Assisted Robust Reward Design

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Abstract: Real-world robotic tasks require complex reward functions. When we define the problem the robot needs to solve, we pretend that a designer specifies this complex reward exactly, and it is set in stone from then on. In practice, however, reward design is an *iterative* process: the designer chooses a reward, eventually encounters an "edge-case" environment where the reward incentivizes the wrong behavior, revises the reward, and repeats. What would it mean to rethink robotics problems to formally account for this iterative nature of reward design? We propose that the robot not take the specified reward for granted, but rather have *uncertainty* about it, and account for the future design iterations as *future evidence*. We contribute an Assisted Reward Design method that speeds up the design process by anticipating and *influencing* this future evidence: rather than letting the designer eventually encounter failure cases and revise the reward then, the method actively exposes the designer to such environments during the development phase. We test this method in an autonomous driving task and find that it more quickly improves the car's behavior in held-out environments by proposing environments that are "edge cases" for the current reward.

Keywords: Reward Design, Safety, Human-in-the-loop

1 Introduction

One popular way to design robotic agents is to program them to maximize the cumulative reward in their environments. While we have made great progress in solving this optimization problem, we often delegate finding a good reward function to the human designer. In reality, reward design is an iterative and challenging process. Human designers spend tremendous effort iterating on the reward function as they test the robot in more and more environments. What is more, once deployed, reward functions can still be incorrect in edge-case environments, leading to failures.

Take, for instance, autonomous cars. They have to correctly balance safety, efficiency, comfort, and abiding by the law. A human designer starts by looking at some representative traffic scenarios and specifying a reward function that leads to desired behaviors in each of them. But working well in this set of environments is not enough — the reward function has to incentivize the right behavior in *any* environment the car will encounter in its lifetime[1]. The engineer will test-drive the car in both simulation and in the real world. Almost inevitably, optimizing for the specified reward will lead to some undesirable behavior in some further environments. The engineer will then *revise* the initial reward and repeat the process. If they are lucky, they will have converged to a suitable reward function by deployment time. But for many systems, this is a never ending process: the car will encounter some edge-cases in the real world that they did not foresee — an unseen road layout or traffic situation — and the engineer revises the reward again on the new environment.

In this work, we explore what it would mean for the robot to explicitly account for this iterative nature of reward design. Rather than treating the current reward as set in stone, we envision a system in which the robot works together with the designer and helps them design the right reward function, as in Fig. 1: the robot takes the reward function specified by the designer, and proposes a new environment for the designer to investigate where the reward function might fail. To capture this formally, we first enable the robot to explicitly account for the *uncertainty* in the reward function

[1]While there are challenges to building a world model, planning algorithms, etc., for this paper, we assume success in that and focus on designing the reward function.

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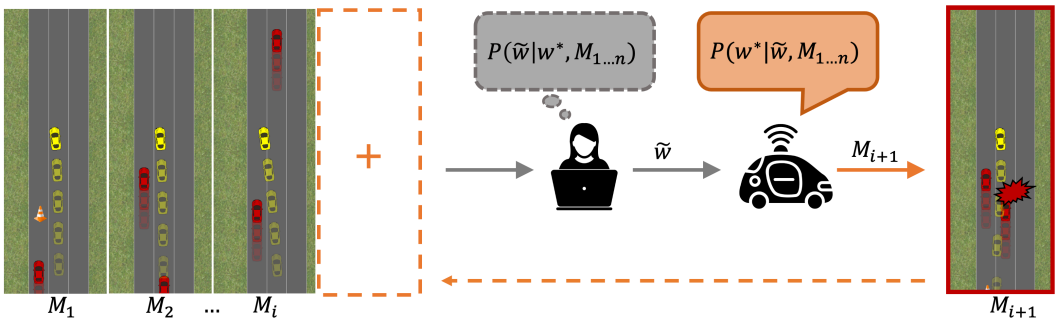

Figure 1: In the Assisted Reward Design process, the reward designer specifies a proxy reward on a set of environments. The robot agent takes the current proxy and queries the designer with a new environment where the proxy fails. The designer then revises her proxy to work on this new environment.

itself: every reward revision does *not* define the reward function fully, but is instead an *evidence* about it. Previous work on Inverse Reward Design [1] incorporates this uncertainty into the reward function with the goal of making the robot plan more conservatively in new environments. In this work, rather than passively updating the robot's estimate of the reward, we argue that it is the robot's job to actively help the engineer design more robust reward functions, with the goal of performing well at deployment time. We refer to this as *Assisted Reward Design*. The key insight is that:

By accounting for the iterative nature of reward design, the robot does not just passively estimate the reward it receives but proactively influences the future evidence it can gather from the designer.

Our contributions are three-fold:

1. Formalizing reward design as an iterative process. We formalize the problem of iterative reward design as a Meta MDP with hidden state. Under this formulation, the robot can and should account for the future iterations of the reward as *future evidence*. The robot can then make these pieces of evidence more informative by exposing the designer to environments where revisions are most likely needed. Rather than letting the designer eventually encounter edge-case environments, our method *proposes* candidate environments and asks for reward designs, inserting itself in the design process loop, as in Fig. 1. This has two implications. In cases where the designer would converge to a good reward before deployment time, our method speeds up the iterations by focusing on informative environments. Perhaps more importantly, in cases where the designer might still otherwise have the wrong reward when deploying the system, our method has the potential to expose the edge-case environments that cause failures, prompting fixes in the reward ahead of time.

2. Providing an approximate algorithm for our method. It is intractable to compute the reward uncertainty given the high-dimensional nature of the reward space and the environment space. We propose an approximate algorithm based on particle filtering to enable efficient computation.

3. Analyzing Assisted Reward Design in an autonomous car domain. We evaluate our method's practicality and effectiveness in designing reward functions for autonomous cars, using the open-source environment proposed by Sadigh et al. [2]. We conduct experiments with both simulated reward designers and robotics experts. We find that our method uncovers more difficult test scenarios and speeds up the reward design process. We also showcase that it proposes interesting environments that tend to be *edge cases* where the current reward estimate fails.

Overall, this paper takes a step towards making our robotic systems understand reward specification as an iterative process. In the end, we would like robotic systems not just to optimize what we design for them but help us design better and more robust reward functions. Even though admittedly more work is needed to put these ideas in real-world systems, we are excited to see our method assist in reward design and produce *edge-case environments* without any hand-coded heuristics.

2 Related Work

Designing robots to work reliably in an open world remains a challenging problem. Our work bridges three lines of work towards this goal: teaching robots the correct behaviors, enabling robots to actively learn from humans, and ensuring safety and robustness when deploying robots.

Learning Rewards from Diverse Human Input Given the difficulty of specifying reward functions, researchers have explored a wide variety of different methods to enable robots to learn rewards instead

from human input, especially demonstrations [3, 4, 5, 6]. Using this idea, recent works have explored learning from a diverse set of modalities. These include language instructions [7, 8], numerical feedback [9, 10], comparisons [11, 12], advice [13], facial expressions [14], collaborative behavior [15], or corrections [16, 17]. In contrast, our work builds on [1], which uses the specified reward function itself as the human input to learn from. We generalize this idea to an iterative, active process.

Active Reward Learning Our work is an instance of active reward learning. Prior work has focused on actively querying for comparisons [18, 19], demonstrations [20, 21, 22, 23], or reward labels [24]. Such queries are typically for trajectories or states in a given environment (MDP). Recent work has proposed active learning to synthesizes the environment itself to gain more information about the reward (either the initial configuration and behavior of other agents in the scene, such as [12], or the entire environment [24]). We also propose to actively query new environments, but the human feedback is a proxy reward designed to work only in that environment. This is interesting for two reasons. First, we show that it leads to the robot proposing edge cases to the designer where the previous reward is likely to fail, thus aiding in revising the reward. Second, we argue that the same active reward learning ideas from the literature can be applied to the reward engineering process — when we design a reward function, we should not just have the robot go optimize it blindly. We should instead think about it as an iterative process through the lens of active reward learning.

Reward Shaping Many prior works have also focused on recovering reward functions for suboptimal planners, given a ground truth reward function that is difficult to optimize, e.g. due to sparsity or non-differentiability [25, 26]. Note that in many real-world problems, such as autonomous cars, there are dangerous situations where no ground-truth reward exists. Assisted Reward Design is different from the reward shaping problem in that we do not assume access to a ground-truth reward function, but seek techniques that leverage proxy rewards that are the designer's best guesses.

Safety in Real-World Robots Robots deployed in the open-world need to handle a large set of possible environment configurations, be it a busy road for an autonomous car or a messy kitchen for a home robot. Given this challenge, there has been a rising number of work on safeguarding robot behaviors by generating edge cases. Koren et al. [27] and O'Kelly et al. [28] studied using black-box optimizers to perform adaptive testing and generate failure cases. [29] trains a generative model of environments from datasets. Uesato et al. [30] generates edge cases by learning a failure predictor. These methods require defining hard constraints that the robot should not violate. Similarly, reward shaping work has looked at how to incorporate such constraints into the reward [31].

In contrast, we focus on settings where such hard constraints are incomplete or difficult to specify. Our method does not assume access to such constraints. We show that our method can learn to develop edge-case scenarios that implicitly violate constraints without having to specify them.

3 Problem Statement

We first describe the Unassisted Reward Design problem works, then we formulate the Assisted Reward Design problem and introduce our method.

3.1 The Unassisted Reward Design Problem

Problem Setup Let an "environment" M be a Markov Decision Process without the reward function. At development time, we assume access to a large set of such environments, $\mathcal{M}_{\text{devel}}$. We assume this is a large set that the designer cannot exhaustively test. This can be, for instance, all the environments in a several-million-mile autonomous driving dataset. Or, it can be a parameteric set of possible environment configurations, such as placements of objects, roads, and other agents. Finally, it can also be a generative model of the world. The robot will run at deployment time in a different set of environments $\mathcal{M}_{\text{deploy}}$, which we do *not* have access to during development time. [2]

We further assume access to a space of reward functions parameterized by $w \in W$ — these can be linear weights on pre-defined features or weights in a neural network mapping raw input to scalar reward. We denote by w^* weights of the ground truth reward function, which induces the desired behavior in $\mathcal{M}_{\text{devel}}$ and $\mathcal{M}_{\text{deploy}}$. We denote by $\xi_{w,M}$ the trajectory (or policy, but for this work, we consider deterministic MDPs with set initial states) optimal to the cumulative reward induced by w

[2] Our method works best when we can induce a vast set $\mathcal{M}_{\text{devel}}$ that includes all possible scenarios in $\mathcal{M}_{\text{deploy}}$. Otherwise, if $\mathcal{M}_{\text{deploy}}$ is allowed to be drastically different, and if $\mathcal{M}_{\text{devel}}$ is not enough to design a robust reward function, this exposes the robot to unanticipated failures after deployment.

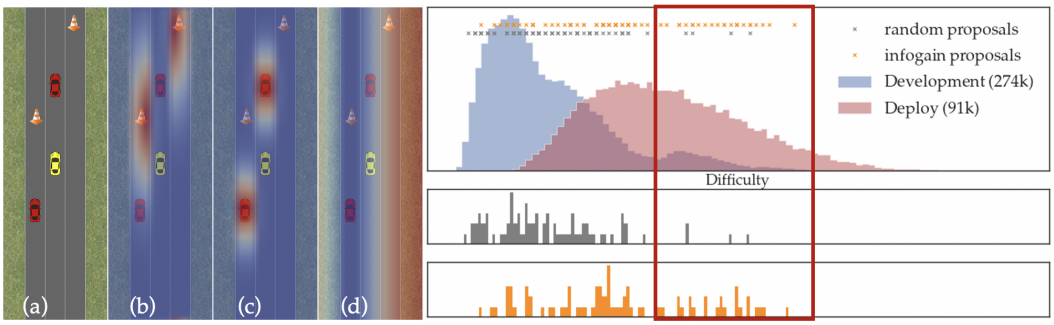

Figure 2: Left: (a) The driving environment with autonomous vehicle (yellow) and human-driven vehicles (red). (b)(c)(d) highlights selected features: obstacle distance, vehicle distance, progress. Right: the distribution of $\mathcal{M}_{\text{devel}}$ (blue) and $\mathcal{M}_{\text{deploy}}$ (pink) based on difficulty metric.

in M, $\xi_{w,M} = \arg\max_{\xi} R_w(\xi; M)$. Our assumption is that there exists a w^* such that $\xi_{w^*,M}$ is the desired behavior for any $M \in \mathcal{M}_{\text{devel}}$ and any $M \in \mathcal{M}_{\text{deploy}}$. We do *not* have access to w^*.

The Process of Unassisted Reward Design The designer takes a subset of environments $\mathcal{M} \subseteq \mathcal{M}_{\text{devel}}$ and specify a reward function (via parameters $\tilde{w}$) that leads to good behavior in those environments. In a one-shot design, they would select a set $\mathcal{M}$, assume it is representative of $\mathcal{M}_{\text{deploy}}$, design a $\tilde{w}$ for that $\mathcal{M}$, and deploy the system with $\tilde{w}$ (never changing the reward again). However, in reality, this is an iterative process. They start with an $\mathcal{M}_0$, design a $\tilde{w}_0$, and eventually encounter during their testing a new environment M' on which optimizing $\tilde{w}_0$ does not lead to desirable behavior. Then, they would augment their set to $\mathcal{M}_1 = \mathcal{M}_0 \cup \{M'\}$, and re-design the reward: $\mathcal{M}_0 \rightarrow \tilde{w}_0 \rightarrow \mathcal{M}_1 \rightarrow \tilde{w}_1 \rightarrow \ldots$. This might continue into deployment if the reward at the time of deployment still fails on $\mathcal{M}_{\text{deploy}}$. Implicitly, at every step along the way, the robot treats the current $\tilde{w}_i$ as equivalent to w^*.

3.2 The Assisted Reward Design Problem

We formulate the Assisted Reward Design Problem by introducing a Meta MDP problem. The system receives proxy rewards as observations from the designer and acts by proposing new environments. The goal is to minimize regret of the reward design over deployment $\mathcal{M}_{\text{deploy}}$.

Meta State, Meta Actions, Observations, Transitions.[3] In the Assisted Reward Design problem, the notion of a "state" is a set $\mathcal{M}$ of environments — this is what changes over time and is directly observable — along with the hidden state w^*. The robot starts at state $(\mathcal{M}_0, w^*)$ (environments either chosen by the designer to be representative, or simply the empty set). It transitions to the next state by "acting", i.e. adding one more environment M_i to the set: $\mathcal{M}_{i+1} = \mathcal{M}_i \cup M_i$. Every time it enters a state $(\mathcal{M}_{i+1}, w^*)$, it receives an observation $\tilde{w}_{i+1}$ about w^* from the designer. For the robot to assist the designer, it needs to treat the observed reward $\tilde{w}_i$ not the same as w^*, but as a proxy that emulates w^* *only* on the current $\mathcal{M}_i$. It can then interpret $\tilde{w}$ as evidence about w^* and use all past evidence to obtain a belief of w^*. To assist the designer, the key step is to account for (and thus influence) the future evidence in order to get a better reward estimate.

Observation Model. Previous work on Inverse Reward Design [1] introduced an observation model that computes the probability of observing proxy reward $\tilde{w}$ under w^* and designer's training environment set $\mathcal{M}$:

$$P_{\text{design}}(\tilde{w}|w^*, \mathcal{M}) \propto \exp\left[\sum_{i=1}^{|\mathcal{M}|} \beta R_{w^*}(\xi_{\tilde{w}_i, M_i})\right] \tag{1}$$

with β controlling how close to optimal we assume the person to be. This distribution informs the robot that it is receiving proxy rewards from an approximately optimal designer who looks at the current $\mathcal{M}$. We can then leverage this model to infer a belief over w^*: $b_{\mathcal{M}}(w^*)$.

Objective. The objective of Assisted Reward Design is to achieve high reward at deployment time. What the robot controls are a sequence of actions, i.e. a sequence of environments $\mathcal{M}_T$ it can propose. These lead to observations about w^*. At deployment time, the robot uses its belief to generate optimal trajectories and accumulates reward according to w^*. We want to find the set of environments $\mathcal{M}_T$ such that when given to the designer, these environments induce a belief that leads to the best performance in $\mathcal{M}_{\text{deploy}}$:

$$\max_{\mathcal{M}_T} \mathbb{E}_{M \sim \mathcal{M}_{\text{deploy}}} \mathbb{E}_{w \sim b_{\mathcal{M}_T}(w^*)} R_{w^*}(\xi_{w,M}) \tag{2}$$

[3]For the rest of this paper, all our references to "state" and "action" stand for "meta state" and "meta action".

where $b_{\mathcal{M}_T}(w^*)$ is the robot's belief at deployment time, based on the evidence gathered from the states $\mathcal{M}_0, .., \mathcal{M}_T$; $\xi_{w,M} = \arg\max_\xi R_w(\xi; M)$ is the optimal trajectory.

As currently stated, this objective is impossible to optimize directly because the robot does not know $\mathcal{M}_{\text{deploy}}$. In what follows, we introduce a solution to Assisted Reward Design based on the heuristic objective of identifying w^* — if the robot used its actions to disambiguate what w^* should be, then it can achieve optimum performance on the objective in Eq. 2 because it can plan optimally to w^*. We discuss this below. First, we introduce the Maximal Information objective. Then we show how the robot can track a belief and perform future belief updates in order to propose new environments.

4 Assisted Reward Design via Active Info-Gathering.

Maximal Information. We invert the probability model of Eq. 1 to obtain a belief over w^*: $P(w^*|\tilde{w}, \mathcal{M})$. Our key insight is that we can reduce the belief uncertainty by proposing future environments to influence the designer. In other words, we would like to find environments that can disambiguate the reward as much as possible — if we can identify w^* exactly, the robot attains zero regret at deployment. Thus, we introduce an approximate strategy for the robot: proposing environments that provide the most information gain over its belief distribution, as commonly done in active learning [32, 33] and robot active exploration [34]. For computational tractability, we do a one-step look-ahead only, although the robot could benefit from reasoning over multiple future iterations. Given an action M (MDP), we compute its mutual information with w:

$$f(M_{i+1}) = \mathbb{I}[w; M_{i+1}] = \mathbb{H}[w|\mathcal{M}_{0:i}, \tilde{w}_{0:i}] - \mathbb{E}_{w^* \sim P_i(w), \tilde{w}_{i+1} \sim P_{\text{design}}(\tilde{w}_{i+1}|w^*, \mathcal{M}_{i+1})}[\mathbb{H}[w|\mathcal{M}_{0:i+1}, \tilde{w}_{0:i+1}]] \tag{3}$$

Here $\mathbb{H}[w|\mathcal{M}_{0:i}, \tilde{w}_{0:i}]$ is the entropy of posterior distribution of $P_i(w)$, and $\tilde{w}_{i+1}$ is a new observation sampled from the updated designer model $P_{\text{design}}(\tilde{w}_{i+1}|w^*, \mathcal{M}_{i+1})$. After observing $\tilde{w}_{i+1}$, we can compute the conditional entropy $\mathbb{H}[w|\mathcal{M}_{0:i+1}, \tilde{w}_{0:i+1}]$ using methods from Sec. 4.1. In our implementation, we set $\tilde{w}_{i+1} = w^*$ to make Eq. 3 more tractable and find that it empirically works well. Next we introduce two update rules to compute conditional entropy — joint and independent mode.

4.1 Updating Beliefs over w^*

Joint reward design. At iteration $i+1$ of Assisted Reward Design, the robot takes an action M_{i+1} (proposes an environment), and receives an observation $\tilde{w}_{i+1}$ – a reward that works over *all* environments $\mathcal{M}_{i+1} = \mathcal{M}_i \cup \{M_{i+1}\}$. Assuming that $\tilde{w}_{i+1}$ is independent from previous observations, we can use $\tilde{w}_{i+1}$ to update the belief over w using Eq. 1:

$$P_{i+1}(w|\tilde{w}_i, \mathcal{M}_i) \propto P_i(w) P_{\text{design}}(\tilde{w}_i|w, \mathcal{M}_i) \tag{4}$$

with P_0 the robot's prior (uniform in our experiments). We take a sequential-importance-resampling particle filtering approach to approximate P_{i+1}: we sample N_p particles from P_i, compute importance weights based on Eq. 1 for each particle, and resample using the importance weights. Note that we need to compute the normalized P_{design}, and we approximate the normalizer in Eq. 1 via samples.

Independent reward design. We also allow designers to provide an observation $\tilde{w}_i$ based solely on the new environment M_i. Prior work [35] finds that this model puts less burden on the designer. Under this assumption, our belief update simplifies to relying on a single new environment:

$$P_{i+1}(w|\tilde{w}_i, M_i) \propto P_i(w) P_{\text{design}}(\tilde{w}_i|w, M_i) \tag{5}$$

5 Experiments with Simulated Designers

We evaluate Assisted Reward Design in an autonomous driving task. In this section, we hypothesize a ground truth reward function and simulate designer behaviors. Note that our method does not require such unique ground truth w^* – this is merely used here for evaluation. In Sec. 6, we conduct an expert study where we do not have the ground truth.

5.1 Experiment Setup

Driving task. As illustrated in Fig. 2, the autonomous car is to merge to the leftmost lane. Since there may be other human vehicles (simplified as constant speed) and obstacles, the autonomous car needs to decide whether to overtake or to slow down. Our reward function based on Sadigh et al. [2] is a weighted sum of six features, including vehicle distance, progress, control effort, etc. Please refer to supplementary material for their details. A good reward function should correctly balance these

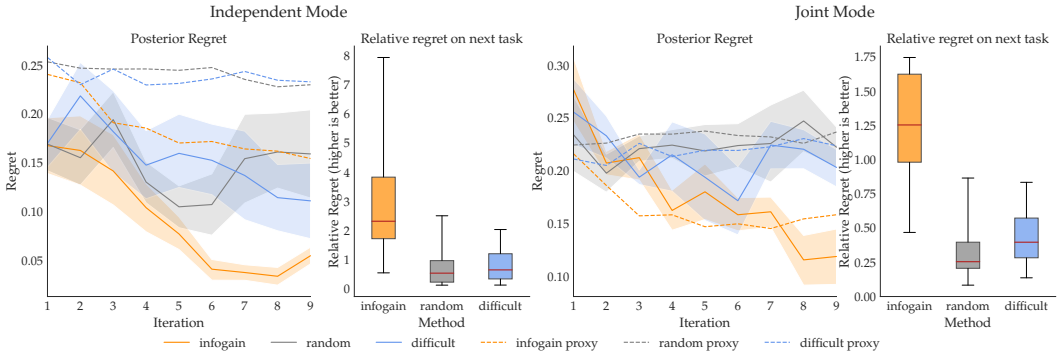

Figure 3: Experiment with simulated designers. Left: independent mode, right: joint mode. (a)(c) shows the regret of the posterior mean compared to true reward under different acquisition functions. (b)(d) shows the efficacy of the proposed environment. The "box" denotes 5th to 95th percentile.

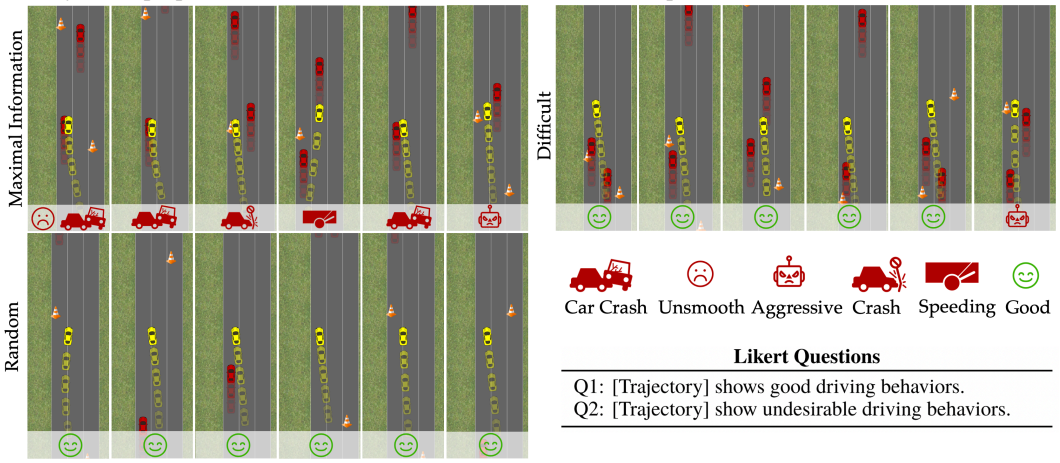

Figure 4: Visualization of the top proposed environments based on each acquisition function.

terms and reflect our desired behaviors in all different situations. To obtain $\mathcal{M}_{\text{devel}}$, we parametrize environments over the initial placements of obstacles and other vehicles.

Environment Difficulty. Successful merging tends to be more difficult when human vehicles and obstacles are closer to the autonomous vehicle. We can use a simple metric to describe each environment: difficulty $= \sum_i 1/d_{\text{human vehicle}_i} + \sum_j 1/d_{\text{traffic cone}_j}$. We visualize the distribution of $\mathcal{M}_{\text{devel}}$ and $\mathcal{M}_{\text{deploy}}$ in Fig. 2 using this metric. Note that both $\mathcal{M}_{\text{devel}}$ and $\mathcal{M}_{\text{deploy}}$ have a "long-tail" distribution of events — events that are rare to encounter daily, but could be highly useful for the reward design. An ideal acquisition function in should be able to identify these events.

Baselines. We compare our Maximal Information acquisition function with two baselines that represent common design paradigms where the designer selects (1) the most difficult tasks ranked by $M \in \mathcal{M}_{\text{devel}}$ (2) random environments from $\mathcal{M}_{\text{devel}}$.

5.2 Experiment Results

Evaluation. A good Assisted Reward Design method should help the reward designer quickly recover high-quality reward functions. To evaluate this, we specify one set of ground truth reward w^*. At every iteration, we simulate the designer using w^* under both *independent* mode and *joint* mode as described in Sec. 4.1. Please refer to the appendix for experiment details. We plot the performance of posterior mean and the proxy reward $\tilde{w}$ under different methods in Fig. 3. To mitigate the effect of the choice of initial environments, we experiment on six random initial environments and find that our active method outperforms the proxy reward $\tilde{w}$, as well as the random and difficult baseline in both joint and independent modes ($p < 0.05$).

Our active method (orange) outperforms both the random baseline (grey) and the difficulty heuristic (blue) as shown in Fig. 3. This means that certain environments, despite being rated "easy" by heuristics, turn out useful for the reward design. These environments are often edge-cases that subtly

trigger undesirable behaviors — in Fig. 1 a rather empty road with two human vehicles triggered the autonomous vehicle to crash. Next we further investigate this.

Edge-Case Nature of Proposed Environments To study why our method performs better than the baselines, we measure the quality of the proposed environments using: $r(M_{\text{next}}) = \mathbb{E}_{\tilde{w}\sim P(w=w^*)}\left[\text{Regret}(\tilde{w}; w^*, M_{\text{next}})\right] / \mathbb{E}_{\tilde{w}\sim P(w=w^*)}\mathbb{E}_{M\sim\mathcal{M}_{\text{deploy}}}\left[\text{Regret}(\tilde{w}; w^*, M)\right]$, the ratio of regret on next environment versus average regret in deployment. Higher $r(M_{\text{next}})$ means the next environment better uncovers the overall regret of the current posterior. As shown in Fig. 3, our active method proposes environments of highest relative regret. This suggests that to find the most useful environment for Assisted Reward Design, simply relying on heuristic environment ranking is not enough. It is more effective to utilize all proxy rewards and their induced uncertainty over w^*.

6 Experiments on Real Reward Design

We conducted a study with 14 robotics experts[4] on the autonomous driving tasks, where we ask them to design reward functions to generate their preferred driving behaviors.

6.1 Experiment Setup

We give the experts 10 minutes to familiarize with the features. We then let them design reward functions over four consecutive iterations, under three different methods and three different random seeds. This gives a total of 36 individual reward designs. We use counterbalancing to randomize the sequence of different methods. All our experiments are conducted over Zoom.

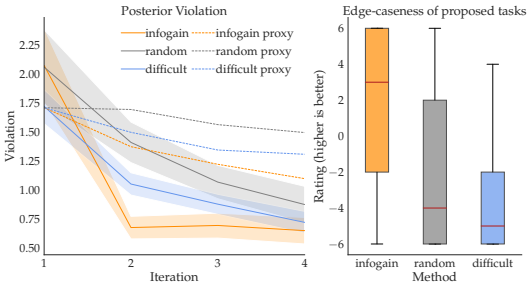

Figure 5: Experiment with robotic experts. The left shows the violation under different acquisition functions. The right compares the relative value of proposed environments.

Violation. Since we do not have the ground truth reward function, we cannot measure posterior regret as in Sec. 5. For evaluation purposes only, we introduce seven violation criteria to measure the quality of our reward design, including collision, driving off track, stopping, etc. Please refer to the appendix for detailed definitions. We use these criteria as unit tests on the behavior to capture unwanted behaviours. We then count the total number of violations of each trajectory. Better reward functions should induce lower violation counts. Although we could explicitly incorporate these tests as hard constraints in the "reward" function [31], we keep the reward features oblivious to them. This is for two main reasons. First, in the real world, constraint violations are acceptable in some edge-case scenarios: slamming on the brake, despite uncomfortable, is justifiable at the sight of traffic accidents. Such trade-offs are difficult to specify and it is our goal to exploit potential edge-cases. Second, violation tests only capture a subset of unwanted behaviors. Tailgating, for instance, does not break the tests. Yet, it is undesirable in most cases for the autonomous vehicle. In Sec. 6.2 we provide qualitative examples from the experiment to illustrate such undesirable behaviors.

6.2 Experiment Results

Evaluation. We perform Assisted Reward Design where experts answer the queries stemming from our algorithm, as well as the baselines. We visualize the result in Fig. 5 left. Maximal Information outperforms the other acquisition functions in causing fewest average violations on $\mathcal{M}_{\text{deploy}}$. This shows that Assisted Reward Design can help us tune a reward function that fails fewer tests as a measurable proxy for the good driving behaviors in the real world.

Edge-Case Nature of Proposed Environments. To measure the quality of the proposed environments at each iteration, we ask the experts to watch the trajectories that their proxy designs generate on the proposed tasks. We then use the Likert scale questions in Fig. 4 and ask the users to rate how much they agree with the statement on a scale of 1-7. We then compute the normalized score $Q1 - Q2$ as a measure of how good the behavior is. A lower score indicates better behavior. We use the inverse of the score to indicate edge-caseness in Fig. 5. Our maximal information method outperforms the heuristic difficulty metric in finding edge-case environments that contain more violations.

Qualitative Analysis of Proposed Environments We randomly sample an initial environment and query designer. We then use maximal information, heuristic difficulty, and random acquisition

[4] from the authors' institution

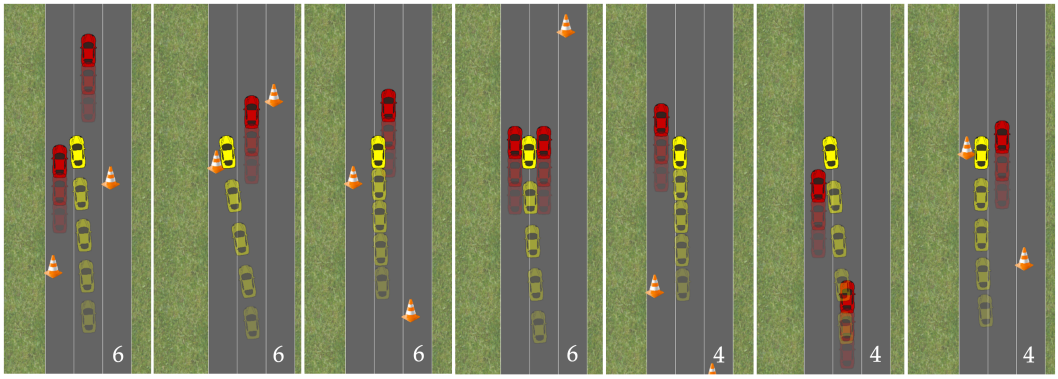

Figure 6: Selected environments proposed by Maximal Information with the highest rating by users. The robot plans a trajectory using previously designed w_{MAP}. Normalized Likert scale rating is shown on the bottom right of each scenario. Higher rating means more likely to be an edge case. Notice that these trajectories are failure cases but do not violate the pre-defined difficulty metrics such as collision.

function to propose the next environments. We visualize the trajectory of MAP estimate w_{MAP} on each of these new environments in Sec. 6. Notice that interestingly, our method tends to find environments where the current MAP estimate fails, even though we do not explicitly optimize for finding failure cases. It turns out that these environments help reward designers effectively narrow down on the true reward. In comparison, heuristic difficulty finds environments with dense interactions. Yet, they do not induce failure in the resulting trajectories likely because such difficulties have been addressed by past reward designs. Heuristic difficulty tends to generate repetitive environments.

Can Violation Count Replace the Maximal Information? Our experiments in Sec. 6.2 use violation counts to evaluate trajectories. One may ask the question: can we simply use the violation count as an acquisition function to find edge-case environments? In other words, environments where the design leads to high collision, off-track counts, etc. should be proposed as edge cases. On a surface level, this seems to be a reasonable approach. In fact, this is commonly used in industry [36]. However, we argue that setting violation counts as the acquisition function limits the scope that we can identify edge cases. We highlight this in Fig. 6, where we visualize selected environments proposed by Maximal Information. They exhibit subtle failures and lead to the highest Likert-scale ratings despite obeying all violation criteria. Interestingly in the second, fourth, and seventh examples, the vehicle narrowly avoids the collision. Such behaviors found by Maximal Information are hard to capture with hand-designed violation metrics. By acting on the edge of violations, the robot pushes the reward designer to better specify her "decision boundaries". As a result, Maximal Information can propose more diverse edge cases and gather designer preference more quickly.

7 Discussion

We contribute Assisted Reward Design, an active reward learning method that generates environments and queries for reward functions as user inputs. We find experimentally that our method exposes edge cases — environments where the current proxy reward leads to high regret. Experiments with robotic experts confirmed that these environments are edge cases that lead to undesirable behaviors. We are excited to contribute a marriage between active reward learning and traditional reward design, and we advocate that reward design should be thought about as an iterative process.

Currently, there are several limitations to our approach. Firstly, our environment proposal algorithm could be made more efficient. This will enable us to search over a larger set of environments. One may also explore synthesis and continuous optimization over the environment parameters instead of exhaustive search. Secondly, despite experimentally showing that we can generate edge cases and reduce regret, we stand in need of formal analysis and guarantee of such results. Thirdly, our method assumes access to an environment model, which could also be practically challenging. Though one can leverage existing simulators [37], simulating realistic environments, e.g., streets with responsive drivers, remain an open problem.

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