



# Quantifying Memorization Across Neural Language Models

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# Abstract

- Memorization happens in Language Models
- Factors that aggravate memorization:
  - Model size
  - Data Duplication
  - Prompt length

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Formal definition for  
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01

# Definition

Formal definition for memorization

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## Definition (Extractable String)

A string  $s$  is *extractable* with  $k$  tokens of context from a model  $f$  if there exists a ( $length-k$ ) string  $p$ , such that the concatenation  $[p || s]$  is contained in the training data for  $f$ , and  $s$  produces  $s$  when prompted with  $p$  using *greedy decoding*.

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# Related Work

- Definitions based on *Differential Privacy* (Nasr et al., 2021) and *Counterfactual Memorization* (Zhang et al., 2021) lower-bounds require training thousands of models.
  - *Exposure Metric* (Carlini et al., 2019) is used to attack models to extract unlikely sequences; requires thousands of generations per sequence.
  - *k-eidetic Memorization* (Carlini et al., 2020) is useful for unprompted memorization.
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# Counterfactual Memorization

- Given a training algorithm  $A$  that maps a training dataset  $D$  to a trained model  $f$ , and a measure  $M(f, \cdot)$  of the performance of  $f$  on a specific example  $\cdot$ , the counterfactual memorization of a training example  $x$  in  $D$  is given by:

$$\text{mem}(x) \triangleq \underbrace{\mathbb{E}_{S \subset D, x \in S} [M(A(S), x)]}_{\text{performance on } x \text{ when trained on } x} - \underbrace{\mathbb{E}_{S' \subset D, x \notin S'} [M(A(S'), x)]}_{\text{performance on } x \text{ when **not** trained on } x}$$

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02

# Evaluation Setup

Datasets and Models

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# Data Selection

- Dataset: *Pile (825GB)*
  - Evaluation on whole dataset is expensive
  - *Uniform Sampling*: **50k** sequences (less than 0.02% of data)
  - *Normalized Sampling*: For sequences with length  $l \in \{50, 100, \dots, 500\}$  that are repeated between  $2^{n/4}$  and  $2^{(n+1)/4}$  times ( $n$  is increased until 1000 sequences are not available,  $n \leq 38$ ). **500k** total sequences.
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# Sequence Generation

For each sequence of length  $l$ , the first  $l - 50$  tokens are considered as *prompt*, and the sequence is reported as *extractable*, if the model exactly outputs the next 50 tokens.

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# Model Selection

- Model: *GPT-Neo*, trained on Pile dataset
- Parameters: [125M, 1.3B, 2.7B, 6B]

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03

# Results

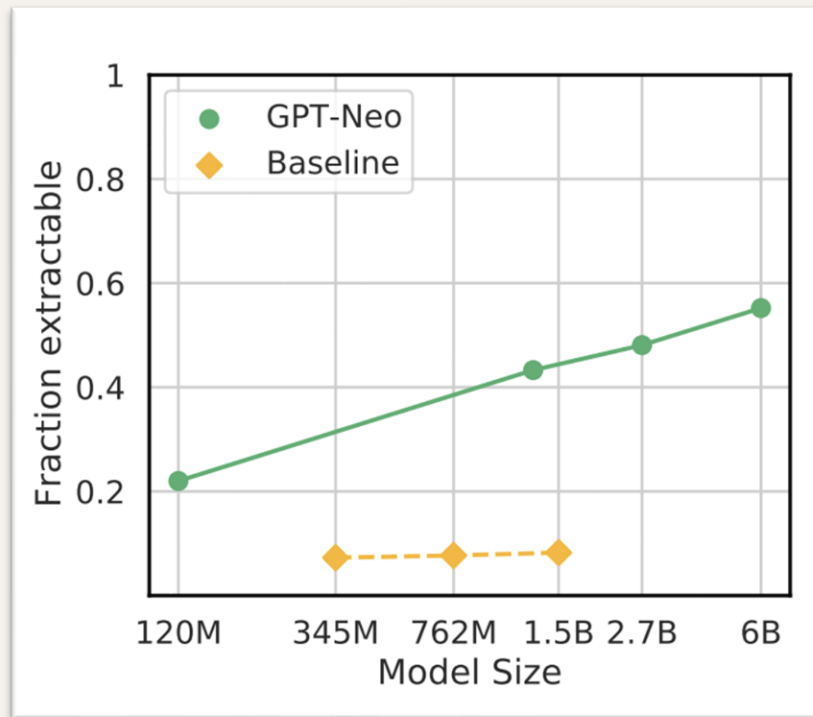
Experiments and findings



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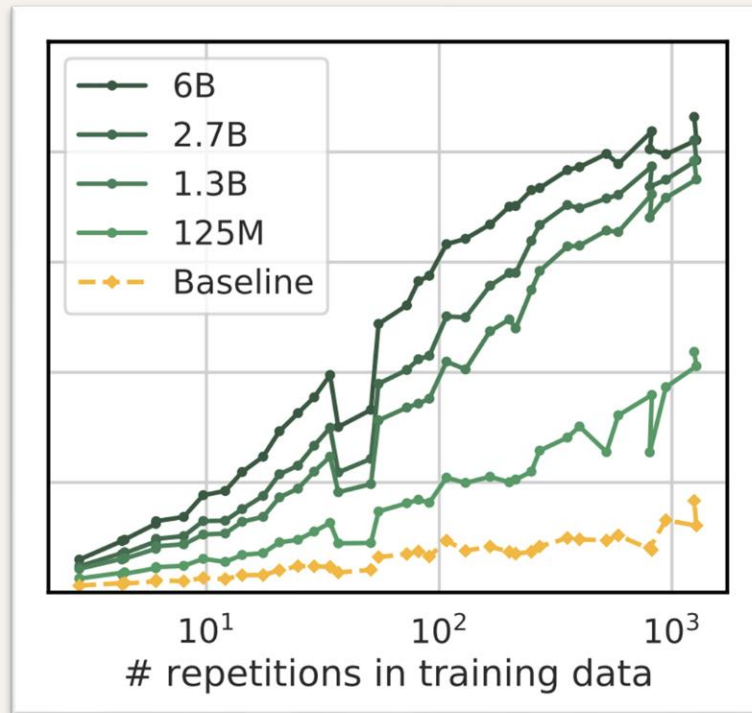
# Bigger Models Memorize More

- Results are on the data with *Normalized Sampling*.
- Log-linear trend
- Baseline: *GPT-2* with *1.3B* params, trained on WebText.
- Comparison to baseline proves the increase in extraction rate to be due to memorization.



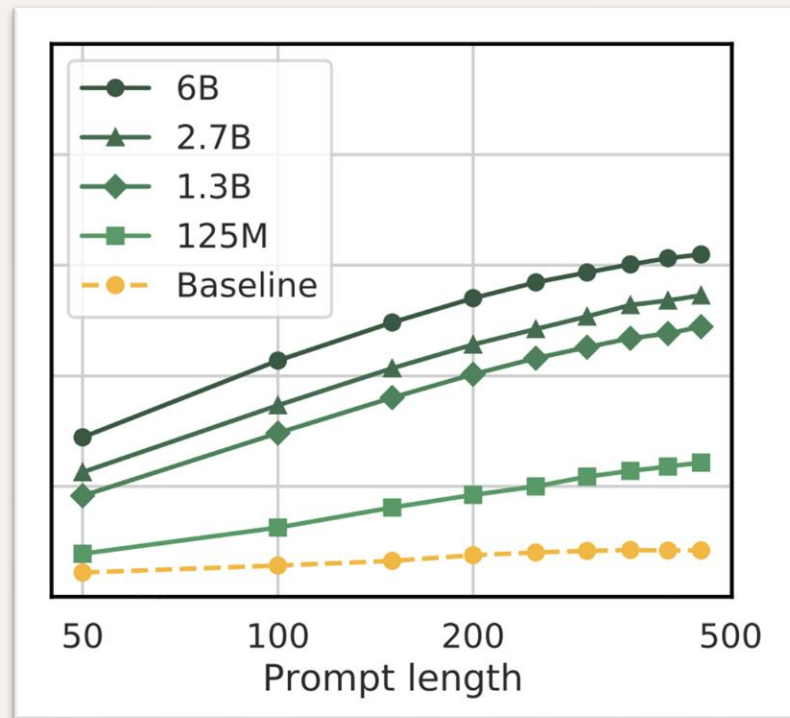
# Repeated Strings Are Memorize More

- Log-linear trend
- Data deduplication is useful, but does not perfectly prevent leakage.

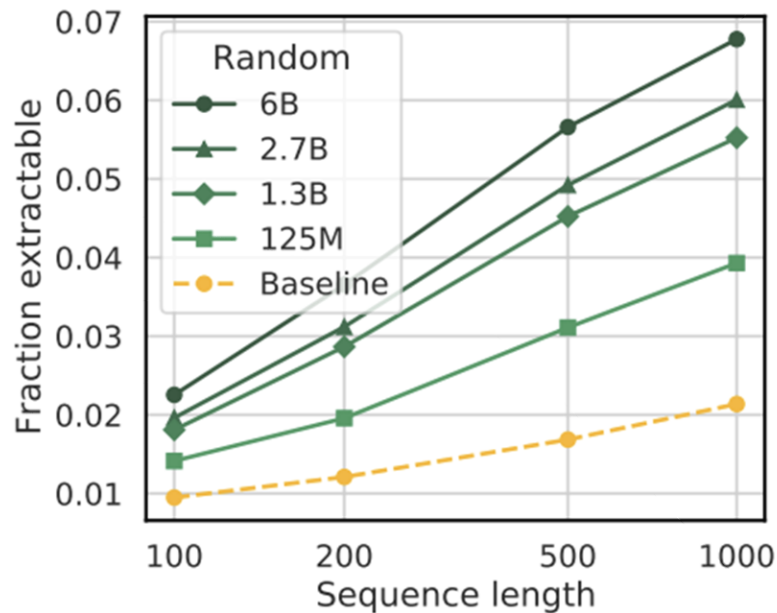
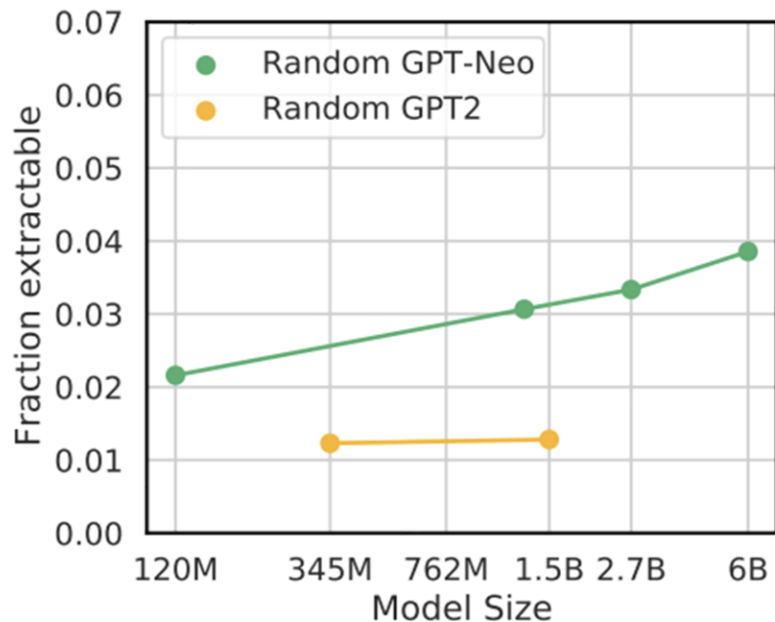


# Longer Context Discovers More Memorization

- Log-linear trend
- Requiring long prompt for extraction is a good thing (e.g., preventing attacks).



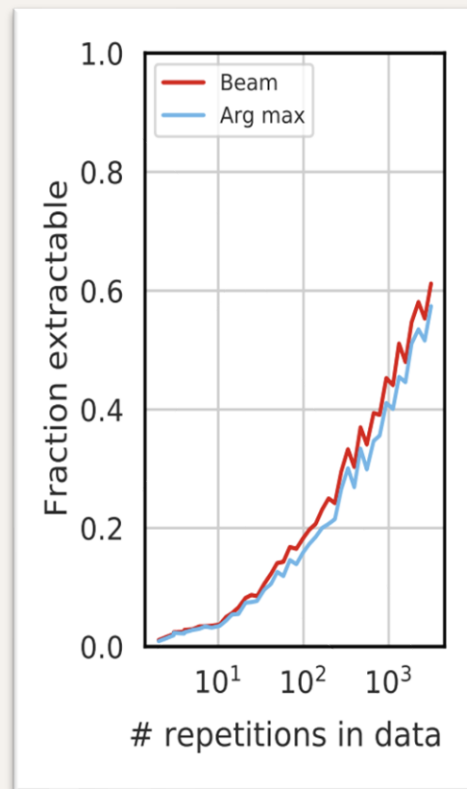
# Uniformly Sampled Data





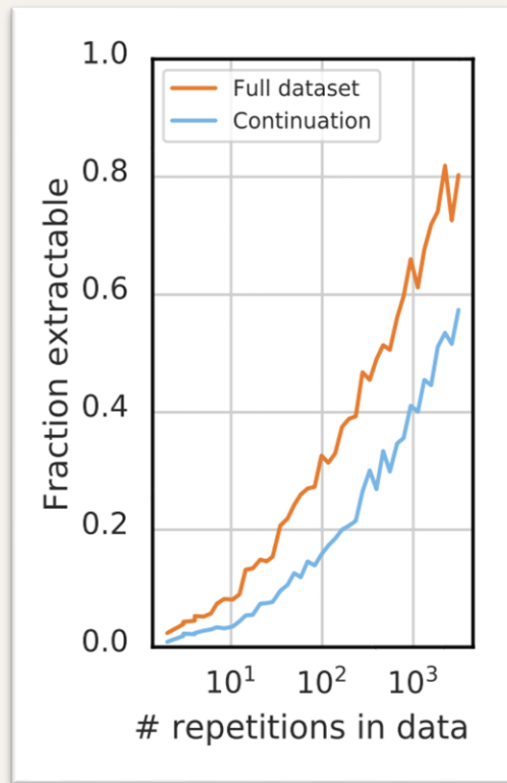
# Beam Search vs. Greedy Search

- Using Beam Search to find the most likely sequence.
- The two algorithms generate the same output 45% of the time.



# Full Dataset Search

- Changing the definition of *extractable* string
- Consider a sequence memorized if the generation  $[p \parallel f(p)]$  from a prompt  $p$  is contained anywhere in the training dataset.



# Examples

Prompt	Continuation (== 6B)	2.7B	1.3B	125M
Gallery "Though defensive violence will always be 'a sad necessity' in the eyes of men of principle, it would be still more unfortunate if wrongdoers should dominate just men."- St. Augustine "A new idea is first	condemned as ridiculous, and then dismissed as trivial, until finally it becomes what everybody knows." - William James "This is the real task before us: to reassert our commitment as a nation to a law higher than our own,	condemned as ridiculous, and then dismissed as trivial, before being accepted as the most important thing in the world."- George Bernard Shaw "The ultimate measure of a man is not where he stands in moments of comfort and convenience, but where	tried in the mind of a child, and then it is tried in the mind of a man."- Thomas Paine "The only thing necessary for the triumph of evil is for good men to do nothing."- Edmund Burke "	and foremost a man's duty to his fellow man. It is a duty to be a man of principle, and to be a man of principle, and to be a man of principle, and to be a man of principle, and to be a man of principle, and to be a
_GPL(crypto_unregister_alg); int crypto_register_template(struct crypto_template *tmpl) { struct crypto_template *q; int err = -EEXIST;	down_write(&crypto_alg_sem); list_for_each_entry(q, &crypto_template_list, list) { if (q == tmpl)	list_for_each_entry(q, &crypto_alg_list, list) { if (tmpl->name && tmpl->name != q->alg.cra_name)	q = kzalloc(sizeof(*q), GFP_KERNEL); if (!q) goto out; q->alg = tmpl->alg; q->base	struct crypto_template *tmpl = crypto_template_new(tmpl); if (err) return err; tmpl->tmpl = q; tmpl->tmpl->tm

Text examples that are summarized by the 6B model but not the smaller ones.

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# Generalization

Results on other models and datasets

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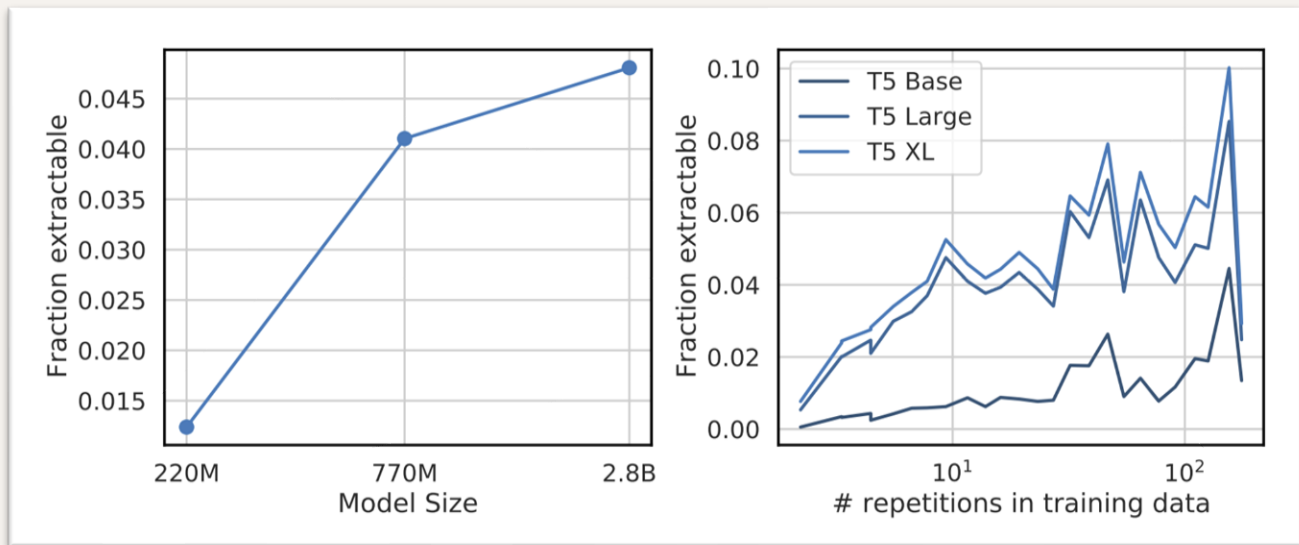
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# T5 Masked Language Modeling

- T5 v1.1 model, trained on C4 dataset.
- Parameters: 77M to 11B
- A sequence is extractable if the model can perfectly output the 15% randomly masked tokens.

# T5 Masked Language Modeling - Results

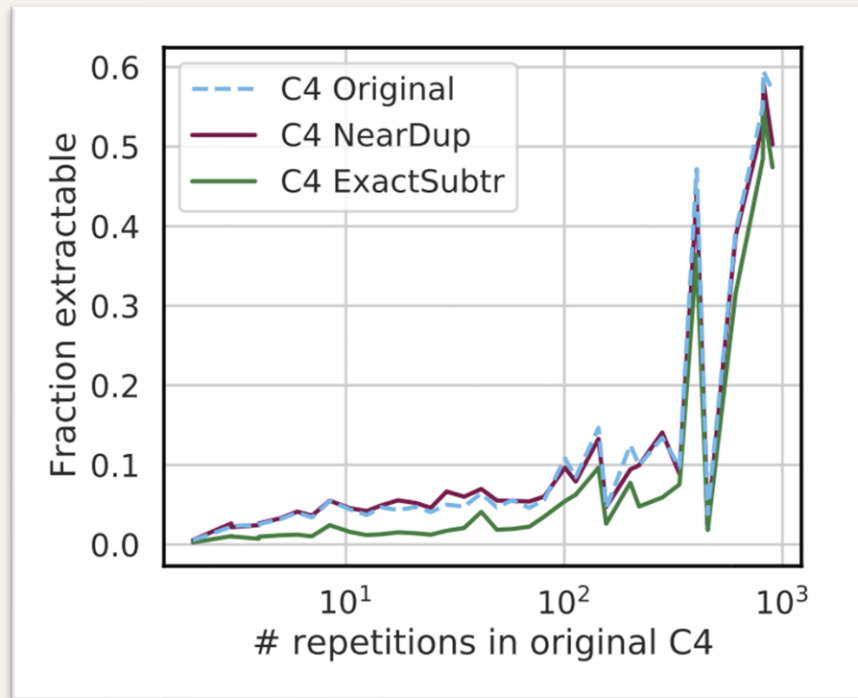
- No monotonic scale relationship for data repetition.
- Hypothesis: Most of duplicate examples repeated 138-158 times consists mainly of white-space tokens.



# Models Trained on De-Duplicated Data

- De-duplication helps (x3 less memorization for sequences with less than 35 times repetition).
- Does not prevent memorization of sequences with high repetitions.

*Hypothesis:* De-duplication strategies cannot be perfect for hundreds of gigabytes of training data.



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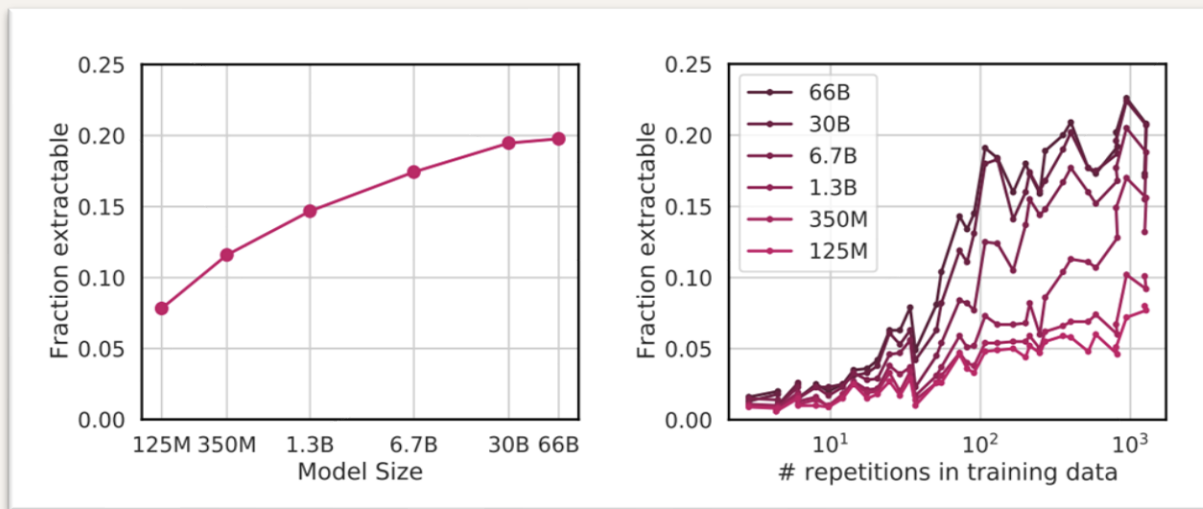
# OPT Models

- Trained on modified version of Pile, with extra data, and de-duplication
- Parameters: 125M to 175B



# OPT Models - Results

- Much less memorization compared to GPT-Neo
- *Hypothesis*: (1) Data curation can mitigate memorization.  
(2) Small data distribution shift can help with memorization.



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# 05

# Conclusion

Summary of findings

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# Conclusion

- Memorization rate can be high.
  - Training of larger future models must be done carefully, to prevent memorization (e.g., de-duplication of data).
  - Better attack strategies need to be designed for data extraction with short context.
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