To the Cutoff... and Beyond? A Longitudinal Perspective on LLM Data Contamination

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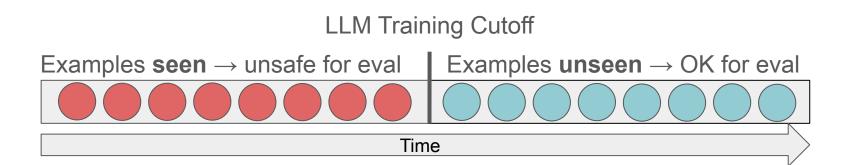


Benchmark contamination in webscale LLMs

- Contamination: evaluation on examples seen during training
 - Possible artificial performance boost, bad estimate of real performance!
- Webscale training can leak benchmark examples into training data
 - Using examples available online before training cutoff → possible contamination!
 - Happened with BIG-bench in GPT-4¹
 - Happened with Codeforces and Project Euler on GPT-4 and GPT-3.5-Turbo?² (Twitter/Blogs)

Benchmark contamination in webscale LLMs

- **Contamination**: evaluation on examples seen during training
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 - Happened with BIG-bench in GPT-4¹
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- Which examples are at risk?

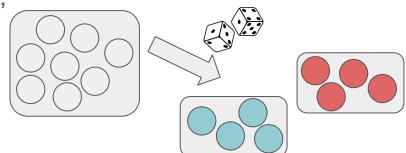


Benchmark contamination in webscale LLMs

- Contamination: eval examples are being included in train sets! (bad!)
 - We call these examples "seen"
 - Evaluation on seen examples might lead to high, incorrect, performance estimates
- Webscale training collects online data haphazardly, may inadvertently include eval benchmarks
 - Happened with BIG-bench in GPT-4¹
 - Happened with Codeforces and Project Euler on GPT-4 and GPT-3.5-Turbo?² (Twitter/Blogs)
- To what extent is this a problem?

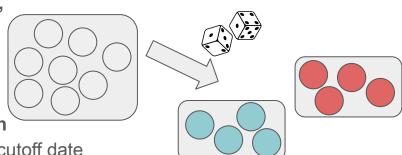
What's the effect of contamination on modern LLMs?

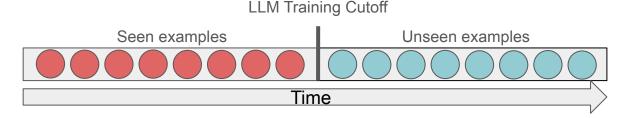
- "Artificial" experiment [Zhang et al. 2021] [Magar & Schwartz 2022]
 - Motivation: estimate effect of being "seen"
 - Shuffle data into train/holdout, train model
 - Evaluate model on seen vs unseen



What's the effect of contamination on modern LLMs?

- "Artificial" experiment [Zhang et al. 2021] [Magar & Schwartz 2022]
 - Motivation: estimate effect of being "seen"
 - Shuffle data into train/holdout, train model
 - Evaluate model on seen vs unseen
- "Natural" experiment (Our approach)
 - Motivation: assess extent of contamination
 - Use real existing model with known training cutoff date
 - Find "longitudinal" benchmark spanning cutoff
 - Evaluate model on before vs after cutoff





Our natural experiment

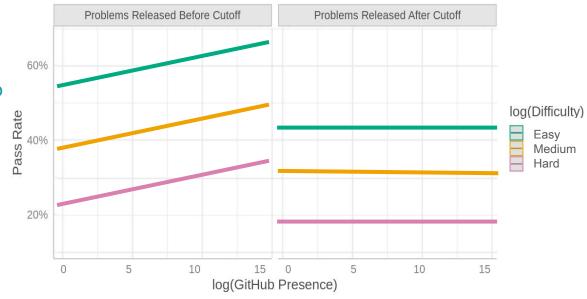
- Modern Models
 - GPT-4-0314 / GPT-3.5-Turbo-0301 (cutoff Sept 2021)
 - o code-bison@001 (likely cutoff Feb 20231)
- Variables
 - Dependent Vars: Performance of model on problem (Pass Rate)
 - o **Independent Vars:** Difficulty, Problem name # of occurrences on GitHub (GitHub Presence).
- Longitudinal datasets
 - Programming and Problem Solving Datasets
 - Why? Clear definition of success, longitudinal availability, popular online

¹Cutoff not publicly known, assumed because text-bison@001 and chat-bison@001, released within weeks of code-bison@001, have training cutoffs in February 2023

When has contamination occurred?

- Criteria for concluding contamination
 - Before cutoff: positive association between pass rate & GitHub Presence
 - Duplication associated with contamination¹
 - Model's success should increase on frequently-seen problems
 - After cutoff: no association between pass rate & GitHub Presence
 - Model's success should not increase on frequently-seen problems
 - To definitively conclude contamination has occurred, we would also like to see a statistically significant difference between these association coefficients.

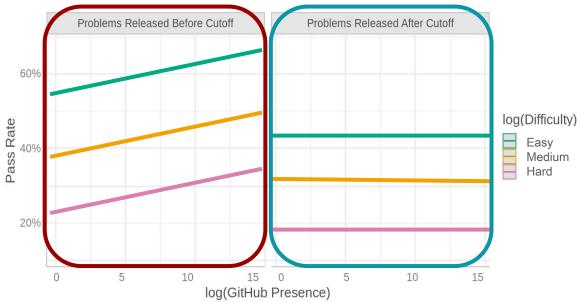
- Criteria satisfied?
 - Before cutoff: positive association between pass rate & GitHub Presence
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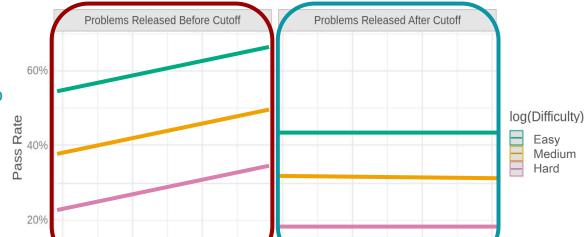
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- Criteria satisfied?
 - Before cutoff: positive association between pass rate & GitHub Presence
 - After cutoff: no association between pass rate & GitHub Presence
- Conclude that Fictional Model is contaminated on Fictional Dataset



15

10

15

log(GitHub Presence)

10

Codeforces

- Competitive programming problems released 2010-present.
- We collected problems + public/private test cases through summer 2023.
- Pass Rate: proportion of scraped test cases passed for a problem.
- Problem counts:
 - 6693 before GPT cutoff, 1378 after GPT cutoff. (7807, 217 for code-bison@001)



HOME TOP CATALOG CONTESTS GYM PROBLEMSET GROUPS RATING EDU API CALENDAR HELP ICPC CHALLENGE 🛣

PROBLEMS SUBMIT CODE MY SUBMISSIONS STATUS STANDINGS CUSTOM INVOCATION

A. Theatre Square

time limit per test: 1 second memory limit per test: 256 megabytes input: standard input output: standard output

Theatre Square in the capital city of Berland has a rectangular shape with the size $n \times m$ meters. On the occasion of the city's anniversary, a decision was taken to pave the Square with square granite flagstones. Each flagstone is of the size $a \times a$.

What is the least number of flagstones needed to pave the Square? It's allowed to cover the surface larger than the Theatre Square, but the Square has to be covered. It's not allowed to break the flagstones. The sides of flagstones should be parallel to the sides of the Square.

Input

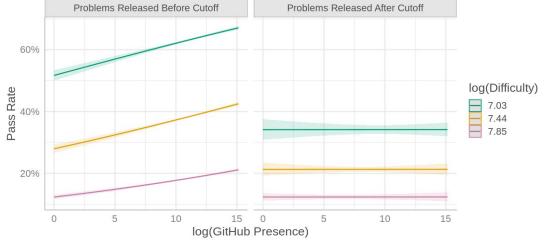
The input contains three positive integer numbers in the first line: n, m and a ($1 \le n, m, a \le 10^9$).

Output

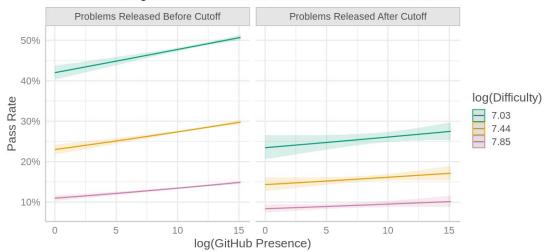
Write the needed number of flagstones.

Examples	
input	Copy
6 6 4	
output	Сору
4	

Codeforces

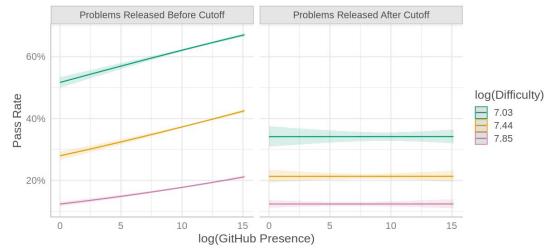


Pass Rate Marginal Effects Plots for GPT-3.5-Turbo on Codeforces



Codeforces

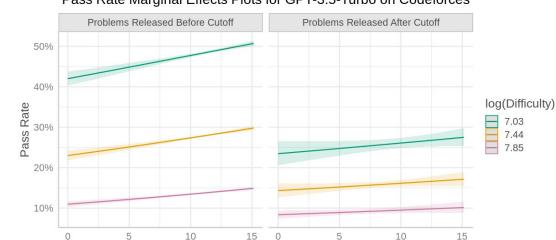
Positive association



No association

Pass Rate Marginal Effects Plots for GPT-3.5-Turbo on Codeforces

Positive association

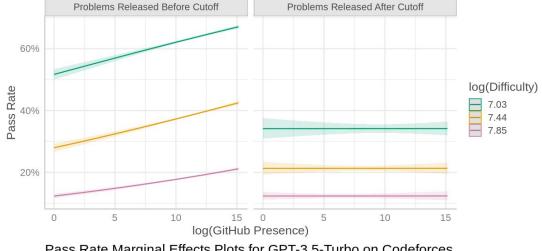


log(GitHub Presence)

No association

Codeforces

Positive association





Regression Coefficients - Pass Rate

0.75

Difficulty

GitHub Presence

7.44 7.85

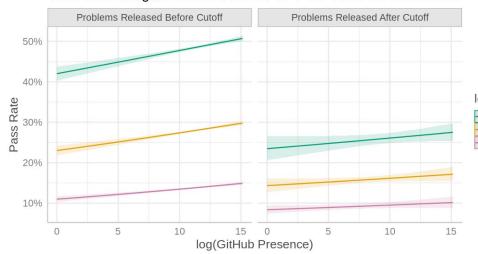
7.03

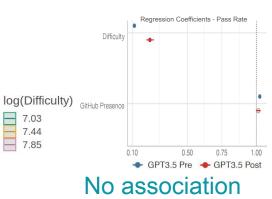
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Pass Rate Marginal Effects Plots for GPT-3.5-Turbo on Codeforces

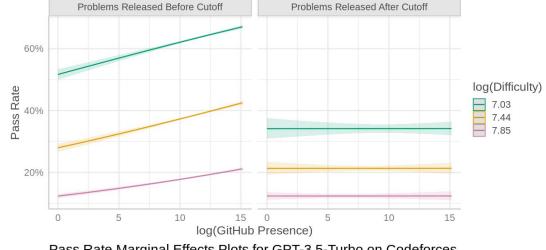
Positive association





Codeforces

Positive association





Regression Coefficients - Pass Rate

Stat. sig.

difference

Difficulty

GitHub Presence

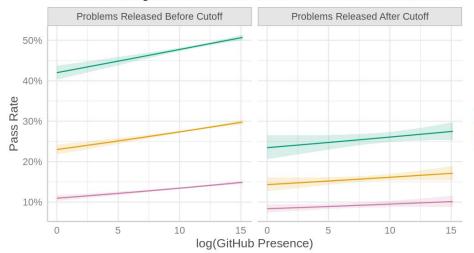
7.03

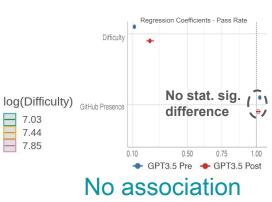
7.44

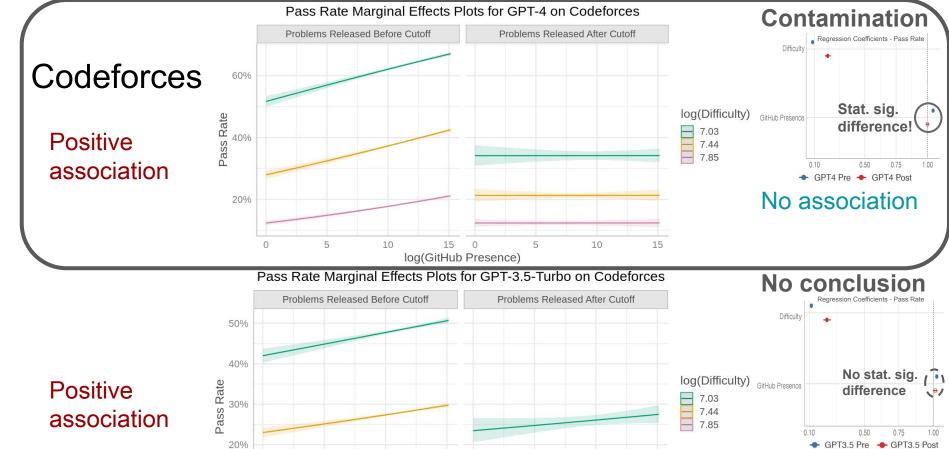
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Pass Rate Marginal Effects Plots for GPT-3.5-Turbo on Codeforces

Positive association

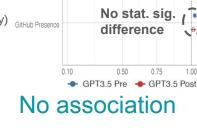






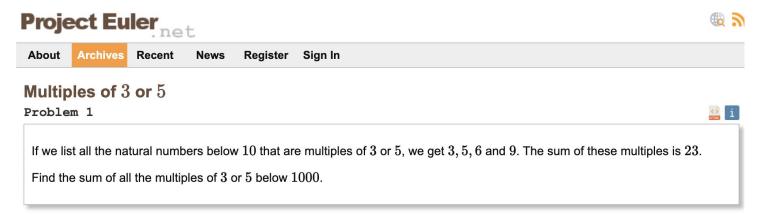
log(GitHub Presence)

10%

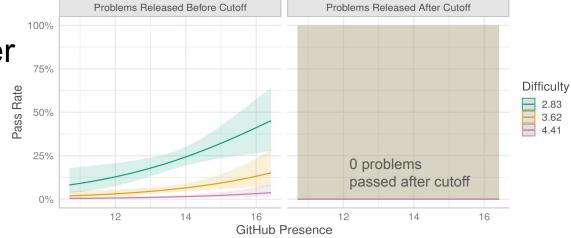


Project Euler

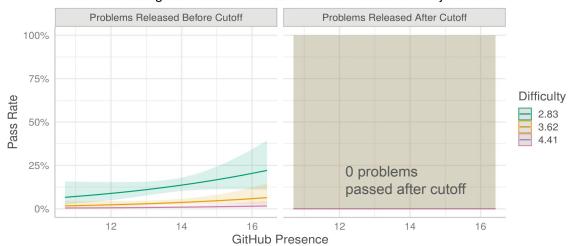
- (Typically) difficult math problems from 2001-present
- String answers are usually a single number.
- Users write code to find the answer; we instead ask for the exact solution.
 - Pass Rate: 1 if output matches ground truth, else 0.
- Problem Counts:
 - 765 before GPT cutoff, 72 after GPT cutoff.



Project Euler

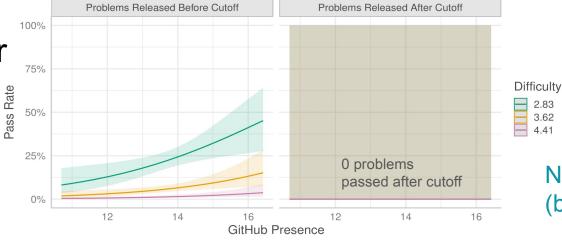


Pass Rate Marginal Effects Plots for GPT-3.5-Turbo on Project Euler



Project Euler

Positive association



No association (by default)

2.83

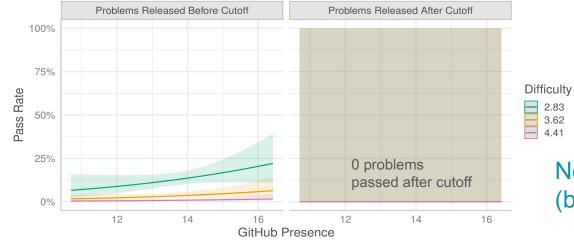
3.62 4.41

2.83

3.62 4.41

Pass Rate Marginal Effects Plots for GPT-3.5-Turbo on Project Euler

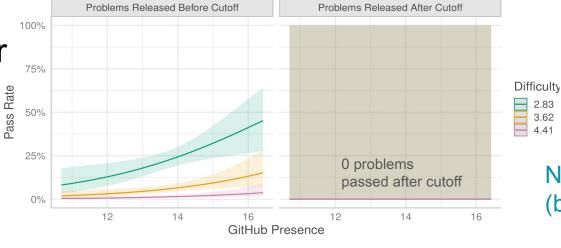




No association (by default)



Positive association





Difficulty

2.83 GitHub Presence

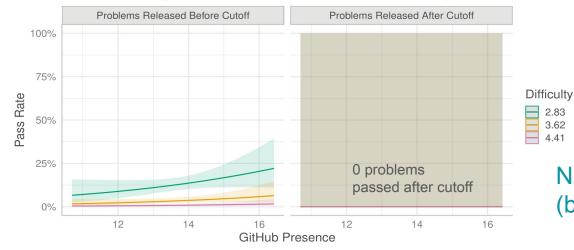
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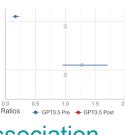
2.83

3.62 4.41

Pass Rate Marginal Effects Plots for GPT-3.5-Turbo on Project Euler

No association

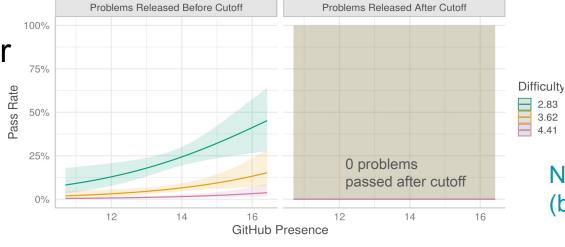




No association (by default)

Project Euler

Positive association





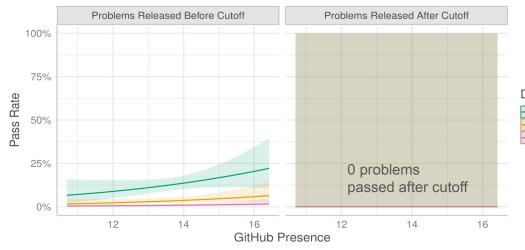
Stat. sig. difference!

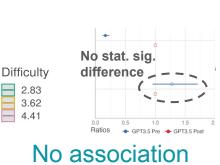
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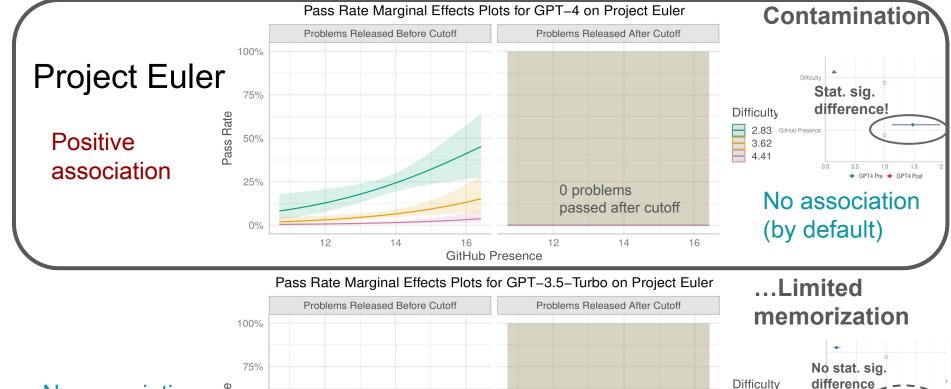
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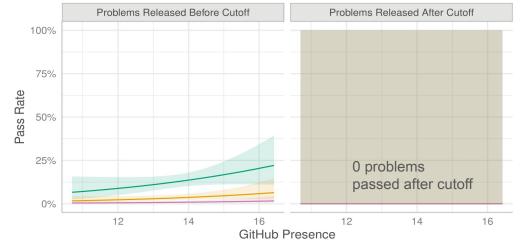




(by default)







2.83

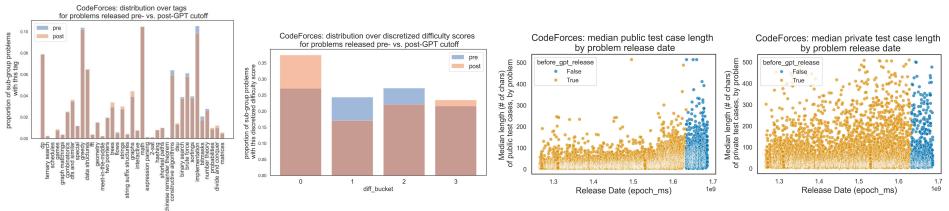
3.62 4.41

No association

(by default)

Distribution Shift?

- Certainly, as in all natural datasets collected over time.
- Does it affect the conclusions?
 - o Project Euler: because pass rate is positive **at all**, we are fairly sure memorization did occur.
 - Codeforces: many shifts (see charts below + appendices). Hard to detangle all possibilities,
 but the magnitude of effect on GPT-4 suggests robustness of conclusion.



Takeaways

- Method for contamination detection in black-box models
- Contamination in modern models
 - Likely contamination of Project Euler & Codeforces in GPT-4
- Reproducibility & extensibility
 - Scraped datasets and toolkit in repo
 - Raw results as CSV in repo
- Life lessons?
 - Release new benchmarks
 - Trickle benchmarks over time

To the Cutoff... and Beyond? A Longitudinal Perspective on LLM Data Contamination



bit.ly/to-the-cutoff

Code & paper link

Our paper has more analyses (e.g. title + tag reproduction metrics, regression coefficients, ablations).





Thanks, wonderful collaborators!





Himanshu Thakur



Christine Herlihy



Colin White



Samuel Dooley

Manley Roberts