Sequence-to-Sequence Modeling & Attention

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Slides are adopted from the Stanford course 'NLP with DL' by C. Manning and UMass course 'Advanced NLP' by M Iyyer

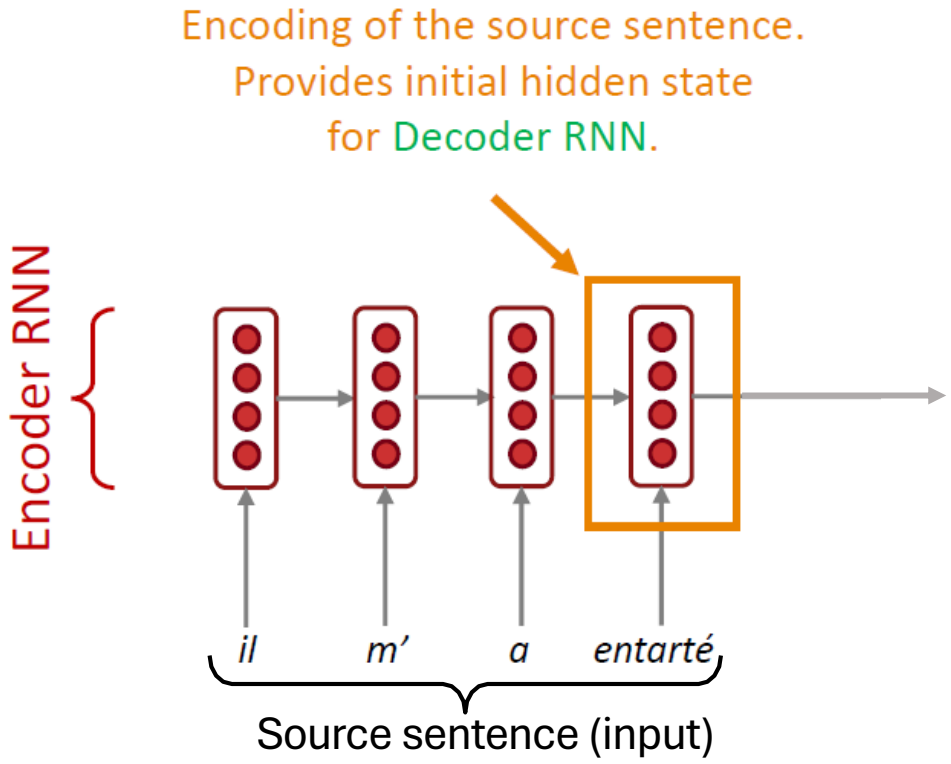
Neural Machine Translation?

- 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) and it involves *two* RNNs.

Neural Machine Translation (NMT)

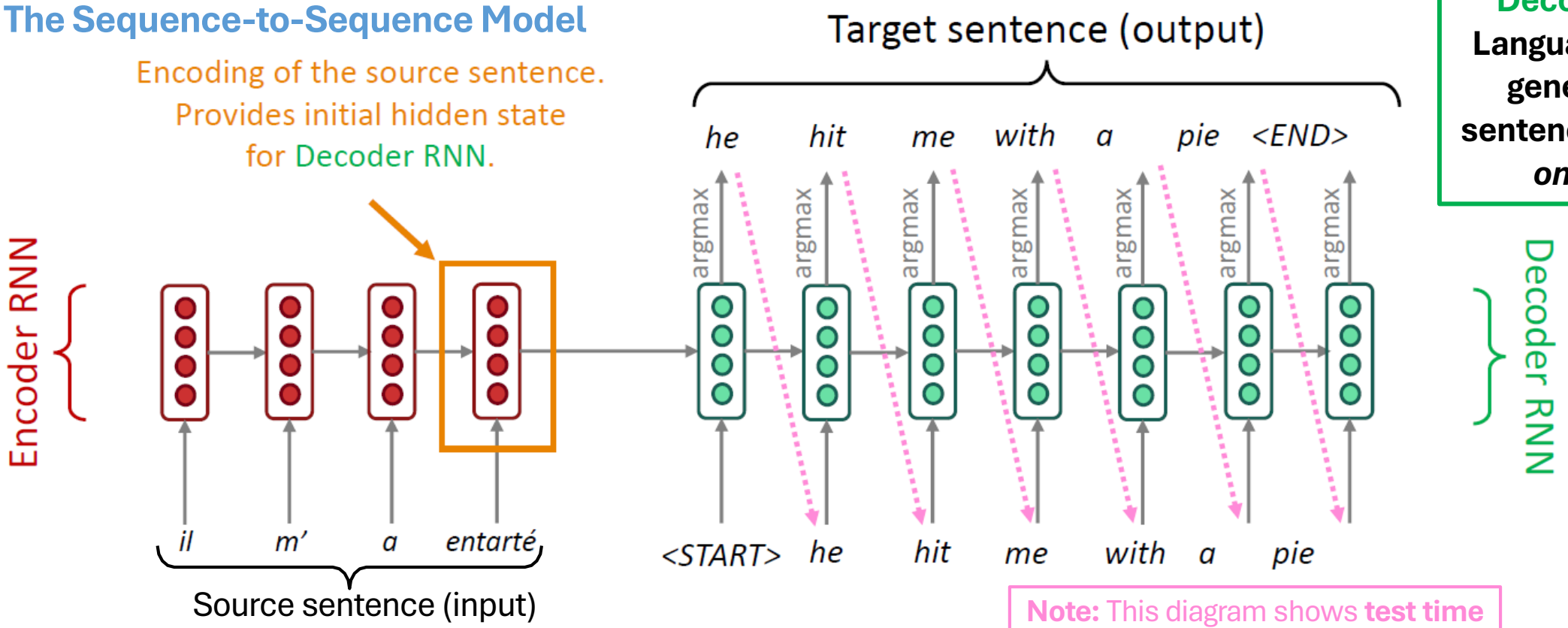
The Sequence-to-Sequence Model



Encoder RNN produces an encoding of the source sentence.

Neural Machine Translation (NMT)

The Sequence-to-Sequence Model



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

Encoder RNN produces an encoding of the source sentence.

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

Sequence-to-Sequence is Versatile!

- The general notion here is an encoder-decoder model
  - One neural network takes input and produces a neural representation
  - Another network produces output based on that neural representation
  - If the input and output are sequences, we call it a seq2seq model
- 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)

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 $P(y|x)$

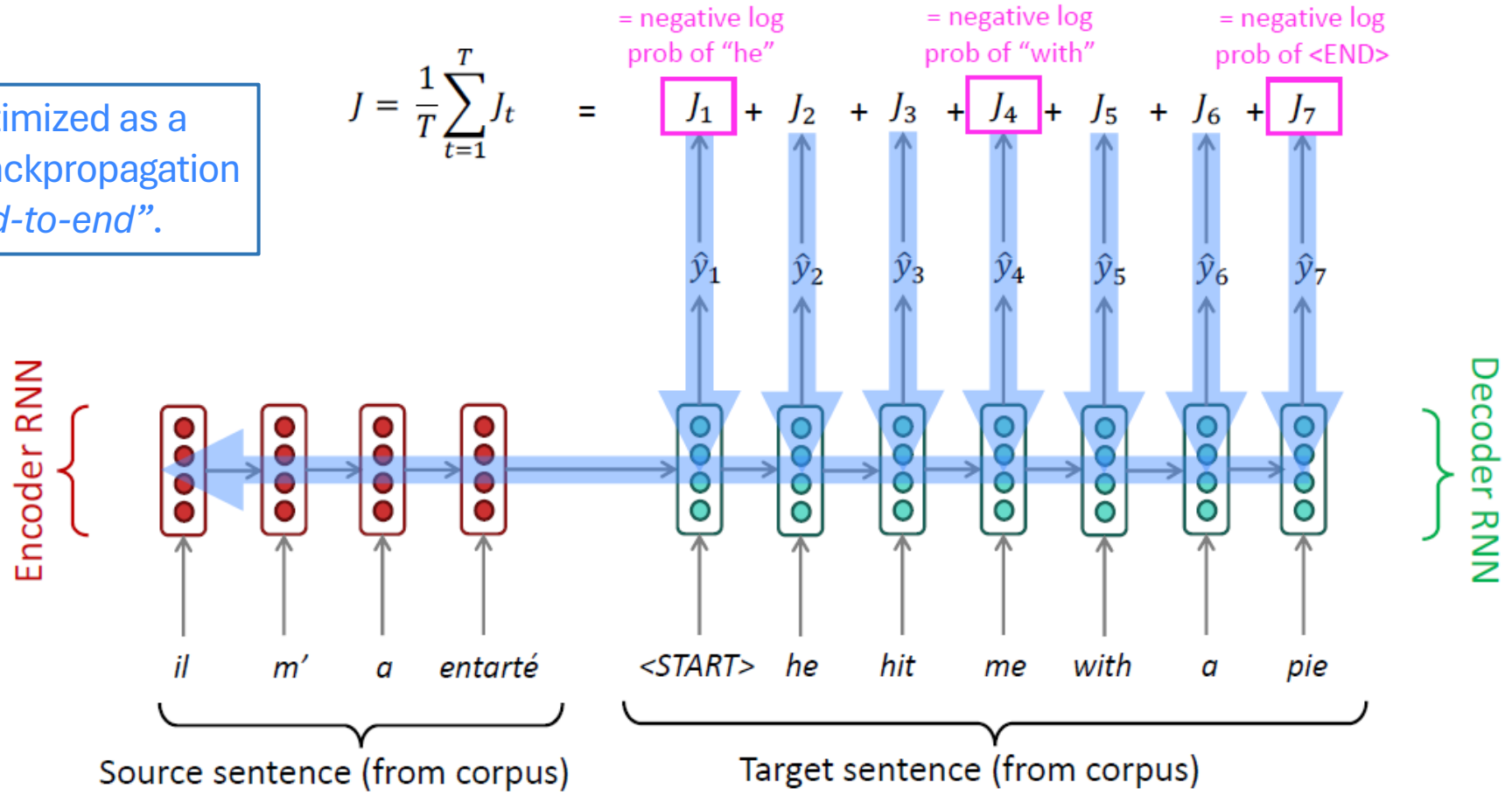
$$P(y|x) = P(y_1|x)\,P(y_2|y_1,x)\,P(y_3|y_1,y_2,x)\ldots\underbrace{P(y_T|y_1,\ldots,y_{T-1},x)}$$

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

- How to train an NMT system?

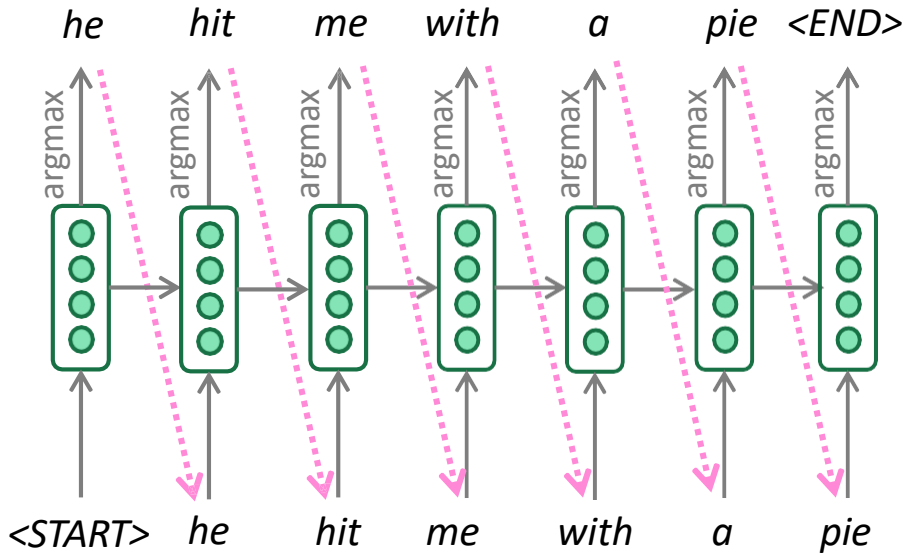
Training an NMT System

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.



- 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…)

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**!

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!

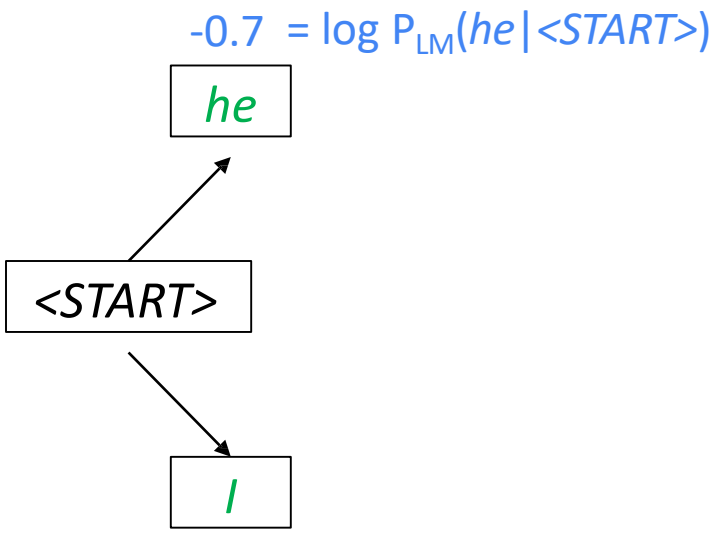
Beam Search Decoding: Example

Beam size = k = 2.

<START>

Calculate prob distribution of next word

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



Take top *k* words
and compute scores

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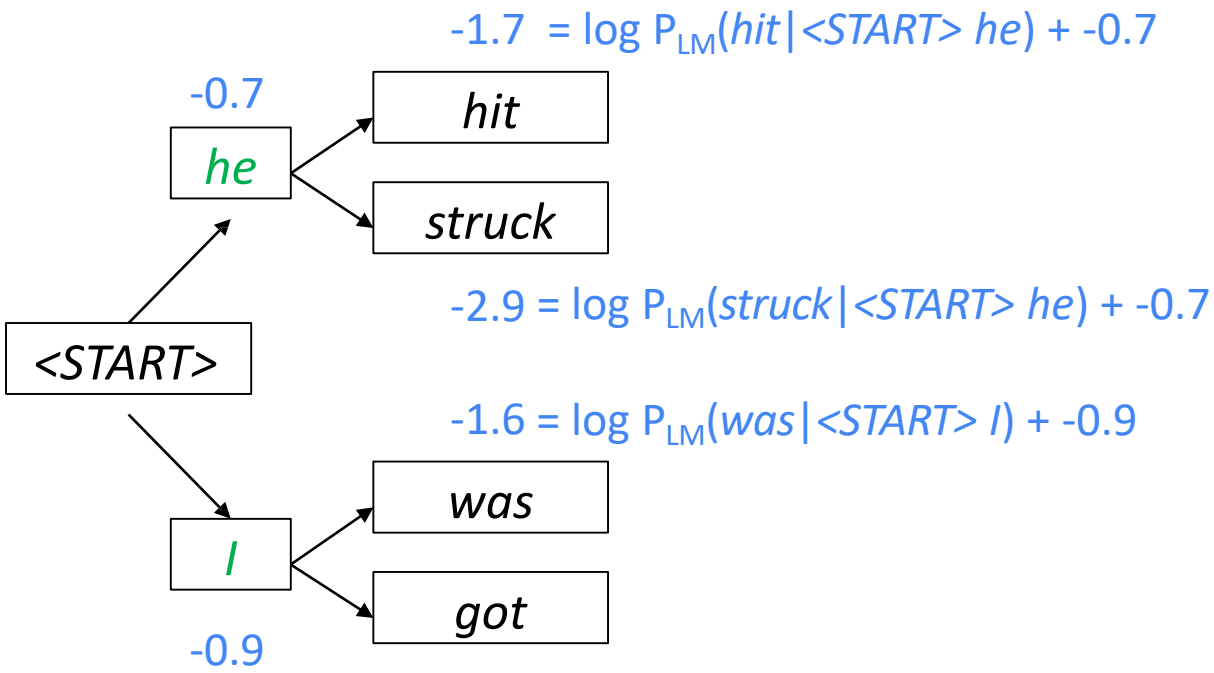

For each of the *k* hypotheses, find top *k* next words and calculate scores

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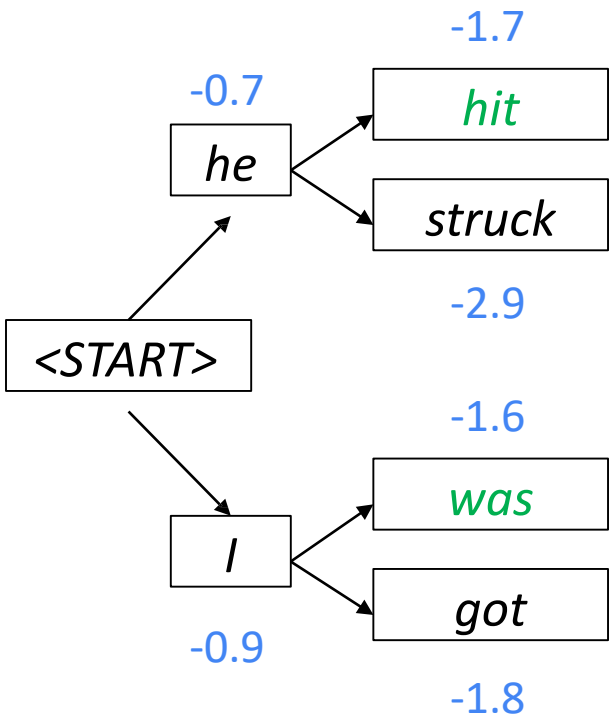

Of these k^2 hypotheses,
just keep k with highest scores

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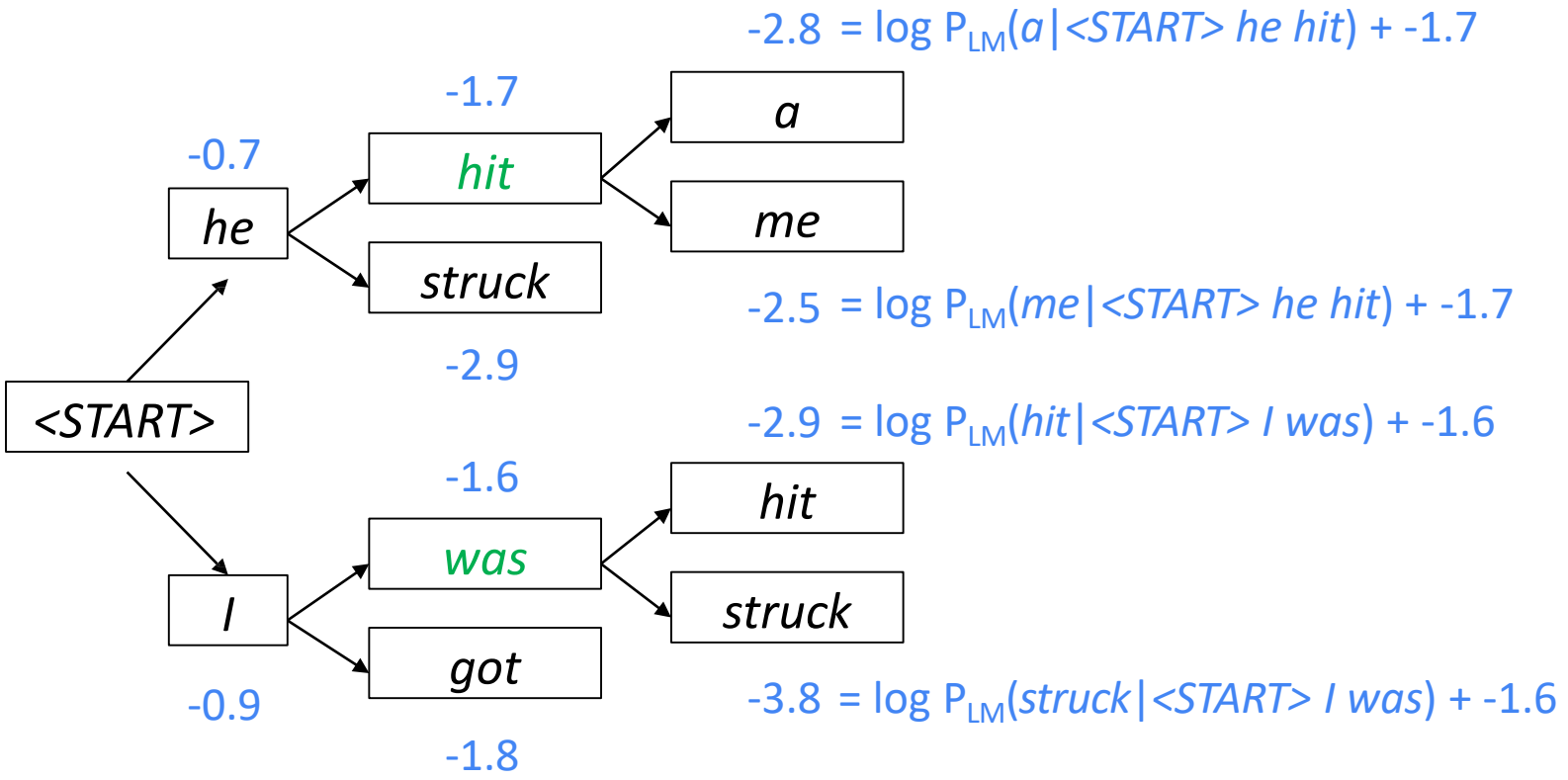

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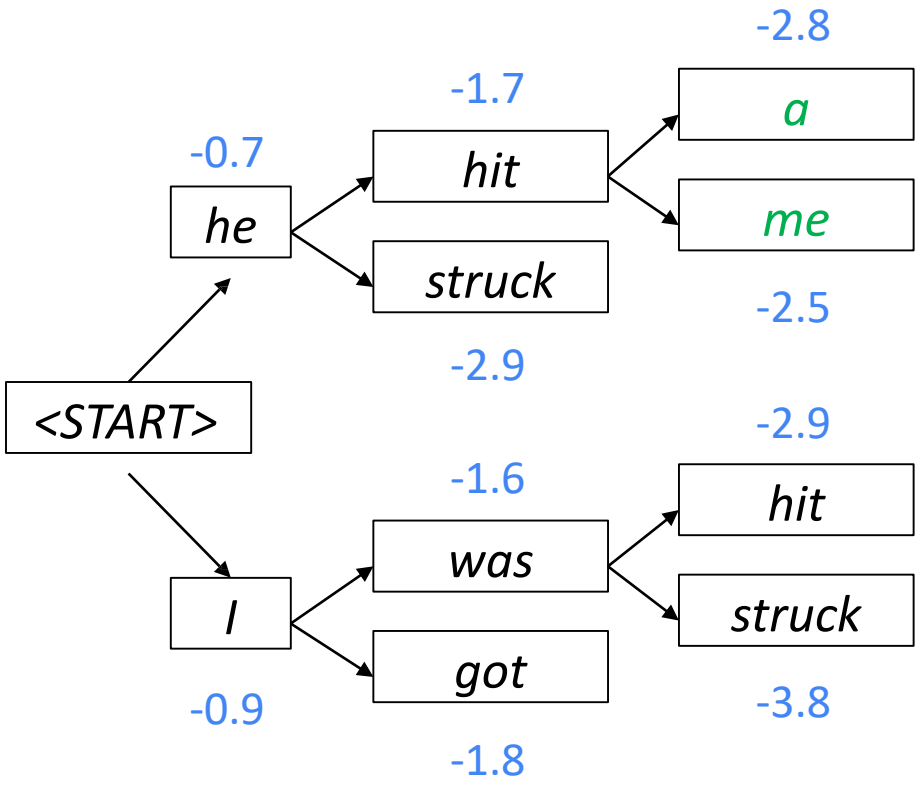

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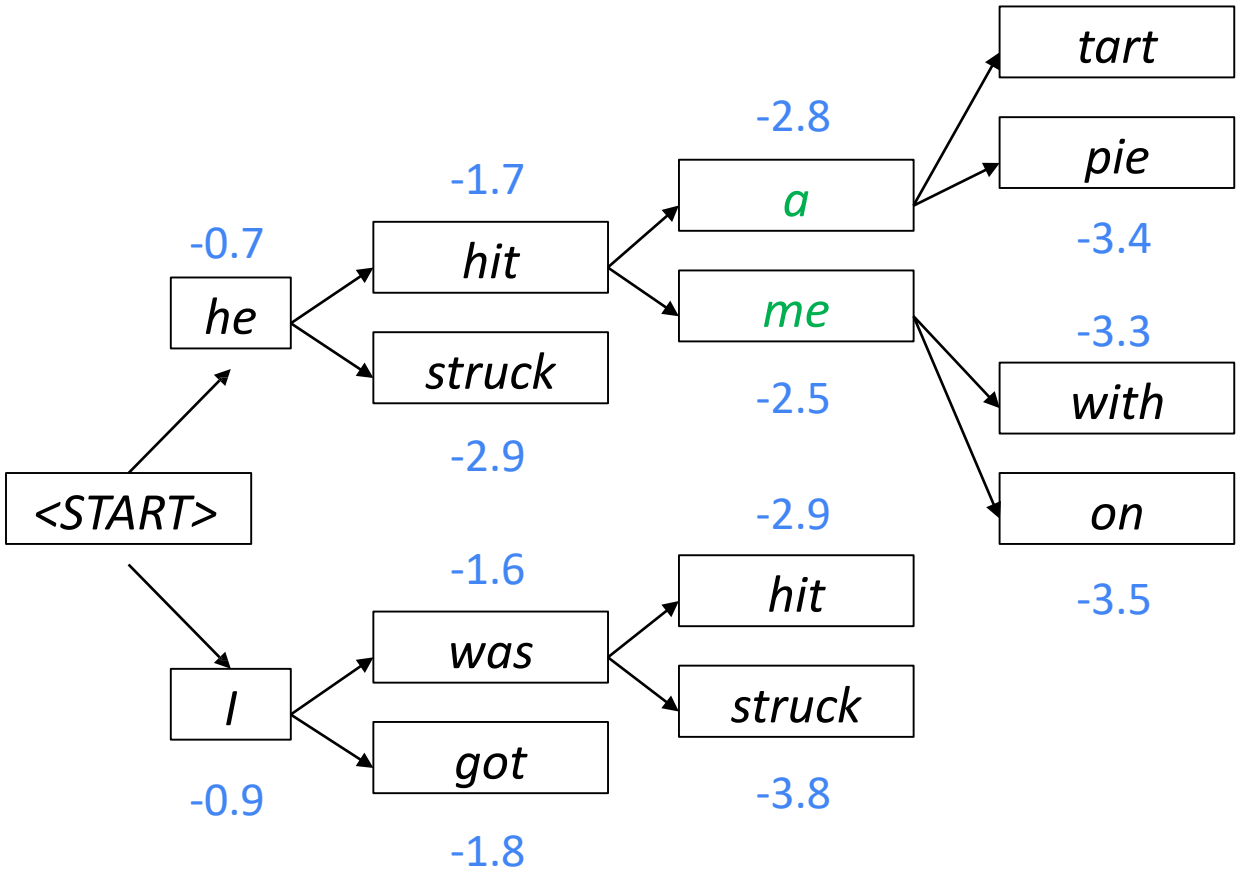

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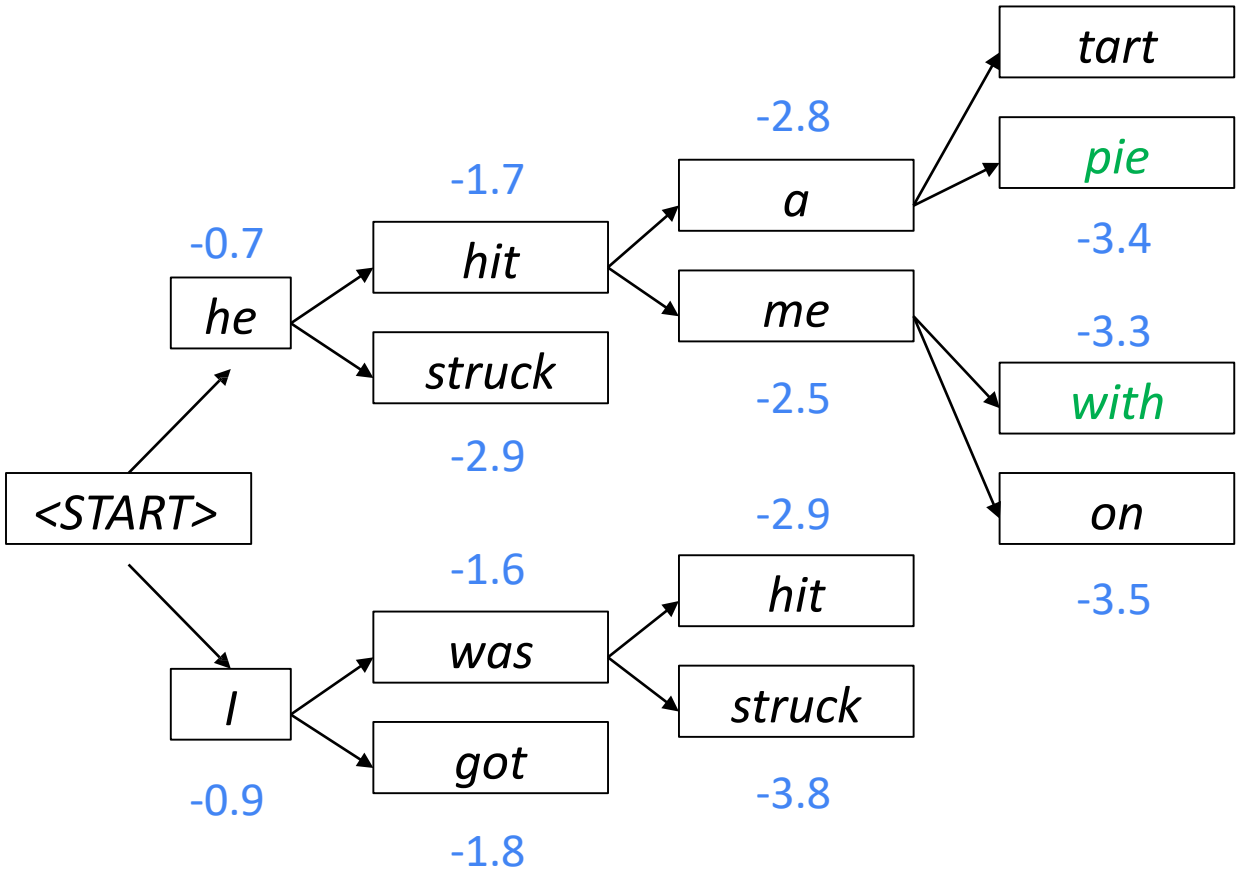

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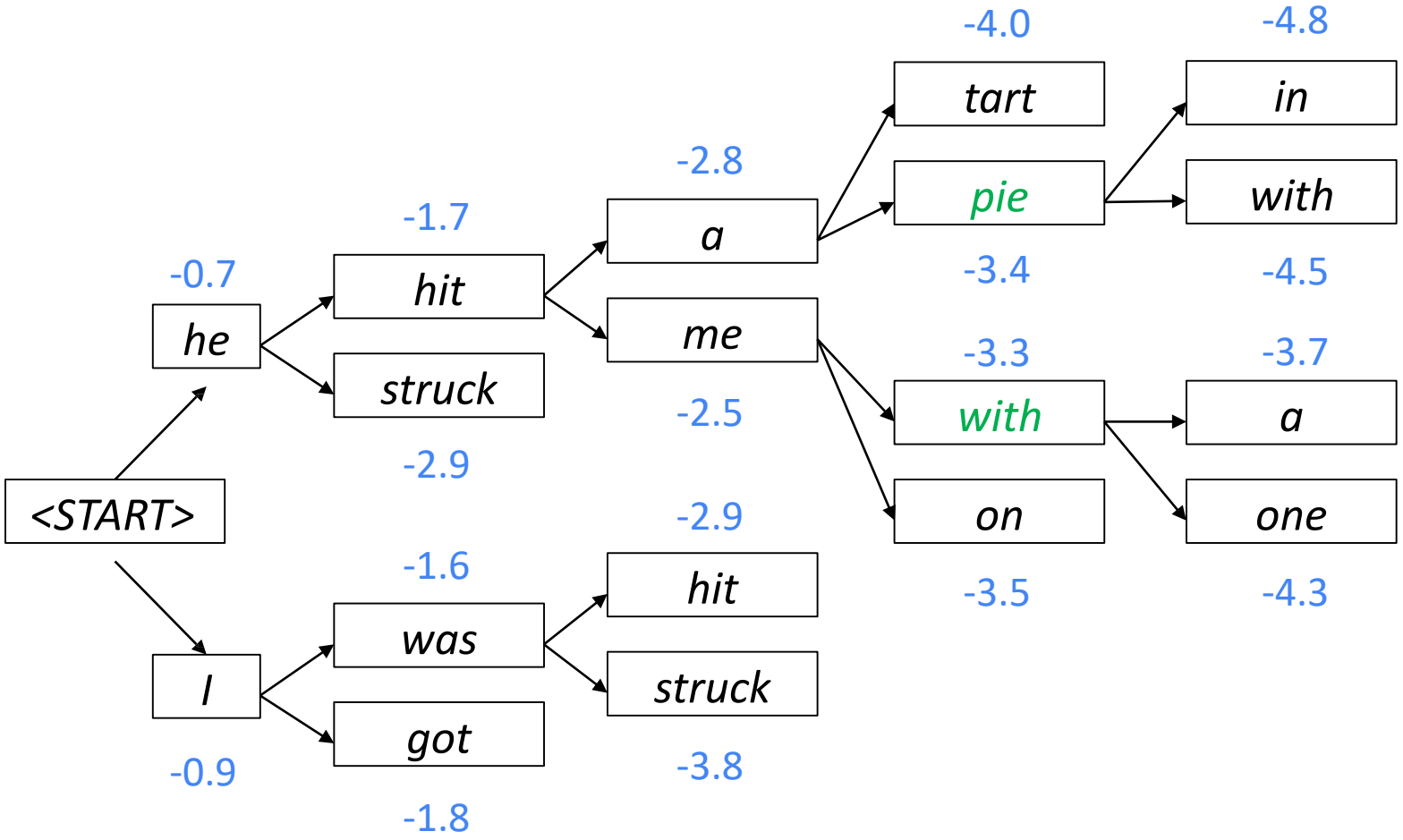

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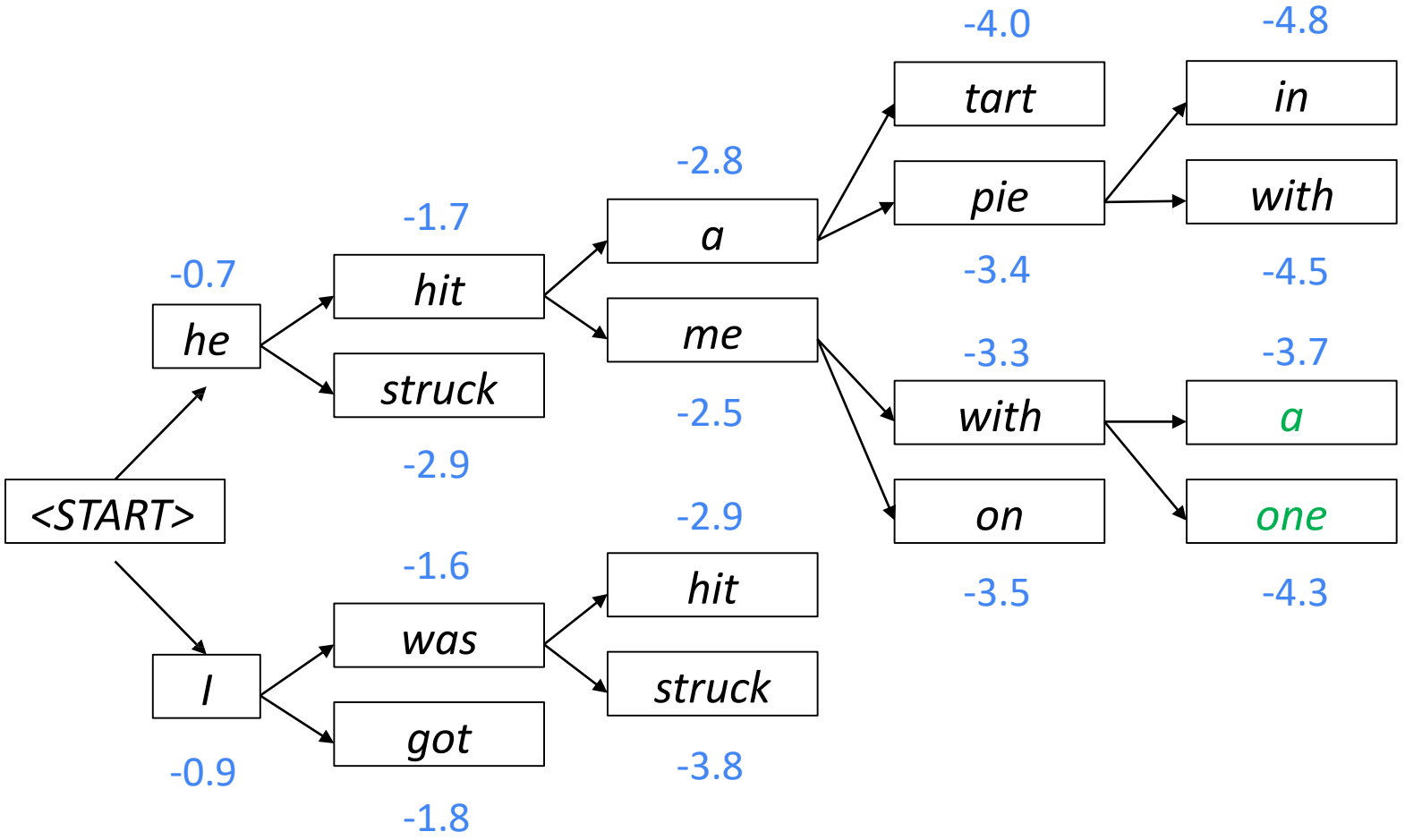

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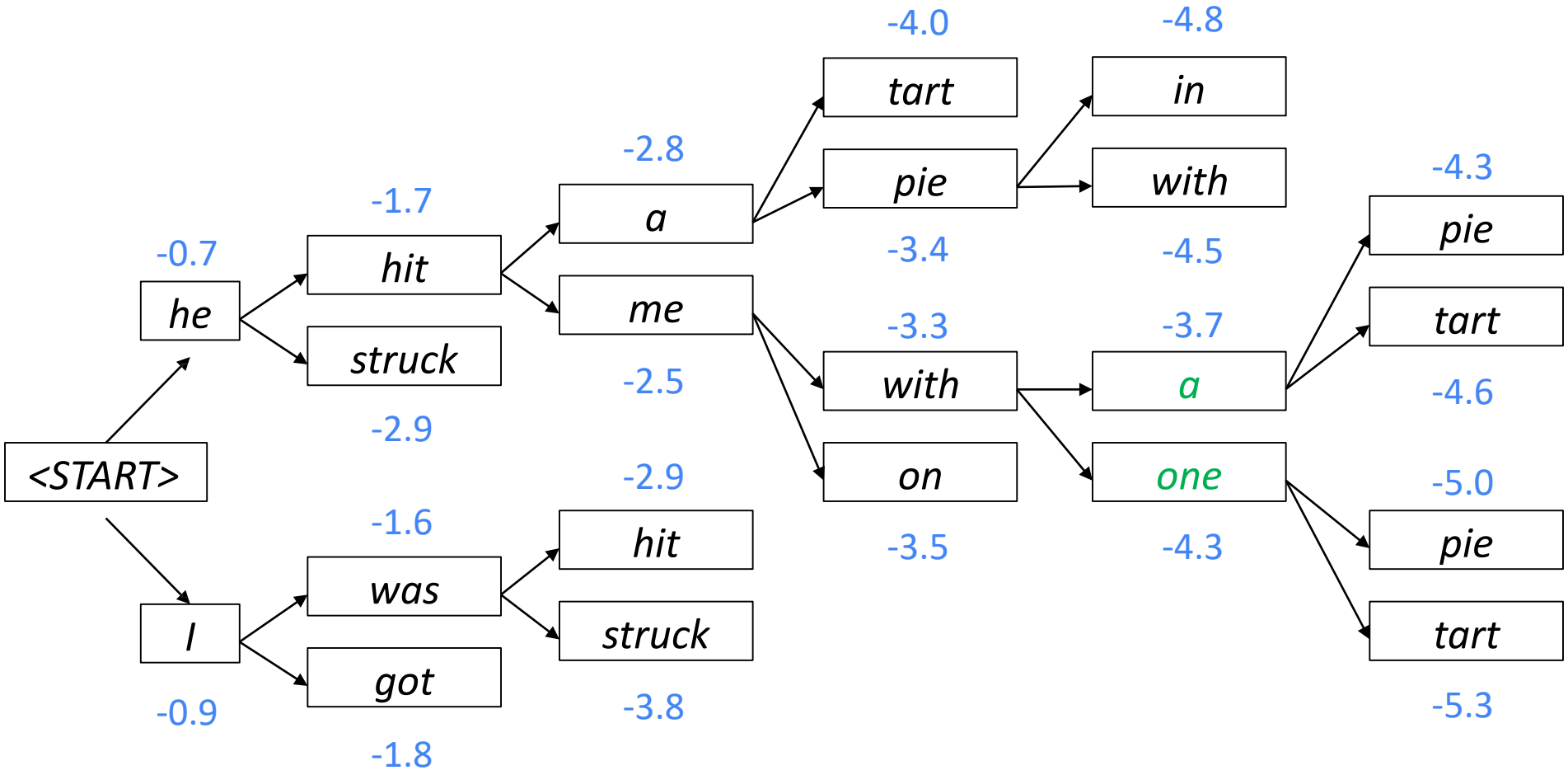

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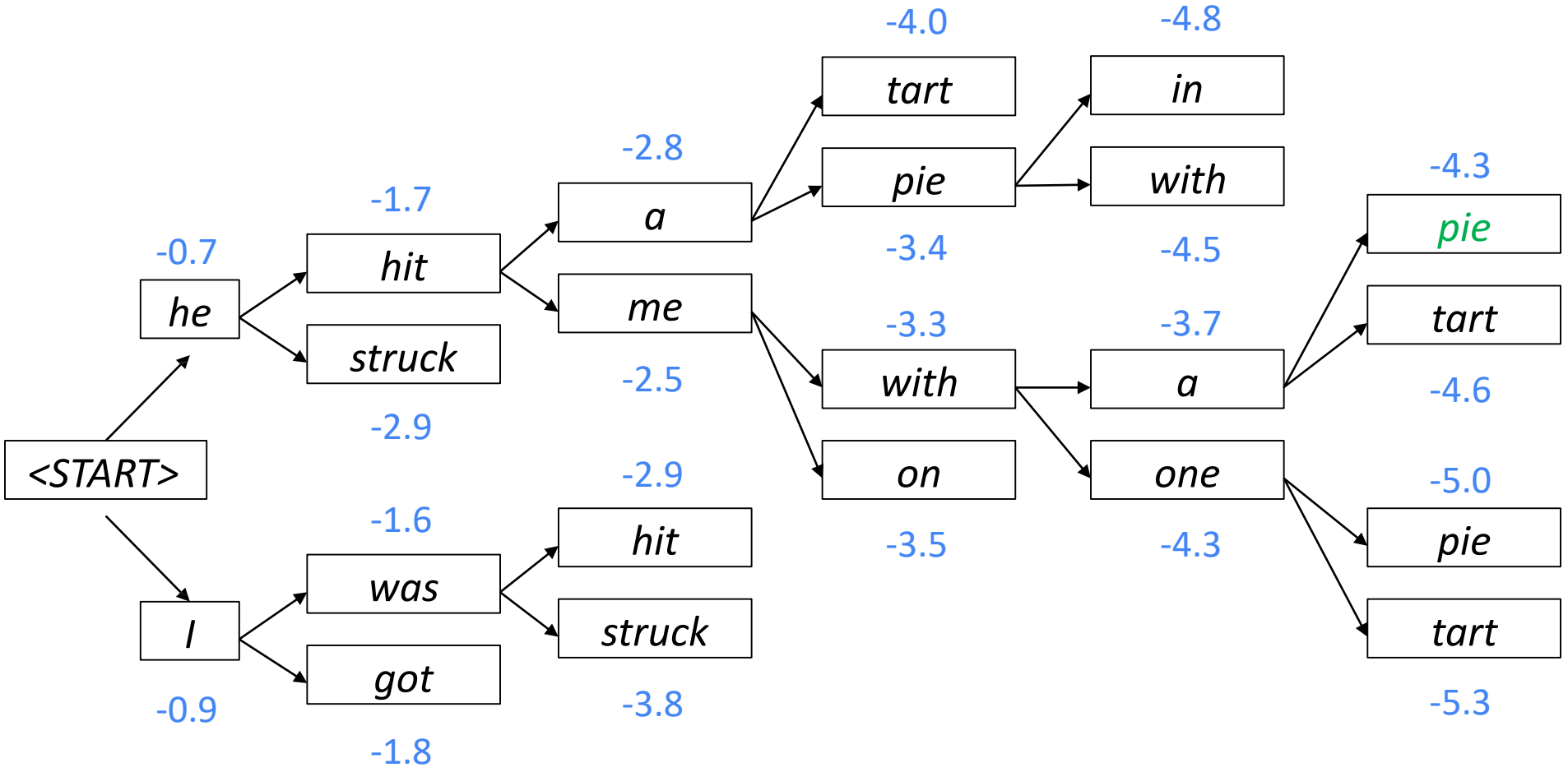
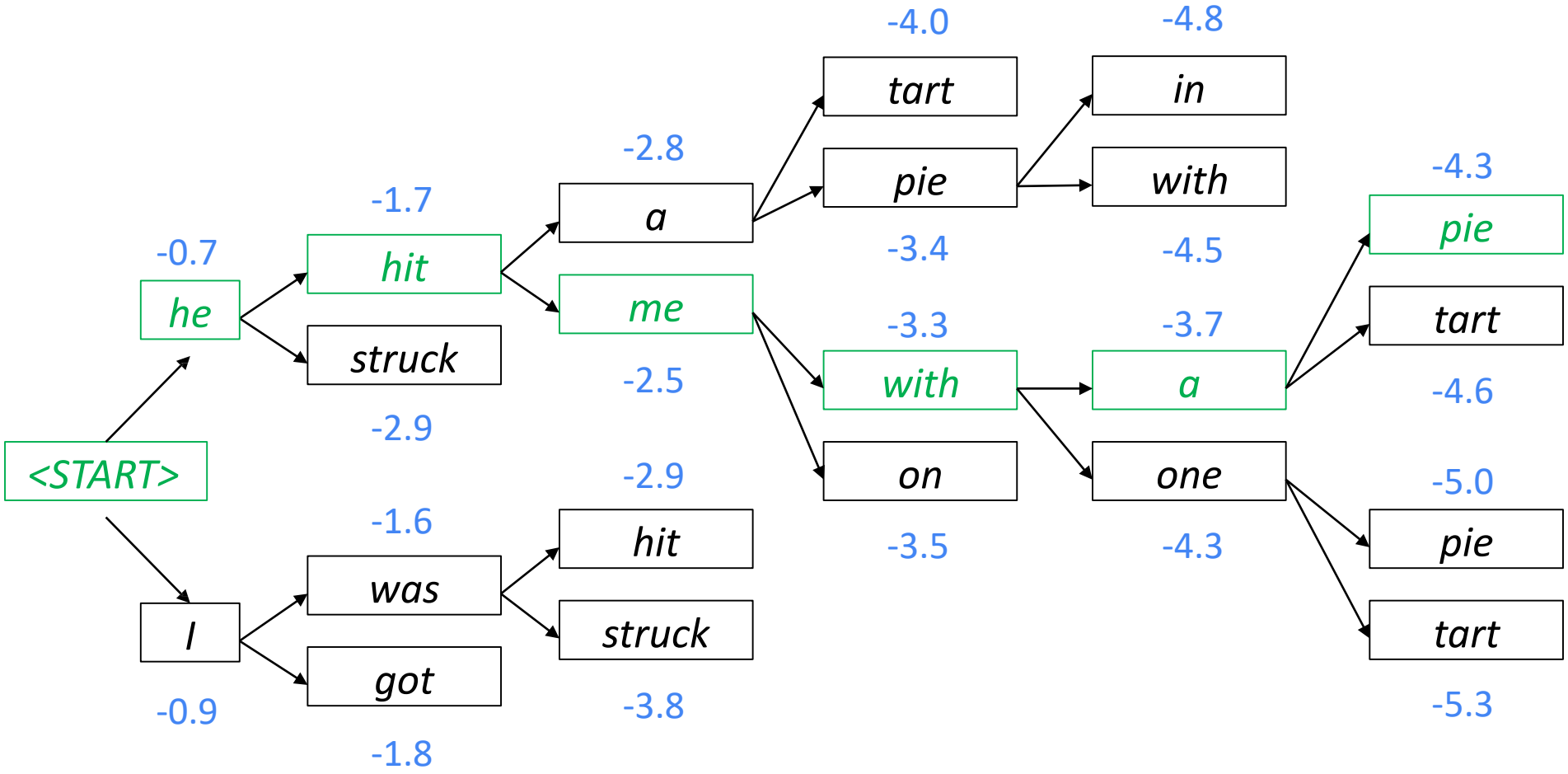


This is the top-scoring hypothesis!

Beam 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 a <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: 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

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

- **Problem:** longer hypotheses have lower scores
- **Fix:** Normalize by length. Use this to select the top one instead:

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

Other Decoding Techniques

Deterministic vs. Stochastic Decoding Strategies

- The decoding methods which we discussed in the previous lecture – greedy decoding, exhaustive search and beam search – are all deterministic, i.e., *given the same model and the same input context, they always generate the same output sequence*.

- However, to ensure diversity of the generated responses we need stochastic decoding strategies.
  - The stochastic decoding strategies generate diverse responses even for the same model and same input context.
- In this lecture, we will look into three stochastic decoding strategies:
  1. Top-k Sampling
  2. Top-p / Nucleus Sampling
  3. Temperature Sampling

Random Sampling

- Before moving onto those three stochastic decoding strategies, let's first look at simple random sampling.
- If we want to generate a sequence of N words w_1, ..., w_N , then *random sampling* can be written formally as the following algorithm:

$i \leftarrow 1$

$w_i \sim P(w_i \mid c)$

while w_i != EOS or i<=N:

$i \leftarrow i + 1$

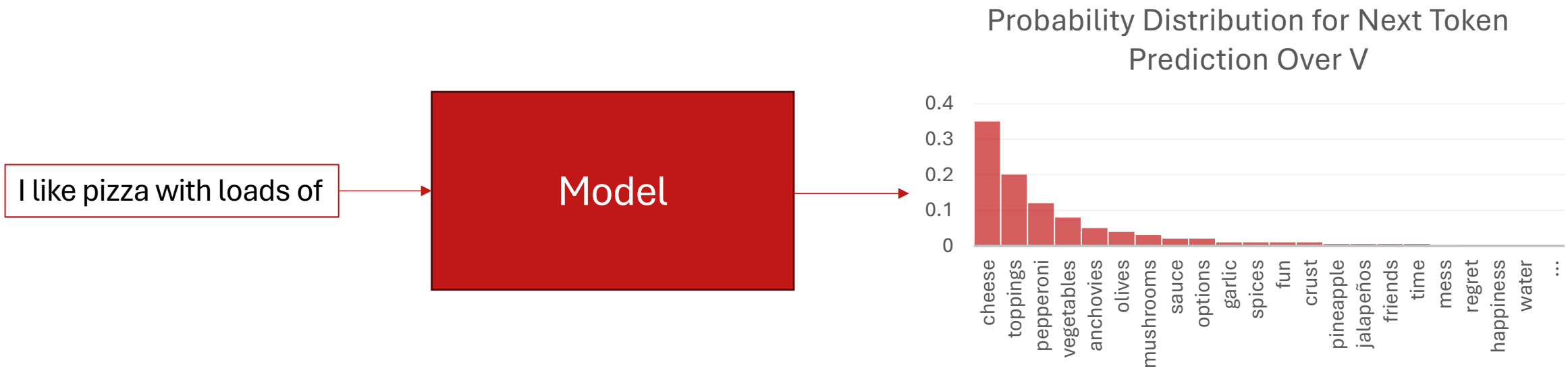
$w_i \sim P(w_i \mid c, w_{<i})$

Intuitively, if say P(*cheese* | c='I like pizza with loads of') = 0.35, then on giving c as input 100 times, on random sampling, 'cheese' is expected to be generated approximately 35 times as the next token, though the exact count may vary due to randomness.

Top-k Sampling

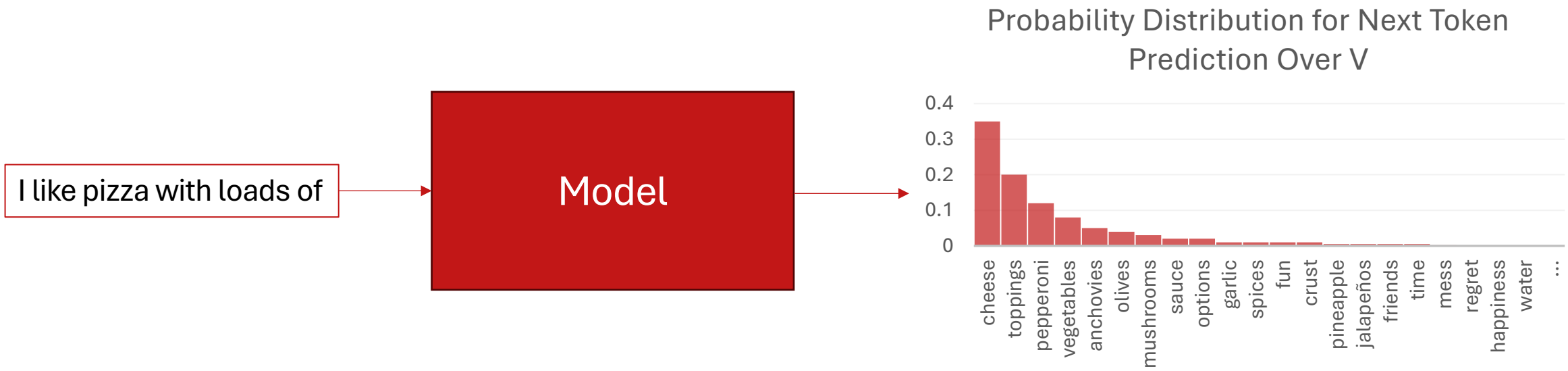
- In greedy decoding, the token with the highest probability was chosen at each step, making it deterministic. Top-k sampling is a stochastic generalization of greedy decoding.
- Top-k sampling involves the following steps:
  1. Choose in advance a number of tokens ***k***
  2. Given the probability $P(w_t | c, w_{<t})$ for all tokens in the vocabulary V, as generated by the model, sort the tokens by their likelihood, and throw away any token that is not one of the top ***k*** most probable tokens.
  3. Renormalize the scores of the ***k*** tokens to be a legitimate probability distribution.
  4. Randomly sample a token from within these remaining ***k*** most-probable tokens according to its probability.
- When k = 1, top-k sampling is identical to greedy decoding.

Top-k Sampling: Working Example



- Let's take **k=3**.
- Step-1: Sort the tokens by their likelihood, and throw away any token that is not one of the top ***k*** most probable tokens.
  - In our example, top-3 tokens with P(w|c) are: **cheese (0.35), toppings (0.20), pepperoni (0.12)**

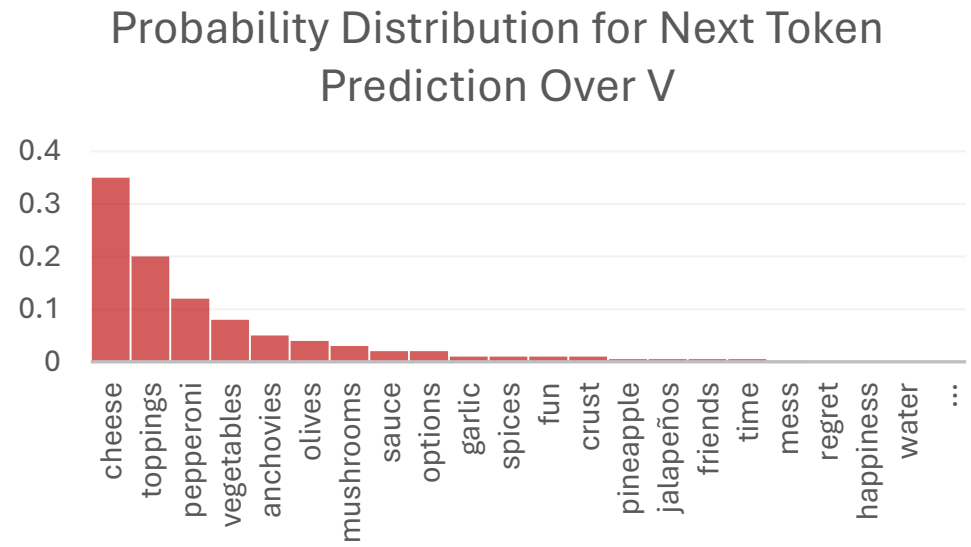
Top-k Sampling: Working Example

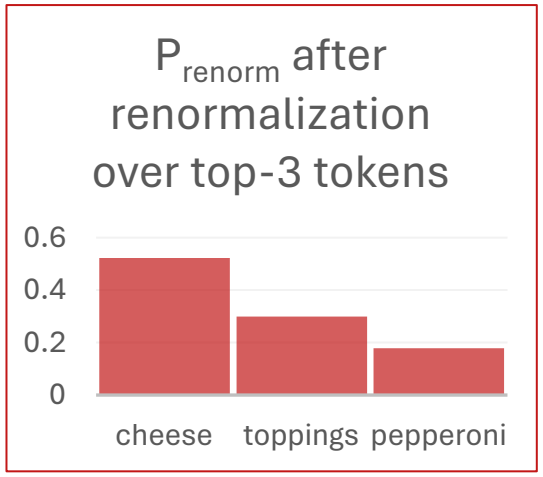


- Step-2: Renormalize the scores of the ***k*** tokens to be a legitimate probability distribution.
- After renormalization, $P_{renorm}(w|c) = \frac{P(w|c)}{\sum_{x \in top-k} P(x|c)}$.
  - Renormalized probabilities: **cheese (0.522), toppings (0.299), pepperoni (0.179)**

Top-k Sampling: Working Example

I like pizza with loads of → Model

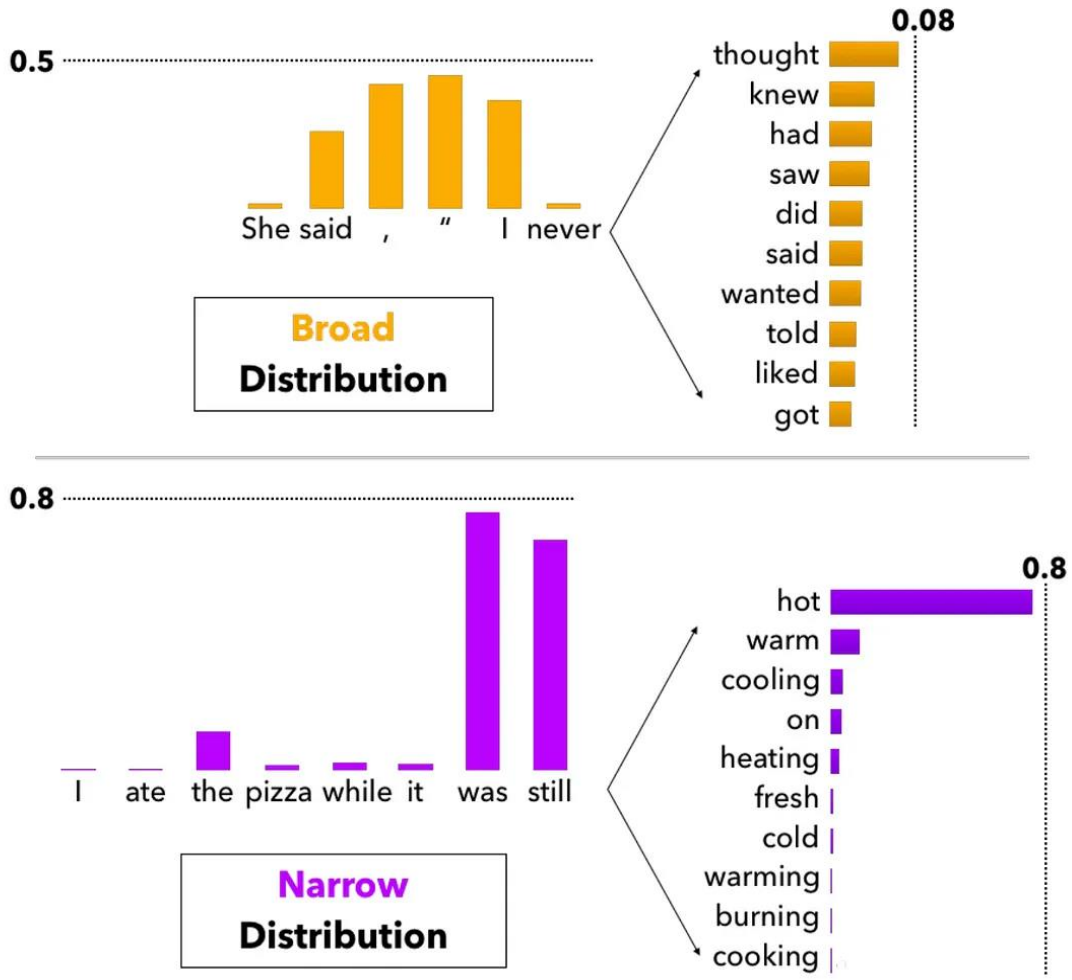




- Step-3: Randomly sample a token from within these remaining ***k*** most-probable tokens according to its probability after renorm.
- For generating the next token, $w_t \sim P_{renorm}(w_t | c)$

Problem With Top-k Sampling

- In top-k sampling ***k*** is fixed, but the shape of the probability distribution over tokens differs in different contexts.
- For example, if we set k = 10:
  - Sometimes the top 10 tokens will be very likely and include most of the probability mass.
  - But other times the probability distribution will be flatter and the top 10 tokens will only include a small part of the probability mass.



Solution: Top-p / Nucleus Sampling

Image source: https://towardsdatascience.com/how-to-sample-from-language-models-682bceb97277

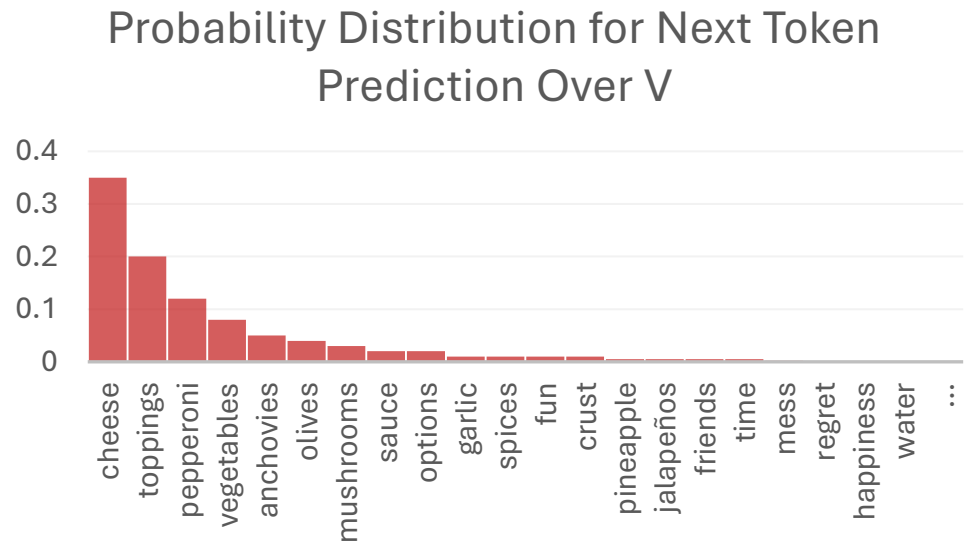
Top-p / Nucleus Sampling

- The goal of nucleus sampling is the same as top-k sampling, which is to truncate the distribution to remove the very unlikely tokens.
- Here, we keep the top ***p*** percent of the probability mass.
  - By measuring probability rather than the number of tokens, the hope is that the measure will be more robust in very different contexts, dynamically increasing and decreasing the pool of token candidates.
- Formally, given a distribution $P(w_t \mid c, w_{<t})$, the top-p vocabulary $\mathbf{V^{(p)}}$ is the smallest set of tokens such that:

$$\sum_{w \in V^{(p)}} P(w|c, w_{<t}) \geq p$$

Top-p Sampling: Working Example

I like pizza with loads of → Model →



Token (w)	P(w|c)	Cumulative P
cheese	0.35	0.35
toppings	0.20	0.55
pepperoni	0.12	0.67
vegetables	0.08	0.75
anchovies	0.05	0.80

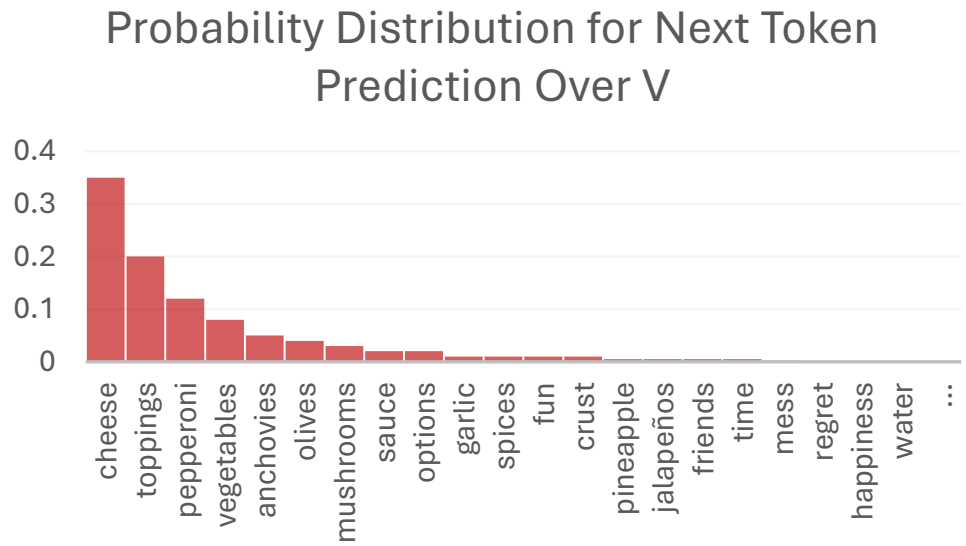
- Let's take **p=0.5**
- Step-1: Get the top-p vocabulary $\mathbf{V^{(p)}}$, which is the smallest set of tokens such that: $\sum_{w \in V(p)} P(w|c, w_{<t}) \geq p$

In our example, $\mathbf{V^{(p)}}$ consists of:

cheese (0.35), toppings (0.20)

Top-p Sampling: Working Example

I like pizza with loads of → Model →

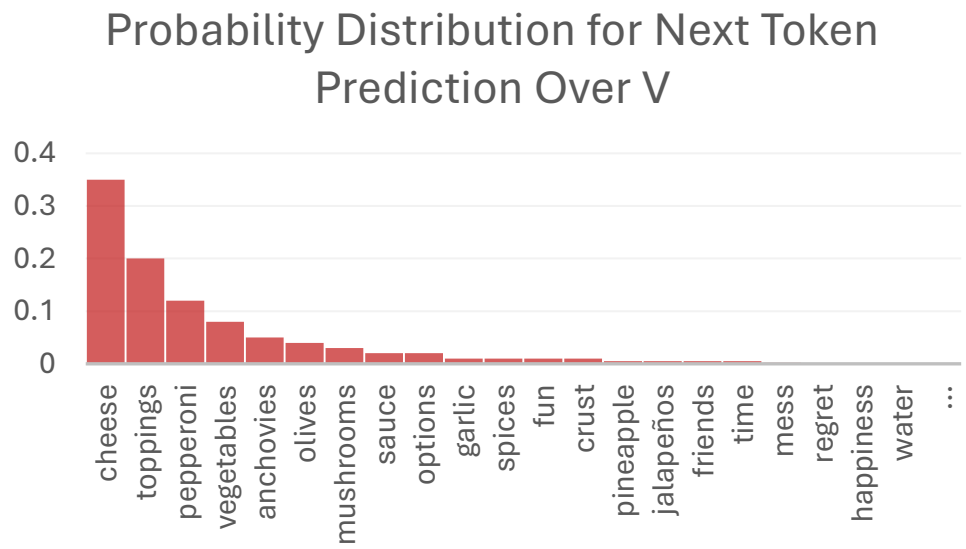


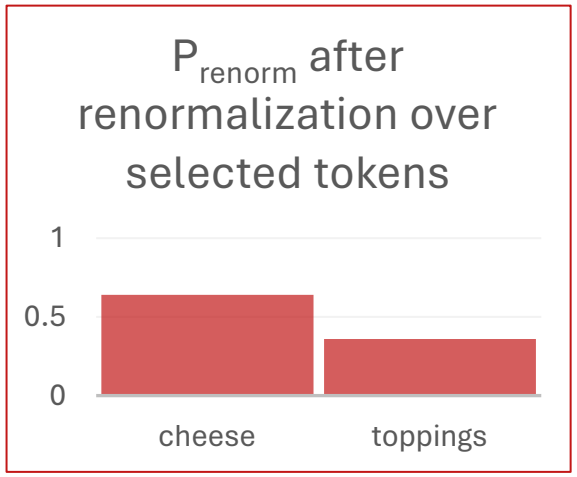
- Step-2: Renormalize the scores of the selected tokens (same procedure as top-k).

Renormalized probabilities: **cheese** $\left(\frac{0.35}{0.35+0.20} = 0.64\right)$, **toppings** $\left(\frac{0.20}{0.35+0.20} = 0.36\right)$

Top-p Sampling: Working Example

I like pizza with loads of → Model → Probability Distribution for Next Token Prediction Over V





- Step-3: Randomly sample a token from within these selected tokens according to its probability after renormalization.
- For generating the next token, $w_t \sim P_{renorm}(w_t | c)$

Temperature Sampling

- In temperature sampling, we don't truncate the distribution but instead reshape it.
- The **temperature parameter (τ)** is incorporated while computing ***softmax*** over the logits of the tokens (for next token prediction).

Normal Softmax

$$P(t_i) = \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

- $P(t_i)$: Probability assigned to token t_i
- z_i : Logit for token t_i

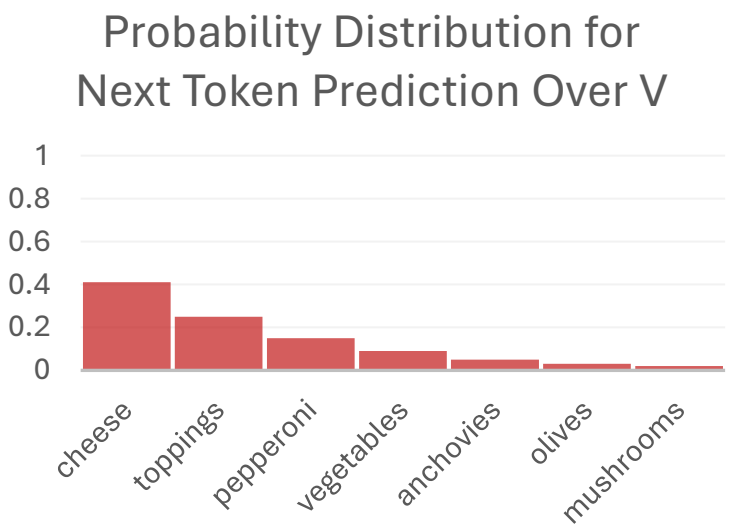
Softmax with Temperature

$$P(t_i) = \frac{\exp(z_i/\tau)}{\sum_j \exp(z_j/\tau)}$$

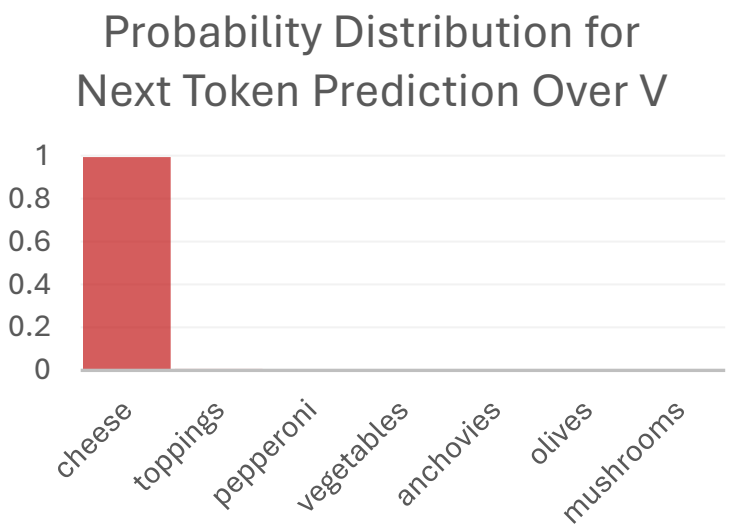
- τ : Temperature parameter
  - $\tau > 0$

Effect of Temperature

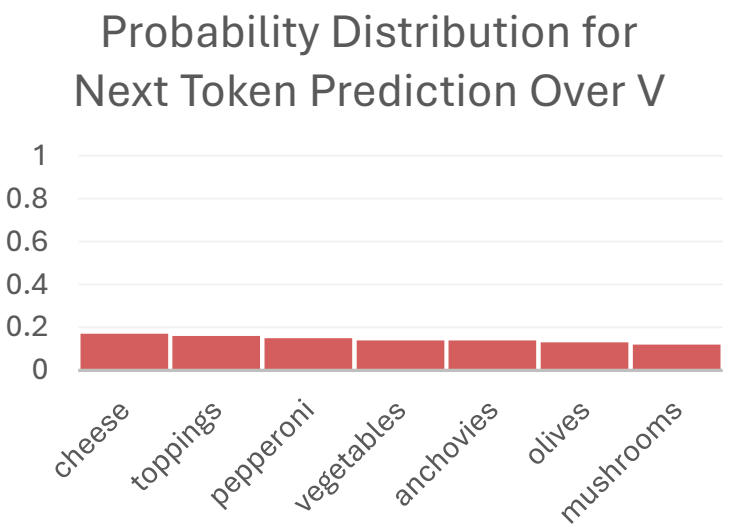
I like pizza with loads of



τ =1

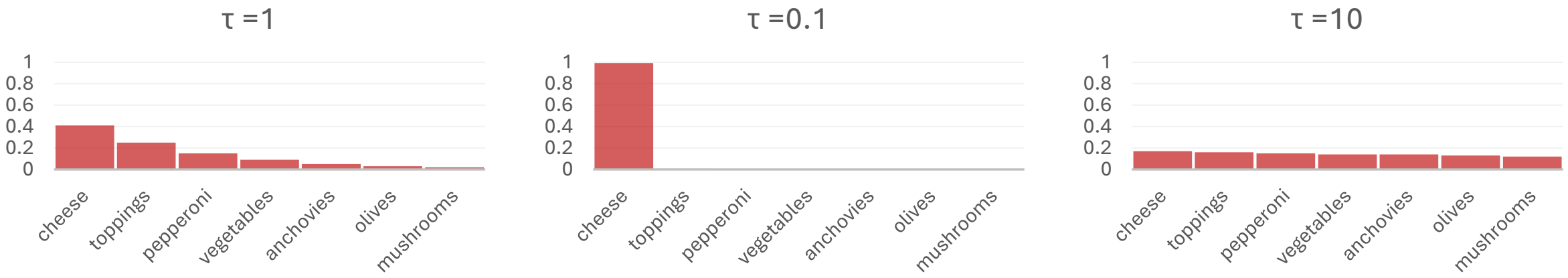


τ =0.1



τ =10

Effect of Temperature



- A low temperature sharpens the probabilities, making the model confident and more deterministic.
  - As τ approaches 0 the probability of the most likely word approaches 1.
  - Lower temperatures make the model more “confident” which can be useful in applications like question answering.
- A high temperature flattens the probabilities, encouraging diversity and creativity in outputs but with a risk of incoherence.
  - Thus, higher temperatures make the model more “creative” which can be useful when generating prose, for example.

NMT: The First 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 [Sutskever et al. 2014]
- 2016: Google Translate switches from SMT to NMT – and by 2018 everyone had
  - https://www.nytimes.com/2016/12/14/magazine/the-great-ai-awakening.html

- This was amazing!
  - SMT systems, built by hundreds of engineers over many years, were outperformed by NMT systems trained by small groups of engineers in a few months

Issues With RNN

- Linear interaction distance
- Bottleneck problem
- Lack of parallelizability

ATTENTION