Leak, Cheat, Repeat: Data Contamination and Evaluation Malpractices in Closed-Source LLMs

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Abstract

Natural Language Processing (NLP) research is becoming increasingly focused on the use of Large Language Models (LLMs), with some of the most popular ones being either fully or partially closed-source. The lack of access to model details, especially regarding training data, has repeatedly raised concerns about data contamination among researchers. Several attempts have been made to address this issue, but they are limited to anecdotal evidence and trial and error. Additionally, they overlook the problem of indirect data leaking, where models are iteratively improved by using data coming from users. In this work, we conduct the first systematic review of work using OpenAI's ChatGPT and GPT-4, the most prominently used LLMs today, in the context of data contamination. By analysing 255 papers and considering OpenAI's data usage policy, we extensively document how much data has been leaked to ChatGPT in the first year after the model's release. At the same time, we document a number of evaluation malpractices emerging in the reviewed papers, including unfair or missing baseline comparisons, reproducibility issues, and authors' lack of awareness of the data usage policy. Our work provides the first quantification of the ChatGPT data leakage problem.

1 Introduction

The recent emergence of large language models (LLMs) that show remarkable performance on a wide range of tasks has led not only to a dramatic increase in their use in research but also to a growing number of companies joining the race for the biggest and most powerful models. In pursuing a competitive advantage, many of the most popular LLMs today are locked behind API access and their details are unknown (OpenAI, 2023a; Thoppilan et al., 2022; Touvron et al., 2023). This includes model weights (OpenAI, 2023a), training data (Piktus et al., 2023), or infrastructural details to assess model carbon footprint (Lacoste et al., 2019).

In particular, the lack of information about the training data being used raises important questions about the credibility of LLM performance evaluation. The training data, typically collected automatically by scraping documents from the web, may contain training, validation, and – most critically – test sets of standard NLP benchmarks, leading to unintended evaluation of the LLM's performance on data it was trained on. This phenomenon, known as data contamination, may not be an issue in the general use of commercial LLMs, where adherence to research principles is not mandatory, but it becomes a serious problem when these tools are widely used and evaluated in research.

Unfortunately, closed-source models are typically locked behind inference-only APIs, which makes detecting data contamination very complex. Because of this, existing work on the matter is limited to detecting extreme forms of overfitting and memorization, where the LLM is mostly probed to reproduce known examples from benchmarks verbatim. These approaches also overlook that recent LLMs get iteratively improved with user interaction data. When users test these models on benchmarks, they may, in fact, be exposing them to the data even if it was not part of the original training data, a phenomenon that we refer to as *indirect data leaking*.

In this paper, we address the issue of data contamination in closed-source LLMs by conducting a systematic literature review. We review 255 papers and carefully detail data leakage emerging from them. We focus primarily on OpenAI's ChatGPT,[1] and secondarily on GPT-4[2] as these are the most frequently used commercial LLMs in NLP research. By considering OpenAI's data usage policy, we assess how much data was reported to be leaked to them in such a way that it could be

[1]https://openai.com/blog/chatgpt

[2]https://openai.com/gpt-4

used for further training, hence giving the models an unfair advantage over open-source LLMs that are usually trained following scientific rigor. We also report a series of emergent evaluation malpractices, including lack of comparison with other models/approaches, differences in the evaluation scale (e.g. closed-source LLMs being evaluated on samples while compared open models are evaluated over an entire benchmark), lack of code and data access, or data leakage even in situations where it could be avoided. To our knowledge, ours is the most comprehensive and extensive quantification of the data leakage issue in LLMs.

In short, our contributions are as follows:

(1) We perform a systematic review of the work evaluating OpenAI's ChatGPT and GPT-4 on a variety of tasks in NLP and other domains (Section 4).

(2) For each work, we estimate the amount of data leaked to these models in such a way that it could be used for further model training (Section 5.1).

(3) We reveal some critical malpractices in closed-source LLM research, affecting both evaluation reproducibility and fairness (Sections 5.2 and 5.3).

(4) Based on our findings, we propose a list of best practices for the evaluation of closed-source LLMs (Section 6).

Furthermore, we believe that the results of our work can help the ongoing efforts in empirical inspection of LLM data contamination by pointing out which datasets are worth investigating. We release our survey results as a spreadsheet with an assessment of the extent of data leakage for each dataset to stimulate further research.[3]

2 Prior Work on LLM Data Contamination

Work on LLMs data contamination traces back to OpenAI's GPT-3 (Brown et al., 2020; Raffel et al., 2020; Magar and Schwartz, 2022), one of the first LLMs with general API access for which only partial training information was released. Despite results hinting at the presence of significant data contamination (Raffel et al., 2020; Magar and Schwartz, 2022), the model has been used extensively in research and the issue was rarely taken into account when interpreting its performance. With the release of ChatGPT and following closed-source models to general public,[4] the data contamination topic became an even more pressing issue.

Because of the implicit complexity of analyzing closed-source LLMs, few practical approaches have been proposed to estimate the leak of known benchmarks into them. One notable example is the LLM Contamination Index,[5] which features a regularly updated list of models along with the extent of their eventual contamination/memorization on popular NLP benchmarks. This approach works by zero-shot prompting the model to generate instances from specific datasets, providing details on the required split and format (Sainz et al.). The premise is that no model should be able to replicate specific benchmark formats without having seen them first.

Recent work (Aiyappa et al., 2023a) also discussed the issue by comparing different ChatGPT versions on known benchmarks, noting that performance on the task improved shortly after the model was exposed to the datasets by previous work (Zhang et al., 2022). More applied approaches have been proposed recently (Golchin and Surdeanu, 2023), where the model is prompted to complete a given sentence coming from a known benchmark. The completion is then compared with the original reference through text overlap metrics and a statistical test is used to assess if the model is contaminated.

Although these preliminary works exploring the task of data contamination detection are promising, they cannot be fully trusted and have some limitations. Most importantly, they are based on an assessment of the model's ability to generate an example from the benchmark. The recall of such methods can be affected by two issues:

(1) Some closed-source models have incorporated special filters into their decoding algorithms that prevent them from generating texts that significantly overlap with their training sets (GitHub, 2022; Ippolito et al., 2023). This creates an additional noise for the detection methods and results in the lack of confidence

[3] https://anonymous.4open.science/r/eacl-data_contamination-BEF1/

[4] Including GPT-4 (OpenAI, 2023a), Google's LaMDA (Thoppilan et al., 2022) and PaLM (Chowdhery et al., 2022), Cohere's Command and Anthropic's Claude.

[5] https://hitz-zentroa.github.io/lm-contamination/

that even the datasets tested negative for data leakage are not present in LLM training data.

(2) Such approaches can only detect the most extreme form of overfitting which results in (almost) complete memorization of data samples by the model. However, even a regular adjustment of the model by training on the leaked data, which does not necessarily lead to its memorization, poses a problem for fair comparisons.

3 The Issue of Indirect Data Leaking

The related work presented in Section 2 approaches the issue of data contamination mainly by backtracking models' training data. It is commonly assumed that the use of benchmarks available only to authorised parties, or datasets being constructed after the ChatGPT release, is a guarantee that they have not been leaked. This ignores the fact that models using reinforcement learning from human feedback (RLHF) (Ouyang et al., 2022), such as ChatGPT, are subject to repeated updates (Aiyappa et al., 2023a) with training data partially coming from user interactions. The collection of user data and online model updates lead to a previously overlooked phenomenon of indirect data leaking. This is a new development of the issue for two main reasons:

(1) Unlike plain text scraped from the internet, data from users might be harder to inspect for contamination as it might involve model prompts, textual alterations, or truncation of benchmark samples.

(2) Users supply the data along with instructions on how to perform the task. In LLMs, this can be considered a novel form of gold-standard data for continued training, even in the absence of target labels. Model updates on such data are likely much more effective than plain in-domain text.

For (1), even with a conscious and targeted effort of the LLM vendors to avoid fine-tuning the model on test data and benchmarks, this issue is particularly complex to trace. When evaluating a closed-source LLM, users often feed the model with test-set samples (with or without labels) surrounded by additional text, such as instructions in the form of prompts. In some cases, especially when evaluating the LLM robustness, the test-set samples are perturbed and hence no longer an exact match of their original version. Therefore, it is unlikely that LLM vendors could effectively exclude leaked benchmarks from further model fine-tuning, especially at scale.

For (2), it would be necessary to understand how the LLM vendor uses the data to improve the model. A very likely scenario is continued pre-training, where the data leaked by users is treated as an in-domain corpus (and thus given more influence than pretraining data). This procedure is known to improve models' performances in the leaked domains (Gururangan et al., 2020). Notably, Shi and Lipani (2023) find that fine-tuning a model on in-domain text enriched by textual instructions leads to an increase in the model performance even if gold labels are not shown to the model. Such a setup perfectly matches the kind of data shown to chat LLMs when evaluated by researchers. This means that closed-source LLMs such as ChatGPT can make use of these gold standard examples from widely used NLP benchmarks to gain an unfair advantage over other models.

With this motivation, we conduct a systematic review to quantify how much of such data ChatGPT could have obtained.

4 Methodology

Following the standard protocol for a systematic work review from the medical domain (Khan et al., 2003) we organize our work into five macro-steps, corresponding to the following subsections.

4.1 Framing questions

In reviewing the existing work on evaluation of ChatGPT and GPT-4, we pose the following research questions:

(1) Which datasets have been demonstrably leaked to ChatGPT and GPT-4 during the last year?

(2) Do all works evaluating these models include a fair comparison with existing baselines?

4.2 Identifying relevant work

We employ commonly used online databases[6] and major NLP conferences proceedings (including ACL, NAACL, EMNLP, NeurIPS), considering

[6]We query Google Scholar, Semantic Scholar, DBLP, arXiV, ACL Anthology.

both peer-reviewed work and pre-prints, as the interaction with LLMs happened regardless of publication status. We filter our queries on work containing the terms "ChatGPT", "evaluation", "large language models" and "AI" either in title, abstract, body, or all of them.

We also do not limit our search to computer science works only, as ChatGPT has been investigated by researchers from many other domains, e.g. healthcare (Kung et al., 2023a), psychology (Cai et al., 2023) and education (Szefer and Deshpande, 2023). Since ChatGPT is our primary focus, we limit our search to works between late November 2022 (when the model was publicly released) and early October 2023. Among all the papers, we first do a preliminary screening, assessing if they effectively run ChatGPT or GPT-4 in any form.[7]

4.3 Assessing quality and relevance

To assess which work effectively leaked data to ChatGPT or GPT-4, we refer to OpenAI's data usage policy,[8] stating that no text sent through or produced from API calls is used for model improvements from 1 March 2023 onwards (coinciding with the first ChatGPT API release). Therefore, only the work interacting with the models through the web interface[9] is considered to leak data.

A small number of works used both the web interface and API access.[10] We carefully review such works to calculate which portion of the data was used in the former setup. We drew our conclusions from the paper draft history on arXiv; in some cases, this information was also transparently disclosed by the authors. In the case of work with multiple drafts dating prior to the model release in November 2022, we consider the earliest draft that includes ChatGPT or GPT-4 for the calculation.

4.4 Summarizing the evidence

We inspect each surveyed paper, looking for information on the used datasets, split, and number of samples. If no mention of sampling or similar information is made, we assume that the whole dataset has been used. Similarly, if no information on the used split is provided, we assume that the authors treated the dataset as a whole. It could be argued that feeding entire datasets to ChatGPT or GPT-4 is unrealistic because of the usage restrictions imposed by OpenAI on the web interface, and the amount of work necessary for manually inputting the data inside the chat. However, we note that quickly after ChatGPT release, many unofficial wrappers have been developed[11] for circumventing said issues, most of which are still in active use. We also point out that many of the papers we surveyed mentioned the use of such tools explicitly.

We also track secondary information relevant to the evaluation – for each work, we inspect: (1) if it has been peer-reviewed[12]; (2) if the used prompts are available; (3) if a repository to reproduce the experiment is provided; (4) if the authors used a whole dataset or a sample; (5) if ChatGPT or GPT-4 were compared to other open models/approaches and if the evaluation scale was the same; (6) if the version of the model used is reported.

4.5 Interpreting the findings

We report the results of our review both quantitatively and qualitatively. Specifically, we report the number of works surveyed leaking data to ChatGPT or GPT-4 in such a way that it can be used by OpenAI to further improve the model (according to their data policy). We also document a series of evaluation practices emerging for the work reviewed that is problematic with respect to objectiveness and reproducibility. Finally, drawing upon our results, we present a series of best practices for researchers evaluating OpenAI's and other closed-source LLMs.

5 Results

Following our methodology, in the first step we identified 255 research papers, 216 of which were found relevant during the initial screening. Among the relevant papers, 72 ($\sim 33\%$) were peer-reviewed while the remainder (144) consisted of pre-prints. We subsequently analysed the retrieved papers to examine the problem of data contamination and the adopted evaluation practices.

5.1 Indirect data contamination

From our analysis, 90 papers ($\sim 42\%$) accessed ChatGPT or GPT-4 through the web interface, hence providing data that OpenAI could have used

[7] We encountered a small number of papers also comparing to other closed-source LLMs, such as Anthropic's Claude.

[8] https://help.openai.com/en/articles/5722486-how-your-data-is-used-to-improve-model-performance

[9] https://chat.openai.com/

[10] Their experiments began prior to March 1st, 2023 and the authors started using the API soon after it was released.

[11] E.g. revChatGPT, PyChatGPT, and ChatGPT-to-API.

[12] We do note that part of the work we reviewed is very recent (with pre-prints published in the last 3 months) and might currently be under review.

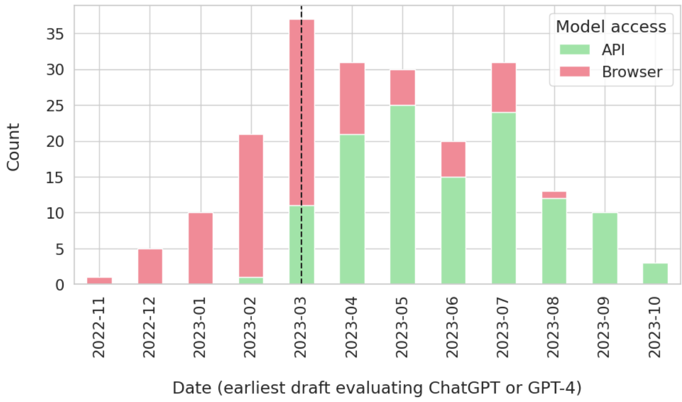

Figure 1: Distribution of the dates when papers evaluating ChatGPT or GPT-4 were first uploaded to arXiv or published. The dotted line represents the ChatGPT API release (March 1st, 2023, dotted line in the chart) as a cutoff point. The single paper shown using the API in February is by a research group who reported having early API access.

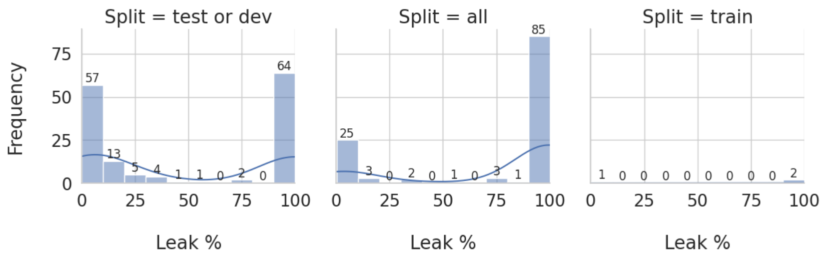

Figure 2: Overview of data leakage distribution. We report the number of times (y) we observed a specific percentage of leaking (x) for the considered split. As some work vaguely describes the used split as "test or dev set", we merge these two values in a unique chart.

to further improve its models. We note that while it is possible to opt out of providing the data for model improvement purposes, we found no evidence suggesting any of the surveyed papers did so.

We first inspected the time distribution of the reviewed works (Figure 1) to gain insight into when most data leaks happened. Unsurprisingly, the majority of the papers leaking data dates before the official release of ChatGPT API, and it can be seen that web interface access rapidly decreased following March 2023. However, we must note that (1) a considerable amount of work kept using the web interface to access ChatGPT until September 2023 and (2) our analysis cannot inspect the preliminary stages of prompt engineering, which are rarely reported and might still be done through the web interface because of its trial-and-error nature.

The presence of leaked data after the API release may indicate that a part of the research community is either unaware of OpenAI's data policy, or does not consider it a problem when conducting experiments. Many works also report on using the web interface for cost reasons, as it allows free ChatGPT access. This might be crucial, especially for small case studies.

As a second step, we quantified leak severity according to the datasets and splits used. For papers specifying the amount of data used or providing a repository with the information, we considered the given value. For the rest, we calculated the value by inspecting the actual datasets.[13] In seven papers, no number of samples used was specified, so we contacted the authors for clarification. In the two cases where the authors did not respond, we assumed the entire split of a dataset was used. We calculated both the number of instances and the percentage of the considered split (or the whole dataset when applicable).

Since only a small number of datasets (18) was used in multiple papers, we always assume that the largest leak for a given dataset is a superset of all smaller ones.[14]

[13] We mainly use HuggingFace Datasets, but also refer to Kaggle or other sources based on availability.

[14] We also tried a pessimistic approach, where we assumed all the leaks were independent, but due to the small number of works covering the same data, the results are virtually

Task name	Lo	M-Lo	M-Hi	Hi
AI safety & ethics	0	0	2	0
Creative NLG	1	0	0	0
Dialogue	2	1	0	5
NLG evaluation	0	0	0	4
Machine Translation	6	4	1	1
Math	0	1	0	8
Natural language generation	2	1	0	14
Natural language inference	6	2	0	15
Language understanding	0	0	0	2
Paraphrasing	2	0	0	0
Politics	0	1	0	3
Programming	0	0	0	1
Psychology	0	0	0	1
Question answering	24	14	5	31
Commonsense reasoning	3	4	0	9
Semantic similarity	2	1	0	3
Sentiment analysis	8	9	1	8
Summarization	5	6	1	1
Text classification	1	0	0	3
Text extraction	2	1	0	7

Table 1: The number of datasets with low (Lo), moderate-low (M-Lo), moderate-high (M-Hi) and high leaks (Hi) is reported for each task, omitting custom datasets. A more detailed table, including specific dataset names, is provided in the Appendix.

Our calculations show that the 90 papers leaked data from 263 unique datasets, for a total of over 4.7M samples.[15] We find most samples ($\sim 93.8\%$) coming from datasets treated as whole (with no split), followed by test and development ($\sim 5.6\%$),[16] and training ($\sim 0.6\%$) sets. In line with what we discussed in Section 3, ChatGPT was presented with millions of samples with instructions that could be considered de-facto novel gold-standard data in some cases.

We also report that several works included the examples' labels when few-shot prompting ChatGPT or when using ChatGPT or GPT-4 as a reference-based evaluation metric. We consider this the worst possible case of data leaking, as it gives the model information about the desired output as well.

To classify leak severity, we examine the frequency distribution of leak sizes (Figure 2). It appears that most works either leak full splits or very small samples, with only a few works leaking intermediate amounts. With this information, we classify a portion of leaked data as *low* ($< 5\%$), *moderate-low* ($5 - 50\%$), *moderate-high* ($50 - 95\%$), or *high* ($> 95\%$).

Consequently, we categorize all leaked datasets into these 4 thresholds. Overall, we find a low leak for 66 ($\sim 25\%$) datasets, moderate-low for 47 ($\sim 18\%$), moderate-high for 10 ($\sim 4\%$) and high for 142 ($\sim 53\%$). This result is particularly worrying as the majority of datasets were nearly fully leaked.

Finally, we inspect which NLP tasks are covered by the leaked data (Table 1). We find that the tasks suffering the most from high leaks are natural language inference, question answering, and natural language generation. These and other tasks (see Tables 4 and 5 in the Appendix) include a lot of very popular NLP benchmarks, as well as high-quality custom datasets created ad-hoc for individual evaluations. The custom datasets were frequently phrased as an exam in a field different from NLP, e.g. medicine, physics, psychology, or law. Other custom datasets explored, for example, the LLMs' sense of humour, philosophical and political leaning, or bias.

5.2 Reproducibility

We assessed the evaluations' reproducibility by checking whether the prompts used to query ChatGPT were provided, whether a repository containing data or code was available, and whether the datasets used were custom-made. Finally, we also checked for sampling of the original data or other practices that make it impossible to exactly reconstruct the data used. Results are shown in Table 2.

196 (91%) works report the prompts used to convert data into a query and possibly to instruct the model on how to perform a given task. The number of works providing a code repository is significantly smaller, at 115 (53%). This figure excludes papers that provided a link to a non-existent or empty repository. Overall, 73 (51%) of the pre-prints and 34 (47%) peer-reviewed papers provided both prompts and a repository.

Another obstacle to reproducibility is that most closed-source LLMs are being regularly updated. Therefore, it is crucial for experiment reproducibility to report a specific LLM version. In the surveyed works, this was generally done by reporting the running period of the experiments when using the web interface, or by reporting which version of the model has been accessed via the API. Unfortunately, as the concept of regular model updates is relatively new, this practice is not yet common. Only 29 (40%) of the peer-reviewed papers and 33 (23%) of the pre-prints provide this information. We consider reporting the running period to be par-

identical.

[15]The survey total is 4,714,753 leaked samples.

[16]As some work vaguely describes the used split as "test or dev set", we merge these two values.

Prompts	Repo	Sampl.	Custom	n. (%)
				3 (2.11%)
			✓	1 (0.70%)
		✓		8 (5.63%)
	✓			3 (2.11%)
	✓	✓		2 (1.41%)
✓				20 (14.08%)
✓			✓	3 (2.11%)
✓		✓		27 (19.01%)
✓		✓	✓	3 (2.11%)
✓	✓			37 (26.06%)
✓	✓		✓	4 (2.82%)
✓	✓	✓		27 (19.01%)
✓	✓	✓	✓	4 (2.82%)

(a) Pre-prints

Prompts	Repo	Sampl.	Custom	n. (%)
				1 (1.43%)
	✓		✓	1 (1.43%)
	✓	✓		1 (1.43%)
✓				14 (20.00%)
✓			✓	7 (10.00%)
✓		✓		9 (12.86%)
✓		✓	✓	3 (4.29%)
✓	✓			8 (11.43%)
✓	✓		✓	4 (5.71%)
✓	✓	✓		16 (22.86%)
✓	✓	✓	✓	6 (6.57%)

(b) Peer-reviewed works

Table 2: Statistics related to the reproducibility of the work reviewed: the availability of used prompts (Prompts) and code/data repository (Repo), the usage of custom datasets (Custom), the application of random sampling or any other practice that does not allow the exact reconstruction of the data used (Sampl.).

Comp.	Scale	n. (%)
		71 (50.00%)
✓		54 (38.03%)
✓	✓	17 (11.97%)

(a) Pre-prints

Comp.	Scale	n. (%)
		30 (42.86%)
✓		34 (48.57%)
✓	✓	6 (8.57%)

(b) Peer-reviewed works

Table 3: Fairness statistics for reviewed work. Statistics related to the practices of performance comparisons between ChatGPT/GPT-4 and other open models: whether such comparisons are performed at all (Comp.) and whether they are of the same scale (Scale).

ticularly important, as Chen et al. (2023b) show that there may be vast differences between model versions.

5.3 Evaluation (mal)practicies

We found that the evaluation of ChatGPT's performance is often conducted without comparing it to any open-source LLM or non-LLM-based method (see Table 3). This is similarly prevalent regardless of the publication status, appearing in 71 (50%) of pre-prints and 30 (43%) of published papers. In addition, among the works that perform a comparison with open models, 23 (21%) compare the results computed on different samples. ChatGPT is typically evaluated on a random sample of the benchmark while other models are compared on its entirety. In many works, ChatGPT's performance is measured on only a handful (10-50) of examples, which substantially lowers the expressive power of the comparison. For instance, considering a simplistic case with binary assessment of model output (correct/incorrect) on 10 examples, the difference should be more than 30% to be statistically significant,[17] which is rarely seen. Statistical analysis of results is almost never performed.

Another practice of some concern is the way in which the size of the evaluation data is reported, especially when sampling is used. The papers often show the size of the whole evaluation dataset upfront (e.g. in a table or in the dataset description section), but they report the actual sample sizes

[17] Assuming Fisher's exact test, typical $\alpha = 5\%$ and moderate model performance around $\hat{p} = 0.5$

used for evaluation only later and in a less obvious way (in footnotes, limitations sections, or appendices). This practice makes the experimental results harder to interpret.

6 Best Practices in Closed-source LLM Evaluation

Our survey revealed both a significant amount of data leakage in ChatGPT and many worrying trends in its evaluation. In light of this, we list a series of best practices that we believe could help mitigate the issues. We believe that researchers looking to objectively evaluate LLMs today should:

Choose the right model access The first step when planning closed LLMs evaluation should be reading their most up-to-date data policies, and access models accordingly (e.g. API instead of web interface for OpenAI's LLMs). We also acknowledge that in some cases this might not be viable due to budget limits, or an overly steep learning curve for the use of APIs by researchers outside of computer science.[18]

Interpret performance skeptically The lack of system specifications, training data information, and other details can make commercial LLMs look like incredibly powerful tools with impressive zero-shot performance. Aiyappa et al. (2023a) already pointed out that this can often be explained by data contamination. In our review, we documented over 4 million samples across over 200 NLP datasets having been leaked to these models. The performance of closed-source LLMs should always be interpreted while keeping this in mind.

When possible, avoid using closed-source models We strongly encourage using the available open-source LLMs. While there has been discussion in the research community about commercial models being consistently better than open-source ones, we note that (1) this is often driven by hype, while there is evidence of the opposite (Kocoń et al., 2023), (2) research done solely on closed LLMs limits scientific progress, bringing benefits mainly to the LLM vendors (3) LLM vendors can arbitrarily make changes to the models, e.g., making previous versions unavailable, changing their behavior in a way that may not be visible to the user (Chen et al., 2023b) or changing the data treatment policy.

[18] In such a case, at the time of writing this paper in mid-October, OpenAI allows users to opt out of providing data for model improvement by using a Google Form.

Adopt a fair and objective comparison Evaluating closed-source LLMs is tied to comparing them with pre-existing approaches. Evaluating LLMs on a limited number of samples while evaluating others on dramatically larger sets is scientifically dubious at best. When sampling is required (for example for budgetary restrictions), it should be applied to all the considered approaches. We also discourage taking state-of-the-art values directly from previous work and suggest to re-run all approaches on the considered data only.

Make the evaluation reproducible In light of the known NLP evaluation reproducibility crisis (Belz et al., 2023) we strongly encourage researchers to report as many details about their setup. Besides the commonly required information such as random seeds, open model parameters, etc., we note that when the evaluation involves closed models, additional details should be disclosed. Prompts, as well as the process leading to them, should be detailed since LLMs are very sensitive to even minor changes in prompts (Lu et al., 2022). The model version and experiment running period should be mentioned as well so that further researchers can use the same model checkpoint if possible. Data, especially if sampled, should be released (ideally in a repository) to avoid potential differences in sampling.

7 Conclusion and Future Work

In this review, we present our findings based on a survey of 255 papers evaluating the performance of ChatGPT and GPT-4. We investigate the problem of indirect data contamination and report that 4.7M samples coming from 263 distinct datasets have been leaked to these models. We also report concerning research practices with respect to reproducibility and fairness. Finally, informed by our survey, we suggest best practices for the evaluation of closed-source LLMs.

Future Work In our future work, we aim to run experiments via the OpenAI API to see the impact of leaked test data on the performance of ChatGPT and GPT-4 on the leaked datasets and the tasks in general.

Furthermore, we consider investigating indirect data leakage in other closed-source models, namely from Anthropic or Cohere, which appeared in a small number of papers reviewed in this work.

8 Limitations

We are aware the list of contaminated datasets we compiled in our work is not fully conclusive for one of several reasons:

(1) We review the information that has been publicly revealed via articles. We postulate more experiments could have revealed test set data to closed-source models but were never published.

(2) In this paper, we focus on the works that use ChatGPT or GPT-4. However, prior to March 1st, 2023, OpenAI's policy stated that they may also use data from the API to improve their models. This would imply that data sent to GPT-3 via the API could have been used for training.

(3) The number of papers investigating the performance of ChatGPT is vast, and despite our best efforts, we could have missed some works.

(4) Information on whether individual works are pre-prints or published is given at the time of writing (early October 2023). This is subject to change, especially given the freshness of many of the works reviewed.

(5) Many datasets released prior to 2021 could have been fully leaked by being a part of the models' pre-training data.

As mentioned in Section 4, in some cases the papers were not clear about some aspects of the experiments. We contacted the authors of such papers for clarification, however, two of them did not respond. For these papers, our best-judgment assumptions may be wrong.

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A Full list of the reviewed work

In this section, we list all the work that we reviewed and classified as relevant.

- LLM-contamination (Sainz et al., 2023)
- Time Travel in LLMs: Tracing Data Contamination in Large Language Models (Golchin and Surdeanu, 2023)
- Don't Stop Pretraining: Adapt Language Models to Domains and Tasks (Gururangan et al., 2020)
- Can we trust the evaluation on ChatGPT? (Aiyappa et al., 2023b)

- How Close is ChatGPT to Human Experts? Comparison Corpus, Evaluation, and Detection (Guo et al., 2023)
- GPTEval: A Survey on Assessments of ChatGPT and GPT-4 (Mao et al., 2023)
- A Systematic Study and Comprehensive Evaluation of ChatGPT on Benchmark Datasets (Laskar et al., 2023)
- Quantifying Memorization Across Neural Language Models (Carlini et al., 2023)
- Preventing Generation of Verbatim Memorization in Language Models Gives a False Sense of Privacy (Ippolito et al., 2023)
- List of various ChatGPT evaluations (Github, 2023)
- GPT-4 Technical Report (OpenAI, 2023b)
- Zeno Chatbot Report (Cabrera and Neubig, 2023)
- A Multitask, Multilingual, Multimodal Evaluation of ChatGPT on Reasoning, Hallucination, and Interactivity (Bang et al., 2023)
- Don't Stop Pretraining? Make Promp-based Fine-tuning Powerful Learner (Shi and Lipani, 2023)
- How Good Are GPT Models at Machine Translation? A Comprehensive Evaluation (Hendy et al., 2023)
- Is ChatGPT A Good Translator? Yes With GPT-4 As The Engine (Jiao et al., 2023)
- Is Chatgpt A General-purpose Natural Language Processing Task Solver? (Qin et al., 2023)
- Extractive summarization via ChatGPT for faithful summary generation (Zhang et al., 2023b)
- Chatgpt or grammarly? evaluating chatgpt on grammatical error correction benchmark (Wu et al., 2023a)
- Will affective computing emerge from foundation models and general ai? A first evaluation on chatgpt (Amin et al., 2023)
- ChatGPT: Jack of all trades, master of none (Kocoń et al., 2023)
- Zero-Shot Information Extraction via Chatting with ChatGPT (Wei et al., 2023)
- Is ChatGPT Good at Search? Investigating Large Language Models as Re-Ranking Agent (Sun et al., 2023b)
- Is ChatGPT a Good NLG Evaluator? A Preliminary Study (Wang et al., 2023c)
- G-EVAL: NLG Evaluation using GPT-4 with Better Human Alignment (Liu et al., 2023g)
- Large Language Models Are State-of-the-Art Evaluators of Translation Quality (Kocmi and Federmann, 2023)
- ChatGPT Outperforms Crowd-workers For Text-annotation Tasks (Gilardi et al., 2023)
- SuperCLUE: A Comprehensive Chinese Large Language Model Benchmark (Xu et al., 2023b)
- C-eval: A multi-level multi-discipline chinese evaluation suite for foundation models (Huang et al., 2023e)
- ChatGPT beyond English: Towards a comprehensive evaluation of large language models in multilingual learning (Lai et al., 2023)
- Zero-Shot Cross-Lingual Summarization via Large Language Models (Wang et al., 2023d)
- A categorical archive of chatgpt failures (Borji, 2023)
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- Is ChatGPT a Good Causal Reasoner? A Comprehensive Evaluation. (Gao et al., 2023a)
- Causal reasoning and large language models: Opening a new frontier for causality (Kıcıman et al., 2023)
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- Boosting Theory-of-Mind Performance in Large Language Models via Prompting (Moghaddam and Honey, 2023)

- Does ChatGPT have Theory of Mind? (Holterman and Deemter, 2023)
- Can ChatGPT Defend the Truth? Automatic Dialectical Evaluation Elicits LLMs' Deficiencies in Reasoning (Wang et al., 2023a)
- Evaluating the logical reasoning ability of chatgpt and gpt-4 (Liu et al., 2023c)
- We're Afraid Language Models Aren't Modeling Ambiguity (Liu et al., 2023b)
- Sparks of artificial general intelligence: Early experiments with gpt-4 (Bubeck et al., 2023)
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- Mathematical capabilities of chatgpt (Frieder et al., 2023)
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- The Wall Street Neophyte: A Zero-Shot Analysis of ChatGPT Over MultiModal Stock Movement Prediction Challenges (Xie et al., 2023b)
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- Performance of ChatGPT on USMLE: Potential for AI-assisted medical education using large language models (Kung et al., 2023b)
- Evaluating the performance of chatgpt in ophthalmology: An analysis of its successes and shortcomings (Antaki et al., 2023)
- Diagnostic Accuracy of Differential-Diagnosis Lists Generated by Generative Pretrained Transformer 3 Chatbot for Clinical Vignettes with Common Chief Complaints: A Pilot Study (Hirosawa et al., 2023)
- Assessing the utility of ChatGPT throughout the entire clinical workflow (Rao et al., 2023a)
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- Can AI tell good stories? narrative transportation and persuasion with ChatGPT (Chu and Liu, 2023)
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- Holistic evaluation of language models (Liang et al., 2023a)
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- How to Design Translation Prompts for ChatGPT: An Empirical Study (Gao et al., 2023e)
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- Analyzing ChatGPT's Aptitude in an Introductory Computer Engineering Course (Deshpande and Szefer, 2023)
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- UZH_CLyp at SemEval-2023 Task 9: Head-First Fine-Tuning and ChatGPT Data Generation for Cross-Lingual Learning in Tweet Intimacy Prediction (Michail et al., 2023)
- Exploring the Feasibility of ChatGPT for Event Extraction (Gao et al., 2023b)
- Does Synthetic Data Generation of LLMs Help Clinical Text Mining? (Tang et al., 2023b)
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- Beyond Black Box AI-Generated Plagiarism Detection: From Sentence to Document Level (Quidwai et al., 2023)
- Comparing Abstractive Summaries Generated by ChatGPT to Real Summaries Through Blinded Reviewers and Text Classification Algorithms (Soni and Wade, 2023)
- MGTBench: Benchmarking Machine-Generated Text Detection (He et al., 2023c)
- Neural Theory-of-Mind? On the Limits of Social Intelligence in Large LMs (Sap et al., 2023)
- What would Harry say? Building Dialogue Agents for Characters in a Story (Chen et al., 2023c)
- Reliable Natural Language Understanding with Large Language Models and Answer Set Programming (Rajasekharan et al., 2023)
- ByGPT5: End-to-End Style-conditioned Poetry Generation with Token-free Language Models (Belouadi and Eger, 2023)
- Transformers Go for the LOLs: Generating (Humourous) Titles from Scientific Abstracts End-to-End (Chen and Eger, 2022)

- Modeling Label Semantics Improves Activity Recognition (Zhang et al., 2023f)
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- Guiding Large Language Mdels via Directional Stimulus Prompting (Li et al., 2023g)
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- Check Your Facts and Try Again: Improving Large Language Models with External Knowledge and Automated Feedback (Peng et al., 2023a)
- ChatGPT for Zero-shot Dialogue State Tracking: A Solution or an Opportunity? (Heck et al., 2023)
- ChatGPT vs Human-authored Text: Insights into Controllable Text Summarization and Sentence Style Transfer (Pu and Demberg, 2023)
- Not The End of Story: An Evaluation of ChatGPT-Driven Vulnerability Description Mappings (Liu et al., 2023f)
- ChatGPT is not a good indigenous translator (Stap and Araabi, 2023)
- You've Got a Friend in ... a Language Model? A Comparison of Explanations of Multiple-Choice Items of Reading Comprehension between ChatGPT and Humans (Duenas et al., 2023)
- Language-Agnostic Transformers and Assessing ChatGPT-Based Query Rewriting for Multilingual Document-Grounded QA (Gowriraj et al., 2023)
- HW-TSC at SemEval-2023 Task 7: Exploring the Natural Language Inference Capabilities of ChatGPT and Pre-trained Language Model for Clinical Trial (Zhao et al., 2023b)
- Can ChatGPT Understand Causal Language in Science Claims? (Kim et al., 2023)
- ChatGPT is fun, but it is not funny! Humor is still challenging Large Language Models (Jentzsch and Kersting, 2023)
- Assessing Cross-Cultural Alignment between ChatGPT and Human Societies: An Empirical Study (Cao et al., 2023)
- Evaluating Reading Comprehension Exercises Generated by LLMs: A Showcase of ChatGPT in Education Applications (Xiao et al., 2023)
- ChatGPT vs. Crowdsourcing vs. Experts: Annotating Open-Domain Conversations with Speech Functions (Ostyakova et al., 2023)
- Leveraging Large Language Models for Automated Dialogue Analysis (Finch et al., 2023)
- Breaking the Bank with ChatGPT: Few-Shot Text Classification for Finance (Liang et al., 2023b)
- Is ChatGPT a Good Teacher Coach? Measuring Zero-Shot Performance For Scoring and Providing Actionable Insights on Classroom Instruction (Wang and Demszky, 2023)
- Credible Without Credit: Domain Experts Assess Generative Language Models (Peskoff and Stewart, 2023)
- SUT at SemEval-2023 Task 1: Prompt Generation for Visual Word Sense Disambiguation (Ghahroodi et al., 2023)
- How Well Do Large Language Models Perform on Faux Pas Tests? (Shapira et al., 2023)
- Zero-Shot Information Extraction for Clinical Meta-Analysis using Large Language Models (Kartchner et al., 2023)
- Can Large Language Models Be an Alternative to Human Evaluation? (Chiang and Lee, 2023)

- RL4F: Generating Natural Language Feedback with Reinforcement Learning for Repairing Model Outputs (Akyurek et al., 2023)
- Toward Human-Like Evaluation for Natural Language Generation with Error Analysis (Lu et al., 2023b)
- Multi-Level Knowledge Distillation for Out-of-Distribution Detection in Text (Wu et al., 2023b)
- MolXPT: Wrapping Molecules with Text for Generative Pre-training (Liu et al., 2023i)
- MUX-PLMs: Pre-training Language Models with Data Multiplexing (Murahari et al., 2023)
- Is GPT-3 a Good Data Annotator? (Ding et al., 2023)
- Language Generation Models Can Cause Harm: So What Can We Do About It? An Actionable Survey (Kumar et al., 2023)
- Detoxifying Online Discourse: A Guided Response Generation Approach for Reducing Toxicity in User-Generated Text (Bose et al., 2023)
- Faithful Question Answering with Monte-Carlo Planning (Hong et al., 2023)
- Nut-cracking Sledgehammers: Prioritizing Target Language Data over Bigger Language Models for Cross-Lingual Metaphor Detection (Schuster and Markert, 2023)
- Generating Faithful Text From a Knowledge Graph with Noisy Reference Text (Hashem et al., 2023)
- Empowering Conversational Agents using Semantic In-Context Learning (Omidvar and An, 2023)
- Can Large Language Models Safely Address Patient Questions Following Cataract Surgery? (Chowdhury et al., 2023)
- Towards Benchmarking and Improving the Temporal Reasoning Capability of Large Language Models (Tan et al., 2023a)
- Generative Pretrained Transformers for Emotion Detection in a Code-Switching Setting (Nedilko, 2023)
- On the Underspecification of Situations in Open-domain Conversational Datasets (Otani et al., 2023)
- Understanding Factual Errors in Summarization: Errors, Summarizers, Datasets, Error Detectors (Tang et al., 2023a)
- Multilingual Language Models are not Multicultural: A Case Study in Emotion (Havaldar et al., 2023)
- Good Data, Large Data, or No Data? Comparing Three Approaches in Developing Research Aspect Classifiers for Biomedical Papers (Chandrasekhar et al., 2023)
- IDOL: Indicator-oriented Logic Pre-training for Logical Reasoning (Xu et al., 2023c)
- PrecogIIITH@WASSA2023: Emotion Detection for Urdu-English Code-mixed Text (Vedula et al., 2023)
- Do PLMs Know and Understand Ontological Knowledge? (Wu et al., 2023c)
- Evaluation of Question Generation Needs More References (Oh et al., 2023)
- A System for Answering Simple Questions in Multiple Languages (Razzhigaev et al., 2023)
- HIT-SCIR at WASSA 2023: Empathy and Emotion Analysis at the Utterance-Level and the Essay-Level (Lu et al., 2023d)
- Pre-trained Language Models Can be Fully Zero-Shot Learners (Zhao et al., 2023c)
- Predicting the Quality of Revisions in Argumentative Writing (Liu et al., 2023k)
- Exploring Effectiveness of GPT-3 in Grammatical Error Correction: A Study on Performance and Controllability in Prompt-Based Methods (Loem et al., 2023)
- When Truth Matters – Addressing Pragmatic Categories in Natural Language Inference (NLI) by Large Language Models (LLMs) (Gubelmann et al., 2023)
- Debiasing should be Good and Bad: Measuring the Consistency of Debiasing Techniques in Language Models (Morabito et al., 2023)

- GPoeT: a Language Model Trained for Rhyme Generation on Synthetic Data (Popescu-Belis et al., 2023)
- Examining Bias in Opinion Summarisation Through the Perspective of Opinion Diversity (Huang et al., 2023c)
- Unsupervised Summarization Re-ranking (Ravaut et al., 2023)
- Improving Dutch Vaccine Hesitancy Monitoring via Multi-Label Data Augmentation with GPT-3.5 (Van Nooten and Daelemans, 2023)
- What Makes a Good Counter-Stereotype? Evaluating Strategies for Automated Responses to Stereotypical Text (Fraser et al., 2023)
- What Makes Good Counterspeech? A Comparison of Generation Approaches and Evaluation Metrics (Zheng et al., 2023c)
- DAMO-NLP at SemEval-2023 Task 2: A Unified Retrieval-augmented System for Multilingual Named Entity Recognition (Tan et al., 2023c)
- UMASS_BioNLP at MEDIQA-Chat 2023: Can LLMs generate high-quality synthetic note-oriented doctor-patient conversations? (Wang et al., 2023f)
- Frontier Review of Multimodal AI (Nan, 2023)
- Is ChatGPT a Highly Fluent Grammatical Error Correction System? A Comprehensive Evaluation (Fang et al., 2023)
- DialogStudio: Towards Richest and Most Diverse Unified Dataset Collection for Conversational AI (Zhang et al., 2023c)

B Detailed List of ChatGPT Data Leak

We show which datasets have been leaked to ChatGPT in Tables 4 and 5.

Task name	Lo	M-Lo	M-Hi	Hi
AI safety & ethics			bbq (all), bold (all)	
Creative text generation	writingprompts (test)			
Dialogue	opendialkg (test), prosocialdialog (test)	multiwoz 2.2 (test)		dstc11 track 5 (dev), dstc7 track 2 (all), multiwoz 2.1 (test), multiwoz 2.4 (test), mutual (test)
Evaluation of generated texts				newsroom (all), openmeva-roc (all), realsumm (all), summeval (all)
Machine Translation	flores-101 (test), wmt20 (test), wmt20 en-de (test), wmt20 robustness task set 2 en->ja (test), wmt20 robustness task set 3 (test), wmt20 zh-en (test), wmt22 (test)	nusax (test), wmt19 biomedical translation task (test), wmt20 robustness task set 2 ja->en (test), wmt2014 ott et al 2018 (test)	flores-200 (dev)	mqm-2022 (test)
Math		numersense (dev)		addsub (all), aqua-rat (test), draw-1k (all), ghosts (all), gsm8k (test), multiarith (all), singleeq (all), svamp (all)
Medical text generation	ddxplus (en) (test), mimic (test)			merck sharpe & dohme (msd) clinical manual (all)
Natural Language Inference	becel-snli (test), commitmentbank (all), mnli (dev), qnli (dev), rte (all), αnli (dev)	becel-rte (test), entailmentbank (test)		med (test), advglue-mnli (dev), advglue-qnli (dev), advglue-rte (dev), anli-r3 (test), ax-g (dev), cb (dev), conjnli (test), control "logical reasoning" (test), help (test), mnli (test), rte (dev), semeval-2023 task 7 (all), taxinli (test), wnli (dev)
Natural Language Understanding				atis (test), snips (test)
Paraphrasing	mrpc (dev), qqp (dev)			
Politics		covid-19-lee (test)		p-stance (test), semeval-2016 task 6 (test), tweet-eval - tweetstance (test)
Programming				quixbugs (all)
Psychology				myers-briggs type indicator (all)

Table 4: The names of datasets with low (Lo), moderate-low (M-Lo), moderate-high (M-Hi), and high (Hi) leakage, categorized according to the task. (1/2)

Task name	Lo	M-Lo	M-Hi	Hi
Question answering	amboss medial questions (all), babi-task16 (test), clutrr (test), e-care (dev), financezhidao (all), freebaseqa (all), hotpotqa (dev), lcquad-2.0 (all), legalqa (all), logiqa (all), math (test), mc-taco (dev), medical dialog (all), medical dialog - zh (all), mkqa (all), pep-3k (all), piqa (test), reclor (all), simplequestions (all), spartqa (test), stepgame (test), timedial (test), webquestionssp (all), webtextqa + baikeqa (all)	babi-task15 (test), bcsc self-assessment program (all), chinese psychological question answering dataset (all), eli5 (all), nlpcc-dbqa (all), openbookqa (dev), ophthoquestions (all), piqa (dev), qasc (dev), race - reading (test or dev), social iqa (dev), squad v2 (dev), truthfulqa gen (test), wikiqa (all)	fiqa (all), gsm8k - mathqa (test), kqapro (all), open-bookqa (test), usmle medial q (all)	advglue-qqp (dev), ar-lsat (test), baidubaike15 (all), boolq (test), boolq-contrast (test), bron (preprocessed) (all), cve-2021 (all), cve-att&ck (all), cwq (all), dblp-bench (all), efficientqa (dev), grailqa (test), graphquestions (all), hc3-chinese (all), hc3-english (all), hofstede cultural survey (all), lc-quad2.0 (all), logiqa 2.0 (test), logiqa 2.0-zh (test), mag-bench (all), nbme medical questions (all), ott-qa (all), protoqa (dev), qald-9 (all), qald-9 (test), reclor (dev), truthfulqa (test), tuce test (all), wiki-csai (all), wqsp (all), yago-bench (all)
Reasoning & common sense	commonsenseqa (test), hellaswag (dev), letter string analogies - webb (all)	arc (dev), coin flip (all), copa (dev), wsc (dev)		cola (dev), commonsenseqa (dev), date (all), last letter (all), matres (test), object (all), strategyqa (all), tddiscourse (test), timebank-dense (test)
Semantic similarity	sts-b (dev), tweeteval - tweetemoji (test or dev)	becel-mrpc (test)		raganato - wsd (test or dev), wic (dev), wic - wordcontext (test or dev)
Sentiment analysis	colbert (test or dev), flipkart (all), imdb (test), sst-2 (dev), unhealthy conv. - unhealthy (test or dev), unhealthy conv. - unhealthyper (test or dev), wikidetox aggr. - aggression (test or dev), wikidetox aggr. - aggressionper (test or dev)	goemotions - goemo (test or dev), goemotions - goemoper0 (test or dev), goemotions - goemoper1 (test or dev), goemotions - goemoper2 (test or dev), goemotions - goemoper3 (test or dev), latenthatred (all), sarcasmania - sarcasm (test or dev), semeval-2023 task 9 (test), tweeteval - tweetsent (test or dev)	realtoxicprompts (all)	advglue-sst-2 (dev), clarinemo (test or dev), first impressions (all), imdb-contrast (all), polemo2 - polemo (test or dev), sentiment140 (all), sst2 (dev), the suicide and depression dataset (all)
Summarization	cnn dailymail (test), crosssum (test), reddit (test), wikilingua (test), xsamsum (test)	cnn/dm (test), covidet (test), newts (test), pubmed (test), qmsum (test), xsum (test)	squality (test)	samsum (test)
Text classification	inverse scaling challenge (11 datasets) (all)			pubmed20k (train), sms spam v.1 (test or dev), symptoms (on kaggle) (train)
Text extraction	ace05 (test), mtsamples (all)	i2b2 2010 (all)		ace05 (all), conll++ (all), conll03 (test), duee1.0 (all), duie2.0 (all), msra (all), nyt11-hrl (all)
Text generation		conll2014 (test)		adveta(add)-spider (dev), adveta(rpl)-spider (dev), cosql (dev), cspider (dev), dusql (all), quiz-design (all), sparc (dev), spider (dev), spider-cg(app) (all), spider-cg(sub) (all), spider-dk (dev), spider-realistic (dev), spider-syn (dev)

Table 5: The names of datasets with low (Lo), moderate-low (M-Lo), moderate-high (M-Hi), and high (Hi) leakage, categorized according to the task. (2/2)