CS 747: Programming Assignment 1

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Code for bandit agent can be found in agent.py.

It consists of a base class **BanditAgent** and subclasses derived from this for each of the algorithms. (**EpsilonGreedyAgent**, **UCBAgent**, etc.)

Following modification was made to **Thompson-Sampling** method for general distributions.

- * Sample arm (like in normal Thompson-Sampling) and get corresponding reward.
- * Do a Bernoulli trial with this reward as success probability.
- * increment #success if you get a 1, else increment #failure.

<>/report/experiment_logs/*: contains rewards and cumulative regrets corresponding to each experiment.

From the experiments, it seems like epsilon-greedy with appropriate ϵ value performs better than other algorithms when the horizon in small. But as the number of pulls increases Thompson-Sampling performs best in almost all cases.

For arms with beta distribution, performance of UCB algorithm does not seem to be very good. KL-UCB performs slightly better. But epsilon-greedy with $\epsilon=0.05$ performed better than these two. Thompson sampling performed better than other algorithms.

For bernoulli distribution, KL-UCB is the second best algorithm in minimizing regret with thompson sampling minimizing the regret most again.

In case of histogram-based bandits, all the algorithms seem to perform poorly with cumulative regret almost being linearly dependent on the horizon.

In epsilon-greedy algorithm, choice of ϵ greatly impacts the performance. In many experiments with $\epsilon=0.05$ performance was comparable to UCB.

Plots

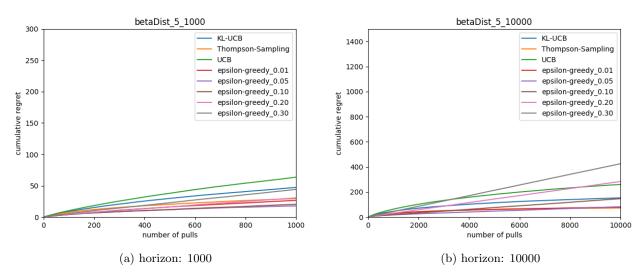


Figure 1: 5 armed bandit, Beta distributed

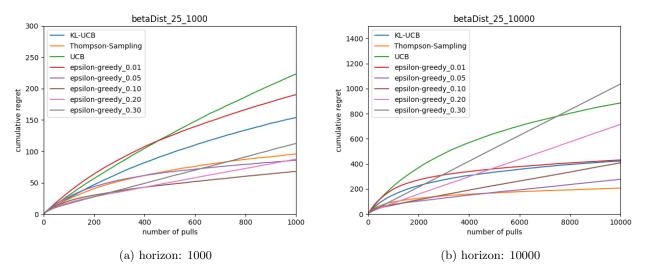


Figure 2: 25 armed bandit, Beta distributed

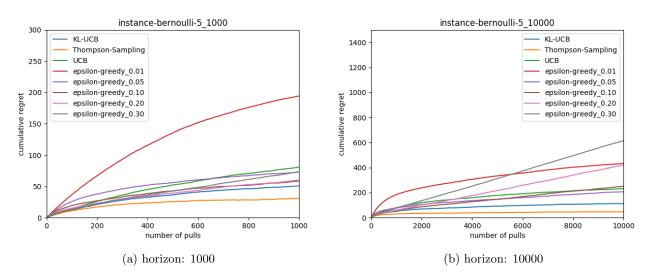


Figure 3: 5 armed bandit, Bernoulli

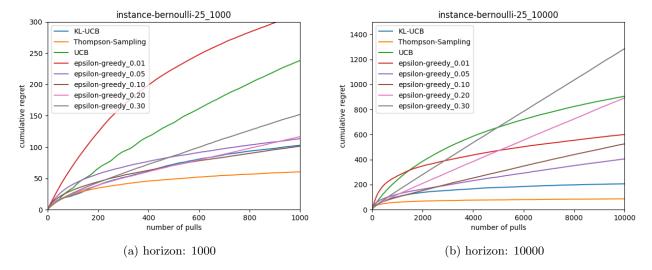


Figure 4: 25 armed bandit, Bernoulli

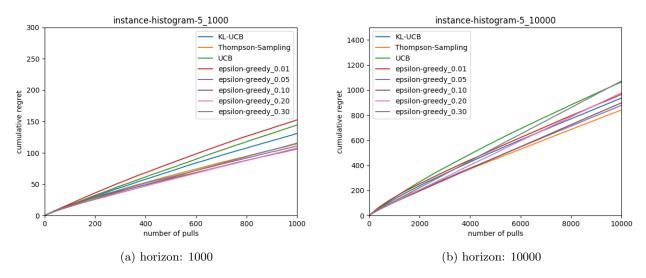


Figure 5: 5 armed bandit, Histogram

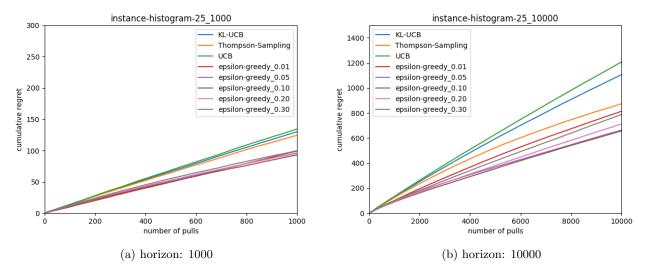


Figure 6: 25 armed bandit, Histogram