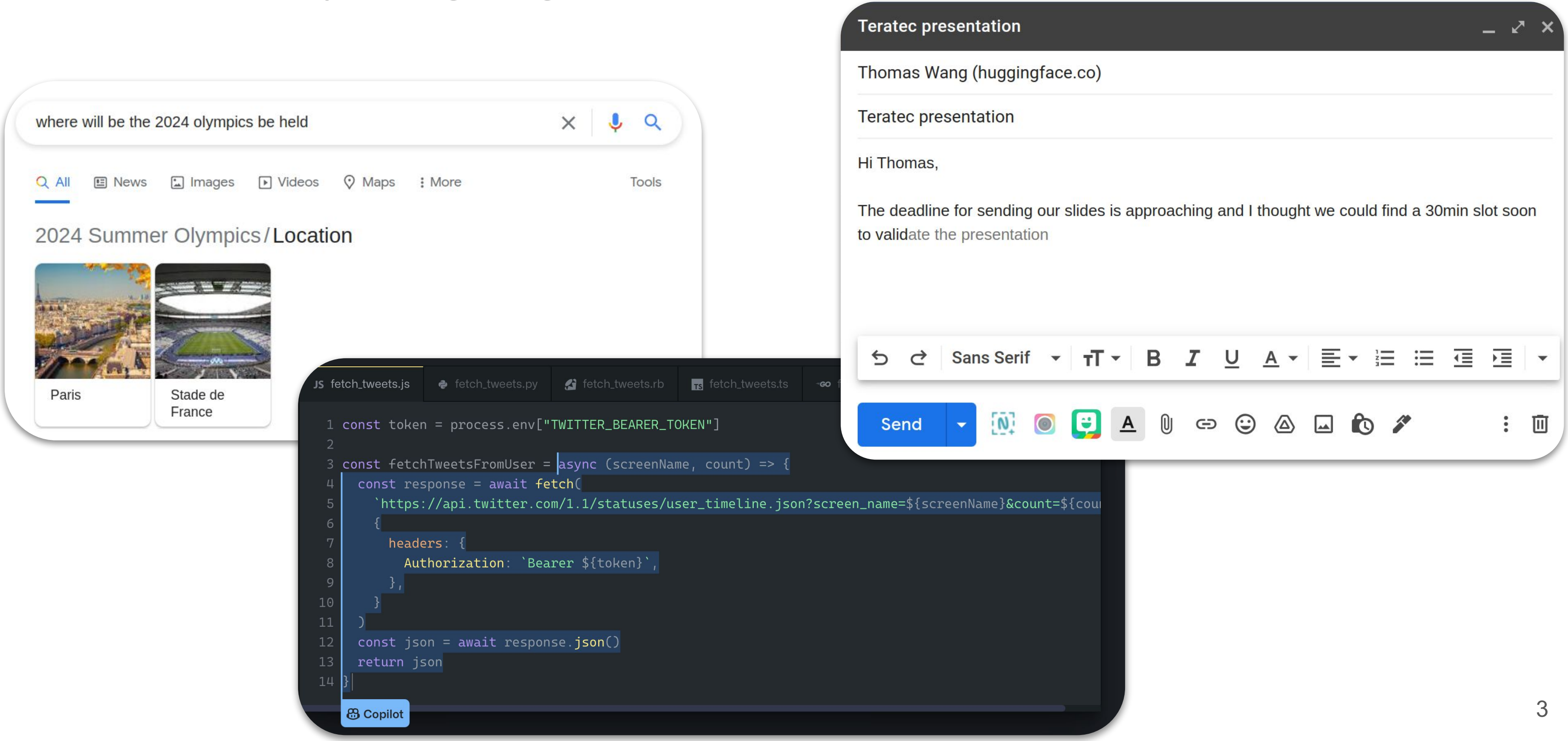
# BigScience Collaboratively training a large multilingual language model

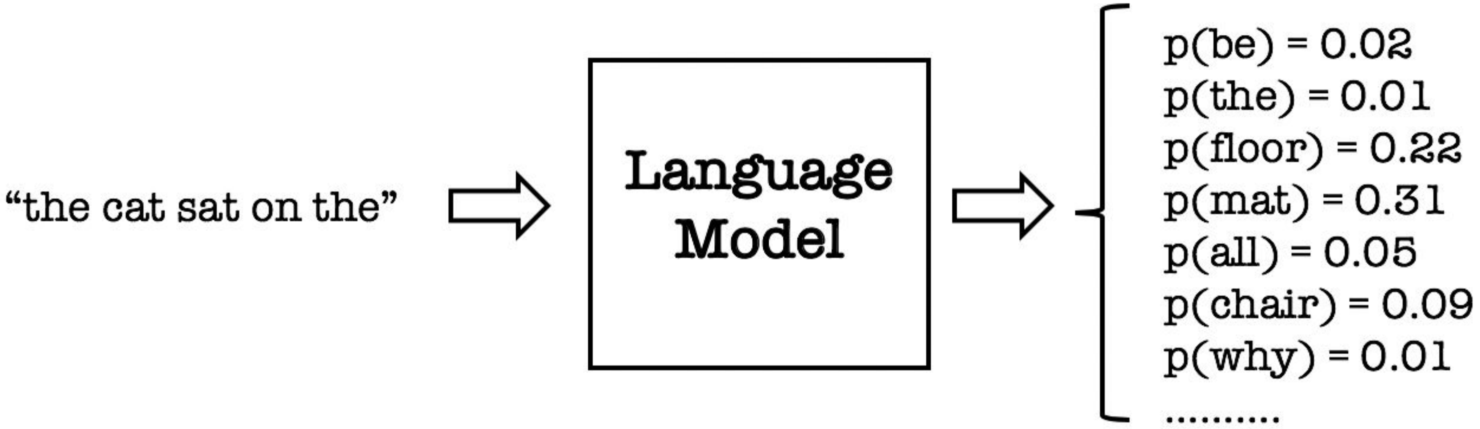
Lucile Saulnier, Thomas Wang

# What motivated us to do BigScience?

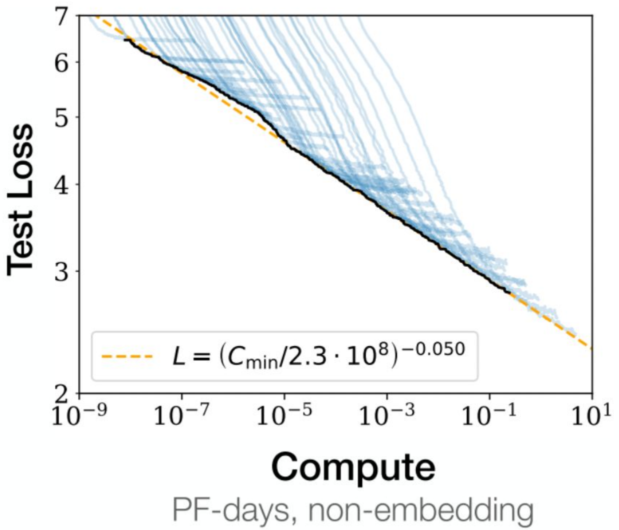
# Context: why language models are useful?

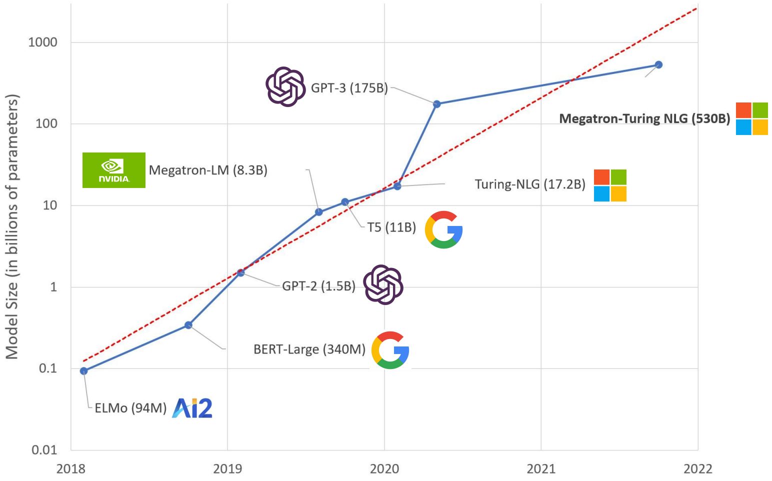


# Context: what is a language model?



# Large Language model: why train one?




GPT-3's generation example:

```
[...]
To do a "farduddle" means to jump up and down really fast. An example of a sentence that uses the word farduddle is:
One day when I was playing tag with my little sister, she got really excited and she started doing these crazy farduddles.
```

# Large Language model: why research on LLMs is hard today?

## Training cost

- typically $2-5M
- million of gpu hours

## Closed access for most of them

**VB** VentureBeat

Naver trained a ‘GPT-3-like’ Korean language model

Naver claims the system learned 6,500 times more Korean data than OpenAI's ... Some experts believe that while HyperCLOVA, GPT-3, PanGu-α, ...

1 Jun 2021

**TC** TechCrunch

Anthropic is the new AI research outfit from OpenAI’s Dario Amodei, and it has $124M to burn

Anthropic, as it's called, was founded with his sister Daniela and its goal is to create “large-scale AI systems that are steerable, ...

28 May 2021

**VB** VentureBeat

AI21 Labs trains a massive language model to rival OpenAI’s GPT-3

“AI21 Labs was founded to fundamentally change and improve the way people read and write. Pushing the frontier of language-based AI requires ...

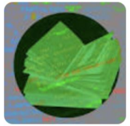
1 month ago

**FC** Fast Company

Ex-Googlers raise $40 million to democratize language AI

This story has been updated with more information about Cohere's approach to responsible AI. About the author. Fast Company Senior Writer Mark ...

2 days ago



# Large Language model: why opacity in LLMs is an issue today?

**Research**

- Difficult to do real research: no access to data, training artifacts, checkpoints
- Academic researchers: not involved
- Lack of fields diversity: English/Chinese only, ML-only teams

**Environmental**

- Training similar models: Duplication of energy requirements

**Ethical and societal around datasets/design**

- Shortcomings in the text corpora used to train these models: Representativeness, stereotypes, PII
- Ethical/bias/usage questions: Only asked a-posteriori

# BigScience: what is it?

“During **one-year**, from May 2021 to May 2022, 1000+ researchers from 60 countries and more than 250 institutions are **creating together a very large multilingual neural network language model** and a **very large multilingual text dataset** on the 28 petaflops Jean Zay (IDRIS) supercomputer located near Paris, France.

During the workshop, the participants plan to investigate the dataset and the model from all angles: bias, social impact, capabilities, limitations, ethics, potential improvements, specific domain performances, carbon impact, general AI/cognitive research landscape.”

# BigScience: what is it?

**Endeavour to generate momentum on research over LLMs**

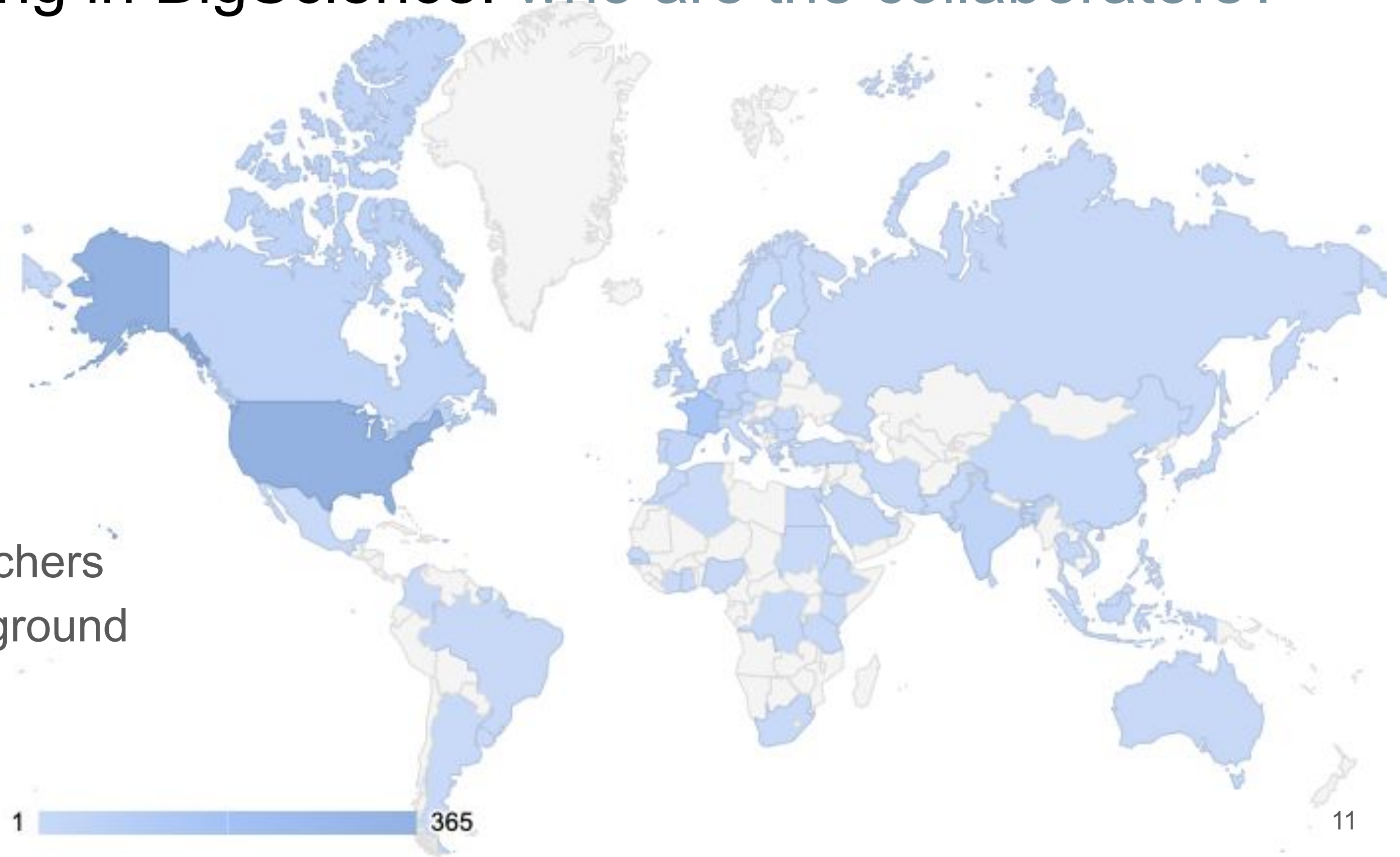
- Open-sourcing
- Collaborative / transparent
- Create working groups over scientific questions

**Training big models is hard from an engineering perspective**

- Train a 176B multilingual model
- Openly discuss engineering problems and solutions throughout the project

# BigScience is a collaborative effort

# People working in BigScience: who are the collaborators?




- 1000+ researchers
- Diverse background

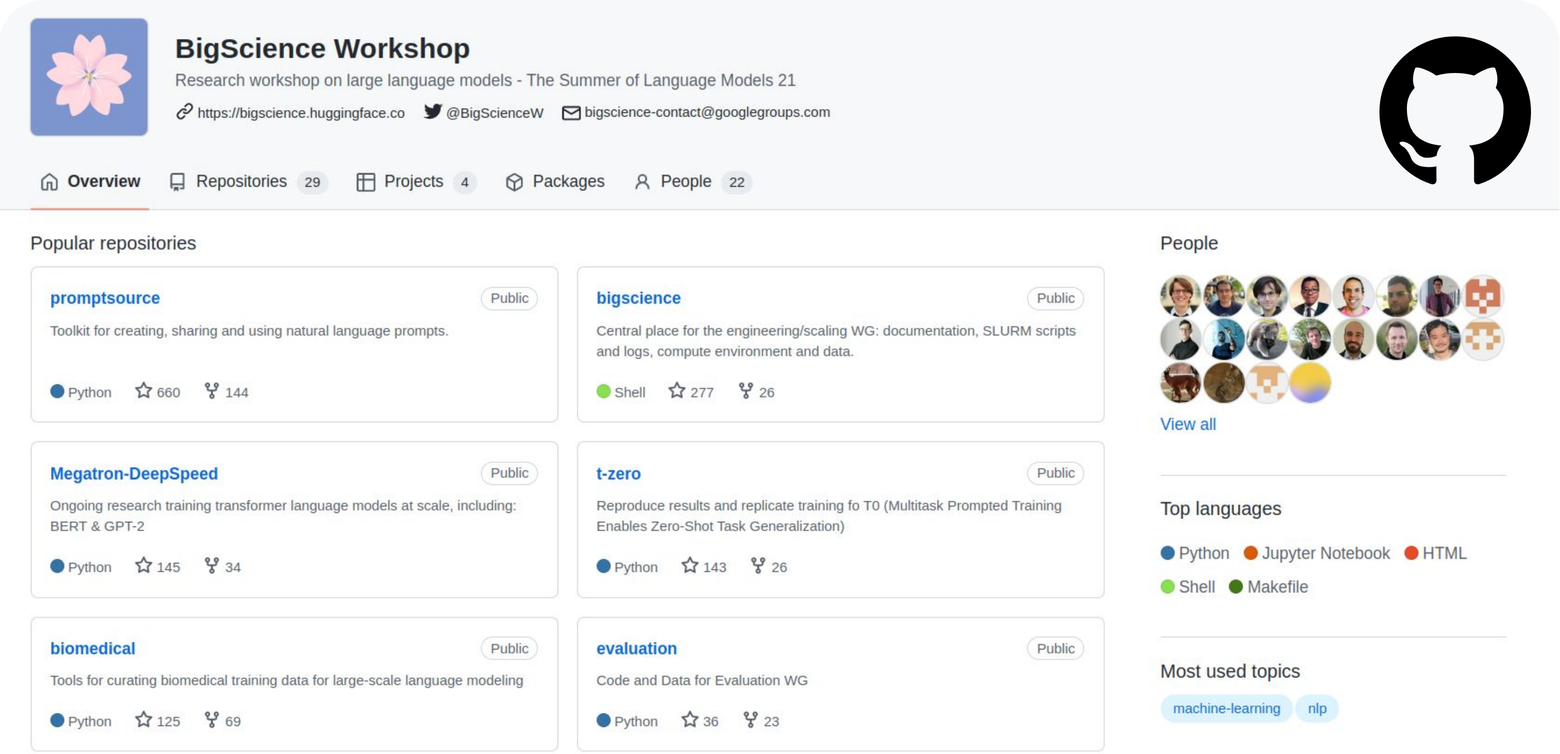
# BigScience's collaborators: what are they working on?

## WORKING GROUPS

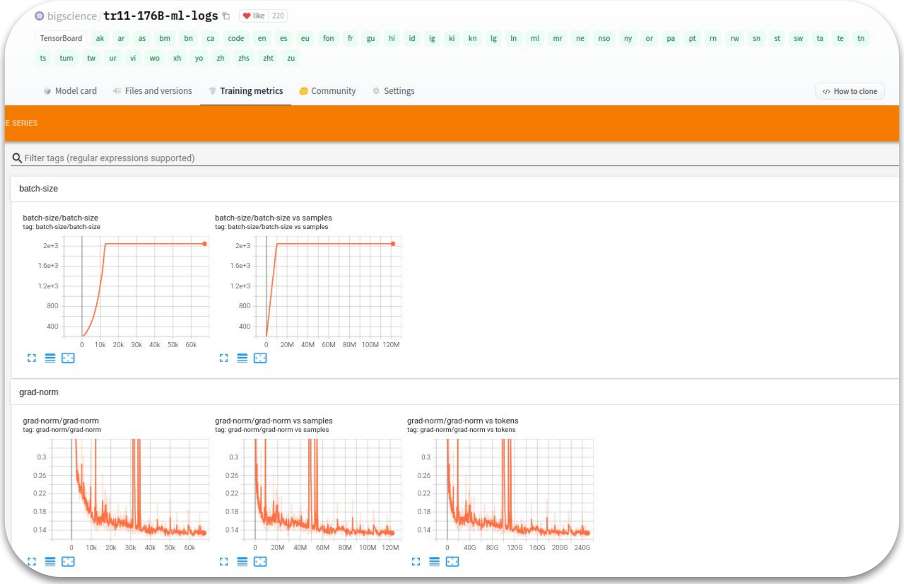
| PROJECT | DATA | TOKENIZATION | MODELING | EVALUATION | DOMAINS |
|---|---|---|---|---|---|
| Organization | Sourcing | **INTERPRETABILITY** | Architecture and Scaling | Intrinsic | Biomedical |
| Ethical and Legal Scholarship | Governance | **ENGINEERING** | Multilinguality | Extrinsic | Historical Texts |
| Accessibility | Tooling | **CARBON FOOTPRINT** | Prompt Engineering | Multilinguality | Math |
| Collaborations and Education | Privacy | | Retrieval | Bias, Fairness, Social Impact | |
| | Analysis and Visualization | | Metadata | Few-shot | |

BigScience

# Artifacts: what came out of BigScience? (1/4)



# Artifacts: what came out of BigScience? (1/4)




https://huggingface.co/bigscience/tr11-176B-ml-logs

```python
from transformers import AutoModel, AutoTokenizer

model_name = "bigscience/bloom"
tokenizer = AutoTokenizer.from_pretrained(model_name)
model = AutoModel.from_pretrained(model_name)
```

https://huggingface.co/bigscience/bloom

# Artifacts: what came out of BigScience? (2/4)

**BigScience**

## BigScience RAIL License v1.0

This is the home of the BigScience RAIL License v1.0.If you would like to download the license you can get it as **.txt**, **.docx**, or **.html** file.

https://huggingface.co/spaces/bigscience/license

# Artifacts: what came out of BigScience? (3/4)

## What Language Model to Train if You Have One Million GPU Hours?


The BigScience Architecture & Scaling Group

Teven Le Scao[1*] Thomas Wang[1*] Daniel Hesslow[2*] Lucile Saulnier[1*] Stas Bekman[1*]
M Saiful Bari[3] Stella Biderman[4,5] Hady Elsahar[6] Jason Phang[7] Ofir Press[8] Colin Raffel[1]
Victor Sanh[1] Sheng Shen[9] Lintang Sutawika[10] Jaesung Tae[1] Zheng Xin Yong[11]
Julien Launay[2,12†] Iz Beltagy[13†]

[1] Hugging Face [2] LightOn [3] NTU, Singapore [4] Booz Allen [5] EleutherAI [6] Naver Labs Europe [7] New York University
[8] University of Washington [9] Berkeley University [10] Big Science [11] Brown University [12] LPENS [13] Allen Institute for AI


...deling methods
...ecture has been a
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...ameters models,
...reasingly expen-
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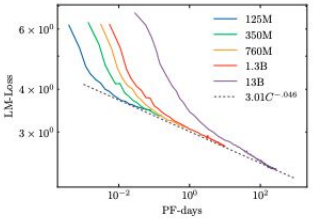



Figure 1: **Smooth scaling of language modeling loss as compute budget and model size increase.** We observe a power-law coefficient $\alpha_C \sim 0.046$, in-line with pre-

## Multitask Prompted Training Enables Zero-Shot Task Generalization


Victor Sanh* Hugging Face | Albert Webson* Brown University | Colin Raffel* Hugging Face | Stephen H. Bach* Brown & Snorkel AI

Lintang Sutawika BigScience | Zaid Alyafeai KFUPM | Antoine Chaffin IRISA & IMATAG | Arnaud Stiegler Hyperscience | Teven Le Scao Hugging Face
Arun Raja I²R, Singapore | Manan Dey SAP | M Saiful Bari NTU, Singapore | Canwen Xu UCSD & Hugging Face | Urmish Thakker SambaNova Systems
Shanya Sharma Walmart Labs | Eliza Szczechla BigScience | Taewoon Kim VU Amsterdam | Gunjan Chhablani BigScience | Nihal V. Nayak Brown University
Debajyoti Datta University of Virginia | Jonathan Chang ASUS | Mike Tian-Jian Jiang ZEALS, Japan | Han Wang NYU | Matteo Manica IBM Research
Sheng Shen UC Berkeley | Zheng-Xin Yong Brown University | Harshit Pandey BigScience | Michael McKenna Parity | Rachel Bawden Inria, France
Thomas Wang Inria, France | Trishala Neeraj BigScience | Jos Rozen Naver Labs Europe | Abheesht Sharma BITS Pilani, India | Andrea Santilli University of Rome
...lan Fries ... & Snorkel AI | Ryan Teehan Charles River Analytics | Tali Bers Brown University
Leo Gao EleutherAI | Thomas Wolf Hugging Face | Alexander M. Rush Hugging Face



### Abstract

...ls have recently been shown to attain reasonable zero-shot ...verse set of tasks (Brown et al., 2020). It has been hypothe... ...sequence of implicit multitask learning in language models' ...t al., 2019). Can zero-shot generalization instead be directly ...ultitask learning? To test this question at scale, we develop


## Masader: Metadata Sourcing for Arabic Text and Speech Data Resources


Zaid Alyafeai[1], Maraim Masoud[2], Mustafa Ghaleb[1], and Maged S. Al-shaibani[1]

[1] King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia
[2] Independent Researcher



### Abstract

The NLP pipeline has evolved dramatically in the last few years. The first step in the pipeline is to find suitable annotated datasets to evaluate the tasks we are trying to solve. Unfortunately, most of the published datasets lack metadata annotations that describe their attributes. Not to mention, the absence of a public catalogue that indexes all the publicly available datasets related to specific regions or languages. When we consider low-resource dialectical languages, for example, this issue becomes more prominent. In this paper we create *Masader*, the largest public catalogue for Arabic NLP datasets, which consists of 200 datasets annotated with 25 attributes. Further-

and so on. This study attempts to identify the publicly available Arabic NLP datasets and to provide a catalogue of Arabic datasets to researchers. The catalogue will increase the discoverability and provide some key metadata that will help researchers identify the most suitable dataset for their research questions.


We...

## Between words and characters: A Brief History of Open-Vocabulary Modeling and Tokenization in NLP


Sabrina J. Mielke[1,2] Zaid Alyafeai[3] Elizabeth Salesky[1]
Colin Raffel[2] Manan Dey[4] Matthias Gallé[5] Arun Raja[6]
Chenglei Si[7] Wilson Y. Lee[8] Benoît Sagot[9*] Samson Tan[10*]
*BigScience Workshop Tokenization Working Group*

[1]Johns Hopkins University [2]HuggingFace [3]King Fahd University of Petroleum and Minerals [4]SAP
[5]Naver Labs Europe [6]Institute for Infocomm Research, A*STAR Singapore [7]University of Maryland
[8]BigScience Workshop [9]Inria Paris [10]Salesforce Research Asia & National University of Singapore
sjm@sjmielke.com



### Abstract

What are the units of text that we want to model? From bytes to multi-word expressions, text can be analyzed and generated at many granularities. Until recently, most natural language processing (NLP) models operated over words, treating those as discrete and atomic tokens, but starting with byte-pair encoding (BPE), subword-based approaches have become dominant in many areas, enabling small vocabularies while still allowing for fast inference. Is the end of the road character-level model or byte-level processing? In this survey, we connect several lines of work from the pre-neural and neural era, by showing how hybrid approaches

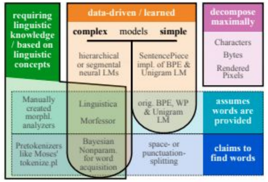




Figure 1: A taxonomy of segmentation and tokenization algorithms and research directions

## What Language Model Architecture and Pretraining Objective Work Best for Zero-Shot Generalization?


The BigScience Architecture & Scaling Group

Thomas Wang[1*] Adam Roberts[2*]
Daniel Hesslow[3] Teven Le Scao[1] Hyung Won Chung[2]
Iz Beltagy[4] Julien Launay[3,5†] Colin Raffel[1†]

[1] Hugging Face [2]Google [3]LightOn
[4]Allen Institute for AI [5]LPENS, École Normale Supérieure



### Abstract

Large pretrained Transformer language models have been shown to exhibit *zero-shot generalization*, i.e. they can perform a wide variety of tasks that they were not explicitly trained on. However, the architectures and pretraining objectives used across state-of-the-art models differ significantly, and there has been limited systematic comparison of these factors. In this work, we present a large-scale evaluation of modeling choices and their impact on zero-shot generalization. In particular, we focus on text-to-text models and experiment with three model architectures (causal/non-causal decoder-only and encoder-decoder), trained with two different pretraining objectives (autoregressive and masked language modeling), and evaluated with and without multitask prompted finetuning. We train


And many mores..

# Artifacts: what came out of BigScience? (4/4)

**Stas Bekman**
@StasBekman

The embed matrix with 250k multi-lingual vocab is on par in size with the transformer block, so rebalancing the pipeline to count embedding matrices as transformer blocks leads to even faster throughput and less memory usage on ranks 0 and -1

Benchmarks:

bigscience-workshop/
**bigscience**

Central place for the engineering/scaling WG: documentation, SLURM scripts and logs, compute environment and data.

13 Contributors · 2 Issues · 272 Stars · 24 Forks

github.com
bigscience/chronicles-prequel.md at master · bigscience-workshop/bigscience
Central place for the engineering/scaling WG: documentation, SLURM scripts and logs, compute environment and data. - bigscience/chronicles-prequel.md a...

6:34 AM · Mar 4, 2022 · Twitter Web App

**BigScience Large Model Training**
@BigScienceLLM

Currently doing live surgery on the 176B model during training

While testing the checkpoint weights for integration in transformers we discovered that layer norms were not in sync across TP ranks contrary to what expected - trying to fix this while training

Wish us luck!

12:38 PM · Mar 25, 2022 · Twitter Web App

https://github.com/bigscience-workshop/bigscience/blob/master/train/lessons-learned.md

# Training a 176B model

# Jean Zay: accessing the french public supercomputer compute

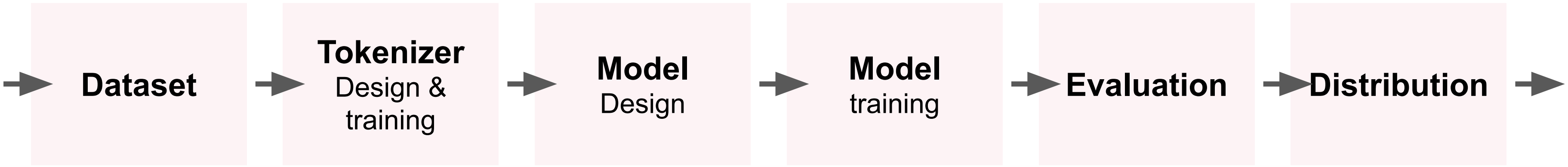
🌸 This work was granted access to the HPC resources of *Institut du développement et des ressources en informatique scientifique* (IDRIS) du *Centre national de la recherche scientifique* (CNRS) under the allocation 2021-A0101012475 made by *Grand équipement national de calcul intensif* (GENCI).

🌸 Compute grant:

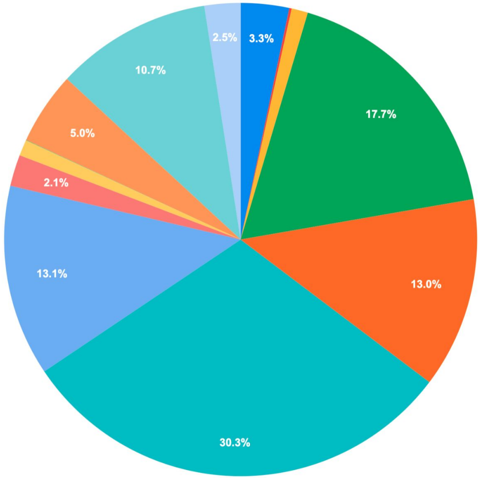
- 2.5M V100 hours
- 1.25M A100 hours: a reserved allocation of 416 A100 (80GB)
- and a ton of CPU

🌸 Technical support - Thanks Rémi Lacroix!

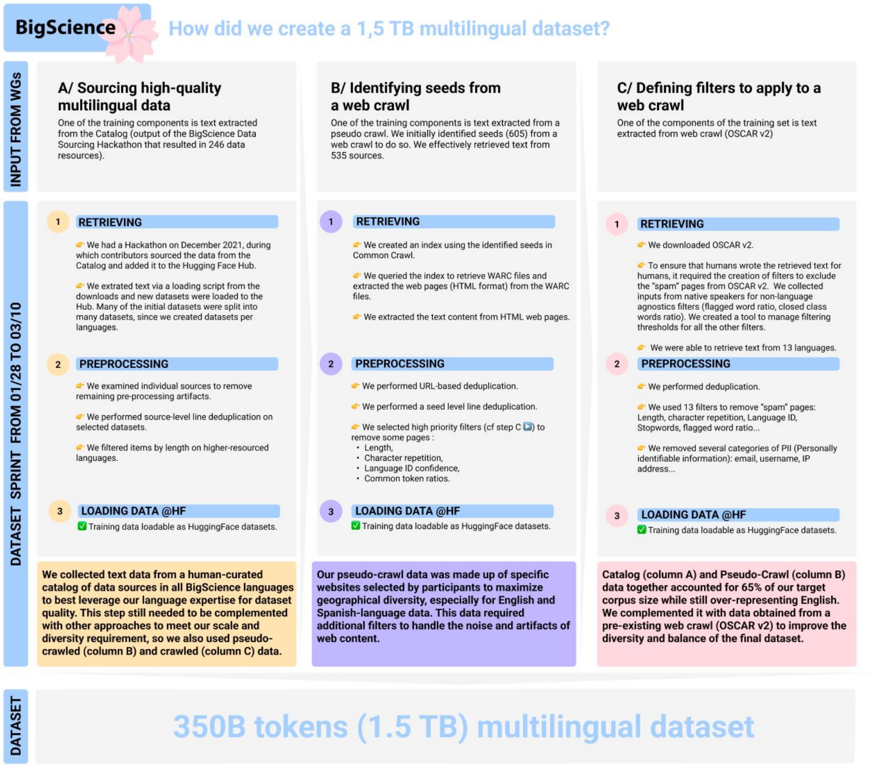
# DL pipeline: what do we need to train a language model?



# Training dataset: building a 1.5T multilingual dataset




- Arabic (3,3%)
- Basque (0,2%)
- Catalan (1,1%)
- Chinese (17,7%)
- Code (13%)
- English (30,3%)
- French (13,1%)
- Indic (2,1%)
- Indonesian (1,1%)
- Niger Congo (0,03%)
- Portuguese (5%)
- Spanish (10,7%)
- Vietnamese (2,5%)



# Modeling: why are we training a GPT-3 like model?

GPT3

RESEARCH

## Democratizing access to large-scale language models with OPT-175B

May 3, 2022

Publication

## An empirical analysis of compute-optimal large language model training

Download | View publication

Google AI Blog

The latest from Google Research

## Pathways Language Model (PaLM): Scaling to 540 Billion Parameters for Breakthrough Performance

Monday, April 4, 2022

## Announcing AI21 Studio and Jurassic-1 Language Models

AI21 Labs' new developer platform offers instant access to our 178B-parameter language model, to help you build sophisticated text-based AI applications at scale

Research

## Language modelling at scale: Gopher, ethical considerations, and retrieval

December 8, 2021

## YUAN 1.0: LARGE-SCALE PRE-TRAINED LANGUAGE MODEL IN ZERO-SHOT AND FEW-SHOT LEARNING

Shaohua Wu* Xudong Zhao Tong Yu
Rongguo Zhang Chong Shen Hongli Liu Feng Li
Hong Zhu Jiangang Luo Liang Xu Xuanwei Zhang

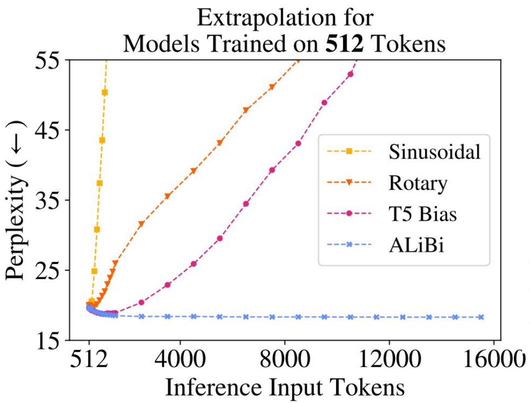
## Announcing GPT-NeoX-20B

Announcing GPT-NeoX-20B, a 20 billion parameter model trained in collaboration with CoreWeave.

February 2, 2022 · Connor Leahy

# Modeling: what did we choose?

- **ALiBi** positional embeddings which allows to do good extrapolations




| Positional Embedding | Average EAI Results |
|---|---|
| None | 41.23 |
| Learned | 41.71 |
| Rotary | 41.46 |
| ALiBi | **43.70** |

Table 2: **ALiBi significantly outperforms other embeddings for zero-shot generalization.** All models are trained on the OSCAR dataset for 112 billion tokens.

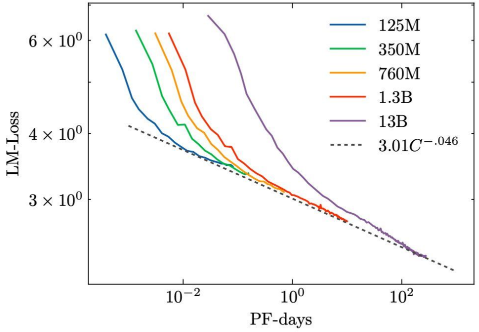
- **GELU** activation which are 30% faster than SwiGLU

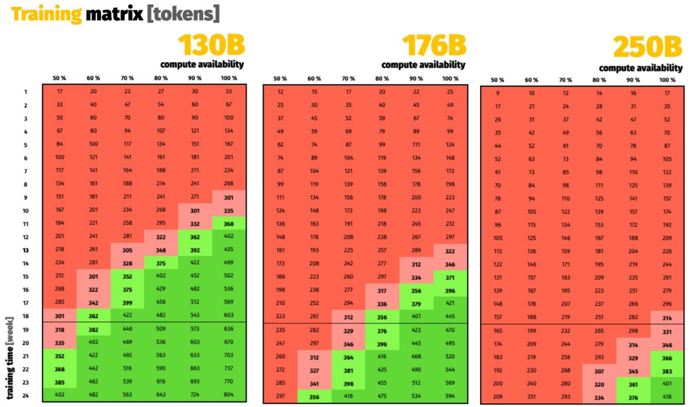
| Activation function | Average EAI Results |
|---|---|
| GELU | 42.79 |
| SwiGLU | **42.95** |

Table 3: **SwiGLU slightly outperforms GELU for zero-shot generalization.** Models trained on The Pile for 112 billion tokens.

# Modeling: how did we decide on the final dimensions of the model?

Perform scaling law on English…




… Create fixed budget scenarios for different model sizes …

| Model | Size [Bparams.] | Pretraining [Btokens] | Budget [PF-days] | Layers | Hidden dim. | Attention heads num. | Attention heads dim. |
|---|---|---|---|---|---|---|---|
| LaMDA (Thoppilan et al., 2022) | 137 | 432 | 4,106 | 64 | 8,192 | 128 | 64 |
| GPT-3 (Brown et al., 2020) | 175 | 300 | 3,646 | 96 | 12,288 | 96 | 128 |
| J1-Jumbo (Lieber et al., 2021) | 178 | 300 | 3,708 | 76 | 13,824 | 96 | 144 |
| PanGu-$\alpha$ (Zeng et al., 2021) | 207 | 42 | 604 | 64 | 16,384 | 128 | 128 |
| Yuan (Wu et al., 2021) | 245 | 180 | 3,063 | 76 | 16,384 | | |
| Gopher (Rae et al., 2021) | 280 | 300 | 4,313 | 80 | 16,384 | 128 | 128 |
| MT-530B (Smith et al., 2022) | 530 | 270 | 9,938 | 105 | 20,480 | 128 | 160 |

arxiv.org/abs/2001.08361
arxiv.org/abs/2006.12467

… Read the scientific literature…

| Model | Size [params.] | Layers | Hidden dim. | Attention heads num. | Attention heads dim. | Memory [GB] | Performance [sec/iter.] | Performance [TFLOPs] |
|---|---|---|---|---|---|---|---|---|
| (1) | 178 | 82 | 13,312 | 64 | 208 | 63 | 104 | 152 |
| (2) | 178 | 82 | 13,312 | 128 | 104 | 60 | 109 | 146 |
| **(3)** | **176** | **70** | **14,336** | **112** | **128** | **59** | **105** | **150** |

… Take into account engineering constraint

# Training a 176B Model from an engineering perspective:
## how do we train effectively models at this scale?

```
~checkpoints/tr11-176B-ml/checkpoints/main> du -h global_step63600/
2.3T  global_step63600/
```

🏋 Including optimizer states and checkpoints

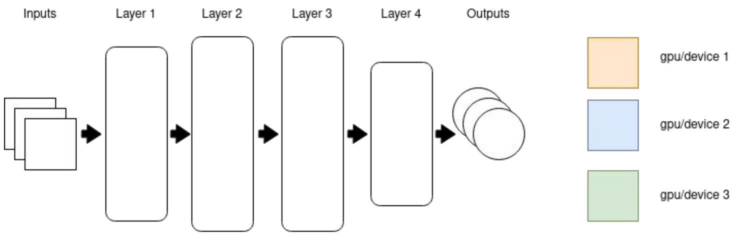
After preliminary studies, we selected:

microsoft / **Megatron-DeepSpeed** Public

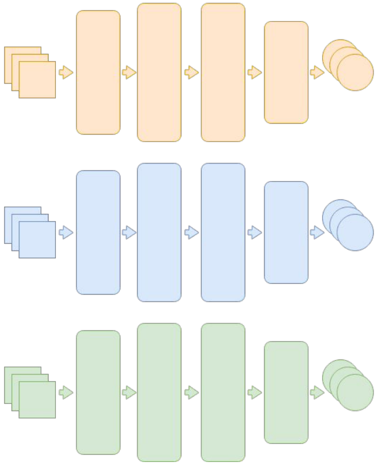
forked from NVIDIA/Megatron-LM

deepspeed

# Parallelism:
## how to use a cluster wisely for DL?



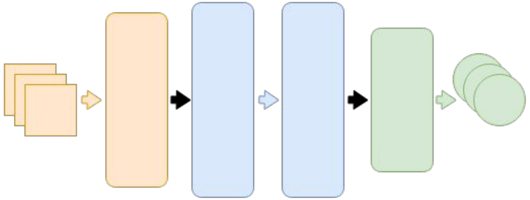

**Data parallelism**
to accelerate the training speed



Each device has a replica of the model and receives a different batch of training data on which it performs a forward and backward pass

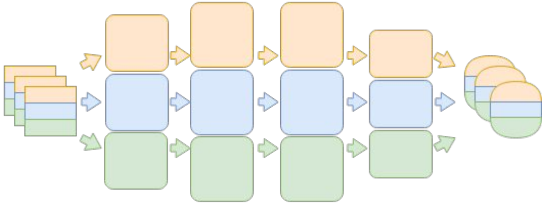
**Model parallelism**
to train models that don't fit in the memory of one device

**Pipeline parallelism**



Only one or several consecutive layers of the model are placed on a single GPU

**Tensor parallelism**

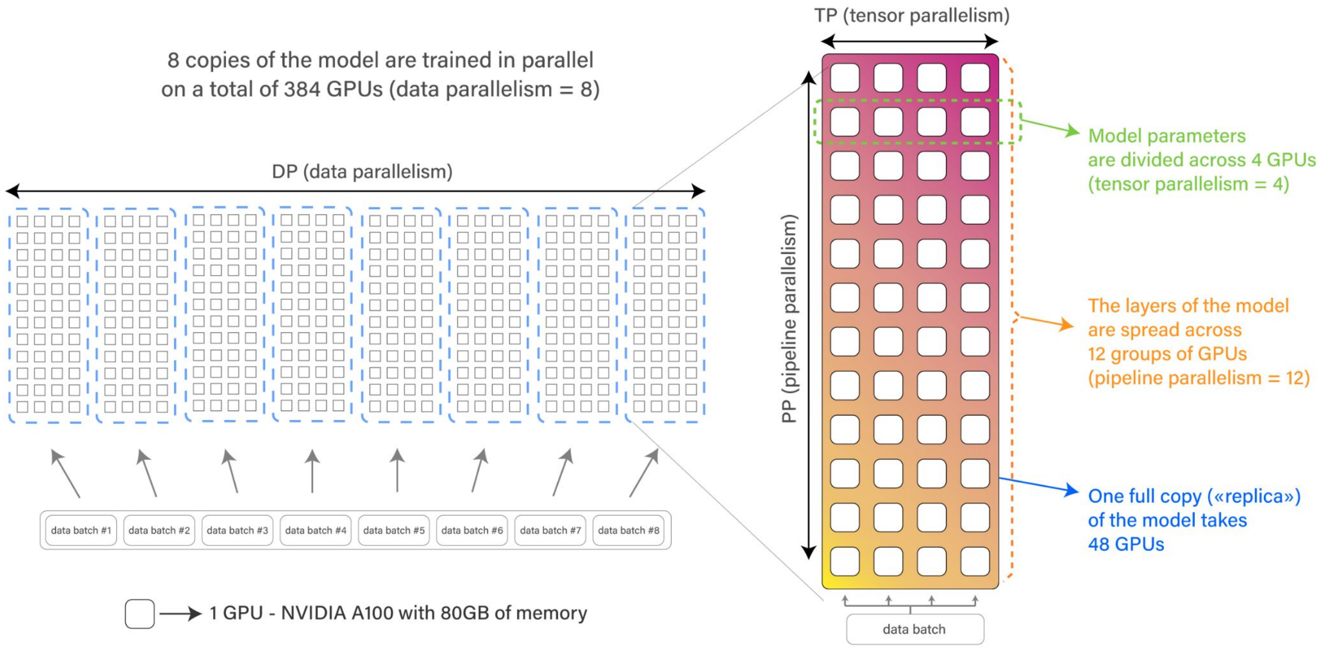


Each tensor is divided into several pieces so that instead of having the whole tensor residing on a single GPU each piece of the tensor resides on a different GPU

# Parallelism:
## how to use a cluster wisely for DL?

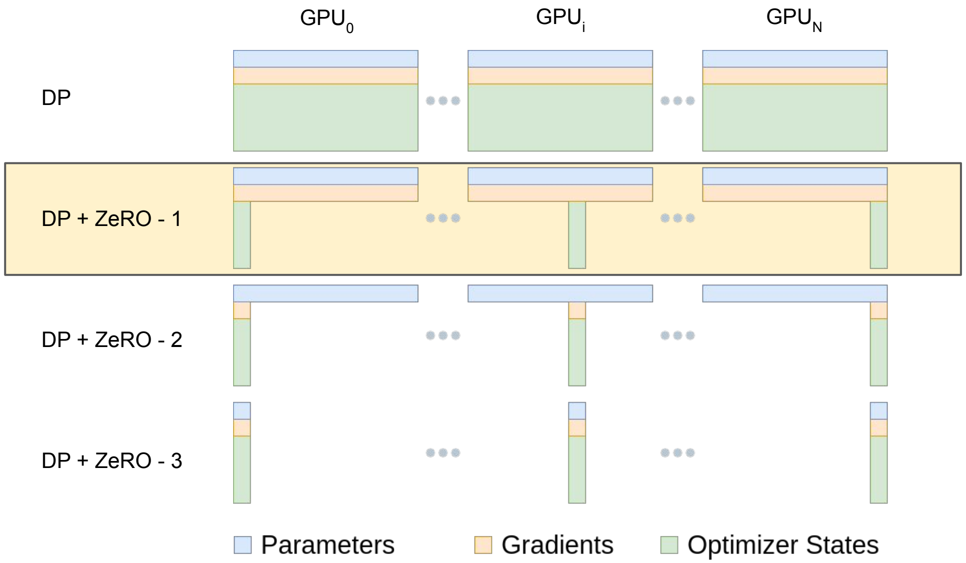
DP?
TP?
PP?

All 3 techniques were used!



# ZeRO data parallelism: to make the most of data parallelism

- instead of replicating everything each GPU stores only a slice of it
- free the gpus for larger batch sizes or more layers




👈 The one we used

https://huggingface.co/docs/transformers/parallelism#zero-data-parallelism

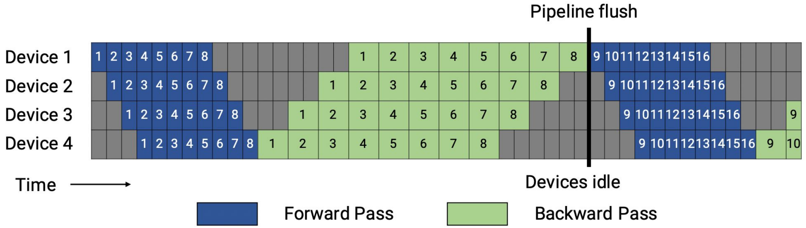
# Pipeline scheduling: improving memory footprint

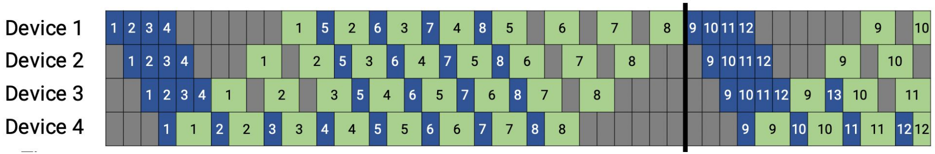
👇The one we used

## All forward, all backward

Reduce memory →

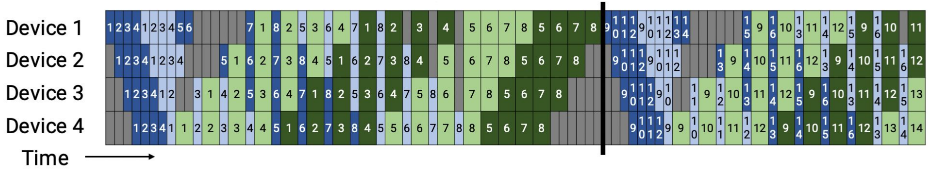
## One forward, one backward (1f1b)



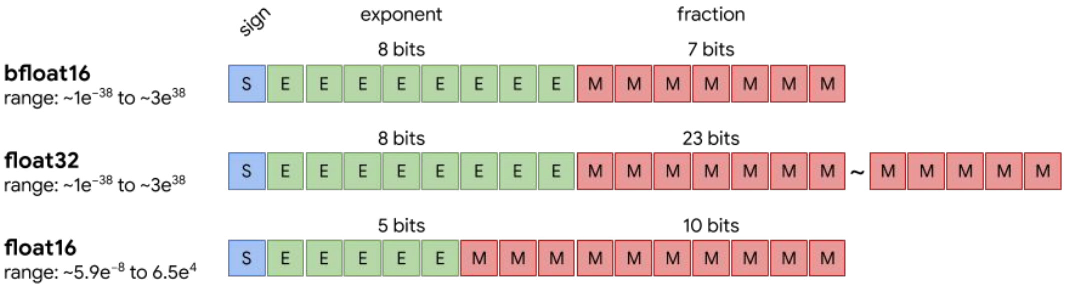

Reduce bubble at the cost of communication

## Interleaved 1f1b



# BF16 (+ clean data):

## a mixed precision enabling stable training

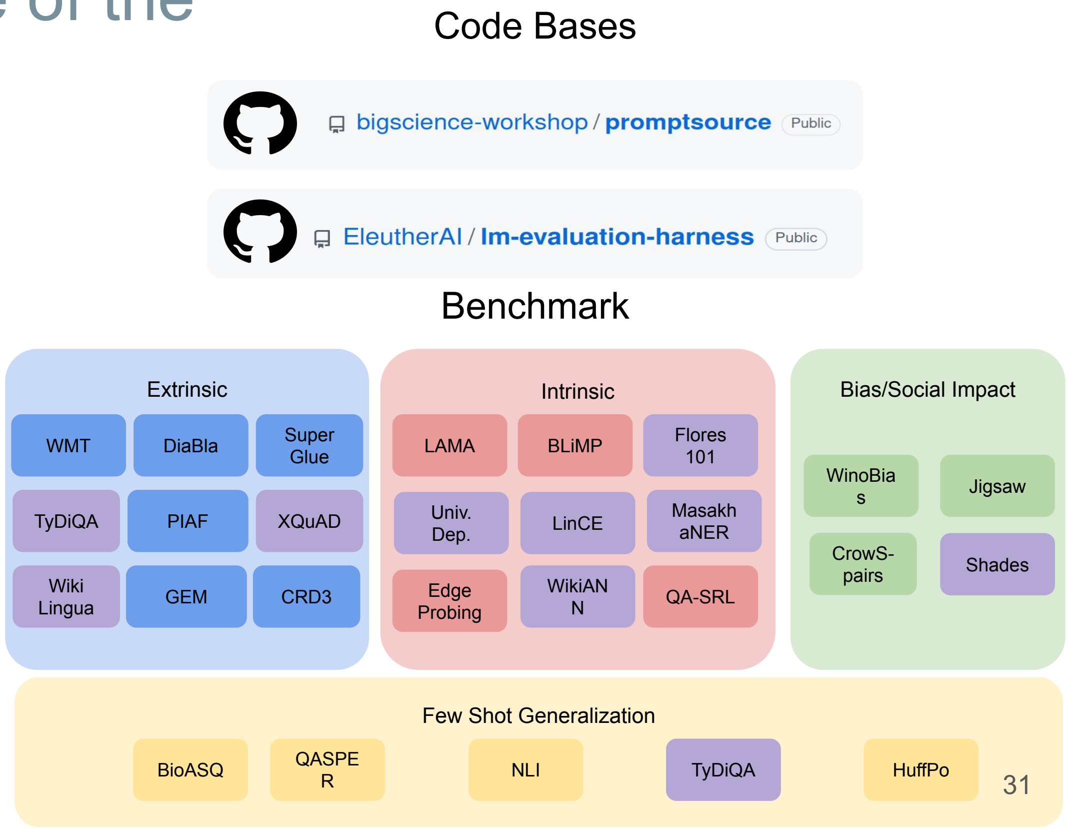



Source: https://moocaholic.medium.com/fp64-fp32-fp16-bfloat16-tf32-and-other-members-of-the-zoo-a1ca7897d407

Trade-off between memory footprint, dynamic range and precision

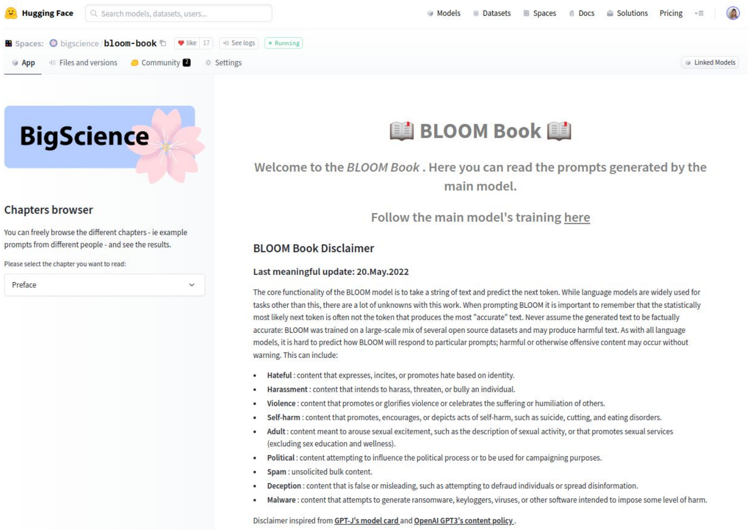
# Evaluation: A new benchmark to measure the performance of the model - WIP

- 🚘 **Extrinsic Evaluation**: Focus on downstream, user-facing tasks
- ⚙️ **Intrinsic Evaluation**: Focus on encoding of linguistic and world knowledge
- 🌈 **Bias/Social Impact**: Quantify encoding of stereotypes and risk of user harm
- 🗣️ **Multilingualism**: Ensure coverage of training and unseen language in all evaluations
- 🍎 🍊**Few-Shot Generalization**: Focus on evaluation on distributions not seen in pretraining



# Evaluation: possibility to prompt the model

📖 BLOOM Book 📖




📖 BLOOM Book 📖

Welcome to the *BLOOM Book* . Here you can read the prompts generated by the main model.

Follow the main model's training here

BLOOM Book Disclaimer

**Last meaningful update: 20.May.2022**

The core functionality of the BLOOM model is to take a string of text and predict the next token. While language models are widely used for tasks other than this, there are a lot of unknowns with this work. When prompting BLOOM it is important to remember that the statistically most likely next token is often not the token that produces the most "accurate" text. Never assume the generated text to be factually accurate: BLOOM was trained on a large-scale mix of several open source datasets and may produce harmful text. As with all language models, it is hard to predict how BLOOM will respond to particular prompts; harmful or otherwise offensive content may occur without warning. This can include:

- **Hateful** : content that expresses, incites, or promotes hate based on identity.
- **Harassment** : content that intends to harass, threaten, or bully an individual.
- **Violence** : content that promotes or glorifies violence or celebrates the suffering or humiliation of others.
- **Self-harm** : content that promotes, encourages, or depicts acts of self-harm, such as suicide, cutting, and eating disorders.
- **Adult** : content meant to arouse sexual excitement, such as the description of sexual activity, or that promotes sexual services (excluding sex education and wellness).
- **Political** : content attempting to influence the political process or to be used for campaigning purposes.
- **Spam** : unsolicited bulk content.
- **Deception** : content that is false or misleading, such as attempting to defraud individuals or spread disinformation.
- **Malware** : content that attempts to generate ransomware, keyloggers, viruses, or other software intended to impose some level of harm.

Disclaimer inspired from GPT-J's model card and OpenAI GPT3's content policy .

https://hf.co/spaces/bigscience/bloom-book

Checkpoint: 65k steps (240B tokens)

Prompt

```
To do a "farduddle" means to jump up and down
really fast. An example of a sentence that uses
the word farduddle is:
```

Generated

```
We were on a Kindrex toyshop hop and we got to
see if Kindrex toys were built to withstand
constant jumping, lots of jumping! To do this
part, I had to farduddle to simulate jumping.
```

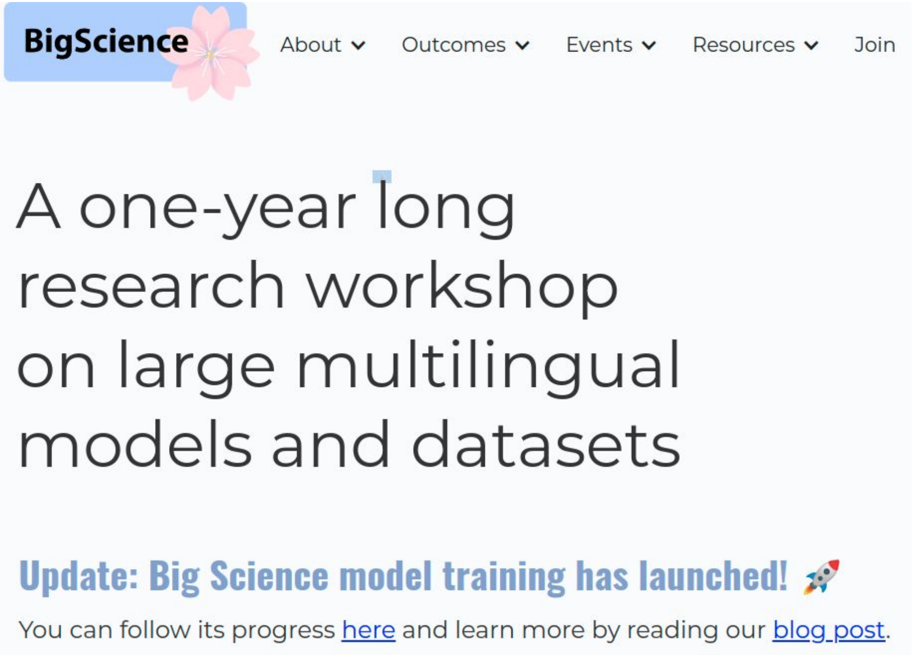
# What’s next?

🌸 Finish training


🌸 Finish evaluation benchmark and perform evaluation

🌸 Make the model more accessible - ZeRO off-loading, Distillation, …

# Follow us!




🌸 Website

https://bigscience.huggingface.co

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