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Comparative Analysis of Recommendation System for Social Media Analysis

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Abstract

Since the growing population uses social networks in their everyday lives, so its generated data is analyzed and visualized in various fields. The way of production, transfer, and consumption of the information, is represented by online social media. Elements like tweets, posts, and comments, set up a connection between the maker and the user of the generated data. Social networks like Facebook generate 4 petabytes of data per day, 511,200 tweets per minute on Twitter, 240MB of data usage per hour on YouTube.

Predictive decisions are taken using social data in many applications such as e-commerce, business, travel, news, micro-blogging, etc. Thus, the social media website facilitates linking people, having similarities, exchanging ideas, and forming groups, and encouraging many social and commercial activities. Due to the information overload, finding the correct information gets demanding. The recommender system is a type of refining system that filters primary information, considering the user choices or feedbacks. The main purpose of the analysis is to give an outline of the recommender system, its types, and the related algorithm. We present, in this analysis, a review of some papers published between 2013 and 2019 in the social media field. Finally, we have mentioned their key aspects with employed techniques. Due to the explosion of social media data, we focus on the recommender system study. We will conclude by pointing out a set of machine learning algorithms that will be used for the contributions towards future work.

Keywords: *machine learning algorithm, recommender system, social media, micro-blogging.*

1. Introduction

In this age of ever-increasing social media innovation, many technologies are used for digital communication. This progress is used for virtual communities and networks to establish channels, which facilitate data generation, creation, exchange, and private-public dealings on a community basis. In Figure 1, below we present the grouping of social media by its categories.

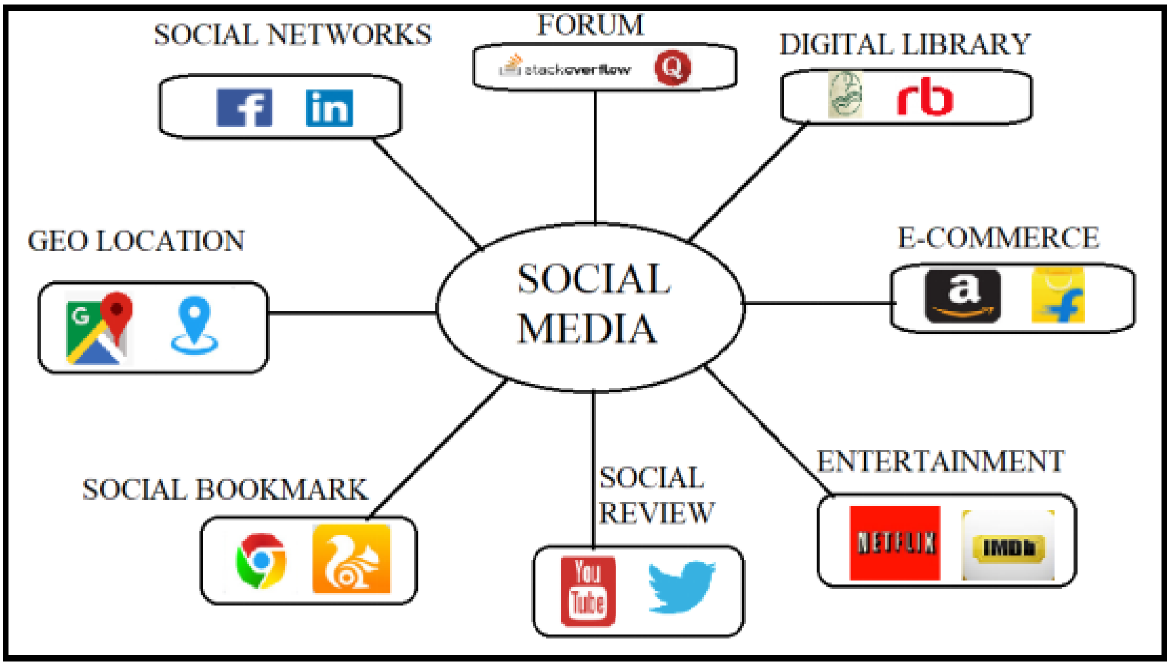

Figure 1. Grouping of Social Media

Thus, the above icons illustrate e-library, e-commerce, commercial meetings, bookmark, entertainment, reviews, and networks [1]. So, these are increasingly being analyzed and developed. However, along with the characteristic of a huge volume of information, they are also heterogeneous. They originate from many points and occur in real-time. According to the analysts, this is referred to as 'Big Data'. This has three main features: Volume, Variety, and Velocity, also noted as '3V'. Some analysts add two other features: Value and Veracity, summing up to '5V' [2]. Thus, for these features, the traditional technology finds difficulty in processing this form of big data. Big data discovered new technologies such as Map-Reduce [3], [4], Hadoop [3], HDFS [3], NoSQL [5], [4], etc.

Users can share their photos, posts, videos on social media like Twitter, YouTube, etc. This activity is useful for creating groups of users having similarities. However, these networks produce noisy and heterogeneous content, and information can be extracted from it [6]. Items and opinions are increasing day by day. So, experts face difficulties while detecting items in a specific area. RS (Recommender system) comes out as a needed resolution. This identifies the nearby users of the target taking into account their profiles in social media sites. The following article is arranged as **Section 2** outlines the literature survey. **Section 3** describes the recommender system with its types. **Section 4** compares the recommendation approaches in social media.**Section 5** highlights the algorithms being identified in the analysis of the selected articles, with the conclusion drawn in **Section 6**.

2. Literature Survey

The Global Internet Population grew 7% from 2019-2020 and now represents 4.54 billion users. Social media is jammed and it's essential to investigate the results to discover strategies. Social media innovations are available as e-commerce networks, enterprise, blogging, portals, review portals, video sharing, and virtual worlds.

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Table 1. Articles Summary

REFERENCE	AUTHOR	YEAR	DESCRIPTION	ALGORITHM	DATA SCOPE/ SOURCE	TOOLS AND TECHNIQUES	APPLICATION DOMAIN
[8]	Rafal Rzepka, Yuki Urabe, and Kenji Araki	2013	Effective Communication by application of Emoticon Recommendation system	Supervised learning	Twitter, Facebook	Emoticon database, affect analysis system, ML-Ask,	Media, Commerce & business
[9]	Ioannis Pipilis, Ioannis Pitas and Ioannis Tsingalis	2014	Study on Youtube 2D and 3D video recommendation graph by using statistical and clustering method	Power-law distribution,BFS, DFS	Youtube	Semi-supervised, unsupervised	Media, Business & commerce
[10]	Fatima EL Jamiy, Abderrahmane Daif, Mohamed Azouazi, and Abdelaziz Marzak	2015	The potential of challenges of big data –recommendation system next level application	Clustering, matrix factorization	Google, amazon, yahoo	CRM, Salesforce automation, content-based, Collaborative Filtering	Business & Commerce, Science & research, Health, Smart cities

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[11]	Nilesh Kumbhar, Krushnadeo Belerao	2017	Microblogging Reviews Based Cross-Lingual Sentimental Classification for Cold-Start Product Recommendation	Cross-lingual joint sentiment/topic model (CLJST)	Amazon, Twitter	collaborative filtering, matrix factorization method	Microblogging, Media, Commerce & business
[12]	Anitha Anandhan, Liyana Shuib, Maizatul Akmar Ismail and Ghulam Mujtaba	2018	Social media recommender system: Review and open research issues	Matrix factorization, Clustering, link analysis, association rule, decision tree	Movie lens, IMDB, Flixster	Content-based, collaborative, hybrid, knowledge-based filtering, KNN, regression	Business &Commerce, Science & research
[13]	Muskan Banthia, Shipra Goel, Adwitiya Sinha	2018	Real-Time Analysis of Social Media Dynamics by the recommendation system	Naïve Bayes, Probabilistic, Supervised Learning	Amazon, twitter	Visualization in RMap reduce, Sentiment based Score calculation, Ensemble learning	Media, Commerce & business
[14]	Murtaza Ashraf, Mustafa Abdulaali, Ghalib Ahmed Tahir, Saqib Mushtaq, Sundus Abrar, Hamid Mukthar	2018	Personalized News Recommendation based on Multi-agent framework using Social Media Preference	Sentiment analysis/ supervised learning	Twitter, Facebook	Information filtering, collaborative filtering, Sentiment analysis, machine learning, data mining, Pie	Business & Commerce, Science & research, Health, Smart cities

						RSS,DOM parser	
[15]	Praveen Madiraju, Paromita Nitu, and Joseph Coelho	2018	Personalized Travel Recommendation System Using Social Media Analysis	Sentiments analysis/ supervised learning	Twitter, Facebook	TextBlob (for sentiment analysis), sklearn (machine learning), data mining, Travel Tweet Classifier, google API	Media, Business & commerce
[16]	Will Serrano	2019	Intelligent recommender system for big data application based on the random neural network	Gradient Descent, Reinforcement Learning	Facebook, LinkedIn, Group lens file, Trip Advisor	Apache Tomcat, Java servlet, Hadoop, data mining methods, ANN	Business & commerce

Thus, by scanning semi-structured as well as unstructured data in social media, valuable hidden insights can be taken out. Today, the social networks Facebook and Twitter handle 250 million and 330 million active users per month respectively throughout the world. Smartinsights.com has proclaimed that more than 4.5 billion people are active users in social media at the start of 2020 [7]. About 2.4 billion people are on Facebook platform, while about 1 billion are available on Instagram, and 330 million are Twitter users.

To fulfill the objective of this analysis, an overall assessment and study were accomplished on the mentioned papers to inspect different techniques in the Recommendation System. Table 1 shows the approaches being used year wise in social media, along with the algorithms used.

3. Recommender System

This section elaborates on the importance of the recommender system along with its types. Useful recommendations of articles and items are being generated by the social media recommender system. This system helps users in collaborating with other users. They recommend the target user of the chosen products by nearby users [17]. So these factors help in predicting whether the user will accept it or not. Nevertheless, information overload creates new research topics, like huge datasets of communities and e-libraries. Recommender system uses these resources for recommending e-commerce products, contents, articles, news, and users. Collaborative and content type systems are the most common methods in the RS. In general, there are four different approaches to develop this system that consists of content-based, collaborative, hybrid-based, and knowledge-based methods. It can be either personalized or non-personalized.

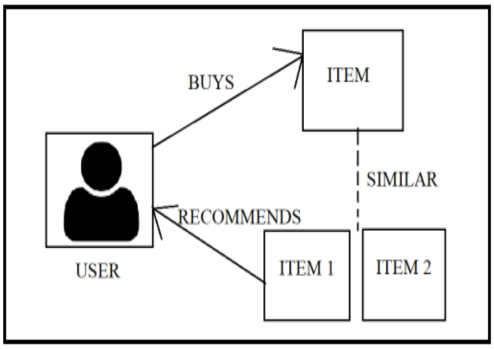

Figure 2. Content-Based

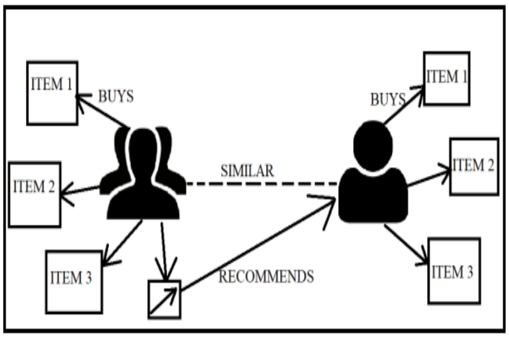

Figure 3. Collaborative Based

3.1. Content-based recommendation

In CB filtering, shown in Figure 2, also called a cognitive method. This suggests items on comparison of profile and product. Content similarity is preferred more than users' similarity [17]. The content of each product is indicated as a set of descriptors, present in a document. The user profile represents the same descriptors. This profile is built up by comparing it with the content of the product, being seen by the user.

3.2. Collaborative based recommendation

CF (Collaborative filtering), represented by Figure 3 above, used to refer like-minded users as active users. Previously stated interest and opinions of similar users are used in this system. This type of approach, also called a social method, as it filters data using the suggestions of other users. It is assumed that users who agreed for certain terms previously, could agree again on the same. Users having similar interests will be trusted more for recommendations than others, which is used for further decision making.

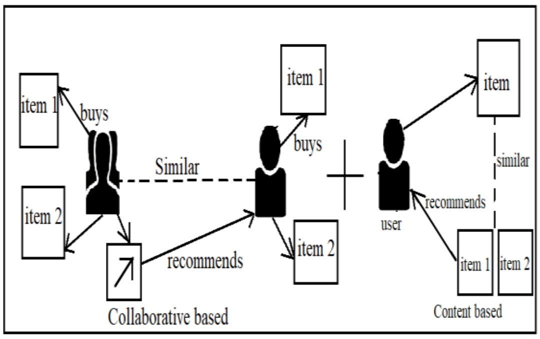

Figure 4. Hybrid Based

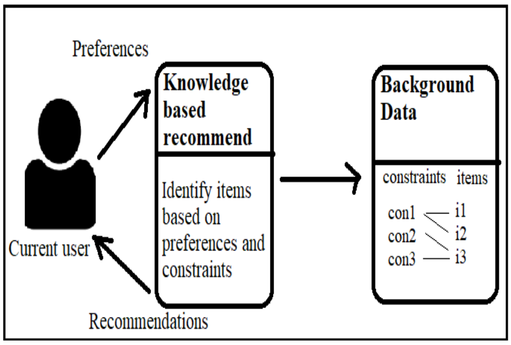

Figure 5. Knowledge-Based

3.3. Hybrid recommendation

An association of collaborative and content-based filtering is known as hybrid filtering, as shown in Figure 4. This is an exceptional approach as it removes the defects of collaborative and content-type methods. Its suggestion accuracy is generally higher in this approach. Both are combined to ensure an increase in acquiring common knowledge, for better recommendations. These advancements facilitate to relate collaborative techniques with the content and content-based techniques with the data of user actions.

3.4. Knowledge-based

Knowledge-based filtering as depicted by Figure 5 given above, is analyzed over the specific learning of user preferences, product varieties, and recommendation basis. Thus, mainly RS filtering is built either over user-similarity rates (CF) or content-similarity rates (CB).

3.5. Personalized

It relates to the insights of user's interests in a particular area. An automated personalized recommender system would focus on a particular user. For example, Twitter as a platform allows a person to post long tweets that may include videos, user namings, hashtags, links, etc. Hash-tags specify tweet subjects that are helpful in clustering tweets. Users can be connected among themselves on twitter and this connection is used for the user-collaborative approach.

3.6. Non-personalized

A personalized recommendation system suggests the items to a person based on their earlier history, while a non-personalized recommender system displays the products among the users according to their popularity in general during that particular time frame. The recommender system used to suggest a product so that the customer may potentially choose. To predict the next day sales, various machine learning algorithms, like linear regression, random forest regression, etc., can be used to train models using input features, such as historical sales, views, sold units, available stock, daily price, discount, rating, number of reviews, number of clicks, etc.

4. Classification

This section represents a classification based on the dimensionality that follows for representing the recommendation system being divided into two-dimensional and multi-dimensional approaches. The two-dimensional approach can further be classified into content-based, collaborative, hybrid-based, and knowledge-based filtering. Content-based can be referred to according to the description of data and user preferences. Collaborative filtering can be of model-based CF (latent factor) and memory-based CF (memory-based). Matrix factorization technique is established over the model-based CF and specifies user and item as a 2D matrix (sparse) using social data. Further, under collaborative filtering, the memory-based model is divided into user and item approaches. Model-based consists of clustering, association, bayesian, regression, matrix factorization methods. Figure 6, depicts the overview of the classification of the recommender system by analyzing the research literature.

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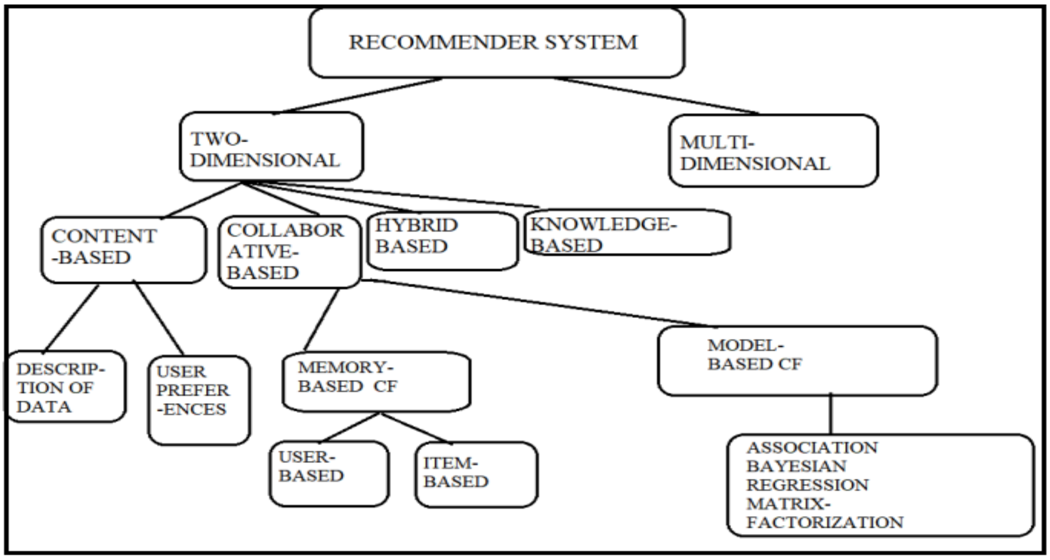

Figure 6. Classification of Recommender System

4.1. Classical approach (2D)

Traditional recommender system works over two entities, users and items. Firstly, some ratings specified by users are collected by the systems. Using these records, the systems estimate a rating function. Mathematically the rating function is given by:

$$U \times I \rightarrow R \qquad (1)$$

where U: users, I: items, R: rating function

So, for the entire $Users \times Items$ domain, the rating function is constructed. Then a system can recommend the items to the user with maximum ratings.

Table 2. Applicability among entities

$R = Item \times User$	Applicability: item &user
$R = User \times Item$	Applicability: user & item
$R = User \times Tag$	Applicability: user &tag
$R = User \times User$	Applicability: user &user.

Estimating the unknown ratings of the items is a costly function for services having many users as well as items. So it is not necessary to estimate it or the entire $Users \times Items$ space beforehand in practice. Table 2, shows the types of applicability or relevance between these entities.

4.2. Contextual or multidimensional

Context have a vital role in estimating the applicability of an item to a user's need and is useful to the recommendation techniques. As indicated in computational methods, contextual information makes better recommendations by using a new rating function, which is represented by the equation :

$$U \times I \times C \rightarrow R \qquad (2)$$

where U: users, I: items, C: contexts, R: rating function

This contextual information estimates the unknown rating values of the multidimensional model through the available values. The classical method is categorized into CB, CF, and HB filtering, that refers to these relations, $Items \times User$, $User \times Item$ and $User \times User$. Mostly ratings are based on the item, tag and user. For the two-dimensional approach, a content-based approach is studied over the content of items while collaborative filtering is studied over users. Hybrid filtering is to remove the demerits. Knowledge-based is studied over items and users. Contextual approaches refer $User \times Tag \times Items$. Overall rating of this method is given by the below equation :

$$R = D1 \times D2 \times D3 \times D4 \times ...... \times Dn \qquad (3)$$

where R: rating function, D1, D2… Dn: dimensions.

Generally, the user-item approach is used. Then comes the user-tag approach accompanied by the user-user approach.

5. Algorithm

Many techniques and algorithms are applied in social media RS to investigate the explosion of data and represent in the form of rules and patterns [18]. In some articles, CB filtering applies Bayesian Network and logistic regression methods. Mainly CF filtering uses decision tree, K-NN, link analysis, matrix factorization, clustering, and association rule. Rankings are then estimated for every community. Whereas HB filtering uses kNN, Clustering, fuzzy methods, matrix factorization, etc. Other techniques like trust techniques, link analysis, etc are least applied in the chosen articles. Figure 7 shows the framework of the algorithm used in the analysis.

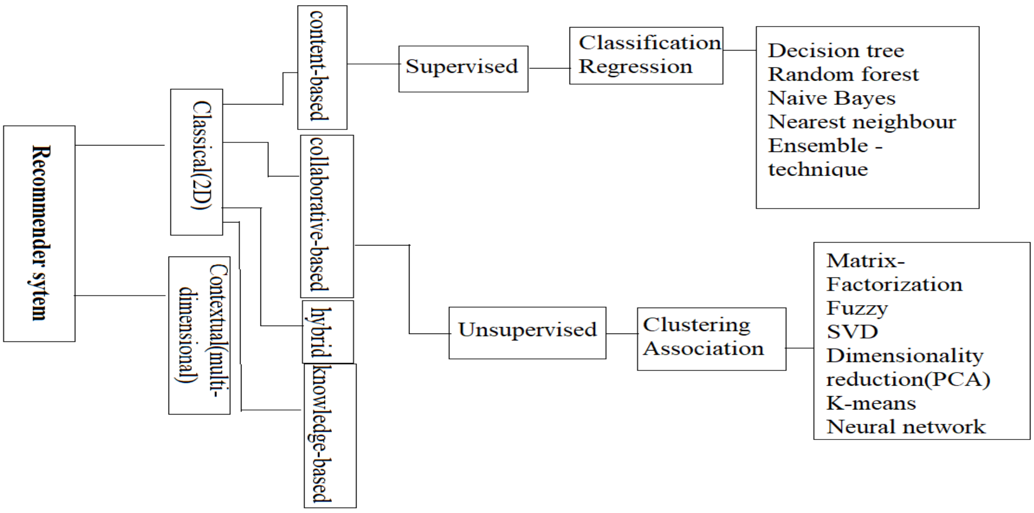

Figure 7. Overview of the algorithm used in recommender system

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The frequently used algorithms in the selected articles are described below.

5.1. Decision tree

This is used for the decision-making process where decision trees are visualized. A tree-like structure involves deciding features to be chosen and conditions to be used for splitting. It contains conditional control statements that are internal nodes checking any conditional attribute. An arm to the condition shows the outcome of the test and an end node is displayed as a group title. Thus, this predicts with high accuracy and ease of interpretation. They are referred to as CART(Classification and Regression Trees).

5.2. Random forest

In this algorithm, detecting the root and splitting the feature nodes will run randomly as compared to decision trees. Overfitting is a kind of critical problem but in this case, if there are enough trees, the classifier would not overfit the mechanism. It can also operate missing values and can also be managed for categorical values.

5.3. Naive Bayes

Bayes theorem relates to this algorithm, as it comprised of many algorithms having the same rules. That means, every entity pair should not be dependent on each other. Bayes theorem finds the probability of an event if other has already occurred, given by :

$$P(X \mid Y) = \frac{P(Y \mid X)P(X)}{P(Y)} \tag{4}$$

where X, Y : events, P(X): probability (prior) of X, P(X|Y): probability (posterior) of Y
Types of Naive Bayes classifiers are multi nominal, Bernoulli, Gaussian naive Bayes classifier, etc. This algorithm used for sentiment analysis, spam filtering, recommendations, etc. But they have demerits while performing classification as the predictors are dependent.

5.4. Ensemble

These methods are used to create multiple models for combining to produce better results. Voting and averaging are the two easiest ensemble techniques where voting is used for classification and averaging for regression purposes. Using some training datasets, both techniques form models. In the case of voting (majority), the model predicts the votes for each test instance and provides a final output that gets more than half of the votes. Thus, it makes stable predictions otherwise not when the situation finds the opposite outcome. In the case of averaging, for every event of test dataset, average predictions are estimated. These techniques often reduce overfit and gives a smooth regression model.

5.5. Matrix Factorization

Various input data are organized as a matrix representing users and products of interest. The most important data are feedback, which consists of direct input of users' choices in items [19]. It is a collaborative based filtering that discovers latent aspects among entities. Correlation measures are taken to check accuracy between item and user recommendations [20]. The defect lies in memory management for maximized data and mathematical estimation. Thus, memory management for large feature sets and excess processing time is required.

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5.6. Fuzzy Techniques

Fuzzy technique uses a particular rating scale to indicate the products. For example, ratings between low to high, where lower value e.g 1 specifies the less interest and higher value e.g 5 specifies the most interest to rate any product. Sometimes linguistic ways relate to the choices, such as 'like' or 'dislike' or 'old' or 'young'. Suggestions for the technique are estimated by the uncertainty of indistinct data. Imprecise information of users and items are fuzzy; thus, many fuzzy functions or applications are applied to the system to acquire accuracy [21].

5.7. Singular Value Decomposition

This technique needs working knowledge of both matrix algebra and vector calculus. SVD of a matrix is a factorization of that matrix into three matrices. It uses algebraic properties and provides geometrical and theoretical insights about linear transformations. It has also important applications in the data science field. Mathematical applications of the SVD include finding range, null space, rank, and matrix approximation.

5.8. Dimensionality Reduction (LDA & PCA)

This method is used to decrease the measurements of the feature set (data set) with a large no of columns or an array of three-dimensional space. That is to reduce the number of variables of the data set by obtaining a set of principal variables. Its major motivation is to avoid overfitting and to remove redundant features and noise. This technique is done by the feature selection method as well as feature engineering methods. They identify and select relevant features for the sample by using transformation or operating the samples. This can be of LDA and PCA types that is, Linear Discriminant Analysis relates the data set with less dimensional space by maintaining separability. Whereas Principal Component Analysis explains the variance of data to maximize that separability. LDA refers to a supervised algorithm while PCA considers to unsupervised algorithm. The objective of PCA is to identify strong patterns in a dataset and raise its variation.

5.9. Clustering

Clustering mainly splits up the products or data into sets of clusters using ratings given by the user. "K-means clustering" has become more preferable. K-means creates groups of objects in the form of k clusters. These groups have members with small distances among each other and have dense data areas. It is an iterative method performed on large sets of data to discover knowledge. Hence, this technique is highly active in statistics, pattern recognition, image or text classification, and machine learning. Various cluster-based approaches face difficulty while relating to large data items and dimensions.

5.10. K-Nearest Neighbor (kNN)

This framework is a CF-based system that suggests the following steps: RS makes a user profile using ratings. Then, a statistical technique is used to find out neighbors i.e., k users, that display similarities with the past. It is formulated using the degree of similarity by a target and its neighbors. While a neighborhood is chosen for a marked user, this system makes a set of products for that user who may purchase by analyzing neighbors [22]. Besides, the accuracy of kNN is quite good. Memory parameters may be used for search issues to find k neighbors that are nearer to the marked one. It is estimated costly due to memory needs for storing every trained data.

6. Conclusion

We began by discussing the Big Data current status and exposing various social media research techniques. We then presented a classification of works related to these parameters. All major research efforts assist researchers in acquiring an improved understanding. Interest in social media research for the recommender system will develop significantly in the future. Non-personalized RS is useful but personalizing recommendations add value. With this assortment of articles on recommendation systems, there can be seen an uprise in its trend. The highly used dataset is MovieLens as it provides seamless access to data. Thus, on comparing all kinds of filtering, it is observed that the collaborative filtering technique is mostly used. So the inspection of this area of business and big data analytics comes up with comprehensive prospects by centralizing over the current aspects in the recommender system.

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