

Open and responsible development of Large Language Models for code

## Today's talk

- 1 The BigCode Community
- 2 The Stack
- 3 StarCoder

## 1. The BigCode community



### BigCode: open-scientific collaboration

We are building LLMs for code in a collaborative way:

- 500+ participants
- 30+ countries





#### NTARCODER:

MAY THE SOURCE BE WITH YOU!

 1Hugging Face
 2ServiceNow Research of Mila
 3ServiceNow 4Northeastern University
 5Independent Mortheastern University
 6Independent Mortheastern University
 6Independe

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### Developing Code LLMs is not only a technical problem!

- Consent of data subjects
  - Do machine learning models comply with copyright laws?
- Privacy risks
  - Scraped data likely contains personal identifiable information
- Software safety and security
  - Code LLMs may be used to generate malware or may provide code suggestions that are less secure

## Closed development of LLMs

- Model only available through API, which limits research on:
  - Safety and alignment
  - The model's inner workings (i.e. representations)
  - Adaptation methods like LoRA, and continuous prompt-tuning

- Training data and filtering is not disclosed:
  - Limits scientific reproducibility
  - Potential benchmark contamination
  - People don't know if their data is used, and there's no way to remove it

## Open & Responsible Research on LLMs

- Distributing the training data
  - Data licensing needs to permit this
- Allow people to inspect the collected data + opt-out
  - See The Stack
- Transparency builds trust in AI systems:
  - Be open about shortcomings in PII detection models
  - Be open about Code LLM limitations: Model cards

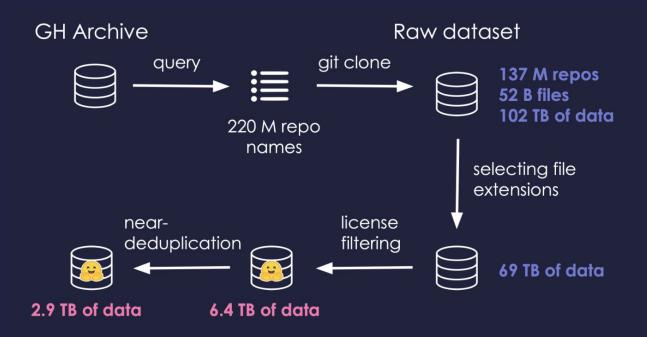
## 3. The Stack



#### The Stack

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

#### **Data Collection**



Find the filtered and deduplicated datasets at: <a href="https://www.hf.co/bigcode">www.hf.co/bigcode</a>

#### Am I In The Stack?





The Stack is an open governance interface between the AI community and the open source community.

#### Am I in The Stack?

As part of the BigCode project, we released and maintain <u>The Stack</u>, a 3.1 TB dataset of permissively licensed source code in 30 programming languages. One of our goals in this project is to give people agency over their source code by letting them decide whether or not it should be used to develop and evaluate machine learning models, as we acknowledge that not all developers may wish to have their data used for that purpose.

This tool lets you check if a repository under a given username is part of The Stack dataset. Would you like to have your data removed from future versions of The Stack? You can opt-out following the instructions <u>here</u>.

The Stack version:		
v1.1		~
Your GitHub username:		
	Check!	

Yes, there is code from 5 repositories in The Stack:

Ivwerra/datasets

lvwerra/jupyterplot

lvwerra/pandas-profiling

lvwerra/transformers

lvwerra/trl

#### Opt-out

If you want your data to be removed from the stack and model training open an issue with <a href="mailto:this.link">this.link</a> (if the link doesn't work try right a right click and open it in a new tab) or visit <a href="https://github.com/bigcode-project/opt-out-v2/issues/new?&template=opt-out-request.md">https://github.com/bigcode-project/opt-out-v2/issues/new?&template=opt-out-request.md</a>.



# StarCoder

#### Training Data - The Stack

- Strong near-deduplication
  - language agnostic and shows consistent performance gains
- Language selection
  - 86 languages out of 358
  - Includes GitHub issues, git commits, structured Jupyter notebooks.
- Data quality inspection
  - o inspect 100 samples per source and derive filtering heuristics
- Removing PII
  - StarPII: Model to detect/remove emails, password and keys

#### **Architecture choices**

#### What do people want from a code model?

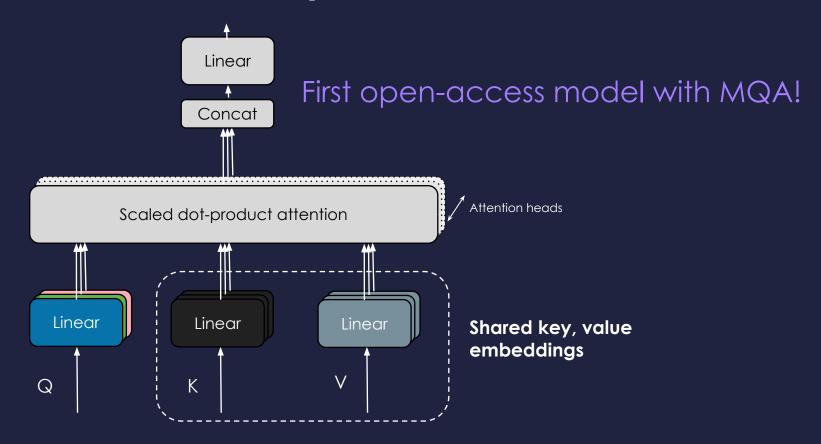
- Fast inference
  - Integrated into an IDE very low latency
- Cheap generations
  - Generating batches or long sequences requires lot of memory
- Long context
  - Including code from repo can improve performance
- Bi-directional context
  - Code before and after cursor can be important for completion.

#### **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
  - $\rightarrow$  Flash Attention to scale to 8,192 tokens context
- Bi-directional context
  - → Fill-in-the-middle training objective

#### Architecture choices: MQA



#### Training setup

Infrastructure: 512 GPUs

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

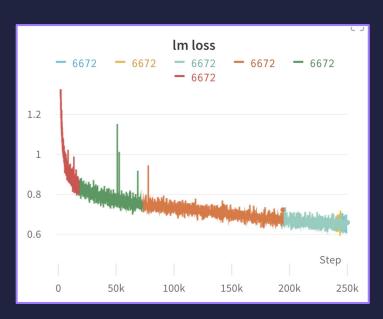
Batch size: 4M tokens

(or 512 at 8,192 sequence length)

**Training length:** 1T tokens / 250k steps

**Training time:** 24 days

**Tool:** Megatron-LM (w/ MQA + FlashAttn) (https://github.com/bigcode-project/Megatron-LM)



"smooth sailing"



#### **StarCoderBase**

Trained on 1T tokens in 80+ languages

#### **StarCoder**

Additionally trained on 35B Python tokens

#### Evaluation - HumanEval/MBPP

#### Common observed failure mode:

# solution here

#### Prompt fix:

<filename>solutions/solutions\_1.py

# Here is the correct implementation of the code exercise

Didn't observe similar gains for

CodeGen-Mono or StarCoderBase

Model	HumanEval	MBPP
LLaMA-7B	10.5	17.7
LaMDA-137B	14.0	14.8
LLaMA-13B	15.8	22.0
CodeGen-16B-Multi	18.3	20.9
LLaMA-33B	21.7	30.2
CodeGeeX	22.9	24.4
LLaMA-65B	23.7	37.7
PaLM-540B	26.2	36.8
CodeGen-16B-Mono	29.3	35.3
StarCoderBase	30.4	49.0
code-cushman-001	33.5	45.9
StarCoder	33.6	<b>52.7</b>
StarCoder-Prompted	40.8	49.5

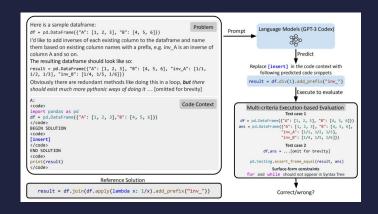
#### **Evaluation - MultiPL-E**

#### MultiPL-E contains translated versions of HumanEval

Language	CodeGen-16B-Multi	CodeGeeX	code-cushman-001	StarCoder	StarCoderBase
срр	21.00	16.87	30.59	31.55	30.56
c-sharp	8.24	8.49	22.06	21.01	20.56
d	7.68	9.15	6.73	13.57	10.01
go	13.54	11.04	19.68	17.61	21.47
java	22.20	19.14	31.90	30.22	28.53
julia	0.00	0.29	1.54	23.02	21.09
javascript	19.15	16.92	31.27	30.79	31.70
lua	8.50	10.96	26.24	23.89	26.61
php	8.37	13.51	28.94	26.08	26.75
perl	3.42	8.09	19.29	17.34	16.32
python	19.26	21.62	30.71	33.57	30.35
r	6.45	3.92	10.99	15.50	10.18
ruby	0.00	3.34	28.63	1.24	17.25
racket	0.66	3.31	7.05	0.07	11.77
rust	4.21	7.88	25.22	21.84	24.46
scala	2.37	8.95	27.62	27.61	28.79
bash	0.61	2.75	11.74	10.46	11.02
swift	1.25	7.26	22.12	22.74	16.74
typescript	20.07	10.11	31.26	32.29	32.15

- outperforming open-access models
- competitive with code-cushman-001

#### Evaluation - DS-1000



- benchmark with data science problems
- **StarCoder / StarCoderBase** competitive edge
- fine-tuning improves completion mode

		Matplottib	04	.25	, ch		, it	TensorFlo	A
Format	Model	Matpi	NumPy	Pandas	PyTorch	SciPy	Scikit. Learn	Tensor	Overall
	Number of problems:	155	220	291	68	106	115	45	1,000
Completion	InCoder-6B	28.3	4.4	3.1	4.4	2.8	2.8	3.8	7.4
Completion	CodeGen-16B-Mono	31.7	10.9	3.4	7.0	9.0	10.8	15.2	11.7
Completion	code-cushman-001	40.7	21.8	7.9	12.4	11.3	18.0	12.2	18.1
Completion	StarCoderBase	47.0	27.1	10.1	19.5	21.7	27.0	20.5	23.8
Completion	StarCoder	51.7	29.7	11.4	21.4	20.2	29.5	24.5	26.0
Insertion	InCoder-6B	28.3*	4.6	2.9	4.4	2.8	3.1	7.8	7.5
Insertion	StarCoderBase	$47.0^{*}$	26.3	10.9	16.6	20.2	30.2	22.3	24.0
Insertion	StarCoder	51.7*	30.8	10.3	21.0	20.2	27.4	20.0	25.4

#### **VSCode** extension

#### Auto-complete

```
Users > swayam > Desktop >  main.py > ...

1    def is_prime(num):
2         return False

        def is_prime(num):
        if num == 2:
            return True
        if num % 2 == 0:
            return False
        for i in range(3, num, 2):
            if num % i == 0:
                 return False
```

https://marketplace.visualstudio.com/items?itemName=HuggingFace.huggingface-vscode

#### Membership test

```
Users > swayam > Desktop > ₱ main.py > ₱ is_prime
       def is_prime(num):
        for i in range(3, num, 2):
        if num % i == 0:
 10
        return False
 11
(i) Highlighted code was found in the stack.
Source: HF Code Autocomplete (Extension)
                                     Go to stack search
```

#### Jupyter extension

The estimated image  $\tilde{f}$  using hard thresholding suffers from many artifacts. It is possible to improve the result by using soft thresholding, defined as:

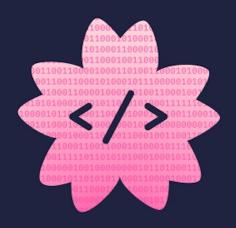
$$\begin{split} \tilde{f} &= S_T^1(f) = \sum_m s_T^1(\langle f, \psi_m \rangle) \psi_m \\ where s_T^1(\alpha) &= \max \left(0, 1 - \frac{T}{|\alpha|}\right) \alpha. \end{split}$$

Display the soft thresholding function  $S_T^1(\alpha)$ .

```
In [1]: import numpy as np
       import matplotlib.pvplot as plt
       def soft thresholding(alpha, T):
           return np.maximum(0, 1 - T / np.abs(alpha)) * alpha
        def plot soft thresholding(T):
           x = np.linspace(-3, 3, 100)
           v = soft thresholding(x, T)
           plt.plot(x, y)
           plt.title('Soft thresholding function')
           plt.xlabel('alpha')
           plt.vlabel('s T^1(alpha)')
           plt.show()
       plot soft thresholding(1)
       plot soft thresholding(2)
       plot soft thresholding(3)
        NameError
                                                 Traceback (most recent call last)
        Cell In [1], line 13
                   plt.ylabel('s T^1(alpha)')
                   plt.show()
        ---> 13 plot soft thresholding(1)
             14 plot soft thresholding(2)
             15 plot soft thresholding(3)
       Cell In [1], line 5, in plot soft thresholding(T)
             4 def plot soft thresholding(T):
        ----> 5 x = np.linspace(-3, 3, 100)
                   y = soft thresholding(x, T)
                   plt.plot(x, y)
       NameError: name 'np' is not defined
```

- The markdown context is passed to the model as well as cell outputs
- Leverages the commit format of starcoder to fix bugs and errors

## Thank you!



## Questions?

www.bigcode-project.org

hf.co/bigcode

#### Feedback from the opt-out form

- "It should be opt-in instead of opt-out"
- "It is unfair to use my code without compensation"
- "There's PII in my code and I don't want it to be publicly exposed"
- "My code is of poor quality and unsuitable for training your AI model"
- "I am not confident about the current state of AI code generation. I
  am concerned that the generated code could be traced back to
  me and I'm held liable for issues in that code."

Jennifer Ding's <u>community research</u>: it's both **better to know** AND **better to have a choice**.

#### **Training Data - Formatting**

#### Code

<reponame>REPONAME<filename>FILENAME<gh\_stars>STARS\nCode<eos>

#### Git commits

<commit\_before>code<commit\_msg>text<commit\_after>code<eos>

#### Jupyter Notebooks

<jupyter\_start><jupyter\_text>TEXT<jupyter\_code>CODE<jupyter\_output>
OUTPUT<jupyter\_text> ...

#### GitHub Issues

<issue\_start>title + USERID: comment<issue\_comment>USERID: Comment
... <issue\_closed (optional)> <eos>

#### **Evaluating Infilling**

- StarCoder supports infilling or fill-in-the-middle: condition generation on code before and after the insertion point
- One of a handful of recent open models that support infilling
- Applications
  - Docstring generation
  - Type prediction
  - o Many more
- StarCoder outperforms other infilling models significantly on three infilling tasks

Model	Java	JavaScript	Python
InCoder-6B	0.49	0.51	0.31
SantaCoder	0.62	0.60	0.44
StarCoder	0.73	0.74	0.62

Model	Non-None F1	All F1
InCoder-6B	59.1	46.8
SantaCoder	66.9	78.5
StarCoderBase	77.4	86.6
StarCoder	77.1	86.4

	Packages type check				
	<b>✓</b>	Total	%		
InCoder	30	128	23.4		
StarCoderBase	49	128	38.3		

Single-line code completion for three languages (SantaCoder/InCoder benchmarks)

Python return-type prediction (InCoder/TypeWriter benchmarks)

TypeScript type inference (TypeWeaver benchmarks)

## Perplexity with long contexts

Window Size	Language									
, indo i sine	срр	c-sharp	c	go	java	javascript	php	r	ruby	rust
2K tokens	2.01	1.90	1.71	1.35	1.65	1.98	1.73	1.72	2.16	1.84
8K tokens	1.79	1.66	1.61	1.21	1.54	1.68	1.43	1.48	2.02	1.65

- Derived test data from GPL repositories on GitHub. GPL was excluded from training data.
- Demonstrates StarCoder can benefit from information within long files or repositories.
- Longer contexts provides noticeable decreases in perplexity.

#### GSM8K

**Problem:** Beth bakes 4, 2 dozen batches of cookies in a week. If these cookies are shared amongst 16 people equally, how many cookies does each person consume?

**Solution:** Beth bakes 4.2 dozen batches of cookies for a total of 4\*2 = <<4\*2=8>>8 dozen cookies

There are 12 cookies in a dozen and she makes 8 dozen cookies for a total of 12\*8 = <<12\*8=96>>96 cookies

She splits the 96 cookies equally amongst 16 people so they each eat 96/16 = <<96/16=6>>6 cookies

Final Answer: 6

Model	Size	GSM8K CoT	+maj1@100	GSM8K PAL	+maj1@40
StarCoderBase	15.5B	8.4	_	21.5	31.2
CodeGen-Multi CodeGen-Mono	16B 16B	3.18 2.6	_	8.6 13.1	15.2 22.4
LLaMA	7B 13B 33B 65B	11.0 17.8 35.6 <b>50.9</b>	18.1 29.3 53.1 <b>69.7</b>	10.5 16.9 38.7 —	16.8 28.5 50.3

- StarcoderBase performs better with PAL than with CoT
- Outperforms CodeGen-16B and LLaMA-13B

## **MMLU**Multiple-choice questions in 57 knowledge domains

Model	Size	MMLU 5-shot acc, %
CodeGen-Multi	16B	27.8
GPT-NeoX	20B	32.9
StarCoder	15.5B	33.9
StarCoderBase	15.5B	34.2
LLaMA	7B	35.1
LLaMA	13B	46.9

#### CoQA

Conversational question answering on diverse text passages

Model	Size	CoQA zero-shot F1 score
CodeGen-Multi	16B	0.59
StarCoderBase	15.5B	0.67
StarCoder	15.5B	0.67
LLaMA	7B	0.71
LLaMA	13B	0.73
GPT-NeoX	20B	0.73

 StarCoder models significantly outperform other open code LLMs but still fall short of text-only LLMs like LLaMa

#### Harmful generations

#### StereoSet:

3 sentence completions (stereotypical, anti-stereotypical, unrelated), which one did the model prefer?

Model	Stereotype Score	Language Model Score	ICAT Score
LLaMA-13B	63.40	87.62	64.14
CodeGen-Multi-16B	61.29	87.25	67.55
StarCoderBase	55.53	86.18	76.65

- StarCoder is less Stereotypical (overall) than LLaMa and CodeGen
- With slightly lower Language Model Score
- On average (ICAT) StarCoder is better than both LLaMa and CodeGen

#### RealToxicityPrompts:

Given toxic prompts (10k), how much toxicity the model generates?

Model	Classifier	<b>Word List</b>
LLaMA-13B	0.74	1.43
CodeGen-Multi-16B	0.21	0.82
StarCoderBase	0.42	1.12

- Classifier: percentage of responses with toxic score > 0.5
- WordList: percentage of responses with 1+ offensive word
- StarCoder generates less toxic content than LLaMa, but little more than CodeGen

## Reasoning tasks in HELM

Model	Size	Open Access	Synth. Reason. (AS)	Synth. Reason. (NL)	bAbI	Dyck	GSM8K	МАТН	MATH (CoT)	LSAT	Legal Support
code-davinci-002	175B		54.0	68.4	68.6	80.5	56.8	41.0	43.3	_	
text-davinci-003	175B		50.2	73.4	65.3	75.1	50.6	39.0	44.9	23.3	62.2
Luminous Supreme	70B		31.2		50.4	72.9	11.2	14.9	5.7	21.2	53.0
StarCoderBase	15.5B	/	44.0	21.0	50.4	85.4	8.4	15.1	7.0	19.0	53.2
Cohere Command Beta	52.4B		24.3	24.5	47.3	42.1	13.8	13.3	7.5	22.9	60.6
J1-Jumbo v1	178B		26.3	17.4	54.3	44.5	5.4	8.9	3.3	23.2	48.4
J1-Grande v2 beta	17B		28.6	13.9	47.0	61.7	9.6	12.7	6.8	19.1	56.2
code-cushman-001	12B		34.1	16.4	48.1	45.1	4.9	9.9	7.2	_	_
OPT	175B	1	22.5	24.8	50.7	49.4	4.0	6.5	2.6	22.0	53.2
GPT-NeoX	20B	1	20.4	16.7	46.8	74.7	5.3	14.1	7.1	19.1	51.5
BLOOM	176B	1	30.4	19.7	44.7	54.5	9.5	4.3	5.5	20.9	54.3
GLM	130B	1	25.2	25.4	44.3	54.9	6.1	0	5.9	19.3	45.1
UL2	20B	1	20.5	21.7	50.1	14.0	2.4	0	0	20.7	50.6
OPT	66B	1	19.3	21.3	40.8	47.1	1.8	4.8	2.9	17.5	52.7
YaLM	100B	1	5.6	6.1	34.6	63.3	0	0	0	2.3	48.4
T5	11B	/	19.6	10.1	41.2	34.7	2.3	0	0	15.9	55.8

- StarCoderBase substantially outperforms other open LLMs
- State-of-the-art performance on Dyck benchmark



### **Prompting StarCoder**

an AI technical assistant. The assistant tries to be helpful, polite, honest, sophisticated, emotionally aware, and humble-but-knowledgeable. The assistant is happy to help with code questions, and will do its best to understand exactly what is needed. It also tries to avoid giving false or misleading information, and it caveats when it isn't entirely sure about the right answer. That said, the assistant is practical and really does its best, and doesn't let caution get too much in the way of being useful. Human: Write a function that takes two lists and returns a list that has alternating elements from each input list. Assistant: Sure. Here is a function that does that. def alternating(list1, list2): results = [] 12 for i in range(len(list1)): results.append(list1[i]) 13 14 results.append(list2[i]) 15 return results 16 17 Human: Can you write some test cases for this function? 19 20 Assistant: Sure, here are some tests. 21 22 assert alternating([10, 20, 30], [1, 2, 3]) == [10, 1, 20, assert alternating([True, False], [4, 5]) == [True, 4, False, 5] assert alternating([], []) == [] 26 27 Human: Modify the function so that it returns all input elements when the lists have uneven length. The elements from the longer list should be at the end. Assistant: Here is the modified function.

Below are a series of dialogues between various people and

Inspired by Anthropic's HHH prompt: the TA prompt can make the model act as a tech assistant!

```
Can you give me Python code that tells me the weather in the city Bern?

Sure. Here is a simple script that uses the OpenWeatherMap API to retrieve data about the weather forecast in Bern.

import requests
import json

api_key = "<KEY>"

url = "http://api.openweathermap.org/data/2.5/forecast"

params = { "q": "Bern", "units": "metric", "APPID": api_key }

response = requests.get(url, params=params)

json_data = response.json()

print("Temperature:", round((json_data["main"]["temp"] - 273.15)))

print("Wind speed:",round(json_data["wind"]["speed"]))

print("Humidity:",round(json_data["main"]["humidity"], 1))
```

#### CodeML OpenRAIL-M v1

- Royalty free access and use of the model
- Enables downstream distribution of derivatives
- Includes ethical use restrictions based on technical capabilities of the Model (e.g malware generation)
- Improved OpenRAIL license for commercialization

### Chinchilla Scaling Laws

Loss Parameters Tokens 
$$L(N,D) = E + \frac{A}{N^{\alpha}} + \frac{B}{D^{\beta}}$$

 $E = 1.69, A = 406.4, B = 410.7, \alpha = 0.32, \beta = 0.28.$ 

## Compute-optimal Parameters and Tokens

$$C = 6ND$$

+ set the partial derivative of L with respect to N/D = 0

$$N_{opt}(C) = G\left(\frac{C}{6}\right)^{\frac{\beta}{\alpha+\beta}}, D_{opt}(C) = G^{-1}\left(\frac{C}{6}\right)^{\frac{\alpha}{\alpha+\beta}}, G = \left(\frac{\alpha A}{\beta B}\right)^{\frac{1}{\alpha+\beta}}$$

## Compute vs model-size trade-off

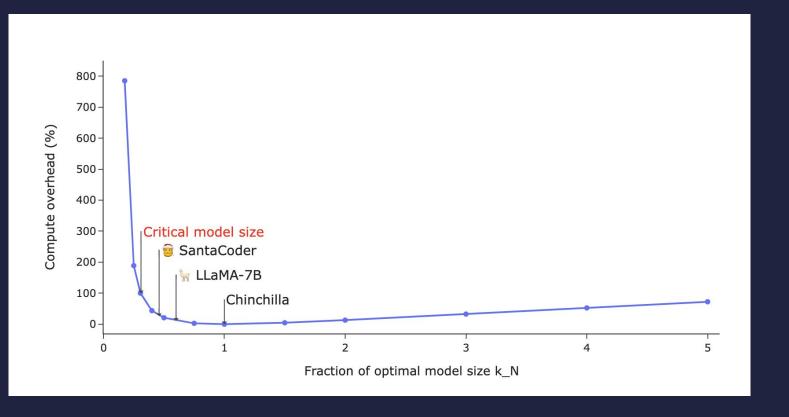
$$L(N_{opt}, D_{opt}) = L(k_N N_{opt}, k_D D_{opt})$$

with some math:

$$k_D = \left(1 - (k_N^{-\alpha} - 1) \frac{AN_{opt}^{-\alpha}}{BD_{opt}^{-\beta}}\right)^{\frac{1}{-\beta}}$$

$$C_{new} = 6(k_N N_{opt})(k_D D_{opt})$$

## The compute vs model-size curve



## **Updated Chinchilla table**

	$k_N=1$		$k_N=0.5$		$k_N=0.3$		
С	N	D	N	D	N	D	
2.21e+19	0.40 B	9.22 B	0.20 B	22.28 B	0.12 B	63.20 B	
1.62e+20	0.99 B	27.20 B	0.50 B	65.70 B	0.30 B	186.35 B	
2.46e+22	9.87 B	415.53 B	4.93 B	1003.77 B	2.96 B	2847.27 B	
1e+23	18.73 B	889.63 B	9.37 B	2149.02 B	5.62 B	6095.86 B	
1.71e+24	68.60 B	4154.24 B	34.30 B	10035.16 B	20.58 B	28465.50 B	

## Next steps



#### StarCoder+

 StarCoder+: StarCoder fine-tuned on 600B tokens from the Falcon English Web dataset & the Stack

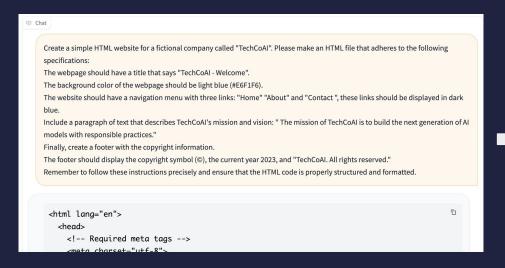
- Strong natural language performance and coding capabilities

 StarChat-Beta: StarCoder+ instruction-tuned

Model	MMLU	ARC	HellaSwag	TruthfulQA	HumanEval
Falcon-7B	35	47.9	78.1	34.3	-
LLaMA-7B	34.2	46.6	75.6	34.1	10.5
LLaMA-13B	37.7	50.8	78.9	39.9	15.8
Stable-Vicuna	38.8	48.1	76.4	46.5	-
Vicuna 13B 1.1	39.6	47.4	78	49.8	-
StarCoderPlus	45.1	48.9	77.3	37.9	26.9
StarChat-Beta	44.7	52	80.6	47.2	26.7

https://hf.co/bigcode/starcoderplus

#### StarChat Beta





https://huggingface.co/spaces/HuggingFaceH4/starchat-playground