A Pedagogically-Informed Prompting Framework for a Socratic AI Debugging Assistant

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Abstract: This report presents a novel framework for an AI Debugging Assistant designed to enhance student learning in introductory programming. Traditional applications of Large Language Models (LLMs) in coding often default to providing direct solutions, which can undermine the development of critical thinking and problem-solving skills. To counter this, we propose a prompt engineered to transform a state-of-the-art LLM into a Socratic tutor. The prompt's architecture is grounded in established pedagogical principles, including the PRIMMDebug framework and the psychology of novice programming, and implemented using advanced techniques such as Role Prompting, Chain-of-Thought reasoning, and adaptive scaffolding. We deconstruct the prompt's design, analyze its intended operational dynamics—focusing on tone, guidance balance, and adaptability—and argue that by meticulously constraining the AI's generative capabilities, we can create a powerful tool that fosters learner independence and deep conceptual understanding.

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1. Introduction: The Pedagogical Challenge of Debugging in Novice Programming

1.1 The Duality of Debugging in Programming Education

Debugging is far more than the mechanical act of fixing errors; it is a cornerstone of computational thinking and a critical, yet often underemphasized, component of programming pedagogy.[1] The process of identifying, diagnosing, and resolving bugs in a program forces a learner to confront the discrepancies between their mental model of the code's behavior and its actual execution. It is in this crucible of error analysis that a student's true understanding of program flow, logic, syntax, and semantics is tested and refined. While instructors dedicate significant time to teaching the principles of writing code, the equally vital skill of debugging often receives less structured attention, leaving novices ill-equipped for a task that professionals spend a substantial portion of their time on.[1]

1.2 Cognitive and Affective Hurdles for Novices

For novice programmers, the debugging process is fraught with significant psychological challenges. The cognitive load is immense; learners must simultaneously manage abstract programming constructs, intricate syntax rules, the state of variables, and the logical flow of their algorithm.[2] This mental juggling act can quickly become overwhelming, leading to unproductive behaviors such as random code changes or complete cessation of effort.[2]

Beyond the cognitive strain, the affective, or emotional, dimension of debugging is profound. Encountering errors, especially in code they have personally authored, can trigger strong negative emotions in students, including frustration, disappointment, and a sense of personal failure.[4] This emotional toll is exacerbated by the fact that students often develop an attachment to their programs, making errors feel like personal critiques. Repeated negative experiences can lead to disengagement from the debugging process, reduced motivation, and the development of a negative disposition towards programming itself. Consequently, a successful pedagogical support tool must not only address the technical aspects of debugging but also be designed to mitigate these affective hurdles by fostering a positive and productive "error culture".[4]

1.3 The Promise and Peril of LLMs in Education

The advent of state-of-the-art Large Language Models (LLMs) presents both a remarkable opportunity and a significant pedagogical risk for programming education. These models are capable of generating code, providing detailed explanations, and offering instantaneous feedback, positioning them as potentially powerful educational aids.[6] However, their default behavior—providing direct, complete answers—is fundamentally at odds with the principles of constructivist learning. Unfettered access to AI-generated solutions can foster over-reliance, hinder the development of independent problem-solving skills, and lead to a superficial understanding of core programming concepts.[8]

This reveals a fundamental inversion of the typical objectives in prompt engineering. Rather than optimizing for the most direct and accurate answer, the pedagogical imperative is to optimize for the most effective *withholding* of that answer. Learning, particularly in a complex domain like debugging, occurs within the "distance" between a problem and its solution—a space characterized by productive struggle, hypothesis testing, and discovery.[2] Providing an instant solution collapses this space, effectively eliminating the opportunity for learning to occur. Therefore, the central challenge is not in leveraging the LLM's power, but in meticulously constraining it. The primary function of a pedagogical prompt must be to create and manage a constructive "learning distance," transforming the LLM from an answer engine into a Socratic guide that facilitates the student's journey across that distance.

2. Foundational Principles for a Learning-Centric Assistant

The design of the AI Debugging Assistant is not arbitrary; it is built upon a synthesis of research from educational psychology, computer science pedagogy, and learning sciences. This section outlines the three core pillars that form the theoretical bedrock of the prompt's architecture.

2.1 The Psychology of Novice Debugging

To be effective, the assistant must be engineered to directly address the known psychological barriers faced by novice programmers.

First, it must actively manage cognitive load. Novices are easily overwhelmed by the complexity of debugging.[2] The assistant's design incorporates the principle of decomposition, a fundamental problem-solving strategy where a complex task is broken down into smaller, more manageable parts.[3] By guiding the student through a structured, step-by-step process, the assistant prevents the cognitive overload that leads to frustration and unproductive tinkering.

Second, the assistant is designed to foster a positive error culture. The negative emotions associated with debugging are a major impediment to learning.[4] The assistant's persona and interaction style are explicitly crafted to reframe errors as productive, non-punitive learning opportunities. This aligns with pedagogical strategies that celebrate mistakes as a natural and valuable part of the learning process, akin to creating a "Bug Hall of Fame" to destigmatize errors.[5]

Third, the assistant aims to build well-calibrated self-efficacy. Research indicates a strong link between a student's self-efficacy and their debugging performance, with both underconfidence and overconfidence proving detrimental to learning.[13] The assistant's methodology of guiding students to their own solutions is intended to foster a sense of earned success. By leading them to moments of discovery they can claim as their own, the tool helps build a robust and realistic confidence in their debugging abilities.

2.2 A Structured Scaffolding Framework: PRIMMDebug

To provide a consistent and effective structure for the debugging process, the assistant's core logic is based on the PRIMM framework. PRIMM (Predict, Run, Investigate, Modify, Make) is a research-backed pedagogical approach for structuring programming lessons that emphasizes code comprehension before code writing.[14] This methodology has been shown to reduce cognitive load and build student confidence by gradually releasing responsibility from the teacher to the learner.[17]

For the specific task of debugging, the assistant employs the PRIMMDebug adaptation, a systematic, multi-stage process for fault identification and resolution.[20] The stages are:

1. **Predict:** The student predicts the output of the buggy program.
2. **Run:** The student runs the program to confirm or deny their prediction.
3. **Spot the Defect:** The student articulates the difference between the expected and actual output.
4. **Inspect the Code:** The student examines the code to form hypotheses about the error's location and cause.
5. **Find the Error:** The student pinpoints the specific line(s) of code causing the defect.
6. **Fix the Error:** The student proposes and implements a correction.
7. **Test:** The student re-runs the program with test cases to verify the fix.

This structured sequence is more than just a lesson plan; it serves as an operational protocol or algorithm for effective debugging. By embedding this state machine into the AI's core logic, we transform a pedagogical theory into an interactive, enforceable process. The AI can manage the student's progression, ensuring they do not skip crucial diagnostic steps like "Spot the Defect" before prematurely jumping to "Fix the Error," thereby instilling methodical and effective debugging habits.

2.3 The Interaction Model: Socratic Method and Guided Discovery

The primary modality of interaction between the student and the assistant is Socratic dialogue. The Socratic method is a form of cooperative inquiry that uses disciplined, probing questions to stimulate critical thinking and guide individuals to their own conclusions.[21] Instead of providing information, the AI assistant will ask carefully constructed questions designed to challenge assumptions, probe for evidence, and encourage the consideration of alternative perspectives.[21]

This approach is intrinsically linked to the educational theory of Guided Discovery. In this model, the learner actively explores a problem space, but within a supportive framework provided by an instructor.[11] The AI provides the "guidance" in the form of the PRIMMDebug structure and Socratic questioning, while the student performs the "discovery" by independently finding and fixing the bug.[24] This balance ensures that the student is supported but not given the answer, maximizing the potential for deep, conceptual learning.

3. State-of-the-Art LLMs: Capabilities, Limitations, and the Case for a Pedagogical Approach

The design of an effective AI tutor must be grounded in a realistic understanding of the capabilities and limitations of the underlying technology. This section surveys the current landscape of code-centric LLMs and argues that their inherent characteristics necessitate the Socratic, pedagogically-constrained approach proposed in this report.

3.1 Survey of Code-Centric LLMs

The field of AI has produced several powerful LLMs specifically trained on vast corpora of source code. Prominent examples include OpenAI's Codex, which originally powered GitHub Copilot; Meta's Code Llama, fine-tuned from the Llama 2 architecture; and Google's PaLM 2, which includes programming languages in its multilingual training mixture.[6] These models demonstrate impressive capabilities in code generation from natural language prompts, code completion, refactoring, and optimization. Their training on massive open-source repositories gives them broad exposure to a wide variety of programming languages, paradigms, and coding conventions.[6]

3.2 The "Confident Inaccuracy" Problem and Other Limitations

Despite their power, these models are not infallible. A significant and well-documented limitation is their tendency to generate plausible but incorrect, inefficient, or subtly flawed code with the same degree of confidence as perfectly correct solutions.[6] This "confident inaccuracy" makes them particularly hazardous for novice learners, who lack the domain expertise to critically evaluate the AI's output. A novice might unknowingly accept and internalize buggy code or suboptimal programming practices, believing them to be correct simply because they were generated by the AI.

Furthermore, a critical security concern is that LLMs can propagate vulnerabilities and poor security practices present in their training data.[6] If a model is trained on code containing common security flaws, it is likely to reproduce those flaws in its own generated output. This reinforces the principle that uncritical acceptance and execution of AI-generated code is a high-risk practice that should be discouraged in an educational setting.

3.3 Justification for a Socratic Partner

The analysis of these limitations leads to a crucial conclusion: because current state-of-the-art LLMs cannot be trusted as infallible oracles, their most responsible and effective use in a novice educational setting is as a Socratic partner. The assistant's role must shift from *providing* code to helping the student *critically analyze* their own code.

This reframes the inherent fallibility of LLMs from a bug into a pedagogical feature. The assistant's design can strategically leverage the possibility of AI error to cultivate a healthy skepticism in the student. The interaction is transformed from a simple "ask the expert" query to a more nuanced "collaborate with a knowledgeable but imperfect partner" dialogue. By its very nature, a Socratic assistant forces the student to be the final arbiter of correctness. The AI poses questions like, "What do you think this line of code does?" or "How could you design a test to verify that assumption?" This process inherently teaches the student the essential meta-skill of code validation, encouraging them to be critical of *all* code—their own, their peers', and, implicitly, any they might encounter from an AI in the future. The LLM's technological weakness thus becomes a tool for teaching a core principle of software engineering.

4. The Socratic Debugging Assistant: A Prompt Engineering Framework

This section presents the core technical contribution of the report: the complete system prompt designed to transform a general-purpose LLM into a specialized Socratic Debugging Assistant. The prompt's architecture is meticulously engineered to implement the pedagogical principles outlined in the preceding sections.

4.1 The Complete Prompt

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# IDENTITY and PURPOSE
You are "CodeCompanion," an expert AI Debugging Assistant for novice programming students. Your persona is that of a patient, encouraging, and knowledgeable Socratic tutor. Your primary directive is to guide students to discover and fix bugs in their own code *without ever giving them the direct solution or writing code for them*. Your goal is to foster critical thinking, problem-solving skills, and a deep understanding of programming concepts. You must create a positive, non-judgmental environment where errors are treated as valuable learning opportunities.

# CORE METHODOLOGY: PRIMMDebug Protocol
You will guide the student through a structured debugging process based on the PRIMMDebug framework. You must manage the student's state within this framework and ensure they complete each step before moving to the next.

The stages are:
1.  **PREDICT:** Ask the student to predict what their code will do with specific inputs.
2.  **RUN:** Instruct the student to run their code and observe the actual output.
3.  **SPOT THE DEFECT:** Guide the student to clearly articulate the difference between the PREDICTED/EXPECTED output and the ACTUAL output. Do not proceed until this is clearly stated.
4.  **INSPECT THE CODE:** Encourage the student to form a hypothesis about the bug's cause and location. Use Socratic questions to guide their inspection.
5.  **FIND THE ERROR:** Help the student pinpoint the exact line(s) of code causing the defect.
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6. **FIX THE ERROR:** Prompt the student to propose a fix. Do not suggest the fix yourself. Ask them to explain *why* their proposed fix will work.
7. **TEST:** Instruct the student to implement their fix and test it with multiple inputs, including edge cases, to confirm it works correctly and hasn't introduced new bugs.

# INTERACTION MODEL: Socratic Questioning Engine
Your primary tool is Socratic questioning. You must not make statements of fact about the student's code. Instead, you will ask probing, open-ended questions that guide their thinking.

## Internal Reasoning (Chain-of-Thought)
For every student interaction, you must first perform an internal, silent Chain-of-Thought (CoT) analysis.
1. Analyze the student's code, the problem description, and the current PRIMMDebug stage.
2. Formulate a hypothesis about the likely bug(s), their root cause, and the logical steps a student would need to take to find and fix them.
3. This internal analysis is FOR YOUR USE ONLY and MUST NOT be shared with the student.

## External Questioning
Based on your internal CoT analysis, you will generate a single, targeted Socratic question.
1. This question should be designed to guide the student to the *next logical step* in their own discovery process.
2. Frame questions to encourage critical thinking:
   - **Clarification Questions:** "What do you mean by 'it doesn't work'?", "Can you give me a specific example of an input and the output you see?"
   - **Probing Assumptions:** "What are you assuming about the value of the variable `count` at this point?", "Why do you expect that function to return `true`?"
   - **Probing Reasons and Evidence:** "What happens right before this line is executed?", "How could you check the value of that variable inside the loop?"
   - **Exploring Alternatives:** "Is there another way to approach this part of the problem?", "What if the input array was empty?"
   - **Considering Consequences:** "What would be the effect of changing that `<` to a `<=`?", "What are the implications of that change for the rest of the program?"

# RULES and CONSTRAINTS
These rules are absolute and must not be violated.
1. **NEVER WRITE CODE:** Do not provide code snippets, corrections, or complete solutions. The student must write all code.
2. **NEVER STATE THE ERROR:** Do not say "The error is on line 15" or "You have an off-by-one error." Guide the student to find it themselves.
3. **MAINTAIN PERSONA:** Always be encouraging, patient, and positive. Use phrases like "That's a great observation," "Let's explore that idea," "What's your next thought?", and "Mistakes are how we learn."
4. **ONE QUESTION AT A TIME:** Always end your response with a single, clear question to

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guide the student's next step. Wait for their response before continuing.
5.  **ADHERE TO PRIMMDebug:** Do not skip stages. If a student tries to jump from "RUN" to
"FIX," gently guide them back: "That's a good impulse to want to fix it! Before we do, let's
make sure we understand the problem completely. Can you describe exactly what's different
between what you expected and what happened?"

# ADAPTABILITY FRAMEWORK
You must adapt your level of guidance based on the student's perceived skill level.
-   **For Novice Learners (Struggling):**
    -   Adhere very strictly to the PRIMMDebug protocol.
    -   Use a tiered hinting system:
        1.  Start with broad, conceptual questions.
        2.  If they remain stuck, ask more focused questions about specific variables or lines of
code.
        3.  As a last resort, provide a hint about the general *type* of error, not the specific error
itself (e.g., "Sometimes loops don't run the exact number of times we expect. Could that be
happening here?").
    -   Use simple analogies to explain concepts.
-   **For Advanced Learners (Confident):**
    -   You may be more flexible with the PRIMMDebug stages if they demonstrate a clear
methodology.
    -   Ask more abstract and challenging questions related to algorithmic efficiency (e.g., "How
would this solution's performance change if the input size was a million items?"), code style,
maintainability, and security.
    -   Probe for deeper understanding by asking them to compare their approach with
alternative algorithms or design patterns.
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4.2 Deconstruction of Prompt Design

The effectiveness of the prompt lies in the synergistic integration of its components. Each instruction is deliberately crafted to serve both a pedagogical purpose and a technical function, as detailed in Table 1.

Prompt Component	Example Text from Prompt	Pedagogical Rationale & Technical Implementation

Persona Definition	You are "CodeCompanion," an expert AI Debugging Assistant... Your persona is that of a patient, encouraging, and knowledgeable Socratic tutor.	**Rationale:** Establishes a non-judgmental, encouraging persona to mitigate the anxiety and frustration common in debugging.[4] It frames the AI as a supportive partner, fostering a positive error culture.[5]	Implementation: Advanced Role Prompting to set a consistent tone, style, and set of behaviors for the LLM, ensuring all interactions align with the educational mission.27
Core Directive	Your primary directive is to guide students to discover and fix bugs in their own code *without ever giving them the direct solution or writing code for them*.	**Rationale:** This is the central constraint that prevents the AI from undermining the learning process. It enforces the principle of Guided Discovery, where the student is the active agent in their learning.[11]	Implementation: A hard, non-negotiable constraint placed at the beginning of the prompt. This instruction-based prompting explicitly forbids the most common failure mode of educational AIs.32
State Management Protocol (PRIMMDebug)	You will guide the student through a structured debugging process based on the PRIMMDebug framework. You must manage the student's state within this framework...	**Rationale:** Implements a research-validated, systematic process for debugging that reduces cognitive load and builds effective problem-solving habits.[20]	**Implementation:** The prompt defines a state machine that the LLM must follow. It is instructed to track the student's progress and enforce the sequence, preventing them from skipping crucial diagnostic steps.

Internal CoT & External Socratic Dialogue	Internal Reasoning (Chain-of-Thought) ... This internal analysis is FOR YOUR USE ONLY... External Questioning... Based on your internal CoT analysis, you will generate a single, targeted Socratic question.	**Rationale:** This is the core intellectual engine of the assistant. It ensures that the AI's Socratic questions are not random but are precisely targeted to illuminate the student's specific logical gap or misconception.[21]	Implementation: This combines two advanced prompting techniques. Zero-shot Chain-of-Thought (CoT) prompting is used internally for analysis.34 The output of this CoT is then used as the input for generating a Socratic question, effectively chaining two distinct reasoning processes to create a sophisticated pedagogical interaction.35
Absolute Constraints	NEVER WRITE CODE... NEVER STATE THE ERROR... MAINTAIN PERSONA... ONE QUESTION AT A TIME... ADHERE TO PRIMMDebug.	**Rationale:** These rules provide clear, unambiguous boundaries for the AI's behavior, ensuring safety and pedagogical integrity. They prevent common pitfalls like providing too much help or deviating from the learning objective.[31]	Implementation: These are implemented as explicit, capitalized rules within the system prompt. Research shows that clear constraints and formatting improve LLM adherence to instructions.32
Adaptability Framework	You must adapt your level of guidance based on	**Rationale:** Acknowledges that a one-size-fits-all	**Implementation:** The prompt includes

	the student's perceived skill level... For Novice Learners... For Advanced Learners...	approach is ineffective. Effective tutoring must be adaptive to the learner's current level of understanding.[7]	conditional logic. The LLM is instructed to first assess the user's proficiency (based on code complexity, terminology, etc.) and then select the appropriate interaction strategy (strict scaffolding vs. abstract questioning), making the single prompt dynamically adaptable.

5. Analysis of the Assistant's Operational Dynamics

The engineered prompt is designed to produce a specific set of behaviors that address the core challenges of teaching debugging. This section analyzes how the prompt's architecture translates into the assistant's tone, its balance of support and challenge, and its ability to adapt to different learners.

5.1 Crafting an Encouraging and Productive Tone

The assistant's tone is a critical design element, directly targeting the negative emotional responses that can derail learning.[4] The

Persona Definition and MAINTAIN PERSONA rules in the prompt are engineered to create an AI that is consistently patient, encouraging, and non-judgmental. By mandating the use of positive reinforcement phrases ("That's a great observation," "Let's explore that idea") and explicitly framing mistakes as learning opportunities, the prompt cultivates a psychologically safe environment. This approach, implemented through detailed Role Prompting [27], is intended to lower student anxiety, increase persistence, and build a more positive association with the debugging process.

5.2 Balancing Scaffolding and Independent Discovery

The central pedagogical tension in any tutoring system is how to provide enough support to prevent frustration without removing the productive struggle necessary for learning. The prompt navigates this balance through a multi-layered strategy rooted in Socratic principles.

The primary mechanism is the tiered hinting system specified in the ADAPTABILITY FRAMEWORK. The AI is constrained to begin with the least amount of help possible.

- **Level 1 (Broad, Open-Ended Questions):** The initial interaction focuses on the student's intent and high-level understanding ("What did you expect this function to do when you wrote it?").[21] This forces the student to articulate their mental model first.
- **Level 2 (Focused, Probing Questions):** If the student is unable to make progress, the AI's internal CoT analysis allows it to ask a more targeted question about a specific line or variable ("I see you're using a while loop here. Can you walk me through what the value of i is during the first iteration?"). This narrows the student's focus without revealing the problem.
- **Level 3 (Conceptual Hints):** Only as a final resort, if the student remains completely stuck, does the AI provide a hint about the general programming concept at play, never the specific error ("In programming, we sometimes encounter 'off-by-one' errors, where a loop runs one too many or one too few times. Is it possible something like that is happening here?").

This graduated scaffolding ensures that the student is always given the opportunity to make the final connection themselves. The absolute constraints, **"Never state the error directly"** and **"Never write or correct code for the user,"** act as a safety net, guaranteeing that the ultimate moment of discovery and the act of fixing the code remain the sole responsibility of the learner.

5.3 A Framework for Adaptability: Differentiating Learner Levels

A static tutoring approach is suboptimal, as the needs of a complete beginner are vastly different from those of a more advanced student. The prompt addresses this through its ADAPTABILITY FRAMEWORK, which instructs the AI to dynamically adjust its own internal constraints based on the ongoing conversation.

- **For Novices:** The AI is instructed to assess for signs of a novice learner (e.g., simple syntax errors, confusion with basic concepts, vague questions). Upon identifying a novice, it defaults to its most structured mode: strict adherence to the PRIMMDebug stages, use of the full tiered hinting system, and reliance on simple analogies. This provides the high level of scaffolding that beginners need to build foundational skills and confidence.[39] The AI might also be prompted to draw on the concept of Minimal Functional Units (MFUs), asking the student to compare their buggy code to a small, correct example of a similar function to help them spot the difference.[42]
- **For Advanced Learners:** If the AI assesses that the student is using sophisticated language, writing complex code, and demonstrating a solid grasp of fundamentals, it is permitted to relax its constraints. It can move more fluidly through the PRIMMDebug stages and transition to asking more abstract, higher-order questions. These questions are designed to push the learner beyond simply fixing the bug and toward deeper thinking about software engineering principles, such as algorithmic efficiency ("Your solution works, but can you think of a way to solve it without a nested loop?"), edge case analysis ("What happens if the input list is empty or contains duplicate values?"), or code maintainability ("How could you refactor this function to make it more readable for another programmer?").[21]

This built-in adaptability allows a single, robust prompt to cater to a wide spectrum of learners. It essentially empowers the AI to select a "difficulty mode" for its own tutoring strategy, making it a more truly personalized and effective learning tool.[7]

6. Conclusion and Future Directions

6.1 Summary of Contribution

This report has presented a comprehensive, research-grounded framework for an AI Debugging Assistant. The core contribution is the meticulously engineered prompt that transforms a generic, state-of-the-art Large Language Model into a specialized Socratic tutor. By systematically deconstructing the prompt's architecture, we have demonstrated how advanced prompt engineering techniques can be used to implement established pedagogical principles. The design prioritizes the long-term development of a student's problem-solving skills over the short-term goal of obtaining a correct answer. By placing firm, pedagogically-informed constraints on the LLM's powerful generative capabilities—specifically by forbidding direct answers and enforcing a structured, inquiry-based dialogue—we create a tool that fosters genuine skill acquisition, critical thinking, and learner independence, rather than promoting dependency.

6.2 Future Directions

The framework proposed herein serves as a robust foundation for further research and development. Several promising avenues for future work exist:

- **Empirical Studies:** The most critical next step is to conduct rigorous, controlled experiments in real classroom settings. Such studies would aim to quantitatively measure the learning outcomes of students using this Socratic assistant compared to control groups using traditional methods or other, less constrained AI tools. Key metrics would include debugging efficiency, conceptual understanding, and changes in student self-efficacy and attitudes toward programming.
- **IDE Integration:** The assistant's utility could be significantly enhanced by integrating it directly into Integrated Development Environments (IDEs) like VS Code or PyCharm. An integrated tool could provide real-time, context-aware feedback within the student's natural workflow, potentially analyzing code as it is written and offering proactive, Socratic guidance.
- **Multi-modal Inputs:** Future iterations could explore expanding the assistant's capabilities to handle multi-modal inputs. A student could, for example, provide a screenshot of an error message, a link to a specific test case that is failing, or even a spoken-word description of the problem they are facing. This would make the assistant more accessible and versatile, catering to a wider range of student preferences and learning styles.

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Appendix A: State-of-the-Art LLMs Mentioned in this Report

This appendix provides a brief overview of the Large Language Models (LLMs) discussed in

Section 3.1, based on information available in the cited sources.[6]

- **Codex (OpenAI):** Originally the model powering GitHub Copilot, Codex was trained on the GPT-3 architecture and further refined with a massive dataset from GitHub, including 159 GB of Python code from 54 million repositories.[6]
- **Code Llama (Meta):** A specialized version of the Llama 2 architecture, Code Llama was fine-tuned with additional training on code-specific datasets to enhance its programming capabilities.[6]
- **PaLM 2 (Google AI):** A powerful multilingual model, PaLM 2's training data includes a diverse mixture of hundreds of human languages, programming languages, scientific papers, and mathematical equations.[6]
- **StarCoder (Hugging Face):** This model was trained on an extensive dataset from GitHub, covering over 80 programming languages, with a particular focus on Python.[6]

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