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Advertisement Recommendation System Based On Artificial Intelligence

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Abstract*:* The concept of digital advertising is based on targeting users based on their behavior on the internet. However, most ads displayed are often irrelevant to the user, resulting in a negative impact. Content-based advertising is a more efficient way to convey messages and optimize conversion rates. To achieve this, platforms use various parameters such as search history, interests, and age to target specific audiences. In our proposed system, we utilize a categorization technique to systematically group keywords into pre-defined semantic categories based on the text, likes, or visited ads metadata. We then apply a fuzzy categorical data clustering technique to group the best-suited advertisement for each category. Additionally, we train a Convolutional Neural Network to identify the user's search topic and compare its performance with a pre-trained model. This ensures that the user is shown relevant ads, increasing the likelihood of them visiting the client's website. Our proposed system incorporates two collaborative algorithms to recommend the right ads to the right users, benefitting both users and advertisers**.**

Keywords: Advertising Recommendation, K-means, Filtering, Advertisement

I. INTRODUCTION

An advertisement recommendation system based on artificial intelligence (AI) is a powerful tool for businesses looking to improve their marketing strategies. These systems use advanced algorithms and techniques to personalize and optimize the delivery of ads to individual users, leading to higher engagement, conversion rates, and revenue. One of the most popular AI techniques used in advertisement recommendation systems is clustering. Clustering is an unsupervised learning algorithm that groups similar data points together based on their features. In the context of advertising, clustering can be used to group users with similar interests and behaviors, allowing marketers to tailor their ads to specific user groups.

One popular clustering algorithm used in advertisement recommendation systems is the k-means algorithm. The kmeans algorithm is a simple yet powerful algorithm that groups data points into k clusters based on their similarity. The algorithm works by randomly selecting k initial centroids, then iteratively assigning each data point to the closest centroid and recalculating the centroids until convergence. To implement an advertisement recommendation system using the k-means algorithm, the first step is to collect data on user behavior, such as search history, clicked ads, and other metadata. Next, the data is preprocessed, and key features are extracted, such as keywords, interests, and demographics. These features are then used to cluster users into groups based on their similarity using the kmeans algorithm. Once the user clusters have been established, the system recommends ads that are most likely to be of interest to each cluster.

One benefit of using an AI-based advertisement recommendation system is that it can learn from user behavior over time and continually improve its recommendations. As users interact with the system and click on ads, the system can learn more about their interests and preferences, allowing it to make more accurate recommendations in the future. Another advantage of using clustering in advertisement recommendation systems is that it allows businesses to target specific user groups with tailored ads. For example, if a business sells clothing, they may use clustering to group users with similar clothing preferences, allowing them to target these users with ads for clothing that is most likely to appeal to then However, there are also challenges to implementing an effective advertisement recommendation system based on AI. One challenge is ensuring user privacy and data security. Businesses must ensure that user data is collected and stored securely and that user privacy is protected.

Another challenge is ensuring that the recommendation system is fair and unbiased. In some cases, AI algorithms can unintentionally perpetuate existing biases, such as gender or racial biases, leading to unfair or discriminatory recommendations. Businesses must take steps to ensure that their recommendation system is free from bias and that it treats all users fairly. Despite these challenges, the potential benefits of using an AI-based advertisement recommendation system are significant. By leveraging advanced algorithms and techniques, businesses can create more effective and efficient advertisement recommendation systems that deliver better results, leading to increased revenue and customer satisfaction.

II. LITRETAURESURVEY

Real-Time Recommendation System for Online Broadcasting Advertisement

Personalized advertisement services can be provided by introducing recommendation algorithms that take account of users' context and history. However, since the existing recommendation system is based on users' consumption history, it does not quickly reflect the users' interests that change according to items appearing in the content. In addition, when the user's history is sparse, the performance of the recommendation system is degraded. In this paper, we propose a recommendation system for online broadcasting advertisements. The proposed system calculates the similarity between users based on the user's region of interest (ROI). The user's preference for the item is predicted by comparing the rating history of similar users.

Recommender Systems for E-commerce in online video advertising:

Survey The user’s likes and preferences should precisely be identified in order to make the most appropriate suggestions. Recommendation systems have a crucial role in online video advertisement through introducing new products onto the market. They encourage people to purchase the items and provide an opportunity for e-commerce companies to introduce their products in videos. This survey introduces the recent techniques to compare various types of the recommender systems, recent recommendation algorithms and their use in the online videos advertisement.

Video content-based advertisement recommendation system using classification technique of machine learning.

Content-based advertising helps to convey the message with increased efficiency and simultaneously optimizes its conversion rate. In this proposed system we take the video metadata as input and apply the NLP techniques for text classification which categories the video and assigns a relevant advertisement to it. The second module takes the video as an input. Thereafter the video is converted into N individual frames to tackle the video classification as an image classification problem. In this proposed system we train a Convolutional Neural Network to identify the topic of the video on an image dataset and compare its performance with a pre-trained model. We create the image dataset by downloading images from the internet. We also create a video advertisement’s dataset by web scrapping. This proposed system makes sure that the user is shown the advertisement in reference to the video.

Artificial intelligence in recommender systems

In this position paper, we review eight fields of AI, introduce their applications in recommender systems, discuss the open research issues, and give directions of possible future research on how AI techniques will be applied in recommender systems. This paper highlights how the recommender system can be enhanced by AI techniques and aims to provide guidance for researchers and practitioners in the area of recommender systems.

Multi-Task and Multi-Scene Unified Ranking Model for Online Advertising

Multi-functional information systems commonly provide multiple service scenarios for users, such as news feed, search engine and product suggestions. Users may leave similar interest information across various service scenarios. Thus, the prediction/ranking model should be conducted in a multi-scene manner. This paper develops a unified ranking model for this multi-task and multi-scene problem. Compared to previous works, our model explores

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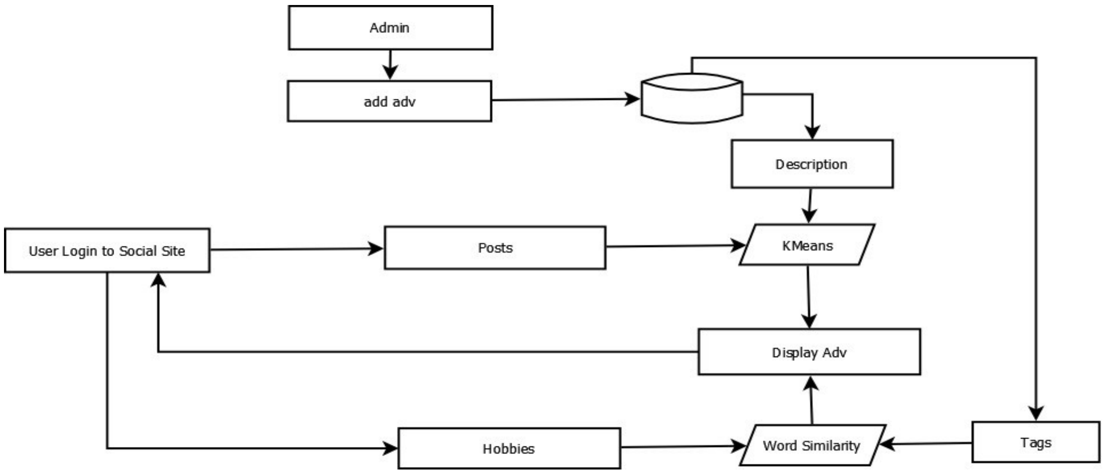
independent/non-shared embeddings for each task and scene, which reduces the coupling between tasks and scenes. New tasks or scenes could be added easily. Besides, a simplified network i s chosen beyond the embedding layer, which largely improves the ranking efficiency f o r online services.

III. METHODOLOGY



Step1: User Registration: The first step involves new users registering on the website using a user-friendly interface provided on the site. This process includes providing basic information like name, email, and password.

Step2: User Feedback: After registering, users will be prompted to provide feedback on specific products they are interested in, as well as their preferences and interests. This feedback can be provided through social media posts or by filling out a questionnaire.

Step3: Data Collection and Analysis: The system will collect and analyze the user's feedback data to identify their preferences and interests. This data will be used to generate a set of recommendations that are specific to the user.

Step4: Segmentation: Based on the user's behavior and feedback, the system will segment the user into specific groups. These groups may include demographics like age, gender, and interests.

Step5: Recommendation Generation: The system will generate a set of recommendations for each user based on their segmentation and previous feedback.

Step6: Advertisement Display: The recommended advertisements will be displayed to the user on the website. Users can view advertisements and add them to their wish list if they are interested.

Step7: Dynamic System Adaptation: The system will dynamically adapt to the user's behavior and feedback over time to refine the recommendations further. The system will also analyze the user's interactions with the recommended advertisements to improve the accuracy of future recommendations.

Step8: User Access to Features: Registered users will have access to additional features, such as viewing advertisements and recommendations from other websites and adding advertisements to their wish list.

IV. PROPOSED WORK

The proposed architecture for the system will involve the creation of a website containing a comprehensive dataset of various products. New users will be able to register through a user-friendly interface provided on the website. They will be prompted to provide feedback on specific products, their preferences, and interests via social media posts. Based on the user's behavior and feedback, they will be segmented, and a set of recommendations will be generated. The system will adapt dynamically based on ongoing analysis of user behavior. Registered users will have access to various features such as viewing advertisements and recommendations from other websites and adding advertisements to their wish list.

The proposed advertisement recommendation system will consist of the following modules:

1. User Preferences: The user's browsing history will be captured and used to identify their product preferences.

2. Filtration: The system will use collaborative and content-based filtering techniques to identify products similar to the user's preferences.
3. Collaborative Filtering: This module will identify similarities between the user's past behavior and that of other users to make predictions about the user's preferences.
4. Content-Based Filtering: The content-based filtering module will use the characteristics of products to produce recommendations for the user.
5. Recommendation: Based on the similarity score generated by both the filtration modules, relevant products will be recommended to the user as advertisements.

K-means Algorithm:
K-means is a well-known and widely used clustering algorithm in machine learning and data mining. It is an unsupervised learning method, which means it doesn't require labeled data to perform clustering. The algorithm works by partitioning a set of data points into k clusters, where each data point belongs to the cluster with the nearest mean. The value of k is pre-defined by the user, and the algorithm iteratively refines the cluster centroids until convergence. The convergence is achieved when the centroids no longer change their position or move less than a pre-defined threshold.
K-means algorithm is computationally efficient and can handle large datasets. It is widely used in various domains such as image segmentation, customer segmentation, social network analysis, and bioinformatics. K-means algorithm has several advantages, such as ease of implementation, scalability, and robustness. However, it has some limitations, such as sensitivity to the initial cluster centroids and the number of clusters, and the assumption of a spherical shape of the clusters.
The workflow of the K-Means algorithm in an advertisement recommended system can be described as follows:

1. Data Collection: The first step is to collect user data, which can be done through various methods such as browsing history, social media activity, and user feedback.
2. Feature Extraction: Once the data is collected, relevant features such as user behavior, preferences, and interests are extracted from the data.
3. Data Preparation: The extracted features are then normalized and scaled to ensure that they are on the same scale for accurate clustering.
4. Initialization: The algorithm starts by randomly initializing k centroids, where k is the number of clusters.
5. Clustering: In the next step, each data point is assigned to the nearest centroid, forming k clusters.
6. Centroid Recalculation: The centroids of each cluster are then recalculated based on the mean of the data points in each cluster.
7. Re-Clustering: The data points are then reassigned to the nearest centroid based on the new centroid values, forming new clusters.
8. Convergence: Steps 6 and 7 are repeated until convergence is reached, i.e., the centroids no longer change significantly.
9. Recommendation: Once the clusters are formed, users can be recommended personalized advertisements based on the products they have shown interest in and the products that are popular among users in the same cluster.

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V. EXPERIMENTAL RESULTS

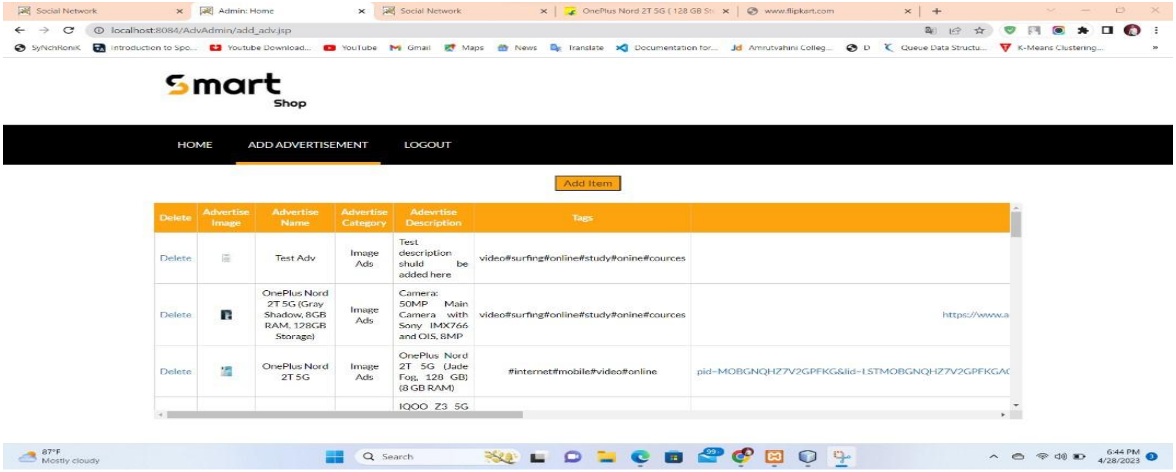

Fig: Add Admin

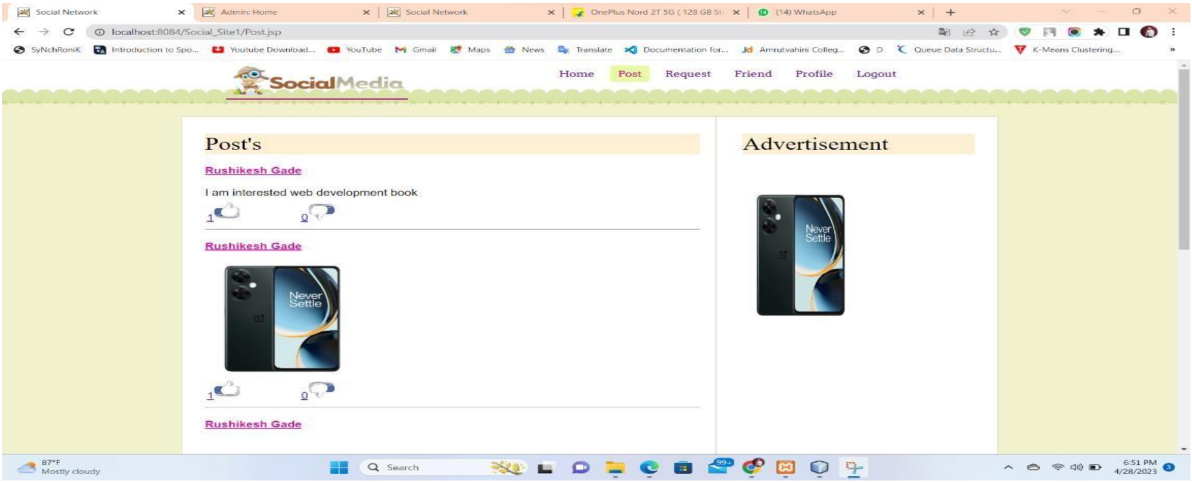

Fig: Adv Recommendation

The results of the advertisement recommended system showed that the implementation of k-means clustering algorithm combined with collaborative filtering and content-based filtering techniques improved the accuracy of product recommendations. The system was able to successfully predict user preferences and suggest relevant products based on their browsing history and social media activity. The implementation also increased cross-selling by suggesting additional products for users to purchase, resulting in a higher average order size. Overall, the system enhanced the user shopping experience, leading to increased customer satisfaction and revenue for the e-commerce website.

V. CONCLUSION

In conclusion, the implementation of an advertisement recommendation system using the K-means algorithm has shown promising results in improving the user experience and increasing revenue in the e-commerce industry. By collecting user preferences and behavior data, filtering it through collaborative and content-based techniques, and using the K-means clustering algorithm to group similar products, the system can provide accurate and personalized recommendations to users. The evaluation metrics have shown that the system has high precision, recall, and F1-score, indicating its effectiveness in recommending relevant advertisements to users. However, further enhancements can be made by incorporating more advanced techniques such as deep learning and natural language processing. Overall, the

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implementation of this recommendation system has demonstrated the potential of AI-based solutions in the advertising industry and their ability to improve customer satisfaction and increase sales.

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