AI for Social Good: Between My Research and the Real World

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Abstract

AI for social good (AI4SG) is a research theme that aims to use and advance AI to improve the well-being of society. My work on AI4SG builds a two-way bridge between the research world and the real world. Using my unique experience in food waste and security, I propose applied AI4SG research that directly addresses real-world challenges which have received little attention from the community. Drawing from my experience in various AI4SG application domains, I propose bandit data-driven optimization, the first iterative prediction-prescription framework and a no-regret algorithm PROOF. I will apply PROOF back to my applied work on AI4SG, thereby closing the loop in a single framework.

From Research to the Real World: AI for Food Waste and Security

In the US, over 25% of the food is wasted, with an average American wasting about one pound of food per day. Meanwhile, 11.8% of the American households struggle to secure enough food. The ongoing COVID-19 pandemic is only making things worse. Even after the pandemic hits its peak, the struggle with basic food security will not subside quickly on our long way back to normal. Thus, now more than ever, there is an urgent call for action to address the food waste and security problem. My experience working with practitioners in this domain poses me in a unique position to address this problem with AI.

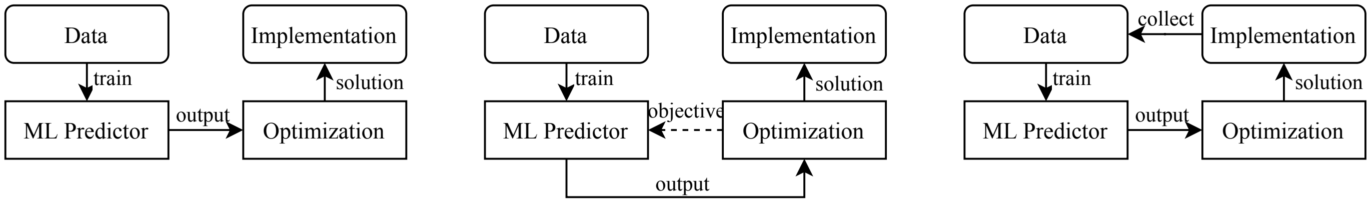
Food rescue organizations (FR) handle real-time or scheduled food donations and match them to recipient organizations that serve under-privileged communities. FRs rely on volunteers to transport the food. After the dispatcher matches a donation with a recipient, they will post this rescue trip on the FR's mobile app so that all volunteers can see it or receive notifications. They may also call some selected volunteers to ask for help. In the US alone, there are FRs operating in over 55 cities, affecting over 11 million people.

However, relying on volunteers to deliver the food comes with inherent uncertainty. What if no volunteer will claim the rescue? What if the volunteer somehow fails to deliver the food after they claimed it? These common uncertainties have serious consequences because they may lead to lost faith in the program from the donor and recipient organizations. It would greatly reduce the FR dispatchers' uncertainty if they have a better idea of when a rescue will be claimed, so that they can better prepare for interventions. Thus, with my collaborators and 412 Food Rescue in Pittsburgh, we developed a machine learning model, which predicts how likely any volunteer is going to claim a given rescue trip in, e.g., 1 hour. This knowledge helps the dispatchers decide on the intervention scheme – when to step in when no one has claimed a rescue and which volunteers should be notified via push notification at what time. In our IAAI-20 paper, we described this data-driven optimization framework to find the optimal intervention scheme (Shi et al. 2020c). 412 Food Rescue has adopted our recommended intervention scheme since January 2020.

FRs typically advertise the rescue trips through mobile app push notifications. It is thus crucial that they send notifications to volunteers who are likely to claim the rescue, but they also do not want to notify everyone all the time because the users would get annoyed and leave the platform. I am building an AI tool to recommend the most probable volunteers for a given rescue. This task is challenging in several ways. First, since each rescue only happens once, the problem stays in the "cold start" phase of a recommender system forever, rendering collaborative filtering-based methods inapplicable. I leverage a rich set of contextual features, an adaptive under-sampling technique, and neural architecture to improve the hit rate from 45% to 79%. Second, since donations arrive in a sequential fashion, FRs have to make decisions without knowing future rescues. I am developing an online algorithm to sequentially select the volunteers to notify while assuring that no volunteers get too many notifications and keeping the hit rate up. Our models and algorithms are slated for field test.

From the Real World to Research: Bandit Data-driven Optimization

More broadly, my research is focused on AI for social good (Shi, Wang, and Fang 2020). Having also worked on AI4SG projects in security, sustainability, and public health with non-profit partners (Shi et al. 2018, 2020a; Wang et al. 2019), I observed a common challenge across all these domains. Based on this observation, I proposed bandit data-



(a) Two-stage prediction-prescription (b) One-shot data-driven optimization (c) Bandit data-driven optimization

Figure 1: Paradigms of how machine learning systems are used in realistic settings.

driven optimization, a novel technical research topic which will be widely applicable across many AI4SG projects.

The success of modern machine learning largely lies in supervised learning. However, it often does not translate directly into a perfect solution to a real-world AI4SG problem. One reason is that supervised learning focuses on prediction, yet real-world problems, by and large, need prescription. For example, rather than predict which food rescue trip will likely be missed using donor and recipient information, dispatchers need to know when to call which volunteers to ask for help. The common practice is a two-stage procedure, as shown in Fig. 1a. After training a prediction model, the user makes decisions based on some optimization problem which takes the prediction output as parameters. The training objective and the optimization objective are completely detached. In the emerging topic of (one-shot) data-driven optimization, the learning problem incorporates the downstream optimization objective into its loss function (Fig. 1b).

However, this is still far from the full picture of many AI4SG applications. As shown in Fig. 1c, after getting data from the collaborator, we train a predictive model and, based on it, recommend an intervention. The workflow does not stop here, though. After the collaborator implements the intervention, they collect more data points. Using these additional data, we then update the predictive model and make a new intervention recommendation to be implemented, so on and so forth, resulting in an iterative process.

Why is such an iterative process necessary? First, often in AI4SG domains there may not be enough data to begin with. A small dataset leads to inaccurate predictions and hence suboptimal decisions. Second, too often the initial dataset has some default intervention embedded, while our goal is to find the optimal intervention. If the data distribution is different under different interventions, it is necessary to at least actively try out some interventions and collect data under them. Third, the communication gaps between researchers and domain practitioners make it difficult to formulate the correct objective at the beginning. Fourth, interventions may have unexpected consequences, further showing the inherent impossibility of fully modeling the problem in one shot.

In my recent work with Steven Wu, Rayid Ghani, and Fei Fang, we propose bandit data-driven optimization, the first iterative prediction-prescription framework (Shi et al. 2020b). It combines the relative advantages of online learning and offline predictive analytics. We achieve this with our algorithm PRedict-then-Optimize with Optimism in Face of uncertainty (PROOF). PROOF is a modular algorithm which can work with a variety of predictive models and optimization problems. Under specific settings, we formally prove that PROOF achieves no-regret. We also propose a variant of PROOF to handle the scenario where the intervention affects the data distribution, which also enjoys no-regret. Our numerical simulations show that PROOF achieves superior performance over a pure bandit baseline. This shows the promise of combining online learning and offline learning in a principled way. In my ongoing work, I am applying PROOF to several applied AI4SG projects including my food rescue ones mentioned earlier, thereby closing the loop from the real world to research and back to the real world. I expect to complete this by AAAI-21.

Anticipated Contributions

1. I have finished an extensive survey of the AI4SG research literature in the past decade (Shi, Wang, and Fang 2020).
2. I am working with two non-profits on food waste and security, one of the first applications of AI to food rescues. My work has reached the deployment stage.
3. I proposed bandit data-driven optimization, a research topic distilled from AI4SG applications across various domains. I will apply it back to my applied AI4SG projects.
4. I believe my work will be a meaningful contribution to AI4SG. My only hope is that, because of my work, at least someone's life gets a bit easier. This is my best reward.

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