Contrastive Explanations for Comparing Preferences of Reinforcement Learning Agents

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Abstract

In complex tasks where reward function is not straightforward and consists of a set of objectives, multiple reinforcement learning (RL) policies that perform task adequately, but employ different strategies can be trained by adjusting the impact of individual objectives on the reward function. Understanding the differences in strategies between policies is necessary to enable users to choose between offered policies, and can help developers understand different behaviors that emerge from various reward functions and training hyperparameters in RL systems. In this work we compare behavior of two policies trained on the same task, but with different preferences in objectives. We propose a method for distinguishing between differences in behavior that stem from different abilities from those that are a consequence of opposing preferences of two RL agents. Furthermore, we use only data on preference-based differences in order to generate contrasting explanations about agents’ preferences. Finally, we test and evaluate our approach on an autonomous driving task and compare the behavior of a safety-oriented policy and one that prefers speed.

1 Introduction

During the last decade, deep reinforcement learning algorithms (DRL) have shown notable results in a variety of applications, ranging from games to autonomous vehicles (Arulkumaran et al. 2017). However, DRL algorithms rely on neural networks to represent agent’s policy, making their decisions difficult to understand and interpret. This lack of transparency stands in the way of wider adoption of DRL methods in high-risk areas, such as healthcare or finance. Additionally, enabling agents to explain their decision-making process to humans is necessary to facilitate trust and collaboration between RL agent and user.

To address this issue, various approaches for interpreting behavior of DRL agents have been proposed in the recent years. Depending on their scope, methods for explaining a DRL system can either be local or global (Du, Liu, and Hu 2019). Local methods interpret a single decision of the RL model (Greydanus et al. 2018; Fukuchi et al. 2017), while global approaches explain policy behavior as a whole (Amir and Amir 2018; Hayes and Shah 2017). Although these methods have shown to increase human understanding of agent’s decision-making process, they have been mostly limited to explaining a single RL policy. However, comparing and interpreting differences in policy behavior is necessary in situations where the user is confronted with a choice between alternative policies. Additionally, enabling developers to discover differences between policies could help them debug imperfect models by locating situations where they differ from a known expert model. Finally, comparing policies corresponds with the human tendency to prefer contrasting explanations which analyze differences in alternative scenarios (Miller 2019).

In this work we distinguish between two ways in which behaviors of two RL policies can differ: ability-based and preference-based. If one policy is trained to a higher standard and exhibits generally superior behavior compared to the other one, then differences between the two are ability-based. On the other hand, if both policies perform the task competently, but follow different strategies based on their individual inclinations then we consider their differences to be preference-based. Current methods for comparing RL policies assume that differences between policies are ability-based and completely disregard the notion of preference (Squeiria and Gervasio 2020; Amitai and Amir 2021). However, in complex domains where defining the optimal behavior is not straightforward, it is possible to train multiple RL policies that perform the task adequately, but rely on different strategies. Interpreting differences between those policies is necessary from the perspective of personalisation – if user needs to choose a policy that suits them best from a set of offered alternatives, understanding differences between them is crucial for making an informed decision. Furthermore, recognizing differences between multiple policies could aid developers in understanding the different behaviors that stem from various reward functions and hyperparameter combinations (Amitai and Amir 2021).

In RL, multiple different strategies can be the result of different reward functions in a task where the objective cannot be precisely defined, and certain trade-offs between goals have to be made (Huang et al. 2019). For example, consider the problem of training a RL policy for driving an autonomous vehicle. Defining the reward function for this task is not straightforward and can involve multiple objec-
tives that need to be satisfied. Consequently, multiple capable policies could be trained on different reward functions that slightly favor a specific objective over the others. These policies will achieve high average reward according to their individual reward function, but due to their opposing preferences in terms of objectives they may also exhibit different strategies for performing the task. Specifically, a policy which was trained on the reward function that severely penalizes close contact with another car will develop a safety-oriented strategy, and prefer slower driving and keeping distance from other vehicles. On the other hand, policy that was penalized for not arriving to the destination on time will likely prefer faster driving, and will have a more relaxed understanding of safety concerns. If a user is given a choice between these two policies it is necessary that the they recognize the differences between their strategies to choose the one best fitting for them.

In this work, we focus on comparing two policies trained on the same task and interpret their preference-based differences. We choose the global approach to explainability, and attempt to discover the differences in overall behavior of two RL agents as opposed to analysing their differences in a single state. Our approach attempts to uncover differences between two policies by analysing situations where policies disagree on the best strategy to follow. We propose an algorithm for distinguishing between disagreements that stem from difference in ability between two agents and those that arise from their opposing preferences. We then analyse only the preference-based disagreements in order to extract conditions in terms of state features that specific agents favour and generate global explanations contrasting agents' behavior. We test and evaluate our approach in an autonomous driving environment, where agent’s task is to merge into another lane currently occupied by a non-autonomous vehicle, and we compare policies of a safety-oriented vs speed-oriented agent.

Our contributions are as follows:

• We propose a method for distinguishing between ability-based and preference-based differences in behavior between two RL agents.
• We present a method for generating contrasting explanations based on the contrast in preferred state feature values between two policies.
• We test and evaluate our approach in an autonomous driving environment.

## 2 Related work

In the recent years various methods for explaining either one decision or the entire behavior of RL system have been proposed (Puiutta and Veith, 2020). However, despite the fact that research shows humans tend to seek contrasting explanations when reasoning about an event (Miller, 2019), there is still limited work in the field of comparing alternative behaviors of reinforcement learning systems. Madumal et al. (2020b) approached the problem of explainability from a causal perspective and proposed a method for generating local explanations that contrast alternative actions in a specific state. The approach however requires a hand-crafted causal model of the environment, which may be difficult to obtain and requires expert knowledge. Additionally, authors focus on generating local explanations, while we interpret and compare global behavior of agents.

Summarisation methods, one of the most notable global approaches for condensing and explaining the agent behavior have also been used to compare multiple RL policies. Sequeira and Gervasio (2020) generated contrasting summaries of agents’ behavior in order to highlight the differences in their capabilities. Similar to our work, Amitai and Amir (2021) used the notion of disagreement between policies to detect and analyse situations where two policies pick different actions, but opted for explaining policies’ differences through contrasting summaries. However, both approaches focus only on extracting discrepancies between agents’ abilities, and disregard the potential difference in their strategies. Additionally, applicability of summarisation methods is limited to tasks with visual input.

Most relevant to our work, van der Waa et al. (2018) compare the outcomes of following different policies from a specific state to justify agent’s choice of action. However, their work focuses only on local explanations, and requires manual encodings of states and outcomes. In contrast, in our work we aim to provide global comparisons of policies and do not rely on hand-crafted interpretable features.

## 3 Preference-based contrastive explanations

In this section we propose a set of conditions for distinguishing between ability and preference-based differences between two policies and offer a method for extracting explanations that highlight feature values that specific agents favour. Throughout this section we assume oracle access to two policies $\pi_A$ and $\pi_B$, their $Q$ action-value functions and the transition function of the environment $T$. Our approach consists of three steps presented in this section. Firstly, policies are unrolled in the environment to collect data on situations where two policies disagree on the best course of action (Section 3.1). Afterwards, collected data is filtered so that only data illustrating preference-based differences between the policies is obtained (Section 3.2). Finally, we analyse and compare preference-based disagreement data from both policies to extract explanations that indicate which conditions agents prefer to end up in (Section 3.3).

### 3.1 Disagreement data

We adopt the definition of disagreement state from Amitai and Amir (2021) and consider two policies to disagree in a state if they do not choose the same action in that state.

With that in mind, we collect three different types of disagreement data from policies’ interaction with the environment. We follow the method for gathering disagreement data presented in Amitai and Amir (2021) which assumes unrolling policy $\pi_A$ in the environment and at every step comparing decisions of $\pi_A$ and $\pi_B$ until a disagreement is reached, then following both policies separately for a set number of steps $k$, and finally returning control to $\pi_A$.

Specifically, we start by executing policy $\pi_A$ in the environment. In each state $s$ that $\pi_A$ encounters we compare the
decisions of both policies and record those states in which policies choose different actions:

**Definition (Disagreement states)** Given two policies \( \pi_A \) and \( \pi_B \), state \( s_d \) is a disagreement state if:

\[
\pi_A(s_d) \neq \pi_B(s_d) \tag{1}
\]

After encountering a disagreement state \( s_d \), we also unroll both policies for a set number of steps \( k \) starting from \( s_d \) and record the resulting pair of trajectories:

**Definition (Disagreement trajectories):** Given two policies \( \pi_A \) and \( \pi_B \) and a disagreement state \( s_d \), a pair of disagreement trajectories is a tuple \( (\mathcal{T}_{\pi_A}(s_d), \mathcal{T}_{\pi_B}(s_d)) \) where:

\[
\begin{align*}
\mathcal{T}_{\pi_A}(s_d) &= \{s^i_d, \ldots, s^{i+k}_d\} \\
\mathcal{T}_{\pi_B}(s_d) &= \{s^i_d, \ldots, s^{i+k}_d\}
\end{align*}
\tag{2}
\]

Finally, upon collecting disagreement trajectories, we also record the last states in each trajectory pair:

**Definition (Disagreement outcomes):** Given two policies \( \pi_A \) and \( \pi_B \) and a pair of disagreement trajectories \( (\mathcal{T}_{\pi_A}(s_d), \mathcal{T}_{\pi_B}(s_d)) \), where \( \mathcal{T}_{\pi_A}(s_d) = \{s^i_d\}_{i=1}^{n} \) and \( \mathcal{T}_{\pi_B}(s_d) = \{s^i_d\}_{i=1}^{n} \), pair of disagreement outcomes is a tuple \( (o_{\pi_A}(s_d), o_{\pi_B}(s_d)) \) where:

\[
\begin{align*}
o_{\pi_A}(s_d) &= \mathcal{T}_{\pi_A}[k] \\
o_{\pi_B}(s_d) &= \mathcal{T}_{\pi_B}[k]
\end{align*}
\tag{3}
\]

In other words, an outcome is a state in which agent ends up after following its policy for a set number of steps from a disagreement state. After individually unrolling two policies from disagreement state \( s_d \) for \( k \) steps, control is returned to policy \( \pi_A \) which continues to progress in the environment, until a new disagreement state or episode terminates. Entire collection process is repeated for \( n \) episodes. The approach is further detailed in Algorithm 1.

Throughout this section we use the term disagreement to denote a tuple \( (s_d, \mathcal{T}_{\pi_A}(s_d), \mathcal{T}_{\pi_B}(s_d), o_{\pi_A}(s_d), o_{\pi_B}(s_d)) \) where \( s_d \) is a disagreement state, \( \mathcal{T}_{\pi_A}(s_d) \) and \( \mathcal{T}_{\pi_B}(s_d) \) disagreement trajectories starting in \( s_d \) and \( o_{\pi_A}(s_d) \) and \( o_{\pi_B}(s_d) \) their outcomes. Output from this section of the approach is a set of collected disagreements \( D(\pi_A, \pi_B) \).

### 3.2 Ability vs. preference-based disagreement

In order to generate preference-based explanations using the gathered disagreement data, we need to distinguish between disagreement that comes from different abilities of two agents and that which is a consequence of different preferences. Specifically, we aim to detect a particular type of disagreement that can be representative of discrepancy in preferences between two policies. Intuitively, we would like to select only those disagreements \( (s_d, \mathcal{T}_{\pi_A}(s_d), \mathcal{T}_{\pi_B}(s_d), o_{\pi_A}(s_d), o_{\pi_B}(s_d)) \) where both agents see the same potential in the state \( s_d \) and fulfil that potential to the same extent over the next \( k \) steps, but disagree strongly on the course of action in \( s_d \). In other words, we select disagreements where agents feel similarly optimistic in state \( s_d \) and policy \( \pi_A \) feels similarly as satisfied being in \( o_{\pi_A} \) as \( \pi_B \) is with reaching \( o_{\pi_B} \), while both agents have high confidence in their chosen path. This would indicate that agents estimate and realize the same potential in the environment, but strongly disagree on their preferred way to do so.

To precisely define these conditions, we need to introduce a metric for measuring how strongly two policies disagree in a specific state. For this purpose we define state importance as follows:

**Definition (State importance)** Given two policies \( \pi_A \) and \( \pi_B \), a disagreement state \( s_d \), and if \( Q_A(s_d) \) and \( Q_B(s_d) \) are vectors of \( Q \) action-values in state \( s_d \) according to policies \( \pi_A \) and \( \pi_B \) respectively, the importance of \( s_d \) with regards to policies \( \pi_A \) and \( \pi_B \) can be defined as:

\[
I(s_d|\pi_A, \pi_B) = \frac{\max(\text{softmax}(Q_A(s_d))) + \max(\text{softmax}(Q_B(s_d)))}{2}
\tag{4}
\]

We compute the softmax over a vector of \( Q \) action-values in order to emphasise the contrast between the first-ranked action and the others, and select the maximum value to represent how sure the policy is in its decision.

Furthermore, in order to quantify the potential that policy sees in a specific state we employ the idea of a state-value function. Since we do not assume direct access to state-value functions of policies, we simulate them with the help of the available \( Q \) action-value functions:

\[
V_\pi(s) = \max_{a \in A} (Q_\pi(s, a))
\tag{5}
\]
Before using them for estimating state-value function, Q action-values are normalized to $[0, 1]$ range, so that they can be compared between different agents.

Finally, we formalize the conditions for considering disagreement $d = (s_d, T_A(s_d), T_B(s_d), o_A(s_d), o_B(s_d))$ to be preference-based:

**Definition (Preference-based disagreement)** Given two policies $\pi_A$ and $\pi_B$ and disagreement between them $d = (s_d, T_A(s_d), T_B(s_d), o_A(s_d), o_B(s_d))$, disagreement is considered to be preference-based if the following conditions are fulfilled:

1. Both policies are highly confident in their decision in the disagreement state $s_d$:
   \[ I(s_d | \pi_A, \pi_B) > \alpha \]  
2. Both policies have similar evaluations of the disagreement state $s_d$:
   \[ V_{\pi_A}(s_d) \approx V_{\pi_B}(s_d) \]  
   To estimate this similarity we evaluate the expression:
   \[ |V_{\pi_A}(s_d) - V_{\pi_B}(s_d)| < \beta \]  
3. After unrolling policies in the environment for $k$ steps from state $s_d$, both policies have similar evaluations of their outcomes:
   \[ V_{\pi_A}(o_A) \approx V_{\pi_B}(o_B) \]  
   To estimate this similarity we evaluate the expression:
   \[ |V_{\pi_A}(o_A) - V_{\pi_B}(o_B)| < \gamma \]

where $\alpha$, $\beta$ and $\gamma$ are threshold values.

Selected values for threshold parameters $\alpha$, $\beta$ and $\gamma$ affect how selective the algorithm is. Some suitable values to use in practice would be: $0.8 \leq \alpha \leq 1.0$, $\beta \leq 0.1$ and $\gamma \leq 0.1$. Decreasing $\alpha$ would result in including disagreements where policies are not confident in their choice and evaluate some alternative actions as similarly promising. These situations indicate that the disagreement is not a consequence of strong preferences of the agents. On the other hand increasing parameters $\beta$ or $\gamma$ would result in allowing more ability-based disagreements into the end result. For example, consider a situation where two agents encounter state $s_d$ which they evaluate similarly, but disagree strongly on the best course of action. If after unrolling these policies separately for a number of steps they arrive at different states, and one policy is far more satisfied with its outcome than the other, that indicates that the disagreement in $s_d$ was not a consequence of opposing preferences, but rather of inferior abilities of the second policy.

Finally, we can use the defined measures to filter the set of disagreements to obtain only those that are preference-based:

\[ D_p(\pi_A, \pi_B) = \{ d \in D(\pi_A, \pi_B) | I(s_d | \pi_A, \pi_B) > \alpha, \ |V_{\pi_A}(s_d) - V_{\pi_B}(s_d)| < \beta, \ |V_{\pi_A}(o_A) - V_{\pi_B}(o_B)| < \gamma \} \]

Output from this stage is the set of preference-based disagreements $D_p(\pi_A, \pi_B)$.

3.3 Generating contrastive explanations

Data set $D_p(\pi_A, \pi_B)$ is rich with information on preference-based differences between $\pi_A$ and $\pi_B$. Therefore, there are multiple ways to approach generating contrastive explanations using $D_p(\pi_A, \pi_B)$ – we could exploit differences in disagreement trajectories or disagreement outcomes. In this work we choose the latter and focus on analysing and comparing outcomes of following the two policies to uncover which states agents prefer to reach. More specifically, we address the question: “What conditions (in terms of state features) does agent A prefer to end up in, compared to agent B?”.

To answer this question, we start by creating two sets of values $O^A_f$ and $O^B_f$ for each state feature $f$, storing values of feature $f$ in outcomes from policies $\pi_A$ and $\pi_B$ respectively:

\[ O^A_f = \{ o_A[f] | o_A \in D_p(\pi_A, \pi_B) \} \]
\[ O^B_f = \{ o_B[f] | o_B \in D_p(\pi_A, \pi_B) \} \]

Finally, we include in our explanations only those features for which there is a significant difference in distributions of $O_A$ and $O_B$. Since we deal with continuous state features in the example presented in Section 3.4, we use a paired T-test to assess the difference in the two distributions. If $f$ is not continuous, alternative appropriate statistical tests can be used to determine statistical relationship (McNemar 1947; Pearson 1900). Provided that there is a significant difference in distribution of feature $f$ in outcomes of the two policies, we consider $f$ to be indicative of agent’s preference and we use it in the explanations. For example, if there is a significant difference between $O_A[f]$ and $O_B[f]$ for some feature $f$ and mean value of $O_A[f]$ is larger than mean value of $O_B[f]$ then the explanation will include that $\pi_A$ prefers to end up in states where feature $f$ has larger values. Final explanation is generated by combining all feature-specific preferences using a natural-language template.

4 Experiments

To evaluate the method proposed in Section 3.5 we employ a simplified version of the merging task in autonomous driving presented in [Huang et al. 2019]. In this environment, the autonomous vehicle navigates a three-lane road. Agent begins the episode in the center lane, and is tasked with merging safely into the right lane, currently occupied by a non-
autonomous vehicle. Episode ends upon successful completion of the task, or if agent fails catastrophically by crashing into another car. Reward of +1000 is awarded for successfully merging in the right lane, while −1000 penalty is received for crashing into the non-autonomous vehicle. Additionally, driving off the road yields −10 penalty. There are two suitable ways to approach this task. Agent can either employ a safety-oriented strategy and merge behind the non-autonomous vehicle, minimizing its chances of collision or it can speed up and merge in front of the other car, depending on its preference in the trade-off between speed and safety.

Agent’s observation is a vector describing both the agent and the non-autonomous vehicle. Specifically, agent observes location of its rear axle \((x, y)\), as well as its heading \(h\), velocity \(v\) and steering wheel angle \(\theta\). Additionally, agent can observe the same features for the non-autonomous vehicle denoted by \(x', y', h', v'\) and \(\theta'\). At each step agent chooses between 5 discrete actions – agent can increase or decrease its speed by 10\%, it can change its steering angle by 3 degrees in any direction, or it can choose to alter nothing. Non-autonomous vehicle, however, drives straight ahead in the right lane with the same velocity throughout the episode.

We start by training a baseline policy \(\pi_{safe}\) with reward function parameters \(\theta_{safe} = [5, 10, 20, 50, 0]\). This policy is safety-oriented – it prefers to keep a distance to the non-autonomous vehicle and chooses to slow down and merge behind it. All policies in this section are trained using DQN algorithm (Mnih et al. 2013).

Furthermore, to obtain policies with different strategies we vary the value of the parameter \(\theta_4\) which affects how important progress is to the agent. Small values of this parameter indicate a safety-oriented policy which prefers to slow down and merge behind the non-autonomous vehicle, decreasing its chances of collision. This strategy is identical to that of \(\pi_{safe}\). On the other hand, increasing the value of this parameter results in a more aggressive policy which values progress over keeping greater-than-necessary distance to the other vehicle. Such policy prefers to speed up and merge in front of the non-autonomous car. For each value \(p \in [0, 1, 2, 3, 4]\) we train 3 different models \(\pi_A^p, \pi_B^p\) and \(\pi_{rand}^p\) using the reward function with parameters \(\theta_p = [5, 10, 20, 50, p]\). In other words, we keep all other reward feature parameters same as in the baseline model, and change only the parameter corresponding to progress. Models \(\pi_A^p\) and \(\pi_B^p\) are trained for the same number of steps and achieve near-optimal performance on the task. To ensure we also generate a policy with inferior capabilities, \(\pi_{rand}^p\) is trained for significantly less time, and does not fully learn the task. Training parameters are given in Table 2.

## 5 Evaluation

We set up experiments to show that the method presented in Section 3 captures and explains only preference-based differences in behavior of the two agents. In other words, we do not want our method to detect difference in behavior when comparing two policies employing the same strategy, or two policies with significantly different capabilities. Therefore, we set up three different evaluation goals:

1. The method detects differences between two policies with different preferences.
2. The method does not detect differences between two policies with same preference.
3. The method does not detect differences between two policies of significantly different capabilities.

To test all three evaluation goals, we set up three different evaluation scenarios. To evaluate our method against the first goal, we compare the behavior of policies \(\pi_{safe}\) and \(\pi_A^p\) for each \(p \in [0, 1, 2, 3, 4]\). Since we expect \(\pi_A^p\) to exhibit more aggressive behavior compared to \(\pi_{safe}\) for larger values of \(p\), this scenario tests whether this difference in strategy will
In this work we focused on the problem of explaining differences in behavior of two RL agents that stem from their opposing preferences. We proposed a method for distinguishing between ability-based and preference-based differences and generated contrasting explanations about state feature values that agents prefer. We also evaluated our approach on a merging task in autonomous driving.

Although we have shown that our method can successfully differentiate between ability and preference-based differences in behavior, our approach relies on the choice of threshold values $\alpha$, $\beta$ and $\gamma$. Additionally, our approach focuses on comparing only two RL policies. In future work we hope to address these two limitations, and extend the method to allow for end-to-end approach for learning threshold parameters and to support multiple policies.

### Table 3: Parameters for data collection and analysis process presented in Section 3

| Parameter | Description | Value |
|-----------|-------------|-------|
| $n_i$     | Number of data-collection episodes | 1000 |
| $k$       | Maximum length of disagreement trajectory | 10 |
| $\alpha$  | State importance threshold | 0.8 |
| $\beta$   | Disagreement state evaluation similarity threshold | 0.1 |
| $\gamma$  | Disagreement outcome similarity threshold | 0.1 |
| $p_{thres}$ | p-value threshold | 0.05 |

### Table 4: Total number of disagreements and number of preference-based disagreements obtained by applying method from Section 3 on the three evaluation scenarios.

| Parameter $p$ | Evaluation scenario | Total number of disagreements | Number of preference-based disagreements |
|---------------|---------------------|-------------------------------|----------------------------------------|
| $1$           | $\pi_A$ vs $\pi_{safe}$ | 1490                          | 0                                       |
|               | $\pi_A$ vs $\pi_3$    | 2910                          | 0                                       |
|               | $\pi_A$ vs $\pi_{rand}$ | 2691                       | 0                                       |
| $2$           | $\pi_A$ vs $\pi_{safe}$ | 2779                          | 182                                     |
|               | $\pi_A$ vs $\pi_3$     | 2000                          | 0                                       |
|               | $\pi_A$ vs $\pi_{rand}$ | 2001                       | 0                                       |
| $3$           | $\pi_A$ vs $\pi_{safe}$ | 2464                          | 216                                     |
|               | $\pi_A$ vs $\pi_3$     | 1843                          | 0                                       |
|               | $\pi_A$ vs $\pi_{rand}$ | 2006                       | 0                                       |
| $4$           | $\pi_A$ vs $\pi_{safe}$ | 2756                          | 927                                     |
|               | $\pi_A$ vs $\pi_3$     | 2000                          | 0                                       |
|               | $\pi_A$ vs $\pi_{rand}$ | 3000                       | 0                                       |
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