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# Rankers, Rankees, & Rankings: Peeking into the Pandora’s Box from a Socio-Technical Perspective

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Algorithmic rankers have a profound impact on our increasingly data-driven society. From leisurely activities like the movies that we watch, the restaurants that we patronize; to highly consequential decisions, like making educational and occupational choices or getting hired by companies– these are all driven by sophisticated yet mostly inaccessible rankers. A small change to how these algorithms process the rankees (i.e., the data items that are ranked) can have profound consequences. For example, a change in rankings can lead to deterioration of the prestige of a university or have drastic consequences on a job candidate who missed out being in the list of the preferred top- $k$  for an organization. This paper is a call to action to the human-centered data science research community to develop principled methods, measures, and metrics for studying the interactions among the socio-technical context of use, technological innovations, and the resulting consequences of algorithmic rankings on multiple stakeholders. Given the spate of new legislations on algorithmic accountability, it is imperative that researchers from social science, human-computer interaction, and data science work in unison for demystifying *how* rankings are produced, *who* has agency to change them, and *what* metrics of socio-technical impact one must use for informing the context of use.

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## POSITION CONTEXT: SOCIO-TECHNICAL IMPACT OF RANKINGS

Algorithmic rankers that learn from data are now ubiquitous and they influence a myriad socio-technical contexts of use. For example, Artificial Intelligence (AI)-based hiring systems employ rankers that match applicants with relevant job profiles and help companies assess quality of fit. Yet, to the job candidate, who is one in a teeming million of data items which are ranked (we term them *rankees*), the rankers are obscure and inaccessible.

As another example, US News [5] collects data from educational institutions about their own performance and about their ratings of peers, in order to produce institutional rankings. Here, high rankings are indicative of societal prestige, where elite universities at the top are in demand, often more expensive, and highly selective. People, including students and parents, are consumers of these rankings but have little agency in how they are constructed. These scenarios, indicative of socio-technical inequity, are summarized in Figure 1; they serve as basis for our position statements in this paper, which are also informed by the team’s prior work and experience with design and applications of responsible algorithmic rankers [6–8, 10, 14, 16, 17, 19–23].

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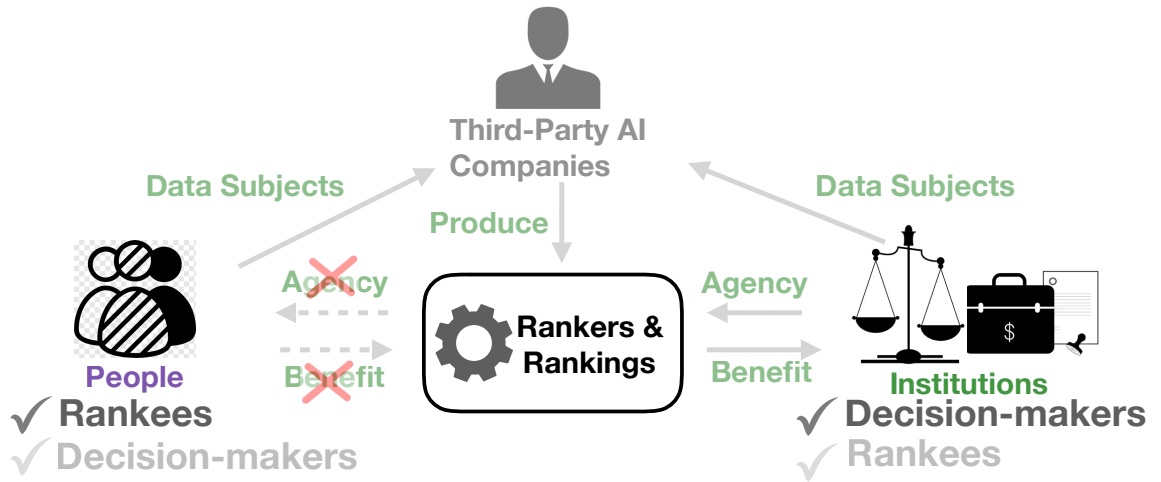


Fig. 1. The ecosystem of ranking producers and consumers.

**Statement 1:** Socio-technical practices of ranking-based decision-making need to be informed by a combination of qualitative field studies and quantitative analysis of the risks and benefits of algorithmic rankers, in particular, with respect to rankees who lack agency and visibility into how their data is used for decision-making.

**Are data subjects empowered?** Government officers behind the criminal justice systems [2], or the hiring manager who controls the recruiting system [1] have disproportionate power over people as rankees or data subjects. In the case of institutional rankings, universities can at least make educated guesses about what data to report that affect their rankings. For stakeholders such as university ranking publishers, it is a typical process to question the quality of the data reported by the university administrators. When the data reported from the university does not satisfy the requirements or the university does not comply with the requirements, the particular university or rankee may be omitted from the ranking. However, such interaction in the data collection stage is not transparent [9] between the rankers and rankees.

**Who has agency?** Ranking publishers typically do not provide the closed-form mathematical formulas but instead a methodology describing the factors considered in the ranking formulation such as *Graduate and Retention rates* 22% or *Faculty Resources* 20% [5]. Although they are the decision-makers, students and their parents may not have agency in the ranking process, but rather are influenced by the social impact of the popular rankings. The rankers and decision-makers may represent the same stakeholders in a different use case. For example, hiring managers may design the ranking formula for job candidates. However, the rankees' representatives, potential or current employees, do not have the agency or the knowledge for evaluating the rankers, and are often prone to biases towards candidates [1, 3].

**Can the decision-makers be held accountable?** We might make an assumption that hiring managers are equipped with the knowledge to understand and evaluate the behavior of rankers. However, such an assumption is questionable. Note that some rankers learn the ranking of items, while others are simpler, based on a scoring formula that computes a weighted sum of attribute values of the items being ranked. Yet, even with a simple scoring formula, the intention of the hiring manager may not be followed, or it may even be reversed in certain subsets of the data [15]. The hiring managers may evaluate the ranker based on accuracy in the top candidates and gain false confidence in the ranker's

accuracy in the lower ranked candidates, raising accountability concerns. The situation worsens when the ranker uses a complex learned model, as is becoming increasingly widespread in the industry.

**Statement 2:** Technological innovation and acceptance need to be guided by democratizing interpretability approaches where ranking processes are made explainable to people who are impacted and, as a result, the outcomes adhere to higher ethical standards and new legislations [4].

**Are institutional explanations sufficient?** Some representatives of the rankers, such as the university ranking publishers, may provide explanations via disclosing the methodology of their ranking process. However, the methodology is typically lengthy yet lacks details. There is neither a way to validate the methodology nor to modify the methodology from rankees’ or decision-makers’ perspective, who may not completely agree with the methodology’s emphasis. For example, a student may want to put more emphasis on *teaching* than *research* when choosing universities.

**Can we explain inaccessible rankers using available data?** Publicly available data (e.g., about hiring practices or college admissions) might provides opportunities to get data-driven explanations about decisions made by inaccessible rankers. For example, decision-makers may build proxy ranking models using machine learning [11] approaches to mimic the behavior of rankers. Decision-makers can learn about the unknown rankers by manipulating the inputs manually and observing the output, as shown in Google’s What-if tool [18]. Alternatively, such manipulating of the input data can be conducted systematically with proper statistical sampling approaches to derive each data attribute’s impact on advancing a rankee’s rank position. The recent development of model-agnostic instance-wise explanation methods such as LIME [13] and SHAP [12] is proven to be effective in explaining behaviors of complicated Machine Learning/Deep Learning models without knowing the model process under the hood. Lack of effective explanation methods leads to concerns of fairness, accountability and transparency [6, 10, 22].

**How can we abstract information that enlighten people about rankers?** Even though the data-driven explanation approaches are promising, we need information abstractions that are informed by data science, social science, and principles of human-data interaction. Nutritional label for ranking [22] is a promising approach in that direction, where explanations about score-based rankings are communicated at different levels of abstraction, inspired from food science, where nutrition facts, ingredients, and recipes, communicate different levels of detail about food, without requiring expert knowledge from the consumer.

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