

FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Software Repository Mining for Estimating Software Component Reliability

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Abstract

TODO

Keywords: *Software-fault Localization, Software Repository Mining, Machine Learning, Classification*

Classificação: *Software and its engineering - Software creation and management - Software verification and validation; Computing methodologies - Machine Learning - Machine Learning Approaches*

Resumo

Dada a crescente necessidade de identificar a localização dos erros no código fonte de *software*, de forma a facilitar o trabalho dos programadores e a acelerar o processo de desenvolvimento, muitos avanços têm sido feitos na sua automação.

Existem três abordagens principais: *Program-spectra based* (PSB), *Model-based diagnosis* (MDB) e *Program slicing*.

Barinel, solução que integra tanto o PSB como o MDB, é, até hoje, com base na investigação feita, a que apresenta melhores resultados. Contudo, a ordenação de conjuntos de candidatos (componentes faltosos) não tem em conta a verdadeira qualidade do componente em causa, mas sim o conjunto de valores que maximizam a probabilidade do conjunto (*Maximum Likelihood Estimation* - MLE), devido à dificuldade da sua determinação.

Com esta tese pretende-se colmatar esta falha e contribuir para uma melhor ordenação dos conjuntos, classificando, com recurso a técnicas de Machine Learning como *Naive Bayes*, *Support Vector Machines* (SVM) ou *Random Forests*, a qualidade e fiabilidade de cada componente, através das informações disponíveis no sistema de controlo de versões (*Software Repository Mining*), neste caso *Git*, como por exemplo: número de vezes que foi modificado, número de contribuidores, data de última alteração, nome de últimos contribuidores e tamanho das alterações.

A investigação já feita, revelou a existência de algumas soluções de análise preditiva de *software*, como *BugCache*, *FixCache* e *Change Classification*, capazes de identificar componentes com grande probabilidade de falhar e de classificar as revisões (*commits*) como faltosas ou não, mas nenhuma soluciona o problema.

Este trabalho visa também a integração com o *Crowbar* e a contribuição para a sua possível comercialização.

Palavras-chave: *Software-fault Localization, Software Repository Mining, Machine Learning, Classification*

Classificação: *Software and its engineering - Software creation and management - Software verification and validation; Computing methodologies - Machine Learning - Machine Learning Approaches*

“Software is eating the world.”

Marc Andreessen

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Abbreviations

MSR	Mining Software Repositories
SFL	Spectrum-based Fault Localization
PSB	Program-spectra based
MDB	Model-based diagnosis
MLE	Maximum Likelihood Estimation
SVM	Support Vector Machines
MHS	Minimal Hitting Set
SMOTE	Synthetic Minority Over-sampling Technique

Chapter 1

Introdução

[TODO] Translate...

Pretende-se com este capítulo enquadrar o tema, explicar as motivações e descrever sucintamente a estrutura deste documento.

1.1 Contexto/Enquadramento

Com o elevado crescimento da indústria de desenvolvimento de software, torna-se cada vez mais importante a existência de ferramentas que auxiliem os programadores a desenvolvê-lo mais eficientemente.

Estima-se que a economia dos Estados Unidos perca entre 60 mil milhões de dólares por ano em custos associados ao desenvolvimento e distribuição de correções para defeitos de *software* e na sua reinstalação [ZC09]. Pelo que, podemos afirmar que as ferramentas de localização das falhas de *software* (*Software Fault Localization*), ajudando a reduzir o tempo investido nesta tarefa, poderão ter um impacto significativo na economia. Nesta área os avanços são consideráveis. *Ochiai*, *Tarantula*, *Bayes-A* e *Barinel* são apenas algumas das soluções existentes, sendo o algoritmo *Barinel* aquele que apresenta melhores resultados. [AZG09] Apesar dos bons resultados apresentados pelo *Barinel*, este poderá apresentar resultados ainda mais rigorosos se tivermos informações relativas ao projeto, como a probabilidade média de erro ou a probabilidade de dado componente, que o constitui, ter defeitos.

Ferramentas de controlo de versões, como o *Git*, uma vez que mantêm todo o histórico do projeto e informações relacionadas com as diversas alterações (p.e. conteúdo, data e autores), em conjunto com técnicas de *Machine Learning*, poderão ser a chave para a melhoria deste algoritmo.

1.2 Motivação e Objetivos

Tendo em conta as possibilidades que a extração de dados de repositórios de controlo de versões e o *Machine Learning* nos dão, pretende-se com esta dissertação:

- Being able to predict the defect probability of each component in a given software project, that uses Git, with an useful precision, regardless of the programming language used.
- Optimize the order of results of Barinel.

1.3 Estrutura

Chapter 2

State of the art

Neste capítulo é feita uma revisão bibliográfica e descrito o estado da arte do *software* de localização de falhas, como o *Barinel*, das diferentes abordagens de predição de defeitos e ainda de *Software Repository Mining*.

2.1 *Fault Localization Software*

O *Fault Localization Software* auxilia na localização automática do código que origina falhas na sua execução, diminuindo o custo desta identificação que teria de ser feita manualmente pelo programador. Existem três categorias principais: *Program Slicing*, *Spectrum-based diagnosis* e *Model-based diagnosis*. Sendo que as abordagens *Spectrum-based diagnosis* serão analisadas mais ao detalhe devido à sua maior importância para este trabalho.

2.1.1 *Program Slicing*

Introduzida por Mark Weiser em 1981 [Wei81, Wei82], esta técnica começa a análise a partir da falha e através do fluxo de dados e de controlo do programa tenta chegar à origem do problema.

Removendo todas as operações que não afetam os dados ou o fluxo do programa, este método define uma porção de código (*slice*) que diz respeito às operações que poderão ser a causa do problema e que terão de ser inspecionadas [PAW04]. Ao reduzir o número de operações que necessitam de ser analisadas, o tempo necessário para a correção do erro diminui.

Normalmente uma análise estática do programa resulta numa porção de código grande, havendo outras técnicas, dinâmicas, que reduzem consideravelmente o seu tamanho, como *program dice* ou *dynamic program slicing* [PAW04].

2.1.2 Spectrum-based diagnosis

Spectrum-based Fault Localization (SFL) é uma técnica estatística de detecção de falhas que calcula a probabilidade de cada componente de *software* conter falhas, através da análise de informação relativa às execuções, bem sucedidas ou falhadas [AZV07]. Esta técnica apresenta bons resultados quando o projeto têm um número elevado de casos de teste e é capaz de executar num tempo reduzido, escalando bem para projetos grandes [MS08].

Esta técnica gera uma matriz, com base nos dados guardados durante a execução (*program spectrum* [RBDL97]), que relaciona as execuções de casos de teste, com os componentes que executou e com o sucesso ou insucesso do mesmo.

	<i>obs</i>			<i>e</i>
	<i>c</i> ₁	<i>c</i> ₂	<i>c</i> ₃	
<i>t</i> ₁	1	1	0	1
<i>t</i> ₂	0	1	1	1
<i>t</i> ₃	1	0	0	1
<i>t</i> ₄	1	0	1	0

Table 2.1: *Hit-spectra matrix*

Com esta matriz, também denominada *hit-spectra matrix*, é calculado o coeficiente de similaridade (*similarity coefficient*) para cada um dos componentes [AZG09], que corresponde à probabilidade desse componente ter uma falha. A forma como este coeficiente é calculado difere de algoritmo para algoritmo. Dando como exemplos o *Pinpoint* [CKF⁺02], o *Tarantula* [JH05] e o *Ochiai* [AZV07], que têm os coeficientes respetivamente calculados do seguinte modo

$$s_J(j) = \frac{a_{11}(j)}{a_{11}(j) + a_{01}(j) + a_{10}(j)} \quad (2.1)$$

$$s_T(j) = \frac{\frac{a_{11}(j)}{a_{11}(j) + a_{01}(j)}}{\frac{a_{11}(j)}{a_{11}(j) + a_{01}(j)} + \frac{a_{10}(j)}{a_{10}(j) + a_{00}(j)}} \quad (2.2)$$

$$s_O(j) = \frac{a_{11}(j)}{\sqrt{(a_{11}(j) + a_{01}(j)) * (a_{11}(j) + a_{10}(j))}} \quad (2.3)$$

2.1.3 Model-based diagnosis

O princípio base do diagnóstico baseado no modelo (*Model-based diagnosis*) é o de comparar o modelo, isto é a descrição de funcionamento do sistema, ao comportamento efetivamente observado [MS08]. Sendo depois a diferença entre os dois usada para identificar os componentes que possam explicar os erros. Isto na prática requer uma descrição formal do sistema, o que torna a tarefa bastante difícil [PAW04].

De forma a facilitar o uso deste método recorre-se por vezes à inferência do modelo, através do próprio *software*, mais especificamente através dos testes definidos neste [PAW04].

Apesar da elevada fiabilidade dos resultados que resultam desta técnica, o esforço computacional necessário na criação do modelo de uma programa de grande dimensão impede, maior parte das vezes, o seu uso em projetos reais [MS08].

2.1.4 *Barinel*

O *Barinel* é um algoritmo que se inspira nos dois métodos descritos anteriormente, *program-spectra based* e *model-based diagnosis*, e que com isto consegue melhores resultados que as outras soluções com um custo pouco superior [AZG09].

O algoritmo começa por analisar uma *hit-spectra matrix*, que representa os testes executados em relação aos componentes que foram executados e ao seu resultado final.

	<i>obs</i>			
	c_1	c_2	c_3	e
t_1	1	1	0	1
t_2	0	1	1	1
t_3	1	0	0	1
t_4	1	0	1	0

Table 2.2: *Hit-spectra matrix*

Na tabela 2.2, temos identificados 3 componentes distintos (c_1 , c_2 e c_3), 4 testes executados (t_1 , t_2 , t_3 e t_4) e o respectivo resultado da execução (e). O valor 1 em qualquer uma das colunas das observações (*obs*) indica que o dado componente foi executado nesse teste e o valor 0 indica o contrário, que o componente não foi executado. Na coluna e , o algarismo 1 declara que o teste correspondente falhou. Pelo que, por exemplo, o teste t_4 executou os componentes c_1 e c_3 e foi concluído com sucesso.

2.1.4.1 Geração de candidatos

Com base nesta matriz, uma lista de conjuntos de candidatos (d) é gerada, sendo esta reduzida ao número mínimo de candidatos possível, dado que estes subsumem todos os outros candidatos e minimizam o espaço de pesquisa. Este problema denominado *minimal hitting set* (MHS) é só por si um problema *NP-hard* o que levou à necessidade de criação de heurísticas próprias [Rui09, CA13]. O algoritmo usado pelo *Barinel* na resolução deste problema é o *Staccato*.

Neste caso, seriam gerados apenas dois candidatos:

- $d_1 = \{c_1, c_2\}$
- $d_2 = \{c_1, c_3\}$

2.1.4.2 Ordenação de candidatos

Para cada candidato d , é calculada a probabilidade de acordo com a regra de *Naïve Bayes*:

$$\Pr(d \mid obs, e) = \Pr(d) \cdot \prod_i \frac{\Pr(obs_i, e_i \mid d)}{\Pr(obs_i)} \quad (2.4)$$

$\Pr(obs_i)$ é apenas um termo normalizador idêntico para todos os candidatos, pelo que não é usado para proceder à ordenação.

Sendo p_j a probabilidade *a priori* do componente c_j originar uma falha, também denominada *prior*, podemos definir $\Pr(d)$, probabilidade do candidato ser responsável pelo erro, não tendo em conta evidências adicionais, como

$$\Pr(d) = \prod_{j \in d} p_j \cdot \prod_{j \notin d} (1 - p_j) \quad (2.5)$$

Sendo g_j (*component goodness*) a probabilidade do componente c_j executar de forma correta dado o facto de c_j integrar o conjunto de componentes faltosos, temos que

$$\Pr(obs_i, e_i \mid d) = \begin{cases} \prod_{j \in (d \cap obs_i)} g_j & \text{if } e_i = 0 \\ 1 - \prod_{j \in (d \cap obs_i)} g_j & \text{otherwise} \end{cases} \quad (2.6)$$

Tendo em conta o nosso exemplo

$$\Pr(d_1 \mid obs, e) = \overbrace{\left(\frac{1}{1000} \cdot \frac{1}{1000} \cdot \left(1 - \frac{1}{1000} \right) \right)}^{\Pr(d)} \times \overbrace{\underbrace{(1 - g_1 \cdot g_2)}_{t_1} \times \underbrace{(1 - g_2)}_{t_2} \times \underbrace{(1 - g_1)}_{t_3} \times \underbrace{g_1}_{t_4}}^{\Pr(obs, e \mid d)} \quad (2.7)$$

$$\Pr(d_2 \mid obs, e) = \overbrace{\left(\frac{1}{1000} \cdot \frac{1}{1000} \cdot \left(1 - \frac{1}{1000} \right) \right)}^{\Pr(d)} \times \overbrace{\underbrace{(1 - g_1)}_{t_1} \times \underbrace{(1 - g_3)}_{t_2} \times \underbrace{(1 - g_1)}_{t_3} \times \underbrace{g_1 \cdot g_3}_{t_4}}^{\Pr(obs, e \mid d)} \quad (2.8)$$

Quando existem valores g_j desconhecidos, é maximizado o valor de $\Pr(obs, e \mid d)$ usando o algoritmo *Maximum Likelihood Estimation* (MLE).

Neste caso, todos os valores de g_j são desconhecidos. Executando o algoritmo MLE para ambas as funções e calculando o resultado final temos que:

- $\Pr(d_1, obs, e) = 1.9 \times 10^{-9}$ ($g_1 = 0.47$ e $g_2 = 0.19$)
- $\Pr(d_2, obs, e) = 4.0 \times 10^{-10}$ ($g_1 = 0.41$ e $g_3 = 0.50$)

2.1.4.3 Crowbar

*Crowbar*¹, anteriormente conhecido como *GZoltar*², é a ferramenta que materializa o algoritmo *Barinel* e que permite uma análise de projetos *Java* [CRPA12].

Através de injeção de código e da execução dos testes *JUnit*, o *Crowbar* é capaz de identificar os componentes que foram executados e associá-los aos testes falhados.

A representação dos resultados pode ser feita de várias formas, sendo a principal a visualização *Sunburst* que podemos ver na Figura 2.1 e que apresenta em cada anel um grau de granularidade diferente, desde o projeto à linha de código [GCA13].

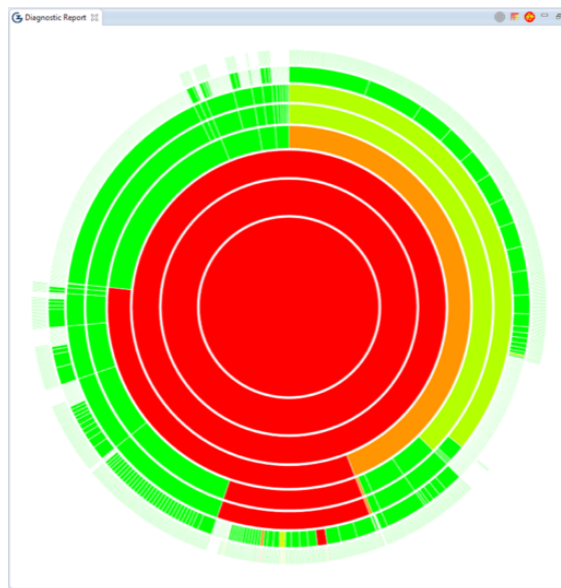


Figure 2.1: Visualização Sunburst do Crowbar

Para além desta informação, a ferramenta apresenta-nos também com a lista de componentes ordenada de acordo com a probabilidade de este ter falhas.

2.2 Software Repository Mining

Entende-se por *Software Repository Mining* todo o *software* que é capaz objetivo de extrair dados de repositórios, como *Git* ou *SVN*.

2.2.1 Identificação de correções e defeitos

Na extração de informações de repositórios de código, como o *Git*, torna-se importante identificar o tipo de alterações feitas. A descrição textual associada à alteração é bastante importante nesta

¹ <http://crowbar.io>

² <http://www.gzoltar.com/>

identificação e permite fazê-lo com um elevado grau de precisão, dependendo do projeto em causa [MV00].

É estimado que 34 a 46% de todas as alterações correspondam a correções e que estas representem 18 a 27% das linhas adicionadas e removidas [MV00]. Foram também encontrados padrões que relacionam as correções com o seu tamanho, em termos de código, e com o dia da semana em que foram executadas [SZZ05].

Após esta identificação é possível identificar as alterações que introduziram os erros usando o algoritmo *SZZ* [SZZ05]. Este algoritmo recorre ao histórico e à análise do código em questão para corretamente localizar o *commit* (alteração) que introduziu o defeito, ignorando, por exemplo, alterações que apenas introduzam comentários.

2.2.2 Ferramentas

Existem diversas ferramentas que facilitam este processo, pelo que destacamos duas.

2.2.2.1 *libgit2*

Libgit2³ é uma biblioteca multi-plataforma, sem dependências, que permite a interação direta com o repositório *Git* com uma performance nativa.

Esta biblioteca pode ser usada em qualquer linguagem que permita ligação a *C*, pelo que existem dezenas de implementações em linguagem como *Python*⁴, *Javascript*⁵ e *Java*⁶.

2.2.2.2 *GHTorrent*

GHTorrent⁷ é um projeto que tem por objetivo criar um armazém de dados escalável, facilmente pesquisável, mesmo *offline*, que replique a informação obtida através da API REST do GitHub⁸.

Esta ferramenta funciona de uma forma distribuída e monitoriza a API do GitHub através da página <https://api.github.com/events>. Cada evento, despoleta a extração de informação e conteúdo para uma base de dados *MongoDB* e outra *MySQL* [GS12].

2.3 Abordagens à previsão de defeitos

Foram já exploradas algumas abordagens para a predição da qualidade do código. Salientam-se neste capítulo algumas técnicas como *BugCache*, *FixCache* e *Buggy Change Classification*, que são técnicas que se incluem no tipo de abordagem que pretendemos seguir (*change log*) e que permitem, em conjunto com outras técnicas, otimizar a localização dos defeitos.

³<https://libgit2.github.com/>

⁴pygit2 - <http://www.pygit2.org/>

⁵nodegit - <https://github.com/nodegit/nodegit>

⁶Jagged - <https://github.com/ethomson/jagged>

⁷<http://ghtorrent.org/>

⁸<http://developer.github.com/>

2.3.1 *BugCache/FixCache*

Com base na premissa de que as falhas nunca ocorrem isoladamente e que portanto onde existe um defeito existem outros, o *BugCache* cria uma lista de componentes onde a probabilidade de conterem erros é elevada, com base na análise em todo o histórico de alterações do projeto.

Este algoritmo destaca-se pela sua precisão, conseguindo uma exatidão de 73 a 95% quando usado com uma granularidade ao nível do ficheiro, sendo portanto o melhor até à data [?].

Os defeitos são identificados por ordem temporal e adicionados à lista. Quando esta lista atinge o tamanho máximo, os componentes vão sendo removidos de acordo com o método de substituição escolhido. Existem diversos métodos que utilizam diferentes métricas como última utilização (*Least Recent Used - LRU*), número de defeitos recentes e número de alterações recentes [?].

Conclui-se com este algoritmo que [?]:

- Caso tenha sido introduzido um defeito, há uma tendência para serem introduzidos mais defeitos em breve. (*temporal locality*)
- Caso um componente tenha sido acrescentado ou modificado recentemente este tem uma maior probabilidade de ser defeituoso (*changed-entity locality, new-entity locality*)
- Caso um componente tenha introduzido um erro, os componentes ligados mais diretamente a este introduzirão também erros no futuro (*spatial locality*)

A diferença entre o *BugCache* e o *FixCache* é o momento em que cada um atualiza a lista. Sendo que o primeiro atualiza a lista quando um defeito é introduzido, o segundo atualiza apenas quando o erro é corrigido. Devido a esta diferença a implementação do *FixCache* torna-se mais fácil.

2.3.2 *Buggy Change Classification*

Change Classification tem uma abordagem fundamentalmente diferente e tem um objetivo também distinto. O *Change Classification*, com recurso a técnicas de *Machine Learning* e às informações disponíveis quanto a erros anteriores, é capaz de prever se uma alteração introduziu ou não um novo defeito. Esta previsão é feita com um rigor muito elevado de 78% [Whi08].

Numa primeira fase, todas as alterações feita até ao momento são classificados como *buggy* ou *clean*. Com esta classificação feita e com a extração de dados para cada também concluída, procede-se à criação de um modelo através do treino de um algoritmo de classificação.

O tipo de dados usados dividem-se em sete grupos: métricas de complexidade, código adicionado, código removido, nome do ficheiro e diretório, novo código e meta-dados [Whi08].

Tanto *Support Vector Machine* (SVM) como *Naïve Bayes* foram usados no estudo, tendo sido o classificador feito com recurso a SVM aquele que apresentou melhores resultados [Whi08].

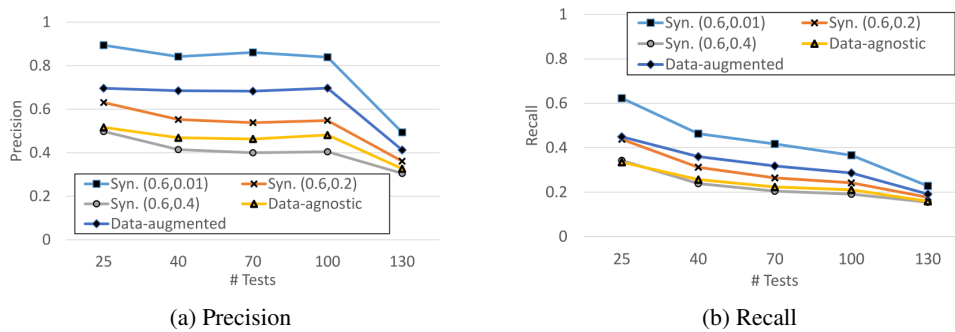


Figure 2.2: Diagnosis accuracy as a function of # tests given to the diagnoser

2.3.3 Data-Augmented Software Diagnosis

A different approach that also aims to help predict the location of software faults is Data-Augmented Software Diagnosis [ESK15].

Model-based and spectrum-based approaches are able to identify faulty components with high precision and recall, but there is still room for improvement and since most projects use some kind of Version Control Software (VCS), there is a big amount of information that is not used. This opportunity is the foundation of the approach.

Barinel assumes that the defect probability, known as the prior, of every component is uniform, 0.001. However, this approach proved it is possible to optimize Barinel results for Java projects by leveraging information about the project and supervised machine learning algorithms to predict the real component's defect probability.

First, healthy and faulty components are identified across the entire project's history according to Bug Trackers. For each component, a list of features, which is not specified, is extracted. The list is composed of traditional and object-oriented software complexity metrics, such as number of lines of code and cohesion, and values extracted from the software change history, like lines added or removed in last version and age of the file.

With the help of a supervised machine learning algorithm (either Random Forest, J48 or Naive Bayes) a model is created and used to classify each component in the project as healthy or buggy. The confidence that a component is faulty is then used as prior.

Experimental results revealed an increment both on precision and recall, see Figure 2.2. However, the solution was tested just on one project.

[TODO] Talk about the Amir Elmishali's paper

[TODO] Add Background about Machine Learning?

Chapter 3

Estimating Defect Probabilities

In order to estimate the defect probability of each software component we developed a data mining application, agnostic to the project's language. It automatically extracts data from the current state and about older defects from a *Git* repository, creates a model and predicts the probability. The project is written in Javascript (Node.js) and Python 3 and heavily uses *node-git* and *scikit-learn*.

In this chapter, we will explain the concept behind it, approach the process used in each of the steps and will explain how to install and use this application.

3.1 Concept

Some patterns are easily recognizable when trying to identify faulty components on a software project and this information could be helpful for software such as Barinel.

We might say, for example, that having a high number of recent changes or having been changed by a given junior developer new to the project probably increases the chances of a file having an error, due to past experiences. So, deep down we are just assuming that the knowledge of the metadata of old faulty components may allow us to predict which components are more probable to be faulty, now.

Based on that assumption, the application, for a given repository state, extracts metadata knowledge from past commits with faulty components, the parent commits of a fix. For each of these commits, all of components are analyzed and labeled as faulty or clean, if it was or not changed on the fix, respectively.

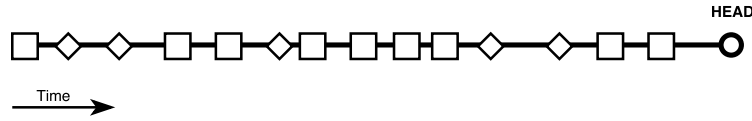


Figure 3.1: Example representation of commits history, with fix commits illustrated in a diamond shape

Since the application should be able to predict the defect probability for any given software project that uses *Git*, static analysis is not used. The only information that is used is information directly related to the file changes, authors, number of lines or bytes.

Along with the extraction of the metadata information from the past faulty states, it must also extract the metadata of the given repository state. The data from the first extraction must be used to create a machine learning model, that should be able to predict the defect probability of each component present in the current state of the project.

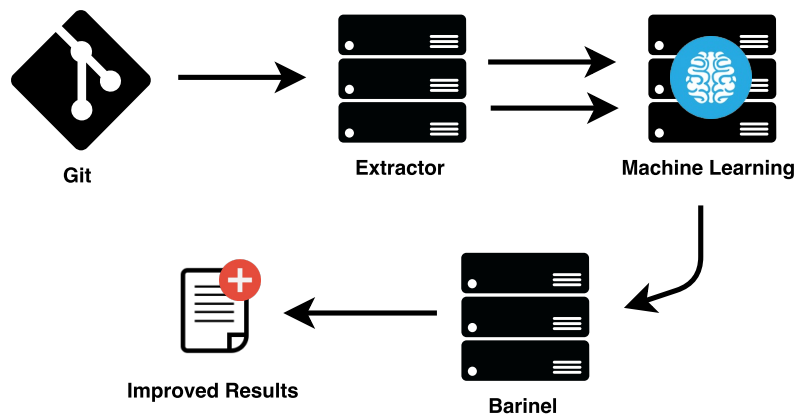


Figure 3.2: Representation of data flow

This concept differs from Data-Augmented Software Diagnosis (Subsection) by being language agnostic, requiring a different set of features mostly focused on number of changes, categorized by type and authors, and weighted according to size and date. It also differs by not requiring that the project uses a bug tracking software and also, as explained in the following section.

3.2 Install

The application relies on *Redis*, *Git*, *Node.js* and *Python 3* and requires some dependencies such as *SciPy*, *scikit-learn*, *numpy*.

```
1 $ git clone --depth 1 https://github.com/atduarte/master-thesis.git
2 $ cd master-thesis/app
3 $ npm install --prod
```

3.3 Usage

After all the dependencies installed the usage is very straight-forward. In order to automatically execute all the steps (extraction, data preparation, modeling and prediction) the following command should be used by replacing "{project-name}" and "{repository-path}" respectively with the chosen project name and the path to the folder containing the repository we want to analyze:

```
1 $ node index.js all {project-name} {repository-path}
```

It is possible to specify a different classification label (e.g. "--classification-label=_mostChanged", default is "_mostChanged25"), a different number of estimators used when modeling (e.g. "--estimators=100", default is 5) or even to define the level of logging by appending, for example, "--log-level=verbose". The existing levels available, from higher to lower priority, are "error", "warn", "info", "verbose" and "silly". The default log level is "info".

```
1 $ node index.js all math ../../tests/Math001
2 info extract/extract Raw Extraction started
3 info extract/extract 499 fix commits found
4 info prepareJson/prepare JSON Preparation started
5 info prepareJson/prepare Will prepare 639 files
6 info results/prepare CSV Preparation started
7 info results/prepare Got 552 files
8 info results/prepare Got 203 columns
9 info results/ml Modeling
```

Some extra configurations are also available by creating a project configuration file, in the folder "project-config/", with the same name as the project-name plus ".js". It allows to change the *regex* used to identify the fix commits, to define a file filter and to define an email normalizer, in order to improve the quality of the extracted data .

```
1 'use strict';
2
3 module.exports = {
4   fileFilter: (filename) => {
5     filename = filename.toLowerCase();
6
7     return filename.endsWith('.java') // Is Java
8     && !filename.startsWith('src/test'); // Aren't tests
9   },
10  };

```

Estimating Defect Probabilities

Before terminating, the application will create a file ("prediction.e500._mostChanged25.csv", by default) in the repository folder containing the predicted defect probability for each source code file.

```
1  ...
2  src/main/java/org/joda/time/Chronology.java,0.0
3  src/main/java/org/joda/time/DateMidnight.java,0.21
4  src/main/java/org/joda/time/DateTime.java,0.484
5  src/main/java/org/joda/time/DateTimeComparator.java,0.0
6  src/main/java/org/joda/time/DateTimeConstants.java,0.0
7  src/main/java/org/joda/time/DateTimeField.java,0.006
8  src/main/java/org/joda/time/DateTimeFieldType.java,0.002
9  src/main/java/org/joda/time/DateTimeUtils.java,0.966
10 src/main/java/org/joda/time/DateTimeZone.java,0.414
11 src/main/java/org/joda/time/Days.java,0.0
12 ...
```

In order to be able to execute only some step of the process, there is the possibility of executing only one operation. The available commands are:

- "raw" - Extracts data from *Git* and saves it to "out/{project-name}/raw"
- "json" - Processes the raw data and converts it to a new JSON structure. Results are saved to "out/{project-name}/json"
- "results" - Creates the CSV files for training and prediction data, based on the JSON files, creates the model and predicts the defect probability. Final result is saved at "{repository-path}/prediction.csv".

3.4 Process

As stated before the process is divided in extraction, data preparation, modeling and prediction steps. We will now dive deep into each.

3.4.1 Extraction

The first objective is to get the list of commits to analyze: the HEAD commit and all the fix commits that preceded it. So, first, the *HEAD* commit is identified. The application then walks recursively through each parent commit or commits and, if its message matches the defined regex, does not contain any word from the stop words list, such as "typo" or "javadoc", and it is not a merge, adds it to the list of commits to analyze.

[TODO] Regex

Estimating Defect Probabilities

Having this list, it analyzes each commit individually, ignoring the ones that were already extracted or that have no changed files after filtering according to configuration. First the information directly related to the commit and its tree is extracted:

- id - Id
- message - Message
- date - Date
- author - Author
- components - List of components

Then, the application walks through the changes history of each component, following name changes and extracting this info for each commit:

- id - Id
- date - Date
- author - Author
- parentCount - Parent count
- isFix - Is it a fix?
- filename - Filename
- lines - Number of lines
- byteSize - Size of file in bytes
- linesAdded - Number of lines added
- linesRemoved - Number of lines removed

Since this procedure has a high computation cost, some enhancements have been made. It relies heavily on *Redis* for caching and the number of components analyzed is reduced when possible. Considering that the modeling step will balance the training data, reducing the number of *clean* components according to the number of existing *buggy* components, the system randomizes the list and limits the extraction of *clean* components up to a maximum of four times the number of *buggy* components on the given commit.

[TODO] Formula representing the maximum number of components

[TODO] Explain Cache Details

This data is then saved to a file named according to the commit id, in the "raw" folder (e.g "out/math/raw/17d6f2163db436518f953166c1e9d495232f90b6").

Estimating Defect Probabilities

```
1  {
2    "id": "0b1b9a9dc86da871ce5e7839b1b2df13c99dd9f8",
3    "message": "Submitted Javadoc fixes from Andreou Andreas ...",
4    "date": 1055343030,
5    "author": "tobrien@apache.org",
6    "components": {
7      "src/java/org/apache/commons/math/ContractableDoubleArray.java": {
8        "linesAdded": 3,
9        "linesRemoved": 3,
10       "changes": [
11         {
12           "id": "8b62ed457040b6a1b4562aa0d0df88e1e77bddce",
13           "date": 1053499586,
14           "author": "tobrien@apache.org",
15           "parentCount": 1,
16           "isFix": false,
17           "filename": "src/java/org/apache/commons/math/ContractableDoubleArray.
18             java",
19           "lines": 322,
20           "byteSize": 12970,
21           "linesAdded": 54,
22           "linesRemoved": 3
23         },
24         ...
25       ]
26     }
27 }
```

3.4.2 Data Preparation

This step is the simplest. The only task is to convert the raw JSON structure, focused on the commit, to a JSON structure, focused on the component. 7 Iterating through each file at the "raw" folder and creating a new one with the same name in the "json" folder.

The data contained in this new file will be ready for being converted to CSV and to be used for modeling or prediction.

The following columns are prepared for each component:

- __changed - Was it changed?
- __filename - Component name
- _lines - Number of lines
- _bytes - File size in bytes
- _mostChanged - Was it the most changed file in this commit?

Estimating Defect Probabilities

- `_mostChanged25` - Was this file in top 25% of most changed files in this commit?
- `_mostChanged50` - Was this file in top 50% of most changed files in this commit?
- `_mostChanged75` - Was this file in top 75% of most changed files in this commit?
- `changes` - Number of changes made in the past
- `changes:date-weighted` - Sum of the result of the time-weighted function applied to each change
- `changes:size-weighted` - Sum of the number of lines added and removed in each change
- `changes:date+size-weighted` - Sum of the result of the time-weighted function applied to each change multiplied for the number of lines added and removed in it
- `authors` - Number of authors that changed this file
- `authorChanges::author` - Number of changes made in the past by a specific author. E.g. `authorChanges::luc@apache.org`
- `authorChanges:date-weighted:author` - Sum of the result of the time-weighted function applied to each change made by a specific author. E.g. `authorChanges:date-weighted::luc@apache.org`
- `authorChanges:size-weighted:author` - Sum of the number of lines added and removed in each change made by a specific author. E.g. `authorChanges:size-weighted::luc@apache.org`
- `authorChanges:date+size-weighted:author` - Sum of the result of the time-weighted function applied to each change made by a specific author multiplied for the number of lines added and removed in it. E.g. `authorChanges:date+size-weighted::luc@apache.org`

[TODO] Time-weighted function

In order to improve modeling results, we also created the columns `"changes-others"`, `"changes-others:date-weighted"`, `"changes-others:size-weighted"`, `"changes-others:date+size-weighted"`, `"changes-fixes"`, `"changes-fixes:date-weighted"`, `"changes-fixes:size-weighted"` and `"changes-fixes:date+size-weighted"` that are equal to the already existing columns starting with `"changes"`, but refer only to changes that were not fixes and changes that were fixes, respectively.

Plotting the results we noticed that the date influenced significantly the data related to changes, since older commits have less history behind. So for each, we added a normalized version by the commit.

Estimating Defect Probabilities

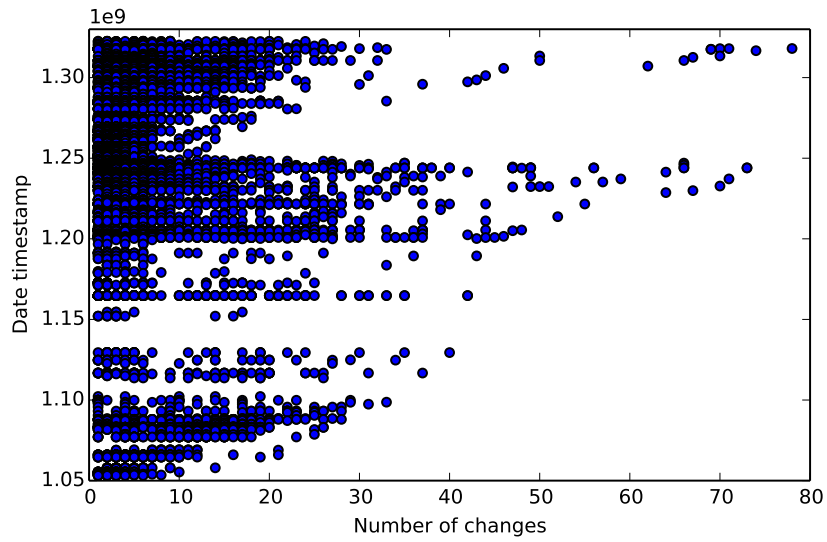


Figure 3.3: Example of the influence of the date on number of changes. (Project Math, Defect 1)

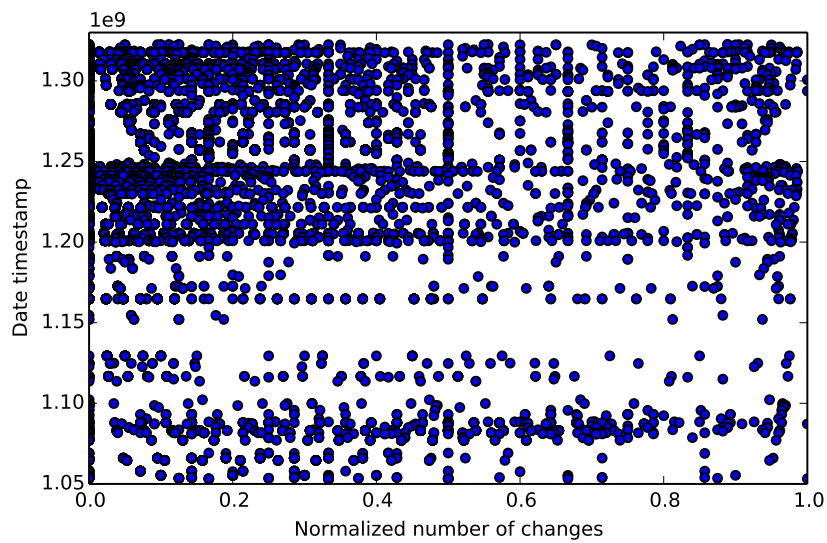


Figure 3.4: Example of the relation between the date on the normalized number of changes. (Project Math, Defect 1)

```
1 [
2   {
3     "__changed": true,
4     "__date": 1364521362,
5     "__filename": "src/main/java/org/apache/commons/math3/distribution/fitting/
6       MultivariateNormalMixtureExpectationMaximization.java",
7     "__lines": 441,
```

Estimating Defect Probabilities

```
7   "_bytes": 18211,
8   "_mostChanged": false,
9   "_mostChanged25": true,
10  "_mostChanged50": true,
11  "_mostChanged75": true,
12  "changes:raw": 3,
13  "changes:normalized": 0.2857142857142857,
14  "changes-fixes:raw": 0,
15  "changes-fixes:normalized": 0,
16  "changes-others:raw": 3,
17  "changes-others:normalized": 0.3333333333333333,
18  "changes:date-weighted:raw": 2.979453,
19  "changes:date-weighted:normalized": 0.290809968305134,
20  "changes:size-weighted:raw": 481,
21  "changes:size-weighted:normalized": 0.4746494066882416,
22  "changes:date+size-weighted:raw": 477.701982,
23  "changes:date+size-weighted:normalized": 0.4831911672918317,
24  "changes-fixes:date-weighted:raw": 0,
25  "changes-fixes:date-weighted:normalized": 0,
26  "changes-fixes:size-weighted:raw": 0,
27  "changes-fixes:size-weighted:normalized": 0,
28  "changes-fixes:date+size-weighted:raw": 0,
29  "changes-fixes:date+size-weighted:normalized": 0,
30  "changes-others:date-weighted:raw": 2.979453,
31  "changes-others:date-weighted:normalized": 0.3394176672358086,
32  "changes-others:size-weighted:raw": 481,
33  "changes-others:size-weighted:normalized": 0.4845814977973568,
34  "changes-others:date+size-weighted:raw": 477.701982,
35  "changes-others:date+size-weighted:normalized": 0.49340824785460163,
36  "authors:raw": 3,
37  "authors:normalized": 0.6666666666666666,
38  "authorChanges::luc@apache.org:raw": 1,
39  "authorChanges::luc@apache.org:normalized": 0,
40  ...
41  "authorChanges:date-weighted::luc@apache.org:raw": 0.993164,
42  "authorChanges:date-weighted::luc@apache.org:normalized":
    0.00025474141229450394,
43  "authorChanges:size-weighted::luc@apache.org:raw": 33,
44  "authorChanges:size-weighted::luc@apache.org:normalized": 0.5454545454545454,
45  "authorChanges:date+size-weighted::luc@apache.org:raw": 32.774417,
46  "authorChanges:date+size-weighted::luc@apache.org:normalized":
    0.5455704368440787,
47  ...
48 },
49 ...
50 ]
```

The data from the multiple fix commits is then combined in a file named "history.csv" and the data from the *HEAD* commit is placed at "master.csv". These two files will be only files required

to execute the next step.

3.4.3 Modeling and Prediction

For modeling and predicting *Python 3* and *scikit-learn* is used. Random Forests, Decision Trees and Naive Bayes were tried, but the former achieved significantly better results as it is presented in the Experimental Results chapter 5. Neural Networks were not used since the training set is normally small.

Before training the model, the training set is randomized and balanced, first to a ratio of 5 *clean* component for each *buggy* component and then SMOTE is used to create more *buggy* component entries. In order to train the model a *Stratified KFold* (4 folds) is used and run 10 times, generating 40 different models. Performance of these 40 models is measured according to the difference of the mean defect probability of buggy test data and clean test data. The 15 models with the highest difference are then used to predict the defect probability of each component in the current project state and a mean is calculated.

As referred before, the results are saved directly at the repository folder.

Chapter 4

Barinel Integration

One of the objectives is to improve Barinel results and for doing so integrations with the existing Barinel project were made. Priors replacement and results modification were the approaches chosen.

4.1 Priors Replacement

Barinel by default uses $\frac{1}{1000}$ as the defect probability (prior) for all software components (4.1).

$$\Pr(d) = \prod_{j \in d} \frac{1}{1000} \cdot \prod_{j \notin d} (1 - \frac{1}{1000}) \quad (4.1)$$

With this integration the Barinel project is now capable of receiving specific priors for each component, reading it from a CSV file located at the root of project being analyzed, and attributing them to the corresponding probes (4.3).

$$\Pr(d) = \prod_{j \in d} p_j \cdot \prod_{j \notin d} (1 - p_j) \quad (4.2)$$

Maximum Likelihood Estimation (MLE) continues to be used in order to maximize the probability, by defining the best possible goodness values.

4.2 Results Modification

The second approach maintains the priors at $\frac{1}{1000}$ and directly modifies the final result calculated by Barinel ($\Pr(d_j, obs, e)$) by multiplying it by 2 if considered faulty.

$$\Pr'(d_j, obs, e) = \Pr(d_j, obs, e) \cdot \begin{cases} 2 & \text{if } j \text{ is faulty} \\ 1 & \text{otherwise} \end{cases} \quad (4.3)$$

Barinel Integration

Chapter 5

Experimental Results

In order to reliably validate the defect probability prediction we used an existing database of faults, *Defects4J*. This database contains a list of commits with defects and their location from five different projects (JFreechart, Closure compiler, Apache commons-lang, Apache commons-math and Joda-Time). Since compatibility with *Barinel* and using *Git* is required, only the last three projects were used, making a total of 184 commits.

Project name	Shortname	Defects
Apache commons-lang	Lang	59
Apache commons-math	Math	101
Joda-Time	Time	25

Table 5.1: Test Set

5.1 Estimating Defect Probability

First we must know the characteristics of each project in order to better interpret the results, so a table was made containing information about the first and last commit of each project.

Project	Defect	Files	Previous commits	Previous fix commits	Contributors
Lang	1	108	3569	366	40
Lang	59	81	1533	190	25
Math	1	813	4877	564	28
Math	103	370	957	66	15
Time	1	162	1717	234	27
Time	26	733	1474	195	9

Table 5.2: Examples of project states from the test set

Three different classification algorithms were tested: Support Vector Machines, Random Forests and AdaBoost. Our preliminary tests showed that Random Forests is the algorithm that provides

Experimental Results

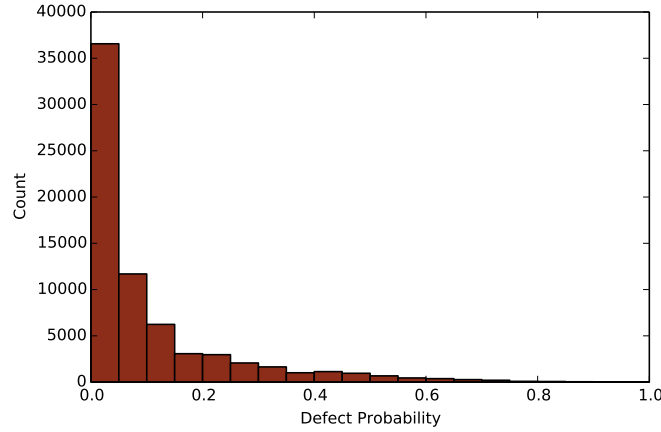


Figure 5.1: Distribution of predicted defect probabilities for probably clean components

an higher accuracy, that using the normalized values did not help and the best label to use for training is `_mostChanged`, so we will focus on this test case.

Figures 5.1 and 5.2 illustrate the different defect probabilities distributions of faulty and probably clean components, across all the 184 defects, respectively. However since we want the faulty component to be the one with the highest defect probability, it is important not only to verify the defect probability for the faulty component, but also to compare it to the probabilities of the other, probably clean, components in the project. Figure 5.3 illustrates a case where the faulty component has a low defect probability, 12%, but it still is on the top 17%.

Figure 5.4 exhibits the relative position of the faulty component for all the 184 defects and allowed to concluded that the average percentage of components with higher defect probability than the faulty component is just 16.6% and the median is 10.6%.

5.2 Barinel Integration

Two types of integration with Barinel were tested so the results will be presented separately in the following two sub-chapters. However, in the interest of better understanding the results, an analysis of the results of the unmodified Barinel was made.

The unmodified Barinel analysis, represented on figure 5.5, showed that on 44.57% of the 184 project states the faulty component already are on the first position and on 5.98% it has associated a 0% probability of being faulty. So, no improvements can be made on 50.55% of the examples of the test set. It also showed that in 88.04% of the results the component with the defect is above the 10th position. For the sake of this analysis, in case of draw, we consider the best position and will not consider on the graphics the cases where the associated probability is 0%.

Experimental Results

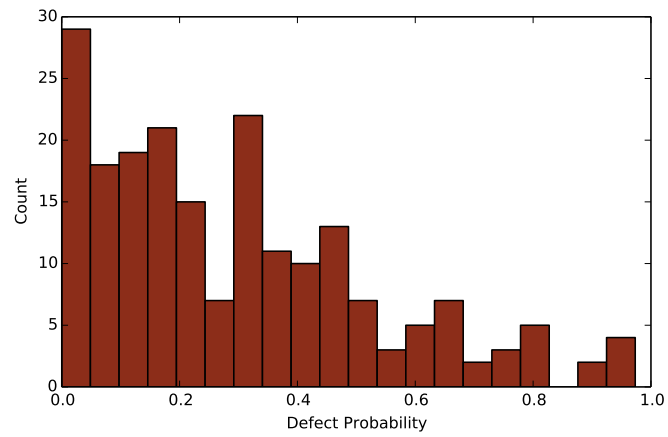


Figure 5.2: Distribution of predicted defect probabilities for faulty components

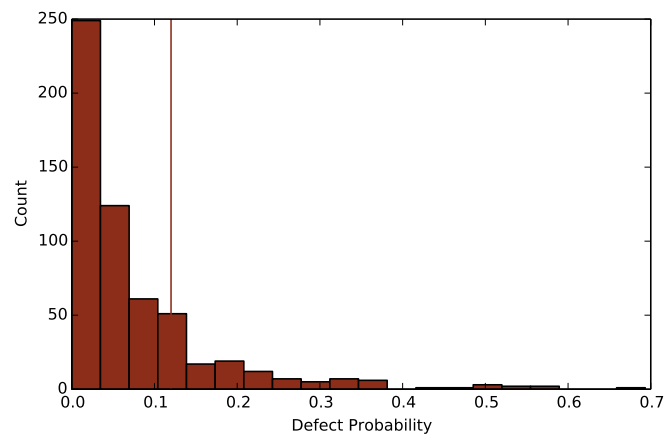


Figure 5.3: Histogram of predicted defect probabilities for Project Math (Defect 50), with a vertical line identifying the faulty component prediction

Experimental Results

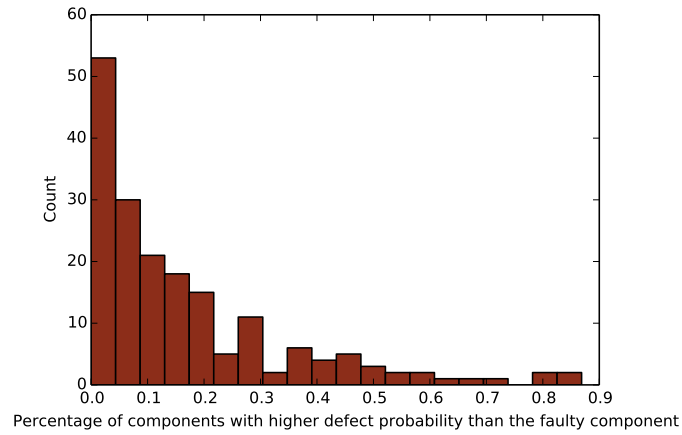


Figure 5.4: Histogram of the percentage of components with higher defect probability than the faulty component for all 184 defects

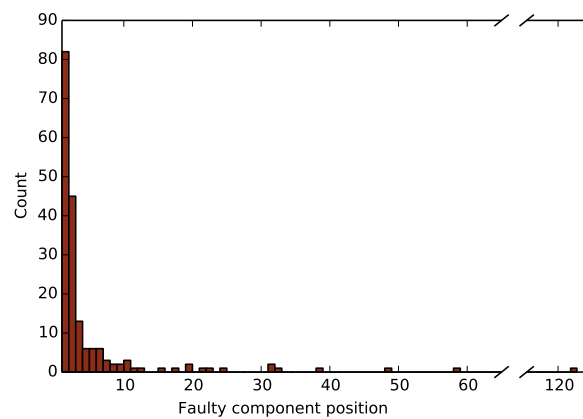


Figure 5.5: Histogram of the relative position of all faulty components, with a probability above zero, reported by the unmodified barinel

Experimental Results

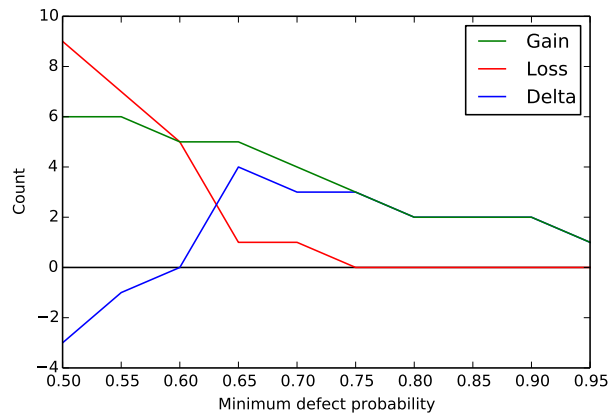


Figure 5.6: Results modification effect on Barinel results, by minimum defect probability

5.2.1 Results Modification

First, to be able to contextualize the results, the best and worst scenarios were tested. If the predicted defect faulty was 1 to all the faulty components and 0 for all the others, there would be an improve on 37 cases. If, for instance, the probabilities were totally wrong, it would worsen 54 cases.

Given the predicted defect probabilities is important to determine the best value to use as the minimum for a component to be considered possibly faulty. When considered possibly faulty, as explained in 4, the Barinel fault probability is doubled. For each value from 0.5 to 1, at 0.05 steps, the gain, loss and delta was calculated, as we can see in 5.6.

5.2.2 Priors Replacement

[TODO] ... Waiting ... Flaky tests ...

Experimental Results

Chapter 6

Discussion

The experimental results acknowledged that extracting the component changes metadata is valuable by allowing to predict, with good precision and independently of the language, which files are more probable to have defects (Figure 5.4).

6.1 Estimating Defect Probability

In figures 5.1 and 5.2 we clearly see two distinct types of distributions. Probably clean components predicted defect probability tends to 0, as intended, but the same can not be interpreted for the buggy components, whereas the distribution is more uniform. Preferably, the buggy components predicted defect probability distribution would tend more expressively to 1, being the reverse of figure 5.1, but this may have been affected by the data imbalance and noise.

Since in each fix commit just a small percentage is changed and all the others are considered clean, extracted data is extremely unbalanced and the number of fault components in the training set is small. Using SMOTE improved the results, but the tendency to 0 continues to be noticeable.

The assumption that all unmodified files are clean may also introduce noise in the data, by labeling faulty components as clean. This along with the uncertainty of the identification of fix commits by the commit message, that may lead to wrongly labeling clean components as faulty, may blur the difference between the two types and lower the prediction accuracy.

Besides, the faulty component may be defectuous just because of a recent change in a related component and since the data set does not contain any information about the components relations, it would be difficult for it to have a high predicted defect probability.

Further more, one important aspect that can be observed on figure ?? and was verified by experimentation is that the model that allows to predict the faulty components now may not work in the future. The model must be trained with the most recent data, because the patterns that allow to identify to distinguish clean and fault component appear to change along with the project.

Yet, even with so much aspects that may affect our prediction accuracy, the figure 5.4 shows that, in fact, the faulty components tends to be classified as one of the components with the highest defect probability. Which is crucial to our goal of improving Barinel results.

6.2 Barinel Integration

Analysis of the unmodified Barinel, illustrated in 5.5, showed how good the results are and the tenuous percentage of tests that can be improved by using our approach to modify Barinel results. 14.67% in the best case scenario. While in the worst case scenario, 29% of the tests would worsen.

Figure 5.6 shows that when considering as faulty all the components with a predicted defect probability above 0.6 the Barinel results improve, with little or no error. Examining for example the results for 0.65 of minimum predicted probability, where the delta is higher, 13.5% of the possible improvements occurred and just one test worsened. Increasing the minimum diminishes both the number of improvements and errors, but starting at 0.75 errors are completely eliminated.

Given this data, we can concluded with some confidence that components with a predicted defect probability above 0.65 have in fact a high real defect probability.

[TODO] The other barinel integration. + Flaky tests

6.3 Threats to Validity

There are some threats to the validity of this research. The first is the fact that the Math project (101 tests of 184) appeared to have flaky tests, since with the exact same configuration Barinel, which is deterministic, reported some value changes.

Using three open source Java projects, with 184 tests, may also not be sufficient to predict the application behaviour in other different projects

Being this research all about defect probabilities, we know that the application made to estimate the defect probability can also have defects and may somehow affect the predictions. Although the application was heavily tested and many results were manually checked for validity.

Last but not least, the data mining application is nondeterministic. It creates models every time and chooses the most accurate ones, in order to avoid being able to predict completely different results, but there will be most certainly differences as expected in a data mining project.

Chapter 7

Conclusions and Further Work

As said before, we consider that building tools to help developers do a better job is crucial and have a huge impact on the global economy. With this research we make one more step in the right direction.

The data mining application developed is based only on metadata information from the files on the Git repository, what makes it language agnostic, and showed that is capable to identify components with an high defect probability, the code hotspots

This capacity of identifying hotspots is highly valuable and can save help save time. It can be used, for example, to advise software developers doing code reviews to be more careful about some file, or to improve results from Fault Localization Software, such as Barinel .

7.1 Goals Satisfaction

The application is able to to predict the defect probability for any component on any software project, that uses Git, with a precision that also allowed to improve some results of Barinel.

So we can conclude that the project was successful and achieved the defined goals.

[TODO] Chourigo++

7.2 Further Work

This project can be further improved and can also be used to create new or integrate with existing applications for which defect probability is important. There are plenty relevant opportunities to further work:

- Improving fix commits identification
- Improving precision by adding static code analysis features

Conclusions and Further Work

- Improving machine learning model accuracy, by reducing the noise, removing outlier and better managing the unbalanced data
- Integrating with GitHub Pull Requests to help identify code hotspots
- Improving extracting performance

[TODO] Add more and explain each deeply

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