Adapting Static Fairness to Sequential Decision-Making: Bias Mitigation Strategies towards Equal Long-term Benefit Rate

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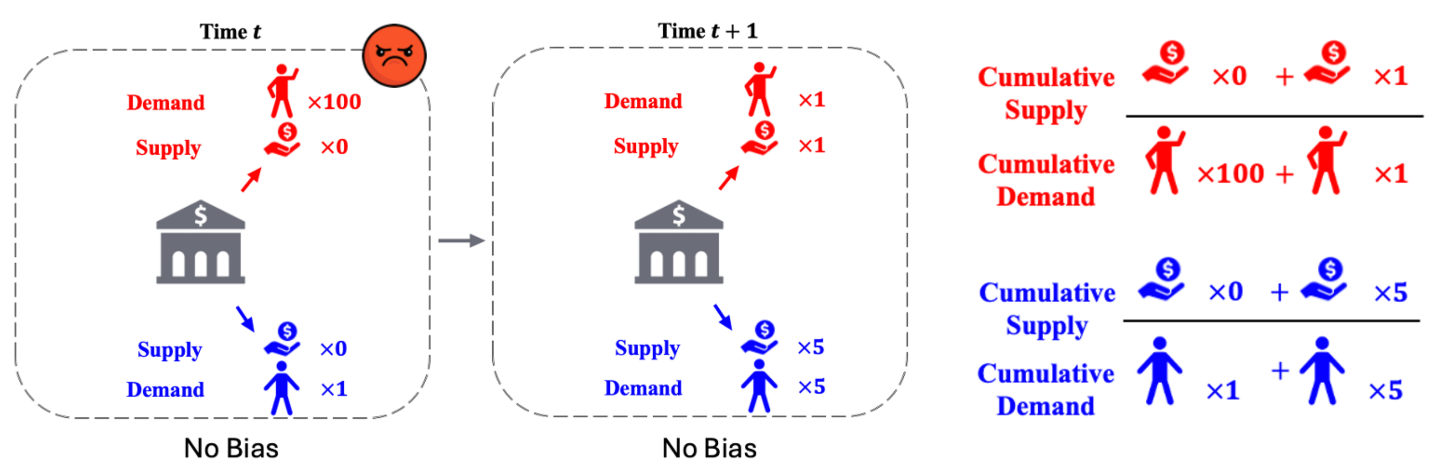
Introduction

❖ Long-term fairness: A bank lending example

- *Demand*: number of applicants; *Supply*: number of loans



Both acceptance rates = 0 (Fair at Time t) | Both acceptance rates = 1 (Fair at Time t+1) | Not fair in the long run!

❖ Future impact matters

❖ Previous long-term fairness notions: summing up step-wise biases

- Temporal discrimination within groups
- Short-term fairness implies long-term fairness (Incorrect!)

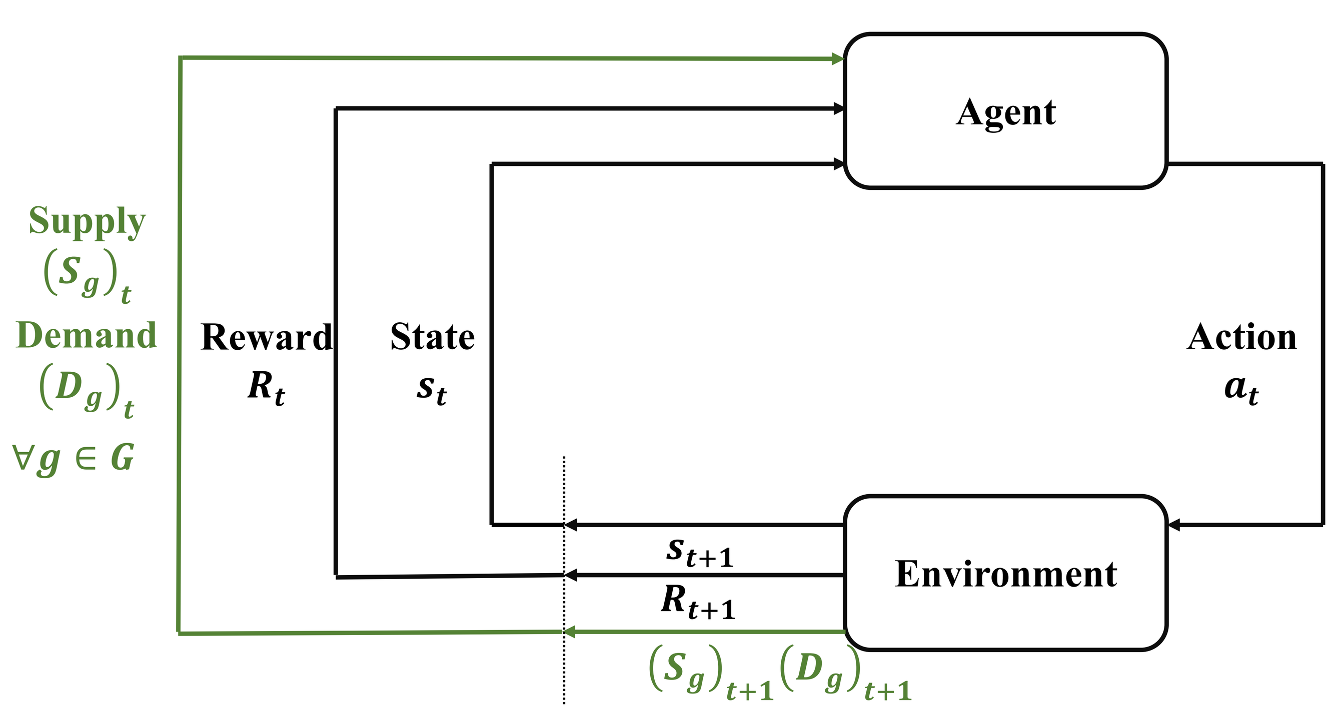
Contributions

- Long-term fairness notion: Equal Long-term Benefit Rate
  - Adapts multiple static fairness notions (e.g., Equal Opportunity)
  - A framework in Markov Decision Process (MDP)
- Bias mitigation algorithm using policy optimization

Equal Long-term Benefit Rate (ELBERT)

❖ Supply-Demand Markov Decision Process

- Additionally returns group demand and group supply as fairness signals



- Cumulative group supply and group demand

$$\eta_g^S(\pi) := \mathbb{E}_\pi\Big[\sum_{t=0}^{\infty} \gamma^t S_g(s_t,a_t)\Big], \eta_g^D(\pi) := \mathbb{E}_\pi\Big[\sum_{t=0}^{\infty} \gamma^t D_g(s_t,a_t)\Big]$$

❖ (Definition) Long-term Benefit Rate: $\frac{\eta_g^S(\pi)}{\eta_g^D(\pi)}$

- Ratio between cumulative group supply and demand

❖ (Definition) Bias of a policy

$$b(\pi) = \max_{g\in G} \frac{\eta_g^S(\pi)}{\eta_g^D(\pi)} - \min_{g\in G} \frac{\eta_g^S(\pi)}{\eta_g^D(\pi)}$$

- Discrepancy of Long-term Benefit Rate among groups

Bias Mitigation Algorithm

❖ Training objective (two groups)

$$\max\ J(\pi) = \eta(\pi) - \alpha b(\pi)^2 = \eta(\pi) - \alpha\Big(\frac{\eta_1^S(\pi)}{\eta_1^D(\pi)} - \frac{\eta_2^S(\pi)}{\eta_2^D(\pi)}\Big)^2$$

- Increase reward & decrease bias
- Challenge: policy gradient of Long-term Benefit Rate $\frac{\eta_g^S(\pi)}{\eta_g^D(\pi)}$

❖ Policy Optimization (PO)

- Key: reduction to standard policy gradient

$$\nabla_\pi\Big(\frac{\eta_g^S(\pi)}{\eta_g^D(\pi)}\Big) = \frac{1}{\eta_g^D(\pi)}\nabla_\pi \eta_g^S(\pi) - \frac{\eta_g^S(\pi)}{\eta_g^D(\pi)^2}\nabla_\pi \eta_g^D(\pi)$$

- Advantage function

$$\nabla_\pi J(\pi) = \mathbb{E}_\pi\{\nabla_\pi \log \pi(a_t|s_t) A_t^{fair}\}$$

  - Can be plugged into any PO methods, like PPO
  - Result

$$A_t^{\text{fair}} = A_t - \alpha \sum_{g\in G} \frac{\partial h}{\partial z_g}\Big(\frac{1}{\eta_g^D(\pi)} A_{g,t}^S - \frac{\eta_g^S(\pi)}{\eta_g^D(\pi)^2} A_{g,t}^D\Big)$$

$$\text{where}\quad b(\pi)^2 = h\Big(\frac{\eta_1^S(\pi)}{\eta_1^D(\pi)}, \frac{\eta_2^S(\pi)}{\eta_2^D(\pi)}\Big)$$

❖ Extension to multi-group setting

- Challenge: non-smoothness in max/min

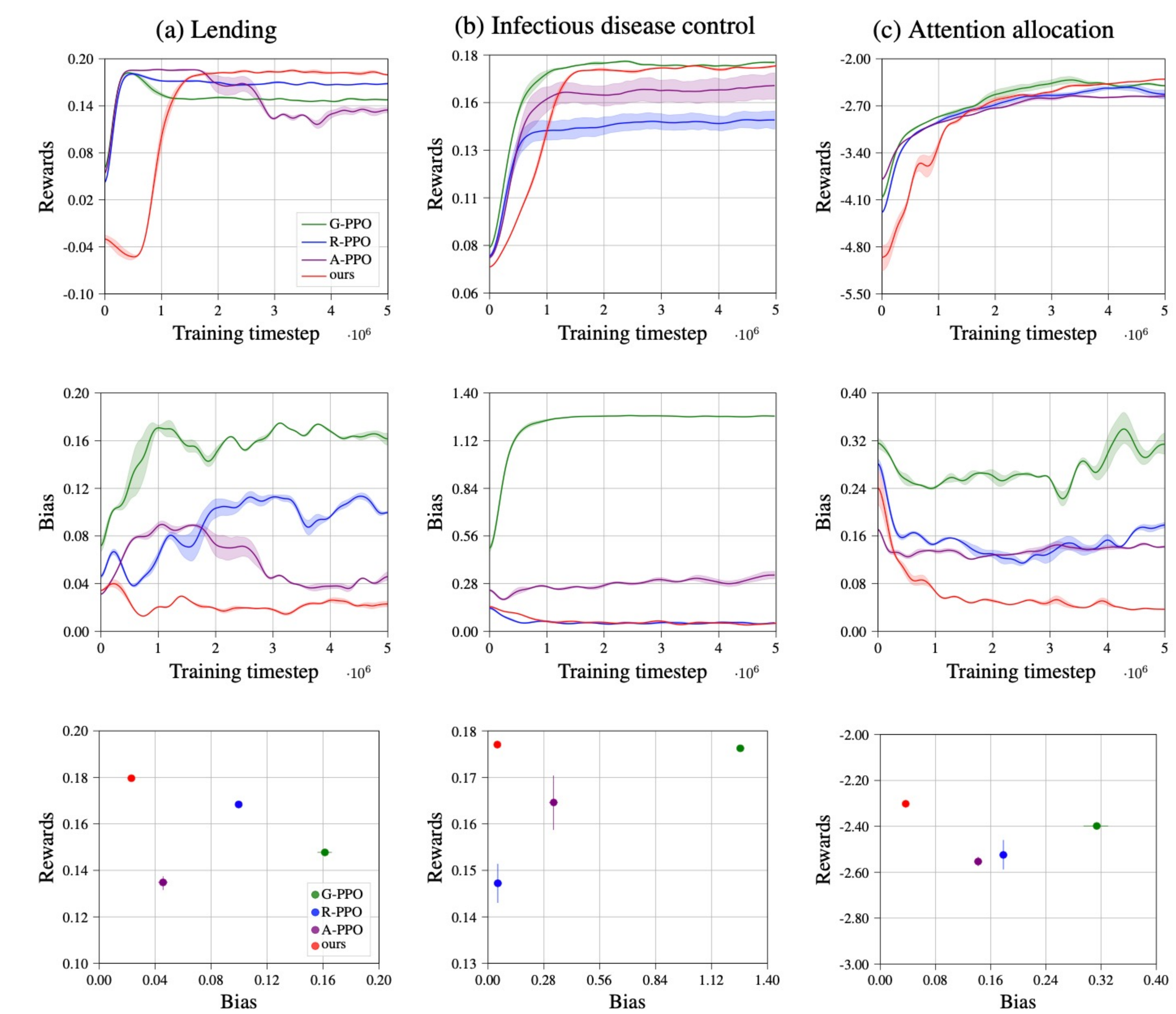
$$J(\pi) = \eta(\pi) - \alpha b(\pi)^2 = \eta(\pi) - \alpha\Big(\max_{g\in G} \frac{\eta_g^S(\pi)}{\eta_g^D(\pi)} - \min_{g\in G} \frac{\eta_g^S(\pi)}{\eta_g^D(\pi)}\Big)^2$$

- Solution: define soft bias

$$b^{\text{soft}}(\pi) = \frac{1}{\beta}\log\sum_{g\in G}\exp\Big(\beta\frac{\eta_g^S(\pi)}{\eta_g^D(\pi)}\Big) - \frac{1}{-\beta}\log\sum_{g\in G}\exp\Big(-\beta\frac{\eta_g^S(\pi)}{\eta_g^D(\pi)}\Big)$$

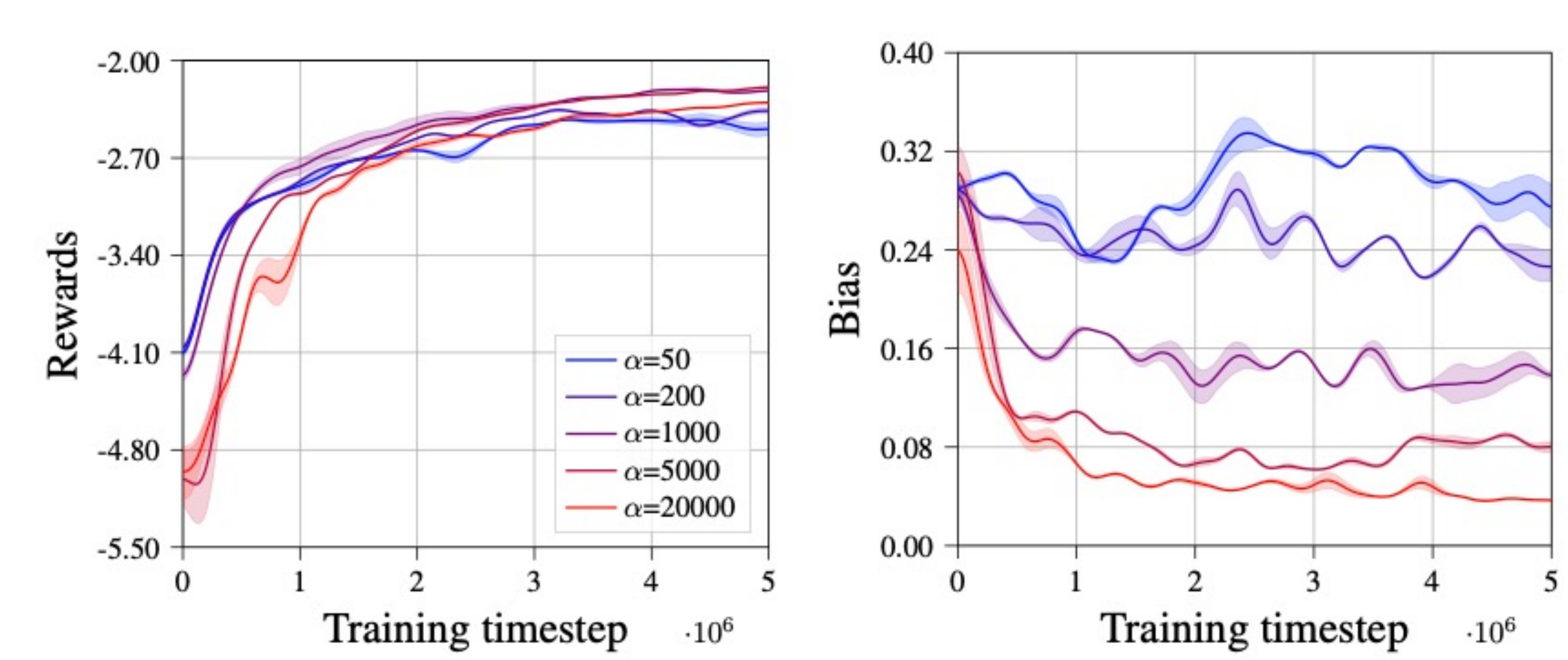
Experiments

❖ ELBERT-PO significantly reduces bias while maintaining high reward



Rewards and bias of ELBERT-PO and baselines in three environments

❖ Effect of the bias coefficient α



(a) Rewards (b) Bias

Larger the bias coefficient α

- Lower bias.
- Slower convergence of reward.
- Final reward could be either higher or lower.