BiasFinder: Metamorphic Test Generation to Uncover Bias for Sentiment Analysis Systems

Muhammad Hilmi Asyrofi, Imam Nur Bani Yusuf, Hong Jin Kang, Ferdian Thung, Zhou Yang and David Lo

Abstract—Artificial Intelligence (AI) software systems, such as Sentiment Analysis (SA) systems, typically learn from large amounts of data that may reflect human biases. Consequently, the machine learning model in such software systems may exhibit unintended demographic bias based on specific characteristics (e.g., gender, occupation, country-of-origin, etc.). Such biases manifest in an SA system when it predicts a different sentiment for similar texts that differ only in the characteristic of individuals described. Existing studies on revealing bias in SA systems rely on the production of sentences from a small set of short, predefined templates.
To address this limitation, we present BiasFinder, an approach to discover biased predictions in SA systems via metamorphic testing. A key feature of BiasFinder is the automatic curation of suitable templates based on the pieces of text from a large corpus, using various Natural Language Processing (NLP) techniques to identify words that describe demographic characteristics. Next, BiasFinder instantiates new text from these templates by filling in placeholders with words associated with a class of a characteristic (e.g., gender-specific words such as female names, “she”, “her”). These texts are used to tease out bias in an SA system. BiasFinder identifies a bias-uncovering test case when it detects that the SA system exhibits demographic bias for a pair of texts, i.e., it predicts a different sentiment for texts that differ only in words associated with a different class (e.g., male vs. female) of a target characteristic (e.g., gender). Our empirical evaluation showed that BiasFinder can effectively create a large number of realistic and diverse test cases that uncover various biases in an SA system with a high true positive rate of up to 95.8%.

Index Terms—sentiment analysis, test case generation, metamorphic testing, bias, fairness bug

1 Introduction

MANY modern software systems comprise of AI systems to make decisions. In AI systems, fairness is considered to be an important non-functional requirement; bias in AI systems, reflecting discriminatory behavior towards unprivileged groups, can lead to real-world harms. To address this requirement, software engineering research techniques, such as test generation, have been applied to detect bias [1]–[5]. While various techniques have been proposed for test generation of machine learning systems [1]–[4], there have been limited studies on detecting biases in text-based machine learning systems [5]. Text-based ML systems have numerous applications, for example, NLP techniques have been used for Sentiment Analysis (SA). It is, therefore, important that biases in these systems can be detected before these systems are deployed.

SA systems are used to measure the attitudes and affects in text reviews about an entity, such as a movie or a news article [6], [7]. In this work, we focus on uncovering bias in SA for two reasons.

Firstly, SA has widespread adoption in many domains [8], [9], including politics [10], [11], finance [12]–[15], business [16], education [17]–[19], and healthcare [20]–[22]. In the research community, SA continues to be widely studied [23]–[28]. In the industry, many companies, such as Microsoft[1] and Google[2], have developed and provided APIs for software developers to access SA capabilities. This suggests the prevalence of SA in real-life applications.

Secondly, SA has generalizability to other areas of NLP. Some NLP researchers have considered SA to be “mini-NLP” [9], as research on SA techniques builds on top of a wide range of topics and tasks in the NLP domain. Cambria et al. [29] argues that SA is a problem with a composite nature, requiring 15 more fundamental NLP problems to be addressed at the same time. Therefore, we believe that tackling bias in SA is a suitable first step that could lead to a more general approach to detect bias in textual data.

Modern SA models have outstanding performance on benchmark datasets, which demonstrates their effectiveness. However, there has been a growing understanding in both the Software Engineering [3] and Artificial Intelligence [5] research communities that it is important to study non-functional requirements, such as fairness, which have been overlooked. AI systems learn from data generated by humans. In the case of SA, the training data is typically a dataset of human-written reviews. The training data may reflect human biases. SA systems may, therefore, exhibit biases towards a demographic characteristic, such as gender [30], [31]. For example, the sentiment predicted by an SA system may differ for a piece of text after a perturbation in the text to replace words that describe a demographic characteristic, e.g., changing “I am an Asian man” into “I am a black woman” may cause a predicted sentiment to change from

• *M.H. Asyrofi, I.N.B. Yusuf, H.J. Kang, F. Thung, Z. Yang, D. Lo are with the School of Computing and Information Systems, Singapore Management University*
E-mail: mhilmia@smu.edu.sg, imamy.2020@phdcs.smu.edu.sg, hjkang.2018@phdcs.smu.edu.sg, ferdianthung@smu.edu.sg, zyang@smu.edu.sg, davidlo@smu.edu.sg

Manuscript received April 19, 2005; revised August 26, 2015.

[1]https://azure.microsoft.com/en-us/services/cognitive-services/text-analytics/
[2]https://cloud.google.com/natural-language/docs/analyzing-sentiment

positive to negative, therefore, showing that the SA system reflects demographic bias.

As SA systems are used in many domains, including sensitive areas such as healthcare, and may be used for business analytics to make critical business decisions, it is important to detect biases in these systems. Early discovery of these biases will help to prevent the perpetuation of human biases, and aid to prevent real-world harms. To do so, SA systems should be tested for fairness (i.e., absence of unintended bias), as existing studies suggest [5], [30]. Prior studies have relied on a small number of templates to generate short texts that may uncover bias. Specifically for SA systems, Kiritchenko and Mohammad [30] propose EEC, which generates test cases produced from 11 handcrafted templates. These test cases help to detect if an SA system predicts a different sentiment given two texts that differ only in a single word associated with a different gender or race.

These test cases are limited in number and may not adequately uncover biases in a system. Very recently, SA researchers [9] have noted that "the templates utilized to create the examples might be too simplistic" and identifying such biases "might be relatively easy". They suggest that "Future work should design more complex cases that cover a wider range of scenarios." In this work, our goal is to address these limitations of handcrafted templates by automatically generating test cases to uncover biases.

We propose BiasFinder, a framework that automatically generates test cases to discover biased predictions in SA systems. BiasFinder automatically identifies and curates suitable texts in a large corpus of reviews, and transforms these texts into templates. Each template can be used to produce a large number of mutant texts, by filling in placeholders with concrete values associated with a *class* (e.g., male vs. female) given a *demographic characteristic* (e.g., gender). Using these mutant texts, BiasFinder then runs the SA system under test, checking if it predicts the same sentiment for two mutants associated with a different class (e.g. male vs. female) of the given characteristic (e.g. gender). A pair of such mutants are related through a metamorphic relation where they share the same predicted sentiment from a fair SA system.

The key feature of BiasFinder is its automatic identification and transformation of suitable text in a corpus to a template. This allows BiasFinder to produce a large number of test cases that are varied and realistic compared to previous approaches. Identifying suitable texts to transform to a template is challenging. For instance, all references to an entity should be replaced in a consistent way that does not make the text (e.g., a paragraph) incoherent. An example is shown in Figure 1, in which all expressions referring to an entity ("Jake") need to be updated. The name "Jake" and its references (bolded and underlined) need to be updated together for the text to remain coherent. BiasFinder addresses this challenge through the use of Natural Language Processing (NLP) techniques, such as coreference resolution and named entity recognition, to find all words that require modification.

Our framework, BiasFinder, can be instantiated to identify different kinds of bias. In this work, we show how BiasFinder can be instantiated to uncover bias in three different demographic characteristics: gender, occupation, and country-of-origin. We empirically evaluate the 3 instances

Original Text
It seems that **Jake** with all **his** knowledge of the great outdoors didn't realize the danger! **He** enters a mine shaft that's leaking with dangerous gas!

Mutant Text
It seems that **Julia** with all **her** knowledge of the great outdoors didn't realize the danger! **She** enters a mine shaft that's leaking with dangerous gas!

Fig. 1. An example of how all references to the same entity has to be considered when mutating a text to be associated with a different gender.

of BiasFinder by running it on a SA model based on BERT [32] – a state-of-the-art text analysis engine. By running BiasFinder on a IMDB Dataset of 50K Movie Reviews [33], we produce test cases of texts (paragraphs) resembling movie reviews. We show the effectiveness of BiasFinder in uncovering biases in an SA system; BiasFinder can generate many pairs of texts revealing biases exhibited by the SA system. Additionally, we evaluate whether the pairs of texts are coherent and should have the same sentiment (although predicted to be of different sentiments by the SA system) by performing a user study. We find that BiasFinder's achieves a reasonable true positive rate of of up to 90%.

The contributions of our work are:

- We propose BiasFinder, a framework that uncovers bias in SA systems through the automatic generation of a large number of realistic test cases given a target characteristic. The source code of BiasFinder is publicly available.[3]
- BiasFinder automatically identifies and curates appropriate and realistic texts (of various complexity) and transforms them into templates that can be instantiated to detect bias. Prior work only considers a small set of manually-crafted simple templates.
- We evaluate BiasFinder on IMDB Dataset of 50K Movie Reviews [33], and generate 129,598 bias-uncovering test cases over 3 demographic characteristics, gender, occupation, and country-of-origin.

The rest of this paper is organized as follows. Section 2 introduces the necessary background related to our work. Section 3 presents BiasFinder. Section 4 elaborates GenderBiasFinder, an instantiation of BiasFinder to detect gender bias. Section 5 briefly discusses instantiations of BiasFinder for detecting occupation and country-of-origin bias. Section 6 describes the results of our experiments. Section 7 presents related work. Finally, Section 8 concludes this paper and describes some future work.

2 Preliminaries

This section provides more details of the benchmark dataset that motivates our work (Section 2.1), as well as basic NLP operations that we use as building blocks of our proposed approach (Section 2.2).

2.1 Equity Evaluation Corpus (EEC)

The Equity Evaluation Corpus (EEC) is a benchmark dataset proposed by Kiritchenko and Mohammad [30] to reveal

[3]https://github.com/soarsmu/BiasFinder

bias in natural language systems. The EEC consists of 8,640 sentences designed to reveal gender and race bias. These sentences are constructed instantiating placeholders in the templates shown in Table 1. The placeholders in templates 1-7 can be replaced with words to produce sentences that lean towards positive or negative sentiment, while the templates in 8-11 result in sentences with a neutral sentiment.

TABLE 1
Templates in EEC

No	Template	# Sentence
Sentences with emotion words:		
1	$\langle person \rangle$ feels $\langle emotion \rangle$	1,200
2	The situation makes $\langle person \rangle$ feel $\langle emotion \rangle$	1,200
3	I made $\langle person \rangle$ feel $\langle emotion \rangle$	1,200
4	$\langle person \rangle$ made me feel $\langle emotion \rangle$	1,200
5	$\langle person \rangle$ found himself/herself in a/an $\langle emotion \rangle$ situation	1,200
6	$\langle person \rangle$ told us all about the recent $\langle emotion \rangle$ events	1,200
7	The conversation with $\langle person \rangle$ was $\langle emotion \rangle$	1,200
Sentences with no emotion words:		
8	I saw $\langle person \rangle$ in the market	60
9	I talked to $\langle person \rangle$ yesterday	60
10	$\langle person \rangle$ goes to the school in our neighborhood	60
11	$\langle person \rangle$ has two children	60

Templates in the EEC have two placeholders: $\langle person \rangle$ and $\langle emotion \rangle$. Mutant texts are generated by instantiating each placeholder with a predefined value. Predefined values for the placeholder $\langle person \rangle$ are:

- Common African American female or male first names; Common European American female or male first names; taken from Caliskan et al. [34]
- Noun phrases referring to females, such as 'my daughter'; and noun phrases referring to males, such as 'my son'.

The second placeholder, $\langle emotion \rangle$, corresponds to four basic emotions: anger, fear, joy, and sadness. For each emotion, EEC selects five words from Roget's Thesaurus[4] with varying intensities.

Although the EEC has successfully revealed bias in NLP systems [30], it is limited only to gender and race bias. It does not explore bias against other demographic information (e.g., occupation, etc.) that may also lead to inappropriate behavior of Sentiment Analysis and other NLP systems. Furthermore, the templates used to create the text dataset may be too short and simplistic as argued by Poria et al. [9]. We suggest that a system that has the capability to automatically create templates to produce more diverse and more complex sentences can aid in better uncovering bias in Sentiment Analysis systems.

2.2 Natural Language Processing (NLP) Techniques

2.2.1 Part-of-speech Tagging

Part-of-speech tagging (PoS-tagging) is the process of identifying the part of speech (e.g. noun, verb) that each word in a text belongs to [35]. An example of PoS-tagging is shown in Figure 2. In the example text, "Maria" is tagged as a proper noun (PROPN); "has" and "loves" are tagged as verbs (VERB); and "She" and "him" are tagged as pronouns (PRON).

[4]http://www.gutenberg.org/ebooks/22

2.2.2 Named Entity Recognition

Named entity recognition (NER) automatically identifies named entities in a text and groups them into predefined categories. Examples of named entities are people, organizations, occupations, and geographic locations [36]. An example of NER can be found in Figure 2, where the word "Maria" is assigned to the "PERSON" category. In this work, we are mainly interested with the person (for gender and country-of-origin bias) and occupation (for occupation bias) categories.

2.2.3 Coreference Resolution

Finding all expressions that refer to the same entity in a text is known as coreference resolution [37]. Linking such expressions is useful for many NLP tasks where the correct interpretation of a piece of text has to be derived (e.g. document summarization, question answering). Coreference resolution only links expressions together, and does not identify the types of the referenced entities, which is done through NER. An example of coreference resolution can be found in Figure 2, in which the expressions "Maria" and "She" are linked. Likewise, the expressions "a friend" and "him" are linked as they refer to the same entity. Given an input text, running a coreference resolution on it will produce n lists of references; each list corresponds to references to a single entity.

Input Text
Maria has a friend. She loves him.

POS-tagging
Maria|PROPN has|VERB a|DET friend|NOUN .|PUNCT
She|PRON loves|VERB him|PRON .|PUNCT

NER
Maria | PERSON

Coreferences Resolution

```
 +----------------+
 |                |
Maria has a friend. She loves him.
          |                 |
          +-----------------+
```

Coreferences
Maria, She
a friend, him

Fig. 2. Example of POS-tagging, NER, and coreference resolution. There are two entities identified by the coreference resolution, "Maria" and "a friend", and the expressions referring to these entities are linked.

2.2.4 Dependency Parsing

The process of assigning a grammatical structure to a piece of text and encoding dependency relationships between words is known as dependency parsing [38], [39]. Encoding such information as a parse tree, words in a text are connected such that words that modify each other are linked. For example, a dependency parse tree connects a verb to its subject and object, and a noun to its adjectives.

Figure 3 shows an example of a parse tree that is output by performing a dependency parsing of an input text: "That guy from Blade Runner also cops a good billing". The directed, labeled edges between nodes indicate the

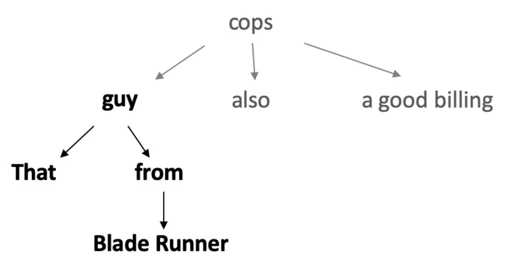


Fig. 3. Example of a dependency parse tree for the sentence "That guy from Blade Runner also cops a good billing". The root word of the phrase "That guy from Blade Runner" (bolded in the above image) is "guy".

relationships between the parent and child nodes. From the parse tree, the root word of a phrase can be identified. For example, the root word of the phrase "That guy from Blade Runner" represented in Figure 3 is "played"", as its node does not have any incoming edges from the nodes of other words in the phrase.

3 BIASFINDER

Figure 4 shows the architecture of our proposed approach: BiasFinder. It takes, as input, a collection of texts and a sentiment analysis (SA) system, and produces, as output, a set of *bias-uncovering test cases*. BiasFinder has three components: (A) *template generation engine*, (B) *mutant generation engine*, and (C) *failure detection engine*. The template generation engine generates *bias-targeting templates* from a collection of texts. These templates are designed to target bias towards a specific characteristic (e.g., gender). The generated templates are input to the mutant generation engine. This engine generates text variants (*mutants*) that differ in a target bias characteristic (e.g., two paragraphs, which are otherwise identical, but describe an individual using words associated with a different gender) and should have the same sentiment. These mutants are then input to the failure detection engine. This engine makes use of the metamorphic relation between mutants (i.e., they have the same sentiment as they are generated from the same template) to infer failures (i.e., bias). This engine identifies mutants that uncover bias in the SA system. These mutants are output as the bias-uncovering test cases.

3.1 Template Generation Engine

The template generation engine follows the workflow in Figure 5. It takes a collection of texts as the input and produces *bias-targeting templates*. Each template is a text unit (e.g., a paragraph) that contains one or more placeholders; the placeholders can be substituted with concrete values to generate different pieces of text that should have the same sentiment.

This engine generates templates for detecting bias in a target characteristic (e.g., gender, occupation, etc.). It extracts linguistic features such as named entities, coreferences, and part-of-speech (*Step 1*). Using these features, it identifies entities related to the characteristic of the targeted bias (*Step 2*). If such entities exist in the texts, BiasFinder replaces references to these entities with placeholders. Essentially, the texts are converted to templates which will be used to generate mutant texts for uncovering the targeted bias (*Step 3*).

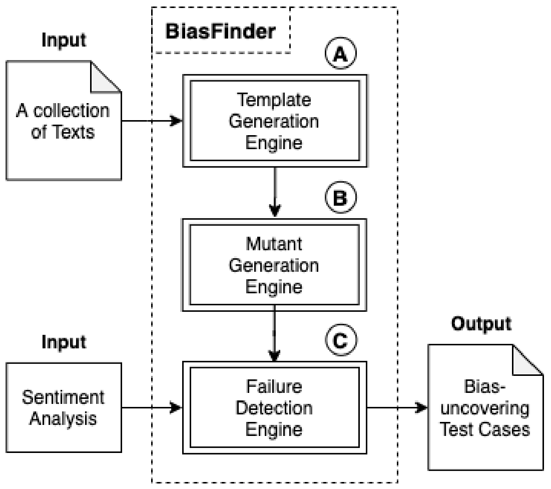


Fig. 4. Architecture of BiasFinder

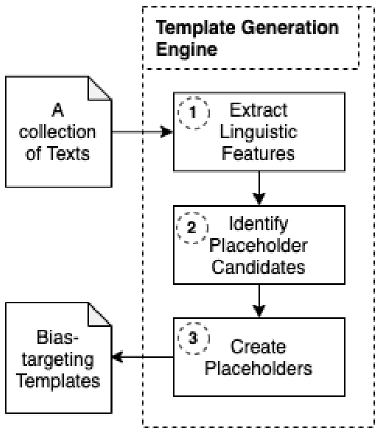

Template Generation Engine
A collection of Texts
1 Extract Linguistic Features
2 Identify Placeholder Candidates
3 Create Placeholders
Bias-targeting Templates

Fig. 5. Workflow of Template Generation Engine

3.2 Mutant Generation Engine

To generate mutant texts from a bias-targeting template, this engine replaces template placeholders with concrete values taken from pre-determined lists of possible values. These lists differ based on the target bias under consideration. The engine substitutes the placeholders with concrete values while ensuring that the generated mutants are valid. A mutant is valid iff the values that are assigned to the placeholders are in agreement with each other. For example, we do not want to generate the following text: "The <u>man</u> speaks to <u>herself</u>". The engine ensures this does not occur by picking only values from a single *class* (e.g., male-related words) to substitute related placeholders to generate a mutant. Each generated mutant is thus associated to a class; and BiasFinder's goal is to check if an SA discriminates against one of the classes (e.g., male or female) associated with a target characteristic (e.g. gender).

3.3 Failure Detection Engine

The failure detection engine takes as input a set of mutant texts along with their class labels, and produces a set of bias-uncovering test cases. le of a dependency parse tree for tThen, it feeds the mutants one-by-one to the SA system, which outputs a sentiment label for each mutant. Mutants of

Algorithm 1: Generating a Template for Detecting Gender Bias

```
   Input: s: a text, gn: gender nouns
   Output: t : a template or null
1  t = s;
2  corefs = getCoreferences(s);
3  names = getPersonNamedEntities(s);
4  coref = filter(corefs, names, gn);
5  if coref ≠ null then
6      for r ∈ coref do
7          if isPersonName(r, names) then
8              t = createPlaceholder(t, s, r, names);
9          end
10         else if isGenderPronoun(r) then
11             t = createPlaceholder(t, s, r);
12         end
13         else if hasGenderNoun(r, gn) then
14             t = createPlaceholder(t, s, r, gn);
15         end
16     end
17 end
18 return $t == s ? null : t$
```

differing classes that are produced from the same template are expected to have the same sentiment. Therefore, if the SA predicts that two mutants of different classes to have different sentiments, they are an evidence of a biased prediction. Such pairs of mutants are output as *bias-uncovering test cases*.

3.4 Instantiating BiasFinder to Different Biases

BiasFinder can be instantiated in various ways to uncover different kinds of biases. In this work, we investigate 3 instances of BiasFinder that can uncover gender, occupation, and country-of-origin biases of a sentiment analysis (SA) system. To instantiate BiasFinder to a particular target characteristic, we need to customize its three components: template generation engine, mutant generation engine, and failure detection engine. We elaborate on how we create GenderBiasFinder, an instance of BiasFinder targeting gender bias in Section 4, and briefly describe the two other instances of BiasFinder in Section 5.

4 GENDERBIASFINDER

An SA system exhibits gender bias if it behaves differently for texts that only differ in words that reflect gender. GenderBiasFinder generates mutants by changing words associated with the gender of a person, and uncovers gender bias when the SA system predicts differing sentiments for a pair of mutants of different gender classes. In this work, we focus on *binary* genders: male and female; but our approach can be extended and generalized for *non-binary* genders. To uncover gender bias, we customize the three main engines of BiasFinder: Template Generation Engine, Mutant Generation Engine, and Failure Detection Engine.

4.1 Template Generation Engine

Algorithm 1 shows the process for generating templates for uncovering gender bias. Given an input text, GenderBiasFinder extracts linguistic features in the form of parts-of-speech, named entities referring to person names, and coreferences. GenderBiasFinder uses coreference resolution (see Section 2.2.3) to find references of entities in the text (Line 2). References to a unique entity are grouped together in a list. The output of the coreference resolution is n lists where n is the total number of entities mentioned in the text, which we refer to as *corefs*. We also run named entity recognition (see Section 2.2.2) to identify person named entities (e.g., person names) in the text (Line 3).

Next, we filter coreference lists in *corefs* by performing two checks embedded inside function *filter* (Line 4):

1) There is *only one* list in *corefs* that refers to a person. In this work, we consider any of the following as a reference to a person: (i) a person name, (ii) a gender pronoun (i.e. he, she), or (iii) a phrase containing a gender noun (e.g., "that guy from Blade Runner").
2) *All references* in the list identified above must be a reference to a person.

If both conditions are met, *filter* returns a coreference list *coref* satisfying the condition; otherwise, it returns *null*. These checks are done to avoid the generation of unsound templates due to coreference resolution's limitations, e.g., detecting a set of references to the same entity as two disjoint lists. If there is a *coref* returned, GenderBiasFinder iterates all its references and creates placeholders depending on the type of each reference r (Lines 7-15). At the end of the iteration, we output a template t generated from the input text s (Line 18). For each iteration, we have three cases depending on the type of each r:

Case 1: *The Reference is a Person Name (Line 7-9)*

At line 7, GenderBiasFinder checks whether the reference r is a person's name in the list of names $names$ extracted using named entity recognition (see Section 2.2.2). If this is the case, GenderBiasFinder generates a template by replacing the person's name with the $\langle name \rangle$ placeholder (Line 8). In the example shown in Figure 6, "Drew Barrymore" is a person's name and is replaced with this placeholder.

Text
'Never Been Kissed' is a real feel good film. If you haven't seen it yet, then rent it out. I am going to buy it when its released because I loved it. **Drew Barrymore** is excellent again, **she** plays **her** part well. I felt I could relate to this film because of the school days I had were just as bad.

Coreferences
Drew Barrymore, she, her

Person Named Entity
Drew Barrymore

Generated Template
'Never Been Kissed' is a real feel good film. If you haven't seen it yet, then rent it out. I am going to buy it when its released because I loved it. ⟨**name**⟩ is excellent again, ⟨**pro-spp**⟩ plays ⟨**pro-pp**⟩ part well. I felt I could relate to this film because of the school days I had were just as bad.

Fig. 6. An Illustrative Example for Case 1 and 2 of GenderBiasFinder

Case 2: *The Reference is a Gender Pronoun (Lines 10-12)*

GenderBiasFinder checks if the reference r is a gender pronoun (Line 10). If so, GenderBiasFinder converts the gender pronoun into ⟨*pro-id*⟩ (Line 11), where *id* can take several values according to the type of the gender pronoun that the placeholder replaces: (1) *spp* for subjective personal pronoun (i.e., he and she), (2) *opp* for objective personal pronoun (i.e., him and her), (3) *pp* for possesive pronoun (i.e., his and her), and (4) *rp* for reflexive pronoun (i.e., himself and herself). In the example shown in Figure 6, "she" is converted to ⟨*pro-spp*⟩ placeholder, while "her" is converted to ⟨*pro-pp*⟩ placeholder.

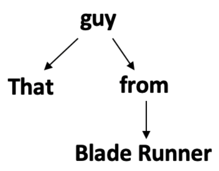
Case 3: *The Reference has a Gender Noun (Lines 13-15)*

GenderBiasFinder checks if the *root word* of the reference r is a gender noun (Line 13). GenderBiasFinder utilizes dependency parsing (see Section 2.2.4) to find the root word and performs POS-tagging (see Section 2.2.1) to confirm that the root word is a noun. Next, it checks that the word exists in gn, a collection of gender-related nouns, and if it does, converts the root word to ⟨*gaw*⟩ placeholder (Line 14). In the example shown in Figure 7, the reference is "That guy from "Blade Runner"". By performing dependency parsing and POS-tagging, "guy" is identified as the root word and is a noun. GenderBiasFinder checks whether "guy" exists in gn. As it does, GenderBiasFinder replaces "guy" to a ⟨*gaw*⟩ placeholder. Some examples of gender nouns are shown in Table 3. In total, we use 22 gender nouns.

Text
Even the manic loony who hangs out with the bad guys in "Mad Max" is there. **That guy from "Blade Runner"** also cops a good billing, although **he** only turns up at the beginning and the end of the movie.

Coreferences
That guy from "Blade Runner", he

Dependency Parsing of The Reference



POS-tagging of The Reference
That|DET guy|NOUN from|ADP "|PUNCT Blade|PROPN Runner|PROPN "|PUNCT

Generated Template
Even the manic loony who hangs out with the bad guys in "Mad Max" is there. That ⟨**gaw**⟩ from "Blade Runner" also cops a good billing, although ⟨**pro-spp**⟩ only turns up at the beginning and the end of the movie.

Fig. 7. An Illustrative Example for Case 3 of GenderBiasFinder

4.2 Mutant Generation Engine

For each generated template, the mutant generation engine produces multiple mutants by replacing placeholders with concrete values. As our objective in GenderBiasFinder is to create test cases related to gender, each mutant is associated with a gender class (i.e., male or female) and the mutant generation engine is restricted to values associated with the given gender class when filling in all placeholders for one mutant. The engine iterates over all possible combinations of the values. Each placeholder can be substituted by a value from a set. We describe the values that each placeholder can be substituted with below:

TABLE 2
Example Names from GenderComputer

Name	Gender	Country-of-origin
Matrosov	Male	Russia
Kapoor	Female	India
Andrea	Male	Italy
Zeynep	Female	Turkey

TABLE 3
Example of Gender Nouns

Male	Female
boy, brother, father, dad, . . .	girl, sister, mother, mom, ...

⟨***name***⟩ **Placeholder:** Values to be substituted for this placeholder are taken from the set of names from GenderComputer[5]. GenderComputer provides a database of male and female names from several countries. Each name in the GenderComputer provides information about its gender and its country-of-origin. It is possible that a name may be used by both genders in the same or different countries. Thus, we filter the names to make sure that the selected names are only used for one gender globally. We randomly take $2N$ names from this filtered set: N male names and N female names. By default, N is set to 30. Examples of names from GenderComputer are shown in Table 2.

⟨***pro-id***⟩ **Placeholder:** Values to be substituted for this placeholder depend on the gender class of the mutant and the id. For male mutant, the values are he for id-*spp*, him for id-*opp*, his for id-*pp*, and himself for id-*rp*. For female mutant, the values are she for id-*spp*, her for id-*opp*, her for id-*pp*, and herself for id-*rp*.

⟨***gaw***⟩ **Placeholder:** Values to be substituted for this placeholder are the set of gender nouns taken from several English resources[6][7][8] Examples of these gender nouns are shown in Table 3.

4.3 Failure Detection Engine

The Failure Detection Engine runs the SA system, using the generated mutants as inputs. It receives, from the SA system, a label for each mutant indicating the predicted sentiment of the mutant. Mutants generated from the same template are expected to have the same predicted sentiment and are grouped together. Each group of mutants is further divided into two classes, depending on the gender associated with the mutant. Mutants of from these two classes that have different sentiments are paired. In other words, the engine find pairs of mutants generated from the same template that differ in both the gender class they are associated with, and the sentiment predicted by the SA system. These pairs of mutants are the bias-uncovering test cases and are the output of GenderBiasFinder.

[5]https://github.com/tue-mdse/genderComputer
[6]https://7esl.com/gender-of-nouns/
[7]http://www.primaryresources.co.uk/english/PC_gen.htm
[8]https://ielts.com.au/articles/grammar-101-feminine-and-masculine-words-in-

Algorithm 2: Generating a Template for Detecting Occupation Bias

```
Input: s: a text
Output: t : a template or null
1  t = s;
2  occs = getOccNamedEntities(s);
3  for occ ∈ occs do
4      if isNoun(occ) then
5          if hasAdjective(t, occ) then
6              t = removeAdjective(t, occ);
7          end
8          t = createPlaceholders(t, occ);
9          occCorefs = getCoreferencesOf(s, occ);
10         for r ∈ occCorefs do
11             if isRefContainsOcc(r, occ) then
12                 if hasAdjective(t, r) then
13                     t = removeAdjective(t, r);
14                 end
15                 t = createPlaceholders(t, r);
16             end
17         end
18         return t;
19     end
20 end
21 return null
```

5 Other Instances of BiasFinder

In this section, we describe how BiasFinder can be instantiated for occupation and country-of-origin biases.

5.1 Occupation Bias

Occupation bias occurs when an SA system favors an honest (i.e., non-criminal) occupation over another. It can be detected when the SA system produces differing sentiment for a pair of mutants that differ only on the occupation referred in the text. We perform these customizations to uncover occupation bias:

Template Generation Engine: We generate occupation templates following Algorithm 2. We first extract the list of occupations *occs* mentioned in the input text s using named entity recognition (Line 2). We then iterate each occupation *occ* from *occs* (Line 3). We then confirm that *occ* is a noun and check whether *occ* has adjectives (Lines 4-5). For example, the adjective of *"driver"* in the *"race car driver"* noun phrase is *"race car"*. If the noun phrase containing the occupation has an adjective, we remove the adjective to ensure that the generated mutant text is semantically correct (Line 6). Leaving the adjective intact may produce a text that describes a non-existent occupation such as *"race car* secretary". We then convert *occ* to $\langle occupation \rangle$ placeholder (Line 8). We also convert determiner "a" or "an" in front of *occ* (if it exists) to $\langle det \rangle$ placeholder to ensure the produced mutant template is grammatically correct. Next, we extract *occCorefs* (Line 9); *occCorefs* is the list of references in s that refer to the same entity that *occ* refers to. We then iterate each reference r from *occRefs* (Line 10). We check whether r is a mention of *occ* (Line 11). For such r, we again create $\langle occupation \rangle$ and $\langle det \rangle$ placeholders (if necessary), after removing adjectives (if necessary) (Lines 12-15). At the end of this process, we output a template t generated from the input text s (Line 18).

In the example below, we detect "doctor" and "journalist" as occupations. We only use the first occupation to form a template. As "doctor" is a noun, and it is not preceded by any adjective, we replace it directly to $\langle occupation \rangle$ placeholder. We then replace its determiner with $\langle det \rangle$ placeholder. In this case, there are no coreferences of "doctor", so the template generation process ends.

Text
The beautiful Jennifer Jones looks the part and gives a wonderful, Oscar nominated performance as **a doctor** of mixed breed during the advent of Communism in mainland China.

Occupation Named Entity
doctor

Generated Template
The beautiful Jennifer Jones looks the part and gives a wonderful, Oscar nominated performance as **⟨det⟩ ⟨occupation⟩** of mixed breed during the advent of Communism in mainland China.

Fig. 8. An Illustrative Example for OccupationBiasFinder

Mutant Generation Engine: To generate occupation mutants, the engine substitutes the $\langle occupation \rangle$ placeholder with a value from a set of 79 honest (i.e., non-criminal) and gender-neutral occupation names that are taken from [40]–[42]. The value of $\langle det \rangle$ is linked with the value of $\langle occupation \rangle$ placeholder. For example, the values of $\langle det \rangle$ for "teacher" and "engineer" occupations are "a" and "an", respectively.

Failure Detection Engine: The engine inputs the generated mutants to the SA system. The SA system labels each mutant with a predicted sentiment. Mutants from the same template are grouped together and mutants in the same group that have a different sentiment are paired. By doing so, the engine finds pairs of mutants that differ both in the occupation they mentioned and the sentiment predicted by the SA system. These pairs of mutants are the bias-uncovering test cases for occupation bias.

5.2 Country-of-Origin Bias

Country-of-origin bias occurs when the SA system favors a person who originates from one country over a person originating from another country. This bias is detected when the SA system produces different sentiments for texts differing only in country-of-origin of the person referred in the text. To uncover country-of-origin bias, we customize BiasFinder as follows:

Template Generation Engine: For generating country-of-origin templates, we follow Algorithm 3. We first run coreference resolution to find *corefs*, which contains references of persons mentioned in the input text s (Line 1). We also run named entity recognition to extract the list of person names mentioned in s (Line 2), which we refer to as *names*.

Next, we filter coreference lists in *corefs* by using the same *filter* function described in Algorithm 1 in Section 4. This is done to avoid the generation of unsound templates due to coreference resolution's limitations. The *filter* function

Algorithm 3: Generating a Template for Detecting Country-of-Origin Bias

```
   Input: s: a text
   Output: t : a template or $null$
1  t = s; corefs = getCoreferences(s);
2  names = getPersonNamedEntities(s);
3  coref = filter(corefs, names);
4  if coref $\neq$ null then
5      g = inferGender(coref);
6      if g $\in \{Male, Female\}$ then
7          for r $\in$ coref do
8              if isPersonName(r, names) then
9                  t = createPlaceholder(t, s, r, g);
10             end
11         end
12         return t
13     end
14 end
15 return $null$
```

returns either a coreference list *coref* or *null*. We stop the template generation process if *null* is returned.

Otherwise, if the references in *coref* refer to a consistent gender g (Line 6) – i.e., by checking that there is a gender pronoun in *coref* and all gender pronouns in it are of the same gender (e.g., he, him, his, himself for male gender) – we iterate each reference r in *coref* (Lines 7-11). If r is the person name in $names$, we replace r with a placeholder representing the gender that was detected (Lines 8-10). A $\langle$*male*$\rangle$ or $\langle$*female*$\rangle$ placeholder is created if a male or a female gender was detected, respectively.

In the example below, "Lauren Holly" is detected as a person name and the coreferences consistently refer to female gender. Thus, we replace "Lauren Holly" with $\langle$*female*$\rangle$ placeholder.

Text
I loved this movie, it was cute and funny! **Lauren Holly** was wonderful, she's funny and very believable in her role.

Coreferences
Lauren Holly, she, her

Person Named Entity
Lauren Holly

Generated Template
I loved this movie, it was cute and funny! $\langle$**female**$\rangle$ was wonderful, she's funny and very believable in her role.

Fig. 9. An Example of Text in CountryBiasFinder

Mutant Generation Engine: To generate country-of-origin mutants, the engine substitutes $\langle$*male*$\rangle$ and $\langle$*female*$\rangle$ placeholders with values from a set of people names taken from GenderComputer[9]. GenderComputer provides the country-of-origin and the gender of each name. Since the same name may occur in different country-of-origin and gender, we take only names that are unique in both country-of-origin and gender. We pick only a male name and a female name from each country. In total, we have 52 names taken from 26 countries of origin. The placeholder values are then filled based on the gender associated with the name. Male and female names are used to fill $\langle$*male*$\rangle$ and $\langle$*female*$\rangle$ placeholders, respectively.

Failure Detection Engine: The engine accepts the generated mutants as input and feed them to the SA system, which gives a sentiment label for each mutant. Mutants from the same template that have a different sentiment are then paired. Here, the engine finds pairs of mutants that differ both in the country-of-origin of the person they mentioned and the sentiment predicted by the SA system. These pairs of mutants are the bias-uncovering test cases for country-of-origin bias.

6 Experiments

In this section, we describe our dataset, experimental settings, evaluation metric, and our research questions. Next, we answer the research questions, and mention threats to validity.

6.1 Dataset and Experimental Settings

We focus on a binary sentiment analysis task, i.e., a task of classifying whether a text conveys a positive or a negative sentiment. A popular dataset to evaluate a sentiment analysis system's performance for this task is the IMDB Dataset of 50K Movie Reviews [33]. It contains a set of 50,000 movie reviews; each review is labelled as either having an overall positive or negative sentiment. Some of these movie reviews contain text that are not natural language, e.g., HTML tags. We remove these text from the movie reviews. Then, we split the 50,000 movie reviews evenly to train and test sets.

We use a Transformer-based model as the sentiment analysis system in our experiments. Transformer-based models have achieved state-of-the-art performances on many NLP tasks in recent years [26], [43], [44]. We pick BERT [32] as a representative model. It is not our goal to evaluate and compare bias over all sentiment analysis systems – we leave such extensive comparative evaluation for future work.

BERT is a pre-trained language model that can be *fine-tuned* to solve many downstream NLP tasks. We fine-tuned BERT for binary sentiment analysis following Sun et al. work [27] and used the implementation they provided.[10] We fine-tuned the BERT sentiment analysis (SA) model using the train set and use the test set as input for three instances of BiasFinder to generate mutants.

We performed our experiments on a computer running Ubuntu 18.04 with Intel(R) Core(TM) i7-9700K CPU @ 3.60GHz processor, 64GB RAM, and NVIDIA GeForce RTX 2080. For coreference resolution, we use NeuralCoref[11]. We use both SpaCy[12] and Stanford CoreNLP[13] for Part-of-Speech (PoS) Tagging and Named Entity Recognition (NER).

Our objective in the study is to produce test cases that reveal bias. As earlier defined, a bias-uncovering test case is a pair of mutants from a bias-targeting template that should

[9]https://github.com/tue-mdse/genderComputer

[10]https://github.com/xuyige/BERT4doc-Classification
[11]https://github.com/huggingface/neuralcoref
[12]https://spacy.io/
[13]https://stanfordnlp.github.io/CoreNLP/

have the same sentiment, but are labelled with a different sentiment by the SA system. To validate our results, we also performed a user study to ensure that the test cases produced are coherent pieces of text and that the mutants of the same template should, indeed, have the same sentiment label.

6.2 Research Questions

RQ1. *How many BTCs can BiasFinder generate?*

BiasFinder is the first approach to automatically generate templates for uncovering multiple biases. We report the number of generated BTCs produced by each instance of BiasFinder for the BERT-based SA system.

RQ2. *How many BTCs are true positives?*

We count the number of BTCs that are true positive via a user study. The user study involves two participants, both of whom are native English speakers and are not authors of this paper. The participants were asked to label mutant texts from randomly sampled BTCs for the three characteristics. We computed the number of samples required for a statistically representative sample given a margin of error of 5% and 95% confidence for the three populations (of 14,916, 109,386, 5,296 generated BTCs). Therefore, we sampled 400 BTCs for each characteristic, which is a number greater than the representative sample sizes (375, 383, 358). The users were asked to label if the mutant texts involved in each BTC are coherent and to provide sentiment labels. We consider a BTC a true positive if its mutants are labelled as coherent texts and are of the same sentiment.

6.3 Results

RQ1. *How many BTCs can BiasFinder generate?*

TABLE 4
BiasFinder's Performance in Generating BTCs

Target Bias	# Templates	# BTCs
Gender	3,057	14,916
Occupation	8,867	109,386
Country-of-Origin	2,344	5,296
Total	**14,268**	**129,598**

Table 4 shows the number of templates generated by and BTCs found by BiasFinder for each its instance. BiasFinder discovered a total of 129,598 BTCs across the three characteristics. Among the three characteristics, it generated the highest number of BTCs for occupation bias and the fewest number of BTCs for the country-of-origin bias. Overall, our experimental results suggest that bias of each characteristic occurs in the target SA system. BiasFinder can also find more BTCs for each bias by generating more templates from another corpus. The templates range in their complexity depending on the text in the corpus. Figures 10, 11, 12 show examples of bias-uncovering test cases for gender, occupation, and country-of-origin, respectively.

RQ2. *How many BTCs are true positives?*

Mutant Text - Using a uniquely male name
What is **he** supposed to be? **He** was a kid in the past, ... and the future? This movie had a lot of problems. Is **he** a ghost, or just a strong kid. Man, ... what a piece of crap. I'm still confused. Also, is **he** supposed to be an abortion? Strange. Very strange. This movie will mess with your mind, ... and it's not very scary, ... just confusing. Why was **he** , ... Where did, ... What was the, ... oh, who cares, ... **Benedetto** isn't worth it, ... My score: 10

Mutant Text - Using a uniquely female name
What is **she** supposed to be? **She** was a kid in the past, ... and the future? This movie had a lot of problems. Is **she** a ghost, or just a strong kid. Man, ... what a piece of crap. I'm still confused. Also, is **she** supposed to be an abortion? Strange. Very strange. This movie will mess with your mind, ... and it's not very scary, ... just confusing. Why was **she** , ... Where did, ... What was the, ... oh, who cares, ... **Elaisha** isn't worth it, ... My score: 10

Fig. 10. BTC Example for Gender

Mutant Text - Housekeeper
Great underrated movie great action good actors and a wonderful story line. Wesley is verry good and the **housekeeper** the bad guy is wonderful The girl plays a nice role and the comedy mixed with blakness!

Mutant Text - Programmer
Great underrated movie great action good actors and a wonderful story line. Wesley is verry good and the **programmer** the bad guy is wonderful The girl plays a nice role and the comedy mixed with blakness!

Fig. 11. BTC Example for Occupation

TABLE 5
Results of our user study. TPR stands for True Positive Rate.

Target Bias	TPR by Annotator 1	TPR by Annotator 2
Gender	76.3%	58.8%
Occupation	65.0%	78.0%
Country-of-Origin	95.8%	65.0%

Table 5 shows the result of the user study. We find that the true positive rates range from 65.0% to 95.8%. We investigated the false positives produced by BiasFinder and we show an example in Figure 13. Although BiasFinder identified the word "director" as an occupation, it cannot be transformed into a placeholder. The usage of the word is specific to the context described in the text, and replacing it with a different occupation results in an incoherent sentence.

To determine the level of agreement between the two human annotators in the user study, we computed Cohen's Kappa [45] and obtained an average value of 0.485 – usually interpreted as moderate agreement [46], [47].[14]

6.4 Threats to Validity

[14]According to Landis and Koch [48], a Kappa value between 0.40 to 0.6 is moderate agreement, while 0.6 to 0.8 is substantial agreement, and a value above 0.8 represents almost perfect agreement.

Mutant Text - Male Name from Somalia
I consider this movie as one of the most interesting and funny movies of all time (...) Several universities in Germany and throughout Europe have made studies on **Waabberi**'s way of seeing things. By the way, **Waabberi** is a very intelligent and sensitive person and on of the Jazz musicians in Germany

Mutant Text - Male Name from Iran
I consider this movie as one of the most interesting and funny movies of all time (...) Several universities in Germany and throughout Europe have made studies on **Keyghobad**'s way of seeing things. By the way, **Keyghobad** is a very intelligent and sensitive person and on of the Jazz musicians in Germany

Fig. 12. BTC Example for Country-of-Origin. (...) is a truncated piece of the original text.

Original Text
I believe the story felt very plain because the **director** failed to focus on character development

Mutant Text
I believe the story felt very plain because the **banker** failed to focus on character development

Fig. 13. Example of a false positive. The usage of the "director" word is context specific, and cannot be replaced with another occupation to produce a coherent mutant text.

We have only experimented with an SA system based on BERT and generated templates from the IMDB dataset. The results may not be generalize to other SA systems and datasets. However, BERT is among the top performing models for text classification in recent years [26], [32], [43], [44], and the IMDB dataset is a common dataset used for studying sentiment analysis [28], [49], [50]. Thus, we believe the threats to validity are minimal as we show that the biases occur on mutants of texts from a common dataset and the biases are exhibited by one of the top models.

While we investigated only the IMDB dataset, it is a large dataset and is commonly used to evaluate sentiment analysis techniques. Thus, we believe IMDB is a good representative dataset for investigating biases in sentiment analysis. Furthermore, the IMDB dataset contains high polarity reviews (i.e., reviews with strong positive/negative sentiments) and, as such, there is minimal risk of mislabelling them.

7 Related Work

In this section, we first describe related work on understanding and detecting bias in AI systems (Section 7.1). Next, we describe some of the related work testing AI systems (Section 7.2).

7.1 Bias in AI Systems

The importance of studying bias in AI systems has been described by many researchers [1], [2], [30], [51], [52]. An AI system may perpetuate human biases and perform differently for some demographic groups than others [1], [31], [51], [52]. As such, many existing studies on uncovering bias [1]–[3], [5], [30] focus on finding differences in the system's behavior given a change in a demographic characteristic (aka. attribute). Our approach has the same high-level objective of uncovering differences in behavior when demographic characteristic is modified, however, our approach differs in several ways, which will be described in the following paragraphs.

Themis [1], Aeqitas [2], and FairTest [3] are approaches aiming to generate test cases that detect discrimination in software. Fairway [4] mitigates bias through several strategies, including identifying and removing ethical bias from a model's training data. Unlike our approach, these strategies do not target NLP systems but focus on systems that take numerical values or images as input, while BiasFinder targets Sentiment Analysis systems which take natural language text as input.

Specific to NLP applications, CheckList [5] has been proposed for creating test cases to evaluate systems on their capabilities beyond their accuracies on test datasets. Fairness is among the capabilities that CheckList tests for, and CheckList relies on a small number of predefined templates for producing test sentences. Our work is complementary to this approach as it can be used to produce test cases without the restriction of predefined templates.

For Sentiment Analysis systems, the EEC [30] has been proposed to uncover bias by detecting differences in predictions of text differing in a single word associated with gender or race. However, as described earlier in Section 2, other researchers [9] have pointed out that the EEC [30] relies on predefined templates that may be too simplistic. We address this limitation as our approach dynamically generates many templates to produce sentences that are varied and realistic. Moreover, our approach uncovers bias through mutating words in text associated with characteristics other than gender and race.

7.2 AI Testing

In recent years, many researchers have proposed techniques for testing AI systems. There are too many of them to mention here. Still, we would like to highlight a few, especially those that are closer to our work. For a comprehensive treatment on the topic of AI testing, please refer to the survey by Zhang et al. [53].

Existing studies have applied metamorphic testing to AI systems [54]–[57]. Many of these systems focus on finding bugs, for example, in machine translation [54], [57] or autonomous driving systems [55], [56]. Our work is related to these studies as BiasFinder is based on metamorphic testing, but differs in that we focus on finding fairness bugs (gender, occupation, and country-of-origin bias) in Sentiment Analysis systems.

In the NLP domain, some research efforts have developed methods for generating adversarial examples [58], [59], while other researchers have proposed techniques to test robustness to typos and other forms of noise [60], or changes in the names of people mentioned in text [61]. Our work differs from these studies as it focuses on uncovering bias rather than testing the correctness of an NLP system.

8 Conclusion and Future Work

There is growing use of Artificial Intelligence in software systems, and fairness is an important requirement in Artificial Intelligence systems. Testing is one way to uncover unintended biases [4], [53]. Our research contributes to the body of work on fairness testing and motivates future research to build automatic fairness testing methods for various machine learning tasks, including sentiment analysis (that we consider in this work).

We propose BiasFinder, a metamorphic testing framework for creating test cases to uncover demographic biases in Sentiment Analysis (SA) systems. BiasFinder can be instantiated for different demographic characteristics, such as gender or occupation. Given a target characteristic, BiasFinder curates suitable texts from a corpus to create bias-uncovering templates. From these templates, BiasFinder then produces mutated texts (mutants) that differ only in words associated with different classes (e.g., male vs. female) of the target characteristic (e.g., gender). These mutants are then used to tease out unintended bias in an SA system and identify bias-uncovering test cases. By analyzing a realistic and diverse corpus, BiasFinder can produce realistic and diverse bias-uncovering test cases.

Existing work [30] use only a small set of simple test cases, testing only for ethnicity bias by swapping names of two geographical characteristics, i.e. African American names and European American names, in a small set of templates of simple sentences. Our work generates templates of test cases involving other characteristics, including gender and country-of-origin. Our mutant generation constructs test cases representing names from 30 countries. Together, the template and mutation generation produces test cases that cover a wider range of scenarios.

We empirically evaluated three instances of BiasFinder on an SA model based on BERT. BiasFinder identifies 14,916, 109,386, and 5,296 bias-uncovering test cases for gender, occupation, and country-of-origin bias. Through a user study, we find that the true positive rates of BiasFinder are reasonably high. In other words, BiasFinder produces a high percentage of bias-revealing pairs of texts that a human annotator considers to have the same sentiment and are coherent.

In the future, we plan to instantiate BiasFinder on more biases and expand the experiments (e.g., by considering other text corpora). Moreover, we will evaluate BiasFinder to determine if it generalizes to tasks beyond SA, for example, testing general text classifiers.

References

[1] S. Galhotra, Y. Brun, and A. Meliou, "Fairness testing: testing software for discrimination," in *Proceedings of the 2017 11th Joint Meeting on Foundations of Software Engineering*, 2017, pp. 498–510.

[2] S. Udeshi, P. Arora, and S. Chattopadhyay, "Automated directed fairness testing," in *Proceedings of the 33rd ACM/IEEE International Conference on Automated Software Engineering*, 2018, pp. 98–108.

[3] F. Tramer, V. Atlidakis, R. Geambasu, D. Hsu, J.-P. Hubaux, M. Humbert, A. Juels, and H. Lin, "Fairtest: Discovering unwarranted associations in data-driven applications," in *2017 IEEE European Symposium on Security and Privacy (EuroS&P)*. IEEE, 2017, pp. 401–416.

[4] J. Chakraborty, S. Majumder, Z. Yu, and T. Menzies, "Fairway: a way to build fair ml software," in *Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, 2020, pp. 654–665.

[5] M. T. Ribeiro, T. Wu, C. Guestrin, and S. Singh, "Beyond accuracy: Behavioral testing of nlp models with checklist," *Association for Computational Linguistics (ACL 2020*, 2020.

[6] B. Pang, L. Lee, and S. Vaithyanathan, "Thumbs up? sentiment classification using machine learning techniques," in *Proceedings of the ACL-02 Conference on Empirical Methods in Natural Language Processing - Volume 10*, ser. EMNLP '02. USA: Association for Computational Linguistics, 2002, p. 79–86. [Online]. Available: https://doi.org/10.3115/1118693.1118704

[7] P. D. Turney, "Thumbs up or thumbs down? semantic orientation applied to unsupervised classification of reviews," in *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics*, ser. ACL '02. USA: Association for Computational Linguistics, 2002, p. 417–424. [Online]. Available: https://doi.org/10.3115/1073083.1073153

[8] W. Medhat, A. Hassan, and H. Korashy, "Sentiment analysis algorithms and applications: A survey," *Ain Shams engineering journal*, vol. 5, no. 4, pp. 1093–1113, 2014.

[9] S. Poria, D. Hazarika, N. Majumder, and R. Mihalcea, "Beneath the tip of the iceberg: Current challenges and new directions in sentiment analysis research," *IEEE Transactions on Affective Computing*, 2020, accepted (early access at: https://ieeexplore.ieee.org/document/9260964).

[10] M. Haselmayer and M. Jenny, "Sentiment analysis of political communication: combining a dictionary approach with crowdcoding," *Quality & Quantity*, vol. 51, pp. 2623 – 2646, 2017.

[11] J. A. Caetano, H. S. Lima, M. F. Santos, and H. T. Marques-Neto, "Using sentiment analysis to define twitter political users' classes and their homophily during the 2016 american presidential election," *Journal of Internet Services and Applications*, vol. 9, pp. 1–15, 2018.

[12] S. Krishnamoorthy, "Sentiment analysis of financial news articles using performance indicators," *Knowl. Inf. Syst.*, vol. 56, no. 2, p. 373–394, Aug. 2018. [Online]. Available: https://doi.org/10.1007/s10115-017-1134-1

[13] T. Renault, "Sentiment analysis and machine learning in finance: a comparison of methods and models on one million messages," *Digital Finance*, 09 2019.

[14] M. Day and C. Lee, "Deep learning for financial sentiment analysis on finance news providers," in *2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, 2016, pp. 1127–1134.

[15] S. Sohangir, D. Wang, A. Pomeranets, and T. M. Khoshgoftaar, "Big data: Deep learning for financial sentiment analysis," *Journal of Big Data*, vol. 5, pp. 1–25, 2017.

[16] M. Rambocas, "Marketing research: The role of sentiment analysis," *FEP WORKING PAPER SERIES*, 04 2013.

[17] S. Rani and P. Kumar, "A sentiment analysis system to improve teaching and learning," *Computer*, vol. 50, no. 05, pp. 36–43, may 2017.

[18] N. Altrabsheh, M. Gaber, and E. Haig, "Sa-e: Sentiment analysis for education," in *Frontiers in Artificial Intelligence and Applications*, vol. 255, 06 2013.

[19] F. S. Dolianiti, D. Iakovakis, S. B. Dias, S. Hadjileontiadou, J. A. Diniz, and L. Hadjileontiadis, "Sentiment analysis techniques and applications in education: A survey," in *Technology and Innovation in Learning, Teaching and Education*, M. Tsitouridou, J. A. Diniz, and T. A. Mikropoulos, Eds. Cham: Springer International Publishing, 2019, pp. 412–427.

[20] V. S. Gupta and S. Kohli, "Twitter sentiment analysis in healthcare using hadoop and r," in *2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom)*, 2016, pp. 3766–3772.

[21] O. Oyebode, F. Alqahtani, and R. Orji, "Using machine learning and thematic analysis methods to evaluate mental health apps based on user reviews," *IEEE Access*, vol. 8, pp. 111 141–111 158, 2020.

[22] S. Yadav, A. Ekbal, S. Saha, and P. Bhattacharyya, "Medical sentiment analysis using social media: Towards building a patient assisted system," in *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*. Miyazaki, Japan: European Language Resources Association (ELRA), May 2018. [Online]. Available: https://www.aclweb.org/anthology/L18-1442

[23] M. Chen, "Efficient vector representation for documents through corruption," *arXiv preprint arXiv:1707.02377*, 2017.

[24] Y. Zhang, Q. Liu, and L. Song, "Sentence-state lstm for text representation," in *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2018, pp. 317–327.

[25] J. Gong, X. Qiu, S. Wang, and X. Huang, "Information aggregation via dynamic routing for sequence encoding," *arXiv preprint arXiv:1806.01501*, 2018.

[26] Z. Yang, Z. Dai, Y. Yang, J. Carbonell, R. R. Salakhutdinov, and Q. V. Le, "Xlnet: Generalized autoregressive pretraining for language understanding," in *Advances in neural information processing systems*, 2019, pp. 5753–5763.

[27] C. Sun, X. Qiu, Y. Xu, and X. Huang, "How to fine-tune bert for text classification?" in *China National Conference on Chinese Computational Linguistics*. Springer, 2019, pp. 194–206.

[28] J. Howard and S. Ruder, "Universal language model fine-tuning for text classification," in *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2018, pp. 328–339.

[29] E. Cambria, S. Poria, A. Gelbukh, and M. Thelwall, "Sentiment analysis is a big suitcase," *IEEE Intelligent Systems*, vol. 32, no. 6, pp. 74–80, 2017.

[30] S. Kiritchenko and S. Mohammad, "Examining gender and race bias in two hundred sentiment analysis systems," in *Proceedings of the Seventh Joint Conference on Lexical and Computational Semantics*, 2018, pp. 43–53.

[31] M. Díaz, I. Johnson, A. Lazar, A. M. Piper, and D. Gergle, "Addressing age-related bias in sentiment analysis," in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 2018, pp. 1–14.

[32] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," in *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 2019, pp. 4171–4186.

[33] A. L. Maas, R. E. Daly, P. T. Pham, D. Huang, A. Y. Ng, and C. Potts, "Learning word vectors for sentiment analysis," in *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*. Portland, Oregon, USA: Association for Computational Linguistics, June 2011, pp. 142–150. [Online]. Available: http://www.aclweb.org/anthology/P11-1015

[34] A. Caliskan, J. Bryson, and A. Narayanan, "Semantics derived automatically from language corpora contain human-like biases," *Science*, vol. 356, pp. 183–186, 04 2017.

[35] E. Brill, "Transformation-based error-driven learning and natural language processing: A case study in part-of-speech tagging," *Comput. Linguist.*, vol. 21, no. 4, p. 543–565, Dec. 1995.

[36] D. Nadeau and S. Sekine, "A survey of named entity recognition and classification," *Lingvisticae Investigationes*, vol. 30, pp. 3–26, 2007.

[37] W. M. Soon, H. T. Ng, and D. C. Y. Lim, "A machine learning approach to coreference resolution of noun phrases," *Computational Linguistics*, vol. 27, no. 4, pp. 521–544, 2001. [Online]. Available: https://www.aclweb.org/anthology/J01-4004

[38] J. Nivre and S. Kübler, "Dependency parsing," *Synthesis Lectures on Human Language Technologies*, vol. 2, 01 2009.

[39] D. Chen and C. Manning, "A fast and accurate dependency parser using neural networks," in *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Doha, Qatar: Association for Computational Linguistics, Oct. 2014, pp. 740–750. [Online]. Available: https://www.aclweb.org/anthology/D14-1082

[40] T. Bolukbasi, K.-W. Chang, J. Zou, V. Saligrama, and A. Kalai, "Man is to computer programmer as woman is to homemaker? debiasing word embeddings," in *Proceedings of the 30th International Conference on Neural Information Processing Systems*, ser. NIPS'16. Red Hook, NY, USA: Curran Associates Inc., 2016, p. 4356–4364.

[41] A. Caliskan-Islam, J. Bryson, and A. Narayanan, "Semantics derived automatically from language corpora necessarily contain human biases," *Science*, vol. 356, 08 2016.

[42] J. Zhao, T. Wang, M. Yatskar, V. Ordonez, and K.-W. Chang, "Gender bias in coreference resolution: Evaluation and debiasing methods," in *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*. New Orleans, Louisiana: Association for Computational Linguistics, Jun. 2018, pp. 15–20. [Online]. Available: https://www.aclweb.org/anthology/N18-2003

[43] T. B. Brown, B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell *et al.*, "Language models are few-shot learners," *arXiv preprint arXiv:2005.14165*, 2020.

[44] C. Raffel, N. Shazeer, A. Roberts, K. Lee, S. Narang, M. Matena, Y. Zhou, W. Li, and P. J. Liu, "Exploring the limits of transfer learning with a unified text-to-text transformer," *arXiv preprint arXiv:1910.10683*, 2019.

[45] J. Cohen, "A coefficient of agreement for nominal scales," *Educational and psychological measurement*, vol. 20, no. 1, pp. 37–46, 1960.

[46] M. V. Mäntylä, B. Adams, F. Khomh, E. Engström, and K. Petersen, "On rapid releases and software testing: a case study and a semi-systematic literature review," *Empirical Software Engineering*, vol. 20, no. 5, pp. 1384–1425, 2015.

[47] M. Joblin, S. Apel, C. Hunsen, and W. Mauerer, "Classifying developers into core and peripheral: An empirical study on count and network metrics," in *2017 IEEE/ACM 39th International Conference on Software Engineering (ICSE)*. IEEE, 2017, pp. 164–174.

[48] J. R. Landis and G. G. Koch, "The measurement of observer agreement for categorical data," *Biometrics*, vol. 33, no. 1, pp. 159–174, 1977. [Online]. Available: http://www.jstor.org/stable/2529310

[49] T. Thongtan and T. Phienthrakul, "Sentiment classification using document embeddings trained with cosine similarity," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop*, 2019, pp. 407–414.

[50] D. S. Sachan, M. Zaheer, and R. Salakhutdinov, "Revisiting lstm networks for semi-supervised text classification via mixed objective function," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, 2019, pp. 6940–6948.

[51] L. Dixon, J. Li, J. Sorensen, N. Thain, and L. Vasserman, "Measuring and mitigating unintended bias in text classification," in *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*, 2018, pp. 67–73.

[52] M. Hardt, E. Price, and N. Srebro, "Equality of opportunity in supervised learning," in *Advances in neural information processing systems*, 2016, pp. 3315–3323.

[53] J. M. Zhang, M. Harman, L. Ma, and Y. Liu, "Machine learning testing: Survey, landscapes and horizons," *IEEE Transactions on Software Engineering*, 2020.

[54] Z. Sun, J. Zhang, M. Harman, M. Papadakis, and L. Zhang, "Automatic testing and improvement of machine translation," in *International Conference on Software Engineering (ICSE)*, 2020.

[55] Z. Q. Zhou and L. Sun, "Metamorphic testing of driverless cars," *Communications of the ACM*, vol. 62, no. 3, pp. 61–67, 2019.

[56] M. Zhang, Y. Zhang, L. Zhang, C. Liu, and S. Khurshid, "Deeproad: Gan-based metamorphic testing and input validation framework for autonomous driving systems," in *2018 33rd IEEE/ACM International Conference on Automated Software Engineering (ASE)*. IEEE, 2018, pp. 132–142.

[57] L. Sun and Z. Q. Zhou, "Metamorphic testing for machine translations: Mt4mt," in *2018 25th Australasian Software Engineering Conference (ASWEC)*. IEEE, 2018, pp. 96–100.

[58] Z. Zhao, D. Dua, and S. Singh, "Generating natural adversarial examples," in *International Conference on Learning Representations*, 2018.

[59] M. Iyyer, J. Wieting, K. Gimpel, and L. Zettlemoyer, "Adversarial example generation with syntactically controlled paraphrase networks," in *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, 2018, pp. 1875–1885.

[60] M. T. Ribeiro, S. Singh, and C. Guestrin, "Semantically equivalent adversarial rules for debugging nlp models," in *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2018, pp. 856–865.

[61] V. Prabhakaran, B. Hutchinson, and M. Mitchell, "Perturbation sensitivity analysis to detect unintended model biases," in *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, 2019, pp. 5744–5749.