Building Large Language Models For Code





Let's start with some Context 📑



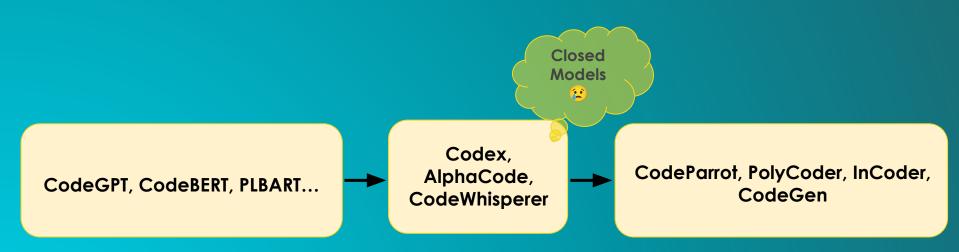
```
тs sentiments.ts
                             parse_expenses.py
                                                ddresses.rb
               ∞ write_sql.go
1 import datetime
3 def parse_expenses(expenses_string):
      """Parse the list of expenses and return the list of triples (date, value, currency).
      Ignore lines starting with #.
      Parse the date using datetime.
      Example expenses_string:
          2016-01-02 -34.01 USD
          2016-01-03 2.59 DKK
          2016-01-03 -2.72 EUR
      expenses = []
      for line in expenses string.splitlines():
          if line.startswith("#"):
          date, value, currency = line.split(" ")
          expenses.append((datetime.datetime.strptime(date, "%Y-%m-%d"),
                           float(value),
                           currency))
      return expenses
  ⊞ Copilot
                                                 Replay
```

From GitHub Copilot to open Code Models 🔑





From GitHub Copilot to open Code Models





From GitHub Copilot to open Code Models

CodeParrot, PolyCoder, InCoder, CodeGen

Open questions: Performance, Transparency about training data, Multilinguality, Evaluation, User experience ...



Hugging Face: From CodeParrot to StarCoder 🔑



CodeParrot

- 1.5B code generation model
- Python only
- **4%** Python score
- Permissive data
- Open Access



StarCoder

- 15B code generation model
- 80+ languages
- 33% Python score: beats code-cushman-001 (Codex)
- Permissive data
- Open Access





BigCode: open-scientific collaboration

We are building LLMs for code in a collaborative way:

- 500+ participants
- 30+ countries



Closed LLM development

Training data and sources not disclosed

Model weights not public

Sending data to external APIs

Not reproducible

Open LLM development 🚢

Public data with inspection and opt-out tools

Model weights public for fine-tuning

On-prem deployment

Full documentation



Training LLMs for Code from scratch

Hundreds of GPU-hours, terabytes of data

But not just that!





StarCoder

Dataset: The Stack

Public dataset with 6.4TB of permissively licensed source code from GitHub in 358 programming languages with a data inspection tool and opt-out mechanism



Training Data Curation

- Language selection & quality inspection
 - 86 languages
 - GitHub issues, git commits & Jupyter notebooks
- Deduplication
- Decontamination
- Personal Identifiable Information (PII) removal



How to run preprocessing on large datasets

- Load datasets from the Hub using multiprocessing
- filter() and map() to apply a transformation using multiprocessing
- Batched mapping: Dataset.map() in batch mode

```
from datasets import Dataset

dataset = Dataset.from_dict({"a": [0, 1, 2]})

# new column with 6 elements: [0, 1, 2, 0, 1, 2]
dataset.map(lambda batch: {"b": batch["a"] * 2}, batched=True)
```



Training



Architecture choices

What do people want from a code model?

- Fast inference
 - → 15B parameters with code optimizations
- Cheap generations
 - → Multi-Query Attention for reduced memory footprint
- Long context
 - → Flash Attention to scale to 8,192 tokens context
- Bi-directional context
 - → Fill-in-the-middle training objective



Training setup

Infrastructure: 512 GPUs

Model Distribution: TP=4, PP=4, DP=32

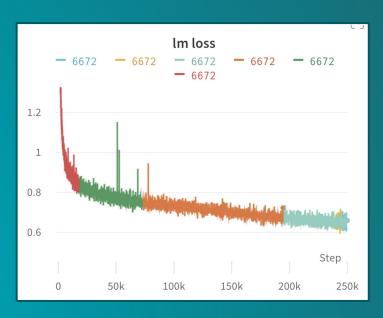
Batch size: 4M tokens

(or 512 at 8,192 sequence length)

Training length: 1T tokens / 250k steps

Training time: 24 days

Tool: Megatron-LM



"smooth sailing"



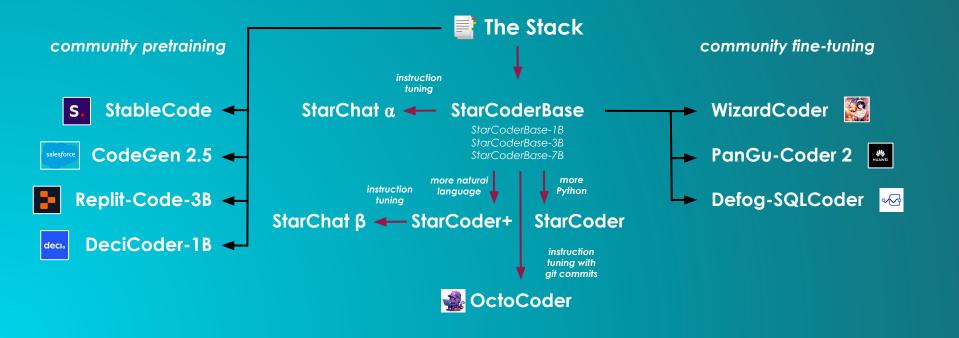
Fine-tuning models on low resources: PEFT 😣

 Fine-tune a small number of (extra) parameters at low computational cost parameters with comparable performance to full fine-tuning

Only push and load adapter weights for inference -- low storage cost

https://github.com/bigcode-project/starcoder

BigCode Ecosystem



Deploying Large Language Models (for Code)





Hugging Face Inference endpoints

A Better Way to Go to Production

Scale your machine learning while keeping your costs low

Before



Struggle with MLOps and building the right infrastructure for production.



Wasted time deploying models slows down ML development.



Deploying models in a compliant and secure way is difficult & time-consuming.



87% of data science projects never make it into production.

After



Don't worry about infrastructure or MLOps, spend more time building models.



A fully-managed solution for model inference accelerates your ML roadmap.



Easily deploy your models in a secure and compliant environment.



Seamless model deployment bridges the gap from research to production.



Text-generation-inference (TGI)



Tensor Parallelism



Quantization



Token Streaming



Optimizations



Metrics and monitoring



Security

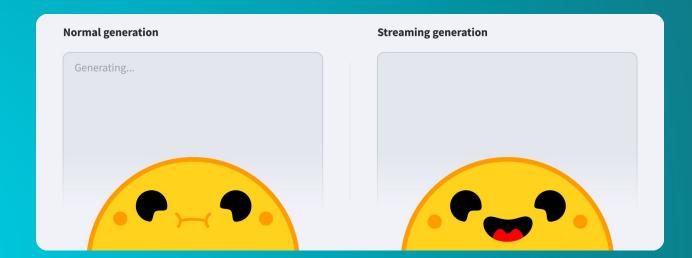
TGI supports most popular LLMs, such as

Production ready: Tracing mechanism & Warmup



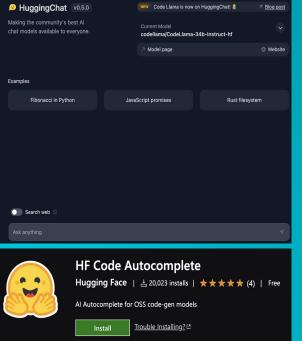
Optimizations & user experience

- Optimized for latency
- Continuous batching: for handling concurrent requests
- Token streaming: reduce perceived latency and improve interactivity



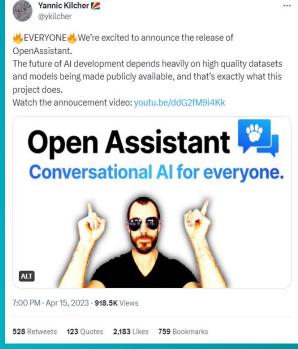
Some users



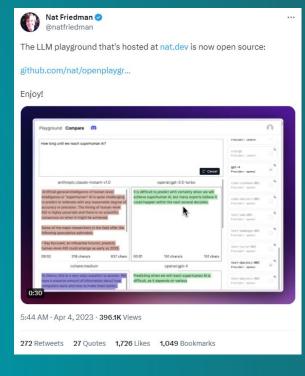




OpenAssistant













- All Hugging Face Infrastructure uses Kubernetes
 - o 8 production clusters, 800 nodes
 - Hub, API Endpoints, Dataset Server, Spaces...



Very dense clusters:

- Use of memory swap feature
- Up to **250 pods** in a node



Re-compilation of containerd to pull images faster

30% faster checksum operations https://go-review.googlesource.com/c/go/+/353402

Questions



