

Assignment-I Report

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The submission folder contains 3 python files -

1. init.py which is the script which starts the code execution
2. banditAlgorithms.py which contains the algorithms for solving multi-arm bandit problem
3. bandit.py which simulates the pulling of a Bernoulli bandit arm

Bandit.sh runs init.py taking instance and other parameters as an argument and calls run_function in banditAlgorithms.py to run the specific algorithm. The algorithms use a Bernoulli arm (reward $\in \{0, 1\}$) to simulate a bandit. It returns 1 with probability μ and 0 with probability $1-\mu$ (μ is the mean of the arm provided in the bandit instance).

For KL-UCB, 20 iterations have been assumed in order to find the maximum $Q \in [0, 1]$ such that the KL divergence is less than $\log(t) + 3\log(\log(t))$.

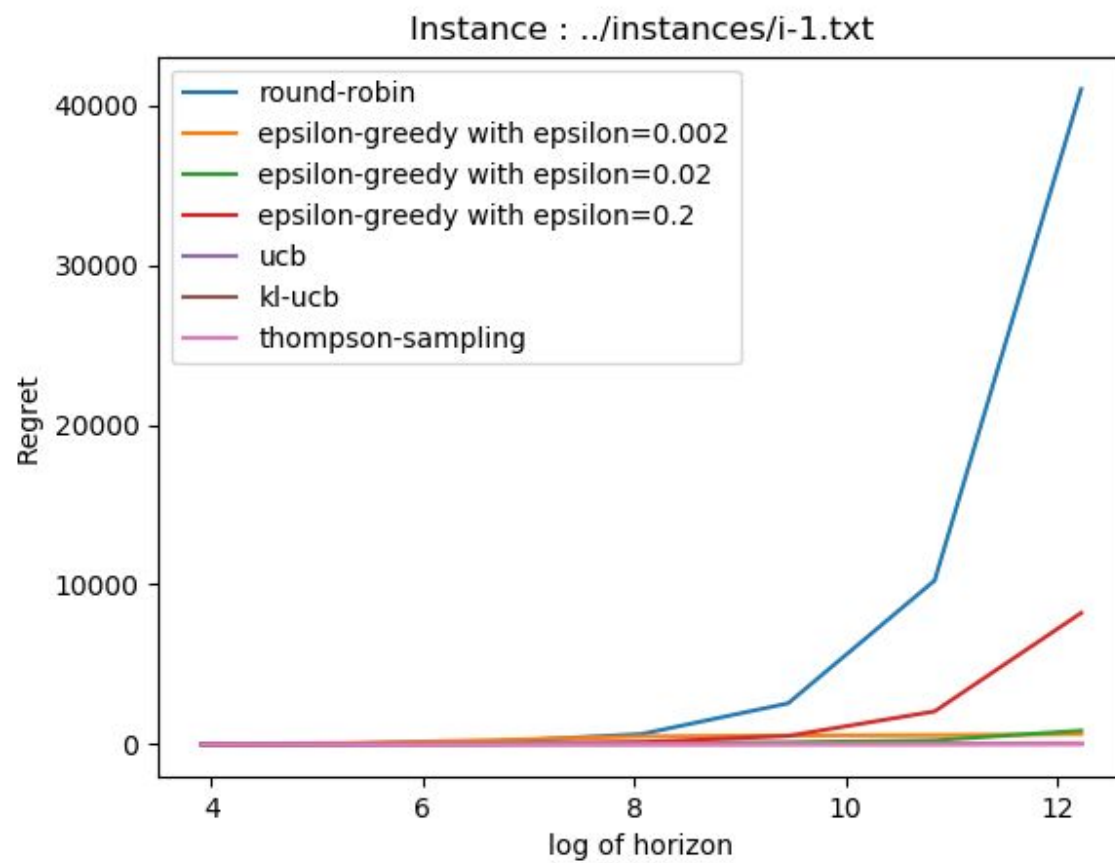
Necessary documentation has been provided in the code for the functions.

The graphs are attached in the report. The interpretation from the graphs is as follows -

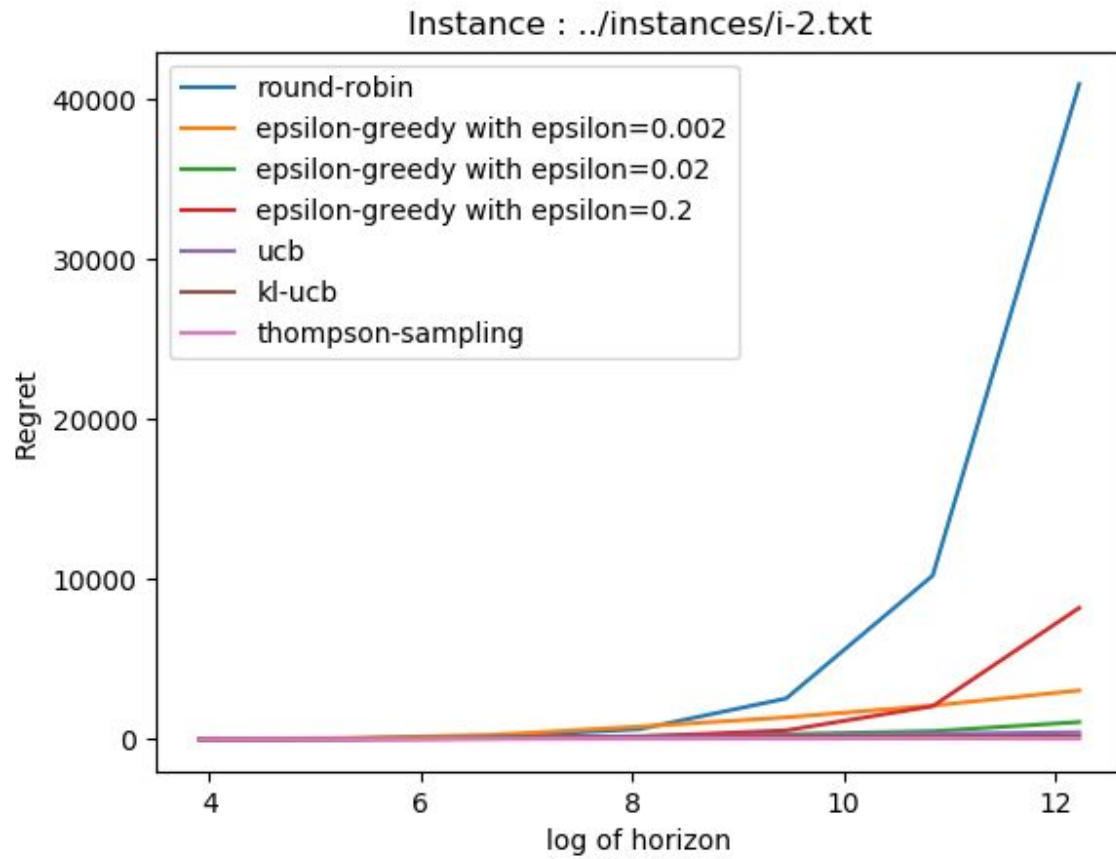
- Thompson Sampling seems to perform better in all 3 of the instances, giving the minimum regret for all horizons.
- Round-robin performs similar to Thompson sampling for low values of horizon, but the regret increases as the horizon value increases.
- ϵ -greedy seems to perform with intermediate results as that of Thompson Sampling and Round-robin. ϵ -greedy performs worse for large values of ϵ for all instances.
- For instance-1, ϵ -greedy with low ϵ values perform as good as UCB and KL-UCB.
- UCB and KL-UCB perform at par with Thompson sampling but with a little more regret.
- For instance-3, KL-UCB performs similar to that of ϵ -greedy with a large epsilon value, implying that KL-UCB is not optimal for that instance.

Graphs :-

Instance-I



Instance-2



Instance-3

