



Neural Network Based Bug Priority Prediction Model using Text Classification Techniques

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Abstract: As open source software systems are becoming larger and more complicated, the task of bug detection and fixing to improve the performance of the software is also getting more complex, time consuming and inefficient. To improve the quality and efficiency of the software, developers allow users to report bugs that are found by them using bug tracking system such as Bugzilla. In Bugzilla users specify the details of the bug, such as the description, the component, the version, the product and the severity. Depending on this information the developers assign the priority levels to the reported bugs. The task of prioritizing the bug reports is manual, therefore it is time-consuming and inconsistent. In this dissertation, Neural Network technique is used for developing prediction models for five different versions (2.0, 2.1, 3.0, 3.1, and 3.2) of Eclipse that will assign the priority levels based on the information provided in each bug report. The features that potentially affect the priority of a bug are temporal, textual, author-related, severity, product and component. Collected dataset is used to train and test the classification algorithms. ROC and F-measure is used to interpret the results.

Keywords: Neural Network, Priority Prediction, Machine Learning, Textual Analysis, MLP, Naïve Bayes, Eclipse, Bugzilla.

1. INTRODUCTION

In the present scenario, there are situations where the size of the software is increasing at an exponential rate and that implies complexity too is growing. As a result, defects enter the software and lead to functional failures. Furthermore, the defects that are initiated by the software are of varying severity levels. There are various bug tracking systems that contain detailed information about these defects along with their ID's and associated severity level. These defects range from mild to catastrophic based on their effects, wherein catastrophic defects are most severe defects and may lead the entire system to go to a crash state. Hence, the defects introduced in the software should be assigned priority levels which will help in investigating bug reports easily by their priority.

There are considerable amount of resources that are involved in software improvement. The task of assigning priority to reported bugs is by and large a manual one and accrues the cost of billions of dollars every year. Still, many software systems are released with defects due to lack of testing. Therefore, to improve and address upcoming versions, developers need to get feedback on defects that are present in released systems [1]. Thus, depending on the complexity of the software system, developers allow end users to report defects using bug reporting systems such as Bugzilla, Jira et al. It is a standard practice in both open source software development and closed source software development. Bug tracking systems help in continuous monitoring and reporting of bugs [2]. Machine learning techniques are just the right kind of algorithms that make the task of bug prediction and classification straightforward and efficient. Further, to enhance the efficiency of a bug classifier by using feature extraction techniques that will help in supplying the refined information to the machine which is achieved by using text mining algorithms. Text mining algorithms extract keywords from bug reports by picking up high importance words- these processed words along the original bug reports are used to improve the accuracy of a classifier. Our approach predicts the priority level of bug reports from Bugzilla using text classification

method considering several factors/fields that affect the priority of a bug report. These factors are as follows [3]:

- Temporal: other bug reports that are reported at the same time as the bug report.
- Textual: the textual component of the bug report.
- Author: the author of the bug report.
- Related-report: related bug reports.
- Severity: the estimated severity of the bug.
- Product: the affected product in which the bug is invoked.

2. TEXT PRE-PROCESSING

The standard text pre-processing techniques are specifically used to extract the textual content of data into a set of features that are meaningful. These methods include tokenization, stop word removal, and stemming [4].

A. Tokenization: Tokenization is a process that is used to separate tokens from a textual document by splitting the text into tokens.

B. Stop-Word Removal: Stop words are removed as they might reduce the effectiveness of machine learning or information retrieval solutions due to their skewed distributions. There is a significant portion of such stop words including “am”, “are”, “is”, “I”, “he”, etc. These stop words should be removed from the set of tokens that are extracted through tokenization (in the previous steps).

C. Stemming: There are many forms of words; in English, grammatical rules dictate if a root word appears in singular, plural, present tense, past tense, future tense, or many other forms. Words beginning from the same root word yet are not identical with one another are semantically related, for example, in “write”, “writes” or “writing”. Stemming tries its best to reduce a word to its *ground* level form. For example, “usability”, “usable”, and “use” would all be reduced to “use”. In this work, Porter’s stemming algorithm [5] is used to process the text and is used many prior studies, for instance, [5], [6] and [7].

3. LITERATURE SURVEY

Till date, there are very few studies on finding such relationship taking the severity of faults into account. The most popular study in the field of fault severity has been done by the authors [8]. They analysed the performance of models at three levels of severity such as high, medium and low severity faults and concluded that the model predicted at high severity faults is less accurate as compared to the models predicted at other severities. It was summarised that the models predicted using DT and ANN methods are better than the models predicted using LR method. Also, it was seen that the metrics such as CBO, WMC, RFC and SLOC are necessary for the faults at all the severity levels. Support Vector Machine (SVM), cascade correlation network, group method of data handling polynomial method, gene expression programming) [9]. AUC calculated the performance from a ROC Curve. Many researchers use ROC curves for the modules for predicting fault-prone or not fault-prone [10].

The work was done [10] is similar to the work of Menzies [11]. Permata have also developed a model for the assignment of the bug severity level. They have used the same pre-processing tasks (tokenization, stop words removal and stemming) and feature selection method, but, have used SVM as their classification method.

In this study, [12] the authors automatically assign priorities to Firefox crash reports in Mozilla Socorro server based on the frequency and entropy of the crashes. When Firefox fails, crash reports are automatically submitted to the Socorro server, and it contains a stack trace and relevant information about the environment to help developers debug the crash. In the study, the authors investigated bug reports that are manually submitted by users. These reports are different from a crash report, a bug report contains natural language descriptions of a bug and might not include any stack trace or environment information. They employ a text mining based solution to assign priorities to bug reports. Some studies [13] group bugs into different categories. Huang et al. propose a text mining solution to categorising bug reports as either capability, security, performance, reliability, requirement, or usability related bugs.

In the year 2012, [14] Tian also predicted the severity of bug reports by using the nearest neighbor approach to predict fine-grained bug report labels. Different from work by Menzies which analyses a collection of bug reports in NASA, Tian applies the solution to a larger collection of bug reports consisting of more than 65,000 Bugzilla reports. Severity levels are given by users, while priority levels are assigned by developers. Severity levels relate to the impact of the bug on the software system as understood by users and priority levels relate to the importance bug reports that are received [15]. Tian [14] used automatically detects and analyse bug reports, which had been reported in the past seven days with severity levels, and taking these reports in consideration severity levels to newly reported bug reports are assigned. They determine the similarity between used duplicate bug reports with relative information and features. This similarity in information helps in assigning the severity levels accurately and quickly.

In the area of similar bugs, a study is presented by [16]. Some research in the field of bug triaging support by

recommending appropriate developers to fix a particular bug. Levenberg-Marquardt (LM) algorithm based on neural network predicts the software defects at an early stage of the SDLC is described by [17]. They use data available on the PROMISE repository of empirical software engineering dataset. The dataset uses the CK (Chidamber and Kemerer) [18] metrics. The study concludes that the Levenberg-Marquardt (LM) neural network based algorithm gives better accuracy (88.09%) as compared to every polynomial function-based neural networks (pF-NNs), linear function-based neural network (lf-NN) and quadratic function-based neural network (qf-NN) respectively. A defect prediction model using data mining. Gayathri [19] worked on an enhanced Multilayer Perceptron, Neural Network technique are proposed, in which comparative analysis of modelling of defect proneness predictions using a dataset of different metrics from NASA MDP (Metrics Data Program) was performed.

CART algorithm and Bayesian logistic regression. Kapila & Satwinder, in their study, use Bayesian inference with six individual software metrics for early prediction of the software fault. They use Bayesian inference model to identify a posterior probability of fault occurrence [20].

In [21] an approach is described for static reliability modelling, and for modelling of software reliability from software complexity regarding the predictive quality and the quality of fit. The performance is compared with more traditional regression modelling techniques. The work concluded that the neural network model is superior as compared to traditional regression-based techniques and had a less standard error.

Other tasks of Tian [14] presented an automated approach with the help of machine learning in suggesting a priority level by information in bug reports. They consider multifactor temporal, textual, author, related reports, product and severity, as potential factors, which affect the priority level of reported bug reports. They use these factors as features to train a model with the help of a classification algorithm (thresholding and linear regression), which can perform well in ordinal class labels and imbalanced data. They conducted their experiment on more than 100,000 reports collected from Eclipse. This experiment shows an improvement of 58.61% regarding average F-measure by outperforming baseline approach. [22] Extended their previous work by using extracted features to train a discriminative model via a new classification algorithm (linear regression) and their framework named DRONE. The new work provides a way to handle ordinal class labels and imbalanced data. They managed to improve their work on 100,000 bug reports from Eclipse regarding F-measure by 209%, which outperform baseline approach.

In addition to this, [23] presented an approach, in which they implement an improved method of detecting duplicate bug reports using the textual similarity features and binary classification. They used a total of 25 textual features, then run their classification method to categorise pairs of bugs into two types: duplicate and non-duplicate. They used new textual elements, derived based on text similarity measures, and trained several binary classification models. After training the models, they tested their work on bug reports collected from Eclipse, OpenOffice and Mozilla to analyse the effectiveness of the improved method. They also compared it with the current state-of-the-art and highlighted

the similarities and differences. They were able to achieve an improvement of 6.32% in duplicate bug report detection even without considering context-based features.

4. RESEARCH METHODOLOGY

Neural Network MLP (Multilayer Perceptron)

A neural network consists of a pool of simple processing units which communicate by sending signals to each other over a large number of weighted connections. Each unit performs a relatively simple job: receive input from neighbors or external sources and use this to compute an output signal which is propagated to other units. Apart from processing, a second task is the adjustment of the weights. The system is inherently parallel in the sense that many units can carry out their computations at the same time. Within neural systems, it is useful to distinguish three types of units: input units which receive data from outside the neural network, output units which send data out of neural network, and hidden units whose inputs and output signals remain within the neural network.

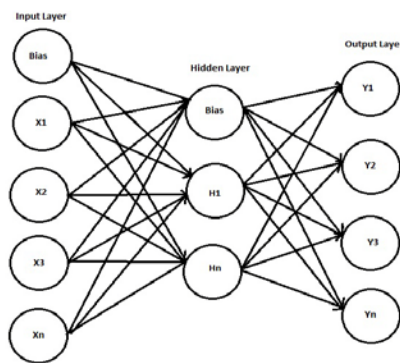


Fig. 1: General Architecture of Neural Network

The figure shows general architecture of neural network with one input, hidden and an output layer.

Mathematically,

$$\text{Net}_k = W_{1k}X_1 + W_{2k}X_2 + \dots + W_{mk}X_m + b_k$$

Sigmoid Activation Function:

The backpropagation algorithm focuses on the minimum error function in weight space. The error function is minimised by the combination of weights that are solutions of the learning problem. The activation function is used in perceptrons, because the composite function produced by interconnected perceptrons is discontinuous, and therefore the error function too. One of the most popular activation functions for backpropagation networks is the sigmoid, defined by the expression

$$S_c(x) = \frac{1}{1 + e^{-cx}}$$

The constant c can be selected arbitrarily and its reciprocal $1/c$ known as the temperature parameter in stochastic neural networks. The shape of the sigmoid changes according to the value of c , as can be seen in Figure 2.

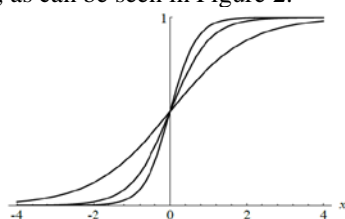


Fig. 2 Three Sigmoids for $c=1$, $c=2$, $c=3$

The graph shows the shape of the sigmoid for $c = 1$, $c = 2$ and $c = 3$. A higher value of c brings the shape of the sigmoid closer to that of the step function, and when $c \rightarrow \infty$ the sigmoid converges to a step function at the origin.

Naïve Bayes Classifier

Naïve Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem (from Bayesian statistics) with strong (naïve) independence assumptions. A more descriptive term for the underlying probability model would be "independent feature model". In simple terms, a Naïve Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature [28]. Depending on the precise nature of the probability model, Naïve Bayes classifiers can be trained very efficiently in a supervised learning setting. In many practical applications, parameter estimation for Naïve Bayes models uses the method of maximum likelihood; in other words, one can work with the Naïve Bayes model without believing in Bayesian probability or using any Bayesian methods [29].

5. EVALUATION MEASURES

Precision, recall, and F-measure, which are commonly used to measure the accuracy of classification algorithms, are used to evaluate the effectiveness of MLP and Naïve Bayes algorithms. In this work, precision, recall, and F-measure are used to evaluate the results for each of the priority levels. The same measures are used in the experiments of Menzies and Marcus to evaluate the results of Severis [11]. Mathematically, precision, recall, and F-measure can be represented as below:

1. Precision = $TP / (TP + FP)$
2. Recall = $TP / (TP + FN)$
3. F-measure = $2 * Precision * Recall / (Precision + Recall)$

Validation Method Used

In this section, for all the versions, both the algorithms are tested by performing 10-fold cross-validation tests with 10 repetitions, which means 100 runs for each combination. The process for cross-validation is chosen for this work because it is a standard that guarantees a stratified sampling of the dataset [24], [25] and reduces overfitting [26]. The performance values such as precision, recall, F-measure, area under ROC are produced with each run.

6. DATA COLLECTION

Eclipse projects focus on building extensible frameworks, tools and runtimes for building and managing software throughout its lifetime. It has many products and components. The versions that are selected for this work are 2.0, 2.1, 3.0, 3.1, and 3.2. There are five main products of Eclipse from which only three are selected for data collection process, namely JDT, PDE and Platform. The Bugzilla database contains all errors (bugs) that have been found in the lifetime of the Eclipse project with the detailed information that includes the release number, bug severity, summary, long description, priority, status, changed the date, reported date, the name of the reporter, etc.

7. RESULTS AND DISCUSSIONS

In this section, the results of various experiments carried out during the research are listed and discussed. The listed experiments were performed with the objective of

classifying the priorities of bugs using MLP and Naïve Bayes. The tests have been performed on five versions of Eclipse project viz 2.0, 2.1, 3.0, 3.1, 3.2.

Table 1: Results of MLP and Naïve Bayes for 10-fold cross-validation

Versions	Algorithms	Priority	Precision	Recall	F-measure	ROC	Algorithm	Priority	Precision	Recall	F-measure	ROC
2.0	MLP	P1	0.743	0.491	0.591	0.895	Naïve Bayes	P1	0.743	0.491	0.591	0.895
		P2	0.742	0.641	0.688	0.911		P2	0.742	0.641	0.688	0.911
		P3	0.944	0.981	0.962	0.986		P3	0.944	0.981	0.962	0.986
		P4	0.523	0.246	0.335	0.876		P4	0.523	0.246	0.335	0.876
		P5	0.600	0.851	0.703	0.924		P5	0.600	0.851	0.703	0.924
2.1	MLP	P1	0.200	0.033	0.056	0.597	Naïve Bayes	P1	0.200	0.033	0.056	0.597
		P2	0.725	0.458	0.561	0.809		P2	0.725	0.458	0.561	0.809
		P3	0.780	0.933	0.849	0.844		P3	0.780	0.933	0.849	0.844
		P4	0.000	0.000	0.000	0.514		P4	0.000	0.000	0.000	0.514
		P5	0.015	0.015	0.023	0.595		P5	0.015	0.015	0.023	0.595
3.0	MLP	P1	0.382	0.153	0.219	0.807	Naïve Bayes	P1	0.382	0.153	0.219	0.807
		P2	0.534	0.482	0.507	0.785		P2	0.534	0.482	0.507	0.785
		P3	0.876	0.913	0.894	0.913		P3	0.876	0.913	0.894	0.913
		P4	0.333	0.707	0.453	0.830		P4	0.333	0.707	0.453	0.830
		P5	0.000	0.000	0.000	0.868		P5	0.000	0.000	0.000	0.868
3.1	MLP	P1	0.000	0.000	0.000	0.742	Naïve Bayes	P1	0.000	0.000	0.000	0.742
		P2	0.613	0.795	0.692	0.860		P2	0.613	0.795	0.692	0.860
		P3	0.916	0.969	0.942	0.948		P3	0.916	0.969	0.942	0.948
		P4	0.188	0.053	0.082	0.720		P4	0.188	0.053	0.082	0.720
		P5	0.455	0.247	0.320	0.789		P5	0.455	0.247	0.320	0.789
3.2	MLP	P1	0.736	0.804	0.768	0.907	Naïve Bayes	P1	0.736	0.804	0.768	0.907
		P2	0.692	0.686	0.689	0.809		P2	0.692	0.686	0.689	0.809
		P3	0.872	0.895	0.883	0.951		P3	0.872	0.895	0.883	0.951
		P4	0.000	0.000	0.000	0.515		P4	0.000	0.000	0.000	0.515

It can be easily inferred from the above table that the model performs efficiently in classifying the priority P3. Priority P3 is the most abundant type of priority that has been found in the bug reports. The classifier also performs best in classifying P3 with an average precision of about 79 percent and a recall of about 80 percent (in Eclipse 2.0). The MLP based model is also performing efficiently in performing the classification of different priorities with ROC varying around 87.6 percent to 98.6 percent. The ROC values in this range denote good to excellent perceptiveness.

It can be easily inferred from the above table that the model performs efficiently in classifying the priority P3 and P5. The classifier also performs best in classifying P3 with an average precision of about 82.7 percent and a recall of about 80.9 percent (in Eclipse 2.0) which is 1.5 to 3 percent better as compared to MLP. The Naïve Bayes based model is also performing efficiently in performing the classification of different priorities with ROC varying around 89 percent to 98 percent. The ROC values in this range denote good to excellent perceptiveness. Therefore, it can be concluded that the results of both the algorithms are efficient for predicting bug priorities.

8. CONCLUSION AND FUTURE WORK

Bug reports of three components of Eclipse are chosen for this research, four main processes performed in experiments are: dataset acquisition, pre-processing, feature selection and classification. Then classification is done using MLP and Naïve Bayes and basis of precision and recall their performance is compared. The prediction models are developed with the 10-fold cross-validation. It was evident from the results that the model has performed very well in predicting the priorities.

The research used only five versions and three products of Eclipse project for bug priority prediction. Therefore in future, other products and versions of Eclipse, Mozilla et al may be used and cross component could be applied by creating a global dictionary of Eclipse.

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