Using counterfactual queries to improve models for decision-support

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Abstract

In this extended abstract, we generalize active learning to tasks where a human has to choose which action a to take for a target after observing its covariates $\tilde{x}$ and predicted outcomes $p(\tilde{y}|\tilde{x}, a)$. An example case is personalized medicine and the decision of which treatment to give to a patient. We show that standard active learning, which is not aware of the final task, would be very inefficient, and we introduce a new problem of decision-making-aware active learning. We formulate the problem as finding the query with the highest information gain for the specific decision-making task, assuming a rational decision-maker. The problem can be solved particularly efficiently assuming an expert able to answer queries about counterfactuals. We demonstrate the effectiveness of the proposed method in a binary outcome decision-making task using simulated data, and in a continuous-valued outcome task on the medical dataset IHDP with synthetic treatment outcomes. The outcomes are predicted using Gaussian processes.

1. Introduction

In this extended abstract we study active learning for tasks where causal models are used for decision support by providing predictions of outcomes under alternative actions. To fit such a model, we need data recording previous actions a, observed outcomes y, and any features relevant to the context of the decision x. When the data are collected *retrospectively* (i.e., the action policy in the training data is not under our control, and may even be unknown), then predicting the effects of interventions requires careful assumptions about the data generating process. In this work, we will assume that there are no unmeasured confounders. Even in this simplified setting, however, there is the issue of *imbalance* in the observed actions in the data. Imbalance arises when our training data contain certain contexts x where not all actions have been taken. Intuitively, this means that we have high *model uncertainty* for certain combinations of actions and contexts that may nevertheless be of interest to the decision-maker. This is illustrated in Figure 1.

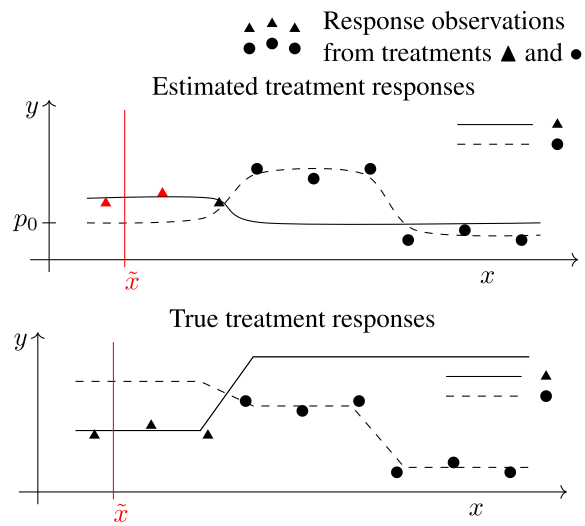

Figure 1. Sample decision-making task is to choose a treatment for a specific $\tilde{x}$ (red mark). Lower y is better. The problem is that there are no observations about one of the treatments close to $\tilde{x}$, which causes the treatment ● appear to be the best choice, although that may be incorrect as shown at the bottom. We propose counterfactual elicitation to acquire from an expert an observation on what would have been the outcome had one training sample received a different treatment. Expected information gain, a traditional active learning criterion, would acquire a sample that is maximally informative across the whole training set, hence in this case around the center of the figure. Decision-making aware active learning, proposed in this work, will know to ask about ● close to $\tilde{x}$ instead, at the red points.

Given that human experts are in the loop for the decision-making tasks, a natural question to ask is can their expertise be tapped on to help solve the imbalance issues. Assuming an expert is able to give (even noisy) answers we propose eliciting their knowledge with *counterfactual queries*, "what would have happened if." Choosing which questions to ask is an active learning question, to which standard active learning approaches would be very inefficient as they do not

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take the decision-making task into account, as demonstrated in Figure 1. For solving the problem a new active learning criterion needs to be formulated, and the elicited feedback needs to be incorporated to correct the predictions.

2. Active Learning from Counterfactuals for Decision-Making

We introduce a new active learning setup where the goal is to maximize the expected information gain for a specific decision-making task, here deciding on the action for $\tilde{x}$. When we assume that the user chooses the action with the highest expected utility, the expected information gain in querying the counterfactual outcome of an action a^* of a training data unit x^* is

$$\mathbf{E}_{p(y^*|x^*,a^*,\theta_k)}\left[u_{x^*,a^*}\right], \text{ where}$$
$$u_{x^*,a^*} = \mathrm{KL}\left[p\big(\tilde{y} \mid \tilde{x}, a_{k+1}, \theta_{k+1}\big) \,\Big\|\, p\big(\tilde{y} \mid \tilde{x}, a_k, \theta_k\big)\right]$$

and KL is the Kullback-Leibler divergence. The a_{k+1} denotes the action of decision-maker's choice after soliciting a counterfactual observation, a_k is the decision-makers choice in the current model (i.e. at iteration k), and similarly θ_k and θ_{k+1} are the model parameters at iteration k and $k+1$. What is new here is that we consider targeted information gain, for the target $\tilde{x}$, and taking the expectations not only over the uncertainty in the expert's answer y^*, but also with respect to the modelled decision of the decision-maker.

3. Experiments

We validate the performance of the proposed method experimentally in two problems, and compare the performance to two widely-used earlier active learning approaches, uncertainty sampling and maximum expected information gain (EIG) (Culotta & McCallum, 2005; Roy & McCallum, 2001). The first experimental problem is a simulated binary-outcome decision-making task in which the difficulty is due to high imbalance in the generated data. The results in table 1 show that the proposed active learning criterion Decision-IG, for information gain for decision-making, achieves a significant increase in correct decisions after just one query.

The second problem is deciding on medical interventions on real medical data with continuous-valued synthetic outcomes. We use the Infant Health and Development Program (IHDP) dataset from (Hill, 2011) (also used e.g. in (Alaa & van der Schaar, 2017)). To make the problem even more realistically hard, we reduce the training sample size to N=100 randomly chosen observations. We fit separate GPs to the outcomes of each treatment with GPy (version 1.9.2) (GPy, since 2012), and use mixed noise likelihood to learn the noise in the counterfactual feedbacks.

Table 1. Comparison of active learning criteria as a function of number of queries. The figures show the proportion of correct decisions in 100 repetitions, averaged over 9 targets. Soliciting even one outcome using active learning increases the number of correct decisions. Information-gain-based approaches are more effective than uncertainty sampling, and decision making-aware Decision-IG is the best.

Number of queries	Uncertainty sampling	EIG	Decision-IG
0	0.58	0.58	0.58
1	0.61	0.65	**0.72**
5	0.63	0.72	**0.79**
10	0.64	0.75	**0.81**

Decision-making performance improves clearly faster when the decision-making task is taken into account in active learning, compared to standard active learning approaches (Figure 2, Decision-IG vs EIG and uncertainty sampling).

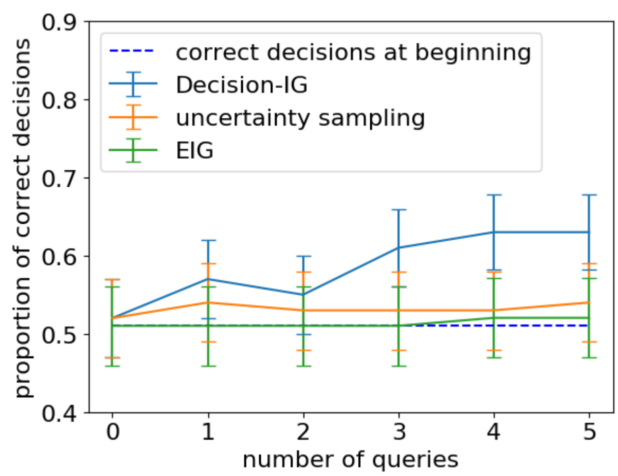

Figure 2. Proportion of correct decisions (higher is better) in IHDP data as a function of the number of counterfactual queries to the simulated, noisy expert, averaged over 100 decision-making tasks. Errorbars show the standard error of mean.

4. Discussion

The results of this work have important implications for the design of decision-support tools backed by machine learning systems. They suggest that the users of such systems may be an important source of on-demand causal knowledge that can be used to incrementally improve the tool and make it more reliable.

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