Moral reinforcement learning using actual causation

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Abstract—Reinforcement learning systems will to a greater and greater extent make decisions that significantly impact the well-being of humans, and it is therefore essential that these systems make decisions that conform to our expectations of morally good behavior. The morally good is often defined in causal terms, as in whether one's actions have in fact caused a particular outcome, and whether the outcome could have been anticipated. We propose an online reinforcement learning method that learns a policy under the constraint that the agent should not be the cause of harm. This is accomplished by defining cause using the theory of actual causation and assigning blame to the agent when its actions are the actual cause of an undesirable outcome. We conduct experiments on a toy ethical dilemma in which a natural choice of reward function leads to clearly undesirable behavior, but our method learns a policy that avoids being the cause of harmful behavior, demonstrating the soundness of our approach. Allowing an agent to learn while observing causal moral distinctions such as blame, opens the possibility to learning policies that better conform to our moral judgments.

Index Terms—Causality, Reinforcement learning, Actual Causation, Ethical reinforcement learning

I. INTRODUCTION

Reinforcement learning deals with a problem where in time step \( t \) the Agent observes a state, selects an action using a policy, and obtains a reward \( r_{t+1} \) before transitioning to the next state. Current formulations of reinforcement learning determine the optimal policy as the one which maximizes the accumulated reward \( \sum_{t=0}^{T-1} r_{t+1} \).

It has been argued that reward maximization is enough to acquire behavior that mimics all known facets of natural intelligence, including motor, perception, social behavior and general intelligence [2]. However, describing morally good behavior in terms of reward maximization is an extreme form of utilitarianism, which is known to lead to paradoxical behavior [3], [4].

Instead, what is morally (and often legally [5]) permissible is commonly described in causal language: was the agent’s action a sufficient cause? Could the outcome be anticipated as a consequence of the agent’s action? [6], [7]. Furthermore, cognitive science indicates that causality plays a crucial role in attribution of blame [8]. We hypothesize that in order to lead to morally acceptable behavior, the reward function of a reinforcement learning agent should be informed by these causal distinctions.

Recent work on actual causality (see section II-A) shows exciting promise on this front, by providing operational meanings to morally significant terms such as cause, intent and blame, albeit in a non-temporal process, where the outcome of all relevant variables is known at once [9], [10].

In this paper, we propose a way to apply definitions of cause, found in actual causality, to the reinforcement learning setting, thereby letting the agent learn a policy which is informed by morally significant causal distinctions [1].

We accomplish this by letting the states in reinforcement learning affect the exogenous variables in a relevant causal model and, based on the notion of actual cause derived from the model, issue a modified terminal reward signal to the agent: the relevant notion of cause is therefore described in the diagram, while the agent learns how and whether its policy affects the state of the causal model.

The principle we want the agent to follow is that one is to blame for outcomes of events one causes, but not to blame for events one did not cause. Although by no means do we suggest that this provides a sufficient account of morality, it does touch upon key distinctions found in moral philosophy, such as cause and blame [7], [11].

Philosophers and experimental psychologists commonly illustrate, test and challenge our moral intuition using vignettes such as the trolley problem [3], [12], and we will similarly illustrate and test our method using a vignette (camping in a dry forest, fig. (a)), which is inspired by [9], [13].

\[ \text{Code to reproduce the results of this paper can be found at } \]
\[ \text{https://gitlab.compute.dtu.dk/tuhe/moral_agent/}. \]
Albert is camping and wants to start a fire. Albert can set up camp at either a safe or unsafe location. The unsafe location is easier to get to, but it will also cause the forest to burn down. A pyromaniac is on the loose, and will always burn down the forest.

(Camping in a dry forest)

The vignette illustrates a problem of simple consequentialism, namely that although the consequence of Albert’s two options (camping safely and unsafely) is the same (the forest will burn down), Albert’s decision to camp at an unsafe location still deserves blame: what matters in the example is whether Albert caused the forest to burn [13].

The above vignette can be considered a reinforcement learning problem with the same conclusion (see fig. 1 (b)), where the environment is described using states $s_t$ (the state could contain the agent’s state, the pyromaniac’s actions, and so on), and actions $a_t$. We assume a natural reward structure in which the agent obtains a reward $r = 10$ for camping at the safe camping spot, $r = 20$ for unsafe camping spot (camping unsafely is less strenuous) and finally, a reward of $r = -100$ for the bad outcome of the forest burning down. In this scenario, the pyromaniac eventually burns down the forest, and therefore the possible accumulated reward the agent will obtain is either $-100$ (no camping), $r = -90$ (safe camping) and $r = -80$ (unsafe camping). An agent which maximizes the reward will therefore learn to always camp unsafely.

The point of the example is not to argue that the behavior cannot be avoided by suitable manipulations of the reward signal (indeed, this is exactly what our approach does). Rather, we suggest that this modification of the reward signal should be grounded in causal analysis, using a relevant causal diagram (fig. 2) and an objective definition of cause [9]. The agent must then learn which causal variables in the diagram it can manipulate and therefore may be blamed for (see section II-D), and this will form the basis for the modified reward signal. When a variable is cause for a bad outcome, the agent obtains a negative reward, but otherwise it does not obtain a negative reward, since it is not to blame. For this reason, we have dubbed the method morally aware reinforcement learning.

The contributions of this paper are therefore threefold:

- We use an example to illustrate how reward maximization can lead to morally impermissible behavior in a concrete reinforcement learning problem.
- We propose a general variant of Q-learning which uses causal information to modify the reward signal so as to avoid blameworthy actions.
- We use experiments to demonstrate how this method can avoid morally impermissible behavior.

A. Related work

The problem of assigning blame in a sequential, team-plan setting was considered in [14], where structural equations and actual causality were used to assign blame to each agent for its contribution to the overall outcome. However, this work differs from ours in that it does not consider learning, and is concerned with the combined actions of a team.

Several other references consider a combination of reinforcement learning and ethics/morality in which ethics is introduced as a weighting factor in the reward function. For instance, [15] consider how different weighting procedures allow moral theories (functions) to vote for particular behaviors, but otherwise leave the specification up to a designer. Other approaches specify these functions through learning from (external) demonstrations [16] or from queries to an idealized (hidden) ethical utility function [17], or supervised using text-based data [18] in a text-based game. Although the objective is similar to ours, the above work differs in that the ethical theories are externally specified to the agent, whereas our procedure has a built-in notion of blame, which it combines with a learning procedure of which variables may be influenced.

In [19], actual causation is used as a way to explain human judgments about intention (but with a different definition of intent than [10]) in problems with a fixed number of states and decisions. This approach differs from ours in that the goal is to explain judgments, and not to learn a policy which conforms to limitations imposed by the definitions of intent.

II. Methods

Causation can be understood in two ways: as general statistical causality (i.e., does smoking cause cancer?) or as actual causality which focuses on specific events (did Bob’s smoking cause his lung-cancer?) [9], [20]. Clearly, the latter form of causality is the more relevant one when it comes to moral dilemmas, since these should always be decided with a specific situation in mind [19].

Both types of causality are mathematically expressed using variations of structural causal models (SCMs) [21], and we will briefly review the main definitions below as they relate to the Camping example.

A. Actual causation

Our discussion of actual causation and SCMs will closely follow [9]. Actual causation assumes that there exists a rel-
event model of the world described in terms of variables, their values and how they influence each other. Variables are classified as either exogenous variables, whose values are determined by factors outside the causal model itself, or endogenous variables, whose values are determined by the exogenous variables. Specifically, a structural causal model $M$ is a tuple $(S, F)$. $F$ is a set of structural equations, which denote a deterministic relationship between the variables, and $S$ is the signature consisting of the triplet $(U, V, R)$, where $U, V$ are the exogenous/endogenous variables respectively, and for any variable $X \in U \cup V$ then $R(X)$ is the range of values the $Y$ can take.

In the case of the camping example, the endogenous variables are discrete variables such as Fire $F$, easy to set up campfire $A$, and including the no-camping option $C$ set up campfire. In the scenario, unsafe camping (no campfire), is a formula of the form $X = x$. That is, $F_X$ determines the value of $X$, given the other variables in $U \cup V$.

We limit ourselves to acyclic models and the model is commonly drawn as a directed graph, where $U \cup V$ are the vertices and there is a directed arrow from $Y$ to $X$, provided that $F_X$ has $Y$ as an input argument.

An assignment of value to all exogenous variables $U$ is called a context and is denoted $\vec{u}$ (in our case simply $\vec{u} = (u^A, u^F)$), and the context will uniquely define the value of all endogenous variables.

### B. Interventions and causation

Given a causal model, the effect of external interventions is defined as follows: suppose we set a variable $X \in V$ to $x$, the result is a new causal model, denoted $M_{X \leftarrow x}$, which is identical to $M$, except the equation $F_X$ is replaced by the constant $F_X = x$. We can generalize this idea to define effects of interventions as follows:

In a causal model $M = (S, F)$ with signature $S = (U, V, R)$, a primitive event is a formula of the form $X = x$ for $X \in V$ and $x \in R(X)$. A causal formula is of the form $[Y_1 \leftarrow y_1, \ldots, Y_k \leftarrow y_k] \varphi$, where

- $\varphi$ is a Boolean combination of primitive events
- $Y_1, \ldots, Y_k$ are distinct variables in $V$
- $y_i \in R(Y_i)$ is a legal value of $Y_i$.

The intuitive meaning of a causal formula is that $\varphi$ would hold (be true) if $Y_i$ was assigned to $y_i$ for all $i = 1, \ldots, k$. A causal formula is abbreviated as $[Y = y] \varphi$ and the special case $k = 0$ as just $\varphi$. Whether a causal formula $\varphi$ is true or false in a causal model depends on the context. We write $(M, \vec{u}) \models \varphi$ provided that $(M_{\vec{u}}) \models \varphi$. Where $\varphi$ is any Boolean combination of primitive events. Given these definitions, cause can be defined as follows:

**Definition 2.1:** $\vec{x} \equiv \vec{y}$ is an actual cause of $\varphi$ in $(M, \vec{u})$ provided that

- $(AC1)$ $(M, \vec{u}) \models [\vec{x} \equiv \vec{y}]$ and $(M, \vec{u}) \models \varphi$
- $(AC2a)$ There is a partition of the endogenous variables $V$ into two disjoint subsets $W$ and $\vec{Z}$ such that $\vec{X} \subset \vec{Z}$ and $\vec{Z}$ and $\vec{x}' = \vec{w}'$ of $\vec{X}$ and $\vec{W}$ such that $(M, \vec{u}) \models [\vec{x} \equiv \vec{x}', \vec{W} \leftarrow \vec{w}'] \models \varphi$.

AC2b) If $\vec{z}$ is such that $(M, \vec{u}) \models \vec{Z} = \vec{z}$, then for all subsets $Z'$ of $\vec{Z}$

- $(M, \vec{u}) \models [\vec{x} \equiv \vec{z}, \vec{W} \leftarrow \vec{w}, \vec{Z}' - \vec{z}'] \varphi$.

AC3) No subset of variables in $\vec{X}$ satisfy condition AC1 and AC2.

This definition is quite technical, and it is best understood through examples. Here, we will limit ourselves to the campfire example. Suppose we want to say unsafe camping $\vec{x} \equiv \vec{y}$ is a cause of fire $\varphi = F = 1$, even when the pyromaniac is on the loose $P = 1$. AC3 says our cause should be minimal (trivially true since it is a singleton), and AC1 says that both $A = 2$ and $F = 1$ had to occur for $A = 2$ to be considered a cause of $F = 1$.

It is AC2 which does the hard work. For $\vec{x} \equiv \vec{y}$ to be a cause, we want to say that if $\vec{y}$ had not occurred, then the effect ($\varphi = F = 1$) would not occur either (a basic but-for condition).

Since $P = 1$ only ensures $F = 1$, the definition must introduce a contingency $\vec{W} = \vec{w}$ under which $F \neq 1$; In our example, $\vec{W} = \{P\} = \{0\}$ will satisfy AC2a.

Since this loosens the condition for something to be a cause, AC2b is required to rule out certain counterexamples, however in our example $\vec{Z} = \{C, F, A\}$ is irrelevant since $\vec{X} = A = 2$ alone is sufficient to ensure $F = 1$. As we can see, in the scenario, unsafe camping $A = 2$ (and by symmetry, the pyromaniac setting the forest alight, $P = 1$) is considered a cause of fire $F = 1$, even though if any one of them did not occur, the forest would still burn.

It should be mentioned that other definitions of cause are possible (see e.g. [22]), however, the practical differences are minute, and the following discussion applies equally to such modifications of theorem 2.1.
C. Overview of our approach

We will consider a standard episodic reinforcement learning setup where the environment evolves between states $s_t$ over time steps $t = 0, \ldots, T$. The agent takes action $a_t$ and, upon transition to state $s_{t+1}$, obtains a reward $r_{t+1}$. The states/actions/rewards are assumed to follow a Markov Decision Process [1].

The crucial point is how the states, actions and rewards, which occur over time, are connected to causation as defined on the non-temporal SCM as discussed in section [11-A]. Our assumptions will be similar to those in other work on structuring reward signals, such as reward machines [23]. That is, we assume that the basic structure of endogenous/exogenous nodes of the SCM is a given, and that it is known how the states $s_t$ affect the value of the exogenous nodes $\mathcal{U}$. As is the case in reward machines for reinforcement learning, this type of identification between states and course-grained variables is often natural to define [23], and we do not make assumptions that the outcome of the policy is known.

The identification between states and exogenous variables is also natural from the point of actual causation, where the role of the exogenous variables is exactly to model all factors affecting the assignment of the endogenous variables, like chance events, motives and other contingent factors (see discussion in [9]).

To deal with the temporal aspect, we observe that in other causal vignettes such as the original forest scenario [10], or the trolley-cart scenario [12], there is an implicit assumption that the exogenous variables $\mathcal{U}$ obtain their value during some temporal process (examples include a trolley-cart driving down a track and hitting a person, a person setting a forest alight and so on), and once this process has assigned them their value they do not change. This suggests a process where for each $u_k \in \mathcal{U}$, we define the temporal (assigned) value as an absorbing process $u_k(t), t = -1, \ldots, T$ as

$$u_k(t) = \begin{cases} u_k(t - 1) & \text{if } u_k(t - 1) \neq u_k(-1) \\ h_{u_k}(s_t) & \text{otherwise} \end{cases}$$

(3)

That is, an exogenous variable $u_k \in \mathcal{U}$ is given a default value $u_k(-1)$, and can then possibly be assigned a different value $h_{u_k}(s_t)$ at a later point, but after this assignment has occurred it will not change. The actual value of the exogenous variables is then defined as $u_k = u_k = u_k(T)$. In our example, $u_k(-1) = 0$ will be used as the natural default value. Once assigned, we can compute the value of all endogenous values and use these to compute the reward signal.

Crucially, this assignment of credit must take into account whether the agent was responsible for the negative outcome (in this case the fire $F$). As discussed in the introduction, the agent is considered responsible exactly if the agent’s actions were an actual cause of the event. Therefore, when a particular event $F$ occurs, we use theorem [2,1] to compute all actual causes of the event $X_t^F, \ldots, X_T^F$. In the camping example, these can be $A = 2$ and $P = 1$. For each cause $X_k$, we compute the degree to which the agent is blameworthy of the cause $B_{\hat{X}_k}$ (defined in section [11-D]) and finally let the reward signal be the maximum blameworthiness of the causes of the outcome – the intuition being that if the agent is fully responsible for just one true cause of the outcome, the agent is responsible for the outcome. The contribution to the terminal reward $r_T$ is therefore:

$$\max_{\hat{X}_k} B_{\hat{X}_k} r(F)$$

(4)

where $r$ is a reward function affecting the exogenous variables, in our case simply $r(F) = -100F$.

D. Blame and manipulation

In order to assign blame to the agent for outcomes $\hat{X} = \hat{e}$, for instance $A = 2$ or $P = 1$, the agent must be able to manipulate the events through its actions. This basic definition of blame can be made more detailed to account for trade-offs in rewards/costs [10]. However, for simplicity we will use the simpler manipulation criteria, which will suffice for our example, and illustrate the main difficulties in applying the definition to reinforcement learning.

The main obstacle in defining blame is that the probability of an event occurring (or not) under different policy choices $P(\pi | \pi)$, does not by itself capture important aspects of whether an event can be manipulated or not (see fig. [3]). For instance, suppose we know that safe camping, given enough time, will eventually burn down the forest, it will still be true that unsafe camping, by hastening the fire, is a blameworthy action. At the same time, whether the pyromaniac burns down the forest may appear within our control, because we can choose to burn down the forest before the pyromaniac is given
a chance (fig. 3 bottom), so our definition should exclude this case.

Our criteria for when a variable can be manipulated will therefore focus on whether the agent’s actions reduces the (estimated) number of steps \( T^{(\eta)}_{\tilde{X}=\tilde{x}}(s_t, a_t) \) until \( \tilde{X}=\tilde{x} \) is expected to occur, given the agent is in state \( s_t \) and takes action \( a_t \). The parameter \( \eta \) measures how conservative the estimate is. We will return to the practical estimation of \( T^{(\eta)}_{\tilde{X}=\tilde{x}}(s_t, a_t) \) in section 4.3 but for now we assume it is given, and focus on how it can be used to define blame.

Intuitively, blame for \( \tilde{X}=\tilde{x} \) increases when we take actions which decrease the time until \( \tilde{X}=\tilde{x} \) occurs, relative to actions which seek to postpone \( \tilde{X}=\tilde{x} \). A tentative definition of blame is therefore:

\[
1 - \frac{T^{(\eta)}_{\tilde{X}=\tilde{x}}(s_t, a_t)}{T^{(\eta)}_{\tilde{X}=\tilde{x}}(s_t)}, \quad T^{(\eta)}_{\tilde{X}=\tilde{x}}(s_t) = \max_{a'} T^{(\eta)}_{\tilde{X}=\tilde{x}}(s_t, a') \tag{5}
\]

That is, simply the relative reduction in time compared to the action \( a' \), which seeks to maximally postpone \( \tilde{X}=\tilde{x} \). However, two situations should be taken into consideration:

1. A potentially catastrophic action and its effect may be separated by several steps; furthermore, if the intermediate actions are optimal, this does not reduce the blame for the catastrophic action.

2. Blame is not simply cumulative over time: a driver who normally drives recklessly, but is involved in an accident on a day that he/she happens to drive safely, should not incur blame.

Both factors can be accounted for by tracking the longest known time until \( \tilde{X}=\tilde{x} \) under actions that seek to delay \( \tilde{X}=\tilde{x} \) as much as possible:

\[
T^{(\eta)}_{\tilde{X}=\tilde{x}}(s_t) = \begin{cases} T^{(\eta)}_{\tilde{X}=\tilde{x}}(s_t) & \text{if } t = 0 \\ \max\left\{ T^{(\eta)}_{\tilde{X}=\tilde{x}}(s_{t-1}) - 1, T^{(\eta)}_{\tilde{X}=\tilde{x}}(s_t) \right\} & \text{if } t > 0 \end{cases} \tag{6}
\]

and then define blame analogous to eq. (5) as:

\[
B_{\tilde{X}=\tilde{x}}(s_t, a_t) = 1 - \frac{T^{(\eta)}_{\tilde{X}=\tilde{x}}(s_t, a_t)}{T^{(\eta)}_{\tilde{X}=\tilde{x}}(s_t)}. \tag{7}
\]

The maximum in eq. (6) ensures this quantity is always between 0 and 1. The definition accounts for the above-mentioned situations as follows:

- Suppose that at an earlier time step \( t \) the time until \( \tilde{X}=\tilde{x} \), \( T^{(\eta)}_{\tilde{X}=\tilde{x}} \), is very large and that a bad action \( a_t \) reduces this time. Although subsequent actions by the agent are optimal, the left argument of the maximum in eq. (6) will ensure that \( T^{(\eta)}_{\tilde{X}=\tilde{x}} \) remains large in subsequent steps, thus ensuring that the agent is still blamed for the earlier (bad) action in eq. (7).

- On the other hand, suppose that the agent has taken several bad actions, thereby resulting in a blameworthy state according to eq. (7). If a good action brings the agent to a state \( s_t \) which is safe, i.e. \( T^{(\eta)}_{\tilde{X}=\tilde{x}} \) is large, then eq. (6) (right-hand part of the maximum) will reset the maximum time \( T^{(\eta)}_{\tilde{X}=\tilde{x}} \) to a large value, and the agent will no longer be blamed.

### E. Estimating temporal delays

To estimate \( T^{(\eta)}_{\tilde{X}=\tilde{x}}(s_t, a_t) \), the expected number of steps until \( \tilde{X}=\tilde{x} \), assuming that the agent starts in state \( s_t \) and takes action \( a_t \), we will use an iterative method similar to Q-learning. To see how, first note that a simple application of the rules of probability shows that the time until an event \( \tilde{X}=\tilde{x} \), denoted by \( T^{(\eta)}_{\tilde{X}=\tilde{x}} \), follows the distribution:

\[
P_{\pi}(T^{(\eta)}_{\tilde{X}=\tilde{x}} = t|s_t, a_t) = \delta_0(t) P(\tilde{X}=\tilde{x}|s_t, a_t) + \frac{1 - \delta_0(t)}{1 - P(\tilde{X}=\tilde{x}|s_t, a_t)} \mathbb{E}_{s_{t+1}, \pi} \left[ T^{(\eta)}_{\tilde{X}=\tilde{x}} - 1|s_{t+1} \right],
\]

where \( s_{t+1} \) is the next state in the MDP and \( P(\tilde{X}=\tilde{x}|s_t, a_t) \) is the chance \( \tilde{X}=\tilde{x} \) in this very same time step. The expectation is taken with respect to \( s_{t+1} \) and \( a_{t+1} \) as generated by the MDP and policy \( \pi \). For terminal steps \( s_{t+1} \), the estimate \( P_{\pi}(T^{(\eta)}_{\tilde{X}=\tilde{x}}|s_{t+1}) \) on the right-hand side is replaced.
by a dispersed (normal) prior\(^3\) reflecting our belief of when \(T\vec{X} = \vec{x}\) occurs after the episode has terminated.

This expression is computationally inefficient, as it would require us to keep track of the probability of each value of \(T\vec{X} = \vec{x}\). However, this would also be unnecessary, since what matters is the mean time until the event occurs and not the overall shape of the distribution. We will therefore use a normal approximation so that: \(T\vec{X} = \vec{x}\) \(\sim \mathcal{N}(m_1(s_t, a_t), \sigma(s_t, a_t))\) and simply track how the mean/variance is updated.

This allows us to simplify eq. (5) by plugging in the normal distribution and performing matching. Using the shorthand \(p_{s_t, a_t} = P(\vec{X} = \vec{x}| s_t, a_t)\) (this value is easily estimated as the sample average) we obtain the following expressions for the first and second moments:

\[
egin{align*}
  m_1 &= (1 - p_{s_t, a_t})(1 + E m_{s_{t+1}, a_{t+1}}^{(1)}) \quad (9a) \\
  m_2 &= (1 - p_{s_t, a_t}) \left( E \sigma_{s_{t+1}, a_{t+1}}^2 + (1 + E m_{s_{t+1}, a_{t+1}}^{(1)})^2 \right). \quad (9b)
\end{align*}
\]

Since the right-hand side only involves simple expectations, we can obtain asymptotically convergent estimates iteratively using \(\alpha\)-soft updates as in \(Q\)-learning. The updates are\(^2\)

\[
egin{align*}
  p_{s_t, a_t} &\leftarrow 1_{\vec{X} = \vec{x}} \quad (10a) \\
  m_{s_t, a_t}^1 &\leftarrow (1 - p_{s_t, a_t})(1 + m_{s_{t+1}, a_{t+1}}^1) \quad (10b) \\
  m_{s_t, a_t}^2 &\leftarrow (1 - p_{s_t, a_t})(1 + m_{s_{t+1}, a_{t+1}}^2 + 2m_{s_{t+1}, a_{t+1}}^1) \quad (10c)
\end{align*}
\]

Since the time estimates are uncertain, we define \(T\vec{X} = \vec{x}\) \(\sim \mathcal{N}(m_{s_t, a_t} + \eta \sigma_{s_t, a_t}, \alpha)\) as the \(\frac{1}{2} + \eta\) percentile of the estimated number of steps until \(\vec{X} = \vec{x}\) occurs in state \(s_t\) under action \(a_t\). Together with the definition of blame in section II-D.

\(^2\)In the experiments, the mean and variance is set to 10, and the method was robust to different choices.

\(^3\)The symbol \(x \leftarrow y\) is understood either as a running average of all \(y\)-values or \(\alpha\)-soft updates \(x = x + \alpha(x - y)\).

\section{Experiments}

We test the proposed method (\textit{AC Agent}) on a MDP variant of the camping vignette. To avoid unnecessary details, we will consider a case where the states and actions are similar to the deterministic case shown in fig. 2 but where the effect of actions is not deterministic, so that the interaction with the environment will occur over an (unknown) number of time steps. We assume that there is a chance \(p_{\text{pyro}} = 0.1\) that the pyromaniac will set the forest alight in each step, and with probability \(p_A\) the agent’s actions will have no effect (and otherwise have the effect of camping safely and unsafely).

We compare the method against tabular \(Q\)-learning\(^4\). For both methods, we set the learning rate to \(\alpha = 0.05\), the \(\epsilon\)-greedy exploration rate to \(\epsilon = 0.1\), and the discount factor to \(\gamma = 0.99\). We selected \(\eta = 0\) in the definition of blame. The choice of these parameters is not important, and only affects speed of convergence; the full code listing is available online.

We first examine the convergence of the methods by plotting the accumulated return per episode during training. The result can be found in fig. 4 (using 2000 steps per episode. The plot is the average over 50 restarts, and the shaded regions indicate the standard deviation of the mean). We see that the \(Q\)-agent converges to the optimal policy (to always burn down the forest) which, as discussed in the introduction, is associated with a higher reward. The AC agent chooses a responsible policy (safe camping) and therefore obtains a lower reward. Although the results are noisy due to the \(\epsilon\)-greedy exploration, we verify that the methods indeed converge by testing the 50 trained agents on 100 episodes each, with exploration. The average return is shown in table 1 and indicates that the only variation occurs when the pyromaniac burns down the forest before the agent has a chance of performing safe camping.

To verify that this indeed occurs, because the agent attributes blame correctly, we extract the blame factor (eq. (4)) for the two actual causes of \(F\), namely the agent setting up an unsafe campfire (\(A = 2\)) and the pyromaniac setting the forest alight, \(P = 1\) (same settings as above). The result can be found in table 1 and we see the agent correctly identify the pyromaniac’s actions as being outside its control (i.e. a blame of 0 when they are an actual cause of the forest burning down), while its own choice of unsafe camping has a high degree of blame. That this factor is not identical to 1 is due to blame being computed as a fraction of reduced time until an event occurs, and since the estimated times are all finite, this naturally places an upper limit on the degree of blame.

\begin{table}[h]
\centering
\caption{Average return without exploration}
\begin{tabular}{|c|c|c|}
\hline
Condition & AC Agent & Q Agent \\
\hline
\(p_A = 1\) & \(-90.008(4)\) & \(-80.000(\) \\
\hline
\(p_A = 0.7\) & \(-90.640(193)\) & \(-82.286(377)\) \\
\hline
\end{tabular}
\end{table}
(compared to a similar choice in the degree of intent, as defined in [10]).

IV. CONCLUSION

In this paper, we have proposed a method which allows a reinforcement learning agent to distinguish between morally good and bad behavior, namely that the agent is behaving badly if its actions are an actual cause of a bad outcome, so that even if a bad outcome is unavoidable, the agent should not be responsible for it in any case.

We have formalized this using a definition of cause taken from the theory of actual causality, and our main contribution has been to apply this to a temporal sequence of events, using our proposed definition of blame. The latter is particularly important in a reinforcement learning setting, where the policy must be trained from data and therefore the effect of the policy, i.e. which of the actual causes are actually under control, cannot be known beforehand.

Our definition of blame rests on a criteria of whether the time an event occurs can be hastened or postponed. This view of blame is quite rudimentary compared to views found in philosophy (c.f. [4], [11]). Elsewhere, blame has been defined as a trade-off that involves the cost to the agent [10]. The trade-off between costs and blame will factor into our method in the reward function eq. [4]. In other words, the agent will in its choice of actions factor in the cost, but not in its definition of being blameworthy.

Our method ultimately learns by using a modified reward signal, so it is natural to ask if “reward is enough” [2]. We don’t claim that morality challenges whether reward-maximization is the best way to train agents, but rather that if we want the agent to take blame or responsibility into account, the modification to the reward should be based on its formal definition. To the extent that causal moral notions such as blame can be specified using SCMs, we believe that our approach illustrates a plausible way to integrate them with reinforcement learning, thereby allowing machine-learning models to learn and act using these moral intuitions. This opens up a possibility both to create machines that are more moral, and also to concretely see what actual behaviors philosophical formulations of moral principles will lead to when implemented.

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