

e-ISSN: 2319-8753 | p-ISSN: 2320-6710

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International Journal of Innovative Research in SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

800

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 10, Issue 3, March 2021

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.512

9940 572 462

6381 907 438

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| e-ISSN: 2319-8753, p-ISSN: 2320-6710| <u>www.ijirset.com</u> | Impact Factor: 7.512|

|| Volume 10, Issue 3, March 2021 ||

DOI:10.15680/IJIRSET.2021.1003184

A Venue Recommender System for Events Based on User Preference

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ABSTRACT: Event-based online social platforms, such as Meetup and Plancast, have experienced increased popularity and rapid growth in recent years. In EBSN(Event Based Social Network) setup, selecting suitable venues for hosting events, which can attract a great turnout, is a key challenge. In this project, we present a deep learning based venue recommendation system Deep Venue which provides context driven venue recommendations for the Meetup event-hosts to host their events. The crux of the proposed 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(Location Based Social Network) service Yelp to extract rich venue related content. For hosting an event, the proposed Deep Venue model computes a success score for each candidate venue and ranks those venues according to the scores and finally recommend the top k venues. Our rigorous evaluation on the Meetup data collected for city Chicago shows that Deep Venue significantly outperforms the baselines algorithms. Precisely, for 84% of events, the correct hosting venue appears in the top 5 of Deep Venue recommended list.

KEYWORDS: Group recommendation, Probabilistic generative model, Event recommendation, Event-based social networks

I. INTRODUCTION

Deep learning enjoys a massive hype at the moment. The past few decades have witnessed the tremendous success of the deep learning (DL) in many application domains such as computer vision and speech recognition. The academia and industry have been in a race to apply deep learning to a wider range of applications due to its capability in solving many complex tasks while providing start-of-the-art results . Recently, deep learning has been revolutionizing the recommendation architectures dramatically and brings more opportunities to improve the performance of recommender. Recent advances in deep learning based recommender systems have gained significant attention by overcoming obstacles of conventional models and achieving high recommendation quality. Deep learning is able to effectively capture the non- linear and non-trivial user-item relationships, and enable the codification of more complex abstractions as data representations in the higher layers. Furthermore, it catches the intricate relationships within the data itself, from abundant accessible data sources such as contextual, textual and visual information.

1.1 OVERVIEW OF THE PROJECT

With the ever-growing volume of online information, recommender systems have been an efective strategy to overcome such information overload. The utility of recommender systems cannot be overstated, given its



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widespread adoption in many web applications, along with its potential impact to ameliorate many problems related to over-choice. In recent years, deep learning has garnered considerable interest in many research fields such as computer vision and natural language processing, owing not only to stellar performance but also the attractive property of learning feature representations from scratch. The insurance of deep learning is also pervasive, recently demonstrating its effectiveness when applied to information retrieval and recommender systems research. Evidently, the field of deep learning in recommender system is flourishing. This article aims to provide a comprehensive review of recent research efforts on deep learning based recommender systems. More concretely, we provide and devise a taxonomy of deep learning based recommendation models, along with providing a comprehensive summary of the state-of-the-art. Finally, we expand on current trends and provide new perspectives pertaining to this new exciting development of thefield.

II. LITERATURE SURVEY

In the year 2008, Probabilistic Matrix Factorization by Ruslan Salakhutdinov, Andriy Mnih .Many existing approaches to collaborative filtering can neither handle very large datasets nor easily deal with users who have very few ratings. In this project we present the Probabilistic Matrix Factorization (PMF) model which scales linearly with the number of observations and, more importantly, performs well on the large, sparse, and very imbalanced Netflix dataset. We further extend the PMF model to include an adaptive prior on the model parameters and show how the model capacity can be controlled automatically. Finally, we introduce a constrained version of the PMF model that is based on the assumption that users who have rated similar sets of movies are likely to have similar preferences. The resulting model is able to generalize considerably better for users with very few ratings. When the predictions of multiple PMF models are linearly combined with the predictions of Restricted Boltzmann Machines models, we achieve an error rate of 0.8861, that is nearly 7% better than the score of Netflix's own system.

In the year 2012, Event-based Social Networks: Linking the Online and Offline Social Worlds byXingjie Liu, Qi Hey, Yuanyuan Tiany.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. By analyzing real data collected from Meetup, we investigated EBSN properties and discovered many unique and interesting characteristics, such as heavy-tailed degree distributions and strong locality of social interactions. We subsequently studied the heterogeneous nature (co-existence of both online and online social interactions) of EBSN's on two challenging problems: community detection information. We found that communities detected in EBSN's are more cohesive than those in other types of social networks (e.g. location-based social networks). In the context of information , we studied the event recommendation problem. By experimenting various information dimension patterns, we found that a community-based dimension model that takes into account of both online and online interactions provides the best prediction power.

In the year 2015, Participant Selection for Offline Event Marketing Leveraging Location-Based Social Networks by Zhiyong Yu, Daqing Zhang, Zhiwen Yu. Offline event marketing invites people to participate in a sponsored gathering, thus allowing marketers to face-to-face, direct, and close contact with their current and potential customers. This paper presents a framework that supports marketers in improving marketing effectiveness by carefully selecting invitees to such sponsored offline events by leveraging location-based social networks. In particular, we first transform the participant selection task into a combinatorial optimization problem. Second, we propose a marketing effect quantitative model that considers the distance and overlapping social influence. Third, we introduce algorithms to determine a participant team that can maximize the marketing effect while fulfilling the scale and item coverage constraints. We finally evaluate the effectiveness of the framework and validate the proposed marketing effect of the quantitative model with -worlddata.



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III. PROPOSED SYSTEM

In existing system depending on the target users, the recommendation systems on EBSN can broadly be categorized into two classes (a) recommendation for general Meet up members and (b) recommendation for Meet up group organizers and event hosts. Where most of the endeavors focused on recommending suitable events to a single or collection of Meet up users, few attempts have been made in recommending potential Meet up groups to the members for joining. In the context of Location Based Social Networks (LBSN), stand-alone point-of-interest (POI) recommendation recommends customers with individual venues (say restaurant or shopping mall) for future visits, depending on their past visits and preferences. In the proposed system,

In the User Authentication & Create Groups, User has an initial level Registration Process. The users provide their own personal information for this process. The server in turn stores the information in its database and user can create a group to add people from their contact list of people in theirlist.

In the Add Events And View Nearby Events, Proprietor can add the events hosted in their venue and also the guest Attended the event can add event in database, user hosting events in their house can also select and addevent detail, User can see list of events hosted within 2km radius from their location. In the Single User

Recommendation, User can select their preference on which type of place they wish to attend an event, All the nearby events which suits the user preference will be displayed in Google map User can select and view the location and event hosted in that venue based on the user preference the venues are recommended

In the Group Recommendation end user can select list of people going to participate in an event, location of all the selected members will be collected and center point of location gathered calculated and based on user preference venue will be recommended user can select the venue and send place details to the group the route map for the location will be displayed for the users.

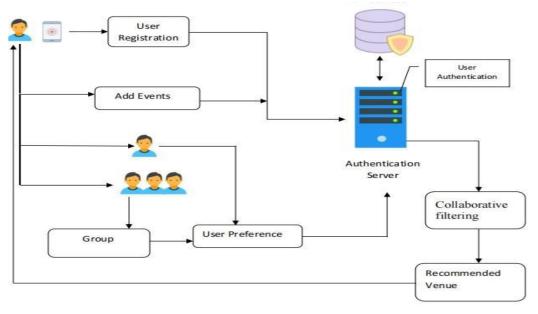


FIG. NO 3.1 PROPOSED ARCHITECTURE DIAGRAM

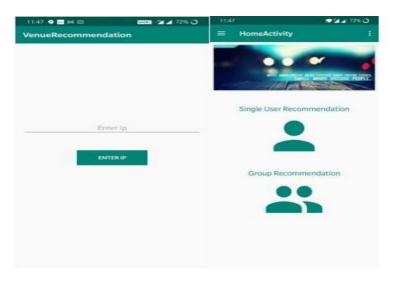


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IV. EXPERIMENTAL RESULTS



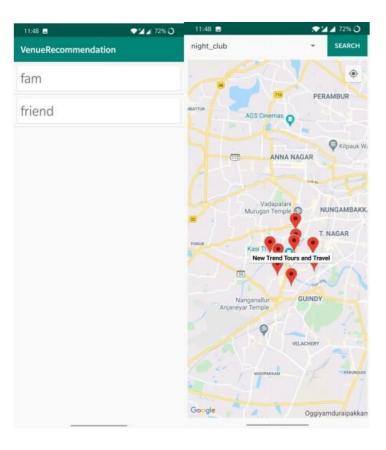
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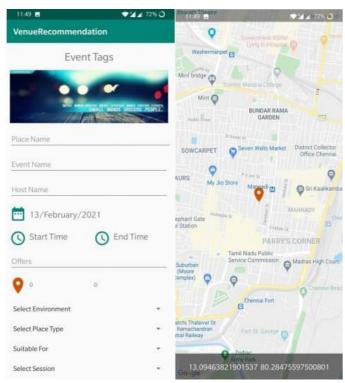


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V. CONCLUSION

Recommendation engine which recommends a ranked list of venues for hosting a target event. To the best of our knowledge, this is the first attempt involving deep learning for handling multi-entity interactions. The functionality of DeepVenue is based on a simple idea. A Meetup event can be successfully hosted by a group at a particular venue if (a) similar type of events have been recently hosted by similar type of groups at the same venue successfully (b) the venue is similar to the type of venues where similar type of events have been recently hosted by sevents have been recently. Evidently, the proposed model relies on the notion of similarity between multiple entities (events, venues, groups etc.). However, each of these entities carry multiple complex perspectives, which makes its representation challenging.

VI. FUTURE ENHANCEMENT

The group event recommendation based on the proposed model has a relative high time complexity and cannot support real-time recommendation on large dataset. In our future work, we will study fast offline training algorithm and efficient online recommendation method for our proposed model.

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