Leveraging static analysis for evaluating code-generation models

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Project Background

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- Our project performs static analysis on code samples derived from XLCoST dataset and completed using CodeLlama-7b-hf and CodeLlama-7b-Instruct-hfmodel models, focusing on **C++** and **Python** languages.

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   - Feeding the errors obtained by our re-developed static evaluation framework back to the model, in the form of engineered prompts, and re-evaluating the generated code.
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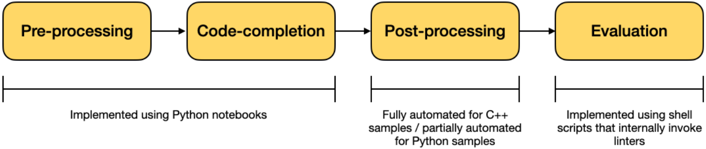
- The model pipeline[†] comprises four stages: **pre-processing**, **code-completion**, **post-processing**, and **evaluation**.



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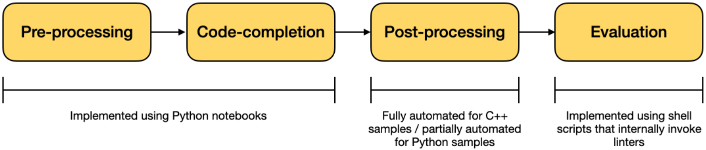

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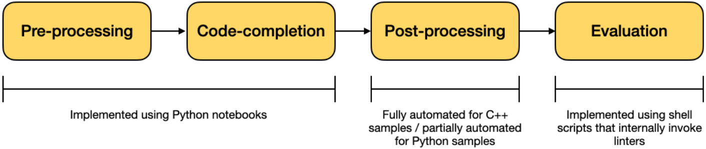

- While quantized versions of the models are more manageable due to their smaller size and faster generation time, for our current and future analyses to be fair across languages and models, we persist with full-size models for our experiments.
- Our experiments were run on T4 GPUs accessible through Google Colaboratory, and on P100 GPUs accessible through Kaggle.

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Broadening horizons

Expanding the scope of static analysis to C++ samples using Cppcheck and Code Llama

Frequency	Defect ID
54	`syntaxError`
2, 2, 2	`shadowFunction`, `unreadVariable`, `variableScope`
1, 1, 1, 1, 1	`arrayIndexOutOfBoundsCond`, `constParameter`, `missingInclude`, `negativeIndex`, `passedByValue`

Broadening horizons

Reproducing results on Python samples using flake8 and Code Llama

Frequency	Error Code(s)	Description
1301, 189, 15, 7, 6	W291, W293, E225, E275, E712	white-space related
56, 32, 53, 26	E305, E302, W292, W391	blank/newline related
40	E501	line too long
61	W191	indentation contains tabs
17	F821	undefined name
12	F401	imported, unused
11	E999	SyntaxError – cannot generate AST
6	E712	`if` condition related
3	F841	assigned, not used
2	F405	Undefined fuction
2, 1	E741, F403	Miscellaneous

Code generation improvement through feedback to model and fine-tuning

Code generation improvement through feedback to model [Python, 300 samples]

Freq. Before f/b	Freq. After f/b	Difference	Error Code
290	0	290 ↓	W292
48	40	8 ↓	F401
11	4	7 ↓	F821
10	6	4 ↓	E999
3	0	3 ↓	E231
17	16	1 ↓	E501
4	4	0	E741
2	2	0	F403
1	1	0	F523
2	2	0	F821
21	22	1 ↑	E225

Table: Coarse-grained statistics — Improvement with feedback — Python

Code generation improvement through feedback to model and fine-tuning

Code generation improvement through feedback to model [Python, 300 samples]

Repetition Freq.	Error Code
30	F401
19	E225
9	E501
8	E302
4, 4	E741, E999
2, 2	F403, F821
1, 1, 1, 1, 1	F523, F841, W292, E231, F811

Table: Fine-grained statistics — Errors that have repeated despite feedback — Python

Code generation improvement through feedback to model and fine-tuning

Code generation improvement through feedback to model [C++, 300 samples]

Freq. Before f/b	Freq. After f/b	Difference	Defect ID
65	14	51 ↓	`constParameter`
159	114	45 ↓	`unusedFunction`
46	16	30 ↓	`syntaxError`
21	7	14 ↓	`passedByValue`
5	4	1 ↓	`variableScope`
3	3	0	`negativeIndex`
1	1	0	`arrayIndexOutOfBounds`
4	6	2 ↑	`shadowVariable`
11	13	2 ↑	`unreadVariable`

Table: Coarse-grained statistics — Improvement with feedback — C++

Code generation improvement through feedback to model and fine-tuning

Code generation improvement through feedback to model [C++, 300 samples]

Repetition Freq.	Defect ID
111	`unusedFunction`
12	`syntaxError`
5	`unreadVariable`
4	`variableScope`
3	`negativeIndex`
2	`shadowVariable`
1, 1, 1, 1, 1	`constParameter`, `arrayIndexOutOfBounds`, `unusedVariable`, `zerodiv`, `legacyUninitvar`

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Remains to be done!

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- Furthermore, our analysis of Python samples suggests that the repetition errors constitute only $\sim$ **20%** of the errors before feedback, implying that repetitions do not occur often post feedback. For C++ samples, this figure is $\sim$ **45%**.
- Our results indicate that the feedback works better for Python samples than C++, and is expected as C++ is a stricter language.

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   - Addressed through the introduction of the post-processing stage in the pipeline.
3. Accurate data cleaning in Python was deemed essential but proved tricky due to the risk of introducing subtle errors, especially in indentation.
   - We ensured that the observed errors were genuine and not artifacts of our evaluation pipeline.

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Remaining Work

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- Cleaning-up code, automating the entire pipeline, and documenting the work.

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Thank you!