

# **Mining Software Repositories to Improve Refactoring Assistants**

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# What is Refactoring?

Refactoring is “a change made to the internal structure of software to make it easier to understand and cheaper to modify without changing its observable behavior.”<sup>1</sup>

1

Identify an Issue

2

Select Refactoring

3

Apply the Refactoring

# Motivation

**Traditional  
Refactoring  
can be seen  
as**

Error Prone

Tedious

Time Consuming

Solutions



Automated  
Testing



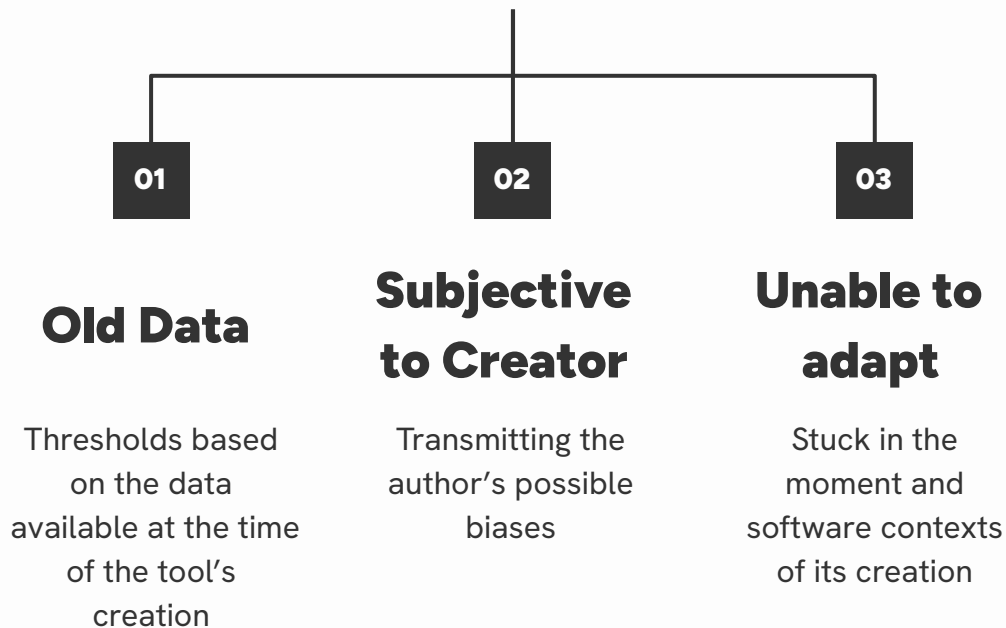
Automated  
Refactoring  
Tools



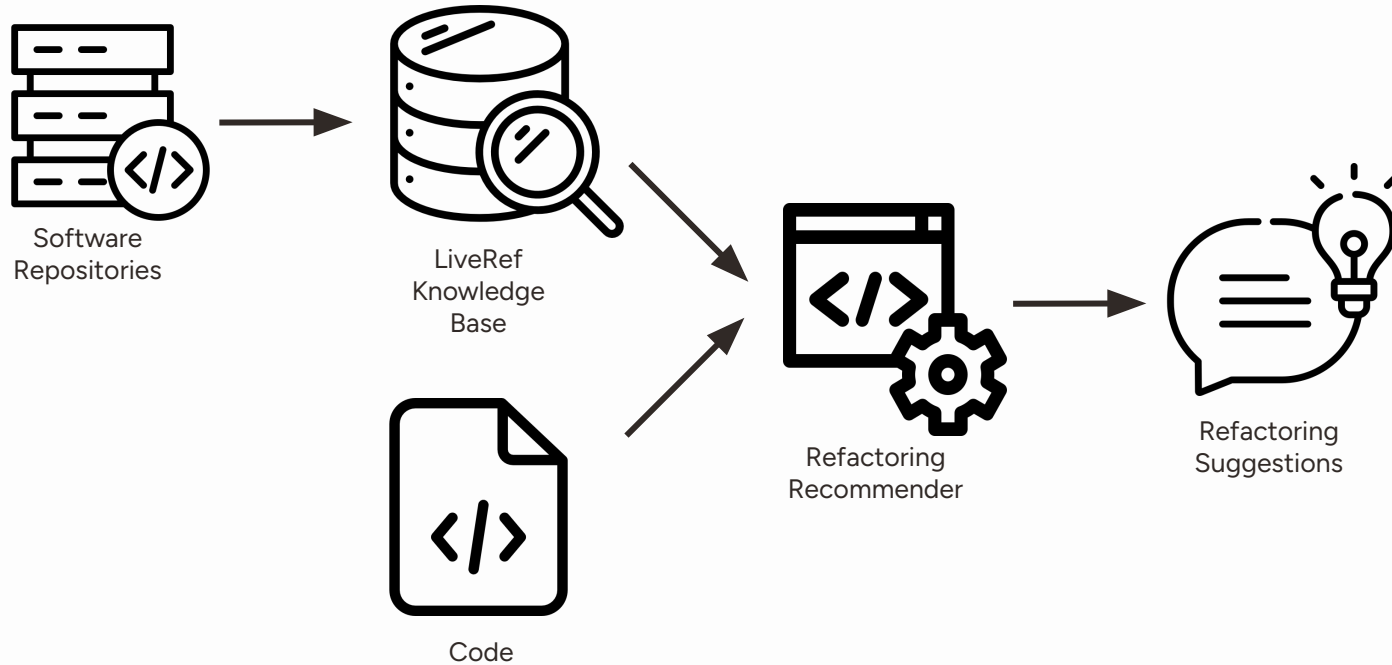
Refactoring  
Metrics

# Problem

## Threshold-Based Refactoring Tools Problems



# Objective



# Problem Statement

*“A refactoring recommendation system based on a dynamic classification model, built with real-life data, will lead to more accurate suggestions when compared to threshold-based methods.”*

## RQ1

*“How do threshold-based refactoring recommendations compare to the refactoring practices developers employ in real-life contexts?”*

## RQ2

*“Is a classification model based on real data able to improve on the refactoring recommendations when compared to a threshold method?”*

# Mining Software Repositories (MSR)

## Approaches

- Repositories contain a myriad of information suited to many purposes, including software maintainability and refactoring.<sup>2</sup>
- Tools such as SemDiff<sup>3</sup> and SysRepoAnalysis<sup>4</sup> analyse the repositories to provide change recommendations or static analyses.

## Improvements

- DISDRILLEY can increase performance in data extraction in MSR.<sup>5</sup>
- Reverted commits have a high impact on noise data in refactoring detection.<sup>6</sup>

2. Mário André de F. Farias, Renato Novais, Methanias Colaço Júnior, Luis Paulo da Silva Carvalho, Manoel Mendonça, and Rodrigo Oliveira Spinola. A systematic mapping study on mining software repositories, 2016.

3. Barthélémy Dagenais and Martin P. Robillard. Recommending adaptive changes for framework evolution. ACM Trans. Softw. Eng. Methodol., 20(4):Article 19, 2011.

4. Armando Sousa, Gisele Ribeiro, Guilherme Avelino, Lincoln Rocha, and Ricardo Britto. Sysrepoanalysis: A tool to analyze and identify critical areas of source code repositories, 2022.

5. Martin Steinhauer and Fabio Palomba. Speeding up the data extraction of machine learning approaches: a distributed framework, 2020.

6. Fengcai Wen, Csaba Nagy, Michele Lanza, and Gabriele Bavota. Quick remedy commits and their impact on mining software repositories. Empirical Software Engineering, 27(1):14, 2021.

# Refactoring Activity Detection

## Mining Commit Logs

- Developers report their own refactorings in the commit logs.
- Approaches identify and Self Affirmed Refactoring (SAR) patterns that indicate refactoring activity.<sup>7</sup>

## Mining the Source Code

- Analysing the version of the code before and after modifications to identify refactorings.
- Either through the use of code metrics that change in specific ways.<sup>8</sup>
- Or through defined code similarity thresholds.<sup>9</sup>

(1) Modif*	(15) Fix* quality flaw	(1) Typo	(15) Formatted
(2) Simplif*	(16) Remov* dependency	(2) Tidy*	(16) Cleaned up
(3) Polish* code	(17) Code improvement*	(3) Spell* code	(17) Code clean
(4) Chang* design	(18) Fix* quality issue	(4) Tidied	(18) Get rid of
(5) Us* less code	(19) Renam* consistency	(5) Polish*	(19) Getting rid of
(6) Simplif* code	(20) Reorganiz* structure	(6) Clarif*	(20) Meaningful
(7) Pull* some code	(21) Fix* technical debt	(7) Separat*	(21) Modulariz*
(8) Us* better name	(22) Remov* unused classes	(8) Optimiz*	(22) Pulled out
(9) Code cosmetic*	(23) Remov* redundant code	(9) Organiz*	(23) Cleaning up
(10) Delet* old stuff	(24) Improv* code quality	(10) Clean-up	(24) Better name
(11) Simplif* design	(25) Mov* more code out of	(11) Pull out	(25) Pulling out
(12) Fix* code smell	(26) Fix* naming convention	(12) Structur*	(26) New structure
(13) Nam* improvement	(27) Chang* package structure	(13) Correct*	(27) Duplicate code
(14) Modulariz* class	(28) Improv* naming	(14) Normaliz*	

Fig 1. Lists of SAR patterns<sup>7</sup>

Refactoring type	Rule
Change Method Signature $m_a$ to $m_b$	$\exists (M, U_1, U_2) \vdash \text{matching}(m_a, b, m_b, b) \mid m_a \in M^+ \wedge m_b \in M^+ \wedge m_a.c \neq m_b.c \wedge \left[ \begin{array}{l} \text{① } (U_1 \neq \emptyset \wedge U_2 = \emptyset \wedge \text{allExactMatches}(M)) \vee \text{② } ( M  >  U_1  \wedge  M  >  U_2  \wedge \text{locationHeuristic}(m_a, m_b) \wedge \text{compatiblesignatures}(m_a, m_b)) \vee \text{③ } ( M  >  U_1  \wedge \text{locationHeuristic}(m_a, m_b) \wedge \exists \text{extract}(m_a, m_c) \vee \text{④ } ( M  >  U_1  \wedge  M  >  U_2  \wedge \text{locationHeuristic}(m_a, m_b) \wedge \exists \text{inline}(m_c, m_b)) \end{array} \right]$
Extract Method $m_b$ from $m_a$	$\exists (M, U_1, U_2) \vdash \text{matching}(m_a, b, m_b, b) \mid (m_a, m_{a'}) \in M^+ \wedge m_b \in M^+ \wedge m_a.c \neq m_b.c \wedge \neg \text{calls}(m_a, m_b) \wedge \text{calls}(m_{a'}, m_b) \wedge  M  >  U_1 $
Inline Method $m_b$ to $m_{a'}$	$\exists (M, U_1, U_2) \vdash \text{matching}(m_b, b, m_{a'}, b) \mid (m_a, m_{a'}) \in M^+ \wedge m_b \in M^+ \wedge m_{a'}.c \neq m_b.c \wedge \neg \text{calls}(m_a, m_b) \wedge \text{calls}(m_{a'}, m_b) \wedge  M  >  U_1 $
Change Class Signature $td_a$ to $td_b$	$\exists (td_a, td_b) \mid td_a \in TD^+ \wedge td_b \in TD^+ \wedge (td_a.M \supseteq td_b.M \vee td_a.M \subset td_b.M) \wedge (td_a.F \supseteq td_b.F \vee td_a.F \subset td_b.F)$
Move Method $m_a$ to $m_b$	$\exists (M, U_1, U_2) \vdash \text{matching}(m_a, b, m_b, b) \mid m_a \in M^+ \wedge m_b \in M^+ \wedge m_a.c \neq m_b.c \wedge  M  >  U_1  \wedge  M  >  U_2  \wedge \left[ \begin{array}{l} \text{① } (td_a, td_b) \in TD^+ \wedge m_a \in td_a \wedge (td_b, td_b) \in TD^+ \wedge m_b \in td_b \wedge \text{importType}(td_{a'}, m_a.c) \vee \text{importType}(td_b, m_a.c) \end{array} \right]$
Move Field $f_a$ to $f_b$	$\exists (f_a, f_b) \mid f_a \in F^+ \wedge f_b \in F^+ \wedge f_a.c \neq f_b.c \wedge f_a.t \neq f_b.t \wedge f_a.n \neq f_b.n \wedge (td_a, td_a) \in TD^+ \wedge f_a \in td_a \wedge (td_b, td_b) \in TD^+ \wedge f_b \in td_b \wedge \text{importType}(td_{a'}, f_a.c) \vee \text{importType}(td_b, f_a.c)$
Extract $m_b$ from $m_a$ & Move to $m_b.c$	$\exists (M, U_1, U_2) \vdash \text{matching}(m_a, b, m_b, b) \mid (m_a, m_{a'}) \in M^+ \wedge m_b \in M^+ \wedge m_a.c \neq m_b.c \wedge \neg \text{calls}(m_a, m_b) \wedge \text{calls}(m_{a'}, m_b) \wedge  M  >  U_1  \wedge (td_a, td_a) \in TD^+ \wedge m_a \in td_a \wedge \text{importType}(td_{a'}, m_b.c)$
Extract SuperType $td_b$ from $td_a$	$\exists (td_a, td_b) \mid (td_a, td_a) \in TD^+ \wedge td_b \in TD^+ \wedge \text{subType}(type(td_a), type(td_b))$
Change Package $p_a$ to $p_b$	$\exists (p_a, p_b) \mid \text{path}(p_a) \in D^+ \wedge \text{path}(p_b) \in D^+ \wedge \exists \text{MoveClass}(td_a, td_b) \mid td_a.p = p_a \wedge td_b.p = p_b$

Fig 2. Refactoring detection rules in RMiner<sup>3</sup>

7. E. AlOmar, M. W. Mkaouer, and A. Ouni. Can refactoring be self-affirmed? An exploratory study on how developers document their refactoring activities in commit messages. In 2019 IEEE/ACM 3rd International Workshop on Refactoring (IWorR), pages 51-58.

8. Raimund Moser, Witold Pedrycz, Alberto Sillitti, and Giancarlo Succì. A model to identify refactoring effort during maintenance by mining source code repositories. In Andreas Jedlitschka and Outi Salo, editors, Product-Focused Software Process Improvement, pages 360-370. Springer Berlin Heidelberg

9. Nikolaos Tsantalis, Matin Mansouri, Laleh M. Eshkevari, Davood Mazinanian, and Danny Dig. Accurate and efficient refactoring detection in commit history. 2018.



# Refactoring Recommendation

## Analysing the Source Code

- Analysing the structure of the code, like the Abstract Syntax Tree (AST), to identify possible need for refactoring.

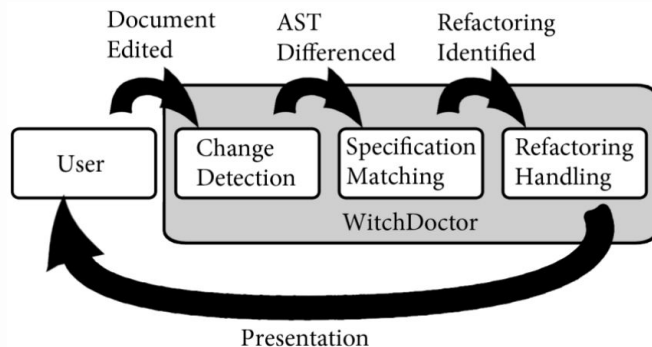


Fig 3. Graphical representation of WitchDoctor's workflow<sup>10</sup>

## Code Quality Metrics

- Define code quality metrics which, depending on their values, for example using thresholds, may indicate the need for a specific refactoring.

Type of Metric	Code Quality Metric
File Metrics	Number of Lines of Code, Number of Comments, Number of Classes, Number of Methods, Average Number of Long Methods, Average Lack of Cohesion, Average Cyclomatic Complexity
	Number of Fields, Number of Public Fields, Number of Methods, Number of Long Methods, Class Lack of Cohesion, Average Cyclomatic Complexity
Class Metrics	Number of Parameters, Number of Lines of Code, Number of Comments, Number of Statements, Method Lack of Cohesion, Cyclomatic Complexity, Halstead Length, Halstead Vocabulary, Halstead Volume, Halstead Difficulty, Halstead Effort, Halstead Level, Halstead Time, Halstead Bugs Belivered, Halstead Maintainability
Method Metrics	

Fig 4. Code quality metrics supported by LiveRef<sup>11</sup>

10. S. R. Foster, W. G. Griswold, and S. Lerner. Witchdoctor: Ide support for realtime auto-completion of refactorings. In 34th International Conference on Software Engineering (ICSE), International Conference on Software Engineering, pages 222-232, 2012. Foster, Stephen R. Griswold, William G. Lerner, Sorin 0270-5257.

11. Sara Fernandes, Ademar Aguiar, and André Restivo. A live environment to improve the refactoring experience, 2022.

# LiveRef Knowledge Base Development Strategy

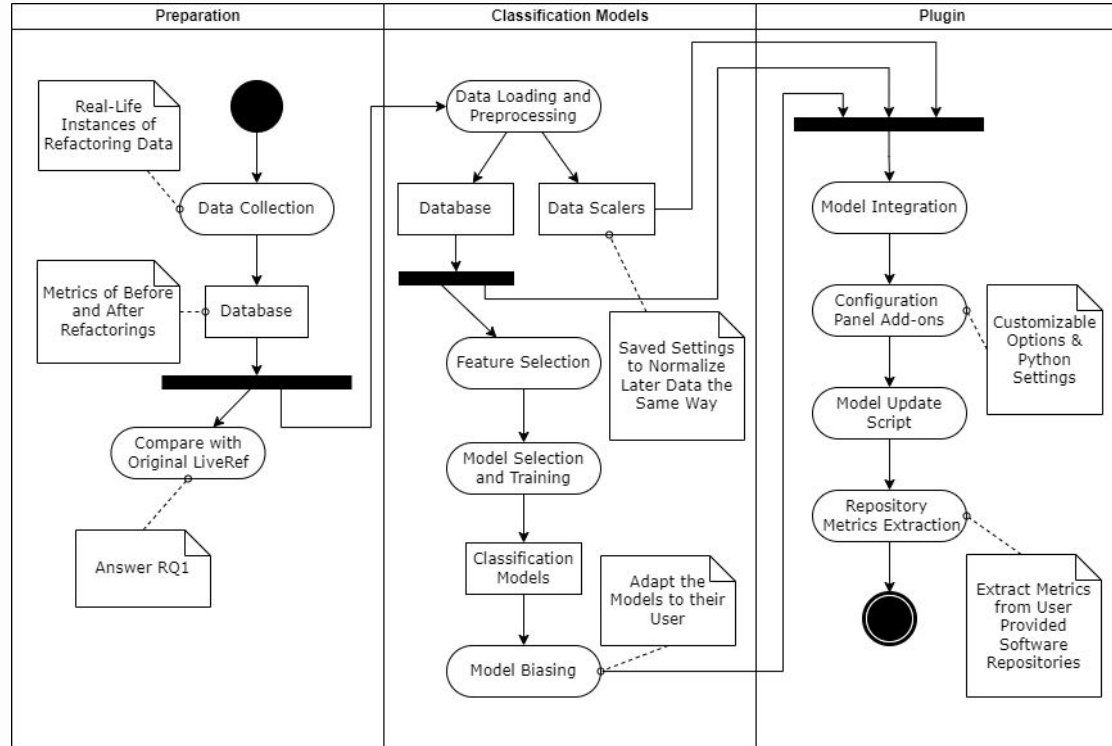


Fig 5. Activity diagram for solution development

# Data Collection

Real-life instances of refactoring operations.

Extract Method:

- ≈ 25,000 rows
- 18 metrics

Extract Class:

- ≈ 2,500 rows
- 20 metrics

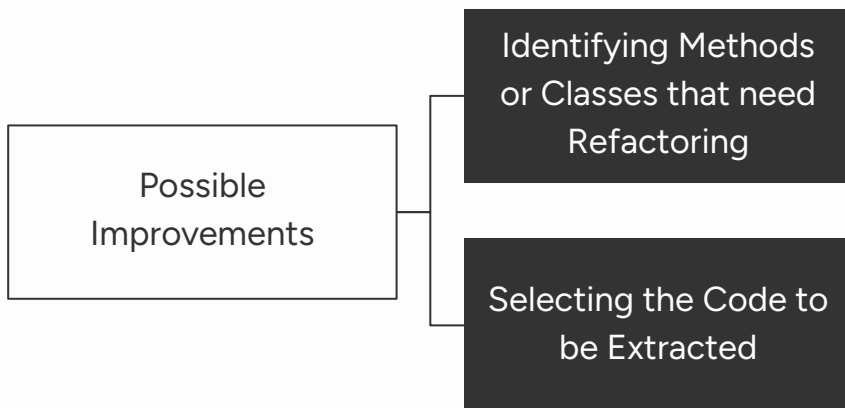
Metric	Extract Method	Extract Class
Number of Lines of Code	✓	✓
Number of Comments	✓	
Number of Blank Lines	✓	
Total Lines	✓	
Number of Parameters	✓	
Number of Statements	✓	
Halstead Length	✓	✓
Halstead Vocabulary	✓	✓
Halstead Volume	✓	✓
Halstead Difficulty	✓	✓
Halstead Effort	✓	✓
Halstead Level	✓	✓
Halstead Time	✓	✓
Halstead Bugs Delivered	✓	✓
Halstead Maintainability	✓	✓
Cyclomatic Complexity	✓	✓
Cognitive Complexity	✓	✓
LCOM	✓	
Number of Properties		✓
Number of Public Attributes		✓
Number of Public Methods		✓
Number of Protected Fields		✓
Number of Protected Methods		✓
Number of Long Methods		✓
Number of Methods		✓
Number of Constructors		✓

Fig 6. Collected Metrics

# Threshold Model Baseline

Comparison of collected data with LiveRef:

- 56% of opportunities found by LiveRef
- Worse end result by LiveRef



Metric	Real-Life	LiveRef
Total Lines	-13.38	-9.75
Halstead Length	-11.54	-9.98
Halstead Vocabulary	-87.54	-77.02
Halstead Volume	-85.74	-75.02
Halstead Difficulty	-2.86	-2.60
Halstead Effort	-2763.38	-2440.33
Halstead Level	0.06	0.03
Halstead Time	-153.52	-135.57
Halstead Maintainability	4.94	4.03
Cyclomatic Complexity	-2.13	-1.90
Cognitive Complexity	-42.96	-13.69
LCOM	-0.04	0.001

Fig 7. Comparison of Average Differences for Various Metrics when Compared to Baseline Code

# Model Development

## Data Loading and Preprocessing

- Cleaning faulty data;
- Normalizing the data.

## Feature Selection

- Removing features based on covariance.

Metric	Extract Method	Extract Class
Number of Lines of Code	✓	
Number of Statements	✓	
Halstead Effort	✓	✓
Halstead Length	✓	✓

Fig 8. Removed Features for each Refactoring Type

# Model Development

## Model Selection & Training

- There is only data for a single class, when a refactoring is meant to occur;
- Selected 3 one-class classification models, all effective in high dimensional datasets;
- Elliptic Envelope performed better in both scenarios, though One Class SVM was also kept for further consideration.

Model	Extract Method	Extract Class
One Class SVM	0.904	0.903
Isolation Forest	0.897	0.899
<b>Elliptic Envelope</b>	<b>0.989</b>	<b>0.988</b>

Fig 9. Comparison of Recall of the Different Models

# Model Integration

- Models were created with Python, thus requiring integration with Java;
- User is required to provide Python path;
- LiveRef is now using created models to identify methods/classes that require refactoring;
- Models are updated after a certain amount of executed refactorings.

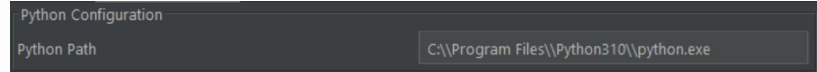


Fig 10. Set Python Path in LiveRef Configuration Panel

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**Algorithm 1** Get Extractable Fragments for Extract Method from Source File

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```
1: function GETEXTRACTABLEFRAGMENTS(sourceFile)
2:   fragments  $\leftarrow$  empty list
3:   for each metrics in Values.before.methodMetrics do
4:     if sourceFile.name does not contain metrics.methodName then
5:       if metrics.method.body is not null then
6:         if PredictionModel.predictEM(metrics, editor.project) then
7:           statements  $\leftarrow$  metrics.method.body.statements
8:           for each statement in statements do
9:             fragments.add(getFragmentsFromStatement(statement, metrics))
10:          end for
11:        end if
12:      end if
13:    end if
14:  end for
15:  return fragments
16: end function
```

---

Fig 11. Pseudocode for GetExtractableFragments function

# Model Biasing

- Large amount of training data impedes the model from being attuned to the user in a reasonable timeframe;
- Sample weights allow for the process to become quicker;
- Allows for the creation of profiles, such as individual, team, and organisation.

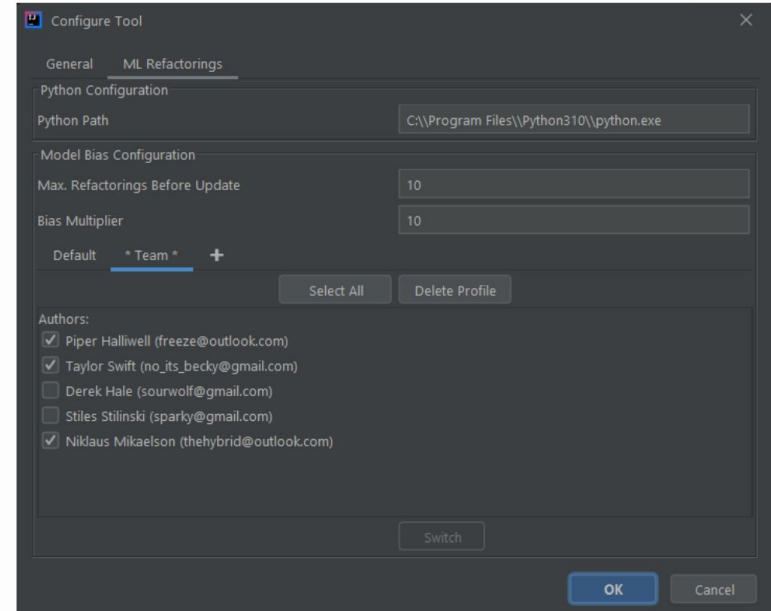


Fig 12. ML Refactorings tab in Configuration Panel



# Repository Metrics Extraction

- Another way to attune the model to the user;
- Allows them to provide a repository, from which the refactoring data will be extracted;
- Updates the models and the authors for the bias profiles.

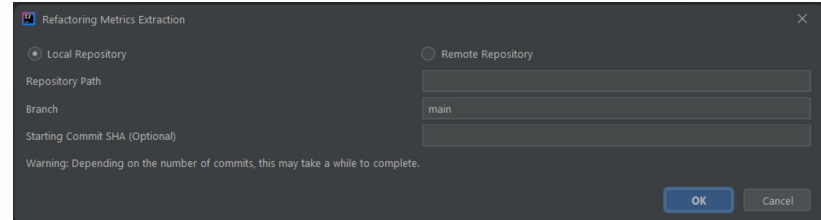


Fig 13. Pop-up for Repository Metrics Extraction

# Validation

## Extract Method

- 13% increase with Elliptic Envelope;
- 5% increase with One-Class SVM.

Method	Percentage of Opportunities
Original Plugin	55.98%
One-Class SVM	60.43%
Elliptic Envelope	69.08%

Fig 14. Comparison of Percentage of refactoring opportunities found for Extract Method

## Extract Class

- 17% increase with Elliptic Envelope;
- 12% increase with One-Class SVM;

Method	Percentage of Opportunities
Original Plugin	5.75%
One-Class SVM	17.12%
Elliptic Envelope	22%

Fig 15. Comparison of Percentage of refactoring opportunities found for Extract Class

# Conclusions



## **RQ1**

Threshold-based refactoring recommendation tool missed a large number of refactorings and provided worse quality recommendations.



## **RQ2**

When compared to real-life data, the classification model missed less suggestions than the threshold-based method.

# Main Contributions



## Literature Review

State-of-the-art research performed.



## Plugin

Updated version of LiveRef.



## Refactoring data

Training and testing dataset.

# Future Work

Adding Refactoring Types

Profile Synchronisation

Diversifying the Data

Extended Testing

# References

1. Fowler, M. Refactoring: Improving the Design of Existing Code. Pearson Education, 2018.  
[https://books.google.pt/books?id=2H1\\_DwAAQBAJ](https://books.google.pt/books?id=2H1_DwAAQBAJ).
2. Mário André de F. Farias, Renato Novais, Methanias Colaço Júnior, Luís Paulo da Silva Carvalho, Manoel Mendonça, and Rodrigo Oliveira Spínola. A systematic mapping study on mining software repositories, 2016.
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# References

8. Raimund Moser, Witold Pedrycz, Alberto Sillitti, and Giancarlo Succi. A model to identify refactoring effort during maintenance by mining source code repositories. In Andreas Jedlitschka and Outi Salo, editors, *Product-Focused Software Process Improvement*, pages 360–370. Springer Berlin Heidelberg
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10. S. R. Foster, W. G. Griswold, and S. Lerner. Witchdoctor: Ide support for realtime auto-completion of refactorings. In *34th International Conference on Software Engineering (ICSE), International Conference on Software Engineering*, pages 222– 232, 2012. Foster, Stephen R. Griswold, William G. Lerner, Sorin 0270-5257.
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**Thank you!**  
**Any Questions?**