Predicting Aging-Related Bugs using Software Complexity Metrics

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Abstract

Long-running software systems tend to show degraded performance and an increased failure occurrence rate. This problem, known as *Software Aging*, which is typically related to the runtime accumulation of error conditions, is caused by the activation of the so-called Aging-Related Bugs (ARBs). This paper aims to predict the location of Aging-Related Bugs in complex software systems, so as to aid their identification during testing. First, we carried out a bug data analysis on three large software projects in order to collect data about ARBs. Then, a set of software complexity metrics were selected and extracted from the three projects. Finally, by using such metrics as predictor variables and machine learning algorithms, we built fault prediction models that can be used to predict which source code files are more prone to Aging-Related Bugs.

Keywords: Software Aging, Fault Prediction, Software Complexity

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Metrics, Aging-Related Bugs

1. Introduction

Software aging is a phenomenon occurring in long-running software systems, which exhibit an increasing failure rate as their runtime increases. This phenomenon is typically related to the accumulation of errors during execution, that leads to progressive resource depletion, performance degradation, and eventually to the system hang or crash. This kind of problems has been observed in several software systems (e.g., web servers, middleware, spacecraft systems, military systems), causing serious damages in terms of loss of money, or even human lives [1, 2].

Software aging is due to the activation of a particular type of software faults, called *Aging-Related Bugs* (ARBs) [3, 4], which tend to cause a failure only after a long period of execution time. For example, ARBs can manifest themselves as leaked memory, unterminated threads, unreleased files and locks, numerical errors (e.g., round-off and truncation), and disk fragmentation.

Due to their nature, it is difficult to observe the effects of such bugs during testing, and to detect and remove ARBs before the software is released. In the literature, most research work has been focused on how to mitigate the negative effects of aging occurrence at runtime. This objective is typically pursued by estimating the time to aging failure (also referred to as *time to exhaustion*), in order to promptly trigger proactive recovery actions to bring the system in a safe state (e.g., rebooting the system). This strategy is known as *software rejuvenation* [5]. The optimal schedule to perform rejuvenation is usually assessed by adopting analytical models and/or by monitoring resource consumption. It has been demonstrated that rejuvenation is an effective strategy to mitigate the effects of ARBs, since the scheduled downtime cost is typically much lower than the cost of an unforeseen downtime caused by a failure [5]. However, this cost cannot be avoided, and the only approach to further reduce the system downtime is to prevent the presence of ARBs in the source code.

Rather than focusing on mitigating the aging effects, this paper is focused primarily on predicting the location of Aging-Related Bugs in complex software systems, in order to aid their identification during testing by assessing which modules are most probably affected by ARBs. This is an important concern when developing complex and large systems that are made up of several thousands of modules and millions of lines of code. The proposed approach uses source code metrics of software modules as predictive features, and exploits binary classification algorithms with the goal of identifying the ARB-prone modules among the ones under test. The prediction can improve the effectiveness of verification and validation activities, such as code reviews [6, 7], stress tests [8, 9], and formal methods [10], which can be focused on the most problematic parts or functionalities of the system.

The driving research hypothesis is that some static software features, such as the software size, its complexity, the usage of some kinds of programming structures related to resource management, and other features, might be related to the presence of ARBs. The underlying principle is that "complexity" may affect the number of bugs committed by programmers; for instance, it is more likely for a developer to omit release operations (e.g., to release locks or memory, causing an aging-related bug) in complex and large code than in a relatively simple and small piece of code; similarly, round-off errors may be related to the amount of operations, fragmentation to the number of files opened, and so on.

In order to investigate the relationship between complexity metrics and ARBs, and thus to confirm/reject the hypothesis, we conducted an empirical analysis on three large software projects, namely the Linux kernel[1], the MySQL DBMS[2], and the CARDAMOM middleware platform for mission-critical systems[3]. More specifically, we: (i) manually analyzed the bug reports of these projects to identify ARBs in their individual software modules; (ii) computed well-known complexity metrics, as well as specific metrics, e.g., memory-related ones, defined for this study; (iii) built fault prediction models using binary classification approaches and the collected data, in order to investigate whether it is possible to predict ARB-prone modules, and to figure out which classification model is best suited for this purpose. Results showed that the ARB-prone files can be effectively predicted (achieving a high percentage of detected ARBs and a low percentage of false alarms), especially when the naive Bayes classifier with logarithmic transformation is adopted. Moreover, we found that the complexity metrics specifically proposed in this study (Aging-Related Metrics) contribute to achieve good performance for all software projects.

The rest of the paper is organized as follows. In Section 2, past work

[1]Linux kernel 2.6, `http://www.kernel.org`
[2]MySQL 5.1, `http://www.mysql.com`
[3]CARDAMOM 3.1, `http://cardamom.ow2.org`

on software aging and software complexity metrics is reviewed. Section 3 describes the software projects considered in this study, and how data about software complexity metrics and ARBs were collected. Section 4 describes the classification models adopted in this work. Section 5 presents the detailed results of the empirical analysis. Section 6 summarizes the findings of the study.

2. Related work

2.1. Software aging

Software aging has been observed in a variety of systems, such as web servers [1], telecommunication billing applications [11], military systems [12], mail severs [13], virtual machines [14, 15], and even in the Linux kernel code [16].

The term Aging-Related Bug has been formalized by Grottke *et al.* [3, 17], who distinguished between *Bohrbugs*, i.e., bugs that are easily isolated and that manifest consistently under a well-defined set of conditions (its activation and error propagation lack complexity), and *Mandelbugs*, i.e., bugs that are difficult to isolate, and not systematically reproducible (its activation and/or error propagation are complex). Mandelbugs include the class of *Aging-Related Bugs*, i.e., bugs leading to the accumulation of errors either inside the running application or in its system-internal environment (see also Section 3.2). A recent analysis of the distribution of bug types has been conducted in the on-board software of JPL/NASA space missions [4]. The analysis highlighted that the presence of ARBs is not negligible. They were found to account for 4.4% of the total bugs found.

Besides these recent works on ARBs, the greatest slice of the literature so far focused on how to mitigate the effects of aging when the system is running, rather than investigating its causes. To this aim, the basic approach to counteract aging developed in these years is known as *software rejuvenation*, i.e., a proactive approach to environmental diversity that was first proposed in 1995 by Huang et *al.* [5]. Its purpose is to restore a "clean state" of the system by releasing OS resources and removing error accumulation. Some common examples are garbage collectors (e.g., in Java Virtual Machines) and process recycling (e.g., in Microsoft IIS 5.0). In other cases, rejuvenation techniques result in partial or total restarting of the system: application restart, node reboot and/or activation of a standby spare.

Along this trend, most of research studies on software aging, such as [18, 19, 20], try to the figure out the optimal time for scheduling the rejuvenation actions. This is typically done by either *analytical approaches*, in which the optimal rejuvenation schedule is determined by models [18, 19], or by *measurement-based approaches*, in which the optimal schedule is determined by statistical analyses on data collected during system execution (e.g., the DBMS performance degradation analysis [21], and the evaluation of Apache Web Server [1]). Vaidyanathan and Trivedi [20] also proposed a solution that combines modeling with a measurement-based approach.

Several works have also investigated the dependence of software aging on the workload applied to the system, such as [22, 23]. These results confirm that aging trends are related to the *workload states*. In [24], the authors address the impact of application-level workload on aging trends. They apply the Design of Experiments approach to investigate the effect of controllable application-level workload parameters on aging. Silva *et al.* [25] highlight the presence of aging in a Java-based SOAP server, and how it depends on workload distributions. Our previous work [14, 16] reports the presence of aging trends both at JVM and OS level; results pointed out the relationship between workload parameters and aging trends (e.g., object allocation frequency for the JVM, number of context switch for the OS). In [13], we also analyzed the impact of application-level workload parameters on aging, such as intensity of requests and size of processed data, and confirmed the presence of aging in Apache, James Mail Server, and in CARDAMOM, a middleware for air traffic control systems.

In the work that we carried out in [26], we pursued a different goal: we investigated the relationship between the static features of the software, as those expressed by software complexity metrics, and *resource consumption trends*. That preliminary study showed that resource consumption trends are related to the static features of software, although the study was limited by the assumption that trends are correlated with the number and the severity of ARBs. The work presented here extends that study: this paper presents an empirical analysis where software complexity metrics are related to *actual Aging-Related Bugs* in the source code, rather than to resource consumption trends. To achieve this objective, we analyzed a dataset of Aging-Related Bugs collected from three real-world software projects. We then built fault prediction models that can be used to predict which source code files are more prone to Aging-Related Bugs. Finally, several classification models were evaluated and compared, in order to identify the classifier most suitable to the purpose of ARB prediction.

2.2. Fault prediction

Software metrics have been widely used in the past for predictive and explanatory purposes. Much work is on investigating relationships between several kinds of software metrics and the fault proneness in a program. Statistical techniques are adopted in order to build empirical models, also known as fault-proneness models, whose aim is to allow developers to focus on those software modules most prone to contain faults.

In [27], authors used a set of 11 metrics and an approach based on regression trees to predict faulty modules. In [28], authors mined metrics to predict the amount of post-release faults in five large Microsoft software projects. They adopted the well-known statistical technique of Principal Component Analysis (PCA) in order to transform the original set of metrics into a set of uncorrelated variables, with the goal of avoiding the problem of redundant features (multicollinearity). The study in [29], then extended in [30], adopted logistic regression to relate software measures and fault-proneness for classes of homogeneous software products. Studies in [31, 32] investigated the suitability of metrics based on the software design. Subsequent studies confirmed the feasibility and effectiveness of fault prediction using public-domain datasets from real-world projects, such as the NASA Metrics Data Program, and using several regression and classification models [33, 34, 35].

In many cases, common metrics provide good prediction results also across several different products. However, it is difficult to claim that a given regression model or a set of regression models is general enough to be used even with very different products, as also discussed in [28, 36]. On the other hand, they are undoubtedly useful within an organization that iteratively collects fault data in its process. If a similar relationship is found for ARBs, developers would better address this phenomenon before the operational phase, e.g., by tuning techniques for detecting ARBs according to such predictions.

3. Empirical data

3.1. Case studies

The analysis focuses on three large-scale software projects, namely the Linux kernel, the DBMS MySQL, and CARDAMOM, a CORBA-based middleware for the development of mission critical, near real-time, distributed applications. These are examples of large-scale software used in real-world scenarios, including business- and safety-critical contexts. MySQL is one of the most used DBMSs, accounting for a significant market share among IT organizations [37]. Linux is one of the most prominent examples of open-source software development, and it is adopted in every domain, from embedded systems [38] to supercomputers [39]. CARDAMOM is a multi-domain platform, as it is intended to be used in different industrial domains for Command and Control Systems (CCS), such as civil Air Traffic Control (ATC) systems, or Defense Command and Control Systems. Table 1 summarizes the main features of the software projects that we analyzed (version, language, number of files and of physical lines of code at the time of writing).

3.2. Aging-Related Bugs

This Section presents the procedure adopted to identify and collect the Aging-Related Bugs analyzed in this paper. We rely on the notion of *Aging-*

Table 1: Software projects considered in this study.

Project	Version	Language	Size (LoC)	# files
Linux	2.6	C	13.2M	30,039
MySQL	5.1	C/C++	1.5M	2,272
CARDAMOM	3.1	C++	847K	4,185

Related Bugs as defined by Grottke *et al.* [4]. According to that scheme, bugs can be classified as follows:

- **Bohrbugs** (BOH): bugs which can be easily isolated. Their activation and error propagation lack "complexity" (see the explanation below).
- **Aging-Related Mandelbugs** (ARB): bugs whose activation and/or error propagation are "complex", and they are able to cause an increasing failure rate and/or degraded performance.
- **Non-Aging-related Mandelbugs** (NAM): bugs whose activation and/or error propagation are "complex", and are not aging-related.

Aging-Related Bugs are considered a subtype of Mandelbugs. The activation and/or error propagation are considered "complex" if there is a time lag between the fault activation and the failure occurrence, or they are influenced by indirect factors such as the timing and sequencing of inputs, operations, and interactions with the environment [4]. A bug can be considered as an ARB if: *i)* it causes the accumulation of internal error states, or *ii)* its activation and/or error propagation at some instance of time is influenced by the total time the system has been running.

In the case of Linux and MySQL, data about ARBs were collected from publicly available bug repositories[4,5]. As for CARDAMOM, no bug repository was publicly available at the time of this study. Therefore, we based our analysis on ARBs found during a testing campaign reported in our previous study [8]. In order to identify Aging-Related Bugs among all bug reports in the repositories (for Linux and MySQL), we conducted a manual analysis. According to the definition of ARBs, the following steps have been carried out to classify these bugs:

1. extract the information about the activation and the error propagation from the bug report;
2. if there is not enough information about the activation and the error propagation to perform the classification (e.g., developers did not reproduce or diagnose the fault), the fault is discarded;
3. if at least one of them can be considered "complex" (in the sense given above) and it is aging-related, the fault is marked as **Aging-Related Bug**.

The inspection focused on bug reports that are related to unique bugs (i.e., they are neither duplicates of other reports nor requests for software enhancements) and that have been fixed (so that the bug description is reliable enough to be classified). To this aim, we inspected the reports marked as CLOSED (i.e., a fix was found and included in a software release). Moreover, the inspection focused on bug reports related to a specific subset of *compo-*

[4]Linux kernel bug repository: `http://bugzilla.kernel.org`

[5]MySQL DBMS bug repository: `http://bugs.mysql.com`

nents (also referred to as *subsystems*), since it would be unfeasible to inspect bug reports for all components of the considered systems. Components were selected among the most important components of system (i.e., those ones that are required to make the system work or that are used by most users of the system), as well as with the goal of covering different functionalities of the system and a significant share of the system code. We analyzed 4, 3, and 8 subsystems, respectively for Linux, MySQL, and CARDAMOM. The subsystems of Linux kernel selected for the analysis are: *Network Drivers* (2,043 KLoC), *SCSI Drivers* (849 KLoC), *EXT3 Filesystem* (22 KLoC), and *Networking/IPV4* (87 KLoC). Subsystems of MySQL are: *InnoDB Storage Engine* (332 KLoC), *Replication* (45 KLoC), and *Optimizer* (116 KloC). Table 2 provides the number of bug reports from Linux and MySQL (related to the subsystems previously mentioned) that we analyzed, and the time span of bug reports; in total, we analyzed 590 bug reports. As for CARDAMOM, we considered the 8 subsystems that were tested in our previous study [8]: *Configuration and Plugging* (3 KLoC), *Event* (10 KLoC), *Fault Tolerance* (59 KLoC), *Foundation* (40 KLoC), *Lifecycle* (6 KLoC), *Load Balancing* (12 KLoC), *Repository* (27 KLoC), and *System Management* (142 KLoC).

The analysis identified 36 ARBs in the bug repositories referring to Linux and MySQL. Additionally, 3 ARBs belong to the CARDAMOM case study. For each identified ARB, we collected its identification number, a short description summarizing the report content, the type of ARB, and the source files that have been fixed to remove the ARB.

Table 3 summarizes the details of the datasets that we obtained in terms of number of files, their total size, and percentage of ARB-prone files per

Table 2: Inspected Bug reports from the Linux and MySQL projects.

Project	Time Span	Subsystem	# Bug Reports
Linux	Dec 2003 - May 2011	Network Drivers	208
		SCSI Drivers	61
		EXT3 Filesystem	33
		Networking/IPv4	44
MySQL	Aug 2006 - Feb 2011	InnoDB Storage Engine	92
		Replication	91
		Optimizer	61

dataset. The MySQL dataset includes 261 additional files that do not belong to a specific component (e.g., header files). Table 4 reports the ARBs that we found in these projects, along with their type. Most of the ARBs were related to memory management (e.g., memory leaks). Bugs were marked as "*storage-related*" when the ARB consumes disk space (as in the case of the EXT3 filesystem). Another subset of faults was related to the management of system-dependent data structures (marked as "*other logical resource*" in the table), such as the exhaustion of packet buffers in network drivers' code. Finally, ARBs related to numerical errors were a minor part: this is likely due to the scarcity of floating point arithmetic in the considered projects, which is not used at all in the case of the Linux kernel [40]. Both "numerical" ARBs caused the overflow of an integer variable. Appendix A describes some examples of ARBs.

3.3. Software complexity metrics

As mentioned, the study intends to analyze the relationship between ARBs and software complexity metrics, for the purpose of fault prediction.

Table 3: Datasets used in this study.

Project	**Size (LoC)**	**# files**	**% ARB-prone files**
Linux	3,0M	3,400	0.59%
MySQL	765K	730	2.74%
CARDAMOM	298K	1,113	0.27%

Table 4: Aging-Related Bugs.

Project	**Subsystem**	**ARB type**	**# ARBs**
Linux	Network Drivers	Memory-related	7
		Numerical	1
		Other logical resource	1
	SCSI Drivers	Memory-related	4
	EXT3 Filesystem	Memory-related	3
		Storage-related	2
	Networking/IPv4	Memory-related	1
		Other logical resource	1
MySQL	InnoDB Storage Engine	Memory-related	2
		Other logical resource	3
		Numerical	1
	Replication	Memory-related	4
		Other logical resource	1
	Optimizer	Memory-related	5
CARDAMOM	Configuration and Plugging	-	-
	Event	-	-
	Fault Tolerance	-	-
	Foundation	Memory-related	2
	Lifecycle	-	-
	Load Balancing	Memory-related	1
	Repository	-	-
	System Management	-	-

The software metrics considered[6] are summarized in Table 5. We include

[6]These metrics are automatically extracted by using the *Understand* tool for static code analysis, v2.0: http://www.scitools.com

several metrics that in the past were revealed to be correlated with bug density in complex software. We aim to evaluate if these metrics are correlated also with the more specific class of *Aging-Related Bugs*. Since each target project encompasses several minor versions (e.g., minor versions 2.6.0, 2.6.1, etc., in the case of the Linux kernel), we computed the average value of each complexity metric across all minor versions, in a similar way to [41].

Table 5: Software complexity metrics.

Type	**Metrics**	**Description**
Program size	*AltAvgLineBlank*, *AltAvgLineCode*, *AltAvgLineComment*, *AltCountLineBlank*, *AltCountLineCode*, *AltCountLineComment*, *AvgLine*, *AvgLineBlank*, *AvgLineCode*, *AvgLineComment*, *CountDeclClass*, *CountDeclFunction*, *CountLine*, *CountLineBlank*, *CountLineCode*, *CountLineCodeDecl*, *CountLineCodeExe*, *CountLineComment*, *CountLineInactive*, *CountLinePreprocessor*, *CountSemicolon*, *CountStmt*, *CountStmtDecl*, *CountStmtEmpty*, *CountStmtExe*, *RatioCommentToCode*	Metrics related to the amount of lines of code, declarations, statements, and files
McCabe's cyclomatic complexity	*AvgCyclomatic*, *AvgCyclomaticModified*, *AvgCyclomaticStrict*, *AvgEssential*, *MaxCyclomatic*, *MaxCyclomaticModified*, *MaxCyclomaticStrict*, *SumCyclomatic*, *SumCyclomaticModified*, *SumCyclomaticStrict*, *SumEssential*	Metrics related to the control flow graph of functions and methods
Halstead metrics	*Program Volume*, *Program Length*, *Program Vocabulary*, *Program Difficulty*, *Effort*, *N1*, *N2*, *n1*, *n2*	Metrics based on operands and operators in the program
Aging-Related Metrics (ARMs)	*AllocOps*, *DeallocOps*, *DerefSet*, *DerefUse*, *UniqueDerefSet*, *UniqueDerefUse*	Metrics related to memory usage

The first subset of metrics is related to the "size" of the program in terms of lines of code (e.g., total number of lines, and number of lines containing comments or declarations) and files. These metrics provide a rough estimate of software complexity, and they have been used as simple predictors of fault-prone modules [33]. In addition, we also consider other well-known metrics, namely McCabe's cyclomatic complexity and Halstead metrics [42]. These metrics are based on the number of paths in the code and the number of operands and operators, respectively. We hypothesize that these metrics are connected to ARBs, since the complexity of error propagation (which is the distinguishing feature of ARBs [4]) may be due to the complex structure of a program.

Finally, we introduce a set of metrics related to memory usage (*Aging-Related Metrics*, ARMs), that we hypothesize to be related with aging since most of ARBs are related to memory management and handling of data structures (see also Table 4). The *AllocOps* and *DeallocOps* metrics represent the number of times a memory allocation or deallocation primitive is referenced in a file. Since the primitives adopted for memory allocation and deallocation vary across the considered software projects, these metrics were properly tuned for the system under analysis: the *malloc* and *new* user-library primitives are adopted for allocating memory in MySQL and CARDAMOM; instead, Linux is an operating system kernel and therefore it adopts kernel-space primitives, such as *kmalloc*, *kmem_cache_alloc*, and *alloc_page* [40]. The *DerefSet* and *DerefUse* metrics represent the number of times a pointer variable is dereferenced in an expression, respectively to read or write the pointed variable. The *UniqueDerefSet* and *UniqueDerefUse* have a similar meaning as *DerefSet* and *DerefUse*; however, each pointer variable is counted only one time per file. These metrics can potentially be expanded to consider system-specific features (e.g., files and network connections), although we only consider metrics related to memory usage due to the predominance of memory-related ARBs and to their portability across projects.

4. Classification models

Since modern software is typically composed by several thousand modules with complex relationships between them, as in the case of the software projects considered in this work (see also Table 3), the process of locating ARBs should be automated as much as possible. As mentioned in the previous sections, we assess whether it is possible to locate ARBs by using software complexity metrics. Since the relationship between software metrics and ARBs is not self-evident and depends on the specific problem under analysis, we adopt machine learning algorithms to infer this relationship, which are widely applied to knowledge discovery problems in industry and science where large and complex volumes of data are involved [43].

In particular, we formulate the problem of predicting the location of ARBs as a *binary classification problem*. Binary classification consists in learning a predictive model from known data samples in order to classify an unknown sample as “ARB-prone” or “ARB-free”. In this context, a data sample is represented by a program unit in which software faults may reside. In particular, *files* (also referred to as *modules* in the following) are the basic unit of our analysis: they are small enough to allow classifiers to provide precise information about where ARBs are located [33], and they are large enough to avoid sparse and excessively large datasets. We did not focus on predicting the exact number of ARBs per file, but only on the presence or absence of ARBs in a file, since the percentage of files with *strictly more than one ARB* is extremely small, amounting to 0.19% of data samples (this is a frequent situation in fault prediction studies [35]). In this section, we briefly describe the *classification algorithms* (also referred to as *classifiers*) adopted in this study. These algorithms, which are trained with examples, try to extract from samples the hidden relationship between software metrics and "ARB-prone" modules. *We consider several algorithms in this study, since they make different assumptions about the underlying data that can significantly affect the effectiveness of fault prediction.* We focus on classification algorithms that could be easily adopted by practitioners and that require to manually tune only few or no parameters. Classification algorithms are then evaluated and compared in Section 5.

4.1. Naive Bayes

A *Naive Bayes* (*NB*) classifier is based on the estimation of *a posteriori* probability of the hypothesis H to be assessed (e.g., "a module is ARB-prone"). In other words, it estimates the probability that H is true given that an evidence E has been observed. The *a posteriori* probability can be obtained by combining the probability to observe E under the hypothesis H, and the *a priori* probabilities of the hypothesis H (i.e., the probability $P(H)$ when no evidence is available) and of evidence E:

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)}. \tag{1}$$

The evidence E consists of any information that is collected and analyzed for classification purposes. Many sources of information are typically considered, which are referred to as *features* or *attributes* of the instances to classify. In the context of this work, software complexity metrics represent the evidences used to classify a software module. Let E_i be a fragment of evidence, i.e., a software complexity metric. A fundamental assumption of a Naive Bayes classifier is that each feature E_i is conditionally independent of any other feature E_j, $j \neq i$. Given this assumption, the *a posteriori* probability can be obtained as:

$$P(H|E) = \left[\prod_i P(E_i|H) \right] \frac{P(H)}{P(E)} \tag{2}$$

since the probability $P(E|H)$ can be obtained from the product of individual probabilities $P(E_i|H)$. This assumption is apparently oversimplifying, since features usually exhibit some degree of dependence among each other. Nevertheless, the Naive Bayes classifier performs well even when this assumption is violated by a wide margin [44], and it has been successfully adopted in many real-world applications [43].

4.2. Bayesian networks

A *Bayesian network* (*BayesNet*) is a directed acyclic graphical model representing a set of random variables (i.e., the graph nodes) and their conditional dependency (i.e., the graph edges). A conditional dependency exists between two nodes if the corresponding random variables are not conditionally independent. In a Bayesian network, each node is associated with a *conditional probability distribution* that depends only on its parents. It is thus assumed that:

$$P(\text{node}|\text{parents plus any other nondescendants}) = P(\text{node}|\text{parents}). \quad (3)$$

The joint probability distribution for a set of random variables $X_1, \ldots, X_n$ of the Bayesian network (which can be ordered to give all ancestors of a node X_i indices smaller than i) can be expressed as:

$$P(X_1, \ldots, X_n) = \prod_{i=1}^{n} P(X_i|X_{i-1}, \ldots, X_1) = \prod_{i=1}^{n} P(X_i|X_i\text{'s parents}). \quad (4)$$

Equation 4 can be used to compute the probability of a hypothesis H represented by a node of the network, given the conditional probability distributions of each node, and given a set of observed values. In this study, a Bayesian network is made up of nodes that represent software complexity metrics and the hypothesis "a module is ARB-prone". A Bayesian network represents a more accurate model than a naive Bayes classifier, since it makes weaker assumptions about independence of random variables: in a Bayesian network model, the structure of the network and the conditional probability distributions can be tuned to model complex dependency relationships between random variables. A Bayesian network is considerably more complex to build than a naive Bayes classifier, since both the network structure and conditional probability distributions have to be inferred from the data. In this work, we consider a simple and common algorithm for building Bayesian networks, namely *K2* [43]. This algorithm processes each node in turn and greedily considers adding edges from previously processed nodes to the current one. In each step it adds the edge that maximizes the probability of the data given the network. When there is no further improvement, attention turns to the next node. Because only edges from previously processed nodes are considered, this procedure cannot introduce cycles. Since the result depends on the order by which nodes are inspected, the algorithm should be executed several times with different node orderings in order to identify the best network structure.

4.3. Decision trees

A *decision tree* (*DecTree*) is a hierarchical set of questions that are used to classify an element. Questions are based on attributes of elements to classify, such as software complexity metrics (e.g., "is LoC greater than 340?"). A decision tree is obtained from a dataset using the C4.5 algorithm [43]. The C4.5 algorithm iteratively splits the dataset in two parts, by choosing the individual attribute and a threshold that best separates the training data into the classes; this operation is then repeated on the subsets, until the classification error (estimated on the training data) is no further reduced. The root and inner nodes represent questions about software complexity metrics, and leaves represent class labels. To classify a component, a metric of the component is first compared with the threshold specified in the root node, to choose one of the two children nodes; this operation is repeated for each selected node, until a leaf is reached.

4.4. Logistic regression

Regression models represent the relationship between a dependent variable and several independent variables by using a parameterized function. In the case of *logistic regression*, the relationship is given by the function

$$P(Y) = \frac{e^{c+a_1X_1+\ldots+a_nX_n}}{1+e^{c+a_1X_1+\ldots+a_nX_n}} \tag{5}$$

where the features $X_1, \ldots, X_n$ are independent variables, and c and $a_1, \ldots, a_n$ are parameters of the function. This function is often adopted for binary classification problems since it assumes values within the range $[0, 1]$, which can be interpreted as the probability to belong to a class. The function parameters have to be tuned in order to model the data properly. The model can be trained using one of several numerical algorithms: a simple method consists in iteratively solving a sequence of weighted least-squares regression problems until the likelihood of the model converges to a maximum.

5. Data analysis

The effectiveness of ARB prediction is assessed by training a classification model using empirical data (namely *training set*), and by using this model to classify other data that have not been used during the training phase (namely *test set*), in order to estimate the ability of the approach to correctly predict ARB-proneness of unforeseen data instances. These sets are obtained from the available dataset (described in Section 3) by dividing it between a training set and a test set. The division is performed in several ways to evaluate the approach in different scenarios, which are discussed in the following of this Section.

For each data sample in the test set, the predicted class is compared with the actual class of the sample. We denote the samples of the test set belonging to the *target class* (i.e., "a module is ARB-prone") as *true positives* if they are correctly classified, and as *false negatives* if they are not correctly identified. In a similar way, the samples belonging to the other class (i.e., "a module is ARB-free") are denoted as *true negatives* if they are correctly classified, and as *false positives* otherwise. We adopt performance indicators commonly adopted in machine learning studies [43], including works on fault prediction [33, 34, 35]:

- **Probability of Detection (PD)**. It denotes the probability that a ARB-prone module will actually be identified as ARB-prone. A high PD is desired in order to identify as many ARB-prone modules as possible. PD is defined as:

$$PD = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}} \cdot 100 \quad [\%]. \tag{6}$$

- **Probability of False alarms (PF)**. It denotes the probability that a non-ARB-prone module is erroneously identified as ARB-prone. A low PF is desired in order to avoid the cost of verifying a module that is not ARB-prone. PF is defined as:

$$PF = \frac{\text{false positives}}{\text{true negatives} + \text{false positives}} \cdot 100 \quad [\%]. \tag{7}$$

- **Balance (Bal)**. PD and PF are usually contrasting objectives (e.g., a classifier with high PD can also produce several false positives and therefore high PF), and a trade-off between them is needed for any practical purpose. Bal is based on the Euclidean distance from the ideal objective $PD = 100[\%]$ and $PF = 0[\%]$ [34], and it is defined as:

$$Bal = 100 - \frac{\sqrt{(0 - PF)^2 + (100 - PD)^2}}{\sqrt{2}} \quad . \tag{8}$$

It should be noted that there exist other performance indicators that can be obtained from true/false positives/negatives, such as the *precision* of a classifier, which is the percentage of true positives among all modules identified as ARB-prone, and its harmonic average with PD, namely the *F-measure*. We do not consider these measures since precision provides unreliable rankings for datasets where the target class occurs infrequently (as showed in [45]), like the ones considered in this study. In fact, precision is insensitive to variations of PD and of PF when the percentage of ARB-prone files is very low, which makes precision unsuitable for comparing different algorithms. However, in the following we also discuss problems related to precision, and this measure can be derived from the data provided in this section using [45, eq. 1]. Other performance indicators not included here, such as the *Receiver Operational Characteristic*, provide similar information to the PD and PF measures since they describe the performance of a classifier in the PD, PF space.

We first evaluate fault prediction when data about ARBs in the project under analysis is available, that is, ARB-proneness of a set of files is predicted by training a classification model using files (of which ARB-proneness is already known) from the same project, such as past versions of the files under analysis or different files that were already tested. In order to perform this evaluation, we split the dataset of a given project in two parts: a training set representing the files for which ARB-proneness is known, and a test set representing the files to be classified [34]. We assume that the training set is representative of data available to developers that collect historical data about ARBs of a software system with a long lifecycle, since the datasets have been obtained by analyzing real bug reports of large, long-life software systems over a large time period (see Table 2).

Since results can be affected by the selection of the data samples used for the training and test sets, the evaluation has to be repeated several times using different, randomly-selected training and test sets. This approach, which is referred to as *cross-validation* [43], repeats the evaluation N times for each classifier (*NB*, *BayesNet*, *DecTree*, *Logistic*) and for each dataset (*Linux*, *MySQL*, *CARDAMOM*), and computes the average results. In each repetition, 66% of the random samples are used for the training set and the remaining for the test set. In order to assure that the number of repetitions is sufficient to obtain reliable results, we computed the 95% confidence interval of the measures using *bootstrapping* [46]. Given a set of N repeated measures, they are randomly sampled M times *with replacement* (we adopt $M = 2000$), and the measure is computed for each sample in order to obtain an estimate of the statistical distribution of the measure and of its 95% confidence interval. The number of repetitions is considered sufficient if the error margin of the estimated measure (i.e., the half-width of the confidence interval) is less than 5%. We performed $N = 100$ repetitions, which resulted to be sufficient to satisfy this criterion.

Table 6 provides the average results for each dataset and for each classifier using cross-validation. Classification experiments were performed using the WEKA machine learning tool [43]. Each classifier was evaluated both on the *plain* datasets without preprocessing (e.g., "*NB*"), and on the datasets preprocessed with a *logarithmic transformation* (e.g., "*NB + log*"). The logarithmic transformation replaces each numeric value with its logarithm; if the value is zero or extremely small ($< 10^{-6}$), the value is replaced with $ln(10^{-6})$. This transformation can improve, in some cases, the performance of classifiers when attributes exhibit many small values and a few much larger values [34]. Aging-Related Metrics are not considered at this stage.

We performed a *hypothesis test* to identify the best classifier(s), in order to assure that differences between classifiers are *statistically significant*, i.e., the differences are unlikely due to random errors. In particular, we adopted the non-parametric *Wilcoxon signed-rank test* [47]. This procedure tests the *null hypothesis* that the differences Z_i between repeated measures from two classifiers have null median (e.g., when comparing the PD of the NB and *Logistic* classifiers, $Z_i = PD_{NB,i} - PD_{Logistic,i}$, $i = 1 \dots N$). The procedure computes a *test statistic* based on the magnitude and the sign of the differences Z_i. Under the null hypothesis, the distribution of the test statistic tends towards the normal distribution since the number of samples is large (in our case, $N = 100$). The null hypothesis is rejected (i.e., there is a statistically significant difference between classifiers) if the *p-value* (i.e., the probability that the test statistic is equal to or greater than the actual value of the test statistic, under the null hypothesis and the normal approximation) is equal to or lower than a significance level α. This test assumes that the differences Z_i are independent and that their distribution is symmetric; however, the samples are not required to be normally distributed, and the test is robust when the underlying distributions are non-normal. For each column of Table 6, we highlight in bold the best results according to the

Wilcoxon signed-rank test, with a significance level of $\alpha = 0.05$. For some datasets and performance indicators, more than one classifier may result to be the best one.

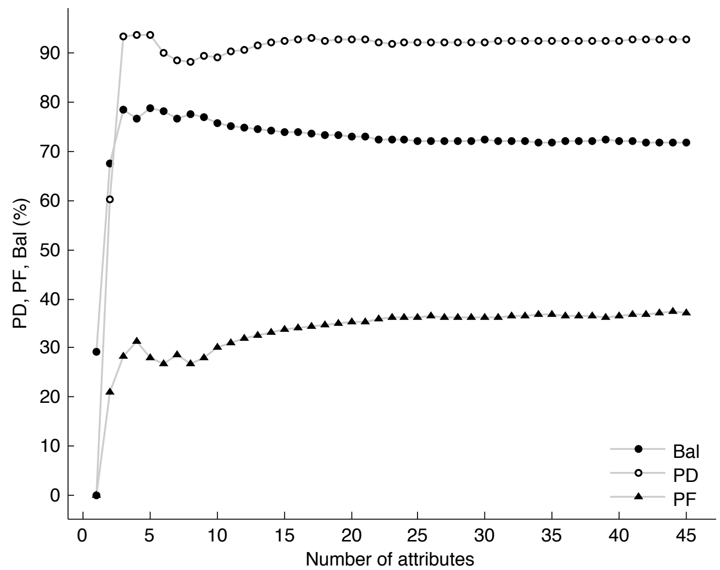
Table 6: Comparison between classifiers.

Algorithm	**Linux**			**MySQL**			**CARDAMOM**		
	PD	**PF**	**Bal**	**PD**	**PF**	**Bal**	**PD**	**PF**	**Bal**
NB	60.13	12.46	**69.24**	49.14	10.46	63.02	0.00	7.18	29.08
NB + log	**92.66**	**37.09**	**72.28**	**88.30**	**34.67**	**73.53**	**54.50**	**25.15**	**53.25**
BayesNet	3.72	1.85	31.91	44.57	8.65	60.26	0.00	0.00	29.30
BayesNet + log	5.34	1.95	33.06	44.50	8.65	60.21	0.00	0.00	29.30
DecTree	0.00	0.03	29.30	11.21	2.64	37.17	0.00	0.00	29.30
DecTree + log	0.00	0.00	29.30	11.28	2.65	37.22	0.00	0.00	29.30
Logistic	1.00	0.63	30.01	22.93	4.43	45.40	0.00	1.21	29.30
Logistic + log	3.84	0.62	32.01	25.07	5.13	46.88	0.00	0.65	29.30

Table 6 points out that the naive Bayes classifier with logarithmic transformation is the best classifier for the *Linux* and *MySQL* datasets with respect to PD (i.e., it correctly identifies the highest percentage of ARB-prone files). In all the cases except the naive Bayes classifier with and without logarithmic transformation, $PD < 50\%$ (i.e., most of ARB-prone files are missed). The high PD comes at the cost of a non-negligible amount of false positives (i.e., PF is higher that other classifiers). This fact is consistent with other studies on fault prediction [33, 34, 35]: in order to detect ARB-prone modules, classifiers have to generalize from samples and can make mistakes in doing so. This problem is exacerbated by the high skew towards ARB-free modules in our datasets (Table 3), since it is a challenging problem for a classifier to be so precise to identify few ARB-prone files without incurring non-ARB-prone files [35]. As a result, the precision of classifiers tends to be low, that is, there are several false positives among the modules flagged as ARB-prone (actually, less than 25% are ARB-prone). However, the prediction is useful even if precision is low. For instance, a classifier that generates false positives in 33% of cases (and thus has a low precision due to the small percentage of ARB-prone files), and that detects most of the ARB-prone files, is useful to improve the efficiency of the V&V process, since it avoids to test or to inspect the remaining 67% of non-ARB-prone files (true negatives). The high *Bal* values highlight that the "$NB + log$" classifier provides the best trade-off between PD and PF. The reason for the low performance of other classifiers is that they are negatively affected by the small percentage of ARB-prone files in the datasets [35].

The classifiers were less effective in the case of the *CARDAMOM* dataset compared to the *Linux* and *MySQL* datasets. The only classifier able to achieve $PD > 0\%$ is naive Bayes, although PD is lower than the cases of *Linux* and *MySQL*. The same result was also observed for the *Bal* indicator. This is likely due to the fact that the *CARDAMOM* dataset is even more skewed than the other datasets (Table 3).

Since classification performance can be affected by the selection of software complexity metrics included in the model (for instance, discarding a redundant metric could improve performance), we analyze what is the impact of attribute selection. In particular, we consider the *Information Gain Attribute Ranking* algorithm [48, 49], in which attributes are ranked by their *information gain*, which is given by:



Top 10 metrics
AvgLineComment
AltAvgLineComment
AvgLine
AvgCyclomaticModified
SumCyclomaticStrict
Dif
CountLineComment
SumEssential
AltCountLineComment
AvgCyclomatic

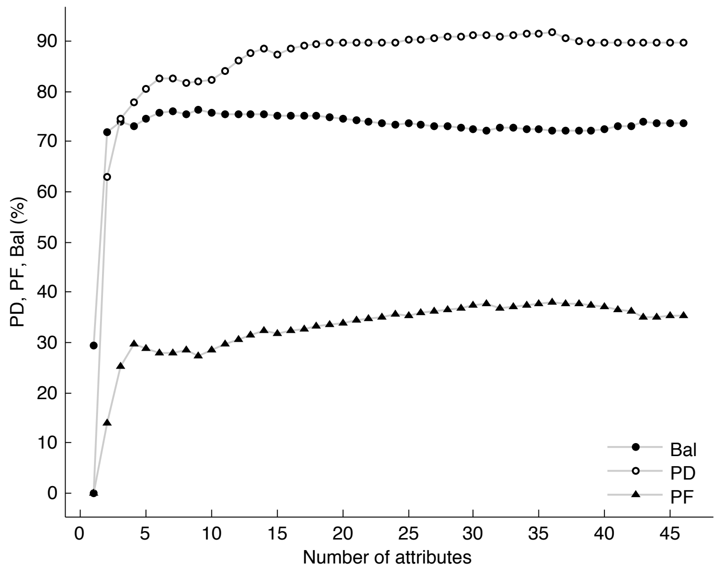
Figure 1: Impact of attribute selection on Linux.

$$\begin{aligned} InfoGain(A_i) &= H(C) - H(C|A_i) \\ &= -\sum_{c \in C} P(c) \cdot \log_2 P(c) - \left[-\sum_{a \in D(A_i)} P(a) \sum_{c \in C} P(c|a) \cdot \log_2 P(c|a) \right] \end{aligned} \quad (9)$$

where $H()$ denotes the entropy, $C = \{\text{ARB-prone}, \text{non-ARB-prone}\}$, $D(A_i)$ is the set of values[7] of attribute A_i, and the information gain measures the number of bits of information obtained by knowing the value of attribute A_i [49].

The sensitivity of performance indicators of "$NB + log$" with respect to the size of the attribute set (i.e., the top n attributes ranked by information

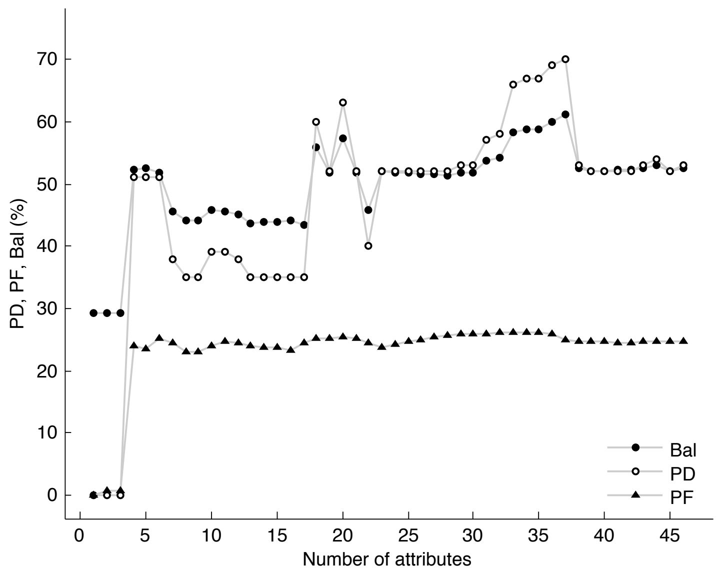
[7]Numeric data are discretized in 10 bins.



Top 10 metrics
CountLineBlank
CountLineCode
CountStmt
AltCountLineBlank
CountSemicolon
MaxCyclomaticModified
AltCountLineCode
CountStmtEmpty
MaxCyclomatic
CountLineComment

Figure 2: Impact of attribute selection on MySQL.

gain, for increasing values of n) is showed in Figure 1, Figure 2, and Figure 3 for the three projects. It can be seen that at least 5 metrics are required to achieve a high probability of detection for all datasets. The CARDAMOM project is the most sensitive to the number of attributes with respect to PD and PF, although the balance stabilizes when more than 5 metrics are considered. It can be observed that there is no individual metric that can be used alone for classification, but the best performance is obtained when considering several metrics and letting the classifier ascertain how to combine these metrics. Since the impact of attribute selection on classifier performance is small (i.e., considering 5 metrics gives similar results to the full set of metrics), we do not apply attribute selection in the subsequent analyses.



Top 10 metrics
CountDeclFunction
CountLine
AvgLineCode
CountDeclClass
AvgLineComment
CountLineCodeExe
CountLineInactive
CountLineComment
CountLineBlank
CountLineCodeDecl

Figure 3: Impact of attribute selection on CARDAMOM.

Table 7: Classification performance without and with Aging-Related Metrics (ARMs).

Algorithm	**Linux**			**MySQL**			**CARDAMOM**		
	PD	**PF**	**Bal**	**PD**	**PF**	**Bal**	**PD**	**PF**	**Bal**
NB	60.13	12.46	69.24	49.14	10.46	63.02	0.00	7.18	29.08
NB + log	**92.66**	**37.09**	72.28	**88.30**	**34.67**	73.53	54.50	**25.15**	53.25
NB + ARMs	58.13	11.88	68.34	48.42	10.06	62.61	0.00	6.57	29.12
NB + log + ARMs	**93.56**	35.90	**73.25**	**88.37**	32.99	**74.69**	**68.00**	10.22	**70.32**

Table 7 analyzes the performance of the naive Bayes classifier obtained by extending the set of attributes in Table 5 with Aging-Related Metrics. When using ARMs with logarithmic transformation, a statistically significant decrease of PF can be observed for both *Linux* and *MySQL*, without affecting PD which was already very high; this leads to a statistically significant increase of Bal. The greatest benefit is obtained for $CARDAMOM$: the naive Bayes with logarithmic transformation and ARMs provides $PD = 68\%$ and reduces PF at the same time, therefore achieving much better performance. In this specific case, the *AllocOps* metric is responsible for the improvement of prediction. This metric contributes to ARB prediction since ARBs in CARDAMOM are all related to misuses of the *new* C++ operator. However, it should be noted that ARMs for ARB-prone files in this project do not take on values far from the average values, and that the *AllocOps* metric alone is not sufficient to identify ARB-prone files but it has to be combined with non-aging-related metrics in order to achieve good performance. In conclusion, since ARMs improved ARB prediction in all three projects (reducing PF in every case and increasing PD in CARDAMOM), these metrics can be considered a useful support for predicting this category of bugs and should be adopted wherever possible.

Table 8: Cross-component classification in Linux.

Component	**Linux**		
	PD	**PF**	**Bal**
Network drivers	88.9	41.7	69.5
SCSI drivers	75.0	27.6	73.7
EXT3	100.0	29.2	79.4
IPv4	100.0	52.2	63.1

Finally, we analyze the effectiveness of the naive Bayes classifier when training data about ARBs in the component or project under analysis are not available. In such scenarios, training data from different components of the same project, or from different projects should be adopted. In these

Table 9: Cross-component classification in MySQL.

Component	MySQL		
	PD	**PF**	**Bal**
InnoDB	65.6	16.5	73.0
Replication	100.0	28.6	79.8
Optimizer	100.0	69.7	50.7

Table 10: Cross-component classification in CARDAMOM.

Component	CARDAMOM		
	PD	**PF**	**Bal**
Foundation	0.0	0.0	29.3
Load Balancing	100.0	9.0	93.7

cases, the test set is made up of data from the target component (respectively, target project), and the training set is made up of data from the remaining components of the same project (respectively, from the remaining projects). This evaluation process is repeated several times, each time with a different target component or target project. It should be noted that this evaluation process does not require to randomly split data between a training and a test set (this was the case of cross-validation), since the training and the test data are determined by component/project boundaries. First, we analyze the scenario in which a classifier has to be deployed for a specific component for which data is unavailable, and the classifier is built using data from the remaining components. The logarithmic transformation and ARMs are adopted.

Table 8, Table 9 and Table 10 show the results for each dataset. In the case of *CARDAMOM*, we only consider the *Foundation* and *Load Balancing* components because ARBs were found only in these components. It can be seen that in most cases performance indicators are comparable to the previous ones, i.e., $PD \geq 60\%$ and $PF \leq 40\%$ (see Table 7). Exceptions are *Linux/IPv4* and *MySQL/Optimizer* ($PF > 50\%$), and *CARDAMOM/Foundation* ($PD = 0\%$), which represents an extreme case of skewed dataset since there is only one ARB in that component. Although ARB data from the component under analysis should be the preferred choice, cross-component classification seems to be a viable approach when no such data is available.

Table 11: Cross-project classification.

Test / Train	Linux			MySQL			CARDAMOM		
	PD	**PF**	**Bal**	**PD**	**PF**	**Bal**	**PD**	**PF**	**Bal**
Linux	-	-	-	82.9	23.8	79.3	0.0	0.2	29.3
MySQL	100.0	50.7	64.2	-	-	-	33.3	11.8	52.1
CARDAMOM	0.0	0.1	29.3	0.0	0.6	29.3	-	-	-

We provide a similar analysis for cross-project classification, i.e., the test set is made up of data of a specific project, and the training set is made up of data from another project. Table 11 reports performance indicators for each possible project pair (e.g., the cell at the first row and second column provides the results when *Linux* is used as training set and *MySQL* is used as test set). It can be seen that good performance is obtained when *Linux* is used as training set and *MySQL* is used as test set. When *MySQL* is adopted as training set, all ARB-prone files are identified for the *Linux* test set ($PD = 100\%$), although the number of false positives is higher than the previous cases ($PF \approxeq 50\%$). The *CARDAMOM* dataset does not seem to be compatible with the remaining two, since low performance values are obtained when it is adopted as either training set or test set. The expected probability of detection for the *CARDAMOM* test set is low ($PD = 33.3\%$), and no ARBs in MySQL and Linux can be detected using *CARDAMOM* as training set. This fact confirms the results from other studies about cross-project classification [28, 36], in which fault prediction does not perform well when the training set and the test set come from projects with very different characteristics. *CARDAMOM* differs from the other two projects with respect to the programming language (it is a pure C++ project, while MySQL is a mixed C/C++ project and Linux is a pure C project), age (it is a younger project) and development process (it is an open-source project developed by industrial organizations, and it is close to commercial software). The state-of-the-art on fault prediction currently lacks an accurate, widely applicable and computationally efficient cross-project prediction approach, and researchers are still actively investigating this problem [50, 51]. Therefore, cross-project classification represents an open issue and it is not advisable if the involved projects exhibit significantly different characteristics. However, this issue does not affect the adoption of ARB prediction in other important scenarios, such as prediction based on historical data and cross-component prediction.

6. Conclusion

In this paper, we investigated an approach for predicting the location of Aging-Related Bugs using software complexity metrics. The approach adopts machine learning algorithms to learn a classification model from examples of ARBs; the classifier is then used on new files to mark them as either "ARB-prone" or "ARB-free". To this purpose, we adopted both well-known software complexity metrics and metrics specifically tailored for ARBs (Aging-Related Metrics, ARMs), and 4 different machine learning algorithms. The approach has been applied to predict ARBs in three real-world complex software systems (the Linux operating system, the MySQL DBMS, and the CARDAMOM middleware). The experimental analysis highlighted that the approach is effective at predicting ARB-prone files (in terms of percentage of detected ARBs and percentage of false alarms) when the naive Bayes classifier with logarithmic transformation is used. Moreover, ARMs were necessary to achieve good performance for one of the three systems (CARDAMOM). We also explored the effectiveness of ARB prediction when the approach is fed with training data from different components or projects than the one under analysis. We found that cross-component classification within the same project is feasible with few exceptions, but that cross-project classification does not achieve acceptable performance in most cases due to the different characteristics of the analyzed projects. A future research direction is represented by the integration of the proposed approach in the V&V of complex software projects, and the study of how defect resolution techniques (e.g., model checking, stress testing, code reviews) can benefit from it:

- **Model Checking**. This kind of techniques allows to formally prove that complex program properties hold in every state of the program [52, 53]. With respect to ARBs, a model checker can ensure the property that resources should be eventually deallocated on every execution path [10]. Unfortunately, model checking suffers the *state space explosion* problem and it is practical only for small amounts of code.

- **Stress Testing**. This kind of testing is a common approach to point out software aging issues in complex software [8, 9], by executing long-running intensive workloads and then pinpointing ARBs by using memory debugging tools [54, 55]. This approach requires that workloads are able to cover and activate ARBs, but devising effective workloads can be challenging in complex, large software.

- **Code Reviews**. Manual code reviews tailored for ARBs can be adopted, based on *checklists* or *perspective-based reading* [6, 7]. Since code reviews are labor-intensive, they should focus on most critical software modules [34].

Distributing judiciously efforts for V&V according to the predicted ARB density would significantly reduce the cost of applying such techniques in large software systems, since resources would be devoted to those parts of the code that are more likely affected by ARBs.

Appendix A. Bug Report Examples

The presented study is based on a process of manual classification carried out on bug reports, which are in turn textual descriptions reported by the application users (end-users, testers, developers, etc.). Thus, like other similar empirical studies the process may be subject to bias, since it relies on the accuracy and completeness of the bug reports and the related materials (e.g. patches, forums), and on the correctness of a manually performed classification. In order to clarify the analysis and classification process adopted to reduce such bias, this appendix provides some examples of bugs that we classified as Aging-Related Bugs. We recall that the steps carried out to identify ARBs are the following:

- the report is first examined looking for any information related to the activation conditions of the bug and/or on error propagation.

- once identified, information about the *complexity*, as intended by the definition, of the activation and/or propagation is looked for. Specifically, there is complexity in fault activation and/or error propagation if one of the two following conditions stands [4]:

  - there is a time lag between the fault activation and the failure occurrence;

  - they are influenced by indirect factors, namely by: *i)* the timing of inputs and operations; *ii)* the sequencing of operations (i.e., the input could be submitted in different order and there is an order of the inputs that would not lead to a failure); *iii)* interactions with the environment (hardware, operating system, other applications).

  if the bug is complex in this sense, it is considered a *Mandelbug*.

- Then, in order to be an ARB, one of these two conditions must be true: the fault causes the accumulation of internal error states, or its activation and/or error propagation at some instance of time is influenced by the total time the system has been running. Thus, the bug report is further examined for one of these two conditions (e.g., the length of a queue continuously increased before the failure, a buffer overflowed, a numerical error accrued over time, the size of a resource, such as table, cache, progressively increased before the failure, resources expected to be freed have not been freed, and so on). In such a case, the bug is classified as an ARB.

Table A.12: Examples of ARBs.

Bug ID	Subsystem	Description
5137	Linux/Network Drivers	FIFO queue overflow causes a hang when network errors accumulate
3171	Linux/EXT3	Disk space leaks
5144	Linux/EXT3	Memory (slabs) leaks
46656	MySQL/InnoDB	InnoDB plugin: memory leaks detected by Valgrind
40013	MySQL/Replication	A temporary table cannot be dropped and cleaned up at end of the session
45989	MySQL/Optimizer	Memory leak after EXPLAIN encounters an error in the query

Table A.12 lists some bugs considered as aging-related. Note that the brief description always suggests an accrued error state over time, which is typical of aging problems. It basically regards memory not freed or resources not cleaned up.

As a counter-example, let us consider the bug #42101 in MySQL InnoDB subsystem, in order to explain what may look like an ARB but was not classified as ARB. This bug concerns a race condition occurring on the global variable `innodb_commit_concurrency`; if this is set to 0 while a commit, `innobase_commit()`, is being executed, some threads may remain stuck.

From the description it is not clear what are the effects of the activation of this fault. Some threads may remain stuck, and this could lead to performance degradation inducing to classify the bug as an ARB. However, even if a performance degradation may be experienced due to some threads not executing their task, it is clear that in this case there is not a progressive *error accumulation* leading to a failure; the threads remaining stuck during a computation was a failure itself. Thus, to be conservative, this bug is not classified as ARB.

To help distinguishing various ARBs, in Section 3 we categorized different types of ARBs, such as memory-related, storage-related, or related to other logical resources in the system. Table A.13 reports some further examples of ARB distinguishing these subtypes.

The first two bugs are examples of memory-related ARBs, being directly related to memory leaks. The last three bugs in the Table are examples of *other logical resources* involved in the manifestation of the ARB. In particular, the first one leads to an increasing number of sockets made unavailable, the second one is about the query cache not being flushed, whereas the last one reports that open connections are not cleaned up, causing degraded performance and eventually the failure.

Finally, note also that in some cases, as mentioned in Section 3, there has not been enough information in the report to perform the classification, and thus it has not been possible to judge if the bug is an ARB or not (e.g., developers did not reproduce or diagnose the fault). In this case the fault is discarded. For instance, the bug #3134 in the Linux EXT3 subsystem reports that after a few day of activity, the journal is aborted and the filesystem is

Table A.13: Examples of ARBs of different types.

ID	**Subsys.**	**Description**	**Type**
11377	Linux Net Drivers	Buffer management errors triggered by low memory	Memory-related
48993	MySQL Replication	Memory leak caused by `temp_buf` not being freed	Memory-related
32832	Linux IPV4	Socket incorrectly shut down cannot be reused	other logical resources
40386	MySQL InnoDB	While truncating table query cache is not flushed. TRUNCATE TABLE on an InnoDB table keeps an invalid result set in the query cache	other logical resources
52814	MySQL InnoDB	InnoDB uses thd_ha_data(), instead of thd_{set|get}_ha_data(): UNISTALL PLUGIN does not allow the storage engine to cleanup open connections	other logical resources

made read-only, and that the system must be rebooted: it may appear to be an ARB, but the root cause of the failure was not identified since subsequent minor releases of the system do not exhibit the failure (it is likely that the bug disappeared after major modifications of the faulty code). Cases similar to this one have been conservatively classified as UNK.

For allowing the reproduction/extension of this study, in Table A.14 we report all the ID numbers of aging-related bugs in the inspected reports (note that some IDs are repeated, meaning that more ARBs are found in that bug description).

Table A.14: Bug IDs of ARBs.

Bug ID	Subsystem	Bug ID	Subsystem
5137	Linux-Network Device Driver	32832	Linux-IPV4
5284	Linux-Network Device Driver	34622	Linux-IPV4
5711	Linux-Network Device Driver	34335	MySQL-InnoDB
7718	Linux-Network Device Driver	40386	MySQL-InnoDB
9468	Linux-Network Device Driver	46656	MySQL-InnoDB
11100	Linux-Network Device Driver	49535	MySQL-InnoDB
11377	Linux-Network Device Driver	52814	MySQL-InnoDB
13293	Linux-Network Device Driver	56340	MySQL-InnoDB
20882	Linux-Network Device Driver	32709	MySQL-Replication
1209	Linux-SCSI Device Driver	33247	MySQL-Replication
3699	Linux-SCSI Device Driver	40013	MySQL-Replication
6043	Linux-SCSI Device Driver	48993	MySQL-Replication
6114	Linux-SCSI Device Driver	48993	MySQL-Replication
2425	Linux-EXT3 FS	38191	MySQL-Optimizer
3171	Linux-EXT3 FS	45989	MySQL-Optimizer
3431	Linux-EXT3 FS	56709	MySQL-Optimizer
5144	Linux-EXT3 FS	56709	MySQL-Optimizer
11937	Linux-EXT3 FS	56709	MySQL-Optimizer

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