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Prediction for Resolution Time of Software Defect

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Prediction for Resolution Time of Software Defect

Da Wang

Problem Report submitted to the
College of Engineering and Mineral Resources
at West Virginia University
in partial fulfillment of the requirements
for the degree of

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in
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ABSTRACT

Prediction for Resolution Time of Software Defect

Da Wang

In practical software development projects, solving test issues efficiently during Software Development Life Cycle is critical to release software products on time. Different test environments, test resources and test requirements could result in different outcomes. Therefore, getting accurate prediction of the software defects' resolution time could be beneficial to the practical projects. .

In our study, data mining techniques offer great promise in prediction of software defects' resolution time. Our research is conducted based on the NASA Metrics Data Program (MDP). We first calculate the resolution time for available projects. Using unsupervised discretization methods, we split resolution time into certain interval as response variable. Then, investigating the relationship between metric properties and time intervals, we fit a model that attempts to produce prediction on resolution time. Experiments and analysis successfully demonstrate the feasibility of our approach.

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Chapter 1 Introduction

1.1 Motivation

In practical software development projects, controlling the Software Development Life Cycle (SDLC), especially the software test period, and then release the software on time would be a difficult challenge for project managers. Different test environments, test resources and test requirements could result in different outcomes for software test period, thereby the whole SDLC. Therefore, getting accurate prediction of the software defects' resolution time could be beneficial to the practical projects..

In this study, we want to investigate proper methodology to generate accurate prediction of resolution time based on metrics properties, such as the number of operators in a modul, the number of decision points, design density, design complexity, and other attributes, in our datasets.

Data mining techniques have been used in software engineering area for many years. In software quality assurance area, the fault-prone module prediction is one of the topics that many researchers are interested in [1]. Module metrics have been successfully used for predicting fault-prone modules. A study of data mining in module metrics, which is the topic of our research, will be effective for predicting resolution time of software defects accurately.

1.2 Goal

Based on previous motivation, the goal of this study is to provide evidence that we could get an accurate prediction for resolution time of software defects after implementing data mining techniques in module metric datasets. We do not have related literature that can be used as reference to guide our research. Thus we need to design our own experiments and validate the assumption in our models. After comparing the performance of different models we can confirm an optimal solution to predict resolution time of software defects accurately.

1.3 Contribution

To build prediction model about software defects' resolution time, a series of experiments studying on NASA Metrics Data Program (MDP) are conducted in this thesis to find the potential relationship between software metrics and defect resolution time. The result shows that with appropriate algorithm and methodology we may achieve a good model to predict the resolution time on the basis of metrics data.

1.4 Organization

The rest of the thesis is organized as follows. Chapter 2 presents a literature review, which covers the usage of prediction in software engineering area as well as the general information about the data sets in MDP depository and general idea of data mining techniques. It also mentions the classification method, Random Forest algorithm and the evaluation of classification results,

which are utilized in this study. Chapter 3 illustrates the experiment result and conducts the evaluation and discussion on the result. Finally, Chapter 4 provides the conclusion and discusses the methods that can be implemented to further optimize the analysis.

Chapter 2 Related Works

2.1 Prediction in Software Engineering

As more data are gathered, with the amount of data doubling every three years, data mining is becoming a significant important tool to transform data into information. Although M. Mendonca and N. L. Sunderhaft have applied data mining techniques on software engineering data during 1990s [2], the idea of using data mining skills has attracted a great deal of interest recently within software engineering. We could dig into software engineering data (such as code bases, execution traces, historical code changes, and bug databases) to find out a large amount of information about a software project's status, progress, and evolution. Using this wealth of information could help us on programming, static defect detection, testing, debugging, and maintenance tasks in software engineering.

In software engineering field, many different data mining techniques (such as association rules, classification, and clustering) have been utilized to analyze the data [3].

Studying association rules that identify library components that are often used by application components could be helpful in discovering library reuse patterns in user-selected applications [4]. In 1999, Amir Michail proposed to explore data mining techniques which are designed to find patterns in vast collections of data. The association rules can help a developer discover patterns for reusing library components. Moreover, these rules can be used

to warn developers automatically when their application reuses library components in a different way from others’.

Classifying data could help do prediction in software engineering field. Amir Michail and Tao Xie used a tool-based approach to help users avoid bugs in GUI applications [5]. In this approach, it incorporates Distance Weighted Nearest Neighbor Learner in the tool to generate bug prediction (bug or not bug) automated. This idea makes sure the user could use the application normally and report defect that they encounter to prevent anyone from encountering those defects again.

Software failure prediction could also be executed by cluster analysis of execution profiles [6]. Andy Podgurski, et al, [7, 8], suggested that using cluster filtering together with stratified random sampling could estimate software reliability efficiently. William Dickinson, et al, [6], evaluated the effectiveness of this method for finding failures. The results show that cluster filtering is a more effective approach for identifying failures in populations of operational executions than simple random sampling.

Besides association rules, classification, and clustering, other methods are also widely used in software engineering area, such as texting mining used for static code analysis [9], and texting mining used for bug report analysis [10].

2.2 Metrics Data Program

The data sets used in this study come from the NASA Metrics Data Program (MDP) data repository [22]. Thirteen projects shown in Table 1 are used in this study. Same data sets are available through the PROMISE [25] repository too.

These data sets provide module metrics that describe 13 different NASA projects. In this study, since we need to predict the defect resolution time period for each project, the projects without resolution time would be removed. Projects MC1, MC2 and PC5, which contain no date data, are not used. Moreover, the number of faulty modules in projects KC3, MW1 and PC2 are 25, 27 and 22 instances respectively, too small sample to predict result correctly. We ignore these three projects too.

The remaining seven data sets contain *defect_id*, *entry_type* and *entry_date* attributes. We calculate the resolution time for each defect and divide the values by seven to generate a new attribute *weeks* as predicted variable. We confirm that only the longest resolution time exists for each module, and then remove *module_id*, *defect_id*, *entry_type* and *entry_date* metrics prior to modeling. After removing and replacing these attributes, KC1 has 22 attributes that can be used as predictor variables, JM1 has 25, and the other five data sets have 44 metrics.

Reverse engineering tool calculates metrics from flowcharts [23], dividing the module metrics into three groups: design, code and other metrics (see table 2) [1]. We use all the metrics in our study, regardless of the metric

groups. In future work, we may study metric groups separately. It could lead to further research on the relationship between metrics properties and our response variable.

Data	Modules	% Faulty	# of Faulty Modules	# of FM with Resolution Time	Project Description	Lang.
CM1	505	16.04%	81	75	Spacecraft instrument	C
KC1	2407	12.17%	293	286	Storage management for receiving/processing ground data	C++
KC4	125	48%	60	57	A ground-based subscription server	Perl
PC1	1107	6.59%	73	63	Flight software from an earth orbiting satellite	C
PC3	1563	10.23%	160	160	Flight software for earth orbiting satellite	C
PC4	1458	12.24%	178	178	Flight software for earth orbiting satellite	C
JM1	10878	18.34%	1995	1350	A real time predictive ground system	C
MC2	161	32.30%	NA	No date data	A video guidance system	C++
MC1	9466	0.64%	NA	No closed date for faults	A combustion experiment of a space shuttle	C(C++)
PC5	17186	3.00%	NA	No date data	A safety enhancement of a cockpit upgrade system	C++
KC3	458	6.3%	29	25	Storage management for ground data	Java
MW1	433	6.24%	27	27	A zero gravity experiment related to combustion	C
PC2	5589	0.393%	22	22	Dynamic simulator for attitude control systems	C

Table 1 Datasets Used in This Study

group	metrics	description or formula
code	PARAMETER_COUNT	Number of parameters to a given module
	NUM_OPERATORS:N1	The number of operators contained in a module
	NUM_OPERANDS:N2	The number of operands contained in a module
	NUM_UNIQUE_OPERATORS: μ_1	The number of unique operators contained in a module
	NUM_UNIQUE_OPERANDS: μ_2	The number of unique operands contained in a module
	HALSTEAD_CONTENT: μ	The halstead length content of a module $\mu = \mu_1 + \mu_2$
	HALSTEAD_LENGTH:N	The halstead length metric of a module $N = N_1 + N_2$
	HALSTEAD_LEVEL:L	The halstead level metric of a module $L = 2 * \mu_2 / (\mu_1 * N_2)$
	HALSTEAD_DIFFICULTY:D	The halstead difficulty metric of a module $D = 1/L$
	HALSTEAD_VOLUME:V	The halstead volume metric of a module $V = N * \log_2(\mu_1 + \mu_2)$
	HALSTEAD_EFFORT:E	The halstead effort metric of a module $E = V/L$
	HALSTEAD_PROG_TIME: T	The halstead programming time metric of a module $T = E/18$
	HALSTEAD_ERROR_EST: B	The halstead error estimate metric of a module $B = E^{(2/3)}/1000$
	NUMBER_OF_LINES	Number of lines in a module
	LOC_BLANK	The number of blank lines in a module
	LOC_CODE_AND_COMMENT:NCSL OC	The number of lines which contain both code and comment in a module
	LOC_COMMENTS	The number of lines of comments in a module
	LOC_EXECUTABLE	The number of lines of executable code for a module (not blank or comment)
	PERCENT_COMMENTS	Percentage of the code that is comments
	LOC_TOTAL	The total number of lines for a given module
design	EDGE_COUNT:e	Number of edges found in a given module control from one module to another
	NODE_COUNT:n	Number of nodes found in a given module
	BRANCH_COUNT	Branch count metrics
	CALL_PAIRS	Number of calls to other functions in a module
	CONDITION_COUNT	Number of conditionals in a given module
	CYCOMATIC_COMPLEXITY: $v(G)$	The cyclomatic complexity of a module $v(G) = e - n + 2$
	DECISION_COUNT	Number of decision points in a given module
	DECISION_DENSITY	Condition_count/Decision_count
	DESIGN_COMPLEXITY: $iv(G)$	The design complexity of a module
	DESIGN_DENSITY	Design density is calculated as: $iv(G)/v(G)$
	ESSENTIAL_COMPLEXITY: $ev(G)$	The essential complexity of a module
	ESSENTIAL_DENSITY	Essential density is calculated as: $(ev(G)-1)/(v(G)-1)$
	MAINTENANCE_SEVERITY	Maintenance Severity is calculated as: $ev(G)/v(G)$
	MODIFIED_CONDITION_COUNT	The effect of a condition affect a decision outcome by varying that condition only
	MULTIPLE_CONDITION_COUNT	Number of multiple conditions that exist within a module
	PATHOLOGICAL_COMPLEXITY	A measure of the degree to which a module contains extremely unstructured constructs

others	NORMALIZED_CYLOMATIC_COMPLEXITY	$v(G)/\text{NUMBER\_OF\_LINES}$
	GLOBAL_DATA_COMPLEXITY:gdv(G)	the ratio of cyclomatic complexity of a module's structure to its parameter count
	GLOBAL_DATA_DENSITY	Global Data density is calculated as: $gdv(G)/v(G)$
	CYCLOMATIC_DENSITY	$v(G)/\text{NCSLOC}$

Table 2 Metrics used in this study [1]

2.3 Data Mining Techniques

Generally, data mining (sometimes called knowledge discovery [11]) is the process of analyzing data from different dimensions and summarizing it into useful information. Although there are many different descriptions for this process, rough procedure can be illustrated as pre-processing the raw data, mining the data, and interpreting the results.

2.3.1 Pre-Processing the Data

The raw data in the real world is noisy, that is why we need pre-processing procedure to provide quality data, and then to achieve quality mining results and quality decisions. The preparation of incomplete, inconsistent and noisy data comprises the majority of the work in a data mining application, probably 90%. The tasks in data pre-processing include data cleaning, integration, transformation, reduction and discretization.

At integration step, data from multiple sources are integrated and combined. Detecting and resolving data value conflicts, as well as removing duplicates and abundant data are the key tasks for this part.

At transformation step, data normalization, aggregation, generalization and other techniques are applied. Normalization refers to scaling attribute values to fall within a specified range. Aggregation indicates moving up in the concept hierarchy on numeric attributes and generalization stands for moving up in the concept hierarchy on nominal attributes.

At reduction step, the number of attribute, attribute values and tuples is reduced in order to obtain a smaller volume of data set but yet produce the same or similar analytical results. Attribute subset selection can be used to choose a minimum set of attributes (features) that is sufficient for the data mining task. Sampling can also be used to select a representative subset of the data, but simple random sampling method may have poor performance in conjunction with skewed data.

At discretization step, the continuous features or attributes of data set are converted into discretized or nominal features, since some data mining algorithms only accept categorical attributes. Typically, there are two types of discretization, unsupervised discretization in which the class variable is not used and supervised discretization, in which the value of class variable is used. Unsupervised discretization involves binning methods, wherein equal-interval (equal width) binning splits the whole range of numbers in intervals with equal size while equal-frequency (equal depth) binning uses intervals containing equal number of values. Supervised discretization relates to entropy (information)-based discretization which recursively splits intervals until the information gain of the resulting split “tells” it to stop.

2.3.2 Mining the data

The goal of data mining is to discover useful or interesting models for the user. Commonly, it involves four types of tasks [11]: association rules, regression model, classification and clustering.

Association rule mining, proposed by Agrawal et al, in 1993 [12], is data mining model studied extensively by the database and data mining community, which assumes all data are categorical. Normal association rule mining does not have any target. It will find all possible rules which exist in data and satisfy a user-specified minimum support and a user-specified minimum confidence at the same time.

Regression is the best-known statistical technique that the data mining community utilizes. Basically, regression is to develop a mathematical model that fits the numeric data set. The simplest form of regression, linear regression, uses the model of a straight line ($y = ax + b$) and determines the suitable values for a and b to predict the value of y based upon a given value of x . Other advanced methods, such as logistic regression, allow the use of

more complex models, such as a logistic function $f(x) = \frac{1}{1 + e^{-z}}$. The major limitation of this technique is that it only works well with continuous quantitative data.

Classification is a data mining technique used to predict categorical class labels for data instances, and then classify data (construct a model) based on training set and the values (class labels) in a classifying attribute and use it

in classifying new data. This paper is mainly focus on the usage of classification technique in software metrics, so the detail information about how to construct the classification models and the way to use these models would be discussed later in this chapter.

Clustering is unsupervised classification with no predefined classes. From a machine learning perspective, clusters correspond to hidden patterns and cluster analysis is to group a set of data objects into clusters, the search for clusters is unsupervised learning. *K*-means clustering is one of the simplest methods of cluster analysis, which intends to partition all data objects into k clusters in which each object belongs to the cluster with the nearest mean.

2.3.3 Interpreting the Results

The last step of discovering information from data is to interpret the data mining results and verify the patterns produced by all kinds of algorithms we used in the experiment. Not all results found by the data mining algorithms are positive, which requires us to use some statistical methods or other approaches to evaluate them. Commonly used performance measures for the evaluation of data mining algorithms include, but not limited to, Accuracy, Precision/Recall, Receiver Operating Characteristic (ROC) Curve and Area under the Curve (AUC), which will be covered later in this chapter.

2.4 Classification and Random Forests

Unlike clustering, classification is a supervised machine learning method. It builds a concise model of the distribution of class labels in terms of predictor features. We can state the problem as follows: given training data $T = (y_n, x_n)$, $n = 1, \dots, N$, where the y_n are the responses and x_n are predictors, produce a classifier $C: X \rightarrow Y$. This classifier will map any object $x \in X$ to its true classification label $y \in Y$ defined by some unknown mapping $M: X \rightarrow Y$ [13][14]. The process can be seen in Figure 1.

Figure 1 Classification Process

The most widely used classification algorithms include neural network, k-nearest neighbors, naïve Bayes, boosting and decision tree. In our study, we use Random Forest (RF), an ensemble classifier of decision trees, developed by Leo Breiman and Adele Cutler as the main method. It demonstrates good performance on software engineering studies [15]. Random Forest is a

classifier consisting of a collection of tree structured predictors, where each tree depends on independent identically distributed random vectors [16]. Each tree constructs as following strategy:

1. Draw T bootstrap samples from the original data. For each sample, grows a tree;
2. Choose m -- number of variables used to split each node. $m \ll M$, where M is the number of variables in the classifier. m is a constant while growing the tree;
3. When growing a tree at each node, select m variables at random and use them to find the best split. Grow the tree to a maximal extent without pruning.
4. To classify or predict new data, collect the votes from every tree in the forest and then use majority voting to decide on the class label.

The RF uses randomly selected inputs or combinations of inputs at each node to grow each tree. The resulting forests produce highly accurate results for many data sets in an efficient way. It comprises effective method to estimate missing data and maintain accuracy when large portion of data are missing. It can also balance error in class population unbalanced data sets.

The RF is more robust to noise and outliers than many other methods. Thus, the classification accuracy of random forests is more significant over other methods in larger data sets [15]. It can handle large data sets containing

thousands of input variables without variable deletion, making it a good choice for our study on software engineering metrics data.

2.5 Evaluation of classification results

As we generate a suitable classification for the original data, we need to test whether this classification is the best fit for the data. Thus, we need to introduce more evaluation approaches to prove that our algorithms bring us a correct and meaningful interpretation for the original information. Normally, we can use Accuracy, Precision/Recall, Receiver Operating Characteristic (ROC) Curve and Area under the Curve (AUC) as our evaluation methods.

Before we introduce the evaluation methods, we need to explain confusion matrices. In the field of artificial intelligence, confusion matrix is used to represent the instances showing whether the system is confusing among different classes. Each column of the confusion matrix indicates the components in a predicted class, while each row indicates the components in a true class. With the help of confusion matrix, we may observe directly that how many correct predictions we have made and how many failures we have made. Figure 2 shows us an example of confusion matrix. Here, True Positive (TP) and True Negative (TN) are correct classifications. The number of True Positive is the number of items correctly predicted as belonging to the positive class, and the number of True Negative is the number of items correctly predicted as belonging to the negative class. False Positive (FP) occurs when the outcome is incorrectly labeled as positive when it is not and False Negative (FN) occurs when the outcome is incorrectly labeled as negative when it is actually positive.

In statistical null hypothesis statement, False Negative is known as Type I errors which reject the null hypothesis given that it is actually true. Also, False Positive is known as Type II errors which are failing to reject the null hypothesis given that the alternative hypothesis is actually true.

	<u>Predicted 1</u>	<u>Predicted 0</u>		<u>Predicted 1</u>	<u>Predicted 0</u>
<u>True 1</u>	True Positive	False Negative	<u>True 1</u>	$P(pr1 tr1)$	$P(pr0 tr1)$
<u>True 0</u>	False Positive	True Negative	<u>True 0</u>	$P(pr1 tr0)$	$P(pr0 tr0)$

Figure 2 Confusion Matrix

2.5.1 Accuracy

Accuracy is the degree of closeness of a measured or calculated quantity to its actual (true) value [13]. For confusion matrix, the accuracy is all true results out of the whole population. It could be determined by following equation:

$$Accuracy = \frac{\text{number.of.}(True.Positive + True.Negative)}{\text{number.of.}(True.Positive + True.Negative + False.Positive + False.Negative)}$$

On most problems, obtaining Accuracy is easy. However, 99% accuracy cannot secure a good performance, while 10% accuracy does not necessarily

lead to a bad prediction. It depends on the problem and data, in which other elements may count on higher weight.

2.5.2 Precision and Recall

In statistical classification task, we also use Precision and Recall to evaluate the basic tradeoff. Precision can be considered as a measure of exactness while Recall is a measure of completeness. In definition, the Precision for a class is the number of true positive divided by the total number of observations labeled as belonging to the positive class, i.e. the sum of true positive and false positive. Recall is defined as the number of true positive over the total number of observations that truly belong to positive class, i.e. the sum of true positive and false negative. They can be demonstrated by following equations:

$$\text{Precision} = \frac{\text{number.of.True.Positive}}{\text{number.of.}(True.Positive + False.Positive)}$$

$$\text{Recall} = \frac{\text{number.of.True.Positive}}{\text{number.of.}(True.Positive + False.Negative)}$$

2.5.3 ROC Curves

Receiver Operating Characteristic (ROC) curve is useful for organizing classifiers and provides intuitive way to visualize their performance. In

addition to a useful performance graphing method, it has properties that make itself useful when learning in the presence of unbalanced classes.

ROC curves are two dimensional graphs which plot True Positive Rate (TP Rate) as a function of False Positive Rate (FP Rate) across all possible experimental threshold settings. They describe the relative tradeoffs between benefits (True Positive) and costs (False Positive). The True Positive Rate (also called Probability of Detection pd and Recall) and False Positive Rate (also called Probability of False Alarm pf) of the classifier can be estimated as follows:

$$\text{True.Positive.Rate} = pd = \text{Recall} = \frac{\text{number.of.True.Positive}}{\text{total.Positive}}$$

$$\text{False.Positive.Rate} = pf = \frac{\text{number.of.False.Positive}}{\text{total.Negative}}$$

A typical ROC curve will have a concave shape that starts from point (0, 0) and ends at (1, 1). Point (0, 1) represents perfect classification. Informally, one point in ROC curve is better than another if it has higher TP Rate and lower FP Rate.

The area under the ROC curve, abbreviated AUC [17], is a common method to numerically evaluate the performance of different classifier. Since the AUC is a portion of the area of the unit square, its value should fall between 0 and 1. However, since a random guess can produce a diagonal line between (0, 0) and (1, 1), which has an area of 0.5, the realistic classifier

should have an AUC greater than 0.5. Also, a well performed ROC curve for a classifier should lie on the left side of the diagonal line between (0, 0) and (1, 1).

Within the past two decades, ROC curves and AUC have become the standard tools for analysis and comparison of classifiers for binary classification [18]. The ROC curves conveniently display the tradeoff between TP Rate and FP Rate for two class problems. Thus, when we are dealing with multi-classes problems, we need to make an extension to the ROC analysis. One method for handling multi-classes is to produce n different ROC curves, one for each class [19] [20]. Since AUC is a measure of the discriminability of a pair of classes, the multi-classes' problem will introduce the issue of combining multiple pair wise values, which make it more complicated. Thus, we may calculate AUCs for multi-class problems by generating ROC curve for each class in turn, measuring the area under each curve, and then summing the AUCs weighted by the data: $AUC_{total} = \sum AUC_{ci} \times p(ci)$, where AUC_{ci} is the AUC for each class and $p(ci)$ is the probability of this class [19].

Chapter 3 Experiment and Analysis

3.1 Experiment Design

We build our predictive models using Random Forest algorithm from Weka package to predict software defects' resolution time. Recall that we use 7 datasets from Metrics Data Program (CM1, JM1, KC1, KC4, PC1, PC3 and PC4), each containing three groups of metrics: design, code and all. We use all the metrics in our study, regardless of the metric groups. The predicted (response) variable is *weeks* for each defect, which is calculated from getting resolution days by subtracting the *opened_time* from *closed_time* in *entry_date* metric and then dividing the resolution days by 7. We confirm that only the longest resolution time exists for each faulty module, and then remove the instances without a *weeks* attribute, and *module_id*, *defect_id*, *entry_type* and *entry_date* metrics prior to modeling.

We use 10-fold cross validation to fit the predictive model while using Random Forest learner with 500 trees (the default is 10 trees in Weka, an insufficient number based on prior experience). 90% of the data will work as training set and 10% as testing set. We will use Accuracy, Precision/Recall and ROC curves to measure the performance of decision models. For each ROC curve, the AUC is calculated using the Trapezoid rule. Since we need to deal with models of multi-classes, we generate ROC curve for each class of each data set to visualize the results. The evaluation methods include, but not limited to, weighted average AUC [19]. Recall that weighted average

AUC is calculated by: $AUC_{weighted} = \sum AUC_{ci} \times p(ci)$, where AUC_{ci} is the AUC for each class and $p(ci)$ is the probability of this class [19].

In the remainder of this section, we first briefly analyze the response variable, *weeks*, in our study, and then we execute experiments to determine a suitable discretization method for our data sets. Next, we compare the performance for each model we fit based on Accuracy, ROC curves and AUC. Finally, we conclude the optimal model that best fit most of our datasets.

3.2 Distribution of Response Variable (Resolution Time)

The purpose of this study is to fit a model to help predict the resolution time for a specific software engineering project. The best way to help managers control the project is to tell them how many days the engineers need to finish the test procedure. To predict the exact days that we need to solve all defects in a module or project, however, cannot be precise. Thus, we expand the response variable from days to weeks as resolution time and improve the precision of prediction.

After generating the response variable *weeks* to our dataset, we make a summary of this attribute, see Table 3. The unit for each cell is weeks. The minimum resolution time for one module in dataset PC4, for example, is 1 week, and the maximum is 91 weeks. This table also gives us the 1st and 3rd quartiles, as well as the median and mean. Median clarifies the middle value of resolution time while mean exhibits the average. 1st and 3rd quartiles show

the values on the rank of $\frac{1}{4}$ and $\frac{3}{4}$ from minimum. To visualize the distribution, we use box plots to show this response variable.

	CM1	JM1	KC1	KC4	PC1	PC3	PC4
Min	0	0	1	5	1	6	1
1 st Q	5	15	11	15	3	23	12
Median	14	34	20	20	7	33	48
Mean	15.03	36.84	20.03	24.47	11.86	35.31	39.12
3 rd Q	16	50	27	25	11	41	55
Max	51	131	116	89	74	99	91

Table 3 Summary of Response Variable weeks

From the box plots we may see that there are many statistical outliers in all datasets except PC4. Also, datasets CM1 and PC4 show more severe skewness.

Figure 3 Boxplots of Resolution Time

3.3 Equal Frequency vs Equal Width

Since we need to convert the variable *weeks* into nominal features, we have to implement a suitable unsupervised discretization method for our datasets. Recall that unsupervised discretization involves binning methods, wherein equal-interval (equal width) binning splits the whole range of numbers in intervals with equal size while equal-frequency (equal depth) binning uses intervals containing equal number of values. Because almost all datasets we are studying involve many statistical outliers which bias the mean value, equal width method would generate bins with major portion of the instances

and bins with few instances. The consequence is that we may get high accuracy of prediction for one class but poor result for other classes.

We execute an experiment on dataset PC1 to compare the results of equal width and equal frequency discretization method. For the sake of convenience, we choose 3 as our bin number. Then we discretize the response variable *weeks* in both equal width and equal frequency methods. Table 4 and 5 shows the discretization results. The minimum and maximum resolution times for dataset PC1 are 0 week and 74 weeks, respectively. The range is 74 weeks. For 3bin equal width method, we divide the range by 3 to make sure each bin contains the same width, and then we get 3 intervals of 0 to 25.3 weeks, 25.3 to 49.6 weeks, and 49.6 to 74 weeks. For 3bin equal frequency method, we make sure each bin contains the same number (or close number) of instances. Thus we count the total instance number and divide the total instance by 3 to fit suitable intervals.

Time Interval(Weeks)		# of Instances
a	0-25.3	53
b	25.3-49.6	8
c	49.6-74	2

Table 4 Equal Width

Time Interval(Weeks)		# of Instances
a	0-3.5	20
b	3.5-10.5	22
c	10.5-74	21

Table 5 Equal Frequency

We may see that *Class a* of 3bin equal width method contains 84% of the total instances, and the other two only contain 16%. On the contrary, 3bin equal frequency method assigns almost the same number of instances to each interval. Then, we use the Time Interval (weeks) as our response

variable to execute Random Forest to predict how many weeks should be used to resolve software defects.

For 3bin equal width method, we calculate a result of Accuracy, Precision, Recall and AUC in Table 6 and a confusion matrix in Table 7. For 3bin equal frequency method, we produce a result of similar statistics in Table 8 and 9.

Class	Accuracy (%)	TP Rate	FP Rate	Precision	Recall	AUC
a		1	0.9	0.855	1	0.674
b		0.125	0	1	0.125	0.705
c		0	0	0	0	0.275
Average	85.71	0.375	0.3	0.618	0.375	0.551

Table 6 3bin Equal Width Result

Confusion Matrix			
	a	b	c
a	53	0	0
b	7	1	0
c	2	0	0

Table 7 3bin Equal Width

Class	Accuracy (%)	TP Rate	FP Rate	Precision	Recall	AUC
a		0.45	0.233	0.474	0.45	0.71
b		0.545	0.195	0.6	0.545	0.671
c		0.571	0.286	0.5	0.571	0.711
Average	52.381	0.522	0.238	0.525	0.522	0.697

Table 8 3bin Equal Frequency Result

Confusion Matrix			
	a	b	c
a	9	5	6
b	4	12	6
c	6	3	12

Table 9 3bin Equal Frequency

From the result tables and confusion matrices, we can see that although 3bin Equal Width method yields a better accuracy, it only predicts one correct instance for *Class b* and *c*. Thus, the 85% prediction accuracy cannot lead to any meaningful conclusion for our study. Also, the weighted average AUC for 3 classes of 0.55 is only a little higher than a realistic threshold of 0.5, which further proves that the performance of 3bin Equal Width is really bad. Therefore, for the subsequent experiments, we use Equal Frequency as our discretization methodology.

For the first experiment in our study, we discretize the response variable into 3 bins to verify either Equal Width method or Equal Frequency method is suitable for our model. However, how many bins are suitable for our study is still unknown. Next, we need to implement experiments for all datasets using equal frequency method and then to compare the performance of prediction on different discretized response.

3.4 3 bin Equal Frequency for All Datasets

The narrower each time interval is, the more meaningful our prediction can be. Thus, we care about not only the performance of each model, but also the prediction detail each model can give us. In this study, we discretize the response variable (weeks) into 3 bins and execute the experiments for all

datasets first. The following tables and graphs demonstrate our important statistics and results.

Table 10 shows the discretized response variable for each data set. Table 11 exhibits the confusion matrix and performance result for each data set. Figure 4 displays the ROC curve for each data set.

Classes	CM1		JM1		KC1		KC4	
	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances
a	0-7.5	24	0-27.5	455	0-15.5	94	0-17.5	20
b	7.5-17	37	27.5-42.5	439	15.5-22.5	92	17.5-21.5	20
c	18-51	14	42.5-131	456	22.5-116	100	21.5-89	17
Classes	PC1		PC3		PC4			
	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances		
a	0-3.5	20	0-27.5	54	0-28.5	60		
b	3.5-10.5	22	27.5-37.5	51	28.5-54.5	43		
c	10.5-74	21	37.5-99	55	54.5-91	73		

Table 10 Instances in Each Bin for 3Bin

From Table 11, we can see that all data sets, except PC3, demonstrate accuracy over 50%. That means more than half of the instances are classified into correct classes. Both CM1 and KC4 achieve accuracy of 65%. Also, weighted average AUC over 0.7 and ROC curves close to upper axes prove that 3Bin Equal Frequency offers a sound performance on prediction of software resolution time for these data sets. The results of accuracy and AUC are consistent of inconsistent.

CM1						JM1						KC1					
Confusion Matrix				Result		Confusion Matrix				Result		Confusion Matrix				Result	
Classes	a	b	c	Accuracy (%)	AUC		a	b	c	Accuracy (%)	AUC		a	b	c	Accuracy (%)	AUC
a	18	5	1		0.8	a	278	100	77		0.79	a	45	27	22		0.67
b	7	28	2		0.78	b	101	221	117		0.72	b	35	43	14		0.71
c	4	7	3		0.79	c	93	103	260		0.76	c	20	16	64		0.8
Weighted Average				65.333	0.79	Weighted Average				56.889	0.76	Weighted Average				53.147	0.73
KC4						PC1						PC3					
Confusion Matrix				Result		Confusion Matrix				Result		Confusion Matrix				Result	
	a	b	c	Accuracy (%)	AUC		a	b	c	Accuracy (%)	AUC		a	b	c	Accuracy (%)	AUC
a	15	5	0		0.84	a	9	5	6		0.71	a	21	16	17		0.61
b	7	11	2		0.78	b	4	12	6		0.67	b	15	18	18		0.57
c	2	4	11		0.84	c	6	3	12		0.71	c	17	11	27		0.66
Weighted Average				64.912	0.82	Weighted Average				52.381	0.7	Weighted Average				40	0.61
						PC4											
						Confusion Matrix				Result							
							a	b	c	Accuracy (%)	AUC						
						a	25	18	17		0.7						
						b	18	14	11		0.71						
						c	14	5	54		0.79						
						Weighted Average				53.977	0.74						

Table 11 Confusion Matrices & Results for 3Bin

Figure 4 ROC Curves for 3Bin

3.5 5Bin Equal Frequency vs 3Bin vs 2Bin

In previous experiment, we evaluate the performance of 3Bin Equal Frequency method. In this study, we want to compare the impact of different class (bin) numbers on prediction performance. The bin numbers are 5 bins (denoted by *5Bin*), 3 bins (*3Bin*) and 2 bins (*2Bin*).

To clearly compare the performance of *5Bin*, *3Bin* and *2Bin*, we summarize the results into Table 12. In Appendix A, Table 13 and 14 shows the discretized response variable for *5Bin* and *2Bin*, respectively; Table 15 exhibits the confusion matrices for *5Bin* while Table 16 for *2Bin*. Figure 5 and 6 visually demonstrates the prediction performance for *5Bin* and *2Bin*.

In Table 12, we use Accuracy, Recall and AUC to evaluate the performance of the prediction. Here, Recall and AUC are both weighted average for 5 bins and 3 bins equal frequency methods.

	5 bins equal frequency			3 bins equal frequency			2 bins equal frequency		
Datasets	Accuracy	Recall	AUC	Accuracy	Recall	AUC	Accuracy	Recall	AUC
CM1	58.667	0.5870	0.799	65.3	0.5737	0.788	78.667*	0.7865*	0.838*
JM1	46.9	0.4676	0.774	56.9	0.5613	0.756	69.7*	0.6970*	0.778*
KC1	40.91	0.3998	0.7234	53.1469	0.5287	0.727	69.5804*	0.6960*	0.771*
KC4	47.368	0.4618	0.74	64.9123	0.6490	0.819*	71.9298*	0.7105*	0.769
PC1	46.0317	0.4422	0.722*	52.381	0.5220	0.697	61.9048*	0.6195*	0.688
PC3	25.625	0.2694	0.621	40	0.4110	0.614	60.625*	0.6005*	0.674*
PC4	47.7273	0.4152	0.768*	53.9773	0.4943	0.737	65.9091*	0.6590*	0.753

Table 12 Performance Comparison

Figure 5 ROC Curves for 5Bin

We compare the prediction performance among 5 bins, 3 bins and 2 bins equal frequency methods. In Table 12, the cell with asterisk (*) means it

performs the best in Accuracy, Recall or AUC when comparing to other methods. *5Bin* method shows the worst accuracy. Only one data set achieves accuracy higher than 50%. *2Bin* method demonstrates the best score on accuracy and recall. All three methods exhibit adequate AUC.

Figure 6 ROC Curves for 2Bin

In Figure 5, several classes in data sets KC4, PC1 and PC3 do not present a good ROC curves since they are too close to the threshold line. This reflects a bad classification for certain instance. In Figure 6, except for data set PC1 and PC3, most ROC curves are in a good shape and imply acceptable performance.

3.6 Discussion

Because we use Accuracy to measure the percentage of observations that have been correctly classified, this metric is intended to indicate how well the prediction model works in the sense of how close to true value that the classifications as faulty or not faulty actually are. When the Accuracy is low, most of our predictions are incorrect. Therefore, it is quite important to have a high Accuracy. As we discussed in Experiment Design section, however, a high Accuracy value does not necessarily imply good predictions. Thus we can conclude that although relatively high Accuracy is important and necessary, it is not sufficient to consider a model with high Accuracy as good prediction because of the paucity of faults in the system [21].

Precision focuses on labeling an observation as belonging to one class that does indeed belong to that class, but does not care about the observation in that class which are labeled incorrectly. For this reason, we conclude that low Precision might infer the inefficiency but is not equivalent to poor prediction. On other hand, Recall emphasizes the percentage of true positives that have been correctly identified as such. Therefore, although the

definition for Precision and Recall are similar to some extent, the consequence of low Recall is far more important than low Precision [21].

As stated above, Thomas J. Ostrand and Elaine J. Weyuker [21] suggested that high Accuracy and high Recall are good measures for a successful prediction. Thus, from above comparison we can see that for 5 bins equal frequency method, the prediction Accuracy and Recall for 6 out of 7 datasets are below 50% and 0.5 respectively. The low Accuracy of below 50% shows that more than 50% observations are labeled as a wrong class, which is a really depressing result. However, it is understandable, since 5bin equal frequency method discretizes the response into 5 bins which make the width of each interval narrower and more difficult to specify.

In contrast, the Accuracy and Recall for 3 bins and 2 bins equal frequency methods are better for analysis. Although 2 bins equal frequency method demonstrates much higher scores for these two metrics, both methods yield similar and favorable ROC curves and AUC. According to the result of AUC, only one dataset using 2 bins equal frequency method is superior to 3 bins equal frequency method by 5%. For other datasets, the differences are not distinct and even the performance of 2 datasets using 3 bins method is better.

Figure 7 Performance Comparison Boxplot

Figure 7 graphically depicts numerical data distributions of Accuracy, Recall and AUC for *5Bin*, *3Bin* and *2Bin* methods. It shows the smallest instance, lower quartile, median, upper quartile and the largest instance. The line inside the box displays the median which follows the central tendency. Based on these plots, *2Bin* method is significantly superior to *3Bin* and *5Bin* methods upon Accuracy and Recall. All three methods present similar AUC distributions.

The reason that 2 bins equal frequency method performs better is understandable, because this approach divide the response into only two bins which make each interval larger than other methods and is easier to classify an observation in this range. For practical usage of this study, we not only want to figure out the best model, but also expect to bring out more interpretation for the prediction. Thus, if we process a prediction which does not require especially high prediction performance, but pursue more meaningful explanation for the data, then 3 bins equal frequency method could be a good fit for the model.

Chapter 4 Summary and Future Work

4.1 Summary

The goal of this thesis is to study the metrics data which involves different code and design metric features and to find the relationship among these factors, and thus further implement the predicting model to help software development project managers better organize their project schedules.

We have analyzed seven data sets from NASA MDP which offer defect and product metrics. The algorithm we used for classification is Random Forest [16], which has demonstrated superior performance on software fault-proneness prediction [15].

First, we identify the discretization method used for classifying response variables into nominal feature. Although Equal Width method generates much better result on Accuracy and other metrics, the skewness of the data suggests that labeling the majority of observations as one class and generating better prediction for this class does not make any meaningful interpretation for the data. This backups our conclusion that pure high performance does not lend any support to the interpretation of prediction. We favor not only the performance of prediction, but also the meaningful explanation for predicted classification.

Next, after confirming the methodology, we fit the models for the data sets with 5 bins, 3 bins and 2 bins discretization and compare the performance for each method. Our experiments indicate a general trend for MDP data sets that the performance of models which have wider bin width is better. This is understandable, since wider width helps decrease the precision and makes it easier to predict. Although 2 bins discretization shows the best performance, 3 bins discretization also demonstrates acceptable result. Because 3 bins discretization provides more detail information about the classification, in case the best prediction performance does not stand the highest priority, then this model would be a good fit for the data.

Based on the insights we obtained from experiments, we conclude that using predictive model to predict software resolution time based on code and design metrics is reasonable and efficient. The proposed algorithm of Random Forest already generates a favorable result when dealing with binary classification. The algorithm also performs well confronting multi-classes problems, though the decrease of the prediction performance occurs as the increase of the classes we defined.

4.2 Future Work

Although our experiments have shown that using Random Forest algorithm to fit a predictive model based on metrics data performs favorably for binary classification, the less prediction detail still has its limitation. Thus, other methodologies need to be implemented in future work to further improve the prediction performance for multi-classes' classification.

Yue, et al [1] suggested that the metrics in our study should be divided into three groups: design, code, and other metrics. We may fit predictive models with each group of metrics respectively to see the relationship between the predictors and the response variable. With less predictor, the model could be easier, and the connection between predictor variables and response variable may be also easier to construct. No matter whether we use one group of the metrics or all metrics to fit a predictive model, we can always remove irrelevant attributes before we execute the prediction. Statistical methods of Mallows C_p statistics, Akaike Information Criterion and Bayes Information Criterion [24] can be good measurement of variable selection. Principal Components built-in algorithm in some machine learning software package is also helpful to perform attribution selection and obtain robust principal variables. All above methods can be used in data pre-processing section to improve the prediction performance for our data.

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Appendix A Tables and Matrices

Classes	CM1		JM1		KC1		KC4	
	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances
a	0-4.5	16	0-10.5	293	0-7.5	65	0-14.5	12
b	4.5-11.5	15	10.5-29.5	305	7.5-16.5	58	14.5-17.5	8
c	11.5-15.5	7	29.5-41.5	268	16.5-21.5	57	17.5-20.5	11
d	15.5-17.5	23	41.5-55.5	245	21.5-28.5	66	20.5-29.5	14
e	17.5-51	14	55.5-131	239	28.5-116	40	29.5-89	12
Classes	PC1		PC3		PC4			
	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances		
a	0-1.5	11	0-21.5	33	0-10.5	38		
b	1.5-4.5	12	21.5-30.5	33	10.5-40.5	33		
c	4.5-9.5	11	30.5-35.5	30	40.5-54.5	32		
d	9.5-13.5	15	35.5-47.5	32	54.5-56.5	40		
e	13.5-74	14	47.5-99	32	56.5-91	33		

Table 13 Instances in Each Bin for 5Bin

Classes	CM1		JM1		KC1		KC4	
	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances
a	0-15	38	0-34.5	684	0-18.5	141	0-20.5	31
b	16-51	37	34.5-131	666	18.5-100	145	20.5-89	26
Classes	PC1		PC3		PC4			
	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances	Time Interval (Weeks)	# of Instances		
a	0-7.5	32	0-32.5	75	0-48	88		
b	7.5-74	31	32.5-99	85	49-91	88		

Table 14 Instances in Each Bin for 2Bin

CM1						JM1				
	Confusion Matrix					Confusion Matrix				
Classes	a	b	c	d	e	a	b	c	d	e
a	11	3	0	2	0	144	68	37	14	30
b	4	6	0	4	1	58	148	46	23	30
c	1	1	4	1	0	35	52	114	36	31
d	0	2	0	18	3	30	43	37	116	19
e	3	1	0	5	5	35	36	35	22	111
KC1						KC4				
	Confusion Matrix					Confusion Matrix				
Classes	a	b	c	d	e	a	b	c	d	e
a	23	14	14	6	8	7	3	1	1	0
b	15	22	10	9	2	2	6	0	0	0
c	12	6	24	11	4	3	1	3	4	0
d	7	5	13	36	5	1	0	4	4	5
e	6	5	8	9	12	1	1	1	4	5
PC1						PC3				
	Confusion Matrix					Confusion Matrix				
Classes	a	b	c	d	e	a	b	c	d	e
a	4	1	1	2	3	4	1	1	2	3
b	0	5	2	2	3	0	5	2	2	3
c	2	1	3	2	3	2	1	3	2	3
d	0	1	1	12	1	0	1	1	12	1
e	0	3	3	3	5	0	3	3	3	5
PC4										
	Confusion Matrix									
Classes	a	b	c	d	e					
a	17	5	4	10	2					
b	2	21	6	4	0					
c	4	8	12	4	4					
d	8	3	1	19	9					
e	4	3	1	9	16					

Table 15 Confusion Matrices for 5Bin

CM1			JM1		KC1		KC4	
	Confusion Matrix		Confusion Matrix		Confusion Matrix		Confusion Matrix	
Classes	a	b	a	b	a	b	a	b
a	31	7	474	210	99	42	25	6
b	9	28	199	467	45	100	10	16
PC1			PC3		PC4			
Classes	a	b	a	b	a	b		
a	19	13	38	37	59	29		
b	11	20	26	59	31	57		

Table 16 Confusion Matrices for 2Bin