Experimental Analysis of Recommendation System in e-Commerce

Neha Verma, Devanand, Bhavna Arora

Abstract**:** ***Recommendation System (RS) are generally used in e-commerce industry to solve the complication of information overloading. Large amount of information is generating now, days due to which user face the difficulty in finding the relevant information of product and services matching to their taste and preferences. Data mining (DM) is the process of mining and extracting useful knowledge from large datasets. The tasks of DM are to do description and prediction of data to retrieve the information. RS is a subfield of information retrieval (IR) and IR is subfield of DM. Recommendation engines basically are data filtering and IR tool that make use of algorithms and data to recommend the most relevant item to particular user. The various technique and approaches used by RS are content-based (CB) filtering, Collaborative Filtering (CF) and hybrid filtering techniques. This paper illustrates the role of Data Mining in Recommendation System and proposes a workflow of RS. Also describes the review of techniques, challenges of RS & compares recommendation systems of various e-commerce websites.***

Index Terms**:** ***Data Mining, Recommendation System, Recommendation Technique, e-commerce.***

I. INTRODUCTION

Data Mining is cogent tool used by Recommendation Systems that helps e-commerce industry to increase their sales and maintaining the business relationships between customer and organization. It is a discipline of criss-crossing of computer science and statistics used to find hidden pattern into the information banks [1]. The central objective is to dig and extract useful information from large datasets and frame it into knowledgeable structure for future use. This technique can be applied to any kind of unstructured data like multimedia data, network data and transactional data etc. [2]. DM is a core of knowledge discovery in database (KDD) process. The key steps of knowledge discovery are data cleaning, data integration, data selection, data information, data mining, pattern evaluation, knowledge presentation [3]. The various predictive data mining techniques are classification, regression, time series analysis, prediction and descriptive techniques are clustering, summarization, association rule, sequence discovery [4]. The gigantic growth of products and service in e-commerce industry over the web has turned it strenuous for the user to search for the product which is reasonable to the user. RS is the software that provide the suggestion to the user regarding products and services in the e-commerce industry [5] and suggestion helps the user in decision making like selecting books, cloths, shoes, watches etc. RS plays a very critical role in highly rated e-commerce sites and applications like Amazon, Flipkart, YouTube, Netflix and many e-learning sites etc. Here are some motivation as to why e-services provider introduce RS like increment in sale, user satisfaction, sell sundry items, user fidelity, more understanding of what user want? Various functions of RS are to express self, recommend a sequence and bundle of products, annotation in context, find some good item, find all good items, just browsing, improve the profile, help others, influence others [6].

Three phases of recommendation process are:

- **Information Collection Phase:** In this phase RS, initially, have to gather the information regarding user preferences like search history likes/dislikes, rating to an item previously user purchased, current location of the user.
- **Learning Phase:** In this phase RS are trained using information collected in previous phase for better understanding of user taste.
- **Prediction Phase:** In this phase RS finally predicts the user relevant items for recommendation [7].

II. RELATED WORK

In paper [8], recommendation play a very important role in e-commerce websites like Amazon, Flipkart, YouTube, Netflix etc. It helps them in retaining customer and increment in sale of items. The problem of overloaded information is solved by search engines, but the issues of personalization of data remain same. To solve this issue e-commerce industry, introduce RS. It makes the task of online seekers simple by suggesting fine variety and precise recommendation of products. Here author also discusses about different techniques of RS, its advantages and disadvantages.

In paper [9], presents a framework for understanding RS, its approaches. Also, for major issues: a) how user input is obtained & used b) contribution by people & computations, types of communication involved c) algorithms for linking people and computing suggestions d) demonstration of recommendation to users.

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In paper [10], a workflow-based RS model to provide useful knowledge to collaborative team (CT) contexts rather than day to day task, like recommending news, movies etc. The CT contains information about relationship among users, roles, tasks which could combine with CF to obtain user entail. Two workflow-centric methods for mining team members are a) knowledge demand b) determining proper recommendation volume, the limitations for current methods & model are cold start problem.

In paper [11], Rec4LRW is used to facilitate research scholars, it helps in finding research paper for their literature survey. It has three key tasks: a) building a list of papers b) find similar paper c) shortlisting final reading paper. Technique used in proposed work are based on transitional set of protocols that capture the features of a scientific paper.

In paper [12] there are variety of domains where RS are applied like news, books, search queries, social tag and e-commerce sites etc. also discuss various techniques like CF, CB, clustering and classification etc. Used to get better recommendations hence reduction in high precision, MAE & accuracy.

In paper [13], author discusses the top 10 data mining algorithms i.e. SVM, Apriori, EM, k-NN, Naïve Bayes, K-means, PageRank, C4.5, AdaBoost and CART in detail. These algorithms used for clustering, classification, association analysis, link mining and statistical learning.

In paper [14], the author proposes a Hybrid CF recommender algorithm with FCM clustering, slope one and FSUBCF algorithm to solve data sparsity problem. Initially it predicts the rating of items that have note rated yet by the user using slope one algorithm based on FCM cluster. On comparing this algorithm with tradition CF algorithm gave better results.

In paper [15], a radical analysis on research articles of RS from 2011-15, total 61 articles are considered from 434 published in WOS (Web of Science) & Scopus. Also discuss some deficiencies, strengths of various recommendation technique.

In paper [16], author proposes a web-based e-learning systems, focuses on two type of affiliation 1) between user and system 2) system and open web. It is being developed using clustering and CF technique. It finds relevant content on the web, personalize and notify content based on the system consideration. This system is able to spot user's need.

In paper [17], the huge growth of information on web is tough and time-consuming problem. Author purposes a RS for research paper field using DNTC (Dynamic Normalized Tree of Concepts) model. It enhances existing model with tortuous ontology and large number of research paper. This system uses the 20112 version of ACM CCS (Computing Classification System) ontology. The proposed approach is better than previous. Here the user profiling step build a user profile as a DNT (dynamic normalized tree) using dynamic edit tree distance approach to do comparison between unseen research papers and user profile.

In paper [18], the use of RS in academic research is very helpful to research scholars to find papers related to their domain of research. Here author propose a topic analysis of paper using item-based method. Also considering cold start problem. The proposed model is able to generate recommendations with a smaller number of user ratings.

In paper [19], supposes a method that relate the captured input and clustering algorithms to solve cold start problem. It uses cosine similarity measure to similarities between users and build clusters. It selects *top n* items for each cluster of users on the base of average rating of item.

Above Literature survey includes the various recommendation systems and models & also illustrates different techniques that can be used in order to build RS described in the Section IV.

III. WORKFLOW OF RECOMMENDATION SYSTEM

The proposed workflow of RS is divided into two phases: a) Information gathering phase b) analysis and recommendation phase as shown in fig.1. Here firstly, RS is build using various techniques mentioned in section IV and user's information is collected regarding searching, buying habits etc. and this gathered information about user is helpful in analyzing user taste i.e. predicted information about user choice and this prediction is further used for generating recommendations.

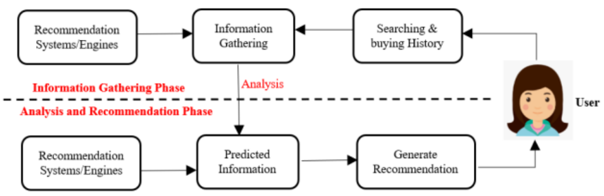

Fig.1 Workflow of RS

IV. TECHNIQUES OF RECOMMENDATION SYSTEM

In this paper RS techniques are divided into three categories: a) Traditional Techniques b) Modern Techniques c) Hybrid Techniques[20]–[24]as shown in Fig 2.

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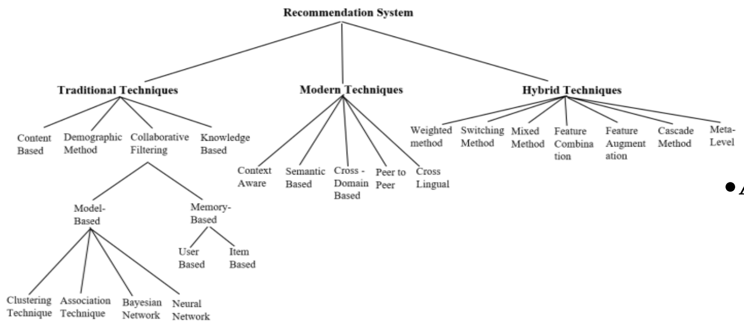

Fig2. Various Techniques of RS

A) *Traditional Techniques*

a. ***Content-Based (CB):*** This approach employs a sequence of different features extracted from contents of item in a order to recommend more items to user with similar features rather than other user's perspective [12],[25].The pivot is on algorithms for learning user preferences [9]. Recommendation approaches used *Top-n* recommendation where n is decided by the organization and rating scale approach where threshold value decided let say t, recommend products greater than or equal to value of t. Various algorithms used by CB like naïve bayes classification, decision tree etc. [8].

b. ***Demographic Method (DM):*** This technique is quick and easy-peasy provide recommendation based on demographic history of user profile with few observations [12].

c. ***Collaborative Filtering (CF):*** This approach build database model i.e. user-item matrix and find user with germane interest or preferences by calculating resemblance between their profiles to make recommendations[7],[26]. Basically it requires the user participation i.e. rating reviews of the item given by millions of user to express the preferences of item for recommendations, but usually user participation is low[9].Let's say if user U_1 likes items say I_1, I_2,I_3 and user U_2 likes I_2 ,I_3, I_4, we can say that they have almost similar taste. So, RS can recommend I_4 to U_1 and I_1 to U_2. CF further divided into two categories and sub categories as shown in figure 2:

➢ ***Model-Based***

- ***Clustering Technique:*** Also known as unsupervised learning[27].It is used to link cluster of users with same predilection. The iterative clustering method that use tie-in between users & items. Using *k-mean* algorithm both users & item are first clustered, then prediction is calculated [28].The taxonomy of clustering methods are: a) partitioning method b) hierarchical agglomerative or divisive methods c) density based d) grid-based e) model-based methods [29].
- ***Association Technique:*** Association rule (AR) relate items having similar features where DM is administering. It uses Apriori algorithm for implementation[30].The taxonomy of AR are: a) multilevel b) multidimensional c) quantitative association rule [29].
- ***Bayesian Network (BN):*** It a probabilistic technique to general training, associates to category of Bayesian classifier[31].It can be predicted as a directed aliphatic graph, with curve represents the integrated possibilities between the variables[32].Formula to calculate Bayes theorem are as follow, where P(m|n) is posteriori probability, P(m) is observing probability of m, P(n) is observing probability of n [33].

$$P(m|n) = \frac{P(m) * P(n|m)}{P(n)}$$

- ***Neural Network(NN):*** Neoteric aid have concern NN for product recommendation in e-commerce industry and demonstrate positive outputs [34].Learning of algorithm of NN is back propagation [29].

➢ ***Memory Based***: Also known as neighborhood-based filtering algorithms.

- ***User Based Neighborhood:*** It find the similarity scores between users and select user with similar taste and prediction ($P_{u,i}$) of an item for a user u is calculated as [35]:

$$P_{u,i} = \frac{\sum_v (r_{v,i} * S_{u,v})}{\sum_v S_{u,v}}$$

Where $P_{u,i}$ is item prediction, $r_{v,i}$ is rating given by user v to item i and $S_{u,v}$ is similarity between users [24].

- ***Item Based Neighborhood***: Its similar as user-based with just a little change i.e. instead of user here we take items and prediction is calculated as:

$$P_{u,i} = \frac{\sum_N (S_{i,N} * R_{u,N})}{\sum_N (|S_{i,N}|)}$$

Where $R_{u,N}$ is rating of item and $S_{i,N}$ is similarity value [35].

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d. ***Knowledge Based (KB):*** This approach suggests items based on uses desire & conjectures entail. This obtained information contain the features of item that meet user taste[12]. The table I: describes about what kind of input has taken in respective techniques for building a recommendation system.

Table I: Overview of traditional techniques

Technique	Inputs
CB	User rating + item attributes
CF	User rating + neighborhood rating
KB	User preferences + item attributes + domain knowledge

B) Modern Techniques

a. ***Context Aware:*** It uses contextual data like weather forecasting, day-night time etc. Most of RS implement this technique for businesslike utilization of information e-commerce industry, social networks etc.

b. ***Semantic Based:*** This kind of system occupy internet in form of metaphysics. Various RS express their behavior concerning semantic methods like trust management, decision making, social interaction groups etc. [37].

c. ***Cross-Domain Based:*** Also known as linked-domain recommendations. This process includes three key points a) domain knowledge transfer b) user-item overlap c) recommendation generation. It utilizes the knowledge learned from source to give recommendations to target [38].

d. ***Peer to Peer (PP):*** This is a suburbanized technique and have ability to solve scalability issue. Here every peer cluster with similar taste associate to other dedicated peer. It utilizes basis of history to give recommendations [33].

e. ***Cross Lingual:*** It uses dictionaries, machine translation for information retrieval. Various classification methods are used for this approach [39].The task of this approach to help user in finding the text, document, news etc. in the language he or she knows rather than the source language [40].

C) Hybrid Techniques (HT)

HT is a fusion of more than two approaches to obtain deficiencies& optimization lone systems. Some stratagem to achieve hybridization are as follow [41]:

a. ***Weighted Method:*** Here score of sundry items is integrated to build solitary recommendation.

b. ***Switching Method:*** This process switches between RS techniques based on contemporaneous state [25].

c. ***Mixed Method:*** Numerous recommendations from divergent system are represent at same time.

d. ***Feature Combination:*** Numerous attributes from divergent knowledge sources are combine together in order to generate single algorithm.

e. ***Feature Augmentation:*** Here output of one approach is considered as the input of next approach.

f. ***Cascade Method:*** Here recommender is given rigid primacy rather than the lower primacy, before breaking the chain of higher scoring.

g. ***Meta-Level:*** Single technique is pertain to build a model whose input used by next approach[42].

V. SIMLARITY MEASURE METHODS

Similarity measure is the process of calculating likeness of products, can be a mutuality or antithetical distance value. Number of methods are there to find similarity matrices, some methods are as follow:

A) Cosine Similarity (C_{sim}): Calculates similarity between two non-zero vectors of inner product space. Suppose 2 vectors U_v user profile vector and I_v item vector respectively[43]:

$$C_{sim}(U_v, I_v) = \cos(\theta) = \frac{Uv \cdot Iv}{|Uv\| \|Iv|}$$

B) Euclidean Distance (ED): It calculate the distance between items, that calculated distance is used for product recommendation. ED ≥ 0. Let say Item x and y with dimensions n is calculated as[44]:

$$ED = \sqrt{(x_1 - y_1)^2 + \cdots\cdots\cdots + (x_n - y_n)^2}$$

C) City-Block Distance (CBD): Also known as MD (Manhattan distance). CBD ≥ 0, unlike ED. It represents distance between two points y and z, with dimension t in the city road grid where you have to move around the building instead of going straight through is calculated as[45]:

$$CBD = \sum_{j=1}^{k} |a_j - b_j|$$

D) Tanimoto Coefficient (TC): Also known as the Jaccard index. It find the similarities between sets of finite sample, formula calculated as[45]:

$$Jaccard(E,F) = \frac{E \cap F}{E \cup F}$$

E) Pearson's Correlation (PC_{sim}): It tells us how much items are correlated to each other. Higher correlation, more similarity between items. Formula calculated as follows[43]:

$PC_{sim}(p,q) =$

$$\frac{\sum(r_{pi}-\bar{r}_p)(r_{qi}-\bar{r}_q)}{\sqrt{\sum(r_{pi}-\bar{r}_p)^2}\sqrt{\sum(r_{qi}-\bar{r}_q)^2}}$$

VI. CHALLENGES IN RECOMMENDATION SYSTEM

RS is beneficial for recommending though it has several challenges. Some of the discuss below:

A) Data Collection: It can be done in two means i.e. explicitly and implicitly. Explicit data is deliberately provided by the user, means user input. Implicit data is collected from easily accessible sources such as user profile data like searching habits, buying history etc. means the information doesn't deliberately provided by the user [46].

B) Data Sparsity: Millions of products sold on web, where most of the active users rated only few products. If user have rated insufficient items, it's pretty difficult to predict user taste [47]and it leads to lack of information to recommend user relevant items [48].

C) Scalability: As in the hike of products and users, the organization needs more resources to process the information and computation ability is often obligatory to calculate the recommendation[49].

D) User Trust: The user with short antiquity may not be relevant as those who have oofy antiquity in their shopping profile. This trust issue arises in order to evaluate a certain user and can be solved by priority distribution [50].

E) Cold Start Problem: The expression derives from automobiles, when its very cold, engine has difficulty with starting up, but once it reaches its optimal state, it will run smoothly. In recommendation engines this problem simply means that the factors not yet optimal for the engine to provide the best possible suggestions or results [48]. It is onerous to give suggestions to new user as using shopping sites first time and has not rated any items yet and also no previous online shopping history. This problem is called cold start problem [51].Above problem can be divide into two ways: a)visitor cold start (VCS): It means new user is introduced into dataset who has no previous history in e-commerce industry & organization also don't know about the user taste. So, it's difficult to recommend items to the user. b) product cold start (PCS): means a new product is introduced in the market and organization must require the user deeds to prompt the value of that product [48].

F) Gray Sheep Problem: The problem refers to the user whose verdict is not consistently accept or reject with group of people which is not worthwhile for RS. Black sheep are the contradictory group whose individualistic taste make recommendations nearly wayward. However, this is a non-success of RS, non-electronic recommenders also have ample problem, in these cases black sheep problem is a permissible failure [48].

G) Synonymy: Most of the RS are unable to detect concealed interdependence, means proclivity of number of akin items with different entries, title, name. Therefore, treat these kinds of items differently. SVD technique→ LSI (latent semantic indexing) method, used to deal with this problem. But this method gives partial solution only because the fact refers that most of the similar words have more than one different meaning[21].

H) Privacy & Security: It is very significant issue. Users are anxious about what kind of information is collected form his profile & how it is used. To provide personalized &precise recommendations, the system must need to know more about user taste. Information like demographic data and user location. Genuinely, question of confidentiality, security & reliability of the given information arises. Various shopping sites provides the security of privacy of user information with the help of dedicated algorithms and programs [51]

VII. COMPARISON OF VARIOUS E-COMMERCE RECOMMENDATION SYSTEMS

Table II provides the Comparison of top-rated websites in terms of: a) technique is used for recommendation system or engine b) how they recommend products and services?

Table II: Comparison of various RS

Website	Technique Used	How they recommend?

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Amazon	Item-Item Collaborative Filtering[52]	RS works based on items rather than users. Initially the list of visited items by any user is sorted in an item-to-item matrix then recommendation algorithm is calculated by using the cosine similarity. Amazon looks at what kind of item user have been searching, viewed earlier, and recommends the very similar item of different shapes, size and brand.
Facebook	CF (Matrix Factorization)[57]	Recommend on the basis of like-minded people like Facebook recommend friends on the basis of mutual friend list i.e. people you may know.
Flipkart	Hybrid Technique[53] (Content-based (CB)+Collaborative Filtering (CF))	Uses CB for item attribute & image in the catalog and CF algorithm is used to analyze user's searching history like pages viewed, Wishlist, add to cart etc. to find more commonly collaborative searched items for a given product.
Netflix	Machine Learning[54]	Netflix recommends the videos on the bases of user watch history, day including time duration of watching a video, and device on which user watch[55].
YouTube	Deep Neural Network[56]	Firstly, it takes implicit data input i.e. user's watch history and then select videos for recommendation in the range of hundreds.

VIII. CONCLUSION

Recommendation systems are high-priority feature in the success of e-commerce age. In the epoch of online shopping, massive number of products are available on the web. Data mining is the businesslike technique of expressing information from user data, with the correct utilization of DM algorithms we can amplify the performance of RS and solve its problems. It actually helpful to untangle the problem of RS in order to find homogeneity between users and items. This paper concludes a step by step process of building a recommendation system with the help of various technique, similarity measure matrices and challenges tackled by the various recommenders.

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