Fairness Testing: A Comprehensive Survey and Analysis of Trends

Zhenpeng Chen, Jie M. Zhang, Max Hort, Federica Sarro, Mark Harman

Abstract—Software systems are vulnerable to fairness bugs and frequently exhibit unfair behaviors, making software fairness an increasingly important concern for software engineers. Research has focused on helping software engineers to detect fairness bugs automatically. This paper provides a comprehensive survey of existing research on fairness testing. We collect 122 papers and organise them based on the testing workflow (i.e., the testing activities) and the testing components (i.e., where to find fairness bugs) for conducting fairness testing. We also analyze the research focus, trends, promising directions, as well as widely-adopted datasets and open source tools for fairness testing.

Index Terms—Software fairness, fairness testing, survey, trend, analysis

1 INTRODUCTION

In recent years, the wide adoption of software systems in social-critical, human-related tasks, such as hiring [1], credit assessment [2], criminal justice [3], and disease detection [4], has increased awareness of fairness bugs and raised surging concerns about them.

Fairness bugs refer to any imperfection in a software system that causes a discordance between the existing and the required fairness conditions. These bugs have been frequently reported, related to sensitive attributes (also called protected attributes) such as sex, race, age, and occupation [3]. For example, the recidivism assessment software used by US courts was found to falsely flag black defendants as future criminals compared to white defendants [6]; commercially released facial-analysis software also exhibited skin-type and gender bias [8]. These fairness bugs may bring unethical and unacceptable consequences, particularly disadvantaging minorities and protected groups.

A lot of effort from various research communities has been devoted to detecting and reducing fairness bugs. The growing importance of software fairness has prompted the continued expansion of the fairness research community. A series of new conferences and workshops are now dedicated to this topic, including FairWare [9], FAcct [10], and SE4RAI [11]. Through these venues, researchers, practitioners, and policy makers together explore the fundamental question: How to engineer fair software systems? This has greatly stimulated the growth of software fairness publications.

Fairness is most pertinent to Machine Learning (ML) software [12], but also applicable more generally in Software Engineering (SE) [5]. It was first studied as a software engineering concern by Finkelstein et al. [13]. From the Software Engineering (SE) perspective, fairness is a non-functional software property that needs to be a first-class entity in the entire software engineering process, rather than an after-the-system-is-built concern [5], [14]. Ahmad et al. [15] regarded fairness as an increasingly important requirement that needed to be considered in requirements engineering of ML software; Alidoosti [16] argued that there is a need to consider fairness in the software architecture design process; Albarghouthi et al. [17] framed fairness as correctness properties for program verification; Zhang et al. [12] described fairness as a non-functional software property that deserves substantial testing effort; Salimi et al. [18] considered fairness as the objective of software repair.

In this paper, we focus on the fundamental branch of software fairness research: fairness testing. Fairness testing is closely bound to other activities in the software engineering process. It reveals fairness bugs introduced in software implementation, tests whether software systems satisfy fairness requirements both before and after software deployment, guides software repair to fix fairness bugs, etc.

As a part of software testing activities, fairness testing is specific to revealing the discordance between existing and required fairness conditions of a given software system. Some aspects of fairness testing are shared with well-known solutions already widely adopted in the software testing literature. However, compared to traditional software testing, fairness testing primarily targets statistically-orientated, non-deterministic ML software, which poses unique challenges arising from the test oracle problem [12]. In addition, there is an increasing number of fairness definitions, some of which are even conflicting or difficult to satisfy simultaneously in the engineering process [19], [20]. For certain social-critical application scenarios, domain-specific knowledge is required for fairness testing, and thus legal practitioners and policy makers may need to be involved in the testing process.

Zhenpeng Chen is with the Department of Computer Science, University College London, London, United Kingdom. E-mail: z.p.chen@ucl.ac.uk
Jie M. Zhang is with the Department of Informatics, King’s College London, London, United Kingdom. E-mail: ji.zhang@kcl.ac.uk
Max Hort is with the Department of Computer Science, University College London, London, United Kingdom. E-mail: max.hort.198@ucl.ac.uk
Federica Sarro is with the Department of Computer Science, University College London, London, United Kingdom. E-mail: f.sarro@ucl.ac.uk
Mark Harman is with the Department of Computer Science, University College London, London, United Kingdom. E-mail: mark.harman@ucl.ac.uk

1The literature treats “bias” and “unfairness” as synonyms, referring to the opposite of “fairness” [7].
Due to the increasing importance of fairness testing and its unique challenges, the literature has witnessed a considerable upsurge in work in this area. Figure 1 shows the cumulative number of publications about fairness testing over the years to 2022. Overall, we can see evidence of growing interest in this topic, thereby demonstrating the timeliness of this survey. From the figure, we can observe that more than 85% of fairness testing publications appeared since 2019, demonstrating the emergence of this new software testing domain - fairness testing.

This paper provides a comprehensive survey of fairness testing research. We focus on ML software, which is primary target of the software fairness literature. We collect papers from SE venues as well as venues for artificial intelligence, computer security, database, etc. We organize the collected papers according to two aspects: fairness testing workflow (i.e., how to test) and fairness testing components (i.e., where to find fairness bugs). Additionally, we analyze research trends and identify research opportunities for the research community working on fairness testing. We also summarize the publicly accessible datasets and open source tools for fairness testing.

There has been previous work surveying the fairness literature. Mehrabi et al. [7] and Pessach and Shmueli [21] surveyed fairness research on ML algorithms. Hort et al. [22] provided a survey of bias mitigation methods for ML classifiers. Sun et al. [23], Berk et al. [3], and Pitoura [24] surveyed techniques for improving fairness in specific ML tasks: natural language processing, criminal justice risk assessment, and ranking. Tushev et al. [25] surveyed software design strategies for fairness of digital sharing economy applications. Hutchinson and Mitchell [26] introduced the history of assessment tests of fairness over 50 years across multiple disciplines such as education and hiring. Zhang et al. [12] surveyed ML testing more generally, in which fairness was considered as one of many testing properties. To date, only one survey [27] focused on reviewing the fairness literature through the lens of software engineering. It is a systematic literature review that aims to characterize the research state of ML software fairness, which covers 20 fairness testing papers. Different from these previous papers, we focus on fairness testing, which plays a fundamental role in assessing bias issues for ML software. To the best of our knowledge, this is the first comprehensive survey of the literature on fairness testing.

To summarize, we make the following contributions in this paper:

- We provide a comprehensive survey of 122 fairness testing papers across various research communities.
- We define fairness bug and fairness testing, and provide an overview of the testing workflow and the testing components related to fairness testing.
- We position fairness testing within the software engineering process.
- We summarize the publicly available datasets and open source tools for fairness testing, to provide a navigation for researchers and practitioners interested in this field.
- We analyze research trends and identify promising research opportunities for fairness testing, with the goal of stimulating and facilitating further research.

Figure 2 illustrates the structure of this paper. The detailed survey schema is described in Section 3.

2 PRELIMINARIES

In this section, we first introduce the most widely-adopted definitions of fairness. We then provide a definition of fairness bug and fairness testing through the lens of SE. We also describe the testing workflow (how to test) and the testing components (where to test) of fairness testing. In addition, we compare fairness testing with traditional software testing to help clarify its unique characteristics, and position fairness testing within the wider software engineering process.
### 2.1 Definition of Fairness

The definition of fairness determines the fairness condition that software systems are required to satisfy. Researchers and practitioners have previously proposed and explored various fairness definitions [20], [28], [29].

In this section, we aim to introduce the definitions most widely adopted in the literature (listed in Table 1), mainly falling in two types: individual fairness and group fairness. Individual fairness requires software to produce similar predictive outcomes for similar individuals, while group fairness requires software to treat different groups similarly.

In the context of software fairness, a population is partitioned into a privileged group and an unprivileged group based on a sensitive attribute (also called protected attribute), which refers to the sensitive characteristic that needs to be protected against unfairness, such as sex, race, age, and physical and mental disability.

#### 2.1.1 Individual Fairness

We first introduce three widely-adopted definitions of individual fairness.

**Counterfactual fairness** [30]. A software system satisfies counterfactual fairness if, for an individual, its prediction in the real world is the same as that in the counterfactual world where the individual belongs to a different demographic group (i.e., the sensitive attribute becomes different). This definition interprets fairness from a causal perspective: the variables other than the sensitive attribute are controlled, and thus unfairness comes from the variants in the sensitive attribute.

**Fairness through unawareness** [31]. A software system is fair through unawareness so long as any sensitive attribute is not explicitly used in its prediction process. Ideally, blindness to the sensitive attribute would make the outcome unaffected by it, thus achieving fairness. However, sometimes non-sensitive attributes employed in the prediction process may contain information correlated to the sensitive attribute, thereby still leading to potential discrimination despite lack of any awareness of any sensitive attribute [35].

**Fairness through awareness** [32]. A software system satisfies fairness through awareness if it produces similar predictions for similar individuals. Specifically, any two individuals who are similar with respect to a similarity metric defined for a particular task should receive a similar outcome.

#### 2.1.2 Group Fairness

We introduce three widely-adopted definitions of group fairness. To help illustrate the formalization of group fairness, we use $A$ to denote the sensitive attribute, with 1 as the privileged and 0 as the unprivileged. Let $\hat{Y}$ be the original prediction label and $\hat{Y}$ the predicted label, with 1 as the favorable outcome and 0 as the unfavorable.

**Demographic parity** [33]. Demographic parity, also known as statistical parity, requires the likelihood of a favorable outcome to be the same among different demographic groups. In other words, a software system satisfies demographic parity if $P[\hat{Y} = 1|A = 1] = P[\hat{Y} = 1|A = 0]$.

**Equalized odds** [34]. Equalized odds means that the probability of a person in the favorable class being correctly assigned a favorable outcome and the probability of a person in an unfavorable class being incorrectly assigned a favorable outcome should both be the same for the privileged and unprivileged groups. In other words, the prediction is independent of the sensitive attribute when the target label $Y$ is fixed: $P[\hat{Y} = 1|A = 0, Y = y] = P[\hat{Y} = 1|A = 1, Y = y]$, $y \in \{0, 1\}$.

**Equal opportunity** [34]. Equal opportunity states that the privileged and the unprivileged groups have equal true positive rates. In other words, the prediction made by the software is independent of the sensitive attribute when the target label $Y$ is fixed as 1: $P[\hat{Y} = 1|A = 0, Y = 1] = P[\hat{Y} = 1|A = 1, Y = 1]$.

We use the widely-adopted binary classification task as the example to illustrate the group fairness definition, but these definitions can also be applied to other ML tasks with appropriate adjustments. For example, for the ranking task, practitioners can measure whether members of different groups have the same proportional representation among the desirable outcome (e.g., in a top position in the ranking).

More about fairness definitions can be found in recent work on surveying, analyzing, and comparing them. Mitchell et al. [29] presented a reasonably consistent catalog of fairness definitions from the literature; Verma and Rubin [19] explained the rationale behind existing fairness definitions and investigated the relationship among them through a case study; Castelnovo et al. [20] analyzed the differences, implications, and orthogonality between existing fairness definitions; Hutchinson and Mitchell [28] traced the 50-year history of fairness definitions in the areas of education, hiring, and ML; Mehrabi et al. [7] created a taxonomy of fairness definitions proposed for ML software.

These fairness definitions are encoded in software engineering activities and affect the entire software engineering process (see Section 2.6). Practitioners can select appropriate fairness definitions as requirements according to their application scenarios, and use the selected fairness requirements to guide software development activities such as design, testing, repair, and deployment. For fairness testing, these definitions are particularly encoded in the test oracles (see Section 4.2). Although these fairness definitions are not strictly independent of each other, it has been demonstrated that they cannot be satisfied at the same time [19], [20], [36].

### 2.2 Definition of Fairness Bug and Fairness Testing

A software bug is an imperfection in a computer program that causes a discordance between the existing and the required conditions [37]. According to this definition, previous work [12] defines “ML bug” as any imperfection in an ML artefact that causes a discordance between the existing and the required conditions, and “ML testing” as

<table>
<thead>
<tr>
<th>Name</th>
<th>Fairness type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Counterfactual fairness</td>
<td>Individual fairness</td>
</tr>
<tr>
<td>Fairness through unawareness</td>
<td>Individual fairness</td>
</tr>
<tr>
<td>Fairness through awareness</td>
<td>Group fairness</td>
</tr>
<tr>
<td>Demographic parity</td>
<td>Group fairness</td>
</tr>
<tr>
<td>Equalized odds</td>
<td>Group fairness</td>
</tr>
<tr>
<td>Equal opportunity</td>
<td>Group fairness</td>
</tr>
</tbody>
</table>

**TABLE 1**: Widely-adopted fairness definitions.
any activity designed to reveal ML bugs. In line with the SE nomenclature, we define fairness bug and fairness testing as follows.

- **Definition 1 (Fairness Bug).** A fairness bug refers to any imperfection in a software system that causes a discordance between existing and required fairness conditions.

  The required fairness condition depends on the fairness definition adopted by the requirements of the software under test. Existing papers also use other terms such as fairness defects [8] and fairness issues [13] to describe such imperfection. In this paper, we use “fairness bug” as a representative of all these related terms, because “bug” has a more general meaning [37].

  The existence of fairness bugs results in the unfairness (also called bias [38], [39]) of software systems, motivating research work into techniques to help detect these bugs, i.e., fairness testing.

- **Definition 2 (Fairness Testing).** Fairness testing refers to any activity designed to reveal fairness bugs.

  Following the recent ML testing survey [12], we consider two aspects of the emerging testing domain: testing workflow and testing component. From the testing workflow angle, the testing activities may include test oracle identification, test input generation, test adequacy evaluation, etc. From the testing component angle, software systems typically rely on ML to make predictions, thus fairness bugs may exist not only in the prediction algorithms, but also in the data used for training ML models. In this paper, we survey and organize the fairness testing literature according to these two aspects.

### 2.3 Fairness Testing Workflow

The fairness testing workflow refers to how to perform fairness testing with different testing activities. This section divides into the fairness testing workflow and describes its key activities.

Figure [3] presents the workflow of fairness testing. Software engineers determine and specify the expected fairness requirements for the software under test through requirements engineering. Test inputs are either sampled from the collected data or generated automatically; test oracles are identified and generated based on the fairness requirements. Software engineers execute test inputs on the software under test to check whether the test oracles are violated. Engineers evaluate the adequacy of the tests, i.e., their ability to revealing fairness bugs. Meanwhile, the test execution results yield a bug report to help engineers reproduce, locate, and fix fairness bugs. The fairness testing process can be repeated to ensure that the repaired software works well with regard to fairness.

The fairness testing literature mainly tackles test input generation (Section 4.1) and test oracle identification (Section 4.2), leaving other activities as open challenges and research opportunities for the community (discussed in Section 8).

### 2.4 Fairness Testing Components

The fairness testing components refer to where to find fairness bugs. Traditional software testing aims to detect bugs in the code. In the fairness literature, researchers use the term “algorithmic fairness” [28], [29], [40], [41] to indicate that fairness bugs often exist in the algorithms of ML systems. According to the fairness literature, we consider algorithms an important testing component of fairness testing.

ML systems are enabled or assisted by ML models trained using large-scale data with learning algorithms written based on ML frameworks (e.g., scikit-learn [42], TensorFlow [43], and Keras [44]). In other words, an ML system is the result of the interaction among several components (i.e., data, algorithm, and ML framework) that are closely bonded with each other. Therefore, developers need to conduct fairness testing on each of them to ensure a fair outcome.

**Algorithm Testing:** Algorithm testing reveals fairness bugs based on the input-output behaviors of ML software systems. On the one hand, algorithm testing can detect fairness bugs introduced by a particular part of the algorithm, including improper data processing [45], training algorithm selection [38], and hyper-parameter settings [46]. On the other hand, algorithm testing can view the software under test as a combined entity and detect fairness bugs in the algorithm of the software no matter which part causes these bugs, which we call “fairness integration testing” in this paper. The algorithm can be tested in a white, black, or gray-box manner. Black-box testing is a technique of testing without having any knowledge of the internal working of ML software (e.g., code and data); white-box testing tests an ML software system taking into consideration its internal working; gray-box testing is to test with limited knowledge of the internal working of the software under test [47].

**Data Testing.** ML software is developed following the data-driven programming paradigm. Therefore, data determine the decision logic of ML software to a large extent [12], and data bias is considered a main root cause of ML software bias [48]. Data testing aims to detect different types of data bias, including checking whether the labels of training data are biased (label bias) [35], whether the distribution of training data implies an unexpected correlation between the sensitive attribute and the outcome label (selection bias) [49], whether the features of training data contain bias (feature bias) [50].

**Framework Testing.** ML frameworks play an important role in ML software development, as they support engineers with designing, training, and validating ML models. Therefore, a lot of studies [51], [52], [53] have detected ML framework bugs that lead to problems in the final ML software systems. However, these bugs are primarily related to ML performance (e.g., accuracy). To the best of our knowledge, to date, there has been no framework testing work that detects fairness bugs.

### 2.5 Software Testing vs. Fairness Testing

Fairness testing is an emerging software testing domain, which aims at revealing fairness bugs in ML software. Compared to traditional software testing, fairness testing has its unique characteristics. This section summarizes the relationship and difference between traditional software testing and fairness testing from several aspects.

1. **Components to test.** As described in Section 2.4, traditional software testing detects bugs in the code, while fairness testing can detect fairness bugs in algorithms, data, and ML frameworks.
(2) **Test input.** In traditional software testing, test inputs are usually the input data for detecting bugs in the code. For detecting fairness bugs in algorithms, test inputs can include data instances, while for detecting fairness bugs in data, test inputs can include learning programs. Moreover, fairness is a relative concept that considers different demographic groups at the same time, so the test inputs are often in the form of paired data instances, each of which is in a different group, making fairness testing an instance of metamorphic testing [54].

(3) **Test oracle.** Traditional software testing often assumes the presence of a test oracle and determines the oracle beforehand. For a given input, it compares the output of the software under test with the output that the oracle determines, to reveal software bugs. Compared to traditional software testing, the oracle problem for fairness testing is more challenging.

On the one hand, the ground-truth labels of inputs need to be manually confirmed, which is time-consuming and labor-intensive. Moreover, because fairness testing is often conducted for social-critical, human-related tasks, the manual confirmation needs to be treated with caution and requires domain-specific knowledge about the application scenarios, and even help from legal practitioners and policy makers.

On the other hand, even if we have the actual labels of inputs, it is still challenging to determine the concrete oracle for fairness testing, because there is no firm consensus on what is fair and how to formalize fairness.

In addition, it is difficult to determine the test oracle for an individual input, because fairness is a relative concept that considers different demographic groups at the same time. For example, engineers cannot judge whether a system is fair to women if they are unaware of the outcomes that the system provides to men. In practice, metamorphic relations and statistical measurements are adopted to tackle the oracle problem of fairness testing [48], [55].

(4) **Test adequacy.** Test adequacy criteria measure whether existing tests exercise certain aspects of the software under test. In traditional software testing, various test adequacy criteria have been proposed and adopted, such as line coverage, branch coverage, and dataflow coverage [56], which measure the degree to which the code of a system is executed by a test suite. However, we did not find any research on evaluating test adequacy on coverage concepts for fairness bug revelation. Therefore, there is a need of new test adequacy criteria for fairness testing.

(5) **Testers.** Traditional software testing is performed by test engineers. Considering that fairness bugs may be caused by data or algorithms, data scientists and algorithm designers may also need to take on the role of testers for fairness testing. In addition, fairness is an important software requirement that has been encoded in laws, regulations, and policies, so legal practitioners, compliance officers, and policy makers may also contribute to test the fairness of software systems.

### 2.6 Fairness Testing in Software Engineering Process

This section positions fairness testing within the entire software engineering process.

Fairness is a non-functional software property that needs to be a first-class entity in the entire software engineering process, rather than an after-the-system-is-built concern [5], [14]. Figure 3 illustrates the fairness-aware software engineering process. Indeed, fairness influences each software engineering activity. Fairness testing plays an important role both before and after the deployment of software systems, called offline fairness testing and online fairness testing, respectively.

**Requirements:** Software engineers need to (1) elicit fairness requirements through interviews, workshops, policy analysis, etc. (requirements elicitation), (2) perform requirements triage and prioritization, taking possible conflicts between different fairness requirements into account (requirements analysis), (3) represent and store fairness requirements in a well-organized fashion to facilitate effective communication and change management (requirements specification), and (4) trace, evaluate, and deal with the fairness requirements changes (requirements management).

**Design:** With requirements in hand, the next step for software engineers is to decide the software architectural styles and design patterns to meet these requirements. In recent years, ethics has received increasing attention from the SE community [57], [58], [59], [60], and thus been employed to guide the software design decisions. As an important principle of ethics [61], fairness needs be considered in the software design process.

**Implementation:** Software engineers develop and implement the fairness-aware software systems through computer programming. Implementation involves fairness-related tasks such as generating or identifying/selecting fairness-aware algorithms.

**Offline Testing:** Engineers can use historical or generated data to perform online testing to check whether the
system meets the fairness requirements. Because such data usually fail to fully represent future data, offline testing is unable to cover and test some circumstances that may be problematic in real-world application scenarios.

Repair: Software engineers produce fixes that can be adopted to repair the system. The fixes often both explain the reason of unfairness and provide a possible solution to improve software fairness. The process of software repair for fixing fairness bugs is also called “bias mitigation” in the literature [22], [38], [62]. Testing needs to be repeated after bias mitigation, to check whether the repaired software meets the required fairness conditions.

Deployment: The deployment process may introduce fairness bugs. For example, recently, there is a great demand of deploying deep learning (DL) software to platforms with limited computing resources such as mobile devices [63], [64]. However, because DL software is often computation-intensive and thus cannot be directly executed on such platforms, it has been common during the deployment process to compress the DL model. The compression may result in software unfairness [65], [66], [67].

Online Testing: Online testing employs run-time monitoring to keep checking whether the software can still yield fair outcomes for real-world input data [68]. During this process, user feedback is also a common data source to detect fairness bugs. Another typical way for online testing is A/B testing [69], which splits users to use the new and the old software and thus compares the two versions. The A/B testing results can help software engineers determine which version of software is better and devote more resources to the better one.

Maintenance: If fairness bugs are detected in online testing, software maintenance is needed to modify and update the software in order to improve software fairness. In addition, due to the dynamic environments where software systems operate and the changing needs of stakeholders, fairness requirements may evolve. Software engineers need to maintain the software to keep up with the changing fairness requirements and customer needs.

3 Survey Methodology

In this section, we introduce the survey scope, the paper collection approach, and the organization of our survey.

3.1 Survey Scope

We aim to define, collect, and curate the disparate literature, arguing and demonstrating that there does, indeed, exist a coherent area of research in the field that can be termed “fairness testing”.

We apply the following inclusion criteria when collecting papers. The papers that satisfy any of these criteria are included in this survey.

- The paper introduces the general idea of fairness testing or one of the related aspects of fairness testing.
- The paper presents an approach, study, framework, or tool that targets at fairness testing.

We do not include papers about the issues of fairness in network systems and hardware systems. Moreover, we filter out papers that are about fairness definitions, but do not consider them in the context of testing. We also do not include papers about gender diversity/inclusion and cognitive bias in software development, because our survey focuses on software engineering product fairness, not software engineering process fairness.

3.2 Paper Collection

We collected papers by using keyword searching on the DBLP publication database [70], which covers arXiv (a widely-used open-access archive), 1,803 journals, and 5,836 academic conferences in computer science. DBLP is widely used in software engineering surveys [12], [71], [72], [73], [74], and a recent survey [12] demonstrates that papers collected from other popular publication databases are a subset of those collected from DBLP.

We defined the keywords through a trial-and-error procedure [75] performed by the first two authors and a discussion among the first four authors. The final keywords used for searching included (“fair” OR “bias” OR “discrimination”) AND (“software” OR “learning” OR “bug” OR “detect” OR “fault” OR “algorithm” OR “test” OR “detect” OR “evaluative”). As a result, we conducted a total of $3 \times 9 = 27$ searches on DBLP on March 17, 2022, and obtained 5,694 hits. Then, the first two authors manually inspected each hit paper to check whether it is in the scope of our survey, and selected 59 relevant papers.

We further performed snowballing [76] based on the collected papers, to ensure a high coverage of fairness testing papers, because keyword searching might omit relevant papers. Specifically, we employed both backward snowballing and forward snowballing [76]. In backward snowballing, we analyzed the references in each collected paper and identified those lying in our scope; in forward snowballing, we identified papers of our interest from those that cite the collected papers with the help of Google Scholar. We repeated the snowballing process until we reached a transitive closure fixed point; no new relevant papers were identified. We collected additional 54 papers through snowballing.

To ensure that our survey is comprehensive and accurate, we also contacted the authors of the 113 papers we
collected via keyword searching and snowballing. We asked them to check whether our description about their work is correct. They also pointed us to 14 additional papers, among which 9 papers met our inclusion criteria and were further included in the collected paper repository.

Table 2 shows the statistics of the paper collection process. In summary, we consider 59 + 54 + 9 = 122 papers for this survey.

3.3 Paper Organization

As shown in Table 3, we review the collected papers in the following way:

Section 4 (Fairness Testing Workflow): We organize the collected papers from the testing workflow angle, i.e., we summarize existing fairness testing work according to test input generation and test oracle identification. For each dimension, we further categorize related work. For example, we categorize test input generation work into random test input generation, search-based test input generation, verification-based test input generation, and domain-specific test input generation.

Section 5 (Fairness Testing Components): We organize the collected papers from the testing component angle, i.e., we summarize existing work according to data testing and algorithm testing. For each of the two dimensions, we perform a more fine-grained categorization. For example, for data testing, we introduce the testing effort with regard to fairness bugs in the data features, data labels, and data distribution.

Section 6 (Datasets and Tools): We summarize the publicly available datasets and open source tools for fairness testing, to provide a navigation for (1) researchers who would like to engage in fairness testing research, and (2) test engineers who would like to select an appropriate dataset or tool for their use case.

Section 7 (Research Trends and Distributions): We analyze the research trends of fairness testing and compare the numbers of publications in different research venues, ML categories, data types, and fairness categories, and classify existing fairness testing techniques according to the software access level (white-box or black-box).

Section 8 (Research Opportunities): Finally, we discuss open challenges and highlight potential research avenues in fairness testing.

4 Fairness Testing Workflow

We first introduce existing techniques that support the key activities involved in fairness testing, i.e., test input generation and test oracle identification.

4.1 Test Input Generation

In the area of fairness testing, test input generation aims to automatically produce instances that can induce discrimination and reveal fairness bugs of software systems. We organize relevant research based on the techniques adopted.

4.1.1 Random Test Input Generation

Galhotra et al. [55], [77] presented the first test input generation approach for detecting fairness bugs. Specifically, they proposed Themis, which generates values for non-sensitive attributes randomly, and then iterates over the values for sensitive attributes. Themis can also use the behavior of the system under test on test inputs to measure the frequency of discriminatory instances in the input space.

4.1.2 Search-based Test Input Generation

Despite the effectiveness of Themis, random generation may lead to a low success rate of the discriminatory input generation [78], so the following fairness testing work [78], [79], [80], [81], [82], [83], [84] generates test inputs using search-based techniques. Search-based test generation uses meta-heuristic search techniques to guide the generation process and make this process more efficient and effective [85], [86], [87]. It has been employed in an increasing number of fairness testing techniques to explore the input space of the software under test.

Udeshi et al. [79] proposed Aequitas, a two-phase search-based individual discriminatory instance generation approach. In the global search phase, Aequitas randomly searches for discriminatory instances in the input space. In the local search phase, Aequitas perturbs the discriminatory instances identified in the global phase to search their neighbors. It uses three strategies, i.e., random, semi-directed, and fully directed, to update the probability used to guide the selection of attributes to perturb.

Aggarwal et al. [80] presented Symbolic Generation (SG), which combines symbolic generation and local explainability for search-based discriminatory instance generation. First, SG uses a local model explainer to construct a decision tree to approximate the decision-making process of the ML software under test. Then, SG leverages symbolic execution to cover different paths in the decision tree to discover discriminatory inputs, and perturbs these discovered inputs to search for their neighborhood in the input space, thus generating more discriminatory inputs.

Xie and Wu [81] relied on reinforcement learning to achieve an optimal black-box search strategy for individual fairness test input generation. This approach regards the ML model under test as a part of the environment of reinforcement learning. The reinforcement learning agent takes actions to the environment to produce discriminatory inputs, and then observes the state and feedback from the environment in terms of a reward. Through iterations of such interactions, the agent learns an optimal policy to generate discriminatory inputs with high efficiency.
Fan et al. [78] proposed ExpGA, an explanation-guided discriminatory instance generation approach. First, ExpGA uses interpretable methods to search for seed instances that are more likely to derive discriminatory instances by slightly modifying feature values than other instances. Then, with the seed instances as inputs, ExpGA employs a genetic algorithm to efficiently generate a large amount of discriminatory offspring.

Perera et al. [82] presented SBFT, a search-based fairness testing approach for regression-based ML systems. They first defined fairness degree, which is measured as the maximum difference in the predicted values for all pairs of instances that are similar apart from the sensitive attribute. Then they searched for test inputs that reveal the fairness degree using a genetic algorithm.

In addition to these techniques, there have been several search-based test input generation approaches specifically proposed for Deep Neural Networks (DNNs), such as Adversarial Discrimination Finder (ADF) [82], Efficient Individual Discriminatory Instances Generator (EIDIG) [83], and NeuronFair [84], which are described as follows.

Zhang et al. [82], [89] proposed ADF, a gradient-guided search-based discriminatory instance generation approach for DNNs. It contains two search phases. In the global search phase, ADF locates the discriminatory instances near the decision boundary by iteratively perturbing a seed input towards the decision boundary with the guidance of gradient. In the local search phase, ADF further uses gradients as the guidance to search the neighborhood of the found individual discriminatory instances to discover more discriminatory instances.

EIDIG [83] inherits and improves ADF by integrating a momentum term into the iterative search for identifying discriminatory instances. The momentum term enables the memorization of the previous trend and helps to escape from local optima, which ensures a higher success rate of finding discriminatory instances. In addition, EIDIG reduces the frequency of gradient calculation by exploiting the prior knowledge of gradients to accelerate the local search phase.

Zheng et al. [84] proposed NeuronFair, which uses the identified biased neurons to guide the generation of discriminatory instances for DNNs. First, NeuronFair identifies the biased neurons that cause discrimination via neuron analysis. Then, it generates discriminatory instances with the optimization object of increasing the ActDiff (activation difference) values of the biased neurons. Finally, NeuronFair uses the generated discriminatory instances as seeds and perturbs them to generate more discriminatory instances near the seeds.

Tao et al. [90] proposed RULER for fairness testing and repair of DNNs. For a given input, RULER searches for individual discriminatory instances with different perturbation constraints on sensitive and non-sensitive attributes. Specifically, the perturbation constraints require that sensitive attributes shall be within their valid value ranges, and that non-sensitive ones shall be in the neighborhood of the original input within a small bound. The generated instances are then used in training to improve DNN fairness.

### 4.1.3 Verification-based Test Input Generation

Since our survey focuses on fairness testing, we do not discuss work focusing solely on formal verification of fairness properties (see e.g., [17], [91], [92], [93], [94], [95], [96]). Nevertheless, there is a research stream focusing on generating discriminatory test inputs through fairness verification using Satisfiability Modulo Theories (SMT) solving. These techniques are called verification-based test input generation [97].

Sharma et al. [97], [98] proposed two verification-based test input generation techniques for fairness, named fairCheck and MLCheck. Both fairCheck and MLCheck approximate the black-box model under test by a white-box model, based on its predictions. Then, the fairness property and the white-box model are translated to logical formulæ by SMT solvers. Test cases are then automatically generated attempting to violate the specified fairness property with the help of the SMT solver Z3 [99] to check for satisfiability.
4.1.4 Domain-specific Test Input Generation

Recently, an increasing number of approaches have been proposed for test input generation in specific application domains. These approaches aim to generate natural inputs that belong to the data distribution of a practical application scenario. This section introduces such domain-specific test input generation in two typical domains: natural language processing and computer vision.

### Natural language processing

The test input generation for Natural Language Processing (NLP) systems is mainly based on the metamorphic relation that a fair NLP system should produce the same result for two pieces of text that differ only in sensitive attributed-related features.

Diaz et al. [100] collected sentences containing the word “old” and replaced “old” (as well as “older” and “oldest”) with “young” (as well as “younger” and “youngest”). The sentence pairs were used as test inputs to detect age-related fairness bugs in sentiment analysis systems.

Another method, which is commonly used in fairness testing for NLP systems, is to manually design a set of templates for generating test inputs. These handcrafted templates often consist of short sentences with placeholders, such as “<person> goes to the school in our neighborhood”. Test inputs can be generated by instantiating the placeholder.

Kiritchenko and Mohammad [101] created 11 such templates for gender and race, and pre-defined values for the placeholder <person> as common African American female or male first names, common European American female or male first names, and noun phrases referring to females (e.g., “my daughter”) or males (e.g., “my son”).

Similarly, Sheng et al. [102], Huang et al. [103], Dhamala et al. [104] designed templates for detecting fairness bugs in natural language generation systems. These templates are sentence prefixes containing a placeholder that can be replaced by different values of a sensitive attribute, such as “<XYZ> went to the school in our neighborhood”.

Mehrabi et al. [105] created templates to detect the difference in the ability of name entity recognition systems to recognize male and female names. The templates are sentences that start with a placeholder for names followed by a sentence that represents a human-like activity.

Wang et al. [106] created 30 templates to test machine translation systems with regard to a specific type of fairness bugs, i.e., the inability to determine the gender of a name correctly. Each template includes a person name slot that can be replaced with a name from a list of male and female names.

Sharma et al. [107] manually designed templates to test gender-related fairness bugs in natural language inference systems, which aim to determine whether a hypothesis is true, false, or undetermined given a premise. These templates are gender-specific hypothesis with the placeholder <gender>, such as “This text talks about a <gender> occupation”, where <gender> corresponds to male or female.

Another well-known approach is CheckList [108], which has been proposed for producing test cases to evaluate NLP systems with respects to their capabilities beyond accuracy. Fairness is of these capabilities. Like previous work, CheckList relies on a small number of predefined templates for generating test sentences.

Although handcrafted templates successfully detect fairness bugs in NLP systems, researchers argue that the generated test inputs relying on them may be simplistic and limited [109]. To tackle this problem, Ma et al. [54] proposed an automated framework MT-NLP to generate discriminatory inputs for NLP systems. First, MT-NLP identifies human-related tokens in the input text using advanced NLP techniques. Second, it uses word analogy techniques in manipulating word embeddings to mutate the identified tokens and thus generate the test inputs. Finally, it uses language fluency metrics to rule out unrealistic test inputs.

Asyrofi et al. [110] proposed an automated template creation approach BiasFinder for producing more diverse and complex test inputs to better uncover fairness bugs in NLP systems. BiasFinder first uses NLP techniques, such as coreference resolution and named entity recognition, to automatically identify all the words (e.g., person names, gender pronouns, and gender nouns) associated to demographic characteristics in given texts. Then, it replaces the identified words with placeholders to transform these texts into templates. Finally, it fills in placeholders in each template with concrete values of demographic characteristics to produce a large number of test mutants and test whether the metamorphic relationship is satisfied for the mutants in the system under test.

Ezekiel et al. [111] proposed ASTRAEA, a grammar-based fairness testing approach for generating a large number of discriminatory inputs for NLP systems automatically. ASTRAEA contains the input grammars covering various NLP tasks (i.e., coreference resolution, sentiment analysis, and mask language modeling) and bias (e.g., gender bias, religion bias, and occupation bias). It randomly explores the input grammars to generate initial test inputs, and mutates the words associated with the sensitive attribute using alternative tokens. Finally, ASTRAEA checks whether the generated test inputs and their mutants satisfy the metamorphic relations.

Sun et al. [112], [113] proposed TransRepair and CAT, which can be applied for test input generation for fairness testing of machine translation systems. For each input sentence, TransRepair conducts sentence mutations via context-similar word replacement; CAT identifies and conducts word replacement using isotopic replacement. The mutants as well as the original input sentence are used as test inputs for the machine translation system under test.

### Computer vision

To detect fairness bugs in a Computer Vision (CV) system, researchers typically check how the output changes when the sensitive attribute of the person in the input image changes (e.g., transforming from dark hair to light hair) while keeping everything else constant. The test input generation for CV systems is underpinned by this idea.

To perform image transformations, it is common to use Generative Adversarial Networks (GANs) [114], which can generate superficially authentic images and has been widely adopted in ML testing [12]. However, it is challenging for conventional GANs to generate the precise changes to the image.
images as fairness testing requires. Taking changing the hair color as an example, it is difficult to change the hair color without changing the hair style or other features of the face.

To tackle this problem, there is some recent effort in adapting and improving conventional GANs for test input generation of CV systems. Denton et al. [115] used a progressive GAN [116] to mutate attributes for a given image by linear interpolations of latent variables. Joos and Kärkkäinen [117] used the FaderNetwork architecture [118] that inputs specific known attributes of an image separately to the generator. Zhang et al. [119] adopted CycleGAN [120], whose objective function limits the changes to non-sensitive attributes, in order to generate discriminatory inputs. Denton et al. [121] built a face generative model that maps latent codes, sampled from a fixed prior distribution, to images, and then infers directions in latent code space that correspond to manipulations of a particular sensitive attribute in pixel space. They generated input images by traversing these inferred directions.

However, these approaches ignore the causal relationships between attributes when generating discriminatory images. To generate test inputs that may be encountered in the real world, it is important to consider the downstream changes caused by changing a sensitive attribute. For example, for a chest MRI classification system, age of the patients may affect the relative size of their organs [122]. Therefore, it is not realistic to change the age of a patient without considering the causal relationship between age and the organ size. Based on this insight, Dash et al. [122] proposed ImageCFGen, a fairness testing method that combines knowledge from a causal graph and uses an inference mechanism in a GAN-like framework to generate discriminatory images.

4.2 Test Oracle Identification
Given an input for a software system, the challenge of distinguishing the corresponding desired behaviour from the potentially incorrect behavior is called the “test oracle problem” [122]. The test oracle of fairness testing enables the judgement of whether a fairness bug exists. Compared to traditional software testing, the test oracle problem for fairness testing is more challenging, as described in Section 2.5. We find that existing work employs two types of test oracles for fairness testing: metamorphic relations and statistical measurements.

4.2.1 Metamorphic Relations as Test Oracles
A metamorphic relation is a relationship between the software input change and the output change that we expect to hold across multiple executions [123].

Suppose a system that implements the function \( \sin(x) \), then \( \sin(x) = \sin(\pi - x) \) is a metamorphic relation. This relation can be used as a test oracle to help detect bugs. If \( \sin(x) \) differs from \( \sin(\pi - x) \), we can conclude that the system under test has a bug without the need for examining the specific values output by the system.

Metamorphic relations have been widely studied to uncover fairness bugs. Specifically, existing work mainly performs fairness-related metamorphic transformation on the input data or training data of ML software, and expects these transformations do not change or yield expected changes in the prediction. Next, we classify and discuss this work according to whether the metamorphic transformations operate on sensitive attributes.

1) Metamorphic transformations based on mutating sensitive attributes. For classification systems, the most common metamorphic relation used for fairness testing is that pairs of instances with different sensitive attributes but similar non-sensitive attributes should receive the same classification outcome. For example, we expect that a fair loan application system produces the same decision for two applicants differing only in their gender.

This metamorphic relation has been widely used to test the fairness of software systems and to guide the fairness test generation process in tabular data classification [55]. [77], [79], [80], [81], [82], [83], [89], text classification [54], [101], [103], [106], [107], [108], [110], [111], image classification [84], [115], [117], [119], [121], [122], etc. For tabular data, researchers can directly select the sensitive attributes that they care about in the dataset (e.g., gender and race), and mutate the sensitive attribute values (e.g., from “male” to “female”) of instances to detect whether the software violates the fairness metamorphic relation for these instances. For text, researchers need to identify the entities related to the target sensitive characteristics and transform all the identified entities at the same time to generate legitimate test inputs in the real world. For example, for gender, we need to detect and transform the person name, gender pronoun, gender noun, etc. For images, researchers mainly leverage state-of-art deep learning techniques such as Generative Adversarial Network (GAN) [114] to transform images across the sensitive attributes. The methods for changing the sensitive attributes for different types of data have been introduced in details in Section 4.1.

For software systems that perform regression tasks, the prediction outcomes are continuous values, not concrete labels, making it challenging to determine the metamorphic relations. Specifically, it is difficult to determine whether two predicted continuous outcomes are sufficiently different to judge that the software under test has fairness bugs. To tackle this problem, Udeshi et al. [29] used a threshold to determine the metamorphic relations, i.e., the outcome difference of two similar instances that differ in the sensitive attribute needs to be smaller than the manually-specified threshold. Similarly, Perera et al. [88] proposed the concept of fairness degree, which is measured as the maximum difference in the predicted values for all pairs of instances that are similar apart from the sensitive attribute. The fairness degree can be used and specified to construct metamorphic relations and guide the test input generation.

For software systems that perform generation tasks, it is more challenging to determine the metamorphic relations. For example, for natural language generation systems, it is difficult to evaluate whether the generated text is identical or similar. To measure text similarity, researchers [102], [103] have applied existing natural language processing techniques, including sentiment classification, perplexity and semantic similarity measurement, and regard classification, on machine-generated text. As a result, the metamorphic relations require that pairs of inputs that are identical apart from the sensitive attribute should obtain generated text with the same sentiment polarity, perplexity, semantics, and
regard. For machine translation systems, which generate translations based on the input sentences, Sun et al. [112], [113] generated test oracles relying on the metamorphic relationship between translation inputs and translation outputs. Specifically, translation outputs for the original input sentence and its mutants with regard to sensitive characteristics should have a certain degree of consistency modulo the mutated words. They used similarity metrics that measure the degree of consistency between translated outputs as test oracles.

(2) Metamorphic transformations based on mutating non-sensitive attributes. Metamorphic relations for fairness testing can also be based on the mutation of non-sensitive attributes.

Díaz et al. [100] presented a metamorphic testing approach to detecting age-related fairness bugs in sentiment analysis systems through mutating common adjectives, instead of mutating words related to age. They used the word embedding technique to produce a set of “older” and “younger” analogs for common adjectives. For example, they found that in one embedding “stubborn” – “young” + “old” gives “obstinate”, while “stubborn” – “old” + “young” gives “courageous”. They thus used “obstinate” as the “old” variant of “stubborn”, “courageous” as the “young” variant, and checked whether the use of the two variants in the input sentence influences the output of sentiment analysis systems. If so, they judged that the systems under test might lead to fairness bugs with regard to age.

Rajan et al. [124] proposed metamorphic testing for speech recognition systems to detect fairness bugs. Specifically, they identified eight metamorphic transformations (e.g., noise, drop, and low/high pass filter), which are common in real life, for speech signals. Then they calculated the increase in error rates of speech recognition for different demographic groups after metamorphic transformations. The recognition system has fairness bugs if the difference in the increase for different groups exceeds a given threshold.

Sharma and Wehrheim [125] presented metamorphic transformations to test the fairness of the learning phase of ML software. These transformations are applied to the training data of ML models, including changing the ordering of data rows/columns, permuting the feature names, and replacing categorical features by numerical ones. The learning phase is considered fair if the application of the transformations results in equivalent predictors.

4.2.2 Statistical Measurements as Test Oracles

Researchers have proposed various statistical fairness measurements according to different fairness definitions and requirements. Although these measurements are not direct oracles for fairness testing, they provide a quantitative way for test engineers to evaluate the fairness of the software under test. For example, for demographic parity, researchers calculate the favorable rate among different demographic groups and detect fairness violations by comparing these rates. If the rate difference, called Statistical Parity Difference (SPD) in the software fairness literature [33], [38], [48], [50], [126], is beyond a threshold, the software under test is identified as containing fairness bugs.

There are a large number of existing statistical fairness measurements. A complete description of each is beyond the scope of this survey. For example, to date, the IBM AIF360 toolkit [127] has provided more than 70 statistical measurements for fairness. Verma and Rubin [19] have surveyed and categorized widely-adopted statistical measurements for fairness. Here, we extend their categorization based on our collected papers, and introduce each category with representative measurements.

Measurements based on predicted outcomes. Some measurements are calculated based on the predicted outcomes of the software for privileged and unprivileged groups. For example, the aforementioned Statistical Parity Difference (SPD) [33] measures the difference in favorable rates among different demographic groups; Disparate Impact (DI) [28] measures the ratio of the favorable rate of the unprivileged group against that of the privileged group.

Measurements based on predicted and actual outcomes. Some measurements not only consider the predicted outcomes for different demographic groups, but also compare them with the actual outcomes recorded in the collected data. For example, the Equal Opportunity Difference (EOD) [54] measures the difference in the true-positive rates of privileged and unprivileged groups, where the true-positive rates are calculated by comparing the predicted and actual outcomes. Another widely-adopted measurement that lies in this category is Average Odds Difference (AOD) [54], which refers to the average of the false-positive rate difference and the true-positive rate difference between unprivileged and privileged groups.

Measurements based on predicted probabilities and actual outcomes. Some measurements take the predicted probability scores and actual outcomes into account. For example, for any given predicted score, the calibration measurement calculates the difference in the probability of having a favorable outcome for privileged and unprivileged groups [129]; the measurement of balance for positive class calculates the difference of average predicted probability scores in the favorable class between privileged and unprivileged groups [130].

Measurements based on neuron activation. As DNNs are widely used in software systems to support the decision-making process, researchers have started to leverage the internal behaviors of DNNs to design statistical fairness measurements. Tian et al. [131] proposed a new statistical measurement based on neuron activation for DNNs. First, they computed a neuron activation vector for each label class based on the test inputs. Specifically, for a class $c$, each element of its neuron activation vector represents how frequently a corresponding neuron is activated by all members in the test inputs belonging to class $c$. Then they computed the distance between neuron activation vectors of different classes as the fairness measurement. If two classes do not show a similar distance with regards to a third class, they consider that the DNN under test contains fairness bugs.

Measurements based on situation testing. Some researchers designed statistical measurements to approximate situation testing, which is a legal experimental procedure of seeking for pairs of instances that are with similar characteristics apart from the sensitive attribute value, but obtain different prediction outputs. Thanh et al. [132] leveraged the k-nearest neighbor classification to approximate situation testing. They first divided the dataset into the
privileged group and the unprivileged group, based on the sensitive attribute. Then, for each instance \( r \) in the dataset, they found the k-nearest neighbors in the two groups and denoted them as sets \( K_p \) and \( K_u \), respectively. Finally, they calculated the proportions of instances, for which the outcome is the same as \( r \) in \( K_p \) and \( K_u \), and measured the difference between the two proportions. If the difference is larger than a given threshold, the instance \( r \) is considered unfairly treated. Zhang et al. [133] improved the measurement proposed by Than et al. [132]. They designed a new distance function that measures the distance between data instances, to improve the k-nearest neighbor classification. Their function considers only the set of attributes that are identified as the direct causes of the outcome by Causal Bayesian Networks [134].

**Measurements based on optimal transport projections.** Several measurements [135], [136], [137] are proposed based on optimal transport projections [138], which seek for a transformation map between two probability measures. Black et al. [135] mapped the set of women in the data to their male correspondents, with the optimal transport projection to minimize the sum of the distances between a woman and the man to which she is mapped (called her counterpart). Then they extracted the positive flipset, which contained the women with favorable outcomes whose counterparts are not. They also extracted the negative flipset, which was the set of women with unfavorable outcomes whose counterparts are favorable. Finally, they calculated the size difference of the positive and the negative flipsets to measure the unfairness of the system under test.

**Measurements for ranking systems.** It is difficult to apply the aforementioned measurements directly to ranking systems, which are also used extensively online. Such ranking systems are typically relied on as critical tools for decision making across various domains such as filtering for hiring and university admissions [139], [140]. To tackle this problem, some work reduced the ranking problem to a classification problem, and then applied existing statistical measurements. For example, researchers [141], [142], [143] used the statistical parity difference as the fairness requirement, and measured whether members of different groups have the same proportional representation among desirable outcomes, e.g., in a top position in the ranking. Another typical type of statistical metric is based on pairwise fairness [144], [145], [146], which requires a ranking system to ensure that the likelihood of a clicked item being ranked above another relevant unclicked item is the same across groups.

Using statistical measurements as test oracles poses unique challenges for fairness testing:

**It is difficult to determine the threshold for statistical measurements to detect the fairness bugs.** For example, for the aforementioned SPD, it would be too strict to consider the software under test to be fair only when SPD equals to 0. In practice, practitioners can set a threshold for the measurement under consideration [147]. If the measurement result for the software under test is above or below the specified threshold, the software is considered to have a fairness bug. Although the threshold could be empirically specified by the requirements engineers, it is challenging to determine the appreciate threshold for each fairness measurement.

To alleviate this problem, researchers attempt to use statistical testing, based on the measurements to detect fairness bugs. Tramèr et al. [148] proposed FairTest to analyze the associations between software outcomes and sensitive attributes. The software under test is deemed to have a fairness bug, if the associations are statistically significant. Taskesen et al. [136] and Si et al. [137] employed a statistical hypothesis test for the fairness measurements based on optimal transport projection. DiCiccio et al. [147] presented a non-parametric permutation testing approach for assessing whether a software system is fair in terms of a fairness measurement. The permutation test is used to test the null hypothesis that a system has equitable performance for two demographic groups (e.g., male or female) with respect to the given measurement.

In addition, some researchers construct the baseline for the fairness measurement, and detect fairness bugs by comparing the measurement value with the baseline. Zhao et al. [149] used the fairness measurements calculated based on training data as their baseline against which to evaluate. Specifically, they used the obtained ML model to annotate unlabeled data instances, and revealed situations when the ML process amplified existing bias by comparing the fairness measurements on training data and those on the annotated dataset. Wang and Russakovsky [150] showed that the bias amplification measurement proposed by Zhao et al. [149] conflated different types of bias amplification and failed to account for varying base rates of sensitive attributes. Then they proposed a new, decoupled metric for measuring bias amplification, which takes into account the base rate of each sensitive attribute and disentangles the directions of amplification. Wang et al. [151] presented a fairness testing approach for visual recognition systems that predicted action labels for images containing people. They trained two classifiers to predict gender from a set of ground truth labels and model predictions. The difference in the predictability of the two models indicated whether the ML process introduced fairness bugs.

**It is difficult to determine which measurements to use to ensure the sufficiency of testing, considering a plethora of candidate fairness measurements available.** To tackle this problem, researchers have investigated the relationship among different fairness measurements. If a cluster of fairness assessments measure very similar things, test engineers can use a single metric from the cluster, which largely simplifies the testing process. To this end, Majumder et al. [36] used the clustering algorithm and correlation analysis to group existing fairness measurements. Verma and Rubin [19] divided fairness measurement into different groups based on the theoretical definitions.

Cachel and Rundensteiner [152] presented FINS, a fairness auditing framework for subset selection (i.e., selecting a subset of items), which is integral to AI-enabled decision-making applications including shortlisting items, top-k queries, data summarization, and clustering. FINS provides a unified easy-to-understand interpretation across different fairness measurements for subset selection, and develops guidelines to support stakeholders in determining which measurements are relevant to their problem context and fairness objectives.
5 Fairness Testing Components

Existing fairness testing work primarily resides in data testing and algorithm testing.

5.1 Data Testing

ML software is developed following the data-driven paradigm. This paradigm makes ML software vulnerable to fairness bugs present in data. Specifically, fairness bugs in data can be learned and propagated throughout the ML software development pipeline, leading to the creation of biased and unfair software systems. To tackle this problem, approaches have been proposed that target the ML software training data. They detect the bias in data features, data labels, and data distribution.

(1) Detection of feature bias. Feature bias occurs when some features in the training data are highly related to the sensitive attribute, and these correlated features can thus become the root cause of software unfairness [50]. Zhang et al. [126] explored how the feature set influences ML software fairness. The results showed that the feature set plays a significant role in fairness, which motivates the fairness work about testing data features.

To detect which features result in fairness bugs, it is intuitive to think that the software discriminates against a certain demographic group because it takes the demographic information (i.e., the sensitive attribute) into account during the training and prediction process [35]. To test whether the sensitive attribute is the root cause of fairness bugs, Chakraborty et al. [35] removed sensitive attribute information from the data and found that the obtained ML software exhibits a similar level of unfairness as before.

A similar finding has been derived from a real-world application: In 2016, the same-day delivery service provided by Amazon was demonstrated to discriminate against neighborhoods in which there resided a disproportionally high number of black people [153]. The ML model underpinning this service did not consider race information, but the presence of correlated attributes in the training data meant that bias remained possible nevertheless. That is, “Zipcode” information used for model training turned out to be highly correlated with race, and the ML model induced race information from it.

To tackle this problem, Li et al. [50] aimed to identify all the biased features that are correlated with sensitive attributes. Specifically, they applied linear regression to analyze the association between each feature and sensitive attributes, and identified those features that may thereby induce bias.

Peng et al. [154] used logistic regression and decision tree algorithms as models to extrapolate the correlations among dependent variables that might cause bias in training data.

Black et al. [135] employed optimal transport projections [138] to map the data instances belonging to the unprivileged group to the ones in the privileged group (i.e., the counterparts). Then they extracted the positive flipset (i.e., the set of the unprivileged group members with favorable outcomes whose counterparts were unfavorable). They also computed the negative flipset (i.e., the set of the unprivileged group members with unfavorable outcomes whose counterparts were favorable). Then they analyzed the members of the positive and the negative flipsets to determine which features contributed to inconsistent classifications.

(2) Detection of label bias. Label bias occurs when the process that produces the outcome labels is influenced by factors that are not germane to the determination of the labels [49]. The data for developing ML software are often historically collected over many years. In the collection process, the data labels are typically determined by human beings or algorithms. As a result, these labels can end on encoding human and algorithmic bias.

To mitigate label bias, Chakraborty et al. [35], [48] leveraged situation testing to identify biased data points and remove them from the training data. Specifically, they divided the dataset into the privileged and unprivileged groups based on the sensitive attribute. Then, they trained two separate models on the data in the two groups. For each training data instance, they checked the prediction of the two models obtained. If the two models produced different results, there is a probability that the label of the data point would be biased.

Chen and Joo [155] detected label bias in common datasets for facial expression recognition. They demonstrated that many expression datasets contain significant label bias between different gender groups, especially when it comes to the expressions of happiness and anger. They also found that traditional fairness repair methods cannot fully mitigate such bias in trained models.

(3) Detection of selection bias. Selection bias occurs when the processing of sampling training data introduces an unexpected correlation between the sensitive attribute and the outcome [49]. For example, the Compas dataset [156] can be used for predicting whether defendants will re-offend within two years. It is widely studied in the software fairness literature, and has been demonstrated to contain unintended correlations between race and recidivism [49].

To detect selection bias, researchers mainly test the distribution of the data with regard to the sensitive attribute and the outcome. Chen et al. [39] tested whether the training data satisfy the “We Are All Equal” worldview, which holds the belief that there is no statistical association between the outcome and the sensitive attribute, and has been widely advocated in the literature and law [157]. Specifically, they tested whether the favorable rates of privileged and unprivileged groups are equal. Chakraborty et al. [48], [158] not only analyzed the difference in the favorable rates between privileged and unprivileged groups, but also compared the numbers of data instances in the two groups.

Kärkkäinen and Joo [159] detected bias in public face datasets, and found that these datasets are strongly biased toward Caucasian faces, whereas other races (e.g., Latino) are significantly underrepresented. Such bias would tend to risk the introduction of fairness bugs into any facial analytic system trained on them, and limit the applicability of these systems.

Wang et al. [160] detected the selection bias in visual datasets along three dimensions: object-based bias, gender-based bias, and geography-based bias. Object-based detection considers statistics about object size, frequency, context, and diversity of object representation; gender-based detection reveals the stereotypical portrayal of people of
different geographic locations. Torralba and Efros investigated the computer vision datasets. To test whether existing datasets are really unbiased representations of the real world, they evaluated how well an object detector trained on one dataset generalizes when tested on a representative set of other datasets.

Yang et al. collected perceived demographic attributes on a popular dataset for face detection and observed skewed demographic distributions. The face detectors trained based on this dataset thus exhibited demographic bias measured by performance disparity between different groups.

Mambreyan et al. analyzed the datasets used for lie detection, and found that these datasets contain significant sex bias. Specifically, the percentage of instances labelled with lies for females is larger than that for males in the dataset. They further analyzed the effect of such bias on lie detection. Specifically, they trained a classifier to predict the sex of the identity appearing in a video, and used the sex as a proxy for lie, i.e., predicting lie for females and truth for males. This deception detector simulated a classifier that used nothing but dataset bias. The results showed that the performance of this biased classifier was comparable to the state-of-the-art and thus suggested that the recent techniques claiming almost perfect results may exploit the dataset bias.

5.2 Algorithm Testing

Algorithms may encode data processing, decision-making logic, and run-time configurations (e.g., hyper-parameters for ML). Each part of the algorithm may introduce fairness bugs to the final software system. Algorithm testing can be applied to determine which part of the algorithm causes the unfairness.

1) Testing data processing. It is a common practice in ML software to include data processing stages to manipulate and transform the training data for the downstream learning tasks. Biswas and Rajan and Valentim et al. tested whether data processing methods introduce fairness bugs using causal reasoning. Specifically, they employed each commonly-used data processing method as an intervention into the development process of ML software and kept other settings unchanged. Then they found that certain pre-processing methods do, indeed, introduce fairness bugs into ML software, while other pre-processing methods may improve software fairness.

2) Testing hyper-parameters. Some researchers argue that the hyper-parameters specified in the ML programs play an important role in software fairness, and test whether different hyper-parameter settings result in different levels of software fairness. The testing process is considered as a search-based problem, whose goal is to find optimal settings in the hyper-parameter space. Chakraborty et al. proposed Fairway, which combines the situation testing method with a multi-objective optimization technique. Because there is often a trade-off between fairness and ML performance, Fairway leverages sequential model-based optimization to search for hyper-parameters that make ML software as fair as possible while also not degrading other performance measures.

Similarly, Tizpaz-Niari et al. took both fairness and accuracy into account. They proposed Parfait-ML, which provides three dynamic search algorithms (independently random, black-box evolutionary, and gray-box evolutionary) to approximate the Pareto front of hyper-parameters that trades fairness and accuracy. Parfait-ML not only provides a statistical debugging method to localize hyper-parameters that systematically influence fairness, but also contains a fairness repair method to find improved hyper-parameter configurations that simultaneously maximize fairness and accuracy.

3) Testing ML model internals. Some studies aim to test the internals of the learned ML models. Zhang et al. detected the paths related to fairness in the decision tree and random forest models and repaired them. Specifically, they used a MaxSMT solver to decide which paths in the tree could be flipped or refined, with both fairness and semantic difference as hard constraints. Then they refined the decision tree paths and changed their leaf labels as needed to output a repaired fair model as a solution. The approach is sound and complete with respect to the input dataset.

As for the emerging DL models, researchers detect the neurons (the fundamental units of DNNs) that are responsible for unfair outcomes. NeuronFair identified the biased neurons that are responsible for unfairness through neuron analysis, and then generated discriminatory instances with the goal of increasing the activation difference values of the biased neurons. It has good performance in terms of interpretability, generation effectiveness, and data generalization.

DeepFAIT applied significance testing to detect the activation differences of neurons for instances in the privileged and the unprivileged groups, to identify fairness-related neurons.

Vig et al. employed Causal Mediation Analysis (CMA) to test which parts (such as neurons or attention heads) of a DNN model are causally implicated in its unfair predictions. CMA is a classic technique that measures how a treatment effect is mediated by intermediate variables (i.e., mediators). Consider each neuron in a neural network to be an intermediate mediator, the neuron is affected by the input and, in turn, affects the model output; however, there also exist direct pathways from the input to the output that do not pass through the neuron. CMA enables them to detect the direct and indirect effects of targeted neurons on the final unfair predictions.

Gao et al. proposed FairNeuron for DNNs. FairNeuron first uses a neuron slicing technique to identify conflict paths, i.e., the paths that contain a lot of neurons that select sensitive attributes to make predictions. Then it uses these paths to identify biased instances that trigger the selection of sensitive attributes. Finally, it retracts the model by selective training. In the selective training process, for the identified biased instances, FairNeuron forces the conflict paths to learn all features that are important for prediction rather than the biased ones; for the other instances, FairNeuron keeps the original training way.

4) Testing fairness repair algorithms. As fairness has been an increasingly important requirement for software systems, engineers may include the fairness repair algo-
rithms (i.e., bias mitigation algorithms) in their programs to ensure the fairness of their software systems. Some researchers focus on testing whether these fairness repair algorithms reduce fairness bugs without introducing side effects (e.g., accuracy decrease).

Biswas and Rajan [173] applied seven fairness repair algorithms to 40 top-rated ML models collected from a crowd-sourced platform, and then compared the individual fairness, group fairness, and ML performance before and after these algorithms were applied.

Qian et al. [174] applied fairness repair techniques on five widely-adopted ML tasks, and investigated the variance of fairness and ML performance of these techniques, i.e., whether identical runs with a fixed seed produce different results. The results showed that most fairness repair techniques have some other undesirable impacts on the ML software such as reducing accuracy, increasing fairness variance, or increasing accuracy variance.

Zhang and Sun [175] evaluated existing fairness repair techniques on DNNs and found that they may improve fairness by paying the price of huge accuracy drop. These techniques may even worsen both fairness and accuracy. Then they proposed an approach that adaptively chooses the fairness repair method for a DNN based on causality analysis [176].

Hort et al. [38] proposed a benchmarking framework named Fairea. Existing work often measured the impacts of fairness repair algorithms on fairness and ML performance separately. In this way, it was unclear whether the improved fairness was simply the unavoidable cause of ML performance loss. To tackle this problem, Fairea provided a unified baseline to evaluate and compare the fairness-performance trade-off of different repair methods. Hort et al. [38] used Fairea to empirically evaluate state-of-the-art fairness repair methods implemented in the IBM AIF360 toolkit [177] with different settings. They investigated whether ML algorithms (e.g., RF and SVM), decision-making tasks, and fairness definitions influence the detection of fairness bugs.

Chen et al. [178] employed Fairea to conduct a large-scale, comprehensive empirical evaluation of 17 representative bias mitigation methods from both ML and SE communities, evaluated with 12 ML performance metrics, 4 fairness metrics, and 24 types of fairness-performance trade-off measurements, applied to 8 widely-adopted benchmark software decision/prediction tasks.

Hort and Sarro [179] observed another side effect of fairness repair: it could cause loss of discriminatory behaviours of anti-protected attributes. Anti-protected attributes refer to the attributes that one might want the ML decision to depend upon (e.g., students with homework should receive higher grades).

Orgad et al. [180], [181] evaluated the fairness repair approaches for NLP models from two aspects: extrinsic bias (performance difference across different demographic groups) and intrinsic bias (bias in models’ internal representations, e.g., word [182] or sentence [183] embeddings). They found that the two types of bias may not correlated with each other and that the choice of bias measurement and dataset can affect the evaluation results significantly.

(5) Testing compression algorithms. A computation-intensive DL software system can be executed efficiently on PC platforms with the GPU support, but it cannot be directly deployed and executed on platforms with limited computing power, such as mobile devices [63]. To tackle this problem, model compression algorithms are proposed to represent DL models in a smaller size with minimal impact on their performance [64]. Common model compression algorithms include quantisation (representing the weight values of DL models using a smaller data type), pruning (eliminating redundant weights that contribute little to the model behaviors), and knowledge distillation (transferring knowledge from a large model to a smaller one) [184]. The wide adoption of model compression in DL software motivates researchers to detect fairness bugs introduced by model compression algorithms.

Because model compression is often applied to DL models with large sizes, existing fairness testing of model compression algorithms is typically applied to complex NLP models [65] and computer vision models [65], [66], [67], [185]. Hooker et al. [66] showed that pruning and quantisation can amplify gender bias when classifying hair color on a computer vision dataset. Xu and Hu [186] tested the effect of distillation and pruning on the bias of generative language models, and presented empirical evidence that distilled models exhibited less bias. Stoychev and Gunes [67] detected fairness bugs introduced by different model compression algorithms on various facial expression recognition systems, and did not observe a consistent finding across different systems.

(6) Fairness integration testing. Fairness testing work that detects fairness bugs in software system as a whole is referred to as fairness integration testing, which can be performed in a black-box or white-box fashion. We distinguish between white-box testing and black-box testing according to the access level to the training data and internal knowledge of ML models.

Black-box testing. Black-box testing detects the fairness bugs of ML software without the need of training data and knowing the internal structure of the model.

The typical stream of fairness testing work uses statistical measurements to uncover the fairness bugs in black-box models based on their prediction behaviors. Tramer et al. [148] analyzed the associations between prediction outcomes and sensitive attributes to detect if fairness bugs exist; Biswas and Rajan [173] used existing statistical measurements for individual fairness and group fairness to reveal fairness bugs in public ML models.

In addition, as described in Section 4.2.1 several researchers have detected fairness bugs by performing morphic transformations of the software inputs. They check whether the transformations result in unexpected changes in the predictions. Most of the work uses black-box testing. For example, the Themis tool [55], [7] randomly generates test inputs and checks whether the software system produces the same output for every two individuals who differ only in sensitive attribute values. Similarly, Aequitas [79] and ExpGA [78] search the input space of the software for discriminatory instances that reveal unfair predictions.

Black-box testing is frequently employed to detect fairness bugs in complex software systems or commercial software whose internal knowledge is unseen to testers, such as NLP, computer vision, and ranking systems.
Many researchers designed text templates to detect fairness bugs in various NLP systems, including sentiment analysis systems [101], [110], machine translation systems [106], text generation systems [102], [103], [104], natural language inference systems [107], name entity recognition systems [105]. This work has been described in Section 4.1.4 in details. For example, Asyrofi et al. [110] employed BiasFinder (a fairness testing method described in Section 4.1.4) to build a template for the input text of sentiment analysis systems, and used the template to generate mutant texts. Then, they analyzed whether the system makes the same prediction for equivalent mutants to reveal fairness bugs.

For computer vision systems, state-of-the-art fairness techniques [114], [115], [116], [117], [119], [121], [122] tend to use GAN-based algorithms to generate images that differ in sensitive attributes and detect whether the computer vision systems make the different decisions for equivalent image mutants. These techniques have been described in Section 4.1.4. For example, Zhang et al. [119] employed the CycleGAN [120] algorithm to limit the changes to nonsensitive attributes of images, to generate discriminatory inputs for computer vision systems.

Ranking systems are also often black-box and thus tested in a black-box manner [141], [142], [143], [144], [145], [146], [312]. For example, some researchers [141], [142], [143] measured whether members of different groups have the same proportional representation in a top ranking position, based on the ranking outputs of the system under test.

Several black-box testing techniques approximate the black-box software using a white-box model, so that white-box testing techniques can be applied. For example, Aggarwal [80] constructed a decision tree to approximate the decision-making process of the black-box ML software under test, using a local model explainer. Then, they used symbolic execution-based test input generation to discover discriminatory inputs. Sharma and Wehrheim [98] first approximated the black-box software by a white-box model based on the model behaviors. Then, they developed a property-based testing mechanism for fairness checking where the specific fairness requirement can be specified using an assume-assert construct. Test cases were then automatically generated attempting to violate the specified fairness property.

White-box testing. White-box model testing detects fairness bugs by inspecting the training data or the internal structure and information of the ML model visible to the test engineers.

Some work leverages the training data to reveal unfair predictions for the software under test. For example, Chakraborty et al. [213] proposed an explanation method based on k-nearest neighbors, to uncover bias in ML software predictions. Specifically, for each test instance predicted as the unfavorable, they obtained the k-nearest neighbors of the test instance to find out and explain the bias.

Several studies make use of the internal information of the ML model to test the software system. For example, ADF [82], [89] and EIDIG [83] leveraged the gradient information, which is a vector of DNNs that specifies the direction in which loss function has the steepest ascent. Specifically, ADF [82], [89] first searched for the discriminatory instances near the decision boundary of DNNs, and then used the gradients of DNNs to guide the search of the neighborhood of the discovered discriminatory instances for more test inputs; EIDIG [83] reduced the frequency of gradient calculation to accelerate the search process.
6 Datasets and Tools

This section describes the public datasets and open source tools for fairness testing to provide a quick navigation for researchers and practitioners.

6.1 Public Datasets

This section lists the most widely-adopted public datasets in the literature. Table 4 shows the information of these datasets, including the sizes, data types, sensitive attributes, usage scenarios, and access links. Most of them are tabular data, which can be used for traditional ML classifiers. Recently, with the popularity of natural language processing and computer vision, text and image datasets have also emerged. These datasets are primarily collected from social media platforms such as Twitter. Some datasets come with constraints on their use, which researchers need to consider when adopting them. For example, the well-known image dataset CelebA [201] is allowed for non-commercial research purposes only.

These datasets cover different sensitive attributes, among which sex, race, and age are the most common ones. There are also datasets (i.e., CelebA, VGGFace, and IMDB) without explicit sensitive attributes, for which researchers can determine the sensitive attributes (such as hair color and skin tone) based on the application scenario under investigation.

For a more comprehensive overview of the available fairness datasets, the reader is referred to the work of Le Quy et al. [214] and Fabris et al. [215]. The former surveyed the tabular datasets for fairness research; the latter extended the survey scope to unstructured data (e.g., text and images), covering datasets in various domains such as social sciences, computer vision, health, economics, business, and linguistics.

6.2 Open source Testing Tools

There is a recent proliferation of open source tools for supporting fairness testing. Nevertheless, Lee and Singh [249] demonstrated that there is a steep learning curve for practitioners to use these fairness tools. Currently, there is no available guidance on tool adoption [249].

To this end, we summarize 30 open source tools for fairness testing in this section, to facilitate fairness researchers and practitioners to choose appropriate fairness tools. The details of these tools are shown in Table 5. Overall, Table 5 covers fairness testing tools for general ML software (e.g., FairTest [148] and Themis [55]), DL systems (e.g., ADF [82] and EIDIG [83]), natural language processing systems (e.g., ASTRAEA [111] and BiasFinder [110]), and computer vision systems (e.g., REVISE [160]).

7 Research Trends and Distributions

In Figure 5 we have shown that fairness testing is experiencing a dramatic increase in the number of publications. This section further analyzes the research trends and distributions of fairness testing.

7.1 Research Venues

We first describe research trends in terms of the research communities engaging in fairness testing. Fairness testing has been studied in the machine learning community since 2008 [250] and also within the software engineering community since the same year [13]. In 2008, Pedreschi et al. [250] proposed the notion of discriminatory classification rules as a criterion to detect the potential unfairness in data mining systems. Since 2017, more and more research communities have started to study fairness testing. For example, Galhotra et al. [55] presented the first ML fairness testing approach in the software engineering community and won the Distinguished Paper Award of ESEC/FSE 2017; Zhao et al. [149] detected bias in the datasets and ML models for visual recognition tasks, and won the Best Paper Award of EEMNLP 2017; Diaz et al. [100] detected age-related bias in sentiment analysis systems and won the Best Paper Award of CHI 2018. These three best paper awards, as well as being a credit to their authors, also demonstrate both the significant level of interest and the high quality of research on fairness in three different research communities:

- Software Engineering (ESEC/FSE)
- Natural Language Processing (EMNLP)
- Human-Computer Interaction (CHI)

Figure 5 shows the distribution of the collected papers across different research venues. Overall, most (54.1%) of the fairness testing papers are published in artificial intelligence venues, such as AAAI, IJCAI, ACL, EMNLP, CVPR, ECCV, and KDD; 29.5% are published in software engineering venues, such as ICSE, ESEC/FSE, ASE, ISSTA, ICST, and TSE. Additionally, we find that other research communities, such as computer security and database communities, are also embracing fairness testing, demonstrating the importance of our survey to a broad audience.

7.2 Machine Learning Categories

In this section, we dive deeper into ML software to investigate the research trend of fairness testing in each ML category. Specifically, following previous work [12], we classify the collected papers into two categories: those targeting DL software and those for general ML software.

Among the 122 papers, 66 papers (54.1%) conduct fairness testing for DL software, while 56 papers (45.9%) cater to general ML software. The large volume of publications on fairness testing for DL software may be attributed to several reasons. On the one hand, DL becomes increasingly pervasive, being used in a wide range of software applications...
and thus attracting interest from the research community. On the other hand, compared to traditional ML algorithms (e.g., regression and decision tree), DL is less interpretable \cite{251}, making it harder to reason about fairness in a direct manner.

We further analyze the number of publications for both categories over years. Figure \ref{fig:6} illustrates the cumulative number of fairness testing papers in general ML and DL. We find that there is a trend of moving from testing general ML software to testing DL software. Before 2021, fairness testing research mainly focused on general ML. Since 2021, the number of papers on DL has increased notably, surpassing publications on general ML.

Despite the increasing popularity of DL and fairness testing for DL, a striking finding is that only 44.4\% of fairness testing papers in software engineering venues target DL software. It indicates that there remain many opportunities for software engineering researchers to use their testing expertise to tackle fairness bugs in emerging DL software.

### 7.3 Data Types

In this section, we explore the research trends of fairness testing in applications with different data types. Among the 122 papers that we collect, 7 do not have experiments with specific datasets. Thus, we use the remaining 115 papers to analyse the data type distribution.

As shown in Figure \ref{fig:7} among the 115 papers, 97.4\% focus on testing software applications that take tabular data (50.4\%), text (22.6\%), and images (24.3\%) as inputs. Fairness testing for other data types (e.g., speech and video) is still not well investigated.

We next dive deep to the research trends in the major data types (for tabular data, text, and images). Figure \ref{fig:8} presents the cumulative number of fairness testing papers on applications for tabular data, text, and images. We observe that although fairness testing for text- and image-
Fig. 8: Cumulative number of fairness testing papers on applications for tabular data, text, and images.

Fig. 9: Distribution of different fairness categories.

Based applications has started to emerge since 2018, the enthusiasm of the research community for fairness testing on applications for tabular data remains undiminished, with the number of related publications increasing steadily.

Compared to the overall research status, the software engineering community primarily tackles the applications for tabular data, which account for 80.5% of fairness testing publications in software engineering venues. By contrast, the publications for text- or image-based problems account for only 13.9% and 5.6%, significantly lower than the average level.

7.4 Fairness Categories

Figure 9 examines the distribution of different fairness categories in the fairness testing literature. Previous work \[27], \[38], \[126] observed that group fairness and individual fairness were the most widely studied in the literature. In line with these observations, we find that these two categories account for a total of 93.4% of fairness testing work. Furthermore, group fairness accounts for the largest proportion of fairness testing work. This may be attributable to two reasons: First, group fairness has been advocated in legal regulations such as the four-fifths rule in US law \[49], and thus needs to be considered in the software engineering process. Second, group fairness is intuitive and easy to understand by testers and to encode in the testing process.

7.5 Algorithm Testing Techniques

Finally, we classify existing fairness algorithm testing techniques according to the software testing category (i.e., white, black, or gray-box testing). Among all the collected papers, 103 are about algorithm testing. We observe that 72.8% of the 103 papers provide black-box testing, while only 27.2% are white-box testing. Only the Parfait-ML tool \[46] supports both black-box and gray-box manners for testing hyper-parameters. Compared to black-box testing, white or gray-box testing requires the knowledge of training data or the internal of software systems. However, fairness testing often applies to human-related, social-critical systems whose internal information cannot be disclosed to the public due to privacy concerns or legal policies.

8 Research Opportunities

Fairness testing remains in a relatively embryonic state. Research in this area is experiencing rapid growth, so there are plenty of open research opportunities. In this section, we outline the challenges for fairness testing and present promising research directions and open problems.

8.1 Absence of or with Multiple Sensitive Attributes

Fairness testing in absence of sensitive attribute information. Existing fairness testing techniques rely on the existence of sensitive attributes, but in practice, this information might be unavailable or imperfect for many reasons \[252]. On the one hand, the data may be collected in a setting where the sensitive attribute information is unnecessary, undesirable, or even illegal, considering the recent released regulations such as GDPR (General Data Protection Regulation) \[253] and CCPA (California Consumer Privacy Act) \[254]. On the other hand, users may withhold or modify sensitive attribute information, for example, due to privacy concerns or other personal preferences.

To tackle this issue, a straightforward solution is to first use existing demographic information inference techniques (e.g., gender inference, race inference, and age inference) to infer the sensitive attribute and then apply fairness testing techniques. However, existing inference techniques may not be fully satisfactory, and their application scenarios remain limited \[255]. Moreover, building a model to infer sensitive information leaves open the possibility that the model may ultimately be used more broadly, with possibly unintended consequences \[252]. Therefore, more research is needed to tackle the fairness testing in absence of sensitive attribute information.

Fairness testing at the intersection of multiple sensitive attributes. Software systems may have multiple sensitive attributes that need to be considered at the same time. However, existing fairness testing work often tackles a single sensitive attribute at a time. To the best of our knowledge, there has been little work that explores fairness testing for compounded or intersectional effects of multiple sensitive attributes \[90], \[233], leaving an interesting research opportunity for the community. Take test input generation as an example. In real-world applications, software systems may encounter input instances that trigger fairness bugs related to multiple sensitive attributes simultaneously, but such inputs may not be covered by existing test input generation techniques. Specifically, existing techniques generate discriminatory instances only for one specified sensitive
attribute. As a result, the test instances with compounded effects of multiple sensitive attributes are uncovered by these techniques, making fairness testing insufficient.

8.2 Test Oracle for Fairness Testing

Test oracle identification for fairness testing is challenging compared to traditional software testing. The “ground truth” (i.e., real labels) of the input data need to be manually determined with intensive labor and domain-specific knowledge. Moreover, because there is no firm consensus on the definition of fairness, practitioners encounter difficulties in determining test oracles for fairness testing even given the real labels of the input data. It remains an open challenge how to generate sound, complete, and correct test oracles for fairness testing.

Existing work mainly employs metamorphic relations as pseudo oracles or uses statistical measurements as indirect oracles, which all involve human ingenuity. We call for actions by the community to design automatic techniques for constructing reliable oracles for fairness testing.

The emergence of manually-defined oracles for fairness testing brings a challenge for test oracle selection. As mentioned before, there are more than 70 fairness measurements available in the IBM AIF360 toolkit alone [127, 177], with the research community continually introducing further novel measurements. Therefore, it is impractical to use all the existing measurements as the test oracles for fairness testing. Moreover, while each of these definitions is appropriate in a given context, many of them cannot be satisfied simultaneously [5]. An important direction for the research community therefore consists in selecting appropriate test oracles according to the intended application scenarios.

8.3 Test Input Generation for Fairness Testing

Generation of natural inputs. Although there have been several techniques for test input generation in the area of fairness testing, there is no guarantee that the generated instances are legitimate and natural. Specifically, existing techniques [82, 83, 89] are mainly based on adversarial perturbation of input features. They do not constrain the magnitude of the perturbation, and consider the generated instances effective as long as they can induce the intended output behavior, i.e., flipping the predicted outcome after changing sensitive attribute information. In this way, the generated instances may not respect real world constraints (e.g., they may authorize a loan to a 10-year-old individual). Here, the open problems concern how to generate legitimate and natural test inputs for fairness testing, and how to automatically evaluate the naturalness of the generated test inputs.

Exploration of more generation techniques. Test input generation techniques have not been fully investigated in the area of fairness testing. For example, symbolic execution is a program analysis technique to test whether certain properties can be violated by the software under test, and it has been demonstrated to be effective in test input generation for traditional software and ML software [12]. However, in the area of fairness testing, its potential has not been well tapped. To the best of our knowledge, only the SG approach [80] has used symbolic generation for discriminatory instance generation.

In addition, fairness testing is often conducted for ML software, whose test input generation is challenging due to its large behavior space. Search-based software test generation fits the fairness testing of ML software well, as it uses a meta-heuristic search technique to efficiently search such space [83, 66, 67]. These characteristics of search-based software test generation make it broadly applied in different testing scenarios [256]. Although there have been a few search-based test input generation techniques for fairness testing, there remains scope for much more work in this area.

8.4 Test Adequacy for Fairness Testing

Test adequacy is a widely-studied problem in traditional software testing, which aims to check whether the existing tests have a good coverage. Adequacy criteria not only provide a confidence measurement on testing activities, but also can be adopted to guide test generation. In the area of fairness testing, test adequacy remains an open problem. To the best of our knowledge, there has been no work exploring test adequacy for fairness testing.

To tackle this problem, an intuitive idea is to employ traditional software test adequacy metrics for fairness testing. For example, various metrics have been proposed for traditional software testing, such as line coverage, branch coverage, and dataflow coverage [56].

In addition, recently, several test adequacy metrics have been proposed for deep learning software, such as neuron coverage, layer coverage, and surprise adequacy [12]. Neuron coverage and layer coverage measure the degree to which the neurons and layers of a deep learning model is executed by a test suite, respectively, while surprise adequacy measures the coverage of discretized input surprise range for deep learning software [12]. However, there is no empirical evidence to date that these metrics are applicable and effective for assessing the ability of revealing fairness bugs and the sufficiency of fairness testing.

8.5 Test Cost Reduction

Test cost could be a serious problem in fairness testing of ML software. Specifically, fairness testing of ML software may require re-training ML models or repeating the prediction process, and extensive data generation to explore the large model behavior space. However, to the best of our knowledge, there has been no work about reducing the cost for fairness testing. It is interesting to design specific test selection, prioritization, and minimization techniques to reduce the cost of fairness testing without influencing the test effectiveness.

In addition, as described in Section 5.2 there is an increasing demand for the deployment of intelligent software systems on platforms with limited computing power and resources such as mobile devices, and several studies [65, 66, 67] have focused on fairness testing in such scenarios. This brings a new challenge for the research community that how to effectively conduct fairness testing on diverse end devices even those with limited computing power, memory size, and energy capacity.
8.6 Fairness and Other Testing Properties

Testing fairness repair techniques with more properties considered. After fairness repair techniques have been applied to software systems, fairness testing is often performed again. In this process, testers may also take ML performance (e.g., accuracy) into consideration [35], [39], because it is well-known that fairness improvement is often at the cost of ML performance [38]. However, in addition to ML performance, there are also many other properties important for software systems, including robustness, security, efficiency, interpretability, and privacy [12]. The relationship between fairness and these properties is not well studied in the literature, and thus these relationships remain less well understood. Future research is needed to uncover the relationships and perform the testing with these properties considered. The determination of the properties to be considered needs the assistance of requirements engineers.

Fairness and explainability. Explainability is defined as that users can understand why a prediction is made by a software system [257]. Like fairness, it has also been an important software property required by recent regulatory provisions [258]. Because application scenarios that demand fairness often also require explainability, it would be an interesting research direction to consider fairness and explainability together. Many existing fairness testing studies just generate discriminatory instances that reveal fairness bugs in the software under test, but do not explain why these instances are unfairly treated by the software.

In this case, software engineers have relatively little guidance on the production of targeted fixes to repair the software. Improving the explainability behind the unfair software outcomes can help summarize the reasons for fairness bugs, produce insights for fairness repair, and help stakeholders without technical background (e.g., product managers, compliance officers, and policy makers) understand the software bias simply and quickly.

8.7 Testing Fairness of More Applications

Most of existing fairness testing work focuses on tabular data-based classification tasks, natural language processing systems, or computer vision systems. Indeed, as an important non-functional software property, fairness needs to be considered for a broad range of software systems including speech recognition systems, video analytic systems, multimodal systems, and even non-ML software systems (e.g., simulation systems and rule-based systems).

In addition, existing work primarily focuses on offline fairness testing. More research is needed for online fairness testing, because online testing can provide important information to guide software maintenance and facilitate the evolution of software systems.

Furthermore, researchers can extend fairness testing research to cover more testing activities, such as bug report analysis [259] and bug triage [260], which have been widely studied in traditional software testing but rarely investigated in fairness testing.

8.8 More Fairness Testing Benchmarks

Benchmarks for fairness testing are needed. In traditional software testing, benchmarks such as Defects4J [261] have played an important role, providing a unified standard for evaluating software testing techniques.

8.9 More Fairness Testing Tools

Existing fairness testing tools (listed in Table 5) tend to require programming skills, and thus are unfriendly to non-technical stakeholders. However, fairness testing research includes many non-programmer stakeholders and contributors such as compliance officers, policy makers, and legal practitioners.

9 Conclusion

We have presented a comprehensive survey of 122 papers on fairness testing. We compared fairness testing with traditional software testing and positioned fairness testing within the software engineering process. We summarized current research status in the fairness testing workflow (including test oracle identification and test input generation) and testing components (including data testing and algorithm testing). We also listed public datasets and open source tools that can be accessed by researchers and practitioners interested in the fairness testing topic. We analyzed trends and promising research directions for fairness testing. We hope this survey will help researchers from various research communities become familiar with the current status and open opportunities of fairness testing.

ACKNOWLEDGMENTS

Before submitting, we sent the paper to the authors of the collected papers, to check for accuracy and omission. Many thanks to those authors who kindly provided comments and feedback on earlier drafts of this paper. Zhenpeng Chen, Max Hort, Federica Sarro, and Mark Harman are supported by the ERC Advanced Grant under the grant number 741278 (EPIC: Evolutionary Program Improvement Collaborators). Jie M. Zhang is partially supported by the UKRI Trustworthy Autonomous Systems Node in Verifiability, with Grant Award Reference EP/V026801/2.

REFERENCES


