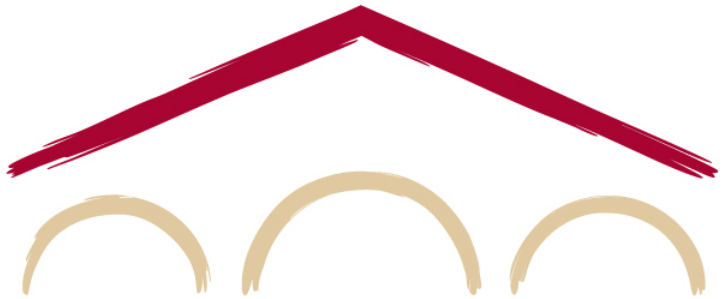
Natural Language Processing with Deep Learning CS224N/Ling284



Christopher Manning

Lecture 7: Machine Translation, Sequence-to-Sequence and Attention

Lecture Plan

<Lecture 7 : p.1~74>
1. Machine Translation (MT)
2. Seq2Seq: major use case = MT
3. Attention: improvement of Seq2Seq

Today we will:

1. Introduce a **new task**: Machine Translation [15 mins], which is a major use-case of
2. A **new neural architecture**: sequence-to-sequence [45 mins], which is improved by
3. A **new neural technique**: attention [20 mins]

- Announcements
  - Assignment 3 is due today – I hope your dependency parsers are parsing text!
  - Assignment 4 out today – covered in this lecture, you get 9 days for it (!), due Thu
    - Get started early! It's bigger and harder than the previous assignments 😰
  - Thursday's lecture about choosing final projects

Section 1: Pre-Neural Machine Translation

Machine Translation

Machine Translation (MT) is the task of translating a sentence *x* from one language (the source language) to a sentence *y* in another language (the target language).

x: *L'homme est né libre, et partout il est dans les fers*

source language X

y: *Man is born free, but everywhere he is in chains*

target language Y

– Rousseau

The early history of MT: 1950s

- Machine translation re
  powerful than high sc
- Foundational work on
  information theory
- MT heavily funded by
  systems doing word s
- Human language is m
  languages!
- Little understanding c
- Problem soon appeare

1 minute video showing 1954 MT:
https://youtu.be/K-HfpsHPmvw

earliest Machine Translation work from 1954
- during Cold War
- translate Russian to English with computers
  - very simple rule based,
  - word lookup dictionary

1990s-2010s: Statistical Machine Translation

- Core idea: Learn a probabilistic model from data
- Suppose we're translating French → English.
- We want to find best English sentence *y*, given French sentence *x*

$$\text{argmax}_y P(y|x)$$

- Use Bayes Rule to break this down into two components to be learned separately:

$$= \text{argmax}_y P(x|y)P(y)$$

$$P(y|x) = \frac{P(y)P(x|y)}{P(x)}$$

(just thinking)
x = given sentence ==> P(x) = 1

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)}$$

A, B = events
$P(A|B)$ = probability of A given B is true
$P(B|A)$ = probability of B given A is true
$P(A), P(B)$ = the independent probabilities of A and B

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.

break down into two components for more tractable
left:
prob of words or phrases being translated between the two languages
without bother of structural word order of languages

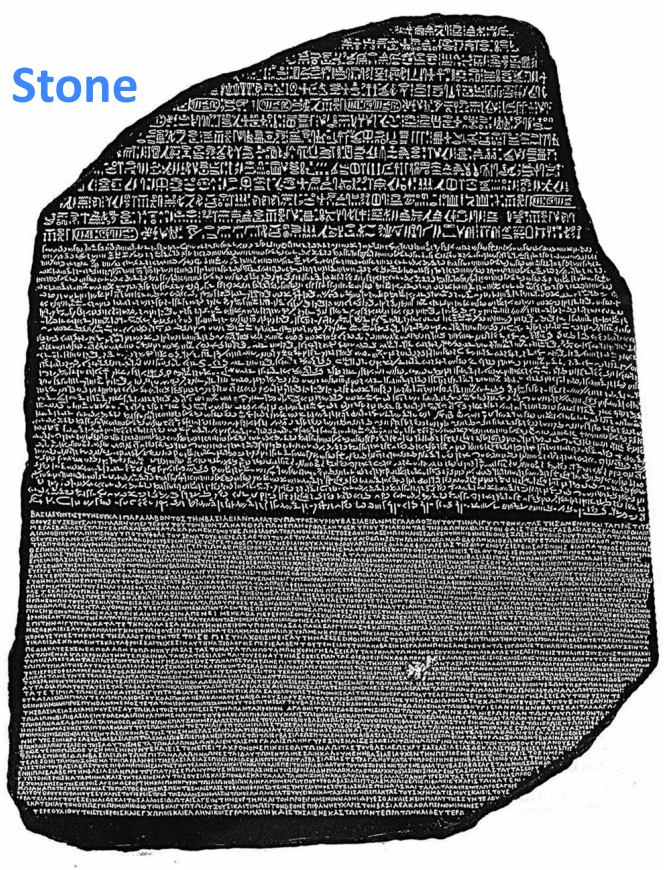
right:
probabilistic language model
make sure whether or not making good model of fluent English sentences
while translation model hopefully puts the right words into them

1990s-2010s: Statistical Machine Translation

- Question: How to learn translation model $P(x|y)$?
- First, need large amount of parallel data
  (e.g., pairs of human-translated French/English sentences)

in modern time, parallel data is produced in large quantities
(ex)
European Union - European languages
French - French/English
Hon Kong: English/Chinese

The Rosetta Stone



Ancient Egyptian

Demotic

Ancient Greek

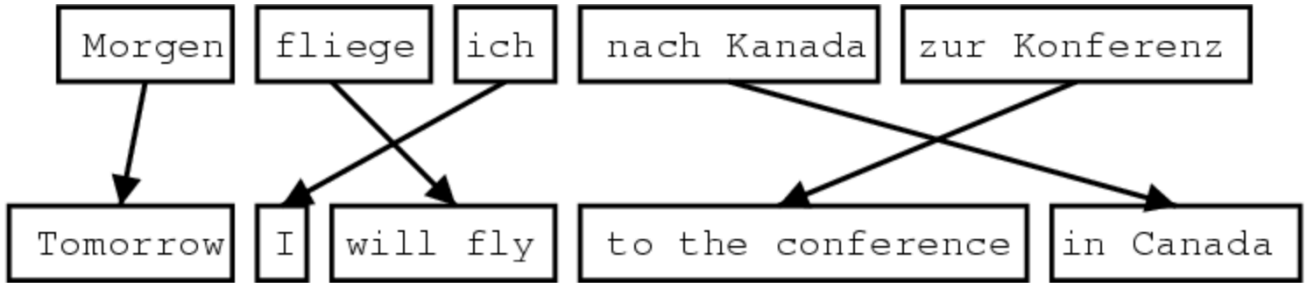
Learning alignment for SMT

- Question: How to learn translation model $P(x|y)$ from the parallel corpus?

- Break it down further: Introduce latent *a* variable into the model: $P(x, a|y)$

  where *a* is the alignment, i.e. word-level correspondence between source sentence *x* and target sentence *y*

alignment
can have prob of pieces of how likely a word or a short phrase is translated in a particular way



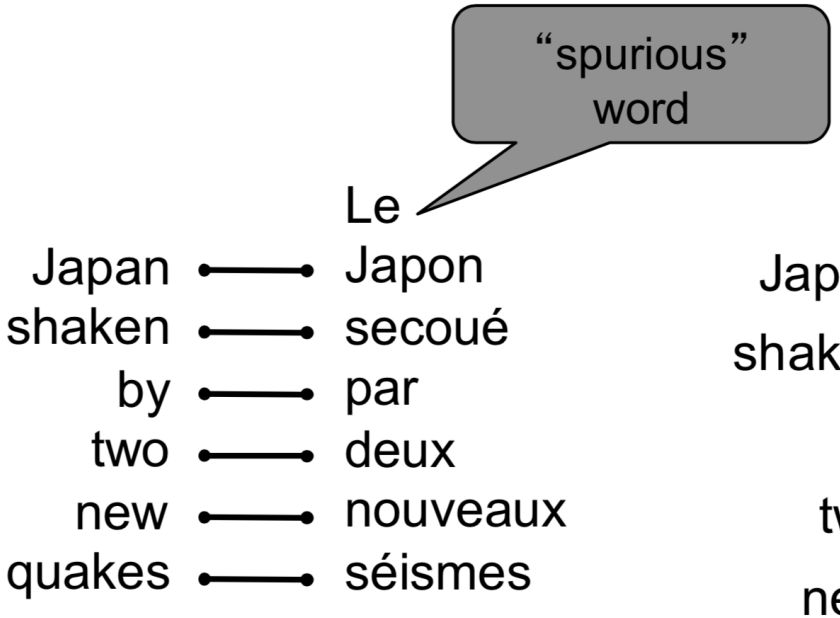
What is alignment?

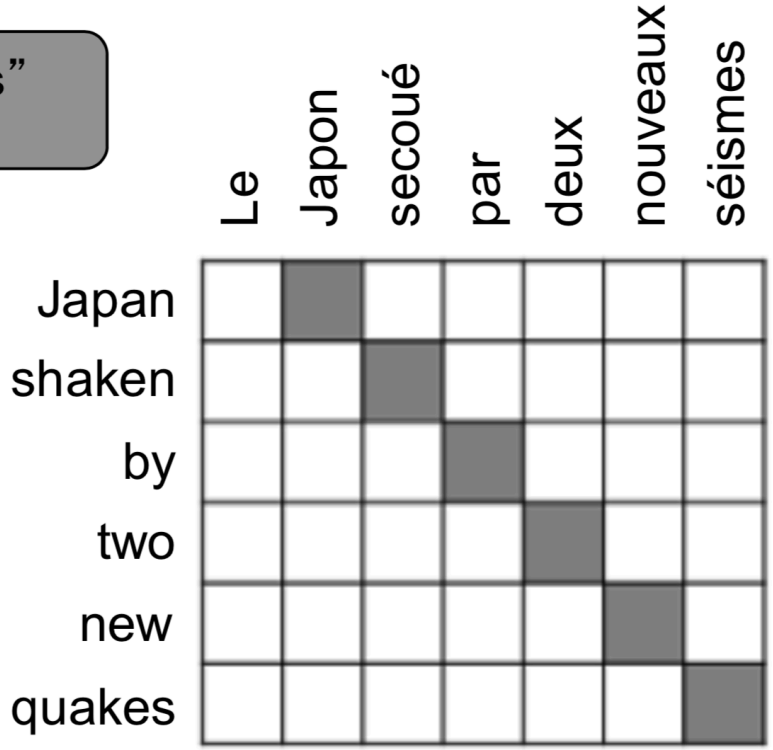
Alignment is the correspondence between particular words in the translated sentence pair.

- Typological differences between languages lead to complicated alignments!
- Note: Some words have no counterpart

Alignment:
capturing grammatical difference between languages
different order (S V O orders)
==> find every possibility of how words can
align between languages

not translation in 'the' when French into english



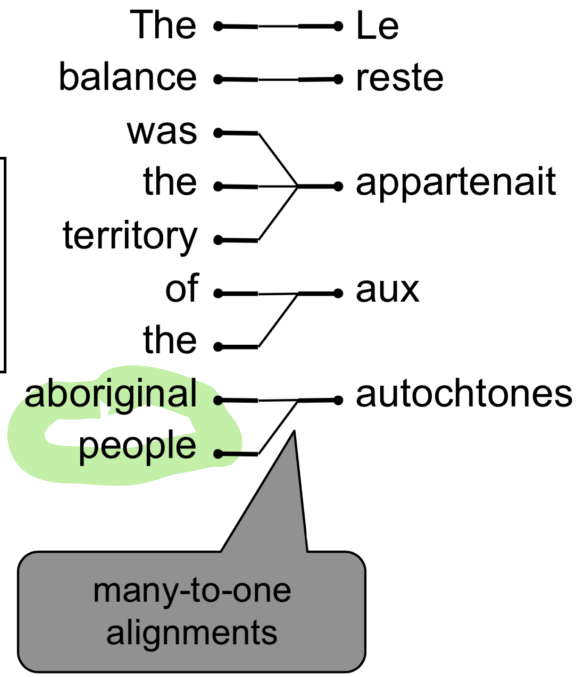


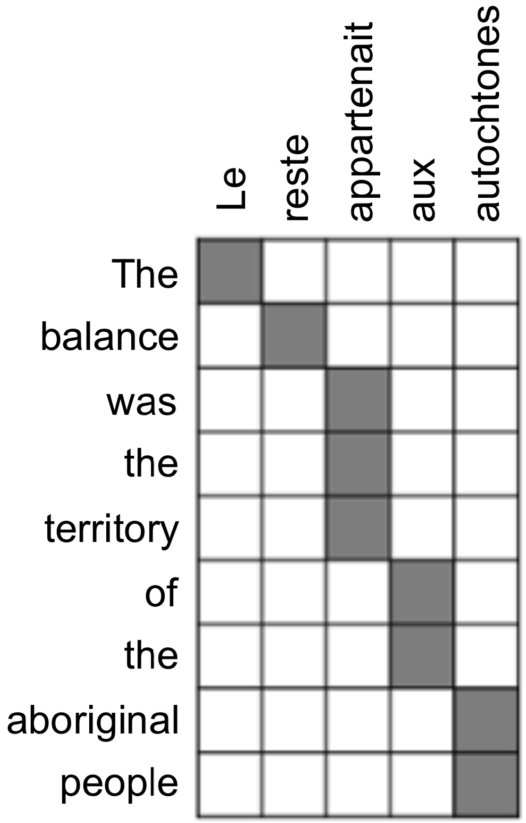
Examples from: "The Mathematics of Statistical Machine Translation: Parameter Estimation", Brown et al, 1993. http://www.aclweb.org/anthology/J93-2003

Alignment is complex

Alignment can be many-to-one

translated as 'Aboriginal people' as multiple words





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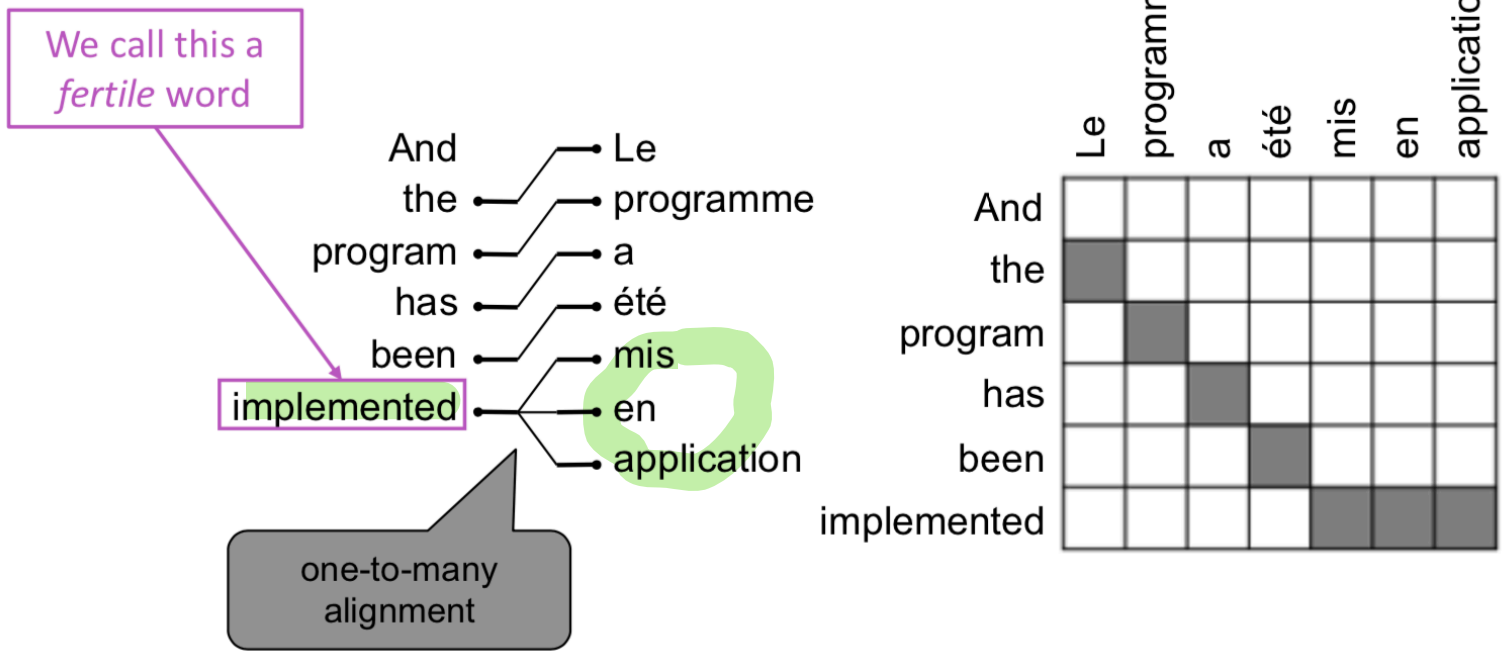
Alignment is complex

Alignment can be one-to-many

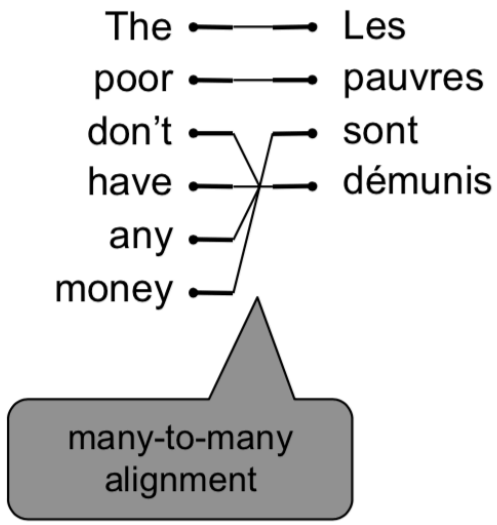


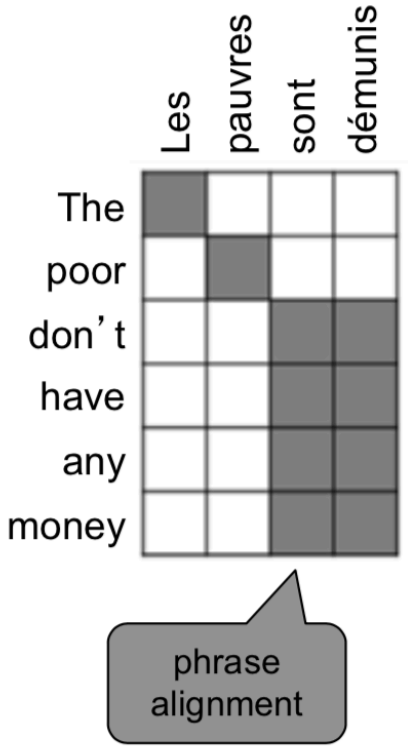
Examples from: "The Mathematics of Statistical Machine Translation: Parameter Estimation", Brown et al, 1993. http://www.aclweb.org/anthology/J93-2003

Alignment is complex

Alignment can be many-to-many (phrase-level)

more complicated
don't beak down and translate each other well
--> this alignment problem can happen within in same language (Eng to Eng)





Examples from: "The Mathematics of Statistical Machine Translation: Parameter Estimation", Brown et al, 1993. http://www.aclweb.org/anthology/J93-2003

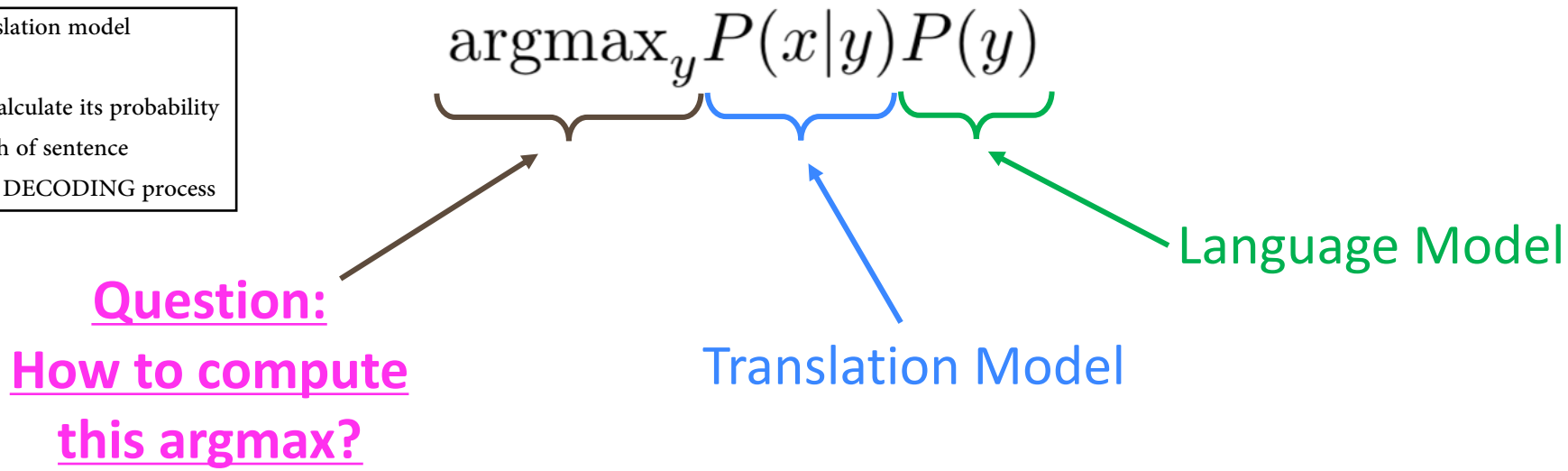
Learning alignment for SMT

- We learn $P(x, a|y)$ as a combination of many factors, including:
  - Probability of particular words aligning (also depends on position in sent)
  - Probability of particular words having a particular fertility (number of corresponding words)
  - etc.
- Alignments *a* are **latent variables**: They aren't explicitly specified in the data!
  - Require the use of special learning algorithms (like Expectation-Maximization) for learning the parameters of distributions with latent variables
    - In older days, we used to do a lot of that in CS 224N, but now see CS 228!

want to learn alignments:
if starts with parallel sentences --> can see how often words/phrases co-occur in parallel sentences
==> figure out what are good ALIGNMENTS
BUT alignments: categorical (not probabilistic) latent variables --> need algorithms for learning (ex: Expectation-Maximization algorithm)

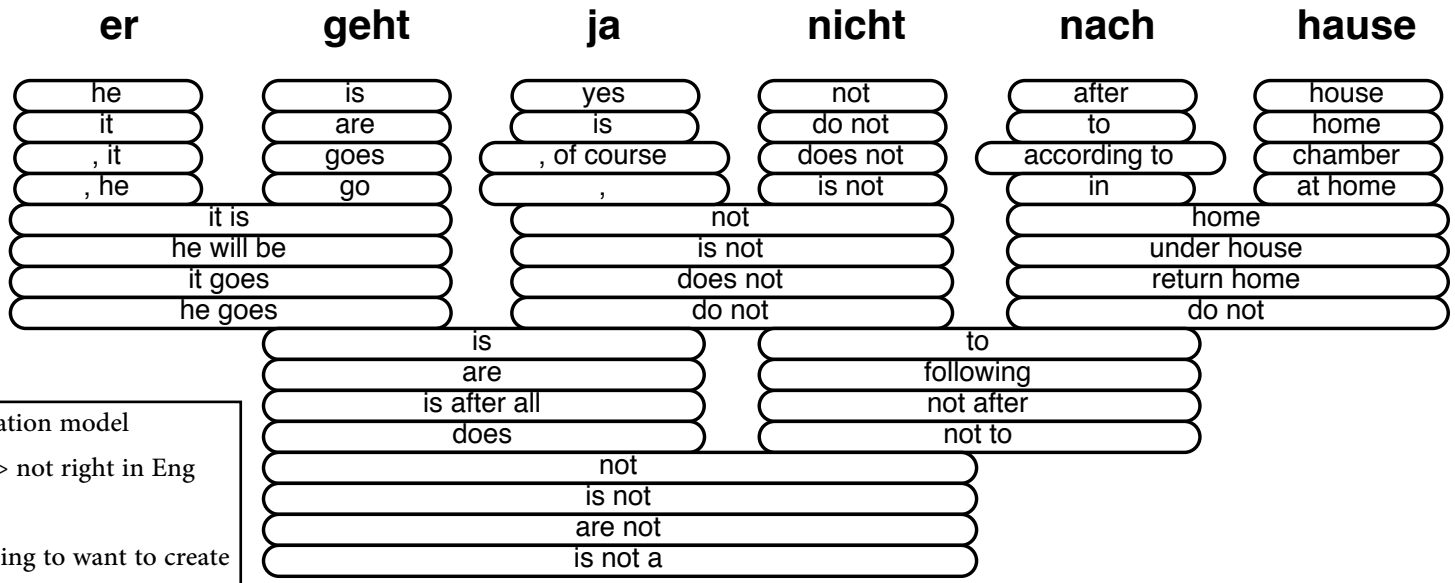
Decoding for SMT

want to pick out most likely translation model
(argmax)
enumerate every possible y and calculate its probability
--> BUT exponential in the length of sentence
==> need a way to break down = DECODING process



- We could enumerate every possible *y* and calculate the probability? → Too expensive!
- Answer: Impose strong independence assumptions in model, use dynamic programming for globally optimal solutions (e.g. Viterbi algorithm).
- This process is called *decoding*

Decoding for SMT



German to English based on translation model

second position verb in German --> not right in Eng

==> need rearrangement

LEGO pieces out of which we're going to want to create the translation

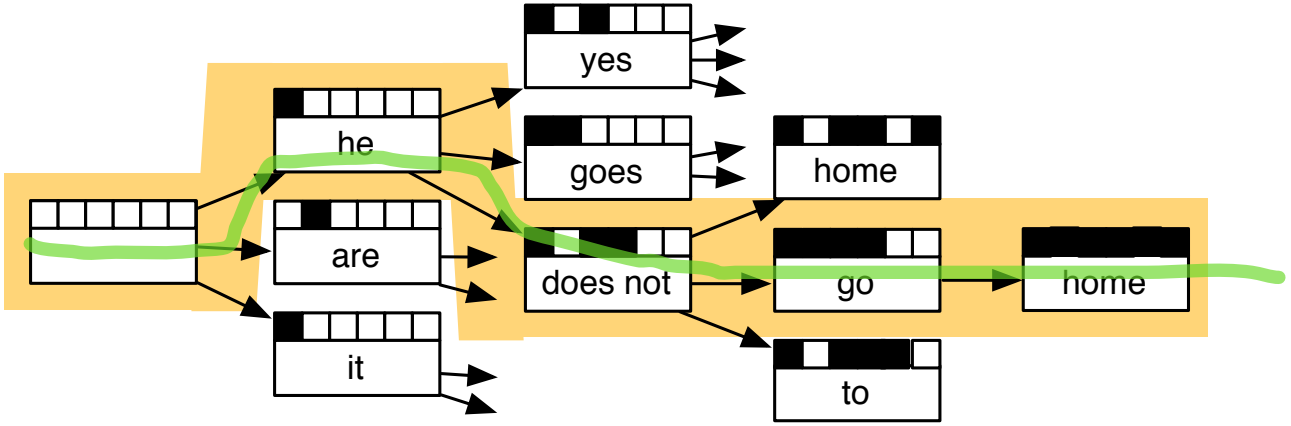
==> gernerate the translation piece by piece

start with empty translation

use one of these LEGO pieces

--> search process ==> guided by language model, the start of sentence becomes 'he'

--> various probabilities and prune, and finally can get the likely continuation and prune



Source: "Statistical Machine Translation", Chapter 6, Koehn, 2009.
https://www.cambridge.org/core/books/statistical-machine-translation/94EADF9F680558E13BE759997553CDE5

1990s-2010s: Statistical Machine Translation

- SMT was a huge research field
- The best systems were extremely complex
  - Hundreds of important details we haven't mentioned here
  - 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
    - Like tables of equivalent phrases
  - Lots of human effort to maintain
    - Repeated effort for each language pair!

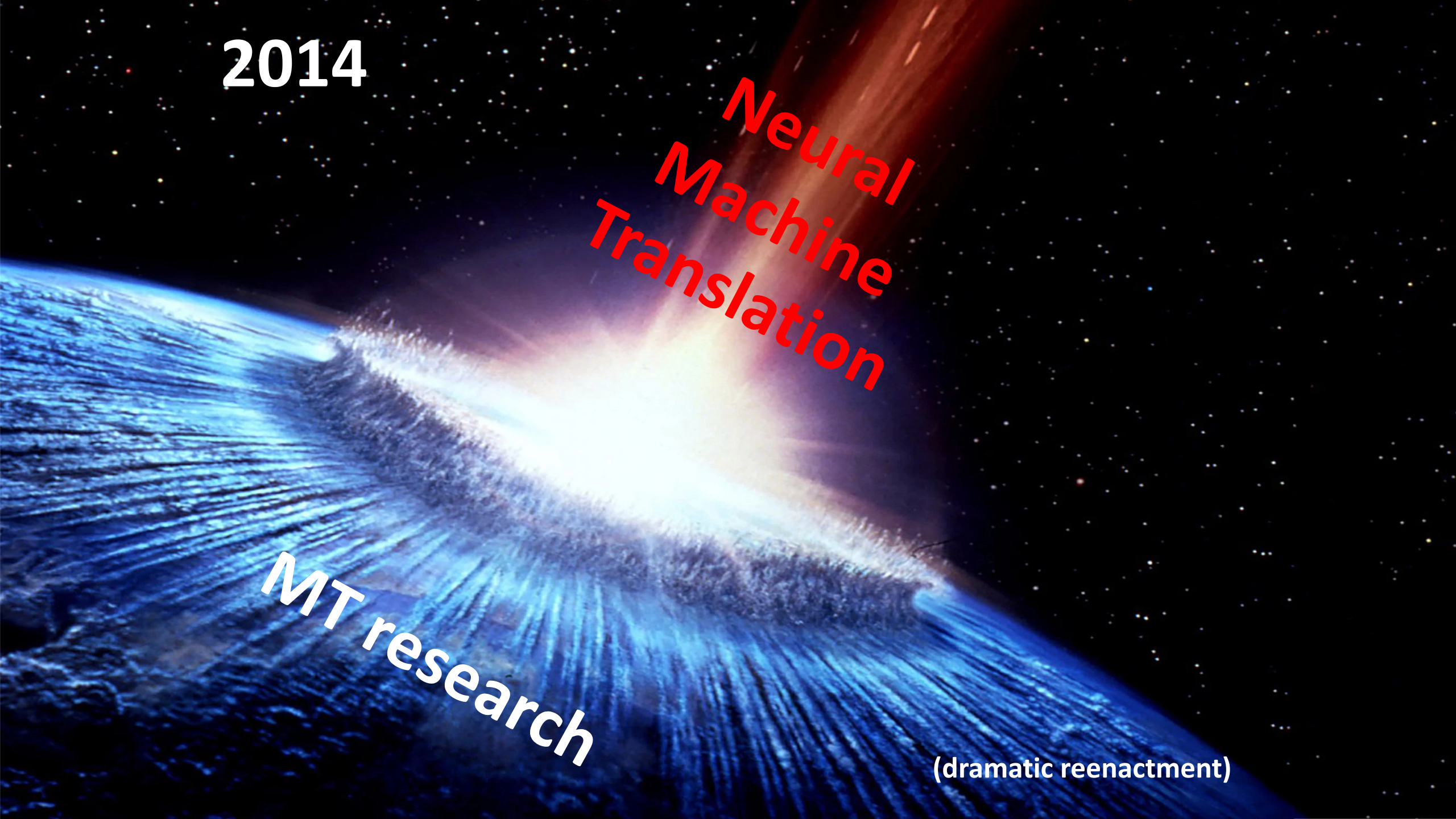
1997~2013: SMT was a huge research field
- problem: complex
- BUT successfully solved

mid 2000s: Google Translation launched

Section 2: Neural Machine Translation

2014

(dramatic reenactment)


2014
Neural
Machine
Translation
MT research
(dramatic reenactment)

What is Neural Machine Translation?

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

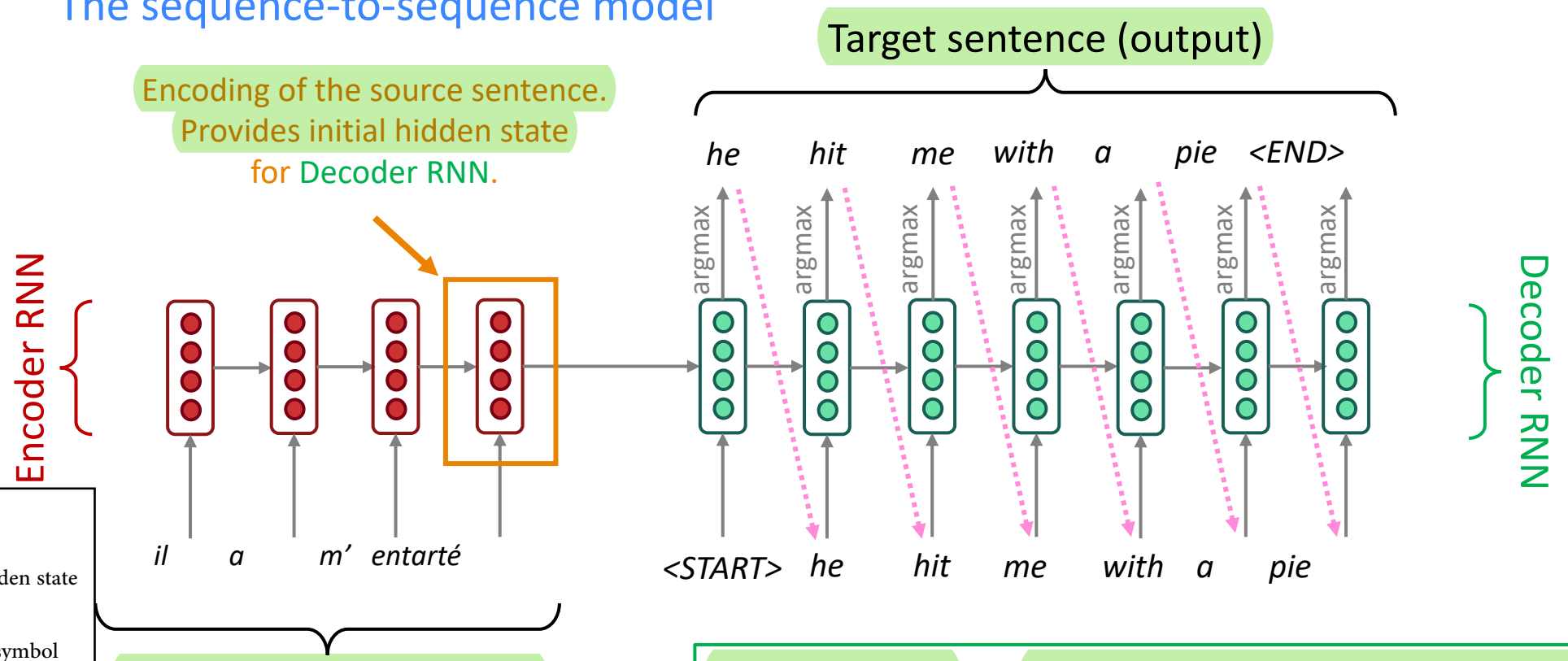
- The neural network architecture is called a sequence-to-sequence model (aka seq2seq) and it involves *two* RNNs

one very large NN to do complete end-to-end
translation = Seq2Seq
train NN model end-to-end to parallel sentences

(vs)
old-fashioned SMT had lots of separate components

Neural Machine Translation (NMT)

The sequence-to-sequence model



<Decoder RNN>
generates a target sentence
conditioned on the final hidden state
of the Encoder RNN
start with the input of start symbol
- LSTM generation: copy that down as the next input. run the next step
LSTM generating another word
--> generating the next sentence
(translated sentence)

==> Decoder RNN: Language Model
- that teacher forces and predict
next sentences

Encoder RNN produces an encoding of the source sentence.

Decoder RNN is a Language Model that generates target sentence, *conditioned on encoding*.

Note: This diagram shows **test time** behavior: decoder output is fed in as next step's input

Sequence-to-sequence is versatile!

- Sequence-to-sequence is useful for *more than just MT*

- Many NLP tasks can be phrased as sequence-to-sequence:
  - Summarization (long text → short text)
  - Dialogue (previous utterances → next utterance)
  - Parsing (input text → output parse as sequence)
  - Code generation (natural language → Python code)

seq2seq is used for many other NLP tasks
(ex) Parsing (dependency parser etc.)

Neural Machine Translation (NMT)

- The sequence-to-sequence model is an example of a **Conditional Language Model**
  - **Language Model** because the decoder is predicting the next word of the target sentence *y*
  - **Conditional** because its predictions are *also* conditioned on the source sentence *x*

- NMT directly calculates $P(y|x)$:

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

Probability of next target word, given target words so far and source sentence *x*

- **Question**: How to train a NMT system?
- **Answer**: Get a big parallel corpus…

transferring information about source sentence from encoder to trigger what the decoder should do
feed in a hidden state as the initial hidden state to Decoder
feed something in as the initial input to the decoder

during word by word generation,
predict target sentence based on
1) previous words, and 2) each time on source x
==> give more information about what's generated sentence should be like [perplexities form]

take batches of source sentences & target sentences

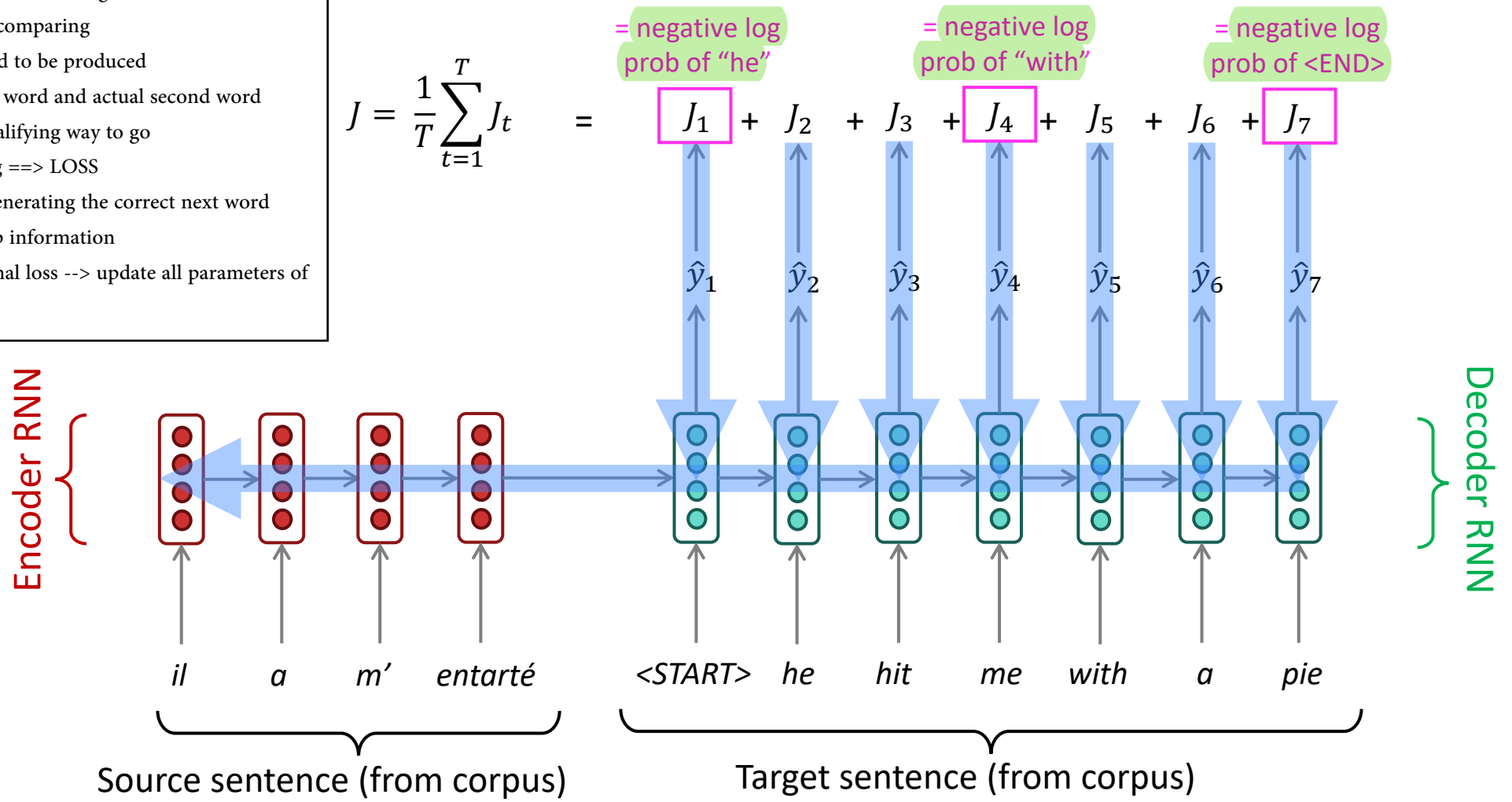
(process)

1. encode the source sentence with Encoder LSTM
2. feed its final hidden state into a target LSTM
3. train word by word by comparing
   - what's most likely word to be produced
   - (vs.) what's actual first word and actual second word

translation is the most qualifying way to go

4. extent that going wrong ==> LOSS
   - negative log prob of generating the correct next word
   - loss--> gives back prop information
5. back Prop: start with final loss --> update all parameters of Decoder and Encoder

Machine Translation system



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

Multi-layer RNNs

- RNNs are already "deep" on one dimension (they unroll over many timesteps)

- We can also make them "deep" in another dimension by applying multiple RNNs – this is a multi-layer RNN.

- This allows the network to compute more complex representations
  - The lower RNNs should compute lower-level features and the higher RNNs should compute higher-level features.

- Multi-layer RNNs are also called *stacked RNNs*.

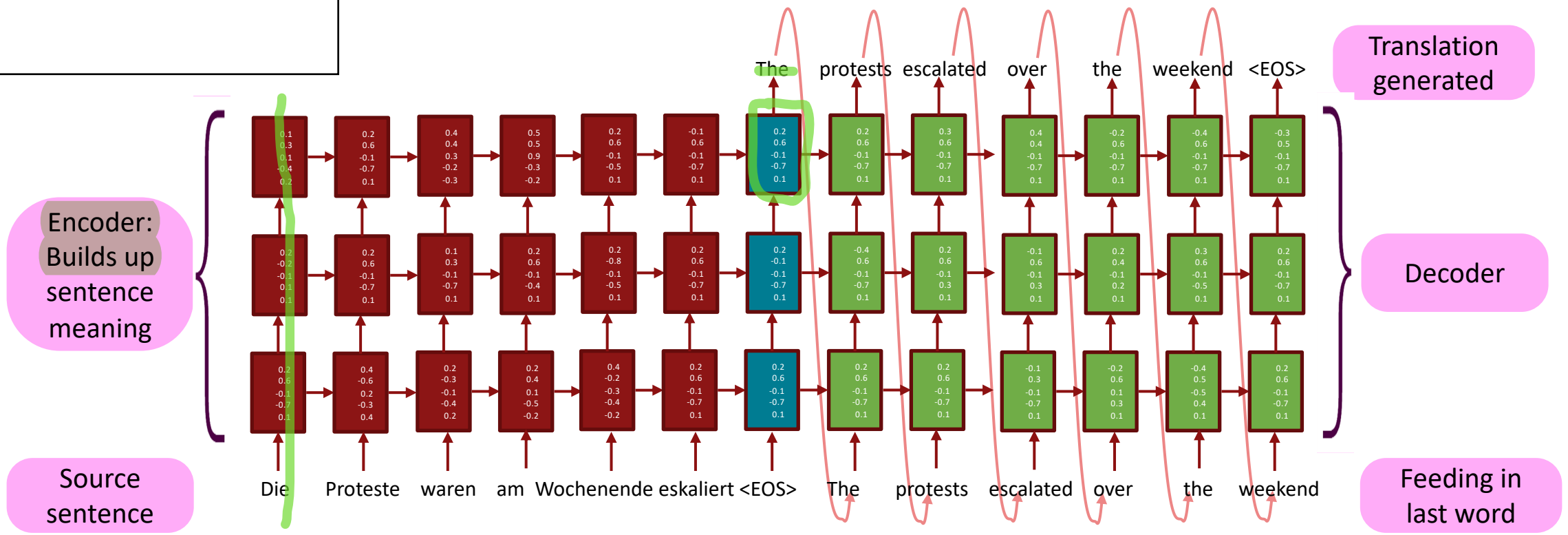
<Multi-layer RNN>: more POWERFUL than one layer
- multi-layer RNN = Stacked RNN
(ex)
1-layer LSTM with 2,000 hidden state
(vs.) 4-layers LSTM with 500 hidden state each
--> looks same because of having same parameters BUT that's not true

Multi-layer deep encoder-decoder machine translation net

[Sutskever et al. 2014; Luong et al. 2015]

The hidden states from RNN layer *i* are the inputs to RNN layer *i*+1

multi-layer stacked LSTM NMT performs powerfully



Conditioning = Bottleneck

Multi-layer RNNs in practice

- High-performing RNNs are usually multi-layer (but aren't as deep as convolutional or feed-forward networks)

- For example: In a 2017 paper, Britz et al. find that for Neural Machine Translation, 2 to 4 layers is best for the encoder RNN, and 4 layers is best for the decoder RNN
  - Often 2 layers is a lot better than 1, and 3 might be a little better than 2
  - Usually, skip-connections/dense-connections are needed to train deeper RNNs (e.g., 8 layers)

deep LSTM models usually gets even better results
: BUT need adding extra skip-connection

- Transformer-based networks (e.g., BERT) are usually deeper, like 12 or 24 layers.
  - You will learn about Transformers later; they have a lot of skipping-like connections

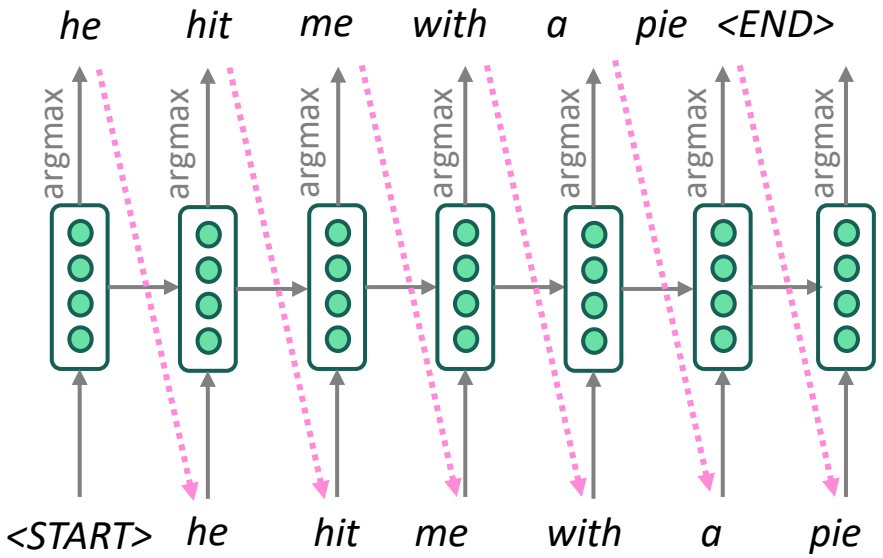
"Massive Exploration of Neural Machine Translation Architecutres", Britz et al, 2017. https://arxiv.org/pdf/1703.03906.pdf

Greedy decoding

- We saw how to generate (or “decode”) the target sentence by taking argmax on each step of the decoder

<Greedy Decoding>: methods that we have seen so far

generate a hidden state that haves prob dist over words
--> choose more probable word (argmax) in each step



- This is greedy decoding (take most probable word on each step)
- **Problems with this method?**

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…)*

<Problem of Greedy Decoding>
- stuck in argmax decision And no way to undo it
(=) once you generated it, then no way to go backwards

- How to fix this?

Exhaustive search decoding

- Ideally, we want to find a (length *T*) translation *y* that maximizes

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

- We could try computing all possible sequences *y*
  - This means that on each step *t* of the decoder, we're tracking V^t possible partial translations, where *V* is vocab size
  - This $O(V^T)$ complexity is far too expensive!

<purpose> find a translation y that max P(y|x)

at least if we know length of translation sentence
--> product of generating word at a time
--> prob dist --> get a full model

Beam search decoding

- Core idea: 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 $y_1, \ldots, y_t$ has a score which is its log probability:

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

  - Scores are all negative, and higher score is better
  - We search for high-scoring hypotheses, tracking top *k* on each step

- Beam search is not guaranteed to find optimal solution
- But much more efficient than exhaustive search!

<Beam Search Decoding>
keep some hypothesis to make better generation while keeping the search tractable
- choose beam size (normally small 5~10)
- each step of Decoder, keep track of the k most probable partial translation
- initial sub-sequences of what we're generating
(=) hypotheses: sort of the prefix of translation has a score which is the log prob up to what's been generated so far
on conditional language model
least negative one = best one

search high probability hypothesis
no guarantee to find the highest prob decoding, but gives more shot than simple greedy decoding

Beam search decoding: example

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

scores of prefix = log probability of prefix

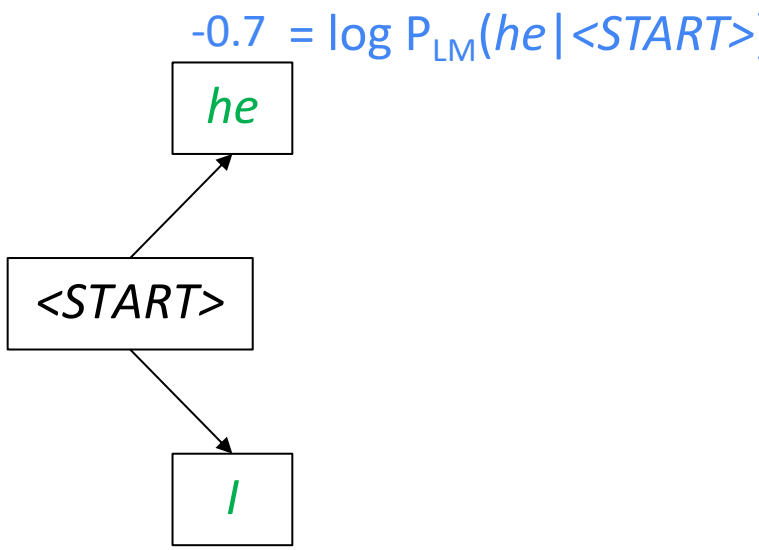
<START>

Calculate prob dist of next word

Beam search decoding: example

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

what's the most likely first word, based on our language model = he, I
then search which would be followed

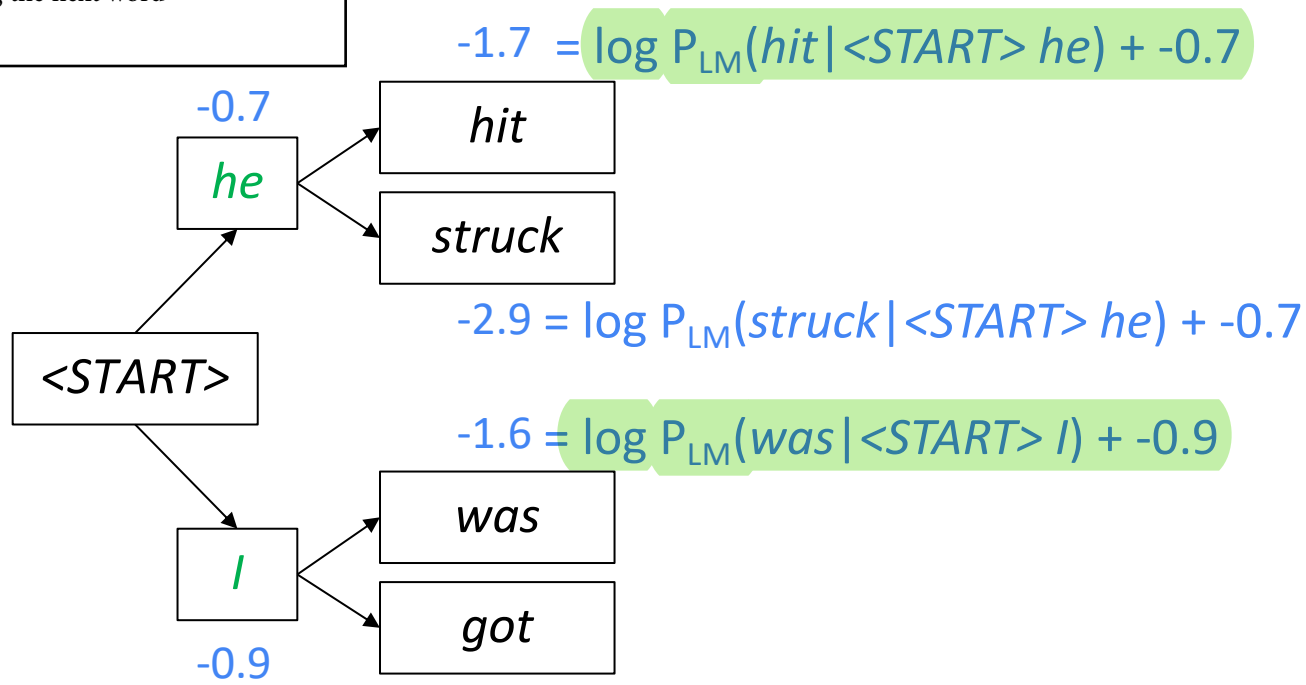


Take top *k* words and compute scores

Beam search decoding: example

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

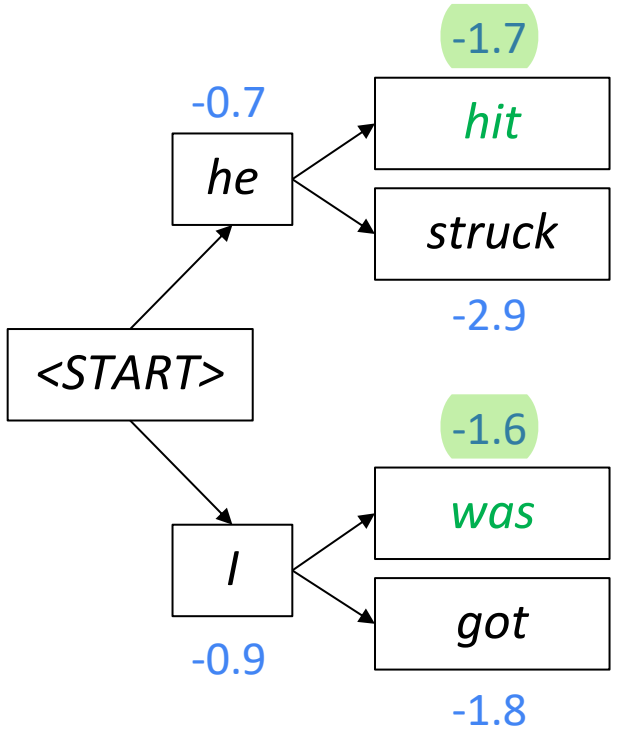
4 partial hypothesis = have each log probability
: previous score that we have the partial hypothesis
(+) log prob of generating the next word



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

Beam search decoding: example

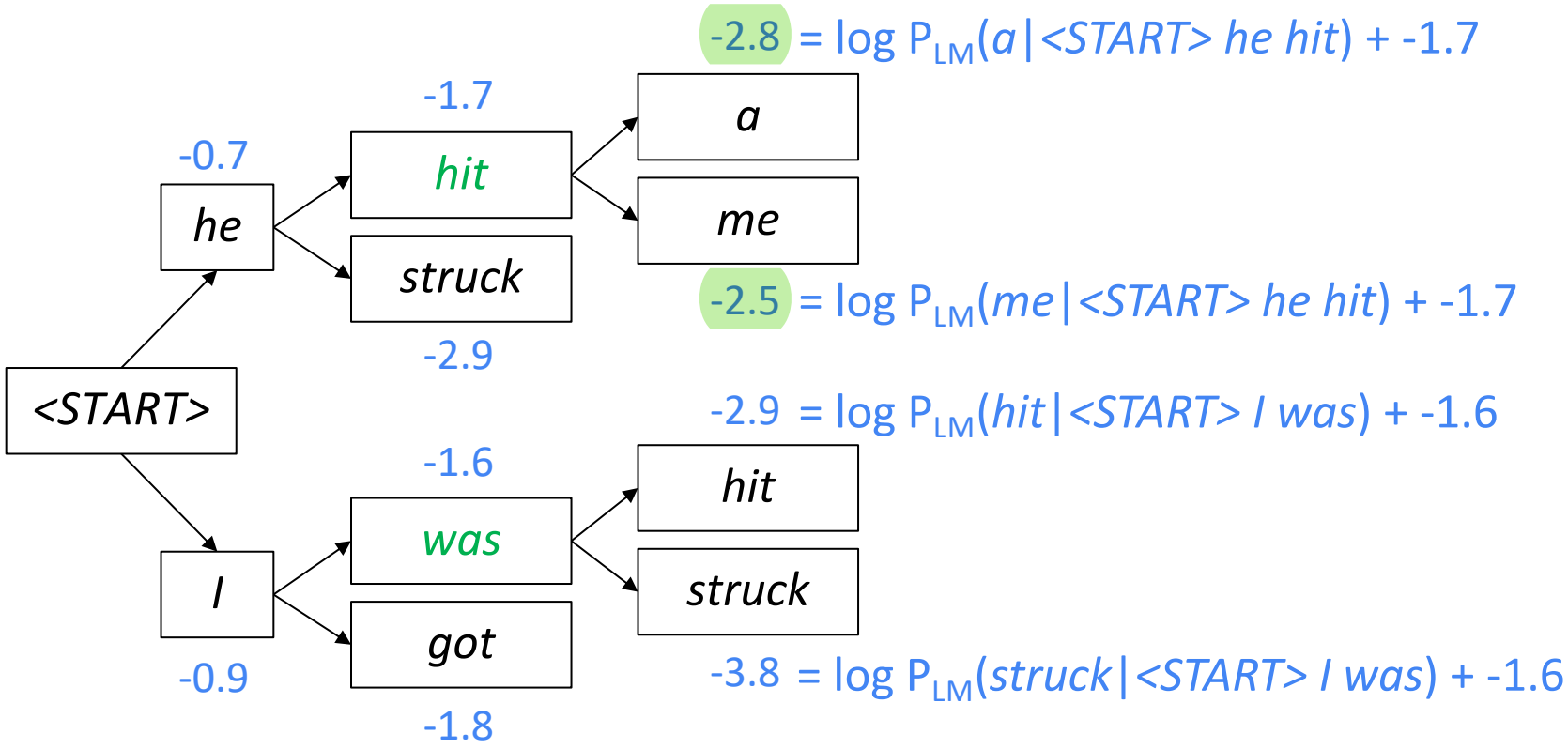
Beam size = k = 2. Blue numbers = $\text{score}(y_1, \ldots, y_t) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$



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

Beam search decoding: example

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



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

Beam search decoding: example

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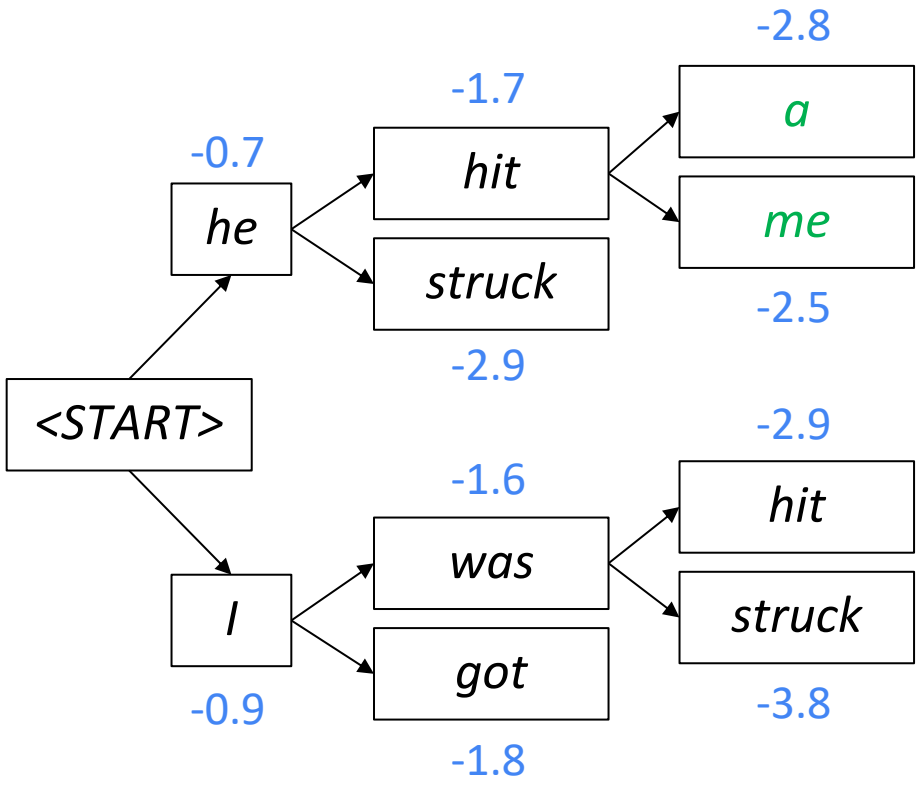
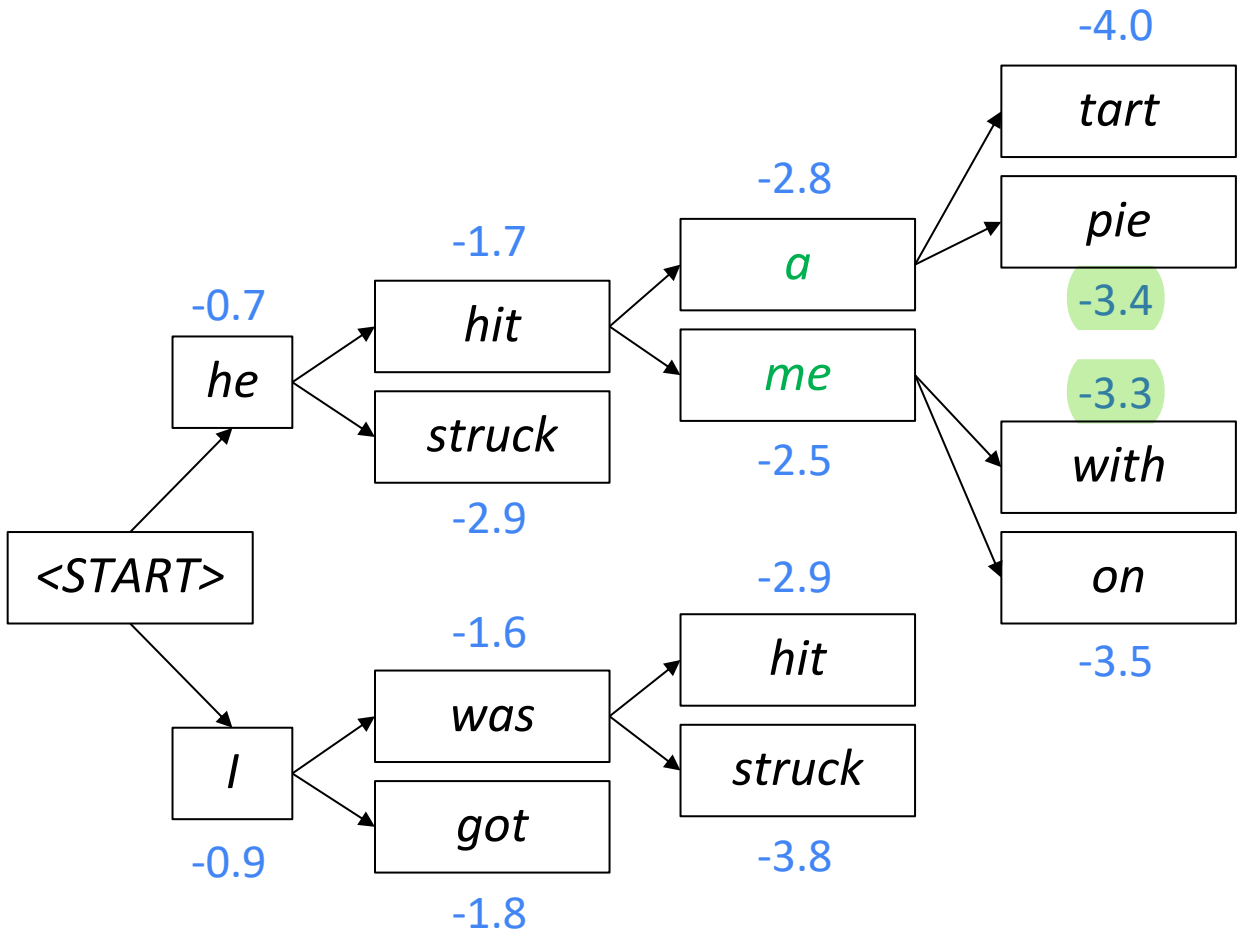


Of these k^2 hypotheses,
just keep k with highest scores

Beam search decoding: example

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



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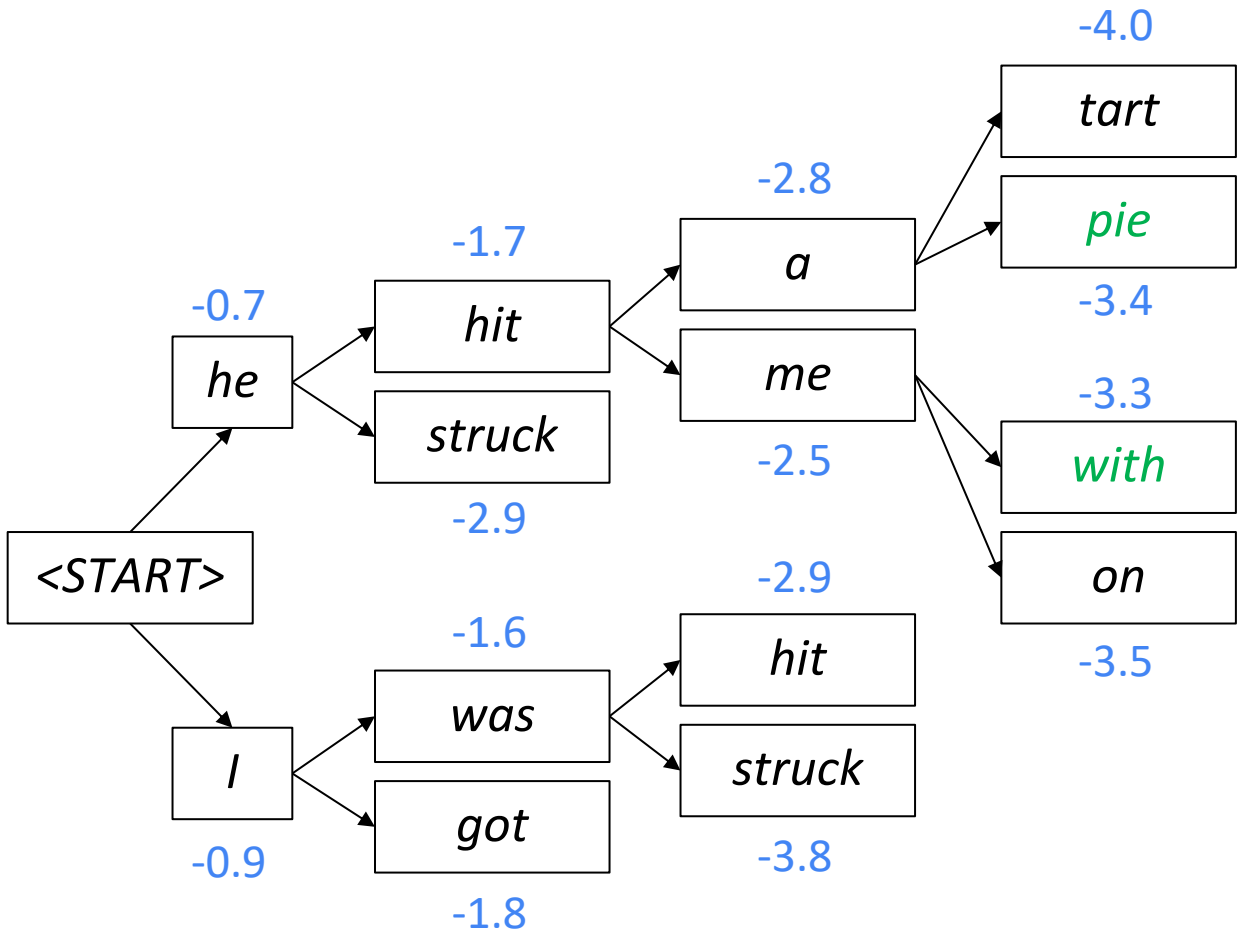

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Beam search decoding: example

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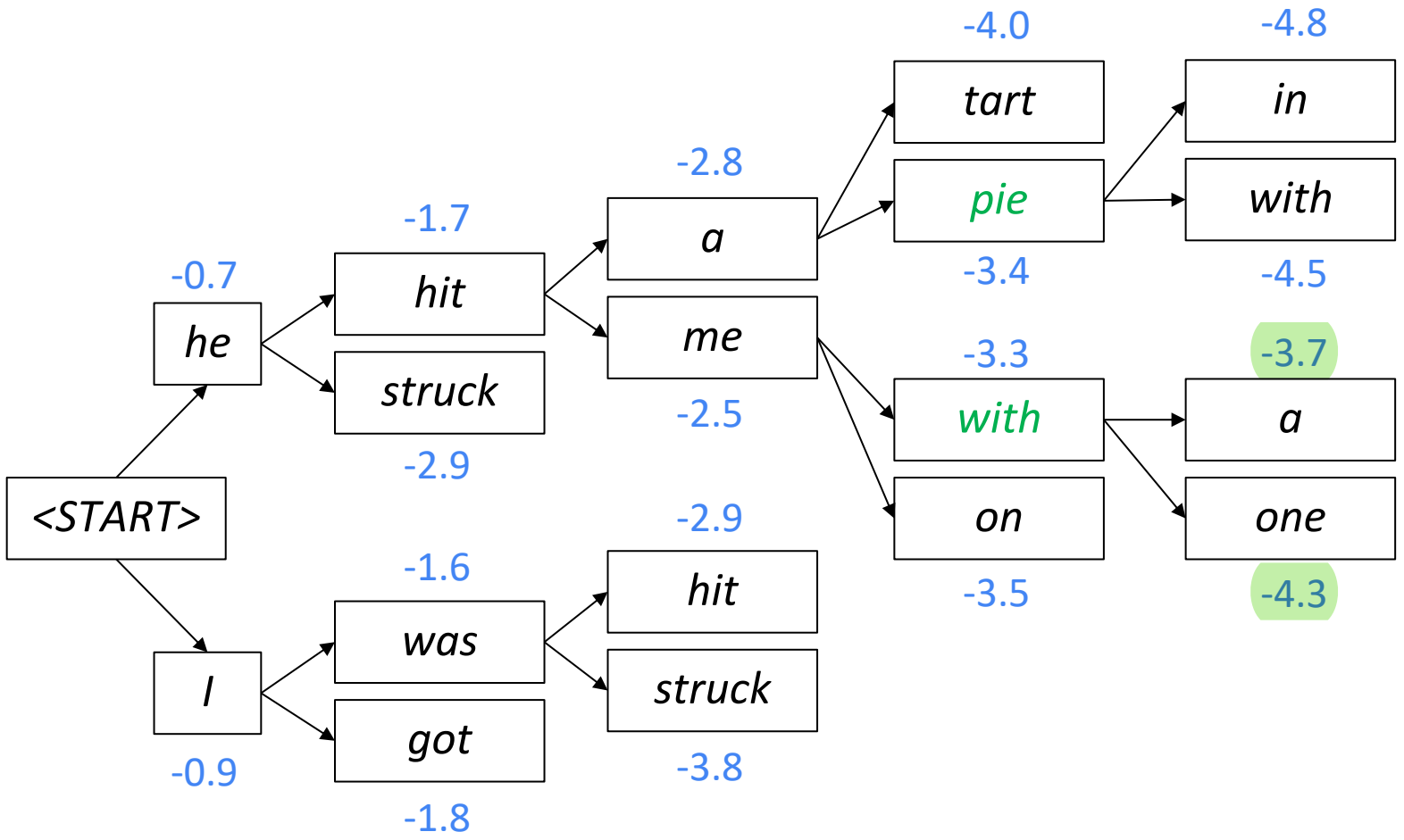

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Beam search decoding: example

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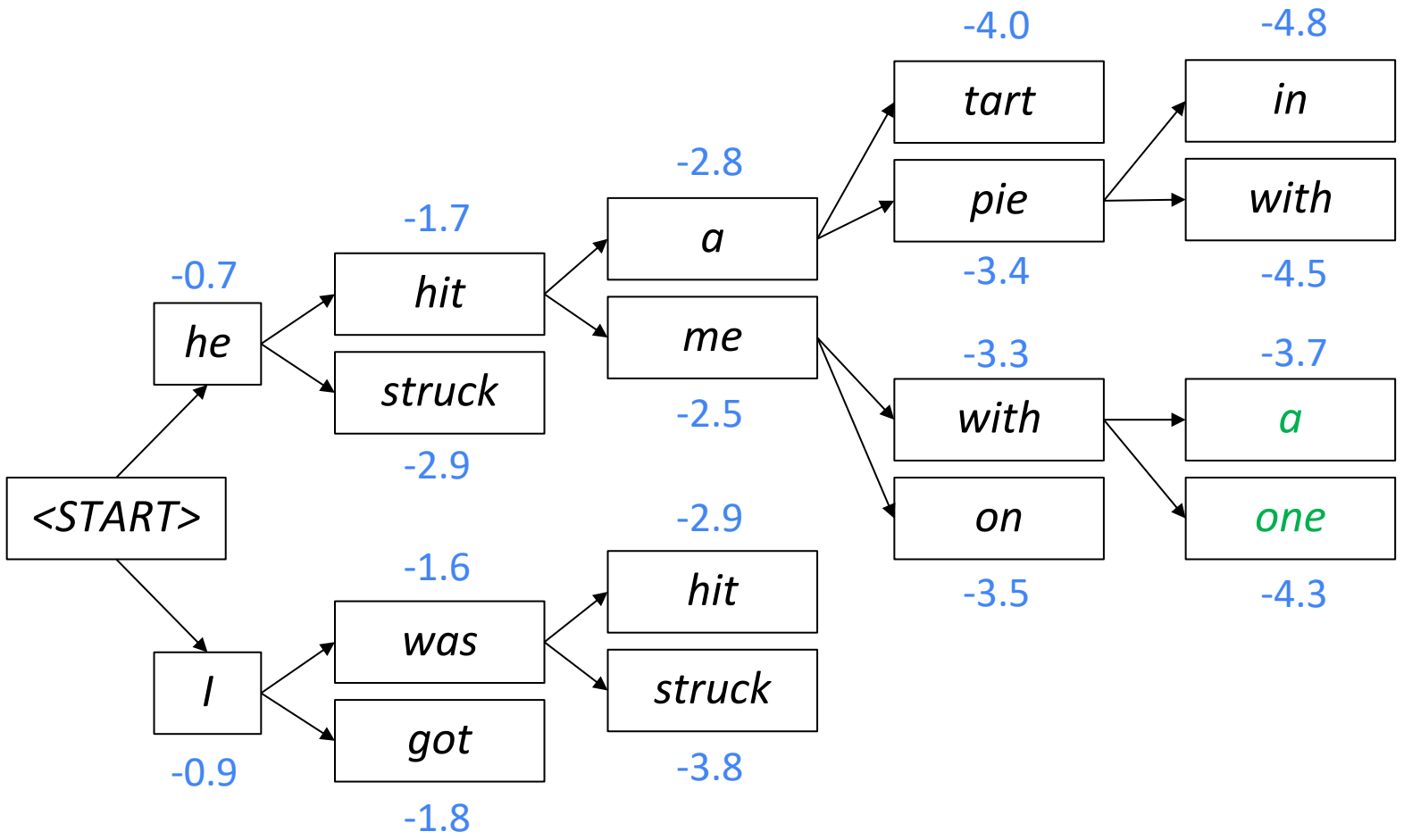

Of these k^2 hypotheses, just keep k with highest scores

Beam search decoding: example

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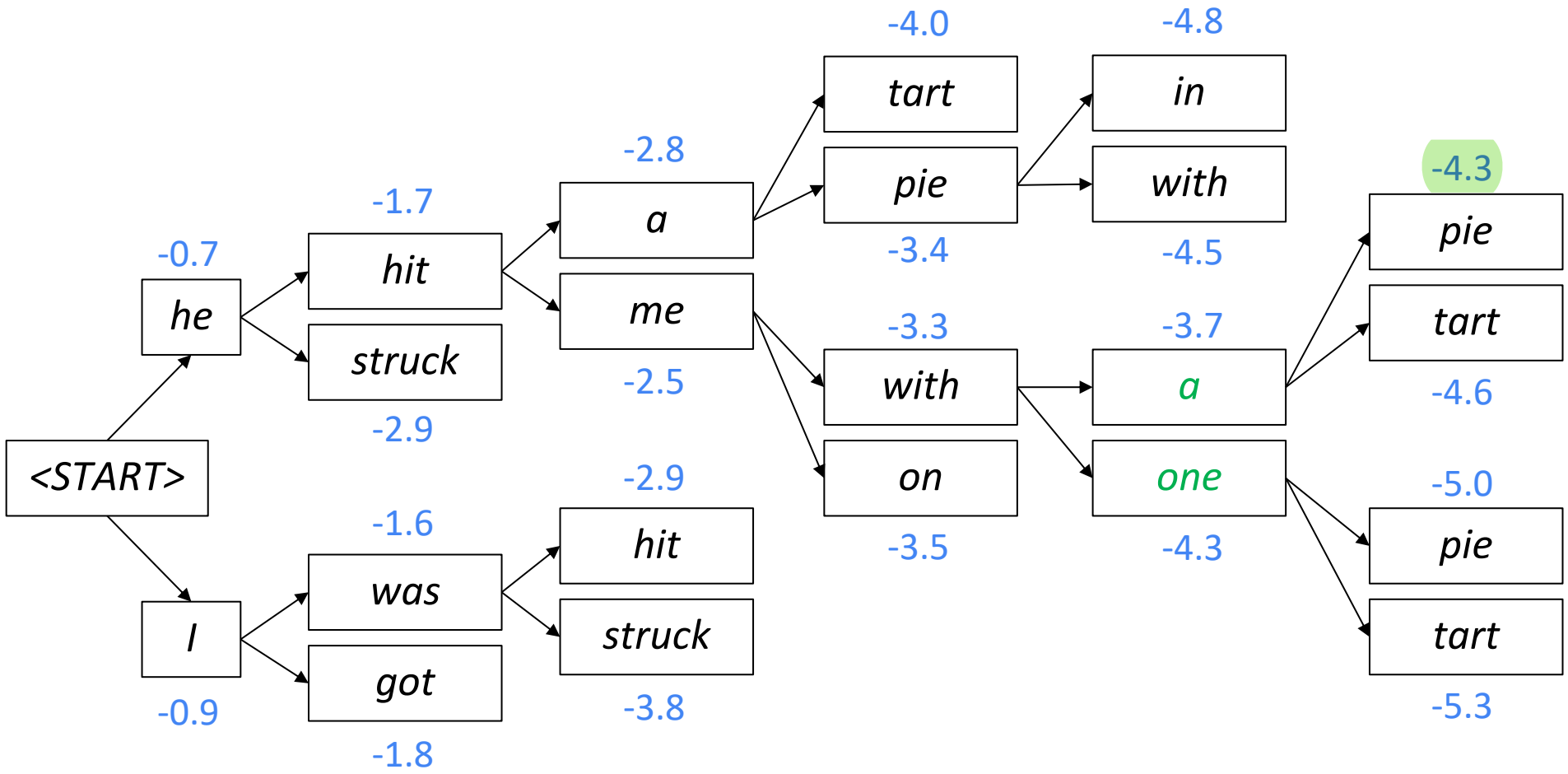

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Beam search decoding: example

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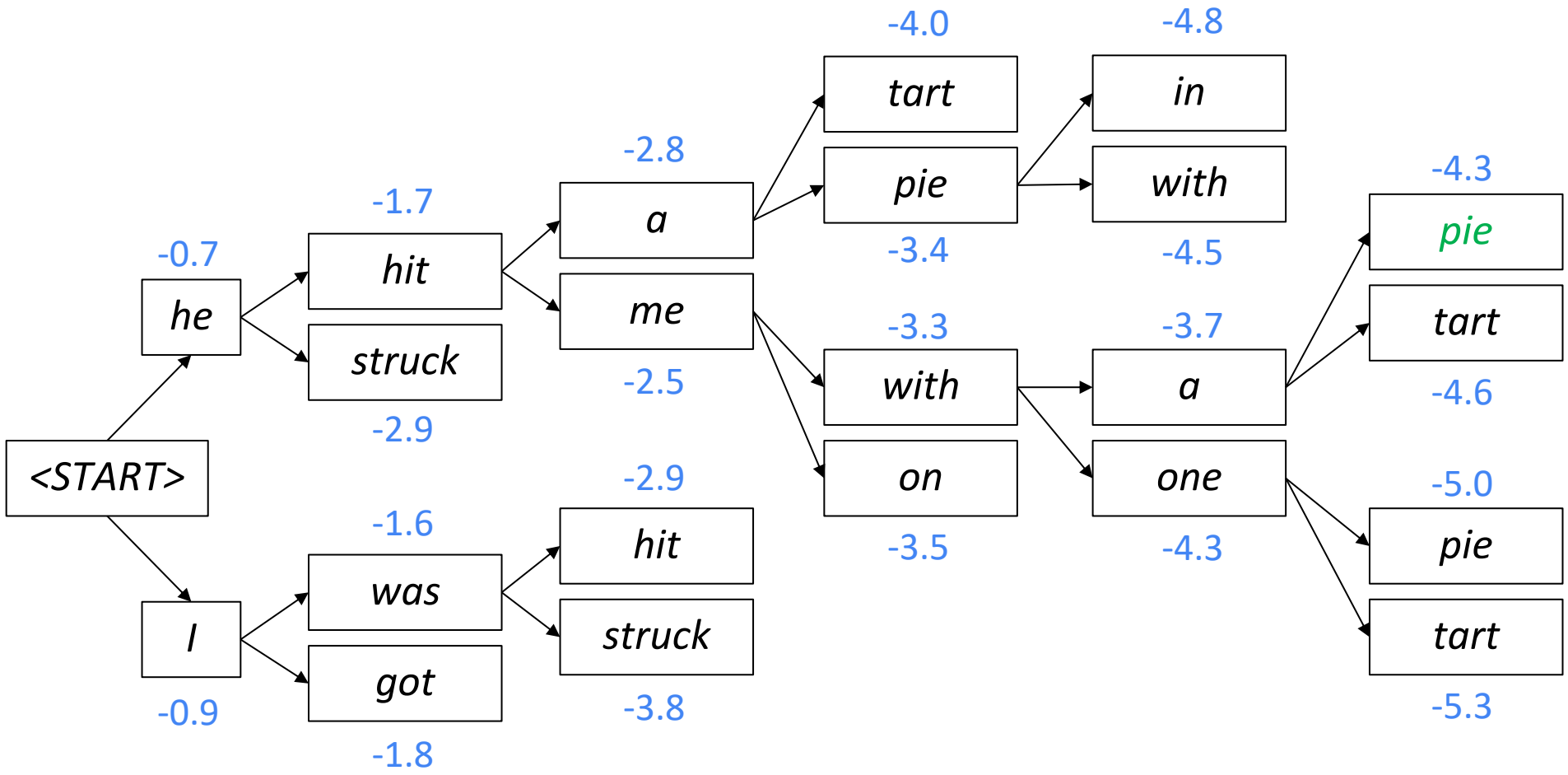
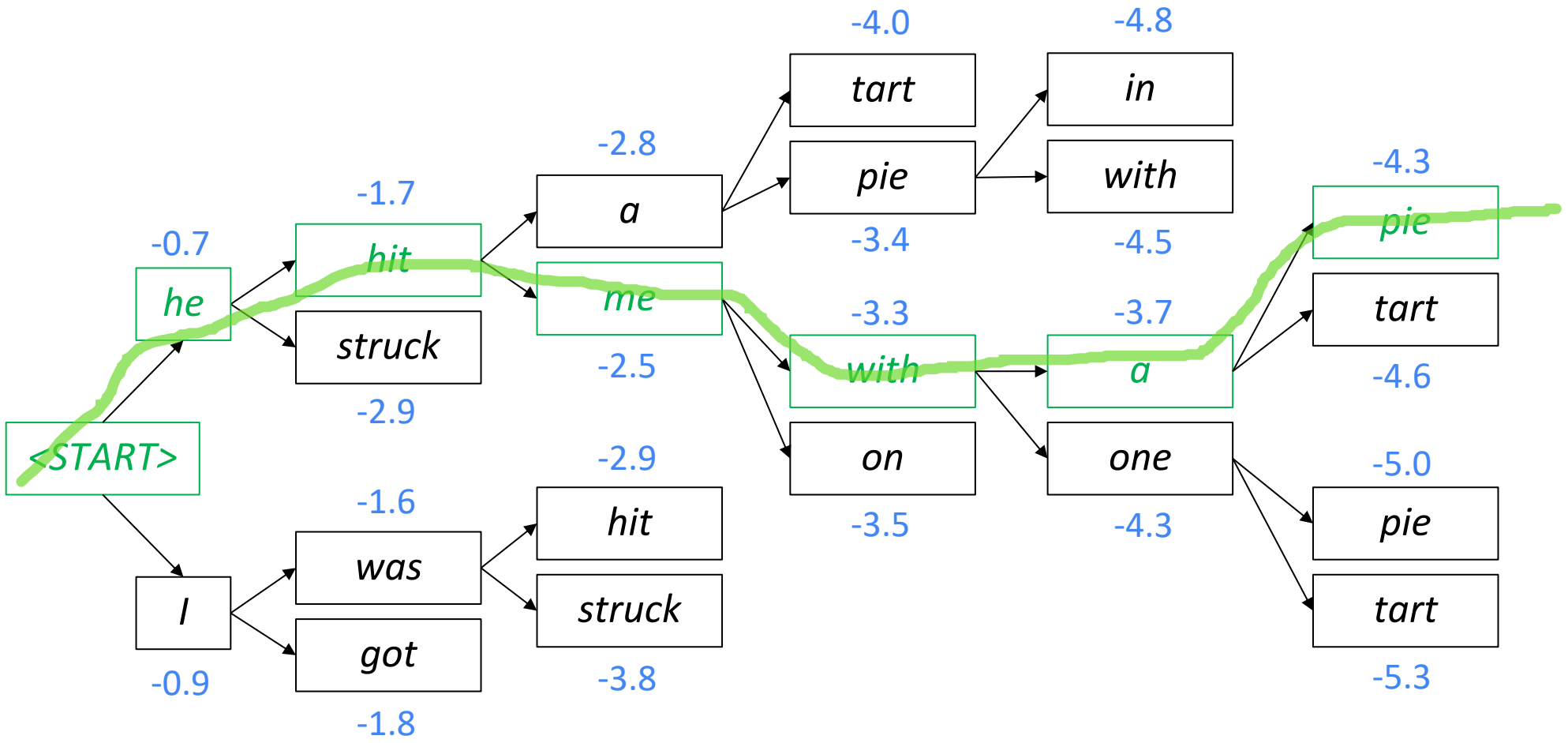


This is the top-scoring hypothesis!

Beam search decoding: example

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



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* (where *T* is some pre-defined cutoff), or
  - We have at least *n* completed hypotheses (where *n* is pre-defined cutoff)

beam search decoding:
different hypothesis may produce <END> tokens on different time steps
don't want to stop as soon as one path through the search tree has generated END
cuz, it could turn out the different path through the search tree to be better
==> put it aside the complete hypothesis,
and continue exploring other hypotheses via the beam search
==> until reaching to N completed hypotheses,
then choose the best one among them

Beam search decoding: finishing up

- We have our list of completed hypotheses.
- How to select top one with highest score?

- Each hypothesis $y_1, \ldots, y_t$ on our list has a score

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

sentence length --> prob longer
ex) news article sentence length = 20~
<Fix> Normalize by length

- **Problem with this:** longer hypotheses have lower scores

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

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

Advantages of NMT

Compared to SMT, NMT has many 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

better use of context: condition on many contexts

single NN works end-to-end --> then performs better than complex-wise model

Disadvantages of NMT?

1. harder to see what they're doing
2. can't give more specifications
- hard to know what they'll generate --> safety concerns

Compared to SMT:

- 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!

How do we evaluate Machine Translation?

BLEU (**Bi**lingual **E**valuation **U**nderstudy)

You'll see BLEU in detail in Assignment 4!

- BLEU compares the machine-written translation to one or several human-written translation(s), and computes a similarity score based on:
  - *n*-gram precision (usually for 1, 2, 3 and 4-grams)
  - Plus a penalty for too-short system translations

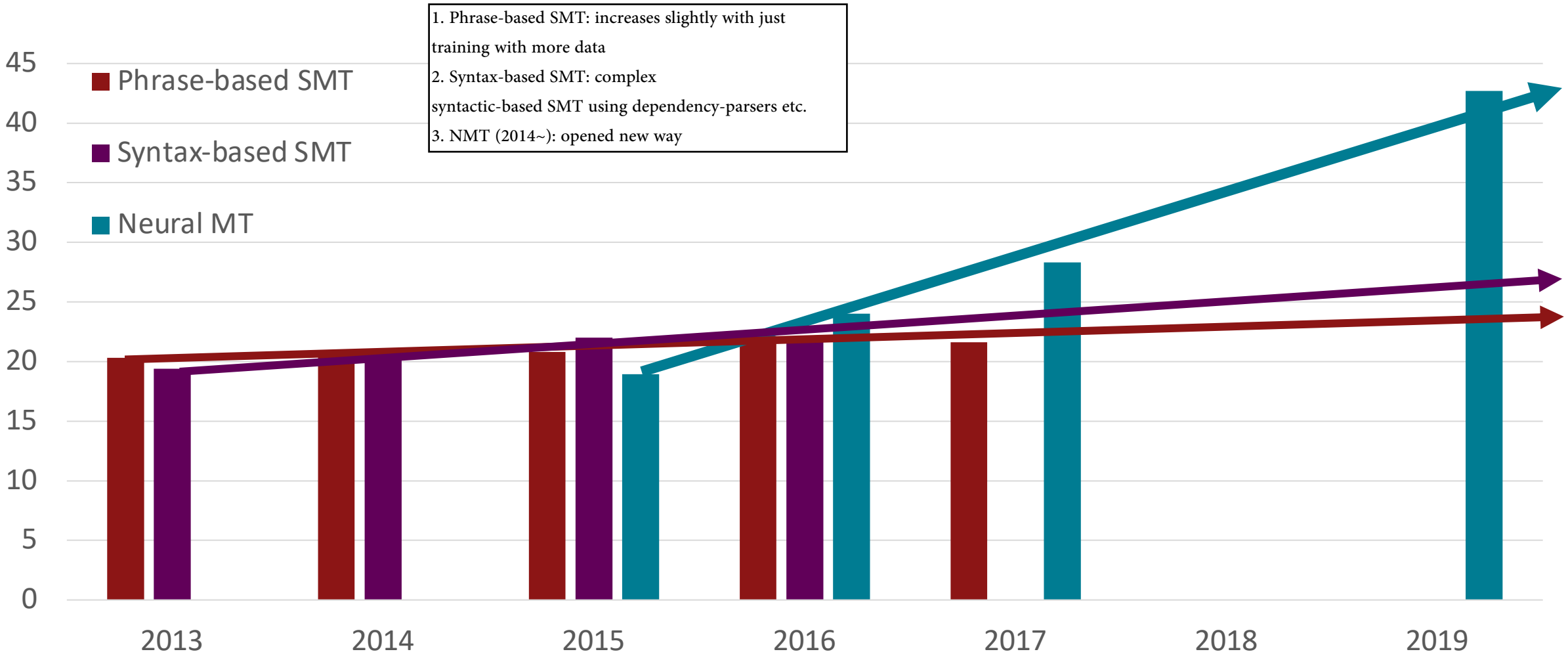
similarity score: (0~100)
geometric average between overlaps of n-grams
(+) penalty for too short system translations

- BLEU is useful but imperfect
  - There are many valid ways to translate a sentence
  - So a good translation can get a poor BLEU score because it has low *n*-gram overlap with the human translation ☹

Source: "BLEU: a Method for Automatic Evaluation of Machine Translation", Papineni et al, 2002. http://aclweb.org/anthology/P02-1040

MT progress over time

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



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

NMT: perhaps the biggest 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

- This is amazing!
  - **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

So, is Machine Translation solved?

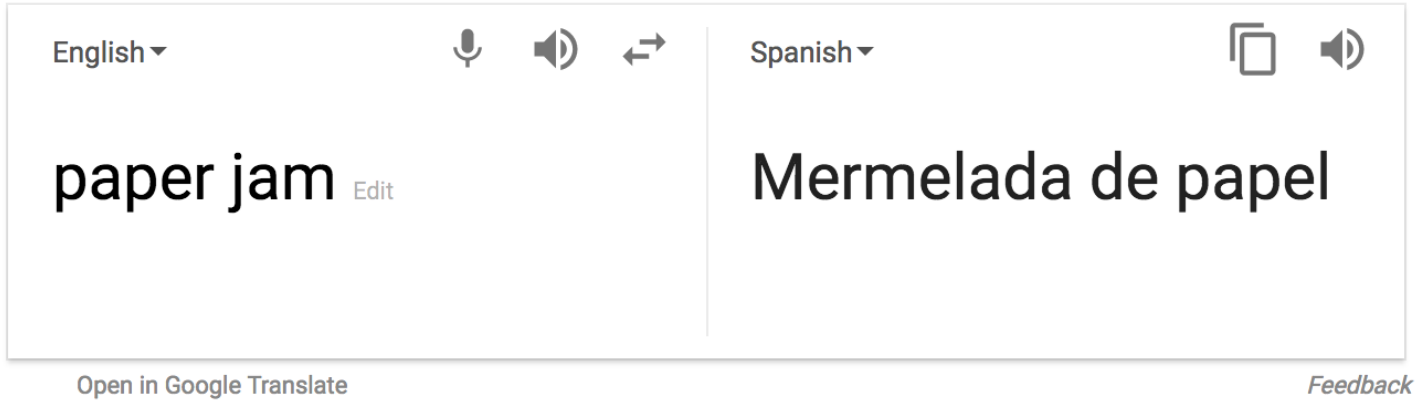
- **Nope!**
- Many difficulties remain:
  - Out-of-vocabulary words
  - Domain mismatch between train and test data
  - Maintaining context over longer text
  - Low-resource language pairs
  - Failures to accurately capture sentence meaning
  - Pronoun (or zero pronoun) resolution errors
  - Morphological agreement errors

2. (ex) use new for SNS messages
6. languages that have lots of inflectional forms of nouns, verb, adj --> get systems wrong

Further reading: *"Has AI surpassed humans at translation? Not even close!"*
https://www.skynettoday.com/editorials/state_of_nmt

So is Machine Translation solved?

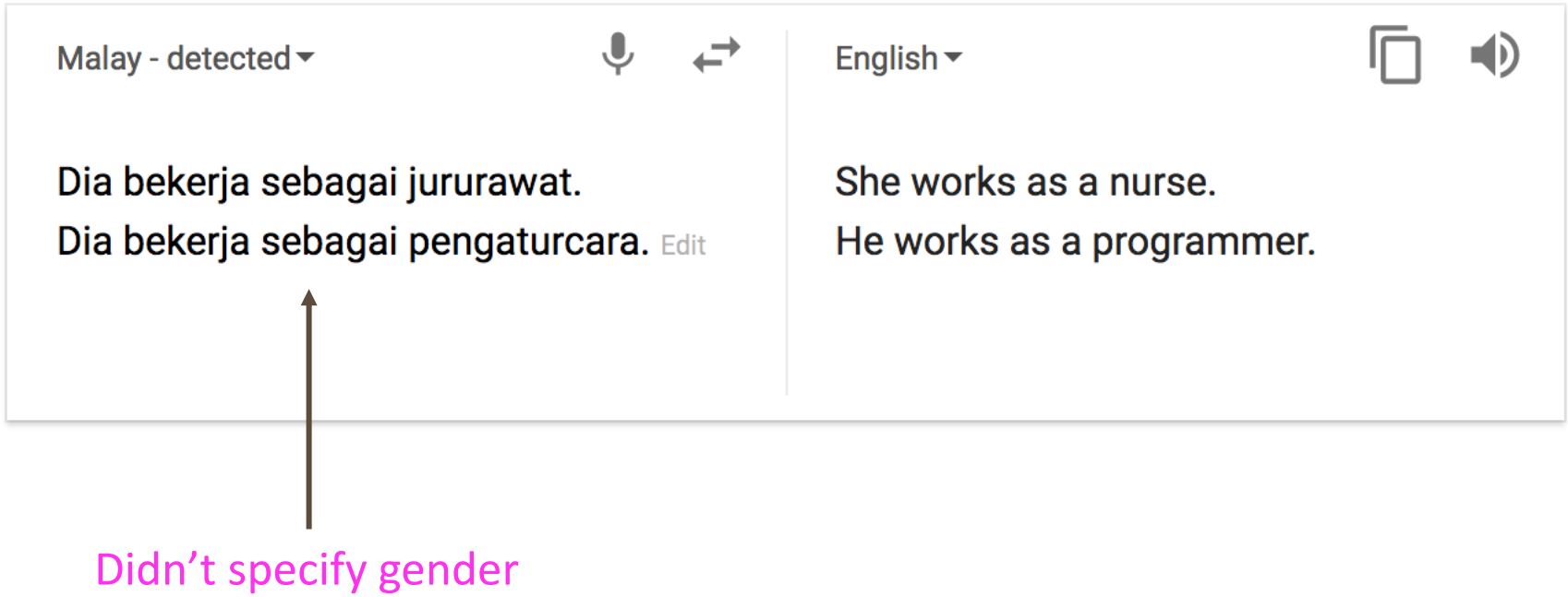
- **Nope!**
- Using common sense is still hard



?

So is Machine Translation solved?

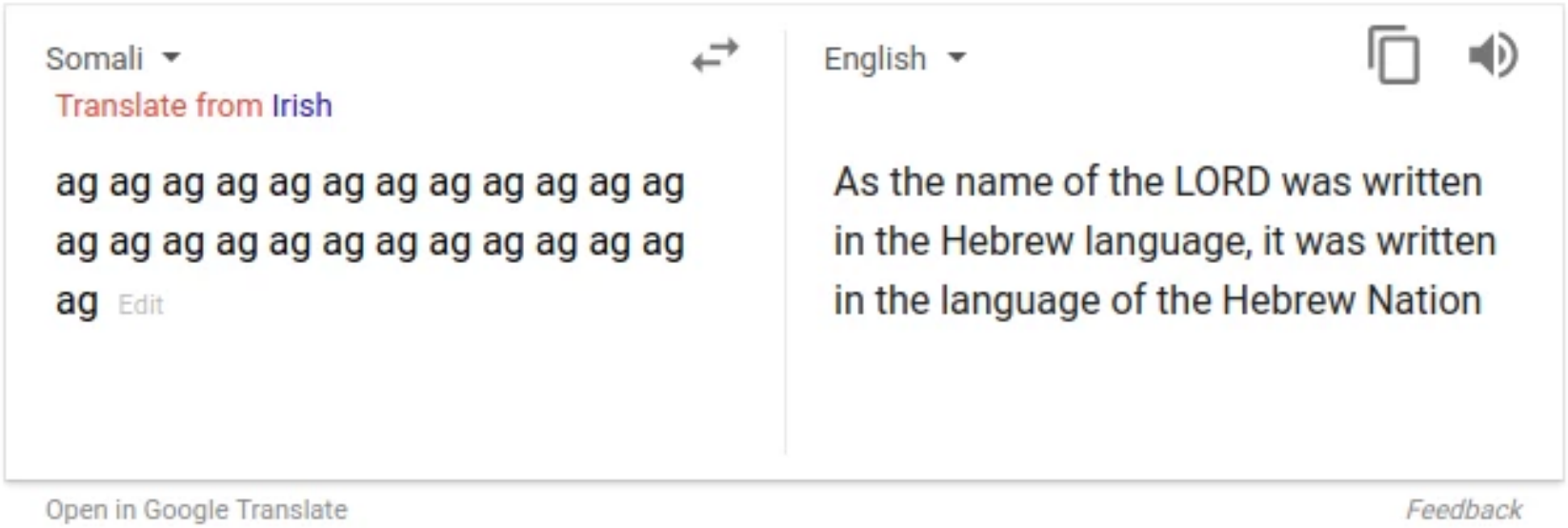
- **Nope!**
- NMT picks up biases in training data



Source: https://hackernoon.com/bias-sexist-or-this-is-the-way-it-should-be-ce1f7c8c683c

So is Machine Translation solved?

- Nope!
- Uninterpretable systems do strange things
- (But I think this problem has been fixed in Google Translate by 2021?)



Picture source: https://www.vice.com/en_uk/article/j5npeg/why-is-google-translate-spitting-out-sinister-religious-prophecies
Explanation: https://www.skynettoday.com/briefs/google-nmt-prophecies

NMT research continues

NMT is a **flagship task** for NLP Deep Learning

- NMT research has pioneered many of the recent innovations of NLP Deep Learning
- In **2021**: NMT research continues to thrive
  - Researchers have found *many, many* improvements to the "vanilla" seq2seq NMT system we've just presented
  - But we'll present in a minute one improvement so integral that it is the new vanilla…

ATTENTION

Assignment 4: Cherokee-English machine translation!

- Cherokee is an endangered Native American language – about 2000 fluent speakers
- Extremely low resource: About 20k parallel sentences available, most from the bible
- ᎠᏍᎩᏴ ᏥᏞᎡᎢ ᎦᏚᏉᎩ ᎢᏯᎾᏂᎢ ᎠᏂᏧᏀ. ᏥᎪᎯᏐᎢ ᏗᎦᎳᎾᎢᏅᏗᎢ ᏀᏂᏯᎡᎢ ᏓᎾᏁᏀᏔᏋᎢ ᏫᎾᏯᎡᎢ ᎪᏢᎳᎾᎢ ᎠᏫᎾᎢ ᎦᏚᏓᏁᏗᏗᏙᎢ ᎠᏆ ᎤᏓᏅᏛᏗᏗ ᎦᎾᏅᏗ ᎠᎾᏗᏅᏅᏞᎢ ᎠᎾᏂᏔᎢ.

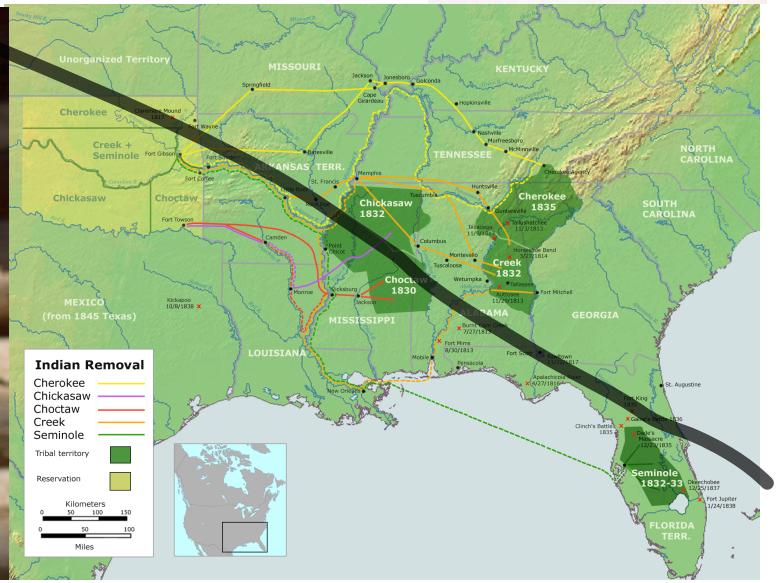
  Long ago were seven boys who used to spend all their time down by the townhouse playing games, rolling a stone wheel along the ground, sliding and striking it with a stick
- Writing system is a syllabary of symbols for each CV unit (85 letters)
- Many thanks to Shiyue Zhang, Benjamin Frey, and Mohit Bansal from UNC Chapel Hill for the resources for this assignment!

- Cherokee is not available on Google Translate! 😭

Cherokee

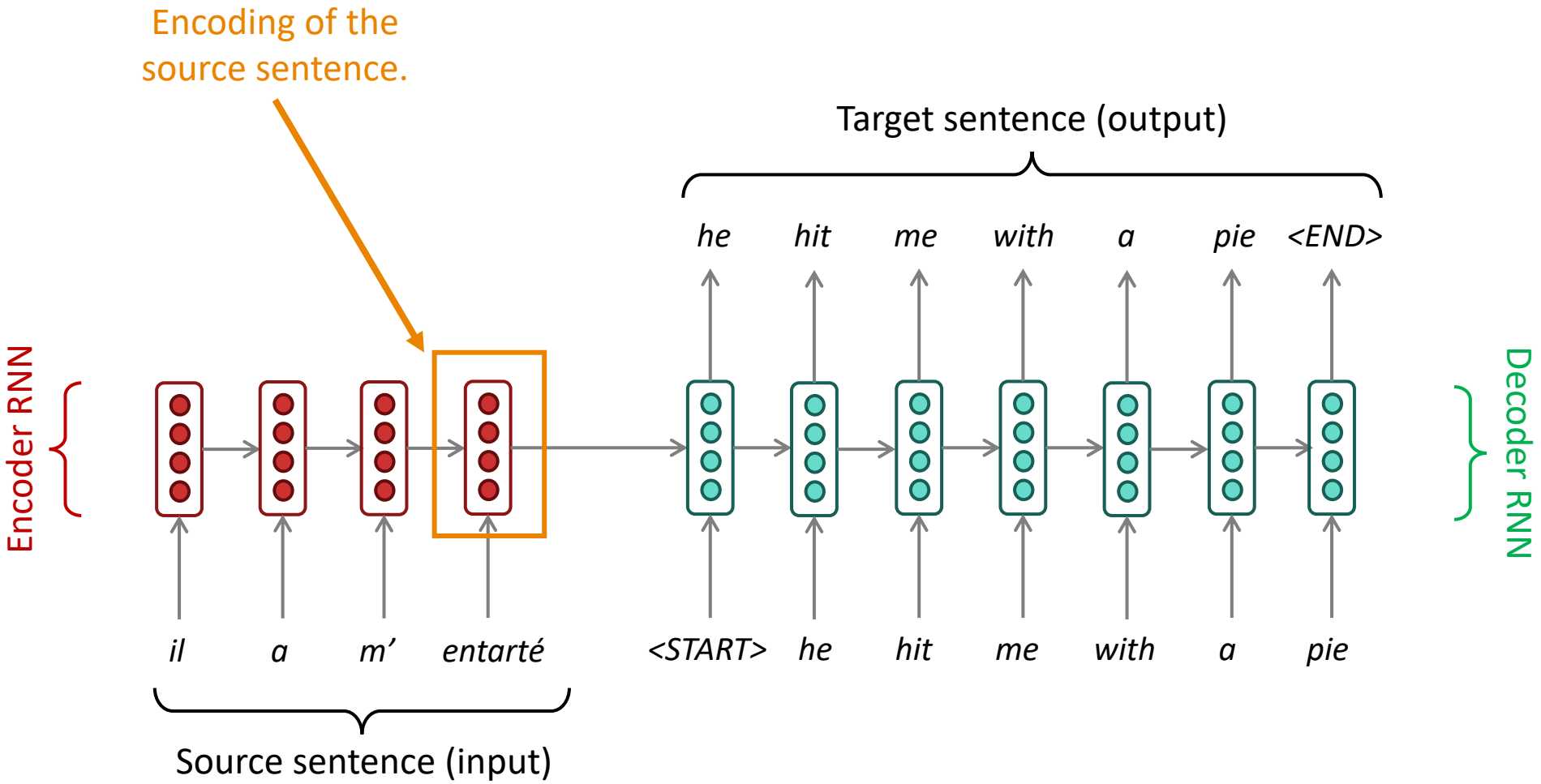
- Cherokee originally lived in western North Carolina and eastern Tennessee
- Most speakers now in Oklahoma, following the Trail of Tears; some in NC
- Writing system Invented by Sequoyah around 1820 – someone who was previously illiterate
  - Very effective: In the following decades Cherokee literacy was higher than for white people in the southeastern United States

- https://www.cherokee.org



Section 3: Attention

Sequence-to-sequence: the bottleneck problem

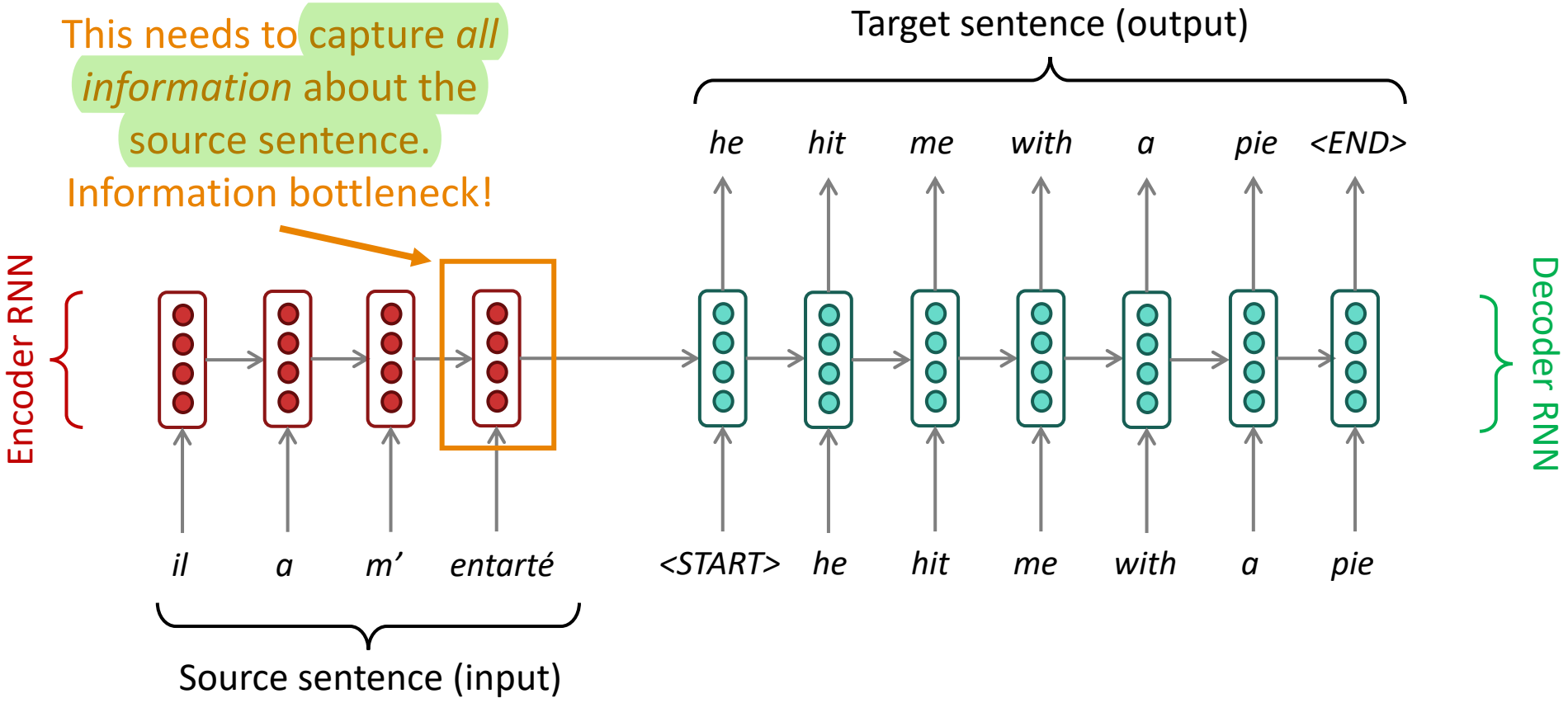


Problems with this architecture?

Sequence-to-sequence: the bottleneck problem

one hidden state has to encode all the information of source sentence ==> BOTTLENECK
order of words is important to preserve

Encoding of the source sentence. This needs to capture *all information* about the source sentence. Information bottleneck!



Attention

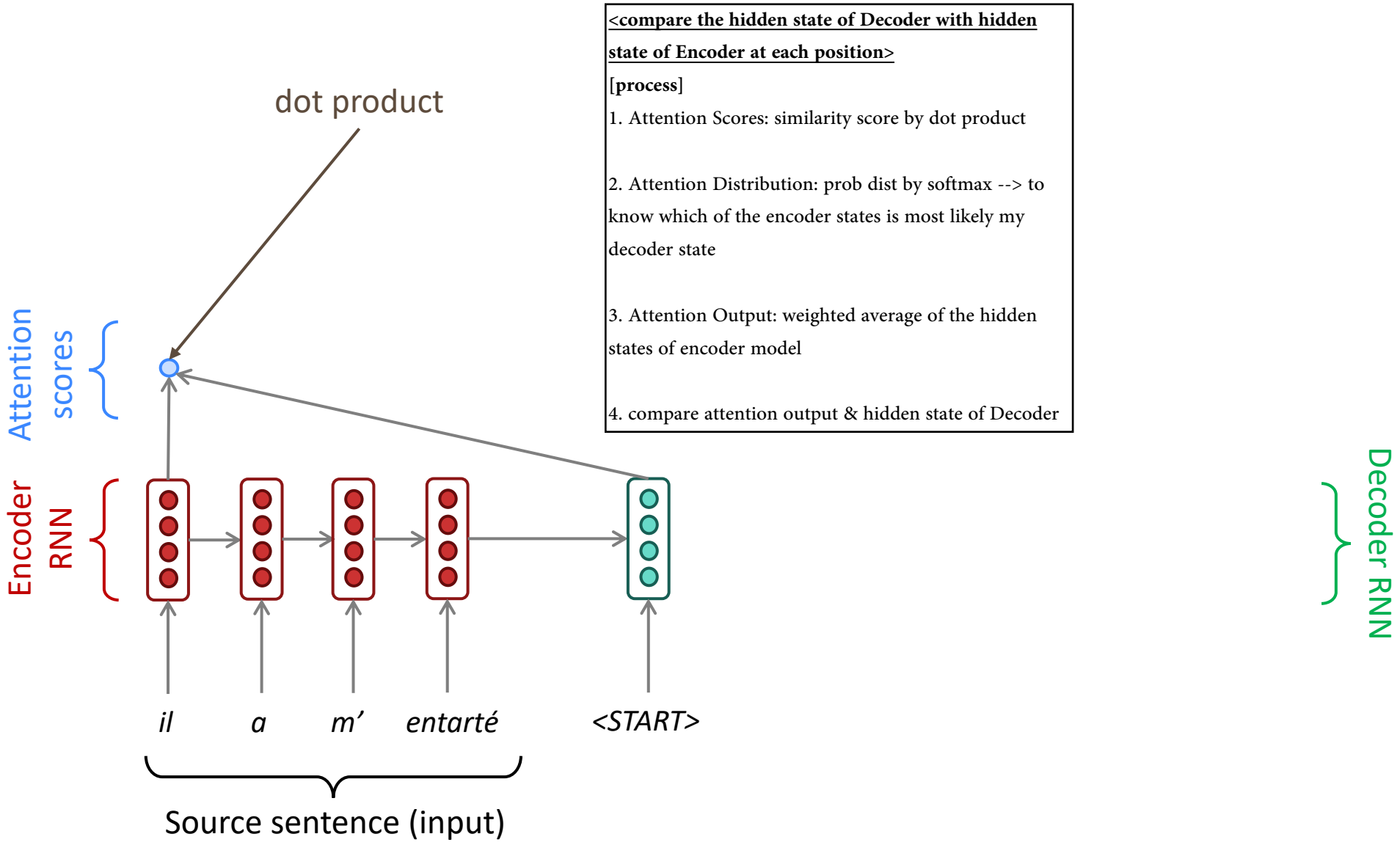
- **Attention** provides a solution to the bottleneck problem.

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

direct connection between Encoder to Decoder

- First, we will show via diagram (no equations), then we will show with equations

Sequence-to-sequence with attention



<compare the hidden state of Decoder with hidden state of Encoder at each position>

[process]

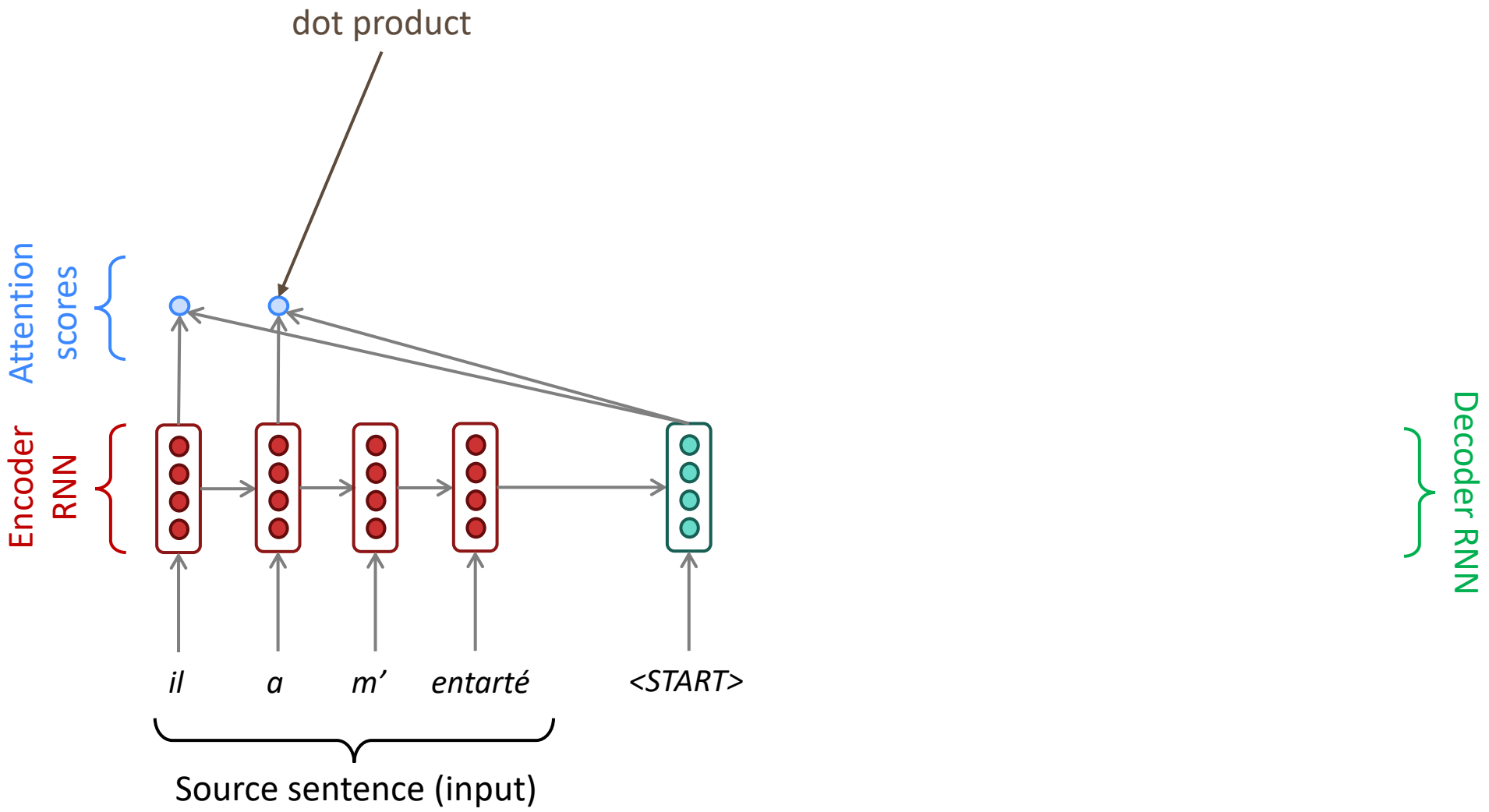
1. Attention Scores: similarity score by dot product

2. Attention Distribution: prob dist by softmax --> to know which of the encoder states is most likely my decoder state

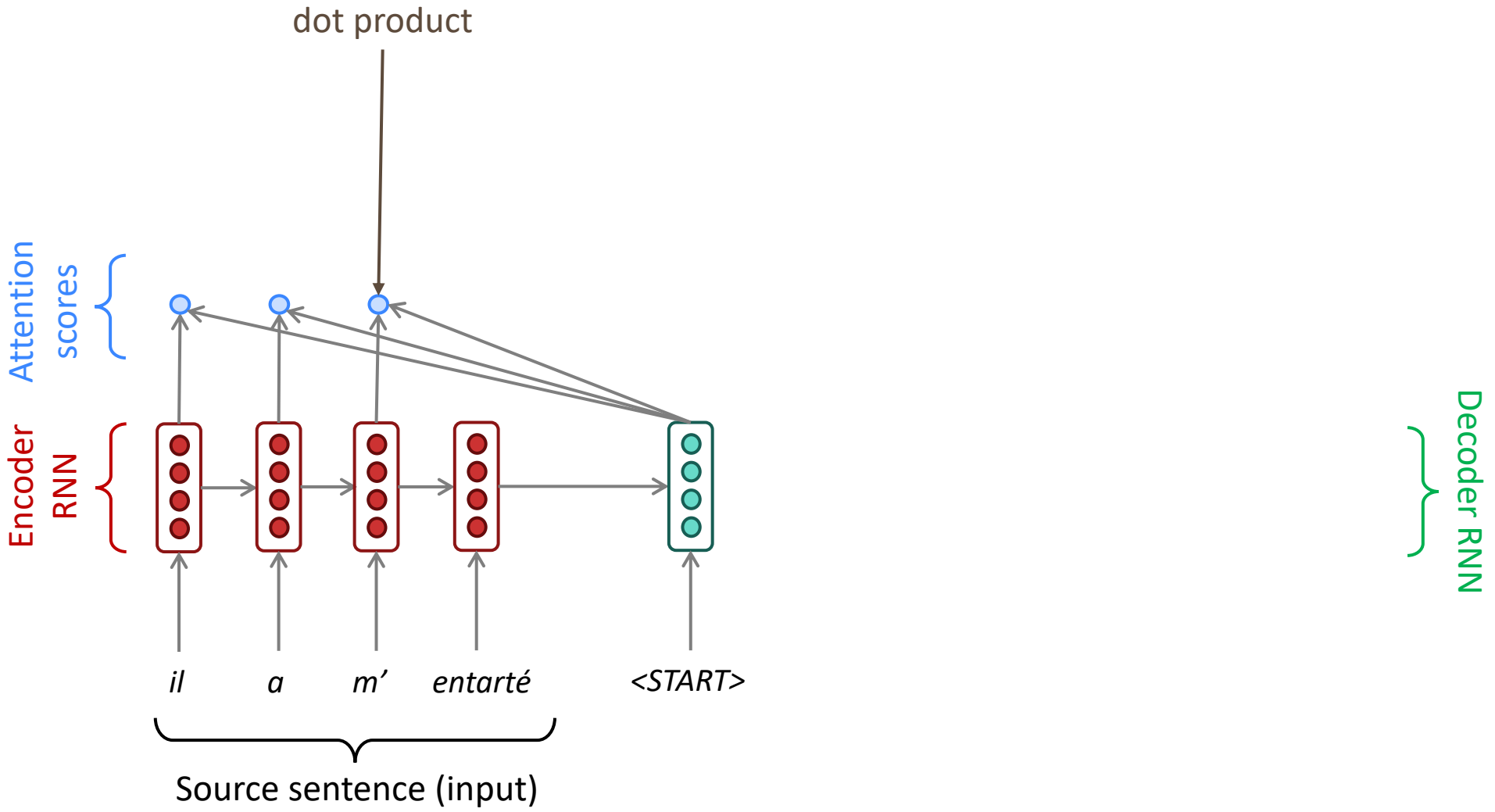
3. Attention Output: weighted average of the hidden states of encoder model

4. compare attention output & hidden state of Decoder

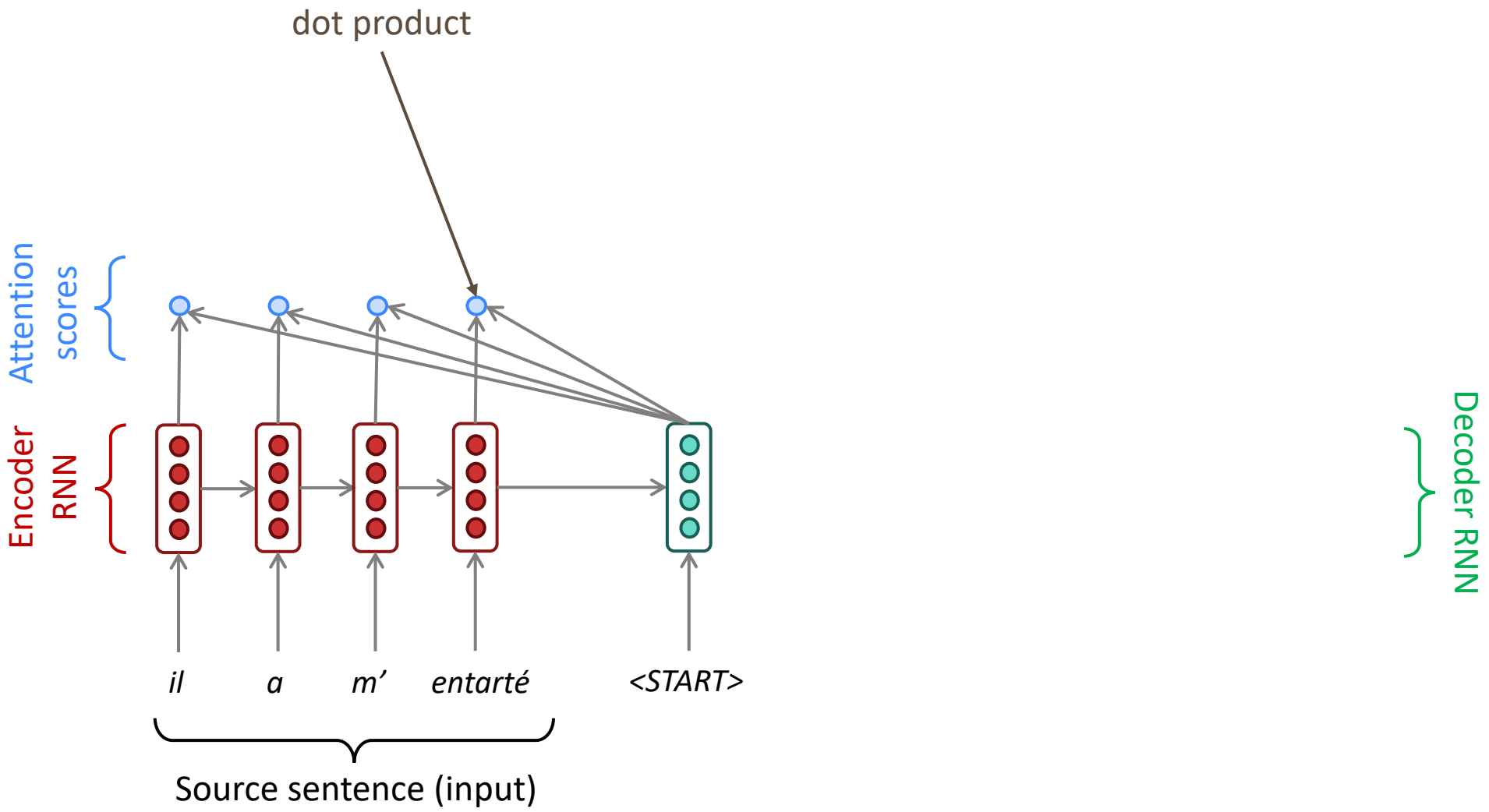
Sequence-to-sequence with attention



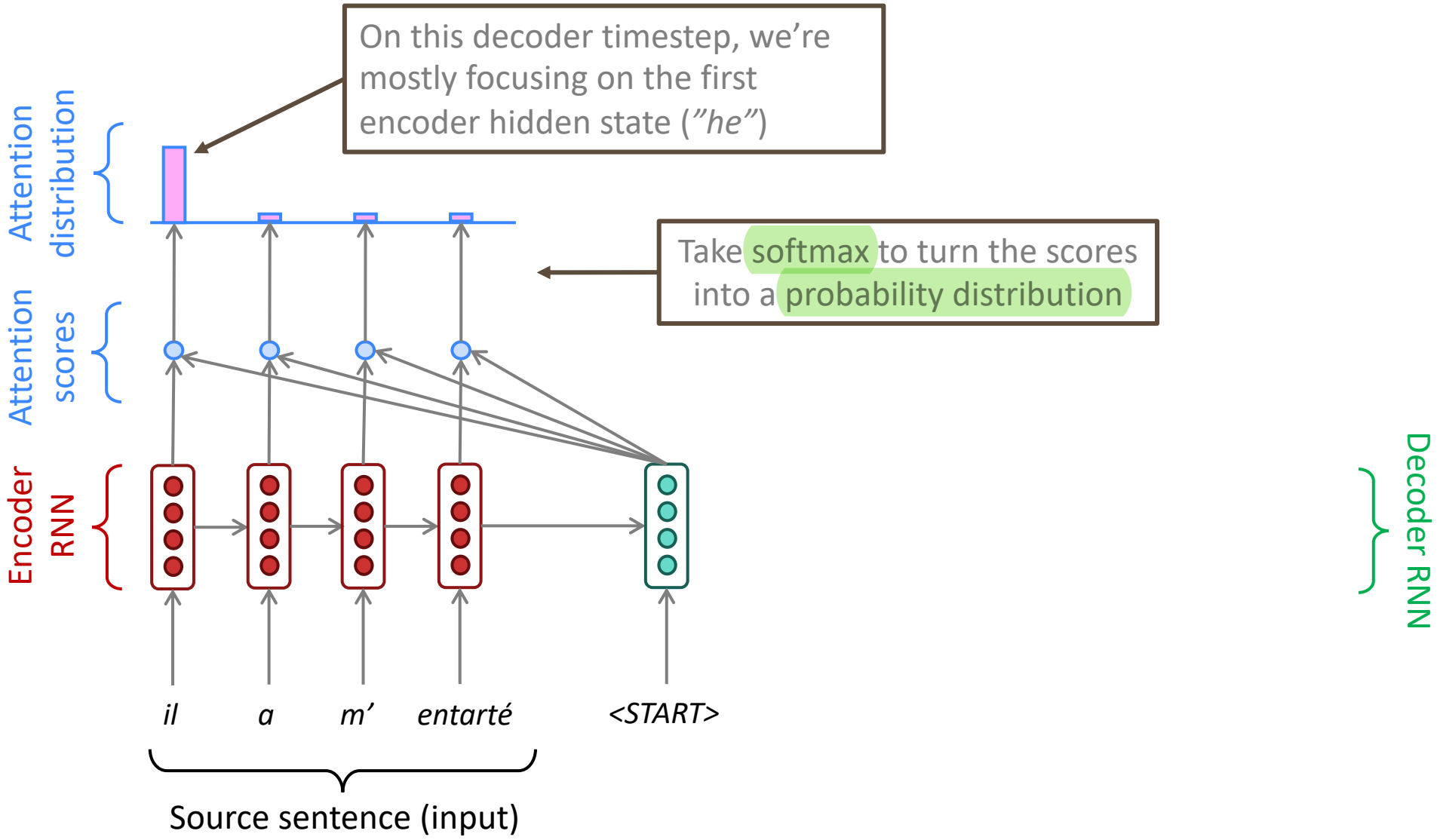
Sequence-to-sequence with attention



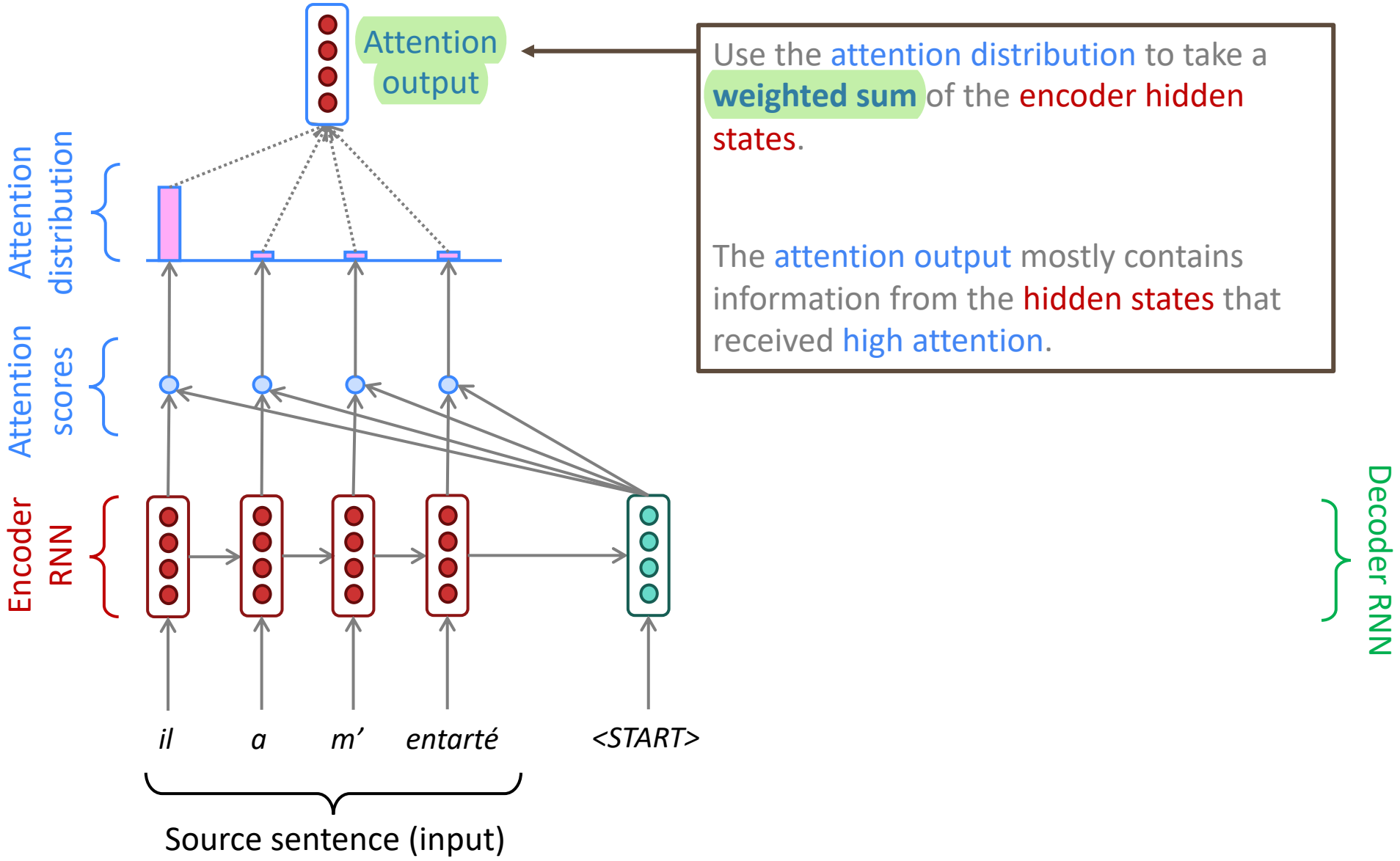
Sequence-to-sequence with attention



Sequence-to-sequence with attention



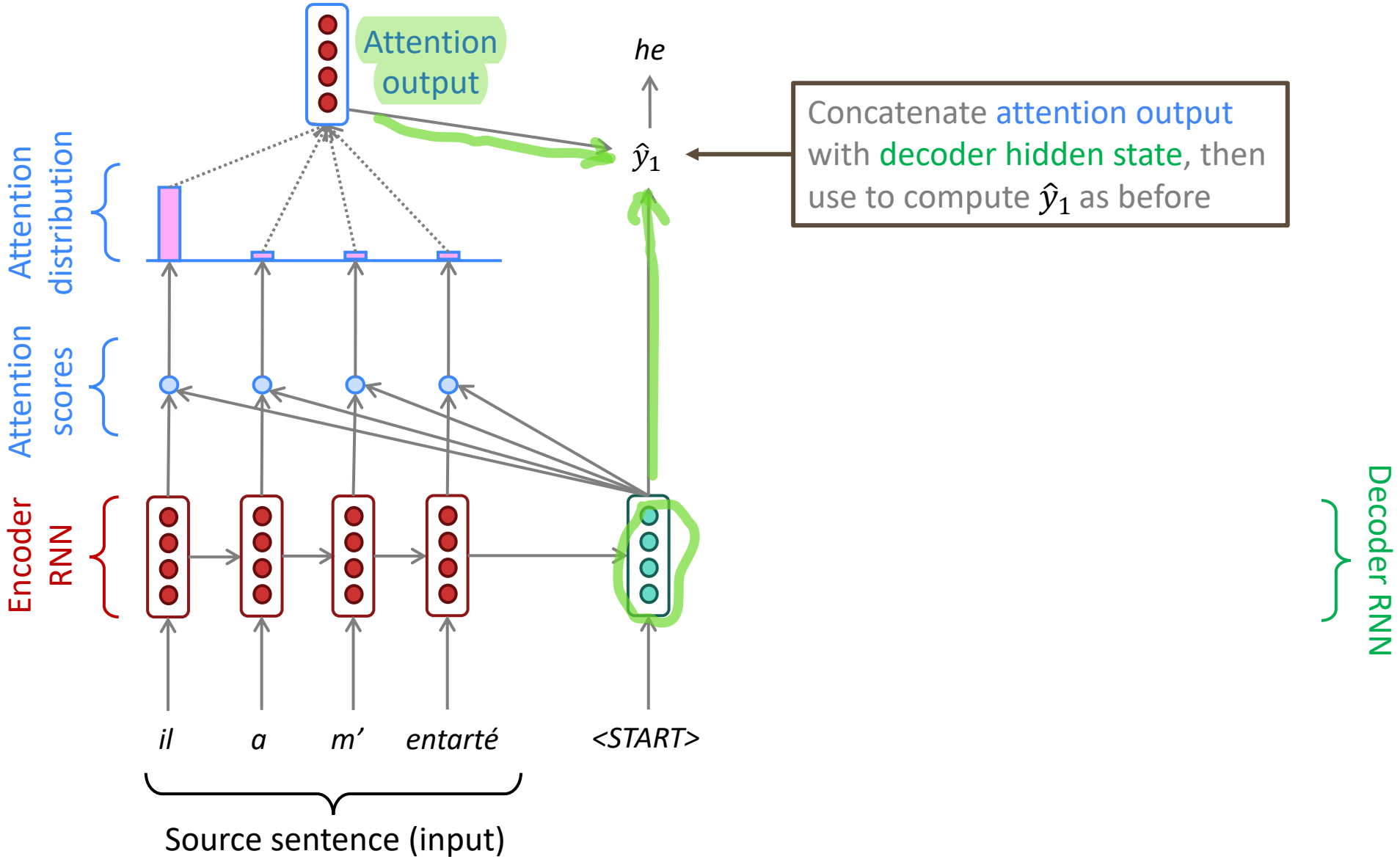
Sequence-to-sequence with attention



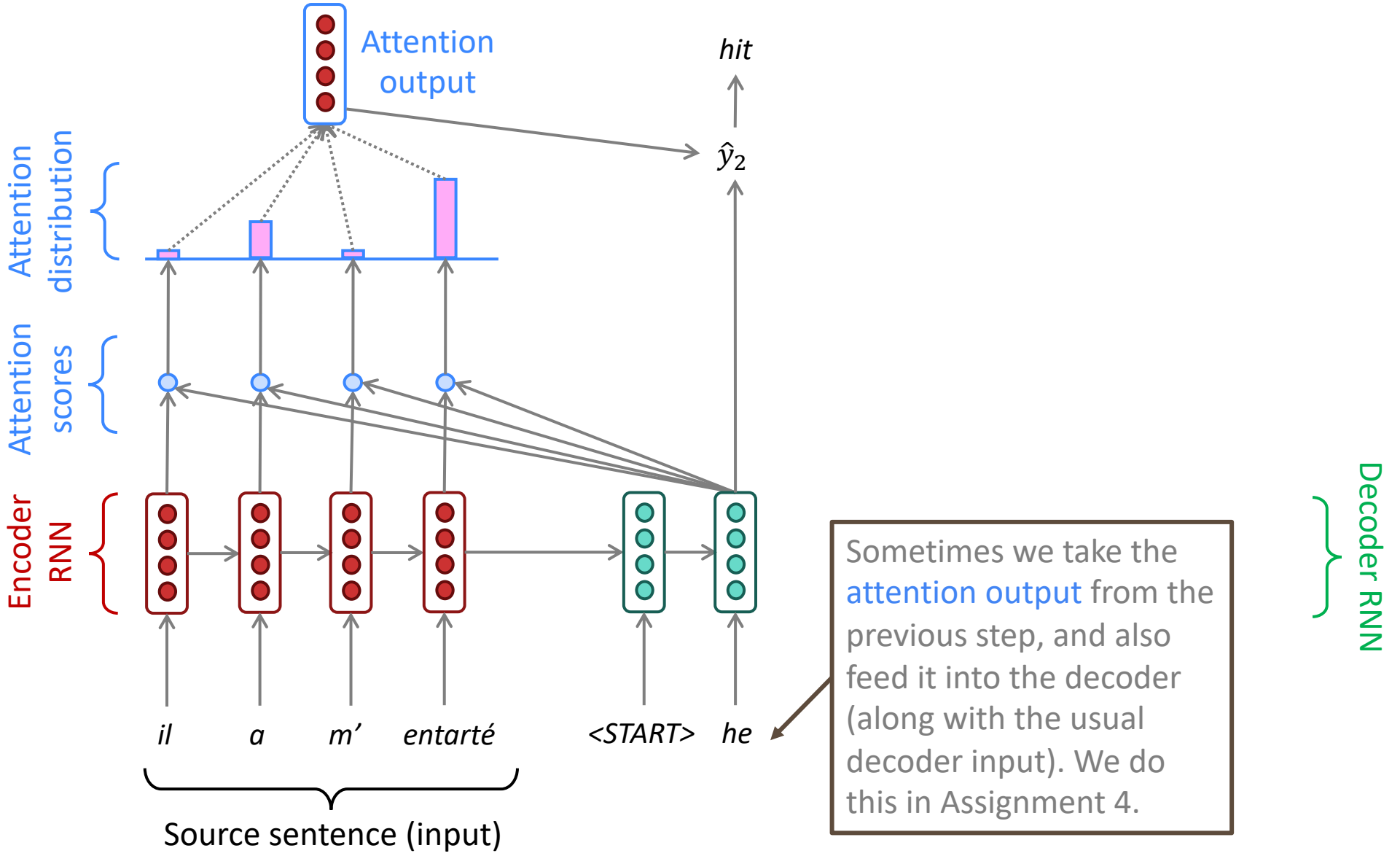
Use the attention distribution to take a **weighted sum** of the encoder hidden states.

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

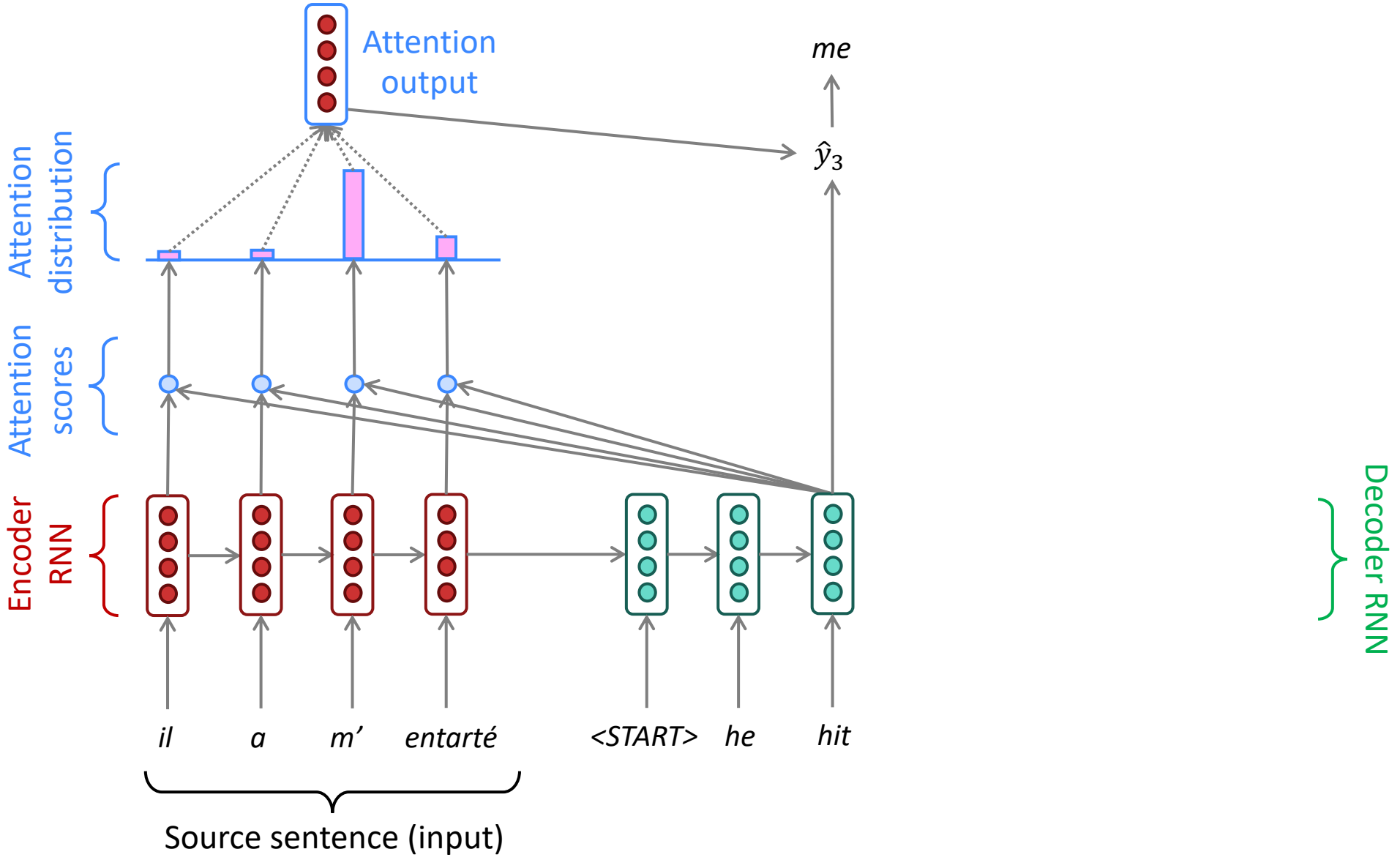
Sequence-to-sequence with attention



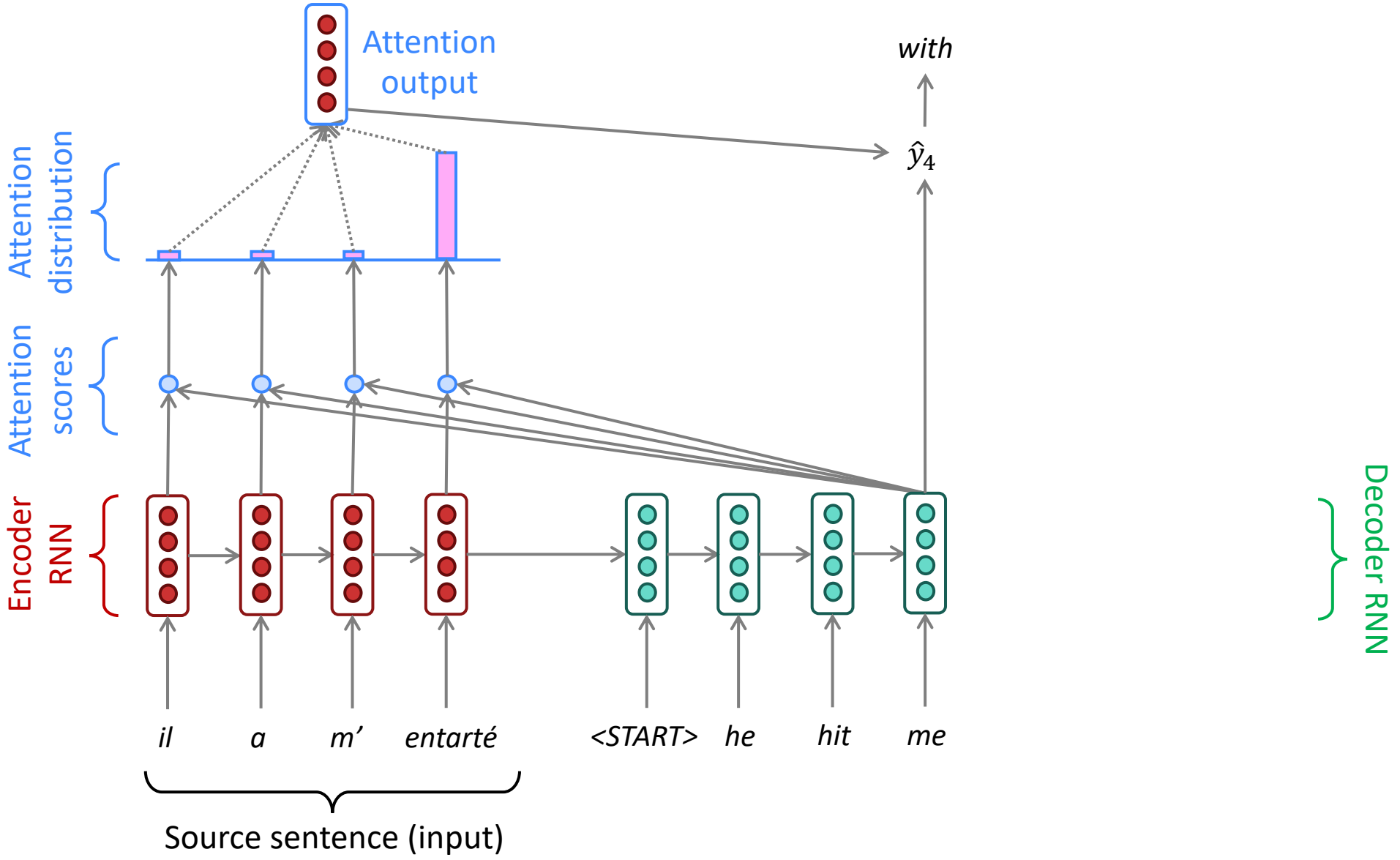
Sequence-to-sequence with attention



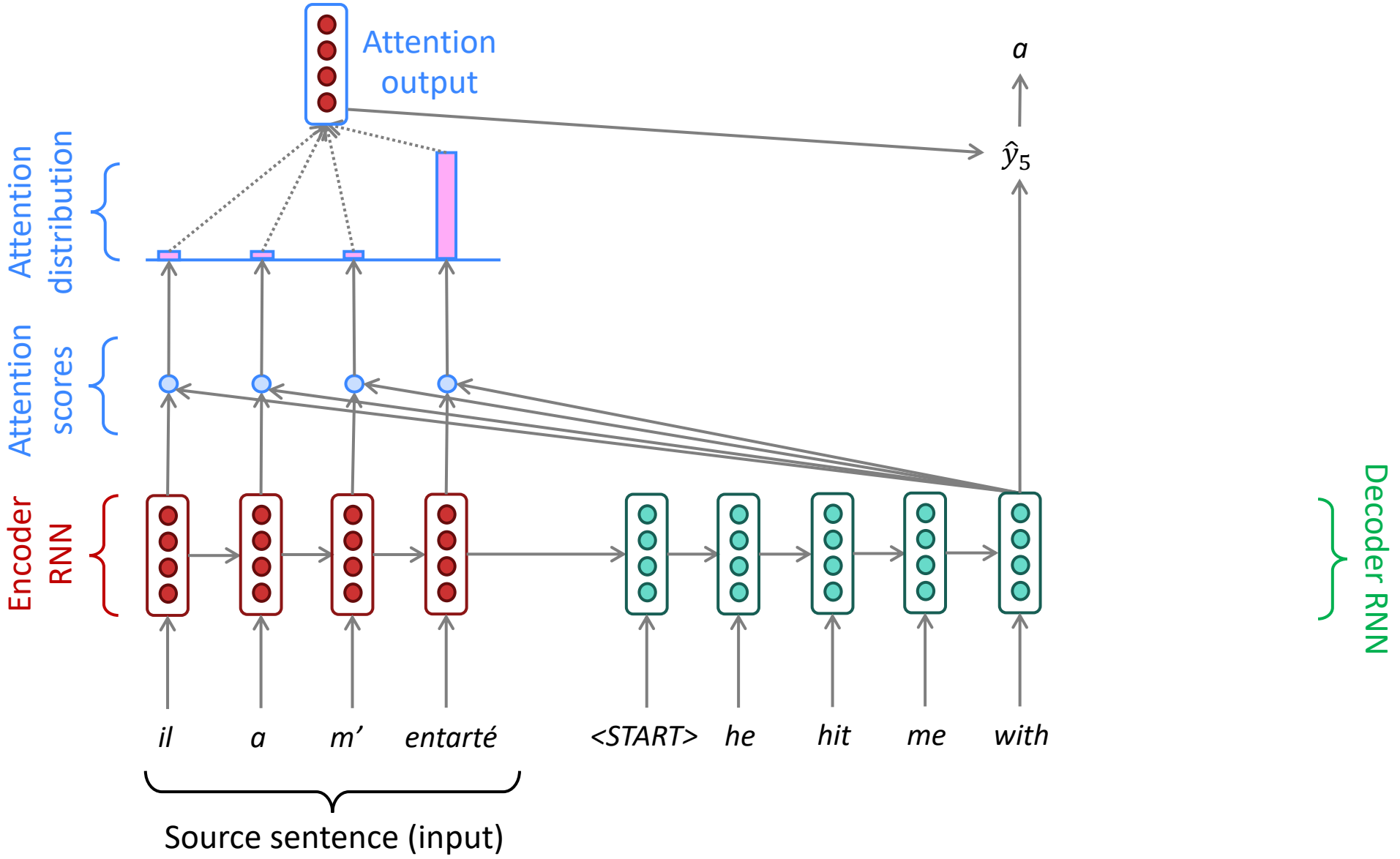
Sequence-to-sequence with attention



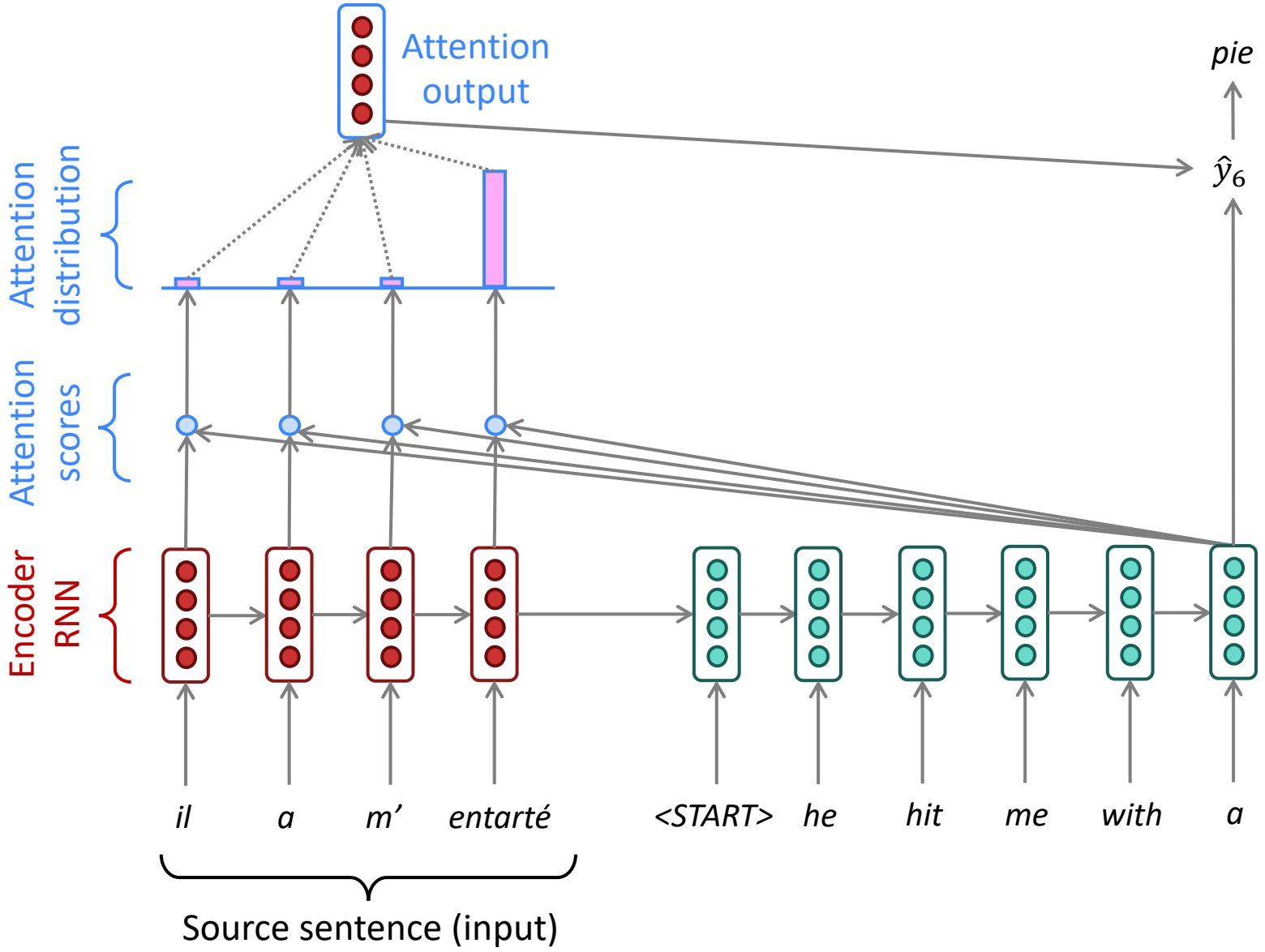
Sequence-to-sequence with attention



Sequence-to-sequence with attention



Sequence-to-sequence with attention



repeat same computations for each Decoder words

==> **Attention:**

1) give more information about the source sentence

2) give more flexible translation

END

Attention: in equations

- We have encoder hidden states $h_1, \ldots, h_N \in \mathbb{R}^h$
- On timestep *t*, we have decoder hidden state $s_t \in \mathbb{R}^h$
- We get the attention scores $\boldsymbol{e}^t$ for this step:

$$\boldsymbol{e}^t = [\boldsymbol{s}_t^T \boldsymbol{h}_1, \ldots, \boldsymbol{s}_t^T \boldsymbol{h}_N] \in \mathbb{R}^N$$

- We take softmax to get the attention distribution α^t for this step (this is a probability distribution and sums to 1)

$$\alpha^t = \text{softmax}(\boldsymbol{e}^t) \in \mathbb{R}^N$$

- We use α^t to take a weighted sum of the encoder hidden states to get the attention output $\boldsymbol{a}_t$

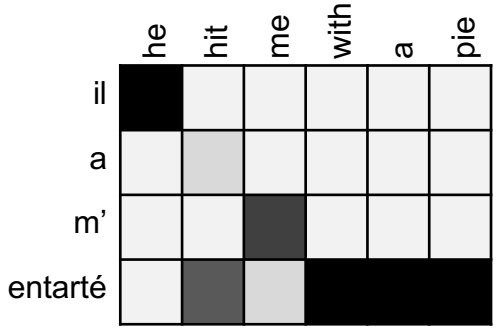
$$\boldsymbol{a}_t = \sum_{i=1}^{N} \alpha_i^t \boldsymbol{h}_i \in \mathbb{R}^h$$

- Finally we concatenate the attention output $\boldsymbol{a}_t$ with the decoder hidden state s_t and proceed as in the non-attention seq2seq model

$$[\boldsymbol{a}_t; \boldsymbol{s}_t] \in \mathbb{R}^{2h}$$

Attention is great

- Attention significantly improves NMT performance
  - It's very useful to allow decoder to focus on certain parts of the source
- Attention solves the bottleneck problem
  - Attention allows decoder to look directly at source; bypass bottleneck
- Attention helps with vanishing gradient problem
  - Provides shortcut to faraway states
- Attention provides some interpretability
  - By inspecting attention distribution, we can see what the decoder was focusing on
  - We get (soft) alignment for free!
  - This is cool because we never explicitly trained an alignment system
  - The network just learned alignment by itself



Attention is a *general* Deep Learning technique

- We've seen that attention is a great way to improve the sequence-to-sequence model for Machine Translation.
- However: You can use attention in many architectures (not just seq2seq) and many tasks (not just MT)

- **More general definition of attention**:
  - Given a set of vector *values*, and a vector *query*, **attention** is a technique to compute a weighted sum of the values, dependent on the query.

- We sometimes say that the query *attends to* the values.
- For example, in the seq2seq + attention model, each decoder hidden state (query) *attends to* all the encoder hidden states (values).

Attention is a *general* Deep Learning technique

More general definition of attention:

Given a set of vector *values*, and a vector *query*, **attention** is a technique to compute a weighted sum of the values, dependent on the query.

Intuition:

- The weighted sum is a *selective summary* of the information contained in the values, where the query determines which values to focus on.
- Attention is a way to obtain a *fixed-size representation of an arbitrary set of representations* (the values), dependent on some other representation (the query).

There are *several* attention variants

- We have some *values* $\boldsymbol{h}_1, \ldots, \boldsymbol{h}_N \in \mathbb{R}^{d_1}$ and a *query* $\boldsymbol{s} \in \mathbb{R}^{d_2}$

- Attention always involves:
  1. Computing the *attention scores* $\boldsymbol{e} \in \mathbb{R}^N$ ← There are multiple ways to do this
  2. Taking softmax to get *attention distribution* α:

$$\alpha = \text{softmax}(\boldsymbol{e}) \in \mathbb{R}^N$$

  3. Using attention distribution to take weighted sum of values:

$$\boldsymbol{a} = \sum_{i=1}^{N} \alpha_i \boldsymbol{h}_i \in \mathbb{R}^{d_1}$$

  thus obtaining the *attention output* $\boldsymbol{a}$ (sometimes called the *context vector*)

Attention variants

You'll think about the relative advantages/disadvantages of these in Assignment 4!

There are several ways you can compute $\boldsymbol{e} \in \mathbb{R}^N$ from $\boldsymbol{h}_1, \ldots, \boldsymbol{h}_N \in \mathbb{R}^{d_1}$ and $\boldsymbol{s} \in \mathbb{R}^{d_2}$:

- Basic dot-product attention: $\boldsymbol{e}_i = \boldsymbol{s}^T \boldsymbol{h}_i \in \mathbb{R}$
  - Note: this assumes $d_1 = d_2$
  - This is the version we saw earlier
- Multiplicative attention: $\boldsymbol{e}_i = \boldsymbol{s}^T \boldsymbol{W} \boldsymbol{h}_i \in \mathbb{R}$
  - Where $\boldsymbol{W} \in \mathbb{R}^{d_2 \times d_1}$ is a weight matrix
- Additive attention: $\boldsymbol{e}_i = \boldsymbol{v}^T \tanh(\boldsymbol{W}_1 \boldsymbol{h}_i + \boldsymbol{W}_2 \boldsymbol{s}) \in \mathbb{R}$
  - Where $\boldsymbol{W}_1 \in \mathbb{R}^{d_3 \times d_1}, \boldsymbol{W}_2 \in \mathbb{R}^{d_3 \times d_2}$ are weight matrices and $\boldsymbol{v} \in \mathbb{R}^{d_3}$ is a weight vector.
  - d_3 (the attention dimensionality) is a hyperparameter

More information: "Deep Learning for NLP Best Practices", Ruder, 2017. http://ruder.io/deep-learning-nlp-best-practices/index.html#attention
"Massive Exploration of Neural Machine Translation Architectures", Britz et al, 2017, https://arxiv.org/pdf/1703.03906.pdf

Summary of today's lecture

- We learned some history of Machine Translation (MT)
- Since 2014, Neural MT rapidly replaced intricate Statistical MT

- Sequence-to-sequence is the architecture for NMT (uses 2 models: encoder and decoder)
- Attention is a way to *focus on particular parts* of the input
  - Improves sequence-to-sequence a lot!