Predicting Pull Request Acceptance on GitHub from Social Factors

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1 Introduction

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 social factors may affect the acceptance of code changes from first time contributors.

1.1 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. [9] 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][13]. 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.

Outline The remainder of this article is organized as follows. Section 2 begins with a description of some of the terminology specific to GitHub, since many of the features in our models rely on an understanding of this terminology. We then describe how we measured various social factors and present our hypotheses. In Section 3 we describe our experiments. We find that the variables we chose lack predictive power of pull request acceptance. Section 4 describes why our models may have failed and presents some observations from the data. Finally, Section 5 presents our conclusions and ideas for future work.

2 Data

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 receieve 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.

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. We then filter this data set to include only the first pull request a user submitted, which results in 13,383 pull requests. Of these, 4,352, or 32.5% of the pull requests were merged. We consider several features, both on the pull request itself as well as the repository.

2.1 User Participation

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, [13] 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 the case of GitHub, we consider the act of commenting on previous pull requests to be the main peripheral activity a user can participate in before submitting a pull request of their own. For each pull request in our data set, we then count the number of previous pull request discussions the user participated in before submitting their own pull request, and present our first hypothesis.

Hypothesis 1 *Community members who have been active in previous discussions are more likely to have their code changes accepted.*

2.2 Reputation of User

In addition to participation within the community, we also suspect that a developer's reputation can affect whether or not his pull request is accepted. In particular, we hypothesize that a user who has popular projects of his

[1] http://developer.github.com/

own is more likely have his pull requests accepted. To measure this property, we use the total number of stars a user's repositories has received. This seems to be a good proxy for measuring the popularity of projects. Unfortunately, we cannot retrieve historical data for stars from the GitHub API. It is therefore not possible to know how many stars a user's projects had at the time he submitted his pull request. We do, however, know the when repositories were created. Therefore, to measure a user's reputation, we look at repositories that were created at the time his pull request was submitted, and sum the current number of stars those projects have at the time our data was collected. This is not a perfect approximation, as some of these projects may have gained many more stars long after the pull request was submitted. However, since we cannot access historical data, we rely on this as an approximation for user reputation.

Hypothesis 2 *Community members who have other popular projects are more likely to have their code changes accepted.*

2.3 Attention Pull Request Recieves

We consider the attention the pull request receives, which we measure as the total number of comments on the pull request. Our intuition is that a high number of comments indicates the pull request is generating interest within the community and is therefore more likely to be merged.

Hypothesis 3 *Pull requests with a high number of comments are more likely to be accepted.*

2.4 Number of Other Contributors

[12] 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 recieve less modifications than following contributions. They hypothesize that the first user sets the tone of the article and their contributions therefore are more likely to survive. We predict a similar effect in pull requests, where the first persons to submit pull requests are more likely to be accepted.

Hypothesis 4 *The likelihood a pull request is accepted declines as the number of contributors to a repository increases.*

2.5 Number of Previous Commits

Similar to the above hypothesis, we also measure the number of commits that have occurred in a repository prior the submission of the pull request. In addition to counting the number of previous contributors, we believe that commits here can be used as an estimate of how much activity has taken place in a codebase, and that as more activity occurs and project complexity grows, the likelihood of a pull request being accepted decreases.

Hypothesis 5 *The likelihood a pull request is accepted declines as the number of commits to a repository increases.*

2.6 Size of the Pull Request

We use two metrics to measure the size of the commit, both the number of commits and the number of changes. As mentioned previously, a commit is a snapshot of the code at a certain point in time. Different developers might have different commit habits, but in general, larger changes will probably include more commits. The number of changes is calculated simply as the number of lines added and the number of lines deleted. As an example to help differentiate these two metrics, imagine the scenario of changing the name of a widely used variable across the code base. Every line where this variable name appears would be treated as being deleted and re-added using the new variable name by git, resulting in a large number of changes. The developer, however, would likely only make one commit to capture this change. We predict that smaller pull requests are more likely to be accepted, since they can be reviewed quickly and are unlikely to introduce new complexity.

Hypothesis 6 *The likelihood a pull request is accepted declines as the size of the pull request increases.*

3 Methods

To test the relationship between the variables identified in Section 2, we apply a logistic regression model using these variables as indepedent variables and the binary outcome of merged or not as the dependent variable. We create categorical independent variables by binning the data. The results from the regression are shown in Table 1. In general, we do see the correlations we

expect in the model, with the exception of the number of comments that the pull request receives, where we see a negative correlation.

Examining the decrease in deviance from the null deviance from our parameters indicates our model significantly ourperforms a null model. However, the χ^2 value for the residual deviance is approximately equal to 1, indicating that the logit model overall may be a poor fit.

4 Discussion

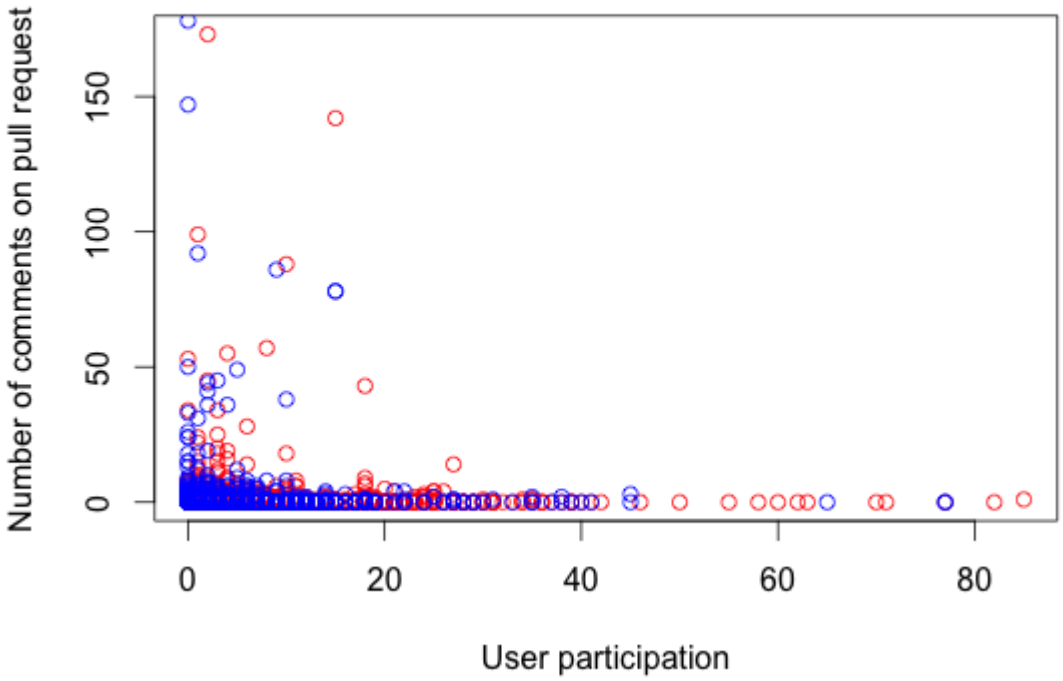
Visualizing some variables demonstrates that they may be a poor choice in attemping to distinguish between merged and not merged pull requests. In Figure 1, we see a scatter plot of user activity and the number of comments on pull requests for both merged and not merged pull requests. In both cases, most of the values for these features are zero. This in itself is an interesting observation. In evaluating the types of activity which take place in developer joining scripts, [13] note that the most common type of activity is to join an ongoing technical discussion, rather than suggest a technical solution. 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 both cases, developers first participate in peripheral activities. Both of these studies examine CVS repositories and project mailing lists. 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 [9]. It is possible this interface lowers the barrier of entry for a developer who wants to contribute to a project.

Another interesting observation is the negative relationship between the number of comments on a pull request and the likelihood of it being merged. Manual inspection of some of these pull requests suggests there are several causes for this. For example, it may be the case that the owner of a repository is not interested in merging a change, but other community members think the change is valuable, so they leave comments on the pull request to encourage the repository owner to merge it. In other cases, a discussion might develop between only the person who submitted the pull request and the repository owner where the two of them debate the value of the submitted change. It would be interesting to see if inclusion of things like number

Table 1: Logistic Regression Results

	Dependent variable:
	merged
User participation$_1$	0.242
	(0.421)
User participation$_2$	0.912*
	(0.513)
User participation$_3$	1.729***
	(0.617)
Attention pull request receives$_1$	−0.795***
	(0.155)
Attention pull request receives$_2$	−0.053
	(0.325)
Attention pull request receives$_3$	−0.019
	(0.524)
User reputation$_1$	0.185*
	(0.101)
User reputation$_2$	0.192
	(0.130)
User reputation$_3$	0.342**
	(0.143)
Number of commits$_1$	−1.195***
	(0.416)
Number of commits$_2$	−3.218***
	(1.013)
Number of commits$_3$	−13.219
	(114.104)
Number of changes$_1$	−0.221**
	(0.108)
Number of changes$_2$	−0.609***
	(0.148)
Number of changes$_3$	−0.620***
	(0.192)
Number of repository commits$_1$	−0.306***
	(0.050)
Number of repository commits$_2$	−0.037
	(0.060)
Number of repository commits$_3$	0.245***
	(0.085)
Number of contributors$_1$	−0.103*
	(0.055)
Number of contributors$_2$	−0.657***
	(0.098)
Number of contributors$_3$	−0.526***
	(0.140)
Constant	−0.547***
	(0.031)
Observations	13,383
Log Likelihood	−8,282.562
Akaike Inf. Crit.	16,609.120
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 1: Visualization of number of comments on a pull request and user participation variables. Merged pull requests are blue. Not merged are red.



of people who commented on a pull request and analysis of linguistic features along with the number of comments on the pull request help make it more predictive.

5 Conclusion and Future Work

Although the results of the logistic regression indicate the positive correlation posited in our first two hypotheses, the predictive power of that model and all our other models are weak, suggesting that these variables are not useful to predict whether or not a pull request is merged or not. Future work should find better features to improve the accuracy of these predictive models.

In this paper, we examined the first pull request users submitted to repositories. It might be useful to further discriminate the types of users who submit pull requests. [10] describe eight different roles members of an open source community assume, including bug reporter, bug fixer, and peripheral developer. In future work, we might continue to examine users' first pull requests, but only those users who go on to become active, stable members, rather than just one off bug fixers. It may be the case that this fixes the problem of our independent variables in both cases clustering around 0, if a majority of those cases come from those one time contributors.

Finally, future work should work to identify how the way both contribution by members outside the community and acceptance of their changes by those in the community change over time. [11] notes that for new members, control and fit are important in deciding whether or not to contribute. It may be that as projects grow, more rigid control structures are put in place, and contribution patterns change over that time.

In all these cases, GitHub as a social platform enables new forms of collaboration and a wealth of data about how that collaboration is taking place, and much more work can be done to explore the social nature of the collaborative efforts of open source developers.

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