Abstract

Counterfactual interventions are a powerful tool to explain the decisions of a black-box decision process, and to enable algorithmic recourse. They are a sequence of actions that, if performed by a user, can overturn an unfavourable decision made by an automated decision system. However, most of the current methods provide interventions without considering the user’s preferences. For example, a user might prefer doing certain actions with respect to others. In this work, we present the first human-in-the-loop approach to perform algorithmic recourse by eliciting user preferences. We introduce a polynomial procedure to ask choice-set questions which maximize the Expected Utility of Selection (EUS), and use it to iteratively refine our cost estimates in a Bayesian setting. We integrate this preference elicitation strategy into a reinforcement learning agent coupled with Monte Carlo Tree Search for efficient exploration, so as to provide personalized interventions achieving algorithmic recourse. An experimental evaluation on synthetic and real-world datasets shows that a handful of queries allows to achieve a substantial reduction in the cost of interventions with respect to user-independent alternatives.

1 Introduction

Automated decision systems are becoming ubiquitous in our daily lives. Through machine learning technologies, we have been able to build systems to aid humans in performing many tasks: university admissions [1], rejecting or accepting a job applicant [2], prescribing medications or treatments [3]. Some of these tasks are also high-risk, such as bail approval [4] or granting a loan request [5]. However, these systems have several shortcomings that need to be addressed. First, users affected by these automated systems usually have no means to overturn a potentially bad decision. The decision systems do not provide explanations or recommendations to act on their decision. Second, many of the models employed are black-box, which means that even the designers of such systems cannot explain their reasoning process. These issues raise substantial concerns about the trustworthiness and fairness of these methods.

Being able to provide explanations or suggestions about how to overturn a given decision made by a machine learning model has even become a legal requirement [6] in certain countries. To address this, a number of approaches have recently been developed to reach algorithmic recourse
Figure 1: Overview of the complete procedure. (1) Given initial $s^{(0)}$ and $w^{(0)}$, we compute a set of candidate interventions (2) We generate a choice-set $O^{(t)}$ which will be presented to the user (3) The user chooses the best action (4) Given the user’s choice, we improve the weights $w^{(t+1)}$ and (5) we also update the user’s state $s^{(t+1)}$. After $q$ questions, we use the estimated weights to compute the final optimal intervention $I^∗$.

7 8 9 10 11 12 13 14, which is the ability to give “explanations and recommendations to individuals who are unfavourably treated by automated decision-making systems” 15. They all follow a general framework: they want to find a counterfactual intervention 16, which is a sequence of actions that, if applied by the user, can overturn the decision given by a machine learning model. Moreover, they want to provide the shortest sequence of actions which produces the least effort, or cost, upon the user. Finally, they aim to rely on causal relationships to determine the best interventions. Indeed, recent research has shown that it would be impossible to achieve recourse without considering a causal structure 17. However, most of these systems generate interventions by placing hard assumptions on the user. For example, the individual cost of the actions is defined a-priori, or even the causal graph is fixed. The generated interventions, while successful, do not take into consideration the potential preferences of the users (e.g., “I do not want to change job”) and tend to patronize them.

In this work, we propose the first human-in-the-loop method to generate counterfactual interventions specifically tailored to a given user. We show how it is possible to refine generic interventions to provide better recommendations through preference elicitation 18 under a Bayesian setting. We relax the initial assumptions in our setting by keeping the causal graph structure fixed while iteratively learning the user’s specific costs. At each algorithm iteration, we ask the user to choose the best action available from a choice set. The choice set is computed to maximize the Expected Utility of Selection (EUS). Given the user’s answers, we improve our estimate of the weights, which will enable us to generate interventions closer and closer to the optimal sequence for the user. We exploit a Reinforcement Learning technique coupled with Monte Carlo Tree Search (MCTS) for an efficient search to find the interventions given the user’s state. See Figure 1 for a high-level overview of our method.

The main contributions of the paper are the following:

- We provide the first human-in-the-loop method to generate personalized counterfactual interventions by casting the problem through the lens of preference elicitation.

- We provide a greedy procedure which builds an optimal choice-set, maximizing the Expected Utility of Selection (EUS) in polynomial time.

- We experimentally show how our interactive approach can generate substantially cheaper interventions than the user-independent counterpart with just a handful of queries.
2 Related work

Counterfactual interventions, (or explanations) [16, 19, 20, 21, 22, 23] are powerful tools to explain the decision of machine learning models. They are model-agnostic, local and human-friendly, thus suited to be given as an explanation to an affected user [24]. Several works propose different methods to obtain algorithmic recourse via counterfactual interventions [9]. They exploit various techniques: program synthesis [7, 10], integer programming [12], probabilistic models [13] or reinforcement learning [11, 7, 10]. Unfortunately, most of the presented works assume fixed costs which are not learned from data (7, 8, 10, 11 and many more). It is a very strong assumption that is rarely met in practice and can introduce bias in the proposed interventions. Our proposal is to learn these costs by interacting with the user during the intervention generation phase. Most existing counterfactual intervention generation approaches are ill-suited to incorporate an interactive elicitation stage, as they would need explicitly model costs as features in order to converge to a solution (for example 10, 11), substantially increasing the complexity of the search procedure and the computational budget needed to converge, especially in purely heuristic methods [8]. On the other hand, neuro-symbolic approaches, such as [7], can be adapted to generate personalized interventions even if trained in a user-agnostic way, by integrating the search procedure with a preference elicitation strategy and using the neural output as a prior to drive the explorations. We follow this strategy in designing our personalized counterfactual intervention generation method.

Reasoning with preferences and their elicitation are important topics in AI. Modern approaches to preference elicitation adopt some forms of measure of uncertainty on preferences in order to ask informative queries (questions to the user) with the goal of converging to near-optimal recommendations with just a few answers to queries. While an important line of research in preference elicitation deals with minimax regret [25, 26, 27, 28], Bayesian methods [29, 30, 18] have the advantage of modeling imprecision in users answers. Choice queries, prompting the user to select a preferred item among a set, are often used in elicitation; informative choice queries can be selected using some informative measure [31, 28]. Research works dealing with uncertain preferences and preference elicitation include works dealing with decisions under risk [26], sequential decision problems [32], non linear aggregation functions [27], social choice problems [33], constructive domains [34, 35], recommendations in large datasets with deep learning architecture [36].

3 Problem Setting

A user state \( s \in S \) is defined as a vector of \( d \) features. A feature \( s_i \) can be categorical or real-valued. Given a user state \( s \), an action \( a \in A \) changes a single feature \( s_i \) to a new value \( s'_i \). Let us also define a cost function \( C : A \times S \rightarrow \mathbb{R}^+ \). The cost function models the effort required by a user to change a feature given a user state. As features are causally related to each other, the cost of changing a feature also depends on the value of a subset of other features.

The cost function \( C \) is defined in terms of a linear structural causal model (SCM) [37]. An SCM is a directed graph \( G = (V, E) \) which represents causal relationships as edges between nodes. In our setting, each node represents the cost of changing a single user feature \( s_i \). We denote the nodes as \( C_i \). A directed edge \( e \in E \) represents a causal relationship between two nodes \( (C_i, C_j) \). Each edge \( e \) has associated a weight \( w_{ij} \in \mathbb{R} \). Moreover, each node has its internal weight \( w_i \). We represent the full weights of the linear SCM as a vector \( w \in \mathbb{R}^m \), where \( m = |E| + |V| \). The SCM is linear, which means that the cost of changing a feature \( s_i \) is assumed to be a linear combination of other costs. We denote with \( C(a, s|w) \) the cost of changing a given feature \( s_i \in s \) to its value \( s'_i \) by applying action \( a \in A \), given the weights \( w \). More formally:

\[
C(a, s|w) = w_i(s'_i - s_i) + \sum_{j \in Pa_i} w_{ji}s_j
\]

where \( s_i \) and \( s'_i \) are respectively the old and new value of the feature modified by \( a \), and \( Pa_i \) are the parents of the \( s_i \) node. See Figure 2 for an example of SCM and associated cost functions.

An intervention \( I \) is a sequence of actions \( \{a_0, \ldots, a_T\} \). Let us define the intervention cost, \( C(I|w) \) as:

\[
C(I|w) = \sum_{t=0}^{T} C(a^{(t)}, s^{(t)}|w).
\]
**Figure 2:** A Linear Structural Causal Model for cost modelling. Given a user state, $s = [s_1, s_2, s_3]$, the cost of changing a feature (e.g., $C_3$) depends on its parents in the graph. The weight vector $w$ models the user preferences. Red weights refer to the node components, while the blue weights refer to the edge components.

where $s^{(t)}$ is the state obtained by applying action $a^{(t-1)}$ to state $s^{(t-1)}$, and $s^{(0)} = s$ is the initial state of the user. We denote with $I(s^{(0)})$ the operation of applying each action $a \in I$ sequentially. Given a user profile $s$ with the corresponding weightings $w$, we are interested in finding the optimal intervention sequence $I^*$, which minimizes the intervention cost for the user and enables algorithmic recourse. More formally, given a black-box binary classifier $h : S \rightarrow \{0, 1\}$ we want to find an intervention $I^*$ such that:

$$I^* = \arg\min_I C(I|w) \quad \text{s.t.} \quad h(I^*(s^{(0)})) \neq h(s^{(0)})$$

4 Background

We employ a strategy similar to De Toni et al. (2022) to achieve recourse, which uses a combination of reinforcement learning (RL) coupled with Monte Carlo Tree Search (MCTS). This strategy exploits RL to learn a generalized policy that can be applied to multiple users to provide interventions. The approach is highly scalable, and it was shown to learn successful policies to obtain recourse by reducing the training budget and the number of queries made to the black-box classifier with respect to competitors.

Following [7] we define an action $a \in A$ as a tuple $(f, x)$. $f$ represents a function, while $x$ represents the argument of such function, such as $(\text{change\_income}, \$1000)$. Each action $a$ has an associated precondition which tells us when the action can be called given the state $s$. Given the user state $s$, the RL agent produces two policies $\pi_f(s)$ and $\pi_x(s)$, over the potential functions and arguments spaces. The two policies are used as a prior to drive the MCTS search procedure when choosing the next action $a^{(t+1)}$. During training, we use MCTS to find successful interventions, and we train the two policies such to imitate the found interventions. Then, during inference, the RL agent and the MCTS work together to generate the intervention, which achieves recourse and minimizes the cost for the user.

In the original setting, the RL agent is trained by assuming a fixed causal graph and fixed weights shared by all the users. The following shows how to adapt this strategy to deal with unknown user-specific costs by integrating it with a preference elicitation procedure. We notice that MCTS improves the ability of the RL agent to generalize with different $w$. While the agents’ policy is transparent to the user’s weights, the MCTS search procedure can take them into account.

5 Personalized Counterfactual Intervention Generation

We now describe in detail each step of the procedure to build personalized interventions. First, we formalize the notion of expected cost given the user’s weights $w$. Second, we show how to formalize user feedback elicitation in terms of choice set queries. Last, we integrate the resulting preference elicitation strategy into the counterfactual intervention generation process.
5.1 Expected Intervention Costs

While we can fully know the user state $s \in S$, we are not usually also able to know the associated weights $w$, nor it is possible to infer them directly from the state. For example, users with the same initial state $s \in S$ might favour different actions.

We model our uncertainty on the costs of the user in terms of a probability distribution $P(w)$ over the weights in the SCM (see Figure 2). Initially, this distribution is set to a multivariate standard normal $N(0, I)$. In our interactive algorithmic recourse setting, this estimate is progressively refined by interacting with the user, collecting the resulting feedback into a dataset $D^{(t)}$ and computing the posterior of the weights given the feedback, $P(w|D^{(t)})$. In this setting, the cost of an action is replaced with an expected action cost, $E[C(a^{(t)}, s^{(t)})|D^{(t)}]$, computed by marginalizing over all the possible weightings $w \in \mathbb{R}^m$:

$$E[C(a^{(t)}, s^{(t)})|D^{(t)}] = \int_w C(a^{(t)}, s^{(t)}|w)P(w|D^{(t)}) \, dw$$

(4)

Analogously, the cost of an intervention $I$ is replaced by its expected intervention cost:

$$E[C(I)|D^{(t)}] = \sum_{t=0}^T E[C(a^{(t)}, s^{(t)})|D^{(t)}]$$

(5)

The integral defined by Equation 4 cannot be easily computed analytically because of the difficulty of finding a closed-form for $P(w|D^{(t)})$. We will resort to Monte Carlo sampling to obtain an approximate estimation of the integral. In the next sections, we will outline how to build the dataset $D^{(t)}$ and how the preference elicitation process is carried out.

5.2 Eliciting user preferences

In order to incorporate user preferences, we need to define the notion of partial and candidate interventions. These constructs will be useful when querying the user for feedback.

Definition 5.1 (Partial Intervention). A partial intervention $I^{(t)}$ is a sequence of actions $\{a_0, \ldots, a_t\}$, where $a_t \in A$, that does not achieve recourse yet. Given an initial user state $s^{(0)}$, we have $h(s^{(0)}) = h(I^{(t)}(s^{(0)})).

Definition 5.2 (Candidate Intervention). A candidate intervention $\hat{I}_{a}$ is a sequence of actions, $\{a_0, \ldots, a_t, a, a_{t+2}, \ldots, a_T\}$, that is built starting from a partial intervention $I^{(t)}$, which requires to perform action $a \in A$ at time $t + 1$, and (eventually) enables recourse for a given user state $s^{(0)}$.

Given a user state $s^{(0)}$, we need to rely on our inaccurate estimate of $P(w|D^{(t)})$ to compute the optimal intervention $I^*$. We want to improve our initial estimate, $P(w|D^{(t)})$, by incrementally building upon a partial intervention by asking to the user to pick the preferred next action from a choice set. This set contains a collection of candidate interventions. We will give more details about how to generate candidate interventions from partial interventions in the next sections. We iterate this procedure for each time step until we either reach the maximum number of questions or an early stopping criterion based on the expected loss, which will be defined in detail in the next section.

Definition 5.3 (Choice set). A choice set $O^{(t)}$ for a given partial intervention $I^{(t)}$ is a collection of $k$ tuples, $(a, \hat{I}_{a})$, which are made by an action $a \in A$ and a candidate intervention $\hat{I}_{a}$, built from $I^{(t)}$. A choice set only contains actions which we are sure will lead to recourse.

Given a partial intervention $I^{(t)}$, we build at each time step the corresponding choice set $O^{(t)}$, and we ask the user to pick the preferred action $a$. The associated candidate intervention is not shown to the user since it might bias the selection. However, the user is aware of the partial intervention up to that point. Then, we concatenate $I^{(t)}$ with the user’s choice $a$ to obtain $I^{(t+1)} = I^{(t)} \circ a$, and we repeat until we obtain recourse or we reach the maximum number of questions available.

In our setting, the dataset $D^{(t)}$ becomes the set of choices, candidate interventions and associated choice sets $\{(a, \hat{I}_{a}, O)^{(0)}, \ldots, (a, \hat{I}_{a}, O)^{(t)}\}$ made by the user up to timestep $t$. Therefore, $p(w|D^{(t)})$
measures the probability that the user’s SCM has the weights \( \mathbf{w} \), based on the provided answers. The peculiarity of this setting is that the data is ordinal information about which item is preferred within each set.

### 5.2.1 Generating the choice set

Given our estimate \( P(\mathbf{w}|D^{(t)}) \), we need to show to the user the best choice set available, which maximizes the information gain. Presenting the user with a poorly chosen choice set could slow down the estimation process or make it fail.

Following the preference elicitation setting \([18]\), we define the expected utility of a candidate intervention \( \hat{I}_a \) under a belief \( P(\mathbf{w}|D^{(t)}) \) as the negation of its expected cost:

\[
\text{EU}(\hat{I}_a|s^{(t)}, D^{(t)}) = -\mathbb{E}[C(\hat{I}_a)|D^{(t)}] = -\int \mathbf{w} C(\hat{I}_a|\mathbf{w}) P(\mathbf{w}|D^{(t)}) \, d\mathbf{w}
\]  

For each time step \( t \), we have to provide to the user the optimal choice set \( O^* \) that has the highest value of information \([29]\). For choice set, the maximally informative query is the one that maximizes expected utility of a selection \((\text{EUS})\) \([31]\). Intuitively, we should choose a choice set that maximises the user’s expected utility, which means minimizing the overall expected cost of the successful interventions. However, we cannot assume the user will always choose the best action. Therefore, we model the user’s choice with a noise model \( R \). We define \( P_R(O^{(t)} \sim a|\mathbf{w}) \) as the probability of choosing \( a \) from \( O^{(t)} \) under the user response model \( R \) and weighting \( \mathbf{w} \). In our case, we choose the logistic response model \((L)\) which is commonly used in choice modelling \([38]\):

\[
P_L(O^{(t)} \sim a|\mathbf{w}) = \frac{\exp(-\lambda C(\hat{I}_a|\mathbf{w}))}{\sum_{\hat{I}_a \in O^{(t)}} \exp(-\lambda C(\hat{I}_a|\mathbf{w}))}
\]  

where \( \lambda \in \mathbb{R} \) is a temperature parameter. Intuitively, under the logistic response model, two actions producing interventions with similar costs will have a similar probability to be chosen by the user. Lastly, we can define the EUS over a choice set \( O^{(t)} \) as:

\[
\text{EUS}_L(O^{(t)}|s^{(t)}, D^{(t)}) = \sum_{a, \hat{I}_a \in O^{(t)}} P_L(O^{(t)} \sim a) \text{EU}(\hat{I}_a|s^{(t)}, D^{(t)})
\]

\[
= -\int \mathbf{w} \left[ \sum_{a, \hat{I}_a \in O^{(t)}} P_L(O^{(t)} \sim a|\mathbf{w}) C(\hat{I}_a|\mathbf{w}) \right] P(\mathbf{w}|D^{(t)}) \, d\mathbf{w}
\]  

Generally, the naive maximization of the \( \text{EUS} \) is computationally intensive and intractable in practice. It is possible to prove that the task is \( \text{NP-hard} \) \([39, 40]\). However, under quite broad response models \( R \), the \( \text{EUS} \) function defined by Equation\([38]\) is \( \text{submodular} \) \([40]\), and there exists a procedure that can determine an approximation of the optimal set \( O^* \) with proven accuracy bounds. We have a greedy polynomial algorithm that achieves \( \text{EUS}_R(O^*|s, D) \geq (1 - e^{-1}) \text{EUS}_R(O^*|s, D) \), where \( O^* \) is the optimal choice set \([18, 39, 40]\).

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**Algorithm 1** Greedy choice set computation.

1. **procedure** SUBMOD-CHOICE(s, k, A, D, I, w)
2. \( O \leftarrow \emptyset \)
3. **while** \( |O| < k \) **do**
   4. Compute the feasible actions \( \mathcal{F} \subseteq A \) given \( s \).
   5. Generate the candidate interventions \( \mathcal{I} = \{(a, \hat{I}_a) : a \in \mathcal{F}\} \) given \( s \) and \( w \).
   6. Given \( \Delta \text{EUS} = \text{EUS}_{NL}(O \cup (a, \hat{I}_a)|s, D) - \text{EUS}_{NL}(O|s, D) \)
   7. \((a, \hat{I}_a) \leftarrow \text{argmax}_{(a, \hat{I}_a) \in 2^A \times \mathcal{I}} \Delta \text{EUS} \)
   8. \( O \leftarrow O \cup (a, \hat{I}_a) \)
9. **end while**
10: **return** \( O \)
11: **end procedure**
Algorithm 2 Generate personalized interventions given the user’s feedback.

1: procedure INTERVENE(s(0), q, k, h, A)
2: \( w \sim \mathcal{N}(0, I) \)
3: Initialize \( t \leftarrow 0 \), \( I(0) \leftarrow \emptyset \), \( D(0) \leftarrow \emptyset \)
4: for \( t \leq q \land h(I(t)(s(0))) = h(s(0)) \) do
5: \( O(t) \leftarrow \text{SUBMOD-CHOICE}(s(t), k, A, D(t), I(t), w) \)
6: Compute the average loss \( R \) over \( O(t) \)
7: if \( R \approx 0 \) then
8: Stop asking questions and break
9: end if
10: Ask the user to pick the best intervention \((a, \hat{I}_a) \in O(t)\)
11: \( D(t+1) \leftarrow (a, \hat{I}_a, O(t)) \cup D(t) \)
12: \( I(t+1) = I(t) \circ a \)
13: \( s(t+1) = I(t)(s(t)) \)
14: Update weight estimate \( p(w | D(t+1)) \)
15: \( t \leftarrow t + 1 \)
16: end for
17: Given the expected mean \( \mathbb{E}_{p(w | D(t))}[w] \), compute the final intervention \( I^* \) with RL+MCTS.
18: return \( I^* \)
19: end procedure

Unfortunately, the EUS
\( _L \) under the logistic model is not submodular. However, it is possible to prove that we can compute EUS greedily by using the noiseless response model (NL) as a proxy \[18\] with worst-case guarantees; that is EUS
\( _L \) − EUS
\( _{NL} \) is always smaller than a problem independent bound. The noiseless response model is such that\[1\]

\[
P_{NL}(O(t) \rightarrow a) = \prod_{a', \hat{I}_{a'} \in O(t)} \mathbb{I}[C(\hat{I}_{a'})|w] < C(\hat{I}_a|w)]
\]

which in turn produces a new EUS formulation:

\[
\text{EUS}_{NL}(O(t)|s(t), D(t)) = - \int_{w} \min_{a, \hat{I}_a \in O(t)} \{C(\hat{I}_a|w)\} P(w | D(t)) \, dw
\]

In practice, following the submodularity property, we can build a choice set \( O(t+1) \) by iteratively adding the tuple \((a, \hat{I}_a) \in 2^A \times \hat{I}_{O(t)} \) that maximally increases the EUS:

\[
(a, \hat{I}_a) = \arg \max_{(a, \hat{I}_a) \in 2^A \times \hat{I}_{O(t)}} \text{EUS}_{NL}(O(t) \cup (a, \hat{I}_a)|s(t), D(t)) - \text{EUS}_{NL}(O(t)|s(t), D(t))
\]

The procedure is repeated until we reach \(|O(t+1)| = k\), where \( k \) is the maximum size of the choice set. Algorithm\[1\] shows the pseudocode of the SUBMOD-CHOICE procedure that generates a choice set greedily. We consider only feasible actions \( F \subseteq A \) for building the set. Given a state \( s(t) \), an action \( a \in A \) is feasible if it has its precondition satisfied (see Section 4).

5.3 Generating the personalized interventions

Algorithm\[2\] shows the complete procedure to refine the interventions given the user’s feedback. The procedure takes as arguments: \( s(0) \), the initial state of the user, \( q \), how many questions we will ask, \( k \), the size of the choice sets, and \( A \), the available actions.

Building \( O(t) \) greedily requires to compute the candidate interventions for each action \( a \in A \) given the partial intervention \( I(t) \). In order to do so, we employ a pre-trained RL agent, coupled with the Monte Carlo Tree Search (MCTS) procedure, to efficiently explore the search space based on our

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\[1\] For sake of presentation, we assume that there are no ties. Note that the EUS formula is invariant to the way ties are broken. In our implementation, ties are broken uniformly at random.
Figure 3: Evaluation results on the synthetic (a) and german (b) datasets for an increasing number of queries to the user. The "T" value indicates the results when using the ground-truth weights. From left to right: accuracy (fraction of successful interventions), intervention cost and intervention length. Results are averaged over all users, and the error bars indicate the standard deviation.

current estimate $p(w|D^{(t)})$. The agent itself was trained assuming fixed costs. However, the MCTS procedure ensures it has the flexibility to adapt to the new costs while we are estimating them.

In order to estimate the weights, we should compute the Bayesian update $P(w|D^{(t)}) \propto P(D^{(t)}|w)P(w)$. However, computing analytically the likelihood is problematic, since $D^{(t)}$ is a set of preferences. Therefore, we use Monte Carlo methods to sample from the posterior. We employ ensemble split sampling [41, 42] and then we average over all the particles to get an estimate of $w$ after each iteration.

The procedure ends when $I^{(t)}$ achieves recourse or we finish the query budget $q$. As an additional stopping criterion, we measure the expected loss of each choice set. The expected loss of a candidate intervention $R((a, \hat{I}_a)|w)$ is defined as the loss in utility we will occur by choosing the tuple $(a, \hat{I}_a)$ instead of the optimal choice [29]. Thus, we have $R((a, \hat{I}_a)|w) = C(\hat{I}_a|w) - \min_{(a',\hat{I}_{a'}) \in O} C(\hat{I}_{a'}|w)$. It captures the diversity of the choice set. If the average expected loss is low, or close to zero, for many iterations, it means that each action in the choice set has the same utility for the user, and we cannot learn much from it.

As the last step, when the elicitation stage is finished, we re-run the RL agent and the MCTS procedure to compute the final intervention to be recommended to the user.

6 Experiments

We evaluated our approach on two dataset taken from the relevant literature, one synthetic and one real-world: synthetic, [7] and german credit [43]. We sampled 100 and 34 instances with an unfavourable classification, respectively. The german dataset is very small, so we ended up with few examples. The datasets have both categorical and numerical features. They also come with fixed costs and a fixed causal graph each. We kept the corresponding causal graphs, but we randomly generated
We want to underline that these results are obtained thanks to the estimation of the weights. In general, which achieve recourse. In practice, we estimate only a subset of the weights \( \tilde{w} \). The choice set \( \mathcal{D} \) contains candidate interventions with sequences of (previous) actions that have been generate from inaccurate weight estimates \( P(w|\mathcal{D}) \), making the interventions suboptimal. Therefore, at the end of the preference elicitation stage, we have to recompute the interventions using the now better estimated \( P(w|\mathcal{D}) \).

### 7 Conclusions

In this work, we have shown the first, to the best of our knowledge, human-in-the-loop approach for generating personalized counterfactual interventions for algorithmic recourse through preference elicitation. We developed a framework to iteratively estimate uses costs in a Bayesian setting by asking targeted questions from a choice set. We also provided a polynomial procedure to build greedily choice sets which maximize the Expected Utility of Selection (EUS), and integrated the resulting preference elicitation strategy in a counterfactual intervention generation approach leveraging RL and MCTS. Our experimental evaluation showed how we can achieve a sensible reduction in the intervention costs by asking a handful of questions to the user. Interestingly, we can obtain these results by employing a model trained in a cost-agnostic way.

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The code will be released at a later date.
As for all methods dealing with algorithmic recourse, the effectiveness of the approach should in principle be evaluated on real users. However, this evaluation is highly non-trivial (and thus still missing in the algorithmic recourse literature) because it requires to create a realistic scenario where a user feels to be unfairly treated in some machine-driven decision involving her life. The legal requirements that are progressively being introduced to regulate AI systems could contribute to make the information needed to setup such a scenario available in the near future.

In principle, we develop these methods to increase the fairness of the current machine learning systems. However, we need to consider the potential bad ethical ramifications of these technologies. Eliciting users’ preferences might entail asking sensitive questions, or malicious entities could exploit these procedures to "hack" and twist the intervention generation. These considerations can be mitigated by research on adversarial attacks to ensure the method’s robustness. Moreover, legal advice might be needed to manage personal user data and to ensure the safety of the user’s preferences during the procedure.

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