The Birth, Growth, Death and Rejuvenation of Software Maintenance Communities

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ABSTRACT

Background: Though much research has been conducted to investigate software maintenance activities, there has been little work characterizing maintenance files as a community and exploring the evolution of this community. **Aims:** The goal of our research is to identify maintenance communities and monitor their evolution—birth, growth, death and rejuvenation. **Method:** In this paper, we leveraged a social community detection algorithm—clique prelocation method (*CPM*)—to identify file communities. Then we implemented an algorithm to detect new communities, active communities, inactive communities and reactivated communities by cumulatively detecting and constantly comparing communities in time sequences. **Results:** Based on our analysis of 14 open-source projects, we found that new communities are mostly caused by *bug* and *improvement* issues. An active community can be vigorous, on and off, through the entire life of a system, and so does an inactive community. In addition, an inactive community can be reactivated again, mostly through *bug* issues. **Conclusions:** These findings add to our understanding of software maintenance communities and help us identify the most *expensive* maintenance spots by identifying constantly active communities.

CCS CONCEPTS

• **Software and its engineering** → *Software evolution*;

KEYWORDS

Software Evolution, Maintenance Communities

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1 INTRODUCTION

Much research [15, 17, 21, 24] has been conducted to investigate software maintenance activities within groups of files. Xiao et al. [24]

proposed a model called DRSpace, which is a set of architectural-connected files. They claimed that a few DRSpaces can capture most buggy files in a project, and can furthermore reveal the structural relations among these buggy files. Silva et al. [21] studied co-changed files in software maintenance and classified them into 3 patterns: Encapsulated, Crosscutting, and Octopus. Based on these patterns, they further investigated developers' perceptions of co-change clusters and detected design anomalies reflected by these co-change patterns. Negara [17] proposed a new algorithm to mine previously unknown patterns from fine-grained sequences of code changes; they summarized and evaluated 10 popular types of transformations. Jiang et al [15] presented an approach to group and aggregate relevant code changes into six types of trajectory patterns and detected underlying rules with these patterns. While patterns in a group of either structurally-related or co-changing files have been extracted, there is little study characterizing co-changing files as a *community* and exploring the evolution of this community.

In this paper, we leverage a social community detection algorithm—called clique prelocation method (*CPM*) [8, 19]—to identify file communities in maintenance. The file communities detected by *CPM* have two characteristics: (1) files in the same community co-change with each other very frequently; (2) files in the same community are more likely to be located in the same packages. In other words, files in the same community are more likely to share some key characteristics and to be changed together. These file communities, we claim, should be analyzed as a group, to understand a system's evolution.

We have implemented an algorithm to detect new communities, active growing communities, active closed communities, inactive communities, and reactivated communities. We do this by detecting and constantly comparing communities in a time sequence. We treat each issue as a unit and each issue's resolution time as a time stamp. For example, in our study, the Avro project has 689 issues from i_1 to i_{689} so we have 689 time stamps from t_1 to t_{689} . We run the *CPM* algorithm to cumulatively detect communities at each time stamp. For example, at t_1 , we detect communities using i_1 's files; at t_2 , we detect communities using i_1 's files and i_2 's files, etc. A new community is deemed to be born at t_{x+1} when this community exists at t_{x+1} but does not exist at t_x . An *active open community* at t_{x+1} is a community whose size is growing from time t_x to time t_{x+1} . An *active closed community* at time t_{x+1} is a community in which files are modified in issue i_{x+1} but no new files are subsequently added to this community. Since its last activity, if files in a community have no activities and this community is not growing for a period of time (Δt), at a settable threshold, we call this an *inactive community*. If an inactive community becomes alive again (either new files are added or existing files are modified), we call this a *reactivated community*.

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Based on our analysis of 14 open-source projects, we found that the majority (74.5% to 92.5%) of maintenance files can be clustered into communities. So community evolution can reflect most of a system's evolution. New communities are typically formed by *bug* and *improvement* issues. An existing community can grow, on and off, through the entire life of a system. An inactive community, usually containing a small set of files, can start as early as the project's beginning and last till the final time stamp in our analysis. And an inactive community can be activated again, typically through *bug* issues.

The contributions of this paper are as follows:

- (1) Our work is the first empirical study of software file maintenance communities and their evolution by using a social community detection algorithm (*CPM*).
- (2) We implemented an algorithm to monitor the life cycle of maintenance communities: their birth, growth, death and rejuvenation. This algorithm is general and can be applied to detect the life cycle of any sets of files, and not just file community detection.
- (3) Our algorithm can detect the most *expensive* growing maintenance communities, where file interactions can be visualized. Developers can look into these problematic communities and try to find a refactoring solution.

The rest of the paper is organized as follows. Section 2 lists work related to our research. Section 3 presents how communities are extracted and communities' characteristics. Section 4 defines the stage of a community's life cycle. Section 5 states the 5 research questions and section 6 demonstrate the experiments and the answers to these research questions. Section 7 discusses the results and our future work. Finally this paper concludes by section 8.

2 RELATED WORK

2.1 Software Communities

Software communities have been extensively studied [1, 2, 4, 9, 10, 12, 13, 22]. Barcellini et al. [1, 2] studied how members of OSS communities, and especially users, participate in the design process and to identify whether or not some participants are the key to connect the user and the developer communities. Ducheneaut [9] explored the communications in the email and code databases of OSS and characterized successful participants. Fang and Neufeld [10] conducted qualitative analyses and concluded that sustained participations are not caused by the initial condition to participate, but due to situated learning and identity construction behaviors. Bird et al. [4] extracted and studied latent sub-communities from the email social network. Their results show that subcommunities do indeed spontaneously arise as the projects evolve. Heller et al. [13] analyzed user profiles and repository metadata from the GitHub source code hosting service and summarized 3 patterns based on developer relationships, social connectivity and influence among cities, and variation in project specific contribution styles (e.g., centralized vs. distributed). Hahn et al. [12] explored how developers choose to contribute to newly initiated OSS projects. Their results claimed that a project is more likely to attract a developer if the project's initiator has strong collaborative ties with the developer. Tamburri et al. [22] described a set of community smells that can plague an architecture, as well as a set of mitigations for each.

All of the above studies have provided valuable insights on developers or users' communities, however, none of these studies have considered software source files as members in a community. Files co-change with each other in the project's revision history, just as developers communicate with each other via email. In this paper, we treat each file as an element of a maintenance community to learn how files interact with each other in a community and how maintenance communities communicated with each other.

2.2 Software Evolution

Software evolution, especially software evolution modeling, has attracted substantial attention. Chapin et al. [6] proposed a method to classify evolution types based on a semi-hierarchical manner of the change in 4 different aspects from documentation to functionality. Godfrey et al. [11] compared software evolution with biological evolution, and examined how software evolves in response to environmental pressure and emergent design. Tu et al. [23] claimed the evolution of the Linux kernel at the system level and within the major subsystems is fast, and discussed why they think Linux continues to exhibit such strong growth. Robles et al. [20] studied the evolution of a Linux distribution, Debian, with respect to its overall size, use of programming languages, maintenance of packages, and file sizes over seven years.

Architectural evolution has also been explored [5, 25, 26]. Chaikalas et al. [5] incorporated structural information and domain information, such as the creation of relations among existing and new classes and the removal of edges, into a network-based prediction model. 10 open-source projects were used to evaluate this model and they showed that their derived models can provide insight into the future trends and can potentially form the basis for eliciting improved or novel laws of software evolution. Zimmermann [26] examines architectural refactoring as an evolution technique that revisits architectural decisions and identifies related design, implementation, and documentation tasks. Xiao et al. [25] also studied software evolution in terms of architectural debt. They proposed 4 types of architectural issues and showed how these issues evolve into architectural debt over time.

The above studies on software evolution focus on the evolution of software architecture, knowledge bases, and so forth. Our study is complementary to these studies, by investigating software evolution through maintenance file communities.

2.3 Co-change Patterns in Maintenance

Much prior research [15, 17, 18, 21] has studied co-change patterns in maintenance. Silva et al. [21] studied co-changing files software maintenance and classified them into 3 patterns: Encapsulated, Crosscutting, and Octopus. Based on these patterns, they further investigated developers' perception of co-change clusters and detected design anomalies reflected by these co-change patterns. Negara et al. [17] proposed an algorithm to mine previously unknown patterns from fine-grained sequences of code changes; they then summarized and evaluated 10 popular types of transformations. Jiang et al. [15] presented an approach to group and aggregate relevant code changes as six types of trajectory patterns and detected underlying rules with these patterns. Nguyen et al. [18] studied

Table 1: Subjects

Subject	Start Time	# Files	# Commits	# Issues
Avro	2009-04	1458	1560	689
Camel	2007-03	24466	28899	6396
Cassandra	2009-03	3027	23026	5018
Cxf	2008-04	10905	13135	3321
Derby	2004-08	4430	8088	2069
Hadoop	2009-05	10027	16103	2457
Hbase	2007-04	4436	13564	6516
Mahout	2008-01	2328	3799	694
Openjpa	2006-05	5211	4820	1188
Pdfbox	2008-02	1672	6239	1771
Pig	2009-03	2452	3076	1639
Tika	2007-03	2062	3794	1033
Wicket	2004-09	5619	19846	3146
Zookeeper	2008-05	1192	1557	786

repetitive changes within and across projects by comparing old and new AST subtrees.

While these co-change studies have successfully captured co-change patterns among multiple files with co-change relations in maintenance, none of these studies are characterizing co-change maintenance files as a community and exploring the evolution of this community. These patterns can change or disappear as software evolves. Our paper investigates a maintenance community's life cycle, including how it is born, grows, achieves stability and eventually becomes inactive.

3 MAINTENANCE COMMUNITIES

3.1 Subjects

For our study we selected 14 open source projects from Apache, as evaluation subjects. These projects differ in terms of size, domain, and length of evolution history. They range in domains, from a distributed database (Hadoop) to a content analysis toolkit (Tika). Table 1 shows the “demographic” information for each project. We studied each project from the start dates listed in the *Start Date* column of the table until 2017-07-07. Their ages vary from 13 years old (Wicket) to 8 years old (Hadoop).

The *#Files* column lists the number of files found in their latest version, varying from 1458 files in Avro to 24466 files in Camel. The number of commits recorded in their evolution history, that is, the number of revisions made to each project, ranges from 1560 in Avro to 28899 in Camel. Column *#Issues* lists the number of bug issues recorded in their respective JIRA databases.

3.2 Extraction of Maintenance Communities

In this section, we describe how software maintenance communities are extracted. The data in the paper can be accessed via Zenodo (<https://doi.org/10.5281/zenodo.1321253>). Given a project and a time range, we conduct the following steps.

Step 1: Extract issue keys from its JIRA issue tracking system.

Step 2: Find a set of files for each issue in the revision log where the commit message matches the issue key. In this step, all test files are filtered out as we focus our investigation on just source files. In this step, we also filter out issues that modified more than 10 source files, to reduce the noise caused by a large set of files (due to changes in formatting, refactorings, etc). We choose 10 because the issues with fewer than 10 files cover around 95% of all issues.

Figure 1: Communities Formed by the First 100 Avro Issues

Step 3: Extract co-change edges for each issue. If two files are in the same file set and modified for the same issue, then we form an edge between these files. We extracted all co-change edges in the system maintenance history.

Step 4: Apply the clique prelocation method (*CPM*) [8, 19] to detect software maintenance communities. “The key features of the communities obtained by *CPM* are that (i) their members can be reached through well connected subsets of nodes, and (ii) the communities may overlap (share nodes with each other).” We choose 3-cliques as a parameter in *CPM* detection, which means that any file is co-changing with at least two other files in this community. Then we use R scripts to visualize the detected communities.

Figure 1 shows detected maintenance communities from the first 100 issues in Avro. One node represents a distinct file and the nodes in the same color means that these nodes belong to the same community. If a node's color is red, it means that this node belongs to multiple communities. If a node's color is white, it means that this node does not belong to any community. If a file does not co-change with any other files and then it can not form an edge; in this case this file should be isolated in the community representation. Figure 1 shows that 12 communities are formed by these 100 issue fixes. The largest community is shown in yellow. One of the red nodes 95 belongs to two communities as it co-changes with nodes (93-94, 96-98) and with nodes (111-113 and 33). There are 6 white nodes without communities (1, 2, 52, 53, 87 and 88), though some nodes co-changed with other other nodes. 2 files (32 and 137) are isolated and they are changing independently.

3.3 Characteristics of Maintenance Communities

Bonding in communities: Suppose C is a superset of communities, containing all communities from c_m to c_n in a system. We calculate the average edge weight inside a community W_c and compare it with the average edge inter community weight W_{ic} . Suppose $edge_m$ is the number of edges between any two files and $file_m$ is

the number of files in the community c_m . The average edge weight in the community c_m is $W_{c_m} = \text{edge}_m / (\text{file}_m \times (\text{file}_m - 1) / 2)$. Then, we calculate the average edge weight inside one community W_c for all communities (C) by $\sum_{c_m \in C} W_{c_m} / \text{Size}(C)$.

Similarly, edge_{mn} is the number of edges between a file in community c_m and a file in community c_n . The average edge inter community weight W_{ic} is $\frac{\sum_{c_m \neq c_n} \text{edge}_{mn}}{\text{Size}(C) \times (\text{Size}(C) - 1) / 2}$.

From figure 1, it is obvious that W_c is significantly larger than W_{ic} , which means that the bonding in the same community is much tighter than between different communities. This indicates that files in same community tend to change together in maintenance activities. Table 2 shows W_c and W_{ic} of the 14 subject projects. The ratio of W_c to W_{ic} ranges from 6.1 to 130.4, with an average of 41.1, meaning that a file co-changes with another file in the same community 41.1 times more often, on average, than a file co-changes with a file in another community. This justifies our community definition.

Location in communities We define the *PathDistance* of two files based on the packages they belong to. If two files are located in the same package, then their distance is 0. Given two files, f_i and f_j , we define Dir_c as the common directories shared by both files, and model their full paths as:

$$\text{Path}(f_i) = \text{ProjRoot} / \text{Dir}_c / \text{Dir}_{A1} / \text{Dir}_{A2} / \dots / \text{Dir}_{An} / f_i$$

$$\text{Path}(f_j) = \text{ProjRoot} / \text{Dir}_c / \text{Dir}_{B1} / \text{Dir}_{B2} / \dots / \text{Dir}_{Bm} / f_j$$

We define the distance as: $\text{PathDistance}(f_i, f_j) = n + m$. Modeling all the files involved in a community, c_m , as a set, FileSets and $f_i, f_j \in \text{FileSets}$, we can compute the average path distance of the file set $\text{AvgPathDistance}(c_m)$ as follows:

$$\frac{\sum_{i \neq j} \text{PathDistance}(f_i, f_j)}{\text{Size}(\text{FileSets}) \times (\text{Size}(\text{FileSets}) - 1)}$$

We get the average path distance for each community and calculate the average path distance inside each community for all communities (D_i). Similarly, we randomly sample a set of files, which has the same size as each community, and formed a random “community”. We calculate the average path distance for all random “communities” (D_r). We compared the results in table 2. As we can see, the average package distance of a community is 4.23, while the random files’ average package distance is 12.66. Files in the same community tend to be more localized, which means files in the same community are closer to each other in terms of physical or package distances. For example, in figure 1, the average path distance for files in communities is 2.9, compared to 4.7 for all files.

Summary: Files in the same community are more likely to share the same characteristics and co-change with each other in revision history. These maintenance communities should be treated together in a system’s evolution and deserve special attention.

4 COMMUNITIES EVOLUTION

D’Ambros et al. [7] states that one view of software evolution is to cover all the work done to update and fix a software system after its first release. In this paper, we also adopt this view and use all types of issues to investigate communities’ evolution. We detected maintenance communities over time and compare their differences to monitor their evolution. For example, Avro has 689 issues; we applied CPM to detect communities 689 times in time sequence.

Table 2: Characteristic in vs inter Communities

Project	W_c	W_{ic}	W_c/W_{ic}	D_i	D_r
Avro	0.75	0.02	30.8	1.71	11.57
Camel	0.76	0.01	130.4	5.56	17.49
Cassandra	0.86	0.11	7.8	1.56	4.75
Cxf	0.87	0.01	66.6	7.81	21.24
Derby	0.92	0.05	17.9	3.44	7.89
Hadoop	0.89	0.01	68.4	6.25	15.35
Hbase	0.89	0.03	32.6	4.41	14.55
Mahout	0.8	0.01	63.9	4.7	13.68
Openjpa	0.95	0.16	6.1	5.66	12.95
Pdfbox	0.85	0.06	14.1	4.51	12.4
Pig	0.88	0.06	14.8	2.38	8.54
Tika	0.84	0.06	14.5	4.27	12.49
Wicket	0.83	0.01	100.5	4.73	16.71
Zookeeper	0.76	0.12	6.4	2.18	7.58
Average	0.85	0.05	41.1	4.23	12.66

Figure 2: Types of Communities

4.1 New Communities

We define that a new community is born at time $t + 1$ if at time t it does not exist but at time $t + 1$ it is there, as shown in figure 2.A. For example, the issue Wicket-14 modified 3 files (*AbstractWebRequestCodingStrategy.java*, *WebRequestCodingStrategy.java*, *org.eclipse.core.resources.prefs*). These 3 files have not been touched before issue Wicket-14 and thus these files formed a new community.

4.2 Active Communities

We define a community as *active* at time $t + 1$ if it meets either one of these two conditions:

1. At time t it exists but at $t + 1$ its size is larger than its size at t , as shown in figure 2.B. For example, before issue Avro-60, there was a maintenance community consisting of 7 files: (*json_tokenizer.h*, *json.c*, *avro.h*, *json.h*, *lempar.c*, *json_tokenizer.c* and *lemon.c*). Avro-60 modified 3 files (*avro.c*, *json_tokenizer.c*, *json.h*). *avro.c* is co-changed with *json_tokenizer.c* and *json.h* and joined this maintenance community and became a new member.

2. At time t it existed and at $t + 1$ its size is the same as at t , and a member in this community is active at time $t + 1$, as shown in figure 2.C. For example, before issue Pig-881 on 2009-07-10, there was a community consisting of 3 file members (*MRCompiler.java*, *POPackage.java* and *PhysicalOperator.java*). Pig-881 touched *MRCompiler.java* and *JarManager.java*, in which *MRCompiler.java* makes this community active at time $t + 1$.

4.3 Inactive Communities

We consider a community is inactive at time $t + \Delta t$ if this community exists at time t and the files in this community have not been active for a continuous time range (from t to $t + \Delta t$). Δt is a

threshold we can set. If we set Δt to 100, this means 100 consecutive issues. For an example, in the Tika project, a 13 member community (*MimeTypesFactory.java*, *PowerPointExtractor.java*, *WordParser.java*, *XMLParser.java*, *OpenOfficeParser.java*, *ExcelParser.java*, *PowerPointParser.java*, *AppendableAdaptor.java*, *Word6Extractor.java*, *OfficeParser.java*, *WordTextBuffer.java*, *CauseIOException.java* and *PDF2XH-TML.java*) has not been active since the issue Tika-186 on 2009-02-14 to 2017, a span of about 940 issues.

4.4 Reactivated Communities

If a new member joined in an inactive community or an existing member in this community is active again, we say this community is reactivated. For example, in Cassandra project there is a community consisting of 4 file members (*TypeParser.java*, *CompositeType.java*, *DynamicCompositeType.java* and *AbstractCompositeType.java*). Since the issue Cassandra-2355 on 2011-05-17, this community has been inactive for over 340 issues. However, on 2012-01-13, the issue Cassandra-3625 modified the file *AbstractCompositeType.java* and thus this community is deemed to have been reactivated.

5 RESEARCH QUESTIONS

RQ1: How many files are clustered into communities? The answer to this question will identify the scope of our study. If files are not in any communities, it means that these files are modified relatively independently in maintenance activities, which suggests good modularization in the system. If a large percentage of maintenance files falls into communities, then these communities should be given higher priority considering their tight bonding.

RQ2: When and why is a new community born? If we can identify when new communities are born, we can alert developers of this new community as soon as it appears. And we are also investigating which types of issues will incur new communities, as a way of getting more insights about new communities.

RQ3: How long can an existing community stay active? An existing active community is a *hot* maintenance spot in a project. If an active community has been growing and becoming larger, it will cost much more maintenance effort. If files in an existing community keep getting modified, these modified files are *hot* files, which deserve developers' attention. We are interested in finding the most active communities and investigating how long their activity can last in a project's life.

RQ4: When does a community become inactive? After a period of activity, it is possible that the focus of new development tasks has shifted, or that the old community has been refactored. A community can then be inactive. We are investigating the time when a community becomes inactive.

RQ5: How does an inactive community get reactivated? We are investigating which kinds of issues can reactivate an inactive community. This may help developers find the *technical debt* that remains in previously inactive communities.

6 RESULTS

6.1 Files in Maintenance Communities

We have found that the majority of modified files in a project can be clustered into maintenance communities. As shown in figure 3, in a software revision history, there are 3 types of files in the maintenance history after applying CPM: *IsolatedFiles*, *FilesNotInCommunity* and *CommunityMemberFiles*. *IsolatedFiles* are files which are modified independently in issues; they did not co-change with other files in the revision history. *FilesNotInCommunity* represents files that do not belong to any community, although they co-change with other files. For example, in figure 1's Avro's communities, file52 and file 53 co-changed with each other, but this does not meet the threshold of 3 to qualify as a community member. *CommunityMembersFiles* is the set of files in any communities (the colored files in figure 1), which are co-changed with at least two other files in the same community. Figure 3 shows that the majority of all files (74.5% to 92.5%) are in maintenance communities during evolution. We can see that Cassandra has the lowest percentage (7.5%) of *IsolatedFiles* and *FilesNotInCommunity* and the highest percentage (92.5%) of *CommunityMemberFiles*, which means that most files in Cassandra are highly coupled in the revision history. This result is consistent with the results in [16], that Cassandra has the lowest decoupling level, a metric which measures to what extent the source files of a system are decoupled.

Answer to RQ1: 74.5% to 92.5% of all files in the project revision histories studied can be clustered into communities. Monitoring these non-trivial communities will help developers better access and evaluate the majority of software maintenance activities.

6.2 The Birth of New Communities

A new community usually means a shift from old tasks, bugs or issues to new tasks, bugs or issues, which deserves close attention of developers' teams. In this section, we are investigating when and why new communities start to be born.

As we detect new communities continuously, we extract issue information (such as resolution time, issue type, etc.) when a new community is born. Table 3 lists all types of issues that led to a new community. A cell with a gray background means this type of issue is the most in one project. We can see that *bug* issues causes most new communities, followed by *improvement* issues and *feature* issues. If a *bug* issue causes a new community, either it has new files or its old files have not been touched in the prior revision history and this could cause the birth of a new community. *Improvement* issues mean refactoring, new classes or files, so it is easy to understand that *improvement* issues can lead to new communities. When *feature* issues involve implementation of new classes or files, these issues can lead to new communities as well.

Next, we investigate whether a community's birth time is related to the release time in a project. We extracted all snapshots and tags of release time, as well as the new community formation time, for each project and plotted these in figure 4. The red circle represents a new community and its birth time and the black circle represents a release/tag time. Figure 4a shows there are no new communities in Avro after Jan. 2014 even though there are releases in Avro, which means that the project has been stable since Jan. 2014. Figure 4c shows that in Hadoop the appearance of new communities slows

Figure 3: Community Member Ratio

Table 3: Issues Types of New Communities

Project	Bug	Feature	Task	Improvement	Test	Others
Avro	10	8	1	20	1	0
Camel	31	128	16	55	1	0
Cassandra	12	3	3	12	0	0
Cxf	55	16	11	50	1	0
Derby	25	0	5	17	0	0
Hadoop	24	10	23	35	1	0
Hbase	31	8	19	25	0	0
Mahout	19	23	5	24	0	0
Openjpa	12	6	1	2	0	0
Pig	23	12	1	8	0	0
Pdfbox	26	5	1	9	0	0
Tika	7	11	1	26	0	1
Wicket	54	20	6	73	0	1
Zookeeper	8	4	1	6	0	0

Table 4: Continuous Open(Growing) Communities Steps

Project	Step1	Step2	Step3	Step4	Step5	Total
Avro	135	2	1	0	0	138
Camel	5703	571	83	12	2(2 ¹)	6373
Cassandra	769	99	35	6	0	909
Cxf	2135	171	18	0	0	2324
Derby	1089	153	19	3	1	1265
Hadoop	312	23	5	1	0	341
Hbase	6808	992	186	40	1	8027
Mahout	117	5	0	0	0	122
Openjpa	212	26	2	2	0	242
Pdfbox	211	15	0	0	0	226
Pig	1061	105	11	0	1	1178
Tika	141	11	0	1	0	153
Wicket	318	8	0	0	0	326
Zookeeper	89	7	1	1	0	98

Figure 4: New Communities Form Time vs Tag Time

between May 2012 and March 2014, although there are frequent releases during this time period. In Camel there is continuous creation of new communities, as shown in figure 4b. Overall, we do not see strong correlations between new communities birth time and project release time. This may be because developers in these open source projects are more flexible about new releases and the implementation of these feature/task/bug issues, which will give birth to new communities. We will study commercial systems in the future to see if there is a difference between open source and commercial systems in this regard.

Answer to RQ2: New communities are formed by *bug*, *improvement* and *feature* Issues. In open-source projects, new communities seems unrelated with planned releases.

6.3 Active Communities

In this section, we investigate 2 types of active communities. One is active open communities, in which new members keep join in. The other is active closed communities in which old members stay active in revision history.

6.3.1 Active Open (Growing) Communities. If a new member joins a community, we define it is an active open/growing community. If a community is growing continuously over time, we define it as a continuous active open community. The continuous active communities we detected are shown in table 4. The number of steps means how many issues a community has continued to attract new members in a time series. Figure 5 shows a continuous 4-step active open community in Hadoop. The first community at time 356 contains 8 files. At time 357, issue hadoop-7250 adds file243 to this community and now it contains 9 files. At time 358 and time 359, file244 and file245 are added. Finally at time 360, this community has 14 files by adding file231, file246 and file49. The longest active open community we have observed has grown over 6 steps. From table 4 we can see most of the continuous active open communities grow in one step but do not continue growing in multiple steps. Only 5 communities in 14 open-source projects have grown over 5 steps and only 2 communities in the Camel project have grown over 6 steps or more.

These continuous active open communities are not mutually exclusive; for example, a continuous active open community may stop growing for a period of time but later will grow again. Our

¹There are 2 communities with 6 or more steps.

Figure 5: A 4-Step Active Open(Growing) Community in Hadoop

Table 5: Merged Active Open(Growing) Communities

Project	Count	MaxTimeRange	MaxIncreasedSize	MaxSteps
Avro	49	424	119	26
Camel	6017	4564	2490	180
Cassandra	338	5011	1577	674
Cxf	2034	3218	1195	149
Derby	1065	2049	934	152
Hadoop	96	1927	617	140
Hbase	7583	3877	2349	433
Mahout	50	599	153	19
Openjpa	99	1164	500	145
Pdftbox	72	1594	486	122
Pig	1089	818	536	55
Tika	44	1009	361	73
Wicket	138	2420	615	88
Zookeeper	15	736	203	89

Figure 6: A Merged Active Open Community in Hbase

algorithm detects these as two separate continuous active open communities. We merge such communities if the latter community contains the last member of the prior continuous active open community. Table 5 shows the statistics of merged active open communities. As we can see from table 4, there are 138 continuous active open communities in Avro. These can be merged into 49 communities, as shown in table 5. Multiple continuous active open communities can be merged into one merged community. For example, 98 continuous active open communities can be merged into 15 communities in Zookeeper, which means that on average 6.5 communities were merged together. There are some projects where continuous active open communities are more separate. For example 6373 continuous active open communities can be merged into 6017 active open communities in Camel; thus, on average, 1.1 continuous active open communities were merged together. Compared to Zookeeper, the active growing communities are more isolated or random in Camel.

Table 5 also presents the MaxTimeRange, MaxIncreasedSize and MaxSteps of a merged active open community. MaxTimeRange and MaxIncreasedSize measure the maximum time and the maximum increased number of files, when a merged active open community starts and ends growing (although during some time periods this community's size may remain the same). MaxSteps measures the maximum steps when a merged active open community continuously grows. We can see from table 5 that the MaxIncreasedSize ranges from 119 in Avro to 2490 in Camel. The MaxTimeRange ranges from 424 in Avro to 5011 in Cassandra, which is almost 90% of its life time. The MaxSteps ranges from 19 in Mahout to 674 in Cassandra, which excludes the time period when a community's size remains unchanged.

Figure 6 shows an example of merged active growing communities in Hbase. As we can see, this community starts at the early stage of the project and continues to grow to time stamp 3882. The size of this community has increased from 5 to 1449 files. But the community stop growing after time stamp 3883, which means this community has achieved a temporary saturation and became stable. The long life span and large size of this community makes it a *hot spot* attracting new members from 433 issues and thus deserves close examination.

6.3.2 Active Closed Communities. If any member in an existing community continues to be changed but the community is not adding new members, it is an active closed community. As with continuous active open communities, most closed communities can stay active continuously in one or two steps as shown in table 6. Some active closed communities even make it to 5 steps. For example, Figure 7 shows an example of active closed community with 5 steps in Pdfbox. From time 39 to time 43, the community's size (20) is unchanged, but at every time step some files in this community had been modified. Compared to active open communities, we have observed some closed communities staying active a little longer. For example, in Cassandra, 173 active closed communities can stay active in 6 or more steps, compared to *zero* active growing communities with 5 steps or more.

As with merged active open communities, we merged continuous active closed communities if the files in the first step of the latter community contains the files in the last step of a previous

Figure 7: A 5-Step Active Closed Community in Pdfbox

Table 6: Continuous Closed Communities Steps

Project	Step1	Step2	Step3	Step4	Step5	Step6+	Total
Avro	299	35	10	1	1	0	346
Camel	2476	393	163	83	50	34	3199
Cassandra	534	218	139	113	76	173	1253
Cxf	1574	156	45	15	4	1	1795
Hadoop	1144	101	14	6	2	2	1269
Hbase	1381	337	211	109	80	91	2209
Pdfbox	654	94	19	12	4	3	786
Wicket	1162	72	8	1	0	0	1243
Derby	693	113	48	27	16	22	919
Mahout	310	13	1	0	0	0	324
Openjpa	221	54	35	21	12	20	363
Pig	605	94	47	13	6	6	771
Tika	432	60	20	10	5	4	531
Zookeeper	172	44	22	22	11	14	285

Table 7: Merged Active Closed Communities

Project	Count	MaxTime	MaxStep
Avro	140	456	27
Camel	1212	5763	89
Cassandra	680	4848	131
Cxf	587	3070	38
Derby	378	1770	104
Hadoop	375	1788	59
Hbase	1049	4215	224
Mahout	156	570	19
Openjpa	192	1042	43
Pdfbox	241	1476	43
Pig	258	1490	62
Tika	165	825	26
Wicket	463	2393	40
Zookeeper	109	526	31

community. Table 7 shows the merged active closed communities. There is no MaxIncreasedSize in this table as the size of an active closed community remains the same. The MaxTimeRange is from 456 - 689 in Avro to 5763 - 6396 in Camel. The MaxSteps of active closed community ranges from 19 in Mahout to 224 in Hbase, which is a little smaller than that in merged active open communities.

Figure 8 shows an example of merged active closed communities in Cassandra. As we can see, this community starts at the early stage of the project and continues to be active till the day our data was extracted. This community's size has remained the same: 4 (*concurrent/DebuggableThreadPoolExecutor.java*, *tools/NodeProbe.java*, *concurrent/IExecutorMBean.java* and *db/CommitLogExecutorService.java*). 131 steps means that the files in this community have been modified in 131 issues, which makes this community a persistent maintenance *hot spot* and thus deserves close examination.

Answer to RQ3: Active open communities can keep growing continuously at most 6 steps while active closed communities can

Figure 8: A Merged Active Closed Community in Cassandra

stay active more than 6 steps. Merged active open/closed communities can spread over the entire project history, get involved in hundreds of issues, cost a lot of maintenance efforts, and deserve developers' most attention.

6.4 Inactive Communities

If, during a period of time Δt , existing community members are not active and there are no files joining this community, we define this as an inactive community. If we set Δt to 10%, an inactive community is a community which has no activities in at least 10% of a project's time range. For example, given that Cassandra has 5018 issues and hence a 5018 time span, a community that has no activity in a time span of 502 or more is considered an inactive community. We are interested in *when* a community starts to be inactive. Figure 9 shows the distribution of inactive communities by a Box-and-Whisker plot. The y axis is the ratio of start time of inactive communities to the entire project's length. We can see that a community in some projects, such as Avro, Hbase and Wicket, can become inactive any time in a project's life, from the beginning to the last time stamp. In some other projects, such as Cassandra, Derby and OpenJPA, inactive communities usually happen at the beginning of the project. As shown in Figure 9, in general, 50% of existing communities have been inactive at the beginning of a project's development history. This may due to the fast and unstable nature of development in the early stage of a project. Figure 10 shows the CDF graph of inactive community file sizes in Avro, Cassandra and Wicket. As we can see from Figure 10, around 95% of inactive communities in Cassandra and Wicket and 86% of inactive communities in Avro have fewer than 10 files. These small inactive communities no longer require developer attention; either they are fixed and have become modularized or the function of these

Figure 9: Inactive Communities Starting Time

Figure 10: CDFs of the # of Files in Inactive Communities

Table 8: Statistics of Inactive and Reactivated Communities

Project	#TotalInactive	#Reactivated	%
Avro	67	23	34.3%
Camel	306	187	61.1%
Cassandra	23	7	30.4%
Cxf	264	141	53.4%
Derby	100	75	75.0%
Hadoop	153	74	48.4%
Hbase	111	39	35.1%
Mahout	166	83	50.0%
Openjpa	45	37	82.2%
Pdfbox	77	46	59.7%
Pig	68	41	60.3%
Tika	55	23	41.8%
Wicket	281	103	36.7%
Zookeeper	33	20	60.6%

modules have shifted. Such inactive communities can “sleep” for a long time. For example, among 67 inactive communities in Avro, 44 have stayed inactive to the end of the project data (i.e., when our data was extracted).

Answer to RQ4: Existing communities can become inactive during any stage of a project. Half of the inactive communities start at the early stage of development. These inactive communities are usually small.

Table 9: Issue Types of Reactivated Communities

Project	Bug	Feature	Task	Improvement	Test	Others	Total
Avro	12	2	2	7	0	0	23
Camel	63	23	3	79	1	0	187
Cassandra	3	0	0	4	0	0	7
Cxf	87	4	3	39	0	2	141
Derby	52	0	4	18	0	0	75
Hadoop	38	4	7	24	0	0	74
Hbase	15	1	4	16	0	0	39
Mahout	47	4	2	30	0	0	83
Openjpa	23	0	4	8	0	1	37
Pdfbox	32	0	1	13	0	0	46
Pig	29	1	1	10	0	0	41
Tika	9	2	3	9	0	0	23
Wicket	52	7	3	41	0	0	103
Zookeeper	9	3	1	6	0	0	20

6.5 Reactivated Communities

Given our definition of inactive communities, at a threshold Δt , provided in the previous section, we now investigate whether an inactive community can become active. That is to say, we are looking into whether files in this inactive community may get modified or a new file is added to this community after a long time of inactivity: more than 10% of a project’s time span. We define such communities as reactivated communities. We first look into how many inactive communities have become reactivated. Then we examine which types of issues can turn an inactive community into a reactivated community.

As shown in table 8, 30.4%-82.2% of inactive communities can become reactivated. These reactivated communities can be considered as prior *technical debt*, which has not been resolved and has incurred additional maintenance costs. The issues which reactivate communities are presented in Table 9. Different from the observation that new communities are initiated by *bug* and *improvement* issues, we can see most inactive communities are triggered by *bug* issues. This justifies our assumptions that these reactivated communities may be paying *technical debts* from a previous stage, through bug fixes.

Answer to RQ5: 30.4%-82.2% of inactive communities in our dataset have been reactivated. Most reactivated communities are initiated by *bug* issues, which indicates possible *technical debt* in previous communities.

7 DISCUSSION

7.1 Threats to Validity

The first threat to validity of our study is that we use threshold 3 in CPM to detect communities. We chose 3 so that a file in each community is co-changed with at least two other files, which is

a strong connection in the revision history. Also, we chose Δt to be 10% of a project life to detect inactive communities and reactivated communities. We will experiment with other thresholds for sensitivity testing in the future.

Another threat is that the accuracy of our study depends on the quality of projects' revision history. Recent studies [3, 14] state that it is possible for one commit to fix multiple bugs, or, for a bug commit to not explicitly link to a bug issue. Our analyses assume that files in fixing an issue are related to each other, though we do remove issues which modified more than 10 source files to reduce noise. We intend to further assess this threat via qualitative analysis.

7.2 Discussion and Future Work

In this paper, 14 open source systems have been studied to analyze communities' evolution. In the future, we intend to study more projects and, in particular, more commercial projects to compare the difference of life cycles between open source systems and commercial systems. We suspect that the birth of new communities may follow a clearer pattern in commercial systems as they have more focused and organized management. It is also possible that active growing communities have better control and evaluation in commercial systems.

We also plan to propose a metric to better evaluate the activeness in a community. As a community is growing bigger and bigger, some files in this community may not be active. In this case, these old files need to be re-accessed to be qualified as the community member. We will work on this case qualitatively and propose a reasonable methodology to calculate a community's activeness in the future.

8 CONCLUSIONS

In this paper, we have presented our empirical study of maintenance communities detection and evolution. Files in maintenance are not isolated. Instead, the majority of these maintenance files co-change with each other and form maintenance file communities. We studied these communities' birth, growth, death and rejuvenation in 14 open source projects. We found new communities are usually formed by *bug* and *improvement* issues. An existing community can stay active through the entire life of a system, either by recruiting new members or by modifying its old members. These active open/closed communities cost a lot of maintenance effort and are spread across the entire project lifetime, affect large numbers of files. For this reason they are *hot* spots worthy of the most attention from developers. An inactive community, usually containing a small set of files, can start as early as the project's beginning. And an inactive community may be activated again, primarily through *bug* issues.

REFERENCES

- [1] Flore Barcellini, Françoise Détienné, and Jean-Marie Burkhardt. 2008. User and developer mediation in an Open Source Software community: Boundary spanning through cross participation in online discussions. *International Journal of Human-Computer Studies* 66, 7 (2008), 558–570.
- [2] Flore Barcellini, Françoise Détienné, Jean-Marie Burkhardt, and Warren Sack. 2007. A socio-cognitive analysis of online design discussions in an Open Source Software community. *Interacting with computers* 20, 1 (2007), 141–165.
- [3] Mike Barnett, Christian Bird, João Brunet, and Shuvendu K Lahiri. 2015. Helping developers help themselves: Automatic decomposition of code review changesets. In *Proceedings of the 37th International Conference on Software Engineering—Volume 1*. IEEE Press, 134–144.
- [4] Christian Bird, David Pattison, Raissa D'Souza, Vladimir Filkov, and Premkumar Devanbu. 2008. Latent social structure in open source projects. In *Proceedings of the 16th ACM SIGSOFT International Symposium on Foundations of software engineering*. ACM, 24–35.
- [5] Theodore Chaikalis and Alexander Chatzigeorgiou. 2015. Forecasting java software evolution trends employing network models. *IEEE Transactions on Software Engineering* 41, 6 (2015), 582–602.
- [6] Ned Chapin, Joanne E Hale, Khaled Md Khan, Juan F Ramil, and Wui-Gee Tan. 2001. Types of software evolution and software maintenance. *Journal of Software: Evolution and Process* 13, 1 (2001), 3–30.
- [7] Marco D'Ambrósio, Harald Gall, Michele Lanza, and Martin Pinzger. 2008. Analysing software repositories to understand software evolution. In *Software evolution*. Springer, 37–67.
- [8] Imre Derényi, Gergely Palla, and Tamás Vicsek. 2005. Clique percolation in random networks. *Physical review letters* 94, 16 (2005), 160202.
- [9] Nicolas Ducheneaut. 2005. Socialization in an open source software community: A socio-technical analysis. *Computer Supported Cooperative Work (CSCW)* 14, 4 (2005), 323–368.
- [10] Yulin Fang and Derrick Neufeld. 2009. Understanding sustained participation in open source software projects. *Journal of Management Information Systems* 25, 4 (2009), 9–50.
- [11] Michael W Godfrey and Daniel M German. 2008. The past, present, and future of software evolution. In *Frontiers of Software Maintenance, 2008. FoSM 2008*. IEEE, 129–138.
- [12] Jungpil Hahn, Jae Yun Moon, and Chen Zhang. 2008. Emergence of new project teams from open source software developer networks: Impact of prior collaboration ties. *Information Systems Research* 19, 3 (2008), 369–391.
- [13] Brandon Heller, Eli Marschner, Evan Rosenfeld, and Jeffrey Heer. 2011. Visualizing collaboration and influence in the open-source software community. In *Proceedings of the 8th working conference on mining software repositories*. ACM, 223–226.
- [14] Kim Herzig and Andreas Zeller. 2013. The impact of tangled code changes. In *Mining Software Repositories (MSR), 2013 10th IEEE Working Conference on*. IEEE, 121–130.
- [15] Qingtao Jiang, Xin Peng, Hai Wang, Zhenchang Xing, and Wenyun Zhao. 2017. Understanding systematic and collaborative code changes by mining evolutionary trajectory patterns. *Journal of Software: Evolution and Process* 29, 3 (2017).
- [16] Ran Mo, Yuanfang Cai, Rick Kazman, Lu Xiao, and Qiong Feng. 2016. Decoupling level: a new metric for architectural maintenance complexity. In *Proceedings of the 38th International Conference on Software Engineering*. ACM, 499–510.
- [17] Stas Negara, Mihai Codoban, Danny Dig, and Ralph E Johnson. 2014. Mining fine-grained code changes to detect unknown change patterns. In *Proceedings of the 36th International Conference on Software Engineering*. ACM, 803–813.
- [18] Hoan Anh Nguyen, Anh Tuan Nguyen, Tung Thanh Nguyen, Tien N Nguyen, and Hridesh Rajan. 2013. A study of repetitiveness of code changes in software evolution. In *Automated Software Engineering (ASE), 2013 IEEE/ACM 28th International Conference on*. IEEE, 180–190.
- [19] Gergely Palla, Imre Derényi, Illés Farkas, and Tamás Vicsek. 2005. Uncovering the overlapping community structure of complex networks in nature and society. *nature* 435, 7043 (2005), 814.
- [20] Gregorio Robles, Jesus M Gonzalez-Barahona, Martin Michlmayr, and Juan Jose Amor. 2006. Mining large software compilations over time: another perspective of software evolution. In *Proceedings of the 2006 international workshop on Mining software repositories*. ACM, 3–9.
- [21] Luciana L Silva, Marco Tulio Valente, Marcelo de A Maia, and Nicolas Anquetil. 2015. Developers' perception of co-change patterns: An empirical study. In *Software Maintenance and Evolution (ICSME), 2015 IEEE International Conference on*. IEEE, 21–30.
- [22] Damian Tamburri, Rick Kazman, and Hamed Fahimi. 2016. The Architects Role in Community Shepherd. *IEEE Software* 33, 6 (Nov./Dec. 2016), 70–79.
- [23] Qiang Tu et al. 2000. Evolution in open source software: A case study. In *Software Maintenance, 2000. Proceedings. International Conference on*. IEEE, 131–142.
- [24] Lu Xiao, Yuanfang Cai, and Rick Kazman. 2014. Design Rule Spaces: A New Form of Architecture Insight. In *Proc. 36th International Conference on Software Engineering*.
- [25] Lu Xiao, Yuanfang Cai, Rick Kazman, Ran Mo, and Qiong Feng. 2016. Identifying and quantifying architectural debt. In *Proc. 38th International Conference on Software Engineering*.
- [26] Olaf Zimmermann. 2015. Architectural refactoring: A task-centric view on software evolution. *IEEE Software* 32, 2 (2015), 26–29.