Lecture 17:
Generating From Language Models II

Instructor: Swabha Swayamdipta
USC CSCI 499 LMs in NLP
Apr 1, Spring 2024

Slides adapted from Chris Manning, Xiang Lisa Li

Logistics / Announcements

Logistics / Announcements

- Today: Quiz 5
- Wednesday: HW4 due
- HW3 Grades: Out latest by tomorrow

- Upcoming Guest Lectures
  - Lecture on Prompting: Qinyuan Ye
  - Lecture on Alignment: Justin Cho

Lecture Outline

- Mid-Semester Feedback
- Recap: Tokenization
- Recap: Natural Language Generation - Basics
- Recap: Classic Inference Algorithms: Greedy, Exhaustive and Beam Search
- Modern Generation Algorithms
- Evaluating Generations
- Quiz 5

Recap: Tokenization in Transformers

Byte-pair encoding

- Byte-pair encoding is a simple, effective strategy for defining a subword vocabulary
- Adapted for word segmentation from data compression technique (Gage, 1994)
  - Instead of merging frequent pairs of bytes, we merge characters or character sequences
- Algorithm:
  1. Start with a vocabulary containing only characters and an "end-of-word" symbol.
  2. Using a corpus of text, find *the most common adjacent characters* "a,b"; add "ab" as a subword
     - This is a learned operation!
     - Only combine pairs (hence the name!)
  3. Replace instances of the character pair with the new subword; repeat until desired vocabulary size.
- At test time, first split words into sequences of characters, then apply the learned operations to merge the characters into larger, known symbols
- Originally used in NLP for machine translation; now a similar method (WordPiece) is used in pretrained models.

BPE in action

Corpus

low	lower	newest
low	lower	newest
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Source: https://www.analyticsvidhya.com/blog/2020/05/what-is-tokenization-nlp/

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Frequency

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e-r (2)	n-e (5)	w-</w> (5)
e-s (8)	o-w (7)	w-e (7)
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USC Viterbi

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es	est	est</w>	lo	low	low</w>	ne	new	newest</w>

After 10 merges

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Recap: Natural Language Generation

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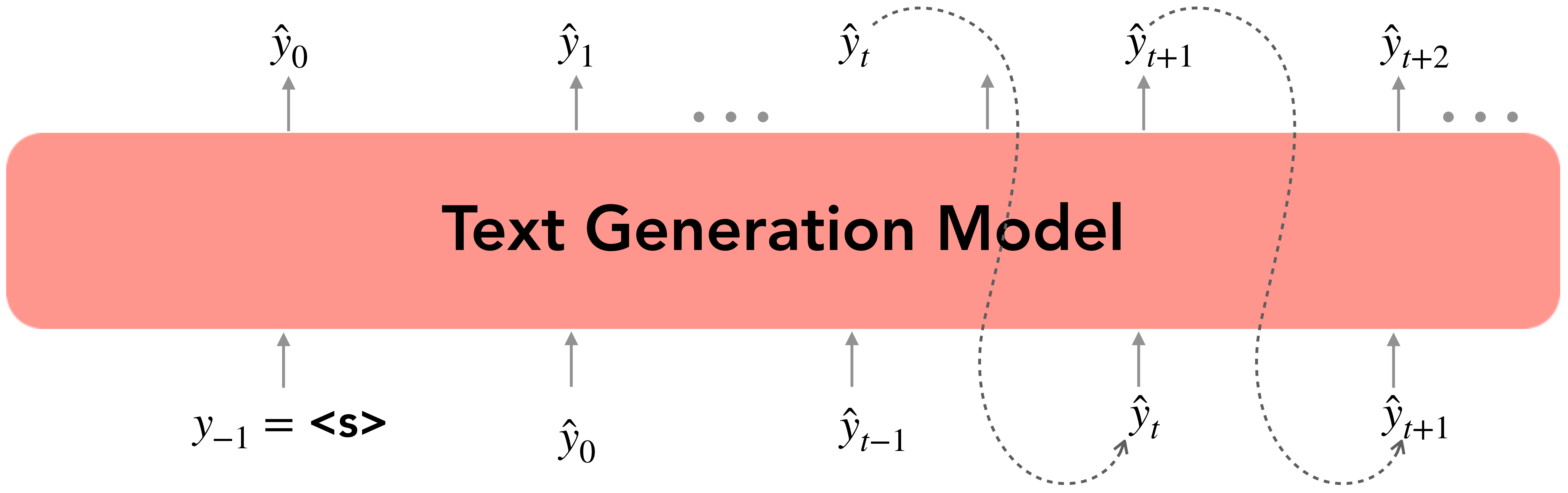
Language Generation: Fundamentals

In autoregressive text generation models, at each time step t, our model takes in a sequence of tokens as input $S = f_\theta(y_{<t}) \in \mathbb{R}^V$ and outputs a new token, $\hat{y}_t$

For model $f_\theta(\cdot)$ and vocabulary V, we get scores $S = f_\theta(y_{<t}) \in \mathbb{R}^V$

$$P(w \mid y_{<t}) = \frac{\exp(S_w)}{\sum_{v \in V} \exp(S_v)}$$

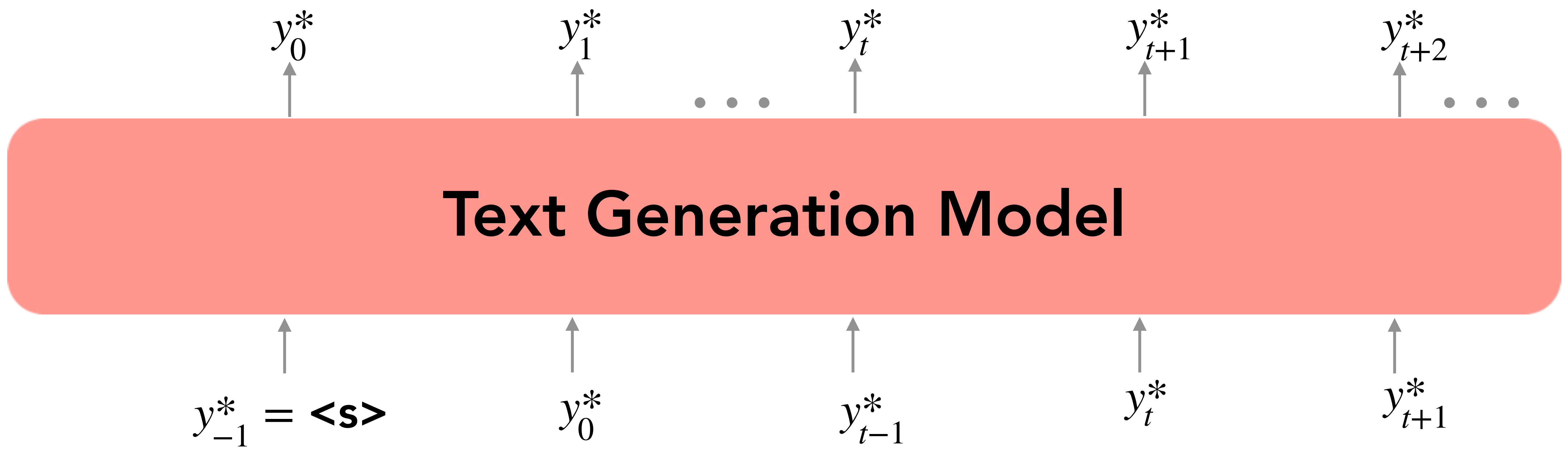


Language Generation: Training

- Trained one token at a time to maximize the probability of the next token y_t^* given preceding words $y_{<t}^*$

$$\mathscr{L} = -\sum_{t=1}^{T} \log P(y_t \mid y_{<t}) = -\sum_{t=1}^{T} \log \frac{\exp(S_{y_t \mid y_{<t}})}{\sum_{v \in V} \exp(S_{v \mid y_{<t}})}$$

- Classification task at each time step trying to predict the actual word y_t^* in the training data
- "Teacher forcing" (reset at each time step to the ground truth)



Language Generation: Inference

- At inference time, our decoding algorithm defines a function to select a token from this distribution:

Inference / Decoding Algorithm

$$\hat{y}_t = g(P(y_t \mid y_{<t}))$$

- The "obvious" decoding algorithm is to greedily choose the highest probability next token according to the model at each time step

$$g = \arg\max$$

$$\hat{y}_t = \arg\max_{w \in V}(P(y_t = w \mid y_{<t}))$$

Recap: Classic Inference Algorithms: Greedy and Beam Search

Decoding

- Generation from a language model is also called decoding / inference
- Strategy so far is **Greedy**: Take $\arg\max$ on each step of the decoder to produce the most probable word on each step
    - Not looking ahead, making the hastiest decision given all the information we have
    - Problem: No wiggle room for errors
    - Problem: Bland / repetitive generations (degeneracy)

Context: In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

Continuation: The study, published in the Proceedings of the National Academy of Sciences of the United States of America (PNAS), was conducted by researchers from the **Universidad Nacional Autónoma de México (UNAM)** and **the Universidad Nacional Autónoma de México (UNAM/Universidad Nacional Autónoma de México/ Universidad Nacional Autónoma de México/ Universidad Nacional Autónoma de México/ Universidad Nacional Autónoma de México...**

Holtzmann et al., 2020

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 the vocabulary size
  - This $O(V^T)$complexity is far too expensive!

Beam Search Decoding

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- 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, in NMT)

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- A hypothesis has a score which is its log probability:

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

  - Scores are all negative, and higher score is better
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- Beam search is not guaranteed to find optimal solution
- But much more efficient than exhaustive search!

Beam Search Decoding: Example

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

<START>

Calculate prob
dist of next word

Slide credit: Chris Manning

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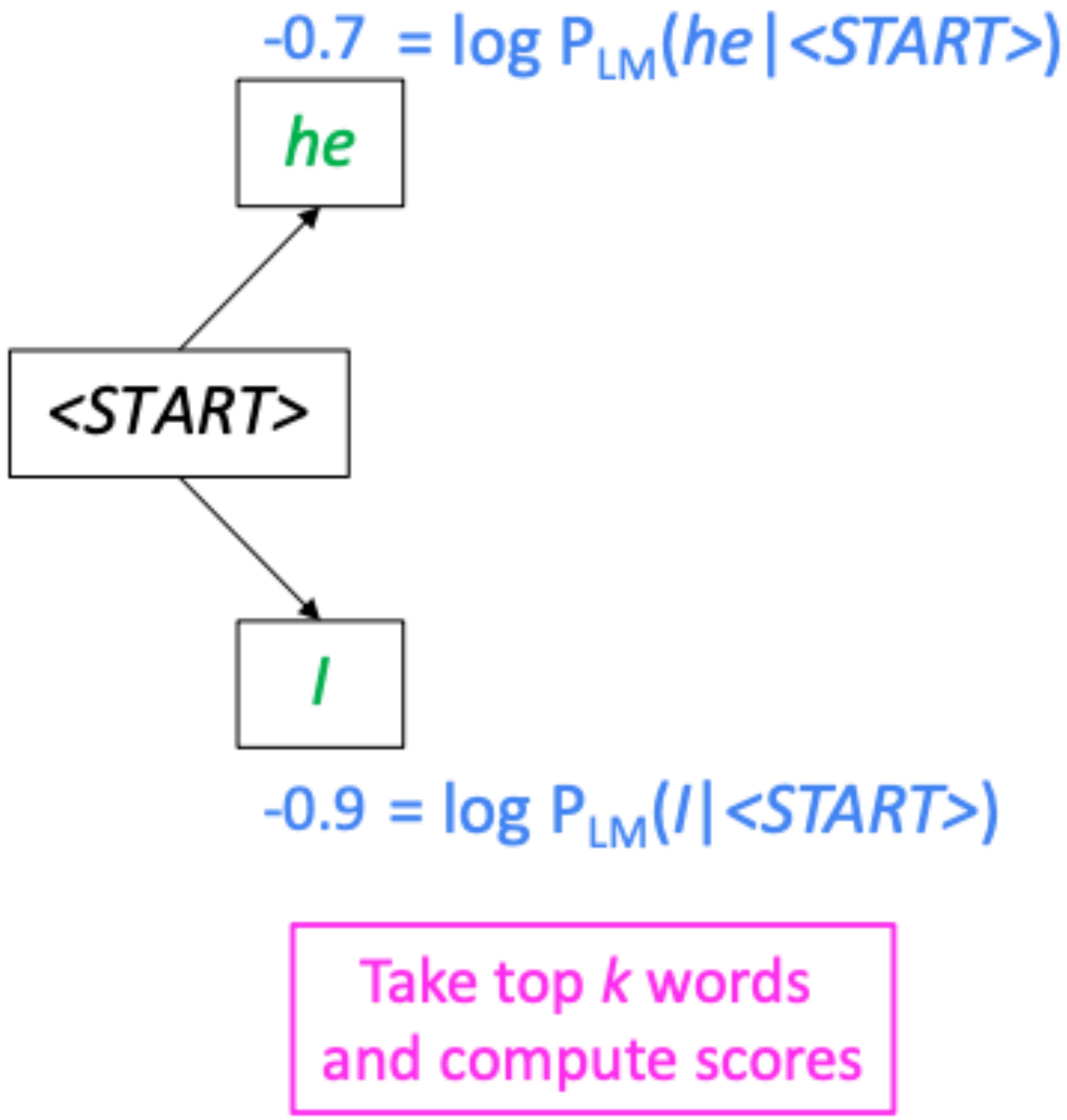

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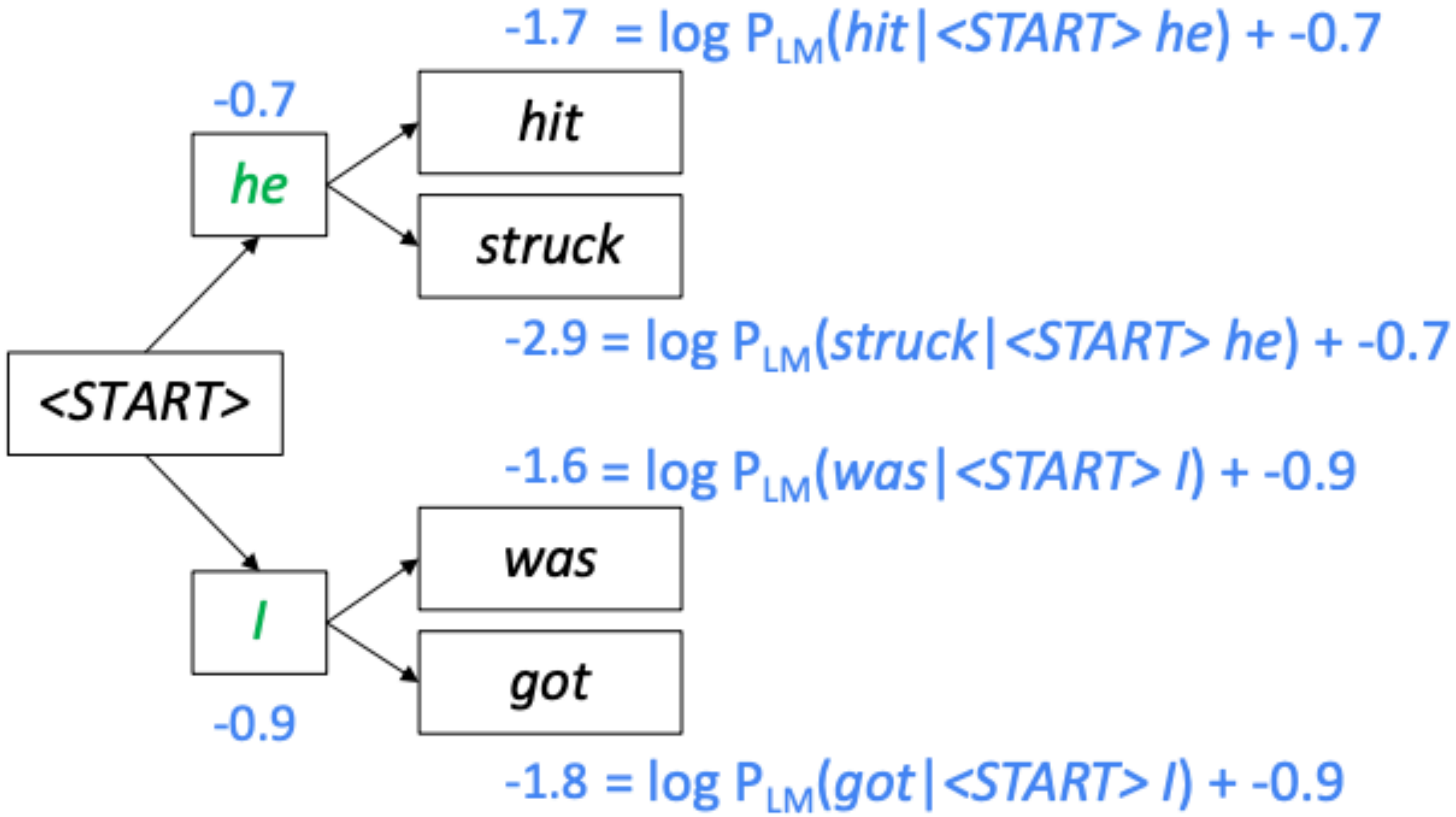

For each of the *k* hypotheses, find top *k* next words and calculate scores

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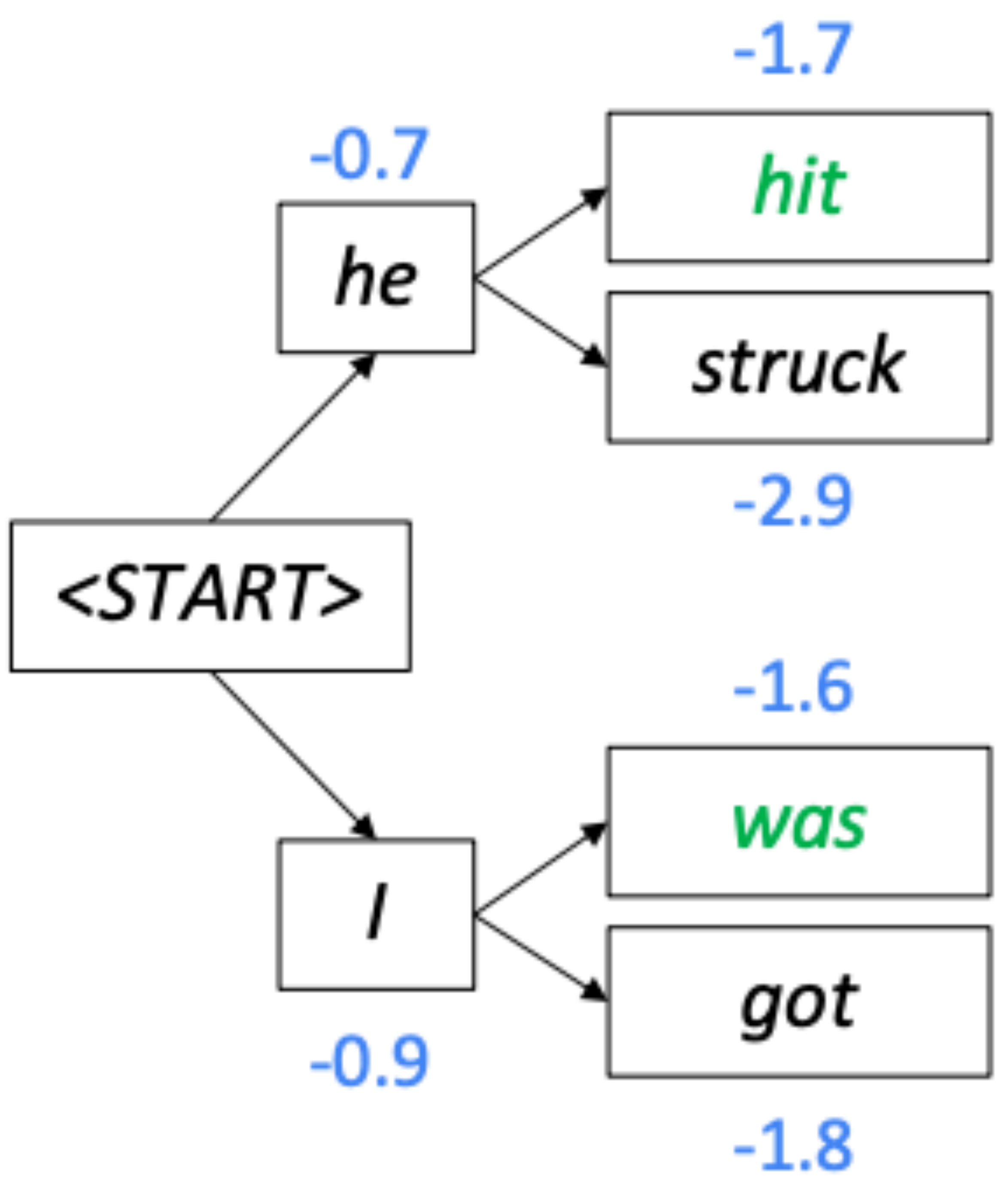

Of these k^2 hypotheses,
just keep *k* with highest scores

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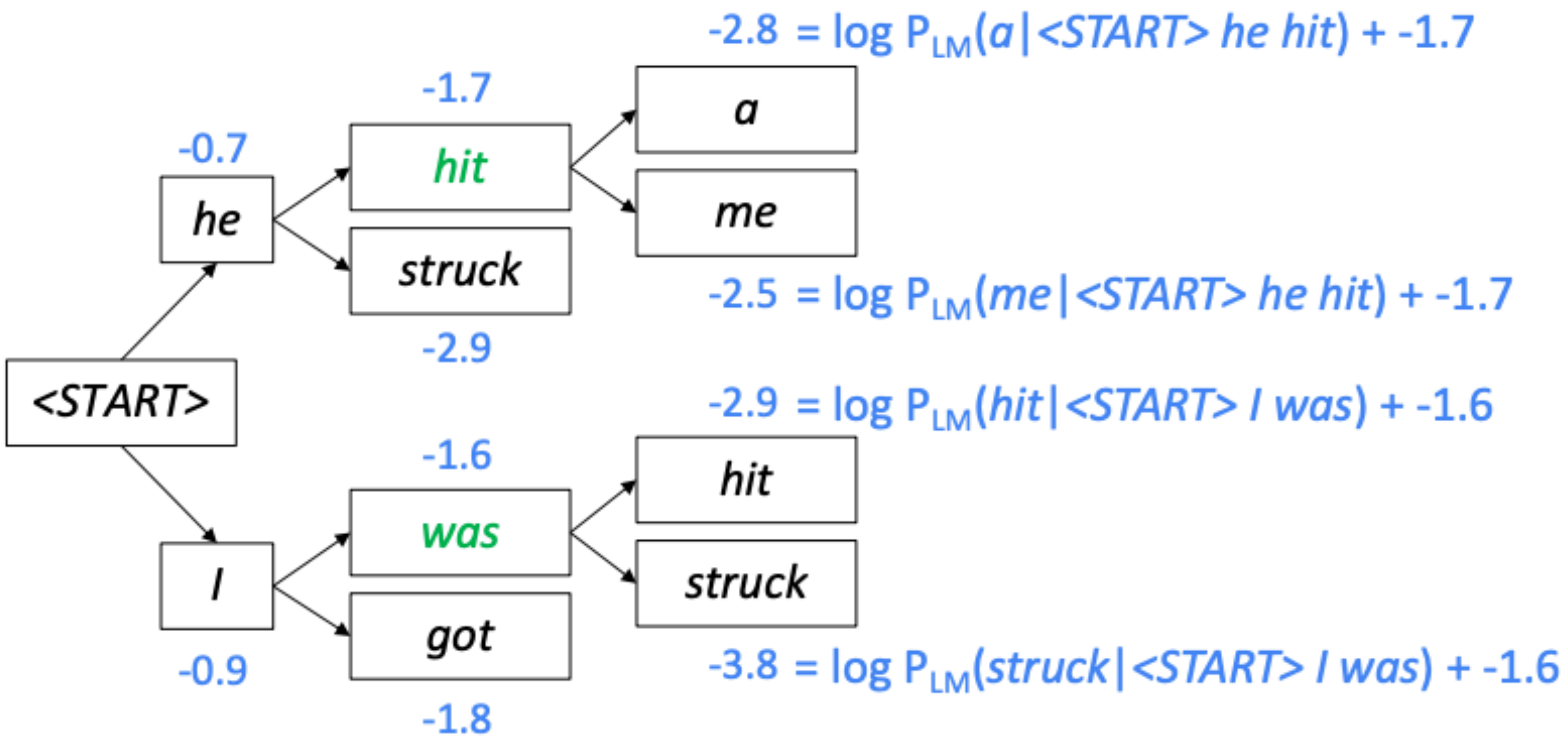

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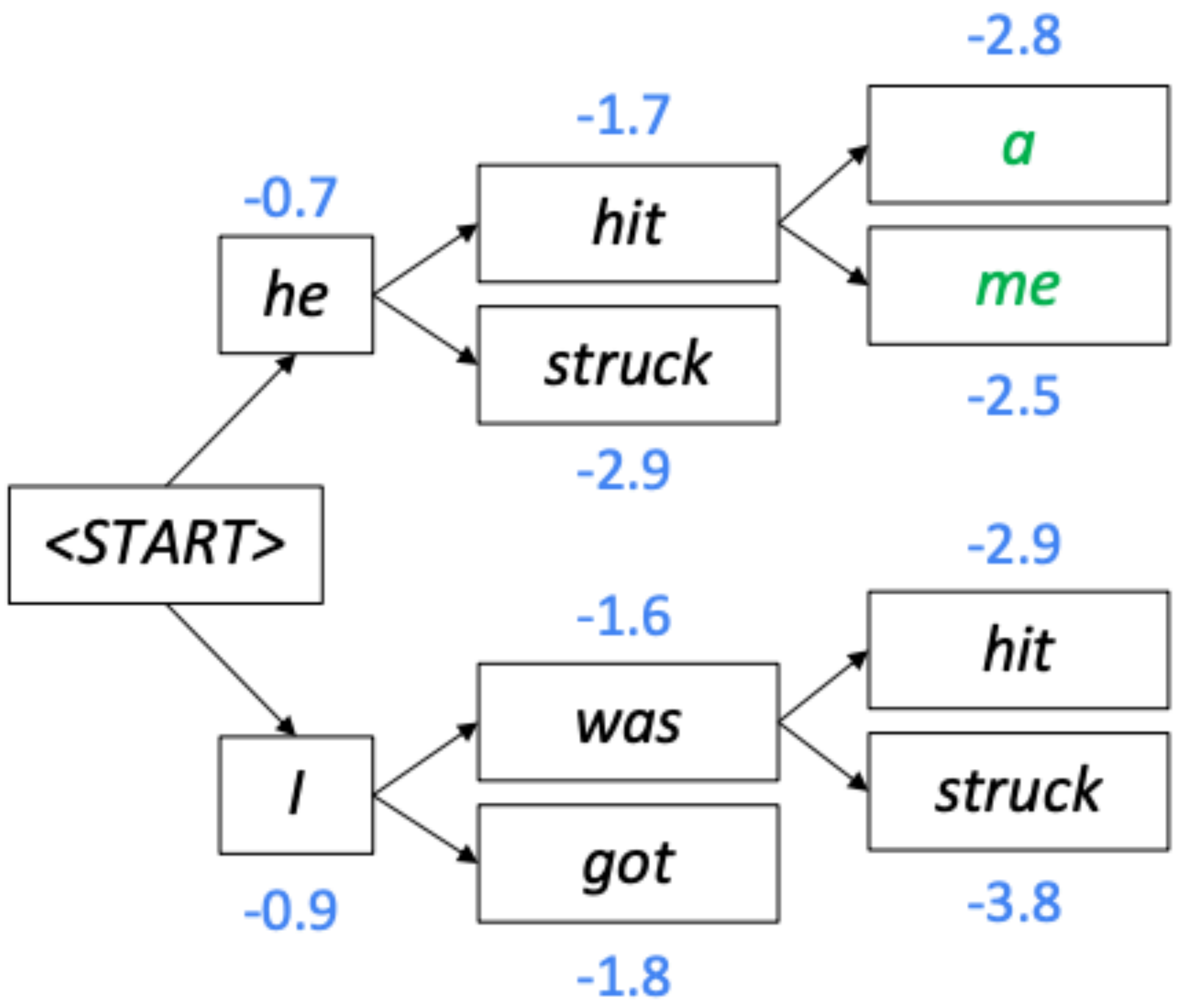

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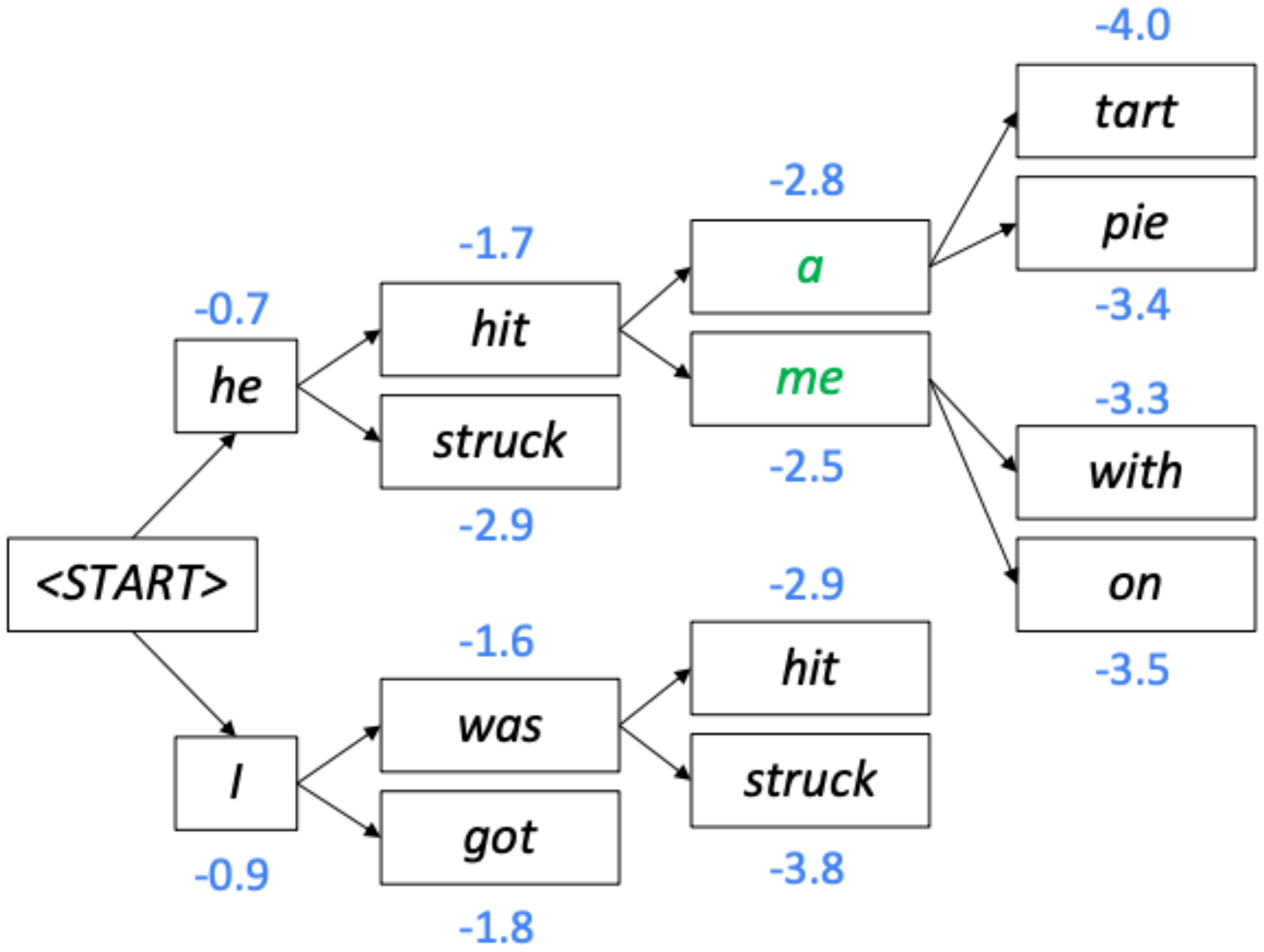

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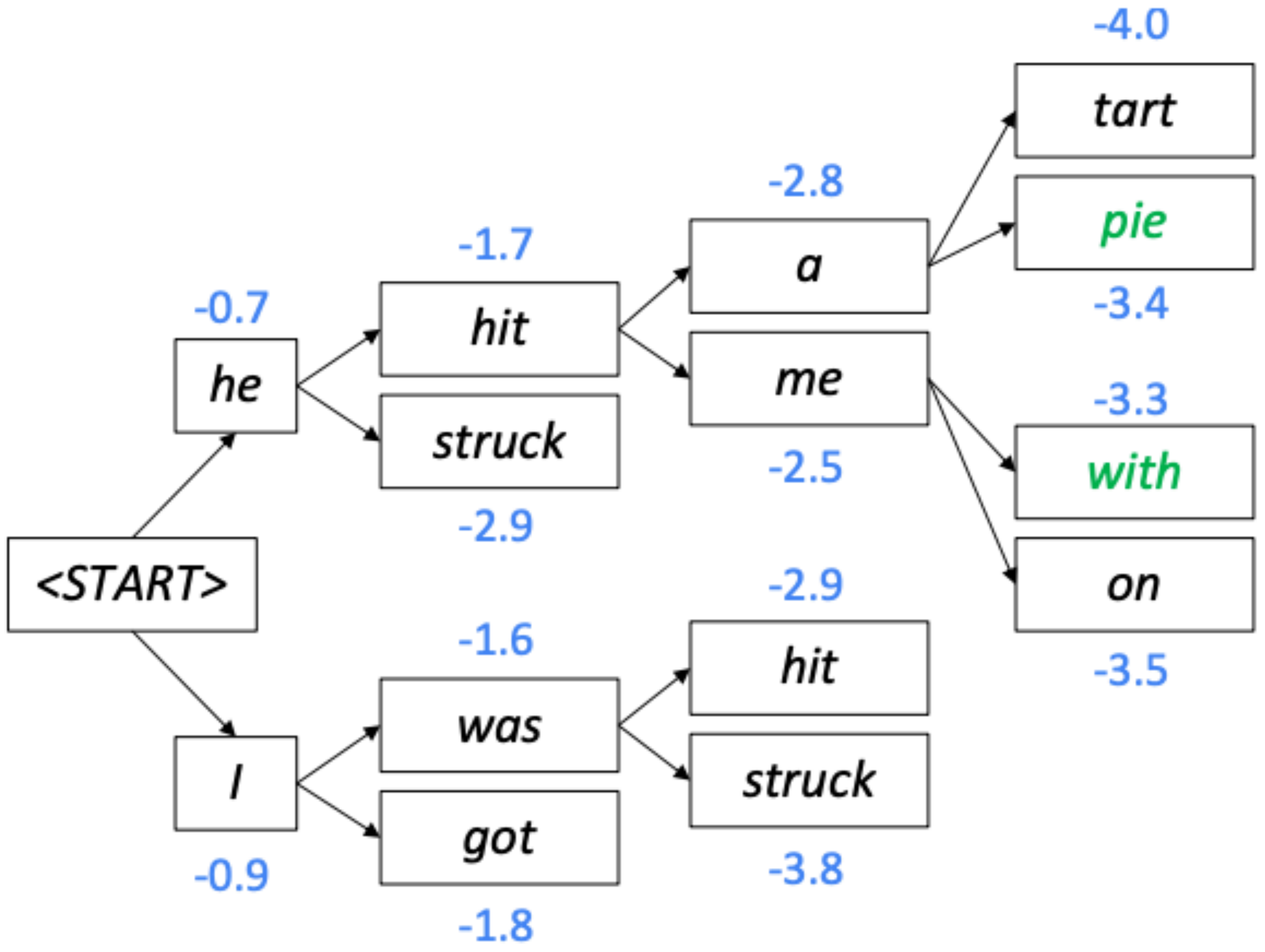

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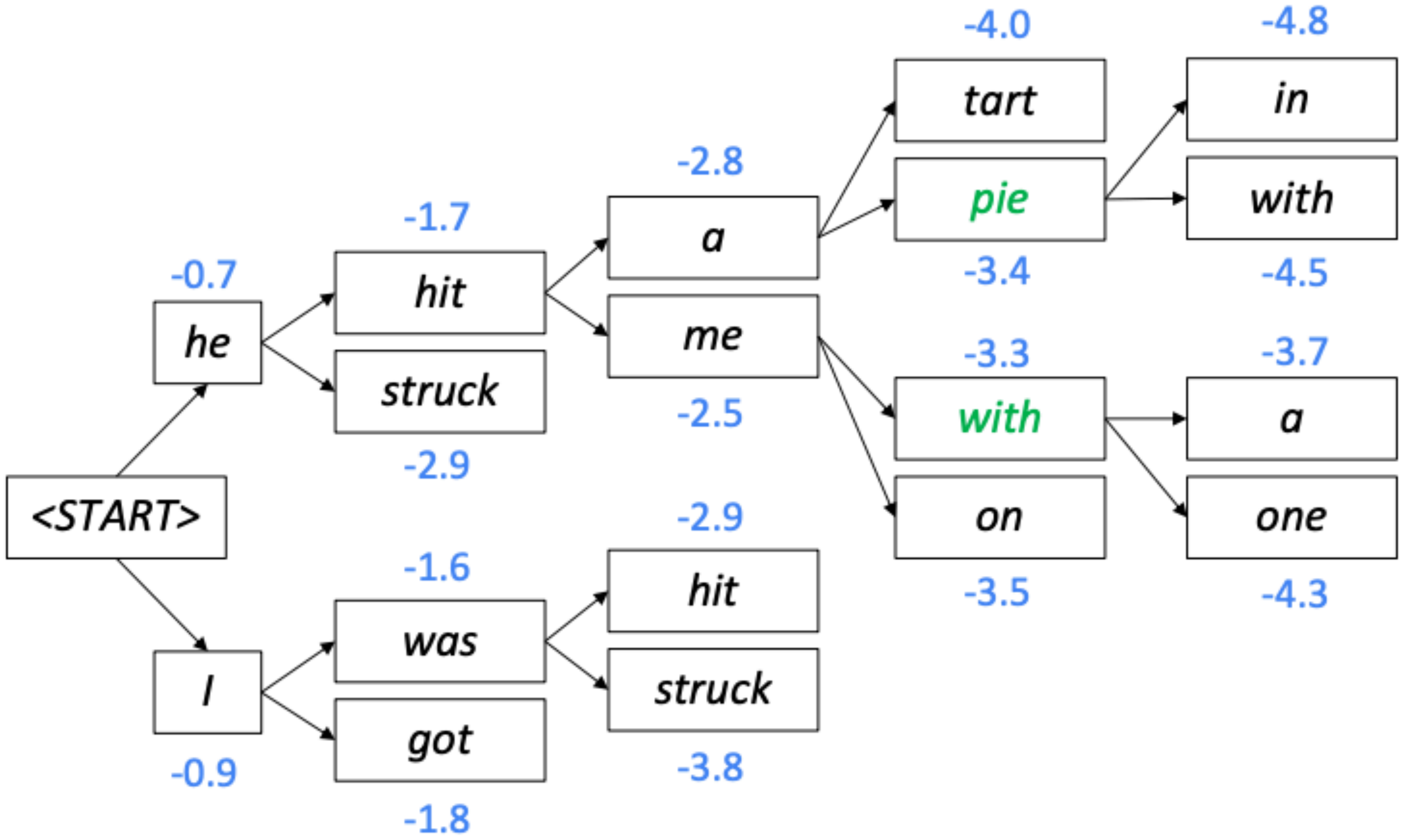

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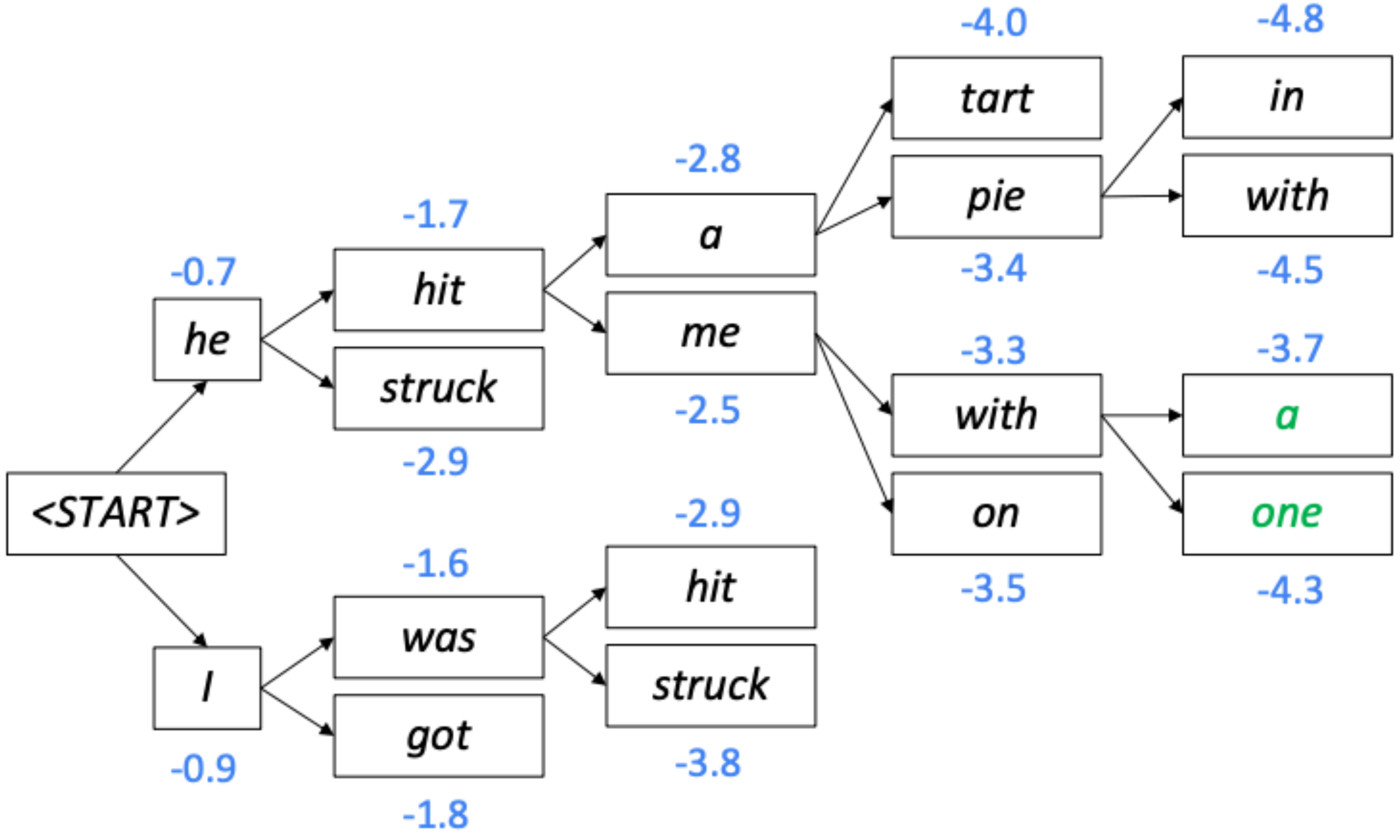

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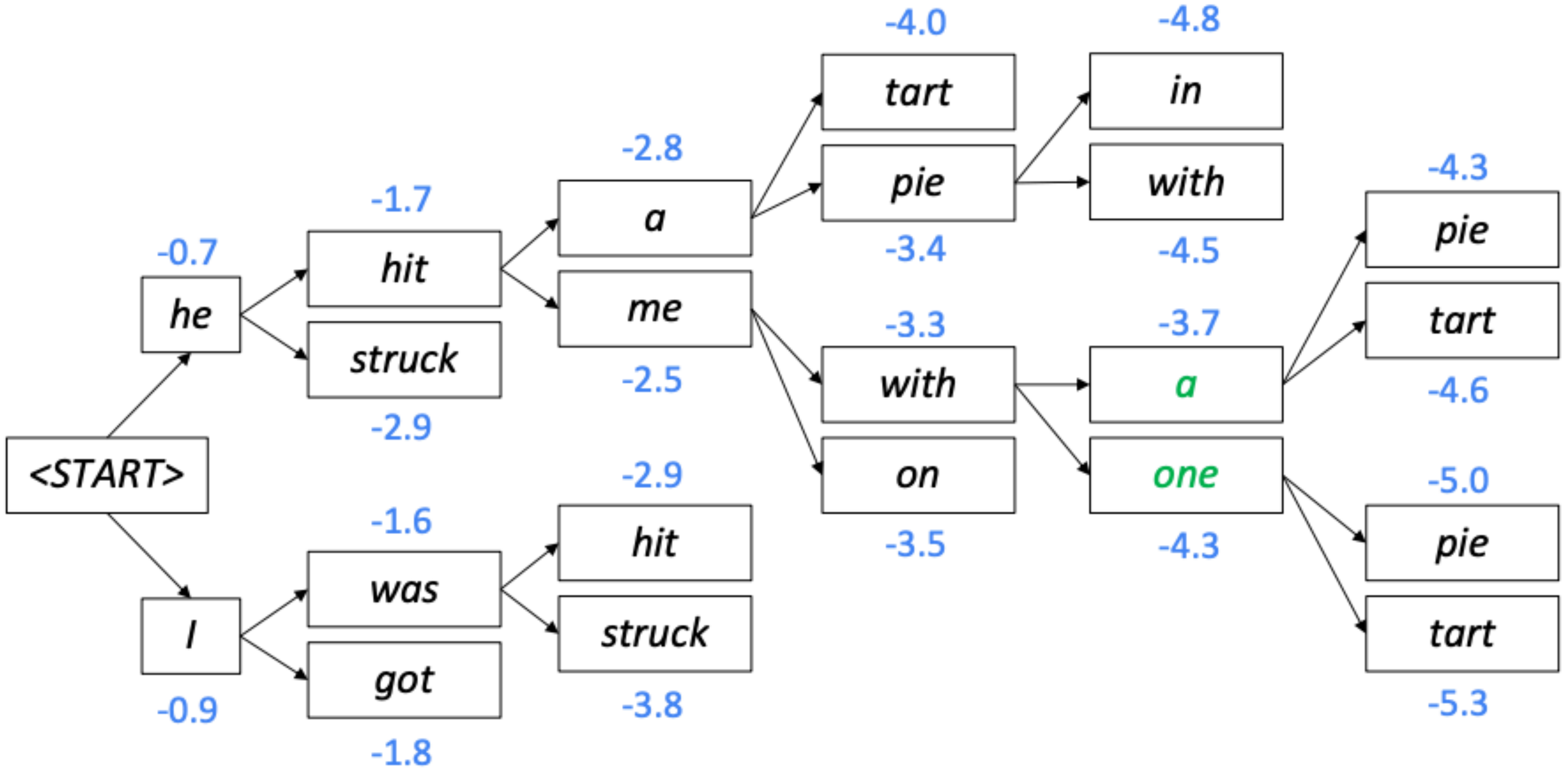

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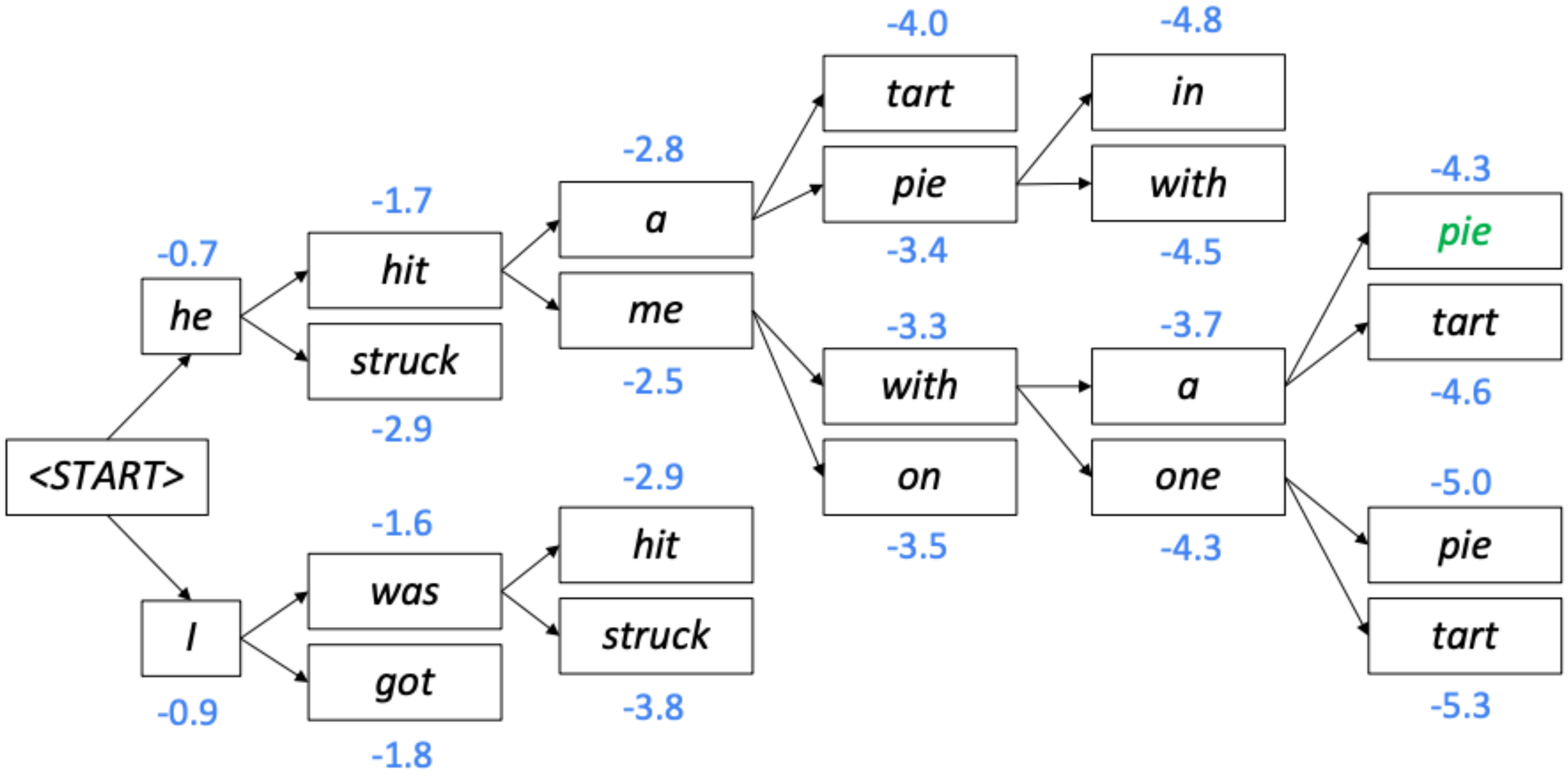

This is the top-scoring hypothesis!

Slide credit: Chris Manning

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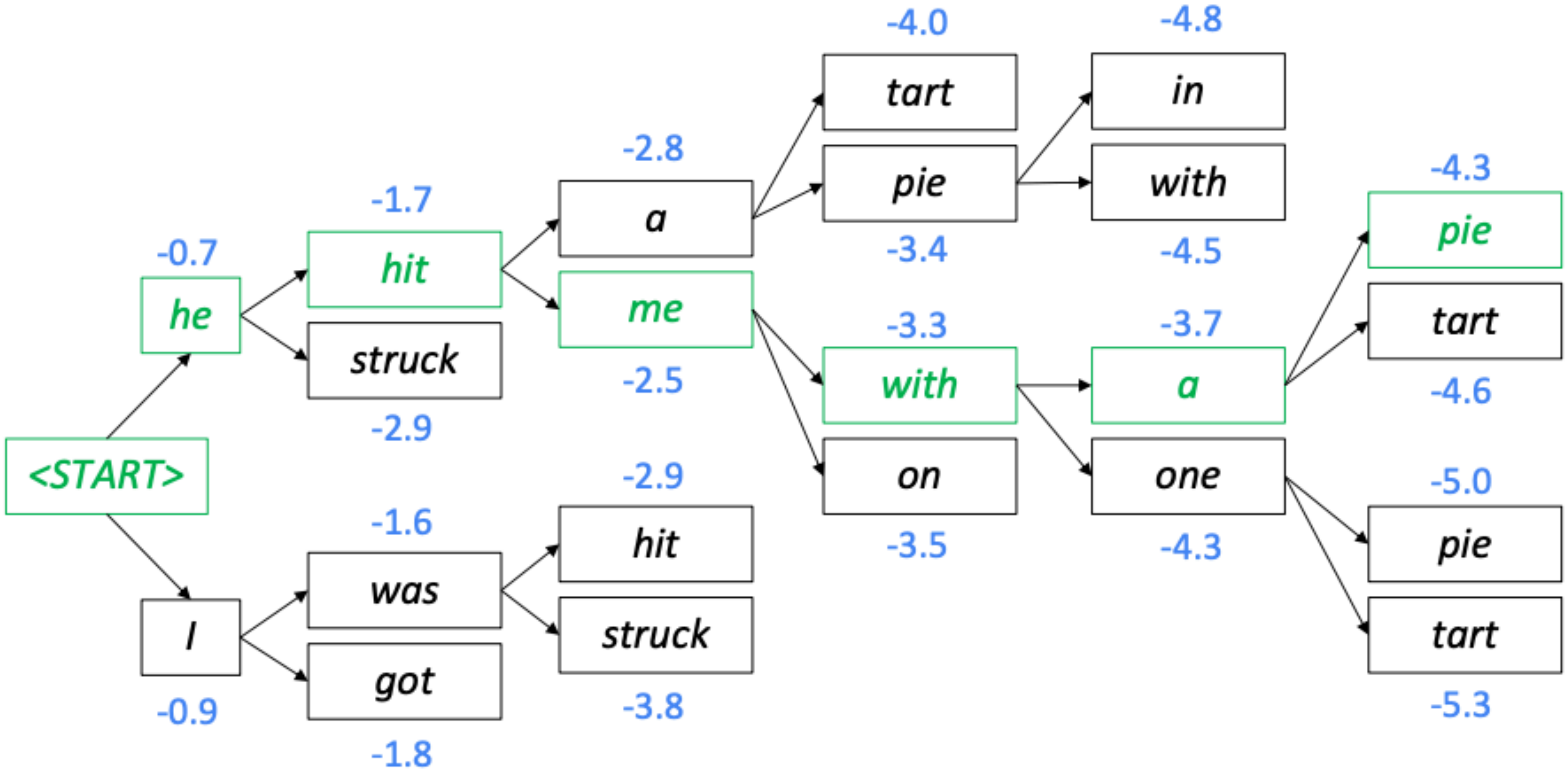

Backtrack to obtain the full hypothesis

Slide credit: Chris Manning

USC Viterbi

Beam Search Decoding: Stopping Criterion

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But this is expensive!

Maximization Based Decoding

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Holtzmann et al., 2020

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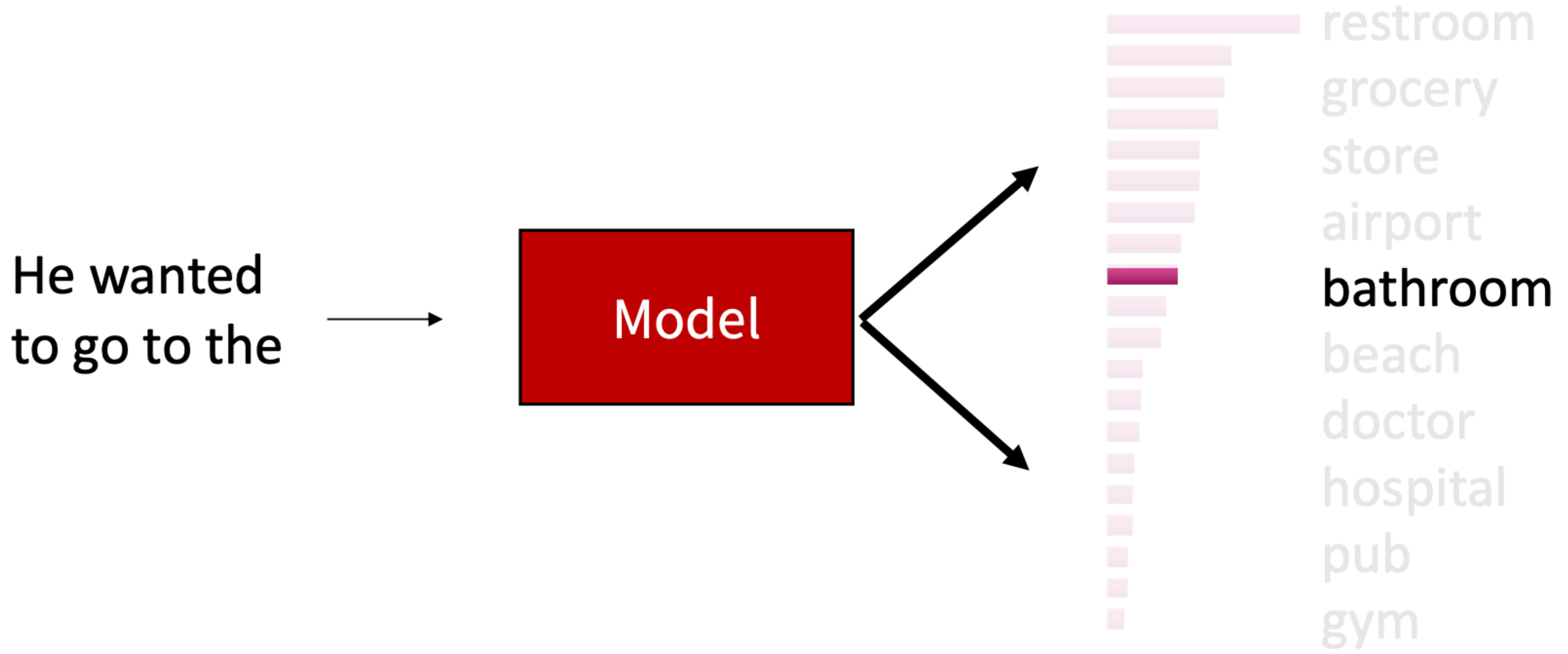
Perhaps we should not really be maximizing!
What else could we do?

Holtzmann et al., 2020

Solution: Don't Maximize, Pick a Sample

- Sample a token from the distribution of tokens.
- But this is not a random sample, it is a sample for the learned model distribution
  - Respects the probabilities, without going just for the maximum probability option
  - Or else, you would get something meaningless
  - Many good options which are not the maximum probability!



Modern Generation: Sampling

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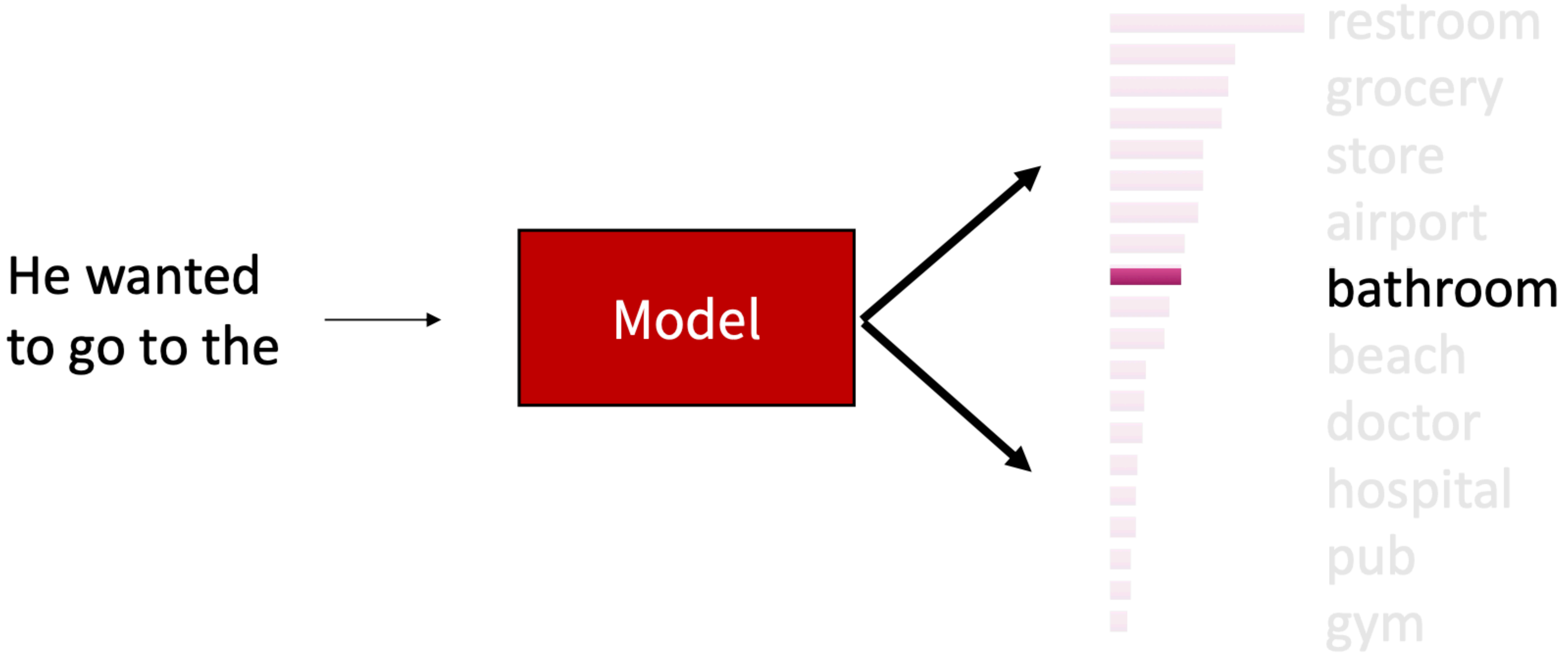
Pure / Ancestral Sampling

$$y_t \sim P_t(w) = \frac{\exp(S_w)}{\sum_{v \in V} \exp(S_v)}$$



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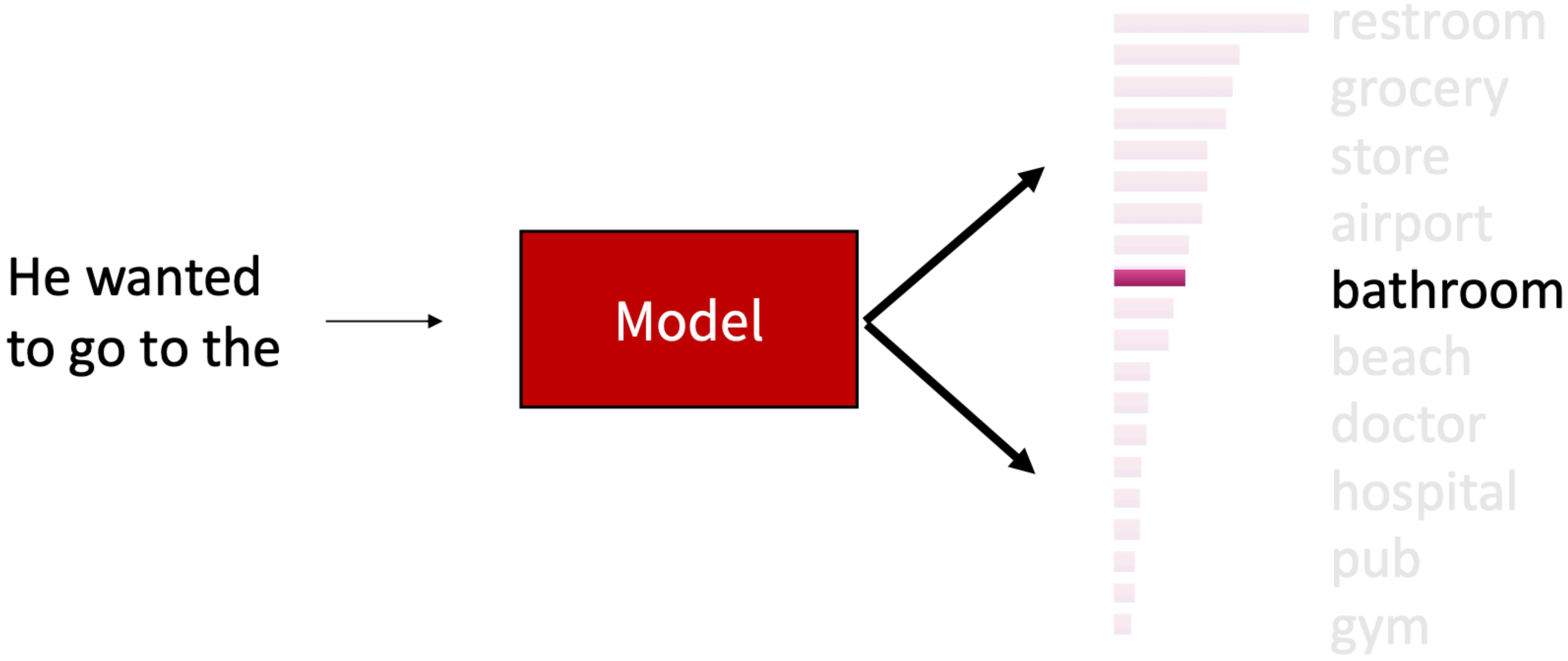

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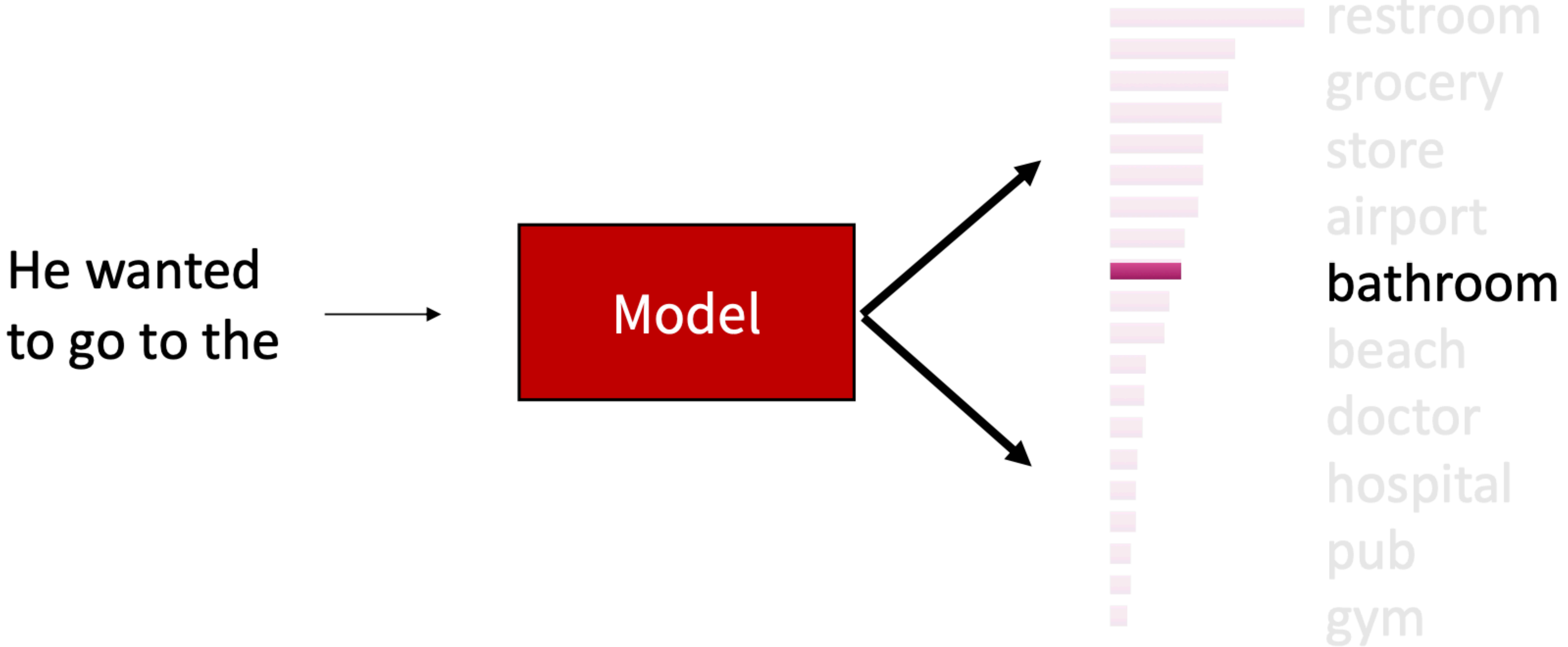

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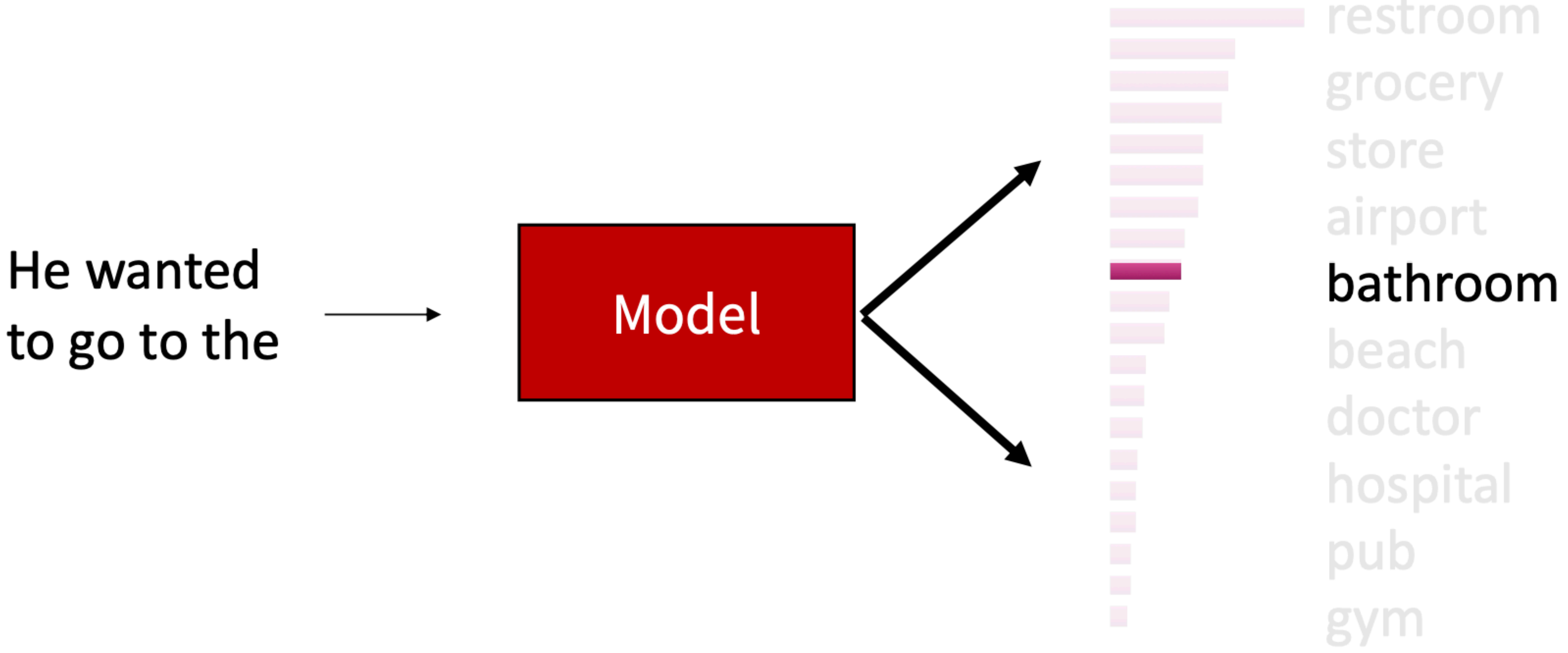

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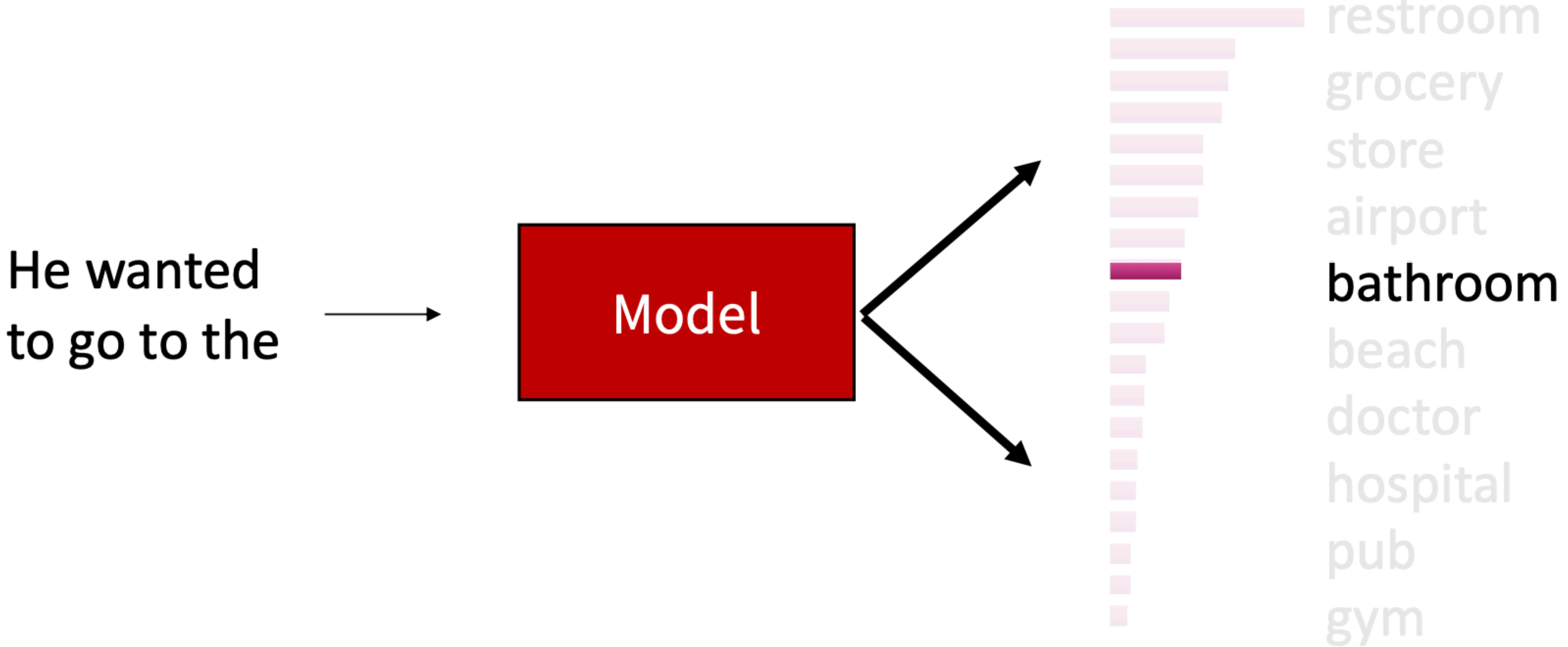

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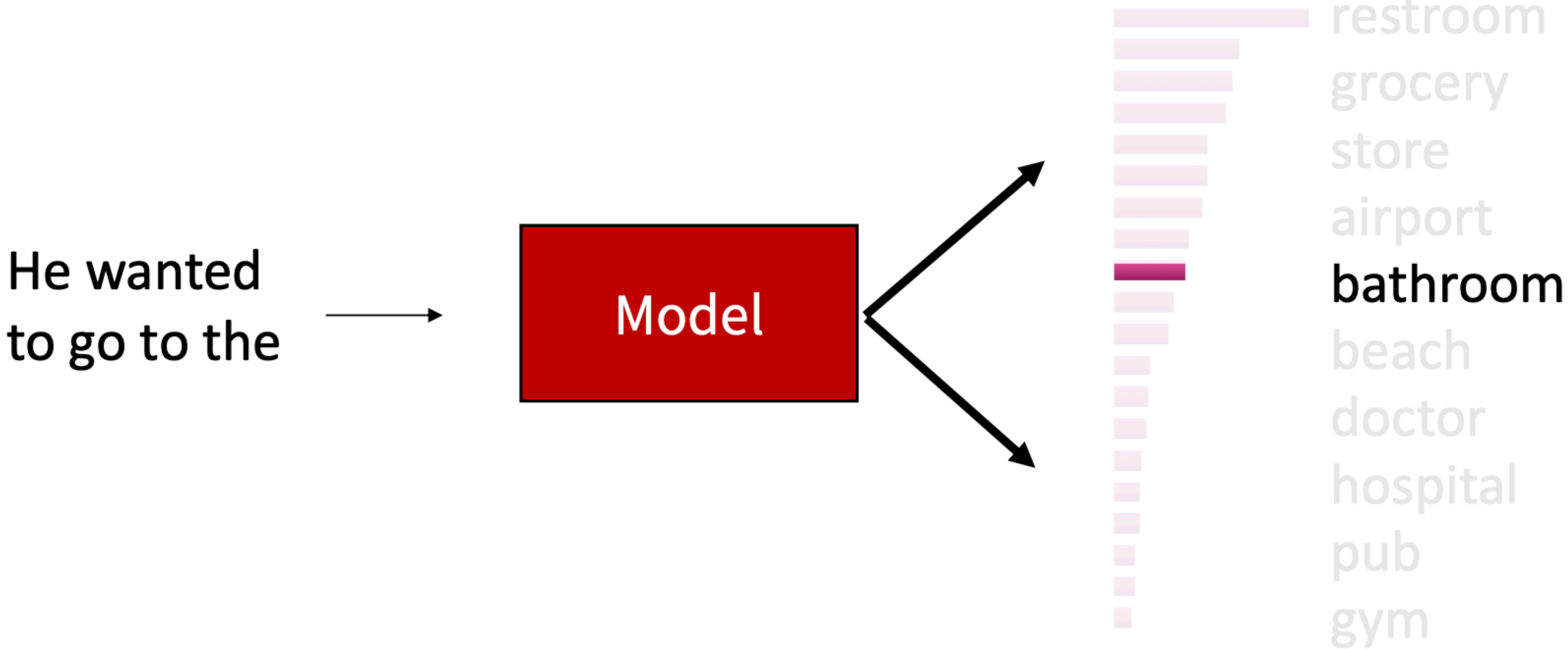
- Often results in ill-formed generations
  - No guarantee of fluency



Fan et al., ACL 2018; Holtzman et al., ACL 2018

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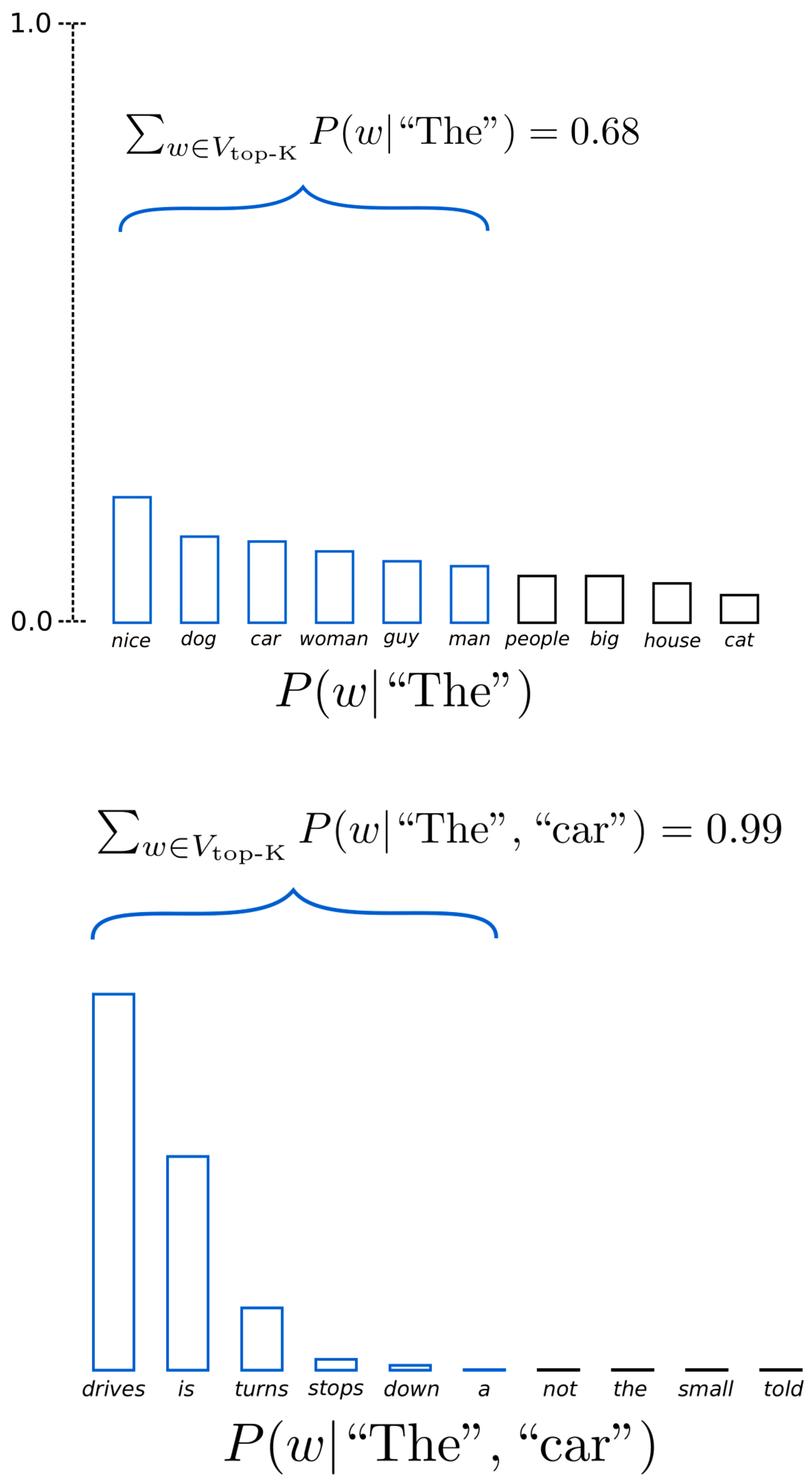

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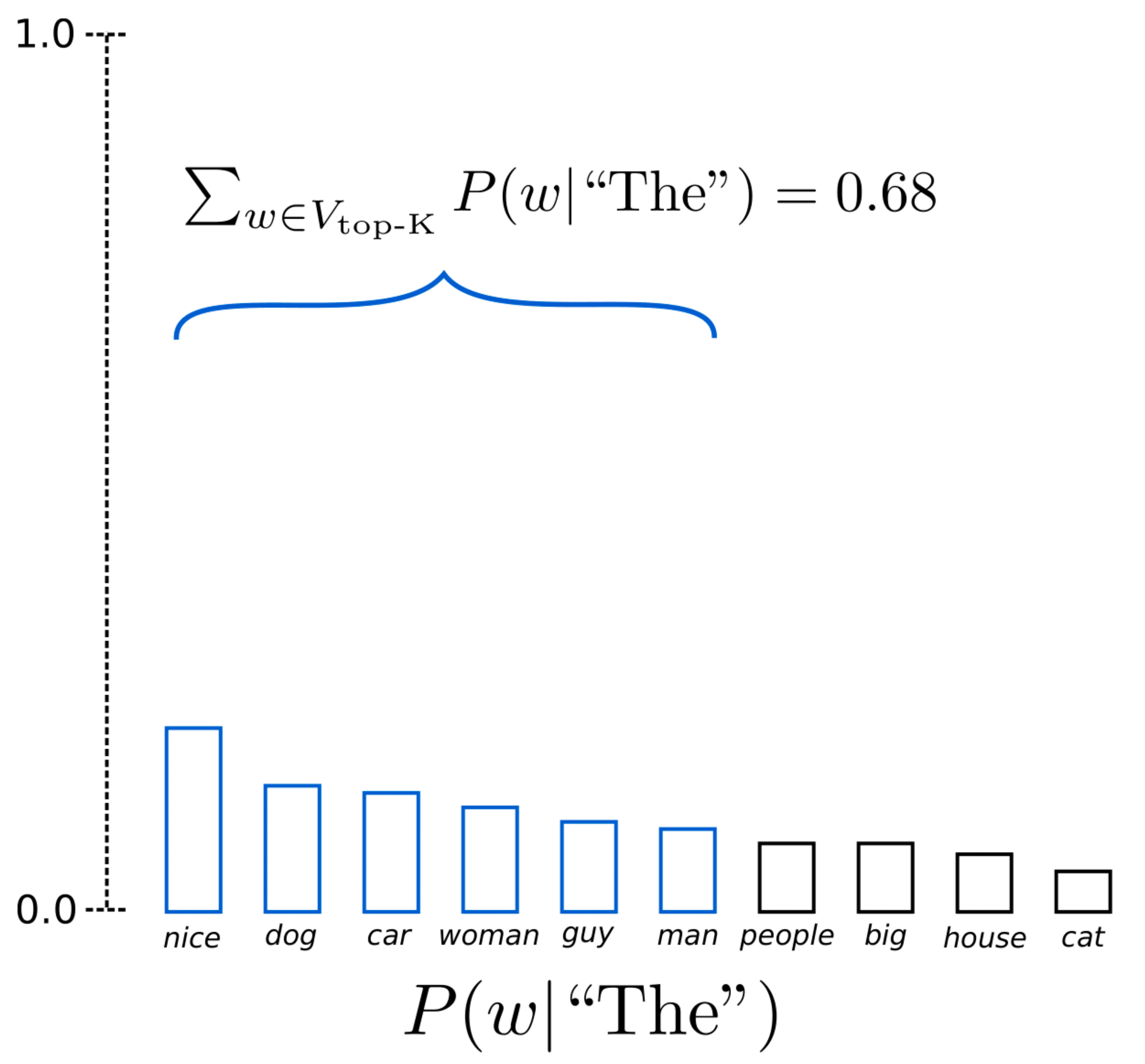

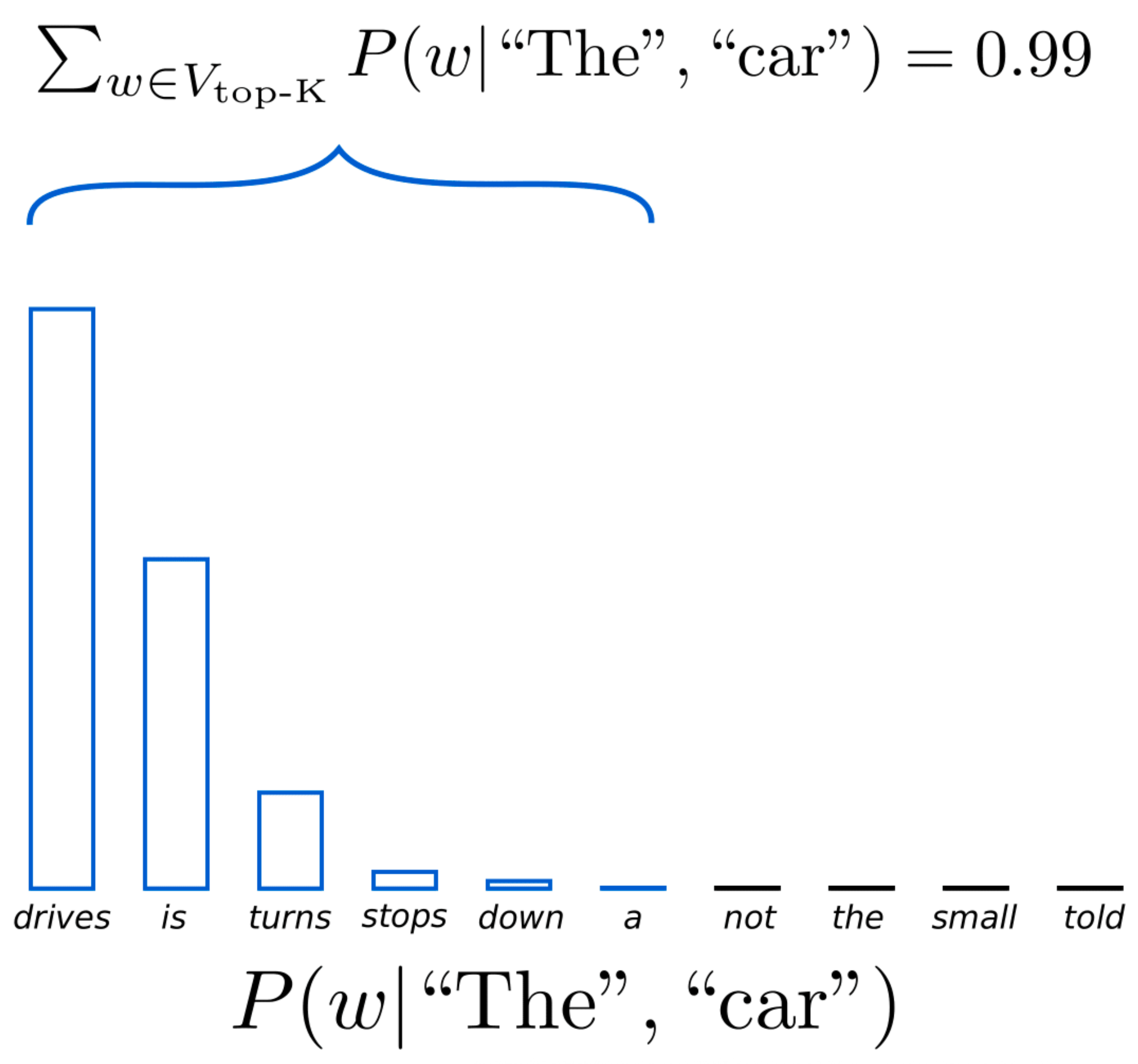

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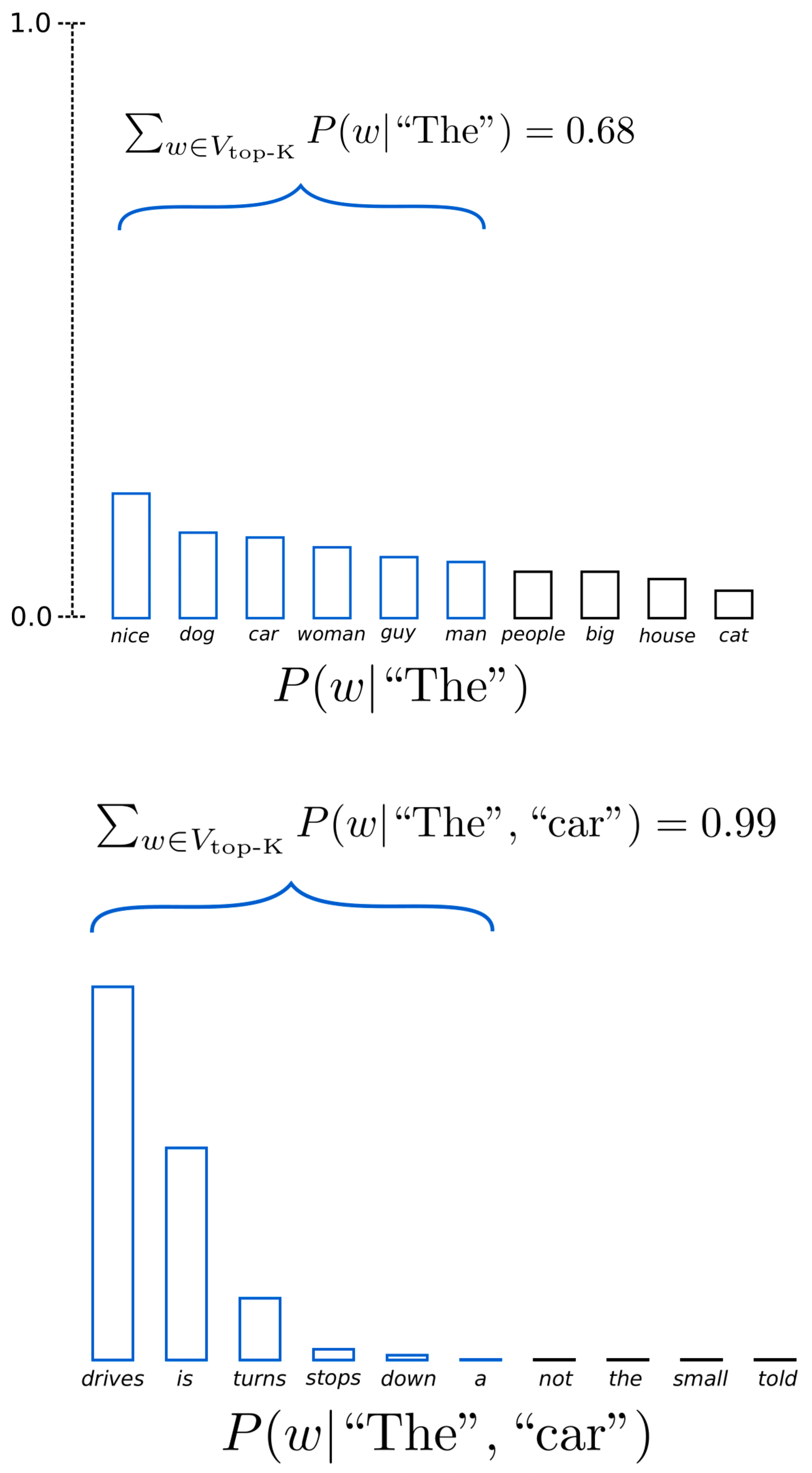

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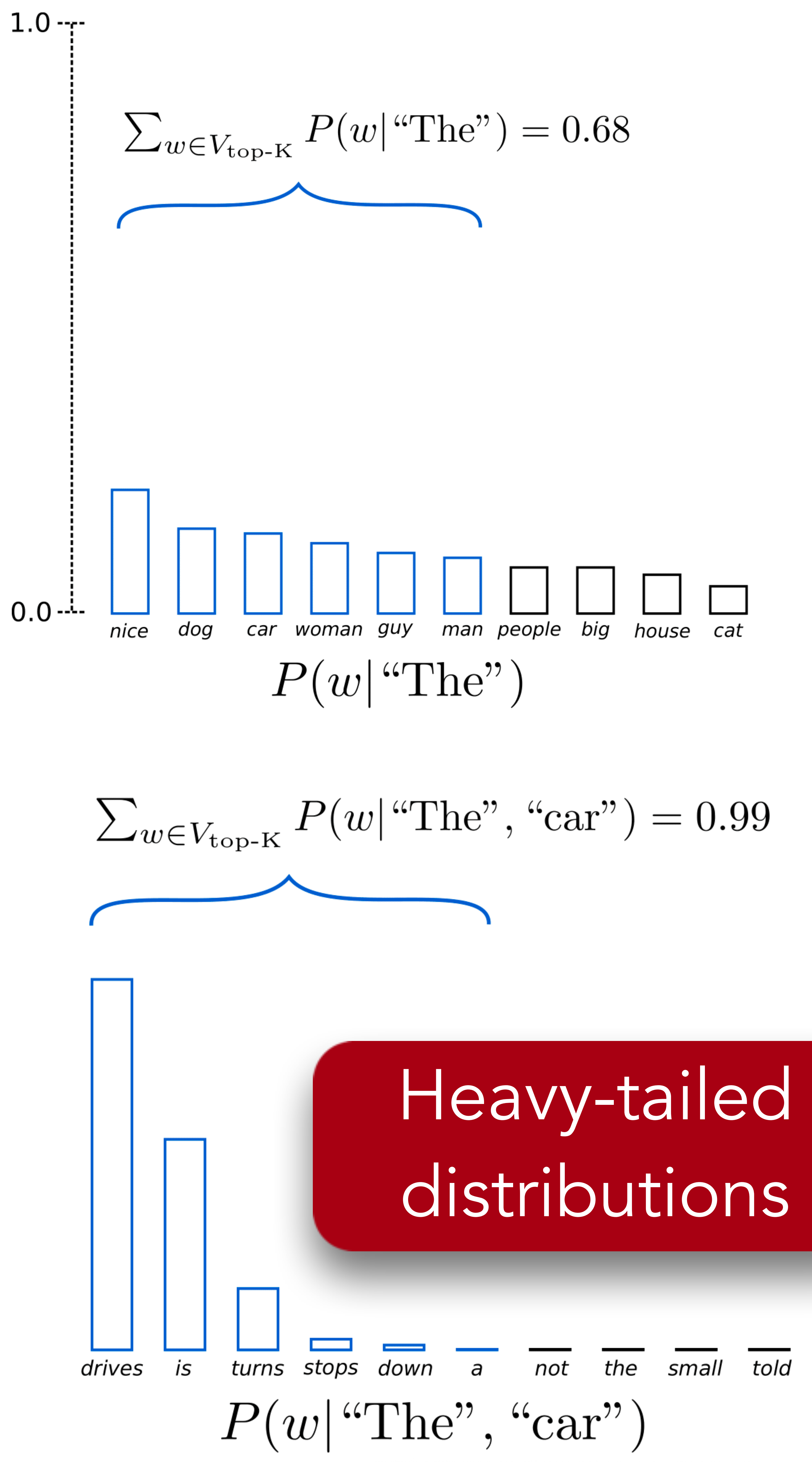

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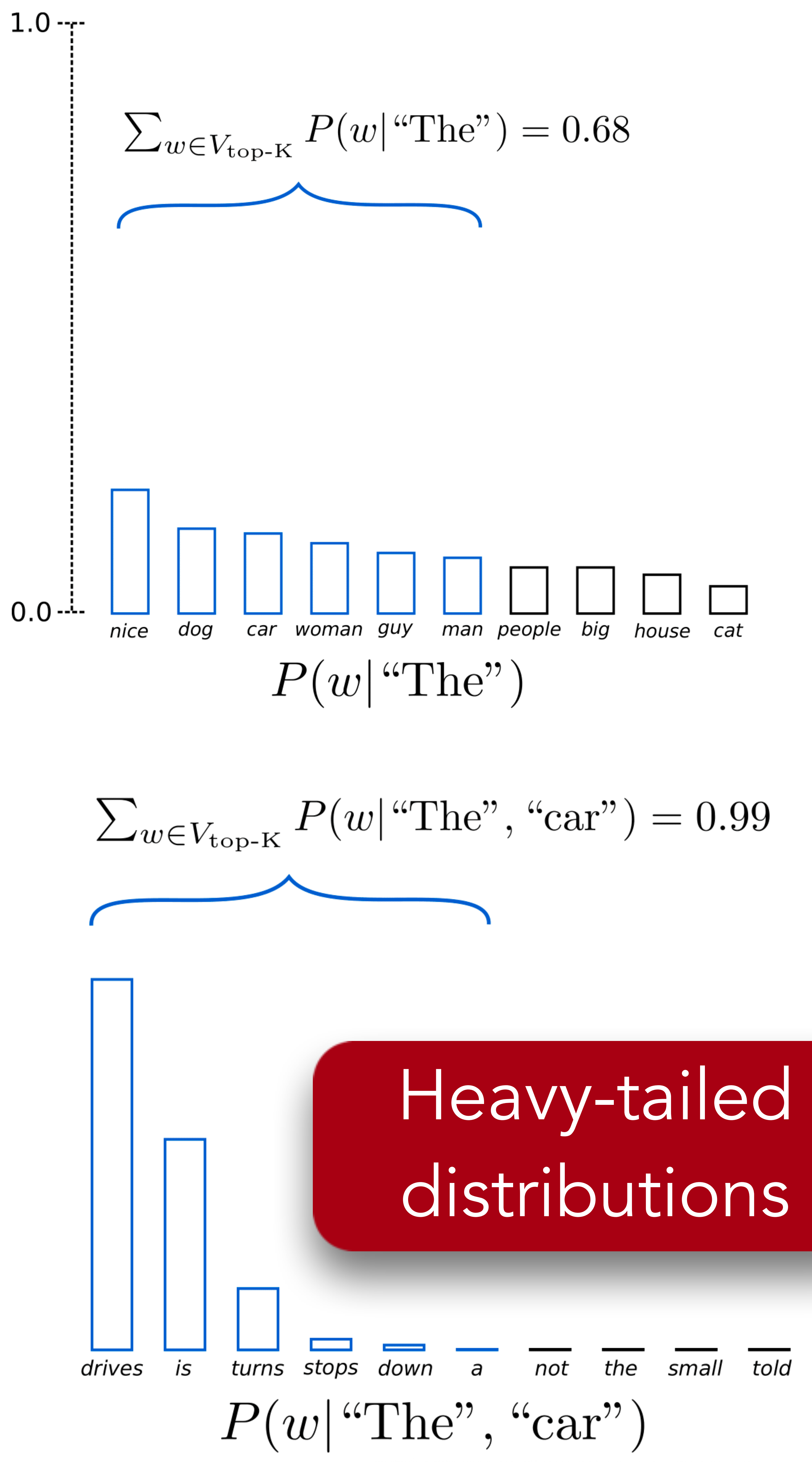

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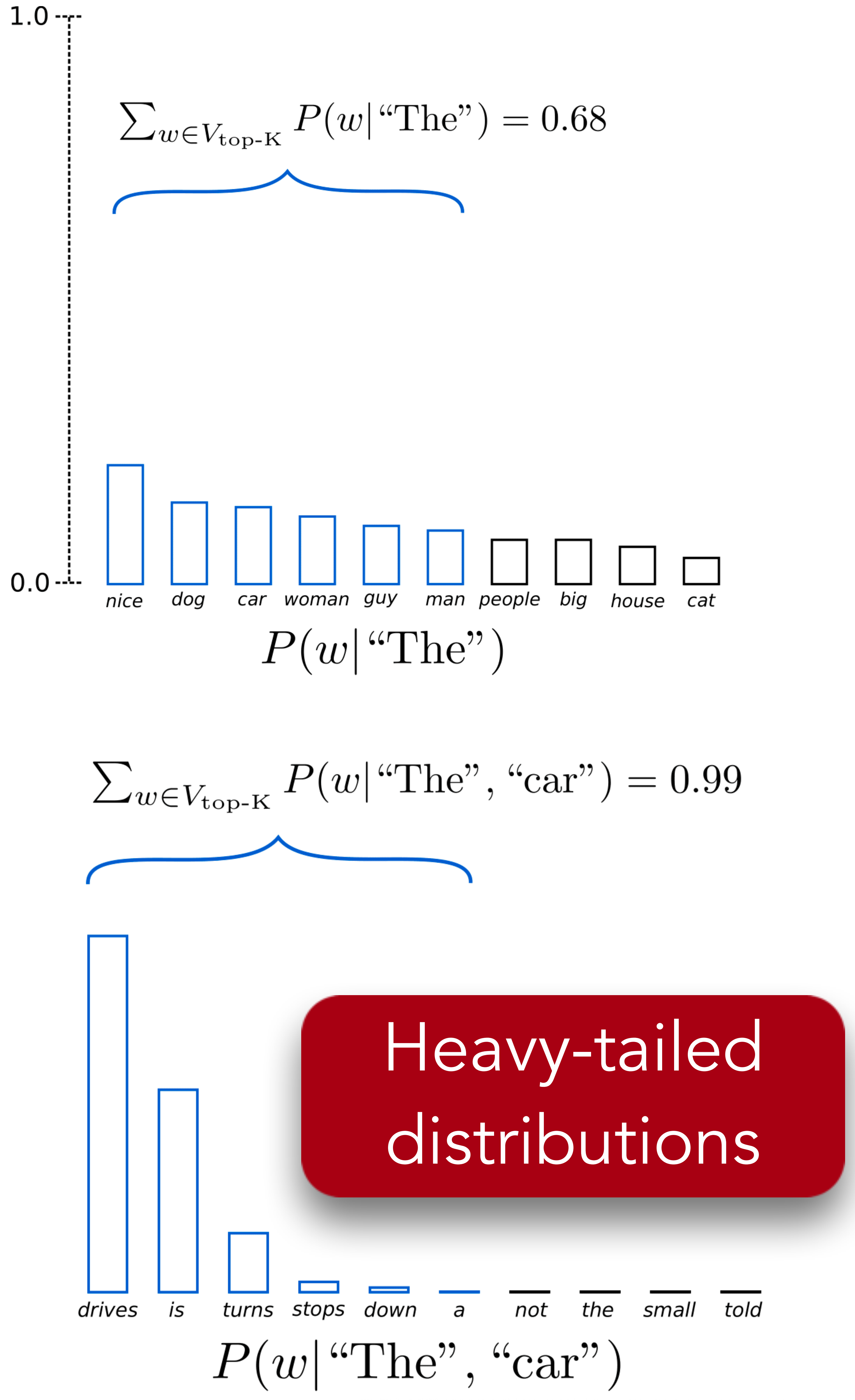

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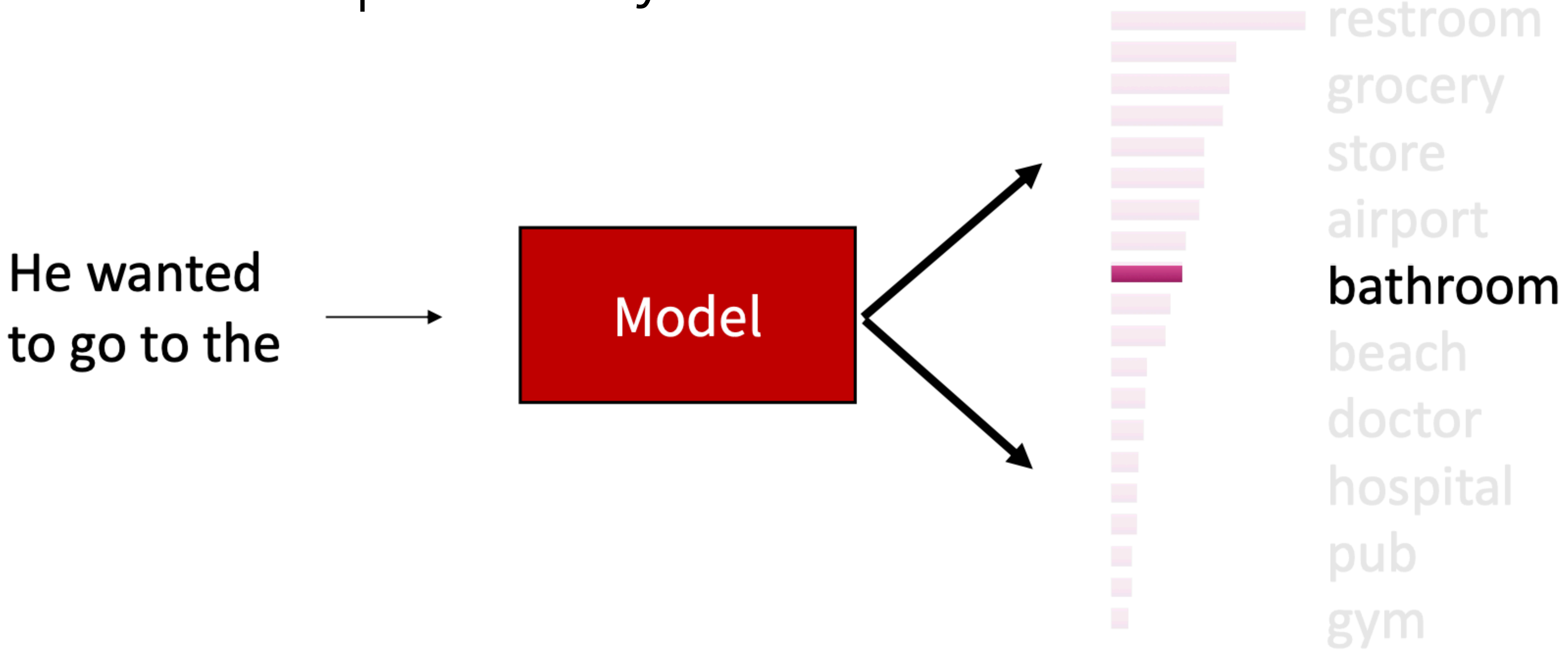

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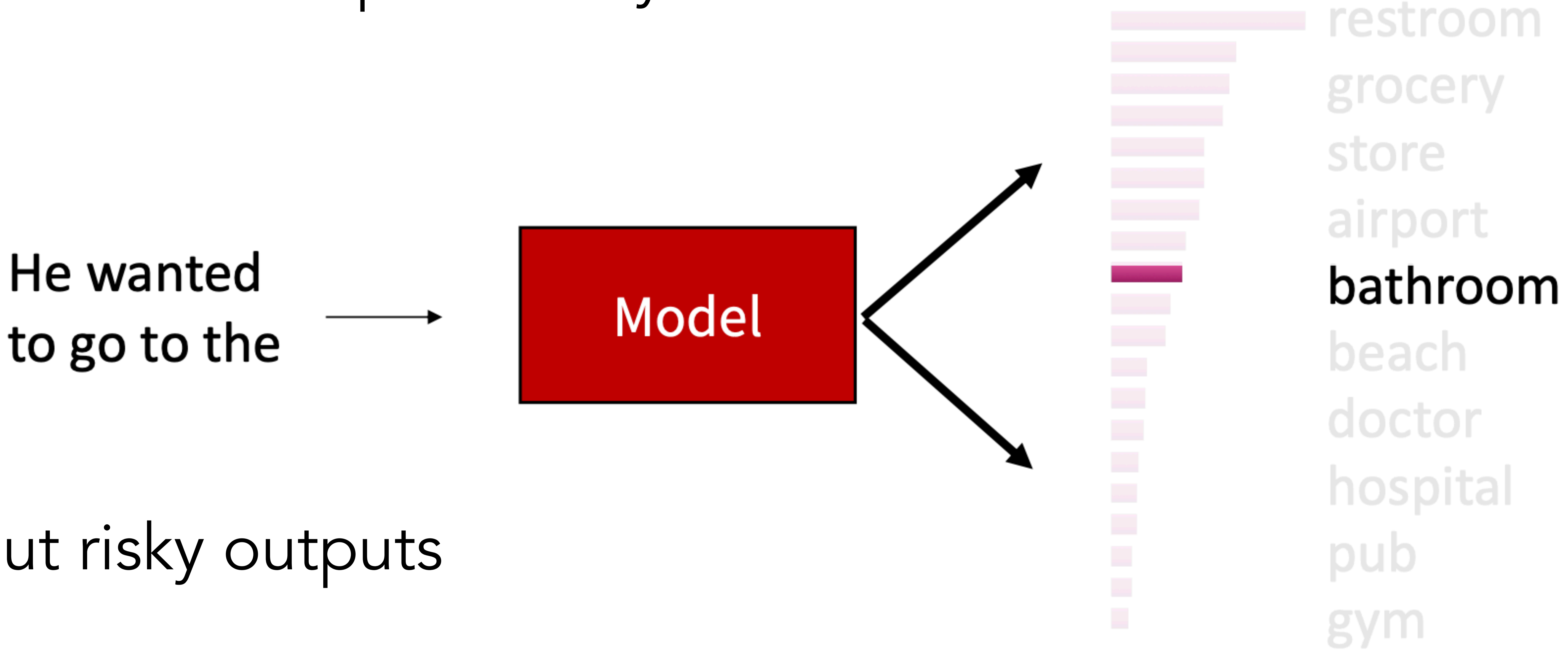

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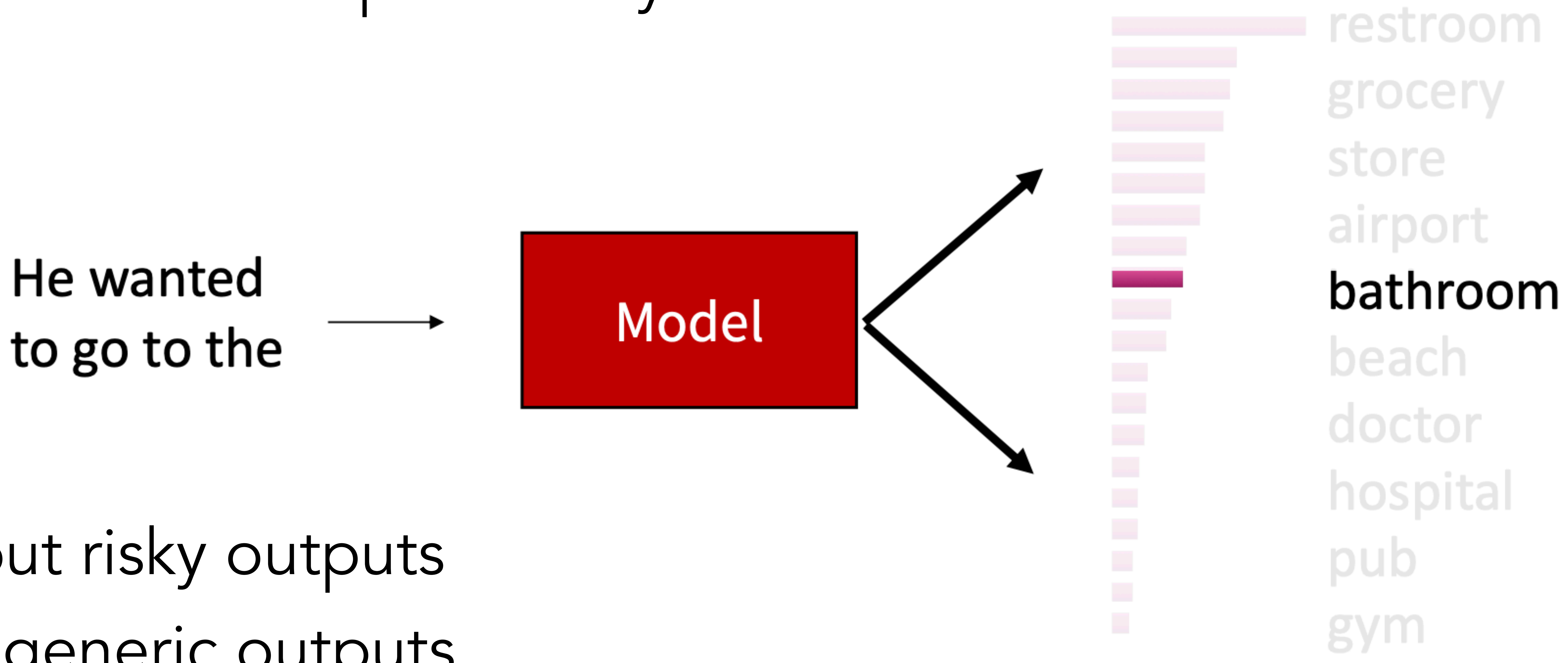

- Increase K yields more diverse, but risky outputs
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Top-K Sampling: Issues

Top-K sampling can cut off too quickly

Image Source: Holtzmann et al., 2019

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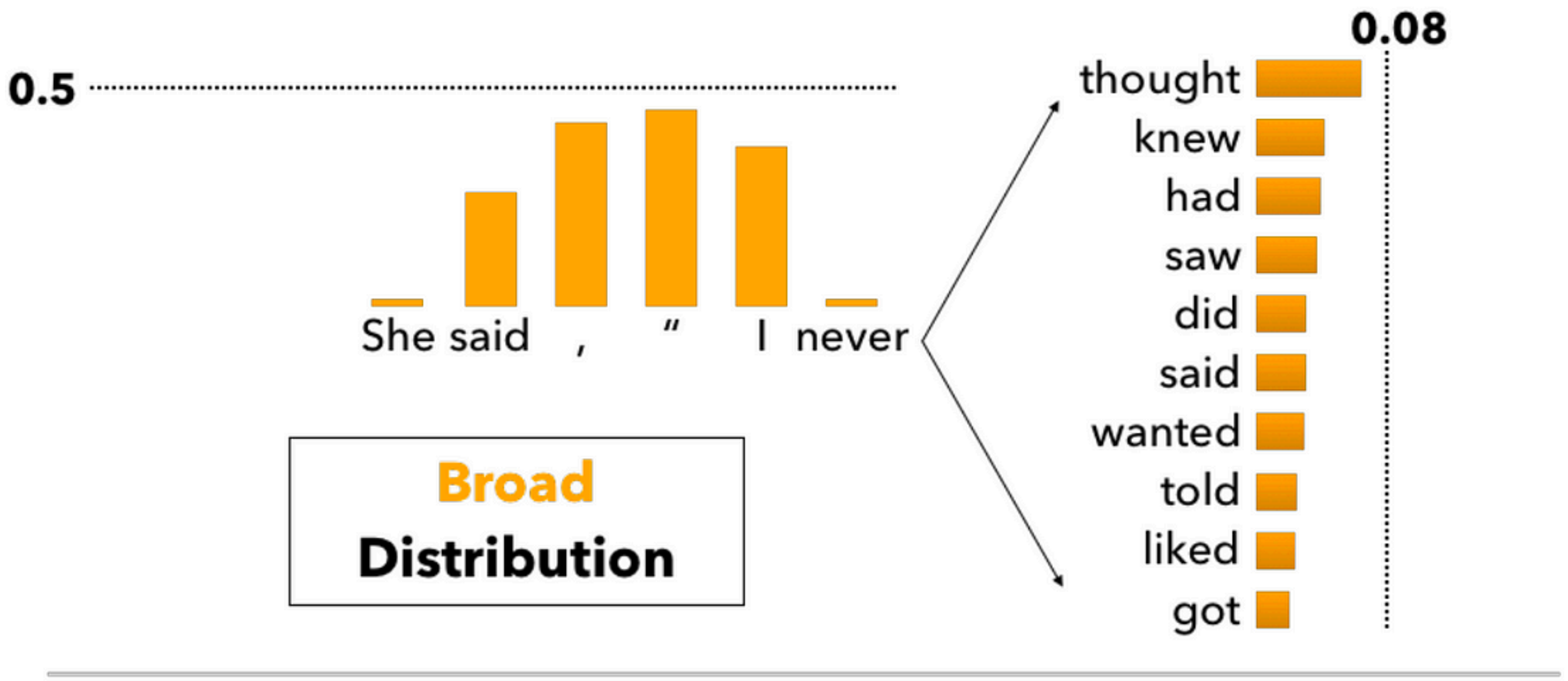

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Top-K Sampling: Issues

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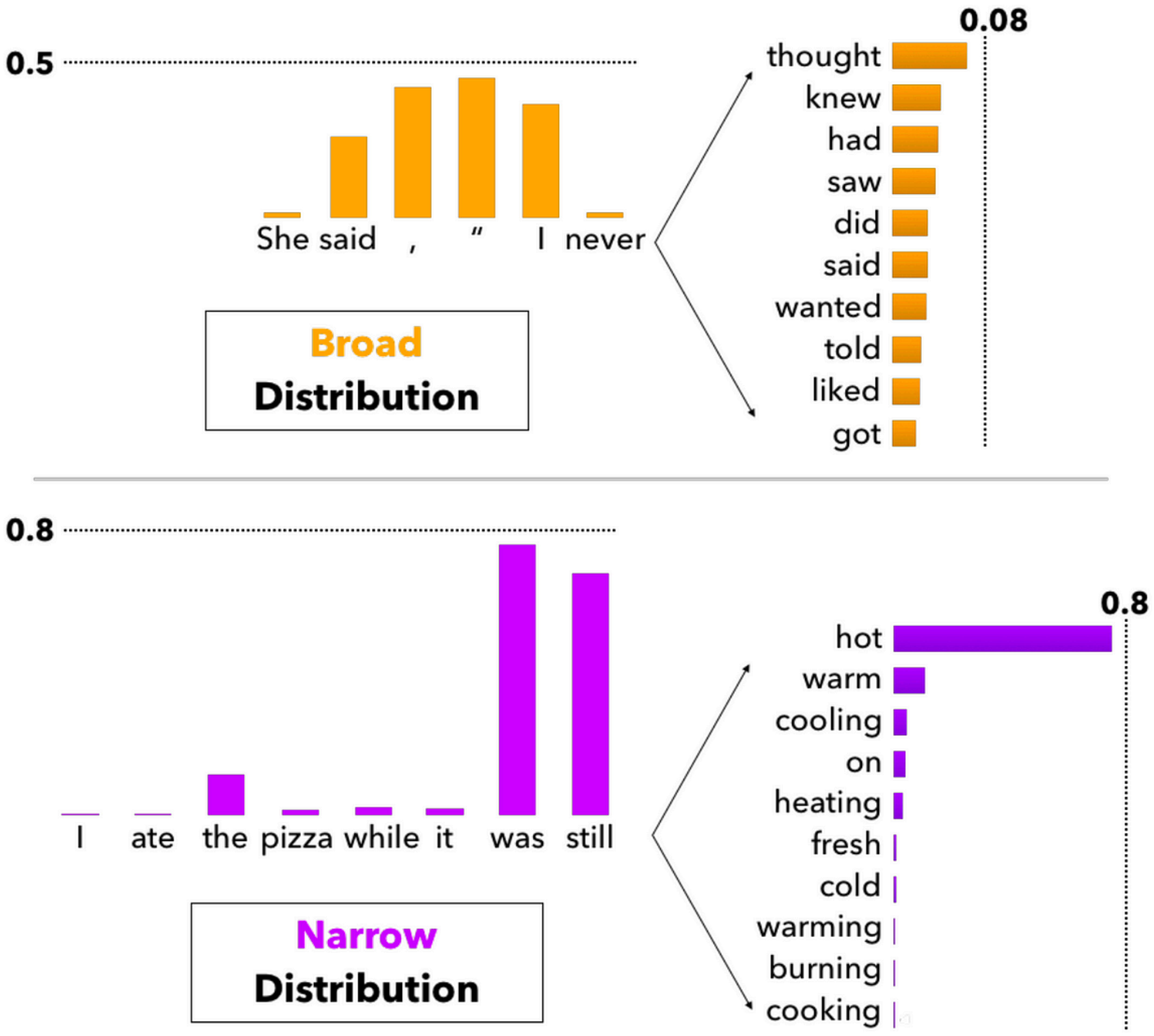

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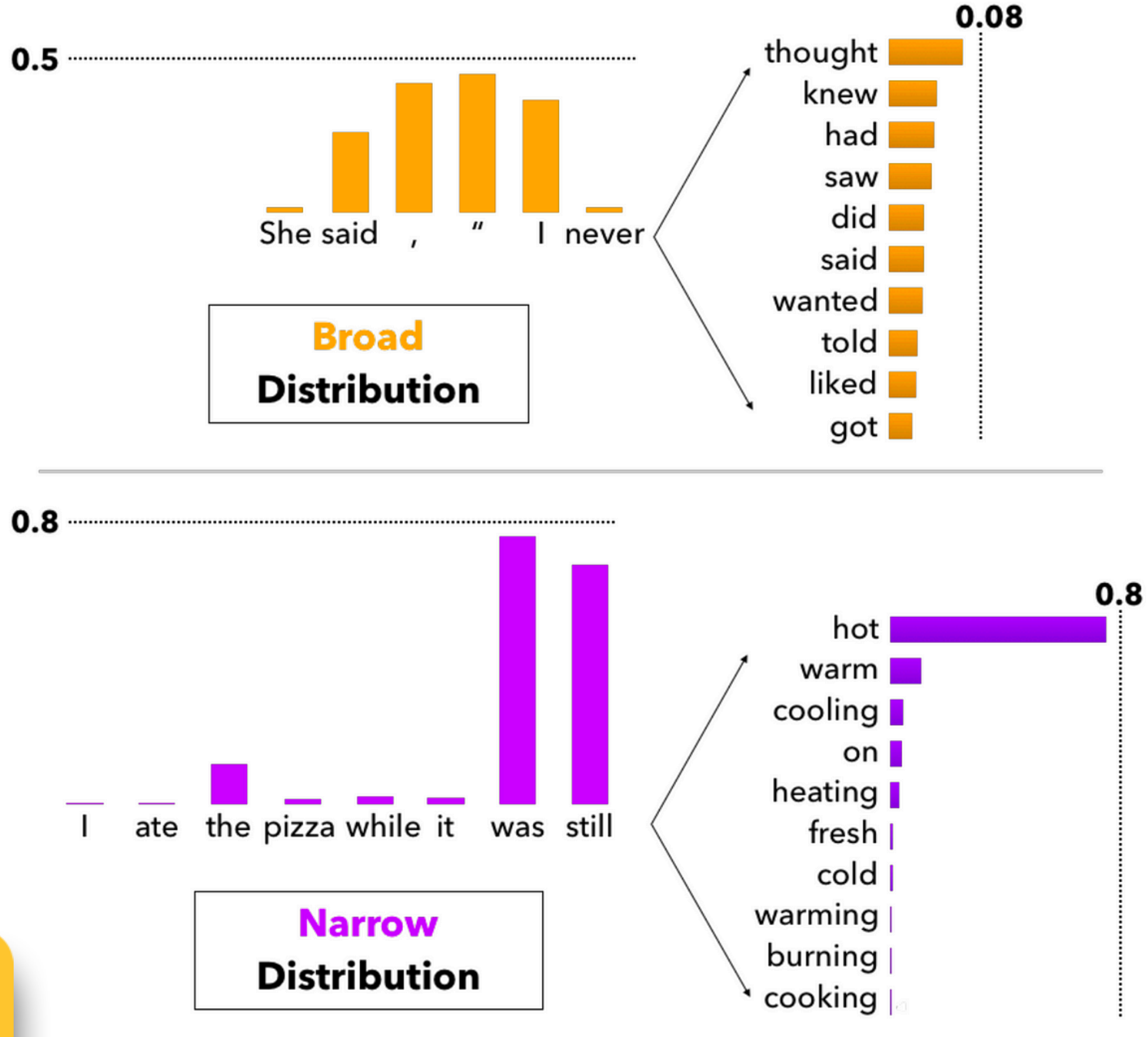
We can do better than having one-size-fits-all: a fixed K for all contexts



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Holtzman et al., ICLR 2020

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Holtzman et al., ICLR 2020

Nucleus (Top-P) Sampling

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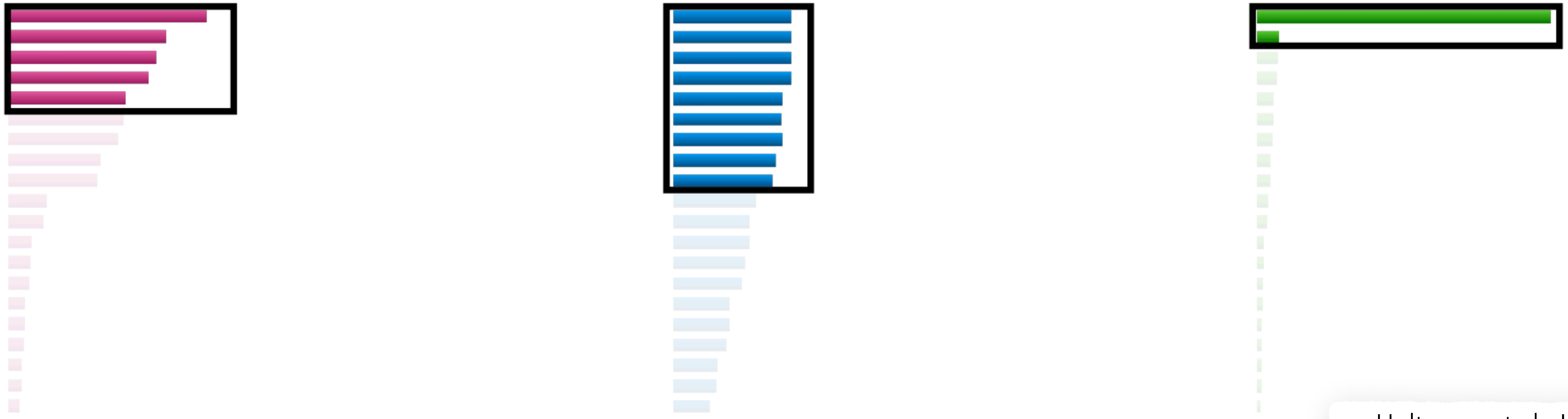
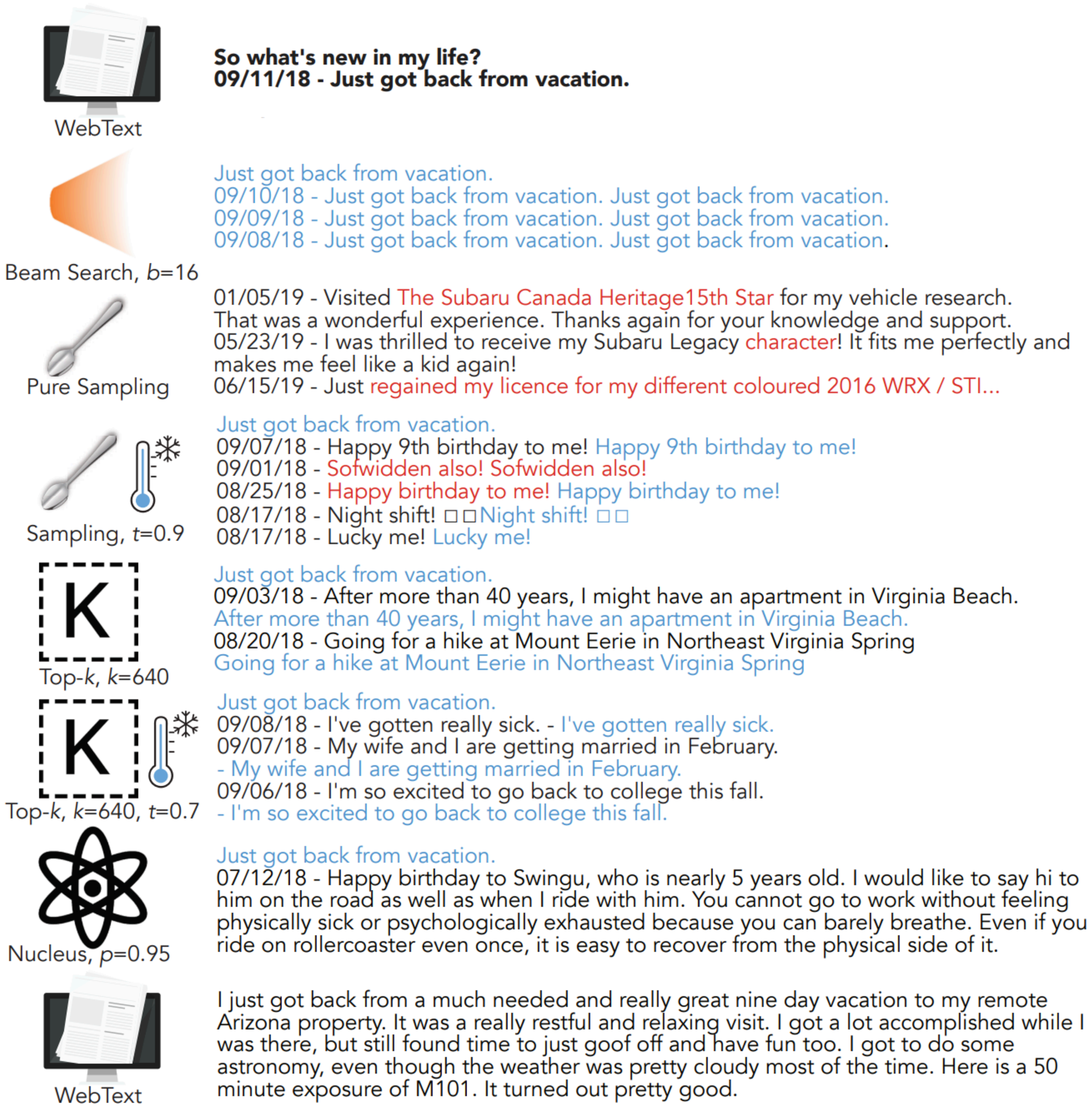


Holtzman et al., ICLR 2020

Comparing different decoding algorithms



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Comparing different decoding algorithms

- Generate text to continue a given context
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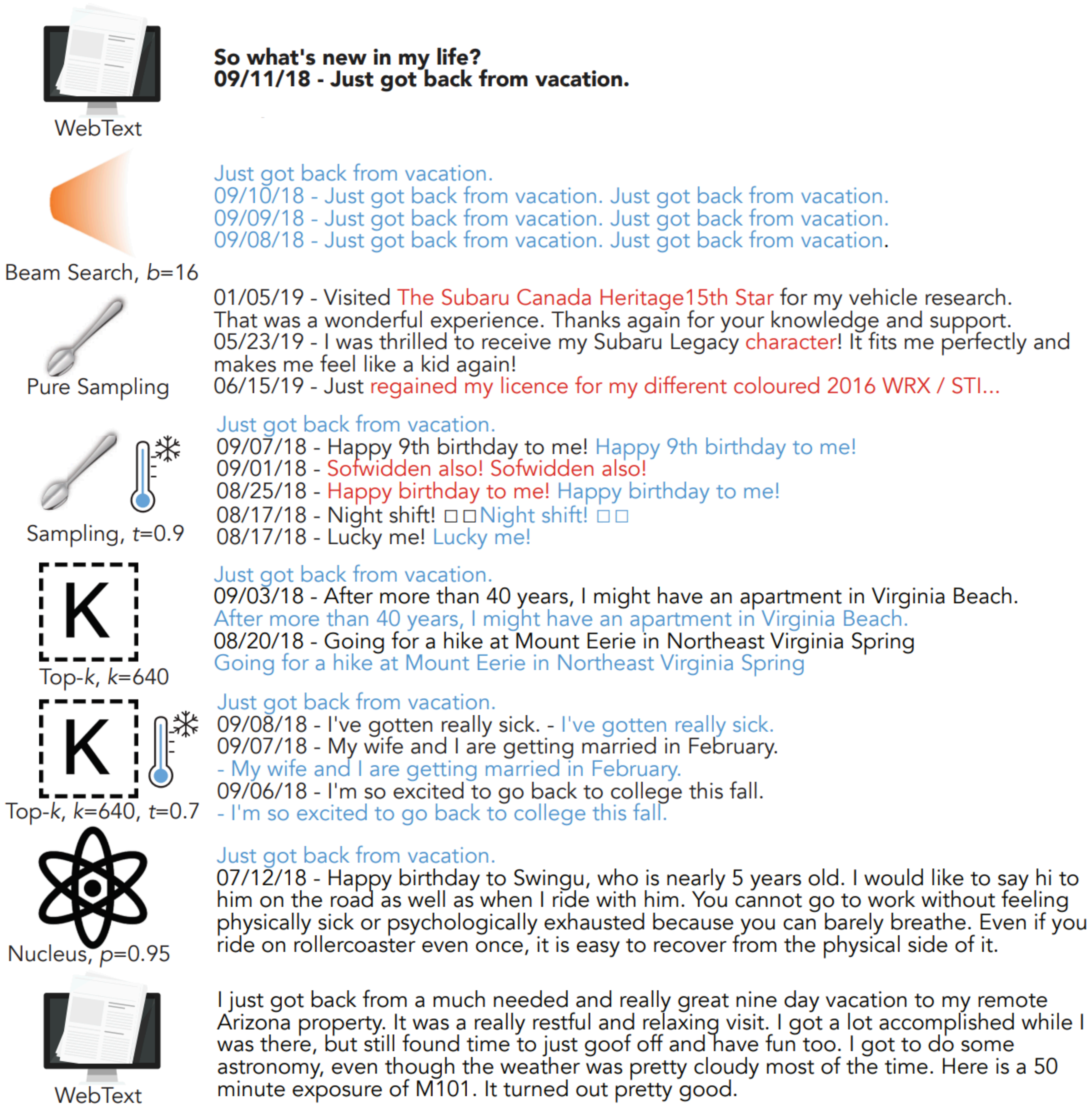

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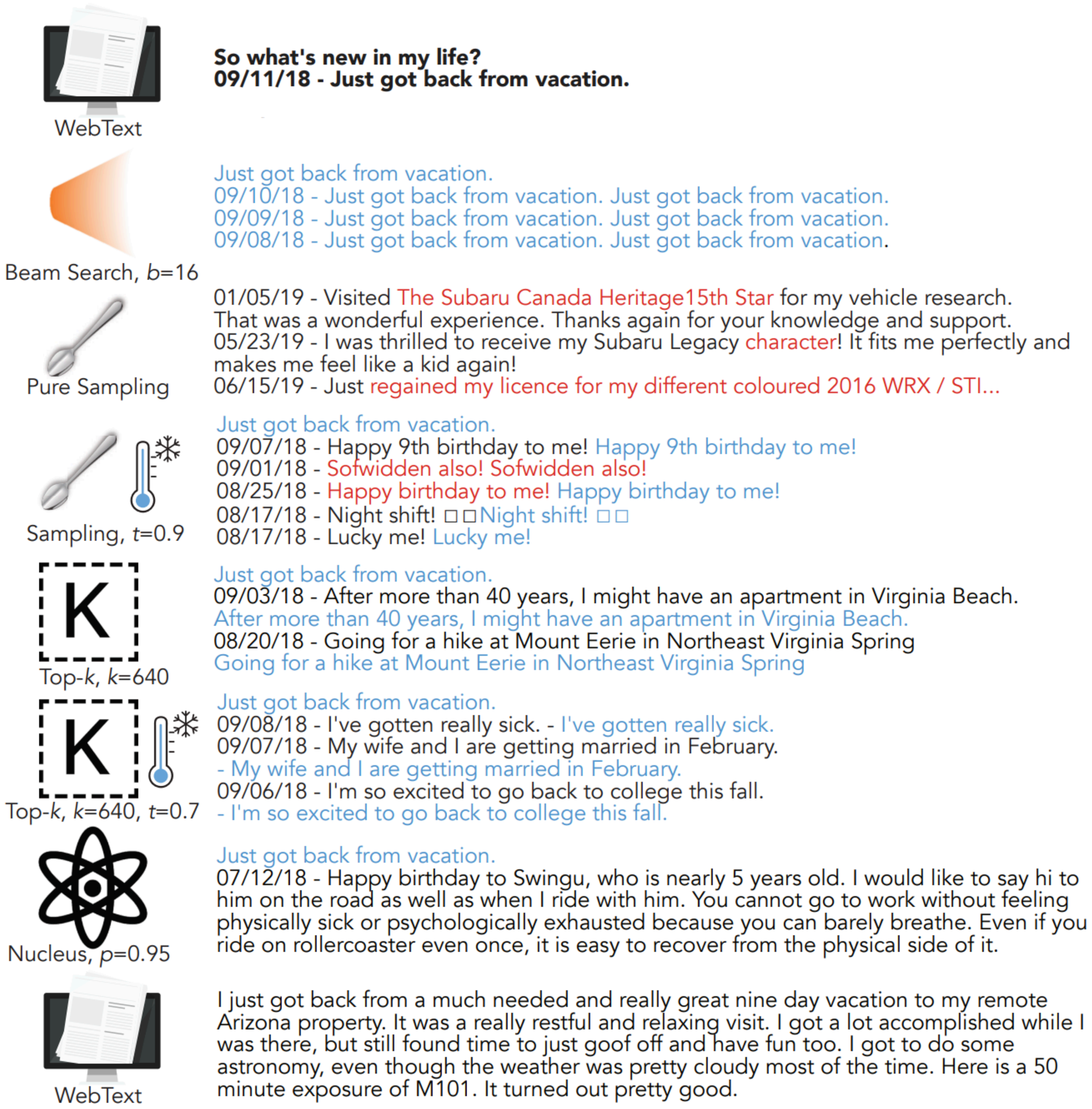
Comparing different decoding algorithms

- Generate text to continue a given context
  - Open-ended generation
- Same decoding algorithms are also useful for close-ended generation tasks



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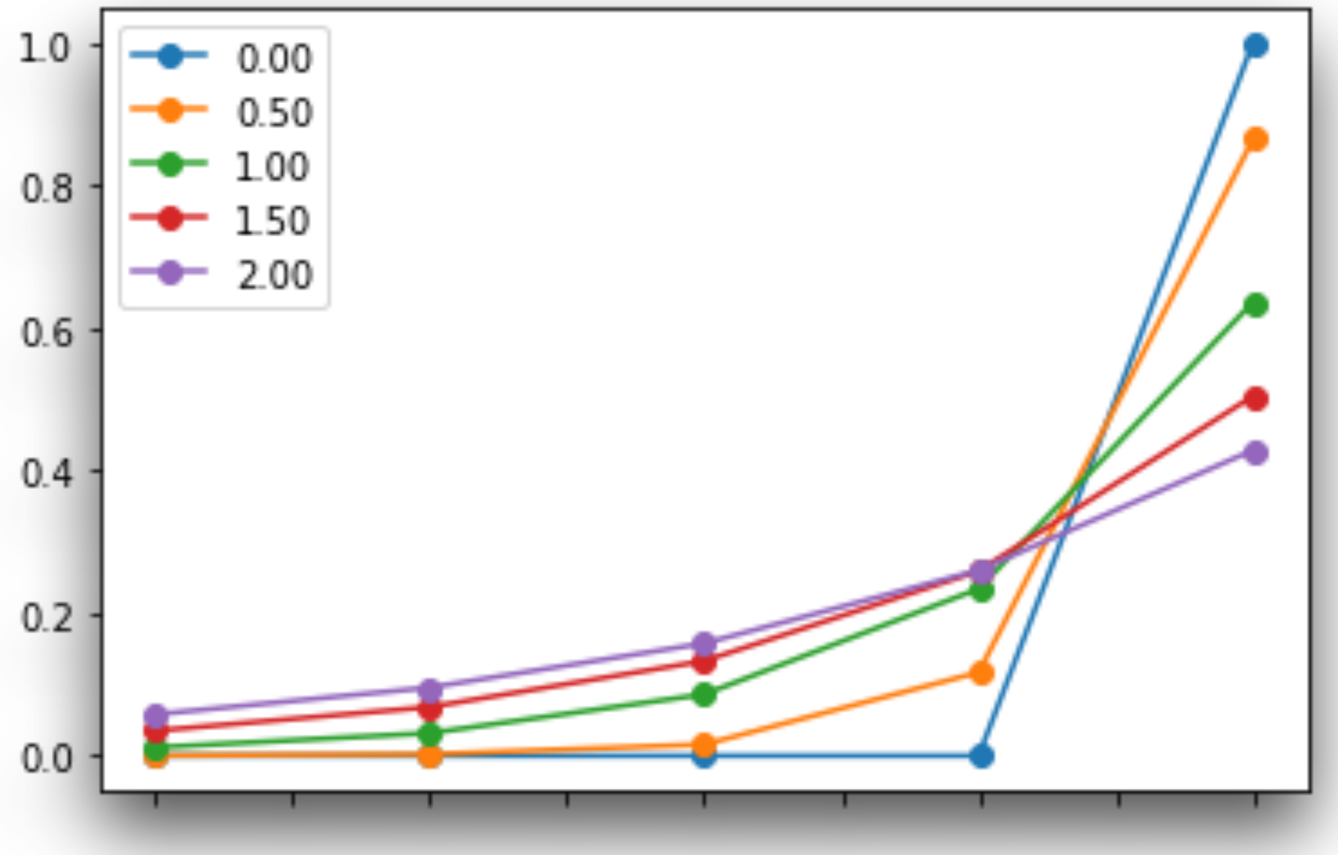

$$P(y_t = w) = \frac{\exp(S_w/\tau)}{\sum_{v \in V} \exp(S_v/\tau)}$$

- Raise the temperature $\tau > 1$: P_t becomes more uniform
  - More diverse output (probability is spread around vocab)

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- Recall: On timestep t, the model computes a prob distribution P_t by applying the softmax function to a vector of scores $s \in \mathbb{R}^{|V|}$
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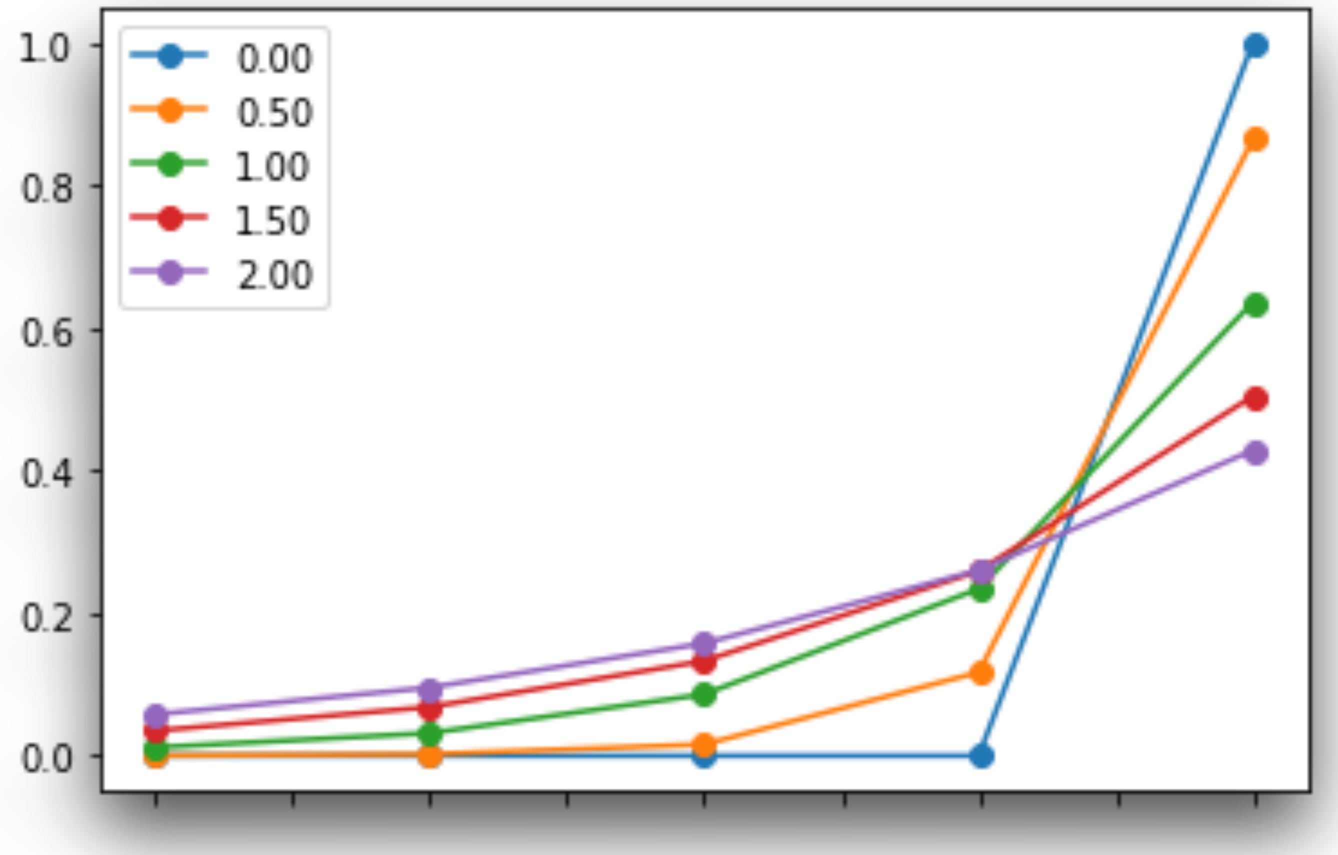
$$P(y_t = w) = \frac{\exp(S_w/\tau)}{\sum_{v \in V} \exp(S_v/\tau)}$$



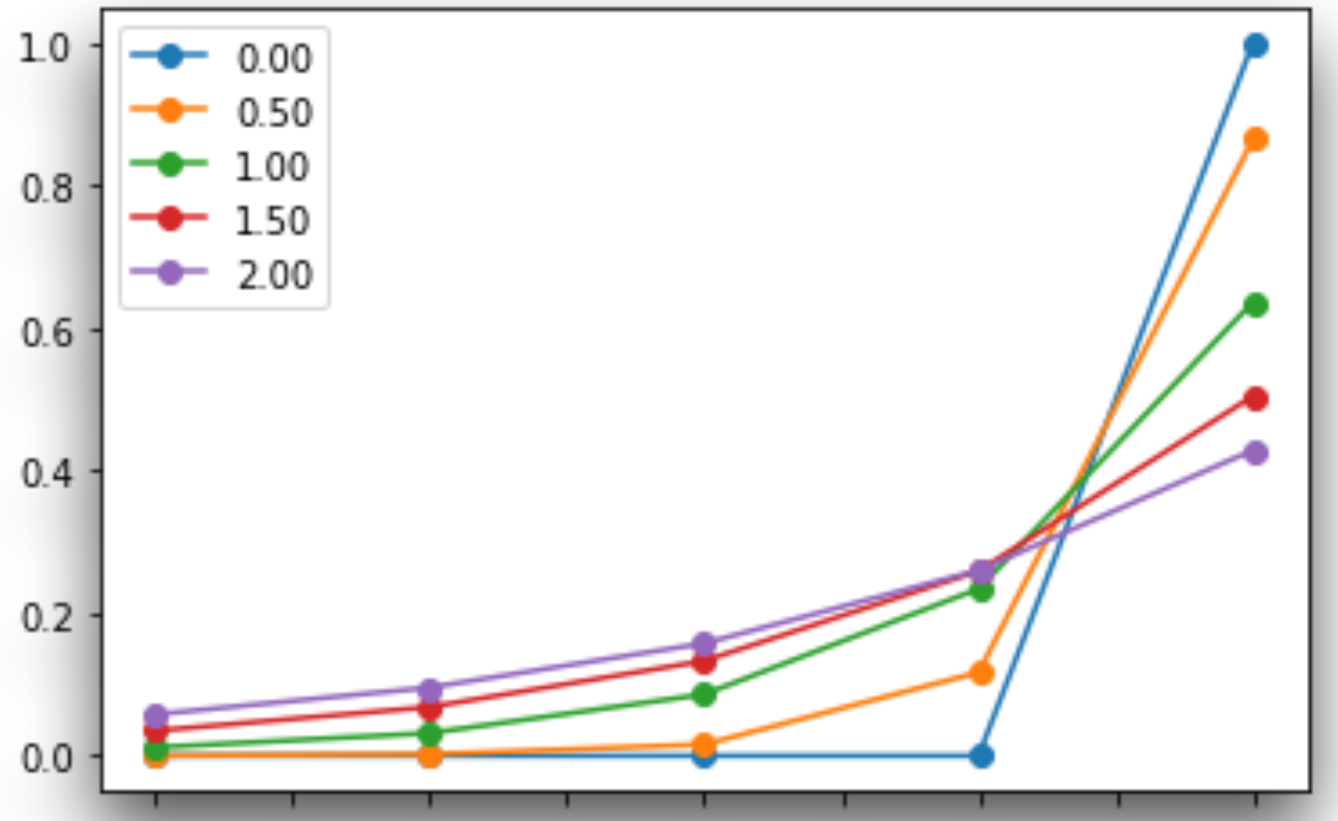
- Raise the temperature $\tau > 1$: P_t becomes more uniform
  - More diverse output (probability is spread around vocab)
- Lower the temperature $\tau < 1$: P_t becomes more spiky
  - Less diverse output (probability is concentrated on top words)

Temperature Scaling

$$P(y_t = w) = \frac{\exp(S_w)}{\sum_{v \in V} \exp(S_v)}$$

- Recall: On timestep t, the model computes a prob distribution P_t by applying the softmax function to a vector of scores $s \in \mathbb{R}^{|V|}$
- We can apply a temperature hyperparameter τ to the softmax to rebalance P_t

$$P(y_t = w) = \frac{\exp(S_w / \tau)}{\sum_{v \in V} \exp(S_v / \tau)}$$



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Temperature is a hyperparameter for decoding: It can be tuned for both beam search and sampling.

Modern Decoding: Takeaways

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- Some properties of the softmax function make truncation based decoding necessary

CLOSING THE CURIOUS CASE OF NEURAL TEXT DEGENERATION

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Next Class: Evaluating Generations (Me), Prompting and Instruction Tuning (Guest Lecture)

Quiz 5