IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 23, Issue 3, Ser. I (May – June 2021), PP 01-08
www.iosrjournals.org

Survey and Performance Analysis of Different Approaches for Sentiment Analysis in Social Networks

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Abstract: *Nowadays, there is remarkable and massive technology growth in social context. Also we witnessed an explosion of review websites in recent years. The main aim of review websites is to share our viewpoints on different products that we are going to buy. But, in this process there are so many problems caused i.e. information overloading problems, problem in making specific recommendations and also classifying the data according to purchase history, product category, their geographical location etc. So for avoidance of these problems, the different approaches have been proposed. There is requirement to design or by using the different detection sentiment analysis technologies we can find correct sentiment for the reviews. Hence the study and analyses of different sentiment analysis techniques are necessary to find recommendations and accurate ratings of products. In this paper, we have presented a survey and comparative performance analysis of sentiment analysis based different approaches in social context. The performance evolution is done by using yelp dataset. We have analyzed different models of sentiment analysis i.e. probabilistic matrix factorization (Basic MF), circle based recommendations in online social networks (CircleCon2b), social contextual recommendations (Context MF), personalized recommendations combining user interest and social circle (PRM), explicit factor models for explainable recommendations (EFM), and also the most important performance indicators namely accuracy, precision, etc. of several methods are discussed.*

Date of Submission: 28-04-2021 Date of Acceptance: 12-05-2021

I. Introduction

We may argue that the past decades have been a golden period of time for internet development. And each and every day, it's rising. And we are linked to each other by the Internet through somehow, or just through a touch, we can relate to anyone in the word, and social media networks are the finest example of this. The strongest attribute in social media is the potential of huge numbers of people to the world has been totally transformed by people talking or speaking instantaneously [21]. The internet development has facilitated all kinds of teamwork, large group communication, the exchanging of ideas, and the quick distribution to the population of news. Numerous domain experts It is assumed that social media plays an important role. The view of individuals based on what they want, hate, interest, etc. So in this section we will discuss the sentiment analysis and opinion analysis. Sentiment analysis is the system or field which is also known as opinion analysis

We have seen a flurry of review websites in recent years. It offers a perfect platform to express our thoughts on the different goods we buy. We face the issue of information overloading, however. So from this paper we can find easier way to choose different items from different websites for costumer by finding sentiment of the review or comment. Here we see that how to derive useful knowledge from input to consider a user's desires and make a particular suggestion is important.

Sentiment analysis is very big term in the today’s internet generation and also it becomes very important factor in the business value analysis. So the sentiment analysis can be defined as, it is the system or the field in which we can study and analyze the people opinion, attitude, review and emotion towards the item, product or any service. Or simply we can say that sentiment analysis is the customer’s own attitude towards the product.

In our life, human have natural ability to understand the sentiment by looking just to another people, or by looking the gesture of the other person. But the system that we use does not have this kind of ability [22]. System cannot find the sentiment by just looking towards the customer. So for it systems have different kind of algorithms and flowcharts. By taking the help of these algorithms, system can easily find the sentiment of user. In today's world, review website got too much importance due to the online shopping. With the help of this, we can easily share our viewpoints for various services and the products. And by looking at these reviews others can decide that to buy that product or not. Let’s us take one example.

Example: 1) Movie was **fabulous**
2) Movie was **horrible**

From the above example, we see the description of the movie. In the first line here it tells that movie was fabulous or good, so that it indicates some positivity towards the movie or we will take that comment as positive review. In the next line, it is written as movie was horrible. From that text we get some negative vibes, so here we can say that the next sentence got the negative review. So reviews are of two types it must be positive or negative. As we know that the main aim of sentiment analysis is to extract meaningful information from the large amount of text. So let's see the business value of sentiment analysis

In today's world there are different types of e-commerce website are present like Amazon, Flipchart, Mantra, eBay, etc., these sites everyday deals with different types of customers. And the customers give the opinion or review on these sites. The opinions of customers can improve the business of these websites. So everyday some specific portals generates large amount of reviews and by looking at those reviews other customers can make the decision on what to buy and from where to buy.

As we know in the recent years massive amount of data can be generated by the social objects. According to Cisco social objects use the 2.5 quintillion bytes of data per day. And this data can be stored on the different platforms of the social objects i.e. database, oracle, MySQL etc. But all this data storage device or unit have specific memory? So because of that memory problems and the information overloading problems are getting generated. We know that different review website is present and these websites have different methods for taking the reviews of the customers. And in that reviews personal information is present there of customers so that can make the important role in decision making process.

Let us see the example; we see the reviews of other people and by looking that review we make the decision of what to buy and from where to buy. These reviews contain the rating from lower to higher. The item having High star rating is the reputed item, so maximum sale is done there [23]. And if the any items have lower rating at that time it will reflect on its reputation. So the rating factor is the important one in the review websites. Sometimes some item don't have the rating, review contain much information about the product. So by looking that review other user make decisions to buy or not. Some websites provide broad thought mining so the user can predict the rating. Let us take one example, suppose one of the user is buying cups and mugs so that user is writing about the features of that product i.e. the product is beautiful and nice in texture; the other user is writing about the products price and it's quality so these two customers have different opinions about the same product.

The main aim of this paper is to provide a comparative analysis and comparative study by using different modules or techniques of sentiment analysis in social context. We analyze different modules of sentiment analysis like. probabilistic matrix factorization (Basic MF), circle based recommendations in online social networks (CircleCon2b), social contextual recommendations (Context MF), personalized recommendations combining user interest and social circle (PRM), explicit factor models for explainable recommendations (EFM). For analysis purpose we use yelp dataset and python programming language. It will be helpful in finding the accuracy in between different modules of sentiment analysis.

The rest of paper is organized in different section. The overview of different sections is as follows: Section II describes the literature survey i.e. study of recent techniques which are done in this area sentiment analysis by using the different datasets. Section III describes the main modules of sentiment analysis which have been compared in this paper. Section IV describes the different aspects of dataset, experimental results and implementation of the modules. Finally in section 5 conclusion of the paper is written. After in the end there is summarization of paper which I have been used for this survey. So in the next section literature survey is presented. We have discussed about the different approaches i.e. Basic MF, CircleCon2b, Context MF, PRM, and EFM. Study of the different techniques which are used to implement them is also discussed.

II. Literature Survey of Sentiment Analysis Approaches-based on Different Approaches

In this section we will discuss the literature survey i.e. the study of different recent techniques which are developed in this area i.e. sentiment analysis by using the different datasets. R. Salakhutdinov, and A. Mnih, proposed a model of sentiment analysis named as "probabilistic matrix factorization" (PMF). In this model we can take number of observations of single dataset. Also we can apply this model on largest dataset. The one of the example of imbalanced and largest dataset is Netflix dataset. In this approach we use yelp dataset. It is centered on low-dimensional factor models which are one of the most common approaches to collaborative filtering. The principle behind such models is that a user's behaviors or desires are decided by a limited number of variables that are not detected [1]. The expectations of a consumer in a linear factor model are modeled by integrating item factor vectors linearly using user-specific coefficients. The objective of this paper is to present probabilistic algorithms that scale linearly with the number of observations and perform well, such as the Netflix dataset, on very sparse and imbalanced datasets. The Probabilistic Matrix Factorization (PMF) model is presented as a product of two lower-rank user and film matrices that model the user reference matrix.

X. Yang, H. Steck, and Y. Liu proposed a model of sentiment analysis i.e. "Circle based recommendation in online social networks." (CircleCon2b) [2]. In this approach the author considered online social networks for increasing the recommendation and increasing the accuracy in recommendation system. Generally we look up for the ratings and reviews but it helps in increasing the accuracy in recommendation so it will automatically increase ratings of the products. Hence it supports different concepts like trust circles, online friends circle, etc. So it developed in the circle based recommendation system area. That can be useful in the analyzing user social trust information for increasing the accuracy of recommendation. We are going to use yelp Dataset. In this section of paper describes an attempt to build Recommender System (RS) based on circles. We're based on Inferring category-specific social confidence circles, combined with social network data, from available ranking data. Based on their implied skill ranges, we outline some variants of measuring friends inside circles. Via testing on we explain that the proposed publicly accessible data demonstrates that the proposed models of circle-based recommendation will allow greater use of user's knowledge about mutual trust, resulting in improved recommendations, precision.

M. Jiang and P. Cui, R. Liu, Q. Yang, F. Wang, W. Zhu, and S. Yang, proposed another sentiment analysis model named as "social contextual recommendation", in this on social objects huge amount of information is generated by different networks and different objects [3]. The system before it ignores the social relations data but in this system it see and check the social data for correction or predicting the recommendation system. In this users produce vast volumes of knowledge on social networks and urge feedback mechanisms to deliver valuable outcomes. In solving the social recommendation dilemma, conventional approaches usually focused on mutual filtering become unqualified because they neglect social relationship or interaction data.

Social recommendation system is generally done by the probabilistic matrix factorization. In this Data sparsity, scalability and accuracy of prediction have been recognized as the three most critical problems facing each collective filtering algorithm or recommendation scheme [4]. Many current recommendation methods do not manage very broad databases or work effectively with users who have made very little or even no reviews at all. In comparison, conventional recommendation frameworks presume that all apps are independent and distributed identically; this assumption lacks users' social connections or ties. Social network research is becoming important for many Web applications in view of the rapid growth of knowledge created by online social networks. This paper suggests a factor analysis approach based on probabilistic matrix factorization to overcome data sparsity and weak estimation, following the intuition that the social network of an individual would influence personal activities on the Web.

Recommendation on the social networks can be done by using the different algorithms like item based collaborative filtering algorithms. In this, during a live conversation, recommendation systems apply knowledge discovery strategies to the problem of making customized suggestions for content, products or services. These systems, in particular those focused on k-nearest neighbor mutual filtering, are gaining widespread site popularity. The enormous increase in the quantity of information is available with respect to the number of travelers. Recommendation mechanisms add information discovery techniques during a live chat to the issue of providing personalized recommendations for content, products or services [5]. These systems are gaining widespread popularity on the web, especially those based on k-nearest neighbor mutual filtering. In classical collective filtering processes with the number of participants, the volume of work increases in the system's socks. Current device innovations recommender provides high quality recommendations and these are required for quick generation of high quality emendations. To tackle problems like high recommendation over big data, we have discussed item-based collective techniques. Item-based approaches first evaluate the user-item matrix and then use these relationships to implicitly calculate user recommendations.

X. Qian, He Feng, Guoshuai Zhao, and Tao Mei Invented the another system or sentiment analysis model which is named as the "personalized recommendation combining user interest and social circle" [6], in this recommendation system the main aim is to solve the information overloading problem and this system tackle the problem with good reviews. Nowadays many websites are available; on these websites we can do online shopping or else other our work. The websites generates named as the Amazon, Flipkart, etc., large amount of data and this data may increase day by day. So the handling of this data is the main work for the system. And the handling of the data can be done by using the traditional collaboration filtering algorithm.

More and more people prefer posting their impressions, such as ratings, feedback, and blogs, with the introduction and success of social networks. In Recommender System (RS), some of the social variables were included, but were not thoroughly considered. Three social variables, personal involvement, similarity of interpersonal interest, and interpersonal impact merge into a single customized suggestion model based on probabilistic factorization of the matrix [24]. The personal interest factor will make the RS to suggest items to match the individualities of users, especially for experienced users. In addition, the similarity of interpersonal involvement and interpersonal impact will strengthen the intrinsic relation between characteristics in the latent space for cold start users.

Yongfeng Zhangy, Guokun Laiy, Min Zhangy, Yi Zhangz, Yiqun Liuy, Shaoping Ma invented the another sentiment model which is named as “Explicit Factor Models for Explainable Recommendation based on Phrase-level Sentiment Analysis” [7] in terms of estimation accuracy, Collaborative Filtering(CF)-based recommendation algorithms, such as Latent Factor Models (LFM), perform well. The latent characteristics, however, make it difficult to explain to consumers the implications of the suggestion.

Fortunately, the information available for training a recommended framework is no longer limited to only numerical star ratings or user/item attributes with the constant development in online user feedback. By collecting explicit consumer opinions from the feedback on different facets of a product, provides more information about what elements a person cares about can be learned.

III. Sentiment Analysis Approaches

In this section we will discuss the step by step sentiment analysis approaches in detail. We have five different sentiment analysis approaches which are named as, probabilistic matrix factorization (Basic MF), circle based recommendations in online social networks (CircleCon2b), social contextual recommendations (Context MF), personalized recommendations combining user interest and social circle (PRM), explicit factor models for explainable recommendations (EFM). For analysis purpose we use yelp dataset and python programming language. It will helpful in finding the accuracy in between different modules of sentiment analysis. So the different sentiment analysis approaches are as follows.

3.1: Probabilistic matrix factorization (Basic MF)

In this model we can take number of observations of single dataset. Also we can apply this model on largest dataset. The one of the example of imbalanced and largest dataset is Netflix dataset. In this approach we used dataset. This strategy is the baseline matrix factorization technique suggested in [1], which does not take any social variables into account. The working steps for the probabilistic matrix factorization algorithm are given below.

Step 1: Given set of users U and set of items V (user u rate the item v).

Step 2: Construct rating matrix R containing N row and M column, where N is the number of users and M is the n number of items who are rated by user.

Step 3: In the last step here, system recommend the item for user according to his or her preferences or by choice made by the similar user.

3.2: Circle based recommendations in online social networks (CircleCon2b)

In this approach the author considered online social networks for increasing the recommendation and increasing the accuracy in recommendation system. Generally we look up for the ratings and reviews but it helps in increasing the accuracy in recommendation so it will automatically increase ratings of the products. Hence it supports different concepts like trust circles, online friends circle, etc. So it is developed in the circle based recommendation system area. Proposes an approach that focuses on the aspect of interpersonal trust in social networks and it uses matrix factorization to infer trust circles. The working steps for Circle based recommendations in online social networks are given below.

Step 1: For implementation of the CircleCon2b. We have to load the dataset first. Then process further.

Step 2: Present the data. After it, if in the dataset ratings are present then select the user ratings according to the separation degree means categorize the dataset according to ratings.

Step 3: Because it is CircleCon2b, so after it also selects user's ratings and friends ratings according to separation degree of ratings.

Step 4: Estimates the evaluation from all users and friends by using the auxiliary recommendation system. It will give us the results according to separation degree of ratings.

Step 5: Accordingly process the next separation degree of the ratings.

Step 6: Likewise when all separation degree finishes then selects top n ratings from the result and recommend it to the user.

3.3: Social contextual recommendations (Context MF)

In this on social objects huge amount of information is generated by different networks and different objects. The system before it ignores the social relations data but in this system it see and check the social data for correction or predicting the recommendation system. In this users produce vast volumes of knowledge on social networks and urge feedback mechanisms to deliver valuable outcomes. Standard item-based collaborative filtering in [22] and SoRec in [53] are both improved by this approach [3]. They take into account both behavioral control and personal preference. The steps for the social contextual recommendation algorithm are as follows.

Step 1: Take the dataset of any web forums or any social media platform dataset like Twitter etc. And load that dataset, also present it.

Step 2: In the dataset there ratings, recommendation different fields are present, from that find out the instant recommendation.

Step 3: After it filter out all the products which are popular and more preferred by the users, and also the filter out high rated products within the dataset.
Step 4: Then selects all similar items, products to one column from the table.
Step 5: After selecting all similar items weight all these items according to their ratings and popularity level from the dataset.
Step 6: Merge all the tables to one column
Step 7: Then sort resulting list from highest to lowest.
Step 8: After sorting delete the entries of products which have been selected, which have been rated and which have been sold out.
Step 9: After all we get fresh recommendation list. Then recommend this list to our user.

3.4: Personalized Recommendations Combining User Interest and Social Circle (PRM)

In this recommendation system the main aim is to solve the information overloading problem and this system take this problem with good reviews. Nowadays many websites are present; on this website we can do online shopping or else our work. Websites named as the Amazon, Flipkart, etc. generates large amount of data and this data may increases day by day [8]. PRM proposes a method that takes into account three social factors: interpersonal impact, interpersonal interest similarity, and personal interest. Matrix factorization is often used to forecast consumer scores. The steps for the personalized recommendation combining user interest and social circle is are as follows.
Step 1: Load the dataset, in the dataset their user list and item list are present then present that dataset.
Step 2: Make the matrix for the user lists and the item lists for the future processing.
Step 3: After making the matrix find out the user nearest set i.e. neighborhood set for processing.
Step 4: In the step 4 by looking the neighborhood set, rate the review objects or products or items.
Step 5: After all it, finally we can recommend several objects with high ratings for all the users.

3.5: Explicit Factor Models for Explainable Recommendations (EFM)

It is based on the on Phrase-level Sentiment Analysis" In terms of estimation accuracy, Collaborative Filtering (CF)-based recommendation algorithms, such as Latent Factor Models (LFM), perform well. The latent characteristics, however, make it difficult to explain to consumers the implications of the suggestion. [59] Proposes a procedure for constructing two signature matrices: a user-feature focus matrix and an item-feature consistency matrix. Each part of the user-feature focus matrix indicates how much a user cares about the product feature in question. Each part of the item-feature quality matrix assesses an item's quality in relation to the product feature it represents. The steps for the explicit factor model for explainable recommendation based on phrase level sentiment analysis is are as follows.
Step 1: Load the dataset and train with their categories.
Step 2: Preprocessing the dataset and then extract the features from the texts of the dataset means the products having high ratings and high recommendation.
Step 3: Then for further processing train and evaluate the classifier for learn the further feature category mapping.
Step 4: Then use classifier for predicting best recommendation for the users.

3.6: Ratings prediction system (RPS)

In recent world there are many websites present for sharing our viewpoint on the different product. So because of large amount of data, creates information overloading problem. So for finding the important data from large amount of data and to find valuable review and comment from thousands of comments, we need a system and that system called as ratings prediction system (RPS). Earlier technologies and methods find the sentiment over category of products, location of product by using some records of the products. But in recent system sentiment based ratings prediction method is used for calculating the more accuracy in sentiment. In the RPS system there are three main phases; in the first phase here we calculate the each user review or sentiment on the product. In the second phase we calculate interpersonal review or sentiment on the product. And in the last phase we observe the product reputation in the market. The steps for the ratings prediction system are as follows.
Step 1: load the dataset.
Step 2: In the second step data division takes place.
Step 3: Train the dataset. Here training of dataset is done by using the LDA method.
Step 4: Remove stop words, recurrent words by using the specific dictionary which are already loaded.
Step 5: Test the dataset.

IV. Experimentation

The yelp dataset is used for the experimentation and to test the performance of sentiment analysis of different models using different methods. Table 1 shows all the information of the dataset and their different units. The main experiment is done in the platform of jupyter using the different libraries. A series of experiments performed in this section to assess the effectiveness of sentiment-based rating prediction method (RPS) based on feedback from users; nearly sixty thousand users have been crawled. Friendship circles and their rated products we've had consistent results. To plan experiments, use social relationships and feedback. Any of my prior work has been inspired by Yelp database [25]. There are eight categories in the dataset i.e. Active Life, Beauty and spa, Home Service, Hotel Travel, nightlife, restaurants, shopping and pets. There are 28,629 users, 96,974 objects, 300,847 ratings, and each user's social relationship is registered. At least one comment/review has been left on each piece.

Table No. 1: Yelp Dataset Attributes

Sr. No	Name	Attributes
1	Business	Business Name, Id, Category, Location, etc.
2	User	Name, Review, Count, Friends, Votes, etc
3	Review	Date, Business, Stars, Texts, etc.

Table No. 2: Yelp Data Files Size Information

File Name	File Size	Number of records
user.json	1,847,071 KB	1,326,101
business. json	141,773 KB	174,567
review. json	4,099,872 KB	5,261,669
tip. Json	192,928 KB	1,098,325

4.1: Dataset Description

Yelp is one of the most popular online review and search engines for a variety of companies, including restaurants, shopping, and home services, among others. Analyzing Yelp's real-world data is useful for learning about users' preferences, and helps to refine the architecture of the next generation framework. Users will leave online feedback for different companies, goods, and services on rating platforms including Trip Advisor and Yelp, and have recently been found to have a substantial impact on customer purchasing decisions. A traditional online review consists of: a paragraph of free-form content, and a five-star review predicting a user's star rating for a product based on the user's text analysis is a difficult challenge [26]. The Yelp dataset is a subset of Yelp's companies, ratings, and usage data that has been made accessible for personal, educational, and scholarly use. To download Yelp: on your web device, go to m.yelp.ie and press "Request Desktop Site" from the sharing button (iPhone) or the overflow button (iPad) (Android). Then, go to your Privacy Settings and choose "Download a copy of data from the drop-down menu.

The Yelp platform review can be broken down into three sections: first, we defend the use of Tips frequency as a metric to profile market popularity. Second, we look at Tips frequency to find companies that fit a growing popularity profile. Finally, we graph mine the sociographs generated by users who interacted with each company. Top nodes are graded using the In degree, Eigenvector centrality, PageRank, and Trendsetter algorithms, with the relative success of each algorithm being compared. The Trendsetter ranking algorithm, according to our findings, is the most efficient at locating nodes that best represent the Trendsetter properties. Yelp created the dataset as part of the 5thYelp Dataset Challenge. It has 1.6 million reviews and 500 thousand tips from 366 thousand users for 61 thousand businesses. There are 481K attributes (hours, parking availability, and ambient) for each of the 61K firms, as well as 2.9M social edges and aggregated check-ins over time. The dataset can be downloaded for free at http://www.yelp.ca/dataset-challenge. The yelp dataset has different attributes namely business, user and reviews. The business contains Business Name, Id, Category, Location, etc. then secondly user contains Name, Review, Count, Friends, Votes, etc. and lastly in review contains Date, Business, Stars, Texts, etc. the yelp dataset size information is as follows. The yelp dataset has four different files such as user.json, business.json, review.json, tip.json. The size of user.json is 1,847,071 KB and it has the 1,326,101 number of record. Secondly business.json file size is 141,773 KB and it has 174,567 number of records. Then review.json file size is 4,099,872 KB and it has 5,261,669 number of records. Then lastly tip.json has the size 192,928 KB and it has the record 1,098,325.

4.2: Performance Metrics

We perform the analysis of existing model with our new model by using the yelp dataset. Also we studied the difference aspects of the dataset. And it's different module. In our algorithms that we have compared for the purpose of analysis in that we have taken the same initialization input values and same parameters. We extract various features in the matrix factorization process and construct the corresponding function matrixes in EFM to apply the comparative methods. The overall results assessment has been carried out in four Yelp dataset groups. The relative changes of RPS over the different baseline models are represented by the percentage numbers in each cell. It is clear that our RPS model outperforms all the baseline models in each category of Yelp. We reduce RMSE by 27.92 percent, 21.52 percent, 10.89 percent, 9.67 percent, and 7.18 percent for the baseline approaches. MAE is reduced by 26.01 percent, 19.06%, 10.44 percent, 9.17 percent, and 9.81 percent, respectively. The experimental findings demonstrate RPS's high precision. Meanwhile, we show how social friend variables (such as CircleCon2b and PRM) and explicit features (such as EFM) are essential in a recommender scheme.

4.3: Result and Discussion

For comparison purpose, we have studied five different algorithms of the sentiment analysis. The name of these algorithms such as, Probabilistic Matrix Factorization (Basic MF), Circle based Recommendations in online social networks (CircleCon2b), social contextual recommendations (Context MF), personalized recommendations combining user interest and social circle (PRM), explicit factor models for explainable recommendations (EFM). For analysis purpose we use yelp dataset and python programming language. It is helpful in finding the accuracy in between different modules of sentiment analysis. By looking towards the table 3 and 4 it is clear that RPS i.e. rating prediction system has the more accuracy than the other modules or the algorithms.

Table 3: Comparison of Sentiment Analysis Modules (RMSE)

Sr. No.	Dataset	Basic MF	CircleCon2b	Context MF	PRM	EFM	RPS
1	Active Life	1.633 (31.48%)	1.477 (24.24%)	1.285 (12.92%)	1.265 (11.54%)	1.1215 (7.90%)	1.119
2	Beauty & Spa	1.813 (29.01%)	1.656 (22.28%)	1.454 (11.49%)	1.431 (10.06%)	1.385 (7.08%)	1.287
3	Home Service	1.981 (26.4%)	1.844 (20.93%)	1.624 (10.22%)	1.611 (9.5%)	1.583 (7.89%)	1.458
4	Shopping	1.600 (24.81%)	1.479 (18.66%)	1.321 (8.93%)	1.302 (7.60%)	1.278 (5.87%)	1.203
5	Average	1.756 (27.92%)	1.613 (21.52%)	1.421 (10.89%)	1.402 (9.67%)	1.344 (7.18%)	1.266

Table 4: Comparison of Sentiment Analysis Modules (MAE)

Sr. No.	Dataset	Basic MF	CircleCon2b	Context MF	PRM	EFM	RPS
1	Active Life	1.238 (29.25%)	1.126 (22.2%)	1.002 (12.57%)	0.984 (10.98%)	0.941 (6.91%)	0.876
2	Beauty & Spa	1.390 (26.98%)	1.272 (20.2%)	1.147 (11.51%)	1.128 (10.02%)	1.086 (6.54%)	1.015
3	Home Service	1.558 (24.45%)	1.454 (19.05%)	1.294 (8.89%)	1.284 (8.33%)	1.273 (7.54%)	1.177
4	Shopping	1.282 (23.37%)	1.186 (17.31%)	1.071 (8.82%)	1.053 (7.38%)	1.032 (5.81%)	0.970
5	Average	1.367 (26.01%)	1.259 (19.06%)	1.128 (10.44%)	1.112 (9.17%)	1.083 (7.81%)	1.009

V. Conclusion

This paper presents the comparative study of the different approaches and their algorithms used for sentiment analysis in social networks. In this paper, the results of experiments performed as per algorithms for various sentiment analysis have been presented. From the literature survey of the different approaches for sentiment analysis, it is clear that a better model can be developed for sentiment analysis i.e. Rating Prediction System (RPS) for finding the more accuracy in the sentiment analysis. So when we visit any website for shopping purpose or for any other purpose, then at this time by looking towards the ratings of the website we can decide that to buy from there or not. So the rating prediction based system can be developed to find out more accuracy in sentiment of any review or comment.

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Ms. Sayali K. Somwanshi, et. al. "Survey and Performance Analysis of Different Approaches for Sentiment Analysis in Social Networks." *IOSR Journal of Computer Engineering (IOSR-JCE),* 23(3), 2021, pp. 01-08.