

Automated Trustworthiness Oracle Generation for Machine Learning Text Classifiers

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Machine learning (ML) for text classification has been widely used in various domains, such as toxicity detection, chatbot consulting, and review analysis. These applications can significantly impact ethics, economics, and human behavior, raising serious concerns about trusting ML decisions. Several studies indicate that traditional uncertainty metrics, such as model confidence, and performance metrics, like accuracy, are insufficient to build human trust in ML models. These models often learn spurious correlations during training and predict based on them during inference. When deployed in the real world, where such correlations are absent, their performance can deteriorate significantly. To avoid this, a common practice is to test whether predictions are made reasonably based on valid patterns in the data. Along with this, a challenge known as the *trustworthiness oracle problem* has been introduced. So far, due to the lack of automated trustworthiness oracles, the assessment requires manual validation, based on the decision process disclosed by explanation methods. However, this approach is time-consuming, error-prone, and not scalable.

To address this problem, we propose TOKI, the first automated trustworthiness oracle generation method for text classifiers. TOKI automatically checks whether the words contributing the most to a prediction are semantically related to the predicted class. Specifically, we leverage ML explanation methods to extract the decision-contributing words and measure their semantic relatedness with the class based on word embeddings. As a demonstration of its practical usefulness, we also introduce a novel adversarial attack method that targets trustworthiness vulnerabilities identified by TOKI. We compare TOKI with a naive baseline based solely on model confidence. To evaluate their alignment with human judgement, experiments are conducted on human-created ground truths of approximately 8,000 predictions. Additionally, we compare the effectiveness of TOKI-guided adversarial attack method with A2T, a state-of-the-art adversarial attack method for text classification. Results show that (1) relying on prediction uncertainty metrics, such as model confidence, cannot effectively distinguish between trustworthy and untrustworthy predictions, (2) TOKI achieves 142% higher accuracy than the naive baseline, and (3) TOKI-guided adversarial attack method is more effective with fewer perturbations than A2T.

CCS Concepts: • **Software and its engineering** → **Software testing and debugging**; • **Human-centered computing**; • **Computing methodologies** → *Natural language processing*; Learning paradigms;

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Warning: This paper contains examples of language that some people may find offensive or upsetting.

1 Introduction

Machine learning (ML) holds significant importance in contemporary advanced systems, such as spam detection, clinical text analysis, and vulnerability detection, with text classification being a primary application. Despite their superior performance during development, ML models can still fail in real-life scenarios [Caruana et al. 2015; Lapuschkin et al. 2019], raising concerns about trusting their decisions. When assessing a model, it is important not only to evaluate its general task-solving ability using metrics, such as prediction uncertainty or classification accuracy, but also to understand its decision-making process [Liao and Wortman 2024]. Indeed, several studies show that these metrics alone are insufficient indicators of model reliability [Canbek et al. 2022; Nguyen et al. 2015], as the model might learn spurious patterns [Ye et al. 2024], leading to overconfident decisions based on irrelevant features [Geirhos et al. 2020].

An ML model relying on irrelevant features, when faced with unseen data, can misclassify in the absence of these features or be fooled by them, leading to problematic predictions. We illustrate this using a Bert-based [Devlin et al. 2019] binary sentiment classifier applied to amazon reviews. Figure 1 shows four review examples, the model's predictions, and the probabilities of each class. We also highlight the important words steering these predictions, which are identified by LIME [Ribeiro et al. 2016], an explanation method. Orange and blue colors highlight words contributing to the negative and positive classes, respectively, with darker shades indicating higher importance. The review in Figure 1a is correctly classified as negative with high confidence. However, a closer look at the most important words the classifier relies on reveals that these words, such as “back”, “the”, “anything”, and “through”, are unrelated to either class. When removing some of them, as shown in Figure 1b, the review is misclassified as positive by the same model, despite negative sentiment in phrases “too slow”, “rough patch”, “sloggin”, and “give up”. To further explore the potential harm of this phenomenon, we synthesise a new review using a positive review shown in Figure 1c. This new review, as illustrated in Figure 1d, is injected with the words “back”, “through”, and “anything”. Although, these injections do not change the original meaning, the confident correct prediction is flipped to its opposite. These shifts underscore the importance of assessing whether the learned patterns are genuinely valid and generalisable or if they are merely based on spurious correlations within the training data, typically referred to as *shortcut learning* [Du et al. 2023]. A shortcut learning model is unlikely to provide correct classifications for the right reasons. Therefore, it becomes ineffective once deployed in the real world, where spurious correlations are absent.

To ensure the quality of ML systems in a reliable and cost-effective way, considerable effort has been focused on automating various aspects of the testing process, particularly through automated test oracles [Barr et al. 2015]. Traditional software testing has inspired automated test oracles for ML to test various properties, such as correctness, fairness, and robustness using techniques like metamorphic testing [Guo et al. 2018; Pei et al. 2017]. However, trustworthiness testing has not received as much attention and consequently remains less resolved [Cho et al. 2024]. Trustworthiness refers to the ability of a model to make reasonable predictions based on relevant features, such as semantically related words in text classification. Developing automated test oracles for trustworthiness testing is a long-lasting challenge hindering the broader adoption

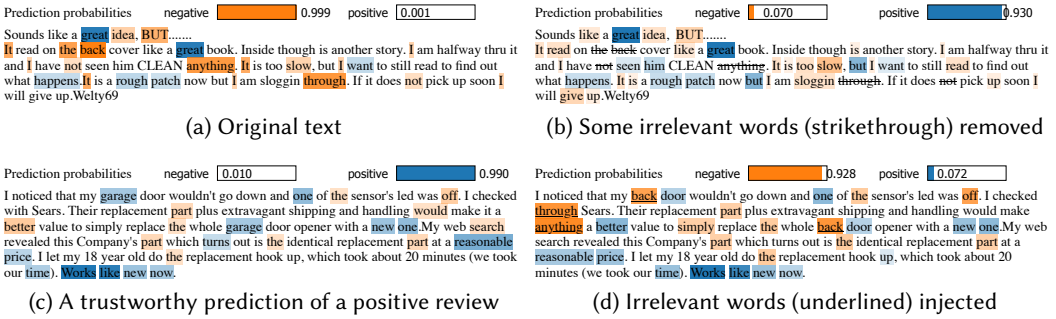


Fig. 1. LIME explanations of predictions analysing amazon reviews. Words highlighted in orange and blue indicate which class, negative or positive, they contribute to, with the shade representing their importance.

of ML models in the real world. Due to the lack of automated trustworthiness oracles, most studies [Du et al. 2021; Lapuschkin et al. 2019; Ribeiro et al. 2016] rely on human-based evaluation as the oracle to assess the ML prediction reasoning uncovered by explanation methods [Zhao et al. 2024]. However, this is time-consuming, error-prone, and not scalable [Ye et al. 2024].

In this paper, we focus on the oracle problem of assessing the trustworthiness of predictions made by text classifiers. Intuitively, trustworthiness assessment can be done by measuring the semantic relatedness between each decision-contributing word and the class name. However, measuring the semantic relatedness between two words is non-trivial, as discussed in Section 2.1. Given a word, there exists a group of words naturally related to it with very similar semantics like its synonyms. Their semantic similarity can be easily measured with existing metrics, such as cosine similarity. Some other words can also be related to the target word, but require a semantic hop, which we call indirectly related words. For example, the words “computer” and “file” are naturally related. Although the word “extension” may not seem naturally related to “computer”, it is strongly semantically connected to “file” and thus indirectly related to “computer”. We argue that examining the distribution of words helps better recognise semantically related words. Based on this, we propose an automated trustworthiness oracle generation method that leverages explanation methods to extract decision-contributing words and assesses their semantic relatedness to the class based on such distribution. The key idea is to identify keywords, which act as anchors for assessing semantic relatedness and indicate what a text classifier should rely on for predictions. A prediction is then deemed trustworthy if it is mainly based on these keywords. For instance, the prediction in Figure 1a is untrustworthy because the top contributing words, “back”, “the”, “anything”, and “through”, are all semantically unrelated to “negative”. To reveal the negative impact of vulnerabilities in trustworthiness, we also design an adversarial attack method guided by trustworthiness oracles. Our main contributions are summarised as follows.

- TOKI, the first approach for generating automated trustworthiness oracles.
- A novel attack method that targets trustworthiness vulnerabilities identified by TOKI.
- A benchmark for trustworthiness assessment for text classification, which contains approximately 8,000 predictions in various domains, such as topic classification, sentiment analysis, clinical mental text classification, hate speech detection, and software issue management.
- An investigation on the relation between the uncertainty and trustworthiness of predictions, revealing that relying on prediction uncertainty metrics, such as model confidence, overlooks untrustworthy high-confidence predictions and trustworthy low-confidence predictions.
- Ablation studies and comparative evaluations of TOKI. For trustworthiness assessment, we compare TOKI with a naive baseline solely based on model confidence. For adversarial attacks,

we compare our method with A2T [Yoo and Qi 2021], a state-of-the-art (SOTA) adversarial attack method. The results show TOKI's superior effectiveness and efficiency.

2 Problem Definition, Preliminary, and Motivation

This section clarifies the definition of trustworthiness used in the paper, the trustworthiness oracle problem, and our intuition to address it.

2.1 Definition of Trustworthiness

Trustworthiness is a complex concept that has raised numerous scholarly debates among researchers. This paper focuses on trustworthiness, in particular, whether a model makes predictions based on valid and reasonable patterns rather than spurious ones. Hence, we adopt the definition of trustworthiness proposed by Kästner et al. [2021] as shown in Definition 1.

DEFINITION 1. *An ML model is trustworthy to a stakeholder in a given context if and only if it works properly in the context and the stakeholder has justified belief in it.*

They also distinguish trustworthiness from trust: trustworthiness is a system's property, as recognised by prior studies as a critical non-functional requirement [Riccio et al. 2020], whereas trust is the perception a person has towards it. Hence, people can still trust an untrustworthy system.

According to Definition 1, understanding a model thoroughly helps justify our beliefs about how well it works. Model explanations can serve as a means to gain this understanding [Wiegrefe and Pinter 2019], thereby promoting trustworthiness [Bussone et al. 2015; Kästner et al. 2021]. There are two main types of model explanations: global [Caruana et al. 2015], which provides insights into the entire model's inner workings, and local [Li et al. 2016; Mohebbi et al. 2021; Ribeiro et al. 2016], which focuses on individual predictions. Local explanations, by breaking down a model into its components, allow users to grasp its functionality and decision-making process in a way that aligns with human cognitive patterns. Hence, they are more readily applicable [Adadi and Berrada 2018]. In text classification, various local explanations have been developed, such as feature attribution-based [Li et al. 2016; Mohebbi et al. 2021], attention-based [Barkan et al. 2021; Yeh et al. 2024], and counterfactual [Treviso et al. 2023] explanations. While other local explanations are subject to extensive debate [Jain and Wallace 2019], feature attribution-based explanations, such as LIME [Ribeiro et al. 2016], have proven to be effective, faithful, and widely used [Mariotti et al. 2024]. Hence, we leverage these explanations to uncover the reasoning behind individual predictions by highlighting the most relevant features contributing to those predictions. Exploring alternative explanations for assessing trustworthiness is an interesting avenue for future work.

A trustworthy model should make correct predictions, and the reasoning behind them, supported by explanations, should also be plausible. We propose the definition of a trustworthy prediction.

DEFINITION 2. *A trustworthy prediction is correct and the reasoning behind it is also **plausible**.*

In the context of text classification, a trustworthy prediction should rely on words in the input text that align with human reasoning. To simulate human judgement, the reasoning behind a prediction can be considered plausible if words contributing the most to the prediction are **semantically related** to the predicted class. We follow the definition of semantic relatedness described by Budanitsky and Hirst [2006]. Words can be semantically related by lexical relationships, such as meronymy (car-wheel) and antonymy (hot-cold), or just by any kind of functional association or other "non-classical relations" (pencil-paper, penguin-Antarctica, and rain-flood) [Morris and Hirst 2004]. It is important to distinguish semantic relatedness from **semantic similarity**. Semantic relatedness is a more general concept [Budanitsky and Hirst 2006] while semantic similarity refers to the degree of overlap or resemblance in meaning between two words [Slimani 2013]. For example,

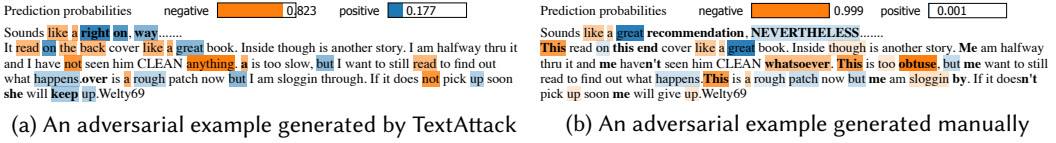


Fig. 2. LIME explanations of predictions analysing amazon reviews. **Bold** words represent perturbations, while words highlighted in orange and blue indicate their contribution to the negative or positive class, with the shade reflecting their importance.

“desk” and “chair” are semantically related but not semantically similar, “desk” and “table”, on the other hand, are both semantically related and semantically similar. It is also important to note that semantically relatedness is contextual, meaning two words are semantically related in a specific context, but might not in others. For instance, “bank” in “*the bank exploits small firms*” is semantically related to economics, while “bank” in “*we walked along the river bank*” is not.

Definition 2 describes a trustworthy prediction, referring to *local* trustworthiness. In contrast, *global* trustworthiness is the ability to make trustworthy predictions across a broad range of inputs. A globally trustworthy model can perfectly interpret every input like human domain experts. Although achieving *global* trustworthiness is the ultimate goal, it is challenging due to the more complex architectures and training procedures required, which result in higher computational costs. Therefore, we focus on *local* trustworthiness of individual predictions. While most observed predictions by a model are trustworthy, this does not directly mean the entire model is trustworthy.

2.2 Trustworthiness and Robustness

Sharing the same goal of improving the model’s generalisability, robustness testing might be able to identify problems that can be spotted during trustworthiness testing. Local robustness measures the model’s ability to retain its prediction on a sample under perturbations, also known as adversarial examples [Zhang et al. 2020b], that do not affect human perception and decision. For example, replacing a few words in Figure 1a with their synonyms should not alter a human’s decision to classify it as negative. If the model fails to maintain its original prediction on this adversarial example, we can conclude that the adversarial example reveals a local robustness issue.

Before investigating the oracle problem of model trustworthiness, one important question we need to answer is that to what extent does the trustworthiness problem differ from the robustness problem? More essentially, are there any issues that can be uncovered during trustworthiness testing but not during robustness testing? When a model’s prediction is trustworthy on a sample, the prediction is correct and based on justifiable reasons. This prediction is not necessarily robust, meaning it might be altered under minor perturbations, such as replacing the decision-essential words with their semantic equivalents, or removing/modifying the decision-unessential ones. On the other hand, when a prediction by the model is robust, it is still possible that the model relies on some justifiable shortcut reasons, resulting in problematic predictions in the future where the shortcuts are absent or the shortcuts appear in samples having opposite classes. Hence, we conclude that the trustworthiness problem overlaps with the robustness problem, but they are not the same.

We differentiate trustworthiness from robustness by revisiting the prediction in Figure 1a, showing that robustness testing is unable to identify issues in the model’s behavior, but trustworthiness testing can. TextAttack [Morris et al. 2020], a framework implementing several SOTA adversarial example generation methods, is applied to attack [Zhang et al. 2020b] the model on the same text input. An additional adversarial example is generated manually to preserve grammar and semantic by replacing orange-highlighted words in Figure 1a with their synonyms from WordNet [Miller 1995]. The substitutions are ① idea–recommendation, ② BUT–NEVERTHELESS, ③ It–This, ④ the–this,

⑤ back-end, ⑥ anything-whatsoever, ⑦ slow-obtuse, ⑧ I-me, ⑨ through-by, ⑩ not-n't. Figures 2a and 2b, with bold words representing perturbations, show LIME explanations for two predictions to adversarial examples generated by TextAttack and manually, respectively. All adversarial examples fail to attack the model since it maintains the same prediction. This indicates that although the model is robust against certain adversarial examples, its prediction can still be untrustworthy.

2.3 Trustworthiness Oracle

ML testing involves providing a model with inputs and observing its responses. The oracle problem in ML testing is the challenge of determining whether these responses are appropriate. In trustworthiness testing, a response is an explainable prediction, as described in Definition 3.

DEFINITION 3. *For the classifier m , x is an individual data input into m , and $p = \langle \hat{y}, e \rangle$ is the **explainable prediction** to x of m , where \hat{y} is the predicted class and e is the explanation.*

The explainable prediction p assigns the input x to the predicted class \hat{y} , with its reasoning explained by the explanation e . The explanation e is a list of decision-contributing words and the corresponding **importance scores** measuring their contribution to the prediction p .

Three cases can occur with an explainable prediction: (1) incorrect, (2) correct due to semantically related words, and (3) correct due to semantically unrelated words. In the first case, investigating incorrectness becomes more important than trustworthiness assessment. Although the explanation might hint at why the prediction is incorrect, we leave this interesting avenue for future work. In this way, this paper only focuses on differentiating the last two cases, meaning that it examines only *correct* explainable predictions in the context of trustworthiness testing. We then adopt the definition of test oracles from Barr et al. [2015]. Definition 4 describes trustworthiness test data while Definition 5 defines trustworthiness oracles.

DEFINITION 4. *For the classifier m , X is the dataset correctly predicted by m and P is the set of correct explainable predictions to an instance of m . Trustworthiness test data forms the set $T = X \uplus P$.*

DEFINITION 5. *A trustworthiness oracle $D : T \mapsto \mathbb{B}$ is a function from an instance of trustworthiness test data t to true or false, indicating whether the prediction p in t is trustworthy according to Definition 2.*

A trustworthiness oracle is a predicate that determines whether the prediction in an individual trustworthiness test data is trustworthy according to Definition 2. The trustworthiness oracle formulated in Definition 5 can be applied to any text classifier, as long as there is an explanation method that uncovers the reasoning behind its predictions in the form of word attributions.

2.4 Applications of Trustworthiness Oracles

The trustworthiness problem exists in various ML applications. For example, a clinical mental text classifier from social media posts shows good held-out performance but might rely on irrelevant clues frequently present in the training data, such as post tags, job positions, and special occasions [Harrigan et al. 2020]. When deployed in the real world, such classifier is unlikely to perform well on unseen data. Hence, it is crucial to assess the reasoning of ML models to detect any behavioral issues before deploying them in real-world scenarios, rather than only evaluating their classification performance using metrics such as accuracy, recall, and F1-score.

Figure 3a shows a traditional development process of ML systems. AI engineers collect all available data, preprocess and split it into training and test sets. The training data is used to train the model, while the test data evaluates its performance. If the model performs poorly, the engineers improve the learning algorithm to enhance performance. Once the model achieves good held-out performance, it can be deployed in the real world. However, its performance often deteriorates due

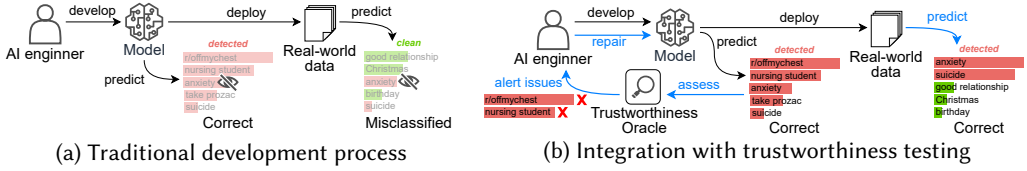


Fig. 3. Comparison between two ML system development processes: without and with trustworthiness testing. Blue lines indicate the differences between these processes.

to the model's reliance on spurious correlations learned during training, making it overconfident in held-out evaluations. In the real world, where these correlations are absent, the model tends to misclassify unseen data. A common solution is to augment the dataset with new manually annotated data and retrain the model, which is costly and inefficient.

Figure 3b shows the process integrated with trustworthiness testing. In addition to evaluating traditional performance metrics, this process also assesses the model's behavior behind correct predictions. In this process, trustworthiness oracles determine whether a prediction is trustworthy or based on spurious correlations. Identifying such issues allows the engineers to mitigate the impact of spurious correlations, ensure the model is correct for the right reasons, and improve its generalizability. If undetected, these issues can lead to problematic predictions in the future. Human annotations often serve as trustworthiness oracles, but this approach is not scalable [Ye et al. 2024]. Integrating automated trustworthiness oracles into the software engineering (SE) lifecycle for ML systems can greatly advance their development and applications. Automated trustworthiness oracles enable the automation of trustworthiness testing, which is vital and closely intertwined with other SE activities [Riccio et al. 2020]. This is especially valuable in the iterative development of ML systems where performance and trustworthiness must be evaluated and refined [Martinez et al. 2022]. Specifically, automated trustworthiness oracles support continuous integration and delivery pipelines by automating trustworthiness testing for ML systems. They also serve as a tool for monitoring ML systems in real-world environments, particularly in online testing or DevOps workflows, to verify whether predictions are trustworthy in real time, and test with real-world and corner-cased inputs. Moreover, the outputs of trustworthiness oracles provide actionable insights for feedback-driven repairing and improving processes, reducing the need for human intervention.

In addition, trustworthiness oracles help assess the trustworthiness of systems in SE that employ ML for text classification. ML has been widely used in SE for text classification, automating numerous tasks to enhance planning, design, and maintenance. For example, sentiment analysis has been applied to various SE artifacts, including git commit comments [Sinha et al. 2016], JIRA issues [Ortu et al. 2015], and apps' reviews [Panichella et al. 2015]. It also helps assess developers' psychological states [Guzman and Bruegge 2013], and analyse sentiment on Q&A sites like StackOverflow to recommend improvements for source code [Rahman et al. 2015] or to identify problematic API design features [Zhang and Hou 2013]. In addition to sentiment analysis, other tasks, such as software requirement classification [Pérez-Verdejo et al. 2020] and project issue categorisation [Schulte et al. 2024], have also been integrated with ML to reduce human effort and improve efficiency. Hence, automated trustworthiness oracles offer opportunities to foster greater trust in these systems, both within SE domains and more broadly.

3 TOKI: Trustworthiness Oracle through Keyword Identification

As outlined in Section 2, a prediction is considered trustworthy if its reasoning is plausible. In text classification, a trustworthy prediction should rely on words semantically related to the predicted class. We argue that examining the distribution of words helps better recognise these semantically

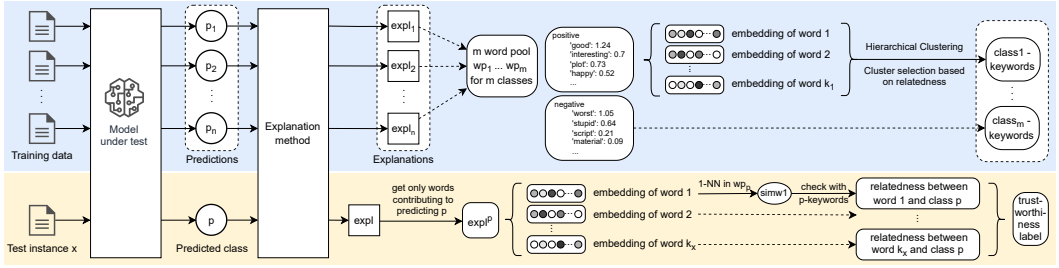


Fig. 4. The process of TOKI, with blue and yellow background colors indicating the first and second pipelines.

related words. Specifically, directly related words can act as anchors, and words indirectly related to the class are likely to form clusters around them. Following this intuition, we present **Trustworthiness Oracle through Keyword Identification (TOKI)**. The key idea of TOKI is to use a list of **keywords** for each class to indicate what a text classifier should rely on for predictions. To identify these keywords, TOKI selects clusters containing directly related words and their surrounding indirectly related words. A prediction is then deemed trustworthy if it mainly relies on the keywords of the predicted class. While the ultimate goal is to identify a complete list of keywords, this is impractical due to resource and computational constraints. Hence, we identify only a partial list of keywords by extracting decision-contributing words from the classifier's responses on the training data and applying clustering analysis to them. Since not all decision-contributing words are genuinely related to the class, clustering analysis also helps separate related words from unrelated ones. Figure 4 describes TOKI with two pipelines: keyword identification and trustworthiness label computation.

3.1 Keyword Identification

ML models learn correlations in training data, including both valid and spurious ones [Geirhos et al. 2020]. Therefore, *not all predictions are solely based on the spurious correlations*. Predictions reflecting the valid correlations rely on *words semantically related to the predicted class, regardless of their importance scores*. While the spurious correlations can make predictions untrustworthy, TOKI identifies keywords for each class through the valid correlations, following four steps.

Step 1: Explaining. To extract keywords, we focus on analysing the reasoning behind correct predictions, as incorrect ones might provide meaningless reasoning. Therefore, TOKI identifies the decision-contributing words from instances that have been predicted correctly in the training set. Let X , $f(\cdot)$, and c represent the training set, the text classifier, and the true class, respectively. The explaining step is formalised in Equation 1, which returns a list of explanations E_c for each class c .

$$E_c = \{e(f, x) \mid x \in X, f(x) = c\} \quad (1)$$

TOKI leverages the explanation method $e(\cdot, \cdot)$ to measure the contribution s of each word w to a prediction. Several methods, such as LIME [Ribeiro et al. 2016], achieve this by locally approximating the model as an interpretable surrogate model. Other methods [Li et al. 2016] perturb input and evaluate model output changes. Another common way [Mohebbi et al. 2021] is to compute the gradient of the output with respect to the input. These methods explain the prediction $f(x)$ in the form of $e(f, x) = \{\langle w, s \rangle\}$, a list of top decision-contributing words with their importance scores.

Step 2: Word pool construction. A word pool of decision-contributing words and their averaged importance scores across explanations is created for each class, as formalised in Equation 2.

$$W_c = \{\langle w, \overline{s_w} \rangle \mid w \in E_c\}, \text{ where } \overline{s_w} = \frac{\sum_{e \in E_c, \langle w, s_i \rangle \in e} s_i}{\sum_{e \in E_c, \langle w, s_i \rangle \in e} 1} \quad (2)$$

Words in the explanations E_c are categorised based on the predicted class c , with their importance scores averaged. This results in a word pool $W_c = \{\langle w, \overline{s_w} \rangle\}$ for the class c , containing words and their averaged importance scores. The averaged importance score $\overline{s_w}$ also indicates the **correlation** between the word w and the class c .

Step 3: Word clustering. The word pool W_c of the class c contains both keywords and unrelated words. To distinguish them and collect both directly related and indirectly related words, TOKI clusters the word pool W_c , as formalised in Equation 3.

$$C_c = \text{hierarchical_cluster}(W_c, \theta_{dist}) \quad (3)$$

Words in W_c are transformed into embeddings by embedding methods. As the number of clusters is unknown, hierarchical clustering [Nielsen 2016] is applied to group these word embeddings based on their cosine similarities. Clusters C_c of the class c are obtained by cutting the dendrogram, a hierarchical tree of relationships between the word embeddings, at the threshold distance θ_{dist} .

Step 4: Keyword selection. The list of keywords is identified by selecting the clusters of words semantically related to the class name, as described in Equation 4.

$$K_c = \bigcup_{C_i \in C_c} \left\{ C_i \mid \text{sim}(\overline{C_i^w}, c) \geq \theta_{relate} \right\}, \text{ and } F_c = W_c \setminus K_c \quad (4)$$

In TOKI, the word cluster C_i is directly related to the class c if $\text{sim}(\overline{C_i^w}, c) \geq \theta_{relate}$. Here, $\overline{C_i^w}$ is the mean vector of all the embeddings of words in C_i , $\text{sim}(\cdot, \cdot)$ measures the cosine similarity between two word embeddings, and θ_{relate} is the threshold relatedness. After this step, the list of keywords K_c of the class c is identified while the remaining words form a list of non-keywords F_c .

While θ_{dist} needs manual configuration, θ_{relate} can be automatically estimated by turning it into a binary classification problem. The key idea to determine θ_{relate} is that related pairs of words can be found via synonyms. To accomplish this, the top 1,000 most common English words are taken from WordNet [Miller 1995]. Then, TOKI uses Merriam-Webster Dictionary [2002] to find all single-word synonyms of each word, resulting in approximately 32,000 pairs of related words. Another 32,000 random pairs of words are generated from WordNet to create a list of unrelated pairs. Finally, TOKI determines the value of θ_{relate} through a binary search on the word embeddings of these lists. At each iteration, all 64,000 pairs are classified, with each pair of words considered as related if the cosine similarity between two word embeddings is higher than or equal to the current θ_{relate} . The search stops when precision and recall for both related and unrelated classifications are balanced. The value of θ_{relate} varies depending on the word embedding method, as different methods have their unique ways of embedding, thereby impacting the measurement of similarity between words.

3.2 Trustworthiness Label Computation

The second pipeline of TOKI, as highlighted in yellow in Figure 4, focuses on assessing the trustworthiness of a correct prediction. The trustworthiness label is determined by comparing the impacts between related and unrelated decision-contributing words based on their total importance scores. To determine whether a decision-contributing word is related to the class, TOKI uses keywords as anchors to assess semantic relatedness. We define an indicator function $r(w, c)$ for this purpose by checking whether the nearest word in W_c to w is a keyword, as shown in Equation 5. We then formalise the second pipeline in Equation 6.

$$r(w, c) = \begin{cases} 1, & \text{if } \max_{\langle w_{i,-} \rangle \in K_c} \text{sim}(w_i, w) \geq \max_{\langle w_{i,-} \rangle \in F_c} \text{sim}(w_i, w), \\ 0, & \text{otherwise.} \end{cases} \quad (5)$$

$$IS_{rel} = \sum_{\langle w_i, s_i \rangle \in e(f, x_t)} s_i * r(w_i, c), \quad IS_{unr} = \sum_{\langle w_i, s_i \rangle \in e(f, x_t)} s_i * (1 - r(w_i, c)), \quad \text{and} \quad D(f, x_t, c, e) = IS_{rel} \geq IS_{unr} \quad (6)$$

TOKI leverages the explanation method $e(\cdot, \cdot)$ to extract decision-contributing words for the prediction to the given input x_t . For each word w , TOKI identifies the most similar word in the word pool W_c of the predicted class c , which is constructed in the first pipeline, by measuring the cosine similarity between their embeddings. The semantic relatedness between each word and the class is determined by checking whether the most similar word is a keyword. Next, TOKI computes the total importance scores IS_{rel} and IS_{unr} for semantically related and unrelated words, respectively. Based on the difference between them, the trustworthiness oracle D finally assigns a trustworthiness label (trustworthy or untrustworthy) to the prediction.

Word embeddings themselves can be biased due to their training data [Torregrossa et al. 2021], potentially affecting the ability to measure semantic relatedness. To mitigate this, TOKI applies ensemble learning [Leon et al. 2017] by employing different word embedding methods. We use both static embedding methods [Bojanowski et al. 2017; Shazeer et al. 2016], which produce a single output for each word and contextual embedding methods [Cer et al. 2018; Devlin et al. 2019], which generate different vectors for the same word based on its context. Each method has a different way of vectorizing words, resulting in different similarity measurements between them. In the first pipeline, this affects the computation of θ_{relate} and the keyword identification. In the second pipeline, different embedding methods identify different similar words in the word pool, leading to different decisions about how the word is related to the class. Decisions made by all embedding methods are combined using plurality voting [Leon et al. 2017] in both pipelines.

Plurality voting is a simple yet effective voting method where each voter selects a single option, and the option with the most votes wins. In the first pipeline, a word receives a vote from an embedding method if the method identifies it as a keyword. The word is ultimately classified as a keyword if it receives the highest number of votes across all embedding methods. Similarly, in the second pipeline, a word is considered related to a class if it is identified as such by the highest number of embedding methods in the ensemble.

4 Targeted Adversarial Attacks on Trustworthiness Vulnerabilities

We introduce a novel adversarial attack method guided by TOKI. The key idea is *to weaken valid correlations* by replacing words with similar ones that are weakly correlated to the original class, while *strengthening spurious correlations* by injecting unrelated words strongly correlated to other classes. Table 1 compares TOKI-guided attack method with existing adversarial attack methods, exemplified by the SOTA A2T [Yoo and Qi 2021].

A2T uses the gradient of the loss to determine the substitution order of words based on their importance scores in the prediction. It then iteratively replaces each word with synonyms generated from a counter-fitted word embedding model [Mrkšić et al. 2016]. This embedding model is injected with antonymy and synonymy constraints into vector space representations to improve its ability to assess semantic similarity. For example, traditional word embedding models like GloVe [Pennington et al. 2014] consider “expensive” similar to its antonyms, “cheaper” and “inexpensive”. In contrast, the counter-fitted word embedding model prefers synonyms like “costly” and “overpriced”. A2T also sets a modification rate to constrain the maximum number of perturbations allowed. The generated texts are subsequently filtered to ensure part-of-speech consistency and semantic preservation by evaluating the cosine similarity between the sentence encodings of the original and perturbed texts. A2T has been validated and demonstrated as a strong adversarial attack method [Zhou et al. 2024].

Our method follows the same architecture as A2T. The key difference is that it finds synonyms in word pools W constructed by TOKI, based on word-class correlations measured by the averaged

Table 1. Comparing TOKI-guided attack method (Ours) and A2T [Yoo and Qi 2021]

Components	TOKI-guided attack method (Ours)	A2T [Yoo and Qi 2021]
Word Ranking Method	Gradient-based Word Importance	Gradient-based Word Importance
Source of Synonyms	<i>Trustworthiness Oracle</i>	Counter-fitted Embedding
Word Substitution	Word Embedding + <i>Word-Class Correlation</i>	Word Embedding
Constraints	Modification Rate	Modification Rate
	DistilBERT Cosine Similarity	DistilBERT Cosine Similarity
	Part-of-Speech Consistency	Part-of-Speech Consistency

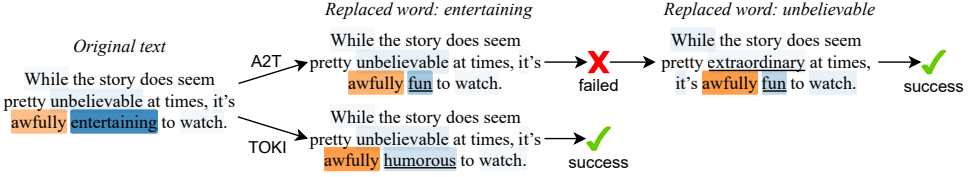


Fig. 5. Adversarial examples generated by TOKI (Ours) and A2T. Words highlighted in orange or blue show their contribution to the negative or positive class, with the shade indicating their level of importance.

importance scores \bar{s} . To replace a word, TOKI-guided attack method checks whether the word is related to the original predicted class. If it is, the word is replaced with a similar keyword of that class that has a *low importance score*. Otherwise, it is replaced with a similar non-keyword from other classes that has a *high importance score*. This mechanism tricks the model into using unrelated words as cues for predictions to cause misclassification, increasing the likelihood of successful attacks while reducing the number of perturbations.

Figure 5 compares adversarial examples generated by TOKI and A2T on the same input, showing that A2T requires more perturbations to succeed. The text is initially predicted as positive mainly based on the words “entertaining” and “unbelievable”. A2T first substitutes “entertaining” with “fun”, a synonym identified by the counter-fitted word embedding model. However, this change fails to attack the model, as the positive clues “fun” and “unbelievable” still dominate. A2T then replaces “unbelievable” with its synonym “extraordinary”. This time, the overall impact of positive clues is reduced, allowing the negative clue “awfully” to dominate. A2T substitutes words based only on the semantic meaning, requiring two substitutions to create a successful adversarial example. In contrast, TOKI-guided attack method replaces “entertaining” with a similar word “humorous”. This word is deemed weakly correlated to the positive class by TOKI in this case, allowing the negative clues to dominate and alter the prediction with just one substitution.

5 Trustworthiness Benchmark

Trustworthiness oracles aim to determine whether a prediction is trustworthy, as described in Section 2. Evaluating them requires datasets containing model predictions, corresponding explanations, and trustworthiness labels (trustworthy or untrustworthy). We call them “trustworthiness datasets” to distinguish them from “datasets” used to train and validate ML models. However, limited trustworthiness datasets are available for such evaluation [Schlegel et al. 2022].

Dong’s trustworthiness dataset. The human-based evaluation conducted by Dong [2018] is one of the most relevant studies. This evaluation uses two datasets: a subset [Ribeiro et al. 2016] of the 20 newsgroups (*20news*) differentiating Christianity from Atheism, and *movie* reviews with sentiment labels. In the evaluation, text inputs, highlighting the top words identified by the explanation method, are shown to crowdworkers. They then guess the system’s output and state their confidence on a five-point Likert scale, ranging from “strongly disagree” to “strongly agree”.

Table 2. Trustworthiness benchmark

Dataset		Data Statistics			Model Under Test		Number of top words	Importance Type
		Trust	Untrust	Total	Model Type	Accuracy		
movie [Dong 2018] 20news [Dong 2018]		311	47	358	Multilayer perceptron (MLPs)	0.832 0.939	10, 20	importance equivalent
CAMS [Garg et al. 2022]		1,206	739	1,945	mentalbert-base-uncased	0.397	10	importance equivalent
HateXplain [Mathew et al. 2021]		3,002	304	3,306	bert-base-uncased	0.797	10	importance equivalent
Issues [Schulte et al. 2024]		2,187	45	2,232	sebert-base	0.945	10	importance different
Ours	amazon_polarity	226	19	245	roberta-base-cased	0.960	5, 10, 20	importance different
	ag_news				bert-base-uncased	0.934		
	rotten_tomatoes				distilbert-base-uncased	0.841		
	yahoo_answers_topics				bert-base-uncased	0.750		
	imdb				distilbert-base-uncased	0.928		
	emotion				distilbert-base-uncased	0.926		

To derive a trustworthiness dataset, only answers, where the model correctly predicts the output, are selected from the original crowdworkers' responses. The answers, where crowdworkers either guess incorrectly with high confidence (4–5) or correctly with low confidence (1–2), are deemed untrustworthy. Other answers, where the crowdworkers guess correctly with high confidence (4–5), are trustworthy. Trustworthiness labels from the crowdworkers for the same prediction are combined using plurality voting [Leon et al. 2017] to determine the final trustworthiness label.

CAMS and HateXplain. CAMS [Garg et al. 2022] is a corpus for classifying mental health issues from social media posts, while HateXplain [Mathew et al. 2021] is a dataset for hate speech detection. Both datasets provide ground-truth explanations for each instance. In CAMS, annotations highlight phrases used as inferences for predictions. In HateXplain, tokens are labeled as 0 or 1 to indicate whether they are part of the explanation. Trustworthiness datasets are created by explaining the models and comparing these explanations with the ground-truth ones. To measure the plausibility of the reasoning behind predictions, we follow Zini et al. [2022] and use *explanation precision* = $|E \cap G| / |E|$, where E is the model explanation and G is the ground-truth explanation. High precision suggests that the model explanation is unlikely to provide a word not in the ground-truth explanation. A prediction is then considered trustworthy if its explanation precision ≥ 0.5 .

Issues: A SE-specific dataset. We adopt the study of Schulte et al. [2024], which analyses explanations for the automated classification of bug and non-bug issues, a critical task in SE. These issues are reported in issue tracking systems, such as JIRA or Github. Each prediction is explained by explanation methods, such as LIME [Ribeiro et al. 2016]. The authors then review the explanation based on multiple criteria, assigning a score of +1 if satisfied, 0 if neutral, and -1 if not. To assess a prediction's trustworthiness, we focus on two criteria: *related* and *unambiguous*. Specifically, *related* means there is a clear relationship between the important words of the explanation and the prediction. On the other hand, *unambiguous* implies there are no words of mixed meaning or all words are used in their correct meaning with respect to the explanation. Predictions are deemed trustworthy if the average score of these two criteria is greater than 0. If the average score is lower than 0, they are deemed untrustworthy. We finally combine these decisions of all annotators using plurality voting [Leon et al. 2017] to determine the final trustworthiness label for each prediction.

Importance-different trustworthiness dataset. We create an additional trustworthiness dataset that considers the distribution of importance scores of words. Six datasets and corresponding models are selected from Huggingface: *amazon_polarity*, *ag_news*, *rotten_tomatoes*, *yahoo_answers_topics*, *imdb*, and *emotion*. We randomly sample 1,000 predictions and have three trained participants

annotating their trustworthiness. For each prediction, the annotators first guess the output of the text input. They then review the model prediction and its explanation generated by LIME [Ribeiro et al. 2016], a SOTA method known for its effectiveness and faithfulness [Mariotti et al. 2024; Zhao et al. 2024]. Finally, the prediction is manually labelled as trustworthy or untrustworthy by annotators. Only predictions where both the model and annotators guess the correct output are considered. The trustworthiness label for each prediction is determined by plurality voting [Leon et al. 2017] based on all annotations. It is observed that the annotators often deem a prediction untrustworthy if unrelated words receive significantly higher importance scores in its explanation.

Explanation method. Three methods are used to extract decision-contributing words.

- *LIME* approximates the model locally with an interpretable model on perturbed samples created around the input [Ribeiro et al. 2016]. Our experiments use 5,000 perturbed samples.
- *Word omission* [Li et al. 2016] estimates the contribution of individual words by deleting them and measuring the change in probability for the predicted class [Dong 2018].
- *Gradient* computes the output gradient with respect to the input [Mohebbi et al. 2021].

Models under test. For our new datasets, popular fine-tuned models from Huggingface are chosen. For the remaining datasets, models provided by the authors are used. Table 2 summarises the final trustworthiness benchmark, the models under test, and their corresponding accuracies.

6 Evaluation

This section describes a series of experiments conducted to evaluate how well TOKI addresses the trustworthiness oracle problem and adversarial attacks text classifiers.

6.1 Baselines

We adopt a naive approach, named **Naive**, which assesses trustworthiness based on model confidence. Naive considers a prediction untrustworthy if its confidence is lower than a threshold θ_{conf} . For ablation studies, we use a TOKI's variant, called **TOKI (-K.I)**, which directly measures the relatedness between decision-contributing words and class names without identifying keywords [Cho et al. 2024]. We also compare TOKI-guided attack method with **A2T** [Yoo and Qi 2021], a SOTA adversarial attack method that has been validated to be strong and effective [Zhou et al. 2024].

6.2 Research Questions

We answer three research questions to investigate the trustworthiness problem and evaluate TOKI.

RQ1. Does a prediction's uncertainty reflect its trustworthiness?

RQ1.1. How are prediction uncertainty and trustworthiness related?

RQ1.2. What is the optimal configuration for θ_{conf} of Naive?

RQ2. How effective and efficient is TOKI in trustworthiness assessment?

RQ2.1. What is the optimal configuration for θ_{dist} ?

RQ2.2. How effective is TOKI compared to Naive?

RQ2.3. How does identifying keywords affect TOKI's effectiveness and efficiency?

RQ2.4. What is the impact of different explanation methods on TOKI?

RQ3. How effective is TOKI-guided attack method compared to A2T?

6.3 Metrics

Trustworthiness assessment. We emphasise that our evaluations focus on the effectiveness of trustworthiness oracles in classifying predictions as trustworthy or not, rather than assessing the trustworthiness of ML models themselves. The effectiveness of trustworthiness oracles is determined by the alignment between their generated trustworthiness labels and human-annotated

ones that reflect human perceptions of trustworthiness in the benchmark shown in Table 2. We frame trustworthiness oracles as binary classifiers with trustworthy and untrustworthy labels and evaluate their effectiveness using standard performance metrics for binary classification.

- *Accuracy*: the proportion of predictions correctly labelled as trustworthy or untrustworthy.
- *Precision, sensitivity, and F1-score*: the performance in detecting trustworthy predictions.
- *Specificity*: the performance in detecting untrustworthy predictions.
- *Geometric mean (G-mean)*: the balance between the classification performance on trustworthy and untrustworthy predictions, computed as $\sqrt{\text{sensitivity} \times \text{specificity}}$.

This usage of these metrics differs from that of model confidence in **RQ1**, which is assumed to be an unsuitable indicator of trustworthiness. G-mean serves as a balanced metric for evaluating classification performance on both trustworthy and untrustworthy predictions. A higher G-mean indicates better alignment between the trustworthiness benchmark and the oracles. Additionally, the efficiency of the trustworthiness oracles is assessed by their processing time in seconds.

Adversarial attack. We report the attack success rate (**ASR**), defined as $\frac{\# \text{ of successful attacks}}{\# \text{ of total attacks}}$, and the number of perturbations (**NP**) to evaluate effectiveness. We also use **Bert** [Devlin et al. 2019] and **USE** [Cer et al. 2018] scores to assess cosine similarity between original and adversarial examples.

6.4 Experimental Setup

We use six word embedding methods for TOKI’s word embedding ensemble model. ① **NNLM** [Bengio et al. 2000] learns embeddings and language models using a feedforward neural network. ② **GloVe** [Pennington et al. 2014] generates word embeddings from corpus word-to-word co-occurrence matrices. ③ **Swivel** [Shazeer et al. 2016] generates low-dimensional embeddings from feature co-occurrence matrices. ④ **FastText** [Bojanowski et al. 2017] represents each word as a bag of character n-grams, capable of embedding misspelled, rare, or out-of-vocabulary words. ⑤ **USE** [Cer et al. 2018] encodes sentences into embeddings for transfer learning to other tasks. ⑥ **Bert** [Devlin et al. 2019] is the first deeply bidirectional, unsupervised language representation, pre-trained on a large text corpus to condition both left and right contexts of each word.

We use the trustworthiness benchmark described in Section 5 to evaluate trustworthiness oracles. For our datasets, 2,000 training instances are randomly sampled for explanations in TOKI’s first pipeline, while all training instances are used in the remaining datasets. Trustworthiness oracles employing LIME, omission, and gradient explanations are denoted by the suffixes “-lime”, “-omis”, and “-grad”, respectively. Regarding adversarial attacks, we implement our method using TextAttack [Morris et al. 2020], which already includes A2T’s implementation [Yoo and Qi 2021], and use A2T’s default settings for both. We then attack random samples of up to 8,000 instances from each dataset in Table 2. Experiments are run 10 times on a Macbook M3 Pro with 12-core CPU, 18-core GPU, 18GB RAM, and 512GB SSD. The final results are averaged across these runs.

6.5 Results

RQ1: Relation between prediction uncertainty and trustworthiness. We use model confidence as a metric to assess the uncertainty of ML predictions. Figure 6 addresses **RQ1.1** by illustrating the distribution of model confidence for two trustworthiness labels on the benchmark shown in Table 2. The majority of high confidence predictions are trustworthy. Highly confident (0.9–1.0) predictions that are trustworthy account for 76%–99% of predictions with highly strong confidence. Similarly, trustworthy predictions with high confidence (0.8–0.9) represent 49%–91% of high confidence predictions. While predictions with strong confidence are likely to be trustworthy, several confident predictions are still untrustworthy. Confident (0.8–1.0) but untrustworthy predictions make up

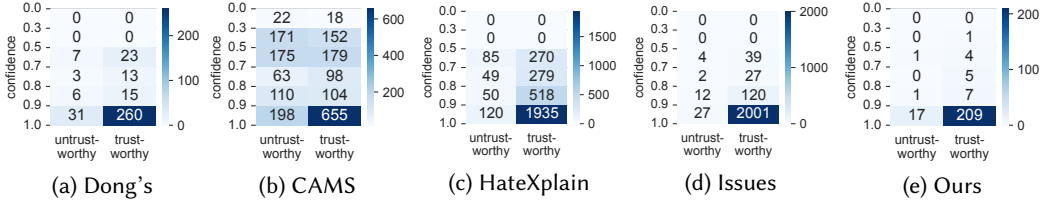


Fig. 6. The distribution of predictions' confidence across trustworthiness labels.

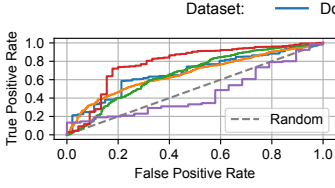
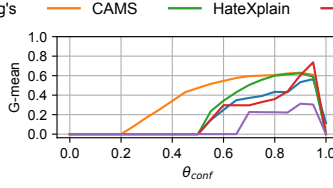
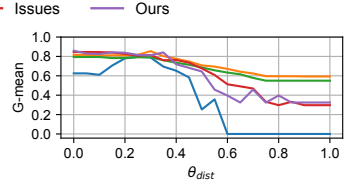


Fig. 7. ROC curves of Naive.

Fig. 8. Naive with different θ_{conf} .Fig. 9. TOKI with different θ_{dist} .

2%–29% of all confident predictions. In contrast, predictions with low confidence (<0.8) can also be trustworthy, with 51%–92% of low confidence predictions being trustworthy.

We now address **RQ1.2**, finding the optimal value of θ_{conf} for Naive, which relies solely on model confidence. Figure 7 shows receiver-operating characteristic (ROC) curves of Naive across trustworthiness datasets. Only the ROC curve for *Issues* is slightly closer to the top-left corner of the plot, while the others are near the random curve. Notably, the ROC curve for the new trustworthiness dataset falls below the random curve. This indicates that model confidence is limited in distinguishing between trustworthy and untrustworthy predictions. Figure 6 further shows that increasing θ_{conf} on the y-axis decreases the false positive rate, where untrustworthy predictions are labeled as trustworthy, but also increases the false negative rate, where trustworthy predictions are labeled as untrustworthy. In other words, increasing θ_{conf} enhances specificity but reduces sensitivity. Hence, we choose to maximise G-mean as the criterion to find θ_{conf} . Figure 8 illustrates Naive's effectiveness in G-mean with different values of θ_{conf} . As the value of 0.9 achieves the best G-mean for Naive, we set θ_{conf} to 0.9 for the remaining experiments.

Answer to RQ1: Uncertainty metrics of ML predictions, such as model confidence, are not suitable for assessing their trustworthiness. Although high confidence predictions tend to be trustworthy, relying on these metrics easily overlooks both trustworthy low confidence predictions and untrustworthy high confidence predictions.

RQ2: Effectiveness and Efficiency of TOKI. Intuitively, increasing θ_{dist} leads to an over-inclusion of words as keywords, which results in a bias towards classifying predictions as trustworthy. This increases sensitivity while reducing specificity. Conversely, decreasing θ_{dist} causes related keywords to be overlooked, leading to a bias towards classifications of predictions as untrustworthy, thereby reducing sensitivity and increasing specificity. Hence, we also address **RQ2.1** by measuring the effectiveness of TOKI-lime with various values of θ_{dist} using G-mean, a metric that balances sensitivity and specificity. Figure 9 reveals that the optimal value of θ_{dist} ranges from 0.2 to 0.4, depending on the models under test. Across all trustworthiness datasets, when θ_{dist} exceeds 0.6, G-mean drops significantly. In this case, TOKI considers all words as keywords and biases for labeling predictions as trustworthy. In the subsequent experiments, we set θ_{dist} to 0.3, as it balances the effectiveness across the benchmark.

Table 3. Comparison between TOKI (Ours), Naive, and a TOKI's variant that is without keyword identification (indicated by the suffix -K.I) against the trustworthiness benchmark

Dataset	Method	Acc (↑)	Pre (↑)	Sen (↑)	F1 (↑)	Spec (↑)	G-mean (↑)	Training Instances	Keyword Identification Time (↓s)	Test Instances	Trustworthiness Label Computation Time (↓s)
Dong's [Dong 2018]	TOKI-lime (Ours)	0.930	0.947	0.974	0.960	0.638	0.789	2,509	4,866	358	1,053
	TOKI-omis (Ours)	0.882	0.912	0.956	0.934	0.392	0.612		98		379
	TOKI-grad (Ours)	0.853	0.944	0.891	0.917	0.387	0.587		41		704
	Naive	0.771	0.893	0.836	0.864	0.340	0.533	✗	✗		✗
	TOKI-lime (~K.I)	0.302	0.985	0.209	0.345	0.915	0.437	✗	✗		1,051
	TOKI-omis (~K.I)	0.285	0.956	0.192	0.320	0.902	0.416				377
	TOKI-grad (~K.I)	0.233	1.000	0.170	0.290	0.968	0.406				702
CAMS [Garg et al. 2022]	TOKI-lime (Ours)	0.878	0.872	0.941	0.905	0.775	0.854	2,158	198,359	1,945	224,540
	TOKI-omis (Ours)	0.735	0.840	0.622	0.715	0.864	0.733		30,030		31,968
	TOKI-grad (Ours)	0.539	0.888	0.499	0.639	0.719	0.599		2,366		3,116
	Naive	0.615	0.768	0.543	0.636	0.732	0.631	✗	✗		✗
	TOKI-lime (~K.I)	0.422	0.648	0.343	0.449	0.551	0.435	✗	✗		224,435
	TOKI-omis (~K.I)	0.442	0.557	0.232	0.327	0.683	0.398				31,912
	TOKI-grad (~K.I)	0.388	0.836	0.356	0.500	0.531	0.435				3,071
HateXplain [Mathew et al. 2021]	TOKI-lime (Ours)	0.933	0.966	0.961	0.963	0.661	0.797	2,364	352,721	3,306	464,720
	TOKI-omis (Ours)	0.855	0.928	0.904	0.916	0.538	0.697		4,630		4,913
	TOKI-grad (Ours)	0.684	0.375	0.385	0.380	0.785	0.550		5,334		7,303
	Naive	0.640	0.942	0.645	0.765	0.605	0.624	✗	✗		✗
	TOKI-lime (~K.I)	0.103	0.953	0.014	0.027	0.984	0.117	✗	✗		464,606
	TOKI-omis (~K.I)	0.137	0.879	0.010	0.020	0.975	0.099				4,818
	TOKI-grad (~K.I)	0.737	0.586	0.020	0.039	0.979	0.140				7,271
Issues [Schulte et al. 2024]	TOKI-lime (Ours)	0.958	0.993	0.963	0.978	0.689	0.815	3,090	585,523	2,232	353,754
	Naive	0.944	0.983	0.959	0.971	0.200	0.312	✗	✗		✗
	TOKI-lime (~K.I)	0.109	0.913	0.010	0.019	0.489	0.007	✗	✗		6,358
Ours	TOKI-lime (Ours)	0.922	0.977	0.938	0.957	0.737	0.831	12,000	1,126,453	245	23,892
	Naive	0.861	0.925	0.925	0.925	0.105	0.312	✗	✗		✗
	TOKI-lime (~K.I)	0.408	0.968	0.403	0.569	0.474	0.437	✗	✗		23,849

The *next* experiment compares TOKI, Naive, and TOKI (-K.I) with different explanation methods against the benchmark outlined in Table 2. The experimental results are presented in Table 3.

- **RQ2.2: Comparing TOKI and Naive.** TOKI consistently outperforms Naive across all datasets. Naive occasionally shows good precision, sensitivity and F1-score but relatively low specificity and G-mean, especially on Dong's, Issues, and our trustworthiness datasets. This indicates that Naive is biased toward labeling predictions as trustworthy, resulting in misclassifying untrustworthy predictions as trustworthy.
- **RQ2.3: Ablation study – the effect of keywords.** TOKI (-K.I) underperforms compared to TOKI with low accuracy and G-mean across all datasets. On Dong's and HateXplain trustworthiness datasets, TOKI (-K.I) shows high specificity and precision, but other metrics remain low. This suggests a bias against labeling predictions as trustworthy, leading to misclassifying trustworthy predictions as untrustworthy. In terms of efficiency, TOKI (-K.I) and TOKI have similar processing times for computing trustworthiness labels, indicating that most of the time is spent on explaining predictions. Although keyword identification is time-consuming, it is only run once to assess the trustworthiness of a batch of predictions.
- **RQ2.4: The impact of explanation methods.** We investigate this using Dong's, CAMS, and HateXplain datasets, as other datasets only use LIME. Overall, TOKI demonstrates the best effectiveness with the SOTA LIME. TOKI-lime achieves higher accuracy and G-mean compared to TOKI-omis and TOKI-grad, while other metrics show no significant differences, except for the CAMS dataset. Explanation methods also impact TOKI's efficiency. TOKI-lime is significantly slower due to LIME's sampling of 5,000 neighbors, while omission and gradient are more lightweight. The model complexity also affects TOKI's efficiency, as the fine-tuned models consume more time than the two simpler MLPs in Dong's dataset.

Table 4. Experimental results comparing TOKI-guided attack method and A2T [Yoo and Qi 2021]

Dataset	Instances	TOKI-guided attack method (Ours)				A2T			
		SAR (↑)	Avg.NP (↓)	Bert (↑)	USE (↑)	SAR (↑)	Avg.NP (↓)	Bert (↑)	USE (↑)
movies	728	0.994	11.399	0.994	0.996	0.994	11.531	0.994	0.996
20news	926	0.458	21.058	0.977	0.979	0.456	21.089	0.976	0.979
CAMS	4,316	0.812	4.807	0.983	0.968	0.765	5.500	0.981	0.966
HateXplain	3,846	0.351	1.887	0.952	0.933	0.325	1.915	0.951	0.931
Issues	3,090	0.220	3.629	0.967	0.975	0.168	4.255	0.960	0.972
amazon_polarity	8,000	0.362	5.976	0.974	0.969	0.187	7.316	0.970	0.963
ag_news	7,600	0.192	2.481	0.965	0.949	0.151	2.668	0.963	0.952
rotten_tomatoes	1,066	0.500	1.626	0.952	0.921	0.334	1.898	0.950	0.919
yahoo_answers_topics	8,000	0.372	4.107	0.955	0.954	0.307	4.726	0.953	0.952
imdb	8,000	0.800	7.473	0.983	0.985	0.650	9.786	0.981	0.982
emotion	2,000	0.643	1.152	0.961	0.927	0.517	1.235	0.957	0.926

Table 5. Several adversarial examples: *blue* words indicate perturbations in the text, ✓ and ✗ represent successful and failed attacks, respectively

Original [toxic]: If I am a moderate muzzy and do not stand against the extremists within my religion, I am a worthless dog who deserves the title of muzzy terrorist period. A2T [normal ✓]: If I am a moderate muzzy and do not stand against the extremists within my <i>cults</i> , I am a <i>pointless</i> dog who <i>merits</i> the title of muzzy terrorist <i>periods</i> . TOKI [normal ✓]: If I am a <i>mild</i> muzzy and do not stand against the extremists within my religion, I am a worthless dog who deserves the title of muzzy terrorist period.	Original [medication]: When I manage to get a small victory against depression and “wake up”, I still have to fight against the pain that doesn’t let me move without moaning. A2T [jobs and careers ✓]: When I manage to get a small <i>win</i> against <i>downturn</i> and “wake up”, I still have to fight against the <i>grief</i> that doesn’t let me move without <i>whining</i> . TOKI [jobs and careers ✓]: When I manage to get a small victory against <i>stressors</i> and “wake up”, I still have to fight against the pain that doesn’t let me move without moaning.
Original [joy]: He is old enough to no longer feel that I am the only acceptable answer in the dark. A2T [sadness ✓]: He is <i>longtime</i> enough to no longer feel that I am the only <i>agreeable</i> answer in the <i>gloomy</i> . TOKI [love ✓]: He is old enough to no longer feel that I am the only <i>accepted</i> answer in the dark.	Original [negative]: Despite its visual virtuosity, “Naqoyqatsi” is banal in its message and the choice of material to convey it. A2T [negative ✗]: <i>Though</i> its visual virtuosity, “Naqoyqatsi” is banal in its <i>messaging</i> and the <i>choices</i> of <i>materials</i> to convey it. TOKI [positive ✓]: Despite its visual virtuosity, “Naqoyqatsi” is <i>insipid</i> in its message and the choice of material to convey it.

Answer to RQ2: TOKI outperforms the naive baseline based solely on model confidence, achieving the best effectiveness with LIME explanations. Without identifying keywords, TOKI’s ability to measure semantic relatedness is limited, which can misclassify trustworthy predictions as untrustworthy. In terms of efficiency, TOKI depends on the explanation methods and the model complexity, as most of its processing time is spent on explaining predictions.

RQ3: Effectiveness of TOKI-guided attack method. Table 4 compares the effectiveness of TOKI-guided attack method and A2T [Yoo and Qi 2021]. Overall, TOKI-guided attack method outperforms A2T, achieving a higher ASR and lower NP across all models. Adversarial examples generated by TOKI also have higher Bert and USE scores than those by A2T, except for the USE score on the ag_news dataset, demonstrating TOKI’s ability to preserve the semantic meaning of the original texts. Table 5 displays several adversarial examples generated by both methods. It is observed that TOKI can effectively find synonyms to attack with fewer perturbed words, while A2T requires more perturbations and sometimes fails. Interestingly, in Dong’s dataset, A2T performs nearly as well as the proposed method, likely because the models are simple MLPs and more easily attacked than transformer-based models in other datasets. However, in other datasets, the proposed method outperforms A2T by 2.6%–17.5% in ASR and requires 0.1–1.34 fewer NP. These results underscore the effectiveness of TOKI-guided attack method, particularly against models using SOTA architectures.

Answer to RQ3: The adversarial attack method guided by TOKI outperforms the SOTA A2T. Our method achieves a higher success rate with fewer perturbations than A2T while preserving the semantic meaning of the original texts.

7 Discussion

7.1 Implications

Prediction uncertainty and trustworthiness. Experimental results show that highly confident predictions are more likely to be trustworthy. However, high confidence does not guarantee trustworthiness, and low confidence predictions can still be trustworthy. Relying on prediction uncertainty is ineffective for trustworthiness assessment, overlooking both trustworthy low and untrustworthy high confidence predictions. Prior work has a complex debate over the impact of prediction uncertainty, mainly on human trust in ML models. Several studies [Bussone et al. 2015; Nguyen et al. 2015] suggest that prediction uncertainty has a limited impact on human trust [Ovadia et al. 2019; Rechkemmer and Yin 2022]. Other studies [Zhang et al. 2020a] show that prediction certainty can improve human trust in ML models and increase the willingness to rely on high confidence predictions. However, we argue that whether prediction certainty increases human trust or not, it does not translate into improving the model’s trustworthiness. Model certainty can lead to overreliance on ML decisions without reflecting the true trustworthiness of the model. The model may make decisions based on spurious correlations, being confident in them rather than valid correlations in the training data. This fits the distinction between trust and trustworthiness defined by Kästner et al. [2021], where people can still trust an untrustworthy model.

Automated trustworthiness oracles. TOKI identifies keywords for each class and uses them to measure the semantic relatedness between words and the class, effectively capturing the characteristics of classes. This makes TOKI outperform the baselines, including its variant that omits keywords to measure relatedness, which is biased for untrustworthy predictions.

Regarding adversarial attacks, examples generated by TOKI are more effective in attacking models than those created by A2T. By leveraging correlations between words and classes, our method generates adversarial examples likely to trigger trustworthiness vulnerabilities. This enables TOKI-guided attack method to achieve a higher attack success rate with fewer perturbations than existing adversarial attack methods. This finding highlights the negative impact of trustworthiness issues and the need for trustworthiness oracles, which remain underexplored in the research community.

Implications for software engineering. Trustworthiness is a crucial non-functional requirement of ML systems [Riccio et al. 2020]. Trustworthiness oracles enable automating trustworthiness testing, which is particularly valuable in the iterative development of ML systems. They support continuous integration and delivery pipelines, monitoring in real-world SE environments, such as online testing or DevOps, and handling corner-cased and real-world inputs. Since TOKI is efficient and lightweight, it can be directly applied in online settings and real-world environments without extensive training, requiring only a one-time keyword identification. This makes TOKI a practical safety net for software systems that rely on ML text classification. TOKI’s outputs also provide actionable insights for feedback-driven improvement, reducing the need for human intervention.

Text classification is also a primary application in SE domains to automate tasks such as sentiment analysis of SE artifacts, including git commit comments, JIRA issues, and app reviews, assessing developers’ psychological states, analysing Q&A sites like StackOverflow, software requirements classification, and project issue categorisation. Integrating such oracles can foster greater trust in ML4SE systems and significantly advance their development and deployment.

7.2 Threats to Validity

Threats to **internal validity** can be related to the faithfulness of explanations, which refers to how accurately the explanations reflect a model's reasoning [Mariotti et al. 2024]. To assess this, we evaluate TOKI using three explanation methods, including LIME, omission, and gradient. Another threat to internal validity is the bias in word embedding methods due to their training data. We mitigate this by using ensemble learning with multiple word embedding methods.

To reduce threats to **external validity**, we evaluate TOKI on approximately 8,000 predictions across 11 models and datasets in various domains, including topic classification, sentiment analysis, clinical mental text classification, hate speech detection, and software issue classification. We also employ TOKI with various explanation methods to assess its performance.

Threats to **construct validity** can arise from the trustworthiness benchmark. We leverage existing studies, which do not directly label predictions as trustworthy or not, by measuring the explanations' plausibility. To mitigate the threats, we collect an additional, more straightforward trustworthiness dataset. The bias in human annotations is addressed by combining all human-annotated trustworthiness labels for each prediction using plurality voting [Leon et al. 2017].

8 Related Work

8.1 Machine Learning Testing

Various testing techniques have emerged to assess different aspects of ML models. For example, test input generation methods [Guo et al. 2018; Pei et al. 2017; Tian et al. 2018] are used to detect defects, guided by test adequacy criteria [Ma et al. 2018; Pei et al. 2017]. Several methods aim to debug and repair models [Dutta et al. 2019; Krishnan and Wu 2017]. Other methods, such as A2T [Yoo and Qi 2021], focus on adversarial attacks [Morris et al. 2020; Zhang et al. 2020b] to assess model robustness. The oracle problem [Barr et al. 2015] is also a significant area of interest. Two main approaches are primarily used to address the oracle problem: metamorphic testing [Ramanagopal et al. 2018; Xie et al. 2020] and cross-referencing [Guo et al. 2018; Pei et al. 2017]. Considerable efforts have been made to test various properties of ML models, such as accuracy, relevance, efficiency, robustness, fairness, and interpretability [Zhang et al. 2022]. However, testing the trustworthiness of ML models remains a significant challenge. Several metrics have been proposed to quantify the concept of trustworthiness [Cheng et al. 2020; Kaur et al. 2021]. However, different from other properties, much of the work on trustworthiness testing relies on human interpretation within their systems.

8.2 Explanation Method

Local explanations, in contrast to global counterparts, focus on how a specific input leads to a prediction. This makes them particularly suitable for understanding ML predictions. In text classification, various methods have been developed to generate local explanations.

Feature attribution-based explanations assess the relevance of individual input features, such as words, to a model's prediction. Some [Dong 2018; Li et al. 2016] achieve this by removing, masking, or modifying input features, and observing the impact on the prediction. Others calculate the gradient of the output with respect to the input [Mohebbi et al. 2021]. Methods like LIME [Ribeiro et al. 2016] approximate the model's behaviour with simpler, interpretable models.

Attention-based explanations leverage the attention mechanism, which often serves as a means to attend to the most relevant part of inputs [Wiegrefe and Pinter 2019]. Intuitively, they can capture meaningful correlations between intermediate states of the inputs, potentially explaining the model's predictions [Zhao et al. 2024]. Hence, many approaches [Barkan et al. 2021; Yeh et al. 2024] aim to explain the predictions solely based on the attention weights or by analysing the knowledge encoded in the attention.

Counterfactual explanations reveal model behavior by demonstrating how slight input changes impact outputs, highlighting key features influencing predictions [Zhao et al. 2024]. Originally applied to ML tasks with explicit features and tabular datasets [Guidotti 2024], these explanations have since been extended to other tasks, including text classification [Treviso et al. 2023].

While other local explanation methods are subject to extensive debate [Jain and Wallace 2019], feature attribution explanations, such as the SOTA LIME [Ribeiro et al. 2016], have proven to be effective, faithful [Mariotti et al. 2024], and widely used by AI practitioners. Therefore, this paper focuses on feature attribution-based explanations. Exploring other local explanations for trustworthiness testing is a promising direction, which we leave for future work.

8.3 Making Use of Explanations

Explanations have served as a valuable tool for testing and improving ML models [Zhao et al. 2024]. Various studies have used explanations to understand and debug models. Ribeiro et al. [2016] demonstrated the usefulness of local explanations in various tasks, such as model comparison and trust assessment. Lapuschkin et al. [2019] introduced a semi-automated approach that characterises and validates classification strategies. Thomas et al. [2019] used explanations to uncover input-prediction patterns. Several studies [Yoo and Qi 2021; Zhang et al. 2020b] have applied explanations in adversarial attacks, primarily to determine word substitution order based on word importance. To the best of our knowledge, this paper introduces the first approach that leverages explanations to make perturbations, specifically, by weakening valid correlations and strengthening spurious ones. Explanations have also been integrated into the learning process to improve model performance and reliability. Ross et al. [2017] proposed an approach to discover multiple models for the same task with different classification strategies, allowing domain experts to choose the best one. Chen and Ji [2022] used explanations to improve the adversarial robustness of language models. Other studies [Ghai et al. 2021; Schramowski et al. 2020] leveraged explanations to make models right for the right scientific reasons. Similarly, Du et al. [2021] developed a framework to mitigate shortcuts, focusing on stop words, punctuation, and numbers. Recent studies [Linhart et al. 2024] have also applied explanation regularisation to mitigate the impact of spurious correlations.

9 Conclusion

We investigate the trustworthiness oracle problem of text classifiers. Statistical evaluation reveals that while highly confident predictions are more likely to be trustworthy, some still lack trustworthiness due to reliance on spurious correlations. We propose TOKI, an automated trustworthiness oracle generation method. Experiments compare the effectiveness and efficiency of TOKI, TOKI's ablation variant and the naive approach against the trustworthiness benchmark on ten models and datasets. Results show that TOKI outperforms other approaches. We also introduce a TOKI-guided adversarial attack method, which proves to be more effective than the SOTA A2T. In addition, several directions remain open for future work. We plan to explore alternative explanations, such as attention-based and counterfactual explanations, as well as other word embedding methods like sentence-transformers [Reimers and Gurevych 2019]. Further experiments on SE-specific datasets are also necessary to gain more insights into the trustworthiness problem in SE. Moreover, adapting TOKI to other data types, such as images and speech, presents a promising avenue in the future.

Data Availability. Our data and replicate package are available at [Lam et al. 2024].

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