A Motivation-Aware Approach for Point of Interest Recommendations

Khadija Ali Vakeel
Indian Institute of Management Indore
Prabandh Shikhar, Indore
India
091-0731-2439-666
f13khadijav@iimidr.ac.in

Sanjog Ray
Indian Institute of Management Indore
Prabandh Shikhar, Indore
India
091-0731-2439-524
sanjogr@iimidr.ac.in

ABSTRACT
Most existing context aware recommender systems primarily use a combination of ratings data, content data like features or attributes of the product or service, context data like location or time and social network data. In this paper, we propose a novel approach for refining the recommendations made by location-aware recommender systems based on user motivations for checking in at locations in location based social networks. Based on a classification that classifies user's motivation for checking in at a Point Of Interest into seven categories we propose an approach that will help refine recommendations in a way that can be better explained to the user. We also show the applicability of our approach by analyzing a dataset extracted from Foursquare.

CCS Concepts
• **H.3.3 [Information Storage and Retrieval]: Information Search and Retrieval—Information Filtering**

Keywords
Location-based social networks; Point Of Interests Recommendations; Motivation-Aware; Explanations.

1. INTRODUCTION
Availability of multiple product choices and easy access to information about them has made the task of making correct purchase decision, by evaluating the information available, a huge problem for the consumers of the products or services. Recommender systems are software that helps customers make these decisions by providing them product recommendations that are relevant. Recommender systems give personalized recommendation to the user by either using explicit data provided by user through ratings or by using implicit data like user browsing behavior, past purchasing behavior etc. The popularity of personalized systems have increased manifold as today the success of e-commerce sites is dependent on the quality of recommendations. Hence, researchers are continuously trying to improve quality of recommendation by integrating more and more data about the customers in the recommendation process [1].

Presently, there is a clear trend towards usage of context-aware recommendation systems as they integrate contextual data like time, location, mood, emotions, companion, purpose etc. with ratings data to provide final recommendation[2]. Among the different contexts, research community has shown most interest towards location-aware recommendations systems. One reason for greater focus on location-aware recommendation systems is the easy availability of GPS data due to increased adoption of smart mobile phones.

Tourism industry is hugely impacted by the ubiquity of mobile phones in consumer lives [3]. Availability of many travel related apps and ease of access of free Wi-Fi spots has made mobile phones the main decision making tool in helping tourists make travel related decisions. Mobiles phones complemented with intelligent travel related apps has completely transformed the travel experience [4]. Among the technologies used for applications created for tourism, location aware and context aware based apps are the most popular as they have helped tourists to enhance their travel experience by making relevant recommendations. There is still a need for developing new approaches for recommending point of interests to tourists based on the variety of contextual and personal data available. This paper tries to address the above need by proposing a novel approach for recommending users places, restaurants, events etc. based on user motivation profile that is derived from his check-in data from location based social networks.

In this paper, we propose a novel approach for refining the recommendations made by location-aware recommender systems based on user motivations. Most existing recommender systems primarily use a combination of ratings data, content data like features or attributes of the product or service, and context data like location or time. We propose to integrate the user checking in motivation at places he has visited places into the location-aware recommendation system, as it will help refine recommendations in a way that can be better explained to the user. This will also lead to increased adoption of the recommendations as prior research has shown that explanation has been found more valuable by the user if they are explained in a more simple and accurate manner[1]. User motivation data is inferred from previous user check-in and comments at different locations. We also show how our approach can be applied through a case study on a real life dataset of 10 users extracted from popular location based recommendation app Foursquare.

2. RECOMMENDER SYSTEMS IN TOURISM
The key problems in recommender systems are the prediction problem and the top-N prediction problem[5]. The prediction problem is about predicting whether a user will like or dislike a new item that the user has not yet consumed or purchased. This prediction is generated using the knowledge of user preferences, past purchases data and interests. The top-N problem in recommender systems attempts to predict the set of N items that a user may like from the set of items he has not yet seen. Recommender systems in tourism industry primarily focuses on the top-N problem. In tourism industry these systems help the tourist or user in information search by recommending

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destinations, point of interests, restaurants, events, travel itineraries etc. The recommendations made are specific to a user as they are personalized according to the user interests and preferences.

The popularity of recommender systems in tourism industry has brought this field into the attention of the academic research community. The increased focus on research in recommender systems in tourism is evident by going through the detailed and exhaustive survey papers [6], [7] that have been published on the topic recently. Among the recommendation problems that are researched in the tourism domain, Point of Interests recommendations (POI) is the most researched problem by the academic community [6].

In Point of Interests recommendations a ranked list of point of interests like tourists attractions in a city, restaurants, events etc. are presented to the user[8]–[11]. POI problem can be classified as top-N recommendation problem. These systems focus on two aspects of the problem, first on how to improve accuracy of the recommendations and the other aspect is how to effectively present the information to the user[8]. Majority of recommender systems in tourism focus on point of interests recommendations. One primary reason for that is the availability of new contextual data that has motivated researchers to focus on ways to improve recommendation accuracy. Location, time of the day, current weather, budget, means of transport, traffic, presence of friends nearby etc. [6]are contextual aspects that have been used in making POI recommendations. Location of the user is one the most popular contextual data that is used in most algorithms, one reason could be the easy access to accurate location data because of widespread use of mobile phones among tourists. Social network data is also used for making POI recommendations[10]–[12]. Social network data provides rich data points that can be used for profiling the user. It also provides data about relationship between users, preferences and views that can be derived from user comments, reviews and other network activity.

Tour Package [13] or Travel destination recommendation and Itinerary Planning [14], [15] are two more problems that have been researched. Travel destination recommendations are designed with tour operators as end users. These systems also recommend hotels, flights in addition to tourist locations. Cost is also one aspect that is considered an important criteria in tour recommendations[13]. Itinerary planning or route planning recommends multiple day personalized tour plans with set of point of interests to be explored each day. Contextual aspects like days of visit, pace of travel, preferred transportation mode [16] have been used for such recommendations.

Among the recommender systems approaches in tourism domain research, content based technique is the more popular as compared to collaborative filtering technique [6]. Unavailability of user rating data for different attractions, restaurants, events etc. may be the reason behind fewer collaborative filtering based approaches. Hybrid algorithms that combine content based and collaborative filtering based may be considered more appropriate for tourism domain recommendations.

3. RELATED WORK

Point of interest recommendations approaches in context based recommender systems is categorized by the type of data the systems process to make recommendations [17], [18]. Combining both the categorization approaches, POI recommendation approaches can be of six types.

Pure check-in data approach: This approach primarily considers check-in frequency data for making recommendations. It assumes that if two users are similar if they have similar checked in history. One demerit in considering check in data frequency as ratings is that during vacations tourists only check in once at a tourist location so it difficult to deduce whether the user liked or disliked the place.

Geographical influenced approach: The current location of the user and distance of POIs not yet visited by the user from the current location is used for making recommendations. This approach is appropriate when availability of time, transport options, traffic condition, weather conditions are used as contextual variables for making recommendation.

Social influence enhanced approach: Popularity of location based social networks like Foursquare, Yelp etc. have resulted in recommendation approaches that utilize social relationships among users to enhance POI recommendation. This approach assumes that friends of a user have similar interests as the user and a user is more likely expected to trust recommendations made by people who they are connected to in the network.

Temporal influence enhanced approach: Some POIs are preferred to be visited at a particular time slot, temporal influence approach considers time information while generating recommendations. For example, there are tourist locations that are primarily visited during sunrise or sunset time. Even closing time and opening time of museums and restaurants are important information that can help improve POIs recommendation.

Sequential influenced approach: These systems assume that users exhibits pattern in the order in which they visit places. For example, some users may prefer going to a restaurant after watching a movie or a game in a stadium. Patterns once identified from past check in data can be used for making recommendations.

Categorical influenced approach: Users preferences for checking in at particular categories of point of interests is leveraged in this approach. A user may prefer going to museums only and another user may have preferences for entertainment parks. The knowledge of a user biases for a particular category of POI is used in this approach for enhancing recommendations.

Among the different approaches for POIs recommendations, check-in data, geographical influenced and temporal influenced approach have significantly enhanced POI recommendation quality. Geographical influence is used the most to improve POI recommendation [17].

In [11] a approach is proposed that combines temporal and geographical data to make POI recommendation. Their approach splits time into hourly slots and mines the user checking in history to get insight about user temporal preferences to visit particular type of POIs at a time slot. As users tend to visit POIs that are closer to their current location, this approach combines the POIs nearby to user location with the insight acquired by the user temporal preferences to make the final recommendation.

Social network data, geographical data as well as check in data is used in the approach proposed in [19]. Their approach challenge the main assumption made in most POIs recommendations approaches that use location based social network (LBSN) data i.e. check-in frequency of user at a particular POI indicates user preference for that POI. This assumption is challenged on the basis that in more than 50 % of the places a user has checked in only once and on the basis of one check in it cannot be implied that the user prefers that POI. In the approach proposed by [19], they extract the preference of POI by mining user comments for that POI. The mining of the comments provide a sentiment polarity for the POI for that user. The sentiment polarity can be positive, negative or neutral. The final recommendation is made by integrating user sentiment polarity towards POIs he has commented on, user social network links and geographical location of the user.

Most approaches use geographical data, check-in data, and temporal data or combine them to make recommendations. An interesting approach [20] uses user personality data to enhance the recommendations. The personality of the user is captured through a questionnaire filled by the user during the registration process on the mobile application. The personality is based on the Five factor model [21]. The Five Factor Model terms personality among the five dimensions of Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to Experience. Along with personality of the user the approach uses a set of contextual factors, such as the weather conditions, the time of day, user's location and user's mood to recommend the final set of POIs.

Our approach uses the concept of user motivation for checking in as the context to refine the final recommendation. To the best of our knowledge, no other research paper has ever used this data for POIs recommendations.

4. MOTIVATION BASED RECOMMENDATION APPROACH

4.1 Motivation

Spatiotemporal mobility among user using location based social networks (LBSN) are driven primarily by social rewards and also by systems rewards [22]. Checking in behavior in LBSN is driven by users seeking status recognition in his network .LSBN enables social recognition as the feature of immediate sharing of location details, pictures etc. generates immediate social reaction among his network friends. Checking in behavior is an important aspect in marketing of services in LBSN. The authors cite the theory of self-concept [23] to explain the behavior of customers. Theory of self-concept indicates that consumers value consumption that results in recognition and that strengthen the conception about themselves. Similarly, we use motivation behind checking in at a location to refine recommendations as we believe that every user may have a different motivation behind checking in at a location. Using user motivation preferences while showing and explaining the final POIs recommendation to the users will result in more effective recommendations.

Our work is based on the foundation that users have a particular motivation when they check-in at a location. In this work, we use the classification done by [24], they found that motivations for a user to share his location or check-in at a particular location can be classified into seven categories.

They identify Social Enhancement, Informational Motive, Social Motivation, Entertainment value, Gameful Experience, Utilitarian motivation, Belongingness as the motives for a user to check-in at a location.

Social enhancement value is the most commonly observed motive, exhibited in more than fifty percent check-ins, where a user check-ins for impressing others and feels important to be at a place [25].

Information Motivation is commonly observed in youth, usually a suggestion or advice. Social Motivation is used when hanging out with friends or for relationship development.

Entertainment value is when user is relaxing or playing, to communicate positive moments.

Gameful experience is using gaming mechanics in non-gaming sense. City spots and achieving a virtual status like Mayor or owner. Utilitarian motivation is for winning promotions and discounts as you share or check-in at a place.

Belongingness is for places like home, school when users are nostalgic.

Scenario: Number of places a tourist can visit is limited because of the constraints of time and effort needed. POIs recommender systems help the users in deciding the POIs to visit using contextual variables. The final list to 2-3 POIs provided to the user as recommendation many times are difficult to justify as multiple contextual variables are evaluated using complex algorithms to generate the final recommendations. In our approach we further refine the final recommendations based on user motivation to checking in at a POI. The justification of the recommendations made through explanations based on user motivation for checking in will be easier for the user to comprehend.

For example, a tourist in Barcelona whose analysis of checking in data in Foursquare suggests that he is motivated by social enhancement will be recommended POIs like Sagrada Familia or Park Guell, while somebody who is motivated by information motivation will be recommended an offbeat attraction or a new restaurant.

4.2 Algorithm

Our aim is to recommend User U_i at location L_i a place of interest P_i that is within a radius of distance R_i from location L_i. We define two kind of motivations for each location or POI and for each user. The two motivations are Dominant explicit motivation and Dominant perceived motivation. Dominant explicit motivation for a user is derived from explicit data like comments and status messages after checking in at a POI on the location based social network. Dominant perceived motivation are generated for a location through survey.
We use the approach of explicit and perceived motivation because many users may not put any comments or status messages after checking in at a location. Using explicit motivation will more likely result in data sparsity.

Step 1: Assigning dominant explicit motivations to users and locations
Dominant explicit motivations for a user are determined based on the motivation inferred from the comments and status messages user have given after check in to different places. Set *DUi* represents the dominant motivations of a user U_i .It contains those motivations which have highest frequency of check-ins with a particular motivation. We have made DU_i a set as a user may have more than one motivation having the max frequency count. Similarly, Dominant explicit motivations to a place is referred as set DP_i and is determined by doing a frequency count of the inferred motivations derived from comments given to the place by users.

Step 2: Assigning dominant perceived motivations to users and locations.

Based on offline assessment of the places by a survey each place P_i is assigned a perceived motivation. PP_i is the set of dominant perceived motivations of a place P_i. It is determined by doing a frequency count of the perceived motivations assigned to the place P_i in the survey. PU_i is the set of dominant perceived motivations for a user U_i. It is determined by doing a frequency count of the perceived motivations assigned to each place the user U_i has checked into.

Step 3: Recommendation Generation
To recommend User U_i at location L_i a place of interest P_i that is within a radius of distance R_i from location L_i. Using collaborative filtering or other POIs recommendation algorithm approaches a set of places within a radius of distance R_i from location L_i are generated that are matching with user preferences based on his ratings or preferences data.

Step 4: Final set of motivation based recommendation
User U_i set of dominant motivations as generated in step 2 is the union of the sets DU_i and PU_i. Place P_i set of dominant motivations as generated in step 2 is the union of the sets DP_i and PP_i. Then the final set of recommendations is based on refining the places selected in step 3 using User U_i dominant motivations. From the set of places selected in step 3 only those places P_i whose dominant motivations matches with user U_i dominant motivations are recommended to the user U_i.

Our proposed algorithm approach applies post filtering contextual approach [2] as motivation context is applied on a list of recommendations generated by traditional recommender systems algorithms. A pre-filtering contextual approach can also be applied but as ratings data is primarily used by traditional algorithms, pre-filtering places of interest based on motivations may lead to data sparsity problem.

5. Case Study

Our approach as mentioned in the earlier section is to refine the recommendation made by an algorithm that is designed for accuracy. Our suggested approach objective is not to improve accuracy further but to improve the way final recommendations are explained to the user. Explanations[26] are an important component of recommender systems as it may increase the adaptability and trustworthiness of the recommender system. In [27], the authors show that there is merit in providing personalized explanations and explanation interfaces should be designed to increase the informativeness of the explanation. We believe our approach will add to the informativeness of the explanation.

Instead of an experimental evaluation of our approach we have done a data analysis on four square data set to check whether our approach is feasible in a real life scenario. Our approach is feasible only if users show variety of motivation while checking in, if all users show the same motivation then motivation cannot be used to refine the final recommendations. Our algorithm uses the concept of perceived and actual motivation, we also want to check through actual data whether there is any difference in actual and perceived motivation.

5.1 Data Collection

Foursquare launched in 2009 is used for check-in and real time location sharing with friends. It has 50 million users in its network and handles millions of check-in in a day. The Foursquare app allows the users to have their own profile and share their comment describing their feelings when they visit a location. The users of the foursquare were selected for the final analysis that has more than 10 check-in in Indore. We could find 10 users with such criteria who had visited in all 97 places including restaurants, pubs, city spots, home and business.

5.2 Comment Classification

The 7 motivations for check-in by [24] are used, Table 1 shows which characteristics of a comment can help us map with which motivation. For example, if a user checks-in at a high end restaurant and puts a comment "Tremendous food". Then his motivation would be classified as social enhancement value as it is a high end restaurant and the user has checked in as he is feeling important. Based on his comment the user motivation will be classified as information motivation. Similarly, all the comments by the user are classified by using characteristics of the motivation. Table 2 shows the result of classifying all the 129 comments made by the users in our dataset. The table shows the distribution of various motivations.

5.3 User Classification

Every user has one motivation from the above 7 categories. The motivation of the user is the highest frequency of motivation in the comments as classified according to the above method. Hence, a user *Ui* has a motivation *Mi*, if the comments posted by the user on foursquare has highest number of comments with *Mi* as motivation. In our dataset of 10 four square users in Indore, 50 per cent had Social Enhancement value as their main motivation. What was surprising was that both social enhancement and Informational motivation together were dominant motivation in 20 per cent user. Hence, for a user it is not necessary to have a single motivation as a dominant motivation but combination of more than one. Table 3 shows classification of users on the basis of 7 motivations.

Table 1. Characteristics of different motivations for location check-ins

Motivation	Characteristics
Social Enhancement	Impressing others Feeling Important To show off Extremely Popular location Night clubs High end restaurants Distinctive Identity or Intellectual Image Celebrity Status
Informational Motivation	Suggestions Advices Information about event or news Location and arrival Important event Give and take recommendation
Social Motivation	Meeting new people Socializing Observing others Meeting a Friend Flirting and relationships Emotional Feeling At Home or Office Know about friends and where they are
Entertainment Value	Playing Relaxing

	Passing Time Less Lonely Positive moments, emotional state Fight boredom Initiate chat Waiting
Gameful Experience	To collect award Points Status in an app More in females Older age(not in youth aged 19-22) City spots(streets, square, roads, bridge, old town) Escape from reality, Virtual Possession
Utilitarian	Win promotions and discounts Check in of family business for marketing
Belongingness	Place with social group Nostalgia or ownership

Table 2. Comments of Four Square dataset classified on motivation for check-in

Motivation	Per cent of comments
Social Enhancement Value	38
Informational Motivation	27
Social Motivation	7.7
Entertainment Value	10.0
Gameful experiences	3.8
Utilitarian Motivation	3.8
Belongingness	9.30

Table 3. Spread of Motivation among users in our dataset

Motivation	Per-cent
Social Enhancement Value	50
Informational Motivation	10
Social Enhancement Value and Informational	20
Social Motivation	10
Belongingness	10

5.4 Perceived & Actual Motivation

While the user giving a comment on a location he visits might be classified into one of the motivation category, but this motivation may differ for the perceived dominant motivation of the location. The perceived dominant motivation of the location is classified based on a survey. This mismatch in perceived and actual motivation in check-in can lead to distorted image of the user. For example, suppose a user checks-in at a high end posh restaurant with a comment "Excellent coffee, Must try." Though, the actual motivation of the user is Information Motivation but the characteristics of the place may make another user who sees this comment assume the motivation behind check-in was Social Enhancement Value. To address this dissonance, in step 4 of the algorithm, for a User $U_{i,}$ the set of dominant motivations is generated by the union of the sets DU_{i} and PU_i. We analyzed the data to check whether this kind of dissonance exists in our data set. Table 4 shows 39% of times the actual motivation is also the perceived motivation but a majority number of times the perceived and actual motivation differs. Also, 12 percent places had multiple classifications which dint allow us to attach them to a specific motivation.

Table 4. Difference between actual and perceived motivation

Perceived & Actual Motivation	Places	Percentage
Equal	35	39.32584
Not Equal	43	48.31461
Not Determined	11	12.35955

6. DISCUSSION & CONCLUSION

Every user has a motivation when the user checks-in at a particular location, if these motivation is taken into account while generating final recommendations then it will be more beneficial to the user. Context variables like time, location and social network data of a user are mainly used to recommend new locations to a tourist. In this paper, we propose an approach that uses user checking in motivation along with the other contextual variables. Motivation can be effectively used if used as a post-filtering contextual variable in combination with the existing recommendation algorithm. Our analysis of real life data shows that our approach can be used as user do show different motivations as they check in into different POIs , the primary motivation among users also differs and there do exist a difference between a user's actual motivation for checking in and perceived motivation for checking in. We believe using our approach will improve the explanation quality of the final recommendations.

Limitations of the study are that we did not experimentally evaluate the accuracy of our approach based on metrics like mean absolute error, precision or recall. Our approach is not designed to improve accuracy, what it offers is the additional explanation for a recommendation to the user, which helps him understand the recommendation given more easily. In future research we aim to operationalize this algorithm on a mobile app and then try to do a qualitative evaluation of the ability of the algorithm in providing more satisfaction to the user. Though, the existing dataset is sufficient for gaining insights on the appropriateness of our algorithm, a qualitative study is required to show the benefit of using checking in motivation for enhancing POIs recommendations.

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