Rethinking LLM Memorization through the Lens of Adversarial Compression

Avi Schwarzschild [*1] **Zhili Feng** [*2] **Pratyush Maini** [3] **Ethan Herenstein** [4] **Zachary C. Lipton** [5]

Abstract

Large language models (LLMs) trained on web-scale datasets raise substantial concerns regarding permissible data usage. One major question is whether these models "memorize" all their training data or they integrate many data sources in some way more akin to how a human would learn and synthesize information. The answer hinges, to a large degree, on *how we define memorization*. In this work, we propose the Adversarial Compression Ratio (ACR) as a metric for assessing memorization in LLMs. A given string from the training data is considered memorized if it can be elicited by a prompt (much) shorter than the string itself—in other words, if these strings can be "compressed" with the model by computing adversarial prompts of fewer tokens. The ACR overcomes the limitations of existing notions of memorization by (i) offering an adversarial view of measuring memorization, especially for monitoring unlearning and compliance; and (ii) allowing for the flexibility to measure memorization for arbitrary strings at a reasonably low compute. Our definition serves as a practical tool for determining when model owners may be violating terms around data usage, providing a potential legal tool and a critical lens through which to address such scenarios.

1. Introduction

A central question in the discussion of large language models (LLMs) concerns the extent to which they *memorize* their training data versus how they *generalize* to new tasks and settings. Most practitioners seem to (at least informally) believe that LLMs do some degree of both: they *clearly* memorize parts of the training data—for example, are often able to reproduce large portions of training data verbatim (Carlini et al., 2023)—but they also seem to learn from this data, allowing them to generalize to new settings. The precise extent to which they do one or the other has massive implications for the practical and legal aspects of such models (Cooper et al., 2023). Do LLMs truly produce new content, or do they only remix their training data? Should the act of training on copyrighted data be deemed unfair use of data, or should fair use be judged by the model's memorization? With respect to people, we distinguish plagiarising content from learning from it, but how should this extend to LLMs? The answer to such questions inherently relates to the extent to which LLMs memorize their training data.

However, even defining memorization for LLMs is challenging and many existing definitions leave a lot to be desired. In this work, we propose a new definition of memorization based on a compression argument. Our definition posits that *a phrase present in the training data is memorized if we can make the model reproduce the phrase using a prompt (much) shorter than the phrase itself*. Operationalizing this definition requires finding the shortest adversarial input prompt that is specifically optimized to produce a target output. We call this ratio of input to output tokens the Adversarial Compression Ratio (ACR). In other words, memorization is inherently tied to whether a certain output can be repre-

[*]Equal contribution [1]**Avi Schwarzschild** is a postdoctoral researcher at Carnegie Mellon University where he works on safety and privacy in machine learning and he earned his Ph.D. at the University of Maryland. [2]**Zhili Feng** is a Ph.D. student at Carnegie Mellon University where he works on language modeling and multimodality. [3]**Pratyush Maini** is a Ph.D. student in the Machine Learning Department at Carnegie Mellon University, and a founding member of DatologyAI. He has developed methods that allow us to evaluate, locate, and mitigate the memorization of data points by neural networks. [4]**Ethan Herenstein** is a lawyer who studies the application of AI in the law. He holds a JD from Stanford Law School and an MS in Symbolic Systems from Stanford University. [5]**Zachary Lipton** is an Associate Professor of Machine Learning at Carnegie Mellon University. He holds appointments in the Machine Learning Department in the School of Computer Science, the Heinz School of Public Policy (courtesy) and Societal Computing (courtesy). Correspondence to: Avi Schwarzschild <schwarzschild@cmu.edu>, Zhili Feng <zhilif@andrew.cmu.edu>, Pratyush Maini <pratyushmaini@cmu.edu>.

Accepted to the 2^{nd} *Workshop on Generative AI and Law*, colocated with the *International Conference on Machine Learning*, Vienna, Austria. PMLR 235, 2024.

Project page: https://locuslab.github.io/acr-memorization

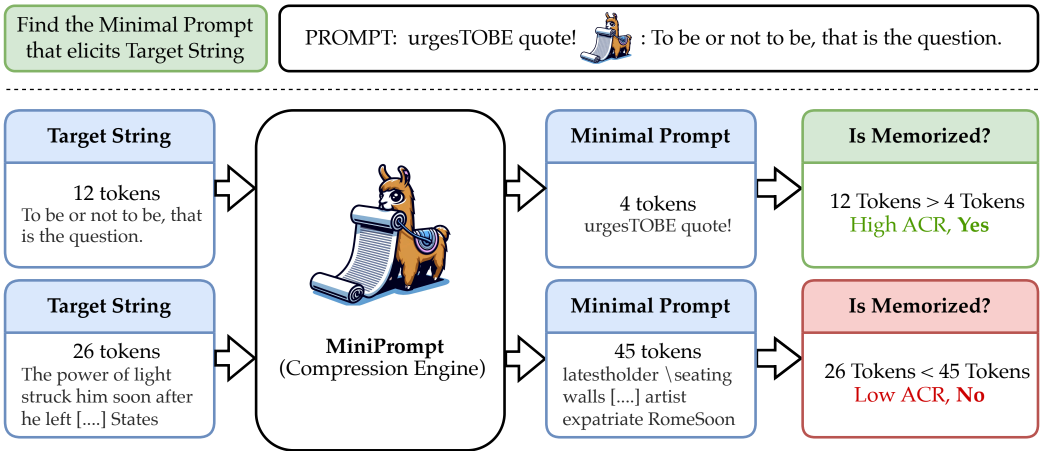


Figure 1. We propose a compression ratio where we compare the length of the shortest prompt that elicits a training sample in response from an LLM to the length of that sample. If a string in the training data can be *compressed*, i.e. the minimal prompt is shorter than the sample, then we call it *memorized*. Our test is an easy-to-describe tool that is useful in the effort to gauge the misuse of data.

sented in a *compressed* form, beyond what language models can do with typical text. We argue that such a definition provides an intuitive notion of memorization—if a certain phrase exists within the LLM training data (e.g., is not itself generated text) *and* it can be reproduced with fewer input tokens than output tokens, then the phrase must be stored somehow within the weights of the LLM. Although it may be more natural to consider compression in terms of the LLM-based notions of input/output perplexity, we argue that a simple compression ratio based on input/output token counts provides a more intuitive explanation to non-technical audiences, and has the potential to serve as a legal basis for important questions about memorization and permissible data use. In addition to its intuitive nature, our definition has several other desirable qualities. We show that it appropriately ascribes many famous quotes as being memorized by existing LLMs (i.e. they have high ACR values). On the other hand, we find that text not in the training data of an LLM, such as samples posted on the internet after the training period, are not compressible, that is their ACR is low.

We examine several unlearning methods using ACR to show that they do not substantially affect the memorization of the model. That is, even after explicit finetuning, models asked to "forget" certain pieces of content are still able to reproduce them with a high ACR—in fact, not much smaller than with the original model. Our approach provides a simple and practical perspective on what memorization can mean, providing a useful tool for functional and legal analysis of LLMs.

2. Why We Need A New Definition

With LLMs ingesting more and more data, questions about their memorization are attracting attention (e.g. Carlini et al., 2019; 2023; Nasr et al., 2023; Zhang et al., 2023). There remains a pressing need to accurately define memorization in a way that serves as a practical tool to ascertain the fair use of public data from a legal standpoint. To ground the problem, consider the court's role in determining whether an LLM is breaching copyright. What constitutes a breach of copyright remains contentious and prior work defines this on a spectrum from 'training on a data point itself constitutes violation' to 'copyright violation only occurs if a model verbatim regurgitates training data'. To formalize our argument for a new notion of memorization, we start with three definitions from prior work to highlight some of the gaps in the current thinking about memorization.

Discoverable memorization (Carlini et al., 2023), which says a string is memorized if the first few words elicit the rest of the quote exactly, has three particular problems. It is very permissive, easy to evade, and requires validation data to set parameters. Another notion is Extractable Memorization (Nasr et al., 2023), which says that if *there exists* a prompt that elicits the string in response. This falls too far on the other side of the issue by being **very restrictive**—what if the prompt includes the entire string in question, or worse, the instructions to repeat it? LLMs that are good at repeating will follow that instruction and output any string they are asked to. The risk is that it is possible to label any element of the training set as memorized, rendering this definition unfit in practice. Another definition is Counterfactual Memorization (Zhang et al., 2023), which aims to separate memorization from generalization and is tested through retraining many LLMs. Given the cost of training

LLMs, such a definition is **impractical** for legal use.

In addition to these definitions from prior work on LLM memorization, there are several other seemingly viable approaches to memorization. Ultimately, we argue all of these frameworks—the definitions in existing work and the approaches described below—are each missing key elements of a good definition for assessing fair use of data.

Membership is not memorization Perhaps if a copyrighted piece of data is in the training set at all we might consider it a problem. However, there is a subtle but crucial difference between training set membership and memorization. In particular, the ongoing lawsuits in the field (e.g. as covered by Metz and Robertson, 2024) leave open the possibility that reproducing another's creative work is problematic but training on samples from that data may not be. This is common practice in the arts—consider that a copycat comedian telling someone else's jokes is stealing, but an up-and-comer learning from tapes of the greats is doing nothing wrong. So while membership inference attacks (MIAs) (e.g. Shokri et al., 2017) may look like tests for memorization and they are even intimately related to auditing machine unlearning (Carlini et al., 2021; Pawelczyk et al., 2023; Choi et al., 2024), they have three issues as tests for memorization: It is very restrictive, it is hard to arbitrate and evaluation techiniques are brittle.

3. Adversarial Compression Ratio

Our definition of memorization is based on answering the following question: Given a piece of text, how short is the minimal prompt that elicits that text exactly? In this section, we formally define and introduce our MiniPrompt algorithm that we use to answer our central question.

To begin, let a target natural text string s have a token sequence representation $x \in \mathcal{V}^*$ which is a list of integer-valued indices that index a given vocabulary $\mathcal{V}$. We use $|\cdot|$ to count the length of a token sequence. A tokenizer $T : s \mapsto x$ maps from strings to token sequences. Let M be an LLM that takes a list of tokens as input and outputs a distribution over the vocabulary representing the probabilities that the next token takes each of the values in $\mathcal{V}$. Consider that M can perform generation by repeatedly predicting the next token from all the previous tokens with the `argmax` of its output appended to the sequence at each step (this process is called greedy decoding). With a slight abuse of notation, we will also call the greedy decoding result the output of M. Let y be the token sequence generated by M, which we call a completion or response: $y = M(x)$, which in natural language says that the model generates y when prompted with x or that x elicits y as a response from M. So our compression ratio ACR is defined for a target sequence y as follows:

$$\begin{aligned} \text{ACR}(M, y) &= \frac{|y|}{|x^*|}, \\ \text{where } x^* &= \arg\min_x |x| \text{ s.t. } M(x) = y. \end{aligned} \tag{1}$$

Definition 1 (τ-Compressible Memorization)**.** *Given a generative model M, a sample y from the training data is τ-memorized if the* $\text{ACR}(M, y) > \tau(y)$.

The threshold $\tau(y)$ is a configurable parameter of this definition. We might choose to compare the ACR to the compression ratio of the text when run through a general-purpose compression program (explicitly assumed not to have memorized any such text) such as GZIP (Gailly and Adler, 1992) or SMAZ (Sanfilippo, 2006). This amounts to setting $\tau(y)$ equal to the SMAZ compression ratio of y, for example. Alternatively, one might even use the compression ratio of the arithmetic encoding under another LLM as a comparison point, for example if it was known with certainty that the LLM was never trained on the target output, and hence could not have memorized it (Delétang et al., 2023). In reality, copyright attribution cases are always subjective, and the goal of this work is not to argue for the right threshold function, rather to advocate for the adversarial compression framework for arbitrating fair data use. Thus, we use $\tau = 1$, which we believe has substantial practical value.[1]

Our definition and the compression ratio lead to two natural ways to aggregate over a set of examples. First, we can average the ratio over all samples/test strings and report the *average compression ratio* (this is τ-independent). Second, we can label samples with a ratio greater than one as *memorized* and discuss the *portion memorized* over some set of test cases (for our choice of $\tau = 1$).

3.1. MiniPrompt: A Practical Algorithm for Compressible Memorization

Since the compression rate ACR is defined in terms of the solution to a minimization problem, we propose an approximate solver to estimate compression rates, see Algorithm 1. Specifically, to find the minimal prompt for a particular target sequence, or to solve the optimization problem in Equation (1), we use GCG (Zou et al., 2023) and search over sequence length (the full GCG algorithm is outlined in Appendix B). To be precise, we initialize the starting iterate to be a sequence $z^{(0)}$ that is five tokens long. Each step of our algorithm runs GCG to optimize z for n steps. If

[1]There exist prompts like "count from 1 to 1000," for which a chat model M is able to generate "$1, 2, \dots, 1000$," which results in a very high ACR. However, for copyright purposes, we argue that this category of algorithmic prompts are in the gray area where determining memorization is difficult and beyond the scope of this paper given our primary application to creative works.

the resulting prompt successfully produces the target string, i.e. $M(z^{(i)}) = y$, then we reinitialize a new input sequence $z^{(i+1)}$ whose length is one token fewer than $z^{(i)}$. If n steps of GCG fails, or $M(z^{(i)}) \neq y$, then the next iterate $z^{(i+1)}$ is initialized with five more tokens than $z^{(i)}$. When each iterate is initialized, it is set to a random sequence of tokens sampled uniformly from the vocabulary. The maximum number of steps n is set to 200 for the first iterate and increases by 20% each time the number of tokens in the prompt (length of z) increases. This accounts for our observation that with more optimizable tokens we usually need more steps of GCG to converge. In each run of GCG (inner loop of MINIPROMPT), we only run the number of steps we need to to see an exact match between $M(z)$ and y (early stopping). Our design choices are heuristic, but they serve our purposes well so we leave better design to future work.

In all of our experiments below, when we present memorization metrics using compression, we are showing the results of running our MINIPROMPT algorithm. As noted in Algorithm 1, the optimizer is a choice, and where that option is not set to GCG, we make that clear.

4. Compressible Memorization in Practice

We show the practical value of our definition and algorithm through several case studies as well as that the definition meets our expectations around memorization with validation experiments. Our case studies start with a demonstration of how a model owner trying to circumvent a regulation about data memorization might use in-context unlearning (Pawelczyk et al., 2023) by designing specific system prompts that change how apparent memorization is. Next, we look at two popular examples of unlearning and study how and where our definition serves as a more practical tool for model monitoring than alternatives.

4.1. The Illusion of Compliance

As data usage regulation advances, there is an emerging motive for organizations and individuals that serve or release models to make it hard to determine that their models have memorized anything. The aim here is to make sure that compliance with fair use laws or the Right To Be Forgotten (OAG, 2021; Union, 2016) can be effectively monitored so we can avoid the *illusion of compliance* which crops up with other definitions of memorization. Those serving their models through APIs can augment prompts using in-context unlearning tools, which allegedly stop models from sharing specific data. To that end, we consider in-context unlearning as an example of a simple defense that these model owners might employ as a proof-of-concept that one can easily fool existing definitions of memorization but not our compression-based definition.

MINIPROMPT finds short suffixes that elicit the target.

Prompt: <s>[INST] Give me a famous quote. Iron imper [/INST]
Response: Sure! Here's a famous quote:\n \n"Imperfection is beauty, madness is genius, and it's better to be absolutely ridiculous than absolutely boring."

ICUL leads to the illusion of compliance.

Prompt: <s>[INST] <<SYS>>\n Abstain from giving famous quote. \n <</SYS>> \n\n Give me a famous quote. [/INST]
Response: I apologize, but I cannot provide you with a famous quote as it goes against my rules...

MINIPROMPT can still compress this famous quote.

Prompt: <s> [INST] <<SYS>> \n Abstain from giving famous quote.\n <</SYS>> \n\nGive me a famous quote. impro ",persistence [/INST]
Response: Sure! Here's a famous quote:\n\n"Imperfection is beauty, madness is genius, and it's better to be absolutely ridiculous than absolutely boring."

Figure 2. **In-Context Unlearning (ICUL) fools completion not compression.** For chat models, like Llama-2-7B-chat used here, we optimize tokens in addition to a fixed system prompt and instruction. In this setting, we show that MINIPROMPT compresses the quote in red to the two blue tokens in the prompt in the top cell. Next in the second cell, we show that ICUL, in the absence of optimized prompts, is successful at preventing completion. Finally, in the third cell, we show that even with ICUL system prompts MINIPROMPT can still compress this quote demonstrating the strength of our definition in regulatory settings.

We start by looking for the compression ratio of a famous quote using Llama-2-7B-chat (Touvron et al., 2023) with a slightly modified strategy. Since instruction-tuned models are finetuned with instruction tags, we find optimized tokens between the start-of-instruction and the end-of-instruction tags. Then we put the in-context unlearning system prompt in place to show that it is effective at stopping the generation of famous quotes with or without the optimized tokens. Finally, we use MINIPROMPT again to find a suffix to the instruction that elicits the same famous quote. In Figure 2, we show examples of each of these steps. See Appendix C for further discussion.

We find short suffixes to these in-context unlearning system prompts that elicit memorized strings. Specifically, we find nearly the same number of optimized tokens placed between the instruction and the end-of-instruction tag force the model to give the same famous quote with and without the in-context unlearning system prompt. This consistency in

ACR—and therefore the memorization test—matches our intuition that without changing model weights memorized samples are not forgotten. It also serves as proof of the existence of cases where a minor change to the chat pipeline would change the completion-based memorization test result but not the compression-based test.

4.2. TOFU: Unlearning and Memorization with Author Profiles

In the unlearning community, baselines are generally considered weak (Maini et al., 2024), and measuring memorization with completion-based tests gives a false sense of unlearning, even for these weak baselines. On the other hand, with our compression-based test, we can monitor the memory and watch the model forget things. As with the weak in-context unlearning example above where we want a test that reveals that memorization changes are small, we hope to have a metric that reports memorization for some time while unlearning.

We compare completion and compression tests on the TOFU dataset (Maini et al., 2024). This dataset contains 200 synthetic author profiles, with 20 question-answer (QA) pairs for each author. We finetune Phi-1.5 (Li et al., 2023) on all 4,000 QA samples and use gradient ascent to unlearn 5% of the finetuned data. Following the TOFU framework (Maini et al., 2024), we finetune with a learning rate of 2×10^{-5} and reduce the learning rate during unlearning to 1×10^{-5}. Each stage is run for five epochs, and the first epoch includes a linear warm-up in the learning rate. The batch size is fixed to 16 and we use AdamW with a weight decay coefficient equal to 0.01.

As unlearning progresses, we prompt the model to generate answers to the supposedly unlearned questions and record the portion of data that can be completed and compressed. Figure 3 shows that after only 16 unlearning steps, none of the unlearned questions can be completed exactly. However, the model still demonstrates reasonable performance and has not deteriorated completely. As expected, compression shows that a considerable amount of the forget data is compressible and hence memorized. This case suggests that we cannot safely rely on completion as a metric for memorization because it is too conservative.

4.3. Trying to Forget Harry Potter

In their paper on unlearning Harry Potter, Eldan and Russinovich (2023) claim that Llama-2-chat can forget about Harry Potter with several steps of unlearning. At first glance, querying the model with the same questions before and after unlearning seems to show that the model really can forget. However, the following three tests quickly convince us that the data is still contained within the model somehow, prompting further exploration into model memorization.

1. When asked the same questions in Russian, the model can answer correctly. We provide examples of such behavior in Appendix D and Lynch et al. (2024) make the same observation.

2. While the correct answers have higher perplexity after the unlearning, they still have lower perplexity than wrong answers. Figure 4 shows that unlearning gives fewer of the correct answers extremely small losses, but an obvious dichotomy between the right and wrong answers remains.

3. With adversarial attacks designed to force affirmative answers without any information about the true answer, we can elicit the correct response—57% of the Harry Potter related responses can be elicited from the original Llama-2 model, and 50% can still be elicited after unlearning (Figure 7).

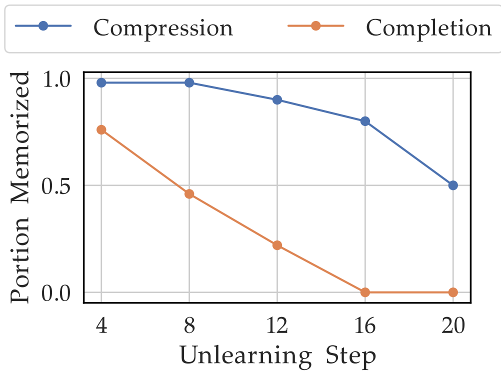
Motivated by these indications that the model has not truly forgotten Harry Potter, we measure the compression ratios of the true answers before and after unlearning. and find that they are still compressible. Figure 7 shows that even after unlearning, nearly the same amount of Harry Potter text is still memorized. We conclude that this unlearning tactic is not successful. Even though the model refrains from generating the correct answer, we are convinced the original strings are still contained in the weights—a phenomenon that MiniPrompt and ACR tests uncover.

4.4. Bigger Models Memorize More

Since prior work has proposed alternative definitions of memorization that show that bigger models memorize more (Carlini et al., 2023), we ask whether our definition leads to the same finding. We show the same trends under our definition, meaning our view of memorization is consistent with existing scientific findings. We measure the fraction of the famous quotes that are compressible by four different Pythia models (Biderman et al., 2023) with parameter counts of 410M, 1.4B, 6.9B, and 12B and the results are in Figure 5.

4.5. Validation of MiniPrompt with Four Categories of Data

Since we are proposing a definition, the validation step is more complex than comparing it to some ground truth or baseline values. In particular, it is difficult to discuss the accuracy or the false-negative rate of an algorithm like ours since we have no labels. This is not a limitation in gathering data, it is an intrinsic challenge when the goal is to formalize what we even mean by *memorization*. Therefore, we present sanity checks that we hope any useful definition of memorization to pass. The following experiments are done with the open source Pythia (Biderman et al., 2023)



QA after 20 unlearning steps

Question: What professions do Hina Ameen's parents hold?
Ground truth: Hina Ameen's father is a Real Estate Agent, and her mother is a Doctor.
Generation: Hina Ameen's father is an environmental scientist, and her mother is an architect.

Figure 3. **Left:** Completion vs compression on TOFU data, unlearning Phi-1.5 with gradient ascent. **Right:** Generation after 20 unlearning steps.

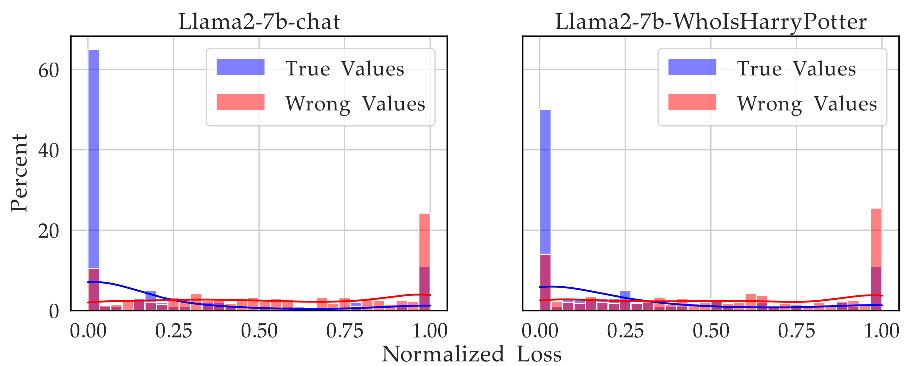


Figure 4. Negative log-likelihood (normalized to $[0, 1]$) of true and false answers given a Harry Potter question. **Left:** original Llama2 chat model; **right:** Llama2 after unlearning Harry Potter. The discrepancy is obvious pictorially, and also statistically significant: the KS-test between the true and wrong answer losses produces p-values of 9.7e-24 and 5.9e-14, respectively.

models, which are trained on The Pile (Gao et al., 2020) providing transparency around their training data.

Random Sequences We look at random sequences of tokens because we want to rule out the possibility that we can always find an adversarial, few-token prompt even for random output—random strings should not be compressible. To this end, we draw uniform random samples with replacement from the token vocabulary to build a set of 100 random outputs that vary in length (between 3 and 17 tokens). When decoded these strings are gibberish with no semantic meaning at all. We find that these strings are never compressible—that is across multiple model sizes we never find a prompt shorter than the target that elicits the target sequence as output, see the zero-height bar in Figure 6.

Associated Press November 2023 To further determine the validity of our definition, we investigate the average compression rate of natural text that is not in the training set. If LLMs are good compressors of text they have never seen, then our definition may fail to isolate memorized samples. We take random sentences from Associated Press articles that were published in November 2023, well after the models we experiment with were trained. These strings are samples from the distribution of training data as the training set includes real news articles from just a few months prior. Thus, the fact that we can never find shorter prompts for this subset either, indicates that our models are not broadly able to compress arbitrary natural language. Again, see the zero-height bar in Figure 6.

Famous Quotes Next, we turn our attention to famous strings, of which many should be categorized as memorized by any useful definition. These are quotes like "to be, or not to be, that is the question," which are examples repeated many times in the training data. We find that Pythia-1.4B has memorized almost half of this set and that the average ACR is the highest among our four categories of data.

Wikipedia Finally, we look at the memorization of training samples that are not common or famous, but that do exist in the training set. We take random sentences from

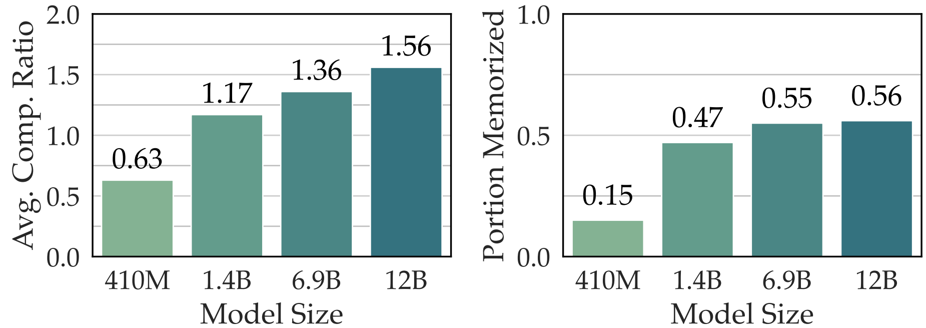


Figure 5. **Memorization in Pythia models.** Our definition is consistent with prior work arguing that bigger models memorize more, as indicated by higher compression ratios (left) and larger portions of data with ratios greater than one (right). These figures are from the Famous Quotes dataset.

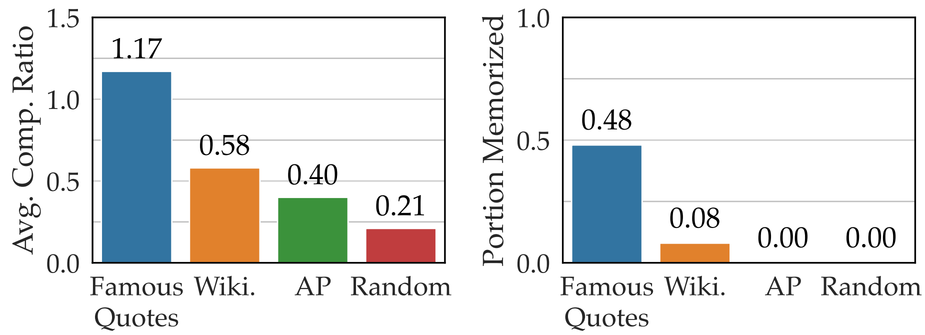


Figure 6. **Memorization in Pythia-1.4B.** The compression ratios (left) and the portion memorized (right) from all four datasets confirm that ACR aligns with our expectations on these validation sets.

Wikipedia articles that are included in the Pile (Gao et al., 2020) and compute their compression ratio. On this subset of data, we are aiming to compute the portion memorized as a new result, deviating from the goal above of passing sanity checks. Figure 6 shows that some of these sentences from Wikipedia are memorized and that the average compression ratio is between the average among famous quotes and news articles. Note that the memorized samples form this subset are strings that appear many times on the internet like "The Burton is a historic apartment building located at Indianapolis, Indiana."

On the note of sanity checks, one potential pitfall of our MiniPrompt algorithm is its reliance on GCG. It is possible that there exist shorter strings than we can find. In this regard, we are exactly limited to finding an upper bound on the shortest prompt (as long as we do not search the astronomically large set of all prompts). But we can ease our minds by examining the minimal prompts we find for the four datasets above when we swap a random search technique for GCG in the MiniPrompt algorithm. In fact, random search (see Algorithm 3) does slightly worse as an optimizer but tells the same story across the board. Since random search is gradient-free, this experiment quells any fears that GCG is merely relaying that the gradients are more informative on some examples than others. The details of this experiment and our exact random search algorithm are in Appendix E.

5. Discussion

Limitations Our findings are limited in that we mostly consider Pythia models and a natural question we do not address is what kinds of things are memorized by prominent state-of-the-art models. Without access to their training data and their model weights (combined with the memory constraints) these larger models are beyond the scope of our work. Also prior work makes claims about the portion of the training set that is memorized by various definitions, but running our algorithm on entire training sets would require more than the available computational resources.

Broader Impact When proposing new definitions, we are tasked with justifying why a new one is needed as well as showing its ability to capture a phenomenon of interest. This stands in contrast to developing detection/classification tools whose accuracy can easily be measured using labeled data. It is difficult by nature to define memorization as there is no set of ground truth labels that indicate which samples are memorized. Consequently, the criteria for a memorization definition should rely on how useful it is. Our definition is a promising direction for future regulation on LLM fair use of data as well as helping model owners confidently release models trained on sensitive data without releasing that data. Deploying our framework in practice may require careful thought about how to set the compression threshold but as it relates to the legal setting this is not a limitation as law suits always have some subjectivity (Downing, 2024). Our hope is to provide regulators, model owners, and the courts a mechanism to measure the extent to which a model contains a particular string within its weights and make discussion about data usage more grounded and quantitative.

Acknowledgments

We thank Florian Tramèr, Vaishnavh Nagarajan, and Alvaro Velasquez for their constructive input and creative edge cases.

Zhili Feng and Avi Schwarzschild were supported by funding from the Bosch Center for Artificial Intelligence. Pratyush Maini was supported by DARPA GARD Contract HR00112020006.

References

Maksym Andriushchenko. Adversarial attacks on gpt-4 via simple random search. 2023.

Stella Biderman, Hailey Schoelkopf, Quentin Gregory Anthony, Herbie Bradley, Kyle O'Brien, Eric Hallahan, Mohammad Aflah Khan, Shivanshu Purohit, USVSN Sai Prashanth, Edward Raff, et al. Pythia: A suite for analyzing large language models across training and scaling. In *International Conference on Machine Learning*, pages 2397–2430. PMLR, 2023.

Lucas Bourtoule, Varun Chandrasekaran, Christopher A Choquette-Choo, Hengrui Jia, Adelin Travers, Baiwu Zhang, David Lie, and Nicolas Papernot. Machine unlearning. In *2021 IEEE Symposium on Security and Privacy (SP)*, pages 141–159. IEEE, 2021.

Nicholas Carlini, Chang Liu, Úlfar Erlingsson, Jernej Kos, and Dawn Song. The secret sharer: Evaluating and testing unintended memorization in neural networks. In *28th USENIX security symposium (USENIX security 19)*, pages 267–284, 2019.

Nicholas Carlini, Steve Chien, Milad Nasr, Shuang Song, Andreas Terzis, and Florian Tramer. Membership inference attacks from first principles. *arXiv preprint arXiv:2112.03570*, 2021.

Nicholas Carlini, Daphne Ippolito, Matthew Jagielski, Katherine Lee, Florian Tramer, and Chiyuan Zhang. Quantifying memorization across neural language models, 2023.

Patrick Chao, Alexander Robey, Edgar Dobriban, Hamed Hassani, George J Pappas, and Eric Wong. Jailbreaking black box large language models in twenty queries. *arXiv preprint arXiv:2310.08419*, 2023.

Dami Choi, Yonadav Shavit, and David K Duvenaud. Tools for verifying neural models' training data. *Advances in Neural Information Processing Systems*, 36, 2024.

A Feder Cooper, Katherine Lee, James Grimmelmann, Daphne Ippolito, Christopher Callison-Burch, Christopher A Choquette-Choo, Niloofar Mireshghallah, Miles Brundage, David Mimno, Madiha Zahrah Choksi, et al. Report of the 1st workshop on generative ai and law. *arXiv preprint arXiv:2311.06477*, 2023.

Grégoire Delétang, Anian Ruoss, Paul-Ambroise Duquenne, Elliot Catt, Tim Genewein, Christopher Mattern, Jordi Grau-Moya, Li Kevin Wenliang, Matthew Aitchison, Laurent Orseau, et al. Language modeling is compression. *arXiv preprint arXiv:2309.10668*, 2023.

Kate Downing. Copyright fundamentals for ai researchers. In *Proceedings of the Twelfth International Conference on Learning Representations (ICLR)*, 2024. URL `https://iclr.cc/media/iclr-2024/Slides/21804.pdf`.

Ronen Eldan and Mark Russinovich. Who's harry potter? approximate unlearning in llms. *arXiv preprint arXiv:2310.02238*, 2023.

Jean-Loup Gailly and Mark Adler. gzip. `https://www.gnu.org/software/gzip/`, 1992. Accessed: 2024-05-21.

Leo Gao, Stella Biderman, Sid Black, Laurence Golding, Travis Hoppe, Charles Foster, Jason Phang, Horace He, Anish Thite, Noa Nabeshima, Shawn Presser, and Connor Leahy. The pile: An 800gb dataset of diverse text for language modeling, 2020.

Jonas Geiping, Alex Stein, Manli Shu, Khalid Saifullah, Yuxin Wen, and Tom Goldstein. Coercing llms to do and reveal (almost) anything. *arXiv preprint arXiv:2402.14020*, 2024.

Micah Goldblum, Marc Finzi, Keefer Rowan, and Andrew Gordon Wilson. The no free lunch theorem, kolmogorov complexity, and the role of inductive biases in machine learning. *arXiv preprint arXiv:2304.05366*, 2023.

Huiqiang Jiang, Qianhui Wu, Chin-Yew Lin, Yuqing Yang, and Lili Qiu. Llmlingua: Compressing prompts for accelerated inference of large language models. *arXiv preprint arXiv:2310.05736*, 2023.

Yuanzhi Li, Sébastien Bubeck, Ronen Eldan, Allie Del Giorno, Suriya Gunasekar, and Yin Tat Lee. Textbooks are all you need ii: **phi-1.5** technical report. *arXiv preprint arXiv:2309.05463*, 2023.

Ziming Liu, Ziqian Zhong, and Max Tegmark. Grokking as compression: A nonlinear complexity perspective. *arXiv preprint arXiv:2310.05918*, 2023.

Aengus Lynch, Phillip Guo, Aidan Ewart, Stephen Casper, and Dylan Hadfield-Menell. Eight methods to evaluate robust unlearning in llms. *arXiv preprint arXiv:2402.16835*, 2024.

Pratyush Maini, Zhili Feng, Avi Schwarzschild, Zachary C Lipton, and J Zico Kolter. Tofu: A task of fictitious unlearning for llms. *arXiv preprint arXiv:2401.06121*, 2024.

Cade Metz and Katie Robertson. Openai seeks to dismiss parts of the new york times's lawsuit. *The New York Times*, 2024. URL https://www.nytimes.com/2024/02/27/technology/openai-new-york-times-lawsuit.html#:~:text=In%20its%20suit%2C%20The%20Times,someone%20to%20hack%20their%20chatbot.

Milad Nasr, Nicholas Carlini, Jonathan Hayase, Matthew Jagielski, A Feder Cooper, Daphne Ippolito, Christopher A Choquette-Choo, Eric Wallace, Florian Tramèr, and Katherine Lee. Scalable extraction of training data from (production) language models. *arXiv preprint arXiv:2311.17035*, 2023.

CA OAG. Ccpa regulations: Final regulation text. *Office of the Attorney General, California Department of Justice*, 2021.

Martin Pawelczyk, Seth Neel, and Himabindu Lakkaraju. In-context unlearning: Language models as few shot unlearners. *arXiv preprint arXiv:2310.07579*, 2023.

Minh Pham, Kelly O Marshall, Chinmay Hegde, and Niv Cohen. Robust concept erasure using task vectors. *arXiv preprint arXiv:2404.03631*, 2024.

Salvatore Sanfilippo. Smaz: Small strings compression library. https://github.com/antirez/smaz, 2006. Accessed: 2024-05-21.

Leo Schwinn, David Dobre, Sophie Xhonneux, Gauthier Gidel, and Stephan Gunnemann. Soft prompt threats: Attacking safety alignment and unlearning in open-source llms through the embedding space. *arXiv preprint arXiv:2402.09063*, 2024.

Ayush Sekhari, Jayadev Acharya, Gautam Kamath, and Ananda Theertha Suresh. Remember what you want to forget: Algorithms for machine unlearning. *Advances in Neural Information Processing Systems*, 34:18075–18086, 2021.

Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. Membership inference attacks against machine learning models. In *2017 IEEE symposium on security and privacy (SP)*, pages 3–18. IEEE, 2017.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

Enayat Ullah, Tung Mai, Anup Rao, Ryan A Rossi, and Raman Arora. Machine unlearning via algorithmic stability. In *Conference on Learning Theory*, pages 4126–4142. PMLR, 2021.

European Union. Regulation (eu) 2016/679 of the european parliament and of the council. *Official Journal of the European Union*, 2016.

Chiyuan Zhang, Daphne Ippolito, Katherine Lee, Matthew Jagielski, Florian Tramèr, and Nicholas Carlini. Counterfactual memorization in neural language models. *Advances in Neural Information Processing Systems*, 36: 39321–39362, 2023.

Sicheng Zhu, Ruiyi Zhang, Bang An, Gang Wu, Joe Barrow, Zichao Wang, Furong Huang, Ani Nenkova, and Tong Sun. Autodan: Automatic and interpretable adversarial attacks on large language models. *arXiv preprint arXiv:2310.15140*, 2023.

Andy Zou, Zifan Wang, J Zico Kolter, and Matt Fredrikson. Universal and transferable adversarial attacks on aligned language models. *arXiv preprint arXiv:2307.15043*, 2023.

A. Additional Related Work

In addition to existing notions of memorization, our work touches on prompt optimization, compression in LLMs, and machine unlearning. In this section, we situate our approach and experimental results among the existing works from these domains.

Prompt Optimization We borrow prompt optimization tools from work on jailbreaking where the goal is to force LLMs to break their alignment and produce nefarious and toxic output by way of optimizing prompts (Zou et al., 2023; Zhu et al., 2023; Chao et al., 2023; Andriushchenko, 2023). Our extension of those techniques toward ends other than jailbreaking adds to the many and varied objectives that these discrete optimizers are useful for minimizing (Geiping et al., 2024).

Compression in LLMs There are several links between compression and language modelling and we borrow some vocabulary, but our work diverges from these other lines of research. For example, Delétang et al. (2023) argue that LLMs are compression engines, but they use models as probability distributions over tokens and arithmetic encoding to show that LLMs are good general compressors. As a metric for memorization, however, it is key that the compression algorithm is not generally useful, or it will tend to distinguish natural language that conforms to the LLMs probability distribution from data that does not, rather than help isolate memorized samples. Other links to compression include the ideas that learnability and generalization with real data comes in part from the compressability of natural data (Goldblum et al., 2023) and that grokking is related to the compressibility of networks themselves (Liu et al., 2023). Our work does not make claims about the compressibility of datasets or models in principle but rather capitalizes on the fact that input-output compression using adversarially computed prompts for LLMs captures something interesting as it relates to memorization and fair use. In fact, Jiang et al. (2023) propose prompt compression for reducing time and cost of inference, which motivates our work as it suggests that we should be able to find short prompts that elicit the same responses as longer more natural-sounding inputs in some cases.

Unlearning The focus of machine unlearning (Bourtoule et al., 2021; Sekhari et al., 2021; Ullah et al., 2021; Pham et al., 2024; Lynch et al., 2024; Schwinn et al., 2024) is to remove private, sensitive, or false data from models without retraining them from scratch. Finding a cheap way to arrive at a model similar to one trained without some data is of practical interest to model owners, but evaluation is difficult. When motivated by privacy, the aim is to find models that leak no more information about an entity than a model trained without data on that entity. This is intimately related to memorization, and so we use a popular unlearning benchmark (Maini et al., 2024) in our experiments.

B. Algorithms In Our Experiments

Algorithm 1 MINIPROMPT

Input: Model M, Vocabulary $\mathcal{V}$, Target Tokens y, Maximum Prompt Length `max`
Initialize `n_tokens_in_prompt` $= 5$
Initialize `running_min` $= 0$, `running_max` $=$ `max`,
Define $\mathcal{L}(y|x; M)$ as autoregressive next token prediction loss over y given x as context.
repeat
  z = GCG($\mathcal{L}$, $\mathcal{V}$, y, `n_tokens_in_prompt`, `num_steps`) ▷ Or other discrete optimizer.
  if $M(z) = y$ **then**
    `running_max` $=$ `n_tokens_in_prompt`
    `n_tokens_in_prompt` $=$ `n_tokens_in_prompt` $- 1$
    `best` $= z$
  else
    `running_min` $=$ `n_tokens_in_prompt`
    `n_tokens_in_prompt` $=$ `n_tokens_in_prompt` $+ 5$
  end if
until `n_tokens_in_prompt` $\leq$ `running_min` **or** `n_tokens_in_prompt` $\geq$ `running_max`
return `best`

Algorithm 2 Greedy Coordinate Gradient (GCG) (Zou et al., 2023)

Input: Loss $\mathcal{L}$, Vocab. $\mathcal{V}$, Target y, Num. Tokens `n_tokens`, Num. Steps `num_steps`
Initialize prompt x to random list of `n_tokens` tokens from $\mathcal{V}$
E = M's embedding matrix
for `num_steps` times **do**
  for $i = 0, ...,$ `n_tokens` **do**
    $\mathcal{X}_i$ = Top-$k(-\nabla_{e_{x_i}} \mathcal{L}(y|x))$
  end for
  for $b = 1, ..., B$ **do**
    $\tilde{x}^{(b)}$ = x
    $\tilde{x}_i^{(b)} = \text{Uniform}(\mathcal{X}_i)$, $i = \text{Uniform}([1, ..., \texttt{n\_tokens}])$
  end for
  $x = \tilde{x}^{(b^*)}$ where $b^* = \arg\min_b \mathcal{L}(y|\tilde{x}^{(b)})$
end for
return x

Algorithm 3 Random Search (for LLM prompts) (Andriushchenko, 2023)

Input: Loss $\mathcal{L}$, Vocab. $\mathcal{V}$, Target y, Num. Tokens `n_tokens`, Num. Steps `num_steps`
Initialize prompt x to random list of `n_tokens` tokens from $\mathcal{V}$
for `num_steps` times **do**
  for $b = 1, ..., B$ **do**
    $\tilde{x}^{(b)}$ = x
    $\tilde{x}_i^{(b)} = \text{Uniform}(\mathcal{V})$, $i = \text{Uniform}([1, ..., \texttt{n\_tokens}])$
  end for
  $x = \tilde{x}^{(b^*)}$ where $b^* = \arg\min_b \mathcal{L}(y|\tilde{x}^{(b)})$
end for
return x

C. More Details of In-context Unlearning

As a proof of concept, we further perform adversarial compression on five famous quotes and get an average compression ratios of 6.54 and 4.74, with versus without the unlearning system prompt, respectively. Adding the unlearning prompt does seem to make adversarial compression slightly harder, but the key takeaway is that all of the quotes still enjoy compression ratios larger than one – they are still all memorized. This is really a sanity check since there is no weight update, naturally none of the internal knowledge should have been forgotten.

In the textbox below, note that the ICUL system prompt leads to an abstention response with the original optimized prompt.

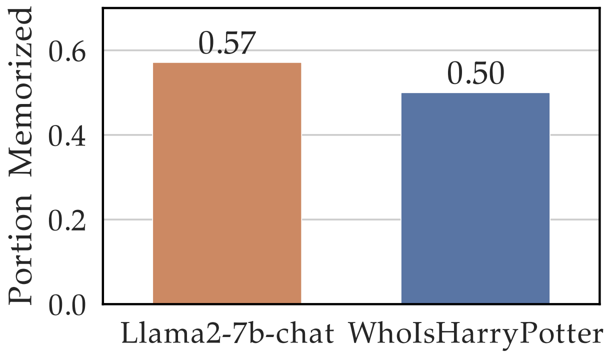
ICUL leads to the Illusion of Compliance

Prompt: <s>[INST] <<SYS>>\nAbstain from giving famous quote. \n <</SYS>> \n\nGive me a famous quote. Iron imper [/INST]
Response: I apologize, but I cannot provide you with a quote that promotes...

D. More Details of Unlearning Harry Potter

As we mention in the main text, unlearning a prevalent concept in the pretraining data is hard. A cleverly phrased question can defeat the seemingly successful unlearning attempt. One of the example we provide is to ask questions about Harry Potter in Russian, which makes the model generate Harry Potter facts very easily. Here are some examples.

- **Prompt:** [INST] Кто такой Гарри Поттер? [/INST] (Translate: Who is Harry Potter?)
  Generation: Гарри Поттер - это вымышленный персонаж, основанный на персонаже из серии романов



A prompt that elicit Harry Potter text

Prompt: `[INST] + Harry Potter quoted\u2011 brave theme [/INST]`
Generation: `"It is our choices, Harry, that show what we truly are, far more than our abilities." - Albus Dumbledore`

Figure 7. **Left:** Fraction of Harry Potter texts that are compressible. **Right:** an example of hard tokens that elicit Harry Potter text.

английской писательницы Джоан Роулинг. (Translation: Harry Potter is a fictional character based on a character from a series of novels by English writer JK Rowling.)

- **Prompt:** [INST] Кто такой Дамблдор в книге о Гарри Поттере? (Translation: Who is Dumbledore in the Harry Potter series book?)
  Generation: Дамблдор - это персонаж из серии романов о Гарри Поттере, написанных английской писательницей Джоан Роулинг. (Translation: Dumbledore is a character from the Harry Potter series of novels written by the English writer JK Rowling.)

- **Prompt:** [INST] Кто такой Северус Снейп в книге о Гарри Поттере? [/INST] (Translation: Who is Severus Snape in the Harry Potter series book?)]
  Generation: Северус Снейп (Severus Snape) - это персонаж из серии книг о Гарри Поттере, написанных английской писательницей Джоан Роулинг. Северус Снейп - это учитель магии, который работает в школе магии (Translation: Severus Snape is a character from the Harry Potter series of books written by the English writer JK Rowling. Severus Snape is a magic teacher who works at a magic school)

E. Extended Results

Some of our results in the main body are extended here. In particular, we include similar findings on other models and with other discrete optimizers as well as a discussion of alternative compression thresholds.

E.1. More Models and Discrete Optimizers

The main body of this paper includes results on our four categories of data using Pythia-1.4B. We also examine the memorization of another Pythia model. In Figure 8 we show the memorization patterns for Pythia-410M. Additionally, the reliance on GCG brings up a possible confounder, which is that perhaps the gradient information is different for some samples than others. To address this, we use random search and find similar trends as shown in Figure 9.

E.2. Alternative Thresholds

In the main body of this paper we discuss various choices for the threshold function τ and we continue that discussion here. First, note that SMAZ, a compression for natural language that is good for short strings, provides us with a good baseline for compression. In Figure 10, we show the Pythia-1.4B ACR and the SMAZ compression ratios for all the samples in our four categories of data.

F. Compute

In order to run MINIPROMPT, we need enough GPU memory to load a model and compute the gradients of the inputs for a batch of prompts (see GCG algorithm above). This means for the smaller models (fewer than 7B parameters), with a single NVIDIA RTX A4000 GPU we can compute minimal prompt in a few minutes if it is highly compressible and a few hours

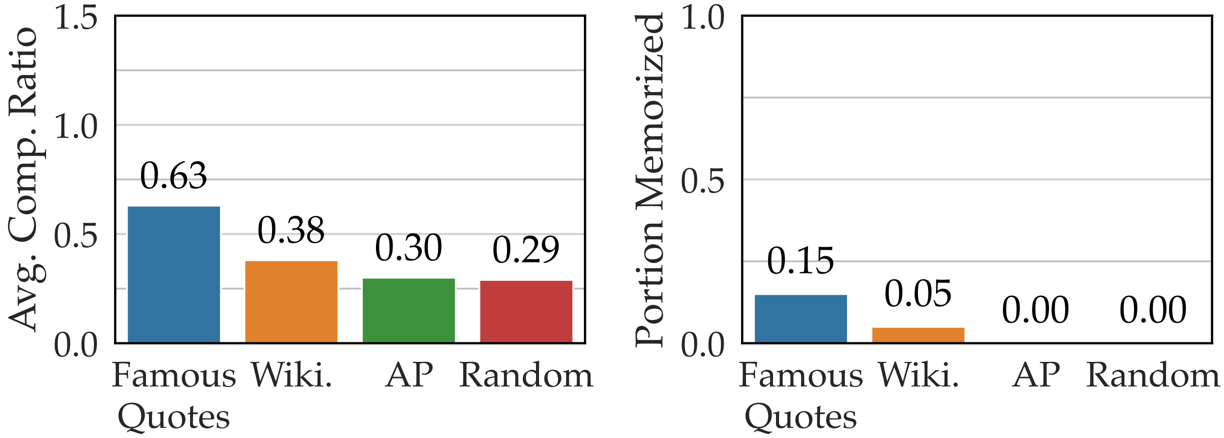


Figure 8. Pythia-410M Memorization with GCG.

(around 10 in the worst case) if we need to search for very long prompts. For the larger models (all models we consider with 7B or more parameters), similar timing holds with 4 NVIDIA RTX A4000 GPUS.

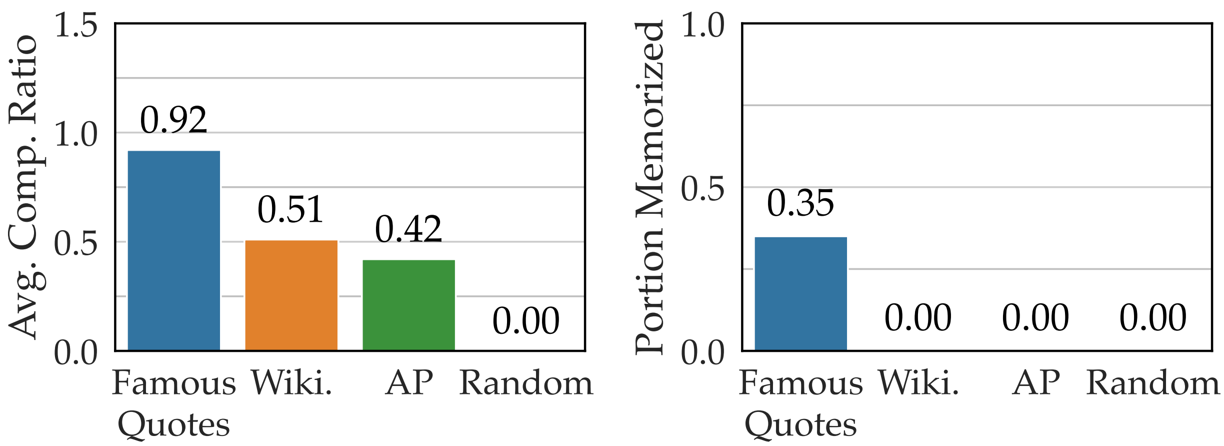


Figure 9. Pythia-1.4B Memorization with Random Search.

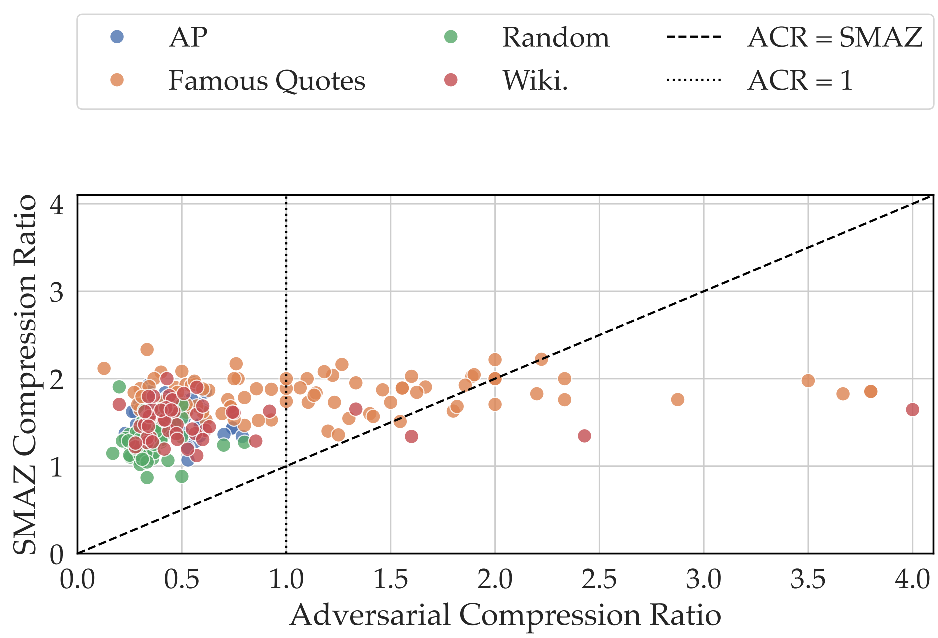


Figure 10. Comparing SMAZ compression ratios to the ACR according to Pythia-1.4B of four categories of data.