Structural Interventions on Automated Decision Making Systems

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Abstract

To address discrimination and inequality in automated decision making systems it is standard practice to implement so-called fairness metrics during algorithm design. These measures, although useful to diagnose and enforce fairness at the decision stage, are not sufficient to capture forms of discrimination arising throughout and from structural properties of the system as a whole. To complement the standard approach, we propose a systemic analysis, aided by structural causal models, through which social interventions can be compared to algorithmic interventions. This framework allows us to identify bias outside the algorithmic stage and propose joint interventions on social dynamics and algorithm design. We show how, for a model of financial lending, structural interventions can drive the system towards equality even when algorithmic interventions are unable to do so. This suggests that the responsibility of decision makers extends beyond ensuring that local fairness metrics are satisfied to an ecosystem that fosters equity for all.

1 Introduction

The widespread use of machine learning algorithms and the practice of data science to support everyday life has brought about unintended consequences. Some of these consequences such as environmental impact [64, 22, 42, 34], extractivism [17, 13], labor exploitation [38, 27, 28, 9, 58, 60, 24], and privacy intrusion [21, 11, 63, 53, 67, 40] are general to the practice and deployment of pervasive computing. A particular problem, salient in the last few years, is the form of discrimination exhibited towards certain population subgroups by data-informed algorithmic decision making systems. Algorithms have been shown to make biased predictions based on race [30, 54, 45, 55, 5, 6, 59], gender [44, 8, 14, 48] and class [25, 66, 29], among other attributes.

Algorithmic discrimination is for the most part unintentional, and much research is being done to correct the problem and identify its nature and origin. Broadly speaking, researchers have recognized two potential sources of bias–bias in algorithms and bias in data [49]. Bad algorithm design

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can disproportionately impact a single subset of the population (see [55] for a prominent example). Most modern algorithms, however, are based on data, so even well-designed algorithms can reproduce discrimination encoded inherently in the data itself [31, 2]. Data, in turn, is the result of mechanisms contingent on institutional norms, laws, ideologies, attitudes, protocols, and overall social dynamics. Likewise, a well-designed algorithm with unbiased data can still be discriminatory by virtue of its use within a biased system of decisions. Discrimination, indeed, is a social problem predating algorithmic decision making. While algorithms may exacerbate the situation and should be designed carefully, it is likely that algorithm design alone cannot fully solve the problem.

There are different perspectives regarding the extent to which computing, as an active part of the problem, can contribute to the solution. As pointed out in [1], fair machine learning research works well as a diagnostic tool to detect problems of discrimination and bias in algorithms [46, 4, 2, 39, 55]. Fairness metrics, however, may fail to properly diagnose discrimination if social context is not taken into account [19]. Although major sources of bias are due indeed to the environment in which algorithms are embedded [61], technologists direct their efforts towards better algorithmic design as the primary point of inquiry [50, 16, 35]. Critics of technology, on the other hand, argue that harmful bias can stem from a variety of situations and optimal design is not sufficient to counteract algorithmic discrimination, which merits different solution approaches [61, 20, 65].

The main criticism of technological solutions is that they don't account for the discriminatory structure inherent to society itself, algorithmic deployment and infrastructure, and differentiated impact. These are criticisms of scope rather than method. By de-centering algorithms as the objects of study, and taking a systemic approach, machine learning research itself can expand its contributions. Some authors propose, for example, considering implementation pipelines to assess discrimination over a linear system of decisions[23, 37]. In this paper, we propose a methodology to account for elements of algorithmic discrimination with social origin. That is, instead of considering the algorithm in isolation, we place it in the social context in which it is deployed. We thereby shift focus from the statistical properties of an algorithm to the properties of the system in which the algorithm resides. This perspective is complementary to fine-scale analysis of algorithmic fairness metrics.

Having placed an algorithm in context, we then explore the potential of different system-level interventions to reduce unequal outcomes. We compare the effect of intervening solely on the algorithm, by constraining it to satisfy fairness metrics, to the effect of interventions on the data generating mechanism and other social aspects of the system. As an example we use the bank loan problem described in [47], and show that social interventions are more effective than algorithmic interventions. Our goal is to show that systemic analysis falls within the scope of machine learning research, and should be carried forward as such.Most fair machine learning research focuses on algorithm-level solutions because the tools at our disposal are already calibrated to this level of analysis. Our intention in this work is to suggest that, with small modifications, we can use those same tools for systemic analysis.

In Section 2, we outline the use of machine learning and causal inference tools in a systemic approach to the problem of algorithmic discrimination. In Section 3, we build on the work of [18] to present the lending example in [47] within this framework, and present experimental results supporting our thesis that structural interventions are transformative when algorithmic interventions fall short. Section 4 presents suggestions for how to implement these principles in practice. We conclude in Section 5.

2 Systems Framework

Our working definition of a system will be a set of objects, possibly with internal structure, and a corresponding set of relationships and constraints these objects have. Let $S = (O, R)$ be the tuple of objects and relationships. Many decision making systems include as a crucial step a binary decision that members of a population are subjected to, for example whether or not to provide a financial loan, a medical treatment, a job offer, or a prison sentence. Automation is possible only because the individual for whom the decision is being taken is represented as a set of features. These representationsare mapped onto the decision contingent on a particular attribute that, purportedly, divides the population into appropriate subgroups (race, sex, class, etc.). That is, for an individual who has been represented by features X and labeled as sharing the characteristics of subgroup A, the decision is taken through a mapping $f(X, A) = Y$ (A need not be used by f). The system itself

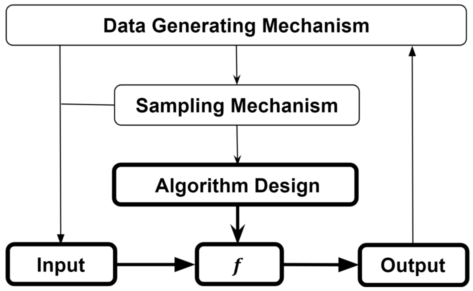

Figure 1: Diagram of relationships among different objects of an automated decision making system. The bolded region indicates where algorithmic local analysis concentrates, leaving out generating mechanisms and feedback effects.

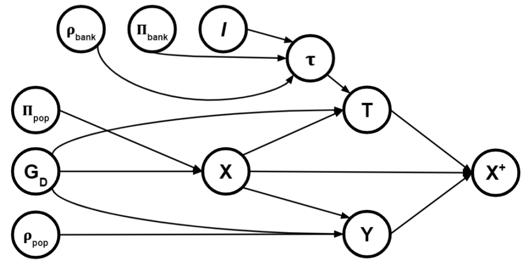

Figure 2: Structural causal model for the lending system studied in Section 3. The inclusion of population characteristics (Π, ρ) and separation between datafied and structural categories permits analysis of extra-algorithmic interventions.

has many components, f being just one of them. For analytical purposes, we can create subdivisions of these components.

Individuals develop the attributes by which they are represented through a complex mechanism of relationships, actions and social and institutional constraints, e.g., educational opportunities and cultural inheritance.We call this process the *data generating mechanism*. We then have the *sampling mechanism*, through which individuals are datafied as a set of features and these features are made available to the decision function, e.g., loan application, doctor visit, criminal sentencing. Then, through the *design mechanism* an algorithm is derived according to a scientific paradigm. Once designed, the *deployment mechanism* makes decisions over individuals. Finally, decisions made for individuals have effects on those individuals and their social groups. The aggregate of these effects is significant enough to elicit a change in the data generating mechanism. We call this the *feedback mechanism*. While for most systems these subdivisions are permeable, we will keep them for practical use. Figure 1 provides a schematic of these mechanisms and their relationship in a decision making system. We note our assumption that each of these has internal structure.

Much of fair machine learning research focuses on the design mechanism (bold region of figure 1), but properties like fairness, discrimination, and inequality are properties of the system as a whole. Indeed, it is possible that achieving a certain property at the algorithmic level is not sufficient to achieve it at the system level, and may instead mask a lack for the overall population [19, 41]. As a particular example consider the design of a classifier we wish not to discriminate based on race. In the design process we have access to data D, a collection of mathematical objects representing individuals. Assume the race attribute is represented as a single categorical variable A. We can then set constraints $\mathcal{C}$ based on this A, and design the classifier f according to a minimization problem that looks like this:

$$\begin{aligned} f = \min_{h \in \mathcal{H}} & \, \mathcal{E}(D, h) \\ s.t. \quad & \mathcal{C} \end{aligned} \tag{1}$$

where $\mathcal{H}$ is an appropriate space of candidate classifiers and $\mathcal{E}$ some error. This system is indeed the bolded subdiagram in figure 1. Notice that while we mention classifiers, f could be something else, like a regression function or clustering assignment, depending on the problem. However, most approaches in fair machine learning have a similar structure as above.

There are two important aspects to the fairness-inducing constraint $\mathcal{C}$. First, that it is based on the variable A which, we recall, represents attributes we wish to protect. Second, that it can guarantee the satisfaction of fairness metrics only with respect to the scope of subsystem 1. Following we explore these aspects further.

2.1 Datafied vs Structural Categories

Consider the constraint $\mathcal{C}$, which is expected to induce fairness or a similar concept. This could be, for example, the exigency of decisions which are independent to the variable A. While we can statistically satisfy independence with respect to A, we cannot satisfy independence with respect to race, or gender, or class, since these are structural relationships in which individuals participate and cannot be detached from the individual. That is, it is imperative not to confuse the categories themselves with A, which is how we operationalize these categories.

Categorization of individuals is for the most part arbitrary, yet has significant consequences as those categories are used for the provisioning of resources and decisions [10, 51]. In demographic and statistical settings, these categories are often represented by a categorical variable, included in the vector of features representing an individual (race, gender, etc.). A basic goal of fair machine learning is to ensure there is no damaging discrimination due to membership to protected categories. Therefore, several fairness metrics are designed to address some type of independence between the variable representing a protected attribute and the algorithm's output. This approach, however, can be deceiving. A category like race, for example, cannot really be encompassed in a single variable. Instead, it is a set of variables, interactions, social biases and experiences, that the individual is subject to throughout their lives, and that influence all the observed variables inscribed in a particular feature vector. Hence, while statistical fairness metrics could enforce independence to a variable indicating race, which is possibly the result of an institutional agent checking a box in a survey or official form, they cannot enforce independence to "race" conceptualized as the structural position in which an individual finds themselves within a social context. This differentiation is seldom discussed in the fairness technical literature. To differentiate between the "check mark" categorical attribute and the real experience of that category, we call the former **datafied** and the latter **structural**. For example, datafied race would be the variable indicating one of the many institutionally defined "races" (white, black, asian, etc.). Structural race on the other hand would be a function of the system structure as a whole, not a variable within the system.

In previous literature [43, 52] fairness has been proposed in terms of blocking the effect of race on the classifier. However, in those instances they refer to *datafied* race, a single variable. While the causal effect of this variable can be blocked by blocking specific paths, structural race cannot, as it would imply blocking most characteristics of the individual with respect to its society, which is impossible. For example, if an individual is represented by their credit score and datafied race (x, a), and we get rid of a, we might be tempted to equalize treatment on all individuals with same x level, however, level x means very different things for different subgroups. Just think about how much harder it is for a person born in poverty to achieve and maintain a high credit score compared to a person born into a wealthy family. To clarify a misconception, attributes like SES, family history, and neighborhood, are not *proxies* for race, meaning variables that exist by themselves outside of race (if correlated), they are indeed part of structural race. Notice that even a completely random classifier would not avoid discrimination because equal decisions have different impact on different subgroups. Therefore, trying to be "blind" to race or other structural categories is not a useful enterprise, and may even be counterproductive [55, 15, 3].

Causal inference does help us identify the differential effects of interventions on subgroups, and we will use a causal model ourselves. However, we will not model structural categories directly. Even if we complexify the concept and define a structural attribute as a set of variables and their connections, the particularities of those connections would be different for each person and context. To acknowledge structural categories but still have a working model, we will simplify them as a set of prior exogenous variables we don't have control over but that influence all observed variables. Other excellent approaches to tackle the problem of datafied versus structural race in machine learning and causal inference can be found in [62, 36, 32, 7].

2.2 Scope of algorithmic subsystem and causal modeling

The other important aspect of $\mathcal{C}$ is that it can only guarantee constraints with respect to subsystem (1). Considering input and output (x, y) during deployment, the objects of this system are $(D, \mathcal{H}, \mathcal{C}, f, x, y) \subset O$. Any property we measure with respect to this system, like fairness, justice, equality, that we may want to optimize, can only be done with respect to these objects. The advantage of circumscribing our focus around f is that we can fine-tune the local behavior of our classifier. However, it has restricted knowledge of the data generating mechanism and the dynamics of a changing population, including feedback effects.

Changing the scale of analysis, we can view algorithms as objects in the system, and study the relationships it has with other objects. In so doing, we can identify if undesired characteristics of the system, for example discriminatory behavior, which are derived from the tuple (O, R), are mostly due to the implementation of a particular algorithm or to the structure of the system as a whole. Identification of such emerging patterns allows us in turn to judge what type of interventions we can do on algorithmic design, with what consequences, and what type of interventions must be done on other objects and relations of the system.

We will use a particular modeling paradigm for (O, R), structural causal modeling. In that case, the transition to the larger system is eased through the concepts of endogenous and exogenous variables. Endogenous variables are those inside the system, these are the ones we assume we can intervene on and for which we can explain causal connections. Exogenous variables are excluded from the modeling in the system but accepted as influences on endogenous variables. Looking at Figure 1, the subsystem of analysis will be limited by the endogenous variables you have access to, often the variables you can observe. Exogenous variables are usually thought of as complicated background conditions that can't be interfered with. Our advocacy for systemic expansion implies co-opting the data generating mechanism–or at least portions of it–into our modeling scope. In a sense, this is equivalent to converting some of those exogenous variables into endogenous variables through modeling assumptions and knowledge from social sciences and related fields that indicate what type of relationships are involved. For more details on causal models, diagrams, exogeneity and counterfactuals see [56, 57].

Consider a property of the system like inequality, our goal is to determine which interventions change that property and to what degree. While the division is porous, we can consider two types of interventions, local interventions and structural interventions. Local interventions involve acting on a specific variable, while structural interventions involve acting on a collection of variables *and* the relationships these have on each other. Local interventions are more likely to be adopted since in general they are easier to implement, for example by enforcing a fairness metric in the design of a classifier, or pre-processing and post-processing data. Structural interventions are generally more expensive and complex. A type of structural intervention would include policies that constrain the behavior of institutions, such as economic, political, and educational reforms. Another type would constrain the behavior of individuals, for example by restructuring strategies for police surveillance and medical diagnosis. The complexity of structural interventions, however, does not preclude us from studying their effect on a system property. If, for a particular scenario, all information is filtered by an observed variable we do not necessarily have control over while designing an algorithm, we can still study interventions on that variable as proxies for having implemented a social policy that led to such changes. We will explore this approach for the case of lending.

3 Exemplary application to a lending system

We apply the systemic framework we have described to the lending system described in [47]. In this scenario, people, separated into subgroups according to their datafied race G_D, apply for loans to a bank. Individuals are judged by the bank's classifier according to their credit score X, and the credit score distribution Π and repayment probability ρ of the group they've been assigned to, notwithstanding personal history. T indicates if they were given the loan or not, Y their actually repaying, and X^+ their updated score. The true characteristics of the population (e.g. Π_{pop}) are not necessarily known to the bank, which may use an outdated estimate of these (Π_{bank}). In [18] an SCM of the lending system was constructed. We have made some alterations based on the framework presented here, as seen in Figure 2. Notice we have not identified the structural category G_S with any particular node, and we don't want to commit to such a representation, since it is constituted by both endogenous and exogenous (as well as possibly not measurable) conditions [2]. Details of the model, including time dependency, feedback and functional relations, can be found in the supplementary material. The classifier τ, following the setup in [47], is derived by maximizing the utility: $\tau^* := \arg\max_{\tau=(\tau_A,\tau_B)} U(\tau; \pi)$ (the explicit form of U can be found in supplementary material). The optimal τ is a threshold classifier, meaning that if a credit score is greater than a group-specific threshold the loan is given, and denied otherwise. If fairness metrics are enforced this threshold value changes. The metrics we consider are demographic parity and equal opportunity, as used in [47] and defined in the supplementary material. Both fairness constraints involve an intervention on the node τ. Our interest is not to compare different types of fairness criteria, instead, we want

[2]For now it is important to separate them analytically so we position claims about fairness and causal paths properly.

to compare different types of interventions: algorithmic interventions on the one side (enforcing fairness criteria), and systemic interventions on the other.

Ideally we would use a model of the generating mechanism, with added objects and relations, in which we could intervene. In this example we are not adding such a model but we can still model the effects of structural interventions by appropriate interventions on the original distributions. That is, we have co-opted Π and ρ as endogenous variables, extending the scale of analysis to account for the conditions under which subgroups have different score distributions or financial capabilities for repayment. This variables are often left out of the model as exogenous and taken as essential characteristics of populations. Intervening on these variables reflects an intervention on the data generating mechanism. A full model for their determination would include the family and social support individuals have, wealth, income, financial and educational opportunities, health status, commuting time, neighborhood resources, social capital, etc.[3] As such, Π and ρ represent a network of relationships from which individuals eventual attributes are derived; changing them represents a change in the system as a whole. We will compare systemic interventions, realized through interventions on Π and ρ, to algorithmic interventions, realized through intervention on τ.

Using this model, we initialize the score distributions and probability of repayment for each group with the data provided by [47]. We also borrow and use portions of the code provided by [47] (BSD-3 license) for our implementation of the classifier and fairness metrics constraints. The data contains no personally identifiable information. Specifics of model implementation and parameter choice can be found in the supplementary material. Code can be found online at this url.

The system evolves over time. The initial score distributions for each group are shown in Figure 3 (top). If we enforce any of the fairness metrics described above, or we don't do any intervention, the classifier eventually drives inequality into the system, as shown in Figure 3 (bottom), where the final distributions after $N = 40$ steps are plotted for the case of demographic parity enforcement. Similar distributions result from maximum profit and equal opportunity. The takeaway is that subgroup A does not have the same opportunities as B when it comes to repayment, so most of the population end up with lower credit scores.

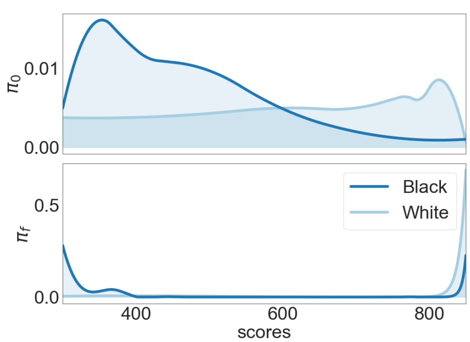

Figure 3: Initial and final distributions of both populations, π_0 and π_f, after $N = 40$ iterations of enforcing DP, smoothed for visualization. The non-privileged population, starting with lower scores, ends with even lower scores; the privileged group's scores concentrate in high regions. Similar results hold for EO and MP.

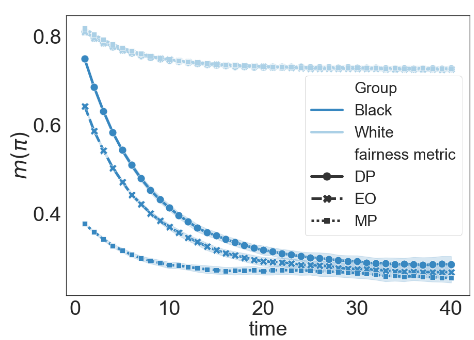

Figure 4: Convergence behavior of the wellness metric m for both groups under different metric constraints, without social interventions. While fairness constraints are better than unrestricted MP, the improvement is marginal, and an inequality gap is formed after several generations of the system.

In order to assess which interventions are more beneficial we need to define a metric m for what a "good" outcome is. Since we don't include other indicators of wellness in our population (health, education, etc.) we will use their credit score distribution as a diagnostic [4]. An ideal distribution

[3]If such a model is available, that is, if a working social theory can work as the basis for the data generation, it can be properly merged with the variables one has access to. A promising direction is to use agent based modeling or other simulation paradigms. See [33, 19, 12].

[4]The use of these proxy variables may be problematic in itself. We acknowledge that limitation but remind the reader that the focus is not on obtaining the best model, but to determine how, under established models, different intervention types affect the population

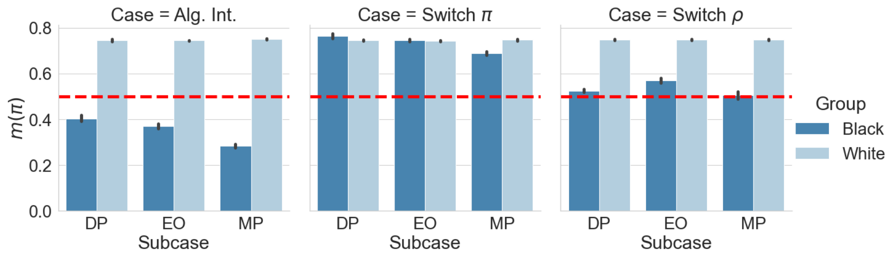

Figure 5: Probability of credit scores being greater than the lending threshold for both subgroups after $N = 40$ generations of the system. (Left panel) Only algorithmic interventions have been applied and inequality prevails. (Middle and right panels) A combination of algorithmic and proxies for systemic interventions is applied, reducing or nullifying the gap.

would be one where everyone in the population has high scores. For our lending scenario we will look instead at the relative number of people whose score exceeds the threshold value set by the bank, that is, the percentage of the population with the opportunity to receive a loan in the first place. Therefore $m(\pi) := P_\pi(X > \tau)$. Note that π and τ change over time. We applied three intervention cases.

Intervention 1. First, we only intervene on the classifier by enforcing different fairness metrics, either equal opportunity (EO) or demographic parity (DP). As a baseline we use the case in which no intervention on the classifier is made (utility is maximized without constraints), we call this baseline maximum profit (MP). Succinctly, the intervention is $f_\tau \leftarrow f'_\tau$.

Intervention 2. Second, we explore the case in which the score distribution of the population is changed, by setting the score distribution of the vulnerable population to that of the privileged population. Succinctly, $\pi_A \leftarrow \pi_B$.

Intervention 3. Finally, we explore the case in which the probability of repayment is changed. In this case, because the bank will still set a threshold based on the heavily skewed π values, a significant percentage of population A will not have the chance to get a loan and improve their scores. Hence, to boost initial lending rate on A, we further adjust ρ to match the initial percentage of people in B who get the loan. Succinctly, $\rho_A \leftarrow \rho_B + \delta$, where δ ensures equal initial percentage of loan opportunities (see supplementary material for details).

For both the second and third interventions, we also explore their combination with the baseline intervention by jointly enforcing EO or DP. Intervention 1 changes the way a classifier is designed, based on fairness principles. This intervention can be considered *local* to the algorithm. It does not intervene directly on any element of the social system outside algorithmic design. The second and third interventions represent actions taken on the social system to change the properties of the population. The particularities of how these would be carried out are beyond the scope of this paper, but if policies were enacted such that as a result the properties of the populations changed in such a way, then we could assess their causal effect. The last two interventions are structural interventions because they encompass a restructuration of the system outside of the algorithmic locus.

Figure 4 shows the evolution of $m(\pi)$ over time for Intervention 1 and both fairness metrics. Even if DP and EO are an improvement over MP, the outcome is still disparity among the groups. We also compute the effect of interventions 2 and 3 in conjunction with fairness sub-interventions. The results after 40 steps are shown in Figure 5 (convergence happens much faster, really). Just as in figure 4, not intervening at the system level results in high inequality among both groups. Indeed, less than half of the unprivileged population even has the further opportunity to get a loan. On the contrary, if we add systemic interventions, inequality is greatly diminished. As a point of clarification, we must point out that our experimental results are limited to the lending model discussed. Like any model, it is bound to miss intricacies of reality. That is OK, since the constant refinement of models, assumptions and hypotheses is inherent part of scientific pursuit.

4 A roadmap

As exemplified in the simulation experiment, interventions applied at the localized algorithm deployment stage are not as impactful in reducing harm as interventions applied to the social mechanism encompassing and sustaining the algorithm itself. This does not imply that algorithm designers have no power to make things better; rather, it suggests they must increase their scope of analysis, e.g., to ensure harms are not reintroduced during algorithm deployment. They might also consider whether the *point of deployment* of the algorithm is displaced. For example, if using machine learning to *predict* recidivism results in harm, we may wish instead to using machine learning to *prevent* recidivism, for example, by reallocating resources to social work and community support [26]. To make concrete the adoption of systemic thinking in algorithmic design, we provide four general principles for the machine learning researcher to incorporate in their practice:

Reformulate. While the discourse surrounding harm in algorithmic systems focuses on fairness, the problem may be rooted in other sources of discrimination and injustice. If that is the case, a proper action to take is to replace the causal inference question "what causes disparity among populations" to "what causes harm to a population". By doing so, efforts towards fairness are complemented by other regulations that diminish noxious impacts.

Identify. Identify the stakeholders involved. In particular, center those who can possibly be harmed by algorithmic deployment in the analysis as opposed to those who profit from it. Furthermore, identify the causal relationships among the agents and variables involved. This modeling should include domain experts. Finally, identify causal relations that are potential sources of harm, these include the locally trained algorithm, the mechanism through which data is obtained, the feedback mechanism, and other stages of the system.

Structuralize. If provided with a datafied category, make explicit the distinction between the structural category it is associated with. If enough information is available to model the dynamics that compose a structural category, add that model to the analysis. Shift efforts from trying to block causal paths from a structural category to identifying which elements harm populations by virtue of the structure of the system.

Expand. Expand spatially, meaning enrich the model to account for context, even by co-opting exogenous variables. Expand temporally, meaning that, if available (often from the social sciences), add a model for the generative mechanism of your data, which comes prior to algorithmic deployment, and add a feedback mechanism by considering the impact of decisions on the population. If not available, explore how changes in the original distribution may reduce harm, as well as long-term effects produced by feedback loops.

These principles make up the easy-to-remember acronym **RISE** (we promise the reader it came up naturally, nice coincidence), we hope these principles help the practitioner reconceptualize the problem of "fairness" in machine learning (or more generally, mitigation of harms) and can be applied in practice to incorporate systems thinking as well as social scientific insights. We know the list is not complete, as more considerations will undoubtedly come up as research and the problem space develops. However, these key principles serve as a basis for a trending shift in perspective from the merely technical to the social systemic.

5 Conclusion

Social systems are composed of many dynamic interrelated parts. To understand the properties emerging from those systems we should complement different analytical frameworks with each other. For systems for which decisions are automated with machine learning technologies we propose expanding the scope of analysis with a structural approach, complementing the standard algorithmic regularization viewpoint. The key advantage of a systemic viewpoint is that we can identify areas of intervention and their consequences inside *and* outside the algorithmic design stage. Using data from a financial lending system in the USA and building on the model of [47, 18], we showed that difference in impact is much greater when applying structural interventions than when only enforcing fairness metrics. Indeed, only constraining an algorithm is not sufficient for changing the state of the system.

To clarify, we do not imply that institutions applying machine learning should be free of accountability. To the contrary, many of the complex social mechanisms that are not seen in the algorithmic stage are nevertheless entangled with the institution's position and practices, including labor, environmental, political and economic actions. We do not think the work on fairness from a localized, algorithmic viewpoint is futile. While fairness metric interventions are not sufficient to solve the problem, they are excellent tools for diagnosing it, and to ensure fair treatment among individuals at that particular stage. We should use them for that, but make companies responsible for more transformative practices. These approaches are part of a larger set of strategies which should be understood jointly to find a real solution to discrimination and inequality. Significant improvements can only be brought about through structural change as a collaboration of technology and social policy designers.

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