RepairLLaMA:Efficient Representations and Fine-Tuned Adapters for Program Repair

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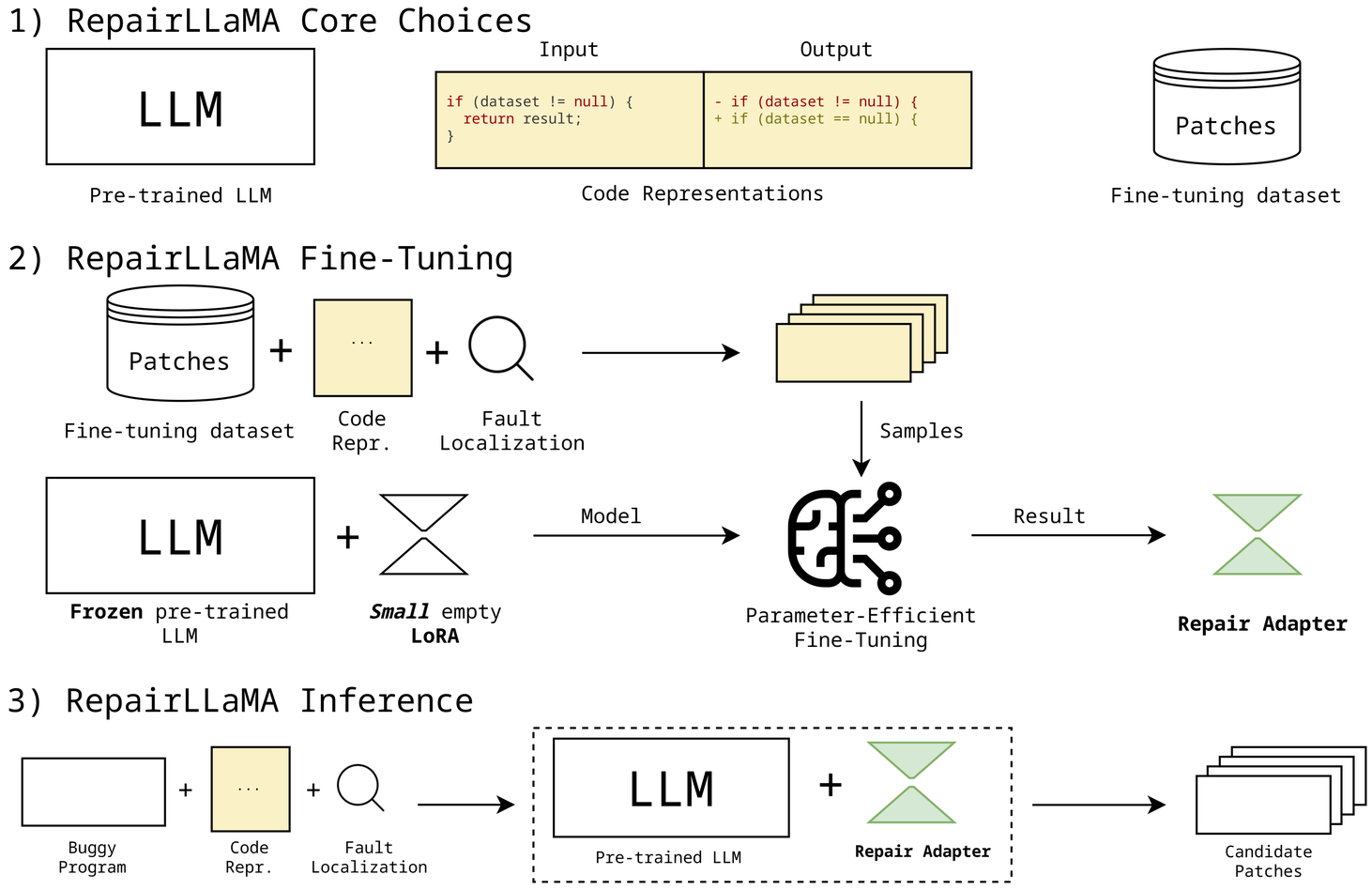
Motivation

- Fine-tuning LLMs for program repair [1] is a recent avenue of research.
- Existing works mostly fine-tune LLMs with naive code representations.
- Existing works do not scale to frontier LLMs due memory requirements.



Results

Model	Defects4J [5] (488 bugs)		
	AST Match	Semantic Match	Plausible
GPT-3.5	33	45	71
GPT-4	60	72	119
RepairLLaMA	**125**	**144**	**195**

RepairLLaMA's effectiveness compared with state-of-the-art ChatGPT-based APR techniques. RepairLLaMA is more effective in finding correct and plausible patches in Defects4J.

- The infilling scheme, supported by code language models, supplemented with the original buggy code, is the best input/output representation pair.
- PEFT outperforms full parameter fine-tuning, avoiding overfitting while optimizing ~1600x less parameters.
- RepairLLaMA outperforms state-of-the-art general purpose models, such as GPT-4, while being much smaller (7B parameters).

Objective

```
@@ -111,9 +111,6 @@
  final double[] lI = lTData[i];
- if (lTData[i][i] < absolutePositivityThreshold) {
-  throw new NotPositiveDefiniteMatrixException();
- }
  for (int j = i + 1; j < order; ++j) {
   final double[] lJ = lTData[j];
@@ -134,6 +131,9 @@
  final double[] ltI = lTData[i];
+ if (ltI[i] < absolutePositivityThreshold) {
+  throw new NotPositiveDefiniteMatrixException();
+ }
  ltI[i] = Math.sqrt(ltI[i]);
  final double inverse = 1.0 / ltI[i];
```

Example of a bug exclusively repaired by RepairLLaMA, Math-86 from Defects4J.

The main objective of RepairLLaMA is to fine-tune LLMs to produce high-quality bug/fix patches.

Methods

- We study two axis in fine-tuning LLMs:
  1) Code Representations
  2) Parameter-Efficient Fine-Tuning (PEFT)
- Fine-tune codellama-7b [2] with six different input-output code representation pairs, tailored for program repair.
- Use LoRA [3], instead of full parameter fine-tuning, reducing the memory requirements.
- Train on ~50k fine-tuning samples from Megadiff [4].

Conclusion

- RepairLLaMA combines PEFT with task-specific code representations.
- RepairLLaMA outperforms larger, state-of-the-art models through specialization in program repair.
- RepairLLaMA correctly repairs 144 real-world bugs from the Defects4J benchmark.

References

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[3] Hu, E. J., Wallis, P., Allen-Zhu, Z., Li, Y., Wang, S., Wang, L., & Chen, W. LoRA: Low-Rank Adaptation of Large Language Models. In International Conference on Learning Representations.
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[5] R. Just, D. Jalali, and M. D. Ernst, "Defects4j: A database of existing faults to enable controlled testing studies for java programs," in Proceedings of the 2014 International Symposium on Software Testing and Analysis, 2014, pp. 437–440.

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