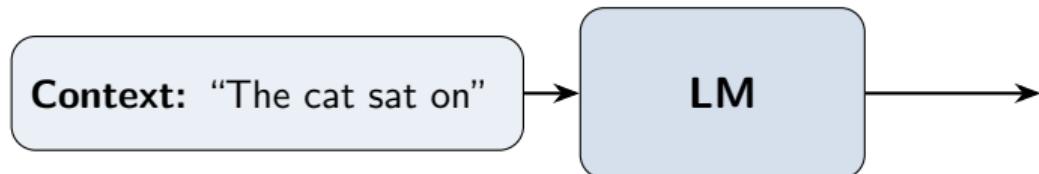


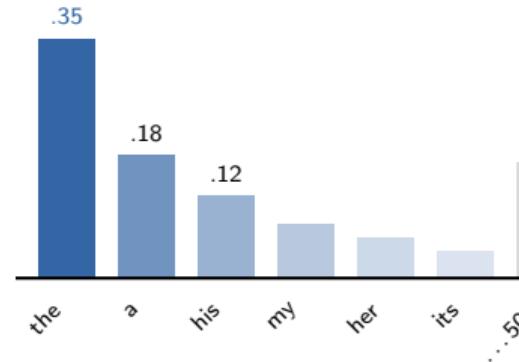
Decoding Strategies

Greedy · Beam Search · Temperature · Top- k · Top- p

The generation problem



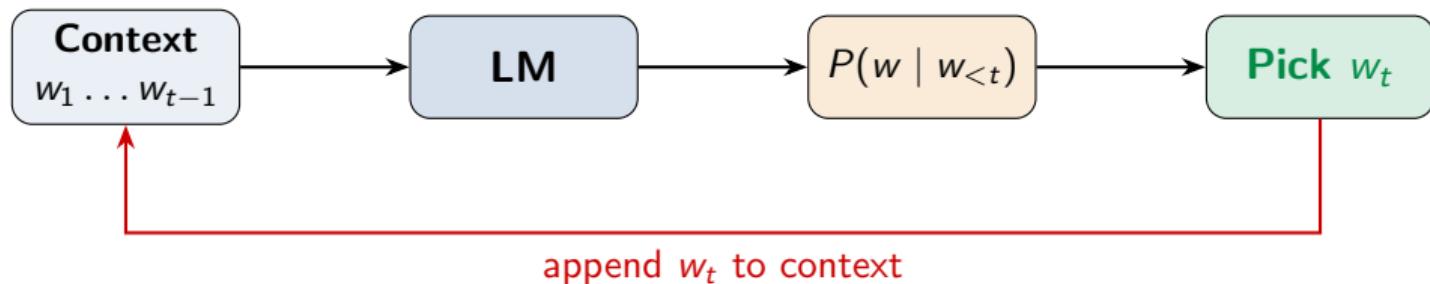
$$P(w | \text{context})$$



How do we pick the next token?

Autoregressive generation

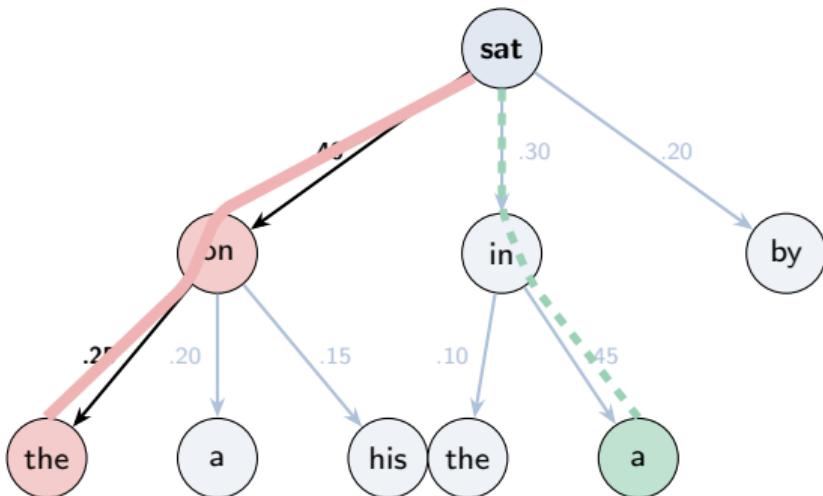
$$P(w_1, w_2, \dots, w_T) = \prod_{t=1}^T P(w_t | w_1, \dots, w_{t-1})$$



Every decoding method differs **only** in the “Pick w_t ” step.
The model and the loop are always the same.

Greedy search

$$w_t = \arg \max_w P(w | w_1, \dots, w_{t-1})$$



Greedy picks the best token at each step, but can miss the **globally** best sequence.

Greedy path

$$.40 \times .25 = .10$$

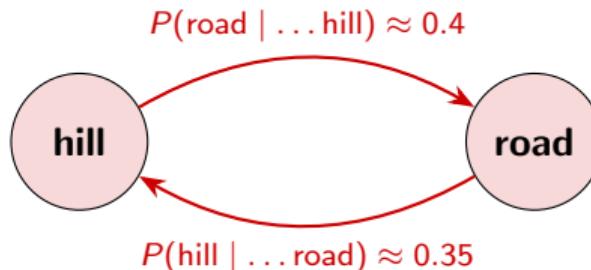
Better path

$$.30 \times .45 = .135$$

Greedy search: the repetition trap

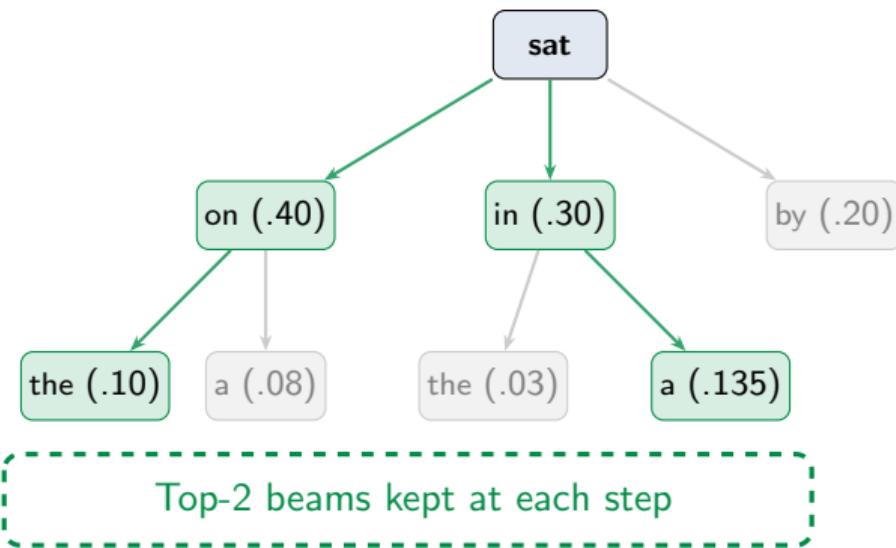
Prompt: "Once upon a time, there was a little cat who"

Greedy output: lived in a small house. The house was on the hill. **The hill was on the road. The road was on the hill. The hill was on the road. The road was on the hill. The hill was on the ...**



Once in a high-probability loop, greedy search **never escape**.
Each token is locally optimal, but the sequence is degenerate.

Beam search ($B = 2$)



Beam search keeps the B most probable *partial sequences*.

Length-normalized score:

$$\text{score} = \frac{1}{T^\alpha} \sum_{t=1}^T \log P(w_t | w_{<t})$$

$\alpha \approx 0.6\text{--}0.7$ prevents preference for short sequences.

Beam search: trade-offs

Works well for:

- Machine translation
- Summarization
- Any task with a “right answer”
- Constrained generation

These tasks want the **most likely** sequence — beam search finds it.

Struggles with:

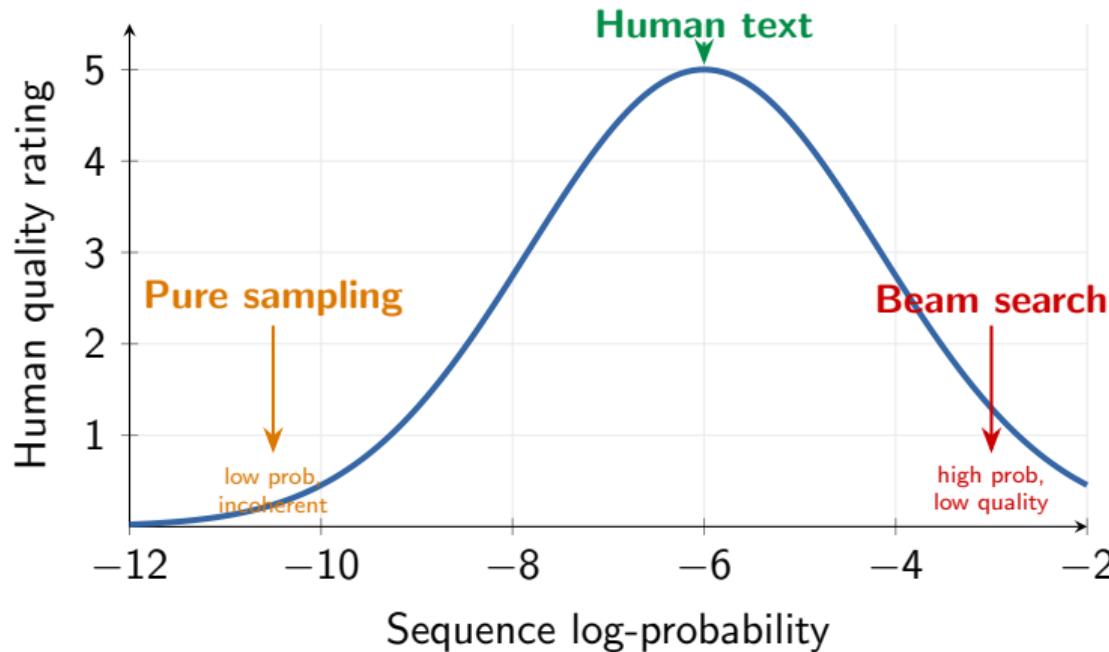
- Open-ended text / stories
- Dialogue / chat
- Creative writing

Output is “safe” but **boring**: generic, repetitive, lacks surprise.

Humans rate beam search text as less natural than sampling.

Repetition fix: n -gram penalty — if generating token w_t would create an n -gram that already appeared, set $P(w_t) = 0$.

The probability trap



The highest-probability text is **not** the best text.

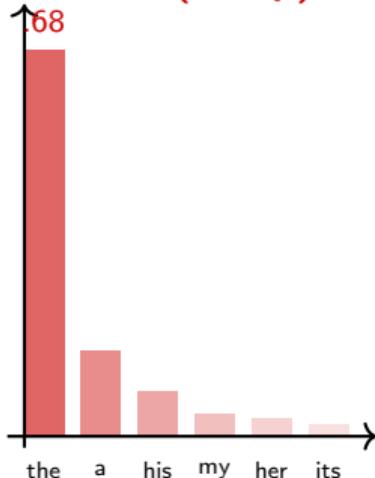
Human language occupies a **sweet spot** of moderate probability.

— Holtzman et al., “The Curious Case of Neural Text Degeneration” (2019)

Temperature scaling

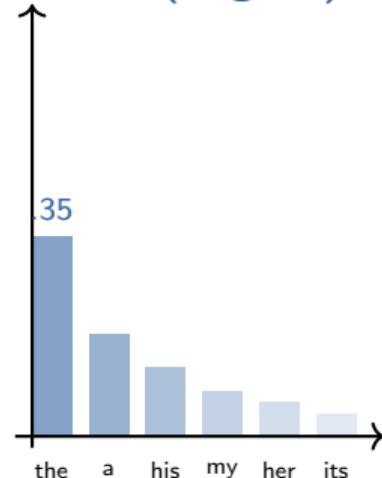
$$p_i = \frac{\exp(z_i / T)}{\sum_j \exp(z_j / T)}$$

$T = 0.3$ (sharp)



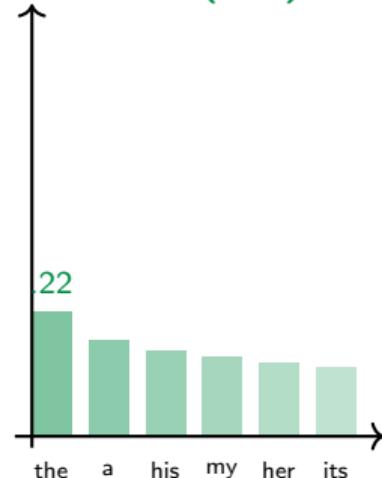
$T \rightarrow 0$: greedy

$T = 1.0$ (original)



$T = 1$: unchanged

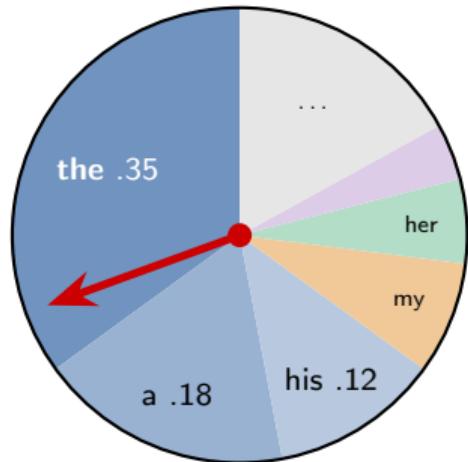
$T = 2.0$ (flat)



$T \rightarrow \infty$: uniform

Sampling from the distribution

$$w_t \sim P(\cdot \mid w_1, \dots, w_{t-1})$$



Sample = “spin the wheel”

The good: introduces diversity, avoids repetition loops, more human-like

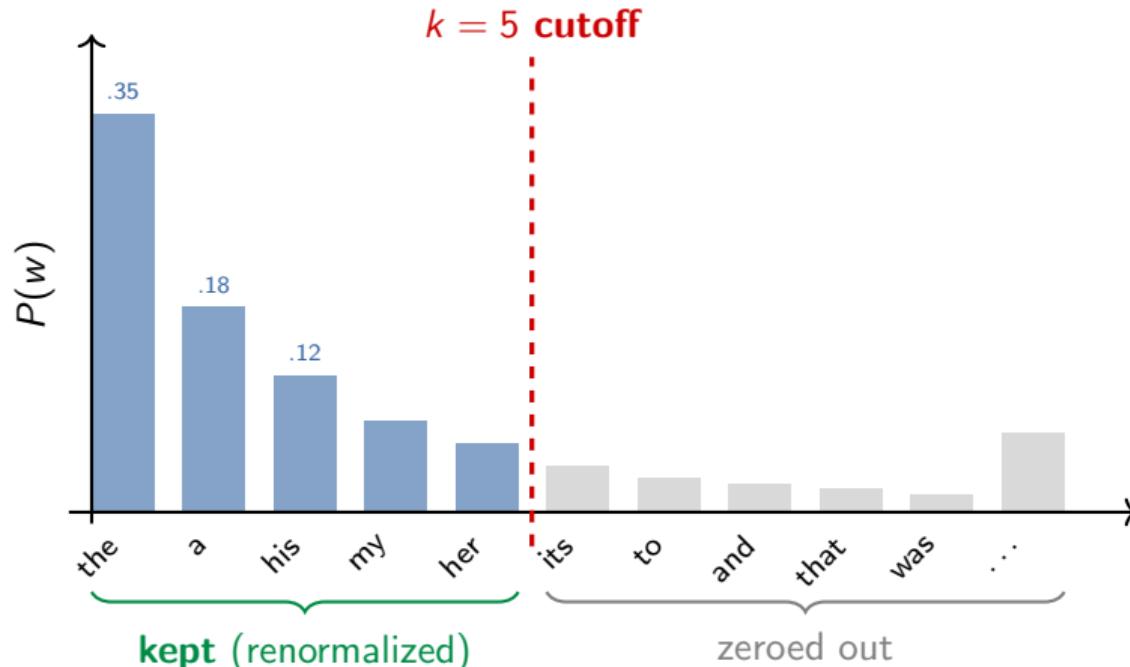
The bad: low-probability tokens (“banana”, “⟨unk⟩”) occasionally get sampled, **derailing** the entire sequence

“The cat sat on **quantum** and then **refrigerator** began to **oscillate** the ...”

We need to sample, but from a **truncated** distribution.
This motivates top- k and top- p .

Top- k sampling

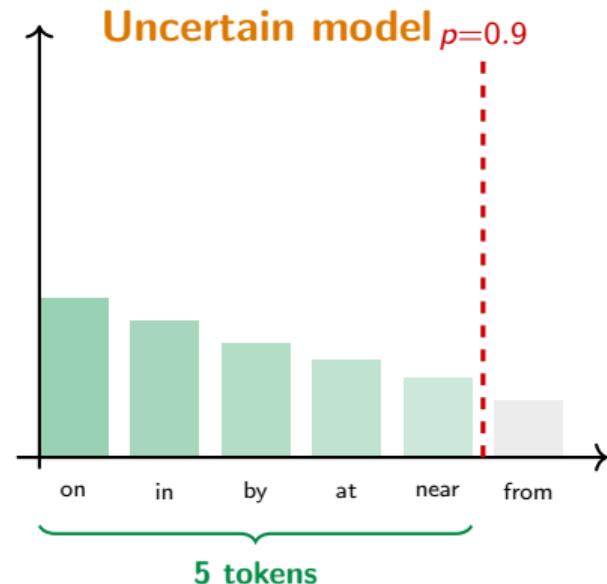
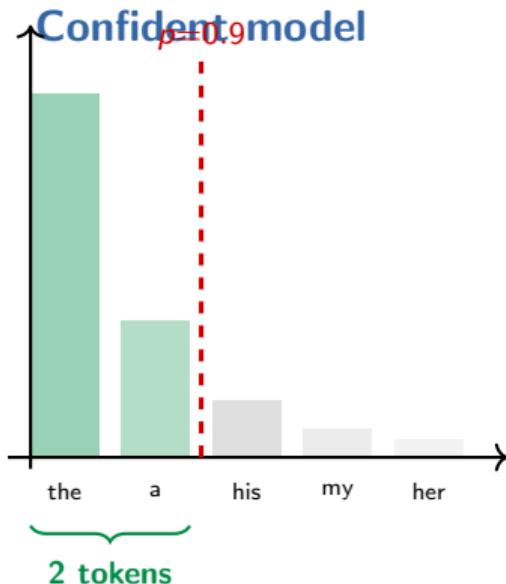
Idea: Keep only the k most probable tokens, zero out the rest, renormalize.



Problem: Fixed k doesn't adapt. When the model is **confident**, $k=50$ includes garbage. When the model is **uncertain**, $k=10$ cuts off good

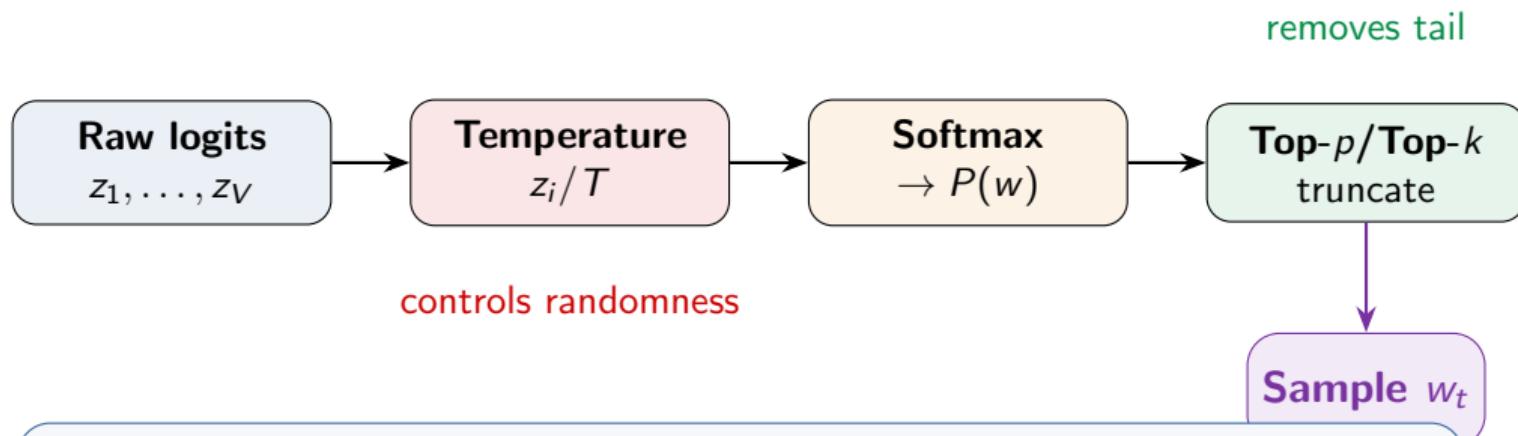
Top- p (nucleus) sampling

Idea: Find the smallest set V_p such that $\sum_{w \in V_p} P(w) \geq p$.



Top- p adapts the number of candidates to the model's confidence.

Combining the knobs



Common combinations:

- Temperature T reshapes the distribution *before* truncation
- Top- k and top- p can be used *together* (intersection of both filters)
- Greedy = $T \rightarrow 0$, or equivalently top- k with $k=1$

Comparison of decoding strategies

Method	Deterministic?	Best for	Main weakness
Greedy	Yes	Quick baseline	Repetitive, local optima
Beam search	Yes	Translation, summary	“Boring” open-ended text
Temperature	—	<i>Modifier, not standalone</i>	Just a knob
Top- k	No	Open-ended generation	Fixed k doesn’t adapt
Top- p	No	Open-ended generation	Slightly slower than top- k

In practice, most LLM APIs use **temperature + top- p** together.
Beam search is reserved for structured tasks (translation, summarization).
Greedy ($T=0$) is used when you want fully deterministic output.

Practical: typical API parameters

```
response = client.generate(  
    prompt = "...",  
    temperature = 0.7,  
    top_p = 0.9,  
    top_k = 50,  # optional  
    max_tokens = 256  
)
```

Creative writing

$T = 0.8\text{--}1.0$
 $\text{top-}p = 0.9\text{--}0.95$

Factual / Code

$T = 0.0\text{--}0.3$
or greedy ($T=0$)

Translation

Beam search, $B = 4\text{--}6$
length penalty $\alpha \approx 0.6$

Questions?

Next: Evaluation — Perplexity, BLEU, ROUGE