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Location and Preference based Recommendation System using Social Network

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Abstract-In recent years, recommended systems have become increasingly evolving suggest to users would give to an items and then whatever users' needs or interests fulfill them request. In this paper, we are proposed collaborative filtering approaches significant make them to implement. Collaborative filtering is a method of making automatic predictions about the interests of a user by gathering preferences or discretioninformation from many users.A mobile social networking service, such as Facebook and Google Latitudeallows a user's to perform a check-in that is feedback about the venue visited by the users.

Index Terms-*Recommendation Systems, Collaborative Filtering, Content-based Filtering.*

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1. INTRODUCTION

The growth of the Internet has made it much morenumerous social networks services, such as Facebook, and Twitter have resulted in the massive volume of data collected by the service providers on daily source.Social networking applications have become very important web services that provide Internet-based platforms for their users to interact with their friends.Collaborative filtering approaches makes a model from a user's already purchased or selected for an items as well as similar decisions made by other users.The integrated recommendation systems provide users with personalized recommendations for various items of users' needs or interest. Recommendation systems utilize several knowledge discovery techniques on a user's historical data and current situation to recommend products and services that match the user's preferences.A mobile social networking service, such as, Facebook and Google Latitudeallows a user to perform a "check-in" that is feedback about the venue visited by the user.In recent years, developments in location-acquisition and wireless communication technologies have enabled the creation of location-based social networking services, such as Facebook, and Twitter. In such a service, users can easily share feedback about their buying products and services in the physical world via online platforms. For example, a user with a mobile phone can share comments with his friends about a restaurant at which hehas said toeaten via an online social site. Other users can expand their social networks using friend suggestions derived from overlapped location histories.

2. RECOMMENDED SYSTEM

Recommendation systems that seek to predict the rating or preferencethat a user would give to an item.A major research challenge for such systems is to process data at the real-time and extract preferred place from an enormously huge and various dataset of users' historical check-ins.Recommender systems have become increasingly popular in recent years, and are utilized in a variety of areas including movies, music, news, books, research articles, search queries, social tags, and purchase products, collaborators, restaurants, garments, financial services, life insurance, and Twitter pages.

2.1 APPROACHES

2.1.1 COLLABORATIVE FILTERING

Collaborative filtering is the process of filtering for information or patterns using techniques involving collaboration among multiple agents, viewpoints, data sources, etc. Applications of collaborative filtering usually involve very large data sets. Collaborative filtering methods have been applied to many different kinds of data including: sensing and monitoring data, such as in mineral exploration, environmental sensing over large areas or multiple sensors;financialdata, such as financial service institutions that integrate many financial sources; or in electronic commerce and web applications where the focus is on user data, etc.Collaborative filtering algorithms often require (1) users' active participation, (2) an easy way to represent users' interests, and (3) algorithms that are able to match people with similar interests. Typically, the workflow of a collaborative filtering system is: A user expresses his or her preferences by rating items (e.g. books, movies or CDs) of the system. Theseratings can be viewed as an approximate representation of the user's interest in the corresponding domain.The system matches this user's ratings against other users' and finds the people with most similar tastes.With similar users, the system recommends items that the similar users have rated highly but not yet beingrated by this user.

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2.1.1.1 CONTRIBUTION

This approach uses user rating data to compute the similarity between users or items. This is used for making recommendations. This was an early approach used in many commercial systems. It's effective and easy to implement. Typical examples of this approach are neighbourhood-based CF and item-based/user-based top-N recommendations. For example, in user based approaches, the value of ratings user 'u' gives to item 'i' is calculatedas an aggregation of some similar users' rating of the item:

$$r_{u,i} = aggru^{'} \epsilon U r_{u^{'},i}$$

Where 'U' denotes the set of top 'N' users that are most similar to user 'u' who rated item 'i'. Some examples of the aggregation function includes:

$$r_{u,i} = \frac{1}{N} \sum_{u^{'} \epsilon U} r_{u^{'},i}$$

$$r_{p,k} = k \sum_{u^{'} \epsilon U} \mathrm{simil}(u,u^{'})\, r_{u^{'},i}$$

$$r_{p,k} = \overline{r_u} + k \sum_{p^{'} \epsilon U} \mathrm{simil}(u,u^{'})(r_{u^{'},i} - \overline{r_{u^{'}}})$$

Where k is a normalizing factor defined as $k = 1/\sum_{u^{'} \epsilon U} |\mathrm{simil}(u,u^{'})|$.and $\overline{r_u}$is the average rating of user u for all the items rated by u.The neighbourhood-basedalgorithm calculates the similarity between two users or items produces a prediction for the user by taking the weighted average of all the ratings. Similarity computation between items or users is an important part of this approach. Multiple measures, such as Pearson correlation and vector cosine based similarity are used for this. The Pearson correlation similarity of two users x, y is defined as

$$\mathrm{simil}(x,y) = \frac{\sum_{i\epsilon I_{xy}} (r_{x,i} - \overline{r_x})(r_{y,i} - \overline{r_y})}{\sqrt{\sum_{i\epsilon I_{xy}} (r_{x,i} - \overline{r_x})^2 \sum_{i\epsilon I\, xy} (r_{y,i} - \overline{r_y})^2}} \qquad (\boldsymbol{r_x},$$

Where I_{xy} is the set of items by both user x and user y.

The cosine-based approach defines the cosine-similarity between two users x and y as:

$$\mathrm{simil}(x,y) = \cos(\vec{x},\vec{y}) =$$

$$\frac{\vec{x}.\vec{y}}{\|\vec{x}\| \times \|\vec{y}\|} = \frac{\sum_{i\epsilon I_{xy}} r_{x,i}\, r_{y,i}}{\sqrt{\sum_{i\epsilon I_x} r_{x,i}^{\,2}}\sqrt{\sum_{i\epsilon I_y} r_{y,i}^{\,2}}}$$

The user based top-N recommendation algorithm uses a similarity based vector model to identify the k most similar users to an active user. After the k most similar users are found, their corresponding user item matrices are aggregated to identify the set of items to be recommended. A popular method to find the similar users is the Locality sensitive hashing, which implements the nearest neighbor mechanism in linear time.The advantages with this approach include: the explain ability of the results, which is an important aspect of recommendation systems; easy creation and use; easy facilitation of new data; contentindependence of the items being recommended; good scaling with curateditems. There are also several disadvantages with this approach. Its performance decreases when data gets sparse, which occurs frequently with web related items. This hinders the scalability of this approach and creates problems with large datasets. Although it can efficiently handle new users because it relies on a data structure, adding new items becomes more complicated since that representation usually relies on a specific vector space.The recommender system compares the collected data to similar and dissimilar data collected from others and calculates a list of recommended items for the user. Several commercial and noncommercial examples are listed in the article on collaborative filtering systems.

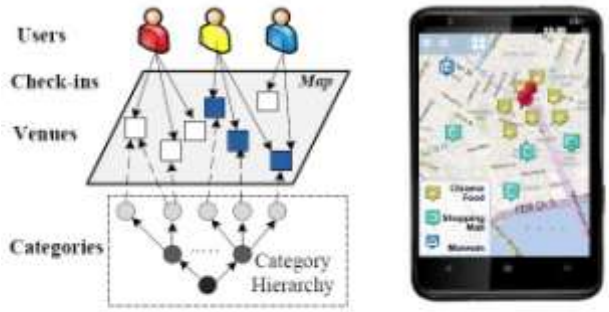

Fig.1 Diagram of various users check-ins venues in various mapping location.

2.1.2 CONTENT-BASED FILTERING

Another common approach when designing recommender systems is content-based filtering. Content-based filtering methods are based on a description of the item and a profile of the user's preference. In a content-based recommender system, keywords are used to describe the items and a user profile is built to indicate the type of item this user likes. To create a user profile, the system mostly focuses on two types of information: 1. A model of the user's preference. 2. A history of the user's interaction with the recommender system. Basically, these methods use an item profile (i.e., a set of discrete attributes and features) characterizing the item within the system. The system creates a content-based profile of users based on a weighted vector of item features. The weights denote the importance of each feature to the user and can be computed from individually rated content vectors using a variety of techniques. Direct feedback from a user, usually in the form of a like or dislike button, can be used to assign higher or lowerweights on the importance of certain attributes.

3. SYSTEM OVERVIEW

Most of existing recommendation systems utilize centralized architecture that are not scalable enough to process large volume of distributed data.The centralized architecture for venue recommendations must simultaneously consider users' preferences, check-in history, and social context to generate optimal venue recommendations.

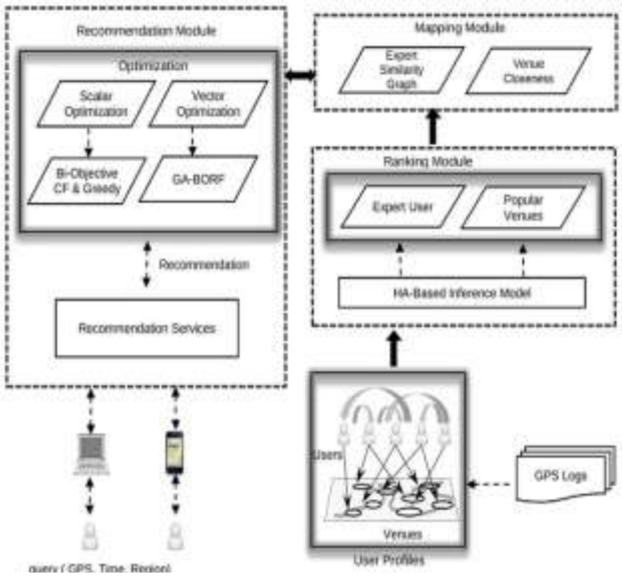

Fig.2 Architecture diagram of preference venue recommendation

3.1 User Profiles

As reflected in Fig. 2, the MobiContext frameworkmaintains records of users' profiles for each geographical region. The arrows from users to venues at lower right ofFig. 1 indicate the number of check-ins performed by each user at various venues. A user's profile consists of the user's identification, venues visited by the user, and check-in time at a venue.

3.2 Ranking Module

On top of users' profiles, the ranking module performs functionality during the pre-processing phase of data refinement. The pre-processing can be performed in the form of periodic batch jobs running at monthly or weekly basis as configured by system administrator. The ranking module applies model-based HA inference method on users' profiles to assign ranking to the set of users and venues based on mutual reinforcement relationships. The idea is to extract a set of popular venues and expert users. We call a venue as popular, if it is visited by many expert users, and a user as expert if (s)he has visited many popular venues. The users and venues that have very low scores are pruned from the dataset during offline pre-processing phase to reduce the online v computation time.

3.3 Mapping Module

The mapping module computes similarity graphs among expert users for a given region during pre-processing phase. The purpose of similarity graph computation is to generate a network of like-minded people who share the similar preferences for various venues they visit in a geographical region. The mapping module also computes venue closeness based ongeographical distance between the current user and popular venues.

3.4RecommendationModule

Recommendation module utilizes bi-objective optimization to make an enhanced list of venues. Suppose a current user A is involved in venue type T that must be located closest to the current location of the current user within an exact region R. In such a set-up, the current user requires the best preferred venues as well as the closest venues from the user's current location. To meet both the aforementioned objectives, we utilize bi-objective optimization in the proposed MobiContext recommendation framework.

3.5Time Complexity Analysis

In this subsection, we compute the time difficulty of the pre-processing phase, CF-BORF, the greedy-BORF, and GA-BORF approach, respectively. For time complexity analysis, in a specific number of regions, the time complexity of the HA inference model is $O(a \times r \times (x'2 + y2)$, where the parameter a presents the total number of iterations for approaching to the convergence, x′ and y present total number of users and the venues in a region r. Therefore, the overall time complexity of the offline pre-processing phase would be $O(r \times ((a \times (x'2 + y2)))$.

4. CHALLENGES

4.1 Data sparsity

In practice, many commercial recommender systems are based on large datasets. As a result, the useritemmatrixused for collaborative filtering could be extremely large and sparse, which brings about the challenges in theperformances of the recommendation.One typical problem caused by the data sparsity is the cold start problem. As collaborative filtering methodsrecommend items based on users' past preferences, new users will need to rate sufficient number of items to enablethe system to capture their preferences accurately and thus provides reliable recommendations.Similarly, new items also have the same problem. When new items are added to system, they need to be rated bysubstantial number of users before they could be recommended to users who have similar tastes with the ones ratedthem. The new item problem does not limit the content-basedrecommendation, because the recommendation of anitem is based on its discrete set of descriptive qualities rather than its ratings.

4.2 Scalability

As the numbers of users and items grow, traditional CF algorithms will suffer serious scalability problems. Forexample, with tens of millions of customers and millions of items, a CF algorithm with thecomplexity of is alreadytoo large. As well, many systems need to react immediately to online requirements andmake recommendations for all users regardless of their purchases and ratings history, which demands a higherscalability of a CF system. Large web companies such as Twitter use clusters of machines to scalerecommendations for their millions of users, with most computations happening in very large memorymachines.

RELATED WORK

In the past, generally work focused on trajectory-based approaches for venue recommendation systems. The trajectory based approaches evidence information about a user's visit pattern to various location, the routes taken, and dwell times. Trajectory-based approach recommends locations to users based on their past trajectories, a main drawback of such approaches is that they are not capable to concurrently consider other influential factors apart from simple GPS trace that makes them manufacture less optimal recommendations. To address such deficit, we utilized multi-objective optimization in our proposed framework. Another issue is that the trajectory-based approaches suffer from data sparseness difficulty as usually a person does not often visits many places, which results in sparse user-venue matrix. Moreover, the trajectory based approaches suffer from scalability issues as huge volumes of trajectory data needs to be processed causing considerable overhead. Some of the approaches are based on the online ratings provided by the users to the visited places. Apart from rating base approaches, few of the techniques have their model built on check-in based approaches where the users provide small feedbacks as check-ins about the spaces they visited.

CONCLUSION

In this paper we are proposed creating social network similar to Facebook and Twitter and then we are implement product and service advertisement notification to the users with various venues. These product and service advertisement are suggested to the interest or expect users with real time happens something like that trends, festivals, etc. If they are need product and service and then expect users must be asked the shop to purchase the product and services.

REFERENCES

[1] M. Ye, P. Yin, and W. Lee, "Location recommendation forlocation-based social networks," In Proceedings of the 18thSIGSPATIAL International Conference on Advances in GeographicInformation Systems, ACM, pp. 458-461, 2010.

[2] C. Chow, J. Bao, and M. Mokbel, "Towards Location-BasedSocial Networking Services," In Proceedings of the 2nd ACMSIGSPATIAL International Workshop on Location Based SocialNetworks, ACM, pp. 31-38, 2010.

[3] A. Noulas, S. Scellato, N. Lathia, and C. Mascolo, "A RandomWalk around the City: New Venue Recommendation inLocation-Based Social Networks," In Proceedings of InternationalConference on Social Computing (SocialCom), pp.144-153, 2012.

[4] J. Bobadilla, F. Ortega, A. Hernando, A. Gutiérrez,"Recommender Systems Survey," Knowledge-Based Systems, vol.46, pp. 109-132, 2013.

[5] Y. Zheng, X. Xie, and W.-Y. Ma.GeoLife: ACollaborative Social Networking Service among User,Location and Trajectory. IEEE Data Eng. Bull.,33(2):32–40, 2010.