Spring 2024 6.8200 Computational Sensorimotor Learning Assignment 1

In this assignment, we will learn about multi-armed and contextual bandits. You will need to answer the bolded questions and fill in the missing code snippets (marked by **TODO**).

Make a copy of this notebook using File > Save a copy in Drive and edit it with your answers.

IMPORTANT: Set your runtime to GPU, otherwise the checkers may fail. Go to Runtime-> Change Runtime type -> Select T4 GPU.

WARNING: Do not put your name or any other personal identification information in this notebook.

There are 165 total points in this assignment, scaled to be worth 6.25% of your final grade.

Setup

Run the following skeleton code (imports, plotting).

```
!pip install git+https://github.com/Improbable-
AI/sensorimotor_checker.git@master
```

```
Collecting
git+https://github.com/Improbable-AI/sensorimotor_checker.git@master
  Cloning https://github.com/Improbable-AI/sensorimotor_checker.git
(to revision master) to /tmp/pip-req-build-h1bff192
  Running command git clone --filter=blob:none --quiet
https://github.com/Improbable-AI/sensorimotor_checker.git /tmp/pip-
req-build-h1bff192
  Running command git checkout -b master --track origin/master
  Switched to a new branch 'master'
  Branch 'master' set up to track remote branch 'master' from
'origin'.
  Resolved https://github.com/Improbable-AI/sensorimotor_checker.git
to commit e02f6303ebf14b5ed27a7b5aeed7e3a5427e22ff
  Installing build dependencies ... ents to build wheel ... etadata
(pyproject.toml) ... otor_checker
  Building wheel for sensorimotor_checker (pyproject.toml) ...
otor_checker: filename=sensorimotor_checker-0.0.9-py3-none-any.whl
size=4298
sha256=bb751c1469a7d3a5f4d2455270e91c0fc1c5a5f2b83ff5c0dbb9eca0bbff08a
f
  Stored in directory:
/tmp/pip-ephem-wheel-cache-k744b5be/wheels/50/00/f1/315b902a24192b47f9
4d124df94d7c064c98abe3c39c44d1a4
Successfully built sensorimotor_checker
```

```
Installing collected packages: sensorimotor_checker
Successfully installed sensorimotor_checker-0.0.9
```

```
%matplotlib inline
import numpy as np
import random
import time
import os
import gym
import json
import matplotlib.pyplot as plt
import matplotlib as mpl
import seaborn as sns
import pandas as pd

import unittest
from copy import deepcopy
from tqdm.notebook import tqdm
from dataclasses import dataclass
from typing import Any
mpl.rcParams['figure.dpi']= 100

from sensorimotor_checker import hw1_tests

# some util functions
def plot(logs, x_key, y_key, legend_key, **kwargs):
    nums = len(logs[legend_key].unique())
    palette = sns.color_palette("hls", nums)
    if 'palette' not in kwargs:
        kwargs['palette'] = palette
    ax = sns.lineplot(x=x_key, y=y_key, data=logs, hue=legend_key,
**kwargs)
    return ax

def set_random_seed(seed):
    np.random.seed(seed)
    random.seed(seed)

# set random seed
seed = 0
set_random_seed(seed=seed)
```

Multi-armed bandits

Let us define a multi-armed bandit scenario with 10 arms. There are two slightly different formulations that are useful:

- Stochastic Case: Each arm has a reward of 1, with probability $p \in [0,1)$.

- Deterministic Case: Each arm has a reward $r \in [0,1)$, but the same reward is obtained for every pull.

In this assignment, we will work through the stochastic case. The same insights would apply to the deterministic scenario with variable rewards or even to stochastic setups with variable rewards.

To define our bandit, we arbitrarily select probabilities p for each arm and save them as `probs`.

```
numArms = 10
probs = [np.random.random() for i in range(numArms)]
print(probs)
```

```
[0.5488135039273248, 0.7151893663724195, 0.6027633760716439,
0.5448831829968969, 0.4236547993389047, 0.6458941130666561,
0.4375872112626925, 0.8917730007820798, 0.9636627605010293,
0.3834415188257777]
```

We then define an environment to evaluate different agent strategies.

```
#To simulate a realistic Bandit scenario, we will make use of the
BanditEnv.
@dataclass
class BanditEnv:
    probs: np.ndarray # probabilities of giving positive reward for
each arm

    def step(self, action):
        # Pull arm and get stochastic reward (1 for success, 0 for
failure)
        return 1 if (np.random.random()  < self.probs[action]) else 0

#Code for running the bandit environment.
@dataclass
class BanditEngine:
    probs: np.ndarray
    max_steps: int
    agent: Any

    def __post_init__(self):
        self.env = BanditEnv(probs=self.probs)

    def run(self, n_runs=1):
        log = []
        for i in tqdm(range(n_runs), desc='Runs'):
            run_rewards = []
            run_actions = []
            self.agent.reset()
            for t in range(self.max_steps):
                action = self.agent.get_action()
```

```
                reward = self.env.step(action)
                self.agent.update_Q(action, reward)
                run_actions.append(action)
                run_rewards.append(reward)
            data = {'reward': run_rewards,
                    'action': run_actions,
                    'step': np.arange(len(run_rewards))}
            if hasattr(self.agent, 'epsilon'):
                data['epsilon'] = self.agent.epsilon
            run_log = pd.DataFrame(data)
            log.append(run_log)
        return log

#Code for aggregrating results of running an agent in the bandit
environment.
def bandit_sweep(agents, probs, labels, n_runs=2000, max_steps=500):
    logs = dict()
    pbar = tqdm(agents)
    for idx, agent in enumerate(pbar):
        pbar.set_description(f'Alg:{labels[idx]}')
        engine = BanditEngine(probs=probs, max_steps=max_steps,
agent=agent)
        ep_log = engine.run(n_runs)
        ep_log = pd.concat(ep_log, ignore_index=True)
        ep_log['Alg'] = labels[idx]
        logs[f'{labels[idx]}'] = ep_log
    logs = pd.concat(logs, ignore_index=True)
    return logs
```

Credits: The code for Multi-Arm Bandits is inspired from

- https://github.com/ShangtongZhang/reinforcement-learning-an-introduction/blob/master/chapter02/ten_armed_testbed.py
- https://github.com/lilianweng/multi-armed-bandit/blob/master/solvers.py

Oracle Agent

The best agent we could possibly build is one that has access to all the necessary information to make an optimal decision, even if that information would not be available in a real world problem. We call this an "oracle agent."

Imagine you were to build an Oracle agent for the stochastic multi-armed bandits problem defined by `probs`. What reward would you get from this agent in expectation?

```
#### TODO: find the maximum return with priviledged infromation about
the reward distribution [5pts] ####
oracle_reward = np.max(probs)
```

```
##################################
suite = unittest.TestSuite()
suite.addTest(hw1_tests.TestOracleAgent('check_reward',
oracle_reward))
unittest.TextTestRunner(verbosity=0).run(suite)

----------------------------------------------------------------------
Ran 1 test in 0.000s

OK

<unittest.runner.TextTestResult run=1 errors=0 failures=0>
```

Random Agent

That's pretty high reward! However, let's say that we don't have access to `probs`, and that the only information we can learn about the environment is through interaction. This is more akin to a real world bandits problem.

One baseline agent we should construct is one that chooses a random action at every timestep. Fill in the `TODO` in the below agent code to implement this behavior.

```
#As a baseline, lets first construct a baseline agent that chooses a
random action at every timestep.
#We will measure how much better we can do.
@dataclass
class RandomAgent:
    num_actions: int

    def __post_init__(self):
        self.reset()

    def reset(self):
        self.t = 0
        self.action_counts = np.zeros(self.num_actions, dtype=int) #
action counts n(a)
        self.Q = np.zeros(self.num_actions, dtype=float) # action
value Q(a)

    def update_Q(self, action, reward):
        pass

    def get_action(self):
        self.t += 1
        #### TODO: get a random action index [5pts]####
        selected_action = random.randint(0, len(probs)-1)

        ##################################

        return selected_action
```

```python
#Create the random agent.
agent = RandomAgent(num_actions=len(probs))
'''
In order to measure average behavior of the agent, we are going to run
the agent
multiple times and compute the mean reward. The number of runs will be
denoted
by the variable `n_runs`. The default value is set to 1000, but feel
free to reduce it
it if its taking too much time.
'''
n_runs = 1000
logs = bandit_sweep([agent], probs, ['Random'], n_runs=n_runs)
```

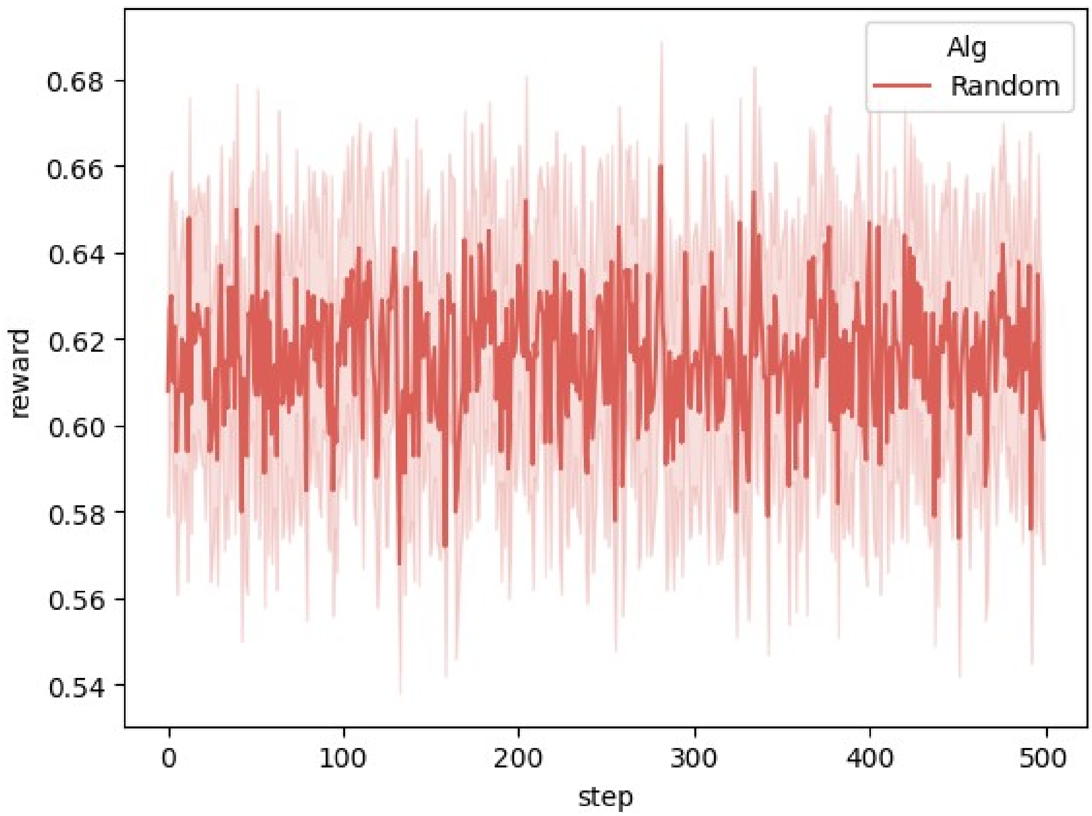
{"model_id":"5bb2328173244067900f88194429681c","version_major":2,"vers
ion_minor":0}

{"model_id":"c208cf1464924dce94e37940b63f219a","version_major":2,"vers
ion_minor":0}

```python
#### TODO: plot the reward curve of a random agent, and print the
average reward over this of this agent [5pts]####
agent_idx = random.randint(0, len(probs)-1)

plot(logs, x_key='step', y_key='reward', legend_key='Alg')

###############################
mean_reward = np.mean(logs['reward'])
print(mean_reward)
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed_cell` argument and any exception that happen during
thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
/usr/local/lib/python3.10/dist-packages/pandas/core/algorithms.py:522:
DeprecationWarning: np.find_common_type is deprecated.  Please use
`np.result_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs
for more information.  (Deprecated NumPy 1.25)
  common = np.find_common_type([values.dtype, comps_array.dtype], [])
/usr/local/lib/python3.10/dist-packages/pandas/core/algorithms.py:522:
DeprecationWarning: np.find_common_type is deprecated.  Please use
`np.result_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs
for more information.  (Deprecated NumPy 1.25)
  common = np.find_common_type([values.dtype, comps_array.dtype], [])
```

```
0.615614
```




```
suite = unittest.TestSuite()
suite.addTest(hw1_tests.TestRandomAgent('check_performance', logs))
unittest.TextTestRunner(verbosity=0).run(suite)

----------------------------------------------------------------------
Ran 1 test in 0.002s

OK

<unittest.runner.TextTestResult run=1 errors=0 failures=0>
```

Analyzing the Results:

- On the x-axis is the number of steps taken by the agent.
- On the y-axis is the average reward at step i.

The reward obtained by the random agent is far less that the oracle agent. Regret is defined as the difference between the the reward collected by oracle and the agent under consideration. In the above example, regret is about 0.35.

Note: that if you use a different random seed to run experiments, you might get a slighly different value of regret. Treat this as a ball park figure.

Explore First Agent

In the class we discussed an algorithm to solve bandits where,

- Exploration Phase: For the first N (defined as `max_explore` in the code) steps the agent takes random actions to estimate the value of different arms.
- Exploitation Phase: In each step after that, the agent identifies the best arm based on the information it aggregated so far. Notice that the agent keeps updating its prediction even after the inital N steps.

We will now implement this agent below. Fill in the missing code in `update_Q` and `get_action`. We will store the average reward for each action in the variable `self.Q` (see slide 43 in Lec 2 slides), and the count of how many times we've taken each action in `self.action_counts`.

```
#Lets now construct the explore first agent
@dataclass
class ExploreFirstAgent:
    num_actions: int
    max_explore: int

    def __post_init__(self):
        self.reset()

    def reset(self):
        self.t = 0
        self.action_counts = np.zeros(self.num_actions, dtype=int) # action counts n(a)
        self.Q = np.zeros(self.num_actions, dtype=float) # action value Q(a)

    def update_Q(self, action, reward):
        # Update Q action-value given (action, reward)
        # HINT: Keep track of how good each arm is
        #### TODO: update Q value [5pts] ####
        self.action_counts[action] += 1
        self.Q[action] += (1/self.action_counts[action]) * (reward - self.Q[action])
        ####################################

    def get_action(self):
        self.t += 1
        #### TODO: get action [5pts] ####
        # select the action with the highest q value
        # selected_action = np.argmax(self.Q)
        ####################################

        if sum(self.action_counts) < self.max_explore:
            selected_action = random.randint(0, self.num_actions-1)
        else:
```

```
            selected_action = np.argmax(self.Q)

        return selected_action
```

Great! Now we'll instantiate the engine, and run it with $N\!=\!5$ (five steps of exploration, followed by entirely greedy policy).

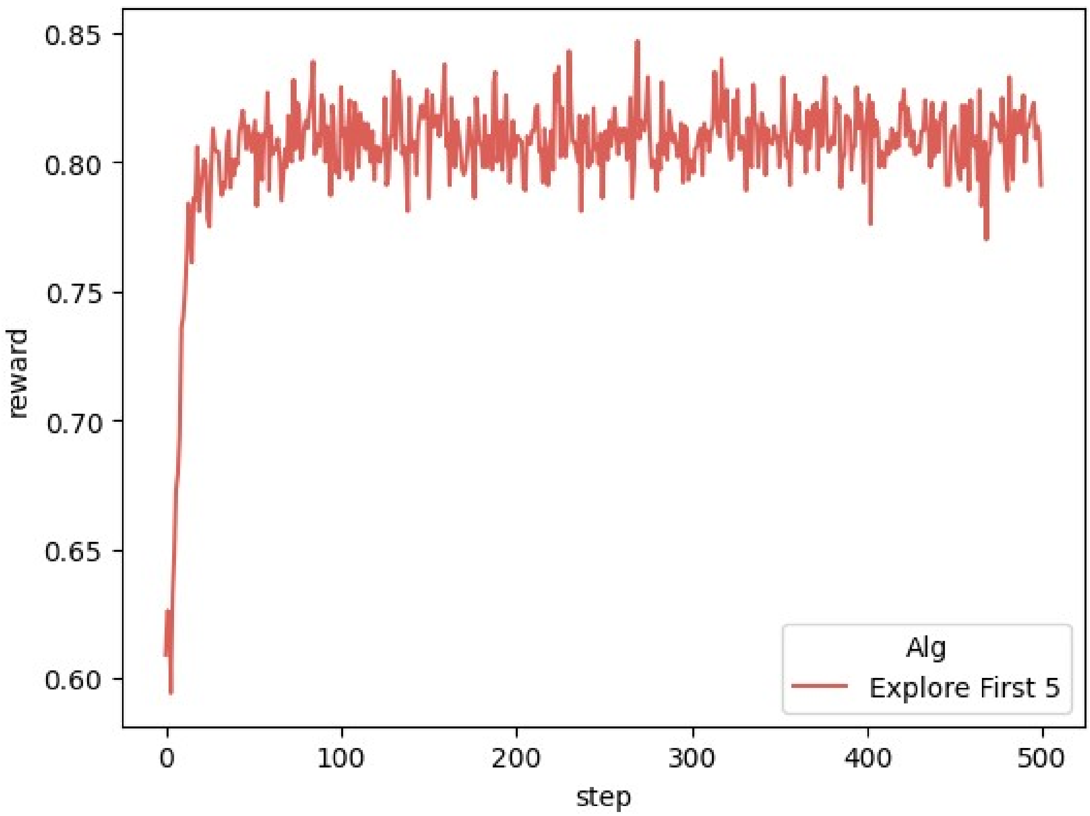
```
max_explore = 5
agent = ExploreFirstAgent(num_actions=len(probs),
max_explore=max_explore)
logs = bandit_sweep([agent], probs, ['Explore First 5'], n_runs=1000,
max_steps=500)
plot(logs, x_key='step', y_key='reward', legend_key='Alg',
estimator='mean', errorbar=None)
```

{"model_id":"4b726b0b28ac483d913738b958563576","version_major":2,"version_minor":0}

{"model_id":"29d2e3b64783486990d9f0eabf88dc25","version_major":2,"version_minor":0}

```
/usr/local/lib/python3.10/dist-packages/pandas/core/algorithms.py:522:
DeprecationWarning: np.find_common_type is deprecated.  Please use
`np.result_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs
for more information.  (Deprecated NumPy 1.25)
  common = np.find_common_type([values.dtype, comps_array.dtype], [])
/usr/local/lib/python3.10/dist-packages/pandas/core/algorithms.py:522:
DeprecationWarning: np.find_common_type is deprecated.  Please use
`np.result_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs
for more information.  (Deprecated NumPy 1.25)
  common = np.find_common_type([values.dtype, comps_array.dtype], [])
```

```
<Axes: xlabel='step', ylabel='reward'>
```



Check your work:

If you pass update_Q but fail in performance, check your get action and ensure that you're on GPU runtime.

```
suite = unittest.TestSuite()
suite.addTest(hw1_tests.TestExploreFirstAgent('check_update_Q',
ExploreFirstAgent))
suite.addTest(hw1_tests.TestExploreFirstAgent('check_performance',
logs))
unittest.TextTestRunner(verbosity=0).run(suite)
```

```
----------------------------------------------------------------------
Ran 2 tests in 0.008s

OK

<unittest.runner.TextTestResult run=2 errors=0 failures=0>
```

Explore First v.s. Random Agent

The results clearly show that the explore first agent performs better than the random agent. However, it still performs much worse than the oracle. How can we improve our performance?

If there are 10 possible actions but the agent only explores for 5 steps, then it is likely it won't find the best arm. Thus, the policy will be suboptimal. Let's see what happens when we allow the agent to explore for more steps.

```
'''
What happens if we allow the agent to explore for only 5, 10, 50, 100,
200 steps respectively?
'''
max_explore_steps = [5, 10, 50, 100, 200]
# max_explore_steps = [5, 10]
n_runs = 1000
all_logs = None
#### TODO: run ExploreFirstAgent with different max_explore steps, and
plot the reward curves [10pts]####
for explore_steps in max_explore_steps:
  agent = ExploreFirstAgent(num_actions=len(probs),
max_explore=explore_steps)
  logs = bandit_sweep([agent], probs, [f'Explore First
{explore_steps}'], n_runs=1000, max_steps=500)
  all_logs = logs if all_logs is None else all_logs.append(logs)

plot(all_logs, x_key='step', y_key='reward', legend_key='Alg',
estimator='mean', errorbar=None)

#########################################
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed_cell` argument and any exception that happen during
thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

{"model_id":"69a97bd045a347f79595edf22437bb12","version_major":2,"version_minor":0}

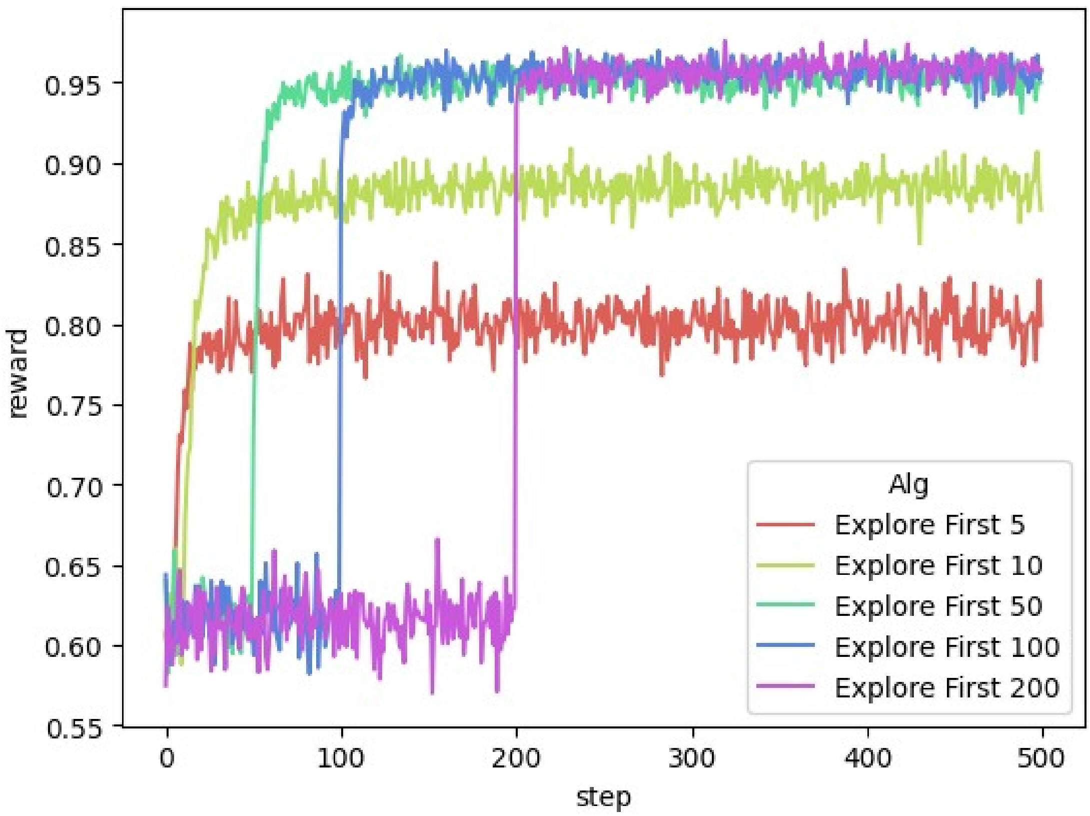
{"model_id":"757c7005c83e439bb748c1bd9560b898","version_major":2,"version_minor":0}

{"model_id":"d8d2540553434e09934497620d8bb5af","version_major":2,"version_minor":0}

{"model_id":"232b464a748d485cb6376d2eda7959ec","version_major":2,"version_minor":0}

```
<ipython-input-44-f52c09d415ec>:12: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  all_logs = logs if all_logs is None else all_logs.append(logs)
```

```
{"model_id":"1af9e8400c6d4f4390ec89c9355a2422","version_major":2,"version_minor":0}

{"model_id":"c5004342ee7f4cb2895851a550a881e2","version_major":2,"version_minor":0}

<ipython-input-44-f52c09d415ec>:12: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  all_logs = logs if all_logs is None else all_logs.append(logs)

{"model_id":"402c16503df445bebc74c8c482bd657a","version_major":2,"version_minor":0}

{"model_id":"5794d97b2ad3443d9362e1ac9f3db46a","version_major":2,"version_minor":0}

<ipython-input-44-f52c09d415ec>:12: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  all_logs = logs if all_logs is None else all_logs.append(logs)

{"model_id":"24a3d8224a034b01a3b9b57f6692eb4e","version_major":2,"version_minor":0}

{"model_id":"8aaa58952963427e84b180adef489974","version_major":2,"version_minor":0}

<ipython-input-44-f52c09d415ec>:12: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  all_logs = logs if all_logs is None else all_logs.append(logs)

<Axes: xlabel='step', ylabel='reward'>
```



Analyzing the Results

- Notice that for all agents there is a jump in performance. This corresponds to the time point when they switch from explore only to exploit mode.
- The agents that explore for 5, 10 steps are unable to accurately identify the best arm everytime. Their scores are lower than that of agents exploring for 50 or 100 steps. These agents find the optimal arm.

Moving to More Realistic Scenarios

Question (5pts): It's unclear how long the agent should explore before switching to exploit mode. Can you come up with a strategy to choose a good value of `max_explore`? Can we use such a strategy to deploy a product?

Answer: A good strategy could be to observe if the environment is stochastic or deterministic. This can be observed by looking at the rewards for the same action. In a situation where the environment is stochastic, if we explore less, a initial high/low reward for an action may bias the agent towards either selection/rejecting that action. In such a situation, we may want to explore more before switching to the exploit mode. In situations where the environment is bit more deterministic, we can switch to the exploit mode much earlier. This could be tracked by noting the variance of the rewards for the actions.

UCB Agent

Rather than having seperate exploration and exploitation phases, an agent should be able to figure out when to explore and when to exploit. This leads us to the UCB agent that we discussed in class.

Implement the `update_Q` and `get_action` methods for a UCB agent using the course notes.

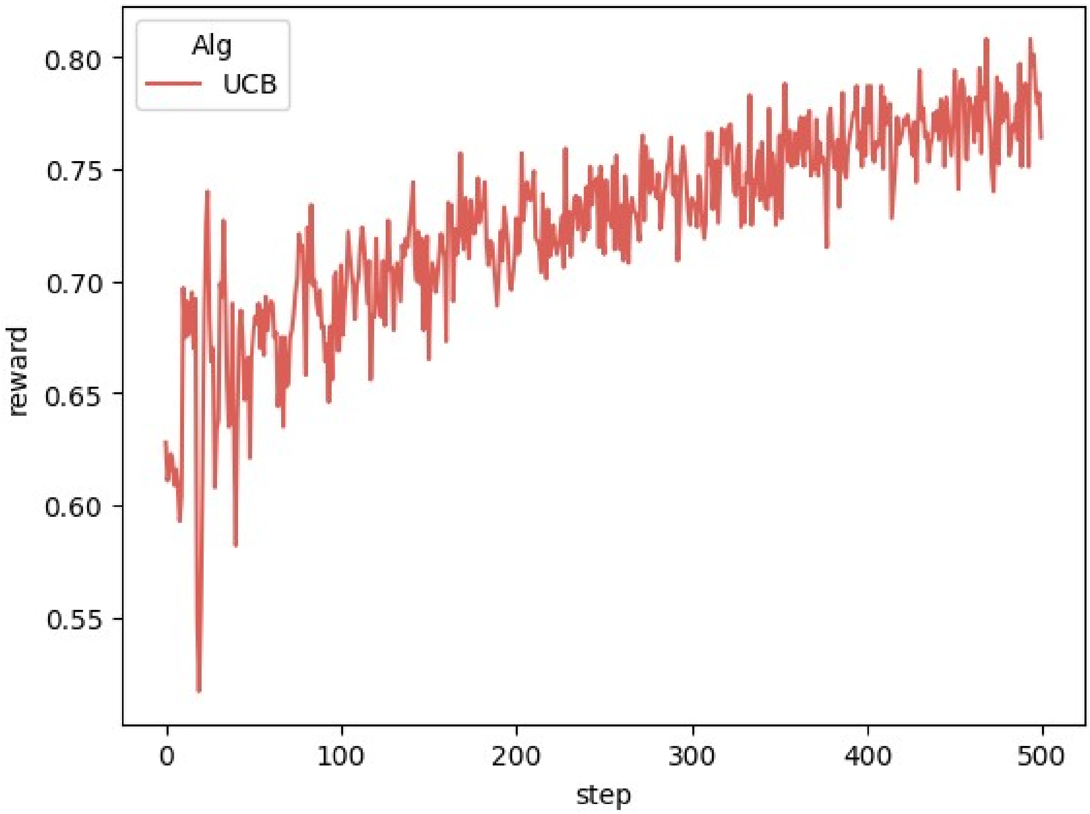
```
#### UCB Agent ####
@dataclass
class UCBAgent:
    num_actions: int

    def __post_init__(self):
        self.reset()

    def reset(self):
        self.t = 0
        self.action_counts = np.zeros(self.num_actions, dtype=int) # 
action counts n(a)
        self.Q = np.zeros(self.num_actions, dtype=float) # action 
value Q(a)

    def update_Q(self, action, reward):
        # Update Q action-value given (action, reward)
        #### TODO: Calculate the Q-value [5pts] ####
        self.action_counts[action] += 1
        self.Q[action] += (reward - self.Q[action]) / 
self.action_counts[action]

        ################################

    def get_bonus(self, t, action_counts):
        #### TODO: Calculate the exploration bonus. To avoid a 
division by zero, add a small delta=1e-5 to the denominator [5pts] 
####

        delta = 1e-5
        exploration_bonus = np.sqrt(4*np.log(t) / (action_counts + 
delta))

        return exploration_bonus

        ################################

    def get_action(self):
        self.t += 1
        Q_explore = self.Q + self.get_bonus(self.t, 
self.action_counts)
```

```
        return np.random.choice(np.where(Q_explore == Q_explore.max())
[0])

#Define the UCB Agent
agentUCB = UCBAgent(num_actions=len(probs))
#Compute Performance
logs = bandit_sweep([agentUCB], probs, ['UCB'], n_runs=1000,
max_steps=500)
#Plot Performance
plot(logs, x_key='step', y_key='reward', legend_key='Alg',
estimator='mean', errorbar=None)
```

{"model_id":"9092e501af084c6984e5b3a4d6c4d441","version_major":2,"version_minor":0}

{"model_id":"9ede032fc43b47ac87db400eac4c1e92","version_major":2,"version_minor":0}

```
/usr/local/lib/python3.10/dist-packages/pandas/core/algorithms.py:522:
DeprecationWarning: np.find_common_type is deprecated.  Please use
`np.result_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs
for more information.  (Deprecated NumPy 1.25)
  common = np.find_common_type([values.dtype, comps_array.dtype], [])
/usr/local/lib/python3.10/dist-packages/pandas/core/algorithms.py:522:
DeprecationWarning: np.find_common_type is deprecated.  Please use
`np.result_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs
for more information.  (Deprecated NumPy 1.25)
  common = np.find_common_type([values.dtype, comps_array.dtype], [])

<Axes: xlabel='step', ylabel='reward'>
```



Check your work:

If all other tests pass but check_performance fails, make sure your runtime type is GPU and then come to OH or post on piazza.

```
suite = unittest.TestSuite()
suite.addTest(hw1_tests.TestUCBAgent('check_update_Q', UCBAgent))
suite.addTest(hw1_tests.TestUCBAgent('check_exploration_bonus',
UCBAgent))
suite.addTest(hw1_tests.TestUCBAgent('check_performance', logs))

unittest.TextTestRunner(verbosity=0).run(suite)
```

```
----------------------------------------------------------------------
Ran 3 tests in 0.004s

OK

<unittest.runner.TextTestResult run=3 errors=0 failures=0>
```

UCB v/s Explore-First

Now let's compare the reward curves of the `UCB` agent and `Explore First` agent with `max_explore=5`.

Analyzing the Results

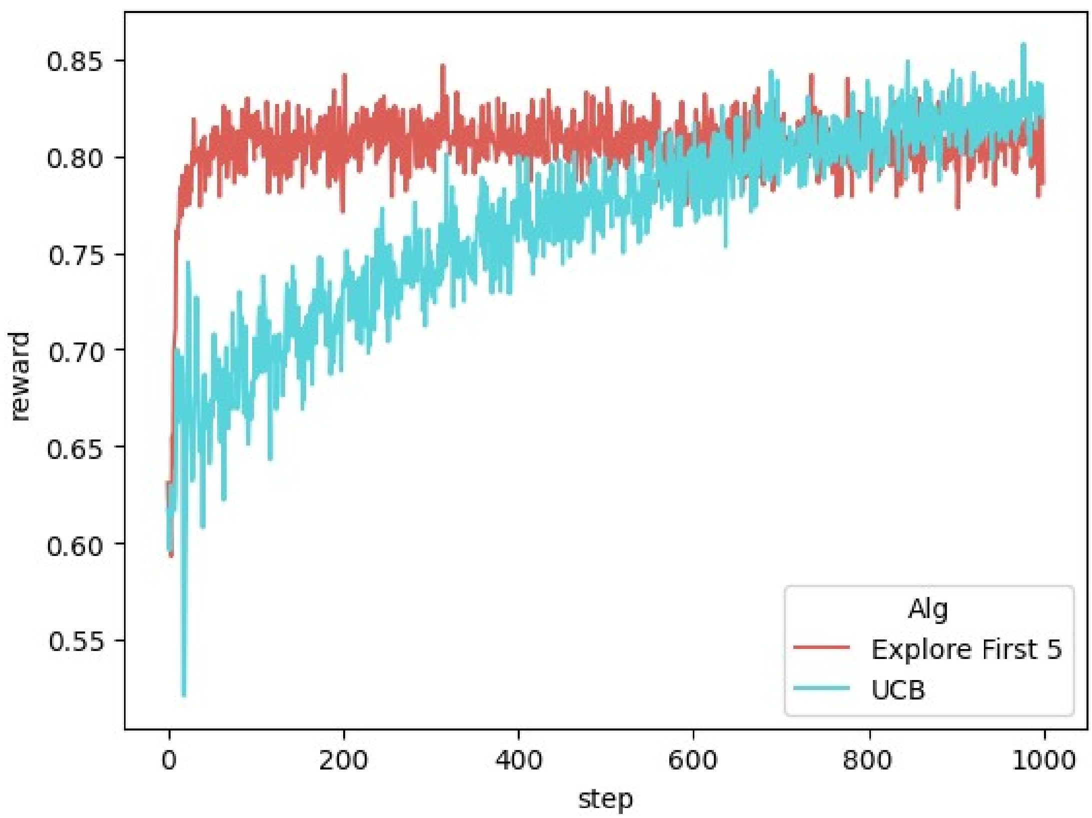
Question [5pts]: Why does the UCB algorithm learn slowly (even after 500 steps, the agent still does not reach the maximum reward)?

Answer: The UCB algorithms is designed to balance between exploration and exploitation. One of the key reasons could be its tendency to explore other actions even if a particular action seems to be the best action based on the current state. This ensures good long-term performance but could slow down the process of choosing the best performing actions. We can control the balance using the alpha hyperparameter. In essence, in some environments, it may take UCB longer to accurately estimate the true value of each action, which means that the algorithm needs to sample more to make accurate choices. Because of these reasons, it still does not reach maximum reward.

```
#Now we will compare the UCB agent against the ExploreFirst Agent that
only explores for 5 steps.
#### TODO: run both algorithms and plot the reward curves
(max_explore=5) [10pts] ####
#### use legends ['UCB', 'Explore First 5'] respectively
#### run each algorithm 1000 times (n_runs=1000), and max_steps=1000
n_runs = 1000
max_steps = 1000
max_explore = 5

# explore first agent
agent = ExploreFirstAgent(num_actions=len(probs),
max_explore=max_explore)
logs = bandit_sweep([agent], probs, ['Explore First 5'],
n_runs=n_runs, max_steps=max_steps)
# plot(logs, x_key='step', y_key='reward', legend_key='Alg',
estimator='mean', errorbar=None)

# ucb agent
agentUCB = UCBAgent(num_actions=len(probs))
#Compute Performance
ucb_logs = bandit_sweep([agentUCB], probs, ['UCB'], n_runs=n_runs,
max_steps=max_steps)
#Plot Performance
logs = logs.append(ucb_logs)
plot(logs, x_key='step', y_key='reward', legend_key='Alg',
estimator='mean', errorbar=None)
##################################

/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed_cell` argument and any exception that happen during
thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

```
{"model_id":"aaf8c27023fd4fbdabdf90a007d1a7e4","version_major":2,"version_minor":0}

{"model_id":"bba079287129457b894854170b5c63f0","version_major":2,"version_minor":0}

{"model_id":"0224b3b1a0da4c519a1594ffb8326b6e","version_major":2,"version_minor":0}

{"model_id":"e47992a1a60048448ff2585257e49d79","version_major":2,"version_minor":0}
```


```
<ipython-input-31-a0b1bd7d9dda>:21: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  all_logs = all_logs.append(ucb_logs)

<Axes: xlabel='step', ylabel='reward'>
```



Result Analysis: UCB outperforms the greedy Explore First agent that only explores for 5 steps.

What happens if we allow the agent to explore for more steps? Run the Explore First agent for 20 steps, and compare the reward to the UCB agent.

```
#Lets compare UCB with an agent that explores for twenty steps.
#### TODO: run both algorithms and plot the reward curves
(max_explore=20) [10pts] ####
#### use legends ['UCB', 'Explore First 20'] respectively
#### run each algorithm 1000 times (n_runs=1000), and max_steps=1000
n_runs = 1000
max_steps = 1000
max_explore = 20

# explore first agent
agent = ExploreFirstAgent(num_actions=len(probs),
max_explore=max_explore)
logs = bandit_sweep([agent], probs, ['Explore First 20'],
n_runs=n_runs, max_steps=max_steps)
# plot(logs, x_key='step', y_key='reward', legend_key='Alg',
estimator='mean', errorbar=None)

# ucb agent
agentUCB = UCBAgent(num_actions=len(probs))
#Compute Performance
ucb_logs = bandit_sweep([agentUCB], probs, ['UCB'], n_runs=n_runs,
max_steps=max_steps)
#Plot Performance
logs = logs.append(ucb_logs)
plot(logs, x_key='step', y_key='reward', legend_key='Alg',
estimator='mean', errorbar=None)
##################################,
```

{"model_id":"dfb20039f1494420a91276ab4f5db8ef","version_major":2,"version_minor":0}

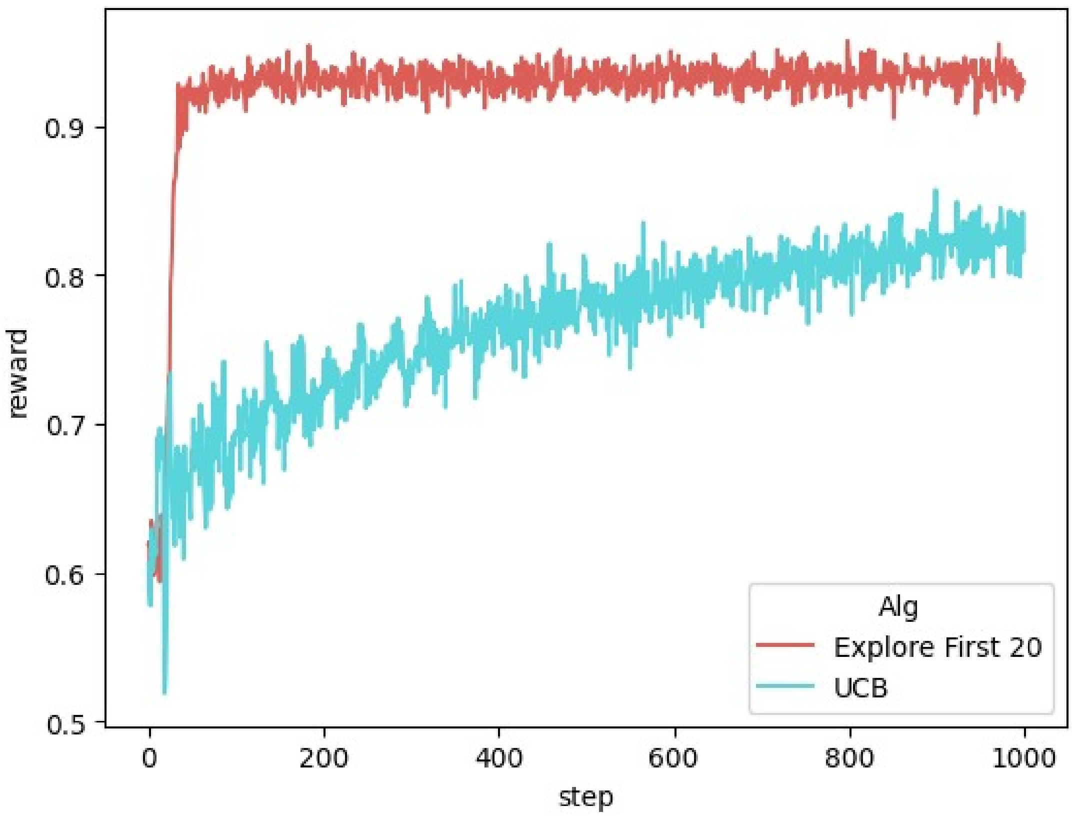
{"model_id":"37930f270d0341368f29f9ab7ad02630","version_major":2,"version_minor":0}

{"model_id":"95dc80a89bcf48e0a3d597616383f480","version_major":2,"version_minor":0}

{"model_id":"a1f3a9ffd6ab4cbb93d668eac9900a22","version_major":2,"version_minor":0}

```
<ipython-input-32-573a52077e10>:19: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  logs = logs.append(ucb_logs)
```

```
<Axes: xlabel='step', ylabel='reward'>
```



Question (5pts): In the lecture we studied that the UCB algorithm is optimal. Why then does Explore First perform better?

Answer: This could be because Explore First has sampled each arm sufficient number of times (given by the explore parameter -- 20 in this case), and has an accurate estimate of each arm's performance.

Skewed Arms Scenario:

In the previous example, the probability of each arm providing a return was sampled uniformly from $[0, 1)$. Because there were only 10 arms, and some arms had similar returns, by performing 20 random actions it is possible to find the best arm by chance. However, if the reward distributions are very skewed (e.g., only one arm returns rewards with high probability, say 0.9), or there are more arms, more actions may be necessary. In this case the initial exploration phase may not succeed at finding the best arm. Lets see this in practice below.

```
skewedProbs = [0.1, 0.2, 0.15, 0.21, 0.3, 0.05, 0.9, 0.13, 0.17, 0.07,
0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01]
#### TODO: compare the reward curves of UCBAgent and ExploreFirstAgent
(max_explore=len(skewedProbs)) [10pts] ####
#### sweep with n_runs=1000, max_steps=1000

n_runs = 1000
max_steps = 1000
```

```
max_explore = len(skewedProbs)

# explore first agent
agent = ExploreFirstAgent(num_actions=len(skewedProbs),
max_explore=max_explore)
logs = bandit_sweep([agent], skewedProbs, ['Explore First 20'],
n_runs=n_runs, max_steps=max_steps)
# plot(logs, x_key='step', y_key='reward', legend_key='Alg',
estimator='mean', errorbar=None)

# ucb agent
agentUCB = UCBAgent(num_actions=len(skewedProbs))
#Compute Performance
ucb_logs = bandit_sweep([agentUCB], skewedProbs, ['UCB'],
n_runs=n_runs, max_steps=max_steps)
#Plot Performance
logs = logs.append(ucb_logs)
plot(logs, x_key='step', y_key='reward', legend_key='Alg',
estimator='mean', errorbar=None)
##################################

/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed_cell` argument and any exception that happen during
thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

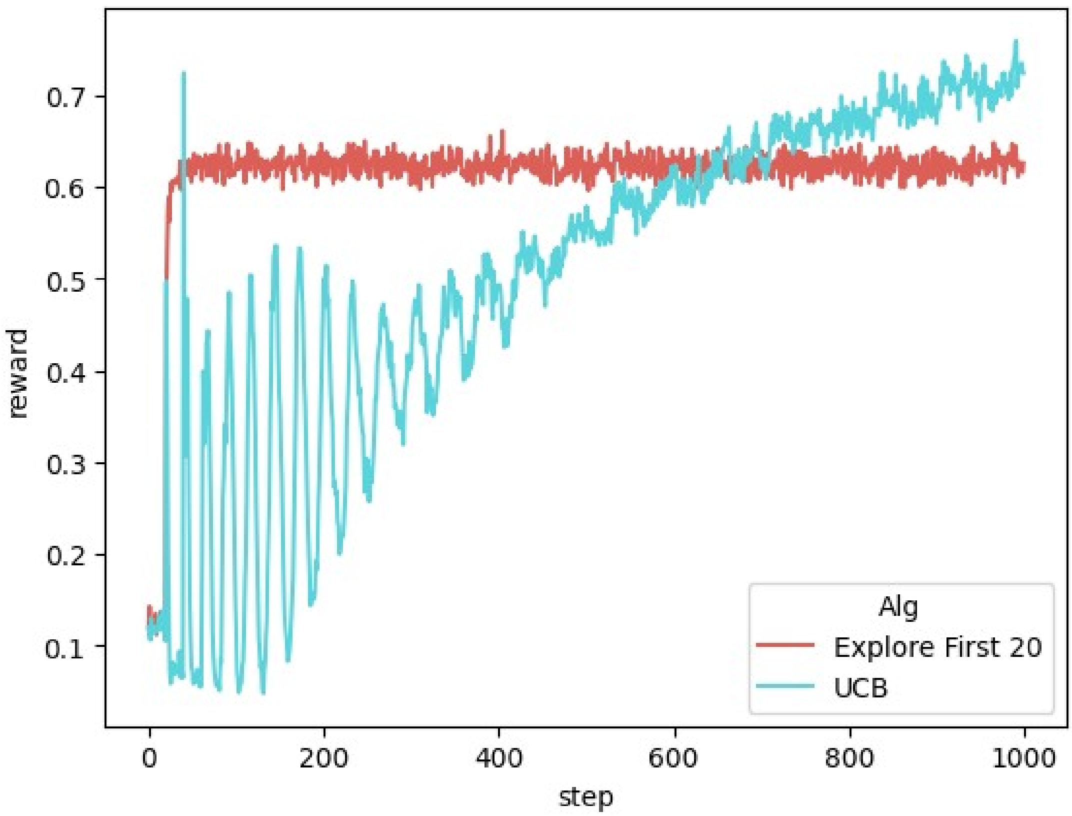
{"model_id":"a1070df9bf084f569f29fb90e926af0e","version_major":2,"version_minor":0}

{"model_id":"0bcb260e420546bca2ccc90904332aa2","version_major":2,"version_minor":0}

{"model_id":"1ff561c06de04528be7d9a38b8c08838","version_major":2,"version_minor":0}

{"model_id":"7fb8468983ab41c48baee7f748a316fc","version_major":2,"version_minor":0}

```
<ipython-input-33-8beea0ebf398>:19: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  logs = logs.append(ucb_logs)

<Axes: xlabel='step', ylabel='reward'>
```



In this case, UCB performs better than *Explore First (20)*. It is because exploring for 20 steps is insufficient for this problem. This problem again illustrates that unless one has access to privileged information about the problem, UCB performs the best!

Also notice that UCB's reward is still increasing and it hasn't converged to the optimal action yet. Try varying the maximum number of steps to see when UCB converges to the optimal / oracle policy.

In other words, `max_explore` is a hyperparameter in the explore-first algorithm. Without "tuning" it, the method may perform well on some problem instances and poorly on others. An advantage of UCB is its lack of hyperparameters. Next, we'll consider another hyperparameter, ϵ.

Epsilon-greedy Agent

Another popular method of simultaneoulsy exploring/exploiting is ϵ-greedy exploration. The main idea is to:

- Sample the (estimated) best action with probability $1-\epsilon$
- Perform a random action with probability ϵ

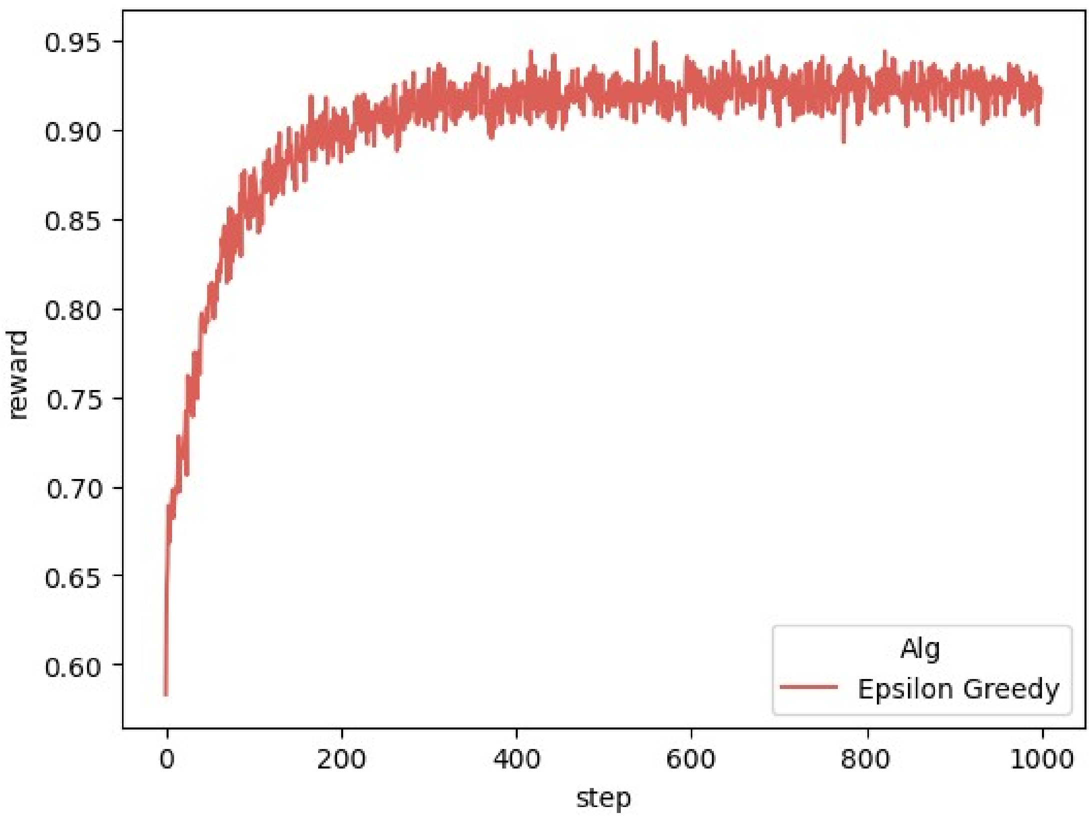
By changing ϵ, we can control if the agent is conservative or exploratory. We will now implement this agent.

```
##EpsilonGreedy Agent
@dataclass
class EpsilonGreedyAgent:
    num_actions: int
    epsilon: float = 0.1

    def __post_init__(self):
        self.reset()

    def reset(self):
        self.action_counts = np.zeros(self.num_actions, dtype=int) #
action counts n(a)
        self.Q = np.zeros(self.num_actions, dtype=float) # action
value Q(a)

    def update_Q(self, action, reward):
        # Update Q action-value given (action, reward)
        self.action_counts[action] += 1
        self.Q[action] += (1.0 / self.action_counts[action]) * (reward
- self.Q[action])

    def get_action(self):
        # Epsilon-greedy policy
        values = ['exploration', 'exploitation']
        choice = np.random.choice(values, p=[self.epsilon, 1-
self.epsilon])
        #### TODO: Code for exploration [5pts] ####
        if choice == 'exploration':
          action_index = random.randint(0, self.num_actions - 1)

        ###########################################
        #### TODO: Code for exploitation [5pts] ####
        else:
          # action_index = np.argmax(self.Q)
          action_index = np.random.choice(np.where(self.Q ==
self.Q.max())[0])

        # self.action_counts[action_index] += 1
        return action_index

        ###########################################

agent = EpsilonGreedyAgent(num_actions=len(probs), epsilon = 0.1)
logs = bandit_sweep([agent], probs, ['Epsilon Greedy'], n_runs=1000,
max_steps=1000)
plot(logs, x_key='step', y_key='reward', legend_key='Alg',
estimator='mean', errorbar=None)
```

{"model_id":"13155facb6f94153800cfd6b13ace793","version_major":2,"version_minor":0}

{"model_id":"600b20a00aac40fd84e09b83c7520441","version_major":2,"version_minor":0}

```
/usr/local/lib/python3.10/dist-packages/pandas/core/algorithms.py:522:
DeprecationWarning: np.find_common_type is deprecated.  Please use
`np.result_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs
for more information.  (Deprecated NumPy 1.25)
  common = np.find_common_type([values.dtype, comps_array.dtype], [])
/usr/local/lib/python3.10/dist-packages/pandas/core/algorithms.py:522:
DeprecationWarning: np.find_common_type is deprecated.  Please use
`np.result_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs
for more information.  (Deprecated NumPy 1.25)
  common = np.find_common_type([values.dtype, comps_array.dtype], [])

<Axes: xlabel='step', ylabel='reward'>
```




```
suite = unittest.TestSuite()
suite.addTest(hw1_tests.TestEpsilonGreedyAgent('check_performance',
logs))
unittest.TextTestRunner(verbosity=0).run(suite)
```

```
----------------------------------------------------------------------
Ran 1 test in 0.004s

OK

<unittest.runner.TextTestResult run=1 errors=0 failures=0>
```

```python
#### TODO: show reward curves of an EpsilonGreedyAgent with
epsilon=[0, 0.1, 0.2, 0.4] [10pts]####

epsilons = [0, 0.1, 0.2, 0.4]
all_logs = None
for epsilon in epsilons:
  agent = EpsilonGreedyAgent(num_actions=len(probs), epsilon = 0.1)
  logs = bandit_sweep([agent], probs, ['Epsilon Greedy'], n_runs=1000,
max_steps=1000)
  all_logs = logs if all_logs is None else all_logs.append(logs)

plot(all_logs, x_key='step', y_key='reward', legend_key='Alg',
estimator='mean', errorbar=None)

###########################################
```

{"model_id":"f557f2f2953643b38eb05392a89259d4","version_major":2,"version_minor":0}

{"model_id":"3848474691244d59b9e7a3459e9c0255","version_major":2,"version_minor":0}

{"model_id":"4c7bb5c53b6342638aa356a3b08574b8","version_major":2,"version_minor":0}

{"model_id":"ef93c3f7b6674fbcb876d1c709ce7fc2","version_major":2,"version_minor":0}

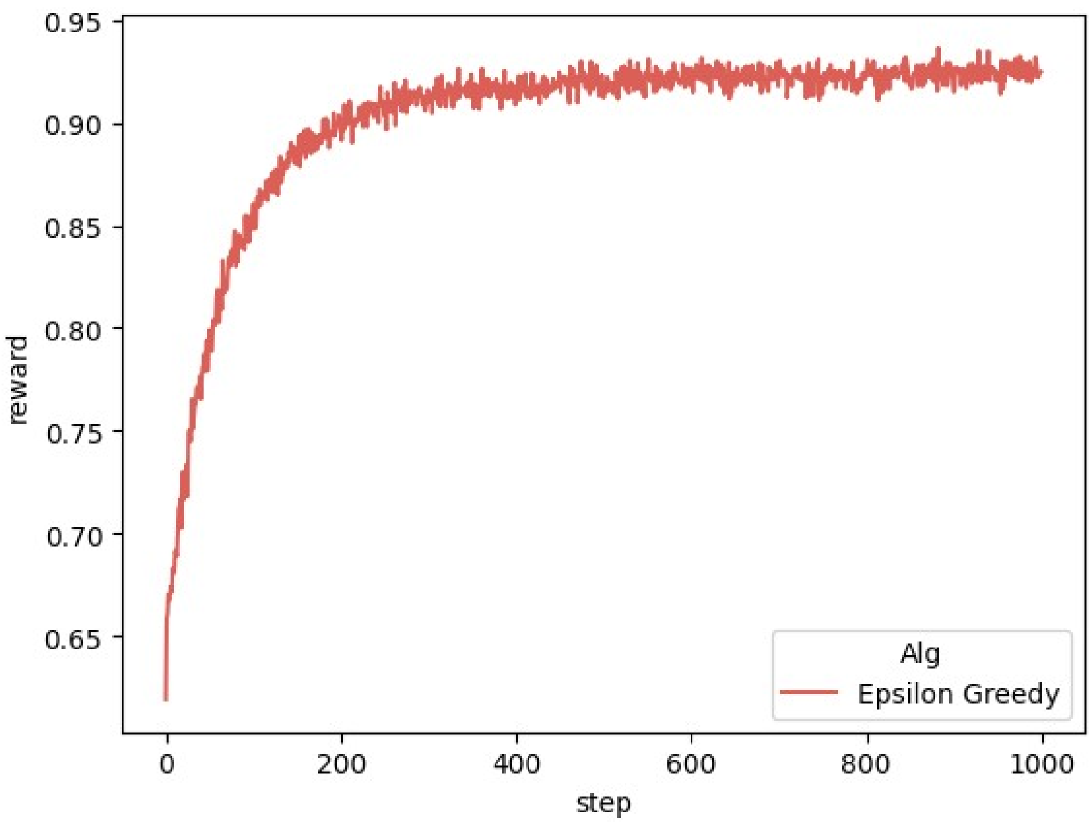
```
<ipython-input-55-80774ae393e4>:8: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  all_logs = logs if all_logs is None else all_logs.append(logs)
```

{"model_id":"74c6c763cbd344da9014ed723271d0dc","version_major":2,"version_minor":0}

{"model_id":"9832785257da40a0a8e1937802228806","version_major":2,"version_minor":0}

```
<ipython-input-55-80774ae393e4>:8: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  all_logs = logs if all_logs is None else all_logs.append(logs)
```

```
{"model_id":"787a37d2e35f400c9becde22f81c688a","version_major":2,"version_minor":0}

{"model_id":"3c0aee08d0fc4e0aaf369a1bef561f10","version_major":2,"version_minor":0}

<ipython-input-55-80774ae393e4>:8: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  all_logs = logs if all_logs is None else all_logs.append(logs)

<Axes: xlabel='step', ylabel='reward'>
```



Analyzing Epsilon-Greedy Agents

Notice that the reward of all agents gradually increases (except for $\epsilon = 0$, which is an extremely greedy agent). Also, notice that reward is maxmium for $\epsilon = 0.1$ but decreases for higher values.

Question [5pts]: Why is the reward lower for higher-values of ϵ?

Answer: It is taking too long to explore (more exploration if epsilon is higher), and its not able to exploit the estimates, and hence the rewards for higher values of epsilon are lower.

Question [5pts]: To overcome the issue above, one can try setting $\epsilon = 0$ after some time or adaptively chaning ϵ. Can you suggest a strategy for varying ϵ with time T?

Answer: When the variability in the probabilities of choosing an action starts to reduce, we can set epsilon to 0. This indicates that we have a good estimate of choosing optimal actions.

Contextual bandits

In this section, we will deal with contextual bandits problem. In contextual bandits, we use contextual information about the observed subject to make subject-specific decisions. The algorithm we will implement is called LinUCB.

As an example, imagine we have a website with 10 products that we'd like to promote. Whenever a user enters the website, the website promotes one product to the user. If the user clicks the product link, then it's a successful promotion (reward is 1). Otherwise, it's a failed promotion (reward is 0). Our goal is to optimize the click through rate (CTR), and thus optimize our $$$.

We will use a dataset from here to explore contextual bandits. The dataset contains a pre-logged array of shape $[10000, 102]$. Each row represents a data point at time step t where $t \in [0, 9999]$. The first column represents the index of the arm a_t that's chosen (10 arms in total). The second column represents the reward $r_t \in \{0, 1\}$ received for taking the selected arm. The last 100 columns represent the context feature vector.

The following code is inspired by this code repository.

```
# Download the dataset
!wget http://www.cs.columbia.edu/~jebara/6998/dataset.txt

--2024-02-23 03:51:44--
http://www.cs.columbia.edu/~jebara/6998/dataset.txt
Resolving www.cs.columbia.edu (www.cs.columbia.edu)... 128.59.11.206
Connecting to www.cs.columbia.edu (www.cs.columbia.edu)|
128.59.11.206|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 2149159 (2.0M) [text/plain]
Saving to: ‘dataset.txt’

dataset.txt         100%[===================>]   2.05M  4.21MB/s    in
0.5s

2024-02-23 03:51:44 (4.21 MB/s) - ‘dataset.txt’ saved
[2149159/2149159]


# load in the dataset
data = pd.read_csv('dataset.txt', sep=" ", header=None)
data = data.iloc[:, :-1]
print(f'Dataset shape:{data.shape}')
data[0] -= 1 # we use 0-based numbering
data = data.to_numpy()
```

```
Dataset shape:(10000, 102)

#### Contextual bandit environment ####
@dataclass
class ContextualBanditEnv:
    dataset: Any
    t: int = 0

    def step(self, action):
        # if the action matches the recorded action in the dataset, it
will
        # return the recorded reward in the dataset. Otherwise, it
will return
        # a reward of None
        if action == self.dataset[self.t, 0]:
            reward = self.dataset[self.t, 1]
        else:
            reward = None
        self.t += 1
        return reward

    def reset(self):
        self.t = 0
```

Fill in the missing code below to implement the LinUCB agent.

```
#### LinUCB Agent ####
@dataclass
class LinUCBAgent:
    num_actions: int
    alpha: float
    feature_dim: int

    def __post_init__(self):
        self.reset()

    def reset(self):
        self.As = [np.identity(self.feature_dim) for i in
range(self.num_actions)]
        self.bs = [np.zeros([self.feature_dim, 1]) for i in
range(self.num_actions)]

    def get_ucb(self, action, state):
        #### TODO: compute the UCB of the selected action/arm, and the
context information [5pts] ####
        A_inv = np.linalg.inv(self.As[action])
        theta = np.dot(A_inv, self.bs[action])
        # x = np.expand_dims(state, axis=1) # not sure why this throws
an error???
        x = state.reshape([-1, 1])
```

```
        ucb = np.dot(theta.T, x) + self.alpha * np.sqrt(np.dot(x.T,
np.dot(A_inv, x)))
        return ucb

        ###########################################

    def update_params(self, action, reward, state):
        #### update A matrix and b matrix given the observed reward,
####
        #### selected action, and the context feature
####
        if reward is None:
            return
        #### TODO: update A and b matrices of the selected arm [5pts]
####
        # x = np.expand_dims(state, axis=1) # not sure why this throws
an error??
        x = state.reshape([-1, 1])

        self.As[action] += np.dot(x, x.T)
        self.bs[action] += reward * x
        ###########################################

    def get_action(self, state):
        #### find the action given the context information (a 1D state
vecotr) ####

        arms_ucb = np.zeros(self.num_actions)
        for arm_id in range(self.num_actions):
            arm_ucb = self.get_ucb(arm_id, state)
            arms_ucb[arm_id] = arm_ucb

        #### TODO: choose an arm a_t=\arg\max_a(p_{t,a}) with ties
broken randomly [5pts] ####
        selected_action = np.random.choice(np.where(arms_ucb ==
arms_ucb.max())[0])
        ###########################################

        return selected_action
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed_cell` argument and any exception that happen during
thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

```
#Code for running the contextual bandit environment.
@dataclass
```

```python
class CtxBanditEngine:
    dataset: Any
    agent: Any

    def __post_init__(self):
        self.env = ContextualBanditEnv(dataset=self.dataset)

    def run(self, n_runs=1):
        log = []
        for i in tqdm(range(n_runs), desc='Runs'):
            # we only record the time steps when the selected arm
matches the arm in the pre-logged data
            aligned_ctr = []
            ret_val = 0
            valid_time_steps = 0
            self.env.reset()
            self.agent.reset()
            for t in tqdm(range(self.dataset.shape[0]), desc='Time'):
                state=self.dataset[t, 2:]
                action = self.agent.get_action(state=state)
                reward = self.env.step(action)
                self.agent.update_params(action, reward, state=state)
                if reward is not None:
                    ret_val += reward
                    valid_time_steps += 1
                    aligned_ctr.append(ret_val /
float(valid_time_steps))
            data = {'aligned_ctr': aligned_ctr,
                    'step': np.arange(len(aligned_ctr))}
            if hasattr(self.agent, 'alpha'):
                data['alpha'] = self.agent.alpha
            run_log = pd.DataFrame(data)
            log.append(run_log)
        return log

#Code for aggregrating results of running an agent in the contextual
bandit environment.
def ctxbandit_sweep(alphas, dataset, n_runs=2000):
    logs = dict()
    pbar = tqdm(alphas)
    for idx, alpha in enumerate(pbar):
        pbar.set_description(f'alpha:{alpha}')
        agent = LinUCBAgent(num_actions=10, feature_dim=100,
alpha=alpha)
        engine = CtxBanditEngine(dataset=dataset, agent=agent)
        ep_log = engine.run(n_runs)
        ep_log = pd.concat(ep_log, ignore_index=True)
        ep_log['alpha'] = alpha
        logs[f'{alpha}'] = ep_log
```

```python
    logs = pd.concat(logs, ignore_index=True)
    return logs

# Run the sweep with alpha = [0, 0.01, 0.1, 0.5] and n_runs=1
logs = ctxbandit_sweep([0., 0.01, 0.1, 0.5], data, n_runs=1)
```


```
{"model_id":"00b060fd9f374a1c80d4608dfa2dcafe","version_major":2,"version_minor":0}

{"model_id":"4e3dc791748f4ac1abc70e484531d7de","version_major":2,"version_minor":0}

{"model_id":"2111f5d8949e4621a44398dcdec337a7","version_major":2,"version_minor":0}
```


```
<ipython-input-68-739f4559280a>:46: DeprecationWarning: Conversion of
an array with ndim > 0 to a scalar is deprecated, and will error in
future. Ensure you extract a single element from your array before
performing this operation. (Deprecated NumPy 1.25.)
  arms_ucb[arm_id] = arm_ucb
```


```
{"model_id":"0fba9e17c3674c3d9dd21625c2751376","version_major":2,"version_minor":0}

{"model_id":"9ec0c2f4ad45462ba66b1e085df8159b","version_major":2,"version_minor":0}
```


```
<ipython-input-68-739f4559280a>:46: DeprecationWarning: Conversion of
an array with ndim > 0 to a scalar is deprecated, and will error in
future. Ensure you extract a single element from your array before
performing this operation. (Deprecated NumPy 1.25.)
  arms_ucb[arm_id] = arm_ucb
```


```
{"model_id":"b432d222934447c3be7419b50dc8a45e","version_major":2,"version_minor":0}

{"model_id":"42ee214092d547589960737a1db0d810","version_major":2,"version_minor":0}
```


```
<ipython-input-68-739f4559280a>:46: DeprecationWarning: Conversion of
an array with ndim > 0 to a scalar is deprecated, and will error in
future. Ensure you extract a single element from your array before
performing this operation. (Deprecated NumPy 1.25.)
  arms_ucb[arm_id] = arm_ucb
```


```
{"model_id":"cf9409e818a549599ef5a8d96d93c99f","version_major":2,"version_minor":0}

{"model_id":"b61eeb412f86418289805d2e047cdc6a","version_major":2,"version_minor":0}
```

```
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an array with ndim > 0 to a scalar is deprecated, and will error in
future. Ensure you extract a single element from your array before
performing this operation. (Deprecated NumPy 1.25.)
  arms_ucb[arm_id] = arm_ucb
```

```
plot(logs, x_key='step', y_key='aligned_ctr', legend_key='alpha',
estimator='mean', errorbar=None)
```

```
/usr/local/lib/python3.10/dist-packages/pandas/core/algorithms.py:522:
DeprecationWarning: np.find_common_type is deprecated.  Please use
`np.result_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs
for more information.  (Deprecated NumPy 1.25)
  common = np.find_common_type([values.dtype, comps_array.dtype], [])
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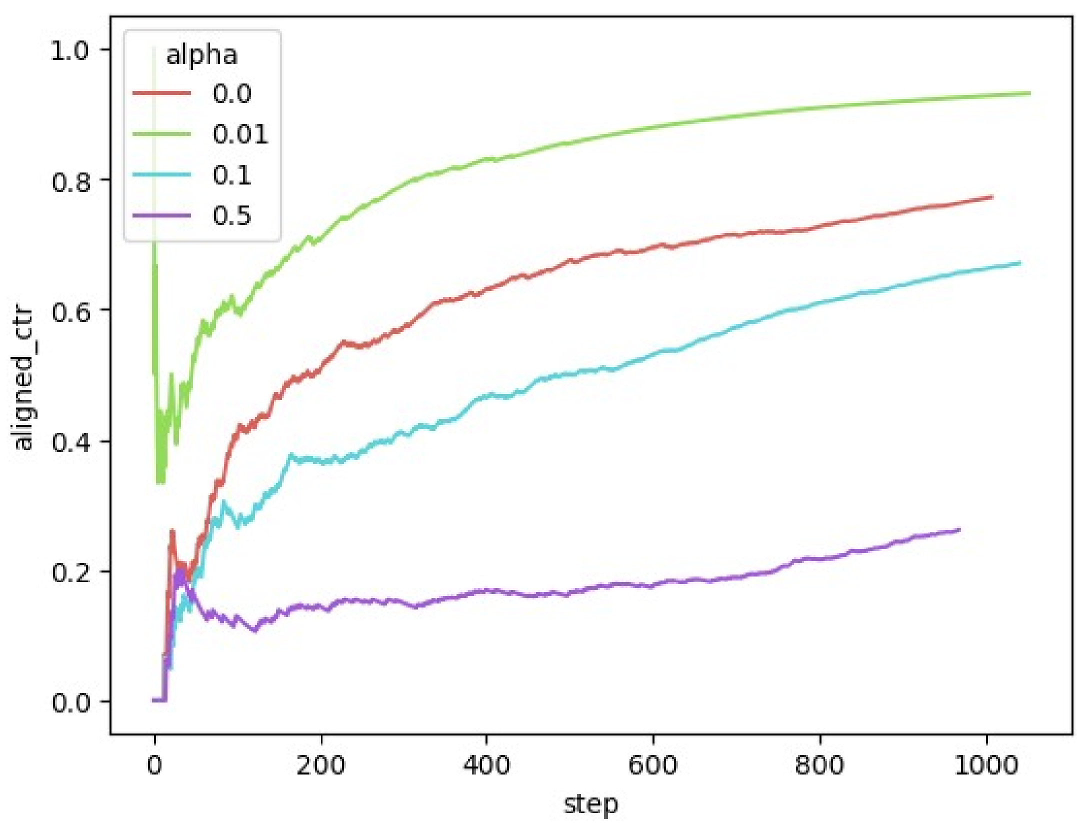
for more information.  (Deprecated NumPy 1.25)
  common = np.find_common_type([values.dtype, comps_array.dtype], [])
```

```
<Axes: xlabel='step', ylabel='aligned_ctr'>
```



Check your work:

```
suite = unittest.TestSuite()
suite.addTest(hw1_tests.TestLinUCBAgent('check_get_ucb', LinUCBAgent))
suite.addTest(hw1_tests.TestLinUCBAgent('check_update_params',
LinUCBAgent))
suite.addTest(hw1_tests.TestLinUCBAgent('check_logs', logs))
unittest.TextTestRunner(verbosity=0).run(suite)
```

```
----------------------------------------------------------------------
Ran 3 tests in 0.005s

OK

<unittest.runner.TextTestResult run=3 errors=0 failures=0>
```

Question [5pts]: What does α affect in LinUCB?

Answer: alpha is a hyperparameter that controls the balance between exploration and exploitation. A higher alpha promotes exploration, and a lower alpha leads to more exploitation of known good actions. In the graphs above, the value of the hyperparameter alpha influences the ctr (click-through rate). We can see that a right balance of alpha (0.01) achieves the highest ctr.

Question [5pts]: Do the reward curves change with α? If yes, why? If not, why not?

Answer: Yes, the rewards curve change with alpha as it influences the balance between exploration and exploitation. For instance, when alpha is set to 0.01, a good balance is achieved between exploration and exploitation. However, we see that in cases where there is no exploration (alpha = 0, red), or more weightage for exploration (alpha = 0.1 and 0.5), the ctr performance degrades.

Finally, let's compare LinUCB to UCB. We want to use the UCB algorithm while ignoring the context. Make a class that modifies the UCB agent which has the same methods as the LinUCB agent called ModUCBAgent. Notice that unlike the LinUCB agent this agent get the context as input but does not use it. Compare the ModUCBAgent to LinUCBAgent with alpha = 0, 0.01, 0.5.

```
@dataclass
class ModUCBAgent:
    num_actions: int

    def __post_init__(self):
        self.reset()

    #### TODO: Implement the necessary function for a UCB agent. This
agent should get the context vector but doesn't use it
    def reset(self):
        self.counts = np.zeros(self.num_actions) # Count of times each
action was chosen
        self.values = np.zeros(self.num_actions) # Total reward of
each action
```

```
    def get_action(self, state):
        # Using UCB formula to select action
        total_counts = np.sum(self.counts)
        if total_counts < self.num_actions:
            # Exploring each action at least once
            return np.argmin(self.counts)
        else:
            ucb_values = self.values + np.sqrt(2 *
np.log(total_counts) / self.counts)
            return np.argmax(ucb_values)

    def update_params(self, chosen_action, reward, state):
        # Update the counts and values
        self.counts[chosen_action] += 1
        # Update the average value of the chosen action
        n = self.counts[chosen_action]
        value = self.values[chosen_action]
        if reward is None:
          return
        new_value = ((n - 1) / n) * value + (1 / n) * reward
        self.values[chosen_action] = new_value
    ###########################################

def ctx_bandit_sweep(agents, labels, dataset, n_runs=2000):
    logs = dict()
    pbar = tqdm(agents)
    for idx, agent in enumerate(pbar):
        pbar.set_description(f'agent:{labels[idx]}')
        engine = CtxBanditEngine(dataset=dataset, agent=agent)
        ep_log = engine.run(n_runs)
        ep_log = pd.concat(ep_log, ignore_index=True)
        ep_log['agent'] = labels[idx]
        logs[f'{labels[idx]}'] = ep_log
    logs = pd.concat(logs, ignore_index=True)
    return logs

agents = [ModUCBAgent(num_actions=10)]
labels = ['ModUCB']
for alpha in [0, 0.01, 0.5]:
    agents.append(LinUCBAgent(num_actions=10, feature_dim=100,
alpha=alpha))
    labels.append(f'LinUCB_{alpha}')
logs = ctx_bandit_sweep(agents, labels, data, n_runs=1)

/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed_cell` argument and any exception that happen during
```

```
thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

{"model_id":"aa9f3e06bb6b4d9daf002e13c20986ee","version_major":2,"version_minor":0}

{"model_id":"3877695707644fa1bf08f215f4e18919","version_major":2,"version_minor":0}

{"model_id":"3c8e3431cead424fba69ba230368a56c","version_major":2,"version_minor":0}

{"model_id":"5a35a6b1914d42ff9d8c22ea9bf5745e","version_major":2,"version_minor":0}

{"model_id":"52b666d7ad9c4e1eb5881d6ea7008e58","version_major":2,"version_minor":0}

```
<ipython-input-68-739f4559280a>:46: DeprecationWarning: Conversion of
an array with ndim > 0 to a scalar is deprecated, and will error in
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  arms_ucb[arm_id] = arm_ucb
```

{"model_id":"67180b165871452c9cb83cbeb696ad1f","version_major":2,"version_minor":0}

{"model_id":"df13ddec433b44afa17b362e14c6af74","version_major":2,"version_minor":0}

```
<ipython-input-68-739f4559280a>:46: DeprecationWarning: Conversion of
an array with ndim > 0 to a scalar is deprecated, and will error in
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performing this operation. (Deprecated NumPy 1.25.)
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{"model_id":"b9f7a66529ef43c9b131245d4a4929ac","version_major":2,"version_minor":0}

{"model_id":"d77fc719da8a4bbdbc141419273eeef1","version_major":2,"version_minor":0}

```
<ipython-input-68-739f4559280a>:46: DeprecationWarning: Conversion of
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future. Ensure you extract a single element from your array before
performing this operation. (Deprecated NumPy 1.25.)
  arms_ucb[arm_id] = arm_ucb
/usr/local/lib/python3.10/dist-packages/pandas/core/dtypes/cast.py:164
1: DeprecationWarning: np.find_common_type is deprecated.  Please use
`np.result_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs
```

```
for more information.  (Deprecated NumPy 1.25)
  return np.find_common_type(types, [])

plot(logs, x_key='step', y_key='aligned_ctr', legend_key='agent',
estimator='mean', errorbar=None)

/usr/local/lib/python3.10/dist-packages/pandas/core/algorithms.py:522:
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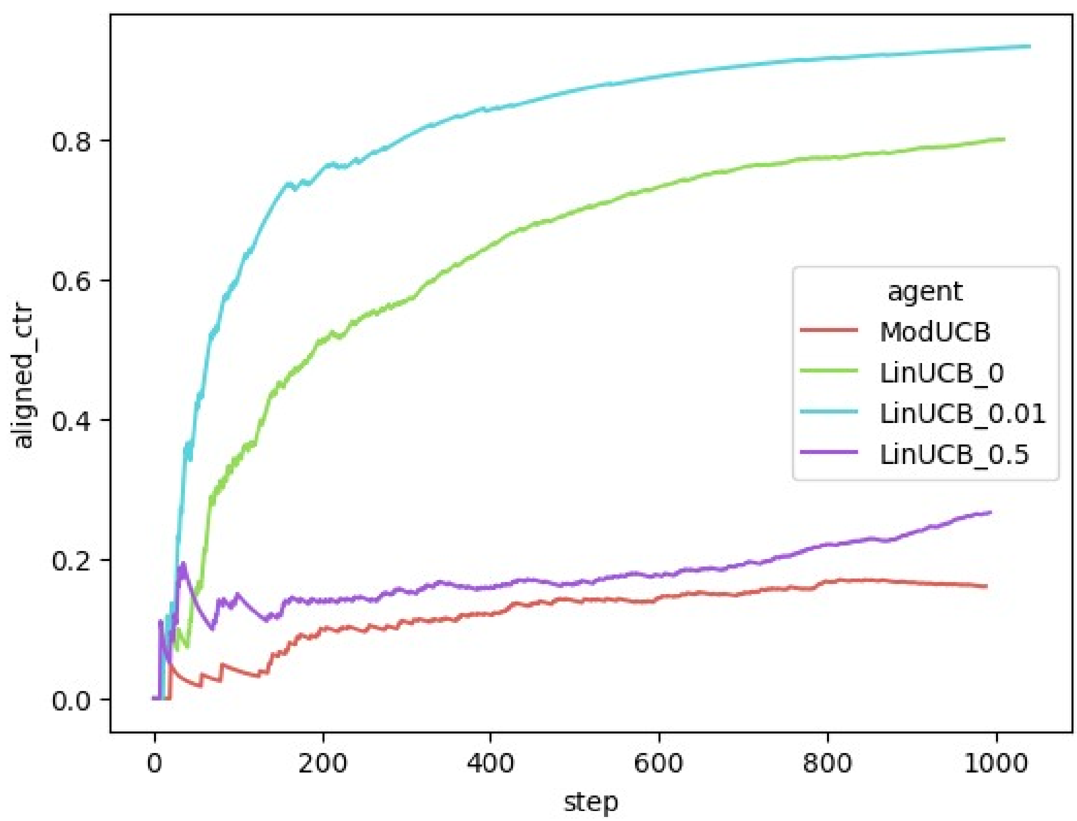
<Axes: xlabel='step', ylabel='aligned_ctr'>
```



Question [20pts]: Does LinUCB outperform UCB? If yes, explain why. If not, explain why not.

Answer: From the graphs, we can see that LinUCB outperforms UCB. LinUCB is a contextual bandit algorithm that leverages additional context or user feature information that provides additional information about the environment or the user's actions. There are cases when the LinUCB algorithm outperforms UCB especially when the context is relevant and provides meaningful information about the rewards of actions, as it can factor the specific context into its choice of actions .

In cases, where the context information is not useful or not available, UCB might perform better or equally as LinUCB, as without the context, LinUCB does not perform better. It may also degrade if the context information provided is noisy or incorrect.

However, in our case (from the graphs), it appears that LinUCB is better, which suggests that the context information is useful.

Survey [BONUS 10pts] Enter the bonus word you get after the survey.

bandit

https://forms.gle/xypvUDsxmQiTEeWy6