Software Defect Prediction Using One Pass Data Mining Algorithm

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Abstract

Software Testing Consumes major percentage of project cost, so researchers focus is "How to minimizes cost of testing in order to minimize the cost of the project". The Software defect prediction is a method which predict defect from historical database. Data mining Techniques are used to predict Software defects from historical databases. This paper describes frame work to produce software defects from the historical database and also present one pass data mining algorithm used to find rules to predict software defects. The experimental results shows that, one pass algorithm generate rules for software defect prediction with consider amount of time and with better performance.

Keywords

Software, Testing, Defect, Data Mining

I. Introduction

Software testing is an investigation conducted to provide stakeholders with information about the quality of the product or service under test. A set of activities conducted with the intent of finding errors in software. Testing is a process used to help identify the correctness, completeness and quality of developed computer software. A Software Defect / Bug is a condition in a software product which does not meet a software requirement (as stated in the requirement specifications) or end-user expectations (which may not be specified but are reasonable). In other words, a defect is an error in coding or logic that causes a program to malfunction or to produce incorrect/unexpected results. Current defect prediction work focuses on (i) estimating the number of defects remaining in software systems, (ii) discovering defect associations, and (iii) classifying the defect-proneness of software components, typically into two classes defect-prone and not defect-prone. The second type of work borrows association rule mining algorithms from the data mining community to re veal software defect associations, which can be used for three purposes. The third type of work classifies software components as defect-prone and non-defect-prone by means of metric-based classification. Being able to predict which components are more likely to be defect-prone supports better targeted testing resources and therefore improved efficiency.

Data mining (sometimes called data or knowledge discovery) is the process of analyzing data from different perspectives and summarizing it into useful information - information that can be used to increase revenue, cuts costs, or both. Association rule mining is to find out association rules that satisfy the predefined minimum support and confidence from a given database. The problem is usually decomposed into two sub problems. One is to find those item sets whose occurrences exceed a predefined threshold in the database; those item sets are called frequent or large item sets. The design and study of one-pass algorithms has a long tradition in many areas of computer science. For example, they are used in the area of data stream processing, where streams of huge amounts of data have to be monitored on-the-fly without prior storing the entire data. But also, e.g., a deterministic finite automaton on words can be viewed as a (very simple) example of a one-pass algorithm whose memory size and processing time per data item is constant, i.e., does not depend on the input size. For most computational problems, however, the amount of memory necessary for solving the problem grows with increasing input size.

The remainder of the paper is organized as follows. Section 2 provides related work. Section 3 describes problem description. Section 4 is devoted proposed framework and one pass algorithm. In Section 5 results are documented. Conclusions and consideration of the significance of this work are given in the final section.

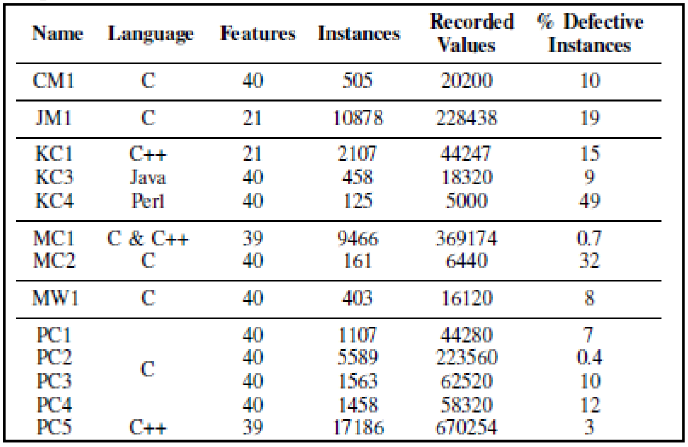
II. Related Work

MGF [1] published a study in this journal in 2007 in which they compared the performance of two machine learning techniques (Rule Induction and Na¨ıve Bayes) to predict software components containing defects. Hall and Holmes [2] concluded that the forward selection search was well suited to Na¨ıve Bayes but the backward elimination search is more suitable for C4.5. Cardie [3] found using a decision tree to select attributes helped the nearest neighbor algorithm to reduce its prediction error. Kubat et al. [4] used a decision tree . That is, which attribute subset is more useful for defect prediction not only depends on the attribute subset itself but also on the specific data set. This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.Filtering attributes for use with a Na¨ıve Bayesian classifier and obtained a similar result. However, Kibler and Aha [5] reported more mixed results on two medical

Classification tasks. Therefore, before building prediction models, we should choose the combination of all three of learning algorithm, data pre-processing and attribute selection method, not merely one or two of them. Lessmann et al. [6] have also conducted a follow-up to MGF on defect predictions, providing additional results as well as suggestions for a methodological framework. However, they did not perform attribute selection when building prediction models. Thus this work has wider application.

III. Problem Description

Association rule mining is to find out association rules that satisfy the predefined minimum support and confidence from a given database. The problem is usually decomposed into two subproblems. One is to find those itemsets whose occurrences exceed a predefined threshold in the database; those itemsets are called frequent or large itemsets. The second problem is to generate association rules from those large itemsets with the constraints of minimal confidence. Suppose one of the large itemsets is Lk, $L_k = \{I_1, I_2, \dots, I_k\}$, association rules with this itemsets are generated in the following way: the first rule is $\{I_1, I_2, \dots, I_{k-1}\} \Rightarrow \{I_k\}$, by checking the confidence this rule can be determined as interesting or not. Then other rule are generated by deleting the last items in the antecedent and inserting it to the consequent, further the confidences of the new rules are checked to determine the interestingness of them. Those processes iterated until the antecedent becomes empty. Since the second subproblem is quite straight forward, most of the researches focus on the first subproblem.



Name	Language	Features	Instances	Recorded Values	% Defective Instances
CM1	C	40	505	20200	10
JM1	C	21	10878	228438	19
KC1	C++	21	2107	44247	15
KC3	Java	40	458	18320	9
KC4	Perl	40	125	5000	49
MC1	C & C++	39	9466	369174	0.7
MC2	C	40	161	6440	32
MW1	C	40	403	16120	8
PC1	C	40	1107	44280	7
PC2		40	5589	223560	0.4
PC3		40	1563	62520	10
PC4		40	1458	58320	12
PC5	C++	39	17186	670254	3

Fig. 1: Stastics of Defect in Softwares

Let I=I1, I2, … , Im be a set of m distinct attributes, T be transaction that contains a set of items such that T ⊊ I, D be a database with different transaction records Ts. An association rule is an implication in the form of $X \Rightarrow Y$, where X, Y ⊂ I are sets of items called itemsets, and X ∩ Y =□. X is called antecedent while Y is called consequent, the rule means X implies Y. There are two important basic measures for association rules, support(s) and confidence(c). Since the database is large and users concern about only those frequently purchased items, usually thresholds of support and confidence are predefined by users to drop those rules that are not so interesting or useful. The two thresholds are called minimal support and minimal confidence respectively. Support(s) of an association rule is defined as the percentage/fraction of records that contain X ∪ Y to the total number of records in the database. Suppose the support of an item is 0.1%, it means only 0.1 percent of the transaction contain purchasing of this item.

Confidence of an association rule is defined as the percentage/fraction of the number of transactions that contain X ∪ Y to the total number of records that contain X. Confidence is a measure of strength of the association rules, suppose the confidence of the association rule $X \Rightarrow Y$ is 80%, it means that 80% of the transactions that contain X also contain Y together.

IV. Proposed Solution

A. Frame Work

The framework consists of two components:

1. Scheme evaluation
2. Defect prediction. historical data are divided into two parts:

A training set for building learners with the given learning schemes, and a test set for evaluating the performances of the learners. It is very important that the test data are not used in any way to build the learners. This is a necessary condition to assess the generalization ability of a learner that is built according to a learning scheme, and further to determine whether or not to apply the learning scheme, or select one best scheme from the given schemes. defect prediction stage, according to the performance report of the first stage, a learning scheme is selected and used to build a prediction model and predict software defect.

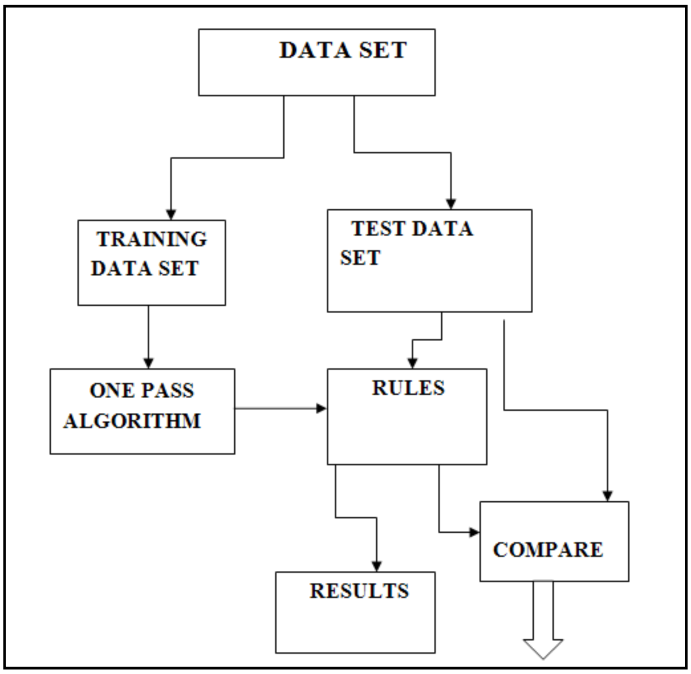


Fig. 2: Frame Work

B. One pass Algorithm for Defect Prediction

ALG Evaluation(historicalData, scheme)
input : historicalData - the historical data;
scheme - the learning scheme.
output: AvgResult - the mean performance over the M×N-way cross-validation.

```
M = 10 ; /*number of repetitions */
N = 10 ; /*number of folds */
repeat
D = Randomize (historicalData); /*randomize the order of instances */
Generate N bins from D ;
for i = 1 to N do
test = bin[i];
train = D − test ;
[learner, bestAttrs ] = Learning (train, scheme);
test' = select bestAttrs from test ;
Result = TestClassifier (test', learner);
/*Compute the performance measures of the learner on data test' */
end
until M times ;
AvgResult = 1/M×N
Result ;
```

Algorithm Learning(data, scheme)
input : data - the data on which the learner is built;
scheme - the learning scheme.
output: learner - the final learner built on data with scheme;
bestAttrs - the best attribute subset selected by the attribute selector of scheme

```
m = 10 ; /*number of repetitions for attribute selection */
n = 10 ; /*number of folds for attribute selection */
d = Preprocessing (data, scheme.preprocessor);
bestAttrs = AttrSelect (d, scheme.algorithm, scheme.attrSelector, m, n);
d' = select bestAttrs from d ;
```

```
6 learner = BuildClassifier (d', scheme.algorithm);
/*build a classifier on d' with the learning algorithm of scheme */
```

```
Algorithm Prediction(historicalData, newData, scheme)
input : historicalData - the historical data; newData - the new data;
scheme - the learning scheme.
output: Result - the predicted result for the newData

1 [predictor, bestAttrs ] = Learning (historicalData, scheme);
2 d = select bestAttrs from newData;
3 Result = Predict (d, predictor);
```

The above functional parts of algorithms describe the generic representations of solutions for predicting defects. In order to generate rules to the following algorithm for one pass frequent pattern mining algorithm is required.

Algorithm MFI-TransSW

```
Input: TDS (a transaction data stream), s (a user-defined minimum support threshold in the range of
[0, 1]), and w (the user-specified sliding window size).
Output: a set of frequent itemsets, FI-Output.
Begin
TransSW = NULL; /* TransSW consists of w transactions */
Repeat:
for each incoming transaction Ti in TransSW do
for each item X in Ti do
Do bit-sequence transform(X);
end for
if TransSW = FULL then
Do bitwise-shift on bit-sequences of all items in TransSW;
end if
end for
for each bit-sequence Bit(X) in TransSW do
if sup(X) = 0 then
Drop X from TransSW;
end if
end for
/* The following is the frequent itemsets generation phase. The phase is performed only when requested by
users. */
FI1 = {frequent 1-itemsets};
for (k=2; FIk−1≠□NULL; k++) do
CIk = CIGA(FIk−1);
Do bitwise AND to find the supports of CIk;
for each candidate ck ∈□CIk do
if sup(ck)TransSW ≥□w□s then
FIk = {ck ∈□CIk | sup(ck)TransSW ≥□w□s};
end if
end for
end for
FI-Output = kFIk;
```

In the above algorithm three stages calculations have to perform

- initialization phase
- window full phase
- frequent pattern finding phase. First phase of algorithm store each transaction that arrive .second phase store incoming transaction remove the old transaction. finally it compute frequent patterns with in threshold.

V. Results

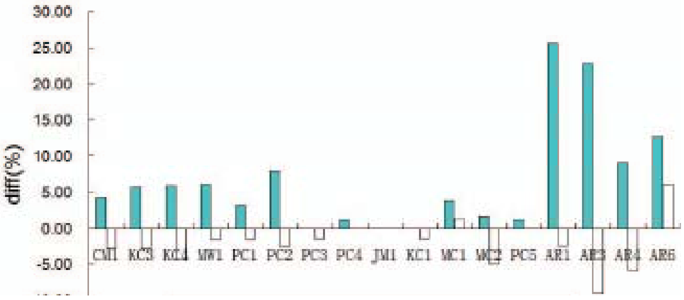


Fig. 3: Differences Existing and Proposed Frame Works

The above fig. shows the balance diff s of the two frameworks on the 17 data sets. From Fig. observe that (1) For MGF framework, the alance diff values are always positive except for the KC1 data. This means the evaluation performance of MGF framework is always higher than the prediction performance.This reveals they overestimated the performance and the result they reported in [23] may be misleading. (2) For the proposed framework, the balance diff values are always negative except for the JM1 and PC5 data are zero, and MC1 and AR6 data are positive. This reveals that our evaluation is a little conservative. The potential reason is that the training data used for learner building in the evaluation is just 90% of the 'historical' data, while the final predictor is built on the whole 'historical' data. That is, the final predictor is built with more sufficiency data than the learner built in the evaluation, hence has a higher balance on average.

VI. Conclusion

This paper, presented a novel benchmark framework for software defect prediction. The framework involves evaluation and prediction. In the evaluation stage, different learning schemes are evaluated and the best one is selected. Then in the prediction stage, the best learning scheme is used to build a predictor with all This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. historical data and the predictor is finally used to predict defect on the new data.

This paper described frame work to produce software defects from the historical database and also presented one pass data mining algorithm used to find rules to predict software defects.

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