Together We Are Better

LLM, IDE and Semantic Embedding to Assist Move Method Refactoring

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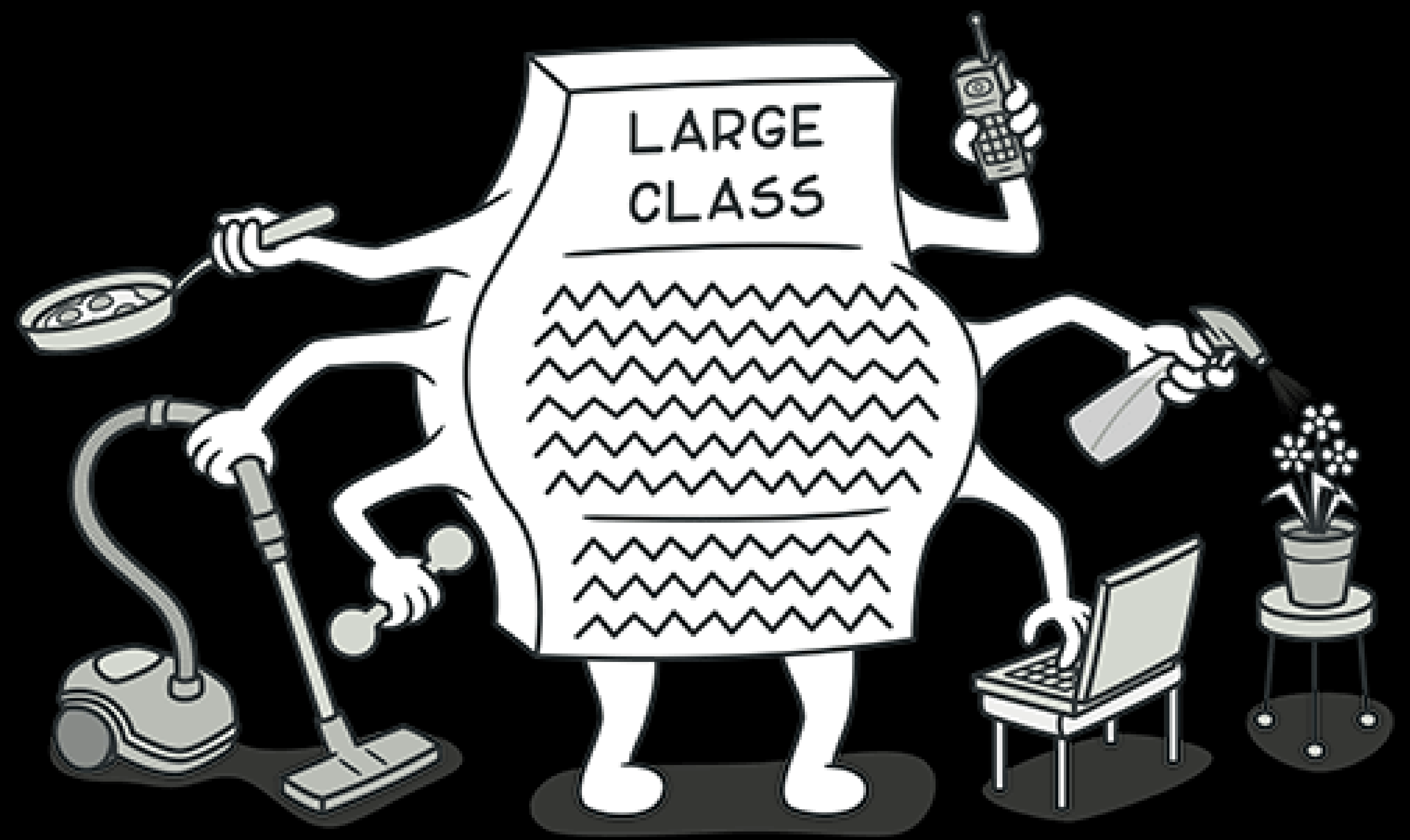
Why MoveMethod Matters

Top-5 most common refactoring

Improves cohesion, reduces coupling

Reduces Technical Debt and removes code smells: God Class, Feature Envy, Duplicate Code



MoveMethod Refactoring to the Rescue

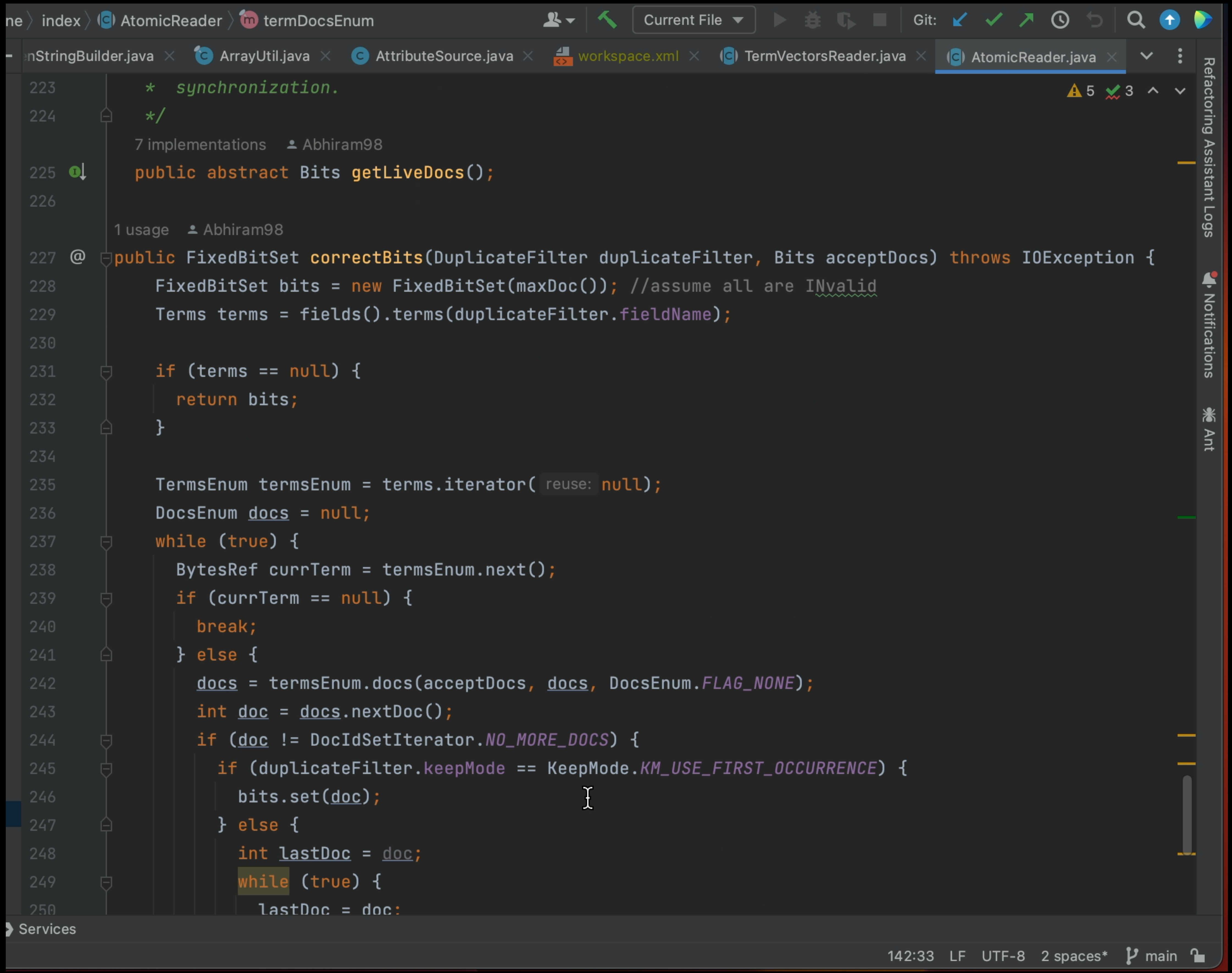
```java
public class Customer {
  private Phone mobilePhone;

  public String getMobilePhoneNumber() {
    return "(" +
      mobilePhone.getAreaCode() + ") " +
      mobilePhone.getPrefix() + "-" +
      mobilePhone.getNumber();
  }
}
```

Move to Phone class

Current Move Method Workflow in IntelliJ

- JetBrains' IntelliJ IDEA has Move Method capabilities
- Semi-automated process
- No automatic recommendations



Approaches for MM Recommendations

Static analysis (JMove, JDeodorant)
- thresholds, slow (hours), poor scalability

ML (RMove, PathMove) / DL (FeTruth, Hmove)
- need retraining, overwhelm users

Optimize software quality metrics

Do not align with how developers refactor code

LLMs
- prolific, capture semantic intuition

Key Challenges

LLM Hallucinations - 80% invalid recommendations

Context window limits – can’t reason over large projects

Workflow fit – needs to be fast and IDE-integrated

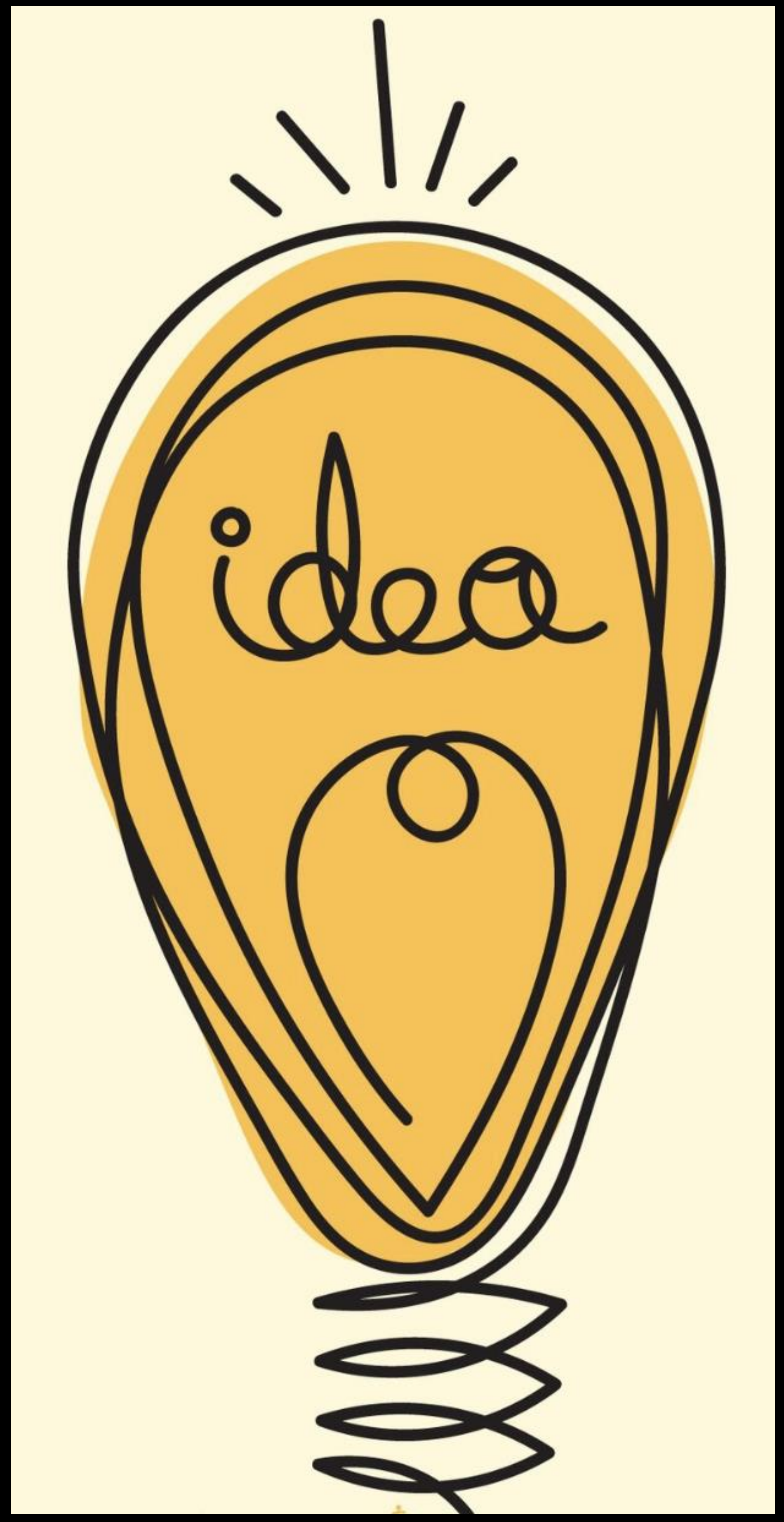
Our Insights

Combine LLM creativity + IDE rigor

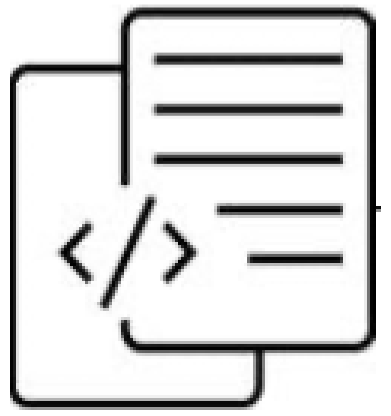
Filter hallucination via static preconditions checks in IDE

Semantic embeddings + Refactoring-aware RAG

Few high-quality recommendations (≤3 per class)



MM-Assist: Workflow



Empirical Evaluation Setup

Two Datasets:

- Synthetic corpus of 235 MM scenarios
- New real-world corpus 210 MM (2024+, OSS), avoids LLM training contamination

Formative study

Baselines: JMove, FeTruth, HMove, Vanilla LLM

User study: 30 participants, 1 week, own project

Results: Synthetic Corpus

235 MM scenarios
Metric: Recall@K for top-K recommendations

MM-ASSIST Recall@1 = 67%, Recall@3 = 75%

Baselines: JMOVE ~40%, HMOVE ~26%, FETRUTH only 2–3%

1.7x improvement over best baseline

LLM alone performed better than old tools but still plagued by hallucinations

Results: Real-World Corpus + User study

Replicated 210 OSS refactorings (uncontaminated by LLM training)

MM-ASSIST Recall@3 = **80% vs 33%** (baselines) → **2.4x improvement**.

Runtime: **~30 seconds** vs hours or days for baselines.

User study: 30 devs, 350 classes analyzed → **83% positive ratings**, avg. 7 accepted refactorings/user.

Dev quote: *"Skeptical about AI, but glad to delegate grunt work."*

Executive Summary

First end-to-end LLM-powered Move Method assistant

Key Idea: LLMs (creative)+ IDEs (validation) + Refactoring-Aware RAG (lookup)

- addresses hallucinations + context limits via IDE + RAG

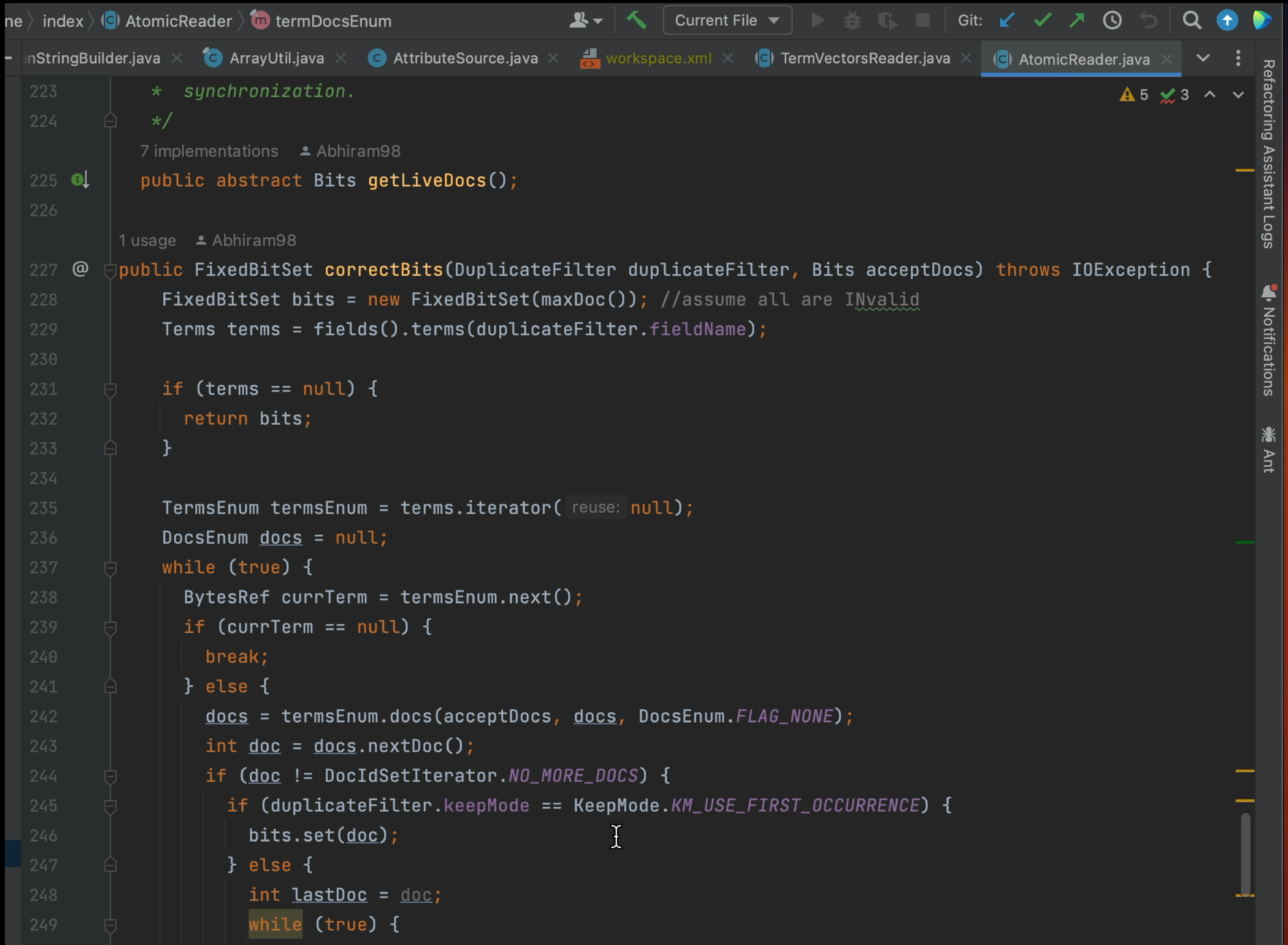
2–4× better recall, 10–100× faster

Trusted by developers (83% positive)

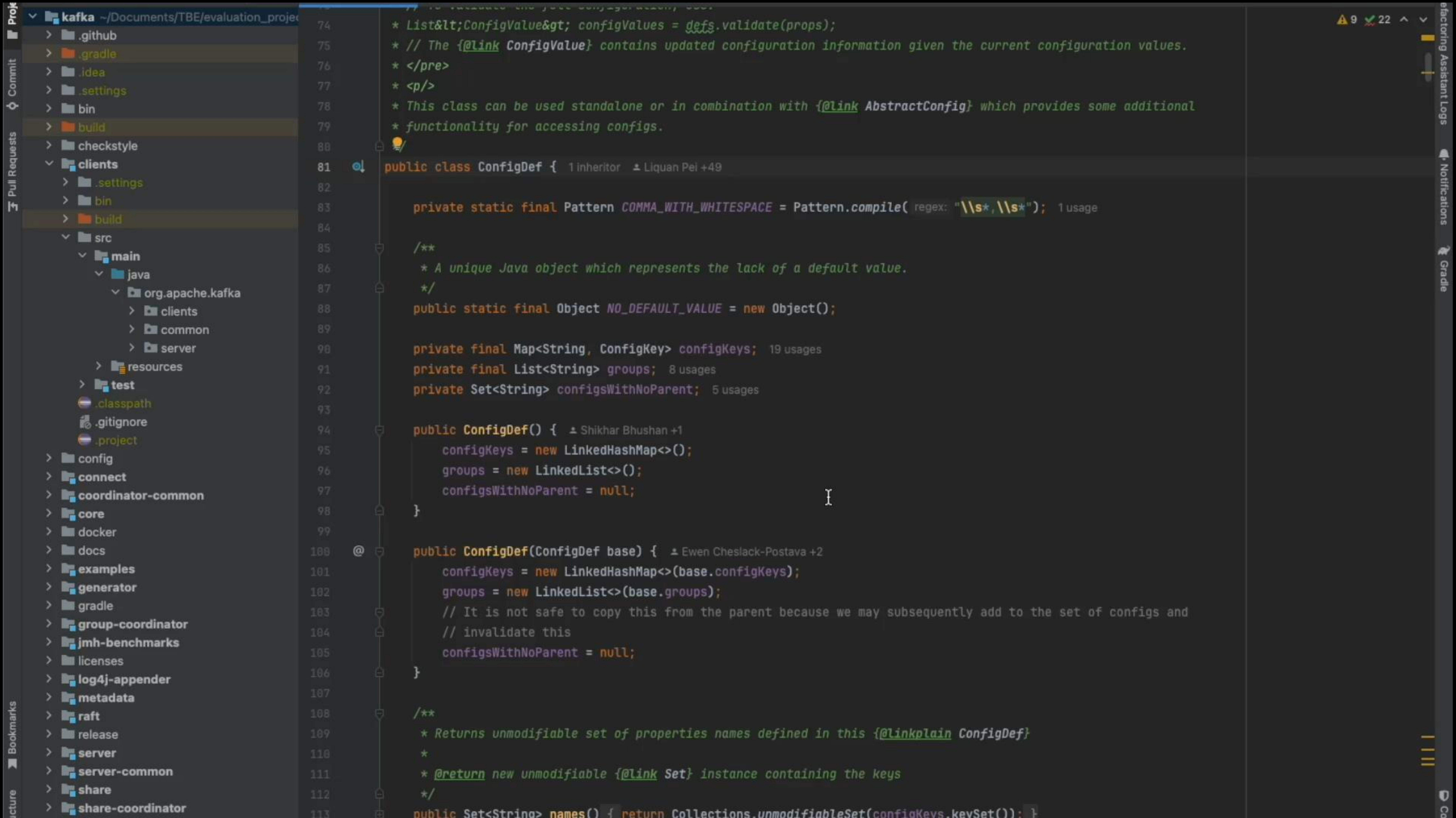
Techniques generalize to other refactorings

Bonus Slides

Move Method Refactoring in IntelliJ



Demo MM-Assist



Lessons Learned

LLM Critique –
Can be too harsh

High hallucination rate 80%

Task Decomposition helped – instead of depending on LLM to do everything

Data leakage problem

LLM Data Leakage

- Gpt-4o training data cutoff: Oct-2023

Approach	$Recall_C$ @1	$Recall_C$ @2	$Recall_C$ @3
MM-Assist	80.6	91.4	93.5
↪ **static method**	90.4	100.0	100.0
↪ **instance method**	77.8	88.9	94.4

Oracle Size	Approach	$Recall_M$			$Recall_C$			$Recall_{MC}$		
		@1	@2	@3	@1	@2	@3	@1	@2	@3
SmallClasses (38)	JMove (19)	5%	5%	5%	0%	0%	0%	0%	0%	0%
	feTruth	20%	20%	20%	**100%**	**100%**	**100%**	20%	20%	20%
	Vanilla-LLM	55%	68	73%	86%	86%	86%	63%	58%	63%
	MM-Assist	**76%**	**92%**	**94%**	86%	89%	89%	**71%**	**82%**	**82%**

Oracle Size	Approach	$Recall_M$			$Recall_C$			$Recall_{MC}$		
		@1	@2	@3	@1	@2	@3	@1	@2	@3
SmallClasses (40)	feTruth	7%	15%	15%	14%	14%	14%	1%	2%	2%
	Vanilla-LLM	43%	57%	65%	7%	7%	7%	3%	4%	5%
	MM-Assist	**55%**	**65%**	**70%**	**21%**	**21%**	**21%**	**12%**	**14%**	**15%**

Your Questions: Core Methodology and RAG Pipeline

Regarding the core methodology, can semantic retrieval meaningfully identify better refactoring targets than traditional dependency graph analysis?

What are the specifics of the RAG pipeline—including the choice of VoyageAI models, the number of retrieved classes, and the prompt optimization strategy, and does using partial class summaries for retrieval significantly degrade recommendation quality?

How effective is cosine similarity for code, and what is the justification for weighting package proximity 2x higher than the utility metric in the RankingScore formula?

Tool Design, Usability, and Edge Cases

From a usability standpoint, how does the tool handle edge cases like finding no suitable candidates (does it fail gracefully or hallucinate?)

What is the workflow for complex "God Classes"?

What was the rationale for limiting suggestions to three candidates, and does this hinder the full exploration of refactoring options without repeated use?

Evaluation, Performance, and Generalizability

In terms of the evaluation, are the reported performance gains primarily due to the novel algorithm, or could they be attributed to failures or limitations in the baseline tools used for comparison?

What were the main reasons developers rejected 17.2% of suggestions?

How does the tool's performance scale to massive codebases?

How would it translate to dynamic languages like Python?

What is the expected gain from using a domain-tuned embedding model?

Cost, Practicality, and Real-World Adoption

Considering practical adoption, what is the tool's financial viability, and how would its performance and cost change if using an open-source LLM instead of a commercial API?

What are the long-term integration complexities and developer privacy concerns?

Crucially, what are the potential implications of the LLM introducing "design hallucinations," especially when applying such a tool to safety-critical codebases?

Future Work and Potential Improvements

For future work, beyond improving method-level suggestions by integrating static metrics or creating a personalized memory system, can this architecture be extended to support more complex tasks?

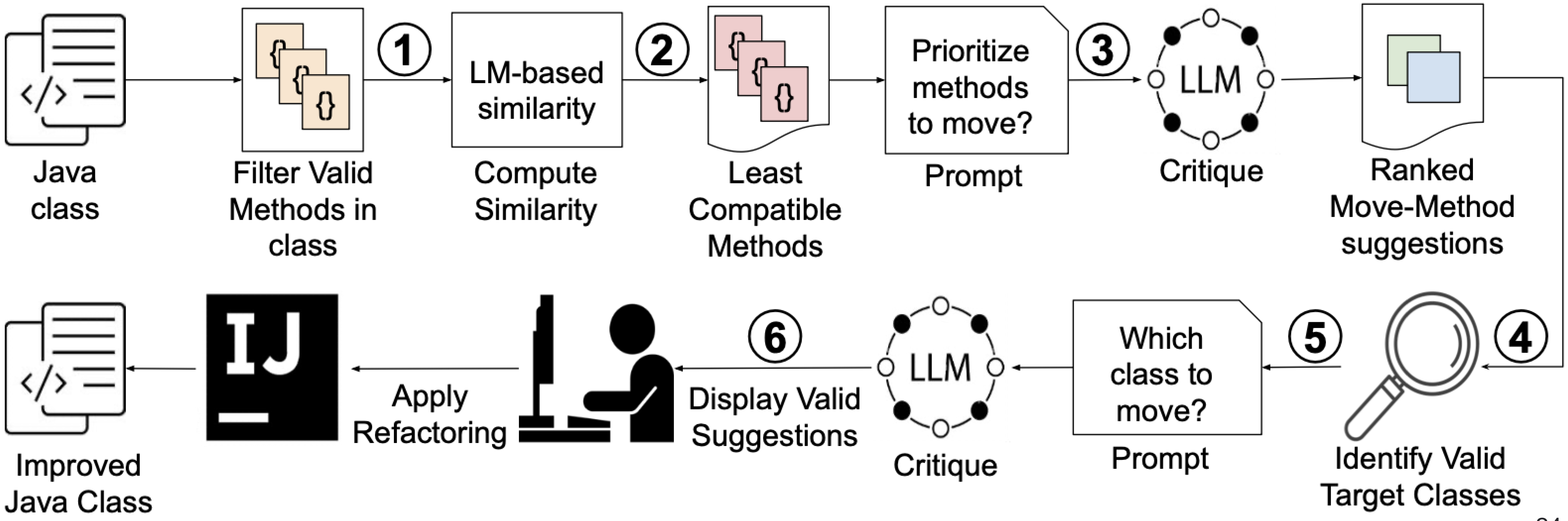
For instance, could it facilitate large-scale architectural refactorings or even serve as a tool for collaborative design sessions among multiple developers?

Research and Development Process

Could you share insights into the development process itself? Was the plugin built from scratch or did it reuse components from EM-assist?

And how did you manage the balance between development and user testing under a tight conference deadline?

Workflow



Java class
Filter Valid Methods in class
1
LM-based similarity
Compute Similarity
2
Least Compatible Methods
Prioritize methods to move?
Prompt
3
LLM
Critique
Ranked Move-Method suggestions
4
Identify Valid Target Classes
5
Which class to move?
Prompt
LLM
Critique
6
Display Valid Suggestions
Apply Refactoring
IJ
Improved Java Class

RQ1: How effective are LLMs at suggesting opportunities for MM refactoring?

TABLE I: Different kinds of hallucinations from Vanilla LLM

Corpus	**# R**	**# H1**	**# H2**	**# H3**
Synthetic (235)	723	362	168	51
Real-world (210)	1293	431	275	320

R: Recommendations, H1: Hall-class, H2: Hall-Mech, H3: Invalid Method.