Large Language Models for Code Refactoring

PhD Thesis Project

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UFMG
UNIVERSIDADE FEDERAL
DE MINAS GERAIS

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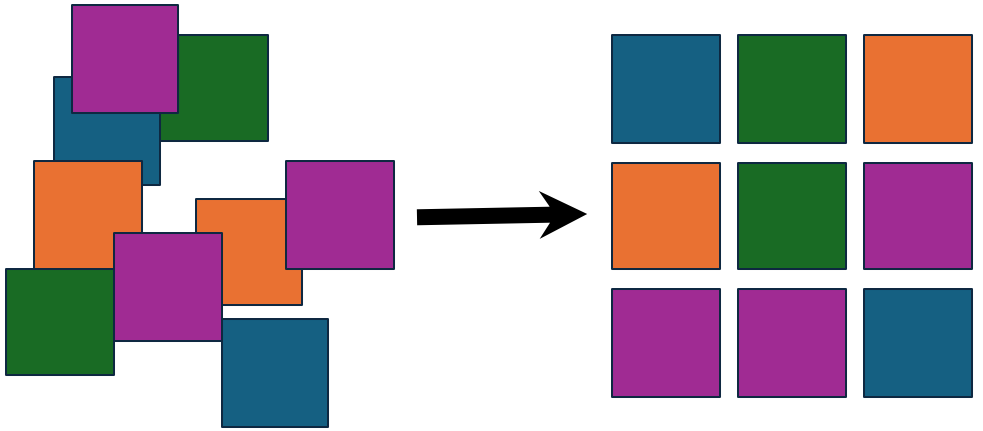
Context of Our Work

Why LLMs for Code Refactoring?

Refactoring

- Refactoring reduces code **complexity** and improves **maintainability**.
- Manual refactoring is costly and slow.
- Refactoring tools are semi-automated, inaccurate and require human intervention.



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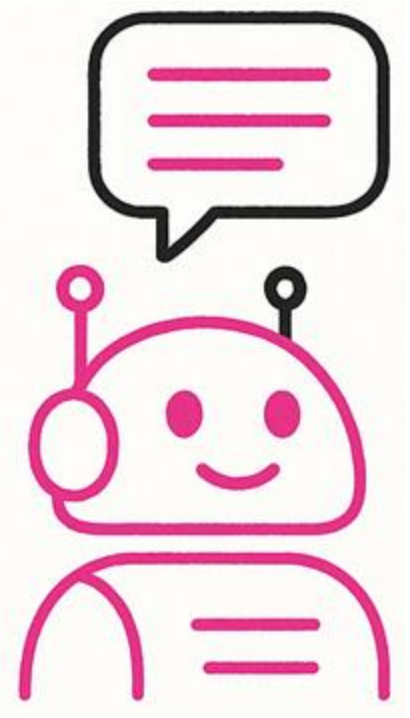
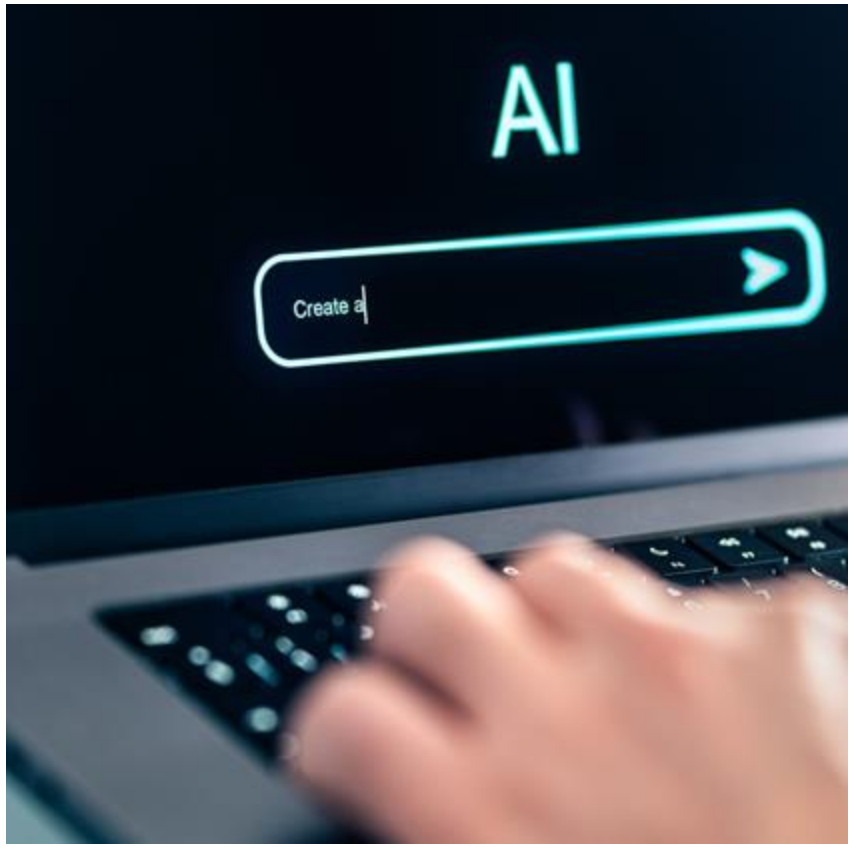
Large Language Models (LLMs)

- LLMs are models trained on a large amount of data and have shown good capability to **write and understand natural language**.
- Studies on LLMs are growing exponentially in software engineering, yet their capability show **limitations** and still need to be explored.



Goals

- We aims to explore the extent to which variation in **prompt techniques** and their combinations affects **different refactoring types**.
- We intend to provide developers and tools with **practical insights** for creating refactoring prompts for real-world projects.



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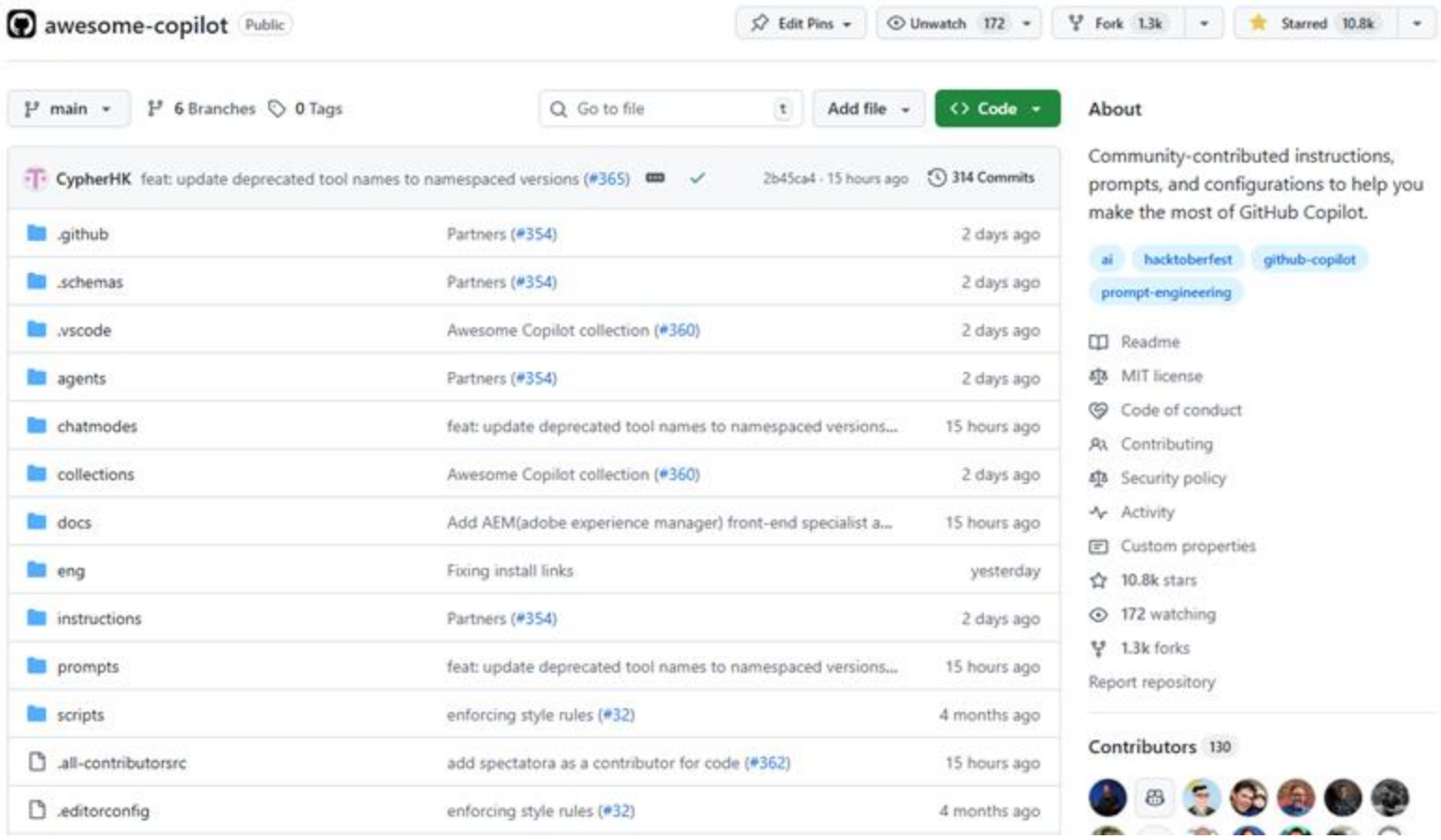
Relevance



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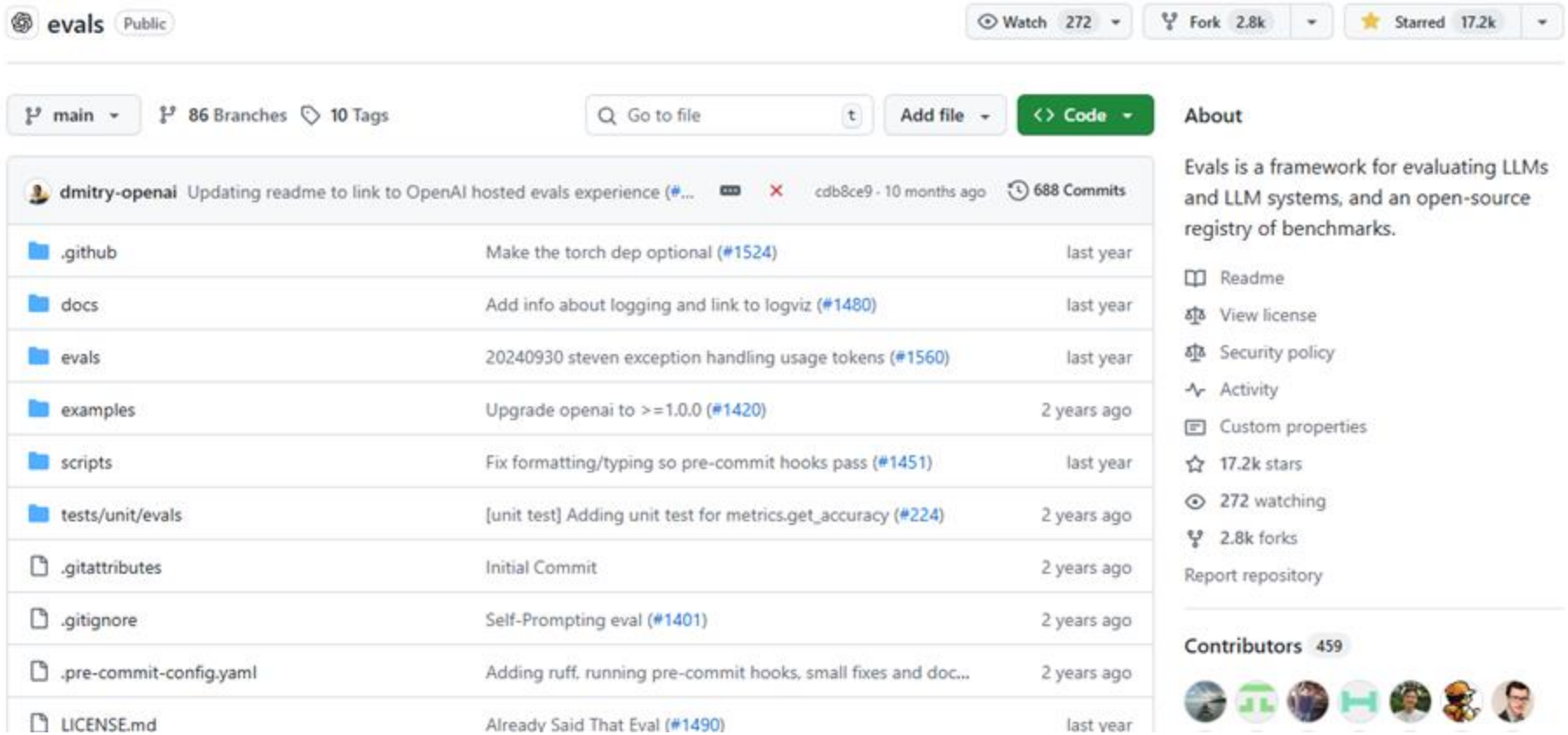
Relevance


evals
Public
Watch 272
Fork 2.8k
Starred 17.2k
main
86 Branches
10 Tags
Go to file
t
Add file
Code
dmitry-openai Updating readme to link to OpenAI hosted evals experience (#...
cdb8ce9 · 10 months ago
688 Commits
.github Make the torch dep optional (#1524) last year
docs Add info about logging and link to logviz (#1480) last year
evals 20240930 steven exception handling usage tokens (#1560) last year
examples Upgrade openai to >=1.0.0 (#1420) 2 years ago
scripts Fix formatting/typing so pre-commit hooks pass (#1451) last year
tests/unit/evals [unit test] Adding unit test for metrics.get_accuracy (#224) 2 years ago
.gitattributes Initial Commit 2 years ago
.gitignore Self-Prompting eval (#1401) 2 years ago
.pre-commit-config.yaml Adding ruff, running pre-commit hooks, small fixes and doc... 2 years ago
LICENSE.md Already Said That Eval (#1490) last year
About
Evals is a framework for evaluating LLMs and LLM systems, and an open-source registry of benchmarks.
Readme
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Security policy
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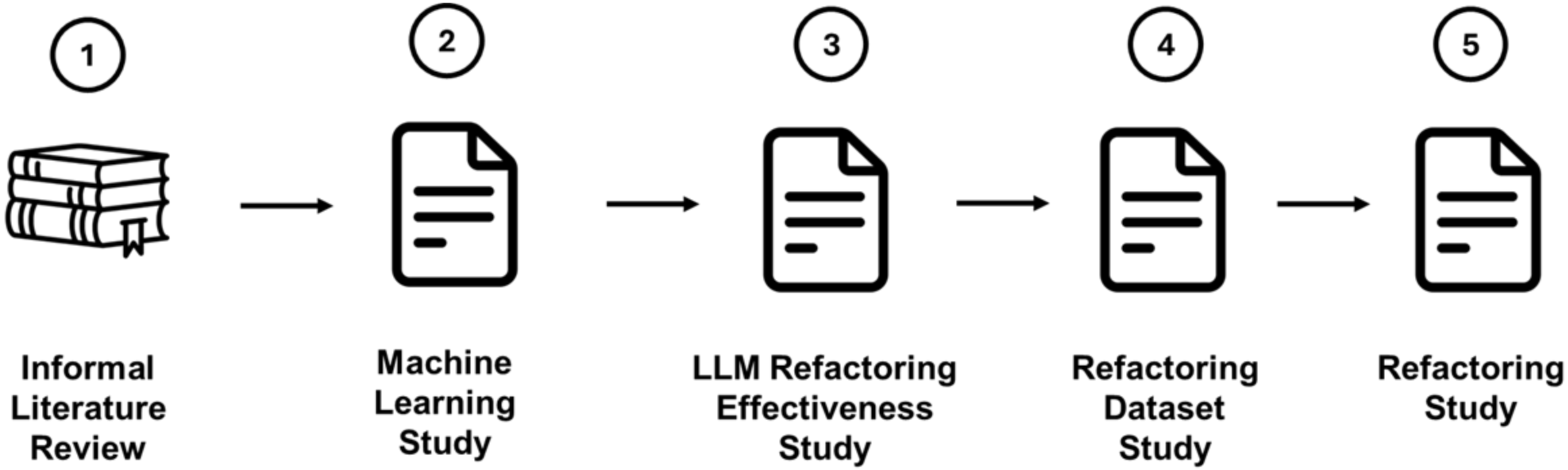
17.2k stars
272 watching
2.8k forks
Report repository
Contributors 459

Research Method



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Contribution Progress

- Nunes, H. G., Santana, A., Figueiredo, E., & Costa, H. *Tuning code smell prediction models: A replication study*. In International Conference on Program Comprehension (**ICPC 2024**) - **Study 1**

- Nunes, H. G., Figueiredo, E., Rocha, L., Nadi S., Ferreira F., & Esteves, G. *Evaluating the effectiveness of llms in fixing maintainability issues in real-world projects*. In International Conference on Software Analysis, Evolution and Reengineering (**SANER 2025**) - **Study 2**

- Nunes, H. G., Sharma, T., Figueiredo, E. *MaRV: A Manually Validated Refactoring Dataset*. In International Conference on AI Foundation Models and Software Engineering (**FORGE 2025**) - **Study 3**

Machine Learning to Detect Code Smells

Study 1

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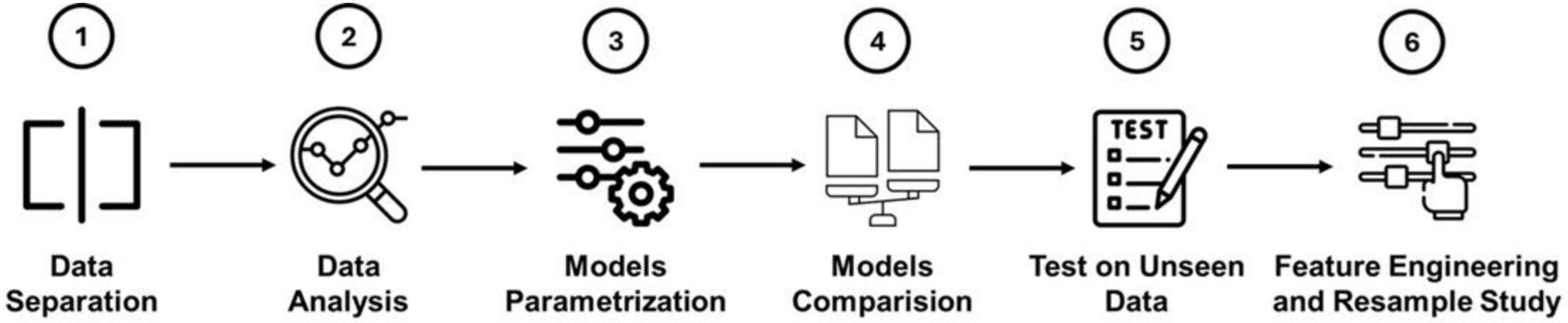
Study Context & Goals

- **Replicate** the study by Cruz et al. (2023), which uses machine learning to detect code smells, but **with a dataset of modern systems**.
- We use **seven traditional machine learning algorithms** to detect **four code smells**.
- We also evaluate how data resampling, feature selection, and polynomial feature techniques affect code smell predictions.

Design of Study 1



Study Result & Conclusion

- The performance of traditional ML algorithms for code smell detection are **limited**.
- ML techniques, especially resampling, improve prediction performance, but **not enough**.
- **This study indicated that we should explore for other solutions. LLMs?**

Large Language Models for Code Refactoring

Study 2

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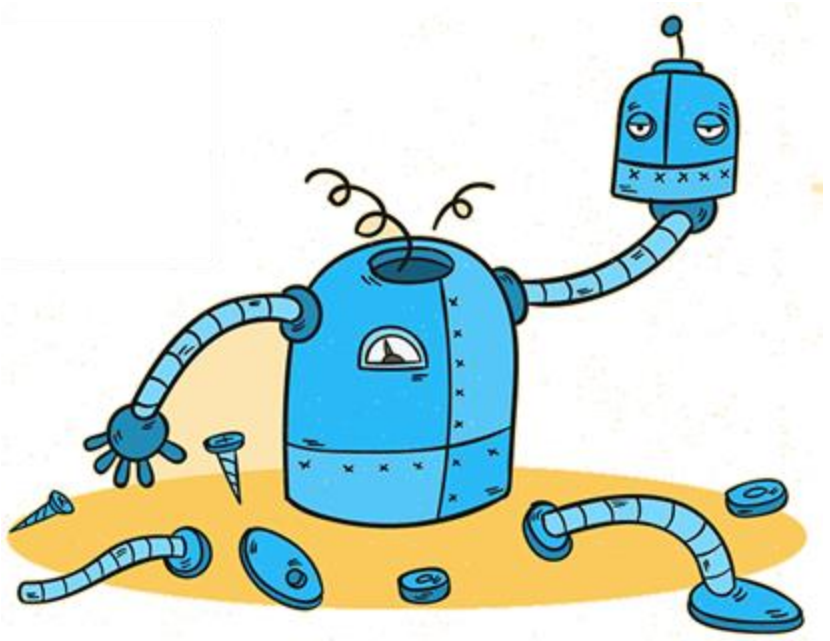
Study Context & Goals

- We evaluated the **effectiveness of LLMs for refactoring** 10 issue categories in real-world projects.
- Furthermore, the study assessed the most common **LLM failures**.
- We also conducted a human **readability evaluation**.



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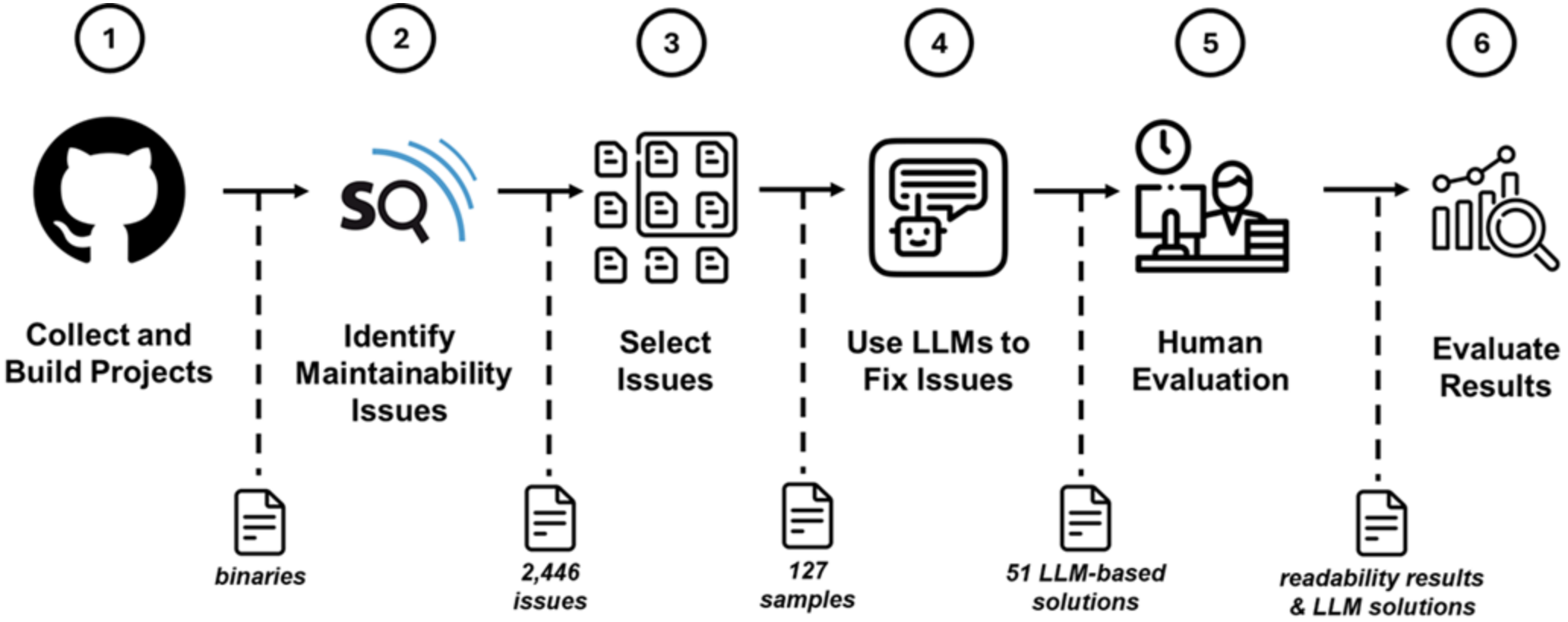
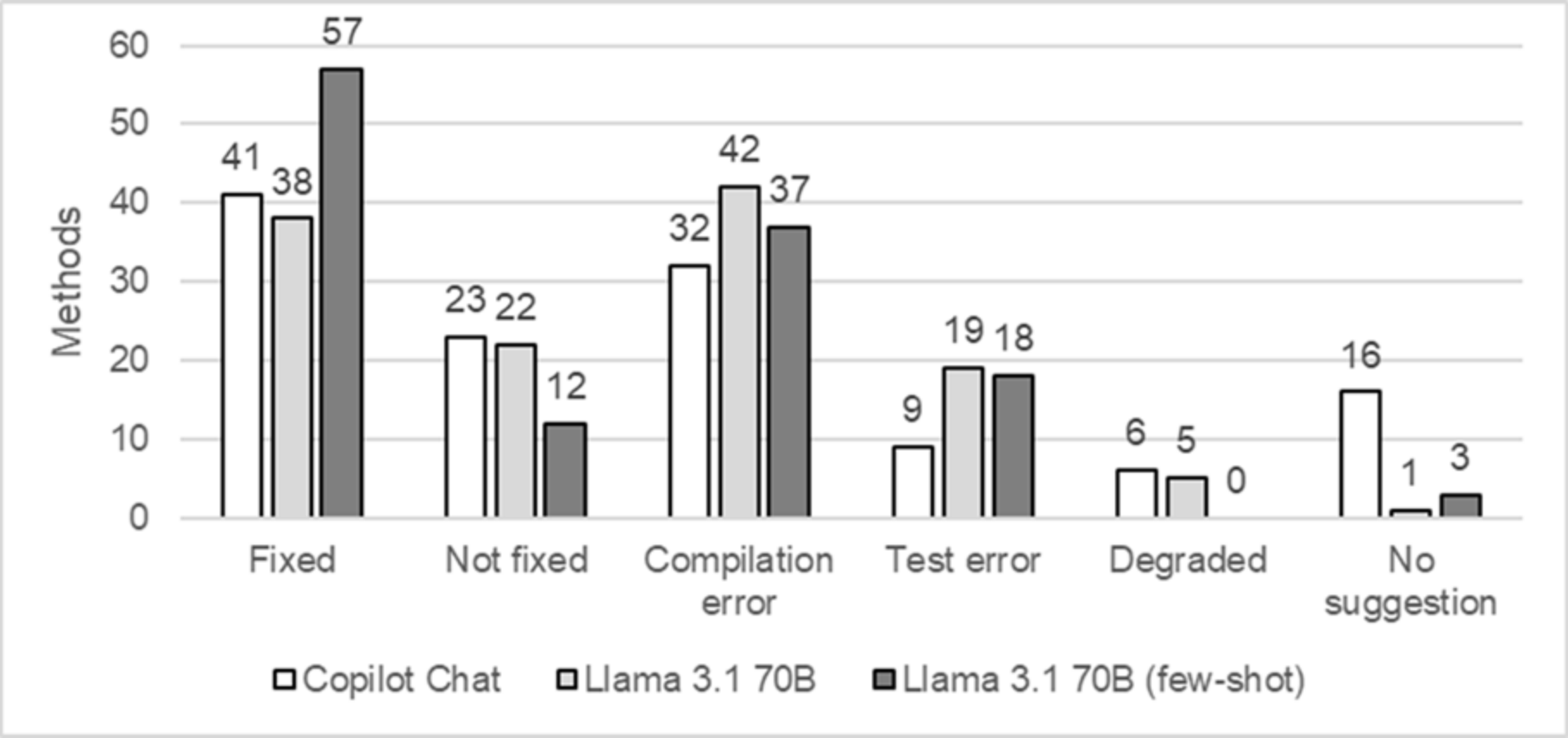
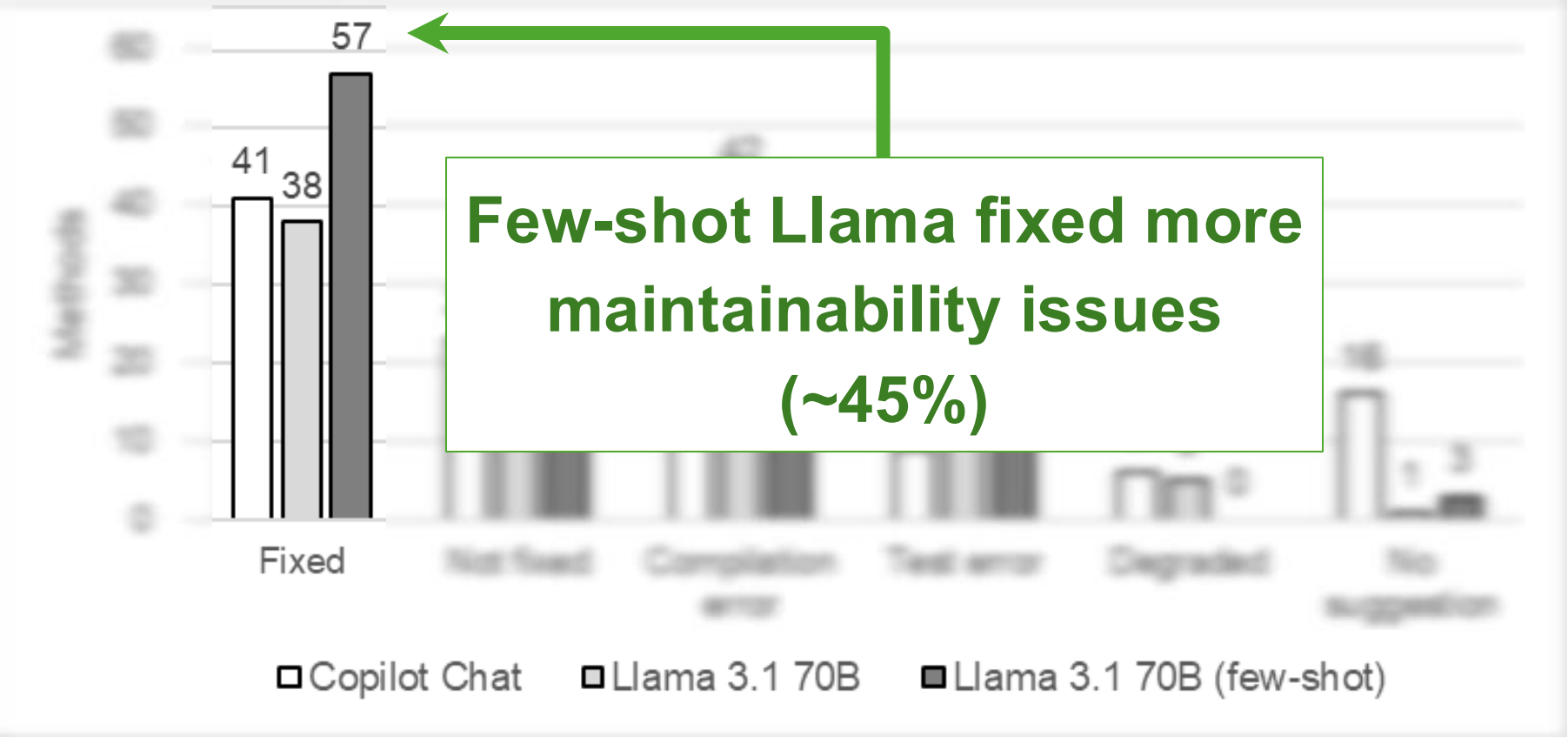
Design of Study 2



Effectiveness of the LLM

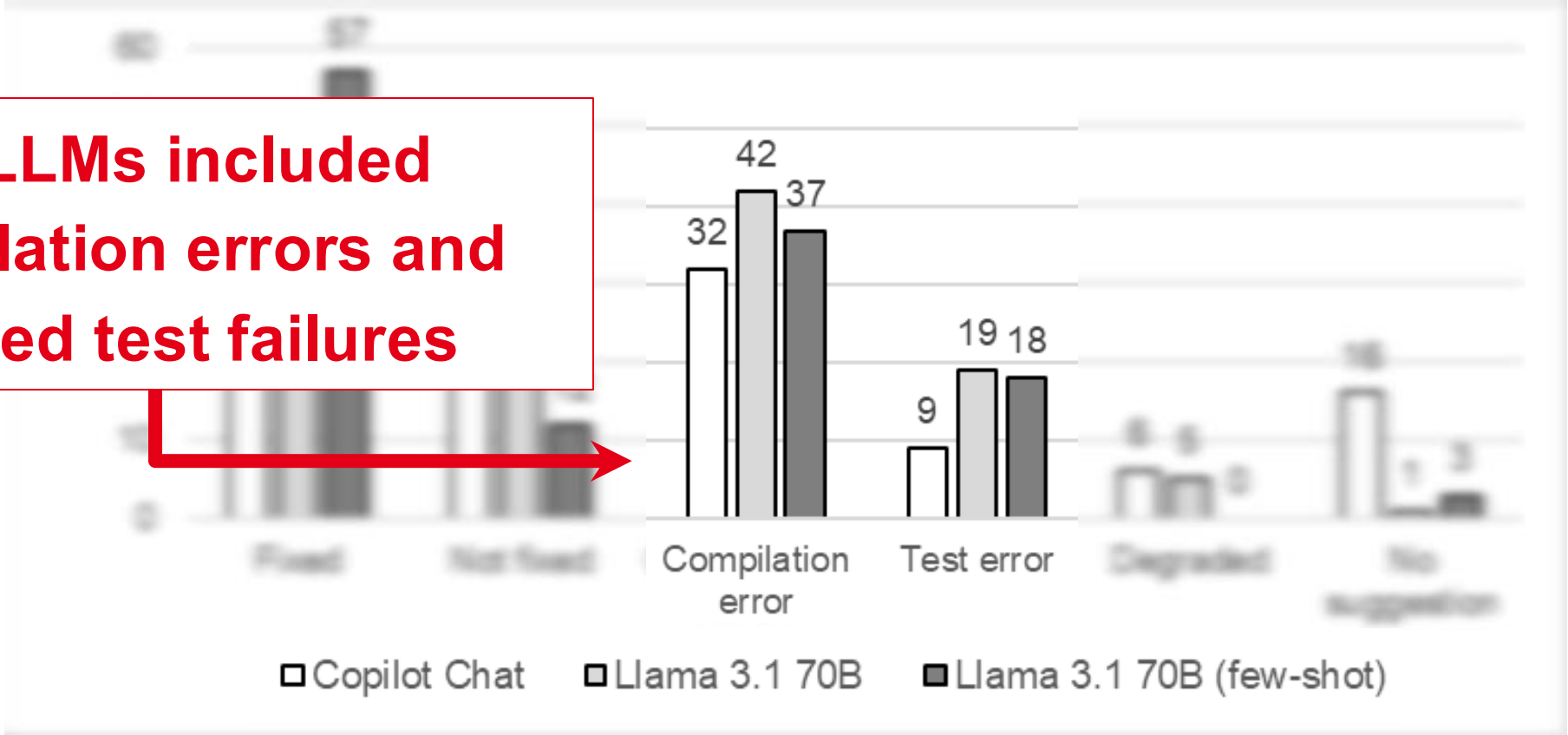


Effectiveness of the LLM



Effectiveness of the LLM

All LLMs included compilation errors and caused test failures



LLM Failures (Hallucination)

Original

```
private void put(DirectoryEntry entry,
    boolean overwriteExisting) {
    DirectoryEntry prev = null;
    [...]
    if (prev != null) {
        prev.next = entry;
    }
    [...]
}
```

LLM

```
private void put(DirectoryEntry entry,
    boolean overwriteExisting) {
    [...]
    overwriteEntry(existingEntry, entry);
    [...]
}

private void overwriteEntry(DirectoryEntry existingEntry,
    DirectoryEntry newEntry) {
    [...]
    if (existingEntry.prev!= null) {
        existingEntry.prev.next = newEntry;
    }
    [...]
}
```

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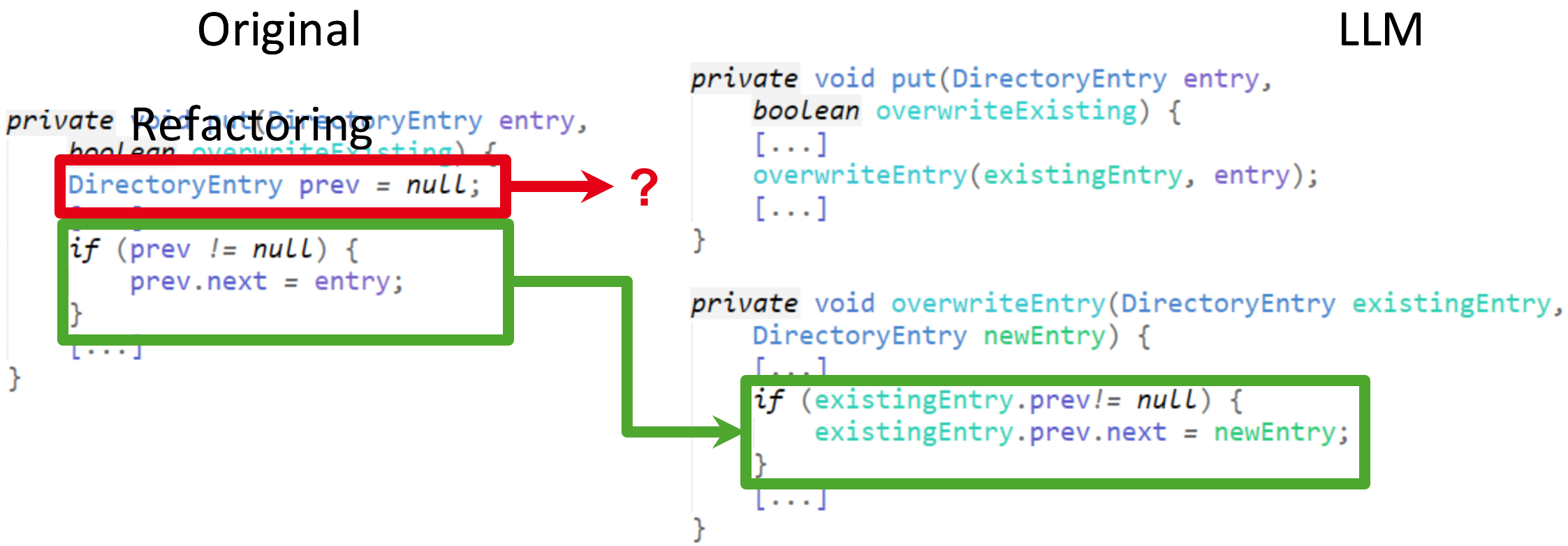
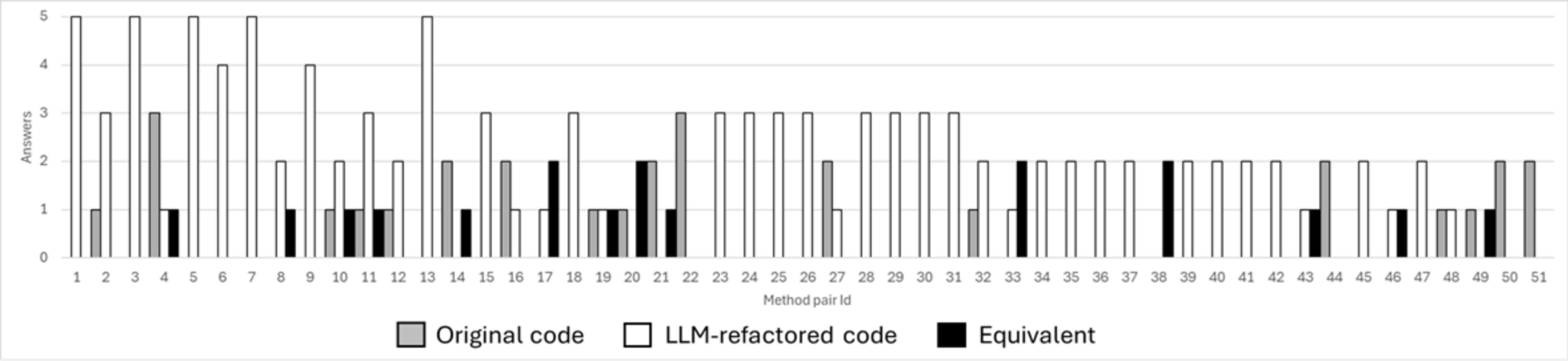
LLM Failures (Hallucination)



Human Evaluation of LLM Readability (RQ3)

Out of 51 method pairs, **~70%** considered LLM-refactored code more readable.



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Study Conclusion

- Despite **limited** effectiveness (below 50%), **few shot learning** presented the highest effectiveness (~40%), if compared with zero shot learning (~30%).
- Overall, participants considered LLM-refactored code **more readable**.
- **The results of this study motivated us to evaluate more deeply the use of prompt techniques for code refactoring.**

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Refactoring Dataset

Study 3

Study Context & Goal

- We used RefactoringMiner to **collect refactorings** and conducted a human evaluation to **select the most representative examples**.
- We aim to produce a high-quality **manually validated dataset** of actual refactorings from open-source projects, **MaRV**.

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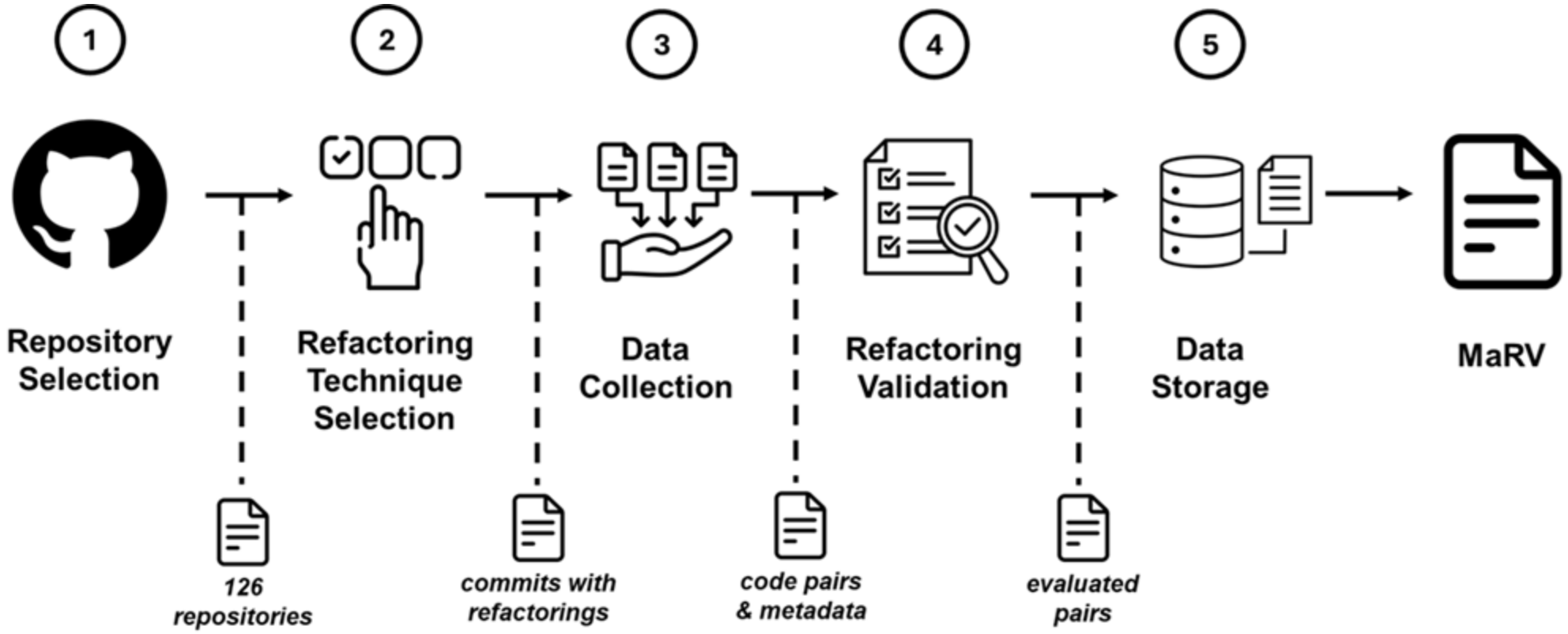
Design of Study 3



Manual Evaluation Results

	Votes	Count	Total
Consensus	[disagree, disagree]	84	405
	[agree, agree]	321	
Conflict	[disagree, agree]	217	285
	[I don't know, disagree]	27	
	[I don't know, agree]	41	
Other	[I don't know, I don't know]	3	3
			693

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Manual Evaluation Results

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	[agree, agree]	**321**	
Conflict	[disagree, agree]	217	285
	[I don't know, disagree]	27	
	[I don't know, agree]	41	
Other	[I don't know, I don't know]	3	3
			693

Both participants agreed in 321 cases (~46%). We considered this cases for MaRV

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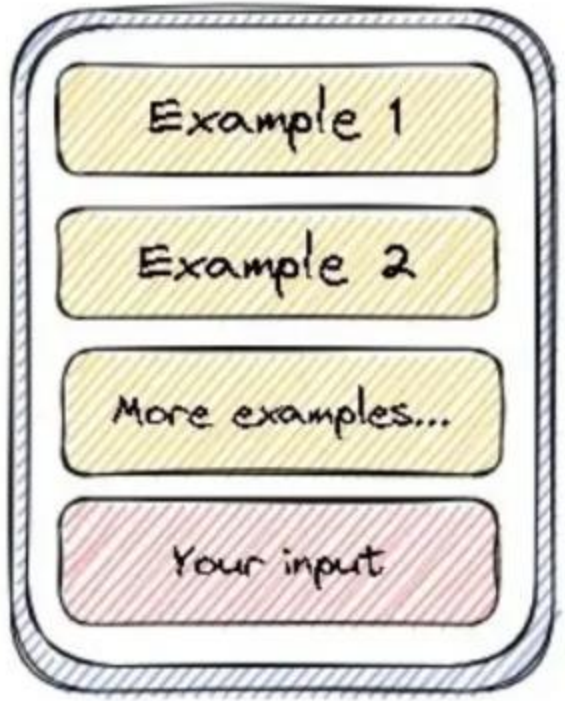
Study Conclusion

- **We aim to use MaRV to support several prompting techniques (e.g., few-shot prompting).**



Agenda

Next Steps

Future Steps

1. Improve MaRV Dataset
2. Select LLMs and Prompting Techniques
3. Define the Prompt Design
4. Execute and Validate LLM-Based Refactorings
5. Evaluate Results and Consolidate in a Paper
6. Extend our LLM Study
7. Write and Submit a Journal Paper
8. Write and Present Thesis

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Improve MaRV

```
@@ -352,9 +352,16 @@ public void testTimeExpireSSK() throws IO

        cachingStore.close();
    }
+
+   public void testOnCollisionsSSK() throws IOException, SSKE
    SSKVerifyException, KeyDecodeException, KeyCollisionExcept
+       // With slot filters turned off, it goes straight to d
+       checkOnCollisionsSSK(false);
+       // With slot filters turned on, it should be cached, i
block.
+       checkOnCollisionsSSK(true);
+   }

    /* Test collisions on SSK */
+   private void checkOnCollisionsSSK(boolean useSlotFilter) t
    InvalidCompressionCodecException, SSKVerifyException, KeyD
        File f = new File(tempDir, "saltstore");
        FileUtil.removeAll(f);

@@ -363,7 +370,7 @@ public void testOnCollisionsSSK() throws I
        new RAMFreenetStore<DSAPublicKey>(pk, keys);
        GetPubkey pubkeyCache = new SimpleGetPubkey(pk);
        SSKStore store = new SSKStore(pubkeyCache);
+       SaltedHashFreenetStore<SSKBlock> saltStore = SaltedHas
     store, weakPRNG, 10, true, SemiOrderedShutdownHook.get(),
        CachingFreenetStore<SSKBlock> cachingStore = new Cachi
    cachingFreenetStorePeriod, saltStore, ticker);
        cachingStore.start(null, true);
        RandomSource random = new DummyRandomSource(12345);
```

```
public void testOnCollisionsSSK() throws IOException, SSKEncodeExcepti
    SSKVerifyException, KeyDecodeException, KeyCollisionException {
    checkOnCollisionsSSK(false);
    checkOnCollisionsSSK(true);
}

private void checkOnCollisionsSSK(boolean useSlotFilter) throws IOExce
    InvalidCompressionCodecException, SSKVerifyException, KeyDecodeExc
        File f = new File(tempDir, "saltstore");
        FileUtil.removeAll(f);
}
```

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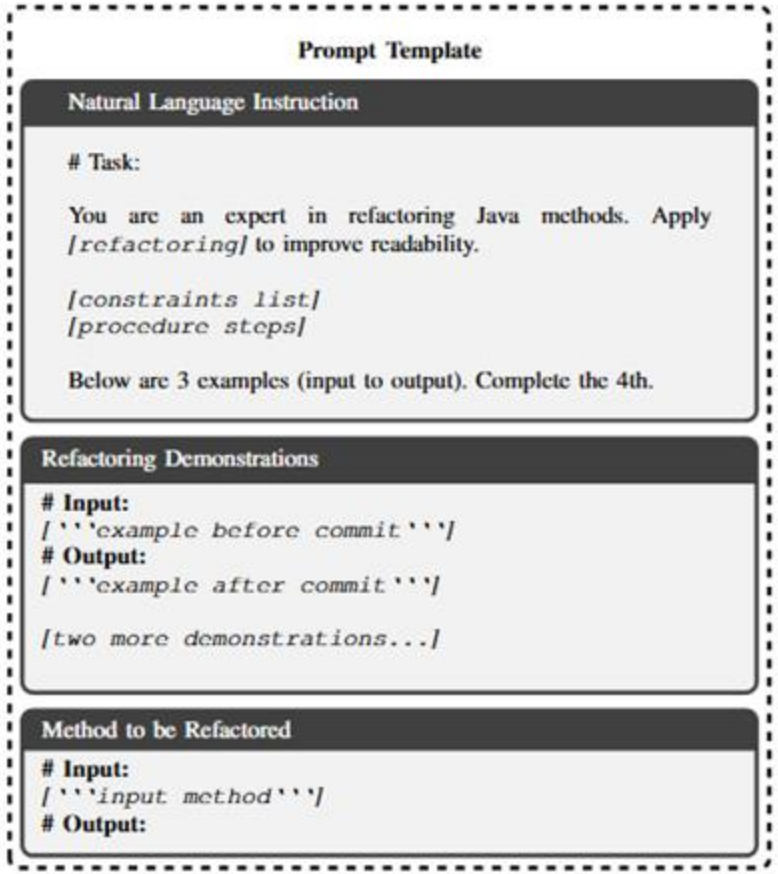
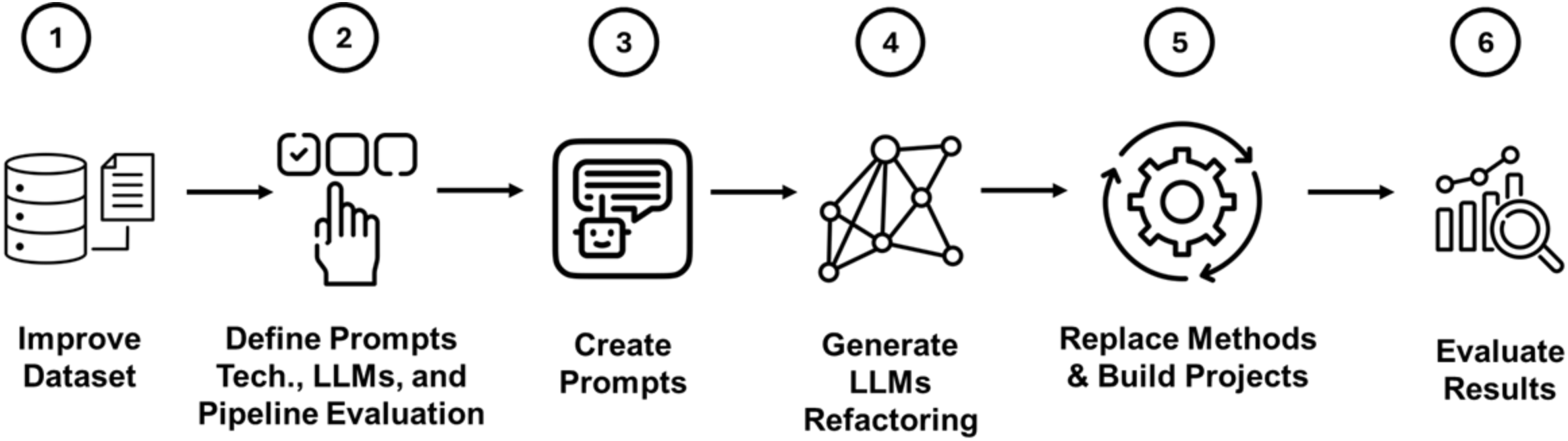
Prompt Evaluation

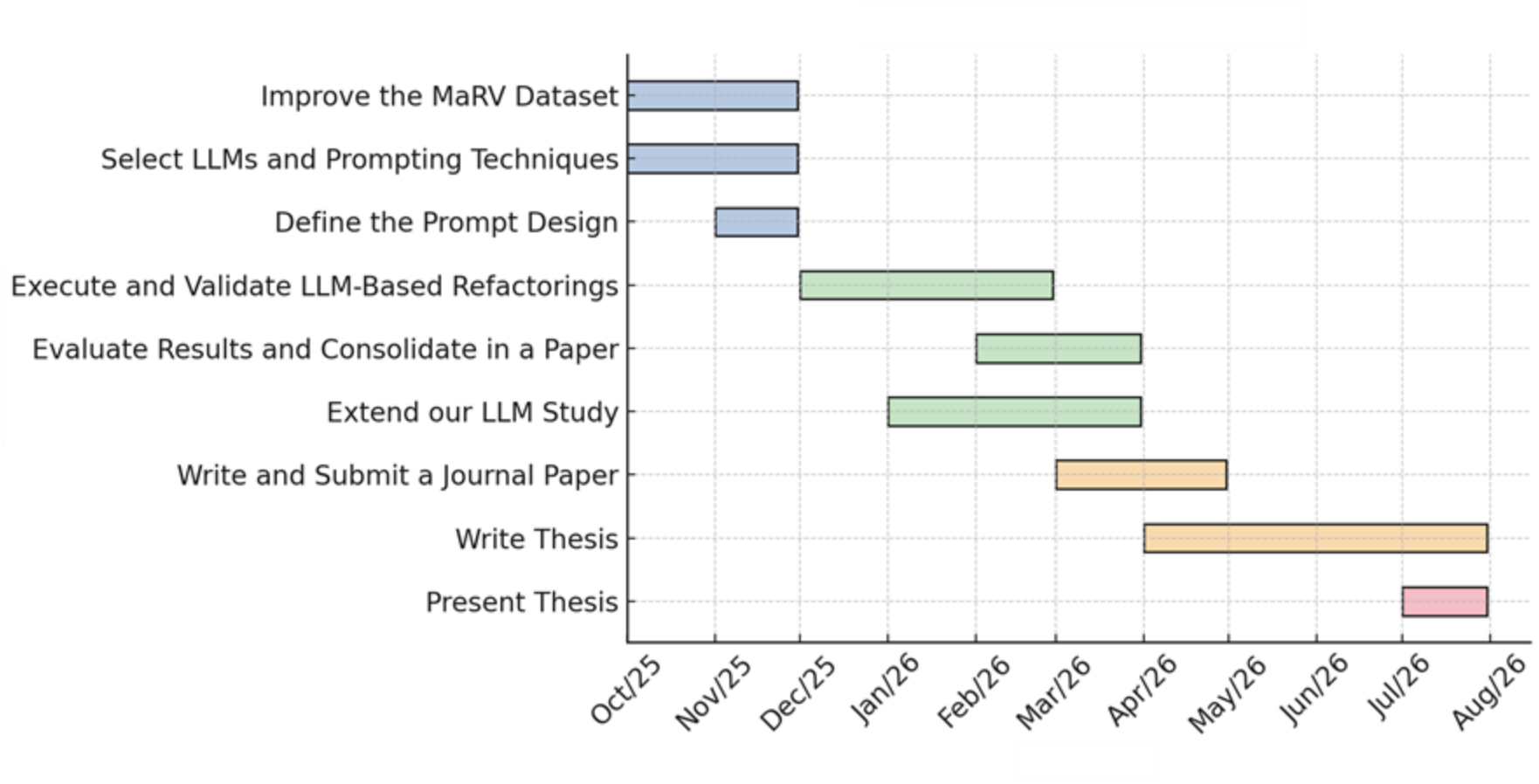
- We aim to evaluate **different prompt techniques** and their variations.
- We will define several prompt designs, **varying and combining techniques**.
- We want to identify **which prompts are most effectiveness** for each different refactoring type.



Next Steps Overview



Agenda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Select LLMs and Prompting Techniques
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Execute and Validate LLM-Based Refactorings
Evaluate Results and Consolidate in a Paper
Extend our LLM Study
Write and Submit a Journal Paper
Write Thesis
Present Thesis
Oct/25
Nov/25
Dec/25
Jan/26
Feb/26
Mar/26
Apr/26
May/26
Jun/26
Jul/26
Aug/26

Thank you!

Henrique Nunes | henrique.mg.bh@gmail.com