Library Adoption Dynamics in Software Teams

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Abstract—When a group of people strives to understand new information, struggle ensues as various ideas compete for attention. Steep learning curves are surmounted as teams learn together. To understand how these team dynamics play out in software development, we explore Git logs, which provide a complete change history of software repositories. In these repositories, we observe code additions, which represent successfully implemented ideas, and code deletions, which represent ideas that have failed or been superseded. By examining the patterns between these commit types, we can begin to understand how teams adopt new information. We specifically study what happens after a software library is adopted by a project, i.e., when a library is used for the first time in the project. We find that a variety of factors, including team size, library popularity, and prevalence on Stack Overflow are associated with how quickly teams learn and successfully adopt new software libraries.

I. INTRODUCTION

The process of learning new information and adopting new technology can be challenging. When new information is acquired, a learning curve often exists until an individual or group becomes proficient in the new technology. These challenges are present throughout society but are especially prevalent in computing and software development, where existing technologies are ever-changing and new innovations are constantly being developed. Further complicating these issues, most major software development occurs in teams where multiple parties collaborate on a project together, and where teammates may or may not know each other. This can lead to teammates having communication issues, which could result in teams which are inefficient and uncooperative. Online collaboration systems like GitHub have provided a powerful setting in which to study this process, because through analyzing the history of commits, whether removed, added, or otherwise, we can reconstruct a story of what happened between the teammates to eventually create the finalized code. By retelling this story, we can further investigate the struggles that occurred as the teammates tried to learn new information together, and see how long it takes for a team to become totally proficient at working together using the same technology.

The present work introduces a new approach to study this problem. By investigating how software developers adopt and use software libraries in this specific context, we may better understand how humans learn new technical information and incorporate concepts previously unknown to the user or group. The findings from this study can be generalized to understand how humans work, learn, and fight together, since GitHub provides a rich dataset which approximates the collaborative process.

Previous work by Kula et al found that programmers adopt new libraries only when they can be assured of the library’s quality and functional correctness [1]. But what happens after the adoption event? When are other group member receptive to new libraries; and when do they resist? What tools can help a team find and learn how to use new libraries? How long does it take a group of people to be successful at learning new information together? And finally, what does it even mean for that group to be successful?

To answer these and other questions, we explore the circumstances surrounding a library adoption, including the number of commits, the size of commits (measured by lines of code), and other related information, including availability of online resources, such as Stack Overflow. We present an in-depth look at commit addition and deletions, and analyze these questions from a variety of different angles.

Additionally, we ask if there exists any competition among team members over the inclusion of a library. When teammates have disagreements about what should be included in a GitHub project, there will ultimately be a winner. Uncovering which user eventually wins these code fights is an interesting research question. We explore competition by examining code fights where two users revert each others code over the course of several commits. Like edit-wars on Wikipedia [2], by looking at the users and libraries that participate in code fights we can learn a great deal about the adoption and diffusion of information. Although the present work focuses specifically on code contributed to public Python projects hosted on GitHub, we hope that other domains can use the methodology of the present work in other explorations of information adoption generally.

In addition to competition, we also aim to find the characteristics of fast adoption. It is preferable to have a short adoption period - in that way, teams can become productive more quickly, since a longer adoption time results in periods of lost production. By finding what combinations of repositories and libraries result in quick adoption times, we can begin to understand how team members work together to learn new information. Therefore, we hope to identify the qualities that create a good team, and what the characteristics of a bad team are. We hope that the findings from our research can be applied to help improve team dynamics and create groups that can work well together.

To summarize, this work aims to answer the following research questions:

What are the events that happen when a team adopts a library for the first time? Learning new information together can be challenging. As a team strives to use a new library together efficiently and correctly, it is one of the aims of this work to uncover the events that happen as the group learns,
and what causes groups to work together well (or poorly!). In the data, we hope to find when library adoptions are successful - and what leads team members to abandon library adoptions as they decide to use other libraries instead.

Are commits containing new libraries more likely to have deletions than other types of commits? One of our research questions is to understand how teams learn to use these new libraries. We expect to find that as teams struggle to use new libraries, commits that contain new libraries will contain many deletions as users attempt to understand how the library works. Eventually, as team members become proficient in using a library, and the library becomes established in a project, we expect to see that there will be less deletions in the project repository code relative to when the library was first adopted. This ratio of positive to negative commits will help us define what it means for a library to be adopted.

Do the answers to these questions vary by library type, team size, or the amount of information available on Stack Overflow? Not all libraries and teams are alike, and we expect to find that as the type of the teams and the libraries change, so will the adoption time. Therefore, we will analyze library adoptions along the axes of team size and library type, and discover the relationship between adoption speeds and resources available on places like StackOverflow. We attempt to show how the speed of library adoptions changes with the addition of easy to use online resources, which we use as a proxy to represent library popularity. We hypothesize that if there exist few resources to learn how to use a library, the time to adoption for that library will be longer than for those libraries that are more well documented.

Do team members fight over the adoption and usage of a new library? We cannot assume that all teams work together well. Fights between team members might result as teammates have differing opinions about what libraries to use or how to implement new code. Therefore, we analyze code fights as part of this work. We wish to uncover what happens in teams when teammates remove code, or remove entire libraries. We examine which libraries are most often fought over, and which team members end up winning code fights. We hypothesize that more experienced team members will win these code fights.

To answer these questions we cloned 259,613 repositories from Github. This data provides us entire commit histories with userids, timestamps and code-diffs across all of the projects. We also downloaded, indexed, and cross-referenced library usage within Stack Overflow. Library adoption in software repositories reveals a natural experiment from which causal relationships between inferred. By following a careful extraction and experimental methodology, the following pages presents answers to these questions and an exploration of this rich resource.

II. DATA AND METHODOLOGY

Characteristics of GitHub.

Since GitHub’s rise to popularity and the growth of the open source software movement, developers have become increasingly comfortable contributing to public repositories [3].

Riding this wave of easily accessible data, researchers have done considerable investigation into GitHub, but many of these studies are limited to a few dozen project repositories in small-scale experiments, thereby limiting their potential generalizability [4]. Instead, our goal is to gather as much data as possible, which, as we shall see, presents different challenges. We summarize our findings from this large-scale collection of data in the subsequent sections of this paper. As future work, further, more specific analysis can be done on smaller datasets, but for the purposes of our research, we wish to treat this work as a big data problem, and try to ingest as much data as possible to answer these questions.

Project Repositories on GitHub

The confluence of GitHub’s online social system and Git’s complete history of pull and commit behavior provides an unprecedented source of information on adoption behavior [5]. We focus on commits that contain imported libraries and their functions. The example code snippet in Fig. 1 shows how a single commit can add and/or remove one or more lines of code. In this example, the 5 additions and 2 deletions result in a net commit size of +3 lines, including the adoption of numpy. We consider usages of libraries \( \ell \) (e.g., numpy, pandas, math) that are imported into Python code through an import statement. An important assumption that we make is that submodule import statements represent the parent library. Therefore, submodules like numpy.random are considered equivalent to numpy in the present work, because the function is included as a part of the parent numpy library, and we are interested in functions which refer to the imported library.

We also consider direct function calls on the imported library. It is important to carefully consider the “scoping” of library aliases (e.g., np, pd, r in Fig. 1) so that we can mine these library functions accurately. Thankfully, the library aliases are included in the import statement, so we can easily find these aliases in the code. In the above example, the functions from the numpy library (linspace and digitize) are referenced in two of the added lines.

Indirect library usage is exemplified by the groupby function of the df object and by the mean function of the groups object in Fig. 1. These objects were created from the same ancestor call to the pandas library (e.g., df = pd.DataFrame(x)) in some other location, but do not directly reference the pandas library themselves. We do not consider indirect library usage in the present work, and only focus on direct library calls.

Data Collection

1+ import numpy as np
2+ from numpy import random as rnd
3+ import math
4+ import pandas as pd
5+ def print_groups(df):
6+ print("function not implemented")
7+ bins = np.linspace(df.a.min(), df.a.max(), 10)
8+ groups = df.groupby(np.digitize(df.a, bins))
9+ print(groups.mean())
First, we issued a query to the GitHub search API for projects written primarily in Python. GitHub returned repository IDs of the 1,000 most popular Python projects on the site. We then found all GitHub users who made at least one commit to a repository in this set and retrieved all their Python projects. We did this breadth-first style crawling two additional times, culminating in 259,923 projects with 89,311 contributing GitHub users.

Of these, we were able to clone 259,613 Python repositories to disk; the remainder were made private or deleted between the time we crawled their project URL and the time that we performed the clone operation. Each cloned repository includes all files, branches, and versions, along with a complete edit history. These repositories constitute about 13% of all Python repositories on GitHub as of September 2018. The full dataset of cloned projects occupies about 8 TB of disk space. For analysis, we parsed the commits to only contain imported functions and libraries, which drastically reduced the size of the dataset.

Because we sampled 13% of the total available public Python projects available on GitHub, it is important to be wary of sampling biases. Our initial GitHub query returned the most popular projects, so our dataset may over-represent highly active repositories compared to the population. It is not our intention to faithfully survey GitHub use nor to represent all Python projects; instead, our goal is to understand how programmers adopt and use new software libraries. Our findings can be applied to projects of all sizes, and small projects are well-represented in our data. However, it is important to remember that private software repositories are not included in our dataset, so we can only investigate team interactions in a public environment.

Additionally, we downloaded all question posts from Stack Overflow from its inception until September 2018. Appropriate tagging tends to increase viewership of questions [7], so we filtered out any posts that were not tagged as Python posts, then extracted all libraries from any code block using the same pattern matching technique as used in the library extraction from Python projects. Only top-level libraries were included. Because Stack Overflow is a free-form text entry platform, this pattern matching procedure may occasionally count extraneous words and misspellings as libraries. Additionally, it is possible that some libraries might not be returned by our query because the library name might have been misspelled, or the question did not include Python code containing a library import.

Recreating the Project Workflow

Each project repository contains files, commits, and users. Each commit is marked with a timestamp \( t \), a message, one (or many) parent-commits (in the event of a merge operation), and a \texttt{diff} specifying lines that were added, edited, or deleted within each file.

An important complication that arises in Git commit histories is that stashes, reverts, branches, and other Git commands can result in a non-monotonic chronology of edits. Because of this, we should not compare commits across different branches to each other until they are merged. Reversions introduce an additional complication. For example, if a user (1) commits code on Monday, (2) commits some new code on Wednesday, and then (3) on Friday reverts the project’s code to Monday’s commit, then the chronology of the repository flows non-monotonically from Monday to Wednesday to Monday again despite the reversion being made on Friday.

Fortunately, each commit keeps a pointer to its parent(s), so we can create the actual lineage of the commits by following the graph of each commit’s parent rather than blindly following the commit timestamps. Because the order of actions is more important than exact times, we enforce a monotonic chronology according to the commit graph. Future work can attempt to explore how this problem can be approached by using timestamps to analyze how the project changes over time.

Text Mining for Libraries

After downloading the data, we combed through each Git commit log to find which libraries had been imported by using Regex pattern matching to identify import statements, such as ‘from \( \ell \) import \( f \)” and ‘import \( \ell \) as \( f \)”. Once we identified which libraries were used in a Git project, we searched the log to find the lines which referenced the functions contained in a library import. To do this, we used pattern matching to search for the libraries \( \ell \) and functions \( f \), along with indicators such as \texttt{.} and \texttt{,} to indicate that the library or function was being used. We gathered the author name, and then stored all this information, including library used, author name, and commit type, in a database for further analysis. This parsing of the data allowed us to perform a relatively quick analysis on a smaller dataset than the entire commit log.

III. LIBRARY ADOPTION

Formally, for a project \( p \), a library \( \ell \), and a time \( t \), we define a library adoption to be an event \((p, \ell, t)\) representing the first time \( t \) that \( \ell \) is found in \( p \).

Some project repositories are simple, containing only a single commit, while others are extremely complex with multiple branches, hundreds of users, and thousands of commits. In 2014, Kalliamvakou et al. found that the median number of commits per project on a small sample of GitHub projects was 6, and 90 percent of projects had less than 50 commits [5]. Our dataset shows a slightly larger distribution of commits, though as mentioned earlier, it is possible that our GitHub data is over-represented by active projects. The distribution of commit-activity per project, illustrated in Fig. 2a, resembles a shifted power law distribution. Because of this dynamic, 50% of projects were found to have 10 or fewer commits \((i.e., \text{median of} \ 10)\) and 90% of projects have 100 or fewer commits.

The distribution of the number of libraries adopted per project, illustrated in Fig. 2b, also resembles a shifted power law distribution, albeit with a larger offset than the commit-activity distribution of Fig. 2a. However, the number of adoptions is less evenly distributed: 54% of projects adopted 10 or fewer distinct libraries and 98% of projects adopted 100 or fewer libraries.

Across all commits of all projects, we find that library adoptions occur more frequently within the first few commits.
Figure 2c shows that a project’s first commit adopts 6.4 libraries on average (with a median of 2 not illustrated). A project’s second through fifth commits adopt 3.3, 1.1, 0.8, and 0.65 libraries on average (with median values of 0 not illustrated). In general, the average number of adoptions per commit appears to follow a Zipfian decay, and commits tend to occur early in a project repository history.

Table I shows there is a wide gap between the average LOC and median lines of code that represent a library \( \ell \), indicating skew caused by large commits. This matches with our analysis which showed earlier than many of the statistics surrounding commits follow a power law distribution. Additionally, average LOC drops quickly after the first commit. Fig. 3 shows the average direct use of an adopted library in lines added and deleted (in green and red respectively) as well as the net change, i.e., insertions minus deletions (in black).

After the initial commit, we find that most of the following commits have only a small positive net productivity. We also find that the volume of activity of lines of code referencing \( \ell \) in Fig. 2c tends towards zero rather quickly after the adoption. This indicates that, on average, the activity surrounding the adoption of a library is brief and oftentimes contradicted quickly. Recall from Fig. 2c that most repositories only adopt a few libraries, with more than half adopting 10 or fewer libraries. Therefore, we can safely deduce that in most repositories, when adoptions occur, they occur early in a repository’s history.

Table I: Statistics surrounding newly adopted library \( \ell \)

| Statistic                                      | Value |
|-----------------------------------------------|-------|
| Avg LOC that reference \( \ell \)             | 31.34 |
| Median LOC that reference \( \ell \)          | 4     |
| Avg insert LOC after 1st adoption to ref \( \ell \) | 2.09  |
| Avg deleted LOC after 1st adoption to ref \( \ell \) | 1.62  |

Stack Overflow

The popularity of software-centric question-and-answer Web sites has spread rapidly. Stack Overflow was created in 2008 [8], which is the same year that GitHub was launched [9]. Because these resources have grown in popularity together, we expect that they have influenced each other in some way. Much of the previous work in this area has focused on understanding user behaviors across Stack Overflow and GitHub [10], [11], modelling user interest [12], or mining for code that users have imported from Stack Overflow posts...
Exemplar libraries are called out in Fig. 4. For example, the standard libraries optparse, json, and os indicate some of the most widely used libraries on GitHub. The sphinx, scrapy, and pandas libraries represent three libraries found on PyPi. The sphinx library is used to create source code documentation files; it is relatively popular on GitHub but has only a few dozen posts on Stack Overflow. This seems to indicate that users have few questions about this library relative to its use (perhaps the library that produces source code documentation is well-documented!). Conversely, the scrapy library, which is used to crawl the Web, and the pandas library, which is used for data analysis, have many questions, potentially indicating that the library is complicated to use. Despite being rather popular on Stack Overflow and GitHub, the contrib “library” is not found in the standard Python libraries nor PyPi. This is a bit of a misnomer because the use of a “contrib” folder/module is a standard way to encourage open source developers to contribute to various projects. As a result, the contrib module is indicated as a common library simply because of its use as a naming convention in many distinct projects, so we see that it is mentioned quite frequently on Stack Overflow as a “local” library, but the functions defined in local “contrib” libraries across GitHub would yield very different functions since each user is writing their own “contrib” library for different purposes.

Our next task is to understand what differences, if any, exist in the net productivity of these various libraries. To help understand the dynamics of library adoption, we calculate the median percentage growth (in LOC) of an adopted library, i.e., the change in the number of added lines containing $\ell$ in a commit minus the number of deleted lines containing $\ell$ in a commit for the first 100 commits after the adoption. This provides us with a simple way to compare growth across teams which are different sizes.

Formally, we compute the growth of a library $\ell$ within a project as follows. If $x = 0$, then let $y_x = 1$; otherwise

$$y_x = y_{x-1} \left( \frac{\sum_{i=0}^{x-1} (n_i) + n_x}{\sum_{i=0}^{x-1} (n_i)} \right),$$

where $n_i$ is the number of changed lines of code (net additions into GitHub projects [13]. In other cases, researchers aim to leverage posts and their answers in order to build tools that aid software development [14], [15]. Further research needs to be done to understand data flows from Stack Overflow to GitHub, and vice-versa.

We plot the number of users of $\ell$ by the mean average number of Stack Overflow posts (across all adoption times) in Fig. 4 that existed when $\ell$ was referenced. This illustration also groups libraries that are (1) included in PyPi, the default library repository used by the pip installer, (2) part of Python’s standard suite of libraries, e.g., os, json, time, and (3) all other libraries. We observe a strong positive correlation between the number of library users and the number of Stack Overflow mentions for standard libraries ($R^2=0.625$, $p<0.001$) and PyPi libraries ($R^2=0.410$, $p<0.001$). There is a small positive correlation between usage of unknown libraries and Stack Overflow posts ($R^2=0.08$, $p<0.001$), most likely due to individuals naming libraries like words and phrases that also happen to appear on Stack Overflow, or perhaps users sharing GitHub repositories that have not made it to PyPi.

Exemplar libraries are called out in Fig. 4.
minus deletions) in commit \( i \) that contain \( \ell \). From this equation \( y_x \) contains the percentage change at commit \( x \) relative to the adoption event (\( x = 0 \)).

Consider as an example the following series of commits \( n = [+2, +1, +4, -1] \). Here, the adoption commit (\( x = 0 \)) introduces two lines of code that reference \( \ell \). We set \( y_0 = 1 \). The next commit contains a net change of +1, rendering \( y_1 = 1(2 + 1)/2 = 1.5 \). In other words, in the second commit the number of lines of code referencing \( \ell \) within this example project grew such that it is now 150% of its original size. The next commit contains a net change of +3, rendering \( y_2 = 1.5((3 + 4)/3) = 3.5 \) indicating that after the third commit the use of \( \ell \) within this example project grew to be 350% of its size over the initial commit, i.e., from 2 lines to 7. The final commit contains a net change of -1, rendering \( y_3 = 3.5((7−1)/7) = 3 \). This normalization of median growth rate helps us compare larger teams to smaller ones.

We plot the median growth (in LOC referencing \( \ell \)) as a function of the number of commits after the adoption in Fig. 5. Note that the adoption commit is not shown; instead, each commit either net-adds or net-subtracts from the initial adoption. Columns represent four groups of Stack Overflow mention sizes: no mention, between 1 and 100, 100 and 1000, and greater than 1000 from left to right respectively. Within each plot, solid lines represent the median, and the dashed lines on top and bottom represent the 3rd and 1st quartiles respectively.

We observe that the use of an adopted library has a complicated relationship with its popularity on Stack Overflow. The primary distinction is in the growth rates for libraries with more than 1000 Stack Overflow posts. 100 commits after the adoption, the adoption of a highly mentioned library on Stack Overflow will have approximately 350% growth (on average) compared to only 250% growth for less mentioned libraries. We can assume that having over 1000 Stack Overflow posts means that the library is highly successful, and highly popular. Over time, it might be easier for users to find new resources about the library online - and add more functionality as the library becomes fully integrated into the project.

When a library does not appear on Stack Overflow, the growth rate is similar to libraries that have over 1000 posts. Libraries that do not appear at all in Stack Overflow mostly consist of libraries that were written by developers who are also the authors committing the library to the repository. This may explain why growth is large in unknown libraries - the adopters know how to use the library because they wrote it. We could also propose that programmers who are using libraries for which there are no online resources available might be more experienced than those that are using more popular libraries, so their growth rate is faster.

**Project Team Size**

Next, we investigate differences in library adoptions as a function of team size. Because library adoptions occur from the perspective of a project, studying how various team sizes adopt libraries is important as we attempt to understand how teams form and work together. Researchers have studied GitHub previously for its team formation attributes. Git and GitHub directly store how team members collaborate and the types of activities that they perform [16]. For example, researchers have found that diversity and team makeup have a significant impact on the productivity of GitHub teams [17], and larger teams tend to process more pull requests on average [18].

We calculate a project’s team size by counting the number of distinct commiters. We observe in Fig. 6 that the distribution of team sizes has a power law-like heavy tail wherein 59% of projects have only a single committer; 24% and 7% of projects have two and three distinct committers respectively. Projects with small teams therefore dominate the GitHub community.
For the 59% of projects with a single committer, we do not have to even consider the team dynamics when a library adoption occurs, because only one individual is adopting a new library for use in the project.

Like in the Stack Overflow analysis, we calculate the median growth over the first 100 commits after a library adoption for various team sizes, which we can see in Figure 7.

We see that smaller teams add more lines of code after the first adoption event than larger teams. A possible explanation for the slower growth of library usage in larger teams is because of perspective differences between two or more committers to a project. Users might feel more comfortable making more commits or experimenting with newly adopted libraries in smaller teams, or if they are working alone, because there are fewer team members to consult before a commit is made - and also a greater need to ensure that all team members understand the purpose of the commit. Also, more communication might be necessary between team members before large commits are made, which would appear to cause slower growth rates for bigger teams. It is possible that in larger teams, the first adoption event is more substantial - and then grow more slowly afterwards.

V. CODE FIGHTS

Fights between committers to a project occur whenever there is a disagreement about how others should structure code, how they should implement features, or any other decision impacting code production. We use this analysis of code fight to understand who wins these arguments by tracking who eventually commits code which eventually stays in the project - or is ultimately removed. Researchers have long analyzed the diffusion and change of information and conventions including work on the adoption of word use in offline textbooks [19], on Twitter [20], and other domains. The experience of the individuals in the group also plays a key role in what ideas are adopted offline [21] and in online social systems [22].

For example, Sumi et al describe edit wars on Wikipedia where two or more Wikipedia editors constantly edit each other’s changes to some article [23]. Investigators have found fights in collaborative science writing where researchers often use and adapt various \LaTeX\ macros and vocabulary. Specifically, based on files obtained from ArXiV, Rotabi et al showed that user experience is a large factor in determining who will win a fight. Less experienced researchers tended to win invisible fights, \textit{i.e.}, fights over \LaTeX\-macros that did not have a high visibility. More experienced researchers, \textit{e.g.}, advisors and senior PIs, tended to win highly visible fights such as fights over the conventions used in the title of the paper [24].

In the software development paradigm, norms tend to develop in software teams, to which developers eventually learn and conform [25].

In the context of library adoptions in collaborative projects, we informally define a code fight as a series of commits that include back-and-forth additions and deletions of the same code containing a newly adopted \(\ell\). For clarity, in the current work we restrict a fight to occur between two committers \(u\) and \(v\), but we encourage follow-up research that lifts this restriction in future analysis. In this context, a fight occurs when user \(v\) removes all (or almost all) of the code that user \(u\) committed that references \(\ell\). Occasionally, the adopting user \(u\) will recommit the original code, which \(v\) may then revert.

A user may add or remove code over a series of contiguous commits, rather than in a single large commit. Therefore, rather than thinking of fights as one commit after another, we model a fight in rounds. A \textit{round} is a series of commits by one user that is uninterrupted by the other user. For example, if \(v\) deletes 5 lines of code in commit 2 and then another 6 lines of code in commit 3, then we represent these two commits as a single round with -11 lines deleted.

We formally define a fight as follows. Let \(n^{(r)}\) represent the net change in lines of code referencing \(\ell\) in round \(r\); \(r = 0\) indicates the round of the adoption event. Also let \(n^{\leq r}\) be the sum of all lines of code referencing \(\ell\) up to and including \(r\), \textit{i.e.}, the running total.

A \textit{code fight} occurs if there exists any \(r\) such that \((1 - \epsilon)n^{\leq r}/(r - 1) \leq n^{\leq r}\), where we set \(\epsilon\) to represent the percent reduction that must occur, with \(\epsilon \in \{.10, .20, .30, .40, .50\}\). Once a fight starts it will continue until there are no more rounds regardless of the size of the change in each round, \textit{i.e.}, further rounds within the same fight do not have to necessarily add or remove \(1 - \epsilon\) LOC.

The probability of a fight, for various sizes of \(\epsilon\) and by project team size, is illustrated in Fig. 8. We observe that fights are relatively rare, occurring between 1 and 3 times for every 100,000 commits on average. We also observe that the choice for \(\epsilon\) has a limited effect on the probability of a fight. The probability of a fight increases with team size, but with diminishing returns that resemble a Zipfian Distribution. In other words, because there are more interactions in a larger team, it is more likely that a fight will occur.

Next, we analyze what happens during a two-person fight. Technically speaking, the first round of a fight is the adoption event and the second round of the fight is the removal of at least 100(1 - \(\epsilon\)) percent lines of the adopter’s code. After this point, the two fighters (the adopter and the deleter) may continue with more rounds of back and forth commits.

Despite the dropoff in number of fights, the adopter tends to fight back with more lines of code. In Fig. 9 we observe that odd-numbered rounds, corresponding to the adopter, have more net LOC referencing \(\ell\) per round, than the deleter’s round that comes afterwards. Also, we see that the larger the original deletion of the code was, the less likely the adoptor is to fight back with lines of code.

We define a fight’s winner as the user who was the last committer referencing \(\ell\). In some cases, the adopter may acquiesce to the deleter and allow the code to remain deleted. In other cases, the deleter may allow the adopter’s reassertion of the library’s addition to stand. By our definition of rounds, it is clear that the deleter wins approximately 90% of the fights because the adopter only fights back 10% of the time. This shows that it is relatively rare for users to counter and re-add code. Perhaps in some cases, the “fight” was not contentious and the result of a mutual agreement to remove a library. Further research is needed to find out how many of these fights are a result of team friction.
Let’s return to our original questions and summarize our results based on our findings.

What does it look like when a team adopts a library for the first time?

In Fig. 2e we observe that library adoptions tend to happen early in a project’s history. Hence, the probability of a new library being adopted later is lower. We can expect that it is difficult to adopt a new library once a project has matured. Perhaps this is because new libraries may introduce instability into a repository, or because the primary innovation within a project occurs early on in its lifespan. Further research is needed to understand this more clearly.

While Fig. 2c shows us that these adoptions happen early on, it would also be interesting to approach this problem from the perspective of percent of project repository history. We see that the commit distribution follows a power law distribution, and many projects have few commits. Therefore, while we measure the commits in a sequential order in Fig. 2c further research should be done to see when library adoptions occur as a measure of project completeness. Early in a project history, do we see that it takes more time for a library to be adopted? Or do we see that a team takes longer to adopt a new project after they have been working using established methods? Further research needs to be done to answer these questions.

Despite these questions, we can see that library adoptions tend to be events that happen in the first few commits - though further research can help us understand when they occur in relation to the length of a project. That would give us another dimension to analyze this problem.

Are commits containing new libraries more likely to have deletions than other types of commits?

Once an adoption has occurred, we track how long it takes for library usage to become stable, or adopted, within the project by examining how many additions and deletions occur in the commits after a library is first used. In Fig. 2c we observe that library adoptions tend to happen early on, it would also be interesting to approach this problem from the perspective of project completeness to understand when these deletions occur over the lifespan of a project. An

| Library   | Prob in Fight |
|-----------|---------------|
| pdb       | 12.4          |
| pprint    | 11.3          |
| telnetlib | 10.5          |
| syslog    | 10.3          |
| distutils | 9.1           |
| glob      | 9.0           |
| poplib    | 8.4           |
| imp       | 7.8           |

TABLE II: Libraries most likely to be involved in a fight.

What role does experience play in winning a fight? To answer this question, we must first ask how to best define experience. Two options are to count 1) the number of commits of a user (in any project) or 2) the time elapsed since the users first commit (in any project). Although these two options obtain similar results, the current work maintains the standard set by prior studies [24] and therefore defines experience as the time since the user’s first commit (in any project). We observe in Fig. 10 which plots only results from $\epsilon = 0.1$, that the more experienced committer wins the fights between 70% and 80% of the time. Results from alternative $\epsilon$ values were nearly identical to $\epsilon = 0.1$ and are omitted for clarity and brevity. The experience difference groupings were selected so that each contained a similar number of fights. Interestingly, the more experienced users have about a 75% win probability even when the experience differences are less than a week or even a day (not illustrated). This suggests that even slightly more familiarity with the project (perhaps an indication of project leadership) results in the more experienced user winning the fight. It appears that it is more common for new people working on a team to be subservient to the person who has been working in the codebase the most.

Finally, we ask: which libraries are the most fought over? To answer this question, we must first ask how to best define experience. Two options are to count 1) the number of commits of a user (in any project) or 2) the time elapsed since the users first commit (in any project). Although these two options obtain similar results, the current work maintains the standard set by prior studies [24] and therefore defines experience as the time since the user’s first commit (in any project). We observe in Fig. 10 which plots only results from $\epsilon = 0.1$, that the more experienced committer wins the fights between 70% and 80% of the time. Results from alternative $\epsilon$ values were nearly identical to $\epsilon = 0.1$ and are omitted for clarity and brevity. The experience difference groupings were selected so that each contained a similar number of fights. Interestingly, the more experienced users have about a 75% win probability even when the experience differences are less than a week or even a day (not illustrated). This suggests that even slightly more familiarity with the project (perhaps an indication of project leadership) results in the more experienced user winning the fight. It appears that it is more common for new people working on a team to be subservient to the person who has been working in the codebase the most.

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analysis such as this would not skew the averages towards smaller projects since the project timeline would be measured from the perspective of percentage of a project completed, instead of absolute commit number.

Additionally, we could ask further questions about the coding history of users that are on the project. To add to this work, we could track the libraries used by the individuals who are contributing to these projects. Other work as shown that user activity rates are higher soon after an adoption event [26]. Tracking user history across GitHub repositories could give us more information about what occurs in an adoption event, and help us learn more about how individuals learn and retain new information.

Do the answers to these questions vary by library type, team size, or the amount of information available on Stack Overflow?

When team sizes are larger, the lines of library code do not grow as quickly relative to the first adoption commit as they do when team sizes are smaller. This may be because larger team projects require more communication and planning and are therefore less agile than small teams or individual projects. As mentioned previously, this is one of the drawbacks of using lines of code as a measurement tool, since it could be argued that the code committed by larger teams is more valuable than the lines of code committed by smaller teams. Additionally, this work only looked at public software repositories. Perhaps an analysis of private software repositories would lead to different conclusions about how various team sizes work together - because the interaction between teammates who know each other personally may be different than those who do not, or may be operating in a public environment.

Further in-depth research is necessary here. While we defined 'large' team sizes as those with 10+ members, it would be interesting to see how teams whose members number in the hundreds or thousands would differ. We would expect these teams to have different adoption behavior. Also, a team size and lifespan analysis would provide unique insights into how long large team repositories survive versus smaller teams. What is the distribution of smaller team projects’ lifespans compared to larger teams?

In addition to team size, we showed that the number of times a library appears in Stack Overflow is highly correlated with the number of adoptions in our data set. Further questions about StackOverflow still need to be answered. In particular, more questions need to be answered about which way StackOverflow and GitHub grow - does StackOverflow influence GitHub, does GitHub influence StackOverflow, or is there information flowing in both directions? How do individuals find new libraries on StackOverflow? What is the distribution of attention given to different StackOverflow questions? Each of these questions requires further analysis as we attempt to understand how groups utilize outside resources to learn about new information.

What does it look like when team members fight over new library usage?

When working on a team, there is bound to be conflict. Different team members have various opinions about which library is best to use in a repository. The probability of these fights occurring increases with team size, as shown in Fig. 8. The winner of these fights tends to be more experienced as shown in Fig. 10.

While we have done an analysis of team size, length of experience, and libraries used in fights, there are still questions to be answered regarding fights. Further research directions could include analyzing when fights occur in a project history. It would be interesting to see if fights are something that occur early or late in a project repository history. Additionally, this research was focused solely on fights between two individuals. Further analysis needs to be done on larger team sizes. Would an analysis of large team fights yield groups of people who are fighting for control on a project? Would larger teams result in more or less fights?

It makes intuitive sense that more experienced teammates would win GitHub fights, since they have more seniority in a project. However, it would also be interesting to investigate the projects in which the individual with less project experience wins the fight. What characteristics do these new, inexperienced team members have that causes them to win code fights? Is there another interesting quality that results in them having more influence over their teammates? More research is needed to answer these questions.

Additionally, in future work we could uncover who is...
bring new libraries into a project. We have seen that more experienced programmers tend to win these code fights. However, we could learn more information about how teammates work together by uncovering which team members are the first to bring in a new library. Would the teammates who have worked longer on the project be the ones to try new approaches with other libraries? Or would new teammates be the ones to suggest new ideas? Additionally, is there a divide between who is using new libraries and the popularity of that library on StackOverflow? We could hypothesize that common libraries, such as os, would be used for the first time equally by both experienced and inexperienced programmers, but a more specialized library like numpy would only be used by veteran team members. Since we have suggested libraries such as pandas have steep learning curves due to the number of posts on StackOverflow about that particular library, we could also track how team members fight over how to use complicated libraries, and if those libraries have a longer time to adoption than others.

**Implications**

There are some important caveats to the findings presented in the present work. We were only able to crawl 13% of all public Python GitHub projects; even if we could obtain all Python projects, these public projects only represent a subset of all Git projects. Therefore, we must temper conclusions to represent a case study of this domain and we caution the reader against drawing broad conclusions about user behavior outside of Python projects from public GitHub repositories. We can hypothesize that private software repositories are written by teams that have higher interpersonal relationships, and library adoption will appear to be different in these groups. Therefore, our conclusions cannot be generalized to all GitHub projects, though they provide a good overview of how libraries are adopted in public GitHub repositories. In particular, fights might look different in private repositories because we can assume that there would be some sort of relationship between the committers in those repositories, which might affect who wins those code fights. Additionally, we might find that people who post only in private repositories might be very different from those who have public GitHub accounts. Understanding the differences between these types of users would yield more interesting takeaways about how individuals work together in teams, as we analyze the difference between people who are more guarded of their work to those who are more open.

From our work, we found some interesting takeaways. We see that the number of commits and adoptions per project, along with team size, follow a power law distribution. We can conclude that power law distributions are common as we understand social behavior - there are many people who contribute little, and only a few that contribute in large amounts. We found positive correlations between the number of times libraries appear in StackOverflow and GitHub. We discovered that popular libraries on StackOverflow have faster rates of adoption for projects in Git. Additionally, smaller teams are more agile and can grow more quickly than larger teams, when productivity is measured as a function of median percentage growth. We also find that code fights are rare, but when they occur, they tend to be won by more experienced coders, and involve libraries which are used for debugging purposes. We can therefore conclude that the availability and proliferation of online resources has helped improve productivity for programmer, and that team characteristics, including size and seniority, have interesting implications for team dynamics. We can only expect resources such as StackOverflow and GitHub to continue growing as they attract new users.

However, just analyzing commit histories of varied team sizes do not tell the whole story. While we see in Figure 7 that larger teams do not grow as quickly, further research needs to be done to conclude if these larger teams are actually more efficient. These smaller teams may be ‘moving fast and breaking things,’ while larger teams could be more cautious in their execution due to the fact that larger teams by definition have more interpersonal relationships which need to be managed. It could be that larger team sizes have a higher percentage of their code that makes its way into the production version, while the multiple, minor commits that smaller teams make might be junk code that winds up being deleted. Therefore, this research needs to be continued to investigate this problem of team productivity from many different angles. This begs the question of what ‘productivity’ means, which could fuel many different research questions.

While this work has focused on the library-centric approach to understanding adopters, more work needs to be done to understand how individuals work to adopt information. Epidemiological models have been used to understand how information spreads across a social network [27], with a SIR model (susceptible, infected, recovered) being used to mimic one’s potential to become ‘infected’ (or viewing a post) and ‘infecting’ it (by sharing it). In these models, individuals have varying levels of susceptibility. Further research could apply these models to GitHub users. Do we see that there are some individuals which have high susceptibility rates, which could enable them to adopt to new libraries more quickly? Also are there some users who are more ‘infecting’ than others, and when they are present on a project, their introduced libraries are adopted more quickly than those introduced by individuals who are less ‘good’ at spreading ‘infections.’ This could be an interesting research topic that could attempt to apply epidemiological models to GitHub projects, where a library could be considered a virus. This type of approach could also help us create a model where we find highly influential GitHub users that are highly successful in implementing new libraries in varied projects. We could also view new libraries as a ‘virus’ that spread throughout GitHub - and track the users that are instrumental in helping them spread.

From this work, we can conclude that the proliferation of online coding resources such as GitHub and StackOverflow have been a positive development for programmers who wish to learn how to use new libraries to accomplish their coding tasks. Observing the growth of individuals who use StackOverflow and GitHub over time shows that the platforms have had tremendous growth over time for those hoping to learn to program. We expect continued high growth rates for both programs.
Future Work

We uncovered some interesting findings, but ultimately end up with more questions than conclusive answers. We encourage the community to explore specific questions raised by our results using the methodology developed in the present work. Specifically, we encourage further probing into how Stack Overflow contributes to the growth of library adoption and popularity. We have uncovered patterns that exist when team members fight over library adoption, and we look forward to further research which investigates code fights at an even greater depth.

We present several facets of analysis, but due to the complexity of varying size of teams and GitHub repositories, there exists virtually limitless possibilities in exploring the data. Since the commit and adoption distribution follow a power law, it might be interesting to investigate what occurs only in projects where these values are very large. This paper attempted to account for this variety of team sizes, but more focused work on investigating either small or large team sizes would yield very interesting results. Additionally, tracking the growth of team sizes could yield some very interesting research.

While this work ignores when commits occurred as a matter of date and time, gathering time stamps of commits might also yield interesting research. There are several questions that could be answered by analyzing time stamps, such as which time of year projects are more productive (students trying to finish semester projects? Teams being more productive at the end of the month?).

Additionally, this work does not attempt to track users across projects. Further research could be done to discover if a person’s prior programming experience results in lower time to adoption, or if sufficiently complex libraries remain hard even for experienced programmers. Some of these questions have been answered by Krohn et al. [25]. Another interesting research topic would be to track how quickly libraries are adopted as a function of time spent in the project, since many projects have short lifespans. Further research could attempt to find if libraries that are adopted later in a project’s repository history will be adopted more quickly, as teams learn how to work together more cohesively.

Conclusion

We have presented an analysis of the dynamics of library adoptions in Python projects pushed to GitHub. We find that when teams attempt to learn new information together, it can be challenging to apply these new concepts and there is often a learning curve needed before the new information can fully stabilize within the group project. We further find that that even though learning curves are unavoidable, it helps to have teammates and other online resources that can guide groups towards learning how to adopt new information. When conflict arises, the more experienced team members usually end up winning disagreements when we track whose code ends up in the final version. Through this work, we confirmed that learning new information together can be a difficult process, and that many of the statistics surrounding GitHub projects follow power law distributions (including team size, commits, and adoptions). This work provides a superficial glimpse into an analysis of teamwork on GitHub, though there are still more in-depth questions to be answered to uncover more information about more complex interactions.

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