

0_Simple_approach

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1 Simple approach to Multi-armed bandit problem

Here I would like to compare three basic approaches to the Multi-armed bandit problem - **Epsilon-Greedy**, **Upper Confidence Bound**, and **Thompson Sampling**. Their implementation codes were taken from this source: <https://www.geeksforgeeks.org/machine-learning/multi-armed-bandit-problem-in-reinforcement-learning/>.

1.1 Approaches

1.1.1 Epsilon-Greedy

```
[1]: class EpsilonGreedy:
    def __init__(self, n_arms, epsilon):
        self.n_arms = n_arms
        self.epsilon = epsilon
        self.counts = np.zeros(n_arms) # Number of times each arm is pulled
        self.values = np.zeros(n_arms) # Estimated values of each arm

    def select_arm(self):
        if np.random.rand() < self.epsilon:
            return np.random.randint(0, self.n_arms)
        else:
            return np.argmax(self.values)

    def update(self, chosen_arm, reward):
        self.counts[chosen_arm] += 1
        n = self.counts[chosen_arm]
        value = self.values[chosen_arm]
        self.values[chosen_arm] = ((n - 1) / n) * value + (1 / n) * reward
```

1.1.2 Upper Confidence Bound

```
[2]: class UCB:
    def __init__(self, n_arms):
        self.n_arms = n_arms
        self.counts = np.zeros(n_arms)
        self.values = np.zeros(n_arms)
        self.total_counts = 0
```

```

def select_arm(self):
    ucb_values = self.values + np.sqrt(2 * np.log(self.total_counts + 1) /
↪(self.counts + 1e-5))
    return np.argmax(ucb_values)

def update(self, chosen_arm, reward):
    self.counts[chosen_arm] += 1
    self.total_counts += 1
    n = self.counts[chosen_arm]
    value = self.values[chosen_arm]
    self.values[chosen_arm] = ((n - 1) / n) * value + (1 / n) * reward

```

1.1.3 Thompson Sampling

```

[3]: class ThompsonSampling:
    def __init__(self, n_arms):
        self.n_arms = n_arms
        self.successes = np.zeros(n_arms)
        self.failures = np.zeros(n_arms)

    def select_arm(self):
        sampled_values = np.random.beta(self.successes + 1, self.failures + 1)
        return np.argmax(sampled_values)

    def update(self, chosen_arm, reward):
        if reward > 0:
            self.successes[chosen_arm] += 1
        else:
            self.failures[chosen_arm] += 1

```

1.2 Simulation

In this simulation the goal is to compare basic properties of these three approaches.

Let's define parameters of the simulation: - **n_arms**: number of arms - **n_simulations**: Number of simulation repetitions - **n_steps**: Number of steps in one run - **epsilon**: Parameter for Epsilon-Greedy approach

```

[4]: # Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import seaborn as sns

```

```

[5]: # Function for simulation

```

```

def simulate_deterministic(agent_class, agent_kwargs, true_rewards, n_steps,
    ↪n_simulations):
    n_arms = len(true_rewards)
    rng_sim = np.random.default_rng()
    total_rewards = np.zeros((n_simulations, n_steps))
    records = []

    algorithm_label = f"{agent_class.__name__} {agent_kwargs}"
    for sim in range(n_simulations):
        agent = agent_class(**agent_kwargs)
        reward_cum = 0

        for t in range(n_steps):
            # Agent
            arm = agent.select_arm()
            reward = true_rewards[arm] # no noise, same reward all the time
            agent.update(arm, reward)

            # Save rewards
            reward_cum += reward
            total_rewards[sim, t] = reward

            # Save record
            records.append({
                "Simulation": sim,
                "Step": t,
                "Algorithm": algorithm_label,
                **agent_kwargs,
                "Reward": reward,
                "Cumulative Reward": reward_cum
            })

        # Calculate some statistics
        cumulative_rewards = np.cumsum(total_rewards, axis=1) # Kumulativní odměny
    ↪v čase pro každou simulaci
        mean_rewards = np.mean(cumulative_rewards, axis=0) # Průměrný průběh
    ↪kumulativní odměny napříč simulacemi
        std_rewards = np.std(cumulative_rewards[:, -1]) # Směrodatná odchylka
    ↪celkové odměny na konci (stabilita výkonu)
        final_mean = np.mean(cumulative_rewards[:, -1]) # Průměrná celková odměna
    ↪na konci simulací (výkon algoritmu)

    return {
        "mean_rewards": mean_rewards,
        "std_rewards": std_rewards,
        "final_mean": final_mean,
        "records_df": pd.DataFrame(records)
    }

```

```
}
```

```
[6]: # Parameters
n_arms = 10
true_rewards = np.array([0.2, 0.5, 0.8, 0.1, 0.3, 0.4, 0.7, 0.6, 0.25, 0.05])
n_steps = 1000
n_simulations = 1000
```

```
[7]: # Run the simulation
results = {}
```

```
[8]: results["Epsilon-Greedy (=0.1)"] = simulate_deterministic(
    EpsilonGreedy, {"n_arms": n_arms, "epsilon": 0.1}, true_rewards, n_steps,
    ↪n_simulations
)
```

```
[9]: results["UCB"] = simulate_deterministic(
    UCB, {"n_arms": n_arms}, true_rewards, n_steps, n_simulations
)
```

```
[10]: results["Thompson Sampling"] = simulate_deterministic(
    ThompsonSampling, {"n_arms": n_arms}, true_rewards, n_steps, n_simulations
)
```

```
[11]: # Check the results
df_all = pd.concat([result["records_df"] for result in results.values()],
    ↪ignore_index=True)
# df_all.head()
df_all
```

```
[11]:
```

	Simulation	Step	Algorithm \
0	0	0	EpsilonGreedy {'n_arms': 10, 'epsilon': 0.1}
1	0	1	EpsilonGreedy {'n_arms': 10, 'epsilon': 0.1}
2	0	2	EpsilonGreedy {'n_arms': 10, 'epsilon': 0.1}
3	0	3	EpsilonGreedy {'n_arms': 10, 'epsilon': 0.1}
4	0	4	EpsilonGreedy {'n_arms': 10, 'epsilon': 0.1}
...
2999995	999	995	ThompsonSampling {'n_arms': 10}
2999996	999	996	ThompsonSampling {'n_arms': 10}
2999997	999	997	ThompsonSampling {'n_arms': 10}
2999998	999	998	ThompsonSampling {'n_arms': 10}
2999999	999	999	ThompsonSampling {'n_arms': 10}

	n_arms	epsilon	Reward	Cumulative Reward
0	10	0.1	0.20	0.20
1	10	0.1	0.20	0.40
2	10	0.1	0.20	0.60

3	10	0.1	0.20	0.80
4	10	0.1	0.20	1.00
...
2999995	10	NaN	0.20	359.95
2999996	10	NaN	0.20	360.15
2999997	10	NaN	0.40	360.55
2999998	10	NaN	0.25	360.80
2999999	10	NaN	0.10	360.90

[3000000 rows x 7 columns]

```
[12]: # Print the mean and std for the approaches
for name, result in results.items():
    print(f"{name}: Final mean = {result['final_mean']:.2f}, Std = {result['std_rewards']:.2f}")
```

Epsilon-Greedy ($\epsilon=0.1$): Final mean = 737.06, Std = 17.25

UCB: Final mean = 653.60, Std = 0.00

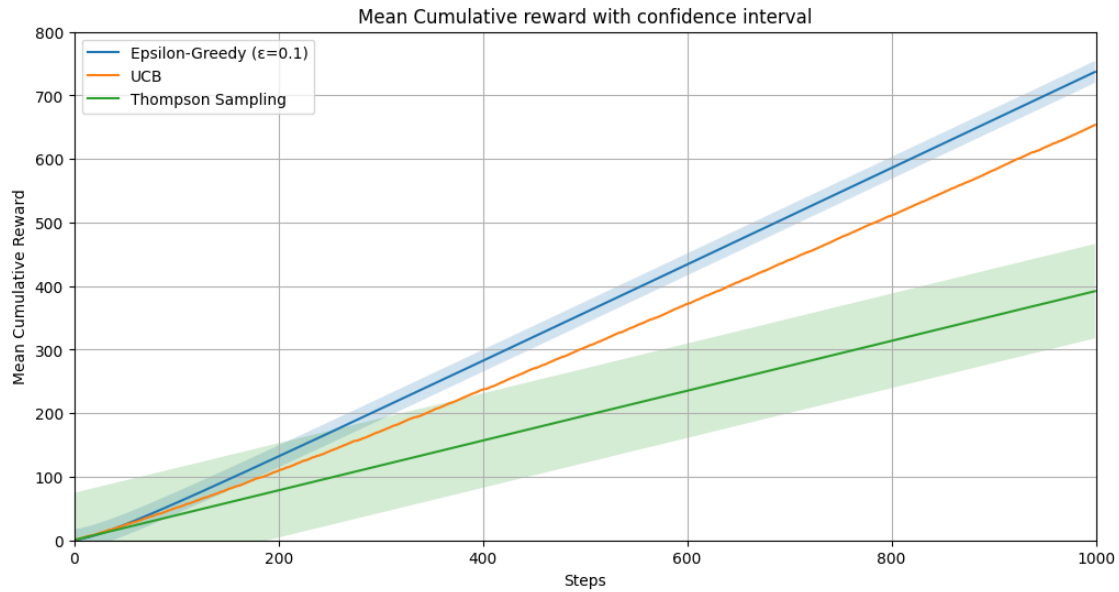
Thompson Sampling: Final mean = 392.07, Std = 74.25

```
[13]: plt.figure(figsize=(12, 6))

for label, result in results.items():
    mean_rewards = result["mean_rewards"]
    std_rewards = result["std_rewards"]

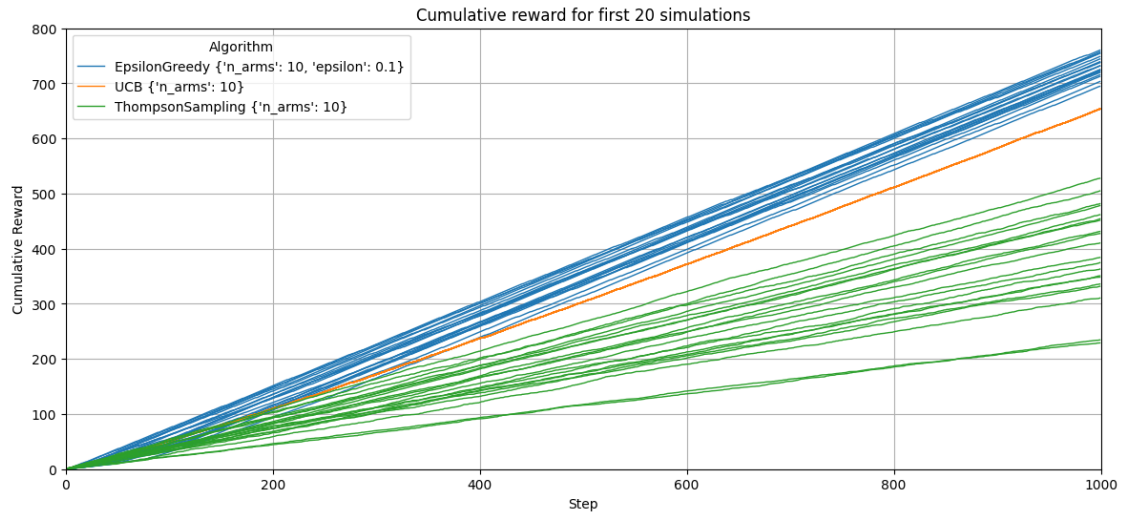
    plt.plot(mean_rewards, label=label)
    plt.fill_between(range(n_steps),
                     mean_rewards - std_rewards,
                     mean_rewards + std_rewards,
                     alpha=0.2)

plt.xlabel("Steps")
plt.ylabel("Mean Cumulative Reward")
plt.title("Mean Cumulative reward with confidence interval")
plt.legend()
plt.xlim(0, 1000)
plt.ylim(0, 800)
plt.ylim(bottom=0)
plt.grid(True)
# plt.show()
```



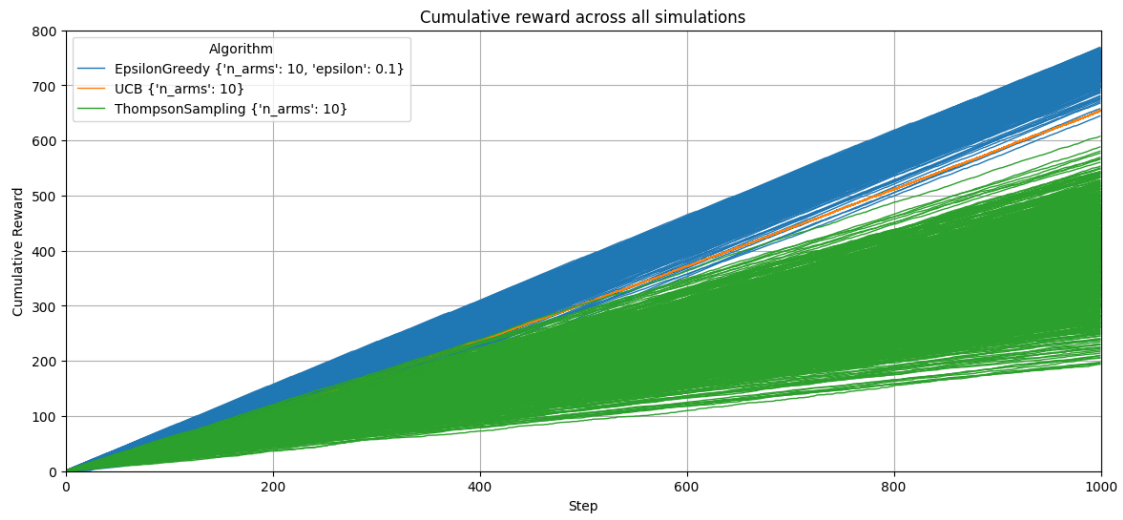
```
[14]: # Visualize first 20 simulations
df_plot = df_all[df_all["Simulation"] < 20]

plt.figure(figsize=(14, 6))
sns.lineplot(
    data=df_plot,
    x="Step",
    y="Cumulative Reward",
    hue="Algorithm",
    units="Simulation",
    estimator=None,
    lw=1
)
plt.title("Cumulative reward for first 20 simulations")
plt.xlim(0, 1000)
plt.ylim(0, 800)
plt.ylim(bottom=0)
plt.grid(True)
# plt.show()
```



```
[15]: # Visualize all simulations
df_plot = df_all

plt.figure(figsize=(14, 6))
sns.lineplot(
    data=df_plot,
    x="Step",
    y="Cumulative Reward",
    hue="Algorithm",
    units="Simulation",
    estimator=None,
    lw=1
)
plt.title("Cumulative reward across all simulations")
plt.xlim(0, 1000)
plt.ylim(0, 800)
plt.ylim(bottom=0)
plt.grid(True)
# plt.show()
```



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