

Why should we ever automate moral decision making?

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Abstract

While people generally trust AI to make decisions in various aspects of their lives, concerns arise when AI is involved in decisions with significant moral implications. The absence of a precise mathematical framework for moral reasoning intensifies these concerns, as ethics often defies simplistic mathematical models. Unlike fields such as logical reasoning, reasoning under uncertainty, and strategic decision-making, which have well-defined mathematical frameworks, moral reasoning lacks a broadly accepted framework. This absence raises questions about the confidence we can place in AI's moral decision-making capabilities.

The environments in which AI systems are typically trained today seem insufficiently rich for such a system to learn ethics from scratch, and even if we had an appropriate environment, it is unclear how we might bring about such learning. An alternative approach involves AI learning from human moral decisions. This learning process can involve aggregating curated human judgments or demonstrations in specific domains, or leveraging a foundation model fed with a wide range of data. Still, concerns persist, given the imperfections in human moral decision making.

Given this, why should we ever automate moral decision making – is it not better to leave all moral decision making to humans? This paper lays out a number of reasons why we should expect AI systems to engage in decisions with a moral component, with brief discussions of the associated risks.

1. Introduction

People are generally quite comfortable with AI making all kinds of decisions in their lives. We are happy for AI to choose a route for us to follow when driving, to choose which articles we read or which videos we see, or even to propose people for us to date. But we often feel less comfortable about the use of AI in settings where there is a significant moral component to the decision.

One good reason to be concerned about this is that we do not currently have a clean, mathematically precise framework for moral reasoning. Indeed, much of the field of ethics concerns how simplistic mathematical frameworks fall short. For example, simplistic versions of act utilitarianism might have us kill a patient with a minor illness to redistribute that patient's organs to other patients, who would die without those transplants. In contexts other than ethics, we do have clean mathematical frameworks. For example, we have such a framework for logical reasoning; and thanks to it, AI techniques (say, using SAT solvers) can help us prove certain kinds of theorems (for a recent example, see [14]). Similarly, we have such a framework

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for reasoning under uncertainty (the theory of probability, graphical models, probabilistic programming, etc.); and thanks to it, we have applications such as monitoring the Comprehensive Nuclear-Test-Ban Treaty [2]. And we have such a framework for strategic reasoning (game theory); and thanks to it, we now have, for example, superhuman-level poker AI [3]. But, again, we lack such a framework for *moral* reasoning – or, to the extent we have such frameworks, they are highly controversial and not broadly endorsed. And it seems unlikely that we will find such a framework soon.¹

Might we be confident in the quality of AI’s moral decision making without such a mathematical framework? It is conceivable, in principle, that in a sufficiently rich environment, AI could learn ethics from scratch. But it seems unlikely that any environments in which AI systems are trained today are sufficiently rich; perhaps something like Melting Pot [9] has many relevant aspects, but still is likely to fall short. Moreover, even if we did have a sufficiently rich environment, it is not clear that we currently know how to train AI systems in such an environment in a way that lets them learn ethics from scratch.

For now, perhaps the most promising approach is for AI systems to learn moral decision making from human beings [5]. They could learn that by aggregating curated human judgments or demonstrations in specific domains [12, 8, 6], or perhaps from a very broad set of data through a foundation model [7]. Still, it is natural to have concerns about this approach, especially given that human moral decision making is surely not perfect.

2. Reasons for automated moral decision making

Given the above, one may well wonder why we should be interested in automated moral decision making at all; can we not simply leave all moral decision making to human beings? In what remains, we cover some reasons why, in spite of the lack of a formal framework, we may yet want to have AI systems do automated moral reasoning, rather than simply leaving the relevant decisions to a human being. As we will discuss, some of these reasons overlap, and some uses of AI can call on multiple of these reasons for support. So, these reasons are not intended to be disjoint from each other; and presumably this list does not exhaust all such reasons. For example applications given below, I will not try to argue that the benefits of automated moral reasoning outweigh the downsides. The intent is that the list of reasons below would be useful even to someone who is opposed to the deployment of AI in any of these applications, if only to understand why others might nevertheless choose to proceed with such deployment.

While each possible application of automated moral decision making comes with its own risks, the reason why automated moral decision making is used in the first place is often informative of the risks faced and the ways to mitigate those risks. Therefore, along with each reason, we present a brief analysis of the risks associated with using automated moral decision making for that reason. There may of course be risks associated with humans making these decisions as well, but we will not get into those here. The first three of the following reasons were also briefly discussed in [6].

¹Perhaps mathematical frameworks that narrowly focus on one particular ethical issue – e.g., [10] – are more likely to be successful, but these will necessarily have limited use as well.

2.1. Speed

In some cases, decisions need to be made *faster* than humans can make them, or faster than humans can make them well. One example is a self-driving car that suddenly faces an unexpected situation. For instance, an accident occurs immediately in front of it, and it needs to make a decision to either brake hard at some risk to the occupants, or attempt to swerve around the accident, which runs the risk of colliding with an adjacent car (possibly depending on the reaction of the adjacent car). This is a moral dilemma. But passing control back to the human occupant, who does not have situational awareness, is likely to do little good. Cybersecurity and cyberwarfare provide additional examples where speed can be of the essence. One might argue that this is a reason to avoid these types of scenarios altogether – maybe we should not have self-driving cars at all, and maybe we should work harder to ensure our systems are not vulnerable to cyberattacks or otherwise prevent such attacks from happening, etc. This is not the place to get into these discussions; all we aim to argue here is that these are settings where simply having a human take over the moral reasoning at the moment that it is needed is not likely to address the problem.

Risks. When AI is adopted for the sake of being able to act faster, there does not seem to be any inherent limit on how bad the consequences can be, because there will be no chance for a human to review the decision.

2.2. Scale

In some settings, *many* decisions need to be made, and it simply is not reasonable to have a human make each of these decisions. For example, consider the decision of whether to show someone a potentially sensitive ad, where the ideal decision requires taking into account detailed features of the user. This, too, can be a moral dilemma. The impact of any one such decision is likely to be small, but as the decisions are made across millions of users, their impact adds up.

Risks. In this context, it seems sensible to periodically review a sample of the decisions; and the more important each individual decision, the more often it makes sense to review. If this is all done well, it naturally limits how badly things may go.

2.3. Complex optimization

In some cases, moral reasoning must be intertwined with complex optimization. A good example of this is the problem faced in a *kidney exchange* [13]. In kidney exchanges, AI is already used to determine which potential kidney donors to match with patients [1]. Even the problem of maximizing the number of transplants is computationally hard, but it is not clear that that is the correct objective to pursue; in making these decisions, maybe we should also take into account other aspects, such as the patients' age, other aspects of their health, perhaps even whether they have dependents or a criminal record, etc. Trading off these varying aspects between feasible solutions poses a moral dilemma.

In this context, the moral reasoning problem does not seem cleanly separable from the optimization problem in such a way that humans can do the moral reasoning when it is needed. In principle, the AI system may propose a selection of feasible solutions, from which (say) a committee of humans then picks one. But without the AI system doing any moral reasoning of

its own, it is not clear how to guarantee that its selection will include the best solution, or even a good one; except, perhaps, if the selection includes *all* reasonable solutions – but there will generally be exponentially many of these, and searching through exponentially many options is what we brought the AI in to do for us in the first place. (In [6], we propose a method for having the AI learn an objective function from human feedback, but there remain a variety of questions about how best to elicit such information from human subjects [4, 11].)

Risks. Here, too, the risks of automated moral decision making could be limited by the fact that decisions can be reviewed. One could, for example, compare the AI-generated decision to a human-generated one in each instance, to make sure the AI-generated one is in fact better.

2.4. Better world models

In some domains, we may not have good intuitions about the actual consequences of decisions. Consider, for example, an AI system tasked with the design of new drugs to treat a disease. It may have better “intuitions” about the effects of various potential drugs than we do; and, for the system, choosing which new drug to propose to us requires trading off that drug’s expected efficacy with its expected side effects. Presumably, we will first still want to conduct a randomized controlled trial on the drug, but even just deciding to start such a trial is a decision with significant consequences. We may want to leave the decision in our own hands, and ask the AI system to tell us the reasons for its choice of proposed drug. But then again, it may not be able to effectively explain these reasons to us, for example because its model of how these drugs work does not translate well to natural language. Even if we as humans *were* able to evaluate the pros and cons of any proposed drug, there is still the issue of how it selects a set of proposed drugs for us to select from; at this point we are back at the issue of complex optimization discussed previously.

A related but different example is an AI system proposing a specific treatment for a specific patient. In this example, we cannot first run a trial; we simply have to decide whether to follow the proposed treatment or not. Again, we may not understand the reasons why the AI system proposed this treatment; moreover, overworked physicians may not have the time and wakefulness to thoroughly study the proposed treatment (see also “humans are poor decision makers under certain circumstances” below). Going one step further, the AI system may control the treatment directly.

It may seem that these examples that involve the treatment of only a single patient do not involve much moral reasoning, as there is no trading off between the welfare of multiple people. Nevertheless, the AI system may still have to trade off, for example, the pain the patient feels against the chances of keeping the patient alive. In some cases, the AI system may need to decide whether to allocate scarce medical resources to the patient even though they could help other patients as well. And perhaps in some cases, we would consider it acceptable for the AI system to try out an unusual course of treatment in part for the purpose of learning more about this course of treatment, to be able to help future patients better.

Risks. To the extent that humans cannot review the decisions effectively because we do not understand the reasons behind them, risks seem significantly higher.

2.5. Transparency of process

Sometimes, it is better to have a clear policy for how to make decisions than it is to make decisions on a case-by-case basis. In particular, human decision making is generally not transparent; human decision makers can be sensitive to bias, and can even be corrupt. In contrast, if a clear policy is set in advance, this helps to evaluate bias and prevent corruption on individual decisions. It can also help to prevent other ways in which ad-hoc decision making might be “gamed” by interested parties.

Committing to use a specific AI system to make decisions has at least some of the benefits of setting a clear policy. While AI systems vary in their transparency and interpretability, they can generally at least be audited by testing them on a variety of inputs, and they cannot be bribed.

Of course, there remain major problems with AI systems displaying unfair biases, for example due to the data they were trained on; at the very least, much more work is needed to address these problems effectively in such systems, and perhaps in the end we will conclude that there should always be a human in the loop in certain applications. The argument here is merely that in principle, there could be an advantage to the use of AI in terms of transparency of process; this is not to say that no further work is needed to attain (most) of these benefits, and it is not to say that these benefits outweigh other concerns.

The use of AI in kidney exchanges can be seen as illustrating the transparency-of-process benefit of using AI (as well as the integrated optimization benefit explained earlier). A human choosing how to match patients and donors might, whether consciously or not, let various biases play a role in the decision; and, at least in principle, such a person might be bribed to make this high-stakes decision work out better for a certain patient.

Other example applications where this benefit could play a role include the allocation of scarce medical resources more generally, or other key resources such as housing; as well as uses in the criminal justice system. Of course, the use of AI in the latter context is extremely controversial, and much work is needed to do this in a responsible way. But at least in principle, the transparency-of-process advantage may yet come to be seen as important enough to justify the use of AI even in this context.

Risks. Human review of decisions interacts with this reason in a tricky way, as the possibility of humans overruling the decision potentially takes away much of the benefit of the transparency of the decision process. For that reason, we may commit ourselves not to overrule the AI system’s decisions – but this increases the risks of these decisions. Perhaps a balance can be struck, for example by allowing overruling only if a supermajority of human judges concludes that this is the right thing to do.

2.6. Humans are poor (moral) decision makers under certain circumstances

This reason overlaps with the “speed” reason above, but there are other circumstances under which humans can be bad decision makers “in the moment.” To illustrate, imagine an AI application that, when someone is trying to send an email after a late night partying and drinking, has the ability to analyze that email and, if the email does not seem wise to send, to prevent it from being sent at that point in time. To be effective, the AI may have to engage in moral reasoning. For example, suppose the message the user is trying to send out late at night

is: “I don’t trust that guy you were just talking with, I recommend that you ditch him.” The AI may have reason to believe that the sender would probably regret sending this message in the morning, but, in making the decision whether to temporarily block the message, has to trade this off against the welfare of recipient in case the sender is in fact onto something.

There are many other conditions under which we humans are poor (moral) decision makers. Besides cases in which our reasoning is obviously compromised – say, due to alcohol consumption, fatigue, illness, etc. – we may also display various biases, in particular when we have a personal stake in the decision.

Risks. As in the case of the “speed” reason above, human review may in some cases not be possible, thereby increasing the risk. On the other hand, in some cases (such as the imagined blocked email message above), we could let another human quickly review the decision if it is deemed important enough, so that if this is set up well, the risk is limited.

2.7. Economic efficiency

Sometimes, we may wish to deploy AI simply to reduce costs. (This reason often overlaps with the “scale” reason above.) For example, consider the project of further automating call centers. To be concrete, consider a government-run healthcare hotline. Let us suppose that in fact, the AI still functions poorly enough that callers would be better served if they were instantly connected to a well-trained human being, so that the primary purpose of using AI to handle calls is to reduce costs. The AI may then face morally challenging decisions when determining which callers to connect to one of the scarce human beings answering calls, and which callers to try to handle itself. While this may sound like an undesirable scenario from the perspective of a caller, the resulting cost savings can of course be valuable; the government could in principle take the savings and apply them towards (say) preventive healthcare education campaigns.

Risks. Similarly to the “scale” reason above, in this context it seems to make sense to periodically review decisions, and to do so more frequently the more important the decisions are; if this is done well, then risks stay limited.

3. Conclusion

It may seem that it is a bad idea to have AI systems make moral decisions, or that at the very least, they should not do so unless and until we have an appropriate, mathematically precise theory for doing so; and that for now, we should leave moral decision making to humans. In this short paper, we have considered a variety of reasons for why we might nevertheless expect AI systems to end up making decisions with a significant moral component. This may be cause for concern, and we have also discussed various risks associated with it; and just that one or more of these reasons apply does not necessarily mean that automating moral decisions is a good idea. But when AI systems do end up making these decisions, we should not close our eyes to the fact that they have a moral component, or naïvely think that we can always effectively bring humans into the loop to make these decisions. The best way for AI systems to learn how to make these decisions may be by observing examples of human moral decision making, but in the end, they are likely to have to make individual decisions themselves.

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