Aaditya Kumar Roll: EE21D411 [CS6700: Tutorial 1 (Bandits)]

```
import numpy as np
import·matplotlib.pyplot·as·plt
import·seaborn·as·sns
import pandas as pd
from IPython.display import display, HTML
from typing import NamedTuple, List

import math
```

## Gaussian Bandit Environment

```
class GaussianArm(NamedTuple):
  mean: float
  std: float


class Env:
  def __init__(self, num_arms: int, mean_reward_range: tuple, std: float):
    """
····num_arms:·number·of·bandit·arms
    mean_reward_range: mean reward of an arm should lie between
                       the given range
    std: standard deviation of the reward for each arm
    """
    self.num_arms = num_arms
    self.arms = self.create_arms(num_arms, mean_reward_range, std)

  def create_arms(self, n: int, mean_reward_range: tuple, std: float) -> dict:
    low_rwd, high_rwd = mean_reward_range
    # creates "n" number of mean reward for each arm
    means = np.random.uniform(low=low_rwd, high=high_rwd, size=(n,))
    arms = {id: GaussianArm(mu, std) for id, mu in enumerate(means)}
    return arms

  @property
  def arm_ids(self):
    return list(self.arms.keys())

  def step(self, arm_id: int) -> float:
    arm = self.arms[arm_id]
    return np.random.normal(arm.mean, arm.std)   # Reward

  def get_best_arm_and_expected_reward(self):
    best_arm_id = max(self.arms, key=lambda x: self.arms[x].mean)
    return best_arm_id, self.arms[best_arm_id].mean

  def get_avg_arm_reward(self):
    arm_mean_rewards = [v.mean for v in self.arms.values()]
    return np.mean(arm_mean_rewards)

  def plot_arms_reward_distribution(self, num_samples=1000):
    """
    This function is only used to visualize the arm's distrbution.
    """
    fig, ax = plt.subplots(1, 1, sharex=False, sharey=False, figsize=(9, 5))
    colors = sns.color_palette("hls", self.num_arms)
    for i, arm_id in enumerate(self.arm_ids):
      reward_samples = [self.step(arm_id) for _ in range(num_samples)]
      sns.histplot(reward_samples, ax=ax, stat="density", kde=True, bins=100, color=colors[i], label=f'arm_{arm_id}')
    ax.legend()
    plt.show()
```

## Policy

```
class BasePolicy:
  @property
  def name(self):
    return 'base_policy'
```

```
  def reset(self):
    """
    This function resets the internal variable.
    """
    pass

  def update_arm(self, *args):
    """
    This function keep track of the estimates
    that we may want to update during training.
    """
    pass

  def select_arm(self) -> int:
    """
    It returns arm_id
    """
    raise Exception("Not Implemented")
```

## Random Policy

```
class RandomPolicy(BasePolicy):
  def __init__(self, arm_ids: List[int]):
    self.arm_ids = arm_ids

  @property
  def name(self):
    return 'random'

  def reset(self) -> None:
    """No use."""
    pass

  def update_arm(self, *args) -> None:
    """No use."""
    pass

  def select_arm(self) -> int:
    return np.random.choice(self.arm_ids)


class EpGreedyPolicy(BasePolicy):
  def __init__(self, epsilon: float, arm_ids: List[int]):
    self.epsilon = epsilon
    self.arm_ids = arm_ids
    self.Q = {id: 0 for id in self.arm_ids}
    self.num_pulls_per_arm = {id: 0 for id in self.arm_ids}

  @property
  def name(self):
    return f'ep-greedy ep:{self.epsilon}'

  def reset(self) -> None:
    self.Q = {id: 0 for id in self.arm_ids}
    self.num_pulls_per_arm = {id: 0 for id in self.arm_ids}

  def update_arm(self, arm_id: int, arm_reward: float) -> None:
    # your code for updating the Q values of each arm
    self.num_pulls_per_arm[arm_id] += 1
    n = self.num_pulls_per_arm[arm_id]
    q = self.Q[arm_id]
    self.Q[arm_id] = q + (arm_reward - q) / n

  def select_arm(self) -> int:
    # your code for selecting arm based on epsilon greedy policy
    if np.random.random() < self.epsilon:
      return np.random.choice(self.arm_ids)
    return max(self.Q, key=self.Q.get)


class SoftmaxPolicy(BasePolicy):
  def __init__(self, tau, arm_ids):
    self.tau = tau
    self.arm_ids = arm_ids
    self.Q = {id: 0 for id in self.arm_ids}
```

```
    self.num_pulls_per_arm = {id: 0 for id in self.arm_ids}

  @property
  def name(self):
    return f'softmax tau:{self.tau}'

  def reset(self):
    self.Q = {id: 0 for id in self.arm_ids}
    self.num_pulls_per_arm = {id: 0 for id in self.arm_ids}

  def update_arm(self, arm_id: int, arm_reward: float) -> None:
    # your code for updating the Q values of each arm
    self.num_pulls_per_arm[arm_id] += 1
    n = self.num_pulls_per_arm[arm_id]
    q = self.Q[arm_id]
    self.Q[arm_id] = q + (arm_reward - q) / n
    return

  def select_arm(self) -> int:
    # your code for selecting arm based on softmax policy
    max_Q = max(self.Q.values())
    probabilities = [np.exp((self.Q[id] - max_Q) / self.tau) for id in self.arm_ids]
    probs = probabilities / np.sum(probabilities)
    return np.random.choice(self.arm_ids, p=probs)

class UCB(BasePolicy):
  # your code here
  def __init__(self, arm_ids):
    self.arm_ids = arm_ids
    self.Q = {id: 0 for id in self.arm_ids}
    self.num_pulls_per_arm = {id: 1 for id in self.arm_ids}
    self.t = 0

  @property
  def name(self):
    return f'UCB'

  def reset(self):
    self.Q = {id: 0 for id in self.arm_ids}
    self.num_pulls_per_arm = {id: 1 for id in self.arm_ids}
    self.t = 0

  def update_arm(self, arm_id: int, arm_reward: float) -> None:
    self.num_pulls_per_arm[arm_id] += 1
    n = self.num_pulls_per_arm[arm_id]
    q = self.Q[arm_id]
    self.Q[arm_id] = q + (arm_reward - q) / n

  def select_arm(self) -> int:
    self.t += 1
    ucb_values = {id: q + math.sqrt(2 * math.log(self.t) / n) for id, q, n in zip(self.Q, self.Q.values(), self.num_pulls_per_arm.values())}
    return max(ucb_values, key=ucb_values.get)
```

## Trainer

```
def train(env, policy: BasePolicy, timesteps):
  policy_reward = np.zeros((timesteps,))
  for t in range(timesteps):
    arm_id = policy.select_arm()
    reward = env.step(arm_id)
    policy.update_arm(arm_id, reward)
    policy_reward[t] = reward
  return policy_reward


def avg_over_runs(env, policy: BasePolicy, timesteps, num_runs):
  _, expected_max_reward = env.get_best_arm_and_expected_reward()
  policy_reward_each_run = np.zeros((num_runs, timesteps))
  for run in range(num_runs):
    policy.reset()
    policy_reward = train(env, policy, timesteps)
    policy_reward_each_run[run, :] = policy_reward

  # calculate avg policy reward from policy_reward_each_run
  avg_policy_rewards = np.mean(policy_reward_each_run, axis =0)
```

```
  # your code here (type: nd.array, shape: (timesteps,))
  total_policy_regret = np.cumsum(expected_max_reward - avg_policy_rewards)
  # your code here (type: float)
  total_policy_regret = total_policy_regret[-1]

  return avg_policy_rewards, total_policy_regret


def plot_reward_curve_and_print_regret(env, policies, timesteps=200, num_runs=500):
  fig, ax = plt.subplots(1, 1, sharex=False, sharey=False, figsize=(10, 6))
  for policy in policies:
    avg_policy_rewards, total_policy_regret = avg_over_runs(env, policy, timesteps, num_runs)
    print('regret for {}: {:.3f}'.format(policy.name, total_policy_regret))
    ax.plot(np.arange(timesteps), avg_policy_rewards, '-', label=policy.name)

  _, expected_max_reward = env.get_best_arm_and_expected_reward()
  ax.plot(np.arange(timesteps), [expected_max_reward]*timesteps, 'g-')

  avg_arm_reward = env.get_avg_arm_reward()
  ax.plot(np.arange(timesteps), [avg_arm_reward]*timesteps, 'r-')

  plt.legend(loc='lower right')
  plt.show()
```

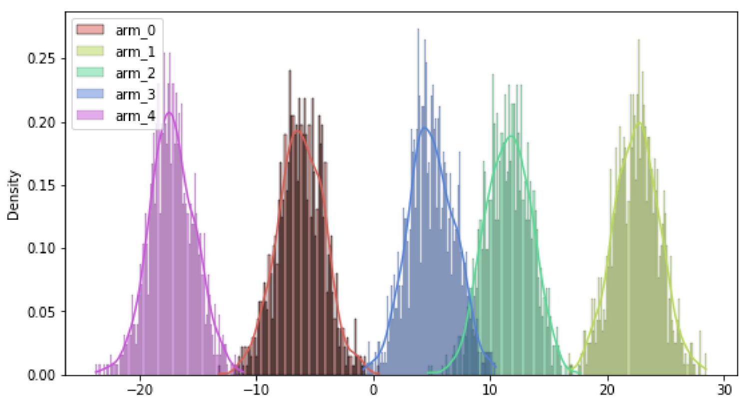
## Experiments

```
seed = 42
np.random.seed(seed)

num_arms = 5
mean_reward_range = (-25, 25)
std = 2.0


env = Env(num_arms, mean_reward_range, std)

env.plot_arms_reward_distribution()
```




```
best_arm, max_mean_reward = env.get_best_arm_and_expected_reward()
print(best_arm, max_mean_reward)
```

```
1 22.53571532049581
```

```
print(env.get_avg_arm_reward())
```

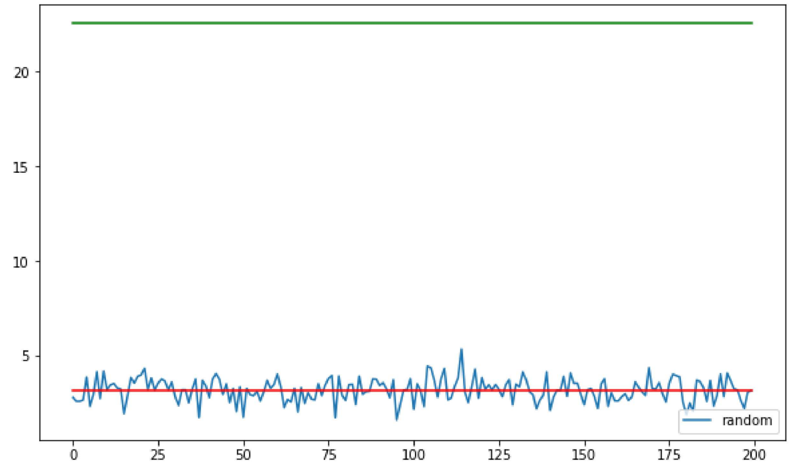
```
3.119254917081568
```

## Please explore following values:

- Epsilon greedy: [0.001, 0.01, 0.5, 0.9]
- Softmax: [0.001, 1.0, 5.0, 50.0]

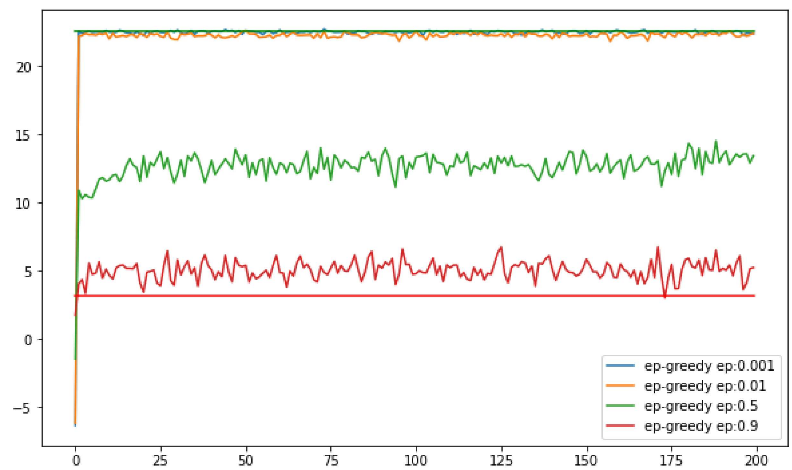
```
random_policy = RandomPolicy(env.arm_ids)
plot_reward_curve_and_print_regret(env, [random_policy], timesteps=200, num_runs=500)
```

```
regret for random: 3871.625
```



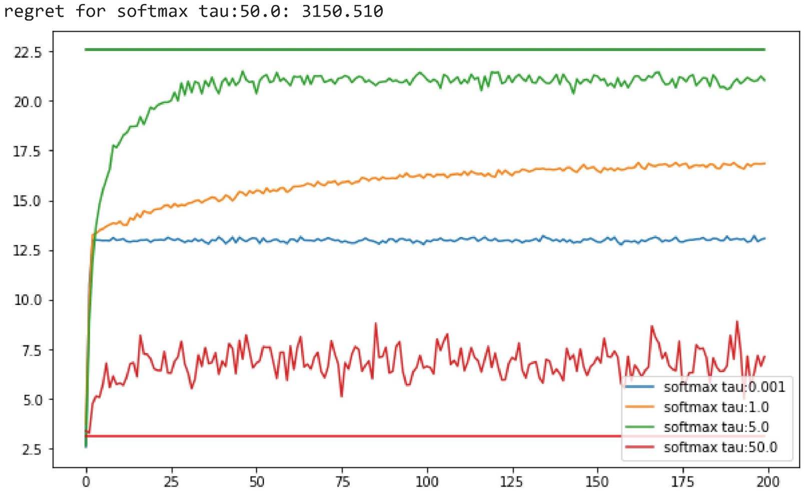

```python
explore_epgreedy_epsilons =  [0.001, 0.01, 0.5, 0.9]
epgreedy_policies = [EpGreedyPolicy(ep, env.arm_ids) for ep in explore_epgreedy_epsilons]
plot_reward_curve_and_print_regret(env, epgreedy_policies, timesteps=200, num_runs=500)
```

```
regret for ep-greedy ep:0.001: 39.590
regret for ep-greedy ep:0.01: 83.511
regret for ep-greedy ep:0.5: 1980.353
regret for ep-greedy ep:0.9: 3505.350
```



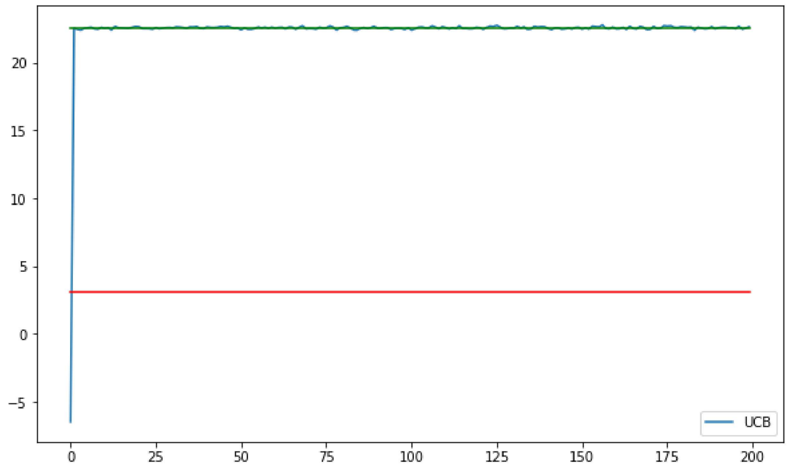

```python
explore_softmax_taus =  [0.001, 1.0, 5.0, 50.0]
softmax_polices = [SoftmaxPolicy(tau, env.arm_ids) for tau in explore_softmax_taus]
plot_reward_curve_and_print_regret(env, softmax_polices, timesteps=200, num_runs=500)
```

```
regret for softmax tau:0.001: 1922.557
regret for softmax tau:1.0: 1344.711
regret for softmax tau:5.0: 411.401
regret for softmax tau:50.0: 3150.510
```



```
plot_reward_curve_and_print_regret(env, [UCB(env.arm_ids)], timesteps=200, num_runs=500)
```

```
regret for UCB: 27.132
```




## Optional: Please explore different values of epsilon, tau and verify how does the behaviour changes.

For epsilon-Greedy algorithm: as we decrease the epsilon (say 0.001), the average reward is higher and the regret is lower because the arm with maximum reward is picked everytime without much exploration meanwhile when the epsilon is increased (say 0.9 or close to 1) the exploration is more and thus the reward is lower and regret is more.

For softmax algorithm: higher tau values resembles the case of uniform distribution and thus its almost always in exploration thereby more regret and lesser average reward where as for lower tau the agent is almost greedy thereby getting comparitively higher reward and lower regret.