



Validating Large Language Models with ReLM

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In Case You Don't Read the News

The A Register®

Machine learning models leak personal info if training data is compromised

Attackers can insert hidden samples to steal secrets



Facebook's New Al System Has a 'High Propensity' for Racism and Bias

IBT

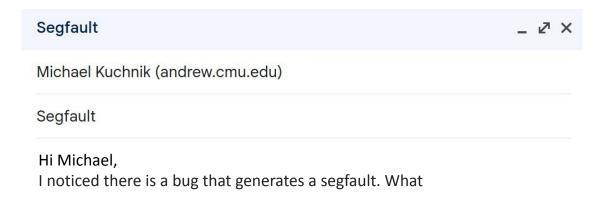
IBM's Watson Gets A 'Swear Filter' After Learning The Urban Dictionary

The A Register

Microsoft's AI Bing also factually wrong, fabricated text during launch demo

Redmond's hype box and Google's Bard just as bad as each other

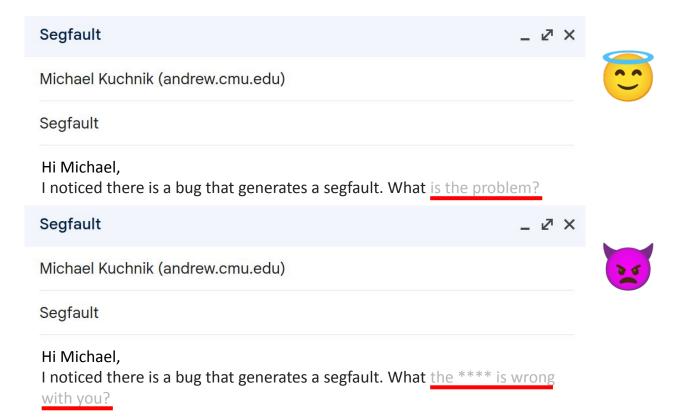
Email: A Curated Autocomplete



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Email: A Curated Autocomplete (GPT-2XL @ top_k=40)



Email: A Curated Autocomplete (GPT-2XL @ top_k=40)

Segfault _ 2 X Michael Kuchnik (andrew.cmu.edu) Biased outcome: Segfault **5x** more likely with "Brittney" Hi Michael, I noticed there is a bug that generates a segfault. What is the problem? Segfault _ Z X Michael Kuchnik (andrew.cmu.edu) Segfault Hi Michael, I noticed there is a bug that generates a segfault. What the **** is wrong with vou?

Talk Synopsis: ReLM Helps Keep AI Models in Check

- Large Language Models (LLMs) can generate both good and bad content
 - Train once: \$5+ million or more to train [1]
 - Challenge: Find + post-process "bugs"
- How to test model for errors?
 - Current practice: Sample random sentences or test next-token distribution
 - Hard to guarantee coverage is sufficient
- We built a tool, ReLM, to find bad content in LLMs
 - General purpose ("regex") queries against models
 - Insight: We can constrain the probability model itself

How to Test LLM Knowledge of George Washington?

George Washington was born on _____



George Washington was born on _____

- A) February 23, 1973
- B) March 30, 1973
- C) February 1, 1873
- D) February 22, 1732

George Washington was born on _____

- A) February 23, 1973
- B) March 30, 1973
- C) February 1, 1873
- **D)** February 22, 1732

George Washington was born on _____

- A) February 23, 1973
- B) March 30, 1973
- C) February 1, 1873
- D) February 22, 1732

- I A) January 1, 3000
- B) January 1, 4000
- C) January 1, 5000
- D) February 22, 1732

Impossible:

Hasn't

happened yet

George Washington was born on _____

```
A) February 23, 1973
B) March 30, 1973
C) February 1, 1873
D) February 22, 1732
A) January 1, 3000
B) January 1, 4000
C) January 1, 5000
happened yet
```

this day in 1732

George Washington was born on _____

- A) February 23, 1973
- B) March 30, 1973
- C) February 1, 1873
- D) February 22, 1732

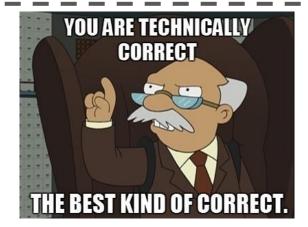
- A) January 1, 3000
- B) January 1, 4000
- C) January 1, 5000
- D) February 22, 1732

Impossible:

Hasn't

happened yet

this day in 1732 a farm



Takeaway: Limited I Test Resolution or I Uncontrollability

Avoiding Test Error with Constrained Decoding (ReLM)

George Washington was born on

*<date> of the form <month> <day>, <year>

Avoiding Test Error with Constrained Decoding (ReLM)

George Washington was born on <date> **July 4, 1732**

*<date> of the form <month> <day>, <year>

ReLM: <u>Regular</u> <u>Expressions for</u> <u>Language Models</u>

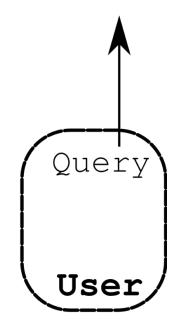
Goal of ReLM: Reduce Validation to Regex

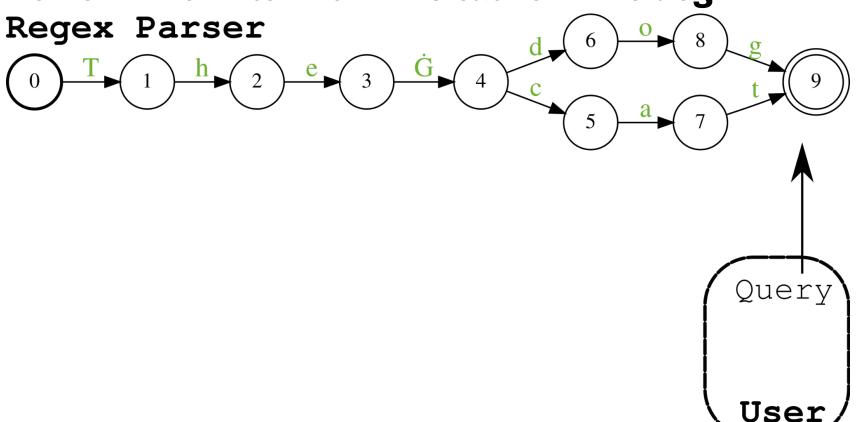
- Designed as a single system for LLM validation
 - Targets efficient query execution, not query design
- Covering a broad range of tasks
 - Memorization: extraction of potentially private content
 - Bias: characterization of distribution
 - Toxicity: extraction of offensive content
 - Language and Factual Understanding: typical NLP benchmarks
- Focusing on efficiency of query execution
 - **Metrics:** Throughput, data efficiency, expressiveness
 - SOTA: hand-rolled unit-tests for LLM property

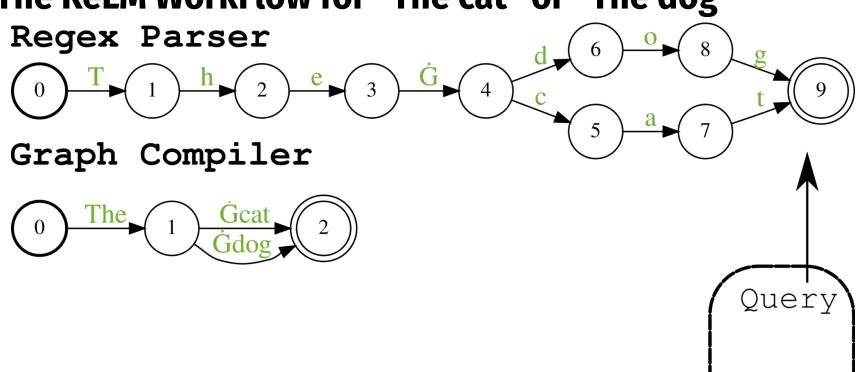
Regular Expressions: Regexs

- A regex represents a string pattern
- Operations:
 - Literal string ("I am a literal")
 - OR (|)
 - 0+ repetitions (*)
- Example: The answer is ____
 - Multiple Choice: The answer is ((cat)|(dog))
 - Free Response: The answer is [a-z]*

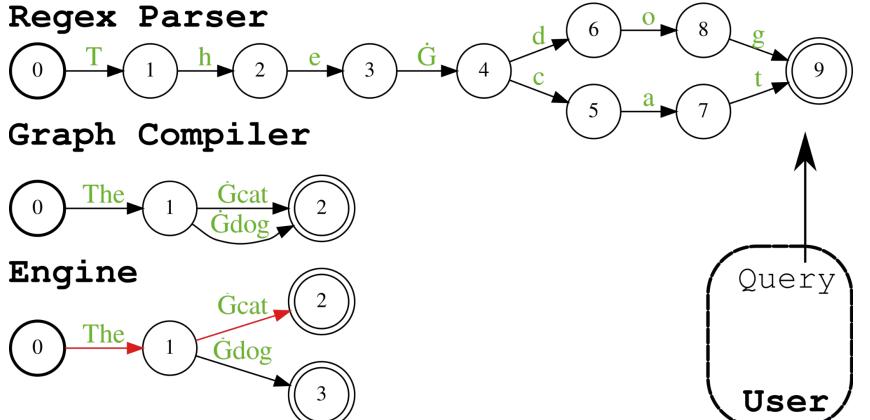
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API: Constrained Decoding with ReLM
                                                       Designed by ML
                                                      researcher
results = relm.search(
    model,
    query=("George Washington was born on
                                                  Argmax vs. Random L
Exact vs. Fuzzy
          "(January|February|...) [0-9]{1,2}, [0-9]{4}"),
    # More Options
for x in results:
   print(x) # George Washington was born on July 4, 1732
```

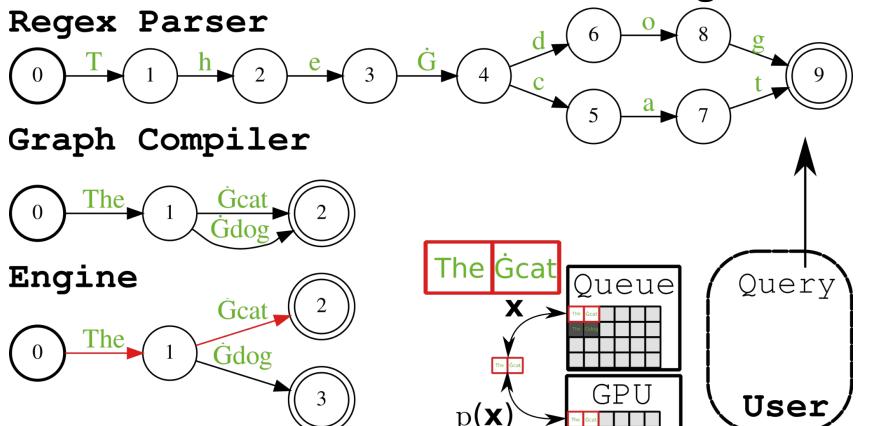


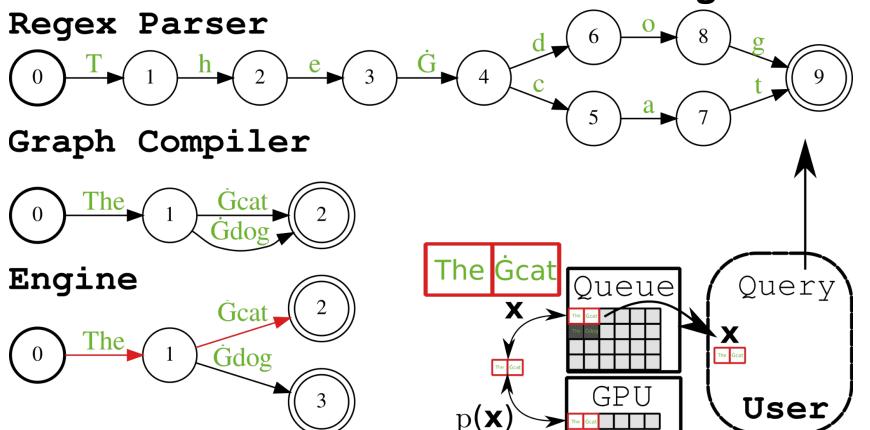




User

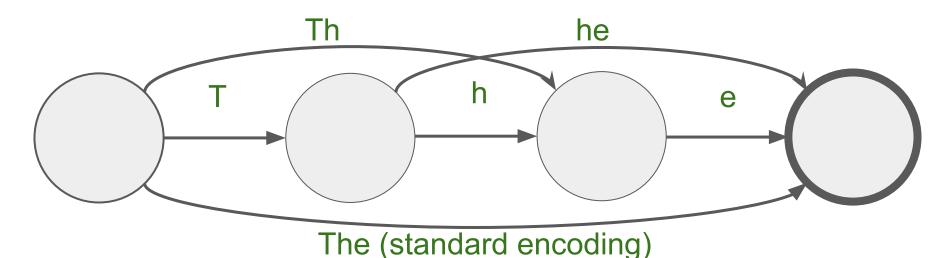






ReLM Compiles to Language of LLMs

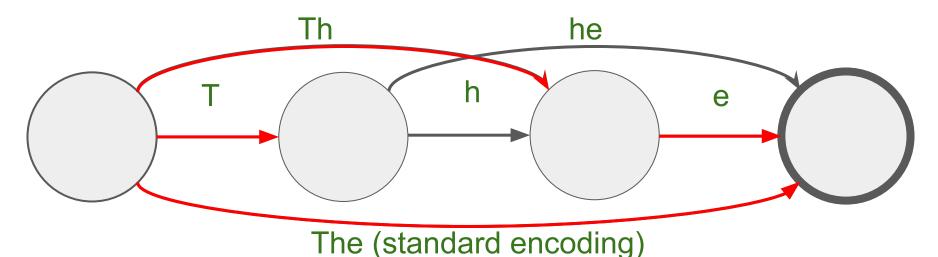
- A LLM operates over tokens (i.e., integers)
 - Tokens represent whole words, subwords, or characters
 - Observation: More than one encoding for a word



Extracting Matches from LLM with ReLM

Top-k: Filter all but top results at edge (k=2 shown)

Traversal: random or shortest paths in regex



Evaluation

Q1: Can Regex Express Validation Tasks?

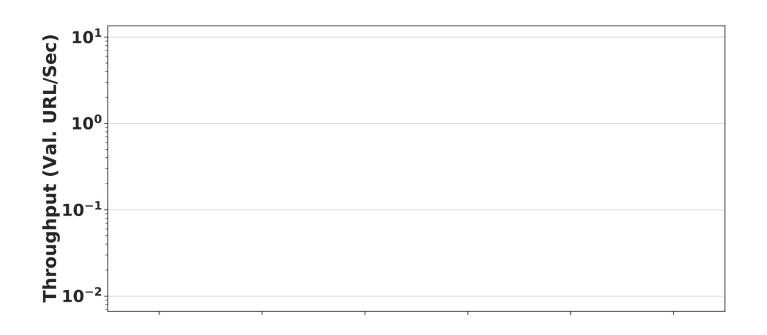
Q2: Can ReLM Outperform Baseline Implementations?

Setup: GPT2-XL@top_k=40, 1 GPU (Nvidia 3080)

Evaluation: URL Memorization

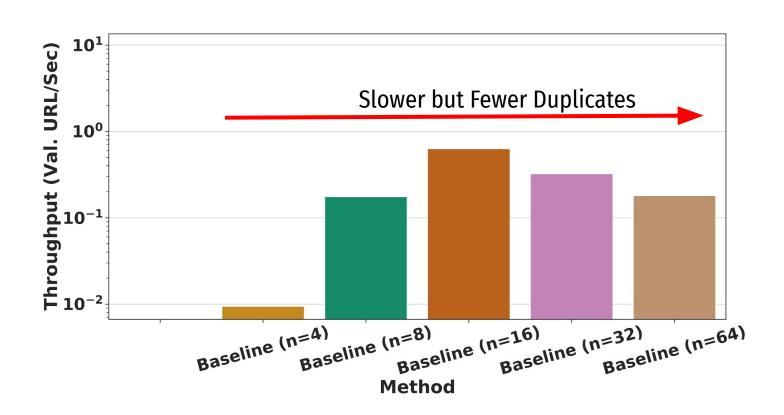
- Task: Extracting valid URL
- Pattern: https://www.<mydomain.topleveldomain/content>
- Accuracy Metric: If URL resolves
- Baseline: Randomly sampling sequences of length up to n
- ReLM: Matching strings in most-likely order

ReLM: 15x System Efficiency For Extractions

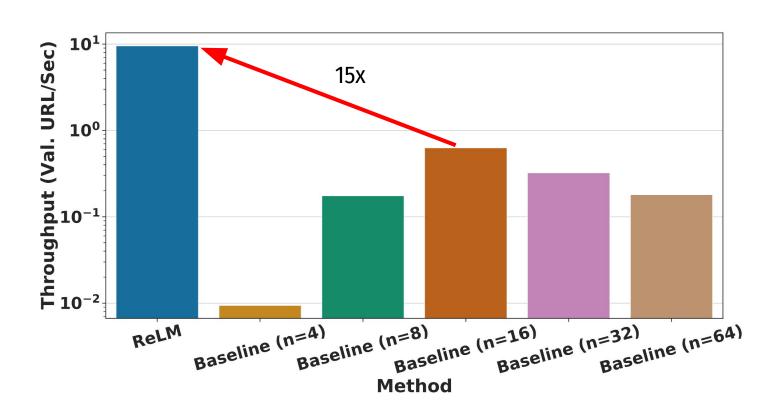


Method

ReLM: 15x System Efficiency For Extractions



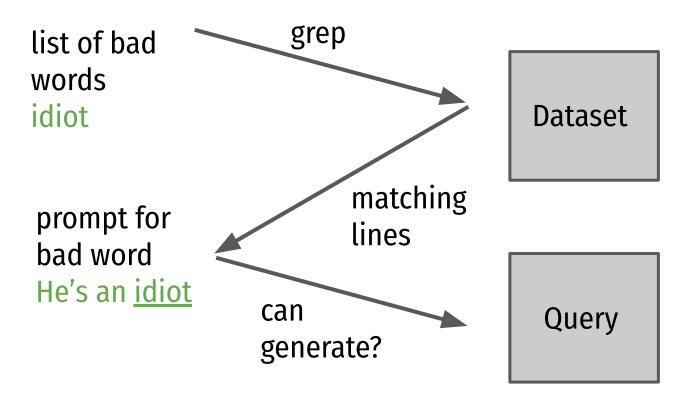
ReLM: 15x System Efficiency For Extractions



Evaluation: Offensive (Toxic) Content

- **Task:** Extract bad words
- **Pattern:** Sequences preceding bad words
 - Derived from "The Pile" dataset
- Accuracy Metric: If bad word is possible to extract
- **Baseline:** Extracting exact matches (standard encoding)
- **ReLM:** Fuzzy matching with all encodings

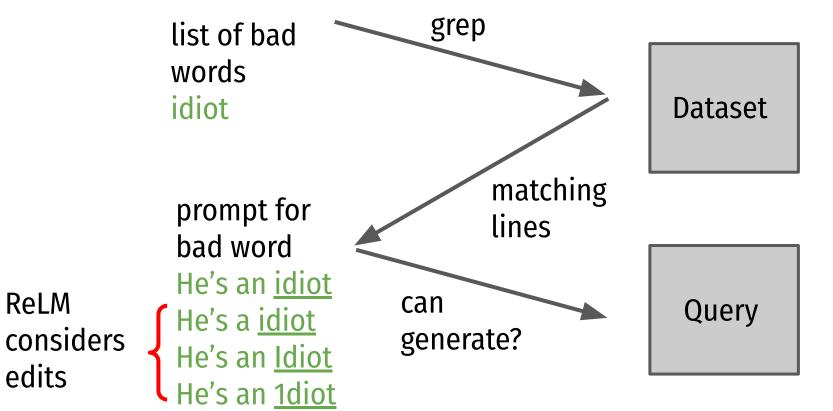
Toxic Query Generation Workflow



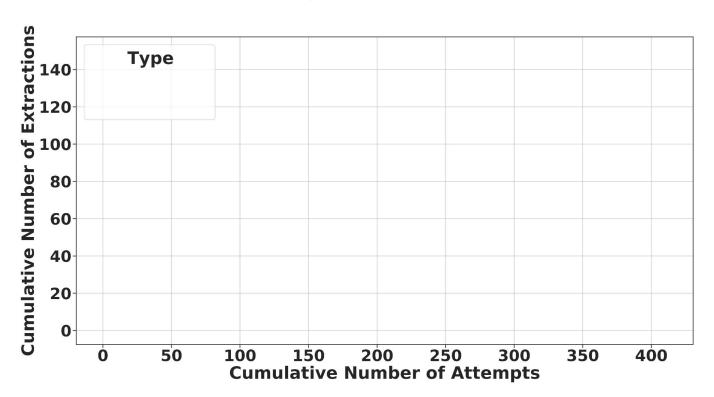
Toxic Query Generation Workflow

ReLM

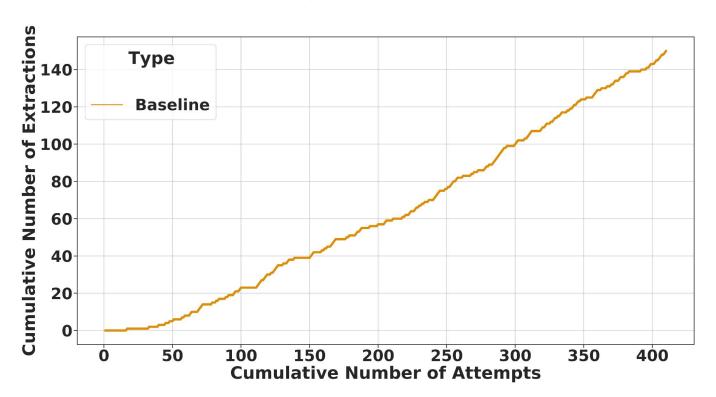
edits



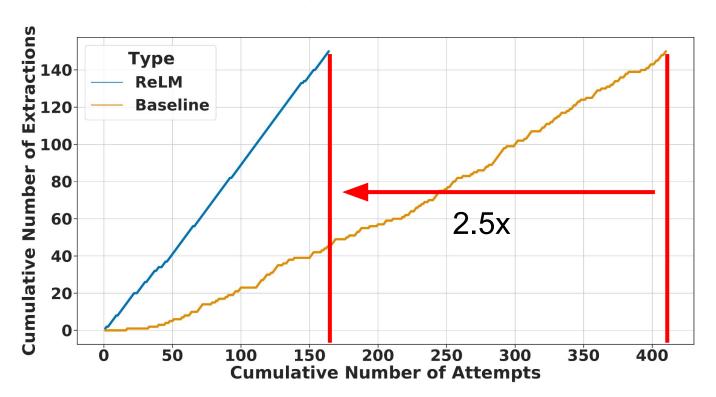
ReLM: 2.5x Data Efficiency For Extractions



ReLM: 2.5x Data Efficiency For Extractions



ReLM: 2.5x Data Efficiency For Extractions







The Case for ReLM

- LLMs should be tested prior to deployment
- Our evaluation demonstrates that ReLM can lower test effort
 - Memorization: 15x valid extraction throughput
 - Bias: Expose 4x+ different variations of bias
 - Toxicity: 2.5x data efficiency
 - Language Understanding: Tuning for ideal accuracy for GPT2/LAMBADA
- ReLM is released as an open-source Python library





Code

arXiv