The Inverse Scaling Effect of Pre-Trained Language Model Surprisal Is Not Due to Data Leakage

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PAPER

Key Takeaways

The inverse scaling effect of pre-trained LM surprisal is unlikely to be due to data leakage. We provide two reasons why:

1. Widely used reading time corpora suffer little from data leakage measured in terms of token n-gram overlap
2. The inverse scaling effect of surprisal is replicated with LMs trained on 'leakage-free' data

Language processing and LM surprisal

People experience processing difficulty at unpredictable words,

The coast guard had seen a shark
The coast guard had seen a zebra

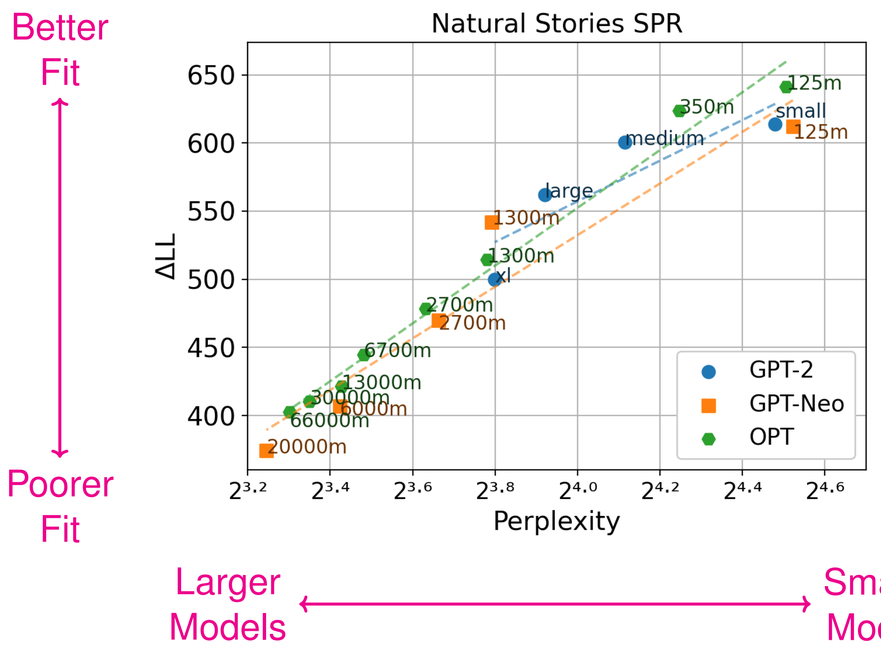
e.g. Ehrlich and Rayner [2]

which has led to research that evaluates LM surprisal (negative log probability) as a predictor of human reading times

Word	*If*	*you*	*were*	*to*	*journey*
Reading Time	571 ms	354 ms	386 ms	383 ms	457 ms
LM1 Surprisal	7.76	0.81	5.42	2.09	14.62
LM2 Surprisal	6.71	0.78	5.22	2.30	13.93
LM3 Surprisal	7.10	0.56	5.15	2.39	15.02

Background: Inverse scaling effect of LM surprisal

Surprisal from larger pre-trained LMs yields a poorer fit to reading times [figure from 9]



However, this may be due to data leakage, as the text material used to collect reading times is often available online [11]

Method: n-gram overlap detection using CDAWGs

Compacted Directed Acyclic Word Graphs [CDAWGs; 8] efficiently return the longest attested suffix of the query sequence

Reference: `h e l l o w o r l d`
Query: `l l o y d`

Output: `1 2 3 0 1`

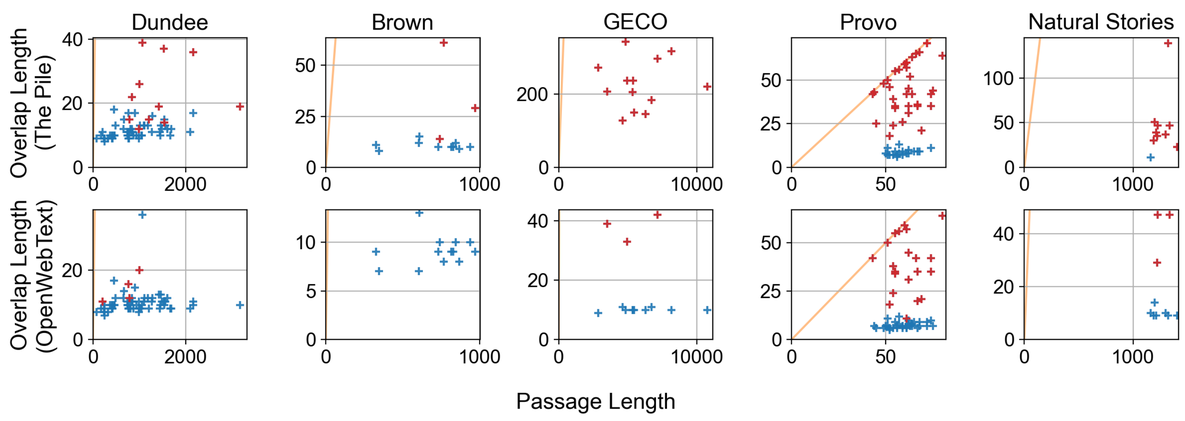
The longest n-gram overlap between reference and query is of length 3

Study 1: Assessment of data leakage

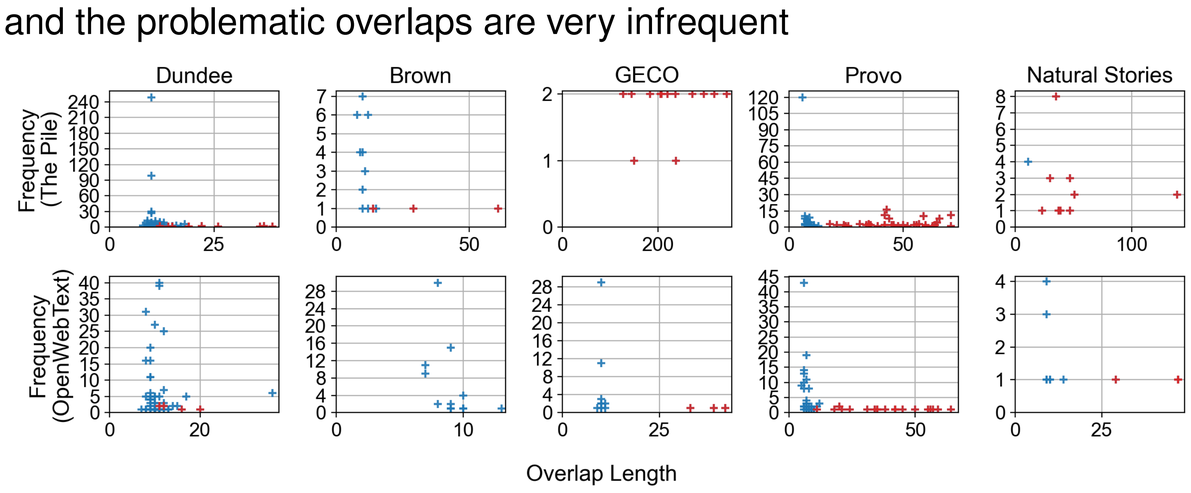
Reference (pre-training data): The Pile, OpenWebText [4, 5]

Query (reading time data): Dundee, Brown, GECO, Provo, Natural Stories [6, 10, 1, 7, 3]

Except for Provo, overlaps are relatively short in light of passage length,



and the problematic overlaps are very infrequent

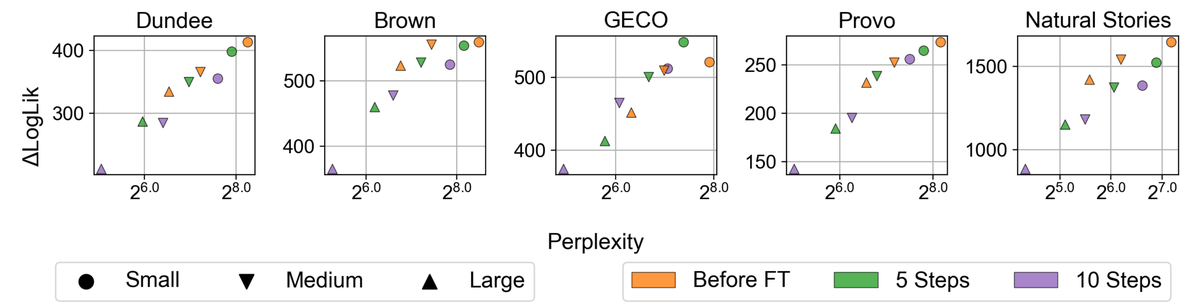


Study 2: Evaluation of LMs trained 'leakage-free'

Clean data: ~21B tokens with at most 11 continuous tokens of overlap

Artificial leakage: Fine-tuning for 5 and 10 steps on reading time corpora

Inverse scaling is replicated with clean data, but leakage strengthens effect



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