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Service Rating Prediction and Sharing by Exploring Social Mobile Users Geographical Locations

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Abstract: ***Social media is in style for classification system currently a day's. Users update share or tag photos throughout their visits. The geographical knowledge set by wise phone bridges the gap between physical and digital worlds. Location knowledge functions as a result of the affiliation between user's physical behaviors and virtual social network structured by the wise phone or internet services user offers ratings to its place and this place become popular the assistance of rating prediction and the user is employed social media for rating. Currently, a day's social media becomes in style. We have a tendency to check with these social networks involving geographical info as location-based social networks (LBSNs). Such info brings opportunities and challenges for recommender systems to unravel the cold begin, exiguity drawback of datasets and rating prediction. During this paper, we have a tendency to alter the use of the mobile users' location sensitive characteristics to hold out rating declaration. The relevancy of user's ratings and user-item geographical location distances, known as user-item geographical affiliation, the relevancy between users' rating variations and user-user geographical location distances, known as a user-user geographical affiliation. In this paper, we've got a bent to change the use of the mobile users' location sensitive characteristics to hold out rating declaration. We are using three factors for rating: user-item geographical connection, user-user geographical connection, and interpersonal interest similarity, are fused into a unified rating prediction model.***

Keywords: Geographical location, KNN Algorithm, K-Means Algorithm, Stop Word Algorithm, Rating prediction, Recommender system, Location-based social networks.

I. INTRODUCTION

With the rapid development of mobile devices and universal Internet access, social network services, such as Facebook, Twitter become prevalent. According to statistics, smartphone users have produced data volume ten times of a standard cell phone. In 2015, there were 1.9 billion smartphone users in the world, and half of them had access to social network services. Through cell phones or online location-based social networks (LBSNs), we can share our geographical position info or check-ins. This service has attracted millions of users. It also allows people to share their experiences, such as reviews, ratings, photos, check-ins, in LBSNs with their friends. Such information brings fighting chance and dares for recommender systems. The geographical location information links the gap between the real world and online services. The first generation of recommender systems with traditional collaborative filtering algorithms is facing great challenges of cold start for users (new users in the recommender system with little historical records) and the sparsity of datasets. If the geographical location factor is ignored, when we search the Internet for a Travel, recommender systems may recommend us a new scenic spot without considering whether there are local friends to help us. But if recommender systems consider geographical location factor, the recommendations may be more humanized and thoughtful. These are the motivations why we utilize geographical Location information to make rating prediction.

II. EXISTING SYSTEM

The first generation of proposed systems with traditional collective filtering algorithms is facing great challenges of cold start for users (new users in the proposed system with little ancient records) and the lack of datasets. Existing system focus on objective evaluation in order to recommend the high-quality services by exploring social user’s contextual information. Except for rating prediction, there are some systems focusing on location recommendation.
Recommender systems are classified into following categories:

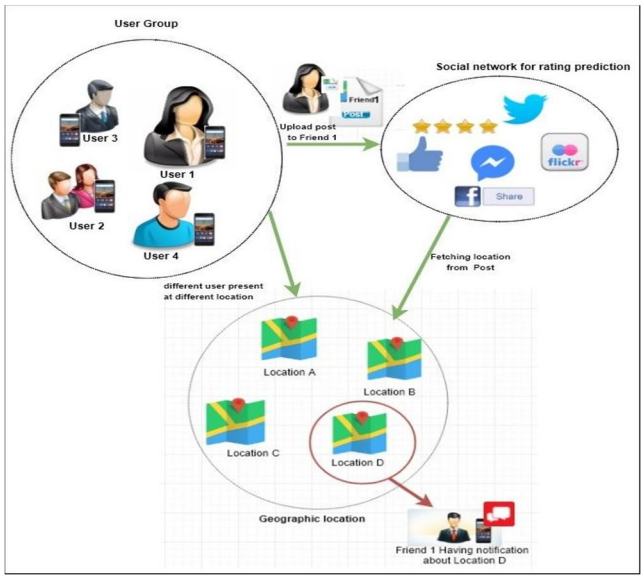
A. Content-based recommendations: The user will suggest items similar to the ones the user preferred in the past.
B. Collaborative recommendations: The user will suggest items that people with similar tastes and preferences liked in the past.

C. Hybrid approaches: These methods merge both collaborative and content-based methods. The drawback of the existing system:
D. Traditional collaborative filtering algorithms are facing great challenges of cold start for users and the sparsity of datasets.
E. Less accuracy and applicability of recommender systems.

III. PROPOSED SYSTEM

If recommender systems consider geographical location factor, the recommendations may be more humanized and thoughtful. These are the motivations why we utilize geographical location information to make rating prediction. Recently, with the rapid development of mobile devices and ubiquitous Internet access, social network services, such as Facebook, Twitter become prevalent. In our system user visit place, if the user like that place then user capture image of that place and gives a rating as per their satisfaction. While capturing an image, our system gets geographical location of that place and allow us to share with friends/groups. In friend side, if he/she near to that place then he/she get a notification that "One of your friends visited that particular place and recommended you to visit that place".

A. Advantages
1) Our system improves the accuracy of recommender systems.
2) Our system improves the applicability of recommender systems.
3) Our System more humanized and thoughtful.



IV. LITERATURE SURVEY

A. Paper 1: Toward The Next Generation Of Recommender Systems: A Survey Of The State-Of-The-Art And Possible Extensions
1) Description: The author gives a summary of recommender systems and suggests that recommendation methods of this generation are classified into three important categories: content-based, collaborative, and hybrid recommendation approaches. Additionally, many limitations of current recommendation methods are focused. Possible extensions that may improve recommendation capability and build recommender systems applicable to a better variety of applications are discussed. These extensions embrace, among others, an improvement of understanding of users and things, incorporation of the discourse info into the advice process, support for multi-criteria ratings, and a provision of additional flexible and fewer intrusive sorts of recommendations.

B. Paper 2: User-Service Rating Prediction by Exploring Social Users Rating Behaviors
1) Description: Authors propose a plan of the rating schedule to represent users' daily rating behaviors. Additionally, we tend to propose the issue of social rating behavior diffusion to deep perceive users rating behaviors. within the projected user-service rating prediction approach, we tend to fuse four factors, user personal interest (related to user and therefore the things topics), social interest similarity (related to user interest), social rating behavior similarity (related to users rating behavior habits), and social rating behavior diffusion (related to users behavior diffusions), into a unified matrix-factorized framework.

C. Paper 3: Circle-Based Recommendation In Online Social Networks

1) Description: In this paper, Author presents an endeavor to develop circle-based RS. The author specializes in inferring category-specific social trust circles from obtainable rating knowledge combined with social network knowledge. We tend to define many variants of weight friends inside circles supported their inferred experience levels.

D. Paper 4: Social contextual recommendation

1) Description: Author investigates social recommendation on the premise of psychological science and social science studies, which exhibit 2 necessary factors: individual preference and social influence. We tend to initial gift the actual importance of those 2 factors in online item adoption and recommendation. Then we tend to propose a unique probabilistic matrix factoring technique to fuse them in latent areas.

E. Paper 5: Personalized Recommendation Combining User Interest and Social Circle

1) Description: In this paper, 3 social factors, personal interest, social interest similarity, and social influence, fuse into a unified customized recommendation model supported probabilistic matrix factorization. The issue of private interest will create the RS suggest things to satisfy users' individualities, particularly for skilled users. Moreover, for cold begin users, the social interest similarity and social influence will enhance the intrinsic link among options within the latent house.

V. CONCLUSION

A personalized Location primarily based Rating Prediction (LBRP) model is projected by combining 3 factors: user-item geographical association, user-user geographical association, and social interest similarity. This method user visit place, if the user like that place then user capture image of that place and provides a rating as per their satisfaction. Whereas capturing an image, our system gets geographical location of that place and permit the North American nation to tag explicit friends. In friend aspect, if he/she regarding that place then he/she get a notification that one in all your friend visited that specific place and counseled you to go to that place.

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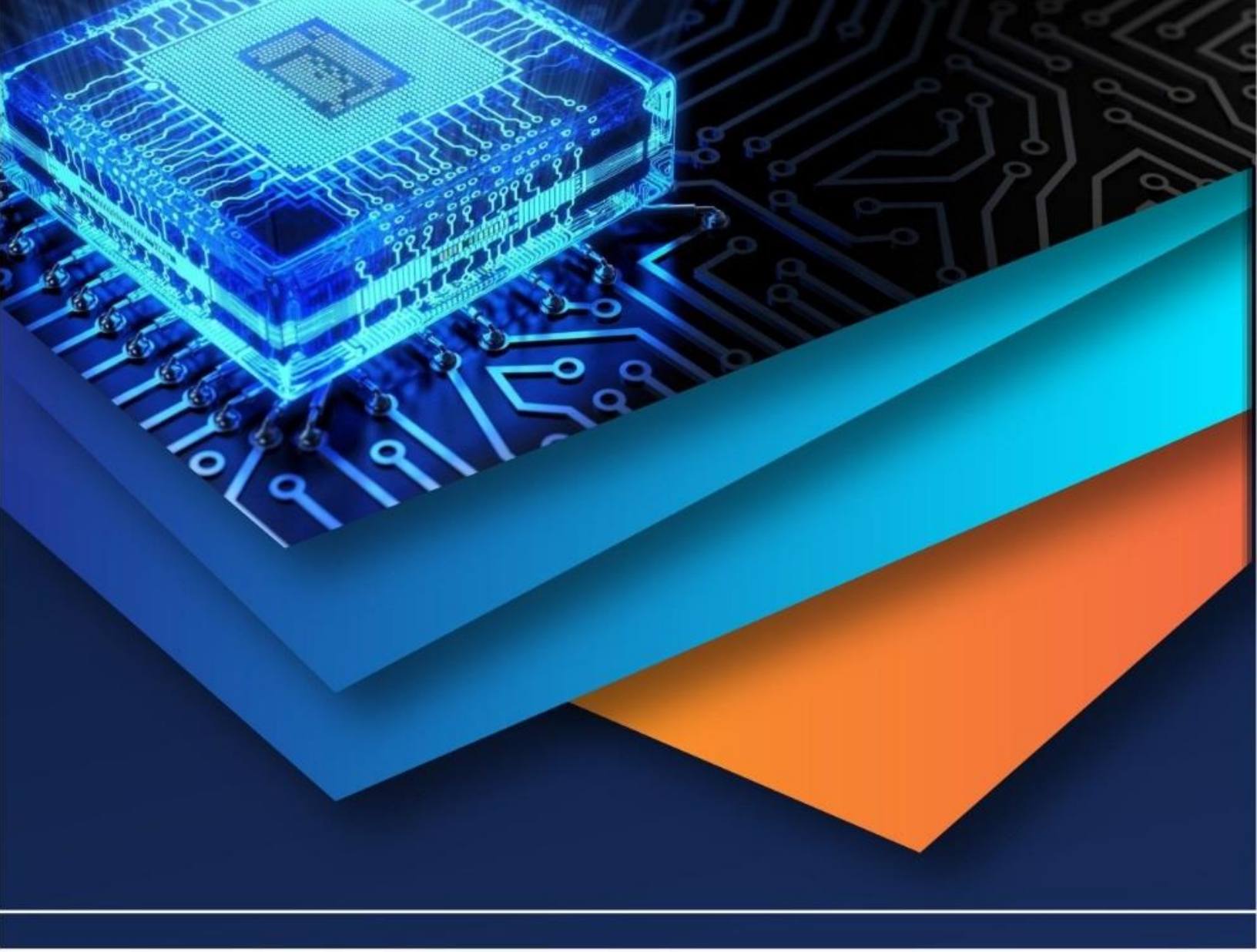

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