

1. Introduction

Software is a fundamental part of the modern life. We depend on the operation of software whether we are watching a video, traveling on a plane, calling a friend or using electricity power. Human life [1] and huge monetary losses [2] may be caused by issues that are not addressed in unreliable software components. Software quality assurance is the collection of activities that ensure the operations of software are complaint with the requirements [3]. Similar to all economical activities, software quality assurance is constrained by the budget of software projects. Efficient allocation of software quality assurance resources is crucial for the development of more reliable software. Development of a large software is beyond the technical capabilities of a single person or a few people. For this reason, large software is built and tested through the collaboration of many developers. Efficient coordination of the developers during the software quality assurance activities is one of the fundamental problems of software engineering.

Delivering a software bug-free is practically impossible since due to budget and time constraints exhaustive testing is not practical . Software are released with an unknown amount of inherent issues. It is a common belief in software engineering that as the number of eyeballs increase bugs become easier to notice [4]. Therefore after the release of a software, one of the most important part of software quality assurance is the publicly available issue management systems. In the issue management process, developers own (or get assigned to) issues reported by testing teams or software users. The key problem of this process is assigning the right developer to the right issue and showing the defect-prone parts of the software to the developers. In organizations twenty five percent of the time is spent while waiting for decisions [5]. We may improve the efficiency of issue management process by building an automated issue recommendation system to reduce the idle waiting time.

1.1. Software Networks

Large software can be classified as complex systems. Artificial and natural complex systems arise from the nature of the relations between many relatively simple entities [6]. Graph is a useful abstraction in computer science used to model complex systems and it is widely used in a range of application areas [7, 8, 9, 10]. In recent years, there has been considerable interest in modeling different complex systems as networks. Various researchers examined the network properties in order to identify similarities among networks from diverse domains [9]. Scale-free networks are a group of networks that are from different domains, and they surprisingly share similar properties [8]. Networks such as academical collaboration, epidemics, world wide web and internet routers show some similar properties such as power-law degree distribution and low network diameter[8]. In the software domain, researchers have found that many dependency networks of large software systems are scale-free networks [11].

In software engineering, research on software networks goes back to early 1980s [12]. In the early years, most of the research has been on building the dependency graph for various programming languages and execution environments. Over the years, interest of researchers moved to investigating the relation of the dependency network and software quality. Therefore, various researchers extracted metrics from dependency graphs based on common global and local properties of the graphs.

More recently, the edits on same software modules have been used to construct a collaboration network among developers similar to scientific collaboration network. This information has been used in empirical context in research on defect prediction models [13] and exploratory studies [14]. One reason behind this surge of interest may be the emergence of global software development [15]. Software network has been mostly studied for exploratory research previously. In this research, we used the software network to model the relation of issues with developers using the co-edits on same defective software modules related to the same category of issues to form the collaboration links among developers.

1.2. Issue Recommendation System

Recommendation systems are a subclass of information filtering system that predicts the rating or preference of a user for an item [16]. The recommendation system we propose is made of two core components namely bug triager and a live defect predictor. Bug triage is defined as assigning a developer to the most relevant issue based on past data [17]. Previous research shows that assigning a bug report to an owner takes five minutes per report on average for large software [17]. For popular projects, this task may make up the entire workload of several people. Previously, bug triage problem has been addressed by estimating the text similarity among issues [17]. This approach has various shortcomings such as language and dependence on issue report content [17]. In our proposed recommender system, we categorize the issues based on their content markings. For each category, we rank the developers based on their collaboration activity and recommend new issues based on this ranking.

Live defect prediction is the prediction of defect-prone modules related to an issue. A defect predictor can be used to present defect-prone modules to the assigned owner of an issue. In most defect prediction models the output of the model is provided at a special snapshot such as the production release or beginning of testing phase [18]. In our model we extend the machine learning based model by using the historical defect proneness data of related software modules using the call-graph of the software to provide defect prone modules *live* (at any point during development).

In order to build such a recommender, the mapping between the issues and defects has also been investigated in order to understand their relation with each other. In addition a new defect predictor has been built in order to detect defective modules live at any point during software maintenance.

If we examine the successful applications of AI that are widely used in practice, we observe that most of them need minimum interference by their users [16]. Successful applications such as movie recommenders, machine translators, image recognizers fit easily to the existing work flow of the users. Since the most common element in the

work flow of developers regarding quality assurance is issue management system, we believe that a practical recommendation system should fit easily to the issue management process. In order to make our issue recommender easily pluggable to the issue management software, we use data that can be extracted with automated tools from the issue and source code repositories.

1.3. Contributions

In this research we built an issue recommendation system using the collaboration network and the call graph of the software in order to increase the efficiency of resource allocation during the software quality assurance activities. Contributions of this research can be summarized as follows:

- *Model the software as the combination of developer collaboration network and the call graph:* We modeled software as the combination of developer collaboration and software call-graph networks. Collaboration is defined as the activity on the similar software modules by two developers during a release. Call graph is formed by the caller-callee relations of software modules. We showed the static and temporal properties of the software collaboration network for a large scale software and their relation with software issues.
- *Build an issue recommendation system using developer collaboration network:* Developer collaboration network shows the experience and centrality of developers within the organization. We used the symptom and category information of the issues to categorize the past issues and built the collaboration network for each cluster. Our model ranked the developers based on their centrality within the collaboration network and recommended the new issue reports based on the ranking.
- *Address developer workload balance problem using the issue recommendation model:* We extended the issue recommendation model to address the issue workload balancing problem. Issue workload balancing is a critical problem in real projects. We initially showed that in two large software, issues are distributed non-uniformly among maintainers especially during the times when active issue count is highest.

One problem of the base recommendation model was the lack of workload balance among developers that may occur when the recommendations of the model were used for issue assignment. We used an approach based on heuristics in order to overcome the problem of issue workload imbalances. Model that used workload balancing heuristics performed worse than the model with no heuristics but distributed issues more uniformly than the original model. Imbalances of the actual issue assignments may be the possible reason for the reduction of performance.

- *Usage of Kronecker networks to estimate the future collaborations of new developers:* Cold start is a common problem in recommender systems and it happens when a new user or item (issue) is added to the system. In our recommender, we solved the item(issue) cold start problem with a content based approach. We categorized the new issue into an existing category and afterwards ran the recommender algorithm.

Recommending new issues to developers is a more serious problem for the issue recommender. It is part of the problem of introducing new people to existing software development teams. As the project progresses initiation of new people gets harder. There is a lot of knowledge to be transferred to the new people reducing the productivity of both old and new employees during initiation. Fred Brooks claims that the addition of new people may even cause later project delivery dates [19].

We used the Kronecker network to address the new people cold start problem in the issue recommendation system. We used a parametric modelling method proposed by Leskovec Et al. [20, 21, 22] named Kronocker network to model the future state of the software collaboration network. We chose Kronecker graph generator since it is the only method that produce networks that conform all the properties of scale free networks. Kronecker networks are formed by fitting Kronecker parameters to the actual network and recursively replicating stochastic Kronecker kernel adjacency matrix by a matrix operation called Kronecker product.

The Kronecker network approach can be used to recommend issues only to a new group of developers since the node labels of the generated network can not be inferred. The state of the future collaboration network can be estimated using

the Kronecker parameters and issues can be recommended to the new group of developers.

- *Live defect prediction:* In traditional defect prediction models the defect prone-ness prediction for software modules is given for certain snapshots during the software project life-cycle such as the release revision or beginning of the testing phase to help managers allocate their testing resources. However, data that is comprised of defect prone modules is also valuable for developers at any time during maintenance. We updated the predictions of the machine learning based prediction model based on the live history of the software modules in the software call-graph to show the defect prone software modules any time during development.
- *Empirical analysis of the issue recommendation system and the live defect prediction model:* In our research, we collected the development data of one industrial large-scale software developed at five international sites as a dataset. The software is produced with the collaboration of more than two hundred developers. We extracted all the issue, collaboration activity and all the code change information over a time span of five years which includes two major releases of the product. We tested the issue recommendation model and its extensions on the extracted datasets and compared its performance with actual issue assignments. We showed that our model performance is better than the state of the art text similarity based issue recommendation systems. We showed the performance of Kronecker networks in addressing the people cold-start problem and the performance of the workload-balancing recommendation system extensions.

2. Problem Definition

Most of the management decisions in software engineering are based on the perceptions of the people about the state of the software and their estimations about its future states. Some of these decisions are; resource allocation, team building, budget estimation and release planning. There are many models and applications in both academia and industry that provide estimations about an aspect of the future state of a software [23]. While useful, most of these models do not recommend actions. In other words, these models mostly act like automated analysts but lack actual management support functionality. Two key reasons of this problem are modeling different aspects of software incompletely and providing output with little information content. Therefore, a problem in software engineering is modeling people, process and product (3P) with a more holistic approach.

In our work, we intend to provide a recommendation system whose output can be directly used to take actions. For this goal, we employ a model of the software that includes information about all aspects of 3P. The problem addressed by this dissertation can be divided into two dimensions: 1) Understanding the structure of software networks, 2) Building a recommender system that helps efficient issue management.

2.1. Understanding the Structure of Software Networks

In this dissertation work we model software projects as two distinct interlinked networks of developers and information elements (software modules) respectively. These two networks, namely the information network and collaboration network, can be seen in Figure 2.1. The *collaboration network* models the cooperation between developers, whereas the *information network* models the dependency relations among the software modules. These two networks together, provide us an abstraction of the software in the form of a *software network*.

The *information network* is a directed network which is based on the relations

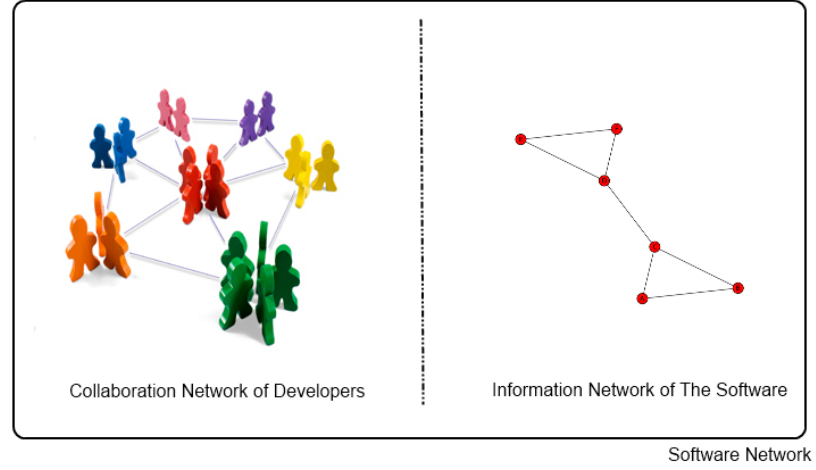


Figure 2.1: *Software network* is represented by the combination of its two underlying networks. a) *Collaboration network* models the interaction among developers, b) *Information network* models the relations between software components.

among software modules. An arc forms from software module a to software module b if a can call b at one point in its execution. The *collaboration network* is an un-directed network in which nodes are developers. An edge forms between two developers if they have contributed on a piece of software at one point.

The nodes in the collaboration network works on a subset of the information network of software modules at a given time . This information is represented in our model by links between software modules and contributor programmers. In the model, software quality is measured by number of defects found in a software module.

Once these two models have been built we aim to investigate the relation of information and collaboration networks in software with software quality. In addition, by modeling how the *software network* model evolves we aim to predict its future states. The *software network* model covers all aspects of 3P. The state of the *information network* provides information about the the product, the state of the *collaboration*

network provides information about people and the evolution of these networks provides information about the processes.

Previously these two networks were mined separately to the best of our knowledge. The evolution of these network has not been modelled either.

2.2. Recommendation System For Issue Management

Defect prediction models provide a list of defect prone modules. However, they recommend no actions about how or by whom to handle them. While in theory providing successful results, defect prediction models face challenges when actively used in practice. One probable reason of these challenges is the difficulty of fitting defect prediction to the existing development environment in an organization.

Issue management is the central element of the software maintenance operations. A practical recommender system should be easily pluggable to the issue management system. Therefore, we propose a recommendation system that triages issues and recommends files that contain defects related to issues. In Figure 2.2 two main parts of the issue recommendation model can be observed. First part of such a system is the bug triage component. The problem of bug triage has been tackled by various researchers as a text mining problem previously [17] [24]. However, to the best of our knowledge no one used past development activity of developers and the issue timelines in triage. After assigning a bug to a developer, the first thing the developer will need would probably be the defective code relevant to the issue. In order to answer this problem we propose a live defect prediction model that predicts the defect prone modules that are relevant to the developer. We believe that with its two components such a model would provide a major boost to the productivity of developers without requiring any input or change to their processes.

In order to develop such a recommendation system one needs to understand the relations between issues and defects and how the issue reports get generated. Therefore our research questions regarding the recommendation model are as follows:

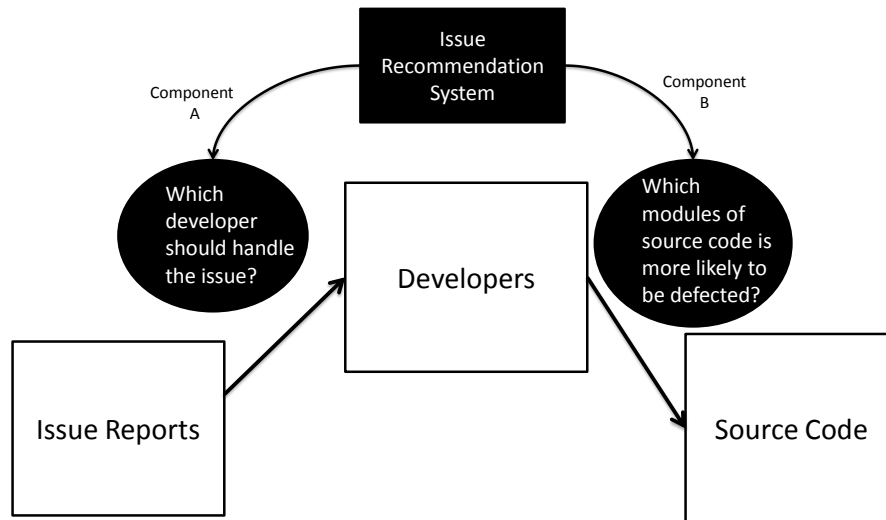


Figure 2.2: The recommendation system and its two components. Component A recommends an issue that is most relevant to a developer. Component B recommends the part of source code that possibly contains a defect related to that issue.

- (i) How can we assign issues to developers?
- (ii) How can developers more efficiently organize their time in solving their issues?

3. Background

The main goal of this dissertation is aiding the process of issue management through an automated issue assignment recommender. In the following section we discuss the literature related to the topics of issue management and defect prediction models. Following these sections we briefly discuss the general literature on recommender systems. We use the software networks of organizations in the issue recommender. For this reason, lastly, we provide an overview of the literature on software networks through a literature survey.

3.1. Issue Management

Issue management systems of large open source software projects have become publicly available since the early 1990s. Issue management systems of some applications with commercial licenses are publicly available to make their issue handling process transparent for their users. Research on issue repository data has started in parallel with the public availability of past software issue management data [25].

Notable areas of research related to issue management include reopened issues, automated issue triage, factors that change the quality of issue reports, detection of duplicate issues and estimation of the issue fix durations [17, 26, 27].

Issue reopening is defined as the process of activating issues that have been previously categorized as fixed. The reopened issues may be an important problem in issue effort management and software quality. Various researchers analyzed issue reopening cases and its possible causes. Shihab et al. [28] analyzed work habits, bug report, bug fix dimensions for Eclipse Project to find the factors that contributed to bug reopening and built a *reopened bug prediction model* using decision trees. Shihab et al. found that *the comment text, description text, time to resolve the bug and the component the bug was found* were the leading factors that caused bug reopening for Eclipse [28]. On the other hand, Zimmermann et al. [29] analyzed Windows Vista and

7 issue repository and conducted a survey on 394 developers in order the important factors that causes bug reopens [29]. Zimmermann et al. built a logistic regression model in order to identify the factors that may cause issue reopening. In their research Zimmermann et al. used organizational and process related factors in addition to factors directly extractable from the issue report. In their logistic regression model nearly all the factors they observed were found to be significant which included factors related to location, work habits and bug report characteristics. We replicated the work of Shihab et al. and Zimmermann et al. on a large scale commercial software [30]. Our results indicated that centrality in the issue proximity network and developer activity are important factors in issue reopening.

One important related research topic about issue repositories is the problem of automated *bug (issue) triage*. Bug triage is the procedure of processing an issue report and assigning the right issue to the right developer. This problem is especially important for large software with millions of users. Anvik et al. found that 300 daily reported issues makes it impossible for developers to triage issues effectively for Mozilla based on an interview with an anonymous developer[17, 31, 27]. Zhang et al. studied the social network of issue reporters and developers to propose a bug triage model [32].

Text mining methods have been used in several studies to find the most relevant developer to handle the bug in the proposed automated bug triage models [17, 24, 33, 34, 35]. Bakir et al. proposed a model that forwarded auto-generated software fault data directly to the relevant developers by mining the patterns in the faults[36]. Measuring the performance of an automated bug triage model is complicated. The benefit is often measured as the percentage of actual owners estimated by the model and the decrease in issue reassignments or *bug tosses*. However, research community is divided about the implications of *bug tosses*. While bug triage studies claim that bug tossing is time consuming, [24], Guo et al. observed on Microsoft Vista dataset that the issue reassignment is in some cases not a problem but beneficial to communication[37].

Effective issue reporting is important for reporters as much as it is for the developers. In an exploratory study, Windows Vista issue repository has been studied

extensively by Guo et al. in order to identify the characteristics of bugs that are getting fixed [31]. Bettenburg et al. also analysed the components of the bug report (such as severity information, stack traces, build information and screenshots) that make a bug more likely to be resolved [26]. They investigated the components of a bug report that are most useful to developers through surveys and data analysis, and built an automated recommender to issue reporters that reminds them to complete missing elements.

Duplicate issue reports are the ones with the same content but different wording. Particularly in popular software, duplicate issues may lead to re-work. Wang et al. proposed a novel method to detect these duplicate reports [38] by mining past issue reports. The model compares a new bug with the patterns of existing bugs and checks if the new bug is a duplicate or not.

The estimation of the issue resolve times is another research area. It is useful for developers in planning their effort and for users in planning their work related to the issue. Giger et al. used k-Nearest Neighbor algorithm to estimate the issue fix times in JBoss project[39]. Weiss et al. used decision trees to estimate the issue fix times on Eclipse, Mozilla and Gnome[27].

3.2. Defect Prediction In Software Engineering

Defect prediction in software engineering can be tracked down to the early work done by researchers in the seventies [40, 41]. In one of the earliest studies Akiyama et. al. found that 23 defects per kLOC occurred in Fujitsu software systems. Using simple linear regression Akiyama proposed a simple defect prediction model for software systems by using LOC as a complexity measure[40]:

$$\text{Defect Count} = 4.86 + 0.018 * LOC \quad (3.1)$$

Over years more complicated metric sets have been proposed by researchers and

various machine learning algorithms have been tried to predict defects on module level. Proponents of defect prediction claim that defect prediction enables better test resource allocation in real software systems[23]. Compared to manual code inspection using static code attributes in defect prediction yields 15 percent better testing efficiency on the average [23]. Some researchers question the general applicability and merits of existing models [42]. A critique of existing defect prediction models in software engineering has been done by Fenton et. al. [42, 43]. Hall et al. gives a structured literature review of the research on defect prediction models [18].

3.2.1. Models In Defect Prediction Studies

Several models have been used in previous defect prediction studies in the literature[23, 44]. Some researchers proposed regression based models using very few metrics or using only LOC [45, 46].

One of the most robust models used in defect prediction is naive bayes. It is shown to be robust on imbalanced datasets. In a benchmark study by Lessmann et. al. it was shown that top 12 algorithms including naive bayes has no statistically significant difference in prediction performance [44]. This can be due to limited information content of static code attributes.

3.2.2. Metric Sets Used In Defect Prediction Studies

3.2.2.1. Static Code Metrics. Static code metrics can be defined as the code metrics that are extracted from the source code in a software project. The major metric sets defined in previous works can be listed as follows[41, 47, 48, 49, 13]:

- **Halstead Metrics:** Halstead metrics are proposed by Halstead in his seminal work about empirical software engineering [41]. They are among the first defined metrics for defect prediction and are used in many regression and classification based defect prediction models [41]. Halstead determines the complexity of a software system by counting the combinations of elements in it. Operands, oper-

ators and statements and derived metrics about their relationships make up the Halstead metric set [50]. Basic metrics of Halstead can be listed as follows:

- (i) total number of operators
- (ii) total number of operands
- (iii) unique number of operators
- (iv) unique number of operands

In appendix B full list of Halstead basic metrics have been explained in detail.

- **McCabe Complexity Metrics:** McCabe metrics are proposed by Thomas McCabe for predicting complexity in a software system by traversing the control flow graph[47]. McCabe metrics provide another view of complexity of software systems from the branching structure of the source code modules. The base McCabe metric is cyclomatic complexity. Cyclomatic complexity is computed using the control flow graph of the program. The nodes of the graph correspond to indivisible groups of commands of a program, and a directed edge connects two nodes if the second command might be executed immediately after the first command. Cyclomatic complexity may also be applied to individual functions, modules, methods or classes within a program. Cyclometric complexity can be computed by formula 3.2 where $v(G)$, e and n denotes complexity of the graph, number of edges and number of nodes respectfully.

$$v(G) = e - n + 2 \quad (3.2)$$

Other metrics of McCabe are derived from cyclomatic complexity of source modules. In appendix C full set of McCabe complexity metrics is given.

- **Chidamber-Kemerer (CK) Metrics :** In the 90s object oriented programming paradigm became the dominant software construction methodology. Chidamber and Kemerer in their seminal work proposed a new metric set based on the class hierarchies and class structures in OOP software[48] In CK metrics, relationships and couplings between objects and classes in an OOP software are counted as a complexity measure. Depth of class hierarchy is measured by calculating depth of the inheritance tree of the classes. In appendix C full set of basic CK metrics are given.

3.2.2.2. Churn (Repository) Metrics. Software version repositories hold a wealth of information that has been harnessed in defect prediction work by researchers[49, 51]. Usage of repository information for defect prediction is a relatively new approach in defect prediction studies and was pioneered by Nagappan and Zimmermann as an alternative software model to static code metrics[49, 51]. In this metric set changes in software modules in terms of software modules are quantified. Change as a changed lines of code is used as an important metric called software churn. Relation of developers to software modules in terms of unique committers and inequality of commit effort is also used in the feature selection.

There are studies that focus on other factors affecting an overall software system such as the dependencies, code churn metrics or organizational (repository) metrics related with the development process [49, 52]. Results of these studies show that the ability of process-related factors to identify failures in the system is significantly better than the performance of size and complexity metrics. Zimmermann and Nagappan challenged the limited information content of data in defect prediction [49, 51]. The authors proposed to use network metrics that measure dependencies, i.e. interactions, between binaries of Windows Server 2003. Results of their study show that the network metrics have higher performance measures in finding defective binaries than code complexity metrics. Moser et al. also used repository metrics and they concluded that repository metrics give better prediction results than static code metrics [53]. In Moser et al.'s work only post-release defect data of Eclipse Project defects are extracted. They trained and tested on the same release. They also applied a cost sensitive classification approach to improve the performance of their model. They stated that cost sensitive approach would be hard to implement in real life. It is also difficult to derive clear conclusions from their results such that whether the cost sensitive classification or usage of repository metrics improved the results. In another study the effect of number of committers have been investigated in a large scale commercial project. The outcome of this study revealed that the number of developers did not have any effect on the defect density [54]. In a recent study decrease in pf rates by using repository metrics have been realised in open source software [55]. That study provide a basis for our Eclipse experiments.

3.2.2.3. Social Network Metrics. Social network metrics consist of the metrics found by modelling development effort of a software in a collaboration graph and calculating common graph metrics like degree, closeness and betweenness [13]. There are just a few works about the usage of social network metrics in defect prediction. Results of these works are not conclusive about the inclusion of these metrics. In their study Meneely et. al. formed a network by examining collaboration at file level and within a release period [13]. Metrics proposed on file level collaboration in this study can be listed as following: When using logistic regression Meneely found that degree and closeness are the most important metrics among several candidates of history and static code metrics.

- (i) **Closeness (max,sum,min,avg)** : Shortest path between one vertex and another vertex
- (ii) **Degree (max,sum,min,avg)** : Number of edges connected to each developer.
- (iii) **Betweenness (max,sum,min,avg)** : Number of geodesic paths including node v divided by all possible geodesic paths.
- (iv) **Number of hub developers** : Number of distinct hub developers who update this file. Hub developers are selected by calculating degree of developers at project level and finding developers with max 10 % of edges.

Weyuker also used developer information and collaborations as metrics on a large scale AT& T project for defect prediction. As a result of the study, using logistic regression no significant improvement on prediction performance of predictors have been realised [56].

Also social network metrics have been used for examining the project governance types in open source software[57, 58]. In this study types of networks that occur in open source projects are associated with the governance types.

3.2.3. Limitations of Defect Prediction Models

Over more than thirty years researchers have proposed defect prediction models using different metric sets, algorithms and data processing techniques with considerable success [18]. However, all defect prediction models have several common limitations which prevent their more general adoption by the software development organizations. We list the main limitations of defect prediction models as follows:

- (i) **Data Collection Challenges:** Data collection is an important barrier for software organizations. For organizations with limited defect tracking capabilities, Turhan et al. proposed cross-company prediction which eliminated the need for defect tracking by using other training datasets [59]. Even with cross company predictors challenges for metric extraction persists.
- (ii) **Lack of Integrated Tool Support:** There is no integrated tool which provides a solution for the measurement and analysis needs with predictive capabilities in the same package. Companies have to manually integrate tools which supports one part of the problem. We built an integrated solution to address this problem [30].
- (iii) **Lack of Information content:** In most cases defect prediction models provide only defective/non-defective predictions for software modules. The content of the output recommends no action for the practitioner. Category based defect prediction can be tried to address a part of this challenge [60].
- (iv) **Focus on Management of the Testing Process:** Benefits of defect prediction is explained in terms of the increase of efficiency in testing resource allocation. However, defect prediction output is also valuable for developers who touch a piece of source code during the product lifecycle. A *live defect predictor* is proposed in this dissertation which updates the model run at any point in time for the developer.

3.3. Recommendation Systems

Recommendation systems attained their current popularity with the popularity of world wide web. One of the common properties of web based recommendation systems is their non-obtrusive nature. Popular sites like stackoverflow, amazon and google employs recommendation systems which guide user decisions with minimal effect on the core functionality [61].

We can group recommendation systems as collaborative, content based and hybrid [62]. The basic idea of collaborative recommendation systems is that if users shared the same interests previously, the previous choices of one user is likely to be chosen by the other *similar* user if he or she has not made the same decision yet. One common method to estimate the similarity is nearest neighbor algorithm. Collaborative recommendation systems are content independent in their nature. All we know is a list of ratings of the users to independent items. Although, such systems provide a robust solution which may eliminate human intervention, pure collaborative recommenders may omit simple clues that can easily be extracted from content. For example, a user who bought science fiction novels in the past may be more likely buy science fiction novels rather than nineteenth century Russian literature. Some problems in collaborative recommender systems include data sparsity, cold start and rating subjectivity. Data sparsity happens when the ratings of users for a lot of items are not defined. Estimating the similarity gets complicated for users who had made a few choices in the system previously. In addition rating based system can be exploited easily by people with malign intentions.

Content based recommenders extract key attributes of the content and offers similar content, based on user's past selections[62]. For example, for a user who likes James Bond movies, the content based recommendation system will likely recommend movies from the spy film genre. There is more human intervention in content based recommenders compared to collaborative recommenders since certain content modelling should be done in model construction. The most important problem of content based recommenders is extracting the important attributes from the content items. Another problem is, similar to collaborative recommender systems, making recommendations

to people with no history in the system. The classic defect predictor in the software engineering literature may be classified as a content based recommender.

There is a final category of recommender systems which uses a hybrid of collaborative and content based approaches [62]. In these recommenders, content knowledge is mixed with the collaborative recommender to use the strengths of collaborative and content based approaches. We believe that the recommender system in our dissertation fits into this category. We used this approach because a content-agnostic approach is not possible in our domain. We do not have the ratings of developers on each issue and every issue is recommended only once by the system. Therefore, there is a issue cold start for every recommendation. In our recommendation we model collaboration implicitly based on code level interaction among people since issue ownership is a non-collaborative activity.

One key problem in most recommendation systems is cold start [63]. Cold start is a special case of the data sparsity problem. It happens when initiating a new user or a new item to the system. In our case since every issue is a new issue we cold start in each issue recommendation. In addition we discuss the problem of new user initiation in our domain for our recommender.

3.4. Literature Survey on Software Networks

A structured analysis of existing literature about social networks, dependency networks and their relations to software quality has been conducted. We used the approach proposed by Brereton Et al. [64] during the survey.

The main motivation in the literature review was highlighting the open problems in the area which have not been addressed by previous research. We focused on two groups of papers in the literature review:

- (i) Papers that analyze the social network of developers and their effect on software quality.

- (ii) Papers that analyze the call-graph of source code and their effect on software quality.

3.4.1. Search Criteria

We queried four well-known online research paper repositories, namely, IEEE Explorer of IEEE, ACM Digital Library by ACM, Springer archive and Elsevier Science Direct. We also manually browsed four major software engineering journals, namely, ACM Transactions on Software Engineering and Methodology (TOSEM), IEEE Transactions on Software Engineering (TSE), Software Quality Journal (SQJ) and Empirical Software Engineering (EMSE). We could not do a full backtrack search of the cited papers from the group of papers initially reachable due to time constraints.

Since some of the terms in software engineering are used interchangeably I constructed my search queries accordingly. I did my survey on learning from connected instances more informally due to time constraints. I limited the publication years to 2000 and onwards. My justification for this short time span is the relative freshness of the topic since the seminal papers that defined the area were published in late nineties. I queried all repositories with similar queries. Our queries in the analysis were as follows:

- (i) ((software engineering) AND ((call graph) OR (dependency)) AND (quality))
- (ii) ((software engineering) AND ((social network) OR (dependency) AND (quality)))

After filtering irrelevant papers, we had 24 papers from the repositories based on my search criteria. In the following sections we will first summarise the papers reached. Afterwards we will analyze some selected papers in depth.

3.4.2. Survey Results

In Table 3.1 an overview of each publication filtered is provided. Properties of the papers are given with the appropriate code values. Overall with 1 exception all the sur-

veyed articles are from 2000s with a higher number of papers from recent years. 7 of the publications were published in scientific journals, 14 are from conference proceedings and 3 are from trade magazines. The distribution among social network and call-graph analysis papers is even with 11 from each type. None of the papers discussed both networks in the same publication or used both networks in a predictive context. In 6 of the papers complex network research has been used and complex network research has been applied to call-graphs. No complex network paper analyses social network of developers. 10 of the papers can be categorized as predictive studies. None of the studies used graph based machine learning algorithms. Every paper analysed instances independently and did not consider inter-instance relationships.

We chose 4 papers based on their relevance to the dissertation for a more detailed review. Following is a brief review of the papers. In Table 3.1 we denoted the papers with in-depth review as alpha.

The first paper we overview is "Mining edge-weighted call graphs to localise software bugs" by Eichinger Et al. [12]. It is the only paper using graph learning techniques in defect localization (prediction) to the best of our knowledge. Eichinger used a dynamical call graph and tried to locate the bugs in software by analysing stack traces. Eichenger weighted directed edges by considering how often they execute during faulty and normal runs. For example a dependence relation which is only executed in faulty runs is given the highest possible weight. 3 programs developed at Siemens and written in C language were used as benchmarks. The dynamical call graph is formed artificially by giving the system different inputs. One limitation of this work is usage of dynamical call-graph. Gathering dynamical call-graph data can be unrealistic (test runs) or impossible (when customer does not share data) in most scenarios.

The second paper we overviewed is "An empirical study of speed and communication in globally distributed software development" by Herbsleb Et al. [15]. Herbsleb Et al. investigated the relations between distributed software teams, increased software development costs and reduced productivity. He also examined if works in different sites can be interdependent and how may the interdependence diminish over time. The

data from 2 multi-site companies have been used as input. Data was collected by surveys and from change management systems. Majority of surveyers point to difficulty of communication between sites. The two surveyed companies could not reduce interdependence of tasks between different sites in the projects. As a result they found that teams located at different sites have reduced overall efficiency by examining the software changes. The study can be extended by proposing ways for effective communication and ways to make tasks independent in order to increase the effectiveness of distributed software teams.

The third paper we overviewed is "Power laws in software" by Louridas Et al. [65]. Lauridas Et al. examined the power-law relation of dependency networks on a variety of open and closed source systems and found that the power-law relation (cx^{-k}) holds for every examined system. One important benefit of finding common patterns in software systems is being able to apply solutions for the common pattern generally.

The last paper we overviewed is "An Empirical Study of the Factors Relating Field Failures and Dependencies" by Zimmermann Et al. [66]. Zimmermann Et al. analysed if there is a correlation of defect proneness between software modules having dependency relations. The results seems to be contradictory in open source project Eclipse and Microsoft Windows. In Microsoft Windows Vista there is no correlation of defect proneness among dependent modules while in Eclipse there is a positive correlation. Investigating the mechanics behind this can be an interesting addition to this work.

After the analysis, we had 2 conclusions about the open problems in the area:

- (i) Lack of an integrated models: None of the researchers examined both the social network and dependence network as a whole.
- (ii) Instances are assumed to be independent: Relational learning has not been tried in software engineering domain.

Table 3.1: Summary of The Literature Survey: Explanation of properties: β -empirical work, λ -social network paper, γ -call graph paper, α major publication analysed in depth, $\sqrt{}$ -estimation, \diamond scale free networks, ϵ evolution of software systems **MAG**-magazine, **JOU**-SCI Journal, **CON**-Referreed conference

	Paper Code	Authors	Paper Name	Publication Year	Published In	Properties
[67]	Applewhite2004	Applewhite, A.	Whose bug is it anyway? The battle over handling software flaws	2004	IEEE Software Vol. 21(2), pp. 94-97	MAG λ
[68]	Barbagallo2008	Barbagallo, D., Francalenei, C., Merlo, F.	The impact of social networking on software design quality and development effort in open source projects	2008	ICIS 2008 proceedings, pp. 201	CON $\lambda \epsilon \beta$
[69]	Benestad2009	Benestad, H.C., Anda, B. Ar- isholm, E.	Understanding software maintenance and evolution by analyzing individual changes: a literature review	2009	Journal of Software Maintenance of Software Maintenance(September), pp. 349-378	JOU ϵ
[26]	Bettenburg2010	Bettenburg, N., Hassan, A.	Studying the Impact of Social Structures on Software Quality	2010	2010 IEEE 18th International Conference on Program Comprehension, pp. 124-133	CON $\beta \lambda \sqrt{}$
[12]	Eichinger2008	Eichinger, F., Bhm, K., Huber, M.	Mining edge-weighted call graphs to localise software bugs	2008	Machine Learning and Knowledge Discovery in Databases, pp. 333-348	CON $\alpha \epsilon \beta \sqrt{}$
[15]	Herbsleb2003	Herbsleb, J., Mockus, A.	An empirical study of speed and communication in globally distributed software development	2003	IEEE Transactions on Software Engineering Vol. 29(6), pp. 481-494	JOU $\alpha \beta \lambda \sqrt{}$
[70]	Ichii2008	Ichii, M., Matsushita, M., Inoue, K.	An exploration of power-law in use-relation of java software systems	2008	Software Engineering, 2008. ASWEC 2008. 19th Australian Conference on, pp. 422-431	CON $\diamond \sqrt{} \beta \gamma \gamma$
[71]	Ko2008	Ko, A.J., Myers, B.A.	Debugging Reinvented : Asking and Answering Why and Why Not Questions about Program Behavior	2008	Human-Computer Interaction, pp. 301-310	JOU $\lambda \gamma$
[72]	Krinke2008	Krinke, J.	Mining execution relations for crosscutting concerns	2008	Software, IET Vol. 2(2), pp. 65-78	MAG $\gamma \beta \gamma$
[73]	Law2003	Law, J., Rothermel, G.	Whole program path-based dynamic impact analysis	2003	25th International Conference on Software Engineering, 2003. Proceedings. Vol. 6, pp. 308-318	CON γ
[65]	Louridas2008	Louridas, P., Spinellis, D., Vlachos, V.	Power laws in software	2008	ACM Transactions on Software Engineering and Methodology Vol. 18(1), pp. 1-26	JOU $\diamond \gamma$

[14]	Madey2002	Madey, G., Freeh, V., Tynan, R.	The open source software development phenomenon: An analysis based on social network theory	2002	Americas Conference on Information, pp. 1806-1813	CON $\beta \diamond \lambda$
[13]	Meneely2008	Meneely, A., Williams, L., Snipes, W., Osborne, J.	Predicting failures with developer networks and social network analysis	2008	Proceedings of the 16th ACM SIGSOFT International Symposium on Foundations of software engineering, pp. 13-23	CON $\beta \lambda \checkmark$
[74]	Palmer1994	Palmer, T., Fields, N.	Computer supported cooperative work	1994	Computer Vol. 27(5), pp. 15-17	MAG λ
[75]	Petersen2010	Petersen, K.	Measuring and Predicting Software Productivity: A Systematic Map and Review	2010	Information and Software Technology	JOU $\diamond \checkmark$
[76]	Turhan2008	Turhan, B., Kocak, G., Bener, A.	Software Defect Prediction Using Call Graph Based Ranking (CGBR) Framework	2008	2008 34th Euromicro Conference Software Engineering and Advanced Applications, pp. 191-198	CON $\beta \gamma \checkmark$
[77]	Wang2009	Wang, L., Wang, Z., Yang, C., Zhang, L., Ye, Q.	Linux kernels as complex networks: A novel method to study evolution	2009	2009 IEEE International Conference on Software Maintenance, pp. 41-50	CON $\diamond \gamma$
[11]	Wen2009	Wen, L., Dromey, R.G., Kirk, D.	Software engineering and scale-free networks.	2009	IEEE transactions on systems, man, and cybernetics. Part B, Cybernetics : a publication of the IEEE Systems, Man, and Cybernetics Society Vol. 39(4), pp. 845-54	JOU \diamond
[78]	Wolf2009	Wolf, T., Schroter, A., Damian, D., Nguyen, T.	Predicting build failures using social network analysis on developer communication	2009	Proceedings of the 2009 IEEE 31st International Conference on Software Engineering, pp. 1-11	CON $\beta \lambda \checkmark$
[79]	Xie2006	Xie, T., Pei, J.	MAPO: mining API usages from open source repositories	2006	Proceedings of the 2006 international workshop on Mining software repositories, pp. 54-57	CON β
[80]	Yang2007	Yang, B., Cheung, W., Liu, J.	Community Mining from Signed Social Networks	2007	IEEE Transactions on Knowledge and Data Engineering Vol. 19(10), pp. 1333-1348	JOU $\beta \lambda \gamma$
[81]	Zimmermann2009	Zimmermann, T., Nagappan, N.	Predicting defects with program dependencies	2009	2009 3rd International Symposium on Empirical Software Engineering and Measurement, pp. 435-438	CON $\beta \gamma \checkmark$

[66]	Zimmermann2010	Zimmermann, T., Nagappan, N., Williams, L., Herzig, K., Premraj, R.	An Empirical Study of the Factors Relating Field Failures and Dependencies	2010	Proceedings of the 4th International Conference on Software Testing, Verification and Validation	CON $\alpha \beta \gamma \checkmark$
[57]	Ohira2005	Ohira, M., N. Ohsugi, T. Ohoka, and K.-i. Matsumoto	Accelerating cross-project knowledge collaboration using collaborative Filtering and social networks	2005	MSR	CON $\beta \lambda$

4. Proposed Solution: Collaboration Based Issue Recommender

In this research, we propose an issue recommender model which uses the software network (call-graph and collaboration network) and software module metrics as input to help developers in organizing their time more effectively while handling software issues. In addition, our recommender can be extended to propose solutions for workload imbalances, employee turnovers and team size changes during maintenance. Ease of extendibility and ease of deployment were the two design goals during the construction of the recommender.

Most of the maintenance operations during the software development life cycle are done reactively i.e. developers work on quality issues as new issues are reported by the users or the testing teams. We observe that the issue management software is the central element of the maintenance operations. We believe that an artificial intelligence based solution which aims to help maintenance of complex software systems should be easily pluggable to the issue management software. During the life-cycle of an issue, it is owned and resolved or terminated in some other way by a developer. A practical recommender plugged to the issue management software can help the ownership and the resolve activities.

We propose a solution which can be used both to recommend issues to developers and to recommend defect prone modules related to an issue to developers. Our solution can be easily integrated to the issue management software and it is independent of the context of the new issues except category information. Our approach and its key differences with the existing solutions in this domain can be explained in three parts:

Issue Recommender: Previous bug triage systems use the unstructured text data in issue reports extensively [17]. These recommenders match new issues with developers based on the text similarity of the issues with the past issues owned by developers. Instead of unstructured text data which may be unreliable in the cases where multiple languages are used, we focus on the activity on the software modules related to different

issue categories. We use the collaboration data on the software modules related to the issues to link the issue reports with new developer groups. Our model ranks developers based on their ranks in the collaboration network. A key strength of our recommender is that we can highlight all the relevant developers to a newly reported issue. Another key strength of our approach is the relative simplicity of the data extraction step since the model uses structured data instead of free format text as the input.

Extensions of the Basic Model: The proposed issue recommender can be extended to eliminate load balancing problem. In a recent study we observed that, the issues owned by developers are distributed non-uniformly particularly during times when many new issues are reported [82]. This trend is not sustainable in the long run since it indicates over-dependence on a few individuals in large projects. We propose to handle workload imbalances in our model by limiting the number of active issues that can be assigned to a developer.

Cold start is a common problem in recommender systems. Cold start is a special case of data sparsity and occurs when new items or users are introduced into the system. Another extension of the model is its ability of recommending issues to a new group of developers. Existing solutions can not handle the cases of user cold start [17]. They can not propose issues to the new developers since, they do not have the activity history of the new developers. We use the stochastic Kronecker networks to model the collaboration network and predict the future collaboration network by using the kernel stochastic adjacency matrix [22]. We use the future network to predict the collaboration structure of a new group of developers and recommend new issues to a the new group based on the predicted future collaboration structure.

Live Defect Prediction: Existing defect prediction models attempt to provide a list of defect prone software modules for the testing teams to help using their testing resources more efficiently [18]. The target users of these models are software testers and testing managers in the companies. In contrast, our proposed model highlights the defect prone modules related to a new issue to help issue resolve activity. Our target users are the developers who maintain software. For this aim, we update the

original predictions of our defect predictor based on historical data during any point during maintenance to highlight the defect prone modules for the developers. We use the software call-graph to weight the defect proneness of nearby software modules.

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