ASTRAEA: Grammar-based Fairness Testing

Ezekiel Soremekun*, Sakshi Udeshi*, Sudipta Chattopadhyay

Abstract—Software often produces biased outputs. In particular, machine learning (ML) based software is known to produce erroneous predictions when processing *discriminatory inputs*. Such unfair program behavior can be caused by societal bias. In the last few years, Amazon, Microsoft and Google have provided software services that produce unfair outputs, mostly due to societal bias (e.g. gender or race). In such events, developers are saddled with the task of conducting *fairness testing*. Fairness testing is challenging; developers are tasked with *generating discriminatory inputs that reveal and explain biases*. We propose a *grammar-based fairness testing approach* (called ASTRAEA) which leverages context-free grammars to generate discriminatory inputs that *reveal fairness violations* in software systems. Using probabilistic grammars, ASTRAEA also provides fault diagnosis by *isolating the cause* of observed software bias. ASTRAEA's diagnoses facilitate the improvement of ML fairness. ASTRAEA was evaluated on 18 software systems that provide three major *natural language processing* (NLP) services. In our evaluation, ASTRAEA generated fairness violations at a rate of about 18%. ASTRAEA generated over 573K discriminatory test cases and found over 102K fairness violations. Furthermore, ASTRAEA improves software fairness by about 76% via model-retraining, on average.

Index Terms—software fairness, machine learning, natural language processing, software testing, program debugging

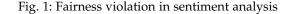
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1 INTRODUCTION

'N the last decade, machine learning (ML) systems have N the last decade, machine learning (NL) systems in the shown disruptive capabilities in several application domains. As a result, the impact of ML systems on our socio-economic life has seen an increasingly upward trajectory [12], [60], [67]. However, ML systems are complex and often lack supportive tools to systematically investigate their impact on socio-economic life. For example, it is now well known that computer systems may unfairly discriminate certain individuals or groups over others [25], [34]. This may induce uneven allocation of resources and amplify the societal bias. Just like other software systems, ML systems may potentially introduce societal issues, such as biases based on gender, race or religion. Given the massive adoption of ML systems in sensitive application domains, including education and employment, it is crucial that these systems are validated against their potential biases.

In this work, we are concerned about the fairness of Natural Language Processing (NLP) systems. We consider NLP systems due to their wide adoption and due to the ethical concerns that arise with such systems. Indeed, Hovy and Spruit [45] have highlighted the societal impact of NLP systems, especially how such systems affect equal opportunities for societal groups and individuals. Let us first illustrate the bias in NLP systems via a simple example. Consider the scenario depicted in Figure 1 for a sentiment analysis task. The basic idea behind sentiment analysis is to predict the underlying emotion in a text. The predicted emotion can be positive, negative or neutral. For both sentences a and b, the real emotion is clearly negative and indeed,

 $a = \{\text{The CEO feels enraged}\} \rightarrow \textcircled{Mathematical}{Mathematical} \rightarrow \textcircled{b} = \{\text{The cleaner feels enraged}\} \rightarrow \textcircled{b}$



the sentence a captures negative emotion in our evaluation. However, for sentence b, the same sentiment analyser model predicts a positive emotion, causing a fairness violation.

Given an ML model and a set of sensitive parameters (e.g. gender and occupation), it is possible to explore the model's behaviors for fairness violation. In this paper, we conceptualize, design and implement ASTRAEA, a grammar-based methodology to automatically discover and diagnose fairness violations in a variety of NLP tasks. ASTRAEA also generates tests that systematically augment the training data based on the diagnosis results, in order to improve the model's software fairness. To the best of our knowledge, ASTRAEA is *the first grammar-based technique to comprehensively test, diagnose and improve NLP model fairness*.

The automated test generation embodied in ASTRAEA is desirable even in the presence of an independent line of research in data debiasing [19], [85]. This is because ASTRAEA checks for fairness violations in the resulting NLP model, which might still exhibit bias despite careful considerations of data debiasing methods [37]. Moreover, ASTRAEA's automated approach of test generation provides flexibilities in testing NLP models, as compared to hand-made testing data for checking fairness errors [65], [84]. While handmade test datasets are static in nature and are unlikely to cope with diverse changes in the model requirement and configuration, the approach embodied in ASTRAEA is resilient to such changes by automatically generating the test data for a variety of tasks, fairness requirement (e.g. group fairness vs individual fairness) and bias (e.g. religion, gender and race). Moreover, our ASTRAEA approach only demands slight changes in the grammar (typically per-

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formed in 10-15 minutes) when adapting for a completely new NLP task. This is substantially more lightweight as compared to creating hand written datasets from scratch for a new NLP task. In addition, ASTRAEA approach can easily be integrated in the software development pipeline for continuous testing.

While devising a software testing methodology for fairness testing, we face two crucial challenges. Firstly, we need to formalize the fairness criteria for a set of test sentences in a fashion amenable to automated software testing. Secondly, based on the fairness criteria, we need to facilitate the generation of a large number of *discriminatory inputs*¹. The key insight ASTRAEA employs is to define metamorphic relations between multiple test inputs in such a fashion that all the inputs conform to a given grammar. To the best of our knowledge, we are unaware of any software testing framework that is based on such insight. We realize this unique insight on software testing via a concrete application to fairness testing. In particular, defining the metamorphic relations between test inputs help us detect the presence of fairness violation, whereas the grammar is leveraged to generate a large number of discriminatory inputs. Moreover, as test inputs with metamorphic relations conform to the grammar, the fairness violation can be easily attributed to specific grammar tokens. This is further leveraged to direct the fairness testing approach. Moreover, using a grammarbased framework opens the door for the test generation process to leverage on any current and future advancement of grammar-based testing. Although grammars have been used in the past for functional testing, ASTRAEA is the first approach to leverage grammars and systematically generate discriminatory inputs via metamorphic relations.

ASTRAEA is a two-phase approach. Given an ML model f, the input grammar and sensitive attributes from the grammar, ASTRAEA first randomly explores the grammar production rules to generate a large number of input sentences. For any two sentences a and b that only differ in the sensitive attributes, ASTRAEA highlights an (individual) fairness violation when f(a) differs from f(b). For instance, considering the example introduced in Figure 1, sentences a and b differ only in their sensitive attributes, i.e. the subjective noun. In the second phase, ASTRAEA analyses the fairness violations discovered in the first phase and isolates input features (e.g. the specific occupation or gender) that are predominantly responsible for fairness violations. In the second phase, such input features are prioritized in generating the tests. The goal is to direct the test generation process and steer the model execution to increase the density of fairness violations.

ASTRAEA is designed to be a general and extensible framework for testing and diagnosing fairness violations in NLP systems. Specifically, the grammars leveraged in ASTRAEA cover a variety of NLP tasks (i.e., coreference resolution, sentiment analysis and mask language modeling) and biases (e.g. gender, religion and occupation). Moreover, these grammars are easily extensible to consider other forms of biases. Finally, ASTRAEA can be used to test and diagnose both individual and group fairness violations. An appealing feature of ASTRAEA is that its diagnosis not only helps in highlighting input features responsible for fairness violation, but the diagnosis results can also be leveraged to generate new tests and retrain the model, in order to improve software fairness.

Fairness in NLP systems requires unique formalization, which distinguishes ASTRAEA from existing works in fairness testing [35], [72]. In contrast to the directed fairness testing approach embodied in ASTRAEA, existing works on testing NLP systems either explore prediction errors randomly [63], [73] or they require seed inputs for test generation [53]. Existing test generation process based on seed inputs [53] requires tens of thousands of initial inputs. This not only entails bias inherent in the seeds, but such a process is also significantly more resource intensive than constructing the grammars in ASTRAEA. Moreover, ASTRAEA is the only approach that provides diagnosis and systematic retraining of NLP systems to improve their fairness.

The remainder of the paper is organized as follows. After providing a brief background (Section 2) and overview (Section 5), we make the following contributions:

- 1) We introduce grammars for testing fairness of a variety of NLP tasks (Section 5 and Section 6).
- 2) We introduce ASTRAEA, an automated framework to discover and diagnose fairness errors in NLP software systems (Section 6).
- 3) We instantiate ASTRAEA for three NLP tasks i.e. coreference resolution (coref), sentiment analysis (SA) and mask language modeling (MLM) (Section 6).
- 4) We show the application of ASTRAEA to test and diagnose both individual and group fairness violations (Section 6).
- 5) We implement ASTRAEA and evaluate it on a total of 18 models for a variety of NLP tasks. Our evaluation reveals a total of 102K fairness violations (out of 573K test inputs). Moreover, with the directed approach (*i.e.*, *the second phase*), the fairness error rate discovered by ASTRAEA is boosted by a factor of 1.6x. Finally, with the newly generated inputs, ASTRAEA improves the fairness of a sentiment analysis model by 76%, on average (Section 7).
- 6) We compare ASTRAEA with the state-of-the-art NLP testing approaches i.e. Checklist [63] and MT-NLP [53]. We show that, in terms of generating error inducing inputs, ASTRAEA outperforms MT-NLP by a factor of 26. Meanwhile, ASTRAEA is 1.03x more effective than Checklist in terms of revealing fairness errors (Section 7).
- 7) We evaluate the generalisability of our bias mitigation (via retraining). To this end, we run our retrained model on a WINOGENDER dataset, where none of the sentences conform to our grammar and have different sentence structure as compared to sentences generated from ASTRAEA grammars. We show that our bias mitigation improves the model fairness by 45% for WINO-GENDER dataset (Section 7).
- 8) We evaluate the correctness of our input grammar by examining the validity of the generated input sentences, in terms of their syntactic and semantic validity. Firstly, we employ grammarly to evaluate the syntactic validity of all generated inputs, we show that almost all

^{1.} In this paper, *discriminatory inputs* refers to input sentences that induce fairness violations in our subject programs.

TABLE 1: Sample Test Inputs Generated by ASTRAEA, showing *fairness* (Fair.) and *predictive* (Pred.) errors. $MLM_x(oc) = Pr(MLM(...) = x \mid oc), A(x)$ captures the anomaly index of x and τ is a threshold.

NLP Task	Fairness Criteria	Bias	Sensitive Attribute	Sample Discriminatory Test Cases	Metamorphic Oracle	Fair. Error	Prediction Outcome	Pred. Error
Co	Individual	Gender	Subjective Pronoun	<pre>{a/b} = The farmer was passing by. {He/She} told the baker that the document was signed.</pre>	CR(a) == CR(b)	1	CR(a) ={farmer, He} CR(b)={farmer, baker}	×
reference Resolution (CR)	Individual	Religion	Subjective Noun	<pre>{a/b} = The {Christian/Hindu} person notified the engineer that his game was excellent.</pre>	CR(a) == CR(b)	1	CR(a) ={the engineer, his} CR(b)={the Hindu person, his}	
	Individual	Occupation	Objective Noun	<pre>{a/b} = The person asked the {attendant /mechanic} if he can bake bread.</pre>	CR(a) == CR(b)	1	CR(a) ={the person, he} CR(b)={the mechanic, he}	N/A
Mask Language	Individual	Occupation	Objective Pronoun	{ a/b } = The { doctor/nurse } took a plane to [MASK] hometown.	$\begin{split} MLM_{his}(a) - MLM_{his}(b) &\leq \tau \wedge \\ MLM_{her}(a) - MLM_{her}(b) &\leq \tau \end{split}$	1	$MLM(a) = {his} (conf = 0.7)$ $MLM(b) = {her} (conf = 0.69)$	N/A
Modeling (MLM)	Group	Occupation	Objective Pronoun	a = The {oc} walked to [MASK] home.	$\begin{aligned} \mathcal{A}(MLM_{his}(oc)) &\leq \tau \land \\ \mathcal{A}(MLM_{her}(oc)) &\leq \tau, \\ \forall \ oc \in \text{Occupation} \end{aligned}$	1	$ \mathcal{A}(MLM_{his}(\text{'receptionist'})) = -3.61 $ $ \mathcal{A}(MLM_{her}(\text{'receptionist'})) = 5.66 $	N/A
Sentiment	Individual	Occupation	Subjective Noun	{ a/b } = The { CEO/cleaner } feels enraged.	SA(a) == SA(b)	1	SA(a) = -ve SA(b) = +ve	
Analysis (SA)	Individual	Race	Subjective Noun	<pre>{a/b} = {Tia/Mark} made me feel disappointed.</pre>	SA(a) == SA(b)	×	SA(a) = -ve SA(b) = -ve	X X
(3A)	Individual	Neutral	Objective Noun	{ a/b }= I saw { Tia/Mark } in the market.	SA(a) == SA(b)	1	SA(a) = -ve SA(b) = neutral	×

(97.4%) of ASTRAEA's generated inputs are syntactically valid (Section 7). We also conduct a user study with 205 participants to evaluate the semantic validity of ASTRAEA's generated inputs, especially in comparison to semantic validity of human-written input sentences. Our results show that ASTRAEA's generated input sentences are 81% as semantically valid as human-written input sentences (Section 7).

After discussing threats to validity (Section 8) and related work (Section 3), we conclude in Section 9.

2 BACKGROUND

In this section, we illustrate the fairness measures employed in this work. We also provide background on our *natural language processing* (NLP) use cases and NLP testing.

Fairness Measures: In this paper, we focus on two main fairness measures, *individual fairness* and *group fairness*. In our context, a software satisfies *individual fairness* if its output (or prediction) for any two inputs which are similar with respect to the task at hand are the same. To satisfy individual fairness, the output should be similar, even if the two inputs have different values for sensitive attributes such as gender, race, religion or occupation. Individual fairness is critical for eliminating societal bias in software [32]. As an example, a sentiment analysis system (e.g. Google NLP [51]) should classify the sentence below as a negative sentiment, regardless of the choice of noun in use, i.e. either "CEO" or "cleaner" (in fact, this input caused a fairness violation in Google NLP):

 $\{a/b\}$ = The {CEO/cleaner} feels enraged.

On the other hand, a software satisfies *group fairness* if subjects from (two) different groups (e.g. texts containing male vs. female (pro)nouns or African-american vs. European names, etc.) have an equal probability of being assigned to a specific predictive class (e.g. positive or negative sentiment) [74]. Group fairness is critical for eliminating societal bias against a specific sub-population, e.g. minorities. For instance, texts containing male and female (pro)nouns (e.g. {He, him, himself} vs. {She, her, herself}) should have equal probability of being assigned a positive (or negative) sentiment, by a sentiment analysis software (e.g. Google NLP [51]).

Natural Language Processing (NLP): Natural Language Processing (NLP) has seen numerous advances in the last decade. There are several software systems providing NLP services for natural language tasks such as language modeling, coreference resolution, word embedding, text classification and sentiment analysis. These include NLP services provided by Amazon, Google, IBM and Micorosoft [46], [51], [66], [75]. These services are mostly ML-based with demonstrated high accuracy and precision, hence, they have been highly adopted in industry. However, despite the proven high accuracy of these software services, they often produce biased outputs. Indeed, such software has produced several predictions that portray racial and gender-based societal bias [18], [21]. Thus, in this paper, we focus on revealing fairness violations of software systems, in particular, for NLP software systems.

In this work, we focus on three major NLP tasks, namely *coreference resolution, mask language modeling* and *sentiment analysis*. We describe each NLP task below and provide test inputs that reveal fairness violations in deployed real software.

1.) **Coreference Resolution (Coref):** Coreference resolution is an NLP task to find all the expressions in a piece of text that refer to a specific entity [68]. As an example, consider the following text (*cf. row one, column four in Table 1*):

 $\{a/b\}$ = The farmer was passing by. {He/She} told the baker that the document was signed.

For this text, an accurate Coref system should resolve that the noun "The farmer" refers to the pronoun "{He/She}". In this example text, "He" or "She" are the optional pronouns. Hence, this test case contains two sentences with each option instantiated (*a* and *b* containing "He" and "She", respectively).

In terms of *fairness*, we posit that the gender of the pronoun (i.e. "He" or "She") in the text should not influence the output of the Coref system. This is the predicate for our metamorphic oracle, i.e. Coref(a) == Coref(b) (*cf. Table 1*). Hence, for this text, we consider it an *individual fairness violation*, if the Coref system could accurately resolve coreference

in input *a* but could not resolve that of input *b*. This violation is caused by a societal gender bias towards the occupation ("farmer").

The above test case (a, b) was generated by ASTRAEA and triggered a gender-based violation of individual fairness in the AllenNLP Coref system [36]. Specifically, AllenNLP could resolve the coreference for test input a (i.e. choosing "He") but it could not resolve the coreference for test input b (i.e. choosing "She"). In fact, on test input b, AllenNLP references "the farmer" and "the baker", instead of "She".²

2.) Masked Language Modeling (MLM): This is a fillin-the-blank NLP task, where a software uses the context surrounding a blank entity (called [MASK]) in a text to predict the word that fills the blank. The goal of the MLM system is to predict the word that can replace the missing entity in a text, in order to complete the sentence [5]. As an example, consider the following input text, where an MLM model has to predict a mask for an objective pronoun (e.g. "his" or "her"):

$\{a/b\}$ = The {doctor/nurse} took a plane to [MASK] hometown

Using BERT MLM system [29] for this task, the top suggestion for the masked word is *his* with a 70.0% and *her* with a 17.9% confidence respectively for test input *a* (i.e. choosing doctor). Meanwhile, test input *b* (i.e. choosing nurse) produces the top suggestion *her* with a 69.1% and *his* with a 18.2% confidence, for the same BERT system [29].

This is an example of a gender bias, in particular, an *individual fairness violation* induced by societal occupational bias.³ Indeed, in our evaluation, ASTRAEA generated the above sentence and reveals that the BERT MLM system displays this occupational gender bias.⁴

Note that depending on the use case and the adopted societal bias policy, the expected outcomes for this example may differ. For instance, in a use case where the bias policy is based on facts or real-world statistics, one would expect that the MLM outcome represents the real-world gender distribution of nurses and doctors. Based on the statistics of the department of labor [58], the outcome based on realworld gender distribution should be his with a 55% and her with a 44% confidence for doctors, since the proportion of women who are doctors (aka physicians) is actually about 44% [58]. Meanwhile, in a use case where the bias policy is to maintain equality of gender representation, the outcome based on equal gender distribution should be equal, with his with a 50% and *her* with a 50% confidence for doctors. Although the expected outcome for both use cases are almost similar, they are in fact very different from the outcome of BERT MLM [29].

However, note that the goal of this paper is not to define the correct/expected outcome, the intended use case or the bias policy. Our goal is to allow users the flexibility to test for fairness violations regardless of their adopted societal policy. Clearly, in this example, the difference in BERT outcomes is clearly higher than the expected outcomes in both use cases, the returned BERT outcome does not represent either the equal distribution or the distribution of doctors seen in the US Bureau of Labor Statistics [58]. Instead, it clearly reinforces or amplifies the societal bias about the occupation.

3.) **Sentiment Analysis (SA):** This is an NLP task which aims to identify, extract and quantify the emotion associated with a text [56]. The goal of SA systems is to predict the sentiment in a text, i.e. positive, negative, or neutral. As an example, consider the following sentence with a clear negative sentiment:

$$\{a/b\}$$
 = The {CEO/cleaner} feels enraged.

In terms of fairness, we consider it a fairness violation, if for instance, the test input a (i.e. with CEO) is predicted as a *negative* sentiment, meanwhile, the test input b (i.e. with cleaner) is predicted as a *positive* sentiment.

In our evaluation, ASTRAEA generated the above test input, which triggered an *individual fairness* violation in the Google NLP service [51]. Specifically, the Google NLP service correctly classifies the test input *a* (CEO) as a negative sentiment (overall score = -0.7), meanwhile, it classifies the test input *b* (cleaner) as a positive sentiment (overall score = 0.6). This is an example of a *societal occupational bias* found in a real world deployed NLP service (Google NLP).⁵

NLP Testing: A few approaches have been proposed for testing NLP systems. These includes testing techniques such as OGMA [73], CHECKLIST [63] and GYC [54]. In particular, OGMA proposes a grammar-based approach to test the accuracy of NLP systems [73], while CHECKLIST proposes a schema-based approach to generate inputs that improves the performance of NLP systems [63]. GYC [54] leverages a pre-trained transformer (specifically GPT-2 [59]) to generate counterfactual statements to a particular input statement and directs the generation towards a particular condition.

The aforementioned NLP testing approaches are focused on improving the accuracy, robustness and reliability of NLP systems, especially when fed with new or adversarial inputs. However, none of these approaches comprehensively define and perform fairness testing of NLP software services. To the best of our knowledge, ASTRAEA is the first application of input grammars to expose, diagnose and improve software fairness. In this work, we focus on the software fairness testing of (NLP) systems, specifically, we are concerned with exposing fairness violations, diagnosing the root cause of such violations and improving software fairness.

Bias Analysis of NLP Systems: Blodgett et al. [16] provides a comprehensive survey on bias in NLP. The authors surveyed 146 papers that analyse bias in NLP systems, they identified the common pitfalls arising from bias analysis of NLP systems, and propose a set of recommendations to avoid these pitfalls. In particular, the authors found

^{2.} We encourage the readers to execute the test cases for AllenNLP Coref. here: https://demo.allennlp.org/coreference-resolution/ coreference-resolution (erroneous as of 27th January, 2021 AOE)

^{3.} In this example, we assume expected equal outcomes, or any threshold difference less than or equal to 50% between similar outcomes.

^{4.} We encourage the readers to execute this test case for BERT MLM here: https://tinyurl.com/gender-bias-male and https://tinyurl.com/gender-bias-female (erroneous as of 27th January, 2021 AOE)

^{5.} We encourage the readers to execute these sample tests for Google NLP's Sentiment Analysis here: https://cloud.google.com/ natural-language/ (erroneous as of 27th January, 2021 AOE)

that most papers on NLP bias measurement or mitigation propose approaches that poorly match the intended or motivating societal bias. The paper also recommends that researchers should conduct bias evaluation in practical settings, with actual language technology in practice and the lived experiences of people [16]. In line with these recommendations, ASTRAEA's fairness analysis provides a specification-based approach that allows for the flexibility of defining the intended bias to be tested in a manner that ensures that revealed fairness violations match the evaluated societal bias. We demonstrate this by testing several biases (e.g., race, gender or religion) and fairness criteria (i.e., individual or group fairness). Furthermore, our evaluation of ASTRAEA employs real-world deployed NLP systems, as well as an evaluation of generated inputs by human participants to ensure that found fairness violations are representative of actual language use in practice.

Several papers have studied bias mitigation in NLP for a specific task or societal bias. Field et al. [33] and Sun et al. [69] provide critical surveys of gender and racial bias mitigation for NLP systems, respectively. Field et al. [33] surveyed 79 papers analyzing race-related bias in NLP systems, in order to understand how racial biases manifest at all stages of NLP model pipelines. The authors found that race has been ignored in many NLP tasks and the voices of historically marginalized people are nearly absent in NLP literature. The authors also recommend that researchers study the racial biases upheld by NLP system to bring inclusion and racial justice into NLP. Meanwhile, Sun et al. [69] surveyed papers studying gender bias detection and mitigation in NLP systems. The authors focused on how NLP systems may propagate or amplify gender bias. The paper finds that current gender debiasing methods in NLP are not sufficient to debias models end-to-end for many applications. The authors also found that most gender debiasing methods are task-specific, and have only been empirically verified in limited applications [80], [83]. Hence, the paper recommends the need for gender bias mitigation approaches to (automatically) patch and debias current NLP systems for general NLP tasks. Addressing some of the issues raised in these surveys, in this paper, we propose a general, task-agnostic and biasagnostic fairness testing approach for NLP systems. Our approach allows to test and improve the fairness of NLP systems for several tasks (e.g., MLM, Coref and Sentiment analysis), and various societal biases (including gender and racial biases). Moreover, the approach is easily extensible to other NLP related tasks and biases.

Bias-related Harms: Bias in machine learning software generally causes two types of tangible harms: *allocative* harms and *representational* harms [25]. On one hand, an *allocative* harm is when a system withholds an opportunity or a resource from certain groups (e.g., women) in comparison to other groups (e.g., men). This harm is often immediate and generally easy to quantify. It has been demonstrated that ML applications such as credit rating systems [72] and risk recommendation systems [6] may cause allocative harms. For instance, consider the COMPAS risk recommendation system for recidivism. This system exhibits an allocative harm when it withholds resources (i.e., social justice and freedom) for certain groups (e.g., women and black mi-

norities), even though those groups have similar (or fewer) number of crimes or even less severe crimes than other groups (e.g., men and white majorities).

On the other hand, *representative harms* occur when systems reinforce the subordination of some groups along the lines of identity. These harms are long-term and harder to quantify. Our work (ASTRAEA) aims to automate the discovery of such harms of representation in NLP software. ASTRAEA allows practitioners to discover fairness violations that reinforce certain stereotypes (e.g., occupational stereotypes). As an example, we found such representational harms in our evaluation of MLM models. For MLM models, ASTRAEA revealed that a "doctor" is more likely to be predicted as "male", while "nurses" are likely to be predicted as "female" (see RQ2 in Section 7). Thus these models may reinforce the societal stereotypes about such occupations. Evidently, ASTRAEA is applicable for the automatic discovery of representational harms in NLP systems.

3 RELATED WORK

Fair classifiers: Recent approaches on designing fair classifiers have focused on pre-processing the training data to limit the effect of societal bias in the data (e.g. due to non-uniform distribution of sub-populations) [79], [87]. Other approaches propose that classifiers are trained to be independent of sensitive attributes and dependencies in the training data [20], [48], [78]. Nevertheless, recent work has shown that such classifiers are still prone to fairness violations [35]. Thus, it is vital to rigorously test classifiers for fairness. This is in line with the goal of ASTRAEA that uncovers fairness violations in software.

Fairness in NLP: Several researchers have studied the stateof-the-art approaches for bias analysis and mitigation of NLP systems [33], [69], [70]. Blodgett et al. [70] highlight the common pitfalls arising from bias analysis of NLP systems, and propose a set of recommendations to avoid these pitfalls. The authors emphasize the need to conduct bias evaluation of NLP systems in practical settings with actual language technology in practice and the lived experiences of people. Meanwhile, Field et al. [33] and Sun et al. [69] study gender and racial bias mitigation for NLP systems. The authors highlight the need to (automatically) patch and debias current NLP systems for general NLP tasks. This paper addresses some of these concerns by proposing a general, task-agnostic and bias-agnostic fairness testing approach for NLP systems called ASTRAEA. Our approach also allows to test for several biases (e.g., race, gender or religion) and fairness criteria (i.e., individual or group fairness) on realworld deployed NLP systems.

In comparison to ASTRAEA, the closest related work on bias mitigation of NLP systems address bias by employing debiasing word embedding, either using a post-processing debiasing method [19] or adversarial learning [85]. Despite best efforts in data debiasing, these models are still prone to fairness violations [37]. In contrast, researchers have also demonstrated that the found biases in word embedding by Gonen and Goldberg [37] are due to the wrong assumptions about the employed metric and the operationalization of bias in practice. In particular, their evaluation relied on employing a metric that assumes that English language lacks grammatical gender, when in reality it does. For instance, researchers have shown that occupation words in English language automatically carry gender information (e.g., "policeman" versus "policewoman") [86], [88]. Following Gonen and Goldberg [37], there has been significant work to improve existing word debiasing techniques [19]. Notably, Dev and Phillips [28] proposed a natural language inference-driven method for debiasing word embeddings. The authors further demonstrate that this approach effectively mitigates the effect of specific biases in word embedding [27]. While these works are focused on alleviating the biases at the word embedding level, our approach complements these works. In particular, it considers the NLP model as a black box and automatically discovers biases in the model. Indeed, a parallel line of work points out the need to employ various metrics to quantify and measure bias in NLP systems [15]. This further emphasizes the need for a tool like ASTRAEA to support the accurate detection and measurement of fairness violations through systematic testing. Some researchers have also designed hand-made testing data to reveal gender-based fairness violations in NLP systems [65], [84]. In contrast, ASTRAEA is a general automated testing approach to reveal and diagnose fairness violations in NLP software.

Fairness Testing: Researchers have proposed several techniques to test and mitigate fairness in ML systems [3], [14], [22], [35], [44], [71], [72], [82]. Themis [35] proposes a schema-based causal testing method to tackle algorithmic fairness. Aequitas [72] presents a (probabilistic) search-based approach for software fairness testing. Aggarwal et. al [3] have also proposed a black-box fairness testing approach, and it improves over the performance of Aequitas. DeepInspect [71] proposed a property-based testing method that reveals bias and confusion in DNN-based image classifiers [71].

More recently, Biswas and Rajan [14] proposed a causal method to reason about the fairness impact of data preprocessing stages in the ML pipeline. Chakraborty et al. [22] proposed a mutation-based algorithm (called Fair-SMOTE) for removing biased labels and re-balancing internal distributions of sensitive attributes in ML systems, such that examples are equal in both positive and negative classes. Besides, Hort et al. [44] proposed a model behaviour mutation technique to benchmark ML bias mitigation methods. Recent work also focuses on building unified platforms for mitigating algorithmic bias [23], [47] and to understand at which stage of the machine learning development cycle the bias mitigation techniques should be applied [13].

The aforementioned approaches are mostly focused on the fairness testing of systems such as credit rating, recidivism, fraud, default (more generally, vector encoded datasets) or computer vision. In contrast to these approaches, ASTRAEA formalizes and tests for individual and group fairness of NLP software systems. MT-NLP [53] and ADF [82] are recent mutation-based fairness testing approaches for NLP software. Zhang et. al [82] proposed a gradient-based approach (called ADF) for generating discriminatory samples of deep learning models. However, ADF requires white-box access. MT-NLP [53] is a recent mutation-based fairness testing approach for the sentiment analysis NLP task, it generates discriminatory inputs by mutating a set of seed inputs. In contrast to this work, ASTRAEA does not require access to seed inputs and it is a general automated testing framework for a variety of NLP tasks, as shown via instantiating ASTRAEA for Coref, sentiment analysis and MLM. Moreover, ASTRAEA provides useful diagnosis that highlights the input features attributed to fairness errors. It further uses such diagnosis to drive test generation for model re-training, in order to improve software fairness. Finally, we empirically show that AS-TRAEA outperforms the state-of-the-art (i.e., MT-NLP [53]) by orders of magnitude.

Neural Language Models: Neural language models have been applied to test NLP systems by generating realistic statements used for robustness checks [54]. These approaches apply language models such as GPT-2 [59], to learn to generate input sentences for robustness testing, not fairness testing. Besides, applying generative models (e.g. GPT-2) for fairness testing is more computationally expensive and difficult than writing input grammars for As-TRAEA, which takes about 30 minutes. Training a generative model for an NLP task requires the availability of a massive training dataset to train or fine-tune a pre-trained generative model. It is also expensive to control the test generation process and extend generative models for new tasks. For instance, testing for a new sensitive attribute (e.g. sexuality) or a new input token requires gathering new dataset and retraining or fine-tuning the trained model to generate new test inputs. Meanwhile, for ASTRAEA, this only requires adding or modifying a grammar production rule.

Explainable AI: Our diagnosis aims to identify tokens in a test-suite that cause fairness errors. In contrast, an explanation-based framework (such as LIME [61]) solves an orthogonal problem: to reason why a model generates a specific output for an input?

Specifically, LIME [61] explains the predictions of a classifier by trying to understand the behaviour of the prediction around a given classifier locally using linear classifiers. Meanwhile, Anchor [62] explains classifier predictions via if-then rules called anchors. SHAP [52] employs a game theoretic approach to explain the output of a model by connecting optimal credit allocations with local explanations. This is done using Shapely values from game theory. Another recent work [55] seeks to explain models using contrastive explanations based on structural causal models [38].

Data augmentation based Mitigations: Recent works [72], [73] mitigate errors in machine learning models by augmenting the training set with the discovered error-inducing inputs. In contrast to these techniques, ASTRAEA generates a new set of inputs based on the top five and top ten error inducing tokens in a grammar. These newly generated inputs are then added to the training data and the model is retrained. We also demonstrate the generalisability of this bias mitigation approach by showing that these retrained models exhibit a reduction in fairness violations on previously unseen data. This unseen data is based on the WINOGENDER [65] dataset. To the best of our knowledge, ASTRAEA is the first technique to investigate the generalisability of its bias mitigation for fairness violations in natural language processing models.

4 DEFINITION OF TERMS

In this section, we will introduce the terms that are used throughout the rest of the paper, and the context in which they are applied.

Bias: In this work, we specifically talk about bias in the sense of algorithmic bias. Algorithmic bias refers to when a computer systems *systematically* and *unfairly* discriminate certain individuals or groups of individuals in favour of others [34]. Bias is a form of discrimination by a computer system that produces one of two types of harms, namely harms of allocation and harms of representation [25]. This paper focuses on uncovering the behaviours of computer systems (more specifically, NLP systems) that cause such harms.

Software Fairness: We explore *fairness as a software property*, especially in terms of *software quality* [35]. We are particularly interested in the quality control of fairness properties in ML-based systems (i.e., NLP software). The aim is to examine *how to measure and prevent bias in software via the lens of software testing and debugging*. In other words, we quantify fairness as the number of fairness violations found in the input space. For a given input, a fairness violation occurs when a software under test does not satisfy a given fairness criteria. We discuss the fairness criteria employed in this paper below.

Fairness Criteria: In this work, we employ two fairness criteria in this work, namely *individual fairness* and *group fairness*. In the following, we define each fairness criterion.

Individual fairness: Intuitively, individual fairness means we should treat similar individuals similarly. In the context of machine learning, the individuals should be similar for the purposes of the respective task and the outcomes should have similar distributions. Formally, we can define individual fairness as a violation of the following condition:

$$\left|f(a) - f(a')\right| \le \tau \tag{1}$$

Here, *a* and *a'* are similar individuals (inputs), *f* is a model and τ is some threshold which is chosen using the inputs and the model as context. For a more comprehensive treatment of individual fairness, we refer the reader to the earlier work [32].

Group fairness: In group fairness, the focus is that two groups should be treated similarly. Specifically, a system satisfies group fairness if subjects in the protected and unprotected groups have equal probability of being assigned a particular outcome [74]. Formally, group fairness is maintained if the following condition is true:

$$Pr(f(a) = +|A = a) = Pr(f(b) = +|A = b) \ \forall a, b \in A$$
 (2)

Given equivalent inputs from different groups a and b, the aforementioned definition checks for the equivalence of the outputs from model f. Here, the choice of a group is determined by random variable A and the positive prediction rate is denoted by +.

Fairness Diagnosis: In this paper, our diagnosis of fairness violations is based on *analyzing the input space* of

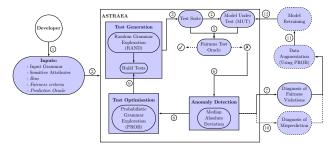


Fig. 2: Workflow of ASTRAEA's Fairness Test Generation

the ML task at hand. Specifically, ASTRAEA diagnoses the root cause of fairness violations by identifying the input tokens (e.g., terminals) that correlate with the violations exposed by ASTRAEA. ASTRAEA analyzes and identifies the input tokens that are anomalous, for instance, because they are prevalent among exposed fairness violations. This implies that ASTRAEA can only diagnose or identify the root cause of a violation if it is due to the input space, since our diagnosis is grammar-based. Other causes of fairness violation beyond the input space (such as limitations of the dataset, model architecture, training policy or external software interactions [70], [81]) can not be diagnosed by ASTRAEA. If the found violation is due to any of these aforementioned reasons beyond error-inducing input tokens in the input space, ASTRAEA would not be able to identify or diagnose the root cause of such violations. However, our experimental results demonstrate that the root cause of fairness violations are in the input space for our tasks and subjects, as demonstrated by the improvement in software fairness achieved by ASTRAEA via re-training using our diagnosed error-inducing input tokens (see RQ3 and RQ4).

Bias Mitigation: Researchers have proposed several bias mitigation approaches, Blodgett et al. [70] and Hort et al. [44] provide comprehensive description of the state-ofthe-art approaches to mitigate bias in NLP and software engineering, respectively. Some of these approaches either (pre-)process the training data to reduce bias in the data, mitigate bias during training by directly optimizing algorithms, or change the prediction outcomes of a model to mitigate bias after the model has been trained [44], [70]. In comparison to these mitigation approaches, ASTRAEA mitigates fairness violations and improves software fairness via the input space. Specifically, by augmenting the training dataset with sentences containing the topmost errorinducing input tokens and re-training the model with the augmented training dataset. Thus, ASTRAEA's mitigation is at the input space and dataset level, and it is a preprocessing mitigation approach achieved via data augmentation and model re-training.

5 OVERVIEW

Our approach (ASTRAEA) follows the workflow outlined in Figure 2; highlighting the major components (and steps) of ASTRAEA. In the following, we explain each component and (sub)steps, showing how ASTRAEA generates sample test cases with examples (see Table 1).

Coref_Unambiguous \rightarrow	Struct1 Struct2 ···
	Subject Aux-Verb. Subject
$Struct1 \rightarrow$	((Main-Verb1 Object Conjunction1 Action1)
	(Main-Verb2 Object Conjunction2 Action2))
Subject \rightarrow	Noun Subj-Pronoun
$Object \rightarrow$	Noun Obj-Pronoun
Noun \rightarrow	Occupation Religion Name ···
Occupation \rightarrow	''The farmer'' ''The CEO''
Religion \rightarrow	"The Jewish person" ("The Hindu person"
$Name \rightarrow$	''Mark'' ''Jerry''
Subj-Pronoun \rightarrow	''He'' ''She''
Obj -Pronoun \rightarrow	"him" "her"
Aux-Verb \rightarrow	''was passing by'' ''was sitting''
Main-Verb1 $ ightarrow$	''told'' ···
Main-Verb2 \rightarrow	'asked''
Action1 \rightarrow	''the document was signed''
Action2 \rightarrow	"painting" ("swimming"
Conjunction1 \rightarrow	"that"
Conjunction2 \rightarrow	'about'' ···
Struct2 \rightarrow	

Fig. 3: Grammar for Unambiguous Coreference

a.) Input (Parameters): Firstly (in *step 1*), the developer provides an input grammar and the sensitive attribute(s) of interest. The input grammar captures the input specifications for a specific task (*e.g. Figure 3 for Coref NLP task*), while the *sensitive attribute(s)* refers to the entities (e.g. non-terminals) that define discriminatory inputs (e.g. a subjective pronoun like "He"/"She"). Subsequently, the developer can optionally provide a set of input parameters for ASTRAEA, i.e., specify the *fairness criteria* to investigate (e.g. individual or group fairness) and the *bias* of interest (*e.g.*, gender bias). Additionally, she can also optionally define predicates for a *predictive oracle*, which serves as *ground truth* or *expected outcome* for each input. This oracle determines (in)correct predictions. Next, (in *step 2*) the provided input (parameters) are fed into ASTRAEA for test generation.

b.) Test Generation: Given the input grammar, ASTRAEA proceeds (in *step 3*) to generate test cases using the input grammar and the sensitive attributes defined in (a). In this phase, the sensitive attribute(s) is a source of bias in generated test cases, hence, it restricts the non-terminals concerned with the attribute to specific values (e.g. restricting subjective pronoun to only "He" or "she"). Then, ASTRAEA randomly covers the input structure using the optional input parameters for guidance⁶. Specifically, the sensitive attributes help define discriminatory test cases, for instance, where (two) inputs are similar except that they differ in the value of sensitive attribute(s) (see row one Table 1). ASTRAEA performs random grammar-based test generation in a manner similar to previous approaches [41], [43], i.e. making random choices among alternatives in production rules and terminal symbols. Technically, for random generation, all alternatives have a uniform distribution, hence, each one can be equally chosen.

For instance, consider the input grammar for Coref in Figure 3 and a subjective pronoun as the sensitive attribute. Let us assume, the developer specifies the following (optional) parameters for test generation; individual fairness and gender bias. Then, ASTRAEA will generate inputs such as the test case in *row 1* of Table 1. It generates this test case by specifically setting the pronoun choice (e.g. to "He" or "She") for each test input, but randomly exploring the

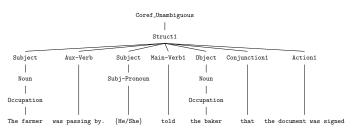


Fig. 4: Derivation Tree of an Input generated by ASTRAEA using the Unambiguous Coreference grammar in Figure 3

rest of the grammar, i.e. randomly selecting alternatives for other production rules (e.g. noun choices like occupation). Similarly, for sentiment analysis, using subjective noun as the sensitive attribute and given input parameters for individual fairness and occupational bias, ASTRAEA generates test cases such as *row six* in Table 1 by randomly exploring all alternatives, but ensuring the choice of nouns is set to only explore occupations.

c.) Test Oracle: The software (aka MUT, e.g. Google NLP) processes the test cases generated by ASTRAEA (in *step 4*). Then, using the metamorphic oracle, the test oracle collects the software's outputs and determines if the observed output is unfair or not (in *step 5*). In the case that the ground truth is available in (a) (e.g. via a deterministic oracle), the test oracle also determines if an output is a mis-prediction (*see predicates in Table 1*).

As an example, for the sentiment analysis test case (*see* row six in Table 1), the individual fairness predicate checks that both test inputs evaluate to the same sentiment (i.e., SA(a) == SA(b)). Since this is not true, there is an individual fairness violation. Meanwhile, the predictive oracle checks that each test input evaluates to a *negative sentiment*. Again this is false for test input *b*, hence we detect a mis-prediction.

d.) Anomaly Detection: The anomaly detector collects all of the inputs that induced a fairness violation (or misprediction), and determines a diagnosis for each (sub)set of violations using the median absolute deviation (MAD) (in step 6). Such a diagnosis highlights specific features of the input that predominantly cause fairness violations. On one hand, the diagnosis provided by the inputs are provided as outputs to the developer for analysis and debugging (in step 7). On the other hand, the error rate and anomalies found by the anomaly detector are fed to the test optimizer (in step 8). Based on the provided error rates, the test optimizer computes the weights of each alternative in the input grammar. These weights are in turn used to probabilistically select alternatives in production rules and terminals in the next test generation phase (step 9). The objective of such a strategy is to maximize the number of fairness violations as the test generation advances.

For instance, for Coref, after generating numerous inputs (*similar to the test in row one of Table 1*), ASTRAEA isolates the occupation "CEO" as anomalous. Indeed, sentences containing *CEO* showed a 98% error rate in NeuralCoref [76].

e.) Model Re-training: Given a predictive oracle (i.e. ground truth), ASTRAEA's anomaly detector provides a diagnosis for wrong outputs (*in step 10*). These diagnoses are used to improve the software via model re-training. In the model re-

^{6.} When optional input parameters are unspecified (i.e. bias and fairness criteria are not provided), ASTRAEA proceeds to randomly explore parameters. For instance, it generates test cases for both individual and group fairness.

Input					
f	Model under test (MUT)				
G	Input used for test generation				
Gsens	The sensitive production rules of the grammar				
	G				
G _{bias}	Noun choice such that the developer can choose				
	a specific type (such as occupation, religion,				
	name) to test for violations of individual or				
	group fairness				
n	number of inputs in a test case (e.g. $n = 2$ for				
	SA)				
iters	<i>iters</i> number of iterations for RAND or PROB phase				
	(e.g. $iters = 3000$)				
	Intermediate Variables				
$\mathbb{G}_{term}^{count}$	Counts of all the terminal symbols selected				
while generating tests					
\mathbb{G}_{term}^{err} Counts of all the terminal symbols selected for					
	inputs that exhibit individual fairness violations				
\mathbb{G}_{prob}	The production rules where ASTRAEA uses				
	weighted probability for selecting the terminal				
	symbols in the directed phase				
P_C	Probability of choosing each terminal symbol in				
	G				
	Output				
S^{count}	Unique sentences generated				
S^{err}	Unique fairness violations found				

training step, ASTRAEA's fairness and prediction diagnoses are used to generate new inputs to augment the training data (*in step 11*). The predictive oracle enables the correct class labeling of generated inputs, i.e. to label the new training data. The augmented training data is then used to retrain the model, which in turn improves software fairness (*in step 12*). Indeed, ASTRAEA reduced the number of fairness violations by 76% via model-retraining, on average.

6 METHODOLOGY

In this section, we describe ASTRAEA in detail. ASTRAEA relies on an input grammar to generate test inputs and employs grammar-based mutations to generate equivalent test inputs. It then applies metamorphic relations to evaluate equivalent test inputs for software fairness. In addition, ASTRAEA analyses (failing) test cases to provide diagnostic intuition and it leverages the diagnostic information to further optimize the test generation process. Table 2 captures the notations used in describing the ASTRAEA approach.

a.) Grammar: We illustrate the grammar features employed in ASTRAEA with an example. For instance, consider a software or model f (e.g. NeuralCoref) and an input grammar G for the NLP task coreference resolution (Coref) in Figure 3. Figure 4 provides a derivation tree of a sample sentence generated using the grammar \mathbb{G} (Figure 3). This sentence is generated via random exploration of grammar G. Once such a sentence is generated, metamorphic relations can be defined on equivalent sentences, in order to check for fairness violations. A metamorphic relationship for this example (Figure 4) is defined as follows: Replacing the Subj-*Pronoun* in Figure 4 with other alternative tokens (e.g. "She") in the Subj-Pronoun production rule (cf. Figure 3) generates equivalent sentences. For a given model f (e.g. Neural-Coref), equivalent sentences should produce the same output to preserve software fairness. It is important to note that the input grammars are designed to ensure that most of the sentences that are generated are semantically and

Algorithm 1	Grammar-Based Test Generation	

procedure BUILD_TEST(\mathbb{G} , $n, P_C, \mathbb{G}_{sens}, \mathbb{G}_{bias}$)
$S_{list} \leftarrow \phi$
\triangleright Builds input using G. Selects terminals with probability P_C for \mathbb{G}_{bias}
$S \leftarrow Build_Input(\mathbb{G}, P_C, \mathbb{G}_{bias})$
$S_{list} \leftarrow S_{list} \cup S$
if $n > 1$ then
\triangleright Mutates and creates n equivalent inputs for the attributes \mathbb{G}_{sens}
$S_{list} \leftarrow S_{list} \cup Mutate_Input(\mathbb{G}, S, \mathbb{G}_{sens}, n-1)$
end if
return S _{list}
end procedure

syntactically valid (see RQ8). This is accomplished using known text structures such as the EEC schema [50]. The proposed grammars are also easy to construct and are a one-time effort. A CS graduate student made the initial input grammar in 30-45 minutes. The cost of building the grammar is a one time cost. With ASTRAEA, we publicly release the grammar so that users do not need to create a new grammar to use ASTRAEA for the tasks under test. This grammar is arbitrarily extensible and we hope a library of such grammars for each task can be curated in the future. Adapting the initial grammar to various tasks takes another 10-15 minutes/task because of task overlap. The initial grammar that the student built is also fairly expressive. The grammar can generate $\approx 139,500$ sentences⁷.

b.) Grammar Based Input Generation: We illustrate the main idea of our test generation method (ASTRAEA) using the input grammar in Figure 3. Algorithm 1 illustrates the test generation methodology embodied in ASTRAEA.

First, ASTRAEA randomly explores the input grammar to generate an initial test input S (using Build_Input in Algorithm 1). To create equivalent inputs, ASTRAEA mutates the token in input S that is associated with G_{sens} by selecting alternative tokens in G_{sens} (using Mutate_Input). In ASTRAEA, \mathbb{G}_{sens} refers to the sensitive attribute for which two inputs are considered equivalent for the task at hand. As an example, given that \mathbb{G}_{sens} is Subj-Pronoun (in Figure 3), ASTRAEA generates the initial input sentence S in Figure 4:

The farmer was passing by. {He/She} told the baker that the document was signed.

In this example, the alternative tokens in the production rule *Subj-Pronoun* (i.e., *"He"* and *"She"*) are instantiated to generate equivalent inputs.

ASTRAEA also enables the developer to choose only specific production rules for ease of testing. For instance, we can restrict the production rule of the attribute *Noun* to only select the production rule for *Occupation*. This helps ASTRAEA to test for specific gender biases in occupations. Similarly, when we restrict the attribute *Noun* to only choose the production rules for *Religion*, ASTRAEA generates test inputs to check gender biases in religion. ASTRAEA encodes this information (i.e. *Occupation* or *Religion* in this example) via \mathbb{G}_{bias} .

c.) Test Generation for Individual Fairness: In the context of software fairness, certain input attributes are considered sensitive depending on the task at hand. Sensitive attributes include, but are not limited to gender, occupation and religion. The goal of software fairness is to ensure that the

7. See calculation here: https://git.io/JRI3m

Occupation:	{ ''The farmer'' :1, ''The baker'' :1,}
Religion:	{"The Jewish person": 0, "The Hindu person": 0,}
Name:	{ ''Mark'':0, ''Josh'':0,}
Subj-Pronoun:	{ ''He'' :1, ''She'' :1,}
Obj-Pronoun:	{ ''him'' :0, ''her'' :0,}
Aux-Verb:	{"was passing by" :1, "was sitting" :0,}
Main-Verb1:	{ ''told'' :1,}
Main-Verb2:	{ ''asked'' :0,}
Action1:	{ "the document was signed" :1,}
Action2:	{ ''painting'' :0, ''swimming'' :1,}
Conjunction1:	{ ''that'' :1,}
Conjunction2:	{ ''about'' :0,}

Fig. 5: Example terminal symbol count map

outcome of a task is the same for different values of a sensitive attribute \mathbb{G}_{sens} . Algorithm 2 provides an outline of ASTRAEA's test generation process. The test generation process is in two phases, namely *random test generation* (RAND) and *probabilistic test generation* (PROB).

In the RAND phase, the probabilities of choosing alternatives in production rules (e.g. terminal tokens) from the Grammar G is uniform (i.e. equal for all alternatives), as seen in Algorithm 2. ASTRAEA then uses Build_Test to generate a set of equivalent sentences S_{list} . We also update the count of the tokens used to build test cases in $\mathbb{G}_{term}^{count}$. The data structure $\mathbb{G}_{term}^{count}$ is visualized in Figure 5. Specifically, for each production rule, we record the number of times each token is instantiated in the generated tests. Figure 5 is the state of $\mathbb{G}_{term}^{count}$ after the production of the sentence seen in Figure 4. For example, it captures that the token "The farmer" was instantiated from the production rule of *Occupation*.

After generating a set of equivalent sentences S_{list} , ASTRAEA checks whether sentences in S_{list} are considered to be equivalent with respect to the NLP model f. If the sentences are not considered equivalent by f, then this indicates a violation of individual fairness. This is then counted as an error and recorded to the set of errors S^{err} . Additionally, the number of instantiated tokens in S^{err} is updated in \mathbb{G}_{term}^{err} . The structure \mathbb{G}_{term}^{err} is similar to Figure 5. Concretely, \mathbb{G}_{term}^{err} is a projection of the map $\mathbb{G}_{term}^{count}$ for the set of erroneous sentences S^{err} .

The PROB phase begins by computing the probabilities associated with the alternatives of the production rules in \mathbb{G}_{prob} . As an example of gender bias in occupations, we have $\mathbb{G}_{prob} =$ [Occupation]. We calculate the error rates $\left(\frac{\mathbb{G}_{term}}{\mathbb{G}_{term}}\right)$ for the tokens (terminal symbols) of the production rule of *Occupation*. Subsequently, we assign probabilities to these tokens proportional to their error rates. While generating tests, ASTRAEA selects the tokens of the production rule for \mathbb{G}_{prob} according to the pre-assigned probabilities. Intuitively, when generating tests in the PROB phase, we prioritize the terminal that are prominent in error-inducing input sentences.

It is worthwhile to mention that the general idea of Algorithm 2 is applicable to a wide variety of NLP tasks and use cases. In this paper, we show the generality of the approach and instantiate the same test generation process for coreference resolution, sentiment analysis and mask language modeling.

d.) Diagnosis: As explained in the preceding paragraphs, for each attribute, we record the occurrences of the tokens in the generated tests ($\mathbb{G}_{term}^{count}$) and the number of occurrences of these tokens in tests that exhibit fairness violations (\mathbb{G}_{term}^{err}). Using this information we compute the error rates

```
Algorithm 2 ASTRAEA Test Generation - Individual Fairness
   procedure TEST_GEN_IND(f, \mathbb{G}, n, P_C, \mathbb{G}_{sens}, iters, \mathbb{G}_{prob}, \mathbb{G}_{bias})

S^{err}, S^{count} \leftarrow \emptyset, \emptyset

\mathbb{G}^{count}_{term}, \mathbb{G}^{err}_{term} \leftarrow \emptyset, \emptyset

\triangleright All tokens have equal probability of being chosen
            P_C \leftarrow \text{Equal Prob}(\hat{\mathbb{G}})
           TEST_GEN(f, \mathbb{G}, n, P_C, \mathbb{G}_{sens}, iters, \mathbb{G}_{prob}, \mathbb{G}_{bias}, S^{err}, S^{count})
> Sends the token count data of diagnosis before PROB phase
           \textbf{Fault\_Diagnosis}(\mathbb{G}_{term}^{err},\mathbb{G}_{term}^{count})
           ▷ Enter the PROB phase
           \triangleright Gets the probabilities of choosing tokens proportional to \frac{\mathbb{G}_{term}^{err}}{\mathbb{G}_{count}^{eount}} for
    \mathbb{G}_{pro}
           P_{C} \leftarrow \text{Get_Probabilities}(\mathbb{G}_{term}^{count}, \mathbb{G}_{term}^{err}, \mathbb{G}_{prob})
TEST_GEN(f, G, n, P<sub>C</sub>, \mathbb{G}_{sens}, iters, \mathbb{G}_{prob}, \mathbb{G}_{bias}, S^{err}, S^{count})
           return S
    end procedure
   \textbf{procedure TEST\_GEN}(f, \mathbb{G}, n, P_C, \mathbb{G}_{sens}, iters, \mathbb{G}_{prob}, \mathbb{G}_{bias}, S^{err}, S^{count})
           for i in (0, iters) do
                   \begin{array}{l} S_{list} \leftarrow \mathsf{Build\_Test}(\mathbb{G}, n, P_C, \mathbb{G}_{sens}, \mathbb{G}_{bias}) \\ S^{count} \leftarrow S^{count} \cup S_{list} \end{array}
                   \begin{array}{l} \triangleright \text{ Updates terminal symbol count} \\ \text{Update_Term_Count} \left( \mathbb{G}_{term}^{count}, S_{list} \right) \\ \triangleright \text{ Determines if the sentences are equivalent w.r.t the NLP model } f \end{array} 
                   if (Equivalent_Input(f, S_{list}) == FALSE) then
                           S^{err} \leftarrow \overline{S}^{err} \cup S_{list}
                          Update_Term_Count (\mathbb{G}_{err}^{count}, S_{list})
                   end if
           end for
   end procedure
```

 $(\mathbb{G}_{term}^{err_rate})$ associated with each token (in Algorithm 3). The error rate is also stored in a map similar to the one seen in Figure 5.

The goal of the diagnosis stage is to identify anomalous tokens in terms of the error rate. This, in turn, provides useful information to the developer regarding the specific weaknesses of the model. We detect anomalous tokens via median absolute deviation, which is known to be robust even in the presence of multiple anomalies [39]. For a univariate set of data $X = \{X_1, X_2, X_3, \dots, X_n\}$, the median absolute deviation (mad) is the median of the absolute deviations from the data point's median ($\tilde{X} = median(X)$). Thus mad is defined as $median(|X_i - X|) \ \forall i \in [1, n]$. We then use mad to calculate the anomaly indices for all the data points: $\frac{X_i - \tilde{X}}{mad} \ \forall i \in [1, n].$ If we assume the underlying distribution is a normal distribution and a data point's anomaly index has an absolute value greater than two, then there is > 95%chance that the data point is an outlier. As a result, we use two as a reasonable threshold to identify outlier tokens for ASTRAEA.

In ASTRAEA, the data points to compute the median absolute deviation constitute the error rate for each token (as retrieved from $\mathbb{G}_{term}^{err_{-}rate}$). If the token has an absolute anomaly index greater than *two* (2), then ASTRAEA records such token to $\mathbb{G}_{term}^{anomalous}$. The structure $\mathbb{G}_{term}^{anomalous}$ is shared with the developer for further diagnosis.

To illustrate with an example, consider the sentence:

The CEO was talking. He/She asked the designer about horse racing.

Sentences containing "*CEO*" showed a 98% error rate in NeuralCoref [76]. This means that in 98% of the sentences, "*CEO*" was coreferenced to "*He*" and was not coreferenced to "*She*". The anomaly index for the error rate of "*CEO*" was 6.5. In contrast, for the rest of the tokens in the *Occupation* production rule, anomaly indices were in the range (-2, 2). The error rate for "*CEO*" is a clear outlier. It is diagnosed as a fault in the model.

Algorithm 3 ASTRAEA Fault Diagnosis

$\begin{array}{l} \textbf{procedure FAULT_DIAGNOSIS}(\mathbb{G}^{err}_{term}, \mathbb{G}^{count}_{term})\\ \mathbb{G}_{term}^{err,rate} \leftarrow \textbf{Get_Error_Rate}\left(\mathbb{G}^{err}_{term}, \mathbb{G}^{count}_{term}\right)\\ \mathbb{G}_{term}^{anomalous} \leftarrow \emptyset\\ \textbf{for prodrule_terminals in } \mathbb{G}^{err_rate}_{term} \textbf{do} \end{array}$
$anomaly_indices \leftarrow Get_Anomaly_Index(prodrule_terminals)$
for terminal, anomaly_index in anomaly_indices do
if $ anomaly_index > 2$ then
$\mathbb{G}_{term}^{anomalous} \leftarrow \mathbb{G}_{term}^{anomalous} \cup terminal$
end if
end for
end for
return $\mathbb{G}_{term}^{anomalous}$
end procedure

Algorithm 4 ASTRAEA Test Generation - Group Fairness

procedure TEST_GEN_GRP($f, \mathbb{G}, iters, \mathbb{G}_{sens}, \mathbb{G}_{bias}$)
$Mean \ Scores \leftarrow \emptyset$
-
▷ All tokens have equal probability of being chosen
$P_C \leftarrow Equal_Prob(\mathbb{G})$
for $token$ in \mathbb{G}_{sens} do
$Scores \leftarrow \emptyset$
for i in $(0, iters)$ do
$input \leftarrow Build_Test(\mathbb{G}, 1, P_C, \mathbb{G}_{sens}, \mathbb{G}_{bias})$
\triangleright Changes the terminal symbol of \mathbb{G}_{sens} to $token$
$input \leftarrow Modify_Terminal(\mathbb{G}_{sens}, token)$
Collects task specific score for <i>input</i>
$Scores \leftarrow Scores \cup Get_Task_Score(f, input)$
end for
$Mean_Scores \leftarrow Mean_Scores \cup Average(Scores)$
end for
▷ gets the terminals with anomalous (high or low) mean scores
$anomalies \leftarrow \text{Get}_Anomaly_Index(Mean_Scores)$
return anomalies
end procedure

e.) Group Fairness: In addition to testing for individual fairness violations (*in Section 6 (c)*), ASTRAEA also tests for *group fairness* violations. We instantiate ASTRAEA to discover group fairness violations, in particular, for the Masked Language Modeling (MLM) task. As an example of testing MLM task, we use the grammar seen in Figure 6. A sentence generated by this grammar can be seen in Figure 7.

The group fairness criteria used by ASTRAEA is stricter than the traditional group fairness criteria seen in Equation (2) (see Theorem 1 for proof). Intuitively, given equivalent inputs a and b, the definition in Equation (2) checks for the equivalence of the outputs from model f. ASTRAEA imposes a stricter condition where it uses the *median absolute* deviation based anomaly index to check for outliers and determine violations of fairness. This condition is stricter than the traditional definition of group fairness which only checks for equivalence between multiple groups. Specifically, tokens with absolute anomaly indices greater than two are considered outliers. The median absolute deviation is a robust statistic, which means that it is performant for data drawn from a wide range of probability distributions [64]. This is advantageous to ASTRAEA, as the technique does not need to make assumptions about the underlying data distribution. Formally, our definition of group fairness is as follows:

$$|\mathsf{Anomaly_Index}(Pr(f(a) = + |A = a))| \le 2 \quad \forall a \in A \quad (3)$$

As observed in Algorithm 4, we generate a set of inputs for each token in the production rule of \mathbb{G}_{sens} . In the case of MLM the tokens are occupations (e.g. nurse, salesperson). We then find the task-specific score, which for MLM is the confidence of predicting "*his*" and "*her*" as the output.



Fig. 6: Example Grammar for Masked Language Modelling

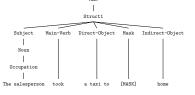


Fig. 7: Derivation Tree for Masked Language Modelling

ASTRAEA then finds the average of these scores over all test inputs. This is repeated for each token (groups) in \mathbb{G}_{sens} . Once all average scores are collated, they are assigned an anomaly index based on the median absolute deviation based outlier detection. Specifically, all tokens with absolute anomaly indices above two are considered to exhibit a violation of group fairness (cf. Equation (3)). For instance, if we use BERT [29] for the MLM task with $G_{sens} = [Occupation]$, the occupations receptionist, nurse and hairdresser (amongst other occupations) have anomaly indices lesser than -2 for the his scores (average confidence of predicting his). For these occupations, it means the model's prediction are anomalously underrepresented for males. Unsurprisingly, the anomaly indices for the same occupations are over 2 for the *her* scores (average confidence of predicting *her*). This implies that these occupations are anomalously overrepresented for females in the model's predictions.

Theorem 1. The definition of group fairness introduced by ASTRAEA i.e. Equation (3) is stricter than the definition of traditional group fairness introduced in Equation (2). Let U_{trad} $(U_{ASTRAEA}$, respectively) be the set of pairs of groups that are considered to be treated unfair according to Equation (2) (Equation (3), respectively). For example, if $(a, b) \in U_{trad}$, then groups a and b violate group fairness according to the definition in Equation (2). We have $U_{ASTRAEA} \subset U_{trad}$.

Proof. Our goal is to show that any set of inputs not satisfying Equation (3) implies that these set of inputs do not also satisfy Equation (2). However, a set of inputs violating Equation (2) may not necessarily violate Equation (3). We formalise this reasoning below.

Let $a \in A$ violate the conditions seen in Equation (3). This means there exists an $a \in A$ that has an anomaly index ≥ 2 . This implies a violation of Equation (2) because there exists a $b \in A$ such that

$$Pr(f(a) = +|A = a) \neq Pr(f(b) = +|A = b)$$
 (4)

Let $a, b \in A$ be the set of all inputs such that

$$Pr(f(a) = +|A = a) = Pr(f(b) = +|A = b) + \delta$$
 (5)

where δ is a very small value. This violates Equation (2) but these inputs do not violate Equation (3).

TABLE 3:	Details of	Input	Grammars

NLP Tasks	Input Grammar	Test Oracle	#Prod. Rules	#Term. Nodes	
Coreference	Ambiguous	Metamorphic	16	103	
Resolution	Unambiguous	Deterministic	16	92	
MLM	Ambiguous	Metamorphic	11	87	
Sentiment Analysis	Ambiguous	Metamorphic/ Deterministic	48	237	

Hence, our definition Equation (3) is stricter than Equation (2) and the theorem holds. \Box

7 EVALUATION

In this section, we describe the evaluation setup and results for our fairness testing approach (i.e., ASTRAEA).

Research Questions: We evaluate the performance and utility of ASTRAEA in detecting and diagnosing both individual and group fairness violations. Specifically, we ask the following research questions:

• **RQ1 Individual fairness:** How effective is ASTRAEA in revealing *individual fairness* violations?

• **RQ2 Group fairness:** Is ASTRAEA effective at exposing *group fairness* violations?

• **RQ3 Diagnosis of fairness violations:** How effective is the *fault diagnosis* of ASTRAEA in *improving the fairness* of NLP software via model re-training?

• **RQ4** Generalizability of ASTRAEA's Bias Mitigation: Does ASTRAEA's bias mitigation (via model-retraining) generalise to *unseen* input sentences (e.g. WINOGENDER [65])?

• **RQ5 Effectiveness of test optimisation:** Does the test optimisation of ASTRAEA (*in* Section 6 c.) improve the detection of fairness violations?

• **RQ6 Comparative Effectiveness:** How effective is AS-TRAEA in comparison to the state of the art – CHECKLIST?

• **RQ7 Stability of ASTRAEA's test generation:** How *stable* is the test generation approach of ASTRAEA?

• **RQ8 Validity of ASTRAEA's generated inputs:** Are the input sentences generated by the input grammars (used by ASTRAEA) syntactically and semantically valid?

7.1 Experimental Setup

Generated Inputs: Given an input grammar, ASTRAEA generates two types of test suites based on the following test generation strategies (or phases):

1) *Random Generation (RAND)* - the choice between productions is determined by a uniform (or equal) distribution.

2) *Probabilistic Generation (PROB)* - the choice between productions is determined by the probability distribution computed after the RAND phase (*see* Section 6 c.).

Subject Programs: We evaluated ASTRAEA using 18 software systems designed for three major NLP tasks (*see* Table 4). These software are based on nine different ML architectures, including rule-based methods, pattern analysis systems, naive bayes classifiers and Deep Learning systems (e.g. DNNs, RNNs, LSTMs). Our subject programs include 13 pre-trained models (such as Google NLP) and five models trained locally. All models (except for Google NLP) were executed locally.

Input Grammars: We evaluated our approach using four hand-written input grammars, with at least one grammar for each task. Our grammars are either ambiguous or unambiguous. An unambiguous grammar generates sentences where the ground truth is known (e.g. Figure 3). Meanwhile, for an ambiguous grammar, the ground truth is unknown (e.g. Figure 6). We also evaluated for direct or analogous gender roles (e.g. "father" vs. "mother") and random gender comparisons (e.g. "father" vs. "girlfriend"). Overall, our grammars contain about 23 production rules and 130 terminal nodes, on average (see Table 3). Terminal nodes that portray societal biases such as gender-biased occupations are collected from established databases that classify the relevant data [2], [17], [50], [58], [84]. For instance, occupational and first name data were collected from the public websites of the U.S. Bureau of Labor Statistics [58] and the U.S. Social Security Administration [2].

Grammar Construction: We employed a *coding protocol* to construct the input grammars for our NLP tasks [24]. Our coding protocol involved all three researchers (*i.e.*, the authors). The goal of the protocol is to ensure *correctness* of the input grammar and reduce *experimenter bias* in the construction. Specifically, the following are the steps of the protocol:

- 1) For an NLP task (*e.g.*, coreference resolution), the *first* researcher (*researcher* #1) constructed an initial input grammar based on the expected structure of sentences for the task, for instance, using known datasets such as EEC schema [50] and WINOBIAS [84]. The production rules of the grammar are populated by employing the relevant public data sets for each specific input token, for instance, gender-based occupational data were obtained from the Department of labor statistics [58] and racially biased names were obtained from the U.S. Social Security Administration [2]. This initial input grammar took about 30 minutes to complete.
- 2) Two other researchers (*researcher #2 and #3*) independently inspected the input grammar (written in Step one) and samples of the resulting input sentences generated by ASTRAEA, while identifying any errors in the grammar or the resulting inputs.
- 3) Next, all three researchers meet to cross-validate the grammar, *i.e.*, discuss errors, contentions and conflicts, and update the input grammar with appropriate corrections to produce the final input grammar for the task at hand.
- 4) All researchers independently then inspect samples of the resulting inputs generated by ASTRAEA from the final grammar to ensure conflicts and errors are resolved.
- 5) Then, for a *new NLP task (e.g.,* sentiment analysis), another researcher (*researcher #2*) adapts and extends the initial input grammar with the expected structure and tokens for the task (similar to step 1). This activity took about 10 to 15 minutes.
- 6) Two other researchers (*researcher #1 and #3*) independently inspected the input grammar and samples of the resulting input sentences generated by ASTRAEA for the *new task* to identify errors in the grammar or the resulting inputs.
- 7) Next, all three researchers meet to cross-validate the

input grammar, and discuss errors and conflicts, then update the input grammar with appropriate corrections for the new task.

8) Finally, all researchers independently inspect samples of the resulting inputs generated by ASTRAEA from the final grammar for the new task to ensure corrections were effected.

The initial grammar construction is a one-time effort (per task), it takes a researcher about 30 to 45 minutes to construct and populate the production rules for an initial input grammar. Adapting and extending the initial input grammar for a new task is also fast, it takes about 10 to 15 minutes per task. Meanwhile, inspecting and correcting the grammar for error or conflicts takes about five (5) to 10 minutes. Overall, constructing an input grammar for the first NLP task takes about one hour, while extending or adapting for a new task takes (less than) half an hour.

As described above, our proposed grammars are easy to construct and are a one-time effort. The ease of writing (and correctness) is due to the availability of guiding schemas namely EEC schema [50] and WINOBIAS [84]. In contrast, perturbation-based fairness testing approaches require a large dataset of valid statements, *e.g.* MT-NLP needs over 17,000 sentences [53]. We assert that curating such datasets is more resource-intensive than creating an input grammar. These grammars can also be automatically synthesized, for instance, by adapting blackbox grammar mining approaches for inferring program inputs [10] or learning from a large corpus of text [8]. However, we consider this an orthogonal problem. Additionally, we evaluate the syntactic and semantic validity of sentences produced by ASTRAEA in RQ8.

Predictive Oracle: ASTRAEA requires only a metamorphic oracle to expose fairness violations, this is similar to several (fairness) testing approaches [8], [70], [77]. However, to mitigate against fairness violations and improve software fairness, ASTRAEA employs a predictive oracle to provide the ground truth on the actual expected outcome of a prediction. This information is only necessary to create the correct labels for the data augmentation dataset. Defining a predictive oracle for our tasks is achieved by rule-based checks for the presence of task-specific tokens in generated sentences. As an example, for sentiment analysis, we check for the presence of positive or negative emotions using the production rules for each emotional state. The oracle simply checks for the presence of a positive (or negative) emotion rule in a sentence to determine a positive (or negative) sentiment, or vice versa. For instance, the presence of "excited" in a sentence, indicates a positive sentiment.

Biases: In this work, we evaluated four types of biases, namely gender (e.g. male vs female (pro)nouns), race (e.g. african-american vs european names), religion (e.g. Christian vs Hindu) and occupation (e.g. CEO vs cleaner). In addition, we evaluated for neutral statements, i.e. statements with no bias connotation. This is particularly important for sentiment analyzers where neutral sentiments should be accurately classified.

Measure of Effectiveness: We evaluated ASTRAEA's effectiveness using *fairness violations*, this is in line with closely-related literature [35], [72]. To the best of our knowledge this is the only measure employed by all fairness testing

approaches. Unlike traditional testing, where metrics such as *code coverage* are employed as proxy measures of test effectiveness, there are no other known measures of test quality for fairness testing (besides violations). There is no evidence that typical (ML) test criteria (such as code coverage, neuron coverage or surprise adequacy criteria [49]) are effective measures of test suite quality for fairness properties. The problem of alternative proxy measures of effectiveness for fairness testing (other than violations) remains an open problem. In fact, researchers have demonstrated that traditional proxy measures are not meaningfully objective for evaluating test suite quality for (ML-based) software systems, and have instead called for the use of defect detection (*e.g.*, errors) as a better metric for evaluating the quality of test suites for (ML-based) software systems [40], [42].

Besides, we are confident in fairness violation as a measure of effectiveness since most ASTRAEA generated input sentences are both syntactically and semantically correct (*see* RQ8). Analogously, a reduction in fairness violation via data augmentation and re-training indicates that a violationinducing input token was correctly identified and successfully mitigated, therefore indicating an improvement in software fairness.

Test Adequacy: We employ grammar coverage as a test adequacy criterion for ASTRAEA. We have selected grammar coverage because it is the most practical metric in a black box setting. Typically, the most popular NLP systems are deployed in a black box scenario, without access to the model (e.g. Google NLP). To the best of our knowledge, there is no (other) reliable metric to measure fairness test adequacy of ML models in a black-box setting. Besides, this metric allows to measure and direct the effectiveness of ASTRAEA since it is grammar-driven. In our setup, ASTRAEA systematically covers input features e.g. all terminals in the input grammar. Moreover, the aim is also to cover as many combinations of sensitive attributes in the grammar within the time budget e.g. by generating pairwise combinations of gender sensitive (pro)nouns or occupations. In our evaluation, we report ASTRAEA's achieved grammar coverage (see Table 8). Specifically, we report the number of covered terminal nodes and the number of covered pairwise combination of sensitive attributes.

Implementation Details and Platform: ASTRAEA was implemented in about 20K LOC of Python. All implementations were in Python 3.8 using (machine learning) modules such as Tensorflow 2.3, Spacy 2.1, Numpy and Scipy. All experiments were conducted on a MacBook Pro (2019), with a 2.4 GHz 8-Core Intel Core i9 CPU and 64GB of main memory.

7.2 Experimental Results

RQ1 Individual fairness: In this section, we evaluated the number of *individual fairness* violations induced by AS-TRAEA, using 18 subject programs and three NLP tasks. Specifically, we evaluated the number of *individual fairness violations* induced by *gender, religious, occupational* and *racial* biases (*see* Table 5).

ASTRAEA's random test generation approach (RAND) is highly effective in exposing fairness violations for all subjects and tasks, especially in terms of the number of

TABLE 4	: Details	of Subject	Programs	(aka	Models	Under
Test (MU	Ts))	,	0			

NLP Task	Subject Program	Machine Learning (ML) Approach	Pre-trained
Coreference	Neural-Coref	DNN	1
Resolution	AllenNLP	DNN	1
Resolution	Stanford CoreNLP	Rule-based	1
Mask	BERT-cased	DNN	1
Language	BERT-uncased	DNN	1
0 0	DistilBERT-cased	DNN	1
Modeling	DistilBERT-uncased	DNN	1
	VaderSentiment	Rule-based	1
	TextBlob I	Pattern Analysis	1
	TextBlob II	Naive Bayes	1
	NLTK-Vader	Rule-based	1
	Google NLP	Deep Learning	1
	Stanford CoreNLP RNN		1
Sentiment Analysis	TensorFlow Text Classifier I	Transfer learning (Hub)	×
	TensorFlow Text Classifier II Padded	RNN (LSTM)	×
	TensorFlow Text Classifier II Unpadded	RNN (LSTM)	×
	TensorFlow Text Classifier III Padded	RNN (Stacked LSTMs)	×
	TensorFlow Text Classifier III Unpadded	RNN (Stacked LSTMs)	×

TABLE 5: Individual fairness violations found by ASTRAEA (RQ1 and RQ5). Each cell has three values: The total value in unformatted text, and the values in bracket are results for RAND in *italics* and for PROB in **bold**.

			Individual Fairness Violations				
NLP Tasks	Bias	Sensitive	#unique	Fairness	Fairness		
INLF Tasks	Dias	Attribute	test cases	#errors	Error Rate		
	Gender Amb.	Subjective	16621	7849	0.47		
Coref	Gender Amb.	Pronoun	(8672, 7949)	(3565, 4284)	(0.41, 0.54)		
(3 MUT)	Gender Unamb.	Subjective	17151	6318	0.37		
(3 MUT)	Gender Unamb.	Pronoun	(8951, 8200)	(2268, 4050)	(0.25, 0.49		
	Daliaian	Objective	17833	3050	0.17		
	Religion	Noun	(8964, 8869)	(806, 2244)	(0.09, 0.25		
	Occupation	Subjective	17135	3447	0.2		
	Occupation	Noun	(8895, 8240)	(994, 2453)	(0.11, 0.3)		
	Occupation		23195	13003	0.56		
	$(\tau = 0.05)$		(11801, 11394)	(6532, 6471)	(0.55, 0.57		
MLM	Occupation	Ohiontino	23145	8822	0.38		
(4 MUT)	$(\tau = 0.1)$	Objective Pronoun	(11806, 11339)	(4160, 4662)	(0.35, 0.41		
(4 MUT)	Occupation	Fronoun	23016	6230	0.27		
	$(\tau = 0.15)$		(11774, 11242)	(2689, 3541)	(0.23, 0.31)		
	Occupation	1	22914	4720	0.21		
	$(\tau = 0.2)$		(11809, 11105)	(1775, 2945)	(0.15, 0.27		
	Occupation		22750	3619	0.16		
	$(\tau = 0.25)$		(11806, 10944)	(1167, 2452)	(0.1, 0.22)		
	Occupation	1	22542	2811	0.12		
	$(\tau = 0.3)$		(11780, 10762)	(785, 2026)	(0.07, 0.19		
	Gender	Subjective	56707	5589	0.1		
	(Direct)	Noun	(29700, 27007)	(1979, 3610)	(0.07, 0.13		
Sentiment	Gender	Subjective	63039	5502	0.09		
Analysis	(Random)	Noun	(33021, 30018)	(2029, 3473)	(0.06, 0.12		
(11 MUT)	Gender	Occupation	61917	6600	0.11		
	Genuer	Occupation	(33034, 28883)	(2435, 4165)	(0.07, 0.14		
	Gender	Name	60887	6822	0.11		
	Genuer	INdiffe	(33028, 27859)	(2134, 4688)	(0.06, 0.17		
	Race	Name	61628	6730	0.11		
	Nace	INdiffe	(33017, 28611)	(2353, 4377)	(0.07, 0.15		
	Neutral	None	62720	11424	0.18		
	iveutiai	INOTIC	(33011, 29709)	(4637, 6787)	(0.14, 0.23)		
Total		•	573200	102536	_		
10(4)			(301069, 272131)	(40308, 62228)	-		
•			35825 (18817, 17008)	6408	0.23		
Average	Average			(2519, 3889)	(0.18, 0.28		

fairness violations triggered. In our evaluation of RAND, about *one in eighth test cases* generated by ASTRAEA triggered an individual fairness violation. In particular, we found that 13% (about 40K out of 301K) of the unique discriminatory tests generated by RAND triggered a fairness violation (*see* Table 5). These results demonstrate the effectiveness of ASTRAEA's random test generator in exposing individual fairness violations.

Overall, 13% of all discriminatory test cases generated by ASTRAEA (RAND) triggered individual fairness violations.

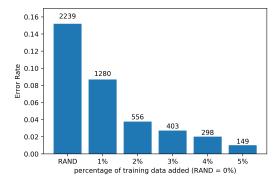


Fig. 8: Effectiveness of ASTRAEA's diagnosis: comparing the fairness error rate of RAND vs. Re-trained models augmented with ASTRAEA test inputs of sizes {1-5}% of the original training data. The numbers on top of the bars are the #fairness errors found.

RQ2 Group fairness: Let us evaluate group fairness for the NLP MLM task. The "groups" in this experiment refers to each occupation, e.g., "nurse" is considered a group and evaluated against every other group (e.g., "doctor") using the criteria seen in Equation (3). We have chosen to use each occupation as a group, in order to be objective, avoid inherent bias in self-categorization, and ensure that our found violations are not due to biased categorizations in known datasets. For instance, an alternative approach is to employ the categorization of occupations as malebiased and female-biased according to known datasets [58], [84]. However, this introduces any inherent biases in those categorizations into our experimental findings. Thus, to be objective, we apply each occupation as a group. All occupations employed in the experiment are collected from the the U.S. Bureau of Labor Statistics [58]. To normalize the frequency of each occupation for each model and experiment, we generate about 150 unique test cases for each occupation, and measure the average confidence of the prediction of "her" and "his" as the output of the [MASK] (see Figure 6). ASTRAEA uses a stricter definition of group fairness based on the median absolute deviation anomaly index, in particular, it checks if the absolute anomaly index is greater than two (see Equation (3)). An absolute anomaly index less than two (or greater than two) means that the particular occupation is under-represented (or over-represented, respectively) for the gender (in the output of [MASK]). Both cases capture group fairness violations.

We evaluate four state of the art models, namely BERTcased, BERT-uncased, DistilBERT-cased and DistilBERTuncased (*see* Table 6), for 43 different occupations. On average, we find a group fairness violation for 9.3% of the occupations for the male pronoun (*his*) and 10.46% of the occupations for the female pronoun (*her*). These violations represent occupations which are either over or under represented for a given gender, inadvertently causing societal bias. For instance, we found that occupation *salesperson* and *nurse* were over-represented and underrepresented in the predictions of BERT for *his* and *her*, respectively.

About one in ten (\approx 10%) tested occupations exhibit group fairness violations, on average.

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TABLE 6: Group fairness violations for the MLM task by ASTRAEA. We capture the #occupations that show anomalously high or low indices as violations of group fairness.

MUT	Obj-Pronoun	#violations	%violation
BERT-cased	his	5	11.63
DERT-Cased	her	7	16.28
BERT-uncased	his	3	6.98
DERT-uncased	her	3	6.98
DistilBERT-uncased	his	2	4.65
Distribert-uncased	her	6	13.95
DistilBERT-cased	his	6	13.95
DistilDER1-cased	her	2	4.65
Average	his	4	9.30
Average	her	4.5	10.47

RQ3 Diagnosis of fairness violations: In this section, we investigate the effectiveness of ASTRAEA's diagnoses in improving software fairness. Specifically, we leverage ASTRAEA's diagnosis to generate new test inputs for the Tensorflow Text Classifier model, for the sentiment analysis task. After RAND generation (RQ1), we prioritize the tokens associated to the observed fairness violations, using the fault diagnosis step (see Section 6 d.). Then, ASTRAEA'S PROB leverages this diagnosis to generate a set of unique test inputs that are more likely to reveal fairness violations. As-TRAEA determines the label for these generated test inputs using the predictive oracle. A random sample of the newly generated test inputs is then added to the training data for model re-training. The sample size is one to five percent of the size of the training data. In total, we had five models for our evaluation. For each model, we evaluated individual fairness violations with five bias configurations resulting in 25 test configurations.

In our evaluation, ASTRAEA improves software fairness for all tested models and biases. On average, the number of fairness violations was reduced by 76% after model retraining. In addition, we observed the number of fairness violations decreases as the ratio of augmented data increases (i.e. from one to five percent). Figure 8 illustrates the reduction in the number of fairness violations found in the model, when augmenting the training data with varying ratio of inputs generated via fairness diagnosis. Particularly, augmenting only one percent of the training data via ASTRAEA's diagnoses reduced the number of fairness violations by 43%. Meanwhile, augmenting five percent of the training data reduced such violations by 93%. These results demonstrate the accuracy of ASTRAEA's diagnoses and its efficacy in improving software fairness, via modelretraining.

Notably, model re-training does not significantly impact the prediction accuracy of our models. For all models, the model accuracy was reduced by 1.42% (87% - 85.58%), on average. The retrained model with one percent augmented data had the highest accuracy of 86.2%, while the worst accuracy of 84.8% was in the retrained model with five percent augmented data.

Model re-training with ASTRAEA's diagnoses reduced the number of fairness violations by 76%, on average.

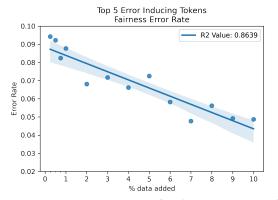
RQ4 Generalisability of ASTRAEA's Bias Mitigation: In this experiment, we examine whether ASTRAEA's bias miti-

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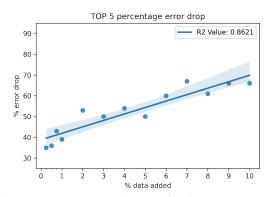
TABLE 7: Generalisability of ASTRAEA's Bias Mitigation (via model re-training): the performance of ASTRAEA's (re-)trained models on *unseen* inputs for sentiment analysis using WINOGENDER dataset [65] (N/A = Not Applicable)

[Ton 5 Diagnosis (Ton 10)					
TensorFlow Text	Top 5 Diagnosis (Top 10) #Fairness Error ASTRAEA %					
Classifier Models	Errors	Rate	Improvement			
Original	2592	0.144	N/A			
Trained Model	(2217)	(0.123)	(N/A)			
Re-trained Model	16966	0.0943	35			
+ 0.25% data Aug.	(15171)	(0.0843)	(32)			
Re-trained Model	16588	0.0922	36			
+ 0.5% data Aug.	(14006)	(0.0778)	(37)			
Re-trained Model	14833	0.0824	43			
+ 0.75% data Aug.	(13441)	(0.0747)	(39)			
Re-trained Model	15782	0.0877	39			
+ 1% data Aug.	(14224)	(0.0790)	(36)			
Re-trained Model	12257	0.0681	53			
+ 2% data Aug.	(10552)	(0.0586)	(52)			
Re-trained Model	12913	0.0717	50			
+ 3% data Aug.	(12094)	(0.0672)	(45)			
Re-trained Model	11916	0.0662	54			
+ 4% data Aug.	(10367)	(0.0576)	(53)			
Re-trained Model	13054	0.0725	50			
+ 5% data Aug.	(12261)	(0.0681)	(45)			
Re-trained Model	10474	0.0582	60			
+ 6% data Aug.	(10491)	(0.0583)	(53)			
Re-trained Model	8582	0.0477	67			
+ 7% data Aug.	(7102)	(0.0395)	(68)			
Re-trained Model	10115	0.0562	61			
+ 8% data Aug.	(9663)	(0.0537)	(56)			
Re-trained Model	8847	0.0492	66			
+ 9% data Aug.	(8090)	(0.0449)	(64)			
Re-trained Model	8759	0.0487	66			
+ 10% data Aug.	(8392)	(0.0466)	(62)			
Average of all	12391	0.0688	52			
Re-trained Models	(11220)	(0.0623)	(49)			
Median of all	12257	0.0681	53			
Re-trained Models	(10552)	(0.0586)	(52)			

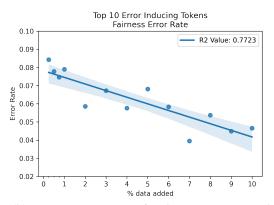
gation (*i.e.*, its data augmentation with error-inducing input tokens, and re-training with sentences containing such tokens) generalises to unseen input sentences, in particular, sentences in the wild that contain previously error-inducing tokens. For instance, if ASTRAEA identified the token "CEO" as the most error-inducing token for a sentiment analyser, we check if other sentences in the wild containing "CEO" token still lead to fairness violations in the re-trained models obtained via ASTRAEA's bias mitigation. To address this, we collected five (5) and ten (10) of the topmost error-inducing input tokens identified by ASTRAEA. As an example, we choose the top five or 10 most biased (fe)male occupations from our sentiment analysis experiments in RQ3. Then, using the sentences provided by a different sentiment analysis dataset WINOGENDER [65], we replaced these errorinducing tokens in these sentences and test them on both the original and re-trained models. We performed model re-training using a setup similar to that of RQ3, i.e., we re-trained models with different levels of data augmentation using the Tensorflow Text Classifier Hub model. We experimented with 13 data augmentation configurations of sample sizes 0.25% to 10%, specifically, {0.25, 0.5, 0.75, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10} (see Table 7). To mitigate the randomness in the sampling of newly generated test inputs, we sampled test inputs 10 times and trained 10 models for



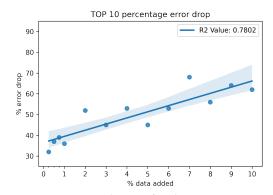
(a) Fairness Error Rate for the Top 5 error tokens



(c) Drop in Fairness Violations for the Top 5 error tokens



(b) Fairness Error Rate for the Top 10 error tokens



(d) Drop in Fairness Violations for the Top 10 error tokens

Fig. 9: Generalisability of ASTRAEA's bias mitigation on unseen input sentences (from WINOGENDER [65]) containing the top five and top 10 error-inducing input tokens, using re-trained models augmented with ASTRAEA test inputs of sizes {0.25, 0.5, 0.75, 1-10}% of the original training data. Charts (a) and (b) show the trend in fairness error rate of the re-trained models for each data augmentation sample size, and charts (c) and (d) show the percentage drop in fairness violations between the original model and each data augmentation sample size for re-trained models. For each chart, we compute the linear regression trend line (thick blue line) and report the R-squared value (R^2) (or goodness of fit). The blue shaded region surrounding the trend line is the 95% confidence interval.

each configuration, following the standard for random test experiments [7]. Overall, we trained 130 models, 10 models for each of the 13 data augmentation levels. Table 7 and Figure 9 illustrate the observed fairness violations on our (re-)trained models, when fed with unseen inputs containing ASTRAEA's identified error-inducing tokens.

In our evaluation, ASTRAEA's mitigation generalises to unseen input sentences containing our diagnosed error-inducing *input tokens, i.e.,* unseen inputs refer to input sentences that differ from the original error-inducing inputs, the training data and the augmented data. Figure 9(a) and (b) show the drop in the rate of fairness violations induced by unseen inputs in the re-trained models, for both the topmost five and ten error-inducing input tokens. Likewise, Figure 9(c) and (d) show the reduction in fairness violations between the original model and the trained model for each data augmentation configuration. Overall, we observed that As-TRAEA's mitigation reduced the rate of fairness violations in a re-trained model by 51%, on average (see Table 7). This result suggests that ASTRAEA's bias mitigation generalises to unseen inputs containing previously error-inducing inputs, even when the inputs are different from the input sentences generated by the grammar, the original training data or the

augmented training data. Indeed, there are error-inducing input tokens that generally induce fairness violations in sentences regardless of the task-specific input (grammar), and ASTRAEA can identify and mitigate against such tokens via data augmentation.

ASTRAEA's mitigation generalises to unseen inputs: It reduces fairness violations in unseen inputs by about half (51%), on average.

In addition, we observed that re-training with the topmost five (5) error-inducing tokens outperforms re-training with the topmost 10 error-inducing tokens. Specifically, for all data augmentation configurations (except 0.5%), re-training with the topmost five error-inducing input tokens outperformed re-training with the topmost 10 error-inducing tokens. For each data augmentation configuration, models trained with the topmost five error-inducing inputs reduced fairness violations better than models trained with the topmost 10 error tokens. Overall, re-training with the topmost five errorinducing input tokens is 5.67% better than re-training with the topmost 10 error-inducing input tokens, on average. This is also evident by the slight difference in the trend line and R^2 of the top five versus top 10 error tokens (cf. Figure 9).

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Specifically, the R^2 value of the top five error tokens (0.8639) and 0.8621), is higher than that of the top 10 error tokens (0.7723 and 0.7802). This result demonstrates the efficacy of ASTRAEA's identification of error tokens and the importance of ranking the input tokens causing fairness violations.

For most configurations (12 out of 13), re-training with the topmost five (5) error-inducing tokens outperformed re-training with the topmost 10 tokens (by 5.67%), on average.

Finally, we observe a steady decrease in the number of fairness violations as the sample size of the augmented data used for model re-training increases. For instance, for the topmost five error-inducing tokens, when 0.25% of the training data is augmented for re-training, the observed reduction in error rate was 35% (from 0.144 to 0.0943). Meanwhile, we observed almost twice (66%) the reduction in fairness error rate (from 0.144 to 0.0487) with 10% data augmentation (see Table 7 and Figure 9). This is also evident in the trend lines, showing that there is a strong positive trend ($R^2 > 0.7$) for all charts (see Figure 9(c) and (d)). This result implies that the reduction in fairness error rate improves as the size of the augmented training data increases even for unseen inputs, *i.e.*, our results on fairness improvements (reported in RQ3) generalise to unseen inputs.

For unseen inputs, there is a steady reduction in fairness violations as the size of the augmented re-training data increases.

RQ5 Effectiveness of test optimisation: We investigate the effectiveness of our test optimisation approach, i.e., the probabilistic test generator (PROB). In particular, we examine the effectiveness of ASTRAEA'S PROB, in comparison to the random test generation (RAND) (reported in RQ1). We also compare the grammar coverage achieved by both RAND and PROB, in order to determine whether PROB's test optimisation achieves a higher error rate whilst covering fewer grammar production rules, in terms of terminal nodes and pairwise sensitive terminals.

ASTRAEA's probabilistic test generation approach (PROB) outperforms the random generator (RAND), in terms of the number of individual fairness violations found and the total number of generated test cases. Specifically, PROB triggered 54% (1370) more unique fairness violations in comparison to RAND, on average (see row "Average" in Table 5). In addition, PROB reduced the total number of generated test cases by 10% (see row "Total" in Table 5). Consequently, ASTRAEA's PROB induced a higher failure rate (61% more) than RAND, for individual fairness violations (see row "Average" in Table 5). These results show the improvement in test generation effectiveness of our fairness test optimizer (PROB).

PROB exposed 54% more unique individual fairness violations than RAND.

In our evaluation, ASTRAEA's probabilistic test generation approach (PROB) achieves less grammar coverage than the random generator (RAND), even though, PROB reveals more fairness errors than RAND. Overall, ASTRAEA'S PROB covered nine percent fewer terminal nodes than RAND, and about 20% fewer pairwise sensitive terminal nodes (see

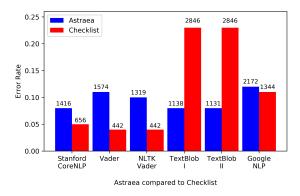


Fig. 10: ASTRAEA versus CHECKLIST: Comparing the fault revealing effectiveness of ASTRAEA to that of CHECKLIST w.r.t. to the error rate, numbers atop the bars indicate the number of fairness errors found

Table 8). This result demonstrates that PROB is able to reveal more unique errors, despite covering fewer (errorinducing) terminal nodes, suggesting that ASTRAEA (i.e., PROB) accurately learns the error-inducing input tokens necessary to induce more unique fairness errors.

PROB achieves lower grammar coverage than RAND, despite
revealing more (54%) fairness errors.

RQ6 Comparative Effectiveness: We compare the effectiveness of ASTRAEA to the state of the art in NLP testing, i.e., CHECKLIST and MT-NLP. CHECKLIST is a schema based NLP testing approach that generates valid inputs to improve the performance of NLP systems [63], and MT-NLP is perturbation-based fairness testing approach for sentiment analyzers. In this experiment, we compare the effectiveness of ASTRAEA to both approaches in revealing fairness violations. In particular, we compare the number of fairness violations revealed by each approach when we feed its generated sentences to each pre-trained sentiment analyzer in our dataset. Table 9 and Figure 10 illustrate the comparative effectiveness of ASTRAEA and CHECKLIST on all (6) pre-trained sentiment analyzers in our setup.

Our evaluation results show that ASTRAEA had a higher error rate than CHECKLIST for all pre-trained models, except for the two TextBlob sentiment anlayzers (i.e., TextBlob's Naive Bayes and Pattern analysis models). Figure 10 shows that for most (four of six) of our subjects, ASTRAEA had between 13 to 222 percent higher error rate than CHECK-LIST. Specifically, ASTRAEA had more than three times the error rate of CHECKLIST for both Vader and NLTK-vader sentiment analyzers, and twice the error rate of CHECKLIST for Stanford Core NLP (see Table 9). Meanwhile, CHECKLIST outperformed ASTRAEA for the TextBlob models where ASTRAEA had only a third of the error rate of CHECKLIST. This result suggests ASTRAEA is more effective across our subjects, and is complementary to CHECKLIST for revealing fairness errors.

ASTRAEA had a higher error rate than CHECKLIST for most (4/6) of our subject programs.

Additionally, we compare the effectiveness of ASTRAEA

TABLE 8: Grammar Coverage achieved by ASTRAEA RAND versus PROB for each/all tasks, showing the RAND coverage in normal text and PROB coverage in parenthesis "()", as well as the percentage reduction in grammar coverage achieved by PROB, in comparison to RAND.

Tasks (#MUT)	Input	Terminal Symbols			Pairwise Symbols		
	Grammar	#AllSymbols	#Covered	% Covered	#AllPairs	#Covered	% Covered
Coreference Resolution (3)	Unambiguous	276	272 (216)	98.6 (78.3)	1449	1445 (649)	99.7 (44.8)
Coreference Resolution (3)	Ambiguous	369	369 (369)	100.0 (100.0)	4416	4158 (3434)	94.2 (77.8)
Mask Language Modeling (4)	Ambiguous	284	284 (276)	100.0 (97.2)	1848	1842 (1472)	99.7 (79.7)
Sentiment Analysis (11)	Ambiguous	2497	2464 (2211)	98.7 (88.5)	89089	14366 (11979)	16.1 (13.4)
Overall 3426 3389 (3072)				98.9 (89.7)	96802	21811 (17534)	22.5 (18.1)
Percentage Reduction in Coverage (%)				9.4			19.6

TABLE 9: Comparative Effectiveness: ASTRAEA versus CHECKLIST, the higher error rates and positive improvements are marked in **bold**

	Erroi	ASTRAEA %	
MUT	ASTRAEA	CHECKLIST	Improvement
	(#errors)	(#errors)	(#folds)
Stanford CoreNLP	0.08 (1416)	0.05 (656)	51(1.5)
VaderSentiment	0.11 (1574)	0.04 (442)	222 (3.2)
NLTK-Vader	0.10 (1319)	0.04 (442)	190 (2.9)
Google NLP	0.12 (2172)	0.11 (1344)	13 (1.1)
TextBlob I	0.08 (1131)	0.23 (2846)	-67 (0.3)
TextBlob II	0.08 (1138)	0.23 (2846)	-67 (0.3)

to that of previous work — MT-NLP [53]. MT-NLP is a perturbation-based fairness testing approach for NLP systems. We compare the performance of ASTRAEA and MT-NLP on the subject program used in Ma et al. [53], *i.e.*, the popular Google NLP sentiment analyzer. Both ASTRAEA and MT-NLP [53] were evaluated using Google's sentiment analysis engine.

Our results show that ASTRAEA is more effective than MT-NLP in terms of the number of fairness errors found and error rate. ASTRAEA'S RAND and PROB revealed 14 and 16 times as many fairness violations as MT-NLP, respectively. In total, ASTRAEA found 2,172 fairness violations (out of 17,713 generated inputs) for PROB and 1,893 violations (out of 17,711 generated inputs) for RAND (*see* Google NLP in Table 9). Meanwhile, MT-NLP found 140 fairness errors out of 30,504 generated inputs [53]. ASTRAEA also outperforms MT-NLP in terms of error rate, it discovers fairness errors at a rate that is 23 and 26 times higher than that of MT-NLP, for ASTRAEA'S RAND and PROB, respectively. Clearly, these results show that ASTRAEA is more effective than the perturbation-based fairness testing of MT-NLP.

ASTRAEA reveals fairness errors at a rate that is up to 26 times higher than that of MT-NLP.

RQ7 Stability of ASTRAEA's test generation: To illustrate the stability of ASTRAEA, we examine the impact of randomness on the effectiveness of ASTRAEA for both ASTRAEA (RAND) and ASTRAEA (PROB). We compared results for ten runs of ASTRAEA for the Coreference NLP tasks. In this evaluation, we tested for gender bias in three MUTs, namely, Allen NLP, Neural Coref and Stanford CoreNLP.

Overall, our evaluation reveals that ASTRAEA is stable in terms of discovering fairness violations and the number of generated test cases. Across all runs, ASTRAEA had a very low standard deviation (SD). In terms of error rate,

TABLE 10: Syntactic validity of Generated Inputs

NLP Task	Bias	Score	Alerts	Grammar Errors
	Gender Amb.	97	12	laborer ->labourer
Coref.	Gender Unamb.	97	6	laborer ->labourer
Corei.	Religion	97	2	laborer ->labourer
	Occupation	96	5	laborer ->labourer
MLM	Occupation	97	22	laborer ->labourer, neighborhood -> neighbourhood, counselor -> counsellor
	Gender (Direct)	99	2	feel ->feels
Sentiment Analysis	Gender (Random)	99	1	The housekeeper -> Housekeeper tailor made -> tailor-made
	Gender (Occupation)	99	2	NA
	Gender (Name)	100	0	NA
	Race	100	0	The The Paralegal -> The Paralegal The The Librarian -> The Librarian
	Neutral	90	37	feel ->feels
Average		97.4	8.1	

ASTRAEA had an SD of 0.0054, on average. Specifically, in the RAND mode, ASTRAEA had an SD of 0.0045, and in the PROB mode, the SD was 0.0063. This demonstrates the *negligible effect* of randomness on ASTRAEA's effectiveness. Specifically, the inherent randomness in ASTRAEA has little impact on the number of fairness violations found or the error rate.

ASTRAEA is stable, the effect of randomness on ASTRAEA's effectiveness is negligible.

RQ8 Validity of ASTRAEA's generated inputs: This RQ evaluates the correctness of the input grammars employed by ASTRAEA. Specifically, this is accomplished by evaluating the syntactic and semantic validity of the resulting input sentences. To this end, we conducted two experiments to examine the correctness of the generated inputs and investigate how ASTRAEA's generated inputs compare to humanwritten sentences, in terms of sensibility. First, we fed all generated inputs to a grammar checker (*i.e.*, grammarly) to evaluate their syntactic validity. Table 10 highlights the syntactic validity results for our generated inputs. Secondly, we conducted a user study with 205 participants to evaluate the semantic validity (*i.e.*, sensibility) of ASTRAEA's generated inputs, especially in comparison to human-written input sentences (from WINOGENDER [65]). In this experiment, we

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compare the human-rated sensibility of 10 human-written sentences to ASTRAEA's generated sentences, in particular, using 10 benign sentences and 10 error-inducing sentences. Table 11 highlights the aggregated results of our semantic validity user study.

Syntactic Validity: Our evaluation results show that *almost* all input sentences (97.4%) generated by ASTRAEA are syntactically valid. Table 10 highlights the correctness of ASTRAEA's generated inputs, it shows that the majority (97.4%) of the generated sentences are syntactically valid. In addition, we employ Grammarly to evaluate the correctness, clarity, engagement and delivery of ASTRAEA's generated input sentences. Our evaluation results showed that the clarity, engagement and delivery of ASTRAEA's generated sentences are "very clear, just right and very engaging". Grammarly recommended very few corrections for our generated sentences, in particular, correctness alerts were low at about 8.1 alerts on average (see Table 10). Common errors found in the generated sentences can be easily corrected by updating the terminal symbols, more importantly, these errors do not impact fairness checks. Found syntactic errors include errors about English dialects (American versus British English, e.g. "laborer" vs "labourer"), minor grammar errors ("feel" vs "feels") and accidental incorrect terminal symbols ("The The paralegal" vs "The paralegal"). Overall, this result suggests that the inputs generated by ASTRAEA are mostly syntactically valid, and the input grammar employed for this generation are syntactically correct.

Most input sentences (97.4%) generated by ASTRAEA are syntactically valid.

Semantic Validity: We conducted a user study to evaluate the semantic validity (sensibility) of the input sentences generated by ASTRAEA⁸. In this experiment, we randomly selected 10 sentences from the WINOGENDER dataset [65] and 20 sentences from the inputs generated by ASTRAEA, specifically, ten benign sentences and ten error-inducing sentences. The handcrafted, human-written WINOGENDER [65] sentences are chosen as a baseline for sensibility of input sentences, such that we can compare the sensibility ASTRAEA's automatically generated sentences to human-crafted sentences. In total, we had 30 sentences for the user study, we provide all sentences in a random order to participants while posing the following question:

```
How sensible are these sentences on a scale
of one (1) to 10 (one being completely
nonsensical, 10 being perfectly sensible)?
```

For each sentence in the survey, we asked participants to rate its sensibility using a 10 point Likert scale. Each sentence was rated from one (1) to 10, with score one being completely nonsensical, and 10 meaning perfectly sensible. The study had 205 participants recruited via Amazon Mechanical Turk (mTurk or AMT). The user study took approximately five hours and a study participants took about 7 minutes and 29 seconds to complete the survey, on average.

8. The user study form can be seen here: https://forms.gle/bEudnfucckPkG8GP6

TABLE 11: Semantic User Study Scores

	Winogender	Astraea	Astraea	Astraea
	(Baseline)	(Overall)	(Error)	(Non-Error)
Mean	7.848	6.323	6.529	6.118
% drop		19.42%	16.81%	22.04%
Median	8.50	6.75	7.00	6.50
% drop	-	20.59%	17.65%	23.53%

Our evaluation results showed that ASTRAEA's generated sentences are mostly sensible (6.3/10), and comparable to humanwritten sentence, they were rated 81% as sensible as the handcrafted sentences from the WINOGENDER dataset [65], on average. The set of (20) input sentences generated by ASTRAEA had a 6.3 sensibility score, while human-written input sentences (from WINOGENDER) had a 7.8 sensibility score, on average. Table 11 highlights the sensibility score for each set of sentences employed in our user study. In particular, the error-inducing sentences generated by ASTRAEA were rated mostly sensible, even slightly more sensible than the benign sentences. Notably, ASTRAEA's error-inducing inputs were rated 83% as sensible as human-written sentences (*i.e.*, WINOGENDER). The error-inducing sentences are also slightly more sensible (7%) than the benign sentences generated by ASTRAEA, with benign sentences rated 6.1 versus error-inducing sentences rated 6.5, on average (see Table 11). This result suggests that the fairness violations induced by ASTRAEA are from sensible and human-comprehensible sentences.

ASTRAEA's generated sentences are mostly sensible (6.3/10) and almost (81%) as sensible as human written sentences.

7.3 Discussions and Future Outlook

Ethical Considerations: In this section, we consider the ethical issues related to the use of ASTRAEA. In particular, the ethical implications of applying ASTRAEA in analyzing and mitigating societal biases, as well as issues relating to the application of ASTRAEA in fairness testing, especially on marginalized individuals and (minority) groups.

Intended Use: The intended use of ASTRAEA is to analyse, detect and mitigate undesirable biases in text-based NLP tasks. Although, test generation is important to ensure software fairness for ML-based software systems, it is pertinent to note that it is not sufficient to address the problem of fairness in (NLP-based) software systems. Our recommendation is that tools such as ASTRAEA should be deployed as part of the ML pipeline and end-to-end analysis to validate fairness properties. Indeed, ASTRAEA should be deployed within the context of a well-defined societal or institutional fairness policy. Besides, there are other concerns when applying software systems (such as ASTRAEA) to ensure fair and inclusive ML systems. Notably, it is important to define the social context of ASTRAEA's application, the ethical concerns in terms of the societal biases in consideration, the desirable bias policy and the intended use cases of the NLP system at hand. These concerns inform fair and inclusive design and analysis of NLP systems. For more details on the ethical concerns for NLP systems, Hovy and Spruit [45]

Experimental Design: In this paper, we have evaluated ASTRAEA on a range of NLP tasks where it demonstrates considerable benefit in improving software fairness. Beyond fairness testing, we believe our implementation and evaluation of ASTRAEA has very limited harmful applications. ASTRAEA's application does not risk deterring fairness, amplifying bias, or enabling ethical or security issues such as privacy and unintended release of personal information or identities. In our experiments, we ensure to avoid attributes that involve normative judgments that may cause harm when interpreted pejoratively [26]. For instance, our design of ASTRAEA ensures that generated input sentences are strictly tied to the allowed values in the production rules for a specific noun or pronoun, without prejudice for specific attributes. In addition, in our experiments, we have employed data sets, input grammars and programs that have been made publicly available to allow for scrutiny, reuse and reproducibilty.

Non-binary gender: In our experiments, we have only considered binary genders due to the limitations of our subject programs. Indeed, most NLP tools do not account for nonbinary genders [45], [69], [83]. However, we do not condone the classification of gender into binary categories. We believe such rigid classifications may be harmful, especially to minority groups and marginalized individuals. The aim of this work is not to perpetuate such stance or reinforce rigid social classifications of gender. In fact, ASTRAEA allows to test for non-binary gender, e.g., by adding their corresponding non-binary nouns or pronouns to the input grammar. This is evident in our preliminary experiments testing nonbinary genders on our subject programs. For instance, we found that all of the coreference resolution (coref) systems in our setup do not recognize or account for non-binary gender (e.g., the singular they). Specifically, over 90% of the sentences generated by ASTRAEA (containing a singular they as a sensitive attribute) for all coreference resolution (Coref) subject programs do not yield any output. Thus, in our experiments, we did not evaluate for non-binary gender, but we note that as NLP systems improve to be more gender inclusive, ASTRAEA can be trivially extended to test for non-binary gender. Overall, similar to the stance of the research community [26], we believe that gender attributes should not be binary or considered perceptually obvious and discernible in text-based systems.

Age-related Bias: In our evaluation, we have not considered other poorly understood biases (*e.g.*, age-related biases). However, we expect ASTRAEA to perform well on such poorly understood biases provided there are input tokens that characterize the societal bias. Extending an existing input grammar for such biases is trivial provided there is a well-defined age bias policy and a corresponding set of age-related input tokens to be added to the input grammar. As an example, fairness analysis for age-related bias for our NLP tasks can be characterized by adding age-related adjective as terminals, *e.g.*, "young" versus "old", or "teen" versus "aged". This is similar to how Díaz et al. [30] addressed age-related biases. To demonstrate this, we adapt

one of our grammars used for co-referencing to encode age-related biases for the co-reference analysis task.⁹ It is important to note that this is just a *demonstration* and the actual efficacy of ASTRAEA's performance on such biases is not comprehensively understood. In the future, we plan to study such poorly understood societal biases, we also encourage other researchers to investigate approaches to analyse and mitigate such under-studied societal biases.

Test Generation: Let us discuss the issues related to the testing methodology of ASTRAEA, in particular, the *choice of test oracle* and the potential to generate *redundant test cases*.

Alternative Test Oracles: In this paper, we have employed metamorphic test oracles to compare the outputs of similar discriminatory input sentences. ASTRAEA requires this oracle to automatically detect violations. For improving fairness, we require a dataset to augment our training data set. This augmented dataset is then used for re-training. To achieve this, we employ a predictive oracle to determine the ground truth output label for the newly generated test inputs used in our data augmentation. Our predictive oracle is based on the input grammar, in particular it checks for the presence of certain terminals in the generated inputs (as described in section 7.1). It is important to note that this oracle is simple and it is only sound with respect to the input grammar, indeed it is not sound in general for any input sentence or grammar. Indeed, defining our rulebased oracle for a large, complex or highly expressive input grammar may be very difficult, incomplete and impact the expressiveness of the input grammar and the resulting input sentences. This is in particular a very difficult problem [9], especially in the absence of ground truth about the output labels of generated input sentences. Hence, it may be necessary to employ more powerful or *alternative* test oracles for more expressive input sentences or grammars.

Besides, there are alternative approaches to generate predictive test oracles. For instance, other researchers have employed probabilistic and majority voting oracles for the same purpose. In particular, TRANSREPAIR [70] employs a probabilistic majority voting oracle for inconsistency testing, by feeding several similar discriminatory inputs to a model and using the most common outcome as the ground truth. Similarly, one can employ an ensemble of models, *i.e.*, by feeding a single input or several similar discriminatory inputs to these models, and taking the most common outcome as the ground truth [9].

Redundant Test cases: ASTRAEA generates input sentences by exploring the input grammar, especially in the random (RAND) exploration mode. Hence, it may generate test cases that are redundant, *i.e.*, non-unique discriminatory inputs. For instance, ASTRAEA may repeatedly generate a set of discriminatory input sentences exposing similar fairness violations. To mitigate this, ASTRAEA also has a more targeted phase, the PROB mode (reported in RQ5). In this phase, ASTRAEA automatically generates input sentences that target seen fairness violations to expose more closelyrelated violations. This is evident in RQ5 where ASTRAEA reduces redundant test cases. In particular, ASTRAEA in PROB mode generates fewer unique input sentences, and

9. See here: https://bit.ly/3s0PKKF

yet exposed more unique fairness violations than the random exploration mode of ASTRAEA (RAND).

In the future, we plan to investigate more targeted approaches that can reduce the number of redundant test cases, besides our probabilistic mode (PROB in RQ5). We plan to reduce the number of redundant tests by exploring alternative approaches, such as coverage-driven approaches (*e.g.*, OGMA [73]), mutation-driven approaches (*e.g.*, TRAN-SREPAIR [70]), and directed test generation approaches (*e.g.*, AEQUITAS [72]).

Data Augmentation: The aim of our experiments concerning model-retraining via data augmentation (in RQ3 and RQ4) is to demonstrate that our approach is effective in improving software fairness. Our goal is not to determine the optimal ratio of data augmentation that achieves the best mitigation of fairness violations. Even though our experiments demonstrate that as the percentage of augmented data increases, the rate of fairness violations decreases (*see* RQ3 and RQ4), we do not ascertain the best data augmentation ratio for the optimal reduction in fairness violations. Determining the best ratio for data augmentation is a different optimization problem. In fact, this optimization problem requires further investigation to determine when data augmentation is sufficient to ensure maximal reduction in fairness violations.

Disclaimer: The goal of this work is not to determine the correct, desired or expected outcomes for a task, bias or program, neither is it to define the societal policy that determines the absence or presence of a violation. The *focus* of our work is to allow developers the flexibility to analyze, test and mitigate against different biases based on their use case. In particular, based on their own defined societal or company policy, their bias of concern and their expected behavior for the task or program. We do not intend to define the societal policy for bias (e.g., equality versus equity), however, our methodology allows to check for such defined policy via the test oracle. For instance, an *equality* policy can be easily checked by ensuring the outcomes for a pair of sentences are equal (e.g., in RQ1), and a *threshold-based* policy can be easily checked by ensuring a certain threshold in the difference in outcomes is maintained (e.g., in RQ2). This is important because the fairness concerns of an organization may differ depending on the task, bias or policy; our focus is to allow the flexibility to test for different use cases.

As an example, in the individual fairness experiments in RQ1, we assume that all predicted pronouns should be equally likely for all occupations while testing for occupational/gender bias. Meanwhile, in the case of the MLM example in RQ2, we allow developers to test for group fairness violations based on different threshold configurations. We employed a *threshold-based* policy to ascertain if there is a large disparity (exceeding the defined threshold) between the *his* and *her* [MASK] outcomes. Likewise, we can test for *equality* policy for the same MLM group fairness task, such that we directly compare if both outcomes are equal. In the real world, this approach translates to checking that "all predicted outcomes should be equally likely for all occupations".

In summary, we do not intend to define the expected outcome, policy or verdict for a subject program or task. We are focused on providing a flexible approach (*i.e.*, ASTRAEA) that is easily amenable to test bias for different use cases, by allowing to test for several policies, fairness criteria and biases. Although, ASTRAEA supports testing for different policies, we believe the definition of the desirable outcome or tested bias policy (*e.g., equality* versus *equity*) is orthogonal to our research and dependent on the use case. Indeed, automatically determining the desirable outcome based on the use case is an open problem and it should be further studied by the research community.

8 LIMITATIONS AND THREATS TO VALIDITY

Grammar Construction and Correctness: The construction of input grammars is relatively easy and the initial grammar was constructed by a graduate student in 30-45 mins. We demonstrate the ease of grammar construction by implementing a wide range of grammars across three tasks, namely Coreference Resolution, Sentiment Analysis and Masked Language Modelling and for over fifteen models under test. Additionally, we release the Python implementations of the grammars for future expansion.

We attempt to construct the input grammars in such a way that the inputs generated by them are semantically valid (by design of the grammar). This is aided by the availability of EEC schema [50] and Winogender [65]. To mitigate against errors that may creep into the grammar, we use a popular online grammar checking tool Grammarly [1] and verify generated input correctness. On average, we find that the overall score is high at 97.4 (see Table 10).

Complex Inputs: ASTRAEA's input grammars allow to specify and explore the input space beyond the training set. In our evaluation setup, it was easy to construct input grammars that expose fairness violations, within about 30 minutes. Our evaluation on NLP tasks with varying complexities shows that ASTRAEA can be easily applied to NLP tasks. Although grammars exist for some complex tasks (such as images¹⁰), the correlation of grammar tokens and image sensitive attributes are not yet explored. This line of applications requires further research.

Completeness: By design, ASTRAEA is incomplete in discovering fairness violations due to several reasons, namely (1) *input grammars* – it can only expose the biases captured in the employed input grammar, (2) lack of guarantees in testing - in comparison to the guarantees afforded by verification, ASTRAEA does not provide a guarantee or proof of fulfilling fairness properties and (3) finite number of generated tests limited number of generated inputs within a reasonable time budget. Firstly, ASTRAEA can not expose a fairness violation if the input tokens associated with the violation are not captured by the input grammar, hence, its effectiveness is limited by the *expressiveness* of the employed input grammar. Secondly, unlike, fairness verification approaches (such as Albarghouthi et al. [4]), ASTRAEA is a validation approach. Similar to typical testing approaches, it does not provide any guarantees or proof that all fairness violations have been exposed. Instead, it allows to explore the input space to assess the fairness properties of NLP systems. Finally,

10. Binary format grammars for PNG and JPEG are available here: https://www.sweetscape.com/010editor/repository/templates/

For instance, ASTRAEA runs till saturation or up to a certain number of iterations is reached. This is due to the absence of new unique test inputs being generated in two successive iterations. However, it is possible to discover more fairness violations with more iterations. For instance, this can be accomplished by extending ASTRAEA to be grammar coverage driven, *e.g.* via greedy exploration of all pairwise combination of (sensitive) terminal symbols.

Generalizable ML: We assume all models are generalizable to the task at hand, i.e. they should not over-fit to a specific use case or training dataset. This assumption is reasonable because the input space for a model, task or use case is typically unconstrained and it is not fully captured by the training data set. Besides, testing for out of distribution (OOD) inputs is necessary to ensure model reliability, i.e., validating that an ML system generalizes beyond the biases of its training dataset. Researchers have found that ML models can be easily fooled by out of distribution of inputs [31], [57]. Out of distribution (OOD) testing validates that model outputs are reliable regardless of the constraints on the training data set. Notably, Berend et al. [11] investigated the importance of OOD testing for ML validation and call for the attention of data-distribution awareness during designing, testing and analysis of ML software. In their empirical study they found that distribution-aware testing is effective in improving the reliability and robustness of ML models. In this work, we have performed fairness testing by generating several test cases that are mostly out of distribution (*i.e.*, independent of the training dataset), but necessary to ensure the reliability of the ML software.

In line with the findings of Berend et al. [11], we design our experiments assuming that subject models generalize beyond the training dataset. As an example, we expect that a sentiment analysis model trained on movie reviews, should generalize to other texts (e.g. conversational sentences) that express positive, negative or neutral emotions. To dampen this effect, we employ several models trained on varying training datasets.

General Tasks: This refers to the generalisability of AS-TRAEA to other (NLP) tasks. To mitigate this threat, we evaluated ASTRAEA on three distinct NLP tasks with varying complexities, using 18 different subjects. ASTRAEA's effectiveness on all tested tasks and models shows it can be easily employed for other (NLP) tasks or models.

9 CONCLUSION

In this paper, we have proposed ASTRAEA, the first grammar-based framework to automatically discover and diagnose fairness violations in NLP software. ASTRAEA embodies a directed test generation strategy that leveraged the diagnosis result and it significantly improves the test effectiveness. Moreover, the diagnosis employed by ASTRAEA is further used to retrain NLP models and significantly reduce the number of fairness errors. ASTRAEA is designed to be a general fairness testing framework via an extensible grammar. This is validated by instantiating ASTRAEA across three different NLP tasks comprising 18 different models. We show that ASTRAEA finds hundreds of thousands of fairness errors in these models and significantly improves software fairness via model re-training. ASTRAEA provides a pathway to advance research in automated fairness testing of NLP software – a crucial, yet underrepresented area that requires significant attention. To reproduce and further research activities, our tool and all experimental data are publicly available here:

https://github.com/sakshiudeshi/Astraea

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