The Contamination Paradox: Why Test Set Leakage Can Be Both Potent and Negligible

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Abstract

Accurately evaluating the capabilities of large language models is critical for both machine learning research and society alike, but is undermined by leakage of benchmark test data into pretraining corpora. Circumstantial and causal evidence alike demonstrate that benchmark performance increases with model size and with the number of benchmark replicas in pretraining corpora. However, recent work by Bordt et al. (2025) demonstrated that test set contamination has little-to-no impact in the "overtrained" regime common to frontier AI systems, raising an apparent paradox of how test set leakage can be both potent *and* negligible. We resolve this paradox with a simple explanation: a language model memorizes a benchmark test set based on its capacity (number of parameters) and its incentive (the relative training loss reduction from memorizing test data). We introduce a novel dose-response framework to quantitatively relate how the "response" of benchmark performance depends on the "dose" of the proportion of benchmark tokens contaminating the pretraining data, mediated by model size. This allows us to extract precise scaling relationships that clarify the effect of test set contamination on model performance.

1 Introduction

Accurately evaluating large language models (LLMs) is increasingly difficult because benchmark test sets leak into web-scale pretraining corpora (Brown et al., 2020; Du et al., 2022; Wei et al., 2022; Chowdhery et al., 2022; Touvron et al., 2023). A growing body of work provides both circumstantial and causal evidence that contamination boosts performance (see Related Work in Appendix A). In particular, memorization rises predictably with model capacity and with the number of times an example is seen (Carlini et al., 2023; Tirumala et al., 2022; Biderman et al., 2023; Duan et al., 2024; Morris et al., 2025), and controlled pretraining experiments show measurable performance improvements (Magar & Schwartz, 2022; Jiang et al., 2024; Yao et al., 2024; Kocyigit et al., 2025).

However, this understanding was recently complicated by Bordt et al. (2025), who found that when models are overtrained—trained on far more tokens than Chinchilla compute-optimal (Hoffmann et al., 2022)—the effect of contamination can diminish or even vanish. Because frontier AI systems are oftentimes pretrained precisely in that regime (Touvron et al., 2023; Sardana et al., 2024; Gadre et al., 2024), the field now faces a paradox: how can contamination be both potent and negligible?

We argue these seemingly inconsistent observations can be unified by a single principle: language models memorize when they are able (i.e., sufficient model capacity by the number of parameters) and incentivized (i.e., relative loss reduction from memorizing benchmarks test sets) to do so. We make this quantitatively precise using a *dose-response relationship*, where the "dose" is the percentage of benchmark tokens in the pretraining corpus and the "response" is the pretrained model's accuracy. Fitting this relationship to the controlled scaling suit of Bordt et al. (2025) yields simple scaling laws: larger models require smaller doses to realize the same contamination-driven gains, while in the limit of unlimited unique data, the dose becomes vanishingly small and thus contamination has a negligible effect, clarifying why contamination can appear both potent and negligible.

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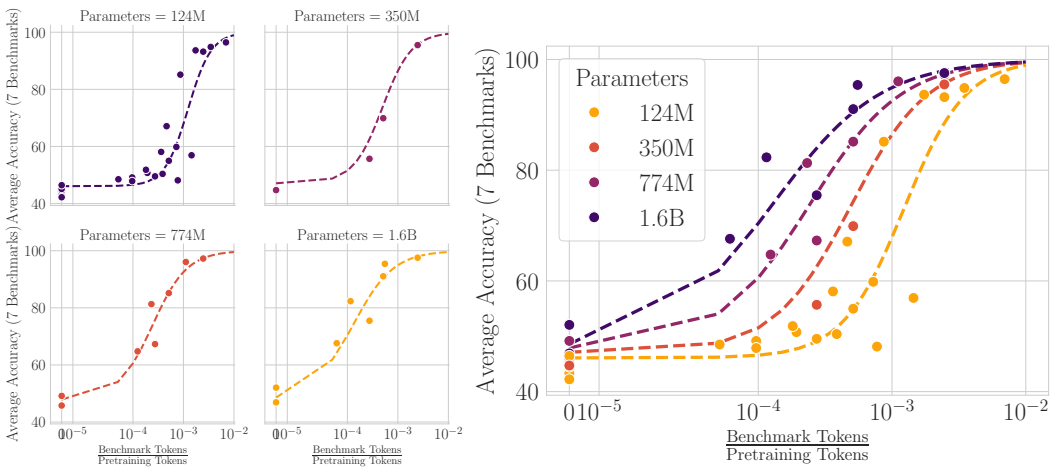

Figure 1: **A Dose-Response Model of Test Set Memorization.** We propose that language models memorize benchmark test sets based on their capacity (number of parameters) and incentive (relative loss reduction) to do so, a relationship we quantitatively capture as a dose-response relationship (Eqn. 2). We fit a functional relationship between the proportion of benchmark tokens in the pretraining data (the "dose") and the average benchmark accuracy (the "response") for different model sizes using the scaling suite from Bordt et al. (2025). These curves unify prior work: larger models have a steeper response and thus require a smaller dose of contaminated data to achieve high accuracy, but in the limit of infinite unique pretraining data (e.g., with overtrained models), the dose falls to 0% and thus test set contamination has little-to-no effect, as shown by Bordt et al. (2025). Note: The kink to the left of 10^{-4} is an artifact from symlog scaling the x-axis, not the fit response.

2 Experimental Setup: Bordt et al. (2025)'s Scaling and Contamination

We study Bordt et al. (2025)'s GPT-3-like (Brown et al., 2020) language models pretrained on FineWeb-Edu (Penedo et al., 2024) in three regimes:

1. **Parameter Scaling**: Four model sizes ($N \in \{124\text{M}, 350\text{M}, 774\text{M}, 1.6\text{B}\}$) are pretrained on a fixed amount of data ($D = 7B$ tokens).
2. **Data Scaling**: One model size (124M) is pretrained on increasing data sizes ($D \in \{5\text{B}, 10\text{B}, 20\text{B}, 37\text{B}\}$, referred to respectively as 2x, 4x, 8x and 15x Chinchilla tokens).
3. **Simultaneous Parameter & Data Scaling**: Models ($N \in \{124\text{M}, 350\text{M}, 774\text{M}, 1.6\text{B}\}$) are pretrained on Chinchilla compute-optimal data ($D \in \{2.5\text{B}, 7\text{B}, 15.5\text{B}, 32\text{B}\}$ tokens, respectively).

"Chinchilla" refers to compute-optimal scaling (Hoffmann et al., 2022), taken as 20 pretraining tokens per model parameter. Each model's pretraining corpus is contaminated *uniformly at random* with test sets taken from 7 different multiple-choice question-answering benchmarks: ARC-Easy (Clark et al., 2018), BoolQ (Clark et al., 2019), HellaSwag (Zellers et al., 2019), MMLU (Hendrycks et al., 2021), PiQA (Bisk et al., 2020), Social-I-QA (Sap et al., 2019) and WinoGrande (Sakaguchi et al., 2021). For each combination of regime, parameters, and tokens, Bordt et al. (2025) trained five models, increasing the number of test set replicas $R \in \{0$ (uncontaminated), 4, 12, 32 or 144$\}$. We report macro-average accuracy across the seven benchmarks using EleutherAI's Language Model Evaluation Harness (Gao et al., 2024). We also re-visualize the average accuracy scores from Bordt et al. (2025) here in Fig. 2 for the following reasons: (i) to provide the information conveniently to the reader, (ii) to remove the confounder introduced by Bordt et al. (2025) plotting *differences* of accuracies, and (iii) to show trends from complementary perspectives: number of test set replicas and the scaling quantity of interest (parameters, tokens, or parameters and tokens).

3 A Dose-Response Model of Test Set Memorization

To quantitatively understand how benchmark contamination affects model performance, we adopt the lens of dose-response relationships. In this framework, the "dose" is the proportion of contaminated

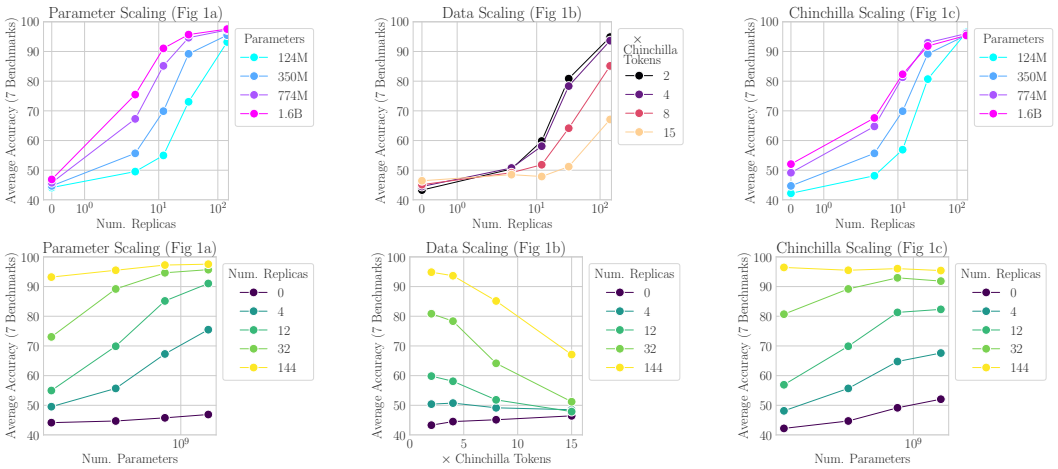

Figure 2: **Average Accuracy of Pretrained Models from Bordt et al. (2025).** We re-visualize the performance of language models pretrained by Bordt et al. (2025). **Left: Model Scaling.** Four increasing model sizes (124M, 350M, 774M, 1.6B) are pretrained on a fixed amount of data (7B tokens). **Center: Data Scaling**: One model size (124M) is pretrained on increasing data sizes (4.96B, 9.92B, 19.84B and 37.2B, referred to respectively as 2x, 4x, 8x and 15x Chinchilla tokens). **Right: Chinchilla Scaling**: Four increasing model sizes (124M, 350M, 774M, 1.6B) are pretrained on their corresponding Chinchilla compute-optimal data (2.48B, 7B, 15.48B, 32B tokens). **Key Takeaway:** When test set contamination is viewed as a function of multipliers of compute-optimal scaling, multiple complicated trends exist; once we reparameterize test set contamination as a function of the ratio of benchmark tokens to pretraining tokens, trends become cleaner (Fig. 1).

test set tokens in each model's pretraining data, and the "response" is the model's resulting accuracy on the contaminated benchmarks. For each pretrained model i, we consider its number of parameters N_i, its average accuracy across the 7 benchmarks $a_i \in [0, 100]$ and the proportion of tokens in the pretraining corpus $p_i \in [0, 1]$ that originate from the benchmarks' test sets. We model the accuracy as

$$a_i \;=\; \mu(p_i, N_i;\, \theta) \;+\; \varepsilon_i, \tag{1}$$

where $\mu(\cdot)$ is the mean function and ε_i is zero-mean noise. For the mean function, we adopt the most commonly used dose-response equation called the "$E_{\max}$ equation" (Hill, 1910; Macdougall, 2006):

$$\mu(p, N;\, \theta) \;\stackrel{\text{def}}{=}\; a_{\min}(N) \;+\; \big(a_{\max}(N) - a_{\min}(N)\big) \cdot \frac{p^{\,h(N)}}{p^{\,h(N)} + p_{50}(N)^{\,h(N)}}. \tag{2}$$

This relationship has four intuitive components:

(i) $a_{\min}(N)$: The baseline accuracy of a model with no test set contamination ($p = 0$).

(ii) $a_{\max}(N)$: The maximum achievable accuracy as the dose of contamination dominates the pretraining corpus ($p \to 100$);

(iii) $p_{50}(N)$: The proportion of contamination necessary to achieve 50% of the accuracy gain.

(iv) $h(N) > 0$: A parameter that controls the curvature or steepness of the dose-response curve.

We parameterize these components as functions of model size N to ensure the relationships are interpretable and well-behaved (i.e., $0 \leq a_{\min}(N) < a_{\max}(N) \leq 100$, $p_{50}(N) > 0$, and $h(N) > 0$):

$$\begin{aligned}
a_{\min}(N) &\stackrel{\text{def}}{=} 100 \cdot \sigma(a_0 + a_1 \log N)\,, \\
a_{\max}(N) &\stackrel{\text{def}}{=} a_{\min}(N) + \big(100 - a_{\min}(N)\big) \cdot \sigma(b_0 + b_1 \log N)\,, \\
p_{50}(N) &\stackrel{\text{def}}{=} \exp(c_0 + c_1 \log N)\,, \\
h(N) &\stackrel{\text{def}}{=} \exp(h_0 + h_1 \log N)\,,
\end{aligned}$$

where $\sigma(x) = 1/(1 + e^{-x})$ is the sigmoid function. The power–law form for $p_{50}(N)$ and $h(N)$ are based on the ansatz that larger models need less benchmark proportion to reach a given fraction

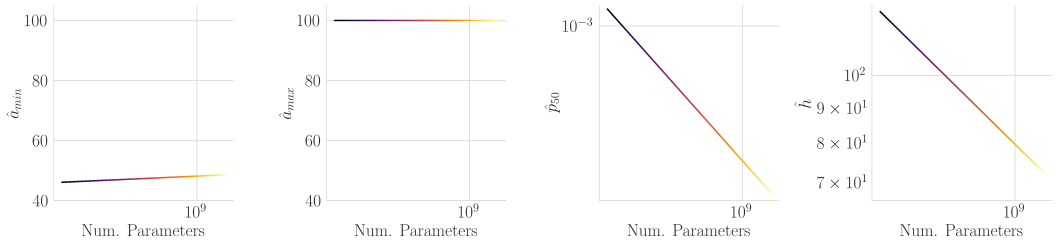

Figure 3: **Fitted Dose-Response Parameters Exhibit Predictable Scaling Laws with Model Size.** Each panel displays a parameter of our dose-response relationship (Eqn. 2) as a function of the number of model parameters N. The baseline accuracy without contamination, $a_{\min}(N)$, trends upward with model size, consistent with normal scaling without contamination. The maximum achievable accuracy, $a_{\max}(N)$, is consistently at 100%, which suggests that any model can achieve perfect accuracy with sufficient test set contamination in its training data. The proportion of contamination needed to achieve half of the possible accuracy gain scales as a power law $\log p_{50}(N) = 9.71 \cdot N^{-0.881}$, showing that larger models need a smaller proportion of benchmark data to achieve a significant accuracy boost. The steepness parameter also scales as a power law $\log h(N) = 4.63 \cdot N^{-0.214}$, indicating that the accuracy of larger models increases more sharply in response to contamination.

of the attainable improvement (Kaplan et al., 2020; Hoffmann et al., 2022). We estimate $\theta = \{a_0, a_1, b_0, b_1, c_0, c_1, h_0, h_1\}$ by robust nonlinear least squares over all points $\{(p_i, N_i, a_i)\}$ using the "soft-ℓ_1" loss to reduce sensitivity to outliers. The fit parameters are $\hat{a}_0 = -0.8877$, $\hat{a}_1 = 0.0392$, $\hat{b}_0 = -35.7432$, $\hat{b}_1 = 17.0654$, $\hat{c}_0 = 9.7100$, $\hat{c}_1 = -0.8807$, $\hat{h}_0 = 4.6277$, and $\hat{h}_1 = -0.2145$.

Fig. 1 includes all models from all three scaling regimes and all number of test set replicas ($\{0, 4, 12, 32, 144\}$). The fitted curves capture the key qualitative pattern visible in the underlying measurements: as the "dose" of benchmark contamination increases, accuracy approaches ceiling performance, and larger models achieve the same accuracy at markedly smaller doses. In contrast with Bordt et al. (2025), who find different test set memorization relationships depending on the scaling regime, Fig. 1 demonstrates that a single unifying relationship appears once one instead considers the test set dosage, i.e., the ratio of benchmark tokens to total pretraining tokens.

Fig. 3 demonstrates how dose-response parameters change with model size: The baseline accuracy with no contamination $\hat{a}_{\min}(N)$ increases gently with model size, reflecting normal scaling without contamination. The maximum achievable accuracy under heavy contamination is estimated near the upper bound ($\hat{a}_{\max}(N) \approx 100\%$ for all sizes), indicating near-perfect recall is attainable when contaminated tokens dominate pretraining. Our ansatz for sensitivity and curve steepness of power law scaling with respect to model size fit the data well: $p_{50}(N) \propto N^{-0.881}$ and $h(N) \propto N^{\hat{-}0.214}$. For practical intuition, the dose needed to realize 50% of the attainable gain is tiny and shrinks with model size: for a 1.6B parameter model, having $\sim 0.01\%$ of pretraining tokens originate from benchmarks captures 50% of the attainable performance improvements, and (assuming the relationship holds for larger models) for a 30B parameter model, a dose of $\sim 0.001\%$ benchmark tokens captures 50% of the attainable performance improvements.

4 Discussion

This work introduces a dose-response framework that resolves seemingly paradoxical findings on test set contamination within a single curve family: minor contamination can yield large gains for high-capacity models, while overtraining with unique new data reduces the dose to zero, thereby rendering contamination negligible. Moreover, our insights (1) yields actionable contamination thresholds (e.g., p_{50}) for auditors, and (2) clarifies why contamination matters most when capacity is high and unique data are scarce (Villalobos et al., 2024).

Future Directions: (1) Future work should test the generalizability of these scaling laws across different tasks and different notions of memorization (Tirumala et al., 2022; Carlini et al., 2023; Hayes et al., 2025; Duan et al., 2025). (2) Because frontier models are often pretrained on multiple epochs (Muennighoff et al., 2023), future work should study how multiple epochs complicates this picture. (3) This framework could also be developed into a practical tool for evaluators to predict and potentially correct for performance inflation caused by contamination.

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A Related Work

Data contamination and its consequences. A growing body of evidence shows that leakage of benchmark material into pretraining corpora can inflate reported performance and compromise evaluation validity. Position and survey papers argue that contamination should be routinely audited and reported for each benchmark, and they document the breadth of leakage modes and impacts (Sainz et al., 2023, 2024; Deng et al., 2024a; Xu et al., 2024a; Reuel et al., 2025). Empirical audits of large web corpora show nontrivial train–test overlap and duplication (Dodge et al., 2021), and work on systematizing benchmark integrity highlights ways LMs can "cheat" on evaluations if contamination is not addressed (Zhou et al., 2023; Dong et al., 2024). Measurements on widely used math benchmarks indicate likely leakage and overfitting signals (Zhang et al., 2024a). Community reports and open-source audits provide broader, ongoing measurements across models and datasets (Li et al., 2024). Beyond evaluation leakage, scaling studies indicate that poisoning risks increase with model size: across dozens of frontier LLMs, larger models learn harmful behaviors from tiny poisoned fractions substantially faster than smaller models, underscoring the need for robust curation and safeguards (Bowen et al., 2025). As a cautionary illustration, Schaeffer (2023) shows that pretraining on the test set trivially yields strong benchmark results, motivating rigorous decontamination and auditing.

Controlled contamination during pretraining. Several studies *causally* probe memorization by deliberately inserting evaluation items into the *pretraining* mix and varying exposure. Magar & Schwartz (2022) interleave task datasets with general text during masked-LM pretraining, systematically varying duplication; they distinguish storing examples ("memorization") from using them to improve test accuracy ("exploitation"), and show that both model size and repetition amplify exploitation on leaked items. Jiang et al. (2024) pretrain GPT-2–style models from scratch on clean corpora augmented with either *text-only* (inputs) or *ground-truth* (input–output) benchmark injections, sweeping contamination frequency; they find sizable gains under ground-truth insertion and show that paraphrases and partial leaks can evade simple n-gram decontamination. Moving beyond monolingual settings, Yao et al. (2024) demonstrate a *cross-lingual* channel: continuing pretraining on non-English translations of English benchmarks yields material improvements on the original English tests, revealing contamination undetectable by string-overlap audits. At larger scale, Bordt et al. (2025) vary (i) repetition of leaked examples, (ii) model size (up to $\sim$1.6B), and (iii) the total token budget from compute-optimal to $\gg$optimal; they recover predictable scaling with size and repeats, and also show that sufficiently long training on abundant *unique* data (with regularization) can attenuate or erase contamination measured earlier. Kocyigit et al. (2025) study machine translation, injecting held-out *source–target* pairs at controlled times and frequencies during pretraining of 1B- and 8B-parameter models; they quantify large BLEU overestimation for full-pair leakage (with weaker effects for source-only/target-only), and observe stronger inflation for larger models and lower-resource settings. Together, these pretraining-time interventions provide *causal* evidence that LMs will memorize and exploit benchmark material.

Repeated data and memorization dynamics. A complementary line of work isolates the effect of repeated training examples. Hernandez et al. (2022) train families of LMs where a small fraction of data is repeated many times, finding strong double descent (Advani et al., 2020; Belkin et al., 2019; Adlam & Pennington, 2020; Bordelon et al., 2020; Schaeffer et al., 2024) and showing that repeating even 0.1% of tokens $100\times$ can substantially degrade generalization. Tirumala et al. (2022) track exact-sequence memorization through training and across scales, showing that larger models memorize faster, memorize more, and forget less. Carlini et al. (2023) quantify log-linear relationships between verbatim emission and (i) model capacity, (ii) duplication count, and (iii) prompt length. Biderman et al. (2023) study *forecasting* whether a specific string will be memorized, showing that reliable prediction often requires using a sizable fraction of the target model's pretraining compute and providing preliminary scaling recommendations for forecast design. Beyond explicit repetition, Duan et al. (2025) uncover *latent memorization*: many memorized sequences persist and can be revealed later (e.g., by weight perturbations) even if not obviously memorized at the final checkpoint, posing privacy risks. Finally, memorization appears task-dependent: Wang et al. (2025) find stronger memorization in knowledge-intensive QA, while machine translation and mathematical reasoning show comparatively greater novelty/"true" generalization. Memorization also interacts with logical reasoning: using dynamically generated Knights & Knaves puzzles, Xie et al. (2025) show that LLMs can interpolate and memorize training puzzles to near perfection after fine-tuning yet remain brittle

to slight perturbations; importantly, fine-tuning also improves true generalization, revealing a shifting balance between reasoning and memorization. These results provide mechanistic and scaling context for the pretraining-injection studies above.

Detecting and proving contamination. Many papers focus on a complementary problem: detecting and/or proving test set contamination. Oren et al. (2023) and Ni et al. (2025) propose statistical tests with provable false-positive control by exploiting exchangeability: without contamination, canonical orderings should not be privileged relative to shuffles. Shi et al. (2024) introduce Min-$k\%$-Prob to determine if a sequence likely appeared in pretraining using only black-box probabilities. Two complementary lines from Golchin & Surdeanu (2023, 2024), respectively, frame detection as a multiple-choice "Data Contamination Quiz" (estimate contamination by asking models to pick the original among perturbations) and use temporal information about model training windows vs. benchmark releases. Broader audits quantify leakage and decontamination across tasks and models (Xu et al., 2024b; Deng et al., 2024b; Li et al., 2024), while Yang et al. (2023) show that rephrasing can evade n-gram filters, underscoring the limits of surface-overlap heuristics. Riddell et al. (2024) quantify contamination across popular code suites and link overlap to performance deltas. Matton et al. (2024) catalog leakage channels (direct, synthetic-pipeline, and model-selection overfitting) and release a dataset (LBPP) to mitigate them. Complementing these audits, Yang et al. (2025) systematically test fine-grained contamination scenarios in code intelligence (input-only, output-only, unpaired, paired) across pretrained language models (RoBERTa, GPT-2) and LLMs (LLaMA, StarCoder), finding that paired contamination has limited effect under the pretrain–finetune–inference pipeline, but substantially affects LLMs under a pretraining-plus-inference paradigm, while other scenarios often have minimal impact. Work tracing the origins of chain-of-thought style sequences provides additional detection instruments (e.g., Li et al., 2025).

Preventing test set contamination Concerns with test-set contamination have led to new approaches to benchmark creation, including dynamically updating benchmarks (Jain et al., 2025; Xia et al., 2024; Zhang et al., 2025; Qian et al., 2024) and private or restricted-access benchmarks (Zhang et al., 2024a; Glazer et al., 2025). Nie et al. (2025) recently released a benchmark of unsolved questions, which, while perhaps not the main motivation, has the nice benefit of preventing models from being trained on the solutions.

Retrieval-/agent-time contamination. As evaluations move from static prompting to tool-augmented agents, contamination risks expand to include search-time. Han et al. (2025) introduce search-time contamination, where an agent retrieves benchmark Q&A pages during evaluation, thereby artificially inflating scores.

Membership Inference Attacks Membership inference attacks (MIA) focus on the idea of determining whether an example has been trained on by a model based on (white-box or black-box) access to the model alone (Shokri et al., 2017). It relates to test set contamination in that detecting contamination can be cast as a membership inference problem. The MIA literature spans computer vision (e.g., Yeom et al. (2018); Salem et al. (2018); Sablayrolles et al. (2019); Jagielski et al. (2024)) and more recently to language modeling (e.g., Carlini et al. (2021); Zarifzadeh et al. (2023); Shi et al. (2024); Mattern et al. (2023); Li et al. (2023)). Despite these attempts, progress of sequence-level MIA on language models is hindered by flawed evaluations (Meeus et al., 2024; Zhang et al., 2024b; Jiang et al., 2025). Duan et al. (2024) argue that membership can be inherently blurry for natural language. Das et al. (2024) and Meeus et al. (2024) report that existing MIA testbeds suffer from distribution shifts. Kong et al. (2023) refute MIAs using a theoretical gradient-space attack. Liu et al. (2025) demonstrates the fundamental limitations of n-gram based membership definitions which hinder downstream tests, with Mangaokar et al. (2025) providing a concrete of exploit of existing MIA tests via poisoning. Due to these challenges, recent work also explore enhancing membership signals by leveraging multiple correlated sequences as inputs (Maini et al., 2021; Kandpal et al., 2023; Maini et al., 2024), which are closely related to detecting contamination of an entire test set rather than individual test examples (Golchin & Surdeanu, 2023; Oren et al., 2023).

Dose–response relationships. Most similar to our idea of a dose–response relationship is Hernandez et al. (2022), which argued that highly repetitive data can be severely damaging if the number of repeats incentivizes memorizing that data and if doing so consumes a meaningful fraction of

the model's capacity. Our framework connects this incentive perspective with model capacity and observed contamination effects.

Positioning. Relative to prior work that asks *whether* models are contaminated and *how* to detect or mitigate it, our contribution is a unified *dose–response* framing that quantifies *how much* performance can be attributed to contamination-driven memorization as a function of exposure (e.g., repeats, paraphrases) and training trajectory. Our measurements and fits operationalize this principle across model sizes and token budgets, connecting the controlled injections above with scaling-law regularities.