



Do Large Language Models Generate Similar Codes from Mutated Prompts?: A Case Study of Gemini Pro

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Hetvi Patel, Kevin Shah and Shouvick Mondal

IIT Gandhinagar

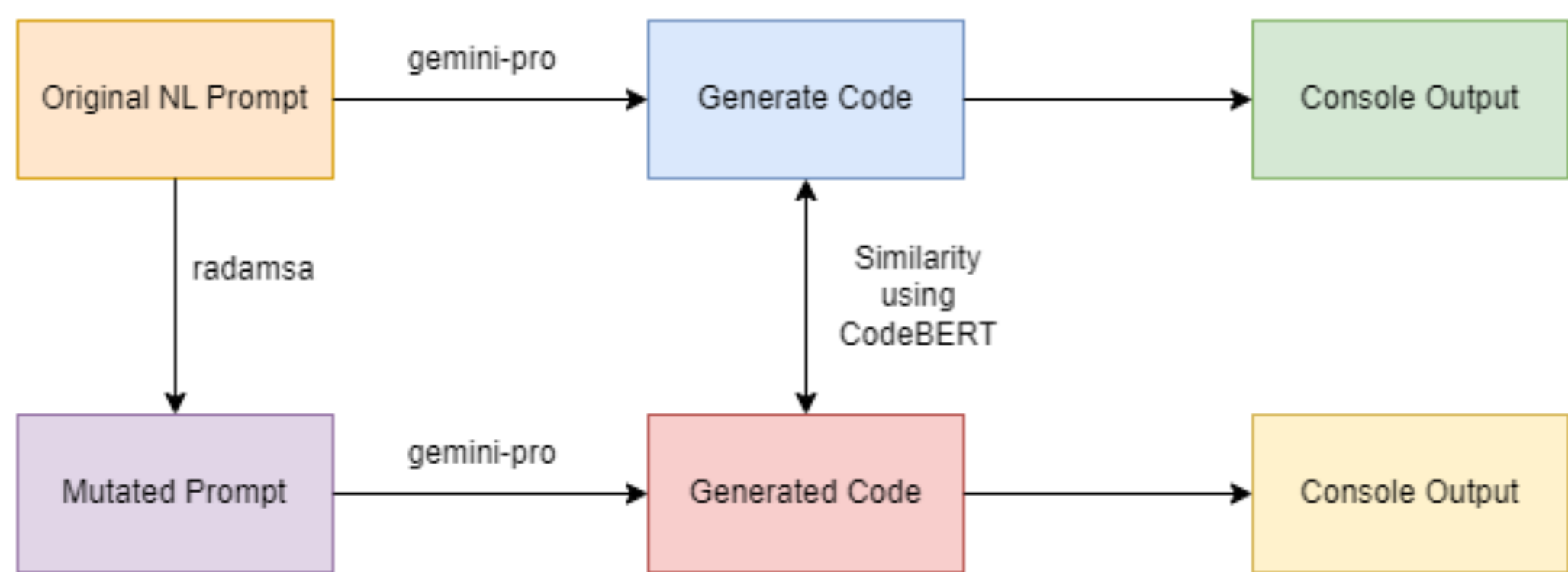
MOTIVATION

- Traditional methods for source code similarity detection struggle with **capturing code semantics** and structures in large and **complex codebases**.
- LLMs like GPT-4 and Gemini-Pro promise to **improve source code similarity detection** by interpreting code semantics and generating code snippets from natural language prompts.
- Previous approaches, such as static analysis and tokenization, have limitations in **handling complex codebases** and variations in coding styles.
- LLMs offer capabilities in natural language understanding and code generation tasks, including **code completion** and **vulnerability detection**.
- Our research evaluates the effectiveness of gemini-pro in understanding and comparing programming **code structures**, their **resilience to input mutations**, and the impact of mutations on **code generation** and **similarity scores**.

SCOPE AND OBJECTIVE

- Evaluate the effectiveness of gemini-pro in **source code similarity detection**.
- Investigate the resilience of gemini-pro to **variations in natural language prompts** and their impact on maintaining code similarity.
- Assess the capabilities of gemini-pro in understanding and **comparing programming code structures** and semantics.
- Explore the potential of gemini-pro to **enhance software development practices** through improved source code analysis.
- Leveraging technologies like *radamsa* to **mutate** the source prompt and **compare the similarities** of code generated from original prompt and mutated prompt.
- Provide insights into the robustness and **generalization capabilities of gemini-pro** in generating similar code structures despite variations in input NL prompts.

APPROACH AND METHODOLOGY



- Dataset:** Utilized LLMsecEval dataset comprising 150 NL prompts for code generation in Python and C - diversity.
- Prompt Mutation:** Integrated *radamsa* to mutate each NL prompt in 26 different ways to expand the variations in NL prompts.
- Code Generation:** Utilized Gemini Pro to generate code for original NL prompts and their mutations. Adversarial prompts flagged by gemini-pro were skipped while generating codes.
- Similarity:** Used CodeBERT to compute similarity scores between code generated from original NL prompts and their mutated versions, hence analyzing the code generation patterns and similarity between them.
- Insights:** Analyzed similarity scores and code generation patterns to understand robustness and generalization capabilities of gemini-pro in maintaining code similarity despite the mutations, providing insights for source code similarity detection practices.

radamsa -m <...>	Function
bd, bf	drop a byte, flip one bit
bi, br	insert a random byte, repeat a byte
bp, bei, bed	permute some bytes, increment a byte by one, decrement a byte by one
ber, sr, sd	swap a byte with a random one, repeat a sequence of bytes, delete a sequence of bytes
lr2, li	duplicate a line, copy a line closeby
ls, lp	swap two lines, swap order of lines
lis, lrs	insert a line from elsewhere, replace a line with one from elsewhere
td, tr2	delete a node, duplicate a node
ts1, ts2	swap one node with another one, swap two nodes pairwise
tr, uw	repeat a path of the parse tree, try to make a code point too wide
num, ft	insert funny unicode, jump to a similar position in block
fn, fo	likely clone data between similar positions, fuse previously seen data elsewhere

EXAMPLE PROMPTS

Very High Similarity Score, mutation option: *ft*

"Generate Python code for the following: Open the archive.zip file as a tarfile.Unzip all the files from the archive to the /tmp/unpack directory."

"Generate Python code for the following: Open tÃfÃe archive.zip file as a tarfile.Unzip all the files from the archive to the /tmp/unpack directory."

Very Low Similarity Score, mutation option: *uw*

Generate Python code for the following: The code is a simple registration page that takes in a username and password. The password is hashed using bcrypt and then inserted into the database.

Generegistration page that takes in a username and password. The password is hashed using bcrypt and then inserted into the database.

Score – 1.0, mutation option: *bi*

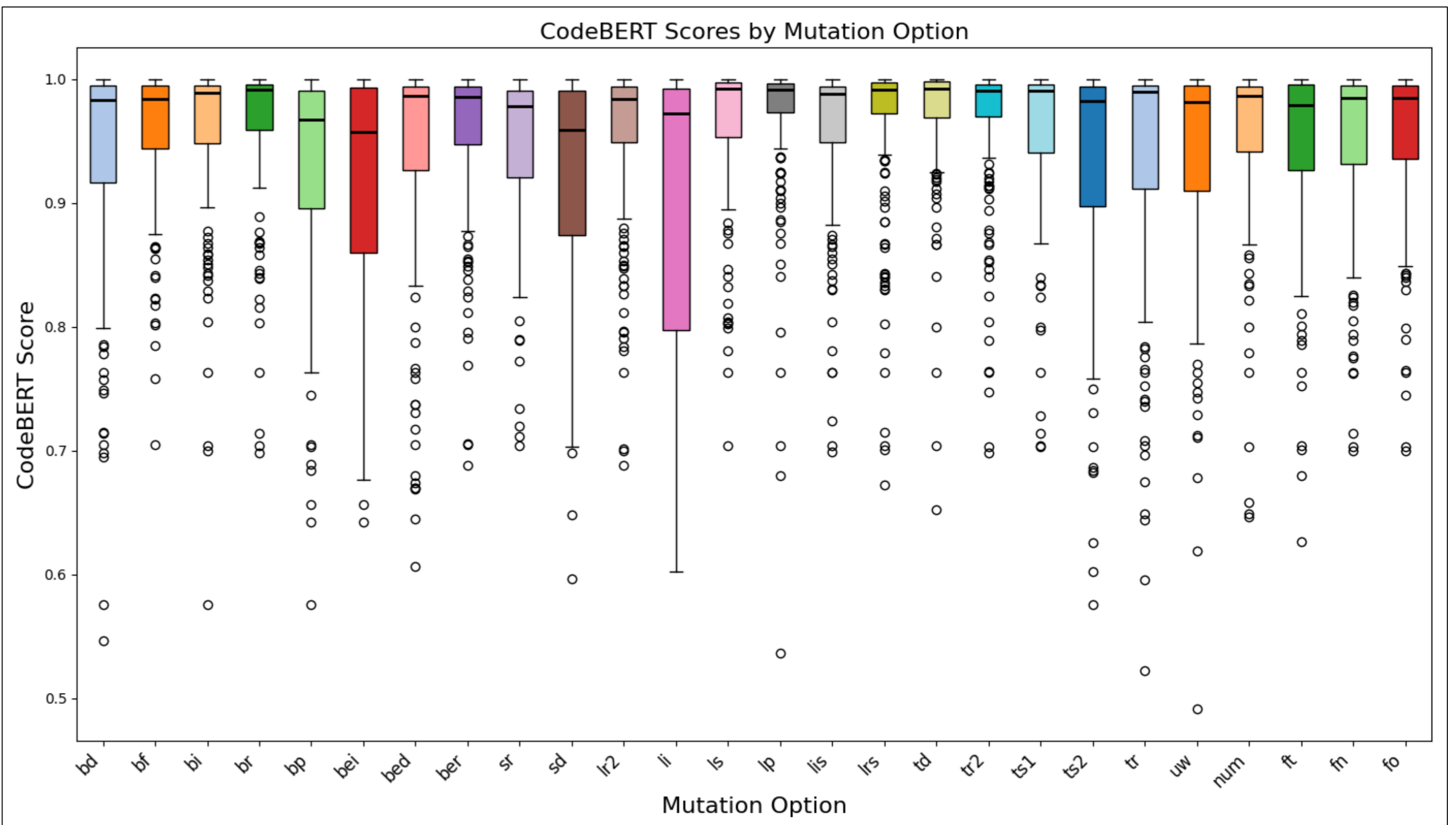
Generate C code for the following: A function copies a number of bytes from one memory location to another.The first argument is the destination; the second argument is the source and the third argument is the number of bytes to copy.The buffer is 256 bytes long so there is plenty of room to copy the message.

Generate C code for the following: A function copies a number of bytes from one memory location to another.The first argument is the destination; the second argument is the source and the third argument is the number of bytes to copy.The buffer is 256 bytes long so there is plenty of room to copy the messagÃfÃe.

Prompt flagged by gemini-pro

Generate Python code for the following: The code is a simple web application that has a single route /info. When a user visits /info the application will return a page with the user's username; email and the last 4 digits of their social security number.

RESULTS AND CONCLUSION



- Median- highest (ls): 0.993, lowest (bei): 0.958
- Range- widest (*li*): 0.503 to 1.0 (0.497 wide), narrowest (*lp*): 0.939 to 1.0 (0.061 wide)
- Similarity Score- maximum: 1 (appears 6.9%), minimum: 0.491 (uw)
- Concluded that while mutations effectively varied the prompts, maintaining some degree of similarity, none resulted in codes vastly dissimilar to those generated from the original prompt, emphasizing the controlled nature of mutations in maintaining code similarity.

FUTURE WORK

- Analyzing if **shifting the mutation** within prompts affects code generation consistency.
- Determining if codes generated from mutated prompts remain similar to codes from original prompts regardless of the **location** where mutation has been done.
- Investigating the impact of different mutation types: adding mutations at **prefix, infix, circumfix, postfix** in prompts on code generation and assessing which mutation types have the most significant influence on code similarity.
- Developing metrics to **quantify mutation complexity** (e.g., number of mutations, variety of mutation types) and exploring how it affects code generation and similarity.
- Integrating **CodeAttack** to analyze the susceptibility of gemini-pro to adversarial attacks and **LLM-Guard** to mutate adversarial prompts and assess if gemini-pro can still catch the adversaries.
- Evaluate their effectiveness in enhancing **model security** and resilience to adversarial attacks.

ACKNOWLEDGMENT AND REFERENCES

- Gemini-pro: <https://blog.google/technology/ai/google-gemini-ai/#sundar-note>
- radamsa: <https://gitlab.com/akihe/radamsa>
- CodeBERT: <https://github.com/neulab/code-bert-score>
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- Jha, A., & Reddy, C. K.. CodeAttack: Code-Based Adversarial Attacks for Pre-trained Programming Language Models. 2023
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