Commit–Defect and Architectural Metrics–based Quality Assessment of C Language

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Abstract: The foundation of any software system is its design and architecture. Maintaining and improving the architecture and design as systems grow are difficult tasks. Many studies on the architecture and design of object-oriented systems exist but only few studies pertain to the architecture and design of procedural systems. Herein we study the quality of systems for the C language, and investigate how dependencies and associated metrics among files, functions, and modules are related to defects. We also investigate whether a set of static, dependency, and social-network metrics are related to problems in the architecture. Additionally, we examine the bug fixing commits from the commit history and the relations among bug-fixing commits and metrics. Thirteen open source systems from trending GitHub projects are used for study. We found that files with a high number of bug fixing commits are correlated to higher cycles and centrality, indicating that key files of the architecture in C systems are the same files causing issues in the development process. We identify some version releases having huge impact on architecture and files which could be considered at high risk and need more attention.

1 INTRODUCTION

Software architecture, which is the backbone of any software system, is error prone. Although costly to maintain and evolve, it directly affects the quality of software systems (Capilla et al., 2016). Bug fixing is just 17% of the maintenance costs, while enhancement is 60% (Glass, 2001). These enhancements include corrective (bug fixing), preventative, perfective and adaptive maintenance comprising fixing and refactoring the architecture at several stages (McCormack, 2019).

Previous studies have investigated software architecture maintenance, improvement, and defect detection/prediction, including architecture recovery (Erdemir et al., 2011; Mancoridis et al., 1999), dependency assessments (Cai et al., 2019), and metrics (E.J. Newman and Girvan, 2004). Bug fixes during the software evolution are also related to the software architecture, since architecture is an abstraction of code.

The evolution of software quality and architecture can largely be encapsulated by version control systems with their whole history of commits and releases (Weicheng et al., 2013; Behnamghader et al., 2017; Tufano et al., 2017). We identified several architecture level metrics in literature, and used them to quantify the dependencies. We also used measures like number of fixing commits and age of file to investigate relation with evolution of architecture.

The majority of previous works on software architecture assessment and risk detection has focused on object-oriented programming languages like C#, C++, or Java. Many tools for architecture systems in these languages are available (Xiao et al., 2014; Lattix, 2019). In contrast, research on the software architecture for procedural languages like C are lacking, although procedural languages are common in industry, like operating systems, embedded systems and several applications. Despite the fact that architecture is idealised to be language independent, developers do develop a bias keeping implementation requirements

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in mind. Moreover, even assuming the architecture to be language independent, improving and refactoring the software require changes at implementation level, unlike to initial goal of architecture. Thus we need to investigate software in flipped manner, from implementation to architecture.

Herein we study C systems to assess their defect-metrics evolution and its relationship with the software architecture. We focus on dependency viewpoint of architecture, which is a controllable aspect, and commit data which is historical behaviour to provide developers with decisive information to alter implementation and conduct refactoring accordingly. We answer the following research questions (RQs):

- ***RQ1.*** What is the distribution of dependency metrics, social network analysis (SNA) metrics and commit history data over a set of C projects?

  This question assesses whether the metrics used in evaluations can identify distinctive quality features and discriminate between different architectures. Visualization techniques are used to verify whether metrics deviations are in sync with architectural abnormalities.
- ***RQ2.*** What are the relations among the metrics? Do these metrics impact the number of bug fixes/defects?

  Here, we determine the importance of each metric to evaluate the architecture. It helps identify whether these metrics are related to defects in the software product.
- ***RQ3.*** How do metrics and defects grow throughout the commit timeline of the software, and do they show relation with dependency and social-network based metrics?

  This question investigates the growth of metrics as the project grows using the commit histories of the system. It helps to determine whether metrics are able to show congruence with architectural developments.

The rest of this paper is divided as follows. Section 2 provides the background and related works. Section 3 reviews the experimental setup and data description. Section 4 presents the results and evaluation. Sections 5 and 6 discuss the threats to validity and conclusions, respectively.

2 RELATED WORK

The architecture has the most profound effect on the technical and financial aspects of software, but most of the architectural studies have investigated objected-oriented systems. Since those systems inherently induce OO design principles, adherence to quality standards is anticipated (Tiwari et al., 2019). Researchers and industries have developed various tools, which provide an architectural-level visualization and quality feedback. Few examples are eUML2[1] and JetBrains IDE[2] or Jetbrains CLion[3]. There is also SonarQube[4], which interestingly has C language support, but unfortunately is not part of an open source project. Moreover, the majority of related work are code-level analysis and lack architecture-level support. Various architecture-level metrics have been defined to quantify the quality. The Q value (E.J. Newman and Girvan, 2004) was introduced to quantify the randomness of the architecture, propagation cost (MacCormack et al., 2006) measures the extent that change can be propagated in a dependency graph, and Decoupling Level (Mo et al., 2016) can tell how easy it is to decouple an architecture. Several other community-based modularity metrics proposed by Newman (Newman, 2006) also help find patterns in the architecture.

The evolution of software systems reveals underlying assumptions, which are usually not documented. Tacit knowledge, or undocumented assumptions used by developers to make design decisions, are major issues when searching for the reasons behind a specified architecture design (Kruchten et al., 2006). Most developers have their own assumptions, which sometimes conflict (Tang, 2011). These types of architecture assumptions should be more prevalent in C due to its highly flexible nature, as developers can exhaustively decide on the structure, complexity, and intricate connections. Although a few recent studies have investigated the C language architecture (Tiwari et al., 2019; Biaggi et al., 2018), they discussed the static state of software with dependencies, but did not explore the defect and evolution aspect.

3 EXPERIMENTAL SETUP AND DATA

Figure 1 shows the flow of our study. It can be divided into four parts: (i) Architecture Representation (ii) Dependency and SNA Metrics (iii) Fixing Commits and Evolutionary Analysis (iv) Project Data

[1] http://soyatec.com/euml2/
[2] https://jetbrains.com/help/idea/module-dependencies-tool-window.html
[3] https://www.jetbrains.com/clion/
[4] https://www.sonarqube.org/

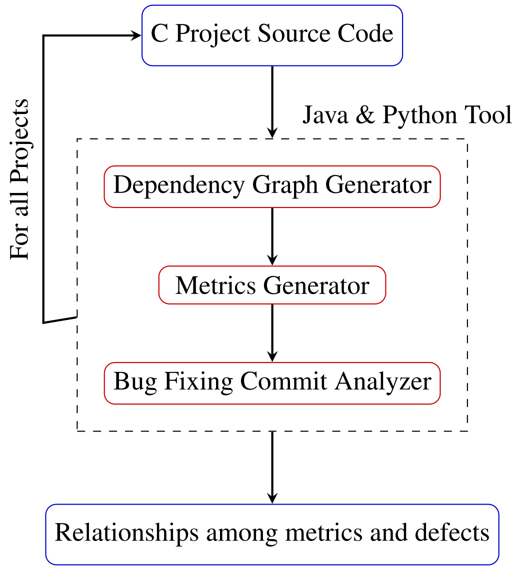


Figure 1: Flow Diagram.

3.1 Architecture Representation

Software architecture representation depends on the language and context. Dependencies in C language are represented as either include dependencies (including files in the header) or symbol dependencies (function calls). It has been shown that symbol dependencies capture the architecture better than include dependencies (Lutellier et al., 2015). We used symbol dependencies to generate dependency graphs. Modules in the case of C language are terminal directories. There may be several abstraction levels of the representation of dependencies, namely function, file, and module based. In our study, we pre-processed C files before generating the architectural representation. We focused mainly on file and module dependency graphs and their associated metrics. These graphs were generated using cflow[5] and ctags[6] which are incorporated in our tool.

3.2 Dependency and SNA Metrics

We used the generated dependency graphs to evaluate several dependency graph-based and social network-based metrics. Table 1 shows the metrics used and the corresponding description. These metrics were evaluated for each file contributing to the dependency graph. We used NetworkX (Hagberg et al., 2008) to assess the social network metrics and PyDriller (Spadini et al., 2018) to extract commit data.

[5]https://www.gnu.org/software/cflow/
[6]http://ctags.sourceforge.net/

Table 1: File Dependency Graph-based Metrics.

Metric Name	Explanation
In–degrees	Number of all incoming function calls from other files.
Out–Degrees	Number of all outgoing function calls to other files.
Fan-in/out visibility (MacCormack et al., 2006)	Fan-in visibility is how much other entities depend on a given file. Fan-out visibility is how much an entity depends on other files.
External Functions Called	Number of functions from other modules called by each file
Average Parameters	Average parameters of functions in a file
Degree Centrality	A Social Network metric indicating the importance of a node using its in-degrees
Load Centrality	This represents the fraction of all shortest paths that pass through a given node
Betweenness Centrality	This is the number of these shortest paths that pass through a vertex
Cycle Inclusions	Number of times the node is included in a cycle in its dependency graph

3.3 Defect–Metric Analysis

The evolution of defects of a project can be captured using the data from the version control. For each file, we looped through all the commits affecting that file from the project and calculated the total commits, bug fixing commits, and average time taken (in weeks) to fix defects. We also extracted the commit data for versions of the product to use in the analysis. We used the following tokens taken from GitHub[7] to tag a commit as bug fixing:

close, fix, resolve, fixed, fixes, closed, resolved, resolves

Table 2 contains the commit measures extracted for the entire commit timeline and the respective explanation. All four of the metrics were normalized using the age of the file (in weeks) to account for higher

[7]https://help.github.com/en/github/managing-your-work-on-github/closing-issues-using-keywords

Table 2: Extracted measures from Commits for Each File.

Metric Name	Explanation
All commits	Number of commits for each file/week
All modifications	Number of modifications for each file/week
Fixing Commits	Number of fixing commits for each file/week
Time taken to fix	Average time taken in weeks to fix the defects/bugs. PyDriller uses the SZZ algorithm to evaluate the time.

commits for older files.

The commit measures and architecture metrics can be divided into dependent and independent variables.

- **Independent:** In/Out degrees, Fan-in/out Visibility, External functions called, Average parameters, Centralities, Cycles, All commits
- **Dependent:** Fixing commits, Time taken to fix

Picking one dependent variable at a time, we conducted regression analysis to determine which factors have large effect on the number of fixing commits and time taken to fix.

3.4 Project Data

We used GitHub's curated popular/trending projects, to select the most popular C projects for our study (on 14 September 2019). These projects were popular due their high community engagement and size. We manually checked the projects to verify that they contained sufficient numbers of C files to generate commit history and dependencies. Table 3 lists summary of these projects. It shows the size of each project in Kilo Lines of Code (KLOC). Next column is lines of code written in C language, and last column is percentage of lines written in C language.

Table 3: Projects Summary.

Project Name	Commits	LOC (k)		
		Total	C	C%
libui	3945	41.9	18.3	43.7
libusb	1403	38.3	23.9	62.3
lvgl	2914	45.0	44.1	98.2
librdkafka	3210	89.1	72.9	81.8
Arduino	3377	134.8	78.0	57.9
mpv	47404	154.2	124.1	80.5
hashcat	6386	607.2	158.2	26.1
raylib	3338	178.9	158.9	88.8
numpy	21433	340.3	166.1	48.8
micropython	10669	254.2	200.0	78.7
nodemcu-firm.	2171	321.5	299.9	93.3
JohnTheRipper	2078	412.5	300.3	72.8
esp-idf	10062	569.0	478.0	84.0

4 RESULTS AND EVALUATION

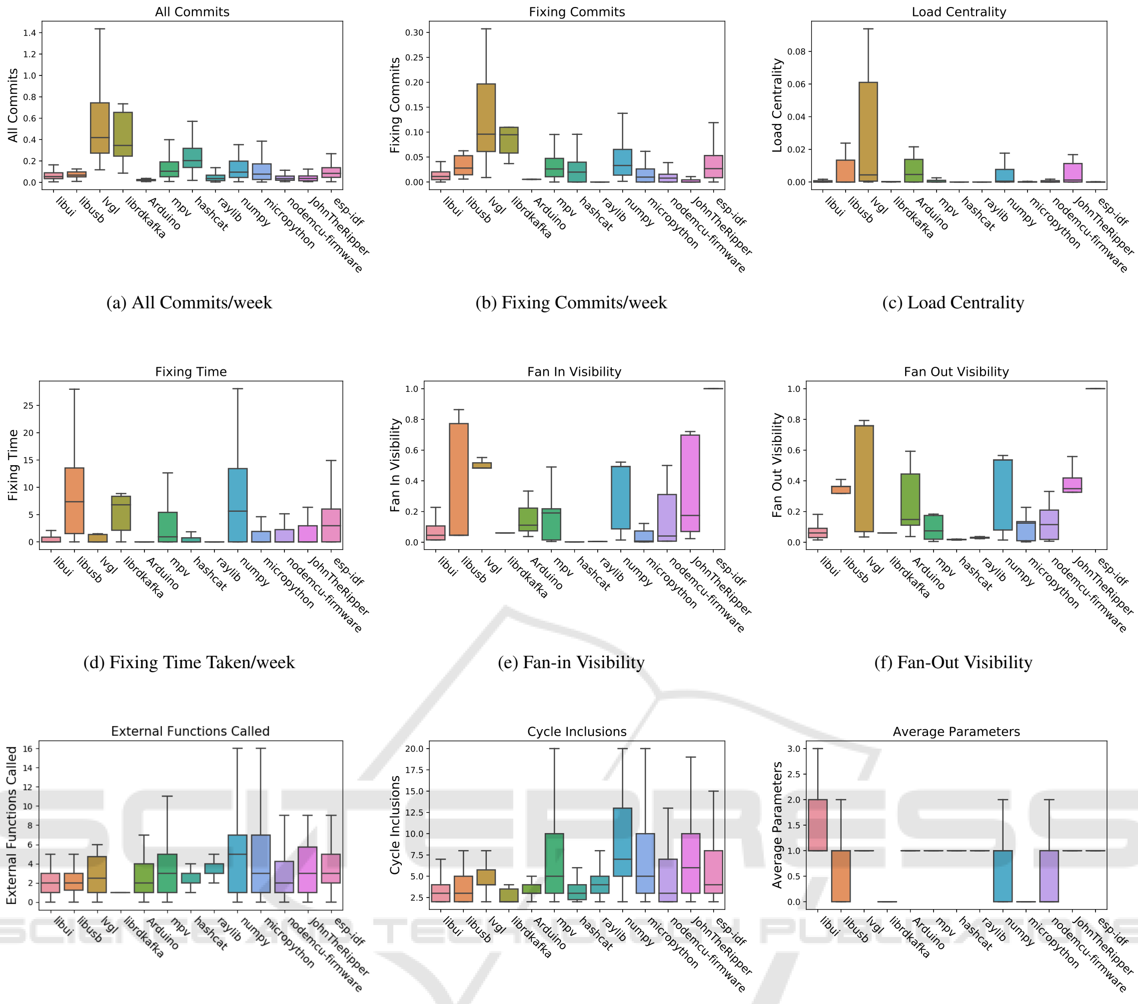
4.1 RQ1: Metrics Distribution

Figure 2 shows the distribution of 9 metrics over 13 projects. The projects are plotted in order of small size to large size (kLoc). The variability of the metrics over all the projects indicates the difference in their underlying assumptions. *lvgl* has the most commits per week (Figure 2a) and is relatively active compared to the other repositories. *Arduino* and *raylib* have very few fixing commits (Figure 2b), indicating these systems have stabilized and do not have frequent releases. Due to the same reason, the time taken (Figure 2d) by these projects to fix bugs is also very small. For fan-in and fan-out visibility (Figure 2e and Figure 2f), *esp-idf*, which is an IoT Development framework, has a really high value. This is because it has a very complex network and is difficult to comprehend. On the other hand, projects like *raylib* and *hashcat* have really low values. These projects have only a few files with high fan-in and fan-out visibilities, and the rest of the files communicate through them, suggesting a better design decision.

> We confirmed that each project has different distribution, but the metrics behave according to characteristics/complexity of each project, which provides higher comprehension of complexity in architecture. This also helps in identification of metric anomalies in files, which should be further investigated by developers.

4.2 RQ2: Metrics Relation

Table 4 shows the Pearson correlation and significance level among the metrics for the project *mpv*. Due to space constraints, the table is truncated to the major metrics and only one project. We selected project *mpv* as an example due to its large size and high numbers of commits. Load centrality is significantly correlated with fixing commits and all commits. External Functions Called is also highly correlated to the fixing commits, indicating files with high dependencies suffer from high defect proneness. In



(a) All Commits/week (b) Fixing Commits/week (c) Load Centrality

(d) Fixing Time Taken/week (e) Fan-in Visibility (f) Fan-Out Visibility

(g) External Functions Called (h) Cycle Inclusions (i) Average Parameters

Figure 2: Metric Distributions.

this case, the fixing time is not highly correlated with any other metric. However, it is somewhat correlated in other projects. For example, in *Arduino*, the fixing time is positively correlated with the number of parameters, indicating the higher the number of parameters in a file's methods, more time is required to fix the file. Files having high fan-in as well as high fan-out are at high risk, as it can be seen in Figure 2 that *esp-idf*, *lvgl* and *numpy* having high number of fixing commits. We also conducted a correlation analysis with project-level metrics like propagation cost, Q Value, and module dependencies and found that the number of fixing commits is highly correlated to the propagation cost.

Table 5 and Table 6 shows a truncated version of the result for regression analysis with target variable fixing commits and time taken to fix, respectively. We identify Fan-out visibility and Load centrality can significantly estimate the number of fixing commits. Moreover, Fan-out visibility and degree centrality have significantly high coefficient in estimating time taken to fix. Hence, files with high fan-out visibility show buggy behaviour than others. Interestingly, degree centrality has high effect on time taken to fix, but negative effect in case of number of fixing commits. It indicates that although the number of bugs encountered in such files are low, fixing them takes long time.

> We identified correlations among centrality, fixing commits, External Functions Called, indicating files with high dependencies suffer from high defect proneness. Fan-out visibility is also identified having high effect on number of fixing commits and corresponding fixing time.

Table 4: Correlation Table for Dependency Metrics and SNA Metrics for Project *mpv*.

	1	2	3	4	5	6	7	8
Out Degrees(1)								
Fan-in Visibility(2)	-0.09							
Fan-out Visibility(3)	0.68***	-0.17						
External Functions Called(4)	1.0***	-0.09	0.68***					
Load Centrality(5)	0.66***	0.09	0.44***	0.66***				
Cycle Inclusions(6)	0.61***	0.47***	0.31**	0.61***	0.57***			
Fixing Commits(7)	0.74***	-0.05	0.5***	0.74***	0.42***	0.46***		
All Commits (8)	0.78***	-0.04	0.5***	0.78***	0.46***	0.5***	0.98***	
Time Given(9)	0.25*	0.01	0.22*	0.25*	0.17	0.13	0.23*	0.21

$p < .0001$ "∗∗∗∗"; $p < .001$ "∗∗∗", $p < .01$ "∗∗", $p < .05$ "∗"

Table 5: Regression Analysis, Target var=Time taken to fix.

Metric Name	Estimate	p value
No. of functions	0.0508	< 0.001
In Degrees	-0.003	0.641
Fan-out Visibility	2.855	< 0.001
Ext. Functions Called	0.209	< 0.001
Average Parameters	0.115	0.268
Degree Centrality	8.371	< 0.001
Load Centrality	-13.708	0.355

Table 6: Regression Analysis, Target var=Fixing Commits.

Metric Name	Estimate	p value
No. of functions	< 0.001	< 0.001
In Degrees	< 0.001	< 0.001
Fan-out Visibility	0.015	< 0.001
Ext. Functions Called	0.004	< 0.001
Average Parameters	0.001	0.233
Degree Centrality	-0.030	0.133
Load Centrality	0.669	< 0.001

4.3 RQ3: Defect–Metrics Analysis

To understand the evolution of metrics, we chose the file named *video.c* from project *mpv* because it has the highest number of fixing commits. This file was fixed once about every 3.3 weeks, which is the highest in all files. This project has 73 released versions. Figure 3 shows how the values of metrics change through the 73 versions. Since *mpv* is a fairly large project, it has also been refactored many times. For easy visualization, the metric values are min-max normalized. The file *video.c* was created around version 12 and the large refactoring around version 24 made it highly dependent. It was later reduced but regained the complexity as the product grew. Fan-out visibility, i.e. dependence on other files was considerably reduced around version 55, but it went high again in few versions. On inspection of version log, we found few complex experimental features were added to the file

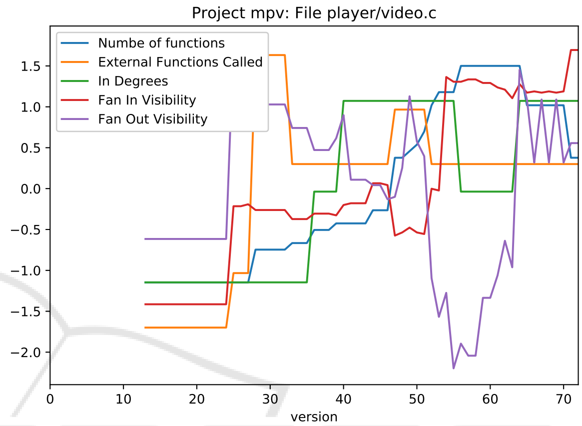


Figure 3: Normalized Metrics variation for Project *mpv*.

during this period, leading to high fan-out visibility. Such observation shows it could be possible to find major releases of the software using the commit data.

> We confirmed that metric inflections can help identify which version release introduced major changes or experimental phases, and whether the complexity in terms of metrics increased/decreased.

5 THREATS TO VALIDITY

Tufano (Tufano et al., 2017) showed that many architectural issues are present in a system since its inception and have a high serviceability. Therefore, analyzing the initial commits in the evolution history might provide some useful insights. We used the commit history from Github for our evolution analysis. However, there is a risk of not capturing the file history properly because what happens between two commits is unknown (Weicheng et al., 2013).

Visualizing every project and their distribution also poses problem of normalization. Even after normalization, few projects' range of metric values still could not indicate the clarity in distribution. In the experiment, we pre-processed the C files before generating dependency graphs, which is helpful in removing the macros, but in turns creates a risk of preprocessing failure. In that case, the whole file poses risk of not getting processed. Another threat is that if a project size is extremely big or very small, the metrics values might not represent the true degree of skewness.

6 CONCLUSION AND FUTURE WORK

We believe that our discussed metrics and evolutionary analysis for C language help identify and localize architecture anomalies in files, functions, version releases as well as provide refactoring support. We used file-based dependency graphs to generate social network and dependency metrics. These metrics are strongly correlated with fixing commits, indicating files with a higher fixing frequency could have unique patterns with the corresponding metrics. This relation helps identify such files beforehand, allowing preemptive actions to mitigate complex files and modules that lead to breakdown to be taken. These actions could include splitting huge files, separating header file interfaces, or investing more resources (developers and time) to specific files/modules. We also showed that the evolution of metrics as a product grows and sudden changes indicate refactoring, major bug fixes, or a defect induction.

Our study excluded module-based and function-based metrics. In the future, we plan to use such dependencies to gain insights on the modular and intricate analysis of the relationships among modules, files, architecture quality, and defects. The density of fixing commits could identify files/modules which face high dependency strain. This information will allow developers to know entities in project that need extra care. Moreover, we plan to add design rules and new metrics, like decoupling level (Mo et al., 2016) which will add additional descriptive ability for the structure of project. The evolutionary phase could use evolution models to quantify change (Aoyama, 2002), determining when and how the files and versions heavily changed, and their consequences in architecture. Understanding the commit messages and investigating phrase patterns in bug fixing and inducing commits could also lead to insightful results.

The studied projects had high numbers of commits, which totaled tens of thousands in some projects. Thus we also plan to analyze the commit messages for phrase pattern in bug fixing/inducing commits. In future, we plan to parallelize our approach and study the evolution of metrics for all commits, instead of versions. We will also include more projects with varying size and different domains, as this will help understand the relationship between metrics, defects and domains.

REFERENCES

Aoyama, M. (2002). Metrics and analysis of software architecture evolution with discontinuity. In *Proceedings of the International Workshop on Principles of Software Evolution*, IWPSE '02, pages 103–107, New York, NY, USA. ACM.

Behnamghader, P., Alfayez, R., Srisopha, K., and Boehm, B. (2017). Towards better understanding of software quality evolution through commit-impact analysis. In *2017 IEEE International Conference on Software Quality, Reliability and Security (QRS)*, pages 251–262.

Biaggi, A., Fontana, F. A., and Roveda, R. (2018). An architectural smells detection tool for c and c++ projects. In *2018 44th Euromicro Conference on Software Engineering and Advanced Applications (SEAA)*, pages 417–420.

Cai, Y., Xiao, L., Kazman, R., Mo, R., and Feng, Q. (2019). Design rule spaces: A new model for representing and analyzing software architecture. *IEEE Transactions on Software Engineering*, 45(7):657–682.

Capilla, R., Jansen, A., Tang, A., Avgeriou, P., and Babar, M. A. (2016). 10 years of software architecture knowledge management: Practice and future. *Journal of Systems and Software*, 116:191 – 205.

E.J. Newman, M. and Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical review. E, Statistical, nonlinear, and soft matter physics*, 69:026113.

Erdemir, U., Tekin, U., and Buzluca, F. (2011). Object oriented software clustering based on community structure. In *2011 18th Asia-Pacific Software Engineering Conference*, pages 315–321.

Glass, R. L. (2001). Frequently forgotten fundamental facts about software engineering. *IEEE Software*, 18(3):112–111.

Hagberg, A. A., Schult, D. A., and Swart, P. J. (2008). Exploring network structure, dynamics, and function using networkx. In Varoquaux, G., Vaught, T., and Millman, J., editors, *Proceedings of the 7th Python in Science Conference*, pages 11 – 15, Pasadena, CA USA.

Kruchten, P., Lago, P., and van Vliet, H. (2006). Building up and reasoning about architectural knowledge. In Hofmeister, C., Crnkovic, I., and Reussner, R., editors, *Quality of Software Architectures*, pages 43–58, Berlin, Heidelberg. Springer Berlin Heidelberg.

Lattix (2019). Lattix.

Lutellier, T., Chollak, D., Garcia, J., Tan, L., Rayside, D., Medvidovic, N., and Kroeger, R. (2015). Comparing software architecture recovery techniques using accurate dependencies. In *2015 IEEE/ACM 37th IEEE International Conference on Software Engineering*, volume 2, pages 69–78.

MacCormack, A., Rusnak, J., and Baldwin, C. Y. (2006). Exploring the structure of complex software designs: An empirical study of open source and proprietary code. *Manage. Sci.*, 52(7):1015–1030.

Mancoridis, S., Mitchell, B. S., Chen, Y., and Gansner, E. R. (1999). Bunch: A clustering tool for the recovery and maintenance of software system structures. In *Proceedings of the IEEE International Conference on Software Maintenance*, ICSM '99, pages 50–, Washington, DC, USA. IEEE Computer Society.

McCormack, J. (2019). Fowler technical debt quadrant. http://users.monash.edu/~jonmc/CSE2305/Topics/13.25.SWEng4/html/text.html. Accessed: 3rd December 2019.

Mo, R., Cai, Y., Kazman, R., Xiao, L., and Feng, Q. (2016). Decoupling level: A new metric for architectural maintenance complexity. In *2016 IEEE/ACM 38th International Conference on Software Engineering (ICSE)*, pages 499–510.

Newman, M. E. J. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences*, 103(23):8577–8582.

Spadini, D., Aniche, M., and Bacchelli, A. (2018). Pydriller: Python framework for mining software repositories. In *Proceedings of the 2018 26th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, ESEC/FSE 2018, pages 908–911, New York, NY, USA. ACM.

Tang, A. (2011). Software designers, are you biased? In *Proceedings of the 6th International Workshop on SHAring and Reusing Architectural Knowledge*, SHARK '11, pages 1–8, New York, NY, USA. ACM.

Tiwari, D., Washizaki, H., Fukazawa, Y., Fukuoka, T., Tamaki, J., Hosotani, N., and Kohama, M. (2019). Metrics driven architectural analysis using dependency graphs for c language projects. In *2019 IEEE 43rd Annual Computer Software and Applications Conference (COMPSAC)*, volume 1, pages 117–122.

Tufano, M., Palomba, F., Bavota, G., Oliveto, R., Penta, M. D., De Lucia, A., and Poshyvanyk, D. (2017). When and why your code starts to smell bad (and whether the smells go away). *IEEE Transactions on Software Engineering*, 43(11):1063–1088.

Weicheng, Y., Beijun, S., and Ben, X. (2013). Mining github: Why commit stops – exploring the relationship between developer's commit pattern and file version evolution. In *2013 20th Asia-Pacific Software Engineering Conference (APSEC)*, volume 2, pages 165–169.

Xiao, L., Cai, Y., and Kazman, R. (2014). Titan: A toolset that connects software architecture with quality analysis. In *Proceedings of the 22Nd ACM SIGSOFT International Symposium on Foundations of Software Engineering*, FSE 2014, pages 763–766, New York, NY, USA. ACM.