Effective Automated Decision Support for Managing Crowdtesting

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Abstract—Crowdtesting has grown to be an effective alternative to traditional testing, especially in mobile apps. However, crowdtesting is hard to manage in nature. Given the complexity of mobile applications and unpredictability of distributed, parallel crowdtesting process, it is difficult to estimate (a) the remaining number of bugs as yet undetected or (b) the required cost to find those bugs. Experience-based decisions may result in ineffective crowdtesting process.

This paper aims at exploring automated decision support to effectively manage crowdtesting process. The proposed iSENSE applies incremental sampling technique to process crowdtesting reports arriving in chronological order, organizes them into fixed-size groups as dynamic inputs, and predicts two test completion indicators in an incrementally manner. The two indicators are: 1) total number of bugs predicted with Capture-ReCapture (CRC) model, and 2) required test cost for achieving certain test objectives predicted with AutoRegressive Integrated Moving Average (ARIMA) model. We assess iSENSE using 46,434 reports of 218 crowdtesting tasks from one of the largest crowdtesting platforms in China. Its effectiveness is demonstrated through two applications for automating crowdtesting management, i.e. automation of task closing decision, and semi-automation of task closing trade-off analysis. The results show that decision automation using iSENSE will provide managers with greater opportunities to achieve cost-effectiveness gains of crowdtesting. Specifically, a median of 100% bugs can be detected with 30% saved cost based on the automated close prediction.

I. INTRODUCTION

Crowdtesting is an emerging trend in software testing which accelerates testing process by attracting online crowdworkers to accomplish various types of testing tasks [1]–[5], esp. in mobile application testing. It entrusts testing tasks to crowdworkers whose diverse testing environments/platforms, background, and skill sets could significantly contribute to more reliable, cost-effective, and efficient testing results.

Trade-offs such as “how much testing is enough” are critical yet challenging project decisions in software engineering [6]–[9]. Insufficient testing can lead to unsatisfying software quality, while excessive testing can result in potential schedule delays and low cost-effectiveness.

Many existing approaches employed either risk-driven or value-based analysis for prioritizing or selecting test cases, and minimizing test runs [10]–[14], in order to effectively plan and manage testing process. However, none of these is applicable to the emerging crowd testing paradigm where managers typically have no control over online crowdworkers’ dynamic behavior and uncertain performance. Worse still, there is no existing method to support crowdtesting management.

Consequently, due to lack of decision support, in practice, project managers typically plan for the close time of crowdtesting tasks solely based on their personal experience. However, it is very challenging for managers to come up with reasonable experience-based crowdtesting decisions. This is because our investigation on real-world crowdtesting data (Section I-C reveals that there are large variations in bug arrival pattern of crowdtesting tasks, and in task’s duration and consumed cost for achieving the same quality level. Furthermore, crowdtesting is typically treated as black box and managers’ decisions remain insensitive to actual testing progress. Hence, managers have significant challenges deciding when to intervene and close the task (and improve cost-effectiveness as well).

To address these challenges, this paper aims at exploring automated decision support to effectively manage crowdtesting. In detail, we focus on exploring dynamical bug arrival data associated with crowdtesting reports, and investigate whether it is possible to determine that, at certain point of time, a task has achieved satisfactory bug detection level (e.g. indicated by a percentage), based on the dynamic bug arrival data.

The proposed iSENSE[1] applies incremental sampling technique to process crowdtesting reports arriving in chronological order, organizes them into fixed-size groups as dynamic inputs, and integrates the Capture-ReCapture (CRC) model and the Autoregressive Integrated Moving Average (ARIMA) model to raise awareness of crowdtesting progress. CRC model is widely applied to estimate the total population based on the overlap generated by multiple captures [15]–[18]. ARIMA model is commonly used to model time series data to forecast the future trend [19]–[22]. iSENSE predicts two test completion indicators in an incrementally manner, including: 1) total number of bugs predicted with CRC model, and 2) required test cost for achieving certain test objectives predicted with ARIMA model. To the best of our knowledge, this is the first study to apply incremental sampling technique in crowdtesting management, so as to better model the bug arrival dynamics.

1iSENSE is named considering it likes a sensor in crowdtesting process to raise the awareness of the testing progress.
tSENSE is evaluated using 218 crowdtesting tasks from one of the largest Chinese crowdtesting platforms. Results show that, the median errors on tSENSE’s prediction performance (of total bugs, and required cost) are both below 3%, with about 10% standard deviation during the second half of the crowdtesting process.

We further demonstrate its applications through two typical decision scenarios, one for automating task closing decision, and the other for semi-automation of task closing trade-off analysis. The results show that decision automation using tSENSE will provide managers with greater opportunities to achieve cost-effectiveness gains of crowdtesting. Specifically, a median of 100% bugs can be detected with 30% saved cost based on the automated close prediction.

The contributions of this paper are as follows:

- Empirical observations on crowdtesting bug arrival patterns based on industrial dataset, which has motivated this study and can motivate future studies.
- Integration of incremental sampling technique to model crowdtesting bug arrival data.
- Development of CRC-based model for predicting total number of bugs, and ARIMA-based model for predicting required cost for achieving certain test objectives.
- tSENSE approach for automated decision support in crowdtesting management, including automating task closing decision, and semi-automation of task closing trade-off analysis.
- Evaluation of tSENSE on 46,434 reports of 218 crowdtesting tasks from one of the largest crowdtesting platforms in China, and results are promising.

II. BACKGROUND AND MOTIVATION

A. Background

In general crowdtesting practice, managers prepare the crowdtesting task (including the software under test and test requirements), and distribute it on certain online crowdtesting platform. Crowdworkers can sign in their interested tasks and submit test reports, typically summarizing test input, test steps, test results, etc.

The crowdtesting platform receives and manages crowdtesting reports submitted by the crowdworkers. Project managers then inspect and verify each report for their tasks manually or using automatic tool support (e.g., [4], [23] for automatic report labeling). Generally, each report will be characterized using two attributes: 1) whether it contains a valid bug or unique bug, 2) if yes, whether it is a duplicate bug that has been previously reported by other crowdworkers.

In the following paper, if not specified, when we say “bug” or “unique bug”, we mean the corresponding report contains a bug and the bug is not the duplicate of previously submitted ones.

B. BigCompany Dataset

Our experimental dataset is collected from BigCompany[4] crowdtesting platform, which is one of the largest platforms in China. The dataset contains all tasks completed between May. 1st 2017 and Jul. 1st 2017. In total, there are 218 tasks, with 46434 submitted reports. The minimum, average, and maximum number of crowdtesting reports (and unique bugs) per task are 101 (6), 213 (26), and 876 (89), respectively.

C. Observations From A Pilot Study

To understand the bug arrival patterns of crowdtesting, we conduct a pilot study to analyze three bug detection metrics, i.e. bug detection speed, bug detection cost, and bug detection rate.

For each task, we first identify the time when K% bugs have been detected, where we treat the number of historical detected bugs as the total number. K is ranged from 10 to 100. Then, the bug detection speed for a task can be derived using the duration (measured in hours) between its open time and the time it receives K% bugs. Next, the bug detection cost for a task can be derived using the number of submitted reports by reaching K% bugs.

To examine bug detection rate, we break the crowdtesting reports for each task into 10 equal-sized groups, in chronological order. The rate for each group is derived using the ratio between the number of unique bugs and the number of reports in the corresponding group.

In addition, for each crowdtesting task, we also count the percentage of accumulated bugs (denoted as bug arrival curve) for the previous K reports, where K ranges from 1 to the total number of reports.

Next, we present two general bug arrival patterns derived from the pilot study.

1) Large Variation in Bug Arrival Speed and Cost: In Figure 1a, we first present four example bug arrival curves randomly selected from 218 crowdtesting tasks, illustrating the diversity of bug arrival curves among different tasks.

In general, there is large variation in bug arrival speed and cost. Figure 1b and 1c demonstrates the distribution of bug detection speed and bug detection cost for all tasks. It is obvious that, to achieve the same K% bugs, there is large variation in both metrics. This is particularly true for a larger K%. For example, when detecting 90% bugs, the bug detection speed ranges from 3 hours to 149 hours, while the bug detection cost ranges from 27 to 435 reports.

2) Decreasing Bug Arrival Rates Over Time: Figure 1d shows the bug detection rate of the 10 break-down groups across all tasks. We can see that the bug detection rate decreases sharply during the crowdtesting process. This signifies that the cost-effectiveness of crowdtesting is dramatically decreasing for the later part of the process.

3Url for tSENSE website with experimental dataset, source code and detailed experimental results is blinded for review.

4Blinded for review.

5Note that, the primary cost in crowdtesting is the reward to crowdworkers, and their submitted reports are usually equally paid [2], [5]. Hence, the number of received reports is treated as the consumed cost for simplicity in this study.
In addition, from Figure 1a we can also see that during the later part of the crowdtesting task, there is usually a flat area in bug arrival curve, denoting no new bugs submitted. This further suggests the potential opportunity for introducing automated closing decision support to increase cost-effectiveness of crowdtesting.

3) Needs of Automated Decision Support: In addition, an unstructured interview was conducted with the managers of BigCompany, with findings shown below.

Project managers commented the black-box nature of crowdtesting process. While they can receive constantly arriving reports, they are often out of clue about the remaining number of bugs as yet undetected, or the required cost to find those additional bugs.

Because they could not know what is going on of the crowdtesting, the management of crowdtesting is conducted as a guesswork. This frequently results in many blind decisions in task planning and management.

In Summary, because there are large variations in bug arrival speed and cost (Section II-C1), current decision making is largely done by guesswork. This results in low cost-effectiveness of crowdtesting (Section II-C2). A more effective alternative to manage crowdtesting would be to dynamically monitor the crowdtesting reports and automatically alert managers or close tasks when certain pre-specified test objectives are met, e.g. 90% bugs have been detected, to save unnecessary cost wasting on later arriving reports.

Furthermore, current practice suggests a practical need to empower managers with greater visibility into the crowdtesting processes (Section II-C3), and ideally raise their awareness about task progress (i.e., remaining number of bugs, and required cost to meet certain test objectives), thus facilitate their decision making.

This paper intends to address these practical challenges by developing a novel approach for automated decision support in crowdtesting management, so as to improve cost-effectiveness of crowdtesting.

III. APPROACH

Figure 2 presents an overview of tSENSE. It consists of three main steps. First, tSENSE adopts an incremental sampling process to model crowdtesting reports. During the process, tSENSE converts the raw crowdtesting reports arrived chronologically into groups and generates a bug arrival lookup table to characterize information on bug arrival speed and diversity. Then, tSENSE integrates two models, i.e. CRC and ARIMA, to predict the total number of bugs contained in the software, and the required cost for achieving certain test objectives, respectively. Finally, tSENSE applies such estimates to support two typical crowdtesting decision scenarios, i.e., automating task closing decision, and semi-automation of task closing trade-off analysis. We will present each of the above steps in more details.

A. Preprocess Data based on Incremental Sampling Technique

Incremental sampling technique [24] is a composite sampling and processing protocol. Its objective is to obtain a single sample for analysis that has an analytic concentration representative of the decision unit. It improves the reliability and defensibility of sampling data by reducing variability when compared to conventional discrete sampling strategies.

Considering the submitted crowdtesting reports of chronological order (Section II-A), when smpSize (smpSize is an input parameter) reports are received, tSENSE treats it as a representative group to reflect the multiple parallel crowdtesting sessions. Remember in Section II-A we mentioned that, each report is characterized as: 1) whether it contains a bug; 2) whether it is duplicate of previously submitted reports; if no, it is marked with a new tag; if yes, it is marked with the same tag as the duplicates. During the crowdtesting process, we maintain a two-dimensional Bug Arrival Lookup Table to record these information (as Table I).

After each sample is received, we first add a new row (suppose it is row i) in the lookup table. We then go through each report contained in this sample. For the reports not containing a bug, we ignore it. Otherwise, if it is marked with the same tag as the duplicates, the report is characterized as a duplicate. For each remaining report (i.e., the report marked with a new tag), we maintain a two-dimensional Bug Arrival Lookup Table to record these information (as Table I).

We present the details about this interview in tSENSE website.
TABLE I: Example of bug arrival lookup table

| Sample # | #1 | #2 | #3 | #4 | #5 | #6 | #7 | #8 | #9 | #10 | #11 | #12 | ... |
|-----------|----|----|----|----|----|----|----|----|----|-----|-----|-----|-----|
| Sample #1 | 1  | 1  |    | 0  | 0  | 0  | 0  | 0  | 0  |    |    |    |     |
| Sample #2 | 0  | 0  | 1  | 0  | 0  | 0  | 0  | 0  | 0  |    |    |    |     |
| Sample #3 | 0  | 0  | 0  | 1  | 0  | 0  | 0  | 0  | 0  |    |    |    |     |
| Sample #4 | 0  | 0  | 0  | 0  | 1  | 1  | 1  | 1  | 1  | 0  |    |    |     |
| Sample #5 | 0  | 0  | 1  | 1  | 0  | 0  | 1  | 1  | 1  | 0  |    |    |     |
| Sample #6 |    |    | 1  | 0  | 0  | 0  | 0  | 0  | 0  |    | 1  |    |     |
| Sample #7 |    |    |    |    |    |    |    |    |    |    |    |    |     |

tag as existing unique bugs (suppose it is column $j$), record $I$ in row $i$ column $j$. If it is marked with a new tag, add a new column in the lookup table (suppose it is column $k$), and record $I$ in row $i$ column $k$. For the empty cells in row $i$, fill it with 0.

B. Predict Total Bugs Using CRC

1) Background about CRC: CRC model, which uses the overlap generated by multiple captures to estimate the total population, has been applied in software inspections to estimate the total number of bugs [15]–[18]. Existing CRC models can be categorized into four types according to bug detection probability (i.e. identical vs. different) and crowdworker’s detection capability (i.e. identical vs. different), as shown in Table II.

Model $M0$ supposes all different bugs and crowdworkers have the same detection probability. Model $Mh$ supposes that the bugs have different probabilities of being detected. Model $Mt$ supposes that the crowdworkers have different detection capabilities. Model $Mth$ supposes different detection probabilities for different bugs and crowdworkers.

TABLE II: Capture-ReCapture models

| Bug detection probability | Crowtherworker’s detection capability |
|--------------------------|--------------------------------------|
| Identical                | Identical $M0$, $MhJK$, $MhCH$       |
| Different                | Different $Mt$, $Mth$                 |

Based on the four basic CRC models, various estimators were developed. According to a recent systematic review [16], $MhJK$, $MhCH$, $MtCH$ are the three most frequently investigated and most effective estimators in software engineering. Apart from that, we investigate another two estimators (i.e., $M0$ and $Mth$) to ensure all four basic models are investigated.

2) How to Use in sENSE: sENSE treats each sample as a capture (or recapture). Based on the bug arrival lookup table, it then predicts the total number of bugs in the software using the CRC estimator. This section first demonstrates how it works with $Mth$ estimator.

$Mth$ estimator predicts the total number of bugs based on Equation 1 [25]. Table III shows the meaning of each variable, how to compute its value based on the bug arrival lookup table in Table I.

\[ N = \frac{D}{C} + \frac{f_1}{C} \gamma^2, \quad C = 1 - \frac{f_1}{\sum_{k=1}^{D} kf_k} \quad (1) \]

\[ \gamma^2 = \max \left\{ \frac{D}{2} \sum_{j<k} n_j n_k - 1, 0 \right\} \quad (2) \]

For the usage of other four estimators, one can find the equation for estimating the total bugs from related work (i.e., for $M0$, for $MtCH$, for $MtCH$, and for $MhJK$). The value assignments for the variables are the same as $Mth$. Due to space limit, we put the detailed illustration on our website.

C. Predict Required Cost Using ARIMA

1) Background about ARIMA: ARIMA model is commonly used to model time series data to forecast the future values [19]–[22]. It extends ARMA (Autoregressive Moving Average) model by allowing for non-stationary time series to be modeled, i.e., a time series whose statistical properties such as mean, variance, etc. are not constant over time.

A time series is said to be autoregressive moving average (ARMA) in nature with parameters $(p,q)$, if it takes the following form:

\[ y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} + \epsilon_t \quad (3) \]

Where $y_t$ is the current stationary observation, $y_{t-i}$ for $i = 1, ..., p$ are the past stationary observations, $\epsilon_t$ is the current error, and $\epsilon_{t-i}$ for $i = 1, ..., q$ are the past errors. If this original time series $\{z_t\}$ is non-stationary, then $d$ differences can be done to transform it into a stationary one $\{y_t\}$. These differences can be viewed as a transformation denoted by $y_t = \gamma^d z_t$, where $\gamma^d = (1 - B)^d$ where $B$ is known as a backshift operator. When this differencing operation is performed, it converts an ARMA (Autoregressive Moving Average) model into an ARIMA (Autoregressive Integrated Moving Average) model with parameters $(p,q,d)$.

2) How to Use in sENSE: Figure 3 demonstrates how ARIMA is applied in predicting future trend of bug arrival. We treat the reports of each sample as a window, and obtain the number of unique bugs submitted in each sample from bug arrival lookup table. Then we use the former $trainSize$ windows to fit the ARIMA model and predict the number of bugs for the later $predictSize$ windows. When new window is formed with the newly-arrived reports, we move the window by 1 and obtain the newly predicted results.

Suppose one want to know how much extra cost is required for achieving $X\%$ bugs. As we already know the predicted total number of bugs (Section III-B), we can figure out how many bugs should be detected in order to meet the test objective...
A. Research Questions

Four research questions are formulated to investigate the performance of the proposed iSENSE.

- RQ1: To what degree can iSENSE accurately predict total bugs?
- RQ2: To what degree can iSENSE accurately predict required cost to achieve certain test objectives?
- RQ3: To what extent can iSENSE help to increase the effectiveness of crowdtesting through decision automation?
- RQ4: How can iSENSE be applied to facilitate the trade-off decisions about cost-effectiveness?

B. Evaluation Metrics

We measure the accuracy of prediction based on relative error, which is the most commonly-used measure for accuracy [23], [30], [31]. It is applied in the prediction of total number of bugs (Section V-A) and required cost (Section V-B).

We measure the cost-effectiveness of close prediction (Section V-C) based on two metrics, i.e. bug detection level (i.e. \%bug) and cost reduction (i.e. \%reducedCost).

\%bug is the percentage of bugs detected by the predicted close time. We treat the number of historical detected bugs as the total number. The larger \%bug, the better.

\%reducedCost is the percentage of saved cost by the predicted close time. To derive this metric, we first obtain the percentage of reports submitted at the close time, in which we treat the number of historical submitted reports as the total number. We suppose this is the percentage of consumed cost. The larger \%reducedCost, the better.

Intuitively, an increase in \%bug would be accompanied with a decrease in \%reducedCost. Motivated by the F1 (or F-Measure) in prediction approaches of software engineering [4], [23], [31], we further derive an analogous metric $F_1$, to measure the harmonic mean of \%bug and \%reducedCost as follows:

$$F_1 = \frac{2 \times \%\text{bug} \times \%\text{reducedCost}}{\%\text{bug} + \%\text{reducedCost}}$$

IV. Experiment Design

Related insights can provide managers with more confidence in making informed, actionable decisions on whether to close immediately, if the required cost is too high to be worthwhile for additional X% more detected bugs, or wait a little longer, if the required cost is acceptable and additional X% detected bugs is desired.
C. Experimental Setup

For RQ1, we set up 19 checkpoints in the range of receiving 10% to 100% reports, with an increment interval of 5% in between. At each checkpoint, we obtain the estimated total number of bugs at that time (see Section III-B). Based on the ground truth of actual total bugs, we then figure out the relative error (Section IV-B) in predicting the total bugs for each task.

For RQ2, we also set 19 checkpoints as RQ1. Different from RQ1, the checkpoints of RQ2 is based on the percentage of detected bugs, i.e., from 10% bugs to 100% bugs with an increment of 5% in between. At each checkpoint, we predict the required test cost (Section III-C) to achieve an additional 5% bugs, i.e., target corresponding to the next checkpoint. For example, at the checkpoint when 80% bugs have detected, we predict the required cost for achieving 85% bugs. Based on the ground truth of actual required cost, we then figure out the relative error (Section IV-B) in predicting required cost for each task.

For RQ3, we analyze the effectiveness of task closing automation with respect to five sample close criteria, i.e., close the task when 80%, 85%, 90%, 95%, or 100% bugs have detected, respectively. These five close criteria are consistent with the commonly-used test completion criteria in software testing, and we believe the similar principles can be adopted in crowdtesting as well.

For RQ4, we use several illustrative cases from experimental projects to show how tSENSE can help trade-off decisions.

D. Baselines

To further evaluate the advantages of our proposed tSENSE, we compare it with two baselines.

Rayleigh: This baseline is adopted from one of the most classical models for predicting the dynamic defect arrival in software measurement. Generally, it supposes the defect arrival data following the Rayleigh probability distribution [32]. In this experiment, we implement code to fit specific Rayleigh curve (i.e., the derived Rayleigh model) based on each task’s bug arrival data, and then predict the total bugs, as well as the future bug trend (and further obtain the required cost for certain test objective), using the derived Rayleigh model.

Naïve: This baseline is designed to employ naïve empirical results, i.e., the median obtained from the experimental dataset. More specifically, for the prediction of total bugs, it uses the median total bugs from 218 experimental tasks. For required cost, it uses the median required cost from 218 experimental tasks, in terms of the corresponding checkpoint (Section IV-C).

E. Parameter Tuning

For each CRC estimator, the input parameter is \( \text{smpSize} \), which represents how many reports are considered in each capture. To determine the value of this parameter, we randomly select 2/3 crowdtesting tasks to tune the parameter, and repeat the tuning for 1000 times to alleviate the randomness.

In each tuning, for every candidate parameter value (we experiment from 2 to 30) and for each checkpoint, we obtain the relative error (>0: overestimate; <0: underestimate) in predicting the total bugs, respectively.

For ARIMA model, we use the same method for deciding the best parameter value. The tuned \( \text{smpSize} \) values are respectively 8 for \( M0 \), 8 for \( MtCH \), 6 for \( MhCH \), 3 for \( MhJK \), and 8 for \( Mth \).

For ARIMA model, we use the same method for deciding the best parameter value. The tuned parameter values are as follows: \( \text{smpSize} \) is 3, \( \text{trainSize} \) is 10, \( p \), \( q \), and \( d \) are respectively 5, 1, 0.

V. Results

A. Answers to RQ1: Accuracy of Total Bugs Prediction

Table IV demonstrates the median and standard deviation for the relative error of predicted total bugs for all five CRC estimators, corresponding to all checkpoints. We highlight (in italic font and red color) methods which have the best two performance with respect to each checkpoint. Due to space

G. Advantages of tSENSE

The proposed tSENSE can help decision makers to predict the total bugs, as well as the future trend, with very small values, very quickly, across the checkpoints.

For RQ2, we also set 19 checkpoints as RQ1. Different from RQ1, the checkpoints of RQ2 is based on the percentage of detected bugs, i.e., from 10% bugs to 100% bugs with an increment of 5% in between. At each checkpoint, we predict the required test cost (Section III-C) to achieve an additional 5% bugs, i.e., target corresponding to the next checkpoint. For example, at the checkpoint when 80% bugs have detected, we predict the required cost for achieving 85% bugs. Based on the ground truth of actual required cost, we then figure out the relative error (Section IV-B) in predicting required cost for each task.

For RQ3, we analyze the effectiveness of task closing automation with respect to five sample close criteria, i.e., close the task when 80%, 85%, 90%, 95%, or 100% bugs have detected, respectively. These five close criteria are consistent with the commonly-used test completion criteria in software testing, and we believe the similar principles can be adopted in crowdtesting as well.

For RQ4, we use several illustrative cases from experimental projects to show how tSENSE can help trade-off decisions.
TABLE IV: Statistics for relative error of predicted total bugs (RQ1)

|                | 10% | 15% | 20% | 25% | 30% | 35% | 40% | 45% | 50% | 55% | 60% | 65% | 70% | 75% | 80% | 85% | 90% | 95% | 100% |
|----------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| **Mh**        | -0.35 | -0.25 | -0.23 | -0.14 | -0.10 | -0.01 | -0.04 | -0.04 | -0.04 | -0.04 | -0.03 | -0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **Mh**        | -0.40 | -0.32 | -0.28 | -0.18 | -0.15 | -0.10 | -0.07 | -0.06 | -0.05 | -0.03 | -0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **Mh**        | -0.36 | -0.23 | -0.17 | -0.12 | -0.09 | -0.05 | -0.05 | -0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **Mh**        | -0.33 | -0.22 | -0.11 | -0.06 | -0.06 | -0.05 | -0.06 | -0.05 | 0.00 | 0.04 | 0.04 | 0.06 | 0.08 | 0.06 | 0.06 | 0.06 | 0.03 | 0.04 |
| **Mh**        | -0.29 | -0.21 | -0.17 | -0.11 | -0.06 | -0.05 | -0.04 | -0.04 | -0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

TABLE V: Comparison with baselines in relative error of predicted total bugs (RQ1)

|                | 10% | 15% | 20% | 25% | 30% | 35% | 40% | 45% | 50% | 55% | 60% | 65% | 70% | 75% | 80% | 85% | 90% | 95% | 100% |
|----------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| **iSENSE**    | 0.40 | 0.40 | 0.40 | 0.40 | 0.38 | 0.37 | 0.34 | 0.32 | 0.29 | 0.26 | 0.23 | 0.21 | 0.20 | 0.17 | 0.13 | 0.07 | 0.05 | 0.03 |
| **Rayleigh**  | 0.31 | 0.32 | 0.32 | 0.29 | 0.26 | 0.21 | 0.17 | 0.13 | 0.14 | 0.13 | 0.09 | 0.08 | 0.08 | 0.07 | 0.07 | 0.04 | 0.04 | 0.04 |
| **Naive**     | 0.36 | 0.40 | 0.39 | 0.39 | 0.38 | 0.31 | 0.28 | 0.25 | 0.20 | 0.19 | 0.22 | 0.20 | 0.21 | 0.16 | 0.20 | 0.18 | 0.17 | 0.09 |
| **Mh**        | 0.47 | 0.42 | 0.42 | 0.42 | 0.38 | 0.35 | 0.33 | 0.27 | 0.24 | 0.19 | 0.19 | 0.16 | 0.11 | 0.13 | 0.12 | 0.07 | 0.07 | 0.04 |

TABLE VI: Results of Mann-Whitney U Test for relative error of predicted total bugs (RQ1)

|                | 10% | 15% | 20% | 25% | 30% | 35% | 40% | 45% | 50% | 55% | 60% | 65% | 70% | 75% | 80% | 85% | 90% | 95% | 100% |
|----------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| **iSENSE vs. Rayleigh** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **iSENSE vs. Naive**    | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **Rayleigh vs. Naive**  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

limit, we only present the detailed performance for **MhJK** (the worst estimator) and **Mh** (the best estimator) in Figure 4. From Table IV and Figure 5, we can see that, the predicted total number of bugs becomes more close to the actual total number of bugs (i.e., the relative error decreases) towards the end of the tasks. Among the five estimators, **Mh** and **MhCH** have the smallest median relative error for most checkpoints. But the variance of **MhCH** is much larger than that of **Mh**. Hence, estimator **Mh** is more preferred because of its relatively higher stability and accurate prediction in total number of bugs. In the following experiments, if not specially mentioned, the results are referring to those generated from iSENSE with **Mh** estimator due to space limit.

**Comparison With Baselines**: Table V compares the prediction accuracy of iSENSE and the two baselines, in terms of the median and standard deviation of relative error. The columns correspond to different checkpoints, and the best performer under each checkpoint are highlighted. Table VI summarizes the results of Mann-Whitney U Test for the relative error of predicted total bugs between each two methods. It shows that the iSENSE significantly outperforms the two baselines (with p-value <0.05), especially during the later stage (i.e. after the 40% checkpoint) of the crowdtesting tasks.

**Answers to RQ1**: iSENSE with the best estimator **Mh** is surprisingly accurate in predicting the total bugs in crowdtesting, and significantly outperforms the two baselines. More specifically, the median of predicted total bugs is equal with the ground truth (i.e., median relative error is 0). Better yet, the standard deviation is about 10% to 20% during the latter half of the process.

**B. Answers to RQ2 : Accuracy of Required Cost Prediction**

Table VII summarizes the comparison of median and standard deviation of the relative error of predicted required cost across iSENSE and the two baselines, with columns corresponding to different checkpoints. We highlight the methods with the best performance under each checkpoint. Table VIII additionally presents the results from the Mann-Whitney U Test between each pair.

As indicated by the decreasing median relative error in Table VII, the prediction of required cost becomes increasingly accurate for later checkpoints. For example, after 50% checkpoint, the median relative error of predicted cost is lower than 3%, with about 15% standard deviation. This implies that iSENSE can effectively predict the required cost to targeted test objectives.

**Comparison With Baselines**: We can see that the median and standard deviation of relative error for two baselines are worse than iSENSE during the second half of the task process. Observed from Table VIII the difference between the proposed iSENSE and two baselines is significant during the second half of crowdtesting process (p-value <0.05). This further signifies the advantages of the proposed iSENSE.

**Answers to RQ2**: iSENSE can predict the required test cost within averagely 3% relative error for later stage of crowdtesting (i.e. after 50% checkpoint).

**C. Answers to RQ3: Effectiveness of Task Closing Automation**

Figure 6 shows the distribution of %bug, %reducedCost, and FI for five customized close criteria for 218 experimental tasks. Table IX lists their median and standard deviation.
Let us first look at the last row in Table IX which reflects a close criterion of 100% bugs being detected (i.e., most commonly-used setup). The results indicate that a median of 100% bugs can be detected with 29.9% median cost reduction. This suggests an additional 30% more cost-effectiveness for managers if equipped with such a decision automation tool as iSENSE to monitor and close tasks automatically at run-time. The reduced cost is a tremendous figure when considering the large number of tasks delivered in a crowdtesting platform. In addition, the standard deviation is relatively low, further signifying the stability of iSENSE in close automation.

We then shift our focus on other four customized close criteria (i.e., 80%, 85%, 90%, and 95% in terms of percentage of detected bugs). We can observe that for each close criterion, the median %bug generated from iSENSE is very close to the targeted close criterion, with small standard deviation. Among these close criteria, 36% to 52% cost can be saved, which further signifies the effectiveness of iSENSE.

We also notice that, the median %bug is a little larger than the customized close criterion. For example, if the project manager hopes to close the task when 90% bugs detected, a median of 92% bugs have submitted at the predicted close time. This implies, in most cases, the close prediction produced by iSENSE do not have the risk of insufficient testing.

Furthermore, we have talked with the project managers and they thought, detecting slightly more bugs (even with less reduced cost) is always better than detecting fewer bugs (with more reduced cost). This is because %bug is more like the constraint, while %reducedCost is only the bonus.

We also analyze the reason for this phenomenon. It is mainly because, before suggesting close, our approach requires the predicted total bugs remain unchanged for two successive captures (Section III-D1). This restriction is to alleviate the risk of insufficient percentage of detected bugs. Besides, this is also because we treat a sample of reports as the unit during the prediction, which can also potentially result in the close time being a little later than the customized close time.

**Answers to RQ3:** The automation of task closing by iSENSE can make crowdtesting more cost-effective, i.e., a median of 100% bugs can be detected with 30% saved cost.

**D. Answers to RQ4: Trade-off Decision Support**

Considering the large number of tasks under management at the same time, a typical trade-off scenario is to strategically allocate limited testing budgets among the tasks. To reflect such trade-off context, we randomly pick a time and slice the experimental dataset to retrieve all tasks under testing at that time, then examine the cost-effectiveness of more testing on those tasks.

Figure 7 demonstrates 4 trade-off analysis examples across 6 tasks (i.e. P1-P6), generated from repeating the above analysis at four different time points (i.e. corresponding to time1 to time4 in a sequential order). The y-axis denotes the next test objective to achieve, while x-axis shows the predicted required cost to achieve that objective.

Generally speaking, the crowdtesting tasks in the right area are less cost-effective than the tasks in the left area. For ex-
ample, at time3, P6 is estimated to require additional 14 cost in order to achieve 90% test objective. If the manager is facing budget constraints or trying to improve cost-effectiveness, he/she could choose to close P6 at time3, because it is the least effective one among all tasks. In another example, at time1, P2 is estimated to only require 3 additional cost to reach the next objective (i.e., 70%). This suggests the investment on 3 extra cost is highly worthwhile in increasing its quality to the next objective.

To facilitate such kind of trade-off analysis on which task to close and when to close, we design two decision parameters as inputs from decision maker: 1) quality benchmark which sets the minimal threshold for bug detection level, e.g. the horizontal red lines in Figure 7; 2) cost benchmark which sets the maximal threshold for test cost to achieve the next objective, e.g. the vertical blue lines in Figure 7.

These two benchmarks split the tasks into four regions at each slicing time (as indicated by the four boxes in each sub-figure of Figure 7). Each region suggests different insights on the test sufficiency as well as cost-effectiveness for more testing, which can be used as heuristics to guide actionable decision-making at run time. More specifically:

- **Lower-Left (Continue):** Tasks in this region are low hanging fruits, only requiring relatively less cost to achieve next test objective, and quality level is not acceptable yet; this indicates the most cost-effective option and testing should definitely continue.

- **Lower-Right (Drill down):** Tasks here have not met the quality benchmark, so continue testing is preferred even though they require significant more cost to achieve quality objective. In addition, it likely suggests that the task is either difficult to test, or the current crowdworker participation is not sufficient. Therefore, managers would probably want to drill down in these tasks, and see if more testing guidelines or worker incentives are needed.

- **Upper-Left (Think twice):** Tasks here already meet their quality benchmark, possibly reaching next higher quality level if with little additional cost investment. Managers should think twice before they take the action.

- **Upper-Right (Close):** Tasks in this region require relatively more cost to reach next test objective, and current bug detection level is already high enough. This indicates that it is practical to close them considering the cost-effectiveness.

Note that, the two benchmarks in Figure 7 can be customized according to practical needs.

**Answers to RQ4:** iSENSE provides practical insights to help managers make trade-off analysis on which task to close or when to close, based on two benchmark parameters and a set of decision heuristics.

**VI. DISCUSSION**

**A. Best CRC Estimator for Crowdtesting**

In traditional software inspection or testing activities, $MhJK$, $MhCH$, and $MtCH$ have been recognized as the most effective estimators for total bugs $[15]$, $[17]$, $[18]$, $[33]–[36]$. However, in crowdtesting, the most comprehensive estimator $Mth$ (see Section III-B1) outperforms the other CRC estimators. This is reasonable because crowdtesting is conducted by a diversified pool of crowdworkers with different levels of capability, experience, testing devices, and the nature of bugs in the software under test also vary greatly in terms of types, causes, and detection difficulty, etc. In such cases, $Mth$, which assumes different detection probability for both bugs and crowdworkers (see Section III-B1), supposes to be the most suitable estimator for crowdtesting.

**B. Necessity for More Time-Sensitive Analytics in Crowdtesting Decision Support**

As discussed earlier in the background and motivational pilot study (Section II-C), challenges associated with crowdtesting management mainly lie in two aspects: uncertainty in crowdworker’s performance and lack of visibility into crowdtesting progress. We believe there is an increasing need for introducing more time-sensitive analytics to support better decision making to fully realize the potential benefits of crowdtesting.

Compared with the two baselines, iSENSE provides additional visibility into the testing progress and insights for effective task management. In particular, during the later stage of crowdtesting process, the performance of iSENSE is significantly better than the baselines (see Table VII).

As discussed in answering RQ4, iSENSE can generate time-based information revealing dynamic crowdtesting progress and provide practical guidelines to help managers make trade-off analysis on which task to close or when to close, based on a set of decision heuristics.

This suggests a significant portion of crowdtesting cost can be saved through employing effective decision support approaches such as iSENSE. This is extremely encouraging and we look forward to more discussion and innovative decision support techniques in this direction.

**C. Threats to Validity**

The external threats concern the generality of this study. Firstly, our experiment data consists of 218 crowdtesting tasks...
collected from one of the Chinese largest crowdtesting platforms. We can not assume that the results of our study could generalize beyond this environment in which it was conducted. However, the diversity of tasks and size of dataset relatively reduce this risk. Secondly, our designed methods are largely dependent on the report’s attributes (i.e., whether it contains a bug; and whether it is the duplicates of previous ones) assigned by the manager. This is addressed to some extent due to the fact that we collected the data after the crowdtesting tasks were closed, and they have no knowledge about this study to artificially modify their assignment.

Internal validity of this study mainly questions the baselines. As there is no existing methods for managing crowdtesting tasks, we choose one commonly-used method for managing software quality, and one method based on empirical observations of crowdtesting, as the baselines to demonstrate the advantage of our proposed tSENSE.

Construct validity of this study mainly concerns the experimental setup for determining the parameter value. We use the most frequent tuned optimal parameter values, which can alleviate the randomness, to examine the performance of our proposed tSENSE.

VII. RELATED WORK

A. Crowdtesting

Crowdtesting has been applied to facilitate many testing tasks, e.g., test case generation [37], usability testing [38], software performance analysis [39], software bug detection and reproduction [40]. These studies leverage crowdtesting to solve the problems in traditional testing activities, some other approaches focus on solving the new encountered problems in crowdtesting.

Feng et al. [41], [42] proposed approaches to prioritize test reports in crowdtesting. They designed strategies to dynamically select the most risky and diversified test report for inspection in each iteration. Jiang et al. [43] proposed the test report fuzzy clustering framework to reduce the number of inspected test reports. Wang et al. [4], [23], [44] proposed approaches to automatically classify crowdtesting reports. Cui et al. [5], [45] and Xie et al. [46] proposed crowdworker selection approaches to recommend appropriate crowdworkers for specific crowdtesting tasks.

In this work, we focus on the automated decision support for crowdtesting management, which is valuable to improve the cost-effectiveness of crowdtesting and not explored before.

B. Software Quality Management

Many existing approaches proposed risk-driven or value-based analysis to prioritize or select test cases [10]–[14], [47], so as to improve the cost-effectiveness of testing. However, none of these is applicable to the emerging crowd testing paradigm where managers typically have no control over online crowdworkers’s dynamic behavior and uncertain performance.

There are also existing researches focusing on defect prediction and effort estimation [31], [48]–[51]. The core part of these approaches is the extraction of features from the source code, or software repositories. However, in crowdtesting, the platform can neither obtain the source code of these apps, nor involve in the software development process of these apps.

Many existing approaches focused on applying oversampling and under-sampling techniques to alleviate the data imbalance problem in predictions [30], [52], [53]. However, what we faced is not the data imbalance problem, but the dynamic and uncertain bug arrival data. This is why we employed incremental sampling in this study.

Several researches focused on studying the time series models for measuring software reliability [9], [54]–[59]. Among these, ARIMA is the most promising model for mapping system failures over time. It has been applied in estimating software failures [19], predicting the evolution in maintenance phase of system project [20], predicting the monthly number of changes of a software project [21], modeling time series changes of software [22], etc. This paper used ARIMA in modeling the bug arrival dynamics in crowdtesting and estimating future trend.

Another body of previous researches aimed at optimizing software inspection by predicting the total and remaining number of bugs. Eick et al. [60] reported the first work on employing capture-recapture models in software inspections to estimate the number of faults remaining in requirements and design artifacts. Following that, several researches focused on evaluating the influence of number of inspectors, the number of actual defects, the dependency within inspectors, the learning style of individual inspectors, on the capture-recapture estimators’ accuracy [15], [17], [18], [33]–[36]. The aforementioned approaches are based on different types of capture-recapture models, and results turned out $M_{JK}$, $M_{CH}$, and $M_{CH}$ are the most effective estimators. We have reused all these estimators and experimentally evaluated them in crowdtesting.

VIII. CONCLUSION

Benefits of crowdtesting have largely been attributed to its potential to get test done faster and cheaper. Motivated by the empirical observations from an industry crowdtesting platform, this study aimed at developing automated decision support to address management blindness and achieve additional cost-effectiveness.

The proposed tSENSE employ incremental sampling technique to address the dynamic, parallel characteristics of bug arrival data, and integrate two classical prediction models, i.e. CRC and ARIMA, to raise managers’ awareness of testing progress through two indicators (i.e., total number of bugs, required cost to achieve certain test objectives). Based on the indicators, tSENSE can be used to automate the task closing and semi-automate trade-off decisions. Results show that decision automation using tSENSE can largely improve the cost-effectiveness of crowdtesting. Specifically, a median of 100% bugs can be detected with 30% cost reduction.

It should be pointed out that the presented material is just the starting point of the work in progress. We are collaborating...
with BigCompany and begin to deploy tSENSE online. Future work includes conducting further evaluation on a broader scope of datasets, incorporating more real-world crowdsourcing application scenarios, conducting more evaluation experiments in industry settings, and improving the usability of tSENSE based on evaluation feedback.

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