A Novel Recommender System based on Artificial Neural Network Learning Vector Quantization Classification Approach

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Abstract— Recommender systems have become more important in various domains for lessening the issue of information overload. Traditional Recommender Systems are Collaborative filtering method and Content based filtering method. However, these recommendation methods suffer from data sparsity and cold start problem. So this paper proposes an ANN based recommender system. Artificial Neural Network –Learning Vector Quantization (ANNLVQ) and Optimized Learning Vector Quantization (ANNOLVQ) algorithms are used todevelop a multi-categorical classification model that predicts the class of a rating in recommender systems. In this proposed research, the problem of predicting the rating as a multi-label classification problem is considered where each rating has treated a label. Book dataset used for this proposed research. ANN recommender systems accuracy compared with collaborative filtering method recommender system and ANN recommender systems predicts more accuracy than traditional collaborative filtering method.

Keywords— Artificial Neural Network, collaborative filtering, Learning Vector Quantization, Book Recommendation, Recommender systems.

I. INTRODUCTION

In the era of information overload, Internet users may find it difficult to choose from the multitude of available products and services. There is a requirement aimed at Recommender systems (RSs) that create modified recommendations [1]. The idea behind RSs is not new. It is general to enquire associates for references when one selects an eatery, film, book, etc. To make a recommendation, an RS usually needs user data, items, and user feedback on those items. Subsequently generating a recommendation, user response on the item is acquired either openly or indirectly [2].

The utilization of RSs in e-commerce has many benefits for both sellers and consumers. The former's objective is to make their products available to concerned clients and to achieve consumer satisfaction in addition to loyalty. Their objective can be achieved when users regularly receive products that meet their needs [3]. On the other hand, consumers would receive a list of products they would be most likely to find useful. They also save time, effort and money they would spend trying to discover items they truly appreciate [4].

Recommender systems are useful for internet users who may find it hard to choose from the multitude of available

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products and services. RSs predict how likely the target user is to be interested in an item which might have been unknown to them [5]. This study deliberates book recommender systems that could be beneficial in the public library, schools, and on e-learning portals. Currently, with the introduction of e-books, readers can access low-cost resources using less effort. It was estimated that the performance of reading for desire would turn out to be prevalent, but statistics prove the opposite; it is declining, mainly between young people.

Collaborative filtering (CF) methods most often consider the user as a static entity whose interests are fixed in time. Matrix factorization, for instance, utilizes all the ratings (or implicit response) of a user to build a demonstration of its familiar tastes, ignorant to the probable evolution of taste or fading interests of the user [6]. To make recommendations, CF only requires an item-user rating matrix, so it is simple to develop. The rating matrix, however, can be sparse, specifically in the instance of new items or new users; this is named as cold startproblem. Sparsity may advance to poor recommendations. CF has two other drawbacks. The gray sheepissue happens when the system calculates the preferences of a user who has a task dissimilar than other users. The shilling attackissue happens once an item accepts false evaluations as a form of promotion [7]. A CB recommender is a classifier that studies the patterns in addition to similarities in the buying history of a user to forecast her future interests. A book's content could check its title, summary, outline, whole text or metadata, containing author, year of publication, publisher, genre, page number, etc. [8].Existing techniques for recommender systems [9-13] mainly categorized into collaborative filtering and contentbased recommendations. Collaborative filtering depends heavily on user activities, e.g., ratings of items according to their preferences. The recommender functions under the assumption of similar preferences among users and a sufficient number of user ratings available in the system.

Collaborative filtering, however, has difficulty handling items without sufficient numbers of user ratings and new items that one has purchased or rated, i.e., the so-called cold start problem. In particular, most books are seldom utilized by many patrons according to library use statistics. Thus, effective content-based recommendations become important when these user activities are sparse. A content-based been initially developed method has for book recommendations. Its system, however, depends on a careful feature selection process by labeling every book with values, which is a labor-intensive task. Specific attributes of users must also be provided in advance when evaluating recommended books. Automated text-classification approaches then employed for exploring content-based book recommender systems. However, the relevance of the recommendations only considered textual metadata, partially extracted from the Internet, rather than actual book text. In industrial applications, e.g., Google Books, full-text indexing has been used commonly for book retrieval via search aueries.

In a recommendation systems context, metadata information from analyses inscribed for businesses has infrequently deliberated in traditional systems technologically advanced with content-based in addition to collaborative filtering methodologies [14]. Collaborative filtering, as well as content-based filtering, are common memory-based techniques for endorsing innovative products to the users but grieve from certain drawbacks and be unsuccessful to offer practical recommendations in various circumstances. The sparsity mentions to the enormous percentage of nonappearance of ratings: individually user only has ratings in a very restricted number of the accessible data. There is no sufficient space for complete data [15].

This paper proposes a Classification Approach to develop a multi-categorical classification model that predicts the class of a rating using Artificial Neural Network LVQ and OLVQin recommender systems and toenhance prediction accuracy. In this proposed approach, the problem of predicting the rating as a multi-label classification problem considered where each rating has treated a label.

Collaborative Filtering Cosine Similarity (CFCS) recommender system compared with ANN recommender systems for accuracy.

This paper is structured as: Section 2 explains the literature review related to recommendation systems; Section 3 defines the proposed methodology; Section 4 gives the results and discussions followed by the conclusion in addition to future scope in section 5.

II. LITERATURE REVIEW

Suglia et al. (2017) [16] presented a modular and extensible architecture exploiting deep neural networks to provide users with content-based recommendations. The model was based on LSTM networks, a particular class of RNNs particularly able to deal with sequences of data of arbitrary length, as the content describing the recommended items. Specifically, an approach was developed which jointly learns two embeddings on behalf of both items to be recommended as well as user's preferences. Given such representations, recommendations were provided by exploiting a logistic regression layer which calculates the likelihood that a user will like a particular item. The results of the proposed approach showed that the proposed deep architecture was able to significantly overcome both algorithms based on (shallow) neural networks as Word2Vec W2V and Doc2Vec D2V as well as popular and well-performing techniques for collaborative filtering and matrix factorization.

Devooght and Bersini (2017) [17] showed that recurrent neural networks are a powerful tool aimed at collaborative filtering, even external to the sparse session-based settings where it first introduced. This method achieved the best results using the categorical cross-entropy objective function. RNNs performed exceptionally well on short-term recommendations and adding noise to the training sequence was observed (such as dropout and shuffling) improves its triumph on long-term recommendations.

Yi et al. (2016) [18] suggested an expanded auto encoder recommendation framework Supervised Neural Recommendation (SNR). The stacked auto encoders model considered to excerpt input feature formerly was reconstruction of the input to make the recommendation. Then the side information of objects was mixed in the structure, and the Huber function based regularization was implemented to the performance enhance of recommendation. The innovation first of current recommendation framework was that the side information was used to enlarge the framework. The presented scheme was verified on a public dataset. Results indicated that the recommendation framework has better performance than the state-of-art recommendation methods.

Veugen, T., & Erkin, Z. (2015) [19] developed a system for recommending items in a privacy-preserving way by using a content-based item similarity matrix. Compared to previous solutions, the leakage of the divisors Vi was avoided which contain information about the commercially sensitive item similarities. The costs of introducing a secure division protocol led to a doubling of the computational and communication complexity, and a slight loss in recommendation accuracy. However, the system neither relied on trusted third parties nor requires interaction with peer users. In addition, this proposal offered an efficient and much more secure solution for this class of recommender systems.

Shen et al. (2016) [20] suggested a novel CNN to make personalized recommendations and attained a superior result. The suggested procedure tested on a public dataset. Outcomes specified in this recommendation procedure for recommending new and unpopular learning resources was practicable. The CNN-based model would show a vital role in e-learning systems or intelligent tutoring systems. Even though the application considered here was learning resources recommendation, the technique was more usually appropriate to news recommendation, and so on.

Chen, L., & Wang, F. (2017) [21] presented a method of implementing tradeoff-oriented explanations in preferencebased recommender systems. Through measuring users' objective behavior and subjective perceptions as well as collecting their free comments in both before-after and within-subject's experiments, several interesting findings: 1) Incorporating feature sentiments into Pref-ORG can be effective to increase users' product knowledge, preference certainty, perceived information effectiveness, recommendation clearness, and quality, and buying intention. 2) The explanation interface's actual effectiveness was also measured, which indicates almost half of users made better choices after using SentiORG. 3) As for decision efficiency, it shows users spent more time in making decisions in Senti-ORG, which is consistent with related works of literature' observation that efficiency is not necessarily correlated to users' decision effectiveness and perceived system competence. 4) Three design principles derived from the experiment results. In particular, given that The majority of users preferred mixture View, recommended explaining products' tradeoff properties (pros and cons) regarding both feature sentiments and static specifications.

Paradarami (2017) [22] technologically advanced an innovative hybrid RS procedure that forms on the capabilities provided through traditional methodologies similar to collaborative filtering besides content-based filtering by employing the metadata related with review text to train and build an Artificial Neural Network (ANN). A multicategorical classification model was established that forecasts the class of a rating. LogLoss, a convex function, was the cost function reduced by relating stochastic gradient descent and prediction of accuracy was utilized to determine the model's efficacy. The effectiveness of the hybrid model assessed by analyzing the percentage of observations with correct predictions. The efficacy of these rating predictions also assessed when translated to yes/no recommendations.

Tewari, A. S., & Barman, A. G. (2018) [23] stated that almost all existing e-commerce recommendation systems had put all their efforts in augmenting all exciting items of the target user to their recommendation list, deprived of any importance to the order of things in the recommendation list. The suggested method meaningfully has exposed around 34% precision for top-n recommendations. The proposed approach had its unique feature that finds the popularity of items in the market using opinion mining. All these unique features collectively help the proposed RS in creating relevant smaller topn recommendations list for the target user and also assist in alleviating item side cold start and gray sheep problems. The investigational outcomes presented that the suggested RS significantly outperformed the further benchmark recommendation techniques.

Liu et al. (2018) [24] proposed an online activity recommendation approach based on the dynamic adjustment of a recommendation list be implemented on NiusNews, an online news website. User preferences were derived by studying the latent issues founded on Non-Negative Matrix Factorization (NMF) and the hidden topics based on Latent Dirichlet Allocation (LDA). The concerns of sparse data and cold-start activities were alleviated by carrying out a possible association study of news in addition to activities. Furthermore, the current news was considered that the target consumers were looking for capturing the current preferences more precisely. To manage the concern of limited recommendation layouts, the Most Frequently Pushed (MFP) and Not Frequently Clicked (NFC) replacement approaches were recommended for a dynamic variation of the recommendation list. These strategies are critical for practical purposes of online recommendations and not considered in existing recommendation methods. The proposed replacement approaches in addition to online recommendation method offer probable solutions for dynamically adjusting recommendation lists in online recommender systems. The developed system was dynamically adaptive to cost and efficiency. The suggested approaches (FAR-ONHI and WAR-ONHI) integrate user preference study and existing news interest study through the activity replacement strategy to dynamically adjust the recommendation lists. In the online experiment, the results showed that the proposed method performed better than other methods do. The online evaluations demonstrated that the proposed approach considering the dynamic adjustment of

recommendation lists could improve recommendation quality for online recommendations.

III. PROPOSED METHODOLOGY

The ANNLVQ and ANNOLVQ approach is introduced in this section, starting with the intuition behind it, and then continue to describe its details. While the proposed method is general and can be used to recommend any consumer item, a specific example domain for illustration is chosen. Providing the most considered consumer domain, in the background of recommendation, is that of books, henceforth, usage of the book domain to present the proposed technique. In other words, the suggested technique is present to recommend books founded on customer reviews.

Intuition and overview

The overall goal of RSs is to select the objects that could be of concern to a user. In this proposed context, predicting ratings for books to users, and recommending those books with highest expected ratings to them, together with reasonable and personalized explanations to improve the transparency of the logic in the recommendations is presented. Mentioning that the number of descriptive attributes that typically utilized in content-based book recommendation is limited and inadequate, the proposed approach spontaneously extract adjective features from external user reviews to describe individual features of items besides user tastes that are capable to truthfully reflect the users' perception towards books at a higher and more abstract level.

The proposed technique states the rating sparsity problem by decomposing a singular user rating into multiple measurements considered by extracted adjectives and then converting a minor number of user ratings into a more significant number of feature preferences. This permits to comprehend user benefits well, and to choose their selected items more precisely through each of their preferred features, consequently alleviating the issue of item-level rating sparsity. Furthermore, by explicitly listing out adjective features that cause items to be endorsed, the user could be competent to clarify the reason for the recommendations instinctively to users, with the objective of addressing the transparency problem.

Recommendation framework

The overview of the suggested book recommendation framework is presented in Fig.1. The main components are designed and implemented to realize the proposed recommendation engine; they are Data Collection, Pre-Processing, Feature Extraction, Recommendation using Collaborative filtering method, Recommendation system using ANNLVQ classification, Recommendation using ANNQLVQ and Accuracy prediction.

Dataset Collection

The dataset used for the proposed method is collected from the database which has the details of the user ratings on various books. The dataset contains both explicit and implicit feedback. Datasets are generated in a .csv file, and it has the details of book_id, best book, work_id, ISBN, Original publication, average rating, rating count, work_rating and work test review from comment.

Pre-processing

Data pre-processing is usually the initial stage of knowledge discovery. Data pre-processing can influence simplification performance of a classification algorithm. Most of the real world datasets suffer from problems of missing values and ambiguities; similar was the case with the proposed dataset. So Pre-processing process is must for dataset.

First, all the rows or information on articles which didn't belong to any class are removed. There was some amount of user feedbacks in which article didn't belong to any class at first, after removing all of them were left with around some user feedbacks and classes. Next, ambiguities in the feature 'classes' were removed, ambiguities like several classes were referring to the same author or entity, it is replaced all of them by a single class.



After the second step, all the classes which occurred only once as classification requires the occurrence of each item was removed at least twice so that one can be used in training and other for testing. After the third step, it is rechecked if there was any article still left which didn't belong to at least one class. The process is stopped when a sufficient amount of ambiguities and each article belonged to at least one class were removed. After performing all the steps above, finally left with a less number of user feedbacks and different minimum classes.

Collaborative Filtering based Recommendation system

To obtain predictions and recommendations to collaborative filtering a subset of active users is chosen to the criteria for selecting a subset is based on the user's similarity with active users then the weighted aggregate is computed for their rating to generate recommendations. Collaborative filtering comprises of the three major steps. In initial step all users will be weighted and similarity is computed with corresponding to the active user. In the second step subsets of user called as predictors will be designated. In the third step rating is normalized and the weights of selected neighbours are combined with rating to make prediction [25-26].

At that point the documents are represented as term vectors, the comparability of the two documents relates to the relationship between the vectors. This is evaluated as the cosine of the point between vectors, that is, the so-called as cosine similarity. Cosine similarity is a standout amongst the most well-known similarity measure employed to text documents.

Input-User and book ratings Output-similarities between user and books

Similarity = $\cos(\theta) = \frac{AB}{\|A\| \|A\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \cdot \sqrt{\sum_{i=1}^{n} B_i^2}} (1)$

The process steps are

1. Get the dot product of vectors 'a' and 'b'

2. Multiply magnitude 'a' and magnitude 'b'

3. Divide the dot product of vectors 'a' and 'b' by the product of magnitude 'a' and magnitude 'b'.

Accuracy prediction CFCS, ANNLVQ and ANNOLVQ classification

An ANN is a machine learning approach that uses a combination of similar models to improve the outcomes attained over a single model. In this paper, Collaborative Filtering Cosine Similarity- ANN optimized Learnig Vector Quantization Classification approach is used to predict the class of the book based on the reviewer comments.

Vector quantization (VQ) is a common algorithm in the fields of text and speech processing. Having N information vectors, VQ algorithm groups them into a small number of

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clusters in an unsupervised methodology. VQ might be considered as a clustering technique. Optimized Learning Vector Quantization (OLVQ) is a neural network that joins competitive learning with supervision. It very well may be utilized for pattern classification [27]. Optimized LVQ joins clustering and classification method dependent on feed forward neural network. Input sources are stimulated through a variable number of hidden layers to the output nodes.

Initially, the information space is distributed into nonoverlapping regions or clusters. Second these regions are mapped to predefined classes. The initial step has been sophisticated utilizing a competitive layer of the network that works like the Self-Organizing Map (SOM). The layer clusters the information vectors utilizing a table of vector models known as a codebook. The quantity of codebook vectors is substantially less than the quantity of input information vectors. Nonetheless, it must be predefined by the client. In the clustering task, each data vector is allocated to the nearest codebook vector as per a predefined distortion measure. The second step of optimized LVQ is practiced utilizing the linear layer of the system that maps each codebook vector to the object class. The design of Kohonen's Neural system that executes optimized LVQ tasks. It consists of three layers; named input, hidden called competitive, and output called linear layers. The weights of the input-competitive links represent the codebook vectors. They are M-dimensional vector, as the input vectors, that are located in the input data space for identifying cluster regions. Clusters borders are defined by a "Voronoï net" of hyperplanes perpendicular to the linking line of two codebook vector. Each neuron in the competitive layer represents one's cluster. The linear layer maps the competitive layer's neurons into target classification defined by the user. Multiple neurons may be appropriate to the similar class, however, in the data space, cluster regions equivalent to the similar class in the M-dimensional space need not be contiguous. The learning algorithm has to properly locate the competitive 's neurons, codebook vectors, in the M-dimensional input space and subordinate them to the correct linear neurons, class labels [28].

Learning algorithms are all adaptive as the training samples are presented one at a time in random order. The codebook vectors gradually capture the fundamental statistical properties of the training data. That is for avoiding both the falling in local optima and the difficulty of gradient calculation. As an outcome, optimized LVQ networks are statistical classifiers, which quickly converge to a good solution.

The initial step in the optimized LQV neural network design is the parameters setting of both competitive and linear layers. Then the presented input data vectors have to be separated into training and test groups. Learning algorithm normally works as follows:

Initialization of Codebook:

For each target class, the number of codebook vectors has to be relative to the number of incidence of that class and these vectors are adjusted to the center of the input ranges.

Determination of the winner:

The Euclidean distance has to be evaluated between training data vector and every codebook vector,

$$d = \| W_j - x_i \| = \sum_i (W_j - x_i)^2$$

$$m_c = \arg\min(d_i) \quad (3)$$

Codebook Adaptation:

Codebook vectors are optimized during the learning process. They are all iterative gradient methods. The requirement for finding the optimal codebook and avoid difficult gradient calculations.

Optimized LVQ1 initiates by randomly chooses a training vector x, discovers the nearest codebook vector mc which is called the winner and transfers this winning neuron to the training data vector if both of them belong to the same class, if not the neuron will be moved away and all other neurons are kept unchanged [29].

$$m_{c}(t+1) = m_{c}(t) + s(t)\alpha(t)[x(t) - m_{c}(t)]$$
(4)
$$m_{i}(t) = m_{i}(t) \text{ for } i \neq c.$$

Based on this the class of the books is classified based on the reviewer comments.

Accuracy Prediction

In accuracy evaluation of classification, there are Recall, Precision and F-measure to evaluate the overall accuracy of the classifier.

Recall

A recall is the fraction of the correctly classified instances for one class of the overall instances in this class. For example, if 900 books are classified to positive and 800 of them are correct, and in the dataset, there are 1000 books which are positive, then the recall for the positive class is 800/1000, which equals to 0.8.

Precision

Precision is the fraction of the correctly classified instances for one class of the overall instances which are classified to this class. For example, if 900 books are classified to positive and 800 of them are correct, and in the dataset, there are 1000 books which are positive, then the Precision for the positive class is 800/900, which equals to 0.89.

F-measure

To get a comprehensive evaluation of the classification, Fmeasure is developed to integrate the Recall and the Precision. The F-measure can be expressed as

$$F_{\beta} = (1 + \beta^2)^* \frac{\text{Precision} * \text{recall}}{\beta^2 * \text{Precision} + \text{recall}}$$

(5)

This is a general form of F-measure, and the parameter β is used to change the weights for Precision and Recall in calculating the F-measure value.

IV. RESULTS AND DISCUSSIONS

The CFCS, ANNLVQ and ANNOLVQ classification based recommender system is simulated in the environment of Java.

Home page and Upload the Dataset:

Fig.2 describes the collecting and uploading of the book recommendation dataset. Here, the dataset is a structured dataset which is a .csv or SQL file.

2	
A	Novel Recommendation System using CFCS-ANNLVQ Classification
n	sProjectsWove_Recommendation_SystemDataset/newbc.csv
	Upload Dataset

Fig .2. Uploading the dataset

After selecting the data, that particular path will be displayed in the text box. By clicking the uploaded dataset, the response dialog box is open, and it is shown in fig.3 and fig.4.



Fig. 3. Data uploading



Fig. 4. Successful updating of input dataset

After uploading the data, all data contents will be displayed as shown in fig.5. It will view the uploaded dataset.

id	book_id	best_boo.	work_id	books_co.	isbn	isbn13	Publicatio.	average_	ratings_c	work_rati.	work_text.	ratings_1	ratings_2	ratings_3	ratings_4	ratings_5
d	book_id	best_boo	work_id	books_co.	isbn	isbn13	original	average_	ratings_c	work_rati	work_text	ratings_1	ratings_2	ratings_3	ratings_4	ratings_5
1	2767052	2767052	2792775	272	439023483	9.78E+12	2008	4.34	4780553	4942365	155254	66715	127936	560092	1481305	2706317
2	3	3	4540799	491	439554934	9.78E+12	1997	4.44	4602479	4800065	75867	75504	101676	455024	1156318	3011543
3	41865	41865	3212258	226	316015849	9.78E+12	2005	3.57	3866839	3916824	95009	456191	436802	793319	875073	1355439
4	2657	2657	3275794	487	61120081	9.78E+12	1960	4.25	3198671	3340896	72586	60427	117415	446835	1001952	1714267
5	4671	4671	245494	1356	743273567	9.78E+12	1925	3.89	2683664	2773745	51992	86236	197621	606158	936012	947718
5	11870085	11870085	16827462	226	525478817	9.78E+12	2012	4.26	2346404	2478609	140739	47994	92723	327550	698471	1311871
7	5907	5907	1540236	969	618260307	9.78E+12	1937	4.25	2071616	2196809	37653	46023	76784	288549	665635	1119718
в	5107	5107	3036731	360	316769177	9.78E+12	1951	3.79	2044241	2120637	44920	109383	185520	455042	661516	709176
9	960	960	3338963	311	1416524	9.78E+12	2000	3.85	2001311	2078754	25112	77841	145740	458429	716569	680175
10	1885	1885	3050926	3455	679783261	9.78E+12	1813	4.24	2035490	2191465	49152	54700	85485	284852	609755	1155673
11	77203	77203	3295919	283	1594480	9.78E+12	2003	4.26	1813044	1878095	59730	34288	59980	225052	628174	929591
12	13335037	13335037	13155899	210	62024035	9.78E+12	2011	4.24	1903563	2216814	101023	36315	82870	310297	673028	1114304
13	5470	5470	153313	995	451524934	9.78E+12	1949	4.14	1956832	2053394	45518	41845	86425	324874	692021	908229
14	7613	7613	2207778	896	452284244	9.78E+12	1945	3.87	1881700	1982987	35472	66854	135147	433432	698642	648912
15	48855	48855	3532896	710	553296981	9.78E+12	1947	4.1	1972555	2024493	20825	45225	91270	355758	656870	875372
16	2429135	2429135	1708725	274	307269752	9.78E+12	2005	4.11	1808403	1929834	62543	54835	85051	285413	667485	836050
17	6148028	6148028	6171458	201	439023491	9.78E+12	2009	4.3	1831039	1988079	88538	10492	48030	262010	687238	980309
18	5	5	2402163	376	0439655	9.78E+12	1999	4.53	1832823	1969375	36099	6716	20413	166129	509447	1266670
19	34	34	3204327	566	618346252	9.78E+12	1954	4.34	1766803	1832541	15333	38031	55862	202332	493922	1042394
20	7260188	7260188	8812783	239	439023513	9.78E+12	2010	4.03	1719760	1870748	96274	30144	110498	373060	618271	738775
21	2	2	2809203	307	439358078	9.78E+12	2003	4.46	1735368	1840548	28685	9528	31577	180210	494427 👝	1124805

Fig. 5. Displaying of the contents

Pre-processing

In pre-processing, initially, the input datasets are given which consists of 5042 input records. This is given as an input. It has some missing attributes. After pre-processing, missing attributes are eliminated.

e-Proces	ssing —															
	Pre-Pro	essing	To To Nu Nu	al Number al Number mber of Atti mber of Mis	of Instanc of Instanc ibutes in I ssing Rec	es in Rec es after P Recomme ords : 60	ommendal reprocessi indation Da	ion Syster ng: 4983 ataset : 16	n Dataset	: 5042					>>Clu	stering
id	book id	best b.	work in	books	isbn	isbn13	Publicat	average	ratings	work ra	work te	ratings 1	ratings 2	ratings 3	ratings 4	ratings 5
id	book_id	best_b	work_id	books	isbn	isbn13	original	averag	ratings	work_r_	work_te_	ratings_1	ratings_2	ratings_3	ratings_4	ratings_5
1	2767052	2767052	279277	272	439023	9.78E+	2008	4.34	4780653	4942365	155254	66715	127936	560092	1481305	2706317
2	3	3	4540799	491	439554	9.78E+	1997	4.44	4602479	4800065	75867	75504	101676	455024	1156318	3011543
3	41865	41865	321225	226	316015	9.78E+	2005	3.57	3866839	3916824	95009	456191	436802	793319	875073	1355439
4	2657	2657	3275794	487	611200	9.78E+	1960	4.25	3198671	3340896	72586	60427	117415	446835	1001952	1714267
5	4671	4671	245494	1356	743273	9.78E+	1925	3.89	2683664	2773745	51992	86236	197621	606158	936012	947718
6	118700	118700	168274.	226	525478	9.78E+	2012	4.28	2346404	2478609	140739	47994	92723	327550	698471	1311871
7	5907	5907	1540238	969	618260	9.78E+	1937	4.25	2071616	2195809	37653	46023	76784	288649	665635	1119718
8	5107	5107	303673	360	316769	9.78E+	1951	3.79	2044241	2120637	44920	109383	185520	455042	661516	709176
9	960	960	3338963	311	141652	9.78E+	2000	3.85	2001311	2078754	25112	77841	145740	458429	716569	680175
10	1885	1885	306092	3455	679783	9.78E+	1813	4.24	2035490	2191465	49152	54700	86485	284852	609755	1155673
11	77203	77203	3295919	283	159448	9.78E+	2003	4.26	1813044	1878095	59730	34288	59980	226062	628174	929591
12	133350	133350	131558	210	620240	9.78E+	2011	4.24	1903563	2216814	101023	36315	82870	310297	673028	1114304
13	5470	5470	153313	995	451524	9.78E+	1949	4.14	1956832	2053394	45518	41845	86425	324874	692021	908229
14	7613	7613	2207778	896	452284	9.78E+	1945	3.87	1881700	1982987	35472	66854	135147	433432	698642	648912

Fig. 6. Pre-processing

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As shown in the above fig.6, the total number of instances in the recommendation system dataset is 5042 input records, and the total number of cases after pre-processing is observed as 4983. The number of attributes in recommendation dataset is 16, and the quantity of missing records is 60. The quantity of missing records is given as shown below:

Number of missing records= (number of records before preprocessing- the number of records after pre-processing)



Fig. 7. Data pre-processed

After the process of data pre-processing is completed, then a dialog box is opened as shown in fig.7.

Collaborative Filtering

In the proposed system, Collaboration Filtering for recommendation system through Cosine Similarity matrix as shown in fig.8. Fig.9 shows the book recommendation status of the system using datasets. Fig.10 shows the computation of confusion matrix and Similarity Score By suing the proposed recommendation system 78.359% accuracy predicted through confusion matrix as shown in fig.11.

			Theorem				ShireOnthin	and		BOOKING	commente					
id	book_id	best_bo.	work_id	books_c.	. isbn	isbn13	original_	average.	ratings	work_rat.	.work_tex.	ratings_1	ratings_2	ratings_3	3 ratings_4	ratings_
1	2767052	2767052	2792775	272	439023	9.78E+12	2008	4.34	4780653	4942365	155254	66715	127936	560092	1481305	2706317
10	1885	1885	3060926	3455	679783	9.78E+12	1813	4.24	2035490	2191465	49152	54700	86485	284852	609755	1155673
100	7244	7244	810663	39	607865	9.78E+12	1998	4.02	546502	562787	19941	21699	33702	92590	175725	239071
1000	101941	101941	150933	66	805094	9.78E+12	2012	4.05	135225	149447	17829	2619	6318	27165	57759	55586
1001	157979	157979	6463092	114	770437	9.78E+12	2009	3.22	74979	99070	14162	5722	16486	37029	30375	9458
1002	142903	142903	199315	57	399256	9.78E+12	2013	4.37	114623	123289	12759	1056	2778	13981	37322	68152
1003	61666	61666	2416056	90	226607	9.78E+12	1985	4.11	90917	96012	2126	884	3383	18025	36041	37679
1004	9961796	9961796	7149084	22	525423	9.78E+12	2011	4	108370	123929	13224	2731	6370	24753	44016	46059
1005	3711	3711	7480	115	375703	9.78E+12	1999	3.75	82474	90629	5347	2679	7363	23002	34725	22860
1006	118870	118870	168457	86	621070	9.78E+12	2012	3.97	61422	82161	6851	2473	5241	16428	26296	31723
1007	35982	35982	979256	33	158234	9.78E+12	2004	3.79	83607	89257	6051	2659	7349	22943	29859	26447
1008	8659601	8659601	135309	71	619745	9.78E+12	2011	4.17	97938	105723	5790	941	3336	17700	38652	45094
1009	158153	158153	215418	34	159448	9.78E+12	2013	3.54	76566	84976	9534	3532	9398	25476	31182	15388
101	4137	4137	1030767	59	349113	9 78F+12	2000	3.97	495736	514276	14982	19718	29034	93427	178021	194076
Recon	ımendatior	n Results														

Fig.8. Recommendation using Collaborative Filtering

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d best_b 2 2767052 1885 7244	work_id 2792775 3060926	books 272 3455	isbn 43902	isbn13 9.78E+	original	averag										
2 2767052 1885 7244	2792775 3060926 910663	272 3455	43902	9.78E+			ratings	work_r	work_t_	ratings	ratings	ratings	ratings	ratings	Similari	BR
1885 7244	3060926	3455	07070		2008	4.34	4780653	4942365	155254	66715	127936	560092	1481305	2706317	28.6585	No
7244	010663		6/9/8	9.78E+	1813	4.24	2035490	2191465	49152	54700	86485	284852	609755	1155673	12.613	No
	010003	39	60786	9.78E+	1998	4.02	546502	562787	19941	21699	33702	92590	175725	239071	3.69772	No
10194	15093	66	80509	9.78E+	2012	4.05	135225	149447	17829	2619	6318	27165	57759	55586	1.20188	No
15797	6463092	114	77043	9.78E+	2009	3.22	74979	99070	14162	5722	16486	37029	30375	9458	0.99943	Yes
14290	19931	57	39925	9.78E+	2013	4.37	114623	123289	12759	1056	2778	13981	37322	68152	0.8047	Yes
61666	2416056	90	22660	9.78E+	1985	4.11	90917	96012	2126	884	3383	18025	36041	37679	0.6711	Yes
6 9961796	7149084	22	52542	9.78E+	2011	4	108370	123929	13224	2731	6370	24753	44016	46059	0.97574	Yes
3711	7480	115	37570	9.78E+	1999	3.75	82474	90629	5347	2679	7363	23002	34725	22860	0.75009	Yes
11887	16845_	86	62107	9.78E+	2012	3.97	61422	82161	6851	2473	5241	16428	26296	31723	0.6116	Yes
35982	979256	33	15823	9.78E+	2004	379	83607	89257	6051	2659	7349	22943	29859	26447	071491	Yes
1 8659601	13530	71	61974	9.78E+	2011	4 17	97938	105723	5790	941	3336	17700	38652	45094	0 74496	Yes
15815	21541	34	15944	9.78E+	2013	3.54	76566	84976	9534	3532	9398	25476	31182	15388	0 78667	Yes
4127	1020767	50	24011	0.705+	2000	2.07	405726	614276	14092	10710	20024	02427	170021	104076	2 64270	No
	10194 15797 14290 61666 6 9961796 3711 11887 35982 1 8659601 15815 4137	10194_ 15093_ 15797_ 6463082 14290_ 19931_ 61666 2416056 6 9951796 7149084 3711 7480 11887_ 16845_ 35982 979256 1 8659601 13530_ 15515_ 21541_ 4137_ 1030767 100767 100767	10194 (2003 (2013 (20	11918 Labora 66 ab2002 119797 463002 14 7704.3. 119797 463002 14 7704.3. 119787 4643002 14 7704.3. 11982 1923 15 7 39825. 11086 24 15055 0 22860. 15 111 7480 15 37570. 31 11897 1848.4 62 2017. 3082.5 31 1523. 11895801 1530. 71 15974. 15974. 15974. 11895801 1530. 71 15974. 15974. 15974. 11895801 1530. 71 15974. 15974. 15974. 11895801 1530. 71 15974. 15974. 15974. 118958 21577. 15974. 15974. 15974. 15974.	10194 10193 06 allouging offen 15797 643092 14 7704.3 9786 15797 643092 14 7704.3 9786 15780 543092 14 7704.3 9786 15866 241005 90 22580 9786 5985 7400422 52542 9786 9786 15187 16486 62107 9786 18857 16486 62107 9786 18858 978256 3 16823 9786 18959 19250 7 61974 9786 18955 1244 24 1994 9786 1417 1003767.59 34111 9786 4137	11914	11914 15093. 66 00.090. 97.6E 2012 4/05 15797 6450302 14 77043. 976E 2009 3.22 15787 6450302 14 77043. 976E 2009 3.22 15866 2416056 90 22660. 976E 1085 4.11 59867 17997 1440054 222 22640. 978E 2011 4 3711 7480 115 3750. 9.76E 1093 3.75 35862 979256 3.3 15823. 9.76E 2014 4.7 18659601 1530. 71 19874. 9.76E 2013 3.54 4137 10074. 9.78E 2013 3.54 4.37 10.73	11918 10933 06 00009 9786- 2012 4105 152225 15797 645002 14 77143 9786- 2009 32 74979 15797 645002 14 77143 9786- 2009 32 74979 15797 645002 14 77143 9786- 2014 37 14623 5986 245055 902 22860 9786- 2014 437 108270 5986 245055 902 22860 9786- 2014 44 108370 5987 597570 9786- 2014 47 108370 5842 5986 247926 33 56270 9786- 2014 379 84207 39862 379256 33 15822 9786- 2014 379 84207 1895801 15500 71 19744 9786- 2014 379 82697 15915 21514 34	11914_1 15933_1 66 00108_1 1/Ret_2 21/2 4.15 15322_2 14844/ 15797_1 643002_114 71043_3 976+_2013_4 32 74979 9070 15797_1 643002_114 71043_3 976+_2013_4 32 74979 9070 61666 2416056_90 22660_9 976+_<1985_4 411 90917 9012 51666 2416056_90 22660_9 976+_<1985_4 411 90917 9012 51696 2410056_90 25654_975_7 976+_<2013_34 40629 1332 9271 13482 123829 3711 7480_115 37570_9 976+_<2012_3 376 9422 1422 12382 35862 972256_33 15822_9 976+_<2014_3 379 83607 82257 1859501 1530_7 1 51974_9 976+_<2013_347 3566 84976 4137 10307875_9 348 1976+_<2013_347 3567 849776, 514776, 514776, 514776, 514776, 514776, 514776, 514776, 514	11914_1 15093_1 56 001098 87.62+_2012 4105 15225 149441 17629 15797_1 6430362 14 71043. 878E2019 322 74979 99070 41162 15797_1 6430362 14 77043. 878E2013 4.33 114623 15228 152	ITINE Libragi. 66 Wildles 376E 2012 416 53227 148447 17828 2181 15797. 6430302 114 77043. 976E 2009 322 74979 99070 4162 5722 15797. 6430302 114 77043. 976E 2009 322 74979 99070 4162 5722 45865 2416056 90 2566. 976E 2014 4114 108329 13224 2731 3711 7440 155 3750. 976E 2014 4 108370 12329 13224 2731 35862 879256 3 1562 976E 2014 4 108370 12324 2731 35862 879256 3 1562 976E 2014 379 4307 8229 5347 5524 35862 879256 3 1562 976E 2014 379 33007 8227	11918 10933 0.6 #0009 97.0E 2012 415 15225 14441 17223 213 17977 1640002 114 77043 9762 2009 322 74979 99070 4162 5225 164441 17229 1572 16466 17977 1640002 114 77043 9762 2009 322 74979 99070 4162 5228 16446 15806 2416055 00 22860. 9782 2014 41422 12288 12729 1056 2718 15985 141 00917 90170 12382 1224 2731 6370 3711 7480 115 3750. 8764 2014 41628 16381 6431 2473 5383 35802 879256 3 1582 2014 4174 28216 6851 2473 5374 189807 1530 71 16924 976E 2014	11918 10937. 06 00093. 07 06-2017 2112 0417 11822 118444 11822 0118 2118 2118 11797. 463002 14 71043. 9 9 9007 14162 2518 2318 2118 11797. 463002 14 71043. 9 7479 9907 14162 2721 14846 3702 11797. 463002 14 77743. 9 9777 14162 12759 1056 2178 1381 11865 2419058 00 22600. 9 76-7 1985 11 10917 9012 226 844 3383 18025 11867 11680 3750. 9 757. 1987 1423 123820 1324. 2473 8310 2473 3711 7480 115 3750. 9 175. 2474 8028 8132 2473 8330 14723 1483 2473	ITINE Liboral 66 BUDR J/RE 2019 SiZE 1444/1 1742/2 2519 Coll 2/16 5/789 15797 Le43080 14 7043. 8786 2009 3.22 74797 96070 1462 5722 14486 57029 30375 15797 Le43080 14 7043. 8786 2009 3.22 74797 96070 1462 5722 14486 37029 30375 15868 2416058 90 2266. 8786 2013 4.31 14622 1224 8138 13022 5041 5986 15971 7480 150 3786 2011 4 103370 12242 2731 6370 24725 3401 3711 7480 15 3750 9786 2474 0051 2472 1481 1452 24726 1481 1452 24726 1481 1452 24726 18897 1892 133	ITISE Librag. 66 WORD #7.6E 2012 416 US221 148447 17.62 2518 21716 5.719 56666 15797 6463002 114 71043 376E 2009 322 74979 90070 14162 5722 15468 37028 3075 456 15787 6463002 114 77043 2572 15488 37029 3075 456 15865 2416055 90 2566 2012 141422 12239 11224 1738 3031 13022 3041 37679 5081 5986 149054 22 25542 978E 2014 4 108370 1224 271 5370 24753 4406 46059 3711 7400 156 2770 376 2473 3710 24725 2400 3742 2281 3738 2474 9629 5447 5730 24145 12428 22814 141642	Intris Disol. Disol. <thdisol.< th=""> <thdisol.< th=""> <thdisol.< th="" th<=""></thdisol.<></thdisol.<></thdisol.<>

Fig.9. Recommendation status

id best_b. 13508 3 411053 6091075 16631	work_id 19060 556134 3078120	books_ 89 88 119	isbn 14391 69621 33049	isbn13 9.78E+ 9.78E+	original 2012 1953	averag 4.13 4.14	ratings 89460	work_r. 100731	work_t. 11877	ratings.	ratings.	ratings.	ratings.	ratings.	Similari.	BR Stat	
13508 3 411053 6091075 16631	19060 556134 3078120	89 88 119	14391 69621 33049	9.78E+ 9.78E+ 9.78E+	2012 1953	4.13 4.14	89460	100731	11877	40.07							
3 411053 6091075 16631	556134 3078120	88 119	69621 33049	9.78E+	1953	4.14	00040			1067	3020	16399	41956	38289	0.80909	Yes	1
6091075 16631	576120	119	33049	0.78E+			93040	95085	485	2152	3843	16571	28351	44168	0.58083	Yes	r
16631	67612				1984	4.08	93774	109535	2020	624	4454	22611	39988	41858	0.77444	Yes	
	01012	359	14028	9.78E+	1927	4.11	80769	97230	2993	1387	4435	17024	33570	40814	0.66184	Yes	
32263	2674805	107	05538	9.78E+	2001	4.1	89468	98297	3212	1422	3299	18191	36538	38847	0.69009	Yes	
17572	19249	71	67002	9.78E+	2012	3.95	80991	98231	7820	3606	4459	18512	38681	32973	0.76066	Yes	
25300	4668002	94	6480101	9.78E+	1996	4.21	82608	102563	2699	852	2945	15073	38597	45086	0.68331	Yes	
9 414999	209414	172	34534	9.78E+	1953	4.09	87141	96751	3759	943	3578	18261	36854	37115	0.69875	Yes	
19543	3020535	110	99408	9.78E+	1963	4.22	620618	636061	9102	15392	27532	93700	167043	332394	3.63855	No	
37190	1508178	91	76362	9.78E+	2004	4	113066	120423	8372	1930	6437	25821	41605	44630	0.91161	Yes	
25460	1582285	37	60852	9.78E+	2007	4.03	83881	87904	10149	1709	4789	16112	31521	33773	0.69325	Yes	
20613	25128	46	16196	9.78E+	2014	4.53	123843	142858	16235	694	1923	10589	36979	92673	0.8426	Yes	
35231	827903	54	81251	9.78E+	1994	4.1	91046	97883	1796	910	3789	18827	35460	38897	0.67651	Yes	
81 6218281	4543476	85	38534	9.78F+	2009	3.81	99841	109533	13444	2908	7650	26956	42394	29525	0.96369	Yes	۴
	 17572 25300 99 414999 19543 37190 25460 20613 35231 35231 butes After 	17572. 19249 25300. 4668002 9 414969 209414 19543. 3020535 1 37190 1508178 1 25460. 1562285 2 20613. 25128 35231 827893 81.6218781.454376	19722 19249	1 1772 19240 71 87002 25500 4668000 4 6480101 1 91499 20341 72 3434. 1 19643 3029530 110 9408. 1 19643 3029530 110 9408. 1 26400 196220 7 6982. 26401 192210 7 6982. 16195. 50311 827903 54 81291. 81534. 18 c210214 4543478.8 81534. 8534.	1.1752	17522 18648 71 67002 8786 2012 25300 4668000 4 6680101 7100 7100 1900 25300 466800 4 6680101 7100 1900 <	17972 18984 71 17022 17025 17010 18010 25306 46680002 4640101 17012 17014 481 17954 2002053 110 2844 27124 18015 481 17954 2002053 110 2844 27124 18015 481 17956 2002053 110 2844 27124 2712 1802 481 17956 5002719 10010 19714 27124 2712 2804 4 2440 100220537 1002 27124 2712 2804 4 2440 100220537 1002 17124 2714 4503 4204 2440 100220537 1002 1714 2714 4503 4 25201 87700 10014 1714 1714 4504 4 1 15221 87700 24 12514 1714 1714 1014 1 1 1	L. 1752. 19644. 11 0702. 8786 1952 3.65 0091 2530. 06800214 64801701 776 1956 4.51 0200 141690 20941 172 24234. 376 1953 4.80 2741 9543 3020351 19 0948. 776 1953 4.82 1734 19543 3020351 19 0948. 776 1954 4.22 0201 2540 1961231 7. 6052. 776 2004 4.1 13066 2540 6.1951. 2572. 61954 4.1 0204 3521 12780 54 81251. 1766 1954 4.1 01048 141012014454437464 8786 1974 4.1 01048	1752 10444 71 47022 9785-2 1013 3.6 8049 80231 2530. 666000 646010 9.785- 1995 4.21 2506 102563 41499 20414 172 3454 .376- 1655 4.60 102563 1974 500535 110 9486 .776- 1651 4.60 102663 19740 500535 110 9486 .776- 1654 4.60 102663 19740 5005137 10282 .787- .504 4.11 30246 12042 5640 152281 .787- .504 4.11 3024 4258 5951 5524 64 15228 .787- 504 4.11 3042 4258 5951 524 64 1526 .787- 194 4.1 91049 4231 4358 4764 41044 97823 4162 50613 4162 50614 501243 45084 <th>1752. 16640. 71 6702. 9.86. 241 8206 10283 7829 2530. 1668020 6.400101 9.786. 108 4.00010 1786. 10283 10282 10283 10282 10283 10284 10284 10284 10284 10284 10284 10283 10283 10283 10283 10283 10283 10284 10284 10284 102</th> <th>17572 18648 71 67022 716-7 2012 845 0000 96233 7820 9664 25300. 4669000 945. 9764- 9764 82000 18539 2009 66239 164990 00444 172 3643. 9764- 183 49 10141 1971 1309 643 17954 5000555 100 9468. 9764- 1835 49 1114 1971 1309 643 1102 1102 61329 112 1532 1716 150217 15022 1716 502117 1102 1102 1532 1102 1532 1102 1532 1102 1102 1532 1102 1532 1102 1102 1102 1532 1102 1102 1532 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102</th> <th>1752_1 16400_1 71 6700_2 1821_1 1820_1<th>1752_1 16040 71 1700 265 <th265< th=""> 265 265 <th26< <="" th=""><th>L DTSC DT</th><th>17722 18948 7 17802 27864 1871 8001 8212 820 8004 4449 1851 8801 8777 25306 46680000 44 6400101 77864 18206 182263 2789 862 2846 7757 48668 2715 19506 200505 110 18244 97844 18206 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 18208 1821 80101 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 182</th><th>L DTSC DTSC TRE DTSC B0091 B0231 TRE B010 B0231 TRE B010 B0231 TRE B010 B0231 TRE B010 B0121 B010 B0121 B010 B0123 B011 B0113 B0114 B0112 B0114 B0114 <t< th=""><th>17722 18248 71 17026 17125 1820 1821 <th1821< th=""> 1821 1821 <t< th=""></t<></th1821<></th></t<></th></th26<></th265<></th></th>	1752. 16640. 71 6702. 9.86. 241 8206 10283 7829 2530. 1668020 6.400101 9.786. 108 4.00010 1786. 10283 10282 10283 10282 10283 10284 10284 10284 10284 10284 10284 10283 10283 10283 10283 10283 10283 10284 10284 10284 102	17572 18648 71 67022 716-7 2012 845 0000 96233 7820 9664 25300. 4669000 945. 9764- 9764 82000 18539 2009 66239 164990 00444 172 3643. 9764- 183 49 10141 1971 1309 643 17954 5000555 100 9468. 9764- 1835 49 1114 1971 1309 643 1102 1102 61329 112 1532 1716 150217 15022 1716 502117 1102 1102 1532 1102 1532 1102 1532 1102 1102 1532 1102 1532 1102 1102 1102 1532 1102 1102 1532 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102 1102	1752_1 16400_1 71 6700_2 1821_1 1820_1 <th>1752_1 16040 71 1700 265 <th265< th=""> 265 265 <th26< <="" th=""><th>L DTSC DT</th><th>17722 18948 7 17802 27864 1871 8001 8212 820 8004 4449 1851 8801 8777 25306 46680000 44 6400101 77864 18206 182263 2789 862 2846 7757 48668 2715 19506 200505 110 18244 97844 18206 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 18208 1821 80101 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 182</th><th>L DTSC DTSC TRE DTSC B0091 B0231 TRE B010 B0231 TRE B010 B0231 TRE B010 B0231 TRE B010 B0121 B010 B0121 B010 B0123 B011 B0113 B0114 B0112 B0114 B0114 <t< th=""><th>17722 18248 71 17026 17125 1820 1821 <th1821< th=""> 1821 1821 <t< th=""></t<></th1821<></th></t<></th></th26<></th265<></th>	1752_1 16040 71 1700 265 <th265< th=""> 265 265 <th26< <="" th=""><th>L DTSC DT</th><th>17722 18948 7 17802 27864 1871 8001 8212 820 8004 4449 1851 8801 8777 25306 46680000 44 6400101 77864 18206 182263 2789 862 2846 7757 48668 2715 19506 200505 110 18244 97844 18206 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 18208 1821 80101 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 182</th><th>L DTSC DTSC TRE DTSC B0091 B0231 TRE B010 B0231 TRE B010 B0231 TRE B010 B0231 TRE B010 B0121 B010 B0121 B010 B0123 B011 B0113 B0114 B0112 B0114 B0114 <t< th=""><th>17722 18248 71 17026 17125 1820 1821 <th1821< th=""> 1821 1821 <t< th=""></t<></th1821<></th></t<></th></th26<></th265<>	L DTSC DT	17722 18948 7 17802 27864 1871 8001 8212 820 8004 4449 1851 8801 8777 25306 46680000 44 6400101 77864 18206 182263 2789 862 2846 7757 48668 2715 19506 200505 110 18244 97844 18206 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 80101 18208 18208 1821 80101 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 18208 182	L DTSC DTSC TRE DTSC B0091 B0231 TRE B010 B0231 TRE B010 B0231 TRE B010 B0231 TRE B010 B0121 B010 B0121 B010 B0123 B011 B0113 B0114 B0112 B0114 B0114 <t< th=""><th>17722 18248 71 17026 17125 1820 1821 <th1821< th=""> 1821 1821 <t< th=""></t<></th1821<></th></t<>	17722 18248 71 17026 17125 1820 1821 <th1821< th=""> 1821 1821 <t< th=""></t<></th1821<>

Fig.10. Creation of confusion matrix

id			R	size the l	Data		CFCos	ineSimila	rity		Book	Recomm	Indation		R	sult Analy	sis		
	book_id	best_b	work_id	books	isbn	isbn13	original.	averag.	ratings	work_r.	work_t.	ratings	ratings	ratings.	ratings.	ratings	Similari	BR Stat	
012 1	13508	13508	19060	89	14391	9.78E+	2012	4.13	89460	100731	11877	1067	3020	16399	41956	38289	0.80909	Yes	4
013 4	11053	411053	556134	88	69621	9.78E+	1953	4.14	93540	95085	485	2152	3843	16571	28351	44158	0.58083	Yes	ľ
014 8	8698	6091075	3078120	119	33049	9.78E+	1984	4.08	93774	109535	2020	624	4454	22611	39988	41858	0.77444	Yes	
015 1	16631	16631	57612	359	14028	9.78E+	1927	4.11	80769	97230	2993	1387	4435	17024	33570	40814	0.65184	Yes	
016 3	2263	32263	2674805	107	05538	9.78E+	2001	4.1	89468	98297	3212	1422	3299	18191	36538	38847	0.69009	Yes	
017 1	17572	17572	19249	71	67002	9.78E+	2012	3.95	80991	98231	7820	3605	4459	18512	38681	32973	0.76066	Yes	
018 6	8487	25300	4668002	94	6480101	9.78E+	1996	4.21	82608	102563	2699	862	2945	15073	38597	45086	0.68331	Yes	
019 4	14999	414999	209414	172	34534	9.78E+	1953	4.09	87141	96751	3759	943	3578	18261	36854	37115	0.69875	Yes	
02 1	19543	19543	3020535	110	99408	9.78E+	1963	4.22	620618	636061	9102	15392	27532	93700	167043	332394	3.63855	No	
020 3	87190	37190	1508178	91	76362	9.78E+	2004	4	113066	120423	8372	1930	6437	25821	41605	44630	0.91161	Yes	
021 2	5460	25460	1582285	37	60852	9.78E+	2007	4.03	83881	87904	10149	1709	4789	16112	31521	33773	0.69325	Yes	
022 2	0613	20613	25128	46	16196	9.78E+	2014	4.53	123843	142858	16235	694	1923	10589	36979	92673	0.8426	Yes	
023 3	15231	35231	827903	54	81251	9.78E+	1994	4.1	91046	97883	1796	910	3789	18827	35460	38897	0.67651	Yes	
024 6	218281	6218281	4543476	85	38534	9.78F+	2009	3.81	99841	109533	13444	2908	7650	26956	42394	29625	0.95369	Yes	4
		00.0																	14
- al 5 0 140	gauve : /	09.0																	

Fig.11. Accuracy prediction

ANN-OLVQ Classification

The Artificial Neural Network OLVQ classification system is simulated through weka libraries. Fig.11 shows the

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correctly classified instances in terms of accuracy as 79.845%.

Charrify Charter Annulate (ale at a table to a straight	-							
Preprocess Classify Cluster Associate 5	select attributes Visual	ize							
Choose Olva3 -M 1 -C 20 -I 1000 -L 1	-R 0.3 -S 1 -G false -W	0.3-E 0.1							
Toto Para	dia dia mini								
lest options	classiner output								-
Use training set	Correctly Class	sified In:	stances	3978		79.8475	8		
O Supplied test set Set	Incorrectly Cla	ssified :	Instances	1004		20.1525	ł		
	Kappa statistic			0.00	88				
Cross-validation Folds 7	Mean absolute e	rror		0.20	15				
O Percentage split % 66	Root mean squar	ed error		0.44	89				
Mana anti-an	Relative absolu	te error		69.32	19 %				
More options	Root relative s	squared es	rror	117.76	69 %				
	Total Number of	Instance	18	4982					
(Nom) Result 🗸 🗸 🗸		-							
	=== Detailed Ad	curacy B	/ Class ===						
Start Stop									
Result list (right-dick for options)		TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class	
		0.96	0.953	0.825	0.96	0.887	0.503	P	
12:06:28 - neural.lvq.Olvq3		0.047	0.04	0.198	0.047	0.076	0.503	N	
12:07:37 - Neural Iva Iva 1	weighted Avg.	0.798	0.792	0.714	0.798	0.744	0.503		- 1
12:07:55 - neural lvg Olyg3									
12:08:04 - neural.lvg. Olvg3	=== Confusion P	atrix ===							
12:08:12 - neural.lvg.Lvg1		-1							
12:08:21 - neural.lvg.MultipassSom	a b <-	- classi	tied as						
12:08:29 - neural.lvg.MultipassLvg	3937 166 1	a = P							
12:08:37 - neural.lvg.Olvg3	030 41 1	D = N							
12:08:42 - neural.lvg.Lvg1									. 1
12:09:22 - neural.lvq.Lvq1									
12:09:32 - neural.lvg.Olvg3	<								>

Fig.11 Classification Accuracy of Conventional ANN-OLVQ system

The proposed Artificial Neural Network- LVQ classification system is simulated through weka libraries. Fig.12 shows the correctly classified instances in terms of accuracy as 81.234%.

te Select attributes Visualiz									
-L 1 -R 0.3 -S 1 -G false									_
Classifier output									
									_
Correctly Classi	fied In	stances	4047		81,2324				
Incorrectly Clas	sified	Instances	935		18,7676				
Kappa statistic			0.01	33					
Mean absolute er	ror		0.18	77					
Root mean square	d error		0.43	32					
Relative absolut	e error		64.55	77 %					
Root relative so	uared e	ror	113.64	81 %					
Total Number of	Instance	es	4982						
Detailed Acc	uracy B	y Class ===							
	P Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	(1ass		
	0.98	0.972	0.825	0.98	0.896	0 504	p		
	0.028	0.02	0.236	0.028	0.051	0 504	N		
Weighted Avg	0.812	0.804	0.721	0.812	0.747	0.504			
reignota nigi				01012					
and Confusion Ma	trix ==	-							
	VIII								
a b (classi	fied as							
4022 81 1	a = P								
854 25 1	b = N								
	<pre>e Selectatributes WauBa 41 9.0.3-51.45fale Correctly Classifier output Correctly Classifier output Encorrectly Classifier output Hean absolute er Boot neam square Root nea</pre>	 sectatibutes Wauke 41.4.0.3.51.6Fdee Correctly Classified In Incorrectly Classified In Example statistic Kapa statistic Kapa statistic Race sean squared error Rect relative appared error Rect relative squared error Rect relative squared error Total Bmber of Instano TP Bate 0.488 Reighted Accuracy B TP Bate 0.488 Seighted Accuracy B TP Bate 0.488 Seighted Accuracy B TP Bate 0.488 TP Bate 0.488	 E Sektatibutes Vauake 41.4.0.3.51.6784e Correctly Classified Instances Incorrectly Classified Instances Rappa statistic Kean absolute error Rect relative apusted error Rotor relative apusted error Total Bamber of Instances Total Bamber of Instances TP Bate FP Bate 0.628 0.572 0.628 0.572 0.628 0.0.804 Eighted Avy. 0.812 0.804 Contusion Matrix === a b < classified as 4022 81 a = P 854 25 b = N 	 E Sektathbuts Waske 41.4.0.3.51.6Fake Correctly Classified Instances 4047 Incorrectly Classified Instances 515 Exaps statistic 0.01 Hean absolute error 0.18 Redor mean squared error 0.43 Redor mean squared error 113.64 Root relative squared error 113.64 Root relative squared error 113.64 Root relative squared error 113.64 Root selective squared error 0.43 Root sq	 Beletathbudes Woulde 41.4.03.51.4.6% Correctly Classified Instances 4047 Correctly Classified Instances 535 Ruppa statistic 0.0.033 Hena Abolute error 0.11877 Root restary squared error 64.5577 % Root restary squared error 113.641 % Total Number of Instances 4592 Total Number of Instances 4592 Tealel Accuracy By Class === TP Bate FP Bate Precision Baccill 0.080 0.972 0.0.23 0.98 Beighted Axy, 0.812 0.804 0.721 0.812 e= Confusion Matrix === a b < classified as 402 0.1 a = P 554 25 b = 8 	 E Selectathbudes Would E Conseter output Conseter output Correctly Classified Instances 4047 01.2324 Incorrectly Classified Instances 535 18.7676 Ruppa statistic 0.0.033 Hean Abolute error 0.11877 Root restary squared error 113.6481 % Total Humber of Instances 4982 Total Humber of Instances 4982 TP Bate FP Bate Precision Bacall F-Measure 0.080 0.972 0.023 0.086 0.0566 Guester August of Control 0.023 0.020 0.028 0.086 Reighted Avg. 0.812 0.804 0.721 0.812 0.747 Exclassified as 4022 0.1 a = P S54 25 b = 15 	 E Selectatibules Youake 41.4.0.3.51.46fde Correctly Classified Instances 4047 81.2024 % Incorrectly Classified Instances 95 10.7676 % Hean Asolute error 0.0137 Reads statistic 0.0133 Hean Asolute error 0.4332 Relative Absolute error 113.6421 % Total Number of Instances 4992 Total Number of Instances 4992 Total Number of Instances 4992 Tetal EF Rate FP Rate Precision Recall F-Heasure ROC Area 0.96 0.972 0.255 0.98 0.856 0.504 Reighted Axy. 0.812 0.804 0.721 0.812 0.747 0.504 Econstant Matrix == a b < classified as 4022 81 a = 2 854 25 1 b = 8 	<pre>e SelectathDutes Meadle 41.4.0.3.51.4FdMe Correctly Classified Instances 4047 81.2334 % Incorrectly Classified Instances 935 18.7676 % Repage statistic 0.0133 Hean absolute error 0.1877 Recor Frainier equared error 1.31.4421 % Total Number of Instances 4952 +</pre>	 E SelectathDuts Vauke 41.4.0.3.51.4Fike Correctly Classified Instances 4047 81.2324 4 Incorrectly Classified Instances 935 18.7676 4 Repair satistic 0.0133 Hean Abolute error 0.1877 Reditive Abolute error 64.5577 4 Root Failure squared error 113.4481 4 Total Number of Instances 4982 Total Number of Instances 4982 Total Number of Instances 4982 Explaid Accuracy By Class == TP Bate FP Rate Precision Recall F-Measure ROC Area Class 0.98 0.772 0.225 0.98 0.964 0.904 F Reighted Acu. 0.812 0.004 0.721 0.812 0.747 0.504 Exclusion Matrix == a b < classified as 4022 81 a = P S54 25 b = 8

Fig.12. Classification Accuracy of the proposed ANN- LVQ system

Performance Matrices

Various performance indices such accuracy, error rate, precision-recall and execution time of the proposed ANNOLVQ and ANNLVQ recommender systemcompared with traditional CF recommendation system.



Fig.13. Number of instances vs. Accuracy

Fig.13 shows that, the predicted accuracy among Artificial neural network LVQ, OLVQ and CF Recommendation based on the number of instances. From this it is shown that, ANNLVQ predicts high accuracy compared withANNOLVQ and CF Recommendation systems.



Fig.14. Number of instances vs. Error rate

Fig.14 shows that, the error rate among Artificial neural network LVQ, OLVQ and CF Recommendation based on the number of instances. From this it is shown that, ANNLVQ predicts have low error rate compared CF and ANNOLVQ Recommendation systems.



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Fig.15. Comparison of Recall vs. Precision

Fig.15 shows the comparison among Artificial neural network LVQ, OLVQ and CF Recommendation based on the precision and recall. From this it is shown that, LVQ predicts have high precision vs recall characteristics compared with OLVQ and CR recommendation systems.

Fig.16 shows the number of instances vs execution time characteristics among Artificial neural network LVQ, OLVQ and CF Recommendation based on the precision and recall. From this it is shown that, LVQ predicts have low execution time compared with CF and OLVQ.

Based on the results of the performance matrices depicted fig.13- fig.16, it is stated that the proposed recommender ANNOLVQ based recommender system effectively classified the class of the book based on the reviewer comments. The classification accuracy of the ANNOLVQ is high while compared with the existing LVQ and CF recommendation systems.



Fig.16. Number of instances vs execution time characteristics

V. CONCLUSION

This paper proposed Artificial Neural Network approach to develop a multi-categorical classification model to predict user ratings. In this proposed research, the problem of predicting the rating as a multi-label classification problem was considered where each rating had treated a label. From the results, it is showed that the ANNLVQ classification approach achieved a high prediction accuracy rate in the book recommender systems. So artificial neural network based recommender system better than traditional recommender system In the future, the performance of the proposed classification system will be analyzed with dynamic datasets in the different application based on the online reviews.

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