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List of Five Most Significant Publications

On Formalizing Fairness in Prediction with Machine Learning [1].

In this article, we analyzed fairness notions from the machine learning literature by juxtaposing them with their corresponding notions from the social sciences literature. This was one of the inaugural works arguing for an interdisciplinary approach to fairness-aware machine learning research and it continues to be used as reading material for related courses at a number of universities [2, 3]. In this article, we provided theoretical as well as empirical critiques of the fairness notions and proposed guiding principles while choosing the fairness notions to use in particular application domains. Furthermore, we suggested two notions of distributive justice (one of which has been used in the foundations of the human development paradigm by the United Nations) which address some of these critiques.

Autonomous Exploration for Navigating in MDPs Using Blackbox RL Algorithms [4].

This article provides the inaugural method to convert any reinforcement learning algorithm with sublinear regret into an exploration algorithm with suitable guarantees on its sample complexity. We consider the problem of navigating in a Markov decision process where extrinsic rewards are either absent or ignored. In this setting, the objective is to learn policies to reach all the states that are reachable within a given number of steps (in expectation) from a starting state. We introduce a novel meta-algorithm that can use any online reinforcement learning algorithm (with appropriate regret guarantees) as a black-box. We prove an upper bound on the sample complexity of our algorithm in terms of the regret bound of the used black-box algorithm. Furthermore, we provide experimental results to validate the effectiveness of our algorithm.

A Relative Exponential Weighing Algorithm for Adversarial Utility-based Dueling Bandits [5].

The main contribution of this article is an algorithm designed for adversarial single-state reinforcement learning using preference feedback. This is in contrast to most of the existing algorithms in the contemporary related literature which assumed a stochastic environment. For the performance measure, we provided a lower bound for the problem and an upper bound for the proposed algorithm. These two bounds match the original bounds for single-state reinforcement learning using conventional absolute feedback. Our experiments on real-world information retrieval datasets show that our proposed algorithm works well in practice.

Corrupt Bandits for Preserving Local Privacy [6].

The main contribution of this article is an efficient learning algorithm providing local differential privacy in applications of reinforcement learning e.g., recommender systems. Our work paved the way for considering a stricter notion of privacy, in contrast to most existing work in the literature of reinforcement learning which considered a milder privacy notion. We proved a lower bound on the performance measure and constructed a frequentist algorithm and a Bayesian algorithm and proved respective near-optimal upper bounds on their performance. We also provided an optimal mechanism using which a user can achieve the desired trade-off between privacy and utility. Our experimental results show that our proposed method could be useful in recommender systems.

Adaptively Tracking the Best Bandit Arm with an Unknown Number of Distribution Changes [7].

In this article, we considered a variant of the stochastic single-state reinforcement learning problem where the stochastic reward distributions may change abruptly several times. In contrast to previous work, we constructed the first algorithm for the considered problem that achieves optimal performance bounds without knowing the number of changes in advance. Our algorithm (without any change) also provides optimal performance guarantees in terms of total variation.

References

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