Announcement

- Homework 2
  - Available in Blackboard -> Homework
  - Due: Mar. 9, 11:59pm (one week)

Sequence to Sequence

SLP3 Ch 10; INLP Ch 18

Sequence to sequence

- Input a sequence, output another sequence
  - Often abbreviated to seq2seq
- Many applications
  - Machine translation (the most well-known seq2seq task)
    - Input: source language text
    - Output: target language text
  - Paraphrase
    - Input: a sentence
    - Output: a restatement of the meaning using other words
  - Style transfer
    - Input: some text
    - Output: a restatement in a specified style (e.g., formal writing, advertisement, positive sentiment, Shakespearean writing style, etc.)

Sequence to sequence

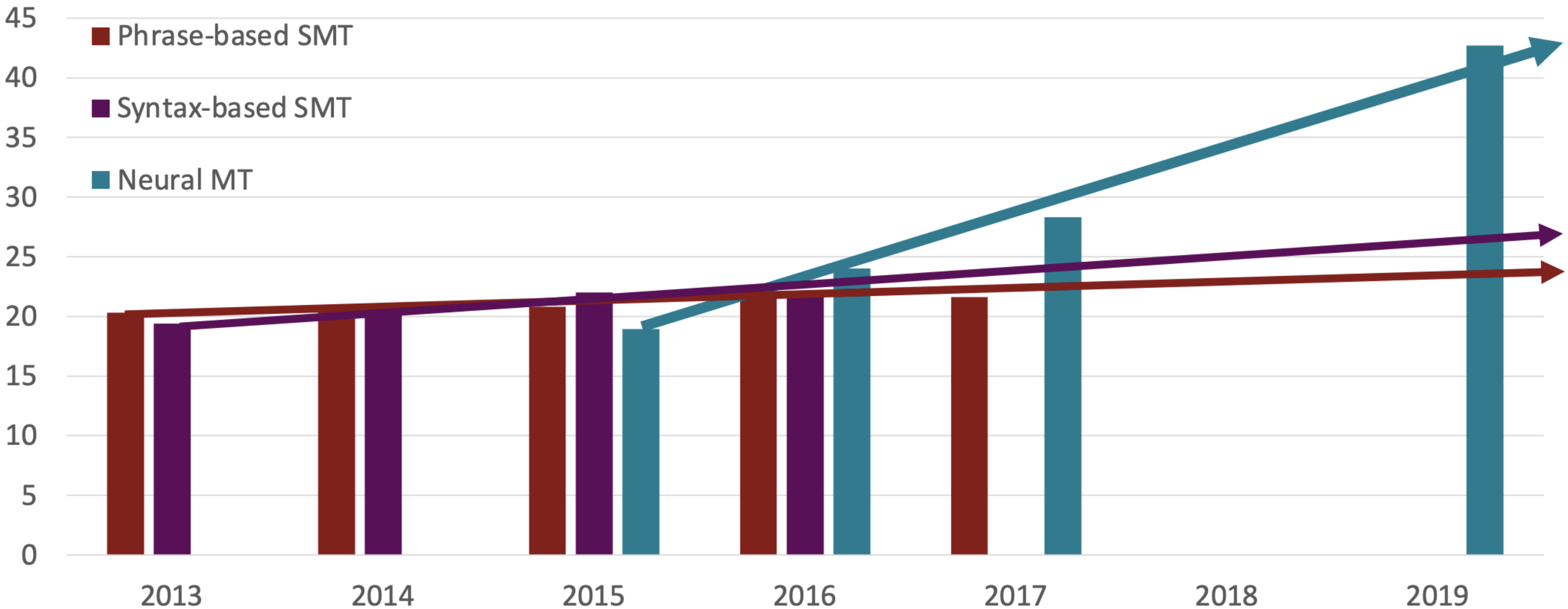
- Input a sequence, output another sequence
  - Often abbreviated to seq2seq
- Many applications
  - Summarization
    - Input: a document
    - Output: a few sentences that summarize the document
  - Question answering
    - Input: a question
    - Output: the answer
  - Dialog
    - Input: previous utterances
    - Output: next utterance

Sequence to sequence

- More applications
  - Input: Tolkien's epic novel The Lord of the Rings was published in 1954-1955, years after the book was completed.
  - Joint entity and relation extraction
    - [Tolkien | *person*]'s epic novel [The Lord of the Rings | *book* | *author* = Tolkien] was published in 1954-1955, years after the book was completed.
  - Semantic role labeling
    - Tolkien's epic novel [The Lord of the Rings | *subject*] [was published | *predicate*] [in 1954-1955 | *temporal*], years after the book was completed.
  - Coreference resolution
    - [Tolkien]'s epic novel [The Lord of the Rings] was published in 1954-1955, years after the [book | The Lord of the Rings] was completed.
  - More on these tasks later…

Paolini, et al. "Structured prediction as translation between augmented natural languages." ICLR 2021

Comparing Methods of Machine Translation



Sources: http://www.meta-net.eu/events/meta-forum-2016/slides/09_sennrich.pdf & http://matrix.statmt.org/

SMT: statistical machine translation
NMT: neural machine translation ⇐ neural seq2seq

[Edinburgh En-De WMT newstest2013 Cased BLEU; NMT 2015 from U. Montréal; NMT 2019 FAIR on newstest2019]

NMT: a big success story of NLP + deep learning

- Neural Machine Translation went from a fringe research attempt in 2014 to the leading standard method in 2016
  - 2014: First seq2seq paper published
  - 2016: Google Translate switches from SMT to NMT - and by 2018 everyone has

Microsoft SYSTRAN beyond language Google facebook

Bai du 百度 網易 NetEase www.163.com Tencent 腾讯 搜狗搜索

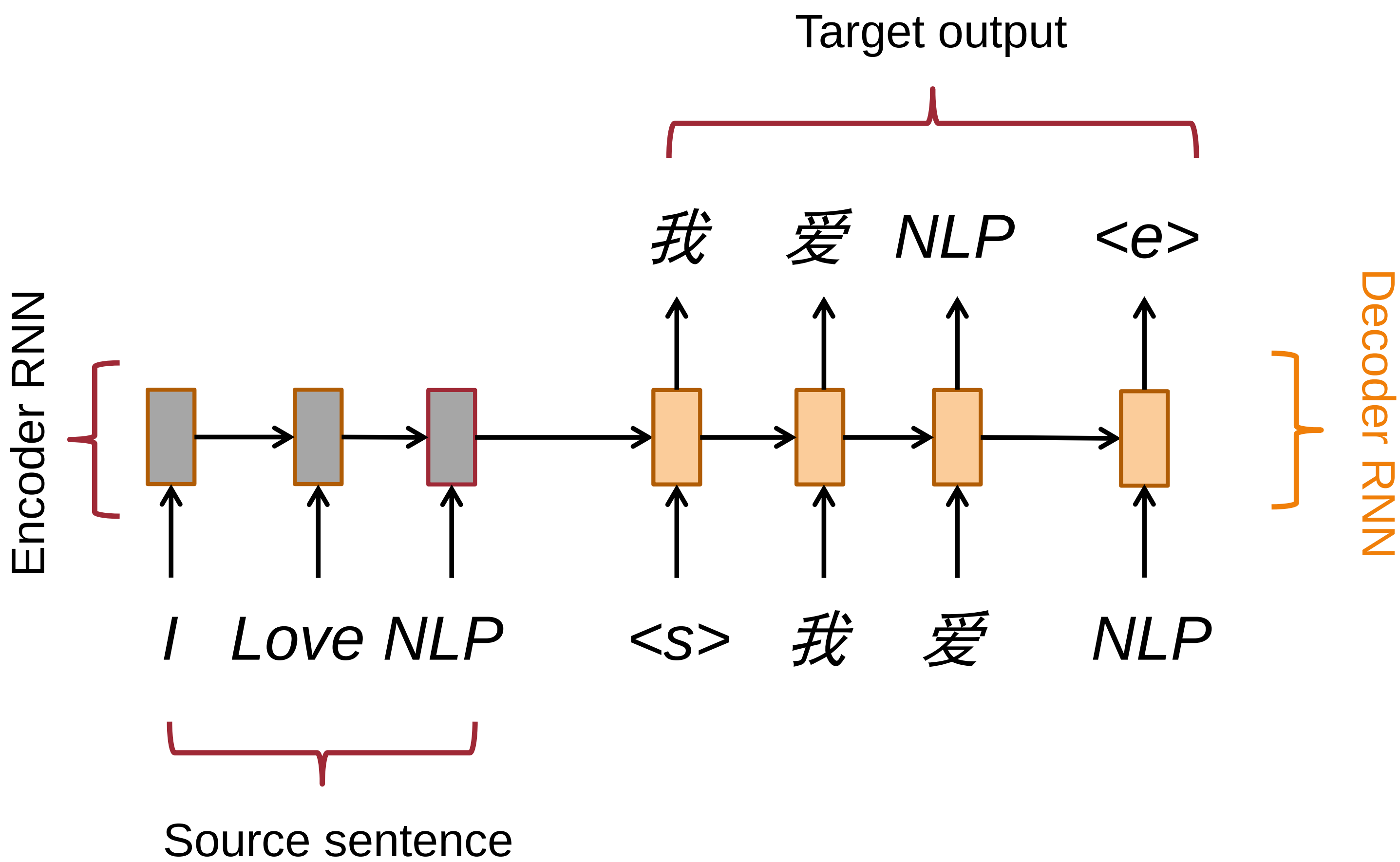
  - SMT systems, built by hundreds of engineers over many years, outperformed by NMT systems trained by a small group of engineers in a few months

Neural Seq2Seq Methods

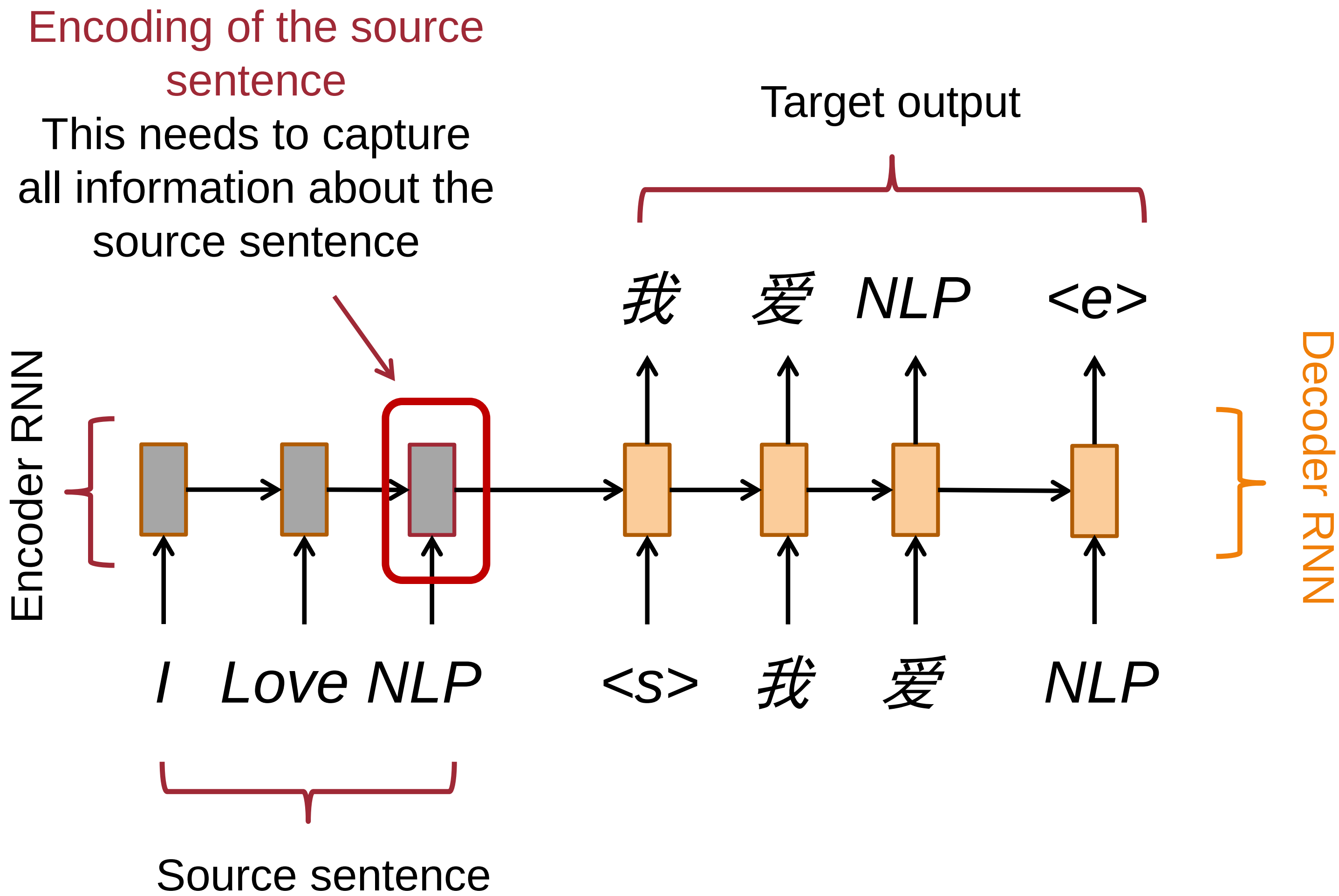
Neural Seq2seq Methods

- Similar to neural language modeling methods
  - Recurrent neural network
  - Attention
  - Transformer
- Difference: now we have an encoder to process the input sequence and a decoder to produce the output sequence

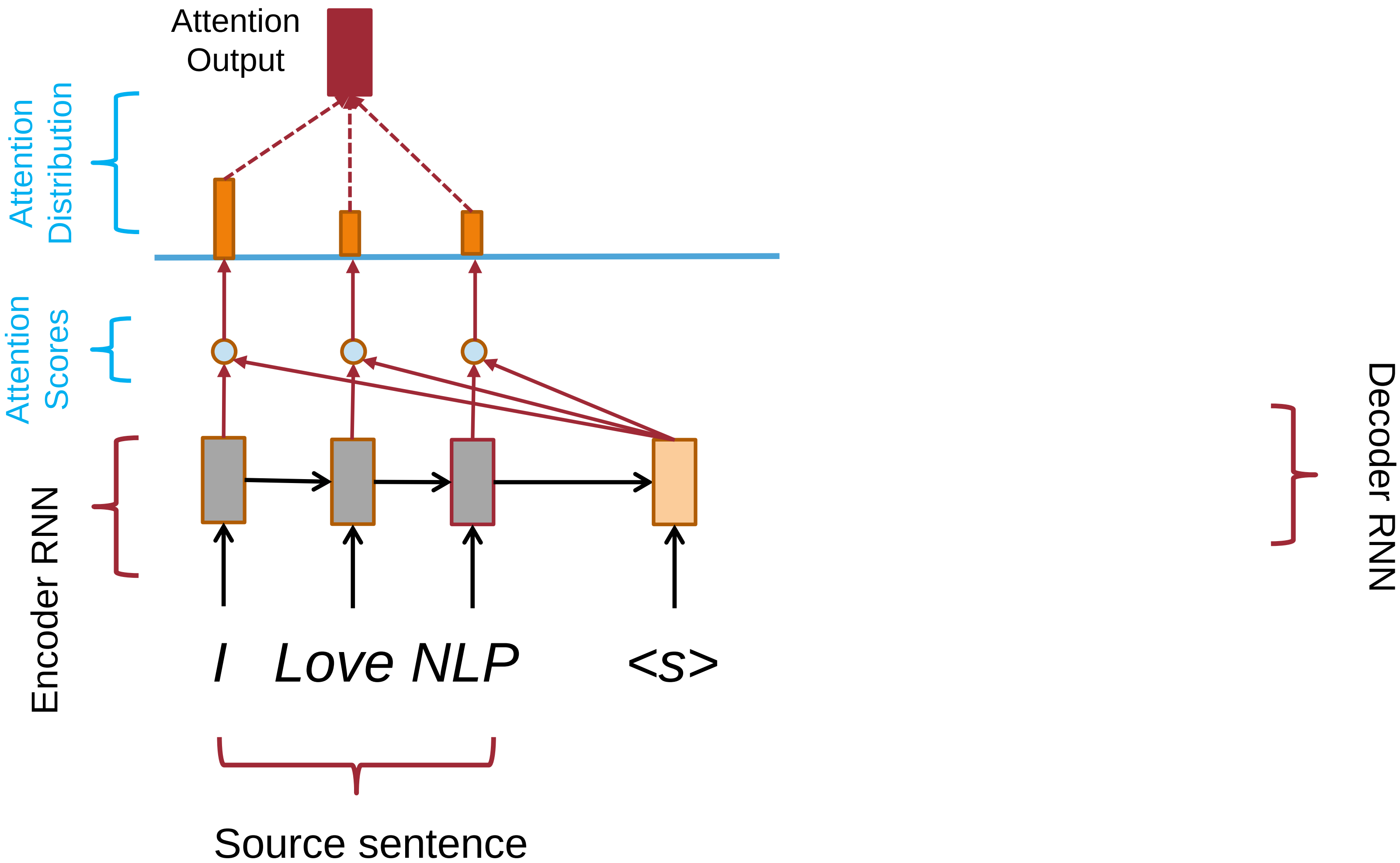
RNN


Target output
我
爱
NLP
<e>
Encoder RNN
Decoder RNN
I
Love
NLP
<s>
我
爱
NLP
Source sentence

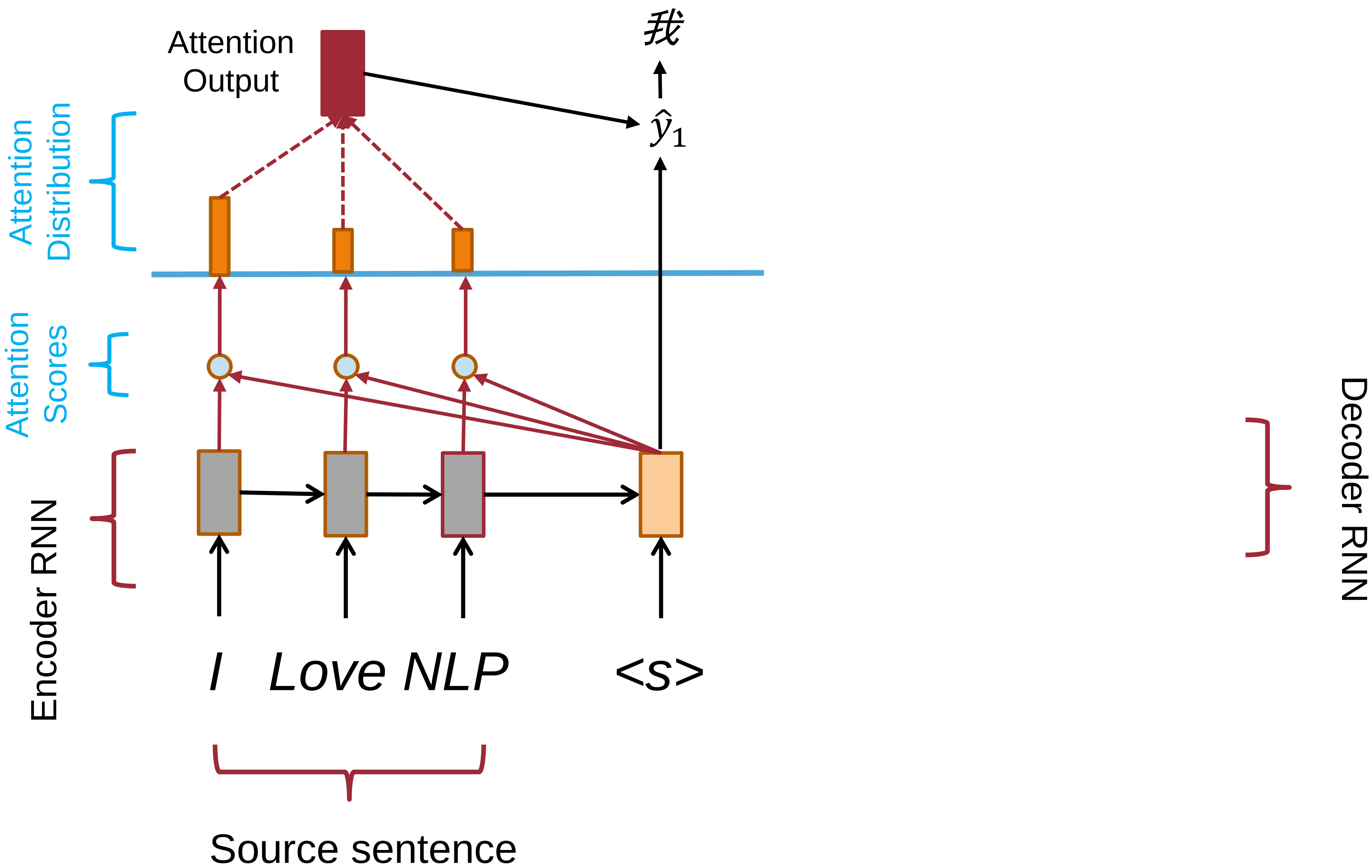
RNN: the bottleneck problem



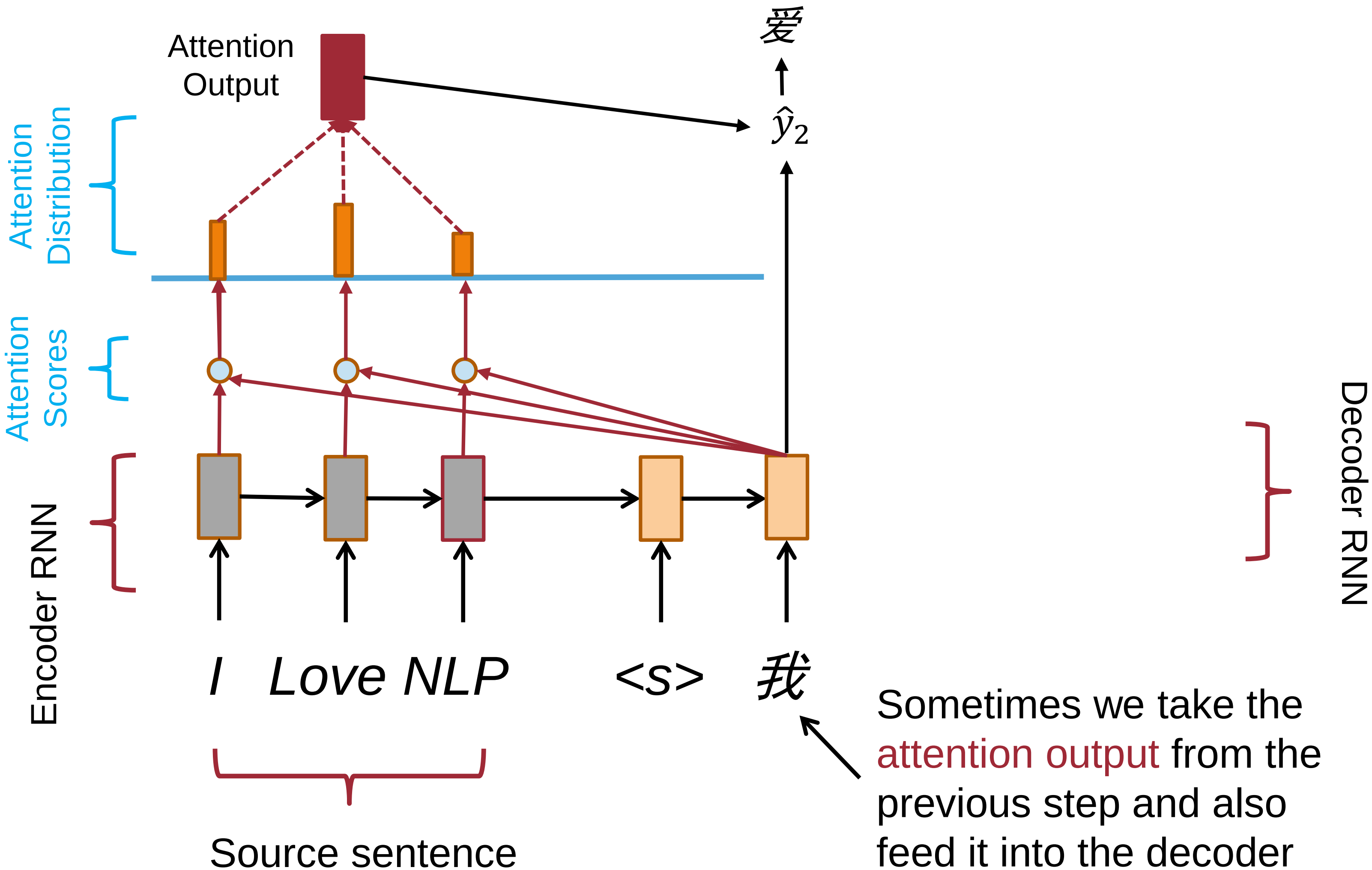
Seq2seq with attention



Seq2seq with attention

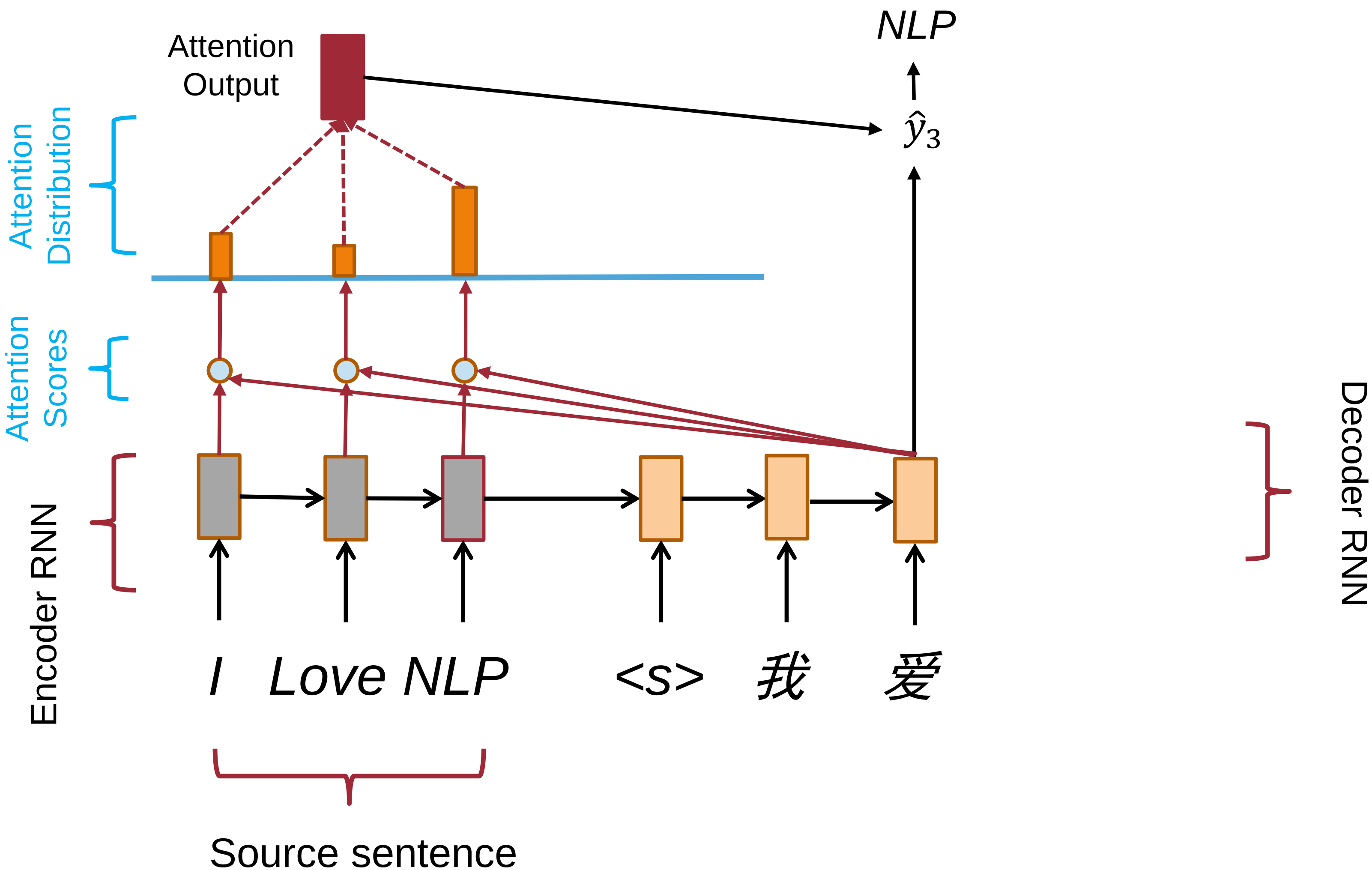


Seq2seq with attention

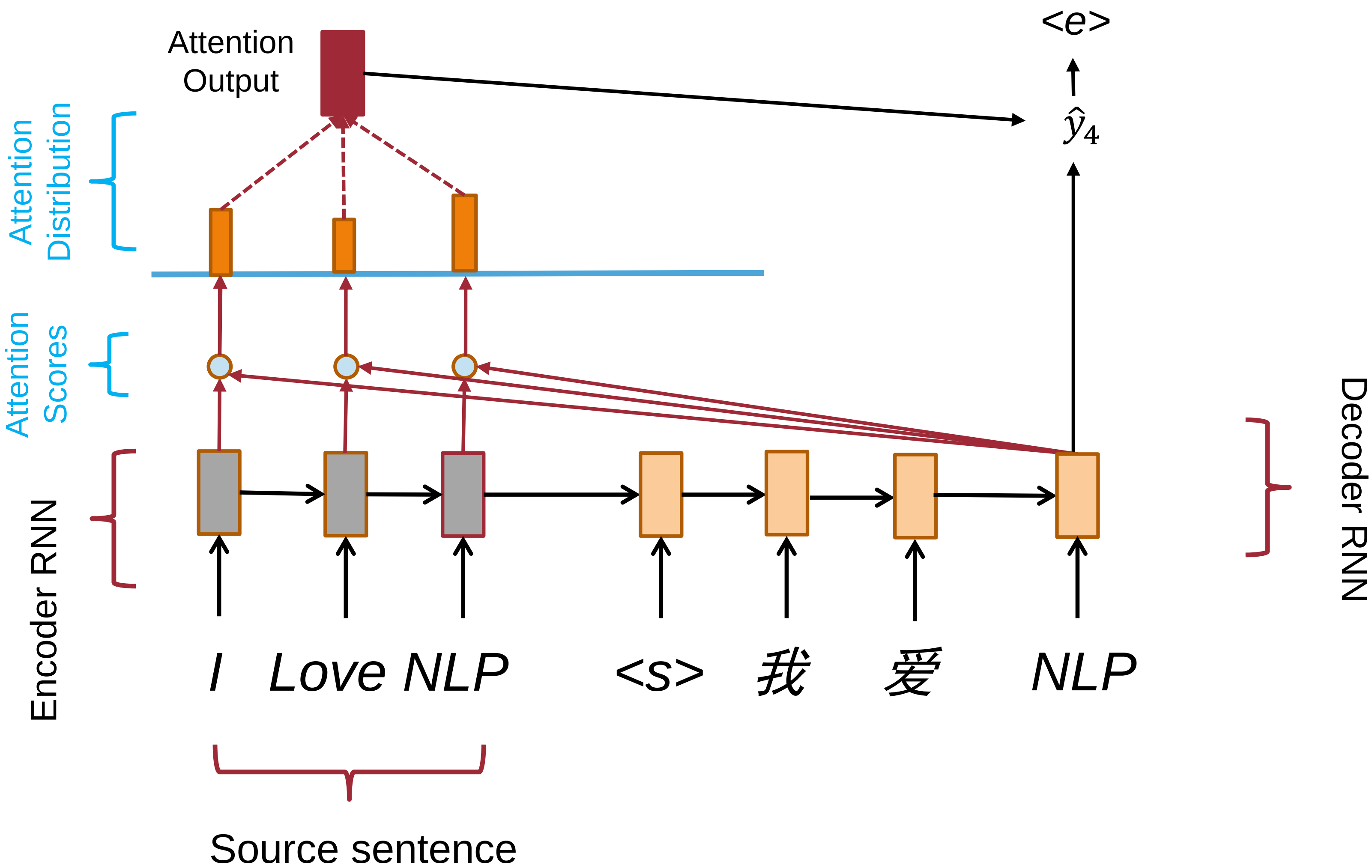


Sometimes we take the attention output from the previous step and also feed it into the decoder

Seq2seq with attention

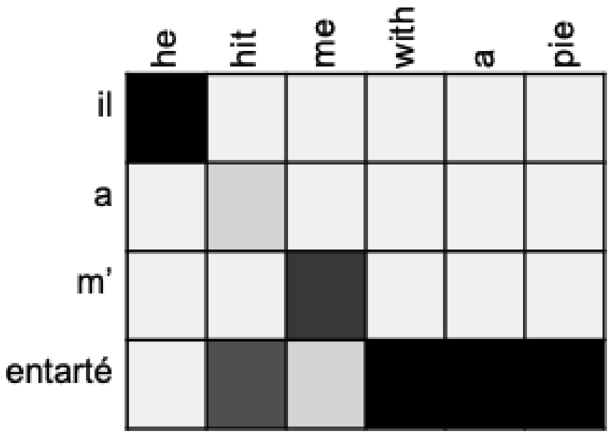


Seq2seq with attention



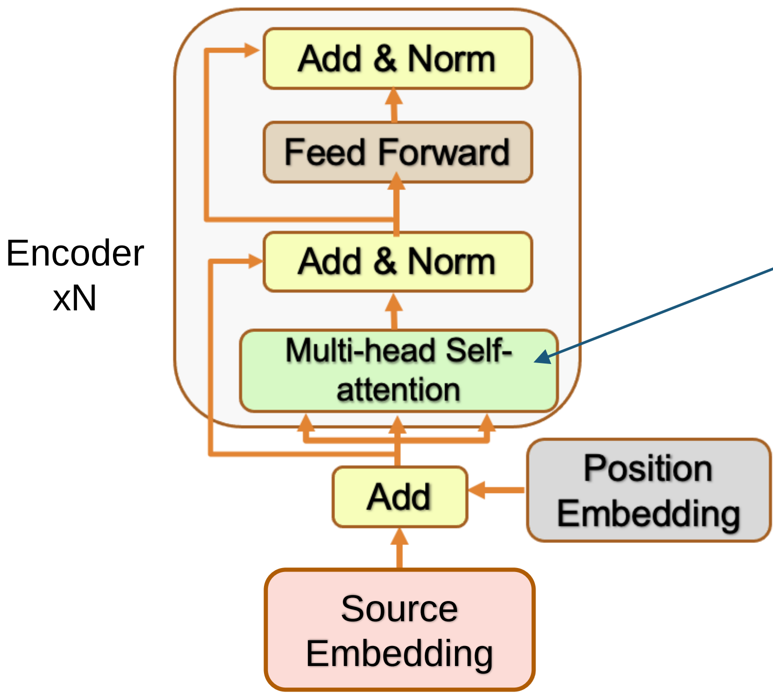
Attention is great

- Attention solves the bottleneck problem
  - It allows decoder to look directly at source, bypassing bottleneck
- Attention helps with the vanishing gradient problem
  - Provides shortcut to faraway states
- Attention provides more "human-like" model of seq2seq
  - You can look back at the source sentence while translating, rather than needing to remember it all
- Attention provides some interpretability
  - Attention distribution reveals what the decoder was focusing on
  - = (soft) source-target sentence alignment.



Replace RNN with Transformer

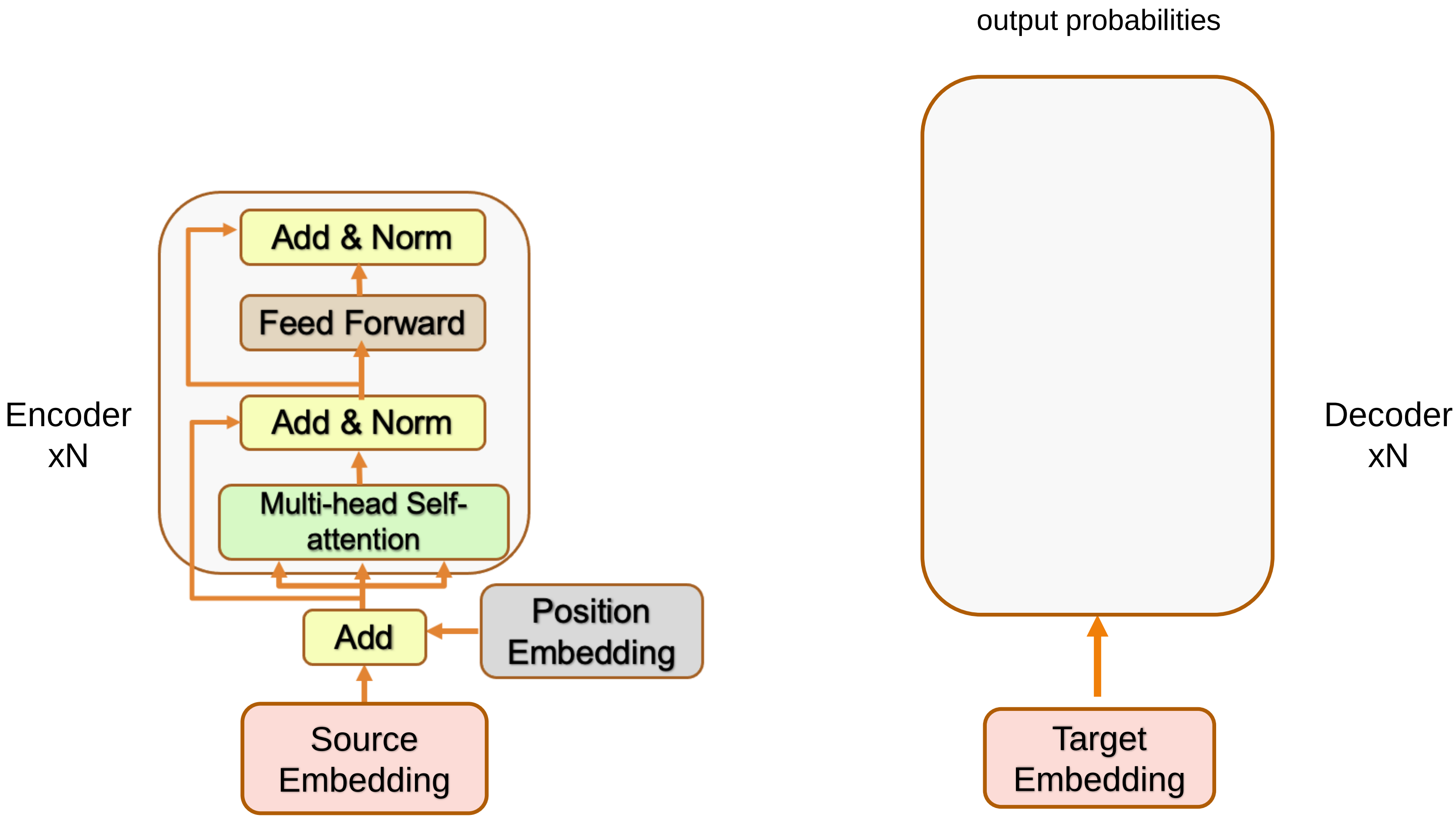
- We have introduced transformer encoder in LM.



No mask, because we are not doing LM and are allow to see the complete sentence.

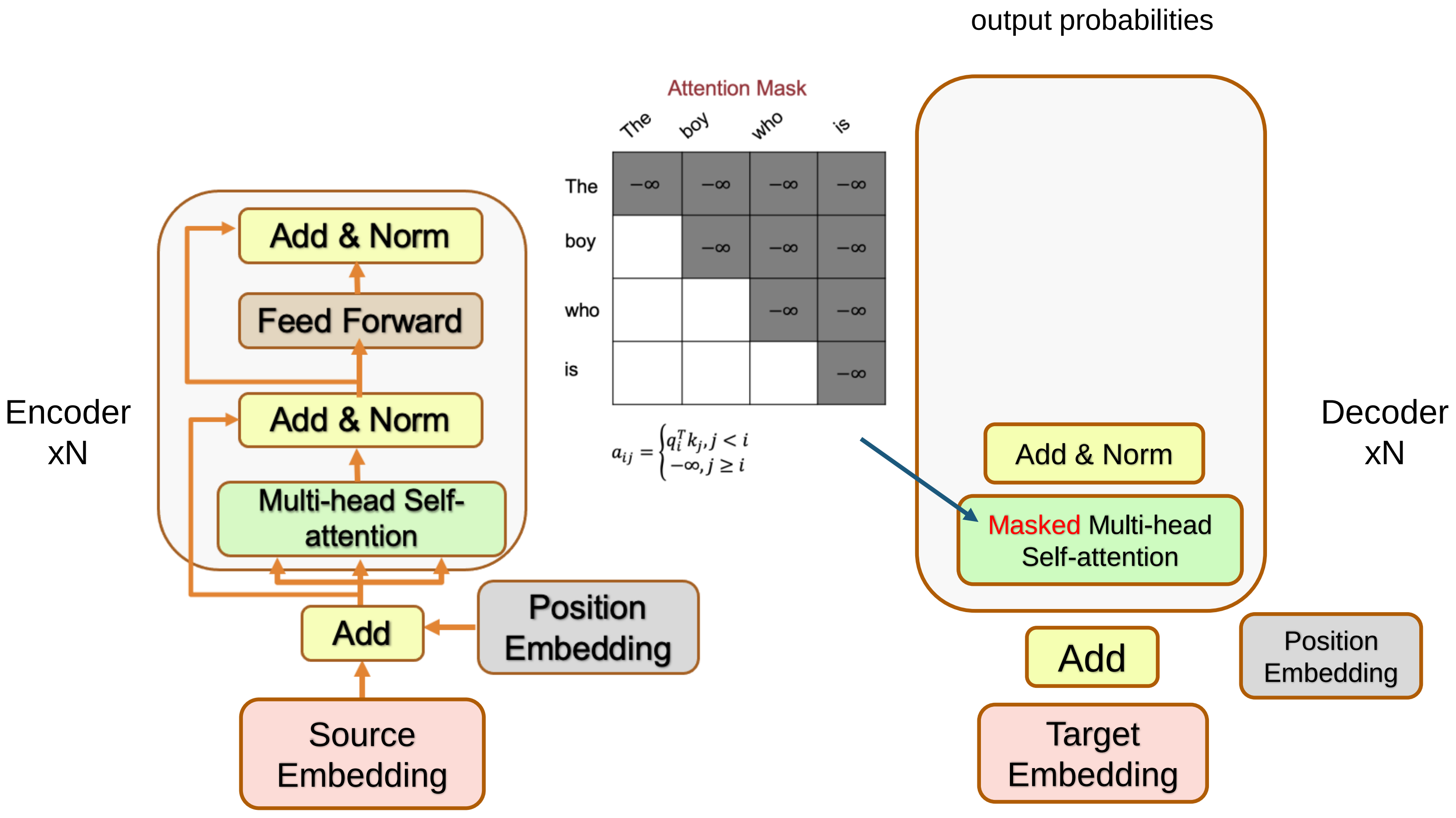
Replace RNN with Transformer

- What about the decoder?



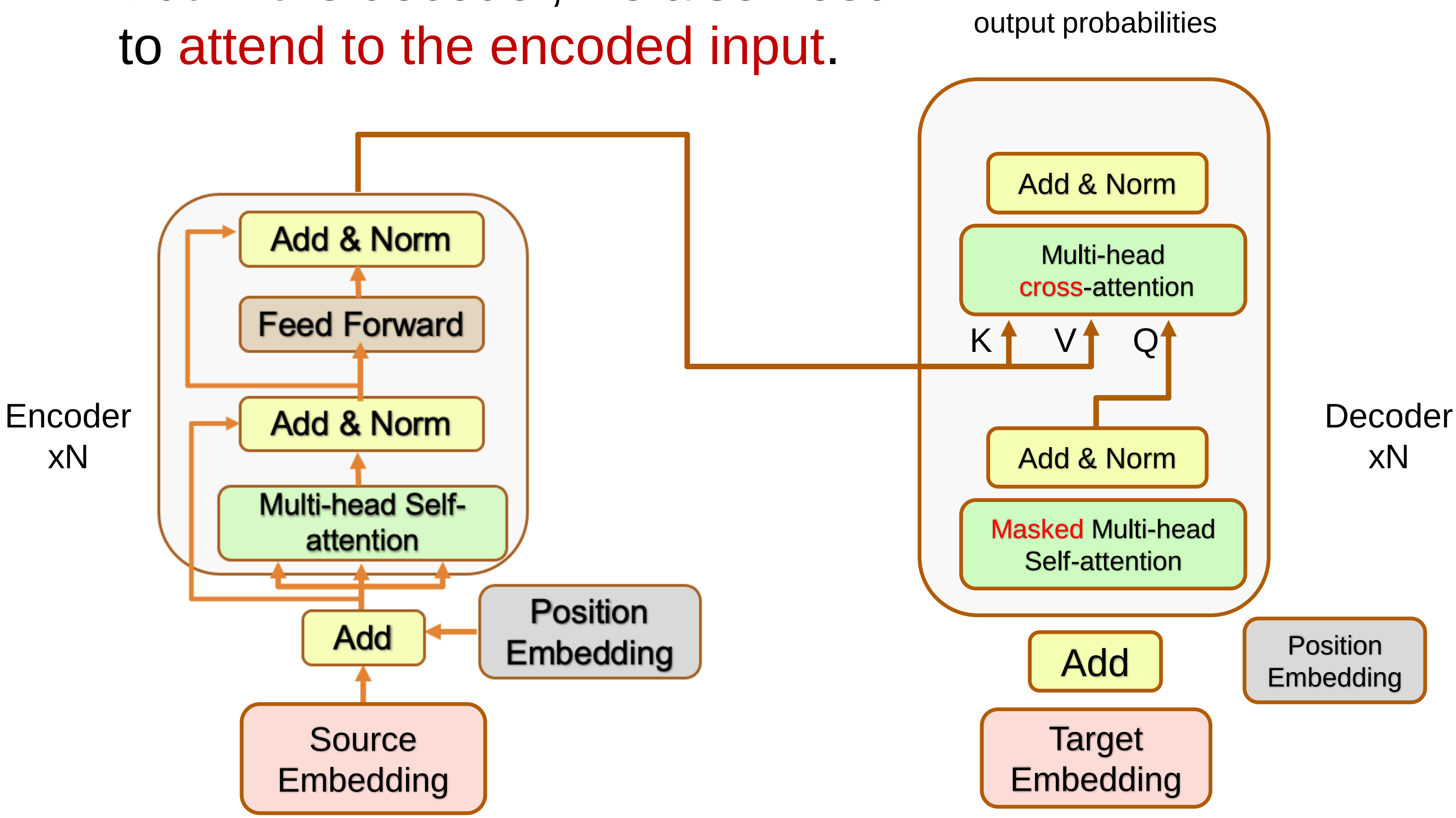
Seq2seq with Transformer

- We ignore the arrows in the decoder for simplicity.



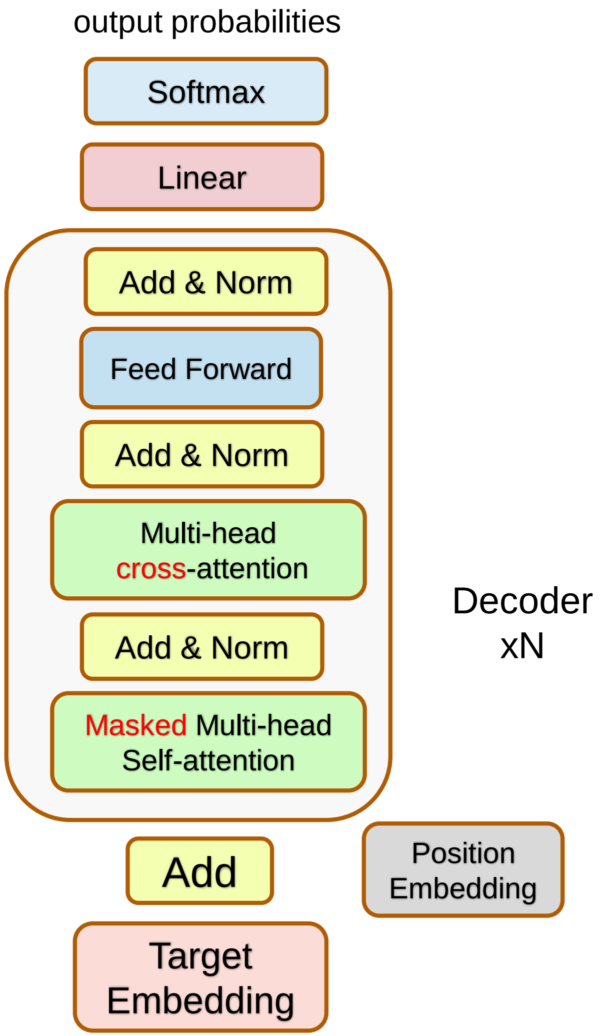
Seq2seq with Transformer

- In self-attention, K/Q/V come from the same sequence.
- But in the decoder, we also need to attend to the encoded input.

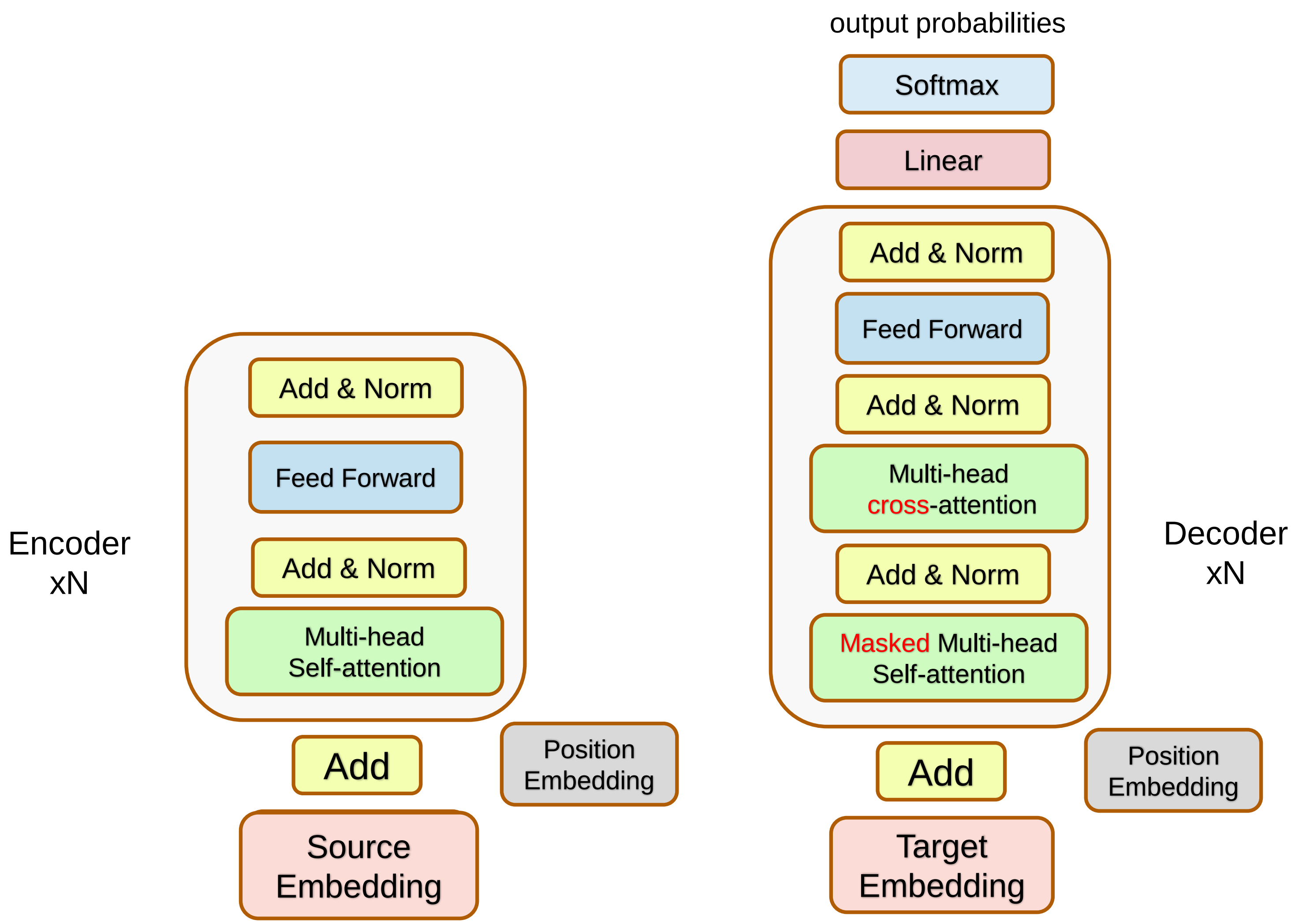


Transformer decoder: finishing touches

- Add a feed forward layer (with residual connections and layer norm)
- Add a final linear layer to project the embeddings into a much longer vector of length vocab size (logits)
- Add a final softmax to generate a probability distribution of next word



Recap of the Transformer Architecture



Learning and Decoding

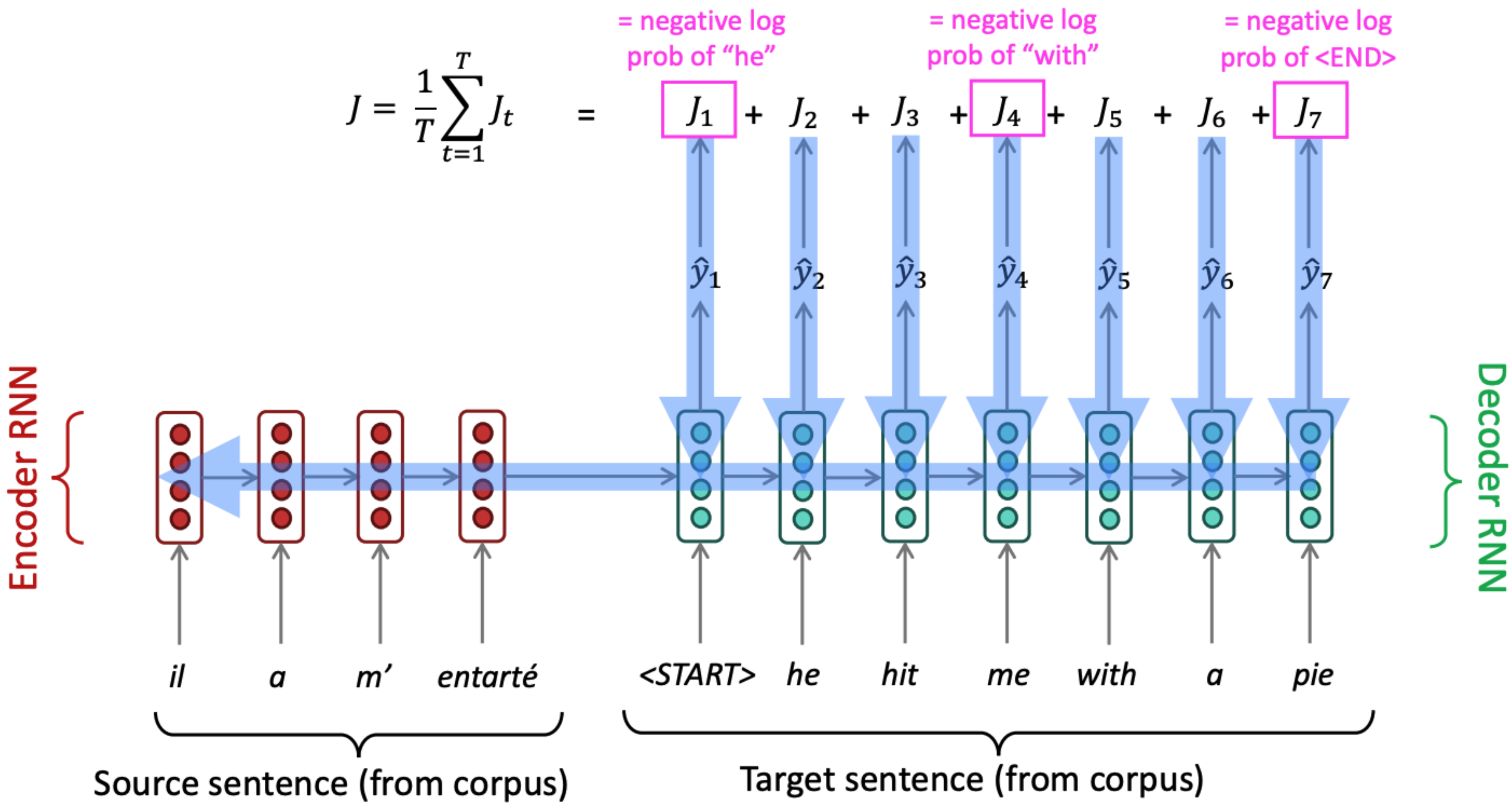
Learning of seq2seq

- The sequence-to-sequence model is an example of a conditional language model
  - "Language model" because the decoder is predicting each word of the target sentence y from left to right
  - "Conditional" because its predictions are conditioned on the source sentence x
- Seq2seq directly calculates $P(y|x)$:

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

- Learning
  - Training data: a parallel corpus (paired input-output sequences)
  - Objective: maximizing the conditional likelihood

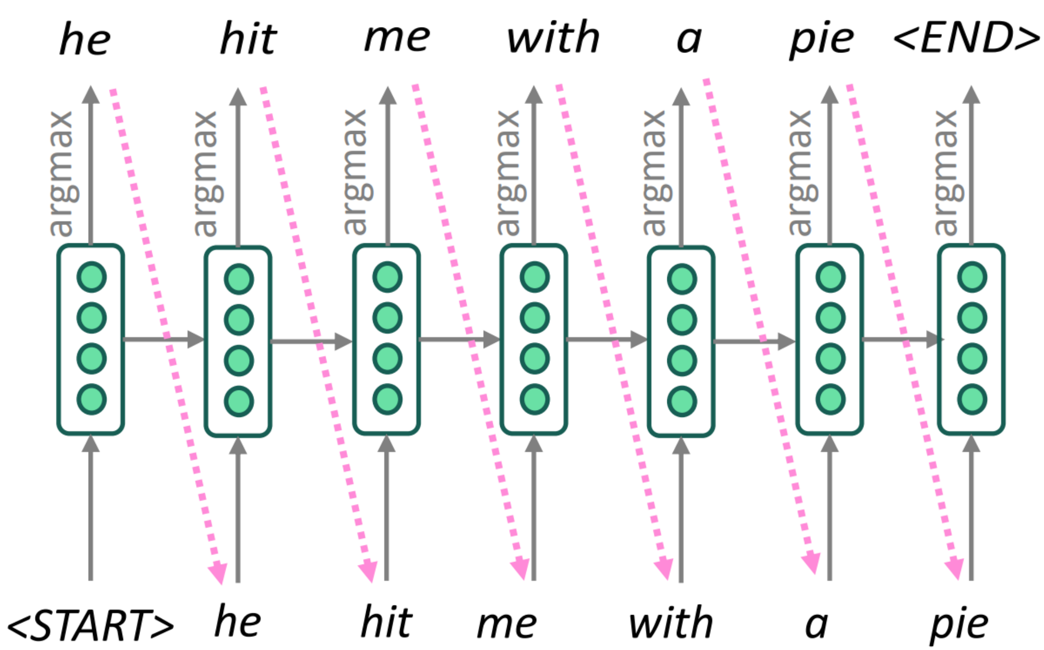
Learning of seq2seq



Seq2seq is optimized as a **single system.** Backpropagation operates “*end-to-end*”.

Greedy decoding

- We saw how to generate (or "decode") the target sentence by taking argmax on each step of the decoder
  - Predict the most probable word at each step



Problems with greedy decoding

- Greedy decoding has no way to undo decisions!
  - Input: *il a m'entarté* *(he hit me with a pie)*
  - → *he* ____
  - → *he hit* ____
  - → *he hit a* ____ *(whoops! no going back now…)*
- How to fix this?

Beam search decoding

- At each step, keep track of the k best partial translations (i.e., hypotheses)
  - k is the beam size (e.g., 5 to 10 in NMT)
- A hypothesis $y_1, \dots, y_t$ has a score which is its log probability:

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

- Beam search is not guaranteed to find optimal solution
- It is even not guaranteed to outperform greedy decoding
  - But it is often better

Beam search decoding: example

Beam size = k = 2.

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

<start>

Calculate prob dist of next word

Beam search decoding: example

Beam size = k = 2.

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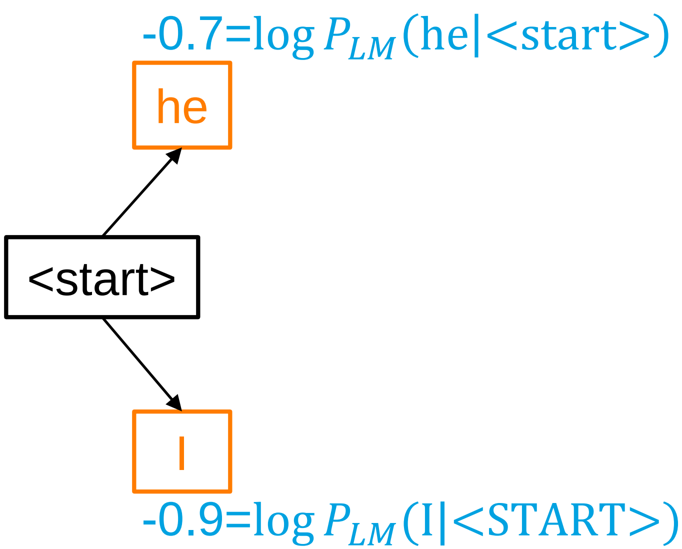

Take top k words

Beam search decoding: example

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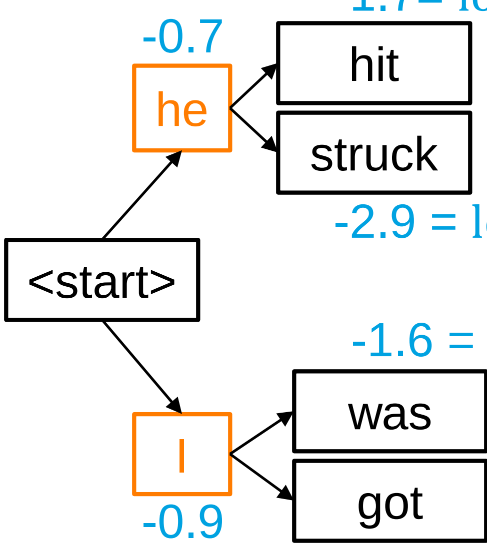

-1.7$= \log P_{LM}(\text{hit}|\text{<start> he}) + -0.7$

-2.9 = $\log P_{LM}(\text{struck}|\text{<start> he}) + -0.7$

-1.6 = $\log P_{LM}(\text{was}|\text{<start> I}) + -0.9$

-1.8 = $\log P_{LM}(\text{got}|\text{<start> I}) + -0.9$

For each of the k hypothesis, find top k next words and calculate scores

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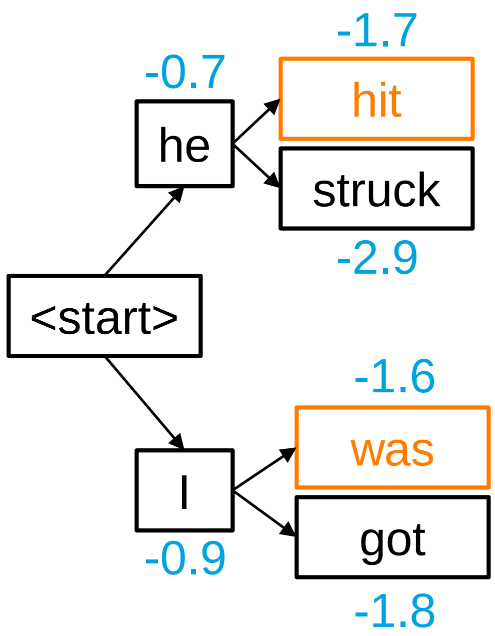

Of these k^2 hypotheses,
just keep k with highest scores

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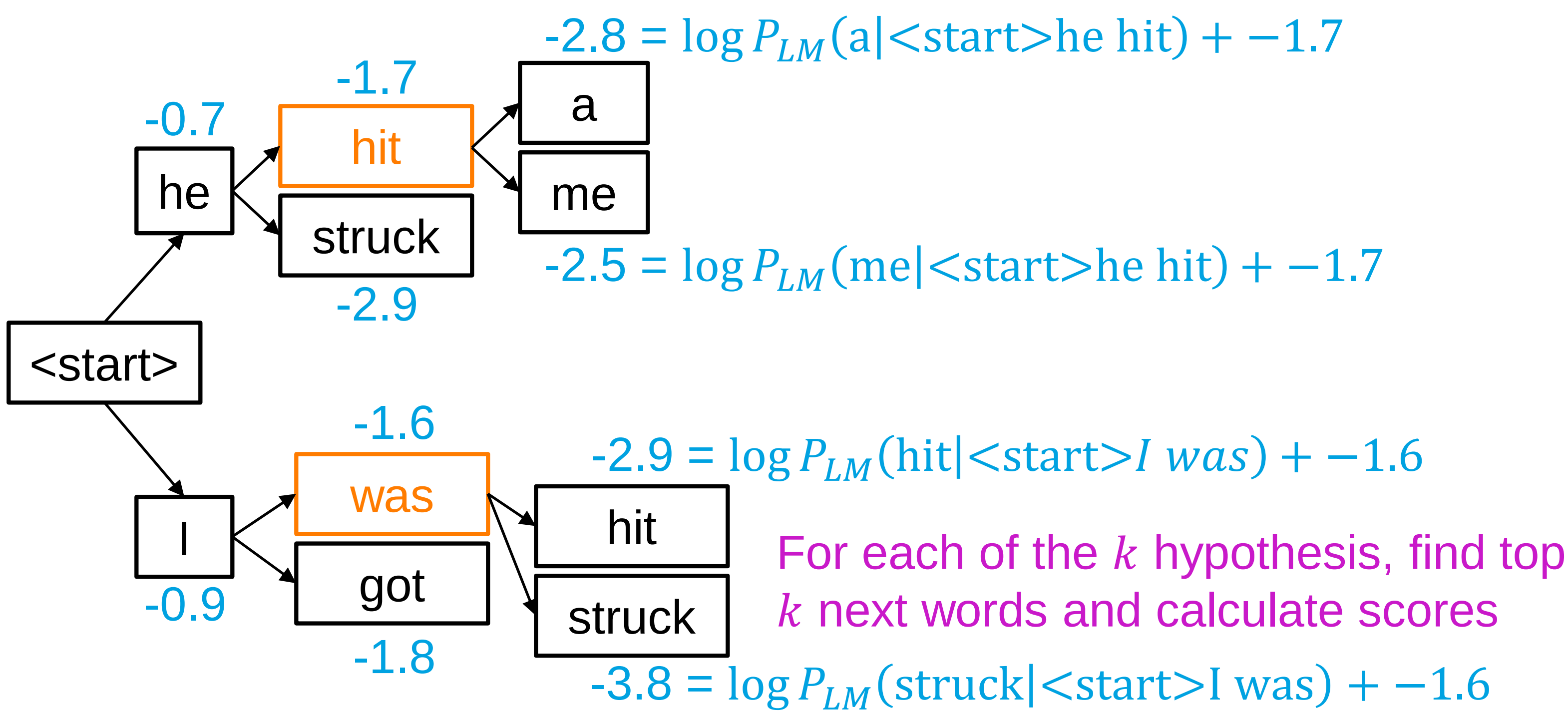

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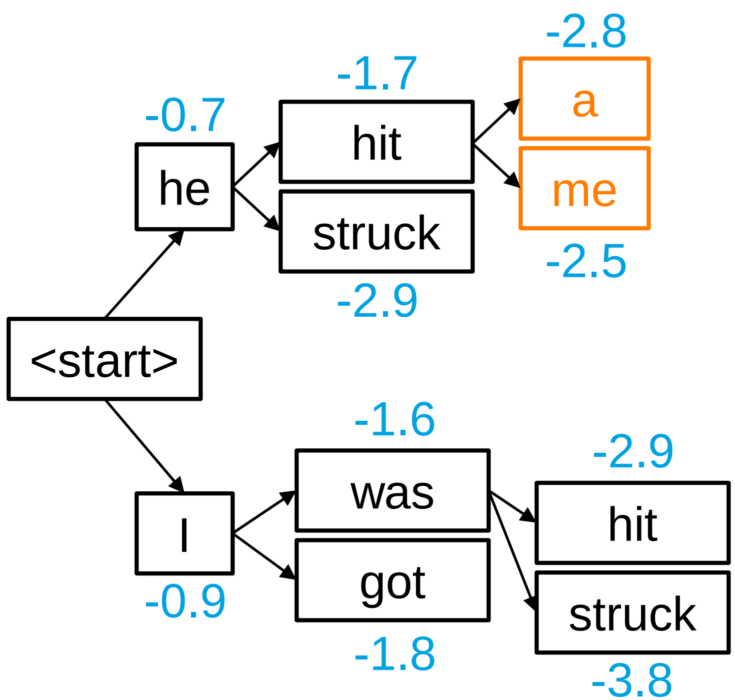

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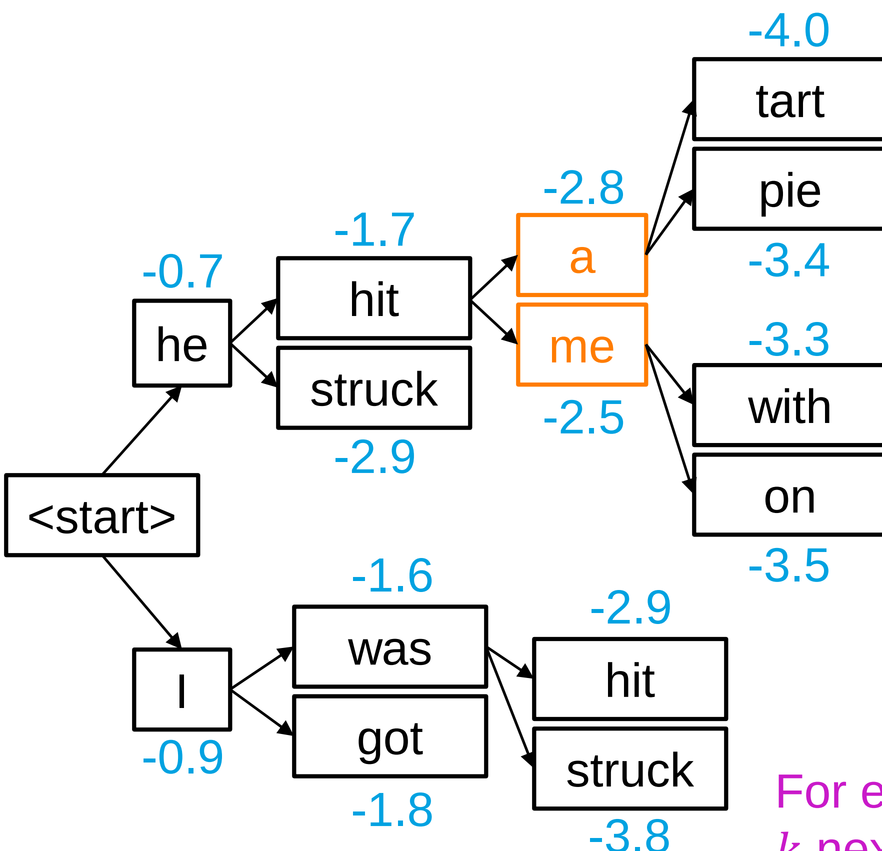

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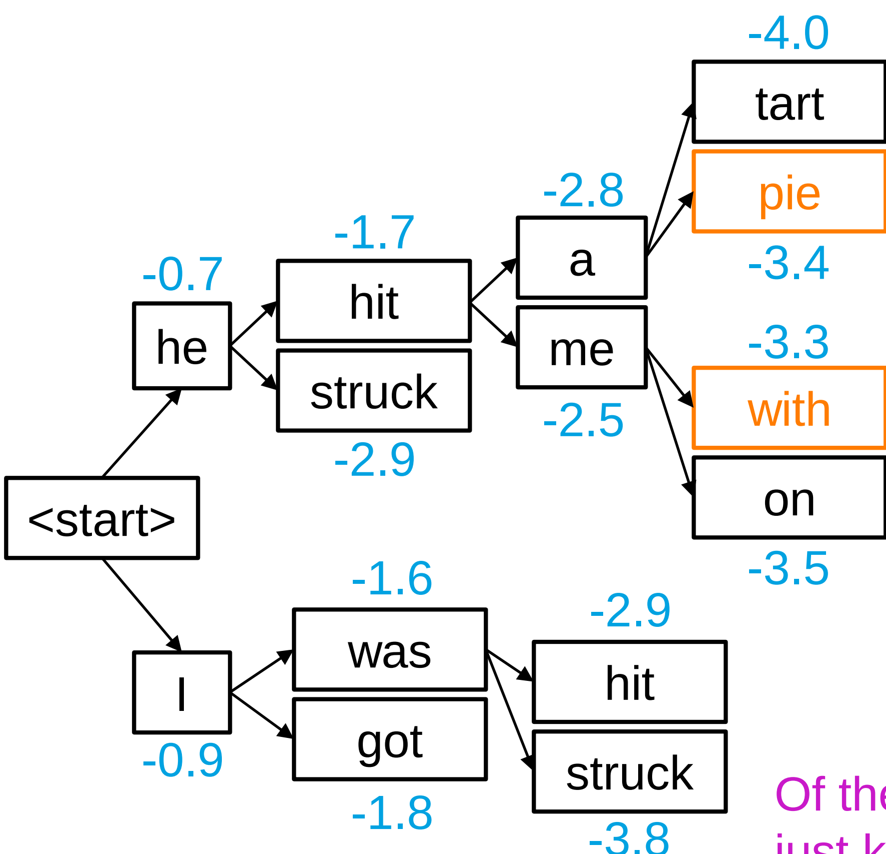

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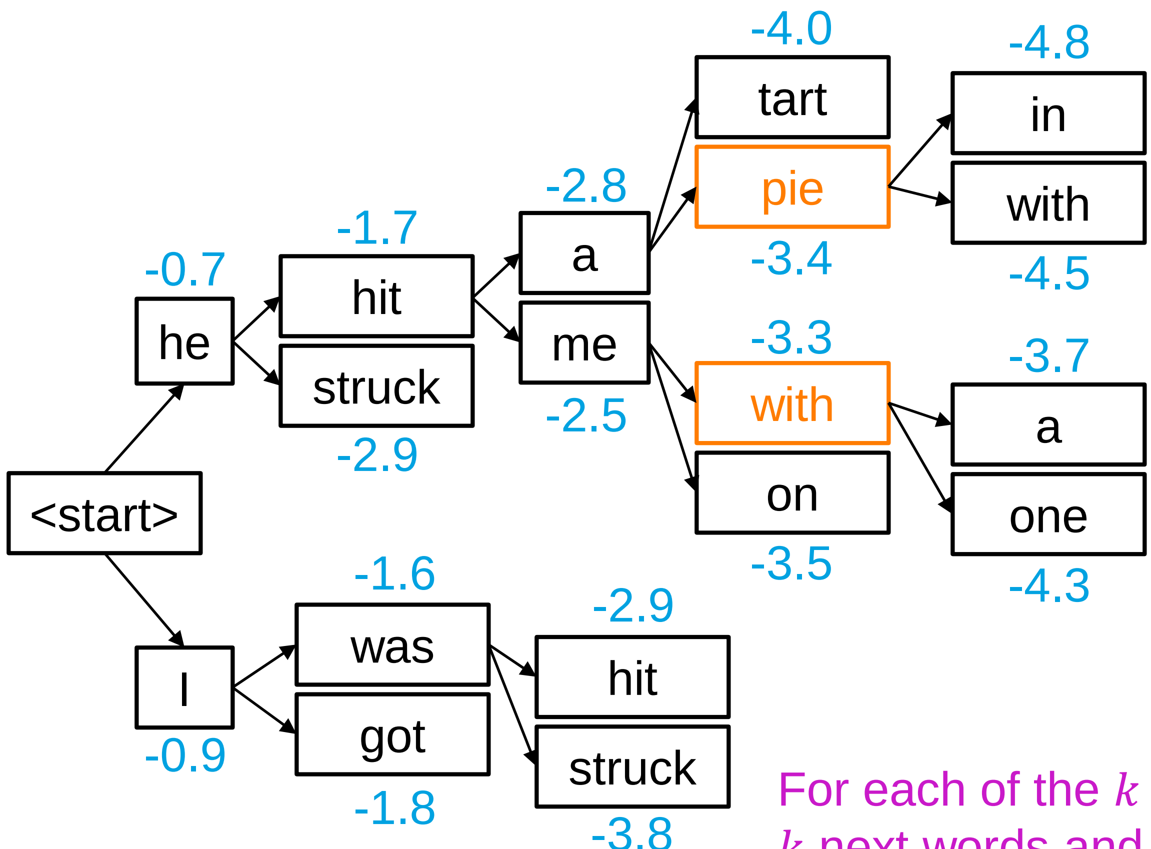

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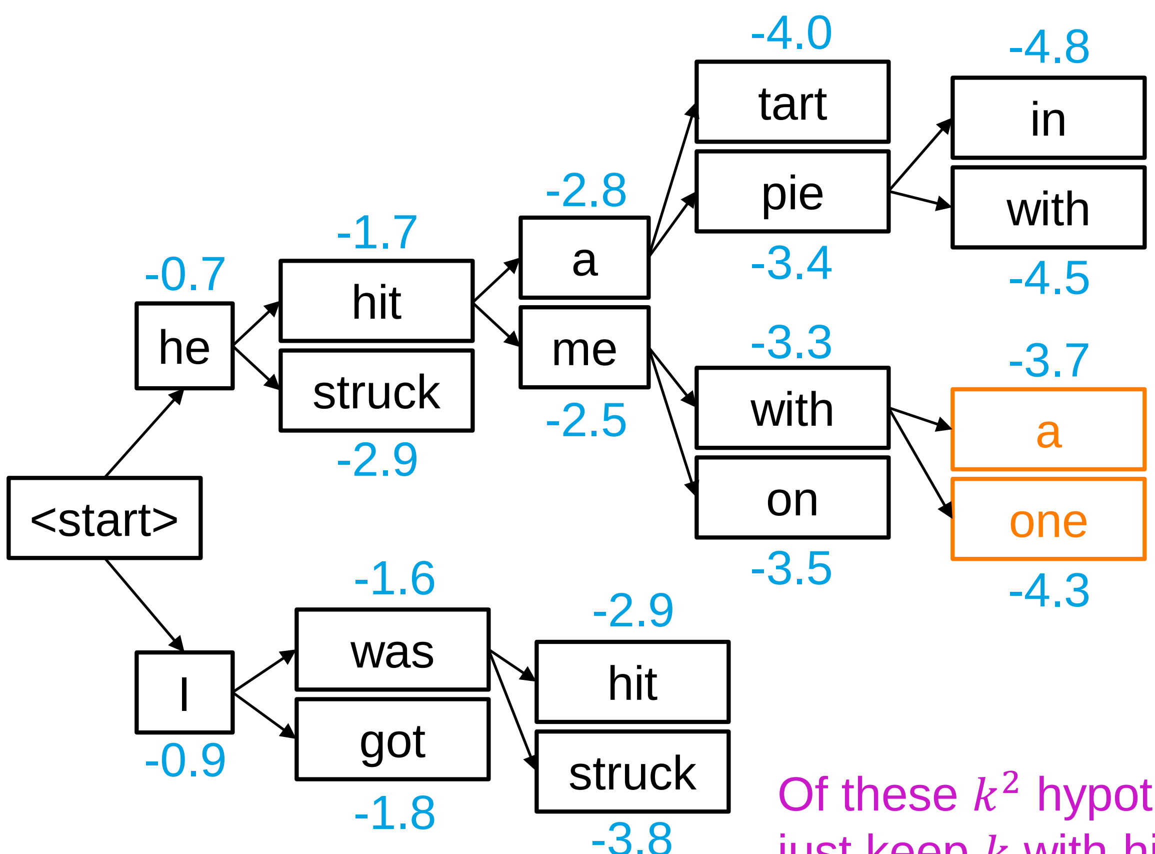

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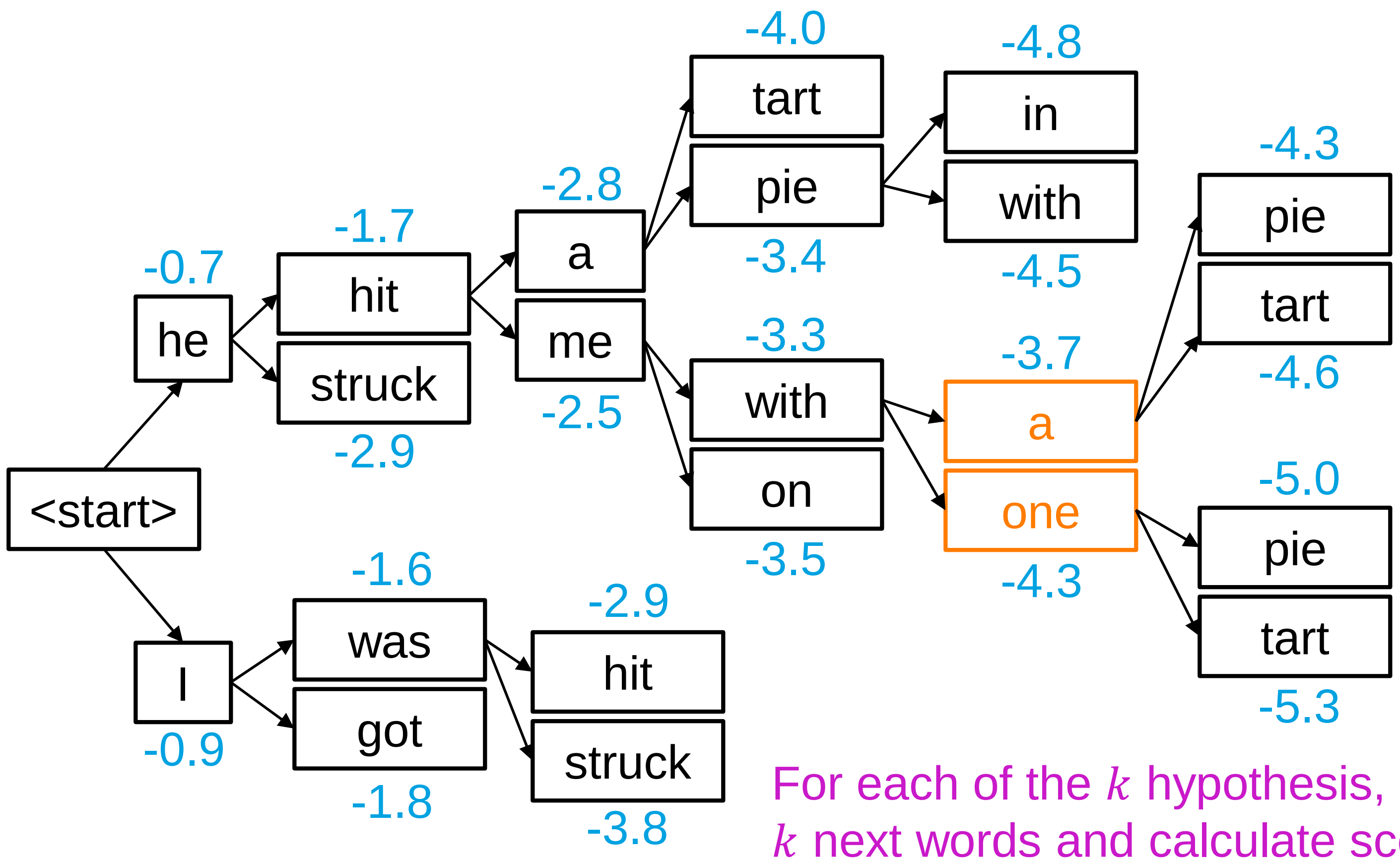

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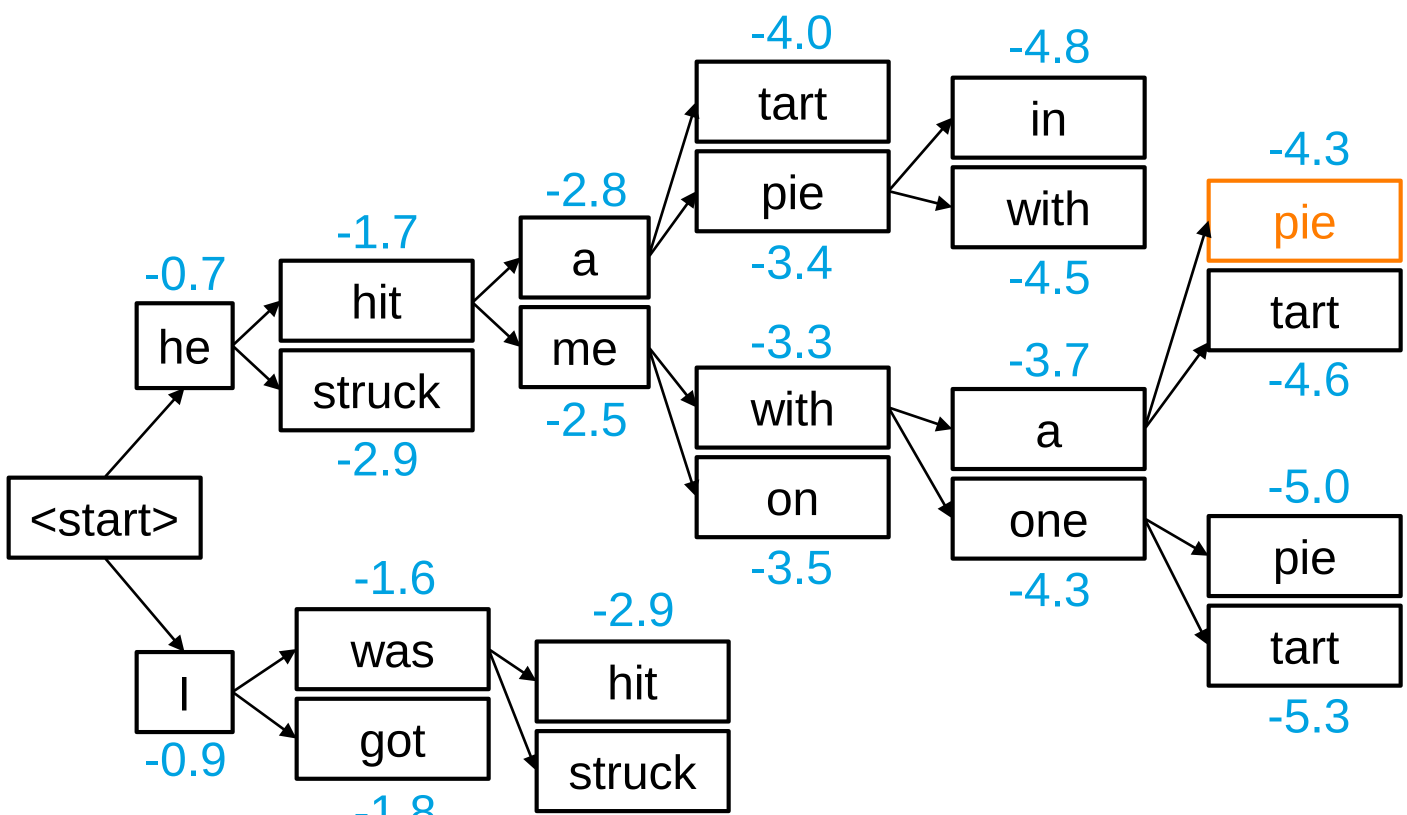

This is the top-scoring hypothesis!

Beam search decoding: example

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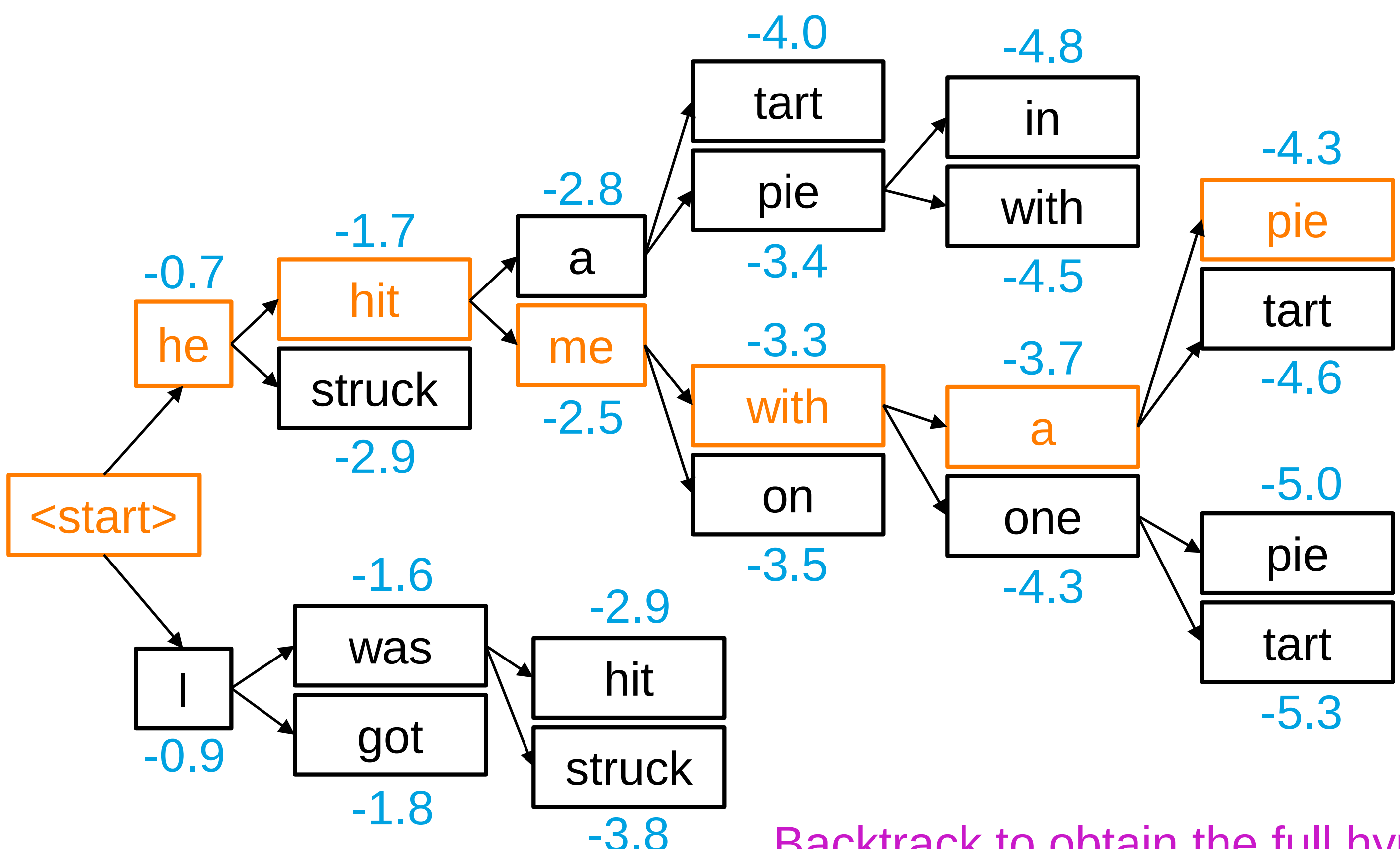


Backtrack to obtain the full hypothesis

Beam search decoding: stopping criterion

- In greedy decoding, usually we decode until the model produces an <END> token
  - For example, "*<START> he hit me with a pie <END>*"
- In beam search decoding, different hypotheses may produce <END> tokens on different timesteps
  - When a hypothesis produces <END>, that hypothesis is complete.
  - Place it aside and continue exploring other hypotheses via beam search.
- Usually we continue beam search until:
  - We reach timestep T, or
  - We have at least n completed hypotheses

T and n are some pre-defined cutoffs

Beam search decoding: finishing up

- With a list of completed hypotheses, how do we select the best one?
- Selecting one with the highest score?

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

  - Problem with this?
  - Longer hypotheses have lower scores
- Fix: Normalize by length. Use this to select the top one:

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

Decoding

- Other desiderata
  - Reduce repetition
    - Penalize generation of already-seen tokens
      - Can also be incorporated into training (unlikelihood objective)
    - Prevent attending to the same words
  - Encourage diversity for certain tasks (e.g., dialog)
    - Sample, instead of being greedy
  - Avoid hallucination (generating things not in the input) for translation, summarization, etc.
    - Multiple causes and solutions

Extensions

Pointer Net / Copy Mechanism

- In some cases, we may wish to copy part of the input to the output
  - Ex: named entities, numbers

Source sentence: Federer suffered a 1-3 defeat to Nadal

Target sentence: Federer a subi une défaite 1-3 contre Nadal

Pointer Net / Copy Mechanism

- In some cases, we may wish to copy part of the input to the output
  - Ex: semantic role labeling as seq2seq

Source sentence:

Tolkien's epic novel The Lord of the Rings was published in 1954-1955 …

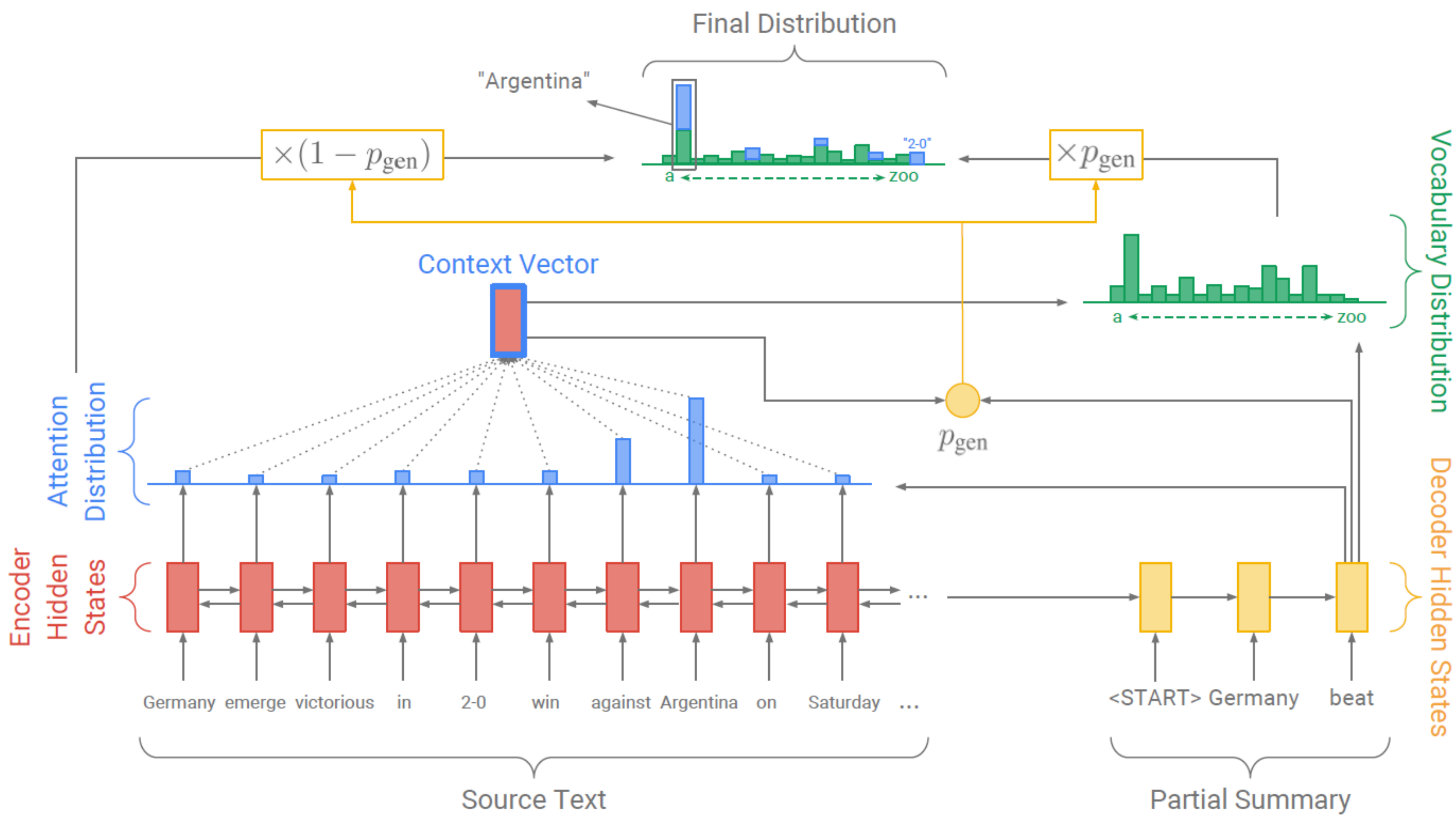
Target output:

Tolkien's epic novel [The Lord of the Rings | *subject*]
[was published | *predicate*] [in 1954-1955 | *temporal*]

Pointer Net / Copy Mechanism

- At each decoding step, calculate a Bernoulli distribution over generation vs. copying and sample from it
  - Generation: the old way of predicting a token
  - Copying: predict a distribution over the input tokens (i.e., a pointer)
    - This is similar to computing the attention distribution

Pointer Net / Copy Mechanism

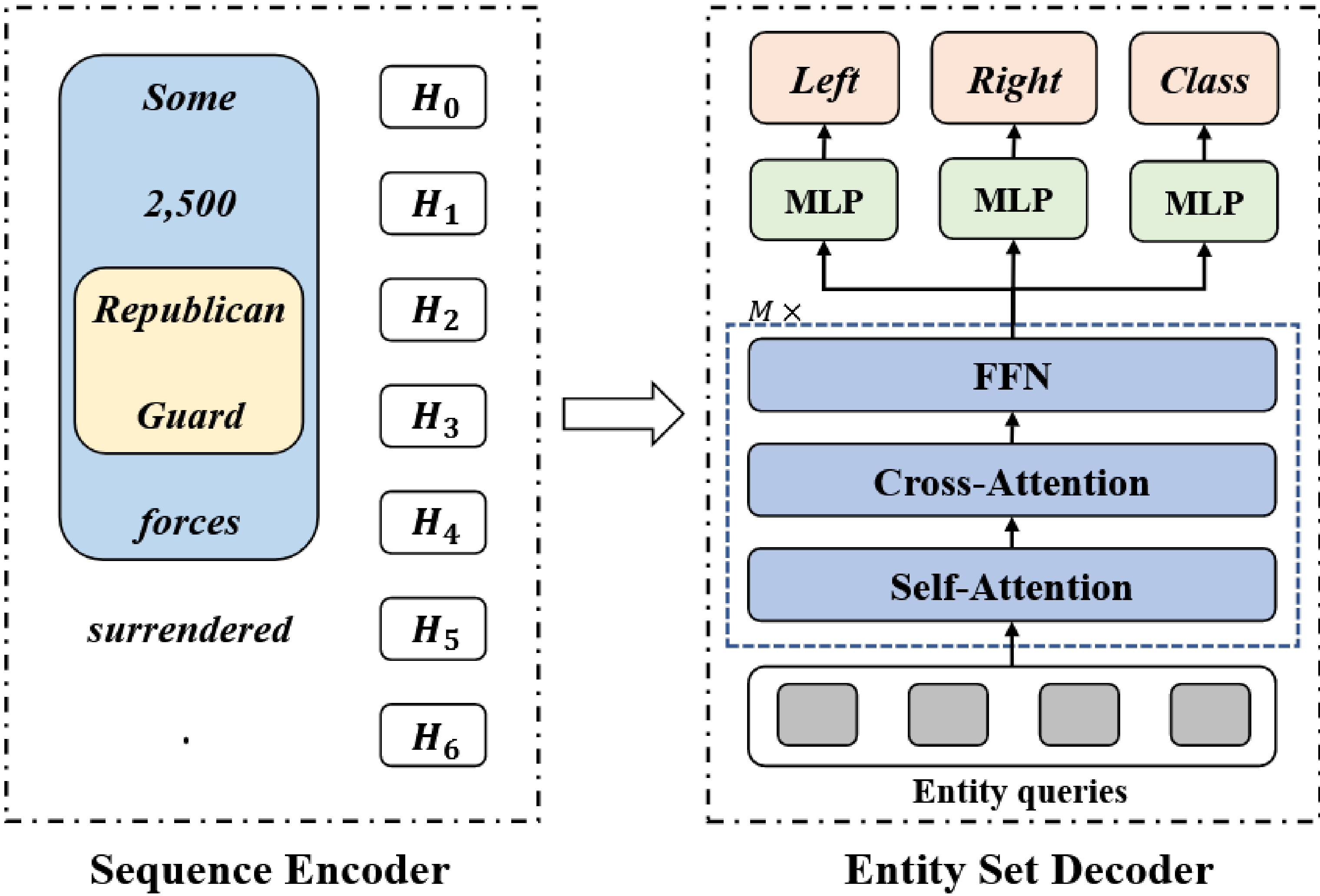


See, et al., "Get To The Point: Summarization with Pointer-Generator Networks", ACL 2017

Extensions of Seq2Seq

- Seq2Set
  - Decoding to a set (e.g., named entities)
  - Still use a Transformer decoder, but the input is a fixed number of "queries"
    - Query vectors are learnable model parameters
    - No position embedding, no mask
    - Simultaneous decoding across all the positions
    - An output can be null, allowing variable set sizes

Extensions of Seq2Seq



Tan, et al., "A Sequence-to-Set Network for Nested Named Entity Recognition", IJCAI 2021

Extensions of Seq2Seq

- X2Seq (requiring an X-encoder)
  - Image captioning
  - Visual question answering
  - Structured data (e.g., table) to text
  - …
- Null2Seq
  - Language modeling!
  - (Unconditional) text generation

Summary

Sequence to Sequence

- Many applications
  - MT, paraphrase, summarization, ...
- Methods: encoder-decoder
  - Recurrent neural network
  - Attention
  - Transformer: cross-attention
- Learning
  - Maximizing conditional likelihood on a parallel corpus
- Decoding
  - Greedy, beam-search
- Extensions
  - Pointer Net / Copy Mechanism
  - Seq2Set, X2Seq, Null2Seq