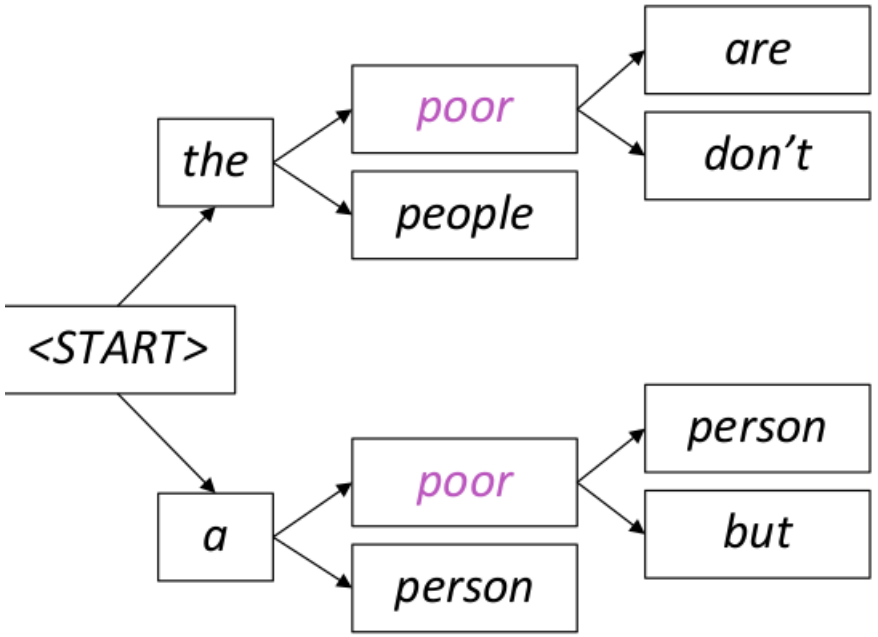
Beam search

Beam size = 2



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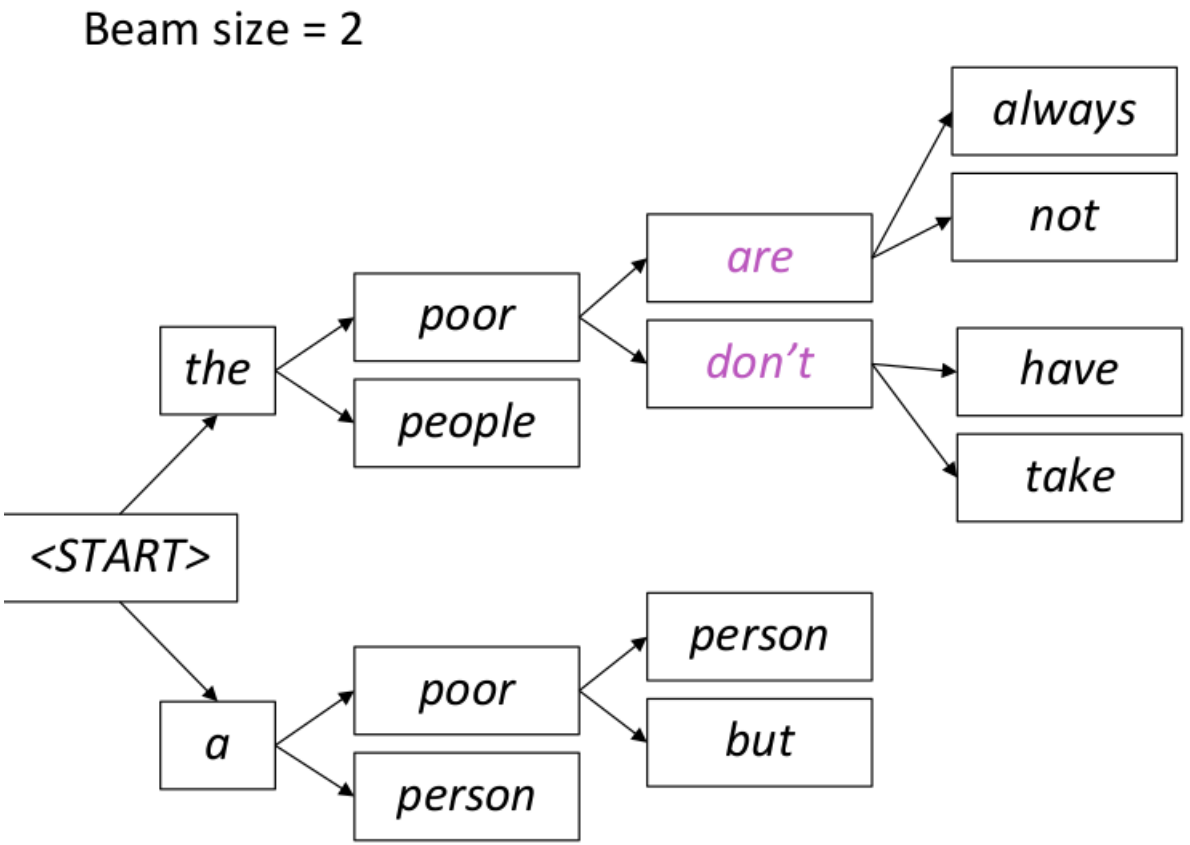
Beam search



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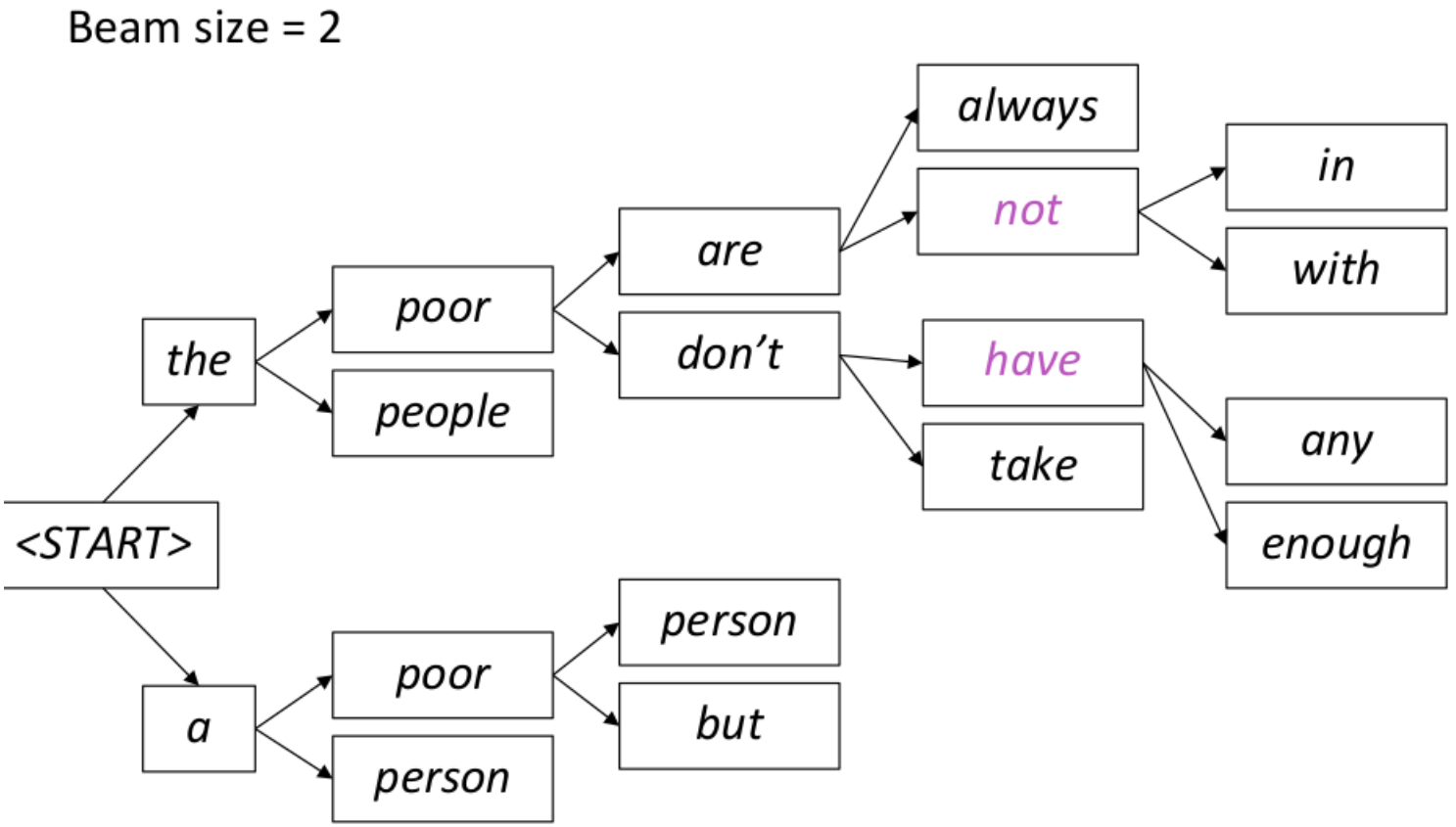

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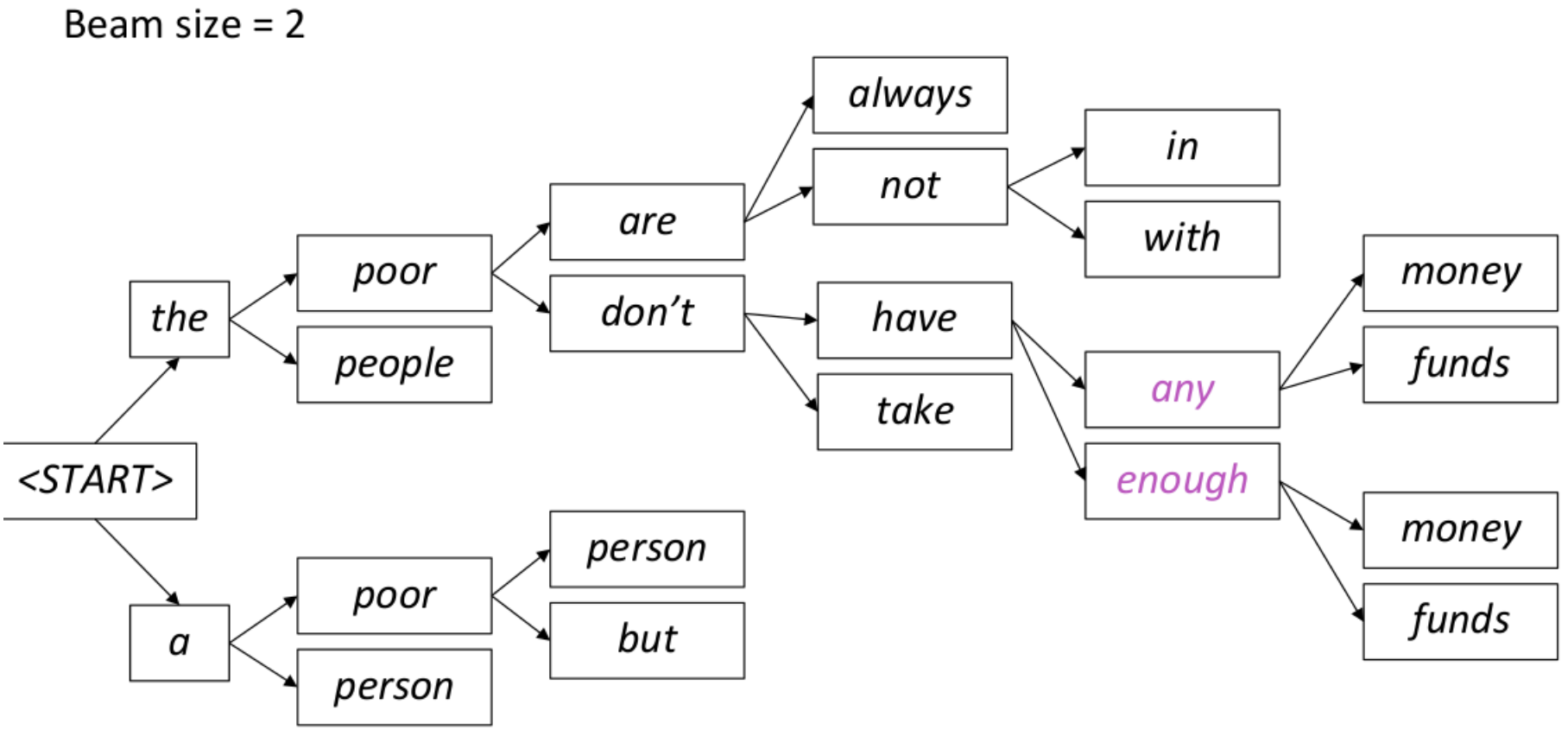

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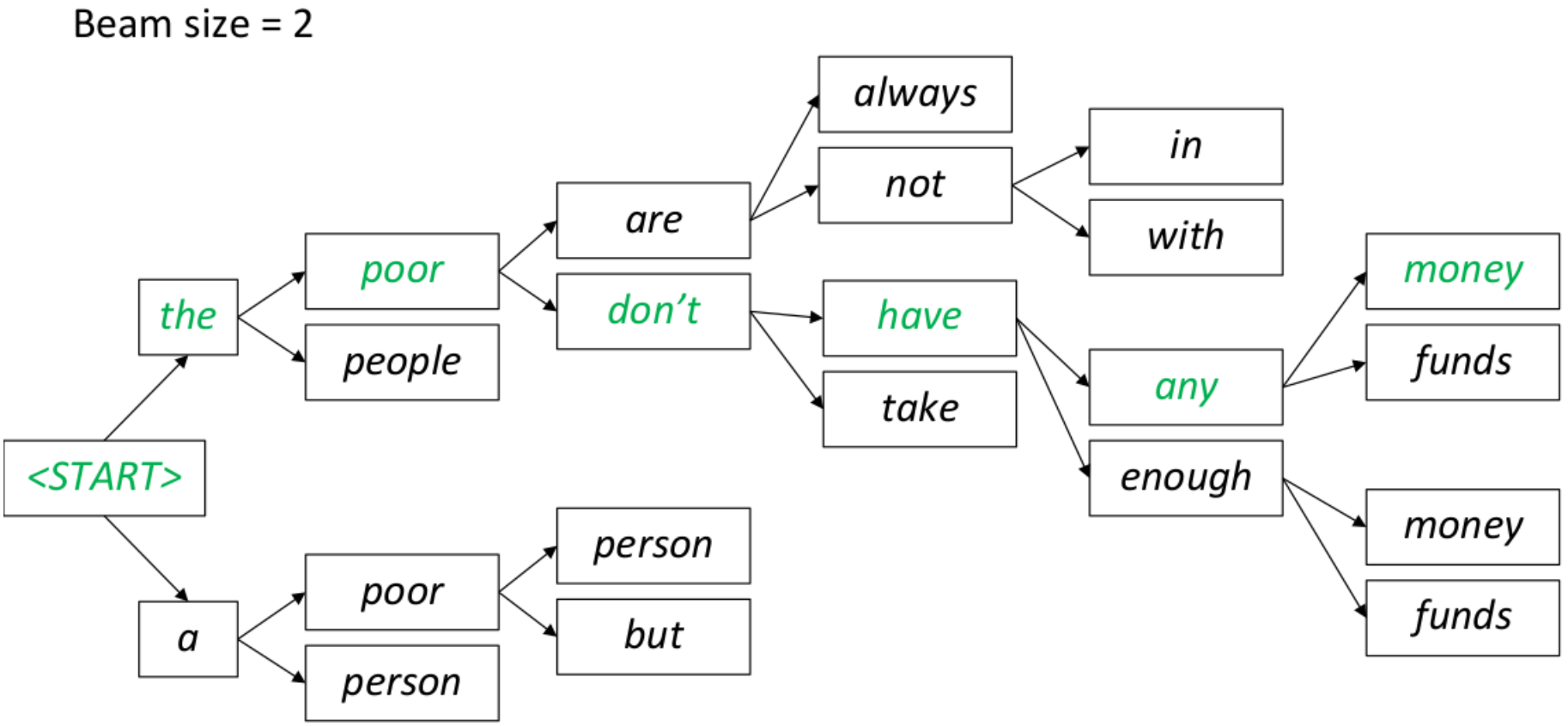

Socher, Manning. Cs224n, 2017

Beam search

- Ideally we want to find *y* that maximizes

$$P(y|x) = P(y_1|x)\, P(y_2|y_1, x)\, P(y_3|y_1, y_2, x) \ldots, P(y_T|y_1, \ldots, y_{T-1}, x)$$

- We could try enumerating all *y* → too expensive!
  - Complexity $O(V^T)$ where *V* is vocab size and *T* is target sequence length

- **Beam search**: On each step of decoder, keep track of the *k* most probable partial translations
  - *k* is the beam size (in practice around 5 to 10)
  - Not guaranteed to find optimal solution
  - But much more efficient!

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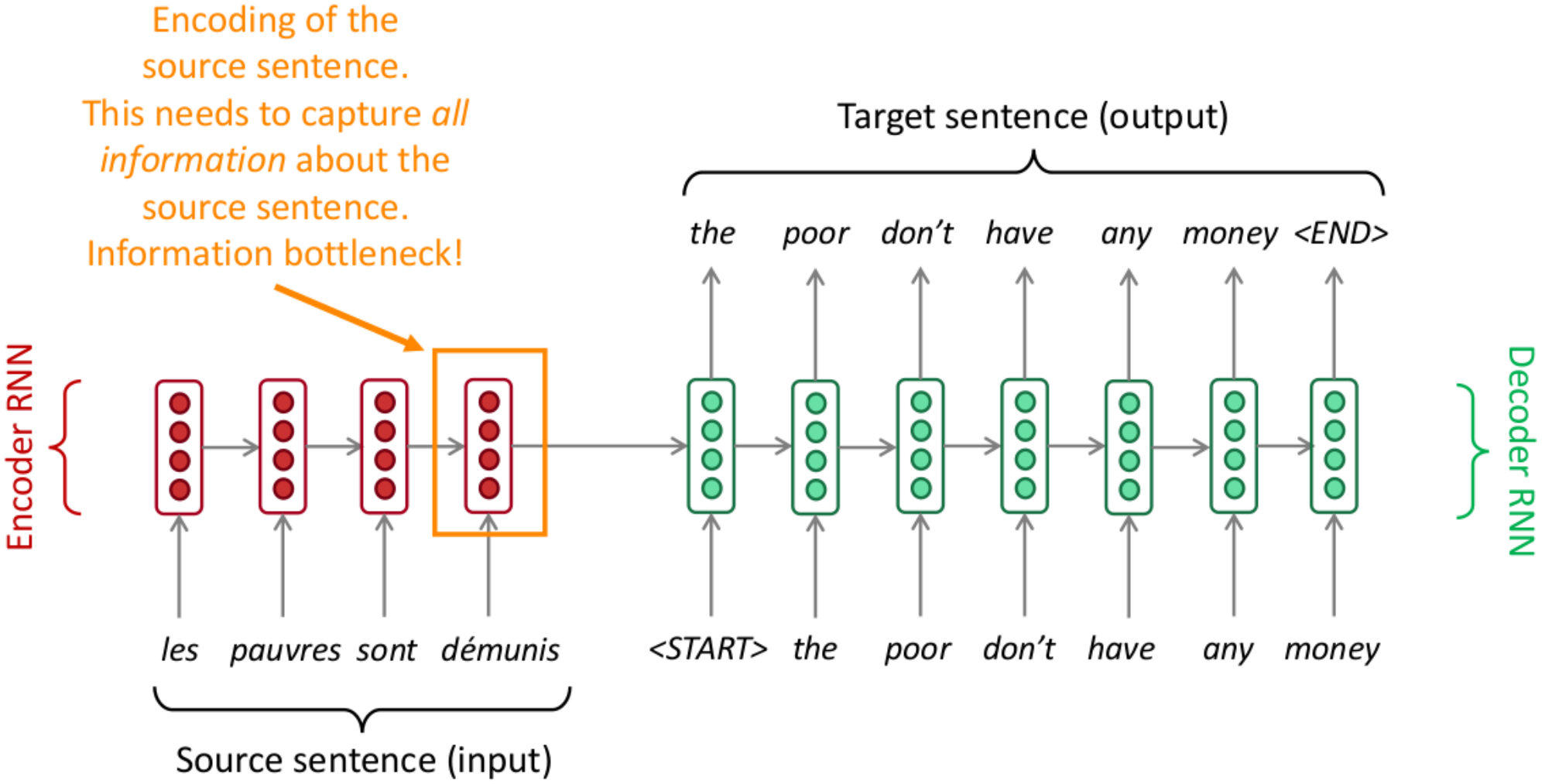
Length bias in NMT

- Maximizing *s(e)=P(e|source):* $s(e) = \sum_{i=1}^{m} \log P(e_i \mid e_{1:i})$

  results in the shorter translations be preferred to longer translations.
- Length normalization: $s'(e) = s(e) / m$
- Google NMT: $s'(e) = s(e) \Big/ \frac{(5+m)^\alpha}{(5+1)^\alpha}$
- Word reward $s'(e) = s(e) + \gamma m$

Murray and Chiang. Correcting length bias in neural machine tranlations, 2018.

Seq2seq bottleneck



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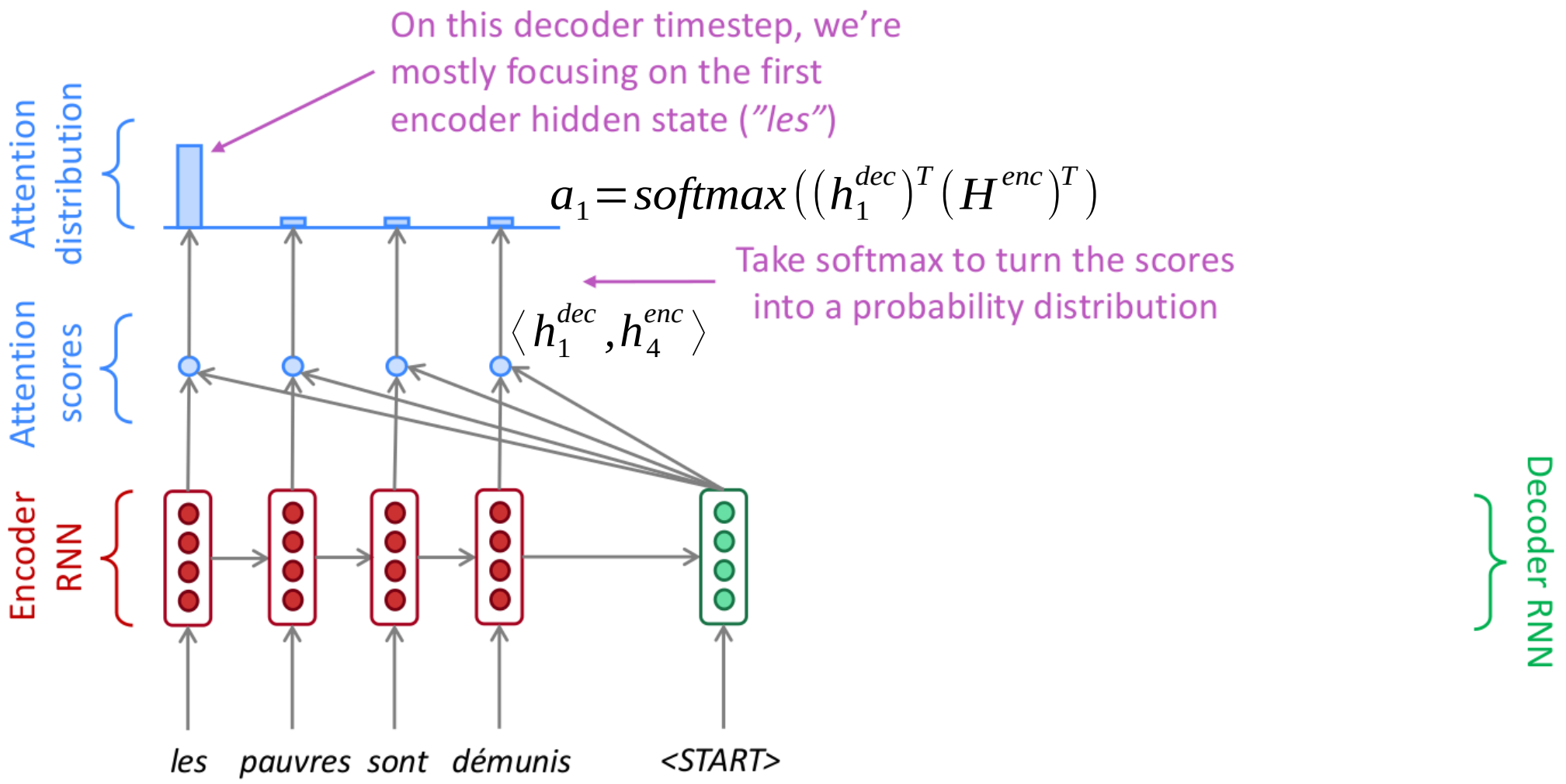
Attention: Idea

- At each timestep (when generating next word) the decoder should focus on the **most relevant (to this timestep) part** of input sequence
- Hidden state of the decoder at each timestep represents a “rough idea” of what it wants to say next
  - Help it to “put this idea into words”: find a part of input sequence relevant to this “idea” and “remind” this part to him

Attention: Example



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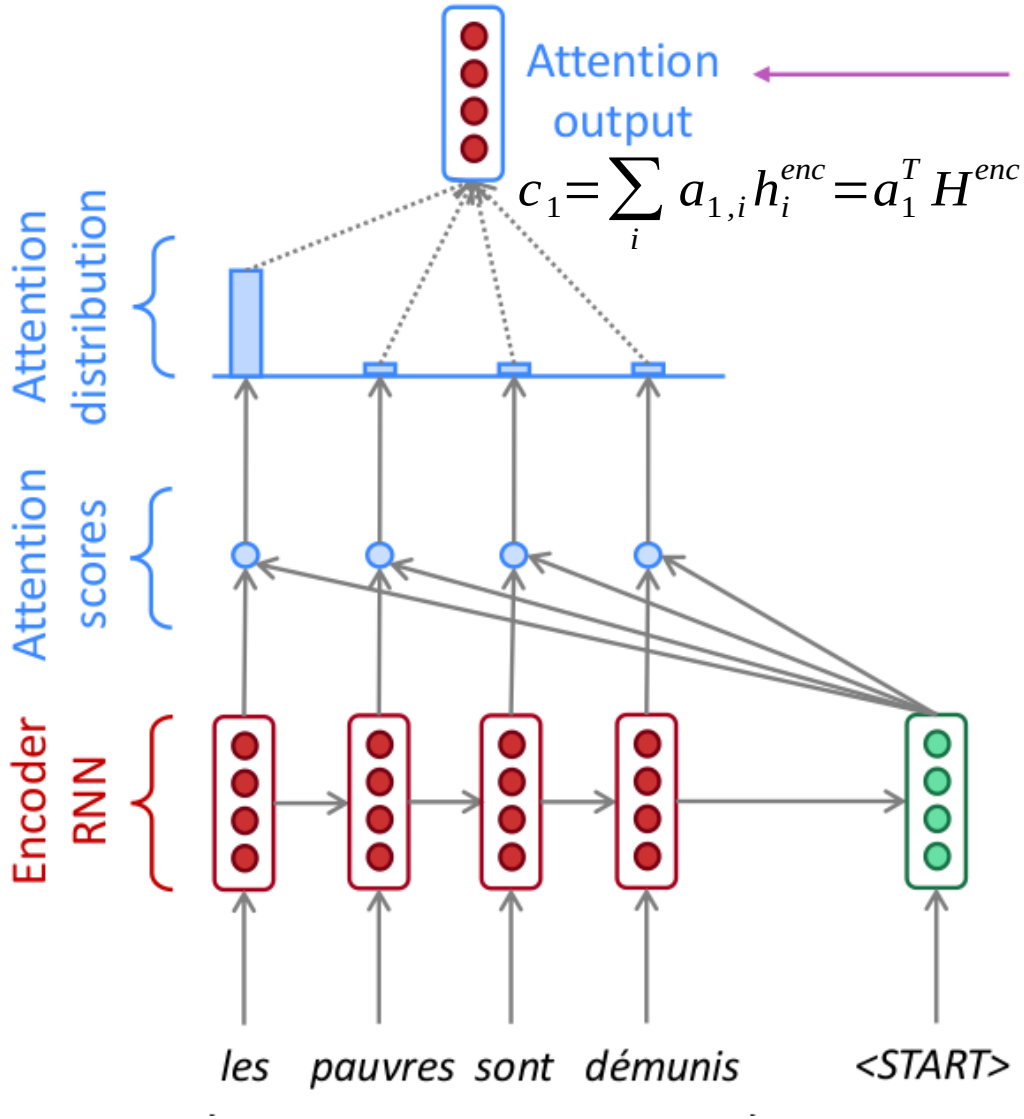

Use the attention distribution to take a **weighted sum** of the encoder hidden states.

The attention output mostly contains information the hidden states that received high attention.

Decoder RNN

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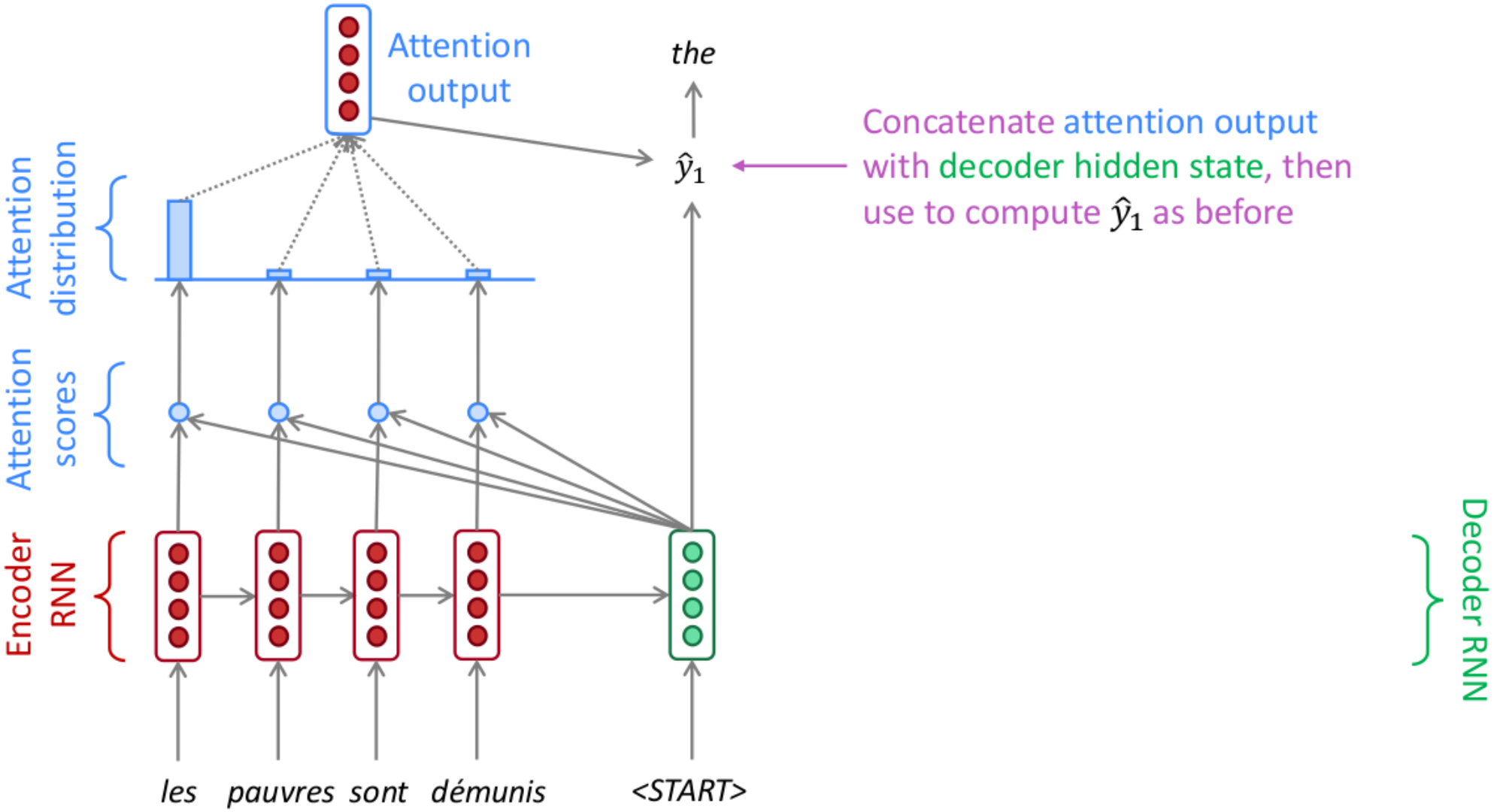
Attention: Example



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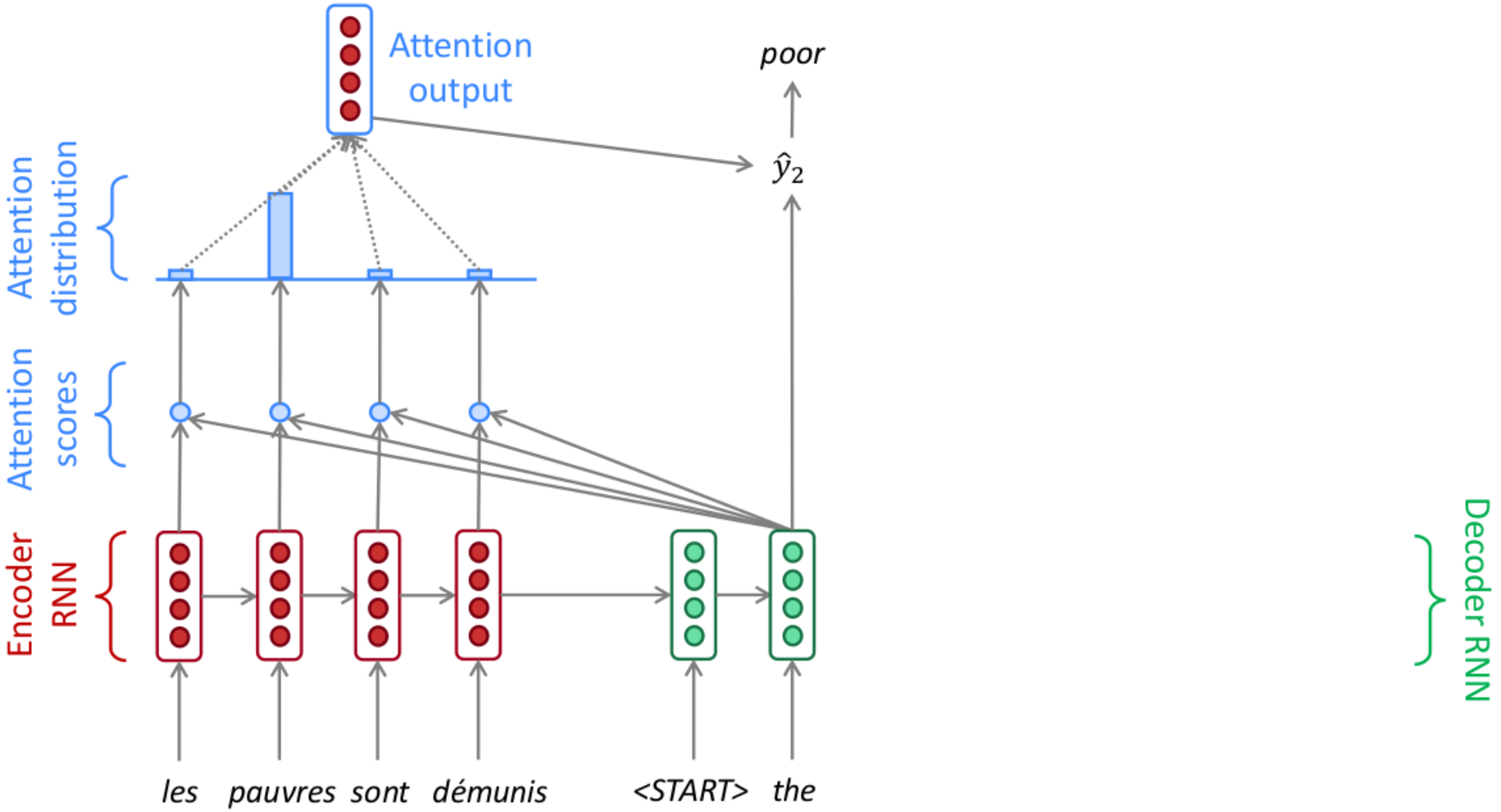

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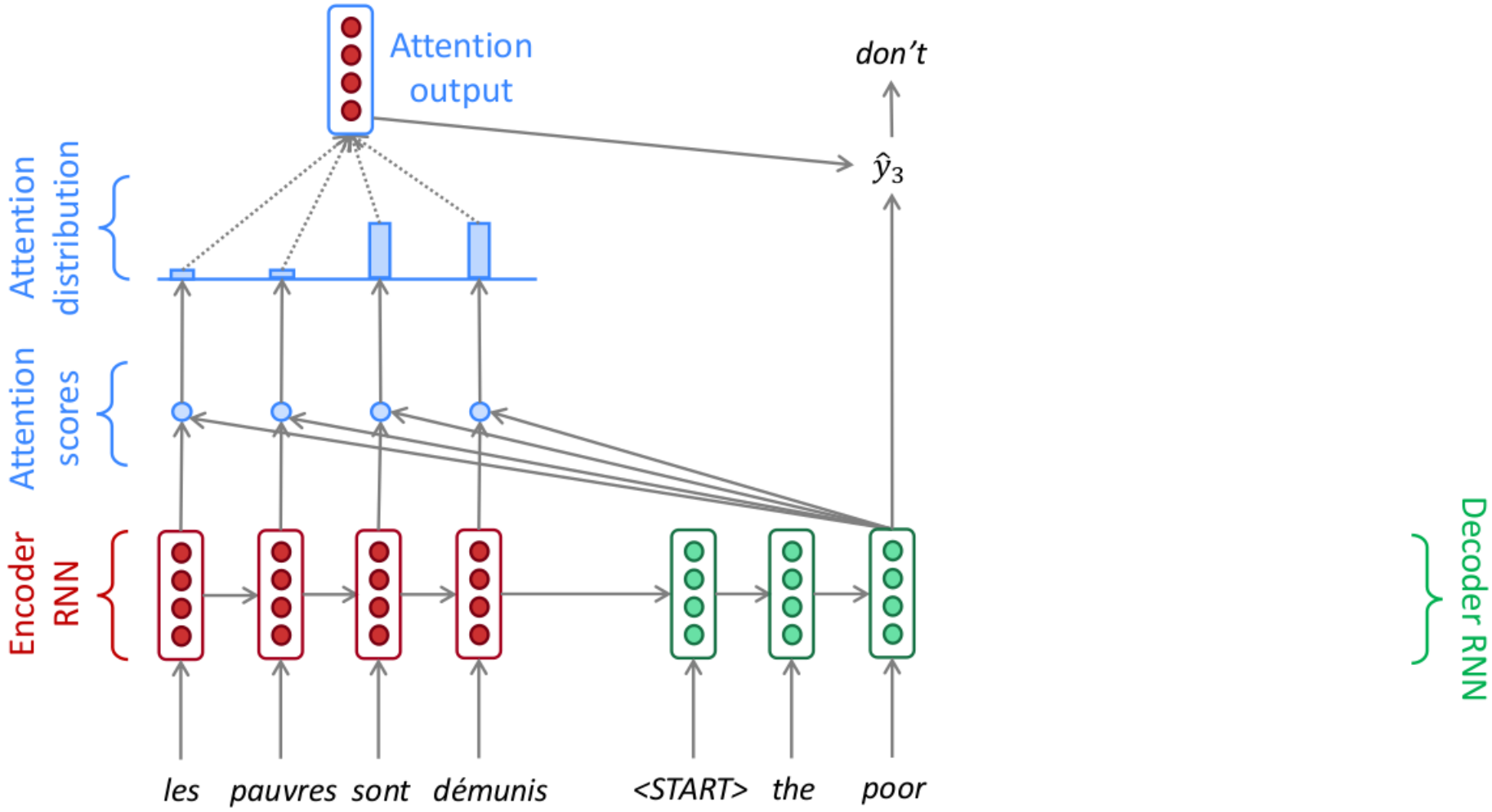

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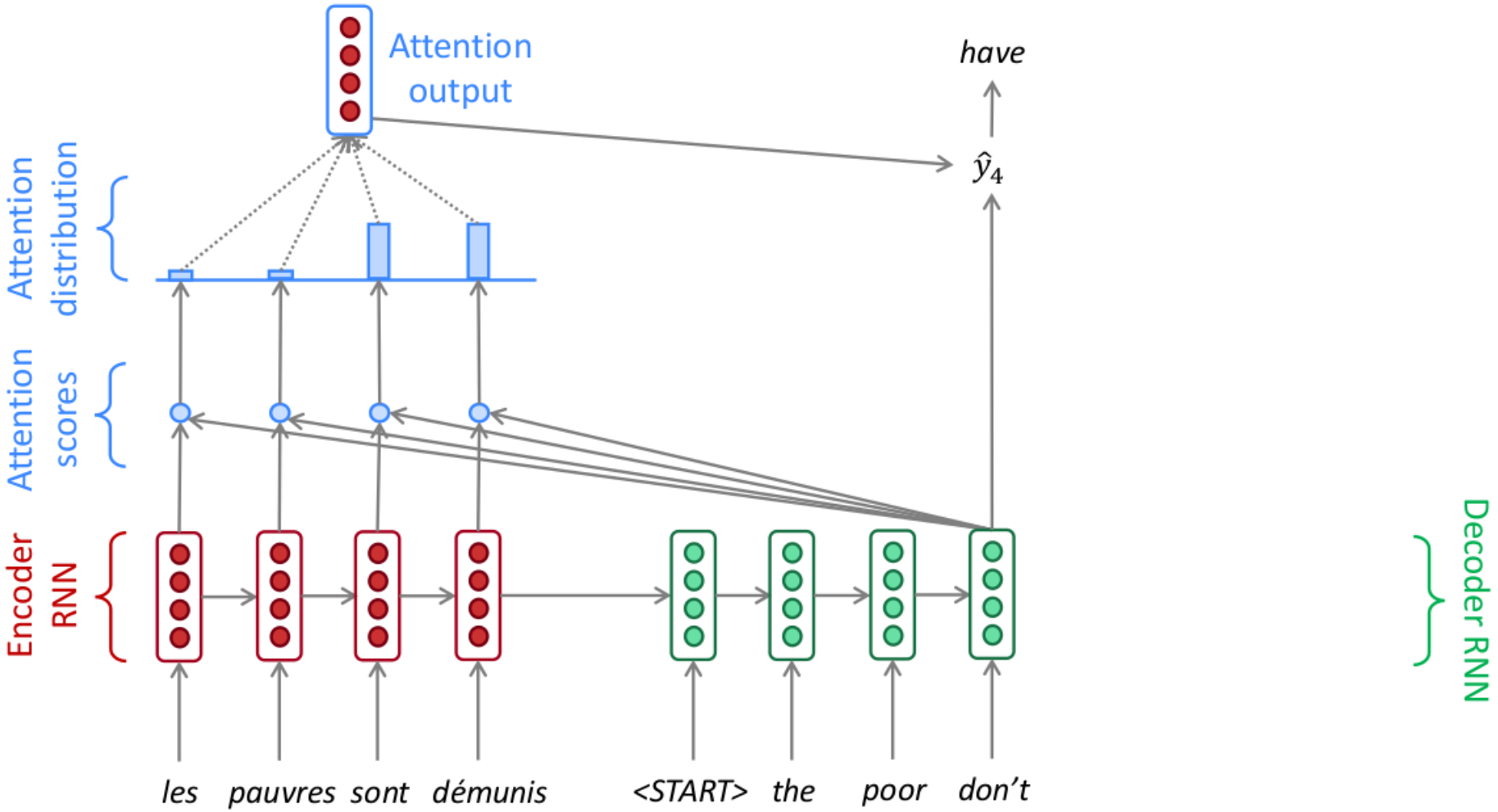

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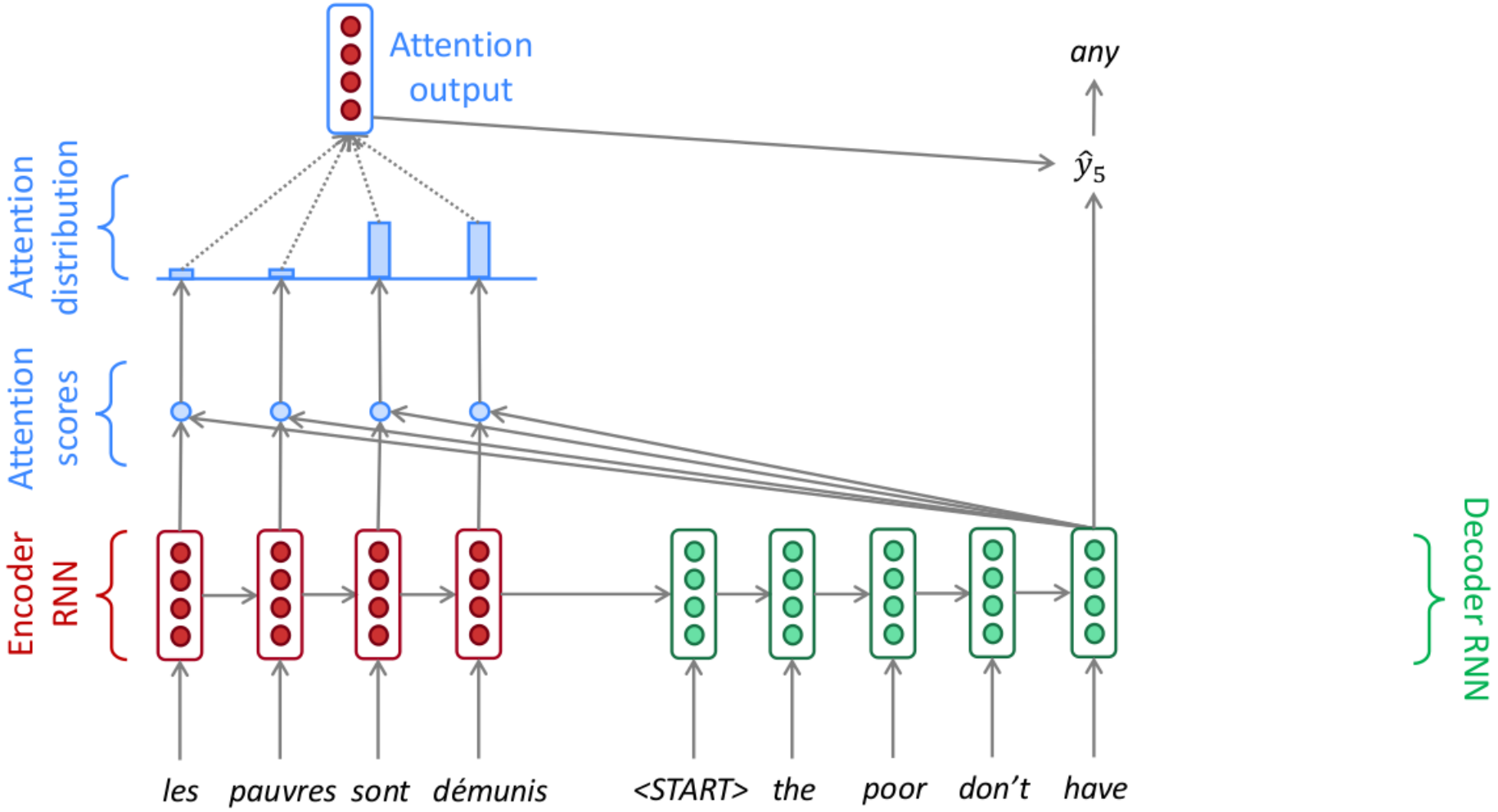

Socher, Manning. Cs224n, 2017

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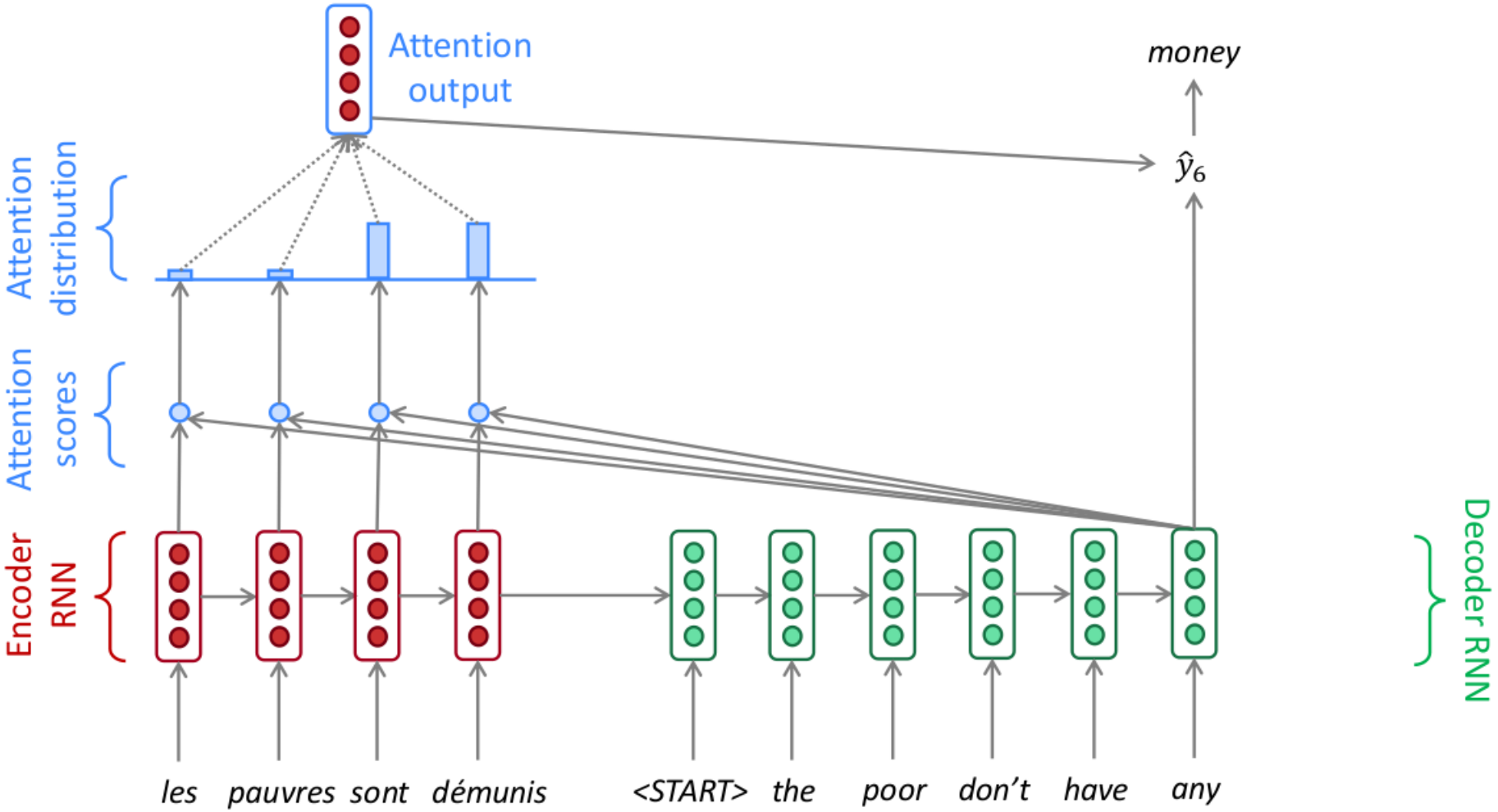
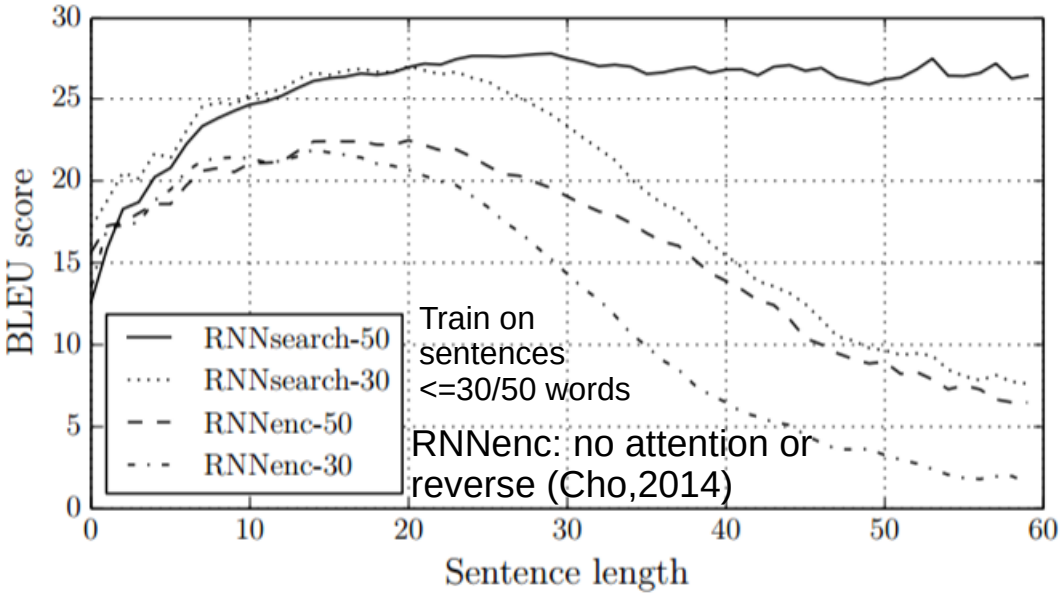


Socher, Manning. Cs224n, 2017

Bahdanau 2015

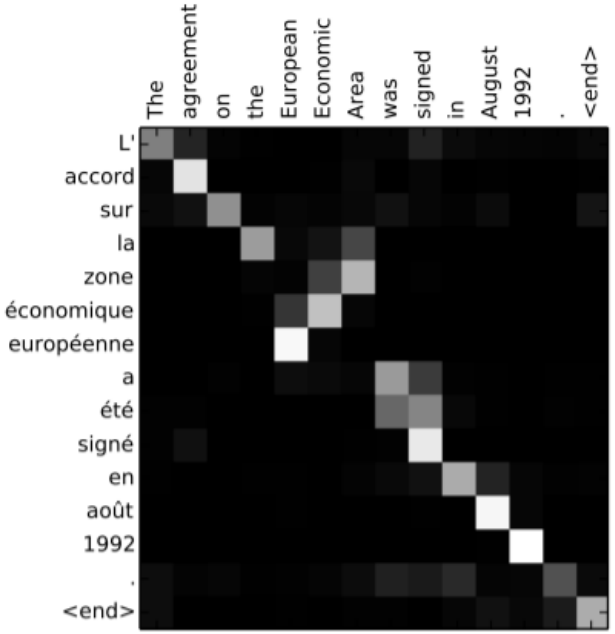
Dzmitry Bahdanau, KyungHyun Cho, Yoshua Bengio. Neural Machine Translation by Jointly Learning to Align and Translate, 2015

- Solves the problem of low quality for long sequences
  - Alternative to reversing

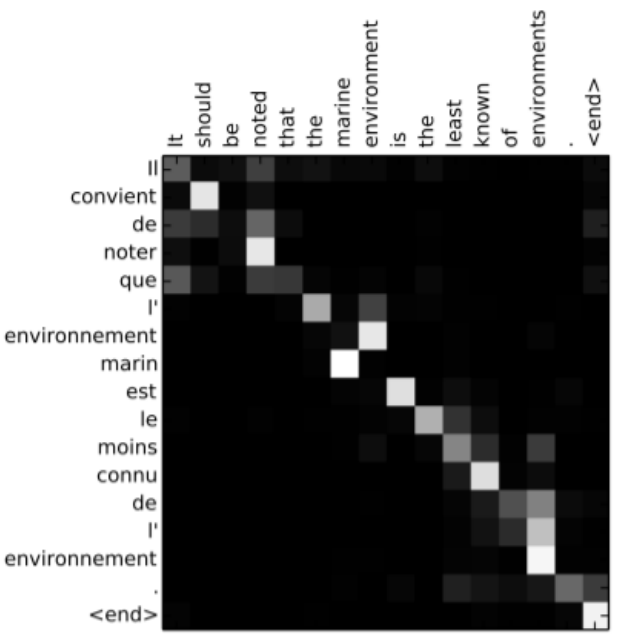


Bahdanau et al. Neural Machine Translation by Jointly Learning to Align and Translate, 2015

Bahdanau 2015



(a)



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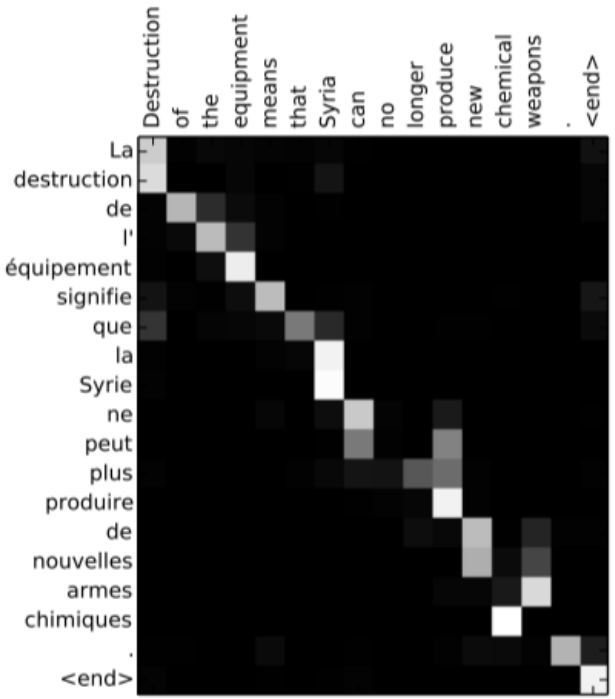
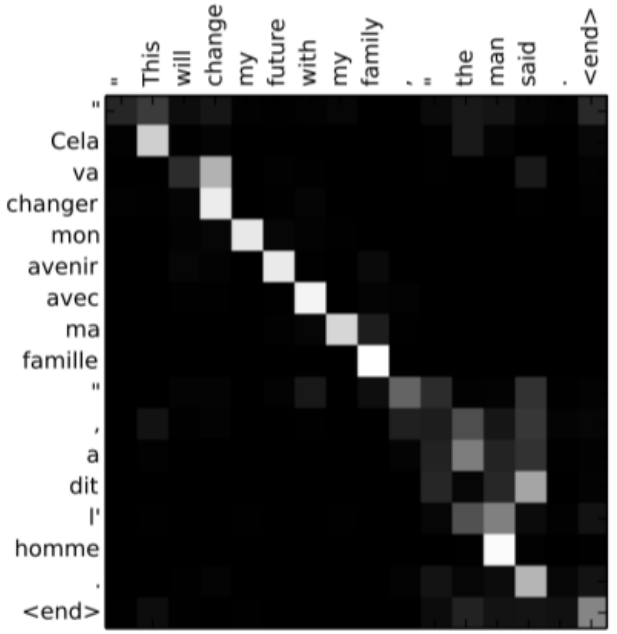
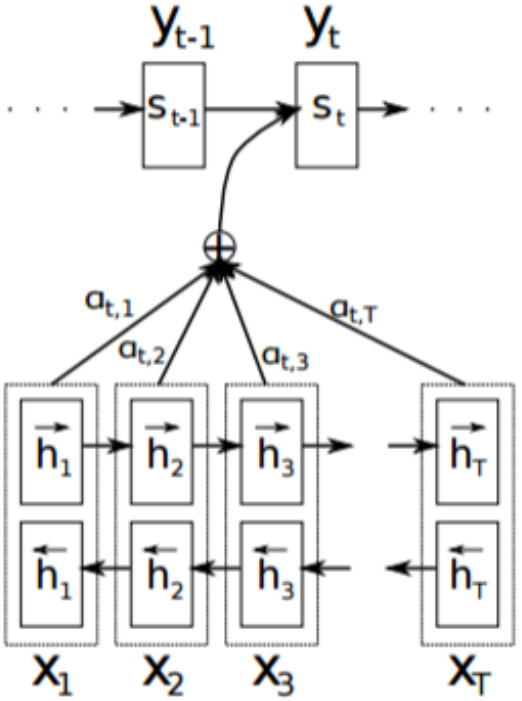






Bahdanau et al. Neural Machine Translation by Jointly Learning to Align and Translate, 2015

Attention

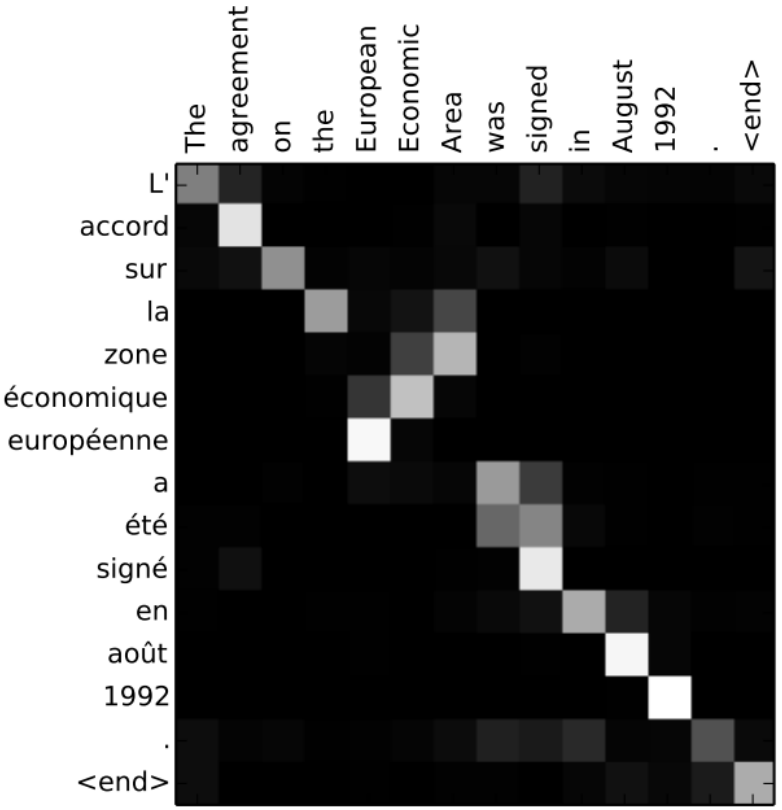
- Improves translation quality significantly
  - Solves **information bottleneck** problem, acts like an unlimited size memory
  - Helps **gradient propagation** from encoder to decoder, especially in long sequences
    - Remember vanishing gradient problem partially solved by LSTMs? But they have sigmoid forget gates! (<1)

Britz et al., 2017. Massive Exploration of Neural Machine Translation Architectures:

“we found that the attention-based models exhibited significantly larger gradient updates to decoder states throughout training. This suggests that the attention mechanism acts more like a ”weighted skip connection” that optimizes gradient flow than like a ”memory” that allows the encoder to access source states, as is commonly stated in the literature”

Attention

- Improves interpretability
  - Networks learns alignment as byproduct of translation
  - We can look at which fragments were translated to which



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Attention

Attention is a new basic layer type (along with feed-forward, convolutional and recurrent)

- Works with variable length inputs (texts)
  - like RNNs, CNNs
  - unlike feed-forward
- Used in SOTA models in lots of tasks (question answering, image captioning, ...)

Do I hold your attention?