

ACCEPTANCE OF CODE CONTRIBUTORS ON GITHUB

BY

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(Don't copy this sample text. Write your own acknowledgement.)

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ABSTRACT

Your Abstract goes here!

CHAPTER 1

INTRODUCTION

1.1 GitHub GitHub is a social website that open source software developers use to host their software projects and to browse other developers' projects. It includes many features that are present on social networking sites, such as the ability to follow other users and leave comments on projects. In the study of computer supported cooperative work, GitHub provides a wealth of data, as it is a centralized location where many different tasks take place. For example, users can create bug reports, submit fixes, and engage in discussions about new features all on one website. In this study, we use statistical and machine learning methods on data from GitHub repositories to explore how different factors may affect the acceptance of code changes from first time contributors.

1.2 Related Work GitHub itself has not been extensively studied. [2] use data from the website to examine what they call *herding behavior* of developers in open source projects. [10] provide a qualitative exploratory study on how developers on the website measure success of projects. Of importance to our study is their findings that developers believe the GitHub interface has changed the way developers are able to participate in the community. While they describe how features of the website are used by developers to measure community involvement and activity, we are concerned with how these features can provide measures that insight into how contributions by new community members are accepted by core members.

While there are not many studies on GitHub itself, there are many studies that explore different open source communities. These include theoretical perspectives on knowledge building and success in open source projects [4] [5] and the motivations of open source developers [6][8].

Our study seeks to which factors contribute to the acceptance of code contributions of first time contributors. We draw on findings from previous studies that describe the joining process of new developers [7][12]. We also draw from work that describes joining processes not only in open source software, but also from other computer mediated collaborative contexts, such as Wikipedia [1]. Our goal is to provide an empirical understanding of community acceptance on a relatively new social platform.

CHAPTER 2

DATA

2.1 Terminology A software project on the website is referred to as a *repository*. Any user on GitHub can *star* a repository. Users star repositories to be able to easily navigate to it and to receive updates on activity from the repository. If a developer wants to contribute to another one of developer’s repositories, he can *fork* the repository, which creates a copy of the project for him to work on. As the developer makes changes to this code, he *commits* his changes. A *commit* is a snapshot of the code at a certain point in time. When the developer is finished, he can submit a *pull request* to the owner of the project. All pull requests for a project are viewable on GitHub, and any user of the site can comment on them. A pull request can have a status of open or closed. A status of open indicates that that owner of the repository has not made a decision about whether or not to include the changes. If the owner of a repository wants to incorporate the changes the developer made, he can *merge* them into the repository. A pull request can be closed without being merged, which means that the changes the developer made were not accepted.

2.2 Data Collection Data was collected using the GitHub API.¹ We collected pull requests from 45 different repositories. The repositories selected came from the top 100 most starred repositories on GitHub. We chose popular repositories with the assumption that they would be maintained by an active community. We only consider pull requests with a status of closed. This resulted in approximately 44,400 pull requests. For most of our experiments, we will use what we refer to as first pull requests, by which we mean the first pull request a user submitted to a repository. Filtering for these pull requests results in a sample size of 13,383. The distribution of these pull requests across repositories ranges from 10 to 1,489, with a median of

¹<http://developer.github.com/>

210. To find merged pull requests, we first filter all pull requests that are marked as merged by the GitHub API, meaning that the project maintainers used GitHub's merge feature to accept the pull request. In some repositories, project maintainers use a different workflow when accepting pull requests, wherein the code changes are accepted, but it is not reflected as merged on GitHub. In most of these cases, there is a standard way of reflecting this in the commit comments, so we use some naive heuristics for identifying these requests by searching commit comments for certain text patterns. This results in finding 5,239, or 39.1% of first pull requests being merged.

CHAPTER 3

METHODS

3.1 Communities of Practice [9] describe learning in communities of practice as taking place through a process of *legitimate peripheral participation*, wherein newcomers join a community by participating in peripheral tasks and forming relationships to move towards the center of the community. This concept has been explored in many studies of computer mediated communication. In their study on members of Wikipedia, [1] note that members initially become involved through peripheral activities. These are simple and low risk activities members can take part in to learn more about the community before trying to become major contributors. Similarly, [12] from observing open source communities generate the construct of a *joining script*, where each project has a set of tasks for new developers to go through before being accepted into the community. In a discussion of successful developers on the Python project, [3] describe the first steps of their trajectory as including peripheral monitoring of development activity and reporting of bugs.

In this section, we explore both how a user engages with the community before submitting their pull request, as well as try to measure the community response to the pull request. We consider the main peripheral activity a user can participate in on GitHub is commenting on other pull requests. For each first pull request in our dataset, we count the number of other pull requests the user commented on before submitting. Based on these previous findings, we would expect to see a positive correlation between this number and the likelihood that a pull request is received. We also count the number of comments that each first pull request receives, with the assumption that this variable can be used to measure the amount of community interest in a given pull request. We plot these variables in Figure 3.1.1.

3.1.1 User Participation. We see that user participation for the majority

of all first pull requests, both merged and not merged, is 0. This indicates that in general, most users are not attempting to engage in the peripheral activity of commenting on other pull requests before submitting their own. The GitHub interface makes it relatively easy for a user to fork a repository, make changes, and submit the changes for consideration. Previous studies on GitHub have shown that the number of contributions did increase for some projects that moved from other hosting options to GitHub [10]. It is possible this interface lowers the barrier of entry for a developer who wants to contribute to a project, and allows them to bypass participating in the joining script described by [12].

We also examine these variables for first pull requests by users who later submit another pull request. Our intuition here is that some users might encounter a bug they fix or desire a feature that they implement, and then submit these changes back to repository. They may not comment on other pull requests as they are not interested in becoming long term members of the community, but rather are just interested in submitting a one time patch. Figure 3.1.1 shows a visualization of the same first pull requests, but only for users who submit at least one other pull request at a later point in our data set, and Figure 3.1.1 shows the data for users who submit at least 5 more times. Looking at users who submit at least one other time cuts our number of observations from 13,383 to 5,207, indicating that approximately 61% of these pull requests come from users who will not contribute any others. Looking at users who will submit at least 10 more times gives us a total of 1,155 observations.

It is clear that in all these cases, regardless of whether or not they will be continuing to submit other pull requests later, at the time of submitting their first pull request, users are generally not participating in the community. The previous graphs only consider the number of pull requests a user commented on before submitting their first pull request, so we do not capture how users who submit multiple pull

request over time comment on other pull requests over time. In Figure 3.1.1 we plot the total number of others' pull requests that a user commented on by how many pull requests they submitted themselves, considering only users who have submitted at least two pull requests. There is not a strong correlation between these variables (Spearman's $\rho = 0.44$), indicating that users do not necessarily participate in more commenting as they continue to submit more pull requests.

3.1.2 Attention Pull Request Receives. In Figure 3.1.1, we see more variance in the number of comments on first pull requests than we did with the number of pull requests users commented on before submitting. However, there is clearly no linear separation of merged and not merged pull requests using this variable, so it seems just viewing the amount of activity a pull request receives is not enough to explain whether or not it gets merged.

To test whether or not the content of these comments is predictive of whether or not a pull request is merged, we collect the comments for each of our first pull requests. We ignore comments made by the user who submitted the pull request, since we are interested in what other users had to say about it. We also ignore the last comment associated with a pull request, since these often will explicitly say whether or not the maintainer is merging the pull request or not. We are more interested in if the type of language used in the discussion of a pull request is predictive of whether or not it is accepted. We ignore pull requests that only have one comment associated with it. This gives us a sample size of 5,674. 3,811, approximately 67% are unmerged. We treat the remaining comments associated with the pull request as one document, and convert them into feature vectors representing the count of each unigram and bigram in the documents, and train both a logistic regression and naive bayes classifier using this feature set. The results of testing these classifiers is shown in Table 3.1.2. The results shown are the result of running 10-fold cross validation.

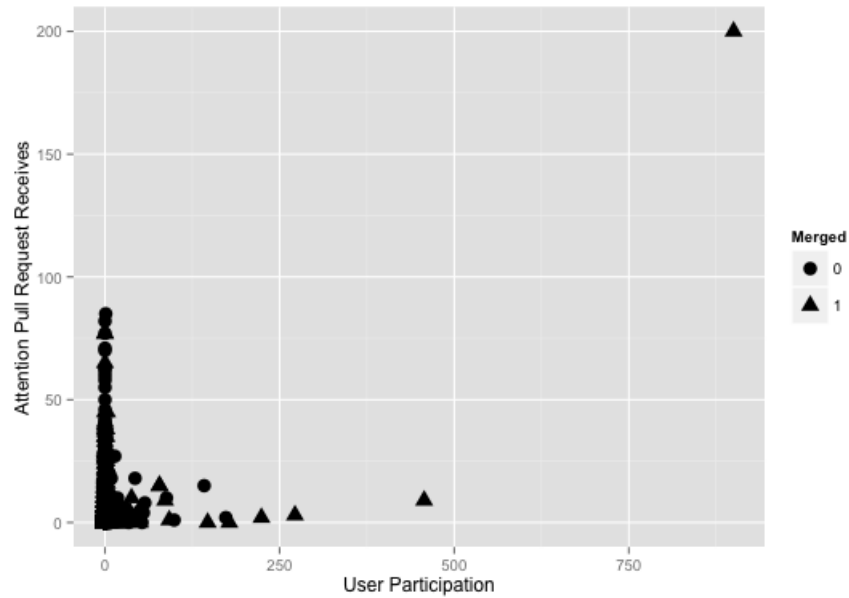


Figure 3.1. User participation and attention a pull request receives for all first pull requests.

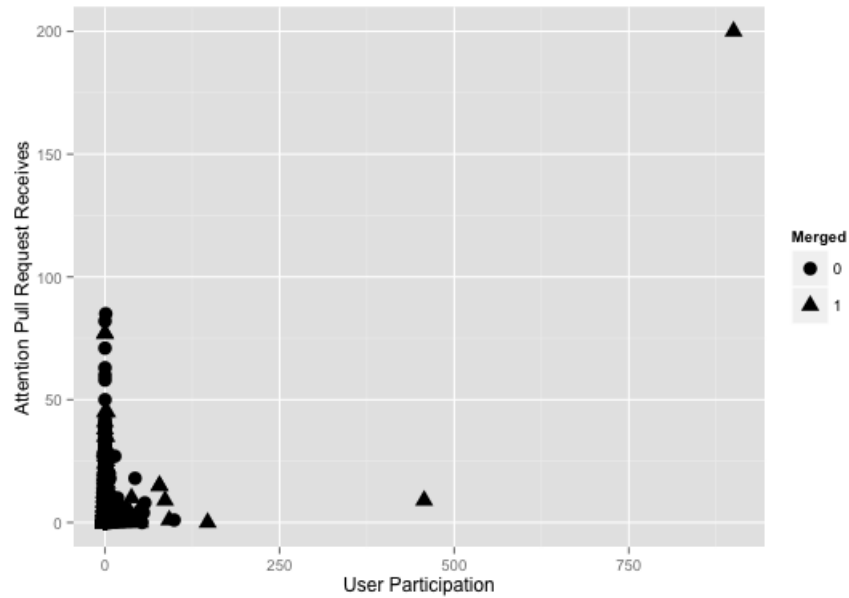


Figure 3.2. User participation and attention a pull request receives variables for users who submit at least one other pull request in our data set.

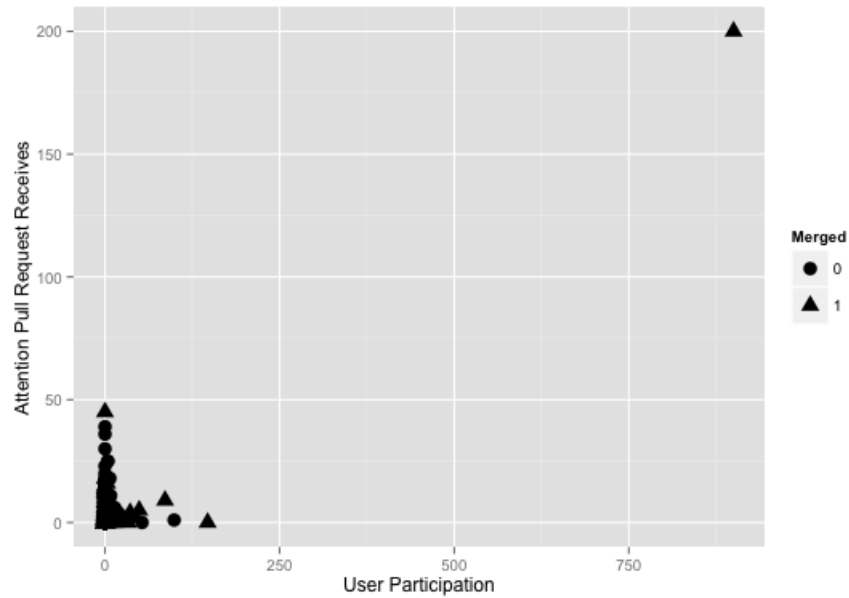


Figure 3.3. User participation and attention a pull request receives variables for users who submit at least 10 other pull requests in our data set.

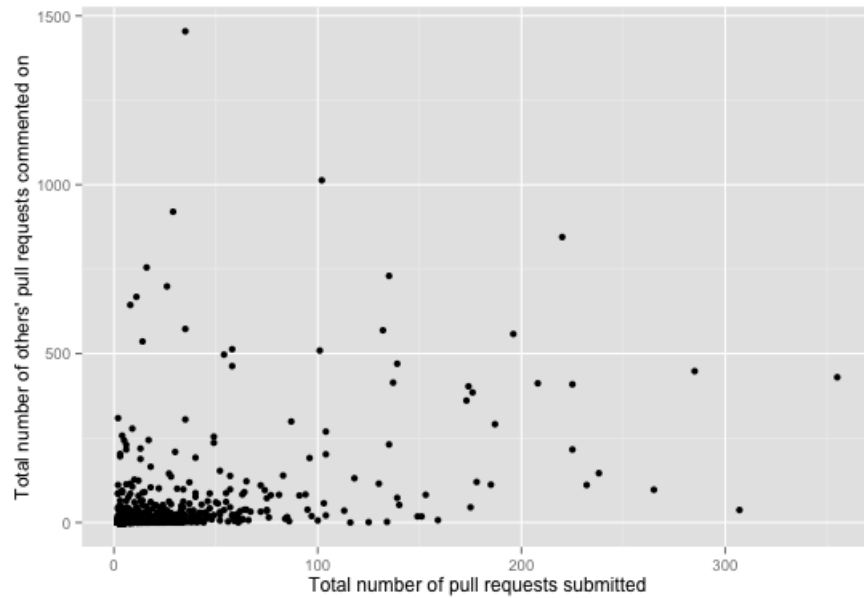


Figure 3.4. Total number of pull requests commented on and total number of pull requests submitted for each user.

The low recall rates indicate that the text data is not sufficient to distinguish positive cases. Of course, our sample size of 5,674 is relatively small, but it is interesting to note that only 42% of the first pull requests in our data set have more than 1 comment associated with them.

Table 3.1. Classifier results

	Logistic Regression	Naive Bayes
Accuracy	69.6%	70.6%
Precision	56.0%	60.3%
Recall	36.1%	30.7%

3.2 First Mover Advantage [11] find what they call a *first-mover advantage* in the editing of Wikipedia articles, wherein the first contribution to a page tends to survive longer and receive less modifications than following contributions. In this section, we explore how the acceptance of pull requests changes over time.

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