Putting Them under Microscope: A Fine-Grained Approach for Detecting Redundant Test Cases in Natural Language

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ABSTRACT
Natural language (NL) documentation is the bridge between software managers and testers, and NL test cases are prevalent in system-level testing and other quality assurance activities. Due to reasons such as requirements redundancy, parallel testing, and tester turnover within long evolving history, there are inevitably lots of redundant test cases, which significantly increase the cost. Previous redundancy detection approaches typically treat the textual descriptions as a whole to compare their similarity and suffer from low precision. Our observation reveals that a test case can have explicit test-oriented entities, such as tested function Components, Constraints, etc; and there are also specific relations between these entities. This inspires us with a potential opportunity for accurate redundancy detection. In this paper, we first define five test-oriented entity categories and four associated relation categories and re-formulate the NL test case redundancy detection problem as the comparison of detailed testing content guided by the test-oriented entities and relations. Following that, we propose Tscope, a fine-grained approach for redundant NL test case detection by dissecting test cases into atomic test tuple(s) with the entities restricted by associated relations. To serve as the test case dissection, Tscope designs a context-aware model for the automatic entity and relation extraction. Evaluation on 3,467 test cases from ten projects shows Tscope could achieve 91.8% precision, 74.8% recall, and 82.4% F1, significantly outperforming state-of-the-art approaches and commonly-used classifiers. This new formulation of the NL test case redundant detection problem can motivate the follow-up studies to further improve this task and other related tasks involving NL descriptions.

CCS CONCEPTS
• Software and its engineering → Software testing and debugging. Acceptance testing.

KEYWORDS
Test Case Redundancy, Entity and Relation Extraction, Natural Language Processing

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1 INTRODUCTION
Software testing is an activity to ensure that an entire system meets its requirements [5]. In the testing phase, testers need to analyze the requirements specification, identify all the test execution scenarios, and then instantiate them in manually written test cases [54]. Such test cases are typically described in natural language (NL). Due to their adjustability and interpretability, the NL test cases are still prevalent in industrial practice [32].

A requirement covers multiple features, and there may be overlapping features among requirements. For a large software project, the requirements are typically tested by different engineers, and engineers are not aware of the feature overlapping. Test redundancy may produce when each test engineer individually designs test case(s) for assigned requirements [14, 36]. As the system evolves, the redundant test cases significantly increase the cost of testing,
as well as maintenance effort[36]. The problem is especially obvious in the manual testing scenario where human testers must read through test steps and carry them out manually by interacting with the system [22].

To alleviate the issue, information retrieval-based approaches have been proposed to automatically detect redundancy among the NL test cases [32, 49, 53]. The general idea is to vectorize the description of the test case with text representing models, e.g., vector space model or Doc2Vec, and conduct the similarity comparison on it. However, these existing approaches suffer from low accuracy because they treat test cases’ textual descriptions as a whole, and thus cannot capture its fine-grained semantic information and inherent meaning. Meanwhile, we have the following two observations which can facilitate the similarity comparison and redundancy detection of the NL test case.

First, the test case has explicit categories of test-oriented entities which can facilitate accurate redundancy detection. Take Figure 1 as an example, the two test cases look similar in their textual descriptions, and would be detected as redundancy with the aforementioned information retrieval-based approaches. However, if putting these two test cases under the microscope, we can find that the executing manners of these two test cases ("mesa-util tool" and "UnixBench tool") are different, based on which, we can distinguish them accurately. More than that, one can easily observe that there are different categories of test-oriented entities, for example, "component", "behavior", "prerequisite", "maneuver", and "constraint", and four relation categories associated with the entities. It considers the global context of the test case for entity extraction, and the local context of the involving entities for relation extraction. After that, Tscope dissects each test case into the structured atomic testing tuple(s) guided by the extracted entities and relations. Finally, Tscope detects redundancy by comparing the entities in each tuple pair, considering the semantic meaning of the entities as well as their involved indicative words.

The new formulation of the NL test case redundant detection problem as the comparison of detailed testing content guided by the test-oriented entities and relations. Following that, we propose a fine-grained redundant test case detection approach Tscope1, which dissects the test case into atomic test tuple(s) with the five entities restricted by their associated relations, and conducts the comparison on them. One example test tuple dissected from Test case #525 in Figure 2 is as follows, Behavior "browse", component "visit history" and Manner "mouse". To achieve this, Tscope first designs a context-aware model for extracting test-oriented entities and relations from test case descriptions, which considers the global context of the test case for entity extraction, and the local context of the involving entities for relation extraction. After that, Tscope dissects each test case into the structured atomic testing tuple(s) guided by the extracted entities and relations. Finally, Tscope detects redundancy by comparing the entities in each tuple pair, considering the semantic meaning of the entities as well as their involved indicative words.

We evaluate Tscope on 3,467 test cases from ten projects. The evaluation results show that Tscope could reach 97.5% precision, 94.8% recall for the entity extraction, and 90.4% precision, 97.6% recall for the relation extraction, which significantly outperforms the two state-of-the-art approaches. For the redundancy detection task, Tscope could achieve 91.8% precision, 74.8% recall and 82.4% F1. Compared with the two state-of-the-art redundancy detection approaches and four commonly-used classifiers, Tscope is 19.8%-23.4% higher in F1. Moreover, the results of ablation experiments show that the five entity categories all play significant roles in Tscope.

The new formulation of the NL test case redundant detection problem can motivate the follow-up studies to further improve this task, and other related tasks involving NL descriptions. Actually, there are several tasks in software engineering domain involving the similarity comparison of two textual documents, e.g., duplicate test reports detection [24, 25], similar Stack Overflow questions identification [55], duplicate requirements detection [38], etc. The previous techniques typically treat the textual descriptions as a whole for the similarity comparison, while ignoring the fine-grained semantic information hidden in the text. The new formulation proposed in this paper, i.e., comparison of detailed content guided by the scenario-related entities and relations, could potentially motivate the researchers in these related fields.

In summary, the key contributions of this paper are as follows:

1. We name our approach as Tscope considering it likes a microscope to inspect the detailed information in test cases to facilitate the redundant detection.

Figure 2: Non-redundant test cases with multiple test-oriented entities

Figure 1: Non-redundant test cases with similar descriptions

Second, there might be multiple test-oriented entities that need to be carefully parsed and matched to ensure accurate redundancy detection. The first observation has motivated us to conduct the comparison within the same category of test-oriented entities for determining redundancy. However, when we put the two test cases in Figure 2 under the microscope, a second observation is made. There are both testing Behavior "browse" and tested Component "visit history" in these two test cases, yet they are expressing different test-oriented operational information. In detail, in test case #346, the Behavior "browse" is targeted at Component "content of each resource directory", and the Component "visit history" is associated with the Behavior "switch", while in test case #525 Behavior "browse" is directly for Component "visit history". The observation implies that the multiple test-oriented entities need to be carefully parsed and matched, and it is necessary to identify the test-oriented operational information, i.e., entities and associated relations when analyzing test cases to achieve accurate redundancy detection.

Motivated by the two findings, we define five test-oriented entity categories, i.e., Component, Behavior, Prerequisite, Manner and Constraint, and four relation categories associated with the entities. We then re-formulate the NL test case redundancy detection problem as the comparison of detailed testing content guided by the test-oriented entities and relations.

Taking into account the two observations, we develop a context-aware model for extracting test-oriented entities and relations from test case descriptions, which considers the global context of the test case for entity extraction, and the local context of the involving entities for relation extraction. After that, Tscope dissects each test case into the structured atomic testing tuple(s) guided by the extracted entities and relations. Finally, Tscope detects redundancy by comparing the entities in each tuple pair, considering the semantic meaning of the entities as well as their involved indicative words.

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In summary, the key contributions of this paper are as follows:

1. We name our approach as Tscope considering it likes a microscope to inspect the detailed information in test cases to facilitate the redundant detection.
• The new formulation of the NL test case redundancy detection problem, i.e., the comparison of detailed testing content guided by the test-oriented entities and relations.
• A fine-grained redundancy detection approach Tscope for NL test cases, which dissects the test case into atomic test tuple(s) with the five entities restricted by their associated relations, and conducts the comparison on them.
• A context-aware model for extracting test-oriented entities and their relations from test case descriptions, which involves the global context of the test case in entity extraction, and the local context of the involved entities for relation extraction.
• Evaluation with 3,467 test cases from ten projects, with promising results. We also publicize the source code for facilitating follow-up studies and other related tasks.

The remainders of the paper are as follows: Section 2 presents the empirical studies of the entity category for redundancy detection. Section 3 elaborates the approach. Section 4 presents the experiment design. Section 5 describes the results. Section 6 discusses the learned lessons. Section 7 introduces the related work and its limitations. Section 8 concludes our work.

2 EMPIRICAL ANALYSIS OF ENTITIES AND RELATIONS

2.1 Categories of Entities and Relations
Motivated by the observations in Section 1, we provide a new formulation of the NL test case redundancy detection problem, i.e., the comparison of detailed testing content guided by the test-oriented entities and relations. To achieve this, we define five categories of entities and four categories of relations associated with the entities. Specifically, we explore entity and relation categories through a bottom-up analysis approach. Specifically, three researchers (details in Section 4.2) are involved in mining the categories of entities and relations that affect redundancy detection in the test case text. If all three researchers agree on adding a category, this entity category is admitted and added to the entity category set. While if their views diverge, the decision is made through a voting mechanism, i.e., the entity category will be added to the set if it is admitted by at least two researchers. Finally, we obtain the five entity categories and corresponding relations among the entity categories. Table 1 shows each entity/relation category and examples.

2.1.1 Categories of Entities. The definition of the five entity categories is based on the purpose and basics of software testing, as well as the observations on NL test cases. First, test cases are driven by the feature(s) in requirements, and a feature specifies the behavior of one or more components in terms of their current conditions. Taken in this sense, the key entities in a feature will also be reflected in the test case descriptions. Therefore, we identify three entity categories “Component”, “Behavior” and “Prerequisite” respectively.

Second, according to our observations, test cases differ by the Manner sometimes. For example, there are descriptions of two non-redundant test cases in Figure 1. The two test cases have the same Prerequisite (“When drawing 3D graphics”) and Component (“gear rotation processing”), but different operation manner (“mesa-util tool” and “UnixBench tool”). To reflect this difference, we define an entity category “Manner”.

Third, in some cases, test cases may differ by the satisfied constraints. For example, there are two descriptions, “Test there are preset applications after the system installation” and “Test the preset applications including FTP application after the system installation”. The two test cases have the same Component (“preset applications”) but the latter additionally involves the constraint (“including FTP application”). Accordingly, we define an entity category “Constraint” to indicate the difference.

2.1.2 Categories of Relations. As shown in Figure 2, there may be multiple test-oriented entities per entity category within a test case, which implies the need for inspecting the entities within the test case a step further. Taking Test Case #346 in Figure 2 as an example, Behavior “browse” is targeting at Components “contents of each resource directory”, and Behavior “switch” is acting on Components “visit history”. This demonstrates the mapping between Components and Behavior, and we define it as the Act relation.

We also observe the relations in terms of the other three categories of entities, e.g., the executing manner of the testing. And considering the components in the test case are the basic object of the testing content, we define other three relations between Component and Prerequisite, Manner, Constraint to indicate the detailed information of the testing (details in Table 1).

2.2 Correlation Analysis
We conduct an empirical study to investigate the effectiveness of the entity categories for redundancy detection. Specifically, we randomly sample 5,000 test case pairs and manually label each test case by comparing each pair. Then, we build five Boolean variables by manual judgment, i.e., EQ\text{com}, EQ\text{beh}, EQ\text{pre}, EQ\text{man} and EQ\text{con}. Each variable represents the entities belonging to each category in the summaries are manually judged as equivalent. At the same time, a variable Redundant is built according to the redundancy label (not based on entity comparison), representing whether a test case is truly redundant.

We analyze the correlation between the above five variables and the variable Redundant. Table 2 shows the Pearson correlation coefficient and p-value of the correlation test. The results show that the five entity categories are significantly correlated to the variable Redundant, which indicates the effectiveness of each entity category for redundancy detection. Moreover, we analyze the consistency of the two variables, i.e., EQ\text{all} and Redundant, where EQ\text{all} represents that the entities belonging to the five entity categories in the test case pair are all equivalent by manual comparison. Cohenkappa coefficient is 0.984, which shows the significant consistency of the two distributions. The results indicate that redundant test cases could be effectively detected using the five entity categories. Motivated by the above considerations, we design a joint extraction model to extract entities and relations belonging to the pre-defined categories, dissect each test case into atomic test tuple(s) based on the extracted entities and relations, and detect the

\footnote{The test case pairs are built from the dataset in Table 1. The pairing and labeling processes are consistent with the descriptions in Section 4.2.}
We adapt the entity and relation joint extraction techniques \[\text{SEP}\], ...,

(4) Detecting Redundant Test Cases by Tuple Comparison, where \(Tscope\) designs three comparison strategies for tuple comparison.

\(Tscope\) designs a context-aware extraction model to extract the test-oriented entities and relations from test case descriptions; (3) Test Case Dissection into Tuples, where \(Tscope\) dissects each test case into test tuples based on the extracted entities and relations, to represent the fine-grained test-oriented operational information; and (4) Detecting Redundant Test Cases by Tuple Comparison, where \(Tscope\) designs three comparison strategies for tuple comparison and detects redundancy by a Tuple Covering Rule. The following introduces the details of the four phases.

### 3 APPROACH

Figure 3 shows the overview of Tscope. Tscope consists of four phases: (1) Data Pre-processing, where it conducts data-processing and constructs samples for the extraction model; (2) Context-aware Model for Test-oriented Entity and Relation Extraction, where Tscope designs a context-aware extraction model to extract the test-oriented entities and relations from test case descriptions; (3) Test Case Dissection into Tuples, where Tscope dissects each test case into test tuples based on the extracted entities and relations, to represent the fine-grained test-oriented operational information; and (4) Detecting Redundant Test Cases by Tuple Comparison, where Tscope designs three comparison strategies for tuple comparison and detects redundancy by a Tuple Covering Rule. The following introduces the details of the four phases.

#### 3.1 Data Pre-processing

Considering test cases are written in natural language, Tscope applies the standard data pre-processing pipeline in NLP field [39]. Specifically, given a test case \(TC\), Tscope first splits the textual contents into sentences \(\{s_1, ..., s_m\}\). For a sentence \(s_i\), Tscope removes special characters, converses into lowercase, and tokenizes it into a token sequence using the NLP toolkit scikit-learn\(^4\). Then, each test case is represented as a token sequence \(T_{TC} = \{T_1, \text{SEP}, T_2, \text{SEP}, ..., T_j, \text{SEP}, ..., T_n\}\), where \(T_j\) is the token sequence for sentence \(s_i\), \(\text{SEP}\) is the placeholder for dividing sentences. After that, \(T_{TC}\) is considered a sample for entity and relation extraction.

#### 3.2 Context-Aware Model for Test-Oriented Entity and Relation Extraction

We adapt the entity and relation joint extraction techniques [13, 50, 61] to design our context-aware model for test-oriented entity and relation extraction. First, the model obtains the candidate entities by iterating all the spans [50] in the input and encodes each candidate span using an embedding layer. Second, it designs an entity classifier, which considers the global context of the test case, to determine whether each candidate is an entity and its category. Third, it designs a relation classifier to decide the relation category for each entity pair, where it introduces the local context information of involved entities to act as the indicators for relation classification.

##### 3.2.1 Embedding Layer

In this layer, the extraction model firstly iterates all the candidate spans [50]. Specifically, the extraction model presets a span length and constructs all the spans by traversing all consecutive word chunks in the input text that do not exceed the span length. Spans are regard as candidate entities (CE\(1\) to CE\(n\) in the Figure 4). Then, the embedding layer encodes each candidate entity into a hidden representation. Please note that the span length is empirically set as 10 in the extraction model since there are no more than ten words for most of the entities according to our observations. After that, our model uses a pre-trained BERT model\(^5\) which is a commonly-used embedding model in the NLP field and shows strong robustness for different domains [35, 47]. Through the embedding layer, Tscope produces a hidden representation for each candidate entity.

##### 3.2.2 Entity Extraction Layer

In this layer, Tscope receives the hidden representations of all candidate entities and outputs whether they are entities and their categories. For the hidden representation of CE\(i\), Tscope leverages a maxpooling function [30] to retain the key semantic information and filter the noise. After that, it is sent to the entity classifier.

Compared with the traditional extraction models which only use the representations of the candidate entities for classification, the entity classifier in our model additionally includes the global context of the input test case to help determine the certain category of an entity belonging to. The reason why we employ this global context is that different types of test cases would have unique nature in the test-oriented entities. For example, a test case targeting at the performance bugs would be more likely to have the Constraints and Prerequisite categories of entities, compared with the test case targeting at the scalability bugs. Specifically, the model applies a vector CLS [41] for signifying the global context. It is the weighted sum of hidden representations for all the tokens in the test case and has been proven to effectively improve the performance of the classification tasks[56]. The entity classifier concatenates the

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\(^4\)https://scikit-learn.org/stable/

\(^5\)https://github.com/huggingface/transformers
representation of each candidate entity and CLS, and uses a softmax function \[\text{softmax}\] to predict whether the candidate entity is an entity and its entity category. The outputs of softmax function are six probabilities, i.e., \(P_{\text{Com}}, P_{\text{Beh}}, P_{\text{Pre}}, P_{\text{Man}}, P_{\text{Con}}\) and \(P_{\text{Non}}\), where the former five represent the probability of the relation categories and \(P_{\text{Non}}\) represents there is no relation between \(E_i\) and \(E_j\).

Traditional models only employ the representations of \(E_i\) and \(E_j\) as input. However, we observe that besides the two entities, the local context information is beneficial for relation extraction. Taking Test Case #525 in the Figure 2 as an example, for the \(\text{Component} \) “visit history” and \(\text{Manner} \) “mouse”, the context “using” could be a trigger word to indicate the \(\text{Use} \) relation between the two entities. Thus, when classifying the relation between \(E_i\) and \(E_j\), our model additionally introduces the local context information \(C_0\) and \(C_1\), where \(C_0\) is the contextual words before \(E_i\), and \(C_1\) is the contextual words between \(E_i\) and \(E_j\). The reason for not including the context words after \(E_j\) is that there are few cases in which trigger words appear after \(E_j\), according to our observations. Then, the relation extraction layer obtains the vector representations \(V(C_0)\), \(V(E_i)\), \(V(C_1)\) and \(V(E_j)\) using the BERT model and concatenates \(V(C_0)\), \(V(E_i)\), \(V(C_1)\) and \(V(E_j)\) for relation classifier. Our model chooses the category with the highest probability. Finally, it produces the extracted test-oriented entities and the relations for each test case.

### 3.3 Test Case Dissection into Tuples

After extracting test-oriented entities and relations, Tscope dissects each test case into test tuples. During dissection, Tscope firstly finds the extracted entities belonging to \(\text{Component}\), and then retrieves the associated entities based on the extracted relations. Finally, a \(\text{Component}\) and an associated \(\text{Behavior}\), an associated \(\text{Prerequisite}\), an associated \(\text{Manner}\), and an associated \(\text{Constraint}\) make up an atomic test tuple for redundancy detection. Please kindly note that if there are no associated entities for an entity \(\text{Component}\), it is marked as “NULL”.

Taking the Test Case #346 as an example, Tscope firstly retrieves two \(\text{Components}\), “contents of each resource directory” and “visit history”. Then, for the \(\text{Component}\) “visit history”, Tscope retrieves the associated \(\text{Behavior}\) “switch”, and the associated \(\text{Manner}\) “mouse”. After that, Tscope constructs a tuple “<visit history”, “switch”, NULL, “mouse”, NULL>”. Following the above process, Tscope iterates all the entities belonging to \(\text{Component}\), and constructs all the tuples. For the two test cases in the Figure 2, Table 3 shows all the tuples after dissection.
3.4 Detecting Redundant Test Cases by Tuple Comparison

3.4.1 Test Tuple Pair Construction. After dissecting test cases into test tuples, Tscope builds all the tuple pairs for comparison. A tuple pair consists of two tuples dissected from different test cases. Take two tuples dissected from two test cases as \(<\text{Com}_i, \text{Beh}_i, \text{Pre}_i, \text{Man}_i, \text{Con}_i>\) and \(<\text{Com}_j, \text{Beh}_j, \text{Pre}_j, \text{Man}_j, \text{Con}_j>\). Then, Tscope judges whether two tuples in each tuple pair are semantically equivalent by comparing entities belonging to five entity categories respectively.

3.4.2 Test Tuple Comparison. For a pair of two tuples, Tscope compares the corresponding entities belonging to the same category and judges whether they are expressing the same meaning. To alleviate the noisiness brought by different expressions and better capture the semantics of the entities, we apply the word embedding technique in modeling the entities and conduct the following comparison. Furthermore, we observe that different categories of test-oriented entities might involve different expression ways, e.g., the \(\text{Component}\) category is usually expressed with the noun phrases as the main linguistic elements, which could influence the comparison accuracy. To tackle this, we design three strategies for the tuple comparison, respectively for three types of expression ways corresponding with the entity categories.

- **Strategy 1.** for entities in form of the verb, represent entities with word embedding and compare with cosine similarity. This strategy is applied for entity category \(\text{Behavior}\).
- **Strategy 2.** for entities expressed with noun phrases as the main linguistic elements, besides Strategy 1, applies the SIF method in representation. This strategy is applied for entity category \(\text{Component}, \text{Manner}, \text{Constraint}\). It can alleviate the noise brought by the modifier around the core noun.
- **Strategy 3.** for entities in form of the adverbial clause, besides Strategy 1, retrieve the indicative word for separate comparison then apply Strategy 1. This strategy is for entity category \(\text{Prerequisite}\). It can better distinguish the meaning of \(\text{Prerequisites}\) for the test case.

**Strategy 1: Word Embedding + Cosine Similarity.** Considering that the entities belonging to \(\text{Behavior}\) are typically described as verbs, such as “browser” and “visit”, and the semantic information could be accurately captured only with the word embedding technique. We train Word2Vec model [37] using the training data (see Section 4.4.1), and the entity \(\text{Beh}_i\) and \(\text{Beh}_j\) are vectored as \(W2V_{\text{Beh}_i}\) and \(W2V_{\text{Beh}_j}\), respectively using the Equation 1:

\[
W2V_E = \text{Average}(W2V_{w_1}, \ldots, W2V_{w_7}, \ldots, W2V_{w_n})
\]

where \(w_i\) is the word in the extracted entity, and \(W2V_{w_i}\) is the vector representation for \(w_i\) returned by the trained Word2Vec model. Then Tscope directly calculates Cosine similarity score [42] between \(W2V_{\text{Beh}_i}\) and \(W2V_{\text{Beh}_j}\). After that, \(\text{Beh}_i\) and \(\text{Beh}_j\) are considered semantically equivalent if the similarity score is larger than the pre-defined threshold \(^6\).

**Strategy 2: Word Embedding + SIF + Cosine Similarity.** For entities belonging to \(\text{Component}, \text{Manner}, \text{Constraint}\), they are typically expressed with noun phrases as the main linguistic elements, and there are usually less informative words bringing the noise to the comparison. For example, there are two semantically equivalent \(\text{Components}\) “browser application” and “browser” described in two test cases. However, the vector representations of the two entities differ a lot due to the general word “application”. To alleviate the noise, Tscope additionally adopts SIF method [2] to filter out the noisy information. It removes the projection of the average of semantic representations of an entity along semantically meaningless directions and has been proven to effectively filter the meaningless information introduced by the general words in short text [19]. Similarly, Tscope judges whether two entities are semantically equivalent by the Cosine similarity and the pre-defined threshold.

**Strategy 3: Indicative Word Comparison + Word Embedding + Cosine Similarity.** The entities belonging to \(\text{Prerequisite}\) category are typically long entities described as adverbial clauses. We observe that there are indicative words in these entities, e.g., the words determining the temporal information. These words differ a little, yet can lead to an entirely different meaning. For example, in two similar test cases “Testing the CPU utilization when no preset applications are installed on the system” and “Testing the CPU utilization when preset applications are installed on the system”, the logic indicative word “no” in the entity \(\text{Prerequisite}\) indicates the test cases are different test cases. Another example is for the two similar test cases “Testing hard disk can be partitioned before the system installation” and “Testing hard disk can be partitioned after the system installation”, where the temporal indicative words “before” and “after” indicate the difference.

Taken in this sense, we summarize two lists of indicative words, i.e., words indicating logic difference and words indicating temporal difference. The example logic indicative words are “no”, “not”, and “without”, while the temporal indicative words are “after”, “before”, “when/while” \(^7\). For the comparison, Tscope first extracts the indicative words from the category \(\text{Prerequisite}\), and if they are different, the corresponding \(\text{Prerequisite}\) are considered as non-consistent. Otherwise, Tscope applies Word2Vec and Cosine similarity as Strategy 1 for the comparison.

3.4.3 Redundancy Detection by a Tuple Covering Rule. After that, Tscope judges whether a test case pair (\(\text{TC}_i\) and \(\text{TC}_j\)) is redundant according to a Tuple Covering Rule: if the tuples for \(\text{TC}_i\) could semantically cover tuples for \(\text{TC}_j\) (there is a semantically equivalent tuple in \(\text{TC}_i\) for every tuple for \(\text{TC}_j\)), \(\text{TC}_j\) is considered as a redundant test case. Using the above rule, Tscope iterates all the test tuple pairs and detects all the redundant test cases. Please note that, for \(\text{TC}_i\) and \(\text{TC}_j\), if there are the same number of tuples in the two test cases and Tuple Covering Rule is satisfied, Tscope considers that they are totally equivalent, and either one could be reconsidered as redundant.

\(^6\)To ensure the high precision, the similarity threshold is set as 0.95 in Tscope.

\(^7\)The full list of indicative words are displayed in our public package.
4 EXPERIMENT

4.1 Research Questions

RQ1: Can Tscope effectively extract entities and relations from the test case descriptions? This research question aims at evaluating the effectiveness of Tscope in extracting five entity categories and four relation categories from test case descriptions.

RQ2: Can Tscope effectively detect the redundant test cases? This research question aims at evaluating the effectiveness of Tscope in detecting redundant test cases.

RQ3: How effective is each entity category for redundancy detection? This research question intends to investigate the performance differences of redundancy detection when removing each entity category from Tscope.

4.2 Subject and Dataset

The dataset comes from our industrial partner, which is a certified third-party testing agency for software testing for over ten years. For each software system, our industrial partner maintains a test case library. After each test, test cases for the system will be included in the corresponding test case library. As the system evolves, it produces redundant test cases in the test case library.

In this study, we collect 3,467 test cases (TCs) from ten systems. We retrieve the textual descriptions of the test case’s summary for the redundant detection, and the average terms of each test case are also in Table 4. In our study, we only use the summary for redundancy detection since the summary almost covers all the target entities based on our observations. In addition, compared with the summary, there is much noisy information in steps and expected behavior, such as testing tool installation steps and configuration steps of the testing environment.

Then, guided by our industrial partner, we iterate the test case pair in the 3,467 test cases and label the redundancy by comparing the test cases in each pair. To guarantee the correctness of the labeling results, a labeling team with one senior researcher, one test engineer in the industrial partner and two Ph.D. students jointly work in this process. The redundancy is labeled according to the whole test case descriptions including summary, steps, and expected behavior. During the labeling process, each test case is labeled by one member and inspected by the other three members of the labeling team. Once different labeling opinions arise, the final result is determined based on a team discussion and a majority voting mechanism. The manually labeled results are considered as the ground truth set. Table 4 shows the details of the redundancy labeling results.

To train and evaluate the extraction model, we select 1,170 test cases using Stratified Sampling from 3,467 test cases according to the projects belonging to. For each test case, we manually label the entities and relations in the descriptions following the same process for redundancy labeling. Finally, we labeled 2,717 entities and 1,426 relations. In detail, for the entities, we label 1,377 Component, 824 Behavior, 102 Prerequisite, 137 Manner and 277 Constraint. For the relations, there are 865 Act, 113 Require, 145 Use and 303 Satisfy.

4.3 Experiment Design

To answer the RQ1, we used the 1,170 test cases with entity and relation labels to train and evaluate the joint extraction model. Specifically, we adopt the randomly sampling strategy to divide the test into the training set and testing set in the ratio of 8:2. We train Tscope using the training set, and extract entities and relations for the testing set. Finally, the extracted entities and relations are compared with the ground truth, and the performance is evaluated. To avoid randomness, the above experiment is repeated five times, and the average performance is considered the final performance. Moreover, we compare with the state-of-the-art extraction approaches, SLM and BLM (illustrated in Section 4.4.1). Mann-Whitney test is used to test whether Tscope could significantly outperform the baselines.

To answer RQ2, we train the extraction model using all the 1,170 test cases whose entities and relations are labeled. Then, we apply Tscope with the trained model to the remaining 2,297 test cases, and the performance metrics are calculated by comparing the detected redundancies with the ground truth. At the same time, we include two state-of-the-art redundancy detection approaches, CTC, Clustep, and four learning-based classifiers (illustrated in Section 4.4.2), as the baselines. Mann-Whitney test is used to test whether Tscope could significantly outperform the baseline approaches.

To answer RQ3, we investigate the effectiveness of five entity categories by ablation experiment. We conduct five groups of experiments in the terms of Tscope − 𝑋, where 𝑋 is each of the five entity categories. For each group of experiments, we train Tscope on the 1,170 test cases and evaluate the performance of redundancy detection using 2,297 test cases.

4.4 Baselines

4.4.1 Entity and Relation Extraction Baselines.

Span-Level Model (SLM) [13]: This is a state-of-the-art approaches for jointly extracting entities and relations. It first obtains the candidate entities using the span strategy, then classifies the category for each entity and the relation among each entity pair. By combining the entity extraction loss and relation extraction loss in the training phase, SLM could avoid the error accumulation problem and outperform the approaches which individually solve the entity extraction and relation extraction tasks [60, 61]. In our study, we implement the approach strictly following its steps.

BIO-Level Model (BLM) [3]: This is another state-of-the-art method for extracting entities and relations. Different from SLM which takes the entity and relation extraction as a classification task.
BLM models the extraction as a sequence tagging task [45], and leverages the deep learning model to predict the label for each token. The predicted label indicates the position of the token relative to an entity, i.e., the beginning of the entity, the inside of the entity, the end of the entity, or the outside of the entity. After entity extraction, BLM uses a classifier to predict the relation between each entity pair. In our study, we reuse the package provided by the paper\(^a\).

4.4.2 Redundancy Detection Baselines.

Clustep [32]: This is the state-of-the-art method for detecting redundant steps in NL test cases, which is similar to our scenario since both of them involve the detection of similar test descriptions. Clustep encodes the descriptions by the Word2Vec model, calculates the distance between text vectors according to the relaxed word mover’s distance model [29], and detects redundant test steps using the Agglomerative clustering and k-means clustering algorithm. We implement the approach strictly following its steps.

Learning-based Classifiers. We additionally employ machine/deep-learning classifiers, which are commonly used in information retrieval, natural language processing and software engineering [20, 23, 27], to predict whether two test cases are redundant. Its basic idea is to vectorize the test cases using the pre-trained BERT model, concatenate the vectors of each test case pair, and conduct the prediction based on it. To provide more comprehensive perspectives of comparison, we experiment with Support Vector Machine (SVM) [52], Random Forest (RF) [31], Decision Tree (DT) [6] and a deep-learning based classifier TextCNN [11]. The implementation is within scikit-learn library and open-source library of TextCNN\(^b\).

4.5 Evaluation Metrics

We evaluate the performance from two aspects, i.e., entity and relation extraction and redundancy detection, using the four evaluation metrics, i.e., Precision, Recall, F1, and Accuracy. (1) Precision, which refers to the ratio of the number of correct predictions to the total number of predictions; (2) Recall, which refers to the ratio of the number of correct predictions to the total number of samples in the ground truth; (3) F1-Score, which is the harmonic mean of precision and recall; (4) Accuracy is the proportion of test cases that are correctly predicted among all test cases. Please note that, for two totally-equivalent test cases (details in Section 3.4.3), either considered redundant is treated as a correct prediction.

\(^a\)https://github.com/hellonlp/classifier_multi_label_textcnn
\(^b\)https://radimrehurek.com/gensim/
\(^c\)https://github.com/hellonlp/classifier_multi_label_textcnn

5 RESULTS AND ANALYSIS

5.1 Entity and Relation Extraction Performance

Table 5 shows the performances of entity and relation extraction of our extraction model and baselines. In general, the extraction model could achieve promising performance with 97.5% precision, 94.8% recall for entity extraction, and 90.4% precision, 97.6% recall for relation extraction.

Compared with the baseline, SLM, our extraction model is 4.5%, 9.5% higher in F1 for entity and relation respectively. The results indicate the effectiveness of introducing global information and context information into the traditional extraction models. There is only one exception appearing in the recall of Prerequisite. It is that the entities belonging Prerequisite are typically described as adverbial clauses whose length is much larger than the other four categories. It is difficult for BERT to encode the long entities. Among the three models, BLM shows the worst performance, which indicates the advantage of the span-based joint extraction approach for test case descriptions. In addition, for each project, the average time to train the Tscope model is 72 seconds, yet it can be done offline.

Table 5: Performance of entity and relation extraction

| Metric   | Model | Entity Categories | Relation Categories |
|----------|-------|-------------------|---------------------|
|          |       | Prec | Rec | F1 | Prec | Rec | F1 | Prec | Rec | F1 |
| Precision| SLM   | 94.8%| 93.7%| 94.4%| 97.9%| 90.3%| 85.9%| 90.3%| 90.1%| 90.2%|
| Recall   | SLM   | 93.8%| 92.1%| 92.5%| 95.2%| 89.8%| 89.1%| 94.0%| 90.1%| 90.4%|
|          | BLM   | 91.2%| 89.7%| 91.5%| 94.9%| 89.2%| 89.1%| 92.6%| 90.1%| 90.5%|
|          | Clustep | 95.2%| 96.0%| 95.5%| 95.6%| 96.0%| 96.0%| 95.9%| 96.0%| 96.1%|
|          | BLM   | 94.2%| 90.9%| 92.8%| 94.1%| 90.1%| 90.1%| 92.6%| 90.1%| 90.5%|
|          | Clustep | 97.1%| 98.0%| 98.4%| 97.7%| 93.9%| 93.1%| 93.9%| 93.9%| 93.1%|

5.2 Redundancy Detection Performance

Table 6 shows the performance of detecting redundant and non-redundant test cases. In general, Tscope could reach 91.8% precision and 74.2% recall for redundant test cases, 86.7% precision and 96.0% recall for the non-redundant test cases. The overall classification accuracy is 88.0%. Figure 5 shows the redundancy detection performance for Tscope and baselines on the ten projects. The results reveal that Tscope outperforms two state-of-the-art redundancy detection approaches (CTC and Clustep), and four commonly-used classifiers (SVM, RF, DT, and TextCNN) in F1. In addition, Tscope shows the smallest variance of the seven approaches in precision and F1, which reflects the high robustness.

Table 6: Performance of redundancy detection

| Metric   | Redundant | Non-Redundant | Accuracy |
|----------|-----------|---------------|----------|
| Precision| 91.8%     | 86.7%         | 88.0%    |
| Recall   | 74.8%     | 96.0%         |          |
| F1       | 82.4%     | 91.1%         |          |

Especially, Tscope shows the great advantages in precision. Compared with the two redundancy detection approaches, Tscope is 39.4% higher than CTC and 30.5% higher than Clustep in precision. Of the four commonly-used classifiers, the precision is not promising (the best precision is 66.6% achieved by TextCNN). The results of the Mann-Whitney test show the differences between Tscope

ESEC/FSE ’22, November 14ś18, 2022, Singapore, Singapore Zhiyuan Chang, Mingyang Li, Junjie Wang, Qing Wang, and Shoubin Li
and each baseline approach are all significant (the significant level is 0.05). It is mainly that the traditional approaches and classifiers can not perceive the subtle differences in the test-oriented entities. The results emphasize the effectiveness of Tscope for accurate redundancy detection.

Figure 5: Redundancy detection performance on ten projects

As for the recall, we notice that the commonly-used classifiers could reach 94.4%-99.1% in the recall. The reason is that the classifiers tend to predict all similar test cases as redundancy. However, it has obvious damage to the precision. In redundancy detection, precision should be guaranteed first compared with recall, since low precision may affect the fault-revealing power of a test suite (discussed in Section 6.1). Compared with CTC and Clustep, Tscope shows no significant differences in the recall, which indicates Tscope could retrieve almost the same magnitude of redundancy with higher precision.

There are 25.2% (100% - 74.8% in recall) redundant test cases in ground truth that are not retrieved. The main reason for true negatives is due to some test-oriented entities are missing. For example, there are two descriptions, i.e., “Test whether the system can display the calendar function correctly” and “Test whether the calendar function in the system is correct”. The test cases have the same component “calendar function”, while the former contains a behavior “display” and no obvious behavior in the latter. The two test cases are both considered non-redundant by Tscope due to the differences in the category Behavior. However, they are labeled as redundancy in the ground truth, due to “display” in the former does not introduce much information for distinguishing. However, to avoid ambiguity, it would be better to clearly describe the necessary test-oriented entities in the descriptions. It is worth noting that for each project Tscope requires an average of 42 seconds for redundant detection, compared to 15 seconds for baselines. For memory, Tscope takes about 400MB, while baselines take 200-250MB. In summary, Tscope consumes comparable cost, yet achieves significantly higher performance.

5.3 Entity Category Effectiveness

Table 7 shows the performance on redundancy detection after removing different entity categories from Tscope. The figure in the bracket is the difference compared to Tscope. In general, the overall performances (F1) significantly decrease after removing most of the entity categories except for Prerequisite, which indicates the necessity of the five entity categories.

In detail, the difference is greatest when removing Component, since the Component is the basic category and the frequency of occurrence in the descriptions is the highest among the five entity categories. The difference is smallest after removing Prerequisite. Although Prerequisite shows the greatest correlation coefficient (0.841) with the variable Redundant, it appears least among the five categories in our dataset. Therefore, the difference is not obvious in F1 after removing Prerequisite. However, the difference is significant in R_Precision, which also indicates the importance of accurate redundancy detection.

Table 7: Performance after removing each entity category

| Experiment Group | Precision | Recall | F1    |
|------------------|-----------|--------|-------|
| Tscope           | 91.8%     | 74.8%  | 82.4% |
| Tscope - Com     | 52.2% (-39.6%) | 32.7% (-42.1%) | 40.2% (-42.2%) |
| Tscope - Beh     | 66.6% (-25.2%) | 67.0% (-7.8%) | 67.2% (-15.2%) |
| Tscope - Pre     | 86.3% (-5.5%) | 67.0% (-7.8%) | 75.2% (-7.2%) |
| Tscope - Man     | 84.1% (-7.7%) | 65.5% (-9.3%) | 73.8% (-8.6%) |
| Tscope - Con     | 83.3% (-8.5%) | 66.4% (-8.4%) | 73.8% (-8.6%) |

### 6 DISCUSSION

#### 6.1 The Importance of High Precision for Redundancy Detection

Our study focuses on redundancy detection for NL test cases, and it could be applied to many research problems, such as test suite reduction (or minimization), test case selection and test case prioritization [34, 57]. In the previous studies, Precision and Recall are two commonly-used metrics to evaluate the performance of the proposed approaches. It has been reported that precision and recall are two competing metrics, and they need to be balanced to achieve promising overall performance in the previous studies [7, 18]. However, we consider that precision has a higher priority compared with recall when designing automatic approaches for redundancy detection.

For example, in the test suite reduction, the detected redundant test cases will be removed from the set to be executed, aiming at reducing the testing cost [22]. The lower precision means that more non-redundant test cases will be removed from the executed set, which may reduce the fault-revealing power of the test suites. Thus, automated approaches should improve performance based on the premise of precision. As we illustrate in Section 1, previous studies suffer low precision since they cannot perceive the subtle differences in the test-oriented entities in test cases. It is also reported that current approaches often complicate fault detection effectiveness of a test suite by existing empirical studies [36, 44]. To overcome the issue, Tscope defines five test-oriented entity categories and detects the redundancy by the fine-grained comparison of the five entities. The evaluation also shows that Tscope could reach promising performance, especially for precision, which indicates that Tscope could be more effective in practice.
3.4.3 The dependence could be detected by their writing quality. According to the definition of test dependence \((TC_A fails)\), the application can not be switched by the taskbar. The summaries of two test cases and the entities extracted by Tscope guide the engineers to write test cases. And our fine-grained approach could be considered as the description items to improve the test engineers of the missing description items to improve the test case descriptions or test specifications in real-time, and remind the test engineers of the missing description items to improve the writing quality.

6.2 Additional Benefits of the Fine-Grained Redundancy Detection

Besides achieving high accuracy, our proposed fine-grained redundancy detection approach also has the following additional benefits.

The interpretability of redundancy detection. Previous approaches for redundancy detection are typically black-box approaches since they can not perceive subtle differences in test-oriented entities. On the contrary, Tscope conducts the comparison for the test-oriented entities, and calculates the similarity scores of the entities belonging to the five entity categories respectively (details in Section 3.4.3). The entities whose similarity score is less than the pre-defined similarity threshold could be considered as the reasons for non-redundancy. Explicitly presenting the reasons for the redundancy can potentially increase the confidence of testers in managing the test cases.

Optimization of the execution sequence of test cases. The execution of the whole test suite usually takes a long time, and optimizing the execution sequence for reducing the time is valuable [15]. The fine-grained test case information can potentially facilitate this task. For example, if some non-redundant test cases have the equivalent entities belonging to Prerequisite, it indicates that they share the same test prerequisite. In practice, prerequisite preparation is cost-consuming, especially for load testing or extreme testing. It could be better to continuously execute test cases with the equivalent prerequisites to avoid repeatedly preparing the testing prerequisites, which potentially reduces the testing cost in practice.

Improving the writing quality. The quality of test specifications and test case descriptions is the premise to ensure test quality. How to write complete and unambiguous test cases or test specifications is a challenging task in practice [59]. The five test-oriented entity categories could be considered as the description items to guide the engineers to write test cases. And our fine-grained approach, Tscope, can be used to check the completeness of the test case descriptions or test specifications in real-time, and remind the test engineers of the missing description items to improve the writing quality.

6.3 Other Applications of Entity Categories

In our study, we define five entity categories for redundancy detection. The entity categories are not limited to redundancy detection, but other tasks, such as test dependence detection [48] and requirements-test linking [51]. For example, Figure 6 shows summaries of two test cases and the entities extracted by Tscope. According to the definition of test dependence \([TC_A fails]\), \(TC_B\) is dependent on \(TC_A\) since if the “taskbar window” can not be displayed (\(TC_A\) fails), the application can not be switched by the taskbar window (\(TC_B\) can not succeed). The dependence could be detected using a heuristic rule: “\(TC_B\) is dependent on \(TC_A\) if \(Component\) in \(TC_A\) is the same as the \(Manner\) in \(TC_B\)”.

The entity categories could also be used to reconstruct the link between test cases and requirements. Users could manually label Component, Behavior, Manner, Prerequisite and Constraint from the requirements descriptions, and trains the model to extract the five entity categories. After that, a link between a test case and a requirement can be reconstructed if the entities in each category are equivalent.

6.4 Validity Threats

External Validity. The external threats are related to the generalization of the proposed approach. First, we experimented with the data taken from one company. The results may be different in other scenarios. However, we evaluate the performance on ten projects from different domains, which could reduce this threat. Second, we only use the summaries for extracting test-oriented entities and relations, which may ignore some entities buried in the other attributes such as steps and expected behavior. However, summaries almost cover all the target entities based on our observations. In addition, the Cohen’s kappa coefficient between EQall and Redundant is 0.984 (details in Section 2.2). The results imply that almost redundancy could be detected by the entities and relations in summaries, which could alleviate the threat.

Internal Validity. The internal threats relate to experimental errors and biases. First, the four relation categories are built around the Component, and the other four entity categories are associated with Component. We find that a few cases that Prerequisite or Constraint is more accurately associated with the combination of a Behavior and a Component rather than a single Component. It may introduce bias when dissection test cases and redundancy detection. However, such cases account for a very small proportion, which could alleviate the threat. Second, for the baselines whose packages are not provided, it may introduce bias in the implementation processes. However, we strictly follow the steps in their studies, which may alleviate the threat.

7 RELATED WORK

Test cases act as the starting point for the test execution and the following quality assurance activities [17, 26, 58]. Redundant test cases frequently appears in the test suite and potential affects many automatic techniques, e.g., test suite reduction [12, 17, 44], test case selection [3, 8, 57] and test case prioritization [15, 16, 46].

Many studies are focusing on the redundant detection of the white-box test. Among them, several approaches employed the test coverage metrics for redundancy detection. For example, Offutt et al. [40] leveraged the statement coverage to detect the redundancy in a test suite. Rothermel et al. [43] proposed an approach to detection redundancy in a test suite based on the branch coverage. The basic assumption of the approaches is that if two test cases have the same test coverage metric, either is considered redundant. Koochakzadeh [28] reported that the coverage information suffers from a large number of false-positive errors. They combined the coverage information with additional tester-assisted information to improve the precision of redundancy detection. Different from our study, these studies focus on the white-box test. Yoo et al.
[57] reported that this white-box coverage with the tester-assisted information is costly or even biased.

There were also approaches applying information retrieval techniques for the white-box test case redundant detection [10, 12, 33, 36]. For these approaches, different similarity metrics are proposed and two test cases with the high measurement metric are considered redundancy. For example, Chen et al. [10] proposed an approach to exploit the diversity among test cases for guiding selection. It first selects a random set of test cases and then filters redundancy based on their distance from the already selected test cases. Cruciani et al. [12] leveraged the vector space model to transform the test case into points in the Euclidean space, and then it detects the redundancy using the clustering algorithms. Different from our study, the inputs of these approaches are typically executable test cases that consist of test source code and command lines, rather than natural language.

There are studies focusing on the redundant detection of black-box tests. Cartaxo et al. [8] and Hemmati et al. [21] proposed approaches to reduce the model-based test suite with similarity comparison. However, they mainly relied on a formal model of program behavior such as LTS and UML diagrams, which are not available in some cases or are biased.

Several studies aimed at detecting redundant NL test cases. Tahvili et al. [49] used an implementation of Doc2Vec algorithm to generate embeddings of test cases and then groups them using two clustering algorithms HDDBSCAN and FCM. Li et al. [32] designed an approach to identify similar text steps in the textual test cases. It leverages the word embedding technique along with Relaxed Word Mover’s Distance to analyze the similarity of test steps, then combines hierarchical and K-means clustering algorithms to detect similar test steps. Viggiani et al. [53] used a combination of text embedding, text similarity, and clustering techniques to identify similar NL test cases based. These approaches suffer from low accuracy because they treat the test case as a whole and cannot capture the fine-grained semantic information as our approach.

8 CONCLUSION

Due to the redundancy of requirements, parallel testing, and tester turnover within long evolving history, there are lots of redundant test cases. As the software evolves, redundant test cases significantly increase the cost of test and maintenance efforts. Previous redundancy detection approaches suffer low accuracy because of their weakness in the capture of the test case’s fine-grained semantic information and inherent meaning. In this study, we re-formulate the problem and propose a fine-grained approach Tscope to detect redundancy from test cases in natural language. Tscope extracts the test-oriented entities and associated relations to dissect the NL test case into atomic test tuple(s), and conduct similarity comparison on them. Evaluation shows Tscope could outperform the state-of-the-art approaches for entity and relation extraction and redundancy detection. Moreover, the results also demonstrate the contribution of our defined fine categories of entities in redundancy detection, which further indicates our problem formulation is promising.

In the future, we will further investigate the cost-effectiveness of Tscope in real-world practice. Apart from that, we will apply the fine-grained approach based on entity and relation extraction to other software engineering tasks, such as duplicate issue report detection, test dependence detection, and requirements-test linking.

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