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# A performance analysis of Rating Prediction System by analyzing sentiments from textual reviews

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**Abstract:** *With the introduction of Web 2.0; The users' generated content like Reviews, Feedbacks, comments, Web Chats, Votes (Likes | Dislikes), Ratings (Stars Ratings) have grown exponentially over time and provided great opportunity for Research Scholars, Organizations, Businesses to mine this useful information and make use of it for variety of novel work like Recommendations. As the time passed, the information overloading problem arrives. There is lot of users' generated data collected by Organizations and Businesses such as Reviews; How to extract useful information from these reviews and make a perfect recommendation is crucial. Traditional Recommender Systems (RS) considering a number of factors, such as product category, Stars Ratings, Location, user purchase history and other social factors. In this paper we have implemented the Recommender System as proposed by Lei et. al. [5]. The dataset was taken from yelp.com. Model Training is done by Latent Dirichlet Algorithm(LDA) along with Sentimental Dictionaries and Score computation methods as proposed by Lei et. al.[5]. The whole work has been implemented on MatLab (2016a) and experimental results were also analyzed.*

**Keywords:** *Recommender system, Rating prediction, Collaborative Filtering, Latent Dirichlet Algorithm (LDA), Sentimental Dictionaries, Machine Learning, Natural Language Processing, MatLab.*

## I. INTRODUCTION

As we all know, in a valuable reputation service customers make decisions that reflect consumers' comprehensive analysis of the real value of specific product. If we want to know the service reputation, text commentary is required. In our daily lives, most of the users buy those items that are quite commendable with positive reviews.

### 1.1 Web 2.0

Web 2.0 is a term used to describe the second generation of the World Wide Web, focusing on people's ability to collaborate and share information online. Web 2.0 mainly refers to the transition from static HTML Web pages more dynamic to a more efficient, and provides Web-based applications to users. The generic name of current Web development is Web 2.0. Developers are familiar to using the software version number, and the term Web 2.0 to ask for a new Web [1]. What is new to me is a major aspect and the focus of my research is user-generated content. It operates a counter with relationships between readers and publishers of traditional media. Mostly there are two suggestions given by readers, first one is that there are a number of readers than traditional publishers, secondly, mainly readers lack the editing and quality assurance of traditional publishers. More content usually means more information and to get more information means that you can make more informed decisions. However, the problem is that you can access almost 6,000 generated user comments 'Harry Potter book,' 1 can be quite overwhelming. You can also read the book together, forming your own opinion. So the question isif there are number of reviews for single product, for instance, if we say there are 10,000 reviews than a recommended system will be provided for analyzing all reviews instead of checking each.

### 1.2 User generated reviews

User-generated reviews play an important role for potential consumers in making purchase decisions. Due to the growth of internet business, more and more web sites are providing services by requesting users leave reviews after they finish a transaction [2]. “Online product reviews provided by consumers who previously purchased products have become a major information source for consumers and marketers regarding product quality”. In fact, user-generated reviews are collectively considered as a rich source of information to help buyers make purchase decisions and are increasingly showing up as a new generation [3].Generally, reviews are mainly divided into two groups named as positive and negative group. However, it becomes tough for buyers to choose the products when all users reflect positive or negative sentiment. But you also need to know how good the product is. This happens because different people have different sentimental expressions. For example, , some users prefer to use 'Good' to describe a 'better product, while others may use 'good' to describe a 'poor ' product [4].

### 1.3 The information overloading problem

In recent years, we have seen abundant review websites. It provides a great opportunity to share ideas we buy a variety of products. However, we are faced with the problem of information overloading. How to tap important information from reviewers, to understand the users’ preferences and make accurate lifelong recommendations is crucial. Traditional system recommendation (RS) system considers different factors like user account purchase history, product category and geographic location and other factors [4]. As seen in fig.1, as the information processing is increased the accuracy of making decision also get increased until it reached at peak. After that when information load get overloaded shown by the darken area the decision making accuracy starts decreasing [5].

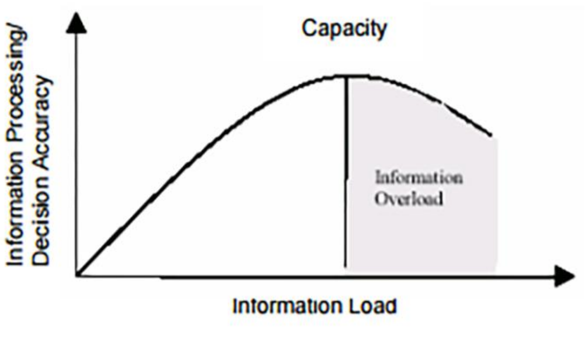


**Fig.1:** Information overload

### 1.4 The recommender systems

Recommended system of research article is useful applications, which help researchers keep track of their field of study. Recommended system usually provides a list of suggestions in one of two ways named as collaboration filtering algorithm and content based algorithm [6].

**Content based algorithm**: In this recommendation system will work with the profile of users that were created at the beginning. A profile contains information about users and their taste. The taste is based on user review points. In the recommendation process, project engines will compares the rate that were already positive rated by the user with the items he did not rate and look for similarities. Thus, the most similar positive project reviews are recommended for the user.

**Collaborative filtering Algorithm:** This system was described by Paul Resnick and Hal Varian in 1997.The recommended system has become one of the most studied technical recommendations of the system, since Paul Resnick and Hal Varian mentioned and described this way in 1997. Collaborative filtering ideas are to find the user in a shared community appreciation. If two users have the same or almost same project review, then they have the same taste. Such customers make a group known as neighborhood. Users get advice on his / her previous projects that did not score, but have been positively reviewed within his/her neighborhood [7].
Importance of recommender system is to overcome the overloading problem that will occur in social media site, books site, movies/videos sites or in online shopping sites like Myntra, Amazon etc.. Recommender system will help the customers to find the products according to their requirement.

### 1.5 Sentimental analysis

In order to obtain the reputation of the products, we must provide a review advice. Under normal circumstances, if a review of projects reflects positive emotions, the project can enjoy a good reputation to a great extent. On the contrary, if the project review is full of negative emotions, then it reflects the bad reputation of the project. For a given product, if we know the user's mood, we can indicate that the reputation is even a comprehensive rating. Whenever users search for any new products, they first read their positive and negative comments that are valuable to be as reference. For positive comments, we can understand the benefits of the product. For negative tests, we can get the disadvantage of being cheated.

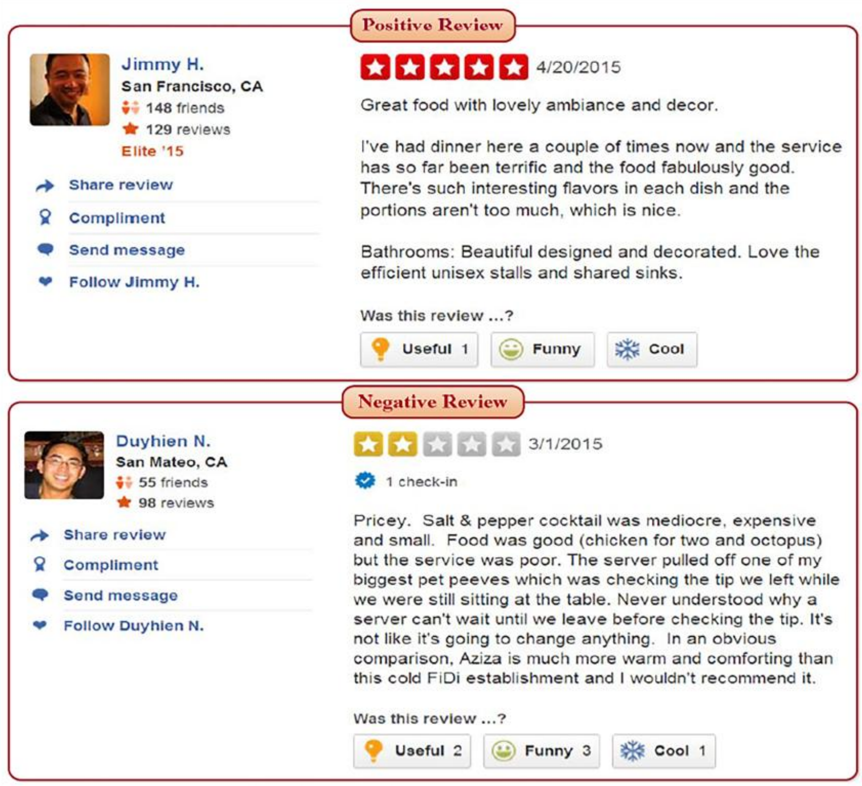


**Fig.2:** An example of positive review and negative review on Yelp website.

However, user's sentiment is hard to predict and the unpredictability of interpersonal sentimental influence makes a great difficulty in exploring social users. Initially, product features are extracted from user's review using LDA. Then their sentimental words have been find out that gives the product features.

**To determine the sentiment of a specific user on an product we use sentiment dictionary.** A shown in fig. 3 the last user is interested in those product features, so based on the user reviews and the sentiment dictionaries, the last item will be recommended and stored into the recommender system.

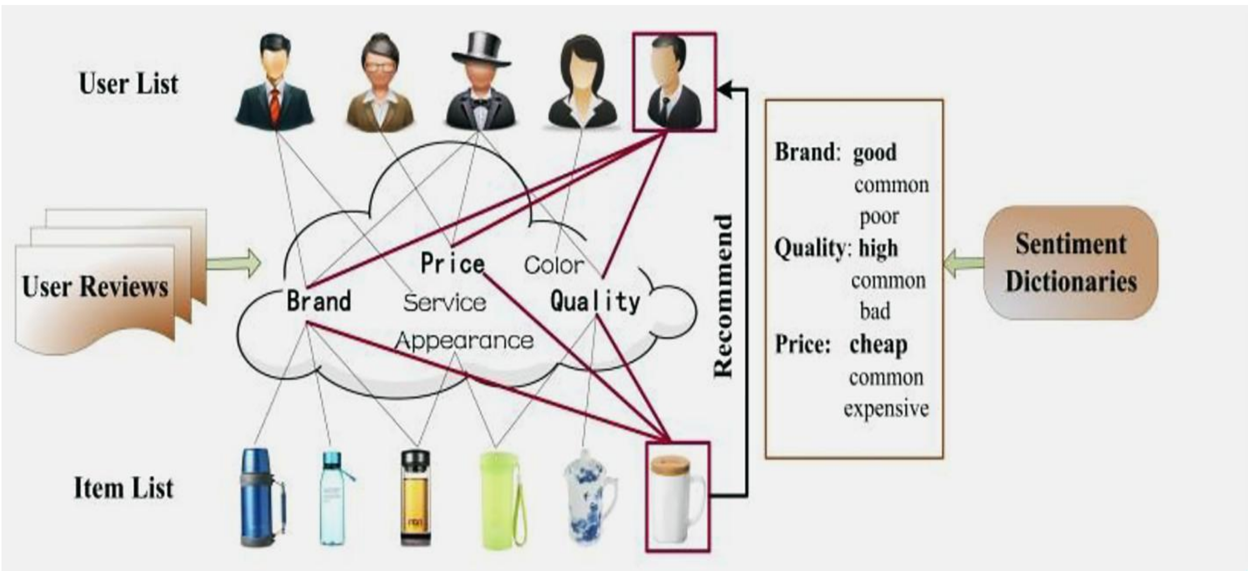


**Fig.3** Recommended system

The product features are collected on the basis of their Brand, price and Quality. Then Sentiment dictionary has been constructed by extracting the sentimental words from the user's review. Thus, at last users choose that product which has more positive sentimental review and then product will be recommended to the customers [8-10].

The remaining paper is organized as follows. Related work about recommender system was presented in section II. In section III, Algorithms and methodology of the proposed work has been discussed, Simulation results and conclusion have been discussed in section IV and V respectively.

## II. Related Work

In this section, we are presenting the previous work done by different authors related to our algorithm. **Karen H. L et al. [11]** proposed a system to combine tag in recommender system by extending the user-item matrix and then applying algorithm that fuses two popular recommended system (RS) algorithms such that the correlations between users, items and tags can be captured simultaneously. The aim of this algorithm was to give basis idea about the product that were used in past. **X. Wang et al. [12]** proposed a POI recommendation algorithm by incorporating venue semantics as a regularizer. **Parisa Lak1 et al. [13]** used Matrix factorization model to solve the cold start problem. Authors used 1M dataset. Matrix factorization is one of the mostly used model for low-dimensional matrix decomposition. **Lin Zhao and Bo Xiao [14]** proposed two methods named as CW-MF that consider user's preference on the basis of categories and NICW-MW consider the impact of user's neighbors so that preferences between users and their neighbor get minimized. **X. Yang et al. [15]** proposed a model to increase the efficiency of the recommendation system by using the concept of indirect circles of friends. **K. Zhang et al. [16]** experiment on customers reviews taken from Amazon.com website as an input data to the product model. On their basis product ranking has been produced that was closely related to the ranking reported by the retailers. **Wenjuan Luo1 et al. [17]** solved the problem of identifying and rating, in unrated reviews. Authors proposed a LDA-style model that produced ratable aspects over sentiment and associates modified with ratings. **Pang et al. [18]** proposed a context insensitive evaluative lexical method. But they did not deal with the mismatch between the base valence of the items and the author's usages.

## III. Proposed algorithms

The algorithms that we have used in the research work are described below:

**Algorithm #1:** Sentiment Dictionaries Construction
Input: How Net Sentiment Dictionary

**How Net Sentiment Dictionary:** Available at http://www.keenage.com/download/sentiment.rar

**Output:** .TXT files holding classified versions of SD, ND, SDD

**Step 1: LOAD How Net Sentiment Dictionary**& Remove Non-Latin Words (E.g. Chinese)

**Step 2: CONSTRUCTION** of **SD (Sentiment Dictionary)**

1. **FETCH POS-Words(Positive Words)** such as: attractive, clean, beautiful from **How Net Sentiment Dictionary**
2. **FETCHNEG-Words(Negative Words)** such as: annoyed, awful, bad, poor, boring, complain, crowed from **How Net Sentiment Dictionary**

**Step 3: CONSTRUCTION** of **ND (Negation Dictionary)**
**FETCH** frequently-used negative prefix words, such as "no", "hardly", "never", etc. from **How Net Sentiment Dictionary** to construct the ND

**Step 4: CONSTRUCTION** of **SDD (Sentiment Degree Dictionary)**
**FETCH** and **CLASSIFY** SDD into 5 Levels (Level-1, Level-2, Level-3, Level-4 and Level-5) from **HowNetSentimentDictionary**

**Step 5: STORE SD, ND** and **SDD** into text files (.**TXT)**

**Algorithm #2**—Sentimental Score Computation and Result Analysis

**Input:** TestDataset

**Output:** .MAT files holding the Results

**Step 1: LOAD** the **TestDataset** into Memory

**Step 2:** For each business category compute the Reviews Sentimental Score as follows

1. Computing Sentimental Score(**Sr**) for a Review(**r**)

a. Divide the original review into several clauses by the punctuation mark.
b. For each clause, firstly look up the dictionary SD to find the sentiment words. A positive word is initially assigned with the score +1.0, while a negative word is assigned with the score −1.0.
c. Find out the sentiment degree words based on the dictionary SDD and take the sentiment degree words into consideration to strengthen sentiment for the found sentiment words.
d. Check the negative prefix words based on the dictionary ND and add a negation check coefficient that has a default value of +1.0. If the sentiment word is preceded by an odd number of

negative prefix words within the specified zone, Reverse the sentiment polarity, and the coefficient is set to −1.0.

e. Now For a review r that user u posts for the item i, sentiment score is obtained as follows:

$$S(r) = \frac{1}{Nc}\sum_{c\epsilon r} \sum_{w\epsilon c} Qw * Dw * Rw \quad (1)$$

**Where:**
**c** denotes the clause.
$Nc$ denotes the number of clauses.
$Q$ denotes the negation check coefficient.
$Dw$ is determined by the empirical rule.

$Dw$ = [0.25, 0.5, 2, 4, 5].

When we have a level-1 sentiment degree word before the sentiment word, $Dw$ is set a value of 5.0; when we have a level-2 sentiment degree word before the sentiment word, $Dw$ is set a value of 4.0, etc. There is a one-to-one correlation between $Dw$ and five sentimental degree levels.

**2.** Computing Normalized Sentimental Score (**E**)

a. After obtaining the review r's basic sentiment score the normalize score is computed as follows:

$$E(u, i) = \frac{10}{1+ e^{-S(r)}} - 5 \quad (2)$$

**Step 3:** The Result Analysis

1. The graph is constructed for each Business categories and "Computed Sentiment Score" for each review is plotted aside "Actual User Supplied Sentiment Score" for the given Review. The X-Axis holds the "No. Of Reviews" whereas Y-Axis holds the "Rating Scores"

**2.** From the Graph the Differences between the Predicted vs the Actual Review Score can be analyzed easily for each business Categories.

Following are the steps used for the proposed work.

**Step 1:** Initially, we collect the data from yelp.com website which is around 3-4 GB. The collected data is in the form of JavaScript Object Notation (JSON) format.

**Step 2:** yelp consist 66,992 numbers of categories out of these categories we select eight categories named as Active life, beauty and spas, home services, hotel and travel, night life, pets, restaurants and shopping.

**Step 3:** clustering of these categories on the basis of star's rating has been done.

**Step 4:** Clusters has been divided into two forms named as Testing and Training Data set.

### Training dataset

a. In this step, features from the files have been extracted using LDA algorithm and then the files are stored in .m format. Here, the LDA algorithm extracts the features of the product like for restaurant category the product features are like, price, discount, waiter, manager, environment etc.

b. Now we will construct sentimental dictionary, which will count social user's sentiment in items. That is how we will manage positive evaluation word, negative evaluation words and sentimental words. For each category of words stores in different dictionary named as POS0words fro +ve word, NEG-words for –ve words and SDD for sentimental words.

### Testing

In testing phase, sentimental score on the basis of trained data has been computed for the test file. Then results have been analyzed for all the eight categories. The results obtained have been shown in the next section.

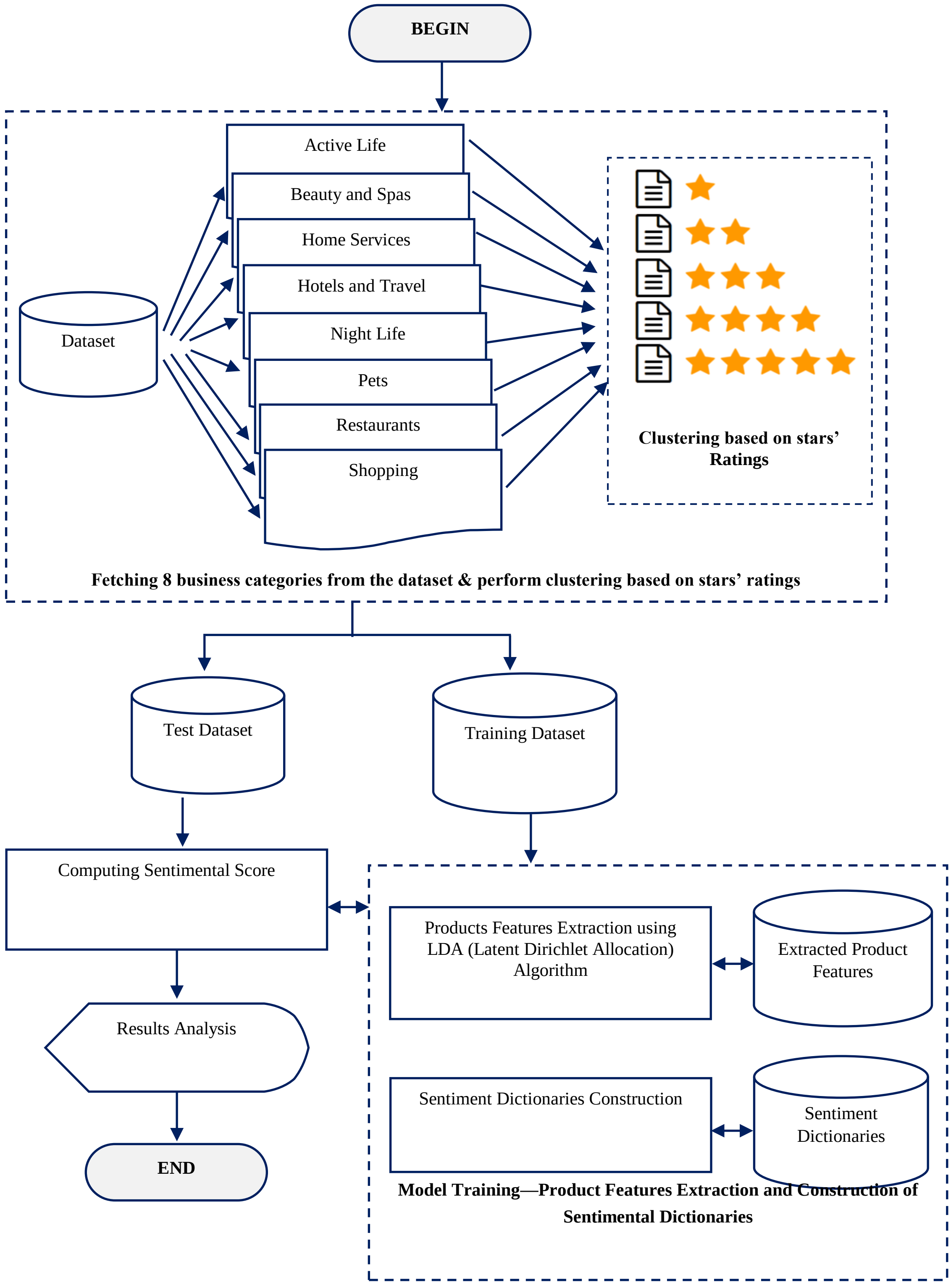


**Fig. 4** Flowchart of the proposed work

## IV. Simulation results

In this section, we are comparing our results with the existing results obtained from Yelp dataset. In table 1, the total performance evaluation of different eight categories of Yelp dataset has been displayed.

| **TheActual Users' Supplied Review Rating Scores** | **The Computed Normalized Sentiment Scores** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Active life** | **Beauty & Spa** | **Home services** | **Hotel & travel** | **Night life** | **Pets** | **Restaurant** | **Shopping** |
| 1 | 2.335091 | 1.224593 | 0 | 0.312094 | 4.801597 | -0.4157 | 1.354236 | 3.150755 |
| 1 | 1.370308 | -0.22712 | 0 | -0.27749 | 0 | 1.168479 | 2.310586 | 2.310586 |
| 1 | 1.742065 | -0.09614 | 0.597136 | 0.440035 | 1.126187 | 0.926666 | 0.49834 | 1.224593 |
| 1 | 3.607375 | 2.310586 | 0 | 3.807971 | -0.8257 | 1.607564 | 0.459228 | 1.976089 |
| 1 | 0.49834 | 0.677623 | -0.13885 | 1.791787 | 1.869104 | 2.310586 | 1.607564 | 1.970593 |
| 1 | -2.02063 | 3.048153 | 0.825702 | 2.05785 | 2.310586 | -0.57042 | 2.090191 | 3.021839 |
| 1 | -1.6342 | 0 | -1.79179 | 4.933071 | -4.77023 | 1.823746 | 3.279872 | 1.224593 |
| 1 | 0.669041 | 0.574376 | 1.403591 | 1.970593 | 0.621765 | 2.05785 | 0.52438 | 1.715307 |
| 1 | 1.224593 | 0.393919 | -0.88349 | 1.607564 | 4.36285 | 0.825702 | 0 | 1.055325 |
| 1 | 0 | 3.021839 | 0.467382 | 1.390927 | -0.62177 | -1.22459 | 0.621765 | 2.502601 |
| 2 | -0.55328 | 2.602127 | 1.700328 | 1.53931 | -0.62177 | 0.709466 | -1.3026 | 0.662744 |
| 2 | 1.171037 | -2.31059 | 4.241418 | 3.772526 | -1.97059 | 0.964331 | 0 | 3.411309 |
| 2 | -0.62177 | 0.059521 | 2.310586 | 1.94985 | 1.750795 | 0.825702 | 3.88095 | 0 |
| 2 | -0.4157 | 2.502601 | 3.807971 | -0.3743 | 0 | 0.283786 | 2.828935 | 1.881891 |
| 2 | 0.479293 | 1.379937 | 1.899745 | -0.26292 | -0.3743 | 3.776111 | 0.986877 | 2.310586 |
| 2 | 2.310586 | 3.519528 | 1.703299 | 1.224593 | 1.607564 | 1.681878 | 3.807971 | 1.791787 |
| 2 | 2.310586 | 3.97216 | 1.390927 | 0.744425 | 2.167854 | 1.224593 | 2.128141 | 3.581489 |
| 2 | 2.272608 | 3.781471 | 0.277492 | 3.519528 | -0.20821 | 4.573487 | 0.986877 | -0.98688 |
| 2 | 2.62542 | 2.62542 | 1.095242 | 1.53931 | 1.41834 | 4.525741 | 1.566583 | -0.4157 |
| 2 | 2.685248 | 0.117166 | -0.46738 | 1.224593 | -0.31209 | 2.733409 | -0.36394 | 1.41834 |
| 3 | 3.621583 | 2.976109 | 1.791787 | 3.242563 | 1.92642 | 1.776637 | 0.621765 | 2.772999 |
| 3 | 1.846015 | 1.472888 | 4.870463 | -0.49834 | 2.43168 | 3.411309 | 2.471243 | 0.544705 |
| 3 | 2.740778 | 4.350308 | 3.411309 | 4.350308 | 3.649636 | 3.109021 | 3.021839 | 3.607375 |
| 3 | 2.689481 | 2.700039 | 3.717663 | 4.046505 | 1.791787 | 3.887588 | 2.963501 | 0 |
| 3 | 1.887148 | 1.899745 | 0.415705 | 3.490632 | 1.560709 | 3.919784 | 0.926666 | 2.380222 |
| 3 | 1.513549 | 1.532449 | 1.607564 | 2.685248 | 3.279872 | 3.004148 | 1.713475 | 4.525741 |
| 3 | 0.883486 | 3.354835 | 1.140304 | 1.314545 | 4.241418 | 3.09142 | 2.844292 | 3.175745 |
| 3 | 3.508986 | 2.582038 | 1.456563 | -1.65411 | 1.818963 | 1.456563 | 3.649636 | 2.812093 |
| 3 | 2.733409 | -0.35654 | 2.595109 | 3.267118 | 2.879312 | 1.945395 | 3.209397 | 3.411309 |
| 3 | 3.112776 | 3.175745 | 2.22788 | 2.834209 | 0 | 4.444507 | 3.125502 | 4.706878 |
| 4 | 3.807971 | 1.026853 | 3.97216 | 3.807971 | 2.310586 | 2.981868 | 3.021839 | 0.866176 |
| 4 | 1.970593 | 3.411309 | 0 | 1.791787 | 2.310586 | 4.241418 | 3.320184 | 0.415705 |
| 4 | -1.60756 | 1.899745 | 2.981868 | 3.01048 | 0.621765 | 2.310586 | 4.538134 | 0.533674 |
| 4 | 0 | 3.807971 | 3.279872 | 4.80876 | 1.85201 | 2.685248 | 0 | 4.655548 |
| 4 | -1.60756 | 1.224593 | 3.021839 | 3.807971 | 1.700328 | 4.788209 | 3.219202 | 2.62542 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 4 | 1.224593 | 2.959402 | 1.607564 | 1.224593 | 1.791787 | 1.791787 | 1.224593 | 4.586263 |
| 4 | 1.224593 | 3.036225 | 2.471243 | 4.015251 | 3.455347 | 4.951952 | 1.55399 | 0.926666 |
| 4 | 4.350308 | 2.346839 | 3.411309 | 0.774954 | 1.395772 | 3.859476 | 3.581489 | 3.807971 |
| 4 | 1.224593 | 4.525741 | 0 | 2.963501 | 3.490632 | 2.05785 | 3.807971 | 4.608343 |
| 4 | 1.916175 | 4.655548 | 0.156199 | 4.09907 | 2.371582 | 2.407749 | 1.607564 | 2.935001 |
| 5 | 3.519528 | 3.175745 | 1.429601 | 4.975274 | 4.579123 | 1.302602 | 2.913915 | 3.411309 |
| 5 | 2.913915 | 0 | 2.310586 | 0.926666 | 2.637007 | 3.686288 | 2.54915 | 1.354236 |
| 5 | 3.97216 | 1.899745 | 2.981868 | 2.54915 | 3.807971 | 4.456867 | 3.09142 | 4.116003 |
| 5 | 4.022274 | 4.655548 | 1.224593 | 1.224593 | 3.613948 | 4.241418 | 4.116003 | 4.595604 |
| 5 | 3.175745 | 2.109495 | 2.310586 | 2.772999 | 2.685248 | 4.90684 | 1.791787 | 4.525741 |
| 5 | -0.69001 | 1.055325 | 4.241418 | 2.310586 | 4.859364 | 3.807971 | 1.224593 | 4.116003 |
| 5 | 3.807971 | 3.237069 | 2.606507 | 2.310586 | 2.310586 | 1.607564 | 2.310586 | 0.49834 |
| 5 | 4.706878 | 2.913915 | 4.046505 | 1.224593 | 3.138904 | 0.986877 | 0.621765 | 1.92642 |
| 5 | 1.945395 | -0.8257 | -1.22459 | 3.649636 | 1.938503 | 3.055034 | 0 | 2.871267 |
| 5 | 3.991214 | 3.807971 | 3.175745 | 4.241418 | 4.350308 | 1.456563 | 1.700328 | 3.324291 |
| | | | | | | | | |

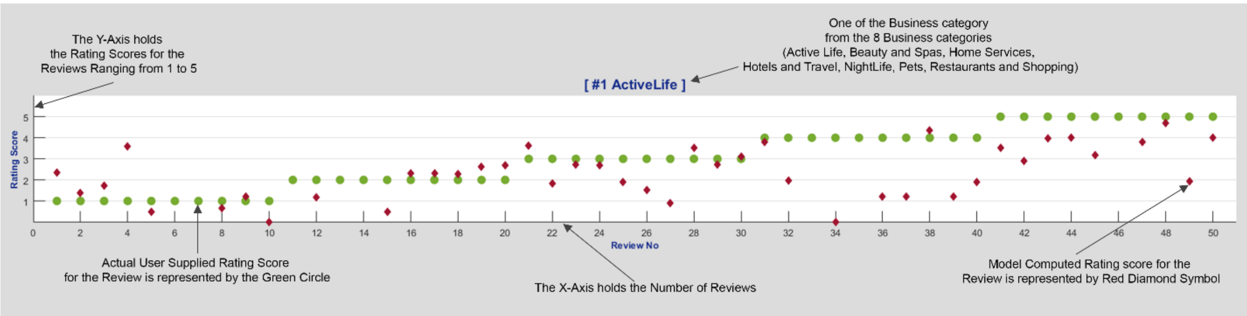


**Fig. 4:** Ratings scores for Category Active Life

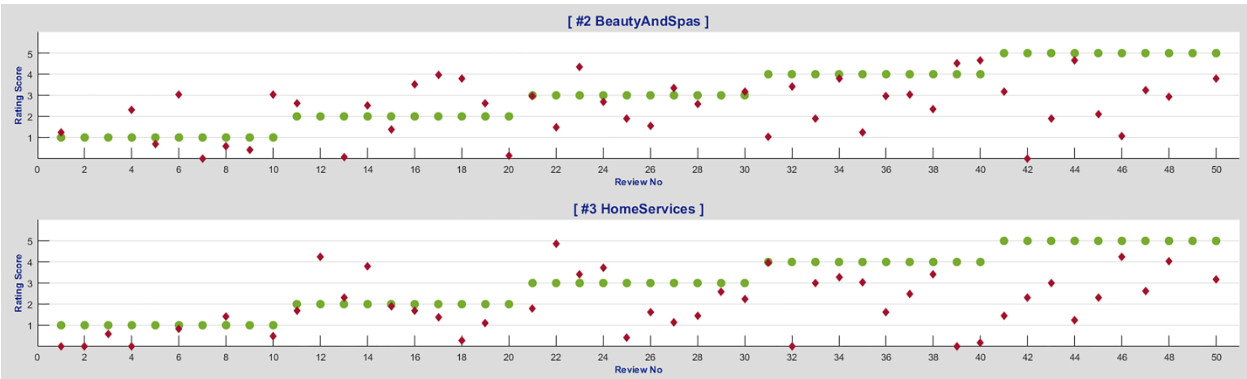


**Fig. 5:** Ratings scores for business Categories: Beauty & Spa, Home service

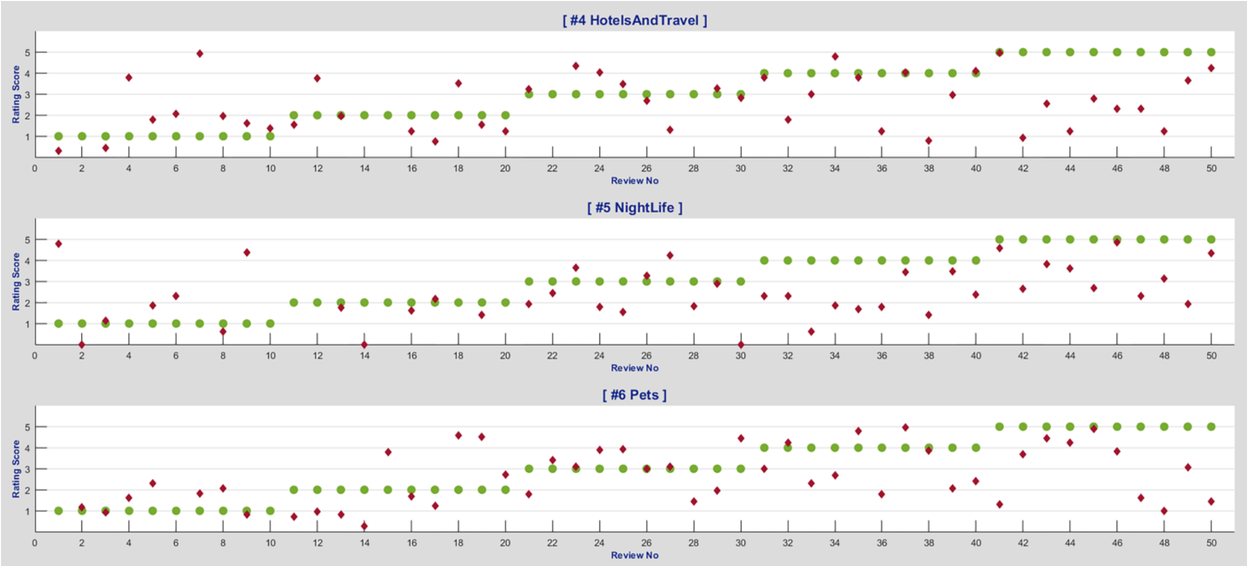


**Fig. 6:** Ratings scores for business Categories: Hotel &Travel, Night life and Pets

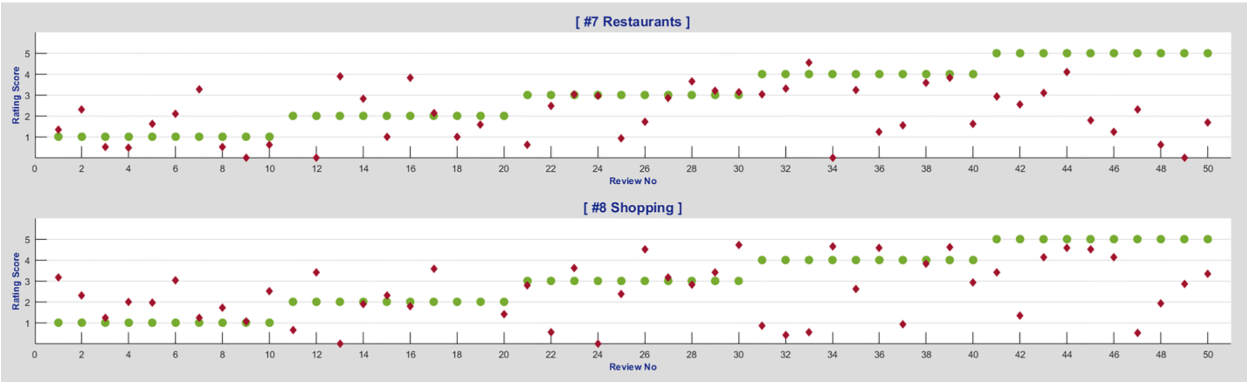


**Fig. 7:** Ratings scores for business Categories: Hotels &Travel and shopping

In the above figure red dots depicts the model Computed rating and green dotes represent the actual rating obtained by the number of viewers. Here, we are considering the 50 number of reviews, those gives rating to different eight categories. In the above figure x-axis depicts the number of reviews and y axis represents the rating score for reviews ranging from 1 to 5. At the top of the graph, business category from the eight categories has been represented.

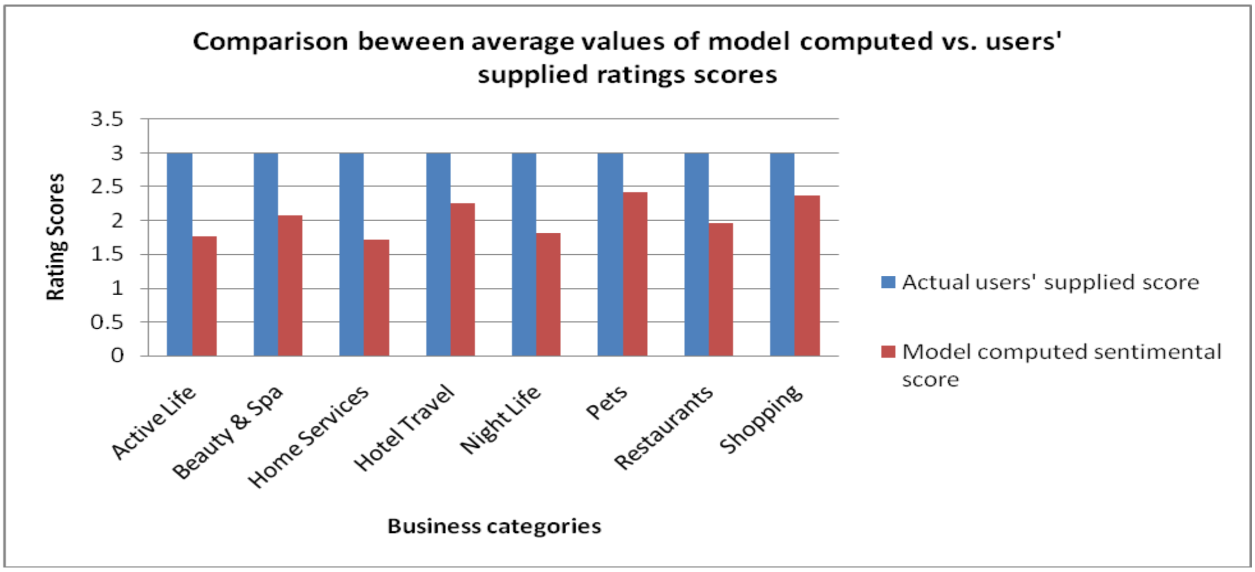


**Fig. 8.**Comparison between average values of model computed vs. users' supplied ratings scores

For active life the average value of rating score obtained for the computed work is 1.76 whereas for the existing work it is 3. Similarly, for Beauty & spa the average value of rating score for the computed work is 2.07 whereas for the existing work it is 3. For home services the average value of rating score for the computed work is 1.71 whereas for the existing work it is 3. For hotel travel, the average value of rating score for the computed work is 2.24 whereas for the existing work it is 3. For night life, the average value of rating score for the computed work is 1.82 whereas for the existing work it is 3. For pets, the average value of rating score for the computed work is 2.42 whereas for the existing work it is 3. For Restaurants, the average value of rating score for the computed work is 3 whereas for the existing work it is 3. For shopping, the average value of rating score for the computed work is 2.36whereas for the existing work it is 3.

## CONCLUSION

In this paper, a Recommendation Model (as proposed by Lei et. el. [5]) was implemented on the dataset; which was fetched from yelp.com. The Model was implemented via MatLab and The Reviews from Eight business categories(Active life, beauty & spa, Home service, hotel travel, night life, pets, restaurants and shopping) were supplied to the model. For Product Features extraction from the Reviews LDA algorithm was used. Scores, Ratings computation was done via Model equations as proposed by Lei et. el. [5] along with LDA Extracted product features and Sentimental Dictionaries (Positive Words, Negative Words, Negation Words, Sentiment Degree words). The Experimental Results showed that there is scope of improvement in the existing model (Lei et. el. [5]) as the Model computed scores lags behind the Actual User supplied scores.

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