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Mapping Bug Reports to Relevant Files and Automated Bug Assigning to the Developer

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ABSTRACT

Then bug means the coding mistake that occurs in the software developing stage. It may occurs because of many reasons and some of the reasons are version mismatch, network incompatibility, and unavailability of supporting documents. And bug report means a user level description about a bug. A bug report mainly having a bug id, summery about a bug and a detailed description about the bug. A tool for ranking all the source files with respect to how likely they are to contain the cause of the bug would enable developers to narrow down their search and improve productivity. The ranking is done on the basis of comparing the source code and the bug report, here 19 features are considering for the bug mapping procedure. And bug triaging refers to the process of assigning a bug to the most appropriate developer in order to fix the bug. The process of bug triaging is based on the interest of the developer and the bug mapping history of each developer. And also avoiding the chances of occurrence of duplication in repository. This method is very useful for java projects working in the netbeans, eclipse, tomcat platforms.

Keywords : Bug Report, Bug Mapping, Bug Triaging.

I. INTRODUCTION

Software bug which results in an incorrect output or unexpected output due to the error or failure in a computer program. To permanently cure a bug we need to change the program. New bugs can be introduced due to the bug fixing process, so it should be the one of the most important step. Most of the cause of the bug are due to the mistakes, errors or due to the components in the operating systems, unavailability of the supporting documents, network incompatibility. Some of them are due to the incorrect code, which is produced by the compiler. Buggy means a program will be containing a huge number of bugs and the will be adversely affecting the functionality of the program. Under a testing environment while in the testing phase when testing the software which is found out by the testers are list of bugs are known as bug report or issue report. The test environment will be similar to the original environment. In the development site the test environment is created similar to the actual environment in which the software is supposed to work or run in live scenario. Bug reports which is used for understanding the developers about the software product defects. Majority of the companies spend their time in resolving the bugs during their day-to-day process. The software companies will be having different teams and these teams will be receiving a large number of bugs. One of the most difficult tasks is that the finding the location of source files with the correct bug. In their daily process as they are receiving a large number of bug reports and it is challenging for them to analyse manually debug and resolve them. So here introducing an automatic system that can rank the

source code files with the relevant bug reports. From the source code will be taking the summary and description. Code and comments are extracted from the source code. This paper, which describes a methodology learning to rank files that is, ranking score, is computed by the weighted combination of the features. Features which specifies the relationship between the source code and bug report. Weights are trained on previously fixed bug reports. Here finding the similarity between the bug reports and the source code files and its methods, API similarities between the bug reports and source code files, semantic similarity between the bug report and source code files, computing collaborative score for recommending systems, bug fixing history, code change history, page rank score, hubs and authority score and local graph features by the dependency graph. That is obtaining ranking as which the pages that can occur the bug is being retrieved effectively. And also method for removing the duplicate bug reports. Manual bug assigning to the correct developer is expensive and usually results in wrong assignment of bug reports to developers. Proposing a method to automatically assign the bug reports to the correct developers by data reduction technique by feature selection that is, improving the quality of bug data. From the historical data sets we will be retrieving the attributes and constructing model that predicts the new bug set. We first applies feature selection technique to preprocess the textual information in bug reports, and then applies text mining technique build statistical models. The approach also includes the usage of the clustering to group the similar bug reports instead of random grouping that make it easy to assign the bug to the appropriate developer. For this process to take place, we have to label the clustered groups in the order of prioritization. Then, the labeled groups will be assigned to the correct developer based on the domain knowledge. The purpose of doing this automation is that if we are considering an example eclipse which will be created by a group of developers. When a bug is occurred that is it will be a bug which is not fixed. To assign whom is a huge work. This process is having overhead. Developers will be working on different modules. So to identify a particular person we should take the previous history, current and we should communicate with peer developers and users. After that we should recreate the problem from that only we can identify the bug. This is time consuming to assign the bug to correct developer within a short span of time. And also expenditure will be also high. Thus we are developing an effective bug system that is finding the relevant pages that can occur the bugs, removing the duplicate bugs, and assigning this ranked pages to the correct developers so they can fix the bug fastly and accurately which can reduce the time consuming. We perform experiments on six large scale open source java projects namely, Eclipse, Aspectj, Tomcat, SWT, JDT, Birt.

II. LITERATURE SURVEY

The paper 'Improving bug localization using structured information retrieval' which is written by Saha[1]. Here uses Bluir method in which source code will be taken as the input and then we will be creating abstract syntax tree (AST) using JDT (Java development toolkit) and parsing through the abstract syntax tree. Dividing the source code into four document fields class, variable, comment, and method. Then performing tokenization splitting into a bag of words using white spaces. And will be stored in the structured Xml document. Then it will be Units indexed into an array using an indexer. From the bug report extracting the summary and description. Performing tokenization as discussed above which is splitting into tokens by a bag of words using the white spaces. Bluir which outperforms bug locator and here computing the similarity between the features as a single sum is having less accuracy than our method. In this method using the fixed revision of source code is used for the evaluation of bug reports which can lead to very bad contamination bug reports in case of future fixing bug information. Next paper 'Where Should the Bugs Be Fixed?' which is written by

Zhou[2]. Here propose a bug locator which is a method for retrieving the information. This is done for finding the location of the bug files. This method ranks all files that is having a textual similarity between the bug report and the source code file using the vector space representation model(VSM). When bug is received we will be computing the similarity between the bug and source code using the similarity measures by analyzing the past fixed bugs. The ranked list of files will be in decreasing order. The top in the list are more likely to contain the result. If contains similar bugs then they are proposing another method that is, three layer heterogeneous graph. First layer which represents the bug reports. Second layer shows previously reported bug reports, and the last layer which is the third layer which represents the source code files. Major disadvantages to the work are if the developer uses non-meaningful names the performance will be severely gets affected. And also bad reports which can cause misleading of the information and also essential information can cause significant delay. And thereby performance will be affected. Next paper 'Mapping Bug Reports to Relevant Files: A Ranking Model, a Fine-Grained Benchmark, and Feature Evaluation' written by Xin ye[3] in this it is being done by using learning to rank algorithm. The ranking score is computed similarity between the source code files and the bug report. So for that using the feature extraction, extracting 19 features.

III. PROPOSED METHOD

For mapping bug reports to source code, first some preprocessing will done on the source code and the bug report. The source code contain the the code for the program and the commented description abiut a program. So we wants to perform the preprocessing on the code and the comments. In case of bug report it contain the summery about a bug and the description about a bug. The preprocessing on the bug report means, do all the preprocessing steps on the summery and the description. The below showing a bug report it having a bug id, summery and the description about the bug.

Bug ID: 339286
Summary: Toolbars missing icons and show wrong menus.
Description: The toolbars for my stacked views were: missing icons, showing the wrong drop-down menus (from others in the stack), showing multiple drop-down menus, missing the min/max buttons ...

Figure 1. Sample bug report

A Preprocessing

Preprocessing in which knowledge extraction is being done. From the bug report use both description and summary. From the source code file use the whole content code and comments. For tokenization we will be splitting into words by using the white spaces. Then we remove thee stop words, punctuation, numbers etc. all words are reduced using porter stemmer as the NLTK[1] package. And by using vector space modeling find out the vector values of each term in a document. By developing a vocabulary of the terms in a document.

In the preprocessing stage first step is to tokenize the bug report and source code then removing the white spaces and special characters in the code and the report. Then by using the If we regard the bug report as a query and the source code file as a text document, then we can employ the classic vector space model (VSM) for ranking, a standard model used in information retrieval. In this model, both the query and the document are represented as vectors of term weights. Given an arbitrary document d (a bug report or a source code file), compute the term weights for each term t in the vocabulary based on the classical tf.idf weighting scheme in which the term frequency factors are normalized. The term frequency can be determined by finding the number of occurrence of a term in a document based on the total number of terms in a document.

Surface Lexical similarity

For a bug report, we use both its summary and description to create the VSM representation. For a source file, we use its whole content—code and comments. To tokenize an input document, we first split the text into a bag of words using white spaces. We then remove punctuation, numbers, and standard IR stop words such as conjunctions or determiners. Cosine similarity function is used for checking the similarity checking between the source code and the bug report.

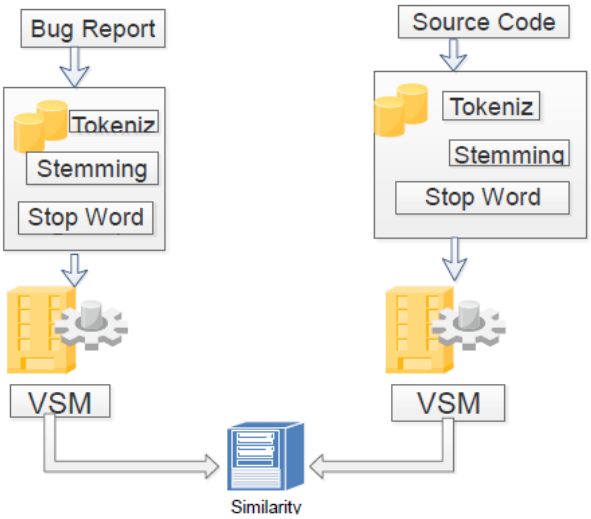

Figure 2

API enriched lexical similarity

Here find out the sematic similarity between the source code and the bug report is done. Which means some library function which including the information about button and user interfacing tools so such errors in the functions can be identified by using this Api enriched lexical similarity.

Collaborative Filtering Score

The file has be fixed before certain type of errors it can be identified by using this method consequently it is expected to be beneficial in our retrieval setting, too.

Class name similarity

Finding the class name similarity between the source code and the bug report. This feature having the high weightage than the all other feature evaluation technique. Both the summary and Description is used for the similarity checking.

Other features

i. Bug -Fixing Recency
ii. Bug-Fixing Frequent
iii. Summery class name Similarity
iv. Summery method name similarity
v. Summery variable name similarity
vi. Summery Comment name similarity
vii. Description class name similarity
viii. Description method name similarity
ix. Description variable name similarity
x. Description Comment name similarity
xi. Page rank score
xii. In-link dependencies
xiii. Out-link dependencies
xiv. Hub score
xv. Authority Score

Page rank score determine the complexity of a source code and it is based on the in-link and out-link dependencies.

The hub score and the authority score are based on the Hyper Linked Induced Algorithm.

A. Weight Computation

For this we are using TF-IDF for calculation. TF which indicates the number of occurrences of specific term in the document. IDF which indicates the number of documents that contain the specific term. After the TF-IDF calculation cosine similarity is being done. Cosine similarity is the similarity between the bug report and the source code file.

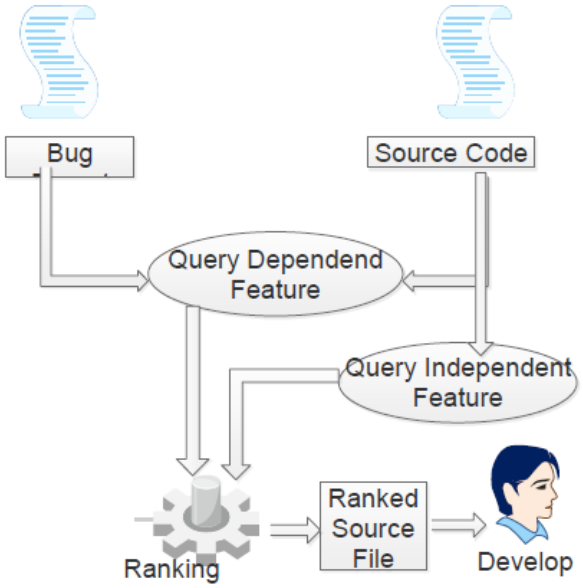

Figure 2. Bug mapping

B. Semantic Similarity

Semantic similarity between two words which means that the two words whose meanings are similar. To find out the meaning between bug report and source code file we use machine learning approach. There are two phases: training phase and testing phase. The training which consist of bug reports and corresponding bug ids which indicates the semantic similarity between bug reports and source code files. Every bug reports in the training data which indicates the set of features. At training time, we range all bug reports and feature extraction functions to compile a feature vector per bug report. The feature vectors are stored in a matrix. We train a supervised learning method from the features and the bug ids of the training examples As the bug ids in the evaluation set that we use are binary, we build a classifier. At testing time, features are generated for the bug ids in the test set in a similar fashion as in the training phase, and a final prediction is made with the classifier trained in the training step.

C. Assigning Correct Developer

In this system we are developing a model to directly assign the bug report to the correct developer. The ranked list of pages that can occur as bug will be given to the correct developer. So for this process to occur we will be performing data reduction. That is reducing the data and also removing the duplicate bug reports. The architecture of the system is shown below.

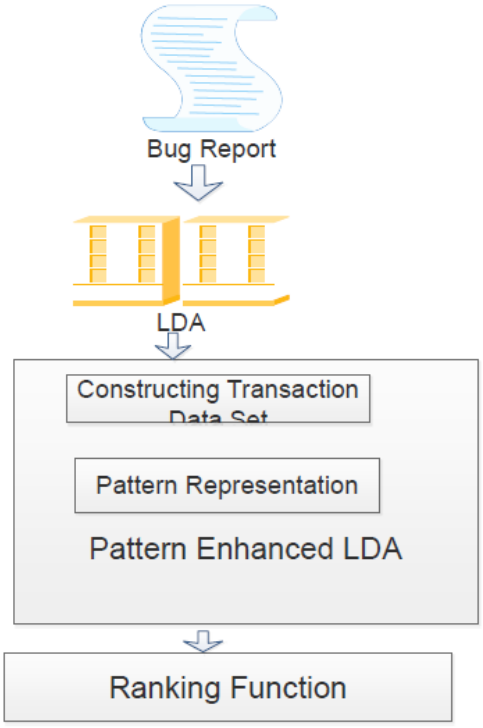

Figure 4. Assign to the Developer

IV. CONCLUSION

Through this work introduced an automated bug system which can be effectively used in the software companies. We will be getting ranked list of pages that can occur the bug and it will be automatically assigned to the correct developer who has developed the code. And also remove the duplication of the bugs. And also computed the semantic similarity between the bug report and source code file. From the previous experiments it was proved that learning to rank approach is having higher accuracy which is being used in our system. In the future work we can use additional types of domain knowledge such as stack traces and also features used in the defect prediction system. Also plan to use ranking svm in

nonlinear kernels. Also to find how to prepare high quality datasets.

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