Object Detection Using Deep Learning

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Table of Contents

Introduction

- Conventional multi arm bandit (MAB) problem:
  - learner pulls one out of $K \in \mathbb{N}_+$ arms
  - reward is obtained (sampled from an unknown-mean distribution)
- Multi-play multi-armed bandits:
  - play multiple arms in a single time slot
- Shareable multi-play multi-armed bandits (*shareable* MP-MAB)
  - Each arm can be played any number of times

Problem Statement

- $K \in \mathbb{N}_+$ arms, indexed by $1, 2, ..., k$
- rewards according to the distribution X_k with means, μ_k (not known to the player)
- finite rewards capacity, m_k, (not known to the player)
- Reward from arm $k = \min\{a_k, m_k\} \times X_k$
- Without loss of generality $\mu_1 \geq \mu_2 \geq ... \geq \mu_k$

Problem Statement

N number of plays are assigned in each time slot, and the player chooses how these N plays are distributed among the K arms.

Objective: estimate the means of the reward distribution and capacity of these arms, while maximising the reward.

Theoretical Background

OrchExplore Algorithm:

Stage 1: Initial iterations: runs PIE in odd time slots, PUE in even time slots

Stage 2: After each run of PIE or PUE, update the upper and lower confidence bounds:

$$m^l_{k,t} := max\{\lceil \hat{\nu}_{k,t}/\hat{\mu}_{k,t} + \phi(\tau_t, \delta)\phi(l_t, \delta)\rceil, 1\}$$
$$m^u_{k,t} := min\{\lceil \hat{\nu}_{k,t}/\hat{\mu}_{k,t} + \phi(\tau_t, \delta)\phi(l_t, \delta)\rceil, N\}$$

Once the PUE set $\mathcal{Y}_t = \phi$, OrchExplore runs only PIE.

Stage 3: Once $\mathcal{Y}_t = \phi$ and $\mathcal{E}_t = \phi$, then pure *exploitation* - it allocates plays to empirical optimal arms according to these arms' reward capacities.

Parsimonious Individual Exploration (PIE)

The Oracle function: input - reward capacity's lower bounds m_t^l and empirical means $\hat{\mu}_k$ of the arms output - a_t^{IE}, assigns the highest mean to the arm with highest lower bound on capacity.

- $\mathcal{S}_t$, the set of all arms that will be played
- L_t to be the least favoured among these
- arms suct that KL-UCB index, $u_{k,t}$ is greater than or equal to the least favoured arm's mean $\hat{\mu}_{k,t} \longrightarrow \mathcal{E}_t$

$$u_{k,t} := \sup\{q \geq 0 : \hat{\tau}_{k,t}, \mathsf{kl}(\hat{\mu}_{k,t}, q) \leq \log t + 4 \log\log t\}$$

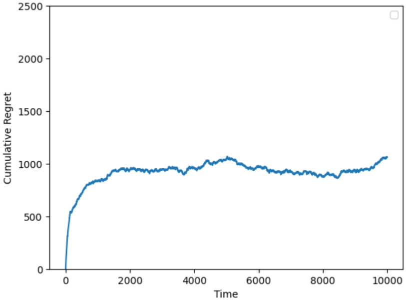
Parsimonious Individual Exploration (PIE)

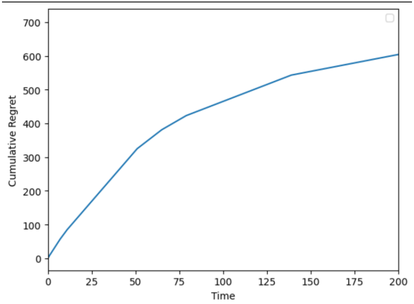
- With a probability of $1/2$, assign one play from L_t to one arm randomly uniformly selected from $\mathcal{E}_t$ The following values are updated:
  - empirical mean, $\hat{\mu}_t$
  - KL-UCB indexes, u_t
  - effective times of IE, $\hat{\tau}_t$
  - time slot index, t

Parsimonious United Exploration (PUE)

- $\mathcal{Y}_t$: all those arms in $\mathcal{S}_t - L_t$ for which $m^l_{k,t} \neq m^u_{k,t}$
- increase the empirical mean of these arms by a large positive value, M.
- Now, $\hat{\mu'}_t$ and the upper capacity bound, $m^u_{k,t}$ are given as input to the Oracle function and the output, a^{UE}_t is used to play the round
-
  - "full load" reward mean, $\hat{\nu}_t$
  - effective times of UE, $\hat{\text{ß}}_t$
  - time slot index, t

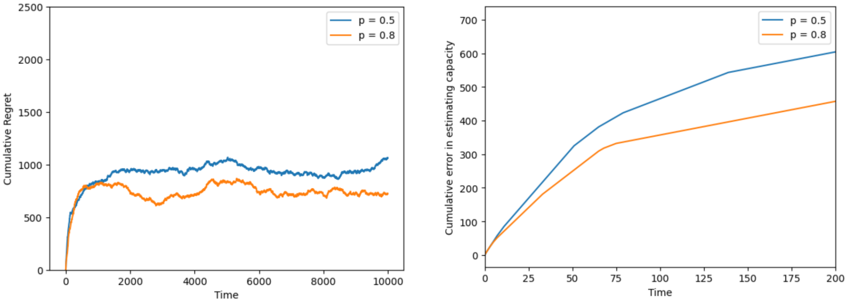
Results and Conclusions





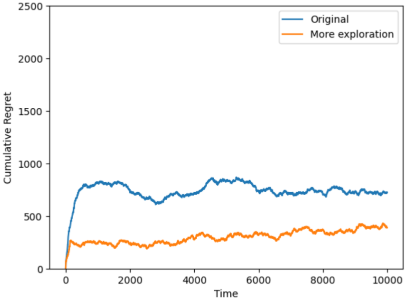
Results of original algorithm

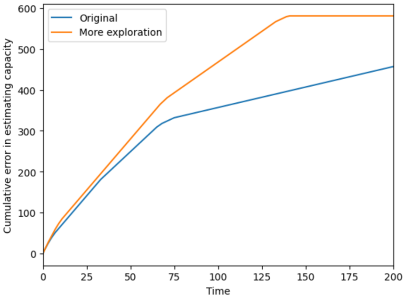
Results and Conclusions



Increasing the probability of random exploration

Results and Conclusions





Exploring more arms

References I

[1] Xuchuang Wang, Hong Xie, and John C. S. Lui. "Multiple-Play Stochastic Bandits with Shareable Finite-Capacity Arms". In: *Proceedings of the 39th International Conference on Machine Learning*. Ed. by Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvari, Gang Niu, and Sivan Sabato. Vol. 162. Proceedings of Machine Learning Research. PMLR, 17–23 Jul 2022, pp. 23181–23212. URL: https://proceedings.mlr.press/v162/wang22af.html.