BANDITS REPORT

Assuming,
- Uniform Distribution = 1/(number of users)
- User weights have started as 0 for all users and they have not been normalized going forward. Probabilities(P(a,i)) have been calculated for users for each content and total probability value has been used to scale it down to between 0 and 1.
- As eta is considered only in static bandits, the results showing rolling bandits only include alpha, beta and n(not eta) as parameters and not eta as it is a part of static bandits.
- Min = 0.0
  Max = 0.9
  Step = 0.1
  Range : 4000(Range is taken in consideration when loading user-engagement data)
  Uniform Distribution = 1/(number of users)
  N(Rolling bandits parameter) = number of times any user has been pulled for a content(Counter is present to calculate this inside content loop).

1.
BEST PERFORMING AGENT TYPE FOR INDIVIDUAL ENGAGEMENT:
- Agent Type : Static Bandit
- Parameters :
  alpha(α) : 0.5 beta(β) : 0.9 Eta(η) : 0.9
- Top 3 users maximum no. of times pulled(In Percentage) over the min and max iteration:
  user_103: 319992 (100.00%)
  user_106: 5 (0.00%)
  user_101: 2 (0.00%)
- BEST CLIENT : user_103 CUMULATIVE REWARD : 238290.5

BEST PERFORMING AGENT TYPE FOR INFLUENCE EFFECTS:
- Agent Type : Rolling Bandit
- Parameters :
  alpha(α): 0.5 beta(β) : 0.99
- Top 3 users maximum no. of times pulled(In Percentage) over the min and max iteration:
  user_104: 320000 (100.00%)
  user_103: 0 (0.00%)
  user_106: 0 (0.00%)
- BEST CLIENT : user_104 CUMULATIVE REWARD : 540375.0

2.
Test-I
File Names - content_engagements.csv(Original file), user_network_connections-Test.csv

BEST PERFORMING AGENT TYPE FOR INDIVIDUAL ENGAGEMENT:

- Agent Type : Static Bandit
- Parameters :
  alpha(α): 0.5 beta(β): 0.9 Eta(η) : 0.9
- Top 3 users maximum no. of times pulled(In Percentage) over the min and max iteration:
  user_103: 319992 (100.00%)
  user_106: 5 (0.00%)
  user_101: 2 (0.00%)
- BEST CLIENT : user_103 CUMULATIVE REWARD : 238285.5

BEST PERFORMING AGENT TYPE FOR INFLUENCE EFFECTS:

- Agent Type : Rolling Bandit
- Parameters :
  alpha(α): 0.5 beta(β): 0.9 N : 40000.0
- Top 3 users maximum no. of times pulled(In Percentage) over the min and max iteration:
  user_102: 319986 (100.00%)
  user_106: 12 (0.00%)
  user_104: 2 (0.00%)
- BEST CLIENT : user_102 CUMULATIVE REWARD : 362980.0

Test-II
File Names - content_engagements.csv(Original File), user_network_connections-Test-1.csv

BEST PERFORMING AGENT TYPE FOR INDIVIDUAL ENGAGEMENT:

- Agent Type : Static Bandit
- Parameters :
  alpha(α): 0.5 beta(β): 0.9 Eta(η) : 0.9
- Top 3 users maximum no. of times pulled(In Percentage) over the min and max iteration:
  user_103: 319992 (100.00%)
  user_106: 5 (0.00%)
  user_101: 2 (0.00%)
- BEST CLIENT : user_103 CUMULATIVE REWARD : 237851.0

BEST PERFORMING AGENT TYPE FOR INFLUENCE EFFECTS:

- Agent Type : Rolling Bandit
- Parameters :
  alpha(α): 0.5 beta(β): 0.9 N : 40000.0
- Top 3 users maximum no. of times pulled(In Percentage) over the min and max iteration:
  user_107: 319995 (100.00%)

user_106: 3 (0.00%)
user_104: 1 (0.00%)

- BEST CLIENT : user_107   CUMULATIVE REWARD : 240060.0

3.
Individual Reward: In a static bandit with individual rewards, the model would prioritize users who consistently show high engagement with the content over time. This approach would treat the problem as a one-time decision: once the bandit determines which users have the highest individual engagement, it will repeatedly exploit those users without considering any time-based changes. Since the network structure doesn't matter for individual rewards, the dense connections will not affect how the static bandit selects users. It will focus purely on users' direct engagement. In a highly connected network, individual rewards may overlook important connections where users with low personal engagement might still be valuable due to their influence on other users.

The rolling bandit with individual rewards will continuously adapt to changes in users' engagement over time. This approach would be more dynamic, making it suitable for situations where user engagement fluctuates. If engagement is volatile and some users periodically increase their activity, the rolling bandit will adjust its strategy. It will initially explore users based on recent engagement scores and shift focus as the data changes.

Influence Reward: Static Bandit will prioritize users based on their followers' engagement, favoring users with many engaged followers. In such a highly connected network, influence rewards will be extremely important. In the initial user network, user_104 was the most influential user but in the new network, users like user_102, user_104 and user_105(even though lower followers than user_104 in the older network) had high influence in the new network.

The rolling bandit will fully leverage the dense connections in the network. In the initial user network, user_104's followers started engaging more, therefore the user_104 was prioritized more. In the newer user network, user_14 followers went down therefore rolling bandit focused on other users like user_102, the rolling bandit shifted its focus.

Noticed that Static Bandits influenced more for Individual rewards and Rolling Bandits Influenced more for Influenced rewards even though graph structure was changed drastically. This can be because static bandits can exploit the same high-performing user without adjusting much for fluctuations therefore it works well for individual rewards and here we don't consider influence reward so it prefers a stable environment. For rolling bandits working well for influence reward type, it might be because of factor 'n' we use for rolling average. It changes as the user is pulled each time. One first content, if it chose the most influential user, it will prioritize it based on the weight it received in the next iterations. Therefore, dynamic changes work on rolling bandits more.

Network Connectivity - In the dense network, the users have a lot of links; a user like user_104, who is following six other users, might go better with a Rolling Bandit because it learns from more varieties of influences adaptively over time. The dynamic nature of engagement could be effectively grasped by weights that keep updating themselves.

In sparse networks, say one or two followers, a Static Bandit might be more effective. Static models can better exploit stable patterns of engagement that do not require continuous adaptation for the most part in low-connectivity scenarios.

Parameter Sensitivity - It may be useful in a dense network to pick a lower alpha, as it weighs the accumulated reward against exploration and gives an advantage to the links possessing high weights. Conversely, in a sparse network, higher values of alpha will encourage exploration in less popular contents leading to higher accumulated rewards.
A large η: It significantly influences the learning rate. On networks featuring high follower activities, a larger η would amplify the influences by followers, thus being more favorable to bandits that capture the influence dynamics better.
Reward Type - If the graph structure allows significant influence to be wielded by followers- for example, where user_102(in newer network) has many followers-influence-susceptible models may set higher rewards in case of the reward type "Influence.". On the other hand, in the case of "Individual" engagement and individual performances being high across the graph, a Static Bandit can give higher performances since it capitalizes on stable scores.
If some users are always more engaging than others, then rewards will have a 'bias' towards a type of bandit that adapts quickly to changes in engagement; hence the need for an adaptable model.
Exploration vs. Exploitation - The right balance between exploration and exploitation depends on the graph structure. If the network is highly interconnected, uncovering new content with Rolling Bandit could make patterns appear that no one could have foreseen. On the other hand, a graph that is less interconnected should be more predictable in its engagement patterns; hence, it may be better to stick with what is already known: Static Bandit.