

An AI Based Event Recommendation & Management System

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ABSTRACT

The study introduces a semantic-enhanced and context-aware hybrid collaborative filtering approach for event recommendation in event-based social networks (EBSN). This method combines semantic content analysis with contextual event influence to optimize user neighborhood selection. The algorithm uses latent topic modeling to analyze event description text, assigning influence weights to each event based on its social impact and semantic uniqueness. It then predicts event ratings for each user based on their neighbors' ratings. The study also introduces "Evento," an online platform that serves as both an event management system and a marketplace. It streamlines administrative tasks such as user registration, ticket sales, event group creation, email notifications, report generation, venue booking, and payment processing. The system prioritizes user security and data protection, making organizing and managing events efficient, seamless, and secure for all involved.

Keywords: Knowledge management, events organization, documented libraries, educational institution.

INTRODUCTION

Event management applications serve as centralized platforms aiding individuals and organizations in planning and executing various events, encompassing conferences, weddings, trade shows, and more. These platforms streamline tasks such as event registration, ticketing, promotion, networking, scheduling, and analytics, which were traditionally handled manually or through disparate services. The advent of such applications addresses several critical needs in event management:

Convenience: Event management applications eliminate the need for juggling multiple tools, thus saving time and reducing confusion.

Efficiency: These platforms enhance coordination between various event activities, ultimately saving time and improving overall efficiency. Cost Savings By automating tasks like registration and ticketing, event management applications help reduce administrative and staffing costs, as well as eliminate the need for purchasing multiple tools. Better Attendee Engagement:

Data Analytics: Event management applications track and analyze data related to attendance, engagement, and feedback, enabling data-driven decision-making to improve future events.

To address these needs comprehensively, we propose "Evento," a marketplace and event management platform. Evento not only simplifies event planning but also offers venues for rent and facilitates the provision and sale of event management services. Additionally, the platform handles all necessary payments, including those for food vendors and service providers, through the app, ensuring seamless transactions and maintaining detailed payment records..

Furthermore, Evento streamlines communication by providing dedicated event groups where administrators can disseminate information and attendees can resolve queries through a Q&A section. Moreover, the platform utilizes multiple channels, including

LITERATURE SURVEY

2.1 Event Based Social Networks

Newly emerged event-based online social services, such as Meetup and Plancast, have experienced increased popularity rapid growth. From these services, we observed a new type of social network {event-based social network (EBSN)}. An EBSN does not only contain online social interactions as in other conventional online social networks, but also includes valuable online social interactions captured in online activities.

2.2 Recommendation based on Content

Recommender systems have the effect of guiding users in a personalized way to interesting objects in a large space of possible options. Content-based recommendation systems try to recommend items similar to those a given user has liked in the past. Indeed, the basic process performed by a content based recommender consists in matching up the attributes of a user profile in which preferences and interests are stored, with the attributes of a content object (item), in order to provide the user with new interesting items.

2.3 Combining Heterogenous Social and Geographical Information for Event Recommendation

With the rapid growth of event-based social networks (EBSNs) like Meetup, the demand for event recommendation becomes increasingly urgent. In EBSNs, event recommendation plays a central role in recommending the most relevant events to users who are likely to participate in. Different from traditional recommendation problems, event recommendation encounters three new types of information, i.e., heterogenous online + offline social relationships, geographical features of events and implicit rating data from users. Yet combining the three types of data for offline event recommendation has not been considered

2.4 Context-Aware Event Recommendation

The Web has grown into one of the most important channels to communicate social events nowadays. However, the sheer volume of events available in event based social networks (EBSNs) often undermines the users' ability to choose the events that matches their interests. Recommender systems appear as a natural solution for this problem, but different from classic recommendation scenarios (e.g. movies, books), the event recommendation problem is intrinsically cold start. Indeed, events published in EBSNs are typically short-lived and, by definition, are always in the future, having little or no trace of historical attendance. To overcome this limitation, we propose to exploit several contextual signals available from EBSNs.

2.5 Deep learning driven venue recommendation

Deep learning based venue recommendation system DeepVenue which provides context driven venue recommendations for the Meetup event-hosts to host their events. The crux of the proposed model relies on the notion of similarity between multiple Meetup entities such as events, venues, groups etc. We develop deep learning techniques to compute a compact descriptor for each entity, such that two entities (say, venues) can be compared numerically. Notably, to mitigate the scarcity of venue related information in Meetup, we leverage on the cross domain knowledge transfer from popular LBSN service Yelp to extract rich venue related content. For hosting an event, the proposed DeepVenue model computes a success score for each candidate venue and ranks those venues according to the scores and finally recommend the top k venues. However, the sheer volume of events available in event based social networks (EBSNs) often undermines the users' ability to choose the events that matches their interests. Recommender systems appear as a natural solution for this problem, but different from classic recommendation scenarios (e.g. movies, books), the

FINDINGS

A. Motivation

An event recommendation system project can enhance user experience by providing personalized recommendations based on preferences, location, and past behavior. It can also help users discover new events, simplify decision-making, and foster community by suggesting activities aligning with their interests. This system can also increase visibility and attendance for event organizers and provide valuable data insights for future improvements.

B. Technologies used

- 3.3.1 Operating System: Windows 11
- 3.3.2 IDE: Eclipse
- 3.3.3 Programming Language: Java, Python

C. System Architecture

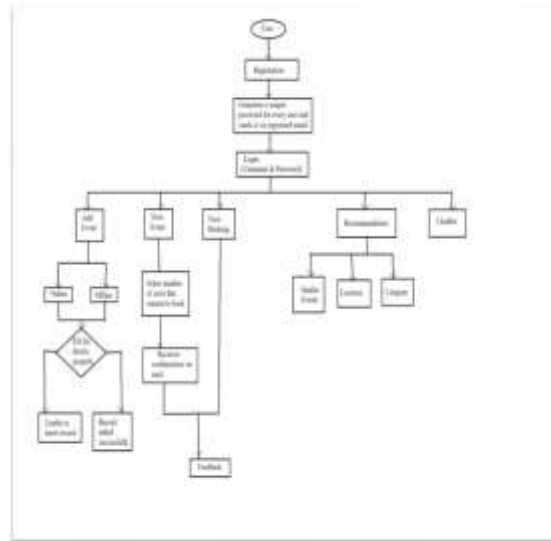


Figure 1. Architectural diagram

METHODOLOGY

The downside of content filtering is that it needs the side information for each item. For example, genres such as romance and action are the side information of movies. It is very expensive to have someone watch movies and add side information for every movie out there and every movie in the future.

The recommendation Techniques available are :

1. Collaborative filtering recommender systems:

Collaborative filtering (CF) is a popular recommendation algorithm that bases its predictions and recommendations on the ratings or behaviours of other users in the system. The fundamental assumption behind this method is that other users’ opinions can be selected and aggregated in such a way as to provide a reasonable prediction of the active user’s preference. Collaborative filtering (CF) based recommender systems must interact with the user, both to learn the user’s preferences and provide recommendations; these concerns pose challenges for user interface and interaction design. Systems must have accurate data from which to compute their recommendations and preferences, leading to work on how to collect reliable data and reduce the noise in user preference data sets. Based on purchase history, browsing history, and the item a user is currently viewing, Amazon recommends items for the user to consider purchasing. Various companies are finding this as a significant motivation to be able to increase sales volume — customers may purchase an item if it is suggested to them but might not seek it out otherwise

2.Content-based filtering (CBF) based recommender systems is another class of systems which uses content-based approaches based on information retrieval,Bayesian inference, and case-based reasoning methods. These methods consider the actual content or attributes of the items to be recommended instead of or in addition to user rating patterns. CBF systems perform recommendations, such as finding items similar to the items liked by a user using textual similarity in metadata. Basically,

3. Hybrid recommender systems are nowadays more standard. They use collaborative Aswell as content-based recommendations and have emerged frontrunner as various recommender strategies have matured, combining multiple algorithms into composite systems that ideally build on the stren0gths of their component algorithms. Collaborative filtering, however, has remained an effective approach, both alone and hybridized with content-based approaches

MODULE

1. Admin Portal: Admin view, add event, delete event, update event, maintain database.

2. User Portal: In this module customer can register to application, login, search event, select places. Register and login is an optional, user can view events without registering to application also. Book event

DATA FLOW

In the Data Flow Diagram (DFD), we illustrate the flow of data within our system. DFD0 depicts the foundational diagram, where rectangles represent inputs and outputs, while circles denote the system components. DFD1 showcases the specific inputs and outputs of the system; inputs can be text or images, while the output is the detection of rumors. Similarly, DFD2 delineates the operations carried out by both users and administrators within the system.

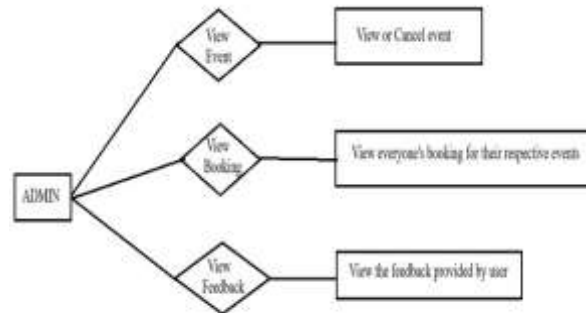


Figure 2. Flow(a)

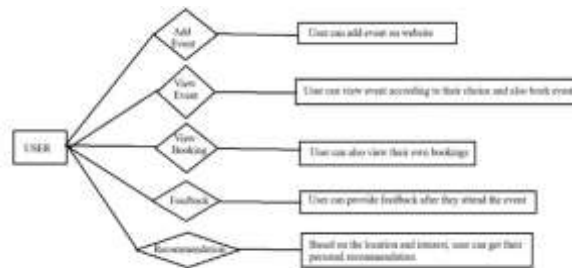


Figure 3. Flow(b)

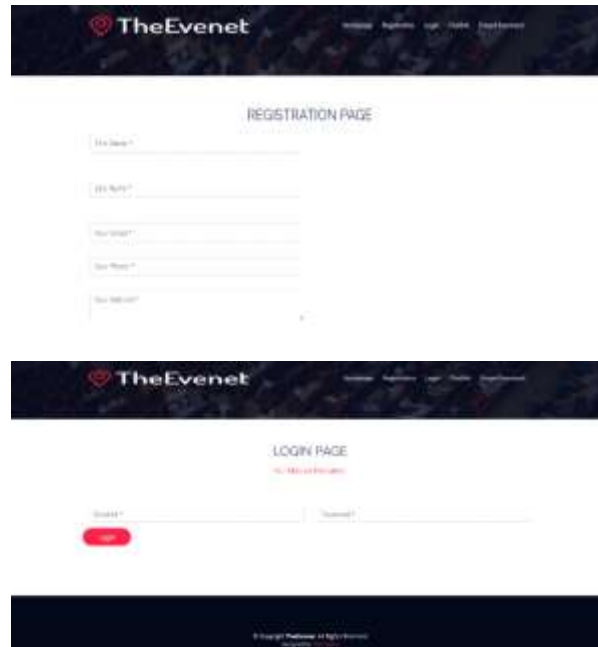
RESULT

As the application is just a prototype of an real time application, which can be in future implemented with more robust user interface and structure.

Some of the major steps or the measures that the user has to follow to use this application are mentioned below-

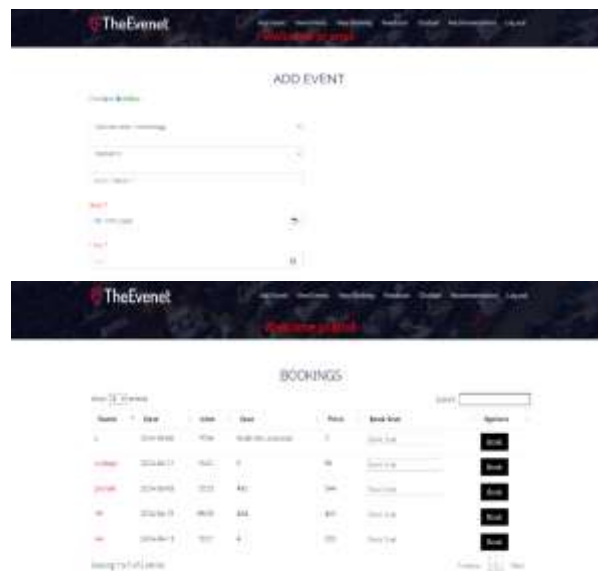
Step 1:-

Whenever user will open the application for very first time, he or she has to register himself first to use the application, after registration passcode will be generated for further login.



Step 2:-

The user can add events, view listed events and book them.



Step 3:-

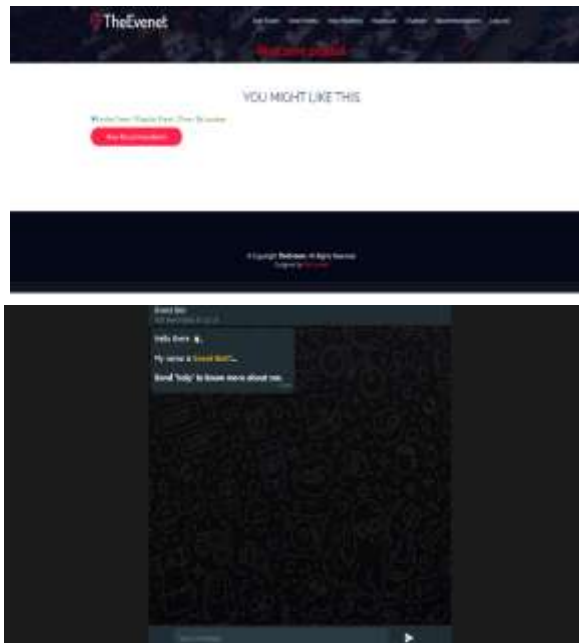
The user gets the recommendation of the events based on three factors:



Step 5:



Admin can access the events by updating and cancelling.



Step 4:-For any queries chatbot is accessible where user can ask the doubt

CONCLUSION

The primary contribution of this system lies in its model, which considers user preferences and their current locations to recommend venues or events of interest. The success of an event in a particular venue is contingent upon two factors: the occurrence of similar events in the venue recently and the venue's similarity to other venues where similar events have taken place. Our model employs collaborative filtering, which factors in a user's interests based on their past event history, as well as content-based filtering, where datasets of suitable yet under-promoted venues are collected. Collaborative filtering relies on user preferences and tendencies, while content-based filtering employs algorithms to recommend events. Furthermore, this system can be extended to recommend movies and applied in various domains involving multiple factors akin to our approach (e.g., venue, event, user, group), making it suitable for addressing multiple-entity recommendation problems. To refine venue recommendations, factors beyond location, such as hobbies and professional details, could be considered to enhance precision. The scHCF scheme proposed in this paper integrates social relationships with content information, while also constructing distinct user interest models for various tasks and considering temporal impact and context-aware event influence. Experiments conducted on Douban Event, a real EBSN, have demonstrated its superiority over comparable schemes in terms of recommendation performance. Nevertheless, certain challenges remain. Notably, parameter training was not automated in our experiments, leading to a considerable time investment in finding suitable parameter values. Additionally, the process of selecting neighbourhood users for a target user involves traversing all users, resulting in significant time consumption with a large user base. Hence, future efforts will explore approaches for automating parameter training and employing Matrix Factorization (MF) to streamline the recommendation system and enhance its performance.

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