# A Search Engine for Algorithmic Fairness Datasets

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Abstract
Algorithmic equity is a key desideratum for systems embedded in a diverse society producing data with embedded patterns of discrimination. This data is leveraged in algorithmic fairness research with the aim of studying the root causes of undesirable discrimination and developing methods to overcome them. Data documentation is central in supporting discoverability and correct use of existing resources. Documentation debt causes suboptimal data usage, with a negative impact on data-driven research and practice. This work introduces a search engine for algorithmic fairness datasets, describing its scope, functionality, and envisioned use cases, calling for inputs and collaboration within the community for the long-term maintenance and exploitation of this resource.

**Keywords**
Algorithmic Fairness, Fairness Datasets, Documentation Debt, Information Access

## 1. Introduction

Algorithmic Fairness is a scholarly field aimed at ensuring equity in algorithmic decision making [1], with dedicated measures [2, 3], algorithms [4, 5], and auditing procedures [6, 7]. Many of the key findings in this field have been data-driven [8, 9]. Therefore, the quality of datasets employed in research and practice are central to the validity of experiments and to the generalization of results in algorithmic fairness. Downstream effects of data issues triggered by poor practice that undervalues data quality are both common and avoidable [10]. Noisy, inaccurate, or otherwise non-representative data inevitably affect the reliability and utility of findings [11, 12]. Algorithmic fairness, as a whole, stands to gain from improvements in its prevalent data practices.

Recent work has shown that algorithmic fairness articles frequently use "off-the-shelf" datasets [13]. Fabris et al. [14] call into question the suitability of these benchmark datasets in algorithmic fairness, documenting over 200 alternative datasets that have been employed in the field. In this work, we develop a search engine that makes the documentation of Fabris et al. [14] readily available and searchable.[1]

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[1]Search engine available at http://fairnessdata.dei.unipd.it/.

## 2. Key Functionality

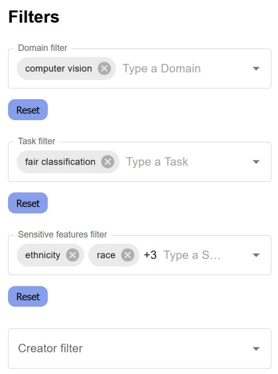


Figure 1: A screenshot summarizing the faceted search result filtering.

Our Web Application (WebApp) realizing the search engine, is depicted in screeshots reported in Figures 1 and 2. Two search modes are concurrently available. Full-text search lets the user specify a text query and returns the datasets whose documentation matches the query. Faceted search (Figure 1) can be used to refine the query or as a *stand-alone* feature. The available filters let the user specify different domains (e.g. "computer vision"), tasks (e.g. "fair classification"), and sensitive attributes. A list of datasets matching all the search requirements is displayed in alphabetical order (Figure 2). Search results can be expanded, as in Figure 2, displaying the data brief for a given dataset, as described in Fabris et al. [14]. It is worth noting that the documentation in the WebApp was hand-curated and sent to dataset creators for verification, as described in Fabris et al. [14]. To favour contributions from a larger community, the WebApp allows for spontaneous reporting of datasets and *donations* of documentation, through a form accessible from the WebApp homepage or the menu available in the search results page.

For each dataset, the WebApp includes the following fields.

- **Description**. A summary of the dataset describing its purpose, features, and labeling procedures.
- **Task**. The algorithmic fairness tasks that have been studied on a given dataset, including both the setting (e.g. "fairness under unawareness") and the task itself (e.g. "fair ranking"), with citations to the respective articles. Notice that this field also summarizes the popularity of a dataset in algorithmic fairness research as measured by its usage in peer reviewed articles.
- **Domain**, annotated from a two-level taxonomy including domain (e.g. health) and subdomain (e.g. radiology).
- **Sensitive Features**. The encoded sensitive attributes, that can be the focus of an algorithmic fairness study.
- **Landing Page**. A link to the website where the resource can be downloaded or requested.
- **Data Specification**. The format of the data.
- **Sample size**. Dataset cardinality.
- **Last Update**. Last known update at the time of writing.
- **Creator Affiliation**, summarizing the provenance of the data.

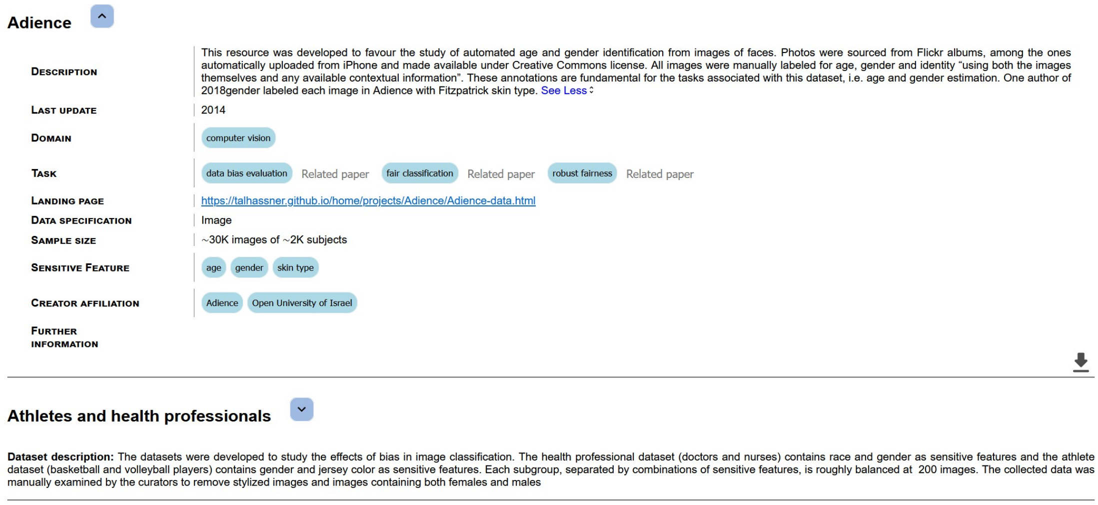


**Figure 2:** A screenshot summarizing the search engine results.

## 3. Use Cases and Applications

The WebApp we developed supports research and practice in algorithmic fairness and critical data studies in several ways. Below are the main use cases we envision.

1. Enabling task-driven and domain-driven search for principled dataset selection. Researchers and practitioners with a specific research angle may use our WebApp to find the most suited datasets for their needs.
2. Supporting multi-dataset studies in identifying relevant resources; for example, studies of how race and gender are encoded in datasets can use our tool to select datasets with the sensitive attributes of interest.
3. Directing data audits and critical data studies towards important resources; for example, datasets used in many research articles are pivotal for the community and deserve deeper scrutiny.
4. Highlighting under-explored domains or tasks, where new contributions, such as algorithms and datasets, can have a larger impact.

## 4. Discussion and Call for Contributions

Documentation debt causes suboptimal data usage and negatively affects data-driven research [10, 15]. Our WebApp aims to empower the algorithmic fairness community, enabling principled approaches to select datasets for research, development, and critical data studies. Our long-term goal is to support easily accessible, up-to-date search along relevant axes. Updating and maintaining this resource with new datasets will certainly be a challenge.

**We call on the algorithmic fairness community, the key stakeholders of this work, to contribute with guidance and collaboration, to help shape and maintain this resource.**

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