***A Hybrid Recommender System with User’s Reviews Sentiment Analysis for Business Recommender System***

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Abstract

In the era of internet where people has access to internet from different devices, providing a good recommendation about the business will be beneficial to the user as well as the business owners and saves an ample amount of time that the user would have spend looking for a place of interest and still may end up unsatisfied. With the global use of mobile applications and websites such recommendation systems are gaining too many active users and while people are searching such systems before spending money on local business. Due to popularity of such business recommendation systems like yelp.com, Groupon, Foursquare, etc. people are searching for businesses over such systems rather than traditionally they were searching over web like google or Bing. With large amount and diversity of information available over such systems, it is getting a time consuming and challenging problem to predict and show the user what can be more useful, valuable and relevant to what they are looking for and how they are feeling at real time. Using customer reviews and ratings can be instrumental in predicting the success and sustainability of businesses. Our system will try to overcome the problem of information overload by providing user with a good recommendation about the business that is in the proximity of the user location. Not only we check the nearest location of interest, we also take in consideration the contexts (time and geo-location, etc.) In which the user is expecting the recommendation. To make a solid recommendation, our system relies on the ratings related to a particular business that is in the vicinity of the user location. But, using only the ratings for a recommendation may end up with the same recommendation to multiple users each time and that violates the norm of a good recommendation. To overcome this issue, we use individual user generated reviews with the help of sentiment analysis to further filter our recommendation so that user doesn’t end up with the same recommendation each time in the same context. Related works that include reviews in recommendation paradigm has shown to provide better and much more personalized recommendation. Therefore, we use the pros of both the user generated reviews and ratings to provide a better-personalized context aware user recommendation. Our work will demonstrate that combining all of the above mentioned features will generate a much better recommendation than solely relying in any one of them.

**Keywords:**

Collaborative filtering; content-based filtering; hybrid recommender systems; Sentiment analysis; Opinion mining; Business review

Introduction

Business Recommendation System has been an interesting area of research soon after the different kinds of recommendation systems have gained popularity. Everybody wants a system that could provide him or her suggestions about which place to visit related to the purpose of their visit. Because Internet has become so omnipresent and mobile devices are becoming ubiquitous; people have different ways of accessing the internet, they would love to have recommendations that could not only save their valuable time but also meet their satisfaction of their visit to an unknown place. Our system tries to fulfill this necessity by providing a solid recommendation about the different places that may be of interest to the users based on the search query that they are typing. Existing base-line recommender systems using content based or collaborative based or context based and totally rely on the ratings given by the user or the businesses as their relevancy criteria.

As number of users are increasing, the number of online business reviews continues to increase. Many social recommendation social site like yelp.com, Groupon, Foursquare, etc. provides both combination of a star rating and a review writing facility to express the feeling and experience of any business services. Rather than believing on word-of-mouth, such online reviews and rating are greatly influencing any new or existing business customers. But the structure of star score and the review might have some contradictions. For example, some business may have a high star rating whereas the review may be not so good to prove it. Furthermore, since these systems totally rely on the ratings that they already have about a particular business, there is a possibility that the businesses manipulate the ratings causing the information that is provided to the user to be not necessarily correct. Therefore, it may be very useful way to classify the review’s content based on the sentiment which can be further used as a parameter to improve the ranking of any search result. Thus before looking any rating, user needs to look at the hidden meaning behind the reviews content which are both informative and expressive and can be very useful for re-ranking of search. Since user intents and purposes essentially vary with individual, business recommendation needs to be both contextual and personalized.

According to survey conducted by Inc. Magazine most reviewers (sometimes called "Yelpers”) are "well-intentioned" and write reviews in order to express themselves, improve their writing or be creative. Many reviews are written in an entertaining or creative manner. So even based on those reviews systems can be irrelevant and noisy while suggesting a good business to customers. According to a study conducted by Nielsen[16], a whopping 85 percent of consumers find local business information online, where reviews, store hours, deals and maps are just a click away. It is found that the proportion of people who visit Yelp will call or visit a local business and also do some purchase is very high. But still the study is only done specifically based on the ratings and reviews. Nielsen[16] found that online reviews are among the most trusted sources for information for consumers, with 70 percent of them finding online opinions somewhat or completely trustworthy. But the trusted level is not analyzed and what might be the real meaning behind those reviews and user’s current context and preference need to be thoroughly analyzed and used for effective ranking the search result. This is one of the main goal of this paper.

Related Work

Recommendation is a ranking problem. A new problem in the form of reliability and trustworthiness of reviews is prevalent that is why we trying to analysis the sentiments underlying the reviews of the customers. Previous research on Recommender Systems (RS), especially the continuously popular approach of Collaborative Filtering (CF), has been mostly focusing on the information resource of explicit user numerical ratings or implicit (still numerical) feedbacks. However, the ever-growing availability of textual user reviews has become an important information resource, where a wealth of explicit product attributes/features and user attitudes/sentiments are expressed therein. [13] There is concern that the Yelp ratings have being manipulated by the businesses with an intention of increasing the revenue.

The analysis which done by Michalis Potamias[1] focusing on Yelp rating by analysis the importance of identifying and removing the biases rating from Yelp reviews. In this way, the possible fair and better result would help both the consumer and the business. Some works has been done to implement a hybrid recommender system for improving e-commerce recommender systems[2][3]. They have grouped the users based on user- specific rating data and use a weighted hybrid recommender system (WRCCF) where RCF (combination of RBR and Collaborative Filtering (CF)) and CCF (combination of case-based reasoning(CBR) and Collaborative Filtering(CF)) schemes are combined to let the system more effective prediction. Moreover, some works have been done on Senti-lexicon and improved Naïve Bayes algorithms for sentiment analysis of restaurant reviews[4] which classify a review based on a positive or negative sentiment using the supervised learning algorithm. Another concern that has been described is the existence of the potential for abuse of this rating system among papers[5]. On the papers they online ratings and reviews the results presented in this paper demonstrate that the cumulative rating of restaurants as a whole converge, whereas the reviews of individual restaurants have fluctuating behavior. Some work related to propose the generic location-aware rank query (GLRQ)[6] are not used on business recommender system where location-aware ranking is make a great influence to the potential customer.

Another similar work is related to classify the user reviews into the “context rich” specific and “context poor” generic reviews and present a word-based and an LDA-based methods of extracting contextual information from the specific reviews[7] which analyze the contextual information in each user reviews. This information can be very helpful to integrate with the ranking model to come up with efficient ranking algorithm. One old research was done on Location Based Context-aware Recommendation System [17] which is immature and based on user preference and personalization this make the recommendation more context-aware but they only consider the implicit user input to get the mode of user’s current transportation mode, spatial location and mood. There is less work done on analyzing the sentiment behind the user’s reviews that can be more subjective and opinionated to some context while posting that particular opinion. Our project will also integrate the missing part for retrieving the search result that will analyze the sentiment and influence of various types of review for different businesses. It will predict the usefulness of a review is the reviewer’s impact metrics score. We propose a regression model that predicts the usefulness rating of each user’s review and its impact on user’s feedback.

Project Description

Specifically, the system should have (1) background data, the dataset that the system has before the recommendation process, (2) input data, the information from user to communicate the system in order to produce the recommendation, (3) the algorithm that combine background and input data to achieve the suggestion. The background data have been organized by Yelp and the dataset is describe on validation section. This project focus on input data and the algorithm to implant the system. Since our system is context aware recommendation system we would like to point out the features that we are going to implement in our system so that they could actually define the particular user preferences. Context is a dynamic set of factors describing the state of the customer at the moment of the customer's experience. The things that we are going to consider while making a context based recommendation to the user are mentioned below. Location: considering the proximity of the user’ location, distance, age, time of day: morning, afternoon or night, day of the week: weekday or a weekend; seasonal trends; type of the place (e.g. club, restaurant/cafe, bar, food/beverages), average rating of the place, and number of reviews in last month.

First, we propose a joint matrix factorization model that not only factorizes the user-business rating matrix but also exploits contextual information. Such context-aware suggestions with Multi-Criteria will make more accurate recommendation based on user’s preference and search and narrow down the decision making problem. For example, in case of Yelp, customer reviews contain valuable contextual information about customer experiences of interacting with Yelp businesses, such as restaurants, bars, hotels, and beauty & spas. By analyzing these reviews, we can discover various types of rich and important contextual information that can subsequently be used for providing better recommendations.

To get the current user location we make use of the Google API to find the current location of the user. This also gives us the distance or the proximity of the user location so that we can recommend user the businesses that will be feasible to the user. For example: the user cannot be recommended the business that is too far or even in another city even if the business most likely to be preferred. Similarly, the day has an impact on the recommendation too. Most people would like to visit a place that may be a bit far in weekends rather than in weekdays. So during weekends they will prefer near place even if that is not as good as the other place. Another thing is the time of the day, they may prefer a place according to the time. They may not want to go to places in the morning which opens late in the day or to places in the night which closes early than users preferred time. Finally, we look at the seasonal trends too. To state it precisely, what is getting famous these days? What kind of businesses are getting popular? What kind of locations people are preferring these days? All of these are taken into consideration while providing a recommendation to the user.

Firstly, we have already mentioned the context-aware features that we are going to take into consideration. The next area we have focused is the content based recommendation This not only narrow down the search domain and understand what actually user want to do but also eliminates the cold start problem that the system faces when there is no information about the current user. This is the advantage of the content based filtering that we are embedding in our system. Next thing that we are including in our system is the collaborative filtering mechanism. Collaborative filtering approaches build a model from a user’s past behavior. Since it has gained a lot of popularity within the recommendation system realm, we will implement the pros of this filtering technique in our system. The advantage of using this method is to personalize a user's need by collecting the data about the user previous recommendations, search queries and his/her reviews.

We can future integrate Association rules like Past check-ins, reviews and rating used to find relationships of common user’s preferences. We can use these information to generate a weight vector for a user and check this vector with all the different vectors that has been clustered based on the features of other users. Then the most similar user is calculated and analyzing the context of the current user, we recommend him/her the business that the most similar users reviewed positively or visited or even rated highly. The idea of personalized recommendations sounds like a great idea, though obviously it’s a hard problem to solve. The social interactions like friends, family, foodies, chefs, or anyone else you trust to be ranked on top position while searching will make the recommendation system more trustworthy. Again this eliminates the cold start and user’s data sparseness problem that we mentioned earlier. But again there is another problem, the review count that is if the review for a particular business is mostly positive does not necessarily imply that the test user will like it. There may be some inclinations of the user that is peculiar to him/herself. Therefore, this need to take in account the previous review that the user had given. Even if both the user fall in the same cluster, they may not be that similar that every places that the trained user likes is also liked by the test user. To eradicate the problem mentioned above we bring the reviews into play. "What is my motivation for writing this review?" Well the problem is people don't do that frequently. Also systems don’t compelled them to write reviews on services like Yelp even they feel satisfied or not. Such lack of sufficient data for a business can cause sparseness of user’s data and can cause cold-start problem i.e. a recommender system doesn't have enough data on the new cool place to confidently recommend it to a user.

How reliable and trustworthy are Yelp reviews for individual users. This may vary with my taste preferences of individual and don't seem to coincide with most reviewers’.  Initially, reviews are also used to generate meaningful recommendation to the user based on the context. The business that are in the user’s vicinity are analyzed with the review count that the business has and if the business matches the user’s mood then the recommendation is most likely to the liked by the user. How about predicting star ratings using sentiment analysis? To answer this question we need to calculate the importance of the reviewers. The reviews and ratings be given a greater weight within that space. We need to sort the unqualified reviewers and their reviews and rating while making a ranking judgment. Based on this trust-level of individual reviewer, we can find out whether it is noise information or valuable information for re-ranking the search results. The recommendation that has the highest similarity is recommended rather than going will the highly rated or positively review recommendation of the similar users. So, now our hybrid system takes a two level collaborative filtering: First one user-based collaborative filtering and the second one item-item collaborative filtering (in our case, business-business collaborative filtering). This is expected to better personalize the user as soon as we have enough data for the particular user and the other users that have been actively reviewing, rating and visiting the large number of business time and again. Using the sentiment analysis on the reviews provided by individual users, we label the places the user visited and reviewed as either positive or negative recommendation for the particular user. This can be then used to refine the recommendation next time when the same user is in the similar context. We think that this can play a vital role in making our hybrid recommendation system a bit different and more of an optimal personalized recommendation system so that the user can use it effectively whenever a business recommendation is needed.

One primary concern we need to focus is the location of the current user and locality of available businesses. If someone travel to a new city or if he/she on a city block, he/she should be able to get great recommendations for places near him/ her. People will likely to go to the business that is near where they are now. Currently it is based on their importance to a customer which is directly derived from the Rating, number of reviews and reviews from someone he/she knows like family or friends. But it seems there is less research done on the implication of what actually the review’s content. So our framework will analysis the content and figure out the real sentiment behind posting that reviews. This can be a valuable insights that can help any business to drag attention of a potential customer and can help to drive profitable growth. But easier said than done, how can we analyze the review so that the user sentiment is taken into consideration and we output the exact polarity of the user content precisely either negative or positive. In recent research, a sentiment lexicon method has been implemented that improves the way we classify the user’s review. An index of sentiment words are presented and it determines the polarity of the relevant word that denotes whether it has a positive sentiment in it or a negative one. We are trying to implement this concept in our sentiment analysis part where the number of positive words and negative words in a review are generated and then we find out which sentiment outrank the other one. The one with most number of words is the label we give to the review. In other words, if the number of positive words are more than negative, the overall review is positive and if the negative ones has higher number it is labeled as negative. The sentiment lexicon represents an index of sentiment words, and it has the polarity information of the relevant word irrespective of whether it carries a positive sentiment or a negative sentiment. Finally, there are occasionally times when the positive classification accuracy and the negative classification accuracy are not accurate in the sentiment analysis. This becomes a factor in lowering the average classification accuracy. Thus there is a need to improve the average classification efficiency by increasing the accuracy of the relatively lower area between the positive and the negative. We will go one step further and classify positive or negative sentiment associated with the word usage in reviews. We will propose an improved Naive Bayes algorithm to measure its effectiveness when the accuracy.

Our framework will integrate the context-aware parameters, social interactions between other existing customers and meaning of the posted reviews and rating in unified way so that it will give an accurate recommendation to user to make a good decision. This approach will be helpful to enhance the ranking efficiency of overall recommender system so that it will promote the accurate business catalog on the top position.

Validation

Evaluation is a key factor to reflect the quality of a recommender system algorithm. For that purpose, we have the Yelp dataset that will help in in our validation process. Most of the data in that dataset contains all the relevant information that we need for training our context aware hybrid recommendation system.

**Experimental Setup**

**Dataset:**

We will analyze the performance of our hypotheses over datasets collected from Yelp. Our project use case is focused on Yelp.com, to extract opinions on different categories, which includes services, shopping or restaurants, etc. Yelp is a crowd-sourced local business review and social networking site and also has mobile app, as of 2012, 45 percent of Yelp searches are done from a mobile device. [18] Where businesses can be listed and customers can review about those local businesses. Users can write a review and rate a business with one to five star rating system. Other users can give a review a "thumbs-up" if it is "useful, funny or cool.” Yelp also offers search functionality: users can search for local businesses using terms and locations. Yelp responds with relevant search results displaying the average review rounded in half stars (e.g., 3.5, 4 stars etc.) and the number of reviews that the business has received. The average rating may be viewed as a metric for the quality of the business while the number of reviews give confidence to that value. The same users can check-in and review a business multiple times, making Yelp’s number of reviews and average review score susceptible to manipulations and biases. Yelp’s number of reviews and average review score susceptible to manipulation. This is the main problem that can be suggest and rank an inaccurate and false business to a customer on top position while searching.

There are 1.6M reviews and 500K tips by 366K users for 61K businesses. Besides, this data provide 481K business attributes, e.g., hours, parking availability, ambience. The Yelp Challenge dataset is much larger and richer. There is 85 percent of small businesses listed on the data have been rated for three stars or better, but some negative reviews are very personal or extreme even most of reviews are written with good manner. This project would setup limitation for activity reviewer and filter the abnormal reviews. However, any customer with a rant should be able to rant to the business, and the business should have a chance to respond before a rant affects their ratings. The project will try to simulate true behavior of business.

The Yelp dataset contains reviews of various businesses, such as restaurants, bars, hotels, shopping, real estate, beauty & spas, etc., provided by various customers of Yelp describing their experiences visiting these businesses, in addition to the customer-specified ratings of these businesses. The available dataset contains the objects below which are the different aspect for the project to approach. Business Objects contain basic information about local businesses, and the 'business\_id' field can be used with the Yelp API to fetch more information for visualization. Review Objects contain the review text, the star rating, and information on votes Yelp users have cast on the review. User Objects contain aggregate information about a single user across all of Yelp.

**Evaluation metrics:**

We can evaluate the performance of our proposed framework by calculating the quality i.e. average ratio of the number of relevant business result of the resulted recommendation business lists. The basic to do it to calculate relevance of the business that is queried on top-n position to the current user and another metrics can be done using mean average precision (MAP) for each query. We will use prediction accuracy metrics and classification accuracy metrics. To evaluate it we can use location-aware rank query include the (k-) nearest neighbor (NN) query and location-aware keyword query (LKQ, a.k.a spatial keyword query). From the dataset of yelp, we can get the context of 'longitude', 'latitude' for user’s location and the local businesses.

Since we have a lot of data we can make use of the every vital piece of information related to the businesses and users from this public dataset. Using these data, we can cluster the group of users into similar clusters that can help us in the user based collaborative filtering and the group of businesses that can aid us in item-based collaborative filtering. This will remove the problems associated with of user’s data sparsity, scalability, neighbor transitivity, and accuracy.

We will experimentally evaluate and assess the outcome with traditional approaches and our novel model. The significant and consistent performance gain will demonstrate the importance of using hybrid context aware model with sentiment analysis on the reviews will outperform the existing baseline models.

The given below methods are used for our system validation and evaluation purpose:

* Category-based diversification of recommendation lists
* Real-time incremental updates for many recommenders based on user implicit feedback
* Evaluation based on user engagement.
* It uses sentiment analysis to isolate the positive and negative sentiments from the reviews. We would use the reviews for sentiment analysis and monitoring. Reviews go hand-in-hand with ratings. The system will do the analysis on the reviews in order to predict an approximate rating for the review for current user based on preference and context.
* We will implement a sentiment engine that will gather opinions or determine sentiment expressed in reviews, a classifier module will filter keywords, sentences and words, and a polarity module will predict the polarity of a sentiment sentence for each reviews, and a scoring module will calculate a total weighted score for the business from users.
* So we can correlate the data from baseline model and proposed model to compare and evaluate which one is best performed.

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