Lecture 17:
Language Generation

Instructor: Swabha Swayamdipta

USC CSCI 544 Applied NLP

Oct 24, Fall 2024

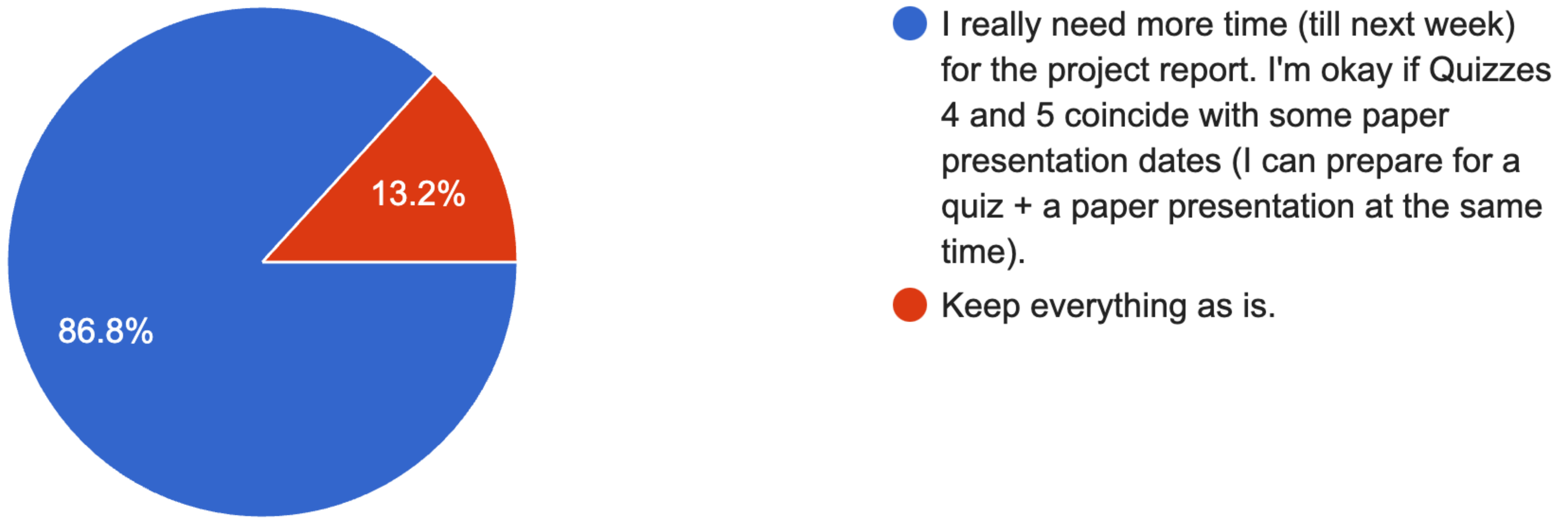
Some slides adapted from Dan Jurafsky and Chris Manning

Announcements

- Tue, 10/29 - Project proposal
- Thu, 11/7 - Quiz 4
- Tue, 11/12 Quiz 5
- Quizzes 4 and 5 - all topics after the midterms
  - Consider these as practice tests for final exams
- Thu, 11/14 Guest lecture by Prof. Willie Neiswanger on 11/14 + HW4 due
- Thu, 10/31 onwards: Paper presentations and project presentations
  - Also two remaining lectures on 10/31 and 11/5

If we delay the project proposal date deadline, this will affect the timeline for quizzes, and paper presentations. Which option is more preferable to you?

121 responses



Lecture Outline

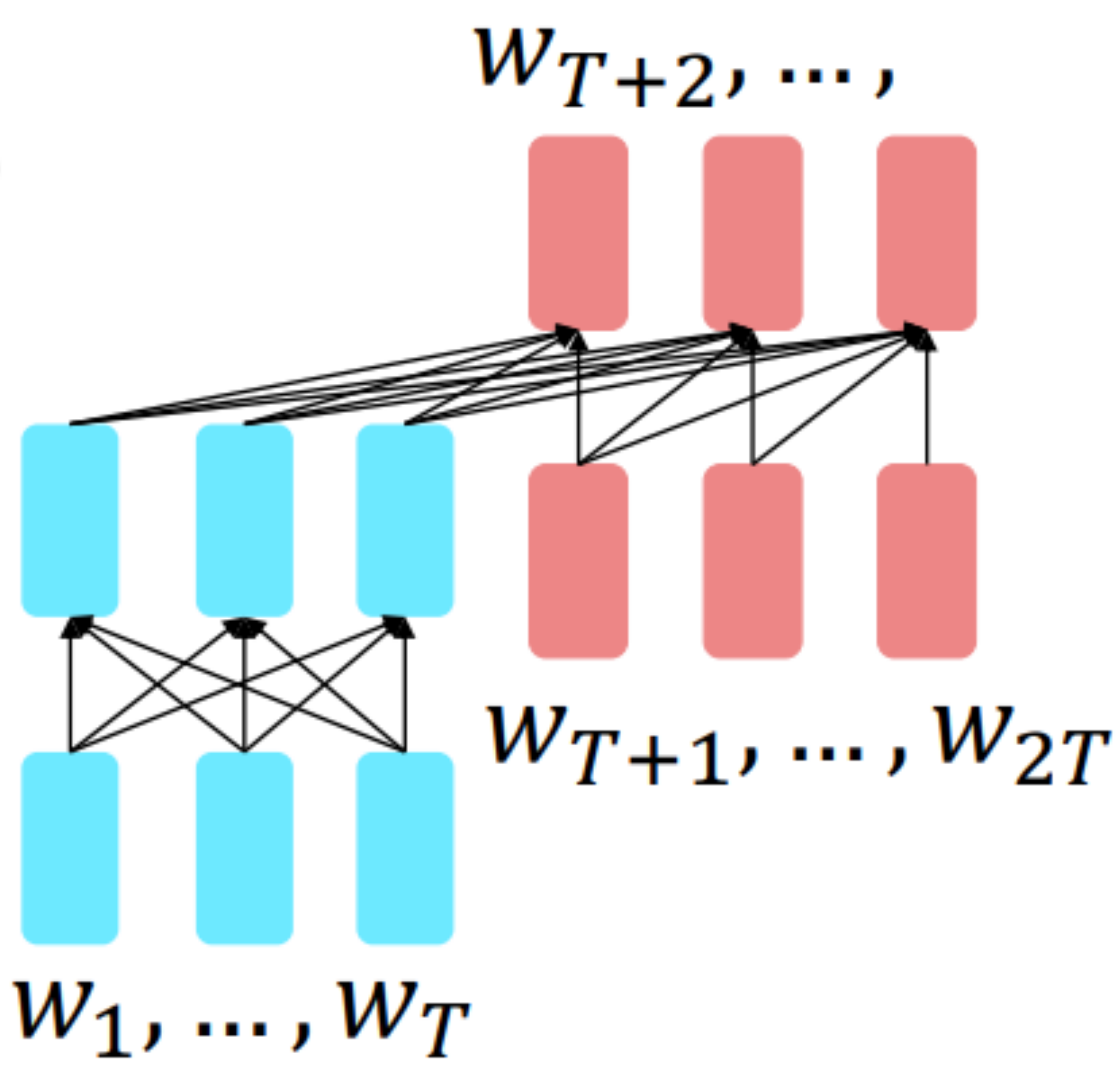
- Announcements
- Recap: The pre-training and fine-tuning paradigm
  - Pre-training Decoder-Only Models
  - Pre-training Encoder-Only Models
- Pre-training Encoder-Decoder Models
- Tokenization
- Natural Language Generation

Recap: Pre-training Encoder-Decoder Models

Pretraining Encoder-Decoder Models

- For encoder-decoders, we could do something like language modeling, but where a prefix of every input is provided to the encoder and is not predicted.

$$h_1, \dots, h_T = \text{Encoder}(w_1, \dots, w_T)$$
$$h_{T+1}, \dots, h_2 = Decoder(w_1, \dots, w_T, h_1, \dots, h_T)$$
$$y_i \sim Ah_i + b, i > T$$

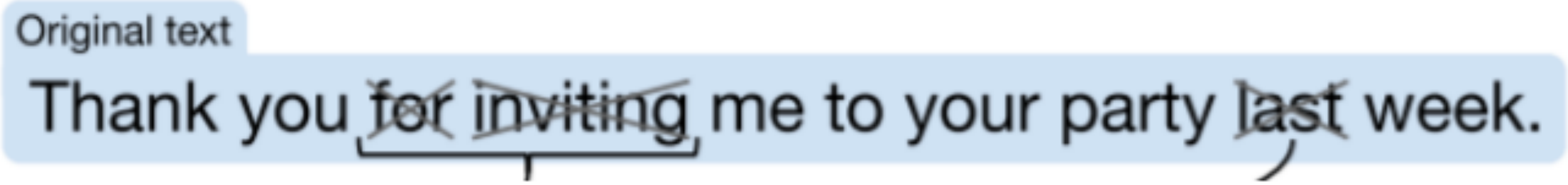


The encoder portion benefits from bidirectional context; the decoder portion is used to train the whole model through language modeling.

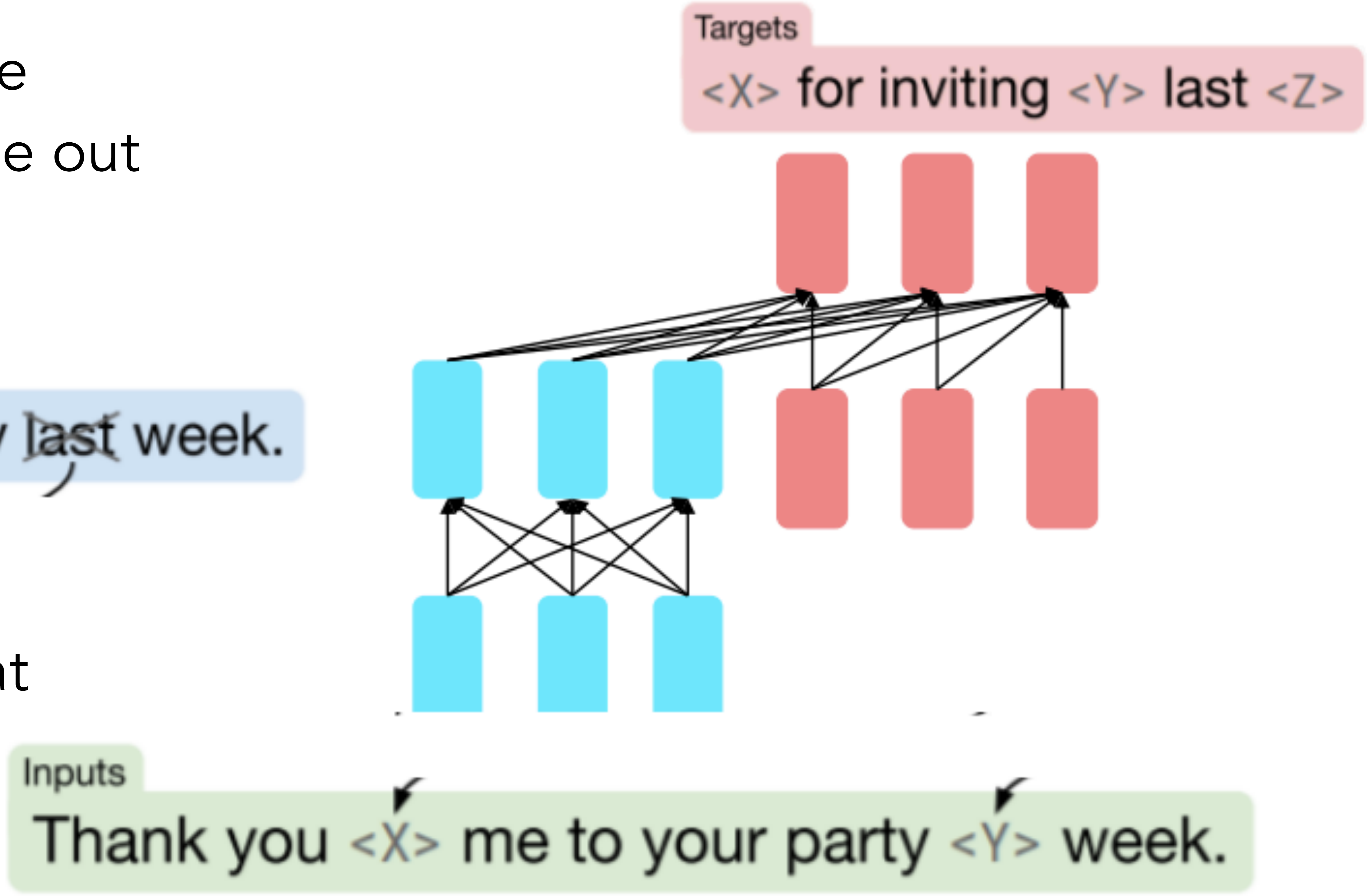
T5: A Pretrained Encoder-Decoder Model

- Raffel et al., 2018 built T5, which uses as a span corruption pretraining objective

Replace different-length spans from the input with unique placeholders; decode out the spans that were removed!



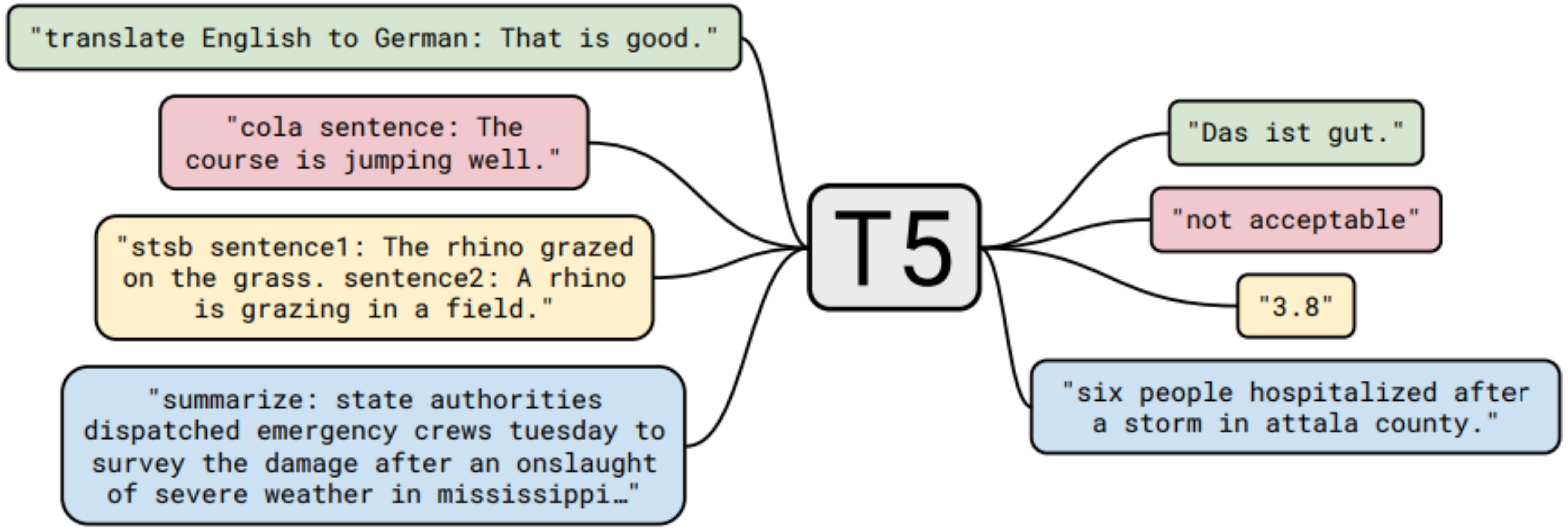
This is implemented in text preprocessing: it's still an objective that looks like language modeling at the decoder side.

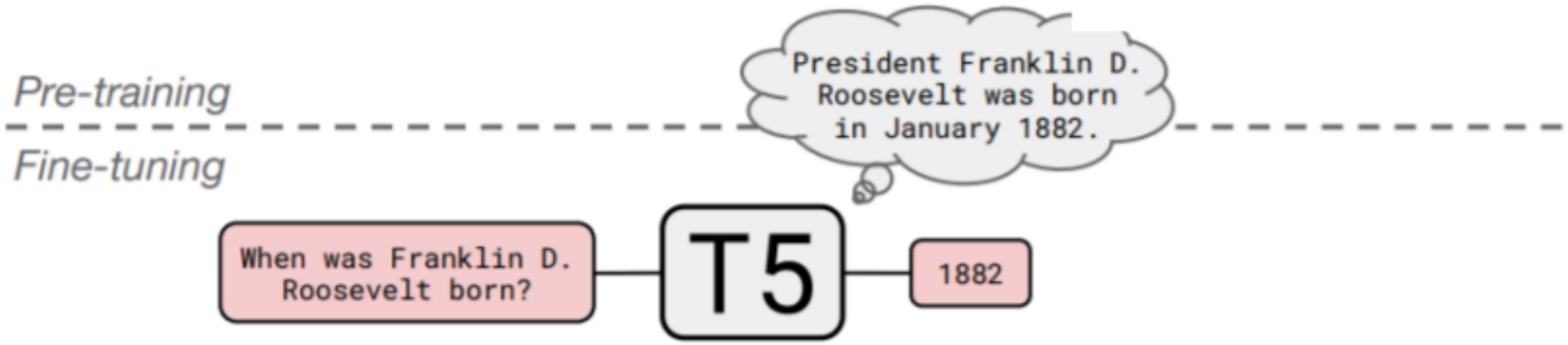


T5: Task Preparation

Pre-training task objective is very different from fine-tuning task objectives!

A fascinating property of T5: it can be finetuned to answer a wide range of questions, retrieving knowledge from its parameters.





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! However, not a parametric function
     - 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
low	widest	newest
low	widest	newest
low	widest	newest

Corpus

low</w>	lower</w>	newest</w>
low</w>	lower</w>	newest</w>
low</w>	widest</w>	newest</w>
low</w>	widest</w>	newest</w>
low</w>	widest</w>	newest</w>

Corpus

l o w </w>	l o w e r </w>	n e w e s t </w>
l o w </w>	l o w e r </w>	n e w e s t </w>
l o w </w>	w i d e s t </w>	n e w e s t </w>
l o w </w>	w i d e s t</w>	n e w e s t </w>
l o w </w>	w i d e s t </w>	n e w e s t </w>

Vocabulary

d	e	i	l	n	o	s	t	w
es								

Frequency

d-e (3)	l-o (7)	t-</w> (8)
e-r (2)	n-e (5)	w-</w> (5)
e-s (8)	o-w (7)	w-e (7)
e-w (5)	r-</w> (2)	w-i (3)
i-d (3)	s-t (8)	

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

BPE in action

Corpus

low	lower	newest
low	lower	newest
low	widest	newest
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Corpus

low</w>	lower</w>	newest</w>
low</w>	lower</w>	newest</w>
low</w>	widest</w>	newest</w>
low</w>	widest</w>	newest</w>
low</w>	widest</w>	newest</w>

Corpus

l o w </w>	l o w e r </w>	n e w es t </w>
l o w </w>	l o w e r </w>	n e w es t </w>
l o w </w>	w i d es t </w>	n e w es t </w>
l o w </w>	w i d es t</w>	n e w es t </w>
l o w </w>	w i d es t </w>	n e w es t </w>

Vocabulary

d	e	i	l	n	o	s	t	w
es	est							

Frequency

d-es (3)	l-o (7)	w-</w> (5)
e-r (2)	n-e (5)	w-es (5)
e-w (5)	o-w (7)	w-e (2)
es-t (8)	r-</w> (2)	w-i (3)
i-d (3)	t-</w> (8)	

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BPE in action

Corpus

low	lower	newest
low	lower	newest
low	widest	newest
low	widest	newest
low	widest	newest

Corpus

low</w>	lower</w>	newest</w>
low</w>	lower</w>	newest</w>
low</w>	widest</w>	newest</w>
low</w>	widest</w>	newest</w>
low</w>	widest</w>	newest</w>

Corpus

l o w </w>	l o w e r </w>	n e w est </w>
l o w </w>	l o w e r </w>	n e w est </w>
l o w </w>	w i d est </w>	n e w est </w>
l o w </w>	w i d est </w>	n e w est </w>
l o w </w>	w i d est </w>	n e w est </w>

Vocabulary

d	e	i	l	n	o	s	t	w
es	est	est</w>	lo	low	low</w>	ne	new	newest</w>

After 10 merges

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

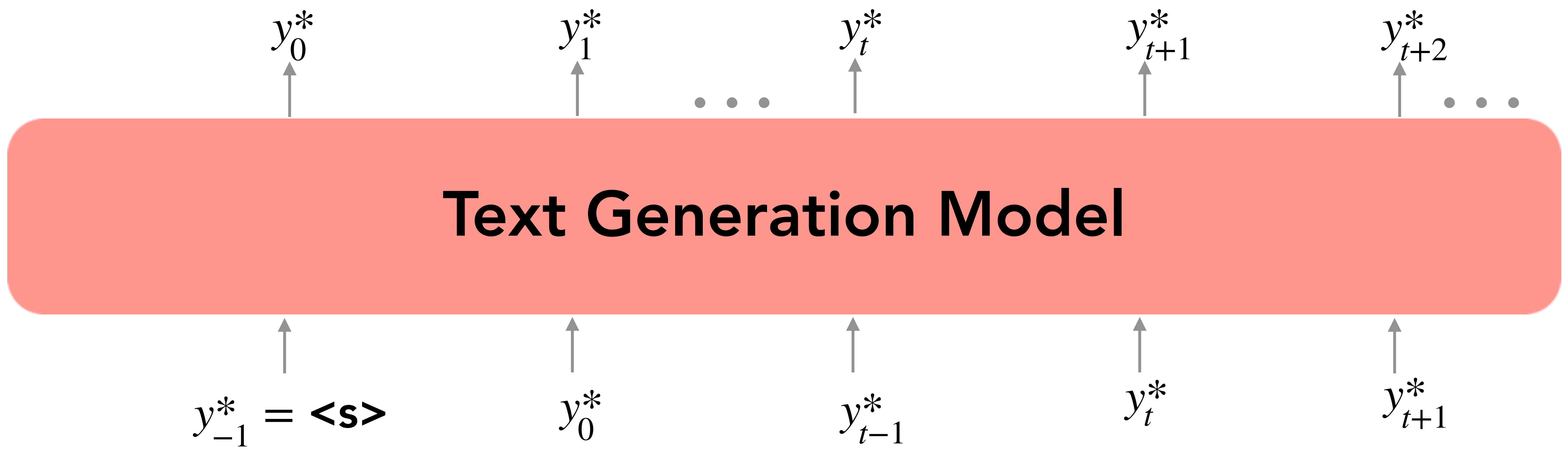
Natural Language Generation

Language Generation: Training

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

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

- 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)



Teacher Forcing

- Strategy for **training** decoders / language models
- At each time step t in decoding we force the system to use the gold target token from training as the next input x_{t+1}, rather than allowing it to rely on the (possibly erroneous) decoder output $\hat{y}_t$
- Runs the risk of **exposure bias**!
  - During training, our model's inputs are gold context tokens from real, human-generated texts
  - At generation time, our model's inputs are previously–decoded tokens
- To avoid:
  - Allow the decoder at training times to occasionally condition on its own outputs

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

$$g = \arg\max$$

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

Classic Inference Algorithms: Greedy and Beam Search

Greedy Decoding: Issues

- Greedy decoding has no wiggle room for errors!
  - Input: the green witch arrived
    - Output: llego
    - Output: llego la
    - Output: llego la verde
- How to fix this?
  - Need a lookahead strategy / longer-term planning

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, in NMT)
- 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
  - 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. 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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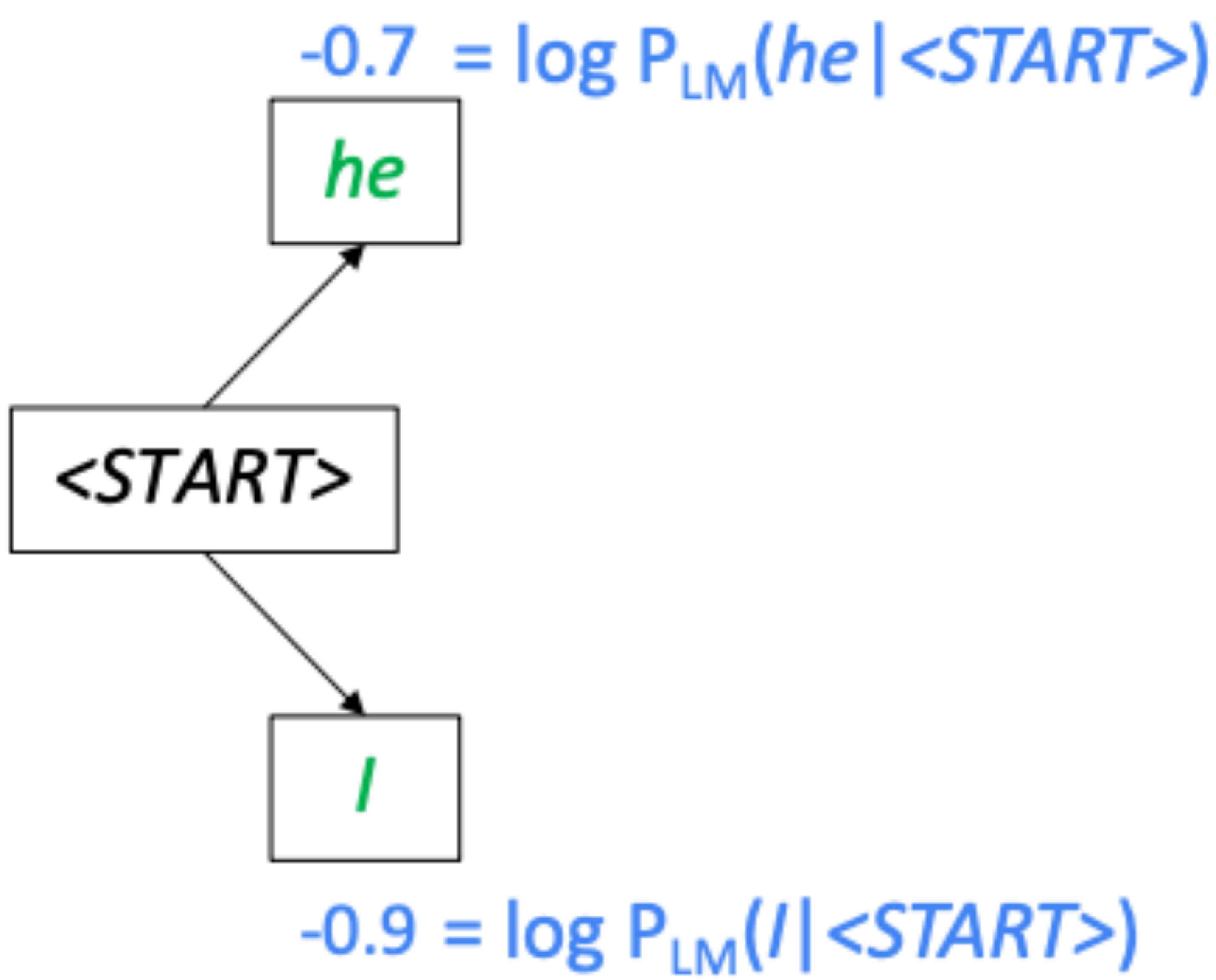

Take top *k* words and compute scores

: Chris Manning

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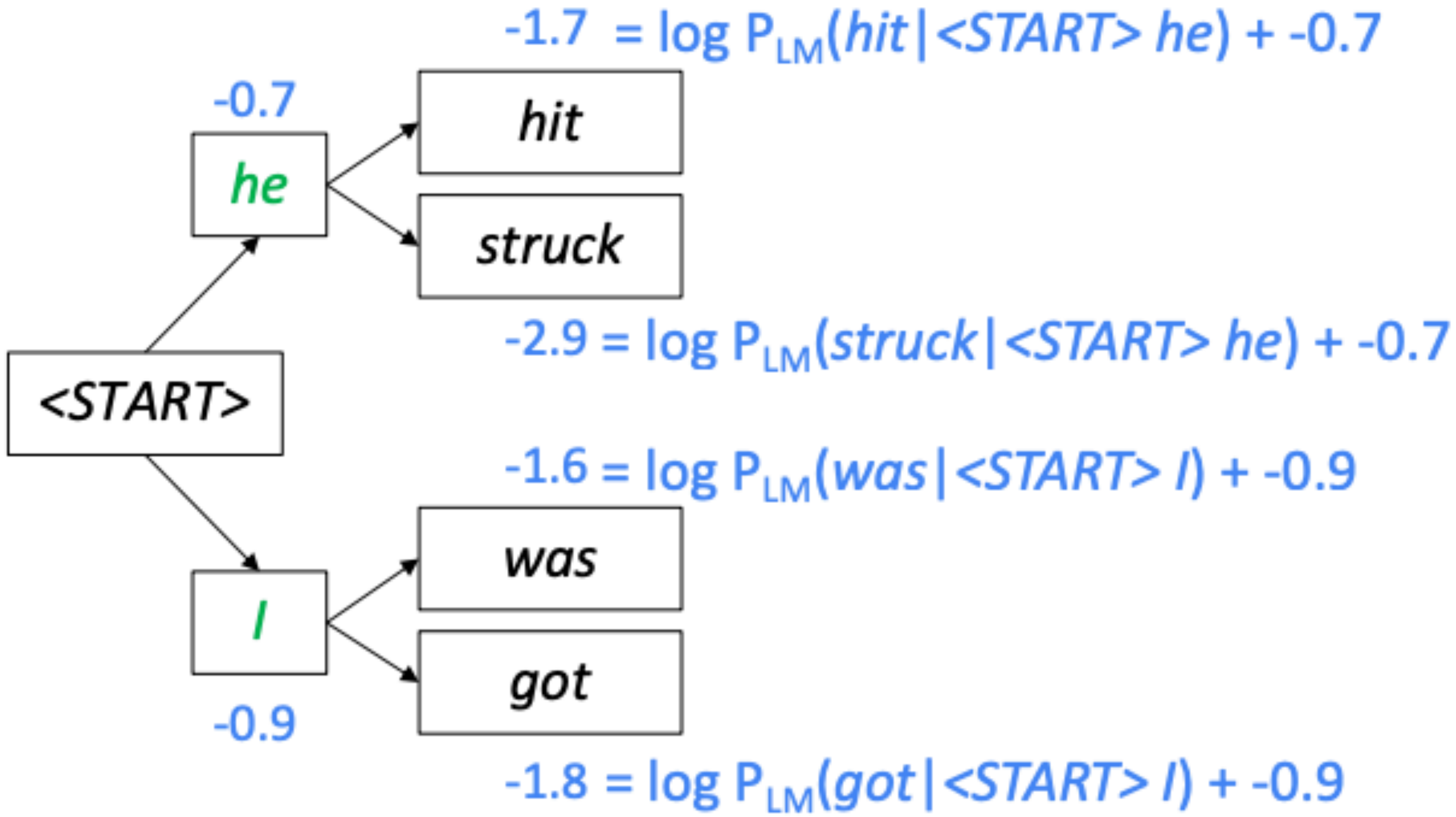

For each of the *k* hypotheses, find top *k* next words and calculate scores

Slide credit: Chris Manning

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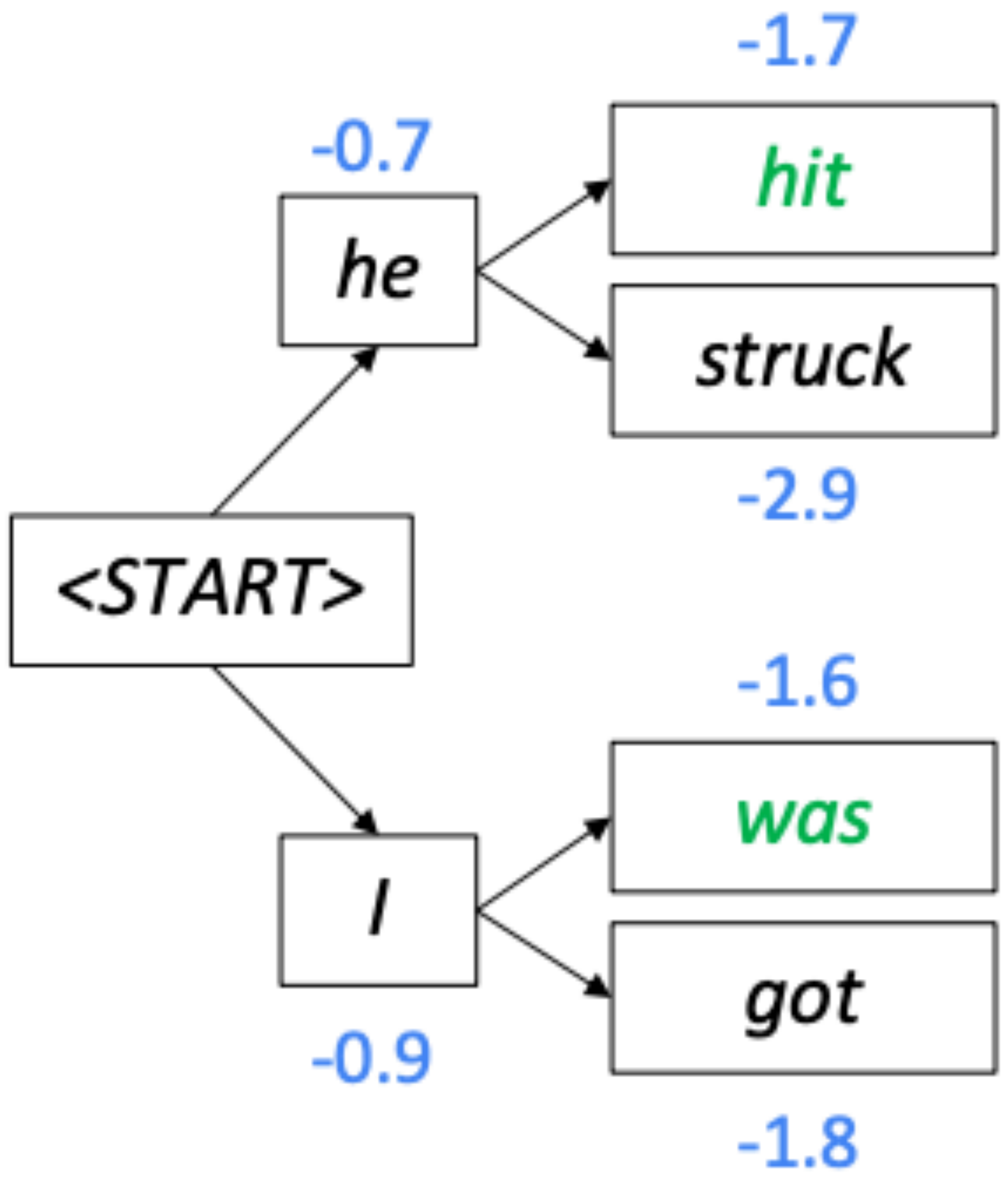

Of these k^2 hypotheses, just keep *k* with highest scores

Slide credit: Chris Manning

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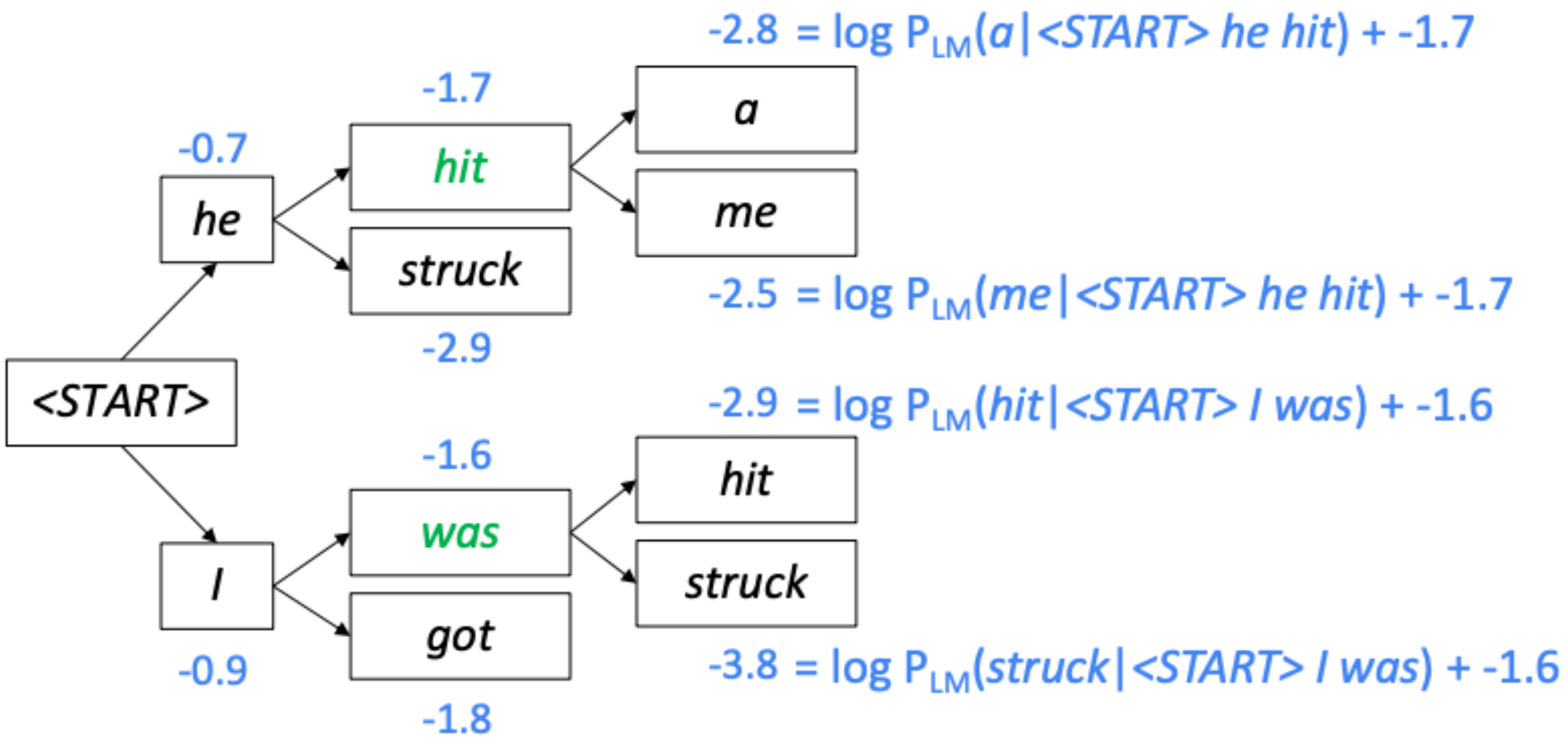

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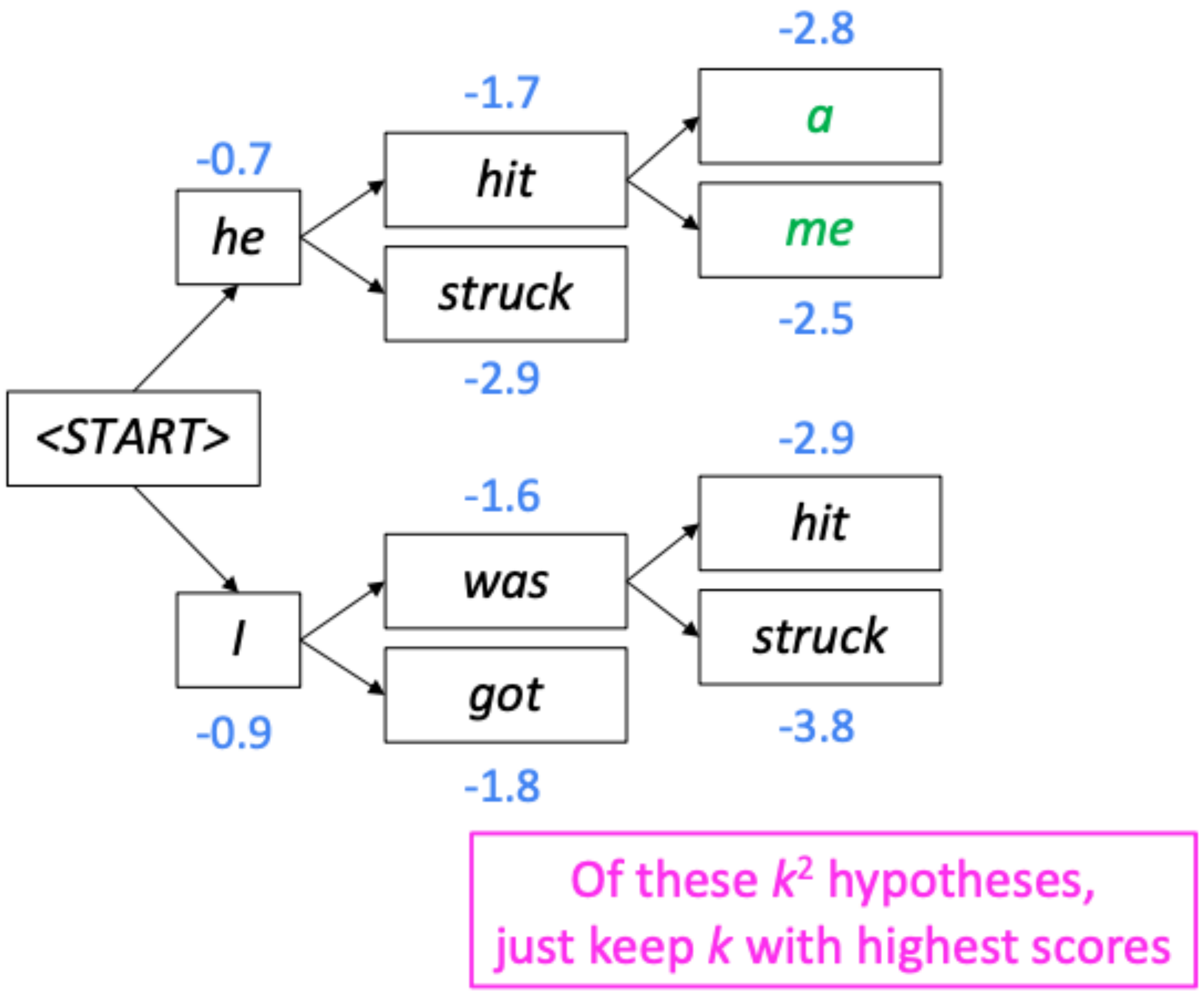

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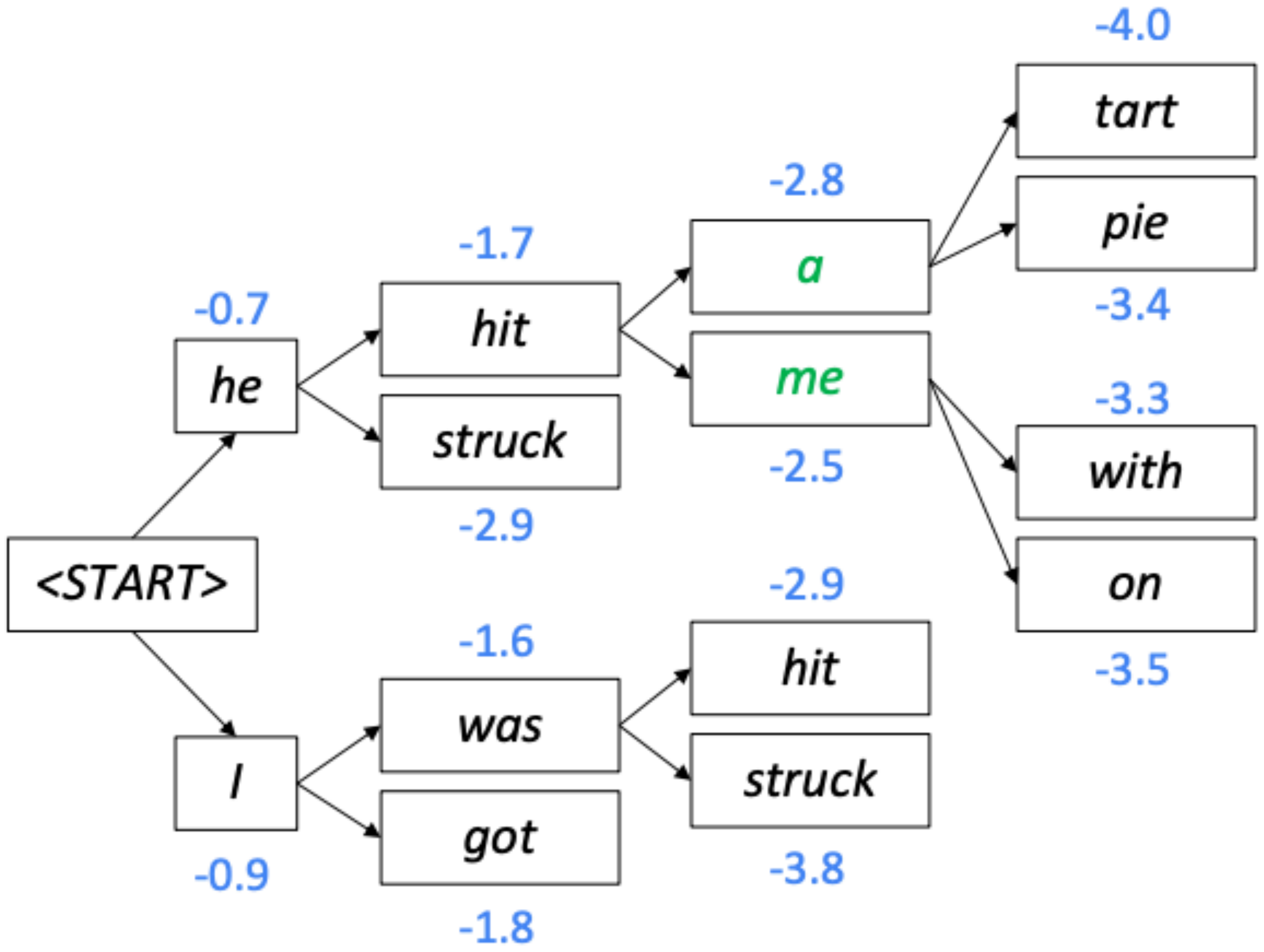

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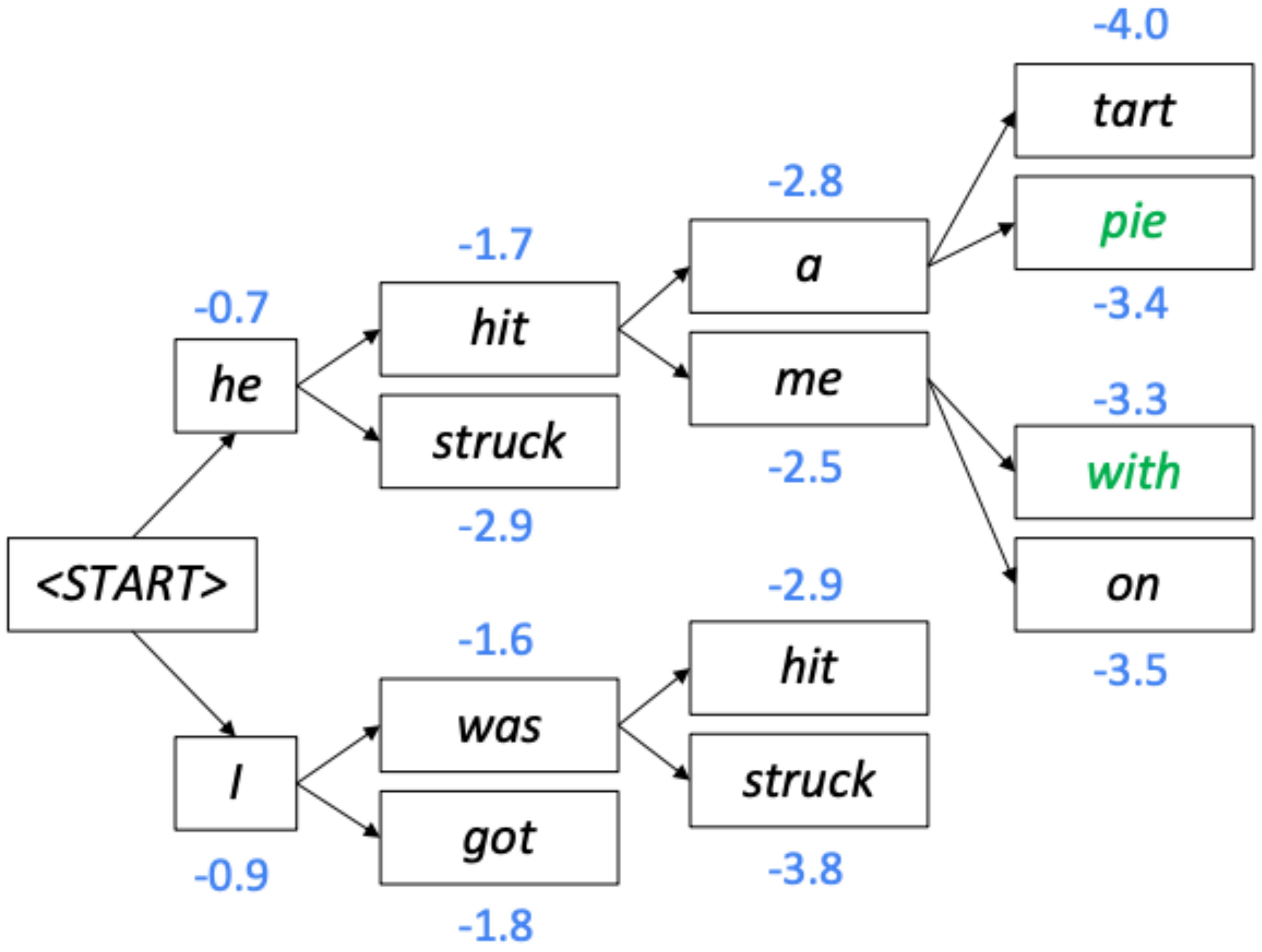

Of these k^2 hypotheses, just keep k with highest scores

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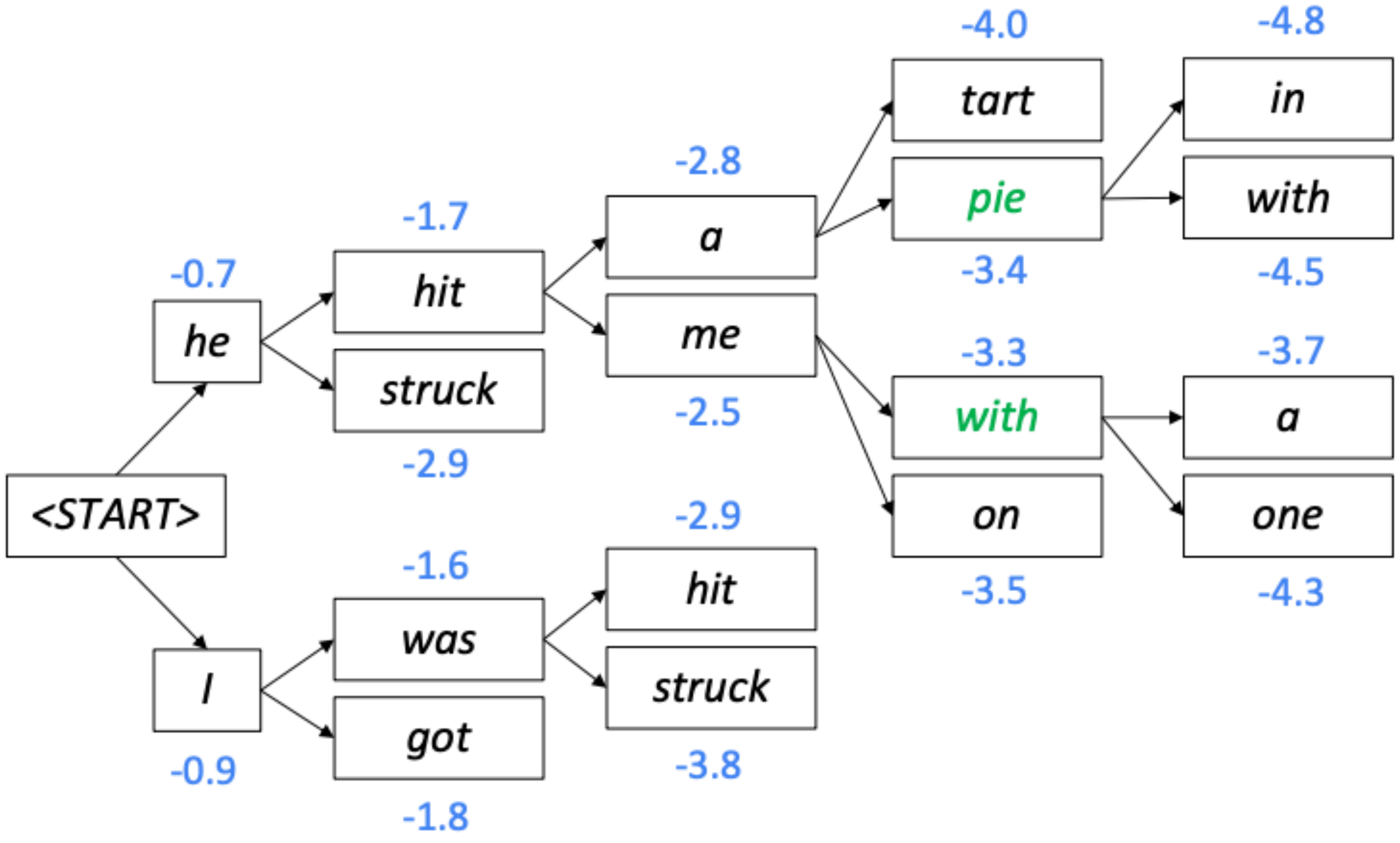

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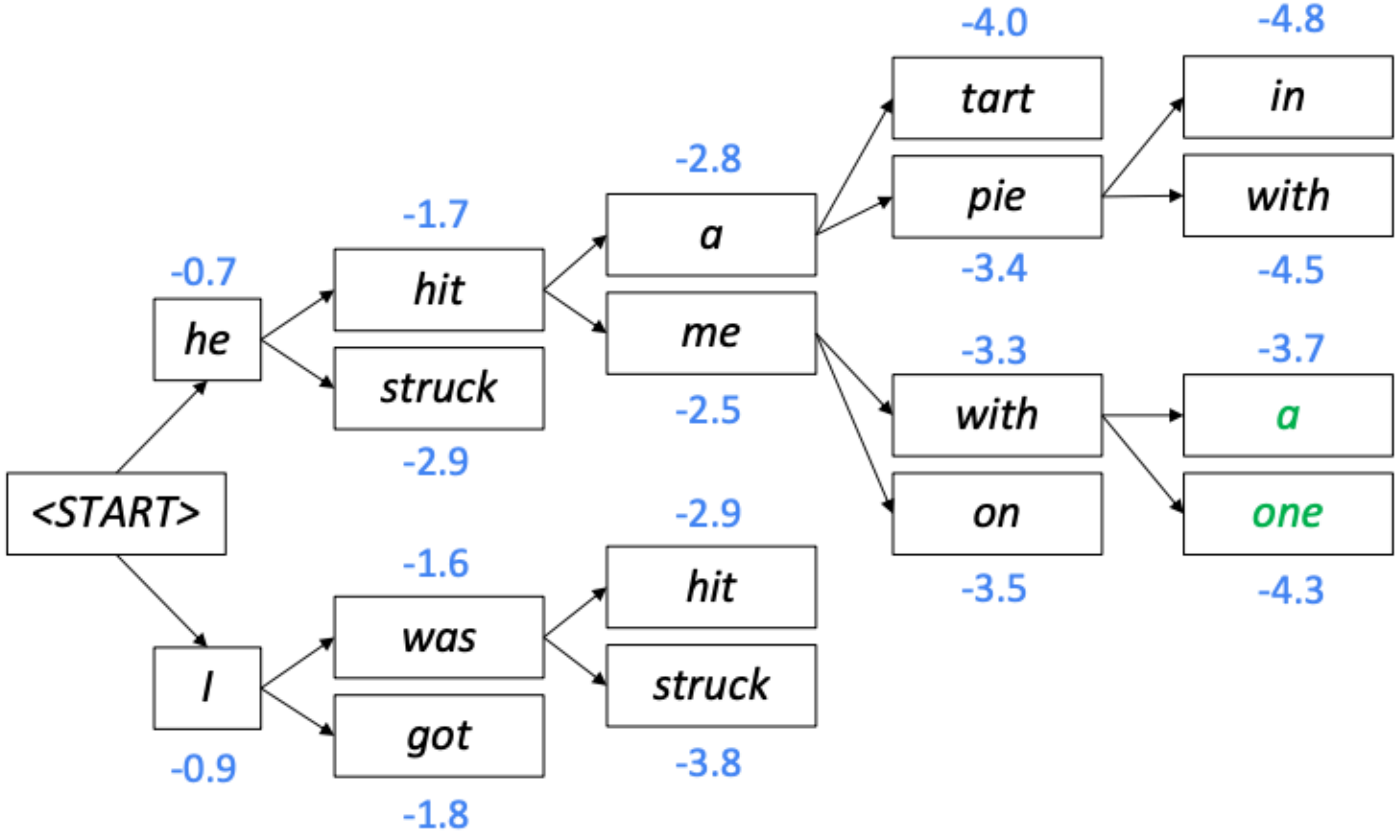

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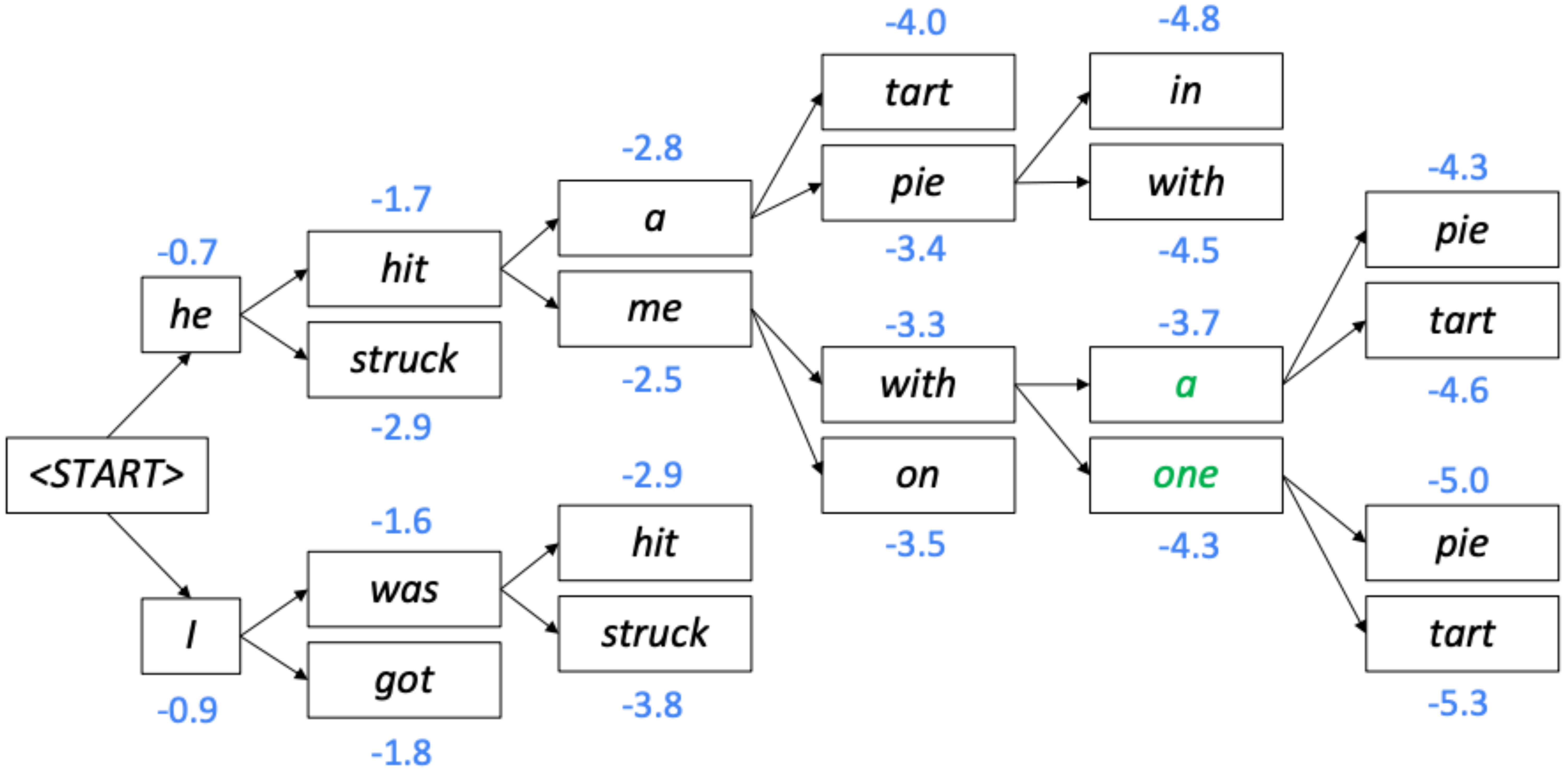

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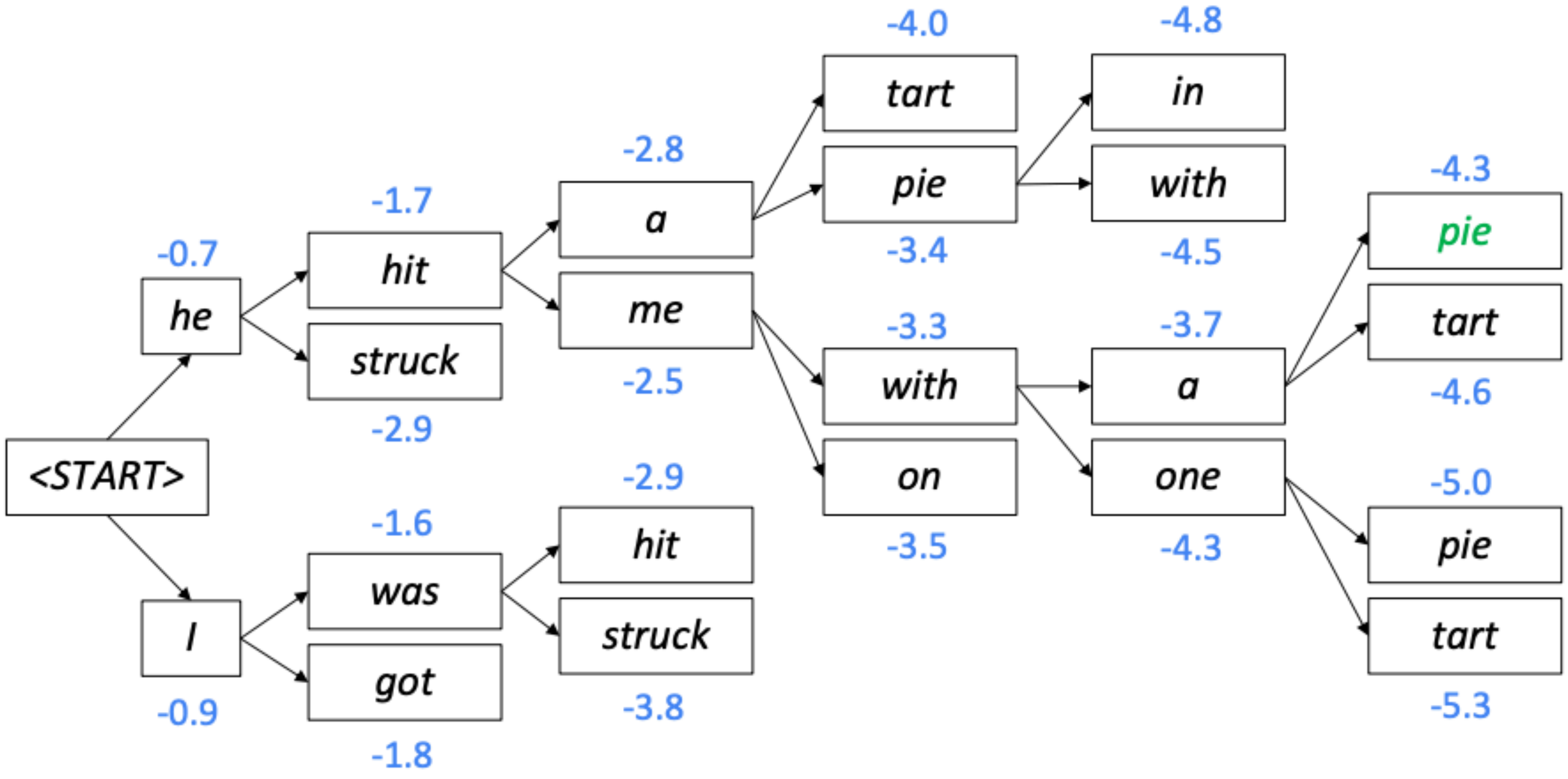

This is the top-scoring hypothesis!

Slide credit: Chris Manning

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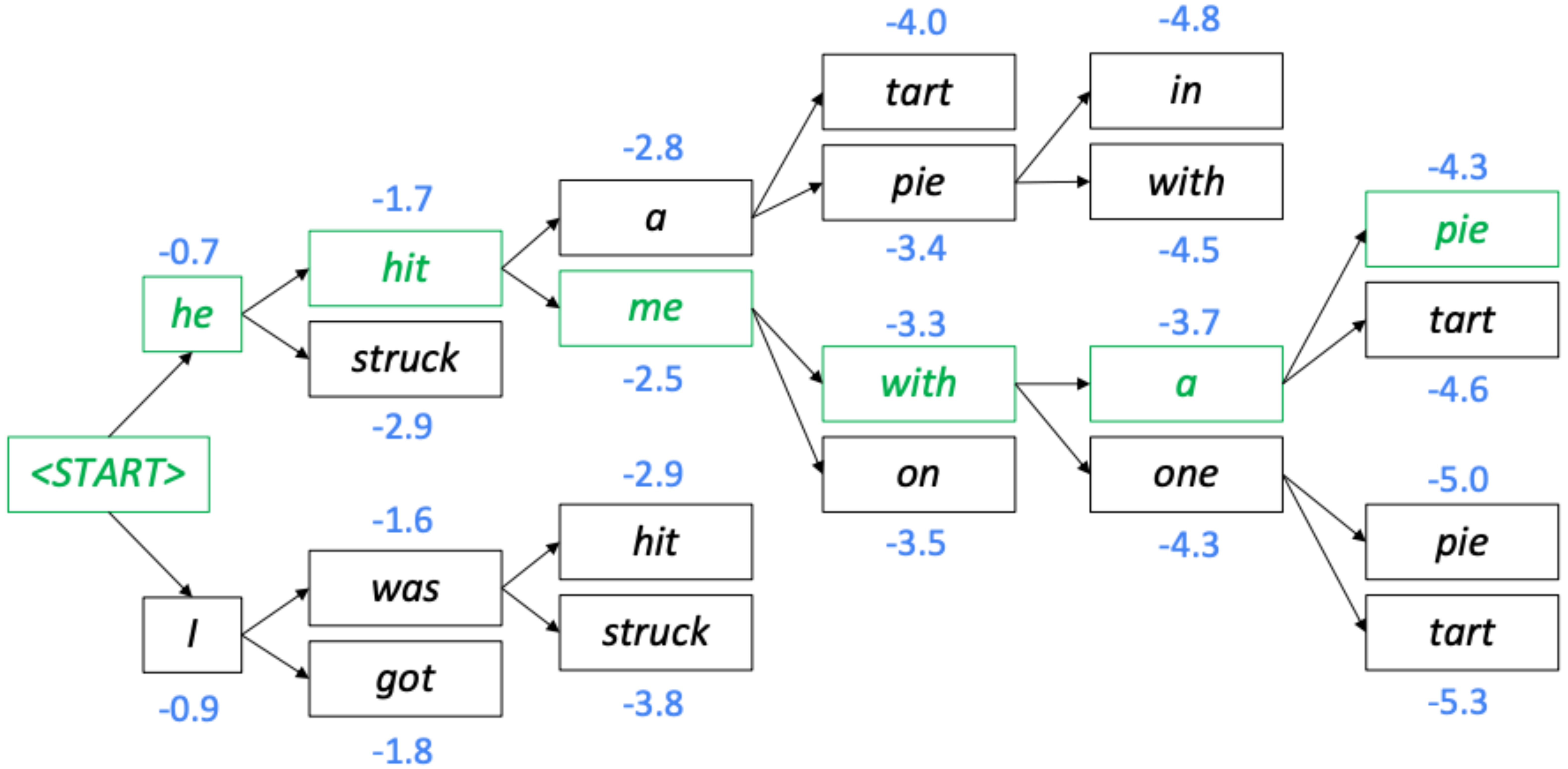


Backtrack to obtain the full hypothesis

Slide credit: Chris Manning

Beam Search Decoding: Stopping Criterion

- Greedy Decoding is done until the model produces an </s> token
    - For e.g. <s> he hit me with a pie </s>
- In Beam Search Decoding, different hypotheses may produce </s> tokens at different time steps
    - When a hypothesis produces </s>, that hypothesis is complete.
    - Place it aside and continue exploring other hypotheses via beam search.
- Usually we continue beam search until:
    - We reach time step 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: Parting Thoughts

- We have our list of completed hypotheses. Now how to select top one?
- 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 with this: longer hypotheses have lower score
- Fix: Normalize by length. Use this to select top one instead

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

But this is expensive!

Maximization Based Decoding

- Either greedy or beam search
- Beam search can be more effective with large beam width, but also more expensive
- Another key issue:

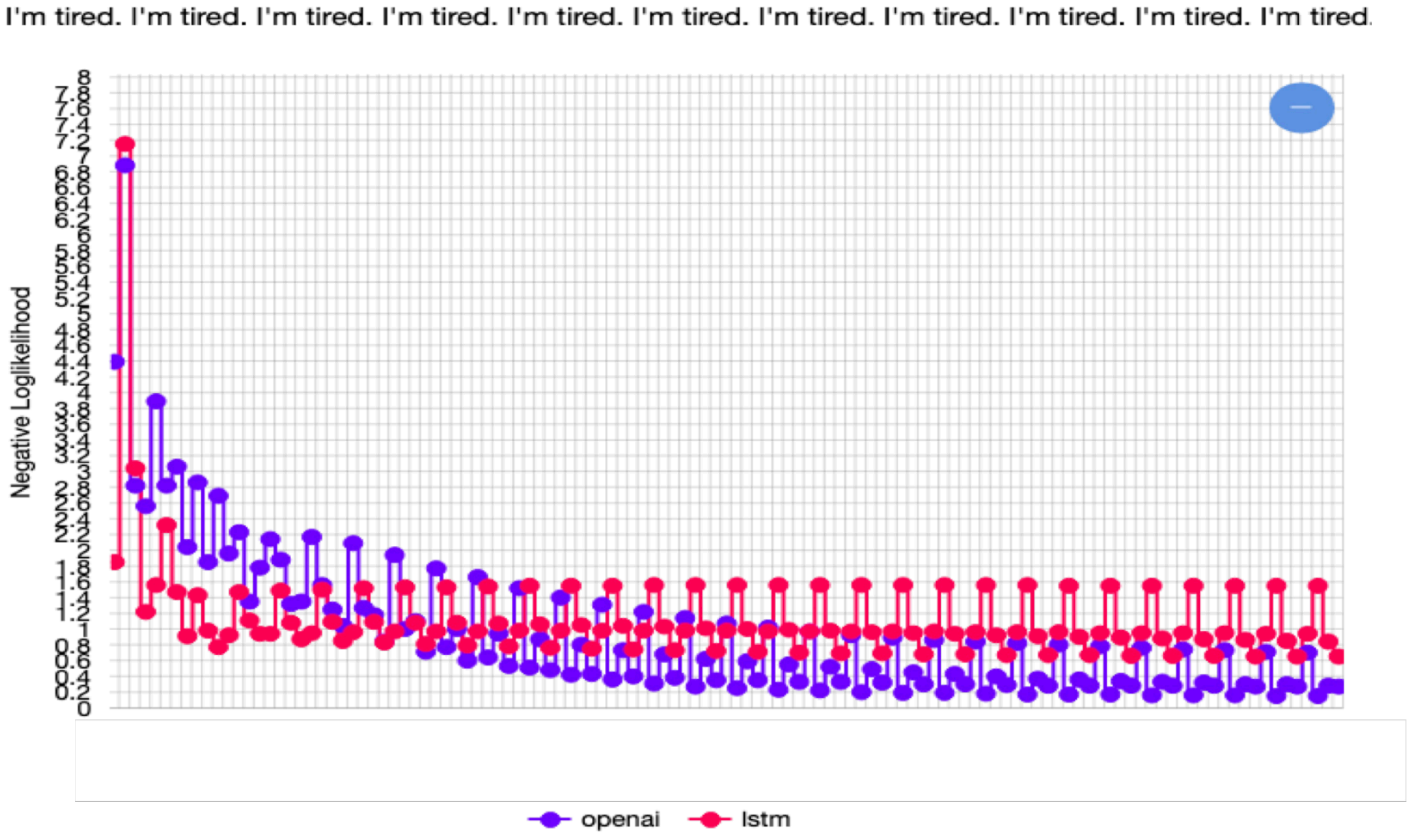
Generation can be bland or repetitive (also called degenerate)

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

Degenerate Outputs

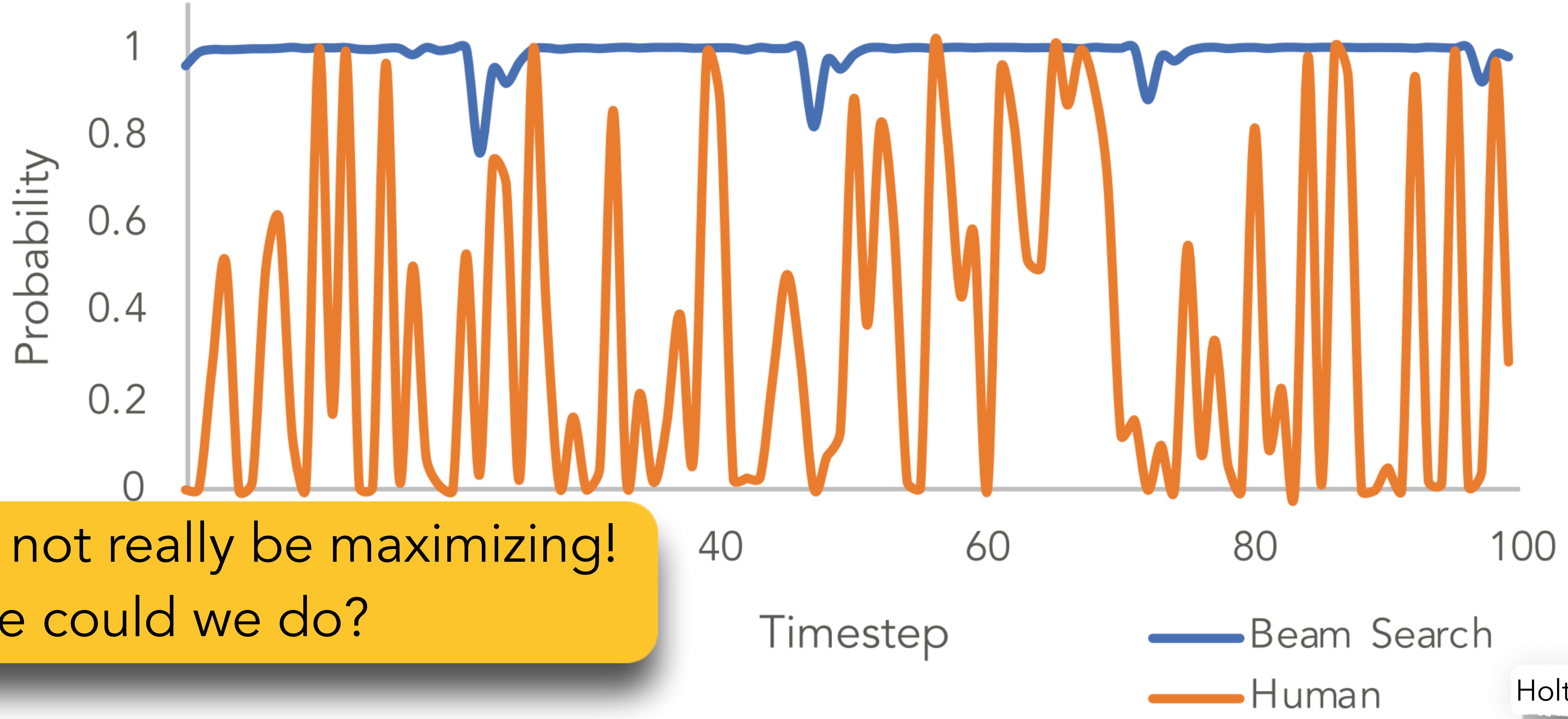


Holtzmann et al., 2020

However, the problem goes away under extreme-scale language models, such as GPT-4 and Llama-3

Why does repetition happen?

- Probability amplification due to maximization based decoding
- Generation fails to match the uncertainty distribution for human written text

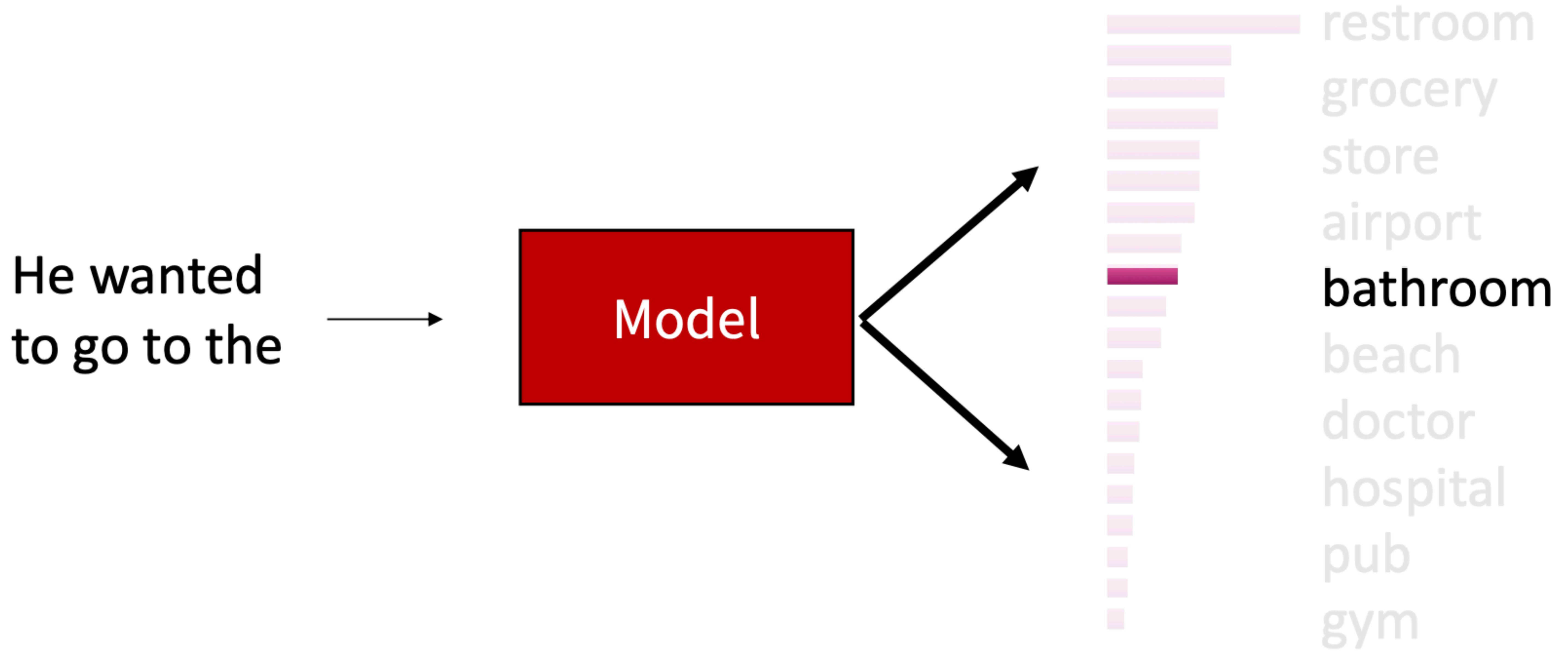


Perhaps we should not really be maximizing!
What else could we do?

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!

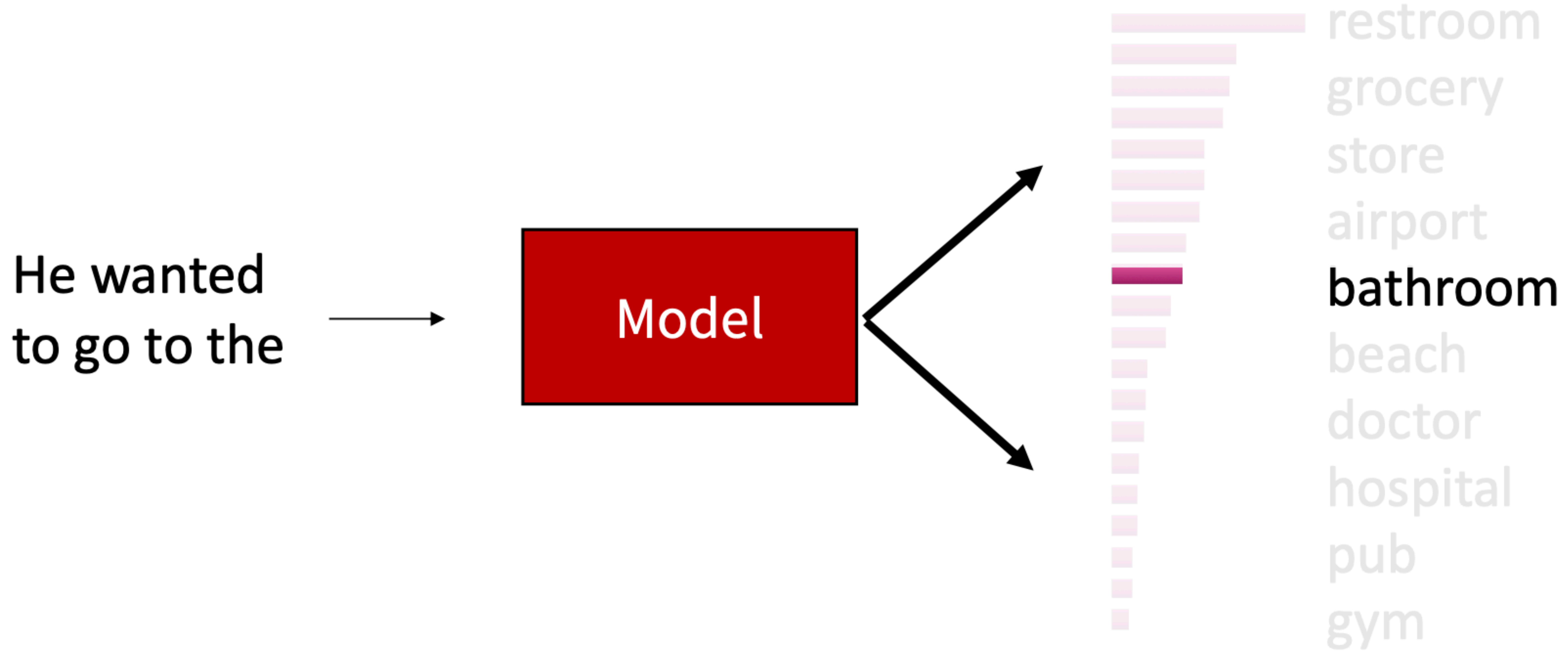


Modern Generation: Sampling

Pure / Ancestral Sampling

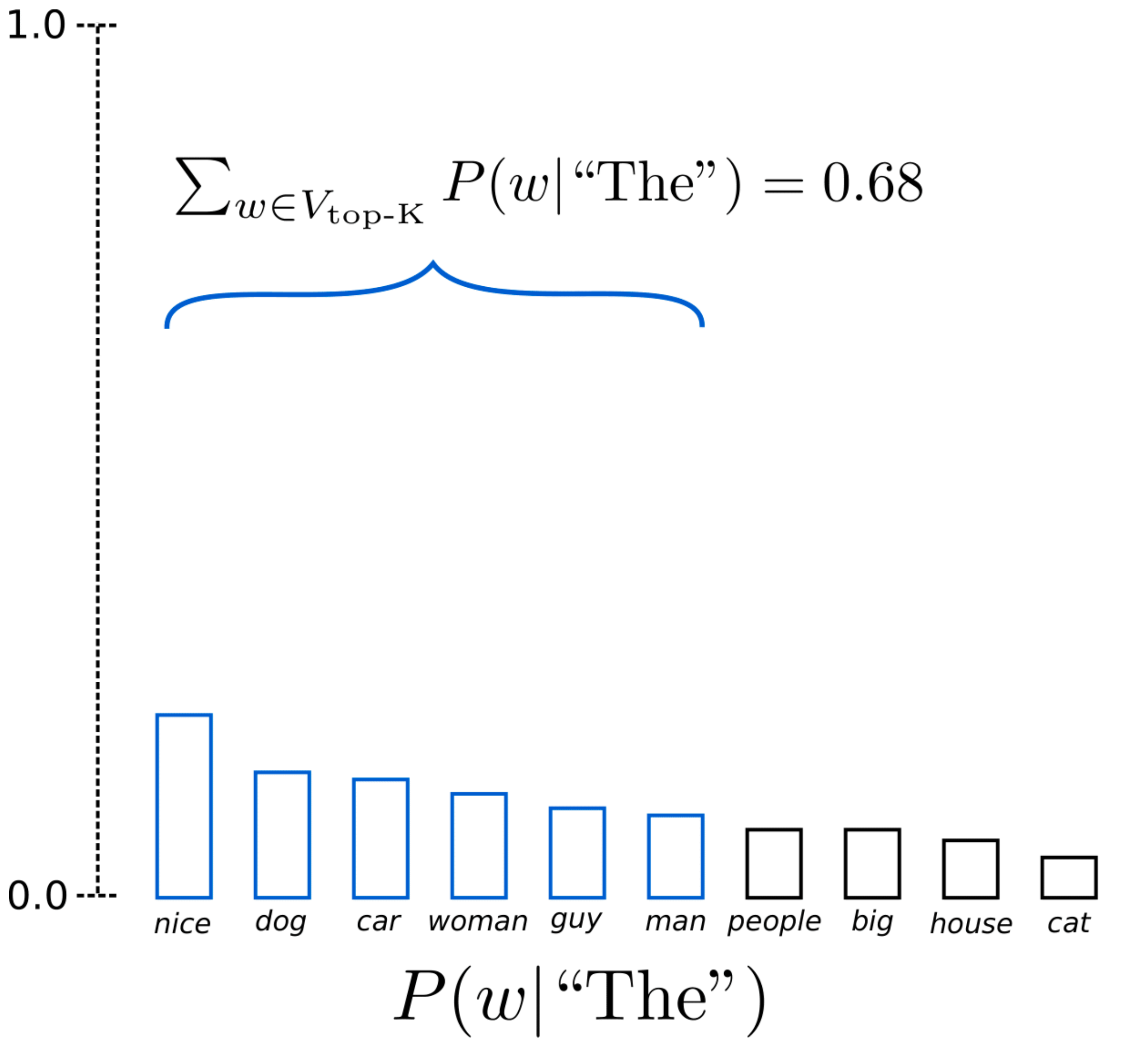
$$y_t \sim P_t(w) = \frac{\exp(S_w)}{\sum_{v \in V} \exp(S_v)}$$

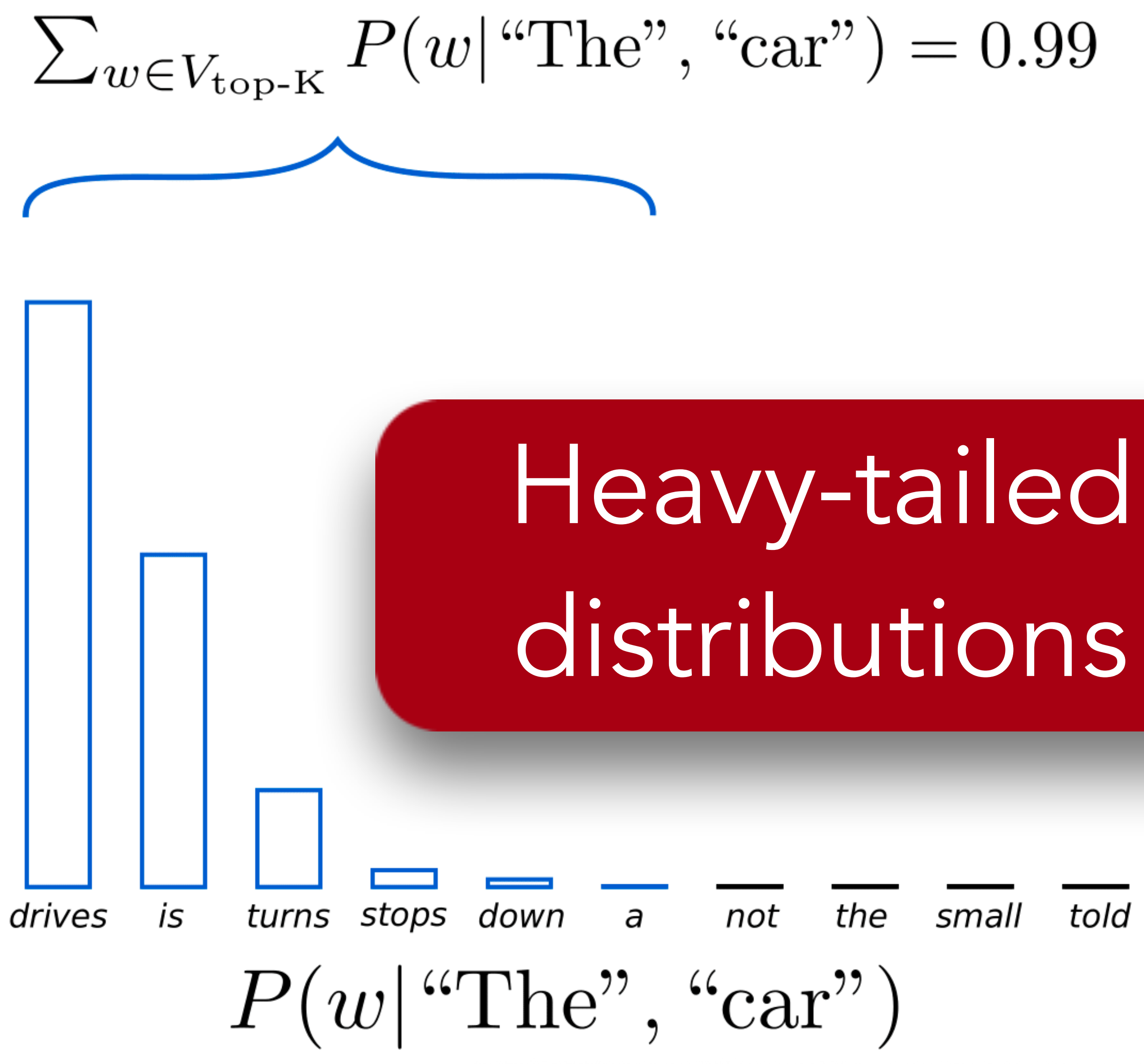
- Sample directly from P_t
- Still has access to the entire vocabulary
- But if the model distributions are of low quality, generations will be of low quality as well
- Often results in ill-formed generations
  - No guarantee of fluency



Top-K Sampling

- Problem: Ancestral sampling makes every token in the vocabulary an option
  - Even if most of the probability mass in the distribution is over a limited set of options, the tail of the distribution could be very long and in aggregate have considerable mass
  - Many tokens are probably really wrong in the current context. Yet, we give them individually a tiny chance to be selected.
  - But because there are many of them, we still give them as a group a high chance to be selected.
- Solution: Top-K sampling
  - Only sample from the top K tokens in the probability distribution





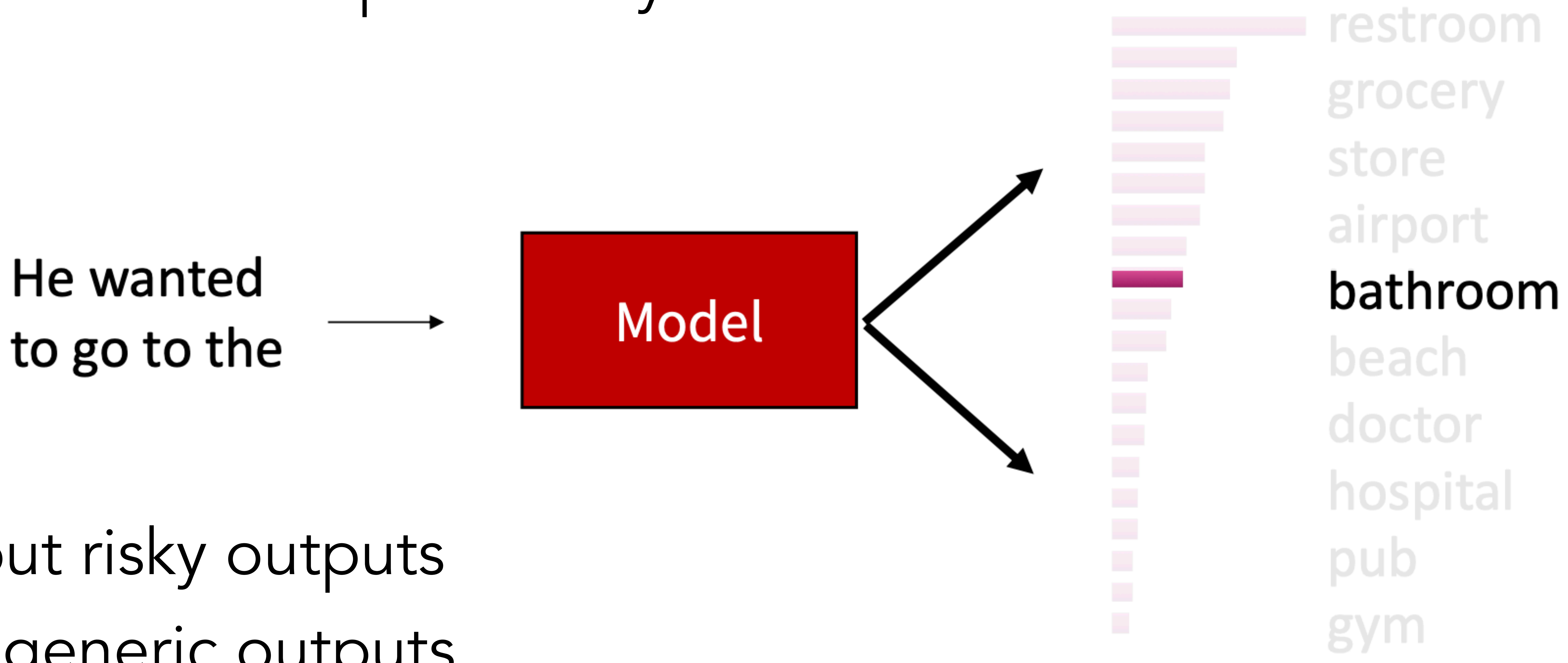
Heavy-tailed distributions

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

Image Source: Huggingface

Top-K Sampling: Value of K

- Solution: Top-K sampling
  - Only sample from the top K tokens in the probability distribution
  - Common values are K = 50



- Increase K yields more diverse, but risky outputs
- Decrease K yields more safe but generic outputs

Top-K Sampling: Issues

Top-K sampling can cut off too quickly

Top-K sampling can also cut off too slowly!

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

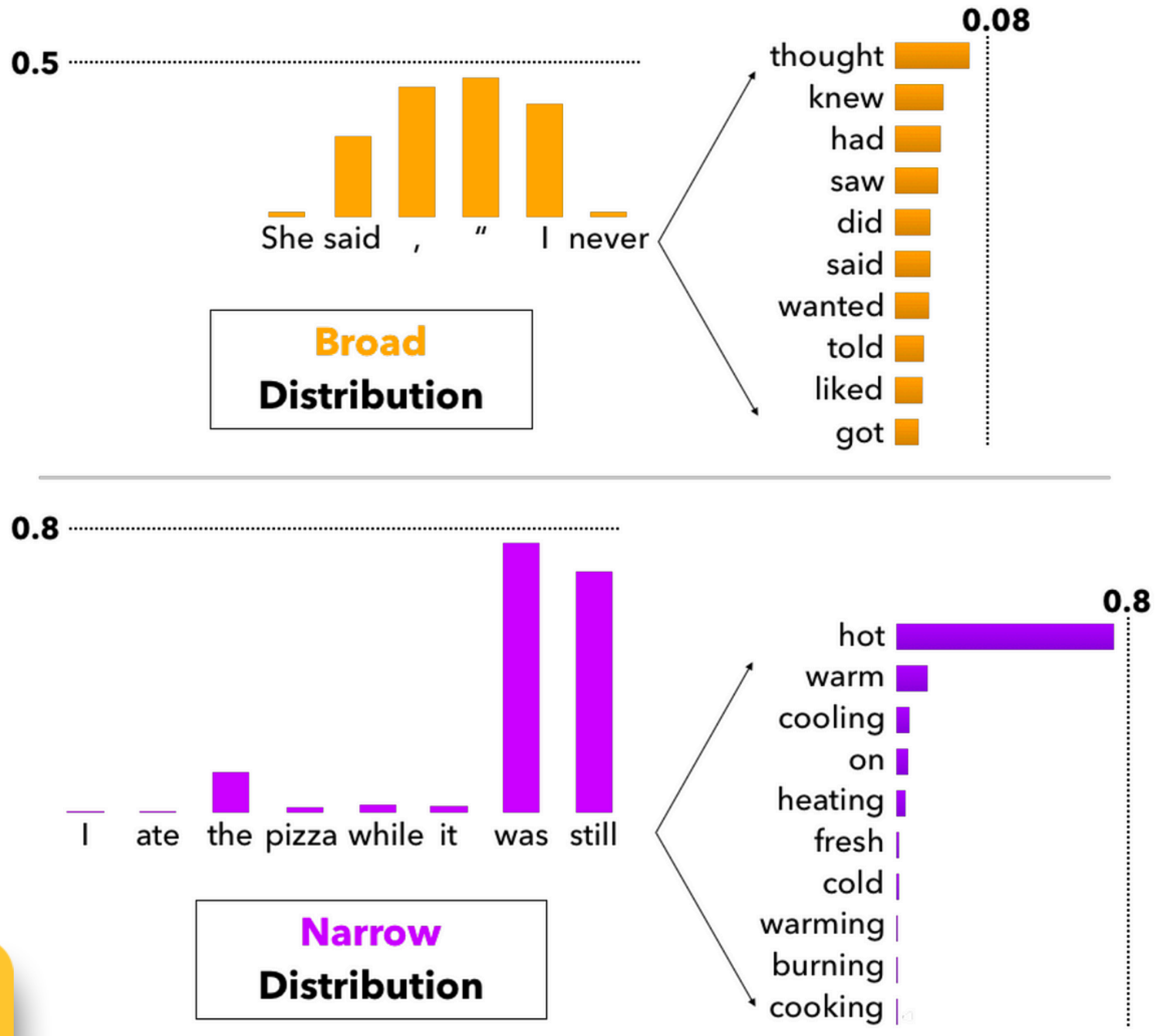


Image Source: Holtzmann et al., 2019

Modern Decoding: Nucleus Sampling

- Problem: The probability distributions we sample from are dynamic
  - When the distribution P_t is flatter, a limited K removes many viable options
  - When the distribution P_t is peakier, a high K allows for too many options to have a chance of being selected

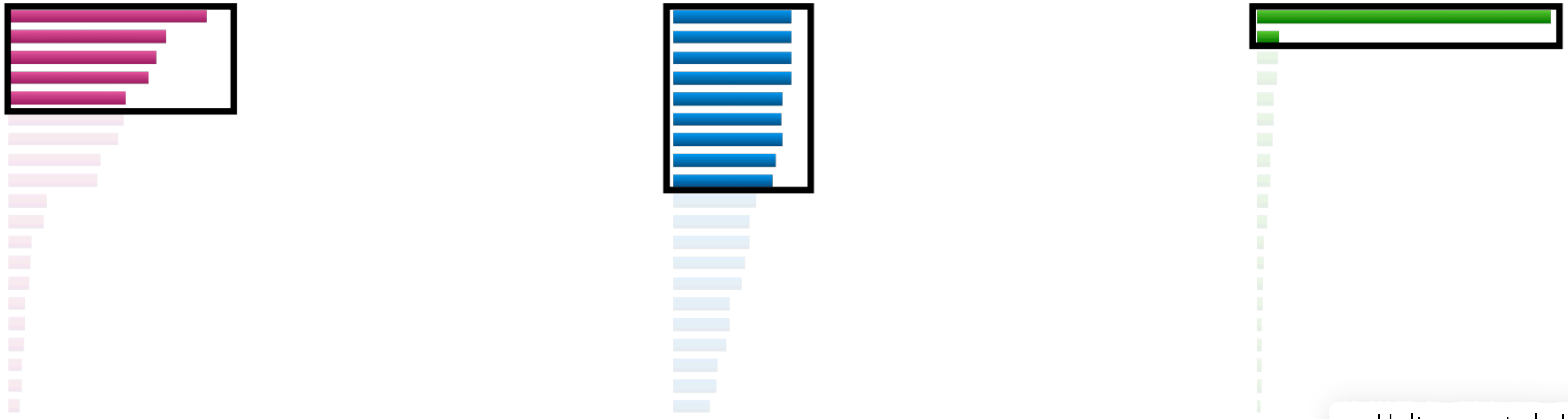
- Solution: Nucleus Sampling / Top-P sampling
  - Sample from all tokens in the top P cumulative probability mass (i.e., where mass is concentrated)
  - Varies K depending on the uniformity of P_t

Holtzman et al., ICLR 2020

Nucleus (Top-P) Sampling

- Solution: Top-P sampling
  - Sample from all tokens in the top P cumulative probability mass (i.e., where mass is concentrated)
  - Varies K depending on the uniformity of P_t

$P_t^1(y_t = w \mid \{y\}_{<t})$ $\quad$ $P_t^2(y_t = w \mid \{y\}_{<t})$ $\quad$ $P_t^3(y_t = w \mid \{y\}_{<t})$



Holtzman et al., ICLR 2020

Temperature Scaling

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

- 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

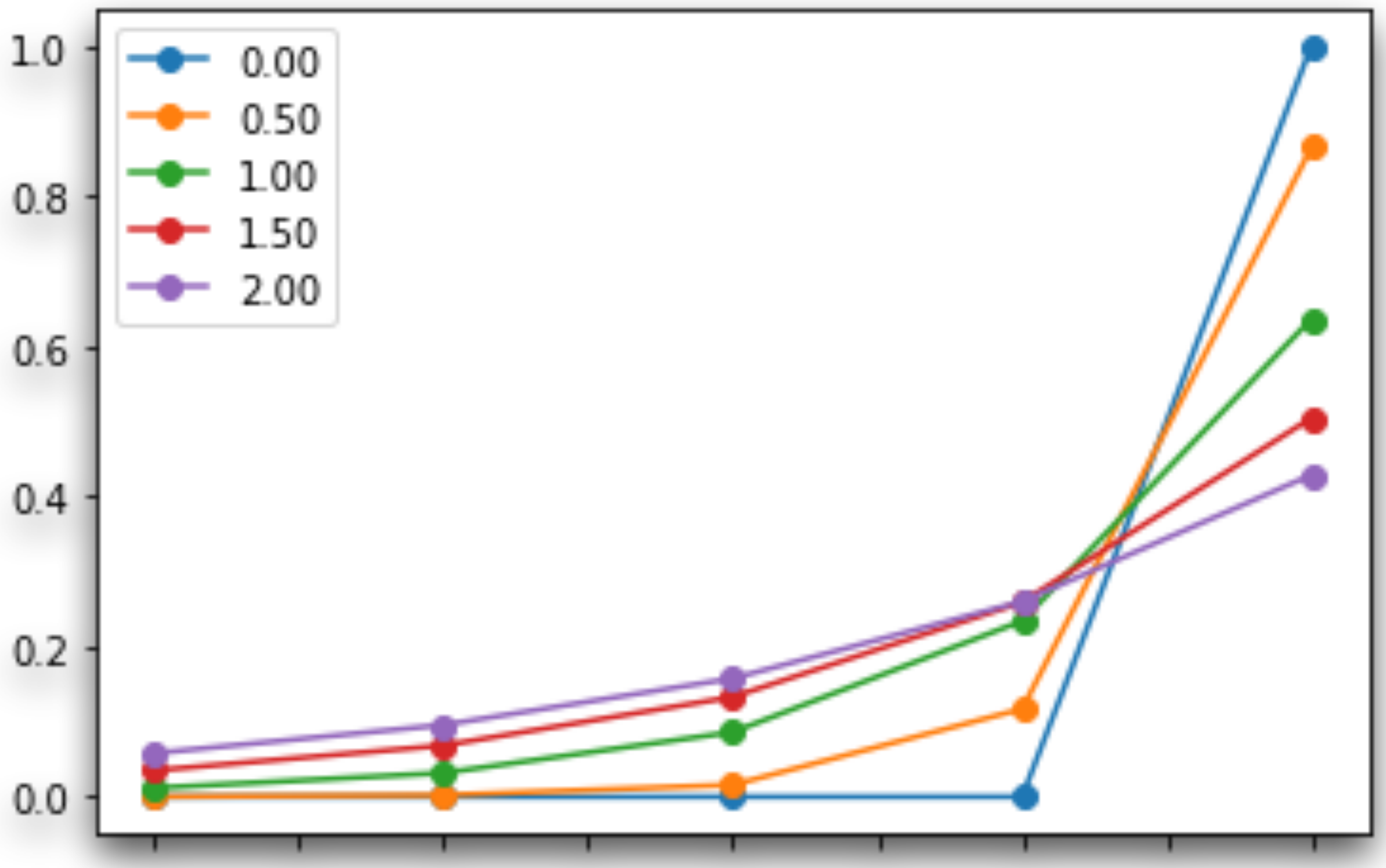
- Let's say initial scores, S_w: (remember these are real-valued)
  - 0.1912, 0.7492, 0.5966, 0.5528, 0.8324, **0.9409**
- After softmax, p:
  - 0.1031, 0.1802, 0.1547, 0.1480, 0.1958, **0.2182**
- S_w/τ when $\tau = 0.01$:
  - 19.12, 74.92, 59.66, 55.28, 83.24, **94.09**
- After softmax, p
  - 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, **1.0000**

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

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

Sampling after Temperature Scaling

- 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)



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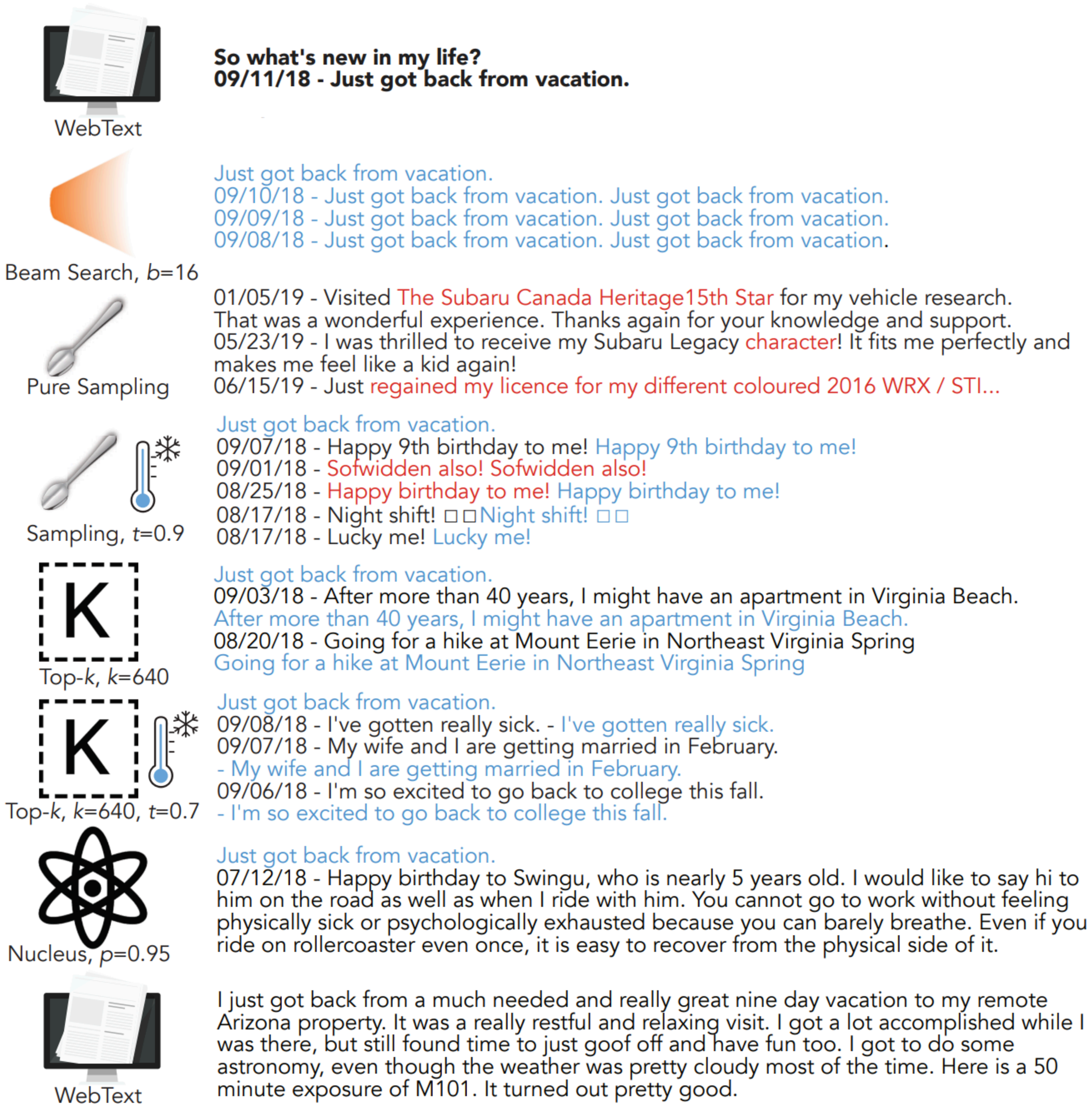
Comparing different decoding algorithms

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



Holtzman et al., ICLR 2020

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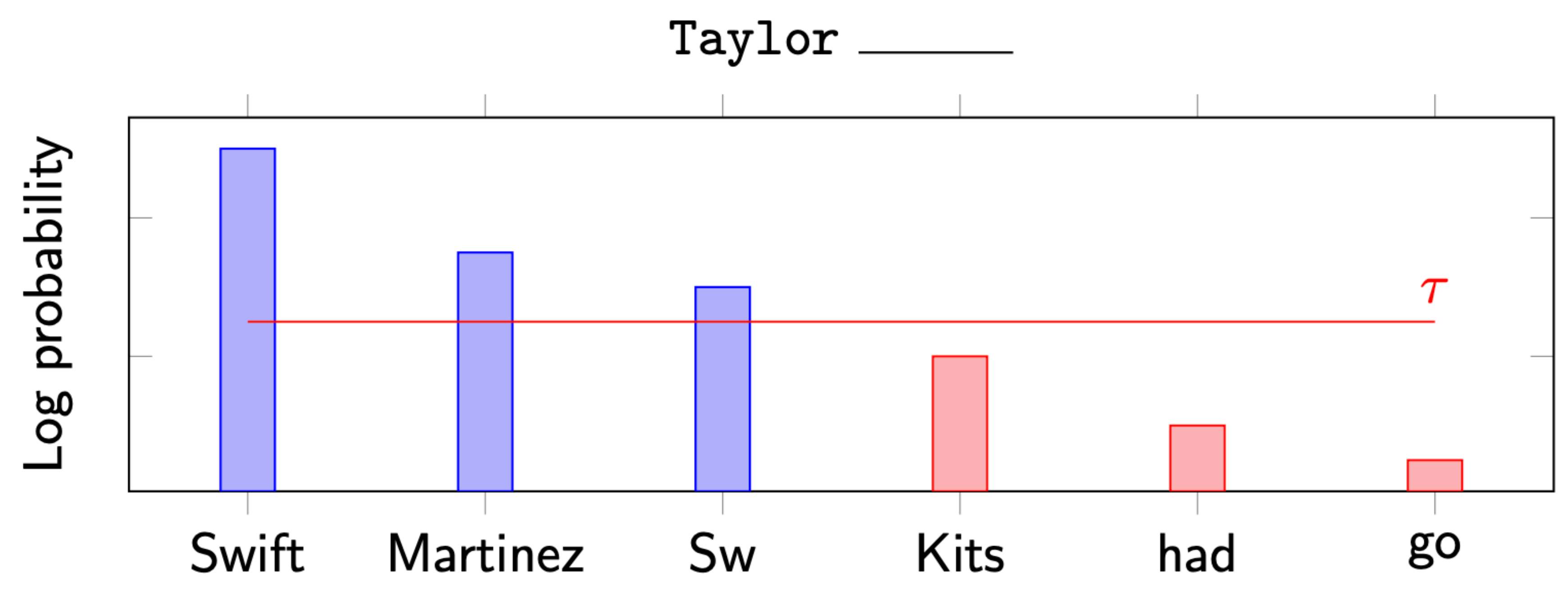
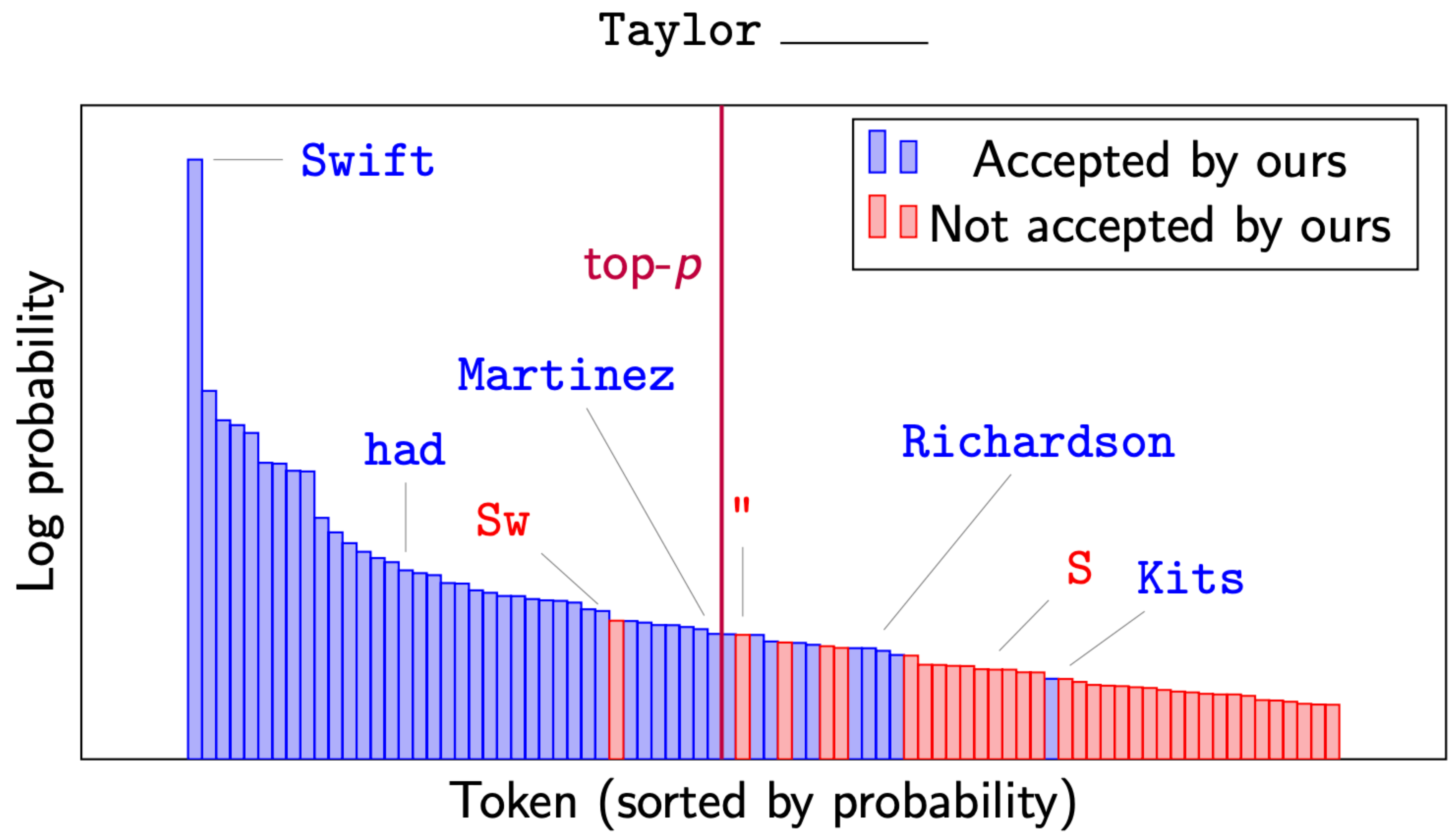
Truncation-based Sampling

- Nucleus Sampling is an example of truncation sampling
  - Certain properties of language models (mismatch between vocabulary size and hidden dimensionality) make threshold sampling a great choice!
  - [Finlayson et al., 2024]
- Locally-Typical Sampling: Similar to Nucleus Sampling, but based on conditional entropy (entropy of a distribution determines its randomness) [Meister et al., 2022]
- η-Sampling: Entropy dependent threshold that also takes into account absolute probabilities [Hewitt et al., 2022]
- BAT Sampling: More flexible than truncation [Finlayson et al., 2024]

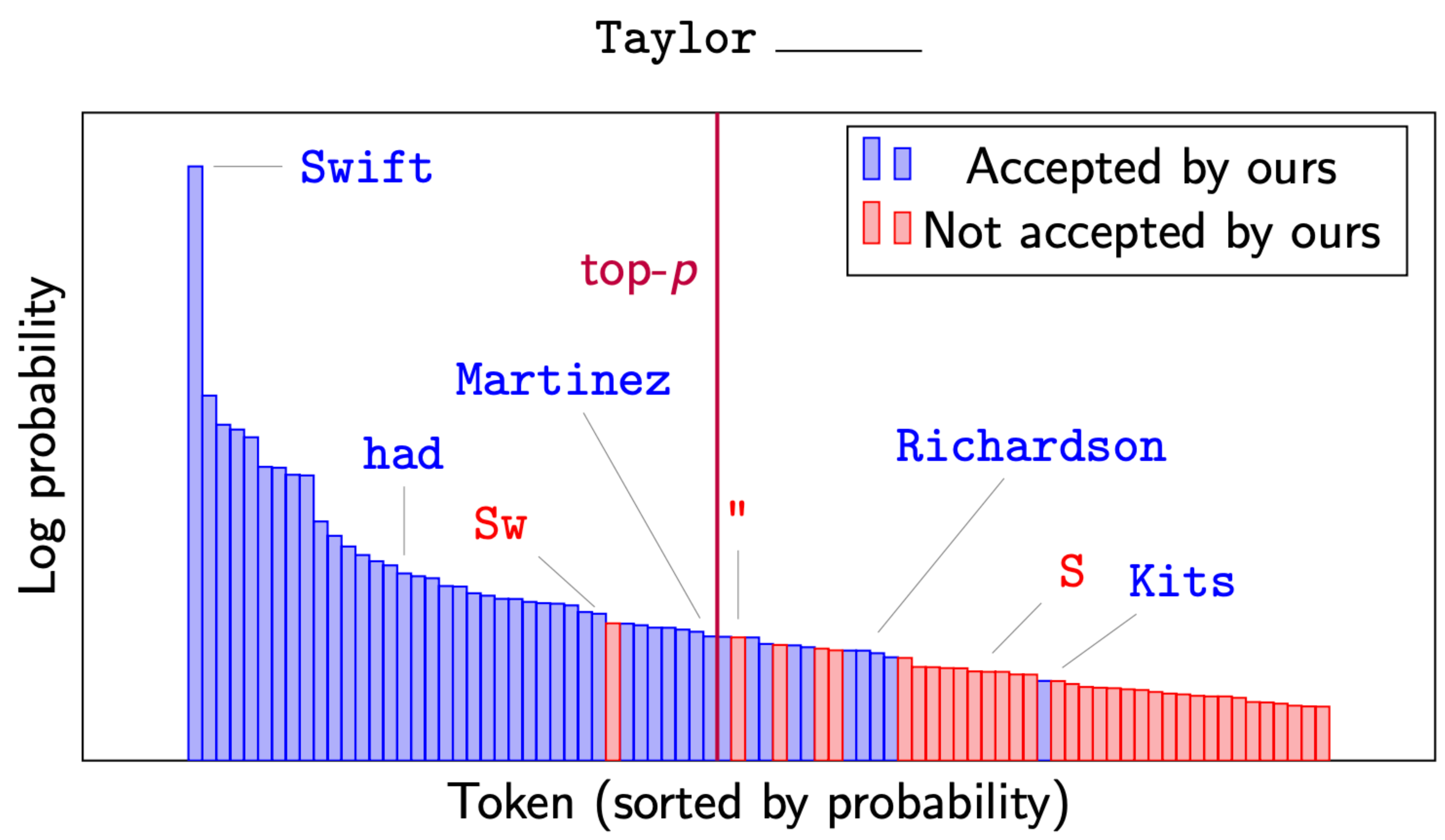


Choose a threshold τ and only sample tokens with probability greater than τ.



Modern Decoding: Takeaways

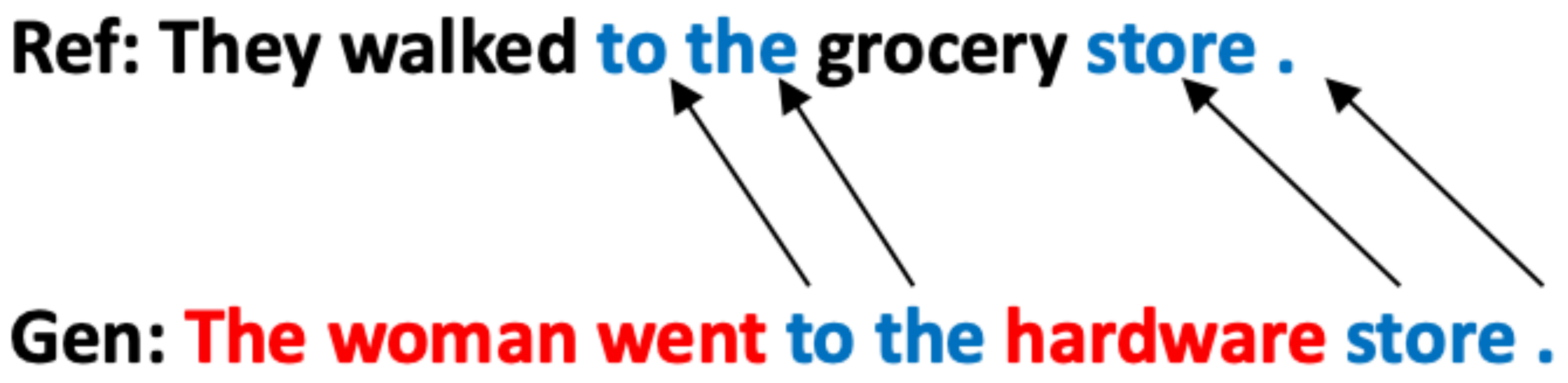
- Natural language distributions are very peaky but the softmax function assigns probabilities to all tokens in the vocabulary
- Hence we need approaches to truncate / modify the softmax distribution
  - Ancestral, Top-k, Top-p (Nucleus), Temperature
- Some properties of the softmax function make truncation based decoding necessary



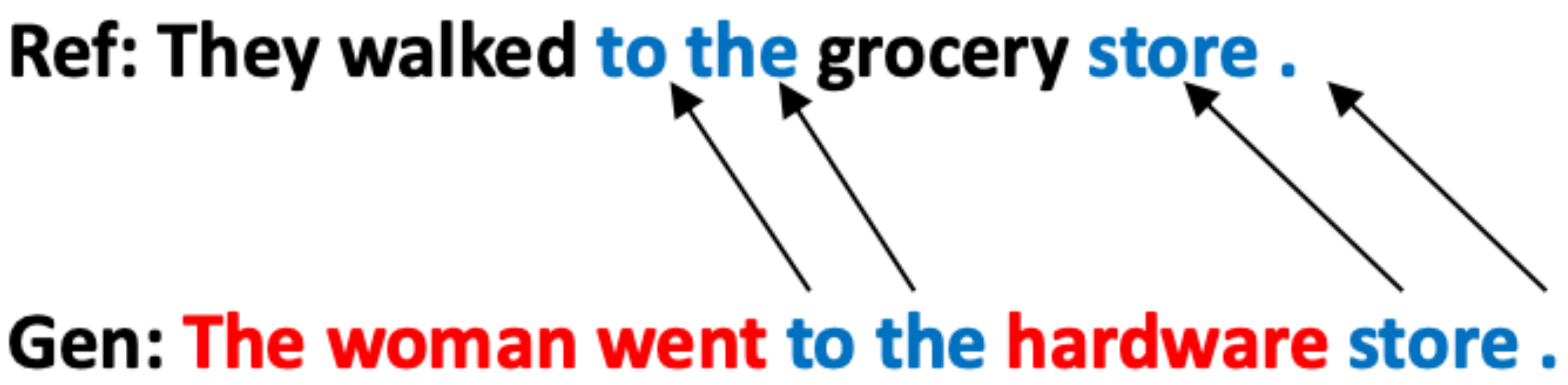
Evaluating Generations

Evaluation Strategies

- With Reference
    - Lexical Matching
    - Semantic Matching
- Without Reference
    - Perplexity
    - Model-Based Metrics
    - Advanced: Distributional Matching
    - Simplest, Most Reliable Strategy to-date: Human Evaluation
    - Even simpler and least reliable: Auto Evaluation



Reference-Based Metrics



- Only possible for close-ended generation tasks
- Compute a score that indicates the lexical similarity between generated and gold-standard (human-written) text
- Fast and efficient and widely used
- n-gram overlap metrics (e.g., BLEU, ROUGE, etc.)