Mining Software Repository for Cleaning Bugs Using Data Mining Technique

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Abstract: Despite advances in technological complexity and efforts, software repository maintenance requires reusing the data to reduce the effort and complexity. However, increasing ambiguity, irrelevance, and bugs while extracting similar data during software development generate a large amount of data from those data that reside in repositories. Thus, there is a need for a repository mining technique for relevant and bug-free data prediction. This paper proposes a fault prediction approach using a data-mining technique to find good predictors for high-quality software. To predict errors in mining data, the Apriori algorithm was used to discover association rules by fixing confidence at more than 40% and support at least 30%. The pruning strategy was adopted based on evaluation measures. Next, the rules were extracted from three projects of different domains; the extracted rules were then combined to obtain the most popular rules based on the evaluation measure values. To evaluate the proposed approach, we conducted an experimental study to compare the proposed rules with existing ones using four different industrial projects. The evaluation showed that the results of our proposal are promising. Practitioners and developers can utilize these rules for defect prediction during early software development.

Keywords: Fault prediction; association rule; data mining; frequent pattern mining

1 Introduction

Mining software repositories is a procedure for examining data based on software development history. This is a developing field for supporting software development teams in performing daily tasks. Mining software repositories discovers interesting and actionable patterns for software development from the rich data available in the repository. Many open-source software repositories, such as source code control systems, archived communications among project personnel,
Software engineers and researchers recognize the benefits of mining software repositories for software system maintenance, reuse, and authenticating new ideas and techniques. Numerous approaches to data mining have been implemented in various data-mining applications [1]. The overall objective is to make accurate predictions or classify repositories to improve the decision-making process from data [2]. Data-mining approaches, such as support vector machines, nearest neighbors, neural networks, Naive Bayes, and logistic regression, can provide exact predictions but still be deficient in clarifying the relationship between objects in a class.

The decision tree algorithm builds a tree in which each node of the tree is an input variable and the path that follows a series of nodes leads to a decision-category label [3]. The Apriori algorithm can generate association rules for each category that requires classified features [4] by looking for frequent items in the data with individual category tags. These algorithms can provide comparable classification accuracies and interpretable results. However, the disadvantages are that the models become complicated if the amount of data increases significantly and takes considerable time, which is not effective for timely prediction [5]. Software quality measures are essential to building high-quality software within a time frame and budget [6]. The best predictor is a model that predicts software defects and has been proven to help quality software development [7,8]. The approach that deals with discovering interesting patterns and correlations among the data in software repositories is known as frequent pattern mining; the most important frequent pattern mining application is mining association rules [9].

Association rule mining (ARM) creates associations among variables in repositories [10] and is used to correlate the presence of one set of objects with another set. It generates the rules that follow set criteria with minimal support and confidence. ARM is applied in many fields such as process mining, protein sequencing, logistic regression, scientific analysis, bio-scientific literature, and customer relationship management (CRM) of credit card enterprises. Existing literature describes that the right decision is critical for extracting practicable patterns among information available using different algorithms (e.g., Apriori, Éclat, and FP-growth) [11–14]. Other than ARM algorithm evaluation measures (e.g., support, confidence, and correlation), Jaccard and F-measure are also calculated and evaluated. Correlation can be calculated with the help of the “lift” measure. The values of other evaluation measures can be generated using mathematical and statistical formulas. The value of the F-measure defines the power of the association rules: the greater the F-measure, the stronger are the rules. These algorithms have some challenges in improving the performance and complexity of mining information, as there is a need to cope with large and complex datasets. Some existing algorithms involve using correlation measures [15], and a few existing algorithms use ARM [16,17]. The Apriori algorithm generates an iterative set of rules to locate the frequent pattern in a dataset and avoid unnecessary transactional statistics [13,14]. Frequent extraction of information from relevant repositories requires error-free relevant data to be reused during ARM software development, which is essential for mining bug-free data. This study applies ARM using the Apriori algorithm to extract the rules for defect prediction. There is a need for a mining algorithm that can clean and discover bug-free relevant data from the repository for correct reuse based on the frequently extracted data. Supporting the allocation of resources for software development and maintenance accurately is necessary to predict error-based information.

To maintain high project quality, project managers and engineers must screen faults during software development. Therefore, software defect prediction tasks should classify software modules as faulty or clean using metric-based classification methods, especially ARM. Software modules
comprise many characteristic metrics (predictors) that can determine whether a module or class is defective or clean. Software modules and classes can be considered as multidimensional vectors and a software system as a dataset. In the dataset, a record is a software module, and a feature is a software index; rich information can be extracted from the module or class. The main contributions of this study are as follows:

• We analyzed defect data extracted from many projects by applying ARM to determine whether a software entity (class) is defective or clean. Association rules that identify buggy or clean classes are evaluated by different interestingness measures such as lift, support, correlations Jaccard, and F-measure.

• Although there is much work in software defect prediction, more focus is needed on accurate software defect predictors; the limitations of current methods need to overcome. As yet, few studies have been presented based on ARM predictors. Therefore, this study developed an ARM for fault prediction and evaluated its effectiveness through experimental results.

• Evaluating an algorithm using the proposed approach rules identified performance metrics for mining repositories using an experimental study of four industrial projects.

• The results showed that the proposed approach efficiently mines error-free information during development using an ARM-based algorithm and provides software practitioners with a guideline for mining repositories.

The remainder of the paper is organized as follows. Section 2 presents related work. The experimental design is discussed in Section 3, and the research methodology is presented in Section 4. Section 5 presents the results and discussions. Section 6 concludes the paper by offering a direction for future work.

2 Related Work

Association rules [18] are commonly implemented in unsupervised scenarios. Numerous classification extensions have been proposed, such as classification based on the association (CBA) method [4], in which class association rules are mined, and the results are class labels. Liu et al. [19] proposed CBA2 to resolve data imbalance issues. Here, the rules have different minimum supports that predict different classes. Ma et al. [4] proposed another CBA2 method to predict faulty modules by performing tests on the NASA dataset [20], and the results were compared with those of other classification models. It was also found that the association rule generated from the data of one project can be used only for similar projects and that cross defect prediction cannot be performed [21]. Kamei et al. [22] proposed a hybrid model based on ARM and logistic regression that checks the rule suitability for a given instance. If suitable, the rules are implemented; if not, then a logistic regression model is implemented to obtain results. In [23], the authors introduced a subgroup discovery (SD) algorithm called the evolutionary decision rules (EDER) for detecting subcategories. This approach depends on evolutionary calculations to generate rules that further describe error-prone modules—tests were conducted on NASA's dataset. The results of the EDER-SD algorithm were better than those of the three other popular SD algorithms. Analysis of different machine learning (ML) algorithms, such as the naive Bayes classifier, One R, and J48, was carried out by Menzies et al. [20]. The results show that log filtering and the naive Bayes algorithm yield superior results on NASA datasets. A literature review focusing on defect prediction methods shows that clustering, classification, and association mining are commonly used for defect prediction [24].
In another approach [25], prediction models for real-time defect datasets of software [20] were evaluated. The results confirmed that the hybrid model of one-rule classification [26] and instance-based learning produced better results in fault prediction than other models. Haghighi et al. [27] performed a comparative study of 37 models of fault detection systems on the NASA dataset; it was shown that the bagging classifier performed better than other classifiers. ROCUS [28] is a semi-supervised learning model that depends on divergence. The authors tested it on eight datasets of the NASA repository. Results were compared with those of other semi-supervised methods. Semi-supervised learning was used because the amount of labeled data in defect prediction is limited, whereas it is easy to collect unlabeled data. Zhang et al. [29] proposed a semi-supervised learning model based on divergence, called ACoForest. This model only needs to mark a part of the module; it then attempts to mark the remaining modules based on the model built from the marking data. Tests on publicly available datasets show that this method is superior to traditional ML algorithms. In [30], the authors suggested using the random forest method to predict whether a module comprises a defect. They applied the method to NASA datasets, analyzed its performance, and found that, compared with other ML algorithms, random forest performed better and was particularly effective on large datasets. Recently, defect prediction has shifted to method formalization and standardization [31]. For data preprocessing, attribute selection methods consisting of a framework were defined for defect prediction. D’Ambros et al. [32] proposed a standard for predicting defects using public datasets. Menzies et al. [20] studied the instability of the outcomes of prediction systems. They suggested the possible causes and solutions that tend to correct for one project but not for other projects. Ma et al. [21] claim that the area under the curve (AUC) approach provides a more suitable indicator, whereas Gray et al. [33] proved that the accuracy should also be reported. However, almost all approaches agree that accuracy alone is not sufficient when the data is skewed.

3 Experimental Design

This study’s principal objective was to identify software metrics that can serve as suitable predictors of software fault and find the best association rules for fault prediction using the Apriori algorithm. To achieve this, we first needed to decide which metrics to choose and how data would be extracted and mined.

3.1 Selection of Software Metrics

The selection of suitable software metrics was a challenge because there are many metrics available. Several studies have employed Chidamber & Kemere (CK) metrics and fault-proneness prediction. Basili et al. [34] used multivariate linear regression (LR) for fault-prone classes. By contrast, Kanmani et al. [35] used a general regression neural network for the fault ratio and multiple linear regression for the fault ratio applied in [36,37]. In this work, we used the CK metrics to measure object-oriented behavior, which helps in software evolution. They are as follows:

- Weighted methods per class (WMC) are the aggregate complexity of methods, which can predict the time and effort needed for the maturity of a class.
- Depth of the inheritance tree (DIT) uses the maximum distance between a node and the root of a tree to evaluate complexity. A high value indicates high complexity, and a low value shows simplicity.
- Number of children (NOC) is a direct subclass in a class ladder. A low value shows a deficiency in communication, and a high value indicates the need for sophisticated tests.
• Coupling between object classes (CBO) uses the count of classes to which it is attached. Low CBO values show ease in reuse and testing.
• Response for a class (RFC) is a count of class methods and other methods that are called. A high RFC value indicates difficulty in testing and maintenance of the class.
• Lack of cohesion of methods (LCOM) tests the variation of procedures in a class using instance variables. High values indicate complexity.

3.2 Selection of Dataset
For this study, we used the GitHub bug database [38] to extract the datasets. This database is useful for working and analyzing defect prediction areas. Java projects were selected with different domains, and features of these projects were mined from the GitHub repository using the SourceMeter tool. Fifteen projects were analyzed to answer different research questions. The SZZ algorithm [39] was used for analyzing commit logs and extracting bug data. Release versions at six-month intervals were used to create a bug database.

4 Research Methodology
This section describes the process for analyzing the selected metrics as the best predictor of software faults for classes, covering steps such as preprocessing, ARM, the Apriori algorithm, receiver operating characteristic curve (ROC) analysis, and rule evaluation. Fig. 1 shows that, first, data extracted from repositories were preprocessed according to the requirements. Next, a data-mining technique was applied to achieve desired objectives. In this study, we applied ARM and generated rules regarding the bugs. Last, the rules were evaluated and tested on the bug dataset of a different project using the GitHub repository.

![Figure 1: Process to analyze selected metrics](image)

4.1 Data Preprocessing
The Apriori algorithm was used to find the best predictor of software faults. This algorithm requires the nominal values of the selected datasets; hence, the quantitative value of data had to be changed to the nominal values by preprocessing for compatibility with the algorithm. The preprocessing algorithm is as follows.
Algorithm

Input: Dataset of required metrics with numerical data
Output: Dataset of required metrics with nominal data
Step 1: For each $x_i \in d_i$ where $d$ are the datasets
Step 2: $M_{min} \in x_i$ (Minimum value of $x_i$)
Step 3: $M_{max} \in x_i$ (Maximum value of $x_i$)
Step 4: Calculate quartiles of metric $Q \in x$ (Quartiles of $x_i$)
Step 5: $Q = q_1, q_2, q_3$ ($q_1, q_2, q_3$ are 1st, 2nd, and 3rd quartiles of metric $x$)
Step 6: If $x_i \leq q_1$ then $x_i = "N"
Step 7: If $x_i \leq q_2$ then $x_i = "L"
Step 8: If $x_i \leq q_3$ then $x_i = "M"
Step 9: If $x_i \leq M_{max} \text{ then } x_i = "H"
Step 10: Repeat the above for each $x_i \in d_i$

4.2 Association Rule Mining (ARM)

Association rules are the characteristics that often occur in an assumed dataset. An ARM can be stated as $X \rightarrow Z$, where $X$ and $Z$ are item sets representing the predecessor and the resulting part of the rules, while $X$ and $Z$ do not intersect. ARM discovers the existing relations and correlations between the variables of a given dataset [40]. According to the evaluation criteria, the rules are evaluated as correlation, support, confidence, lift, and F-measure.

4.2.1 Apriori Algorithm

In this study, the Apriori algorithm is used to produce association rules by finding a repeated pattern in the data. An item is regarded as frequent if its support and confidence are higher than the threshold values. The support rate is the frequency of item set $x$ that exceeds its occurrence in the exercise dataset; confidence is the frequency of item set $x$ with $z$ that satisfies the rule and exceeds the rate of item set $x$.

4.2.2 Why Use Apriori Algorithm

The FP-growth algorithm finds the frequent itemsets using a divide-and-conquer strategy; it then encodes the training data into an FP-tree to represent the frequent itemsets. However, it is expensive to build and may not fit in memory. Prediction using a decision tree starts with the root and proceeds through the nodes until a leaf node (the final class) is found. The drawback of the FP-growth algorithm is that it is easily overfitted. The support vector machine discriminates between classes by creating a separating hyperactive plane or a set of hyperactive schemes in a large dimension space and finds the best hyperactive scheme that attains the maximum margins between the classes. However, it does not work well with many samples and requires many parameters to be tuned. Logistic regression describes the association between the contributing classes and estimates the probabilities for the category-dependent variable using a logit function based on one or more features. Its disadvantages include being prone to overfitting and requiring more training time. The K-nearest neighbor algorithm assigns categories by a majority vote of k neighboring test samples. It uses such similarity measures as distance functions to determine the closeness of the samples. The drawbacks of the algorithm are that it is hard to classify with high dimensionality and that it has weak performance with imbalanced data and large amounts of memory. The Naive Bayes algorithm is successful in a variety of data-mining tasks. It estimates
$P(X \mid Y)$ and $P(Y)$ and classifies new instances into the highest posterior. However, it assumes the independence of features and robustness of outliers.

4.3 Receiver Operating Characteristic (ROC) Curve

The ROC is used as a test of diagnostic accuracy [41]. It is shaped by scheming the true-positive rate contrary to the false-positive rate at multiple predefined values. Thus, the ROC is recalled as a function of fall-out. The ROC is an assessment tool for choosing optimal models and is linked in an ordinary mode to the cost and benefit investigation of analytical results. Initially, the ROC curve was established by electrical and radar engineers to search for opponents on battlefields in the Second World War. ROC studies are now used in medicine, radiology, biometrics, model evaluation, meteorology, ML, and data mining. Its performance through an AUC is assessed as follows: $AUC = 0.5$, no right category; $0.6 \leq 'AUC' < 0.7$, fair category; $0.7 \leq 'AUC' < 0.8$, suitable type; $0.8 \leq 'AUC' < 0.9$, superb type; and $'AUC' \geq 0.9$, manner superb category.

4.4 Proposed Algorithm

The steps of the proposed algorithm are as follows:

| Proposed Algorithm |
|--------------------|
| Step 1: Adjust minimum confidence (40%) and minimum support (30%) to generate association rules with the help of the Apriori algorithm. |
| Step 2: Apply the ROC curve for evaluating suitable metrics. |
| Step 3: Adjust criteria of selecting rules having confidence $> = 0.95$ |
| Step 4: Calculate the confidence, support, and correlation of each generated and selected rule, and calculate the F-measure by statistical methods. |
| Step 5: Adjust F-value as it is significant for producing better association rules. |
| Step 6: Compare the top generated rules reusing all evaluation measures previously used. |
| Step 7: Test the association rules by applying them to experimental projects. |
| Step 8: Find the results of the experimentations. |

The metrics used for the rules’ evaluation are as follows:

- Recall = (support * lift)/confidence
- F-measure = 2 * (confidence * recall)/(confidence + recall)
- Correlation (X and Z) = (support − P(X) * P(Z))/SQRT(P(X) * P(Z) * (1 − P(X)) * (1 − P(Z)))
- P(X) = support/confidence
- P(Z) = confidence/lift
- Jaccard = support/(P(X) + P(Z) − support)
- Correlation: Correlation analysis deals with the relation between variables. Correlation prunes out the negatively associated rules. Correlation = (support − P(A) * P(B))/SQRT(P(A) * P(B)(1 − P(A))*(1 − P(B)))

5 Results and Discussions

Correlation and F-measure evaluation were used to obtain the best ARM cleaning bugs. The Apriori algorithm was used to produce rules based on support = 30% and confidence = 40%. CK
metrics were used for this purpose because they contain the behaviors of cohesion, complexity, coupling, inheritance, and size. Furthermore, we selected the AUC metric to evaluate the predictive power of each CK metric.

5.1 Predictor Analysis in Representative Projects

This section presents the comparative and predictor analysis using three industrial projects employing the aforementioned metrics. The projects were selected because the repositories are mainly used to develop products by reusing their features.

5.1.1 Android Universal Image Loader (AUIL) Project

The Android universal image loader (AUIL) is a library suitable for processing images on an Android device, such as uploading, hiding, and displaying. It delivers many configuration choices and consists of many advanced features for image processing and memory management. Figs. 2–6 show the ROC curve for different versions of the AUIL project.

![Figure 2: ROC curve for AUIL version 13-1](image1)

![Figure 3: ROC curve for AUIL version 13-7](image2)

5.1.2 ANother Tool for Language Recognition (ANTLR) Project

Another tool for language recognition (ANTLR) is a valuable parser that produces organized text and binary files. It is applied in shaping languages, language tools, and language frameworks. ANTLR works by building parse trees from a grammar and generates an interface for ease
of acknowledgment expressions of requirements. Figs. 7–11 show the ROC curve for different versions of the ANTLR project.

Figure 4: ROC curve for AU1L version 13-12

Figure 5: ROC curve for AU1L version 14-05

Figure 6: ROC curve for AU1L version 14-09
5.1.3 Broadleaf Commerce (BC) Project

The Broadleaf Commerce (BC) project is an e-commerce platform written entirely in the Java language. It facilitates the development of commerce-driven websites and provides a robust data model and the required tools. The BC platform is gradually increasing its features for more facilitation. Figs. 12–16 show the ROC curve for different versions of the BC project.
Further, for all the aforementioned three projects (i.e., AUIL, ANTLR4, and BC), the average of averages was calculated for comparison. Tab. 1 shows the average values of metrics for each project as well as the average of the averages. The results show that metrics such as NOC and DIT have a low AUC and are weak predictors, whereas LOC, WMC, RFC, and so on have a comparatively high AUC, and hence are strong predictors. The experiment was performed on three
different real-world projects to overcome cross-project variations. Because NOC and DIT are weak predictors, they were excluded from the association rules. Only those metrics were selected for analysis that have high predictive power for defects. For this part, the R tool and rules with a high evaluation value were used. Evaluation measures such as support, confidence, correlation, Jaccard, and F-measure were used. The value of the evaluation of each rule for analysis of each project is given in Tab. 1.

Figure 13: ROC curve for BC version 2013-09

Figure 14: ROC curve for BC version 2014-03

Figure 15: ROC curve for BC version 2014-10
5.2 Analysis of Rules for Cleaning Bugs

This section presents the analysis of rules for cleaning bugs in all projects.

5.2.1 Analysis of Rules for Cleaning Bugs—BC Project

Table 2 shows the best rules for bug prediction using data from the BC project. This table shows different evaluation measures for each rule.

| Rule No. | LHS | RHS        | SUPPORT | CONF | COUNT | F-measure | Correlation | Jaccard |
|---------|-----|------------|---------|------|-------|-----------|-------------|---------|
| 1       | \{LCOM5 = N\} ⇒ \{bugs = CLEAN\} | 0.811 | 0.971 | 1545 | 0.906 | 0.172 | 0.828 |
| 2       | \{LCOM5 = L\} ⇒ \{bugs = CLEAN\} | 0.439 | 0.773 | 700  | 0.634 | −0.131 | 0.464 |
| 3       | \{CBO = N\} ⇒ \{bugs = CLEAN\}   | 0.375 | 0.965 | 587  | 0.589 | 0.201 | 0.417 |
| 4       | \{LCOM5 = N, CBO = N\} ⇒ \{bugs = CLEAN\} | 0.346 | 0.970 | 542  | 0.557 | 0.197 | 0.386 |
| 5       | \{WMC = N\} ⇒ \{bugs = CLEAN\}   | 0.349 | 0.993 | 665  | 0.534 | 0.133 | 0.365 |
| 6       | \{LCOM5 = N, WMC = N\} ⇒ \{bugs = CLEAN\} | 0.345 | 0.992 | 656  | 0.529 | 0.131 | 0.360 |

5.2.2 Analysis of Rules for Cleaning Bugs—AUIL Project

Table 3 shows the best rules for bug prediction using data from the AUIL project. This table shows different evaluation measures for each rule.
Table 3: Analysis of rules for cleaning bugs using AUIL project data

| Rule No. | LHS | RHS | SUPPORT | CONF | COUNT | F-measure | Correlation | Jaccard |
|----------|-----|-----|---------|------|-------|-----------|-------------|---------|
| 1        | {LCOM5 = N} ⇒ {bugs = CLEAN} | 0.633 | 0.838 | 62,000 | 0.800 | 0.052 | 0.667 |
| 2        | {LCOM5 = N} ⇒ {bugs = CLEAR} | 0.521 | 0.704 | 38,000 | 0.710 | −0.084 | 0.551 |
| 3        | {CBO = N} ⇒ {bugs = CLEAN} | 0.329 | 0.857 | 24,000 | 0.593 | 0.232 | 0.421 |
| 4        | {LCOM5 = N, CBO = N} ⇒ {bugs = CLEAN} | 0.388 | 0.978 | 45,000 | 0.581 | 0.131 | 0.409 |
| 5        | {LCOM5 = N, CBO = N} ⇒ {bugs = CLEAR} | 0.301 | 0.846 | 22,000 | 0.557 | 0.200 | 0.386 |
| 6        | {LOC = M} ⇒ {bugs = CLEAN} | 0.364 | 1.000 | 40,000 | 0.544 | 0.127 | 0.374 |
| 7        | {WMC = N} ⇒ {bugs = CLEAN} | 0.336 | 1.000 | 39,000 | 0.527 | 0.180 | 0.358 |
| 8        | {LCOM5 = N, WMC = N} ⇒ {bugs = CLEAN} | 0.336 | 1.000 | 39,000 | 0.527 | 0.180 | 0.358 |

5.2.3 Analysis of Rules for Cleaning Bugs—ANTLR4 Project

Tab. 4 shows the best rules for bug prediction using data from the ANTLR4 project. In this table, different evaluation measures for each rule are also shown. Tab. 5 lists the best rules for bug prediction by combining the rules for all the projects. This table shows the different evaluation measures for each rule. Rules 1–3 have the top values; hence, they are the best rules of our study. Tabs. 6–8 show the statistics of metrics LCOM5 and CBO for all three representative projects (i.e., AUIL, ANTLR4, and BC).

Table 4: Analysis of rules for cleaning bugs using ANTLR4 project data

| Rule No. | LHS | RHS | SUPPORT | CONF | COUNT | F-measure | Correlation | Jaccard |
|----------|-----|-----|---------|------|-------|-----------|-------------|---------|
| 1        | {LCOM5 = N} ⇒ {bugs = CLEAR} | 0.521 | 0.704 | 38,000 | 0.710 | −0.084 | 0.551 |
| 2        | {CBO = N} ⇒ {bugs = CLEAR} | 0.329 | 0.857 | 24,000 | 0.593 | 0.232 | 0.421 |
| 3        | {LCOM5 = N, CBO = N} ⇒ {bugs = CLEAR} | 0.301 | 0.846 | 22,000 | 0.557 | 0.200 | 0.386 |
| 4        | {LCOM5 = L} ⇒ {bugs = CLEAN} | 0.378 | 0.982 | 165,000 | 0.552 | −0.028 | 0.381 |
| 5        | {RFC = N} ⇒ {bugs = CLEAN} | 0.342 | 1.000 | 149,000 | 0.515 | 0.085 | 0.347 |

Table 5: Combination of all projects’ rules for cleaning bugs

| Rule No. | LHS | RHS | SUPPORT | CONF | COUNT | Recall | F-measure | Correlation | Jaccard |
|----------|-----|-----|---------|------|-------|--------|-----------|-------------|---------|
| 1        | {LCOM5 = N} ⇒ {bugs = CLEAN} | 0.811 | 0.971 | 1545 | 0.849 | 0.906 | 0.172 | 0.828 |
| 2        | {LCOM5 = L} ⇒ {bugs = CLEAN} | 0.439 | 0.773 | 700 | 0.538 | 0.634 | −0.131 | 0.464 |
| 3        | {CBO = N} ⇒ {bugs = CLEAN} | 0.375 | 0.965 | 387 | 0.424 | 0.589 | 0.201 | 0.417 |
| 4        | {LCOM5 = N, CBO = N} ⇒ {bugs = CLEAN} | 0.346 | 0.970 | 542 | 0.391 | 0.557 | 0.197 | 0.386 |
| 5        | {LOC = M} ⇒ {bugs = CLEAN} | 0.364 | 1.000 | 40 | 0.374 | 0.544 | 0.127 | 0.374 |
| 6        | {WMC = N} ⇒ {bugs = CLEAN} | 0.349 | 0.993 | 665 | 0.366 | 0.534 | 0.133 | 0.365 |
| 7        | {LCOM5 = N, WMC = N} ⇒ {bugs = CLEAN} | 0.345 | 0.992 | 656 | 0.361 | 0.529 | 0.131 | 0.360 |
| 8        | {RFC = N} ⇒ {bugs = CLEAN} | 0.342 | 1.000 | 149 | 0.347 | 0.515 | 0.085 | 0.347 |

5.3 Testing of Candidate Rules

The four projects described in this section were compared and analyzed statistically to demonstrate the performance of the best-selected rules.
Table 6: Statistics of LCOM5 and CBO metrics—AUl project

|        | Ver. 13-1 | Ver. 13-7 | Ver. 13-12 | Ver. 14-5 | Ver. 14-19 |
|--------|-----------|-----------|------------|-----------|------------|
| N      | Valid     | 73        | 98         | 109       | 116        |
|        | Missing   | 0         | 0          | 0         | 0          |
| Percentile | 25       | 1.00      | 1.00       | 1.00      | 1.00       |
|        | 50        | 1.00      | 1.00       | 1.00      | 1.00       |
|        | 75        | 2.00      | 4.00       | 1.00      | 4.75       |

Table 7: Statistics of LCOM5 and CBO metrics—ANTLR4 project

|        | Ver. 13-1 | Ver. 13-6 | Ver. 14-2 | Ver. 14-7 | Ver. 15-1 |
|--------|-----------|-----------|-----------|-----------|-----------|
| N      | Valid     | 430       | 436       | 479       | 516       |
|        | Missing   | 0         | 0         | 0         | 0         |
| Percentile | 25       | 0.00      | 0.00      | 0.00      | 0.00      |
|        | 50        | 1.00      | 1.00      | 1.00      | 1.00      |
|        | 75        | 2.00      | 1.75      | 2.00      | 1.00      |

Table 8: Statistics of LCOM5 and CBO metrics—BC project

|        | Ver. 13-2 | Ver. 13-9 | Ver. 14-3 | Ver. 14-10 | Ver. 15-3 |
|--------|-----------|-----------|-----------|------------|-----------|
| N      | Valid     | 1904      | 1566      | 1593       | 1901      |
|        | Missing   | 0         | 0         | 0          | 0         |
| Percentile | 25       | 1.00      | 1.00      | 1.00       | 1.00      |
|        | 50        | 1.00      | 2.00      | 1.00       | 1.00      |
|        | 75        | 1.00      | 6.00      | 1.00       | 1.00      |

5.3.1 Test of Ceylon IDE for Eclipse Project

This project is a plugin for Eclipse. David Festal developed it from SERLI, a French software house, and donated it to the Ceylon project. By employing ARM, we extracted the best rules for each project and then filtered them using the selected rules from the previous analysis. Tab. 9 shows the best rules for bug prediction using data from the Ceylon IDE project for Eclipse. These promising results are significant. Tab. 10 shows F-measures and other performance measures for best rules discovered in the Ceylon IDE project for Eclipse. Here, we calculated the F-measure of the selected rules and found that its values were outstanding. The F-measure for rule \{LCOM5 = N\} is 0.811, which is excellent, and that for \{CBO = N\} is 0.655, which is very good. The rules are also valid for the Ceylon IDE project.

5.3.2 Test of Elasticsearch Project

Elasticsearch is a dispersed search engine specially made for the cloud environment. It is reliable, real-time, consistent, and easy to use. Other characteristics are a distributed and
highly accessible search engine. It is multi-tenanted and supports a variety of APIs. It is also
document-oriented and does not need

Table 9: Best rules found from Ceylon IDE project for eclipse

| Rule No. | LHS                | RHS                | Support     | Confidence  | Lift         | Count |
|----------|--------------------|--------------------|-------------|-------------|--------------|-------|
| 2        | \{CBO = M\}       | \{Number of bugs = CLEAN\} | 0.1080745   | 0.9613260  | 1.0037191   | 174   |
| 3        | \{CBO = L\}       | \{Number of bugs = CLEAN\} | 0.1608696   | 0.9700375  | 1.0128147   | 259   |
| 4        | \{CBO = H\}       | \{Number of bugs = CLEAN\} | 0.2167702   | 0.9064935  | 0.9464686   | 349   |
| 5        | \{CBO = N\}       | \{Number of bugs = CLEAN\} | 0.4720497   | 0.9781210  | 1.0212547   | 760   |
| 1        | \{LCOM5 = L\}     | \{Number of bugs = CLEAN\} | 0.9577640   | 0.9577640  | 1.0000000   | 1542  |
| 2        | \{LCOM5 = H\}     | \{Number of bugs = CLEAN\} | 0.1229814   | 0.9166667  | 0.9570904   | 198   |
| 3        | \{LCOM5 = M\}     | \{Number of bugs = CLEAN\} | 0.1670807   | 0.9438596  | 0.9854825   | 269   |
| 4        | \{LCOM5 = N\}     | \{Number of bugs = CLEAN\} | 0.6677019   | 0.9693417  | 1.0120883   | 1075  |

Table 10: Performance measures for best rules from Ceylon IDE project for eclipse

| Rule No. | LHS                | RHS                | Support | Confidence | Lift   | F-measure | Correlation |
|----------|--------------------|--------------------|---------|------------|--------|-----------|-------------|
| 5        | \{CBO = N\}       | \{bugs = CLEAN\}   | 0.472   | 0.978      | 1.021  | 0.655     | 0.098       |
| 4        | \{LCOM5 = N\}     | \{bugs = CLEAN\}   | 0.668   | 0.969      | 1.012  | 0.811     | 0.086       |

upfront schema definition. Schemas can be defined for customizing the indexing process, asynchronous write-behind for long-term persistency, near real-time search, and operational consistency. Tab. 11 shows the best rules for bug prediction using data from the Elasticsearch project. This table shows the evaluation for each rule using different performance metrics. Tab. 12 shows the F-measure and other performance indicators for the best rules discovered for Elasticsearch. The F-measure value for rule \{LCOM5 = N\} is 0.819, which is excellent, and for \{CBO = N\} it is 0.457, which is significant. Hence, these rules are also valid for the Elasticsearch project.

Table 11: Best rules found–elasticsearch project

| Rule No. | LHS                | RHS                | Support     | Confidence  | Lift         | Count |
|----------|--------------------|--------------------|-------------|-------------|--------------|-------|
| 2        | \{CBO = M\}       | \{Number of bugs = CLEAN\} | 0.2194593   | 0.9535176  | 1.0128196   | 1518  |
| 3        | \{CBO = L\}       | \{Number of bugs = CLEAN\} | 0.230013    | 0.970122   | 1.0304566   | 1591  |
| 4        | \{CBO = H\}       | \{Number of bugs = CLEAN\} | 0.2115079   | 0.8525641  | 0.9055875   | 1463  |
| 5        | \{CBO = N\}       | \{Number of bugs = CLEAN\} | 0.2804684   | 0.9852717  | 1.0465486   | 1940  |
| 1        | \{LCOM5 = L\}     | \{Number of bugs = CLEAN\} | 0.9414486   | 0.9414486  | 1.0000000   | 6512  |
| 2        | \{LCOM5 = H\}     | \{Number of bugs = CLEAN\} | 0.1178256   | 0.8679446  | 0.9219246   | 815   |
| 3        | \{LCOM5 = M\}     | \{Number of bugs = CLEAN\} | 0.1516553   | 0.9258605  | 0.9834425   | 1049  |
| 4        | \{LCOM5 = N\}     | \{Number of bugs = CLEAN\} | 0.6719676   | 0.9593395  | 1.0190036   | 4648  |
5.3.3 Test of Hazelcast Project

Hazelcast is an open-source distributed in-memory data store and computation platform. It provides a wide variety of distributed data structures and concurrency primitives. Tab. 13 shows the best rules for bug prediction using data from the Hazelcast project. This table shows the different performance metrics evaluated for each rule. Tab. 14 shows the F-measure and other performance measures for best rules discovered for the Hazelcast project. The F-measure for rule \{LCOM5 = N\} is 0.852, which is excellent, whereas for \{CBO = N\}, it is 0.534, which is good. Hence, these rules are also valid for Hazelcast.

### Table 13: Best rules found—hazelcast project

| Rule No. | LHS          | RHS                          | Support | Confidence | Lift  | Count |
|----------|--------------|------------------------------|---------|------------|-------|-------|
| 2        | \{CBO = L\}  | \{Number of bugs = CLEAN\}  | 0.1533453 | 0.9701705 | 1.049075 | 683   |
| 3        | \{CBO = M\}  | \{Number of bugs = CLEAN\}  | 0.2411316 | 0.9496021 | 1.026834 | 1074  |
| 4        | \{CBO = N\}  | \{Number of bugs = CLEAN\}  | 0.3403682 | 0.9711723 | 1.050158 | 1516  |
| 1        | \{LCOM5\}    | \{Number of bugs = CLEAN\}  | 0.9247867 | 0.9247867 | 1.000000 | 4119  |
| 2        | \{LCOM5 = H\} | \{Number of bugs = CLEAN\}  | 0.2025146 | 0.8869223 | 0.9590561 | 902   |
| 3        | \{LCOM5 = N\} | \{Number of bugs = CLEAN\}  | 0.7222721 | 0.9359907 | 1.0121152 | 3217  |

### Table 14: Performance measures for best rules—hazelcast project

| Rule No. | LHS          | RHS                          | Support | Confidence | Lift  | F-measure | Correlation |
|----------|--------------|------------------------------|---------|------------|-------|-----------|-------------|
| 4        | \{CBO = N\}  | \{Number of bugs = CLEAN\}  | 0.340   | 0.971      | 1.050 | 0.534     | 0.129       |
| 3        | \{LCOM5 = N\} | \{Number of bugs = CLEAN\}  | 0.722   | 0.936      | 1.012 | 0.852     | 0.078       |

5.3.4 Test of JUnit Project

This project is used extensively for testing. Tab. 15 shows the best rules for bug prediction using data from the JUnit project. This table shows the different performance metrics for each rule. Tab. 16 shows the F-measure and other performance measures for the best rules discovered for the JUnit project.

The F-measure for rule \{LCOM5 = N\} is 0.792, which is excellent, and for \{CBO = N\}, it is 0.414, which is significant. Hence, these rules are also valid for the JUnit project. The F-measure of the two selected rules for each of the projects selected is very promising. Hence, these rules provide the best guidelines for defect prediction to improve the quality of software projects. We compared the results of the proposed approach with the results of the nearest neighbors...
and decision tree methods. The comparison shows a significant difference between the F-measure values of the proposed approach (i.e., greater than 60%) and current methods (i.e., less than 60%).

Table 15: Best rules found—JUnit project

| Rule No. | LHS          | RHS                                    | Support      | Confidence   | Lift        | Count |
|----------|--------------|----------------------------------------|--------------|--------------|-------------|-------|
| 4        | {CBO = N}    | {Number of bugs = CLEAN}               | 0.2503       | 0.968254     | 1.016945    | 183   |
| 5        | {CBO = L}    | {Number of bugs = CLEAN}               | 0.3638851    | 0.9672727    | 1.015914    | 266   |

Table 16: Performance measures for best rules—JUnit project

| Rule No. | LHS          | RHS                                    | Support      | Confidence   | Lift        | F-measure | Correlation |
|----------|--------------|----------------------------------------|--------------|--------------|-------------|-----------|-------------|
| 4        | {CBO = N}    | {Number of bugs = CLEAN}               | 0.2503       | 0.968254     | 1.016945    | 0.414     | 0.045       |
| 4        | {LCOM5 = N}  | {Number of bugs = CLEAN}               | 0.6429549    | 0.9572301    | 1.0053667   | 0.792     | 0.034       |

6 Conclusion and Future Work

In this study, we applied ARM and statistical analysis to determine whether a software class can be classified as clean or buggy. The rules selected through ARM are further evaluated in terms of their ability to classify the class as either impact error or zero impact error. Using the selected rules to classify classes will help improve software quality and reduce project costs. The rules were extracted from three projects according to their high-value F-measures and then tested on four other projects for their effectiveness. The experimental results demonstrate the applicability of the selected rules. Those metrics with a large AUC are used for extracting rules. This study also proposes a heuristic method for ranking association rules according to four constraints – support, confidence, F-measure, and correlation. The proposed approach produces the top association rules for any type of field. The predictor selected from this method also demonstrated promise in predicting the classes of the software projects selected using the ROC curve. Therefore, the proposed approach is useful for software evolution. For example, a software quality manager can allocate resources for any specific module based on the best association rules to save cost and time. Our method can find commercial and industrial solutions or a solution where the best choice is needed. We would like to extend this approach to future work by incorporating and analyzing more metrics such as complexity, inheritance, coupling, and size.

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