# Generating Diverse Code Explanations using the GPT-3 Large Language Model

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## KEYWORDS

large language models, natural language processing, code explanations, computer science education

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## 1 ABSTRACT

Good explanations are essential to efficiently learning introductory programming concepts [10]. To provide high-quality explanations at scale, numerous systems automate the process by tracing the execution of code [8, 12], defining terms [9], giving hints [16], and providing error-specific feedback [10, 16]. However, these approaches often require manual effort to configure and only explain a single aspect of a given code segment. Large language models (LLMs) are also changing how students interact with code [7]. For example, Github's Copilot can generate code for programmers [4], leading researchers to raise concerns about cheating [7]. Instead, our work focuses on LLMs' potential to support learning by explaining numerous aspects of a given code snippet. This poster features a systematic analysis of the diverse natural language explanations that GPT-3 can generate automatically for a given code snippet. We present a subset of three use cases from our evolving design space of *AI Explanations of Code*.

## 2 USE CASES

To understand the types of explanations GPT-3 [2] can generate, we issued over 700 prompts across numerous code snippets. An example prompt and resulting explanation is shown in Figure 1. We discovered eight explanation types and Figure 2 includes three explanation types to illustrate the explanatory power of GPT-3. The additional types include: 1) tracing the execution of code, 2) fixing bugs and explaining how they were fixed, 3) generating analogies to real world settings, 4) listing relevant programming concepts, and 5) predicting the console output.

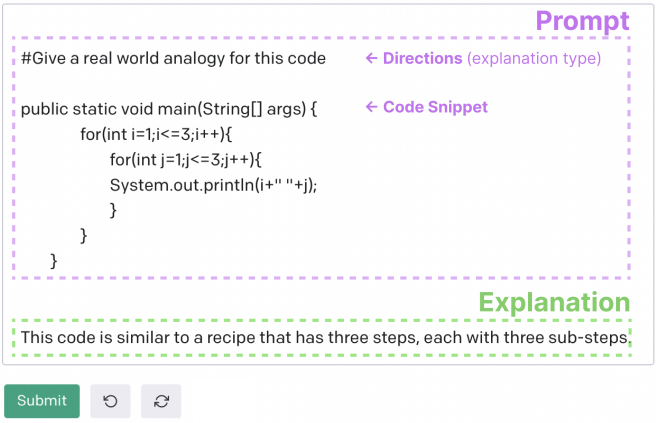


**Figure 1: A prompt and explanation based on analogy.**

### 2.1 Analyzing and explaining time complexity

Instructors rate time complexity as the most difficult programming topic [17]. However, understanding time complexity is important [6, 13] because it facilitates decision-making so students choose an appropriate algorithm for a given problem. This use case shows GPT-3 can identify and explain time complexity.

### 2.2 Identifying common mistakes made by beginner programmers

Commonality exists in how students solve programming problems [15] and the mistakes they make [1, 11]. Pedagogical techniques, such as the 'muddiest point' highlight these common and most confusing concepts [3, 14]. GPT-3 can automatically create a checklist of common mistakes students might make regarding a given code snippet.


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**Code Snippet**

Given Java Code:

```
int algorithm (int arr[], int l, int r, int x)
 {
   if (r >= l) {

     int mid = l + (r - l) / 2;

     if (arr[mid] == x)
       return mid;

    if (arr[mid] > x)
      return algorithm(arr, l, mid - 1, x);

    return algorithm(arr, mid + 1, r, x);
  }
   return -1;
}
```

**1. Time Complexity**

**What is the time complexity of this code and why?**

The time complexity of this code is O(log n). This is because the code is using a Binary Search algorithm, which halves the search space each time it is called.

**2. Identifying Common Mistakes**

**List the common mistakes a beginner programmer might make while writing this code. How can a beginner programmer avoid each of these mistakes?**

A beginner programmer might make the following mistakes while writing this code:

1. Not understanding how binary search works - Binary search is a search algorithm that searches for an element in a sorted array by repeatedly dividing the array in half and comparing the element to the middle element of the array. If the element is not found, the search continues in the lower or upper half of the array, depending on whether the element is less than or greater than the middle element, respectively.

2. Not correctly implementing the binary search algorithm - In order to correctly implement binary search, the programmer must ensure that the array is sorted before beginning the search. Furthermore, the programmer must correctly handle the case when the element is not found in the array.

3. Not using the proper data structures - Binary search can only be performed on an array. If the programmer is using a linked list, for example, binary search cannot be used.

4. Not using the proper variable types - Binary search requires that the array be of type int. If the programmer is using a different data type, binary search will not work.

5. Not understanding the time complexity of binary search - Binary search has a time complexity of O(log n), which means that it is a very efficient algorithm. If the programmer is not aware of this, they may try to improve the efficiency of the algorithm by making unnecessary changes.

**3. Summarizing Code**

**Summarize and explain the goal of this code.**

The goal of this code is to find the index of a given element in an array using a binary search algorithm. The code takes in an array, the left and right indices of the array, and the element to be found as parameters. If the element is found, the code returns the index of the element. If the element is not found, the code returns -1.

**Figure 2: Three example explanations automatically generated by GPT-3 for an 'anonymized' Binary Search code snippet.**

## 2.3 Summarizing code at multiple levels of abstraction

Before understanding how a code snippet executes, it is often useful to understand the purpose of the code [5]. The summary generated by GPT-3 and shown in Figure 2 defines the goal, traces the execution, and highlights relevant CS concepts such as arrays.

# 3 DISCUSSION

Our three use cases demonstrate the potential for GPT-3 to explain code for intro CS students. Our poster presentation will feature all eight explanation types as a design space of explanations to convey the diversity of explanations that can be generated by LLMs. We will highlight best practices for generating effective explanations and pitfalls that lead to less effective explanations. We are evaluating the usefulness of these explanations in a series of summer classes.

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