ReplitLM: using Open-source from Training to Production for a Code Completion LLM

Michele Catasta

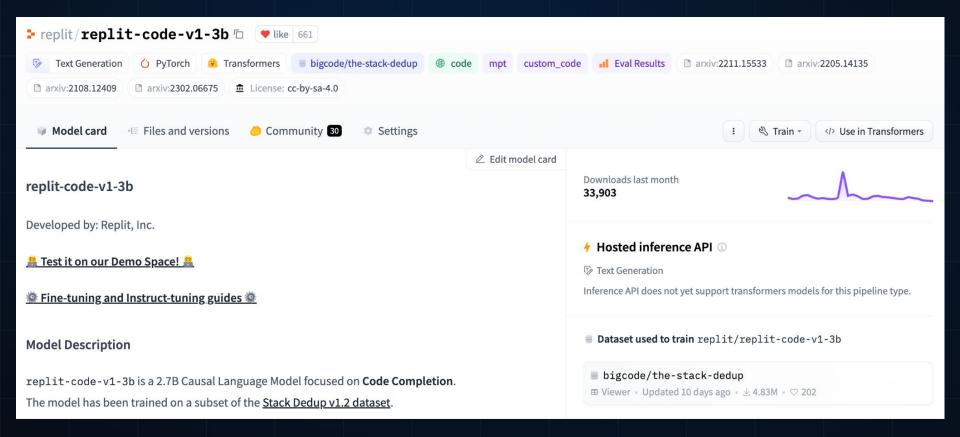
https://twitter.com/pirroh

https://pirroh.fyi

Code Completion on Replit

```
⋾ style.css × +
 3
11
13
14
```

In early May 2023 we released replit-code-v1-3b, our bespoke Code Completion LLM serving a large number of Replit users



replit-code-v1-3b / Data

First Llama-style	
LLM for code	

~195 tokens per parameter

Trained on 525B tokens of code

175B tokens over 3 epochs

20 languages

Markdown, Java,
JavaScript, Python,
TypeScript, PHP, SQL,
JSX, reStructuredText,
Rust, C, CSS, Go, C++,
HTML, Vue, Ruby,
Jupyter Notebook, R,
Shell

The Stack

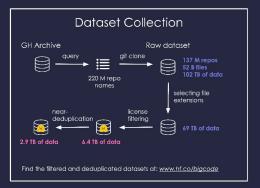
6 TB of permissive code data



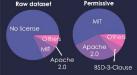
https://www.bigcode-project.org/



contact@bigcode-project.org



Licensing + Governance Raw dataset **Permissive**



Opt-out: If users would like to mechanism, Visit:

https://www.bigcode-projec

Permissive license distribution of licenses used to filter the dataset:

MIT (67.7%) | Apache-2.0 (19.1%) | BSD-3-Clause (3.9%) | Unlicense (2.0%) CC0-1.0 (1.5%) | BSD-2-Clause (1.2%) | CC-BY-4.0 (1.1%) | CC-BY-3.0 (0.7%) OBSD (0.4%) | RSA-MD (0.3%) | WTFPL (0.2%) | MIT-0 (0.2%) | Others (166) (2.2%)



Evaluation

We trained several GPT-2 models (350M parameters) on different parts of the dataset both with and without near-deduplication. The models trained on the Python subset of The Stack performed on par with CodeX and

Dataset	Filtering	pass@1	pass@1	0 pass@100
Codex (300M)	unknown	13.17	20.17	36.27
CodeGen (350M)	unknown	12.76	23.11	35.19
Python all-license	None	13.11	21.77	36.67
	Near-dedup	17.34	27.64	45.52
Python permissive-license	None	10.99	15.94	27.21
	Near-dedup	12.89	22.26	36.01

*results obtained with The Stack v1.0

- Pretraining data mixture based on The Stack v1.2 (released in March 2023)
- Selected the top 20 languages used on Replit
- Large number of code quality heuristics to filter the dataset (e.g., Codex paper, stripping long content from HTML/CSS files, etc.)
- Data processing on Spark, vocabulary training with Google SentencePiece

Scaling Data-Constrained Language Models

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Data-Constrained Scaling Laws

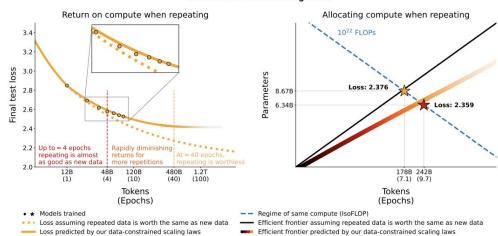


Figure 1: *Return* and *Allocation* when repeating data. (*Left*): Loss of LLMs (4.2B parameters) scaled on repeated data decays predictably (§6). (*Right*): To maximize performance when repeating, our data-constrained scaling laws and empirical data suggest training smaller models for more epochs in contrast to what assuming Chinchilla scaling laws [42] hold for repeated data would predict (§5).

- Published coincidentally just a few weeks after we released our LLM
- Highly recommended paper, confirming our ablation studies on repeated data
- This intuition allowed us to train to completion using only permissively-licensed code, hence we could release our model under CC BY-SA-4.0

replit-code-v1-3b / Model Training

2.7B parameters	256 A100-40GB	LLM best practices
	GPUs	
Custom 32k		Flash Attention,
vocabulary	For ~3 days on	<u>AliBi positional</u>
focused on code	the <u>MosaicML</u>	embeddings,
	platform	LionW optimizer,
		etc.











LLM Foundry

This repository contains code for training, finetuning, evaluating, and deploying LLMs for inference with Composer and the MosaicML platform. Designed to be easy-to-use, efficient *and* flexible, this codebase is designed to enable rapid experimentation with the latest techniques.

About

LLM training code for MosaicML foundation models

nlp deep-learning pytorch
neural-networks IIm

- ☐ Readme
- ♠ Apache-2.0 license
- Activity
- ☆ 3k stars
- 37 watching
- **약 326** forks

Report repository

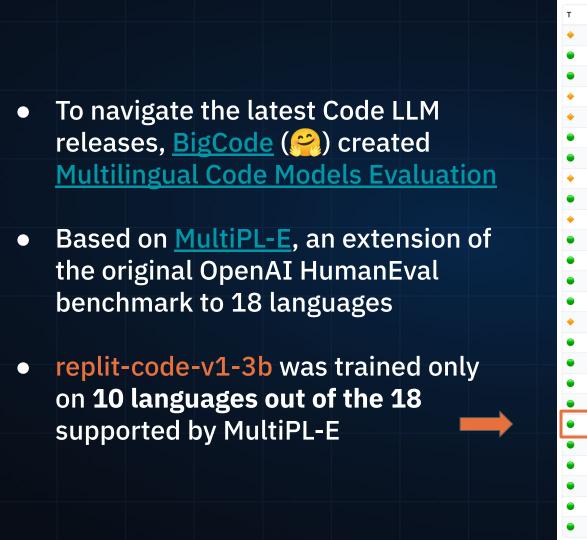
Releases 3

- v0.2.0 Latest
- + 2 releases

- All training runs based on an early release of <u>LLM</u>
 Foundry by
 MosaicML
- Same library used to train larger open-source models like MPT-7B and MPT-30B

replit-code-v1-3b / Evaluation

	Score pass@1
Python (OpenAI HumanEval)	22.56%
Python (MultiPL-E)	20.49%
Java (MultiPL-E)	20.25%
JavaScript (MultiPL-E)	19.25%
C++ (MultiPL-E)	18.63%
Rust (MultiPL-E)	16.02%
PHP (MultiPL-E)	13.04%



CodeLlama-34b	33.89
CodeLlama-34b-Python	33.87
WizardCoder-15B-V1.0	32.07
CodeLlama-13b-Instruct	31.29
CodeLlama-13b-Python	28.67
CodeLlama-13b	28.35
CodeLlama-7b-Instruct	26.45
CodeLlama-7b	24.36
OctoCoder-15B	24.01
CodeLlama-7b-Python	23.5
StarCoder-15B	22.74
StarCoderBase-15B	22.4
CodeGeex2-6B	21.23
OctoGeeX-7B	20.79
StarCoderBase-7B	20.17
CodeGen25-7B-multi	20.04
StarCoderBase-3B	15.29
CodeGen25-7B-mono	12.1
Replit-2.7B	11.62
CodeGen-16B-Multi	9.89
StarCoderBase-1.1B	9.81
StableCode-3B	8.1
DeciCoder-1B	5.86

4.92

CodeLlama-34b-Instruct

SantaCoder-1.1B

Average score

35.09

replit-repltuned-v1-3b / Data & Training

Further pretraining on 111B tokens of code

Code authored by our users in public Repls

Same languages, same data filtering heuristics

37B tokens over 3 epochs

A lot of Python and Javascript

The problem



Nowadays everybody finetune / continue train LLaMA. A practical problem is learning rate re-warm: the pretraining learning rate schedule stops at 3e-5, naively increasing the continue train Ir to 3e-4 typically causes double descent. Is there a good way to mitigate this issue?

11:09 AM · Aug 15, 2023 · **46K** Views



Our experience



Yam Peleg 🔮 @Yampeleg · Aug 15

I just schedule (& warmup) the gradient clipping along the Ir and it works fine

Also: suboptimal training is usually not that suboptimal.. yolo just go for it, worse case the initial steps won't be the best and you end up with only 97% of the performance you could have..

The solution?

- Continual Pre-Training
 of Large Language
 Models: How to
 (re)warm your model?
- A pragmatic hack explained by <u>Shital</u> <u>Shah</u> in <u>this thread</u>, inspired by the LR schedule from "<u>Scaling Vision</u> Transformers"

replit-repltuned-v1-3b / Evaluation

	Score pass@1	Base model
Python (OpenAI HumanEval)	30.48%	22.56%
Python (MultiPL-E)	29.81%	20.49%
Java (MultiPL-E)	19.62%	20.25%
JavaScript (MultiPL-E)	27.95%	19.25%
C++ (MultiPL-E)	26.08%	18.63%
Rust (MultiPL-E)	15.38%	16.02%
PHP (MultiPL-E)	23.60%	13.04%

replit-*-v1-3b / Inference

~ 200 tokens / s on a single A100-40G (no batching)

We made explicit architectural choices to support:

- https://github.com/NVIDIA/FasterTransformer
- https://github.com/triton-inference-server

for optimized inference on NVIDIA GPUs

Reliable inference evaluation across model architectures is still really HARD



CodeLlama-34b-Pvthon 15.1 CodeLlama-13b 25.3

Models

CodeLlama-34b

CodeLlama-7b

StarCoder-15B

CodeGeex2-6B

StarCoderBase-3B

StarCoderBase-1.1B

CodeGen25-7B-mono

CodeGen-16B-Multi

StableCode-3B

DeciCoder-1B

SantaCoder-1.1B

Replit-2.7B

CodeLlama-13b-Python

CodeLlama-7b-Python StarCoderBase-15B

StarCoderBase-7B CodeGen25-7B-multi

46.9

32.6 50

42.2

71.4

Throughput (tokens/s)

15.1

25.3

33.1

43.9

33.1 43.8

32.7

34.1

17.2

30.2

54.6





 Instruct fine tuned on CodeAlpaca and GPTeacher Code-Instruct:

https://huggingface.co/teknium/Replit-v2-CodeInstruct-3B

 Quantization + ggml support to boost local inference for VSCode plugins



The first GPT4All powered code copilot has launched

@morph_labs allows you to use the recently released Replit GPT4All model on Apple Metal to perform privacy aware

- Code completion (23 tok/second)
- Chatting and asking questions

all through the Rift VSCode extension.

Local LLMs power the future of software development.



The future of AI code assistants is open-source, private, secure, and on-device. That future starts today. We're excited to release Rift, an open-source AI-native language server and VSCode extension for local copilots.

morph.so



Links

https://github.com/replit/ReplitLM

https://huggingface.co/replit/replit-code-v1-3b

https://blog.replit.com/llm-training

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- Madhav Singhal, Juan Sigler Priego, Bradley Heilbrun, Samip Dahal,
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