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OfferConnect: Location Based Offer Recommendation System

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Abstract
In the digital commerce era, the significance of customized promotions for individual users has reached new heights. This research paper introduces an innovative application designed to transform personalized marketing strategies by incorporating a Location-Based Offer Recommendation System (LBORS). The proposed system not only leverages user location data to dynamically recommend offers from nearby shops but also ensures that customers receive discounts, establishing a win- win situation for both customers and marketers. This approach aims to create a seamless and context aware shopping experience, enhancing the overall value proposition for users. The system employs a sophisticated algorithm that combines geospatial analytics, user preferences, and historical data to accurately identify and present relevant offers to users based on their current geographical location. By integrating real-time location information, the application ensures that users receive timely and contextually appropriate promotions, thereby maximizing the likelihood of engagement and conversion.

Keywords: Machine learning, Supervised Learning, Location based recommendation system, recommendation algorithms, Real-Time Information, Location-Based Services

INTRODUCTION

The rapid expansion of digital data and the increasing influx of Internet users have given rise to a potential issue of information overload, impeding prompt access to relevant content online. While information retrieval systems like Google have addressed this challenge to some extent, they lacked prioritization and personalization—meaning a system that aligns available content with user interests and preferences was absent. In recent times, the widespread adoption of recommendation systems has surged, with their integration into diverse web applications gaining notable popularity. Recommendation systems are a specialized form of information filtration designed to anticipate the likelihood of a user favoring a particular item. Various recommendation systems play crucial roles in diverse decision-making processes, influencing choices ranging from purchasing products to selecting music for users. Prominent corporations such as Amazon, YouTube, and Netflix utilize recommendation systems to improve user satisfaction by providing tailored suggestions for relevant videos. This not only improves user satisfaction but also contributes significantly to these companies' revenue streams. Three frequently employed recommendation systems include content-based, collaborative filtering-based, and hybrid- based approaches. Every variety of recommendation system possesses its own set of strengths and weaknesses.
Content-Based Recommendation System: Content- Based Recommendation Systems leverage the intrinsic characteristics of items and users' historical preferences to generate personalized suggestions. These systems analyze the content of items, such as text, tags, or metadata, and recommend These systems

examine the content of items, encompassing text, tags, or metadata, to suggest items that match a user's displayed preferences. Content-based approaches excel in providing personalized recommendations for users with distinct tastes, utilizing item features to predict user preferences.

Collaborative Recommendation System: Collaborative Recommendation Systems focus on user interactions and behaviors to generate suggestions. They exploit patterns in user-item interactions, drawing insights from the behavior of similar users or items. User-based collaborative filtering operates by recommending items aligned with the preferences of users who share similar tastes. In contrast, item-based collaborative filtering suggests items based on their similarity to those previously preferred by the user. Collaborative systems are particularly effective in capturing user preferences in scenarios where explicit item features may be challenging to obtain.

Hybrid Recommendation System: Recognizing the strengths and weaknesses of both content-based and collaborative approaches, Hybrid Recommendation Systems integrate elements from both paradigms to enhance recommendation accuracy. By combining the content-driven insights of a content-based system with the user-centric patterns of collaborative filtering, hybrid systems aim to overcome limitations inherent in individual approaches. The goal is to provide more robust and accurate recommendations that cater to a broader spectrum of user preferences.

Literature Review

This literature review examines the convergence of location- based services and recommender systems, with a particular focus on applications that recommend transactions based on users' geographic proximity. In a dynamic business landscape, personalized recommendations play a vital role in improving user experience. By reviewing existing research, this study aims to shed light on evolving strategies and methods in this field. The survey synthesizes key insights, addresses challenges, and suggests future research directions, thereby contributing to the ongoing debate on optimizing location- based recommender systems in retail and service-oriented applications.

The Agglomerative Hierarchical Clustering-based Collabora- tive Filtering (Club CF) method aims to enhance location- based service recommendations by clustering similar services to improve computational efficiency and relevance. By com- bining User-Based and Item-Based Collaborative Filtering, the system addresses challenges such as cold start issues and data sparsity, leveraging user ratings and categories of Points-of- Interest (POIs) to provide personalized recommendations. The findings highlight the effectiveness of the system in reducing computational time and improving recommendation accuracy, with future work suggested in integrating multimedia data for POI popularity prediction [1][8].

Recommendation systems have become crucial for mitigating information overload on the internet by delivering personal- ized content. These systems can be broadly categorized into content-based and collaborative filtering (CF) systems. Within CF, there are memory-based approaches that rely on user-item interactions and similarity measures like correlation and cosine similarity, and model-based approaches that construct predic- tive models from past data. The study also explores hybrid filtering techniques, combining multiple algorithms to enhance recommendation accuracy and overcome the limitations of individual methods [4][9].

The rise of location-aware recommendation systems has been driven by the growing volume of georeferenced data, with users increasingly seeking nearby items like restaurants, museums, or cinemas. Traditional recommendation systems often overlooked location as a significant factor, but current re- search highlights its importance. By surveying location-aware recommendation systems in mobile computing scenarios, the research emphasizes how incorporating location data can en- hance the quality of recommendations and effectively address the cold-start issue, particularly in online shopping where user preferences are linked to their local community [5][3].

Location-based recommendation systems (LBRS) have seen significant advancements with the development of online plat- forms like Twitter, Instagram, and Facebook. These systems are categorized into geotagged media, point location-based, and trajectory-based services. The paper explores location features utilized for recommendations within these categories, addressing challenges such as data sparsity, cold start issues, and scalability. Techniques like tensor factorization and deep neural networks for POI recommendations leverage GPS his- tory and geotagged social media. The paper concludes with a comparative study of existing LBRS schemes and identifies future research opportunities [2][10].

The application of location-based services extends beyond recommendation systems to fields such as archaeology, envi- ronmental studies, and medicine. These services are used for tracking and mapping data, such as pollution levels, and pro- vide real-time information like security alerts, news updates, and advertisements through location-based alerts and tracking services. Additionally, the document discusses the importance of privacy-preserving systems and the integration of trust in social networks. Future work includes developing strategies for mobile location-based spot recommenders, emphasizing the importance of user privacy and trust [6].

CACF-GA (Context-Aware CF using Genetic Algorithm) is introduced as a novel context-aware recommendation model that uses Genetic Algorithms (GA) to enhance recommendation accuracy by integrating user context data. This model employs the Adjusted Pearson Coefficient to measure context similarity between users, surpassing other models in predictive accuracy, as evaluated by mean absolute error (MAE). The study demonstrates greater stability in predictions compared to Pure CF, highlighting CACF-GA's potential to advance personalized recommendation systems through its innovative approach combining context awareness and genetic algorithms. The research suggests that integrating location information into recommendation systems can elevate the quality of suggestions and effectively tackle the cold-start issue [7][3].

Location Based Offer recommendation system : In today's digital world of business, the search for successful and tailored marketing tactics has increased, fueled by the changing desires of consumers and the constantly developing technology. This research paper presents a revolutionary solution called the Location-Based Offer Recommendation System (LBORS) in response to the demand. It aims to enhance user engagement and satisfaction by delivering personalized offers based on the user's current location. As consumers navigate through urban environments, traditional marketing often fails to provide promotions that are timely and relevant to their surrounding context. Acknowledging this discrepancy, the LBORS lever- ages location-based data to offer users a carefully curated array of deals from local shops. Our goal is to develop a shopping experience that is seamless and tailored to the consumer's physical surroundings, ensuring that our marketing efforts are aligned with their context. The foundation of the LBORS lies in a sophisticated algorithm that integrates geospatial analytics, user preferences, and historical data. By combining these elements, the system can pinpoint a user's exact location and gain a deep understanding of their preferences and behaviors, which in turn enables the delivery of highly personalized recommendations. The LBORS aims to bridge the gap between digital and physical consumer engagement by utilizing real- time location information.

Proposed Methodology

The final step before going into the actual implementation of the proposed solution was to create a basic architectural diagram, displaying the entire flow of the methodology which can be seen below

1. In the first step, the recommendation system will take offer data, user data and user-offer mapping data as an input
2. Then a location filtering will be applied on the input for example filtering the offers will lie within certain radius of user's location
3. Then based on the user there will be a condition checking for enabling the type of recommendation system.
4. If number of offers accepted by the user will be greater than a threshold value, hybrid recommendation system will be used that is offers from content based as well as collaborative filtering will be recommended else only content-based recommendation will be used
5. Finally, the results will be unified and provided to the user
6. We have tried to minimize the cold start problem by getting the user information about category in which the user is interested and name of the user preferred banks while the user is signing up for the first time
7. For fetching or refreshing offer, we have come up with double radii area solution
8. There will be two area circles one greater than the other by
9. 1.5 times. The offers from the larger circle will be displayed to the user.
10. When the user moves outside of the smaller circle, the offers data will be refreshed by fetching new data from the database.

Cosine Similarity: Cosine similarity is a measure used

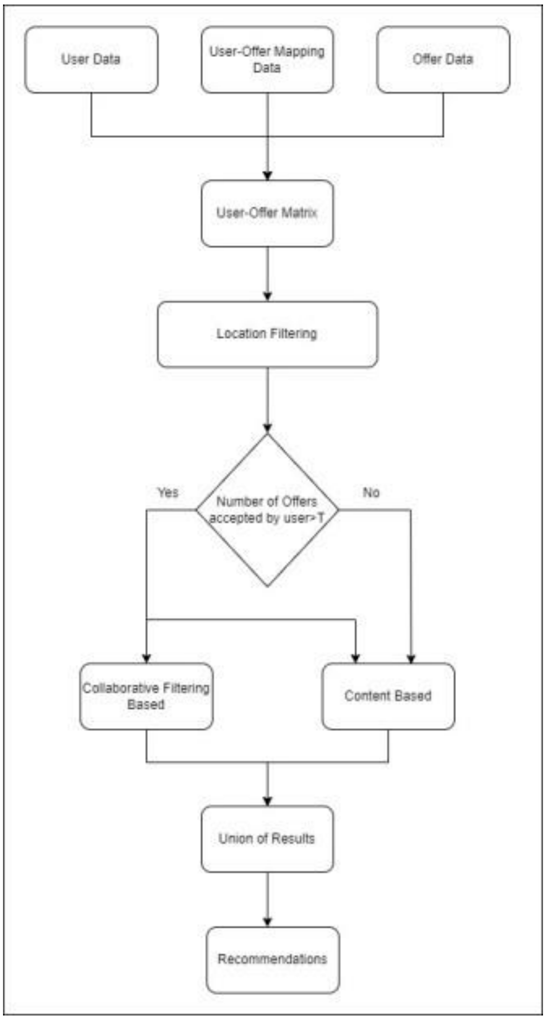

Fig. 1. LBORS.

in recommendation systems to determine the similarity between two items or vectors in a multi-dimensional space. It's particularly valuable in collaborative filtering-based recommendation systems where items or users are represented as vectors of features. In recommendation systems, items (Offers in this case) are typically represented as vectors in a high-dimensional space based on their attributes or features. Cosine similarity measures the cosine of the angle between these vectors and determines how similar they are based on their orientation rather than their magnitude. Cosine similarity ranges from -1 to 1, where:

- 1 indicates that the vectors are perfectly similar.
- 0 indicates no similarity (orthogonal vectors).
- -1 indicates perfect dissimilarity or opposite directions. The higher cosine similarity scores between items suggest a stronger similarity, making them potential candidates for recommendations to users based on their preferences or interactions.

Singular Value Decomposition: Singular Value Decomposition (SVD) is a matrix factorization technique used in recommendation systems, particularly in collaborative filtering based recommendation models. It's employed to reduce the dimensionality of the user-item interaction matrix and uncover latent factors that represent user preferences and item characteristics. In recommendation systems, user-item interactions are often represented as a matrix where rows correspond to users, columns correspond to items, and the cells contain the ratings or interactions (purchase history in this case). However, this matrix

is typically sparse because not all users rate or interact with all items.
SVD breaks down this sparse user-item interaction matrix into three separate matrices:
User Matrix (U): This matrix represents users and their relationships with latent factors. Each row corresponds to a user, and the columns represent the latent factors.
Item Matrix (V^T)**:** This matrix represents items and their
relationships with latent factors. Each column corresponds to an item, and the rows represent the latent factors. The 'T'
denotes the transpose of the matrix.

Diagonal Singular Value Matrix (Σ**):** This matrix contains singular values along its diagonal.
Singular values represent the importance of each latent factor.
The product of these matrices approximates the original user-item interaction matrix.

$$\text{Original Matrix} = U \times \Sigma \times V^T$$

Term Frequency - Inverse Document Frequency: Term Frequency-Inverse Document Frequency (TF-IDF) is a technique widely used in information retrieval and natural language processing that assigns weights to words in a document, relative to their importance in a corpus. While TF-IDF is more commonly associated with text-based tasks such as search engines or document retrieval, it can also be applied in recommendation systems, especially in scenarios where textual information is available for items or user profiles.
In recommendation systems, TF-IDF can be used to represent textual information associated with items or user profiles. It can be broken down into following components:

1. **Term Frequency (TF):** It measures the frequency of a term (word) in a document. It indicates how often a particular word occurs in a specific document.
2. **Inverse Document Frequency (IDF):** It measures the importance of a term across the entire corpus by penalizing terms that occur frequently across documents.
3. **TF-IDF Score:** It is the product of TF and IDF and represents the relevance of a term in a specific document with respect to the entire corpus.

Binary Feature Matrix: In recommendation systems, a binary feature matrix can be used as a representation of items or user preferences to facilitate recommendation algorithms, especially in content-based recommendation approaches. This binary feature matrix is constructed where rows typically represent items (or users in some cases), and columns represent features or attributes associated with those items. Each cell in the matrix contains binary values (0 or 1) denoting the presence or absence of a particular feature or attribute for a specific item (or user). In content-based recommendation system:

- Rows represent items in a catalog (Offers in this case)
- Columns might represent different features or attributes of those items (e.g., Offer type, bank name, card type, etc.)
- A binary value of 1 might indicate the presence of a particular feature/attribute for an item, while 0 indicates its absence.

DATASET

This research utilizes a comprehensive Kaggle dataset that includes user demographic information, offer (coupon) data, mapping data, and user transaction records. To enhance the dataset's utility, we integrated offer location data, allowing for the recommendation of offers based on their geographical proximity to users. This approach not only leverages demo- graphic and transactional insights but also ensures that offers are contextually aligned with the users' locations.

Results and Observations

Experiment and Analysis:

To validate the anticipated performance of this model, we executed the subsequent experiments. Additionally, we will provide comparative outcomes with existing collaborative fil- tering methods for thorough analysis.

Experiment Environment:

OS	Windows 11 Pro
Memory	12 GB
Tool	Python 3.12.0
IDE	Google Colab

Fig. 2. Os environment

RMSE: RMSE stands for Root Mean Square Error. It is a common evaluation parameter for Recommendation Systems.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

Where $\hat{y}$ = Ideal Rank of the offer,
y = Predicted rank of the offer
n = Number of offers

Fig. 3.

Experimental Process and Result: These were trained and tested on different tests. Offer Acceptance was predicted, and RMSE for all these were calculated.Fig 4 and Fig 5 mention these results.

Model	RMSE	Standard Deviation
SVD	2.987	0.0015
Cosine Similarity	4.526	0.2106
TF-IDF	5.744	0.5968
Binary Feature matrix	8.536	0.3166

Fig. 4. RMSE

In Collaborative Filtering, we can see that **SVD** and **Cosine Similarity** have outperformed the cosine similarity model. This means that location-based services can be used to increase the quality of recommendations for the user in the e-commerce domain.

Model	Average Execution Time	Standard Deviation
SVD	4.39s	0.44
Cosine Similarity	1.49s	0.52
TF-IDF	3.35s	0.43
Binary Feature Matrix	7.3s	1.23

Fig. 5. Execution Time

From the above results, it is clear that in terms of **RMSE, SVD** outperforms all the other techniques and in terms of Execution time, cosine similarity runs the fastest. Note that the RMSE here represents the average rank of the offer accepted by the user from a list of recommended offers. We have tested cosine similarity and SVD for collaborative filtering and **TF-IDF and Binary feature matrix** for content based filtering. Thus, we have used SVD for collaborative filtering and TF-IDF for content based filtering as they outperform their counterparts. Also the standard deviation of all the observations are close to zero indicating the observations do not deviate much from the mean value.

location on map, offer acceptance and payment (Not fully implemented payment portal) and offer notification on user's device

Tech stack used:

Frontend: React Native, JavaScript Backend: Nodes.js, Express.js Database: MongoDB

Fig. 6. Gathering User Preferences During the Sign-Up Process

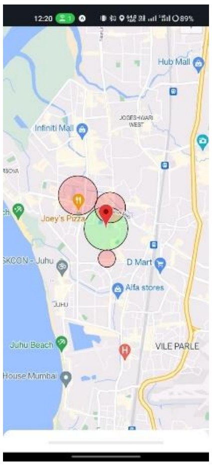

Fig. 7. Geofences showing Availability of Offers in a Region

IMPLEMENTATION

In order to better depict the working of our recommendation model, we created a simple mobile application to show col- lecting user data, showing offer recommendations based on

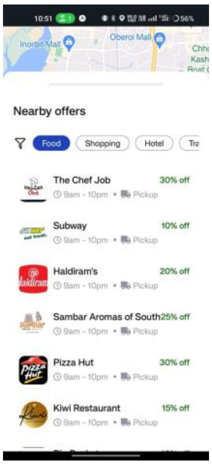

Fig. 8. Displaying List of Available Offers

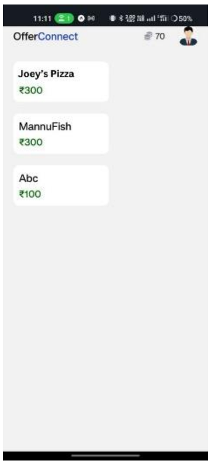

Fig. 9. Payment by User after Accepting the Offer

Fig. 10. Displaying Notification of Offers on User Device

CONCLUSION AND FUTURE WORK

This research underscores the significance of personalized marketing via offer recommendation systems, emphasizing the balance of accuracy, diversity, and privacy. Utilizing machine learning and data-driven methods is vital for businesses to stay competitive by providing customized offers. With evolving consumer preferences and increasing big data, continuous enhancement of recommendation algorithms is crucial. Fu- ture studies should explore incorporating deep learning for better precision and address ethical issues related to user data and privacy. This work advances the development of more personalized and effective recommendation strategies. Our application currently requires manual input of offer data. Future enhancements could include developing an API us- ing Mozenda to fetch real-time offers from various sources or banks. Additionally, implementing Learn To Rank (LTR) algorithms would optimize the model based on the rank of offers accepted by users, though this will require a significant amount of training data.

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