LLM Inference

How to generate text from LLMs?

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Today's learning outcomes

After today's lecture, you should be able to:

- Understand how to **generate text** with a Transformer-based language model.
- Explain differences between **decoding algorithms** and the role of decoding parameters.
- **Choose a suitable LLM** for your task.
- **Run a LLM** locally on your computer or computational cluster.

Text generation

Overview: training

Model stages:

random neural network

1

“autocomplete on steroids”

base / foundational model

2

assistant

instruction-tuned model

3

helpful assistant

Training stages:

1 Pre-training 🌍

Prague is the capital of Czechia (...)

2 Instruction tuning 💬

user: What is the capital of Czechia?

assistant: **Prague**

3 Human preference optimization 🧑‍⚖️

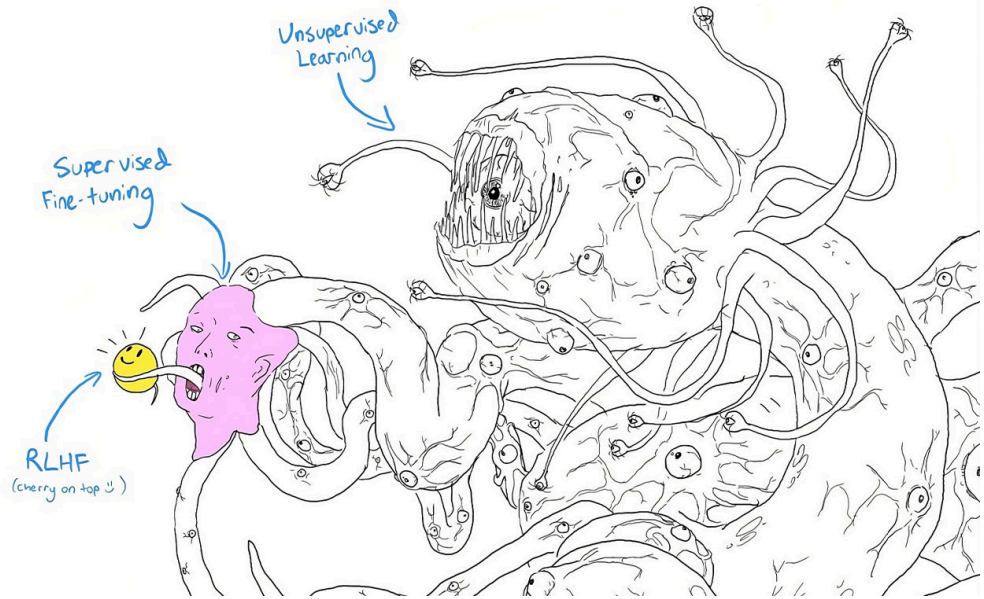
user: What is the capital of Czechia?

answer #1: Prague.

answer #2: The capital of Czechia is Prague. It is the largest (...)

LLM inference

This lecture: **LLM inference** = we have a trained model and we want to **use it**.



Question

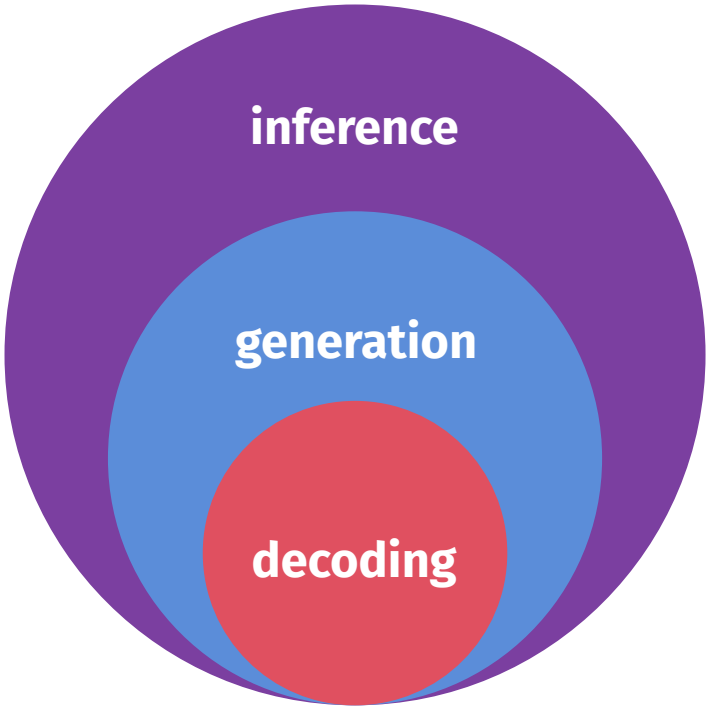
What is the difference between inference, generation, and decoding?

LLM Inference

Inference – The concept of using a trained model for **making predictions** on new data (for classification, sequence tagging, text generation, ...).

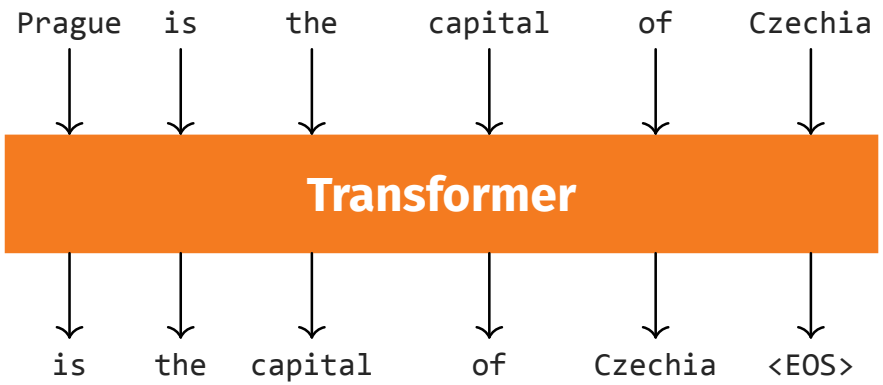
Generation – The process of using a trained model for **producing a sequence of tokens**.

Decoding – The algorithm of **selecting the next token** using the model's internal representation.



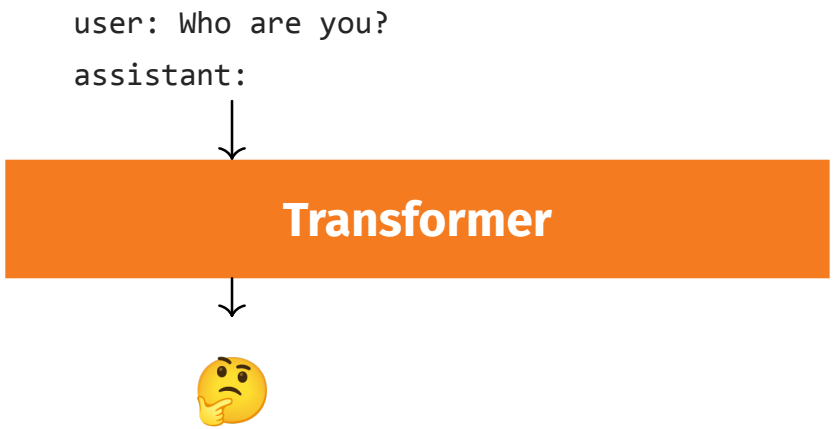
Training vs. inference

Training



Teacher forcing: We know what token should come next, so we use it to train the model.

Inference



Decoding: We need to *select* what token should come next.

👨‍🍳 Recipe: How to generate text autoregressively

1. **Start with the context**: a sequence of tokens (a “prompt” if instruction-tuned).
2. **Feed the context** into the LLM.
3. **Select the next token** from the model-generated probability distribution.
4. **Append the selected token** to the sequence.
5. **Repeat** from (3) until the EOS (end-of-sequence) token is selected.

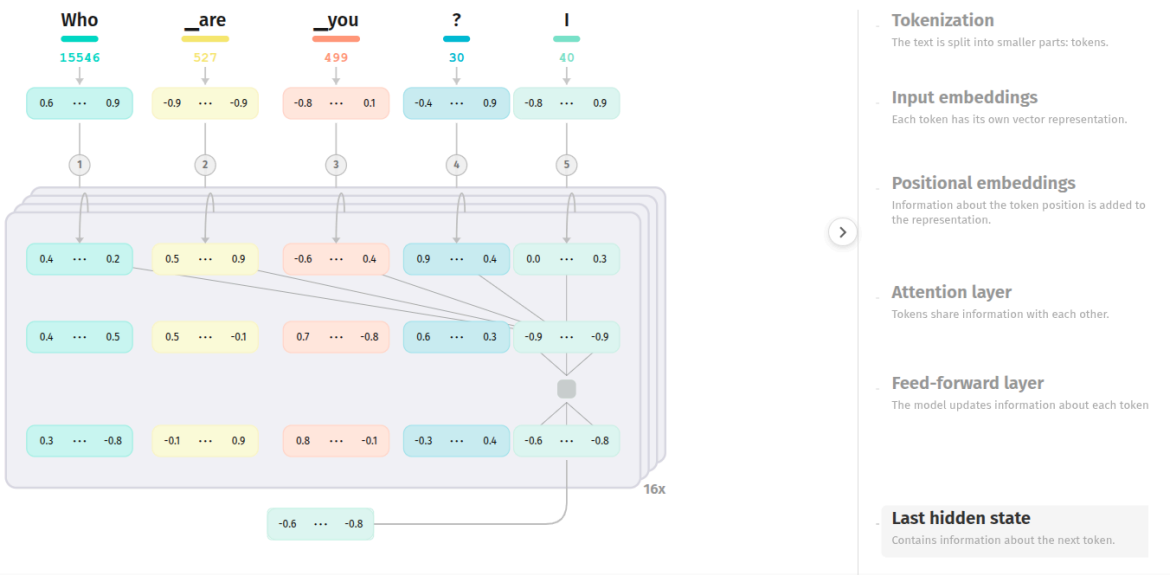
What happens during LLM inference?

Inference for dummies 🐥

https://animatedllm.github.io/generation-simple

What happens during LLM inference?

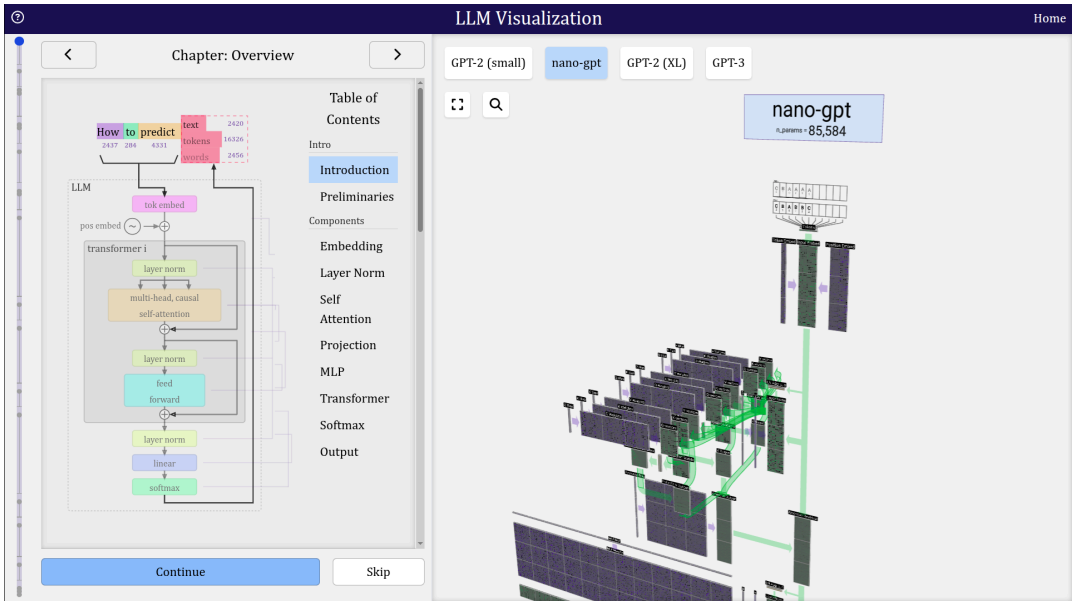
Advanced version 🎓



https://animatedllm.github.io/generation-model

What happens during LLM inference?

Hardcore version 🤘

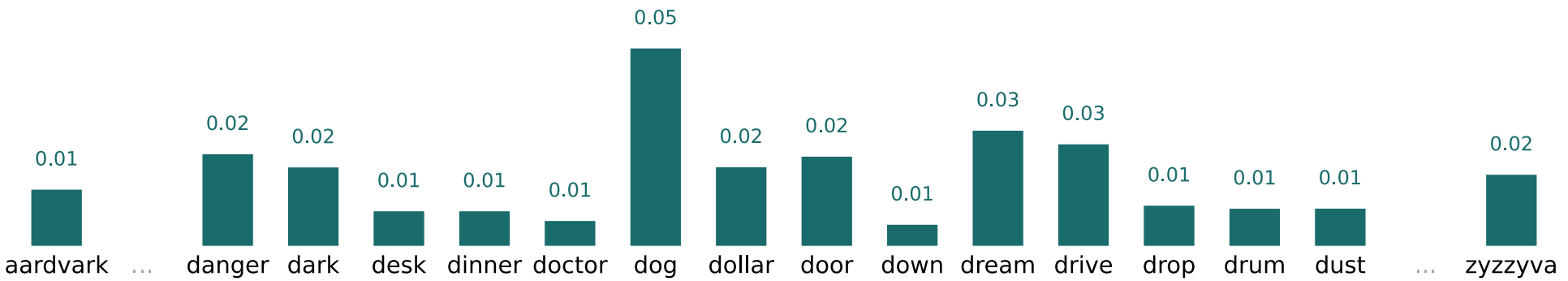


https://bbycroft.net/llm

Decoding algorithms

Decoding the next token

For each time step t, the decoder outputs **probability distribution** over the tokens given the previous context $P(y_t \mid y_{1:t-1}, X)$.



That is where the “job” of the Transformer decoder ends → it is up to us (or our decoding algorithm) to **use the distribution for decoding the next token**.

Exact inference

🏆 **Holy grail**: Find the most probable continuation to our prompt:

$$y^* = \arg\max_{y \in \mathcal{Y}} P(y) = \arg\max_{y \in \mathcal{Y}} \prod_{i=1}^{t} P(y_i \mid y_1, \ldots, y_{t-1})$$

Question

Why is this not possible in practice?

Intractable (exponential search space) → we need to approximate it.

Question

And is it even our goal?

Decoding algorithms

Two approaches we typically combine in practice:

Approximating the most probable sequence 🤔

Greedy search / beam search

Adding stochasticity 🎲

Temperature / top-k sampling / nucleus (top-p) sampling

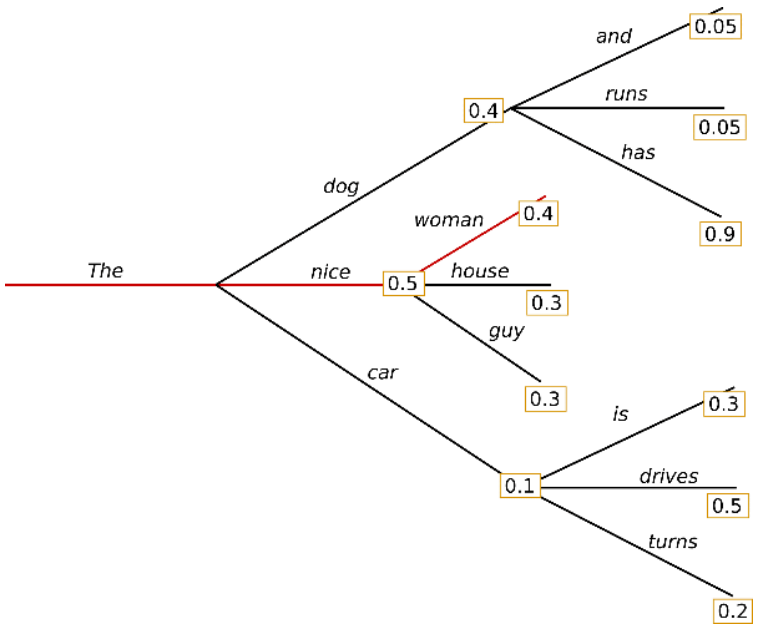
Greedy decoding

source: HF Blog

Algorithm

In each step t, select the most probable token: $y_t = \arg\max_{y_t \in \mathcal{V}} P(y_t \mid y_1, ..., y_{t-1})$

- Very fast, often works satisfactorily (especially with LLMs).
- Non-parametric (no hyperparameters to tune).
- But: may produce sequences that are too generic.



Beam search

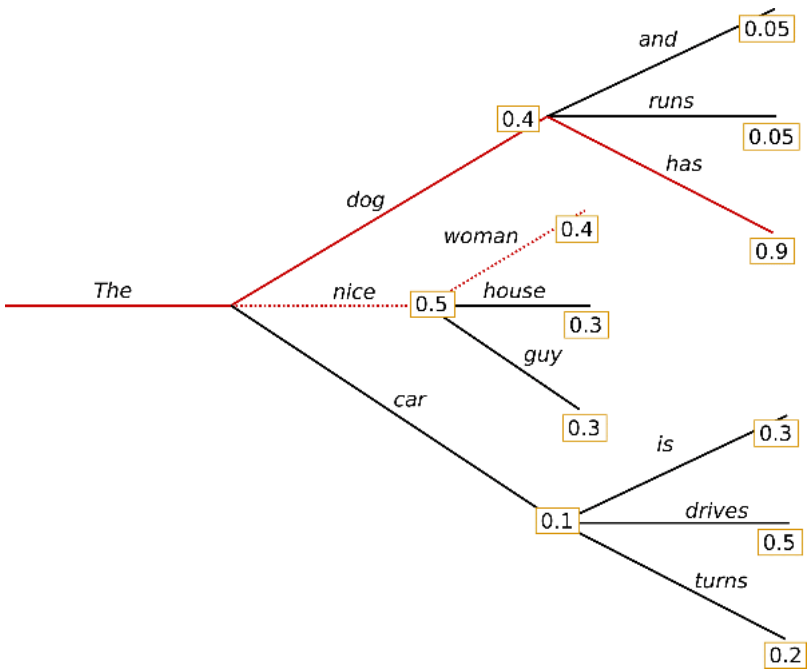
source: HF Blog

Algorithm

Parameter k: number of sequences (beams).

Each step t:

1. Extend the sequences from step $t-1$ with all possible tokens.
2. Select the k most probable sequences for step $t+1$.



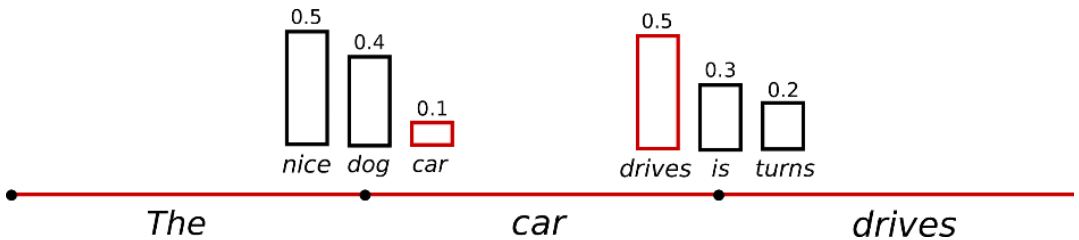
- $k = 1$ → greedy decoding; larger k → slower, but better approximation.
- $k > 1$ allows re-ranking results.

Adding stochasticity

source: HF Blog

Instead of picking the most probable token, we can randomly sample the next token y_t according to its conditional probability distribution:

$$y_t \sim P(y_t \mid y_1, \ldots, y_{t-1})$$



Question

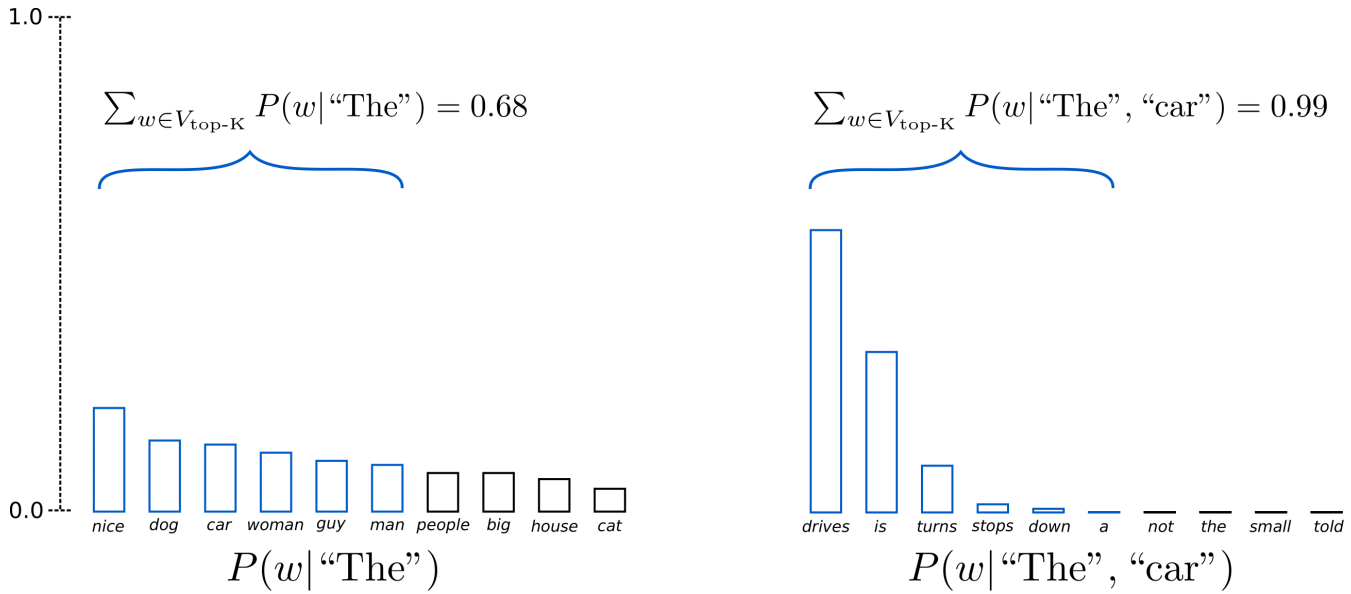
Why is this sampling from the entire vocabulary not a good idea?

Top-k sampling

source: HF Blog

Selecting the token in each step randomly from $k \in \{1, ..., |\mathcal{V}|\}$ most probable tokens.

The truncated distribution is re-weighted using softmax.

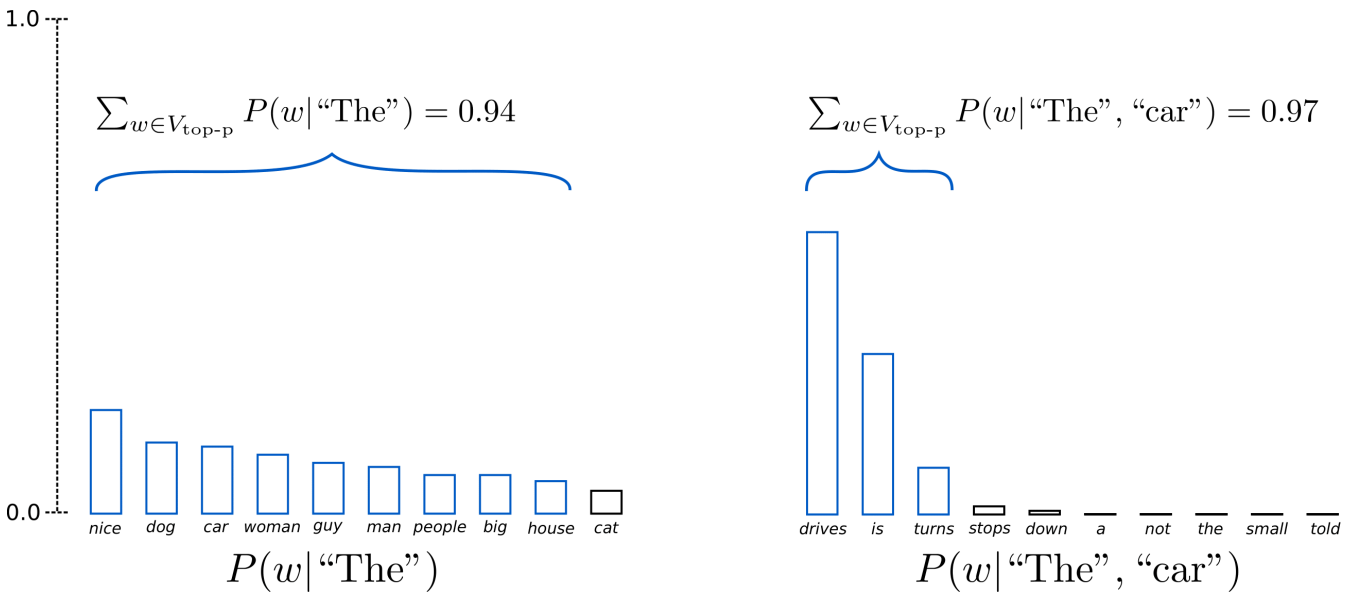


Top-p (nucleus) sampling

source: HF Blog

Sampling from the **nucleus**: set of the most probable tokens with combined probability summing to $p \in (0, 1]$.

Similar to top-k, but with a **variable** k in each step.



Temperature

source: CME295

The shape of the output distribution can be adjusted using the **temperature** T:

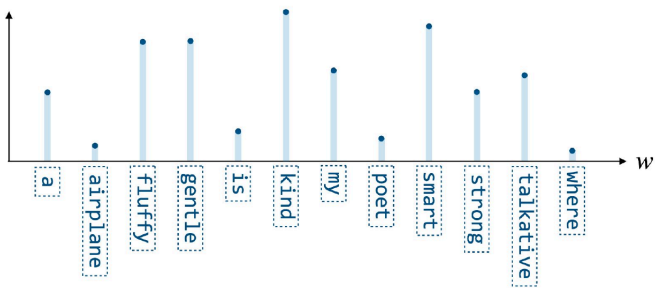
$$\text{softmax}(z) = \frac{\exp\left(\frac{z_t}{T}\right)}{\sum_j \exp\left(\frac{z_j}{T}\right)}$$

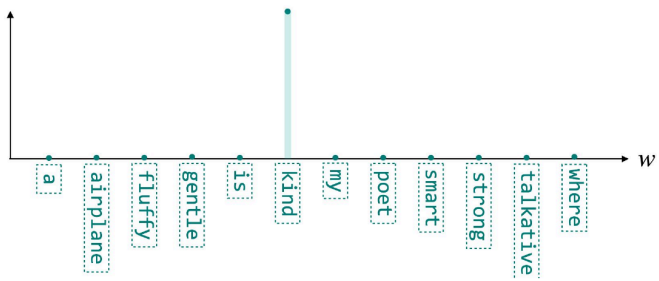
$T = 1$: **original distribution**

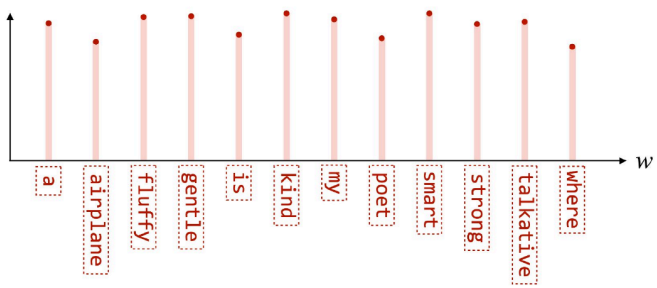
$T < 1$: **more peaked**

($T = 0$ → greedy decoding)

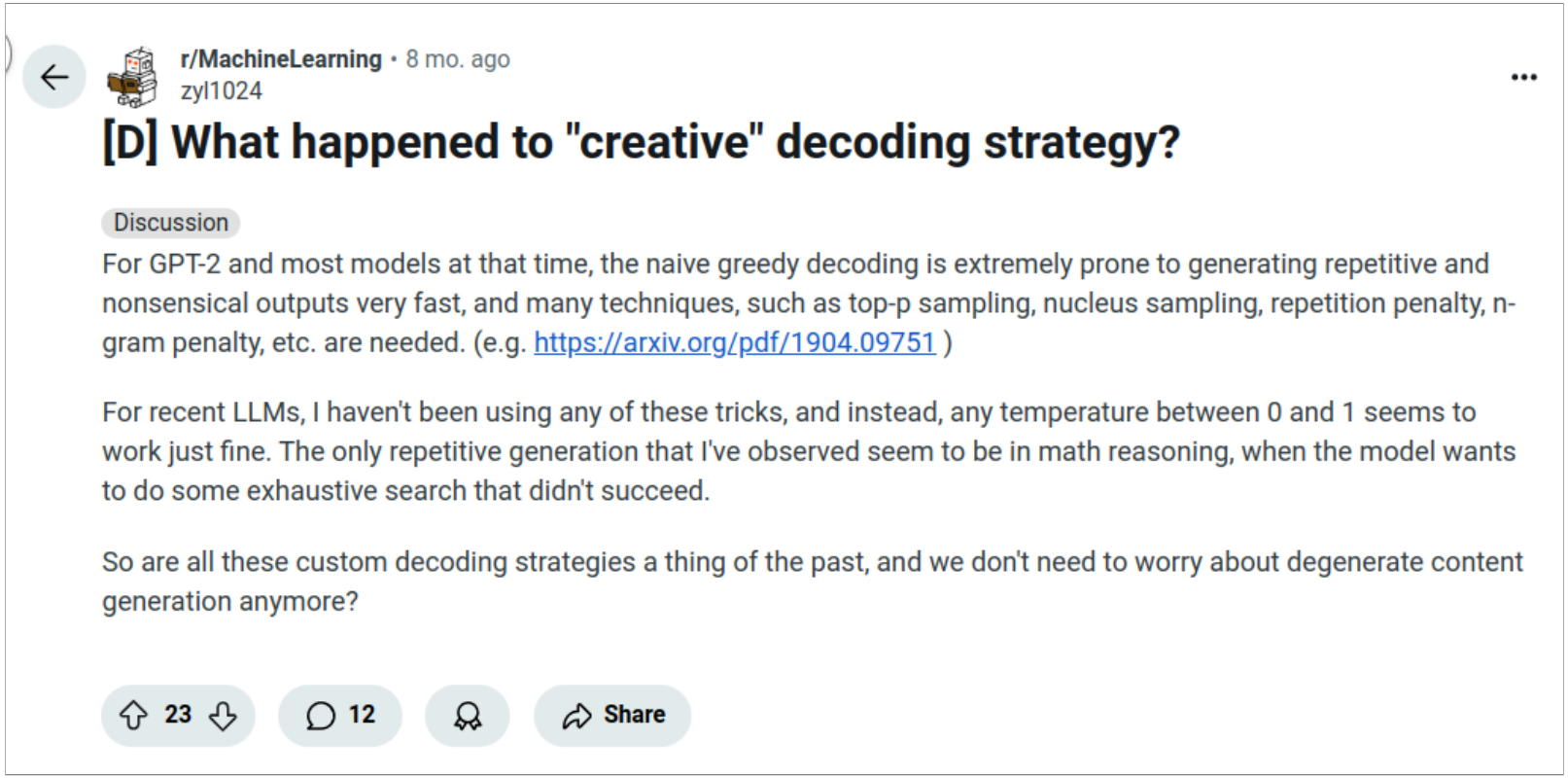
$T > 1$: **more uniformly random**







Is greediness all you need?



r/MachineLearning • 8 mo. ago
zyl1024

[D] What happened to "creative" decoding strategy?

Discussion

For GPT-2 and most models at that time, the naive greedy decoding is extremely prone to generating repetitive and nonsensical outputs very fast, and many techniques, such as top-p sampling, nucleus sampling, repetition penalty, n-gram penalty, etc. are needed. (e.g. https://arxiv.org/pdf/1904.09751)

For recent LLMs, I haven't been using any of these tricks, and instead, any temperature between 0 and 1 seems to work just fine. The only repetitive generation that I've observed seem to be in math reasoning, when the model wants to do some exhaustive search that didn't succeed.

So are all these custom decoding strategies a thing of the past, and we don't need to worry about degenerate content generation anymore?

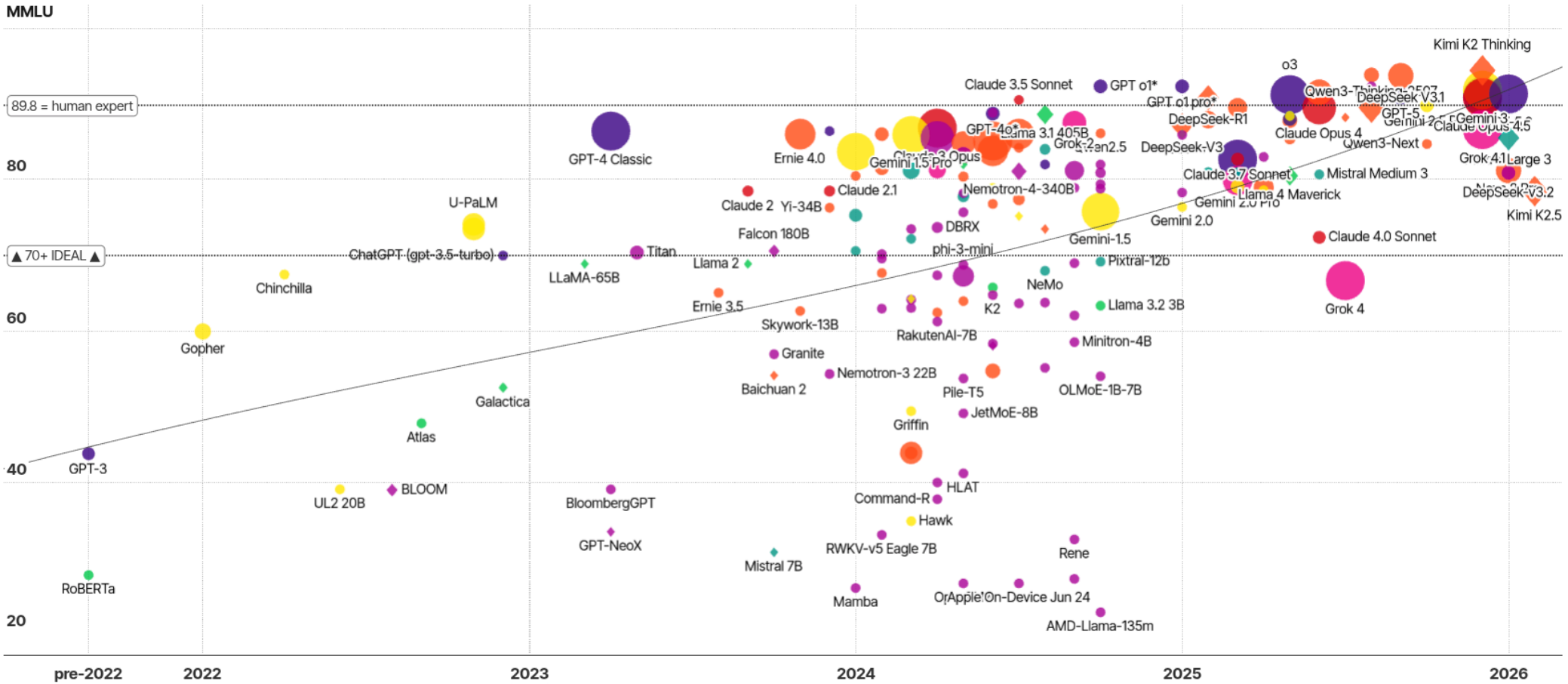
23 12 Share

source: Reddit

Navigating the LLM zoo

LLM size and capabilities

source: informationisbeautiful.net

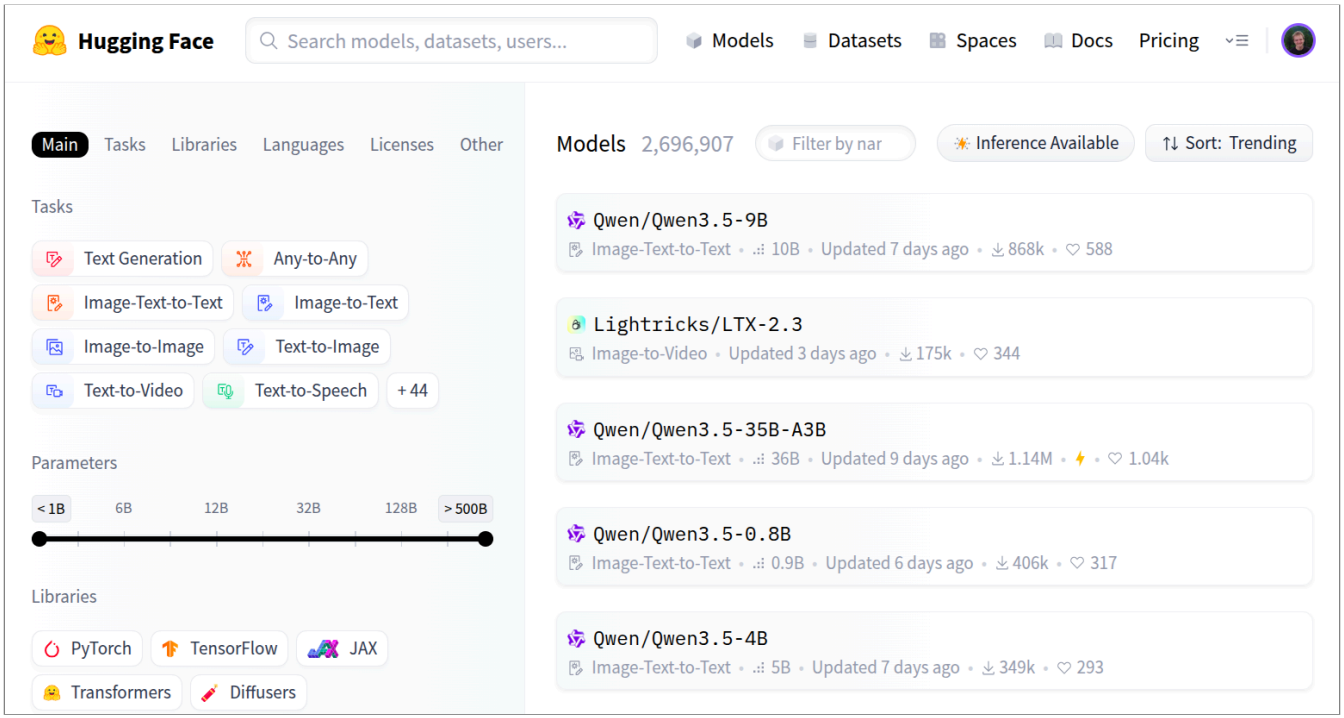


HuggingFace: source of open LLMs

source: HuggingFace Models

HuggingFace: the largest repository of open LLMs.

As of March 2026, it contains 2.7M models (many of these are derivatives).



Model sources and leaderboards

source: Artificial Analysis

Artificial Analysis LLM Leaderboard: rating LLMs across many dimensions (context, window size, price, speed, performance…).

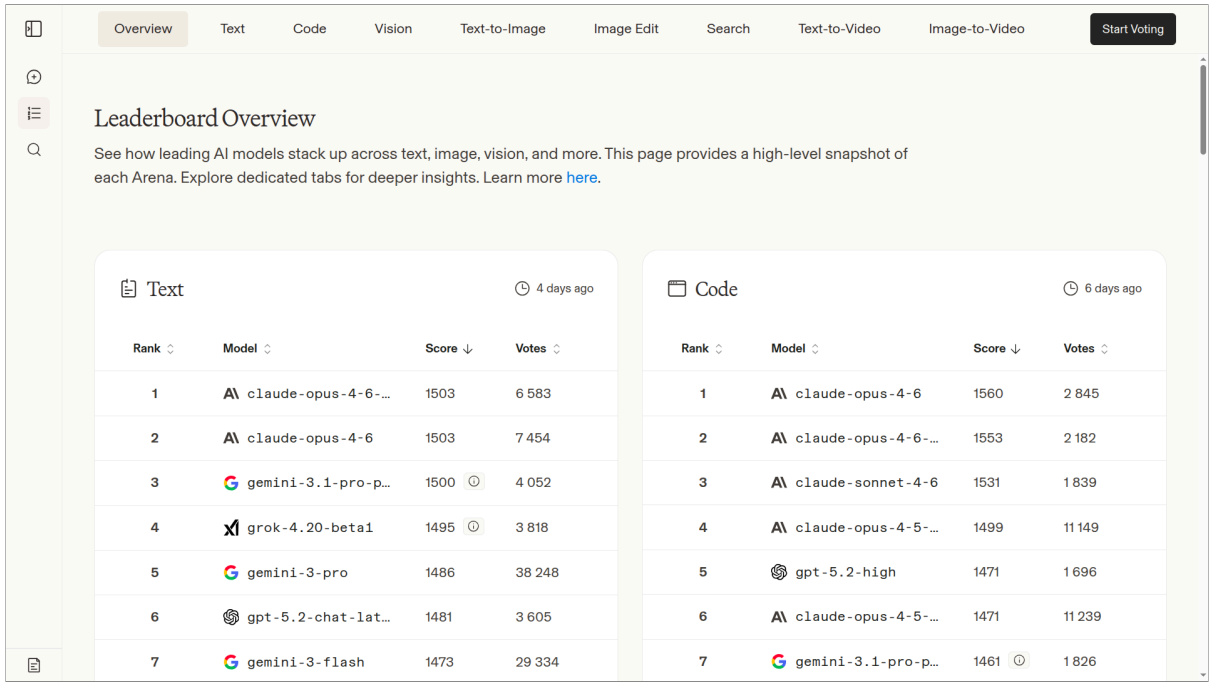
Model performance is grouped under a single “Intelligence index” (=combined score from 10 benchmarks).

	Features		Intelligence	Price	Speed	Latency	
Model	Context Window	Creator	Artificial Analysis Intelligence Index	Blended *USD/1M Tokens*	Median *Tokens/s*	Latency *First Answer Chunk (s)*	Further Analysis
Gemini 3.1 Pro Preview	1m	Google	57	$4.50	119	33.59	Model Providers
GPT-5.4 (xhigh)	1m	OpenAI	57	$5.63	78	184.99	Model Providers
GPT-5.3 Codex (xhigh)	400k	OpenAI	54	$4.81	65	96.73	Model Providers
Claude Opus 4.6 (max)	200k	Anthropic	53	$10.00	46	15.33	Model Providers
Claude Sonnet 4.6 (max)	200k	Anthropic	52	$6.00	47	100.63	Model Providers
GPT-5.2 (xhigh)	400k	OpenAI	51	$4.81	67	81.58	Model Providers
GLM-5	200k	Z AI	50	$1.55	61	1.54	Model Providers
GPT-5.2 Codex (xhigh)	400k	OpenAI	49	$4.81	92	57.75	Model Providers

Model sources and leaderboards

source: Arena.ai

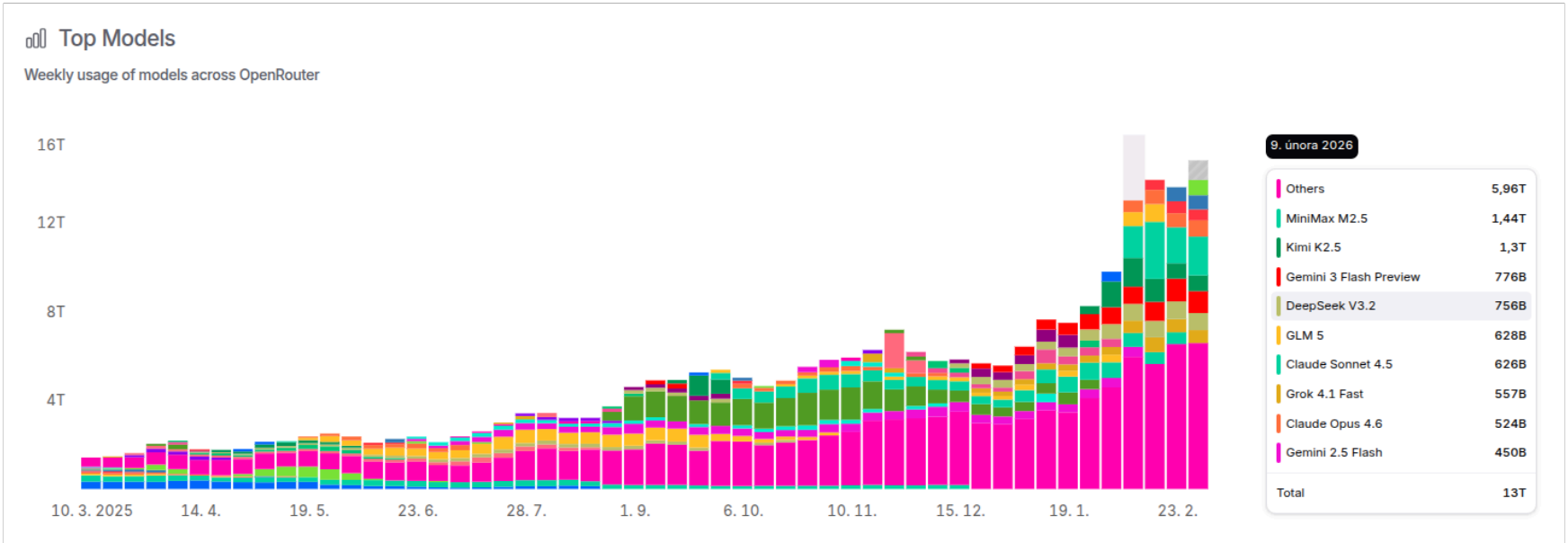
Arena.ai: Elo rating of LLMs: for a pair of answers from different models, users decide which is better.



Model sources and leaderboards

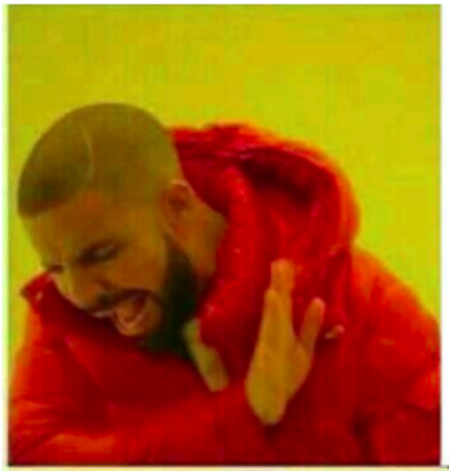
source: OpenRouter

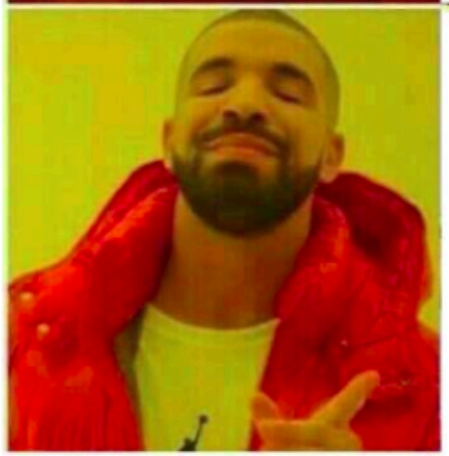
OpenRouter: routing traffic to various LLM providers, tracks real model usage through their proxy.



Deploying LLMs

How to use LLMs





How to use LLMs

Proprietary APIs

- OpenAI (ChatGPT, GPT-4o)
- Anthropic (Claude)
- Google (Gemini)
- …

✅ Easy to use, no hardware needed

❌ Paid, no control over the model

Open models (local)

- Meta (Llama)
- Mistral
- Qwen
- …

✅ Free, full control

❌ Requires hardware (GPU)

Frameworks for running open LLMs

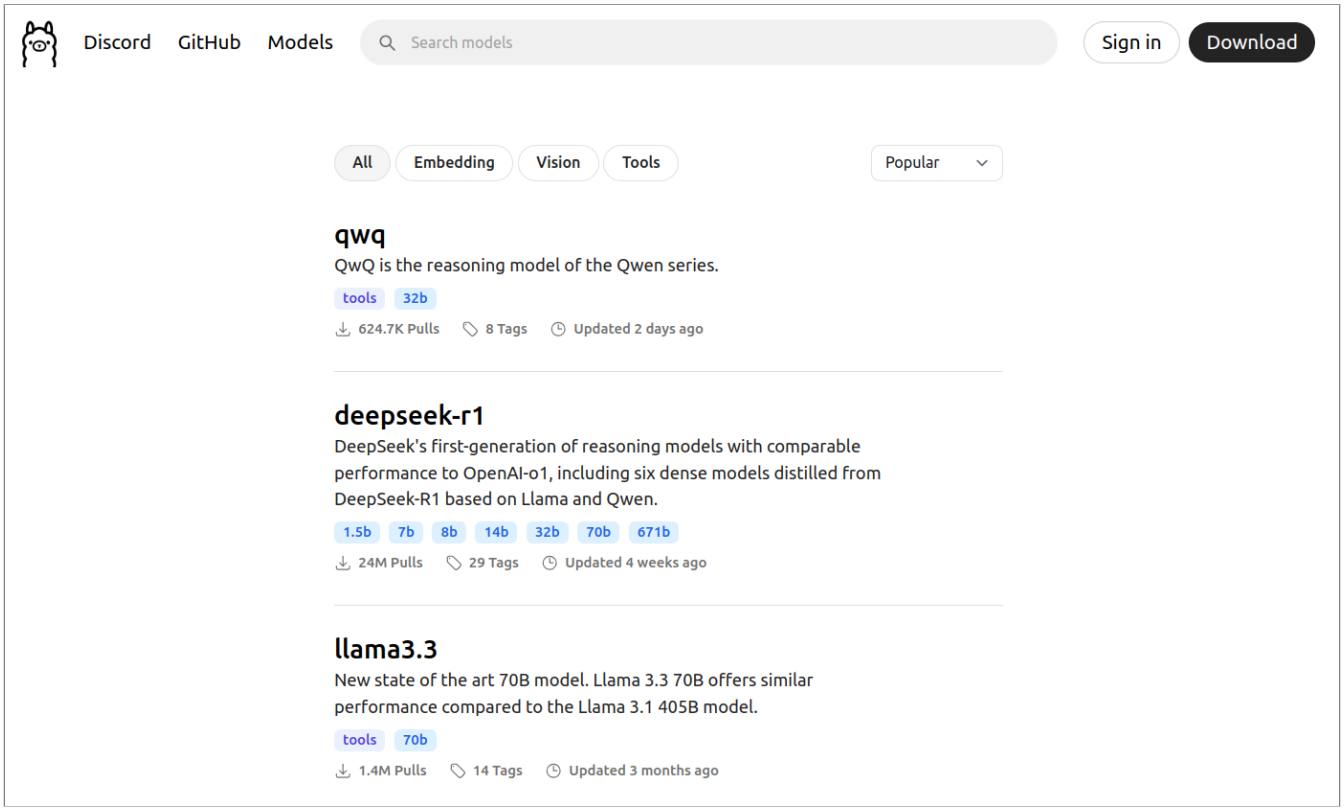
source: HF Transformers

HuggingFace transformers: Python library for loading models from the HuggingFace model repository.

Frameworks for running open LLMs

source: Ollama

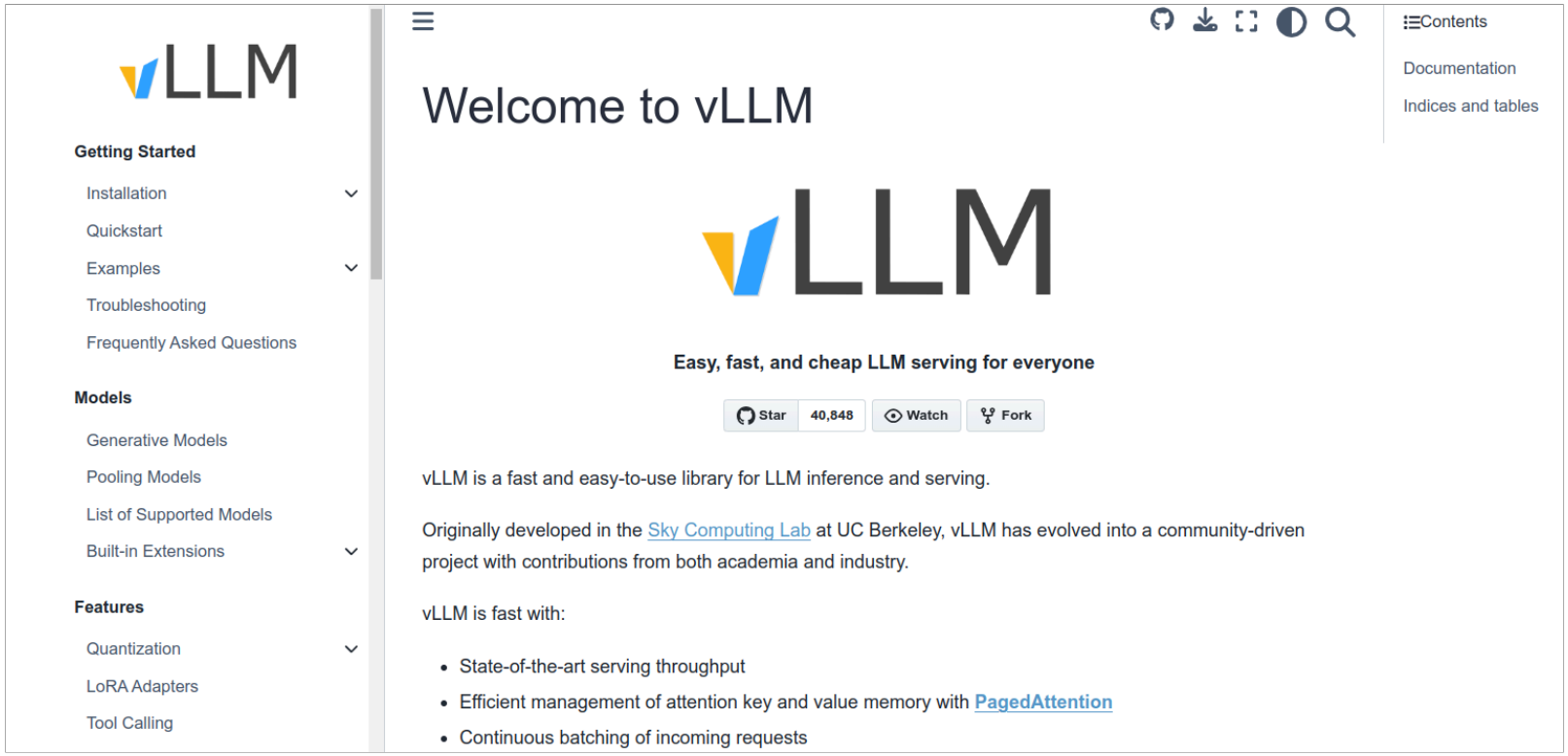
Ollama: running LLMs locally, easy to use, focus on quantized models.



Frameworks for running open LLMs

source: vLLM

vLLM: efficient library for serving of LLMs at scale.



Demo time 🧑‍💻

👉 HuggingFace LLM tutorial

Summary

Summary

- **Terms**:
  - **inference** = using a trained model for predictions
  - **generation** = producing a sequence of tokens
  - **decoding** = selecting the next token.
- **Greedy decoding** is the simplest approach
- **Beam search** improves it by keeping k hypotheses.
- **Stochastic methods** (top-k, top-p, temperature) add randomness to avoid repetitive and dull outputs.
- Open LLMs can be run locally using **HuggingFace transformers**, **Ollama**, or **vLLM**.

Links and resources

- HuggingFace models
- Awesome LLM: curated list of resources
- Transformer inference: 3D visualization
- HuggingFace decoding algorithms overview
- HuggingFace text generation strategies
- Common pitfalls when generating text with LLMs
- Visualizing decoding strategies
- Minimum Bayes Risk decoding

Further reading

- **On NMT Search Errors and Model Errors: Cat Got Your Tongue?** (Stahlberg and Byrne, 2019) – what happens if one manages to approximate exact inference
- **On decoding strategies for neural text generators** (Wiher et al., 2022) – language generation tasks vs. decoding strategies.
- **If beam search is the answer, what was the question?** (Meister et al., 2020) – why does beam search work so well?
- **Understanding the properties of Minimum Bayes Risk decoding in neural machine translation** (Müller and Sennrich, 2021) – when can MBR be useful?

Bonus: extra decoding algorithms

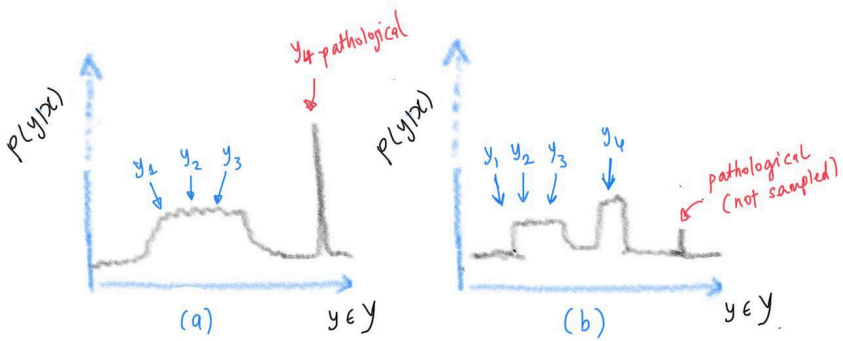
Minimum Bayes Risk (MBR) decoding

source: Minimum Bayes Risk Decoding

Selecting the sequence **most similar to other sequences** = “consensus decoding”:

$$y^* = \arg\max_{y_k \in \mathcal{Y}} \sum_{y_\ell \in \mathcal{Y} \setminus \{y_k\}} \mathrm{sim}(y_k, y_\ell)$$

- Useful for minimizing pathological behavior.
- Intractable → we need a sampling algorithm.
- Application in ASR and machine translation.



Mirostat

source: Basu et al. (2021)

Aims to eliminate **repetition and incoherent text** in stochastic algorithms.

Adapting the k parameter based on the desired text perplexity.

Parameters:

- τ – the target perplexity
- η – learning rate

Algorithm 1: Adaptive top-k sampling for perplexity control

Target cross entropy τ, maximum cross entropy $\mu = 2 * \tau$, learning rate η

while *more words are to be generated* **do**

- Compute $\hat{s}$ from (40): $\frac{\sum_{i=1}^{N-1} t_i b_i}{\sum_{i=1}^{N-1} t_i^2}$
- Compute k from (41): $k = \left(\frac{\hat{\epsilon} 2^{\mu}}{1 - N^{-\hat{\epsilon}}} \right)^{\frac{1}{\hat{s}}}$
- Sample the next word X using top-k sampling
- Compute error: $e = \mathfrak{S}(X) - \tau$
- Update μ: $\mu = \mu - \eta * e$

end

Mirostat

"mirum" = surprise, "stat" = control

(Locally) typical sampling

source: Meister et al. (2023)

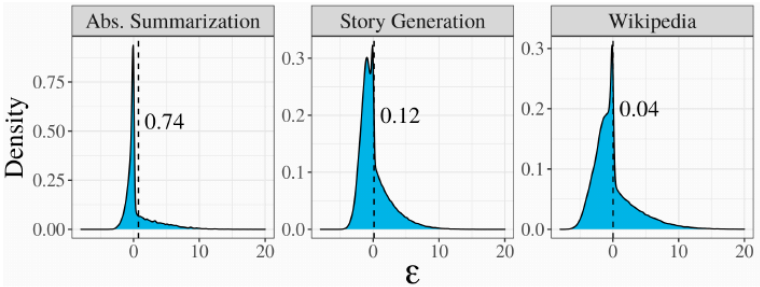
Similar to Mirostat, but **dynamic**: the perplexity is not pre-specified.

Ensures that in each decoding step, text perplexity is **close to the model perplexity**.

Example: coin toss

$p(H) = 0.75, p(T) = 0.25$:

- $HHHH$ → most probable sequence
- $HTHH$ → typical sequence



Originates from the information theory: **typical messages** are the messages that we would expect from the process.