Programming Language Representation with Semantic-level Structure

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ABSTRACT

Natural language processing (NLP) technique has become one of the core techniques for developing text analytic applications. These applications are required to achieve high reliability to be useful in practice. 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 with the held-out accuracy is limited in validating its overall quality because the held-out datasets are often not comprehensive. Along with this, evaluating an NLP model on task-specific behaviors defined on empirical linguistic capabilities has been introduced. However, such evaluation relies on manually created test cases, and is still limited to measure the model performance on biased dataset. In this work, we introduce S^{2}LCT, an NLP model testing infrastructure. Given a linguistic capability that users want to evaluate for a NLP model, S^{2}LCT finds suitable seed inputs from existing datasets, generates sufficient number of new test inputs by fuzzing the seed inputs based on their context-free grammar (CFG). We evaluate S^{2}LCT by showing its reliability on generated inputs and its generalization ability. In our experiments, we also show that S^{2}LCT facilitates identification of critical failures and its origins in the NLP models for sentiment analysis task.

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1 INTRODUCTION

Natural language processing (NLP) applications are growing exponentially. As a result, trustworthiness in the quality of NLP applications has become critical for its practical use in the real world. Therefore, quality assurance of NLP applications is an essential process in the software development processes. Researchers aim to improve the current practices of testing NLP models from three perspectives: (i) *Test input generation*, (ii) *Automated test oracle*, and (iii) *Meaningful quality metrics*.

Test input generation. Currently, most testing of an NLP model reuses existing large textual corpus as the testing dataset to evaluate the model. This practice will often overestimates the model performances from the hold-out set [8, 10, 14]. The overestimation comes from the discrepancy between the distribution of the used dataset and the actual data distribution in real world. Oftentimes, the hold-out dataset is not representative and is likely to introduce specific biases, leading to the decreased robustness of NLP models. In this regard, prior works have proposed techniques for testing the robustness of NLP models by crafting adversarial examples and attacking a model with them intentionally [1, 4, 13, 16].

Automated test oracle. The current testing practice requires manual work for labelling the test oracles of the hold-out data. The manual work is costly in terms of time consumption and its impact on market price. Therefore, it necessitates automated test oracle generation for improving the testing process of NLP models. However, automatically generated test oracles may not always be feasible; predicting the correct test oracles remains one of main challenges. Along with this, software metamorphic testing approach has been introduced [18] to alleviate the test oracle discrepancy between expected and observed test oracles.

Meaningful quality metrics. Traditionally, the quality of NLP models are represented by numbers in quality metrics. Especially, accuracy (i.e., the fraction of outputs that the model correctly predicts) is the most widely used metric for assessing the quality of classification models. Generally, higher accuracy number suggests better quality of a model. However, all NLP models have their strength and weakness and forcing aggregation statistics into a single number makes the users difficult to assess the capabilities of NLP models. Not to mention localizing and fixing the bugs found from the hold-out set (i.e., testing dataset, as opposed to training dataset). Therefore, this forced aggregation method not only fails to validate the linguistic capability of the model, but it also makes the localization of the causes of the inaccuracy more costly [20]. To address this limitation, Ribeiro et al. introduced CHECKLIST, a behavioral testing framework for evaluating NLP model on multiple linguistic capabilities [14]. CHECKLIST defines task-relevant linguistic capabilities and generates test cases for each linguistic capability.

However, none of the above approaches satisfy all three requirements at the same time. First, adversarial testing approaches merely focus on evaluating model robustness. They measure how sensitive the models are to input perturbations while do not evaluate linguistic functionalities. Second, the metamorphic testing approach is required to understand the characteristics of metamorphic relations between inputs and outputs. However, finding these remains one of the most challenging problem in metamorphic testing [18]. Along with this, such relation in textual data in NLP domain has not been evaluated despite its importance. Third, CHECKLIST relies on manually generated input templates, which need to be preset before test input generation. Consequently, CHECKLIST templates are distributed in a limited range of their structures. This restricts CHECKLIST's ability to comprehensively test the linguistic capabilities.

Despite CHECKLIST's limitations, assessing the quality of NLP models through the linguistic capabilities is a promising direction.

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Each linguistic capability explains the functionality of the input and output behavior for the NLP model under test. Typically, it describes certain type of inputs and outputs observed in real world for the target NLP task ranging from simple to complicated behaviors, so the model developers can better understand the capabilities and potential issues of the NLP models. For example, a linguistic capability of "Negated neutral should still be neutral" measures how accurately the sentiment analysis model understands the negative neutral input as an neutral sentiment [14]. Therefore, it requires the sentiment analysis model to output neutral sentiment on the negated neutral input. Such methodology of evaluation on the specified functionalities avoids the overestimation of the model performance as it equivalently measures the model performance on each functionality. In the end, testing through linguistic capabilities provides not only the overall model performance, but also the malfunction facets of the model.

To satisfy all three requirements mentioned above, we present S^2LCT, an automated NLP model evaluation method for comprehensive behavioral testing of NLP models on sentiment analysis task. There are three main challenges that S^2LCT overcomes to satisfy all three aforementioned requirements.

C1 The test suite should cover diverse syntactic structures;
C2 Each test case should be categorized into a linguistic capability;
C3 The label of each test case should be automatically and accurately defined.

C1. generating sentences with diverse syntactic structure is challenging since text have a higher order of its structure. However, the structures are obscured by word usage. To address the challenge, S^2LCT establishes specifications for evaluating a linguistic capability and searches suitable sentences that satisfy the specification from existing public dataset. In this process, S^2LCT generates new inputs by mutating the searched sentences, used as seed inputs. S^2LCT expands seed input grammar structures and determines its available part-of-speech to maintain structural naturalness.
C2. Suitability of test case for evaluating NLP model on a linguistic capability is obtained from its high relevancy to the linguistic capability. Relevancy between test case and linguistic capability is difficult to be measured because the linguistic capability is defined on a specific phenomenon appeared in the mixture of textual structure and semantic, and understanding each test case with respect to the phenomenon and measuring its relevancy are not trivial. To address the difficulty, S^2LCT implements search rules and the transformation templates of linguistic capabilities. In addition, anlyzing parse tree of seed sentence is used for its expansion identification.
C3. Last challenge is on estimating the appropriateness of test oracle. For sentiment analysis task, test oracle is determined by understanding meaning from text. The meaning of text is sensitive to its semnatic, structure, and the combination of two. Therefore, generation of test case ought to ensure the correctness of its oracle allocation. In this work, S^2LCT obtain the appropriateness of test oracle by implementing domain-specific knowledge on word sentiment dataset and word suggestion model pre-trained on large corpus for validation of generated sentence and its oracle.

We demonstrate its generality and utility as a NLP model evaluation tool by evaluating well-known sentiment analysis models:

```
air_noun = [
    'flight', 'seat', 'pilot', 'staff',
    'service', 'customer service', 'aircraft', 'plane',
    'food', 'cabin crew', 'company', 'airline', 'crew'
]
pos_adj = [
    'good', 'great', 'excellent', 'amazing',
    'extraordinary', 'beautiful', 'fantastic', 'nice',
    'incredible', 'exceptional', 'awesome', 'perfect',
    'fun', 'happy', 'adorable', 'brilliant', 'exciting',
    'sweet', 'wonderful'
]
neg_adj = [
    'awful', 'bad', 'horrible', 'weird',
    'rough', 'lousy', 'unhappy', 'average',
    'difficult', 'poor', 'sad', 'frustrating',
    'hard', 'lame', 'nasty', 'annoying', 'boring',
    'creepy', 'dreadful', 'ridiculous', 'terrible',
    'ugly', 'unpleasant'
]

t = editor.template('{it} {air_noun} {be} {pos_adj}.',
                    it=['The', 'This', 'That'], be=['is', 'was'],
                    labels=2, save=True)
t += editor.template('{it} {be} {a:pos_adj} {air_noun}.',
                    it=['It', 'This', 'That'], be=['is', 'was'],
                    labels=2, save=True)
t += editor.template('{i} {pos_verb} {the} {air_noun}.',
                    i=['I', 'We'], the=['this', 'that', 'the'],
                    labels=2, save=True)
t += editor.template('{it} {air_noun} {be} {neg_adj}.',
                    it=['That', 'This', 'The'], be=['is', 'was'],
                    labels=0, save=True)
t += editor.template('{it} {be} {a:neg_adj} {air_noun}.',
                    it=['It', 'This', 'That'], be=['is', 'was'],
                    labels=0, save=True)
t += editor.template('{i} {neg_verb} {the} {air_noun}.',
                    i=['I', 'We'], the=['this', 'that', 'the'],
                    labels=0, save=True)
```

Figure 1: Example of CHECKLIST templates on linguistic capability of "Short sentences with sentiment-laden adjectives".

BERT-base [3], RoBERTa-base [7] and DistilBERT-base [17]. We show that ...

2 BACKGROUND

In this section, we provide a brief background on CHECKLIST test-case generation via an example. Quality of software is verified by ensuring the proper working of all functionalities without knowing the internal workings of the software. Knowing performances of model on the multiple functionalities provides users with better

understanding and debugging the software. The same principle applies to the NLP model. traditional NLP model evaluation relying on a test set is lack of specification of model functionality. However, In NLP domain, there are many phenomena on linguistic input such as negation, questionization. Given a NLP task, the phenomena determine task-relevant output. Traditional evaluation method neglects them, thus, it becomes less efficient to detect and analyze which aspect the model yields unexpected outcome. To tackle this limitation, CHECKLIST introduces task-dependent linguistic capabilities for monitoring model performance on each linguistic capability. It assumes that the linguistic phenomena can be represented into the model behaviors as they provide what input and output are desired and how the model works with them. For each linguistic capability, CHECKLIST makes testcase templates and generate sentences by filling-in the value for each placeholder. We show an example of the templates in Figure 1. The templates in the figure is used for evaluating a sentiment analysis model on "Short sentences with sentiment-laden adjectives". For the templates defined from line 22 to 33 have placeholders such as it, air_noun, pos_adj. Values for the placeholders are defined at line 23, 1 and 6. Ater all, all combinations of the values of placeholders in a template are filled-in the template, and the senteneces are generated such as "The flight is good", "That airline was happy" and so on. Finally, these are used for evaluation of linguistic capability. Despite its simplicity of testcase generation, it still has limitations: it first relies on manual work for defining template structure and its values. Therefore, the manual work for testcase generation keeps the process costly. Extended from it, Second, such manual work produces the imitative forms between test cases, and it is likely to introduce bias on the testcases. We will show that these observations contribute to the performance of our models.

3 SPECIFICATION- AND SYNTAX-BASED LINGUISTIC CAPABILITY TESTING

We design and implement a new NLP model testing method, *Specification- and Syntax-based Linguistic Capability Testing (S^2LCT)*, that automatically generate test cases with oracles to test the robustness of sentiment analysis models. S^2LCT addresses all three challenges discussed above.

Figure 2 shows the overview of S^2LCT, which consists of two phases. The *specification-based seed generation* phase performs rule-based searches from a real-world dataset and template-based transformation to obtain the initial seed sentences. The search rules (e.g., search for neutral sentences that do not include any positive or negative words) and transformation templates (e.g., negating a sentence) are defined in the *linguistic capability specifications*, which guarantee that each resulting seed conforms to a specific linguistic capability (**C2**) and is labelled correctly (**C3**).

The *syntax-based sentence expansion* phase expands the seed sentences with additional syntactic elements (i.e., words) to cover many real-world syntactic structures (**C1**). It first performs a syntax analysis to identify the part-of-speech (PoS) tags that can be inserted to each seed, by comparing the PoS parse trees between the seed sentence and many other sentences from a large reference dataset. Each identified tag is inserted into the seed as a *mask*. It then uses an NLP recommendation model (i.e., BERT []) to suggest possible words. If a resulting sentence is validated to be consistent with the specification which additionally defines the rules for expansion (e.g., the expanded word should be neutral), **C2** and **C3** are still satisfied. Last, because some validated sentences may include unacceptable suggested words given the context, we use a heuristic (i.e., the confidence score from the NLP recommendation model) to select the more realistic context-aware expanded sentences into S^2LCT's test suite.

We now describe each phase of S^2LCT in detail.

3.1 Specification-based Seed Generation

The seed generation phase of S^2LCT starts by searching sentences in a real-world dataset that match the rules defined in the linguistic capability specification, and then transforming the matched sentences using templates to generate seed sentences that conform to individual linguistic capabilities. The reasons for this design choice are twofold. First, while generally judging which linguistic capability any sentence falls into and which label it should have is infeasible, there exist simple rules and templates to allow classifying the resulting sentences into individual linguistic capabilities and with the correct labels, with high confidence. This enables us to test each linguistic capability individually. Second, searching from a real-world dataset ensures that the sentences used as test cases for testing linguistic capabilities are realistic and diverse. The diverse test cases are more likely to achieve a high coverage of the target model's functionality in each linguistic capability, thus detecting more errors. In this phase, S^2LCT first search and selects sentences applicable to the linguistic capability in a given real-world dataset with search rules. In case that the search rules only fulfill portion of the linguistic capability specifications, the selected sentences are not yet appropriate to become seed, we transform the selected sentences into seed sentences using the heuristic templates. Table 1 shows the search rules and the transformation templates of all 11 linguistic capabilities we implemented in S^2LCT. The first column shows the linguistic capability type and its description, and the second column shows the search rule and transformation template used in each linguistic capability. For LC1 and LC2, the NLP models are evaluated in the scope of short sentences with selective sentiment words. It does not require any transformation because the search rule alone is sufficient to conform to the linguistic capabilities. On the other hand, search rules of LC3 to LC11 are not enough to match their linguistic capability specification, thus S^2LCT uses heuristic templates to conform the searched sentences to the linguistic capability. For example, in LC3's transformation template, the searched sentences become seeds by preturbing them with the defined templates. In LC4's transformation template, the searched demonstrative sentences are negated.

3.2 Syntax-based Sentence Expansion

The simple search rules and transformation templates used to generate the seed sentences may limit the syntactic structures these seeds may cover. To address this limitation, the syntax-based sentence expansion phase extends the seed sentences to cover syntactic structures commonly used in real-life sentences. Our idea is to differentiate the parse trees between the seed sentences and the reference sentences from a large real-world dataset. The extra PoS

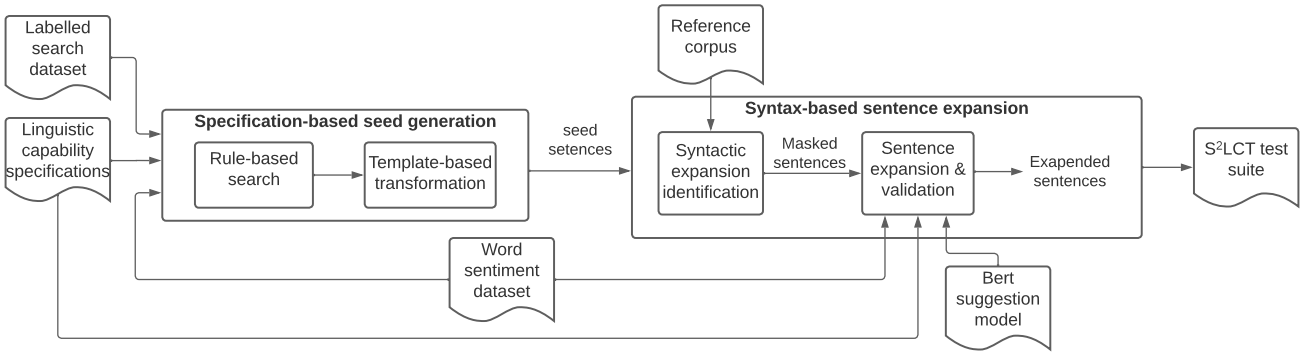

Figure 2: Overview of S^{2}LCT.

tags in the reference parse trees are identified as potential syntactic elements for expansion and inserted into the seed sentences as masks. We then use masked language model to suggest the fill-ins. If the resulting sentences still conform to the linguistic capability specification, they are added to S^{2}LCT's test suite.

3.2.1 Syntax Expansion Identification. Algorithm 1 shows how masks are identified for each seed sentence. It takes the parse trees of the seeds, generated by the Berkeley Neural Parser [5, 6], and a reference context-free grammar (CFG) from the Penn Treebank corpus dataset [] as inputs. The reference CFG is learned from a large dataset [] that is representative of the distribution of real-world language usage. The algorithm identifies the discrepancy between the seed syntax and the reference grammar to decide how a seed can be expanded.

Algorithm 1 Syntax expansion identification algorithm.

```
1:  Input: Parse trees of seed sentences S, reference context-free grammar R
2:  Output: Set of masked sentences M
3:  for each part tree s from S do
4:      for each production s_prod from s do
5:          s_lhs = s_prod.lhs
6:          s_rhs = s_prod.rhs
7:          for each r_rhs from R[s_lhs] do
8:              if s_rhs ⊂ r_rhs then
9:                  M = M ∪ insertMask(r_rhs-s_rhs, s)
10:             end if
11:         end for
12:     end for
13: end for
14: return random(M, k)
```

For each production of in each seed's parse tree (lines 3 and 4), we extract its non-terminal at the left-hand-side (line 5), *s_lhs*, and the grammar symbols at the right-hand-side (line 6), *s_rhs*. In line 7, the algorithm iterates through all productions in the reference context-free grammar and match these that have the same non-terminal at the left-hand-side as *s_lhs*. The right-hand-side of each matched production is called *r_rhs*. If *s_rhs* consists of a subset of the grammar symbols in *r_rhs* (line 8), the additional symbols in the *r_rhs* are inserted as masks in the parse tree of seed sentence, in their respective positions in the expanded production. The left to right traversal of the leaves of an expanded parse tree forms a masked sentence. Lastly, due to the inefficient cost of accessing full list of the masked sentences, we randomly select k masked sentences for the next sentence expansion and validation phase when the masked sentences are more than maximum number of masked sentences. The random sampling is unbiased approach since it gives same chance to be chosen. Thus, the random sample becomes representative of the population of the masked sentences, and it efficiently shows the usefulness of the S^{2}LCT.

Running example. Figure 3 shows an example using Algorithm 1 to generate a masked sentence. The sentence "Or both." is a seed of linguistic capability of "Short sentences with neutral adjectives and nouns". The tree on the left shows the parse tree of this seed; it consists of two productions: "FRAG->[CC, NP, .]" and "NP->[DT]". When matching the left-hand-side non-terminal of the second production (i.e., "NP") in the reference CFG, we found that it includes a production "NP->[DT, NNS]" which has an additional symbol "NNS" on the right-hand-side. The algorithm thus expands the parse tree with this symbol, shown in the second tree. The masked sentence "Or both {MASK}." is the result of the left-to-right traversal of this expanded parse tree.

3.2.2 Sentence Expansion and Validation. In this phase, the words to fill in the masks in the masked sentences are suggested by the BERT pretrained model [3]. The BERT is a transformer-based natural language model. It is pretrained on two tasks of masked token prediction and next sentence prediction. As a result of the training process, the BERT model suggests word for the mask token according to its surrounding context in sentence. For each masked token, multiple words are suggested ranked by their confidence scores. Because BERT model is not aware of the linguistic capability specification and the grammar symbol in the expanded parse tree, an expanded sentence using the suggested words may no longer satisfy the linguistic capability specification. Therefore, we perform validation on the suggested words and only accept them if the following three criteria are met.

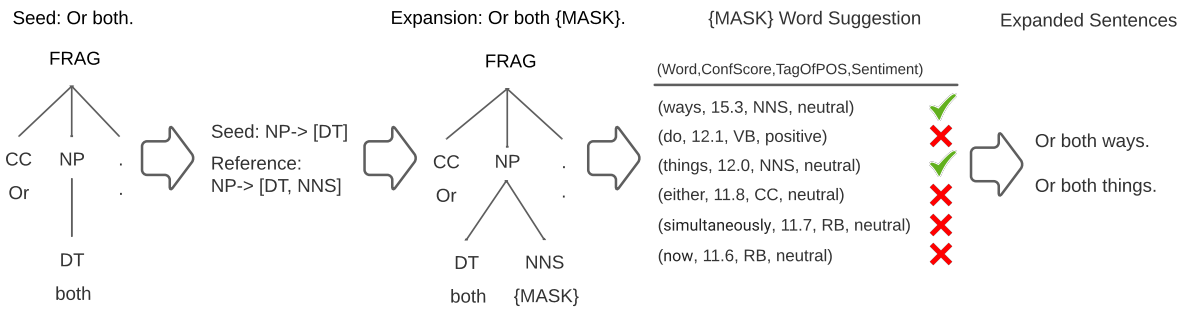

Figure 3: Example of masked sentence generation. Shiyi: Expansion: Or both {MASK}. -> Masked sentence: Or both MASK.

First, the PoS tag of the suggested word must match the PoS tag of the expanded symbol in the parse tree. For the example in Figure 3, the masked symbol is a "NNS" (i.e., plural noun); thus, the suggested word must also be a "NNS". In this work, we use SpaCy, a free open-source library for natural language processing, for extracting PoS tags for each suggested word.

Second, it is required that the sentiment of the expanded sentence becomes the same as the seed sentence. To ensure this, the suggested words must be neutral.

Third, we additionally verify that the expanded sentences satisfied the same search rules for the seed sentence in LC1 and LC2. This criteria cannot be applied to other linguistic capabilities because they have additional transformation templates.

In this work, out of the BERT suggested words, we randomly selects words that matches their PoS tag of the expanded symbol in the parse tree. The words that meets the second and third criteria are finally employed for the expanded sentences.

Running example. The third step in Figure 3 shows the words suggested by BERT. For this masked sentence, BERT suggested six words. Each word is associated with the confidence score provided by BERT, the PoS tag, and the sentiment. Among the six words, only "ways" and "things" are validated by S^{2}LCT because they have the Pos tag "NNS" and are neutral. In addition, it is found that both sentences meets the search rule of the associated linguistic capability of "Short sentences with neutral adjectives and nouns". In the end, two sentences of "Or both ways" and "Or both things" are generated.

4 EXPERIMENTAL SETUP

In this section, we present the setup of the experiments to evaluate the effectiveness of S^{2}LCT. We address the following research questions (RQs):

Shiyi: We may miss a RQ for the test results using S^{2}LCT. In the setup, we have not said which sentiment analysis models we tested, and how we measure the results (e.g., number of misclassified test cases).

RQ1 : Can S^{2}LCT generate consistent test sentence and its oracle?

RQ2 : Are S^{2}LCT generated test cases relevant to be used for their linguistic capability evaluation?

RQ3 : Can S^{2}LCT generate more diverse test cases than CHECKLIST?

RQ4 : Can S^{2}LCT be useful to find root causes of bugs in the sentiment analysis models?

Shiyi: Make clear (earlier in the paper): a test case is a sentence in a linguistic capability with a sentiment label.

4.1 Experimental Subjects

NLP Models & Dataset. We evaluate our approach on three leaerning-based sentiment analysis models implemented in Transformer library from the Hugging Face centralized Model Hub.[1]: `BERT-base` (textattack/bert-base-uncased-SST-2), `RoBERTa-base` (textattack/roberta-base-SST-2), and `DistilBERT-base` (distilbert-base-uncased-finetuned-sst-2-english). They are pre-trained on English language using a masked language modeling (MLM) objective, and fine-tuned on sentiment analysis task. In this experiment, we use Stanford Sentiment Treebank version 1 dataset for searching seeds and expanding the seeds in S^{2}LCT.

Comparison Baselines. We compare our approach with CHECKLIST[2], which is a manual template-based approach to generate test cases. In this experiment, we used the CHECKLIST released sentiment analysis test cases which are generated from its publicly available jupyter notebook implementation.

4.2 Experimental Process

RQ1 and RQ2. As described in Section 3, S^{2}LCT generates test cases in two steps: specification-based seed generation and syntax-based sentence expansion. These automated steps may generate seed/expanded sentences marked with incorrect sentiment labels or categorized into wrong linguistic capabilities. For example, the search rule and template defined in a linguistic capability may not always generate seed sentences in that capability or with the correct label. To answer RQ1 and RQ2, we perform a manual study to measure the correctness of the sentiment labels and linguistic

[1]https://huggingface.co/models
[2]https://github.com/marcotcr/checklist

capabilities associated with the seed/expanded sentences, produced by S^{2}LCT.

In the manual study, we randomly sample three sets of pairs of seed sentences and corresponding linguistic capability from seed test cases. For each set, we also select expanded sentences that S^{2}LCT generated from the formerly sampled seed sentences. In this experiment, each set has 100 sentences (50 from seed sentences and 50 from expanded sentences) and 200 sentences, in total, are used for the manual study. For each sampled set, two subjects are provided with the same set of sampled sentences. The subjects are asked for scoring the two following: **1. relevancy score between sentence and its associated linguistic capability**: this score measures the amount of appropriateness of the use of sentence for evaluating the model on its linguistic capability. The scores are discrete ranging from 1 to 5, and each represents "strongly not relevant" to "strongly relevant" respectively. **2. sentiment score of sentence**: this score measures the level of sentence sentiment. It is also discrete, and it ranges from 1 to 5 representing "strongly negative" to "strongly positive" respectively. In this work, we collect manual study scores from 3 subjects in total. In case of different scores with a same sentence from different subjects, we used their average score as a score of the sentence. From the collected scores, we measure the following metrics:

$$sentiment\_relecancy = \sum_i \delta(label_{S^2LCT}! = label_{human}) \quad (1)$$

$$LC\_relevancy_{AVG} = \frac{1}{\#data} \cdot \sum_i LC\_relevancy_i \quad (2)$$

The equation 1 represent the number of test cases that their labels assigned from are different between S^{2}LCT and human. Higher number of this metric indicates worse correlation of test oracle that S^{2}LCT generated with human. In addition, the equation 2 represents the average score of the relevancy score between sentence and its associated linguistic capability. Higer average score means that higher human-level agreement of the use of sentence for its linguistic capability, resulting in higher suitability of the use of the testcases for evaluating model on the linguistic capability. Given the metrics, we answer RQ1 and RQ2 by the metrics from the equation 1 and equation 2 respectively, thereby, show its ability of S^{2}LCT to understand human intelligence.

RQ3. Recall that a key limitation of CHECKLIST is that its template-based approach that relies on significant manual efforts may not generate test cases that comprehensively cover the sentences in a linguistic capability. S^{2}LCT, instead, automatically generates test cases based on a search dataset and the syntax in a large reference corpus. We expect S^{2}LCT can generate a more diverse test suite than CHECKLIST. To measure diversity, we follow the approach presented by Ma et al. [**?**], where the authors measure the coverage of NLP model intermediate states as corner-case neurons. Because the matrix computation of intermediate states impacts NLP model decision-making, a test suite that covers a greater number of intermediate states can represent more NLP model decision-making, making it more diverse. Specifically, we used two coverage metrics in existing work [**?**], *boundary coverage* (BoundCov) and *strong activation coverage* (SActCov), as our metrics to evaluate the test suite diversity. TODO: It is worth noting that a test sample with a statistical distribution similar to the training data would rarely be found in the corner case region. As a result, covering a larger corner case region means that the test suite is more likely to be buggy.

$$\begin{aligned} \text{UpperCorner}(\mathcal{X}) &= \{n \in N | \exists x \in \mathcal{X} : f_n(x) \in (high_n, +\infty)\}; \\ \text{LowerCorner}(\mathcal{X}) &= \{n \in N | \exists x \in \mathcal{X} : f_n(x) \in (-\infty, low_n)\}; \end{aligned} \quad (3)$$

Eq. 3 shows the formal definition of the corner-case neuron of the NLP model $f(\cdot)$, where $\mathcal{X}$ is the given test suite, N is the number of neurons in model $f(\cdot)$, $f_n(\cdot)$ is the n^{th} neuron's output, and $high_n, low_n$ are the n^{th} neurons' output bounds on the model training dataset. Eq. 3 can be interpreted as the collection of neurons that emit outputs beyond the model's numerical boundary.

$$\begin{aligned} BoundCov(\mathcal{X}) &= \frac{|UpperCorner(\mathcal{X})| + |LowerCorner(\mathcal{X})|}{2 \times |N|} \\ SActCov(\mathcal{X}) &= \frac{|UpperCorner(\mathcal{X})|}{|N|} \end{aligned} \quad (4)$$

The formal definition of our coverage metrics are shown in Eq.4, where BoundCov measures the coverage of neurons that produce outputs that exceed the upper or lower bounds, and SActCov measures the coverage of neurons that create outputs that exceed the lower bound. Higher coverage indicates the test suite is better for triggering the corner-case neurons, thus better test suite diversity.

To answer **RQ3**, for each NLP model under test, we first feed its training dataset to compute each neuron's lower and upper bounds. After that, we select the same number of test cases from S^{2}LCT and CHECKLIST as the test suite and compute the corresponding coverage metrics.

RQ4. To answer RQ4, we conduct experiments to demonstrate that S^{2}LCT can help developers understand the bugs in the NLP models. Recall that S^{2}LCT generates test cases by mutating seed sentences (e.g. by expanding one token in the seed input). Still, it is unclear why mutating one token will cause the model to produce misclassified results. We seek to help developers to understand why such mutation will result in the misclassification. Existing work [2**?**] has demonstrated that the ML model prediction is dominated by a minimal set of input features (i.e. tokens in input sentences). Motivated by such intuition, we seek to identify a minimal set of input tokens that dominate the model prediction.

Formally, given a input sentence $x = [tk_1, tk_2, \cdots, tk_n]$, and the NLP model under test $f(\cdot)$, our goal is to find a masking template $T = [t_1, t_2, \cdots, t_n]$, where t_i is 0 or 1, representing masking the i^{th} token in x or not. The template T can mask some tokens in x with attribute tokens, and the masked input has a high probability of retaining the original prediction x, denoted as

$$P(f(T(x)) = f(x)) \geq P_{thresh} \quad (5)$$

To create such a template T, we first compute the contribution score of each input token using an existing explainable ML technique []. Following that, we begin with the full mask template (i.e., all tokens are masked); such full mask template definitely does not satisfy Eq. 5. We then iteratively shift one position from mask to non-mask based on the order of each token's contribution score, until the template T satisfies Eq. 5 Because we iterate the size of our mask, the generated template T will keep the minimum number of

tokens in x. Moreover, since the input x is an incorrect prediction, the generated template T is likely to produce misclassification (i.e., the probability to be misclassified is larger than P_{thresh}).

Implementation Details.

Shiyi: Missing: environment running these experiments.

5 RESULT

6 EXPERIMENTAL RESULTS

6.1 RQ1: S^{2}LCT Sentiment Label Consistency

6.2 RQ2: Correctness of Linguistic Capability Categorization

6.3 RQ3: Test Suite Diversity

Table **??** shows that ....

6.4 RQ4: Use S^{2}LCT for Debugging

7 RELATED WORK

NLP Testing. With the increasing use of NLP models, evaluation of NLP models is becoming more important. Wang *et al.* [19] propose multiple diagnostic datasets to evaluate NLP models. Few recent works have also considered model robustness as an aspect for model evaluation. Different methods like adversarial set generation [1, 4, 13, 16], fairness evaluation [9, 15], logical consistency evaluation [11], prediction interpretations [12] and interactive error analysis [20] have been proposed to evaluate model robustness. More recently, CHECKLIST introduces input-output behaviors of linguistic capabilities and generates behavior-guided inputs for validating the behaviors. [14] However, the approach only relies on manually generated input templates, thus the template generation becomes expensive and time consuming. Also, it does not guarantee the comprehensive evaluation.

8 CONCLUSIONS

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Table 1: Search rules and transformation templates for linguistic capabilities. Shiyi: Add transformation templates. May need to find a better specification language..

Linguistic capability	Search rule and transformation template
LC1: Short sentences with neutral adjectives and nouns	**Search** seed={length: <10; include: neutral adjs & neutral nouns; exlcude: pos adjs & neg adjs & pos nouns & neg nouns; label: neutral} **Transform** N/A
LC2: Short sentences with sentiment-laden adjectives	**Search** seed={length: <10; include: pos adjs; exlcude: neg adjs & neg verbs & neg nouns; label: pos} | {length: <10; include: neg adjs;exclude: pos adjs & pos verbs & pos nouns & neg verbs & neg nouns; label: neg} **Transform** N/A
LC3: Sentiment change over time, present should prevail	**Search** pos_sent={label: pos}, neg_sent={label: neg} **Transform** seed={[‘Previously, I used to like it saying that’,‘Last time, I agreed with saying that’,‘I liked it much as to say that’]+[pos_sent | neg_sent]+[‘but’, ‘although’, ‘on the other hand’]+[‘now I don’t like it.’, ‘now I hate it.’]} | {[‘I used to disagree with saying that’,‘Last time, I didn’t like it saying that’,‘I hated it much as to say that’]+[neg_sent, pos_sent]+[‘but’, ‘although’, ‘on the other hand’]+[‘now I like it.’]}
LC4: Negated negative should be positive or neutral	**Search** demonstrative_sent={start: [This, That, These, Those] + [is, are]; label: neg} **Transform** seed=negation of demonstrative_sent ([‘is’] -> [‘is not’, ‘isn’t’], [‘are’] -> [‘are not’, ‘aren’t’])
LC5: Negated neutral should still be neutral	**Search** demonstrative_sent={start: [This, That, These, Those] + [is, are]; label: neutral} **Transform** negation of demonstrative_sent
LC6: Negation of negative at the end, should be positive or neutral	**Search** neg_sent={label: neg} **Transform** seed={[‘I agreed that’, ‘I thought that’]+[neg_sent]+[‘but it wasn’t’, ‘but I didn’t’]}
LC7: Negated positive with neutral content in the middle	**Search** pos_sent={length: <20; label: pos}, neutral_sent={length: <20; label: neutral} **Transform** seed={[‘I wouldn’t say,’, ‘I do not think,’, ‘I don’t agree with,’]+[neutral_sent]+[‘,’]+[pos_sent]}
LC8: Author sentiment is more important than others	**Search** pos_sent={label:pos}, neg_sent={label: neg} **Transform** seed={[temp1]+[pos_sent]+[temp2]+[neg_sent]} | {[temp1]+[neg_sent]+[temp2]+[pos_sent]} where temp1={[‘Some people think that’, ‘Many people agree with that’, ‘They think that’, ‘You agree with that’], temp2=[‘but I think that’]}
LC9: Parsing sentiment in (question, yes) form	**Search** pos_sent={label: pos}, neg_sent={label: neg} **Transform** seed={[‘Do I think that’, ‘Do I agree that’]+[pos_sent | neg_sent]+[‘? yes’]}
LC10: Parsing positive sentiment in (question, no) form	**Search** pos_sent={label: pos} **Transform** seed={[‘Do I think that’, ‘Do I agree that’]+[pos_sent]+[‘? no’]}
LC11: Parsing negative sentiment in (question, no) form	**Search** neg_sent={label: neg} **Transform** seed={[‘Do I think that’, ‘Do I agree that’]+[neg_sent]+[‘? no’]}

Table 3: Comparison of evaluation of BERT-base, RoBERTa-base and DistilBERT-base on S^{2}LCT and CHECKLIST testcases. Due to the spatial constraints of table, BERT-base, RoBERTa-base and DistilBERT-base models are denoted as Model1, Model2 and Model3 respectively.

Linguistic capability	Cklst #TCs	Cklst #Fails	S^{2}LCT #Seeds	S^{2}LCT Seed #Fails	S^{2}LCT #Exps	S^{2}LCT Exp #Fails	S^{2}LCT #PassToFail
LC1: Author sentiment is more important than of others	8528	Model1: 3741 Model2: 2692 Model3: 3535	50	Model1: 22 Model2: 13 Model3: 20	2323	Model1: 1163 Model2: 725 Model3: 1040	Model1: 134 Model2: 78 Model3: 31
LC2: Negated negative should be positive or neutral	6786	Model1: 799 Model2: 218 Model3: 734	50	Model1: 46 Model2: 41 Model3: 44	1784	Model1: 1680 Model2: 1537 Model3: 1579	Model1: 49 Model2: 64 Model3: 26
LC3: Negated neutral should still be neutral	2496	Model1: 2427 Model2: 2304 Model3: 2450	26	Model1: 24 Model2: 24 Model3: 24	1009	Model1: 932 Model2: 939 Model3: 961	Model1: 62 Model2: 38 Model3: 74
LC4: Negated positive with neutral content in the middle	1000	Model1: 860 Model2: 416 Model3: 865	50	Model1: 42 Model2: 21 Model3: 38	1634	Model1: 1438 Model2: 664 Model3: 1280	Model1: 40 Model2: 54 Model3: 9
LC5: Negation of negative at the end, should be positive or neutral	2124	Model1: 1871 Model2: 445 Model3: 2124	50	Model1: 50 Model2: 50 Model3: 50	1486	Model1: 1486 Model2: 1486 Model3: 1486	Model1: 0 Model2: 0 Model3: 0
LC6: Sentiment change over time, present should prevail	8000	Model1: 1680 Model2: 829 Model3: 2532	50	Model1: 12 Model2: 28 Model3: 39	-	Model1: - Model2: - Model3: -	Model1: - Model2: - Model3: -
LC7: Short sentences with neutral adjectives and nouns	1716	Model1: 1330 Model2: 1391 Model3: 1661	19	Model1: 15 Model2: 17 Model3: 19	210	Model1: 182 Model2: 160 Model3: 198	Model1: 19 Model2: 9 Model3: 0
LC8: Short sentences with sentiment-laden adjectives	8658	Model1: 26 Model2: 139 Model3: 125	50	Model1: 2 Model2: 2 Model3: 1	394	Model1: 17 Model2: 19 Model3: 11	Model1: 4 Model2: 5 Model3: 8
LC9: Parsing positive and negative sentiment in (question, no) form	7644	Model1: 4056 Model2: 4576 Model3: 6440	100	Model1: 71 Model2: 79 Model3: 93	2379	Model1: 1723 Model2: 1947 Model3: 2216	Model1: 40 Model2: 18 Model3: 12
LC10: parsing sentiment in (question, yes) form	9204	Model1: 1793 Model2: 1262 Model3: 1557	50	Model1: 2 Model2: 1 Model3: 3	1373	Model1: 37 Model2: 57 Model3: 76	Model1: 43 Model2: 46 Model3: 14