Sampling and Generation

Ling 282/482: Deep Learning for Computational Linguistics

C.M. Downey

Fall 2025

Generation / Decoding

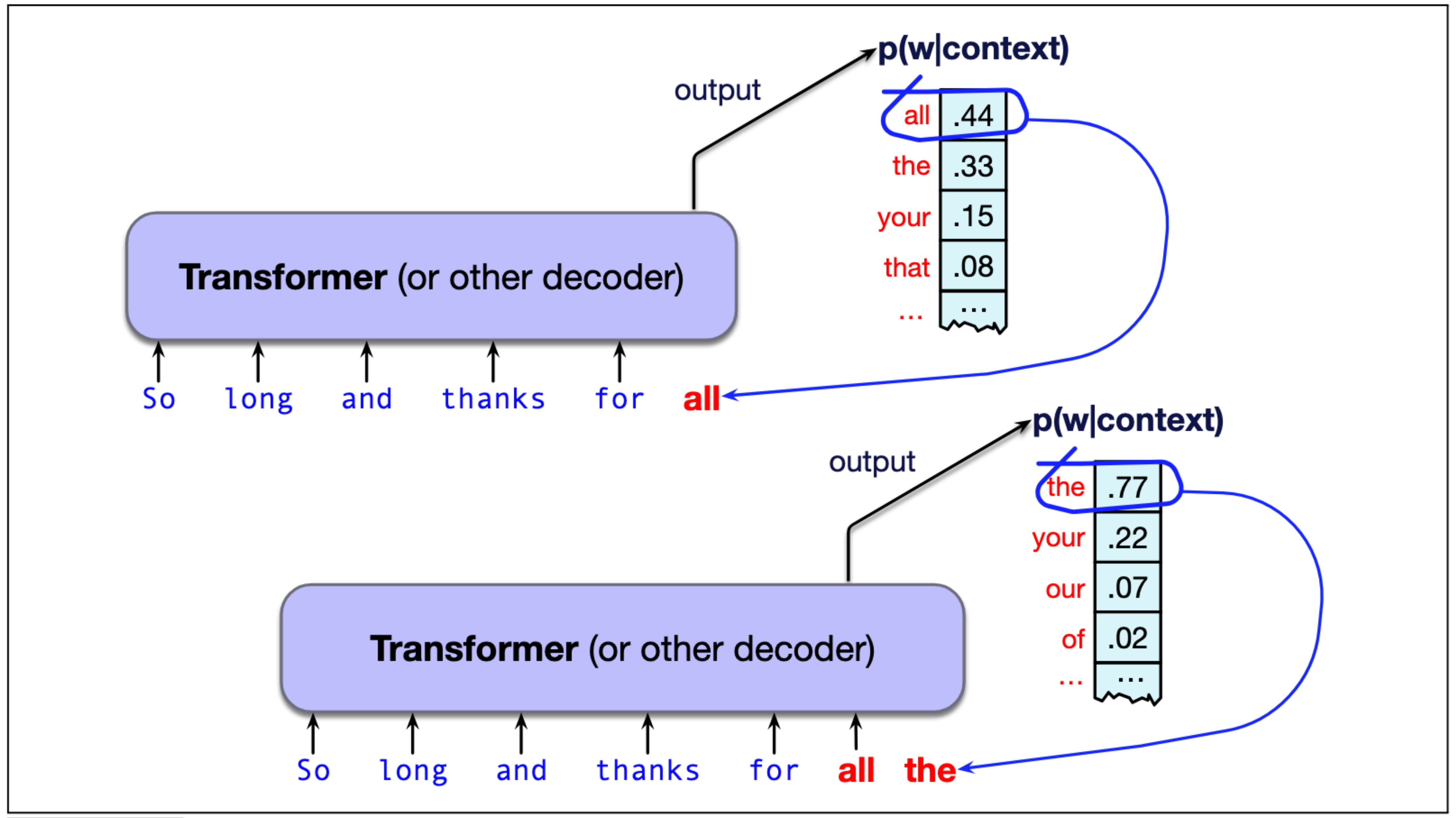
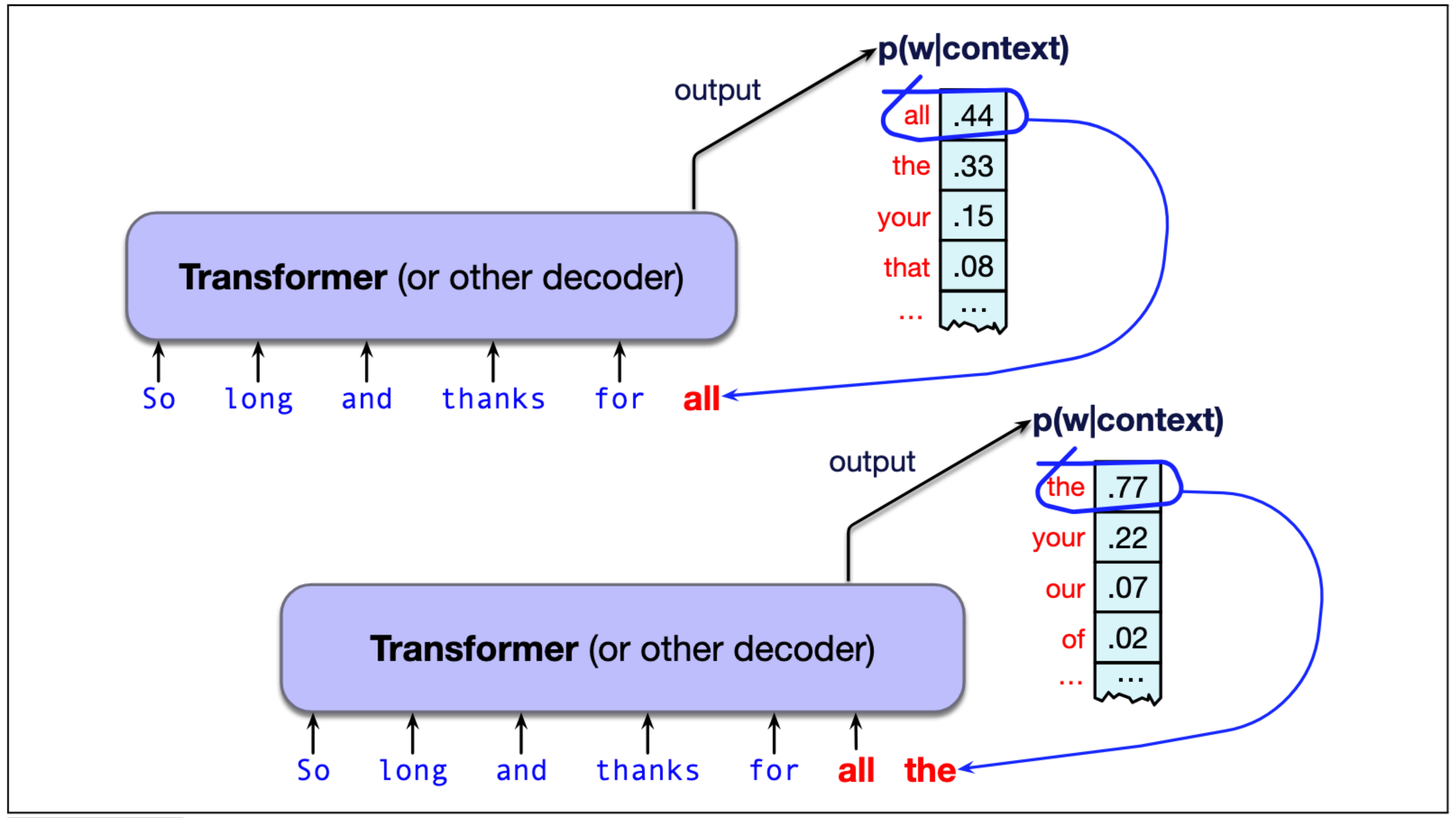


Figure 7.2 Turning a predictive model that gives a probability distribution over next words into a generative model by repeatedly sampling from the distribution. The result is a left-to-right (also called autoregressive) language models. As each token is generated, it gets added onto the context as a prefix for generating the next token.

Generation / Decoding

- A Language Model outputs a **probability distribution** over possible words
  - The LM encodes the probability for **all possible sequences**
  - Given this, how do we decide what the **predicted sequence** should be? (This process is often called **"decoding"**)



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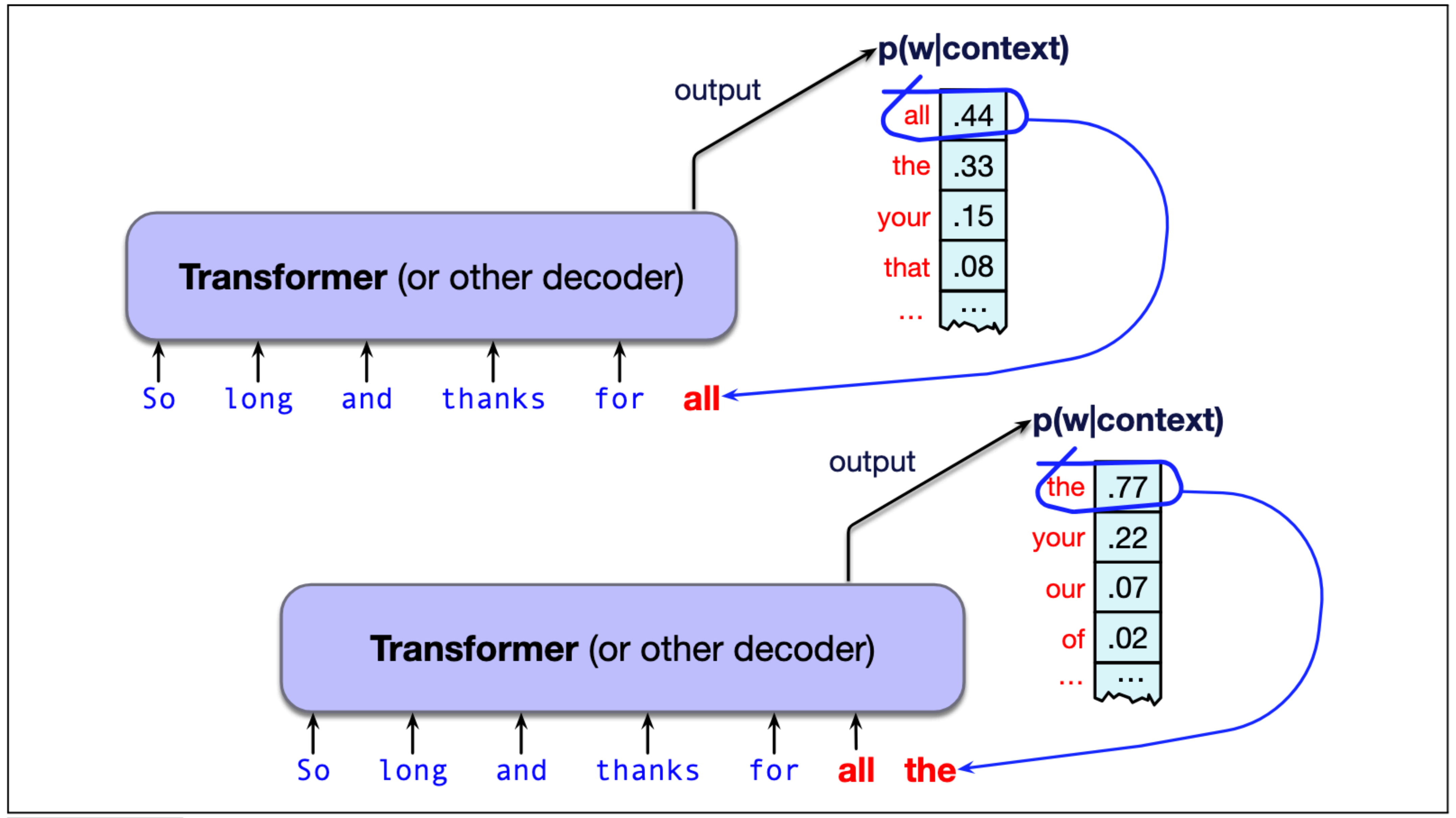
  - Given this, how do we decide what the **predicted sequence** should be? (This process is often called **"decoding"**)
- How do we generate **new sequences?**
  - During training, we always know what the next word should be
  - For many real-world tasks (e.g. Chatbots), we want the model to **generate novel text**



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Greedy Decoding

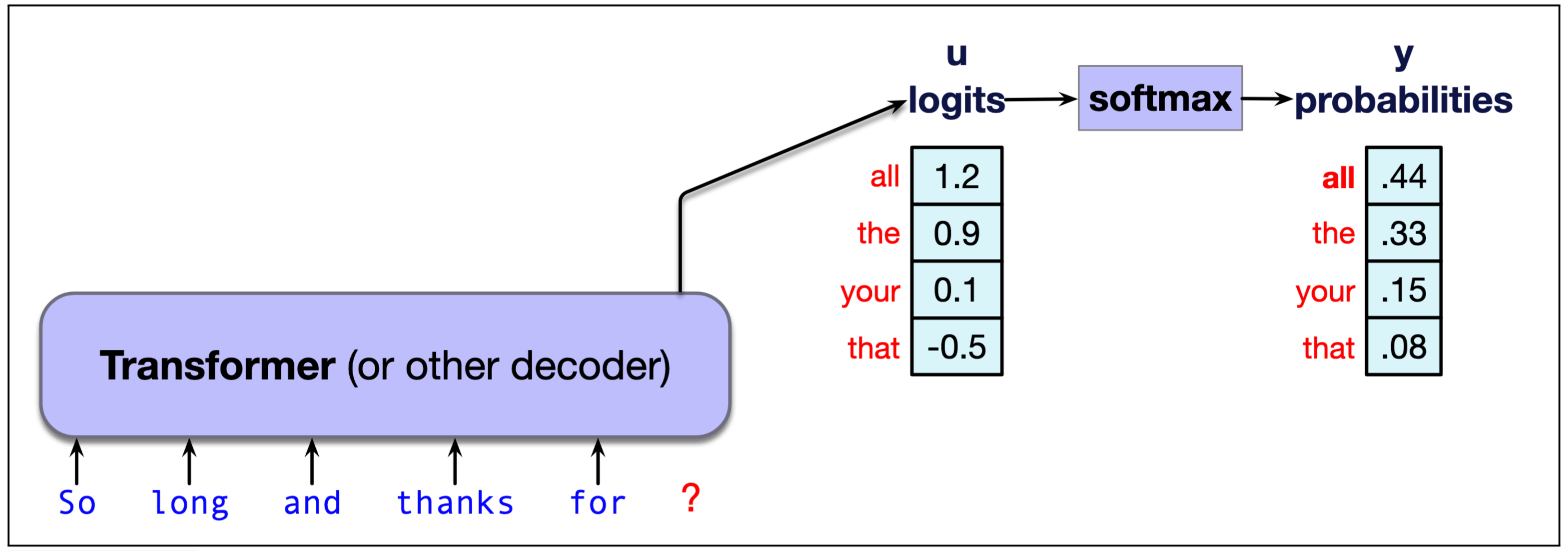
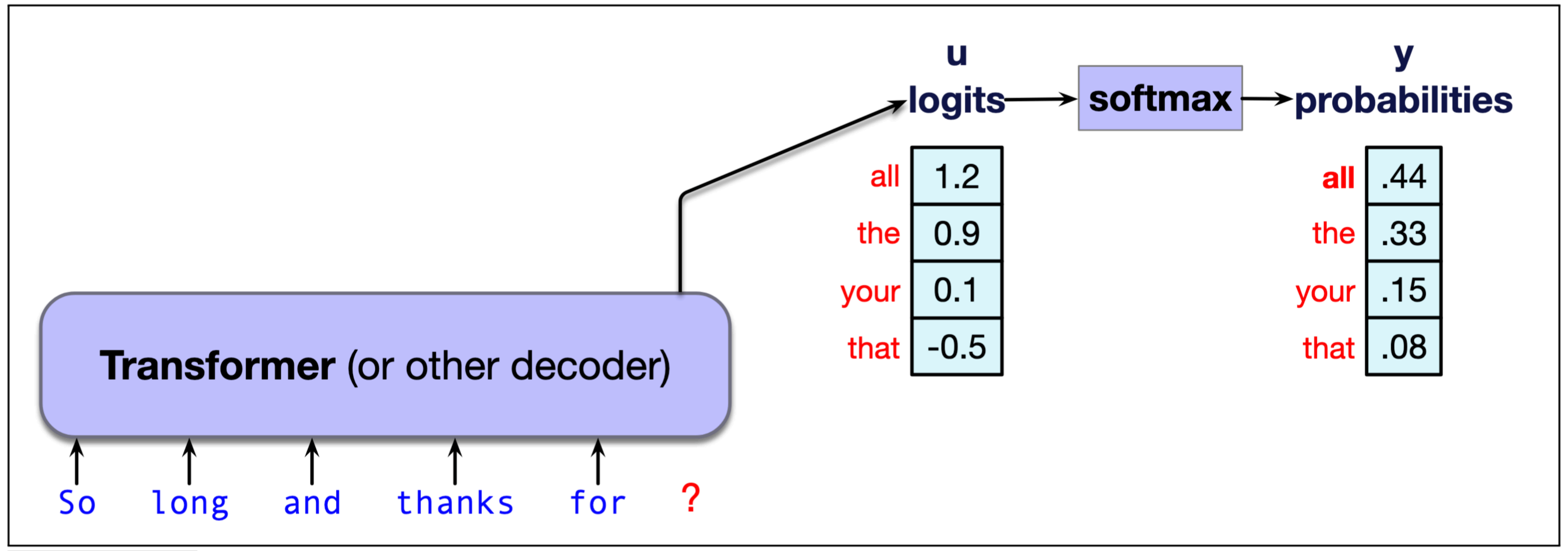


Figure 7.7 Taking the logit vector **u** and using the softmax to create a probability vector **y**.

$$\hat{w}_t = \text{argmax}_{w \in V} P(w \mid w_{<t})$$

Greedy Decoding

- **"Greedy" decoding** is the simplest strategy
  - At each time step, choose the **highest-probability word**
  - "Greedy" because it does **NOT** guarantee the highest-probability sequence



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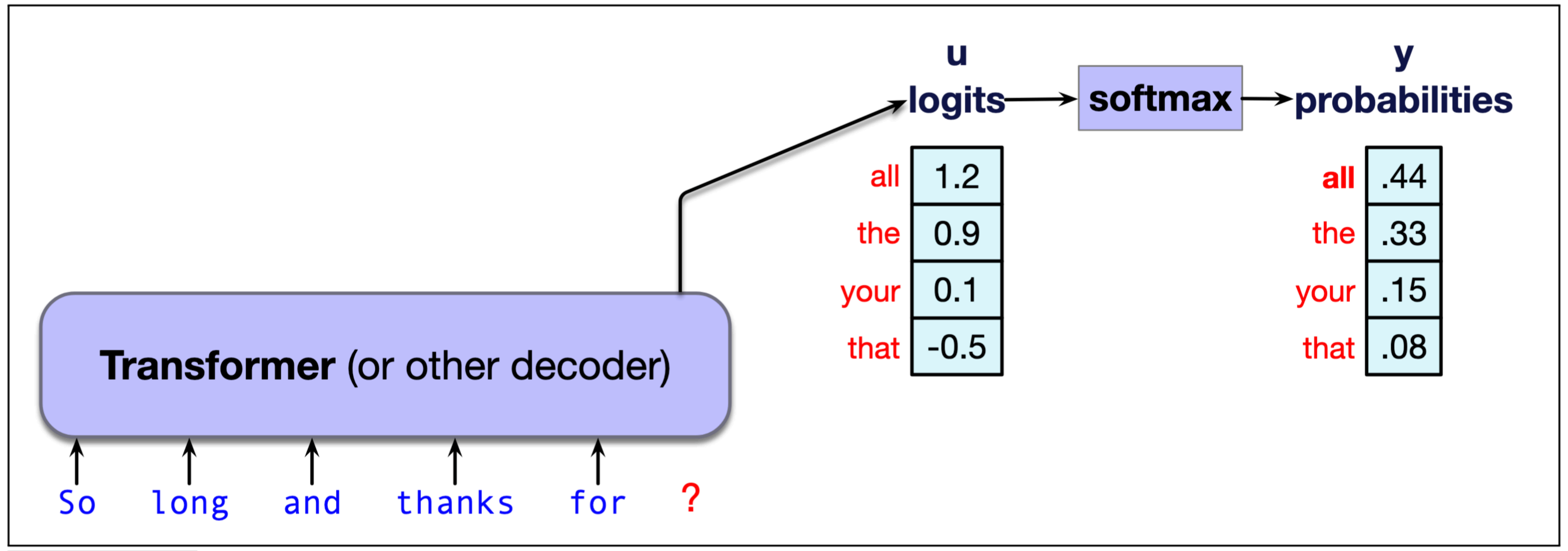

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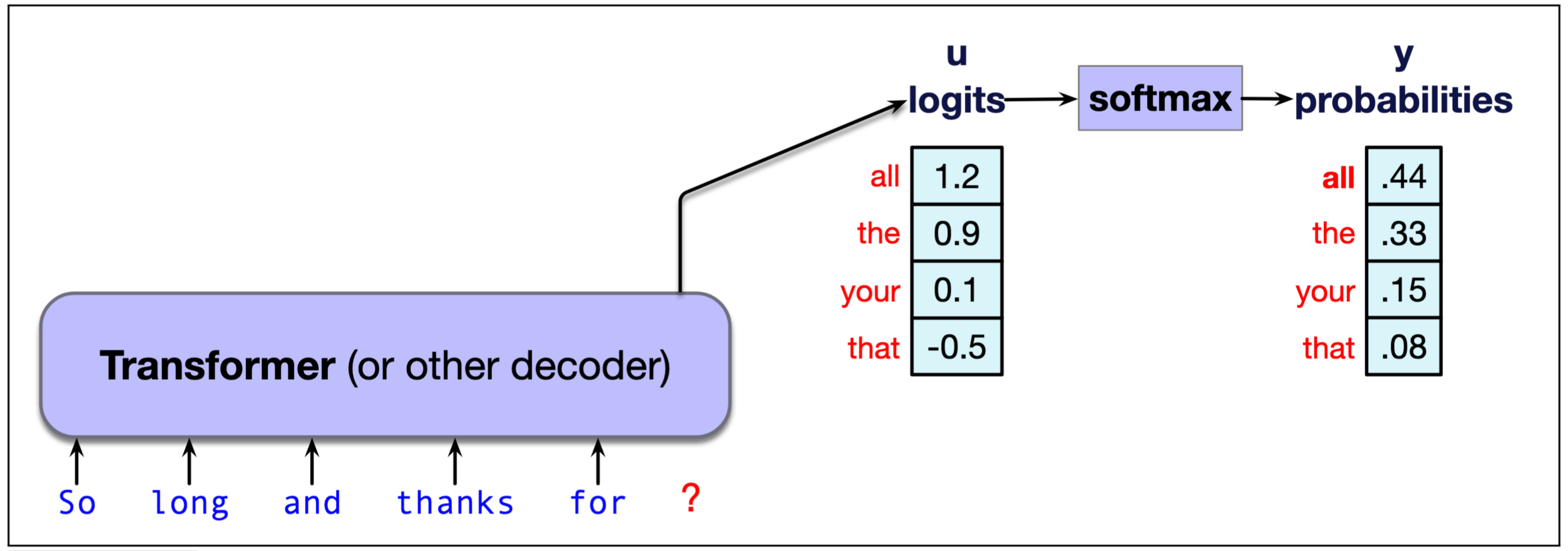
  - "Greedy" because it does **NOT** guarantee the highest-probability sequence
- **No randomness** involved (same context gives the same completion)
- Tends to generate **boring or repetitive** text
  - Or text that's been **exactly copied** from the training data



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Random Sampling

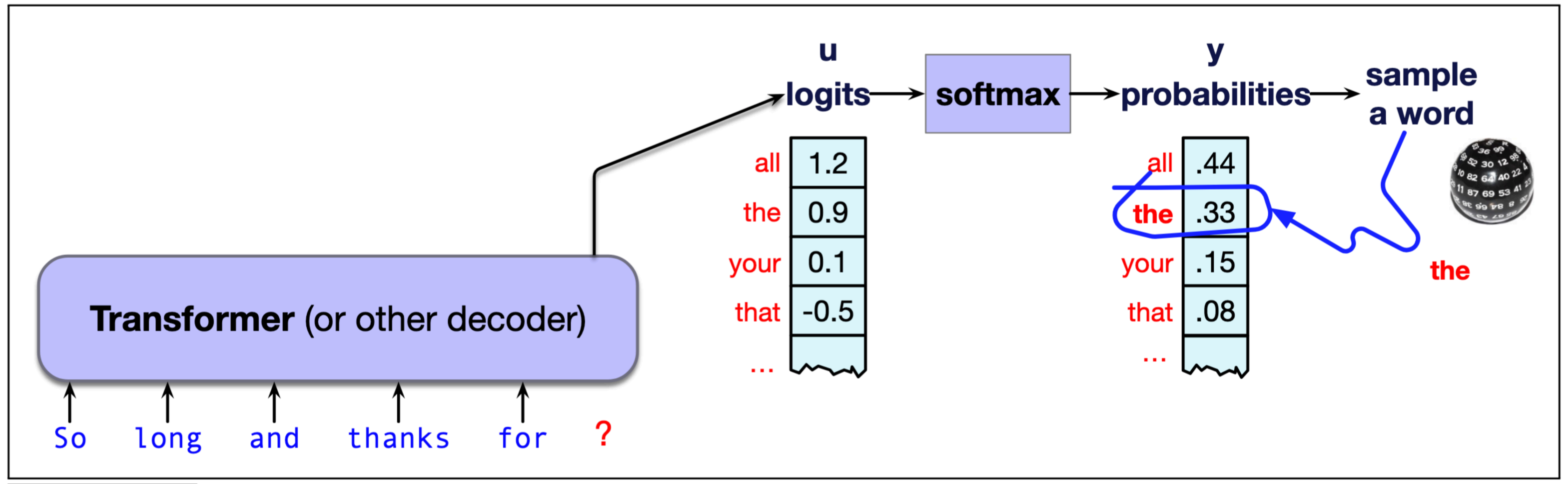

Figure 7.9 Random multinomial sampling: we randomly chose a word according to its probability.

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\begin{aligned}
&\mathrm{i} \leftarrow 1 \\
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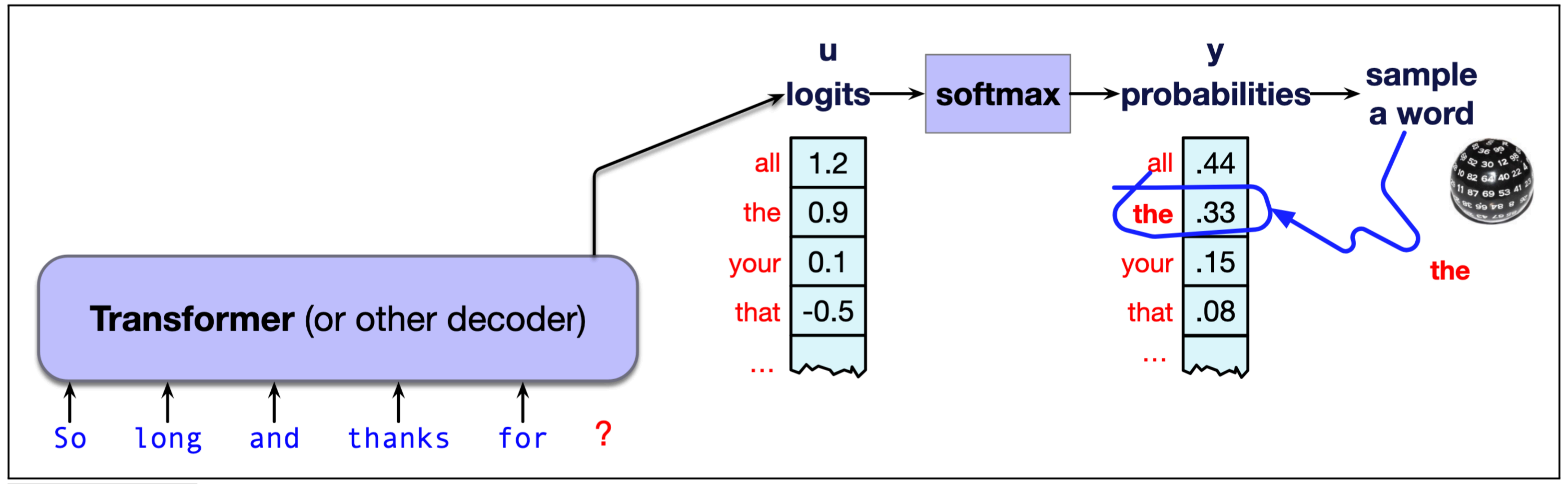
Random Sampling

- **Sampling:** taking **random draws** from a **probability distribution**



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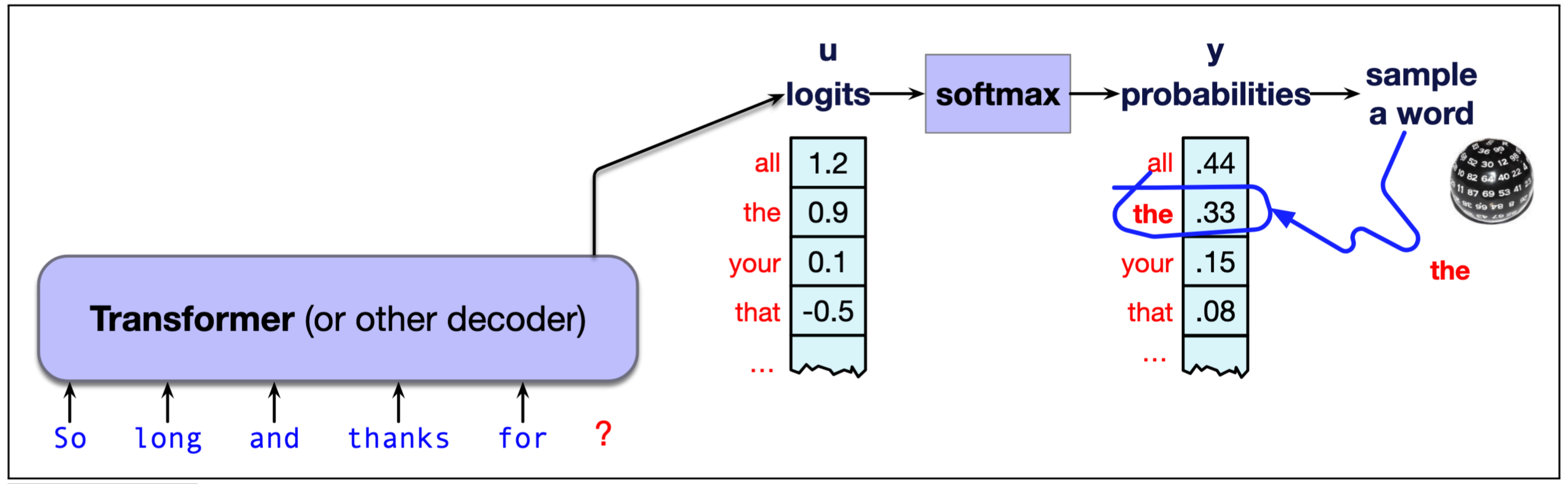

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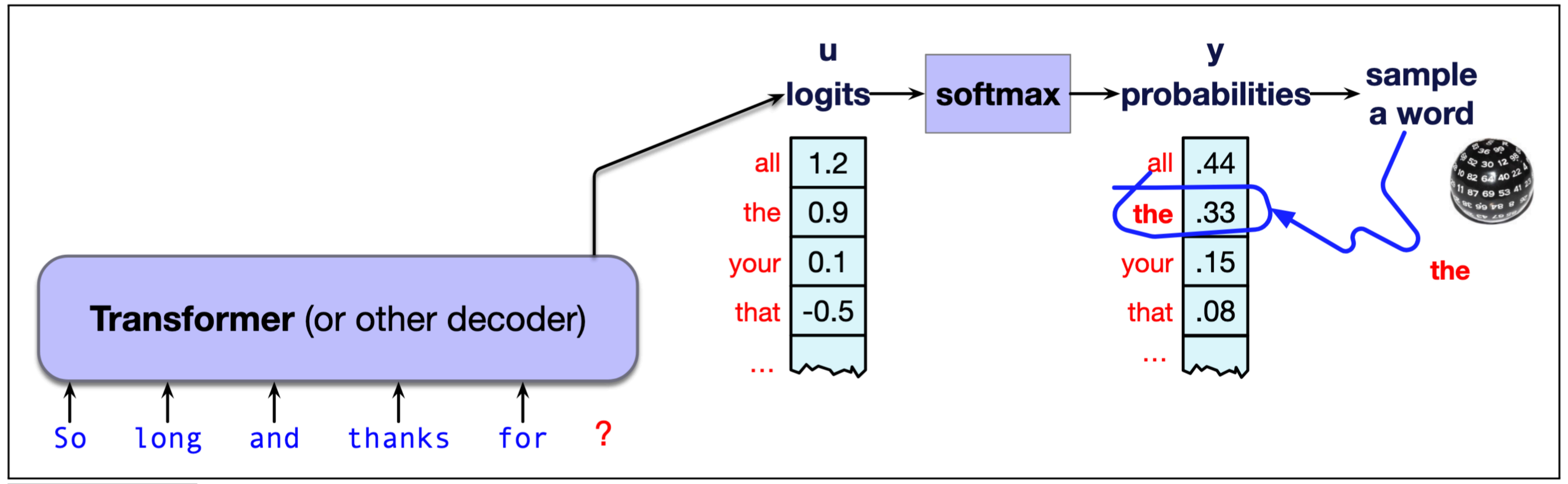

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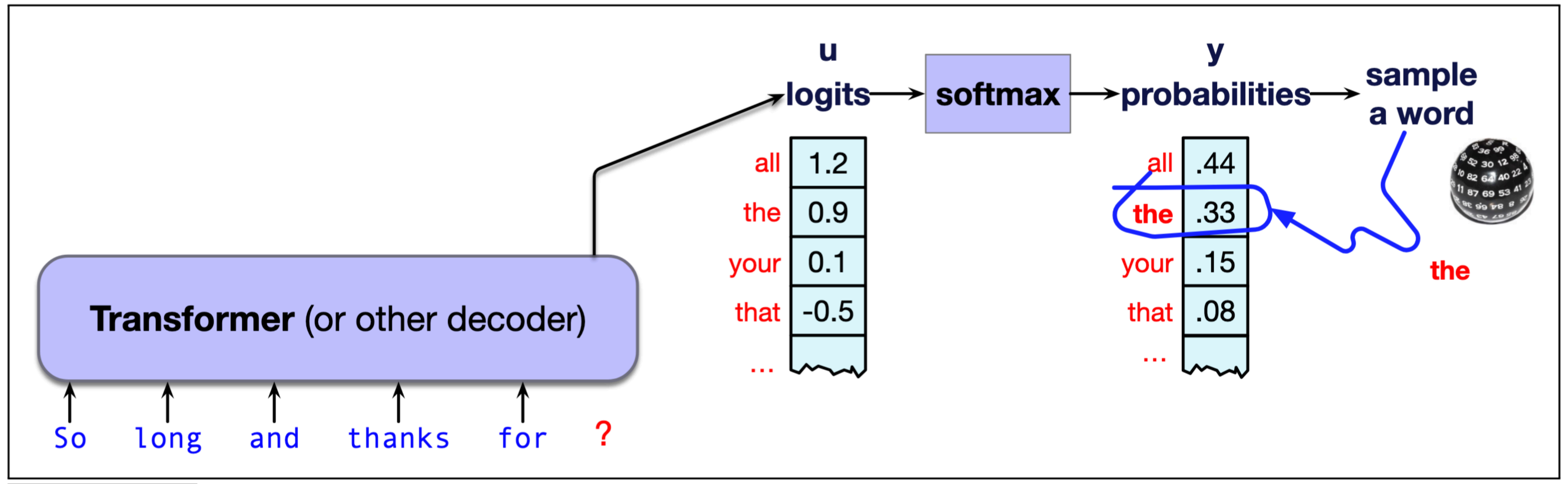

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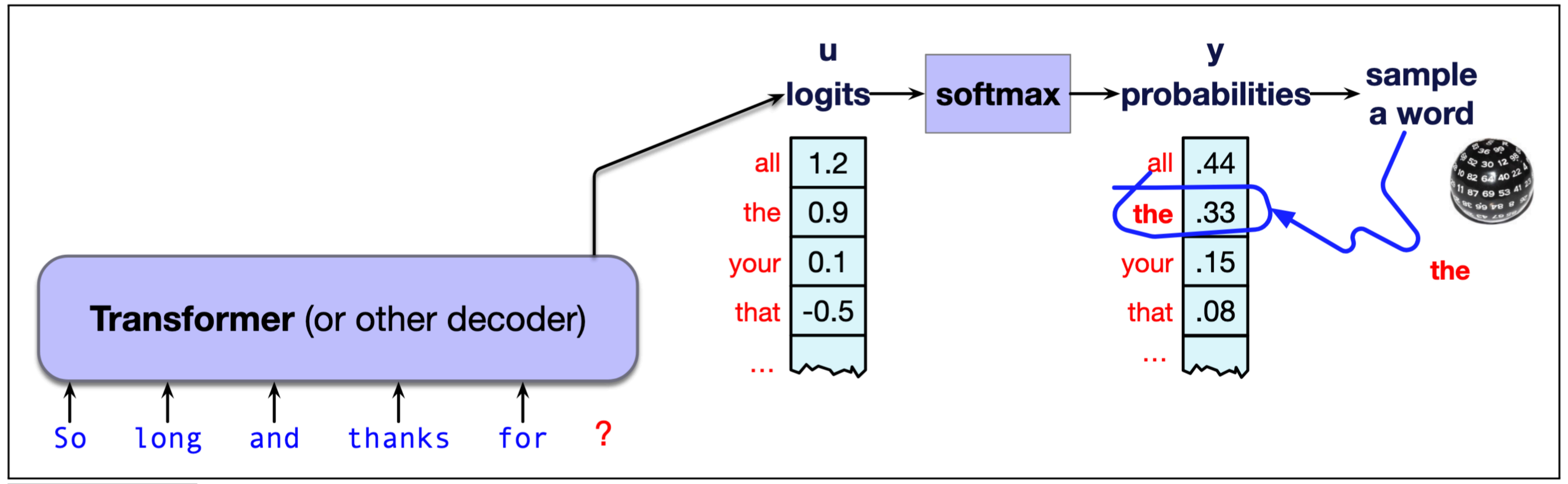

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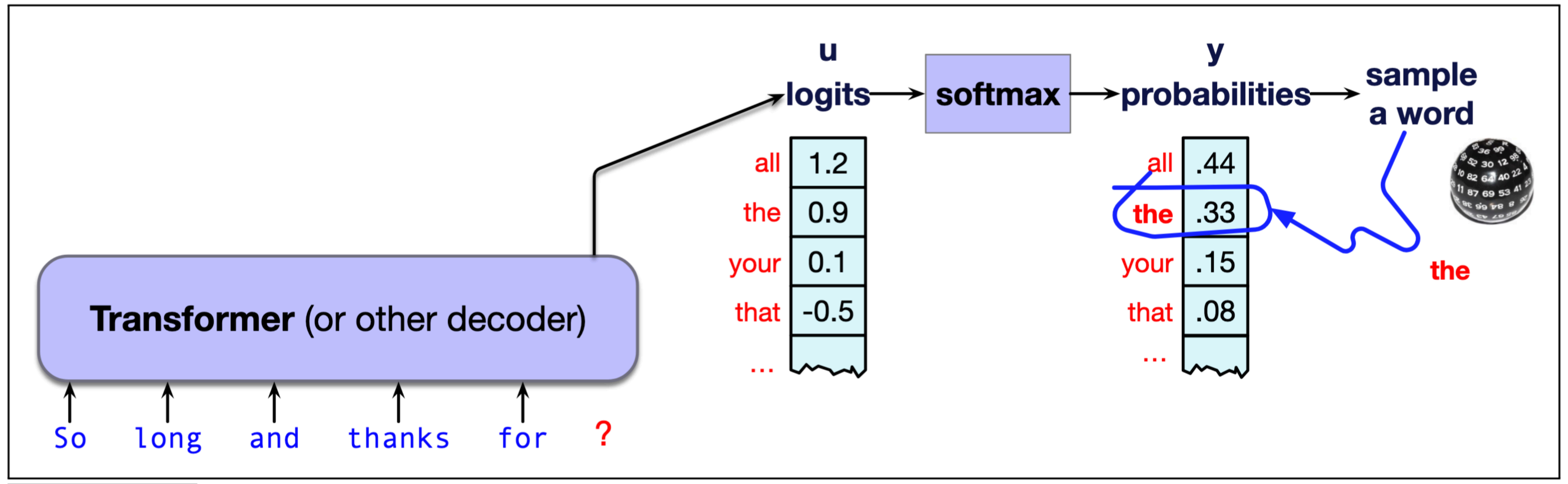

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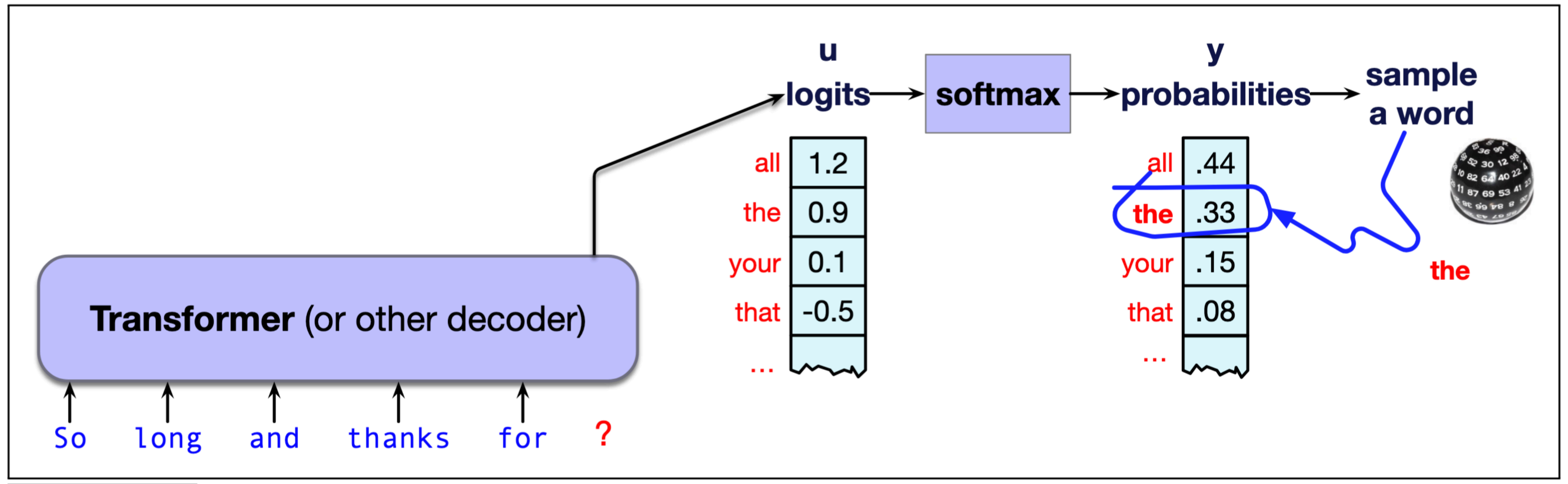
- Is there something in-between this and greedy?



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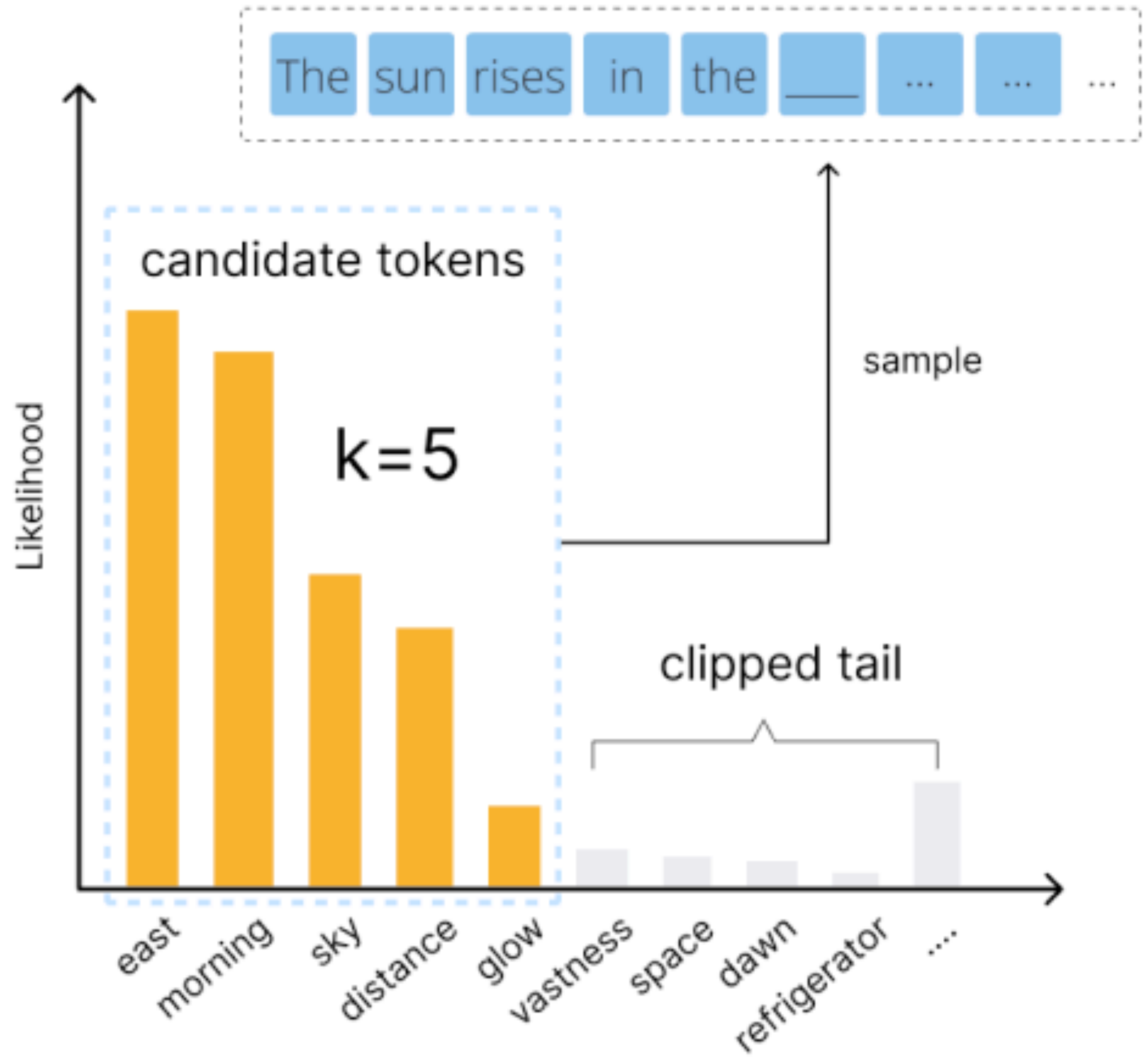
Top-k Sampling



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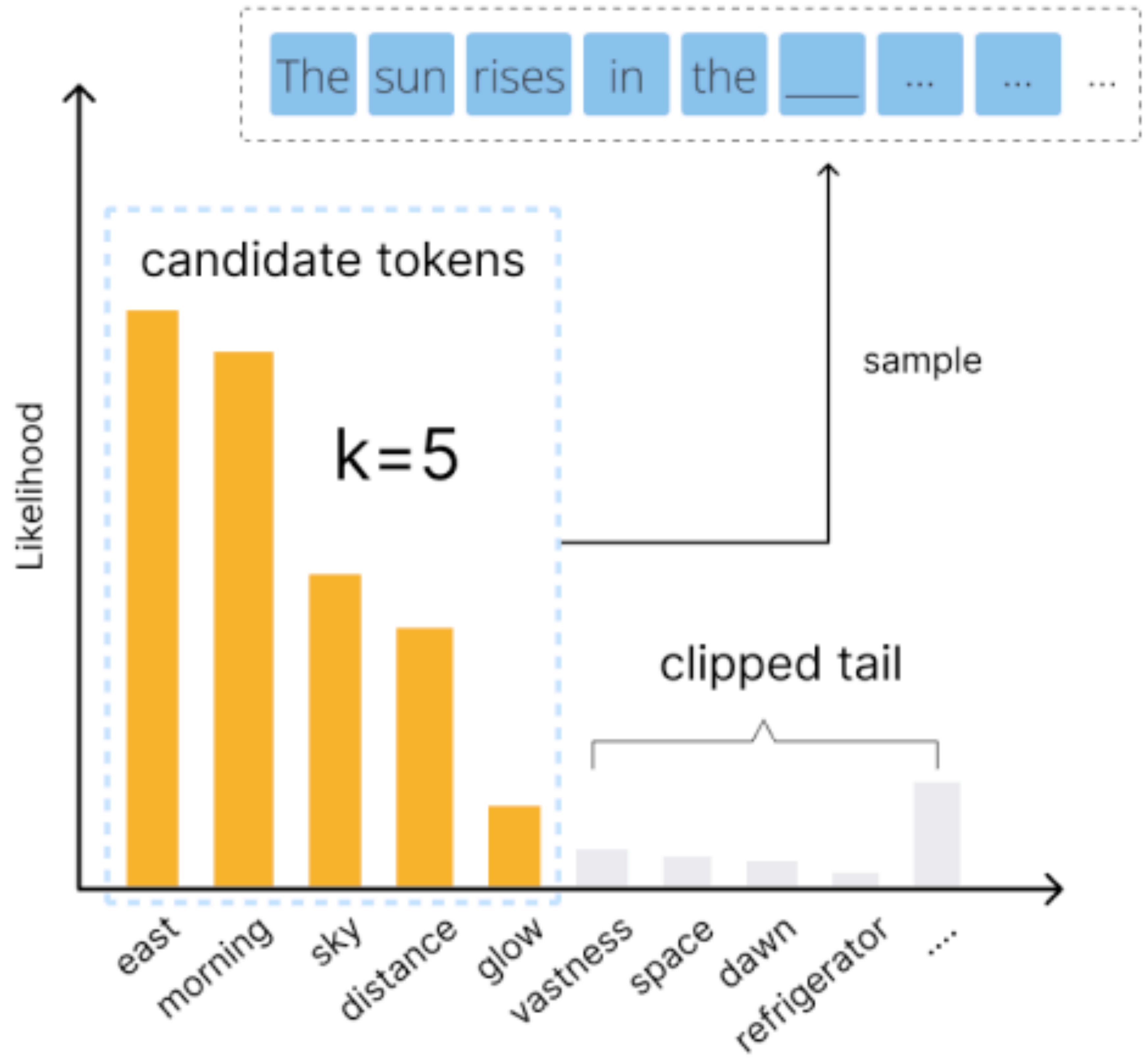
Top-k Sampling

- Instead of considering the whole distribution, what about the **top few words?**



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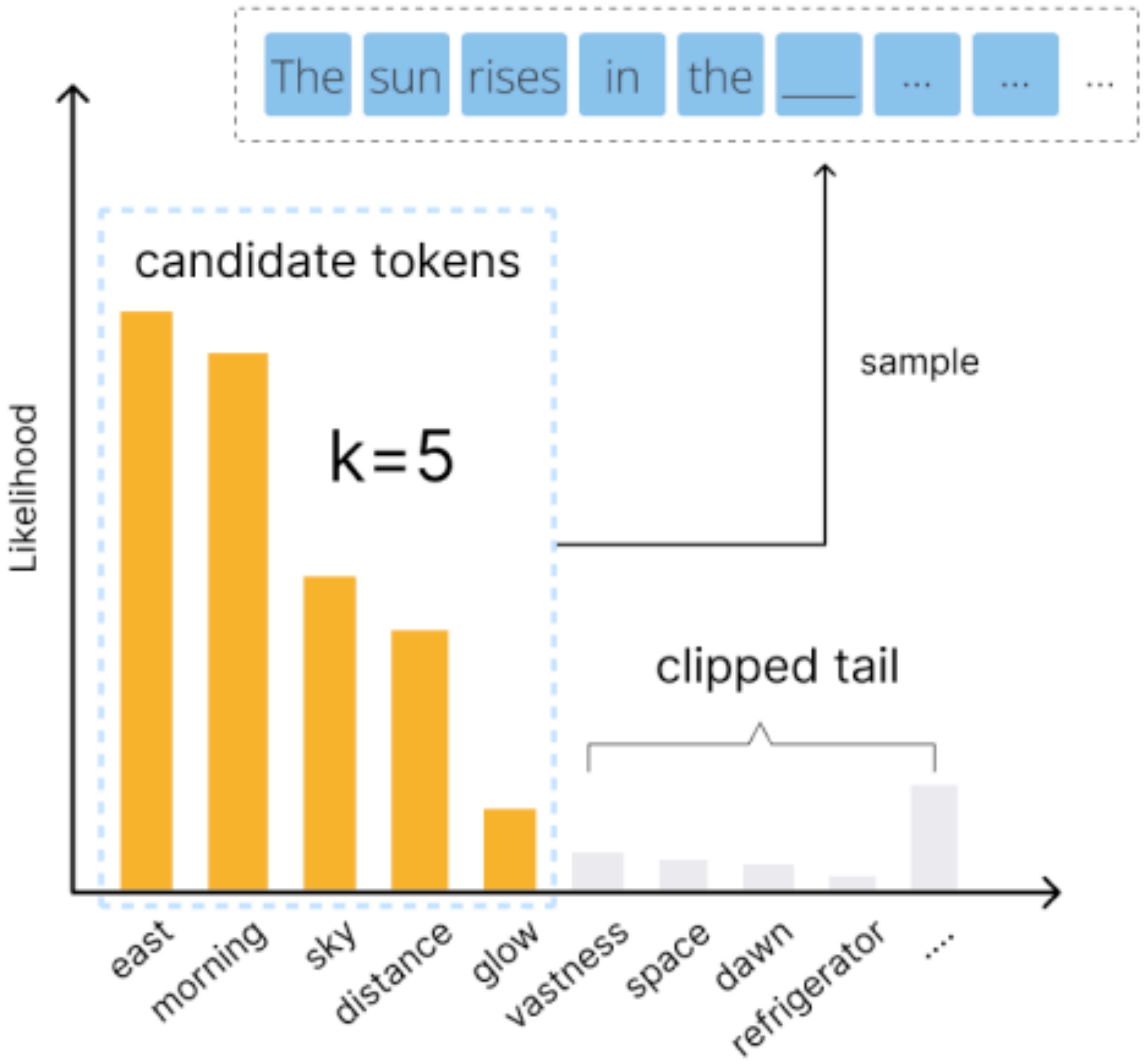

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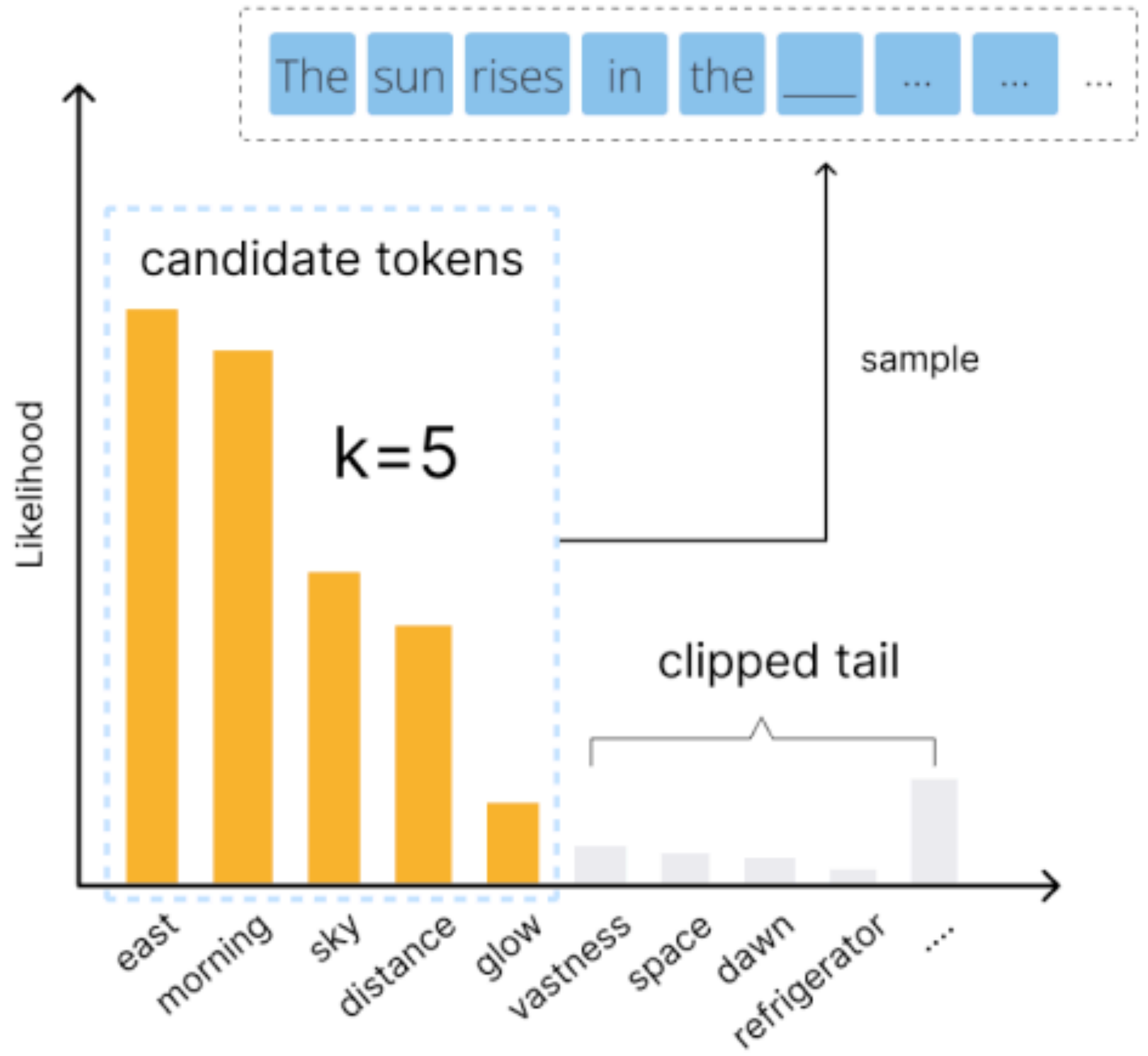
- **Cuts off** the long tail of the distribution



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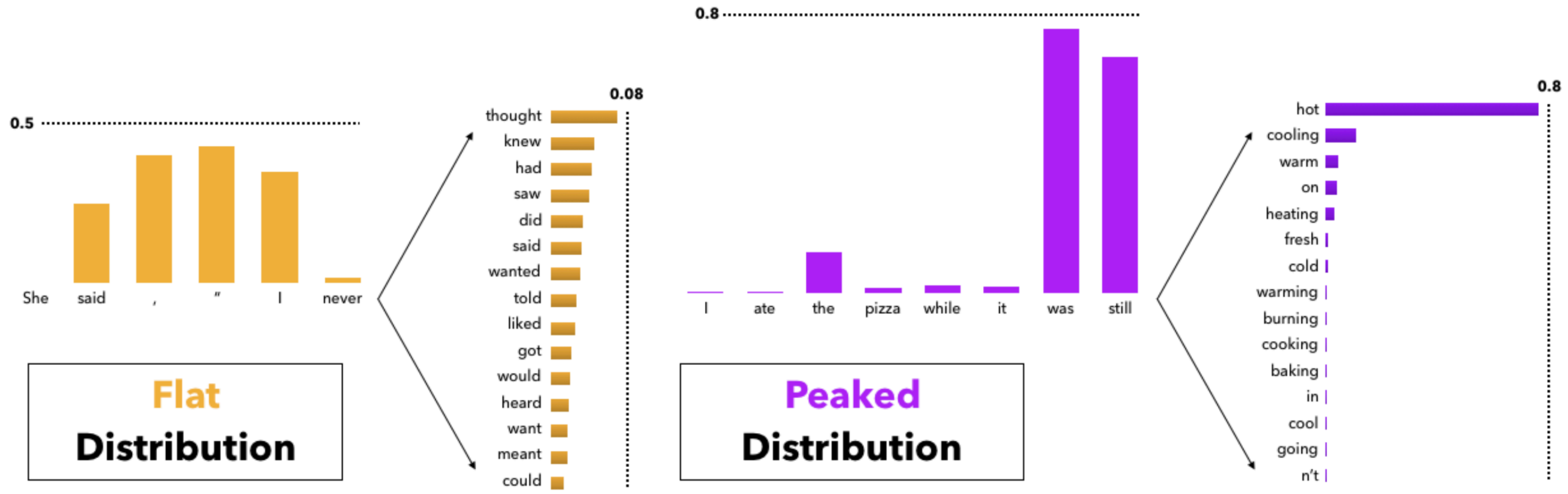

Figure 5: The probability mass assigned to partial human sentences. Flat distributions lead to many moderately probable tokens, while peaked distributions concentrate most probability mass into just a few tokens. The presence of flat distributions makes the use of a small k in top-k sampling problematic, while the presence of peaked distributions makes large k's problematic.

[Holtzman et al (2020)]

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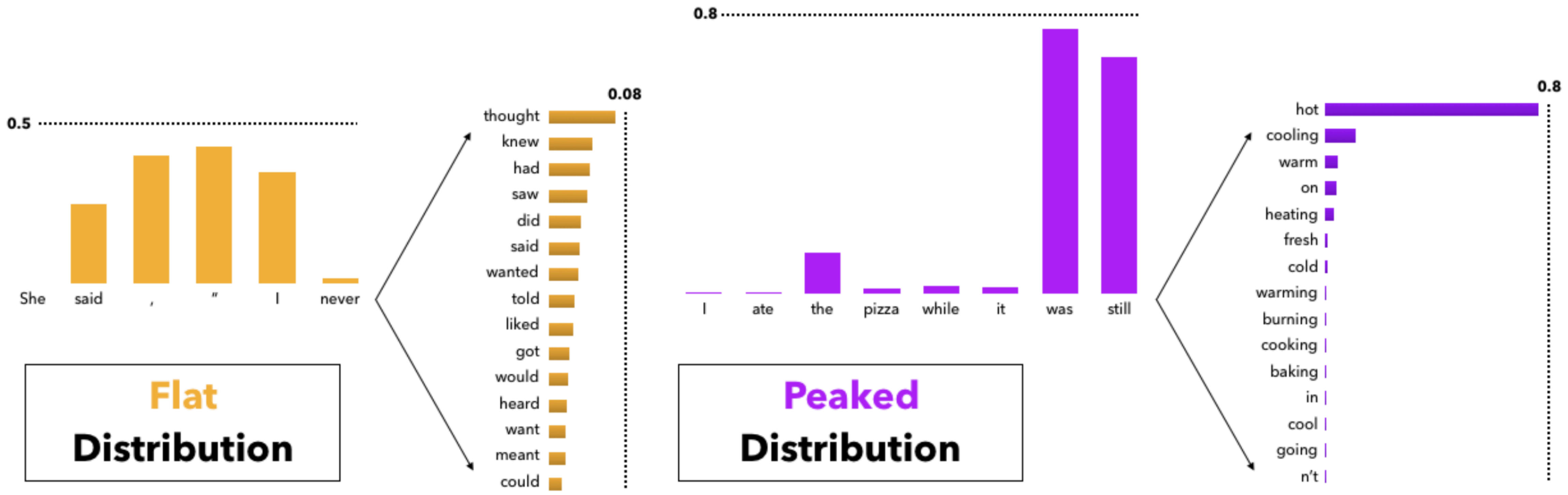

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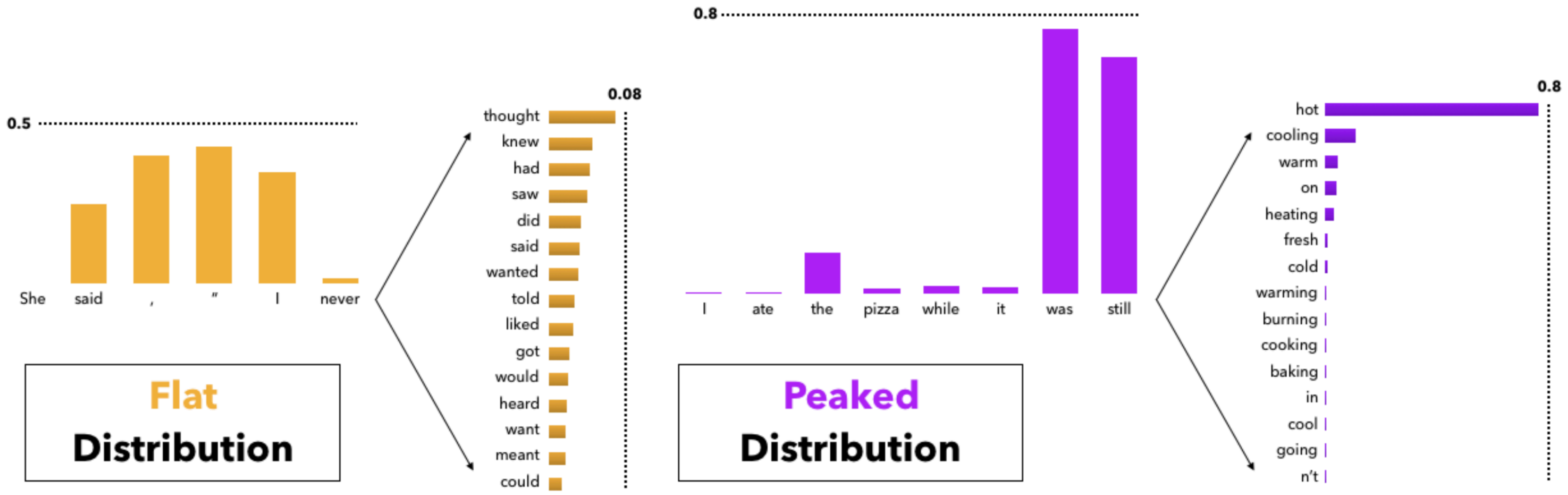

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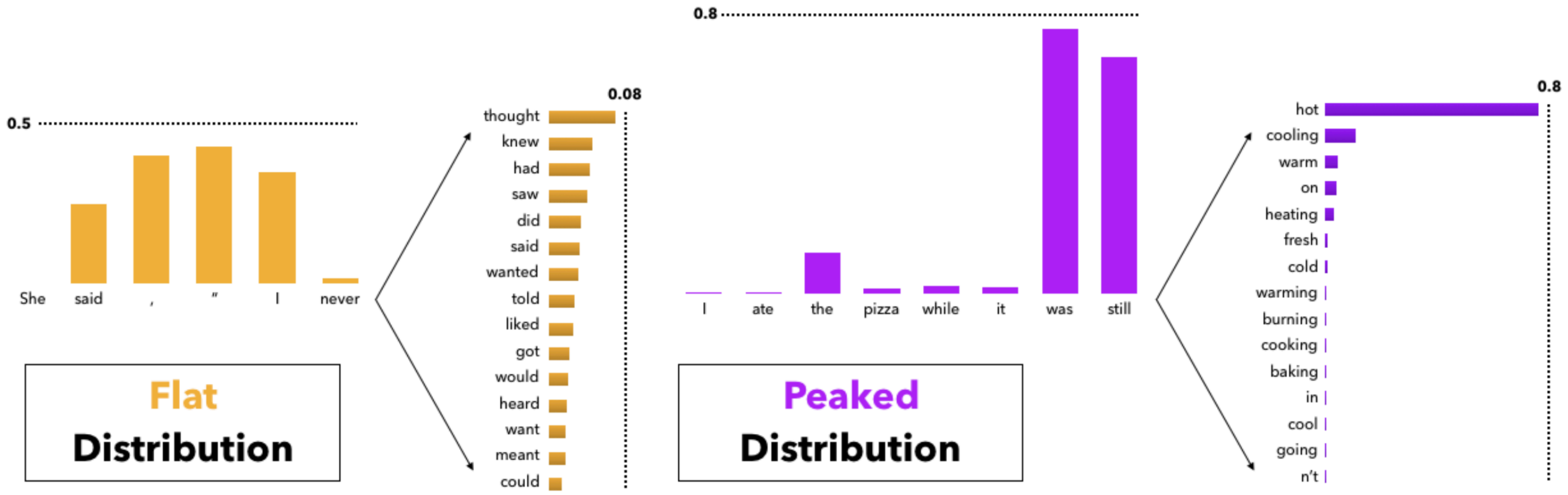

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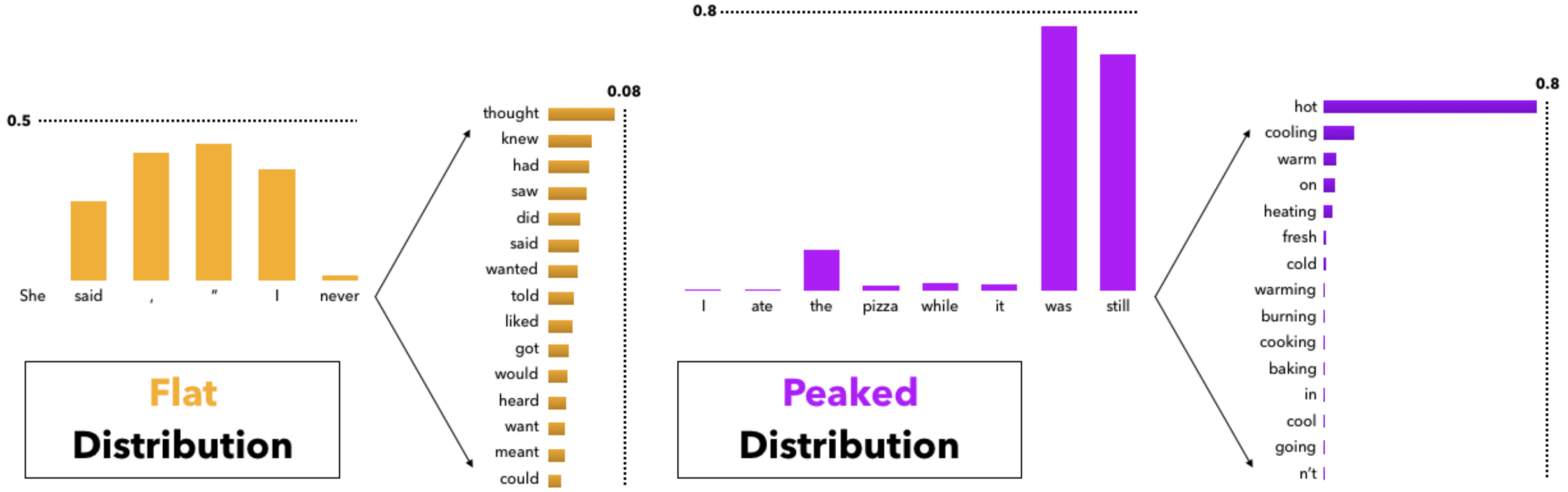

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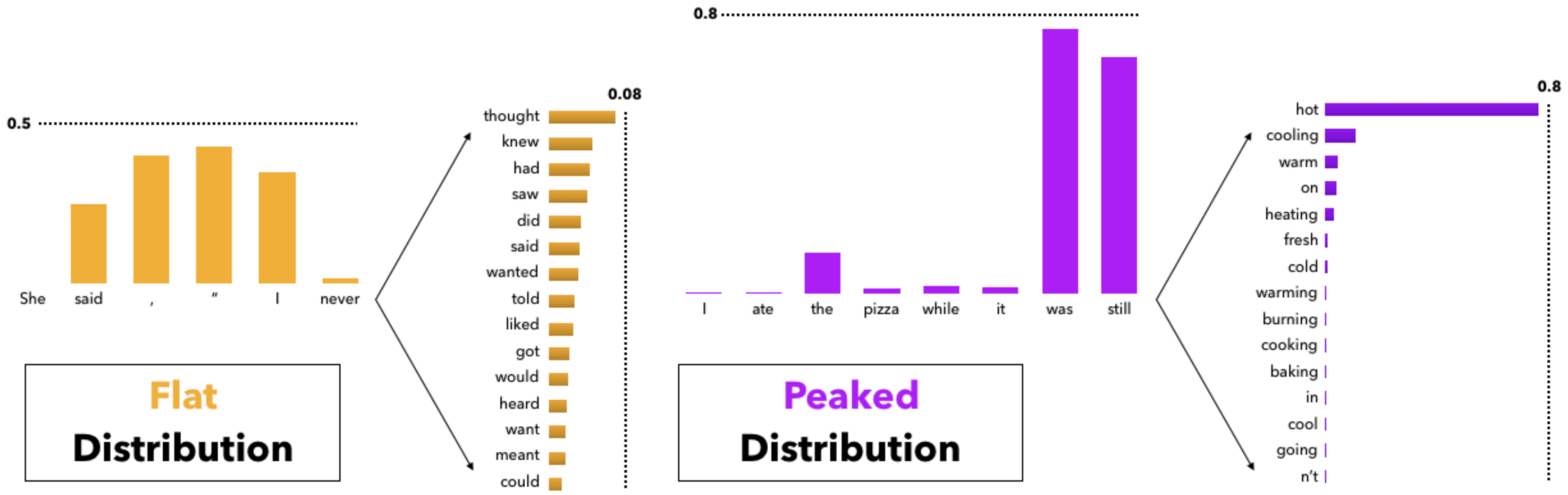

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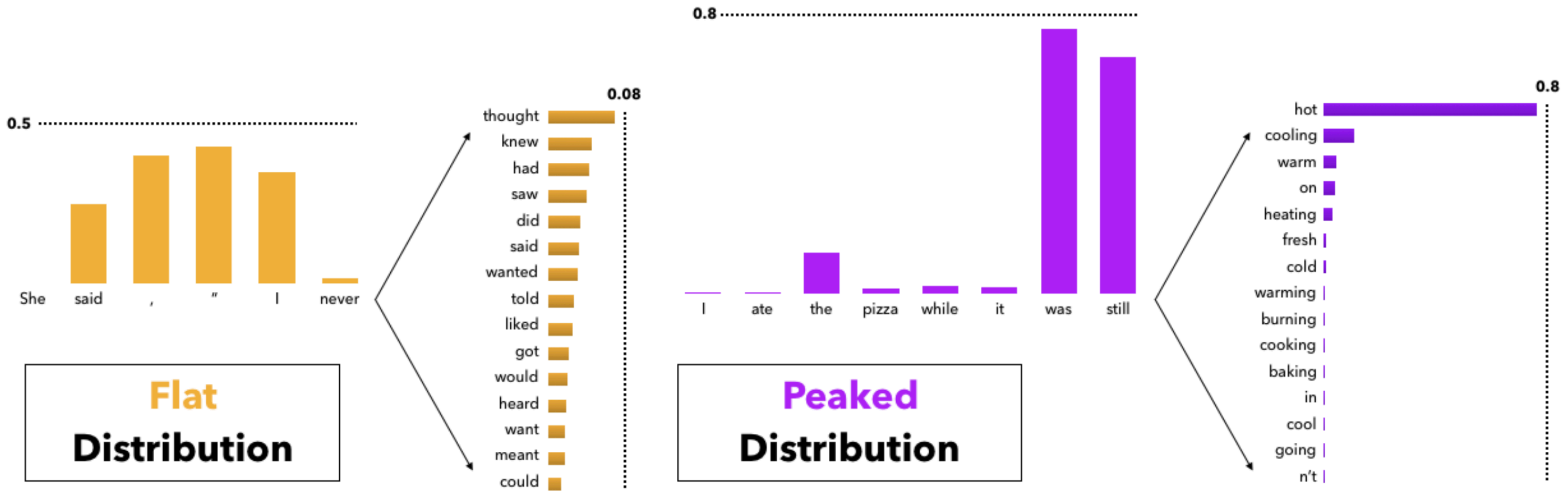
  - Adaptable to different distribution shapes



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Softmax Temperature

$$\text{probs} = \text{softmax}(\mathbf{x}/\tau)$$

close to greedy

normal softmax

close to uniform

	logits	τ=0.1	τ=0.5	τ=1	τ=10	τ=100
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the	0.9	.05	.32	.33	.26	.25
your	0.1	0	.07	.15	.24	.25
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low temperature sampling (towards greedy)

high temperature sampling (towards uniform)

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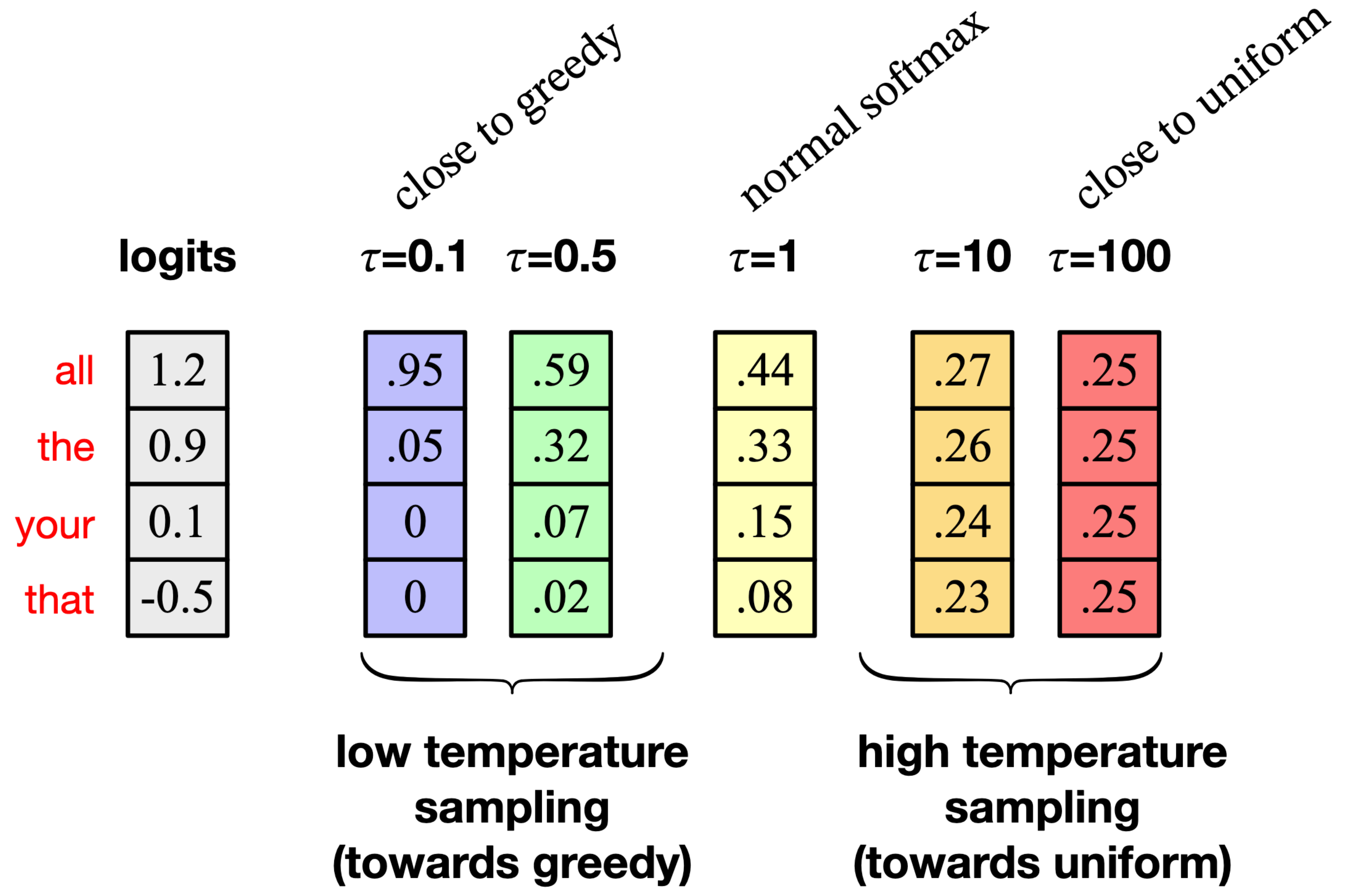

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  - $\tau = 1.0$ $\rightarrow$ **regular softmax**
- Can be **tuned** to give more/less deterministic outputs

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close to greedy — normal softmax — close to uniform

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