Fairness of Exposure in Online Restless Multi-armed Bandits

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Healthcare Intervention

Need to provide medical intervention to patients, but only have a limited budget to do so (number of doctors, number of available rooms, etc.). There are many things to consider for any potential solution.

- The patient's condition may change.
- The doctor may not have a good estimate of how a patient's condition might evolve.
- The limited budget.

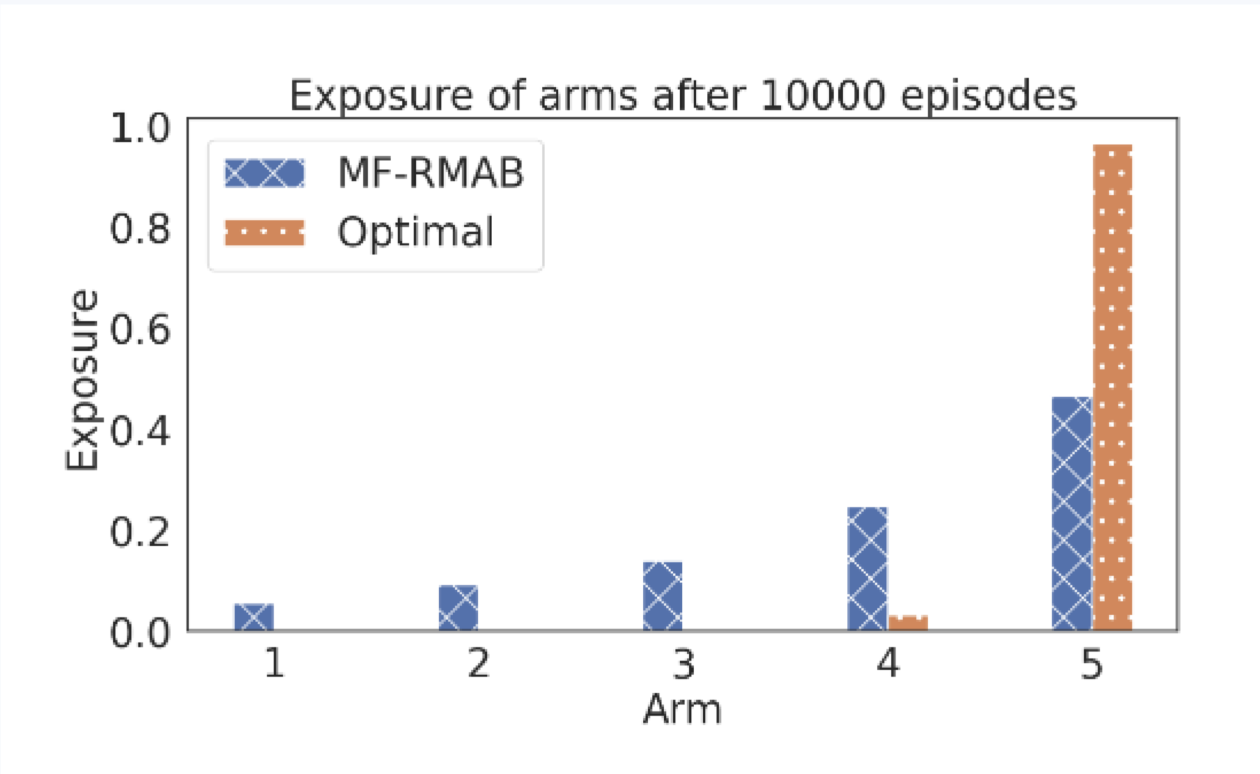
Restless Multi-armed Bandit

- Each patient is modelled as an 'arm'. Total number of arms = N
- Providing intervention to a patient is called 'pulling' that arm.
- Each arm has two states: 'good' and 'bad'.
- Arms transition from one state to another based on their 'transition probabilities' P.
- We run our algorithm (policy) for total T episodes.
- We can only pull K (< N) arms at one-time step.
- Ideally, we want to pull the arm which will go from bad to good state due to our intervention.
- We can define the 'reward' of an arm as the benefit the arm receives from getting pulled.

The Optimal Policy need not be fair!

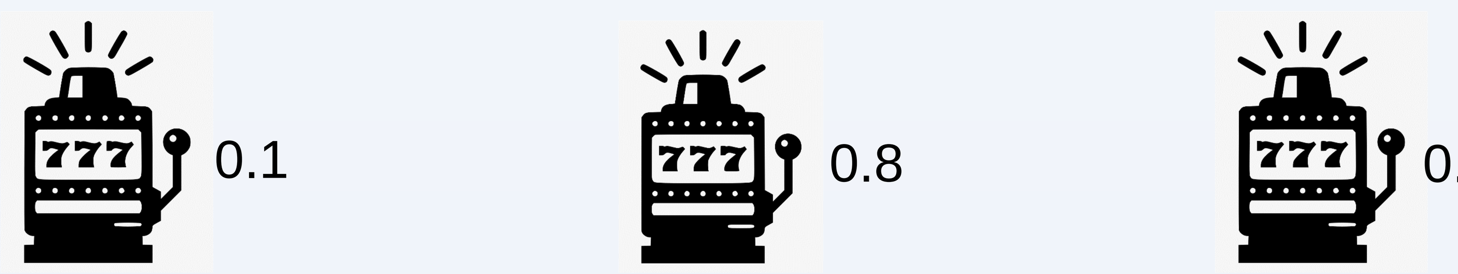
Meritocratic Fairness

- Pulling arms with the highest reward leads to some arms getting starved of attention.
- In healthcare, this would imply that some patients barely receive medical help!
- There is a need for policies that provide fair exposure to each arm.



Pull each arm with probability proportional to their reward.

Motivation



Optimal Allocation: Arm 3 with reward 0.9

Fair Allocation: Pulling probabilities of 0.055, 0.44, and 0.5 respectively

Proposed Algorithm: MF-RMAB

For each episode t,

1. Learn the transition probabilities P_i^t for each arm i via Upper Confidence Bound approach [1].
2. Find out steady state probability $f_i(P_i^t, p_i)$ of arm being in 'good' state (when hypothetically pulled with probability p_i) [2].
3. Estimate reward $\mu_i^t = f_i(P_i^t, 1) - f_i(P_i^t, 0)$.
4. Define meritocratic fair policy π, where π_i is the probability of arm i being pulled. $\pi_i^t = \frac{g(\mu_i^t)}{\sum_j g(\mu_j^t)}$, where $g(.)$ is a non-decreasing positive Lipschitz-continuous function [3].
5. Sample K arms from π^t.

Fairness Regret

Suppose we already know the true transition probabilities P^* of all the arms. The subsequent policy according to MF-RMAB is denoted by π^*.

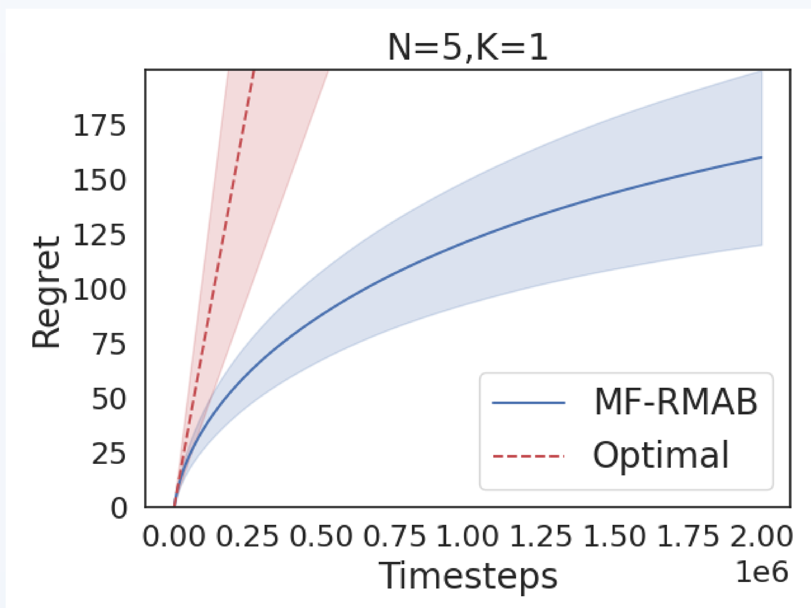
The Fairness Regret (FR) is defined as the difference between the policies when all information is known vs when we have to estimate the transition probabilities.

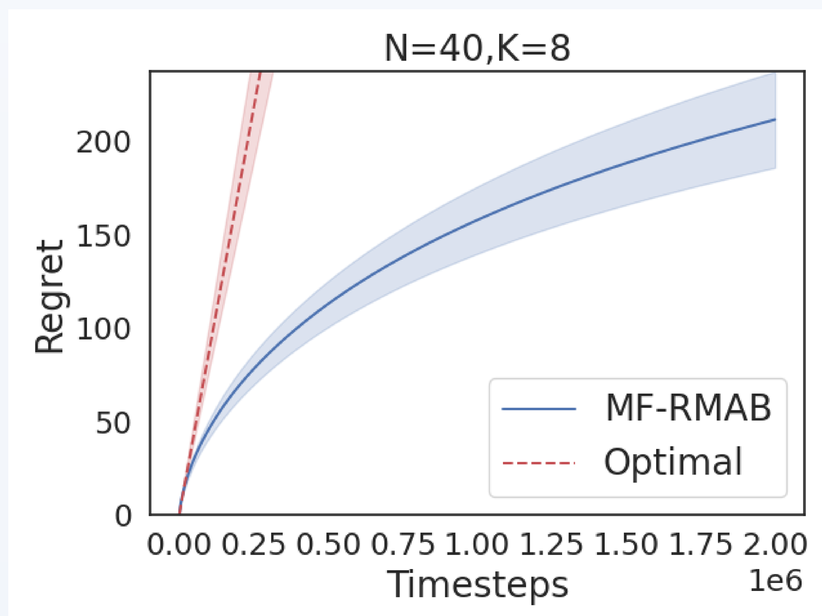
$$FR^T = \sum_{t=1}^{T} \sum_{i \in [N]} |\pi_i^* - \pi_i^t|$$

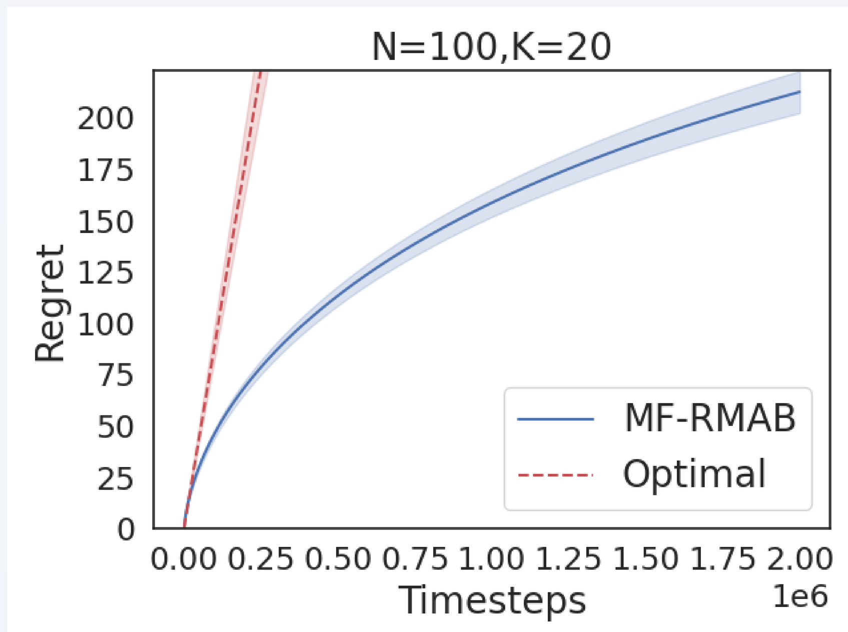
Theoretical Results

Theorem: MF-RMAB incurs $O(\sqrt{T \ln T})$ fairness regret for sufficiently large T and $K = 1$.

Experimental Results







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