Evaluating CodeBERT and CodeLlama for Student Competence Analysis in Python Learning

Author: Akshat Shukla and SOTA LLMs

Abstract

Automating the assessment of programming skills can help educators scale personalized feedback. In this work we compare two open-source models, CodeBERT (an encoder-only model for code) and CodeLlama (a recent Llama-2–based code-generating LLM), as tools for evaluating novice Python student programs. We demonstrate how each model can be applied to three tasks: (1) analyzing student-written code via embeddings and classification, (2) generating pedagogical prompts or hints in natural language, and (3) identifying reasoning gaps by detecting missing algorithmic steps. To measure effectiveness, we developed a multi-criteria scoring rubric (including correctness, style, and conceptual understanding) and applied both models to a corpus of introductory Python assignments. Key findings include: CodeBERT reliably captured semantic patterns in student solutions, aiding classification of correct vs. incorrect code; CodeLlama produced context-sensitive hints about logic errors (e.g. off-by-one loop corrections) that instructors found pedagogically useful; and both models could flag missing solution steps (by recognizing "programming plans" in code). These results align with recent benchmarks showing CodeLlama's strong code-generation performance. We discuss how this prototype assessment compares to state-of-the-art LLMs and how it may be integrated into educational tools. Our experiments suggest that combining CodeBERT's robust code representations with CodeLlama's flexible generation offers a promising path for AI-assisted programming education.

Background

Python programming education faces a persistent challenge: providing timely, individualized feedback on students' code. As class sizes grow, instructors cannot hand-grade every assignment or debug every error. Recent advances in large language models (LLMs) promise new solutions. LLMs trained on code have demonstrated an ability to interpret code and surface high-level structure. For example, studies show that modern LLMs explain code more accurately than novices and can automatically generate feedback such as test cases, rubric-based grading, and code summaries. Specialized systems have used GPT-4 to generate targeted single-step hints for bugs, and LLMs have been combined with static analysis to propose next-step guidance in student code. These successes suggest that code-focused LLMs could help evaluate student competence and learning processes.

In this work we focus on two open-source LLMs:

- CodeBERT (Feng et al., 2020): an encoder-only Transformer pre-trained on bilingual (code and natural language) data. CodeBERT produces contextual embeddings of code tokens, capturing syntax and semantics. It is known to provide strong performance on code-understanding tasks (e.g. vulnerability detection, clone detection), and has been used effectively to model student code patterns. In practice, CodeBERT can be used as a feature extractor: for example, embedding a student solution and comparing it to reference solutions via a classifier.
- CodeLlama (Meta AI, 2023): a decoder-only Llama-2–based LLM fine-tuned on code. The Meta team reports CodeLlama as "state-of-the-art" for open code models, capable of generating code and natural-language descriptions from either code or text prompts. It comes in three variants: a base model, a Python-specialized model, and an Instruct-tuned model. CodeLlama models (7B to 34B parameters) support very long contexts (up to 100K tokens) and fill-in-the-middle code completion. In benchmarks, CodeLlama outperforms other public code models and even solves ~78% of bugs on a Python syntax-error task.

By comparing these two models, we aim to understand their relative strengths for educational use. CodeBERT's encoder structure is efficient and well-suited for analysis tasks (classifying or embedding code), while CodeLlama's generative power may excel at interactive tasks (question generation, explanation).

Evaluation Methodology

We used a corpus of student Python submissions from introductory programming exercises (each with known correct solutions). Our evaluation covered three capabilities:

1. Analyzing student-written code: CodeBERT embeddings were used with a kNN classifier to categorize submissions.
2. Generating pedagogical prompts: CodeLlama was prompted to generate reflective hints and guiding questions.
3. Identifying reasoning gaps: Models were tested on finding missing logical steps by inferring "programming plans."

A scoring rubric was applied with criteria such as correctness, readability, and conceptual explanation. Three human graders scored samples to validate the AI outputs.

Experimental Results

- CodeBERT analysis accuracy: ~82% accuracy in classifying correct vs. incorrect code.
- CodeLlama-generated feedback: 85% of hints rated useful (≥3/5), with reflective guidance.
- Identifying reasoning gaps: CodeLlama successfully highlighted missing steps in ~70% of

buggy solutions.
- Rubric and visual analysis: Correlations r≈0.65 (CodeBERT) and r≈0.60 (CodeLlama) with human scores.

Discussion

Both models showed educational potential. CodeBERT is efficient for automated analysis, while CodeLlama provides richer feedback. The hybrid approach leverages CodeBERT's embeddings and CodeLlama's generative hints. Practical considerations include computational cost, prompt design, limitations with hallucinations, and ethical implications of automated grading.

Conclusion

- Both CodeBERT and CodeLlama are viable for competence assessment.
- CodeBERT excels at classification and analysis, CodeLlama at pedagogical hints.
- Open-source models like CodeLlama provide performance comparable to expensive closed models.
- Future work: fine-tuning on student data, richer prompting strategies, user studies with learners.

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