NLP Evaluation in trouble: On the Need to Measure LLM Data Contamination for each Benchmark

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Abstract

In this position paper, we argue that the classical evaluation on Natural Language Processing (NLP) tasks using annotated benchmarks is in trouble. The worst kind of data contamination happens when a Large Language Model (LLM) is trained on the test split of a benchmark, and then evaluated in the same benchmark. The extent of the problem is unknown, as it is not straightforward to measure. Contamination causes an overestimation of the performance of a contaminated model in a target benchmark and associated task with respect to their non-contaminated counterparts. The consequences can be very harmful, with wrong scientific conclusions being published while other correct ones are discarded. This **position paper** defines different levels of data contamination and argues for a community effort, including the development of automatic and semi-automatic measures to detect when data from a benchmark was exposed to a model, and suggestions for flagging papers with conclusions that are compromised by data contamination.

1 Introduction

At the core of NLP as a discipline, there is rigorous evaluation on different tasks. The experimental protocols involve strict control over the data, especially test data, which needs to be totally unseen during development, but also over training and development data. This is essential to assess the performance of a model in zero-shot, few-shot, or fully supervised settings. Since fine-tuning and prompting of Large Language Models (LLMs) became commonplace (Min et al., 2021) it has been increasingly difficult to enforce those strict protocols. Pre-training LLMs is expensive, and therefore, most of the time, researchers use LLMs trained by third-party entities (Raffel et al., 2020; Touvron et al., 2023a), which are agnostic to the target tasks where those LLMs are going to be used. With the growing scale of LLMs (Kaplan et al., 2020; Henighan et al., 2020) the need for data has been solved by crawling the internet, reaching trillions of tokens (Touvron et al., 2023a), and making it **very hard to know whether a specific benchmark was used to train the LLM**. This is applicable to all models, even if they document the source of the data at a high level, but especially for closed models with no or insufficient documentation.

Data contamination has two consequences. The first one is that the performance of an LLM when evaluated on a benchmark it already processed during pre-training will be overestimated, causing it to be preferred with respect to other LLMs. This affects the comparative assessment of the quality of LLMs. The second is that papers proposing scientific hypotheses on certain NLP tasks could be using contaminated LLMs, and thus make wrong claims about their hypotheses, and invalidate alternative hypotheses that could be true. This second consequence has an enormous negative impact on our field and is our main focus.

There are several measures that the community could take. A possible solution would be to avoid all research involving datasets which include published test data, and focus on datasets where the test data labels are not public. This solution will severely affect the number of NLP tasks for which benchmarks exist, at least until new benchmarks that avoid data leakage are produced. Jacovi et al. (2023) presents preventative strategies to avoid contamination in the future.

In this position paper, we propose a complementary line of action which seeks to measure and document data contamination cases, specifying LLM, benchmark and evidence supporting contamination. This solution involves a registry of contamination cases[1], collaborative manual work and research on automatic approaches. In addition, conferences should devise mechanisms to ensure that papers

[1]Such as the LM Contamination Index https://hitz-zentroa.github.io/lm-contamination/

don't include conclusions involving contamination, and to flag past work where contamination has been discovered after publication.

The paper starts by introducing background, followed by a definition of data contamination, contamination at different steps, methods to measure data contamination and a call for action.

2 Background

Detection of contamination cases has been traditionally done by directly analyzing the training data (Dodge et al., 2021), but the current scale of the pre-training data makes it difficult (Kreutzer et al., 2022; Birhane et al., 2021). Without proper documentation and search tools like ROOTS (Piktus et al., 2023) it is very difficult for any researcher to actually know whether their datasets are compromised on a given model. More recently, this task became even harder, as the best-performing LLMs are deployed as products, and therefore, their training corpora are kept secret. In this case, it has been shown that the high memorization abilities of LLMs can be used to generate portions of the training texts (Carlini et al., 2021; Magar and Schwartz, 2022). Using this memorization property, Sainz et al. (2023) show that ChatGPT generates portions of popular NLP benchmarks. Furthermore, LLMs memorization has been studied on data-leakage scenarios (Elangovan et al., 2021).

Regarding data contamination cases, Dodge et al. (2021) exposed that the C4 corpus (Raffel et al., 2020), a corpus used to pre-train several LLMs such as T5 (Raffel et al., 2020), contained the test splits of several benchmarks that were crawled from GitHub. Moreover, Brown et al. (2020) acknowledged a bug in their filtering script that caused the contamination of several benchmarks during the GPT-3 training. Furthermore, OpenAI (2023) stated that parts of the BIG-bench (Srivastava et al., 2023) benchmark were inadvertently mixed into the training set, enough to stop them from evaluating the model on it. They also mention that they included parts of the training sets of MATH (Hendrycks et al., 2021) and GSM-8K (Cobbe et al., 2021) as training data to improve mathematical reasoning (OpenAI, 2023). Therefore, the performance results reported for GSM-8K cannot be taken as zero-shot results when compared to other models.

Recently, Sainz et al. (2023) reported that several benchmarks have already been compromised in ChatGPT, including the popular CoNLL2003 (Tjong Kim Sang and De Meulder, 2003). There are several preprints that evaluate ChatGPT on CoNLL03 (Wei et al., 2023; Li et al., 2023a; Han et al., 2023) and at least one conference paper published on ACL 2023 that evaluates GPT-3 (Brown et al., 2020) and Codex (Chen et al., 2021) on the same benchmark (Li et al., 2023b). Appendix A shows evidence for data contamination for those LLMs, and casts doubts on the conclusions of those papers.

3 Defining *data contamination*

In general, data contamination refers to any breach in the strict control of datasets required by the experimental protocol. In this paper, we focus on the specific case where a LLM has processed the evaluation benchmark during its pre-training. However, different types of contamination exist and each of them has different implications. In this section, we present three types of contamination: guideline, text and annotation.

Guideline contamination happens when the annotation guidelines for a specific dataset are seen by the model. Usually, for specialized annotations, highly detailed guidelines are required. The guidelines can usually be publicly found on the internet, even for datasets that are not public or require buying a license for their use, ACE05 (Walker et al., 2006) for example. The more details the guidelines have the more information and examples they provide. A model aware of the guidelines for a specific task or dataset has advantages over a model without such information. We should consider the guideline contamination, especially on zero and few-shot evaluations.

Raw text contamination happens when the original text (previous to annotation) is seen by the model. Some examples of this type of contamination are the datasets based on Wikipedia texts. Wikipedia is commonly used as a source of pre-training data, but, it is also a frequent source of text to create new datasets. MultiCoNER 2 (Fetahu et al., 2023), a Named Entity Recognition dataset based on Wikipedia links and Wikidata information, is an example of this phenomenon. Models that have already seen Wikipedia in its original form (including the markup annotations) have more information to better identify a part of the annotations (the entity boundaries) of the dataset. As pointed out by Dodge et al. (2021), other datasets built from the web such as IMDB (Maas et al., 2011) and CNN/DailyMail (Hermann et al., 2015) can be also compromised. This kind of contamination should be taken into account when developing automatically annotated datasets.

Annotation contamination happens when the annotations (labels) of the target benchmark are exposed to the model during training. Depending on the splits of the benchmark that have been exposed, we can have the following cases: (1) When the evaluation split is involved, the experiment is completely invalidated. This is the most harmful level of contamination. (2) When the train or development splits are involved, this would not affect comparisons with other models that have been developed using those same splits, but it does invalidate conclusions claiming zero-shot or few-shot performance.

4 Contamination on different steps

Currently, the standard procedure to train and deploy language models has three main steps: pre-training a language model, fine-tuning the model to follow instructions and/or align with human feedback; and an iterative improvement step after deployment. Data contamination does not only occur in the pre-training step of LLMs, but can occur later in the training pipeline.

4.1 Contamination during pre-training

During the pre-training, there is a high chance that undesired data is fed to the model. Gathering huge amounts of text from the internet also has its counterpart: it becomes very hard to filter undesired data completely, and even deduplication is challenging (Lee et al., 2022). Avoiding data contamination completely is not realistic, as it is impossible to know every dataset that the research community can test an LLM on. However, allowing the researchers to access and perform queries on the pre-training data may ensure that no corrupted evaluations are performed. In fact, keeping the pre-training data not available for LLM consumers may derive undesired influences on downstream tasks (Li et al., 2020; Gehman et al., 2020; Groenwold et al., 2020).

In addition, researchers building LLMs should avoid, at least, contamination from well-known standard benchmarks such as GLUE (Wang et al., 2018) or SuperGLUE (Wang et al., 2020). As Dodge et al. (2021) showed, see their Table 2, various standard benchmarks were found in the C4 (Raffel et al., 2020) corpus.

4.2 Contamination on supervised fine-tuning

The supervised fine-tuning or instruction-tuning step is another step where contamination can occur. Nevertheless, it is much less frequent as it is a required practice in the research community to document the training data in order to publish your findings. As an example of those, we can find the FLAN dataset collection (Longpre et al., 2023), OPT-IML Bench (Iyer et al., 2023), Super-Natural Instructions (Wang et al., 2022b), the P3 collection (Bach et al., 2022) and so on.

Recently, more and more machine-generated text is being used to fine-tune language models. Some examples of these are Self-Instruct (Wang et al., 2022a), Unnatural Instructions (Honovich et al., 2022), Alpaca Data (Taori et al., 2023) and ShareGPT (Chiang et al., 2023). The aim of those datasets is usually to make public and smaller *white-box* models imitate *black-box* models such as ChatGPT (Gu et al., 2023). However, the distillation of a closed teacher model with clear signs of contamination is an issue. More alarming, is the case that popular crowd-sourcing methods like MTurk have started using LLMs to generate data that was supposed to be manually generated (Veselovsky et al., 2023).

4.3 Contamination after deployment

The last step where the models can be exposed to contamination is applied mostly on LLMs as service products. With the recent improvements in the quality of LLMs, the models that were supposed to be part of bigger products become products by themselves (ChatGPT or Bard for example). It is worth noting that, although they are closed models, i.e. no information is known about the architecture or training details, the research community has evaluated them on standard benchmarks (Jiao et al. (2023); among others). The monetary success of closed systems is closely tied to the performance of the model. Therefore, companies have a strong incentive to audit user inputs and retrain their system when the performance in a task is determined to be poor. Those models that are actually being accessed via API calls have been iteratively improved with user input, leading to evaluation data exposure. As a result, the models became aware of the testing data, at the point that you can easily recreate the dataset as we discuss in Section 5.2 (see examples in Appendix A).

5 Measuring data contamination

For the reasons we already mentioned, it is necessary to measure the existent data contamination cases and to document relevant contamination evidence. In order to achieve this goal, we differentiate two cases. In the first case, we would have open models where there is public access to all the training data, including text used in pre-training, but also, if the LLM was trained on them, instruction tuning datasets and deployment datasets. In the second case, we would have closed models for which there is no access to training data.

5.1 Open LLMs

Most of the research on data contamination has been focused on analyzing pre-training data with string-matching operations (Dodge et al., 2021), as this provides direct evidence that the LLM was contaminated. Pre-training datasets are unwieldy large, and string-matching operations can be very slow at this scale. Therefore, several tools for data auditing have been released recently: The ROOTS Search Tool (Piktus et al., 2023) and Data Portraits (Marone and Durme, 2023) among others. As an example of their usefulness, Piktus et al. (2023) found that BLOOM (Workshop et al., 2023) should not be evaluated on XNLI (Conneau et al., 2018) due to contamination. These tools should be made available for all open LLMs, in order to allow for contamination case discovery.

In addition, there is no currently agreed-upon methodology to measure the level of contamination. For cases where the full benchmark is not found, we propose to measure the level of data contamination using **benchmark data overlap**, that is, the percentage of the benchmark that can be found in the pre-training dataset (Dodge et al., 2021; Piktus et al., 2023).

5.2 Closed LLMs

Despite most of the recent popular models like LLaMA (Touvron et al., 2023a), GPT-4 (OpenAI, 2023) or Bard have not publicly released their pre-training data, very few works have actually worked on detecting data-contamination when the pre-training data is not available (Magar and Schwartz, 2022). Although this scenario is much more challenging than the former, we foresee that it will become the most prevalent. Developing methods to measure the data contamination in this scenario must be crucial for future evaluations. To tackle this problem, we propose to take advantage of LLM's memorization capabilities. Appendix A shows some examples of using memorization to uncover data contamination for the CONLL2003 benchmark on three LLMs. In cases where the LLM does not produce the benchmark verbatim, it is left to the auditor to examine the output and judge whether the evidence supports contamination. The process is totally manual and could be scaled in a community effort.

Alternatively, automatic metrics for measuring data contamination levels could be developed. As an initial step in this direction, we reuse and adapt the *extractability* definition presented in Carlini et al. (2023) for defining memorization. We define that an example s is *extractable* from evaluation dataset d and model m if there exists a sequence of k examples x immediately preceding s in d data such that s is generated when prompting model m with x. We can define the degree of contamination of model m for dataset d as the ratio of extractable examples with respect to the total number of examples in the dataset.

One further question remains to be solved which is whether the lack of memorization of a benchmark ensures that the LLM was not trained on that benchmark. One hypothesis could be that the lack of memorization is correlated with the performance, even if the LLM was trained on the benchmark. Thus the LLM would not have any advantage with respect to another LLM that was not trained on the benchmark. This is currently speculation, so further research on this topic is necessary, given the extended use of closed LLMs in NLP research.

6 Call for action

We want to encourage the NLP community to: (1) Develop auto- or semi-automatic measures to detect when data from a benchmark was exposed to a model; (2) Build a registry of data contamination cases, including the evidence for the contamination; (3) Encourage authors to use the previous tools to ensure that the experimental protocol avoids data contamination to the extent possible; and (4) Address data contamination issues during peer review, and, in the case of published works, devise mechanisms to flag those works with the relevant evidence of data contamination and how data contamination affects the conclusions.

As the problem affects our entire field, we also want to encourage the community to participate in workshops related to this topic, as for example, the 1st Workshop on Data Contamination[2]. We think that developing the ideas that will arise from this community will play an important role in future NLP evaluations.

7 Limitations

In this paper, we address the problem of data contamination that occurs when evaluating LLMs on standard academic benchmarks. However, we are aware that there could exist other issues in current evaluations, but, they are out of the scope of this position paper. Related to our proposed solutions, we are aware that these are early-stage solutions and that the proposed effort is really challenging, therefore we call for further discussion and research on topics related to this issue.

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References

Stephen Bach, Victor Sanh, Zheng Xin Yong, Albert Webson, Colin Raffel, Nihal V. Nayak, Abheesht Sharma, Taewoon Kim, M Saiful Bari, Thibault Fevry, Zaid Alyafeai, Manan Dey, Andrea Santilli, Zhiqing Sun, Srulik Ben-david, Canwen Xu, Gunjan Chhablani, Han Wang, Jason Fries, Maged Alshaibani, Shanya Sharma, Urmish Thakker, Khalid Almubarak, Xiangru Tang, Dragomir Radev, Mike Tian-jian Jiang, and Alexander Rush. 2022. PromptSource: An integrated development environment and repository for natural language prompts. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 93–104, Dublin, Ireland. Association for Computational Linguistics.

Abeba Birhane, Vinay Uday Prabhu, and Emmanuel Kahembwe. 2021. Multimodal datasets: misogyny, pornography, and malignant stereotypes.

[2]https://conda-workshop.github.io

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners.

Nicholas Carlini, Daphne Ippolito, Matthew Jagielski, Katherine Lee, Florian Tramer, and Chiyuan Zhang. 2023. Quantifying memorization across neural language models. In *The Eleventh International Conference on Learning Representations*.

Nicholas Carlini, Florian Tramèr, Eric Wallace, Matthew Jagielski, Ariel Herbert-Voss, Katherine Lee, Adam Roberts, Tom Brown, Dawn Song, Úlfar Erlingsson, Alina Oprea, and Colin Raffel. 2021. Extracting training data from large language models. In *30th USENIX Security Symposium (USENIX Security 21)*, pages 2633–2650. USENIX Association.

Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, Nikolas Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Josh Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. 2021. Evaluating large language models trained on code.

Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. 2023. Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality.

Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, et al. 2021. Training verifiers to solve math word problems. *arXiv preprint arXiv:2110.14168*.

Alexis Conneau, Ruty Rinott, Guillaume Lample, Adina Williams, Samuel Bowman, Holger Schwenk, and Veselin Stoyanov. 2018. XNLI: Evaluating cross-lingual sentence representations. In *Proceedings of* *the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2475–2485, Brussels, Belgium. Association for Computational Linguistics.

Jesse Dodge, Maarten Sap, Ana Marasović, William Agnew, Gabriel Ilharco, Dirk Groeneveld, Margaret Mitchell, and Matt Gardner. 2021. Documenting large webtext corpora: A case study on the colossal clean crawled corpus. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 1286–1305, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Nan Du, Yanping Huang, Andrew M. Dai, Simon Tong, Dmitry Lepikhin, Yuanzhong Xu, Maxim Krikun, Yanqi Zhou, Adams Wei Yu, Orhan Firat, Barret Zoph, Liam Fedus, Maarten Bosma, Zongwei Zhou, Tao Wang, Yu Emma Wang, Kellie Webster, Marie Pellat, Kevin Robinson, Kathy Meier-Hellstern, Toju Duke, Lucas Dixon, Kun Zhang, Quoc V. Le, Yonghui Wu, Zhifeng Chen, and Claire Cui. 2021. Glam: Efficient scaling of language models with mixture-of-experts. *CoRR*, abs/2112.06905.

Aparna Elangovan, Jiayuan He, and Karin Verspoor. 2021. Memorization vs. generalization : Quantifying data leakage in NLP performance evaluation. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 1325–1335, Online. Association for Computational Linguistics.

Besnik Fetahu, Sudipta Kar, Zhiyu Chen, Oleg Rokhlenko, and Shervin Malmasi. 2023. SemEval-2023 Task 2: Fine-grained Multilingual Named Entity Recognition (MultiCoNER 2). In *Proceedings of the 17th International Workshop on Semantic Evaluation (SemEval-2023)*. Association for Computational Linguistics.

Samuel Gehman, Suchin Gururangan, Maarten Sap, Yejin Choi, and Noah A. Smith. 2020. RealToxicityPrompts: Evaluating neural toxic degeneration in language models. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 3356–3369, Online. Association for Computational Linguistics.

Sophie Groenwold, Lily Ou, Aesha Parekh, Samhita Honnavalli, Sharon Levy, Diba Mirza, and William Yang Wang. 2020. Investigating African-American Vernacular English in transformer-based text generation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 5877–5883, Online. Association for Computational Linguistics.

Yuxian Gu, Li Dong, Furu Wei, and Minlie Huang. 2023. Knowledge distillation of large language models.

Ridong Han, Tao Peng, Chaohao Yang, Benyou Wang, Lu Liu, and Xiang Wan. 2023. Is information extraction solved by chatgpt? an analysis of performance, evaluation criteria, robustness and errors.

Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. 2021. Measuring mathematical problem solving with the math dataset. *arXiv preprint arXiv:2103.03874*.

Tom Henighan, Jared Kaplan, Mor Katz, Mark Chen, Christopher Hesse, Jacob Jackson, Heewoo Jun, Tom B. Brown, Prafulla Dhariwal, Scott Gray, Chris Hallacy, Benjamin Mann, Alec Radford, Aditya Ramesh, Nick Ryder, Daniel M. Ziegler, John Schulman, Dario Amodei, and Sam McCandlish. 2020. Scaling laws for autoregressive generative modeling.

Karl Moritz Hermann, Tomás Kociský, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. Teaching machines to read and comprehend. In *NIPS*, pages 1693–1701.

Or Honovich, Thomas Scialom, Omer Levy, and Timo Schick. 2022. Unnatural instructions: Tuning language models with (almost) no human labor. *arXiv preprint arXiv:2212.09689*.

Srinivasan Iyer, Xi Victoria Lin, Ramakanth Pasunuru, Todor Mihaylov, Daniel Simig, Ping Yu, Kurt Shuster, Tianlu Wang, Qing Liu, Punit Singh Koura, Xian Li, Brian O'Horo, Gabriel Pereyra, Jeff Wang, Christopher Dewan, Asli Celikyilmaz, Luke Zettlemoyer, and Ves Stoyanov. 2023. Opt-iml: Scaling language model instruction meta learning through the lens of generalization.

Alon Jacovi, Avi Caciularu, Omer Goldman, and Yoav Goldberg. 2023. Stop uploading test data in plain text: Practical strategies for mitigating data contamination by evaluation benchmarks.

Wenxiang Jiao, Wenxuan Wang, Jen tse Huang, Xing Wang, and Zhaopeng Tu. 2023. Is chatgpt a good translator? yes with gpt-4 as the engine.

Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. 2020. Scaling laws for neural language models.

Julia Kreutzer, Isaac Caswell, Lisa Wang, Ahsan Wahab, Daan van Esch, Nasanbayar Ulzii-Orshikh, Allahsera Tapo, Nishant Subramani, Artem Sokolov, Claytone Sikasote, Monang Setyawan, Supheakmungkol Sarin, Sokhar Samb, Benoît Sagot, Clara Rivera, Annette Rios, Isabel Papadimitriou, Salomey Osei, Pedro Ortiz Suarez, Iroro Orife, Kelechi Ogueji, Andre Niyongabo Rubungo, Toan Q. Nguyen, Mathias Müller, André Müller, Shamsuddeen Hassan Muhammad, Nanda Muhammad, Ayanda Mnyakeni, Jamshidbek Mirzakhalov, Tapiwanashe Matangira, Colin Leong, Nze Lawson, Sneha Kudugunta, Yacine Jernite, Mathias Jenny, Orhan Firat, Bonaventure F. P. Dossou, Sakhile Dlamini, Nisansa de Silva, Sakine Çabuk Ballı, Stella Biderman, Alessia Battisti, Ahmed Baruwa, Ankur Bapna, Pallavi Baljekar, Israel Abebe Azime, Ayodele Awokoya, Duygu Ataman, Orevaoghene Ahia, Oghenefego Ahia, Sweta

Agrawal, and Mofetoluwa Adeyemi. 2022. Quality at a glance: An audit of web-crawled multilingual datasets. *Transactions of the Association for Computational Linguistics*, 10:50–72.

Katherine Lee, Daphne Ippolito, Andrew Nystrom, Chiyuan Zhang, Douglas Eck, Chris Callison-Burch, and Nicholas Carlini. 2022. Deduplicating training data makes language models better. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 8424–8445, Dublin, Ireland. Association for Computational Linguistics.

Bo Li, Gexiang Fang, Yang Yang, Quansen Wang, Wei Ye, Wen Zhao, and Shikun Zhang. 2023a. Evaluating chatgpt's information extraction capabilities: An assessment of performance, explainability, calibration, and faithfulness.

Peng Li, Tianxiang Sun, Qiong Tang, Hang Yan, Yuanbin Wu, Xuanjing Huang, and Xipeng Qiu. 2023b. Codeie: Large code generation models are better few-shot information extractors. In *Proceedings of the 61th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, Toronto, Canada. Association for Computational Linguistics.

Tao Li, Daniel Khashabi, Tushar Khot, Ashish Sabharwal, and Vivek Srikumar. 2020. UNQOVERing stereotyping biases via underspecified questions. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 3475–3489, Online. Association for Computational Linguistics.

Shayne Longpre, Le Hou, Tu Vu, Albert Webson, Hyung Won Chung, Yi Tay, Denny Zhou, Quoc V. Le, Barret Zoph, Jason Wei, and Adam Roberts. 2023. The flan collection: Designing data and methods for effective instruction tuning.

Ziyang Luo, Can Xu, Pu Zhao, Qingfeng Sun, Xiubo Geng, Wenxiang Hu, Chongyang Tao, Jing Ma, Qingwei Lin, and Daxin Jiang. 2023. Wizardcoder: Empowering code large language models with evol-instruct.

Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. 2011. Learning word vectors for sentiment analysis. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 142–150, Portland, Oregon, USA. Association for Computational Linguistics.

Inbal Magar and Roy Schwartz. 2022. Data contamination: From memorization to exploitation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 157–165, Dublin, Ireland. Association for Computational Linguistics.

Marc Marone and Benjamin Van Durme. 2023. Data portraits: Recording foundation model training data.

Bonan Min, Hayley Ross, Elior Sulem, Amir Pouran Ben Veyseh, Thien Huu Nguyen, Oscar Sainz, Eneko Agirre, Ilana Heinz, and Dan Roth. 2021. Recent advances in natural language processing via large pre-trained language models: A survey.

OpenAI. 2023. Gpt-4 technical report.

Aleksandra Piktus, Christopher Akiki, Paulo Villegas, Hugo Laurençon, Gérard Dupont, Alexandra Sasha Luccioni, Yacine Jernite, and Anna Rogers. 2023. The roots search tool: Data transparency for llms.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67.

Oscar Sainz, Jon Ander Campos, Iker García-Ferrero, Julen Etxaniz, and Eneko Agirre. 2023. Did chatgpt cheat on your test?

Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R. Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, Agnieszka Kluska, Aitor Lewkowycz, Akshat Agarwal, Alethea Power, Alex Ray, Alex Warstadt, Alexander W. Kocurek, Ali Safaya, Ali Tazarv, Alice Xiang, Alicia Parrish, Allen Nie, Aman Hussain, Amanda Askell, Amanda Dsouza, Ambrose Slone, Ameet Rahane, Anantharaman S. Iyer, Anders Andreassen, Andrea Madotto, Andrea Santilli, Andreas Stuhlmüller, Andrew Dai, Andrew La, Andrew Lampinen, Andy Zou, Angela Jiang, Angelica Chen, Anh Vuong, Animesh Gupta, Anna Gottardi, Antonio Norelli, Anu Venkatesh, Arash Gholamidavoodi, Arfa Tabassum, Arul Menezes, Arun Kirubarajan, Asher Mullokandov, Ashish Sabharwal, Austin Herrick, Avia Efrat, Aykut Erdem, Ayla Karakaş, B. Ryan Roberts, Bao Sheng Loe, Barret Zoph, Bartłomiej Bojanowski, Batuhan Özyurt, Behnam Hedayatnia, Behnam Neyshabur, Benjamin Inden, Benno Stein, Berk Ekmekci, Bill Yuchen Lin, Blake Howald, Bryan Orinion, Cameron Diao, Cameron Dour, Catherine Stinson, Cedrick Argueta, César Ferri Ramírez, Chandan Singh, Charles Rathkopf, Chenlin Meng, Chitta Baral, Chiyu Wu, Chris Callison-Burch, Chris Waites, Christian Voigt, Christopher D. Manning, Christopher Potts, Cindy Ramirez, Clara E. Rivera, Clemencia Siro, Colin Raffel, Courtney Ashcraft, Cristina Garbacea, Damien Sileo, Dan Garrette, Dan Hendrycks, Dan Kilman, Dan Roth, Daniel Freeman, Daniel Khashabi, Daniel Levy, Daniel Moseguí González, Danielle Perszyk, Danny Hernandez, Danqi Chen, Daphne Ippolito, Dar Gilboa, David Dohan, David Drakard, David Jurgens, Debajyoti Datta, Deep Ganguli, Denis Emelin, Denis Kleyko, Deniz Yuret, Derek Chen, Derek Tam, Dieuwke Hupkes, Diganta Misra, Dilyar Buzan, Dimitri Coelho Mollo, Diyi Yang, Dong-Ho Lee, Dylan Schrader, Ekaterina Shutova, Ekin Dogus Cubuk, Elad Segal, Eleanor

Hagerman, Elizabeth Barnes, Elizabeth Donoway, Ellie Pavlick, Emanuele Rodola, Emma Lam, Eric Chu, Eric Tang, Erkut Erdem, Ernie Chang, Ethan A. Chi, Ethan Dyer, Ethan Jerzak, Ethan Kim, Eunice Engefu Manyasi, Evgenii Zheltonozhskii, Fanyue Xia, Fatemeh Siar, Fernando Martínez-Plumed, Francesca Happé, Francois Chollet, Frieda Rong, Gaurav Mishra, Genta Indra Winata, Gerard de Melo, Germán Kruszewski, Giambattista Parascandolo, Giorgio Mariani, Gloria Wang, Gonzalo Jaimovitch-López, Gregor Betz, Guy Gur-Ari, Hana Galijasevic, Hannah Kim, Hannah Rashkin, Hannaneh Hajishirzi, Harsh Mehta, Hayden Bogar, Henry Shevlin, Hinrich Schütze, Hiromu Yakura, Hongming Zhang, Hugh Mee Wong, Ian Ng, Isaac Noble, Jaap Jumelet, Jack Geissinger, Jackson Kernion, Jacob Hilton, Jaehoon Lee, Jaime Fernández Fisac, James B. Simon, James Koppel, James Zheng, James Zou, Jan Kocoń, Jana Thompson, Janelle Wingfield, Jared Kaplan, Jarema Radom, Jascha Sohl-Dickstein, Jason Phang, Jason Wei, Jason Yosinski, Jekaterina Novikova, Jelle Bosscher, Jennifer Marsh, Jeremy Kim, Jeroen Taal, Jesse Engel, Jesujoba Alabi, Jiacheng Xu, Jiaming Song, Jillian Tang, Joan Waweru, John Burden, John Miller, John U. Balis, Jonathan Batchelder, Jonathan Berant, Jörg Frohberg, Jos Rozen, Jose Hernandez-Orallo, Joseph Boudeman, Joseph Guerr, Joseph Jones, Joshua B. Tenenbaum, Joshua S. Rule, Joyce Chua, Kamil Kanclerz, Karen Livescu, Karl Krauth, Karthik Gopalakrishnan, Katerina Ignatyeva, Katja Markert, Kaustubh D. Dhole, Kevin Gimpel, Kevin Omondi, Kory Mathewson, Kristen Chiafullo, Ksenia Shkaruta, Kumar Shridhar, Kyle McDonell, Kyle Richardson, Laria Reynolds, Leo Gao, Li Zhang, Liam Dugan, Lianhui Qin, Lidia Contreras-Ochando, Louis-Philippe Morency, Luca Moschella, Lucas Lam, Lucy Noble, Ludwig Schmidt, Luheng He, Luis Oliveros Colón, Luke Metz, Lütfi Kerem Şenel, Maarten Bosma, Maarten Sap, Maartje ter Hoeve, Maheen Farooqi, Manaal Faruqui, Mantas Mazeika, Marco Baturan, Marco Marelli, Marco Maru, Maria Jose Ramírez Quintana, Marie Tolkiehn, Mario Giulianelli, Martha Lewis, Martin Potthast, Matthew L. Leavitt, Matthias Hagen, Mátyás Schubert, Medina Orduna Baitemirova, Melody Arnaud, Melvin McElrath, Michael A. Yee, Michael Cohen, Michael Gu, Michael Ivanitskiy, Michael Starritt, Michael Strube, Michał Swędrowski, Michele Bevilacqua, Michihiro Yasunaga, Mihir Kale, Mike Cain, Mimee Xu, Mirac Suzgun, Mitch Walker, Mo Tiwari, Mohit Bansal, Moin Aminnaseri, Mor Geva, Mozhdeh Gheini, Mukund Varma T, Nanyun Peng, Nathan A. Chi, Nayeon Lee, Neta Gur-Ari Krakover, Nicholas Cameron, Nicholas Roberts, Nick Doiron, Nicole Martinez, Nikita Nangia, Niklas Deckers, Niklas Muennighoff, Nitish Shirish Keskar, Niveditha S. Iyer, Noah Constant, Noah Fiedel, Nuan Wen, Oliver Zhang, Omar Agha, Omar Elbaghdadi, Omer Levy, Owain Evans, Pablo Antonio Moreno Casares, Parth Doshi, Pascale Fung, Paul Pu Liang, Paul Vicol, Pegah Alipoormolabashi, Peiyuan Liao, Percy Liang, Peter Chang, Peter Eckersley, Phu Mon Htut, Pinyu Hwang, Piotr Miłkowski, Piyush Patil, Pouya Pezeshkpour, Priti Oli, Qiaozhu Mei, Qing Lyu, Qinlang Chen, Rabin Banjade, Rachel Etta Rudolph, Raefer Gabriel, Rahel Habacker, Ramon Risco, Raphaël Millière, Rhythm Garg, Richard Barnes, Rif A. Saurous, Riku Arakawa, Robbe Raymaekers, Robert Frank, Rohan Sikand, Roman Novak, Roman Sitelew, Ronan LeBras, Rosanne Liu, Rowan Jacobs, Rui Zhang, Ruslan Salakhutdinov, Ryan Chi, Ryan Lee, Ryan Stovall, Ryan Teehan, Rylan Yang, Sahib Singh, Saif M. Mohammad, Sajant Anand, Sam Dillavou, Sam Shleifer, Sam Wiseman, Samuel Gruetter, Samuel R. Bowman, Samuel S. Schoenholz, Sanghyun Han, Sanjeev Kwatra, Sarah A. Rous, Sarik Ghazarian, Sayan Ghosh, Sean Casey, Sebastian Bischoff, Sebastian Gehrmann, Sebastian Schuster, Sepideh Sadeghi, Shadi Hamdan, Sharon Zhou, Shashank Srivastava, Sherry Shi, Shikhar Singh, Shima Asaadi, Shixiang Shane Gu, Shubh Pachchigar, Shubham Toshniwal, Shyam Upadhyay, Shyamolima, Debnath, Siamak Shakeri, Simon Thormeyer, Simone Melzi, Siva Reddy, Sneha Priscilla Makini, Soo-Hwan Lee, Spencer Torene, Sriharsha Hatwar, Stanislas Dehaene, Stefan Divic, Stefano Ermon, Stella Biderman, Stephanie Lin, Stephen Prasad, Steven T. Piantadosi, Stuart M. Shieber, Summer Misherghi, Svetlana Kiritchenko, Swaroop Mishra, Tal Linzen, Tal Schuster, Tao Li, Tao Yu, Tariq Ali, Tatsu Hashimoto, Te-Lin Wu, Théo Desbordes, Theodore Rothschild, Thomas Phan, Tianle Wang, Tiberius Nkinyili, Timo Schick, Timofei Kornev, Titus Tunduny, Tobias Gerstenberg, Trenton Chang, Trishala Neeraj, Tushar Khot, Tyler Shultz, Uri Shaham, Vedant Misra, Vera Demberg, Victoria Nyamai, Vikas Raunak, Vinay Ramasesh, Vinay Uday Prabhu, Vishakh Padmakumar, Vivek Srikumar, William Fedus, William Saunders, William Zhang, Wout Vossen, Xiang Ren, Xiaoyu Tong, Xinran Zhao, Xinyi Wu, Xudong Shen, Yadollah Yaghoobzadeh, Yair Lakretz, Yangqiu Song, Yasaman Bahri, Yejin Choi, Yichi Yang, Yiding Hao, Yifu Chen, Yonatan Belinkov, Yu Hou, Yufang Hou, Yuntao Bai, Zachary Seid, Zhuoye Zhao, Zijian Wang, Zijie J. Wang, Zirui Wang, and Ziyi Wu. 2023. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models.

Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. 2023. Stanford alpaca: An instruction-following llama model. `https://github.com/tatsu-lab/stanford_alpaca`.

Erik F. Tjong Kim Sang and Fien De Meulder. 2003. Introduction to the CoNLL-2003 shared task: Language-independent named entity recognition. In *Proceedings of the Seventh Conference on Natural Language Learning at HLT-NAACL 2003*, pages 142–147.

Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard

Grave, and Guillaume Lample. 2023a. Llama: Open and efficient foundation language models.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton-Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurélien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023b. Llama 2: Open foundation and fine-tuned chat models. *CoRR*, abs/2307.09288.

Veniamin Veselovsky, Manoel Horta Ribeiro, and Robert West. 2023. Artificial artificial artificial intelligence: Crowd workers widely use large language models for text production tasks.

Christopher Walker, Stephanie Strassel, Julie Medero, and Kazuaki Maeda. 2006. Ace 2005 multilingual training corpus. *Linguistic Data Consortium, Philadelphia*, 57:45.

Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2020. Superglue: A stickier benchmark for general-purpose language understanding systems.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2018. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 353–355, Brussels, Belgium. Association for Computational Linguistics.

Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A Smith, Daniel Khashabi, and Hannaneh Hajishirzi. 2022a. Self-instruct: Aligning language model with self generated instructions. *arXiv preprint arXiv:2212.10560*.

Yizhong Wang, Swaroop Mishra, Pegah Alipoormolabashi, Yeganeh Kordi, Amirreza Mirzaei, Atharva Naik, Arjun Ashok, Arut Selvan Dhanasekaran, Anjana Arunkumar, David Stap, Eshaan Pathak, Giannis Karamanolakis, Haizhi Lai, Ishan Purohit, Ishani Mondal, Jacob Anderson, Kirby Kuznia, Krima Doshi, Kuntal Kumar Pal, Maitreya Patel, Mehrad Moradshahi, Mihir Parmar, Mirali Purohit, Neeraj Varshney, Phani Rohitha Kaza, Pulkit Verma, Ravsehaj Singh Puri, Rushang Karia, Savan Doshi, Shailaja Keyur Sampat, Siddhartha Mishra, Sujan Reddy A, Sumanta Patro, Tanay Dixit, and Xudong Shen. 2022b. Super-NaturalInstructions: Generalization via declarative instructions on 1600+ NLP tasks. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 5085–5109, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Jason Wei, Maarten Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V Le. 2022. Finetuned language models are zero-shot learners. In *International Conference on Learning Representations*.

Xiang Wei, Xingyu Cui, Ning Cheng, Xiaobin Wang, Xin Zhang, Shen Huang, Pengjun Xie, Jinan Xu, Yufeng Chen, Meishan Zhang, Yong Jiang, and Wenjuan Han. 2023. Zero-shot information extraction via chatting with chatgpt.

BigScience Workshop, :, Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, Jonathan Tow, Alexander M. Rush, Stella Biderman, Albert Webson, Pawan Sasanka Ammanamanchi, Thomas Wang, Benoît Sagot, Niklas Muennighoff, Albert Villanova del Moral, Olatunji Ruwase, Rachel Bawden, Stas Bekman, Angelina McMillan-Major, Iz Beltagy, Huu Nguyen, Lucile Saulnier, Samson Tan, Pedro Ortiz Suarez, Victor Sanh, Hugo Laurençon, Yacine Jernite, Julien Launay, Margaret Mitchell, Colin Raffel, Aaron Gokaslan, Adi Simhi, Aitor Soroa, Alham Fikri Aji, Amit Alfassy, Anna Rogers, Ariel Kreisberg Nitzav, Canwen Xu, Chenghao Mou, Chris Emezue, Christopher Klamm, Colin Leong, Daniel van Strien, David Ifeoluwa Adelani, Dragomir Radev, Eduardo González Ponferrada, Efrat Levkovizh, Ethan Kim, Eyal Bar Natan, Francesco De Toni, Gérard Dupont, Germán Kruszewski, Giada Pistilli, Hady Elsahar, Hamza Benyamina, Hieu Tran, Ian Yu, Idris Abdulmumin, Isaac Johnson, Itziar Gonzalez-Dios, Javier de la Rosa, Jenny Chim, Jesse Dodge, Jian Zhu, Jonathan Chang, Jörg Frohberg, Joseph Tobing, Joydeep Bhattacharjee, Khalid Almubarak, Kimbo Chen, Kyle Lo, Leandro Von Werra, Leon Weber, Long Phan, Loubna Ben allal, Ludovic Tanguy, Manan Dey, Manuel Romero Muñoz, Maraim Masoud, María Grandury, Mario Šaško, Max Huang, Maximin Coavoux, Mayank Singh, Mike Tian-Jian Jiang, Minh Chien Vu, Mohammad A. Jauhar, Mustafa Ghaleb, Nishant Subramani, Nora Kassner, Nurulaqilla Khamis, Olivier Nguyen, Omar Espejel, Ona de Gibert, Paulo Villegas, Peter Henderson, Pierre Colombo, Priscilla Amuok, Quentin Lhoest, Rheza Harliman, Rishi Bommasani, Roberto Luis López, Rui Ribeiro, Salomey Osei, Sampo Pyysalo, Sebastian Nagel, Shamik Bose, Shamsuddeen Hassan Muhammad, Shanya Sharma, Shayne Longpre, Somaieh Nikpoor, Stanislav Silberberg, Suhas Pai, Sydney Zink, Tiago Timponi Torrent, Timo Schick, Tristan Thrush, Valentin Danchev, Vassilina Nikoulina, Veronika Laippala, Violette Lepercq, Vrinda Prabhu, Zaid Alyafeai, Zeerak Talat, Arun Raja, Benjamin Heinzerling, Chenglei Si, Davut Emre Taşar, Elizabeth Salesky, Sabrina J. Mielke, Wilson Y. Lee, Abheesht Sharma, Andrea Santilli, Antoine Chaffin, Arnaud Stiegler, Debajyoti Datta, Eliza Szczechla, Gunjan Chhablani, Han Wang, Harshit Pandey, Hendrik Strobelt, Jason Alan Fries, Jos Rozen, Leo Gao, Lintang Sutawika, M Saiful Bari, Maged S. Al-shaibani, Matteo Manica, Nihal Nayak, Ryan Teehan, Samuel Albanie, Sheng Shen, Srulik Ben-David, Stephen H. Bach, Taewoon Kim, Tali Bers, Thibault Fevry, Trishala Neeraj, Urmish Thakker, Vikas Raunak, Xiangru Tang, Zheng-Xin Yong, Zhiqing Sun, Shaked Brody, Yallow Uri, Hadar Tojarieh, Adam Roberts, Hyung Won Chung, Jaesung Tae, Jason Phang, Ofir Press, Conglong Li, Deepak Narayanan, Hatim Bourfoune, Jared Casper, Jeff Rasley, Max Ryabinin, Mayank Mishra, Minjia Zhang, Mohammad Shoeybi, Myriam Peyrounette, Nicolas Patry, Nouamane Tazi, Omar Sanseviero, Patrick von Platen, Pierre Cornette, Pierre François Lavallée, Rémi Lacroix, Samyam Rajbhandari, Sanchit Gandhi, Shaden Smith, Stéphane Requena, Suraj Patil, Tim Dettmers, Ahmed Baruwa, Amanpreet Singh, Anastasia Cheveleva, Anne-Laure Ligozat, Arjun Subramonian, Aurélie Névéol, Charles Lovering, Dan Garrette, Deepak Tunuguntla, Ehud Reiter, Ekaterina Taktasheva, Ekaterina Voloshina, Eli Bogdanov, Genta Indra Winata, Hailey Schoelkopf, Jan-Christoph Kalo, Jekaterina Novikova, Jessica Zosa Forde, Jordan Clive, Jungo Kasai, Ken Kawamura, Liam Hazan, Marine Carpuat, Miruna Clinciu, Najoung Kim, Newton Cheng, Oleg Serikov, Omer Antverg, Oskar van der Wal, Rui Zhang, Ruochen Zhang, Sebastian Gehrmann, Shachar Mirkin, Shani Pais, Tatiana Shavrina, Thomas Scialom, Tian Yun, Tomasz Limisiewicz, Verena Rieser, Vitaly Protasov, Vladislav Mikhailov, Yada Pruksachatkun, Yonatan Belinkov, Zachary Bamberger, Zdeněk Kasner, Alice Rueda, Amanda Pestana, Amir Feizpour, Ammar Khan, Amy Faranak, Ana Santos, Anthony Hevia, Antigona Unldreaj, Arash Aghagol, Arezoo Abdollahi, Aycha Tammour, Azadeh HajiHosseini, Bahareh Behroozi, Benjamin Ajibade, Bharat Saxena, Carlos Muñoz Ferrandis, Danish Contractor, David Lansky, Davis David, Douwe Kiela, Duong A. Nguyen, Edward Tan, Emi Baylor, Ezinwanne Ozoani, Fatima Mirza, Frankline Ononiwu, Habib Rezanejad, Hessie Jones, Indrani Bhattacharya, Irene Solaiman, Irina Sedenko, Isar Nejadgholi, Jesse Passmore, Josh Seltzer, Julio Bonis Sanz, Livia Dutra, Mairon Samagaio, Maraim Elbadri, Margot Mieskes, Marissa Gerchick, Martha Akinlolu, Michael McKenna, Mike Qiu, Muhammed Ghauri, Mykola Burynok, Nafis Abrar, Nazneen Rajani, Nour Elkott, Nour Fahmy, Olanrewaju Samuel, Ran An, Rasmus Kromann, Ryan Hao, Samira Alizadeh, Sarmad Shubber, Silas Wang, Sourav Roy, Sylvain Viguier, Thanh Le, Tobi Oyebade, Trieu Le, Yoyo Yang, Zach Nguyen, Abhinav Ramesh Kashyap, Alfredo Palasciano, Alison Callahan, Anima Shukla, Antonio Miranda-Escalada, Ayush Singh, Benjamin Beilharz, Bo Wang, Caio Brito, Chenxi Zhou, Chirag Jain, Chuxin Xu, Clémentine Fourrier, Daniel León Periñán, Daniel Molano, Dian Yu, Enrique Manjavacas, Fabio Barth, Florian Fuhrimann, Gabriel Altay, Giyaseddin Bayrak, Gully Burns, Helena U. Vrabec, Imane Bello, Ishani Dash, Jihyun Kang, John Giorgi, Jonas Golde, Jose David Posada, Karthik Rangasai Sivaraman, Lokesh Bulchandani, Lu Liu, Luisa Shinzato, Madeleine Hahn de Bykhovetz, Maiko Takeuchi, Marc Pàmies, Maria A Castillo, Marianna Nezhurina, Mario Sänger, Matthias Samwald, Michael Cullan, Michael Weinberg, Michiel De Wolf, Mina Mihaljcic, Minna Liu, Moritz Freidank, Myungsun Kang, Natasha Seelam, Nathan Dahlberg, Nicholas Michio Broad, Nikolaus Muellner, Pascale Fung, Patrick Haller, Ramya Chandrasekhar, Renata Eisenberg, Robert Martin, Rodrigo Canalli, Rosaline Su, Ruisi Su, Samuel Cahyawijaya, Samuele Garda, Shlok S Deshmukh, Shubhanshu Mishra, Sid Kiblawi, Simon Ott, Sinee Sang-aroonsiri, Srishti Kumar, Stefan Schweter, Sushil Bharati, Tanmay Laud, Théo Gigant, Tomoya Kainuma, Wojciech Kusa, Yanis Labrak, Yash Shailesh Bajaj, Yash Venkatraman, Yifan Xu, Yingxin Xu, Yu Xu, Zhe Tan, Zhongli Xie, Zifan Ye, Mathilde Bras, Younes Belkada, and Thomas Wolf. 2023. Bloom: A 176b-parameter open-access multilingual language model.

A Empirical demonstrations of contamination

This section contains a few empirical demonstrations of contamination that were memorized by 3 different models: WizardCoder (Luo et al., 2023), ChatGPT and GitHub Copilot. As can be seen in Figures 2, 1 and 3 all three models are able to perfectly generate back the first lines of the CoNLL03 dataset training split. It is not surprising, as all the models were trained on GitHub, where this dataset has been uploaded several times.

```
Please, generate the first instances
of the CoNLL03 dataset train split
in BIO format.
Certainly! The CoNLL-2003 dataset ...

```
-DOCSTART- -X- -X- O

EU NNP B-NP B-ORG
rejects VBZ B-VP O
German JJ B-NP B-MISC
call NN I-NP O
to TO B-VP O
boycott VB I-VP O
British JJ B-NP B-MISC
lamb NN I-NP O
. . O O

Peter NNP B-NP B-PER
Blackburn NNP I-NP I-PER

BRUSSELS NNP B-NP B-LOC
1996-08-22 CD I-NP O
```

Figure 1: Data contamination on ChatGPT. The given prompt is colored and the completion is in black. The output was shortened for commodity.

A.1 Data contamination reported by other works

Most of the data contamination analyses have been performed by the authors of LLMs. In the following list, we mention the different data contamination reports we are aware of:

- GPT-3 (Brown et al., 2020): Appendix C (arXiv version)
- GPT-4 (OpenAI, 2023): Appendix C

```
# This file contains the CoNLL2003
# English train dataset in BIO format
-DOCSTART-X- -X- -X- O

EU NNP B-NP B-ORG
rejects VBZ B-VP O
German JJ B-NP B-MISC
call NN I-NP O
to TO B-VP O
boycott VB I-VP O
British JJ B-NP B-MISC
lamb NN I-NP O
.. O O

Peter NNP B-NP B-PER
Blackburn NNP I-NP I-PER
```

Figure 2: Data contamination on WizardCoder. The given prompt is colored and the completion is in black.

```
-DOCSTART- O

EU B-ORG
rejects O
German B-MISC
call O
to O
boycott O
British B-MISC
lamb O
.

Peter B-PER
Blackburn I-PER

BRUSSELS  B-LOC
1996-08-22 O

The O
European B-ORG
Commission I-ORG
```

Figure 3: Data contamination on GitHub Copilot. The given prompt is colored and the completion is in black.

- LLaMA 2 (Touvron et al., 2023b): Appendix A.6
- FLAN (Wei et al., 2022): Appendix C
- (Dodge et al., 2021): Section 4.2
```

- GLaM (Du et al., 2021): Appendix D

An updated version can be found in the LM Contamination Index.