Fairness in Clustering

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Introductory Information

Keywords: Fairness; Clustering; Unsupervised learning
Expected Participants: 150 (if in person); more (if virtual)
History of Tutorial: A version of this tutorial was already successfully presented at AAAI 2022, with 394 registrants.
Website: For additional information check our website.

Goal of the Tutorial

Clustering problems are fundamental in areas ranging from Unsupervised Learning and Operations Research, to Data Mining and Optimization. Even more importantly, due to the numerous practical applications of this family of problems, algorithms developed for them are employed on a daily basis in settings affecting the lives of millions of individuals. Because of this, a flurry of research has emerged on guaranteeing that the aforementioned clustering problems will explicitly take into account the issue of fairness, thus providing solutions that mitigate socially harmful biases. This research endeavour has led to a vast collection of results, where multiple and often unrelated or conflicting definitions of fairness are considered.

The goal of this tutorial is to introduce a wide audience interested in algorithmic fairness to the nascent research area of *fair clustering*. Specifically, we wish to: (1) present a variety of fairness notions used in the context of clustering, (2) argue about the necessity of each of those through corresponding applications, (3) discuss the relationships between different notions, (4) sketch the algorithmic ideas that were developed in order to address the corresponding computational problems, and (5) finally share our thoughts about the future of research in algorithmic fairness. By the end of the tutorial, the audience will have achieved a significant level of familiarity with multiple definitions of fairness in the unsupervised learning context, and we hope that researchers will use these ideas in contexts both within and adjacent to the clustering context, in both industrial and academic applications.

Brief Outline of the Tutorial

We will begin the tutorial by formally introducing standard variants of clustering problems. Moving on, we will discuss applications in which unfairness may naturally arise, and for each such application we will discuss the corresponding notion of fairness that was introduced in order to mitigate the aforementioned situation. Furthermore, we will sketch the high-level algorithmic ideas that were developed in order to solve each corresponding fair clustering problem. However, we plan on putting more emphasis on presenting the actual mathematical definitions of fairness, and not on the algorithmic aspects of the results. The reason for this is that we want to expose the audience to as many notions of fairness as possible, while discussing the necessity of each of them and the relationships between them. The last section of the tutorial will involve a broader discussion of the future of research in algorithmic fairness, by proposing specific directions.

Prerequisite Knowledge

We will cater our tutorial to the modal *junior* participant (e.g., an early-stage PhD student or similar). That is, we will assume the audience has a basic CS and AI/ML background, but not necessarily deep clustering experience. Specifically, any participant who has had an undergraduate- or early graduate-level Algorithms and Machine Learning course will be able to follow the entirety of the tutorial. This is because, as mentioned earlier, the emphasis will be put into the definitions of fairness and their corresponding relationships, and relatively less on the algorithmic aspects of (traditional, constrained, and/or fair) clustering.

Content

The first part of the tutorial will consist of introducing classical clustering paradigms, together with appropriate applications for each of them. These paradigms define what we call the unfair clustering problem, where fairness is not part of the computational problem. The unfair clustering problems we will discuss are well-studied and longstanding, however we will only need their definitions and not algorithmic results on them. Specifically, in the first part of the tutorial we will present the formal definitions for:

- Metric k-clustering: k-center, k-median and k-means.
- Clustering with outliers.
- Hierarchical clustering.
- Correlation clustering.

In the second part of the tutorial we will start discussing specific notions of fairness for clustering, and we will see how these are incorporated in the classical/unfair models. For each such notion we will present realistic applications demonstrating its importance. One of the biggest take-home messages of our tutorial will be that these different definitions of fairness are equally important and they are introduced in order to capture different and unique scenarios. In addition, besides simply enumerating different concepts of fairness, we will present a more structured taxonomy. The full list of the work we are going to cover can be found in the References section below.

The third part of the tutorial will revolve around some of the main algorithmic techniques that were developed in order to tackle fair clustering problems. Our description of those will be on a high-level, nonetheless we would still like to make the audience aware of the kind of approaches that have been used throughout the literature. Examples of techniques we want to cover include the widely-used two-step approach of (Bercea et al. 2019; Bera et al. 2019), the fairlet decomposition of (Chierichetti et al. 2017), and network-flow roundings such as those in (Bercea et al. 2019).

The final part of the tutorial will feature a discussion of where fair clustering and the broader field of algorithmic fairness is going. We will explore important questions, criticisms, and developing norms in this growing research area. Emphasis will be placed on connecting foundational research in fair clustering more closely to real applications and communities served. This discussion will conclude with exciting future directions and open problems.

Presentation Details and Differences from Previous Runs of the Tutorial

This tutorial involves ongoing research and the work is led by all members of our team. For the actual tutorial presentation we choose a subset of at most four members that are tasked with giving the talks. Given the two hours limit, we plan on allocating 20 minutes to the first section, 50 minutes to the second one, 20 minutes to the third one, and 30 minutes to the last one.

Compared to the first time we presented this tutorial at AAAI 2022, we plan on making it more interactive. Specifically, we are working on creating Jupyter Notebooks that are going to be incorporated in our website. This Notebooks will give the audience the opportunity to see in real time the behavior of fair and unfair algorithms on actual datasets. We hope that these implementations will help the participants better visualize concepts of algorithmic fairness in clustering. Furthermore, they may be useful as pedagogical tools in undergraduate and graduate courses taught or taken by attendees of the tutorial.

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