Improving Software Defect Assignment Accuracy

With the LSTM and Rule Engine Model

by

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Submitted in partial fulfillment
of the requirements for the degree of
Doctor of Professional Studies
in Computing

at

Seidenberg School of Computer Science and Information Systems

Pace University

2019

We hereby certify that this dissertation, submitted by Robert Zhu, satisfies the dissertation requirements for the degree of *Doctor of Professional Studies in Computing* and has been approved.

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Abstract

After a software defect is reported with a title and a text description, a competent developer needs to be assigned to fix it. The accuracy of this assignment has big impact on the quality of the resulting software, and the speed of the debugging process. Traditionally this software defect assignment process is conducted by product managers based on his/her knowledge of the software and the developers, which is not very scalable. In the recent years, this defect assignment problem has been formulated as a problem of (1) feature extraction from the defect title and description, and (2) classification of the resulting feature sets to the developers. Machine learning has been used to automate this software defect assignment problem.

The research improves the existing approaches in automatic defect assignment by (1) improving the feature extraction by NLP and Vector for Words technology, (2) introducing rule-based engine aka expert system to better character the strength of each developer, instead of the traditional characterizing a developer only by the descriptions of the bugs he/she has resolved; (3) combining the two layers model of our model (Layer 1, NLP and Vector for Words and Layer 2, Long Short-Term Memory and Rule-based Engine).

The optimal results are achieved on the CHROME dataset based on our new model of Long Short-Term Memory(LSTM) with Rule-based Engine in comparison with the traditional ML model - Naïve Bayes model.

The proposed neural network model extracts text features on its own, considering not only the word order messages that the word bag model ignores, but also the grammatical and semantic characteristics of the text. Rule-based Engine has absorbed developers' history data, and activity information.

The structure of these two layers network model with Rule-based Engine is relatively simple, i.e. the model is parallel structure, ideal for parallel computing, plus a dedicated hardware processing accelerator GPU makes the model not only high accuracy, but also faster.

The new approach that we introduced in the research shows that it has better accuracy than traditional Naïve Bayes model and pure LSTM model.

The new model can expand and migrate the system to generic bug assignment problems. The model is expandable and migratable.

Acknowledgements

First and foremost, I want to thank my wife, my daughters and parents for putting up with my time spent on this dissertation. I can still hear the complaints from them pointing out another weekend thrown away. More importantly I want to thank Dr. Lixin Tao. His patience and guidance were the light that shone my path. Also, all my friends and family who kept asking me when the day would come, well, it finally comes.

Trademarks

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Chapter 1 Introduction

As the complexity of software continues to increase, the probability of software defects will increase exponentially. In order to ensure the quality of computer software and enhance the reliability and usability of software, software defects must be assigned accurately.

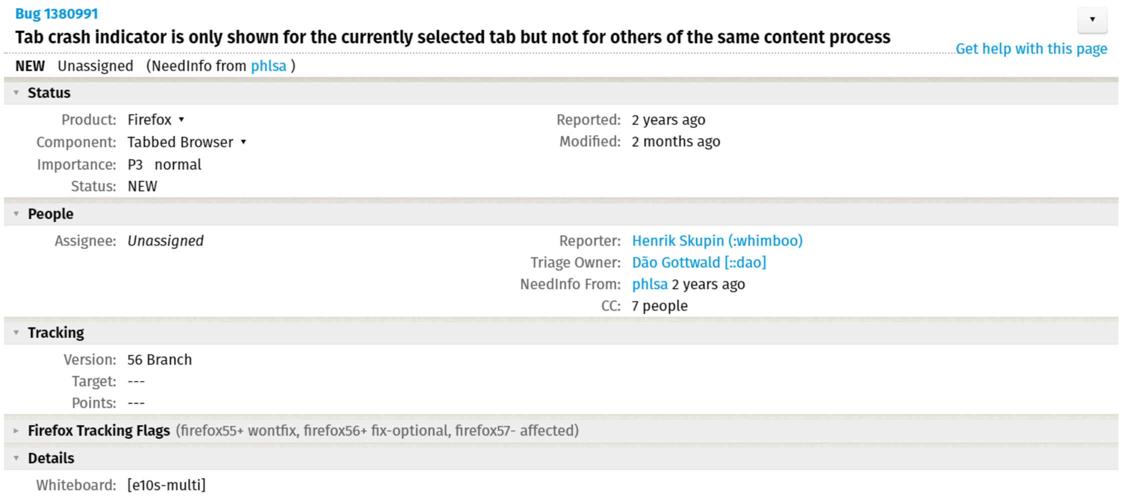
1.1 Research Background

The goal of software maintenance is to fix defects in the software or to develop new features for the software. Software defects in production software each year can cause billions of dollars in losses. At the same time many software companies have spent huge amount of money on software maintenance and software evolution. Therefore, it is necessary to pay more attention to the research and practice of software defect fix. Later part of the dissertation will use defect and bug interchangeably as in the software industry, they are the same.

Moreover, in large software development projects, developers use bug repositories to manage and perform normal software development. At the heart of the defect tracking system are software artifacts, such as defect reports, source code, and change history.

Those artifacts are important parts of the defect repairing task, because software developers in the project often use these software artifacts to manage and repair software defects.

In the maintenance of large software projects, bug reporting in software products is an important tool to help software developers to fix defects. Users, developers, software test engineers, program managers and others can create and fill out a software defect report with what they have found, and log them into bug database once they have discovered some defects in the software during the process of using or developing the software in order to facilitate software engineers to quickly verify and repair defects. In general, a complete defect report should consist of three parts: predefined fields like bug title, owner fields, status, type of bug, priority, severity, release milestone, area path, resolution, fixes, and history, etc. The second part is the bug description field including repro steps, which is natural language text, and the third party is the related attachments including repro picture, videos, crash dump or trace files, and etc. The bug report's fields can be configurable and system administrators of the bug database can define what fields are needed to satisfy all the software engineering process, as shown in Figure 1 and Figure 2.


Bug 1380991
Tab crash indicator is only shown for the currently selected tab but not for others of the same content process
Get help with this page
NEW Unassigned (NeedInfo from phlsa)

Status

Product:	Firefox	Reported:	2 years ago
Component:	Tabbed Browser	Modified:	2 months ago
Importance:	P3 normal		
Status:	NEW		

People

Assignee:	Unassigned	Reporter:	Henrik Skupin (:whimboo)
		Triage Owner:	Dão Gottwald [::dao]
		NeedInfo From:	phlsa 2 years ago
		CC:	7 people

Tracking

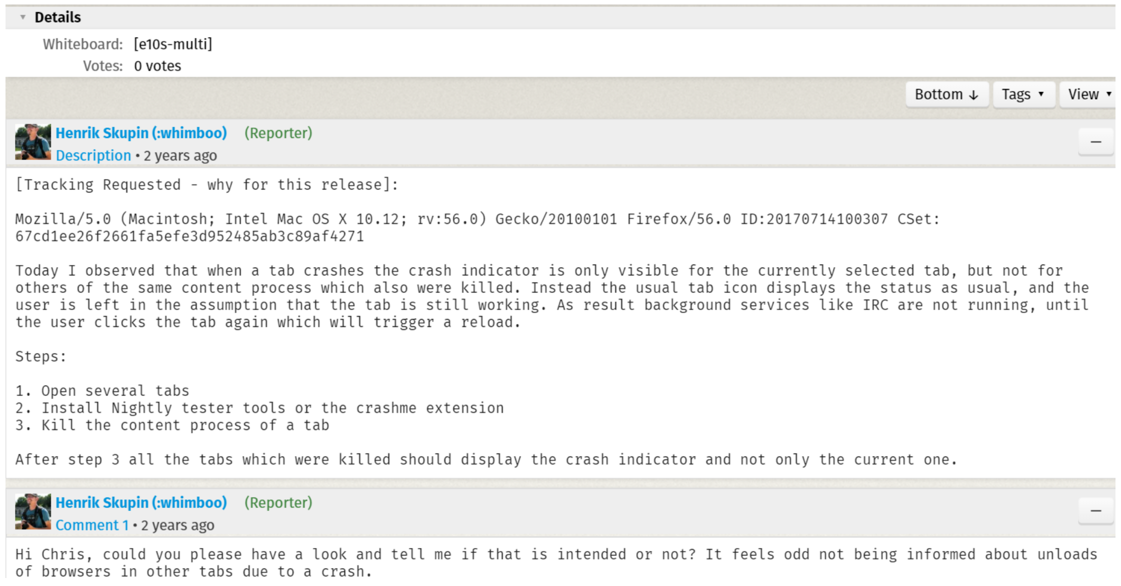
Version:	56 Branch
Target:	---
Points:	---

Firefox Tracking Flags (firefox55+ wontfix, firefox56+ fix-optional, firefox57- affected)

Details

Whiteboard: [e10s-multi]

Figure 1 Bug Report Fields - Bug 1380991's fields in Firefox Browser project


Details

Whiteboard: [e10s-multi]
Votes: 0 votes

Henrik Skupin (:whimboo) (Reporter)
Description • 2 years ago

```
[Tracking Requested - why for this release]:

Mozilla/5.0 (Macintosh; Intel Mac OS X 10.12; rv:56.0) Gecko/20100101 Firefox/56.0 ID:20170714100307 CSet:
67cd1ee26f2661fa5efe3d952485ab3c89af4271

Today I observed that when a tab crashes the crash indicator is only visible for the currently selected tab, but not for
others of the same content process which also were killed. Instead the usual tab icon displays the status as usual, and the
user is left in the assumption that the tab is still working. As result background services like IRC are not running, until
the user clicks the tab again which will trigger a reload.

Steps:

1. Open several tabs
2. Install Nightly tester tools or the crashme extension
3. Kill the content process of a tab

After step 3 all the tabs which were killed should display the crash indicator and not only the current one.
```

Henrik Skupin (:whimboo) (Reporter)
Comment 1 • 2 years ago

```
Hi Chris, could you please have a look and tell me if that is intended or not? It feels odd not being informed about unloads
of browsers in other tabs due to a crash.
```

Figure 2 Bug Report Description - Bug 1380991 description text in Firefox Browser project

The predefined fields of the defect report are primarily metadata describing the defect report. For example, status as "resolved by fix" means that the bug has been resolved. Importance as “P0” means is very high and developers need to drop everything and start to work on the bug now. Assignee is whom the defect shall be assigned to, Triage Owner is the person who is charge of triaging the bug, and Reporter is the person who initially reported the bug.

All bug reports constitute the basic characteristics of the defect. The natural language text part can be divided into three parts: Summary, Description, and Comments. Summary is mainly to make a proper title for the defect content, so that others can browse and view it. Description will detail how to reproduce defects, as well as some basic analysis about defects. Comments are generally free discussions by relevant software developers on current bug, which are either long or short.

In general, these discussions are very helpful in fixing defects. In addition, software developers provide attachments, such as repro videos, crash dumps, pictures, test cases, and others.

As mentioned earlier, the bug fix process has a life cycle. It starts with bug creation, then to bug distribution, to bug fix and final resolution phase and bug close phase. The process is also reflected in the predefined field status of the defect report, as shown in Figure 3. After the reporter submits a new bug report, the bug reviewer, who usually is the program manager or product manager, in Microsoft for instance, will verify the bug. After the bug reviewer has verified the bug is not a duplicate bug, the bug reviewer will change the status of the bug “unconfirmed” to “new defect”. Next, the bug reviewer will assign it to the appropriate software developer for a fix based on the content of the defect report and the relevant developer information. After that, the bug status will be changed to “in progress” state.

If the bug is successfully fixed, the corresponding status in the bug report becomes “Resolved”. Finally, after the software test engineer verifies that the defect was successfully repaired, the corresponding status in the bug report will become "closed". However, this does not mean the end of the life cycle of the bug.

After that, if it is found that the defect has not been completely repaired, for example a regression has been found, then the corresponding state will be changed to "active" state again. If the bug reviewer verifies the bug is a real bug, the bug will go to "new defect" state and repeat the above steps.

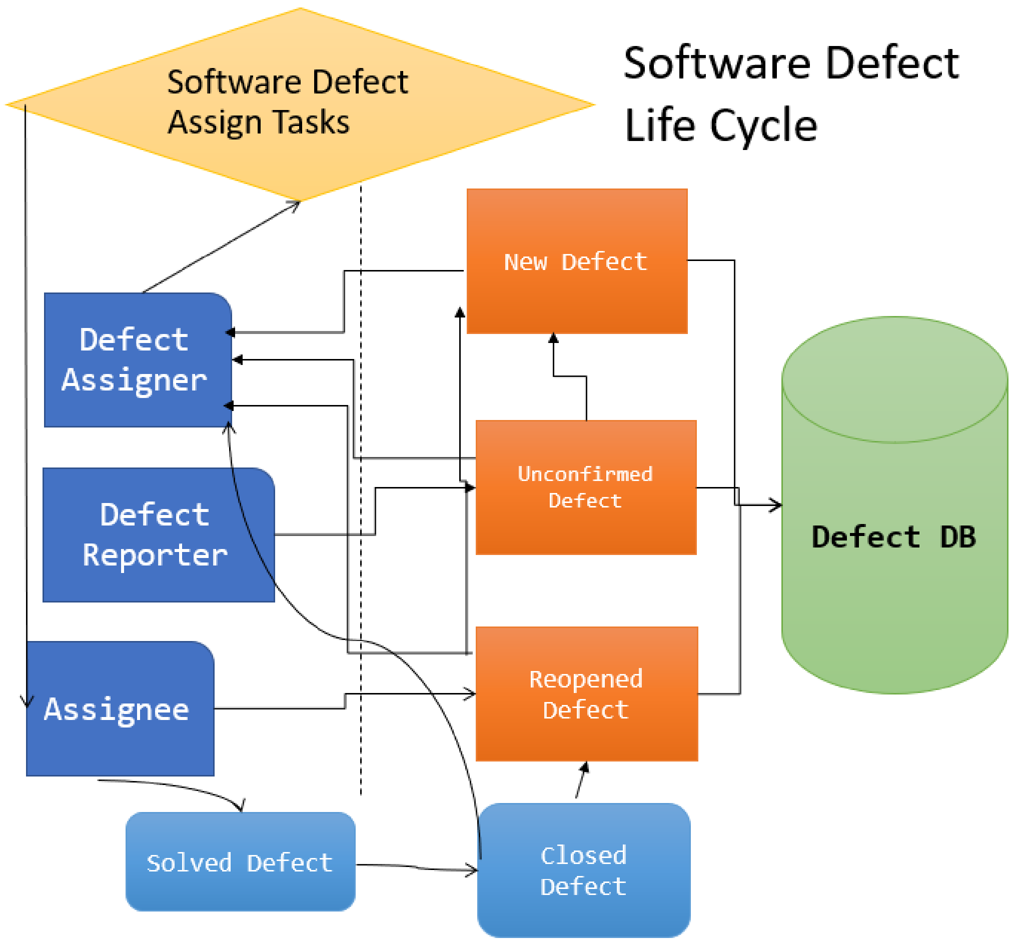


Figure 3 Software defect life cycle

From the perspective of the life cycle of bug management, the bug repair process is roughly divided into three stages: the bug understanding phase, the bug triage and assignment phase, and the bug fixing phase. When the bug report changes from the "unconfirmed" status to the "new defect" status, the bug reviewer needs to fully understand the content of the bug report. By capturing important information of the bug, the bug reviewer can duplicate the bug to another bug, or simply add a bug hit count number to increase the bug's frequency or file a new bug report.

Some important feature fields (such as Priority, Severity, etc.) are ultimate relevant for future bug fix work, and the corresponding phase is called the bug understanding phase. After the bug is fully be understood, the bug will enter the triage and assignment stage.

In the triage and assignment phase, usually the software development manager, senior software engineers will look into the bug report. They will manually assign the bug to software engineers based on the bug reviewers' understanding of the report and the reviewers' empirical experience and knowledge on relevant developers' expertise. Many times, those tribal knowledges are not accurate and results in assigning the bug to the wrong software engineer and leads to delaying of bug fix.

The software developer who is assigned to the bug will perform the repair work based on the understanding of the bug report and his or her related experience. Then the bug goes into the bug fixing phase.

Finally, the bug fixing phase is further divided into two steps: the first step is to complete the root cause analysis of the bug aka, RCA work. The second step is to come up a solution and create a service pack or patch for the bug and complete the bug fixing life cycle.

1.2 Research Challenges

The dissertation is designed to improve the automatic bug assignment accuracy for large software projects. The improvement of the bug assignment accuracy and efficiency is of great significance to alleviate the burden of the bug assignment engineering staff and improving the quality of the software.

Traditionally managers will assign the defects to their developers and assign the defects to the components according to managers' experience. However, this method of manual assignment not only consumes a lot of valuable time for managers, moreover, the accuracy of the assignment is bad. Later on, researchers started automatic defect assignment models which mostly gives a general empirical estimation formula through empirical analysis. Such prediction methods often have certain limitations, and their accuracy is not ideal. With the emergence of machine learning and data mining techniques, these theories or methods are gradually used in software defect assignment prediction. The way of defect assignment prediction has also evolved from the early empirical formula estimation to the prediction of defect assignment classic data mining science.

In order to improve the efficiency of defect assignment, it is necessary to fully understand the details of the bug report, understand the competency, capacity, and resources like tools and equipment of the relevant software developers have, and other necessary information like the environment and location he or she is at, for example, if the software engineer is trying to do a root cause analysis on a mobile phone bug with cellular issue in AT&T cellular network, but the engineer has no AT&T cellular signal in his or her location, so the bug reviewer needs to find a proper engineer with the access of the cellular network available to re-produce the bug. Those requirements are the criteria for the bug to be root cause analysis (RCA), and be properly fixed and verified.

From the above requirements, we can imagine we need to have a very experienced engineering manager and rich experienced engineers triage the bugs, while they have huge burden to triage the high volume of incoming bug reports.

Even so, the accuracy of assigning bug reports to the right developers is difficult to guarantee. The bugs are often like hot potatoes being passed around and are never earned a chance to be fixed. The study by Jeong et al. [1] shows that the more re-routing of the bugs, the less chance of the bug will be fixed. Sometimes, the bug has never found a right host to address its problem.

In order to solve the above problems, the researcher began to propose various methods and models for automatically assigning bugs, and they hoped to use automated methods to recommend bugs to the appropriate software engineers, thereby reducing the work pressure of the bug reviewers and software engineering managers and solving the low efficiency and inaccuracy of bug assignment problems.

Undoubtedly, the existing models have achieved some reasonable and limited results on the automatic assignment of defects. It can also reduce the probability of multiple re-routing of bug assignments. However, some of the existing methods do not make full use of text information (such as word classification based on the word bag model), and some require a large amount of manual feature selection work (such as C4.5 based text classification method). Therefore, there is still a long way to go to achieve efficient, accurate and smart automatic bug assignments.

Firstly, the existing models are usually impossible to effectively deal with many mixed and irregular natural language texts in bug reports.

Secondly, the existing methods are often based on the word bag model and its transformation of words usually cannot effectively deal with word order and the models are too sparse in terms of word hashing.

Thirdly, the current traditional approach usually requires a large number of human interfered feature extraction or labor-intensive work on feature selections to achieve their bug assignment efficiency, which adds the burden of bug assignment engineering process.

Recently thanks to the rapid development of artificial intelligence especially in the area of deep learning neural network, the field of natural language processing has undergone tremendous breakthroughs. Deep learning has achieved remarkable results in many aspects of natural language processing (such as text modeling, text categorization, machine translation, etc.) and has gone beyond traditional methods.

Therefore, with the idea of deep neural network (DNN) in combination of rule-based engine research, the dissertation introduces the successful experience of deep learning in the field of text classification into the field of automatic software bug assignment to improve many shortcomings of the previous automatic bug assignment models. The rule-based engine on top of DNN further tunes the models.

With the hybrid of advanced deep learning neural networks with rule-based engine technology, the research actively explores how to make full use of the hybrid model to address the above shortcomings in order to achieve the high accuracy and high efficiency of smart automatic software bug assignments.

The key is to incorporate and rate the right candidate developers for bugs through rule-based engine. After applying DNN model at the first layer, the research uses the rule-based engine in the second layer of the hybrid model to evaluate the developer's experience and rate the developers. Then the hybrid model gives out its recommended developer to be chosen based on rule-engine ranker to further modify the DNN's preliminary suggested developer data.

1.3 Research Problem Statement

The research is aimed at improving the existing approaches in automatic defect assignment by (1) improving the feature extraction by NLP and Vector for Words technology, (2) introducing rule-based engine aka expert system to better character the strength of each developer, instead of the traditional characterizing a developer only by the descriptions of the bugs he/she has resolved; (3) combining two layers model (Layer 1, NLP and Vector for Words and Layer 2, LSTM and Rule-based Engine).

1.4 Research Methodology

How to improve the accuracy of automatic bug assignment process? Firstly, good training data must be collected. The researcher believes that the bug report can be used as the effective bug assignment basis for the bug assignment. It can be used as the training set. The text information in the bug report can provide insightful knowledge for bug assignment. The bug assignment prediction model learns these inside knowledge through training, the accuracy of bug assignment can be effectively improved.

How can we learn this insightful information that is crucial to the assignment of defects? The question raises a challenge for us to find deep learning model with rule-based engine of the defect text for the bug assignment model. The current work is still far from meeting this challenge. The research has already clarified this point in Section 1.2.

Therefore, this dissertation aims at the hybrid model of Layer 1: natural language processing (NLP) and Layer 2: deep learning neural network model, and rule engine method. The deep learning neural network is currently widely used in the field of natural language processing. It is expected to learn from the well-developed text processing ideas and model methods. The combination of deep learning neural network with rule-based engine is the new methodology to try it on bug assignment area. The hybrid approach is introduced into the field of automatic bug assignment problem space and is developed as a more accurate model to fit the real engineering bug practice. The hybrid model includes the layer 1 – vector for words, and layer 2 – LSTM and rule-based engine. The new model is shown in Fig 4.

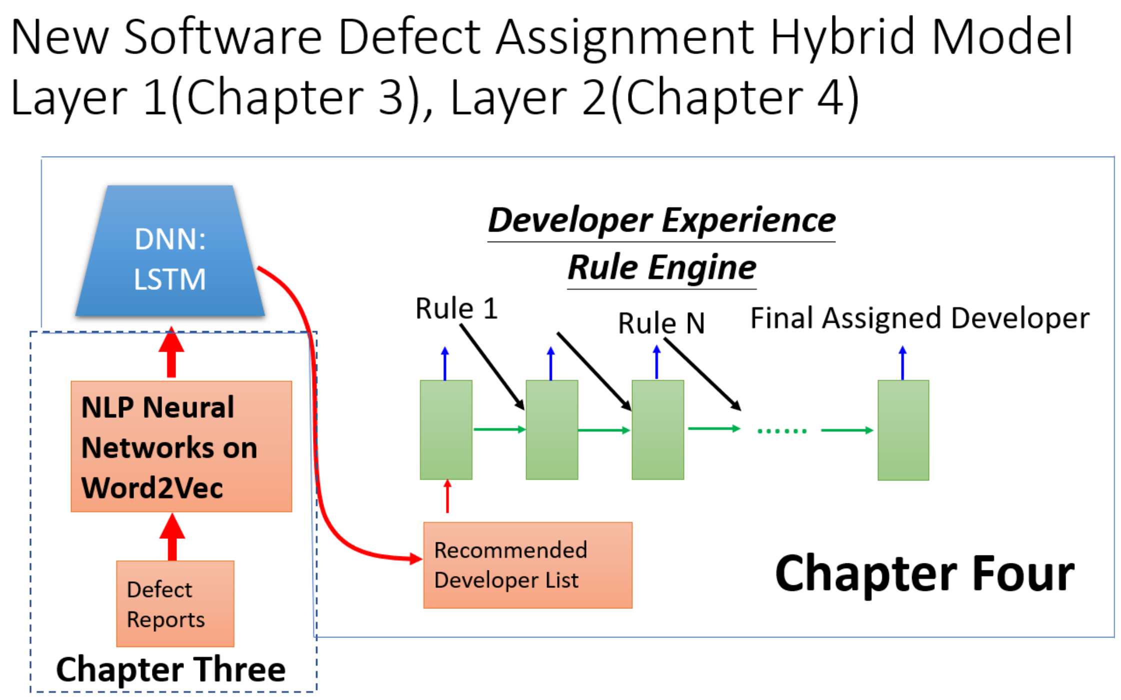

New Software Defect Assignment Hybrid Model
Layer 1(Chapter 3), Layer 2(Chapter 4)
DNN: LSTM
NLP Neural Networks on Word2Vec
Defect Reports
Chapter Three
Developer Experience
Rule Engine
Rule 1
Rule N
Final Assigned Developer
......
Recommended Developer List
Chapter Four

Figure 4 New Software Defect Assignment Hybrid Model

Researchers found that deep neural networks such as FFN, CNN, RNN, especially long-short-time memory (LSTM) proposed by Dyer et al. [6][7] LSTM has strong advantages in the field of natural language processing, especially in text classification.

Firstly, it has the natural advantage of dealing with local features selection. Moreover, this advantage is more prominent in the field of natural language processing, a lot of work [2][3][4][5] indicates that texts are based on deep learning models based on RNN, and it variant LSTM.

When classifying, the optimal effect can be achieved at that time. It can be also seen that DNN has a good ability to capture local text features. Moreover, LSTM operation can take full advantage of the text information, for example, the regional word order can be learned. LSTM can also have the ability to mine grammatical and semantic information, which cannot be achieved by the traditional word bag model. LSTM can automatically capture text features without any manual involvement, which can automatically assign the bugs to right owners.

Secondly, the hybrid model of NLP, LSTM with rule engine runs reasonable fast by using modern GPU, and the neuron weight and bias computation can not only reduce a large number of network model parameters, but also make the model have parameter sharing characteristics, which helps to quickly train the model.

Finally, there is also a special operation accelerator GPU to provide parallelized acceleration for neuron computation, SoftMax operations and cross entropy calculations in DNN in order to have the entire model built quickly and easily.

After reading a large number of references and researches, the dissertation is aimed at designing a deep learning model based on natural language processing (NLP), LSTM neural network and rule-based engine.

In the research, a dependency syntax analysis model to create word representations using shallow neural network [61] is created to get the word vectors. It reconstructs linguistic contexts of words. It is named as Word2vec and used to produce word embeddings. Word2vec uses the text corpus as input values to produce a vector space in serval hundred dimensions. Each individual word in the corpus is assigned a specific vector in the space. Word vectors are positioned in the vector space, so the words share common contexts in the corpus are located in close to each other in the vector space.

The accuracy is improved after adding Rule-based Engine on top of pure LSTM, for example, a bug with the real issue_title and description:

{

"id" : 8942,

"issue_id" : 68953,

"issue_title" : "Use after free in PepperPluginDelegateImpl::GetTextInputType on Mac OS",

"reported_time" : "2008-08-31 02:47:11",

"owner" : "",

"description": "\n[89950,1056861440:11:24:19.994000] Fatal error in file /Users/glider/src/chrome-commit/src/ppapi/native_client/src/shared/ppapi_proxy/ppb_rpc_client.cc, line 293: !(ppapi_proxy::PPBCoreInterface()->IsMainThrea\r\nd())\r\n[89950,1056861440:11:24: …EOF is received instead of response. Probably, the other side (usually, **nacl** module or **browser plugin**) **crashed**.\r\n[89947,2953392128:15:24:20.063623]…, freed by thread T0 here:\r\n #0 0x7365 in AsanThread::Init() (in Chromium Helper) + 229\r\n #1 0x964d15f9 in **free** (in libSystem.B.dylib) + 261\r\n, previously allocated by **thread** T0 here:\r\n … [89950,1056861440:11:24:19.995000] ReleaseResourceMultipleTimes: **PPAPI** calls are not supported off the main thread\r\nLOG_FATAL **abort** exit\r\n … "

}

Pure LSTM model assigns the bug's owner field with email alias: scherkus@chromium.org, a wrong developer. The reason of why we know it is wrong is because the pre-collected data has the right answers(email aliases) in the owner field in the training set. LSTM is a supervised learning, and the training model gives a confusion matrix, and it shows that record has the wrong owner prediction scherkus@chromium.org. But after the Rule-based engine, since there are many words including **nacl**, **browser, plugin**, **crashed**, **free**, **thread, PPAPI** and **abort** in the bug's description are matching the attributes aka keywords list of developer kinaba@chromium.org. According to a preconfigured threshold value on overlapping of the bug's title, description keywords with the developer's attributed keywords, the Rule-based engine on top of LSTM correctly assigns it to kinaba@chromium.org, a correct developer. With more records running through Rule-based engine, the accuracy of confusion matrix becomes higher and higher for the hybrid model.

The dissertation adds LSTM and rule-based engine with expert system and fuzzy logic basic idea to design a new bug assignment model. LSTM uses deep neural networks to perform all encoding on such transition states as stack, cache, history transfer sequence state, and current dependent subtree collection state. By this way, it makes full use of historical transfer information. More fine-grained modeling of words, stacks, caches, transfer sequences, etc. It has more flexible control of parameters tuning in a multitasking learning framework.

With a little more complexity by adding additional memory gates storages and introducing Rule-based engine, the hybrid of Layer 1 and Layer 2 model proves that it has better accuracy and generalization in the experiment to compare with traditional ones.

1.5 Dissertation Roadmap

The research is divided into six chapters, the content of each chapter is arranged as follows:

Chapter 1 Introduction The research introduces the background of the field of software bug fix engineering system and process. It states the main problem space of this dissertation is addressing, the automatic defects assignment related work, and briefly introduces the main researches on how deep learning neural networks and Rule-based engine aka expert system can solve the automatic defect assignment challenges.

Chapter 2 Software defect assignment traditional theory and approaches The traditional defect assignment models divides the current research work into four categories:

1) Model Based on Fuzzy Logic

2) Model based on Traditional Machine-learning

3) Expert System Model

4) Tossing-graph model

5) Social-network model

6) Topic-model.

Chapter 3 New Software Defect Assignment Model – Layer 1: NLP and Vector for Words The chapter introduces the methods of automatic software defect assignment based on text classification aka natural language processing. The method of defect is assignment fundamentally based on the text classification and how to create word vector dictionary. Generally, the defect report is the main feature to be used for the text classification and the developer acts as a label, and then the defect assignment problem is converted into the text classification problem.

Chapter 4 New Software Defect Assignment Model – Layer 2: LSTM and Rule-based Engine Inspired by LSTM, decision trees, and expert systems theories on software defect assignment, the chapter decided to apply LSTM, rule engine approach to the automatic of defect assignment research areas. The combination of text classification training on LSTM with developer productivity rule architecture is discussed for bug assignment project.

Chapter 5 Data Collection and Experiments Result Many comparative studies are presented. Through experiments, it is found that the hybrid model not only has a significant effect on text classification, but also has a higher accuracy rate than the traditional learning method for the problem of automatic defect assignment.

Chapter 6 Summary and Future Work This paper summarizes the work of the dissertation, explains the main contribution of the research in the field of defect assignment field, and future looks to the next step (like BERT, GPT 2 system) based on the current research topics.

Chapter 2 Software defect assignment traditional theory and approaches

It is the major and complex task for bug reviewers to assign defects to appropriate assignees in order to achieve the purpose of rapid repair defects. Automating the distribution of bugs can reduce the probability of re-routing of bugs and save valuable time for bug fixing.

However, how to identify candidates of bug assignee and the order of appropriate bug assignees will be a huge challenge. At present, there are a large number of methods based on segmentation and classification (such as traditional Machine-learning algorithm, social network matrix, etc.) to evaluate the experience of software developers, so that you can select the right candidate and pick the most suitable bugs for them.

The traditional defect assignment models divide the current research work into six categories: 1) Model Based on Fuzzy Logic 2) Model based on Traditional Machine-learning 3) Expert System Model 4) Tossing-graph model 5) Social-network model 6) Topic-model. The details are as follows.

2.1 Model Based on Fuzzy Logic

The Bugzie method proposed by Tamrawi et al. [8][9] is a method for automatic bug assignment based on fuzzy set and Cache-based model. Bugzie extracts a number of technical aspects of the software system, each technical aspect has a number of technical terms (Technical terms).

Technical capabilities are characterized by a fuzzy set of terminology. Specifically, for developers, fuzzy collections represent the expertise of a developer or the ability to resolve defects; for defect reporting, a fuzzy collection represents a defect report that requires the expertise of a software developer or the ability to resolve defects, and the matching relationship between them, is measured using the membership score. Finally, sorting the candidate developers according to the value of the Membership score and selecting the most suitable developer. Experiments show that Bugzie is superior to other models in research.[10][11][12][13] For example, in the open source Eclipse dataset, when the recommended number is tops, Bugzie only reached it in 22 minutes. 72% accuracy, 49 times faster than SVM [12], and accuracy rate has increased by 19%.

Fuzzy logic absorbs the ambiguity of human thinking, and uses the functions of membership function, fuzzy relationship and decision-making in fuzzy mathematics to obtain control actions, which are generally classified into functions, fuzzy reasoning and fuzzy decision making. Fuzzy logic technology has been widely used in the software and hardware industries. It has the following characteristics:

1. Simple

   Human thinking has the characteristics of ambiguity, and fuzzy logic is similar to human thinking. It does not need to first analyze the mathematical model of the system like software bug assignment system and can directly use the opinions of experts. It allows designers to describe inputs, rules, and outputs with IF...THEN... statements. Its fuzzy subset and membership functions (such as cold, hot, etc.) are generally very intuitive. Each input requires only 3 to 8 fuzzy subsets. The membership function can also use a simple triangle or trapezoidal form, and often only it takes ten to dozens of rules. But using these simple modules can form a control system that performs very complex tasks.[14]

2. The software for implementing fuzzy control is short and requires less storage space.

   The fuzzy control system generally requires only a short program and less storage space, which requires much less storage space than the control system using the look-up table method and requires less storage space than the control system using mathematical calculation methods. There are also fewer.[15]

3. High speed

   Fuzzy logic software systems can perform complex tasks in a short period of time, rather than requiring a large amount of mathematical calculations using mathematical methods. In this way, a simple 8-bit microcontroller can be used to perform functions that may require a 32-bit or RISC processor. It also performs tasks that were previously too complicated to complete due to mathematical calculations. Moreover, since the fuzzy calculation itself is a parallel structure, each input can be fuzzified at the same time, or each rule can be reasoned. This allows fuzzy reasoning to be done at high speed using parallel processing hardware. For example, the existing fuzzy \ logic chip can complete a fuzzy control within tens of microseconds.

4. Easy and fast development

   With fuzzy logic, you can start designing the approximate fuzzy subset and rules, and then adjust the parameters step by step to optimize the system. The various components of the fuzzy inference process are functionally independent, so that the system such defect assignment can be easily modified. For example, you can add rules or input variables without having to change the overall design. For a conventional software defect assignment, adding an input variable will change the overall algorithm. When developing a fuzzy bug assignment system, you can concentrate on functional goals rather than analyzing mathematical models, so you have more time to enhance and analyze the system. [16]

5. Different from Neural Networks

   The basic unit of neural network is a neuron. The two layers of networks are connected by weights. Therefore, the knowledge information after learning is distributed in the middle of the weight, while the fuzzy logic system stores the knowledge in a regular way, as shown in Fig. 5. The input in the figure is the fuzzy variable A, which is an n-dimensional vector, which is mapped to the dimensional fuzzy vector B by m set of rules, and each rule gets a value like B1, …Bm. The total decision vector B as shown below. The system has more human factors in the form of rule sets, the size of regional division and the formulation of rules. If the experience and expert knowledge are used, the structure and result of fuzzy logic software system are better than neural network. The neural network is obtained by learning by itself. The result is related to the sample set. If the sample set is atypical (i.e., the selection is unreasonable), the knowledge storage is not optimal. [17]

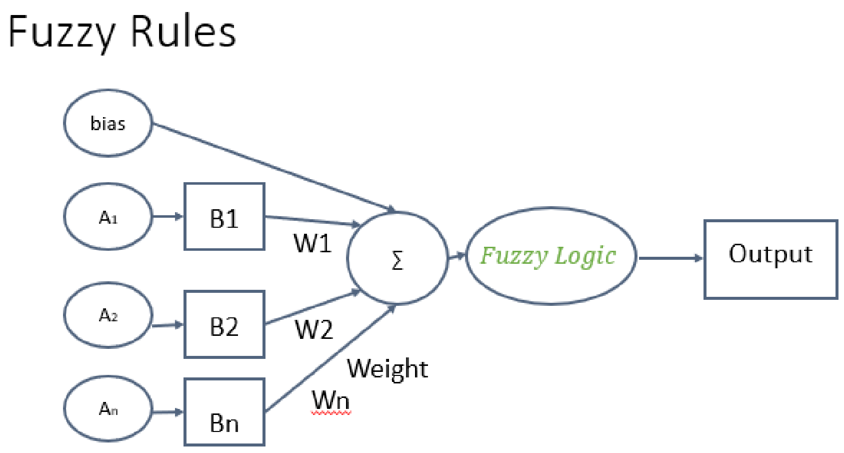


Figure 5 Fuzzy Software Defect Assignment System Inputs and Output

2.2 Model based on Traditional Machine-learning

Traditional Machine-learning model, which is different from deep learning neural networks model, can learn from the data and create a model. Early work such as Naive Bayes, SVM, and etc. uses traditional machine learning methods to determine the appropriate defect assignment.

The earliest work was a solution proposed by Murphy and Cubranic [18] to automate the distribution of software defects. Specifically, they regard the defect assignment task as a text classification problem, each defect assignee is a category, and each defect report corresponds to only one category. They used one of the most commonly used models in machine learning -the Naive Bayes model. It is more appropriate to predict which software developers should be assigned to a bug. However, the accuracy of their method is not very high. In the large open source software Eclipse, the accuracy of 859 defect reports is only 30%.

To further improve the accuracy of automatic assignment of defect reports, Anvik and his colleagues used a variety of different Machine-learning models to predict and recommend defect assignment. They used the Naive Bayes model, the SVM model, and the C4.5 model.

Experiments show that the SVM model is in the open source software Eclipse, Mozilla Fire x [19] is superior to the other two models in the data set. Specifically, in the literature [20], the Precision rate reached 57% and 64% on the Eclipse and FIREFOX datasets respectively. In the literature [21], they used the Component-based method to set the Precision index of the two datasets. They have increased to 97% and 70% respectively.

Lin et al. [22] proposed two methods for automatic defect assignment models based on text information and developer recommendation based on non-text information. Non-text information mainly includes defect types, defect submission personnel, defect priority, and so on. It is worth mentioning that this is the first time that text in Chinese language is used to automatically assign software defects. They use SVM algorithm automatically assigns defects based on Chinese text while using C4 · 5 decision tree algorithm automatically assigned based on the bug's non-text information.

Ahsan et al. [23] used feature selection and Latent semantic indexing (LSI) to reduce the dimensions of the Term-to-document matrix. They used a variety of machine learning algorithms to recommend defect fixers. The final results show that the LSI-based SVM model achieves the best results with an average Precision and Recall values of 30% and 28%, respectively.

Xuan et al. [24]proposed a semi-supervised text classification method. In order to effectively improve the inefficiency of defect class labeling in supervised learning, they use the EM (Expectation-Maximization) algorithm to improve the classification performance of the Naive Bayes classifier, using a small number of marked bug reports and a large number of unmarked defect reports to complete the auto bug assignment task. Experiments have shown that this semi-supervised model can improve the accuracy of 6% compared to the normal Naïve Bayes method.

In order to filter the noise data reported by the defect filing process, Zou et al [25]. used the feature selection model and the instance selection model to reduce the scale of the training set and improve the quality of the training data. They use the Naive Bayes method to verify the effect of automatic defect assignment. The results show that the Naive Bayes method using the feature selection model is 5% better than the normal Naive Bayes, while the Naive Bayes method using the instance selection model is not as effective as the normal Ne Bayes.

Xia et al. [26] proposed a precise assignment model called DevRec to implement the recommendations of defect repairers. DevRec comprises two analysis methods, one is based on the analysis method of Bug reporting, abbreviated as BR assay (BR- based analysis), the other is based on analysis of the Developer, referred to as D assay (D-based analysis). Using feature values in defect reports, such as Terms, Product, Component, Topics, etc., BR analysis can use Multi-Label KNN to find K historical defects related to newly found defects. D analysis uses the characteristics of Terms, Product, Component, and Topic to calculate the similarity between developers. Finally, the BR analysis method and the D analysis method are combined to complete the automatic assignment task of the defect report. Experiments show that the average Recall rate of the DevRec method is increased by 39.39% and 89.36% compared with the Bugzie [27] model and the DREX [28] model, respectively, under the recommendation of top 10 developers.

2.3 Expert System Model

Matter et al [29]. modeled the software developer's source code vocabulary and the vocabulary in the defect report and used the Cosine measure to calculate the similarity of two-word vectors. Experiments show that, in the case of the recommended number is top 1, Precision rate may reach 33.6%; in the case of the recommended number is top10, recall rate may reach 71%.

Servant et al. [30] developed a tool for implementing the automatic bug assignment, which consists of bug line location, history mining, and expertise assignment. Specifically, the historical information of the source code change is combined with the diagnosis information about the defect location, and the candidate developers are sorted to achieve the recommendation purpose. Experiments show that under the condition that the recommended number is top3, the accuracy rate of 81.44% can be achieved.

Expert system model and neural network system have different precision. Both systems can map a nonlinear system, but their mapping surfaces are different. The neural network uses point-point mapping, so the functional relationship between its output and input is different, and the expert system is different. It is a reflection between the rule regions. If the regions are relatively coarse, the surface of the mirror output has low precision. For example, if each rule is a trapezoidal step, the output will be coarse. Therefore, for the mapping with higher precision, the artificial neural network is better, and for the lower precision requirement, the expert system can be used for mapping. For software defect assignment, we need high precision, therefore neural network will work better.

Neural networks need to calculate multiplication, accumulation, and exponential operations, while expert system calculations are relatively small, and the rules involved in each iteration are generally small. However, when the accuracy of the expert system needs to be improved, the number of rule subsets increases correspondingly, and the amount of calculation increases.

Furthermore, the neural network is connected to the feed-forward network. For example, once the input and output and the hidden layer are determined, the connection structure is determined. After learning, almost every neuron is associated with the previous layer of neurons, so it is controlled. In each iteration of iteration, each weight and bias must be learned. In expert system model, each input may be related to only a few rules, so the connection is not fixed, and the rules for each input and output are changeable.

2 .4 Tossing-graph Model

In general, the process of assigning a defect begins with the first assignee and then passes to the next developer until the last fixer. Each pass is called a Tossing step, and a set of pass steps is called a Tossing path. Assuming that the transmission path of a defect is A-B-C-D, the goal of Jeong et al [31]. is to predict a shorter transit path from A to D will speed up the process of defect repair. Experiments show that on the open source software Eclipse and Mozilla datasets, compared to pure machine learning-based models (such as Naive Bayes and Bayesian Network [32]), the Tossing model can greatly improve the accuracy of automatic defect assignment.

Bhattacharya and Neamtiu [33] use a variety of techniques to shorten the length of the delivery path , including the use of additional features for Refined classification and update model during real time training, using more accurate ranking methods, and Multi-features of Tossing graph, etc. Experiments show that the accuracy rates of the open source software Eclipse and Mozilla datasets are 84% and 82.59%, respectively.

In the literature [34], Bhattacharya uses the Naive Bayes model based on the product-component feature and combines the Tossing graph and the incremental learning (Incremental learning) method to complete the task of automatic defect allocation. The accuracy rate on the Mozilla dataset has increased to 85 % and the accuracy rate on the Eclipse dataset has increased to 86%. Compared to the previous work, the automatic allocation effect is greatly improved.

2 .5 Social-network model

In recent years, social network (Social network) technology began to be used defect assignment research area. Usually people use the comment and social chat and rating activity in the defect web site or reports to build a social network, and then through the social network between the developers to analyze, you can know which developers have a wealth of repair experience in solving certain defects. With that information, the model can give right defects to proper developer to fix.

Wu et al. [35] use the KNN model to search for historical defect reports similar to newfound bugs. Then the reviewers involved in the historical defect report are used as candidates, and the last use frequency and other six social network indicators (In-degree centrality, Out-degree centrality, Degree centrality, PageRank, Betweenness centrality, Closeness centrality) to recommend a suitable defect repairer. After comparing the frequency and the distribution of the other six social network indicators, the authors believe that the frequency and Out-degree indicators can achieve the best results.

Xu et al. [36] analyzed the social network to explore the developer prioritization information and then integrated it into the SVM model or Naive Bayes model to automatically assign defects. The results show that the analysis of the developer priority information obtained by the social network can effectively improve the accuracy of the SVM model and Naive Bayes model defect assignment.

2.6 Topic-model

The more similar topic the bugs have, the closer the bugs are related. Therefore, the topical modeling of the defect report (Topic model) can be used to evaluate the similarity between the new defect and the historically fixed defect. Researchers hope to further improve the accuracy of the defect assignment model by introducing relevant methods of topic modeling.

Xie et al. [37] proposed a defect repairer recommendation method called DRETOM, which uses Stanford Topic Modeling Toolbox (TMT). [38]

Given a new defect report, it is easy to confirm which set of topics the defect report should belong to, and then by analyzing the interests and experience of the developers in each set of topics, you can assign appropriate repairers to the new defects. Experimental results show that the DRETOM method works better than general machine-based learning (such as SVM model, KNN model) and social network-based methods.

The LDA [39] model is a probability generation model that generates different topics for discrete data. Naguib et al. [40] used the LDA model to classify defect reports into different topics, then created an activity profile for each developer by mining historical log records and topic models, and finally they used activity profiles and new defects information. The topic models and their own sorting algorithms are used to find the most appropriate defect fixers. Experiments show that the average hit rate (Hitrate) of this model can be reached 88%.

Yang et al. [41] used TMT to model the defect assignment, and then extracted historical defect reports with the same subject as the new bug. Based on multiple features of the new bug such as Product, Component, Priority, the model re-screens those bugs. Then it rebuilds the social network model based on the developers in the remaining historical defect reports. Finally, it uses the bugs' comment activity related to the source code and the activity of change lists for defect assignment. Experimental results show that this method is better than DRETOM and social network-based methods.

Zhang et al. [42] also used the LDA method to extract historical information from defects reports. It obtains information on whether developers are interested in a topic by understanding the code check-in of activities of relevant developers under the same area. In addition, Zhang et al. analyzed the relationship between relevant developers (such as defect reporters and defect fixers) and then combined the topic model with the relationship model. Experiments show that on the open source software Eclipse dataset, this method is 3 % and 16.5% higher than the DRETOM and the previous mentioned activity summary-based models.

2.7 Chapter summary

The chapter mainly introduces the mainstream methods in the field of automatic assignment of software defects. They are the following six principal methods: 1) Model Based on Fuzzy Logic 2) Model based on Traditional Machine-learning 3) Expert System Model 4) Tossing-graph model 5) Social-network model 6) Topic-model.

Firstly, fuzzy logic methods are applied to bug assignments in the early stage of research topic.

Secondly, the traditional machine learning method was the mainstream of defect assignment, many improved methods are based on it.

Thirdly, feature selection or composite models can improve the accuracy of machine learning-based methods like Expert System Model and Tossing-graph model.

Finally, the introduction of new technologies (such as social networks and topic models) can further enhance the effects of machine learning-based models.

Next two chapters the paper will introduce a new software defect assignment model. It includes the layer 1 – vector for words, and layer 2 – LSTM and rule-based engine. The new model flow diagram is shown in Fig. 6.

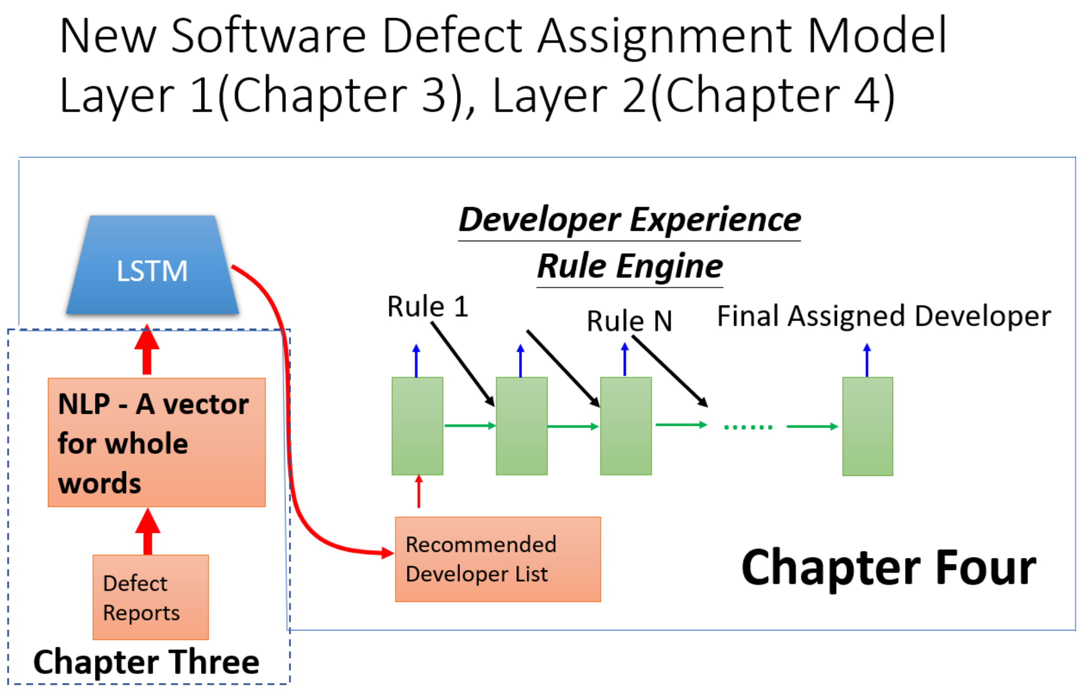

New Software Defect Assignment Model
Layer 1(Chapter 3), Layer 2(Chapter 4)
LSTM
Developer Experience
Rule Engine
Rule 1
Rule N
Final Assigned Developer
NLP - A vector for whole words
......
Recommended Developer List
Defect Reports
Chapter Four
Chapter Three

Figure 6 The model of new software defect assignment system

Chapter 3 New Software Defect Assignment Model – Layer 1: NLP and Vector for Words

The method of defect assignment is fundamentally based on the text classification. Generally, the defect report is the main feature to be used for the text classification and the developer acts as a label, and then the defect assignment problem is converted into the text classification problem. Therefore, in the following descriptions of text classification and defect assignment, the two problems of text classification and defect assignment are deemed as the same problem space we are addressing, we use the two wordings interchangeably.

The traditional practice of text categorization is to use a bag model to represent text features and then use standard machine learning's classification models (such as SVM models) for classification. As we all know, the word bag model does not contain the word order information of the text, and then lacks the representation of the grammatical and semantic aspects of the text, resulting in limited accuracy of the final classification model.

The literature [43][44][45] use two-word phrases (Bi-grams) instead of single words (Unigrams) to make up for the lack of text on the lack of word order information.

However, the work of the document [46] proves to use a multi-word phrase (N-Grams, the method of N>1) is not a very effective method. Although this method alleviates the problem of missing word order, it greatly increases the sparseness of text representation.

Therefore, it is a challenge to make full use of the word order information of the text, and learn the grammatical and semantic knowledge of the text sequence, while at the same time cannot increase the sparseness of the text representation.

3.1 Model Overview

In the text classification algorithm introduced in the previous chapter, most algorithms need to construct text features manually. Such feature construction is very labor-intensive, and the scalability is not good, and it is not easy to obtain during the process of feature extraction. Therefore, the models presented in this chapter do not use these classic text features. The paper is proposing two layers model to solve the problem.

The word vector representation is the first layer in my software defect assignment problem space, followed by the second layer which is modeled with LSTM and rule-engine which will be discussed by Chapter 4 in details.

The first layer for word vector model maps discrete words in each text into a fixed-dimensional feature vector to get the word direction. They are accessed by the second layer hierarchical LSTM to get a vectorized representation of the entire document.

Chapter 3 will focus on my model research on the layer 1: Defect Reports and Vector for Whole Words areas.

For our bug text reports, we need to build a word vector to feed into the LSTM described above so in the text, each word has its own probability and statistics. Therefore, word vector representation, also named as Word Embedding needs to be introduced. Before elucidating the vector model, the first thing to determine is the size of the text and how to represent text sequences. The model that solves such problems is called a vector representation, because the process of text sequence representation is the process of vectorizing the text sequence. This paper is designed to explain it as much as possible, which is beneficial for later understanding of the LSTM neural network model.

New model summary with focus on layer 1 is described in the following diagram Fig 7.

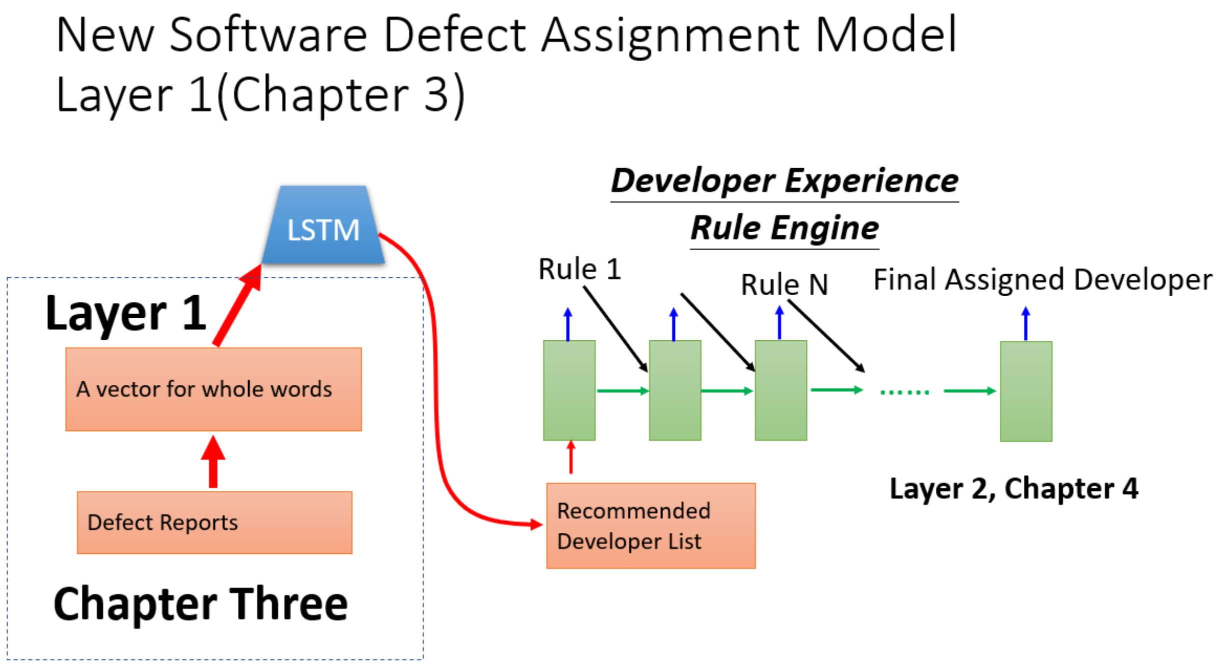


Figure 7 Defect Assignment Model Layer 1

Algorithm 1: Dataset Preprocessing by word2vector

Input:
Untriaged bug set and triaged bug set
Output:
A set of unique words that occurred for at least k-times in the corpus

```
1: BEGIN
2: Set up the min_count, size, window of word2vec function
3: Set up the batch_size, epoch, iteration of classifier hyper parameters
4: Preprocess the untriaged bug set and extract the vocabulary and learn the word2vec representation
5: FOR each sample in untriaged bug set
6:        Remove the return character "\r"
7:        Remove the URLs of online resource
8:        Remove the stack trace
9:        Remove the hex code
10:       Change all letters to lower case
11:       Handle the tokenize
12:       Remove the punctuation marks
13: END FOR
14: PRINT a set of unique words
15: Learn the word2vec model and extract vocabulary
16: Preprocess the triaged bug set and use the extracted the vocabulary
17: FOR each sample in triaged bug set
18:       Remove the return character "\r"
19:       Remove the URLs of online resource
```

```
20:         Remove the stack trace
21:         Remove the hex code
22:         Change all letters to lower case
23:         Handle the tokenize
24:         Remove the punctuation marks
25: END FOR
26: Add all values of label “owner” to array all_owner
27: END
```

Let’s go through the implementation of our approach. The necessary packages for the implementation are: *Numpy, NLTK, Gensim, Keras* and *Scikit-learn*. They can be imported into python as following:

```
import numpy as np
import warnings
warnings.filterwarnings(action='ignore', category=UserWarning, module='gensim')
np.random.seed(1337)
import json, re, nltk, string
from nltk.corpus import wordnet
from gensim.models import Word2Vec
from keras.preprocessing import sequence
from keras.models import Model
from keras.layers import Dense, Dropout, Embedding, LSTM, Input, merge, Concatenate,
concatenate
from keras.optimizers import RMSprop
from keras.utils import np_utils
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.naive_bayes import MultinomialNB
from sklearn import svm
from sklearn.linear_model import LogisticRegression
from sklearn.multiclass import OneVsRestClassifier
from sklearn.metrics.pairwise import cosine_similarity
from keras.utils import to_categorical
```

First, we hard-coded the dataset absolute path first to ensure our system could get the source of data needed to process. In this project, we use two datasets: 1. Untriaged bug dataset is used to learn the target deep learning model in an unsupervised manner. 2. Triaged bug dataset is used for classifier training and testing by cross validation. Another web data is used for bug triage improvement by custom rule engine.

```
open_bugs_json = 'C:\dataset\TestData.json'
closed_bugs_json = 'C:\dataset\TrainData.json'
web_data_address = 'C:\dataset\webData.json'
```

Second, we set up the initialization of global variable, which divides into two parts. The parameters of first part is for word2vector function as following:

```
min_word_frequency_word2vec = 5
embed_size_word2vec = 200
context_window_word2vec = 5
```

min_word_frequency_word2vec means a set of unique words that occurred for at least specific times is extracted as the vocabulary. *embed_size_word2vec* means dimension of the embedding vector. *context_window_word2vec* means how many words to consider left and right. The parameter of second part is to define the number of cross validations, the number of iteration times and the batch size of parallel computing.

```
numCV = 5
max_sentence_length = 50
min_sentence_length = 15
rankK = 10
batch_size = 32
myEpochs = 5
```

numCV means the number of cross validations, *myEpochs* means the number of iteration times for all the training examples, *batch_size* means the number of samples that will be propagated through the network. The higher the batch size, the more memory space you'll need. For instance, let's say you have 1000 training samples and you want to set up a batch_size equal to 100. The algorithm takes the first 100 samples (from 1st to 100th) from the training dataset and trains the network. Next, it takes the second 100 samples (from 101st to 200th) and trains the network again. We can keep doing this procedure until we have propagated all samples through of the network. *rankK* means the user can configure your own specific times for accuracy. *min_sentence_length* means the minimum processing range of time steps in LSTM model. *max_sentence_length* means the maximum processing range of time steps in LSTM model.

Third, there are *id*, *issue id, issue title, reported time, owner* and *description* options in each bug sample of the untriaged dataset, one case is shown in the following table. It is necessary to preprocess them so that we can process the valid data easier. For untriaged dataset, we only focus on the *issue title* and *description*. We removed the return character "\r", the URLs of online resource, the stack trace, the hex code and so on, and store these scattered words into an array: *all_data* as following:

[testing, if, chromium, id, works, what, steps, will, reproduce, the, problem, is, expected, output, do you see instead, please, use, labels, and, text, to, provide, additional, information]

```
{
        "id" : 1,
        "issue_id" : 2,
        "issue_title" : "Testing if chromium id works",
        "reported_time" : "2008-08-30 16:00:21",
        "owner" : "",
        "description" : "\nwhat steps will reproduce the problem\n1\n2\n3\n\r\nwhat is the expected
output what do you see instead\n\r\n\r\nplease use labels and text to provide additional information\n
\n"
}
```

We use the *Word2Vec* method to learn a bug representation (Continuous Bag of Words) model, then extract *vocabulary*. The vocabulary is in the *vocab* field of the Word2Vec model's *wv* property, as a dictionary, with the keys being each token (word).

```
wordvec_model = Word2Vec( all_data, min_count=min_word_frequency_word2vec,
size=embed_size_word2vec, window=context_window_word2vec)
vocabulary = wordvec_model.wv.vocab
```

Fourth, to preprocess the triaged dataset is very similar to the operation of processing the untriaged dataset. We store the title and description of every bug into an array, and the owner into another array as well for the following computing. The use-case of triaged dataset is shown below.

```
{
	"owner" : "amit@chromium.org",
	"issue_title" : "Scrolling with some scroll mice (touchpad, etc.) scrolls down but not up",
	"description" : "\nProduct Version : <see about:version>\r\nURLs (if applicable) :0.2.149.27\r\nOther browsers tested: Firefox / IE\r\nAdd OK or FAIL after other browsers where you have tested this issue:\nSafari 3:\n    Firefox 3: OK\r\n        IE 7:OK\r\n\r\nWhat steps will reproduce the problem?\n1. Open any webpage on compaq 6715s running vista.\r\n2. Try scrolling with the touchpad\r\n3. Scrolling down will work , but up will not.\r\n\r\nWhat is the expected result?\nThe page to scroll up.\r\n\r\nWhat happens instead?\nThe page doesn't move.\r\n\r\nPlease provide any additional information below. Attach a screenshot if \r\npossible.\r\nOnly a minor bug.\n "
	}
```

After preprocessing, the *all_data* and *all_owner* will be:

All_data = [scrolling, with, some, scroll, mice, touchpad, etc, scrolls, down, but, not, up, product, version, see about, if, applicable, other, browsers, tested, firefox, ie, add, ok, or, fail, after, other, browsers, where, you, have, tested, this, issue, safari, 3, 7, what, steps, will, reproduce, the, problem, open, any, webpage, on, cmpaq, 6715s, running, vista, 2, try, touchpad, down, but, is, expected, result, page, to, happens, instead, doesn't, provide, any, additional, information, below, attach, a, screenshot, possible, only, a, minor, bug]

All_owner = [amit@chromium.org]

3.2 Word Vector Representation

Text granularity is generally divided into characters, words, phrases, even paragraphs and even an article, which are theoretically acceptable. They correspond to character vectors, word vectors, and phrase vectors respectively (some papers are also called region vectors), paragraph vector and article vector. My paper uses a word vector model based on word granularity, which is also a commonly used vector model in the field of natural language processing.

The first method for word embedding is one-hot method. The model treats words as an indivisible individual, and then use a dimension equal to the number of words, only the position corresponding to the word is 1 and the rest of the sparse vector is 0. This representation is called a "one-hot representation". However, this method also has a serious flaw, that is, the words exist in isolation, and the similarity between two words cannot be quantified.

For example, there are three words software, networking, kernel. Then generate a three-dimensional vector, each word occupies a position in the vector, software: [1,0,0] networking: [0,1,0] kernel: [0,0,1]. So if an article now has 1000 words, then each vocabulary will be represented by a 1000-dimensional vector, where only the position of the word is 1, and the rest of the positions are all 0, and each word vector is irrelevant.. The benefits of doing this are simple, but not very realistic. It ignores the correlation between words, ignoring the tense of English words, such as get and got have the same meaning, but the tense is different.

The second method is n-gram method. N-gram refers to consecutive n items in the text (item can be phoneme, syllable, letter, word or base pairs). In n-gram, if n=1, it is unigram, n=2 is bigram, and n=3 is trigram. After n>4, it is directly referred to by numbers, such as 4-gram, 5-gram. These are the linear relationships of the semantic space. We can do addition and subtraction. Moreover the language model for n-gram is to estimate the probability of word sequence, for a word sequence: W1, W2, W3, …., Wn, it can get the Probability of (W1, W2, W3, …., Wn).

For example, we have a sentence, “We are going to assign the UI crash bug to Peter”, if bigram is used, it will be: We are, are going, going to, to assign, assign the, the UI, UI crash, crash bug, bug to, to Peter. In Python code to implement bigram model:

```
sent= “We are going to assign the UI crash bug to Peter”
bigram = []
for i in range(len(sent)-1):
   bigram.append(sent[i] + sent[i+1])
print(bigram)
```

Output will be:

```
We are, are going, going to, to assign, assign the, the UI, UI crash, crash
bug, bug to, to Peter
```

and the language model for bi gram:

```
P (“We are going to assign the UI crash bug to Peter”) =P(We|START)
P(are|We) P(going|are) P(to|going) P(assign|to) P(the|assign) P(UI|the)
P(crash|UI) P(bug|crash) P(to|bug) P(Peter|to)
P(Peter|to) = Count (to Peter) / Count(to)
```

It is easy to generalize to trigram and n-gram. If trigram is used, it will be: We are going, are going to, going to assign, to assign the, assign the UI, the UI crash, UI crash bug, crash bug to, bug to Peter. In Python code to implement trigram model:

```
sent= “We are going to assign the UI crash bug to Peter”
trigram = []
for i in range(len(sent)-2):
   trigram.append(sent[i] + sent[i+1] + sent[i+2])
print(trigram)
```

Output will be:

```
We are going, are going to, going to assign, to assign the, assign the UI,
the UI crash, UI crash bug, crash bug to, bug to Peter
```

Finally, n-gram implementation will be as follows:

```
def nGram(lst,n):
    ngram = []
    for i in range(len(lst)-n+1):
        ngram.append(lst[i:i+n])
print(ngram)
```

Call nGram(), sent==" We are going to assign the UI crash bug to Peter ", n can be a number less than len(lst).

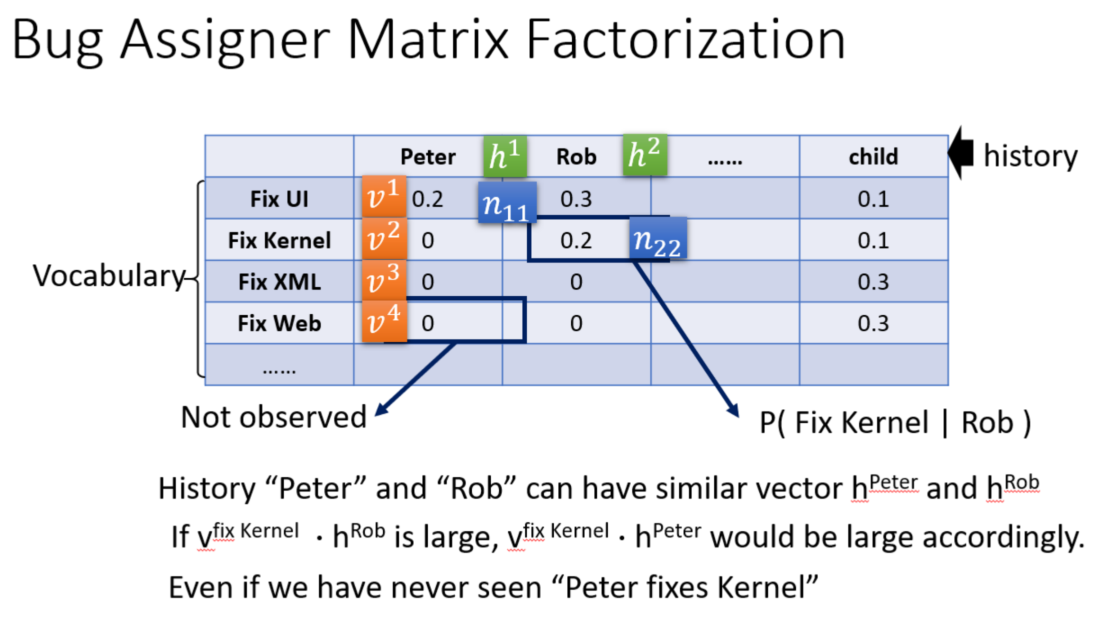
The challenge of n-gram is the estimated probability is not accurate, especially when we consider n-gram with large n because of data sparsity, shortage of training data, and uncontrollable size of dictionary. Though there is some solution like language model smoothing by giving some small probability to address the challenge, the results are not ideal.

There is a very successful view in the field of modern statistical natural language processing: the word can be well studied using only the words around the word. This provides a new idea: one of the easiest and quickest ways is to use a window-based co-occurrence matrix to represent text, using different window lengths to capture different syntax and semantics about text. The final co-occurrence matrix can get some generalized topics (such as software words, engineering words, etc.), which is equivalent to a shallow semantic analysis (Latin Semantic Analysis, LSA).

However, as the size of vocabulary in the corpus continues to increase, the co-occurrence matrix will become larger and larger, which will not only cause large-scale storage problems, but also encounter large-scale sparse matrix problems during training, which is more important. The model is not robust enough and does not have good generalization capabilities.

This is because the dimensions of the model are too high. Is it possible to use a fixed, low-dimensional vector to store text information? In fact, this model is real, and this vector is generally called a dense vector. There are two main ways to get a dense vector: the first one, using dimensionality reduction to reduce the sparse high-dimensional data into dense low-dimensional data, the typical method is singular value decomposition (SVD); the second, direct learning can be used to represent dense vectors of words. In related models (including deep learning models), there are many models that can learn the dense vector of words by model training. This dense vector is not only very effective, but also plays an important role in the field of natural language processing.

To solve the above problems, many neural networks model uses the matrix factorization language model including the following Word2Vec method.   The following Figure 8 shows how matrix factorization works. From the table in the following diagram, the history of developer “Peter” and “Rob” can have similar h^{Peter} and h^{Rob}. If $v^{fix\ Kernel} \cdot h^{Rob}$ is large, $v^{fix\ Kernel} \cdot h^{Peter}$ would be large accordingly, even though we have never seen “Peter fixes Kernel bug”. The neural network has the smoothing automatically done.



	Peter	Rob	......	child
Fix UI	0.2	0.3		0.1
Fix Kernel	0	0.2		0.1
Fix XML	0	0		0.3
Fix Web	0	0		0.3
......				

History “Peter” and “Rob” can have similar vector h^{Peter} and h^{Rob}
If $v^{fix\ Kernel} \cdot h^{Rob}$ is large, $v^{fix\ Kernel} \cdot h^{Peter}$ would be large accordingly.
Even if we have never seen “Peter fixes Kernel”

Figure 8 Bug Assigner Matrix Factorization

Mainstream of NLP prediction method is based on neural network models. On the contrary to traditional Statistics Method such as N-gram model, the neural network models are based on many parameters, and a judgment model. It employs the word vectors of text context as inputs and compute the current word probability distribution through the neural network. The current popular method is the third one, Word2Vec, which my research has chosen for defect assignment model. This is a method that Tomas Mikolov invented when working at Google and is also the name of a toolkit that is open sourced by

Google. Specifically, Word2Vec involves two algorithms, one is CBOW and the other is Skip-Gram. This is also the Word Embedding method based on neural networks after deep learning is popular. The reason why Word2Vec is so popular now is different from some previous Word Embedding methods, which can automatically implement: 1) the measurement of semantic similarity of words; 2) the analogy of semantics of vocabulary. Here, the semantic analogy reflects a relationship. Word2vec is a two-layer neural net that processes text. Its input is a text corpus and its output is a set of vectors: feature vectors for words in that corpus.

While Word2vec is not a deep neural network, it turns text into a numerical form that deep nets can understand. Word2vec's applications extend beyond parsing sentences in the wild. It can be applied just as well to genes, code, likes, playlists, social media graphs and other verbal or symbolic series. Because words are simply discrete states like the other data mentioned above, and we are simply looking for the transitional probabilities between those states: the likelihood that they will co-occur.

The purpose and usefulness of Word2vec is to group the vectors of similar words together in vector space. That is, it detects similarities mathematically. Word2vec creates vectors that are distributed numerical representations of word features, features such as the context of individual words. It does so without human intervention. Given enough data, usage and contexts, Word2vec can make highly accurate guesses about a word's meaning based on past appearances. Those guesses can be used to establish a word's association with other words (e.g. "developer" is to "tester" what "coder" is to "verifier"), or cluster documents and classify them by topic. Those clusters can form the basis of search, sentiment analysis and recommendations in such diverse fields as scientific research, legal discovery, e-commerce and customer relationship management.

The output of the Word2vec neural net is a vocabulary in which each item has a vector attached to it, which can be fed into a deep-learning net or simply queried to detect relationships between words. Measuring cosine similarity, no similarity is expressed as a 90-degree angle, while total similarity of 1 is a 0-degree angle, complete overlap. The detailed code for bug defect on word2vec in my project is implemented in the Table 1. Those noise words are removed from the model.

```
from gensim.models import Word2Vec
# Word2vec parameters
min_word_frequency_word2vec = 5
embed_size_word2vec = 200
context_window_word2vec = 5
wordvec_model = Word2Vec (all_data,
min_count=min_word_frequency_word2vec, size=embed_size_word2vec,
window=context_window_word2vec)
# vocabulary
vocabulary = wordvec_model.wv.vocab
vocab_size = len(vocabulary)
```

Table 1 Function to preprocess the text in bug report

A vector representation refers to a multi-dimensional vector table for an objective natural language (eg, a word). It is usually characterized by low dimensionality, continuous, and dense properties. In fact, there are two definitions in the field of natural language processing for word distribution. First one is called " distributional representation " and can be traced back to Semantic distributional Hypothesis (Distributional Hypothesis) proposed last century Firth: "You shall know a word by the company it keeps” [48][50]. The hypothesis states that the meaning of a word is determined by its context. That is to say, words with similar contexts usually have similar meanings. The definition is called “distributed representation” was first proposed by Hinton [51].

Hinton considers the activation vector of the middle-hidden layer neurons in neural network as “distributed representation” of the input data. Bengio firstly uses the "word embedding" method, which maps words to their distributed representation vectors, and then passes the neural network language model as Neural Network Language Model, referred NNLM., its iterative update [52]. Therefore, this lexical distribution representation is also known as word embedding.

we first build a word-context (word-context) occurrence matrix, then using the matrix decomposition technique to reduce the dimension, to get the score of each word's distributional representation vector.

There are three important technical details:

1. The choice of context. Different contexts determine the nature of the resulting word distributional representation. The more commonly used context is the documents model [53], or the model on words in the context of a certain window [54].

In general, if the context is a document or a disordered context, then the word representation is more inclined to show the subjective or semantic level characteristic. If the context is a word that is closer to the target word, or the word order information is preserved, then the word distributional representation will contain more syntactic properties.

Feature on the context syntax tree constructs semantic spaces that take syntactic relations into account. [55] From the model, the word representation will contain more properties of the dependent syntactic relations.

2. Determination of the median value of the co-occurrence matrix. It is generally necessary to weight the co-occurrence matrix to make the matrix's every element able to express the better interaction between words and context. Commonly used weighting methods are, Pointwise Mutual Information (PMI), logarithm, and so on.

3. Dimension reduction. In the co-occurrence matrix, each word corresponds to a high-dimensional and sparse vector representation. Therefore, it is necessary to reduce the dimension. The most commonly used dimension reduction methods are SVD described before, Non-negative Matrix Factorization (Non-negative Matrix Factorization, NMF), Canonical Correlation Analysis (CCA), and Hellinger

PCA [56], etc. In addition, some nonlinear dimension reduction methods can also be used, such as self-encoders Autoencoder.

Dimension reduction can eliminate some of the noise contained in the original vector, and it will also lose some of the information that may be valuable. Therefore, in real practices, it needs to be properly adjusted for the vector dimension after dimension reduction. It is worth mentioning that the Glove model proposed by Pennington et al. [57] Glove model can be considered a matrix decomposition on word to word basis, which uses regression to fit the model on the weighted co-occurrence matrix. Unlike other matrix decomposition methods, Glove only considers non-zero values in the matrix.

For the following example, there is an article with 1000 words, but we don't need 1000-dimensional representation now, but map these 1000 words to 100-dimensional or other smaller dimensions, and then each word is a 100-dimensional vector. Each vector is not as sparse as the one-hot method but has specific values. We can see that the n words after mapping are similar in semantics, such as fix xml and fix kernel, which are verbs, and both developers Peter and Rob are software engineers. Then the word vector of the two words (the vector where the line where the word is located is connected to the origin) is relatively close. The advantage of doing this is that synonyms or words with different tenses will have their word vectors very close, preserving the semantics of the article.

The following Figure 9 shows how neural network works for language modelling.

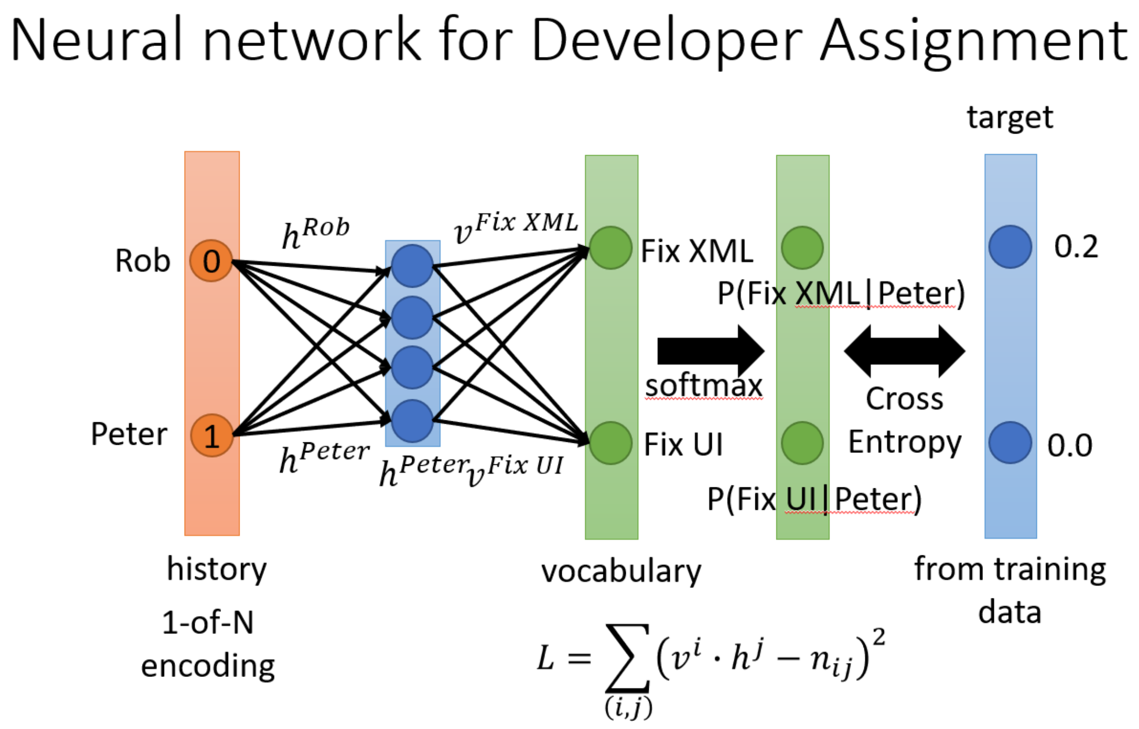


Figure 9 Neural network for Developer Assignment

The model uses Maximum likelihood estimation, MLE or other proper loss function to train the network parameters. After training, every line in the matrix E has corresponding word vector distribution representation.

If the model is used to train the text or description in bug report, the inputs are the words. If the model is aimed at obtaining distribution representation, the inputs can be anything, can be any words including predicting words, phrases before or after the training sentence, or other information. Word embedding concepts are applied to RNN language model (RNNLM). [58]RNNLM is a time sequence model that allows the language to be built by feedback from the hidden layer to the input layer. The model can take advantage of longer historical information. In addition, Mnih and Hinton propose log-bilinear Introduction model (referred to LBL) [59][60], to remove the non-linear transformation operation in hidden layer, at the same time, the output layer directly uses the word vector matrix as the weight matrix.

LBL model's training efficiency is significantly better than the feedforward neural network language model and the RNNLM. Based on similarity theory, Mikolov proposed word2vec [61], which greatly simplified the structure of the feedforward neural network language model and optimized the learning efficiency of the model, made the model easily train big data to obtain the distribution function of training words.

Two important models are used in word2vec, one is Continuous Bag-of-Words Model, referred as CBOW and the other is Skip-gram Model. For the CBOW model, conditions on context, and generate center word as shown below, Figure 10.

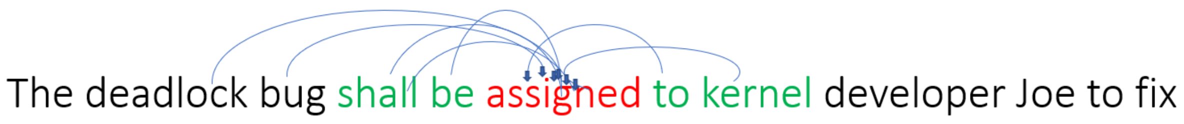

The deadlock bug shall be assigned to kernel developer Joe to fix

Figure 10 CBOW model in word2vec model

Compared with the previous model, the CBOW model has simplified the networks in two ways: 1. Removed the nonlinear hidden Layer; 2. Compared with LBL , CBOW does not consider the word order information of the context, but sums the input context words' vectors and averages, and gets the product of the vector and the target word vector.

word2vec uses two distribution matrices, one for word vectors' input and the other for output. In addition, word2vec actually is a directed graph, all of "context" to "word" connections are all directed edges. Therefore, it has different matrices for input and output, as in the LSA.

In fact, similar to "counting" model, word2vec prediction model can also use richer contexts, such as the context of dependencies [62].

For the Skip-Gram model, it is to generate each word in context given center word as shown below, Figure 11. The Skip-gram model can be considered as a special case of the CBOW model. In the Skip-gram model, we only select one-word c from the context set C each time and use its word vector as a model to predict the target word.

Similarly, maximum likelihood estimation can be used for training. So, in the Skip-gram model, actually it is directly modeling the context co-occurrence relationship between "word" and "word" and is similar to LSA. Since it is time inefficient to traverse the entire vocabulary in output layer, word2vec provides two methods in order to improve training efficiency. Firstly, hierarchical SoftMax [63], and secondly negative sampling technology. It has been proven that the Skip-gram model using negative sampling technique is equivalent to an implicit matrix decomposition [64].

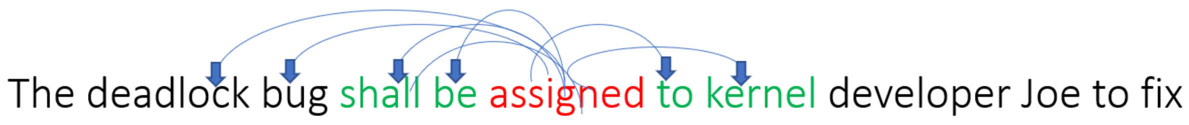

The deadlock bug shall be assigned to kernel developer Joe to fix

Figure 11 Skip-Gram model in word2vec model

In recent years, the academic community has been discussing the advantages of the "counting" model and the "prediction" model. For example, Baroni et al. demonstrated with experimental results on lexical semantic related tasks the fact that the "prediction" model is significantly better than the "counting" "Model" [65].

While Levy et al. prove that if similar technical methods in word2vec are applied to the “counting” model, there is no significant difference in the performance of the “predicting” and “counting” models

[66]. But overall, because "counting" model involves matrix decomposition operations with high memory overhead, it limits its extensibility to bigger data size.

At the same time, the “counting” model generally requires detailed adjustments to the details in order to reach high efficiency, as comparable to “predicting” model. Therefore, researchers are using more "predicting" models, especially such as word2vec.

To get a closer look at Skip-Gram and CBOW, we will actually use Word2Vec in Python. Note that the corpus we use to train the model is the Brown corpus in NLTK. In practice, obtaining a higher quality model often means a larger corpus, which of course means more training time shows in Table 2. Those noise words are removed from the model.

```
Import gensim, logging, os
logging.basicConfig(format='%(asctime)s : %(levelname)s : %(message)s'
, level=logging.INFO)
Import nltk
Corpus = nltk.corpus.brown.sents()
Fname = 'brown_skipgram.model'
If os.path.exists(fname):
    Model = gensim.models.Word2Vec.load(fname)
Else:
    Model = gensim.models.Word2Vec(corpus, size=10, min_count=5,
workers=4, iter=30)
    Model.save(fname)
Now that we have the model, let's evaluate the quality of the model.
We want to evaluate the similarity between the following words.
Words = "kernel drivers sensor hardware gps location productivity
bug".split()
For w1 in words:
    For w2 in words:
        Print(w1, w2, model.similarity(w1, w2))
```

Table 2 Code to predict next word probability

The output sample is as follows:

```
Kernel kernel 1.0
Kernel drivers 0.3451595268
Kernel sensor 0.607956254336
Kernel hardware 0.761190251497
Kernel gps 0.55852293015
Kernel location 0.24118403927
Kernel productivity 0.178044251325
Kernel bug 0.0751838683173
```

The output content is long, not all listed here, the reader can perform the experiment and observe the output. The Word2vec model can easily and quickly fuse new sentences and documents or add new words to the vocabulary. It not only encodes the similarity of words well, but also captures more complex text features. Such as grammatical features. More importantly, the trained word vector can enhance the effect of other text tasks and has a strong ability to generalize and migrate.

In general, to get a good set of dense word vectors, we not only need good representation models and parameter debugging, but the model also uses a large amount of corpus data. This paper uses the pre-trained word vector as the reference vector, that is, the word vector model trained on the Google News dataset (about 100 billion words) based on the CBOW model of Word2Vec (download URL: https://code.googIe.com/ Arch1ve/p/word2vec).

Moreover, Distribution representation has a wide range of applications in natural language processing tasks. Firstly, the distribution representation is intended to comprehensively describe the semantics of natural language processing objects, so they can be easily used for semantic similarity evaluation.

Secondly, the distribution representations learned from unlabeled text can be traditional statistical natural language processing model provides additional features. Those features can alleviate the discrete symbolic representations' data sparse problem.

Finally, the distribution representation can be combined with nonlinear models such as deep neural networks. With the powerful feature combination and learning ability of deep neural networks, the distribution of basic features can obtain a higher level, more abstract, and more related representation of target words. There are three perspectives are explained as follows.

1. Semantic similarities characteristic

The low-dimensional, continuous vector representation of the distribution representation makes it ideal for word objects' semantic similarity degree calculation (such as the most commonly used cosine distance). In fact, in the early vocabulary distribution study, semantic similarity degree calculation has been used to evaluate the quality of distributed representations [67][68]. Also, the commonly used evaluation sets are WordSim-353 [69] and the corresponding Chinese version [70] and so on. Moreover, the semantic similarity calculation of vocabulary can support many upper-level applications, such as language modelling, word meaning discrimination elimination, information retrieval, and rehearsal recognition, etc. [71].

An interesting property derived from semantic similarity is the table of distribution representations for semantic relations. Mikolov et al. firstly discovered that for the two-word pairs satisfying the same semantic relationship, their distributions are also very close [72].

For example, word embedding has a feature that can be analogized, such as

```
V("worse") - V("bad") ≈ V("tougher") - V("tough")
V("client") - V("server") ≈ V("frontend") - V("backend")
```

It has also inspired the Relational Learning research study on the relationship between the distribution representation. For example, Fu et al found that the word contains a distribution which represents a hierarchic relationship between an entity and concept can be effectively used for the word embeddings [73].

2. Semi-supervised learning model characteristic

   The vocabulary distribution representation is usually trained from unlabeled text, and the dependency on labeled text is very small. This characteristic makes semi-supervised linear learning low cost and exceptionally simple. Research has found that a number of natural language processing tough problems are solved by semi-supervised linear learning from big unlabeled data to get word clustering such as Brown clustering [74] and related information.

Specifically, great success has been achieved in the areas such as sequence labeling (word segmentation, Part-of-Speech tagging for online conversational text with word clusters, real name word recognition [75][76][77] and dependency syntax parsing and analysis [78] and so on. The basic idea of word clustering is to label a context similar word as a discrete label, equivalent to a fine-grained part of speech, but it limits the semantics information. However, the study of the distributional representation provides a semi-supervised linear learning model a new approach to look at the problem.

For the first time, Turian et al. incorporated a word based on neural network language model in the sequence labeling model for distributional representation and achieved significant higher accuracy in the word entity recognition and chunking problem [79].

Their approach is to directly combine the original feature word vector (discrete, sparse, high-dimensional) and distribution representation feature vectors (continuous, dense, low-dimensional) together to form a new set of feature vectors.

Wang et al. have done much research on the comparative study of the linear representation and the nonlinear model [80]. Their experiments show that for the distributional representation of feature spaces, the nonlinear model is far superior to the linear model.

If it is represented by a graph, it is as shown below Figure 12.

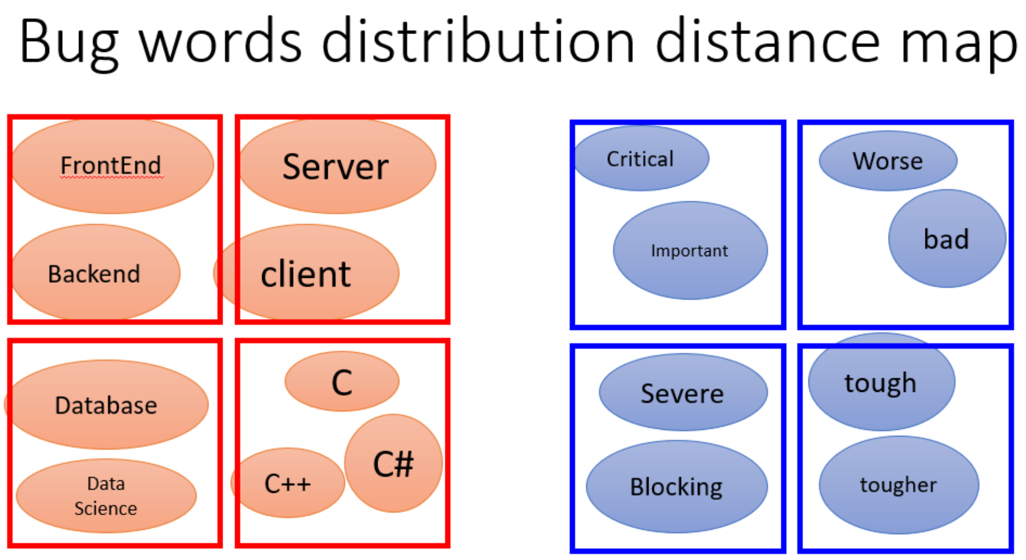


Figure 12 Bug words distribution distance map

3. Non-linear model feature learning (FFN, CNN, RNN, LSTM, ELMo, BERT and GPT-2)

   Feature learning using nonlinear models is based on the collection of combined features. Natural language processing research, especially structural prediction problems on sequence labeling and syntax analysis use huge hypothesis space.

   Therefore, a good feature representation is crucial to learning for statistical models. In the traditional method, because the linear model cannot effectively express the combination of features, therefore, engineers has used their empirical knowledge and engineering practices to design complex combination feature models.

   Taking Semantic Role Labeling (SRL) as an example, the best system in CoNLL 2009 uses more than 50 features. [81]. This labor-intensive feature analysis engineering, which relies heavily on expert knowledge, is not only costly but also suffers from incomplete selection of high dimension features space, and inefficient feature extraction.

Therefore, for natural language processing, deep neural networks with the strength of nonlinear modelling provides huge advantages. The case, especially the neural network language model introduced before such as NNLM model which uses context distributional representation vector as an input, the vector goes through a nonlinear hidden layer tanh activation function and becomes intermediate vector. The probability distribution of the target word is calculated by the output layer with SoftMax - a generalized linear model.

In the feedforward neural network (FFN), the intermediate distributional representation vector is obtained by the hidden layer to process context segment input vector and combine and abstract them. The same idea can be applied to other NLP areas such as syntactic analysis. In a dependency semantic parser system research, Chen and Manning has non-linear hidden layer cube activation function calculate the distributional representation of the transition state, and SoftMax is used to predict the transition action.

Their model only needs to use a small number of basic features of the distributional representation as input, but in the hidden layer it implementation the aggregation of feature vectors, which greatly improves the efficiency of dependency parsing. It can process 1,000 sentences per second.

In addition to the relatively simple structure of the feedforward neural network, the network structure commonly used in natural language processing are recurrent neural networks, convolutional neural networks (CNN) and recursive neural networks (RNN).

CNN [86] is based on the simulation of biological neural networks' local reception field effects. In CNN model, hidden neurons are connected to only a portion of input layer neurons are connected, while the local connection weights of the different hidden layer neurons are shared. CNN is mainly composed of convolutional layer and pooling layer.

The local connection property of CNN makes it change for the translation, scaling, and tilting of the data highly invariant and is now widely used in the field of image processing [87] .

At the same time, this advantage of CNN can be applied in many natural language processing tasks, such as classifying the review text, the blog comments like Amazon book reviews which are often determined by some local phrases, without regard to the context or the position of these phrases in the text. Therefore, CNN has also been widely used in text classification related tasks in recent years and has achieved reasonable results [88][89][90].

In fact, the earliest application of CNN in natural language processing was proposed by Collobert et al. to handle NLP by deep neural networks with multitasking learning. The framework is also known as the C&W model. [91][92]

C&W model is mainly designed for word labeling tasks to use the distributional representation features such as words, word affixes, POS, etc. as multi-tasking deep neural network input, automatically learn the aggregation and interaction between features through CNN, then through the non-linear hidden layer fully connected layers, make the final prediction label at the output layer in the end.

However, because word sequence labeling tasks are very sensitive to information such as word order, so CNN is not necessarily the most ideal feature learning model. The later research shows that a more ideal solution is to use the recursive neural network.

RNN has achieved great success in natural language processing. As early as the last century, RNN was just proposed. At the time, researchers have successfully applied it to natural language processing such as word tagging and oral language analysis. However, limited by the computing power at that time, RNN did not attract widespread attention. In recent years, with the excellent performance of RNN on language model [82][83], researchers notice that RNN is highly applicable to text processing, which is sensitive to long-distance dependence.

Currently, RNN is used in almost all-natural language processing problems, including traditional structural predictions (lexical, syntactic, semantic analysis, etc.) and hot topics like NLP - machine translation.

Simultaneously, RNN also shed lights on many tough research areas that are difficult to achieve with traditional techniques, such as text summaries, poems generation, dialogue system, picture caption generation, and more.

However, we found if RNN has too extreme deep layers, it has severe gradient vanish or gradient explosion problem during training process. It is not ideal for the RNN to capture long-distance dependence in practice.

To solve the above issues, Hochreiter and Schmidhuber proposed Long Short-Term Memory (LSTM) which is a gated RNN, re-emphasize or forget a certain input vectors to a gate in a network. [84]

These controlled inputs enable the flow of information in the RNN to be efficiently transmitted over long distances. Furthermore, coder-decoder framework is proposed [85] to solve a series of sequence-to-sequence problems with a simple and effective end-to-end solution. The above two proposals have made great breakthroughs on solving gradient vanishing and explosion problems.

In recent NLP development, a new model ELMo is created in 2018 by AllenNLP. [93] It employees a deep, bi-directional LSTM model to gain word representations. Instead of a dictionary of words and their corresponding vectors, ELMo studys words within the context that they are used and use the model to form representations of out-of-vocabulary words.

ELMo is used is quite different to word2vec or fast Text. Instead of having a dictionary ‘look-up’ of words and their corresponding vectors, ELMo builds vectors on-the-fly by passing text through the deep learning model.

Google researchers create a deep bidirectional transformer model for 11 natural language processing tasks that surpasses human performance in the area of question answering. The system is called BERT which is a bidirectional encoder to capture long-distance dependencies compared to a RNN architecture.[94] It is an outstanding feature that differentiates BERT from OpenAI GPT (a left-to-right Transformer) and ELMo (a concatenation of independently trained left-to-right and right- to-left LSTM).

BERT pre-trains a binarized next sentence prediction task that can be trivially generated from any monolingual corpus. It is a huge model, with 24 Transformer blocks, 1024 hidden layers, and 340M parameters. Moreover, BERT pre-trains on 40 epochs over a 3.3-billion-word corpus, including BooksCorpus (800 million words) and English Wikipedia (2.5 billion words).

In early 2019, OpenAI GPT-2 (Generative Pretrained Transformer-2) model recently achieved leading results across several language modeling benchmarks in a zero-shot setting. [95] The model has the ability to generate coherent text in areas of question answering, summarization, and etc.

Word2vec is an algorithm used to obtain distributed representations of words. Unfortunately, it does not address polysemy, or the co-existence of many possible meanings for a given word or phrase. For example, go is a verb and it is also a board game. The meaning of a given word type such as go varies according to its context such as the words that surround it.

ELMo, BERT and GPT-2 can obtain much better results in natural language processing tasks by encoding the context of a given word, by including information about preceding and succeeding words in the vector that represents a given instance of a word.

3.3 Chapter summary

The chapter mainly introduces the mainstream methods in the field of natural language processing especially in the areas of word vector representation. They are the following principals in word vector model: 1) CBOW and NGram 2) Skip Gram 3) LSA

Firstly, word vectors form the basis in natural-language processing. Word2vec is an algorithm used to produce distributed representations of words. By that, the word types, for instance, any given word in a vocabulary, such as get or grab or go has its own word vector, and those vectors are stored in a lookup table or dictionary.

Secondly, word2vec library is applied to bug assignments in the codes for my dissertation's experiments. The model can be tuned with the following consideration: the choice of context, determination of the median value of the co-occurrence matrix, and dimension reduction.

Thirdly, word distribution representation can be categorized as many characteristics, empirical, linear, and nonlinear models. Therefore, the chapter discusses semantic similarities characteristic, semi-supervised learning model characteristic and non-linear model feature learning (FFN, CNN, RNN, LSTM, ELMo, BERT and GPT-2).

Next chapter the paper will introduce a new software defect assignment model's layer 2 – LSTM and rule-based engine.

Chapter 4 New Software Defect Assignment Model – Layer 2: LSTM and Rule-based Engine

From Figure 4, the paper starts with defects reports analysis by building a vector for the defect report. We will analyze the defect report and choose the method to build the vector for word. There are many methods below this paper presents. Then it finds the Word2Vec model built upon neural networks can have the best results.

Our defect assignment LSTM Framework has two neural networks connected, the first one is the Word2Vec neural network, on top of Word2Vec neural network, is the LSTM for the final label prediction on assignment to developer.

At present, the text classification field introduces a brand-new model-Recurrent neural network model. Recurrent neural networks (RNN) [47] have achieved great success in the field of natural language processing. RNN has the recurrent feature in its network model and can store the relationship between the previous neuron and current neuron. It is a feedback structured neural network, which output not only depends on the value of current inputs and their weights, but the output also counts the weights and values of the previous neurons. By this way, RNN learns more and trains recurrently.

In traditional neural networks, the model starts from input layer to hidden layer, then to output layer. The layers are connected but the nodes in each layer is not connected. Because of the missing connections between nodes in each layer, the traditional neural networks are unable to handle many problems. For example, if you want to predict what next word the sentence is going to be, you need to know the previous words because the words before and after in a sentence are not independent.

However, RNN can preserve the relationship between the previous node and current node in a sequence of words. Moreover, RNN calculates the output value with the consideration of previous hidden layer's nodes' interrelation. RNN's current hidden layer's inputs capture not only the output of its input layer information, but also the output of the previous hidden layer's output information. It can also handle unlimited length sentence's weight and bias computation.

Though feedforward neural network has good ability to fit the curve with nonlinear function, it has no state information. RNN has FFN advantage but also can keep the signal from one neuron to another one, and will not lose it, and has the signal preserved for a period of time, like having memory capability.

RNN has three categories, 1) Fully recurrent neural networks. 2) Locally recurrent neural network. 3) Long short-term memory neural networks. Among the above three categories, LSTM has the great benefits, because it has solved other RNN's shortcoming, which is not able to store the neuron to neuron relationship for a long term **Error! Reference source not found.**.

LSTM structure has unparalleled natural advantages in extracting features such as natural language sentences. It is good at capturing local parts of words (can be easily understood). For a small part of phrases, such as short phrases, LSTM extract and combine these layers, from basic features to complex features, to finally identify its meaning, in other words, the local features of the extracted text sequence. The specific introduction is as follows.

The biggest feature of LSTM model is to allow memory operations to quickly learn useful context features and filter out other useless words. Our auto bug assignment takes advantage of the context memorization operation.

4.1 Model Overview – Layer 2: LSTM and Rule-based Engine

The layer 1 - word vector representation is connected to layer 2 – LSTM and rule-based engine. The word vector model maps discrete words in each text into a fixed-dimensional feature vector to get the word direction. They are accessed by the layer 2 - LSTM to get a vectorized representation of the entire document.

In order to solve the problem that existing LSTM does not perform well in modeling long sequences and cannot describe the natural existence of documents. This paper improves the ordinary LSTM model with one additional rule engine layer. LSTM models text in the sentence level, meanwhile the weights of the LSTM model are shared with the additional rule engine layer in the evaluation of developers' experience.

The LSTM that models each sentence is to read the word direction of each sentence. The quantity then produces the sentence vector corresponding to each sentence, so that the entire text becomes a sequence of sentence vectors. Then, in this level of developers' experience modeling, another rule engine will read the output of LSTM model, resulting in vectorized representation of the entire final output.

In this process, the structural information between the words in each sentence is very good. The location is preserved, and the structural information between each sentence vectorization is expressed.

After getting the vectorized representation of the bug report, the model begins text label classification of the document. One multi-label classification strategy is proposed, the first is a multi-label classification strategy based on label confidence ranking, which performs multiple logistic regression on bug report features after vectorization expression, and obtains a confidence level for each label. , representing the probability that the document belongs to the tag, on the basis of which a dynamic threshold is used to select those tags whose confidence is higher than the threshold as the prediction result. The dynamic threshold is obtained by the lease square multiplication regression, which can be dynamically adjusted according to the various confidence values obtained by multiple logistic regression.

Then a classifier is trained on each non-leaf node on the hierarchical tag tree, and the classifier defines the overhead of moving from that node to each of its child nodes by the developer experience rule engine. In the prediction, similar to the classification method of the decision tree, the algorithm gradually selects the child node from the root through the classifier on the non-leaf node, and finally obtains a path with the best cost, and all the nodes on the path serve as the output prediction.

Chapter 4 will focus on my model research on the Layer 2: LSTM and Rule-based Engine areas.

Layer 2 Model summary is described in the following diagram Fig 13:

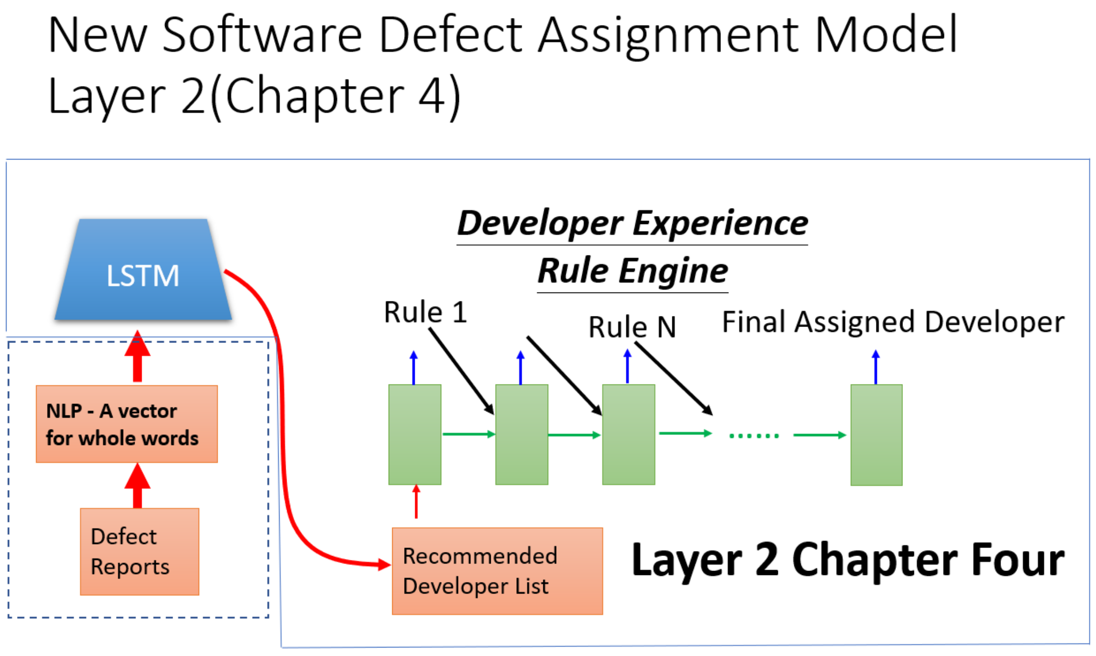


Figure 13 Software Defect Assignment Model Layer 2

Algorithm 2: Construct deep learning model

Input:
The data set of the removed noise
Output:
The validation result of the untriaged data

```
1: BEGIN
2: Get the sample length of cross validation of each time
3: FOR each cross validation
4:     Divide triaged dataset into training set and testing set according to the concept of cross validation
5:     FOR each sample of training data set
6:         IF the length of current train filter is larger than minimum sentence length
7:             Remove words outside the vocabulary from training data set
8:             Remove words outside the vocabulary from the owner array of training data set
```

```
9:              END IF
10:       END FOR
11:       FOR each sample of testing data set
12:             IF the length of current test filter is larger than minimum sentence length
13:                 Remove words outside the vocabulary from testing data set
14:                 Remove words outside the vocabulary from the owner array of testing data set
15:             END IF
16:       END FOR
17:       FOR each sample of processed test_owner array
18:             IF the owner of testing sample doesn't exist in (test_owner – train_owner)
19:                 Remove data from test set that is not there in train set
20:                 Remove owner of test set that is not there in train set
21:             END IF
22:       END FOR
23:       Create train and test data for deep learning model
24:       Construct the deep learning model by LSTM
25:       Test the testing data set and print out the test accuracy
26: END FOR
27: END
```

According to the result of triaged dataset preprocessing, we can get the arrays *all_data* and *all_owner*. and the triaged dataset is split into training data and testing data with a specific number of cross validations you provide to remove training bias. Let's say the number of cross validations is 3, the whole triaged bug dataset is divided into three parts, we can call them, *sub1*, *sub2* and *sub3*. In the first iteration, we use *sub1* as training data, in the meantime, use *sub1* as testing data as well. In the second iteration, we use *sub1* + *sub2* as training data and use *sub2* as testing data. In the third iteration, we use *sub1* + *sub2* + *sub3* as training data and use *sub3* as testing data. The process above is a classic concept of cross validation.

```
train_data = all_data[:i * splitLength - 1]
test_data = all_data[(i-1) * splitLength:i * splitLength - 1]
train_owner = all_owner[:i * splitLength - 1]
test_owner = all_owner[(i-1) * splitLength:i * splitLength - 1]
```

For each bug of training data, we would remove words outside the vocabulary (generated by untriaged bug dataset) from training data, and also remove words outside the vocabulary from the owner array if the length of current train filter is larger than minimum sentence length. For each bug of testing data, we will make the same operations as each bug of training data.

The following block is for owner operations. We would remove invalid bugs from testing set that is not there in the training set, and also remove owners of testing set that is not there in the training set if the owner of testing bug doesn't exist in *(test_owner – train_owner).*

It's time to create training and testing data for deep learning.

```
## Trainning Data
X_train = np.empty(shape=[len(updated_train_data), max_sentence_length,
embed_size_word2vec], dtype='float32')
Y_train = np.empty(shape=[len(updated_train_owner), 1], dtype='int32')

## Testing Data
X_test  =  np.empty(shape=[len(updated_test_data),  max_sentence_length,
embed_size_word2vec], dtype='float32')
Y_test = np.empty(shape=[len(updated_test_owner), 1], dtype='int32')
```

In this process, we create the empty storage space according the specific parameters individually, for example, *embed_size_word2vec*, *max_sentence_length*, for training and testing data. The next step is to store trained and tested sentence or content of training and testing dataset.

The data is ready. We start to construct the deep learning model. This model considers the word sequence both in forward direction and in back-ward direction so that a context of a particular word includes both the previous few words and following few words making the representation more robust. Long short-term memory (LSTM) cells are used in the hidden layer which have a memory unit that can remember longer word sequences and can solve the vanishing gradient problem.

```
sequence = Input(shape=(max_sentence_length, embed_size_word2vec), dtype='float32')
forwards_1 = LSTM(1024)(sequence)
after_dp_forward_4 = Dropout(0.20)(forwards_1)
backwards_1 = LSTM(1024, go_backwards=True)(sequence)
after_dp_backward_4 = Dropout(0.20)(backwards_1)
merged = concatenate([after_dp_forward_4, after_dp_backward_4], axis=-1)
after_dp = Dropout(0.5)(merged)
output = Dense(len(unique_train_label), activation='softmax')(after_dp)
```

```
model = Model(inputs=sequence, outputs=output)
rms = RMSprop(lr=0.001, rho=0.9, epsilon=1e-08)
model.compile(loss='categorical_crossentropy', optimizer=rms, metrics=['accuracy'])
```

4.2 Artificial Intelligence Neural Networks/Recurrent Neural Network

Artificial intelligence neural networks are computational models that mimic the structure of biological nervous systems. The most basic structural unit in the biological nervous system is neurons, which mimic the structure of neurons in the biological nervous system.

In 1943, McCulloch and Pitts [96] abstracted biological neurons as “M-P neuron model” that has been used today. A single neuron accepts multiple inputs from other neurons and gives different weights to each input. The input is subtracted from the threshold of the neuron by summing the weights, and an activation function is used to generate the output of the neuron. Though a single neuron is calculated in such a simple way, artificial neural network with multiple neurons connected to each other can be used to fit complex function maps.

Although the prototype of the neural network was proposed as early as 1943, it has never been popular until the Back Propagation [97] (referred to as the BP calculation) was proposed and BP’s successful application in neural network systems. In 1988, Hinton et al. successfully used BP algorithm to effectively trains some shallow networks [98], and then artificial neural network research has begun widely.

Recurrent Neural Network is a special kind of neural network. In FFN network, the edges between nodes in the neural network could not form a loop, because if there is a loop, the nodes of the entire network could not be topologically ordered, so that a logical calculation order cannot be defined for the network. RNN relaxes this restriction by allowing nodes to form loops through time steps.

Moreover, the calculation process of the RNN is divided into multiple stages according to the time step. At time T, the network performs a calculation. The internal state of the network and the calculated result can be used as the input of the T+1 time. The calculation at time T+1 affects its outcome. Figure 14 is an example of a time expanded RNN network. At each timed step, the network accepts an external input and accepts some calculations from the previous timed step to produce the output of the current time step.

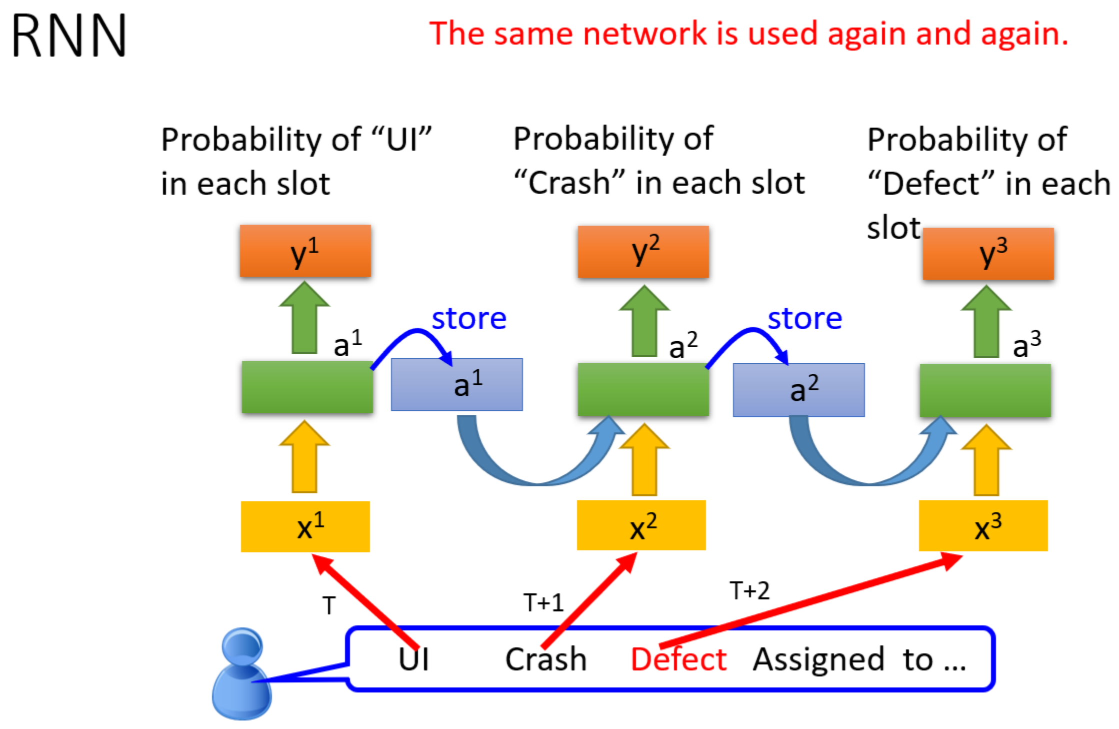

RNN
The same network is used again and again.
Probability of "UI" in each slot
Probability of "Crash" in each slot
Probability of "Defect" in each slot
y^1
y^2
y^3
store
store
a^1
a^2
a^3
a^1
a^2
x^1
x^2
x^3
T
T+1
T+2
UI Crash Defect Assigned to ...

Figure 14 Time-expanded RNN Network

During the time expansion of the RNN, an output sequence is generated step by step by an input sequence. At any T+1 time, the output of the network is the interaction of all the inputs and outputs of the former T and the internal states of the nodes in the network.

The results of such a feature allows the network can "see" the sequence of historical information that can be modeled RNN time series.

There is no essential difference between training RNN and the training of ordinary neural networks. After the RNN is expanded based on time steps, the entire network becomes a common neural network. It has inputs sequences and output sequences.

It can be trained by using the BP algorithm for this expanded network. From this perspective, RNN is just a common neural network that shares weights over multiple time steps while delivering network state between adjacent time steps. RNN is more like a recursive call to a traditional neural network.

4.3 LSTM

Although RNN can “see” all the historical information before time T+1, it can get blurred when the recursive deep first traverse call to its network. To be specific, when the network is trained by BP algorithm, the influence of these historical information on the network will gradually disappear with the network’s expansion. RNN’s such drawback is described as "vanishing gradient problem".[99]

In practice, this flaw can cause the RNN network to be unable to learn events at a certain moment with an event that happens after more than 10 hours.[99]

In order to solve this defect of RNN, many methods have been proposed like Time Delays [101], principle of history compression [102], etc. But so far, the most effective solution is the Long Short-Term Memory Artificial Neural Network Architecture as LSTM. Figure 15 shows the layer 2’s modified LSTM architecture.

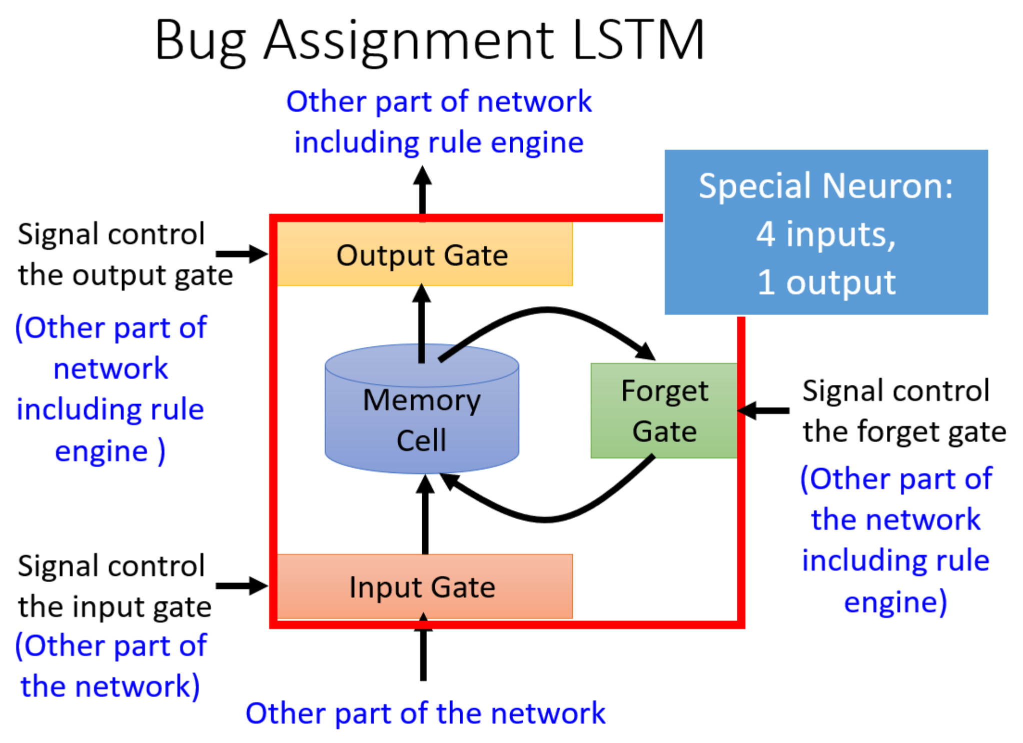

Bug Assignment LSTM
Other part of network including rule engine
Special Neuron: 4 inputs, 1 output
Signal control the output gate
(Other part of network including rule engine)
Output Gate
Memory Cell
Forget Gate
Signal control the forget gate
(Other part of the network including rule engine)
Input Gate
Signal control the input gate
(Other part of the network)
Other part of the network

Figure 15 LSTM connected with other part of network including rule engine

One reason for the problem of gradient disappearance is that the network has no memory of the input data. Over time, the network "forgets" the previous input and the state of the network. LSTM introduces the concept of "memory block".

The memory block can be regarded as a micro-version of the memory chip in the computer. Each memory block contains one or more memory units and three multiplicative units: input gate, output gate and forgetting gate, respectively corresponding to the computer storage block. The write controller, the read controller, and the reset controller, just as the controllers in the computer memory block.

Those controllers' functions are to control the reading, writing, and resetting of information stored in the LSTM memory block. After introducing the memory blocks, LSTM is a special RNN network with a replacement of ordinary neurons in RNN to memorable block. Memory blocks in LSTM can selectively remember a portion of historical information, thereby solved RNN's "vanishing gradient problem". The detailed code for bug defect on constructing LSTM layer in the project is implemented in the Table 3.

```
sequence = Input(shape=(max_sentence_len, embed_size_word2vec),
dtype='float32')
forwards_1 = LSTM(1024)(sequence)
after_dp_forward_4 = Dropout(0.20)(forwards_1)
backwards_1 = LSTM(1024, go_backwards=True)(sequence)
after_dp_backward_4 = Dropout(0.20)(backwards_1)
merged = merge([after_dp_forward_4, after_dp_backward_4],
                     mode='concat', concat_axis=-1)
after_dp = Dropout(0.5)(merged)
output = Dense(len(unique_train_label), activation='softmax')(after_dp)
       model = Model(input=sequence, output=output)
rms = RMSprop(lr=0.001, rho=0.9, epsilon=1e-08)
model.compile(loss='categorical_crossentropy', optimizer=rms,
metrics=['accuracy'])
hist = model.fit(X_train, y_train,  batch_size=batch_size,
epochs=myEpochs)
predict = model.predict(X_test)
```

Table 3 The code of constructing LSTM for software bug assignment model

With the increase of length of LSTM and limitation of inputs, its functionality decreases and is limited. To improve its accuracy, recall rate, and precision rate, the paper proposes a new component rule based engine with the consideration of developer's experience and productivity. Figure 16 shows the LSTM to connect with developer experience rule engine.

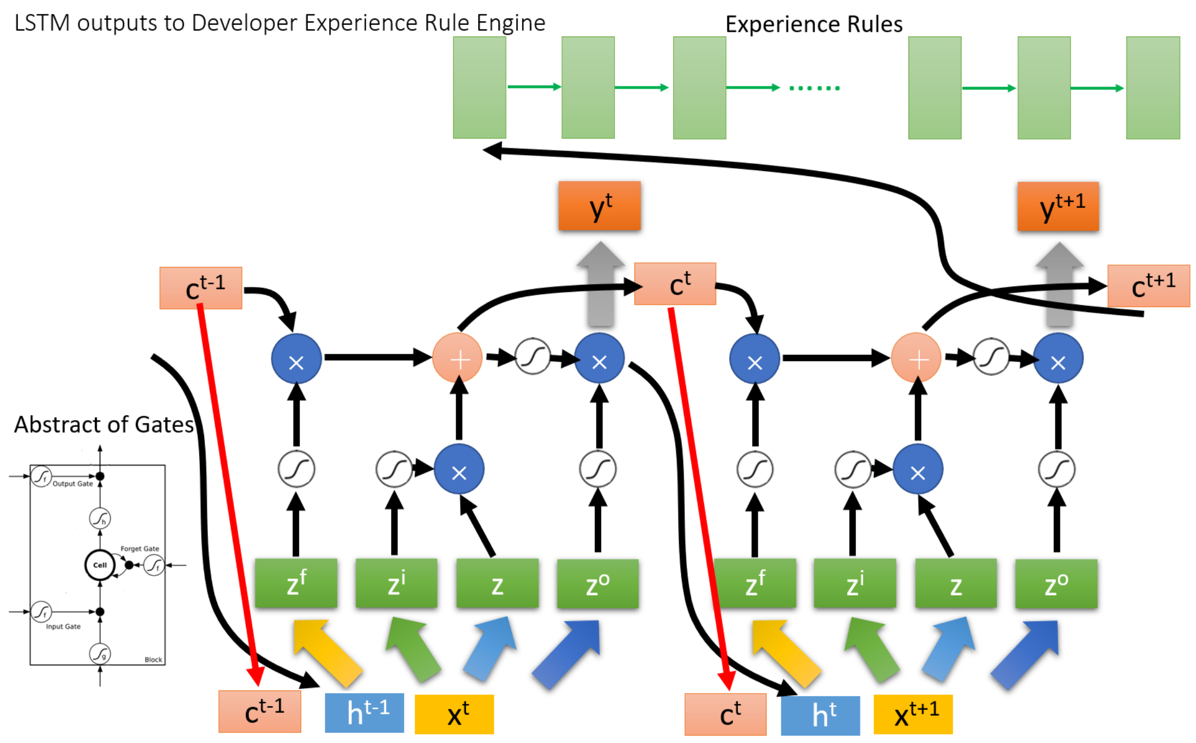


Figure 16 LSTM feeds into developer experience rule engine

4.4 Rule Engines

Knowledge representation is the area of A.I. concerned with how knowledge is represented and manipulated. Rule Engines use knowledge representation to facilitate the codification of knowledge into a knowledge base which can be used for reasoning, i.e., we can process data with this knowledge base to infer conclusions. Rule Engines are based on Expert Systems, which are also known as Knowledge-based Systems and Knowledge-based Expert Systems and are considered to be "applied artificial intelligence".

Algorithm 3: Rule Engine Algorithm

```
Input:
The absolute path of target file
Output:
Generate 'Rule Prediction' result

1: BEGIN
2: Create the translation table
3: IF exists target file
```

```
4:      Read this file by configure parser
5: **ELSE**
6:      return **NULL**
7: Use rule table to define BI rules
8: Read the new failure, new pattern and bug zero from dataset
9: **FOR each row of sample**
10:       **IF** it is a new failure
11:           Update the final result according to rule result
12:       **END IF**
13:       **IF** it is a new pattern
14:           Update the final result according to rule result
15:       **END IF**
16:       **IF** match set to "Infrastructure" issue
17:           Update the final result according to rule result
18:       **END IF**
19:       Check if it belongs to an item in missed training set table
20: **END FOR**
21: Saving new failures and new patterns
22: **IF** exclude new failure
23:     Delete new failure.
24: **END IF**
25: **IF** exclude new pattern
26:     Delete new pattern.
27: **END IF**
28: **END**
```

The process of developing with an Expert System is Knowledge Engineering. EMYCIN was one of the first "shells" for an Expert System, which was created from the MYCIN medical diagnosis Expert System. Whereas early Expert Systems had their logic hard-coded, "shells" separated the logic from the system, providing an easy to use environment for user input. Drools is a Rule Engine that uses the rule-based approach to implement an Expert System and is more correctly classified as a Production Rule System. The algorithm for rule engine’s core runtime is listed in the Table 4.

```
# Ruleset
class TableRuleset(Rule):
    def __init__(self, rules, translations=None):
        self.rules = rules or {}
        if translations:
            translator = Translator(translations)
            for rule in self.rules:
                for key in rule.keys():
                    rule[key] = [translator.replace(item) for item in
rule[key]]

    def should_trigger(self, context):
        return True

    def perform(self, context):
        """Iterate and evaluate all rules in table set, execut
corresponding action
        Args:
            context which has variables and target.

        Returns:
            Result in context (target).
        """
        count = 0
        for rule in self.rules:
            # Check if all conditions are TRUE (Logcial AND) in one
'if' clause
            count = count + 1
            if all([eval(condition, context.as_dict) for condition in
rule['if']]):
                self._current_ruleid = rule.get('id', count)
                for action, target in zip(rule['then'],
rule['target']):
                    if context._translations:
                        action = context._translations.replace(action)
                        target = context._translations.replace(target)
                    result =
context[target.replace('context.','').strip()]=eval(action,
context.as_dict)
                    self.record(context, result)
                # break on any matched rule in rules
                break
            else:
                continue
        else:
            self._current_ruleid = None
            return False
        return True

    @property
    def ruleid(self):
        if self._current_ruleid:
            return "%s.%s" % (super(TableRuleset, self).ruleid,
self._current_ruleid)
        return super(TableRuleset, self).ruleid

class RuleEngine(object):
    def execute(self, ruleset, context):
        for rule in ruleset:
            if rule.should_trigger(context):
                result = rule.perform(context)
                rule.record(context, result)
        return context
```

Table 4 Algorithm of Rule Engine Core

There are two methods of execution for a rule system: Forward Chaining and Backward Chaining; systems that implement both are called Hybrid Chaining Systems. Understanding these two modes of operation is the key to understanding why a Production Rule System is different and how to get the best from it. Forward chaining is "data-driven" and thus reactionary, with facts being asserted into working memory, which results in one or more rules being concurrently true and scheduled for execution by the Agenda.

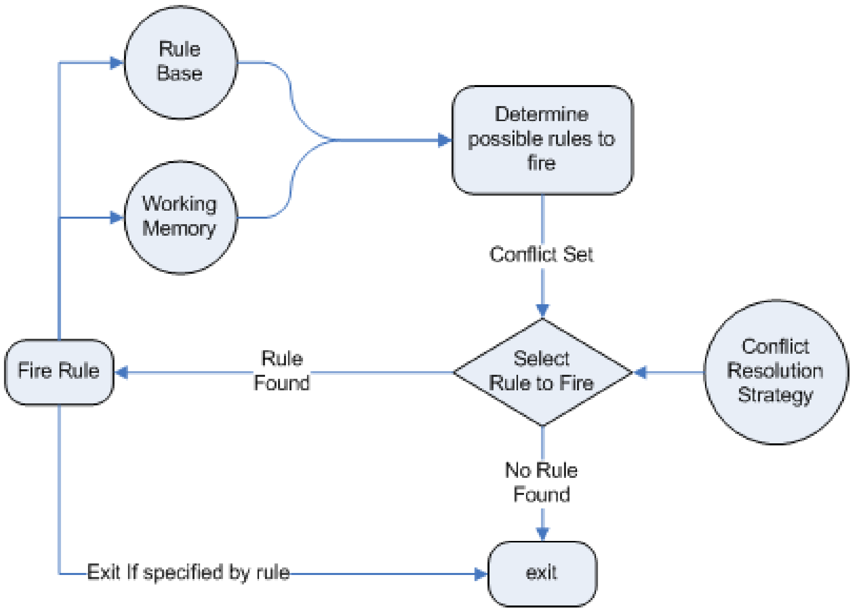


Figure 17 Forward Chaining

Backward chaining is "goal-driven", meaning that we start with a conclusion which the engine tries to satisfy. If it can't it then searches for conclusions that it can satisfy; these are known as sub-goals, that will help satisfy some unknown part of the current goal. It continues this process until either the initial conclusion is proven or there are no more sub-goals. Prolog is an example of a Backward Chaining engine. Drools can also do backward chaining, which we refer to as derivation queries.

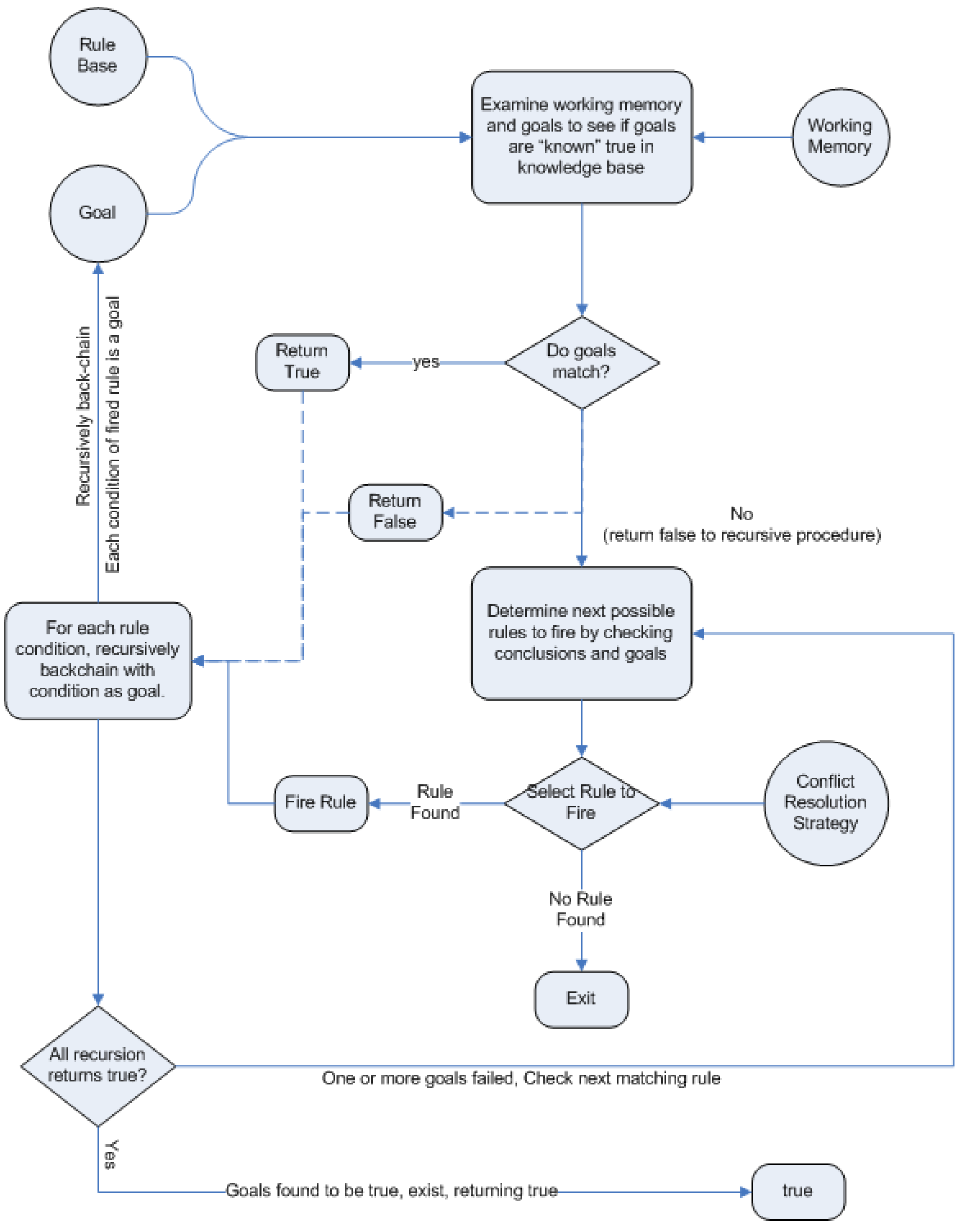

Rule Base
Goal
Examine working memory and goals to see if goals are "known" true in knowledge base
Working Memory
Do goals match?
yes
Return True
Return False
No (return false to recursive procedure)
Recursively back-chain
Each condition of fired rule is a goal
For each rule condition, recursively backchain with condition as goal.
Determine next possible rules to fire by checking conclusions and goals
Fire Rule
Rule Found
Select Rule to Fire
Conflict Resolution Strategy
No Rule Found
Exit
All recursion returns true?
One or more goals failed, Check next matching rule
Yes
Goals found to be true, exist, returning true
true

Figure 18 Backward Chaining

The proposed software defect assignment rule engine has used both forward chaining rule and backward chaining model, and captured the experience of developer, and developer's productivity, developer's context switching time, and dwelling time on the previous bugs. It uses the developers' social networking, membership in technical areas, his/her relationship and decision-making in domain areas to obtain rule engine actions. Their expertise is generally classified into their core competency, core capability, their reasoning and decision making. Rule engine has been effectively used in the experimental work for bug assignment.

It has the following characteristics. Firstly, just obtains the characteristics of developers' activity. It does not need to first analyze the mathematical model of the system like software bug assignment system and can directly use the opinions of experts. It allows system to describe rules with IF...THEN... statements. The rules are generally very intuitive. Inference rules are derived from the experience of experts. Its form is as follows:

```
If X1 AND X2 AND ......Xn then Y1 AND Y2 AND ...... Ym
```

Here n is equal to the number of system input variables, and m is equal to the number of system output variables. The sample code for rule engine's rules is implemented in the Table 5.

```
[rule]
# To determine if it's new failure, check failure table
db_newfailure_table = ChromeJob
db_newpattern_table = FireFoxPattern
# use RulesTable to correct result or not
RulesTable = { 'if': ['DeveloperInBlog >= 1', 'rerun >= 1', 'staticset == 1'], \
               'then' : ['Increase Defect Assignment by 50'],\
               'target':['rulepredict']\
              },\
             { 'if': ['EngineerinStackoverflow >= 1', 'rerun >= 1', 'staticset == 1'], \
               'then' : ['Add Code Defect to dev more weight by 20'], \
               'target': ['rulepredict']\
              }
```

Table 5 Rule Definition Format

Secondly, the software for implementing rule engine is easy and requires less storage space and computation. Production rule system generally requires only a small number of code lines and less storage space such as using the look-up table method.

Using the detected information such as developers' comments on stackoverflow.com sites, developers' code snippets in git, developers' tag in software engineering forum, developers' interest groups, and so on, then the rule reasoning is performed according to the inference rule, and finally the rule engine makes decision according to the activated rules to assign bug to the appropriate developer.

Each input variable is divided into three levels:

Developer degree of expertise in certain technical area: low, medium and high

Developer quantity of comments in stackoverflow.com site: less, medium and more

Developer quality of reviews in staockoverflow.com site: low, medium and high

Developer involvement in certain interest group: light, medium and heavy

For the output variables, Confidence in assigning the right developer to the bug into 5 levels: very low, low, medium, high, very high; Name of developer to be assigned to the bug; List of candidate developers to be assigned to the bug.

The algorithm of Rule Engine Initialization design is shown in the Table 6.

```
import os
import sys
import pandas as pd

class DictObject(object):
    """class to convert dictionary access as object's members
    """
    def __init__(self, initial=None):
        self._data = {}
        if initial:
            self.update(initial)
    def __getattr__(self, name):
        return self._data.get(name)
    def __setattr__(self, name, value):
        if name.startswith('_'):
            object.__setattr__(self, name, value)
        else:
            self.__dict__['_data'][name] = value
    def update(self, other):
        for k in other:
            self.__setattr__(k, other[k])

    def to_dict(self):
        return self._data

class Translator(object):
    def __init__(self, translations):
        self.translations = translations
    def replace(self, input):
        input = " %s " % input
        for source, target in self.translations:
            input = input.replace(" %s" % source, " %s " % target)
        return input
    def rreplace(self, input):
        input = "%s" % input
        for target, source in self.translations:
            input = input.replace("%s" % source, "%s" % target)
        return input
```

Table 6 Algorithm of Rule Engine Initialization Design

For bug assignment developer rules, firstly the rules, which have more data and fact supported by experts and more reasonable to be understood, will have higher precedence over those rules which are not vigorously verified. When the rules are used to calibrate the bug assignment system, their contribution to the accuracy, precision and recall rates can be more effective.

Developers' rules and other rules like bug-to-tech areas, bug-to-component lookup rules, etc. can be obtained based on the hierarchical set of input variables and output variables. For example, developer's assignment can be expressed by the following 27 rules:

Rule 1: If the bug report says UI, the bug has low priority, and the bug is not very severe, then a junior developer in UI area will be assigned.

Rule 2: If the bug is critical, the bug is in kernel area, and it requires developers with a lot of experience, as the developers need to contribute 20K lines codes in git code repository, then a senior developer in Kernel area, and he has met the line of codes in git criteria will be assigned.

......

In the same way, the combination of the bug’s component area, which code path the bug is in, the developer’s activity requirement can obtain the rule representation of the bug assignment as well as the Layer1 and LSTM output evaluation. The combination of the degree of developers’ social networking and stack overflow comments, and other blog history property can obtain the rule representation of which area of the bug belongs to.

Rule engine can perform complex tasks in a short period of time, rather than requiring a large amount of mathematical calculations using mathematical methods. Moreover, since the rule engine calculation itself is a parallel structure, each input can be computed at the same time, or each rule can be reasoned. The algorithm of Rule Engine Execution design is shown in the Table 7.

```
class RuleContext(DictObject):
    """
    Rule context to store values and attributes (or any object).
Used when applying rule engine
    """
    def __init__(self):
        super(RuleContext, self).__init__()
        self._executed=[]
    def __setitem__(self, item, value):
        self.__setattr__(item, value)
    def __getattr__(self, item):
        if not item in self.__dict__ and not item in self._data:
            return None
        return super(RuleContext, self).__getattr__(item)

    @property
    def as_dict(self):
        return {'context' : self}

# Single rule
class Rule(object):
    """
    Rule class - virtual class for table rule set
    """
    def should_trigger(self, context):
        pass
    def perform(self, context):
        pass
    def record(self, context, result):
        context._executed.append((self.ruleid, result))
    @property
    def ruleid(self):
        return self.__class__.__name__.split('.')[-1]
```

Table 7 Algorithm of Rule Engine Execution Design

With rule engine, the operators of the hybrid model can start designing the approximate rule subset and rules, and then adjust the parameters step by step to optimize the system. The various components of the rule inference process are functionally independent, so that the system such defect assignment can be easily modified. For example, you can add rules or input variables without having to change the overall design. For a conventional software defect assignment, adding an input variable will change the overall algorithm. When developing a rule engine bug assignment system, you can concentrate on functional goals rather than analyzing mathematical models, so you have more time to enhance and analyze the system. Figure 19 shows the End to End Bug Assignment with developer experience rule engine.

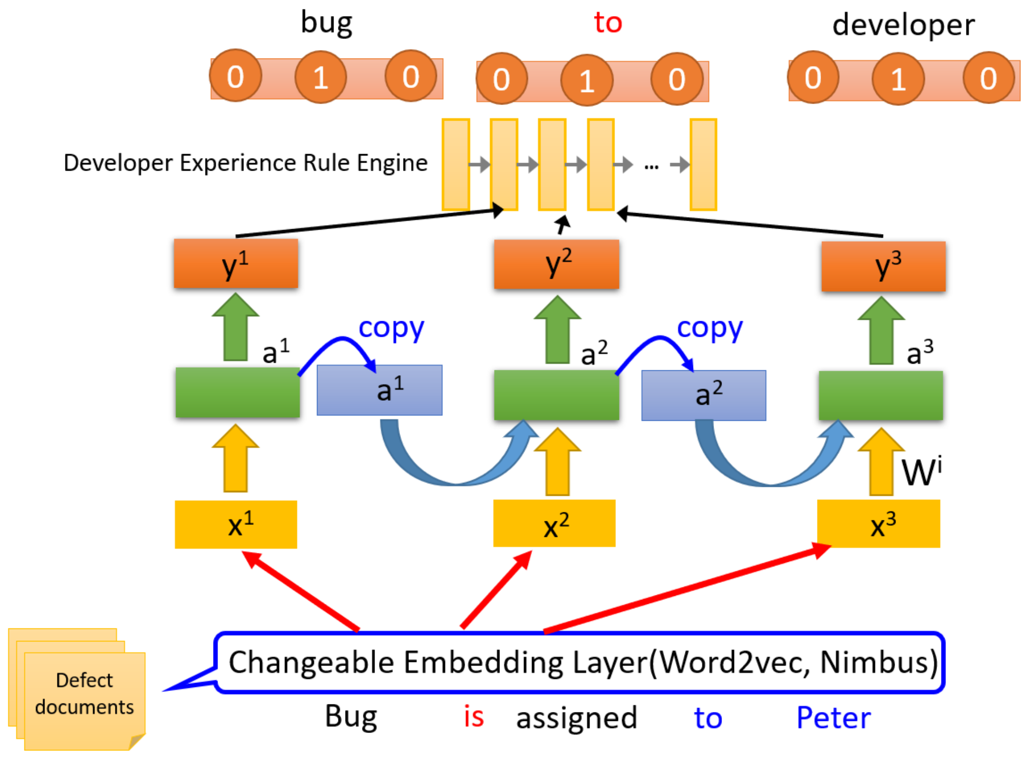


Figure 19 End to End Bug Assignment with developer experience rule engine

```
print('=====Deep learning + rule engine method=====')
            for k in range(1, rankK + 1):
                id = 0
                user_index = 0
                runs = 100
                trueNum = 0
                lableOwner = []
                lableOwnerId = []
                for sortedInd in sortedIndices:
                    pred_classes.append(classes[sortedInd[:k]])
                    if Y_test[id] in sortedInd[:k]:
                        trueNum += 1

                    # store error data
                    elif user_index < runs and k == rankK:
                        lableOwner.append(classes[Y_test[id]])
                        lableOwnerId.append(id)

                        # Base url setup
                        #print('rule engine start')

                        # u_email = 'abarth@chromium.org'

                        u_email = ' '.join(map(str,
lableOwner[user_index]))
                        base_url = 'https://monorail-
prod.appspot.com/p/chromium/issues/list?can=1&q='
                        url = base_url + u_email

                        try:
                            # Get the webpage
                            f = requests.get(url, timeout=5)
                            soup = BeautifulSoup(f.content, "lxml")

                            # Get the key words
                            res = []
                            for keywords in soup.find_all('td',
class_='col_8'):
                                a = (keywords.find_all('span'))
                                b = str(a[0].string).split()
                                for val in b:
                                    res.append(val)

                            unique_result = list(set(res))

                            # Get test set
                            test =
testedContent[lableOwnerId[user_index]]

                            # Get overlap percentage
                            overlap = set(unique_result) &
set(list(filter(None, test)))
                            percentage_overlap = float(len(overlap)
/ len(test))

                            # The customize rule
                            bar_percentage = 0.3
                            rule_flag = True if percentage_overlap >
bar_percentage else False
                            if rule_flag:
                                trueNum += 1
                            #print('user_index:  ', user_index)
                            #print('overlap percentage:::   ',
percentage_overlap)
                            #print('rule result:::  ', rule_flag)
                            #print('rule engine end')
                        except requests.exceptions.RequestException
as e:  # This is the correct syntax
                            print (e)

                        user_index += 1

                    else:
                        lableOwner.append(classes[Y_test[id]])
                        lableOwnerId.append(id)

                    id += 1
                accuracy.append((float(trueNum) / len(predict)) *
100)
            print('Test accuracy:', accuracy[-1])
```

Table 8 Python Code of Rule Engine Web Request and Keyword Overlaps Design

After the running of the LSTM model on the training set, and the model is applied to real data, and with the real data, a HTTP web request is called to retrieve the developer's experience such as the bugs he has fixed and the bugs' description. From the HTTP content, the Python code is used to extract the keywords of the developers' experience. Meanwhile a configured value is used, such as bar percentage = 0.3, that means if the developers' keywords has 30 percent overlap with the on-field bugs' description, that the model overwrites the LSTM results with the developers' experience values and reassign the bug to that developer. Overall with the rule engine, the confusion matrix accuracy has drastically increased.

```
overlap = set(unique_result) & set(list(filter(None, test)))
percentage_overlap = float(len(overlap) / len(test))
bar_percentage = 0.3
rule_flag = True if percentage_overlap > bar_percentage else False
```

We call the above process that is “online” mode. Sometimes, the user cannot connect the internet, we also provide a “offline” mode to ensure the efficiency of our system. First, we collect the valuable information of each bug owner by web crawler. Second, store them to a JSON file: *webData.json*, the reason that selecting JSON as storage format is the transition and searching speed is very fast between JSON and Python. Third, the system may get the information from the file webData.json directly, the processing speed is faster than getting data by HTTP requests.

4.5 Chapter summary

The chapter mainly introduces the hybrid model’s layer 2: LSTM and Rule-based Engine,

Firstly, it gives an overview on Artificial Intelligence Neural Networks/Recurrent Neural Network. It describes the history of Artificial Intelligence Neural Networks and its evolution. FFN and RNN are illustrated briefly. RNN’s shortcoming such as "vanishing gradient problem" is pointed out, and LSTM is introduced to solve the problem.

Secondly, one reason for the problem of gradient disappearance is that the network has no memory of the input data. Over time, the network "forgets" the previous input and the state of the network. LSTM introduces the concept of "memory block".

Thirdly, rule engine is the core of the Layer 2 of the paper’s hybrid model, and is based on Expert Systems, which are also known as Knowledge-based Systems. Knowledge-based Expert Systems and are considered to be "applied artificial intelligence". The proposed software defect assignment rule engine has used both forward chaining rule and backward chaining model, and captured the experience of developer, and developer’s productivity, developer’s context switching time, and dwelling time on the previous bugs. It uses the developers’ social networking, membership in technical areas, his/her relationship and decision-making in domain areas to obtain rule engine actions.

Fourthly, for bug assignment developer rules, the rules, which have more data and fact supported by experts and more reasonable to be understood, will have higher precedence over those rules which are not vigorously verified. When the rules are used to calibrate the bug assignment system, their contribution to the accuracy, precision and recall rates can be more effective.

Finally, with rule engine, the operators of the hybrid model can start designing the approximate rule subset and rules, and then adjust the parameters step by step to optimize the system. The various components of the rule inference process are functionally independent, so that the system such defect assignment can be easily modified.

Chapter 5 Data Collection and Experiments Result

Software defect assignment is a process of reporting that potentially contain defects, analyzing them, and assigning developers to fix potentially buggy code. Figure 20 presents a typical software defect assignment process which is commonly adopted. As the process shows, the first step is to collect source code files (instances) from software archives and label them as buggy or clean. The labeling process is based on the number of post-release defects of each file. A file is labeled as buggy if it contains at least one post-release bug. Otherwise, the file is labeled as clean. The second step is to extract features from each file. There are many traditional features defined in past studies, which can be categorized into two kinds: code metrics and process metrics. The instances with the corresponding features and labels are subsequently employed to train predictive classifiers using various machine learning algorithms such as SVM, Naive Bayes, and Dictionary Learning. Finally, new instances are fed into the trained classifier, which can predict whom the bug should be assigned to. In our case, it employs the hybrid model of NLP, LSTM and rule-based engine.

The set of instances used for building the classifier is training set, while test set includes the instances used for evaluating the learned classifier. In this work, we focus on within-project defect assignment, i.e., the training and test sets belong to the same project. Following the previous work in this field, we use the instances from an older version of this project for training, and instances from a newer version for test.

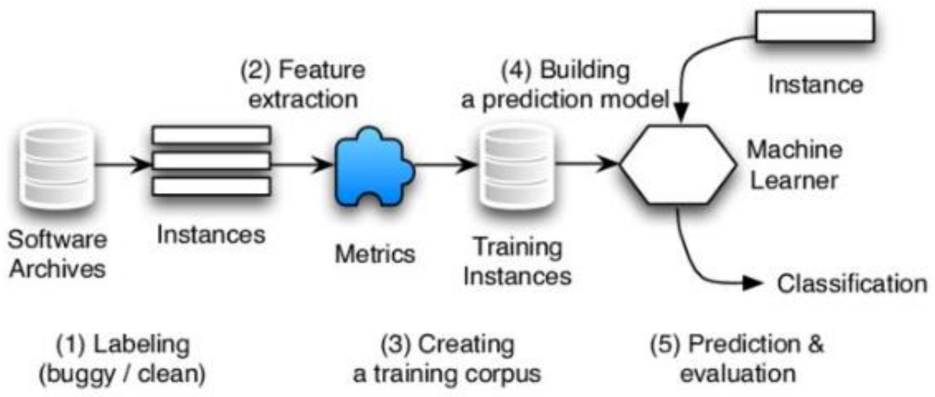

(2) Feature extraction
(4) Building a prediction model
Instance
Machine Learner
Software Archives
Instances
Metrics
Training Instances
Classification
(1) Labeling (buggy / clean)
(3) Creating a training corpus
(5) Prediction & evaluation

Figure 20 The process of software defects prediction

5.1 Data preparation and preprocessing

In the software development process, once the software is found to be defective and needs to be repaired, the relevant personnel will submit it to the defect library in the form of a report to form a defect report. A defect report mainly consists of three parts: 1) the summary and predefined fields (mainly including status, product, component, etc.); 2) is a description, describes how to achieve the recurrence of defects, to help developers understand the occurrence of defects. The process is to find out the cause of the defect; 3) the comment, which mainly records some suggestions and suggestions from the developer for the defect.

This paper selects the defect data of large open source software projects of Chrome as the experimental data set. TrainData.json file contains training sets for using training and validation. That file has 114750 records which is downloaded from https://www.kaggle.com/crawford/deeptriage#classifier_data_0.csv. That file might be updated since last time downloaded.

TrainData.json file has the following field descriptions for each row

Email address	Bug owner (person who will fix it)
issue_title	Title of bug description

Description	Description of the bug

For training set, an example of row in the JSON file as follows:

```
{
            "owner" : "robhogan@chromium.org",
            "issue_title" : "Alt texts are rendered horizontally in
vertical writing mode",
            "description" : "\nUserAgent: Mozilla/5.0 (Macintosh; Intel
Mac OS X 10_9_4) AppleWebKit/537.36 (KHTML, like Gecko)
Chrome/38.0.2107.2 Safari/537.36\r\n\r\nExample URL:\r\n\r\nSteps to
reproduce the problem:\r\nOpen a page contains missing image in vertical
writing mode.\r\n\r\nAlt texts for missing images are not rendered
vertically in vertical writing mode and orientation of text is incorrect.
\r\n\r\nAlt texts should be rendered vertically.\r\n\r\nWhat is the
expected behavior?\r\n- Alt text: rendered vertically in vertical writing
mode\r\n- Japanese characters (fullwidth): glyphs are not rotated\r\n-
Latin characters (halfwidth): glyphs are rotated clockwise 90
degrees\r\n\r\nWhat went wrong?\r\n- Alt text: rendered horizontally in
vertical writing mode\r\n- Japanese characters (fullwidth): glyphs are
rotated counter-clockwise 90 degrees\r\n- Latin characters (halfwidth):
glyphs are not rotated\r\n\r\nDoes it occur on multiple sites:
Yes\r\n\r\nIs it a problem with a plugin? No \r\n\r\nDid this work
before? No \r\n\r\nDoes this work in other browsers? Yes \r\n\r\nChrome
version: 38.0.2107.2  Channel: canary\r\nOS Version: OS X 10.9.4\r\nFlash
Version: Shockwave Flash 14.0 r0\r\n\r\nSame issue in
WebKit\r\nhttps://bugs.webkit.org/show_bug.cgi?id=135383\n "
      }
```

Cross validation number numCV is defined in our python code.   If numCV = 3, that means 33% of TrainData.json will be validation data to verify the model, 67% will be used in LSTM to build the model.

After the running of the LSTM model on the training set in supervised training mode, and rule engine is coming into picture to validate the wrong assignment which is shown in the confusion matrix.

Since it is the supervised learning, the confusion matrix knows the wrong assignment. Rule engine is applied to real data, and with the real data. Rule Engine is set for using to correct the wrong owner assignment during the validation. The more developers to be run and the more developers' keywords info, the better of accuracy

There are two modes of Rule Engines validation, one is the online mode, and the other is the offline mode. If it is online mode, a HTTP web request is called to retrieve the developer's experience such as the bugs he has fixed and the bugs' description. The code call the https://monorail-prod.appspot.com/p/chromium/issues to get the owners' keywords. From the HTTP content, the Python code is used to extract the keywords of the developers' experience from the training set. Meanwhile a configured value is used, such as bar percentage = 0.3, that means if the developers' keywords has 30 percent overlap with the on-field bugs' description, that the model overwrites the LSTM wrong prediction results with the developers' experience values and reassign the bug to that developer. Overall with the rule engine, the confusion matrix accuracy has drastically increased.

Sometimes, the user cannot connect the internet, or we want to have consistent model benchmark, we also provide a "offline" mode to ensure the efficiency of our system. First, we collect the valuable information of each bug owner by web crawler. Second, store them to a JSON file permanently: *webData.json*, the reason that selecting JSON as storage format is the transition and searching speed is very fast between JSON and Python. Third, the system may get the information from the file webData.json directly, the processing speed is faster than getting data by HTTP requests. WebData.json is obtained by our data populator and get them from the https://monorail-prod.appspot.com/p/chromium/issues for only one time and then we can train the data offline. getownerjson.py is the code to create the above WebData.json.

WebData.json has the following field descriptions for each row

Email address	Developer (person who will fix it)
Keywords list	Developer's activity, technical ability and key attributes

TestData.json contains all the bug reports, and Owner field is the developer's email alias which is empty before running our model. Once our model is deployed in production to predict the Owner field, the model will predict which email alias and fill the email address in the Owner field.

TestData.json has the following field descriptions for each row

Id	Bug id
issue_id	issue id
issue_title	Title of bug description
reported_time	Time bug was reported
Owner	email address of owner of the bug (person who will fix it)
Description	Description of the bug

Bug reports from the Google Chromium project were downloaded for the duration of 2008-09-02 (Bug ID: 3) - 2013-09-05 (Bug ID: 633012).

For test set to be predicted after using our bug assignment model, an example of row in the JSON file as follows:

```
{
                "id" : 3,
                "issue_id" : 5,
                "issue_title" : "Java not working yet",
                "reported_time" : "2008-09-02 19:04:27",
                "owner" : "",
fariie\r\nadd ok or fail after other browsers where you have tested this
issue\n     safari 3 ok\r\n    firefox 3 ok\r\n        ie 7 ok\r\n\r\nwhat
steps will reproduce the problem\n1 go to any site using java
technology\r\n2 it will tell you there is no plugin yet\r\n\r\nwhat is the
expected result\njava to run\r\n\r\nwhat happens instead\ngives an error
for plugin\r\n\r\nplease provide any additional information below attach a
screenshot if \r\npossible\r\n \n"
}
```

First, the English text of each defect report is extracted, and a series of texts such as word segmentation, stop words, stemming, and word vectorization are preprocessed to obtain a relatively "normative" text. Second, assuming the length of a text is S, where each word can be represented by the vector of Word2Vec training (or vector representation using random numbers) as D dimensions. Therefore, the text can be represented as a vector matrix of S × D.

The high-level text data process can be summarized in Figure 21. I have to build the data pipeline and extract data from the documents and transform the text into the right format by building the dictionary, and load preprocessed text into the next step of LSTM network and rule engine to do the training and gain the prediction model.

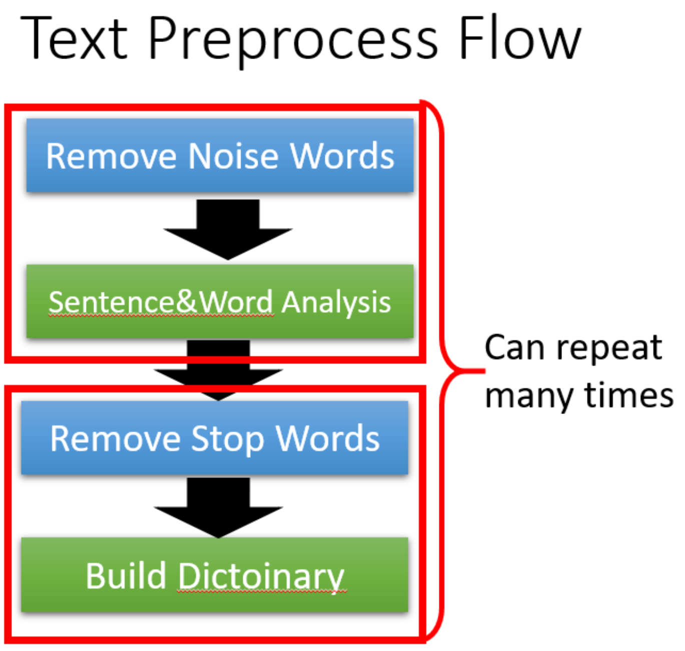


Figure 21 High-level Text Data Process

Since the original text contains irregular words, extra punctuation marks, and meaningless pause words, the algorithm first needs to filter the noise in the text. When filtering the noise, it also needs to perform sentence segmentation and word segmentation on the text. The model in my research treats the document as a sequence of sentences. For each sentence, the model is processed separately, so the process of clauses is necessary. After the clauses and participles are completed, each word needs to be processed and becomes case-insensitive, and the number of times they appear is counted, and a dictionary is constructed. The words with very low number of occurrences in the dictionary are considered to be low-frequency noise words. Those noise words are removed from the model. The detailed code is implemented in the Table 9.

```
with open(closed_bugs_json) as data_file:
    data = json.load(data_file, strict=False)
all_data = []
all_owner = []
```

```
for item in data:
    # Step 1. Remove \r
    current_title = item['issue_title'].replace('\r', ' ')
    current_desc = item['description'].replace('\r', ' ')
    # Step 2. Remove URLs
    current_desc = re.sub(r'http[s]?://(?:[a-zA-Z]|[0-9]|[$-
_@.&+]|[!*\(\),]|(?:%[0-9a-fA-F][0-9a-fA-F]))+', '', current_desc)
    # Step 3. Remove Stack Trace
    start_loc = current_desc.find("Stack trace:")
    current_desc = current_desc[:start_loc]
    # Step 4. Remove hex code
    current_desc = re.sub(r'(\w+)0x\w+', '', current_desc)
    current_title= re.sub(r'(\w+)0x\w+', '', current_title)
    # Step 5. Change to lower case
    current_desc = current_desc.lower()
    current_title = current_title.lower()
    # Step 6. Tokenize
    # A sentence or data can be split into words using the method
word_tokenize()
    current_desc_tokens = nltk.word_tokenize(current_desc)
    current_title_tokens = nltk.word_tokenize(current_title)
   # Step 7. Strip punctuation marks
    current_desc_filter = [word.strip(string.punctuation) for word in
current_desc_tokens]
    current_title_filter = [word.strip(string.punctuation) for word in
current_title_tokens]
    # Step 8. Join the lists
    current_data = current_title_filter + current_desc_filter
    ###########################
    # current_data = filter(None, current_data)
    current_data = list(filter(None, current_data))
    ###########################
    all_data.append(current_data)
    all_owner.append(item['owner'])
```

Table 9 Function to preprocess the text in bug report

In this paper, only the words in the dictionary after removing the low frequency words mentioned above are vectorized, and other words are represented by vectors of all 0s. In the subsequent processing, the model is implemented to automatically ignore all 0s. Text entered into the subsequent model is the word after all low frequency words are removed. The specific process can be summarized in Figure 22.

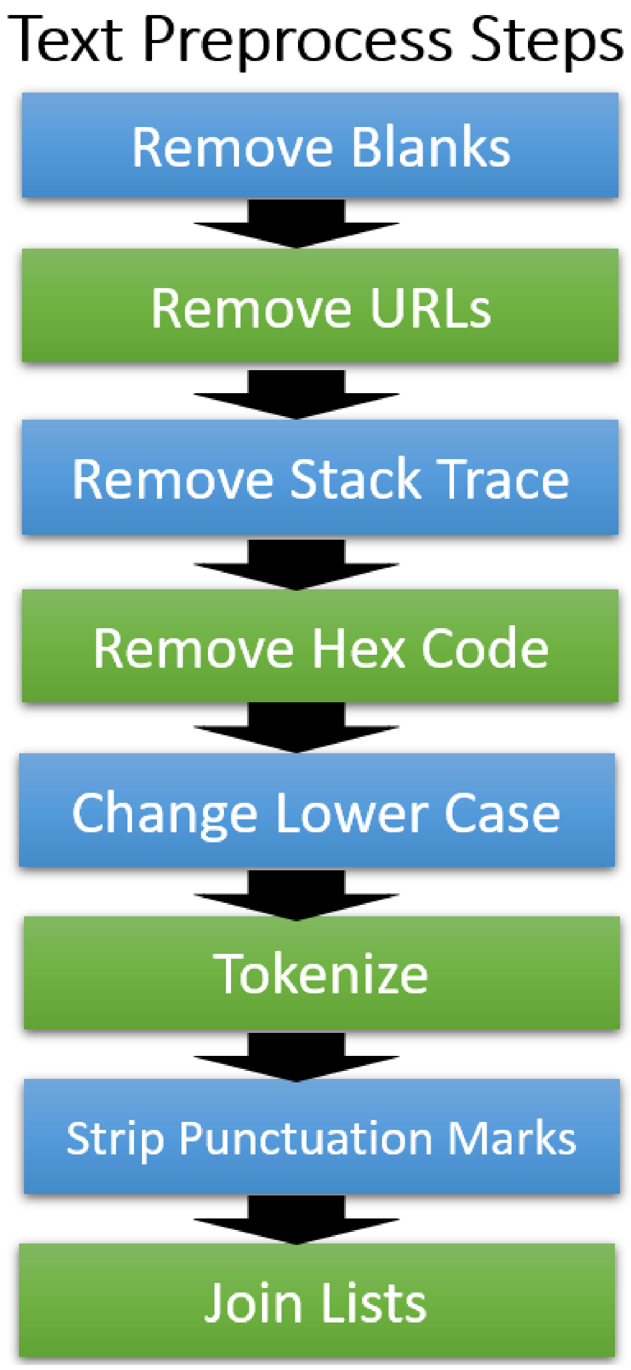
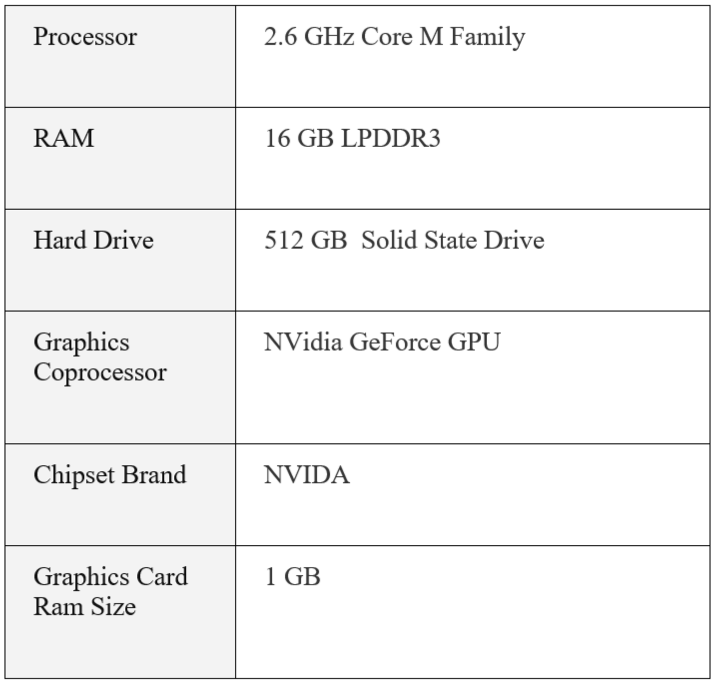


Figure 22 Text Extracting, Transforming, and Loading Process

5.2 Experimental design

The experiment in this paper is carried out on the Surface Book 2, and its configuration is listed in Table 10.



Processor	2.6 GHz Core M Family
RAM	16 GB LPDDR3
Hard Drive	512 GB Solid State Drive
Graphics Coprocessor	NVidia GeForce GPU
Chipset Brand	NVIDA
Graphics Card Ram Size	1 GB

Table 10 Hardware specification for experiments

The operating system is Window 10, the software requirements: Python 3.6.5, "Visual Studio Community 2015 with Update 3", and NVIDIA® GPU drivers —CUDA 9.0 requires 384.x or higher, CUDA® Toolkit, TENSORFLOW, and Keras.

The increment (ten-fold incremental) method is used for training. The data sets are ordered by time and they are equally divided into 11 copies. First, in the first round, the first fold is used as the training set, the second fold is used as the test set. In the second round, the first and second data are used as the training set, and the third fold is used as the test set, and so on. In the 10th round, the data from 1st fold to the 10th fold is used as the training set, and the 11th data is used as the test set. By this way, different training sets can be trained N times, Finally, the average of the N round results is used as the end result.

The following is Tensorflow GPU Installation tutorial.

1. Prerequisite

a. "Visual Studio Community 2015 with Update 3" link
b. Python 3.6.5 [x64] link
Choose" Windows x86-64 executable installer",
and check the box "add to the path" when install

2. GPU Config

a. NVIDIA® GPU drivers —CUDA 9.0 requires 384.x or higher (use latest version).
Chose `Custom install` and check the box `clean install`.

b. CUDA® Toolkit —TensorFlow supports CUDA **9.0**
Also, install all the upgrade packages (if patch_1 cannot install, delete the folder *C:\Program Files\NVIDIA Corporation\Installer2*, and reinstall)

c. cuDNN SDK (latest) with CUDA **9.0**
Extract the files create a folder "tool" in *C:\*, put the cuba folder into to *C:\tool\*
Copy the file *C:\tool\cuba\bin\cudnn64_7.dll*
Paste it into *C:\Program Files\NVIDIA GPU Computing Toolkit\CUDA\v9.0\bin*

d. Edit environment path, make sure these four exist in your path, if not add it.

C:\Program Files\NVIDIA GPU Computing Toolkit\CUDA\v9.0\bin
C:\Program Files\NVIDIA GPU Computing Toolkit\CUDA\v9.0\libnvvp
C:\Program Files\NVIDIA GPU Computing Toolkit\CUDA\v9.0\extras\CUPTI\libx64
C:\tools\cuda\bin

e. Test GPU installation

Open CMD, type *nvcc -V*
If you can see the cuda version, you're good to go.

3. virtual environment

a. install virtualenv, Open CMD as administrator

pip install virtualenv

b. Create a new virtual environment by choosing a Python interpreter and making a *C:\tensorflow* directory to hold it:

In CMD type
virtualenv --system-site-packages -p python C:\tensorflow

4. **Install tensorflow and keras**

a. Activate the virtual environment: <u>(Every time you start use tensorflow)</u>

In CMD type
C:\tensorflow\Scripts\activate

b. Install packages, In CMD type

pip install --upgrade pip
pip list

# Installing tensorflow

pip install --upgrade tensorflow-gpu==1.11.0

# Verify the install:

python -c "import tensorflow as tf; tf.enable_eager_execution();print(tf.reduce_sum(tf.random_normal([1000, 1000])))"

# Installing keras, genism, punkt, scikit-learn, beautifulsoup4, lxml

pip install keras==2.2.4

pip install gensim==3.6.0

pip install nltk==3.3

pip install scikit-learn==0.20.0

pip install beautifulsoup4

pip install lxml

python >>> import nltk

python >>> nltk.download('punkt')

c. When you finish using tensorflow to exit environment

In CMD type

deactivate

5.3 Experiment Results

This section conducts experiments and compares bug assignment models using Naïve Bayes, LSTM and "LSTM + Rule Engine".

1) Bag of words (BOW) + Naïve Bayes (NB)

The bag of words (BOW) feature representation of the bug report creates a Boolean array marking true or false for each vocabulary word in the bug report. During training, the Naïve Bayes classifier will learn this representation to the corresponding owner label. The Naïve Bayes classifier uses only the classifier training and testing data and do not use the un-triaged bug reports and is implemented using the Python *scikit-learn* package.

Naïve Bayes algorithm is implemented using the scikit package of python. It is implemented as following:

```
classifierModel = MultinomialNB(alpha=0.01)
classifierModel = OneVsRestClassifier(classifierModel).fit(train_feats, updated_train_owner)
predict = classifierModel.predict_proba(test_feats)
classes = classifierModel.classes_

 accuracy = []
 sortedIndices = []
 pred_classes = []


 for ll in predict:
     sortedIndices.append(sorted(range(len(ll)), key=lambda ii: ll[ii], reverse=True))

 for k in range(1, rankK + 1):
      id = 0
      trueNum = 0
      for sortedInd in sortedIndices:
          pred_classes.append(classes[sortedInd[:k]])
          if(id < len(Y_test)):
              if Y_test[id] in sortedInd[:k]:
                  trueNum += 1
              id += 1
      accuracy.append((float(trueNum) / len(predict)) * 100)
```

```
print ('Naive Bayes accuracy:', accuracy)
```

The multinomial Naive Bayes classifier is suitable for classification with discrete features (e.g., word counts for text classification). The multinomial distribution normally requires integer feature counts. Firstly, we create a classifier model for multinomial Naïve Bayes. Secondly, we use *OneVsRestClassifier* strategy to fit underlying estimators. This strategy consists in fitting one classifier per class. For each classifier, the class is fitted against all the other classes. In addition to its computational efficiency, one advantage of this approach is its interpretability. Since each class is represented by one and one classifier only, it is possible to gain knowledge about the class by inspecting its corresponding classifier. Third, according to term frequency-based bag-of-words model features, we will make the probability estimates. Finally, we use the real data to get test accuracy. The experiment result is shown in the following table.

2) LSTM

Our deep learning model can learn sentence representation to keep the sequence and syntax of words (title + description), also retain the semantic relationship using LSTM, which are used in the hidden layer of the whole model. At the same time, LSTM also can solve the vanishing gradient problem. The model is implemented using the Python *keras* package. The experiment result is shown in the following table.

3) LSTM + Rule Engine

Comparing with traditional method, we have obtained the remarkable experiment results. But there is still a lot of room to improve the accuracy of recognition. We provide a rule engine over our deep learning model to add the customize rules and improve the test accuracy. In our first use cases (only process first 1000 incorrect owners), we use web crawler to collect the additional information of owners and calculate the overlapping between collected information of owners and the content of predicted sentences. The customize rule uses the parameter bar_percentage. The rule is “if the overlapping rate is greater than 0.35”(bar_percentage = 0.35), we would assign the correct owner to the bug report.

The experiment results are shown in two categories, offline and online. As the research mentions before, the offline is using all data locally, and can be rerun and achieve the similar number except some minor randomness, but it is reproducible. The online result is more dynamic depending on the latest http web request to get the developers’ keywords data.

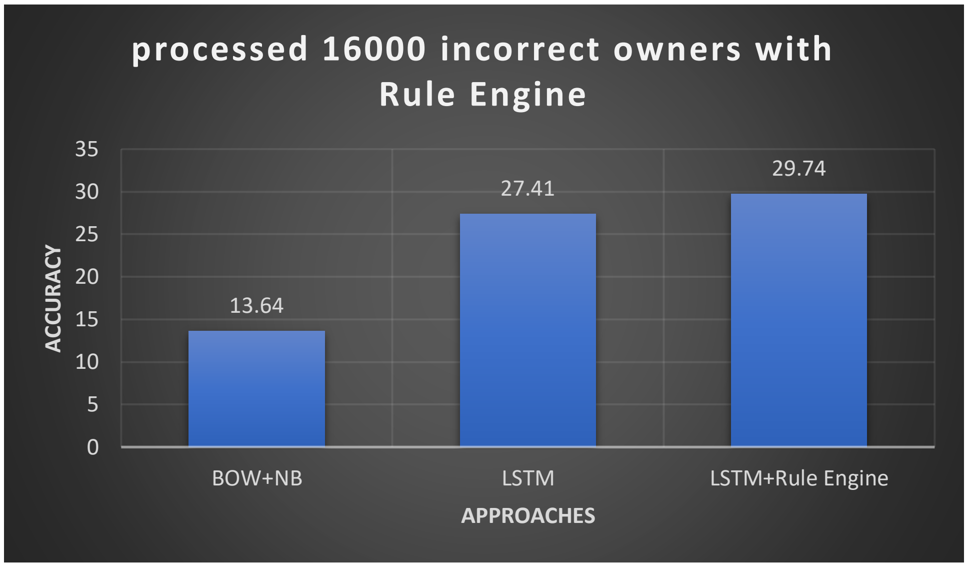
The first one is the benchmark for how to do just run one number of cross validation, and one epoch, and is run as offline. The second result table is also run as offline but number of cross validation is 5 and number of epochs is also 5, other parameters are listed as well. The third one is run as online mode, and other parameters are listed in the configuration table as well.

The following experiment configuration arguments are following and run offline:

```
numCV = 1
max_sentence_length = 50
min_sentence_length = 15
rankK = 10
batch_size = 32
myEpochs = 1
bar_percentage = 0.3
```

In the following use case, we processed 16000 incorrect owners and it takes about 30 minutes to finish. The experiment result is shown in the following table.

Classifier	BOW + NB	LSTM	LSTM + Rule Engine
1st Cross Validation	13.64	27.41	29.74



The above graph shows that in offline mode, pure LSTM has a better result than BOW+NB model, the hybrid LSTM+Rule Engine has the best accuracy overall.

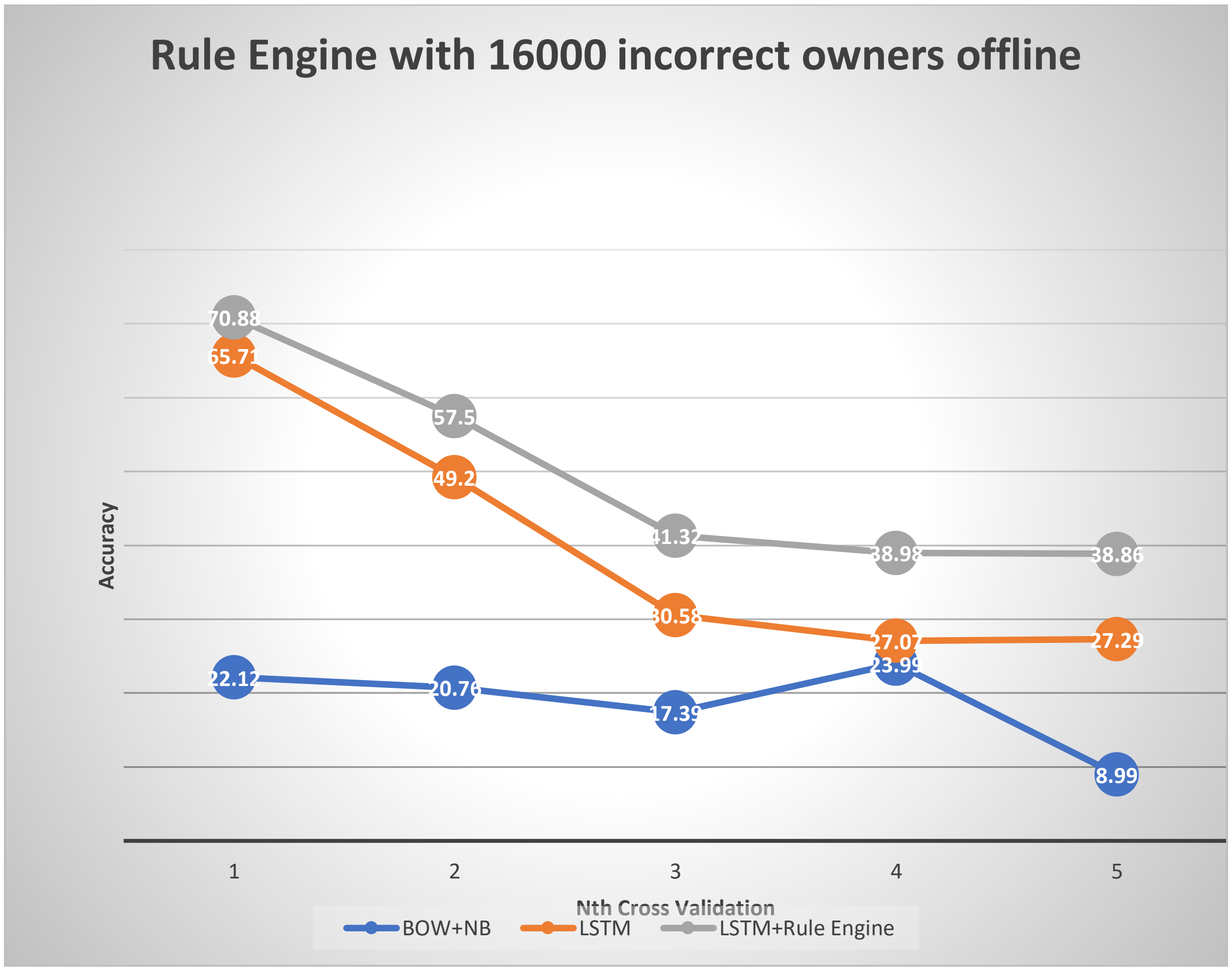
The following experiment configuration arguments are following and run offline:

```
numCV = 5
max_sentence_length = 50
min_sentence_length = 15
rankK = 10
batch_size = 32
myEpochs = 5
bar_percentage = 0.3
```

In the following use case, we processed 16000 incorrect owners and it takes about 10 hours to finish. The experiment result is shown in the following table.

Classifier	BOW + NB	LSTM	LSTM + Rule Engine
1st Cross Validation	22.12	65.71	70.88
2nd Cross Validation	20.76	49.20	57.50
3rd Cross Validation	17.39	30.58	41.32

4th Cross Validation	23.99	27.07	38.98
5th Cross Validation	8.99	27.29	38.86



The above graph shows that in offline mode for 5 cross validations, pure LSTM has a better result than BOW+NB model, the hybrid LSTM+Rule Engine has improved the accuracy over pure LSTM further.

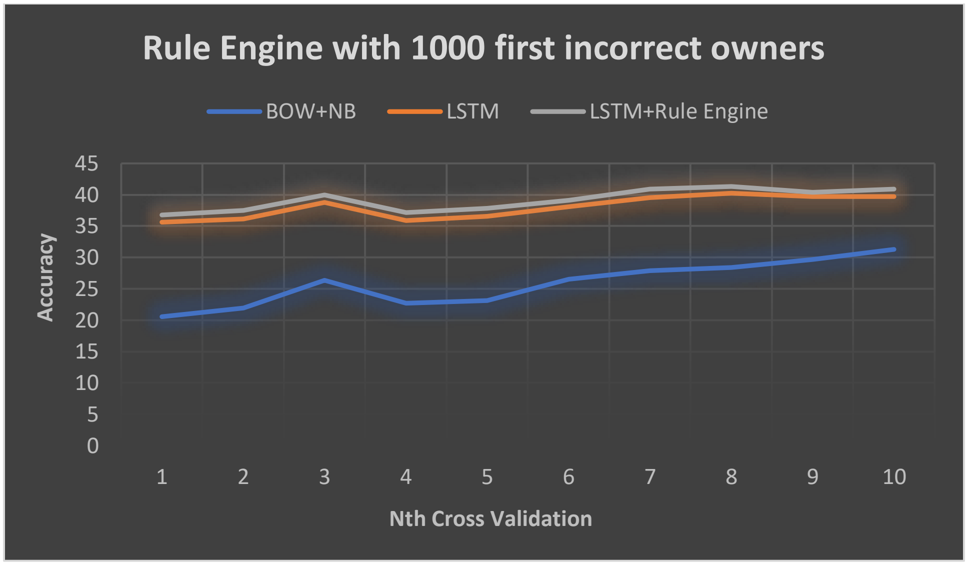
The following experiment configuration arguments are following and run online:

```
numCV = 10
```

```
max_sentence_length = 50
min_sentence_length = 15
rankK = 10
batch_size = 32
myEpochs = 10
bar_percentage = 0.35
```

In the first use case, we processed 1000 incorrect owners. The experiment result is shown in the following table.

Classifier	BOW + NB	LSTM	LSTM + Rule Engine
1st Cross Validation	20.56	35.63	36.78
2nd Cross Validation	21.93	36.12	37.52
3rd Cross Validation	26.38	38.74	39.99
4th Cross Validation	22.69	35.92	37.15
5th Cross Validation	23.14	36.53	37.85
6th Cross Validation	26.57	38.11	39.15
7th Cross Validation	27.89	39.56	40.89
8th Cross Validation	28.42	40.25	41.32
9th Cross Validation	29.67	39.68	40.36
10th Cross Validation	31.29	39.70	40.88
Average	25.85	38.02	39.19

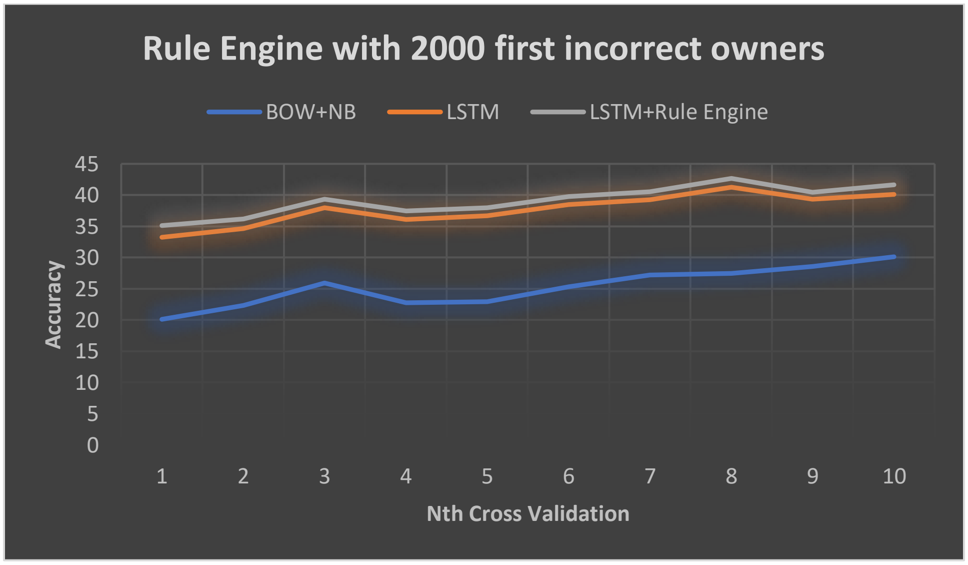


The above graph shows that in online mode for 10 cross validations, pure LSTM has a better result than BOW+NB model, the hybrid LSTM+Rule Engine has applied its rules to 1000 incorrect owners and has improved the accuracy over pure LSTM further.

In the second use case, we processed 2000 incorrect owners. The experiment result is shown in the following table.

Classifier	BOW + NB	LSTM	LSTM + Rule Engine
1st Cross Validation	20.12	33.25	35.12
2nd Cross Validation	22.34	34.63	36.21
3rd Cross Validation	25.94	37.98	39.34
4th Cross Validation	22.78	36.13	37.43
5th Cross Validation	22.97	36.72	37.98
6th Cross Validation	25.37	38.45	39.76
7th Cross Validation	27.18	39.26	40.57

8th Cross Validation	27.45	41.26	42.67
9th Cross Validation	28.59	39.32	40.47
10th Cross Validation	30.13	40.12	41.65
Average	25.29	37.71	39.12

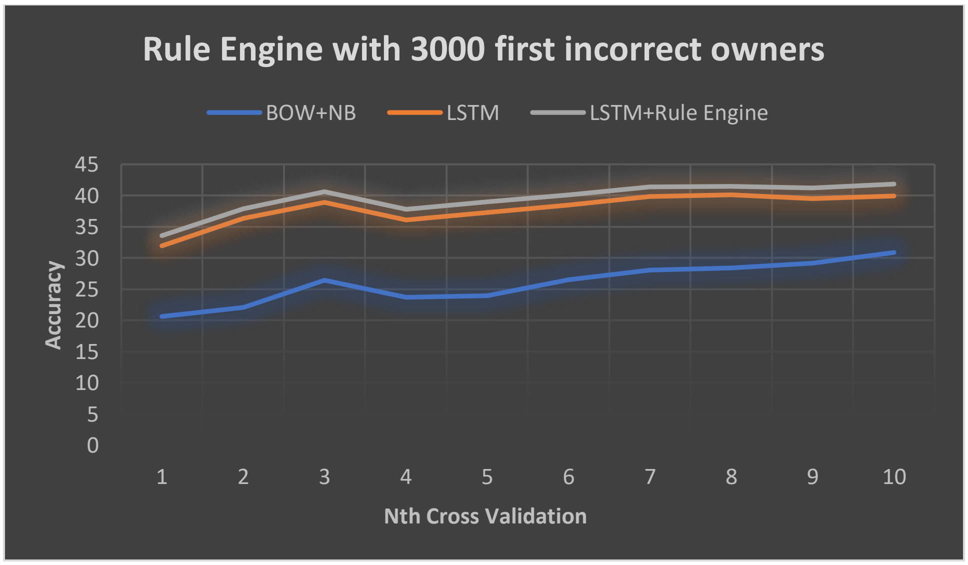


The above graph shows that in online mode for 10 cross validations, pure LSTM has a better result than BOW+NB model, the hybrid LSTM+Rule Engine has applied its rules to 2000 incorrect owners and has improved the accuracy over pure LSTM further.

In the next use case, we processed 3000 incorrect owners. The experiment result is shown in the following table.

Classifier	BOW + NB	LSTM	LSTM + Rule Engine
1st Cross Validation	20.63	31.95	33.58
2nd Cross Validation	22.08	36.34	37.92

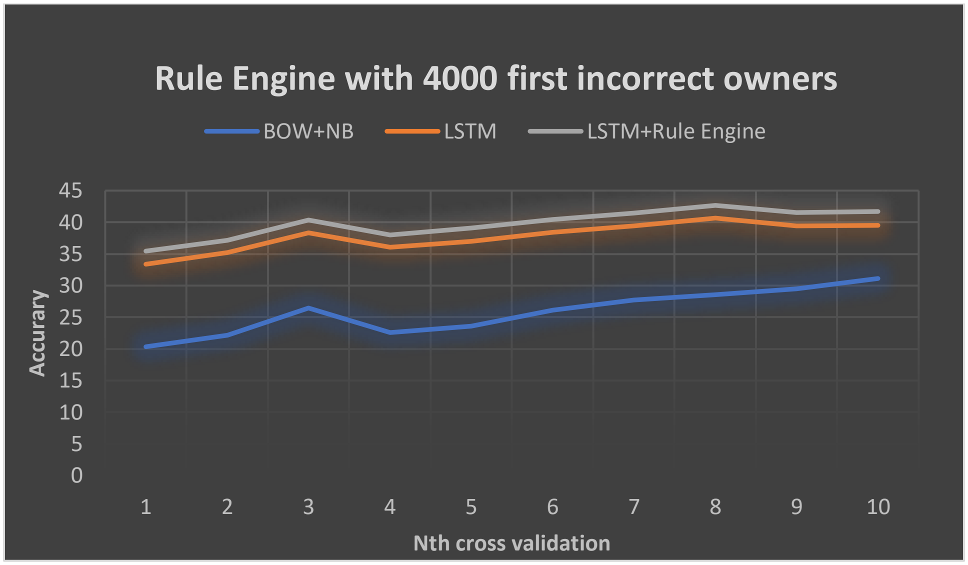
3rd Cross Validation	26.45	38.92	40.59
4th Cross Validation	23.74	36.13	37.76
5th Cross Validation	23.98	37.32	38.99
6th Cross Validation	26.56	38.45	40.07
7th Cross Validation	28.04	39.88	41.43
8th Cross Validation	28.43	40.12	41.48
9th Cross Validation	29.21	39.54	41.23
10th Cross Validation	30.88	39.92	41.84
Average	26.01	37.86	39.49



The above graph shows that in online mode for 10 cross validations, pure LSTM has a better result than BOW+NB model, the hybrid LSTM+Rule Engine has applied its rules to 3000 incorrect owners and has improved the accuracy over pure LSTM further.

In the fourth use case, we processed 4000 incorrect owners. The experiment result is shown in the following table.

Classifier	BOW + NB	LSTM	LSTM + Rule Engine
1st Cross Validation	20.34	33.38	35.45
2nd Cross Validation	22.12	35.24	37.19
3rd Cross Validation	26.45	38.35	40.38
4th Cross Validation	22.57	36.03	38.03
5th Cross Validation	23.56	37.02	39.11
6th Cross Validation	26.13	38.43	40.46
7th Cross Validation	27.76	39.42	41.43
8th Cross Validation	28.58	40.66	42.67
9th Cross Validation	29.45	39.45	41.56
10th Cross Validation	31.12	39.54	41.68
Average	25.81	37.75	39.80

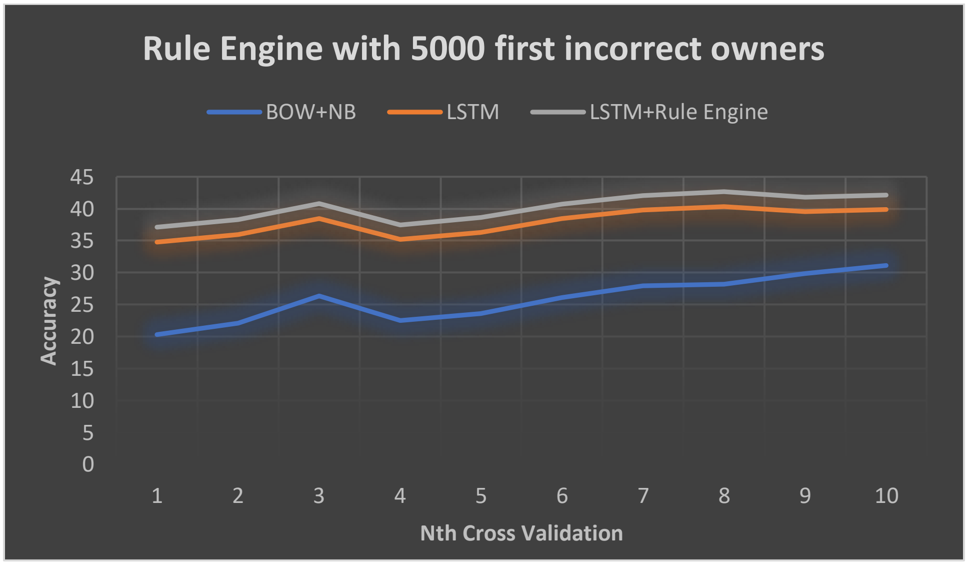


The above graph shows that in online mode for 10 cross validations, pure LSTM has a better result than BOW+NB model, the hybrid LSTM+Rule Engine has applied its rules to 4000 incorrect owners and has improved the accuracy over pure LSTM further.

In the fifth use case, we processed 5000 incorrect owners. The experiment result is shown in the following table.

Classifier	BOW + NB	LSTM	LSTM + Rule Engine
1st Cross Validation	20.31	34.78	37.12
2nd Cross Validation	22.08	35.98	38.27
3rd Cross Validation	26.32	38.46	40.79
4th Cross Validation	22.48	35.17	37.50
5th Cross Validation	23.57	36.32	38.65
6th Cross Validation	26.12	38.45	40.73

7th Cross Validation	27.97	39.76	42.03
8th Cross Validation	28.23	40.33	42.67
9th Cross Validation	29.85	39.54	41.84
10th Cross Validation	31.12	39.88	42,15
Average	25.80	37.88	40.18



The above graph shows that in online mode for 10 cross validations, pure LSTM has a better result than BOW+NB model, the hybrid LSTM+Rule Engine has applied its rules to 5000 incorrect owners and has improved the accuracy over pure LSTM further.

5.4 Chapter summary

This chapter conducts experiments and comparative analysis of the performance of three models, Naïve Bayes, LSTM and Hybrid model proposed in the paper. It introduces the hybrid NLP, LSTM and Rule-based Engine model into the experimental verification flied of defect automatic assignment software engineering. Use the textual information such as summary, description, and commentary of the defect report to train the developer to predict the model for Chromium.

Experiments data show that the proposed hybrid model has obvious advantages in accuracy compared with the machine learning NB algorithm and the pure deep learning LSTM model. It proves the validity of the hybrid model and provides a new solution for automatic defect assignment problem.

Chapter 6 Conclusion

6.1 Major Achievements and Research Contributions

In this research we have designed and implemented a reusable software two-layer new model to assign bugs to right developers. The combination of both layers Layer 1: NLP and Vector for Words and Layer 2: LSTM and Rule-based Engine cover a wide spectrum of validation requirements making our model a versatile research or business value. For the problem of software defects and AI assignment based on text classification, below is a bulleted list of these contributions:

- Leveraged the combination of both layers Layer 1: NLP and Vector for Words and Layer 2: LSTM and Rule-based Engine is successfully introduced into the field of defect self-assignment. The traditional method of defect self-assignment is based on the traditional text word bag model and the machine learning model, which is not only inefficient, but also labor-intensive. If you use deep learning models such as LSTM-based networks, you don't need to spend a lot of time and effort on the feature extraction engineering required for a machine study model, you just need to put text into a simple line, and then enter the model.
- The proposed neural network model extracts text features on its own, taking into account not only the word order messages that the word bag model ignores, but also the grammatical and semantic characteristics of the text, improving the effect of the defect allocation model. Moreover, more importantly, the structure of these two layers network models with rule-based engine is relatively simple, i.e. the model, with only NLP network architecture, word2Vec, LSTM, Rule-based engine parallel structure, ideal for parallel computing, plus a dedicated hardware processing accelerator GPU the use of this paper makes the model not only high accuracy, but also faster.

- My work contributes three different model comparison Naïve Bayes, LSTM and LSTM with Rule-based Engine neural network model structures. LSTM model is more effective than the Naïve Bayes algorithm commonly used in machine learning for bug assignment. Rule Engine is a new attempt, and the model works well, and has been designed on the basis of LSTM model. The optimal results were achieved on both the CHROME dataset. In general, the three models, from simple to complex, from traditional to more advanced hybrid approach gradually increase the accuracy of the bug assignment.
- The model based on the combination of both layers Layer 1: NLP and Vector for Words and Layer 2: LSTM and Rule-based Engine proposed in this paper is simple, but highly effective in defect self-assignment and has the ability to expand and migrate the system to other datasets. The model simply relies on defect text, does not use other complex techniques and tribal knowledge of defect analysis, and the traditional method is based on feature extraction engineering approach, which is only valid for special datasets, making it difficult to be applied to other datasets. The model is expandable and migratable.

6.2 Future Work

The research can still be improved to allow it to stay relevant with the changing technology trends. Below is a list of potential future work examples.

- Although the text classification method based on convolutional neural network proposed in this paper has achieved great results in the automatic assignment of defects, this method still has certain limitations, such as only considering the text keywords features of defect reports overlapping with developers' keywords, but ignoring other possible data source such as developers' blogging activities, their Facebook, and other data.
- Although the two layers models training has achieved some achievements, it does not involve the latest methods in the field of natural language processing, such as BERT (Bidirectional Encoder Representations from Transformers) is a recent paper published by researchers at Google AI Language.

Moreover, it can include GPT-2[103], a powerful NLP model in the layer 1 in the future study as well. For training models, there are new models such as GAN and Transfer Learning are recently proposed as well. It indicates that there is room for further improvement in the methods proposed in this paper.

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