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Master Thesis

Collaboration networks in open-source software development

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DEPARTMENT FÜR INFORMATIONS-VERARBEITUNG UND PROZESS-MANAGEMENT DEPARTMENT OF INFORMATION SYSTEMS AND OPERATIONS

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Abstract

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1 Introduction

In recent years open source software solutions have become widely popular and frequently used in both scientific and enterprise use, which can be attributed to a number of factors, most importantly the ease of development and deployment of IT projects, improved cybersecurity and enhanced scalability [29]. This increases the contribution to open source projects from enterprises and individuals alike. Due to its nature, open source software projects are driven by community contributions, and depend heavily on active participation in all phases of the project.

Software development in a corporate environment usually follows a strict hierarchial structure, where each participant is given a precise position and responsibility, like project manager, scrum master, senior or junior developer, and employees do not tend to work outside of their assigned tasks and territories. The main purpose of maintaining software development structures is for the company to ensure that the outcome of the project is in accordance with the business objective, adheres to the pre-set quality criteria and it is completed in a given timeframe; in other words to asses the risks associated with the business objective of the software project [32]. This is achieved by breaking down the developed software into smaller, less complex components, and grouping the developers into managable teams, where the communication is moderated between teams [9].

As opposed to commercial software development, Free/Libre Open Source Software (FLOSS) projects usually do not follow an organizational hierarchy, and are usually self-organizing and dynamic [9]. Issues, bugs and progress are tracked openly, and everyone is encouraged to contribute based on the current topics and expertise, but purely on a volunteering basis. The lack of access restriction to certain modules allows for much more spontaneous interaction between developers, which generate large, complex networks [22]. These complex networks can be seen as large social networks of developers based on collaboration.

Because contribution to FLOSS projects are voluntary, participants have a different motivation for taking part than in commercial software development. According to El Asir et al. [13], FLOSS participation can be motivated by internal and external factors. Internal factors include self-improvement,

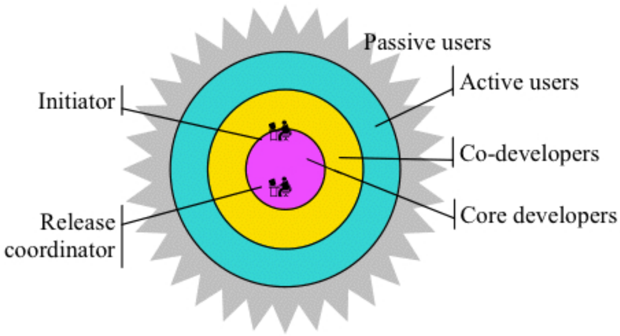


Figure 1: Onion model of collaboration types in FLOSS projects [11].

learning and contribution as a hobby or pass-time activity [4, 34], whereas external factors are motivated by marketing and demonstrating certain skills, thus increasing and improving employability [4].

2 Background and rationale

2.1 Collaboration in FLOSS projects

Collaboration networks of open source software (OSS) have been a subject of many academic research. Raymond [11] has defined collaboration based on bug report interaction, and observed the collaboration network of 124 large-scale SourceForge projects. The generated networks have widely different centralization properties, but it was observed that larger sized projects tend to be more decentralized. The broad community roles contributors tend to take have been also identified in [11], which have been coined as the *onion model* in [22] (Figure 1).

The onion model describes the types of participants in an OSS project as layers. The center represents the small group of core developers, who are responsible for the majority of contributions to the software. They are surrounded by a larger group of co-developers, whose main contributions are usually bug fixes reported by the active users. The passive users are usually the largest in numbers, who do not contribute or report any bugs. In a healthy FLOSS project, each layer of contributors are about one magnitude larger in numbers than the preceeding inner layer [25].

El Asir et al. [13] used a K-means classification to categorise project participants into a similar core-periphery structure (core, gray in-between area, and periphery) based on SNA metrics with a montly timeframe, and analysed how and why contributors transition between groups. They found that technical contributions like code commits and lines added have a much heavier impact on becoming a core developer as opposed to other activities, such as testing, reviewing and commenting.

A literature review conducted by McClean et al. [24] systematically analysed the state-of-the-art research of 46 scientific papers in the field of FLOSS social networks, and categorised them into three groups based on topic: structure, lifecycle and communication. They conclude, that the existence of core-periphery structure in OSS projects is well established in the field, which is also an indicator of a healthy FLOSS software. Regarding the lifecycle, generally the core development team does not change significantly over time, however, the project becomes more decentralised and distributed as it matures. A lack of research regarding temporal analyses were identified in the most current knowledge, which was suggested as a future research area in this field.

2.2 Social network of Open-source projects

In a larger FLOSS project, developers usually cannot understand every part of the project, therefore collaboration is required with eachother. The network created by the collaborators can be considered as a social network, because collaboration requires some kind of social interaction with eachother. Social network theory describes how social interaction patterns affect the individual behaviour [23]. We can model an OSS project's social network as a graph, where nodes represent collaborators (developers, bug reporters, etc...) and edges represent the social interaction between them. In mathematical terms...

The type of the social interaction determines the created network, therefore choosing the basis of collaboration can have a significant impact on the network structure. The common types of developer social networks (DSNs) are Version Control System-based (VCS-DSN), Bug Tracking System-based (BTS-DSN) networks and DNSs, that are purely based on social elements [5]. The VCS-DSN take the version control application as a source for network generation by recording collaboration based on co-edits of the same module, file or code section. Choosing the granularity can impact the precision of true collaborations represented in the network. Co-edits by multiple developers to a single module or file does not necessarily mean actual collaboration was required from the authors, as the parts edited could work functionally independent from eachother. By increasing the granularity to file sections (classes or functions within a single file) or even lines, we can be more certain, that coordination was required, but we risk leaving out semantically connected parts of the project [19]. In contrast to VCS-DSNs' purely technical approach, the BTS-DSNs use semi-technical bases for connecting participants, such as comments on issues, bugs or reviews [13]. These artifacts, although being tightly related to specific sections of the source code, allow for taking into account conversational elements as contribution. For example, participants, who do not contribute directly to the software source code, but actively review and comment, are also considered. Lastly, social networks of developers can be constructed on project participation, following, starring or through communication means like mailing lists. The technical aspect of collaboration is minimized in such DNSs, and they are more fit for project organization and communication analyses in FLOSS projects (mailing list vs file file edits vs line edits)

2.3 OSS project success

community maturity ([21] in [5])

"Successful projects will likely have modular structure from the start or after refactoring as the source code grows larger and more unwieldy" [6]

success factors: Average Time Efforts, Number of Developers, Comments, Total Code Lines, Comment Ratio, Number of Rater [33] Truck Factor [7]

3 Motivation of research problem and research questions

Because there is a high dependency on the community in open source software projects, by understanding how contributions are included and what patterns emerge we can gain valuable insight into the project's current state and its trajectory. As stated before, SNA analysis of OSS have been extensively studied, but there is a lack of research regarding temporal models analyzing the lifecycle of a FLOSS project.

The goal of this paper is to fill in this gap by examining OSS project collaboration networks over time using SNA metrics. More specifically, one part of the research will focus on the evolution of such collaboration networks and comparing and contrasting these networks with the software outcome. The second part will focus on events during a project, and how it affects the developer collaboration. The research questions, which are broken down into subquestions, are as follows:

1. **How does the temporal lifecycle information of a project influence its success?**

    (a) *Based on temporal models of collaboration, is it possible to predict the outcome of the project?* Since it has been proven that the core collaborators do not change much over the course of the OS software development, our assumption is that any sudden or long-term change, that is not consistent with the other observed projects, can have a significant impact on the outcome (negative or positive alike).

    (b) *Can stages of a FLOSS project with a maturity model be observed?* As most OS software starts with a small collaborator basis and grows over time, it can be assumed, that each project goes through the same steps of open source maturity levels. On the other hand, it is also possible that due to the uniqueness of each project, no such stages are observable.

2. **How do major events in the project lifecycle change the collaboration network of the project?**

    (a) *Do planned or foreseeable events change the collaboration structure?* Major software version releases can be considered foreseeable events of the project lifecycle, which could have an effect on the developer collaboration. For example, there might be a higher rate of interaction between contributors just before a new version is released to clear up the backlog of tasks. But it is also possible, that commit and change rates drop during this time, because the focus shifts to stability and testing instead of new features.

    (b) *How unforeseeable internal or external events affect FLOSS collaboration?* Sudden shocks to the project, such as an announcement of disinterest from major users of the software, discontinued enterprise support of the project, large-scale global events like the pandemic, or sudden employee firings can have significant effect on the core and periphery collaborators alike. By analysing the collaboration network before, during and after such changes, we might be able to recognise patterns, that regularly occur around these events.

3.1 Research methodology

To find answers to the research questions above, first we build a repository analyzer tool, which mines collaboration data from FLOSS projects, generates static snapshot collaboration networks at each given time interval and calculates SNA metrics for each snapshot. Then these metrics can be aggregated over time, or plotted against time to discover changes in the network. The `git2net`[1] [14] Python library provides the necessary tools to mine any project repository that uses git version control. It also incorporates temporal network generation capability, which can be used as a source for creating static collaboration networks aggregated over a given period of time.

We apply a hybrid methodology of qualitative and quantitative research. First, as part of the qualitative research, we choose a small number of repositories to be analyzed. We observe the number of connected components, centrality, number of nodes and mean degree SNA metrics in order to discover the core and peripherial collaborators over the project lifecycles. The basis of collaboration, due to the unavailability of other means of communication, is coediting files. Based on the state of the art research in this field, file coediting proves to be an effective and easy way to represent collaboration between developers.

After discovering the collaboration structure over time, we will match the breakpoints and unexpected spikes or troughs to events within the lifespan of the project. We expect that the key SNA metrics will show a periodicity around planned releases and other reoccurring events (e.g. holiday season). Outstanding values without reoccurrence, on the other hand, are more likely to be consequences of unexpected events. In these cases, it should be observed whether the network is capable of reorganizing itself, or does the event leave a permanent mark on the collaboration structure. A categorization of unexpected events and the level of impact each category has should be observed.

For the quantitative research to be conducted, we will gather a large set

[1] `https://github.com/gotec/git2net`

of repositories along with major events in its lifecycles. We will then run the miner for all repositories, and with the findings of the qualitative research, we will try to detect all major events and their type (planned or unexpected). We will utilize the `ruptures` [2] library to detect changes in the continuous SNA metrics. If the model is capable to accurately recognise events, then we can also apply it on any repository to detect changes, which will allow us to discover changes in the collaboration network that are not related to publicly known events or releases.

4 Gitminer implementation

To find answers to the research questions, we implement an analysis tool to mine and analyze project repositories, which allows us to generate collaboration networks and network metrics for the analysed projects.

4.1 `git2net` miner

The process begins with the project mining. After cloning the repository, the `git2net` [14] library is used to collect data related to commits. Specifically, who is the author of each commit, which files were modified (created, edited, deleted) with the commit, and when was the commit created. Additionally, the lines edited by the author within each commit are collected separately, allowing for a more fine-grained collaboration network generation if necessary. The results are collected into an `sqlite` [3] database file's *commits* and *edits* tables.

The `git2net` mining process by default collects all the commits throughout the project's lifecycle. However, the processing time of each commit differs based on the number of edits, the affected number of files and the file types as well, which makes collecting certain commits very resource-intense and time-costly. Therefore, we exclude every commit, which contains more than 100 file modifications, during each repository mining using the *max_modifications* parameter. As observed by Gote et al [14], this exclusion criteria does not affect significanly the generated network, because they are mostly merge commits or project restructurings, which do not mark any

[2] `https://github.com/deepcharles/ruptures`
[3] `https://www.sqlite.org/index.html`

true collaboration effort between developers. During the data mining in certain repositories, we encountered commits, that were not mineable with this method and the mining process halted, presumably due to processing error because of binary file changes in these commits. We also excluded these commits from our data mining process.

This exclusion criteria resulted in an average of 3% of commits excluded in all repositories subject to our analyses, with the highest excluded commit rate being 20%.

4.2 `repo_tools` miner

We use the `repo_tools` [4] Python library to query the Github API for additional repository data extraction, such as:

- Releases
- Tags
- Issues
- Stars and followers

The mining output is also stored in a `sqlite` relational database, which is queried later on during the analysis.

4.3 Data preprocessing

The collaboration networks with the `git2net` library connect the authors to their edited files using only file and author names instead of IDs. This creates an issue when generating the networks, because authors with the same name will show up as one node, and they will be connected to the files they touched combined. Furthermore, authors that change their displayed name ('author_name' field in the mining database) or log in from diferent accounts, where they have different names, will show up as multiple nodes instead of a single vertex.

We utilize the `gambit` [15] rule-based disambiguation tool to resolve the author names. Furthermore, the created networks have issues when the node names contain special characters or spaces. Therefore, after disambiguation,

[4] `https://github.com/wschuell/repo_tools/`

we replace every unique author name with its ID number.

As the files are also labelled by their filename property in the network outputs, the same filenames but in different folders are also displayed as single nodes. In order not to create false collaborations, we simply remove the files from the network with filenames, that occur more than once in all the repository subdirectories. We argue that this does not remove any significant collaboration data, since most files sharing their name with other files are technicaly files, like `__init__.py` for a Python project.

4.4 Collaboration networks

When creating a DSN from the mined data, we have multiple methods at hand. The `git2net` library provides its own co-editing network function, which returns a temporal network of collaborators. This uses the co-authorship algorithm developed by Gote et. al. [14], however, we would like to have more control over the network generation method, such as simple file-based co-authorship in order to customize the network for our needs, like weighing each relation or generating undirected graphs.

4.4.1 Temporal bipartite network

As a first step, we generate a temporal bipartite network of authors and their edited files with the `git2net` built-in *get_bipartite_network* method. A temporal network is a `pathpy` [5] graph object, which contains a collection of timestamped graphs of a single network at each point in time within the observed timeframe. Such a snapshot $S_t = (U, V, E_t)$, where U is the set of authors, V is the set of files and E_t is the set of file edits as edges at t timestamp. By connecting the authors, who touched the same files, and removing the nodes representing the edited files (converting the bipartite network to a regular network), we can observe the evolution of the collaboration over time, represented in Figure 2.

Although a temporal network preserves the time aspect of the graph by the edges being tied to the time dimension of the graph, calculating network metrics like centrality on such networks is infeasible. Visualization also proves to be difficult in representations where animation is not possible.

[5] `https://www.pathpy.net/`

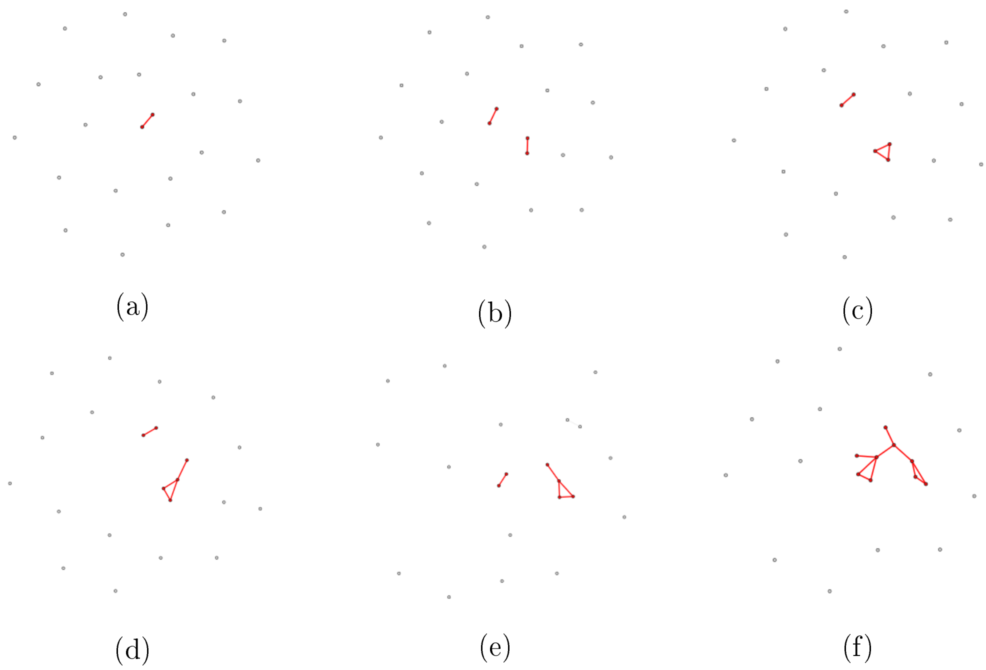


Figure 2: Sequential snapshots of the `networkx` collaboration network with a moving time-window of 30 days and 7-day steps.

Therefore, we aggregate the bipartite network over a given timeframe into a static network. All nodes within the temporal net are preserved, and all directed edges are added to the network with the edge weight representing how many times that author edited the file.

4.4.2 Static networks

The generated static weighed bipartite network looses its time-varying component, but now we are able to manipulate and calculate complex statistics over it. Figure 3 is an example of such a network. As a next step, we convert the the bipartite network into an authors' network by removing the nodes representing files.

We have multiple methods to convert the directed and weighted bipartite network into a projection of authors. We could simply remove the files and connect each author, that worked on the same file, however, the end result would be an unweighted graph. This would falsely show, that all collaborations are weighed equally, which is clearly not the case, as multiple continuous

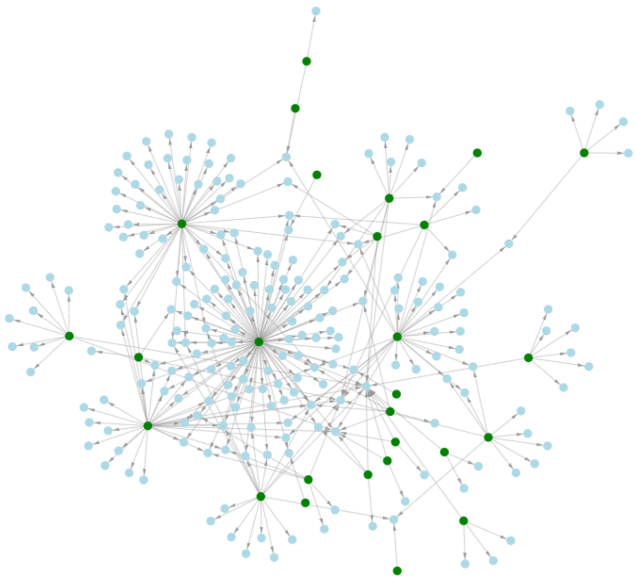


Figure 3: A bipartite network of authors (green) and edited files (light blue) in the `pandas` project within the timeframe 31/01/2021 and 15/02/2021

edits on the same file from both parties should represent a stronger collaborative connection. Therefore, firstly we implement the Weighted One-Mode Projection (WOMP) method [31], The WOMP method converts the bipartite network $G(A, F, E)$, where E is the edge list containing tuples (a_i, f_i, w_{ij}), and $w_{ij} \in E$ is the weight between author $a_i \in A$ and file $f_i \in F$. With this notation, a weighted directed edge can be calculated for any $a_a, a_b \in A$ as follows:

$$w_{ab}^{A \to A} = \sum_{j=1}^{m} \frac{w_{aj}}{W_a^F},$$

where W_a^F is the sum of all outgoing edge weights from author a to all files F denoted as $W_a^F = \sum_{i=1}^{n} w_{ai}$. This creates a bidirectional weighted collaboration network between authors a_1 and a_2, where the weight w_{12} represents the relative collaboration effort of a_1 towards a_2 compared to all the other developers a_1 has collaborated with. Conseqently, every edge is in the rage $[0, 1]$ in the resulting WOMP network.

A disadvantage of the WOMP method is, that the generated collaboration network is bidirectional, meaning if there was any common authored files between a_1 and a_2, then there will be both w_{12} and w_{21} connecting them.

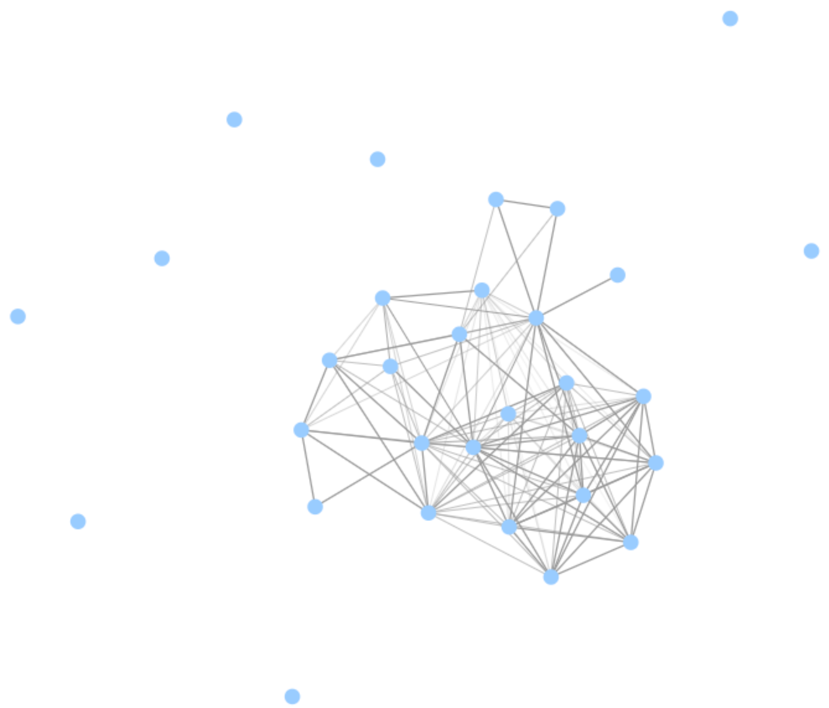


Figure 4: Weighted Jaccard similarity collaboration network of `pandas` generated from the bipartite network in Figure 3.

To simplify the network, we want to generate an authors network, where the edges are undirected. For this, we are using the weighted Jaccard method on the files-authors bipartite network:

$$w_{ab} = \frac{\sum_{f \in F} min(f_a, f_b)}{\sum_{f \in F} max(f_a, f_b)}.$$

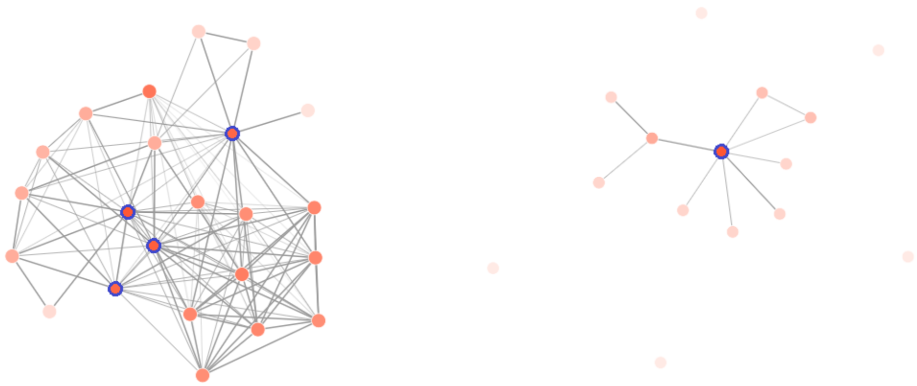
For each file f that a_1 and a_2 authors touch, we sum up the minimum and maximum weights the authors have towards each file, then we divide the sum of minimums with the sum of maximums. This results in the undirected author-author network with edge weights in range $[0, 1]$. By default, this method removes isolated contributors, who do not collaborate with eachother, but are actively editing the files. We add these nodes manually. Figure 4 shows the final author network.

4.5 Core and periphery, centralization

A critical part of the OSS software projects is the existence of core and periphery developers. It has been observed, that in each FLOSS project there are a small number of developers, who provide the vast majority of development effort into the project. It has been also established, that the members of core developers do not change substantially during the project's lifecycle. However, there was no effort on whether there is a change in the collaboration pattern, especially before, during or after a major lifecycle event. Therefore, we make efforts identifying the core developer network to observe these changes.

4.5.1 Degree centrality

We use the degree centrality of each node (i.e. developer) to identify the core members. Degree centrality of a node is the fraction of all possible nodes it is connected to. We can calculate it by dividing the degree with $n - 1$, where $n = |G|$ the number of nodes within the network. Since the core developers contribute the majority of commits and edits of the project, they are expected to be connected with more nodes. Joblin et. al. [18, 19] have also identified degree centrality as the best predictor of core developers. In cases, where binary classification of core or periphery is needed, we assign developers to the core network if their degree centrality score is in the top 20th percentile, otherwise they are considered as periphery. We also take note, that this method does not consider the weighted edges, only the number of edges (degree) a node has. Although this method could be refined to consider the node degree weighted with the edges, we argue that this could lead to invalidity. In case of two developers, who only contributed to one file, they will be represented with a strong connection and would receive a high weighted degree value, whereas a core contributor, who edits many files, can have many weak connections but these might not add up to one strong connection of the two isolated developers when weighted with the edge weights. It is clear, that a developer with many connections, regardless of the strength of the collaboration, should be considered core. Figure 5 shows two examples for degree centrality within a collaboration network. In the figure, darker colors represent a higher degree centrality value. The highlighted nodes are in the highest 20th percentile of degree centrality, classifying as members of the core developers. We can observe in both one-month periods, that `pandas` is much more decentralized, whereas `curl` is largely dependent on one developer.



(a) Pandas (b) Curl

Figure 5: Degree centrality within the `pandas` and `curl` projects' collaboration networks.

4.5.2 Degree centralization

The degree *centrality* can be calculated for every node, however, through our analysis we would also like to measue a global *centralization* metric, which is applicable to the whole network. As suggested by Crowston and Howison [12], we calculate the degree *centralization* by summing the differences between the maximum and each node's degree *centrality*.

$$C_D(A) = \frac{\sum_{i=1}^{n}(C_d(a*) - C_d(a_i))}{H},$$

where $C_d(a)$ is the degree *centrality* of an author a, $a*$ is the author with the highest degree *centrality* value, and n is the number of authors in the collaboration network A. The value H is for normalizing the sum by dividing by the theoretical maximum *centralization*. Since the *centrality* values are already in the range $[0, 1]$, we only need to normalize for the network's size. We get the highest centrality score with a star graph, where each node is only connected to a single central node, which has exactly one edge to all other nodes. The central node has a centrality of 1 in this case, whereas all the other $n-1$ nodes have $C_d(a) = \frac{1}{n-1}$. This means that in case of a star graph:

$$H = (n-1)(1 - \frac{1}{n-1}) = n - 2.$$

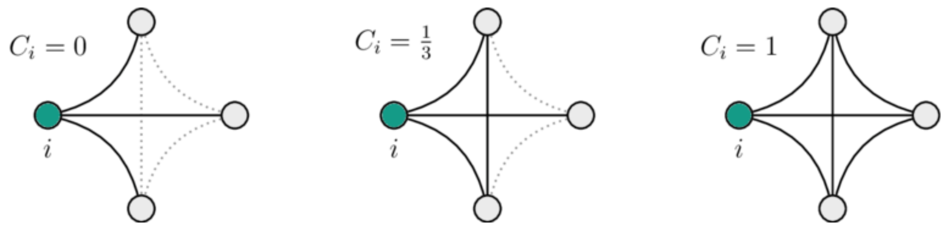


Figure 6: The local clustering coefficient demonstrated on an unweighted network of 4 vertices [17].

Within certain timeframes, when a project is inactive, it could happen, that the network contains 2 nodes or less. We define $C_D(A) = 0$ if $|A| = n <= 2$. The resulting output will always have a value in $[0, 1]$, where 1 means a completely centralized network (star graph) and 0 means a completely decentralized network. It is important to emphasize that a centralization score of 0 does not necessarily mean that there is no collaboration and every developer is isolated. Rather it means that each developer is co-authoring with just as many authors, as the others do.

4.5.3 Clustering coefficient

While centralization helps us describe the centralness of the network and how much it is centered around a single, or a small number of developers, it does not help us describing the structure of the network in more detail. Our goal is to gain an understanding of also the modularity of our network, meaning how much developers tend to cluster together [19]. We expect that authors form smaller clusters, which are more tightly connected together, and these clusters have somewhat weaker ties to other clusters. This builds on the assumption that the social network of the software follows the modules which build up the software itself, thus authors of a specific function should also cluster together within the network [10, 19]. To measure this "clusteredness", we calculate the *local clustering coefficient* for each node.

The *local clustering coefficient* quantifies on a scale $[0, 1]$ how likely it is that a node's neighbours are also neighbours. We use the number of how many triangles (also called clique, triplet) is every node a part of. This is illustrated for unweighted networks on Figure 6 with the formula:

$$C_i = \frac{2T(i)}{deg(i)(deg(i) - 1)},$$

where $T(i)$ is the number of triangles through node i and $deg(i)$ is the degree of i. However, in a weighted network we also have to consider the edge weights, since it is easy to see that a clustering coefficient of 1 with also the maximum weighted edges in a triplet does not represent the same clustering as being connected with a weak links. We expect weaker links connecting larger clusters, whereas stronger links within each cluster. Therefore, we use geometric averaging of the subgraph edge weights (as implemented by the `networkx`[6] library [27]):

$$c_i = \frac{\sum_{jk}(\hat{w}_{ij}\hat{w}_{ik}\hat{w}_{jk})^{1/3}}{deg(i)(deg(i)-1)}.$$

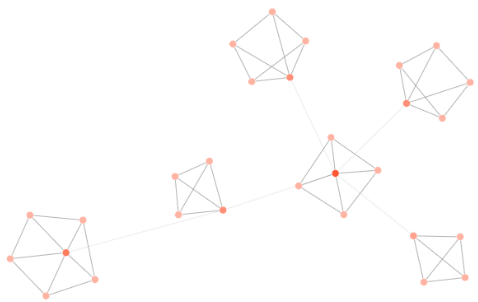
The $\hat{w}_{ij}$ represents the normalized weight of edge e_{ij} over the maximum weight in the network.

4.5.4 Hierarchy

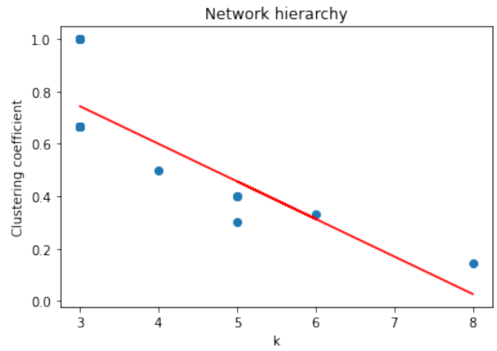
The degree centrality and the clustering coefficient are in themselves able to express meaningful aspects of the developer social network, however, by combining the two metrics, we can also assess how hierarchical the network is. In a scale-free social hierarchical network (such as the collaboration network), nodes tend to cluster around a single or a few hubs, which are more likely to have weak connections to other hubs [30, 19]. The nodes within these formed groups are relatively stronger than the connections connecting the hubs, but they are less likely to connect to nodes outside of their group. Therefore in a hierarchical network, the hubs have a high degree number and a low clustering coefficient, whereas the group members clustering around the hubs have a high clustering coefficient, but low degree numbers.

We can visualize the degree of hierarchy by plotting each node's clustering coefficient against the number of degrees, shown in Figure 7. In hierarchical networks, the plotted linear regression trendline will decrease steeply, as there is a negative correlation between the degree and clustering coefficient. In networks, where this cannot be observed, the trendline stays flat, meaning these two metrics are independent from eachother and the structure is not hierarchical. To measure the hierarchical level numerically within a network, we take the trendline's slope, which is β_1 in the $y = \beta_1 x + \beta_0$ general linear regression equation.

[6] `https://networkx.org/documentation/stable/reference/algorithms/generated/networkx.algorithms.cluster.clustering.html`



(a) Highly hierarchical network



(b) Network hierarchy

Figure 7: Hierarchical network and its corresponding degree number vs clustering coefficient plot.

In every network isolated authors can be observed, who are only working on files that noone else has edited (in the given timeframe). These nodes can skew the hierarchy score, because an isolated node's degree and clustering coefficient are by definition 0, which disproportionately makes the trendline much flatter. Therefore, we remove the isolated nodes from the network. If the network only contains isolated nodes, and there is no linear regression to be calculated, we set the hierarchy value to 0.

4.6 Project measures

One of our assuptions is that the collaboration network structure changes depending on the project's lifecycle. In order to discover cause and effect relationships between the network structure and project lifecycle, we gather basic project metrics to pinpoint the time and date of events, as well as the effort required within the project. We achieve this by gathering the dates of each release, and the quality and relative stress is measured by the issues within the project (create and close times).

4.6.1 Release and release measures

To measure the network changes around releases, first we collect the list of releases for the given project. Our goal is to gather the version number of each release, as well as the dates they were released. There are two relevant APIs regarding the release version numbers: GitHub releases and Git tags. Tags are marked and annotated commits supported by Git, therefore other projects, that are not on GitHub can also have tags. *Tags* are most

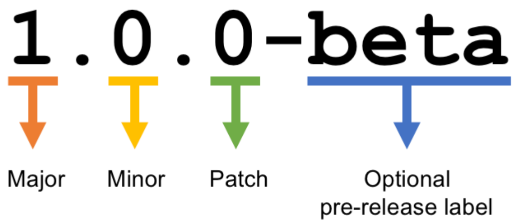


Figure 8: Semantic versioning. Figure source: [2].

commonly used to mark new release versions, but they can also be used to annotate other information, such as release editions or milestones. On the other hand, a *Release* is a high-level GitHub concept, which allows the project organizers to announce Git tags as project releases by adding a version number, release notes and binary artifacts [26]. A commit, that represents a new GitHub release, must be tagged, but a tagged commit does not necessarily need to be a new GitHub release.

Throughout our analysis, we use the tags as indicators of a new release, because there could be new versions of a software, that are not released publicly, and therefore do not have a GitHub release. Furthermore, GitHub only announced the Releases workflow in 2013, when the release versioning by Git tags was already a common practice. This means, that releases before 2013 can only be analysed via the repository tags.

Most large-scale OSS proejcts follow the semantic versioning convention, but only to a certain extent. The majority of tags follow the major-minor-patch (also known as breaking-feature-fix) semantic version naming convention in the format of X.Y.Z, where X is the major number, Y is the minor number, and Z is the patch number [28]. At the end, optionally pre-release and build data can be marked, for example: *1.11.6-pre*. The major number signifies an API-breaking change compared to the previous release, meaning backwards compatibility is not guaranteed for depending applications. Minor releases add new features, but compatibility is ensured with the older version. Patch releases usually handle bugs and security updates within the package.

During the network analysis, we expect the network measures to change around a release, but it is also expected, that a larger release, that required more collaboration, will have a greater impact, while smaller changes have smaller or no impact at all. The issue with the semantic versioning and re-

Index	Name	Tag name	Created	Type	Modifications	Lines added	Lines removed	Total change
0	Pandas v0.13.0	v0.13.0	2013-12-30 17:02:51	unknown	20031	1.665357e+09	1.624343e+09	3.289700e+09
1	Pandas v0.13.1	v0.13.1	2014-02-03 04:52:01	patch	836	2.231875e+06	2.349833e+06	4.581708e+06
2	Pandas v0.14rc1	v0.14.0rc1	2014-05-16 22:28:09	minor	1861	2.251189e+07	2.050846e+07	4.302035e+07
3	v0.14.0 final	v0.14.0	2014-05-30 11:47:40	unknown	318	3.220804e+06	5.314470e+05	3.752251e+06
4	v0.14.1 final	v0.14.1	2014-07-10 23:46:19	patch	720	1.660133e+06	3.796690e+05	2.039802e+06
5	v0.15.0 Pre-release	v0.15pre	2014-09-07 12:52:01	unknown	826	1.028779e+07	2.458664e+06	1.274645e+07
...	...	...	...	...	...	...	...	...
66	Pandas 1.1.5	v1.1.5	2020-12-07 11:42:10	patch	2167	4.251057e+06	4.611365e+06	8.862422e+06
67	Pandas 1.2.0rc0	v1.2.0rc0	2020-12-08 12:31:44	minor	41	1.060500e+04	8.850000e+02	1.149000e+04
68	Pandas 1.2.0	v1.2.0	2020-12-26 13:47:00	unknown	683	5.782570e+05	2.989310e+05	8.771880e+05
69	Pandas 1.2.1	v1.2.1	2021-01-20 11:21:02	patch	1306	1.864636e+07	9.228629e+07	1.109326e+08
70	Pandas 1.2.2	v1.2.2	2021-02-09 10:55:19	patch	844	6.783283e+06	1.827142e+07	2.505470e+07
71	Pandas 1.2.3	v1.2.3	2021-03-02 09:43:36	patch	959	1.002189e+07	5.783745e+06	1.580563e+07
72	Pandas 1.2.4	v1.2.4	2021-04-12 15:59:13	patch	289	3.402820e+05	1.704960e+05	5.107780e+05

Table 1: Releases collected information.

lease names is that there are no constraints, which would enforce a strict version naming, and it is entirely up to the developers to set the tag names. This leads to inconveniences when measuring collaboration effort through release version number, because a patch might require more collaboration effort than a minor release, and a minor release within one project could require significantly more teamwork than in another. Furthermore, tag names can be inconsistent, and there could be version numbers, that do not adhere to the major-minor-patch naming convention at all (e.g. test releases, or releases like 'latest-release-v11'). The possibility to add extra information at the end of tag names, like `-beta` or `rc` further complicates tracking the collaboration effort, because the majority of collaboration effort might happen before the `rc` version, or it might happen after it. As it can also be seen in Table 1, the `v0.14.0rc1` tag contains more modifications than the final `v0.14.0` version, whereas the `v1.2.0rc0` only contains a small fraction of modifications compared to `v1.2.0`.

In order to have a more fine-grained measure of how much effort a release required (besides the semantic versioning), we measure the number of lines added and lines removed in that release. This is calculated by adding up each commit's 'total lines added' and 'total lines removed', which was authored after the previous release but up to and including the current release tag's commit. The total change of lines for a release is simply the sum of lines added and lines removed, which are provided by the `git2net` miner. The miner also provides the number of modifications for each commit. A modification is a section of the source code modified, which can mean multiple lines added and deleted at the same part of the document. For example, if a new function is added to the project, which requires 20 new lines and removes 2 lines (e.g. empty space that was there before), then it will be considered as 1 modification, but 22 total line change. Changes to binary files are due to generated artifacts, which do not carry any collaboration effort, therefore they are excluded, and commits, that do not have a hash are also removed.

The release type contains the semantic version of the release, which was gathered from the tag name with a Regular Expression matching the conventional versioning X.Y.Z. We also capture the version number in tags, that contain additional notations such as `beta` or `rc`, then we compare the current release to the previous to identify whether the release is a major, minor or patch release. When the found version numbers in the previous and in the current release are the same, we leave that as unknown, as this is mostly the case in pre-releases. The first release doesn't have a preceeding tag, therefore we consider every modification before the tag as part of the release. This leads to the first tag seeming to have significantly more edits than the rest of the releases, whereas in fact this is just the result of not tracking from the beginning (see example in Table 1). Therefore, in our analyses we remove the first release, as this would lead to falsely weighing the network results.

4.6.2 Project issues and measures

To measure the productivity within the project, we collect some basic information regarding the GitHub issues. Issues keep track of bugs, beatures and tasks, contributors can comment and discuss the task at hand within an issue, and it can be assigned to users and milestones can be set. We collect the following information of issues:

- Issue title
- Issue number
- Created at
- Closed at
- Open for
- Bug or feature

The *issue title* is a short description of the issue. Most projects create their own convention of naming and tagging issues, for example each issue starts with a 3-letter abbreviation of a category, e.g. `BUG` or `DOC`. *Issue number* is a unique number for each issue, that is increased sequentially. *Created at* is the date and time of the issue being created, and *closed at* is the time when it was closed. If the issue was still open on the day of data mining (May

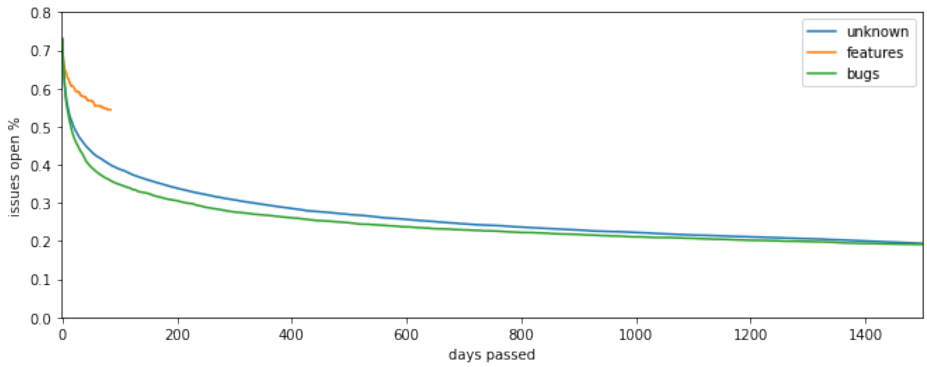


Figure 9: Survival curves of the `pandas` library.

9 2021), this field is empty. The *open for* field is the difference between the *closed at* and *created at* dates, or it is empty if the issue was never closed.

The last measure is *bug or feature*. Because issues can cover a wide range of possible topics, from discussions to performance, it is worth categorizing them to analyse the differences. However, categorization in practice proves to be difficult due to the different conventions each project uses, and because GitHub does not apply any constraints to the text of the title. We are searching for specific keywords in the *issue title* to categorize each issue into either a bug or a feature. We also drop some of the words from the text, because they would give us 'false positive' matches. If keywords for both or neither categories are found, the issue is marked as unknown. The dropped words, as well as the bug and feature keywords can be seen in Table 2 Although this simple method can already classify 10-15 percent of issues, it would require extensive manual effort to further improve this ratio. In future research, sentiment analysis of issue titles and issue descriptions could achieve much higher percentages.

Statistics for issues like average close time also prove to be difficult, because there are continuously open issues, which inevitably leads to the fact that a large portion of issues were still open and continue to be open. For these issues, we cannot know the issue close time, and if we try to calculate global measures by aggregating all (or portion) of issues, we have to consider the *survival bias* [16]. Figure 9 shows the issues survival curve of the `pandas` library. It is clearly visible, that a large portion (20 percent) of issues are not closed, and if we left them out of aggregate values such as average open time, our data will be skewed. Nevertheless, we can see in the example, that the categorization of issues makes a difference, as bugs get closed a bit earlier

Drop words	Bug keywords	Feature keywords
debug	bug	feature
debugger	defect	enhancement
debugging	incorrect	improvement
	unexpected	suggestion
	error	wishlist
	missing	wish list
	warning	
	problem	

Table 2: Keywords and drop words for *bug* and *feature* categorization.

than an average (unknown) issue, because after the same amount of days passign for both categories, more bugs tend to be closed in this example. In contrast, features have a high life expectancy, as they are more likely to be still open than a bug, if the same number of days pass. The reason could be that features take longer to develop and plan than bugs, which is consistent with the findings of Jarczky et. al. [16].

5 Collaboration pattern analysis

The focus of our analysis is how the collaboration network of FLOSS projects changes during their lifecycle. Moreover, we are also interested in the cause of the changes, rather than just observing the changes. Therefore we determined two types of events, that we want to observe in order to see the effects on the collaboration. The events during a project's lifecycle can be one of two types: regular or irregular event. Regular events repeat over time with roughly the same time passing between events. This can be a holiday season (e.g. summer holidays or at the end of the year) or regular software releases. In our research, we will focus on only the software releases, and we suggest the analysis of collaboration and seasonality as a future research topic. In contrast to releases, which are usually well documented and easily discoverable when exactly they were released, irregular events are harder to discover, as these do not necessarily stem from within the developer community, but from external sources. Examples could be a supporting company's organizational restructuring, the sudden increase of work from home during the COVID pandemic, or mass layoffs within the support team. In our analysis, we will mainly focus on layoff events, because of our expectation that this will have the largest effect on collaboration. Usually when a company develops an open-source software, the company relies on the external community of the project, but the core developers are mainly from the company. Therefore, when a company officially pulls out from further development, this results in the removal of most core developers in a short amount of time. Our main goal is to identify how this affects the collaboration network, how the network restructures itself, or if any restructuring occurs at all.

As a first step, we conduct a qualitative analysis on a number of hand-picked repositories to observe the network statistics in detail and to identify cause and effect relationships. In order to avoid bias when selecting repositories, we choose projects based on a variety of factors:

- *Project size:* We define the project's size as small, if it has less than 100 contributors, medium sized if the number of collaborators are between 100 and 500, and large if it has more than 500 collaborators.
- *Centralization:* Although it is hard ot measure how decentralized a project is, based on the literature review, very large projects tend to be decentralized. For now, we consider those projects centralized, which have been identified as centralized in the current state-of-the-art literature.
- *Event occurrences:* Whether there is a regular release cycle within the project or not based on the release dates, or if there are known and confirmed cases of unexpected layoff events.

Based on these criteria, we try to select a wide variety of projects, so that each type (small, medium or large size, centralized or decentralized, regular or irregular or abandoned projects) has at least one example. We acknowledge the fact that this inclusion criteria leaves room for selection bias, as an observed correlation between events and the network in one project might not hold true for all projects. However, later we confirm our hypotheses with a quantitative analysis.

5.1 Project selection and descriptions

All together we choose 8 projects to analyse, these can be seen in Table 3. Due to the repository miner's limitation, we are only considering projects maintained on GitHub. The `pandas` and `numpy` repositories are well-known and popular data science tools for data manipulation in Python. They are very similar in size and popularity, both with a huge base of collaborators.

Name	Contributors	Size	Commits	Stars	Issues	First release
pandas	2333	large	26792	29700	3518	Feb 20, 2011
numpy	1135	large	26392	17200	2030	Jan 5, 2002
networkx	469	medium	6470	9100	166	Jul 17, 2005
seaborn	140	medium	2780	8400	82	Oct 28, 2013
curl	701	medium	27159	20600	27	Mar 14, 2000
servo	1101	large	44084	19600	3305	May 22, 2017
wasmtime	243	medium	8334	5200	341	Oct 18, 2016
py-junos-eznc	69	small	2486	583	76	Nov 3, 2013

Table 3: Collaboration analysis projects and basic statistics.

Since also the number of issues are really high, our expectation is that these projects are highly decentralized, where the developers mainly work on their own parts of the project. They also have fairly regular release cycles, with a minor release in every 5-6 months.

`Networkx` and `seaborn` are both middle-sized repositories based on the number of contributors, and they are both used for data visualization and statistical analysis in Python-based software, but `networkx` visualizes networks and their related statistics, while `seaborn` creates various plot images. Each release date follows the previous with 4 to 10 months, which means their releases are not as regular as the first two repositories.

The project `curl` is an example for a highly centralized project, as its source code is famously maintained by a single developer [12]. Based on the number of contributors, it is a medium-sized project, although the number of commits are much higher than `networkx` or `seaborn`. Being the oldest project from the selection might contribute to the large number of commits.

`Servo` and `wasmtime` are both based on the Rust programming language, and they are both used for web applications: `Servo` is a browser engine, whereas `wasmtime` is a runtime environment for WebAssembly. Both projects were led by Mozilla and maintained in an open-source environment. The Rust developer team was heavily affected by the Mozilla layoffs on January 15$^{\text{th}}$, 2020 and August 11$^{\text{th}}$, 2020 [1, 20], with the second round of layoffs affecting all Rust employees. The `py-junos-eznc` project is considered small, since it has less than 100 contributors, and it is a Python-based library for automatizing devbices running on Juno OS. On May 27$^{\text{th}}$, 2020, the sponsoring company Juniper Networks laid off its entire open source developers [3]. These three projects will be the main focus of analysing unexpected, one-time events and layoffs, where we will take a close look at the network statistics around the mentioned dates.

To reliably compare the projects, we have to consider only a slice of each project, so all of them are compared within the same time period. We take a 3-year period from 2018 to the end of 2020. All projects had their first release before this period, which means this should filter out the initial irregular activities, such as creating directories and restructuring.

5.2 Commits analysis

For the selected period, we check the number of commits in each project as a first step. This can be seen on Figure 10. To smooth out the stacked area plot, we summed up the number of commits in every 28 days. Purposefully a multiple of 7 was chosen in order to even out the possible irregularities caused by the weekdays and weekends. We can see that all projects are active, with varying magnitude of commits generated each month. The number of commits are consistent with the size of the project, but we can also see that the number of contributors and the number of commits are not completely dependend on eachother, as `servo` consistently receives more commits than the other large repositories, despite the fact that it has the same number of contributors as `numpy` and half as many as `pandas`. Our assumption is, that this is highly dependent on the type of software being developed, the used programming language(s) and on other project-specific properties.

There is a noticeable decrease in the number of commits to `servo` at the time of the layoffs (August 2020), which signals that the project could have been affected. This cannot be observed for `wasmtime`. We do not see any evidence of reoccurring trends within the number of commits, e.g. decreased activity during holiday season. There is a reduction in all repositories at the end of 2018, but this is contradicted by a spike in the number of commits at the end of 2019. However, we cannot rule out any periodicity, because this could be hidden due to the 28-day aggregation.

5.3 Releases

As a next step, we take a look at the regular lifecycle events, which are the releases in the open source projects. We generate the collaboration networks for the same time period (between 2018 and 2020) and contrast them with the time of releases.

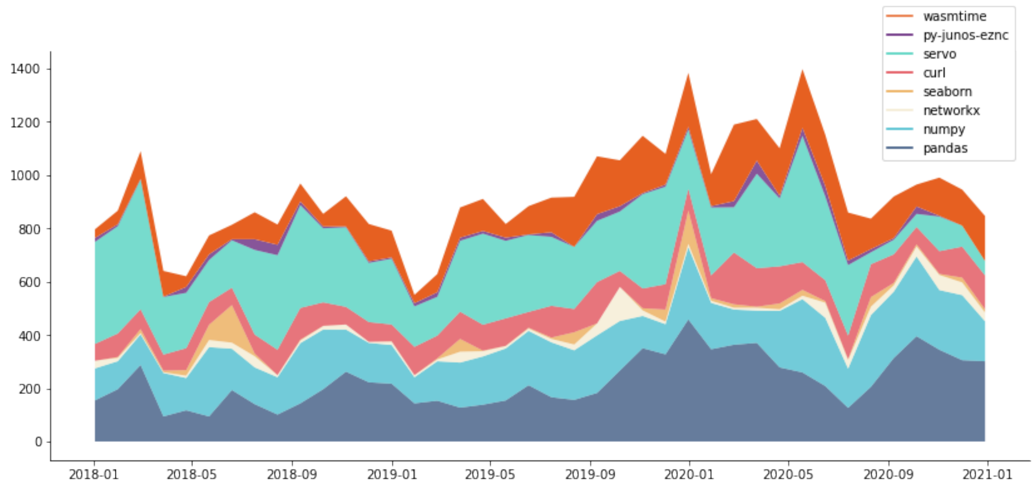


Figure 10: Number of commits in each month.

The issue with generating the collaboration network is the time aspect: we cannot observe any collaboration network if we take a single point in time and create the network for a given timestamp, as this will only contain a handful of connections, who authored an edit in the same file at the exact same time. Therefore, we need to aggregate the edits and commits over time, which requires us to use a time window to scan through the observed time period, and for each step, we generate a snapshot of the network. The first parameter is the time window length and the second is the step size. By choosing a large time window, we observe more connetion within the generated graph, but with a too large value, the network becomes too much grouped together, with almost every node connecting to almost all other nodes. By setting this value too low, the result is a disconnected network. The step size determines how often we take a screenshot of the network for the time window. By default, we use one-day steps, but sometimes this results in too radical changes. Therefore in some cases we use a 7-day or a 28-day step value to smooth out the curves. However, a too high step value can obscure the changes we want to observe.

5.3.1 Node counts

First we take a look at the number of developers in the network over time. The number of nodes (i.e. developers) in the network indicates the level of activity within the project, where a relatively high number of nodes imply a peak in project activity, and a low number can imply a decreasing activity,

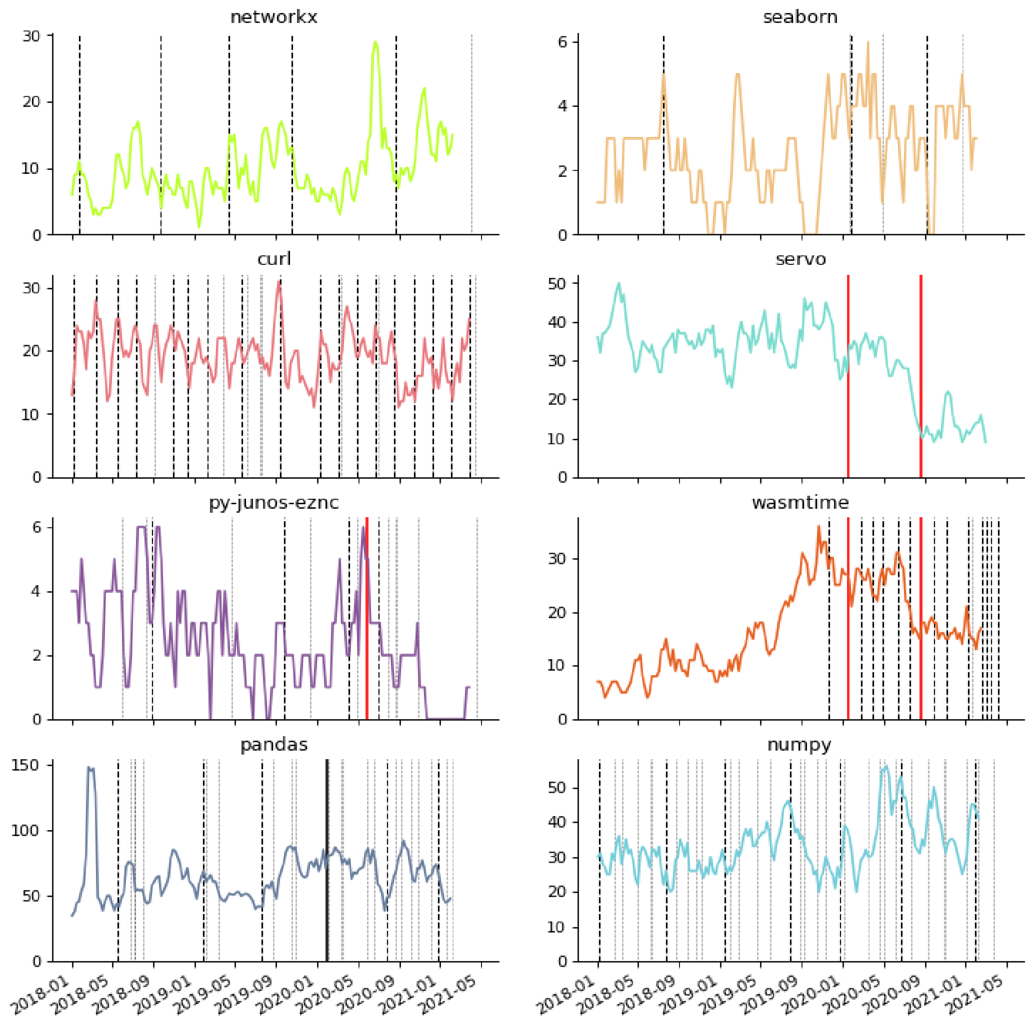


Figure 11: Number of nodes over time.

or that the project has become more centralised. It is easy to see, that if the only source of activity is one single developer over the observed period, then the network will only have one node, whereas if the same activities are distributed, more developers will be shown in the network, and the number of nodes will rise. However, this does not describe the relationship between developers, they could be completely isolated, or they could be relying a lot on eachother regarding collaboration.

In Figure 11 the number of nodes are plotted with the time of releases marked with a vertical black line for each project. The type of release corresponds to the type of line: major releases are shown with a continuous line, minor releases are thick dashed lines, and patch releases are thin dotted lines. The red continuous lines mark an unexpected layoff event, which might had an effect on the project. Each node count data point at t time represents the number of nodes within the collaboration network that is generated between t and $t+28$ days, with a 7-day step size. The average node counts correlate with the size of the project, as the smaller repositories like `py-junos-eznc` and `seaborn` have the number of nodes consistently below 10, while the larger projects can reach 30, 50 or even 100 at certain time periods.

Regarding the releases, we can see that each project can have completely different release planning and schedule, which makes it hard to compare them. Some projects, like `networkx`, `pandas` or `numpy` release a minor version in approximately every 6 months, while `curl` does the same in every 2 months. `wasmtime`'s release schedule regaring minor releases is even shorter, but we do not have any data available before 2020, which does not allow us to confirm whether this is a long-term trend. The release data for `servo` was available to us, however, the repository has a very high frequency of releases, with sometimes multiple minor releases in the same week, and displaying this information on the chart would have obscured the number of nodes plot, therefore we only display the unexpected events. Also, releases can be arbitrarily named by the developers, therefore a minor release in one project might be considered a patch or a major release in others.

Comparing the events with the number of nodes, we can observe, that before or around a minor release, most projects experience an uptick in node count, which is then usually followed by a drop - although not in every case. This can be contributed to the increased activity from the community before the release. There could be a number of factors that cause this activity change: first, if the release date is fixed, the pressure on developers to include the planned features increases, which prompts more activity (pull model). Secondly, the rise in activity could be a newly implemented feature or a recently found bug, which needs immediate attention from developers. In this case it is possible, that the increased activity and larger volume of edits prompts a new release version (push model). Our assumption regarding whether a release follows a push or a pull model is that it can be highly dependent on the project, and within each project there could be a mixture of releases following both models. We cannot observe this trend for the patch releases, and we cannot draw a definitive conclusin regarding major releases, as there was only one major release among all the repositories subject to our analysis.

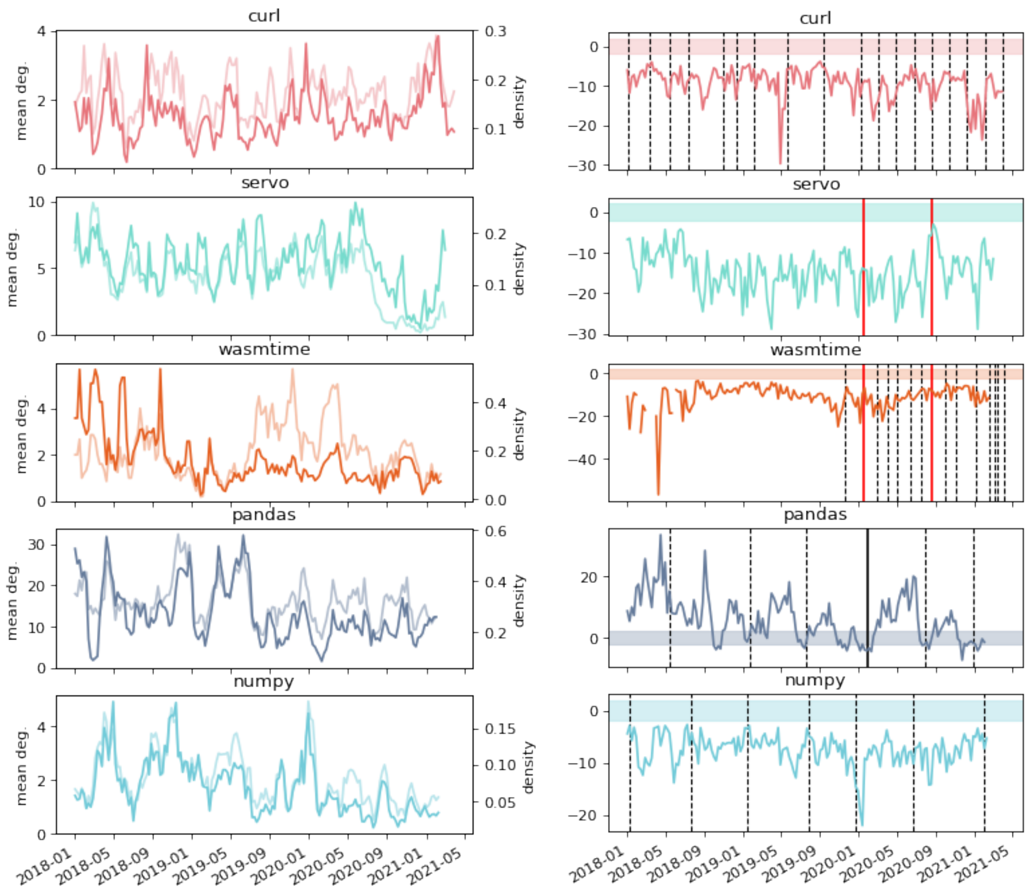
Regarding the layoff events marked with red vertical lines, a significan drop in the number of nodes can be observed shortly before the event in all projects. After the companies stop supporting the project and lay off the development team or they are reassigned to other topics, the number of nodes within the projects drop and stay low, never reaching the same numbers as before. In case of `servo` and `wasmtime`, the first wave of layoffs do not seem to have a significant impact on the number of nodes, however, we do not have reliable information regarding how much the Rust development team was impacted by the first wave, on which both projects depend.

5.3.2 Network density and mean degree

As a next step, we plot the network density and mean degrees of the projects. The network density tells us how densely connected is the network in a scale of $[0, 1]$, where 1 means every node is connected to all other nodes, and 0 means there are no edges in the graph. It refers to the ratio between all the possible connections and the actual connections. Although the generated networks are weighted, we do not consider the edge weight when counting each node's degree, meaning every connection is counted. We expect this value to rise if developers need to reach out to more members of the community and collaborate on more files with others. Similarly to the density, the mean degree value also only takes the number of nodes (N) and the degree number (k) of each node as inputs, so we expect similar results between the two measures.

By plotting the two measures on the same figure in Figure 12a, we can confirm, that they are closely correlated. The values are also highly sensitive regarding the number of nudes within the graph, and a low node count makes the graph values change radically. This is why the smaller projects are not shown, as their graph did not convey any meaningful observations. We can identify some troughs at the release times of minor releases, however, these could also be the results of the changes in the number of nodes.

In order to adjust the network statistics for their sizes, we compare the network with a randomly generated, same-sized network. If we see a significant difference between the two values, we can confidently state that the changes we observe in the network statistics are independent from the network size. To measure the significance, we calculate the *Z-value* of the actual network statistic and a 'general' network of the same size. In our implementation, we randomly generate 10 networks with the same number of edges



(a) Density (dark) and mean degree (light). (b) Z-values for density and releases.

Figure 12: Network density, mean degree and Z-values over time with significance threshold highlighted.

and nodes as the original network, and use them to calculate the Z-value. The Z-value's formula is:

$$Z = \frac{x - \mu}{\sigma}$$

where x is the actual value we are comparing (in this case the network density), μ is the average network density of the randomly generated networks, and σ is the standard deviation of the random graphs. We consider a network significantly different than a random network if its Z-value is greater than 2 in absolute terms. When the Z-value of network density is lower than -2, the network has a lower density than a same-sized general network, meaning the edges are more dispersed. Similarly, a Z-value greater than 2 signals that the graph has more central hubs than the random network.

We plot the Z-values over time in Figure 12b, where the area between -2 and 2 are colored to show at which times the network is significantly different than a randomly generated one: when the plot line is within this range, it is not significantly different, otherwise it is. In some cases, there is a break of continuity within the plot. This occurs, when the standard deviation of the randomly generated network is 0, which would result in a zero-division error. The standard deviation can only be 0 when all the values are the same, which means in these cases our randomly generated networks have exactly the same density. This usually happens in extreme cases, when there is a very low number of nodes or edges.

Almost all projects have a significantly low network density, meaning that the edges are more distributed between the nodes. The notable exception is the `pandas` repository, which has an overall positive Z-value over time, with sometimes crossing the insignificant zone. These points are mostly troughs at the time of minor releases. We can also see on all projects, that around a release, the Z-value approaches (or crosses) the threshold, which signals that the networks behave more like random networks around releases. The same can be observed for the layoff events, as `servo` gets really close to -2 at the time of the announcement.

5.3.3 Clustering coefficient

The weighted global clustering coefficients explained in Section 4.5.3 is plotted over time in Figure 13. Because it would be difficult to show both the Z-values and the the clustering coefficients on the same graph for each project,

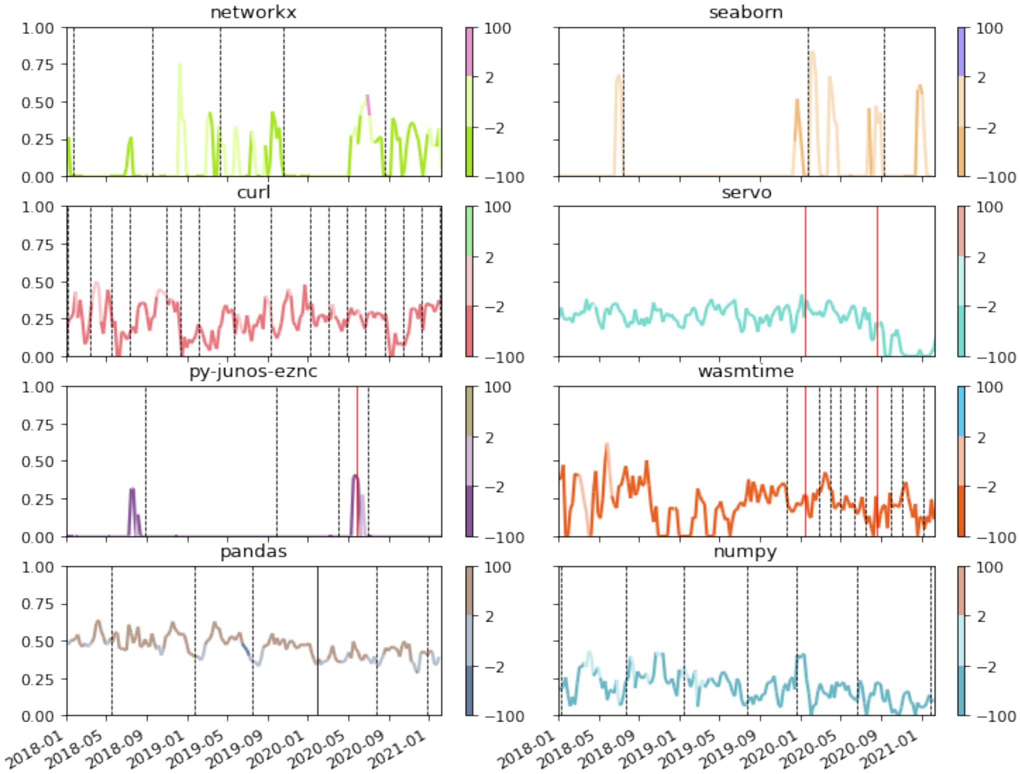


Figure 13: Clustering coefficients over time.

we change the color of the line to indicate the statistical significance. Where the clustering coefficient is significantly different from a random network to the negative side (meaning the Z-value at the corresponding date is less than -2) the line uses the project's dark shaded color. Likewise, when there is a significant difference and the Z-value is over 2, the dark complementer color is used. Within the range of $[-2, 2]$ a light color is used to signal the statistical indifference from a random network of the same size. The color label also indicates the associated Z-value within each subgraph.

We receive mixed results for the clustering coefficients. The smaller libraries (`networkx`, `seaborn` and `curl`) show a sudden spike before a release, which means that the network gets clustered before a release. However, the Z-value is always showing a negative sign being less than -2 in these cases (with the notable exception of `pandas`, which is mainly above 2), signaling that the increase in clustering coefficient is significanly less than a same-sized random network. This shows, that the spike and then a drop in the clustering coefficient before a release is caused by a sudden increase and then decrease of activity within the project, but this activity is decentralized and affects all developers roughly the same. One of the reasons is the more decentralized workflow: as Crowston et. al. [12] have identified, smaller projects early in their lifecycles tend to be more centralized, as there is less specialization to only one area of the project.

Interestingly, almost all of the larger projects have consistently lower clustering coefficient than of a random network, which indicates, that there is a significant overlap of the edited files within the projects, and there is less specialization. Another explanation could also be the use of shared files, which relates to the project structure. If an implementation of a new feature requires developers to edit almost all existing files by adding new functions, then the clustering coefficient will be low. On the other hand, if every new feature requires a new file to be added, developers will be mostly isoated in the collaboration network around the files, which will show up as a higher clustering coefficient than in a random network. This would explain why the `pandas` library has consistently a positive Z-value: the project structure does not require contributors to edit eachother's files. Additionally, we can observe a drop in the clustering around releases, but without statistical significance. This also confirms, that the network becomes more random-like around releases, but we can further extrapolate that a likely factor to this phenomenon is the feature integration: between releases, contributors center around their specialization editing only a limited number of isolated files, but before the release, the effort shifts towards integrating these features together, which requires editing files outside of the 'usual folder'.

5.3.4 Mean path length

Another measure that could be affected by a releaase is the length between nodes in the network. From an organizational perspective, a path between two contributors represent the information flow regarding a specific part of the project. If in a network every vertex tends to be close to the other nodes, meaning less jumps are required, then they are able to gather information about a specific part of the project quicker. Smaller projects with less contributors naturally have relativel short connections to all other developers, and as the software gets larger with more contributors, the average shortest path between nodes is expected to get longer. However, if the project structure maintains central connecting 'hubs' (in this case: developers), the growth in length can remain lower.

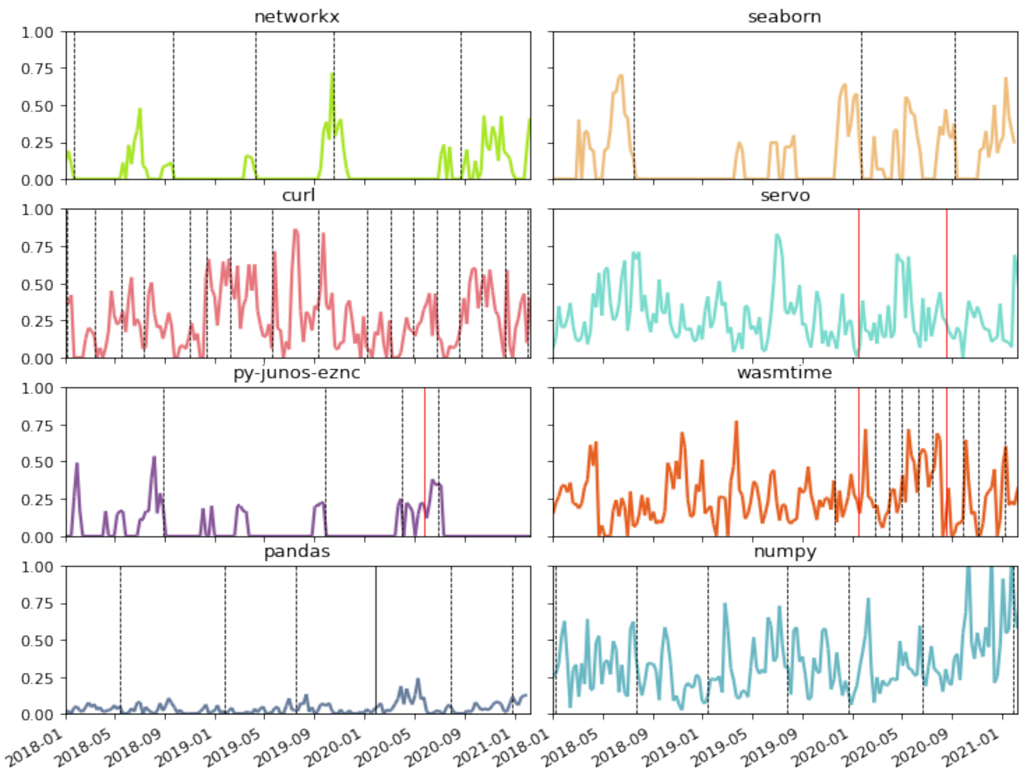


Figure 14: Mean longest path length over time with statistical significance.

In an undirected unweighted graph, the shortest path between two nodes is the least amount of edges needed to be touched in order to get from one node to the other. However, our collaboration network is a weighted undirected graph, where the edge weights represent the collaboration effort between two developers. A strong collaboration is represented as a higher edge weight, whereas a lower edge weight means there is less collaboration between the two contributors. The shortest path between two nodes in a weighted graph is the path, which has the least summed weight of the edges touched. In our case, we want to measure how far away each developer are from all the others in order to quantify the effort for reaching out to eachother in case they want to involve a specific community member. To select the closest connection, we need to look for the strongest connection, meaning we have to consider the longest path between nodes.

We calculate the average longest path P by first summing up all the longest paths from a given node to all other nodes, then dividing by the number of connections, which is $n-1$ in a connected graph. Then we sum up all of these averages for all nodes, and divide by the number of nodes n:

$$P = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} - w_{ij} + 1}{n(n-1)}$$

where w_{ij} is the edge weight between a_i and a_j in range $[0, 1]$. We multiply the weights by -1 and add 1 in order to calculate for the longest, and not the shortest path.

It is clearly visible in the smaller projects (`networkx`, `py-junos-eznc`, `seaborn`), that the path length increases before a release due to the increased activity, and otherwise it stays 0. This indicates a 'push-type' release process, where the releases are sporadic, and a new release is created to incorporate and deploy the changes implemented. With the other projects, we do not see any correlation between releases and mean path length.

...

5.3.5 Core and periphery analysis

5.3.6 Release regularity

- time window
- network stats plots (with major-minor-patch)
- results (e.g. degree centrality, clustering coeff, hierarchy) for each project

5.4 External events

5.5 Observed projects and events

5.6 SNA metrics analysis

5.6.1 K-cores

Besides taking the 20th percentile of the top clustering coefficients to identify the number of core developers in the network, we .... [8]

5.7 Results

6 Quantitative analysis of projects during crunch time

6.1 Collaboration network changes

6.2 Prediction of outcome based on collaboration changes

7 Discussion and results

8 Conclusion and future work

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Appendices

A Connected components

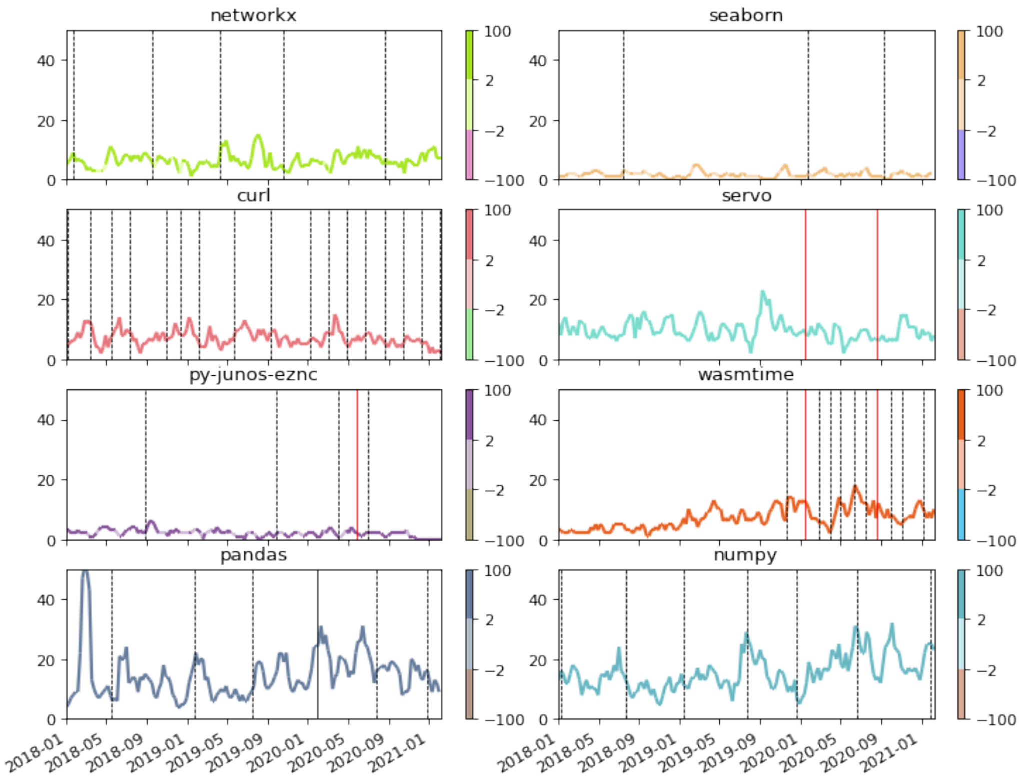

Figure 15: Connected components