Recommendation System
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Abstract:
Nowadays personalization of web content establishes the aim and enthusiasm of a client (or a group of clients) to content they want, while advancing a lot of target commitment measurements. With improved substance utilization following by means of web investigation, such personalization isn't just practical yet additionally important for a content distributor/proprietor with enormous volumes of substance to browse. As the number of users are increasing exponentially everyday and the data security and privacy is becoming a important issue, a model is required that takes care of both personalized experience with data privacy. Recommendation systems are everywhere in our regular day to day existence on the web — they can be amazingly helpful, efficient, and help in our disclosure of things pertinent to our inclinations. As the recommendation systems are present everywhere there is need for confidentiality of own data also. There are also certain advantages to introducing privacy in recommendations/search. We can leverage better metadata, which the user doesn't share, such as app information on the phone, location, etc. We can also unlock better adoptions of the machine learning models in newer domains such as healthcare, financial services, once the user is comfortable in using the system without the hesitations of the data being shared or looked at by other people. In this paper, we introduce a simple yet efficient extension of recommender systems to improve on personalization that picks a subset of substance things (from an enormous assortment) that are pertinent to a given client and decides their separate sizes and relative situations to build a format that is advanced for a picked commitment metric. Also according to The General Data Protection Regulation (GDPR) it requires users to be both fully informed about, and consent to the collection, storage, and utilization of their personal data by other parties.

I. INTRODUCTION

We are currently living in exciting times, where access to the internet has become a cakewalk. As the internetwork is expanding, more and more users are coming online to consume content of various forms. This expansion has led to tremendous growth in the field of recommendations to simplify human decision making. Traditionally recommendation algorithms are broadly divided into three categories: Collaborative Filtering, Content Filtering, and Hybrid.

1. Content filtering: These algorithms focus on building on understanding user interests by making user's portraits by dividing the user, item into certain information features.

2. Collaborative filtering: These algorithms work on without prior information of either user or item and builds user interests only on interaction data of the users. In recent years, Collaborative filtering via Matrix factor is ation has become the default choice to build recommendation systems.

3. Hybrid filtering: These algorithms area combination of the above two algorithms. It encompasses methodologies to take pros from both the above techniques to build better recommendation systems. The traditional methods of coming up with recommendation systems is centralised in a way that does not reserve the privacy of individuals’ collected data and data models are trained in a centralised way. However, in today’s fast paced world where recommendation systems are quite a lot, users also understand the need for privacy and confidentiality of their own data. We are proposing a privacy preserving movie recommendation system using collaborative filtering where we are using matrix factor is ation method.

We are using federated data extracted out of MOVIELENS 1M dataset:

https://grouplens.org/datasets/movielens/1m/ We are using tensor flow federated to implement federated machine learning models.

II. RELATED WORK

Effective personalization of web experience comprises of coordinating the expectation and enthusiasm of a client (or clients) to content they devour, while advancing a lot of target commitment measurements. With improved substance utilization following by means of web examination, such personalization isn't just possible yet additionally important for a substance distributor /proprietor with enormous volumes of substance to browse. Anyway the large number of media (work area, portable, and so on.) and the decent variety of clients' inclinations requires computerization in this procedure of developing customized content encounters. In this paper, we propose a hereditary calculation based system that picks a subset of substance things (from a huge assortment) that are pertinent to a given client and decides their separate sizes and relative situations to develop a format that is streamlined for a picked commitment metric. Correlations against existing structures dependent on publicly supported explanations show improved noticeable quality of key substance (in light of memorable commitment measurements) by the proposed approach, while improving the data assorted variety of the substance introduced in the design.
III. EXISTING WORK

There are various applications that use the browsing history of the user and when they open that application they can see recommendations based on that history, such applications include Myntra, Flipkart, IMDb etc. These applications use a centralized database and a centralized model to achieve their goal, so every time user-specific data is sent to the central system it gets trained from it. But as the model is central, user-specific recommendation is not properly achieved and the data is also not secure. So users don’t get a personalized experience according to their interests. The applications which exist as Movie Recommender systems currently apply from Amazon to Netflix and the two approaches through which recommendation systems are designed (Deshmukh, 2018)

1. Content Based Recommendation

2. Collaborative Filtering

IV. PROPOSED WORK

To overcome the shortcomings of the existing system described, Federated Learning (McMahan et al., 2017) can be used. Instead of using a centralized database, we will train our model on decentralized data across several end devices, which will help in generating a more user-specific movie suggestion rather than a universal suggestion. We can then generate a more user-specific dataset and use that data to optimize the layout based on the interest of the user. Things in which the user has more interest will have a relatively larger size compared to the other. The size of all items will be relative to the users’ interest and will be different for every user.

VI. SYSTEM IMPLEMENTATION

In this implementation, a centralized model will be maintained with a central database. When a user logs in, he uses his/her login credentials so that the system will know which user is using it now. When the user logs in, he can see a layout of movies that will be present there on the basis of his previous likes and ratings. Once the user logs in, a model is downloaded on his/her device. The user will now use the application in searching movies, giving likes and dislikes on different movies, and giving them ratings according to his/her interest. Based on his/her ratings and all the responses, the local model is trained at the users end device only. Training of the model on the users end device improves the security of the data, as the model trains data specific to the user, so there are fewer chances of privacy breach and the data is secured. Once the model is trained, it is then sent as an update to the central model where all the updates from different users are also present. In the central model, the updates are combined and helps in training that model. When the user again logs in into the application he/she can see the movies recommended as per the model trained on the device. This comes when he local model is sent to device, it contains the information of the user with respect to his history of usage of that application and the movies are displayed on the screen with respect to a front-end tool. The front-end tool takes the names of the movies from the backend code and also fetches the images of those movies from the database, merges them and then displays them on the home screen of the application. The home page with the specific recommendation will be different for different users and will be fetched with respect to the users credentials. Once the user gives new ratings and trains the model, new recommendations can be seen for the same user with respect to the model trained on the device where he is running the application.

V. SYSTEM FLOW

The below system flow demonstrates the overall flow in which all the activities will take place when a user uses this model. After login the user will get a model downloaded on his end device, when he gives ratings he actually runs the model locally and trains the model and improves it. Once the trained model is sent back to the server and merged with other updates. And according to the update of the user the recommendation will be made to him on his/her device.

VII. RESULT AND DISCUSSION

As the amount of users on the internet increases, the most important thing that arises is the data security which is of utmost importance. Using the model that we have made, the user will be able to login by using his/her credentials and give ratings to all
the movies, based on his pattern of ratings a model will be trained which will send an update to the centralized model. As the model is trained at the user side the the data security will be high and as the model will be trained with respect to the pattern demonstrated by the user the recommendation will be according to the user and will be specific to him.

VIII. CONCLUSION AND FUTURE WORK

We hereby conclude that with the development of current applications, personalized recommendations has got more and more attention. Data security, optimized layout, user specific contents are not well considered in the current system. It aims to provide solutions to all these problems that the users face in the existing system. The solution can be then expanded in various sectors for customer satisfaction. Till now we have understood the drawbacks of the existing system and found solutions for them till the design phase. We have introduced a calculation to consequently design a lot of pieces across various formats by at the same time improving for various measurements and substance factors. Human comments of the subsequent conveyance show better execution of the proposed approach over existing baselines. Future work incorporates further subjective investigations to remove parts of designs that oversee clients’ commitment with them. Once these have been distinguished, these components should be consolidated into the format age calculation.

IX. REFERENCES


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