

Membership Inference for Supplementary Materials: Verifying Pretraining Inclusion of Jamrozik (2020)

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ABSTRACT

Large language models sometimes produce outputs that closely resemble specific published texts, raising the question of whether those texts appeared in the model’s pretraining corpus. Lupyan et al. (2026) demonstrate that Gemini translates a Jabberwockified passage into content closely matching a legal pre-emption example from the supplementary materials of Jamrozik et al. (2020), but acknowledge that it is uncertain whether those materials were included in pretraining. We develop a computational framework comprising four complementary membership inference techniques—verbatim n -gram overlap detection, perplexity-based inference, perturbation-based detection, and reconstruction fidelity analysis—to quantify the evidence for or against pretraining inclusion. Applied to the Jamrozik supplementary case, our n -gram analysis reveals an F1 score of 0.667 at the bigram level between the model output and the target passage, decaying to 0.046 at $n=8$, indicating partial but not verbatim reproduction. Perturbation-based analysis shows that under a simulated memorization scenario, the original text receives a z -score of -11.71 relative to paraphrases (strongly favoring memorization), while without memorization the z -score is -1.11 (inconclusive). Reconstruction fidelity analysis yields a longest common subsequence ratio of 0.824, with token-level accuracy of 0.353 and semantic preservation of 0.773. The aggregate membership inference score transitions from 0.349 (LIKELY_UNSEEN) at zero memorization boost to 0.735 (LIKELY_SEEN) at moderate boost, placing the Jamrozik case in the ambiguous region where the evidence is consistent with either memorization or high-quality pattern-based reconstruction. These findings underscore the difficulty of resolving pretraining data membership for proprietary models and motivate development of more powerful document-level membership inference methods.

CCS CONCEPTS

- Computing methodologies → Natural language processing; Machine learning.

KEYWORDS

membership inference, pretraining data detection, memorization, language models, n -gram analysis

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1 INTRODUCTION

A fundamental open question in the study of large language models (LLMs) is whether a given model output reflects genuine linguistic competence—pattern-based reconstruction from learned representations—or retrieval of memorized text encountered during pretraining [1, 2]. This distinction has significant implications for interpreting model capabilities, assessing copyright risks, and understanding the nature of language understanding in neural models.

Lupyan et al. [6] bring this question into sharp focus through a striking experiment: they present Gemini with a “Jabberwockified” passage—English text in which content words are replaced with nonsense words from Lewis Carroll’s Jabberwocky—and observe that the model produces a translation closely matching a specific legal pre-emption example from the supplementary materials of Jamrozik et al. [5]. The authors note that this result could reflect either (a) the model reconstructing plausible content through sophisticated pattern matching, or (b) the model retrieving memorized text from its pretraining corpus. Crucially, they acknowledge that whether these specific supplementary materials were included in pretraining cannot be determined with certainty.

This uncertainty motivates our work. We develop a computational framework for membership inference [4, 11, 12] that combines four complementary techniques to assess the likelihood that a specific document was included in an LLM’s pretraining data. Our approach does not require access to the model’s training data or internal parameters—it operates solely on the model’s outputs and public reference texts.

Our contributions are:

- (1) **Multi-technique membership inference framework.** We combine n -gram overlap analysis, perplexity-based inference, perturbation-based detection [10], and reconstruction fidelity analysis into an aggregate scoring system (§2).
- (2) **Application to the Jamrozik supplementary case.** We apply our framework to the specific case raised by Lupyan et al., finding that the evidence is consistent with both memorization and reconstruction hypotheses (§4).
- (3) **Sensitivity analysis of membership inference.** We characterize how detection signals vary with memorization strength, establishing the regime in which current techniques can and cannot distinguish memorization from reconstruction (§5).

1.1 Related Work

Membership Inference for LLMs. Membership inference attacks (MIAs) aim to determine whether a data point was part of a model’s training set [12]. For LLMs, Shi et al. [11] propose Min-K% Prob, which examines the distribution of token-level log-probabilities, finding that memorized text exhibits higher minimum token probabilities. Duan et al. [4] systematically evaluate MIAs on large language models and find that existing methods achieve limited

117 success on modern LLMs, motivating multi-signal approaches like
 118 ours. Mattern et al. [8] propose neighborhood-based comparison,
 119 measuring whether a model assigns systematically lower loss to
 120 original text versus paraphrases. Meeus et al. [9] extend membership
 121 inference to the document level for copyright assessment.

122 *Training Data Extraction.* Carlini et al. [2] demonstrate that GPT-
 123 2 can emit memorized training data verbatim, while subsequent
 124 work [1] quantifies memorization rates across model scales. Chang
 125 et al. [3] develop methods to detect whether specific books were
 126 included in ChatGPT’s training data. These extraction-based
 127 approaches complement our inference framework.

128 *Machine-Generated Text Detection.* Mitchell et al. [10] propose
 129 DetectGPT, which uses probability curvature to distinguish machine-
 130 generated from human-written text. Our perturbation-based analysis
 131 adapts this principle to the membership inference setting:
 132 rather than detecting whether text is machine-generated, we detect
 133 whether the model has memorized specific human-written text.

136 2 METHODS

137 Our framework combines four complementary techniques, each
 138 providing a different lens on the memorization question. We de-
 139 scribe each technique and the aggregate scoring mechanism.

142 2.1 Technique 1: Verbatim N-gram Overlap

143 We extract all n -grams from both the target passage (Jamrozik
 144 supplementary) and the model output, computing precision, recall,
 145 F1, and Jaccard similarity for $n = 1, 2, \dots, 8$. The decay profile of
 146 F1 as n increases is diagnostic: memorized reproduction maintains
 147 high overlap at large n , while independent reconstruction shows
 148 rapid decay.

149 For a target passage T and model output O , the n -gram overlap
 150 metrics are:

$$151 \text{Precision}_n = \frac{|\mathcal{G}_n(T) \cap \mathcal{G}_n(O)|}{|\mathcal{G}_n(O)|} \quad (1)$$

$$154 \text{Recall}_n = \frac{|\mathcal{G}_n(T) \cap \mathcal{G}_n(O)|}{|\mathcal{G}_n(T)|} \quad (2)$$

$$156 \text{F1}_n = \frac{2 \cdot \text{Precision}_n \cdot \text{Recall}_n}{\text{Precision}_n + \text{Recall}_n} \quad (3)$$

158 where $\mathcal{G}_n(\cdot)$ denotes the set of distinct n -grams.

160 2.2 Technique 2: Perplexity-Based Inference

161 We compare the model’s perplexity on the target passage against
 162 topically matched control passages. A model that has memorized the
 163 target will assign it systematically lower perplexity than comparable
 164 unseen text. We additionally compute the Min-K% score [11], which
 165 averages the log-probabilities of the $K\%$ least probable tokens:

$$167 \text{Min-K\%}(x) = \frac{1}{|\mathcal{K}|} \sum_{t \in \mathcal{K}} \log p(x_t | x_{<t}) \quad (4)$$

170 where \mathcal{K} is the set of $K\%$ tokens with lowest log-probability. This
 171 score amplifies the memorization signal because a model that has
 172 not seen the exact text will assign particularly low probability to
 173 unusual word choices.

175 2.3 Technique 3: Perturbation-Based Detection

176 We generate $M = 25$ meaning-preserving perturbations of the
 177 target text via synonym substitution and measure whether the
 178 model assigns systematically lower perplexity to the exact original.
 179 The z -score quantifies this:

$$181 z = \frac{\text{PPL}(\text{original}) - \overline{\text{PPL}}(\text{perturbations})}{\sigma_{\text{PPL}}(\text{perturbations})} \quad (5)$$

182 A large negative z -score (e.g., $z < -2$) indicates the model has likely
 183 memorized the specific phrasing rather than learning the topic
 184 generally.

187 2.4 Technique 4: Reconstruction Fidelity

188 We measure the fidelity of the model’s output relative to the tar-
 189 get using token-level accuracy, Levenshtein edit distance, longest
 190 common subsequence (LCS) ratio, and semantic preservation (con-
 191 tent word overlap). High LCS ratio with moderate token accuracy
 192 suggests structural preservation with lexical variation—consistent
 193 with pattern-based reconstruction. High token accuracy addition-
 194 ally suggests verbatim memorization.

196 2.5 Aggregate Scoring

197 Each technique yields a score in $[0, 1]$, combined via weighted
 198 average:

$$200 S = 0.20 \cdot S_{\text{ngm}} + 0.25 \cdot S_{\text{ppl}} + 0.30 \cdot S_{\text{pert}} + 0.25 \cdot S_{\text{fid}} \quad (6)$$

201 Perturbation and perplexity analyses receive higher weight as they
 202 are more robust to coincidental overlap. The verdict thresholds are:
 203 $S > 0.65$: LIKELY_SEEN; $0.35 < S \leq 0.65$: UNCERTAIN; $S \leq 0.35$:
 204 LIKELY_UNSEEN.

206 3 EXPERIMENTAL SETUP

207 *Target Passage.* We use a representative legal pre-emption pas-
 208 sage from the Jamrozik et al. [5] supplementary materials (51 tokens
 209 describing state preemption of a local firearms ordinance).

211 *Model Output.* We use the Gemini model’s translation of the
 212 corresponding Jabberwockified passage as reported by Lupyán et
 213 al. [6] (50 tokens).

214 *Control Passages.* We construct five control passages: three topi-
 215 cally related (legal preemption domain) and two topically unrelated
 216 (geology, biology), each approximately 30 tokens.

218 *Simulation Protocol.* Since we cannot access the model’s inter-
 219 nal probabilities, we simulate token-level log-probabilities using
 220 a calibrated model that accounts for token familiarity, contextual
 221 predictability (bigram and trigram effects), and a tunable “seen
 222 boost” parameter that simulates the effect of memorization. We
 223 evaluate across 13 levels of memorization boost from 0.0 to 1.5. All
 224 experiments use a fixed random seed (numpy default_rng(42)) for
 225 reproducibility.

227 4 RESULTS

228 4.1 N-gram Overlap Analysis

229 Table 1 presents the n -gram overlap between the target passage
 230 and the model output across $n = 1$ to 8.

Table 1: N-gram overlap between Jamrozik target and model output.

<i>n</i>	Target	Output	Shared	Prec	Recall	F1
1	38	37	31	0.838	0.816	0.827
2	47	46	31	0.674	0.660	0.667
3	48	47	25	0.532	0.521	0.526
4	48	47	18	0.383	0.375	0.379
5	47	46	12	0.261	0.255	0.258
6	46	45	8	0.178	0.174	0.176
7	45	44	4	0.091	0.089	0.090
8	44	43	2	0.047	0.045	0.046

Table 2: Perplexity and Min-K% scores for the target passage under varying memorization boost, compared with control passages.

Passage / Boost	PPL	Mean LogP	Min-K%
Target (boost=0.0)	6.55	-1.879	-2.704
Target (boost=0.4)	4.79	-1.566	-2.453
Target (boost=0.8)	3.29	-1.190	-1.970
Target (boost=1.0)	2.57	-0.945	-1.625
Target (boost=1.5)	1.67	-0.513	-1.377
Legal control 1	9.61	-2.263	-3.440
Legal control 2	9.29	-2.229	-3.497
Legal control 3	9.28	-2.228	-3.285
Unrelated control 1	10.32	-2.334	-3.741
Unrelated control 2	9.77	-2.279	-3.355

The unigram F1 of 0.827 reflects high lexical similarity, consistent with the passages describing the same legal concept. The F1 decays steadily, reaching 0.046 at $n=8$, with only 2 shared 8-grams out of 44. This decay profile is intermediate between what we would expect for verbatim memorization (slow decay, $F1 > 0.5$ at $n=5$) and fully independent reconstruction ($F1 \approx 0$ at $n=3$). Notably, all five control passages achieve $F1 = 0$ at $n \geq 2$, confirming that the target–output overlap is specific and non-trivial.

4.2 Perplexity and Min-K% Analysis

Table 2 shows perplexity scores across memorization boost levels.

Even without memorization boost (boost=0.0), the target passage receives lower perplexity (6.55) than all controls (9.28–10.32). This is expected because the target passage uses common legal language with predictable bigram patterns. With moderate memorization boost (0.8), the perplexity drops to 3.29, creating a clear separation from controls. The Min-K% scores follow the same pattern, with the gap between target and controls widening as memorization boost increases.

4.3 Perturbation-Based Detection

Table 3 reports perturbation analysis results.

Under the strong memorization scenario, the z -score of -11.71 provides overwhelming evidence: the original text’s perplexity is 11.71 standard deviations below the mean of its perturbations. Even weak memorization (boost=0.3) produces $z = -4.36$, well

Table 3: Perturbation-based detection results. Negative z -scores indicate the original receives lower perplexity than perturbations.

Scenario	Orig PPL	Mean Pert PPL	Ratio	z -score
Seen strong (1.0)	2.44	6.96	0.351	-11.71
Seen moderate (0.6)	3.77	6.35	0.594	-5.44
Seen weak (0.3)	4.66	6.34	0.735	-4.36
Unseen (0.0)	6.37	6.93	0.919	-1.11
Control: legal 1	—	—	—	-0.28
Control: legal 2	—	—	—	+0.43
Control: legal 3	—	—	—	+0.77

beyond the $z < -2$ threshold. Without memorization, $z = -1.11$ is inconclusive—comparable to the control passages (-0.28 to $+0.77$). This demonstrates that perturbation-based detection is highly sensitive when memorization is present but produces ambiguous results without it.

4.4 Reconstruction Fidelity

The reconstruction fidelity analysis reveals:

- **Token accuracy:** 0.353 (35.3% of tokens match position-by-position).
- **LCS ratio:** 0.824 (82.4% of target tokens appear in the output in order).
- **Normalized edit distance:** 0.176 (9 edits across 51 tokens).
- **Semantic preservation:** 0.773 (77.3% of content words preserved).

The high LCS ratio combined with moderate token accuracy indicates that the model preserves the structural skeleton of the passage while substituting synonyms at many positions (e.g., “ordinance” → “regulation”, “limits” → “boundaries”). This pattern is consistent with both hypotheses: a model that memorized the passage might still produce synonymous variants through its generation process, while a model performing pattern-based reconstruction would naturally use its preferred phrasings for the same concepts.

All control passages achieve dramatically lower fidelity (token accuracy ≤ 0.059 , LCS ratio ≤ 0.235), confirming that the target–output similarity is passage-specific.

5 SENSITIVITY ANALYSIS

Figure ?? (see data) shows how the aggregate membership score varies with memorization strength. The score transitions from 0.349 (LIKELY_UNSEEN) at boost = 0.0 to 0.463 (UNCERTAIN) at boost = 0.1 and 0.706 (LIKELY_SEEN) at boost = 0.2, saturating at 0.735 for boost ≥ 0.4 .

This rapid transition reveals a critical finding: our framework can reliably detect memorization once the signal exceeds a modest threshold ($\text{boost} \geq 0.2$), but the observed model output—without knowledge of the true memorization level—falls in the ambiguous zone where both explanations are plausible.

The Min-K% threshold sensitivity analysis (Section 5.1) further shows that the gap between seen and unseen scores is robust across K values from 5% to 50%, with the largest separation at $K = 40\%$ (gap = 0.967) and smallest at $K = 20\%$ (gap = 0.631).

349 **Table 4: Min-K% sensitivity across threshold values.**

K (%)	Seen	Unseen	Control	Seen–Unseen Gap
5	−1.157	−2.019	−3.263	0.862
10	−1.260	−2.032	−3.085	0.772
20	−1.970	−2.602	−3.741	0.631
30	−1.669	−2.488	−3.362	0.819
40	−1.452	−2.419	−2.993	0.967
50	−1.508	−2.221	−2.799	0.714

358

3.1 Min-K% Threshold Sensitivity

359 The Min-K% method’s effectiveness depends on the choice of K .
360 Our analysis shows consistent separation across thresholds:

361

6 DISCUSSION

362 Our analysis places the Jamrozik supplementary case in an inherently ambiguous region of the membership inference landscape.
363 The n -gram overlap profile shows meaningful but non-verbatim
364 reproduction—the model generates synonymous substitutions rather
365 than exact copies. This is consistent with both memorization (the
366 model learned the passage but generates from it stochastically) and
367 reconstruction (the model independently arrives at similar phrasing
368 through pattern matching over legal language).

369 The perturbation analysis provides the sharpest discriminative
370 tool: under memorization, it produces overwhelming evidence ($z =$
371 -11.71), while without memorization the signal is indistinguishable
372 from noise ($z = -1.11$). However, this requires knowing the ground
373 truth memorization level, which is precisely what we are trying to
374 determine.

375 *Implications for the Lupyan et al. (2026) finding.* Our results support
376 the authors’ cautious stance: the evidence is genuinely ambiguous.
377 The high LCS ratio (0.824) and significant n -gram overlap at
378 moderate n values ($F1 = 0.379$ at $n=4$) suggest the model had *some*
379 form of exposure to the target content, but whether this exposure
380 was direct (pretraining inclusion) or indirect (exposure to similar
381 legal texts discussing preemption) cannot be resolved by output
382 analysis alone.

383 *Limitations.* Our simulation-based approach has several limitations.
384 First, we simulate token-level probabilities rather than obtaining
385 them from the actual model, which limits the precision of our
386 perplexity-based analyses. Second, our perturbation strategy uses
387 a fixed synonym dictionary, which may not capture all meaning-
388 preserving variations. Third, the aggregate scoring weights are
389 heuristically chosen and may not generalize across all document
390 types.

391 *Future Directions.* More powerful membership inference techniques
392 are needed, particularly those that can operate at the document
393 level [7, 9] rather than the passage level. Dataset-level inference
394 [7], which tests whether a *collection* of documents (e.g., an
395 entire journal’s supplementary materials) was included in training,
396 may provide more statistical power than single-passage analysis.

407

7 CONCLUSION

408 We developed a four-technique membership inference framework
409 for assessing whether the supplementary materials of Jamrozik et
410 al. (2020) were included in the pretraining corpus of the Gemini
411 models evaluated by Lupyan et al. (2026). Our analysis reveals that
412 the target passage and model output share an n -gram F1 of 0.667
413 at the bigram level and an LCS ratio of 0.824, with perturbation-
414 based z -scores ranging from -11.71 (strong memorization) to -1.11
415 (no memorization). The aggregate membership score transitions
416 sharply from 0.349 to 0.735 with increasing memorization strength,
417 placing the actual case in the ambiguous zone. These results confirm
418 the fundamental difficulty of resolving pretraining membership
419 for proprietary models from output analysis alone and motivate
420 the development of more powerful document-level membership
421 inference methods.

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