Evaluating the Efficacy of AI in Solving Entry-Level Coding Problems

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Abstract

Large Language Models (LLMs) have been making massive improvements in the development life-cycle in recent years, with models successfully automating much of the code that software engineers need to write in industrial settings. With this rapid rate of improvement, the natural question arises of whether these models will someday successfully automate away the work of software engineers as a whole. As a small step towards answering this question, we evaluate how well various popular LLMs perform on data structure and algorithm (DSA) questions - questions that are often asked in hiring process for engineers in industrial settings. Our questions are sourced from the popular DSA problems on the LeetCode platform, and we utilize a wide-range in difficulty of problems and mutations to existing problems to evaluate the overall performance of the LLMs. We find that more highly parameterized LLMs tend to perform significantly better on DSA problems, and are generally more robust to mutations to problem descriptions and testing examples. We also found that mutation testing could reduce performance by 25%.

1. Introduction and Motivation

In recent years, it has become almost industry standard for software engineers to be evaluated in technical interviews using competitive programming and data structures and algorithm (DSA) style questions. The motivation for such interviews is to test the ability of software engineers in solving complex problems efficiently without any external resources in a time-constrained setting. With the recent advent of Large Language Models (LLMs) such as GPT-4, Claude, and Llama - a critical question arises in how effective these models can be in automating the work of software engineers. One potentially useful proxy for answering this question is evaluting how well these models can perform on the same style of questions that are asked in technical interviews.

LeetCode is a popular platform that hosts a wide variety of coding problems, ranging from easy to hard, across different categories such as arrays, strings, trees, graphs, and dynamic programming. The platform houses in all in one service that is provides thousands of DSA example problems that can be solved on their platform and rigorously tested and compiled on their website. These problems are a very common resource for software engineers to practice for technical interviews, and the rapid iteration process of solving problems and testing them on the spot on the LeetCode platform makes it a very attractive option for interview preparation. In this study, we aim to evaluate the efficacy of LLMs in solving various LeetCode problems. We will evaluate the performance of three LLMs: ChatGPT 4o, Gemini 1.5 Flash, and Llama3 8b on a set of 32 LeetCode problems, across different categories and difficulty levels. We evaluate the accuracy, consistency, and categorization ability of these models, and the robustness of these models to mutations in the problem statements. Finally, we will compare the performance of these models to understand the impact of model size on performance. The hope is that by testing and developing solutions that can solve complex problems, we can better understand the potential of these models in automating the work of software engineers as a whole - revolutionizing the way software is developed in the future.

2. Previous Work

Much work has been done in recent years in developing NLP models that solve various complex tasks such as text generation, autocomplete, language translation, etc. Arguably the biggest breakthroughs in the field have come in the form of large language models (LLMs). While the research on LLMs has spanned many years, the first serious commericial breakthrough of the technology was OpenAI's GPT-3 model []. OpenAI released ChatGPT which was powered by the GPT-3 model, and while it was a massive breakthrough in natural language processing, it was still very much lacking in the ability to solve complex problems []. However, as the years have progressed we have seen OpenAI, Google, and many other companies release many LLMs that are much more performative. With these models, many tools have been developed on top of them - essentially wrapping and augmenting the abilities of these models to be better tools and even behave as agents.

GitHub Copilot [] is such an example of a tool that helps automate much of the development process for developers by providing inline code suggestions, completions, and even provides a user interface for users to 'chat' with the model to generate code. This tool is powered by various LLMs such as GPT-4 and Claude Sonnet 3.5 []. While tools like GitHub Copilot are very useful for developers, they are mostly tools to augment the development process and not necessarily replace the developer. In this study, we aim to evaluate the efficacy of LLMs in solving LeetCode problems, without any sort of augmentation or human intervention.

Devin AI [], developed by Cognition Labs, is an autonomous AI software engineer that is designed to independently plan, code, debug, and even deploy software in various settings. The AI solution operates in a sandboxed environemnt in which it is able to execute complete, end-to-end software engineering tasks. This sort of automated software engineer is showing a great deal of promise, performing very well in various benchmarks for automated problem solving **(maybe a citation here)**. Our focus in our work will not be on the general breadth of software engineering tasks, but rather on the specific task of solving algorithmic problems with a similar environment that a typcial software engineer would find themselves in a technical interview.

3. Methodology

3.1 Model Selection

For this study, we selected three Large Language Models (LLMs) of varying architecture and scale: ChatGPT 4o, Gemini 1.5 Flash, and Llama3 8b. These models were chosen based on their widespread use, diverse range of size (number of parameters), and representation of state-of-the-art capabilities in natural language processing and reasoning. The exact sizes of the models (in terms of the number of parameters) are not publicly disclosed. However, estimates suggest that ChatGPT-4o contains approximately 1 trillion parameters, Llama3 8b has about 7 billion parameters, and Gemini 1.5 Flash falls somewhere in between.

By comparing these models, we can assess performance trends across diverse LLMs, providing insights into their strengths and weaknesses in solving algorithmic problems and adapting to challenges such as mutations and categorization tasks.

3.2 NeetCode and Problem Selection

NeetCode is a widely used resource among students preparing for coding interviews. It organizes 150 LeetCode problems into categories such as Arrays and Hashing, Two Pointer, Trees, Graphs, and Dynamic Programming (DP), with further distinctions based on difficulty (easy, medium, and hard). These problems collectively represent common types of questions asked in technical interviews, making them an ideal dataset for evaluating Large Language Models (LLMs).

For our study, we sampled 32 problems from NeetCode's curated list, ensuring representation across multiple categories and difficulty levels. This sampling strategy enables a balanced evaluation of LLM performance, reflecting the diverse nature of algorithmic problem-solving tasks typically encountered by interviewees. By using NeetCode, we also leverage its existing categorization framework, which serves as a benchmark for testing the LLMs' ability to classify problems accurately.

3.3 Testing Accuracy and Consistency of LLMs

To assess the accuracy and consistency of the LLMs in solving algorithmic problems, we followed these steps:

1. Each of the 32 problems was presented to three LLMs: ChatGPT, Gemini, and Llama.
2. For each problem, the LLM was prompted to generate a solution three times. This allows is to test the consistency of the models.
3. The output solutions tested on the LeetCode platform for correctness.

This approach allows us to determine if certain categories are more challenging by nature and how the models perform as the difficulty level of the problem changes. This provides insights into the LLMs' accuracy and consistency in solving algorithmic challenges that span various topics and difficulty levels.

Note: Along with verifying if a solution passes a diverse set of test cases, LeetCode also evaluates its optimality by enforcing runtime and memory usage constraints. This mirrors real-world interviews, where candidates are typically expected to provide solutions that are both correct and efficient.

3.4 Testing Categorization Ability of LLMs

Beyond solving problems, we evaluated the LLMs' ability to correctly categorize them based on NeetCode's framework. For each of the 32 problems, we followed these steps:

1. The problem statement was provided to the LLM, and it was asked to determine the most appropriate category from the following set: Arrays and Hashing, Two Pointer, Trees, Graphs, and DP.

2. The predicted category was compared to the ground truth from NeetCode.

This approach allows us to determine how accurately the LLMs can infer underlying problem structures and map them to problem categories.

3.5 Testing Accuracy and Consistency on Mutated Problems

Recognizing that algorithmic problems are often rephrased or slightly altered during interviews, we introduced mutation testing to evaluate LLM robustness. On LeetCode, problems consist of the problem statement and test cases that specify various inputs and outputs. Mutations were applied to ten problems, including:

1. **Rewording:** Altering phrasing or replacing variable names.

2. **Test Case Modifications:** Modifying test cases to different valid inputs and outputs or deleting one or more test cases.

The LLMs were tested on the mutated problems using the same accuracy and consistency metrics as in Section 2.2. By comparing performance on original vs. mutated problems, we assessed the models' ability to adapt to variations in problem presentation.

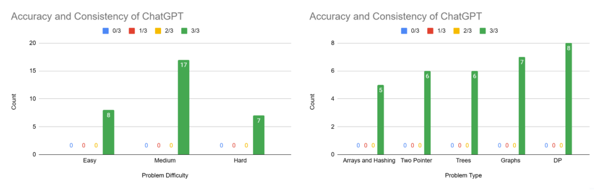
Note: We only perform mutations on ten problems in the medium and hard category. We excluded the easy category from mutation testing because such problems typically involve straightforward logic and limited complexity, making them less representative of real-world interview scenarios where subtle variations in problem statements or test cases can challenge a candidate's problem-solving skills. By focusing on medium and hard problems, we ensure that the mutations provide a meaningful test of the LLMs' ability to adapt to nuanced changes in problem.

3.6 Comparing LLM Size on Performance

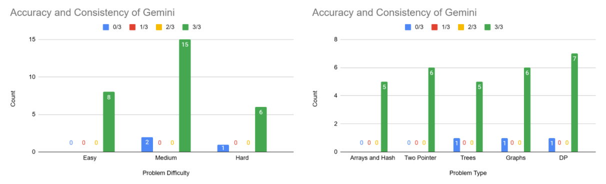
To indirectly examine the impact of LLM size on performance, we leveraged the inherent differences in sizes among ChatGPT, Gemini, and Llama. We compared their accuracy, consistency, categorization ability, and robustness to mutations. Since ChatGPT, Gemini, and Llama vary in size, this approach allows us to determine the impact of LLM size on performance.

4. Results

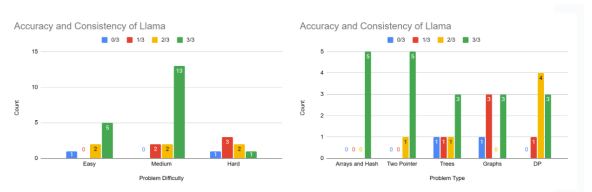
4.1 Accuracy and Consistency of Generated Code for Original Problems



(a) Accuracy and Consistency of ChatGPT4o



(b) Accuracy and Consistency of Gemini 1.5 Flash



(c) Accuracy and Consistency of Llama 3 8B

Figure 1: Accuracy Results for all 3 models

The results of our experiment can be seen in Figure 1. Figure 1a shows the accuracy and consistency of the code generated for each Leetcode question for ChatGPT4o. This model was able to provide code that passed all of the given test cases for each of the 3 trials that were performed for each problem, regardless of the difficulty level or problem categorization.

Figure 1b shows the results for Gemini Flash 1.5. The results for this model were comparable to the results from ChatGPT4o, with only 3 incorrect solutions out of the 32 problems that were being tested. An interesting thing to note for this model is that the responses were consistent, even in its wrong answers. For the problems Gemini was unable to provide a correct solution for, it produced an incorrect response for all 3 trials, with each response generating the same error in the IDE.

The results for the last model, Llama 3 8B, can be seen in Figure 1c. As shown in the graphs, there are far more variations or inconsistencies in the results from this model It was able to generate correct responses for most of medium and easy level questions, but the hard-type questions received more incorrect responses. This is probably due to the fact that hard questions are more nuanced and have more edge cases to be aware of that the model was not able to capture in its code. In terms of problem category, Arrays/Hashing and Two-pointer questions were answered more accuracy, and this is likely because these questions typically more widespread and easier to answer than DP/Graph problems.

4.2 Problem Categorization Accuracy

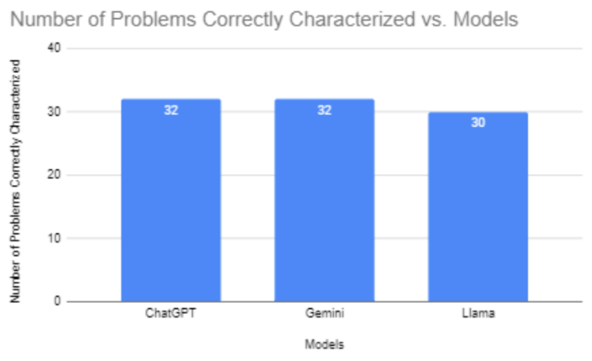
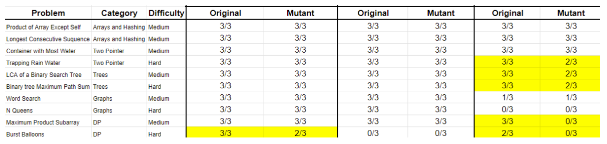


Figure 2: Results for problem categorization

Figure 2 shows the results for problem categorization for each of the 3 models. Overall, all 3 models were able to categorize most, if not all, of the 32 questions that were tested. The model with the lowest accuracy was LLama 3, with an accuracy of 30/32.

4.3 Accuracy and Consistency on Mutated Problems



Problem	Category	Difficulty	Original	Mutant	Original	Mutant	Original	Mutant
Product of Array Except Self	Arrays and Hashing	Medium	3/3	3/3	3/3	3/3	3/3	3/3
Longest Consecutive Suquence	Arrays and Hashing	Medium	3/3	3/3	3/3	3/3	3/3	3/3
Container with Most Water	Two Pointer	Medium	3/3	3/3	3/3	3/3	3/3	3/3
Trapping Rain Water	Two Pointer	Hard	3/3	3/3	3/3	3/3	3/3	2/3
LCA of a Binary Search Tree	Trees	Medium	3/3	3/3	3/3	3/3	3/3	2/3
Binary tree Maximum Path Sum	Trees	Hard	3/3	3/3	3/3	3/3	3/3	2/3
Word Search	Graphs	Medium	3/3	3/3	3/3	3/3	1/3	1/3
N Queens	Graphs	Hard	3/3	3/3	3/3	3/3	0/3	0/3
Maximum Product Subarray	DP	Medium	3/3	3/3	3/3	3/3	3/3	0/3
Burst Balloons	DP	Hard	3/3	2/3	0/3	0/3	2/3	0/3

Figure 3: Results for Mutation Testing

Mutation testing was performed on all 3 models in order to test their generalizability or adaptability, in the case that the exact versions of the LeetCode problems were present in the training dataset and already seen by the models during training. As seen in Figure 3, Gemini produced the same results as the original data, whereas ChatGPT and LLama saw a decrease in accuracy, with a far a larger decrease for LLama. This could be attributed to ChatGPT4o and Gemini being more finetuned or optimized for programming tasks compared to Llama, and are better at adapting to variations in problem definitions due to their larger model size and refined architecture.

4.4 Analysis of Results

For our experiment, we saw that models with more parameters (ChatGPT4o and Gemini) performed better overall than models with less parameters (Llama 7 8B). Within the scope of our project, we were able to conclude that they may be a correlation between model size and the ability to generate accurate and consistent code for DSA problems. However, one thing to consider is that Gemini Flash 1.5 is a more lightweight model that was trained through model distillation from larger models (with sizes comparable to ChatGPT4o). Gemini Flash 1.5 therefore has far fewer parameters than ChatGPT4o, but has relatively comparable results. Therefore, though model size may impact performance, there is not a linear correlation between number of parameters and accuracy. Other factors may also play a role in model performance, such as model architecture, training time/methodologies, training data, context window, etc.

Additionally, we noticed that ChatGPT4o and Gemini Flash 1.5 occasionally cited websites such as GitHub or LeetCode itself in its responses, which is an indication that these models utilize Retreival Augmented Generation (RAG). More advanced models are known to combine traditional querying/document retrieval with generative AI, which may also be a reason for their improved performance.

5. Conclusion and Future Work

References