Searching for Better Test Case Prioritization Schemes: a Case Study of AI-assisted Systematic Literature Review

Zhe Yu · Jeffrey C. Carver · Gregg Rothermel · Tim Menzies

Abstract Given the large numbers of publications in the SE field, it is difficult to keep current with the latest developments. In theory, AI tools could assist in finding relevant work but those AI tools have primarily been tested/validated in simulations rather than actual literature reviews. Accordingly, using a realistic case study, this paper assesses how well machine learning algorithms can help with literature reviews.

The target of this case study is to identify test case prioritization techniques for automated UI testing; specifically from 8,349 papers on IEEE Xplore. This corpus was studied with an incrementally updated human-in-the-loop active learning text miner. Using that AI tool, 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.

The foregoing results were validated by having six graduate students manually explore the same corpus. Using data from that validation study, we determined that without AI tools, this task would take 53 hours and would have found 27 extra papers. That is, with 6% of the effort of manual methods, our AI tools achieved a 90% recall. Significantly, the same 12 state-of-the-art test case prioritization techniques were found by both the AI study and the manual study. That is, the 27/242 papers missed by the AI study would not have changed our conclusions. Hence, this study endorses the use of machine learning algorithms to assist future literature reviews.

Keywords Systematic Literature Review · Test Case Prioritization · Software Engineering · Active Learning · Primary Study Selection

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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, if not more so, 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, 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) [17, 29]. Following a set of guidelines, researchers conducting SLRs manually examine all the papers relevant to some research questions and summarize the research area. Other researchers can then get a general idea about current activity in their field of interest by reading the published SLRs. However, SLRs are not conducted frequently because of their labor-intensive and time-consuming nature [55]. 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.

We (the authors of this article) were faced with the same problem when we were exploring the state-of-the-art in applying TCP techniques to automated UI tests [54]. There was no available SLR summarizing these TCP techniques; thus, we needed to conduct our own literature review. 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. To reduce this time, we applied a state-of-the-art human-in-the-loop machine learning algorithm called FASTREAD [55, 57] to assist in selecting relevant papers. By considering and labeling 470 papers suggested by the machine learning algorithm in three hours, we included 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 10% recall (missing 24 relevant papers).

Because this was the first time FASTREAD 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 FASTREAD, we found:

- The FASTREAD selection process included 85% of the relevant papers with human errors contributing to 5% of the missing papers. That said, FASTREAD was responsible for
missing 10% of the relevant papers, which is very close its estimation of having missed 9% of the relevant papers.

- The distributions of the missing relevant papers are very different from the distribution of papers that FASTREAD included. This suggests that FASTREAD 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. As a result, the overall conclusions of the literature review were not affected by the missing relevant papers.

In conclusion, FASTREAD 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 [54]. Therefore, we believe that it was worth saving 50 hours in selecting relevant papers with 10% of the relevant papers omitted, in our literature review, and this may extend to other situations in which SLRs are conducted. When conducting studies such as system mappings, however, where the actual number and distribution matters, AI assistants such as FASTREAD may need to be avoided until the bias issue has been resolved.

The main contributions of this paper are as follows:

- We conducted the first systematic literature review using FASTREAD. This is also among the very few SLRs assisted by machine learning algorithms.
- We validated the use of FASTREAD in an SLR and observed its strengths and weaknesses.
- We scripted our entire SLR process and we provided it in a public Github repo (https://github.com/fastread/SLR_on_TCP) so that other researchers can use the data for reproduction and improvements on machine-learning-assisted primary study selection.

The remainder of this paper explores the research questions shown in Table 1. Section 2 presents background material and related work. Section 3 reports on the SLR process and answers RQ1 with SLR results. Section 4 reports the selection results of FASTREAD and answers RQ2. Section 5 concludes the paper and discusses the potential future work.

2 Background and Related Work

In this section, we provide background information on systematic literature reviews, and introduce the FASTREAD algorithm.

2.1 Systematic Literature Reviews

Systematic Literature Reviews (SLRs) have become a well established and widely applied review method in Software Engineering since Kitchenham, Dybø, and Jørgensen first adopted them to support evidence-based software engineering in 2004 and 2005 [17,29]. 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 [55]); 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 [4].
Table 1: Research questions and main motivations

| Research question | Main motivation |
|-------------------|-----------------|
| **RQ1:** What are the state-of-the-art TCP techniques that can be applied to automated UI testing? | Through exploring RQ1a-d, we aim to identify TCP techniques that prioritize for failure detection rate, use real failure data, and do not rely on source code information. |
| **RQ1a:** What are the prioritization goals? | Identify the goals of the TCP techniques, e.g., higher fault detection rate, failure detection rate, or code coverage. |
| **RQ1b:** What types of data are used? | Identify the various data sources used in TCP papers. |
| **RQ1c:** What information is used to prioritize the test cases? | Identify the sources of independent variables (features) used in different TCP techniques. |
| **RQ1d:** What methods do not rely on source code information? | Identify the algorithms and strategies applied by TCP techniques when no source code, changes in source code, or requirements information is available. |
| **RQ2:** What are the wins and losses of using FASTREAD to guide the selection of relevant papers? | Study the use of FASTREAD for human effort reduction in paper selection. |
| **RQ2a:** What percentage of relevant papers does FASTREAD actually retrieve? | Determine whether using FASTREAD, user-defined target recall can be achieved by screening only a small portion of the search results. |
| **RQ2b:** What information is missing in the final report because of FASTREAD? | Validate whether retrieving and analyzing a certain percentage of relevant papers significantly shifts the conclusions of the SLR. |

2.2 Machine Learning Algorithms 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 [8, 9, 22, 36, 52, 55, 57]. 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 [23], the total recall problem can be described as follows [56].

**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 [23]. 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 [44]. 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 [8, 12, 22, 48, 52, 55, 57]. 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 [55, 57] 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 [57]. 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 machine learning algorithms have actually been applied in real systematic literature reviews. To the best of our knowledge, only Xiong et al. [53] 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 (FASTREAD [55, 57]) to perform primary study selection. We chose to apply FASTREAD to assist the SLR in our case study because in previous work, (1) it outperformed other approaches in terms of inclusion rate [55], and (2) its recall estimation provides a confidence level that indicates what the algorithm has missed when the selection stops [57].

2.3 FASTREAD

FASTREAD is an active learning tool [4] that helps reduce the cost of primary study selection in SLRs [55, 57]. 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 \((L \subseteq E)\).
- \( L_R = L \cap R \): the set of included papers.

Instead of reviewing and classifying all candidate papers in a random order, a primary study selection with FASTREAD follows the procedure used in active learning frameworks for total recall problems as shown in Figure 3 and benefits from three features:

1. **Higher inclusion rate:** FASTREAD incrementally trains/updates a machine learning model (in Step 4) on the human classification results \((L \text{ and } L_R \text{ from Step 3})\). With the help of the machine learning model, FASTREAD dynamically adjusts the order of papers

https://github.com/fastread/src
Fig. 3: Active learning framework for total recall problems.

2. Recall estimation: FASTREAD estimates the total number of relevant papers $|R_E| \approx |R|^{3}$ 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: FASTREAD 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 version of FASTREAD that we implemented for our case study is shown in Algorithm 1.

3 Case Study: A Systematic Literature Review on Test Case Prioritization with FASTREAD

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 [5]. 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; for example, Elbaum et al. [18] 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;

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3 Here, $|R_E| \approx |R|$ means that $R_E$ is an estimation of the value of $|R|$. 

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Algorithm 1: Pseudo Code for FASTREAD [57] 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

1. \( L \leftarrow \emptyset \);
2. \( L_R \leftarrow \emptyset \);
3. \( |R_E| \leftarrow \infty \);
   // Keep screening until target recall \( T_{rec} \) has been achieved.
4. \( \text{while } |L_R| < T_{rec} |R_E| \text{ do} \)
   // Start training when first relevant paper is found
5. \( \text{if } |L_R| \geq 1 \text{ then} \)
   // Alleviate bias in negative training examples
6. \( L_{pre} \leftarrow \text{Presume}(L, E \setminus L) \);
7. \( CL \leftarrow \text{Train}(L_{pre}) \);
   // Estimate #relevant papers
8. \( |R_E| \leftarrow \text{SEMI}(CL, E, L, L_R) \);
9. \( X \leftarrow \text{Query}(CL, E \setminus L, L_R) \);
   // Select unscreened papers for human to screen
10. \( \text{foreach } x \in X \text{ do} \)
    // Include paper if relevant
11. \( \text{if Screen}(x) \text{ then} \)
12. \( L_R \leftarrow L_R \cup x \);
13. \( L \leftarrow L \cup x \);
14. return \( L, L_R \);

Function \text{Presume}(L, E \setminus L)

// Randomly sample \(|L|\) points from \( E \setminus L \), presume those as non-relevant
15. return \( L \cup \text{Random}(E \setminus L, |L|) \);

Function \text{Train}(L_{pre})

// Train linear SVM with Weighting
16. \( CL \leftarrow \text{SVM}(L_{pre}, \text{kernel=linear, class_weight=balanced}) \);
17. \( \text{if } L_R \geq N_2 \text{ then} \)
18. \( L_I \leftarrow L_{pre} \setminus L_R \); // Aggressive undersampling
19. \( \text{tmp} \leftarrow L_I \text{argsort}(CL \text{. decision function}(L_I))[:|L_R|] \);
20. \( CL \leftarrow \text{SVM}(L_R \cup \text{tmp}, \text{kernel=linear}) \);
21. return \( CL \);

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

// Certainty Sampling (highest predicted probability of failing)
22. \( \text{if } L_R \geq N_2 \text{ then} \)
23. \( X \leftarrow \text{argsort}(CL \text{. decision function}(E \setminus L))[:|L_R|] \);
24. \( \text{else} \) // Uncertainty Sampling
25. \( X \leftarrow \text{argsort}(\text{abs}(CL \text{. decision function}(E \setminus L)))[:|L_R|] \);
26. return \( X \);

Function \text{Screen}(x)

// If human thinks \( x \) is relevant then
27. return True;
28. \( \text{else} \)
29. return False;
it schedules test cases for execution in an order that attempts to increase their effectiveness at meeting some performance goal [42]. Unlike other techniques such as test case selection, TCP techniques use the entire test suite and reduce testing cost by achieving parallelization of testing and debugging activities [14]. By retaining all test cases, TCP techniques do not run the risk of omitting some important test cases.

There are four attributes that distinguish papers on TCP techniques:

- What is prioritized for: the goal of the TCP technique. Common goals include increased fault detection rate [42], increased failure detection rate [25], and the faster achievement of coverage [32]. Different performance goals lead to different evaluation criteria.
- What information is used: TCP techniques rely on different types of information to schedule test cases, e.g., they may rely on data showing the coverage of source code for each test case [27] or on the execution history of test cases in previous runs [25].
- What method is applied: different methods can be applied to utilize the foregoing information to achieve the goals of techniques, such as search-based algorithms [38], greedy algorithms [42], or supervised learning algorithms [25].
Test search for 1+1:
● Given the user has entered search term "1+1"
● When the user clicks on the search button
● Then single result is shown for "2"

```java
@Given("the user entered search term '")
public void searchFor(String searchTerm){
    document.getElementById("searchInput").sendKeys(searchTerm);
}

@When("the user clicks on the search button")
public void clickSearchButton(){
    document.getElementById("searchButton").click();
}

@Then("Single result is shown for '")
public void assertSingleResult(String searchResult){
    assertTrue(document.getElementById("searchResult").innerHTML==searchResult);
}
```

(a) UI test  (b) test description  (c) test code

Fig. 4: To test a page shown at the left (a), programmers write a test description (b) which is converted to test code (c).

Data type for evaluation: what type of data is applied to evaluate different TCP techniques. Most important, are the data synthesized with injected faults [15] or based on real testing results with failure and fault information [47]?

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 4a 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 requirements for such papers are: (1) they must present techniques that prioritize for failure detection rate, (2) they must use real failure data, and (3) then cannot rely on source code information. While (3) is essential for such techniques, (1) and (2) can be relaxed if too few techniques satisfy all the requirements. 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,
Validation, and
Reporting.
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 (RQ1)

We established four research questions by which to identify the primary papers that explore test case prioritization. Research questions and their primary motivations are shown in Table 1 as RQ1a-d.

3.1.2 Search strategy

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:

[software AND test AND (rank* OR optimi* OR prioriti*)]

We executed this search string in the IEEE Explore 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.

3.1.3 Inclusion and exclusion criteria

This review included papers 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. FASTREAD 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 FASTREAD suggest that 90-95% recall is appropriate because the cost required to reach higher recall increases exponentially [55,57]. 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 the properties and categories listed in Table 2. Details on each category will be provided in Section 3.3. The categories for RQ1a and RQ1c are non-exclusive. For example, one paper may utilize both source code and history information.

* https://ieeexplore.ieee.org
Table 2: Classification of papers

| Property                          | Categories                                      |
|-----------------------------------|-------------------------------------------------|
| RQ1a: What is prioritized for     | Fault detection rate, failure detection rate, coverage, none. |
| RQ1b: Data type for evaluation    | No fault or failure, injected faults, real fault or failure. |
| RQ1c: What information is used    | Source code, change, requirement, history, test case, feedback. |
| RQ1d: What method is applied      | History-based, test case-based, feedback-based   |

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 FASTREAD: this is the first SLR study conducted with FASTREAD, 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 FASTREAD tool, we performed the following steps to select the primary studies with a target recall $T_{rec} = 90\%$:

1. We loaded the search results of 8,349 papers with their titles and abstracts into FASTREAD.
2. We 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. 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 5. Meanwhile, the estimated recall was $\frac{|L_R|}{|R_E|} = 242/266 = 91\%$. 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 FASTREAD 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 Table 2 in Section 3.1.4. Among the 242 papers, three were determined to be not relevant to our research questions based on their full text and were thus excluded. The paper classification process required approximately 40 hours of effort by one person.

3.3 Phase 3—reporting

In this phase, the analytical results of the systematic literature review are discussed based on research questions RQ1a – RQ1d. 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 6.

3.3.1 RQ1a: What are the prioritization goals?

Figure 7 shows the distribution of the prioritization goals for the TCP techniques each paper considered. Different goals can overlap when one technique prioritizes for multiple goals and these are evaluated by multiple performance metrics. From the distribution in Figure 7, we observe the following:
– **Fault detection rate**: Most of the papers (close to 75%) present techniques that prioritize test cases to achieve higher fault detection rates. An improved rate of fault detection during testing can provide faster feedback on the system under test and let software engineers begin correcting faults earlier than might otherwise be possible [42]. The most popular performance metrics for evaluating early fault detection is average percentage of faults detected (APFD), proposed by Rothermel et al. [42] in 2001. APFD is calculated as (1):

\[
APFD = 1 - \frac{TF_1 + TF_2 + \cdots + TF_m}{nm} + \frac{1}{2n}
\]

where \( TF_i \) is the first test case that reveals fault \( i \), \( m \) is the total number of faults revealed by the test suite, and \( n \) is the total number of test cases in the test suite. Ranging from 0% to 100%, higher APFD values mean better ordering of test cases in terms of early fault detection.
– Failure detection rate: A few (seven) papers present techniques that prioritize test cases to achieve higher failure detection rate [1, 25, 45–47, 59, 60]. This is a compromise prioritization target when failure to fault mapping information is not available. Usually, APFD can also be applied to measure the failure detection rate [33].

– Coverage: Some (13%) of the TCP techniques presented in the papers attempt to order test cases such that higher coverage can be achieved earlier. Here, coverage can refer to requirements coverage [26], statement coverage [32], decision coverage [32], block coverage [32], branch coverage [42], and so forth.

– None: 23 papers present TCP techniques without explicitly assigning them a goal.

3.3.2 RQ1b: What types of data are used?

Figure 8 shows the distribution of the type of data applied to evaluate the TCP methods. From the distribution in Figure 8 we observe the following:

– No fault or failure: For those papers evaluating TCP techniques only by coverage and those without evaluation, data with fault or failure information is not required. Thus 53 out of 239 of the papers analyzed do not use data providing fault or failure information.

– Injected faults: Most (close to 75%) of the papers evaluate TCP techniques by manually injecting faults to see how early these injected faults can be detected by the prioritized test suite. Most of the papers presenting TCP techniques that prioritize for fault detection rate use this type of data.

– Real faults or failures: A few (10) papers apply data with real faults or failures to evaluate the fault/failure detection rate of TCP techniques. Most of these papers (seven out of 10) are prioritizing for failure detection rate (having no failure to fault mapping) [1, 25, 45–47, 59, 60] while three out of 10 papers state that their data contain real fault information [13, 34, 40].

Table 3 shows the relation between data type and prioritization goal. As the Table shows, there is a strong correlation between the data type used for TCP technique evaluation and the prioritization goal:
Table 3: Relation between data type and prioritization goal

| Goal                        | No fault or failure | Injected faults | Real faults or failures |
|-----------------------------|---------------------|-----------------|-------------------------|
| Coverage only or none       | 53                  | 0               | 0                       |
| Fault detection rate        | 0                   | 176             | 3                       |
| Failure detection rate      | 0                   | 0               | 7                       |
|                             | 53                  | 176             | 10                      |
|                             |                     |                 | 239                     |

Fig. 9: Distribution of information used

- When no fault or failure information is available in the data, techniques can be evaluated only by coverage.
- Most real world data has only failure information, in these cases TCP techniques can be evaluated only by failure detection rate.

3.3.3 **RQ1c: What information is used to prioritize the test cases?**

TCP techniques utilize various information to reorder test suites for their prioritization goals. Figure 9 shows the distribution of each category of information being used by the techniques presented in the 239 papers. The six 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 [3], code coverage [16].
- **Changes**: 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 [30].
- **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 [43].
- **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 [20].
– **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 [58].

– **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 [7].

| Information     | Data             | No fault or failure | Injected faults | Real faults or failures |
|-----------------|------------------|---------------------|-----------------|-------------------------|
| White box       |                  | 53                  | 132             | 6                       | 211                     |
| Black box       | 0                | 24                  | 4               | 28                      |                         |
|                 |                  | 53                  | 176             | 10                      | 239                     |

Table 4 shows the relationship between data type and information used. For our convenience, we categorize the information used as:

– **White box** if source code, code change information, or requirements information, which are not available when prioritizing test cases for automated UI testing, are used;

– **Black box** if only history, test case, and feedback information, which are available when prioritizing test cases for automated UI testing, are used.

In most of the papers (211 out of 239) that we surveyed, the TCP techniques presented require **white box** information; only 28 of 239 present TCP techniques that rely on **black box** information (which is necessary when prioritizing automated UI tests). Interestingly, when considering only the papers in which real faults or failures are utilized a higher ratio of papers (four out of 10) explore TCP techniques that use only **black box** information. This suggests that it is more common than not that **white box** information is unavailable when prioritizing test cases in a real-world testing scenario, just as is the case for the automated UI test case prioritization problem.

3.3.4 **RQ1d: What methods do not rely on source code information?**

Most of the papers that present TCP techniques (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 [2]. However, these coverage-based methods are not applicable when **white box** information (source code, changes, requirements) is not available. Because only **black box** information is available when prioritizing automated UI test cases, we are more interested in TCP techniques that are applied for black box testing. Figure 10 shows the distribution of the papers that utilize such techniques. The techniques applied for black box testing are:

– **History-based**: only history information is utilized. The history-based techniques presented in 13 out of 28 of the papers apply different metrics extracted from past test execution results to predict fault/failure exposing potential, and to prioritize test cases [21].
– **Test case-based**: test case information and history information is utilized. The test case-based techniques presented in seven out of 28 of the papers 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 [6].

– **Feedback-based**: feedback and history information is utilized. The feedback-based techniques presented in eight out of 28 of the papers utilize the execution results (pass/fail) in a current test case run to dynamically reorder those test cases that have not yet been executed [41].

### 3.3.5 **RQ1**: What are the state-of-the-art TCP techniques that can be applied to automated UI testing?

Summarizing from RQ1a-RQ1d, only four papers [1, 25, 47, 60] were dealing with the same scenario in which automated UI testing applies: prioritizing for failure detection rate, using real failure data and only **black box** information. However, techniques that prioritize test cases for fault detection rate can also be applied to prioritize them for failure detection rate in automated UI testing, as long as they do not rely on source code information. As a result, we summarized the 28 **black box** papers and 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 5. In our prior work [54] 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.

Aside from identifying the state-of-the-art TCP techniques that can be applied to automated UI testing, there are other informative findings that can be derived from the systematic literature review:

– Most existing papers on TCP techniques utilize **white box** information and are evaluated by data with injected faults. This type of evaluation has clear drawbacks—the injected faults may not resemble real faults and the **white box** information may not be available in practice.
Table 5: Black Box 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 [24][31].               | ✓                    |
| B2 | Execute test cases in descending order of number of times failed/number of times executed [1][17][24]. | ✓                    |
| B3 | Execute test cases in descending order of exponential decay metrics [28].               | ✓                    |
| B4 | Execute test cases in descending order of ROCKET metrics [35].                         | ✓                    |
| 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 [1]. | ✓                    |
| C1 | Execute test cases in ascending order of the estimated test case runtime [29].           | ✓                    |
| D1 | Supervised learning with Simple History (SH) [25].                                    | ✓ ✓                  |
| D2 | Supervised learning with All History (AH) [25].                                        | ✓ ✓                  |
| D3 | Supervised learning with Weighted History (WH) [25].                                   | ✓ ✓                  |
| E1 | Dynamic test case prioritization with co-failure information [60].                      | ✓ ✓                  |
| E2 | Dynamic test case prioritization with flipping history [7].                             | ✓ ✓                  |
| E3 | Dynamic test case prioritization with rules mined from failure history [41].            | ✓ ✓                  |

On the other hand, fewer papers rely on data that involves real faults or failures (10 out of 239) or present TCP techniques that utilize only black box information (28 out of 239). Only four papers present techniques that prioritize test cases based on black box information on real failures. This is an under-explored area where results can be directly (or most easily) applied to industry.

Therefore, scenarios similar to the one that holds for automated UI testing are under-explored in the TCP literature. Specifically, there is a dearth of papers that (a) use real failure/fault data and that (b) assume the information starved black box scenario defined above.

4 Validation

We now address RQ2, by first validating the primary study selection results of FASTREAD by having six other graduate students manually screen the candidate papers, and then analyzing the missing information with a full-text review of the relevant papers included by the six students but missed by FASTREAD.
4.1 RQ2a: What percentage of relevant papers did FASTREAD 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

\[ \text{software AND test AND prioriti*} \]

a validation set of 783 papers was retrieved. Among the 470 of these papers that had been screened with FASTREAD, 318 were in the validation set; while among the 242 papers classified as relevant by FASTREAD, 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 FASTREAD. This full-text validation required the students to spend six hours to review 70 papers; they found that 39 of these were relevant. These full-text validation results were treated as the ground truth for the validation set.

Table 6 summarizes the validation results of FASTREAD, the majority vote, and the ground truth with labels explained in Table 7. From Table 6 we can derive the performance of FASTREAD on the validation set:

\[
\text{Human Precision} = \frac{234}{234 + 3} = 0.99
\]

\[
\text{FASTREAD Precision} = \frac{234}{237 + 81} = 0.74
\]

\[
\text{Recall} = \text{FASTREAD Recall} \times \text{Human Recall} = \frac{234 + 12}{274} \times \frac{234}{234 + 12} = 0.90 \times 0.95 = 0.85
\]

\[
\text{Cost} = \frac{237 + 81}{783} = 0.41
\]

Here, the recall involved in selecting primary studies consists of two parts—FASTREAD recall and human recall. The FASTREAD 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 FASTREAD was accurate in this SLR study.

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

\[
\text{Precision} = \frac{259}{259 + 34} = 0.88
\]

\[
\text{Recall} = \frac{259}{274} = 0.95
\]

\[
\text{Cost} = \frac{783 \times 2 + 174}{783} = 2.22
\]

This data shows that the human working with FASTREAD (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 research questions RQ1a-d. 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.

4.2 RQ2b: What information is missing in the final report because of FASTREAD?

To determine what information is lost by excluding the 39 relevant papers not discovered by FASTREAD 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 11, we observe:

- Distributions of the missing papers into categories are quite different from those obtained for the 239 papers identified as relevant by FASTREAD. This suggests that when using FASTREAD, 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 FASTREAD, e.g., when 70% of the training data (relevant papers found) uses injected faults, it is likely that FASTREAD would predict that a paper using injected faults has a higher probability of being relevant than otherwise.

- Distributions of the relevant papers into categories are still similar to those obtained for the 239 papers identified as relevant by FASTREAD – especially with respect to the rankings of number of papers in each category. This suggests that, despite the bias introduced by FASTREAD, the overall conclusions of the SLR are still representative when using the 90% relevant papers selected with FASTREAD. 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 presenting a black box TCP technique [37] was identified in the papers omitted by FASTREAD, that technique is similar the D2 technique [25] listed in Table 5; thus, including that paper did not add any new information to the conclusions of the SLR case study.

4.3 RQ2: What are the costs and benefits associated with using FASTREAD to guide the selection of relevant papers?

To summarize, in answer to RQ2, the benefits associated with the use of FASTREAD to guide the selection of relevant papers are as follows:

- With the help of FASTREAD, 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 FASTREAD 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 FASTREAD.

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 FASTREAD to guide the selection of relevant papers are as follows:

- There were more missed relevant papers when applying FASTREAD with a target recall lower than 100%. The higher the target recall is, the higher the cost will be [57]. Researchers need to consider the tradeoff between the screening effort they are willing to spend and the recall they can achieve with FASTREAD.
- Using FASTREAD 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

This paper investigated 242 papers on test case prioritization 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 FASTREAD. This systematic literature review study was conducted for two reasons: (1) to investigate the costs and benefits of selecting relevant papers by using a machine learning tool as represented by FASTREAD; and (2) to determine the state-of-the-art in research on TCP techniques that can be applied to automated UI testing.

Regarding the first point, FASTREAD 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 of 783 candidate papers, the FASTREAD 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 on primary study selection with only 10% loss on recall, and the fact that the missing relevant papers did not affect the final conclusions of the case study SLR, this data supports the suggestion that FASTREAD can be used to cost-effectively select primary studies in SLRs. However, we did find that using FASTREAD can introduce a sampling bias in the included relevant papers. Thus, when conducting systematic mapping studies, it may be best to avoid using FASTREAD.

Regarding the second point, this systematic literature review identified 12 state-of-the-art TCP techniques that rely only on black box information, and that can be applied directly to prioritize automated UI tests. These 12 techniques have since been used as baselines in another already published work [54]. Meanwhile, this SLR also found that TCP techniques that (1) utilize only black box information (no source code, change, or requirements), (2) prioritize for higher failure detection rate, and (3) are validated on real world failure data are under-explored and require more research attention, because these techniques could better meet the needs of large organizations such as Google [19] and Cisco [35].

As for future work, we intend to encourage other software engineering researchers to conduct systematic literature reviews using FASTREAD. We also intend to find ways to improve the efficiency (higher recall and lower cost) of our machine learning 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 FASTREAD. A possible solution in this context may be to replace FASTREAD’s learner with some instance-based classifiers such as K-Nearest Neighbors.

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