Thompson-Sampling

January 17, 2025

[ ]:
```
'''
    Thompson Sampling -->

    Thompson Sampling is a popular reinforcement learning and
    decision-making algorithm used for solving the multi-armed
    bandit problem. It is designed to balance the trade-off between
    exploration (trying new options to gain more information) and
    exploitation (choosing the option that currently seems best).
'''
```

[ ]:
```
'''
    How Thompson Sampling Works -->

    Thompson Sampling uses a probabilistic approach to determine which
    arm to pull at each step. It models the uncertainty of rewards
    using a prior distribution and updates this distribution based on
    observed outcomes (Bayesian updating).

    Assume Prior Distributions :
    Initially, assume a prior distribution (e.g., Beta distribution for
    Bernoulli rewards) for each arm's probability of reward.

    Sampling :
    For each arm, sample a value from its posterior distribution.
    The posterior combines prior beliefs with the data observed so far.

    Select Arm:
    Choose the arm with the highest sampled value (argmax of samples).

    Observe Reward:
    Pull the chosen arm, observe the reward, and update the posterior
    distribution for that arm.

    Repeat:
    Continue this process, balancing exploration and exploitation
    automatically as the posterior distributions converge.
'''
```

```
[ ]: '''
    Key Advantages -->

    Efficient Balance: Thompson Sampling inherently balances
    exploration and exploitation.
    Bayesian Approach: Uses probabilistic reasoning to model uncertainty.
    Adaptable: Works with various reward distributions.

    Applications -->

    Online Advertising: Optimizing click-through rates by choosing
    which ad to display.
    Recommendation Systems: Deciding which products to recommend to users.
    Clinical Trials: Testing new drugs or treatments.
'''
```

```
[4]: #   Importing Libraries -->

import pandas as pd
import numpy as np
import random
import matplotlib.pyplot as plt
```

```
[5]: #   Importing Dataset -->

data = pd.read_csv('Data/Ads_CTR_Optimisation.csv')
data.head(10)
```

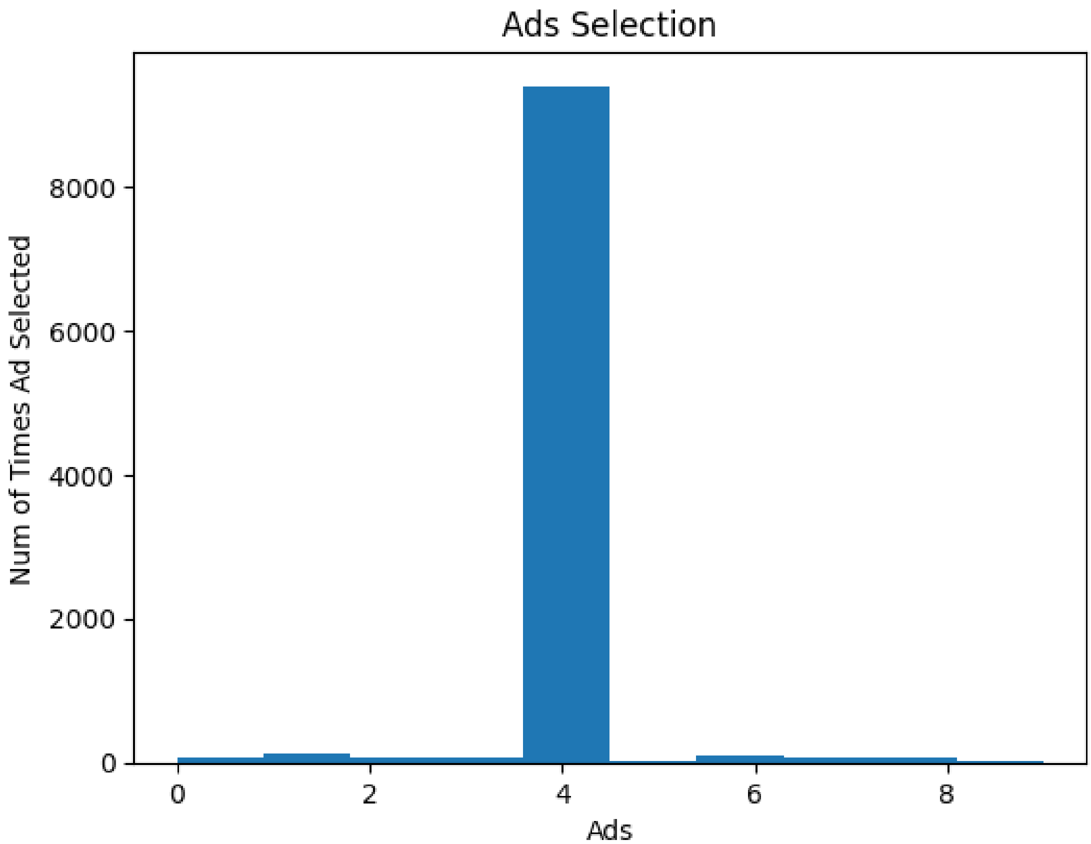
[5]:

	Ad 1	Ad 2	Ad 3	Ad 4	Ad 5	Ad 6	Ad 7	Ad 8	Ad 9	Ad 10
0	1	0	0	0	1	0	0	0	1	0
1	0	0	0	0	0	0	0	0	1	0
2	0	0	0	0	0	0	0	0	0	0
3	0	1	0	0	0	0	0	1	0	0
4	0	0	0	0	0	0	0	0	0	0
5	1	1	0	0	0	0	0	0	0	0
6	0	0	0	1	0	0	0	0	0	0
7	1	1	0	0	1	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0
9	0	0	1	0	0	0	0	0	0	0

```
[8]: #   Implementing Thompson Sampling -->

num_users = 10000
num_ads = 10
ads_selected = []
num_rewards_1 = [0] * num_ads
num_rewards_0 = [0] * num_ads
```

```
total_reward = 0

for rounds in range(0, num_users):
    ad = 0
    max_random = 0

    for ads in range(0, num_ads):
        random_beta = random.betavariate(num_rewards_1[ads] + 1,␣
 ↪num_rewards_0[ads] + 1)

        if (random_beta > max_random):
            max_random = random_beta
            ad = ads

    ads_selected.append(ad)
    reward = data.values[rounds, ad]

    if (reward == 1):
        num_rewards_1[ad] += 1

    else:
        num_rewards_0[ad] += 1

    total_reward += reward
```

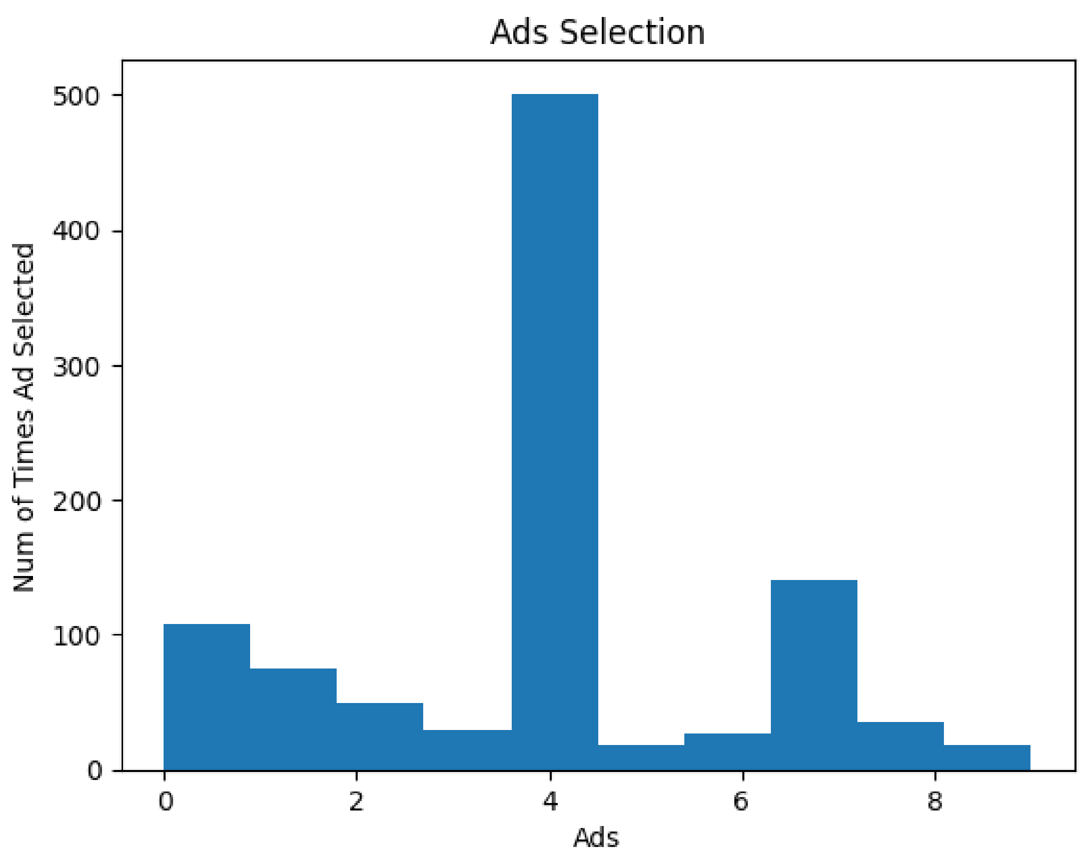
[9]:
```
#   Visualzing The Results -->

plt.hist(ads_selected)
plt.title('Ads Selection')
plt.xlabel('Ads')
plt.ylabel('Num of Times Ad Selected')
plt.show()
```



[10]:
```
#   Let's Try It With 1000 Rounds -->

num_users = 1000
num_ads = 10
ads_selected = []
num_rewards_1 = [0] * num_ads
num_rewards_0 = [0] * num_ads
total_reward = 0

for rounds in range(0, num_users):
    ad = 0
    max_random = 0

    for ads in range(0, num_ads):
        random_beta = random.betavariate(num_rewards_1[ads] + 1,␣
↪num_rewards_0[ads] + 1)

        if (random_beta > max_random):
            max_random = random_beta
```

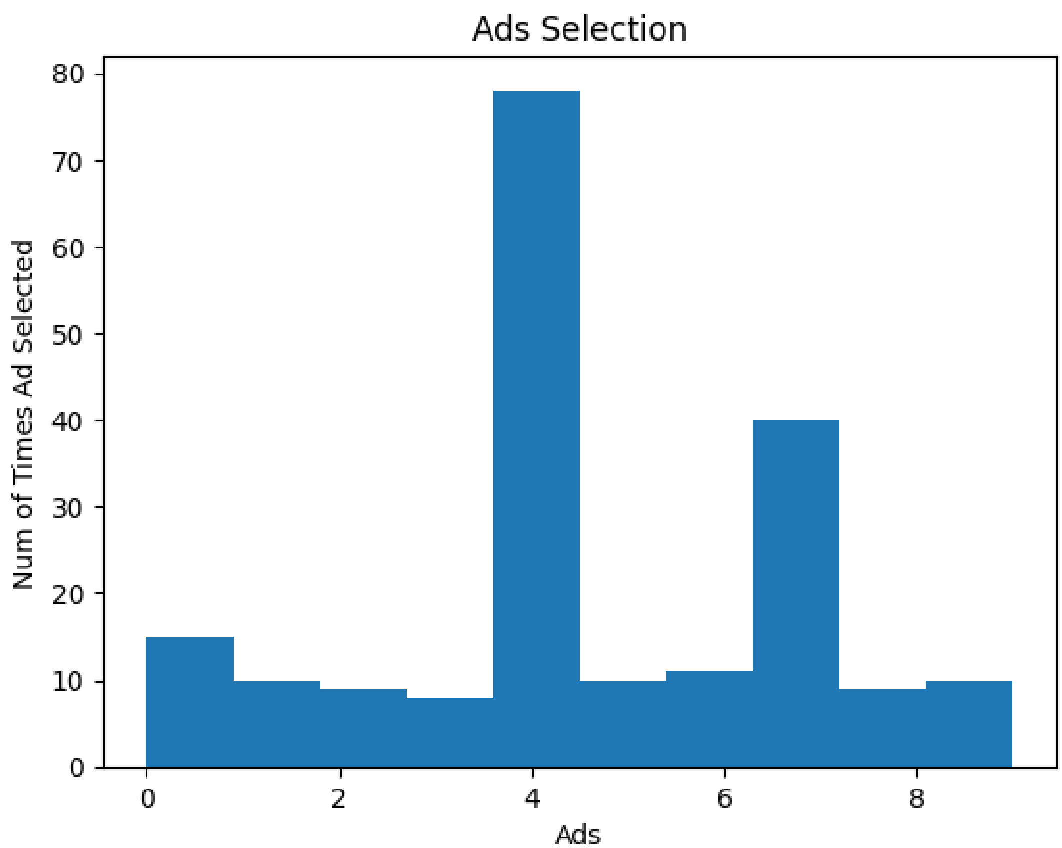
```
            ad = ads

    ads_selected.append(ad)
    reward = data.values[rounds, ad]

    if (reward == 1):
        num_rewards_1[ad] += 1

    else:
        num_rewards_0[ad] += 1

    total_reward += reward
```

[11]:
```
#   Visualzing The Results -->

plt.hist(ads_selected)
plt.title('Ads Selection')
plt.xlabel('Ads')
plt.ylabel('Num of Times Ad Selected')
plt.show()
```



[15]:
```
#   Let's Try It With 500 Rounds -->

num_users = 200
num_ads = 10
ads_selected = []
num_rewards_1 = [0] * num_ads
num_rewards_0 = [0] * num_ads
total_reward = 0

for rounds in range(0, num_users):
    ad = 0
    max_random = 0

    for ads in range(0, num_ads):
        random_beta = random.betavariate(num_rewards_1[ads] + 1,␣
 ↪num_rewards_0[ads] + 1)

        if (random_beta > max_random):
            max_random = random_beta
            ad = ads

    ads_selected.append(ad)
    reward = data.values[rounds, ad]

    if (reward == 1):
        num_rewards_1[ad] += 1

    else:
        num_rewards_0[ad] += 1

    total_reward += reward
```

[16]:
```
#   Visualzing The Results -->

plt.hist(ads_selected)
plt.title('Ads Selection')
plt.xlabel('Ads')
plt.ylabel('Num of Times Ad Selected')
plt.show()
```




```
[ ]: '''
        Thompson Sampling is Efficient as it is able to identify
        the most selected ad in just around 200 rounds while UCB
        was unable to identify in around 500 rounds.
     '''
```