Repository-Level Prompt Generation for Large Language Models of Code

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Introduction

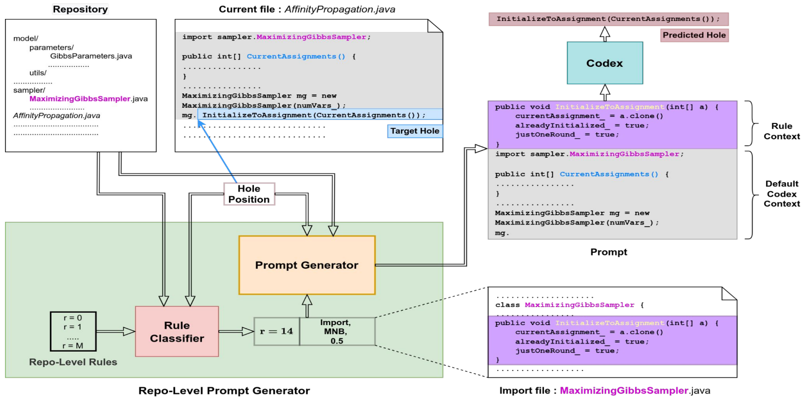
Motivation

- **Black-box access to LLMs.** strongest models *not publicly available*, e.g. no access to model weights for Codex [1] that is deployed in GitHub Copilot[2].
- **Incorporating the repository info:** structure and context from other files.
- **Example-specific discrete prompts:** easy to plug-in human domain-knowledge, easy control.

Repo-Level Prompt Generator (RLPG)

- Learns to generate example-specific prompts **without requiring access** to the model weights.
- We propose a set of repo-level **rules.** A rule consists of (i) rule context location, (ii) rule context type, (iii) rule context ratio. *e.g. get method names and bodies from first import file and fill 50% of the prompt space with this context (see below).*

Methodology



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Experiments and Results

- **Dataset:** Java repositories from Google Code archives[3]
- **Preprocessing:** Deduplication, Parsing the file level AST and collating repo-level meta-info
- **Methods:**
  1. **Codex:** default Codex context.
  2. **Oracle:** use the ground-truth vector that indicates success for each rule per example.
  3. **Fixed Rule:** using a fixed rule for all examples.
  4. **Rule Classifier:** Use a learned model to select the next rule conditioned on the example. Modelled as a multi-label binary classification task.
     - *RLPG-H:* use the hole context
     - *RLPG-R:* use the similarity of the hole context with the rule context.
- **Prompt Generator:** Concatenate the default Codex context with the selected rule's context in the rule context ratio.

Method	Success Rate(%) (hole-wise)	Rel. ↑(%) (hole-wise)	Success Rate(%) (repo-wise)	Rel. ↑(%) (repo-wise)
Codex (Chen et al., 2021)	58.73	-	60.64	-
Oracle	79.63	35.58	80.24	32.31
Fixed Rule ($k = 1$)	65.78	12.00	68.01	12.15
RLPG-H ($k = 1$)	**68.51**	**16.65**	69.26	14.21
RLPG-R ($k = 1$)	67.80	15.44	**69.28**	**14.26**

Performance of different methods averaged across all holes (hole-wise) and individual repositories (repo-wise).

Data Split	SR Codex(%)	SR Oracle(%)	Rel. ↑ over Codex(%)
Train	59.78	80.29	34.31
Val	62.10	79.05	27.28
Test	58.73	79.63	35.58

Performance of the oracle

Conclusions

- An oracle constructed from our proposed rules gives **36% relative improvement over Codex.**
- When we use our rule-classifier to select the best rule, we get **17% relative improvement** over Codex. RLPG also better than fixed rule.
- Future Work: Composition of rules and human-in-the-loop prompt generation.

References:

[1] Chen, Mark, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards et al. "Evaluating large language models trained on code." *arXiv preprint arXiv:2107.03374* (2021).
[2] https://github.com/features/copilot/
[3] https://code.google.com/archive/