A Probabilistic Model for Software Defect Prediction

Thesis Proposal

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1. Introduction

Search-Based Software Engineering (SBSE) is an emerging area of research, where search-based optimization techniques are applied to the Software Engineering problem domain. SBSE problems include The Next Release Problem, Structural Test Data Generation, and Software Cost Estimation[5].

To make SBSE of practical use on a software project, a method is needed to model the practical details of a project in an abstract way so that is amenable to search-based optimization. In this paper, such a model is developed toward making use of algorithms developed for the Next Release Problem (NRP).

In the NRP, proposed features have an associated cost, so that an optimal feature subset can be selected. Now it might be suggested that the estimated cost of a proposed feature can be used directly in a NRP algorithm. But, there is a practical detail that prevents this: the total cost of a feature includes both the cost of implementation *and* the cost of fixing associated defects.

Of course, defects that will be associated with a feature are not known in advance, so determining their exact cost would be impossible. But if associated defects can be predicted, then the cost of such defects can be estimated.

To this end, a model is proposed for predicting the defects associated with some proposed feature, with some level of confidence. The model will be probabilistic, and will be built using a software project's historical data, available from an issue tracking database.

Exploratory data analysis was conducted on a software project, MongoDB, in order to asses the feasibility of such a predictive model.

The remainder of this document is organized as follows. First, the Background section provides details on the Next Release Problem and the methods used software project data collection. Next, the Related Work section describes other approaches used in defect prediction, which mainly center around static code analysis. Then, the Exploratory Data Analysis section presents the methods used, and results obtained for exploratory data

analysis. Finally, the Proposed Work section lays out the specific tasks that are proposed in order to design an effective predictive model, in the context of the results obtained from exploratory data analysis.

2. Background

In this section, first the Next Release Problem will be introduced and described more formally. Then, the methods used for collecting historical data from software projects will be discussed.

2.1. The Next Release Problem (NRP)

The Next Release Problem (NRP) was defined by Bagnall et al[2], and was shown to be NP-Hard. Being abstract in its treatment of feature cost, a broad range of optimization techniques can be applied to the NRP, such as integer programming, hill climbing, simulated annealing, genetic algorithms, etc. The NRP is the subject of academic research in the area of Search-Based Software Engineering[7, 9, 10].

The NRP is designed to aid software project planners, who have multiple customers to satisfy. The project planner would like to maximize the revenue produced from completing the project. This is all described mathematically as follows.

A software project has a set R of all possible requirements (new features and enhancements) that might be included in the next software release. A customer i is satisfied by completing a subset $R_i \subseteq R$. The importance of a customer i is given by the weight, $w_i \in \mathbb{Z}^+$.

Requirements may have acyclic dependencies, or prerequisites, that must be completed first. A subset that includes all prerequisite requirements, recursively, is indicated by $\hat{R}_i$, and should be taken to mean

$$\hat{R}_i = R_i \cup ancestors(R_i) \tag{1}$$

For example, if $R_1 = \{r_2\}$, and r_1 is a prerequisite for r_2, then $\hat{R}_1 = \{r_1, r_2\}$.

A requirement $r \in R$ has a cost $cost(r) \in \mathbb{Z}^+$, associated with its implementation, not considering the cost of any prerequisite requirements. Then, the cost for some subset $R' \subseteq R$ will be

$$cost(R') = \sum \{cost(r) | r \in \hat{R}_i\} \tag{2}$$

Once customer i is satisfied, their weight w_i contributes to the total revenue from the project, as in

$$\sum_{i \in S} w_i \tag{3}$$

So, the NRP is posed as follows: for a group of n customers, select the subset $S \subseteq \{1, 2, ..., n\}$ that maximizes total revenue, while keeping the total cost within some budget

constraint B. This is given by

$$
\begin{aligned}
maximize \quad & \sum_{i \in S} w_i \\
subject\ to \quad & cost(\bigcup_{i \in S} \hat{R}_i) \leq B
\end{aligned}
\tag{4}
$$

2.2. Issue Tracking Systems

The empirical data used to establish a predictive model will be taken from software project historical data, found in an Issue Tracking System (ITS). In addition to tracking bugs, past and present, an ITS can be used to track features, enhancements, or any other type of software process issue.

3. Related Work

Software defect (bug) prediction typically involves a detailed analysis of code or proposed design changes. Akiyama [1] predicted defect counts based on lines of code (LOC), number of decisions, and the number of subroutine calls. Gafney [3] likewise predicted defect count based on LOC. Rather than code itself, Henry and Kafura [6] define metrics that are based on information taken from design documents, to be used in defect prediction.

TODO: discuss more about the above methods

3.1. Other Approaches to Defect Projection

Rather than requiring a detailed code analysis to predict defects, the approach proposed in this paper is to develop a mathematical model based on historical data on defect occurrences. Specifically, the proposed approach is to develop a prediction model using software features as inputs and defects as outputs.

A related approach, used by Li et al.[8], is to study only the defect occurrences themselves, and attempt to develop a mathematical model for defect projection. In their work, functions were fitted to a time series of defect occurrences, then the function parameters themselves were extrapolated for each new release. They found that the Weibull model fit best in 73% of the tested software releases. They attempted to extrapolate model parameters using nave methods, moving averages, and exponential smoothing, but found these techniques to be "...inadequate in extrapolating model parameters of the Weibull model for defect-occurrence projection". The reason given for this ineffectiveness is the changing nature of the software development system For example, development practices, staffing levels, and usage patterns may all change between releases.

In another related approach, Graves et al.[4] develop several models that predict the future distribution of software faults in a given code module. The basis of their predictive models is a statistical analysis of change management data, which describes only the changes made to code files. The best model they found, was a weighted time damp model, where every change in the module files contributed to fault prediction, with

time-damping to account for age of changes. They achieved "slightly less successful performance" by basing a generalized linear model on just the modules age and the number of past changes. They also found factors that did not improve model performance: module length, number of developers making changes in the module, and how often a module is changed simultaneously with another module.

4. Exploratory Data Analysis

This section covers the exploratory data analysis which was performed to asses the feasibility of developing a predictive model for software defects. In this section, first the methods used to collect and analyze the data are presented. Then the analysis results are presented and interpreted.

4.1. Data Collection

The MongoDB project was selected for exploratory data analysis. The criteria for project selection, and also the methods used, are explained in the following subsections.

4.1.1. Project Select Criteria

To facilitate data collection, only projects that have a freely accessible Issue Tracking System (ITS) were considered. Included in this category are open-source software projects. Also, only projects with a consistent and transparent release policy were considered. Last, a long history of project data was an important consideration. MongoDB met all these considerations.

4.1.2. Data Collection Methods

Data collection is semi-automatic. First, there is a manual step is to export data from JIRA as XML. Then, pertinent data is automatically extracted using a Python script and then saved as a delimited table text file for later analysis in R. The pertinent fields to extract were: issue type, priority, and time to resolve (in days).

4.2. Data Analysis

Historical data from each software project was analyzed over both the long term (all releases) and short term (each significant[1] release period). The long-term analysis will provide an overview of each project, and possibly reveal some consistent patterns between projects. The short-term analysis will serve to isolate each significant release period as a cause-and-effect period (changes being the causes, and bugs being the effects).

Before presenting the results of data analysis, next the data analysis methods are discussed.

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[1]For the MongoDB project, a significant release period is comprised of an odd/even-versioned release pair (e.g. 2.1 and 2.2). The odd-versioned release is unstable, for development work, and the even-versioned release is for bug-fixing only.

4.2.1. Data Analysis Methods

Project historical data was analyzed as follows. First, for each period of analysis, data was be separated by category: first, by issue type, and then by priority. The remaining data attribute was the time to resolve (in days). Once separated, each data group was summarized using frequency count and descriptive statistics, represented visually and numerically. Last, a good-fitting probability distribution was found for each data group, and shown set against a histogram of the data.

4.3. Results

The analysis results presented are broken up into subsections for long-term and short-term analysis. Following each will be interpretation of the results.

4.3.1. Long-term Analysis Results

TODO

4.3.2. Short-term Analysis Results

TODO

5. Proposed Work

The Next Release Problem (NRP) is not readily applicable to the release planning process in a software project. This is due to the abstract nature of the NRP. But by modelling the practical details of release planning, the way could be paved for making use of optimization techniques already developed for the NRP.

Feature cost is a critical part of the NRP. An inaccurate cost estimate might mislead a project planner into believing that a feature subset can be implemented inside the budgeted constraint when that may not be the case. And because the cost of fixing defects contributes to the total cost of a feature, the cost of fixing defects should be accounted for.

To this end, the work proposed here is to develop a model for predicting the defects associated with some proposed feature, with some level of confidence. The model will be probabilistic, and will be built using the same data collected for Exploratory Data Analysis.

The breakdown of this work, and the timeline for completing it are discussed next.

5.1. Modelling Work

The modelling work itself can broken up as follows:

1. **Select candidate model structures**. There are potentially many different model structures that can be used. Several structures will be put forth as likely candidates for a model.

2. **Optimize model parameters**. For each candidate model structure, parameters will be chosen using Maximum Likelihood Estimation (MLE).

3. **Validate model**. Models will be validated by: TODO

5.2. Timeline

The proposed modelling work is to be completed over the winter quarter in 2015. A timeline of this work, along with the up-front work of forming a committee and presenting this proposal, is listed in Table 1 below.

Table 1: Timeline for proposed work

Task	Start Date	End Date
Form committee	Nov 10	Dec 5
Present proposal	Jan 6	Jan 16
Respond to committee feedback	Jan 19	Jan 23
Select candidate model structures	Jan 26	Feb 13
Optimize parameters and validate models	Feb 9	Feb 27
Repeat procedures for two more SW projects	Mar 2	Mar 20

A. Software Requirements

The software developed so far has been used for data collection and analysis. The scripts used can be run on any platform that supports Python and R. Besides this basic requirement, here are the other dependencies:

Python dependencies:

- docopt: for defining command-line interfaces and parsers. See the GitHub page for installation instructions.

- BeatifulSoup: for processing XML files. See the support page for installation instructions.

R dependencies:

- devtools: adds github_install function. Install by running "`install.packages("devtools")`" on the R command line.

- docopt: for defining command-line interfaces and parsers. See the GitHub page for installation instructions.

References

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[10] Y. Zhang, M. Harman, and S. A. Mansouri. The multi-objective next release problem. In *Proceedings of the 9th annual conference on Genetic and evolutionary computation*, pages 1129–1137. ACM, 2007.