Data behind LLM

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Data behind large language models

- Large language models are trained on “raw text”. To be highly capable (e.g., have linguistic and world knowledge), this text should span a **broad** range of domains, genres, languages, etc.
- **Web**: a major source.
  - Huge. the Google search index is 100 petabytes (reference).
- **Private datasets** that reside in big companies are even larger than what’s available publicly.
  - WalMart generates 2.5 petabytes of data each hour!

Data behind large language models

- Common Crawl
- WebText and OpenWebText
- Colossal Clean Crawled Corpus (C4)
- GPT-3 dataset
- The Pile

Common Crawl

- **Common Crawl** is a nonprofit organization that crawls the web and provides snapshots that are free to the public.
- Scale: The April 2021 snapshot of Common Crawl has 320 terabytes of data
- Applications: A standard source of data to train many models such as T5, GPT-3, and Gopher.

Common Crawl

Representation harms. Despite the richness of web data, it has been noted in Bender et al, 2021 that:

- Despite the size, large-scale data still has **uneven representation** over the population.
- Internet data overrepresents younger users from developed countries.
- GPT-2's training data is based on Reddit, which according to Pew Internet Research's 2016 survey, 67% of Reddit users in the US are men, 64% between ages 18 and 29.
- 8.8-15% of Wikipedians are female.
- Filtering "bad words" could further marginalize certain populations (e.g., LGBT+).

Takeaway: it is crucial to understand and document the composition of the datasets used to train large language models.

WebText

- WebText: **dataset used in training GPT-2**
- Goal: obtain **diverse but high-quality** dataset.
- Previous work:
  - Datasets were trained on news, Wikipedia, or fiction.
  - Common Crawl contains a lot of junk (gibberish, boilerplate text).
  - Trinh & Le, 2018 selected a tiny subset of Common Crawl based on n-gram overlap with the target task.
- Process for creating WebText:
  - Scraped all outbound links that received at least 3 karma (upvotes).
  - Filtered out Wikipedia to be able to evaluate on Wikipedia-based benchmarks.
  - End result is 40 GB of text.
- WebText was not released by OpenAI

WebText and OpenWebText

- OpenWebText: WebText was replicated (in spirit) by the OpenWebText dataset.
- Process for creating OpenWebText:
  - Extracted all the URLs from the Reddit submissions dataset.
  - Used Facebook's fastText to filter out non-English.
  - Removed near duplicates.
  - End result is 38 GB of text.

Dataset: WebText and OpenWebText

- **Toxicity analysis**.
  - RealToxicityPrompts (Gehman et al. 2020) : a dataset of 100K naturally occurring, sentence-level prompts derived from a large corpus of English web text, paired with toxicity scores from a widelyused toxicity classifier.
  - Analyzed these two datasets and found:
    - 2.1% of OpenWebText has toxicity score >= 50%
    - 4.3% of WebText (from OpenAI) has toxicity score >= 50%
    - News reliability correlates negatively with toxicity (Spearman ρ=−0.35)
    - 3% of OpenWebText comes from banned or quarantined subreddits, e.g., /r/The_Donald and /r/WhiteRights
- Takeaway: We can construct datasets to evaluate toxicity score of large datasets / models.

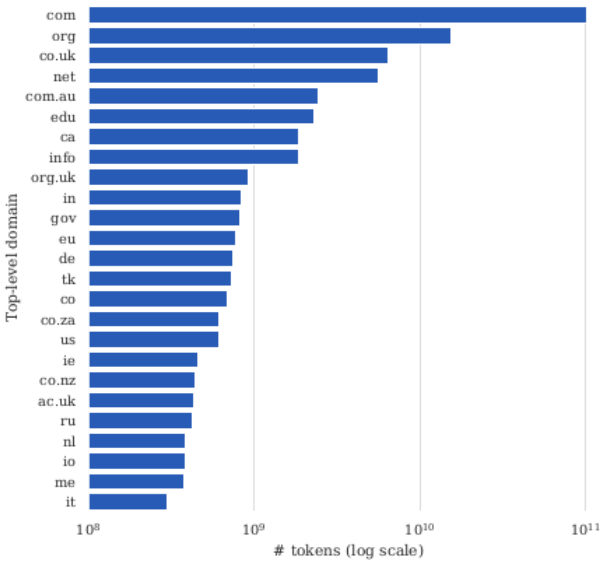
Colossal Clean Crawled Corpus (C4)

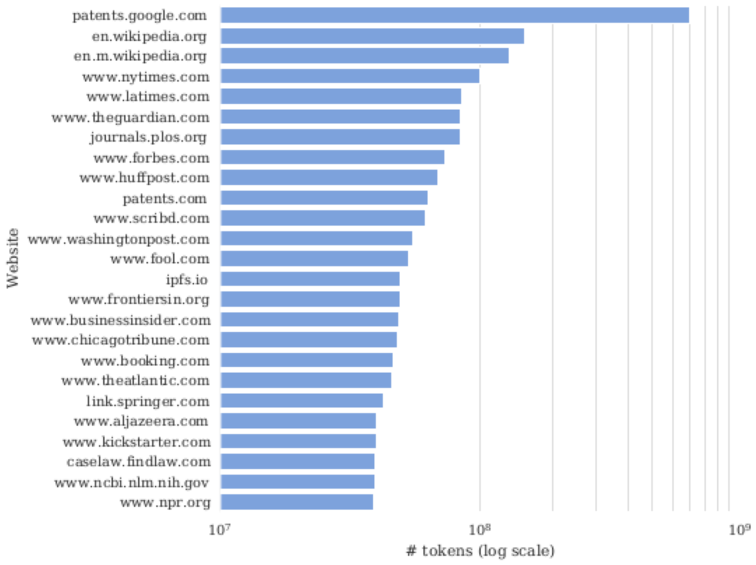
- The Colossal Clean Crawled Corpus (C4) is a larger was created to train the T5 model.
- Processes for constructing C4
  - Started with April 2019 snapshot of Common Crawl (1.4 trillion tokens)
  - Removed “bad words”
  - Removed code (“{“)
  - langdetect to filter out non-English text
  - Resulted in 806 GB of text (156 billion tokens)

Colossal Clean Crawled Corpus

Analysis. Dodge et al. 2021 performed a thorough analysis of the C4 dataset.

- A surprising amount of data from patents.google.com
- 65% pages in the Internet Archive; out of those, 92% pages written in the last decade
- 51.3% pages are hosted in the United States; fewer from India even though lots of English speakers there
- Some text from patents.google.com are automatically created, and thus have systematic errors:
  - Filed in a foreign country's official language (e.g., Japanese) is automatically translated into English
  - Automatically generated from optical character recognition (OCR)





Benchmark data contamination

- When we are evaluating the capabilities of large language models using benchmark data (e.g., question-answer pairs), it makes a difference whether the benchmark data appears in the training data of the language model. If so, then the benchmark performance will be **biased** up.
- Normally, in machine learning, data hygiene (keeping the training data separate from the test) is relatively easy, but **in the case of large language models**, both the training data and benchmark data are derived from the Internet, **it can be difficult to a priori guarantee their separation.**

Benchmark data contamination in C4

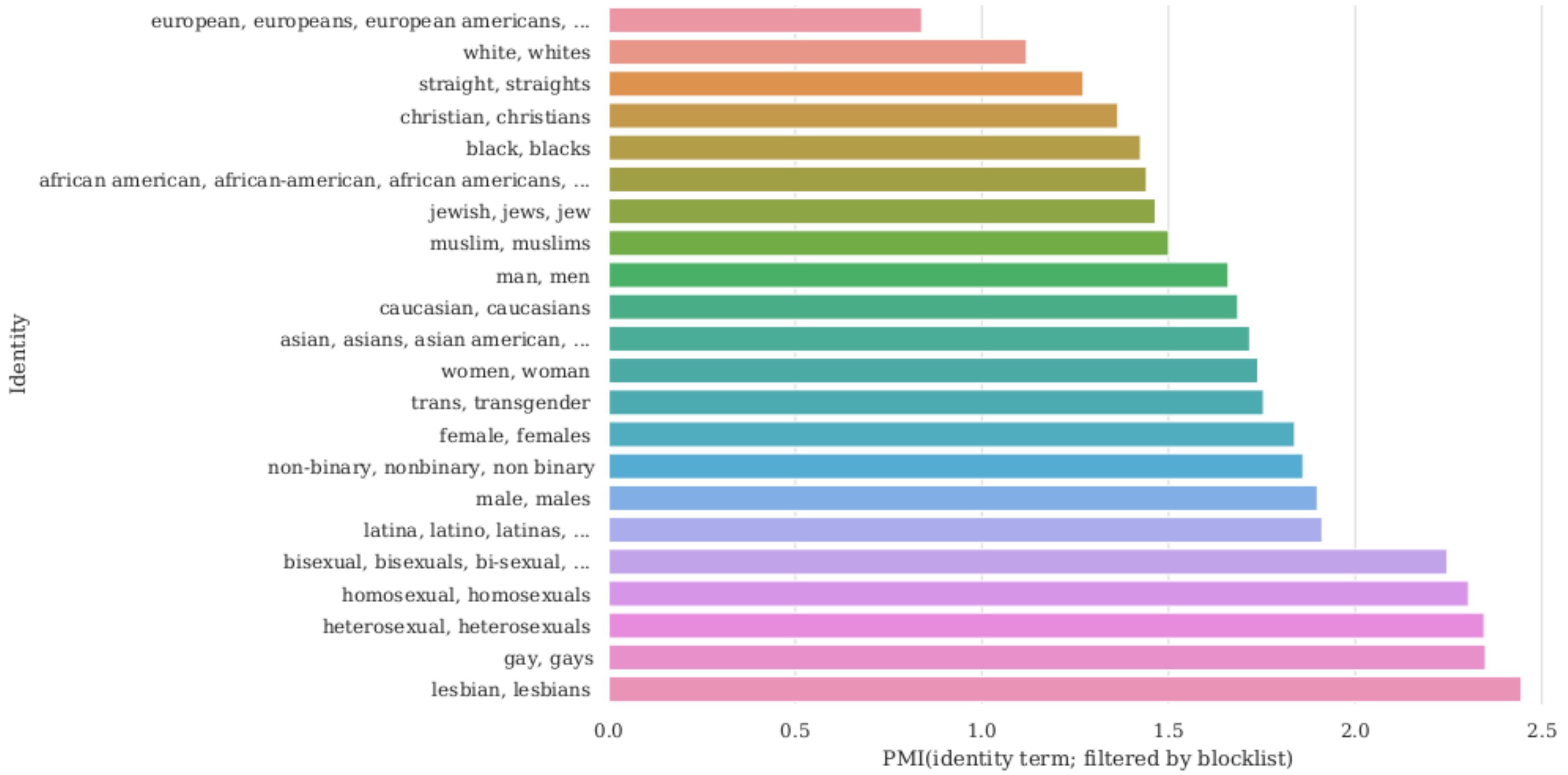
- There are two types of contamination:
  - **Input-and-output contamination**: both the input and output appear in the training data. Varies from 1.87% to 24.88% (XSum is 15.49%).
  - **Input contamination**: the input appears in the training data. Varies from 1.8% to 53.6% (QNLI, which is derived from Wikipedia).
- Note that contamination is not due to hosting datasets (as they are usually stored in a JSON file, not as a webpage).

Harms in C4

- **Representational harms**
  - They look at co-occurrence with ethnicity terms (e.g., *Jewish*) and sentiment-bearing words (e.g., *successful*).
  - *Jewish* has 73.2% positive sentiment, *Arab* has 65.7% positive (7.5% difference).
  - Variation across sites (New York Times had a 4.5% difference, Al Jazeera had 0% difference).
- **Allocational harms**
  - Recall C4 is a filtered version of Common Crawl (only about 10%).
  - Mentions of sexual orientations (e.g., *lesbian*, *gay*) more likely to be filtered out; of those filtered out, non-trivial fraction are non-offensive (e.g., 22% and 36%).
  - Certain dialects are more likely to be filtered (AAE: 42%, Hispanic-aligned English: 32%) than others (White American English: 6.2%)

Allocational harms in C4

- **Pointwise Mutual Information (PMI)** between identity mentions and documents being filtered out by the blocklist. Identities with higher PMI (e.g., lesbian, gay) have higher likelihood of being filtered out.



GPT-3 dataset

1. Selected subset of Common Crawl that's **similar to a reference dataset** (WebText).
   1. Downloaded 41 shards of Common Crawl (2016-2019).
   2. Trained a binary classifier to predict WebText versus Common Crawl.
   3. Sampled (kept) a document with higher probability if classifier deems it more similar to WebText.
2. Performed **fuzzy deduplication** (detect 13-gram overlap, remove window or documents if occurred in <10 training documents), removing data from benchmark datasets.
3. Expanded the diversity of the **data sources** (WebText2, Books1, Books2, Wikipedia).

4. During training, Common Crawl is **downsampled** (Common Crawl is 82% of the dataset, but contributes only 60%).

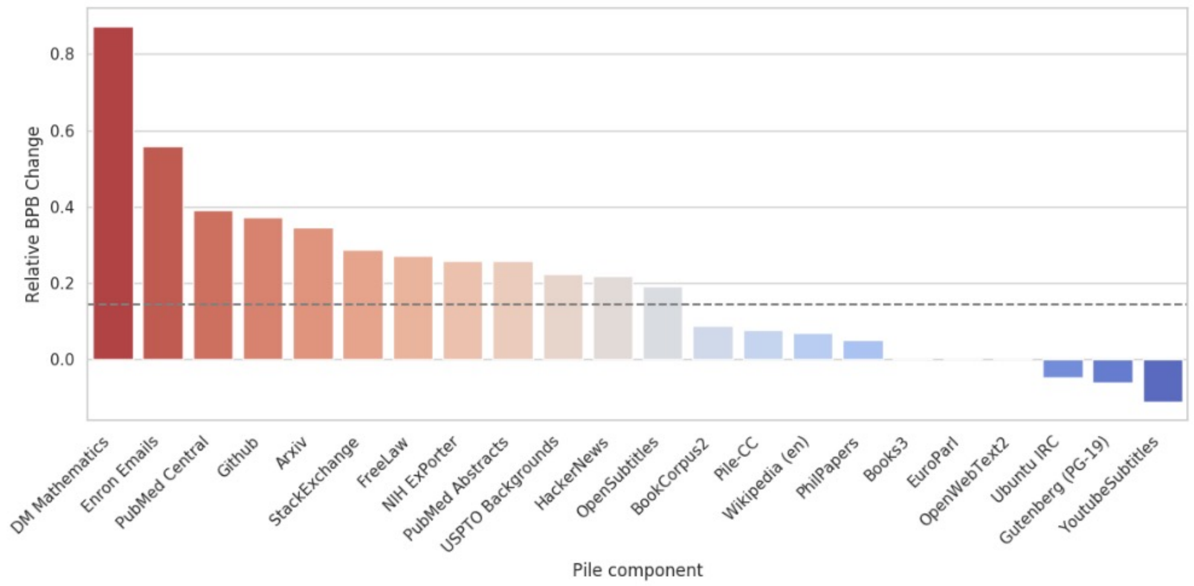
Dataset	Quantity (tokens)	Weight in training mix	Epochs elapsed when training for 300B tokens
Common Crawl (filtered)	410 billion	60%	0.44
WebText2	19 billion	22%	2.9
Books1	12 billion	8%	1.9
Books2	55 billion	8%	0.43
Wikipedia	3 billion	3%	3.4

The Pile

- While a web crawl is a natural place to look for broad data, it’s not the only strategy, and GPT-3 already hinted that it might be productive to look at other sources of higher quality.
- EleutherAI (a nonprofit organization committed to building open language models), pushed this idea even farther. They released The Pile, a dataset for language modeling, where the key idea is to source it from smaller high-quality sources (academic + professional sources).
- **Data composition**.
  - 825 GB English text
  - 22 high-quality datasets

The Pile

- The key idea is to source it from smaller high-quality sources (academic + professional sources).
- contains a lot of information that's not well covered by GPT-3's



They also performed analysis of pejorative content, gender/religion biases. The findings are qualitatively similar to previous work.

Component	Raw Size	Weight	Epochs	Effective Size	Mean Document Size
Pile-CC	227.12 GiB	18.11%	1.0	227.12 GiB	4.33 KiB
PubMed Central	90.27 GiB	14.40%	2.0	180.55 GiB	30.55 KiB
Books3†	100.96 GiB	12.07%	1.5	151.44 GiB	538.36 KiB
OpenWebText2	62.77 GiB	10.01%	2.0	125.54 GiB	3.85 KiB
ArXiv	56.21 GiB	8.96%	2.0	112.42 GiB	46.61 KiB
Github	95.16 GiB	7.59%	1.0	95.16 GiB	5.25 KiB
FreeLaw	51.15 GiB	6.12%	1.5	76.73 GiB	15.06 KiB
Stack Exchange	32.20 GiB	5.13%	2.0	64.39 GiB	2.16 KiB
USPTO Backgrounds	22.90 GiB	3.65%	2.0	45.81 GiB	4.08 KiB
PubMed Abstracts	19.26 GiB	3.07%	2.0	38.53 GiB	1.30 KiB
Gutenberg (PG-19)†	10.88 GiB	2.17%	2.5	27.19 GiB	398.73 KiB
OpenSubtitles†	12.98 GiB	1.55%	1.5	19.47 GiB	30.48 KiB
Wikipedia (en)†	6.38 GiB	1.53%	3.0	19.13 GiB	1.11 KiB
DM Mathematics†	7.75 GiB	1.24%	2.0	15.49 GiB	8.00 KiB
Ubuntu IRC	5.52 GiB	0.88%	2.0	11.03 GiB	545.48 KiB
BookCorpus2	6.30 GiB	0.75%	1.5	9.45 GiB	369.87 KiB
EuroParl†	4.59 GiB	0.73%	2.0	9.17 GiB	68.87 KiB
HackerNews	3.90 GiB	0.62%	2.0	7.80 GiB	4.92 KiB
YoutubeSubtitles	3.73 GiB	0.60%	2.0	7.47 GiB	22.55 KiB
PhilPapers	2.38 GiB	0.38%	2.0	4.76 GiB	73.37 KiB
NIH ExPorter	1.89 GiB	0.30%	2.0	3.79 GiB	2.11 KiB
Enron Emails†	0.88 GiB	0.14%	2.0	1.76 GiB	1.78 KiB
The Pile	**825.18 GiB**			**1254.20 GiB**	**5.91 KiB**

Takeaway

- The total amount of data out there (web, private data) is massive.
- Training on “all of it” (even Common Crawl) doesn’t work well (not effective use of compute).
- Filtering / curation (OpenWebText, C4, GPT-3 dataset) is needed, but can result in biases.
- Curating non-web high-quality datasets is promising (The Pile).
- Important to carefully document and inspect these datasets.

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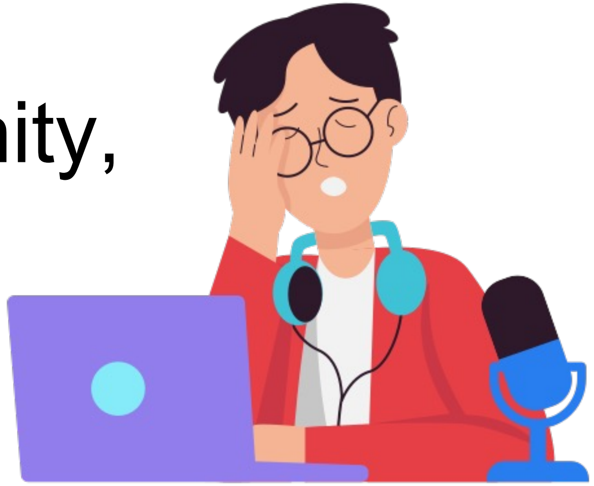
Documentation for datasets

- Documentation is important
  - Examples from other fields:
    - **Electronics industry** has a well-established protocol where every component has a datasheet with operating characteristics, test results, recommended and usage.
    - **Nutrition labels**: The FDA mandates that food be labeled with their nutrition content.
- But within the machine learning community,

it has been a fairly ad-hoc process…



Documentation for datasets

- **Datasheets for datasets** (Gebru et al., 2018) is an influential paper that provides community norms around documentation.
- **Data statements** (Bender & Friedman, 2018) is related framework that is more tailored to language datasets.
- The emphasis is on **transparency**.
- Two purposes:
  1. Dataset creators: reflect on decisions, potential harms (e.g., social biases) when creating the dataset.
  2. Dataset consumers: know when the dataset can and can't be used.

Documentation for datasets

A sample of the questions from each category are provided below:

- **Motivation**
  - For what purpose was the dataset created?
- **Composition**
  - What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)?
  - Is any information missing from individual instances?
- **Collection process**
  - How was the data associated with each instance acquired?
  - Who was involved in the data collection process?

Documentation for datasets

- **Preprocessing/cleaning/labeling**
  - Was any preprocessing/cleaning/labeling of the data done?
  - Is the software that was used to preprocess/clean/label the data available?
- **Uses**
  - Has the dataset been used for any tasks already?
  - Are there tasks for which the dataset should not be used?
- **Distribution**
  - How will the dataset will be distributed?
- **Maintenance**
  - Who will be supporting/hosting/maintaining the dataset?
  - Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)?

As an example, let's look at the datasheet for The Pile.

Thank you！

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http://keg.cs.tsinghua.edu.cn/jietang
https://github.com/THUDM