

Programming Language Representation with Semantic-level Structure

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ABSTRACT

Natural language processing (NLP) technique becomes one of the core techniques for developing text analytics applications. For developing the NLP applications, the applications are required to achieve high reliability before it goes to market. The trustworthiness of the prevalent NLP applications is obtained by measuring the accuracy of the applications on held-out dataset. However, evaluating NLP on testset does with held-out accuracy is limited to show its quality because the held-out datasets are often not comprehensive. While the behavioral testing over multiple general linguistic capabilities are employed, it relies on manually created test cases, and is still limited to measure its comprehensive performance for each linguistic capability. In this work, we introduce Fuzz-CHECKLIST, an NLP model testing methodology. Given a linguistic capability, The Fuzz-CHECKLIST finds relevant testcases to test the linguistic capability from existing datasets as seed inputs, generates sufficient number of new test cases by fuzzing the seed inputs based on their context-free grammar (Context-free grammar). We illustrate the usefulness of the Fuzz-CHECKLIST by showing input diversity and identifying critical failures in state-of-the-art models for NLP task. In our experiment, we show that the Fuzz-CHECKLIST generates more test cases with higher diversity, and finds more bugs.

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1 INTRODUCTION

Software testing is the crucial process when developing software. It evaluates an attribute or capability of the software and determines that it meets the requirements by examining the behavior of the software under test. Software testing in the early stage of the development finds bugs, and fixing them saves amount of costs. In addition, reliable software testing methodology ensures software quality to users in that the software meets requirements by verification and validation. Regarding that, NLP application is a branch of artificial intelligence software, and testing NLP application also becomes important process as well.

The prevalent models of NLP are evaluated via train-validation-test splits. train and validation set is used to train the NLP model

and the hold-out set is used for testing by measuring accuracy. The accuracy is a indicator of the performance of the models.

Despite its usefulness, the main limitation of the testing paradigm is that the hold-out set often overestimates the performances. Each dataset comes with specific biases, and the biases increase the discrepancy of distribution between dataset and real-world [6]. The aforementioned accuracy on hold-out set does not consider the discrepancy and it is limited to achieve comprehensive performance of the NLP model. As a consequence, it is difficult to analyze where the errors comes from [15].

On the subject of the limitation of traditional testing paradigm, a number of methods have been proposed. First, multiple diagnostic datasets for evaluating NLP model were introduced for obtaining generalized evaluation of the NLP model [14]. Not only that, model is evaluated on different aspects such as robustness of the model on adversarial sets [1, 3, 9, 12], fairness [5, 11], logical consistency [7], prediction interpretations [8] and interactive error analysis [15]. Especially, CHECKLIST implements behavioral testing methodology for evaluating multiple linguistic capabilities of NLP model [10]. CHECKLIST introduces input-output behaviors of linguistic capabilities and generates behavior-guided inputs for validating the behaviors. It provides comprehensive behavioral testing of NLP models through a number of generated inputs. However, the approach only relies on manually generated input templates, thus the template generation becomes expensive and time consuming. In addition, the generated templates are selective and often too simple, and it is limited to provide restricted evaluation of linguistic capabilities. Thus, it does not guarantee the comprehensive evaluation.

In this paper, we present Fuzz-CHECKLIST, an automated NLP model evaluation method for comprehensive behavioral testing of NLP models on sentiment analysis task. For each behavior of linguistic capability, Fuzz-CHECKLIST does not rely on the manual input generation. Instead, it establishes input requirement for evaluating a linguistic capability and finds suitable inputs that meet the requirement from existing public dataset. Therefore, Fuzz-CHECKLIST increases input diversity and generality. Further, Fuzz-CHECKLIST applies the fuzzing testing principle to generate inputs by mutating the selected inputs as seed inputs. Fuzzer in Fuzz-CHECKLIST first expands seed input grammar structures and determines its available part-of-speech to maintain structural naturalness. After that, to hold contextual naturalness of the mutated inputs, the fuzzer completes the expanded new structures via data-driven context-aware word suggestion. Additionally, sentiment-independent words in the inputs are replaced with rule-based word suggestion.

We demonstrate its generality and utility as a NLP model evaluation tool by evaluating well-known sentiment analysis models: BERT-base [2], RoBERTa-base [4] and DistilBERT-base [13]. We show that

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2 BACKGROUND

3 RELATED WORK

4 APPROACH

5 RESEARCH QUESTIONS FOR EVALUATION

6 EXPERIMENT

In this section, we present experiments to evaluate the effectiveness of our proposed evaluation methodology. In particular, we address the following research questions:

RQ1: How effective is our proposed evaluation model for finding failures given a linguistic capability?

RQ2: How effective is our proposed model for generating diverse test cases?

RQ3: How effective is our proposed model for detecting diverse type of errors?

RQ4: How effective is our new test case generation using context-free grammar expansion?

6.1 Experiment Setup

For answering **RQ1:** and **RQ2:**, we organize the experiment as follows: **Selection of seed inputs. Context-free grammar expansion. Models.**

In addition, we answer **RQ4:** by organizing the another experiment as follows:

7 RESULT

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