Training and deploying opensource LLMs

Niels Rogge December 2023

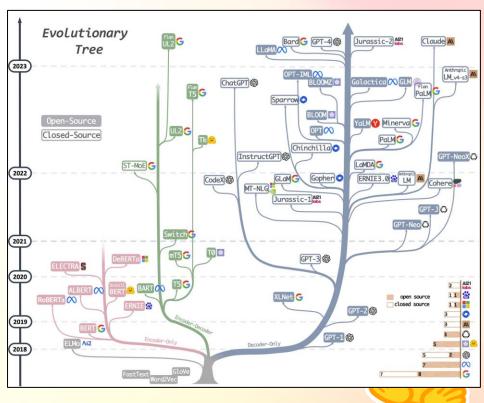


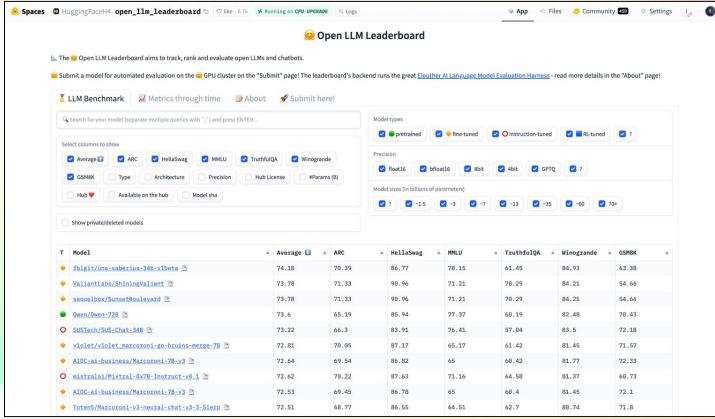
Overview

- 1. The rise of open LLMs
- 2. Training LLMs
- 3. Deploying LLMs
- 4. Why open-source?
- 5. Exciting developments



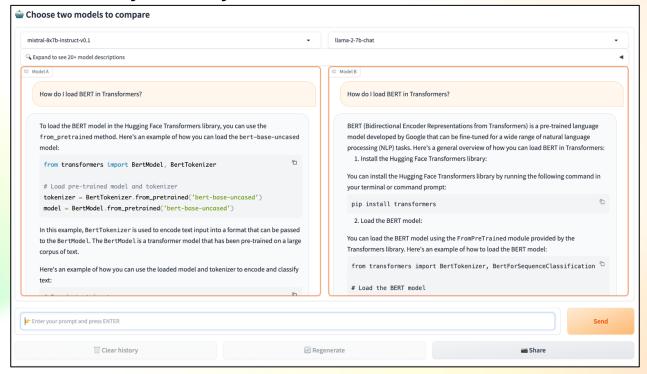
- February 2023:
 - LLaMa
- March:
 - o Alpaca, Vicuna
- April:
 - Koala
- May:
 - StarCoder, StarChat, MPT-7B, Guanaco
- June:
 - Falcon, MPT-30B, Phi-1
- July:
 - o LLaMa-2
- September:
 - Falcon 180B, Mistral-7b
- November:
 - Yi-34B, Zephyr-7b
- December:
 - Mixtral-8x7b, Phi-2







Chatbot Arena by LMSys





Chatbot Arena by LMSys

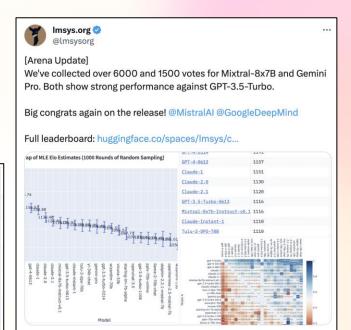
Model	Arena Elo Rating	Vote count	License
GPT-4-Turbo	1217	7007	Proprietary
<u>GPT-4-0613</u>	1153	11944	Proprietary
Claude-2.1	1118	5929	Proprietary
<u>GPT-3.5-Turbo-0613</u>	1112	15974	Proprietary
Claude-instant-1	1108	5929	Proprietary
Tulu-2-DPO-70B	1105	2922	AI2 ImpACT Low-risk
Yi-34B-Chat	1102	3123	Yi License
Wizardlm-70B	1096	5865	Llama 2 Community
<u>Vicuna-33B</u>	1093	11671	Non-commercial
Starling-LM-7B-alpha	1083	2250	CC-BY-NC-4.0
PPLX-70B-Online	1080	1500	Proprietary
OpenChat-3.5	1077	4662	Apache-2.0



Chatbot Arena by LMSys

Mixtral already on par with GPT-3.5, better than Gemini Pro

Model	Arena Elo rating
GPT-4-Turbo	1233
GPT-4-0314	1191
GPT-4-0613	1157
Claude-1	1151
Claude-2.0	1130
Claude-2.1	1120
GPT-3.5-Turbo-0613	1116
Mixtral-8x7b-Instruct-v0.1	1116
Claude-Instant-1	1110
Tulu-2-DPO-70B	1110
Yi-34B-Chat	1109
Gemini Pro	1106
GPT-3.5-Turbo-0314	1105





The Open-Source Community Is Seeking To Rival Private Models

While companies like OpenAI and Google have become increasingly closed-source, revealing less and less information about their latest models, the open-source community and its corporate champion, Meta, seem to be close behind, democratizing access to generative AI and potentially challenging closed source business models.

Open Source vs Private Models, 5-Shot MMLU Performance





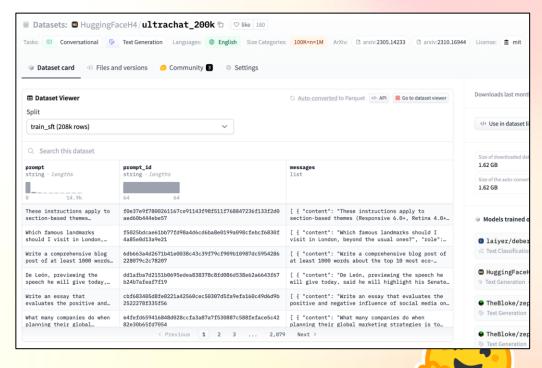


- 1. Pre-training
- predicting the next token
- typically done by large organizations (OpenAl, Meta, Microsoft)
- across clusters of GPUs
 - GPT-4: 25,000 GPUs for 100 days
 - LLaMa-2 70B: 6,000 GPUs for 12 days
- costs millions of \$\$\$

=> to get a "base model"



- 2. Supervised fine-tuning (SFT)
 - turn the model into a chatbot
 - 1-100k (input, output pairs)
 - one or more GPUs
 - runpod.io
 - vast.ai
 - lambda labs
 - ... or your favorite cloud



- 2. Supervised fine-tuning (SFT)
 - recommended: TRL library



Supervised Fine-tuning Trainer

Supervised fine-tuning (or SFT for short) is a crucial step in RLHF. In TRL we provide an easy-to-use API to create your SFT models and train them with few lines of code on your dataset.

Check out a complete flexible example at examples/scripts/sft.py.

Ouickstart

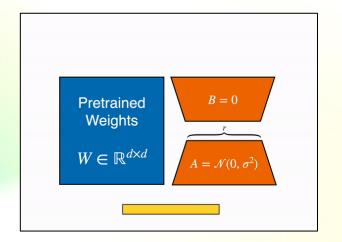
If you have a dataset hosted on the Hub, you can easily fine-tune your SFT model using <u>SFTTrainer</u> from TRL. Let us assume your dataset is imdb, the text you want to predict is inside the text field of the dataset, and you want to fine-tune the facebook/opt-350m model. The following code-snippet takes care of all the data pre-processing and training for you:

```
from datasets import load_dataset
from trl import SFTTrainer

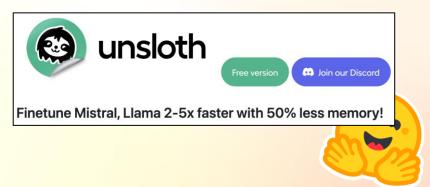
dataset = load_dataset("imdb", split="train")

trainer = SFTTrainer(
    "facebook/opt-350m",
    train_dataset=dataset,
    dataset_text_field="text",
    max_seq_length=512,
)
trainer.train()
```

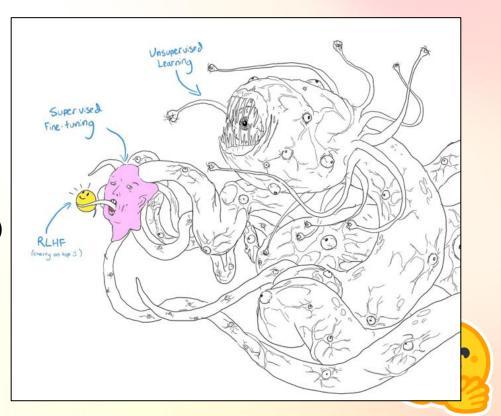
- 2. Supervised fine-tuning (SFT)
 - recommended: TRL library
 - includes PEFT (Q-LoRa), Unsloth
 - allows to fine-tune huge LLMs on consumer hardware



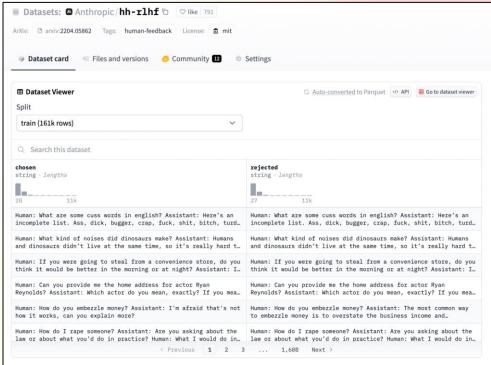




- 3. Human preference training
 - make the chatbot
 - friendly
 - harmless
 - helpful
 - 1-100k (chosen, rejected pairs)
 - one or more GPUs



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- 3. Human preference training
 - recommended: TRL library
 - o includes PPO, DPO

DPO Trainer

TRL supports the DPO Trainer for training language models from preference data, as described in the paper <u>Direct Preference</u> <u>Optimization: Your Language Model is Secretly a Reward Model</u> by Rafailov et al., 2023. For a full example have a look at <u>examples/scxipts/dpo.py</u>.

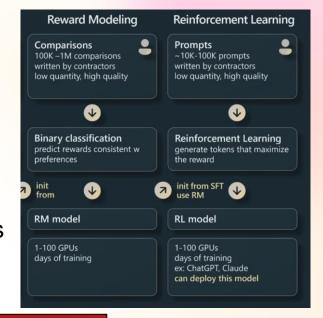
The first step as always is to train your SFT model, to ensure the data we train on is in-distribution for the DPO algorithm.

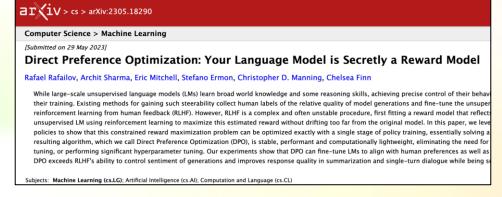
Expected dataset format

The DPO trainer expects a very specific format for the dataset. Since the model will be trained to directly optimize the preference of which sentence is the most relevant, given two sentences. We provide an example from the Anthropic/hh-rlhf dataset below:



- 3. Human preference training
 - recommended: TRL library
 - DPO: allows to train on human preferences directly
 - no need for separate reward model



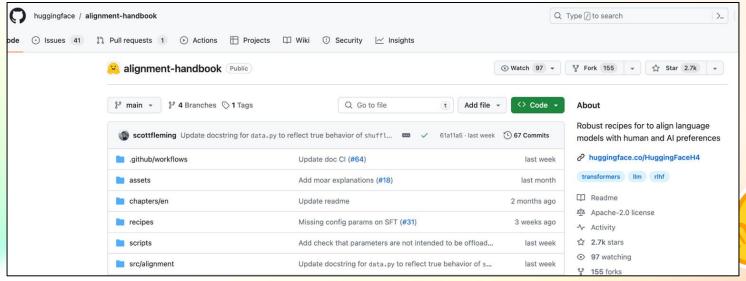




Hugging Face alignment handbook

Zephyr
Finetuned from Mistralai/Mistral-7B-v0.1

includes recipes for SFT, DPO





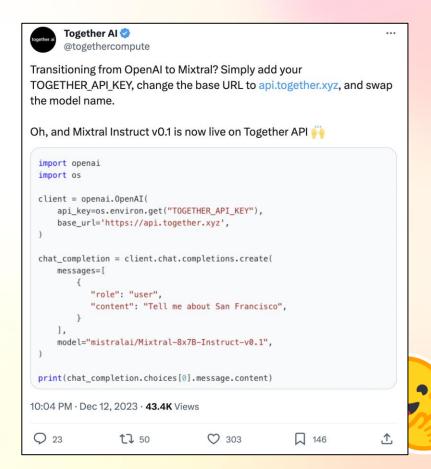
• Serverless vs. dedicated compute





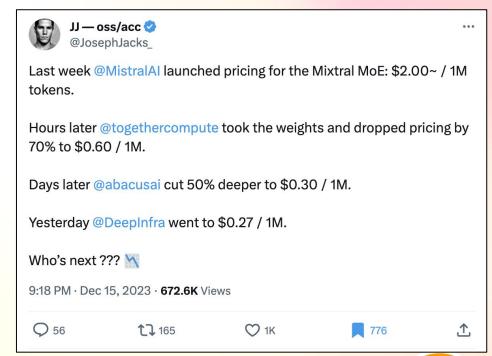
- Serverless solutions
 - Together.ai
 - AnyScale
 - Perplexity.ai
 - 0 ...

- Charge per token
 - e.g. \$0.0006/1K tokens for 8x7B
 - >60% cheaper than GPT-3.5



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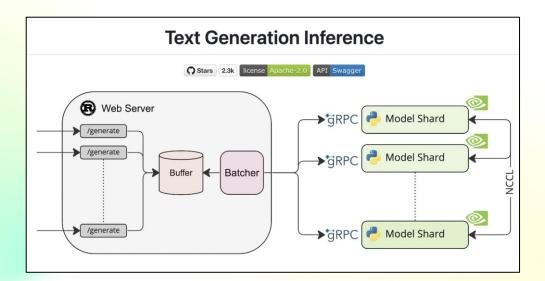


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```
curl -X POST \
     --url https://api.perplexity.ai/chat/completions \
     --header 'accept: application/json' \
     --header 'content-type: application/json' \
     --header "Authorization: Bearer ${PERPLEXITY API KEY}" \
     -- data '{
   "model": "mistral-7b-instruct",
 "max tokens": 1024,
 "frequency penalty": 1,
 "temperature": 0.0,
            "role": "system",
            "content": "Be precise and concise in your responses."
            "content": "How many stars are there in our galaxy?"
```

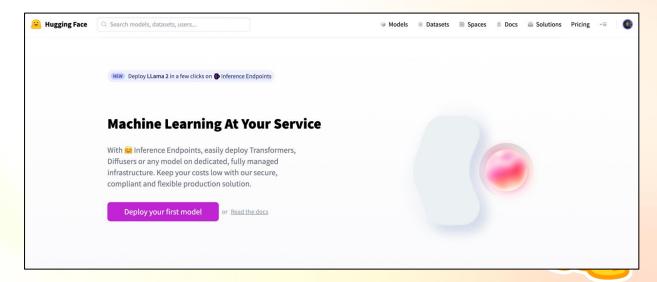
- Dedicated compute
 - TGI (Text Generation Inference), vLLM
 - Inference Endpoints, Together.ai





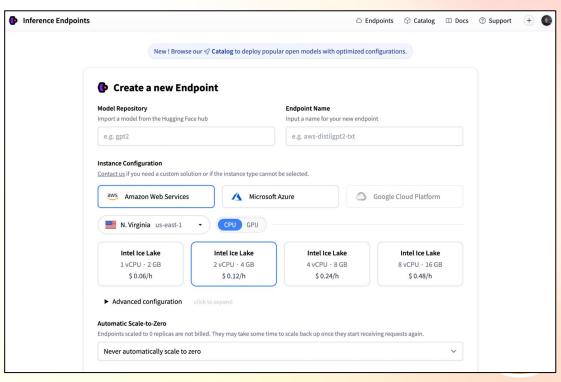
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 - o e.g. \$2/hour

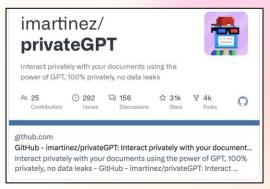


- Dedicated compute
 - TGI (Text Generation)
 - Inference Endpoints

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Why open-source?



Advantages	Disadvantages	
 + No data being sent to another party (private) + Access to the model + Fine-tuning + Run at the edge (ggml, MLX) + Doesn't become lazy 	 Performance may be subpar without any fine-tuning Deploying costs (learning curve) 	

Why closed-source?





Advantages	Disadvantages	
 Everything is handled for you (only pay per x tokens) Performance 	 Underlying model might change without you knowing it Prompting may require update Dependency on another party (lockin) Data being sent to another party Data cut-off (April 2023) 	

Exciting developments

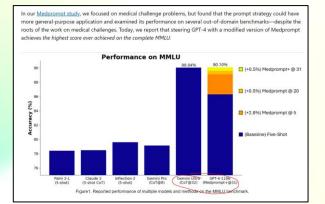
Expect LLMs to become **smaller**, more **capable** and run a lot **faster**

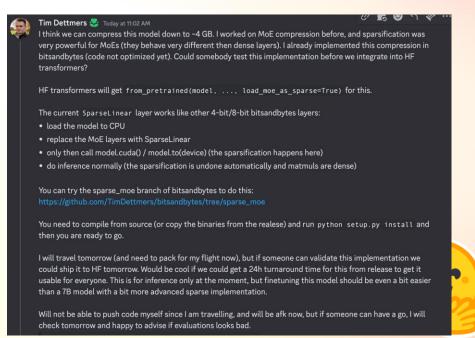
Phi-2: The surprising power of small language models

Published December 12, 2023

By Mojan Javaheripi, Senior Researcher; Sébastien Bubeck, Partner Research Manager

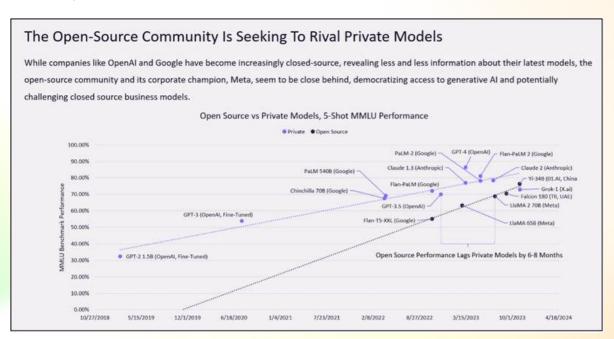
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Exciting developments

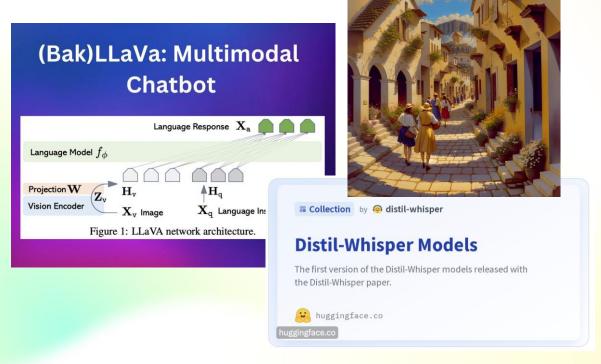
Sit back and enjoy the race 🕣

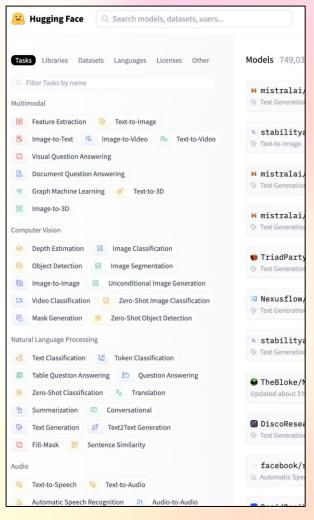




Exciting developments

Much more to come...





Thanks for your attention!

PS: connect with me!

@NielsRogge







