Nudge: Accelerating Overdue Pull Requests Towards Completion

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Pull requests are a key part of the collaborative software development and code review process today. However, pull requests can also slow down the software development process when the reviewer(s) or the author do not actively engage with the pull request. In this work, we design an end-to-end service, Nudge, for accelerating overdue pull requests towards completion by reminding the author or the reviewer(s) to engage with their overdue pull requests. First, we use models based on effort estimation and machine learning to predict the completion time for a given pull request. Second, we use activity detection to reduce false positives. Lastly, we use dependency determination to understand the blocker of the pull request and nudge the appropriate actor (author or reviewer(s)). We also do a correlation analysis to understand the statistical relationship between the pull request completion times and various pull request and developer related attributes. Nudge has been deployed on 147 repositories at Microsoft since 2019. We do a large scale evaluation based on the implicit and explicit feedback we received from sending the Nudge notifications on 8,500 pull requests. We observe significant reduction in completion time, by over 60%, for pull requests which were nudge thus increasing the efficiency of the code review process and accelerating the pull request progression.

1 INTRODUCTION

With the adoption of collaborative software development platforms like GitHub and Azure DevOps, pull requests have become the standard mechanism for distributed code reviews. Pull requests enable the code changes to be reviewed by one or more developers and even automated bots [7, 19]. Once the reviewers have signed off, the changes can be merged with the main branch and deployed. Pull requests have recently become an active area of research in the software engineering community. Various aspects of pull requests have been studied such as reviewer recommendation [5, 41], prioritization [35] and duplication [36]. Additionally, several bots and extensions have been built for platforms like GitHub and Azure DevOps to automate various software development workflows [17, 19].

While pull requests streamline the code review process significantly, they can also slow down the software development process. For instance, if the reviewers are overloaded and lose track of the pull request, it might not be reviewed in a timely manner. Similarly, if the pull request author is not actively working on the pull request and reacting to the reviewers’ comments, pull request completion could be slowed down significantly. Hence, if the pull request’s author and reviewers don’t actively engage, the pull requests can remain open for a long time, slowing down the coding process and even causing side effects like merge conflicts in some cases. Yu et al. [40] did a retrospective study of the factors impacting pull request completion times and found that the size of the pull request and availability of CI pipeline have a major impact. Long lived feature branches
can also cause several unintended consequences [4]. Some of the most common side effects caused by long lived feature branches or pull requests are:

- They hinder communication. Pull requests that are open for longer periods of time hide your work from rest of your team. Making code changes and merging them quickly increases source code re-usability by making the functionality and optimizations built by a developer available to other developers.
- With thousands of developers working on same codebase and with the amount of code churn that happens, in large organizations, the assumptions that a developer make about the state of the code might not hold true, longer they have their feature branches open. There is a greater risk that developers become blind to how their work affect others.
- They cause integration pain. When the code is merged more frequently to the main branch, the pain of integration happens at the beginning of the software development life cycle instead of the end. Integration testing can be done earlier, issues can be detected faster and bugs can be fixed at the earliest possible moment.
- They cause complex merge conflicts. Branches that stay diverged from the main branch for longer periods of time can causes complex merge conflicts that are hard to solve. Dias et al. [18] studied over 70,000 merge conflicts and found that code changes with long check-in time are more likely to result in merge conflicts.
- They prevent the companies from delivering value to the customers quickly. Organizations can deliver more value to the customers by turning on new features or bug fixes that the customers would love to see in a company’s products or services earlier if the code is merged faster. Code changes that address really important customer issues or that have the ability to create differentiation and value proposition to the companies are worth nothing if they are not merged faster and deployed sooner.

In this work, we designed and deployed Nudge, a service for accelerating overdue pull requests towards completion. Nudge leverages effort estimation and activity detection to intelligently predict the completion time for a given pull request. Further, it analyzes the pull request state to determine the actor (i.e. pull request author or reviewer(s)) blocking the pull request from completion. Lastly, it notifies the actor by leveraging the comment functionality in pull request environment. To build Nudge, first we do a correlation analysis to analyze various factors related to the pull request, pull request author, pull request reviewers and even temporal factors which can impact the pull request completion time. Unlike Yu et al. [40], we consider factors which are known at the time of the pull request creation. Next, we use effort estimation for predicting the pull request completion time at the time of pull request creation. Effort estimation models have been long studied in software engineering research. Effort estimation models help organizations and individuals plan and track progress of their software projects and individual tasks to help plan delivery milestones better. We build on the rich body of work in the effort estimation literature, to build a model for predicting the completion time of a pull request. Prior work [20] has also focused on effort estimation at the feature and project level, but not at the level of individual pull requests. We use several metrics from the defect prediction literature like code churn [27], reviewer information [23], ownership information [20] to build our pull request lifetime prediction model.

While effort estimation models have been shown to have been fairly accurate [6], they cannot account for contextual and environmental factors such as work load of the pull request reviewer(s) or the author. So, in order to improve the notification precision, we implement activity detection which monitors any updates on the pull request such as new commits, review comments, etc and adjusts the notification accordingly. Lastly, to make the Nudge notifications actionable, we also implement dependency determination which infers the actor (pull request author or a specific
reviewer(s)) who is blocking the pull request from completion. To summarize, in this paper, we make the following contributions:

1. We build and evaluate a pull request level effort estimation model using various in-product and process metrics.
2. We designed and implemented Nudge, which leverages the effort estimation model along with activity detection and dependency determination to accelerate pull request completion.
3. We share the quantitative and qualitative results from deploying Nudge to over 147 repositories at Microsoft since 2019.
4. We do an ablation study to help understand the contributions of the different components of Nudge.

The rest of the paper is organized as follows. In section 2, we discuss the building of the effort estimation model for pull request lifetime prediction. Section 3 describes the activity detection and Section 4 describes the dependency determination. In Section 5, we present the implementation details of the Nudge service using Azure DevOps extensibility mechanism. In Sections 6 and 7, we describe the large-scale user study of Nudge we conducted at Microsoft. We then conclude the paper with related work and conclusion.

This paper extends our prior publication [24] presented at the 27th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering - Industry Track (ESEC FSE ’19 Industry Track). New materials with respect to the conference version include:

- **Activity detection**: Motivated by the user feedback we received from the prior deployment of the Nudge service at Microsoft, we have implemented activity detection (Section 3) on top of the effort estimation model to improve the notification accuracy. Previously, we had heard from multiple users about being reminded about a pull request even when it was being actively worked on or reviewed.

- **Dependency determination**: Another major feedback we had received was about making the notifications actionable. Since the pull request could be delayed because of different factors, it’s important to highlight the root cause in the Nudge notification. So, we have implemented dependency determination to attribute the delay in pull request completion to make it more actionable (Section 4).

- We do a large-scale deployment and user study at Microsoft to evaluate the efficacy of the Nudge system and compare it with the previous version (Sections 6 and 7).

- Additional details regarding the implementation (Section 5) and related work (Section 8) are provided.

## 2 PULL REQUEST LIFETIME PREDICTION

In this section, we explain the details about how the data needed to train the effort estimation models at pull request level is mined, how the model is developed, validated and deployed. We can broadly classify this activity into 4 steps:

1. Leveraging the rich history of prior work done in the Effort Estimation and Mining Software Repositories community to determine the factors that impact pull request acceptance and defect prediction, we identify a set of attributes that needs to be mined for pull requests.
2. Run the data collection algorithm on multiple repositories and collect the ground truth data.
3. Use the data collected in Step 2 to build a Pull Request lifetime prediction model and evaluate the performance of the model.
4. Deploy the prediction model in the Nudge service and evaluate the user feedback on the notifications.
2.1 Correlation Analysis

We performed correlation analysis to understand the factors that impact the lifetime of pull requests and the magnitude of impact. We collected 22,875 completed pull requests from 10 different repositories at Microsoft. These repositories host the source code of various medium and large scale services with few hundreds to thousands of developers operating off those repositories.

We formulated this as a linear regression problem where we define a dependant variable (pull request lifetime) and a set of independent variables (features listed in table 1). We then used gradient boosting regression algorithm to perform the regression analysis and calculate correlation scores (listed in Table 2). More details about dependant and the independent variables are listed below:

(1) **Dependant variable** The dependant variable in our experiment is the pull request completion time, i.e., the time interval between pull request creation and closing date, in hours. In case of re-opened pull requests, we only consider the date when they are first closed.

(2) **Features** We computed various pull request related, author related, process related and churn related features. Table 1 lists all the features that are used in our correlation analysis. Correlations of these features to pull request completion time is explained in Table 2.

| Feature | Description | Type |
|---------|-------------|------|
| Day of the week | The day of the week when the pull request was created | Categorical |
| Avg age of pull requests Of this developer | The average time for pull request completion by the developer who initiated it | Continuous |
| Number of reviewers | Total number of required reviewers on the current pull request | Continuous |
| Is .csproj file being edited | Is .csproj file being modified? | Categorical (Binary) |
| Average age of pull request with similar paths changed | The average time for completion for the pull requests which have the same project paths changed | Continuous |
| Number of distinct file types | Total number of distinct file types that are being modified | Continuous |
| Pull request description word count. | The word count of the textual description of the pull request | Continuous |
| Setting or config change | Is the pull request modifying any config. files or settings | Categorical (Binary) |
| Number of active pull requests at this time | To understand the overall load on the project with respect to open pull requests | Continuous |
| Feature                  | Description                                                                                 | Type       |
|-------------------------|---------------------------------------------------------------------------------------------|------------|
| Class churn             | Churned LOC per class                                                                       | Continuous |
| Method churn            | Number of methods being churned                                                             | Continuous |
| New feature            | Is this pull request introducing a new feature?                                            | Categorical|
| LOC Changed             | Number of lines changed                                                                     | Continuous |
| Number of paths touched | Number of distinct paths that are being touched in the current change                      | Continuous |
| Conditional statement churn | Number of conditional statements being touched                                              | Continuous |
| Loop churn              | Number of loops being touched                                                                | Continuous |
| Class Member Churn      | Number of classes being added/modified/deleted                                              | Continuous |
| Is It refactoring change | Is the PR doing any refactoring of existing code?                                          | Categorical|
| Reference churn         | Number of references or dependencies (on other libraries / projects) being changed           | Continuous |
| Number of files changed | Number of files that are being modified in pull request                                     | Continuous |
| Is it a merge change    | Is the pull request making any merge changes like forward or reverse integration (FIs / RIs) | Categorical|
| Is it a deprecate change | Is the pull request deprecating any old code?                                               | Categorical|
| Pull request Title Word Count | The word count of the textual title of the pull request.                                    | Continuous |
| Is pull request created during Business Hours? | Whether the pull request is created during business hours or off hours?                   | Categorical|
| Is it Bug Fix           | Is the pull request fixing bugs?                                                             | Categorical|
| Age of the pull request author in current team | Time spent by the developer in the current team.                                            | Continuous |
Detailed description of some of the features and their correlations to pull request completion time is listed below:

**Day of the week:** This is the day of the week on which the pull request is created. This helps us understand if the day on which a pull request is created has an impact on them moving faster. We represent Sunday with 0 and Saturday with 6. A strong positive correlation with this metric indicates that pull request created later in the week (like Friday or Saturday) are taking longer time to complete.

**Average age of pull requests created by the author** - This captures how quickly a specific Author’s pull requests were moving, historically. The idea is, if a developer is junior or new to a particular repository or project they tend to take more time to learn the processes followed in the repository or their changes are subjected to more thorough reviews and testing which potentially delays progression of their pull requests. Over time these developers become better at completing their pull requests and our model captures that. Our correlation analysis shows a strong positive correlation that bolsters the argument that more time a developer’s PRs took to complete historically, more time the current one takes.

**Number of reviewers of the PR** - Number of reviewers actively reviewing the PR. The intuition here is if more people are actively reviewing a PR and are engaged with it, more number of comments and questions are raised (probably more nitpicks too) and that could potentially delay the PR. A strong positive correlation here indicates more the number of reviewers more time it takes for it to be completed / merged.

**Is a .csproj file being edited** - If a .csproj file is being touched? We represent this with 1 if it is and 0 if it is not. A .csproj file in C# context is a project configuration file which tracks files in the current project/solution, external package dependencies and their versions, inter dependencies among different projects in a solution etc. Any modifications to these files indicate that major activity like adding or deleting files / modifying external dependencies or DLLs or modifying dependencies on other projects is happening. A very good positive correlation here indicates that any changes made to these files (represented by value 1) increases the PR’s lifetime.

**Average age of PRs with similar paths changed** - This indicates how PRs that touched same paths as the ones that are being modified in the current PR impacts PR’s completion time. The intuition here is, there are always certain code paths which are known to be riskier and any changes to them usually takes very long time before they are merged. A positive correlation here indicates that more time it took for PRs, that are touching same paths/files as the current PR, in the past to complete, more time it takes to the current PR to be merged.

**Is the PR a Bug fix?** - This is 1 if the PR is doing a bug fix and 0 if it is not. The intuition here is, in large scale service and DevOps environments, bug fixes (especially critical bugs or showstoppers) will always be given higher priority and people just walk around and get all the needed sign-offs and try to push them as soon as possible. A weak negative correlation here indicates that possibly PRs which are bug fixes (with value 1) takes lesser time to complete than the non bug fixes (with value 0).
### Table 2. Correlation analysis

| Feature                                                                 | Correlation score |
|------------------------------------------------------------------------|-------------------|
| Day of the week when PR was created                                    | 0.163             |
| Avg age of PRs by the PR author                                        | 0.159             |
| Number of reviewers of the PR                                           | 0.131             |
| Is csproj being edited                                                 | 0.103             |
| Average age of PRs With similar paths changed                          | 0.089             |
| Number of distinct file types                                          | 0.084             |
| Pr description word count                                              | 0.072             |
| Is settings or config changed in the PR                                 | 0.059             |
| Number of active PRs at the time the PR was created                    | 0.058             |
| Class churn                                                            | 0.055             |
| Total churn                                                            | 0.039             |
| Method churn                                                           | 0.037             |
| Is the PR introducing a new feature                                    | 0.033             |
| Loc changed                                                            | 0.031             |
| Number of paths touched                                                | 0.031             |
| Conditional statements churn                                           | 0.029             |
| Loop churn                                                             | 0.028             |
| Class member churn                                                     | 0.021             |
| Is the PR for refactoring                                              | 0.021             |
| Reference churn                                                        | 0.017             |
| Number of files changed                                                | 0.016             |
| Is it a merge change                                                   | 0.008             |
| Is it a deprecate change                                               | -0.001            |
| PR title word count                                                    | -0.001            |
| Is the PR created during business hours                                 | -0.019            |
| Is it a Bug Fix change                                                 | -0.028            |
| Age of the PR author in current team                                   | -0.031            |
| Age of the PR author in the repository                                 | -0.046            |
| Age of the PR author in Microsoft                                      | -0.056            |
Table 3. Comparison of different prediction models

| Algorithm            | MAE   | MRE  |
|----------------------|-------|------|
| Least squares        | 44.32 | 0.68 |
| Bayesian Ridge       | 46.35 | 0.71 |
| Gradient Boosting    | 32.59 | 0.58 |

**Age of the PR author in the team** - This feature captures how familiar a developer is with the current team, its processes, people, and the product or service the team is working on. Intuitively, more time a developer spends in a team, less difficulty he/she will experience in pushing their change through. A negative correlation here indicates the possibility of the presence of such a relationship.

**Age of the PR author in the repository** - This helps capturing the familiarity of a developer with the repository in which he/she is making changes and the build, deployment processes of that repository. Though this sound similar to the "Age of the developer in current team", this varies a lot with the heterogeneous teams which work on multiple services (especially, micro services) and different members of the same team are mostly making changes that are very specific to the repositories they are actively engaged in. Our correlation analysis has shown that more familiar a developer is with a specific repository, less time it takes for him/her to merge their changes made in that repository.

**Age of the PR author in Microsoft** - This helps capturing the seniority of a developer. Intuitively, senior people who has more experience tend to make less mistakes and doesn’t experience push back on their changes. A negative correlation here is indicating that if someone has more experience, less time it takes them to merge their changes.

### 2.2 Prediction Model

We formulated the task of predicting the lifetime of a PR as a regression problem. We then performed an offline analysis and evaluation with multiple popular regression algorithms like Least Squares linear regression, Bayesian Ridge regression and Gradient boosting. To compare the regression algorithms, we used 2 standard metrics: MAE (Mean Absolute Error), MRE (Mean Relative Error). These metrics are widely used for understanding the performance of regression tasks. We decided to go with gradient boosting algorithm as it has better accuracy with respect to both MAE and MRE. The comparative analysis of the three algorithms, evaluated against MAE and MRE is shown in Table 3.

For training and evaluation, we used Scikit-learn 0.20.0 package for Python 3.7.1. We used a standard evaluation technique called 10-fold cross-validation. The process of 10-fold cross-validation is as follows:

1. Separating the data set into 10 partitions randomly
2. Using one partition as the test data and the other nine partitions as the training data
3. Repeating Step-2 with a different partition than the test data until all data have a prediction result
4. Computing the evaluation results through comparison between the predicted values and the actual values of the data.
Finally, we decided to go with a gradient boosting model with our feature space containing 28 features as described in section 3.1. The details of the model are:

1. Model type: Regression
2. Algorithm used: Gradient boosting
3. Toolkit: Python 3.7.1 - Scikit learn 0.20.0
4. Feature space: 28 features
5. Data points: 2,875 [PRs] from 10 repositories
6. For the training set, Gradient Boosting MAE: 29.29, MRE: 0.52.

Our predictive model is deployed using a Python flask cloud service. Whenever a new PR is created and spent some time (24 hours), we generate a feature vector for that PR and infer its lifetime using the pre-trained model. We discuss various evaluation metrics of our prediction model in the evaluation section.

3 ACTIVITY DETECTION

A good notification system is the one that exactly knows when to send a notification to maximize the probability of target audience to take an action. It is also extremely important for such system to understand when not to send a notification. If the system does not fully understand various activities that are happening inside a pull request environment, and does not know when to back off, it may end up causing more annoyance than being useful. These false positive notifications can impact the usability of the system and potentially make the users lose trust and ignore the recommendations. We conducted a quantitative study to understand how not detecting activity and reacting to it while making recommendations impacts the likeability of the service. Figure 1 shows the distribution of recommendations that are resolved positively or negatively by the developers on pull requests when there was a notification by the Nudge service despite of the fact that there has been activity in the pull request in last 48 hours. 86 out of 119 comments resolved negatively are the ones where we passed notifications without honoring the fact that there was at least one human-generated activity in the pull request. Later, we talked to some of the developers who were...
either authoring or reviewing those pull requests. Majority of them mentioned that they resolved the recommendation negatively as they did not like the fact that they were receiving notifications for something that they already knew and were on top of. Typical pull request environment in large organizations can get really complex with multiple actors performing different activities through various collaboration points. These actors can be human or non-human (bots/automation tools). Or, the activity can be originated at different collaboration points by performing actions like commenting, reviewing, changing state of the pull request etc. So, to determine the activity that happens in a pull request, we should first understand various collaboration or interaction points that are offered by pull request environment. This also changes based on the provider of the source control system (GitHub, Azure DevOps, GitLab etc). However, a good amount of collaboration points / concepts remain similar. In the context of this work, we focused primarily on Azure DevOps which is a source control system used by Microsoft’s developers and offered by Microsoft to third party customers.

States: A pull request will be in ‘Active’ or ‘Draft’ state upon creation. A pull request which is in ‘Active’ state will be reviewed by a set of reviewers. When a reviewer reviews the pull request they can change its state to one of the following states:

1. Approved: which means they agree with the proposed changes in the pull request as-is and willing to let the author merge the changes.
2. Rejected: which means the changes aren’t acceptable.
3. Waiting for author: which means the author has to review the comments left by the reviewer.
   The author should let the reviewer know to review the code again after they address the concerns raised.

Once the review is completed and the pull request is approved, the author can change the state of the pull request to ‘Completed’ which means the pull request is merged into the master branch. At any point of time, during the life of the pull request, the author can change the state of the pull request to ‘Abandoned’ which means the author would like to recall the pull request. A state change in a pull request strongly indicates that one of the actors (Author/Reviewers) has recently acted on the pull request.

Comments: Once the pull request is submitted for review, reviewers can add comments to recommend changes or seek clarification on a specific code change etc. Authors of the pull request can also reply to the comment thread that is started by the reviewers if they have any follow up questions. In addition to placing the comments and replying to them, the actors can also change the status of the comments. Typical statuses are: ‘Active’ which means the comment is just placed, ‘Resolved’ which means the comment is resolved by the author of the pull request by making the changes prescribed by the reviewers, ‘Won’t fix’ which means the author would like to discard the review recommendation and not going address it, finally, ‘Closed’ which means the comment thread is going to be closed as there are no more follow up action items or discussions needed.

Updates: After a pull request is created, authors can keep pushing new updates in the form of commits. These commits are collection of changes that authors are making in response to review recommendations for which the author has agreed to make changes or something the authors themselves has decide to push into the pull request. Under some special circumstances someone other than the author or the reviewer can also push new updates into a pull request but that is a rare occurrence. New updates or iterations are a very strong indicator that the author is making progress on the pull request.

We selected a random sample of 200 pull requests from 20 repositories ranging from medium to large to very large in size. These repositories are the ones which experience continuous development activity, in them, in the last one year i.e., new pull requests are created, commits are pushed, review
comments are added and pull requests are closed on a daily basis. We performed a retrospective analysis to understand how magnitude of activity in pull requests changes overtime, with the age or lifetime of the pull request.

As shown in figure 2, pull requests experience more activity in the beginning (when their age is couple of days) and slowly the activity reduces followed by a slight increase before the pull request gets completed. This is because of the fact that some of these pull requests are getting closed gradually as time progresses. Even if they are open, the process of reviewing, addressing the reviews, activity induced by reviews (comments, replies to comments, pushing new updates etc) and the updates that matter are pushed into the pull request by this time. As one can observe, while the trend of activity is clearly reducing, which is expected. However, there are a good amount of pull requests that still record some activity even after 7 days. To better understand the extent of pull requests that exhibit this kind of pattern as shown in figure 3, we performed a manual analysis and found that 55 pull requests in our data set (i.e., 22.5%) exhibit similar pattern i.e., record some activity within first week, followed by no activity for a while and then see some activity again.

This is a strong indication that activity patterns are not always monotonic or linear in nature but have some spiky behavior which can be explained by various factors like developer schedules, day of the week, holidays, urgency of the pull requests and the behavioral aspects of the developers and reviewers themselves. So, any system that is intended to notify the author or reviewers about making progress on their outstanding changes has to keep in mind the activity patterns that are being recorded in their respective pull requests and decide on what is the most appropriate action (hold back or proceed with the notification) that can be taken accordingly. Based on a user study described in Section 7, we find that activity detection improves user experience, reduces false positives and thus increases the likeability of the Nudge service.

4 DEPENDENCY DETERMINATION

In a pull request, there are different actors involved that can influence the outcome i.e., approved or rejected or abandoned etc. and the speed with which a pull request progresses. Below is the list of such actors and a brief description about their roles:

Authors Authors of the pull request are the ones who creates a pull request in first place. They send the pull request for review and keep working on the pull request by reacting to the review comments by pushing new changes (in the form of commits or iterations). Once all the reviewers are satisfied, they take the final decision to merge or not merge a change. They have a significant influence on the pace of the pull request. If they react to the review comments quickly and resolve them, pull request will have a better chance of making progress quickly.
Reviewers

Reviewers are added by the authors or any other automation tools (based on certain conditions) to pull requests. Reviewers can be individuals in the same team or people with more experience and expertise with the area of source code that is being changed or groups which are a collection of individual reviewers. When a pull request is submitted for a review, reviewers can either approve or reject or make suggestions which needs to be acted upon by the author of the change and resolve the comments made by the reviewers. By virtue of their role, reviewers can significantly impact the outcome of the review and the velocity of the pull request.

Non-human actors

With the increased use of bots and automation tools, there are lot of non-human actors that play a vital role in determining the velocity with which change progression happens. Tools that enforce security & compliance policies, bots that enforces styling guidelines, ensures dependencies are not broken etc are some of the examples.

We focus on understanding the human change blockers i.e., authors and reviewers, and the extent to which they influence the change progression. We collected 200 pull requests from 20 medium to large to very large repositories and manually analyzed them to understand on whom they were waiting before they were completed. These are pull requests whose age is at least 14 days and have not been completed yet. We find there are 5 mutually exclusive classes that explain the cases in which a pull request is awaiting completion. Table 4 lists the classes and who is the actor that is responsible and the number of pull requests that fall under each class. As shown in figure 4, 70 pull requests i.e., 35% of the pull requests are actually blocked by the reviewers while remaining 65% are awaiting on the author to make progress.

Encouraged by the findings, we devised an algorithm that helps determine the actor that needs to be notified to make progress on a given pull request. The flow chart shown in figure 5 explains the control flow and how the actors that are responsible for making progress on the change are determined.

The algorithm has to evaluate various decision points along the way to determine the blockers of the change. These decision points represent different states that a pull request or review or review
Table 4. Classes that explains change blockers and responsible actors

| Class                                               | Awaiting on actor | # of PRs |
|-----------------------------------------------------|-------------------|----------|
| Review comments are not addressed                   | Author            | 34       |
| PR Author has pending action items                  | Author            | 47       |
| PR is approved but author is not merging it         | Author            | 49       |
| Review has not been started yet                     | Reviewer          | 51       |
| Review comments are addressed but reviewers has not approved yet | Reviewer          | 19       |

comments in the pull request take during the lifetime of a pull request. Some of the decision points are explained below.

**PR is approved** A pull request is approved when the reviewers are satisfied with the changes and have no more comments or concerns about the change. Reviewers can approve the change without even passing any review comments if they feel the change is already looking good and no more work needs to put in. In this case it is very clear that the author has to decide whether they want to complete the pull request and merge the changes. In some cases, authors may want to wait due to an external blocker e.g., certain restrictions imposed by the process.

**Author has pending action items** This condition is met when the reviewer does not want to approve the changes, and ask the author to review the comments left by the reviewer. The author should let the reviewer know to review the code again after they address the concerns. So, in this case the author is expected to make necessary changes and push them through subsequent updates or iterations. Typically, the reviewers change the state of a pull request to ‘waiting for author’ or they leave a comment in the pull request by ‘@ mentioning’ the authors to indicate that authors has pending action items.

**Unresolved review comments** In this case, reviewer has left comments seeking some clarity or proposing recommendations. Author is responsible to address the review comments. Authors typically will have two choices: If they agree with the review comment, they can resolve it or if they disagree, they can mark it as ‘wont’ fix’. In either cases authors has to address the comments and unblock the change progression.

In remaining cases, reviewers has to act on the pull request to unblock the change. They are,

**Review has not started** Upon creating the pull request. authors typically add the reviewers that they would like to get a review from for the specific change. The reviewers are supposed to act on it and provide their comments. If they do not have any comments, they could just approve the pull request which will let the author complete it if they would like to. Providing reviews is considered as important as making the change itself. If the reviewers are not acting on the pull
request after requesting a review the onus is going to be on the reviewers to act on the pull request and unblock it.

**Review comments are addressed** Once the reviewer has provided their review, author will act on it and resolve/won’t fix the comments by making any changes as necessary. Then the responsibility shifts back to the reviewer to re-verify the changes and provide sign-off. If that is not happening, reviewers are held accountable and should be notified to unblock the change.

5 IMPLEMENTATION

In this section we present the details about how Nudge Service is implemented. We first discuss Azure DevOps, a GIT based DevOps solution offered by Microsoft, which we used to deploy Nudge as an extension. Further, we describe major constructs of the Nudge Service: 1) Nudge service’s workflow 2) Determining dependencies 3) Detecting activity 4) Notifying developers. Figure 6 shows the service architecture and gives an overview of various components involved. Listed below are the seven steps that explains the high level architecture and interaction between various components in the Nudge system.

1. Developer creates a pull request or updates an existing pull request by pushing a new commit or iteration into it.
2. A pull request creation or update event is triggered through the service hook.
A new message will be sent and queued in Azure service bus.

Azure worker role picks up all the new messages in first come first serve (FCFS) basis.

Worker role runs effort estimation models (inference), saves the result to the database. Activity detection and dependency determination algorithms are also run.

Based on the outcome of step-5, worker role sends notification using Azure DevOps APIs in the form of pull request comments.

Notification email is sent to the developer.

5.1 Azure DevOps

Azure DevOps is a DevOps platform providing Git-based VCS (version control system). In addition to repositories, it also offers planning tools such as work item and bug report management, facilitates code review management. It also has features such as build and release management to facilitate continuous integration and deployment (CI/CD). Azure DevOps is heavily used by lot of fortune 500 customers and lot of small and mid sized companies too. Nudge service is deployed as an extension of Azure DevOps because of the rich collaboration features offered by Azure DevOps. Below are the details about some of the key features that Azure DevOps offers that helped materializing Nudge service:

1. **Collaboration points**: Azure DevOps offers a rich set of collaboration points through which third party services or extensions can interact with pull requests in Azure DevOps. The collaboration points allows services to add comments on pull requests, add labels to the pull requests, add or remove reviewers.

2. **Service hooks**: Azure DevOps offers service hooks which helps any third party service to listen to the events that are happening inside pull request environment. Events can be pull request creation events that fires an event through service hooks when a pull request is created or pull request update events that are fired when the pull request experiences any updates such as pushing new commits or iterations.

3. **APIs**: Azure DevOps exposes a rich set of REST APIs [2] that helps third party services to access information about various artifacts in Azure DevOps environment. These APIs can be called through a rest client and return metadata about pull requests (id, title, author, reviewer information, comments, labels, status, commits that are included in the pull request).
commits (title, files changed in a commit), build and release (status, test outcomes, deployment outcomes).

5.2 Nudge Service Workflow

The Nudge Service is built on top of Microsoft Azure cloud services such as Azure Batch [1], Azure Active Directory, Azure SQL, Application Insights. We provide the details on how we implemented our dependency determination algorithm (explained in section 4) and activity detection algorithm (explained in section 3). Nudge is run on Azure Batch [1] as a batch job which is triggered for every six hours.

Figure 7 explains the overview of the Nudge system’s workflow. It consists of 4 steps:

1. Nudge service’s workflow starts with calculating the effort needed for a pull request using effort estimation models. When the batch job is triggered, it first scans all the active pull requests and runs effort estimation model (described in Section 2) to determine the lifetime of a pull request and save it to the back end SQL database.

2. Once a pull request’s age becomes equal to estimated effort, next module i.e., activity detection is activated which checks for any activity. If there is activity, the workflow is going to be terminated.

3. Once the activity detection algorithm determines that there is no activity, dependency determination algorithm kicks in which determines the change blockers and dependant actors who should take appropriate actions to facilitate the movement of the pull requests.

4. Finally, notifications are sent to the list of actors (which is enumerated in the previous step) in the form of pull request review comments and email based notifications.

5.3 Activity detection

We use Azure DevOps’s REST APIs [2] extensively to collect data that is required to understand if there has been any activity in a pull request. We gather data about various actions or activities that happen inside a pull request (as explained in section 3) to determine if there has been any activity.

- **Commit activity** We use Azure DevOps’s GetPullRequestIterationsAsync API which provides details about all the commits that are ever pushed into a pull request. We first get a list of all the commits that are pushed using the GetPullRequestIterationsAsync API then take the timestamp of the latest iteration as the latest commit timestamp of a pull request.

- **Comment activity** To determine whether there has been any commenting activity like adding new comments or replying to existing comments, we use Azure DevOps’s GetThreadsAsync API. This API returns all the comments that are ever placed in a pull request in the form of threads. We check if any new threads are created or any new comments are placed in an existing thread. We take the maximum of both of them to determine the latest comment activity that has happened in a pull request. While doing this we exclude any comments that are placed by system accounts or non-human actors.
• **State changes in pull requests** Changes in pull request state is another important signal that helps determining activity in a given pull request. Unfortunately, there is no direct way of determining state changes in pull requests. We use Azure DevOps’s GetThreadsAsync API to collect all the comments placed in a pull request. Comments whose content property contains the word "voted" indicates that a state change has happened. We use that to determine when was the last time a pull request’s state has changed.

### 5.4 Dependency determination

We rely on Azure DevOps’s REST APIs to collect data for determining the dependencies. As explained in section 4, we need to understand these three primary constructs to determine dependencies:

1. **Is pull request waiting on the Author?** To determine if pull request’s author has any pending action items, we check if the state of the pull request is set to ‘Waiting on Author’. We use Azure DevOps’s GetPullRequestReviewersAsync API to get the votes of all the reviewers. We check if there are any votes with status "-5" which indicates that the pull request is marked as ‘Waiting on author’ by one of the reviewers.

2. **Check for existence of unresolved comments** Understanding the existence of unresolved comments is important to understand if the blocker of the pull request is the author or the reviewer. We use Azure DevOps’s GetThreadsAsync API to get all the threads and then we check for existence of threads with statuses ‘Active’ or ‘Pending’. Presence of threads with any of these two statues indicates that there are unresolved comments.

3. **Enumerate the list of change blockers** We first use GetPullRequestReviewersAsync API offered by Azure DevOps to query the list of reviewers on a given pull request. We then use GetThreadsAsync API to determine list of all the reviewers who commented on the pull request at least once and who comments are resolved by the author of the pull request. We prepare two lists: commented reviewers and all reviewers and choose one of them to use based on the state of the pull request. If there are no reviews on a pull request, we send notifications to the reviewers in the ‘all reviewers’ list. If there has been review activity (placing comments on the pull request by a reviewer), we prioritize notifications to the reviewers in the commented reviewers list.

Figure 8 shows the screenshot of how the Nudge notification looks like. An interesting thing to note is that the dependent actor (in this case the reviewer but not the author) is being ‘@ mentioned’ in the notification. This triggers a separate email addressing to the reviewer of this pull request is sent requesting them to unblock the pull request. As we can notice, The pull request was created and had been waiting for the reviewer’s approval for four days. After the Nudge service tagged the reviewer and pushed them to act on the pull request, the reviewer has approved it and the pull request got completed on the same day.

### 6 USER STUDY

In this section, we describe the experiments we conducted to assess the value of a pull request level effort estimation system, the value of a system like Nudge that leverages the effort estimation models to notify developers about their overdue pull requests and the impact Nudge has on large development teams and organizations. We propose three research questions:

- **RQ1** What is the accuracy of effort estimation models in predicting the lifetime of pull requests?
- **RQ2** What is the impact of Nudge service on completion times of pull requests?
- **RQ3** What are developers’ perceptions about usefulness of Nudge service?
6.1 Data collection and methodology

We obtained data from the large scale deployment of the Nudge service for 9 months on 147 repositories in Microsoft. These repositories are owned by various product and service teams and they are of different sizes, geographies and products. We have made notifications on 8,500 pull requests till now. First we discuss the results from an experiment we conducted on the first version (v1) of the Nudge service (without activity detection and dependency determination). Later we present the analysis of metrics collected from the deployment of enhanced version of the service specifically focusing on how the enhancements helped increasing the positive feedback and customer satisfaction.

For RQ1, we collect data from pull requests that are completed, from historic pull request data. It is important to collect data for completed pull requests as we need the start and end timestamps to help us calculate the lifetime for each pull request and construct our ground truth data set. We collected 2,875 pull requests from 10 different repositories that are merged and completed. These repositories host the source code of various services with developers ranging from a few hundred to a few thousand contributing to those repositories.

For RQ2, we collect data from the 147 repositories on which we operationalized Nudge. We collect data about how the lifetime of pull requests is varying between pull requests which received a Nudge notification and pull requests that did not. We also collect data about how long each pull request takes after a Nudge notification takes before the author either completes or abandons the pull request.

For RQ3, we collect data through our automated pipeline that actively tracks every single inline reply that is posted by the developers in response to Nudge notification and whether they positively or negatively resolved a comment. We do this for all the 8,500 pull requests on which we made notifications.
6.2 Study participants

There is no selection methodology or algorithm that is used to pick the pull requests for which we sent notifications or notifications, through Nudge service. Notifications are sent when a pull request meets the criteria needed to be nudged, as imposed by the Nudge model and algorithm. All the developers on whose pull requests a Nudge notification is sent are given equal opportunity to provide feedback i.e., either to positively or negatively resolve the comment or to provide anecdotal feedback by replying inline to the Nudge notification. An important point to note is, majority of the repositories on which Nudge is operationalized are organizationally away from the developers of the Nudge service. The notifications does not reveal the names or identities of the developers of the Nudge service to avoid response bias [16].

Fig. 9. A Pull Request with PRLifetime prediction notification in Azure DevOps
7 RESULTS

7.1 RQ1: What is the accuracy of effort estimation models in predicting the lifetime of pull requests?

To answer this research question, we generate metrics and charts that explain how accurate our prediction model is. We also list the anecdotes that received from developers about the accuracy of the prediction model. To get qualitative feedback, we randomly select pull requests on which we are about to send a Nudge notification and add more details in the notification comment. These are details like Nudge model’s predicted lifetime for a given pull request, how long the pull request has been open for past the estimated lifetime by the Nudge model. Figure 9 shows the details about the predicted lifetime of a sample pull request, as predicted by the Nudge model, and the reason for sending the notification at a given point of time.

Model Evaluation - We evaluated our prediction model against standard metrics: Mean Absolute Error (MAE) and Mean Relative Error (MRE). For the pull request level effort estimation model, the MAE is 32.60 hours and MRE is 0.58. To put these numbers in perspective, we have done an experiment by considering mean lifetime of our training data as the predicted lifetime of every PR in our testing data. Our random model’s MAE is 36.43 hours and MRE is turned out to be 0.68. We are doing 11.8% better with MAE and 17.7% better with MRE compared to the random model. To understand if a MAE of 32.60 hours is reasonable, we should also understand few important metrics of the data on which we are training and doing inference against. The data set we are dealing with has a mean PR Lifetime of 107.63 hours and the earliest a PR is completed is in 24 hours (minimum) & a maximum lifetime of a PR is 336 hours. Basically, we have a prediction MAE of 32.60 for data points (PRs) ranging from 24 hours to 336 hours. Figure 10 shows the MAE distribution. A very interesting thing to note is, a significant portion of our MAE lies within the range of 50 hours and only a very little portion of our absolute error exceeds order of 107 hours (which is the mean of this distribution).

Fig. 10. MAE distribution

Fig. 11. MRE distribution
Table 5. Tolerance level distribution

| Tolerance level | % of predictions within tolerance level |
|-----------------|----------------------------------------|
| +/- 0%          | 0.7                                    |
| +/- 5%          | 7.17                                   |
| +/- 10%         | 13.97                                  |
| +/- 15%         | 21.33                                  |
| +/- 20%         | 28.44                                  |
| +/- 30%         | 41.06                                  |
| +/- 50%         | 62.91                                  |
| +/- 70%         | 74.44                                  |
| +/- 90%         | 79.82                                  |
| +/- 100%        | 81.29                                  |

An important point to note is, majority of our MRE (close to 90%) falls under a relative error of 1. Figure 11 shows the MRE distribution. As with any regression problems, one of the other important metrics to understand is tolerance. Based on the domain we are operating in and the users who are consuming our prediction results, tolerance levels may vary. For instance, in real estate or in finance, a tolerance of 50% is not acceptable. However, in effort estimation, going off by +/- 50% hours is reasonable since we are only alerting developers for acting on pending Pull Requests. In our Qualitative analysis section (4.3), we list anecdotes from users which supports this argument. The distribution of our prediction accuracy based on the tolerance level is listed in Table 5.

User feedback about model’s prediction accuracy We received a very positive feedback from the developers of the randomly selected pull requests for which we added more details about the model prediction. One of the developers said

This was reasonable. This PR sat stale while doing work for FHL, so it was untouched for an extended period.

Here, the developer is acknowledging the fact that model’s prediction (110 hours) is pretty reasonable and, noticeably, providing an explanation for why the pull request is taking long to wait. As we see in figure 9, the developer ended up completing the pull request within couple of hours after the notification was sent. Similarly, another developer said,

I totally agree with the model saying this pull request should take not more than 120 hours to complete. The code change is slightly complex and the estimation seems reasonable.

In this case, the developer is pretty happy about the fact that the model is predicting the lifetime by taking into account the complexity of the change and giving enough breathing room for the developers to act on it before nudging them. Another developer passed feedback by acknowledging the fact that the model adapts to the changes happening inside the pull request by comparing two of her pull requests.
Table 6. Comparison of average pull request lifetime (hours)

| Service                  | Average PR lifetime | Number of PRs |
|--------------------------|---------------------|---------------|
| No notification service  | 197.2               | 3856          |
| Nudge                    | 112.6               | 4117          |
| Nudge with new features  | 77.65               | 4383          |

I see the estimation is 176 hours on this pull request and it was 64 hours on another pull request of mine where I was editing lesser number of files and not pushing critical code changes. I do not know if your model is taking these facts into account. But, it seems like...interesting!!

This anecdote supports the fact that the model adapts to the pull request in question and the users starts to notice and appreciate the fact that the model is doing a good job in adapting to the change in context.

7.2 What is the impact of Nudge service on completion times of pull requests?

To measure the impact, we came up with two metrics which we believe are the most appropriate indicators of whether Nudge service is really helping developers and yielding intended benefit:

1. Average pull request lifetime: This is the average of the time difference (in hours) between pull request creation date and closed date. A service like Nudge is expected to introduce positive effects like reduction in pull request lifetime by notifying the change blockers about making progress and closing the pull requests.

2. Distribution of number of pull requests that are completed within a day, in three days, within a week and after a week since Nudge sent a notification. This explains if developers are really reacting to the Nudge notifications, if so, how quickly they are reacting.

While measuring and comparing the metrics above, it is important to make sure to nullify the effects of all the other variables such as month of the year (changes move faster in some months and slower during some), typical code velocity in a given repository (Some repositories naturally experience faster code velocity because of the nature and criticality of the service), team or organization culture (some teams typically are more agile and ship things faster) etc. So, if we compare pull requests from two different repositories or from two different time periods, we cannot really say the increase or decrease in average lifetime is due to the presence/absence of the Nudge service or due to other factors explained above. So, we conducted A/B testing by choosing one of the three configurations listed below to turn on on each pull request. The selection process, that picks a specific configuration to be turned on for a given pull request, is determined based on a randomization algorithm.

1. Turn the Nudge service off for a set of randomly selected pull requests.
2. Turn on the basic version of the Nudge service i.e., without dependency determination and activity detection.
3. Turn on the dependency determination and activity detection features along with the effort estimation model in the Nudge service.

Table 6 explains the difference in average pull request lifetime for each of these configurations.

We see a clear decrease in average lifetime for the pull requests for which Nudge notifications are sent. Average lifetime of the pull requests on which Nudge notifications are sent is 112.6 hours which is 42.9% decrease compared to the set of pull requests on which we did not send the
notification (where the average life time is 197.2 hours). Dependency determination and activity detection further brought the average lifetime down to 77.65 hours which is a reduction of 60.62% in average pull request lifetime. Similarly, we see a clear increase in positive feedback (number of comments that are resolved positively) after we rolled out dependency determination and activity detection, on a set of randomly selected pull requests. We see that the positive feedback from the end users is increased to 73% (from 43%). This is a strong indicator that users are receiving the enhancements, activity detection and dependency determination, positively.

In figure 12, we plotted the distribution of pull requests that are completed within a day, three days, a week and takes more than a week after Nudge sent the notification. Only 1570 pull requests out of 8500 pull requests (18.47%) have taken more than a week to close. 81.53% of the pull requests are closed with in a week. An important observation to make is 2300 pull requests i.e., 27.05% of the pull requests on which Nudge sent the notification were completed within a day. This distribution indicates that majority of the pull requests on which Nudge sends notifications are completed relatively quickly.

7.3 RQ3: What are developers’ perceptions about usefulness of Nudge service?

To understand the likeability of the users towards Nudge system, we pursued a mixed methods approach where we calculate the likeability of the system by quantifying the like/dislike percentages from all the notifications that the nudge system sends. We also gather customer anecdotes by mining the replies to Nudge notification comments:

- Number of notifications that are positively resolved: This is the number of Nudge notifications that are resolved positively by the end users of the service (developers). This is synonymous to clicking on Facebook like button. Users are encouraged to ‘like’ a Nudge notification if they like or agree with it. Similarly, users are provided with an option to ‘dislike’ or convey their dissatisfaction by resolving the notification as ‘Won’t Fix’.
- We analyzed the textual responses that we received from our end users. These are the inline replies posted by the developers within a Nudge notification comment.

To better understand how users are perceiving the differences between original version of Nudge and Nudge with new features, we categorized the results and the responses received from the users into two groups. We explain how the new features, activity detection and dependency determination, are perceived and appreciated by the developers which helped driving the favorability towards the system by a good margin.
Table 7. Difference in percentage of positively resolved notification

| Service type                          | Percentage of positive feedback |
|---------------------------------------|---------------------------------|
| Nudge                                 | 47%                             |
| Nudge with new features               | 73%                             |

7.3.1 Percentage of positively resolved comments. We measure is percentage of comments that are positively resolved. This signifies the positive feedback that we receive from the end users. Table 7 shows the difference in percentage of comments that are resolved positively for the original version of Nudge and Nudge with new features. As seen, the new version got 73% comments positively resolved which is an increase of 55.3% on top of the original Nudge system. 73% positive feedback is also pretty significant even if we look at it alone. Various studies has shown that users tend to provide explicit negative feedback when they do not like or agree with a recommendation while not so explicit about positive feedback [22, 31]. 73% of the developers who received Nudge notifications explicitly resolving the notifications positively indicates a significant positive sentiment that the developers exhibit towards the Nudge service.

7.3.2 Nudge user feedback (original version). We tried to understand how helpful our suggestions are and whether they are yielding intended benefits i.e., driving PRs towards a terminal state which is Completion or Abandonment. We received very positive feedback (comments/anecdotes from the developer) and observed that intended actions are happening on the PRs. To provide a glimpse, we listed some of the quotes that we received from the developers that are appropriate to discuss in the context of this paper. On one of the PRs, a developer said

"I agree. Making few more changes and pushing this PR through! Thanks for the notification!"

Then we saw this developer acting on this PR by pinging the reviewers and driving this PR towards completion. And within 8 minutes this PR got completed. In another PR, the developer has acknowledged our nudge and completed it within a day. In another PR, the developer has done something very interesting. First, he replied to our comment saying

"The pipeline is failing and blocking this check in. Followed up with an ICM incident and completed the PR!"

then, soon enough (within a day) the PR was abandoned. Here, it is not just about completion, people are making progress on their PRs by pushing them towards a terminal state (completion / abandonment) and in turn maintaining the repository hygiene. So, we are clearly seeing that people are responding to the comments and most importantly, taking an action to push the PRs towards completion/abandonment thus expediting the deployment of changes and achieving repository hygiene. We also received feedback that says the notification is not useful because it is blocked by a reviewer. The exact comment is

"The comment does not add any value to me personally because I already know that the PR I’ve authored has been open for a long time. It is not me who is blocking this but the reviewer"

As the developer above has mentioned, sometimes a PR is set to wait due to few external factors like, dependency on other PRs or management decisions like feature planning and road-maps etc. In these cases, pinging the developer and re-iterating the fact that their PR is safe to complete (especially when they are staying on top of that PR) doesn’t seems to be adding much value. This is
addressed in the new version of Nudge which implements a model, to determine the real change blockers through, dependency analysis. Similarly, we see comments about why they think the notification is not so useful in some cases where they interacted with the pull request recently by resolving a comment or pushing a new commit but we ended up nudging them because the lifetime of the pull request is high. One such comment comes from a developer where she says

"I just resolved the comments on this pull request yesterday. I know about this one being pending for a while. This is not helpful!"

In this case the developer is annoyed because they logged into the repository and performed an action (in this case resolving couple of comments) on the pull request. So, they clearly do not appreciate the notification sent by Nudge.

7.3.3 Nudge user feedback (new version). As expected, a lot of users indicated that they love the enhancements made in the new version which implements dependency determination and activity detection models. While there were some differences on how long the service should hold itself back before sending a notification when an activity is seen (24 hours vs 48 hours), we received a unanimous agreement about the usefulness of these features. When asked about determining change blockers and '@ mentioning' them in the notification thus eliminating an extra hop, users said

"Yes it’ll be nice for the tool to ping the reviewers instead of having the person do it."

"yes I think that’s handy to notify specific people. I often see someone “waiting” on a pr for changes, but then forget to revisit and follow up after changes have been pushed."

Another user said the algorithm was very accurate in determining the change blocker for a pull request that he was working on

"change blocker was perfectly identified and notified for pull request 731796. You did my job!"

8 RELATED WORK

Our related work is dived broadly into 3 sections. The first being on effort estimation, then on bots in software engineering and finally on PR acceptance.

8.1 Effort Estimation

Software effort estimation is a field of software engineering research that has been studied a lot in the past four decades [9, 12, 14, 15, 26]. Typically, in this line of research, one tries to predict either the effort needed to complete the entire project or the effort needed to finish a feature. One of the earliest effort estimation models was the COCOMO model proposed by Barry W. Boehm in his 1981 book, Software Engineering Economics [12], which he later updated to COCOMO 2.0 in 1995 [11]. This work was followed up by Briand et al. [13] which compared various effort estimation modelling techniques using the data set curated by the European Space Agency. In all these cases a model was built for the entire software project and effort was estimated for function points. More recently, Menzies et al. [26] and Bettenburg et al. [9] looked at the variability present in the data and therefore built separate models for subsets of the data. Unlike, these past effort estimation studies, in our paper we look into predicting how long it would take for a pull request to be accepted.

8.2 Bots in Software Engineering

The extensibility mechanisms provided by software development platforms like GitHub and Azure DevOps have enabled a huge ecosystem [3] of bots and automated services. It has also spawned active research [32] on understanding and building bots to assist with various software engineering
tasks. Storey et al. [32] have defined a **Software Engineering Bot** as a software which either automates a feature OR performs function which are done by humans OR interacts with humans. Lebeuf et al. [21] have proposed a taxonomy for software bots based on the environment, the intrinsic properties of the bot and based on how the bot interacts with the environment. In terms of applications, lot of prior work has focused on improving the code review process by automating reviewer recommendation [5, 41], diagnosing issues [8, 10, 25], refactoring [29, 39] and even intent understanding of the code changes [37, 38]. In this work, we built and deployed Nudge which is a bot for increasing software development velocity and productivity by accelerating PR completion.

### 8.3 Predicting Pull Request acceptance

More recently there has been interest in predicting pull request acceptance. Soares et al. [30], and Tsay et al. [34] looked at a variety of factors to see which one had an impact on pull request acceptance. More specifically, Terrell et al. [33] and Rastogi et al. [28] looked at gender or geographical location impacts a pull request acceptance. The work closest to our work is by Yu et al. [40], who explored the various factors that could impact how long it took for an integrator to merge a pull request. Unlike their study we do not examine what factors might impact the time taken to accept a pull request, rather how much time it would actually take for a pull request to be accepted. Hence, unlike past papers which were empirical studies on building knowledge with respect to pull request acceptance, we build a system that will predict how long it will take to accept a pull request and provides actionable feedback to the developers leveraging that knowledge.

### 9 CONCLUSION

Pull request are a key part of the collaborative software development process. In this paper, we presented Nudge, a service for improving software development velocity by accelerating pull request completion. Nudge leverages machine learning based effort estimation, activity detection and dependency determination to provide precise notifications for overdue pull requests. To make the notifications actionable, it also infers the actor (pull request author or reviewer(s)) who is delaying the pull request completion. We have done a large-scale deployment of Nudge at Microsoft where it has been used to **nudge** over 8,500 pull requests, over a span of 18 months, in 147 repositories. We have also done a qualitative and quantitative user study which proves the efficacy of the Nudge algorithm compared to prior work which was just based on effort estimation. 73% of the notifications by Nudge have been positively acknowledged by the users. Further, we have observed significant reduction in completion time, by over 60%, for pull requests which were **nudged**.

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