APPLYING SOCIAL NETWORK ANALYSIS TO SOFTWARE FAULT-PRONENESS PREDICTION

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I would like to dedicate this to my loving family – my wife, my father and my mother – each of whom has been instrumental in making this possible.

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by

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FAULT-PRONENESS PREDICTION

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Due to the rapid pace of software development, end-users now anticipate a seemingly limitless expansion of capabilities from their software. As a result, software systems are becoming increasingly complex and more susceptible to failures. Although software fault localization techniques are becoming more comprehensive, it is still expensive to precisely locate, let alone fix, bugs in a program. Hence, fault-proneness prediction can be applied beforehand to alleviate the cost of program debugging by identifying software modules which are likely to contain faults.

Meanwhile, social network analysis (SNA) has been frequently applied in software engineering to depict relations between (1) modules, (2) developers, or (3) modules and developers. Previous studies have shown that these relations have been used to build social networks to predict fault-prone modules and the results are encouraging.

Although these networks are useful for fault-proneness prediction, they are built either by a single relation or by a pair of relations aforementioned. In addition, these networks appear to

neglect an essential factor: developer quality. After all, it is developers who make mistakes and introduce faults into software.

We therefore, propose Tri-Relation Network (TRN), a weighted social network that integrates all three types of relations. Four network node centrality metrics are correspondingly derived from TRN. Moreover, a calibration mechanism for edge weights on TRN is explored as well. Case studies reveal that TRN holds great promise in the context of fault-proneness prediction and the effectiveness improves further after applying the calibration mechanism on current TRN.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS……………………………………………………………………v

ABSTRACT………………………………………………………………………………...vi

LIST OF FIGURES………………………………………………………………………ix

LIST OF TABLES……………………………………………………………………...x

CHAPTER 1 INTRODUCTION 1

CHAPTER 2 SOFTWARE FAULT-PRONENESS PREDICTION 7

2.1 Methods and Techniques to Build Fault-Proneness Prediction Models 7

2.2 Related Issues of Fault-Proneness Prediction 17

CHAPTER 3 SOCIAL NETWORK ANALYSIS 25

3.1 Social Network Analysis in Software Engineering 25

3.2 Network Code Centrality Metrics 26

3.3 Social Networks for Fault-Proneness Prediction 27

CHAPTER 4 THE PROPOSED TRI-RELATION NEWTORK (TRN).......................................31

4.1 The Construction of TRN 31

4.2 Four Network Centrality Metrics and Other Metrics...33

4.3 Evaluation of TRN...36

CHAPTER 5 EDGE WEIGHT CALIBRATION MECHANISM FOR TRN..............................47

5.1 The Proposed CaTRN 47

5.2 Results for R3 49

CHAPTER 6 CONCLUSION AND FUTURE WORK 54

REFERENCES 58

BIOGRAPHICAL SKETCH 83

CURRICULUM VITAE..84

LIST OF FIGURES

Figure 1. Taxonomy of software metrics 2

Figure 2. A DCN with 2 developers and 3 modules 27

Figure 3. A MDN with 4 modules 28

Figure 4. A STN with 2 developers and 5 modules 29

Figure 5. A DN with 4 developers 30

Figure 6. A TRN with 3 developers and 4 modules 32

Figure 7. CaTRN with 3 developers and 4 modules 49

LIST OF TABLES

Table 1. Ten commonly used software metrics 34

Table 2. Notations relevant to metrics, networks, and prediction models 35

Table 3. Network node centrality metrics derived from TRN, DCN, MDN, STN, and DN 35

Table 4. Summary of subject programs used 37

Table 5. Correlation Analysis Using Spearman Rank Correlation Coefficient for Camel 1.4.0 where correlation is significant at the 0.05 level (2-tailed) 41

Table 6. Correlation Analysis Using Spearman Rank Correlation Coefficient for Flume 1.5.0 where correlation is significant at the 0.05 level (2-tailed) 42

Table 7. Correlation Analysis Using Spearman Rank Correlation Coefficient for Tika 1.6 where correlation is significant at the 0.05 level (2-tailed) 42

Table 8. Confidence that $M_{TRN\text{-}Cen}$ is more correlated with the number of bugs than the corresponding $M_{DCN\text{-}Cen}$, $M_{MDN\text{-}Cen}$, $M_{STN\text{-}Cen}$, and $M_{DN\text{-}Cen}$ 42

Table 9. Prediction effectiveness of $\Phi(M_{TRN})$, $\Phi(M_{DCN})$, $\Phi(M_{MDN})$, $\Phi(M_{STN})$, $\Phi(M_{DN})$, and $\Phi(M_{CO})$ with respect to average Recall and average FPR for Camel 1.4.0 44

Table 10. Prediction effectiveness of $\Phi(M_{TRN})$, $\Phi(M_{DCN})$, $\Phi(M_{MDN})$, $\Phi(M_{STN})$, $\Phi(M_{DN})$, and $\Phi(M_{CO})$ with respect to average Recall and average FPR for Flume 1.5.0 45

Table 11. Prediction effectiveness of $\Phi(M_{TRN})$, $\Phi(M_{DCN})$, $\Phi(M_{MDN})$, $\Phi(M_{STN})$, $\Phi(M_{DN})$, and $\Phi(M_{CO})$ with respect to average Recall and average FPR for Tika 1.6 45

Table 12. Confidence that $\Phi(M_{TRN})$ is more effective than $\Phi(M_{DCN})$, $\Phi(M_{MDN})$, $\Phi(M_{STN})$, $\Phi(M_{DN})$, and $\Phi(M_{CO})$ with respect to Recall and FPR 46

Table 13. Spearman Rank Correlation Coefficient for Camel 1.4.0 where correlation is significant at the 0.05 level (2-tailed) 50

Table 14. Spearman Rank Correlation Coefficient for Flume 1.5.0 where correlation is significant at the 0.05 level (2-tailed) 50

Table 15. Spearman Rank Correlation Coefficient for Tika 1.6 where correlation is significant at the 0.05 level (2-tailed) 50

Table 16. Confidence that $M_{CaX\text{-}Cen}$ is more correlated to the number of bugs than the corresponding $M_{X\text{-}Cen}$ 51

Table 17. Prediction effectiveness of $\Phi(M_{CaTRN})$, $\Phi(M_{CaDCN})$, $\Phi(M_{CaMDN})$, $\Phi(M_{CaSTN})$, and $\Phi(M_{CaDN})$ with respect to average Recall and average FPR for Camel 1.4.0 52

Table 18. Prediction effectiveness of $\Phi(M_{CaTRN})$, $\Phi(M_{CaDCN})$, $\Phi(M_{CaMDN})$, $\Phi(M_{CaSTN})$, and $\Phi(M_{CaDN})$ with respect to average Recall and average FPR for Flume 1.5.0 52

Table 19. Prediction effectiveness of $\Phi(M_{CaTRN})$, $\Phi(M_{CaDCN})$, $\Phi(M_{CaMDN})$, $\Phi(M_{CaSTN})$, and $\Phi(M_{CaDN})$ with respect to average Recall and average FPR for Tika 1.6......................52

Table 20. Confidence that $\Phi(M_{CaX})$ is more effective than the corresponding $\Phi(M_X)$..................53

CHAPTER 1

INTRODUCTION

Due to the rapid pace of software development, end-users now anticipate a seemingly limitless expansion of capabilities from their software. Software quality and reliability are becoming critical issues for software systems[1] and have gained much attention in research. It has been reported that, in an attempt to reduce the number of delivered faults, most companies spend between 50-80% of their software development effort on testing [60]. The project failure rate is a major concern in software project development, and it is increasing as software projects grow in complexity. Galorath [81] reports research by the Standish Group revealing that the success rates of software projects in 1994, 1996, 1998, 2000, 2004, and 2009 were 16%, 27%, 26%, 28%, 29%, and 32% respectively, implying that software project development entails a number of risks which need to be taken into consideration. Although software fault localization techniques are becoming more comprehensive [246], [247], [250], [251], [252], it is still expensive to precisely locate, let alone fix, bugs in a program. As a result, implementing fault-proneness prediction as early as possible has a significant impact on controlling software budgets and software quality [118]. To achieve this, software metrics are collected and used to build fault-proneness prediction models to identify fault-prone modules so that potential problems can be further prevented and a basis for planning and controlling software testing and maintenance can be created.

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[1] In this dissertation, we use "program", "application" and "software system" interchangeably. We use "method" and "function" interchangeably. We use "bugs", "faults", and "defects" interchangeably. We also use "metric", "feature", and "attribute" interchangeably. A software system consists of various modules. A software module can have different representations depending on how a software system is described on a particular architecture level. For example, it can represent a single function, a single class, or a single file.

The purpose of using software metrics is to obtain knowledge of target software programs and to get insight during software development life cycle. A number of studies on metrics development, investigation, and implementation have been conducted to help better assess software quality as well as identify module fault-proneness over the past twenty years [20], [62], [68], [87], [96], [110], [122], [151], [152], [154], [156], [172], [183], [194], [202], [204], [205], [211], [214], [222], [248], [249], [255], [256], [268], etc.

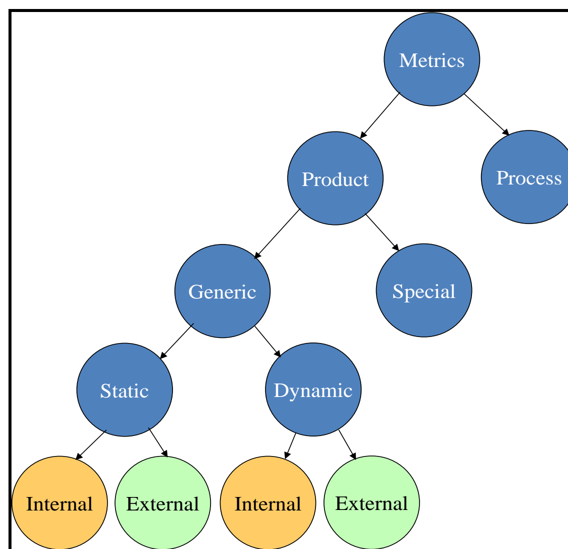

Figure 1. Taxonomy of software metrics

As shown in Figure 1, metrics that can be used for model construction are generally categorized into two types: product metrics and process metrics [262]. Product metrics are used to analyze software from different aspects. For instance, object-oriented metrics can reflect the impact of using object-oriented mechanisms such as inheritance, coupling, cohesion, polymorphism and encapsulation [6]-[13], [26], [40]-[44], [58], and [59]). Product metrics can be divided into generic metrics and special metrics. Generic metrics consist of two types of metrics: static metrics and dynamic metrics. Static metrics are used to measure static attributes of software and can be collected at compile time. Dynamic metrics can only be collected and

evaluated at run-time (e.g., dynamic coupling metrics [17], run-time cohesion metrics [162], and code coverage-based metrics [165] and [254]). Both static metrics and dynamic metrics can be further divided into internal and external metrics. Internal metrics focus the internal structure of a software module (e.g., Lines of Code [181], McCabe's cyclomatic complexity [157], Halstead complexity [98], and Wong's internal design metrics [253]). External metrics emphasize the interactions between a software module and the rest of the system (e.g., information flow [104] and Wong's external design metrics [253]). Special metrics are used to measure the attributes that are unique to the target software (e.g., temporal complexity metrics for concurrent and real-time systems [16]). Process metrics are used to describe how a software system is built and operated such as code churn [174], developer-based metrics [192], [243], [257], organizational metrics [34], [171], [179], etc. Generally speaking, the measurement of product metrics is repeatable, objective, and can be automated while for process metrics different people may have different assessments which are more subjective compared to product metrics. It is also more challenging to automate the collection of process metrics.

However, the effectiveness of these product and process metrics in identifying fault-prone modules is inconsistent or contradictory on different projects. For example, there are many studies investigating the relationship between lines of code and number of faults. Zhang [263] found that 20% of the largest modules were responsible for 51%~63% of the defects on three versions of Eclipse. Ostrand et al. [191] reported that on average 73% and 74% of the faults contained in the 20% of the files that were the largest in terms of the number of lines of code on two large industrial systems. However, a replicated study by Grbac et al. [92] reported that size metrics are not useful as predictors of fault proneness based on the data from five consecutive

releases of a large software system in the telecommunications domain. Fenton and Ohlsson [78] used two versions of a telecommunication software and found that 20% of the modules were responsible for nearly 60% of the faults but contained just 30% of the code. Koru et al. [142], [143] reported that fault proneness increases with size, but at a slower rate. This makes smaller modules proportionally more problematic compared with larger ones. Radjenovic´ et al. [202] observed a strong correlation between the LOC and fault proneness in pre-release and small dataset, while in post-release and large dataset, only a weak association was found. McCabe's cyclomatic complexity was a good indicator of software fault proneness in [11], [108], [161], [162], [177], [188], and [272] but not in [10], [87], and [258]. Radjenovic´ et al. [202] reported that cyclomatic complexity was fairly effective in large post-release environments using OO languages but not in small pre-release environments with procedural languages. One potential explanation for this could be that in large data sets, modules are more complex than in small data sets. Also, the modules used in OO programming languages (usually class) are generally bigger than modules used in procedural languages (usually method) and may, therefore, be more complex. Studies in [125], [160], and [162] indicated that Halstead's metrics were good indicators of fault proneness but not in [174] and [260]. According to [160], Halstead's metrics were not as good as McCabe's cyclomatic complexity or LOC. Studies in [77], [91], [267], and [271] indicated that complexity metrics are useful in identifying fault-prone modules but are not as well as some OO metrics or process metrics. CK metrics are the most frequently used OO metrics. However, not all CK metrics performed equally well. Authors of [5], [20], [43], [44], [71], [95], [114], [185], [195], [211], [222], [262], and [266] found that CBO, WMC, and RFC in the CK metrics suite are good indicators of software fault proneness, while the usefulness of

LCOM is mediocre [20], [95], [195], [222] compared to these three metrics. Surprisingly, DIT and NOC were reported as untrustworthy in [75], [88], [95], [185], [195], [211], [222], [227], and [266]. Process metrics were found to be useful in predicting post-release faults in [19], [65], [79], [91], [99], [113], [136], [149], [156], [172], [177], and [179]. Radjenovic´ et al. [202] suggested that industry practitioners looking for effective and reliable process metrics should consider code churn, the number of changes, the age of a module and the change set size metrics. Researchers looking for poorly investigated areas may consider the number of past faults and the change set size metrics. Once again, there are no decisive conclusions regarding the effectiveness of these metrics in predicting fault-prone software modules.

A potential solution is to explore software metrics that harbor features from the perspectives of both software product and process. In other words, we should consider metrics that depict how software modules and developers are related within/to each as a whole. Therefore, interaction is the key. Meanwhile, social networks and its analysis has been used wildly to understand software engineering activities modeling how people communicate and collaborate among others, which provides critical information for a software development project [28]-[32], [35], [56], [115], [147], [158], [159], [180], [200], [232], [245], [270], [271]. It investigates not only the social organization of the work but also the technical information infrastructures.

In this dissertation, we propose applying social network analysis in fault-proneness prediction by first constructing a network, namely Tri-relation Network (TRN), which depicts the social/ technical relationship between (1) software modules, (2) developers, and (3) modules and developers. Later, four centrality network node metrics are derived from TRN and used to

build our fault-proneness prediction model. Additionally, an edge weight calibration mechanism is proposed and applied on TRN to construct CaTRN to further enhance the effectiveness of fault-proneness prediction.

The remainder of this dissertation is organized as follows. First CHAPTER 2 presents a literature survey on software fault-proneness prediction providing a brief overview of methods and techniques that have been used to conduct fault-proneness prediction activities. CHAPTER 3 generally introduces the use of social network analysis in software engineering, and some related work that has been in fault-proneness prediction. CHAPTER 4 describes our proposed TRN along with an empirical evaluation, followed by CHAPTER 5 which discusses the notion of our edge weight calibration mechanism and the proposed CaTRN based on this mechanism followed by empirical evaluation. Finally, we conclude with a summarization of ongoing work and future work in CHAPTER 6.

CHAPTER 2

SOFTWARE FAULT-PRONENESS PREDICTION

We provide a brief overview of methods and techniques that have been used for predicting software fault-proneness.

2.1 Methods and Techniques to Build Fault-Proneness Prediction Models

We summarize the methods and techniques that have been used to build fault-proneness prediction models and categorize them into different group.

2.1.1 Statistics-based Techniques

Regression analysis is a statistical method used to describe the nature of the relationship between a dependent variable and independent variables [38]. A regression model developed by an estimated regression equation is used to predict the value of the dependent variable given values for the independent variables. For a linear regression model, the dependent variable y, denoted as $\hat{y}$, can be expressed as a linear combination of n independent variables, x_1, x_2, x_3, x_4,…, x_n, in the form of Equation 1.

$$\hat{y} = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + ... + \alpha_n x_n + \varepsilon \quad (1)$$

In this equation, ε is the error term, and parameters α_1, α_2,…, α_n can be estimated from the observation data. R^2, also known as the coefficient of determination, is a commonly used statistic to evaluate the model fit of a regression equation; that is, to show how good the independent variables are at predicting the dependent variable. The value of R^2 ranges from 0 to 1 – the higher the value the better the fit between the regression model and the data. The most

general definition of the coefficient of determination is shown in Equation 2. SS_{tot} is the total sum of squares, and SS_{err} is the residual sum of squares.

$$R^2 = 1 - \frac{SS_{err}}{SS_{tot}} \tag{2}$$

With respect to software fault-proneness prediction, Hassan [99] built linear regression models using data from the second and third years of the source control repository to predict the number of faults in the fourth and fifth years of a software project. Tomaszewski et al. [230] built linear regression models with a number of software metrics as independent variables to predict fault density and the number of faults on a telecommunication system. Basili and Hutchens [21] employed linear regression analysis to examine the relationship between software metrics and program changes on 19 compiler projects. Goel and Singh [88] built linear regression models to predict the number of faults using a public data set, KC1, from NASA Metrics Data Program. In addition, Li and Henry [153] applied linear regression analysis to examine the relationship between software metrics and software maintenance effort (in terms of the number of lines changed per class) on two commercial software systems.

Logistic regression is another frequently used regression modeling method in which the dependent variable takes on one of two different values. By dividing the software module classes into two categories, fault-prone (FP) and non-fault-prone (NFP), logistic regression can be used for building software fault-proneness prediction models. A logistic regression model is shown in Equation 3.

$$\pi(x_1, x_2, ..., x_n) = \frac{e^{\beta_0 + \beta_1 x_1 + ... + \beta_n x_n}}{1 + e^{\beta_0 + \beta_1 x_1 + ... + \beta_n x_n}} \tag{3}$$

In this equation, the x_is are the software metrics included as independent variables, the β_is are the regression coefficients corresponding to x_is, and π is the probability that a module is faulty. Studies [18], [25], [42], [44], [69], [71], [88], [112], [149], [166], [173], [185], [216], [220], [221], [237], [266], and [267] have been conducted to apply logistic regression to predict fault-prone software modules as well as to determine the usefulness of a software metric as an indicator of software module fault-proneness. Rather than logistic regression models, Gao et al in [82] and [132] presented an empirical study on count models (such as a Poisson regression model and a negative binomial regression model) to predicate the number of faults in a file on two Windows-based embedded software applications.

Couto et al. [63] proposed a model by using the Granger causality test to evaluate the causality between source code metrics and the occurrence of defects. The proposed model predicts defects introduced in the source code via triggering alarms whenever a change performed to a class reproduces similar variations that cause defects in the past.

2.1.2 Machine Learning-based Techniques

Artificial neural networks (ANNs) are based on learning algorithms inspired by biological neural networks and can be used to build software fault-proneness prediction models. Prior to training, the user must decide on the network topology such as the number of units in the input layer, the number of hidden layers, the number of units in each hidden layer, and the number of units in the output layer. A neural network is then applied to a given data set of training tuples (software modules with known classes represented by a set of software metrics with known values). An iterative learning procedure is later followed to minimize the difference between the predicted value (the training output) and actual target value (the actual output). With respect to software

fault-proneness prediction, Khoshgoftaar and Szabo [137] built a Backpropagation (BP) network, Thwin and Quah [228] built a BP network and a General Regression Neural Network to predict the number of defects in a software module. Bezerra et al. [30] built a Radial Basis Function (RBF) network to predict the probability of defect existed in a software module. Researchers of 0, [29], [57], [89], [106]-[109], [119], [123], [128], [133], [134], [146], [189], [198], and [264] built different neural networks to predict fault-prone software modules. Zhou et al. [269] explored another five neural network-based techniques (Batch Gradient without momentum, Batch Gradient with momentum, Variable Learning Rate without momentum, Variable Learning Rate with momentum, and Resilient Backpropagation) for the modeling of fault severity in a software module. Generally speaking, the accuracy of the resulting trained network relies on the network design, which is a trial-and-error process. If the accuracy is not acceptable, then it is necessary to repeat the training process with a different network topology.

A large software system may consist of hundreds of software modules, each of which possesses quite different characteristics. It is sometimes not the particular value but specific ranges that significantly identify the qualitative difference. In this way, high-defect modules with different characteristics for different partitions can be identified, and different actions can be carried out to correct the problems. Tree-based modeling handles data partitions and relation analysis. The model construction involves recursively partitioning the data set into smaller subsets using split conditions defined on independent variables, resulting in increasing homogeneity of the dependent variable. Each subset of data associated with a tree node is uniquely described by the path of associated split conditions. The results presented in such forms are natural to the decision process and, consequently, are easy to interpret and use. Researchers

of [27], [86], [94], [95], [116], [124], [127], [129], [131], [135], [138], and [266] applied different algorithms to building decision trees [201] in order to identify fault-prone software modules and predict the number of bugs in a software module. Knab et al. [141] predicted defect densities in source code files with different decision tree learners. Shin et al. [218] built decision tree learning models to predict vulnerable files in Mozilla Firefox and Linux kernel. Tian and Troster [229] constructed tree-based models to identify and characterize high-defect software modules in both a legacy and a new software system, while Koru and Tian [144], [145] built their tree-based models to analyze the relationship among high-change software modules, high-defect software modules, and modules with high measurement values. Similar to tree-based models, Briand et al. in [39] introduced a pattern matching technique called optimal set reduction (OSR) to help predict fault-prone software modules. However, patterns defined by OSR are not mutually exclusive and can be used in conjunction to identify risky areas.

The Naïve Bayesian classifier and the Bayesian Belief Network are two classification algorithms based on Bayes' theorem that can also be used for software fault-proneness prediction. For the Naïve Bayesian classifier, let D be a training set of tuples with associated class labels. Each tuple in D and in the testing set is in the form of n-dimensional attribute vector, $X = (x_1, x_2, \ldots, x_n)$, where x_i (i=1, 2,…, n) is a value of an attribute A_i that characterizes a software module. There are two classes, fault-prone (C_1), and non-fault-prone (C_2) in a Naïve Bayesian classifier. Given a tuple X in the testing set, the classifier will predict that the X belongs to a class (e.g., fault-prone) having the higher posterior probability conditioned on X than the other class (e.g., non-fault-prone) [53], [116], [155], [160], [189], [233], [236]. When using the Naïve Bayesian classifier, it is assumed that the value of an attribute of a given class is independent of

the values of other attributes. If dependencies exist between attributes, a Bayesian Belief Network (BBN) is used instead. Bayesian Belief Networks are also known as Belief Networks, Bayesian Networks, or Probabilistic Networks. A belief network consists of two components: a directed acyclic graph and a set of conditional probability tables (CPTs). Both may be given in advance or inferred from the data. Rather than returning a single class label, the trained network can return a probability distribution that gives the probability of each class. Researchers of [14], [67], [76], [77], [86], [187], and [195] built different BBN models to estimate fault content in software modules of different applications.

Authors of [93] and [196] proposed using Dempster-Shafer (D-S) belief networks to predict fault-prone modules. The structure of the D-S network does not represent causal relationship as in the Bayesian network. Instead, it represents implication relationship among the nodes. Each node represents an individual attribute that characterizes a software module. Each arc in the graph signifies the existence of a direct implication rule between two adjacent nodes. The class label of a software module is dependent on the values of all attributes that influence it.

Support vector machine (SVM) is another machine learning-based technique used for data classification. Given a set of training tuples, it uses nonlinear mapping to transform these tuples into a higher dimension. Within this new dimension, it searches for the linear optimal separating hyperplane (the decision boundary), known as the maximum marginal hyperplane (MMH), to separate the new tuples of one class from another (fault-prone from non-fault-prone) with minimum classification error [72], [86], [89], [139], and [258].

Mizuno and his colleagues [102], [168]-[170] proposed fault-prone filtering where a software module is considered as an e-mail message and all software modules are categorized as

either spam emails (fault-prone modules) or regular emails (non-fault-prone modules). After learning of existing FP and NFP modules, a new module will be classified into as either FP or NFP by applying a spam filter.

Discriminant analysis is often applied as another useful statistical analysis technique. With regard to software fault-proneness prediction, it classifies software modules characterized by a set of software metrics into two groups: fault-prone or non-fault-prone [25], [84], [106], [126], [130], [175], [177], [186], [226]. This classification is made by building a discriminant function from the training dataset to assign data points (software modules characterized by a set of software metrics) in the testing set to either the fault-prone or the non-fault-prone group.

2.1.3 Miscellaneous Techniques

Pandey and Goyal [197] built a fuzzy inference system (FIS) to learn the relationship between used software metrics and software module fault-proneness and later was used to predict fault-proneness degree of an unlabeled module (e.g., low, medium, or high fault-prone). Rodriguez et al. [207] proposed a descriptive approach using a subgroup discovery (SD) algorithm for software fault-proneness prediction which allows characterizing defective software modules with rules that can describe thresholds and relationships between software metrics. Jing et al. in [120] introduced a supervised dictionary learning-based technique for software fault classification and prediction. Czibula et al. [64] applied relational association rules to define different types of relationships between the values of used software metrics and fault-proneness of software modules. Such relationships will be used as useful patterns to predict if a new software module is fault-prone or not.

Seliya and Khoshgoftaar [210] proposed a constraint-based semi-supervised clustering scheme that uses the K-Means clustering method to cluster software modules into different clusters based on several modules whose labels (fault-prone or non-fault-prone) are already decided by an expert. Yang et al. [261] reported that using an affinity propagation clustering algorithm can achieve a better performance in clustering software modules into fault-prone or non-fault-prone cluster than using K-Means based on case studies of two real-world software projects. In addition, Catal et al. [51], [52] and Bishnu et al. [37] proposed a clustering and metrics thresholds-based approach for software fault-proneness prediction without previous fault data. First, a clustering technique is applied to cluster software modules. Then, the representative software module of the cluster is checked against a set of predefined software metrics thresholds. A cluster is predicted as fault-prone if at least one software metric of the representative module is higher than the specified threshold value of that software metric. Last but not least, Scanniello et al. [209] applied a graph clustering algorithm, BorderFlow, to group software modules based on their dependencies (e.g., there is a dependency between class c_j and class c_i if there is any class instantiation, method invocation, or field access of c_j in the body of the class c_i or vice versa). The idea behind BorderFlow is to maximize the number of dependencies to the nodes within the same cluster while minimizing the number of dependencies to the nodes in a different cluster. Data from one cluster is used to train the model, which is later used to predict fault-proneness for software modules in other clusters.

He et al. [103] built software fault-proneness prediction models from the selected data of other projects when historical data for the target project is not available and concluded that cross-project software fault-proneness prediction was feasible as long as it involved a careful selection

of training data. Rahman et al. [203] also reported that cross-project prediction performance is no worse than within-project prediction performance using project data from the GIT and JIRA repositories. However, Zimmermann et al. [272] ran 622 cross-project predictions and found that only 3.4% actually worked. Herbold [105] reported that although the quality of cross-project-based software fault-proneness prediction can improve with an appropriate training data selection strategy, it still cannot compete with the quality of within-project software fault-proneness prediction. Cotroneo et al. [61] also found that cross-project software fault-proneness prediction does not achieve acceptable performance in most cases compared to the results of within-project software fault-proneness prediction due to the different characteristics of the analyzed projects. Turhan et al. [235] combined within- and cross-project data from 73 versions of 41 projects to build software fault-proneness prediction models and found that collecting data from other projects is not feasible in terms of practical performance improvement when there is already an established within-project software fault predictor using full project history. However, when there is limited project history (e.g., early phases of development), mixed project predictions (e.g., using only 10% of available within project data) may perform as well as full within-project models. A major issue in cross-project software fault-proneness prediction is how to find the right training data in a software repository. Nagappan et al. in [178] conducted an empirical study of the post-release defect history of five Microsoft software systems. The results indicate that predictors are accurate only when obtained from the same or similar projects. Regarding this issue, Burak et al. [234] and Peters et al. [199] proposed two filters respectively to select appropriate training data. The former selects instances using KNN to measure the similarity (with Euclidean distance) between test instances and training data set instances. While

the latter finds nearest test instances for each training data set instance and then a test instance chooses the closest training data instance as a candidate for the filtered training data set while rejecting all the others. Bell et al. [23] reported that models could not be applied to other systems while Denaro and Pezzè [70] reported that good predictive performance only across homogenous applications. Nagappan et al. [178] also found that models are only accurate when trained on the same or similar systems. However, other studies report more promising transferability. Mizuno and Hirata [167] used 28 versions of 8 projects to conduct experiments of the cross-project and intra-project prediction. They found that intra-project prediction had better precision than cross-project. In contrast, recall is better using cross-project prediction.

Zhong et al. [265] proposed an unsupervised learning method for expert-based software quality estimation. It first clusters hundreds of software modules into a small number of groups. The representative of each group is then inspected by a software quality expert, who labels each cluster as either fault-prone or non-fault-prone based on his/her domain knowledge as well as other data statistics. They found that the proposed method could achieve comparable prediction accuracies with other fault-proneness classifiers. Tomaszewski et al. [231] invited eleven experts involved in the development of two telecommunication systems to perform fault-proneness prediction in the latest releases of both systems. On the contrary, they reported that the prediction accuracy of fault-proneness prediction models using historical fault data outperformed expert estimations. The biggest disadvantage of expert-based fault-proneness prediction is that its performance is largely dependent on the size of the dataset since estimating the fault-proneness of all modules in a system can be both time- and labor-consuming especially when the system is large and complex. As reported in [231], invited experts were confident when it comes to

ranking the first couple of components. Beyond a certain number of components, they admitted they would put remaining components in a random order. In addition, it is quite possible that experts do not agree with each other on determining the fault-proneness of same modules which makes such prediction even more challenging.

Wong et al. [254] proposed a static and a dynamic risk model to identify high-risk code in a program. The static model is constructed by using software metrics related to the static structure of the code, such as the number of c-uses, p-uses, definitions, decisions and function calls. The dynamic model utilizes additional dynamic test coverage of the code such as decision, c-use and p-use coverage to calibrate the metric values used in the model. Users have the choice to select either a summation scheme, which builds a risk model by using the sum of the selected software metrics, or a product scheme, which uses the product of the selected software metrics. Additionally, the two model schemes allow users to assign different weighting factors to the selected metrics based on their understanding of the target software product. These two models are able to identify the fault-proneness at a very fine granularity level (e.g., a basic block), which differs from other studies that identify fault-proneness at a method or class level.

2.2 Related Issues of Fault-Proneness Prediction

In this section, discussions on the related issues of fault-proneness prediction are presented.

2.2.1 Fault Severity in Fault-Proneness Prediction

Although some faults are more important to be identified than others, few studies consider fault severity when into evaluating the fault-proneness prediction performance. Shatnawi and Li [211] reported a model that is able to predict high and medium severity faults (these levels of severity

are based on those reported in Bugzilla by Eclipse developers). Lamkanfi et al. [148], Singh et al. [222], and Zhou and Leung [266] had also investigated fault severity when conducting their fault-proneness prediction studies. This lack of studies that consider severity is probably because, although acknowledged to be important, severity is considered a difficult concept to measure. For example, Menzies et al. [163] said that severity is too vague to reliably investigate. Nikora and Munson [182] said that without a widely agreed definition of severity we could not reason about it, and Ostrand et al. [190] stated that severity levels are highly subjective and can be inaccurate and inconsistent. These problems of how to measure and collect reliable severity data may have limited the usefulness of fault-proneness prediction models.

2.2.2 Challenges on Data Quality

Data quality challenges exist in both literature and applied research when investigating software fault-proneness prediction. In published research, papers may demonstrate inconsistencies that make the conclusions difficult to interpret. Fenton and Martin [77] pointed that in some cases definitions of defects, errors, faults, and failures differs widely between studies; defect rate, defect density, and failure rate are used almost interchangeably. It can also be difficult to tell whether a model is predicting discovered defects or residual defects. In other cases, strong theoretical or practical justification is required in order to remove data points during analysis, but it is sometimes difficult to tell whether any such points have been removed.

Similarly, some papers may acknowledge removed data points but provide no explanation. Moreover, they argued that the use of “averaged” data in analysis rather than the original data prejudices many studies. When using averages instead of raw data, the amount of information available to test the conjecture under study is reduced. However, any corresponding

conclusions may be weakened. In an extreme case, the conclusion reached by using averages can be completely contrary to that of using raw data. For example, the study in [22] used average fault density of grouped data to suggest a trend that was not supported by the raw data.

Additionally, inconsistency regarding the size of the same program reported in different studies posts another challenge on data quality. A typical example is the LOC of project Xerces, an XML parser, reported in [7] and [206]. The former reported that the LOCs of Xerces 1.2 and 1.3 are 60,032 and 64,503 respectively while the LOCs provided by the latter are 159,254 and 167,095 (which means the sizes reported in [206] are twice larger than those reported in [7] even though the subject programs are identical). The discrepancy is even more alarming considering the fact that these two papers were published in the same conference and in the same year. Jiang et al. [118] investigated the impact that the size of the training and test dataset has on the accuracy of fault-proneness predictions. The experiment results indicated that if the study is performed using the data from a small project, or an unreasonable distribution of modules between model training and testing, high variance will indicate that the results are unstable, prompting the need for better software engineering data or improved experimental design. Gray et al. [90] reported that the bulk of fault-proneness prediction experiments based on the NASA Metrics Data Program datasets might have led to erroneous findings due to repeated data points that potentially caused substantial amounts of training and testing data to be identical. Once data collection is complete, it is important to conduct data cleansing to remove noise (e.g., inaccurate/incorrect data points or data points with missing values) and outliers (e.g., data points with faulty class label if all the metrics are within their corresponding thresholds levels) to make the data sets suitable for machine learning.

By and large, it is important to anticipate and address any data quality challenges, as they may compromise the outcome of a given fault-proneness prediction model. To aid in identifying potential obstacles, researchers in [47] and [48] proposed a taxonomy of data quality challenges in empirical software engineering and reviewed techniques for assessing and addressing quality issues. And Hall et al. [97] proposed a set of criteria that can be served as guidance to conduct a reliable study on software fault-proneness prediction.

2.2.3 No Single Set of Software Metrics or Single Model Fits All Projects

Nagappan et al. [178] reported that different subsets of complexity metrics relate to faults in different projects and that no single set of metrics fits all projects. Arisholm et al. [9] found that the choice of fault-proneness modeling technique has limited impact on the resulting classification accuracy or cost-effectiveness. There are large differences between the individual software metric sets and their cost-effectiveness, and the best model is highly dependent on the criteria used to evaluate and compare the models. Similarly, Shepperd et al. [213] concluded that it is not the choice of fault proneness classifier but the people who conduct the research have a significant impact on the final fault-proneness prediction performance. Moreover, Shepperd and Kadoda [215] argued that the accuracy of a specific software fault-proneness prediction model is very much dependent on the attributes of the dataset. The study results observed in [223] also indicate that different learning schemes should be selected for different datasets, since no scheme dominates. Likewise, experiments conducted by Wong et al. [253] suggest that there is no particular metric having a clear advantage over the others in determining which function is fault-laden. As a result, it is better to ask which model is the best in a specified context rather than asking which one is the best in general [215]. More reliable research procedures need to be

developed before confident conclusions can be reached for comparative studies of software fault-proneness prediction models [176].

2.2.4 New and Modified Modules Seem More Fault-Prone

In [99], Hassan built software fault-proneness prediction models using change complexity metrics on six open-source software systems. The results indicate that a complex code change process negatively affects the software system. The more complex changes to a file, the higher the chance the file will contain faults. Tomaszewski et al. [230] also found that the modified code can be an important source of faults. They built fault density prediction models using data from two large telecommunication systems produced by Ericsson and reported that the faults found in the modified code accounted for more than 60% of the total number of faults found in the systems. Kim et al. [140] found that if a method was changed or had been added recently, it tended to introduce faults soon. Illes-Seifert and Paech [113] used nine open source Java projects to investigate the relationship between history characteristics of files and their defect count. They reported that the number of changes, the number of distinct authors performing changes to a file, and the file's age are positively related to a file's defect count. Another study conducted by Basili and Perricone [22] on a software project containing 90,000 lines of code indicate that: (1) both modified and new software modules have a high percentage of interface errors, (2) new software modules have a higher percentage of control errors, (3) modified software modules contain a high percentage of commission errors, and (4) modified software modules appeared to be more vulnerable to errors due to misunderstanding of the specifications, which is consistent with Endres's result [74]. Shin et al. in [217] made three observations: (1) the more method invocations in a file, the more fault-prone the file might be, (2) new files that have less chance to

be tested are more fault-prone than existing files, and (3) new and modified methods are more likely to be faulty than other methods. Bell et al. in [24] found that most faults in the system analyzed occurred in files that had been changed in the prior release. Similarly, Shen et al. [212] also found that new and modified modules are more fault-prone than unchanged modules from a previous release of the same product. In [100], Hassan et al. highlighted that some of the most susceptible subsystems (directories) that may have a fault such as Most Frequently Modified (MFM), Most Recently Modified (MRM), Most Frequently Fixed (MFF), and Most Recently Fixed (MRF).

2.2.5 The Pareto Law Universally Applies

In a telecommunication system produced by Ericsson Telecom AB, Fenton and Ohlsson [77] found that 20% of software modules contain approximately 60% of the total faults found. Similarly, Tomaszewski et al. in [230] conducted their research based on data from two different telecommunication systems developed by Ericsson and found that 60% of faults can be found in 20% of the codes. Kim et al. studied seven open source projects in [140] and found that 10% of the source code files account for 73%-95% of the total faults. Bell et al. [23] performed an empirical study of software fault-proneness prediction for an industrial voice response system and found that 20% of the files contained 75% of the faults. English et al. [75] carried out an empirical study for an open-source software project based on the information retrieved from the CVS repository and the Bugzilla database and found that Pareto's Law holds: 82% of faults occurred in 20% of the classes. Carrozza et al. [50] investigated how to predict the location(s) of Mandelbugs (faults that are triggered by complex conditions, such as interaction with hardware and other software, and timing or ordering of events) on an industrial software system developed

for the military domain and found that, on average, 60%-80% of Mandelbugs could be identified in the top 20% failure-prone components. Researchers of [15], [89], [190], [189], [241]-[244] also found that the faults contained in the 20% of the files roughly contains 60%~94% of the faults.

2.2.6 Findings Related to Code Management

Binkley et al. [33] derived three language-processing-based measures from the comments and identifiers in the source code to do software fault-proneness prediction. The first measure calculates the percentage of natural language used in a program's identifiers. The second measure calculates percentage of identifiers violating a variant of Deissenboeck and Pizka's rules [66] for concise and consistent identifiers. The third, referred to as the QALP score, is named after a project aimed at providing quality assessment using language processing [148]. Aman [7], [8] investigates the impact of comment statements on the fault-proneness of software modules. Their results showed that software modules containing comments are more likely to be faulty than non-commented software modules. Abede et al. in [4] found that Lexicon Bad Smells (LBS), anomalies that reduce the quality of identifier names, contribute to the identification of fault-prone modules. Good quality identifiers contribute to the understanding of the software and hence make it less susceptible to the introduction of faults. In [225], Taba et al. observed that files containing antipatterns have higher bug density than other files through a case study on multiple versions of Eclipse and ArgoUML. Antipatterns are specific design and implementation styles that can identify poor system designs. They are usually introduced in software systems due to the lack of knowledge or experience of developers when solving a particular problem. In [36], Bird et al. point out that ownership can also have a strong relationship to software defects.

Changes made by minor contributors, as well as components with low ownership, should be reviewed more carefully. Minor contributors should communicate with experienced developers or major contributors on the desired changes before taking any further actions.

CHAPTER 3

SOCIAL NETWORK ANALYSIS

3.1 Social Network Analysis in Software Engineering

Social network analysis (SNA) investigates social structures using network and graph theory [193]. It characterizes networked structures in terms of nodes and the edges that connect them. In the field of software engineering, SNA has been adopted as both a useful approach to understand software engineering activities. A social network models how people communicate and collaborate among others, which provides critical information for a software development project. It investigates not only the social organization of the work but also the technical information infrastructures. For example, Ghosh [85] reports that many open source projects at SourceForge are organized as social networks. Xu et al. [259] classify people working an open source project at SourceForge into project leader, core developer, co-developer, and active user. Ohira et al. [184] apply social network analysis and collaborative filtering to identify experts across different projects. Howison et al. also [111] use data collected from SourceForge to investigate how the social structures in projects are changing. In addition, Sarma et al. [208] have developed a tool that visualizes many different aspects of development artifacts. Cataldo et al. [54] propose the socio-technical congruence framework which examines the relationship between the structure of technical and work dependencies and the impact of dependencies on software development productivity. Their study indicates that when developers' coordination patterns are congruent with their coordination needs, the resolution time of modification requests is significantly reduced. In addition, logical dependency is a more accurate representation of product dependency affecting the development effort than call and data dependencies. Later, they

report that the logical dependency explains most of the variance in fault-proneness [55]. Many researchers have conducted different studies to analyze the interaction between developer and software module. Bird et al. [36] point out that ownership can have a strong relationship to software defects. Changes made by minor contributors, as well as components with low ownership, should be reviewed more carefully. Minor contributors should communicate with experienced developers or major contributors regarding the desired changes before taking further action. Ell [73]and Simpson [219] use the Failure Index (FI) to determine the failure-inducing possibility of developer pairs in developer social networks. Nagappan et al. [179] propose eight organizational metrics that quantify the complexity of a software development organization (e.g., the absolute number of unique engineers who have touched a binary and are still employed by/have left the company) to identify fault-prone binaries in Windows Vista.

3.2 Network Code Centrality Metrics

Network node centrality metrics stem from social network theory and are used to quantify the location of a node to the rest of the network [45]. There are three types of network node centrality [239]: (1) degree centrality, (2) closeness centrality, and (3) betweenness centrality. Degree centrality metrics are computed based on the number of edges that a node has [49]. The more edges a node has, the more central is the node. Closeness centrality emphasizes the distance of a node to other nodes in the network [80]. Betweenness centrality denotes the extent to which information flows through a node to get from one node to another [101]. The more information flows through a node the higher is its betweenness centrality.

3.3 Social Networks for Fault-Proneness Prediction

This section gives a brief overview of some existing social networks that have been proposed for fault-proneness prediction.

3.3.1 Developer Contribution Network (DCN)

In [200], Pinzger et al. represent developer contributions with a developer-module network that is called a contribution network. Case studies based on data collected from Windows Vista indicate that centrality metrics derived from the contribution network are good indicators of the number of post-release faults.

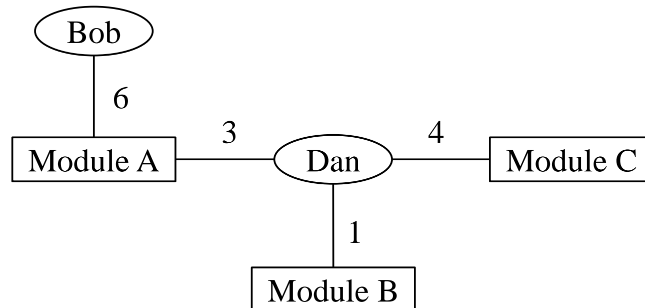

Figure 2. A DCN with 2 developers and 3 modules

A contribution network is an undirected graph G that is formally defined as $G = (D, N, E)$. D and N are the two sets of vertices that represent the two partitions of the graph, and E is a set of edges between vertices $E \subseteq \{(d, n) \mid d \in D \wedge n \in N\}$. D represents the set of developers and N the set of software modules. An edge $e \in E$ denotes a contribution of a developer $d \in D$ to a module $n \in N$. A contribution refers to a commit of a developer to a module. Edges are always between a developer and a module, and there are no self-loops (i.e., neither modules nor developers can contribute to themselves). Edge weights are used to denote the number of commits a developer

has made to a module. Figure 2 depicts a sample developer contribution network. Circles represent developers, rectangles represent software modules, and edges represent developer contributions to modules. For example, developer *Bob* has made 6 commits to module *A*. Developer *Dan* has made 3, 1, and 4 commits to Modules *A*, *B*, and *C*, respectively.

3.3.2 Module Dependency Network (MDN)

Zimmermann and Nagappan [270],[271] construct a network from dependency information for software modules in Windows Server 2003. They also find that social network analysis-based metrics derived from the dependency network are good indicators of the number of post-release faults and module fault-proneness, which is consistent with the results presented in [180], [200], and [232].

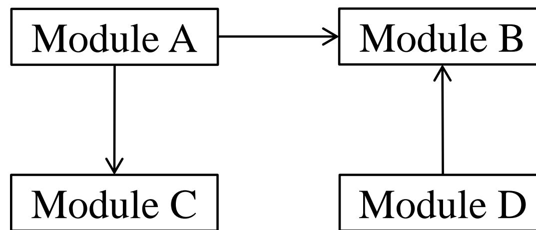

Figure 3. A MDN with 4 modules

Generally, a dependency network models the dependency relationships (e.g., call graphs, class inheritance, class coupling, etc.) between software modules within a software system. It is a directed graph that is formally defined as $G = (N, E)$ where N is the set of software modules and E is the set of directed edges such that $(n_1, n_2) \in E$ if Module n_1 has a dependency on Module n_2. Figure 3 shows a simple dependency network where rectangles represent software modules and directed edges represent module dependency relationships. For example, Module *A* has a

dependency on Modules *B* and *C* respectively. Module *A* and Module *D* are both dependent on Module *B*.

3.3.3 Socio-Technical Network (STN)

In [35], Bird et al. argue that the dependency relations and contribution history should be used together for fault-proneness prediction. They construct a socio-technical network by combining the developer contribution network and the module dependency network.

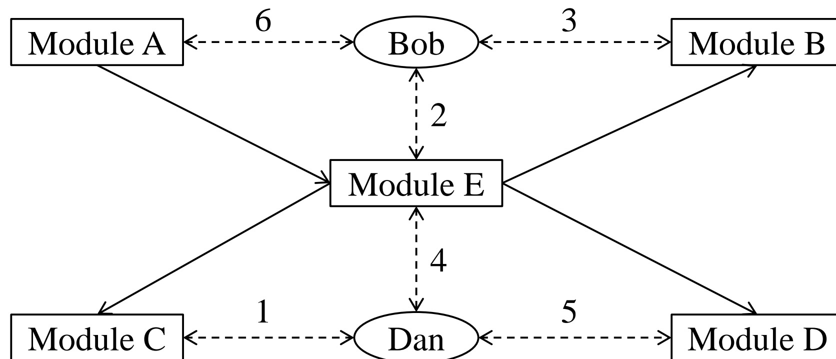

Figure 4. A STN with 2 developers and 5 modules

In the socio-technical network, there is a bidirectional dashed edge (denoted as the contribution edge) between a developer and a software module if the developer has made a commit to the module. The weight on the contribution edge is set as the number of commits from a developer to a module, and the weight of module dependencies is set to 1. Figure 4 shows a sample socio-technical network with 2 developers and 5 modules. For example, developer *Bob* has made 6, 2, and 3 commits to Modules *A*, *E*, and *B*, respectively. Module *E* has dependencies on Modules *B*, *C*, and *D*, respectively.

3.3.4 Developer Collaboration Network (DN)

Meneeley et al. [159] construct a developer collaboration network consisting solely of developers in which edges between developers are based on collaboration on common modules. The authors use social network analysis to assign values of metrics to developers. The value of a metric for a module is based on the values of the developers that contributed to that module (e.g., the sum of a metric for developers for a module).

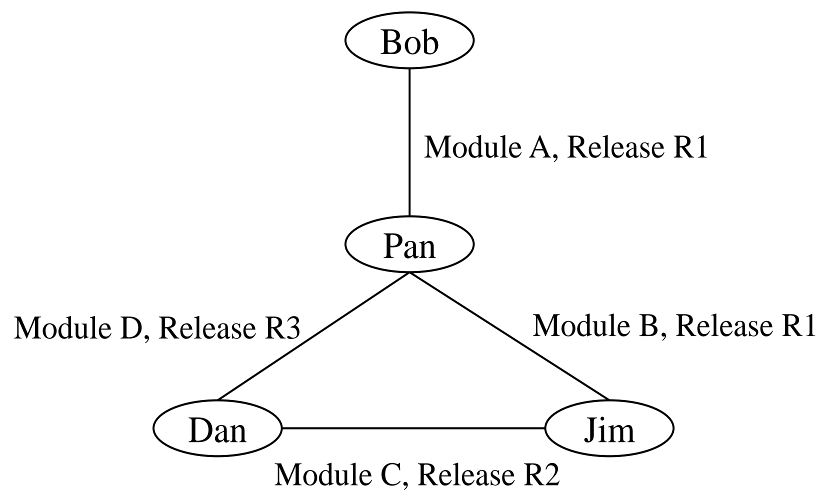

Figure 5. A DN with 4 developers

Figure 5 depicts a sample developer network with 4 developers. Circles represent developers and edges represent common files that two developers have both worked on in a particular release. For example, developers *Bob* and *Pan* have both worked on Module *A* during Release *R*1.

CHAPTER 4

THE PROPOSED TRI-RELATION NEWTORK (TRN)

Having overviewed four exiting social networks used for fault-proneness prediction in general, we are now ready to discuss the proposed TRN in this dissertation. We first present how TRN is constructed and the four network centrality metrics derived come TRN. Later, we move on to evaluate TRN, in terms of the correlation between its centrality metrics and the number of faults as well as the effectiveness of fault-proneness prediction model using these centrality metrics.

4.1 The Construction of TRN

The motivation behind TRN is that a network integrating developer contribution, module dependency, and developer collaboration can provide a more fully comprehensive insight into the interactions between developers and modules than the use of networks based on either a single or a paired relation. This insight is expected to ultimately enhance the effectiveness of software fault-proneness prediction.

In a TRN, there is a directed edge (denoted as the developer contribution) between a developer and a software module if the developer has made a commit to the module between two consecutive releases (e.g., between Release *R* and Release *R*+1). The weight on the contribution edge is set as the normalized[2] number of commits made from a developer to a module between Release *R* and Release *R*+1. Dependencies between modules are represented as directed dash-dot edges with arrows pointing to the modules upon which other modules depend. It is worth noting that we consider two types of dependency: functional dependency (e.g., a file calls another file)

[2] We apply the Min-Max approach for data normalization here.

and logical dependency (e.g., two files are modified in the same commit). We believe the use of both dependency types provides a more accurate representation of module dependencies affecting the development effort. The tool *Understand* from SciTools [238] is used to quantify the normalized dependencies between two modules. The weights for logical dependency between two modules are computed as the normalized number of times that these two modules are modified in the same commit. The resulting module dependency is computed as the sum of normalized functional dependency and normalized logical dependency.

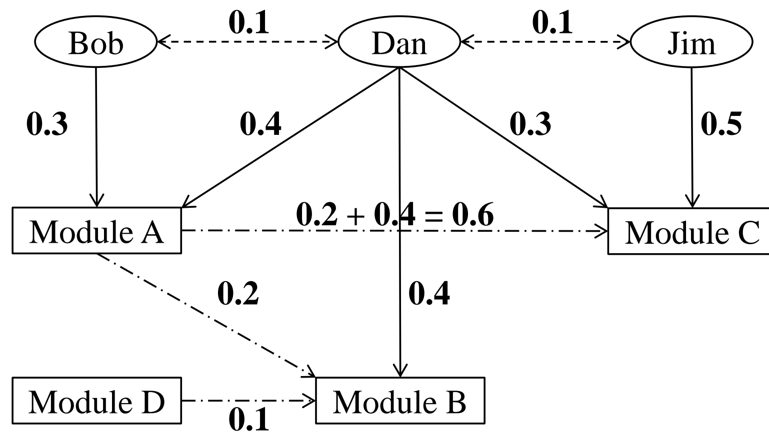

Figure 6. A TRN with 3 developers and 4 modules

In addition, there is a bidirectional dotted edge between one developer and another if these two developers have made at least one commit on the same module between release *R* and Release *R*+1. The weight on collaboration edge is computed as the normalized number of modules two developers have worked on together between Release *R* and Release *R*+1. Figure 6 presents a TRN with 3 developers and 4 modules. For example, the weight on the developer contribution edge *Bob*-to-Module *A* is 0.3. The module dependency edge Module *A*-to-Module *C* is 0.2 (normalized functional dependency) + 0.4 (normalized logical dependency) = 0.6. The developer collaboration edge *Bob*-to-*Dan* is 0.1.

4.2 Four Network Centrality Metrics and Other Metrics

Four centrality metrics, Freeman degree centrality (denoted as M_{FDC}), Bonacich's Power (denoted as M_{BP}), eigenvector of geodesic distances (denoted as M_{EGD}), Freeman node betweenness (denoted as M_{FNB}), which have been widely used in both SNA and fault-proneness prediction [35], [158], [179], [199], [231], [270], [271] are collected in this study. M_{FDC} is calculated as the number of direct edges a node has to its neighbors. M_{BP} is based on the adjacencies. It takes into account the connections of one's connections, in addition to one's own connections. M_{FDC} and M_{BP} focus on the number of developers and other modules it directly connects to, the impact of direct interactions on the module. More people working on the module, higher probability of introducing faults due to inconsistent coding style especially when these people have never worked/communicated with each other before. Due to the direct dependency relationship, more changes made on its neighbor modules higher probability that appropriate changes should be made on the module accordingly, thus more difficult to maintain the module. Closeness centrality emphasizes the distance of a node to other nodes in the network. In this paper, we use one such node distance measure: eigenvector of geodesic distances (denoted as M_{EGD}). M_{EGD} find the most central nodes (i.e. those with the smallest farness from others) in terms of the "global" or "overall" structure of the network, and to pay less attention to patterns that are more "local". Specifically, M_{EGD} applies factor analysis to identify "dimensions" of the distances among nodes. The location of each node with respect to each dimension is called an "eigenvalue", and the collection of such values is called the "eigenvector". Usually, the first dimension captures the "global" aspects of distances among nodes; second and further dimensions capture more specific and local sub-structures.

Betweenness centrality denotes the extent to which information flows through a node to get from one node to another. The more information flows through a node the higher is its betweenness centrality. For betweenness centrality, we use one such metric, Freeman node betweenness (denoted as M_{FNB}). It counts up how frequently each node falls in the geodesic paths between all pairs of nodes. M_{EGD} and M_{FNB} focus on the connection strength of the module to all modules and developers that it either directly or indirectly connects to. The closer the module to other modules and developers, the stronger the connection, the more likely the module can be affected by other modules and developers in a way. We use a tool, *Ucinet* [46], to compute and collect the values of these four centrality metrics.

Table 1. Ten commonly used software metrics

Metric	Description
M_{LOC}	Lines of code
M_{McCabe}	McCabe cyclomatic complexity
M_{LCOM}	Lack of cohesion in methods
M_{DIT}	Depth of inheritance tree
M_{CBO}	Coupling between object classes
M_{NOC}	Number of children
M_{RFC}	Response for a class
M_{WMC}	Weighted methods per class
M_{NC}	Number of commits
M_{ND}	Number of developers

Additionally, we introduce another ten software metrics, as shown in Table 1, that are commonly used for predicting software fault-proneness, including Lines of Code [181], McCabe Complexity [157], all six CK metrics [59], number of commits [177], and number of developers [192], all of which will be used later in our case studies. We use a tool, *Understand* [238], to compute and collect the values of these ten metrics.

Table 2. Notations relevant to metrics, networks, and prediction models

Notation	Description
X	a network
M	a generic software metric
Φ	a generic software fault-proneness prediction model
M_{Cen}	a generic network code centrality metric
$M_{X\text{-}Cen}$	a network code centrality metric derived from X
M_X	a set of four network code centrality metrics derived from X
M_{CO}	a set of ten software metrics that are commonly used for software fault-proneness prediction
$\Phi(M_X)$	a software fault-proneness prediction model using M_X
$\Phi(M_{CO})$	a software fault-proneness prediction model using M_{CO}

Table 3. Network node centrality metrics derived from TRN, DCN, MDN, STN, and DN

$M_{TRN\text{-}FDC}$	$M_{DCN\text{-}FDC}$	$M_{MDN\text{-}FDC}$	$M_{STN\text{-}FDC}$	$M_{DN\text{-}FDC}$
$M_{TRN\text{-}BP}$	$M_{DCN\text{-}BP}$	$M_{MDN\text{-}BP}$	$M_{STN\text{-}BP}$	$M_{DN\text{-}BP}$
$M_{TRN\text{-}EGD}$	$M_{DCN\text{-}EGD}$	$M_{MDN\text{-}EGD}$	$M_{STN\text{-}EGD}$	$M_{DN\text{-}EGD}$
$M_{TRN\text{-}FNB}$	$M_{DCN\text{-}FNB}$	$M_{MDN\text{-}FNB}$	$M_{STN\text{-}FNB}$	$M_{DN\text{-}FNB}$

For the sake of both simplicity and consistency, we use the notations provided in Table 2. For example, X represents a generic weighted network such as TRN, DCN, MDN, STN, or DN. M_{Cen} represents a generic network code centrality metric (e.g., M_{FDC}, M_{BP}, M_{EGD}, or M_{FNB}). $M_{X\text{-}Cen}$ represents a M_{Cen} derived from X. For example, $M_{TRN\text{-}FDC}$ represents the FDC network node centrality metric derived from a TRN. Meanwhile, all four network node centrality metrics derived from a TRN (i.e., $M_{TRN\text{-}FDC}$, $M_{TRN\text{-}BP}$, $M_{TRN\text{-}EGD}$, and $M_{TRN\text{-}FNB}$) can now be simplified to M_{TRN}. We use M_{CO} to denote a metric set that contains the ten software metrics described in Table 2. In addition, we use Φ (M_X) and Φ (M_{CO}) to denote a software fault-proneness prediction model using all four network code centrality metrics derived from X and a prediction model using the ten commonly used metrics, respectively. Since for each network we have four centrality metrics, accordingly, a total of 20 metrics can be derived as shown in Table 3.

4.3 Evaluation of TRN

We first examine the three research questions related to our study followed by a discussion of the software programs and the data analysis techniques used in our case studies. Results are presented at the end of this section.

4.3.1 Three Research Questions

In our study, we answer the following two research questions, which are thoroughly discussed later in this chapter:

R1: Are TRN-based centrality metrics important indicators for the number of post-released bugs in a file?

R2: Do TRN-based centrality metrics effectively improve software fault-proneness prediction models?

R3: Is there any potential enhancement that can be applied to TRN and other networks in order to further improve the effectiveness of fault-proneness prediction?

Answers to these three questions can help determine whether TRN-based centrality metrics are more powerful in building fault-proneness prediction models than not only DCN-, MDN-, STN-, or DN-based centrality metrics, but also software metrics that are commonly used for fault-proneness prediction. Moreover, valuable insights will be gained regarding the contributing factors that can be used to refine current networks in order to further enhance the prediction effectiveness.

4.3.2 Subject Program Studied

Our experiments use three Java programs, Camel 0, Flume [2], and Tika [3]. Camel is an open-source integration framework to define routing and mediation rules in a variety of domain-specific languages. Flume is a distributed service for collecting, aggregating, and moving log data from different sources to a centralized data store. Tika detects and extracts metadata and text from different file types such as PPT, XLS, and PDF.

Table 4. Summary of subject programs used

Project	Release	LOC	Files
Camel	1.3.0	110,113	1,245
Camel	1.4.0	114,621	1,488
Flume	1.4.0	92,437	507
Flume	1.5.0	99,127	547
Tika	1.5	83,502	472
Tika	1.6	87,180	507

Table 4 summarizes the information for these three programs used in our case studies. The columns, starting from the left, give project name, release version, lines of code (including blanks and comments), number of Java files, number of faulty Java files, and the number of faults. Each program contains two consecutive releases. The values of all metrics are collected at file level.

4.3.3 Experimental Methodology

In order to answer R1, the Spearman rank correlation coefficient [224] is used to measure the correlation between each metric (described in Table 5 through Table 7) and the number of post-released bugs for Camel 1.4.0, Flume 1.5.0, and Tika 1.6, respectively. The coefficient is

between +1 and −1, inclusive, in which +1 is total positive correlation, 0 is no correlation, and −1 is total negative correlation.

In order to answer R2, a data mining tool, Weka [240], is used to construct different fault-proneness prediction models. For each program, a total of six datasets are formed based on TRN, DCN, MDN, STN, and DN, as well as a dataset consisting of ten commonly used metrics (denoted as CO-based dataset) from two consecutive software releases (say Release 1 and Release 2). We use all data points collected from Release 1 as the training set and all data points collected from Release 2 as the validation set. Because of the class imbalance issue in the training set we apply SMOTE to oversample the minority class (i.e., classified as fault-prone) so that the size of fault-prone samples is equal to the size of samples that are non-fault-prone. We use BayesNet as our training algorithm. For example, in a TRN-based dataset, each data point is a labeled (i.e., fault-prone or non-fault-prone) file characterized by M_{TRN} (i.e., $M_{TRN\text{-}FDC}$, $M_{TRN\text{-}BP}$, $M_{TRN\text{-}EGD}$, and $M_{TRN\text{-}FNB}$). In a CO-based dataset, each data point is a labeled file characterized by M_{CO}. The same train-predict process is repeated 30 times. For example, we use $\Phi(M_{TRN})$ to represent a fault-proneness prediction model using M_{TRN}. As a result, for each program we have constructed 180 (i.e., 30×6) fault-proneness prediction models including 30 $\Phi(M_{TRN})$, 30 $\Phi(M_{DCN})$, 30 $\Phi(M_{MDN})$, 30 $\Phi(M_{STN})$, 30 $\Phi(M_{DN})$, and 30 $\Phi(M_{CO})$.

Two measures, recall (defined in Equation (4)) and false positive rate (defined in Equation (5)) are used to evaluate the fault-proneness prediction effectiveness of each model. In these two equations, TP (true positive) is the number of fault-prone modules that are correctly predicted, TN (true negative) is the number of non-fault-prone modules that are correctly predicted, FP (false positive) is the number of non-fault-prone modules that are predicted as

fault-prone, and FN (false negative) is the number of fault-prone modules that are incorrectly predicted as non-fault-prone.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{4}$$

$$\text{False Positive Rate (FPR)} = \frac{\text{FP}}{\text{FP+TN}} \tag{5}$$

For discussion purposes, let us assume there are 100 software modules in which 30 are faulty and 70 are non-faulty. Assume also that a fault-proneness prediction model predicts 35 modules as fault-prone, 10 of which are actually non-faulty. This also implies that among the 65 modules predicted as non-fault-prone, 5 are actually fault-prone. Therefore, TP = 25 (25 faulty modules are correctly predicted as fault-prone), TN = 60 (60 non-faulty modules are correctly predicted as non-fault-prone), FP = 10 (ten non-faulty modules are incorrectly predicted as fault-prone), and FN = 5 (five faulty modules are incorrectly predicted as non-fault-prone). Based on Equations (1) and (2), the recall is 25/(25+5) ≈ 83.33% and the FPR is 10/(10+60) ≈ 14.29%. For two different fault-proneness prediction models Φ_1 and Φ_2, if Φ_1 has a higher recall than Φ_2, then it can be said that Φ_1 is more effective than Φ_2 with respect to recall. If Φ_1 has a lower FPR than Φ_2, then it can be said that Φ_1 is more effective than Φ_2 with respect to FPR.

For each program, we compute and compare the respective average recall and FPR of 30 $\Phi(M_{TRN})$, 30 $\Phi(M_{DCN})$, 30 $\Phi(M_{MDN})$, 30 $\Phi(M_{STN})$, 30 $\Phi(M_{DN})$, and 30 $\Phi(M_{CO})$. For example, regarding R2, if $\Phi(M_{TRN})$ has a higher average recall than $\Phi(M_{DCN})$, then $\Phi(M_{TRN})$ is more effective than $\Phi(M_{DCN})$ with respect to average recall.

In addition, we employ the paired Wilcoxon signed-rank test [38] to investigate R1 and R2. For example, regarding R1, we can make the following null hypothesis with respect to the computed Spearman rank correlation coefficient using $M_{TRN\text{-}Cen}$ and the same coefficient using $M_{DCN\text{-}Cen}$:

H_0: the computed Spearman rank correlation coefficient using $M_{TRN\text{-}Cen}$ is equal to or smaller than the computed Spearman rank correlation coefficient using $M_{DCN\text{-}Cen}$

If H_0 is rejected (i.e., the alternative hypothesis is accepted), then it implies that $M_{TRN\text{-}Cen}$ is more correlated with the number of post-released bugs than $M_{DCN\text{-}Cen}$.

Regarding R2, we can make the following null hypothesis with respect to the recall of $\Phi(M_{TRN})$ and $\Phi(M_{DCN})$:

H_0: $\Phi(M_{TRN})$ has equal or lower recall than $\Phi(M_{DCN})$.

If H_0 is rejected (i.e., the alternative hypothesis is accepted), then it implies that $\Phi(M_{TRN})$ will correctly predict more fault-prone files than $\Phi(M_{DCN})$. This also implies that $\Phi(M_{TRN})$ is more effective than $\Phi(M_{DCN})$ with respect to recall.

To answer R3, we propose CaTRN. The motivation behind the construction of the CaTRN is to investigate whether integrating additional factors that describe the development effort in the current TRN will better present the interactions between developers and modules and therefore further improve the fault-proneness prediction using the metrics derived from CaTRN. Consequently, in order to construct a CaTRN, for each type of relation in a TRN, a particular mechanism is applied to further calibrate the corresponding relation strength (i.e., the weight on the corresponding edges). More details regarding CaTRN will be presented the next chapter.

4.3.4 Results for R1

To answer R1, we use the Spearman rank correlation coefficient to measure the correlation between each metric and the number of post-released bugs in a file.[3] The results are shown in Table 5 through Table 7. Each entry in the tables gives the coefficient between a metric and the number of bugs. For example, let us look at the first row of Table 5. The correlation between metric $M_{TRN\text{-}FDC}$ and the number of bugs is 0.79, and the correlation between $M_{DCN\text{-}FDC}$ and the number of bugs is 0.73. The corresponding correlations between metrics $M_{MDN\text{-}FDC}$, $M_{STN\text{-}FDC}$, and $M_{DN\text{-}FDC}$ and the number of bugs are 0.62, 0.71, and 0.63, respectively. Therefore, the centrality metric, M_{FDC}, derived from TRN (i.e., $M_{TRN\text{-}FDC}$) has the strongest correlation with the number of bugs compared to the corresponding M_{FDC} derived from DCN (i.e., $M_{DCN\text{-}FDC}$), MDN (i.e., $M_{MDN\text{-}FDC}$), STN (i.e., $M_{STN\text{-}FDC}$), and DN (i.e., $M_{DN\text{-}FDC}$). Let us now look at the second column of the same table. The correlation between $M_{TRN\text{-}BP}$ and the number of bugs is 0.55, the correlation between $M_{TRN\text{-}EGD}$ and the number of bugs is 0.54, and the correlation between $M_{TRN\text{-}FNB}$ and the number of bugs is 0.44. Therefore, the M_{FDC} derived from TRN (i.e., $M_{TRN\text{-}FDC}$) has the strongest correlation with the number of bugs compared to $M_{TRN\text{-}BP}$, $M_{TRN\text{-}EGD}$, and $M_{TRN\text{-}FNB}$ which are derived from the same TRN.

Table 5. Correlation Analysis Using Spearman Rank Correlation Coefficient for Camel 1.4.0 where correlation is significant at the 0.05 level (2-tailed)

$M_{TRN\text{-}FDC}$	0.79	$M_{DCN\text{-}FDC}$	0.73	$M_{MDN\text{-}FDC}$	0.62	$M_{STN\text{-}FDC}$	0.71	$M_{DN\text{-}FDC}$	0.63	M_{LOC}	0.33	M_{CBO}	0.23	M_{NC}	0.38
$M_{TRN\text{-}BP}$	0.55	$M_{DCN\text{-}BP}$	0.50	$M_{MDN\text{-}BP}$	0.47	$M_{STN\text{-}BP}$	0.50	$M_{DN\text{-}BP}$	0.45	M_{McCabe}	0.31	M_{NOC}	0.03	M_{ND}	0.34
$M_{TRN\text{-}EGD}$	0.54	$M_{DCN\text{-}EGD}$	0.46	$M_{MDN\text{-}EGD}$	0.39	$M_{STN\text{-}EGD}$	0.46	$M_{DN\text{-}EGD}$	0.36	M_{LCOM}	0.11	M_{RFC}	0.10		
$M_{TRN\text{-}FNB}$	0.44	$M_{DCN\text{-}FNB}$	0.37	$M_{MDN\text{-}FNB}$	0.26	$M_{STN\text{-}FNB}$	0.36	$M_{DN\text{-}FNB}$	0.33	M_{DIT}	0.05	M_{WMC}	0.25		

[3] The term "bugs" here are used to refer specifically to post-released bugs.

Table 6. Correlation Analysis Using Spearman Rank Correlation Coefficient for Flume 1.5.0 where correlation is significant at the 0.05 level (2-tailed)

$M_{TRN-FDC}$	0.76	$M_{DCN-FDC}$	0.71	$M_{MDN-FDC}$	0.61	$M_{STN-FDC}$	0.65	M_{DN-FDC}	0.62	M_{LOC}	0.21	M_{CBO}	0.05	M_{NC}	0.58
M_{TRN-BP}	0.69	M_{DCN-BP}	0.60	M_{MDN-BP}	0.49	M_{STN-BP}	0.63	M_{DN-BP}	0.52	M_{McCabe}	0.06	M_{NOC}	0.01	M_{ND}	0.43
$M_{TRN-EGD}$	0.60	$M_{DCN-EGD}$	0.50	$M_{MDN-EGD}$	0.40	$M_{STN-EGD}$	0.50	M_{DN-EGD}	0.40	M_{LCOM}	0.12	M_{RFC}	0.01		
$M_{TRN-FNB}$	0.56	$M_{DCN-FNB}$	0.45	$M_{MDN-FNB}$	0.37	$M_{STN-FNB}$	0.45	M_{DN-FNB}	0.40	M_{DIT}	0.02	M_{WMC}	0.01		

Table 7. Correlation Analysis Using Spearman Rank Correlation Coefficient for Tika 1.6 where correlation is significant at the 0.05 level (2-tailed)

$M_{TRN-FDC}$	0.65	$M_{DCN-FDC}$	0.53	$M_{MDN-FDC}$	0.46	$M_{STN-FDC}$	0.52	M_{DN-FDC}	0.41	M_{LOC}	0.29	M_{CBO}	0.19	M_{NC}	0.62
M_{TRN-BP}	0.52	M_{DCN-BP}	0.42	M_{MDN-BP}	0.39	M_{STN-BP}	0.45	M_{DN-BP}	0.30	M_{McCabe}	0.12	M_{NOC}	0.03	M_{ND}	0.42
$M_{TRN-EGD}$	0.56	$M_{DCN-EGD}$	0.47	$M_{MDN-EGD}$	0.36	$M_{STN-EGD}$	0.46	M_{DN-EGD}	0.39	M_{LCOM}	0.32	M_{RFC}	0.06		
$M_{TRN-FNB}$	0.40	$M_{DCN-FNB}$	0.33	$M_{MDN-FNB}$	0.25	$M_{STN-FNB}$	0.34	M_{DN-FNB}	0.21	M_{DIT}	0.09	M_{WMC}	0.14		

In general, from Table 5 to Table 7, we observe that: (1) $M_{TRN-FDC}$ has the strongest correlation (i.e., 0.79) with the number of bugs among all metrics; (2) for any M_{Cen} derived from TRN, $M_{TRN-Cen}$, it has the strongest correlation with the number of bugs compared to the corresponding M_{Cen} derived from DCN (i.e., $M_{DCN-Cen}$), MDN (i.e., $M_{MDN-Cen}$), STN (i.e., $M_{STN-Cen}$), and DN (i.e., M_{DN-Cen}).

Table 8. Confidence that $M_{TRN-Cen}$ is more correlated with the number of bugs than the corresponding $M_{DCN-Cen}$, $M_{MDN-Cen}$, $M_{STN-Cen}$, and M_{DN-Cen}

	$M_{DCN-Cen}$	$M_{MDN-Cen}$	$M_{STN-Cen}$	M_{DN-Cen}
Camel 1.4.0	98.98%	99.98%	99.98%	99.98%
Flume 1.5.0	97.97%	99.98%	98.97%	99.97%
Tika 1.6	98.98%	99.97%	99.98%	99.98%

In addition, we use the paired Wilcoxon signed-rank test to investigate R1 from a statistical point of view. Table 8 presents the results of a Wilcoxon signed-rank test showing the confidence with which it can be claimed that $M_{TRN-Cen}$ is more correlated with the number of bugs than the corresponding $M_{DCN-Cen}$, $M_{MDN-Cen}$, $M_{STN-Cen}$, and M_{DN-Cen}. Each entry in the table strengthens the conviction that the alternative hypothesis stands. Furthermore, for each program in Table 8, at the 0.05 level, the correlation coefficient distributions are significantly different

between (1) $M_{TRN\text{-}Cen}$ and $M_{DCN\text{-}Cen}$, (2) $M_{TRN\text{-}Cen}$ and $M_{MDN\text{-}Cen}$, (3) $M_{TRN\text{-}Cen}$ and $M_{STN\text{-}Cen}$, and (4) $M_{TRN\text{-}Cen}$ and $M_{DN\text{-}Cen}$.

For example, for Camel 1.4.0, it can be said with 98.98% confidence that $M_{TRN\text{-}Cen}$ is more correlated with the number of bugs than the corresponding $M_{DCN\text{-}Cen}$. Let us look at the third row of Table 8; for Flume 1.5.0, it can be said with 97.97%, 99.98%, 98.97%, and 99.97% confidence that $M_{TRN\text{-}Cen}$ is more correlated with the number of bugs than the corresponding $M_{DCN\text{-}Cen}$, $M_{MDN\text{-}Cen}$, $M_{STN\text{-}Cen}$, and $M_{DN\text{-}Cen}$. In general, from Table 8 it can be claimed with high confidence (at least 97%) that $M_{TRN\text{-}Cen}$ is more correlated with the number of bugs than the corresponding $M_{DCN\text{-}Cen}$, $M_{MDN\text{-}Cen}$, $M_{STN\text{-}Cen}$, and $M_{DN\text{-}Cen}$ for all three programs. If we change our alternative hypothesis to "$M_{TRN\text{-}Cen}$ is equally/more correlated with the number of bugs as/than the corresponding $M_{DCN\text{-}Cen}$, $M_{MDN\text{-}Cen}$, $M_{STN\text{-}Cen}$, and $M_{DN\text{-}Cen}$," then the confidence is 100% for almost very scenario.

***Summary with respect to R1*:**

- Metrics derived from the proposed TRN are significant indicators for the number of bugs in a file
- Metrics derived from the proposed TRN are generally more correlated to the number of bugs than corresponding metrics derived from DCN, MDN, STN, and DN
- The FDC metric derived from TRN, $M_{TRN\text{-}FDC}$, has the strongest correlation with the number of bugs among all metrics used in our case studies. This also indicates that for a software module (a file in our case), (1) the number of direct interactions with its contributing software developers, (2) the contribution frequency of these developers, (3) the number of modules it has a direct dependency (both functional and logical) relationship with, and (4)

their mutual dependence intensity, jointly have a significant impact on the quality of the module itself

4.3.5 Results for R2

To answer R2, for each program, we compute and compare the average recall and FPR of $\Phi(M_{TRN})$, $\Phi(M_{DCN})$, $\Phi(M_{MDN})$, $\Phi(M_{STN})$, $\Phi(M_{DN})$, and $\Phi(M_{CO})$. The results are shown in Table 9 through Table 11. For example, in Table 9, the average recall and FPR of $\Phi(M_{TRN})$ are 69.79% and 4.60%, respectively. In the same table, the average recall and FPR of $\Phi(M_{DCN})$ are 62.95% and 4.86%, respectively. Therefore, $\Phi(M_{TRN})$ has a larger average recall and a lower average FRP compared to $\Phi(M_{DCN})$.

Table 9. Prediction effectiveness of $\Phi(M_{TRN})$, $\Phi(M_{DCN})$, $\Phi(M_{MDN})$, $\Phi(M_{STN})$, $\Phi(M_{DN})$, and $\Phi(M_{CO})$ with respect to average Recall and average FPR for Camel 1.4.0

Prediction Model	Average Recall	Average FPR
$\Phi(M_{TRN})$	69.79%	4.60%
$\Phi(M_{DCN})$	62.95%	4.86%
$\Phi(M_{MDN})$	26.49%	6.23%
$\Phi(M_{STN})$	44.09%	5.66%
$\Phi(M_{DN})$	38.47%	6.63%
$\Phi(M_{CO})$	54.15%	4.90%

From Table 9, we observe that $\Phi(M_{TRN})$ has the highest average recall (i.e., 69.79%) and the lowest average FPR (i.e., 4.60%) among all fault-proneness prediction models in the table. The same also applies to Table 10 and Table 11 where $\Phi(M_{TRN})$ has the highest average recall (i.e., 87.01% and 64.60%) and the lowest average FPR (i.e., 4.51% and 2.10%) among all fault-proneness prediction models in these two tables.

Table 10. Prediction effectiveness of $\Phi(M_{TRN})$, $\Phi(M_{DCN})$, $\Phi(M_{MDN})$, $\Phi(M_{STN})$, $\Phi(M_{DN})$, and $\Phi(M_{CO})$ with respect to average Recall and average FPR for Flume 1.5.0

Prediction Model	Average Recall	Average FPR
$\Phi(M_{TRN})$	87.01%	4.51%
$\Phi(M_{DCN})$	76.91%	6.17%
$\Phi(M_{MDN})$	44.71%	9.96%
$\Phi(M_{STN})$	64.79%	7.05%
$\Phi(M_{DN})$	53.22%	9.58%
$\Phi(M_{CO})$	68.14%	6.39%

Table 11. Prediction effectiveness of $\Phi(M_{TRN})$, $\Phi(M_{DCN})$, $\Phi(M_{MDN})$, $\Phi(M_{STN})$, $\Phi(M_{DN})$, and $\Phi(M_{CO})$ with respect to average Recall and average FPR for Tika 1.6

Prediction Model	Average Recall	Average FPR
$\Phi(M_{TRN})$	64.60%	2.10%
$\Phi(M_{DCN})$	63.78%	2.38%
$\Phi(M_{MDN})$	40.67%	3.79%
$\Phi(M_{STN})$	52.78%	2.78%
$\Phi(M_{DN})$	45.06%	2.97%
$\Phi(M_{CO})$	53.97%	2.52%

Once again, from a statistical point of view, we employ the paired Wilcoxon signed-rank test to compare the recall and FPR of $\Phi(M_{TRN})$ against $\Phi(M_{DCN})$, $\Phi(M_{MDN})$, $\Phi(M_{STN})$, $\Phi(M_{DN})$, and $\Phi(M_{CO})$. Table 12 presents the results of a Wilcoxon signed-rank test showing the confidence with which it can be claimed that $\Phi(M_{TRN})$ is more effective (in terms of recall or FPR) than $\Phi(M_{DCN})$, $\Phi(M_{MDN})$, $\Phi(M_{STN})$, $\Phi(M_{DN})$, and $\Phi(M_{CO})$. Each entry in the table gives the assurance with which the alternative hypothesis stands. Furthermore, for each program in Table 12, at the 0.05 level, the recall/FPR distributions are significantly different between (1) $\Phi(M_{TRN})$ and $\Phi(M_{DCN})$, (2) $\Phi(M_{TRN})$ and $\Phi(M_{MDN})$, (3) $\Phi(M_{TRN})$ and $\Phi(M_{STN})$, (4) $\Phi(M_{TRN})$and $\Phi(M_{DN})$, and (5) $\Phi(M_{TRN})$ and $\Phi(M_{CO})$, respectively. To take an example from Table 12, it can be said with 99.98% and 99.99% confidence that $\Phi(M_{TRN})$ has a higher recall and lower FPR, respectively, than $\Phi(M_{DCN})$ for Camel 1.4.0. It also implies that $\Phi(M_{TRN})$ is more effective than

$\Phi(M_{DCN})$ in terms of recall and FPR, respectively. In general, from Table 12 we observe that it can be said with at least 99.90% confidence that $\Phi(M_{TRN})$ has a higher recall and lower FPR than the corresponding $\Phi(M_{DCN})$, $\Phi(M_{MDN})$, $\Phi(M_{STN})$, $\Phi(M_{DN})$, and $\Phi(M_{CO})$ for all three programs. If we change our alternative hypothesis to consider equalities, then the confidence is 100% for almost very scenario.

Table 12. Confidence that $\Phi(M_{TRN})$ is more effective than $\Phi(M_{DCN})$, $\Phi(M_{MDN})$, $\Phi(M_{STN})$, $\Phi(M_{DN})$, and $\Phi(M_{CO})$ with respect to Recall and FPR

		$\Phi(M_{DCN})$	$\Phi(M_{MDN})$	$\Phi(M_{STN})$	$\Phi(M_{DN})$	$\Phi(M_{CO})$
Camel 1.4.0	Recall	99.98%	99.99%	99.99%	99.98%	99.98%
	FPR	99.99%	99.99%	99.99%	99.98%	99.97%
Flume 1.5.0	Recall	99.98%	99.99%	99.98%	99.99%	99.98%
	FPR	99.98%	99.99%	99.99%	99.98%	99.99%
Tika 1.6	Recall	99.96%	99.99%	99.97%	99.98%	99.98%
	FPR	99.96%	99.99%	99.97%	99.98%	99.99%

***Summary with respect to R2*:**

Fault-proneness prediction models using network node centrality metrics derived from the proposed TRN are more effective than prediction models using the same metrics derived from DCN, MDN, STN, and DN as well as prediction models using the ten common metrics, in terms of recall and FPR.

CHAPTER 5

EDGE WEIGHT CALIBRATION MECHANISM FOR TRN

5.1 The Proposed CaTRN

To answer R3, we propose CaTRN. The motivation behind the construction of the CaTRN is to investigate whether integrating additional factors that describe the development effort in the current TRN will better present the interactions between developers and modules and therefore further improve the fault-proneness prediction using the metrics derived from CaTRN. Consequently, in order to construct a CaTRN, for each type of relation in a TRN, a particular mechanism is applied to further calibrate the corresponding relation strength (i.e., the weight on the corresponding edges).

This section contains material from the following source [150]: S. Lee and Y. Li, "DRS: A Developer Risk Metric for Better Predicting Software Fault-Proneness," in *Proceedings of the 2nd International Conference on Trustworthy Systems and Their Applications*, Hualien, Taiwan, July 2015, pp. 120-127. Specifically, we introduce developer risk score (DRS) [150], which computes the risk of a developer working on the modules, and use it for further edge weight calibration. DRS is based on two heuristics: (1) with respect to a given program, the more frequently a developer has introduced bugs in past releases, and the greater the severity of those bugs, the higher the risk that this program will contain a bug if this same developer makes a commit on the current release; and (2) the greater the complexity of a program, the greater the difficulty a developer has in working on this program and the higher the risk that the developer will introduce a bug into the program. For a given software system, assume that m_j is the jth module in the system, and c_k is the kth bug-introducing commit made by developer d in the jth

module. We retrieve the bug severity of each bug-introducing commit (e.g., *critical*, *major*, *minor*, or *trivial*) from JIRA [121] and use the function *SeverityScore*(f_j, c_k, d, R−1) to map it to one of the following scores: 4 (*critical)*, 3 (*major)*, 2 (*minor)*, and 1 (*trivial*). A score of 4 is assigned to the variable *MaxSeverityScore.* The bug severity ratio of the kth bug-introducing commit made by developer d in the jth module in release R−1 is defined as:

$$SeverityRatio(m_j, c_k, d, R-1) = \frac{SeverityScore(m_j, c_k, d, R-1)}{MaxSeverityScore} \tag{6}$$

The overall complexity value of the jth module in release R−1 is computed by *Complexity*(m_j, R−1) as the sum of normalized LOC [181], McCabe Complexity [157], and all six CK metrics [59]. *TotalCommits*(d, R−1) gives the total number of commits made by developer d in release R−1. *DRS*(d, R), the developer risk score of developer d at release R, is defined as:

$$DRS(d, R) = \frac{\sum \frac{SeverityRatio(m_j, c_k, d, R-1)}{Complexity(m_j, R-1)}}{TotalCommits(d, R-1)} \tag{7}$$

To calibrate the weight of a developer contribution edge, we multiply the original weight (i.e., the number of commits made by a developer) by the DRS value[4] of this developer. To calibrate the weight of a module dependency edge, we multiply the original weight (i.e., the quantified dependency value for a pair of modules) by the sum of DRS values of distinct developers who have worked on the two modules. To calibrate the weight of a developer collaboration edge, we multiply the original weight (i.e., the number of modules on which two

[4] For a newly joined developer, its DRS value is set to the median of the DRS value set which is currently available.

developers have both worked) by the sum of DRS values of these two developers. Let us assume the DRS values for developers *Bob*, *Dan*, and *Jim* are 0.5, 1.2, and 3, respectively. The CaTRN is shown in Figure 7. Compared to TRN, CaTRN contains additional information by considering developer risk, program complexity, and bug severity, thus describing the development effort from a more comprehensive perspective. The same calibrating strategy can also apply to DCN, MDN, STN, and DN. As a result, a total of seven modified networks are obtained (i.e., CaTRN, CaDCN, CaMDN, CaSTN, and CaDN). Once we have these modified networks, the corresponding network centrality metrics from each modified network are derived, respectively.

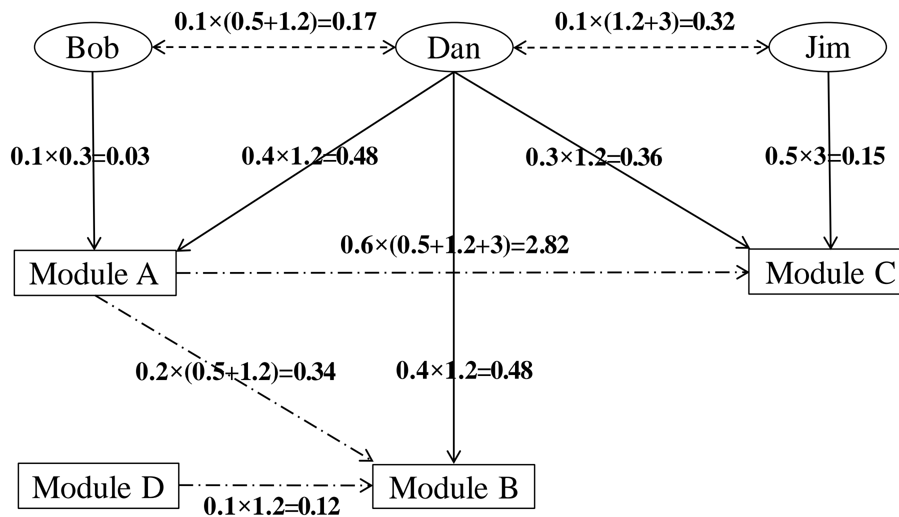

Figure 7. CaTRN with 3 developers and 4 modules

5.2 Results for R3

We answer R3 by re-conducting similar data analysis which has been used to investigate R1 and R2. Table 13 through Table 15 present the Spearman rank correlation coefficient used to measure the correlation between each metric derived from the corresponding modified networks and the number of bugs in a file. For example, in the first row of Table 13, the correlation

between the FDC metric derived from CaTRN (i.e., $M_{CaTRN\text{-}FDC}$) and the number of bugs is 0.87. As you may recall, the same FDC metric derived from TRN (i.e., $M_{TRN\text{-}FDC}$) in Table 5 is 0.79. This indicates that the FDC metric derived from the modified TRN (i.e., $M_{CaTRN\text{-}FDC}$) which consider calibrated edge weight has a stronger correlation with the number of bugs than the same FDC metric derived from the original TRN which does not.

Table 13. Spearman Rank Correlation Coefficient for Camel 1.4.0 where correlation is significant at the 0.05 level (2-tailed)

$M_{CaTRN\text{-}FDC}$	0.87	$M_{CaDCN\text{-}FDC}$	0.80	$M_{CaMDN\text{-}FDC}$	0.67	$M_{CaSTN\text{-}FDC}$	0.75	$M_{CaDN\text{-}FDC}$	0.69
$M_{CaTRN\text{-}BP}$	0.60	$M_{CaDCN\text{-}BP}$	0.51	$M_{CaMDN\text{-}BP}$	0.50	$M_{CaSTN\text{-}BP}$	0.55	$M_{CaDN\text{-}BP}$	0.47
$M_{CaTRN\text{-}EGD}$	0.57	$M_{CaDCN\text{-}EGD}$	0.53	$M_{CaMDN\text{-}EGD}$	0.40	$M_{CaSTN\text{-}EGD}$	0.52	$M_{CaDN\text{-}EGD}$	0.40
$M_{CaTRN\text{-}FNB}$	0.52	$M_{CaDCN\text{-}FNB}$	0.42	$M_{CaMDN\text{-}FNB}$	0.31	$M_{CaSTN\text{-}FNB}$	0.37	$M_{CaDN\text{-}FNB}$	0.38

Table 14. Spearman Rank Correlation Coefficient for Flume 1.5.0 where correlation is significant at the 0.05 level (2-tailed)

$M_{CaTRN\text{-}FDC}$	0.83	$M_{CaDCN\text{-}FDC}$	0.79	$M_{CaMDN\text{-}FDC}$	0.64	$M_{CaSTN\text{-}FDC}$	0.71	$M_{CaDN\text{-}FDC}$	0.69
$M_{CaTRN\text{-}BP}$	0.71	$M_{CaDCN\text{-}BP}$	0.64	$M_{CaMDN\text{-}BP}$	0.56	$M_{CaSTN\text{-}BP}$	0.69	$M_{CaDN\text{-}BP}$	0.55
$M_{CaTRN\text{-}EGD}$	0.64	$M_{CaDCN\text{-}EGD}$	0.58	$M_{CaMDN\text{-}EGD}$	0.48	$M_{CaSTN\text{-}EGD}$	0.57	$M_{CaDN\text{-}EGD}$	0.44
$M_{CaTRN\text{-}FNB}$	0.61	$M_{CaDCN\text{-}FNB}$	0.50	$M_{CaMDN\text{-}FNB}$	0.40	$M_{CaSTN\text{-}FNB}$	0.51	$M_{CaDN\text{-}FNB}$	0.43

Table 15. Spearman Rank Correlation Coefficient for Tika 1.6 where correlation is significant at the 0.05 level (2-tailed)

$M_{CaTRN\text{-}FDC}$	0.67	$M_{CaDCN\text{-}FDC}$	0.57	$M_{CaMDN\text{-}FDC}$	0.52	$M_{CaSTN\text{-}FDC}$	0.54	$M_{CaDN\text{-}FDC}$	0.45
$M_{CaTRN\text{-}BP}$	0.55	$M_{CaDCN\text{-}BP}$	0.49	$M_{CaMDN\text{-}BP}$	0.41	$M_{CaSTN\text{-}BP}$	0.47	$M_{CaDN\text{-}BP}$	0.33
$M_{CaTRN\text{-}EGD}$	0.61	$M_{CaDCN\text{-}EGD}$	0.51	$M_{CaMDN\text{-}EGD}$	0.42	$M_{CaSTN\text{-}EGD}$	0.51	$M_{CaDN\text{-}EGD}$	0.40
$M_{CaTRN\text{-}FNB}$	0.47	$M_{CaDCN\text{-}FNB}$	0.37	$M_{CaMDN\text{-}FNB}$	0.32	$M_{CaSTN\text{-}FNB}$	0.39	$M_{CaDN\text{-}FNB}$	0.25

In general, from Table 13 to Table 15, we observe that: (1) the metrics derived from modified networks (i.e., $M_{CaX\text{-}Cen}$) have stronger correlation with the number of bugs than the corresponding metrics derived from the original networks (i.e., $M_{X\text{-}Cen}$) as shown from Table 5 to Table 7; (2) $M_{CaTRN\text{-}FDC}$ has the strongest correlation with the number of bugs among all metrics derived from modified networks; and (3) for any M_{Cen} derived from CaTRN, $M_{CaTRN\text{-}Cen}$, it has

the strongest correlation with the number of bugs compared to the corresponding M_{Cen} derived from CaDCN (i.e., $M_{CaDCN-Cen}$), CaMDN (i.e., $M_{CaMDN-Cen}$), CaSTN (i.e., $M_{CaSTN-Cen}$), and CaDN (i.e., $M_{CaDN-Cen}$).

In addition, the results of the paired Wilcoxon signed-rank test in Table 16 indicate that with high confidence (at least 98%), $M_{CaX-Cen}$ is more correlated with the number of bugs than M_{X-Cen}. The confidence increases to 100% for almost every scenario when considering equalities. In general, metrics derived from the modified networks which consider calibrated edge weights are more correlated with the number of bugs than the same metrics derived from the corresponding networks which do not.

Table 16. Confidence that $M_{CaX-Cen}$ is more correlated to the number of bugs than the corresponding M_{X-Cen}

	$M_{CaX-Cen} > M_{X-Cen}$
Camel 1.4.0	98.98%
Flume 1.5.0	99.96%
Tika 1.6	99.97%

Similarly, we also compute the average recall and the average FPR of $\Phi(M_{CaTRN})$, $\Phi(M_{CaDCN})$, $\Phi(M_{CaMDN})$, $\Phi(M_{CaSTN})$, and $\Phi(M_{CaDN})$. The results are shown in Table 17 through Table 19. For example, in Table 17, the average recall and FPR of $\Phi(M_{CaTRN})$ are 71.50% and 4.59%, respectively. As stated previously, the average recall and FRP of the corresponding $\Phi(M_{TRN})$ in Table 9 are 69.79% and 4.60%, respectively. This indicates that the fault-proneness prediction models based on modified TRN which consider calibrated edge weights (i.e., $\Phi(M_{CaTRN})$) are more effective than the models based on the corresponding TRN which do not (i.e., $\Phi(M_{TRN})$) in terms of average recall and FPR.

In general, from Table 17 to Table 19, we observe that: (1) fault-proneness prediction models based on modified networks which consider calibrated edge weights (i.e., $\Phi(M_{CaX})$) are more effective than the prediction models based on the corresponding networks which do not (i.e., $\Phi(M_X)$) as shown from Table 9 to Table 11 in terms of average recall and FPR; and (2) $\Phi(M_{CaTRN})$ has the highest average recall and FPR among all modified networks.

Table 17. Prediction effectiveness of $\Phi(M_{CaTRN})$, $\Phi(M_{CaDCN})$, $\Phi(M_{CaMDN})$, $\Phi(M_{CaSTN})$, and $\Phi(M_{CaDN})$ with respect to average Recall and average FPR for Camel 1.4.0

Prediction Model	Average Recall	Average FPR
$\Phi(M_{CaTRN})$	71.50%	3.59%
$\Phi(M_{CaDCN})$	66.59%	4.69%
$\Phi(M_{CaMDN})$	27.77%	5.48%
$\Phi(M_{CaSTN})$	45.65%	5.53%
$\Phi(M_{CaDN})$	38.86%	6.47%

Table 18. Prediction effectiveness of $\Phi(M_{CaTRN})$, $\Phi(M_{CaDCN})$, $\Phi(M_{CaMDN})$, $\Phi(M_{CaSTN})$, and $\Phi(M_{CaDN})$ with respect to average Recall and average FPR for Flume 1.5.0

Prediction Model	Average Recall	Average FPR
$\Phi(M_{CaTRN})$	88.80%	3.93%
$\Phi(M_{CaDCN})$	80.73%	5.18%
$\Phi(M_{CaMDN})$	46.92%	9.10%
$\Phi(M_{CaSTN})$	65.75%	6.43%
$\Phi(M_{CaDN})$	54.61%	8.94%

Table 19. Prediction effectiveness of $\Phi(M_{CaTRN})$, $\Phi(M_{CaDCN})$, $\Phi(M_{CaMDN})$, $\Phi(M_{CaSTN})$, and $\Phi(M_{CaDN})$ with respect to average Recall and average FPR for Tika 1.6

Prediction Model	Average Recall	Average FPR
$\Phi(M_{CaTRN})$	65.73%	1.73%
$\Phi(M_{CaDCN})$	65.01%	2.25%
$\Phi(M_{CaMDN})$	41.66%	3.00%
$\Phi(M_{CaSTN})$	56.77%	2.24%
$\Phi(M_{CaDN})$	45.45%	1.75%

Moreover, the results of the paired Wilcoxon signed-rank test in Table 20 indicate that with high confidence (at least 96%), $\Phi(M_{CaX})$ is more effective than $\Phi(M_X)$ in terms of recall and FPR. If we change our alternative hypothesis to consider equalities, then the confidence is 100% for almost very scenario.

Table 20. Confidence that $\Phi(M_{CaX})$ is more effective than the corresponding $\Phi(M_X)$

		$\Phi(M_{CaX}) > \Phi(M_X)$
Camel 1.4.0	Recall	98.99%
	FPR	99.68%
Flume 1.5.0	Recall	96.88%
	FPR	99.99%
Tika 1.6	Recall	97.93%
	FPR	97.98%

***Summary with respect to R3*:**

- The developer risk score (DSR) which takes bug severity, program complexity, and development difficulty into account contributes to the network refinement and improves the effectiveness of software-fault proneness prediction
- Metrics derived from the modified network which considers calibrated edge weight using DSR are generally more correlated to the number of bugs than the same metrics derived from the corresponding networks which do not consider calibrated edge weight
- Fault-proneness prediction models using metrics derived from the modified networks which consider calibrated edge weight are more effective than prediction models using the same metrics derived from the corresponding networks which do not

CHAPTER 6

CONCLUSION AND FUTURE WORK

The more complex a software system is, the more likely programmers will make mistakes, introducing faults that can lead to execution failures. A risk in a software system can be viewed as a potential problem, and a problem is a risk that has manifested. In order to reduce the risk of software operations, software modules that have the potential to cause problems have to be identified so that necessary actions can be taken to prevent any such problems from occurring. This demand, in turn, has fueled the research and development of software fault-proneness prediction.

Aside from various techniques used for building/training a software fault-proneness prediction model, the key to conducting effective fault-proneness prediction is the software metrics used in the model. Although a vast amount of product and process metrics have been proposed in the past decades, there are still no decisive conclusions regarding their effectiveness in predicting fault-prone modules. A potential solution is to explore metrics that combine the strength of both product and process metrics. In other words, metrics that focus on the relations within/between software developers and modules should be taken into account. As a result, social network analysis can fulfill the need as it investigates not only the social organization of the work but also the technical information infrastructures.

Previous studies have shown that the developer contribution relation, module dependency relation, and developer collaboration relation have been used to build different networks for software fault-proneness prediction. However, these networks either use a single relation or a pair of relations. In addition, these networks appear to neglect an essential factor: developer

quality. After all, it is developers who make mistakes and introduce faults into software. Therefore, we propose TRN which integrates all three relations with additional information in a comprehensive network for effective fault-proneness prediction.

In a TRN, a developer contribution edge connects a developer with a software module if the developer has made a commit to the module between two consecutive releases. The weight on the contribution edge is set as the normalized number of commits made from the developer to the module. A module dependency edge in TRN connects a module to another if dependency exists between these two modules. Different from DN, two types of dependency: functional dependency (e.g., a file calls another file) and logical dependency (e.g., two files are modified in the same commit) are considered instead of just functional dependency. This provides a more accurate representation of module dependencies affecting the development effort. The weights for logical dependency between two modules are computed as the normalized number of times that these two modules are modified in the same commit. The resulting module dependency is computed as the sum of normalized functional dependency and normalized logical dependency. For the developer collaboration edge in TRN, it connects two developers if they have made at least one commit on the same module. The weight on collaboration edge is computed as the normalized number of modules two developers have worked on together.

In addition, we use DRS which computes the risk of a developer working on the modules to further calibrate the edge weights on TRN. The calibrated TRN is called CaTRN. DRS is based on two heuristics: (1) with respect to a given program, the more frequently a developer has introduced bugs in past releases, and the greater the severity of those bugs, the higher the risk that this program will contain a bug if this same developer makes a commit on the current

release; and (2) the greater the complexity of a program, the greater the difficulty a developer has in working on this program and the higher the risk that the developer will introduce a bug into the program. Specifically, we multiply the number of commits made by a developer by his/her DRS value to calibrate the weight on a developer contribution edge. We multiply the quantified dependency value for a pair of modules by the sum of DRS values of distinct developers who have worked on the two modules to calibrate the weight on a module dependency edge. And we multiply the number of modules on which two developers have both worked by the sum of DRS values of these two developers to calibrate the weight on a developer collaboration edge.

Four network node centrality metrics (i.e., M_{FDC}, M_{BP}, M_{EDG}, and M_{FNB}) are derived from the corresponding networks to predict the fault-proneness of a given file on three Java programs. M_{FDC} and M_{BP} focus on the number of developers and other modules it directly connects to, the impact of direct interactions on the module. More people working on the module, higher probability of introducing faults due to inconsistent coding style especially when these people have never worked/communicated with each other before. Due to the direct dependency relationship, more changes made on its neighbor modules higher probability that appropriate changes should be made on the module accordingly, thus more difficult to maintain the module. M_{EGD} and M_{FNB} focus on the connection strength of the module to all modules and developers that it either directly or indirectly connects to. The closer the module to other modules and developers, the stronger the connection, the more likely the module can be affected by other modules and developers in a way. The results of our study indicate that (1) TRN-based centrality metrics are more correlated with the number of bugs than the corresponding DCN-, MDN-, STN-, and DN-based centrality metrics as well as the ten software metrics that are commonly used for

software fault-proneness prediction; (2) fault-proneness prediction models using TRN-based centrality metrics outperform the models using DCN-, MDN-, STN-, and DN-based centrality metrics as well as the models based on ten commonly used software metrics; (3) centrality metrics derived from a modified network which consider calibrated edge weight using developer risk score are more correlated to the number of bugs than those derived from the same network which does not; and (4) fault-proneness prediction models using centrality metrics derived from a modified network outperform the models using centrality metrics derived from the same network which does not. In the future, we plan to repeat our study on a wider variety of programs and include additional software metrics for comparison to further validate the effectiveness of our TRN-based metrics. We also intend to search for potential intelligent algorithms to better train our prediction models. In addition, it is interesting to investigate whether our TRN-based centrality metrics can be used for cross-project software fault-proneness prediction when the historical information is limited or unavailable. Last but not least, we also plan to seek other superior mechanisms to further refine current networks.

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BIOGRAPHICAL SKETCH

Yihao Li was born in Nanchang, Jiangxi, China. After completing his schoolwork at No.1 Railway Middle School in Nanchang in 2005, Yihao entered East China University of Technology (ECUT) in Nanchang. He received a Bachelor of Science with a major in software engineering from ECUT in 2009. During the following one and a half years, he studied at Southeastern Louisiana University in Hammond, Louisiana and received a Master of Science with a major in computer science. In August 2011, Yihao entered the Graduate School of The University of Texas at Dallas.

CURRICULUM VITAE

YIHAO LI

EDUCATION

Ph.D. in Computer Science, University of Texas at Dallas, USA *Aug. 2011 – Aug. 2017*

- Dissertation title: Applying Social Network Analysis to Software Fault-Proneness Prediction
- Supervisor: W. Eric Wong

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RESEARCH INTERESTS

Software Fault-Proneness Prediction, Program Debugging, Quality Assurance, Metrics, Risk Analysis

SKILLS

Programming Language: Java, C#
Quality Assurance: JUnit, xSuds Toolsuite, HP LoadRunner, Understand, Ucinet,
Web Framework: .NET, Joomla
Database: MySQL, SQL Server

PROFESSIONAL EXPERIENCE

- **Academic Service**

– **External Reviewer**
- IEEE Transactions on Software Engineering (TSE)
- ACM Transactions on Software Engineering and Methodology (TOSEM)
- IEEE Transactions on Reliability (TR)
- Elsevier Journal of Systems and Software (JSS)
- Empirical Software Engineering (EMSE)
- Wiley Software Testing, Verification and Reliability (STVR)
- Springer Software Quality Journal (SQJ)
- IEEE International Symposium on Software Reliability Engineering (ISSRE)
- IEEE Computer Society International Conference on Computers, Software & Applications (COMPSAC)
- International Conference on Software Engineering & Knowledge Engineering (SEKE)

– **Conference Organizer**
- 2015, 2016, 2017 International Conference on Software Quality, Reliability, and Security (QRS)
- 2016 IEEE Conference on Software Engineering Education and Training (CSEE&T)
- 2014 IEEE International Conference on Quality Software (QISC)
- 2012, 2013, 2014 International Conference on Software Security and Reliability (SERE)
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- 2015, 2016, 2017 International Conference on Software Quality, Reliability, and Security (QRS)
- 2015 International Conference on Trustworthy Systems and Their Applications (TSA)
- 2012, 2013 International Conference on Software Security and Reliability (SERE)
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HONORS AND AWARDS

- IEEE Reliability Society Service Award
  2016, sponsored by IEEE Reliability Society Dallas Section
- Certificate of Appreciation for Computer Educators in Texas
  2016, sponsored by Association for Computer Educator in Texas
- Best Paper Award
  2012, sponsored by IEEE International Conference on Software Security and Reliability
- Best Student Paper Award
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Research Assistant
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CS6367: Software Testing
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PUBLICATIONS

Book

Chapter Author for "Handbook on Software Debugging− Foundations and Advances", by *Wiley-IEEE Press* (accepted for publication)

Journal Paper

- **Yihao Li**, Shou-Yu Lee, and W. Eric Wong, "Tri-Relation Network for Effective Software Fault-Proneness Prediction," *International Journal of Software Engineering and Knowledge Engineering* (under revision)
- W. Eric Wong, Ruizhi Gao, **Yihao Li**, Rui Abreu, and Franz Wotawa, "A Survey on Software Fault Localization," *IEEE Transactions on Software Engineering*, Volume 42, Issue 8, pp. 707-740, August 2016
- W. Eric. Wong, Vidroha Debroy, Ruizhi Gao, and **Yihao Li**, "The DStar Method for Effective Software Fault Localization," *IEEE Transactions on Reliability*, Volume 63, Issue 1, pp. 290-308, March 2014

Conference Paper

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