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The Relationship of Code Churn and Architectural Violations in the Open Source Software JabRef

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ABSTRACT

The open source application JabRef has been developed since 2003. In 2015, the developers decided to make an architectural refactoring as continued development was deemed too demanding. The developers also introduced Static Architecture Conformance Checking (SACC) to prevent violations to the intended architecture. Measurements mined from source code repositories such as code churn and code ownership has been linked to several problems, for example fault proneness, security vulnerabilities, code smells, and degraded maintainability. The root cause of such problems can be architectural. To determine the impact of the refactoring of JabRef, we measure the code churn and code ownership before and after the refactoring and find that large files with violations had a significantly higher code churn than large files without violations before the refactoring. After the refactoring, the files that had violations show a more normal code churn. We find no such effect on code ownership. We conclude that files that contain violations detectable by SACC methods are connected to higher than normal code churn.

CCS CONCEPTS

• **Software and its engineering** → **Software architectures**; *Software verification and validation*;

KEYWORDS

Software Architecture, Conformance Checking, Repository Data Mining

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1 INTRODUCTION

JabRef¹ is a Java Open Source Software (OSS) desktop application for managing bibliographic references. The first version of JabRef

was released in 2003 and it has since then been under active development; the current version was released in early 2017. JabRef seems to have lacked an explicit software architecture for the majority of its development. In 2015, the developers deemed that further development was too hard so a new software architecture was introduced. During the following releases, more and more of the Java classes in the application were refactored into this new architecture. To facilitate the transition, automated unit tests that analyze the source code were introduced to ensure that the intended structure of packages in the architecture was not violated. These unit tests is one of many possible ways to perform *Static Architectural Conformance Checking* (SACC) [4, 16, 18, 23, 24, 29, 30, 34].

Detection methods for architectural violations is a well-established area of research, but we find that there is a lack of research results that focus on the analysis and tangible impact of architectural violations as well as the effect of refactoring such violations [1, 15]. Source code repository mining provides the opportunity to understand how software evolves, which developers are involved, and what changes are made to the source code of a system [14, 19, 39]. We can use mining to study the effects of refactoring architectural violations by studying changes to source code size (*code churn*) as well as the contributions of different developers (*code ownership*). When code churn and code ownership deviates from what can be observed during “normal evolution”, it might indicate that there are problems [10, 27].

JabRef provides an opportunity for us to study code churn and code ownership in the light of architectural violations in a project that use SACC. Our overall aim is to determine whether there is a difference in code churn and ownership between files that do and do not contain architectural violations as well as how architectural refactoring impacts files with violations. Is there a link between architectural violations and code churn or code ownership? We seek to answer the following research questions:

- RQ1.** Do files with architectural violations have a difference in code churn compared to files without architectural violations?
- RQ2.** Do files that were refactored to remove architectural violations have a difference in code churn compared to files without architectural violations?
- RQ3.** Do files with architectural violations have a difference in code ownership compared to files without architectural violations?
- RQ4.** Do files that were refactored to remove architectural violations have a difference in code churn compared to files without architectural violations?

¹<https://www.jabref.org>

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Figure 1: The intended architecture components and relations in JabRef.

We aim to contribute to fill the research gap by studying tangible effects of using SACC, as well as to understand if there is a link between code churn, code ownership, and architectural violations in the situations where a software architecture was introduced during the development and the source code was subsequently refactored to conform to this architecture.

2 BACKGROUND

During the evolution of a software system, problems that can inhibit a system’s architectural qualities, such as performance, security, reusability, and maintainability arise [20, 21, 35]. These problems are for example caused by a lack of explicit architecture, mistakes in the implementation, new architectural requirements, or new technologies [6, 17, 36]. They can, in themselves be minor, but the long-time accumulation can inhibit the qualities. We refer instances of these problems in the source code as *architectural violations*. One way to avoid these architectural violations in the source code is to use SACC tools. These tools identify where the source code breaks an intended architectural constraint and alert developers to the existence and location [22, 28]. They often rely on dependencies embedded in source code statements, and compare these with the desired and allowed dependencies in the software architecture. Methods such as Reflexion Models [4, 16, 23, 24], Dependency Rules [29, 30, 34], and Dependency Structure Matrices [18] have been used to find and visualize architectural violations.

JabRef introduced SACC to enforce the new architecture following a major refactoring in 2015. The new intended architecture consists of three layers: *Model*, *Logic*, and *GUI*. A fourth component outside the application itself is the *GUI API* (e.g., Java Swing and Abstract Window Toolkit (AWT)).

JabRef uses a simple approach to SACC that is based on unit tests that scan source code files and look at import statements. The architectural tests implement the following rules:

- (1) Model does not import from GUI, Logic, or the GUI API
- (2) Logic does not import from GUI, or the GUI API

Hall and Munson introduce the concept of code churn and code delta to understand the evolution of software metrics [13]. They define code churn as the amount of change of a metric (for example the amount of source code lines added, modified, or deleted) and code delta as the difference of a metric between two revisions of a system, respectively. Studying the evolution of these parameters over time gives insight into what parts of a system are growing or contracting (code delta), and the amount of change needed (code churn) to achieve the growth or contraction. Using Lines of Code (LoC) as the metric for code churn (as we will do for the remainder of this paper), a higher than normal code churn can be linked to faults, code smells, security, and maintenance problems [10, 27, 33].

Code churn is the tangible effect of changes to the source code files of a system as it evolves. Besides studying how the source code evolves, source code repository mining also provides an opportunity to study social aspects like code ownership where a low degree of ownership indicate problematic code [2, 8].

3 METHOD

We perform a retrospective longitudinal case study where we analyze the released versions of JabRef using SACC based on the rules of the intended layered architecture (cf. Fig. 1). We also mine the Git source code repository to ascertain the code churn (added and deleted LoC) and the contributors for each commit. Based on this data, we can determine the accumulated code churn and code ownership for each source code file for each version of the application. Using the results from the SACC, we group files depending on whether they contain architectural violations, are refactored, or are normal.

From our research questions, we formulate the following hypotheses together with their complementing null hypotheses. If there is a link between architectural violations and code churn we expect to be able to refute the null hypothesis of $H(RQ1)$ but not for $H(RQ2)$, i.e. files with violations differ from normal files and become more normal after refactoring. The same reasoning is applied for code ownership and $H(RQ3)$ and $H(RQ4)$, respectively.

$H(RQ1)$: There is a significant difference in code churn for files with violations compared to normal files within releases before introduction of architectural layers.

$H(RQ2)$: There is a significant difference in code churn for files that are refactored compared to normal files after introduction of architectural layers.

$H(RQ3)$: There is a significant difference in code ownership for files with violations compared to normal files before introduction of architectural layers.

$H(RQ4)$: There is a significant difference in code ownership for refactored files compared to normal files after introduction of architectural layers.

3.1 Detection of Architectural Violations

SACC works by mapping each source code entity (e.g., class in an object-oriented system) to a component of the intended architecture (in the JabRef case, one of the layers). The actual dependencies (as implemented) are then checked to see whether they conform to the intended dependencies of the architecture or not. The initial mapping is often done by experts, i.e., the developers or the architect

of the actual system [22, 28]. In our case, this is not feasible for two reasons; we are not system experts and there are too many releases to map. We instead implement an algorithm that can perform this mapping automatically for any version of JabRef. We can then check each version of JabRef for violations.

The algorithm is based on the intended architecture of JabRef as found in the documentation (cf. Fig. 1), in the architectural tests, and in the layers pattern [5]. Its first step is to use the mapping in release 3.7 of JabRef. We use this release to determine the classes in the Model, Logic, and GUI packages respectively. We can then find the same classes in other versions using a simple name comparison. However, while this mapping most likely performs fine for releases near 3.7, it is more unlikely to perform well for earlier versions. For these earlier versions, a large portion of classes would not be mapped and thus not checked. To avoid this problem, we rely on the rules defined in the tests and infer a mapping that minimizes the number of violations, starting with the bottom layer (Model) and then iterate. When no more classes can be mapped, we move on to the next layer. For example, if an unmapped class is used by a class mapped to the Model layer, the unmapped class would be mapped to the Model layer as it would otherwise create a violation (e.g., if mapped to Logic or GUI). After the mapping, we check the conformance of each class and if there is a violation, the class is marked. We finally map classes to the corresponding source code Java file, since we want violations on a file level.

We implemented this using our own tool based on the ASM Java byte code manipulation and analysis framework version 5.0². To ensure that our tool work as expected, we compared the results to the same analysis performed in Visual JArchitect³ 5.0.0. implemented using CQLinq queries. We could not find any discrepancies, so we conclude that our tool is correct.

3.2 Data Collection

To answer the research questions, we need to identify subset of releases before and after the architectural layers were introduced. The files in these subsets form our two main groups, *Pre* and *Post*. We want to compare files that either contains violations or are refactored files with normal files (cf. Fig. 2), so we divide the two main groups into two sub groups. Each file of each release is mapped to one of these two subgroups, i.e., flagged as either containing a violation or not. This means that each file as it transitions from one release to another can be in one of four states:

- (1) The file contains violation in both past and future releases,
- (2) The file contained violations in past, but not in future releases (i.e., the violation is removed),
- (3) The file contained no violation in past, but future releases have violations (i.e., a violation is added),
- (4) The file has no violations, neither in past nor future release.

If we consider H(RQ1) and H(RQ3), files with violations are files in States 1, 2, or 3, and normal files are in State 4. For H(RQ2) and H(RQ4) refactored files are in State 2, and normal files are in State 4.

A confounding factor is that some release might focus on some particular task, such as adding/removing/changing a particular set

Figure 2: Overview of the collected data. Shows main groups and sub groups, arrows indicate hypothesis testing.

of features. This might cause a specific subset of files to be changed to a larger extent, which might skew the results. We address this problem by identifying an as large span of releases as possible for each main group. Another confounding factor to consider is the size of each file (in LoC). Since there are more LoC in larger files, they might also be more likely to have changes, violations, or other problems. To address this issue, we randomly select 100 files of the largest (highest average LoC) 200 files in each of the two main groups.

To test H(RQ3) and H(RQ4), we collect the number of unique contributors and the code churn for each contributor and file in the same subsets as we used for H(RQ1) and H(RQ2) (cf. Fig. 2).

The JabRef repository⁴ is mined using the *git log* command and we measure the size in LoC using *cloc* v.1.7.2⁵.

3.3 Data Analysis

Statistical analysis is performed in R 3.3.2⁶. The goal is to test if the null-hypothesis can be rejected. To test H(RQ1) and H(RQ2), we use the accumulated absolute code churn. We use this rather than relative measures since it is easier to interpret the effect size for absolute measures. To test H(RQ3) and H(RQ4) we compute the biased Gini coefficient based on the accumulated code churn for each contributor to a source code file. The Gini coefficient is a measure of inequality ranging from 0.0 to 1.0, where 1.0 is the most unequal [12, 37]. For example, if there is a file that has seven unique developers that contribute to it, the Gini coefficient gives insight into the distribution of code churn between the contributors, i.e., did they all contribute equally much or not. So, the Gini coefficient allows us to determine if there is a clear code ownership of a file or not. The unbiased Gini coefficient will move towards 1.0 (in a perfect equal distribution) as the number of contributors increase, so we use a bias factor is based on the number of contributors to ensure that the value range of the Gini coefficient is between 0.0 and 1.0.

We assume that neither the churn data nor the Gini coefficient are normally distributed for this data set, so we use the non-parametric Wilcoxon Rank Sum test to perform the tests of our hypothesis. We use $p < 0.05$ to indicate significance. We will perform two tests per main groups and the p-value will not need adjustment.

4 RESULTS

We run our automatic SACC algorithm on all released versions of JabRef, and find that it performs as expected. Initially, the number of

²<http://asm.ow2.org>

³<http://www.jarchitect.com>

⁴<https://github.com/JabRef/jabref>

⁵<https://github.com/AlDanial/cloc>

⁶<https://www.r-project.org>

Table 1: Comparison of LoC in files per group.

	Pre Normal	Pre Violations	Post Normal	Post Refactored
#Files	67	33	80	20
Median	243	265	205	184
Average	335	346	222	225
Min	116	115	82	128
Max	1258	1142	495	476
SD	252	251	82	103

Table 2: Results of hypothesis testing, shows the resulting p-value, r-value, 95% confidence interval, and the median difference.

Hypothesis	p	r	conf. int.	med. diff.
H(RQ1)	0.016	0.241	79–1013	-844
H(RQ2)	0.069	0.180	-52–1472	-737
H(RQ3)	0.827	0.022	-0.057–0.07	-0.001
H(RQ4)	0.301	0.104	-0.079–0.023	0.027

files with violations steadily grows as the system itself grows. This trend is reversed starting with release 2.11, but it takes until some releases after version 3.0 for a majority of files to be refactored.

We select version 2.11 as the version where the architectural refactoring into a layered architecture was initiated. In this release, the number of actual violations start to decline and the Logic package is introduced. Version 3.0 was released only 18 days after 2.11. The subset of releases after the new architecture is introduced (Post) thus consists of the 12 releases from 2.11 to 3.8.2. We use the same number of releases to capture roughly the same amount of work in the releases prior to introduction of the new architecture. This makes release 2.9b2 the first release to be included in the Pre subset.

A Pearson Correlation test between code churn and LoC show a moderate but significant correlation. There is a tendency for large files to have a higher code churn ($p < 0.05$, $r = 0.58$, 95% confidence interval: 0.55 – 0.61).

We removed one file with violations from the data as this was considered an outlier (`Util.java`). The file had a churn of 33,189 while the second most churned file in the Pre group had a churn of 11,183. We then select the 100 files that form the sub groups. Table 1 provides an overview of the LoC in the groups and Figure 3 shows a box plot for the groups.

We use the Wilcoxon Rank Sum test to determine if we can reject the null hypothesis at $p < 0.05$ for our hypotheses. Figure 4 shows the code churn for each sub group. For H(RQ1), we can reject the null hypothesis and find a significant difference in code churn. For H(RQ2), we cannot reject the null hypothesis (cf. Table 2). Figure 5 shows the Gini coefficient for each group. As the box plot suggests, there is no difference within the groups. We cannot reject the null hypothesis for H(RQ3) or H(RQ4) (cf. Table 2).

Figure 3: Average Size (LoC) in the four groups. **Figure 4: Code Churn in the four groups. Normal files are compared to files with violations in the Pre group. Normal files are compared to refactored files in the Post group**

5 RELATED WORK

In [25], a Dependency Structure Matrix is used to form two metrics of modularity based on coupling. The metrics are used to analyze 19 versions, from early 1998 to early 2000, of Mozilla in a longitudinal

Figure 5: Code ownership in the four groups based on the Gini Coefficient. Normal files are compared to files with violations in the Pre group. Normal files are compared to refactored files in the Post group

study during an infamous redesign effort where the all of the old source code was scrapped [38]. In the study, the redesign had a positive impact on both metrics. The focus in [25] is, however, not on architectural violations but rather on managerial impact on system architecture. In [11] Mozilla’s architecture is again analyzed, this time version M9, released August 1999. The conclusion from this analysis is that the architecture has either deteriorated very rapidly or that architecture was not a focal point from the onset in the project. MacCormack et al. do not find this surprising, as the development was under extreme pressure during the “browser wars”. However, this study also does not focus on violations of the architecture per se, but rather at reverse engineering tools and increasing tool interoperability.

In [7], a large dataset of source code (100,000,000 LoC, 50 subsystems and 5,000 modules) and complete change management information for 15 years of releases is investigated to determine whether the developer’s notions of code decay is real. The study analyses a single subsystem (100 modules) and conclude that the code has indeed decayed in relation to changes made to it. There was however no evidence of dramatic or widespread decay. The study is focused on change management data (file updates, additions, deletions) but not on code churn or architectural violations.

An experiment by Knodel et al. [20, 21] indicate that an effect of architectural violations cause unneeded effort when evolving software systems. The setup is an experiment with two versions of the same professionally developed system; one with violations and one without. The same evolutionary task is replicated three times and is performed by randomized development teams consisting of

both professional developers and students. The experiment showed that it was harder both in terms of effort and correctness to evolve the eroded version of the system, though the evolutionary task selected of course is important [20].

In [3] refactorings are guided by architectural violations. An improvement in code metrics is reported and developers found it easier to evolve the system after refactoring. However, no quantitative data is used to show this.

In [32] the architecture of a large scale (25 MLoC) business application is refactored into a layered and more modular architecture. They report on a set of “home-grown gate keeper tools” that check conformance to layer and module rules. They report on a set of metrics and improvements of these during the two-year effort of refactoring parts of the system into the new architecture.

In [9], Faragó et al. find that code that has been heavily modified in the past tend to predict a decrease maintainability in future modifications. They compare the average of the cumulative code churn (the number of added and removed lines up to a certain point in time) for each file with the maintainability change (positive or negative) for each commit. The maintainability is computed as an aggregation of code metrics. They investigate four cases and find a significant relation. This research is especially interesting as it establishes a cause and effect relation, i.e., they use the historical code churn of the files and estimate the effect of a future commit on maintainability.

Churn- and architectural dependency-metrics are combined in [27] to improve prediction of post-release component failures in Windows Server 2003. The code churn measures collected for each component is the sum of the number of lines added, deleted or modified, as well as the number of files touched and the number of changes made (i.e., the number of commits). Using this information in combination with architectural dependencies they build a multiple linear regression model to predict failures post release.

Faragó et al. [8] has also investigated code ownership effect on maintainability in four systems. The measure of maintainability is an aggregation of source code metrics. The measure of code ownership is calculated for each commit and is based on the geometric mean of the accumulated number of different contributors for each file in the commit. This means that the ownership value is based on the files included in the commit. They find a statistically significant relation between a high degree of code ownership and a positive maintainability trend in three of the four cases. Their conclusion is that common code is more likely to accumulate maintenance problems than code with more clear authorship.

Code ownership has also been studied in the large OSS Apache server [26]. It is analyzed in order to find signs of code ownership on file and module-level. Mockus et al. investigate how many developers contribute to each file, with a cut off at 10% to remove very small contributions. They find that there is no code ownership at file or module level, and that the “core team contribute to various modules as needed”. They also put forth the hypothesis that: “For projects that are so large that 10-15 developers cannot write 80% of the code in a reasonable time frame, a strict code ownership policy will have to be adopted to separate the work of additional groups, creating, in effect, several related OSS projects.”

6 DISCUSSION

We found that the amount of change needed (code churn) to files in JabRef that contain architectural violations is often larger than the amount of change needed to files that do not contain architectural violations, if there is a lack of explicit architecture. The size of this effect is medium ($r = 0.241$, median difference = -844), i.e., there is an expectation that a file containing violations require more churn than a file that does not. After the architectural refactoring effort, files that are refactored show a more normal change pattern when compared to normal files for the same time period. In this latter case, it should be noted that the actual refactoring is also included and that there could be some time before the file is actually refactored. This could explain why there still seems to be a difference in churn post refactoring (median difference = -737). It would be interesting to remove the effect of refactoring itself from the analysis. This would, however, require another type of data analysis as different files are refactored at different points in time so a direct comparison of code churn would not be possible. In general, our findings indicate that a tangible effect of architectural violations in source code files is higher code churn compared to normal files. Refactoring to achieve architectural compliance seems to make the code churn of refactored files comparable to normal files. However, there is no implied causality in our analysis, violations might be added because the code is changed a lot or violations drive code churn (i.e., because of these dependencies we need to make changes).

We could not find any difference in code ownership in any of the groups. In general, this could be regarded as contrary to the effects found in Faragó et al. [8], i.e., we should be able to reject the null hypothesis of $H(RQ3)$. However, there are two major differences. First, we compare to architectural violations and not maintenance as measured by code metrics. Second, we measure ownership differently as we are interested in a general difference between groups while Faragó et al. [8] is interested in the accumulated ownership of files in each commit. However, in studying the OSS Apache server, no real code ownership evolved [26]. Our findings support their hypothesis, JabRef is not big or complex enough to need a strict code ownership policy. There could also be team effects, i.e., a few developers working closer together, something that is not visible in our analysis.

We focus on the direct effect of violations, i.e., added responsibility in the file that contain the violations. In some cases, it may be that the violation (e.g., an added attribute) is actually used in other files, i.e., the effect of the violation is not isolated to a single file. It could thus be interesting to combine coupling and code churn as done in [2] and [27].

Before the new architecture was introduced, there was no documented notion of structure that could consciously be violated. Our analysis is rather based on determining the impact of a new architecture on the existing source code. There could be other architectures that would have a larger impact. It should be possible to combine SACC and repository mining to better understand the importance of architectural compliance and the effects of an architectural refactoring. One approach could be to use repository data to determine the effects of a proposed architecture on the source code. This could determine whether the rules proposed by the architecture can actually be used to identify files that are known to

be problematic (for example by measuring code churn), and find trade-offs between major refactorings and possible effect. If no such effect can be found there is no data to support the refactoring effort. This would, in essence, be a way to use SACC to support data driven agile architecting.

7 THREATS TO VALIDITY

We only investigate one case in a retrospective study so our findings are hard to generalize. More cases and studies regarding architectural violations and code churn in similar but different contexts are needed to confirm or refute our findings. However, it is generally not easy to identify suitable subjects that use SACC. Also, in some cases found violations are not removed [3, 31]. In OSS, JabRef could be a unique example of using SACC to rigidly define the architecture, and as such it is worth studying.

There are possible errors in our measurements. Our algorithm to map Java classes to architectural components is conservative as it tries to minimize violations. However, the name-based mapping accounts for the majority of mapping, and this should be correct as per the developers' mapping. We count each LoC as equal, which can be a problem, since in practice, one line might be the result of much effort or one file may encapsulate some really complicated lines. Such differences are not visible in our analysis. This is a general problem in source code metrics and it is important to realize that metrics are an abstraction that do not show every detail in every situation.

Another potential problem in our analysis is subject independence, i.e., a file is not an independent subject and churn in one file may affect churn in other files. We address this by using a large set of commits and releases, and random sampling.

8 CONCLUSION AND FUTURE WORK

In JabRef we could use SACC to find a significant difference in code churn between files that have architectural violations compared to normal files before a new architecture is introduced (RQ1). Code churn for files that contain violations becomes more normal when these files are refactored to remove the violations (RQ2). We could not find any difference in code ownership for files with architectural violations compared to normal files, neither before nor after the new architecture was introduced (RQ3 and RQ4). We conclude that in our case, architectural violations and code churn are linked, but not code ownership. Non-normal code churn can be a tangible, measurable, effect of architectural violations in source code. However, more research is needed regarding this link; if violations are the cause, the size of the effect, the cost of refactoring, and whether it is generalizable to other systems, are examples of what needs to be further investigated.

We will continue our work in combining SACC and repository data mining by studying and evaluating simple and efficient methods for SACC in evolving systems. As a next step, we plan to investigate the more direct effect of refactoring files in JabRef, possibly extending this to include different type or amounts of violations and whether there is an effect on classes that depend on these violations. We also plan to work on visualizations of architectural evolution and SACC, and combine this for efficient semi-automatic code to architecture mapping techniques.

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