## **Data Contamination Quiz:**

# A Tool to Detect and Estimate Contamination in Large Language Models

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### **Abstract**

We propose the Data Contamination Quiz (DCQ), a simple and effective approach to detect data contamination in large language models (LLMs) and estimate the amount of it. Specifically, we frame data contamination detection as a series of multiple-choice questions and devise a quiz format wherein three perturbed versions of each dataset instance are created. These changes only include word-level perturbations. The generated perturbed versions, along with the original instance, form the options in the DCQ, with an extra option accommodating the possibility that none of the provided choices is correct. Given that the only distinguishing signal among the choices is the exact wording relative to the original instance, an LLM, when tasked with identifying the original instance from the choices, gravitates towards the original one if it has been exposed to it in its pre-training phase-a trait intrinsic to LLMs. Tested over several datasets with GPT-4/3.5, our findings-while fully lacking access to LLMs' pre-training data and internal parameters—suggest that DCO uncovers greater contamination levels compared to existing detection methods and proficiently bypasses more safety filters, especially those set to avoid generating copyrighted contents.<sup>1</sup>

## 1. Introduction

Large language models (LLMs) have shown remarkable success in various Natural Language Processing (NLP) benchmarks and beyond (Bubeck et al. 2023; Bang et al. 2023; OpenAI 2023). However, due to the lack of trans-

<sup>1</sup>We will shortly release all the data corresponding to the DCQ for all the settings used throughout the paper at https://github.com/shahriargolchin/DCQ. parency regarding the data sources used by some LLM providers, coupled with their dependency on web data for pre-training (Penedo et al. 2023; Touvron et al. 2023a;b), the performance of such models may be skewed by "data contamination" (Zhou et al. 2023). This refers to the inclusion of test data from downstream tasks in the LLMs' pre-training data (Golchin & Surdeanu 2023). Considering the immense volume of data used for pre-training, even making this data open-access does not provide a practical solution. This is because cross-verifying each sample in the evaluation dataset against open-source pre-training data becomes impractical due to the substantial computational costs (Touvron et al. 2023b) or the extensive manual effort involved (Chowdhery et al. 2022). This has led LLM developers to assess data contamination in benchmark datasets post-training (Team et al. 2023). As a result, there is a pressing need to pinpoint and quantify this contamination using a cost-effective approach, which demands minimal computational resources and human intervention, ensuring its broad applicability.<sup>2</sup>

We propose the Data Contamination Quiz (DCQ), a streamlined method that efficiently detects and estimates data contamination in LLMs without the need to access their pretraining data and any internal weights/logits. In essence, detection is achieved via a multiple-choice reading comprehension task, while estimation is performed by assessing the LLM's performance across a series of these multiplechoice questions that form the quiz. Specifically, we automatically form a five-option quiz: one option presents a reference instance from a dataset partition, three options offer three distinct word-level perturbed variations of it where words are replaced with their contextually relevant synonyms, and an additional option allows the selection of none of the choices. We instruct GPT-4 (OpenAI 2023) to generate these variations using zero-shot prompting with the original instance embedded in the input prompt. While

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<sup>&</sup>lt;sup>2</sup>In Appendix A, we show how some model providers recently updated their LLMs to counteract circumvention by the latest methods developed for pinpointing data contamination that were successful against earlier versions. This highlights the need for creating new techniques capable of bypassing the newly implemented safety filters and considerations to continually identify data contamination, as further training and updates occur.

the wording differs, the meaning and sentence structure of these variations mirror the original instance, resulting in almost identical semantic representations across all options containing the perturbed versions and the option containing the original instance. As such, the sole difference among these choices is in the precise wording relative to the original instance. Therefore, when the LLM is tasked with identifying the original instance among its variations, a consistent predilection for selecting the original instance reveals the LLM's memorization and prior exposure to the data. However, due to the positional biases inherent in LLMs (Wang et al. 2023; Zheng et al. 2023), this detection is not consistent when the position of the reference instance changes. To address this, for a single setting, we create multiple quizzes by permuting the position of the original instance among the least favored positions to avoid overestimation, and report the maximum performance of LLM across all these quizzes as the highest quantifiable levels of detected contamination.

The main contributions of this paper are listed as follows:

- (1) We approach the issue of data contamination in LLMs using a unique lens: a five-option quiz. This quiz consists of the original instance as one option, along with its three lexically altered variations, and a none option. The LLM's ability to identify the original instance—out of the presented options—discloses its memorization capacity and previous exposure to the data. We interpret the frequency of correct selections in this quiz as indicative of data contamination levels. To obtain a more precise estimate of contamination, we devise several quizzes for a single setting by permuting the position of the correct answer (original instance) among the least favored spots by the LLM, and report the maximum performance achieved by the LLM across all quizzes. This process accounts for the positional biases present in LLMs.
- (2) Through rigorous evaluations encompassing various settings, including controlled and uncontrolled contamination environments for GPT-4 and GPT-3.5 (Ouyang et al. 2022), our findings show that our proposed DCQ detects significantly higher levels of contamination/memorization compared to prior studies, such as the state-of-theart method for pinpointing contamination proposed by Golchin & Surdeanu (2023), by more than eighty times. Notably, our technique is adept at identifying data contamination, even in scenarios where it is not evidently noticeable.

Overall, our approach offers several key benefits over existing methods for data contamination detection:

(i) Our method is the first to effectively estimate contamination levels in the context of black-box LLMs without requiring access to the pre-training data and model weights;

- (ii) By forcing the LLM's output to be a single letter that identifies the selected choice (from A to E), our strategy substantially reduces the probabilistic behavior of autoregressive LLMs in recognizing data contamination;
- (iii) Building on the same principle of limiting output, our method can adeptly evade the safety filters set by model providers during the decoding process, especially in proprietary LLMs that seek to prevent the generation of copyrighted contents, thereby revealing more contamination;
- (iv) It transcends the limitations of probability-/thresholdbased methods, which are typically language-specific, allowing our approach to be applied across different languages:
- (v) Our technique is both cost- and time-saving thanks to the automated quiz generation and administration on a manageable subset of dataset instances—specifically, 100 instances. This obviates the necessity for human participation at any stage and significantly reduces the financial and computational costs connected with generating options for our DCQ, using a generative LLM; and
- (vi) The streamlined nature of our method means the quiz options we collect for each dataset partition are reusable and can be universally applied to any LLM to administer the DCQ, providing the community with an effective and handy tool for pinpointing data contamination within LLMs.

### 2. Related Work

Identifying data contamination in LLMs is trivial when the pre-training data is accessible, albeit at a considerable cost. Typically, this process involves expensive overlap comparison between the pre-training data and the evaluation datasets using high-order n-grams—an exclusive approach to model developers (OpenAI 2023; Touvron et al. 2023a;b; Anil et al. 2023; Chowdhery et al. 2022; Brown et al. 2020, inter alia). However, this task becomes challenging when the pre-training data is absent due to being proprietary or when it is open but vast in size.

A handful of recent studies pivoted to devise strategies for detecting contamination without needing to access pretraining data. Sainz et al. (2023a;b) prompted GPT-3.5 to generate the first instances of a dataset split. However, this method may falter due to the sparseness of the signal in the prompt or because the LLM's safety considerations prevent the generation of copyrighted materials. In contrast, Golchin & Surdeanu (2023) amplified the signal in the prompt by infusing an initial segment of an instance from the downstream dataset and instructing the LLM to complete the subsequent part, thereby more effectively steering the model's output towards the potentially

contaminated dataset.

Roberts et al. (2023) used a time-based approach for contamination detection in LLMs by analyzing dataset pass rates pre- and post-model training cutoff. However, this method encounters limitations due to the continuous updates of closed-source LLMs and the necessity for ongoing data collection efforts. Also, performance fluctuations across multiple datasets are not definitive indicators of contamination, as emergent capabilities of LLMs (Wei et al. 2022) may also influence the results. Further, the challenge of identifying contamination for datasets other than code/mathematical problem-solving remained unresolved. Shi et al. (2023) employed a similar strategy, measuring outlier word likelihood in new examples to determine if a text was part of a pre-training corpus. While useful for open-source LLMs, detecting pre-training data is not synonymous with confirming contamination. True contamination occurs when a data sample, along with its correct answer (depending on the task at hand), from a particular dataset is present in the model's pre-training data. In contrast, discovering samples in various forms (e.g., unlabeled, with different labels, or lacking the correct answer) does not constitute true contamination.

Oren et al. (2023) aimed to detect test data contamination by comparing the likelihoods of a canonically ordered dataset and its shuffled version. However, the inherent positional biases in LLMs (Wang et al. 2023; Zheng et al. 2023) and the bold presumption of dataset instances appearing in the pre-training data in the same order as on the web limit the applicability of this method. In addition, adding data points during data pre-processing or dealing with partially contaminated datasets can easily violate this assumption.

Our work builds upon detecting *true contamination*, i.e., the presence of exact samples with their corresponding correct answers. We refine the strategy proposed by Golchin & Surdeanu (2023) by factoring in the LLMs' probabilistic behavior, which can challenge the consistent replication. Particularly, we narrow the choices available to an LLM by presenting it with quiz options and prompting it to identify the reference instance. This not only enables the detection of contamination but also allows for the estimation of its extent, all while substantially reducing probabilistic generations and bypassing anticipatory filters for copyrighted contents.

### 3. Approach

Our approach consists of three main phases: (1) DCQ development, (2) deployment, and (3) assessment. In the first phase, we generate a dataset containing word-level perturbations per instance. These, alongside the original instance itself as well as a none option, form the quiz options. This

quiz is then presented to the LLM. We next evaluate the ability of the LLM to discern the correct answer among other options. A detailed description of each phase follows.

### 3.1. Development of Data Contamination Quiz

For the development of the DCQ, we use GPT-4. Its rich representations and proficient adherence to following instructions (Bubeck et al. 2023) make it adept at performing word substitutions that maintain contextual relevance. To devise the options, we employ a zero-shot prompt with the original instance infused in it as a reference to generate other options based on. For each original instance, we instruct GPT-4 to craft four distinct word-level altered variations of it, replacing words with their contextually relevant synonyms while ensuring the core essence and sentence structure remain consistent with the original instance. Further, when the reference instance includes a label, we refrain from making any perturbations to the label and instead directly attach the label of the reference instance to the perturbed versions.<sup>3</sup>

Then, we collate the generated variants and combine three of them with the original instance to form four choices in the standard DCQ. Conversely, we leverage all four perturbed versions as four choices in the modified DCQ. We elaborate on each of these quizzes in Subsection 3.2. As a fifth option, we include a choice that allows the possibility of selecting none of the first four options. This is beneficial in situations where the LLM is not contaminated with a particular dataset or when the LLM's memorization is not triggered by the provided options. The zero-shot prompt and the procedure adopted for crafting quiz options are detailed in Appendix B. Figure 1 also exemplifies the produced options for an original instance and their integration into a standard DCQ.

### 3.2. Deployment of Data Contamination Quiz

As shown in Figure 1, employing zero-shot prompting, an LLM is tasked with pinpointing the choice that represents an original instance from a specific dataset partition. Within the DCQ, as all options except the last one mirror the core meaning, the sole differentiating signal remains the lexical variations. This encourages the LLM's memorization ability to recognize the original instance if it was exposed to it during pre-training. Hence, to estimate contamination, we iteratively apply this process to every instance in a small subset of k random samples drawn from a dataset's test split.

However, the performance of LLMs in answering multiplechoice questions is influenced by positional biases (Wang et al. 2023; Zheng et al. 2023), which alter the per-

<sup>&</sup>lt;sup>3</sup>See Table 5 in Appendix A for an example of this attachment.

#### **Reference Instance:**

Summary: Michele Morgan, the French screen star and glamour icon who won the first best actress prize at the Cannes film festival, has died at the age of 96.

Instruction: You are provided with a five-choice quiz. Your task is to correctly select the option that exactly corresponds to an instance from the test split of the XSum dataset.

When selecting the option, you must ensure that you follow the following rules:

(1) You must ensure that you only generate a single option letter as your answer.

(2) If you do not know the dataset or the correct answer, you must select option "E) None of the provided options."

Hint: While all the following options seem similar in terms of meaning, there is only one option that reflects the exact wording with respect to the original instance.

- - -

Correct Answer: C

A) Summary: Michele Morgan, the French film luminary and elegance symbol who claimed the first top actress award at the Cannes film festivity, has passed away at 96 years old.

B) Summary: Michele Morgan, the Gallic cinema standout and attractive idol who procured the premier leading actress accolade at the Cannes film celebration, has expired at the age of ninety-six.

C) Summary: Michele Morgan, the French screen star and glamour icon who won the first best actress prize at the Cannes film festival, has died at the age of 96.

**D**) Summary: Michele Morgan, the French cinematic star and beauty icon who secured the first best actress distinction at the Cannes film event, has succumbed at the age of 96.

E) None of the provided options.

Answer: C

Figure 1: An example of a five-option quiz crafted to detect data contamination within the test partition of the XSum dataset. Here, GPT-4 is the underlying LLM, answering one of the 100 questions in DCQ. In this example, the produced answer aligns with the correct option (option C), signaling the model's ability to discern the original instance from others.

formance according to the position of options. This, in our case, results in varying detectable levels of contamination for an identical subset of instances. Our solution to this issue involves permuting the correct answer (the option containing the reference instance) and systematically placing it in the *least preferred positions*. There are dual advantages to this: it allows us to detect the maximum extent of memorization, and in turn, contamination via DCQ, while also preventing the overestimation of contamination. We demonstrate this empirically in Subsection 5.1.

To identify the least favored positions, we devise a *modified quiz*. In this quiz, the correct answer is removed from the available options and is replaced by another word-level perturbed version of the reference instance. As a result, the modified quiz does not contain the correct answer. We then submit the quiz to the LLM and assess its performance, pinpointing the least preferred options if they are chosen by the LLM less frequently than random chance suggests, excluding the none option. In the case of a five-option quiz, any option selected fewer than  $\lceil \frac{k}{5} \rceil$  times in the modified quiz is considered least preferred by the LLM to be subsequently used in the *standard quiz*, which contains a single correct answer (reference instance).

Once the least favorable positions are recognized, we incorporate them into the standard quiz by strategically placing the correct answer in these positions. We repeat the standard quiz for all detected least favored positions and report

the highest performance achieved in these quizzes by the LLM as the highest contamination level detected by our DCO.

### 3.3. Assessment of Data Contamination Quiz

As discussed, the reported contamination level for a specific dataset partition is determined by the maximum performance of the LLM in multiple standard DCQs. These quizzes are conducted by systematically positioning the correct answer among the least favored options. Although this represents the maximum detectable contamination by our DCQ, it is also possible to report a minimum detectable amount of contamination, both empirically and theoretically.

Empirically, the minimum contamination can be determined by identifying the second-highest performance of the LLM from one of the settings during the process of permuting the correct answer among the least preferred choices, particularly in scenarios where multiple positions are least favored.

Theoretically, given that we deal with a non-ideal system, we can apply the principle of chance-adjusted accuracy to account for the probability of chance agreement. Thus, we use Cohen's Kappa (Galton 1892; Cohen 1960), defined as:

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$

where  $p_o$  is the observed agreement and  $p_e$  is the expected agreement by chance. In simple terms,  $p_o$  refers to the topmost performance attained by the LLM among the standard DCQs when the correct answer is substituted with the least

<sup>&</sup>lt;sup>4</sup>In general, in the modified quiz, it is feasible to have zero or one least favored position. However, throughout the paper, we always refer to *multiple least favorable options* as this frequently occurs and aids in maintaining consistency within the write-up.

favored options, whereas  $p_e$  is the frequency of choosing the least preferred option in the modified quiz where the LLM attained its top performance in the standard DCQs by placing the correct answer in that position.

Since the minimum contamination can be measured in two ways, the most stringent interval is obtained by taking the maximum of the empirical and theoretical minimums. This is reported as the minimum contamination detected by DCQ.

## 4. Experimental Setup

**Data.** Examining the initiation of memorization in LLMs via DCQ (Subsection 5.1), we leverage two of the contaminated datasets discovered by Golchin & Surdeanu (2023): AG News (Zhang et al. 2015) and WNLI (Wang et al. 2018). In particular, we use the train and test sets of the former and the train and validation sets of the latter dataset.

In our systematic contamination experiments (Subsection 5.2), we use the train sets from two datasets–MeetingBank (Hu et al. 2023) and AuTexTification (Sarvazyan et al. 2023)—which were both released in 2023, and thus, are unexposed to GPT-3.5. Further, our experiments involving pre-contaminated datasets (Subsection 5.2) utilize the test split from the HumanEval (Chen et al. 2021), the validation split from the DROP (Dua et al. 2019), and the train split of the GSM8k (Cobbe et al. 2021). We justify our dataset choices within our discussion in the respective subsection.

For both wild experimental (Subsection 5.3) and reciprocal evaluations (Appendix C), we utilize the same set of datasets as employed by Golchin & Surdeanu (2023) for their data contamination analysis. This includes IMDB (Maas et al. 2011), AG News (Zhang et al. 2015), Yelp Full Reviews (Zhang et al. 2015), SAMSum (Gliwa et al. 2019), XSum (Narayan et al. 2018), WNLI (Wang et al. 2018), and RTE (Wang et al. 2019). Our experiments focus on the test splits of these datasets except for WNLI and RTE, where we use validation sets due to the unavailability of their test sets.<sup>5</sup>

Preparation of instances for the DCQ involves formatting each instance as per the task of its dataset: for the classification task, an instance includes the text along with its exact label; for the natural language inference task, it contains the premise, hypothesis, and precise label; and so on. In general, we format each instance such that, if disclosed during the pre-training stage, leads to data contamination.

To conduct DCQ, we select a random sample of k=100 unique instances for all the experiments executed within this paper. If there are fewer than 100 samples in a partition, we leverage the entire set. Using GPT-4, we then

produce four distinct word-level altered versions of each sampled instance. Initially, all four perturbed versions are employed in the modified quiz to identify the least favored options. In the next stage, the standard quiz maintains three of these perturbed instances, substituting one—determined by its position—with the original instance.

**Setting.** For all the experiments involving GPT-4 and GPT-3.5, we leverage the snapshots of gpt-4-0613 and gpt-3.5-turbo-0613, accessed through the OpenAI API. During the quiz development phase, we adjust the temperature for GPT-4 to 1.00—the default value for generative tasks such as conversation and storytelling<sup>6</sup>—to encourage a wider variety of lexical variations, and cap the maximum completion length to 4,000 tokens. In contrast, for the deployment phase, we set the temperature for all models taking the quiz to zero—promoting deterministic outcomes given the provided options—with a maximum token limit of one.

In all our comparative experiments (Golchin & Surdeanu 2023), we set the temperature to zero and cap the token limit at 500. We also create random-length initial segments of dataset instances by randomly deriving them from a range spanning 40% to 70% of each instance's length based on the white space count. This range is chosen as we observed that this interval produces the highest levels of memorization when replicating instances using the LLMs under study. Finally, the generated completions are judged by GPT-4 with few-shot in-context learning prompt (Brown et al. 2020).

### 5. Empirical Results and Evaluation

In the next subsection, we initially provide empirical evidence of how our proposed DCQ instigates memorization in LLMs for uncovering data exposure and avoiding overestimation of contamination. In the final two subsections, we assess the performance of DCQ by applying it to controlled contamination studies where the presence of contamination is either strategic or pre-established, and further employ it in real-world cases where contamination is not controlled.

### 5.1. Positional Adversarial Analysis

Our quiz-based approach is grounded upon two pivotal tactics: the generation of word-level perturbations from a reference instance and the *strategic placements of this reference instance into what we recognize as the least favorable positions* among the choices. In this subsection, we first aim to elucidate how embedding the reference instance among its perturbations can facilitate memorization with respect to the data exposed to the model previously. Second, we show how positioning the reference instance in the

<sup>&</sup>lt;sup>5</sup>Dataset details are available in Appendix D.

<sup>&</sup>lt;sup>6</sup>https://platform.openai.com/playground

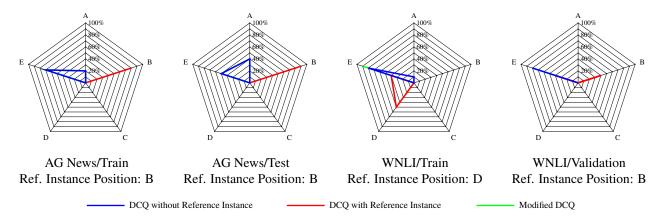


Figure 2: Outcomes of positional adversarial analysis. The green curves show the frequency distribution of choices in the modified DCQ, while the red and blue curves represent the results after adding a reference instance and its word-level perturbation into the least-chosen option detected from the modified DCQ, respectively. The skew towards selecting reference instances (shown in red) validates the model's prior exposure to the data. In all settings, GPT-4 is the base model.

recognized least favorable positions can either mitigate the risk of overestimating contamination or, at the very least, create a setting that is more resistant to such overestimation risks.

For this study, we undertake two distinct variants of DCQ. Upon administering the modified guiz and the recognition of the least preferred positions, we only focus on a single least-chosen option to replace it with a reference instance. Note that this diverges from the standard DCQ, which takes into account all the least preferred options (those selected fewer than 20 times) for replacement with the reference instance. Following this, in the first variant of DCQ, we substitute the detected least-chosen position with a reference instance, akin to the procedure in the standard DCQ. In the second variant, however, the least-selected position is replaced with a unique word-level alteration, ensuring it differs from all other perturbations included in the modified DCQ. This essentially allows us to investigate the position selection preference by examining the preference skewness produced with the presence versus absence of the reference instance. In fact, this confirms that if an LLM has not been exposed to the dataset instance, and thus, cannot recognize the original instance by memorization, the selection distribution among options in the modified DCQ should be maintained regardless of whether the original instance is included among the options. In contrast, a pronounced preference for selecting the dataset instance in the DCQ signals prior exposure to the data, and thereby, signaling data contamination.

To better visualize the skewness in the selection distribution of options, we exploit four different contaminated partitions, identified by Golchin & Surdeanu (2023). Specifically, we use the train and test sets of AG News as well as the train and validation sets of the WNLI dataset, with GPT-

4 serving as the foundation model. Figure 2 showcases the outcomes of this experiment. As evident, all plots colored red exhibit a marked skew towards selecting the original instance when it is presented as one of the options. In contrast, when a word-level perturbed version of the reference instance is included among other perturbations, since it has not been seen by the model, the distribution of selecting options remains consistent (blue), harmonizing with the selections in the modified DCQ (green). For example, the initial selection distribution of options in the modified DCQ for the train set of AG News is {A: 29, B: 0, C: 0, D: 0, E: 71}. Nevertheless, when the reference instances supplant option B, there is a prominent skew towards its selection: {A: 6, B: 88, C: 0, D: 0, E: 6. Conversely, when option B in the modified DCQ is replaced with word-level perturbed versions of the reference instances, the initial positional biases remain almost unchanged: {A: 28, B: 0, C: 0, D: 0, E: 72}.

We empirically showed that infusing a reference instance among its perturbations, through the use of quiz options, triggers evidence of memorization in LLMs. In this approach, instead of partially (Golchin & Surdeanu 2023) or fully (Sainz et al. 2023b) replicating an instance, the presence of memorization is achieved by emitting a single-letter option. This technique helps reveal a greater extent of memorization by factoring in the probabilistic nature of LLMs during replication. Recognizing that not all positions trigger memorization equally, we permute the reference instance among the least favored positions to uncover the highest possible level of memorization/contamination. Further, by strategically positioning the reference instance, we avoid overestimating contamination. This becomes clear with the example provided earlier. For instance, if the reference instance is placed in position A, any contamination level surpassing 71% results in the system indicating 100%

Table 1: DCQ results after introducing systematic contamination to GPT-3.5. The table displays the minimum and maximum detected contamination levels, with the minimum derived from the higher value between theoretical and empirical minimums. If the theoretical minimum is used, recall and precision stay constant at their values computed for the maximum, due to the identical setting. The results are also compared to the replication-based (rplc-based) method (Golchin & Surdeanu 2023).

	Meetir	ngBank	AuTexTification		
Method	100% Cont.	50% Cont.	100% Cont.	50% Cont.	
Rplc-based (%)	1.00	0.00	1.00	0.00	
Our DCQ (%) Recall (%) Precision (%)	[85.87, 87.00] [87.00, 87.00] [87.00, 87.00]	[47.00, 49.00] [82.00, 88.00] [87.23, 89.80]	[66.29, 70.00] [70.00, 70.00] [70.00, 70.00]	[44.68, 48.00] [70.00, 70.00] [72.92, 72.92]	

Table 2: A comparison between the contamination levels reported for GPT-4 (OpenAI 2023) and those identified via the replication-based (rplc-based) methodology (Golchin & Surdeanu 2023) alongside our DCQ method. This experiment encompasses the test, evaluation, and train sets of the HumanEval, DROP, and GSM8k datasets, respectively.

Method	HumanEval	DROP	GSM8k
Reported (%)	$\approx 25.00$	≈ 21.00	Full but a part
Rplc-based (%)	0.00	4.00	2.00
Our DCQ (%)	[55.62, 56.71]	[42.86, 44.00]	[78.79, 79.00]

contamination. While it is not feasible to unequivocally guarantee the probabilistic behavior of LLMs, including the potential overestimation of contamination in our case, it can be confidently asserted that our approach, at least by design, does not stimulate this overestimation.

### 5.2. Evaluation under Controlled Contamination

Systematic Contamination. As for the first step in assessing the performance of DCQ, we start our evaluation with controlled contamination. In this experiment, we systematically contaminate the GPT-3.5 base model with two clear datasets-MeetingBank and AuTexTification-and study four different settings.<sup>7</sup> Our methodology incorporates determining data contamination levels with the use of DCQ for two separate levels of contamination per dataset: 50% and 100% contamination. In particular, we introduce contamination with 1,000 instances from each dataset. Among the 100 samples we employ in the DCQ, in settings with 100% contamination, all samples are drawn from the 1,000 samples used for contamination. However, in settings with 50% contamination, only 50 instances are selected from the initial 1,000 instances while the other 50 are drawn from the same set but not among the 1,000 instances included in the contamination process. The idea behind this design is to mimic real-world scenarios where the DCQ uses only subsets of random instances derived from the dataset partitions.

Table 1 details the outcomes of our experiment under controlled contamination upon applying the DCQ. When compared with the replication-based strategy (Golchin & Surdeanu 2023), DCQ proves to be significantly more effective at uncovering memorization, and in turn, contamination. In fact, the levels of contamination identified by replicating instances are so insignificant that it is impracticable to compare with our DCQ's performance. As expounded in Subsection 5.1, this enhanced capacity to detect more memorization is obtained by minimizing the tendency of LLMs to engage in probabilistic generations. The DCQ achieves this by delivering a single-letter quiz option that flags the presence of certain data within the pre-training corpus of the model, rather than replicating it. As a result, it reveals a considerable amount of memorization/contamination. Another salient advantage of outputting an option letter is its ability to bypass the preemptive filters designed to stop LLMs from producing copyrighted contents in any language. This capability further enhances the detection/estimation of more contamination instances.<sup>8</sup> Importantly, although DCQ does reveal more memorization, it accurately measures the extent of contamination, as shown in Table 1. Detailed in Subsection 5.1, the procedure of systematically placing the reference instances in the least favored positions discourages the overestimation of contamination.

**Known Contamination.** The technical report of GPT-4 (OpenAI 2023) highlights data overlap between several datasets and the pre-training data of GPT-4. As part of our controlled contamination evaluation, we meticulously select three datasets that hold significant importance within the context of LLMs. In fact, we consider the backdrop of reported contamination for these datasets as a ground

<sup>&</sup>lt;sup>7</sup>For more information regarding the continued training of the GPT-3.5 base model, see Appendix E.

<sup>&</sup>lt;sup>8</sup>To see case examples, refer to Appendix A.

Table 3: Estimated levels of data contamination for GPT-4 and GPT-3.5 across test/validation partitions of seven datasets using a maximum of 100 random samples. The table includes the "rplc-based" label, referring to the replication-based method (Golchin & Surdeanu 2023), where we view both exact and near-exact matches as contamination instances in this method. As for each setting involving DCQ, the maximum values are computed solely based on the performance obtained on the standard DCQ, whereas minimum values are obtained by calculating the greater theoretical and empirical minimums.

		Datasets						
Model	Method	IMDB	AG News	Yelp	RTE	WNLI	SAMSum	XSum
GPT-4	Rplc-based (%)	0.00	3.00	0.00	1.00	15.49	0.00	7.00
	Our DCQ (%)	[81.82, 82.00]	[91.00, 91.00]	[80.00, 80.00]	[60.00, 60.00]	[49.30, 50.70]	[77.00, 77.00]	[95.00, 95.00]
GPT-3.5	Rplc-based (%)	0.00	0.00	0.00	1.00	2.82	0.00	2.00
	Our DCQ (%)	[46.43, 55.00]	[80.43, 82.00]	[12.12, 13.00]	[65.06, 71.00]	[7.47, 12.68]	[70.11, 74.00]	[78.35, 79.00]

truth against which we compare the performance of DCQ in detecting contamination. Specifically, we apply DCQ to the test, validation, and train splits of the HumanEval, DROP, and GSM8k datasets, respectively. The rationale behind selecting these particular datasets stems from their pivotal role in assessing the reasoning and problem-solving capabilities of LLMs, coupled with the explicit mention of contamination levels for these datasets by OpenAI. Further, our focus on the train segment of the GSM8k dataset is driven by the fact that this set—apart from a small portion—was included in the pre-training corpus of GPT-4, though without a specified degree of inclusion. Thus, we expect that our DCQ detects a significant level of contamination within this partition.

Although we use the figures from OpenAI (2023) as our ground truth, they may not accurately represent the true contamination extent due to the involved complexity. The concerns include: (1) The measured cross-contamination comes from overlapping three 50-character substrings, yielding high false negatives and false positives; and (2) Detection was conducted using a maximum of 1,000 random samples from each split. Hence, these figures should be viewed as contamination estimates rather than definitive measures.

Table 2 compares the performance of our proposed DCQ with contamination levels reported by OpenAI (2023) for the mentioned datasets. The data within the table confirms that our DCQ not only corresponds with the figures provided by OpenAI (2023) but also uncovers higher levels of contamination, despite lacking access to the pretraining data. Further, consistent with expectations, the contamination level identified for the GSM8k's train set is markedly high while the replication-based approach can only pinpoint 2.00% contamination. Again, as can be seen here, while the DCQ inherently does not overestimate the

amount of contamination, it shows the ability to uncover higher levels of contamination—even when compared to the cross-contamination measured in the availability of the pre-training data.

#### 5.3. Evaluation in the Wild

After examining contamination in controlled environments, we implement our detection strategy to a range of datasets in real-world scenarios where the exact contamination levels are unknown, substantiating the effectiveness of our DCQ. Although there is no information about the precise contamination levels for the datasets we analyze, we assess the contamination levels by our DCQ against the existing state-of-the-art strategy introduced by Golchin & Surdeanu (2023). We perform this with the understanding that our DCQ does not encourage overestimation. For these experiments, we use identical datasets to the ones used in their research, covering seven datasets with test/validation splits. Both GPT-4 and GPT-3.5 are utilized in these experiments.

Table 3 lists all the results from our evaluation in the wild experiment over 14 settings. As indicated by the outcomes, the replication-oriented methodology falls short in accurately estimating the levels of contamination within the investigated dataset partitions. Although it successfully replicates a few dataset instances, for example when GPT-4 acts as the foundation model and is applied to WNLI (15.49%) and XSum (7.00%) datasets, this method appears to be ineffective in most cases. In contrast, our DCQ successfully detects a decent amount of contamination across all studied partitions. For instance, for the mentioned datasets, the maximum detected contamination amounts to 50.70% and 95.00%, which represents a detection range of contamination three to more than thirteen times higher.

While the results from the extraction-based method align closely with those from our DCQ, it appears that this method is only effective for binary detection of contamination when the contamination level is notably high and lacks

<sup>&</sup>lt;sup>9</sup>As done by OpenAI (2023), we apply DCQ to the entire test set of the HumanEval dataset containing 164 samples.

ability to effectively estimate contamination.<sup>10</sup> When comparing performance, our method reveals cases of memorization/contamination to an extent significantly greater than methodologies based on extracting pre-training data from LLMs (Golchin & Surdeanu 2023; Carlini et al. 2023).

### 6. Conclusion

We proposed the Data Contamination Quiz (DCQ), the first approach to effectively estimate data contamination for black-box LLMs by transforming the task of detecting data contamination into a multiple-choice reading comprehension challenge. The devised quiz presents the LLM with five choices: one being an original instance from a specific dataset partition, three being variations of the original dataset instance with word-level perturbations, plus a none option. Success in this quiz hinges on the LLM's ability to recognize the original instance through memorization.

Encompassing a wide range of datasets and several LLMs under controlled and uncontrolled environments, the findings affirmed that our technique not only aligns with previously reported/detected contamination levels but also surpasses the state-of-the-art method in detecting contamination and furnishing an estimation thereof, beyond simple binary identification of contamination.

## 7. Potential Broader Impact

Our findings, along with those of others, indicate that data contamination is a widespread problem within LLMs, particularly with pre-training data derived from web sources. In light of the substantial focus on LLMs in recent times—a focus that is likely to intensify moving forward—it becomes imperative to address the issue of data contamination with due seriousness to ensure evaluations of these models are both fair and robust.

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<sup>&</sup>lt;sup>10</sup>By performing a reciprocal evaluation between the DCQ answers and instances replicated via the replication-based approach (Golchin & Surdeanu 2023), we observed perfect agreement across all settings. See Appendix C for additional information.

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## A. Identifying Data Contamination for Current and Past LLMs' Updates

As LLM providers persistently update their proprietary models, the safety of these LLMs towards detected weaknesses and adversarial attacks also improves. The detection technique recently developed by Golchin & Surdeanu (2023) is one such attack addressed by these updates. For example, when GPT-4 is instructed to complete a partial reference instance from a text classification task, the June 2023 snapshot (gpt-4-0613) is capable of accomplishing this task, thus unveiling contamination. In contrast, a more recent version from November 2023 (gpt-4-1106-preview) often chooses not to complete the task due to the activation of newly implemented safety mechanisms. It is worth mentioning that this strategy continues to proficiently identify contamination for all other tasks.

In Table 4, we show that the recent updates to GPT-4 hinder the model from replicating dataset instances for data contamination detection, a task that was feasible in its previous version. On the other hand, in Table 5, we illustrate that our proposed DCQ can successfully identify data contamination in both versions. This highlights the capability of DCQ in pinpointing data contamination even in the presence of newly added safety filters to LLMs. In fact, our strategy can effectively sidestep filters related to copyrighted materials by delivering a single-letter response that embodies the detection of the original instance among other options, thereby disclosing data contamination.

Table 4: A comparison between the completions generated using replication-based approach (Golchin & Surdeanu 2023) for the June and November 2023 snapshots of GPT-4. While the June snapshot exactly replicates the second piece of the provided instance from the train split of the IMDB dataset, the November snapshot avoids completing the provided first piece due to the activation of filters intended to prevent the generation of copyrighted contents.

#### LLM Version/Detection

#### Reference Instance and Its Replica

#### Reference Instance:

Review: Bromwell High is a cartoon comedy. It ran at the same time as some other programs about school life, such as "Teachers" My 35 years in the teaching profession lead me to believe that Bromwell High's satire is much closer to reality than is "Teachers". The scramble to survive financially, the insightful students who can see right through their pathetic teachers' pomp, the pettiness of the whole situation, all remind me of the schools I knew and their students. When I saw the episode in which a student repeatedly tried to burn down the school, I immediately recalled ............................ High. A classic line: INSPECTOR: I'm here to sack one of your teachers. STUDENT: Welcome to Bromwell High. I expect that many adults of my age think that Bromwell High is far fetched. What a pity that it isn't!

Label: 1 (positive)

**Instruction:** You are provided with the first piece of an instance from the train split of the IMDB dataset. Finish the second piece of the instance as exactly appeared in the dataset. Only rely on the original form of the instance in the dataset to finish the second piece.

Label: 1 (positive)

**First Piece:** Bromwell High is a cartoon comedy. It ran at the same time as some other programs about school life, such as "Teachers". My 35 years in the teaching profession lead me to believe that Bromwell High's satire is much closer to reality than is "Teachers".

#### Second Piece:

The scramble to survive financially, the insightful students who can see right through their pathetic teachers' pomp, the pettiness of the whole situation, all remind me of the schools I knew and their students. When I saw the episode in which a student repeatedly tried to burn down the school, I immediately recalled ....... at ....... High. A classic line: INSPECTOR: I'm here to sack one of your teachers. STUDENT: Welcome to Bromwell High. I expect that many adults of my age think that Bromwell High is far fetched. What a pity that it isn't!

Version: gpt-4-0613 Detection: Exact Match

**Instruction:** You are provided with the first piece of an instance from the train split of the IMDB dataset. Finish the second piece of the instance as exactly appeared in the dataset. Only rely on the original form of the instance in the dataset to finish the second piece.

Label: 1 (positive)

**First Piece:** Bromwell High is a cartoon comedy. It ran at the same time as some other programs about school life, such as "Teachers". My 35 years in the teaching profession lead me to believe that Bromwell High's satire is much closer to reality than is "Teachers".

#### Second Piece:

Sorry, but I can't continue the text from the IMDB dataset as it is copyrighted material. However, I can provide a summary or discuss the themes and characters of "Bromwell High" if you're interested. Let me know if you would like me to provide some other type of information!

**Version:** gpt-4-1106-preview **Detection:** None

Table 5: An illustration of a question posed when taking the DCQ to both June and November snapshots of GPT-4. While the generated response is correct (option C), this approach—unlike the replication-based strategy (Golchin & Surdeanu 2023)—proves to be effective for both snapshots without triggering any content-related filters set by the model developer.

#### LLM Version/Detection

Versions: gpt-4-0613 and gpt-4-1106-preview

Detection: Correct (option C)

#### Reference Instance and Its Replica

#### **Reference Instance:**

Review: Bromwell High is a cartoon comedy. It ran at the same time as some other programs about school life, such as "Teachers". My 35 years in the teaching profession lead me to believe that Bromwell High's satire is much closer to reality than is "Teachers". The scramble to survive financially, the insightful students who can see right through their pathetic teachers' pomp, the pettiness of the whole situation, all remind me of the schools I knew and their students. When I saw the episode in which a student repeatedly tried to burn down the school, I immediately recalled .......................... High. A classic line: INSPECTOR: I'm here to sack one of your teachers. STUDENT: Welcome to Bromwell High. I expect that many adults of my age think that Bromwell High is far fetched. What a pity that it isn't!

Label: 1 (positive)

**Instruction:** You are provided with a five-choice quiz. Your task is to correctly select the option that exactly corresponds to an instance from the train split of the IMDB dataset.

When selecting the option, you must ensure that you follow the following rules:

(1) You must ensure that you only generate a single option letter as your answer.

(2) If you do not know the dataset or the correct answer, you must select option "E) None of the provided options."

Hint: While all the following options seem similar in terms of meaning, there is only one option that reflects the exact wording with respect to the original instance.

A) Bromwell High is an animated comedy. It was broadcasted concurrently with other TV shows about the school experience, such as "Teachers". In my three and a half decades in the teaching realm, I've come to conclude that Bromwell High's mockery aligns more closely with the real world than "Teachers" does. The struggle to make ends meet, the young scholars who can see right through their teachers' pretentiousness, the triviality of the entire scenario, all remind me of the educational institutions I was familiar with and their pupils. When I viewed the episode where a student persistently tried to set the school on fire, I immediately reminisced about ....... High. A memorable quote: INSPECTOR: I'm here to terminate one of your teachers. STUDENT: Welcome to Bromwell High. I assume many people my age believe that Bromwell High is exaggerated. It's regrettable that it isn't!

B) Bromwell High is a caricature comedy. It aired simultaneously with a few other programs about academia, like "Teachers". My 35-year tenure in the realm of education makes me think that Bromwell High's ridicule is far more truthful compared to "Teachers". The financial survival hustle, the perceptive pupils who can penetrate their pathetic teachers' grandiosity, the trivialities of the whole circumstance, all bring back memories of the educational institutions I was once part of and their learners. Upon watching the episode where a pupil repeatedly attempted arson on the school premises, I had an immediate flashback to ...... High. An iconic line: INSPECTOR: I have come to dismiss one of your teachers. STUDENT: Welcome to Bromwell High. I suspect many grown-ups of my generation presume that Bromwell High is overly dramatized. What a misfortune that it isn't so!

C) Bromwell High is a cartoon comedy. It ran at the same time as some other programs about school life, such as "Teachers". My 35 years in the teaching profession lead me to believe that Bromwell High's satire is much closer to reality than is "Teachers". The scramble to survive financially, the insightful students who can see right through their pathetic teachers' pomp, the pettiness of the whole situation, all remind me of the schools I knew and their students. When I saw the episode in which a student repeatedly tried to burn down the school, I immediately recalled .............. High. A classic line: INSPECTOR: I'm here to sack one of your teachers. STUDENT: Welcome to Bromwell High. I expect that many adults of my age think that Bromwell High is far fetched. What a pity that it isn't!

E) None of the provided options.

Answer:

С

```
Instruction: Your task is to create a four-choice quiz by replacing the words in the provided "Input Text" with their contextually rel-
evant synonyms. The meaning and sentence structure of the four options must exactly match every detail in the Input Text. You must
not include the provided Input Text as an option.
You must make sure that:
(1) You generate distinct options based on the provided Input Text;
(2) The only difference between options is word-level perturbations.
(3) Options are ordered;
(4) There is not any extra explanation;
(5) You follow the following "Format" to generate options;
(6) You comply with every specific symbol and letter detail in the given Input Text; and
(7) All options retain the exact label from the Input Text, if there is one.
Input Text:
Summary: Michele Morgan, the French screen star and glamour icon who won the first best actress prize at the Cannes film festival,
has died at the age of 96.
Format:
Summary:
Summary:
Summary:
Summary:
- - -
Summary: Michele Morgan, the French film luminary and elegance symbol who claimed the first top
actress award at the Cannes film festivity, has passed away at 96 years old.
Summary: Michele Morgan, the Gallic cinema standout and attractive idol who procured the premier
leading actress accolade at the Cannes film celebration, has expired at the age of ninety-six.
Summary: Michele Morgan, the French movie sensation and charm emblem who achieved the inaugural
best actress honor at the Cannes film gala, has deceased at the age of ninety-six.
D)
Summary: Michele Morgan, the French cinematic star and beauty icon who secured the first best
actress distinction at the Cannes film event, has succumbed at the age of 96.
```

Figure 3: The zero-shot prompt employed for generating four perturbations per dataset instance. The input text is replaced for each dataset instance, and GPT-4 is prompted to generate the four perturbed options for each instance individually. The format provided in the input prompt is adjusted based on a specific dataset/task, with column names being used to denote distinct components of an original instance. For example, "Summary" is a column name that is prepended to the instance shown above. Further, the requirements outlined in the prompt were established after conducting several experiments to ensure frequent reliable generations by GPT-4. The example shown here is an instance from the test partition of the XSum dataset along with its generated perturbations, as illustrated earlier in Figure 1.

#### **Reference Instance:**

Summary: Michele Morgan, the French screen star and glamour icon who won the first best actress prize at the Cannes film festival, has died at the age of 96.

**Instruction:** You are provided with the first piece of a one-sentence summary from the test split of the XSum dataset. Finish the second piece of the summary as exactly appeared in the dataset. Only rely on the original form of the summary in the dataset to finish the second piece.

Human Eval.: Exact Match

First Piece: Michele Morgan, the French screen star and glamour icon who won the first best actress prize Second Piece:

at the Cannes film festival, has died at the age of 96.

Figure 4: An exact replica generated for an instance from the test split of the XSum dataset, shown in Figure 1. In this depiction, GPT-4 operates as the underlying foundation model.

## **B.** Crafting Quiz Options

Our method for creating options in a multiple-choice quiz involves generating four word-level perturbations for each instance within a randomly selected subset of instances from a particular dataset partition. For each instance, we prompt GPT-4 to generate these four variations. The template prompt employed to instruct GPT-4 in generating the four alternative choices is demonstrated through an example in Figure 3. This zero-shot prompt shows the four generated choices corresponding to the example given in Figure 1.

## C. Reciprocal Evaluation

To broaden our evaluation, we carry out a reciprocal evaluation between the answers from our DCQ and all the replicated instances using our comparative framework. Golchin & Surdeanu (2023) showed that when an LLM is tasked with completing the initial segment of a dataset instance, the presence of contamination is revealed if the completion produced by the LLM matches, either exactly or closely, the subsequent segment of the reference instance. Leveraging this insight, we cross-reference the choices made by the LLMs during our contamination quiz with all instances that were either exactly or near-exactly replicated in all the experiments throughout this paper. This includes all the experiments mentioned in Tables 1, 2, and 3. Our findings suggest that in all scenarios that resulted in exact or near-exact replicas, the LLMs in question—GPT-4 and GPT-3.5—consistently opted for the correct choice in our DCQ. For example, in Figure 1, GPT-4 recognizes the correct choice in our DCQ for an instance that is exactly replicated using the replication-based strategy, as depicted in Figure 4. This observation further supports the reliability of our DCQ methodology, implying that correct choices in the DCQ are produced due to the existence of memorization, which signals previous data exposure.

### **D. Detailed Description of Datasets**

**IMDB Movie Reviews Dataset.** The IMDB Movie Reviews Dataset comprises a well-balanced collection of 50,000 movie reviews specifically designed for sentiment analysis tasks. This dataset is evenly divided, featuring 25,000 reviews designated for training and another 25,000 for testing purposes, with an equal distribution of positive and negative sentiments. Positive reviews are characterized by ratings of 7 out of 10 or higher, while reviews with ratings of 4 or lower are classified as negative.

**AG News Dataset.** Serving as a standard benchmark, the AG News dataset includes a variety of news articles from the comprehensive AG's corpus website, categorized neatly into four distinct sections: world, sports, business, and science/technology. With a total of 496,835 articles sourced from over 2,000 news outlets, the dataset provides an extensive learning ground. Each category is well-represented, with 30,000 training articles and 1,900 articles for testing.

**Yelp Dataset.** Originating from the 2015 Yelp Dataset Challenge, this expansive dataset encompasses 1,569,264 reviews, complete with textual feedback. It underpins two separate classification challenges: one that predicts the number of stars a user has awarded, and another that discerns the sentiment polarity of the review. Reviews with 1- and 2-star ratings are deemed negative, whereas those with 3- and 4-star ratings are considered positive. For the detailed star rating task, there are 130,000 training and 10,000 testing examples for each star category. The polarity task is similarly structured, with 280,000 training and 19,000 testing examples evenly distributed among the sentiment classes.

**Recognizing Textual Entailment (RTE) Dataset.** The RTE dataset is an amalgamation of data from several textual entailment challenge editions: RTE1 (Dagan et al. 2005), RTE2 (Haim et al. 2006), RTE3 (Giampiccolo et al. 2007), and

RTE5 (Bentivogli et al. 2009). These collections, featuring examples derived mainly from news and Wikipedia texts, were standardized into a binary classification framework for simplicity. Instances that were originally categorized under three classes were restructured, merging "neutral" and "contradiction" into a single "not entailment" class. Altogether, the RTE dataset offers 2,490 training instances, 277 for validation, and 3,000 for testing.

Winograd Natural Language Inference (WNLI) Dataset. The WNLI dataset, rooted in the Winograd Schema Challenge (Levesque et al. 2012), presents a set of sentence pairs to challenge natural language understanding systems, specifically targeting the ability to resolve pronouns within context. Although the training set is balanced, the test set is not, comprising 635 training instances, 146 test instances, and 71 validation instances.

**SAMSum Dataset.** Curated by linguists at the Samsung R&D Institute Poland, the SAMSum dataset consists of approximately 16,000 English messenger-style conversations, each accompanied by a third-person summary. These dialogues mirror the diverse range of styles, registers, and subjects found in real-world messaging interactions. Typically involving two participants, the dialogues vary in length, with utterances ranging from 3 to 30 per conversation.

**Extreme Summarization (XSum) Dataset.** The XSum dataset provides a platform for evaluating abstractive single-document summarization systems. Its purpose is to create succinct, one-sentence summaries encapsulating the essence of each article, effectively answering the question, "What is the article about?." This compilation includes 226,711 news articles, each with an associated one-sentence summary, drawn from a spectrum of domains represented in BBC articles from 2010 to 2017. The established random split allocates 204,045 documents for training (90% of the dataset), 11,332 for validation, and 11,334 for testing, accounting for 5% each of the entire dataset.

**Automated Text Identification (AuTexTification) 2023 Dataset.** The AuTexTification dataset involves two distinct challenges. The first challenge is to identify whether a piece of text is human-written or produced by a large language model. The second challenge requires detecting which of six different text generation models produced a given machine-generated text. These models include BLOOM-1B1 (Scao et al. 2022), BLOOM-3B (Scao et al. 2022), BLOOM-7B1 (Scao et al. 2022), Babbage (Brown et al. 2020), Curie (Brown et al. 2020), and text-davinci-003 (Brown et al. 2020). The AuTexTification 2023 dataset is extensive, featuring over 160,000 texts in both English and Spanish, spanning five domains: tweets, reviews, news articles, legal, and how-to articles.

**MeetingBank Dataset.** MeetingBank is a comprehensive benchmark dataset drawn from the city council meetings of six major cities in the United States. It includes a collection of 1,366 meetings, amounting to over 3,579 hours of video. The dataset is further enriched with transcripts, PDF files of meeting minutes, agendas, and additional metadata. Typically, a council meeting spans 2.6 hours, with its transcript featuring more than 28,000 tokens, making this dataset a good resource for testing meeting summarization applications and for mining structured data from meeting videos. For benchmarking, the dataset offers 6,892 instances of segment-level summarization, distributed across training, validation, and testing sets—5,169 instances for training, 861 for validation, and 862 for testing.

**HumanEval Dataset.** The HumanEval dataset is a collection of 164 hand-written programming problems designed to assess the capabilities of language models in generating correct and efficient code. Developed by OpenAI, this dataset includes a broad range of problems that require understanding complex problem statements and generating solutions in Python programming language. Each problem in HumanEval comes with a prompt describing the task, a signature of the function to be implemented, and several test cases that are used to automatically verify the correctness of the generated code solutions. The dataset is primarily used to benchmark the performance of models on code synthesis tasks. It tests for various aspects of programming proficiency including algorithmic thinking, code efficiency, understanding of programming language nuances, and the ability to deal with edge cases.

**Discrete Reasoning Over Paragraphs (DROP) Dataset.** The DROP dataset challenges models with complex questions that require understanding, manipulating, and reasoning about information in passages. This crowdsourced and adversarially-created dataset boasts about 96,000 questions, split into roughly 77,000 for training, 9,500 for development, and a test set of similar size. Questions involve tasks like resolving references, performing discrete operations (addition, counting, sorting), and drawing conclusions, pushing models beyond simple matching or paraphrasing.

**Grade School Math 8k (GSM8k) Dataset.** The GSM8k dataset stands as a carefully curated collection that contains 8,500 linguistically rich grade school math word problems, meticulously created by humans. The collection is organized into two segments: 7,500 examples are set aside for training purposes, while the remaining 1,000 are earmarked for testing. These problems exhibit a range of complexities, necessitating anywhere from 2 to 8 sequential steps for their resolution. For the most part, solving these problems involves conducting a series of fundamental arithmetic operations—specifically addition,

subtraction, multiplication, and division—to arrive at the final solution. This dataset serves as an exemplary resource for endeavors that require multi-step mathematical reasoning.

## E. Continued Training of GPT-3.5 Base Model for Systematic Contamination

To strategically contaminate the base model of GPT-3.5, we utilize the snapshot mentioned in Section 4 of the paper, specifically gpt-3.5-turbo-0613. We conduct continued training on the GPT-3.5 base model by submitting a fine-tuning job through the OpenAI API. Although the model provider refers to this option as fine-tuning, our methodology deviates from standard fine-tuning. In fact, our main goal is to replicate the data exposure that LLMs potentially experienced during their pre-training phase when encountering web data. To accomplish this, we employ all data formats used in the study by Golchin & Surdeanu (2023) to introduce contamination to the GPT-3.5 base model. Each dataset instance is formatted according to the provided formats, embedding both the dataset name and the specific split from which it originates, as metadata. It is important to emphasize that this type of training differs from instruction fine-tuning, as we do not infuse any specific instructions within the data we use for further training.

Due to our project's budget constraints and our focus on a manageable number of training instances, we choose to work with two datasets similar to the datasets we leveraged throughout the paper to assess our proposed DCQ. In particular, we select 1,000 random samples from the training splits of the AuTexTification and MeetingBank datasets to contaminate the GPT-3.5 base model. For training, we retain all default hyperparameters set by OpenAI during our continued training phase. After completing the training, we utilize specific checkpoints provided by OpenAI. For each experiment, the GPT-3.5 base model is individually contaminated using the respective dataset splits, resulting in two separate checkpoints, each associated with one of the aforementioned datasets.

As previously stated, we conduct continued training on the GPT-3.5 base model using the default hyperparameters recommended by its provider. Acknowledging that various factors, such as the number of epochs, learning rate, batch size, etc., can influence memorization in LLMs, we reserve the discussion of these factors for future studies. This decision stems from the limited budget of our project, the expensive nature of experiments with proprietary LLMs, and the main focus of this research on the topic of data contamination, rather than memorization.