iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 6 **Issue:** VI **Month of publication:** June 2018

DOI: http://doi.org/10.22214/ijraset.2018.6053

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 6 Issue VI, June 2018- Available at www.ijraset.com

Geographical Location based Service Recommendation

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***Abstract*: Food recommendation system is an extremely well known service whose precision and advancement continues expanding each day. With the coming of cell phones and web technologies like 3G or 4G, this has turned out to be available by each purchaser. In this paper, we propose a recommendation system which can able to find out best food for users based on the location of that person. Proposed method has various phases such as, feature extraction, feature vectorization and finding cosine similarities for each of the users to best match their tastes.**
Keywords: Machine Learning, Recommendation System, Location Based Service.

I. INTRODUCTION

As of late , with the fast advancement of mobile gadgets and universal Internet get to, social system services, for example, Facebook, Twitter, Yelp, Foursquare, Opinions, wind up pervasive. As indicated by measurements, smart phone users have created data volume ten times of a standard cellphone. In 2015, there were 1.9 billion smart phone users in the world, and half of them had gotten to social network services. Through mobile gadget or online location based social systems (LBSNs), we can share our geographical position data or check-ins. This administration has pulled in a huge number of users. It additionally permits users to share their experiences, for example, surveys, ratings, photographs, check-ins and moods in LBSNs with their companions. Such data brings opportunity and difficulties for recommender systems. Particularly, the geographical location data overcomes any issues between this present realities what's more, online social system services. For instance, when we look through a restaurant thinking about accommodation, we will never pick a faraway one. Additionally, if the geographical location data and social systems can be joined, it isn't hard to find that our mobility might be affected by our social connections as users may incline toward to visit the spots or expend the things their friends visited or consumed previously. As we would like to think, when users take a long journey, they may keep a decent feeling and attempt their best to have a pleasant trip. The greater part of the services they devour are the neighborhood highlighted things. They will give high appraisals more effortlessly than the nearby. This can help us to compel rating prediction. Moreover, when users take a long distance travelling a faraway new city as strangers. They may depend more on their neighborhood companions. Hence, users' and their neighborhood companions' appraisals might be similar. It encourages us to oblige rating prediction. Besides, if the geographical location factor is overlooked, when we scan the Internet for a travel, recommender systems may suggest us another beautiful spot without thinking about whether there are nearby companions to help us to design the outing or not. Yet, in the event that recommender systems consider geographical location factor, the recommendations might be more humanized and thoughtful. These are the inspirations why we use geographical location data to make rating prediction.

A. With the above Inspirations, the Objectives of This Paper Are

1) To mine the relevance between user's ratings and user item geographical location distances, called as user-item geographical connection.
2) To mine the relevance between users' rating contrasts and user-user geographical location distances, called as user-user geographical connection.
3) To discover the similar interest to users.

In this paper, three components are taken into thought for rating expectation: user-item geographical connection, user-user geographical connection, and interpersonal interest similarity. These elements are intertwined into a location based rating prediction model. The curiosities of this paper are user-item and user-user geographical connections, i.e. investigate users' evaluating practices through their geographical location distances. The principle commitments of this paper are condensed as takes after: Mine the significance between ratings and user item geographical location distances. It is found that users more often than not give high scores to the things (or services) which are exceptionally far from their action centers. It can help us to get it users' appraising practices for recommendation. Mine the significance between users' rating contrasts and user-user geographical distances. It is found that users and their geographically far away companions more often than not give the comparative scores to a similar thing. It can help us to comprehend users' rating practices for recommendation. Incorporate three components: user-thing geographical connection, user-user geographical connection, also, relational intrigue likeness, into a Location Based Rating Prediction (LBRP) demonstrate. The proposed show is assessed by broad experiments based on dataset. Experimental outcomes demonstrate critical change analyzed with existing methodologies.

II. LITERATURE SURVEY

Xiaoliang Fan et al. [5], proposes a novel ubiquitous Web service recommendation approach to context-aware recommendation based on user location update (CASR-ULU). First, it model the influence of user location update based on user preference expansion. Second, it perform the context-aware similarity mining for updated location. Third, itpredict the Quality of Service by Bayesian inference, and thus recommend the ideal Web service for the specific user subsequently. Md Farhadur Rahman et al. [6], not only illustrate the design and accuracy of our underlying aggregate estimation techniques, but also showcase how these estimated aggregates can be used to enable exciting applications such as hotspot detection, info graphics, etc. Demonstration system is designed to query real-world LBS (systems or modules) such as Google Maps, WeChat and Sina Weibo at real time, in order to provide the audience with a practical understanding of the performance of ANALOC. Budsabawan Jueajan et al. [7], This project aims to develop a location-aware place recommender system on Android smart phones. Recommender system consists of two major components: 1) place recommendation and 2) Android mobile application component. A user-based collaborative filtering scheme is applied to predict the nearest places for the android user based on his/her GPS position from a mobile device. Chuan Shi et al. [8], first study thecorrelations in real data sets and propose the expenditure aware rating prediction problem. From the data sets crawled from a well-known social media platform Dianping in China, we find some insightful correlations between expenditures and rating scores: 1) transactions or experiences with higher expenditures usually lead to higher rating scores; 2) when the real expenditures are higher than users' normal spending behavior, the users usually give higher scores; and 3) there are multiple grades of expenditure behaviors. Jianxun Liu et al. [9], proposes a location-aware personalized CF method for Web service recommendation. The proposed method leverages both locations of users and Web services when selecting similar neighbors for the target user or service. The method also includes an enhanced similarity measurement for users and Web services, by taking into account the personalized influence of them.

Md Farhadur Rahman et al. [10], considers a novel problem of enabling density based clustering over the backend database of an LBS using nothing but limited access to the kNN interface provided by the LBS. Specifically, a key limit enforced by most real-world LBS is a maximum number of kNN queries allowed from a user over a given time period.

III. METHODOLOGY

In this section we will discuss about the proposed work flow of recommendation system. The system recommends the perfect food for the customers which will result in increase of sales. Fig.1. Shows the proposed system architecture.

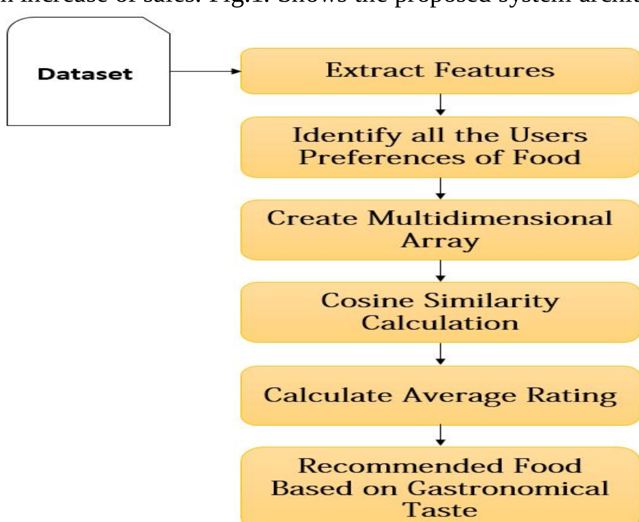

Fig. 1. Proposed System Architecture

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 6 Issue VI, June 2018- Available at www.ijraset.com

In this paper we mainly focused on getting similar taste users and analyzing their food in order to recommend new user based on his/her past food eating habit.

A. Datasets

The database considered are Yelp database. It is the collection of multiple food, restaurants and users lists. The users are also listed based on the location. The detail description of dataset are presented in Result section.

B. Extract Features

In order to construct the multi dimension feature vectors we need to extract the features which are categories. The most common feature among different features are extracted. Feature such as Burger, Pizza, Dosa etc are extracted.

C. User Preference Food Identification

Getting a cumulative score for each feature the user is associated with normalized by the max rating score value available for each particular user to retrieve user preference food.

D. Cosine Similarity

Figuring cosine similarity of all customers towards our reference customers. Cosine similarity may involve values from 0 - 1 => high cosine similarity near 1 implies that 2 customer's preference vectors are of a similar course (clients have comparable inclinations): low cosine similarity near 0 implies that vectors are orthogonal (clients have no comparative preference).

Cosine similarity equation given by:

$$Similarity = \cos(\theta) = \frac{A\,.\,B}{||A||\,||B||}$$

Where, A and B are users preference vector.

E. Weighted Average Rating

Figuring weighted normal business evaluations as a proportion of entirety of quadratically balanced customers ratings and total of squared customer's similitudes. This approach enables us to give more weight to comparable customers and stifle ratings of customers with low similarity.

IV. RESULTS

In this section we present the result of experiments performed by recommendation framework. The dataset used are Yelp dataset which are available online. The snap shot of database is shown in below figure.

{"yelping_since": "2013-07", "votes": {"funny": 4, "useful": 2, "cool": 1}, "review_count": 4, "name": "Dickman", "user_id": "kTpGfnUhc2EBWQCB14Ggkw", "friends": [], "fans": 0, "average_stars": 2.0, "type": "user", "compliments": {"funny": 2}, "elite": []}

Fig. 2. Shows the snapshot of Yelp-User Dataset

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{"business_id": "vcNAWiLM4dR7D2nwwJ7nCA",
"full_address": "4840 E Indian School Rd\nSte
101\nPhoenix, AZ 85018", "hours": {"Tuesday":
{"close": "17:00", "open": "08:00"}, "Friday":
 {"close": "17:00", "open": "08:00"}, "Monday"
: {"close": "17:00", "open": "08:00"},
"Wednesday": {"close": "17:00", "open":
"08:00"}, "Thursday": {"close": "17:00",
"open": "08:00"}}, "open": true, "categories":
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Goldberg, MD", "neighborhoods": [],
"longitude": -111.98375799999999, "state":
"AZ", "stars": 3.5, "latitude":
33.499313000000001, "attributes": {"By
Appointment Only": true}, "type": "business"}
```


Fig. 3. Shows the snapshot of Yelp-Business Dataset

9/2/2014

What a great place for a random night.

I stumbled upon this place on Yelp one night when I was out alone on a work trip to SF. I stopped in for a drink and stayed for a few hours. I love the charm of this place and the welcoming nature. The bar kind of naturally selects for people willing to have a conversation with the person next to them. Also, there's a great burger place nearby that you can go and bring food back from (grab a burger for the bartender too).

Fig. 4. Shows the snapshot of Yelp-Review Dataset

The yelp dataset contain review for each of the users posted on the yelp website. It also contains the longitude and latitude of the users for which they are provided review.

The result is presented in fig.5. Which shows the recommendation of food based on geographical location and taste of user.

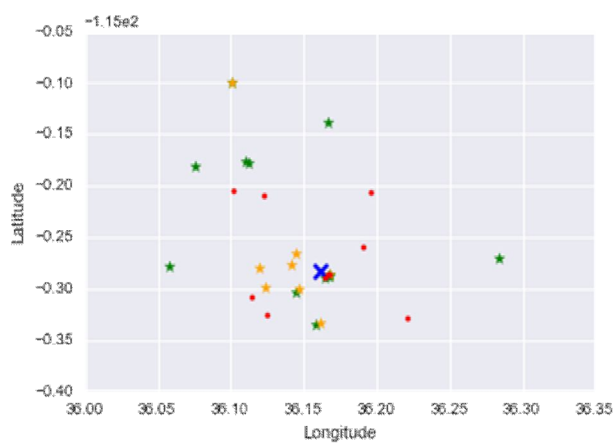

Fig. 5. Shows the geographical position of the user preference of food.

The figure above shows restaurants locations which have been reviewed (green stars) and tipped (orange stars) by the reference user. Red dots correspond to businesses locations that are recommended for the reference user based on user`s preferences and reviews of other users with similar preferences. Blue cross indicates reference user`s median location We can also see that there is one overlapped recommendation for this particular reference user. Overlapped recommendation is the business which has been recommended by the engine and actually reviewed by the reference user.

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V. CONCLUSION

This experiment proposes a model that consolidates confinement, personalization and substance based recommendation in a dynamic and omnipresent condition. An alternate and unsocial type of personalization that is just gotten from the client's conduct and takes into account his needs is composed. In this paper we proposed a Nobel mechanism in order to find the besting matching food for the customers, we find the similar preference and taste of the different users and correlate them in order to extract the useful information. The information are extracted is most suitable food for customer "X" in that particular restaurant based on the location.

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