Assessing Expert System-Assisted Literature Reviews With a Case Study

Zhe Yu\textsuperscript{a}, Jeffrey C. Carver\textsuperscript{c}, Gregg Rothermel\textsuperscript{b}, Tim Menzies\textsuperscript{b}

\textsuperscript{a}Rochester Institute of Technology, Rochester, NY, USA.
\textsuperscript{b}North Carolina State University, Raleigh, NC, USA.
\textsuperscript{c}University of Alabama, Tuscaloosa, AL, USA.

Abstract

Given the large numbers of publications in software engineering, frequent literature reviews are required to keep current on work in specific areas. One tedious work in literature reviews is to find relevant studies amongst thousands of non-relevant search results. In theory, expert systems can assist in finding relevant work but those systems have primarily been tested in simulations rather than in application to actual literature reviews. Hence, few researchers have faith in such expert systems. Accordingly, using a realistic case study, this paper assesses how well our state-of-the-art expert system can help with literature reviews.

The assessed literature review aimed at identifying test case prioritization techniques for automated UI testing, specifically from 8,349 papers on IEEE Xplore. This corpus was studied with an expert system that incorporates an incrementally updated human-in-the-loop active learning tool. Using that expert system, in three hours, we found 242 relevant papers from which we identified 12 techniques representing the state-of-the-art in test case prioritization when source code information is not available. These results were then validated by six other graduate students manually exploring the same corpus. Without the expert system, this task would have required 53 hours and would have found 27 additional papers. That is, our expert system achieved 90\% recall with 6\% of the human effort cost when compared to a conventional manual method. Significantly, the same 12 state-of-the-art test case prioritization techniques were identified by both the expert system and the manual method. That is, the 27 papers missed by the expert system would not have changed the conclusion of the literature review.

Hence, if this result generalizes, it endorses the use of our expert system to assist in literature reviews.

Keywords: Systematic Literature Review, Expert Systems, Software Engineering,
1. Introduction

New papers are being published every day, and in increasing numbers. Knowing what other researchers have done to address a problem has become equally important as, if not more important than, providing a novel solution. However, it is also increasingly difficult to stay current with what other researchers are doing. For example, when searching for work on test case prioritization (TCP) on IEEE Xplore\(^1\), 2,704 results would have been returned in 2009, while in 2019, that number has grown to 8,349. As a result, finding an efficient way to conduct literature reviews and extract useful information from thousands of papers has become a crucial problem for researchers.

To address this problem, software engineering researchers have introduced Systematic Literature Reviews (SLRs) (Kitchenham et al., 2004; Dyba et al., 2005). Following a set of guidelines, researchers conducting SLRs manually examine all of the papers relevant to a set of research questions and summarize the research area. Other researchers can then obtain a general idea about current activity in their field of interest by reading the published SLRs. However, SLRs are conducted infrequently because of their labor-intensive and time-consuming nature (Yu et al., 2018). As a result, when researchers explore a specific problem, they often find that existing SLRs are outdated and they need to carry out their own literature reviews.

In theory, expert systems can assist humans in SLRs and reduce the human effort required. However, those expert systems have primarily been tested in simulations only, rather than in application to actual literature reviews. Consequently, few researchers have faith in such expert systems. To address the above problem, this paper assesses whether it is useful to apply expert systems to actual literature reviews with a literature review case study.

We (the authors of this article) were faced with the same literature review problem when exploring the state of the arts in applying TCP techniques to automated UI tests (Yu et al., 2019). Given the specific nature of automated UI tests, only test history, test description, and test results information are available for prioritizing

\(^1\)https://ieeexplore.ieee.org
the test cases. Therefore, we needed to conduct our own literature review searching for TCP techniques that rely only on the available information. One tedious task we faced in doing this was to find all the relevant TCP papers from among 8,349 search results on IEEE Xplore, using their titles and abstracts. In our estimation, this would require around 53 human hours, as shown in Figure 1. To reduce this time, we applied a state-of-the-art human-in-the-loop expert system called FAST\(^2\) (Yu et al., 2018; Yu and Menzies, 2019) to assist in selecting relevant papers. By screening and labeling 470 papers suggested by the expert system in three hours, the first author identified 242 relevant papers for full-text reviewing. The algorithm indicated that those 242 relevant papers constituted 91\% of all the relevant papers in the 8,349 search results. Finding more, however, would require much more human effort. This was an impressive result because 50 human hours, which is 94\% of the original time required, can be saved by sacrificing 9\% recall (missing 24 relevant papers). Considering the 40 hours required for full-text screening and the 1 hour required for search, using FAST\(^2\) saved about half of the time and effort required for the literature review, as shown in Figure 1.

Since this was the first time FAST\(^2\) was applied in a real literature review, we wished to validate its result. Enlisting six other graduate students to manually screen a subset of the candidate papers and perform full-text reviewing of the missing relevant papers from FAST\(^2\), we explored the following research questions.

**RQ1: What percentage of relevant papers does FAST\(^2\) actually retrieve?**
The FAST\(^2\) selection process included 85\% of the relevant papers with human errors contributing to 5\% (12) of the missing papers. That said, FAST\(^2\) was in fact responsible for missing 10\% (27) of the relevant papers, which is very close to its estimation of having missed 9\% (24) of the relevant papers.

**RQ2: What information is missing in the final report because of FAST\(^2\)?**
The distributions of the missing relevant papers are different from the distribution of papers that FAST\(^2\) included. This suggests that FAST\(^2\) introduced a sampling bias to the relevant papers it identified. On the other hand, with the missing relevant papers added into the included papers, the distribution of the included papers remained roughly unchanged. Additionally, the overall conclusions of the

![Figure 1: Human hours required for conducting the literature review. The targets for the abstract screen are to identify 90\% of relevant papers.](image)
literature review (12 TCP techniques identified suitable for automated UI testing) were not affected by the missing relevant papers (39).

In conclusion, FAST$^2$ was able to include 90% of the relevant papers, as it claimed, and the 242 papers it included were sufficient for our literature review. The set of TCP techniques identified through the literature review was used as a baseline in our published work on prioritizing automated UI tests (Yu et al., 2019). We believe that saving 50 hours in selecting relevant papers with 10% of the relevant papers omitted is a worthwhile result. This may also extend to other situations in which SLRs are conducted. When conducting studies such as system mappings, however, where the actual number and distribution of papers matters, Active learning-based expert systems such as FAST$^2$ may need to be avoided until the sampling bias issue has been resolved.

The main contributions of this paper are as follows:

• We conducted the first systematic literature review using FAST$^2$, a state-of-the-art expert system for assisting with relevant paper selection. This is also among the very few SLRs assisted by machine learning algorithms or expert systems.

• We validated the use of FAST$^2$ in an SLR and observed its strengths and weaknesses via a controlled experiment of only humans performing the same relevant paper selection task.

• We scripted our entire SLR process and provided it in a public Github repository$^2$ so that other researchers can use the data for reproduction and improvements on machine-learning-assisted primary study selection.

The rest of this paper is structured as follows. Section 2 presents background material and related work. Section 3 reports every detail of the performed literature review case study. Section 4 reports the validation results of FAST$^2$ and answers the research questions via a controlled experiment. Section 5 concludes the paper and discusses potential future work.

2. Background and Related Work

In this section, we provide background information on systematic literature reviews, and the state-of-the-art machine learning algorithms and expert systems supporting primary study selection.

$^2$https://github.com/fastread/SLR_on_TCP
2.1. Systematic Literature Reviews

Systematic Literature Reviews (SLRs) have become a well established and widely applied review method in Software Engineering since Kitchenham, Dybå, and Jørgensen first adopted them to support evidence-based software engineering in 2004 and 2005 (Kitchenham et al., 2004; Dyba et al., 2005). SLRs employ a defined search strategy, and an inclusion/exclusion criterion for identifying the maximum possible relevant literature. As a result, compared to traditional literature reviews, an SLR provides thorough, unbiased and valuable summaries of the existing information on specific research questions. However, SLRs also require much more human effort than traditional reviews (weeks to months of work as reported in (Yu et al., 2018)). Therefore, SLRs cannot be conducted or updated very frequently. Primary study selection, where thousands of candidate papers must be reviewed by humans to find the dozens of relevant papers to be included in the SLR, is one of the most time-consuming step in conducting SLRs (Carver et al., 2013).

2.2. Expert Systems for Primary Study Selection

The problem of how to efficiently find the dozens of relevant papers among thousands of candidates is categorized as one type of information retrieval problem called total recall, and has been studied for years (Cormack and Grossman, 2015, 2014; Grossman and Cormack, 2013; Wallace et al., 2010b; Miwa et al., 2014; Yu et al., 2018; Yu and Menzies, 2019). With the goal of optimizing the cost for achieving very high recall— as close as practicable to 100%— with a human assessor in the loop (Grossman et al., 2016), the total recall problem can be described as follows (Yu and Menzies, 2018):

**The Total Recall Problem:**

Given a set of candidates \( E \), in which only a small fraction \( R \subset E \) are positive, each candidate \( x \in E \) can be inspected to reveal its label as positive \( (x \in R) \) or negative \( (x \notin R) \) at a cost. Starting with the labeled set \( L = \emptyset \), the task is to inspect and label as few candidates as possible (min \(|L|\)) while achieving very high recall (max \(|L \cap R|/|R|\)).

Active learning-based approaches, where machine learning algorithms work alongside humans to learn from human classifications and suggest what needs to be reviewed by humans next, are widely applied in solving total recall problems (Grossman et al., 2016). The key idea behind active learning is that a machine
learning algorithm can train faster (i.e. using less data) if it is allowed to choose the data from which it learns (Settles, 2012). The experience in total recall problems explored to date is that such active learners outperform supervised and semi-supervised learners and can significantly reduce the effort required to achieve high recall (Cormack and Grossman, 2017, 2016a,b, 2015, 2014; Grossman and Cormack, 2013; Wallace et al., 2010b,a, 2011; Wallace and Dahabreh, 2012; Wallace et al., 2013; Yu et al., 2018; Yu and Menzies, 2019). To understand active learning, consider the decision plane between the positive and negative data points shown in Figure 2. Suppose we want to find more positive data points and we had access to the model shown in Figure 2. One tactic would be to inspect the unlabeled data points that fall into the region of red circles in this figure, as far as possible from the green squares (this tactic is called certainty sampling). Another tactic would be to verify the position of the boundary, i.e., to inspect the unlabeled data points that are closest to the boundary (this tactic is called uncertainty sampling). Besides the query tactics, state-of-the-art approaches (Yu et al., 2018; Yu and Menzies, 2019) follow the general framework shown in Figure 3 and consider the problem of how to stop the inspection at a target recall and how to efficiently correct human errors. When simulated with reverse-engineered primary study selection datasets, these active learning based algorithms can retrieve 90-95% of relevant papers by reviewing only 5-20% of the search results (Yu and Menzies, 2019). This could save weeks of work for humans who might otherwise need to screen thousands of papers.

Despite the foregoing fact, many years have passed while few expert systems have actually been applied in real systematic literature reviews. To the best of our knowledge, only Xiong et al. (2018) have employed a machine learning aided primary study selection in a systematic review. Even though the machine learning algorithm applied involved a combination of supervised and unsupervised learning (not active learning), they succeeded reducing the cost of primary study selection by around 85%. This motivates the study in this article: we would like to conduct a systematic literature review by utilizing a state-of-the-art active learning approach (FAST² (Yu et al., 2018; Yu and Menzies, 2019)) to perform primary study selection. We chose to apply FAST² to assist the SLR in our case study because in previous work, (1) it outperformed other approaches in terms of inclusion rate (Yu et al., 2018), (2) its recall estimation provides a confidence for the user that what is
missed when the selection stops (Yu and Menzies, 2019), and (3) it has also been shown effective in solving other software engineering problems (Yu and Menzies, 2018) such as inspecting software security vulnerabilities (Yu et al., 2019) and finding defect commits (Tu et al., 2019).

Figure 3: Active learning framework for total recall problems.

2.3. FAST$^2$

FAST$^2$ is an active learning-based tool$^3$ that helps reduce the cost of primary study selection in SLRs (Yu et al., 2018; Yu and Menzies, 2019). Consider a primary study selection with

- $E$: the set of all candidate papers from the search results.
- $R$: the set of relevant papers to be included ($R \subseteq E$).
- $L$: the set of papers already reviewed and classified by humans ($L \subseteq E$).

$^3$https://github.com/fastread/src
• $L_R = L \cap R$: the set of included papers.

Instead of reviewing and classifying all candidate papers in a random order, a primary study selection with FAST$^2$ follows the procedure shown in Figure 3, and benefits from three features:

1. **Higher inclusion rate:** FAST$^2$ incrementally trains/updates a machine learning model (in Step 4) on the human classification results ($L$ and $L_R$ from Step 3). With the help of the machine learning model, FAST$^2$ dynamically adjusts the order of papers to be reviewed and classified by humans next (in Step 8) so that relevant papers will be reviewed and included by humans earlier.

2. **Recall estimation:** FAST$^2$ estimates the total number of relevant papers $|R_E| \approx |R|^4$ with a semi-supervised learning algorithm (in Step 7). The human can then stop the primary study selection process when a pre-determined target recall $T_{rec}$ has been reached by estimation $T_{rec} < |L_R|/|R_E|$. 

3. **Human error correction:** FAST$^2$ also predicts which papers are most likely to have been misclassified by humans (in Step 5). Humans can double check those papers (in Step 6) to correct those errors efficiently.

The pseudo code of FAST$^2$ that we implemented for our case study is shown in Algorithm 1 in the Appendix.

3. Case Study: A Systematic Literature Review on Test Case Prioritization with FAST$^2$

Changes in a version of a software system may affect the behavior of that system. Regression testing is performed to ensure that changes do not adversely affect the behavior (Catal and Mishra, 2013). As a regression test suite grows with the size of a software system, software developers need to wait increasingly longer times before they can get useful feedback on their latest commits. In practice, these times can be quite long. As an example, Elbaum et al. (2003) report on a test suite of software with 20,000 lines of code that requires 7 weeks to run.

Software engineering researchers have explored various techniques for improving the cost-effectiveness of regression testing. Test case prioritization (TCP) is one such technique—it schedules test cases for execution in an order that attempts to increase their effectiveness at meeting some performance goal (Rothermel et al., 2001). Unlike other techniques such as test case selection, TCP techniques use the

\[^4\]Here, $|R_E| \approx |R|$ means that $R_E$ is an estimation of the value of $|R|$.
entire test suite and reduce testing cost by achieving parallelization of testing and debugging activities (Do et al., 2010). By retaining all test cases, TCP techniques do not run the risk of omitting some important test cases.

Automated user interface (UI) testing leads to one special case of regression testing. Compared to unit tests, automated UI tests are more expensive to write and maintain. Worse still, since automated UI tests are expressed in terms of actions taken by a browser user agent, failures do not have a straightforward relationship to the underlying application code or architecture. Figure 4 shows how one automated UI test case is designed to exercise a UI performing a simple search on the string “1+1”. In this example, the test designer wishes to test the search function by (a) verifying that when a user inputs “1+1” and clicks the search button, a result of “2” will appear. To automate this UI test, the test designer would first (c) define the test code for a set of scenarios, then (b) write the automated UI test case with the pre-defined scenarios and expected input and output. In this way, the test designer does not need to know what code will be executed when an automated UI test is executed, and the pre-defined scenarios can be reused in designing other automated UI test cases. As a result, when prioritizing for these automated UI tests, source code information is not available as well as the mapping between a failure of the test case and a fault in the codebase.

We conducted this SLR to identify research papers on TCP techniques that can be applied to automated UI testing. The requirement for such papers is that they can only utilize information available to the prioritization of automated UI tests, i.e.
(1) description of test cases, (2) historical testing results, and (3) testing results of executed test cases in the current build. The SLR investigated papers from January 1, 1956 to January 1, 2019 and included the following phases, which we go on to describe in turn:

- Planning,
- Execution, and
- Reporting.

An overview of the SLR process is shown in Figure 5 where from 8,349 search results, FAST$^2$ cumulatively selected 470 candidate papers for the human to screen. Out of that 470 papers, 242 were included as relevant TCP papers based on titles and abstracts. Then based on full-text screen, 3 were found to be not relevant TCP papers and only 15 were identified as TCP papers that can be applied to automated UI testing, among which 12 TCP techniques were summarized.

3.1. Phase 1—planning

In this phase, we specified research questions, search strategy, inclusion and exclusion criteria, classification of papers, and threats to validity.

3.1.1. Research questions

The only research question of this case study is:

What test case prioritization algorithms utilize only (1) description of test cases, (2) historical testing results, and (3) testing results of executed test cases in the current build information?

3.1.2. Search strategy

In the search process, we want to first find all primary studies on test case prioritization. With Boolean operator OR to link the synonyms of the main terms and Boolean operator AND to combine the main terms, the search string we applied is as follows:
We executed this search string in the IEEE Explore\textsuperscript{5} database to find papers containing the keywords in their titles and abstracts. We chose to search IEEE Explore because it covers a large portion of the software engineering publications and is the only database we know of in which thousands of search results can be downloaded automatically with their titles and abstracts. The “automated UI testing” keywords were not used in this search since (1) it literally generated no result on IEEE Xplore (too narrow), and (2) most test case prioritization techniques should be able to apply to automated UI testing if they are not using the source code related information.

3.1.3. Inclusion and exclusion criteria

This review included papers on test case prioritization published between 1956 and 2018. Papers from peer-reviewed journals, conferences, and workshops were considered. We excluded papers that were not related to test case prioritization in the context of software engineering, such as papers on test case selection or fault localization. The inclusion criteria (IC) and exclusion criteria (EC) are as follows:

IC 1 Primary papers on TCP.
IC 2 Secondary papers on TCP.
EC 1 Primary papers on test case selection or test suite reduction only.
EC 2 Primary papers on test case generation only.
EC 3 Primary papers on fault localization.

Primary study selection was performed by the first author alone. FAST\textsuperscript{2} was applied to help this process include 90\% of the relevant papers ($T_{rec} = 0.9$, $N_1 = 10$, $N_2 = 30$). We targeted 90\% recall because the creators of FAST\textsuperscript{2} suggest that 90-95\% recall is appropriate because the cost required to reach higher recall increases exponentially (Yu et al., 2018; Yu and Menzies, 2019). Whether 90\% recall is in fact sufficient will be examined further in Section 4.

3.1.4. Classification of papers

Classification was also performed by the first author alone. The papers were classified according to what information they utilized during the prioritization. Details on each category will be provided in Section 3.3. These categories are non-exclusive. For example, one paper may utilize both source code and history information.

\textsuperscript{5}https://ieeexplore.ieee.org
3.1.5. Threats to validity

There are two major validity threats to this systematic literature review:

1. Only one data source: we searched for papers in one data source (IEEE Xplore) because retrieving search results in other databases would have been inordinately expensive. Therefore, TCP papers in journals or conference proceedings that are not indexed by IEEE Xplore were not included in this SLR study.

2. Primary study selection with FAST$^2$: this is the first SLR study conducted with FAST$^2$, applied to a single case, and the extent to which results will generalize cannot be determined.

3.2. Phase 2—execution

3.2.1. Search

After applying the search string discussed in Section 3.1.2 in IEEE Xplore, we obtained a result of 8,381 candidate papers. These 8,381 papers were downloaded automatically with their title, abstract, pdf link, and publication year information. Among the 8,381 papers, 32 were not research papers (e.g., they were editorials or prefaces) and were thus excluded. The search process, including the design of the search string and retrieval of all the search result, required approximately 1 hour.

3.2.2. Primary study selection

Following the instructions for using the FAST$^2$ tool$^6$, the first author performed the following steps to select the primary studies with a target recall $T_{rec} = 90\%$:

1. The first author loaded the search results of 8,349 papers with their titles and abstracts into FAST$^2$.

2. The first author searched for keywords “test prioritization” and screened the first ten results by reading the titles and abstracts. Ten papers were included as relevant.

3. Given that $|L_R| = 10 \geq 1$, when the Next button is selected, an SVM model is trained based on the ten screened papers and suggestions for uncertainty sampling and certainty sampling are provided. Because $|L_R| = 10 < 30$, the papers suggested during uncertainty sampling were screened.

4. After 20 more papers were reviewed based on uncertainty sampling (the SVM model was retrained and suggestions were updated for every 10 papers screened by the author), 30 relevant and zero non-relevant papers were screened.

$^6$https://github.com/fastread/src
screened. Because $|L_R| = 30 \geq 30$, certainty sampling was applied for the rest of the papers.

5. Finally, when 440 more papers had been screened based on certainty sampling, 242 relevant papers were found among the 470 reviewed ones ($|L_R| = 242$ and $|L| = 470$), as shown in Figure 6. Meanwhile, the estimated recall was $|L_R|/|R_E| = 242/266 = 91\%$. This was the first time the estimated recall reached the target recall ($T_{REC} = 90\%$). The selection thus stopped and the results were exported.

The primary study selection process with FAST$^2$ required approximately three hours of effort by one person.

3.2.3. Full-text review and paper classification

The 242 papers identified in the search were reviewed in full text and classified according to the information utilized. Among the 242 papers, three were determined to be not relevant (not about test case prioritization) based on their full text and were thus excluded. Then, the rest 239 papers were classified regarding to the information utilized and only 15 papers were found to be applicable to automated UI testing. The paper classification process required approximately 40 hours of effort by one person. Details of the classification process will be introduced in the next subsection.
3.3. Phase 3—reporting

In this phase, the analytical results of the systematic literature review are discussed. These results are collected by a full-text reviewing of the 239 papers identified in the search. The distribution of publication years on the selected papers is shown in Figure 7.

To find out which TCP algorithms can be applied to prioritize automated UI tests, we first categorize each primary study by the information utilized. Figure 8 shows the distribution of each category of information being used by the techniques

Figure 7: Distribution of publication years

Figure 8: Distribution of information used

3.3. Phase 3—reporting

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presented in the 239 papers. The seven categories of information we analyzed are listed in the table as follows:

- **Source code**: source code under test. About half of the analyzed TCP methods extract features from the source code being tested, e.g. software metrics (Carlson et al., 2011), code coverage (Do et al., 2004).

- **Change**: code change from the prior build. Around 16% of the analyzed papers present TCP techniques that utilize information about ”what has been changed in the source code” to decide which test cases should be executed earlier (Kumar and Chauhan, 2015).

- **Requirement**: requirements properties. Around 10% of the analyzed papers present TCP techniques that utilize this type of information, such as customer-assigned priority on requirements, requirement volatility, or developer-perceived implementation complexity of requirements, for prioritization (Salehie et al., 2011).

- **History**: execution results (pass/fail/skip) from previous runs. About 30% of the analyzed papers present TCP techniques that utilize history information such as the fault/failure exposing potential of each test case to reorder the test cases (Engström et al., 2011).

- **Test cases**: information about the test cases, e.g. test descriptions, test code, etc. Some papers (17) present TCP techniques that utilize this type of information to calculate the similarity between test cases, then prioritize the test cases based on the similarity and other types of information (Zhang et al., 2016).

- **Feedback**: execution results (pass/fail/skip) of test cases on current run. A few (10) papers present TCP techniques that learn from the results of already executed test cases to dynamically re-prioritize test cases that have not yet been executed (Cho et al., 2016).

- **Other**: other information such as test dependency (Miller et al., 2013) or test impact (Garg et al., 2012).

From Figure 8 we see that source code is the most frequently used information. What we also found is that most of the papers (around 50%) present coverage-based methods, which prioritize test cases in orders that reach maximum coverage with minimum testing cost, by using greedy or search-based algorithms (Bian et al., 2015).
However, these coverage-based methods are not applicable when information such as source code, change, and requirement is not available. Additionally, although history information is also frequently used, it is actually usually being used along with other information such as source code. As a result, our next step is to identify the TCP algorithms only utilizing history, test case, and feedback information. This gives us only 15 research papers. Among these 15 papers, we identified 12 state-of-the-art TCP techniques that can be applied to automated UI testing, after accounting for similar algorithms and removing inapplicable ones. The 12 TCP techniques thus identified are grouped by the information they use and are listed in Table 1:

- **History-based (B and C):** only history information is utilized. B group algorithms apply different metrics extracted from past test execution results (pass/fail/skip) to predict fault/failure exposing potential, and to prioritize test cases (Hemmati et al., 2015; Kwon and Ko, 2017; Fazlalizadeh et al., 2009; Marijan and Liaaen, 2016; Tsai et al., 2005; Aman et al., 2016; Kim and Porter, 2002; Park et al., 2008; Lin et al., 2013; Marijan et al., 2013). C1 is different from B group algorithms since C1 only utilizes the history information to estimate the runtime of each test case (Park et al., 2008; Marijan and Liaaen, 2016; Choi et al., 2017).

- **Test case-based (D):** test case information and history information is utilized. D group algorithms utilize test case information to calculate the similarity between test cases, and then prioritize the test cases based on both test case similarity and history information (Yang et al., 2017; Hemmati and Sharifi, 2018).

- **Feedback-based (E):** feedback and history information is utilized. E group algorithms utilize the execution results (pass/fail/skip) in a current build to dynamically reorder those test cases that have not yet been executed (Cho et al., 2016; Pradhan et al., 2018; Zhu et al., 2018).

In our prior work (Yu et al., 2019) we then applied these techniques as baselines and compared them against a proposed new TCP algorithm on datasets used in automated UI testing at LexisNexis. Detailed descriptions of how each algorithm work can also be found in that prior work.

4. Validation

We now address the research questions, by first validating the primary study selection results of FAST² with a controlled experiment of the relevant paper
Table 1: Eligible Test Case Prioritization Techniques and Information They Utilize

| ID | Technique Description                                                                 | Utilized Information |
|----|----------------------------------------------------------------------------------------|----------------------|
|    |                                                                                        | Execution history    | Test case description | Feedback |
| B1 | Execute test cases in ascending order of time since last failure (Hemmati et al., 2015; Kwon and Ko, 2017). | ✓                     |                      |          |
| B2 | Execute test cases in descending order of number of times failed/number of times executed (Fazlalizadeh et al., 2009; Marijan and Liaaen, 2016; Tsai et al., 2005; Aman et al., 2016). | ✓                     |                      |          |
| B3 | Execute test cases in descending order of exponential decay metrics (Kim and Porter, 2002; Park et al., 2008; Lin et al., 2013). | ✓                     |                      |          |
| B4 | Execute test cases in descending order of ROCKET metrics (Marijan et al., 2013).         | ✓                     |                      |          |
| B5 | Execute test cases in descending order of the Mahalanobis distance of each test case to the origin (0,0) when considering two metrics—time since last execution and failure rate (Aman et al., 2016). | ✓                     |                      |          |
| C1 | Execute test cases in ascending order of the estimated test case runtime (Park et al., 2008; Marijan and Liaaen, 2016). | ✓                     |                      |          |
| D1 | Supervised learning with Simple History (SH) (Hemmati and Sharifi, 2018).               | ✓                     | ✓                    |          |
| D2 | Supervised learning with All History (AH) (Hemmati and Sharifi, 2018; Yang et al., 2017). | ✓                     | ✓                    |          |
| D3 | Supervised learning with Weighted History (WH) (Hemmati and Sharifi, 2018).            | ✓                     | ✓                    |          |
| E1 | Dynamic test case prioritization with co-failure information (Zhu et al., 2018).        | ✓                     |                      | ✓        |
| E2 | Dynamic test case prioritization with flipping history (Cho et al., 2016).              | ✓                     |                      |          |
| E3 | Dynamic test case prioritization with rules mined from failure history (Pradhan et al., 2018). | ✓                     |                      |          |
selection process. Six graduate students (from our lab with at least 1 year of software engineering research experience) were enlisted to manually screen the candidate papers. A full-text review on the relevant papers included by either the six students or FAST\textsuperscript{2} were performed to provide the final decision on which papers should be included.

4.1. RQ1: What percentage of relevant papers did FAST\textsuperscript{2} actually retrieve?

Considering the prohibitive cost involved in manually screening 8,349 papers, we validate our results on only a subset of the candidate papers. By searching in IEEE Xplore with the following search string 

\textit{[software AND test AND prioriti*]},

a validation set of 783 papers was retrieved. Among the 470 of these papers that had been screened with FAST\textsuperscript{2}, 318 were in the validation set. Among the 242 papers classified as relevant by FAST\textsuperscript{2}, 237 were in the validation set.

Each paper in the validation set was manually screened by at least two graduate students. A third student was asked to screen the paper if the screening results from the first two were inconsistent. A majority vote was then used to determine the final screening results of papers (293 relevant papers) in the validation set. After that, full-text validation was applied to the papers identified by the majority vote that were not identified by FAST\textsuperscript{2}. Six hours were spent on the full-text validation of the 70 papers, and it was confirmed that 39 of the validated papers were relevant. These full-text validation results were treated as the ground truth for the validation set.

Table 2 summarizes the validation results of FAST\textsuperscript{2}, the majority vote, and the ground truth with labels explained in Table 3. From Table 2 we can derive the performance of FAST\textsuperscript{2} on the validation set:

- Human Precision = \frac{234}{234+3} = 0.99
- FAST\textsuperscript{2} Precision = \frac{234}{237+81} = 0.74
Table 3: Labels of Table 2

| Description                                                                                      | FAST² | Majority Vote | Ground Truth |
|------------------------------------------------------------------------------------------------|-------|---------------|--------------|
| Papers suggested by FAST² and included by human                                                | yes   | yes           | yes          |
| Papers suggested by FAST² but excluded by human                                                 | no    | no            | no           |
| Papers ignored by FAST²                                                                       | ignore|               |              |
| Papers included by two humans                                                                  | yes   |               |              |
| Papers excluded by two humans                                                                  | no    |               |              |
| Papers included by full-text validation                                                        | yes   |               |              |
| Papers excluded by full-text validation or by both FAST² and majority vote                     | no    |               |              |

• Recall = FAST² Recall × Human Recall = \( \frac{234+12}{273} \times \frac{234}{234+12} = 0.90 \times 0.95 = 0.85 \)

• Cost = \( \frac{237+81}{783} = 0.41 \)

Here, the recall involved in selecting primary studies consists of two parts—FAST² recall and human recall. The FAST² recall on the validation set is 90%, which is very close to its estimation of 91% recall and is the same as the target recall \( T_{rec} = 90\% \). Therefore, we conclude that the recall estimation of FAST² was accurate in this SLR study.

As for the performance of manual screening with majority votes, the following calculations apply:

• Precision = \( \frac{259}{259+34} = 0.88 \)

• Recall = \( \frac{259}{259+14} = 0.95 \)

• Cost = \( \frac{783 \times 2+174}{783} = 2.22 \)

This data shows that the human working with FAST² (the first author) achieved the same recall as, but higher precision (99%) than, the majority vote results of the other six humans (89%). This probably occurred because the author designed the inclusion and exclusion criteria and had a better understanding of which papers are relevant to the SLR. This result suggests that, although employing more human reviewers for relevant paper selection can effectively reduce the time required for that process, more cost-effective and precise results can be achieved if only the human planning the SLR is employed for the primary study selection, which leads to less unnecessary full-text review effort.
Figure 9: Comparing the distribution of papers in each category (of information utilized), considering (1) the 239 papers considered relevant by FAST\(^2\) (Percentage), (2) the 39 relevant papers missed by FAST\(^2\) (Percentage in missing), and (3) the 278 ground truth relevant papers (Percentage in all).

4.2. **RQ2: What information is missing in the final report because of FAST\(^2\)?**

To determine what information is lost by excluding the 39 relevant papers not discovered by FAST\(^2\) and the human reviewer, we analyzed these papers in the same manner as the 239 papers that were initially included, and classified them based on prioritization goals, data types, information used, and method applied for black box testing. As shown in Figure 9, we observe:
• Distributions of the missing papers into categories are quite different from those obtained for the 239 papers identified as relevant by FAST². This suggests that when using FAST², a bias could be introduced in terms of which relevant papers will be retrieved. This is probably caused by the imbalance of categories in the training data of FAST², e.g., when 30% of the training data (relevant papers found) uses history information, it is likely that FAST² would predict that a paper using history information has a higher probability of being relevant than otherwise.

• Distributions of all the relevant papers into categories are still similar to those obtained for the 239 papers identified as relevant by FAST² – especially with respect to the rankings of number of papers in each category. This suggests that, despite the bias introduced by FAST², the overall conclusions of the SLR are still representative when using the 90% relevant papers selected with FAST². However, in studies like systematic mappings where the exact values of distributions matter, such biases should be avoided by manually screening all of the search results.

• While one more paper (Noor and Hemmati, 2015) in the papers omitted by FAST² was identified to be applicable to automated UI testing, that technique is similar to the D2 technique (Hemmati and Sharifi, 2018) listed in Table 1. Therefore, including that paper did not add any new information to the conclusions of the SLR case study.

To summarize, the benefits associated with the use of FAST² to guide the selection of relevant papers are as follows:

• With the help of FAST², 85% of the relevant papers were included with only \( \frac{470}{8349} = 6\% \) of the candidate papers screened. This saved approximately 50 hours of work.

• The recall of FAST² when the selection stopped was close to the target recall based on the validation result. This suggests that a researcher may be able to choose a level of recall at which to stop the selection with the help of the recall estimation given by FAST².

• The cost of primary study selection was reduced to a reasonable level (three hours for 470 papers), so that it was possible to employ only one human (the one who planned the SLR) to select relevant papers. This reduced the human error rate for the selection process.
The costs associated with use of FAST\(^2\) to guide the selection of relevant papers are as follows:

- There were more missed relevant papers when applying FAST\(^2\) with a target recall lower than 100%. The higher the target recall is, the higher the cost will be (Yu and Menzies, 2019). Researchers need to consider the tradeoff between the screening effort they are willing to spend and the recall they can achieve with FAST\(^2\).

- Using FAST\(^2\) can introduce a sampling bias into the included relevant papers. This may not always affect SLR studies (e.g. the conclusions of the case study SLR in this paper remained unchanged) but it should be avoided in studies such as systematic mappings.

5. Conclusions and Future Work

When researchers report work involving the creation of new approaches, they usually focus on the designed novel approach and how that approach performed compares to other state-of-the-art approaches. However, they seldom discuss how they find these state-of-the-art baseline approaches. In this paper, we want to bring researchers’ attention to this problem— how to find the state-of-the-art baseline approaches— because (1) it is critical to any research (researchers can keep improving the solution to a problem only when they are fully aware of what others have done to attempt to solve that problem), and (2) it is usually a tedious task that consumes large amounts of time and effort. Expert systems have been designed to assist researchers more efficiently in finding relevant papers. However, these expert systems have not been widely applied because of the lack of successful literature review case studies supporting their use.

To this end, we report the process of finding 12 state-of-the-art baseline test case prioritization algorithms, in our lately published test case prioritization paper (Yu et al., 2019). In this literature review case study, we investigated 242 papers on test case prioritization that had been published in conference proceedings and journals, through a systematic literature review process. The 242 papers were selected by manually screening 470 of the 8,349 candidate papers with the help of FAST\(^2\), a human-in-the-loop expert system. During this process, FAST\(^2\) reduced the effort required for paper selection by \(1 - \frac{470}{8349} = 94\%\) (from 53 hours to three hours). Based on the validation results in which six other humans screened a subset (783) of the candidate papers, the FAST\(^2\) selection process included 85\% of the relevant papers with human errors contributing to 5\% of the missing papers. Given the large
reduction of human effort required for primary study selection, with only 10% loss in recall (the same as the FAST²’s estimation), and given the fact that the missing relevant papers did not affect the final conclusions of the case study SLR, this work supports the suggestion that FAST² can be used to cost-effectively select primary studies in SLRs. We did find, however, that using FAST² can introduce a sampling bias in the included relevant papers. Thus, when conducting systematic mapping studies, it may be best to avoid using FAST².

For future work, we intend to encourage other software engineering researchers to conduct systematic literature reviews using FAST². We also intend to find ways to improve the efficiency (higher recall and lower cost) of our expert system-assisted primary study selection approach through simulations on the SLR datasets including this study. Finally, we will attempt to alleviate the sampling bias introduced by FAST². A possible solution in this context may be to replace FAST²’s learner with some instance-based classifiers such as K-Nearest Neighbors.

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Algorithm 1: Pseudo Code for FAST$^2$ (Yu and Menzies, 2019) Implemented in the SLR

Input:
- $E$, the candidate paper set (search results)
- $T_{rec}$, target recall
- $N_1$, batch size
- $N_2$, threshold of query strategy
- $Q$, search query for BM25 to boost initial selection

Output:
- $L$, screened papers
- $L_R$, included relevant papers

L ← ∅;
L_R ← ∅;
$|R_E|$ ← ∞;

// Keep screening until target recall $T_{rec}$ has been achieved.
while $|L_R| < T_{rec}|R_E|$ do
  // Start training when first relevant paper is found
  if $|L_R| ≥ 1$ then
    // Alleviate bias in negative training examples
    $L_{pre}$ ← Presume($L, E \setminus L$);
    CL ← Train($L_{pre}$);
  
  // Estimate #relevant papers
  $|R_E|$ ← SEMI(CL, E, L, L_R);
  // Select unscreened papers for human to screen
  X ← Query(CL, E \setminus L, L_R);
  // Human screen selected papers
  foreach $x$ ∈ X do
    if Screen($x$) then
      L_R ← L_R ∪ x;
      // Add paper into screened set
      L ← L ∪ x;
  
return L, L_R;

Function Presume ($L, E \setminus L$)
  // Randomly sample $|L|$ points from $E \setminus L$, presume those as non-relevant
  return L ∪ Random($E \setminus L, |L|$);

Function Train ($L_{pre}$)
  // Train linear SVM with Weighting
  CL ← SVM($L_{pre}$, kernel=linear, class_weight=balanced);
  if $L_R ≥ N_2$ then
    // Aggressive undersampling
    L_I ← L_{pre} \ L_R;
    tmp ← L_I[.argsort(CL.decision_function(L_I))[|L_R|]];
    CL ← SVM(L_R ∪ tmp, kernel=linear);
  return CL;
Function \( \text{Query}(CL, E \setminus L, L_R) \)

1. if \( L_R \geq N_2 \) then
   - // Certainty Sampling (highest predicted probability of failing)
     2. \( X \leftarrow \text{argsort}(CL.\text{decision}\_\text{function}(E \setminus L))[: -1][: N_1]; \)
   else
     - // Uncertainty Sampling
     3. \( X \leftarrow \text{argsort}(\text{abs}(CL.\text{decision}\_\text{function}(E \setminus L)))[: N_1]; \)

4. return \( X; \)

Function \( \text{Screen}(x) \)

5. if human thinks \( x \) is relevant then
   6. return \( True; \)
   else
     7. return \( False; \)

Function \( \text{SEMI}(CL, E, L, L_R) \)

8. \( |R_E|_{\text{last}} \leftarrow 0; \)
9. \( \neg L \leftarrow E \setminus L; \)
10. foreach \( x \in E \) do
11.    \( D(x) \leftarrow CL.\text{decision}\_\text{function}(x); \)
12.    if \( x \in [L_R] \) then
13.       \( Y(x) \leftarrow 1; \)
14.    else
15.       \( Y(x) \leftarrow 0; \)
16.    \( |R_E| \leftarrow \sum_{x \in E} Y(x); \)
17. while \( |R_E| \neq |R_E|_{\text{last}} \) do
18.    // Fit and transform Logistic Regression
19.    \( \text{LReg} \leftarrow \text{LogisticRegression}(D, Y); \)
20.    \( Y \leftarrow \text{TemporaryLabel}(\text{LReg}, \neg L, Y); \)
21.    \( |R_E|_{\text{last}} \leftarrow |R_E|; \)
22.    // Estimation based on temporary labels
23.    \( |R_E| \leftarrow \sum_{x \in E} Y(x); \)
24. return \( |R_E|; \)

Function \( \text{TemporaryLabel}(\text{LReg}, \neg L, Y) \)

25. \( \text{count} \leftarrow 0; \)
26. \( \text{target} \leftarrow 1; \)
27. \( \text{can} \leftarrow 0; \)
28. // Sort \( \neg L \) by descending order of \( \text{LReg}(x) \)
29. \( \neg L \leftarrow \text{SortBy}(\neg L, \text{LReg}); \)
30. foreach \( x \in \neg L \) do
31.    \( \text{count} \leftarrow \text{count} + \text{LReg}(x); \)
32.    \( \text{can} \leftarrow \text{can} \cup \{x\}; \)
33.    if \( \text{count} \geq \text{target} \) then
34.       \( Y(\text{can}[0]) \leftarrow 1; \)
35.       \( \text{target} \leftarrow \text{target} + 1; \)
36.       \( \text{can} \leftarrow 0; \)
37. return \( Y; \)