Recommendations Engine with Multi-Objective Contextual Bandits (Using Reinforcement learning) for E-Commerce

Harsh Singh[1], Saurabh Yadav[2], Ashish Kumar Banyal[3], Prof Sonali N Deshpande[4]

[1]*Student, Computer Engineering, SIGCE, Navi Mumbai, Maharashtra, India*
[2]*Student, Computer Engineering, SIGCE, Navi Mumbai, Maharashtra, India*
[3]*Student, Computer Engineering, SIGCE, Navi Mumbai, Maharashtra, India*
[4] *HOD, Computer Engineering, Smt. Indira Gandhi College of Engineering, Navi Mumbai, Maharashtra, India*

---***---

Abstract - *This is innovative E-commerce recommending software for user and stakeholder. As in general recommendation engine only aims at optimizing user but not the stakeholders. In this appear we make attempt that satisfy the needs of both user and stakeholders. In this project we use the Reinforcement mechanism and Naive Bayesian probability to seek the subclass of information and by applying the algorithms such as clustering and filtering we recommend the products to user based on the fairness and relevance approach. It helps the user to take correct decision in their browsing experience, increase sales and online transaction.*

Key Words: **E-commerce, Reinforcement mechanism, Bayesian classifier, Fairness, Relevance**

1. INTRODUCTION

A Recommendation system is a sub-part or class of information filtering system that seeks to predict the "Rating" or "Preference" a user want to give to an item[1]. Recommendation system helps the user to get the personalized recommendation and to take correct decision in selecting the item and browsing a website. There are some widely known Recommendation engine available such as- E-bay, Amazon, Facebook, Netflix, YouTube etc. Recommendation systems are based on four main phases i.e. Collection, Storage, Analysis, and Recommendation

1.1 OBJECTIVES

- User centric machine learning is not meant to optimize for different objectives, therefore to provide the solution which is optimal and satisfy different objectives.
- The main purpose is to solve 'Cold Start' problem i.e. the product for which no user given rating to specific product or product which is launch late in the market and which is new to user.
- The another purpose this building this system is to solve the problem when user keep changing its preferences by using the approach of Injecting competitive product and concept of 'Fairness v/s Relevance'

1.2 FEATURES

- Effective in 'Cold Start' problem. • Efficient when user keep changing in preference.
- Support in growing both User and Stakeholder in the E-commerce..

1.3 SCOPES

- Product introduction to customer/user becomes easy as through behavior generation of implicit feedback
- User satisfaction because user are more interested to see there recommends for better product.
- Personalization because, we take recommends from friends because they know better and having trust, Same behaves like Recommendation System.

1.4 CHALLENGES

- If the customer changes its preferences again and again then the clustering of that customer is difficult.
- The customer is sensitive or not it will be not known rather than customer buys minimum two or three products.

1.5 SYSTEM DESIGN

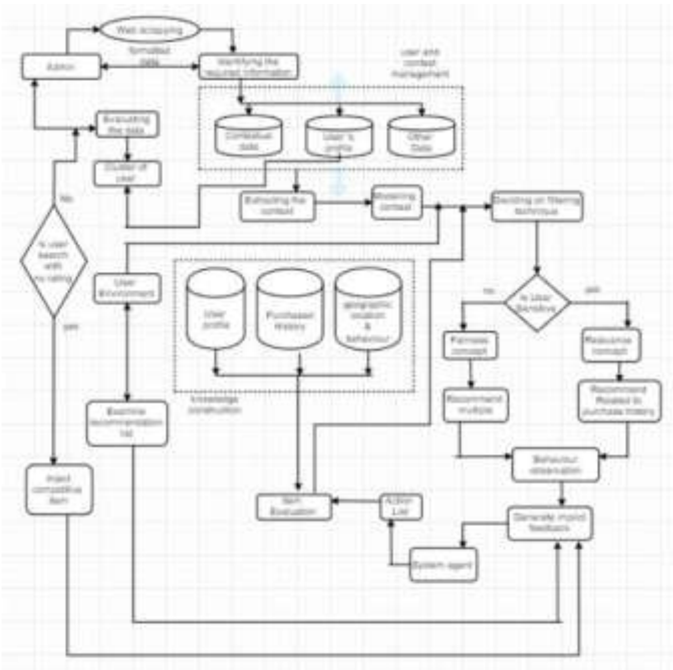

Chart -1: Architecture

2.1 RECOMMENDATION USING REVIEWS.

Attribute Information:

- UserId : Every user identified with a unique id
- ProductId : Every product identified with a unique id
- Rating: Rating of the corresponding product by the corresponding user
- Timestamp : Time of the rating.

Maximum rating is 5 and Minimum rating is 1

Matrix Factorization

Matrix Factorization is commonly known as simplest collaborative filtering. A Model which is higher in status to classic nearest neighbor techniques for producing recommendation with respect to allowance of additional information such as implicit feedback, temporal effects, and confidence levels.[4,5]

$$\min \sum_{ratings\ u,i} (r_{u,i} - x_u \cdot y_i)^2 + \gamma \cdot \overbrace{\left(\sum_{users\ u} \|x_u\|^2 + \sum_{items\ i} \|y_i\|^2 \right)}^{regularization}$$

Exploratory Data Analysis

We do data analysis to extract and know the features along with their data types to have a look at distribution of data. Plotting of data can provide capacity to gain accurate knowledge into the pattern that data follows.[4]

Product Ratings Distribution

Lots of user's have given many ratings, these rating are grouped into categories of number from 1 to 5.From which 1 is lowest and 5 is highest.

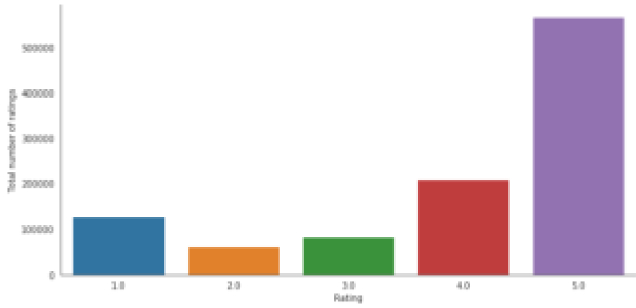

Fig -1: Analyzing Rating

Analyzing the Rating

Here we analysis no of rated product per user given by user so as to estimate how many user have given he same rating of same kind. Helps us to analyze how user are like to give rating to which product and what is the exact population for the same.

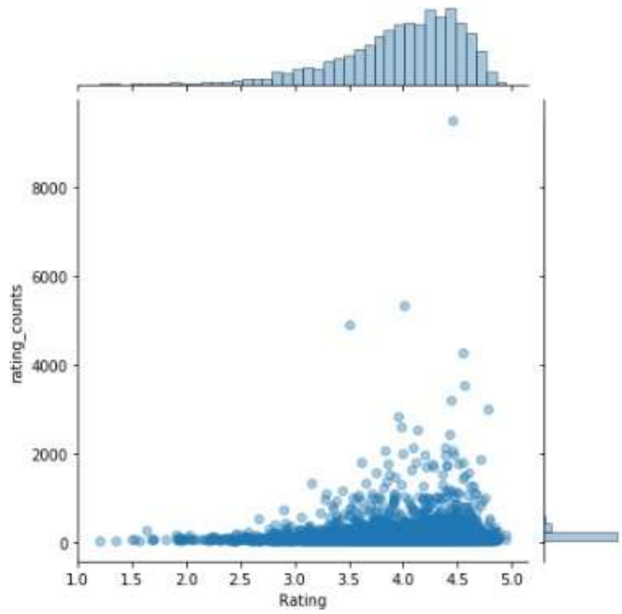

Fig -2: Analysis of Rating Counts.

2.2 BASIC OF CONTEXTUAL BANDITS

Simulate Bandit Performance

Contextual Bandit is prolong of multi –armed bandit problem or version approach to reinforcement learning. Evaluate the performance based on the number of action perceived v/s selection methods by entity on the multi –armed Bandit problem [6,7].

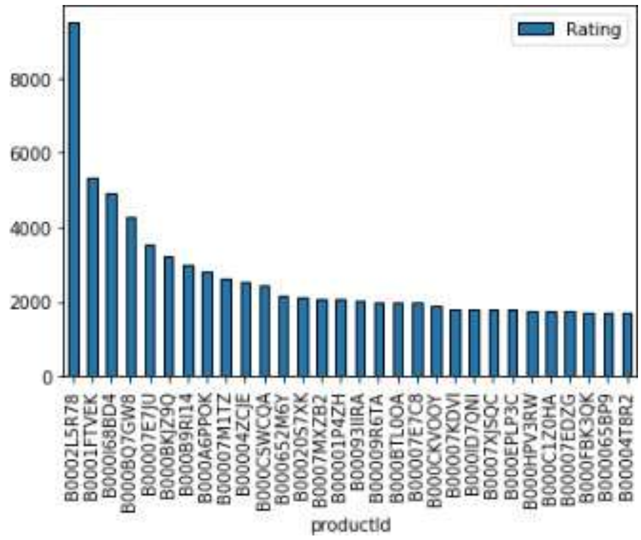

Fig -3: Simulated Bandit Performance.

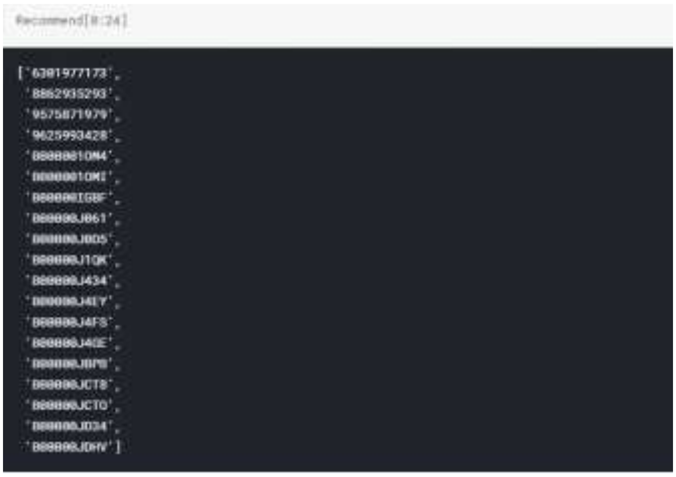

Fig -4: Final Recommendation

2.3: LINUCB + THOMPSON SAMPLING(THE ART OF EXPLORATION-EXPLOITATION DILEMMA)

Generate context vectors for all arms for each of trial n trials : number of trials n arms : number of arms per trials n features : number of features per context vector. Results returns: matrix of size n trials *n arms* n features.

Upper Confidence Bound

The easy and efficient allocation strategies valid on upper confidence bounds for a bandit problem with any yield distribution with known bounded support. Their algorithms produce logarithmic regret performance uniformly over time, not just asymptotically.[5,6]

$$\hat{\mu}_{i,T_i} = \frac{\sum_{t:I_t=i} X_t}{T_i}$$

Thompson Sampling

Thompson's sampling is one of oldest algorithm to address the exploration and exploitation trade-off, but it is surprisingly not popular in the literature.

2.4: GREEDY EXPLORATION – BAYESIAN UCB

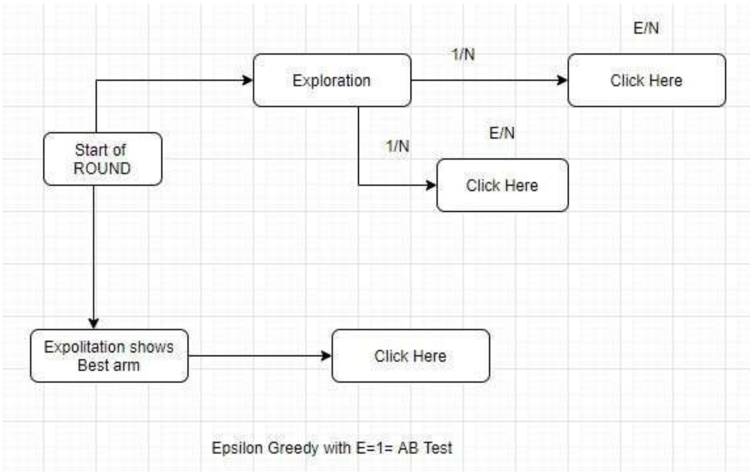

Chart -2: Epsilon-Greedy Algorithm

```
random_agent : 48.795
initial_explore_agent : 65.159
epsilon_greedy_agent : 74.698
decaying_epsilon_greedy_agent : 73.764
optimal_agent : 100.283

<Figure size 640x480 with 1 Axes>
```

Fig -5: Output

2.5: POLICY EVALUTAION IN CONTEXTUAL BANDITS

Adaptive Algorithm.

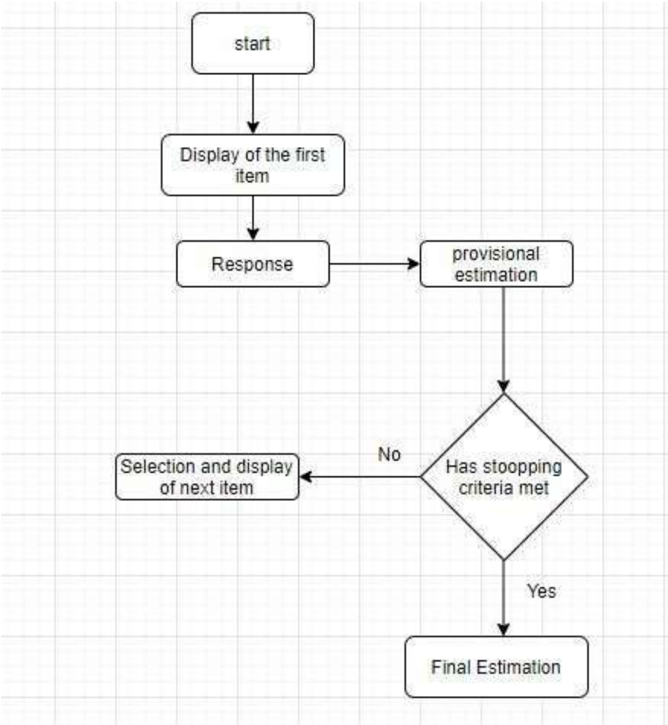

Chart -3 Adaptive Algorithms.

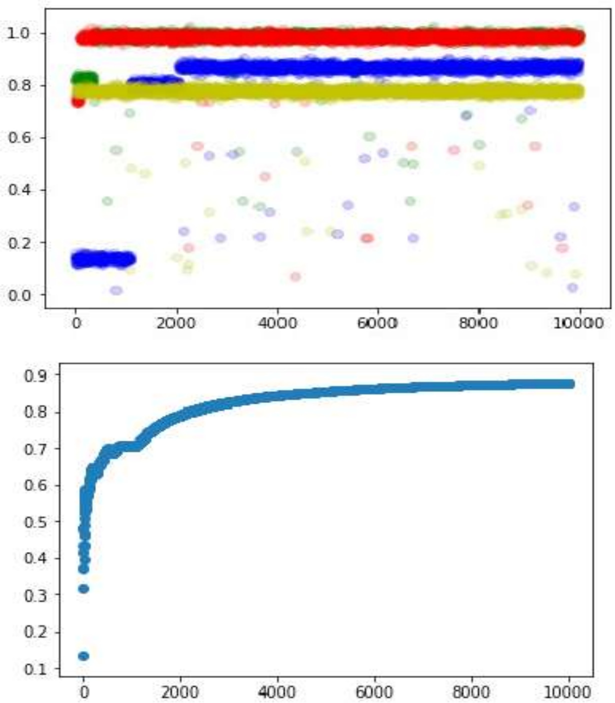

Fig -6: Output

3. CONCLUSION

In this paper, we employed a reinforcement mechanism design to make decision dynamically by concept of 'Fairness and Relevance' in E-commerce websites. We designed a deep reinforcement learning algorithm which overcomes the problem of Seller and User to make decisions in terms of performance and convergence guarantees.

REFERENCES

[1] https://towardsdatascience.com/contextual- bandits-and-reinforcement-learning- 6bdfeaece72a

[2] https://medium.com/emergent-future/simple-reinforcement-learning-with-tensorflow-part-0-q-learning-with-tables-and-neural-networks-d195264329d0

[3] Reinforcement Mechanism Design for e- commerce "Qingpeng Cai Tsinghua , Aris Filos- Ratsikas, Yiwei Zhang"

[4] https://youtu.be/MNVmBgKaROM

[5] https://youtu.be/KoMKgNeUX4k

[6] https://www.youtube.https:// towardsdatascience.com/recommendation- system-with-reinforcement-learning- 3362cb4422c8

[7] Reinforcement Mechanism Design for e- commerce "Qingpeng Cai Tsinghua , Aris Filos- Ratsikas, Yiwei Zhang"

[8] https://youtu.be/MNVmBgKaROM

[9] https://youtu.be/KoMKgNeUX4k

[10] https://www.youtube.https:// towardsdatascience.com/recommendation-system-with-reinforcement-learning-3362cb4422c8

BIOGRAPHIES

Harsh Singh is pursuing Bachelor degree (B.E.) in Computer Engineering from Smt. Indira Gandhi College of Engineering, Navi Mumbai.

Saurabh Yadav is pursuing Bachelor degree (B.E.) in Computer Engineering from Smt. Indira Gandhi College of Engineering, Navi Mumbai.

Ashish Kumar Banyal is pursuing Bachelor degree (B.E.) in Computer Engineering from Smt. Indira Gandhi College of Engineering, Navi Mumbai.

Prof Sonali N Deshpande obtained her Bachelor of Technology degree in year 2001 from SNDTUniversity Juhu, and master's from DR. B.A.M University, Aurangabad. She is HOD of Computer Department in SMT. Indira Gandhi College of Engineering, Navi Mumbai, India. She has more than 17 years of experience and her area of interest is Data structures and Algorithms and Block chain Technology