

# Automated Test Generation to Detect Individual Discrimination in AI Models

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## Abstract

Dependability on AI models is of utmost importance to ensure full acceptance of the AI systems. **One of the key aspects of the dependable AI system is to ensure that all its decisions are fair and not biased towards any individual.** In this paper, we address the problem of detecting whether a model has an individual discrimination. Such a discrimination exists when two individuals who differ only in the values of their protected attributes (such as, gender/race) while the values of their non-protected ones are exactly the same, get different decisions. Measuring individual discrimination requires an exhaustive testing, which is infeasible for a non-trivial system. In this paper, we present an automated technique to generate test inputs, which is geared towards finding individual discrimination. **Our technique combines the well-known technique called symbolic execution along with the local explainability for generation of effective test cases.** Our experimental results clearly demonstrate that our technique produces 3.72 times more successful test cases than the existing state-of-the-art across all our chosen benchmarks.

## 1 Introduction

*Model Bias.* This decade marks the resurgence of Artificial Intelligence where AI Models have started taking crucial decisions in a lot of systems - from hiring decisions, approving loans, etc. to design driver-less cars. Therefore, dependability on AI models is of utmost importance to ensure wide acceptance of the AI systems. One of the important aspects of the dependable AI system is whether decisions are fair and not biased. Bias may be inherent in a decision-making system in multiple ways. It can exist in the form of group discrimination (Feldman et al. 2015) where two different groups (e.g., based on gender/race) gets a varied decision or an individual discrimination (Galhotra, Brun, and Meliou 2017).

*Individual discrimination.* In this paper, we address the problem of detecting whether a model discriminates between two individuals having the values of all their attributes other than the protected ones exactly the same and if such a model yields different decisions for such two individuals. Such cases of bias have been previously noticed in models such as (Galhotra, Brun, and Meliou 2017) and caused

derogatory consequences to the model generator. Therefore, detection of such cases becomes crucial and is of utmost importance. Even though the training data may not contain two instances where such discrimination is noticed, the model can still show such an unintended behavior. The challenge is, therefore, to evaluate and find that for which all values of non-protected and protected attributes, the model demonstrates an individual discrimination behavior.

*Existing Techniques and their drawbacks.* Measuring individual discrimination requires exhaustive testing, which is infeasible for a non-trivial system. The existing technique, such as THEMIS (Galhotra, Brun, and Meliou 2017) generates a test suite to determine if and how much individual discrimination is present in the model. Their approach selects random values from the domain for all attributes to determine if the system discriminates amongst the individuals. Even though such techniques are applicable for any black-box system, our experiments demonstrate that they miss many such combinations of non-protected attribute values for which the individual discrimination may exist. Some of the random inputs may follow the same execution path in the system having the same effect on the output.

*Our approach.* There exists symbolic evaluation (Godefroid, Klarlund, and Sen 2005; Sen, Marinov, and Agha 2005; Cadar et al. 2006) based techniques to automatically generate test inputs by systematically exploring different execution paths in the program. Such methods avoid generation of such inputs which tend to explore the same paths. Such techniques are essentially white-box and leverage the capabilities of constraint solvers (de Moura and Bjørner 2008) to create test inputs automatically. Symbolic execution starts with a random input and analyzes the path to generate a set of path constraints (i.e. conditions on the input attributes) and iteratively toggles (or negates) the constraints in the path to generate a set of new path constraints. It then solves the resultant path constraints using a constraint solver to generate a new input which can possibly take the control to the new path as explained using an example in Section 2. Our idea is to use such a dynamic symbolic evaluation to generate test inputs which can potentially lead to uncovering individual discrimination. However, existing such techniques have been used to generate inputs for procedural programs which are interpretable. Our main challenge is to apply such technique for un-interpretable models. Note that,

similar to THEMIS, our goal is to build a black box and scalable solution, which can be applied efficiently on varied models.

**Challenges.** There exists a few works which try to use symbolic evaluation-based techniques for un-interpretable models such as deep neural networks, although they do not address the problem of finding individual discrimination in the model. Such techniques are essentially white-box and try to approximate the functions (ReLU/Sigmoid) that exist in the network. Therefore, they are catered towards a specific kind of networks and are not generalizable. Other test-case generation techniques (Sun, Huang, and Kroening 2018; Sun et al. 2018) use coverage criteria (like neuron coverage, sign-coverage, etc.) which are structure dependent and therefore such techniques suffer from scalability.

**Solution overview.** In this paper, our key idea is to use the local explanation as the path in the symbolic execution. The local explainer can produce the decision tree corresponding to one input. The decisions in the decision tree are toggled to generate new constraints. Below we list several advantages/salient features of our approach.

- **Black Box.** Unlike other techniques (Gopinath et al. 2018; Sun et al. 2018), our method is black box as the local explainer like LIME (Ribeiro, Singh, and Guestrin 2016) handles black-box models. This enables us to operate on various types of models including deep neural networks.
- **Constraints.** It is possible to use an off-the-shelf local explainer to generate a linear approximation to the path. The linear constraints obtained from the local explainer can be used for the symbolic evaluation which won't require any specialized constraint solver such as in (Sun, Huang, and Kroening 2018).
- **Data-driven.** We use training data as a seed to start the search.
- **Directed and Undirected Search.** Once an individual discrimination is found, We perform directed search to uncover many input combinations which can uncover more discrimination. Otherwise, we perform an undirected search using symbolic execution to cover paths in the model.
- **Optimizations.** The local explainer preserves the important constraints for the decision and omits the unnecessary ones. This removes the need for unnecessary toggling of constraints. Our algorithm performs the selection of constraints for toggling based on its confidence.
- **Scalability.** Our algorithm systematically traverses paths in the feature space by toggling feature related constraints. This makes it scalable, unlike other techniques (Sun, Huang, and Kroening 2018) which consider structure-based coverage criteria.

**Contributions.** Our contributions are listed below:

- We present a novel technique for finding individual discrimination in the model.
- We developed a novel combination of dynamic symbolic execution and local explanation for generating test cases of uninterpretable models.

- We demonstrate the effectiveness of our techniques for several open source classification models containing known biases. We compare our technique with the previous algorithm (THEMIS) and demonstrate that we perform better than their approach.

**Outline.** Section 2 presents the background on dynamic symbolic execution and local explainability. The following section presents the algorithm concentrating on various other challenges in successfully combining the idea of symbolic execution with the local explanation. Section 5 contains the experimental results. This is followed by the related work in Section 6. Section 7 contains the summary, discussion and future work.

## 2 Background

### 2.1 Dynamic Symbolic Execution

Dynamic symbolic execution (DSE) (Godefroid, Klarlund, and Sen 2005; Sen, Marinov, and Agha 2005; Cadar et al. 2006) for automated test generation consists of instrumenting and running a program while collecting path constraint on inputs from predicates encountered in branch instructions, and of deriving new inputs from a previous path constraint by a constraint solver in order to steer next executions toward new program paths. We explain the technique using a simple program, shown in Figure 1.

The technique instruments the program such that the instrumented code performs operation on the symbolic memory which has symbols correspond to all the variables. The symbolic memory is initialized with symbols for the inputs, say  $X$  for  $x$  and  $Y$  and  $y$ . The other variable values are expressed as the expression over input variables. The symbolic constraints along the path generates the path constraints. For example, when started with input  $(x = 2, y = 3)$ , generates the path constraint  $((X + Y > 0) \wedge !(X - Y > 0))$ . It then selects the last constraint (depth-first way of path exploration) and creates the path constraint  $((X + Y > 0) \wedge (X - Y > 0))$  which it solves to get an answer  $X = 3, Y = 2$ . This input, as expected, will go through then branch of the corresponding toggled condition. In the resultant path, it will toggle the first branch condition  $(X + Y > 0)$  and will therefore generate inputs  $(X = -2, Y = 1)$  which will take the else branch of the first condition. This will generate a path constraint  $!(X + Y > 0) \wedge !(X + 2 * Y > 0)$ . It will then solve  $!(X + Y > 0) \wedge (X + 2 * Y > 0)$  to generate the fourth input  $(X = -2, Y = 2)$ .

Figure 1: DSE Example

```
f(x, y)
  z = x + y
  if (z > 0)
    p = x - y
  else
    p = x + 2 * y
  if (p > 0)
    return 1;
  else
    return 0;
```

### 2.2 Local Explainability

Local Interpretable Model-agnostic Explanations (LIME) (Ribeiro, Singh, and Guestrin 2016) consists of explanation techniques that explains the predictions of any classifier or regressor in an interpretable and faithful manner, by approximating it as an interpretable model locally around the pre-

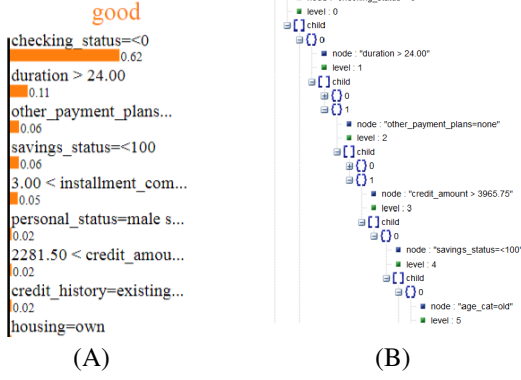


Figure 2: LIME Explanation (A) and decision tree (B) for an instance on German Credit Data

diction. It generates explanation in the form of interpretable models, such as linear models, decision trees, or falling rule lists, which can be easily comprehended by the user with visual or textual artifacts. For generating explanation of an instance, it first converts the representation to an interpretable representation by converting it to a binary vector (0 represents absence of word/image patch). Then it generates data points in the vicinity of the instance by perturbation and learns an interpretable model by minimizing unfaithfulness of the model in approximating the locality of the instance and maximizing local-fidelity and interpretability.

We use LIME to explain a prediction instance for a model and generate a decision tree as interpretable model by combining the explanations across multiple instances. Figure 2 shows an example of LIME explanation for an instance of German Credit Data (Hofmann ). The data contains bias against young people. It is evident from the figure for explanation that age is an important attribute in the prediction for credit risk of a person. Figure 2 shows a snippet of the decision tree we build using LIME for the German Credit Data. The decision tree is built by combining the explanations for a set of instances from the data.

### 3 Algorithm

In this section, we present the algorithm for individual discrimination in an uninterpretable model. We present the algorithm in two steps. First, we present a skeleton algorithm of the symbolic execution which generalizes the symbolic evaluation algorithm from a procedural program to interpretable models. In the next step, we present the full algorithm of generating test inputs for uninterpretable models geared towards discovering different inputs for finding individual discrimination.

#### 3.1 Generalized Symbolic Execution

Algorithm 1 presents the algorithm for symbolic execution such that it can be generalized from programs to models. We explain the changes in this subsection and in the next subsection explain explicit changes are required for models.

The first change is related to the inputs to start with. Instead of starting from a random input, the algorithm finds

#### Algorithm 1: Generalized Dynamic Symbolic Execution

```

1 count = 0;
2 inputs = seed_test_inputs()
3 priorityQ q = empty; q.addAll(inputs,0);
4 while count < limit && !q.isEmpty() do
5     t = deque(q)
6     check_for_error_condition(t)
7     Path p = getPath(t)
8     prefix_pred = true
9     foreach predicate c in order from top of path do
10         path_constraint = prefix_pred ∧ toggle(c)
11         if !visited_path.contains(path_predicate) then
12             visited_path.add(path_predicate);
13             input = solve(path_constraint)
14             r = rank(input, S, p)
15             q.add(input, r)
16         end
17         prefix_pred = prefix_pred ∧ c
18     end
19     count++
20 end

```

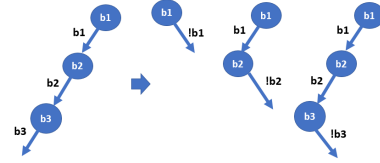


Figure 3: Generation of path constraints

one or more seed inputs to start with (Line 2). The second change (Lines 3, 14, 15) is related to the abstraction of the ranking strategy of selecting which test inputs to execute next. Note that, now the Rank function will determine which inputs should be taken next. In the example illustrated in Section 2, we presented a depth-first strategy for selecting a branch to toggle. And such a decision is taken after each path is executed. Here, for each path, we consider all the conditionals to be toggled and associate ranks to them. The third change is the addition of the check whether the path is already traversed or not (Line 9). Such checks are not required in symbolic execution for programs as the selection of predicates for toggling ensures that an already traversed path will not be traversed again.

Note that, the goal of symbolic execution is to explore as much as paths in the decision space. The generation of constraints (Lines 8-17 is illustrated in the Figure 3. Note that, the other variables, not present in the constraint, can take any value from the domain.

#### 3.2 Test Case Generation for Uninterpretable Model

In this subsection, we describe the various functions that are kept undefined in Algorithm 1.

**Path Creation.** We start with the case of `getPath` function. As illustrated in Section 1, our key idea is to use a local model generated from a local explainer - LIME (Ribeiro, Singh, and Guestrin 2016). Our algorithm generates the decision tree instead of the linear classifier as in LIME.

---

**Algorithm 2:** `getPath(Model m, Input in)`

---

```
1 Set<In, Out> inout = localexp(m, in)
2 return genDecionTree(inout);
```

---

There are a few differences between the decision tree and a program path. 1) Approximation: the decision tree path approximates the actual execution path in terms of interpretable features. 2) Confidence: there is no confidence associated with the predicates in a program path, whereas a decision tree path has such confidence associated with it. 3) Slice: decision tree may not contain some predicates which do not have any effect to the resultant class. This is analogous to dynamic slicing (Agrawal and Horgan 1990) in program analysis literature. Such dynamic slicing removes the redundant state in dynamic symbolic execution (Bugrara and Engler 2013). 4) Non-repeatable: the local explainer is not incremental in nature. In other words, it will not try to preserve the predicates that have occurred in the same path. In symbolic execution for software, predicates in the same path will remain same. The effect of these differences is seen in our algorithm, described subsequently.

**Seed Input Selection.** Symbolic execution in program testing suffers from the path explosion problem (Godefroid 2007), especially the depth-first-search of explanation. It can keep on exploring paths in the depth of the program tree, without exploring the paths in the other parts of the program. Researchers have explored various techniques to address this problem - applying demand driven or directed technique which generates test cases towards a particular location in the program, and compositional techniques which try to analyze various functional modules separately before combining them to generate longer paths in the whole program.

To resolve the path explosion problem, we exploit the distribution present in the training data (Function `seed_test_input()`). Each training data instance can be a good starting point of the symbolic search. However, the order of training data instances become important in search when there is a limit to the search due to which executing all training instances is not possible. Therefore, to increase the diversity in search, we cluster the training data and take seed inputs in round-robin fashion from each cluster.

**Ranking.** Automated test case generation procedure is limit based. It is therefore important to generate non-redundant and effective test cases. We use a ranking scheme based on the confidence of predicates in the decision tree to select which test input to execute next. The confidence of the path is determined by the average confidence of the predicates in it. Therefore, when we toggle a predicate  $p$ , we consider the average confidence of the predicates in the

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**Algorithm 3:** `check_for_error_condition()`

---

```
1 i = 0
2 clusters = KMeans(data, NumberOfClusters)
3 while i < max(size(clusters)) do
4   if q.qsize() == limit then
5     break
6   foreach cluster ∈ clusters do
7     if i ≥ get_cluster_size(cluster) then
8       continue
9     row = cluster.rows.next
10    rows.add(row)
11 return (rows)
```

---

prefix of the path leading to and including  $p$ . This ranking scheme orders the test inputs generated through the undirected symbolic execution. In the next section, we discuss another place in the algorithm for generating input (other than seed inputs and undirected symbolic) and present relative ranking among them.

## 4 Checking Individual Discrimination

Here we discuss few more changes to the generic algorithms above: 1) checking the error condition, 2) directed search, and 3) relative ranking.

**Checking Individual Discrimination.** We begin with the case of checking individual discrimination. Such check will occur in function `check_for_error_condition`. The pseudo code for this function is shown below. The algorithms make the check as per definition of individual discrimination i.e. if a combination of protected attribute values (from the domain) would result in any different class for the non-protected attribute values contained in the test case.

---

**Algorithm 4:** `check_for_error_condition(t)`

---

```
1 class = model.test(t)
2 foreach (val0, ..., valn) | vali ∈ protected_attributei.vals do
3   tnew = Replace value of protected_attributei in t with vali
4   class1 = model.test(tnew)
5   if class1 != class then
6     return Individual Discrimination Found
7 return Individual Discrimination Not Found
```

---

**Directed Symbolic Search.** The undirected symbolic search (discussed previously) tries to find test inputs which can cause individual discrimination. Once such a test case (say  $t$ ) is found, we try to generate more test inputs which can lead to the individual discrimination. The key idea is to negate the low confidence non-protected attribute constraint of  $t$ 's decision tree to generate more test inputs. Low confidence constraints are less prone to change the behavior of the test case and therefore can have the same effect on protected attributes as in  $t$ .



**Algorithm 5: Individual Discrimination**

```

1  count = 0;
2  inputs = seed.test_inputs()
3  priorityQ q = empty; q.addAll(inputs, Rank1);
4  while count < limit && !q.isEmpty() do
5      t = deque(q)
6      found = check_for_error_condition(t)
7      Path p = getPath(t)
8      if found then
9          // directed search
10         foreach predicate c in order from top to bottom of path do
11             path_constraint = p.constraint If c is of protected attribute then
12                 continue
13             if c.confidence < T2 then
14                 path_constraint.remove(c) path_constraint.add(not(c))
15                 if !visited_path.contains(path_constraint) then
16                     visited_path.add(path_constraint);
17                     input = solve(path_constraint)
18                     r = average(path_constraints)
19                     q.add(input, Rank2-r)
20                 end
21             end
22         end
23     end
24     // undirected search
25     prefix_pred = true
26     foreach predicate c in order from top to bottom of path do
27         If c is of protected attribute then continue
28         If c.confidence < T1 then break
29         path_constraint = prefix_pred ∧ not (c)
30         if !visited_path.contains(path_constraint) then
31             visited_path.add(path_constraint);
32             input = solve(path_constraint)
33             r = average_conf(path_constraints)
34             q.add(input, Rank3+r)
35         end
36         prefix_pred = prefix_pred ∧ c
37     end
38     count++
39 end

```

The entire algorithm for individual discrimination is presented in Algorithm 5. Lines 7-22 describe the directed search whereas Lines 24-35 describe the undirected search. **There are two major differences between the directed and undirected search.** The first difference is that in a directed search only low confidence constraints are selected for toggling because of the reason described above (Line 12). In contrast, in undirected search, the high confidence constraints are chosen for toggling. This is because high confidence constraint toggling will result in more chance of diverse coverage of paths. The second difference is that, in undirected search, no constraint exists for suffix of the path, whereas in directed search, all constraints, except the selected low confidence one to toggle, remain as it is.

**Relative Ranking.** In the consolidated algorithm three reference ranks are presented for seed input, directed search, and undirected search. They are chosen in such a way that,

Benchmark	Size	Source
German Credit Data	1000	UCI Machine Learning Repository
Adult census income	32561	UCI Machine Learning Repository
Bank marketing	45211	UCI Machine Learning Repository
US Executions	1437	data.world - US Executions since 1977
Fraud Detection	1100	Kaggle - Fraud Detection
Raw Car Rentals	486	yelp.com - raw-car-rentals
credit data	600	modified German Credit used in THEMIS
census data	15360	modified Adult income used in THEMIS

Table 1: Benchmark Characteristics

the highest priority is given to directed search followed by seed input and finally the undirected search based on their ability to uncover discrimination causing inputs.

In the next section, we experimentally show the effectiveness of various optimizations described in this section.

## 5 Experimental Evaluation

### 5.1 Setup

**Benchmark Characteristics.** We have used 8 open source fairness benchmarks from various sources (see Table 1).

**Configurations.** Our code is written in Python and executed in Python 2.7.12 compiler. All experiments are performed in a machine running Ubuntu 16.04, having 16GB RAM, 2.4Ghz CPU running Intel Core i5. We have used LIME (Ribeiro, Singh, and Guestrin 2016) for local explainability. We have used KMeans clustering in training data with cluster size = 4. For each benchmark, we have created Logistic regression with the default configuration in scikit-learn. The selection of the model is inspired by THEMIS. The two thresholds used in our algorithm T1=0.3 and T2=0.2 as shown in Algorithm 5.

### 5.2 Experiments

**Goals.** Our experiments have two goals, given below:

- Comparison with the existing work. How well we perform compare to existing work in finding individual discrimination in models? We compare our system with the existing system called THEMIS (Galhotra, Brun, and Meliou 2017) which checks the individual discrimination by random test case generation.
- Effect of Algorithmic Features. How well each algorithmic feature (Directed and Undirected symbolic execution, training data) contributed to finding individual discrimination?

**Comparison to THEMIS.** To Compare with THEMIS, we got the code from their GitHub repository and analyzed. It seemed that there is an unintended behavior. THEMIS actually produces duplicate test cases and the result that is reported contains duplicate test cases. We changed THEMIS's code to remove duplicates. Table 2 shows the result of the comparison to THEMIS. *Gen* refers to the set of unique test cases generated. For each such test case, more test cases are generated and executed to check the discrimination by

Bench.	Prot. Attr.	THEMIS		Symbolic	
		#Gen	#InDi	#Gen	#InDi
German Credit	gender	999	166	1000	598
German Credit	age	999	90	1000	359
Adult income	race	999	70	1000	175
Adult income	sex	990	1	1000	462
Fraud Detection	age	999	3	656	0
Car Rentals	Gender	680	198	1000	801
credit	i/gender	598	44	1000	420
census	h/race	999	57	1000	609
census	i/sex	999	7	1000	176
Bank Marketing	age	999	0	1000	1
US Executions	Race	999	2	1000	6
US Executions	Sex	999	8	1000	31

Table 2: Comparison with THEMIS

Bench.	Data		Directed Symb.		UnDirected	
	Gen	InDi	Gen	InDi	Gen	Indi
German Credit(gender)	2	1	998	597	0	0
German Credit(age)	27	2	973	357	0	0
Adult Income(race)	313	24	687	151	0	0
Adult Income(sex)	77	12	923	450	0	0
Fraud Detection	1000	0	0	0	0	0
Car Rentals	18	15	982	786	0	0
credit	20	1	980	419	0	0
census(race)	1	1	999	608	0	0
census(sex)	41	2	959	174	0	0
Bank Marketing	984	1	16	0	0	0
US Executions(Race)	877	0	22	4	101	2
US Executions(Sex)	877	0	74	29	49	2

Table 3: Contribution of different features

changing the value of protected attributes. *InDi* denotes the subset of the generated test cases (*Gen*) which results in individual discrimination. Note that, except in one case our algorithm produces better results than THEMIS.

THEMIS has an average success score (#InDi/#Gen) of 6.4% whereas our symbolic algorithm has 30.3% average success score. It is evident that **across 12 benchmarks, our algorithm generates 3.72 times more** successful (that resulted in discrimination) test cases than THEMIS. This demonstrates advancement in the published state-of-the-art in individual discrimination.

In Table 3, we report the contribution of the test case generation feature (training data, undirected symbolic, directed symbolic) contributed to the above success. The result evidently shows the effect of our relative ranking strategy which specifies the decreasing order of preferences as Indirect, Data, and Direct. Note that, on average, the success percentage for Data and Indirect Symbolic execution are 23% and 37%, respectively.

**Importance of Training Data.** We conducted two experiments for determining the importance of training data by changing the seed input function which instead of taking training data, takes random data from the domain. In the first experiment (shown in Table 4) we switch off the directed and undirected symbolic execution so that all the test cases are

Bench.	Training Data		Random	
	Gen	InDi	Gen	InDi
credit	500	56	500	25
German (Age)	1000	70	1000	46
Census (Sex)	500	20	500	5
Car	500	394	500	190

Table 4: Training data as seed (w/o Symbolic)

Bench.	Random			
	Total	Seed	Dir.	UNdirect.
credit	310/1000	1/21	309/979	0/0
German (Age)	365/100	4/49	361/951	0/0
Census (Sex)	195/1000	3/87	192/913	0/0
Car	803/1000	14/21	789/979	0/0

Table 5: Random seed data (with symbolic) (#InDi/#Gen)

generated from the seed data. In this second experiment (Table 5, we keep both the symbolic searches. In the first experiment, we see that just by getting that training data we get an average improvement of 108% (25% to 12%). The second experiment shows the effectiveness of symbolic evaluation even if we start with the random input. In the `credit` data (Table 5), we see that random data got 310 successful test cases and is less effective than training data which has got 421 successful test cases. However, it’s much better than THEMIS (44).

**Importance of Directed Search** Based on the previous experiments we notice that directed symbolic search has high percentage (37%) of effectiveness. We conduct another experiment to see how we directed search affects the overall execution of the algorithm given a limit on the number of test cases (1000). The results by switching off the directed search feature is presented in Table 6. We should compare this result with the results in Table 3 for the 4 benchmarks. We see that the average effectiveness drops from 43.9% to 25.2% for these 4 benchmarks by removing the directed search feature. This shows the importance of the directed search technique.

**Importance of Clustering** Figure 4 shows the use of diverse seed data ordering got getting individual discrimination. When the number of test cases is limited then we expect that diverse ordering (round-robin) will fetch more discrimination than iterative ordering. It is evident from the Figure 4 that, for most number of test cases, the number of discrimination found is higher for round-robin selection from clusters is more effective than iterative selection. For example,

Bench.	Random			
	Total	Seed	Dir.	Un-direct.
credit	66/603	66/600	0/0	0/3
German (Age)	70/1000	70/1000	0/0	0/0
Census (Sex)	45/994	45/992	0/0	0/2
Car	231/295	91/114	0/0	140/181

Table 6: Without directed search (#InDi/#Gen)

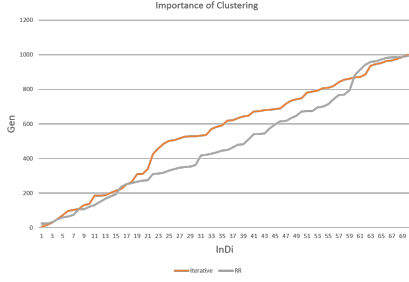


Figure 4: Importance of clustering (German-age)

Bench.	Random			
	Total	Seed	Dir.	Un-direct.
credit	66/607	66/600	0/0	0/7
German (Age)	18/1000	0/1	0/0	18/999
Census (Sex)	45/1000	45/996	0/0	0/4
Car	254/325	75/97	0/0	179/228

Table 7: Undirected search (w/o directed) (#InDi/#Gen)

in the execution of 600 test cases, the round-robin found 45 discrimination compared to 35 for iterative.

**Importance of Undirected Search** We performed an experiment by giving highest priority for undirected search and removing directed search feature. We see that in two cases (German-age and Car) the undirected search extracted successful test cases (see Table 7). In the other two cases, very fewer test cases are even generated 4 and 7 as the confidence of predicates is not high for toggling.

Overall, our experiments demonstrate that directed search uncovers many bias instances after finding the fault. For initial fault finding, training data works better than the undirected symbolic search.

## 6 Related Work

We present the related works in two categories - testing of models and detecting individual discrimination.

**Automated Test Case Generation of AI Models.** We discuss the works which perform symbolic/concolic based test case generation of AI models. *DeepCheck* (Gopinath et al. 2018) uses a white box technique which performs symbolic execution on deep neural networks with the target of generating adversarial images. *DeepCheck<sup>τ</sup>* translates the network  $\mathcal{N}$  to an imperative program  $\mathcal{P}$  that has the same behavior as the neural network  $\mathcal{N}$ . *DeepCheck<sup>Imp</sup>* executes the program  $\mathcal{P}$  and for the execution path  $I$ , taken in  $\mathcal{P}$ , finds the important pixels by 1) first finding a linear expression in terms of the input variables and 2) assigns scores to the input pixels based on the coefficient in the expression, 3) selects the important pixels from the top threshold. A new image is created by changing the  $t$  important pixel such that the label changes. The problem with the technique is that the semantic preserving translation mechanism only

works for a specific network. Concolic execution (Godefroid, Klarlund, and Sen 2005) (Concrete and Symbolic) on deep neural networks is performed by (Sun et al. 2018). Their technique is white box and goal is to perform coverage of deep neural network by systematic test case generation. They model the network using linear constraints and use a specialized solver to generate test cases. Wicker et al. (Wicker, Huang, and Kwiatkowska 2018) aim to cover the input space by exhaustive mutation testing that has theoretical guarantees, while in (Pei et al. 2017; Tian et al. 2018; Ma et al. 2018) gradient-based search algorithms are applied to solve optimization problems, and Sun et al. (Sun, Huang, and Kroening 2018) apply linear programming.

All of the above techniques are white box compare to our black box technique. We use an off-the-shelf solver to generate test cases. Compare to other approaches which try to consider test generation for creating adversarial input in the image space, our technique addresses a new problem trust and ethics domain.

**Individual Discrimination** THEMIS (Galhotra, Brun, and Meliou 2017) uses the causality to define individual discrimination. Even though they use a black box technique, their test case generation technique uses random test generation instead of any systematic test case generation. In fact, they envision the use of systematic test case generation techniques in their paper. FairTest (Tramr et al. 2017) uses manually written tests to measure four kinds of discrimination scores. Their idea is to use indirect co-relation between attributes (e.g., salary is related to age) to generate test cases. FairML (Adebayo and Kagal 2016) uses an iterative procedure, based on an orthogonal projection of input attributes, for enabling interpretability of black-box predictive models. Through an iterative procedure, one can quantify the relative dependence of a black-box model on its input attributes. The relative significance of the inputs to a predictive model can then be used to assess the fairness (or discriminatory extent) of such a model.

None of the existing individual discrimination technique uses systematic test case generation, even though all such methods are black box techniques. Our is the first method which uses systematic test case generation for individual discrimination with the advantage of black box method.

## 7 Conclusion

In this paper, we present a test case generation algorithm for checking individual discrimination in AI models. Our approach combines the idea of symbolic evaluation which systematically generates test inputs and local explanation which approximates the path in the model using linear models. The resultant technique is black box. In future, we would like to apply this technique in various domains including text and images. We would also like to measure the efficacy of symbolic execution in models using the structural metric like neuron coverage, boundary value coverage, etc.

## References

- [Adebayo and Kagal 2016] Adebayo, J., and Kagal, L. 2016. Iterative orthogonal feature projection for diagnosing bias in black-box models.
- [Agrawal and Horgan 1990] Agrawal, H., and Horgan, J. R. 1990. Dynamic program slicing. In *Proceedings of the ACM SIGPLAN 1990 Conference on Programming Language Design and Implementation*, PLDI '90, 246–256. New York, NY, USA: ACM.
- [Bugrara and Engler 2013] Bugrara, S., and Engler, D. 2013. Redundant state detection for dynamic symbolic execution. In *Proceedings of the 2013 USENIX Conference on Annual Technical Conference*, USENIX ATC'13, 199–212. Berkeley, CA, USA: USENIX Association.
- [Cadaru et al. 2006] Cadaru, C.; Ganesh, V.; Pawlowski, P. M.; Dill, D. L.; and Engler, D. R. 2006. Exe: Automatically generating inputs of death. In *Proceedings of the 13th ACM Conference on Computer and Communications Security*, CCS '06, 322–335. New York, NY, USA: ACM.
- [de Moura and Bjørner 2008] de Moura, L., and Bjørner, N. 2008. Z3: An efficient smt solver. In Ramakrishnan, C. R., and Rehof, J., eds., *Tools and Algorithms for the Construction and Analysis of Systems*, 337–340. Berlin, Heidelberg: Springer Berlin Heidelberg.
- [Feldman et al. 2015] Feldman, M.; Friedler, S. A.; Moeller, J.; Scheidegger, C.; and Venkatasubramanian, S. 2015. Certifying and removing disparate impact. In *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 259–268. ACM.
- [Galhotra, Brun, and Meliou 2017] Galhotra, S.; Brun, Y.; and Meliou, A. 2017. Fairness testing: Testing software for discrimination. In *Proceedings of the 2017 11th Joint Meeting on Foundations of Software Engineering*, ESEC/FSE 2017, 498–510. New York, NY, USA: ACM.
- [Godefroid, Klarlund, and Sen 2005] Godefroid, P.; Klarlund, N.; and Sen, K. 2005. Dart: Directed automated random testing. In *Proceedings of the 2005 ACM SIGPLAN Conference on Programming Language Design and Implementation*, PLDI '05, 213–223. New York, NY, USA: ACM.
- [Godefroid 2007] Godefroid, P. 2007. Compositional dynamic test generation. In *Proceedings of the 34th Annual ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages*, POPL '07, 47–54. New York, NY, USA: ACM.
- [Gopinath et al. 2018] Gopinath, D.; Wang, K.; Zhang, M.; Pasareanu, C. S.; and Khurshid, S. 2018. Symbolic execution for deep neural networks.
- [Hofmann ] Hofmann, H. German credit data set.
- [Ma et al. 2018] Ma, L.; Juefei-Xu, F.; Zhang, F.; Sun, J.; Xue, M.; Li, B.; Chen, C.; Su, T.; Li, L.; Liu, Y.; Zhao, J.; and Wang, Y. 2018. Deepgauge: multi-granularity testing criteria for deep learning systems. In *Proceedings of the 33rd ACM/IEEE International Conference on Automated Software Engineering*, ASE 2018, Montpellier, France, September 3-7, 2018, 120–131.
- [Pei et al. 2017] Pei, K.; Cao, Y.; Yang, J.; and Jana, S. 2017. Deepxplore: Automated whitebox testing of deep learning systems. In *Proceedings of the 26th Symposium on Operating Systems Principles*, SOSP '17, 1–18. New York, NY, USA: ACM.
- [Ribeiro, Singh, and Guestrin 2016] Ribeiro, M. T.; Singh, S.; and Guestrin, C. 2016. Why should i trust you?: Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, 1135–1144. ACM.
- [Sen, Marinov, and Agha 2005] Sen, K.; Marinov, D.; and Agha, G. 2005. Cute: A concolic unit testing engine for c. In *Proceedings of the 10th European Software Engineering Conference Held Jointly with 13th ACM SIGSOFT International Symposium on Foundations of Software Engineering*, ESEC/FSE-13, 263–272. New York, NY, USA: ACM.
- [Sun et al. 2018] Sun, Y.; Wu, M.; Ruan, W.; Huang, X.; Kwiatkowska, M.; and Kroening, D. 2018. Concolic testing for deep neural networks.
- [Sun, Huang, and Kroening 2018] Sun, Y.; Huang, X.; and Kroening, D. 2018. Testing deep neural networks.
- [Tian et al. 2018] Tian, Y.; Pei, K.; Jana, S.; and Ray, B. 2018. Deeptest: Automated testing of deep-neural-network-driven autonomous cars. In *Proceedings of the 40th International Conference on Software Engineering*, ICSE '18, 303–314. New York, NY, USA: ACM.
- [Tramr et al. 2017] Tramr, F.; Atlidakis, V.; Geambasu, R.; Hsu, D.; Hubaux, J.; Humbert, M.; Juels, A.; and Lin, H. 2017. Fairtest: Discovering unwarranted associations in data-driven applications. In *2017 IEEE European Symposium on Security and Privacy (EuroS P)*, 401–416.
- [Wicker, Huang, and Kwiatkowska 2018] Wicker, M.; Huang, X.; and Kwiatkowska, M. 2018. Feature-guided black-box safety testing of deep neural networks. In Beyer, D., and Huisman, M., eds., *Tools and Algorithms for the Construction and Analysis of Systems*, 408–426. Cham: Springer International Publishing.