Local Justice and the Algorithmic Allocation of Scarce Societal Resources

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Abstract

AI is increasingly used to aid decision-making about the allocation of scarce societal resources, for example housing for homeless people, organs for transplantation, and food donations. Recently, there have been several proposals for how to design objectives for these systems that attempt to achieve some combination of fairness, efficiency, incentive compatibility, and satisfactory aggregation of stakeholder preferences. This paper lays out possible roles and opportunities for AI in this domain, arguing for a closer engagement with the political philosophy literature on local justice, which provides a framework for thinking about how societies have over time framed objectives for such allocation problems. It also discusses how we may be able to integrate into this framework the opportunities and risks opened up by the ubiquity of data and the availability of algorithms that can use them to make accurate predictions about the future.

Introduction

In a recent paper, Freedman et al. (2020) remark that "efficient and fair allocation of limited resources is a classical problem in economics and computer science." Their specific application is to kidney exchange, a central example of the kinds of domains we are concerned with in this paper, but it also captures many important issues in the development of how we think about the problem today. Computer Science has been concerned for a long time with algorithms that allow for efficient and fair allocation of limited resources (learning about job allocation in time-sharing computers is a long-time staple of operating systems courses, for example). Economics is sometimes defined as precisely the study of the allocation of scarce resources. As a result, most of our ideas for AI-enabled allocation of scarce resources have been driven by the histories of these two fields. This has significant consequences, because it means the measures we develop algorithms to optimize are those that have a pride of place in economics – most of the time utilitarian (or additive) social welfare, but in other cases Rawlsian (max-min) or Nash (multiplicative) social welfare.

However, we have also been building real social and political institutions to allocate scarce resources for centuries, and a central insight is that they often prioritize in ways that do not correspond directly with any of these measures of social welfare. For example, triage in battlefield medicine or rationing of healthcare in emergencies prioritizes greedily by predicted improvement, which can have consequences different from either efficient allocation or max-min allocation. While economics may be the study of the allocation of scarce resources, in the words of Harold Lasswell, politics is "who gets what, when, and how." Thus it is appropriate to turn to political science. The political philosophy of allocation of scarce resources is studied under the moniker of *local justice* (Elster 1992), which systematically considers the question of how institutions allocate scarce resources and necessary burdens (for example, through lotteries, principles of greatest need, best outcome, or most "value added").

While there has been burgeoning interest in defining the objectives of AI systems by taking multiple stakeholders into account (Freedman et al. 2020; Lee et al. 2019), the main theme of this paper is that analyzing AI systems that endeavor to fairly and efficiently allocate scarce resources through the lens of local justice can greatly clarify both the objectives of system design and the parts of the pipeline where algorithmic and data-driven techniques can be particularly helpful. I start by introducing the setting and describing four big questions that should be answered by any allocation system. After providing background on related research in machine learning and fair division, I introduce a formalization of some of the principles of local justice, and then discuss how the four questions can be thought of in that framework, and the roles that AI can play in helping to better assess and design these allocation systems.

Setting

For the purposes of this paper, the problems we are interested in involve the allocation of resources that are (1) controlled or regulated by society; and (2) scarce; we focus on settings where data-driven or algorithmic decision-making is feasible. For various reasons, we have decided that market mechanisms are inappropriate for these settings (Elster 1992; Roth 2007; Currie and Gahvari 2008). Examples include organs for transplantation, resources for homeless populations, and spaces in elite public schools, among others. Note that decisions about the appropriateness of market mechanisms can vary across settings – for example, markets for kidneys exist in Iran. A few other notes: settings can be dynamic (e.g. organ transplantation) or static (e.g. batch matchings of students to schools), and it could be possible to assign different individuals to different types of resources (for example, the level of services provided by homelessness service providers can vary in intensity).

I will argue, through the rest of this paper, that in order to design systems that are improved by the use of AI (and more generally, to consider the benefits and harms of using AI in these domains), we need to think clearly and specifically about a set of related questions. (1) How do we define and quantify desirable outcomes, in terms of efficiency, equity, justice, or fairness? (2) How do we predict outcomes for heterogeneous individuals and households under different feasible allocations? (3) How do we optimize allocation of scarce resources to achieve the best population-level outcomes under constraints defined by our notions of justice or fairness? (4) What can we say about the incentives created by the overall system, and the potential for manipulation or negative long-term outcomes of deployment, considering the preferences of participants?

By specifically engaging elements of each of these questions, we can better consider the ramifications of our technologies – how, precisely, do they help or hurt compared with current practice? – rather than being seen as technological solutionists by the stakeholders we must engage.

Background

It is certainly not a novel observation that we need to think carefully about what it is that we are trying to optimize. Just to give a couple of recent examples, Conitzer (2019) discusses the importance of appropriately designing preferences and optimization goals for AI agents, while a core argument of O'Neil and Gunn (2020) is that many of the problems of "near-term AI" (defined as expert systems that replace human decision-makers) are driven by a mismatch between the performance metrics of the AI (constructed by the algorithm designers) and the true objectives of stakeholders. Nevertheless, it is useful to get a sense of where the academic community has gone in response to these concerns.

Fairness in Machine Learning

A common trope is that the first objective of the engineer is simply to optimize a given objective function. Indeed, standard metrics, for example, accuracy, area under the ROC curve, or return on investment, still drive much research, so the first instinct in many applications of machine learning in society has been to define societal problems in a manner amenable to analysis through the lens of metrics like these. In the recent past, we have learned how machine learning systems that are "in the loop" of human decision-making can have significant unintended consequences. Examples abound: in some cases, instead of reducing crime rates, predictive policing results in more false arrests as police misinterpret algorithmic predictions of suspects as evidence (Saunders, Hunt, and Hollywood 2016). In a number of situations, data-driven allocations have unintentionally introduced systematic biases that perpetuate inequities, such as racial disparities in credit lending, hotspot policing, and crime sentencing (Ensign et al. 2017; Pleiss et al. 2017; Corbett-Davies et al. 2017).

The response of the ML community, while not entirely uniform, has largely revolved around a call for algorithms to satisfy various fairness metrics (Dwork et al. 2012; Kusner et al. 2017; Hardt, Price, and Srebro 2016). However, there has been pushback against this from various perspectives. Notably there have been some impossibility results, showing that several different fairness criteria that all seem intuitively reasonable cannot be satisfied simultaneously (Kleinberg, Mullainathan, and Raghavan 2017; Pleiss et al. 2017; Feller et al. 2016). Corbett-Davies and Goel (2018) discuss the statistical limitations of various fairness criteria, and argue that formal fairness criteria may "harm the very groups they are meant to protect" and advocate instead for treating similarly risky individuals similarly, based on the best risk metrics available. Green and Hu (2018) say that the methodological reliance of machine learning on standard techniques, metrics, and datasets makes it ill-suited to address political and ethical considerations in the deployment of algorithms in socially important contexts. They go on to call for the process of democratic deliberation as much as technical analysis in such deployments.

There is also a rich literature on *fair division* (Bouveret and Lang 2008; Chen et al. 2013, e.g.) that is related, but the connections are, somewhat surprisingly, only beginning to be explored. In typical fair division problems, the analysis is from the perspective of treating all agents as equal priority and focusing on the efficiency and fairness guarantees that can be made with respect to agent preferences. In the types of domains we are looking at, the questions of who receives priority and why are much more central.

Social Policy and Local Justice

In the domain of allocation of scarce resources to individuals (and households, etc.) in need, we do not have to reinvent the wheel in order to examine the effects of different ways of setting social optimization goals. Institutions such as organ donation policy-making bodies and draft boards (among many others) have long grappled with the question of how best to allocate scarce resources (or necessary burdens). Political philosophers have discerned from these cases a set of useful underlying principles of what they call local justice. Our discussion here largely follows that of Elster (1992).

Local vs. global justice To make one distinction clear, local justice is distinguished from theories of global justice and individual rights (notably utilitarianism, Rawl's theory, and Nozick's libertarian theory) by the local nature of decision-making. The ethics of deciding how to allocate scarce resources in one setting does not carry over to others necessarily, and a series of decisions deemed to be locally just may lead to global problems for a particular group. Our concern here is with considerations of ethical decision-making by local institutions.

Principles of Local Justice

Elster categorizes the principles of local justice in several ways. Let us briefly discuss principles for allocation of scarce resources that have been used in society that will not be our focus. These include allocation based on status (quota systems in general), age and gender (women and children first on the lifeboats), waiting time (queueing systems), power and influence (legacy admissions), or lotteries.

If we restrict ourselves to settings in which AI or data-driven decision-making can have most impact, we are most interested in principles that take into account specific properties of individuals, and also the interaction between the individual and the allocated resource. Three types of local decision-making based on the welfare of individuals are prevalent in institutions that allocate scarce resources. In order to present these, first let us assume that individual welfare levels can be reduced to a single-dimension, call it w.

(1) Minimum pre-allocation w: This is the principle of allocating to those with the greatest need. The homelessness system in most of the United States is a good example of a system that mostly works on this principle, with explicit determination and prioritization of the most vulnerable, sometimes based on a score, and sometimes on individual discretion of the case officer. Another example is in cadaveric organ transplantation, where the sickest patients get highest priority, often based on a complex scoring mechanism.

(2) Maximum post-allocation w: This principle allocates resources to those who will be best off after allocation. For example, some elite public magnet schools may select those who are already extremely gifted and would have the highest post-schooling quality (even if the school does not end up contributing much to that final quality itself).

(3) Greatest increase in w: This is the principle of allocating to those who would get the greatest "value added" from the resource, measured by the difference in post- and pre-allocation levels of w (note that this difference could be stochastic rather than deterministic). An example is in emergency medical triage in wars, or when there are insufficient ICU beds or ventilators available in hospitals and care must be rationed. In these settings, those who receive treatment and attention are typically those in the middle-range (leaving aside those who will recover well without attention and those who are too critical to be saved).

It is certainly not the case that one of these is better than the others as a criterion in all situations. Indeed it is worth thinking about societal objectives again, with the example of patients on wait lists for organs from deceased donors. It is common practice to prioritize sicker patients (corresponding to the first principle above) even though overall outcomes may be better if one were to transplant less sick patients earlier in their time on the wait list. However, this creates the societal feeling that one could be abandoned, which is considered harmful to social well-being and cohesion.

Roles for AI

Using the framework of local justice, and in particular of allocation systems based on properties of individuals, we can articulate possible roles for AI by going back to the four defining questions for an allocation system posed above.

Defining and Quantifying Desirable Outcomes

While most of the literature examines the "traditional" utilitarian or Rawlsian notions of welfare, there has been increasing interest in considering different possibilities. The "moral machines" project was among the first to crowdsource moral judgments about algorithmic decisions in the context of ethical dilemmas that could be faced by autonomous vehicles (Awad et al. 2020). There has been recent work on turning such judgments, from experts or from the general public, into objective functions. Notably, Lee et al. (2019) describe a system that allows stakeholders to construct computational models representing their views, and the models then vote in order to create what the authors call "algorithmic policy." One of the benefits, compared to objective functions designed by the algorithm designers, is that this engages stakeholders and increases buy-in. Freedman et al. (2020) propose a principled methodology for eliciting stakeholder preferences for which attributes of individuals should be considered for prioritization of kidney transplant recipients, and propose a method for estimating weights using these preferences. Interestingly, in both of these cases, there is a combination of machine learning for preference learning, and some form of social choice for preference aggregation. These types of ideas highlight the promise of AI to go beyond what we have been able to do societally and come up with methods that could lead to greater social acceptance and more participatory decision-making in these spheres.

Another area where AI has been valuable is in understanding the overall effects of optimizing different welfare criteria through ideas like the price of fairness, which examines the efficiency loss due to implementation of a fairness criterion in allocation (Bertsimas, Farias, and Trichakis 2011; Caragiannis et al. 2012). For example, Nguyen, Das, and Garnett (2021) consider a prioritization method that implements the triage principle of greatest increase in w. They study the price of fairness and show that its price of fairness is often lower than that of the most-vulnerable-first principle. They argue that this could partly explain situations in which society has agreed that the triage principle should be used, e.g. short-term emergency medical situations like those that could occur in a pandemic, in spite of the problem of abandonment. In this type of work, computing acts, in the words of Abebe et al. (2020) "as a formalizer, [shaping] how social problems are explicitly defined — changing how those problems, and possible responses to them, are understood."

There are many risks and caveats to remain aware of. While some may be unanticipated, a few can be seen from the start, and we discuss two here. First: some of the major problems in bias of machine learning systems have arisen as a result of them replicating human biases that we do not want to sustain. Does learning preferences from stakeholders and humans potentially perpetuate injustices? This can vary between contexts, but the famous case of the Seattle "God committee" which decided who would have access to dialysis treatments in the 1960s is a classic cautionary tale. As Levine (2009) says "the committee relied heavily on criteria of social worth heavily weighted toward economic status, reflecting their own values and biases." One of the potential *benefits* of AI is in the potential objectivity of its goals, but nevertheless, this must be in consultation with stakeholders (the veneer of objectivity can also encode biases, of course).

Second, we need to be careful in translating between social objectives and mathematical formalizations. We often benchmark to efficient, or utility maximizing allocations, whether in terms of the price of fairness or not. However, even in some social allocation problems where the goal at first appears to be utilitarian efficiency, it may not be. For example, prioritization by maximum post-allocation welfare is not the same thing as the utilitarian assignment in a system with multiple interventions.

Predicting Outcomes Under Different Allocations

A second part of the local justice framework in which AI, and in particular, machine learning (ML), has potential is in measuring and predicting the welfare level w. While an impossible task in general, in many real-world cases we do use proxies for w. For example, in medical interventions we may use Quality Adjusted Life Years (QALY) as a measure, in homelessness services the VI-SPDAT score (note concerns about validity) has been used to measure vulnerability, and in liver transplantation the MELD score is used to measure severity of liver disease. In the latter two cases, the score is considered inversely related to welfare.

One interesting use of ML is to better capture what such scores seek to measure. In homelessness services, for example, the vulnerability score is often intended to measure how well an individual or household would do without receiving support. In child welfare, one may want to measure any number of negative outcomes (inability to make progress in school, interactions with the criminal justice system or need for emergency medical care). By using ML methods on administrative data, one could predict the probability of successfully remaining housed, or graduating school on time, and these measures may be more directly related to the outcomes we care about than the scores we currently construct.

The prediction problem is in some ways even more interesting, because it asks the question of how well individual A (defined by some characteristics that we can think of as a feature vector) would do when given interventions $\alpha, \beta, \gamma, \ldots$. This is more complex because it asks about the interaction of an individual (or household) with an intervention. While there is much to be done in this area, recently different approaches to this have been taken. In the domain of matching refugees to cities in which they are likely to do well (so A is a refugee family and the Greek letters are different cities), Bansak et al. (2018) take advantage of prior random allocation to learn good models, while Kube, Das, and Fowler (2019) estimate counterfactual probabilities using BART in the case of allocation of homelessness services.

Many of the usual concerns with ML surface when it is used in these domains. Are we learning the right model, and making predictions in ways that are fair to different subgroups, for example (Kearns et al. 2018)? This could be compounded in two separate ways. First, there are many domains where human behavior is fundamentally not very predictable compared with other ML tasks, with low AUC values the norm. Second, the counterfactual problem is particularly difficult. There may be a paucity of data on individuals or households of certain types receiving certain services in the past (whether because of biases or other reasons), making models less valid for those populations.

Optimization With Fairness Constraints

The third question raises interesting algorithmic challenges. Given a plausible, but perhaps "soft" notion of fairness that does not yield a strict priority ordering that must be respected, and also a social goal, how can we optimize towards both objectives? This is a fascinating, and methodologically challenging, problem with a strong practical basis. For example, those fleeing domestic violence are prioritized for spaces in homeless shelters and the immunosuppressed for vaccines. There is exciting work in this space. For example McElfresh and Dickerson (2018) design a rule for balancing a utilitarian objective with preferences for one group over another in kidney exchange, while Azizi et al. (2018) consider a formulation that optimizes efficiency while satisfying fairness constraints specified by a policy-maker in the context of providing resources to homeless youth. There is plenty to be done in this area, where exact solutions that can be computed efficiently are typically hard to find.

Preferences and Incentives

Thus far we have elided the question of preferences. The implicit assumption is that the decision-maker knows, or can acquire, sufficient information about each individual in order to make decisions, and that individuals do not really have the power to affect allocations, and would prefer some allocation to none at all. However, we should also consider the incentives created by such systems, as suggested by Roth (1993) in a review of Elster's book *Local Justice*. Recent work in algorithmic game theory and matching has begun to do so. Two examples are illustrative. Estornell, Das, and Vorobeychik (2021) look at a problem motivated by people lying about self-reported attributes in order to receive a more favorable score (as has been reported, for example, in the context of homelessness services in LA). They show how one can use audits of self-reported features after-the-fact in order to incentivize truthful behavior, and also demonstrate that the scarce resource setting poses fundamentally different challenges than the setting where resources are not scarce but the institution would benefit from setting some score threshold. Aziz and Brandl (2021) consider the problem of allocating scarce healthcare resources when individuals may have different eligibilities for the resources. For example, individuals may become eligible for Covid-19 vaccination under different eligibility categories. They design a mechanism for efficient allocation that complies with eligibility requirements, respects priorities within eligibility categories, and incentivizes truthfulness in the sense that individuals never underreport eligibility categories.

These examples are on the spectrum of the many interesting and challenging problems that arise on the mechanism design side when thinking about how to design end-to-end systems for allocation of scarce societal resources. In addition to the other categories above, this provides a set of possible ideas, and a personal sense of priorities, for future research in the use of AI for such allocation problems.

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