# The Behavior of Large Language Models When Prompted to Generate Code Explanations



Priti Oli, Rabin Banjade, Jeevan Chapagain, Vasile Rus

{poli,rbnjade1,jchpgain,vrus}@memphis.edu University of Memphis, Memphis ,TN, USA

## Introduction

# Experiment and Results

#### **Code Explanation Generation**

- Important task across various domains: Software Engineering, Computer Science Education..
- LLMs for code explanation Generation: Code summarization, Comment generation.

## □ Code Explanation in Computer Science Education:

- Effective in teaching programming to Novices[1].
- Self-Explanation of code induces learning gain.
- Authoring questions, examples and assessment
- □ LLMS for code explanation generation in educational context[2]

### □ **Discrepancy in Code Explanations** across different settings:

 Prompt, Temperature, Programming Language, Explanation Types, LLM settings

## Methodology

## **Quantitative Analysis**

□ Variation with Input Parameter (prompt, code example etc.)

- Vocabulary,
- $\circ$  Token length
- Sentence length

□ Prompt C1 and D2 generate significantly longer explanations.

□ Readability consistent for Python and Java unlike C++

□ Lexical density remains consistent (0.47 on average).

### **Qualitative Analysis**

□ Accuracy: 93%

□ Completeness: 82%

- □ Concision: 58%
- □ Specificity: 77%

Intro to Programming Examples:	Factors	Va
<ul> <li>Programming Languages: Java, Python, C++</li> <li>Code Difficulty: Beginner, Intermediate, Advanced</li> </ul>		P1 P2
<ul> <li>LLMs:</li> <li>ChatGPT-3.5(ChatGPT-3.5-turbo-0613)</li> <li>ChatGPT-4.0(ChatGPT-4-0613)</li> <li>LLAMA2 (LLMa2-chat)</li> </ul>	Prompt	P3 P4 P5 P6 P7
<b>Temperature</b> : 0, 0.5, 1, 1.5, 2.0		P8 pc
Prompt Variations: 12 different types of prompts (Table 1)		C1
Total of 3510 explanations		C2 D1 D2
		DE
Evaluation	Temperature	D3 0
Evaluation           Quantitative Evaluation:           Surface level Properties of Explanations:           Septence length, word length, readability (Elesch Kincaid)	Temperature	D3 0 0.1 1 1.1
<ul> <li>Duantitative Evaluation:         <ul> <li>Surface level Properties of Explanations:</li> <li>Sentence length, word length, readability (Flesch-Kincaid grade), lexical density, and vocabulary.</li> </ul> </li> </ul>	Temperature Model	D3 0 0.1 1 1.1 gp
<ul> <li>Quantitative Evaluation:         <ul> <li>Surface level Properties of Explanations:</li> <li>Sentence length, word length, readability (Flesch-Kincaid grade), lexical density, and vocabulary.</li> </ul> </li> <li>Qualitative Evaluation         <ul> <li>Accuracy: Correct page [2]</li> </ul> </li> </ul>	Temperature         Model	D3 0 0.! 1 1.! gp gp Lla
<ul> <li><b>Quantitative Evaluation:</b> <ul> <li>Surface level Properties of Explanations:</li> <li>Sentence length, word length, readability (Flesch-Kincaid grade), lexical density, and vocabulary.</li> </ul> </li> <li><b>Qualitative Evaluation</b> <ul> <li>Accuracy: Correctness[3]</li> <li>Completeness: Information coverage[3]</li> <li>Conciseness: Brevity[3]</li> </ul> </li> </ul>	Temperature Model Language	D3 0 0.1 1 1.1 3 gp gp Lla 9 y CF

□ Variations with input parameter in Table 2.

	Factors	Values	Complete	Correct	Concise	Specific
		P1	0.92	0.92	0.54	0.85
		P2	0.85	1.00	0.62	1.00
		P3	0.86	0.79	0.57	0.64
		P4	1.00	0.92	0.42	0.88
		P5	0.86	0.43	0.93	0.57
	Prompt	P6	1.00	0.86	0.93	0.79
		P7	1.00	0.86	0.39	0.86
		P8	1.00	0.91	0.36	0.82
		P9	1.00	0.60	0.67	0.47
		C1	0.86	0.86	0.43	0.71
		C2	1.00	0.92	0.62	1.00
		D1	0.86	0.79	0.64	0.75
		D2	0.96	1.00	0.46	1.00
		D3	1.0	0.83	0.62	0.88
	Temperature	0	0.98	0.81	0.62	0.84
		0.5	0.96	0.91	0.56	0.81
		1	0.93	0.84	0.60	0.82
		1.5	0.71	0.44	0.41	0.35
	Model	gpt-3.5-turbo	0.97	0.81	0.75	0.82
		gpt-4	0.96	0.82	0.56	0.88
		Llama2	0.88	0.82	0.41	0.66
	Language	Java	0.95	0.80	0.66	0.80
		Python	0.91	0.78	0.43	0.83
		СРР	0.95	0.87	0.66	0.71
	Code Example	AreaOfCircle	0.91	0.89	0.49	0.92
		AvgOfNumbers	0.96	0.80	0.50	1.00
		Point	0.94	0.83	0.59	0.81
]		BingoBoard	0.93	0.83	0.83	0.80
		BinarySearch	0.96	0.77	0.67	0.66

 $\circ$  Annotated by 2 Graduate Students in binary scale (0/1).

Sym	Prompt	Comment	
P1 P2 P3 P4	Can you explain this code? Can you self-explain this code? Can you explain this code to a learner? Can you explain this code to someone learning to program?	Simple prompts and Variations	Table 2: G
P5 P6 P7	Can you summarize this code? Can you summarize this code for a learner? Can you explain this code at statement level?	Prompts for Summary line-by-line explanation	Explanation influenced by
P8 P9	Can you explain this code at block level? Can you explain this code without breaking down individual statements?	logical/func tional explanation	LLMs exhi based on inpu
C1 C2	<context1>.Given this Java code, explain the code to your students in order to help them understand what the code does and learn the covered programming concepts. <context2>.Given this Java code, read the code carefully and explain what it does to potential students who learn</context2></context1>	Contextual- ized prompt	Llama2.
D1 D2 D3	<ul> <li>programming.</li> <li>Explain the following code line by line as a bulleted list:</li> <li>Give a detailed explanation of the purpose of the following code.</li> <li>Summarize and explain the goal of the above code.</li> </ul>	Prompts used in prior work	<ol> <li>Oli, Priti, et al. "Impr Artificial Intelligence</li> <li>MacNeil, Stephen, et the 2022 ACM Confe</li> <li>Sridhara, Giriprasad, <i>the 25th IEEE/ACM i</i></li> </ol>

Table 1: The input prompts used from simple to contextualized.

Table 2: Qualitative Evaluation Scores Across various factors

## **Discussion and Conclusion**

Explanations for the same prompt vary across example, possibly influenced by the diverse instances available in training data.

□ LLMs exhibit diversity/inconsistency in generated explanations based on input parameters.

□ GPT-4 generates better explanation than ChatGPT 3.5 and Llama2.

□ LLMs' diversity/inconsistency necessitates well-documented parameters and human effort for refining generated explanations.

#### References

- 1. Oli, Priti, et al. "Improving Code Comprehension Through Scaffolded Self-explanations." International Conference on Artificial Intelligence in Education. Cham: Springer Nature Switzerland, 2023.
- MacNeil, Stephen, et al. "Generating diverse code explanations using the gpt-3 large language model." Proceedings of the 2022 ACM Conference on International Computing Education Research-Volume 2. 2022.
- 3. Sridhara, Giriprasad, et al. "Towards automatically generating summary comments for java methods." *Proceedings of the 25th IEEE/ACM international conference on Automated software engineering*. 2010.