LLM Inference

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Today’s learning outcomes

After today’s class, 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.

Generating text

Recap: 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.
```

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

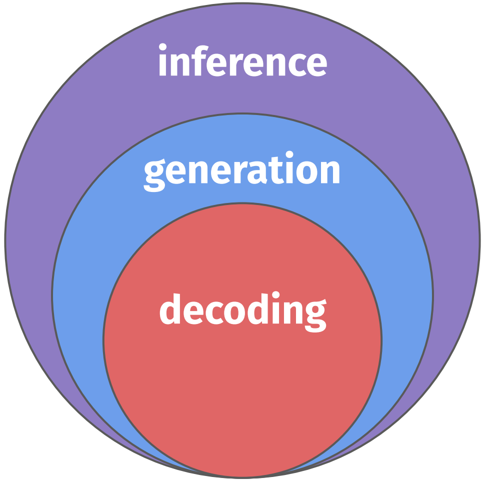
The concept of using a trained model for **making predictions** on new data (for classification, sequence tagging, text generation, ...).

Generation

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

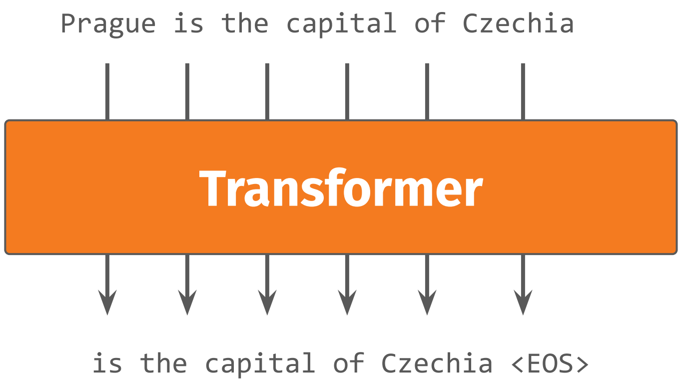
Decoding

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



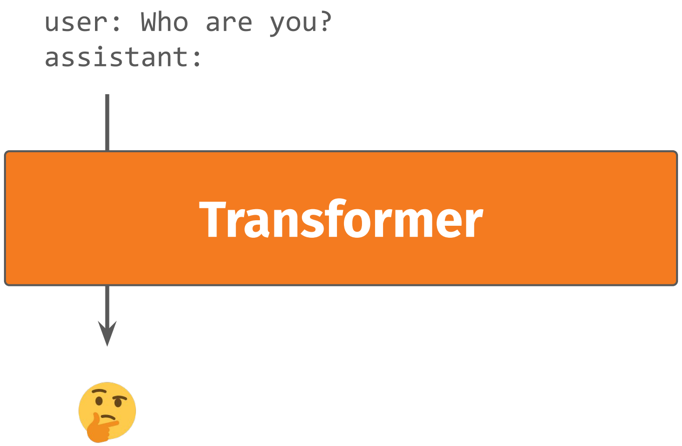
Training vs. inference

Training



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

Inference

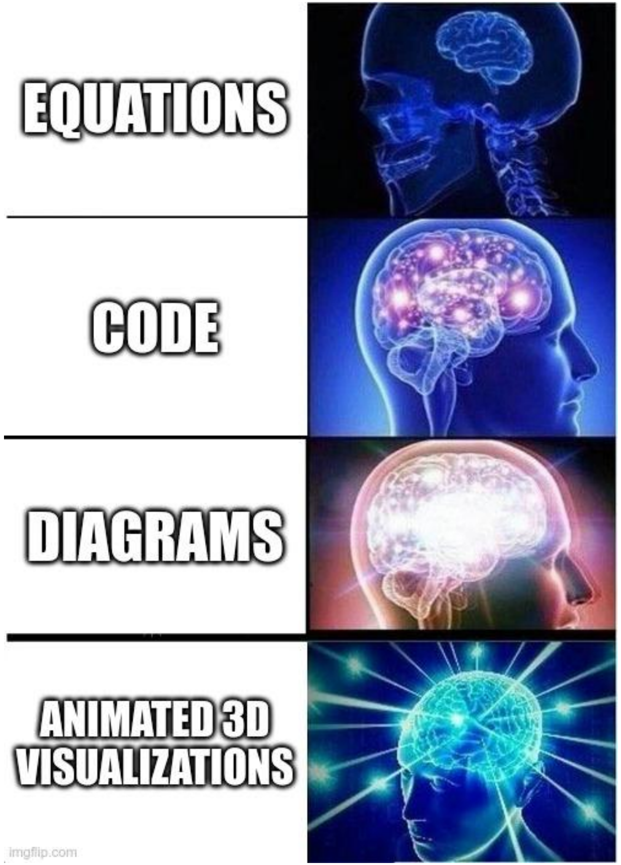


Decoding: We need to select what token should come next.

What happens during LLM inference?

https://bbycroft.net/llm

https://github.com/bbycroft/llm-viz



Generating text

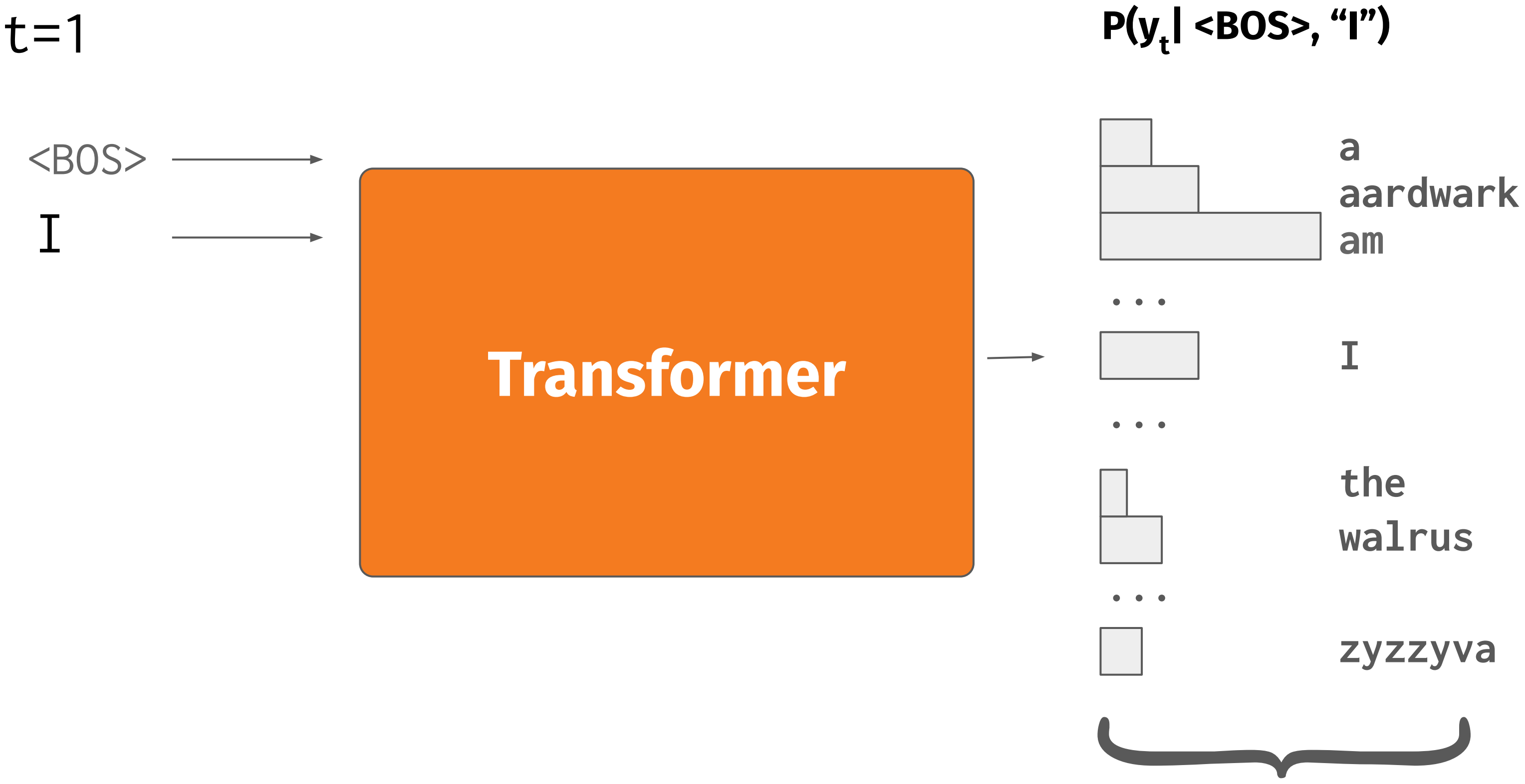
For every sequence, the LLM generates a **probability distribution** over the vocabulary of tokens.

To generate text:

1. Start with a sequence of tokens (“prompt”).
2. Feed the sequence 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 (2).

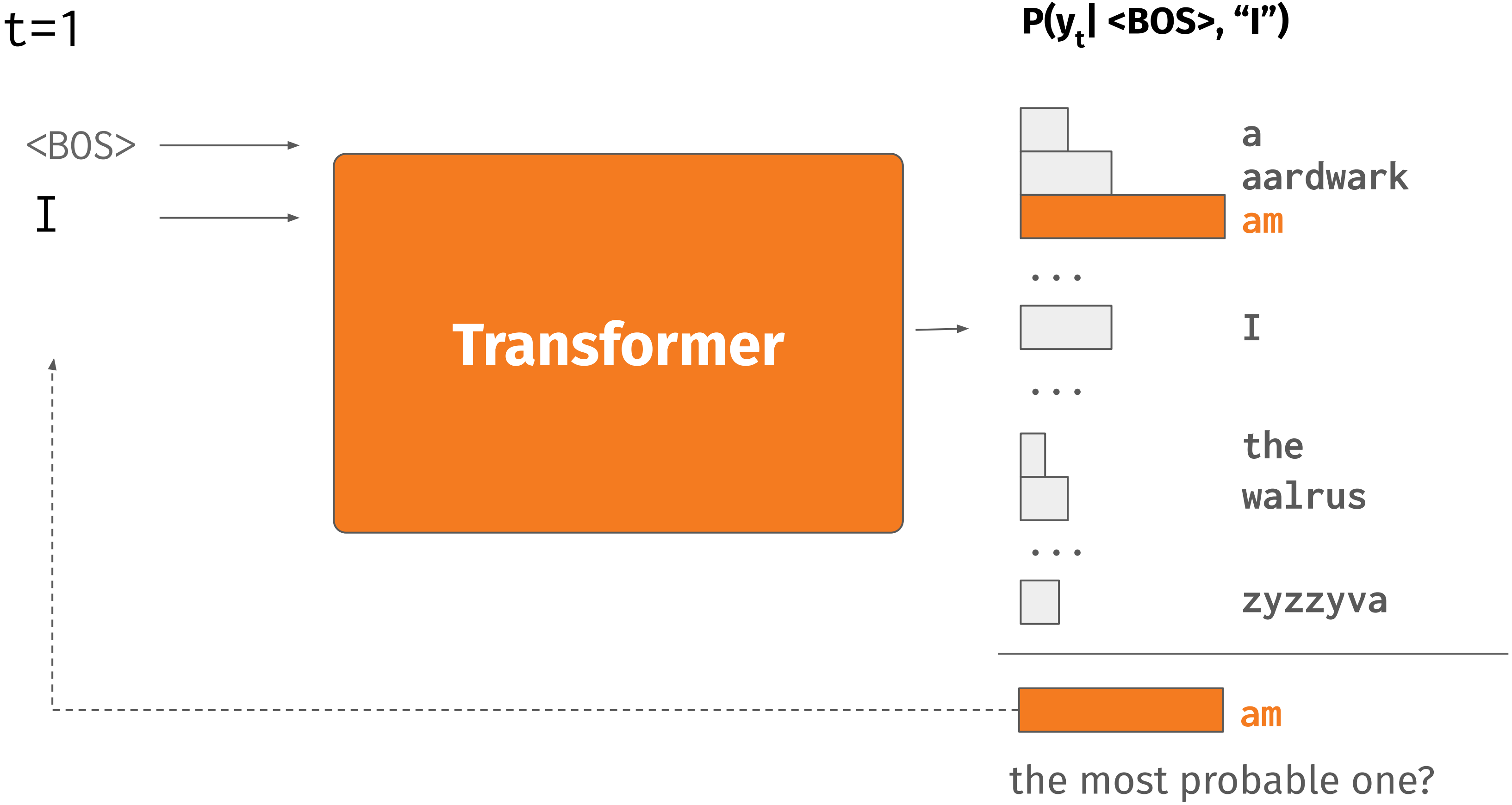
→ Autoregressive decoding

Autoregressive decoding

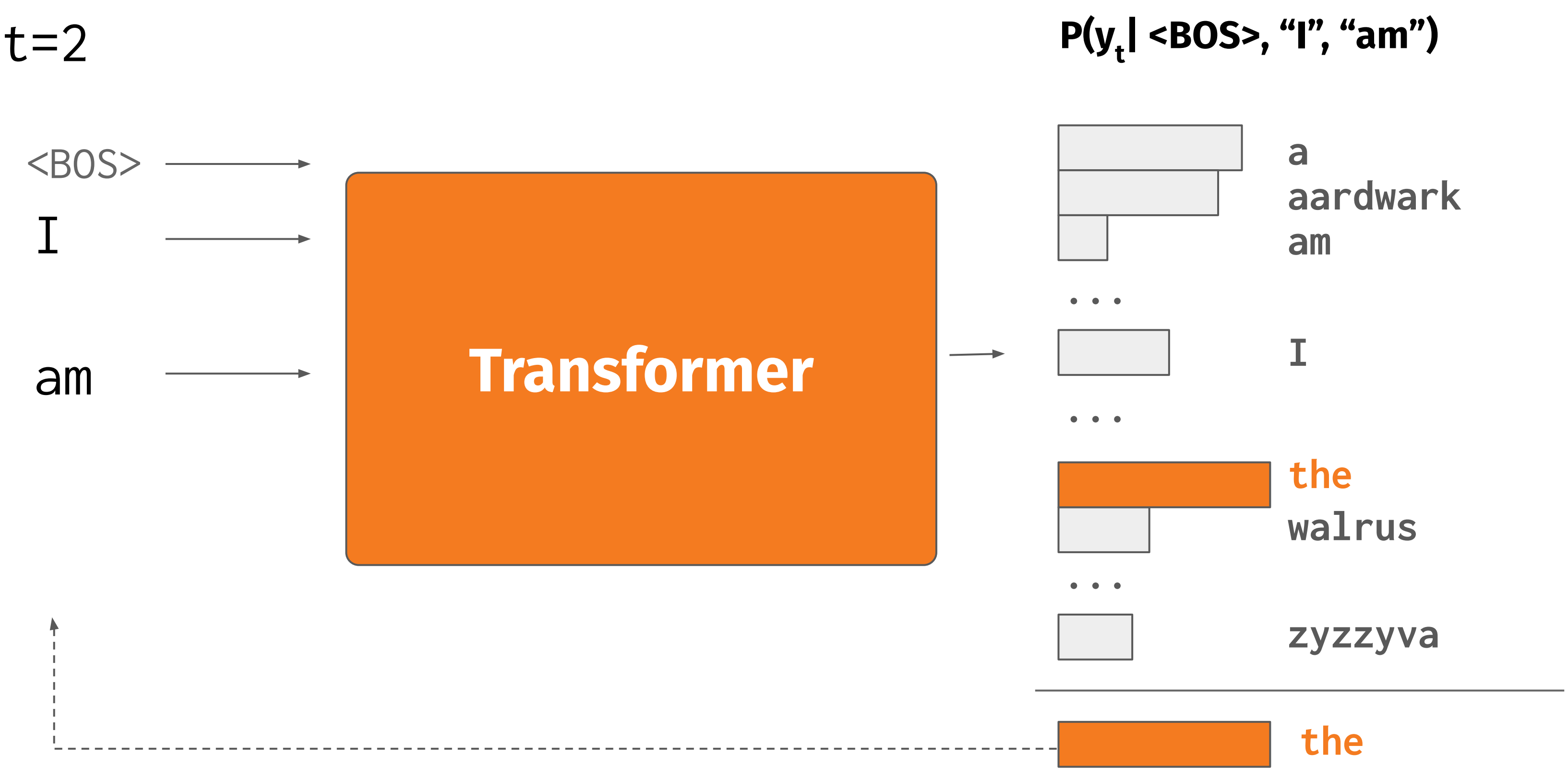


which token to select?

Autoregressive decoding

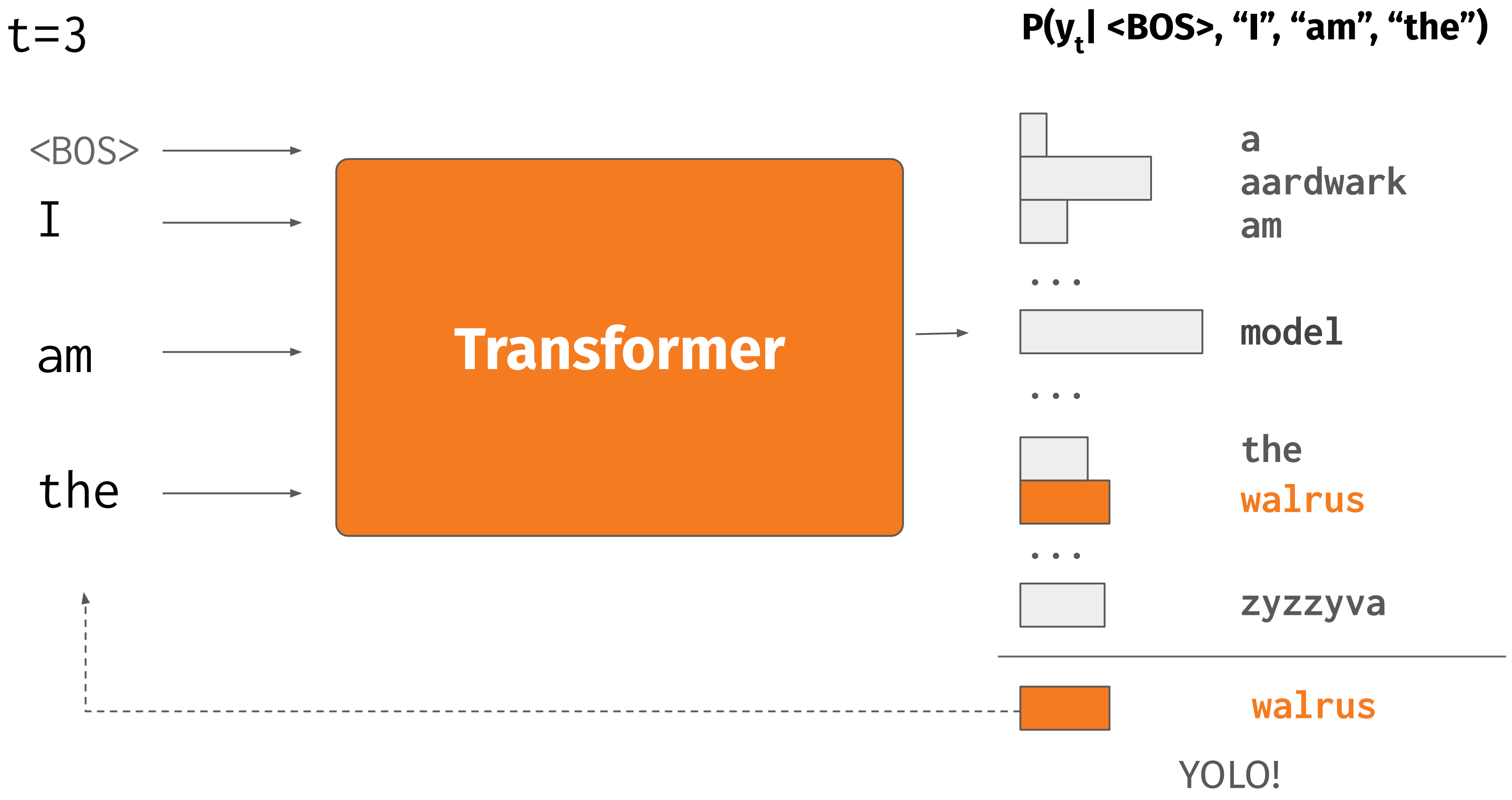


Autoregressive decoding



every single time?

Autoregressive decoding



Autoregressive decoding

t=4

<BOS>

I

am

the

walrus

Transformer

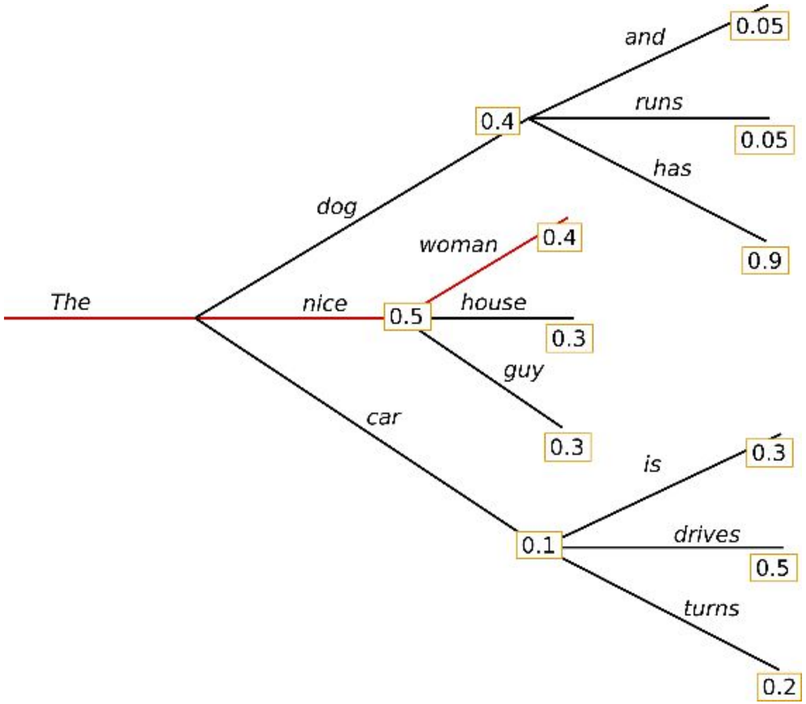
Decoding algorithms

Greedy decoding

- Selecting the **most probable token in each step** *t:*

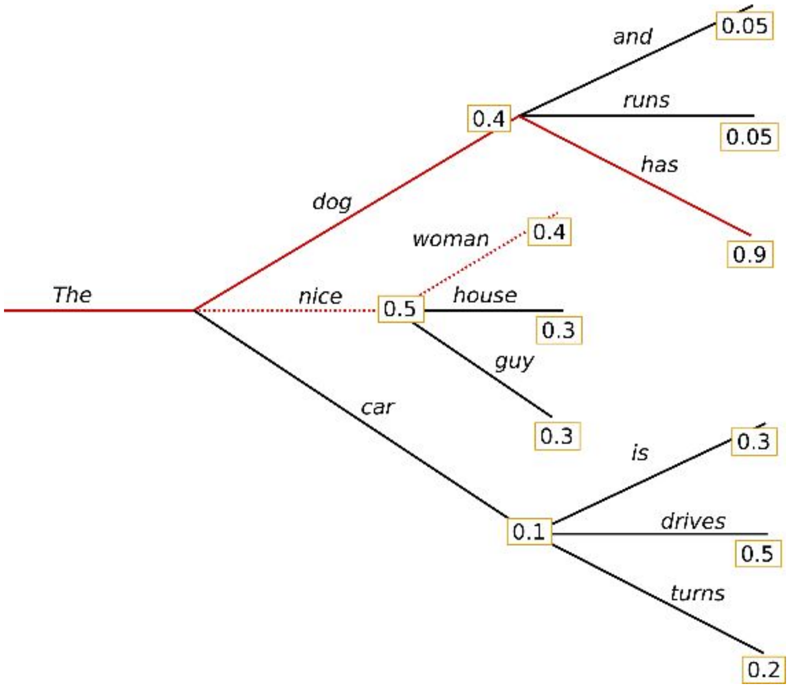
$$y_t = \arg\max_{y_t \in \mathcal{V}} P(y_t | y_1, \ldots, y_{t-1})$$

- Very fast, often works satisfactorily (especially with LLMs)
- Non-parameteric



Beam search

- Parameter ***k*: number of sequences**
- Each step *t*:
  - Extend the sequences from the step *t-1* with all possible tokens.
  - Select the *k* most probable sequences for the step *t+1*.
- Tuning k:
  - *k*=1 == greedy decoding
  - larger *k* → slower algorithm
  - k>1 allows re-ranking results



Exact Inference = Maximum a posteriori (MAP) decoding

- Finding **the most probable sequence** (=mode of the LM distribution) given the step-wise factorization of sequence probability:

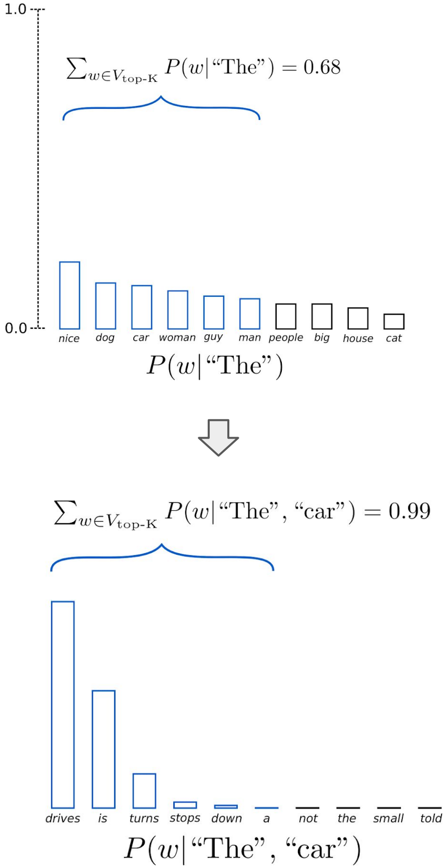
$$y^* = \arg\max_{y \in \mathcal{Y}} P(y) = \arg\max_{y \in \mathcal{Y}} \prod_{i=1}^{t} P(y_i | y_1, \ldots, y_{t-1})$$

- Intractable (exponential search space)
- Can be approximated by greedy decoding or beam search
- The mode may not be a good solution! ([1], [2])
  - e.g. an empty sequence

Top-k sampling

source: https://huggingface.co/blog/how-to-generate

- Selecting the token in each step **randomly from *k* ∈ {1, ..., |V|} most probable tokens**
- The truncated distribution is re-weighed using softmax



step #1

prefix = “The”
→ sampling from {nice, dog, car, woman, guy, man}

cum.prob. = 0.68

step #2

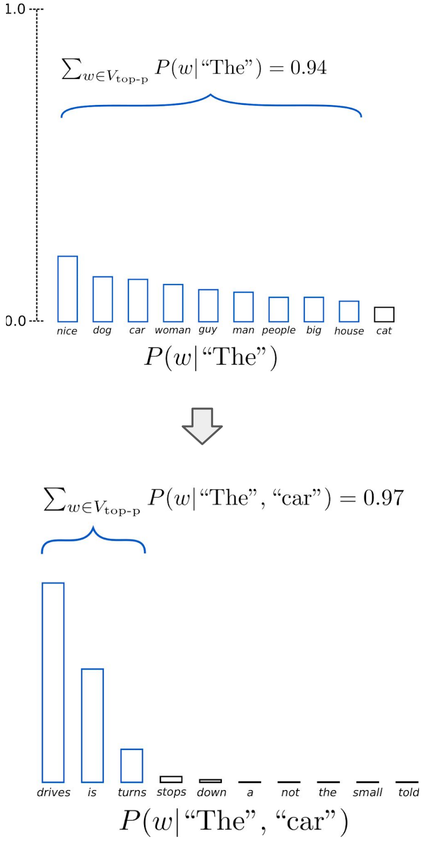
prefix = “The car”
→ sampling from {drives, is, turns, stops, down, a}

cum.prob. = 0.99

Top-p (nucleus) sampling

source: https://huggingface.co/blog/how-to-generate

- Sampling from **“nucleus”:** set of the most probable tokens with combined probability summing to $p \in (0, 1]$
- Similar to top-k sampling, but with a variable *k* in each step.



step #1

prefix = “The”
→ sampling from {nice, dog, car, woman, guy, man, people, big, house}

cum.prob. = 0.94 (>0.9)

step #2

prefix = “The car”
→ sampling from {drives, is, turns}

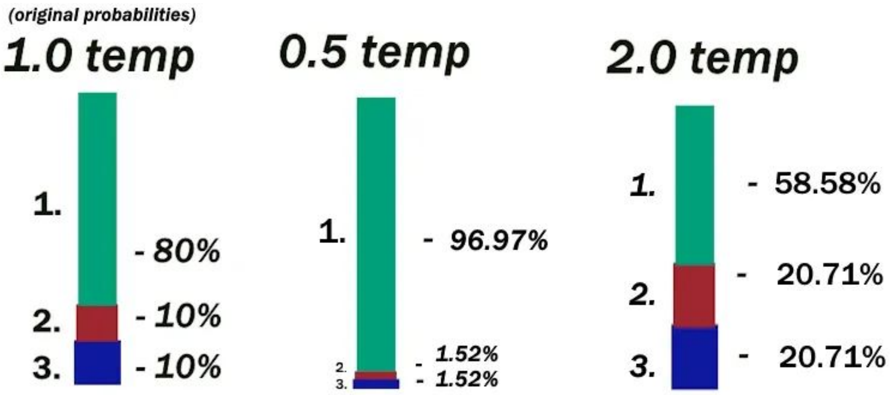
cum.prob. = 0.97 (>0.9)

Temperature

image source: Reddit

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

$$\mathrm{softmax}(y_i) = \frac{e^{y_i/T}}{\sum_{y_j \in \mathcal{V}_{\text{top-k}}} e^{y_j/T}}$$



Is greediness all you need?

source: Reddit

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.

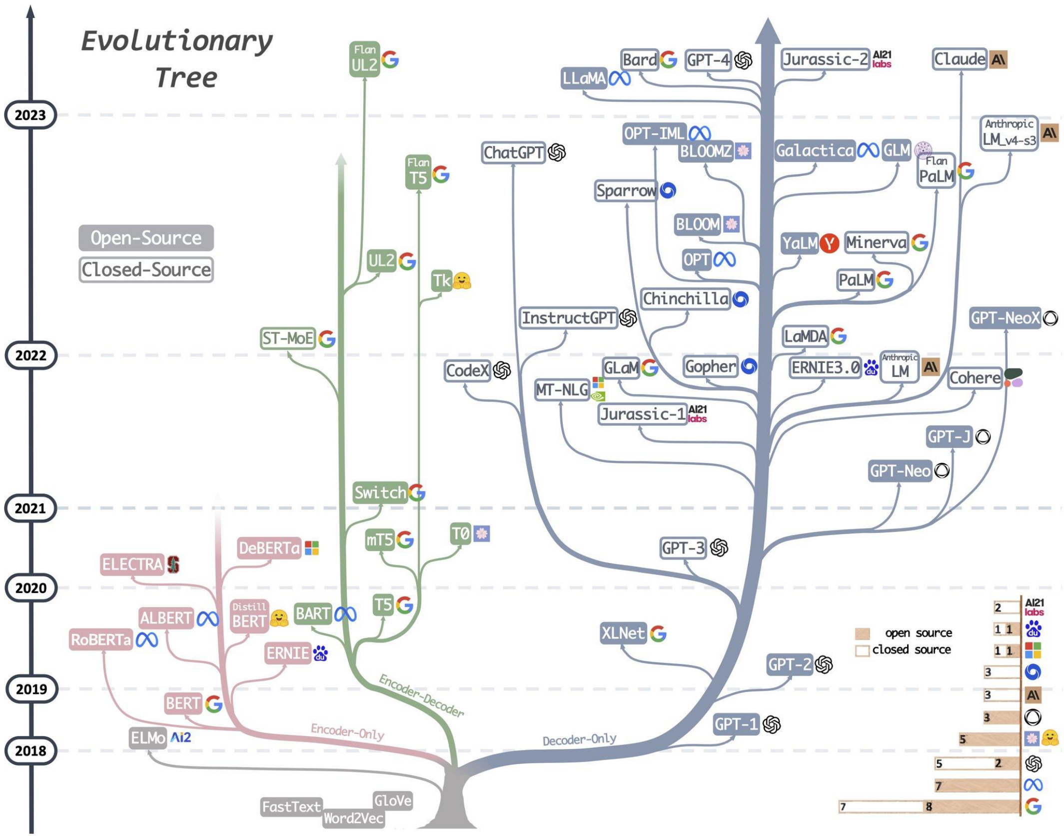
So are all these custom decoding strategies a thing of the past, and we don't need to worry about degenerate content generation anymore?

23 12 Share

Navigating the LLM zoo

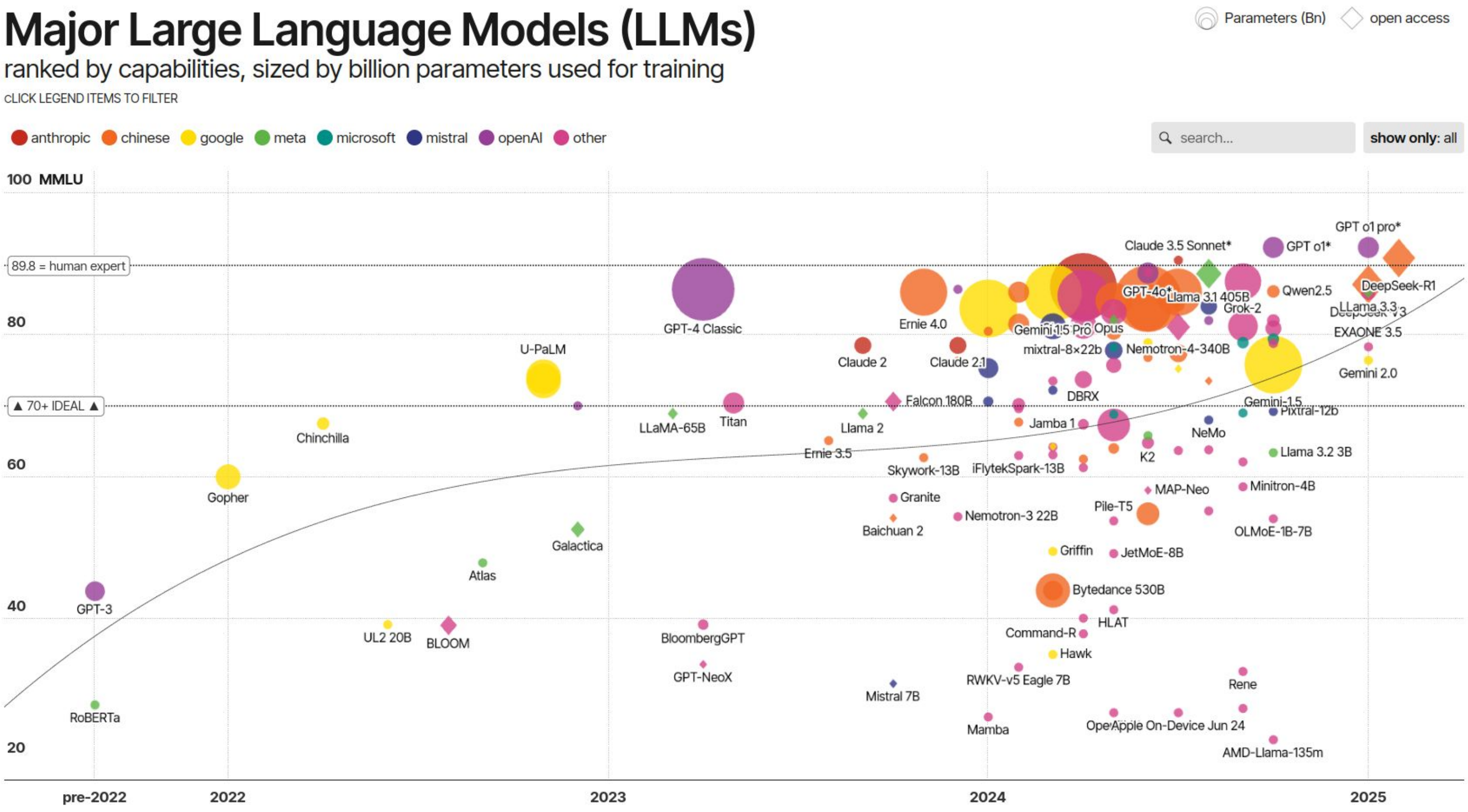
LLM evolutionary tree

source: https://arxiv.org/abs/2304.13712



LLM size and capabilities

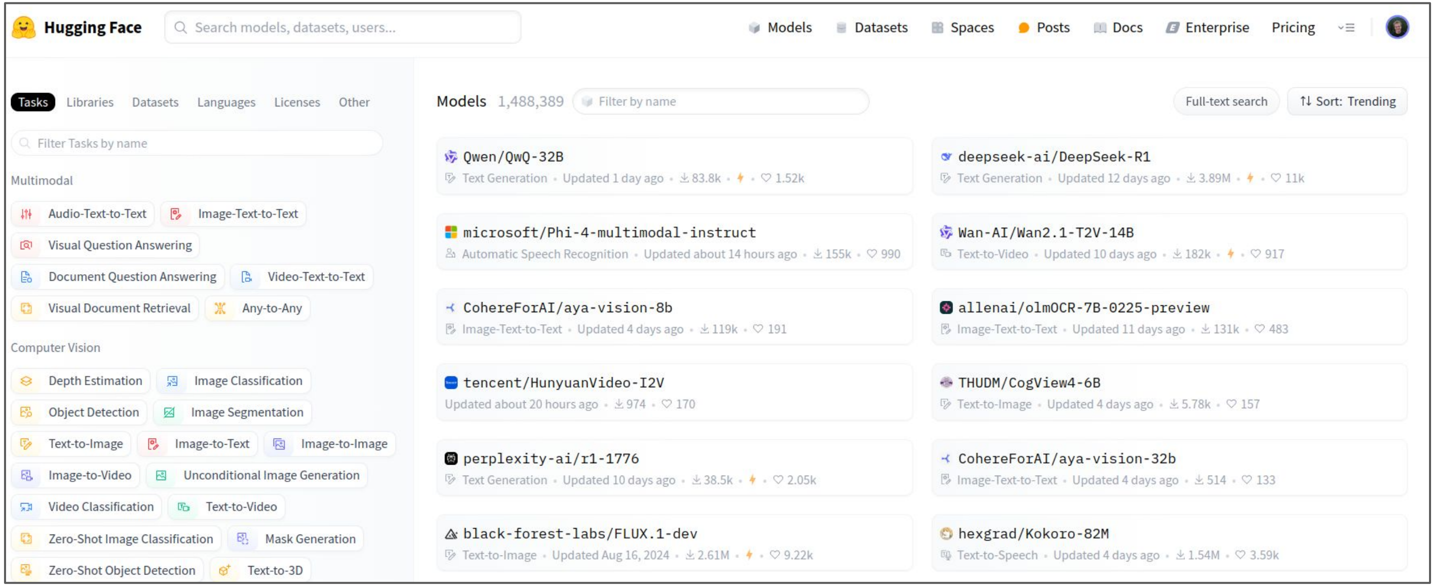
source: https://informationisbeautiful.net/visualizations/the-rise-of-generative-ai-large-language-models-llms-like-chatgpt/



Model sources and leaderboards

HuggingFace: the largest repository of open LLMs.

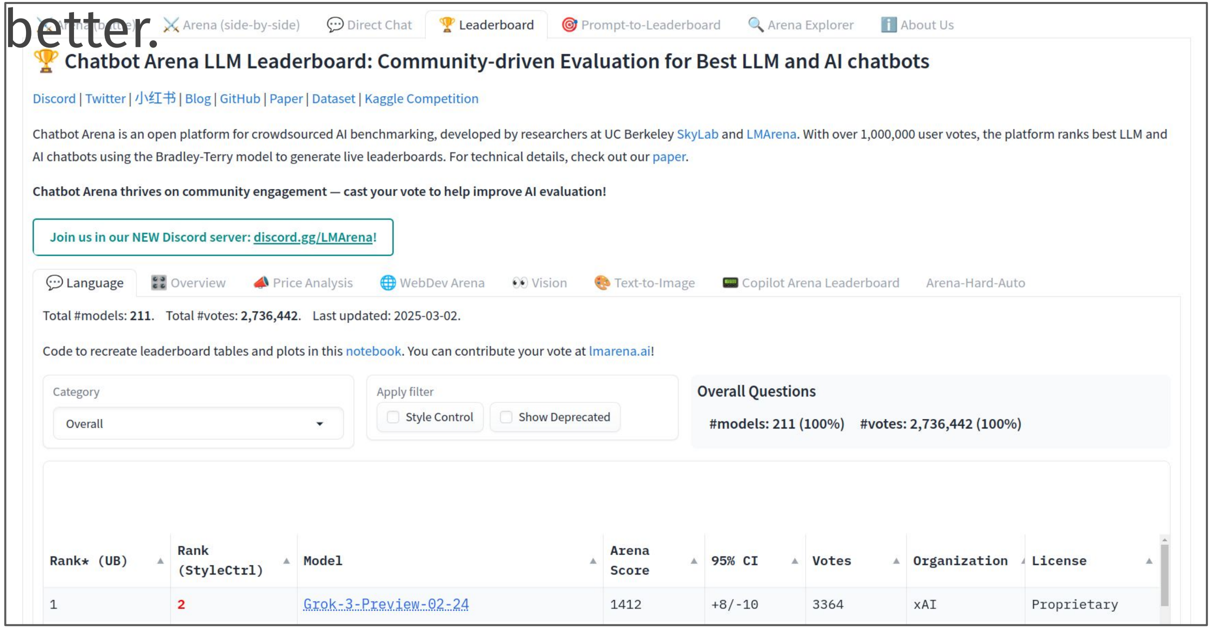
As of March 2025, it contains ~**1.5M models** (many of these are derivatives).



Model sources and leaderboards

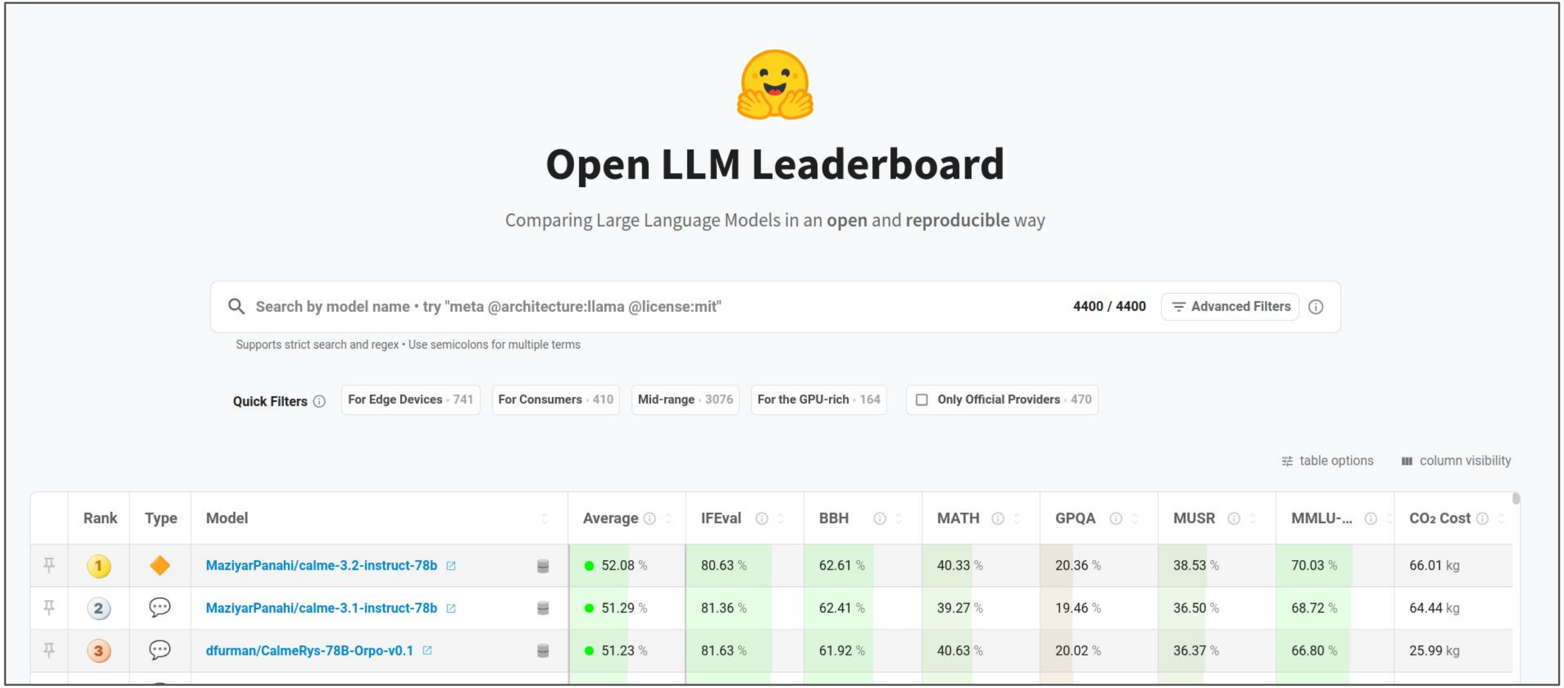
Chatbot Arena: Elo rating of LLMs.

For a pair of answers from different models, users decide which is better.



Model sources and leaderboards

Open LLM Leaderboard: ratings of open LLMs on benchmarks.



Rank	Type	Model	Average	IFEval	BBH	MATH	GPQA	MUSR	MMLU-...	CO_2 Cost
1		MaziyarPanahi/calme-3.2-instruct-78b	52.08 %	80.63 %	62.61 %	40.33 %	20.36 %	38.53 %	70.03 %	66.01 kg
2		MaziyarPanahi/calme-3.1-instruct-78b	51.29 %	81.36 %	62.41 %	39.27 %	19.46 %	36.50 %	68.72 %	64.44 kg
3		dfurman/CalmeRys-78B-Orpo-v0.1	51.23 %	81.63 %	61.92 %	40.63 %	20.02 %	36.37 %	66.80 %	25.99 kg

Rules of thumb for selecting a model

- Try a **general-purpose model** first.
  - You can specify your task using in-context learning.
  - RAG can help you with a custom knowledge base.
- You may want to use a **fine-tuned model**, but think carefully about which data it was finetuned on.
- You probably **do not want an off-the-shelf base model** unless you want to fine-tune it (or you are interested in LM on its own).
- Out of the newest models, select the **largest model you can support.**

Running LLMs locally

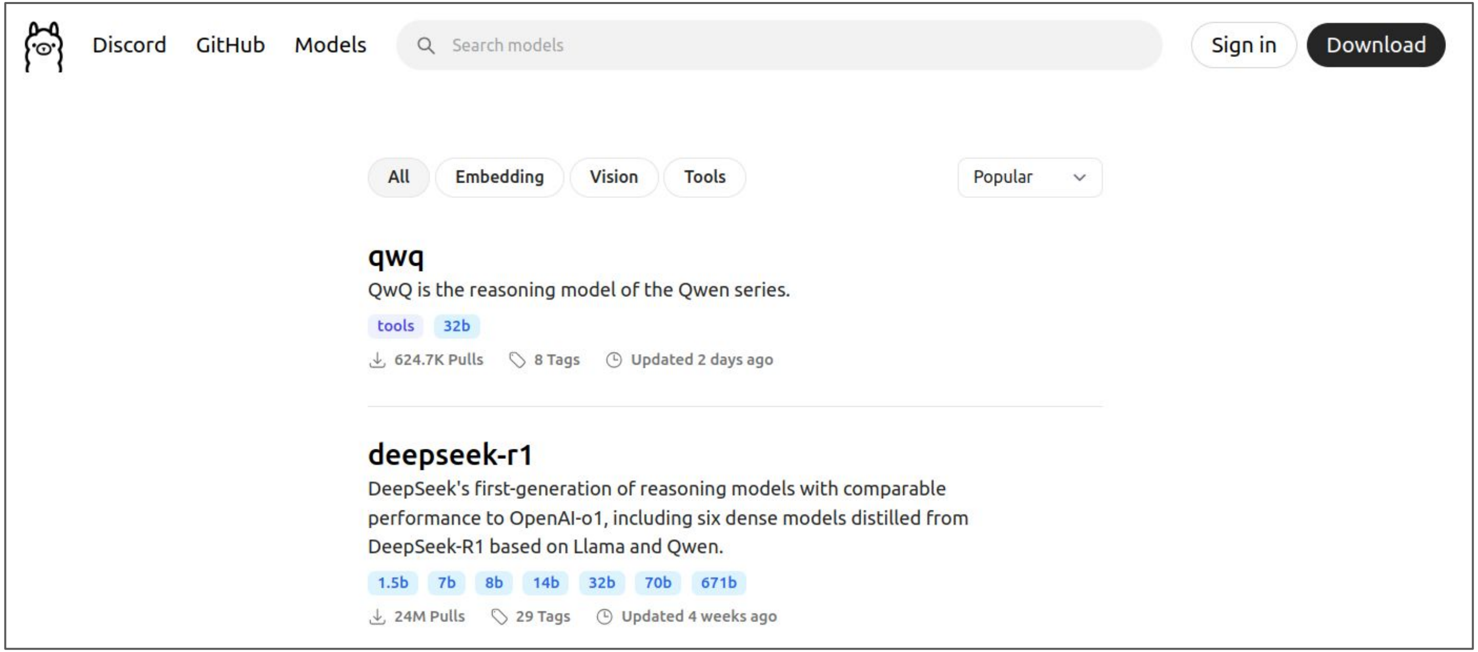
How to use LLMs

Frameworks for running open LLMs

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

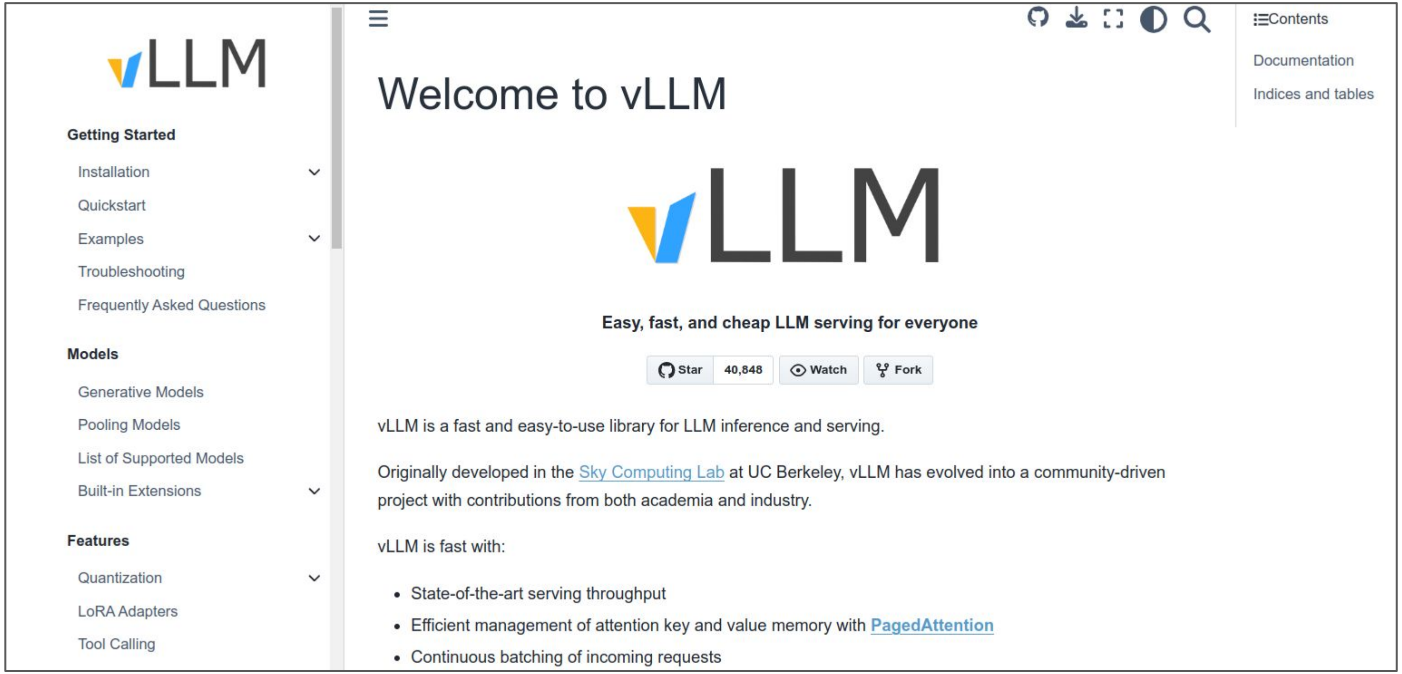
Frameworks for running open LLMs

Ollama: running a local server, easy to use, focus on quantized models



Frameworks for running open LLMs

vLLM: efficient library for serving of LLMs on an enterprise level



Demo time

https://huggingface.co/docs/transformers/llm_tutorial
https://mlabonne.github.io/blog/posts/2023-06-07-Decoding_strategies.html

Links

- Huggingface models
- Awesome LLM: curated list of resources
- Transformer inference: 3D visualization
- Huggingface decoding algorithms overview
- Huggingface text generation strategies (includes a few extra ones)
- Common pitfalls when generating text with LLMs
- Visualizing decoding strategies
- Minimum Bayes Risk decoding

Bonus: Extra decoding algorithms

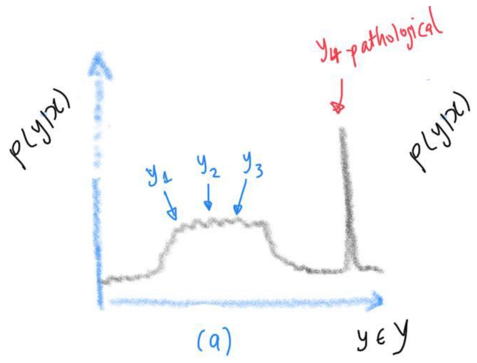
Minimum Bayes Risk (MBR) Decoding

source: [Minimum Bayes Risk Decoding]

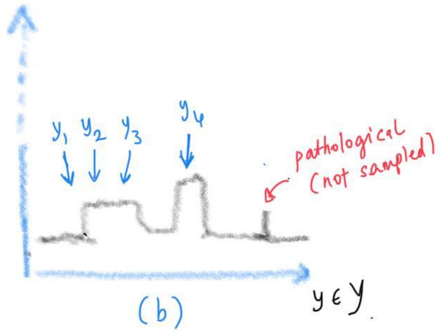
- Selecting the sequence most similar to other sequences = "**consensus decoding**"

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

- Useful for minimizing pathological behavior
- Intractable → we need a sampling algorithm
- Application in automatic speech recognition and machine translation



MAP 😕



MBR 😊

Mirostat

reference: https://openreview.net/pdf?id=W1G1JZEIy5_

- Aims to eliminate repetition and incoherent text in stochastic algorithms
- Adapting the *k* parameter based on the **desired text perplexity** (“mirum” = surprise, “stat” = control)
- Parameters:
  - τ (tau) - the target perplexity
  - η (eta) - learning rate

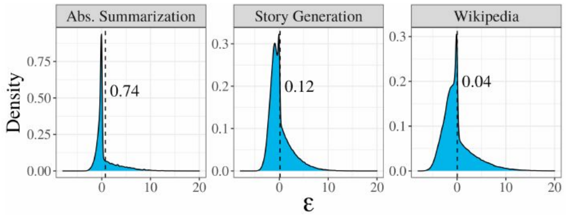
Algorithm 1: Adaptive top-k sampling for perplexity control

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

(Locally) typical sampling

reference: https://aclanthology.org/2023.tacl-1.7/

- Decodes text so that in each step, its perplexity is **close to the perplexity of the model**
  - Similar to Mirostat, but dynamic: the perplexity is not pre-specified
- Information theory: *typical* messages are the messages that we would expect from the process



p(H) = 0.75 H H H H → most probable sequence

p(T) = 0.25 H T H H → typical sequence

Further reading

- 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 (Muller and Sennrich, 2021)
  - When can MBR be useful?