# Bug Report Severity Level Prediction in Free Libre/Open Source Software: A State of Art Survey

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**Abstract**

(i)Establishing a territory. (ii)Indicating a gap. (iii)Announcing present research. (iv)Announce principal findings.

**Index Terms**

software maintenance; bug tracking systems; bug reports; severity level prediction; software repositories.

## I. Introduction

1. show the general area is important, problematic, or relevant in some way (motivations)
2. introduce and review items of previous research in the area
3. Indicate a gap in the previous research, or extend previous knowledge in some way
4. Outline purposes or state the nature of present research
5. Announce principal findings (contributions) and its importance
6. indicate the structure of the research paper

## II. BACKGROUND

This section briefly comments of basic concepts necessary to understand this research area

### A. Related Work

It was find two studies that review, in some way, the literature about bug report severity prediction. Cavalcanti et al. [1] performed a review of 142 papers that investigated challenges and opportunities for software change or bug report request. Just seven out of total papers are related to change request prioritization, which commonly defined by two fields: priority and severity. Four out of them addressed bug report severity prediction. Even though, only two papers (Lamkanfi et al. [2] and Lamkanfi et al. [3]) addressed severity prediction on FLOSS projects. This mapping study shows that all of seven papers used some Information Retrieval Model: that one paper used vector space representation (binary and term count), and all seven used TF-IDF. Besides, it shows that all papers implement learning techniques: SVM (4 out of 7), Decision tree(2 out of 7), KNN(2 out of 7), Naive Bayes (3 out of 7) and Nave Byes Multinomial (1 out of 7).

The review present by Uddin et al. [4] surveyed published articles in bug prioritization. The authors reviewed and analysis in-depth 32 distinct papers published between 2003 and 2015. The aim of this analysis was "to summarize the existing work on bug prioritization and some problems in working with bug prioritization". To depict the results, it classifies the papers by ML algorithms, evaluation measures, data sets, researchers, and publication venue. It can be worth to note that the authors investigated only eight papers about predicting of severity level. In contrast, the current mapping study investigated in depth 27 papers about bug report severity prediction.

Although these reviews present relevant results for research in the theme, they have one essential limitation. There is no explicit focus on bug report severity prediction. In fact, these papers perform a slight review of this topic by addressing mainly bug report priority prediction. The current review has a broader goal of mapping studies addressing many questions about bug report severity prediction. Furthermore, it provides much more classifications for papers data than previous surveys.

## III. Research Method

This section describes the research method used in this mapping study for identifying and analyzing relevant papers. It was based on the software engineering systematic literature review guidelines and recommendations proposed by Kitchenham et al. [5], Brhel et al. [6], Souza et al. [7], and Petersen et al. [8]. They recommend a process with three main steps: planning, conducting, and reporting. In the first step, it should be specified a review protocol, which contains a set of research questions, inclusion and exclusion criteria, sources of papers, search string, and mapping procedures. In the second step, it was selected and retrieved papers to use as basis for data extraction. Finally, in the last step, the results used to address the systematic mapping research questions defined previously are written up.

### A. Research questions

The main goal of this mapping study is to provide a current status view of the research on bug report severity prediction in FLOSS. To ensure an unbiased selection process, it was defined previously the following research questions to be addressed, as well as the rationale for considering them in this study.

**RQ$_1$. When and where have the studies been published?** This research question gives to researcher a perception whether the topic of this mapping study seems to be broad and new, providing an overview about where and when papers were published.

**RQ$_2$. What FLOSS are the most used as report sources in experiments for bug report severity prediction?** This research question names the FLOSS used as report source in bug report severity prediction problems. This overview can be useful for researchers that intend to accomplish new initiatives in this area, and can also motivate adoption of new FLOSS in future research to bridge existing gaps.

**RQ$_3$. Was bug report severity prediction most addressed as either a fine-grained label or coarse-grained label prediction problem?** This research question investigates whether bug report severity prediction was most treated as a fine-grained label (i.e., multi-label) or as a coarse-grained label (i.e., two-label or three-label) prediction problem. This is essential to comprehend each solution provided for each prediction problem type.

**RQ$_4$. What are the most common feature used bug report severity prediction?** This question investigates features used for bug report severity prediction in FLOSS. It can help to map which features have been considered more effective in this prediction problem.

**RQ$_5$. What are the most common features selection methods used for bug report severity prediction?** This question complements the previous one, looking for feature selection methods employed in the papers for bug report severity prediction in FLOSS. This is important to point out which feature selection approaches have been considered more suitable for this prediction problem.

**RQ$_6$. What are the most used text mining or information retrieval methods for bug report severity prediction?** This research question indicates the main text mining approaches used to extract features from textual fields of bug reports. It can guide researchers in the task of selecting text mining methods more suitable to be applied in bug report severity prediction or similar problems.

**RQ$_7$. What are the most used machine learning algorithms for bug report severity prediction?** This research question aims to identify the main ML algorithms adopted bug report severity prediction in FLOSS. What can be useful for any researcher that aim to accomplish further initiatives in this area, as well as to guide him investigating other algorithms to improve current results.

**RQ$_8$. What are the measures typically used to evaluate ML algorithms performance for bug report severity prediction?** This research question aims to find out which measures are used to evaluate ML algorithms performance. It can be helpful to identify the more effective measures to evaluate ML algorithms performance for bug report severity prediction.

**RQ$_9$. Which sampling techniques were employed to improve ML algorithms performance for bug report severity prediction?** This question complements the previous one, investigating sampling techniques, which were used to generate more reliable and accurate ML models. It can be useful to analyze sampling techniques, which might be more suitable to improve the machine learning algorithms performance for bug report severity prediction.

**RQ$_{10}$. What statistical tests were used to compare the performance between two or more ML algorithms for bug report severity prediction?** The answer of this research question can be useful to identify which statistical tests were used in bug report severity prediction context. In addition, it allows to grasp how the comparison between two or more ML algorithms performance using statistical significance was made.

**RQ$_{11}$. What software tools were used to run bug report severity prediction experiments?** This research question highlights the software tools most used to run experiments for bug reports severity prediction in FLOSS projects. This is useful to provide information for researchers and practitioners about technologies that could be used in their own experiments.

**RQ$_{12}$. What solution types were proposed for bug report severity prediction problem?** This research question examines whether the most common solutions proposed in the selected studies are either online or off-line. This is important to separate clearly the solutions that can be applied only in an experimental environment (off-line) from those can be deployed in a real scenario (online).

### B. Study selection

This section describes the selection process carried out through the mapping study. It comprises four steps: (i) terms and search string; (ii) sources for searching; (iii) inclusion and exclusion criteria; and (iv) how to store data.

*1) Terms and search string:* The base string was constructed from three search main terms related to three distinct knowledge areas: "open source project", "bug report" and "severity predict". To build the search string, terms were combined with "AND" connectors. The search string syntax was adapted according particularities of each source (e.g., wildcars, connectors, apostrophes

and quotation marks) before it has been applied on three metadata papers: title, abstract, and keywords. Table I exhibits terms and final search string used in this mapping study.

TABLE I: Search string.

| Area | Search term |
|---|---|
| Bug report | "bug report" |
| Open source | "open source software" |
| Severity prediction | "severity predict" |
| **Search string**: | "open source software" AND "severity predict" AND "bug report" |

*2) Sources:* To accomplish this mapping study, it was selected four electronic databases and one popular search engines recommended by Kitchenham et al. [5]. Table II shows each selected sources, as well as the search date, and the period covered by the search.

TABLE II: Search sources.

| Source | Electronic address | Type | Search Date | Years covered |
|---|---|---|---|---|
| ACM | http://dl.acm.og | Digital library | Dec,18 | 2010 - 2017 |
| IEEE | http://ieeexplore.ieee.org | Digital library | Dec,18 | 2010 - 2017 |
| Google Scholar | http://www.scholar.google.com | Search engine | Dec,18 | 2010 - 2017 |
| Science Direct | http://www.sciencedirect.com | Digital library | Dec,18 | 2010 - 2017 |
| SpringLink | http://www.springerlink.com | Digital library | Dec,18 | 2010 - 2017 |

*3) Inclusion and exclusion criteria:* The inclusion criteria below allow the identification of papers on the existing literature.

**$IC_1$**. The study discusses bug report severity prediction in FLOSS projects.

On the contrary, the following exclusion criteria allows exclude all papers that satisfy any of them.

**$EC_1$**. The study does not have an abstract;
**$EC_2$**. The study is just published as an abstract;
**$EC_3$**. The study is written in a language other than English;
**$EC_4$**. The study is not a primary study (e.g., keynotes);
**$EC_5$**. The study is not accessible on the Web;

*4) Data storage:* The data extracted in the searching phase were stored into a spreadsheet that recorded all relevant details from selected papers. This spreadsheet supported classification and analysis procedures throughout this mapping study.

*5) Assessment:* According to Kitchenham et al. [5], the consistency of the protocol utilized in a mapping study should be reviewed to confirm that: "the search strings, constructed interactively, derived from the research questions"; "the data to be extracted will properly address the research question(s)"; "the data analysis procedure is appropriate to answer the research questions". In this research, the first author is a PhD candidate running the experiments. The review process was conducted by the second and third authors.

### C. Data extraction and synthesis

Figure 1 depicts four stages of selection process carried out in current mapping study. In each stage, the sample size was reduced based on the inclusion and exclusion criteria applicable in this stage. In the first stage, relevant papers were retrieved by querying the databases with the search string presented in Table I. All database queries were issued in December 2017. This yielded a total of 54 initial papers: 13 from **IEEE Xplore**, 5 from **Science Direct**, 17 from **ACM Digital Library**, and 19 from **SpringerLink**. After removing four duplicates, we reduced (around 7%) the initial set to 50 papers. In the second stage, inclusion and exclusion criteria were applied over title, abstract, and keywords, reaching a set of 18 papers (reduction around 64%): 32 papers were rejected for not satisfying $IC_1$ (The study discusses severity prediction of bug reports in FLOSS projects). In the third stage, exclusion criteria were applied considering the full text. However, no study was rejected by taking into account these criteria.

In the fourth stage, the Snowballing [5] activity was conducted, which resulted in 12 additional papers. After applying selection criteria over title, abstract, and keywords, 11 papers remained (reduction of 8.3% over the papers selected by snowballing). For these papers, selection criteria were applied considering the full text, and nine papers remained (reduction of approximately 18.2% over the 11 previously selected papers); $EC_3$ criterion eliminated one paper (the study is written in a language other than English); $EC_6$ eliminated one more paper (the study is inaccessible on the Web), and another one was rejected for not satisfying $IC_1$. The selection phase ended up with 27 papers to be analyzed (18 from the sources plus 9 from

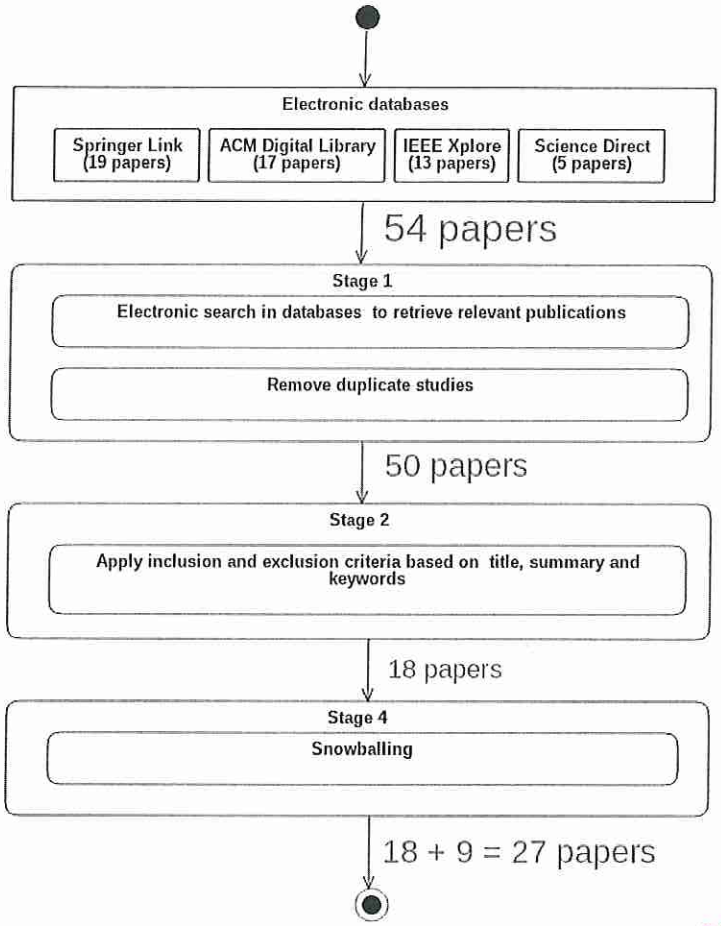



Fig. 1: Study selection phases diagram.

snowballing). Table III shows the bibliographic reference of selected papers and an identifier (#id) for each paper. Throughout the remainder of this text, these identifiers will be used to refer to the corresponding paper.

### D. Classification scheme

Petersen et al. [8] suggest the definition of a classification scheme for conducting a systematic mapping analysis. The categories defined for this mapping study were based on two approaches: (i) categories available in the literature and (ii) taking into account the selected papers. The next sections outline the categories that will be used in this mapping study.

*1) FLOSS software type ($RQ_2$):* This classification organizes the FLOSS used as targets in selected papers experiments by software type. Based on the taxonomy suggested by Pressman [9], FLOSS in studies belongs to three categories:

a. **Application software**: a computer program or group of computer programs designed to solve a specific problem or business need for end users.
b. **System software**: a collection of computer programs (operating systems and utilities) required to run and maintain a computer system.
c. **Programming tools**: computer programs that aid software developers to create, debug, maintain, or perform any development-specific task.

*2) ML classification problem ($RQ_3$):* This classification drills down prediction problems in specific types. Based on studying of selected papers, five categories were defined:

a. **Type 1**: prediction problem whose ML algorithms classify a bug report severity level into severe or non-severe. The default severity level is considered neither into severe nor non-severe classes.
b. **Type 2**: prediction problem whose ML algorithms classify a bug report severity level into severe or non-severe. The default severity level is considered into severe or non-severe classes, or as a separate class.

TABLE III: Selected studies

| #ID, | Bibliographic reference |
|---|---|
| #1 | A. Lamkanfi, S. Demeyer, E. Giger and B. Goethals, "Predicting the severity of a reported bug," 2010 7th IEEE Working Conference on Mining Software Repositories (MSR 2010), Cape Town, 2010, pp. 1-10. |
| #2 | A. Lamkanfi, S. Demeyer, Q. D. Soetens and T. Verdonck, "Comparing Mining Algorithms for Predicting the Severity of a Reported Bug", 2011 15th European Conference on Software Maintenance and Reengineering, Oldenburg, 2011, pp. 249-258. |
| #3 | Y. Tian, D. Lo and C. Sun, "Information Retrieval Based Nearest Neighbor Classification for Fine-Grained Bug Severity Prediction," 2012 19th Working Conference on Reverse Engineering, Kingston, ON, 2012, pp. 215-224. |
| #4 | C. Z. Yang, C. C. Hou, W. C. Kao and I. X. Chen, "An Empirical Study on Improving Severity Prediction of Defect Reports Using Feature Selection," 2012 19th Asia-Pacific Software Engineering Conference, Hong Kong, 2012, pp. 240-249. |
| #5 | Chaturvedi, K. K. and V.B. Singh. "An Empirical Comparison of Machine Learning Techniques in Predicting the Bug Severity of Open and Closed Source Projects." IJOSSP 4.2 (2012): 32-59. |
| #6 | G. Yang, T. Zhang and B. Lee, "Towards Semi-automatic Bug Triage and Severity Prediction Based on Topic Model and Multi-feature of Bug Reports," 2014 IEEE 38th Annual Computer Software and Applications Conference, Vasteras, 2014, pp. 97-106. |
| #7 | C. Z. Yang, K. Y. Chen, W. C. Kao and C. C. Yang, "Improving severity prediction on software bug reports using quality indicators," 2014 IEEE 5th International Conference on Software Engineering and Service Science, Beijing, 2014, pp. 216-219. |
| #8 | Harold Valdivia Garcia and Emad Shihab. 2014. "Characterizing and predicting blocking bugs in open source projects". In Proceedings of the 11th Working Conference on Mining Software Repositories (MSR 2014). ACM, New York, NY, USA, 72-81. |
| #9 | Sharma M., Kumari M., Singh R.K., Singh V.B. (2014) "Multiattribute Based Machine Learning Models for Severity Prediction in Cross Project Context". In: Murgante B. et al. (eds) Computational Science and Its Applications – ICCSA 2014. ICCSA 2014. Lecture Notes in Computer Science, vol 8583. Springer, Cham. |
| #10 | N. K. S. Roy and B. Rossi, "Towards an Improvement of Bug Severity Classification," 2014 40th EUROMICRO Conference on Software Engineering and Advanced Applications, Verona, 2014, pp. 269-276. |
| #11 | Ripon K. Saha, Julia Lawall, Sarfraz Khurshid, and Dewayne E. Perry. 2015. "Are these bugs really "normal"?". In Proceedings of the 12th Working Conference on Mining Software Repositories (MSR '15). IEEE Press, Piscataway, NJ, USA, 258-268. |
| #12 | Tao Zhang, Geunseok Yang, Byungjeong Lee, and Alvin T. S. Chan. 2015. "Predicting severity of bug report by mining bug repository with concept profile". In Proceedings of the 30th Annual ACM Symposium on Applied Computing (SAC '15). ACM, New York, NY, USA, 1553-1558. |
| #13 | G. Sharma, S. Sharma, S. Gujral, "A Novel Way of Assessing Software Bug Severity Using Dictionary of Critical Terms", Procedia Computer Science, pp. 632-639, 2015. |
| #14 | X. Xia, D. Lo, E. Shihab, X. Wang, X. Yang, "Elblocker: Predicting blocking bugs with ensemble imbalance learning", Information and Software Technology, 2015. |
| #15 | S. Gujral, G. Sharma, S. Sharma and Diksha, "Classifying bug severity using dictionary based approach," 2015 International Conference on Futuristic Trends on Computational Analysis and Knowledge Management (ABLAZE), Noida, 2015, pp. 599-602. |
| #16 | M. N. Pushpalatha and M. Mrunalini, "Predicting the severity of bug reports using classification algorithms," 2016 International Conference on Circuits, Controls, Communications and Computing (I4C), Bangalore, 2016, pp. 1-4. |
| #17 | A. F. Otoom, D. Al-Shdaifat, M. Hammad and E. E. Abdallah, "Severity prediction of software bugs," 2016 7th International Conference on Information and Communication Systems (ICICS), Irbid, 2016, pp. 92-95. |
| #18 | Korosh Koochekian Sabor, Mohammad Hamdaqa, and Abdelwahab Hamou-Lhadj. 2016. "Automatic prediction of the severity of bugs using stack traces". In Proceedings of the 26th Annual International Conference on Computer Science and Software Engineering (CASCON '16), Blake Jones (Ed.). IBM Corp., Riverton, NJ, USA, 96-105. |
| #19 | Tian, Y., Ali, N., Lo, D. et al. Empir Software Eng (2016) 21: 2298. https://doi.org/10.1007/s10664-015-9409-1 |
| #20 | Tao Zhang, Jiachi Chen, Geunseok Yang, Byungjeong Lee, and Xiapu Luo. 2016. "Towards more accurate severity prediction and fixer recommendation of software bugs". J. Syst. Softw. 117, C (July 2016), 166-184. |
| #21 | Kwanghue, J., Amarmend, D., Geunseok, Y., Jung-Won, L., Byungjeong, L.: "Bug severity prediction by classifying normal bugs with text and meta-field information". Adv. Sci. Technol. Lett. 129 (2016). Mechanical Engineering. |
| #22 | T. Choeikiwong, P. Vateekul, "Improve accuracy of defect severity categorization using semi-supervised approach on imbalanced data sets", Proceedings of the International MultiConference of Engineers and Computer Scientists, vol. 1, 2016. |
| #23 | Jin, Kwanghue, Dashbalbar, Amarmend Yang, Geunseok, Lee, Byungjeong, Lee, Jung-Won. (2016). "Improving predictions about bug severity by utilizing bugs classified as normal". Contemporary Engineering Sciences. 9. 933-942. 10.12988/ces.2016.6695. |
| #24 | Jin, K, Lee, E.C., Dashbalbar, A, Lee, J, Lee, B. (2016). "Utilizing feature based classification and textual information of bug reports for severity prediction". 19. 651-659. |
| #25 | Geunseok Yang, Seungsuk Baek, Jung-Won Lee, and Byungjeong Lee. 2017. "Analyzing emotion words to predict severity of software bugs: a case study of open source projects". In Proceedings of the Symposium on Applied Computing (SAC '17). ACM, New York, NY, USA, 1280-1287. |
| #26 | V. B. Singh, Sanjay Misra, and Meera Sharma, J. Info. Know. Mgmt. 16, 1750005 (2017) |
| #27 | N. K. S. Roy and B. Rossi, "Cost-Sensitive Strategies for Data Imbalance in Bug Severity Classification: Experimental Results," 2017 43rd Euromicro Conference on Software Engineering and Advanced Applications (SEAA), Vienna, 2017, pp. 426-429. |

c. **Type 3**: The prediction problem whose ML algorithms classify a bug report severity level into one from multi-classes. The default severity level is not considered as a valid class.
d. **Type 4**: The prediction problem whose ML algorithms classify a bug report severity level into one from multi-classes.The default severity level is considered as a valid class.
e. **Type 5**: The prediction problem whose ML algorithms classify a bug report severity level into blocking or non-blocking class. A blocking bug is software defect that prevent other defects from being fixed [10].

*3) Feature data types ($RQ_4$):* This classification groups the features used for bug reports severity prediction into ~~well-known~~ three categories:

a. **Qualitative**: features that can be arranged into categories based on specific characteristics. It cannot be expressed numerically.
b. **Quantitative discrete**: features that contain a finite or a infinite number of values that can be counted.
c. **Quantitative continuous**: features that contain a infinite number of values that can be measured.

*4) Feature selection methods ($RQ_5$):* This classification organizes the feature selection methods used for bug reports severity prediction into three categories, according to taxonomy described in Guyon and Elisseeff [11]:

a. **Filter**: as a selection criterion, this approach score features on a particular metric. The top-scoring features are selected by this score. It selects subsets of features as a pre-processing step, independently of chosen predictor.
b. **Wrapper**: this approach prepares, evaluates and compares feature combinations and selects the best one. It considers the feature selection as a search problem.
c. **Embedded**: this approach perform features selection in the process of training and learn which features best contribute to the accuracy of the model while machine learning creates the model.

*5) Text mining feature representations ($RQ_6$):* This classification organizes the text mining features representations techniques used for bug report severity prediction in four categories. The following categories were employed in this mapping study according to [12]:

a. **Character**: individual component-level letters, numerals, special characters, and spaces are the building blocks of higher-level semantic features such as words, terms and concepts.
b. **Word**: specific words selected directly from a "native" document are at what might be described as the basic level of semantic richness.
c. **Term**: single words an multiwords phrases selected directly from corpus of a native document by means of term-extraction methodologies.
d. **Concept**: features generated for a document by means of manual, statistical, rule-based, or hybrid categorization methodologies.

*6) ML algorithms types ($RQ_7$):* This classification groups ML algorithms used in bug report severity prediction in five categories. The following categories were based on taxonomy proposed by Facelli et al. [13]:

a. **Distance-based**: algorithms that use the proximity between data to generate their predictions.
b. **Probabilistic-based**: algorithms that make their predictions based on the Bayes's theorem.
c. **Searching-based**: algorithms that rely on a searching of a solution in a space to generate their predictions.
d. **Optimization-based**: algorithms whose predictions are based on an optimization function.
e. **Ensemble-method**: algorithms that combine or aggregate classifiers to make the prediction.

*7) Evaluation measures categories ($RQ_8$):* This classification organizes evaluation measures used in selected papers by categories. According to Japkowicz and Shah [14], there are six categories:.

a. **Single class focus**: measures based on confusion matrix information whose focus is on a single class of interest. They are indicated for deterministic classifiers.
b. **Multi-class focus**: measures based on confusion matrix information whose focus is on all the classes of problem domain. They are recommended for deterministic classifiers.
c. **Graphical measure**: measures based on confusion matrix in conjunction with extra information. They enable visualization of the classifier performance under different skew ratios and class priors distribution and are indicated for scoring classifiers.
d. **Summary statistics**: measures based on confusion matrix in conjunction with extra information. They enable quantify the comparative analysis between classifiers and are indicated for scoring classifiers.
e. **Distance/error-measure**: measures based on confusion matrix in conjunction with extra information. They measure the distance of an instance's predicted class label to its actual label and are recommended for continuous and probabilistic classifiers.
f. **Information theoretic measures**: measures based on confusion matrix in conjunction with extra information. They reward a classifier upon correct classification relative to the (typically empirical) prior on the data and are indicated for continuous and probabilistic classifiers.

*8) Sampling techniques ($RQ_9$):* This classification organizes the sampling techniques used for bug reports severity prediction into three categories. Such categories according to Japkowicz and Shah [14] include:

a. **No re-sampling**: techniques that consists of testing the algorithm on a large set of unseen data.
b. **Simple re-sampling**: techniques that tend to use each data point for testing only once.
c. **Multiple re-sampling**: techniques that tend to use each data point for testing more than once.

*9) Statistical Tests($RQ_{10}$):* This classification groups the statistical tests types used for bug reports severity prediction in three categories. Such categories employed in this mapping study according to Japkowicz and Shah [14] include:

a. **Parametric**: make strong assumptions about the distribution of the population
b. **Non-parametric**: do not make strong assumptions about the distribution of the population
c. **Parametric and non-parametric**: both parametric and non-parametric

*10) Experiment software tools ($RQ_{11}$):* This classification groups the software tools used in experiments for bug reports severity prediction in two well-know and popular categories:

a. **Free/Libre Open Source Software (FLOSS)**: software that can be freely used, modified, and redistributed.
b. **Closed Source Software (CSS)**: software that is owned by an individual or a company whose source code is not shared with the public for anyone to look at or change.

### *E. Limitations of this mapping*

We need to consider the following common limitations of all mapping studies to interpret adequately the implications of our results:

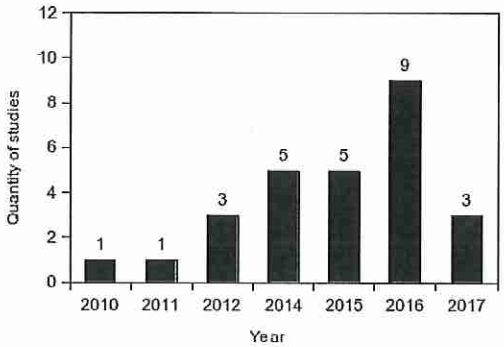
- **Mapping review completeness can never be guaranteed [6]**: Although in this mapping review, it have been observed a strict research protocol to ensure the relatively complete population of the relevant literature, some important papers might be missed.
- **Terminological problems in search string may lead to miss some primary studies [7]**: The terminology we have applied in the database query is normally accepted and used within the scientific community. Nevertheless, different terms may have been used to describe the same relevant information.
- **Subjective evaluation of inclusion and exclusion criteria may cause misinterpretation [6].** Explicit criteria have been defined for assessing the relevance of selected papers III-B. However, the evaluation was based on the perception and experience of the authors. Different people might have other views regarding the relevance of these papers.

## IV. Results

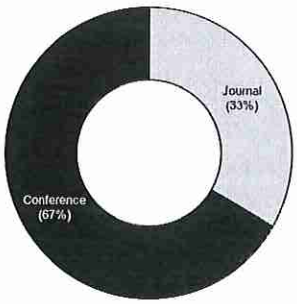
This section summarizes the results of the mapping study. The answers for each research question (RQ1 to RQ12) are presented in tables where each paper is referenced by its id. In addition, extracted data were classified according to criteria defined in Section III.

### *A. When and where have the studies been published? (RQ1)*

Figure 2a shows the temporal distribution of papers. Just over 75% (22/27) of primary selected papers were published after 2012. Table IV presents sources of the selected papers, their types, and their identifiers. Although four studies were published in the MSR and two in the SEAA conferences. It is worth observing that 21 out 27 selected papers were published in 21 different venues. Figure 2b shows that conferences were preferred rooms to publish 67% of the selected papers, while journals were chosen by 33% of the papers.




(a)




(b)

Fig. 2: (a) Paper distribution by year. (b) % of papers by source.

TABLE IV: Papers publication sources.

| Paper source | Publication kind | #ID |
|---|---|---|
| ACM Symposium on Applied Computing | Conference | #21 |
| Advanced Science and Technology Letters & Journal | Journal | #10 |
| Asia-Pacific Software Engineering Conference | Conference | #4 |
| Computational Science and Its Applications (ICCSA) | Conference | #9 |
| Computer Software and Applications Conference | Conference | #6 |
| Contemporary Engineering Sciences | Journal | #23 |
| Empirical Software Engineering | Journal | #19 |
| Futuristic Trends on Computational Analysis and Knowledge Management (ABLAZE) | Conference | #15 |
| Information and Software Technology | Journal | #14 |
| International Conference on Circuits, Controls, Communications and Computing (I4C) | Conference | #16 |
| International Conference on Computer Science and Software Engineering | Conference | #18 |
| International Conference on Information and Communication Systems (ICICS) | Conference | #17 |
| International Conference on Software Engineering and Service Science | Conference | #7 |
| International Information Institute | Journal | #24 |
| International Journal of Open Source Software and Process(IJOSSP) | Journal | #5 |
| International MultiConference of Engineers and Computer Scientists | Conference | #22 |
| Journal of Information & Knowledge Management | Journal | #26 |
| Journal of Systems and Software | Journal | #20 |
| Procedia Computer Science | Journal | #13 |
| Software Engineering and Advanced Applications (SEAA) | Conference | #10, #27 |
| Symposium on Applied Computing (SAC) | Conference | #25 |
| Working Conference on Mining Software Repositories (MSR) | Conference | #1, #2, #8, #11 |
| Working Conference on Reverse Engineering | Conference | #3 |

*B. What FLOSS are the most used as experiment target for bug report severity prediction (RQ2)?*

Table V details the FLOSS found out after analysis of data gathered throughout this mapping study. The details for each FLOSS include a textual description; a classification, according to Section III-D; a BTS name, which hosted it; and an electronic address, from where it can be accessed. Table VI shows FLOSS distribution by selected papers. It can be observed that the top five projects were used for at least 11% of papers. Nearly 92% of papers employed Eclipse (25 out of 27), 70% Mozilla (19 out of 27), 18% Openoffice (5 out of 27), 14% Netbeans(4 out of 27) and 11% Gnome(3 out of 27).

The chart in Figure 3a quantifies the number of papers by FLOSS type. It points out that the most FLOSS type investigated in experiments for bug report severity prediction is Programming Tool (25 out of 27), closely followed by Application Software (21 out of 27). FLOSS classified as System Software are used in only 2 out of 27 papers. The chart in Figure 3b quantifies the number of papers by BTS site. It shows up that all (27 out of 27) experiments published in the selected papers has extracted data from at least one FLOSS hosted on a Bugzilla site. In the same chart, it can be observed that only a few of them used FLOSS hosted on Google (3 out of 27) and Jira (2 out of 27) sites.

*C. Has the prediction of severity of bug reporting been more commonly treated as a two-label, tree-label or multi-label prediction problem (RQ3)?*

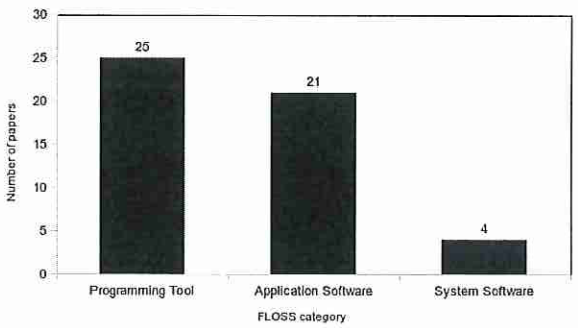
Table VII shows prediction problem types faced by authors in selected papers for bug report severity prediction. It indicates that the most faced prediction problem type was multi-label (13 out of 27 - around 48%), and a significant number of papers (12 out 27 - around 44%) addressed two-label prediction problem as well. Only a few of them handled tree-label problem type.

TABLE V: FLOSS investigated in papers.

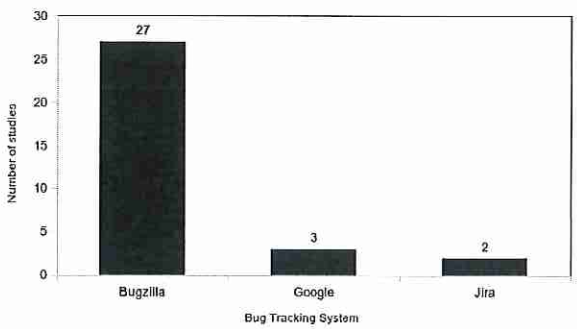
| Project | Description | Classification | BTS | URL (As of May 24, 2018) |
|---|---|---|---|---|
| Android | Mobile operating system | System software | Google | https://issuetracker.google.com |
| Chrominum | Web browser | Application software | Google | https://www.chromium.org/issue-tracking |
| Eclipse | Integrated Development Environment(IDE) | Programming tool | Bugzilla | https://bugs.eclipse.org/bugs/ |
| FreeDesktop | Base platform for desktop for desktop software on Linux and UNIX | Programing Tool | Bugzilla | https://bugs.freedesktop.org/ |
| GCC | C compiler | Programming tool | Bugzilla | https://gcc.gnu.org/bugzilla/ |
| Gnome | Desktop environment based on X Windows System | Application Software | Bugzilla | https://gcc.gnu.org/bugzilla/ |
| Hibernate | Object Relation Mapper(ORM) framework | Programming tool | Jira | https://hibernate.atlassian.net |
| Jboss | Application server | System software | Jira | https://issues.jboss.org/s |
| Mongo-db | No-sql database | System software | Jira | https://jira.mongodb.org/ |
| Mozilla | Internet tools | Application software | Bugzilla | https://bugzilla.mozilla.org/ |
| Netbeans | Integrated Development Environment(IDE) | Programming tool | Bugzilla | https://netbeans.org/bugzilla/ |
| OpenOffice | Office suite | Application software | Bugzilla | https://bz.apache.org/ooo/ |
| Spring | JEE Framework | Programming tool | Jira | https://jira.spring.io |
| WineHQ | Compatibility layer | System software | Bugzilla | https://bugs.winehq.org/ |

TABLE VI: Paper distribution by FLOSS.

| Project | 2010 | 2011 | 2012 | 2014 | 2015 | 2016 | 2017 | Total (%) |
|---|---|---|---|---|---|---|---|---|
| Eclipse | #1 | #2 | #3, #4, #5 | #6, #8, #10 | #11, #12, #13, #14, #15 | #17, #18, #19, #20, #21, #22, #23, #24 | #25, #26, #27 | 92.6% |
| Mozilla | #1 | | #3, #4, #5 | #6, #8, #9, #10 | #12, #14 | #16, #17, #19, #20, #21, #23, #24 | #26, #27 | 70.4% |
| OpenOffice | | | #3 | #8 | #14 | #19, #20 | | 18.5% |
| Netbeans | | | | #6, #8 | #14 | #20 | | 14.8% |
| Gnome | #1 | #2 | #5 | | | | | 11.1% |
| Chrominum | | | | #8 | #14 | | | 7.4% |
| FreeDesktop | | | | #8 | #14 | | | 7.4% |
| Android | | | | | | | #25 | 3.7% |
| GCC | | | | | | #20 | | 3.7% |
| Hibernate | | | | | | | #27 | 3.7% |
| JBoss | | | | | | | #25 | 3.7% |
| Mongo-db | | | | | | | #27 | 3.7% |
| Spring | | | | | | | #27 | 3.7% |
| WineHQ | | | | | | #16 | | 3.7% |




(a)




(b)

Fig. 3: (a) Paper distribution by FLOSS type. (b) Paper distribution by BTS host.

TABLE VII: Paper distribution by prediction problem type.

| Problem Type | 2010 | 2011 | 2012 | 2014 | 2015 | 2016 | 2017 | Total(%) |
|---|---|---|---|---|---|---|---|---|
| Multi-label | | | #3, #5 | #6, #9 | #12 | #16, #18, #19, #20, #22 | #25, #26, #27 | 48.15% |
| Two-label | #1 | #2 | #4 | #7, #8, #10 | #13, #14, #15 | #17, #21, #23 | | 44.44% |
| Tree-label | | | | | #11 | #24 | | 7.41% |

The chart in Figure 4 drills down the paper distribution by prediction problem type. It indicates that the most faced prediction problem in selected papers for bug report severity prediction was type 1 (10 out of 27 - around 37%), second most addressed prediction problem type was type 3 (8 out of - around 37%), and third was type 4 (5 out of 27 - around 18.5%). A few papers regarded about prediction problems type 5 (2 out of 27 - around 7%) and type 2 (2 out of 27 - around 7%).

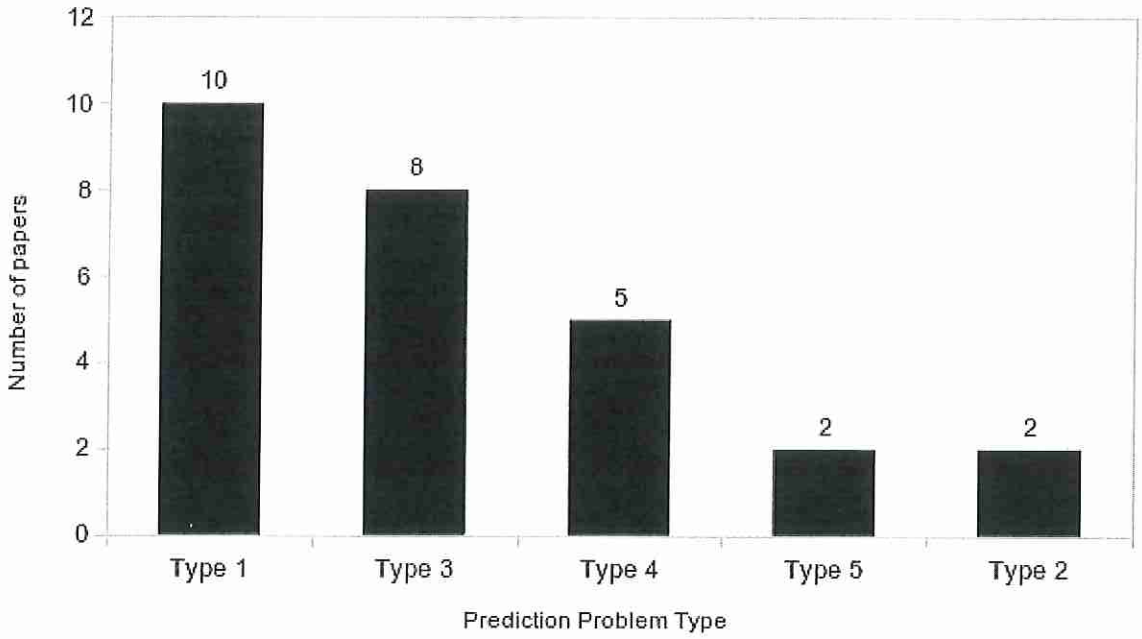



Fig. 4: Paper distribution by prediction problem type.

*D. What are the most common features used bug report severity prediction (RQ4)?*

Table VIII details the features investigated in select papers. The details for each feature include a textual description; a classification, according to Section III-D; whether features are computed from others or not; and whether feature is provided by Bugzilla, Jira and/or Google. Table IX presents the feature distribution by papers. It can be observed that summary (19 out of 27 - 81.5%) and description (17 out of 27 - 63.0%) were the most common features used for bug report severity prediction.

The chart in Figure 5 groups features by data type in three categories: qualitative, quantitative discrete and quantitative continuous. It can be observed that most feature data type used for bug report severity prediction was qualitative.

*E. What are the most common features selection methods employed for bug report severity prediction (RQ5)?*

Table X shows the methods used in selected papers for bug report severity prediction. It can be observed that: (i) few papers utilized a feature selection method and; (ii) only filter method type was used by them.

*F. What are the most used text mining methods for bug report severity prediction (RQ6)?*

Table XI shows text mining methods used in selected papers for bug report severity prediction. It can be observed that the most used text mining method was TF-IDF (9 out of 27 - 33%).

The chart in Figure 6 shows papers by text mining feature model type distribution. It points out that most text mining method used for bug report severity prediction was term model type (12 out of 27 - around 44%).

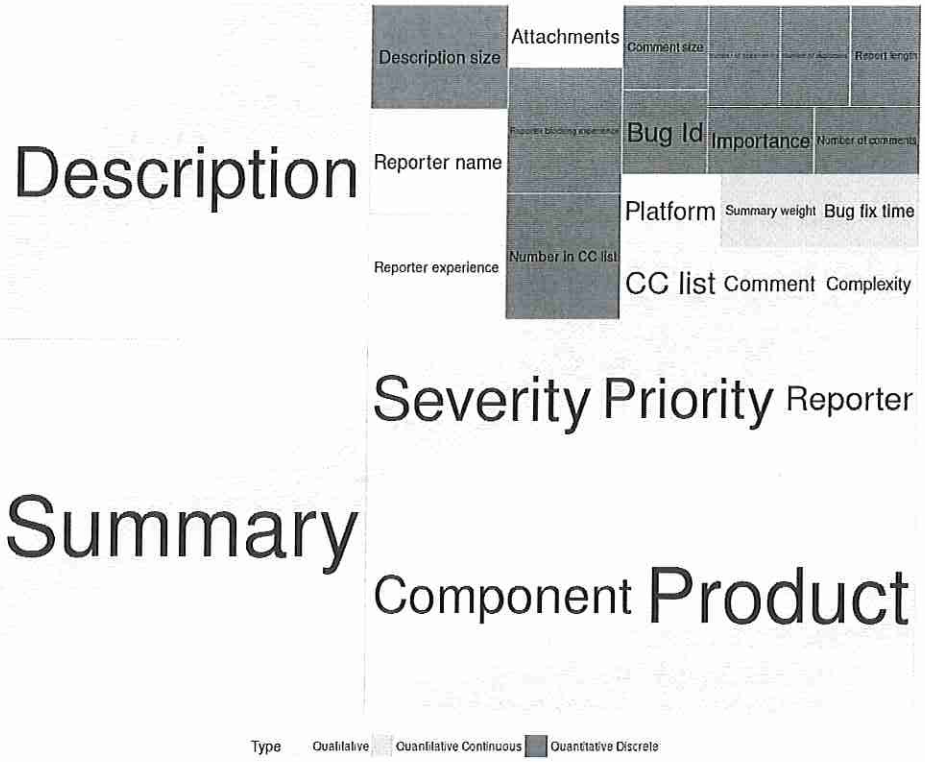



Fig. 5: Papers by feature data type.

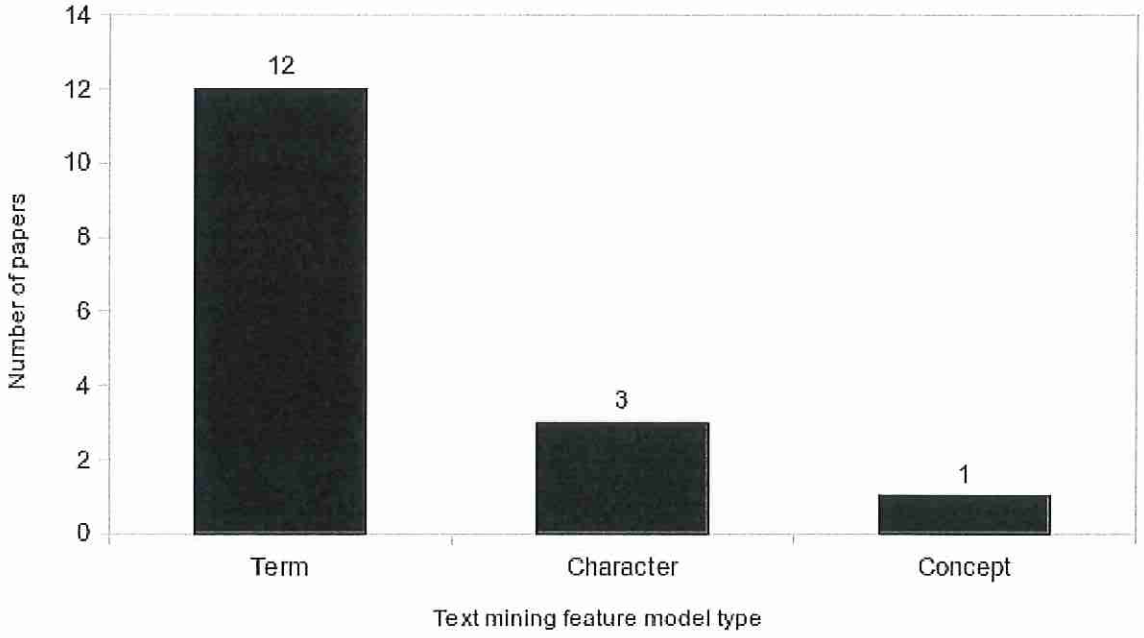



Fig. 6: Papers by text mining feature type

TABLE VIII: Features descriptions.

| Feature | Description | Classification | Is Calculated? | Bugzilla[1] | Jira[2] | Google[3] |
|---|---|---|---|---|---|---|
| Attachments | Files (e.g. testcases or patches) attached to bugs. | Qualitative | No | Yes | No | Yes |
| Bug fix time | Time to fix a bug (Last Resolved Time - Opened Time). | Quantitative Continuous | Yes | Yes | Yes | Yes |
| Bug id | Bug report identifier. | Quantitative Discrete | No | Yes | Yes | Yes |
| CC list | A list of people who get mail when the bugs changes. | Qualitative | No | Yes | No | Yes |
| Comment | Textual content appearing in the comments of bug report. | Qualitative | Yes | Yes | Yes | Yes |
| Comment size | The number of word of all comments of a bug. | Quantitative Discrete | Yes | Yes | Yes | Yes |
| Complexity | Bug level of complexity based on bug fix time. | Qualitative | Yes | Yes | Yes | Yes |
| Component | Each product is divided into different components (e.g. Core, Editor, UI, etc). | Qualitative | No | Yes | Yes | Yes |
| Description | Textual content appearing in the description field of the bug report. | Qualitative | No | Yes | Yes | Yes |
| Description size | The number of words in the description. | Quantitative Discrete | Yes | Yes | Yes | Yes |
| Importance | The importance of a bug is a combination of its priority and severity. | Qualitative | No | Yes | No | No |
| Number in CC list | The number of developers in the CC list of the bug. | Quantitative Discrete | Yes | Yes | No | Yes |
| Number of comments | Number of comments added to a bug by users. | Quantitative Discrete | Yes | Yes | Yes | Yes |
| Number of dependents | Number of report bugs dependents | Quantitative Discrete | Yes | Yes | Yes | Yes |
| Number of duplicates | Number of duplicates of bug report | Quantitative Discrete | Yes | No | No | Yes |
| Platform | These indicate the computing environment where the bug was found (e.g. Windows, GNU/Linux, Android, etc). | Qualitative | No | Yes | Yes | Yes |
| Priority | Priority should normally be set by the managers, maintainers or developers who plan to work, not by the one filling the bug or by outside observers. | Qualitative | No | Yes | Yes | Yes[4] |
| Product | What general "area" the bug belongs to (e.g. Firefox, Thunderbird, Mailer, etc). | Qualitative | No | Yes | Yes | No |
| Report length | The content length of long description providing debugging information. | Quantitative Discrete | Yes | Yes | Yes | Yes |
| Reporter | The account of the user who created the bug report. | Qualitative | No | Yes | Yes | Yes |
| Reporter blocking experience | Counts the number of blocking bugs filed by reporter previous to this bug. | Quantitative Discrete | Yes | Yes | Yes | No |
| Reporter experience | Counts the number of previous bug reports filed by the reporter. | Quantitative Discrete | Yes | Yes | Yes | No |
| Reporter name | Name of the developer or user that files the bug | Qualitative | No | Yes | Yes | No |
| Severity | This indicates how severe the problem is – from blocker ("application unusable") to trivial ("minor cosmetic issue"). | Qualitative | No | Yes | Yes | No |
| Summary | A one-sentence summary of the problem. | Qualitative | No | Yes | Yes | Yes |
| Summary weight | Calculated using information gain criteria | Quantitative Continuous | Yes | Yes | Yes | Yes |

### *G. What are the most used machine learning algorithms for bug report severity prediction (RQ7)?*

Table XII shows ML algorithms used in selected papers for bug report severity prediction. It can be observed that the two most ML algorithms used for bug report severity were KNN and NB (12 out of 27 - around 44%).

The chart in Figure 7 shows ML algorithm types by paper distribution. It points out that the most used ML algorithm type for bug report severity prediction was probabilistic-based (21 out of 27 - around 77%).

### *H. What are the measures used to evaluate ML algorithms performance for bug report severity prediction (RQ8)?*

Table XII shows evaluation measures used in selected papers for bug report severity prediction. It can be observed that the most used evaluation measure for bug report severity prediction was precision (21 out of 27 - around 77%).

The chart in Figure 8 shows paper distribution by ML performance evaluation measure types. It can be observed that the most used evaluation measure type in bug report severity prediction was single class (21 out of 27 - around 70%).

### *I. Which sampling techniques are most applied to generate more reliable predictive performance estimates in severity prediction of a bug report (RQ9)?*

Table XIV shows sampling methods used in selected papers for bug report severity prediction. It can be observed that sampling method preferred by authors of these papers was 10-Fold CV (10 out of 27 - around 37%).

TABLE IX: Features used in selected papers.

| Feature | 2010 | 2011 | 2012 | 2014 | 2015 | 2016 | 2017 | Total (%) |
|---|---|---|---|---|---|---|---|---|
| Summary | #1 | #2 | #3, #4, #5 | #6, #7, #9 | #11, #13 | #16, #17, #20, #21, #23, #24 | #25, #26, #27 | 81.5% |
| Description | #1 | | #3 | #6, #7, #8, #10 | #14, #15 | #16, #17, #18, #20, #21, #23, #24 | #25, #27 | 63.0% |
| Component | | | #3 | #6, #8 | #14 | #16, #20, #21, #23, #24 | | 33.3% |
| Product | | | #3 | #6, #8 | #14 | #16, #20, #21, #23, #24 | | 33.3% |
| Severity | | | | #8 | #14 | #21, #23, #24 | | 18.5% |
| Priority | | | | #6, #8, #9 | #14 | | | 14.8 % |
| Reporter | | | | | | #21, #23, #24 | | 11.1% |
| Description size | | | | #8 | #14 | | | 7.4% |
| Number in CC list | | | | #8 | #14 | | | 7.4% |
| Reporter blocking experience | | | | #8 | #14 | | | 7.4% |
| Reporter experience | | | | #8 | #14 | | | 7.4% |
| Reporter name | | | | #8 | #14 | | | 7.4% |
| Attachments | | | | #7 | | | | 3.7% |
| Bug fix time | | | | #9 | | | | 3.7% |
| Bug Id | | | | | | #22 | | 3.7% |
| CC list | | | | #9 | | | | 3.7% |
| Comment | | | | #8 | | | | 3.7% |
| Comment size | | | | | #14 | | | 3.7% |
| Complexity | | | | #9 | | | | 3.7% |
| Importance | | | | | | #16 | | 3.7% |
| Number of comments | | | | #9 | | | | 3.7% |
| Number of dependents | | | | #9 | | | | 3.7% |
| Number of duplicates | | | | #9 | | | | 3.7% |
| Platform | | | | | #14 | | | 3.7% |
| Report length | | | | #7 | | | | 3.7% |
| Summary weight | | | | #9 | | | | 3.7% |

TABLE X: Paper distribution by feature selection methods.

| Method | Classification | 2010 | 2011 | 2012 | 2014 | 2015 | 2016 | 2017 | Total(%) |
|---|---|---|---|---|---|---|---|---|---|
| Information Gain | Filter | | | #4, #5 | | #13 | #19 | #27 | 18.52% |
| Chi-Square | Filter | | | #4 | #10 | #13 | | | 11.11% |
| Correlation Coefficient | Filter | | | #4 | | | | | 3.70% |

TABLE XI: Paper distribution by text mining methods.

| Technique | Classification | 2010 | 2011 | 2012 | 2014 | 2015 | 2016 | 2017 | Total(%) |
|---|---|---|---|---|---|---|---|---|---|
| TF-IDF | Term | | #2 | #5 | #10 | #12, #13, #15 | #17 | #26, #27 | 33.33% |
| Bigrams | Character | | | #3 | #10 | | #20 | | 11.11% |
| Unigrams | Character | | | #3 | | | #20 | | 7.41% |
| TF | Term | | #2 | #4 | | | | | 7.41% |
| Topic model | Concept | | | | | | #20 | | 3.70% |
| BM25ext | Term | | | | | | #20 | | 3.70% |
| BM25 | Term | | | #3 | | | | | 3.70% |
| Binary Representation | Term | | #2 | | | | | | 3.70% |

TABLE XII: Papers distribution by ML algorithms

| Technique | Category | 2010 | 2011 | 2012 | 2014 | 2015 | 2016 | 2017 | Total(%) |
|---|---|---|---|---|---|---|---|---|---|
| KNN | Distance | | #2 | #3 | #6, #8, #9 | #12, #15 | #18, #19, #20, #22 | #26 | 44.44% |
| NB | Probabilistic | #1 | #2 | #5 | #6, #8, #9, #10 | #11, #12 | #17, #22 | #26 | 44.44% |
| NBM | Probabilistic | | #2 | #4 | #7 | #12, #13, #15 | #19, #21, #23, #24 | #25 | 40.74% |
| SVM | Optimization | | #2 | #5 | #9 | | #19, #22 | #26, #27 | 25.93% |
| Random Forest | Searching | | | #5 | #8 | #14 | #17, #22 | | 18.52% |
| C4.5 | Searching | | | #5 | #8, #16 | | | | 11.11% |
| Bagging Ensemble | Ensemble | | | | | #14, #16 | | | 7.41% |
| Decision Tree | Searching | | | | | | #19, #22 | | 7.41% |
| AdaBoost | Ensemble | | | | | | #17 | | 3.70% |
| RBF Networks | Optimization | | | | | | #17 | | 3.70% |
| RIPPER | Other | | | #5 | | | | | 3.70% |
| Zero-R | Other | | | | #8 | | | | 3.70% |

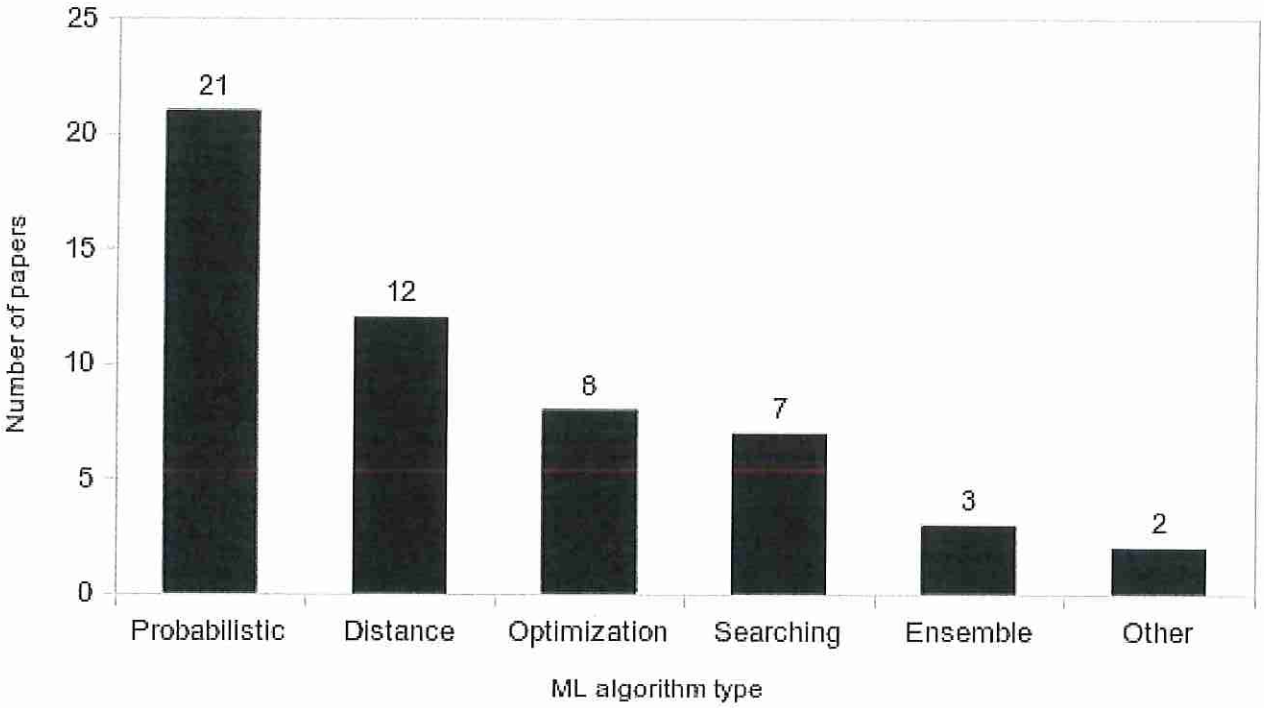



Fig. 7: Papers by ML algorithm categories

TABLE XIII: Papers distribution by evaluation measures.

| Measure | Type | 2010 | 2011 | 2012 | 2014 | 2015 | 2016 | 2017 | Total(%) |
|---|---|---|---|---|---|---|---|---|---|
| Precision | Single class | #1 | | #3, #5 | #6, #8, #9, #10 | #12, #13, #14, #15 | #16, #18, #20, #21, #22, #23, #24 | #25, #26, #27 | 77.78% |
| Recall | Single class | #1 | | #3, #5 | #6, #8, #9, #10 | #12, #14 | #16, #18, #20, #21, #22, #23, #24 | #25, #26, #27 | 70.37% |
| F-measure | Single class | #1 | | #3, #5 | #6, #8, #9, #10 | #12, #14 | #18, #20, #21, #22, #23, #24 | #25, #26, #27 | 66.67% |
| Accuracy | Multi-class | | | #5 | #6, #8, #9, #10 | #11, #13, #15 | #16, #17 | #26 | 40.74% |
| AUC | Summary | #1 | #2 | #4 | #7, #10 | | | | 18.52% |
| ROC | Graphical | #1 | | | #10 | | | | 9.52% |
| MRR | Other | | | | | | #6, #20 | | 7.41% |
| Effectiveness Ratio@20% | Other | | | | | #14 | | | 3.70% |
| Krippendorff's Alpha Reliability | Other | | | | | | #19 | | 3.70% |

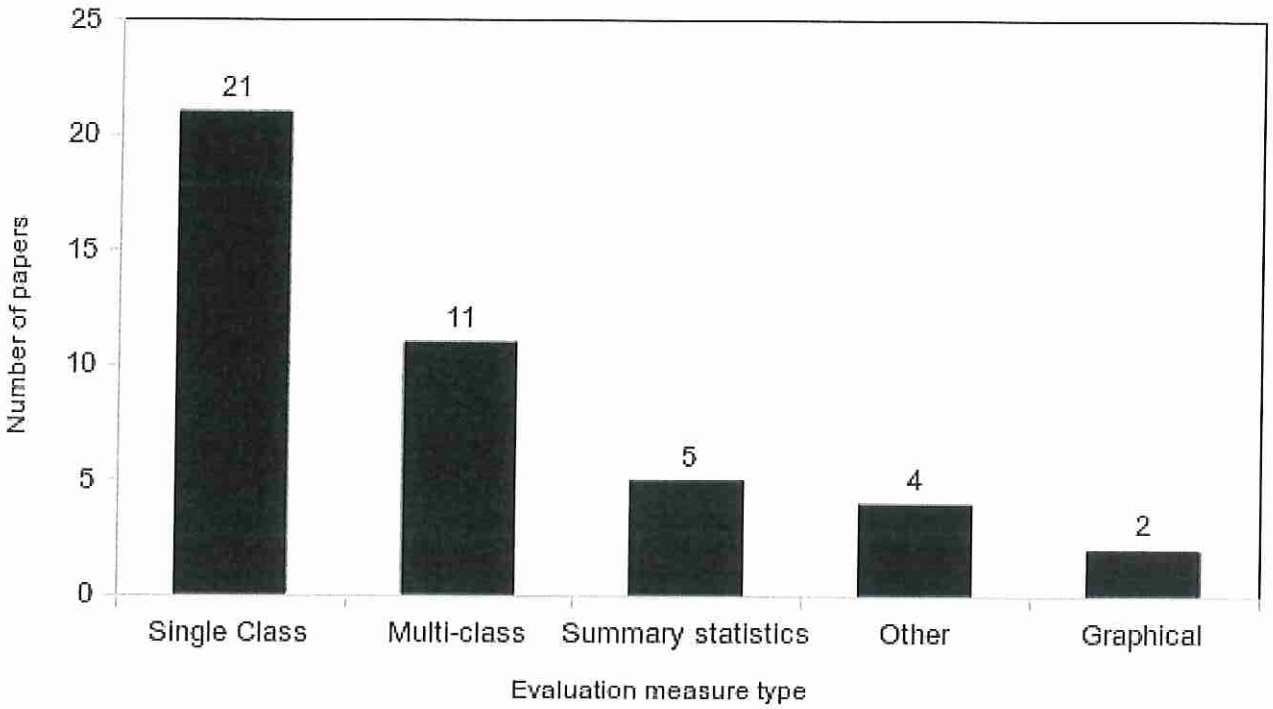



Fig. 8: Papers by evaluate measure types.

TABLE XIV: Paper distribution by sampling methods.

| Sampling Method | Type | 2010 | 2011 | 2012 | 2014 | 2015 | 2016 | 2017 | Total(%) |
|---|---|---|---|---|---|---|---|---|---|
| 10-Fold CV | Simple re-sampling | | #2 | #4, #5 | #7 | #14 | #16, #17, #23 | #25, #26, #27 | 37.04% |
| Stratified 10-Fold CV | Simple re-sampling | | | | #8, #10 | | | | 11.11% |
| Hold-out | No re-sampling | | | | | | #17 | | 3.70% |
| SMOTE | Simple re-sampling | | | | | | #22 | | 3.70% |
| 03-Fold CV | Simple re-sampling | | | | | | #22 | | 3.70% |
| 05-Fold CV | Simple re-sampling | | | | | #13 | | | 3.70% |

The chart in Figure 9 shows papers distribution by sampling method type. It can be observed that the most sampling method type used in bug report severity prediction was simple re-sampling (15 out of 27 - around 55%).

*J. What statistical tests was used to compare the performance between two or more ML algorithms for bug report severity prediction (RQ10)?*

Table XV shows statistical tests used in selected papers for bug report severity prediction. It can be observed that the statistical tests most used by authors of these papers were T-test and Wilcoxon signed rank test (7 out of 27 - around 25%).

TABLE XV: Paper distribution by statistical tests.

| Statistical Test | Type | 2010 | 2011 | 2012 | 2014 | 2015 | 2016 | 2017 | Total(%) |
|---|---|---|---|---|---|---|---|---|---|
| T-test | Parametric | | | | #6 | #12 | #20, #22, #23 | #25, #27 | 25.93% |
| Wilcoxon signed rank test | Parametric and non-parametric | | | | #6, #8 | #12, #14 | #20, #23 | #25 | 25.93% |
| Mann-Whitney U test | Non-parametric | | | | | | | #26 | 3.70% |
| Proportion test | Parametric | | | | | | | #27 | 3.70% |
| Shapiro-Wilk test | Parametric | | | | | | | #25 | 3.70% |

The chart in Figure 10 shows papers distribution by statistical test type. It can be observed that the most statistical test type used in bug report severity prediction was parametric (9 out of 27 - around 33%).

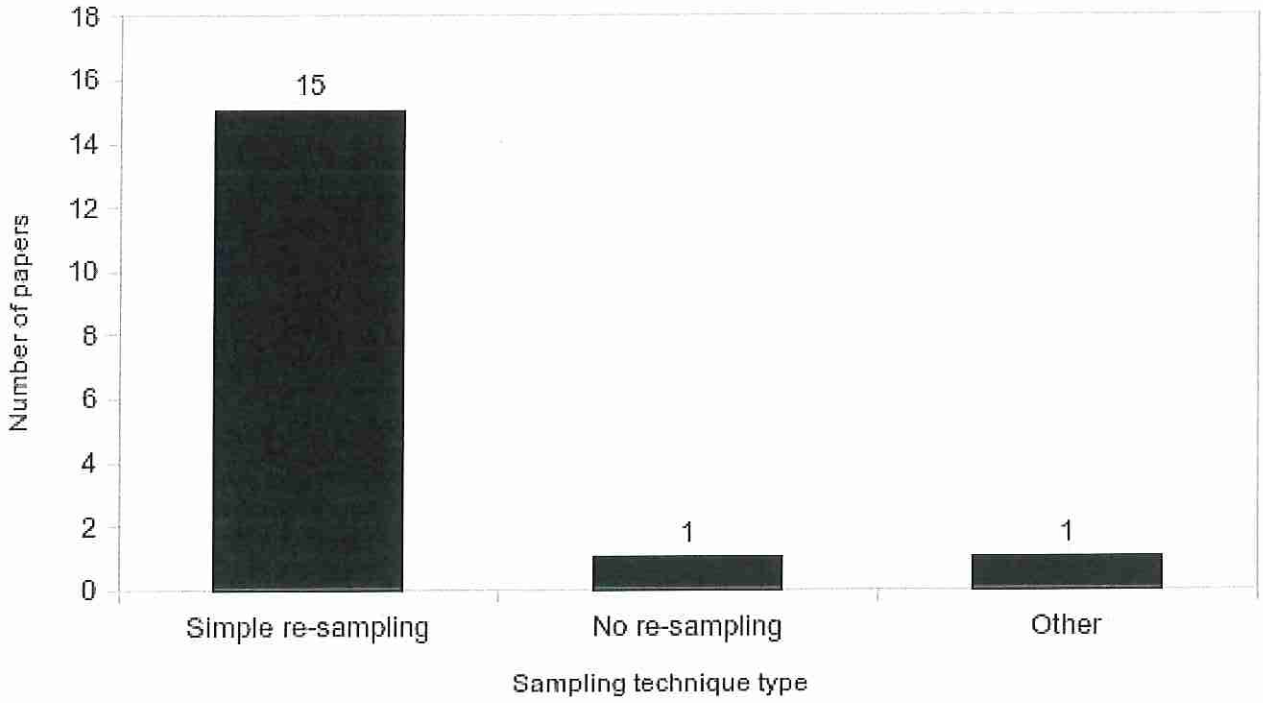



Fig. 9: Papers distribution by sampling method types.

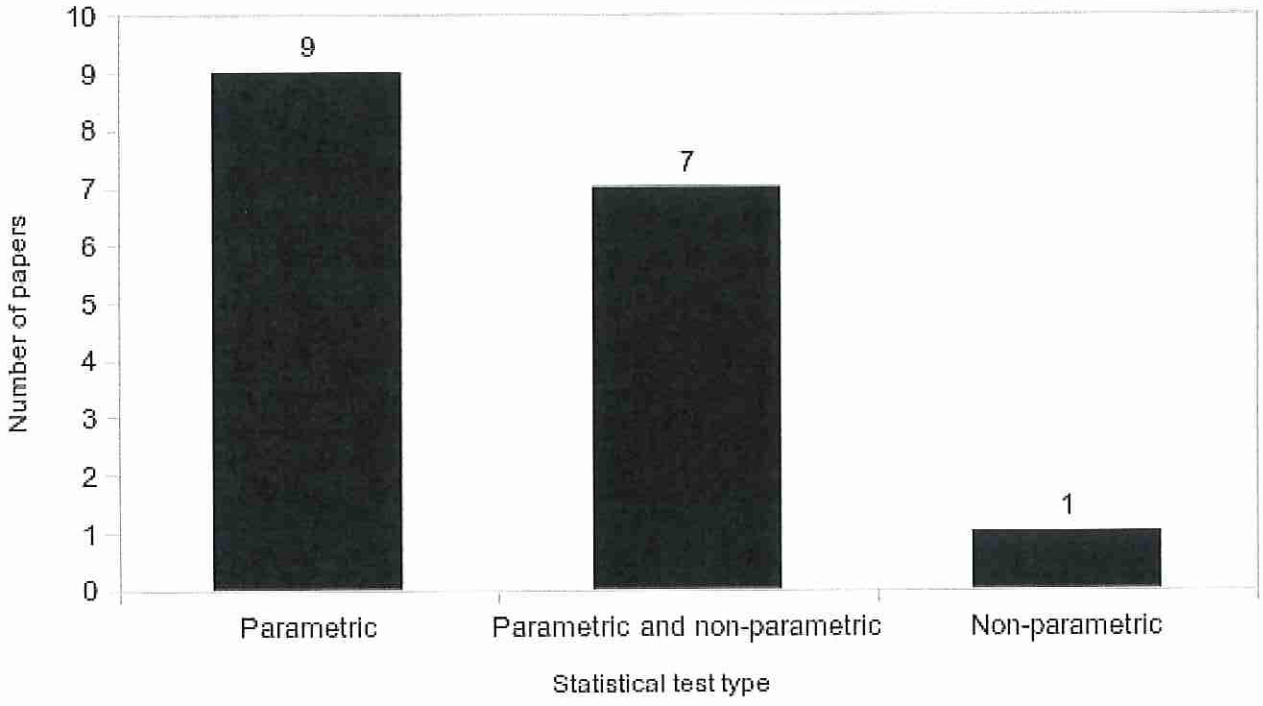



Fig. 10: Papers distribution by statistical test types.

*K. What software tools were used to run bug report severity prediction experiments (RQ11)?*

Table XVI shows software tools used in selected papers for bug report severity prediction. It can be observed that the software tool most used by authors of these papers was RapidMiner (5 out of 18 - around 18%).

TABLE XVI: Software tools used in selected papers.

| Software | Type | 2010 | 2011 | 2012 | 2014 | 2015 | 2016 | 2017 | Total(%) |
|---|---|---|---|---|---|---|---|---|---|
| RapidMiner | CSS | | | #5 | #9 | #13, #15 | | #26 | 18.52% |
| WEKA | FLOSS | | #2 | | #14, #16 | | #19 | | 14.81% |
| R | FLOSS | | | | #6 | #12 | | #25 | 11.11% |
| NLTK | FLOSS | | | | #10 | | #20, #23 | | 11.11% |
| TMT | FLOSS | | | | #6 | | #20 | | 7.41% |
| Statisca | CSS | | | #5 | #9 | | | | 7.41% |
| Ruby | FLOSS | #1 | | | | | | | 3.70% |
| OpenNLP | CSS | | | #3 | | | | | 3.70% |
| WVTool | FLOSS | | | #4 | | | | | 3.70% |
| WordNet | CSS | | | | #10 | | | | 3.70% |
| CoreNLP | FLOSS | | | | | | #25 | | 3.70% |

The chart in Figure 11 shows software tools distribution by select papers. It can be observed that the most software tool type used for bug report severity prediction was FLOSS (11 out of 27 - around 40%).

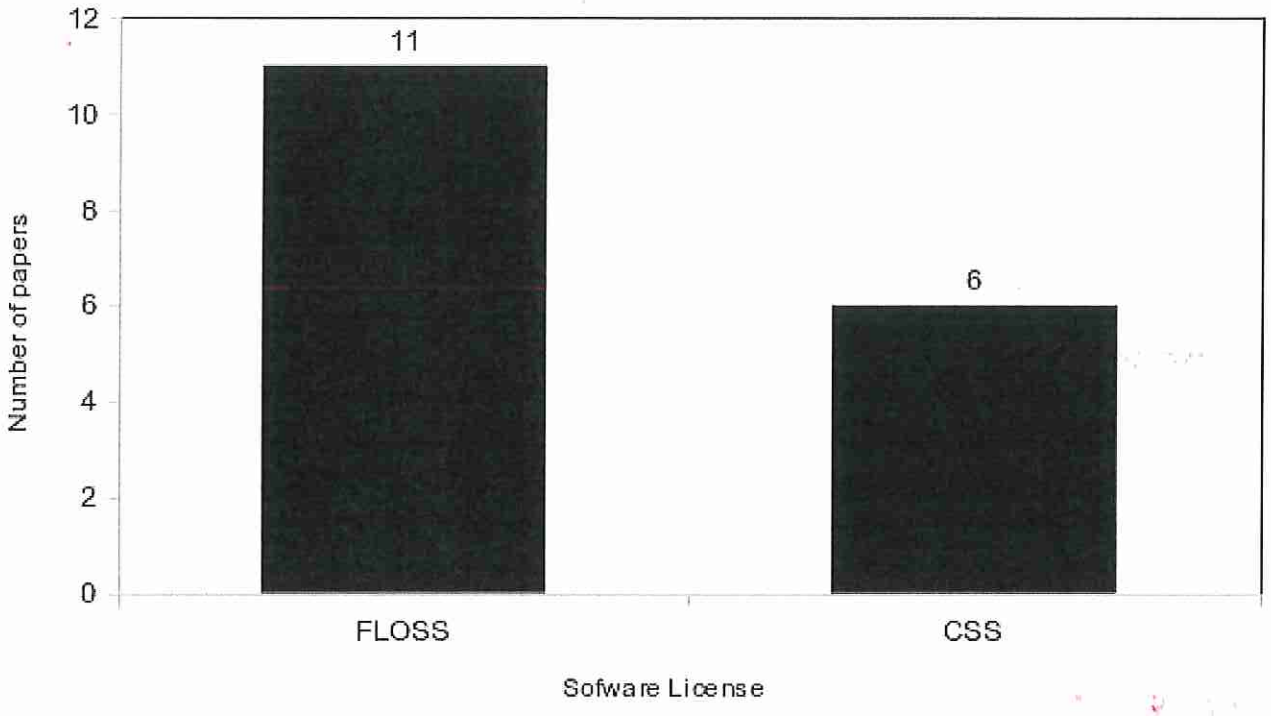



Fig. 11: Paper distribution by software tool types.

*L. What solution types were proposed for bug report severity prediction problem (RQ12)?*

Table XVII shows the solution types proposed in selected papers for bug report severity prediction. It can be observed that the most solution type was off-line (26 out of 27 - around 93%).

## V. Discussion

This section discusses the outcomes which have been found and recommends possible improvements in this research area This mapping study results indicate that research focusing on bug report severity prediction is still recent and relatively stable,

TABLE XVII: Solution types proposed in selected papers.

| Solution | 2010 | 2011 | 2012 | 2014 | 2015 | 2016 | 2017 | Total(%) |
|---|---|---|---|---|---|---|---|---|
| off-line | #1 | #2 | #4, #5 | #6, #7, #8, #9, #10 | #11, #12, #13, #14, #15 | #16, #17, #18, #19, #20, #21, #22, #23, #24 | #25, #26, #27 | 96.30 |
| on-line | | | #3 | | | | | 3.70 |

with the vast majority of the studies developed in the last four years. Also, they suggest that currently, there is no particular place for this type of research or there is no well-established forum for debating this topic. Information Technology, Mining Software Repositories, and Software Engineering publication vehicles seem to be more receptive to papers of bug report severity prediction Repositories.

Despite the number of projects (14 in the total) used as bug reports source, it can notice the lack of prominent FLOSS. For example, Linux Kernel, Ubuntu Linux, and MySQL, among others. Furthermore, the most of papers extracted and processed bug reports from two common projects: Eclipse (approximately 88% of papers) and Mozilla (approximately 70% of papers). The main reason given by many authors is to benchmark their results with those published by Lamkanfi [?], [2], which considered state-of-the-art in this researching area.

The selected projects lead papers to focus on bug reports from Bugzilla. Therefore, they slightly investigated two others cited bug trackers: Jira, responsible for tracking bugs for more than 80% Apache Foundation's projects[5]; and Google, responsible for tracking bugs for many internal and external Google Inc. projects[6]. No paper investigated Github, an outstanding collaborative website which hosted more than 67 million of projects (including many FLOSS)[7]. Hence, it may remain a green field for researching in bug report severity prediction.

From of 14 FLOSS identified in this mapping study, six are programming tools, four are system software, and four are application software. Typically, the bug reporters of two formers are mostly technical users, and the latter are end-users. A bug report can be more or less detailed depends on its reporter [?], [2]. The probability of writing bug reports more accurate is greater for technical users than end-users. It may infer that the most of efforts to severity prediction run over "good" bug reports.

Summary and Description were the most used features for bug report severity prediction. They were utilized respectively in 81.5% and 63.0% of selected papers. These results suggest that proposed solutions are heavily based on unstructured textual information, which leverages advanced text mining and natural language processing methods to extract useful data. Product and Component were other two features reasonably used in papers (33% of them). It may suppose that bug reports collected from separate parts of the same FLOSS affect ML algorithms outcomes differently.

Regarding of available feature data types in bug reports, more than 50% of them are qualitative. SVM and Neural Networks, two popular and essential ML algorithms in modern machine learning [15], do not work with qualitative data [16]. These combined facts bring an extra challenging to use them for bug reports severity prediction. When an input data set has qualitative data, the values of these features should be converted into numeric values before to run these ML algorithms.

The only three used feature selection approaches for bug severity prediction were Information Gain, Chi-Square, and Correlation Coefficient. Yang et al. [17] demonstrated their effectiveness to extract potential severe and no-severe indicators and improve the prediction performance in over half the studied cases. Therefore, it can realize that very few papers (5 out of 27) used at least one method to select features. Furthermore, these papers notably only investigated filter feature selection methods. This approach has two drawbacks [16]: (i) it does not take into account redundancy between features, and (ii) it does not detect dependencies between them.

The most papers used traditional and well-known ML algorithms: KNN [18] or NB [19](around 44% of them), NBM [20] (around 40% of them), and SVM [21](around 25% of them). However, they perform well, and most of the times a paper outperformed the previous one; state-of-art ML algorithms may improve these outcomes in bug report severity prediction. Deep learning, for instance, performs very well when classifying for audio, text, and image data [22].

The most papers used single class measures: precision and recall. As well as, many of these papers also used f-measure, a harmonic mean of precision an recall, to measure ML performance. Typically, a BTS contains many more bug reports with a normal, major, or minor than bug reports with a blocker, critical or trivial severity level [23]. Imbalanced data scenario, as the previous one, strongly skews precision, recall measures [24]. To minimize this distortion, Tian et al. [25], instead, recommends measuring performance using inter-rater agreement based metrics, such as Cohen's Kappa [26] or Krippendorff's Alpha [27]. Despite its well-known issues in an imbalanced dataset [14], around 40% of papers still used accuracy to measure ML performance. AUC, an alternative used by about 18% of papers, seems more robust than accuracy in imbalanced data conditions. Like Kappa and Krippendorff's Alpha, it considers the class distribution on performance evaluation of ML algorithms for bug report severity prediction.

[5]http://www.apache.org/index.html#projects-list
[6]https://developers.google.com/issue-tracker/
[7]https://octoverse.github.com/

The most papers resampled bug reports data using the common 10-fold Cross-Validation technique. About 11% employed the Stratified 10-Fold Cross-Validation, a simple variation of standard 10-fold Cross-Validation which is useful when the class distribution of data is skewed [14]. It is worth to observe that only one paper used SMOTE, considered "de facto" resampling method in imbalanced data scenario [28]. Furthermore, the most of papers, which used at least one sampling technique, utilized a simple re-sampling one. No paper investigated a method of multiple resampling type. Repeated k-fold Cross Validation, a multiple resampling technique, may obtain more stable estimates of algorithm's performance and enhance replicability of results [14].

The most used statistical test was T-test and Wilcoxon Signed Rank test [29]. About 25% of papers employed at least one of them. No paper investigated Analysis of Variance (ANOVA), a robust ranked-based test recommended by Kitchenham et al. [30] for Empirical Sofware Engineering. The statistical test type most used in papers was parametric (around 33% of them), only one paper use a non-parametric test. It is worth to note that, despite their importance, few papers regarded statistical tests to compare ML algorithms performance using statistical significance. In this sense, Japkowicz et al. [14] call attention that to determine whether one algorithm is better than the other by simple exam of superiority or inferiority of means is not advisable.

The most used software tool to run experiments for bug severity prediction was RapidMiner. However, the software company provides a limited free version (w/ 30 days trial), the basic license of this tool costs $2,500 (user/year)[8], which may prohibitive for many research groups. Preventing them from reproducing some experiments reported in papers. In the other hand, a significant portion of experiments run over FLOSS tools (40% of papers). It worth to observe that only one paper used R and no paper used Python, considered two favorite programming language to implement machine learning[9].

The most proposed solutions for bug report severity prediction were off-line. Just one paper's authors (Tian et al. [31]) claimed that the solution provided for them would be fast enough to be embedded in a web browser. Solutions based on Continuous Learning as opposed to algorithms that are trained offline may provide the necessary stuff to overcome these limitations [32].

## VI. Conclusions

i)Familiarize terms, objects, or processes.ii)indicate main purpose. iii) describe methods and materials.iv) describe results and explain them. v) outline research limitations. vi) outline research implications. vii) outline suggestions (future works). viii) cite authors' previous research. ix) cite previous research. x) discuss research contribution/importance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## VII. IDEIAS E DÚVIDAS

*1) IDEIAS:*

- Quais os principais problemas apontados na predição de severidade?
- padronizar as referências bibliográficas.
- de que maneira as publicações comparam o desempenho do ser humano com o problema?
- substituir a classificação de software type por reporter kind (end user, software developer, automatic reporter)
- substituir a classificação de features types(kind) por (categorical, ordinal, quantitative)

*2) DÚVIDAS:*

- Mostrar algoritmos de ML criados ou adaptados no artigos ou mostrar o algoritimo que originou (mais popular) ?
- O que fazer quando um item não possui uma classificação?
- Como classificar TF, TD-IDF e BINARY?
- Estudar relief feature method.
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