Risk-Averse Biased Human Policies in Assistive Multi-Armed Bandit Settings

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ABSTRACT

Assistive multi-armed bandit problems can be used to model team situations between a human and an autonomous system like a domestic service robot. To account for human biases such as the risk-aversion described in the Cumulative Prospect Theory, the setting is expanded to using observable rewards. When robots leverage knowledge about the risk-averse human model they eliminate the bias and make more rational choices. We present an algorithm that increases the utility value of such human-robot teams. A brief evaluation indicates that arbitrary reward functions can be handled.

CCS CONCEPTS
• Mathematics of computing → Probabilistic inference problems; • Computing methodologies → Cognitive robotics.

KEYWORDS
Human-Robot Interaction, Theory of Mind, Multi-Armed Bandit

1 INTRODUCTION

Humans frequently find themselves playing multi-armed bandit (MAB) games. In such settings, an actor repeatedly chooses an action (or pulls an arm) without complete knowledge about the associated reward distribution of each action. During an episode, there is a trade-off between choosing what previously yielded the best results (exploitation) and choosing other actions to improve the estimate of the mean reward (exploration). The goal for the autonomous system is to improve the return for a human by estimating the true expected return of each action by monitoring the human’s behavior as implicit feedback [6, 10], e.g., when choosing music or repeatedly commanding a robot. We might interact with domestic robots in situations, where the human partner is not quite sure what the robot understands as it learns about the different outcomes. Examples include under-specified commands such as “Set the table.” or “Fetch me some food for lunch.”.

This paper focuses on MAB scenarios that model these decision situations. When humans make choices, however, it is known that systematic biases occur, which lead to sub-optimal behavior. One such bias, which occurs in risky uncertain situations, is modeled by the Cumulative Prospect Theory (CPT) [4, 11]. Humans tend to prefer small gains with small variance to large gains with large variance, but are willing to take more risk to avoid big losses. This bias was applied to a human-robot interaction (HRI) [5], where an episode consisted of a single choice, but was not explored in repeated games. On the other hand, human–robot teams in MAB settings have been studied in [2, 8], but their human models were either (noisy) rational, greedy or inconsistent. The solutions would only learn to replicate a bias as proposed by CPT.

The risk-averse biased human MAB policy used in this work is also distinct from MAB policies that explicitly minimize a risk factor [1, 3, 7, 12]. The biased policy’s only goal is to maximize return, but has a biased perception of the estimated means during play, which leads to suboptimal behavior. In this paper we (1) define the assistive MAB with observable reward classes, (2) explore the behavior of a risk-averse biased MAB policy, and (3) present an assistive algorithm for a human-robot team that eliminates the bias of the human and improves the overall return for the team.

2 MULTI-ARMED BANDIT FORMULATION

The MAB is a simplified reinforcement learning problem, where an actor repeatedly picks one of $N$ available actions. In this work, each action is associated with a separate distribution over $M$ different rewards, from which rewards are sampled. The agent thereby weighs exploitation and exploration to finally settle on choosing the best arm. The formalism is presented for discrete random reward variable distributions. Continuous distributions are handled by dividing the continuous reward range into discrete classes.

In the Inverse Multi-Armed Bandit with Observable Reward Classes problem, a passive agent estimates the mean reward of the different actions by observing the MAB choices of another agent. The observer is only allowed to observe the chosen action and the reward class, i.e., no numeric utility, but only a class label. The Assistive Multi-Armed Bandit with Observable Reward Classes is a version of the inverse MAB, where the observer additionally intercepts the action of the other agent and can choose the same action or another to be played in each round. The Upper Confidence Bound (UCB) family of MAB algorithms balance exploration and exploitation by maintaining a statistic about the rewards per available action and calculate an

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Algorithm 1 Robot policy in H + R Team

1: procedure Choose Arm(t)
2: create probability statistic \( P \) for \( i \in [1, \ldots, t-1] \) from \( \mathcal{H} \)
3: perform probability bias on all \( P_i \), initialize \( \hat{R} \) with \( r_0 \)
4: minimize \( \sum_{t'=1}^{t-1} \argmax_{a \in \mathcal{A}} P_t a \neq a_i^H \)
5: inverse reward transformation on \( \hat{R} \)
6: choose \( a_i^R = \argmax P_{t-1} \hat{R} \)
7: observe human choice \( a_i^H \)
8: H and R observe reward \( r_t \) after \( a_i^R \), update \( \mathcal{H} \)

4 EXPERIMENTS
The experiments seek to answer the following research questions:
R1 risky-better: Can the H-R team improve the performance of a risk-averse biased human policy in scenarios, where the risky option has a higher expected return? R2 safe-better: Will the H-R team’s performance deteriorate below the performance of the rational UCB policy when the lower option yields the higher expected return?

5 CONCLUSION
In this paper we motivated the Assistive Multi-Armed Bandit with Observable Reward Classes. This formulation allows a direct observation of the variance of each arm in a MAB. The problem is transformed from a preference learning problem of arm choices to a preference learning of different discrete rewards. This setting is a stepping stone to explore more complex human policies. Future work will include testing algorithms with a supervised training phase before the test phase in the expanded setting and reducing
the error induced by the altered exploration behavior in the human policy.

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