Replicating and Scaling up Qualitative Analysis using Crowdsourcing: A Github-based Case Study

Di Chen, Kathryn T. Stolee, Tim Menzies
North Carolina State University, USA
Raleigh, NC 27606
dchen20@ncsu.edu, ktstolee@ncsu.edu, tim@menzies.us

ABSTRACT
Due to the difficulties in replicating and scaling up qualitative studies, such studies are rarely verified. Accordingly, in this paper, we leverage the advantages of crowdsourcing (low costs, fast speed, scalable workforce) to replicate and scale-up one state-of-the-art qualitative study. That qualitative study explored 20 GitHub pull requests to learn factors that influence the fate of pull requests with respect to approval and merging.

As a secondary study, using crowdsourcing at a cost of $200, we studied 250 pull requests from 142 GitHub projects. The prior qualitative findings are mapped into questions for crowds workers. Their answers were converted into binary features to build a predictor which predicts whether code would be merged with median $F_1$ scores of 68%. For the same large group of pull requests, the median $F_1$ scores could achieve 90% by a predictor built with additional features defined by prior quantitative results.

Based on this case study, we conclude that there is much benefit in combining different kinds of research methods. While qualitative insights are very useful for finding novel insights, they can be hard to scale or replicate. That said, they can guide and define the goals of scalable secondary studies that use (e.g.) crowdsourcing+data mining. On the other hand, while data mining methods are reproducible and scalable to large data sets, their results may be spectacularly wrong since they lack contextual information. That said, they can be used to test the stability and external validity, of the insights gained from a qualitative analysis.

KEYWORDS
Data analytics for software engineering; empirical studies; software repository mining; crowdsourcing; qualitative studies; quantitative studies; mixed method; open source; GitHub; pull request

1 INTRODUCTION
Our ability to generate models from software engineering (SE) data has out-paced our abilities to reflect on those models. Studies can use thousands of projects, millions of lines of code, tens of thousands of programmers [53]. But when insights from human experts are overlooked, the conclusions from the automatically generated models can be both wrong and misleading [47]. After observing case studies where data mining in SE led to spectacularly wrong results, Basili and Shull [59] recommend qualitative analysis to collect and use insights from subject matter experts who understand software engineering.

Shull [1] also warns that traditional methods of finding local beliefs (based on an anthropological-style analysis) does not scale to hundreds of projects. Shull notes that those manual methods have trouble keeping up with the pace of technological change. Such studies can take years to complete – in which time, the underlying technology may have completely changed.

To solve this problem, we propose scalable secondary studies. Such studies are conducted after collecting qualitative insights from an in-depth analysis of a small sample. Next, other method(s) are employed to ensure conclusion stability and external validity in a larger sample. Such scalable secondary studies can be implemented using a variety of methods; in this work, we explore crowdsourcing+data mining.

To demonstrate this approach, we extend a study from FSE’14 by Tsay, Dabbish, Herbsleb (hereafter, TDH) [67]. TDH explored how Github-based teams debate what new code gets merged. To do this, they used a labor-intensive qualitative interview-process of 47 users of GitHub, as well as in-depth case studies of 20 pull-requests.

This papers extends that primary qualitative study of pull requests with a scalable secondary study using crowdsourcing+data mining. Using the terms identified by TDH, crowdsourcing extracted data from 250 pull requests (i.e. an order of magnitude more that TDH). Data mining was applied to that new data resulting in accurate predictors for generating what issues will get merged. Further, when those predictors were compared to another predictor built using more quantitative methods (traditional data mining, no crowd-sourcing, no use initial qualitative insights), this second predictor out-performed the TDH features (the $F_1$ score grew from 68% to 90%).

This is not to say that data mining methods are “better” than qualitative methods. In fact, our key point is:

This secondary studies could not have have happened without the initial qualitative study.

That, in this work, the qualitative inspired and guided the subsequent work. Specifically, the TDH qualitative study defined (a) baseline results and (b) a challenge task addressed in a subsequent secondary study that used crowdsourcing+data mining. In this case, that secondary study is able to build predictors using larger amount of pull requests analyzed. But it would be extremely premature
to use this one result to make some general judgement about the relative merits of different approaches. As James Herbsleb said in his FSE’16 keynote address, “these methods exist and we need to learn to best use them all”. Accordingly, we recommend several years of work where researchers explore combinations of methods. This paper will be a success if it encourages more studies on combinations of primary qualitative studies and subsequent secondary studies.

The contributions of this work are:

- A cost-effective, independent replication of a primary study of pull request acceptance factors using a scaled sample of artifacts (RQ1).
- Analysis of the external validity of the original study, demonstrating stability in some of the results. This has implications for which questions warrant further analysis (RQ2).
- A literature review on factors that impact pull request acceptance and identification of features that reliably predict pull request acceptance (RQ3).

The rest of this paper details our Methodology for Scalable Secondary Studies (MOSSS). The next section introduces empirical methods in software engineering; compares qualitative and quantitative methods in software engineering; describes GitHub and pull requests; and offers an overview on crowdsourcing. Next, in the Methods section, we describe the details of how we apply MOSSS on TDH. Our Results section presents our findings. This is followed by Threats to Validity and Conclusions.

To assist other researchers, a reproduction package with all our scripts and data is available on GitHub¹ and in archival form, tagged with a DOI² (to simplify all future citations to this material).

2 BACKGROUND AND RELATED WORK

2.1 Empirical SE Methods

There are many ways to categorize empirical studies in SE. Sjoberg, Dyba et al. [62] summarize them into two general groups, i.e. primary research and secondary research. The most common primary research usually involves the collection and analysis of original data, utilizing methods such as experimentation, surveys, case studies, and action research. While our paper falls into the secondary research that uses data from previously published studies for the purpose of research synthesis, which involves summarizing, integrating and combining the findings of different studies on a research question [14]. According to Cohen [13], secondary studies can identify crucial areas and questions that have not been addressed adequately with previous empirical research. The core observation it is built on is that no matter how well designed and executed, findings from single empirical studies are limited in the extent to which they may be generalized.

For the methods in empirical SE studies, we have participant observation, interviewing and coding for data collection, constant comparison and cross-case analysis for theory generation and replication for theory confirmation [57]. Our data collection applies the coding method, which is commonly used to extract values for quantitative variables from qualitative data in order to perform some type of quantitative or statistical analysis. Our data analysis falls into the category of replication for theory confirmation. Using replication, we could check the external validity, which focuses on whether claims for the generality of TDH results are justified, and reliability, which focuses on whether our study yields the same results if we replicate it [17].

2.2 Qualitative, Quantitative, and Mixed-Methods in SE

Qualitative methods in SE are typically used for exploratory purpose to generate new theorems or improve existing ones [34, 55]. Due to the involvement of humans when qualitative method are applied, the sample size is often restricted to a very small size. Additionally, the results of a qualitative analysis can be difficult to replicate due to variations in settings or experimenter bias, and therefore engaging in such tasks are risky to researchers [25, 60].

In contrast, quantitative studies are used for explanatory or descriptive purpose to measure and analyze causal relationships between variables [34, 55]. Quantitative methods work with numerical data collected from a representative sample, which could be very large compared to qualitative methods.

A drawback with quantitative methods is that they may operate without any contextual knowledge of the data they are processing. A common study in the mining software repositories community is to apply data miners on information taken from some repository without first interviewing humans familiar with that project or that data. Hence, such quantitative methods may efficiently reach a conclusion over a very large data set, even though those conclusions may not address any current concerns of any living human.

For these reasons, various researchers explore mixed methods to exploit the strengths of all the above approaches. For example, Zimmermann and his colleagues at Microsoft conducted very focused limited-scope interviews with a small number of developers. This primary qualitative analysis is used to refine a set of hypotheses and questions for a secondary study comprising a questionnaire distributed to a very wide audience [6]. The results of that questionnaire are then summarised using a “card sort” (which, we note, is a method commonly used by researchers in interpreting free text responses in survey data [3, 26, 54, 61]). This is a very labor-intensive and somewhat subjective process whereby researchers work through all the questionnaire textual answers, organizing the topics into categories. To the best of our knowledge, even though card sorting is typically done by multiple researchers who reach a consensus, the results of an initial card sort are typically not verified by a second card sort with independent researchers. We speculate that card sorts are such a resource-intensive undertaking that doing it twice is just impractical.

The proposal in this paper is that mixed methods can be improved. Primary studies should remain qualitative since their careful and detailed analysis of human factors within a software project is insightful. Also, they can lead to novel insights they can be overlooked by automatic data mining methods. However, once the primary qualitative study is completed, the stability and external validity of those conclusions should be checked by a scalable secondary method, ideally by an independent research team [60].
example of such a scalable secondary method is the combination of data mining+crowd sourcing explored in this paper.

2.3 GitHub and Pull Requests

With over 14 million users and 35 million repositories as of April 2016, GitHub has become the largest and most influential open source projects hosting sites. Numerous qualitative [5, 15, 22, 24, 39, 44, 50, 67], and quantitative [21, 52, 53, 64–66, 68, 74, 77] and mixed methods studies [8, 30] have been published about GitHub.

Pull requests need to be created when contributors want their changes to be merged to the main repository. After core members receive pull requests, they inspect the changes and decide whether to accept or reject them. This process usually involves code inspection, discussion and inline comments between contributors and repository owners. Core members who have the ability to close the pull requests by either accepting the code and merging the contribution with the master branch, or rejecting the pull requests. Core members could also ignore the pull requests and leave them in the open state. Figure 1 shows an example of pull requests with discussion, inline code comments and final result.

2.4 Crowdsourcing

One of first uses of this term comes from Jeff Howe in 2006 who said:

“crowdsourcing represents the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call.”

Crowdsourcing is being used for many SE tasks including program synthesis [11], program verification [56], and testing [16, 46] using tools such as Amazon Mechanical Turk (MTurk)4, TopCoder5, CrowdFlower6, and ClickWorker7. For an extensive review of crowdsourcing in software engineering, see [37].

There are many reasons to use crowdsourcing. Firstly, it is very cheap. As described later in this paper, this entire study requires just $200 of crowd time. Secondly, crowdsourcing can solve some very hard problems. For example, Minku [45] argues from sampling theory that the union of N slightly different views can be larger than any individual view (see Figure 2). For example, in software engineering studies, it was found that combining crowd answers for writing regular expressions for URLs or email addresses yield better accuracy programs written by a single individual [12].

Surprisingly, the crowd has an unexpectedly coherent understanding of its distributed knowledge. For example, Heikinheimo and Ukkonen’s centroid median theorem shows that if a crowd checks numerous examples for outliers, then items marked least are equal to the mean of a univariate normal distribution [28]. Note that centroid medians work for single numbers in a range or sets of large complex feature vectors. That is, crowds can be used as a human-based data miner to implement, for example, a crowd-sourced K-means clusterer (as done by Heikinheimo and Ukkonen).

Significantly, the crowd can solve problems that have defeated conventional computer science methods. Mason [40] comments that the larger the crowd, the more likely that an individual will offer a (possibly partial) solution to even intractable NP-hard problem.

---

4MTurk focuses on micro-tasks, e.g., labeling an image. Micro-tasks are grouped into one Human Intelligence Task (called HIT). When HITs are defined, they can include the HIT payment, the time constraint for answering, the expiration time for a job to be available on MTurk, and some qualification test. For more, see https://www.mturk.com/mturk/welcome.

5TopCoder is a platform designed to use crowdsourcing for large software engineering tasks, such as website design or implementation. Designers, employed by TopCoder, break down large SE projects into small tasks for crowd workers. For more, see https://www.topcoder.com.

6CrowdFlower is somewhat similar to MTurk but adds some quality control micro-tasks. At CrowdFlower, 20% of the micro-tasks assigned to responders are “golden”, i.e. the answers are already known. For more, see http://www.crowdflower.com.

7ClickWorker is similar to MTurk and CrowdFlower in that it’s a micro-task crowdsourcing platform, but the focus is on surveys, proofreading, web research. Skills are measured by ClickWorker before workers have access to actual tasks. For more, see https://www.clickworker.com.
Two important issues with crowdsourcing are **quality control** and **cost control**. Crowd-based workers may return noisy or incorrect results. One way to address this issue is to use, say, 20% “gold” questions—those for which the answer is known. Workers that perform poorly on the golden set are eliminated, which is also one of the strategies we take in this paper. Alternatively, tasks can be assigned to multiple workers and their results aggregated (e.g., in the TURKIT system [35], one task is performed iteratively, and each worker is asked to improve on the answer of the former, or in AutoMan [4], each task is performed by crowd members until statistical consensus is reached). Other quality control techniques include redundant question formats [63], notifications to workers about the value of their work [33], answer conflict detectors [58], and random click detection [31].

As to cost control, commercial crowdsourcing platforms are not free. Economic incentives for crowd workers strongly effect crowd response quality [18, 32, 36, 38, 41, 42, 72, 73]. To keep the quality high, payments need to be high enough to entice participation [71].

### 3 RESEARCH QUESTIONS

In this work, we evaluate the following research questions:

**RQ1:** Can we use crowdsourcing to replicate TDH’s work, but at faster speeds, with cheaper costs and larger sample sizes? According to Shull’s notes on how to define replication studies in SE[60], in order to show that a given result is robust, the ideal case is for a completely independent set of researchers to replicate a published study using their own experimental design. In this paper, our analysis, which is designed and run by a completely independent set of researchers compared to the primary study, scales well and cost-effectively validates and extends the prior TDH study.

**RQ2:** Does crowdsourcing lead to stable conclusions? This question is important since, given the nature of crowd-based reasoning, it is possible that crowd workers will have different opinions from TDH. We collected the 210 pull requests using similar sampling criteria to the primary study and tested if the crowd reaches the same or different conclusions using the new data set. A conclusion was declared stable if the same conclusions were found in each independent sample. As shown, the analyses in this paper are stable across these two samples.

**RQ3:** Can the pull request features identified in the primary study accurately predict pull request acceptance? Given the larger data set collected and evaluated in this work, there is now an opportunity to evaluate the performance of prediction models based on (1) the features identified as important in the primary study, and (2) features identified as important in previous data mining-only studies.

### 4 METHODS

To leverage the advantages of crowdsourcing, we propose our methodology of scalable secondary studies (MOSSS) for quickly replicating and scaling the time-consuming qualitative works in SE. Our methodology will be introduced and applied on the primary study from TDH on GitHub pull requests. Basically, our methodology shown in Figure 3 is consist of the following steps:

**Step 1:** Literature review on one specific domain, e.g. GitHub pull requests studies, and extract data, insights, features and results from the existing work.
Table 1: A sample of related qualitative and quantitative work. Here, by "quantitative", we mean using data mining with little
to no interaction with project personnel.

| Year  | Source            | Method            | Data                                                                 | Title                                                                 |
|-------|-------------------|-------------------|----------------------------------------------------------------------|----------------------------------------------------------------------|
| 2014  | [33]              | CSW: W Qualitative | Interview of GitHub Users. Pull requests case study 10             | Social coding as GitHub: transparency and collaboration in an open software repository |
| 2013  | [19]              | CSW: W Qualitative | Interview 38 GitHub users. Pull requests case study 10             | Impression Formation in Online Peer Production: Activity Traces and Personal Profiles in GitHub |
| 2014  | [33]              | TSE Qualitative   | Interview of GitHub users. Pull requests case study 20             | Let’s Talk About It: Evaluating Contributions through Discussion in GitHub |
| 2013  | [24]              | ICSE Qualitative  | Online survey 193 integrations. Work Practices and Challenges in Pull-Based Development: The Integrative Perspective |
| 2016  | [22]              | ICSE Qualitative  | Online survey 243 contributors. Work Practices and Challenges in Pull-Based Development: The Contributions Perspective |
| 2014  | [10]              | ICSE Qualitative  | GHTorrent, 166,884 pull requests. An Exploratory Study of the Pull-Based Software Development Model |
| 2014  | [44]              | ICSE Qualitative  | GHTorrent, GitHub Archive. 65,561 pull requests Influence of Social and Technical Factors for Evaluating Contribution in GitHub |
| 2014  | [75]              | ICSE Qualitative  | GHTorrent, 1,200 pull requests. Reviewer Recommendation of Pull-Requests in GitHub |
| 2015  | [26]              | ICSE Qualitative  | Continuous Integration in a SocialCoding World Empirical Evidence from GitHub |
| 2014  | [76]              | AFSEC Qualitative | GHTorrent, 1,200 pull requests. Who Should Review the Pull-Request: Reviewer Recommendation to Explicate Crowd Collaboration |
| 2014  | [77]              | CrowdSoF Qualitative | GHTorrent, GitHub Archive. Investigating Social Media on GitHubPull Requests: A Case Study on Rely on Rails |
| 2014  | [23]              | MSR Qualitative   | GHTorrent. A Dataset for Pull-Based Development Research |
| 2014  | [52]              | MSR Qualitative   | GHTorrent, 74,935 pull requests. An Insight into the Pull Requests of GitHub |
| 2014  | [51]              | MSR Qualitative   | GHTorrent, 74,935 pull requests. Security and emotion sentiment analysis of security discussions on GitHub |
| 2014  | [20]              | MSR Qualitative   | GHTorrent. White boxes denote that a paper examined that feature; Black boxes denote that paper concluded that feature was important; |
| 2014  | [48]              | MSR Qualitative   | GHTorrent, 75,326 pull requests. A study of external community contributions to open-source projects on GitHub |
| 2014  | [50]              | MSR Qualitative   | GHTorrent. Presenting Pull Requests |
| 2014  | [75]              | MSR Qualitative   | GHTorrent, 105,284 pull requests. Wait For It: Determinants of Pull Request Evaluation Latency on GitHub |
| 2014  | [30]              | MSR Qualitative   | Qual: GHTorrent, Qual: 240 Survey, Manual analysis 434 project The promises and perils of mining GitHub |

Step 2: Map insights from qualitative works into questions that could be easily answered by crowd workers and quantitative features should also be easily extracted from these questions. Similarly, map existing data into questions with known answers, which are ‘gold’ queries.

Step 3: Expand the data used in the primary studies with similar selection rules and launch some initial data on crowdsourcing for cost control.

Step 4: Map insights into questions and features

Step 5: Extract features defined in Step 2 from the large amount of answers returned by crowd workers, then apply quantitative analysis on these crowdsourced features and compare those with the quantitative features in Step 1 so as to discover new findings.

### 4.1 Literature Review and Data Extraction

We first set TDH as our primary study and then find all studies related to GitHub pull requests in the literature. We then searched keywords ‘pull’, ‘request’ and ‘GitHub’ on Google Scholar since 2008 and a dataset from [43], which contains 16 software engineering conferences, 1992 to 2016, which includes ICSE, ICSM, WCSE, CSMR, MSR, GPCE, FASE, FSE, ICPC, TSE, SCAM, ASE, SANER, SSBSE, RE, ISSTA, ICST. After manually reviewing the search results, we filtered out the work unrelated to GitHub pull requests. Table 1 lists the remaining research papers that have studied pull requests in GitHub using either qualitative or quantitative methods. Here, we distinguish qualitative and quantitative methods by whether or not there is human involvement during data collection process. Qualitative studies have human involvement and include interviews, controlled human experiments, and surveys. We observe that all previous studies on pull request in GitHub use either qualitative or quantitative methods, while only one mixed approach combining both with a very time consuming manual analysis for the qualitative part [30], which is quite different from ours, because we apply crowdsourcing directly on the results extracted from primary qualitative studies in a relatively much smaller time cost.

Table 2 summarizes the most representative features these studies state are relevant to determining the fate of a pull request. Note that different studies found that different features were most relevant to deciding what happens to pull requests. In that table:

- White boxes denote that a paper examined that feature;
- Black boxes denote that paper concluded that feature was important;

The last column shows what lessons we took from these prior studies.

- If any other column marked a feature as important, then we added it into the set of features we examined. Such features are denoted with a white box in the last column.
- Later in this paper, we run feature subset selectors on the data to determine which features are most informative. Such features are denoted with a black box.

### 4.2 Map Insights into Questions and Features

The tasks performed by the crowd were designed to collect quantitative information about the pull requests, which could be checked against a ground truth extracted programatically (e.g., was the pull request accepted?), and also collect information related to the pull request discussion, described next.

The primary study [67] concluded, amongst other things, that:

*Issues raised around code contributions are mostly disapproval for the problems being solved, disapproval for the solutions and suggestion for alternate solutions.*

*Methods to affect the decision making process for pull requests are mainly by offering support from either external developers or core members.*

In order to use crowdsourcing to do a case study for pull requests, our tasks contained questions related to five concepts. These five concepts reference important findings from TDH’s work, and are also treated as the assumptions we are going to validate:
Table 2: Features Used in Related Works. □ indicates whether the feature is used or not, while ■ indicated the features are found to be heavily related to the results of pull requests in the according paper.

| Category          | Features                                                                 | Description                                                                 | [23] | [20] | [66] | [74] | [77] | [52] | Ours |
|-------------------|--------------------------------------------------------------------------|------------------------------------------------------------------------------|------|------|------|------|------|------|------|
| Pull Request      | time_open_minutes                                                        | Minutes between opening and closing                                            |      |      |      |      |      |      | □    |
| Pull Request      | num_commits                                                             | Number of commits                                                             |      |      |      |      |      |      |      |
| Pull Request      | num_lines_changed                                                        | Number of lines changed (added + deleted)                                    |      |      |      |      | □    |      |      |
| Pull Request      | files_added                                                              | Number of files added                                                         |      |      |      |      |      |      | □    |
| Pull Request      | files_deleted                                                           | Number of files deleted                                                       |      |      |      |      | □    |      |      |
| Pull Request      | files_modified                                                          | Number of files modified                                                       |      |      |      |      |      |      | □    |
| Pull Request      | files_changed                                                           | Number of files touched (sum of the above)                                   |      |      |      |      |      |      | □    |
| Pull Request      | disc_files                                                               | Number of source code files touched by the pull request                      |      |      |      |      |      |      | □    |
| Pull Request      | other_files                                                              | Number of non-source, non-documentation files touched                         |      |      |      |      |      |      | □    |
| Pull Request      | num_commits_comments                                                     | The total number of code review comments                                       |      |      |      |      |      |      | □    |
| Pull Request      | num_issue_comments                                                       | The total number of discussion comments                                        |      |      |      |      |      |      |      |
| Pull Request      | num_comments                                                            | The total number of comments (discussion and code review)                     |      |      |      |      |      |      |      |
| Pull Request      | test_inclusion                                                           | Whether or not the pull request included test cases                           |      |      |      |      |      |      |      |
| Pull Request      | print_interaction                                                        | The number of events the submitter has participated in this project before this pull request |      |      |      |      |      |      | □    |
| Pull Request      | social_distance                                                          | Whether or not the submitter follows the user who closes the pull request     |      |      |      |      |      |      |      |
| Pull Request      | strength_of_social_connection                                           | The fraction of team members that interacted with the submitter in the last three months |      |      |      |      |      |      | □    |
| Pull Request      | description_complexity                                                    | Total number of words in the pull request title and description               |      |      |      |      |      |      | □    |
| Pull Request      | pull_request_first_human_response                                        | Time interval in minutes from pull request creation to first response by reviewers |      |      |      |      |      |      |      |
| Pull Request      | total_CI_latency                                                         | Time interval in minutes from pull request creation to last commit tested by CI |      |      |      |      |      |      | □    |
| Pull Request      | CI result                                                                 | Presence of errors and test failures while running Travis-CI                  |      |      |      |      |      |      | □    |
| Pull Request      | mention_at                                                              | Weather there exist an mention in the comments                                 |      |      |      |      |      |      |      |

(1) Is there a comment showing support for this pull request, and from which party? The crowd’s answer to this question lets us define three binary variables: Q1 support, Q1_spt_core, Q1_spt_other, which stands for “support showed”, “support from core members” and “support from other developers” respectively.

(2) Is there a comment proposing alternate solutions, and from which party? The crowd’s answer to this question lets us define three binary variables: Q2_alternate_solution, Q2_alt_soln_core, Q2_alt_soln_other, which stands for “alternate solution proposed”, “alternate solution proposed by core members” and “alternate solution proposed by other developers” respectively.

(3) Did anyone disapprove the proposed solution in this pull request, and for what reason? The crowd’s answer to this question lets us define four binary variables: Q3_dis_solution, Q3_dis_soln_bug, Q3_dis_soln_improve, Q3_dis_soln_consistency, which stands for “disapproval for the solution proposed”, “disapproval due to bug”, “disapproval because code could be improved” and “disapproval due to consistency issues” respectively.

(4) Did anyone disapprove the problems being solved? E.g question the value or appropriateness of this pull request for its repository. The crowd’s answer to this question lets us define three binary variables: Q4_dis_problem, Q4_dis_prob_no_value, Q4_dis_prob_not_fit, which stands for “disapproval for the problem being solved”, “disapproval due to no value for solving this problem” and “disapproval because the problem being solved does not fit the project well” respectively.

(5) Does this pull request get merged/accepted? The crowd’s answer to this question lets us define a class variable for this system.

The full version of our questions are available on-line. To those questions we also added three preliminary questions that require crowd workers to identify the submitter, core members and external developers for each pull request. These extra questions served two purposes: First, they let a crowd worker grow familiar with analyzing pull request discussions. Second, they let us reject answers from unqualified crowd workers since we could programmatically extract the ground truth from the repository for comparison.

We also extract answers for these questions from the results in TDH. These answers are served as “gold” standard tasks which enable quality control during crowdsourcing and sanity checking for the answers after crowdsourcing.
4.3 Data Expansion and Cost Control

To make sure the pull requests are statistically similar to those of TDH’s work [66, 67], we applied similar selection rules on 612,207 pull requests that were opened during January 2016 from GitHub [19], which is a scalable, searchable, offline mirror of data offered through the GitHub Application Programmer Interface (API).

The selection criteria are stated as follows:

1. Pull requests should be closed (558,480 left).
2. Pull requests should have comments (50,440 left, with 2, 3, and 7 comments as the 25, 50, 75 percentiles, respectively).
3. Pull request comment number should be above 8.
4. Exclude pull requests whose repository are forks to avoid counting the same contribution multiple times.
5. Exclude pull requests whose last update is late than January, 2016, so that we can make sure the project is still active (8,438 left).
6. Retain only pull requests with at least 3 participants and where the repository has at least 10 forks and 10 stars (565 left).

From these 565 pull requests, we sampled 210 such that half were ultimately merged and the other half were rejected.

The 210 pull requests were published on the Amazon Mechanical Turk (MTurk) crowdsourcing platform for analyzing in 2 rounds, together with the 20 carefully studied pull requests from TDH [67] inserted for each round as “gold” standard tasks. The 1st round has 100(80+20) pull requests in total, while 2nd round has 150(130+20) pull requests in total.

Cost Control. We want to make sure the cost is as low as possible but also provide a fair payment for the participants. According to several recent surveys on MTurk [7, 10, 29, 49], the average hourly wage is $1.66 and MTurk workers are willing to work at $1.40/hour. We estimated about 10 minutes needed for each HIT, and first launched our task with $0.25 per HIT but only received 1 invalid feedback after 2 days. So we doubled our payment to $0.50 with a smaller data set for further analysis.

For the rest of this paper, we will refer to the data collected via crowd as the qualitative pull request features.

4.4 Crowdsourcing Quality Control

A major issue in crowdsourcing is how to reduce the noise inherent in data collection from such a subjective source of information. This section describes the three operators we used to increase data quality:

- Audience screening;
- “Gold” standard questions and tasks;
- Feature subset selection.

Quality and experience filters were applied to screen potential participants; only workers with HIT approval rate above 90%, and who had completed at least 100 approved HITs could participate.

Next, a domain-specific screening process was applied. To make sure the crowd participants are qualified to analyze the pull requests in our study, we require them to be GitHub users and answer preliminary questions related to identifying the pull request key players and pull request acceptance on every pull request analyzed. These are questions for which we can systematically extract values from the pull requests; if these golden questions are answered incorrectly, the task was rejected and made available to other crowd workers.

Quality Control. Part of the audience selection relates to quality control since the workers were required to have demonstrated high quality in prior tasks on the MTurk platform and answer simple questions about the pull request correctly. Beyond that, we used (1) redundant question formats [63] and (2) gold standard tasks to control crowd quality.

1. For each question in the task related to the pull request comment discussion, we require workers to answer a yes/no question and then copy the comments supporting their answers from the pull request into the text area under each question. Take question 1 for example (Is there a comment proposing alternate solutions?): if they choose “Yes, from core members”, then they need to copy the comments within the pull requests to the text area we provided.

2. This study was run in two phases, one phase with 80 out of the 210 new pull requests, and one phase with the remaining 130. In each phase, the original 20 pull requests were added to the group. The tasks were randomly assigned to crowd workers. For those crowd workers who got one of the 20 previously studied pull requests, we checked their answers against the ground truth [67]; inaccurate responses were rejected and those workers were blocked. This acted as a random quality control mechanism.

In total, we have 250 highly discussed pull requests from 142 projects and analyzed by 27 workers. After filtering out the unqualified ones using the control processes stated above, 190 pull requests were left with 3,471 comments. The unqualified responses were a result of part (1) above, but an operational error led us to approve the tasks despite the poor comment quality, leaving us with a smaller data set for further analysis.

For the rest of this paper, we will refer to the data collected via crowd as the qualitative pull request features.

4.5 Quantitative Analysis

In this study, we have 2 groups of features (1) all the quantitative features found important in previous works and (2) all qualitative features extracted from the results of studying pull requests in detail by the qualified crowd. For each group of features, we run the CFS feature selector [27] to reduce the features to use for our decision tree classifier. To collect the quantitative features, we started with Table 2 and used the GitHub API to extract the features marked in the right-hand-side column.

CFS evaluates and ranks feature subsets. One reason to use CFS over, say, correlation, is that CFS returns sets of useful features while simpler feature selectors do not understand the interaction between features.

CFS assumes that a “good” set of features contains features that are highly connected with the target class, but weakly connected to each other. To implement this heuristic, each feature subset is
scored as follows according to Hall et al. [27]:

$$merits = \frac{k R_{cf}}{\sqrt{k + k(k - 1) r_{gf}}}$$

where merits is the value of some subset $s$ of the features containing $k$ features; $r_{cf}$ is a score describing the connection of that feature set to the class; and $r_{gf}$ is the mean score of the feature to feature connection between the items in $s$. Note that for this fraction to be maximal, $r_{cf}$ must be large and $r_{gf}$ must be small, which means features have to correlate more to the class than each other.

This equation is used to guide a best-first search with a horizon of five to select most informative set of features. Such a search proceeds as follows. The initial frontier is all sets containing one different feature. The frontier of size $n$, which initialized with 1, is sorted according to merits and the best item is grown to all sets of size $n+1$ containing the best item from the last frontier. The search stops when no improvement have been seen in last five frontiers in merits. Return the best subset seen so far when stop.

Our experiments assessed three groups of features:

1. After CFS feature selector, the selected quantitative features were `commits_on_files_touched`, `requester_succ_rate`, `prev_pullreqs`, which are quite intuitive.
2. The second group of crowdsourced features were `Q3_dis.s`, `Q4_dis.p_nv`.
3. The third group of combined features were the combination of both quantitative and crowdsourced features; i.e. `Q3_dis.s, commits_on_files_touched, requester_succ_rate, prev_pullreqs`.

For each of these three sets of features, we ran a 10x5 cross validation for supervised learning with the 3 different groups of features. These generate three models that predicted if a pull request would get merged/accepted or not. A decision tree learner was used as our supervised learning algorithm. This was selected after our initial studies with several other learners that proved to be less effective in this domain (Naive Bayes and SVM).

5 RESULTS

Using Amazon’s Mechanical Turk micro-task crowdsourcing platform, we collect data for 1) the original 20 pull requests from the primary study [67], and 2) 210 additional, independent pull requests, an order of magnitude more than pull requests than the primary study. This data includes qualitative information about the pull request discussion, such as whether there is a comment showing support, proposing an alternate solution, disapproving of the solution, and disapproving of the problem being solved. The benefits of the larger sample size is two-fold. First, by using similar selection criteria in the secondary study compared to the primary study, we are able to check the stability and external validity of the findings in the primary study using a much larger sample (RQ1, RQ2). Second, in terms for informativeness, we can extract features from crowd’s answers, which is qualitative, and build models to predict pull request acceptance results. This allows us to compare the performance of models built with (a) the features identified as important in the primary study and (b) the features from related, quantitative works (RQ3).

### Table 3: Quality for Crowdsourcing Results from Amazon Mechanical Turk (RQ1).

| Questions | Precision | Recall | F1-Score |
|-----------|-----------|--------|----------|
| Q1        | 0.769     | 0.769  | 0.770    |
| Q2        | 0.818     | 0.750  | 0.783    |
| Q3        | 0.727     | 0.667  | 0.696    |
| Q4        | 0.778     | 0.700  | 0.737    |
| Q5        | 0.833     | 0.714  | 0.770    |
| Total     | 0.801     | 0.742  | 0.770    |

#### 5.1 RQ1: Can the crowd reproduce prior results quickly and cheaply?

RQ1 checks if our analysis in § 4.2 correctly captured the essence of the TDH study.

In this test, we used the 20 “gold” task results from TDH. Each pull request was labeled with the gold results. Next, we checked the performance of the crowd with respect to the gold results. Table 3 shows the precision, recall and F1 scores of the crowd working on the gold tasks. As seen in Table 3, the precision and recall of these ‘human predictors’ on the 20 gold tasks is 80% and 74% respectively (so $F_1 \approx 77\%$). Based on our prior work with data mining from SE data, we assert that these values represent a close correspondence between the TDH results and those from the crowd.

To make sure we did not mistakenly analyze the crowd’s answers, we hand-examined the cases where the crowd disagreed with the TDH. Interestingly, we found several cases that crowd workers appear to be correct. For example, TDH classify the 17th pull request they studied as no support, while the crowd found the comment from the user drolthlis saying ‘This is great news!’, which is an apparent indicator for the supporting this pull request after our examination. Another two cases are the 16th and 20th pull requests they studied. Crowd workers found clear suggestions for alternative solutions (i.e., ‘What might be better is to...’, ‘No, I think you can just push -f after squashing.’), which TDH does not find.

As to the issue of speed and cost, TDH report that they required about 47 hours to collect interview data on 47 users within which, they investigated the practices about pull requests. TDH does not report the subsequent analysis time but, given the qualitative nature of their methods, we conjecture that took hours to weeks.

By way of comparison, we spent $200, to buy 77 hours of crowd time. In that time, 250 pull requests were analyzed (100, 150 pull requests respectively for each round). Note that, in this study, we included the 20 pull requests already studied by TDH.

In summary, we answer RQ1 in the affirmative.

#### 5.2 RQ2: Are the primary study’s results stable?

As described in the introduction, one motivation for this work was checking if crowdsourcing can scale and confirm the external validity of qualitative conclusions. This issue is of particular concern for crowdsourcing studies due the subjective nature of the opinions from the crowd. If those opinions increased the variance of the collected data, then the more data we collect, the less reliable the conclusions.
To test for this concern, we compare the pull requests studied by crowd (excluding the 20 gold tasks) with the 20 pull request studied by TDH (15 merged, 5 rejected). We first randomly select 15 merged and 5 rejected pull requests studied by crowd 100 times, so that we can compare the these 2 independent samples at the same scale and with the same distribution. Then we run another 100 iteration for randomly selecting 87 merged and 29 rejected pull requests studied by crowd, which still has the same distribution but at a 6 times larger scale. *p*-values are collected for each sample comparison in the 2 runs.

Figure 4 shows the results of comparing pull requests from TDH and an independent sample with 2 different scales. As shown, Questions 1, 2, 4 are quite stable for both scales. Moreover, Question 1 and 4 are becoming more stable when scale becomes larger, while Question 2 becomes less stable at a larger scale. For Question 3, all of the *p*-values are lower than 0.05 at the same scale, though the median of its *p*-value is higher than 0.05 at the same scale as TDH. This may indicate that TDH did not cover enough pull requests to achieve a representative sample for the finding, which is mapped into Question 3 about disapproving comments.

Accordingly, we answer RQ2 in the affirmative. The results for Q1, Q2, and Q4 do not differ significantly between TDH and independent samples of the same size or of a larger size. The exception is Q3, for which the results differ significantly when scaling to a larger data set.

5.3 RQ3: How well can the qualitative and quantitative features predict PR acceptance?

The results are shown in Figure 5, expressed in terms of precision, recall, and the $F_1$ score; i.e. the harmonic mean of precision and recall, for each of three feature sets: quantitative, crowdsourced, and a combination. Note that the performances of the predictor using crowdsourced features are not as high or as stable as the one built with quantitative features. We can see that:

- The selected quantitative features achieved $F_1$ score at 90% with a range of 20%;
- The selected crowdsourced features achieved lower $F_1$ score at 68% with a larger range.
- The combined selected features did better than just using quantitative; but performed no better than just using only the quantitative features.

At first glance, the models learned from crowdsourced features performed worse than using quantitative features extracted from numerous prior data mining studies. But is this the case? Do the middle results really reflect the insights taken from Figure 5? As seen in §5.1, we have shown that our analysis in §4.2 correctly captured the essence of the TDH study.

In summary, we answer RQ3 in the affirmative:

(1) The middle results of Figure 5 adequately reflect the TDH results;
(2) Accordingly, we can also conclude that Figure 5 shows the TDH results being out-performed by the purely quantitative features.

6 THREATS TO VALIDITY

As with any empirical study, biases can affect the final results. Therefore, any conclusions made from this work must be considered with the following issues in mind:

**Sampling bias:** This threatens any classification experiment; i.e., what matters there may not be true here. For example, the pull requests used here are selected using the rules described in 4.3. Only 250 highly discussed pull requests from active projects are sampled and analyzed, so our results may not reflect the patterns for all the pull requests. That said, we note that one reason to endorse crowdsourcing is that its sample size can be orders of magnitude larger than using just qualitative methods. For example, TDH reported results from just 20 pull requests.

**Learner bias:** For building the accepation predictors in this study, we elected to use a decision tree classifier. We chose decision trees because it suits for small data samples and its results were comparable to the more complicated algorithms like Random Forest and SVM. Classification is a large and active field and any
Table 4: Comparison of Different Methods for GitHub Pull Requests Studies. '√' stands for True, '×' for False and '?' for Uncertain.

| Measures          | Quantitative Studies: E.g. API-Mining, Data Modeling | Qualitative Studies: E.g. Interview, Case Study | Crowdsourcing Assisted Qualitative Studies |
|-------------------|-------------------------------------------------------|------------------------------------------------|--------------------------------------------|
| Time              | Hours                                                 | Weeks or Months                                | Days                                       |
| Cost              | $10-100                                               | $1,000-3,000                                   | $100-300                                   |
| Perspective       | Objective                                             | Subjective                                     | Combined                                   |
| Purpose           | Descriptive: Reveal General Trends                    | Exploratory: Find Details                      | Confirmatory: Theories                    |
|                   | Explanatory: Summarize Patterns                       | Improving: Study Drawbacks                     | Scale Up & Lower Costs                     |
| Stability         | √                                                     | ?                                               | √                                          |
| Scalability       | √                                                     | ×                                               | √                                          |
| Reproducibility   | √                                                     | ×                                               | √                                          |
| Can Build Predictor | √                                                    | ×                                               | √                                          |

single study can only use a small subset of the known classification algorithms. Future work should repeat this study using other learners.

**Evaluation bias:** This paper uses precision, recall and F1 score measures of predictor’s performance. Other performance measures used in software engineering include accuracy and entropy. Future work should repeat this study using different evaluation biases.

**Order bias:** For the performance evaluation part, the order that the data trained and predicted affects the results. To mitigate this order bias, we run the 5-bin cross validation 10 times randomly changing the order of the pull requests each time.

7 DISCUSSION

We summarize our experience with qualitative, quantitative and crowdsourcing methods in Table 4. As shown, the outstanding benefit of quantitative methods is to find general patterns or underlying trends. They usually work with large amounts of data and are fast to deploy, cheap to run, and easy to replicate. The major drawback is they often ignore the details and often lack a human-level understanding. Besides, it’s also hard to implement a data miner for large projects, and time-consuming for complex systems.

The outstanding benefit of qualitative methods is their exploratory nature to generate new theorems or improve existing ones. They seek details to understand what humans really care about and find insights. While the major drawback is the sample size is restricted to a very small size compared to quantitative method, because of the involvement of human. Therefore, the complexity, time and/or money cost are needed to be taken into consideration. Further, most of the studies with qualitative methods are hard to replicate or scale up for larger sample size.

The outstanding benefit of crowdsourcing methods is they try to mix and match methods in order to exploit the strengths of all the above approaches. They could offer the human-level understanding or intelligence compared with quantitative methods and also scale up and increase the diversity of data size due to its low costs and massive work force compared with qualitative methods. The major concerns of crowdsourcing methods are that the quality and knowledge of the workers from crowd are inadequate, and that the study context cannot be as controlled. Following this, it is unclear if the crowd can serve as a proxy for domain experts. Also, it is important to ask about the right questions for the crowd to get the expected results.

The key point of this paper is that it is misleading to review the benefits and drawbacks of these methods in isolation. Rather, it is more insightful to consider what these methods can achieve in combination. For example, in the original qualitative TDH study, the authors found that 1) supports, 2) alternate solutions, 3) disapproval for the proposed solutions, and 4) disapproval for the problems being solved were important factors that guard pull requests’ acceptance. In this scaled, crowdsourced replication, we found that factors 1, 2 and 4 still hold, but 3 was unstable. Thus, this combination of empirical methods allows us to pinpoint more precisely results that are steadfast against tests of external validity and the results that need further investigation.

In the end, the secondary quantitative study would have been impossible without the primary qualitative work, and we should make best use of the time-consuming qualitative works, instead of stopping after we get results from qualitative results (and vice versa). We find qualitative studies can inspire quantitative studies by carefully mapping out areas of concern. Primary qualitative study can also provide the data needed to control secondary quantitative crowdsourcing studies. We also find a single primary qualitative study can direct the work of many secondary quantitative studies, and our work is just one example of the secondary studies after TDH’s qualitative work.

8 CONCLUSION

In this paper, we designed MOSSS and applied it to one state of art qualitative study from TDH. As seen in Table 1 and Table 2, we reviewed and summarized all related paper on GitHub pull requests from both Google Scholar from 2008 to 2016 and 10 top SE conferences from 1992 to 2016. In §4.2 and 4.3, we show that, with results and data from TDH’s primary study, it is possible to quickly map their insights into micro questions for crowd workers and expand the data they studied to a larger scale. Moreover, from the 20 pull requests studied in TDH, we also extracted answers treated as the ground truth for our questions described in §4.2. These answers served as gold tasks for quality control during our crowdsourcing process in §4.4. With these gold tasks, we not only checked the sanity of the qualified answers from crowd in §5.1, but also checked the stability of the primary results from TDH in §5.2. As seen in Table 3 and Figure 4, we showed an overall 77% of F1 score and three out of the four findings we extracted from TDH are stable from a larger scale. In §4.5, we did quantitative analysis by applying data mining techniques on the large amount
of answers we collected from crowd and build predictors with crowdsourced features, quantitative features from literature review and the combination of both. As shown in Figure 5, we found the crowdsourced features mapped from THD results could do a good job predicting the fate for pull requests, but cannot compete with features selected from related quantitative studies. These results have implications for the value of combining diverse empirical methods and for conducting conceptual replications of empirical software engineering studies in new contexts.

REFERENCES
[1] 2013. Empirical Software Engineering v2.0. (2013).
[2] Ofa Amir, Yuval Shalar, Ya’akov Gal, and Litan Ilani. 2013. On the verification complexity of group decision-making tasks. In First AAAI Conference on Human Computation and Crowdsourcing.
[3] Alberto Bacchelli and Christian Bürd. 2013. Expectations, outcomes, and challenges of modern code review. In Proceedings of the 2013 international conference on software engineering. IEEE Press, 712–721.
[4] Daniel W. Barowy, Charlie Curtinberg, Emery D. Berger, and Andrew McGregor. 2012. AutoMan. A Platform for Integrating Human-based and Digital Computation. SIGPLAN Not. 47, 10 (Oct. 2012), 639–654. DOI: http://dx.doi.org/10.1145/2398857.2384663
[5] Andrew Begel, Jan Bosch, and Margaret-Anne Storey. 2013. Social networking meets software development: Perspectives from github, mdsn, stack exchange, and topecoder. IEEE Software 30, 1 (2013), 52–66.
[6] Andrew Begel and Thomas Zimmermann. 2014. Analyze this! 145 questions for data scientists in software engineering. In Proceedings of the 36th international Conference on Software Engineering. ACM, 12–23.
[7] Adam J Berinsky, Gregory A Huber, and Gabriel S Lenz. 2012. Evaluating online labor markets for experimental research: Amazon’s Mechanical Turk. Political Analysis 20, 3 (2012), 351–368.
[8] Kelly Blinksje, Jyoti Sheoran, Sean Goggins, Eva Petakovic, and Daniela Damian. 2016. Understanding the popular users: Following, affiliation influence and leadership on GitHub. Information and Software Technology 70 (2016), 30–39.
[9] João Brunet, Guil C. Murphy, Ricardo Terra, Jorge Figueiredo, and Dalton Serey. 2014. Do developers discuss design? In Proceedings of the 11th Working Conference on Mining Software Repositories. ACM, 340–343.
[10] Michael Buhmmeister, Tracy Kwang, and Samuel G Gosling. 2011. Amazon’s Mechanical Turk a new source of inexpensive, yet high-quality, data? Perspectives on psychological science 6, 1 (2011), 3–5.
[11] Robert A. Cochran, Loris D’Antoni, Benjamin Livshits, David Molnar, and Margus Veanes. 2015. Program Boosting: Program Synthesis via Crowd-Sourcing. In Proceedings of the 42Nd Annual ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages (POPL ’15). ACM, New York, NY, USA, 677–688. DOI: http://dx.doi.org/10.1145/2676726.2676973
[12] Robert A. Cochran, Loris D’Antoni, Benjamin Livshits, David Molnar, and Margus Veanes. 2015. Program Boosting: Program Synthesis via Crowd-Sourcing. SIGPLAN Not. 50, 1 (Jan. 2015), 677–688. DOI: http://dx.doi.org/10.1145/2775051.2676973
[13] Bernard P. Cohen. 1989. Developing sociological knowledge: Theory and method. Wadsworth Pub Co.
[14] Harris Cooper, Larry V. Hedges, and Jeffrey C Valentine. 2009. Emprical So/ftware Engineering v2.0. (2013).
[15] Laura Dabbish, Colleen Stuart, Jason Tsay, and Jim Herbsleb. 2012. Social coding and the combination of both. As shown in Figure 5, we found the crowdsourced features mapped from THD results could do a good job predicting the fate for pull requests, but cannot compete with features selected from related quantitative studies. These results have implications for the value of combining diverse empirical methods and for conducting conceptual replications of empirical software engineering studies in new contexts.

of answers we collected from crowd and build predictors with crowdsourced features, quantitative features from literature review and the combination of both. As shown in Figure 5, we found the crowdsourced features mapped from THD results could do a good job predicting the fate for pull requests, but cannot compete with features selected from related quantitative studies. These results have implications for the value of combining diverse empirical methods and for conducting conceptual replications of empirical software engineering studies in new contexts.

REFERENCES
[1] 2013. Empirical Software Engineering v2.0. (2013).
[2] Ofa Amir, Yuval Shalar, Ya’akov Gal, and Litan Ilani. 2013. On the verification complexity of group decision-making tasks. In First AAAI Conference on Human Computation and Crowdsourcing.
[3] Alberto Bacchelli and Christian Bürd. 2013. Expectations, outcomes, and challenges of modern code review. In Proceedings of the 2013 international conference on software engineering. IEEE Press, 712–721.
[4] Daniel W. Barowy, Charlie Curtinberg, Emery D. Berger, and Andrew McGregor. 2012. AutoMan. A Platform for Integrating Human-based and Digital Computation. SIGPLAN Not. 47, 10 (Oct. 2012), 639–654. DOI: http://dx.doi.org/10.1145/2398857.2384663
[5] Andrew Begel, Jan Bosch, and Margaret-Anne Storey. 2013. Social networking meets software development: Perspectives from github, mdsn, stack exchange, and topecoder. IEEE Software 30, 1 (2013), 52–66.
[6] Andrew Begel and Thomas Zimmermann. 2014. Analyze this! 145 questions for data scientists in software engineering. In Proceedings of the 36th international Conference on Software Engineering. ACM, 12–23.
[7] Adam J Berinsky, Gregory A Huber, and Gabriel S Lenz. 2012. Evaluating online labor markets for experimental research: Amazon’s Mechanical Turk. Political Analysis 20, 3 (2012), 351–368.
[8] Kelly Blinksje, Jyoti Sheoran, Sean Goggins, Eva Petakovic, and Daniela Damian. 2016. Understanding the popular users: Following, affiliation influence and leadership on GitHub. Information and Software Technology 70 (2016), 30–39.
[9] João Brunet, Guil C. Murphy, Ricardo Terra, Jorge Figueiredo, and Dalton Serey. 2014. Do developers discuss design? In Proceedings of the 11th Working Conference on Mining Software Repositories. ACM, 340–343.
[10] Michael Buhmmeister, Tracy Kwang, and Samuel G Gosling. 2011. Amazon’s Mechanical Turk a new source of inexpensive, yet high-quality, data? Perspectives on psychological science 6, 1 (2011), 3–5.
[11] Robert A. Cochran, Loris D’Antoni, Benjamin Livshits, David Molnar, and Margus Veanes. 2015. Program Boosting: Program Synthesis via Crowd-Sourcing. In Proceedings of the 42Nd Annual ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages (POPL ’15). ACM, New York, NY, USA, 677–688. DOI: http://dx.doi.org/10.1145/2676726.2676973
[12] Robert A. Cochran, Loris D’Antoni, Benjamin Livshits, David Molnar, and Margus Veanes. 2015. Program Boosting: Program Synthesis via Crowd-Sourcing. SIGPLAN Not. 50, 1 (Jan. 2015), 677–688. DOI: http://dx.doi.org/10.1145/2775051.2676973
[13] Bernard P. Cohen. 1989. Developing sociological knowledge: Theory and method. Wadsworth Pub Co.
[14] Harris Cooper, Larry V. Hedges, and Jeffrey C Valentine. 2009. Emprical So/ftware Engineering v2.0. (2013).
[15] Laura Dabbish, Colleen Stuart, Jason Tsay, and Jim Herbsleb. 2012. Social coding in GitHub: transparency and collaboration in an open software repository. In Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work. ACM, 1277–1286.
[16] E. Dolstra, R. Vliegendhart, and J. Pouwelse. 2013. Crowdsourcing GUI Tests. In Proceedings of the 10th Working Conference on Mining Software Repositories (MSR ’13). IEEE Press, Piscataway, NJ, USA, 233–236. http://dx.doi.org/10.1145/2487085.2487132
[17] Steve Easterbrook, Janice Singer, Margaret-Anne Storey, and Daniela Damian. 2008. Selecting empirical methods for software engineering research. In Guide to advanced empirical software engineering. Springer, 285–311.
[18] Gagan Goel, Afshin Nikzad, and Adish Singla. 2014. Mechanism design for E. Dolstra, R. Vliegendhart, and J. Pouwelse. 2013. Crowdsourcing GUI Tests. In Proceedings of the 10th Working Conference on Mining Software Repositories. ACM, 368–371.
[19] Georgios Gousios. 2014. A dataset for pull-based development research. In Proceedings of the 11th Working Conference on Mining Software Repositories. ACM, 285–296.
[20] Georgios Gousios, Andy Zaidman. 2014. A dataset for pull-based development research. In Proceedings of the 37th International Conference on Software Engineering-Volume 1. IEEE Press, 358–368.
[21] Georgios Gousios, Andy Zaidman, Margaret-Anne Storey, and Arie Van Deursen. 2015. Work practices and challenges in pull-based development: the integrator’s perspective. In Proceedings of the 37th International Conference on Software Engineering. ACM, 195–204.
[22] Gousios, M Pinzger, and A Van Deursen. 2013. An exploration of the pull-based software development model. ICSE.
