

Automatic Prediction of Developers' Resolutions for Software Merge Conflicts

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Abstract

In collaborative software development, developers simultaneously work in parallel on different branches that they merge periodically. When edits from different branches textually overlap, conflicts may occur. Manually resolving conflicts can be tedious and error-prone. Researchers proposed tool support for conflict resolution, but these tools barely consider developers' preferences. Conflicts can be resolved by: keeping the local version only (KL), keeping the remote version only (KR), or manually editing them (ME). Recent studies show that developers resolved the majority of textual conflicts by KL or KR. Thus, we created a machine learning-based approach RPREDICTOR to predict developers' resolution strategy (KL, KR, or ME) given a merge conflict.

We did large-scale experiments on the historical resolution of 74,861 conflicts. Our experiments show that RPREDICTOR achieved 63% F-score for within-project prediction and 46% F-score for cross-project prediction. Compared with other classifiers, RPREDICTOR provides the highest effectiveness when using a random forest (RF) classifier. Finally, we proposed a variant technique RPREDICTOR_v, which enables developers to customize its prediction conservativeness. For a highly conservative setting, RPREDICTOR_v achieved 34% effort saving while minimizing the risk of producing incorrect prediction labels.

Keywords: Software merge, textual conflicts, conflict resolution, prediction

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1. Introduction

In collaborative software development, programmers often create separate branches to perform distinct maintenance tasks (e.g., add new features, fix bugs, or refactor code) in parallel. When developers merge edits from different
5 branches, separate edits that were simultaneously applied to the same line of code can conflict with each other.

1.1. Background

Manual resolution of such conflicts is usually challenging and time-consuming. A prior study [49] shows that 56% of developers deferred resolving a merge conflict due to various reasons (e.g., the complexity, large size, or big number of
10 locations of conflicting code). In the period of time between conflicts occur and they get resolved, conflicts can grow and become more difficult to resolve [49]. Vale *et al.* [68] identified factors that make conflicts hard to solve, including the number of conflicting lines of code, the number of conflicting chunks, the number
15 of lines of code changed, and the number of files changed. By conducting surveys with developers, Costa *et al.* [21] showed that the developer performing a merge might not fully understand the changed code or the rationale behind the change, or may not have the expertise to determine the impact of the change. Nelson *et al.* [49] interviewed 10 software developers, and revealed that developers need
20 better tools to facilitate the understanding and resolution of merge conflicts. All these studies motivated us to explore new ways of automatic conflict resolution.

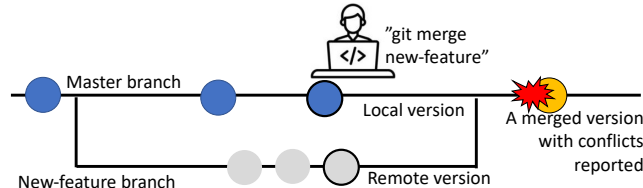


Figure 1: Developers use textual merge (e.g., git-merge) to merge branches and reveal conflicts

As illustrated in Figure 1, developers typically adopt text-based tools (e.g., git-merge [1]) to tentatively merge the latest version of their own branch (i.e.,

local version (L)) with the latest version of a specified branch (*i.e.*, **remote version (R)**), and to detect textual conflicts in this process. Because such tools treat programs as plain text, they can merge the code in ways that are syntactically or semantically incorrect, due to code mismatches between branches [19, 50, 64]. To improve over textual merge, researchers proposed tools that analyze the syntactic structures of programs, to better detect and resolve conflicts [13, 12, 71, 65]. For instance, JDime [12] matches Java code based on abstract syntax trees (ASTs). It conducts tree-based merge instead of text-based merge for each matching node pair, to better align code and integrate as many edits as possible between branches.

Specifically, Yuzuki *et al.* [69] examined 779 Java merge conflicts, and found that developers resolved 99% of conflicting methods by keeping only one of the conflicting versions. Similarly, Ghiotto *et al.* [27] inspected 616 textual conflicts; they observed that developers resolved 56% of cases by keeping only the L or R version. As the studies were done by different researchers on distinct datasets and the adopted granularity (method vs. line) varies, the reported percentages are different.

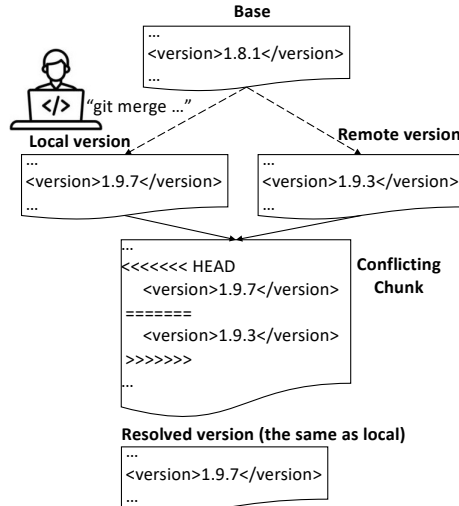


Figure 2: Versions related to a merge conflict

Figure 2 shows an exemplar conflict manually resolved by developers. For this example, L and R simultaneously updated the version number of a library

dependency in distinct ways. As a result, the text-based merge (*e.g.*, git-merge) reveals a conflicting chunk, which uses the format “<<<<<< HEAD
45 ... ===== ... >>>>>>” to mark the conflicting edits between versions. To resolve the conflict, developers simply picked the edit from one version (*i.e.*, L) instead of trying to combine the branch edits somehow.

1.2. Motivation

Generally speaking, developers resolve conflicts via three main strategies:
50 choosing the local version while discarding the remote one (**KL**), choosing the remote version while discarding local (**KR**), or modifying edits from either or both branches for edit integration (**ME**). Inspired by the two studies mentioned above, we wanted to create a novel approach that resolves merge conflicts by considering developers’ preferences. As our new approach predicts the resolution strategy for any given conflict, we expect it to help developers in two ways.
55 First, when it correctly predicts the KL or KR strategy, the approach can automatically apply the strategy and resolve the conflict. This will save developers time and manual effort, which would have been spent on understanding and resolving that conflict. The effort savings provided by this automatic prediction
60 are potentially very high, since past evidence shows that the majority of conflicts get resolved by KL and KR [69, 27]. Second, when our approach predicts the ME strategy, it reminds developers to carefully inspect the local and remote branches, in order to cautiously handle the given conflict.

1.3. Our Research

65 To explore the feasibility of creating a predictor for conflict-resolution strategies, we first did an empirical study to characterize the conflicts in software version history that get resolved with different strategies. We gathered 15,758 conflicts from 100 open-source software repositories, and studied 12 features to characterize each conflict from different perspectives. Our statistical analysis
70 shows a strong correlation between the resolution decisions of developers and

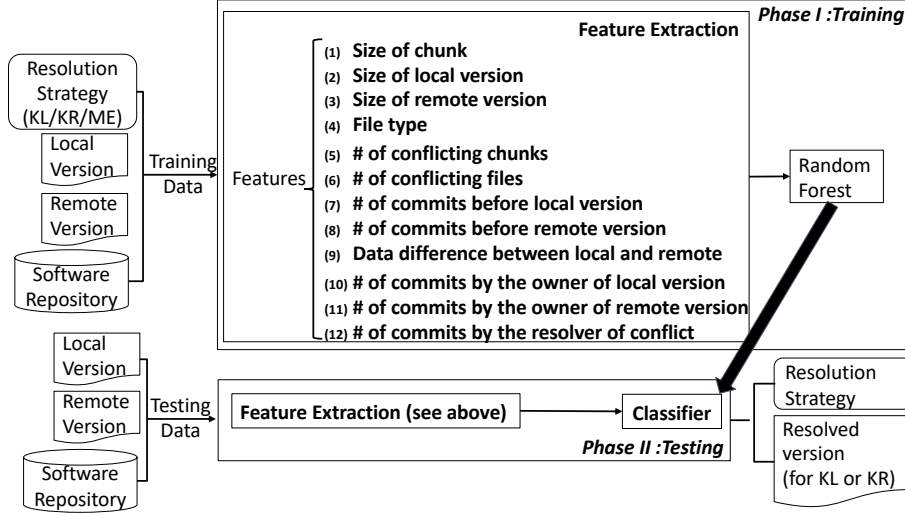


Figure 3: RPREdictor has two phases: training and testing

all features, indicating a strong potential for successfully building a resolution predictor.

Leveraging the 12 features revealed by our study, we designed and implemented an approach—RPREdictor—to automatically predict resolution strategies. As shown in Figure 3, RPREdictor has two phases: training and testing. In Phase I, RPREdictor extracts features for each conflict in a set of merge conflicts that were already resolved in the past, and trains a three-class random forest (RF) classifier. In Phase II, RPREdictor takes in any new conflict together with the software repository holding that conflict, extracts features, and applies the trained classifier to recommend a strategy. When the strategy is KL or KR, RPREdictor also outputs the resolved version.

To evaluate RPREdictor, we conducted large-scale experiments with 74,861 conflicts extracted from the version history of 482 open-source projects. We applied RPREdictor to perform both within-project and cross-project prediction tasks. For the within-project setting, in each repository, we used the oldest 90% of resolved conflicts to train RPREdictor and the remaining 10% of resolved conflicts for testing. RPREdictor predicted resolutions with 63% F-score. For

the cross-project setting, we performed 10-fold cross validation. Namely, we divided the 482 software repositories evenly into 10 folds. In each experiment, we leveraged the conflict data in nine folds for training and used the conflict data from the remaining fold for testing. We repeated the experiment 10 times, with each experiment using a different fold for testing. RPREDICTOR recommended resolutions with 46% F-score.

We also evaluated the sensitivity of RPREDICTOR to different amounts or ages of training data, and to different machine learning (ML) algorithms. We found that as more training data is provided, RPREDICTOR’s effectiveness either increases or stabilizes; nevertheless, it does not change consistently with the age of training data. Compared with other ML algorithms, random forest leads to the best effectiveness of RPREDICTOR. Finally, we designed a customizable variant, RPREDICTOR_v, which allows developers to customize how conservatively they want RPREDICTOR_v to make its predictions, *i.e.*, how inclined it should be to predict the ME resolution, to reduce the ratio of incorrectly predicted KL or KR. For a highly conservative setting (94% C-score), RPREDICTOR_v achieved 34% effort savings; making RPREDICTOR_v less conservative but keeping its conservativeness score (C-score) over 80%, we got RPREDICTOR_v to achieve up to 64% effort savings. We made the following contributions in this paper:

- A novel empirical study of 12 characteristics of 15,758 conflicts, to understand their correlation with resolutions KL, KR, or ME.
- A novel tool RPREDICTOR, that leverages machine learning (ML) to predict the resolution strategy for a given conflict.
- A comprehensive evaluation to assess the prediction effectiveness of RPREDICTOR, with 74,861 conflicts from 482 Java open-source repositories.
- An evaluation of RPREDICTOR’s sensitivity to different configurations related to ML, including (1) the ratio of training and testing data, (2) the balanced or unbalanced data distribution among resolution strategies, (3) the age of training data, and (4) the choice of learning algorithms.

- A customizable variant RPREDICTOR_v , which enables developers to choose more or less conservative results at the trade-off of lower or higher effort savings, respectively.

120 2. Dataset Construction

Ghiotto *et al.* [27] recently conducted an empirical study on merge conflicts, and created a dataset of conflicts from 2,731 GitHub repositories. To study developers’ preferences on conflict resolution and to explore new approaches of resolution prediction, we decided to create our datasets based on their data
125 because of its comprehensiveness and representativeness.

To create the dataset, Ghiotto et al. first used the GitHub API to select 1,997,541 projects. Then they collected information about each project such as the last update date, the size of its development team, and the code size. Next, they selected all Java projects that have at least one commit during January
130 2015 and March 2016. A project is considered a Java project if the percentage of source code written in Java is greater than that of code written in any of the other languages. Finally, they discarded the projects that were forks of other projects in the dataset or had no conflict reported by git-merge in Java files for any merge commits. This led to 2,731 projects with 175,805 conflicting chunks.

135 For our study, we downloaded Ghiotto’s dataset and refined it by taking two steps. First, we removed the projects whose developers resolved conflicts by taking only one or two major strategies e.g., `jsoup` [7] and `platform_frameworks_base` [4]). Namely, if a project (1) has at least 50% of conflicts resolved via a single strategy (KL, KR, or ME) or (2) never uses a certain strategy (*e.g.*, KL), we remove the
140 project. In this way, we ensured that each of the remaining repositories had a relatively balanced distribution of conflicts among KL, KR, and ME. After this step, 609 projects remained in our dataset (*e.g.*, XCoLab [5] and jgralab [6]). Second, we removed the projects whose codebases were no longer available on GitHub, and our final corpus became 582 projects. Table 1 shows some characteristics of the 582 software repositories. As shown in the table, each project
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involves at least 2 developers and at most 426 developers, with the mean value 25 and standard deviation 43. Each repository has at least 24 commits, and at most 190,851 commits. In each repository, there are 2–22,020 merging scenarios, while the number of conflicting chunks varies in 5–5,114. All these numbers imply that the software projects are not toy examples; many of them are large or
150 complex projects involving many developers and having long version histories.

Table 1: Characteristics of the 582 software repositories included by our dataset

	Min	Max	Mean	Standard Deviation
Number of Developers	2	426	25	43
Number of Commits	24	190,851	2,820	9,022
Number of Merges	2	22,020	323	1,045
Number of Chunks	5	5,114	156	368

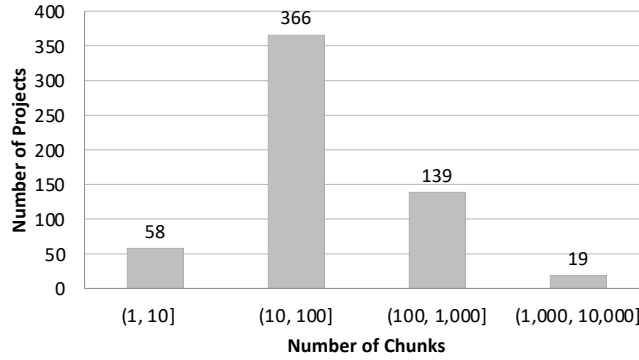


Figure 4: Distribution of conflicting chunks among the 582 projects

Moreover, we analyzed the distribution of conflicting chunks among projects. As shown in Figure 4, 58 out of the 582 projects have 2–10 conflicting chunks in version history; 366 projects have 11–100 chunks; 139 have 101–1,000 chunks; and 19 projects have over 1,000 chunks. Such a distribution implies that some projects contribute a lot more chunks than the others, and may bias our experiment results. However, in total the dataset includes 90,619 conflicting chunks, while the largest number of conflicting chunks contained by any single project is 5,114. It means that there is no project dominating the whole dataset, so the
160 impact of any potential bias is limited.

As shown in Table 2, after refining the original dataset of Ghitto *et al.*, we obtained 582 software repositories. Among the 90,619 conflicts contained by

these repositories, there are 32,065, 24,423, 34,131 conflicts separately resolved via KL, KR, and ME.

165 We randomly sampled 100 repositories in the 582 repositories, to conduct a characterization study of conflicts (see Section 3). This sample set includes 15,758 conflicts, among which 5,519 conflicts were resolved via KL, 4,357 conflicts were resolved via KR, and 5,882 conflicts were resolved via ME. Based on the characterization study, we created RPREDICTOR, and evaluated the tool
170 using all data from the remaining 482 repositories. By making observations on a subset of data and assessing new approaches on the remaining data, we can examine whether the insights gained from some data are generalizable to other unseen data.

Table 2: The datasets used in our research

	# of Repositories	# of Conflicts resolved by			
		KL	KR	ME	Total
Data used in our characterization study	100	5,519	4,357	5,882	15,758
Data used in the tool evaluation	482	26,546	20,066	28,249	74,861
Total	582	32,065	24,423	34,131	90,619

3. Our Characterization Study

175 We characterized all resolved conflicts in the randomly sampled 100 repositories by defining and measuring 12 features. We defined these features based on the insights we learnt from prior studies [27, 49, 16, 68], concerning factors that may impact developers’ decisions on conflict resolution. We organized the features into four categories: (C1) content of the merge conflict, (C2) the scenario in which the conflict happened, (C3) software evolution that led to the
180 conflict, and (C4) experience of the developer(s) involved in the conflict. We describe them in more detail below.

C1. Conflict Content: We hypothesize that developers often observe the conflict content when they try to resolve a conflict [27, 49, 16, 68]. We defined
185 four features to characterize the content of a conflicting chunk:

F1. **Size of Chunk** counts the lines of code (LOC) contained by any given conflicting chunk.

F2. **Size of Local Version** counts the LOC between “<<<<<< HEAD” and “=====”. Namely, for each conflicting chunk, it counts the unique code coming from the local version.

F3. **Size of Remote Version** counts the LOC between “====” and “>>>>>>”. Namely, for each chunk, it counts the unique code derived from remote.

F4. **File Type** reflects the type of the file containing the conflicting chunk. Different resolutions may be popular in different types of files.

Notice that $F1 > F2 + F3$, because a conflicting chunk consists of (1) the unique code from L and R and (2) some common code (*e.g.*, program context) shared between versions. We believe that when developers resolve merge conflicts, the surrounding context is important for them to decide (i) which branch edits fit better and (ii) how to integrate branch edits into the context. Thus, both the conflicting edits and surrounding context can influence developers’ resolution strategies, and we included F1–F3 into our study.

C2. Merging Scenarios: The complexity of a merging scenario (*i.e.*, the scenario where git-merge is applied to merge two branch versions) could make developers defer their responses to conflicts [27, 49, 16, 68]. We defined two features to capture the complexity:

F5. **Number of Conflicting Chunks** counts the conflicting chunks reported by git-merge for a merging scenario .

F6. **Number of Conflicting Files** counts the number of conflicting files in a merging scenario.

C3. Evolution of Changes: It is possible that for a given conflict, how local and remote versions separately evolved can influence developers’ resolution strategies [49, 16]. We hypothesize that branches with longer history are less likely to be discarded,

and defined the following three features accordingly:

215 **F7. Number of Commits before Local** counts the commits or versions standing between the base and local versions, on the branch where the local version resides.

F8. Number of Commits before Remote counts the commits or versions standing between the base and remote versions, on the branch where the
220 remote version resides.

F9. Date Difference between Local and Remote counts the time interval (*i.e.*, days) between the check-in dates of local and remote. We hypothesized that an increasing number of days between the check-in dates of local and remote versions can make a conflict harder to solve, and thus
225 may influence developers' decisions for its resolution.

C4. Developer Experience: The experience of developers can considerably impact how they understand and resolve conflicts [49, 16, 68]. We hypothesize that the number of historical commits checked in by a developer can reflect his/her experience with the software project. We extracted the user IDs of
230 developers, and defined the following three features:

F10. Number of Commits by The Owner of Local: If a developer checked in the local commit for the current merging scenario, we consider that developer as the owner of local. While multiple developers might contribute changes to the local branch, we assign the ownership of local
235 version to the last committer. This is because committers often review all existing code (including other developers' edits) and their modifications before committing changes. This feature counts the commits checked in by the owner of local, before that developer committed the local version.

F11. Number of Commits by The Owner of Remote: If a developer
240 checked in the remote commit for the current merging scenario, we consider that developer as the owner of remote. When multiple developers

contribute changes to the remote branch, we assign the ownership of remote version to the last committer. This is because the last committer typically reviews all existing code and his/her own changes before checking in the commit.

This feature counts the commits checked in by the owner of remote, before that developer committed the remote version.

F12. Number of Commits by The Resolver of Conflict: If a developer checked in the merging commit with conflict resolution for the current merging scenario, we consider that developer as the resolver of conflict. We believe that the resolution strategies vary with resolvers. In reality, to predict developers' resolution strategy for a given conflict, it is hard to know beforehand who will resolve the conflict. However, it is still useful to explore the prediction power of this feature, because the potential predictors-to-build can take in manually entered resolver's user ID to predict the resolution strategy for a specified conflict. This feature counts the commits checked in by the developer who resolved a given conflict, before that conflict resolution.

To study whether these 12 features impact developers' resolution strategies, we applied statistical analysis to compare the values of these features for conflicts separately resolved by KL, KR, and ME. As mentioned in Section 2, in this study, we used in total 15,758 conflicts from 100 randomly sampled repositories.

3.1. Statistical Analysis via H Test

Among the 12 features mentioned above, there are 11 features (except F4) that have numeric values. For each of these features F_i ($i \in [1, 12], i \neq 4$), we measured its value for each conflict. We separated merge conflicts into three groups, according to the resolution strategies applied to them. We use C_L to refer to the conflicts resolved by KL, use C_R to refer to the conflicts resolved by KR, and use C_M for those resolved by ME.

270 To study whether any of these features can be used to predict developers’
resolution strategies, we applied the Kruskal-Wallis H test [46, 43, 8]; it is a
statistical test to decide if three or more groups of samples come from the same
distribution on a variable of interest (*e.g.*, chunk size or number of conflicts). H
test is a non-parametric test, as it does not assume a normal data distribution
275 (none of our studied features follow a normal distribution). For each group
of samples, H test sorts data into ascending order, assigns ranks to the sorted
data points, and thus converts the given values into their ranks. Namely, in the
conversion process, the smallest value gets a rank of 1, the next smallest gets a
rank of 2, and so on. Among the given three or more sample groups, H test is
280 applied to validate the following hypotheses:

- H_0 : The mean ranks of different groups are the same.
- H_1 : The mean ranks of different groups are not the same.

Table 3: The statistical analysis results for F1–F3 and F5–F12

F_i	Mean Ranks			P-value
	C_L	C_R	C_M	
F1. Size of Chunk	25	26	72	0.000046
F2. Size of Local Version	11	13	35	0.000093
F3. Size of Remote Version	14	12	37	0.000129
F5. Number of Conflicting Chunks	55	61	29	0.000000
F6. Number of Conflicting Files	24	28	16	0.000000
F7. Number of Commits before Local	62	62	43	0.000000
F8. Number of Commits before Remote	91	138	96	0.000000
F9. Date Difference between Local and Remote	5	5	4	0.000055
F10. Number of Commits by The Owner of Local	655	558	603	0.000051
F11. Number of Commits by The Owner of Remote	530	530	548	0.002683
F12. Number of Commits by The Resolver of Conflict	621	540	584	0.010751

Table 3 presents the H test results for all features except F4. For any fea-
ture F_i , a p-value lower than 0.05 implies that the groups (i.e., C_L , C_R , and
285 C_M) are from significantly different data distributions, which means that the
corresponding feature could help predict developers’ resolution strategies. As
shown in the table, all of the 11 features have p-values lower than 0.05; thus,
we decided to use these features to train a resolution predictor in Section 4.

Finding 1: The H test shows that all 11 numeric features (F1–F3 and F5–F12) of conflicting chunks can help predict developers’ resolution strategies.

3.2. Statistical Analysis via Chi-Square Test

F4 is different from the other features, because it is a categorical variable to characterize file types for conflicts, while the other features are numeric variables to count numbers related to a given conflict. To study whether file types help predict developers’ resolution strategies, we decided to use the chi-square test [54]—a statistical test applicable to sets of categorical data, to evaluate how possibly any observed difference between the sets happened by chance. Specifically, in our study, after extracting all file-type information for conflicts, we clustered the file types into two big categories: source-code files and non-code files. We then counted the frequency of each category for each resolution strategy to obtain a contingency table (see Table 4). Source-code files include files written in any programming language, such as Java and Python; non-code files include all other kinds of files, such as configuration files and documentation.

Table 4: Data distribution of conflicts between the two file categories

File Category	# of Files in Each Group			Total
	C_L	C_R	C_M	
Source-Code File	3,930	3,375	4,565	11,870
Non-Code File	1,591	983	1,319	3,893

Notice that we decided not to use file types as they are to create the contingency table for two reasons. First, we observed 96 file types in the 100 studied Java projects. Among those types, Java is the biggest one and covers thousands of conflicts, while many rare file types only cover one or two conflicts. Such an extreme unbalanced conflict distribution among file types can make our statistical analysis useless or even misleading. To ensure the relatively balanced data distribution across categories, we decided to create the 2 big categories out of 96 file types. Second, if we used the file types as they are, our statistical analysis results may be limited to the 96 file types we studied, but not generalize well to larger datasets that have a lot more file types. Clustering raw file types into two big categories helps ensure the generalizability of our study results, because

the two big categories remain the same no matter how many more concrete file
315 types are included by larger datasets.

We defined the following hypotheses for our chi-square test:

- H_0 : No association exists between file categories and resolution strategies.
- H_1 : There is association between file categories and resolution strategies.

Our statistical analysis results have chi-square = 77.5874, and $p = 0.0000$. The
320 results imply that file categories are related to developers' resolution strategies,
so we can exploit F4 to train a resolution predictor (Section 4).

Finding 2: *The Chi-square test shows that the file categories of conflicting chunks (F_4) can help predict developers' resolution strategies.*

4. Approach

Our characterization study (see Section 3) shows the feasibility of training
325 a machine-learning model to predict developers' resolution strategies for conflicts. Therefore, we designed and implemented a new approach RPREDICTOR. As shown in Figure 3, RPREDICTOR has two phases: training and testing. Phase I analyzes the conflicts already resolved by developers to train a three-class classifier. Phase II takes a merge conflict from a software repository, and
330 leverages the trained classifier to predict whether developers will resolve it via KL, KR, or ME. If KL or KR is predicted, in addition to outputting the resolution strategy, RPREDICTOR also outputs the resolved version to automate conflict resolution and thus improve programmer productivity. In both phases, RPREDICTOR extracts 12 features for each conflict. For implementation, we
335 used scikit-learn [55]—a Python machine-learning library to train and test a classifier. The scikit-learn library features various classification, regression, and clustering algorithms. By invoking APIs provided by the library, RPREDICTOR uses random forest (RF) to train its three-class classifier.

Because 11 of the 12 features are numeric variables (i.e., F1-F3 and F5-
340 F12), we provided their numeric values as inputs to RPREDICTOR. One feature

(F4) is categorical, with two category labels as “source code file” and “non-code file”. To provide numeric values to RPREDICTOR for F4, we applied one-hot encoding [29] for category-to-vector conversion. Namely, we used the vector [1, 0] to represent the first category, and used [0, 1] to represent the second.

345 5. Evaluation

We conducted a variety of experiments to investigate the following seven research questions (RQs):

- **RQ1:** How effectively can RPREDICTOR predict developers’ resolutions in the within-project setting?
- 350 • **RQ2:** How effectively can RPREDICTOR predict developers’ resolutions in the cross-project setting?
- **RQ3:** How effectively can RPREDICTOR predict developers’ resolutions given projects with unbalanced distributions of resolution strategies?
- **RQ4:** How sensitive is RPREDICTOR to the amount of training data?
- 355 • **RQ5:** How sensitive is RPREDICTOR to the age of training data?
- **RQ6:** How sensitive is RPREDICTOR to the adopted machine-learning algorithm?
- **RQ7:** How sensitive is RPREDICTOR_v to different prediction thresholds?

This section will first introduce our evaluation metrics (Section 5.1), and then
360 present our experiments as well as the results for each research question (Sections 5.2–5.8).

5.1. Evaluation Metrics

In our experiments, we executed our studied techniques to obtain a **prediction** for each one of the merge conflicts in our studied dataset. As **ground**
365 **truth** for each conflict, we observed the resolution strategy employed by the

developer that resolved it in our dataset. We then assessed the effectiveness of a technique by comparing its prediction to the ground truth for each conflict, applying multiple metrics. To facilitate discussion, in this section, we index the three conflict resolution strategies and refer to them as $S_i (i \in [1, 3])$. Namely, S_1 refers to KL (keep the local version); S_2 refers to KR (keep the remote version); S_3 refers to ME (resolution with manual edits). We defined and calculated the following metrics to evaluate effectiveness:

Precision (P_i) measures, among all the conflicts labeled with S_i by a technique, what ratio of them were actually resolved by S_i .

$$P_i = \frac{\# \text{ of conflicts correctly labeled as " } S_i \text{ "}}{\text{Total } \# \text{ of conflicts labeled as " } S_i \text{ "}} \quad (1)$$

Recall (R_i) measures, among all conflicts that were resolved by S_i , what ratio of them were labeled by a technique as S_i .

$$R_i = \frac{\# \text{ of conflicts correctly labeled as " } S_i \text{ "}}{\text{Total } \# \text{ of conflicts that were resolved via } S_i} \quad (2)$$

Both precision and recall vary within $[0\%, 100\%]$. The higher, the better.

F-score (F_i) is the harmonic mean of precision and recall. It provides a way to measure a model's accuracy based on precision and recall. F also varies within $[0\%, 100\%]$. The higher value we get, the better.

$$F_i = \frac{2 \times P \times R}{P + R} \quad (3)$$

Aggregated (Overall) metrics (P , R , F): With the above effectiveness metrics computed for each resolution strategy, we further evaluated the overall effectiveness of a technique by computing the *weighted* average among all strategies. Formally, if we use Γ to represent P or R , and use n_i to represent the number of testing samples in S_i , then the overall effectiveness in terms of precision and recall can be computed as

$$\Gamma_{\text{overall}} = \frac{\sum_{i=1}^3 \Gamma_i * n_i}{\sum_{i=1}^3 n_i} \quad (4)$$

Finally, the overall F is computed with:

$$F_{\text{overall}} = \frac{2 \times P_{\text{overall}} \times R_{\text{overall}}}{P_{\text{overall}} + R_{\text{overall}}} \quad (5)$$

Conservativeness Score (C) or C-score: We defined this metric because different prediction mistakes have different consequences. If a conflict resolved by KL or KR is incorrectly predicted as ME, the technique makes a *conservative* mistake: it misses the opportunity of saving developers’ manual effort, but does not mislead developers to blindly take resolution suggestions. However, if a conflict resolved by ME is incorrectly predicted as KL or KR, the technique makes a more serious mistake: it automatically resolves the conflict using a different strategy than what the developer would have preferred, and thus produces an incorrectly merged version. We created a C metric to measure the ratio of predictions that are *conservative*, *i.e.*, that do not cause any incorrect automatic resolution. Conservative predictions include (1) correct predictions, and (2) any conflict resolved via KL or KR but labeled as ME. C scores range within [0%, 100%]; the higher, the better.

$$C = \frac{\# \text{ of conflicts conservatively labeled}}{\text{All predictions}} \quad (6)$$

5.2. RQ1: Effectiveness of Within-Project Prediction

For each software project in our dataset, we leveraged 90% of the oldest resolved conflicts to train RPREDICTOR, and then used the remaining 10% of resolved conflicts to test RPREDICTOR. We intentionally used older data for training and newer data for testing. This is because such a setting can mimic the real-world scenarios, where RPREDICTOR can only refer to a project’s history data to suggest resolutions for future conflicts of that project.

5.2.1. Baseline

No prior work predicts developers’ resolution preferences, so we could not compare RPREDICTOR with any existing tool. However, we were still interested in how RPREDICTOR compares with a weighted random predictor. Thus, we created a **baseline** technique.

We assumed that baseline somehow knows the ratios of conflicts separately resolved via KL, KR, or ME, and randomly predicts a label each time based on those ratios. As shown in Table 5, in the test set, there are 2,936, 1,979, and

Table 5: The prediction counts for RPREDICTOR and Baseline in the within-project setting

Ground Truth	# of conflicts		RPredictor			Baseline		
	Training	Testing	KL	KR	ME	KL	KR	ME
KL	23,610	2,936	1,815	318	803	1,002	977	957
KR	18,087	1,979	343	931	705	678	649	652
ME	25,472	2,777	361	356	2,060	984	892	901
Total	67,169	7,692	2,519	1,605	3,568	2,664	2,518	2,510

Table 6: Effectiveness measurements for within-project prediction

	# of conflicts		RPredictor				Baseline			
	Training	Testing	P	R	F	C	P	R	F	C
KL	23,610	2,936	72%	62%	67%	-	37%	34%	35%	-
KR	18,087	1,979	58%	47%	52%	-	25%	32%	28%	-
ME	25,472	2,777	58%	74%	65%	-	35%	32%	34%	-
Overall	67,169	7,692	63%	62%	63%	82%	34%	33%	33%	54%

2,777 conflicts separately resolved via KL, KR, and ME. Therefore, given a conflict, baseline predicts KL with a 38% probability (*i.e.*, $2936/(2936+1979+2777)$), and predicts KR and ME with 26% and 36% probabilities, respectively. Notice that the baseline technique is stronger than a naïve random classifier that predicts all resolutions with equal possibilities (*i.e.*, 33%). In reality, it is also hard for any classifier to foresee the conflict distribution among all strategies. We made such a strong assumption to ensure that baseline is nontrivial, and to check whether RPREDICTOR outperforms it.

5.2.2. Comparison with Baseline

Table 5 counts the predictions of both RPREDICTOR and baseline for individual resolution strategies. According to the table, RPREDICTOR correctly labeled 1,815, 931, and 2,060 conflicts with KL, KR, ME, respectively. Meanwhile, baseline correctly labeled only 1,002, 649, and 901 conflicts with KL, KR, ME, respectively. These observations mean that RPREDICTOR predicts resolutions with much higher accuracies than baseline.

With the numbers reported in Table 5, we further measured effectiveness for both techniques using the metrics described in Section 5.1. As shown in Table 6, RPREDICTOR outperformed baseline for all metrics. For instance, for conflicts resolved by KR, RPREDICTOR achieved 58% precision, 47% recall, and 52%

435 F-score; meanwhile, baseline only obtained 25% precision, 32% recall, and 28%
 F-score. RPREDICTOR showed an overall effectiveness of 63% precision, 62%
 recall, 63% F-score, and 82% C-score; in contrast, baseline provided an overall
 effectiveness of 34% precision, 33% recall, 33% F-score, and 54% C-score. Both
 techniques worked more effectively to predict KL and ME, than to predict KR.
 440 This may be because there are fewer conflicts in the training set that were
 actually resolved by KR.

Finding 3: *For within-project prediction, RPREDICTOR’s overall effectiveness
 measurements include 63% precision, 62% recall, 63% F-score, and 82% C-
 score. It outperformed baseline.*

5.3. RQ2: Effectiveness of Cross-Project Prediction

In this experiment, we evaluated the real-world scenarios where a given
 445 project has little version history for RPREDICTOR to leverage. In such sce-
 narios, RPREDICTOR can train a classifier with the conflict data from other
 repositories, and use that classifier to predict resolutions for the given project.
 We conducted 10-fold cross validation to evaluate RPREDICTOR’s effectiveness.
 Namely, we divided the 482 software projects randomly into 10 groups roughly
 450 evenly. For each group $G_i (i \in [1, 10])$, we ran an experiment by using the con-
 flict data in the remaining nine groups for training, and adopting the data in
 G_i for testing. We calculated the effectiveness measurements for each of the 10
 runs, and then computed the aggregated metrics of P, R, F, C among all runs.

5.3.1. Baseline

455 Similar to what we did for RQ1 (Section 5.2.1), we also created a weighted
 random classifier for cross-project prediction. In each of the 10 experiments
 mentioned above, baseline did not involve any training. Instead, it randomly
 assigned labels to conflicts based on the conflict distribution among three strate-
 gies in the test set. By empirically comparing RPREDICTOR with baseline, we
 460 explored how RPREDICTOR improves over weighted random prediction.

Table 7: Effectiveness measurements for cross-project prediction

Experiment Id (Testing Fold #)	RPredictor				Baseline			
	P	R	F	C	P	R	F	C
1	46%	46%	46%	77%	34%	34%	34%	59%
2	49%	51%	50%	81%	35%	35%	35%	56%
3	47%	47%	47%	79%	33%	34%	33%	58%
4	50%	50%	50%	75%	34%	35%	34%	57%
5	41%	41%	41%	64%	38%	35%	36%	60%
6	42%	44%	43%	75%	34%	33%	34%	55%
7	44%	47%	46%	78%	36%	34%	35%	53%
8	47%	49%	48%	79%	36%	35%	36%	55%
9	50%	50%	50%	77%	34%	34%	34%	57%
10	44%	48%	46%	76%	34%	32%	33%	52%
Overall (All folds)	46%	47%	46%	76%	34%	34%	34%	57%

5.3.2. Comparison with Baseline

As shown in Table 7, RPREDICTOR outperformed baseline for all metrics in all 10 experiments. By aggregating our measurements for all folds, we got the overall effectiveness of RPREDICTOR as 46% precision, 47% recall, 46% F-score, and 76% C-score. Meanwhile, the overall effectiveness of baseline is 34% precision, 34% recall, 34% F-score, and 57% C-score. Due to the space limit, we do not present tools’ effectiveness measurements for each resolution strategy. However, when we checked the detailed results for each strategy, we noticed that both tools predicted ME more accurately than predicting the other two strategies. In particular, RPREDICTOR always predicted ME more accurately than baseline; in 8 out of 10 experiments, RPREDICTOR suggested KL more accurately than baseline; in 9 out of 10 experiments, baseline suggested KR more accurately than RPREDICTOR.

Finding 4: *In cross-project prediction, RPREDICTOR achieved 41%–50% precision, 41%–51% recall, 41–50% F-score, and 64%–81% C-score. It outperformed baseline for all studied folds.*

5.3.3. Comparison between Cross-Project and Within-Project Prediction

We also compared RPREDICTOR’s cross-project prediction results (see Table 7) against its within-project prediction results (see Table 6). Generally speaking, both experiments have very similar data-splitting methodologies: they

both use 90% of data (*i.e.*, conflicts or projects) for training and use 10% of data for testing. Nevertheless, RPREDICTOR predicted resolutions more effectively in the within-project setting, for all metrics. This may be because it is easier to predict the future resolution strategies of developers based on their resolution decisions for old conflicts. In contrast, it may be relatively harder to predict these developers' resolution strategies based on the resolution decisions made by other developers in other projects. We also noticed that baseline achieved very similar effectiveness for the within-project and the cross-project settings. This is because the baseline technique does not have a training step. Its predictions are purely based on the random guesses derived from distributions of resolution strategies in test sets. No matter what data distribution we have for any test set, the random guesses typically achieve 33-34% overall F-scores.

Finding 5: RPREDICTOR *predicted resolutions more effectively in the within-project setting than in the cross-project setting.*

5.4. RQ3: Prediction Effectiveness on Unbalanced Data

As mentioned in Section 2, we used the conflict data of 100 repositories to characterize conflicts, and adopted the conflict data of another 482 repositories to train and test RPREDICTOR. All these 582 repositories have balanced distributions of different resolution strategies, which imply that developers did not show strong personal biases towards certain strategies; instead, they might decide upon resolutions solely based on branch edits, program context, and software evolution. To further investigate how effectively RPREDICTOR works given unbalanced data, we conducted another experiment. Specifically, among the 2,122 (*i.e.*, 2,731-609) repositories discarded in Section 2 due to the unbalanced distribution of different resolution strategies, we picked the most popular 100 repositories based on their star counts on GitHub, and experimented with them for both within-project and cross-project prediction. To facilitate discussion, Figures 5 and 6 separately visualize the overall distributions of resolution strategies in the 582 balanced repositories and 100 unbalanced ones. As shown in Figure 6, the unbalanced data has the majority of conflicts (61%) resolved via

KL, and least conflicts (15%) resolved via ME. Meanwhile, the balanced data
 510 has 35%, 27%, and 38% of conflicts separately resolved via KL, KR, and ME.

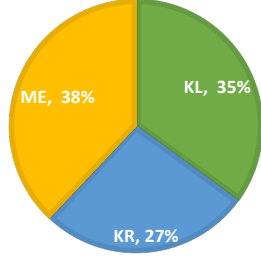


Figure 5: The resolution distributions among 582 balanced repositories

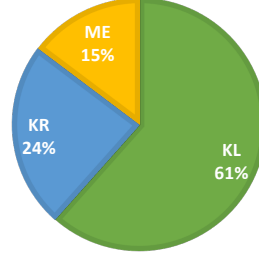


Figure 6: The resolution distributions among 100 unbalanced repositories

Table 8: RPREDICTOR’s effectiveness of within-project prediction given unbalanced data

	P	R	F	C
KL	86%	91%	89%	-
KR	79%	76%	77%	-
ME	64%	53%	58%	-
Overall	81%	69%	74%	86%

5.4.1. Effectiveness of Within-Project Prediction on Unbalanced Data

Similar to what we did for Section 5.2, in each of the 100 repositories with
 unbalanced data, we used the oldest 90% of resolved conflicts to train RPREDIC-
 TOR and used the remaining conflicts for testing. Table 8 shows our experiment
 515 results. By comparing this table against Table 6, we observed that RPREDICTOR
 worked much better when given unbalanced data for within-project prediction.
 Among the 100 repositories, it achieved 81% precision, 69% recall, 74% F-score,
 and 86% C-score; all the measurements are higher than those calculated for
 the balanced dataset (*i.e.*, 63%, 62%, 63%, 82%). In particular, RPREDICTOR
 520 obtained as high as 91% recall when predicting KL in the unbalanced dataset,
 probably because developers demonstrate very strong biases towards KL in that
 dataset and thus make that strategy easier to predict.

Finding 6: *For within-project prediction tasks, RPREDICTOR predicted resolutions more effectively in the unbalanced dataset than in the balanced dataset.*

5.4.2. Effectiveness of Cross-Project Prediction on Unbalanced Data

As with what we did for Section 5.3, we randomly split the 100 repositories into 10 groups with each group having 10 repositories, and performed 10-fold cross validation. As shown in Table 9, overall, RPREDICTOR achieved 53% precision, 43% recall, 47% F-score, and 49% C-score. Meanwhile, its overall metrics in the balanced dataset include 46% precision, 47% recall, 46% F-score, and 76% C-score (see Table 7). Given unbalanced data, RPREDICTOR obtained roughly the same F-score but a much lower C-score than what it did given balanced data; unbalanced data makes cross-project resolution prediction even harder. Namely, if developers show extreme personal biases towards distinct resolution strategies in different projects, it can be very challenging to correctly predict the resolution strategies in one project based on strategies observed in other projects. Actually, among the 10 groups of our unbalanced dataset, there are 4 groups with strong preferences towards KL (*i.e.*, over 50% of conflicts were resolved via KL) and 3 groups with strong biases towards KR. The classifiers trained with such unbalanced data predict KL or KR most of the times but seldom predict ME, although ME is a more conservative strategy than KL and KR. Consequently, such classifiers earn much lower conservativeness scores.

Table 9: RPREDICTOR’s effectiveness of cross-project prediction given unbalanced data

Experiment Id (Testing Fold #)	P	R	F	C
1	41%	42%	41%	55%
2	63%	44%	52%	47%
3	42%	40%	41%	48%
4	52%	46%	49%	51%
5	44%	37%	41%	52%
6	52%	46%	49%	57%
7	34%	31%	33%	50%
8	38%	30%	33%	38%
9	47%	42%	44%	53%
10	51%	38%	43%	59%
Overall (All folds)	53%	43%	47%	49%

Finding 7: For cross-project prediction tasks, RPREDICTOR predicted resolutions less conservatively in the unbalanced dataset than in the balanced one.

Table 10: RPREDICTOR’s effectiveness of within-project prediction, when different amounts of training data are provided in different iterations

Iteration Id	Data Portions		RPredictor			
	Training	Testing	P	R	F	C
1	p_{10}	p_{11}	42%	45%	43%	66%
2	p_9, p_{10}	p_{11}	51%	52%	51%	71%
3	p_8-p_{10}	p_{11}	54%	55%	54%	72%
4	p_7-p_{10}	p_{11}	52%	52%	52%	72%
5	p_6-p_{10}	p_{11}	54%	54%	54%	75%
6	p_5-p_{10}	p_{11}	55%	56%	56%	75%
7	p_4-p_{10}	p_{11}	56%	56%	56%	76%
8	p_3-p_{10}	p_{11}	56%	56%	56%	75%
9	p_2-p_{10}	p_{11}	56%	56%	56%	75%
10	p_1-p_{10}	p_{11}	56%	56%	56%	76%

5.5. RQ4: Sensitivity to The Amount of Training Data

In our experiment settings, by default, we typically used 90% of overall data for training and 10% of data for testing. However, it is unknown how the amount of training data can influence RPREDICTOR’s effectiveness. Therefore, we performed another experiment of within-project prediction, by tuning the amount of training data in use. Specifically, in the balanced dataset (*i.e.*, 482 repositories), we split the conflict data of each repository into 11 portions evenly (each portion having the same number of conflicting chunks): p_1, p_2, \dots, p_{11} . Here, p_1 represents the oldest data portion in history and p_{11} is the newest one. We trained and tested RPREDICTOR 10 times, with each of the iterations using p_{11} as the testing data but using a distinct set of portions for training. As shown in Table 10, the 1st iteration adopts p_{10} for training; the 2nd iteration exploits both p_9 and p_{10} to train RPREDICTOR; the 10th iteration uses 10 portions p_1-p_{10} in training.

RPREDICTOR’s effectiveness increases or roughly remains the same when the amount of training data grows. Specifically when only p_{10} was provided, RPREDICTOR obtained 42% precision, 45% recall, 43% F-score, and 66% C-score. During the first three iterations, as the training data increased from one portion to three portions, all measurements increased steadily. Meanwhile, during the last six iterations, while the training data increased from five to ten

portions, RPREDICTOR’s effectiveness stabilized without much change. One possible reason to explain the observed increase is that when training data is insufficient, providing more data enables RPREDICTOR to better characterize diverse conflicting scenarios and thus better predict resolutions. However, once the training data is sufficient, offering more data does not necessarily improve RPREDICTOR’s effectiveness. Consequently, all measurements stabilize. Based on this experiment, we decided for our other experiments (except for RQ4 and RQ5), by default, we used 90% of data for training and 10% of data for testing, in order to train RPREDICTOR with sufficient data and to observe the best effectiveness measurements achievable by RPREDICTOR.

Finding 8: *RPREDICTOR’s effectiveness improves or stabilizes when more training data is provided.*

5.6. RQ5: Sensitivity to The Age of Training Data

When looking at Table 10, one may be tempted to wonder whether the age of training data also influences RPREDICTOR’s effectiveness. Actually, between different iterations shown in Table 10, both the (1) age and (2) amount of training data are different. To explore the influence of each factor, we conducted an additional experiment with the 11 data portions mentioned in Section 5.5 (each portion having the same number of conflicting chunks). In this experiment, we repetitively trained RPREDICTOR with a distinct data portion but always tested it with p_{11} . As shown in Table 11, the 1st iteration uses p_{10} —the youngest portion within $[p_1, p_{10}]$ —as the training data; the 2nd iteration uses p_9 ; the 10th iteration uses the oldest data p_{10} . Because the training data in each iteration has roughly equal numbers of data points, the comparison of effectiveness measurements across iterations reflects the impact of data age.

According to Table 11, as the training data gets older, the effectiveness measurements either increase or decrease, without presenting a consistent change trend. For instance, in the 1st iteration, RPREDICTOR obtained 43% precision, 44% recall, 43% F-score, and 66% C-score. In the 9th iteration, RPREDICTOR achieved a slightly lower precision (42%), the same recall (44%), the same F-

Table 11: RPREDICTOR’s effectiveness of within-project prediction, when differently aged data is provided for training

Iteration Id	Data Portions		RPredictor			
	Training	Testing	P	R	F	C
1	p_{10}	p_{11}	43%	44%	43%	66%
2	p_9	p_{11}	48%	49%	49%	69%
3	p_8	p_{11}	45%	48%	46%	68%
4	p_7	p_{11}	42%	43%	43%	74%
5	p_6	p_{11}	45%	47%	46%	81%
6	p_5	p_{11}	34%	38%	36%	70%
7	p_4	p_{11}	37%	41%	39%	69%
8	p_3	p_{11}	44%	43%	44%	80%
9	p_2	p_{11}	42%	44%	43%	83%
10	p_1	p_{11}	39%	42%	41%	63%

score (43%), but the highest C-score (83%). However, in the 10th iteration, it acquired the lowest measurements: 39% precision, 42% recall, 41% F-score, and 63% C-score. The phenomena imply that data age does not have a consistently positive or negative impact on prediction results. The prediction effectiveness increased probably because the training data became more similar to the testing data, and decreased probably due to the less similarity between training and test data. Therefore, both the consistent effectiveness improvements and stabilized measurements we observed in Table 10 are mainly contributed by the increase of training data, instead of data aging.

Finding 9: RPREDICTOR’s effectiveness does not consistently change with the age of training data.

5.7. RQ6: Sensitivity to The Adopted Machine-Learning Algorithm

When designing RPREDICTOR, we did not know what machine-learning (ML) algorithm was more suitable. Thus, we experimented with four ML algorithms in both the within-project and cross-project settings, to observe how RPREDICTOR’s effectiveness varies with the adopted algorithm. We studied Adaboost, decision tree (DT), naïve bayes (NB), and random forest (RF). As mentioned in Section 5.2, for the within-project setting, we used 90% of the oldest resolved conflicts in each project’s version history for training, and 10%

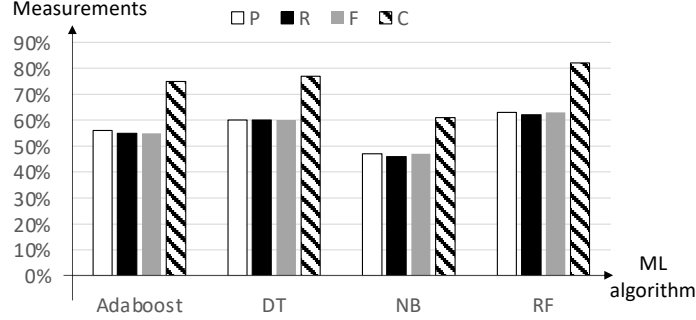


Figure 7: RPREDICTOR using different ML algorithms for within-project prediction

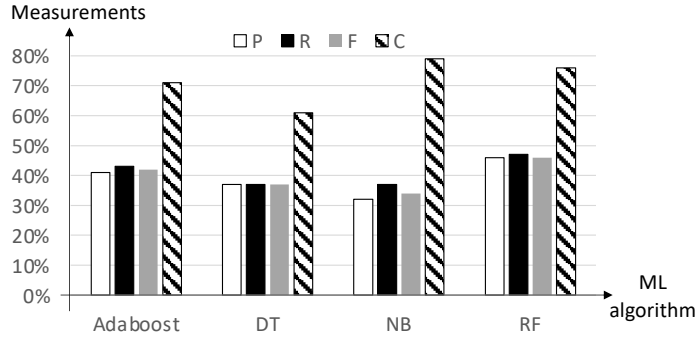


Figure 8: RPREDICTOR using different ML algorithms for cross-project prediction

of conflicts (the most recent ones) for testing. For the cross-project setting, we used 10-fold cross validation (as in Section 5.3). In all of our experiments, we leveraged the ML implementation provided by scikit-learn [55], and used the default parameter settings for all adopted ML algorithms.

As shown in Figures 7 and 8, RPREDICTOR achieved the highest effectiveness when using RF. For within-project prediction, RF obtained 63% precision, 62% recall, 63% F-score, and 82% C-score. DT had lower effectiveness than RF, but better than the other two alternatives; it obtained 60% precision, 60% recall, 60% F-score, and 77% C-score. NB was the least effective and got 47% precision, 46% recall, 47% F-score, and 61% C-score. For cross-project prediction, RF obtained 46% precision, 47% recall, 46% F-score, and 76% C-score. Adaboost performed worse than RF; it got 41% precision, 43% recall, 42% F-score, and 71% C-score. NB achieved the most interesting results. Among the four algorithms studied, NB acquired the lowest precision (32%), lowest recall (37%), and lowest F-score (34%); nevertheless, it acquired the highest C-score

(79%). This is mainly because NB predicted a lot more ME resolutions than the other algorithms. Comparing the effectiveness of distinct algorithms in both within-project and cross-project settings, we decided to use RF as the default ML algorithm in RPREDICTOR because RF often outperformed the others.

Finding 10: *Among the four experimented machine learning algorithms, RF generally outperformed the others when being used in RPREDICTOR.*

5.8. RQ7: Sensitivity to Threshold Setting

In the experiments mentioned above, the highest C-score RPREDICTOR achieved is 82%. It means that 82% of the resolution strategies recommended by RPREDICTOR are conservative; in other words, they correctly predict the developers' preference, or ask developers to resolve the conflict manually. However, some developers may prefer RPREDICTOR to provide lower C-scores (*i.e.*, to predict more KL or KR labels) in order to save more effort, even if the predictions are more risky or less precise. Such preferences are meaningful for projects with very good test suites, in which developers can trust automated testing to reliably decide the correctness of any program version whose conflicts were automatically resolved. Other developers may prefer RPREDICTOR to achieve higher C-scores (*i.e.*, to predict ME more often) in order to avoid prediction errors, even though the predictions save less effort. Such preferences are important for projects with very limited test suites, in which developers cannot blindly trust automated testing to always validate the correctness of programs.

To give developers more control over RPREDICTOR's predictions, we created a configurable variant of RPREDICTOR—RPREDICTOR_v, which offers a parameter th_M so that developers can fine-tune automatic prediction based on their relative tolerance for incorrect KL or KR predictions.

5.8.1. A Threshold-Based Variant Approach: RPREDICTOR_v

Figure 9 shows our approach for RPREDICTOR's customizable variant. Similar to RPREDICTOR, this variant also trains a classifier to predict the resolution strategy for any given merge conflict. However, this variant now allows its users

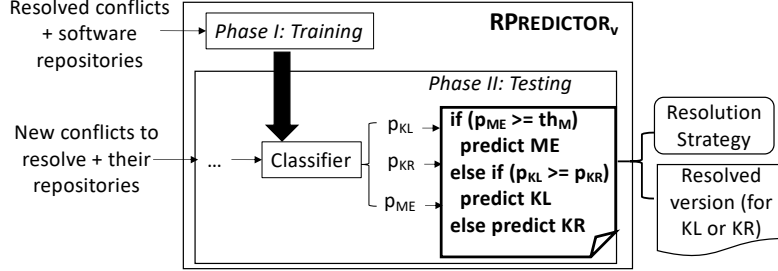


Figure 9: RPREdictor_v—our customizable variant of RPREdictor, which uses a threshold th_M to fine-tune the prediction results

to increase (or decrease) its prediction preference for ME. Given a merge conflict and its related software repository, a classifier generates three predicted likelihoods: p_{KL} , p_{KR} , and p_{ME} . These likelihoods indicate how likely the predictor believes that the conflict should be resolved via KL, KR, or ME. All likelihoods vary within $[0, 1]$; $p_{KL} + p_{KR} + p_{ME} = 1$. The original approach RPREdictor returns its prediction based on the highest likelihood among p_{KL} , p_{KR} , and p_{ME} . In contrast, the customizable variant RPREdictor_v first compares p_{ME} with the user-configured threshold th_M . As shown in Figure 9, if $p_{ME} \geq th_M$, then RPREdictor_v predicts ME; otherwise, it predicts one of the other two strategies, the one with the higher likelihood (KL or KR).

In this way, developers can modify th_M to tune RPREdictor_v's conservativeness. When $th_M = 0$, it predicts all conflicts conservatively as ME. In this scenario, developers would not get any incorrect KL or KR predictions, but they would not benefit from RPREdictor_v automatically acting on the KL or KR predictions (*i.e.*, it would not save effort). On the other extreme, when $th_M = 1.0$, all conflicts are predicted to resolve via either KL or KR. In this scenario, RPREdictor_v would save developers high effort (it would automatically resolve all conflicts by KL or KR), but some of those KL or KR resolutions would not be what the developers preferred (they would be incorrect predictions). With other values of th_M , developers can decide their own personal middle-ground between these two extreme points.

675 5.8.2. Experiment with RPREDICTOR_v

To study the trade-offs between F-score, C-score, and the potential effort-saving by automatic resolution that developers could obtain with RPREDICTOR_v, in this experiment we tuned th_M from 0.1 to 1, with 0.1 increments. For each threshold setting, we applied RPREDICTOR_v to perform both within-project and
680 cross-project prediction. For this section, we defined another metric to measure the potential effort-saving by automatic resolution:

Effort-saving (E) Score or E-score measures among all predictions, for how many of them RPREDICTOR_v outputs KL or KR and automatically resolves the conflict. The score is within [0%, 100%].

$$E = \frac{\# \text{ of conflicts automatically resolved via KL or KR}}{\text{All predictions}} \quad (7)$$

685 Figure 10 shows RPREDICTOR_v's performance for within-project prediction. As th_M increased, C-score consistently decreased and E-score increased. F-score was stable when $th_M \in (0, 0.7]$; it decreased as th_M increased from 0.7 to 1. For the most conservative threshold ($th_M = 0.1$), RPREDICTOR_v labeled many conflicts with ME; it only labeled them KL or KR when the predicted likelihoods
690 were very high (RPREDICTOR_v was quite sure about those predictions). In this scenario, RPREDICTOR_v achieved a C-score of 94%, E-score of 34%, and F-score of 68%. This shows that RPREDICTOR_v can achieve as much as 34% effort savings (E-score) by also very rarely predicting KL or KR incorrectly (with very high C-score). For the most liberal threshold ($th_M = 1.0$), RPREDICTOR_v
695 labeled no conflict with ME. Instead, it only produced KL and KR labels to automate all resolutions. In such scenarios, RPREDICTOR_v incorrectly labeled many conflicts as KL or KR, applying a strategy that was not preferred by the developers. Consequently, the achieved C-score was 50%, E-score was 100%, and F-score was 38%. This option would save all the effort of conflict resolution, but
700 it would likely require additional mechanisms to detect incorrectly applied KL or KR resolutions, *e.g.*, using a very strong test suite that is either manually crafted or automatically generated (*e.g.*, via good fuzzy testing techniques).

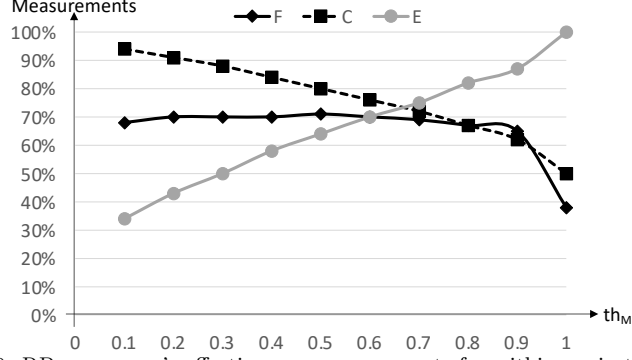


Figure 10: RPREdictor_v's effectiveness measurements for within-project prediction

We believe that other intermediate thresholds would be more popular. Between $th_M = 0.1$ and $th_M = 1.0$, F-score was stable initially and then decreased. As th_M increased, RPREdictor_v achieved different trade-offs between precision and recall for each strategy. Figure 10 also shows that developers could achieve increasing effort savings (E-score), at the cost of accepting increasing ratios of incorrect KL or KR predictions (lower C-scores). However, it is also worth noting that E-scores grew faster than C-scores fell, which means that multiple intermediate thresholds may be attractive for different developers. For example, the thresholds in $(0, 0.5]$ achieved up to 64% effort savings with C-scores no lower than 80%.

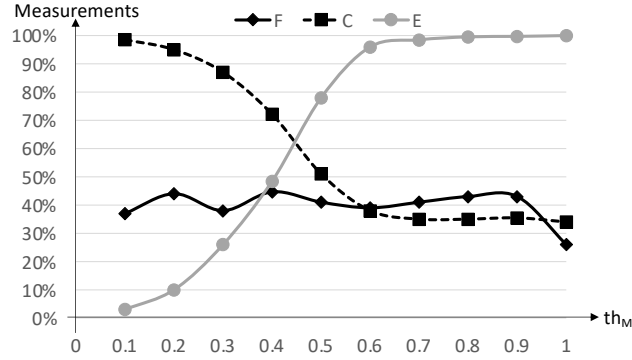


Figure 11: RPREdictor_v's effectiveness measurements for cross-project prediction

Figure 11 shows RPREdictor_v's performance for cross-project prediction. As th_M increased, C-score decreased first and then stabilized when $0.7 \leq th_M \leq 1$; E-score increased first and then stabilized when $0.7 \leq th_M \leq 1$. F-score

vibrated in the range [37%, 45%] when $th_M \leq 0.9$, and dropped afterwards. We saw in RQ2 that RPREDICTOR’s predictions are less effective in the cross-project setting than in the within-project setting. This is also reflected by Figures 10 and 11, since RPREDICTOR_v generally produced a worse trade-off between effort savings and conservativeness. In cross-project prediction, the most conservative threshold ($th_M = 0.1$) provided almost no effort saving, and if we wanted to keep C-score over 80%, we could only achieve up to 26% effort savings ($th_M \leq 0.3$).

Finding 11: RPREDICTOR_v generally achieved better trade-offs between effort savings and conservativeness in the within-project setting than in the cross-project setting. For within-project prediction, RPREDICTOR_v could save up to 63% of efforts by lowering the C-score while keeping it above 80%.

6. Threats to Validity

Threats to External Validity. Our characterization study investigates 12 candidate features, which are defined either based on prior studies or our insights. It is possible that there are other features (*e.g.*, types of edits in branches) that are potentially correlated with developers’ resolution strategies, and can be leveraged to better predict resolutions. In the future, we plan to define and explore more candidate features, so that our characterization study is more representative. By revealing and incorporating new features, we can also strengthen the prediction capability of RPREDICTOR. Our study and experiments are done on Java projects, although the methodology is generally applicable to programs written in any language. It is possible that the results of our study and evaluation do not generalize well to programs written in other languages. In the future, we plan to conduct larger-scale experiments to include non-Java programs.

Threats to Construct Validity. When crawling the owner developers of commits in software repositories, we assumed that there is one-to-one mapping relationship between developers and user IDs (*i.e.*, email addresses). Namely, we assumed that each developer has only one user ID, which is not shared with any

other developer. However, in reality, it is possible that a developer leverages multiple user IDs when checking in different commits (*i.e.*, one-to-many), while some developers share a single user ID when committing program changes (*i.e.*, many-to-one). Such one-to-many and many-to-one relations between developers and user IDs can make our data analysis imprecise. However, we believe that the corner cases of one-to-many and many-to-one mappings are rare, causing little impact on our research findings.

7. Discussion

In this section, we discuss various aspects of our approach to further clarify its applicability.

7.1. The Benefit of RPREDICTOR's Recommendations for Developers

Given a merge conflict, RPREDICTOR predicts the resolution strategy, and even recommends a merged version if the predicted strategy is KL or KR. Readers may be tempted to underestimate the usefulness of RPREDICTOR, because KL and KR seem much simpler to execute than ME. However, we argue that conflict resolution involves not only resolution implementation, but also decision-making; RPREDICTOR helps considerably reduce the manual effort on the decision-making process.

Prior work [49] mentions that 56% of developers have deferred at least once when responding to a merge conflict, which makes conflict resolution more complex as time passes; the key challenges that developers have to overcome when trying to resolve conflicts include (1) understanding the conflicting code, and (2) getting enough metadata information about the conflict (e.g., who made the change, why, and when). RPREDICTOR characterizes software conflicts from 12 distinct aspects, in order to automatically comprehend conflicts and retrieve metadata information related to those conflicts. Therefore, when RPREDICTOR correctly predicts KL and KR, developers do not need to go through the painful process of conflict comprehension and resolution.

As multiple studies [64, 19, 53] show that the majority of conflicts are resolved via KL and KR, RPREDICTOR's good precision of predicting KL/KR can significantly save developers effort, effort that would have otherwise been spent to manually analyze and resolve such conflicts.

775 *7.2. The Impact of Mispredictions and Developers' Trust in Automated Recommendations*

If RPREDICTOR predicts ME and requires developers to manually resolve some conflicts, developers cannot save any manual effort, but it also does not put any extra effort on those conflicts, either.

780 In the scenarios when RPREDICTOR incorrectly predicts KL or KR, developers may need to put extra effort to examine the tool-suggested strategies. However, if the test cases in software projects (1) have sufficient coverage, (2) do not conflict with each other across branches, and (3) reliably express the intended behaviors of merged software, developers do not need to spend more
785 time reasoning about whether tool-generated resolutions work. Instead, they can rely on testing to validate automated resolutions.

Furthermore, developers may choose to manually double-check if they personally agree with RPREDICTOR's prediction before applying it, which can reduce its ratio of mispredictions. This mode of operation would imply a lower
790 effort reduction for developers, but it can still be more efficient than reviewing all the details of the merge conflict.

At the end of the day, we expect different developers to show different preferences in terms of how liberally they want to directly apply RPREDICTOR's recommendations. That is why we proposed a variant of RPREDICTOR in Section 5.8, that gives them flexibility to make RPREDICTOR provide predictions
795 that save higher effort producing more mispredictions, the opposite trade-off, or other points in between.

In future work, we will also explore how to use *explainable machine learning approaches* to increase the trust of RPREDICTOR's recommendations for

800 developers, trying different approaches for explaining why RPREDICTOR is recommending a particular strategy.

7.3. *Applicability of RPREDICTOR on Less-Balanced Projects*

We evaluated RPREDICTOR in a dataset of projects that resolved merge conflicts in a relatively balanced way, *i.e.*, all decisions were taken with relatively
805 similar frequencies. We did this intentionally to evaluate RPREDICTOR in the kinds of projects for which we estimate they would benefit from it most: those projects which do not have a very clear *typical* way to resolve conflicts, *i.e.*, those in which no choice is strongly overrepresented.

However, we believe that RPREDICTOR could also benefit projects in which
810 KL or KR is the *typical* choice to resolve merge conflicts, *i.e.*, in which that strategy is chosen the majority of the time. In such cases, developers would also benefit from RPREDICTOR, because it will capture this bias in its training and it will in fact predict resolution strategies with higher accuracy. We performed an experiment showing RPREDICTOR’s higher accuracy in an unbalanced dataset
815 in Section 5.4 (RQ3).

The only case of projects that would not benefit as much from RPREDICTOR are those which choose ME to resolve their merge conflicts the majority of the time — since RPREDICTOR’s recommendations are most beneficial when it predicts KL or KR. However, such situations are less common — past work
820 [69, 27] showed that KL and KR are the most popular strategies to resolve merge conflicts.

7.4. *What If A Project Has Little Training Data Available?*

When using RPREDICTOR, users do not have to train RPREDICTOR on a large dataset of software repositories. Instead, for the within-project setting,
825 they can use all conflicts extracted from one project’s version history for classifier training, and leverage that trained classifier to predict resolutions for any new conflicts in the same project. For the cross-project setting, users can simply use the trained classifier open-sourced on our project website [3], instead

of training any classifier from scratch. In order to help users decide whether
830 RPREdictor should perform within- or cross- project prediction for their cir-
cumstances, we actually ranked the 482 experimented repositories in descending
order of the number of conflicting chunks they contain in version history. From
that ranked list, we sampled the 1st project (the one with the most conflicts),
the 482th project (the one with fewest conflicts), and 9 projects standing be-
835 tween at roughly 10%-interval of ranks. Table 12 shows all the sampled 11
projects, the total number of conflicts contained by each project, the number of
conflicts used for training (*i.e.*, 90% of the total), and the F-scores achieved by
RPREdictor for within-project prediction.

Table 12: RPREdictor’s F-scores for 11 sampled projects for within-project prediction

Rank	Total # of conflicts	# of conflicts used for training	F-score
1 st	5,114	4,603	92%
48 th	405	365	58%
96 th	150	135	45%
144 th	85	77	37%
192 th	62	56	27%
240 th	44	40	27%
288 th	30	27	17%
336 th	24	22	22%
384 th	17	15	0%
432 th	11	10	0%
482 th	11	10	0%

According to this table, as training data decreases, F-score generally de-
840 creases or stabilizes; this trend coincides with our observation in Section 5.5.
The phenomenon implies that if a user’s software repository has a few resolved
conflicts (*e.g.*, less than 135), she/he can consider using cross-project predic-
tion as the conflicts in version history seem insufficient to train a good within-
project predictor. Otherwise, if the user’s software repository has sufficient
845 resolved conflicts (*e.g.*, hundreds or even thousands of conflicts), she/he can
apply RPREdictor to do within-project prediction for better accuracy.

8. Related Work

Our research is related to empirical studies on merge conflicts, awareness-raising tools, and automated software merge.

850 8.1. Empirical Studies on Merge Conflicts

Several studies were conducted to characterize the relationship between merge conflicts and other aspects of software maintenance [25, 9, 42, 45, 52]. For instance, Estler *et al.* [25] surveyed 105 student developers, and found that the lack of awareness (*i.e.*, knowing “who’s changing what”) occurs more frequently than merge conflicts. Leßenich *et al.* [42] surveyed 41 developers and identified 7 potential indicators (*e.g.*, number of changed files in both branches) for merge conflicts. With further investigation of the indicators, the researchers found that none can predict the conflict frequency. Similarly, Owhadi-Kareshk *et al.* defined nine features (*e.g.*, number of added and deleted lines in a branch) to characterize merging scenarios; they trained a machine-learning model that predicts conflicts with 57%–68% accuracy [52].

Similar to these studies, our study also characterizes merge conflicts. However, it is different in two aspects. First, our study explores how different features characterize developers’ strategies of conflict resolution. Second, our study motivates our research to automatically predict resolution strategies, while existing studies motivate research to automatically predict conflict occurrence.

Some other studies characterize the root causes and/or resolutions of *textual* conflicts [69, 50, 27, 15, 53]. Specifically, Yuzuki *et al.* inspected hundreds of textual conflicts [69]. They observed that conflicting updates caused 44% of conflicts to the same line of code, and developers resolved 99% of conflicts by taking either the left- or right- version of code. Brindescu *et al.* [15] manually inspected 606 textual conflicts. They characterized merge conflicts in terms of the AST diff size, LOC diff size, and the number of authors. They identified three resolution strategies: SELECT ONE (*i.e.*, keep edits from one branch), INTERLEAVE (*i.e.*, keep edits from both sides), and ADAPTED (*i.e.*, change existing edits and/or add new edits). Pan *et al.* [53] explored the merge conflicts

in Microsoft Edge; they classified those conflicts based on file types, conflict locations, conflict sizes, and conflict-resolution patterns. Driven by their empirical study, the researchers further investigated to use program synthesis for conflict resolution. The prototype of their resolution tool only tries to concatenate edits from both branch versions, incapable of suggesting KL or KR resolutions.

These studies inspired us to define and study candidate features that may help predict developers' resolution strategies for conflicts. However, none of these studies conduct statistical analysis between any recognized features and developers' resolutions; our study performed that analysis.

8.2. Awareness-Raising Tools

Tools [56, 63, 14, 17, 28, 18, 40, 37, 44] were created to monitor and compare programmers' development activities, in order to improve team activity awareness. For instance, CASI [63] and Palantír [56] inform a developer of the artifacts changed by other developers, calculate the severity of those changes, and visualize the information. Cassandra [37] is a conflict minimization technique. It observes the super-sub and caller-callee dependencies between program entities. By treating those dependencies as constraints on file-editing tasks, Cassandra identifies tasks that will conflict when performed in parallel. It then appropriately schedules tasks to recommend conflict-free development paths. Crystal [17, 18] and WeCode [28] proactively detect collaboration conflicts via speculative analysis. They eagerly merge the program changes applied to different software branches, even before those changes are all pushed to the master repository in the distributed version control system (DVCS). They leverage textual merge, automatic build, and automatic testing in sequence to reveal the potential conflicts between branches.

The tools mentioned above can proactively detect and report merge conflicts. However, they do not characterize developers' resolution preferences, neither do they automatically recommend any resolution strategy.

905 *8.3. Automated Software Merge*

Tools were proposed to detect or resolve merge conflicts [47, 13, 12, 41, 51, 19, 71, 66, 65, 2, 67, 70, 24]. Mens *et al.* [47] published a survey on software merging techniques. FSTMerge [13, 19, 2] parses code for ASTs, and matches nodes between L and R purely based on the class or method signatures; it then
910 integrates the edits inside each pair of matched method nodes via textual merge. IntelliMerge [65] improves FSTMerge’s effectiveness by detecting and resolving refactoring-related conflicts. Similar to FSTMerge, JDime [12, 41] also matches Java methods and classes based on syntax trees. However, JDime merges edits inside matched methods by matching and manipulating ASTs. AutoMerge [71]
915 improves over JDime. When branch edits are incompatible with each other, AutoMerge attempts to resolve conflicts by proposing alternative strategies to merge L and R, with each strategy integrating the edits between branches in distinct ways. SafeMerge [66] checks if a merging scenario introduced new semantics. RPREDICTOR complements all these techniques, as it models and
920 predicts developers’ resolution preferences.

MergeHelper [51] records the chronological sequence of edit operations made by programmers on the Eclipse Java editor. Given two branch versions—L and R—that conflict with each other, MergeHelper explores the recorded edit sequences before both versions, to locate the most recent snapshot that appears
925 in the evolution history and is consistent with L and R. In other words, MergeHelper rolls back edits applied by both branches, until finding an intermediate version that occurs just before the first conflict was introduced. It provides detailed edit information to help developers understand how conflicts got introduced, but does not suggest resolution strategies as RPREDICTOR does.

930 DeepMerge [24], MergeBERT [67], and GMerge [70] automatically resolve conflicts using deep-learning methods. However, DeepMerge only focuses on conflicts with less than 30 lines [67]; it is not applicable to more complicated conflicts. Given a textual conflict, both DeepMerge and MergeBERT are designed to integrate partial edits from L and R for resolution, instead of proposing
935 KL or KR. GMerge does not focus on textual conflicts; instead, it deals with

a different type of merge conflicts where conflicting edits can be co-applied to the merged version but trigger semantic errors. RPREDICTOR complements the learning-based approaches mentioned above. That is, RPREDICTOR can predict conflicts that get resolved by KL or KR (the majority, according to the literature), and when Rpredictor predicts ME, it can be complemented with an alternative method (like DeepMerge or MergeBERT) to automate a resolution based on the combination of lines.

9. Conclusion

Software merge is complex and time-consuming. People defined the term “Integration Hell” to refer to the challenges of addressing merge conflicts. Although many tools were proposed to detect and even resolve merge conflicts, little tool support is available to automatically resolve conflicts by observing and mimicking developers’ resolution strategies. Consequently, existing tools mainly pinpoint issues of merge conflicts, rarely providing solutions to those issues. In this paper, we conducted the first characterization study to explore any statistical correlation between 12 features of merge conflicts and developers’ resolution strategies. Our study shows for the first time that all of the explored features can help predict developers’ resolution strategies.

Motivated by our study, we also designed and implemented a novel approach—RPREDICTOR—to predict developers’ resolution strategy, given a merge conflict and its related software repository. Our comprehensive evaluation of the tool with a large-scale dataset containing 74,861 resolved conflicts showed that RPREDICTOR effectively predicted resolutions. By training prediction models with the random forest (RF) algorithm, RPREDICTOR could achieve 63% precision, 62% recall, 63% F-score, and 82% C-score for within-project prediction; it also got 46% precision, 47% recall, 46% F-score, and 76% C-score for cross-project prediction. Our sensitivity analysis shows that compared with other machine-learning (ML) algorithms, RF achieved the best results when being used in RPREDICTOR; RPREDICTOR is sensitive to both the amount and age of

965 training data; as more training data is provided, RPREDICTOR’s effectiveness
increases or stabilizes. Developers can also customize RPREDICTOR_v’s th_M
threshold to more or less often predict M resolutions, making it save less or
more effort.

In the future, we will explore more features and more ML algorithms, to
970 further improve the representativeness of our characterization study and to
strengthen the capability of RPREDICTOR. For example, we will explore additional
prediction features related to, *e.g.*, code-change history [58, 59, 57, 61, 62],
testing activity, *e.g.*, [39, 26, 38], decision-making metadata, *e.g.*, [48, 11, 10],
developer expertise, *e.g.*, [60, 20], build failure prediction *e.g.*, [32, 34, 33, 31,
975 35, 36], security issue prediction *e.g.*, [22, 30] or cross-language issues, *e.g.*, [23].

10. Research Artifact

We made available the research artifact for our paper [3].

Acknowledgement

We thank all reviewers for their valuable feedback. This work was partially
980 funded by NSF CCF-1845446, NSF CCF-2046403, Virginia Tech’s hiring pack-
age 117716, Universidad Rey Juan Carlos under the International Distinguished
Researcher award C01INVESDIST, and by Saudi Arabian Cultural Mission
(SACM). This work also served as foundation for award PID2022-142964OA-I00
by the Spanish Agencia Estatal de Investigación.

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