`---------------Mandatory Information to fill------------`

Group ID: 43

Group Members Name with Student ID:

1. SUBHRANSU MISHRA 2023AC05489
2. JAWAHARLAL RAJAN S 2023AC05504
3. SHAILESH KUMAR SINGH 2023AC05475
4. LAKSHMISRINIVAS PERAKAM 2023AC05540

`-------------------Write your remarks (if any) that you want should get consider at the time of evaluation---------------`

Remarks: ##Add here

Background

In the world of online streaming, user satisfaction and engagement are critical metrics for the success of a movie recommendation system. A well-designed recommendation algorithm can significantly enhance user experience by suggesting movies that align with their preferences, leading to higher platform retention and usage. Recommendation systems face the challenge of balancing exploration (discovering new movies) with exploitation (recommending known favourites) to maximize user satisfaction over time.

Scenario

Imagine a leading online movie streaming platform, TrendMovie Inc., that aims to become the go-to destination for personalized movie recommendations. The platform features a vast collection of movies catering to diverse audiences. TrendMovie Inc. wants to optimize its recommendation strategy to deliver maximum user satisfaction while maintaining a high level of engagement. Each movie recommendation is treated as an interaction with the user, and their feedback is used to refine the recommendation strategy dynamically.

Objective

Your objective is to design and implement a recommendation system using Multi-Armed Bandit (MAB) algorithms to maximize cumulative user satisfaction. The system should dynamically allocate recommendations by learning user preferences in real-time, striking the right balance between exploration and exploitation.

Dataset

The dataset contains user ratings for a variety of movies. Key columns in the dataset include:

- **User ID:** A unique identifier for each user.
- **Movie ID:** A unique identifier for each.
- **Rating:** A score provided by the user for a movie (on a scale of 1 to 5).
- **Timestamp:** The time when the rating was given (optional for this assignment).

Link for accessing dataset:
https://drive.google.com/file/d/1gfobhqlVCw8Oo52JCiYpEBGhG5k7cWBr/view?usp=drive_link

Environment Details

Arms: Each movie represents an "arm" in the MAB framework. The probability of a movie being liked by a user is initially unknown and will be estimated based on user feedback during the interactions. For example:

Arm 1: Movie A

Arm 2: Movie B

Arm 3: Movie C

... and so on, for all movies in the dataset.

Reward Function: The reward function is defined based on user ratings:

Reward = 1: The user rates the movie high star (e.g., 4 or 5 stars).

Reward = 0: The user rates the movie low star (e.g., 1, 2, or 3 stars).

Assumptions:

Run simulations for 1000 iterations for each policy

Requirements and Deliverables:

Implement the Multi-Arm Bandit Problem for the given above scenario for all the below mentioned policy methods.

Initialize constants

In [23]:
```
!pip install gym pandas
```

```
Requirement already satisfied: gym in /Users/jawahar/Documents/bitsMTech/s
em2/drl/playground/.venv/lib/python3.12/site-packages (0.26.2)
Requirement already satisfied: pandas in /Users/jawahar/Documents/bitsMTec
h/sem2/drl/playground/.venv/lib/python3.12/site-packages (2.2.3)
Requirement already satisfied: numpy>=1.18.0 in /Users/jawahar/Documents/b
itsMTech/sem2/drl/playground/.venv/lib/python3.12/site-packages (from gym)
(2.2.1)
Requirement already satisfied: cloudpickle>=1.2.0 in /Users/jawahar/Docume
nts/bitsMTech/sem2/drl/playground/.venv/lib/python3.12/site-packages (from
gym) (3.1.0)
Requirement already satisfied: gym_notices>=0.0.4 in /Users/jawahar/Docume
nts/bitsMTech/sem2/drl/playground/.venv/lib/python3.12/site-packages (from
gym) (0.0.8)
Requirement already satisfied: python-dateutil>=2.8.2 in /Users/jawahar/Do
cuments/bitsMTech/sem2/drl/playground/.venv/lib/python3.12/site-packages
(from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /Users/jawahar/Documents/bi
tsMTech/sem2/drl/playground/.venv/lib/python3.12/site-packages (from panda
s) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /Users/jawahar/Documents/
bitsMTech/sem2/drl/playground/.venv/lib/python3.12/site-packages (from pan
das) (2024.2)
Requirement already satisfied: six>=1.5 in /Users/jawahar/Documents/bitsMT
ech/sem2/drl/playground/.venv/lib/python3.12/site-packages (from python-da
teutil>=2.8.2->pandas) (1.17.0)
```

In [24]:
```
import random
import numpy as np
import pandas as pd
import gym

# Constants
no_of_iterations = 1000

seed = 0
random.seed(seed)
```

Load Dataset (0.5M)

In [25]:
```
# Code for Dataset loading and print dataset statistics
#-----write your code below this line---------


# Data Exploration

import pandas as pd

# Load the dataset
dataset = pd.read_csv("TrendMovie.csv")

# Display basic information about the dataset
print("Dataset Info:")
dataset.info()

print("Total Movie count:")
```

```python
print(len(dataset['movieId'].unique()))

# Display the first few rows of the dataset
print("\nDataset Preview:")
print(dataset.head())

# Check for missing values
print("\nMissing Values:")
print(dataset.isnull().sum())

# Summary statistics of the ratings
print("\nSummary Statistics:")
print(dataset["rating"].describe())

# Preprocessing

# Convert timestamp to a readable format
dataset["timestamp"] = pd.to_datetime(dataset["timestamp"], unit="s")

# Sort by user and timestamp for consistent processing
dataset = dataset.sort_values(by=["userId", "timestamp"]).reset_index(dro

print("\nProcessed Dataset Preview:")
print(dataset.head())
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100836 entries, 0 to 100835
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   userId     100836 non-null  int64  
 1   movieId    100836 non-null  int64  
 2   rating     100836 non-null  float64
 3   timestamp  100836 non-null  int64  
dtypes: float64(1), int64(3)
memory usage: 3.1 MB
Total Movie count:
9724

Dataset Preview:
   userId  movieId  rating  timestamp
0       1        1     4.0  964982703
1       1        3     4.0  964981247
2       1        6     4.0  964982224
3       1       47     5.0  964983815
4       1       50     5.0  964982931

Missing Values:
userId       0
movieId      0
rating       0
timestamp    0
dtype: int64

Summary Statistics:
count    100836.000000
mean          3.501557
std           1.042529
min           0.500000
25%           3.000000
50%           3.500000
75%           4.000000
max           5.000000
Name: rating, dtype: float64

Processed Dataset Preview:
   userId  movieId  rating           timestamp
0       1      804     4.0 2000-07-30 18:08:19
1       1     1210     5.0 2000-07-30 18:08:19
2       1     2018     5.0 2000-07-30 18:08:43
3       1     2628     4.0 2000-07-30 18:08:43
4       1     2826     4.0 2000-07-30 18:08:43
```

Design a Movie Environment (0.5M)

In [26]:
```python
import random
import gym
import math

# Define the Movie Recommendation Environment
class MovieRecommendationEnv(gym.Env):
    def __init__(self, data):
```

```
        """
        Initialize the environment.

        Parameters:
        - data: DataFrame containing user ratings with columns: 'userId',
        """
        self.data = data
        self.movies = data['movieId'].unique()  # Unique movie IDs
        self.reset()  # Initialize the state

    def step(self, action):
        """
        Simulate a user's interaction with a selected movie (arm).

        Parameters:
        - action: The selected movie ID (arm).

        Returns:
        - state: Updated state with rewards for each movie.
        - reward: 1 if liked, 0 otherwise.
        - done: Always False, as this is a continuous environment.
        - debug: None for now (can be extended for additional info).
        """
        # Filter ratings for the selected movie
        movie_ratings = self.data[self.data['movieId'] == action]['rating

        # Use the average rating for the movie
        if not movie_ratings.empty:
            avg_rating = movie_ratings.mean()
            reward = 1 if avg_rating >= 4.0 else 0  # High rating gives a
        else:
            reward = 0  # Default to 0 if no ratings are available

        self.state[action].append(reward)  # Update state with reward
        done = False
        debug = None
        return self.state, reward, done, debug

    def reset(self):
        """
        Reset the environment state. Each movie starts with an empty feed

        Returns:
        - state: The initial state of the environment.
        """
        self.state = {movie_id: [] for movie_id in self.movies}
        return self.state

    def render(self, mode="ascii"):
        """
        Display statistics of user feedback for all movies.

        Parameters:
        - mode: The rendering mode (default is "ascii").
        """
        returns = {movie_id: sum(rewards) for movie_id, rewards in self.s
        trials = {movie_id: len(rewards) for movie_id, rewards in self.st
        print(f'===== Total Trials: {sum(trials.values())} =====')
        counter = 0
        for movie_id, total_return in returns.items():
```

```
            # print only for every 50th tried record to save size
            total_trials = trials[movie_id]
            counter += 1
            if counter % 50 != 1 or total_trials <=0:
                continue
            print(f'Movie {movie_id} | Rewards: {total_return}, Trials: {
        print(f'===== Total Rewards: {sum(returns.values())} =====')


# Initialize the environment with the dataset
env = MovieRecommendationEnv(dataset)
```

Using Random Policy (0.5M)

Implement a random policy for movie recommendations and print each iteration. (Mandatory)

In [27]:
```
#  run the environment with an agent that is guided by a random policy
#-----write your code below this line---------

# Random Policy Implementation
def random_policy(env, n_rounds):
    env.reset()

    rewards = []
    cumulative_rewards = []
    total_reward = 0
    for _ in range(n_rounds):
        arm = random.choice(env.movies)
        _, reward, _, _ = env.step(arm)
        rewards.append(reward)
        total_reward += reward
        cumulative_rewards.append(total_reward)
    return np.mean(rewards), cumulative_rewards


# Run the policies
print("Running Random Policy:")
random_avg, random_cum = random_policy(env, no_of_iterations)
# Render final statistics
env.render()
```

```
Running Random Policy:
===== Total Trials: 1000 =====
Movie 2137 | Rewards: 0, Trials: 1
Movie 109487 | Rewards: 0, Trials: 1
Movie 540 | Rewards: 0, Trials: 1
Movie 2072 | Rewards: 0, Trials: 2
Movie 3633 | Rewards: 0, Trials: 1
Movie 2358 | Rewards: 1, Trials: 1
Movie 1672 | Rewards: 0, Trials: 1
Movie 2155 | Rewards: 0, Trials: 1
Movie 8376 | Rewards: 0, Trials: 1
Movie 932 | Rewards: 0, Trials: 1
Movie 66198 | Rewards: 0, Trials: 1
Movie 6006 | Rewards: 0, Trials: 1
Movie 126921 | Rewards: 1, Trials: 1
Movie 213 | Rewards: 0, Trials: 1
Movie 6482 | Rewards: 0, Trials: 1
Movie 104303 | Rewards: 0, Trials: 1
Movie 27820 | Rewards: 1, Trials: 1
Movie 31424 | Rewards: 0, Trials: 1
Movie 7925 | Rewards: 1, Trials: 1
Movie 6530 | Rewards: 1, Trials: 1
Movie 104129 | Rewards: 0, Trials: 1
===== Total Rewards: 262 =====
```

Using Greedy Policy (1M)

Implement a greedy policy that always recommends the movie with the highest estimated reward and print each iteration. (Mandatory)

In [28]:

```python
#  run the environment with an agent that is guided by a greedy policy
#-----write your code below this line---------

# Greedy Policy Implementation
def greedy_policy(env, n_rounds):
    """
    Implements the greedy policy, which selects movies with the highest a
    This policy exploits known rewards but may ignore exploration of less
    """
    env.reset()
    arm_rewards = {arm: [] for arm in env.movies}
    rewards = []
    cumulative_rewards = []
    total_reward = 0

    for _ in range(n_rounds):
        # This line checks whether all movies (arms) have been tried at l
        # It ensures that the policy has sufficient historical data for a
        if all(len(arm_rewards[arm]) > 0 for arm in env.movies):
            avg_rewards = {arm: np.mean(arm_rewards[arm]) for arm in env.
            arm = max(avg_rewards, key=avg_rewards.get)
        else:
            arm = random.choice([arm for arm in env.movies if len(arm_rew

        _, reward, _, _ = env.step(arm)
        arm_rewards[arm].append(reward)
        rewards.append(reward)
```

```
        total_reward += reward
        cumulative_rewards.append(total_reward)

    return np.mean(rewards), cumulative_rewards

print("Running Greedy Policy:")
greedy_avg, greedy_cum = greedy_policy(env, no_of_iterations)
# Render final statistics
env.render()
```

```
Running Greedy Policy:
===== Total Trials: 1000 =====
Movie 2872 | Rewards: 0, Trials: 1
Movie 1894 | Rewards: 0, Trials: 1
Movie 5313 | Rewards: 0, Trials: 1
Movie 46976 | Rewards: 0, Trials: 1
Movie 3822 | Rewards: 1, Trials: 1
Movie 2155 | Rewards: 0, Trials: 1
Movie 1116 | Rewards: 1, Trials: 1
Movie 213 | Rewards: 0, Trials: 1
Movie 5527 | Rewards: 0, Trials: 1
Movie 1707 | Rewards: 0, Trials: 1
Movie 3713 | Rewards: 1, Trials: 1
Movie 3276 | Rewards: 0, Trials: 1
Movie 68945 | Rewards: 1, Trials: 1
Movie 5704 | Rewards: 0, Trials: 1
Movie 112326 | Rewards: 0, Trials: 1
===== Total Rewards: 221 =====
```

Using Epsilon-Greedy Policy (1.5M)

Implement the epsilon-greedy policy, where with probability ε you explore (recommend a random movie) and with probability (1-ε) you exploit (recommend the best-known movie). Try with ε =0.1, 0.2, 0.5 and print each iteration. What value of ε yields the best performance? (Mandatory)

In [29]:

```
#  run the environment with an agent that is guided by a epsilon-greedy p
#-----write your code below this line---------

# Epsilon-Greedy Policy
def epsilon_greedy_policy(env, n_rounds, epsilon):
    env.reset()
    arm_rewards = {arm: [] for arm in env.movies}
    rewards = []
    cumulative_rewards = []
    total_reward = 0

    for _ in range(n_rounds):
        # exploration
        # select random choices until we reach epsilon
        if random.random() < epsilon:
            arm = random.choice(env.movies)
        else:
            # select greedy option by taking the max rewarded
            avg_rewards = {arm: np.mean(arm_rewards[arm]) if len(arm_rewa
            arm = max(avg_rewards, key=avg_rewards.get)
```

```
        _, reward, _, _ = env.step(arm)
        arm_rewards[arm].append(reward)
        rewards.append(reward)
        total_reward += reward
        cumulative_rewards.append(total_reward)

    return np.mean(rewards), cumulative_rewards

epsilon = 0.1
print(f"Running Epsilon Greedy Policy with ε = {epsilon}")
epsilon1_avg, epsilon1_cum = epsilon_greedy_policy(env, no_of_iterations,
# Render final statistics
env.render()
```

```
Running Epsilon Greedy Policy with ε = 0.1
===== Total Trials: 1000 =====
Movie 804 | Rewards: 0, Trials: 7
Movie 2358 | Rewards: 25, Trials: 25
===== Total Rewards: 915 =====
```

In [30]:
```
epsilon = 0.2
print(f"Running Epsilon Greedy Policy with ε = {epsilon}")
epsilon2_avg, epsilon2_cum = epsilon_greedy_policy(env, no_of_iterations,
# Render final statistics
env.render()
```

```
Running Epsilon Greedy Policy with ε = 0.2
===== Total Trials: 1000 =====
Movie 804 | Rewards: 0, Trials: 29
Movie 148626 | Rewards: 0, Trials: 1
Movie 3985 | Rewards: 0, Trials: 1
Movie 2846 | Rewards: 0, Trials: 1
Movie 128991 | Rewards: 1, Trials: 1
Movie 143896 | Rewards: 1, Trials: 1
Movie 6269 | Rewards: 1, Trials: 1
Movie 165343 | Rewards: 0, Trials: 1
===== Total Rewards: 825 =====
```

In [31]:
```
epsilon = 0.5
print(f"Running Epsilon Greedy Policy with ε = {epsilon}")
epsilon5_avg, epsilon5_cum = epsilon_greedy_policy(env, no_of_iterations,
# Render final statistics
env.render()
```

```
Running Epsilon Greedy Policy with ε = 0.5
===== Total Trials: 1000 =====
Movie 804 | Rewards: 0, Trials: 16
Movie 2072 | Rewards: 0, Trials: 1
Movie 3633 | Rewards: 0, Trials: 1
Movie 127146 | Rewards: 0, Trials: 1
Movie 26871 | Rewards: 0, Trials: 1
Movie 72129 | Rewards: 0, Trials: 1
Movie 126921 | Rewards: 2, Trials: 2
Movie 99112 | Rewards: 0, Trials: 1
Movie 41716 | Rewards: 0, Trials: 1
Movie 4711 | Rewards: 1, Trials: 1
Movie 3713 | Rewards: 1, Trials: 1
Movie 2007 | Rewards: 0, Trials: 1
Movie 103085 | Rewards: 0, Trials: 1
===== Total Rewards: 599 =====
```

Using UCB (1M)

Implement the UCB algorithm for movie recommendations and print each iteration. (Mandatory)

In [32]:
```
#  run the environment with an agent that is guided by a UCB
#-----write your code below this line---------

# Upper Confidence Bound (UCB) Policy Implementation
def ucb_policy(env, n_rounds):
    env.reset()
    arm_rewards = {arm: [] for arm in env.movies}
    rewards = []
    cumulative_rewards = []
    total_reward = 0
    total_counts = 0

    for _ in range(n_rounds):
        ucb_values = {}
        for arm in env.movies:
            if len(arm_rewards[arm]) == 0:
                ucb_values[arm] = float('inf')
            else:
                avg_reward = np.mean(arm_rewards[arm])
                ucb_values[arm] = avg_reward + math.sqrt((2 * math.log(to

        arm = max(ucb_values, key=ucb_values.get)
        _, reward, _, _ = env.step(arm)
        arm_rewards[arm].append(reward)
        rewards.append(reward)
        total_reward += reward
        cumulative_rewards.append(total_reward)
        total_counts += 1

    return np.mean(rewards), cumulative_rewards


print("Running UCB Policy:")
ucb_avg, ucb_cum = ucb_policy(env, no_of_iterations)
# Render final statistics
env.render()
```

```
Running UCB Policy:
===== Total Trials: 1000 =====
Movie 804 | Rewards: 0, Trials: 1
Movie 2872 | Rewards: 0, Trials: 1
Movie 1573 | Rewards: 0, Trials: 1
Movie 2137 | Rewards: 0, Trials: 1
Movie 1644 | Rewards: 0, Trials: 1
Movie 109487 | Rewards: 0, Trials: 1
Movie 538 | Rewards: 0, Trials: 1
Movie 2282 | Rewards: 0, Trials: 1
Movie 2763 | Rewards: 0, Trials: 1
Movie 4252 | Rewards: 0, Trials: 1
Movie 350 | Rewards: 0, Trials: 1
Movie 540 | Rewards: 0, Trials: 1
Movie 366 | Rewards: 0, Trials: 1
Movie 354 | Rewards: 0, Trials: 1
Movie 251 | Rewards: 0, Trials: 1
Movie 6539 | Rewards: 0, Trials: 1
Movie 33794 | Rewards: 0, Trials: 1
Movie 187 | Rewards: 1, Trials: 1
Movie 72998 | Rewards: 0, Trials: 1
Movie 61250 | Rewards: 0, Trials: 1
===== Total Rewards: 134 =====
```

Plot the cumulative rewards for all policies on a single graph to compare their performance. (0.5M)

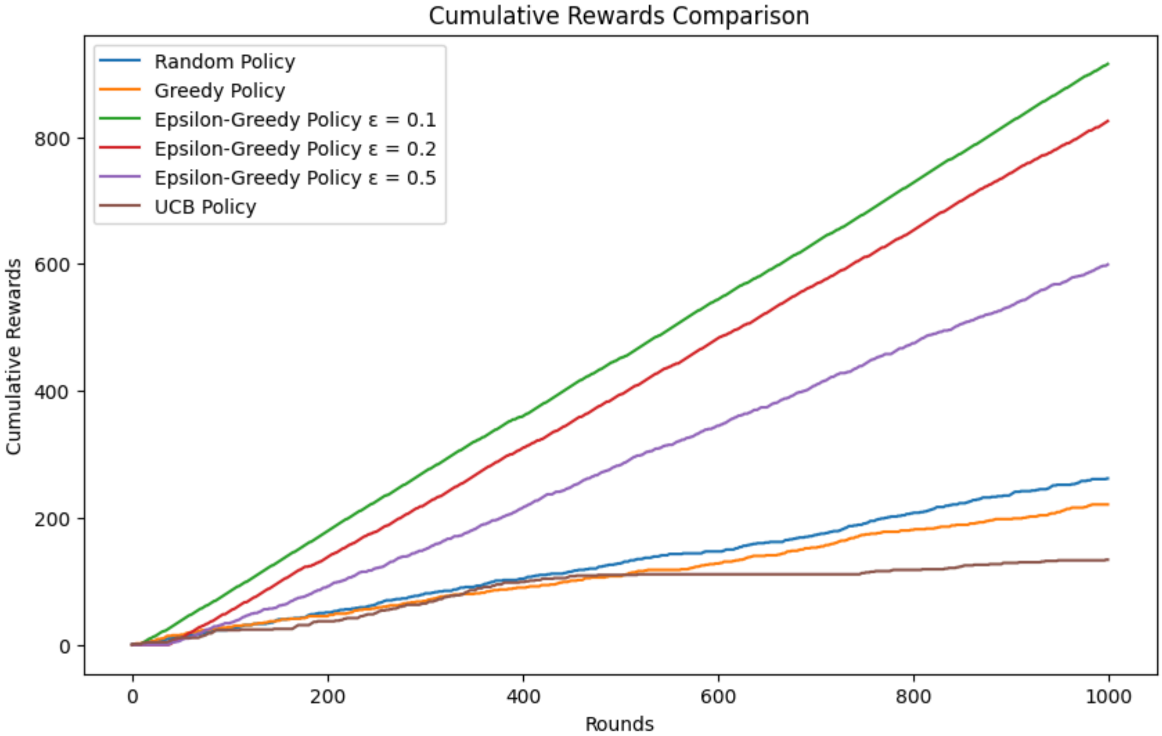
In [33]:

```python
#-----write your code below this line---------
import matplotlib.pyplot as plt

print("Random Policy Average Reward:", random_avg)
print("Greedy Policy Average Reward:", greedy_avg)
print("Epsilon-Greedy Policy Average Reward with ε = 0.1:", epsilon1_avg)
print("Epsilon-Greedy Policy Average Reward with ε = 0.2:", epsilon2_avg)
print("Epsilon-Greedy Policy Average Reward with ε = 0.5:", epsilon5_avg)
print("UCB Policy Average Reward:", ucb_avg)

# Plot cumulative rewards
plt.figure(figsize=(10, 6))
plt.plot(random_cum, label="Random Policy")
plt.plot(greedy_cum, label="Greedy Policy")
plt.plot(epsilon1_cum, label="Epsilon-Greedy Policy ε = 0.1")
plt.plot(epsilon2_cum, label="Epsilon-Greedy Policy ε = 0.2")
plt.plot(epsilon5_cum, label="Epsilon-Greedy Policy ε = 0.5")
plt.plot(ucb_cum, label="UCB Policy")
plt.xlabel("Rounds")
plt.ylabel("Cumulative Rewards")
plt.title("Cumulative Rewards Comparison")
plt.legend()
plt.show()
```

```
Random Policy Average Reward: 0.262
Greedy Policy Average Reward: 0.221
Epsilon-Greedy Policy Average Reward with ε = 0.1: 0.915
Epsilon-Greedy Policy Average Reward with ε = 0.2: 0.825
Epsilon-Greedy Policy Average Reward with ε = 0.5: 0.599
UCB Policy Average Reward: 0.134
```



Conclusion (0.5M)

Determine which policy performs the best based on cumulative reward. Provide a concise conclusion (250 words) summarizing the decision-making process and the trade-offs between exploration and exploitation.

`----write below this line------`

The best-performing policy is Epsilon-Greedy with ε = 0.1, as it achieves the highest average reward by balancing exploration and exploitation effectively. The trade-off here is that too much exploration (high ε) reduces the reward, while too little exploration (greedy or UCB) leads to suboptimal solutions.