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Abstract

"The recommendation system is one of the most popular fields in the research area. The availability of the internet and other devices, the recommendation has become an essential part of the business. A lot of works have been done on this field. For a good recommendation, the recommender algorithm must be good. New algorithms have been also invented and also the existing algorithms are being developed. In our work, we have developed an existing recommender algorithm for a better recommendation. That is why in this book, we presented a hybrid approach two existing algorithms that are considered better algorithms than other existing algorithms. We used the Restricted Boltzmann Machine and Singular Value Decomposition algorithm to train our algorithm."

Acknowledgments

For the better understanding, a sample Acknowledgment is given below.

As it is true for everyone, We have also arrived at this point of achieving a goal in our life through various interactions with and help from other people. However, written words are often elusive and harbor diverse interpretations even in one's mother language. Therefore, We would not like to make efforts to find best words to express my thankfulness other than simply listing those people who have contributed to this thesis itself in an essential way. This work was carried out in the Department of Computer Science and Engineering at East West University, Bangladesh.

First of all, We would like to express my deepest gratitude to the almighty for His blessings on us. Next, our special thanks go to our supervisor, "Mahamudul Hasan Munna", who gave us this opportunity, initiated us into the field of "Recommendation Systems ", and without whom this work would not have been possible. His encouragements, visionaries and thoughtful comments and suggestions, unforgettable support at every stage of our BS.c study were simply appreciating and essential. His ability to muddle us enough to finally answer our own question correctly is something valuable what We have learned and We would try to emulate, if ever We get the opportunity.

We would like to thank "Shaykh Siddique" for his excellent collaboration during performance evaluation studies; "Recommendation Systems" for his overall support; "Rifayet Azam Talukder" for her helpful suggestions in solving tricky technical problems. Last but not the least, We would like to thank our parents for their unending support, encouragement and prayers.

There are numerous other people too who have shown me their constant support and friendship in various ways, directly or indirectly related to our academic life. We will remember them in our heart and hope to find a more appropriate place to acknowledge them in the future.

Asif Zaman

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Table of Contents

Declaration of Authorship i

Abstract i

Acknowledgment ii

Table of Contents iv

List of Figures v

List of Tables vii

List of Algorithms viii

Chapter 1 Introduction 1

1.1 Introduction 1

1.2 Motivation 2

1.3 Our Contribution 3

1.4 Thesis Outline 3

Chapter 2 Literature Review 4

2.1 Literature Review 4

Chapter 3 Proposed Method **10**

3.1 Restricted Boltzmann Machine 10

3.1.1 Model 12

3.1.2 Learning 12

3.1.3 Prediction Making 13

3.2 Singular Value Decomposition 14

3.2.1 Model 14

3.2.2 Learning 14

3.2.3 Prediction 15

3.3 Hybrid Approach 16

Chapter 4 Result and Discussion **17**

4.1 Dataset 17

4.2 Evaluation Matrix 17

4.2.1 MAE 17

4.2.2 RMSE 18

4.3 Graphical Analysis 18

Chapter 5 Conclusion **20**

5.1 Future Work 21

Bibliography **21**

Appendix A List of Acronyms **30**

Appendix B List of Notations **31**

Appendix C List of Publications **32**

List of Figures

3.1 A Restricted Boltzmann Machine with three hidden layers(Simple form of our model). The ratings are inputted into the visible layer of the network. H1, H2 and H3 are the hidden layers. W_{ij} are the weights. 11

4.1 This graph represents the experimental result of our model 19

List of Tables

List of Algorithms

Chapter 1

Introduction

In this chapter, we will introduce the Recommendation Systems and their necessity. We will explain the reason that motivated us to work in this field. After all, we have discussed our contribution to this book.

1.1 Introduction

People's expectations are getting higher with the advancement of modern technology. With the advancement of the internet, a lot of services and businesses have been established based on the internet. For these internet businesses, the recommendation System(RS) plays a vital role to serve both of the industries and their customers. Online based services such as e-commerce, entertainment, riding share, social networking are highly dependent on RS for their business purpose. Filtering relevant items is the main purpose of RS. Collaborative filtering is one of the most applicable approaches. This approach easily predicts users' rating to a specific item using their past activity and the activities of similar minded people[1]. The approach uses similarity factors such as cosine similarity, Jaccard similarity, Pearson similarity, mean square difference and so on to find out similar-minded users or similar categorical items.

A common approach to collaborative filtering is to assign a low-dimensional feature vector to each user and a low-dimensional feature vector to each movie so that the rating that each user assigns to each movie is modelled by the scalar product of the two feature vectors. This means that the $P \times Q$ matrix of ratings that P users assign to Q movies is modelled by the matrix M which is the product of a $P \times R$ matrix U whose rows are the user feature vectors and $R \times Q$ matrix $V\prime$ whose columns are the movie feature vectors. The rank of M is R – the number of features assigned to each user or movie.

However, the collaborative filtering approach sometimes suffers from a cold start problem. The cold start problem occurs when a user is newly registered or an item newly appears. A new user's or a newly appeared item's cannot be measured due to having any past activity or rating[2]. This problem reduces the industry's profit. The cosine similarity matrix is the most used in collaborative filtering. This similarity also has its drawback[3]. Whatever to earn more revenue and more user satisfaction, we have to solve this problem.

The content-based RS, on the other hand, does not require two users. It uses the users' personal profile to track users' preference. That is, depending on a single user's profile and his history, the items are recommended. And that is why the content-based RS does not require any user more than one. Since items are recommended according to the user's personal description, this approach is not as smart as collaborative filtering. Features are extracted from the items' metadata. Sometimes these metadata may be too short to fulfil user's interest. Moreover, some common problems like Polysemy, synonymy, multi-word expressions, named entity recognition and disambiguation make the user demotivated[4].

1.2 Motivation

As RS is necessary for business purpose, any fault or defect may lead to sufficient loss or reduce revenue. A poor recommendation system will cause customer dissatisfaction. As a result, people will not attract to that site of software. On the other hand, there is no such system that does not have any limitation. So, after considering all these measures we have introduced a system that will be helpful to any web-based service to acquire customer satisfaction. We used deep learning algorithm to train our model. Singular

Value Decomposition (SVD) finds the low-rank approximations based on minimizing the sum-squared distance. In the collaborative filtering domain, most of the data sets are sparse [5], this creates a difficult non-convex problem, so a naive solution is not going work.

1.3 Our Contribution

In this paper, we describe two methods one is a class of two-layer undirected graphical models that generalize Restricted Boltzmann Machines to modelling tabular or count data[6] and another is Singular Value Decomposition (SVD) that finds the low-rank approximations based on minimizing the sum-squared distance. Maximum likelihood learning is intractable in these models, but we show that learning can be performed efficiently by following an approximation to the gradient of a different objective function called "Contrastive Divergence"[7].

1.4 Thesis Outline

In this book, we briefly discussed the recommendation system and its classification in chapter 2. Chapter 3 contains the literature review where we have discussed some prior works on the RS field. We have discussed our proposed method in chapter 4 with the illustration. Chapter 5 will represent the evaluation result comparing our model with other existing RS algorithms with figures. We will conclude this book in chapter 6. Last, we will present some references and appendix at the end of the book.

Chapter 2

Literature Review

Recommendation System has become a burning question in recent era of science and technology. Several researches have been taken place on this field. In this section, we will describe some of the research topics and reviewed some research papers.

2.1 Literature Review

In recent years, the Recommender System(RS) has become a very important research field. As various RSs have been used different companies, especially e-commerce, movie & video suggesting and so on, the popularity of the RS field is continuously growing. Deep learning is the most popular approach for designing recommender systems. Fang H. has proposed a novel classification framework that introduces representative Deep learning-based sequential recommendation system[8].

Also, RS is beneficial to the researchers to find out journals, books and articles which are necessary for their research purpose. Bulut [9] has created a new recommendation system using IEEE database data. The RS was performed by various similarity algorithms, and first, it compared the user profiles' similarity by using cosine similarity. The RS was then repeated by a Deep Learning (DL) method named Doc2vec.

Saha J [10] summarized the challenges related to existing RSs in a survey. The survey also presented machine learning and deep learning algorithms that are generally applied in health care RS.

J Mulani [11] introduced deep reinforcement learning-based complete health care RS that even includes medicines to take, doctors to consult, nutrition to acquire and activities to perform like exercises and preferable sports.

B Balasubramanian [12] has shown studies of different deep learning methods for RS highlighting the important aspects of design and implementation.

N Doke [13] designed a personalized RS using the users' profile. His group has also implemented a hybrid approach to gain maximum accuracy and overcome drawbacks of both content-based and collaborative filtering approach.

Aminu Da'u [14] took a survey on RS based on deep learning and found that autoencoder(AE) is the most widely used after CNN and RNN. MovieLens is the most popular dataset after Amazon. The survey also showed that precision and Root Means Square Error (RMSE) are mostly used in the RS research field.

Ruiqin Wang [15] developed a two-stage deep learning model (2019) whose first stage used item and user as features and these features were fed in two separate marginalized stacked denoising auto-encoders to learn feature vectors. Then the feature vectors are combined and used as input vectors for a DNN algorithm in the second stage to optimize his model.

Aminu Da'u [16] proposed an RS using a deep learning approach to increase the accuracy of the RS. The model consists of two parts. In the first part, a multichannel deep convolutional neural network (MCNN) was used to extract aspects and generate aspect specific ratings by computing users' sentiment polarities on various aspects. In the second part, the aspect-specific ratings were integrated into a tensor factorization (TF) machine for the overall rating prediction.

M. Naumov [17] developed a state-of-the-art deep learning recommendation model(DLRM) using PyTorch and caffe2 frameworks (2019).

Batmaz Z. [18] provided a comprehensive review (2018) on the deep learning-based recommendation system that provides a guideline to the new researchers of this field.

Chu H. [1] proposed collaborative filtering of an RS approach using a deep learning algorithm autoencoder(AE) on MovieLens dataset. The algorithm reduced recommendation errors and provided batter recommendations.

Colombo-Mendoza, L. O. [19] has designed a deep learning-based hybrid recommendation system (2018) to enable end-users access to the knowledge base. He has also implemented a prototype of a knowledge base for financial news.

Dai Q. [20] proposed two hybrid recommendation algorithms for B2B medical platforms (2018) for providing the actual recommendation.

Fessahaye, F [21] implemented Tunes Recommendation System (2019), a hybrid RS approach that takes inputs content-based and collaborative filtering to a deep learning algorithm. The algorithm attained precision scores as high as 88% at a balanced discrimination threshold.

Fu M. Qu. [22] presented a deep learning method which imitates an effective recommendation by understanding the user and item formerly.

Guan Y. [23] introduced a multi-view model called Deep Multi-view Information iNtEgration (Deep-MINE). It takes multiple sources of content into an account and designs an end-to-end recommendation system. To implement this model, stacked auto-encoder networks were stretched for mapping multi-view information into unified latent space, a cognitive layer was added to classify consumers' heterogeneity, and an integration module was introduced to interact with multi-view representation.

Huang Z. [24] presented a recommendation system (TRec) with deep neural networks using GPS trajectory big data of taxis (2018) to hunt passengers.

Lee H. [25] discovered novel collaborative filtering based deep neural networks (2018) that takes a normalized user rating vector and normalized item rating vector. Liu J. [26] reviewed on deep learning-based recommendation approaches (2017) and proposed a classification framework. He also gave a possible future research direction in this field.

Liu F. [27] proposed an RS algorithm using a deep learning model in a grid environment.

Nassar N. [28] developed a novel mufti-criteria collaborative filtering based on deep learning. The model has two parts. In the first part, it takes users and items as features to feed them into a deep neural network. In the second part, it predicts ratings.

Kiran R. [29] described a novel hybrid RS approach to overcome the cold start problem using deep neural networks.

Sahoo A.K [30] made an intelligent health recommendation system using a restricted Boltzmann machine (RBM) and convolutional neural network (CNN) that showed how big data analysis can be used for implementing health care recommender systems.

Wei J. [31] proposed two recommendation models to solve the complete cold start and incomplete cold start for new items based on collaborative filtering and deep neural network.

Yi B. [32] proposed a deep learning-based collaborative filtering framework named deep matrix factorization which could integrate any side of information effectively.

Gan M. [33] proposed a deep neural network-based recommendation model named Convolutional and Dense-layer Matrix Factorization (CDMF) model (2019) for the context-aware recommendation.

Huang Z. [24] proposed a novel multimodal representation learning-based model(MRLM) which was trained by two modules simultaneously: global feature representation learning and multimodal feature representation learning

Rutkowski, T [34] designed an RS using neuro-fuzzy approach(2018). The neuro-fuzzy approach allows the system to recommend an item or not.

Qiao B. [35] worked on a content delivery network(CDN) recommendation framework to acquire data-driven and deep learning-based recommendation service. The CDN was built from a deep neural network to improve recommendation service.

Paul Covington [36] described the revolutionary change in youtube recommendation brought by deep learning. He divided the paper into tow-stage information retrieval dichotomy: the deep candidate generation model and the separate deep ranking model.

R.K. Roul [37] designed an algorithm that summarizes the reviews for movie purchases on Amazon. He also proposed a hierarchical summarization method that summarizes large reviews into small sentences.

P.V. Kulkarni [38] took a survey on eLearning and eLearning recommendation systems and also on the available technologies for RS.

V.K. Singh [39] proposed an RS that enables collaborative filtering completes the incomplete matrix of high data sparsity. This RS model was validated on different datasets and was more effective than other existing RS models.

A Dau [40] proposed a weighted Aspect-based Opinion mining using Deep learning method for Recommender system (AODR) which could extract the aspect a product and it's fundamental weighted user review text using a deep learning method. C. Lei [41] worked on Personalized Itinerary Recommendation and made a framework that decides user interest based on point of interest, visit duration and visit sequence to recommend a user his/her next tour. Yichi Lu[42] proposed a recommendation system that uses two CNN model for feature extraction. One for documents and one for images. He did so to improve rating prediction. Jianing Sun [43] proposed a multi-graph convoluted collaborative filtering model which models high-order information via the bipartite user-item interaction graph. The model also integrates proximal information through user-user and item-item graph.

Ruihui Mu [44] made a comprehensive survey on deep learning-based RS in which he included background concepts of deep learning and RS, the research content on deep learning-based RS. He also gave a guideline for future research in the field of Deep learning-based RS.

U.A. Khan [45] proposed a deep learning-based RS that predict the movies with relevant tags and clustering the movies according to the relevant tags.

Yi Caoa [46] assumed position-aware context attention is the solution of attention-based that takes both position information and content information in a sequence.

Guo Wei-wei [47] compared content-based and collaborative filtering recommender systems and proposed a collaborative filtering personality-based algorithm.

Z Huang [48] proposed a multiattention-based group recommendation model that utilizes the multiattention-based deep neural network to accurate group recommendation.

C Gupta [49] focused on searching and selecting relevant requirement on the cloud platform and improved that using KNN and TF-IDF algorithm.

Chao Lei [50] similar domain knowledge based on transfer learning to solve the data security problem on the cloud platform.

P Lops [51] discussed historical aspects of RS, it's recent trends and finally drawn an overview of future development.

G Manogaran [52] presented Multiple Kernel Learning with adaptive Neuro-Fuzzy interface system based on deep learning method.

M Yelo [53] proposed a deep learning model for Recommendation using CNN combined with temporal information to estimate user preference and item properties.

N Nikhil [54] proposed a deep learning-based supervised approach to recommend similar document based on the similarity of contents. The time and space complexity of the model is O(1) and O(n) respectively where n is the number of documents.

L Qinglong [55] made and RS approach identifying the factors of customers' satisfaction. A Deep Neural Network was used to develop the RS.

R Wang [56] proposed a novel Heterogeneous Information Network-based Music Recommendation System model. The model extracts textual data of users' preference to determine topics. After determining the topics Wang's group made a small-scale HIN of songs according to the topic and finally, they used a graph-based model to generate recommendations.

T.W Zhang [57] proposed an RS approach for social networking based on stochastic gradient matrix decomposition to improve accuracy.

Chapter 3

Proposed Method

Collaborative filtering is one of the most common approaches in the area of recommendation system. This approach finds users' similarity to recommend items. Whatever, we chose RBM to implement collaborative filtering to improve the accuracy of the model. In this chapter, we will introduce our model that consists of RBM and Singular Value Decomposition in short SVD. This is a hybrid model consists of tow algorithms.

3.1 Restricted Boltzmann Machine

Restricted Boltzmann Machine(RBM) is a kind of neural network which has only two layers: a visible layer and a hidden layer. An RBM model may also have multiple hidden layers. The input layer of RBM is the visible layer. Data is fed into the visible layer of the RBM for precessing. The data is then passed into the hidden layers. During passing data into the hidden layers, the individual weights of data are combined with the bias term. This process is called the forward pass. The ReLU activation function is used to determine the output of each hidden neuron. Whatever, the input is reconstructed in the output layer(visible layer). Through the backward pass, hidden layers send their result back to the visible layer which is the final output of the RBM model. This model is called restricted because neuron of the same layer cannot connect to each other directly.

Let us assume that, we have I items and U users. A user can rate items 1-5. Let us consider, we have K ratings. The K is an array of length 10. We have taken 10 values to take fractional values.

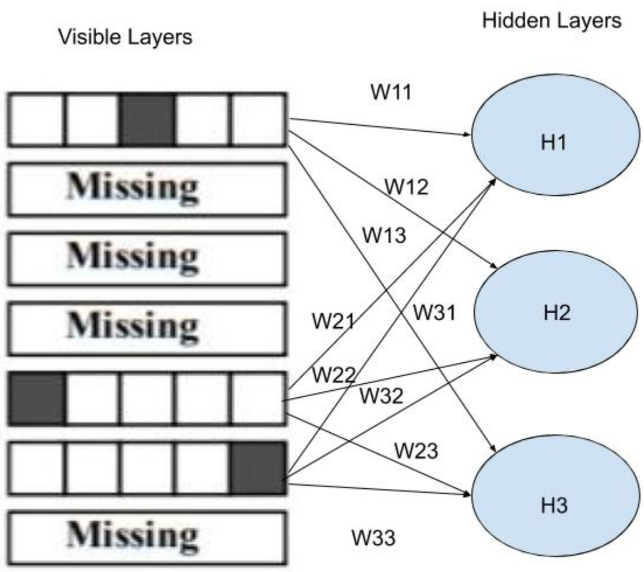

Figure 3.1: A Restricted Boltzmann Machine with three hidden layers(Simple form of our model). The ratings are inputted into the visible layer of the network. H1, H2 and H3 are the hidden layers. W_{ij} are the weights.

3.1.1 Model

We used RBM to predict the ratings of those items that users' have not rated yet. We have used a conditional multinomial distribution for modelling each column of determined visible rating matrix V. We also have a conditional Bernoulli distribution for users' hidden features h.

Let us consider we have U users and I items. The hidden features h_j where j = 1,2,3,.......,F.

$$p(v_i^k = 1|h) = \frac{e^{(b_i^k + \sum_{j=1}^{F} h_j W_{ij}^k)}}{\sum_{l=1}^{K} e^{(b_i^l + \sum_{j=1}^{F} h_j W_{ij}^l)}} \tag{3.1}$$

$$p(h_j = 1|V) = \sigma(b_j + \sum_{i=1}^{m} \sum_{k=1}^{K} v_i^k W_{ij}^k) \tag{3.2}$$

where $\sigma(x) = 1/(1 + e^{-x})$ is the logistic function, W_{ij}^k is a symmetric interaction parameter between feature j and rating k of movie i, b_i^k is the bias of rating k for movie i, and b_j is the bias of feature j. Note that the b_i^k can be initialized to the logs of their respective base rates over all user. The marginal distribution over the visible ratings V is:

$$p(V) = \sum_h \frac{e^{-E(V,h)}}{\sum_{V\prime h\prime} e^{-E(V\prime,h\prime)}} \tag{3.3}$$

Here,

$$E(V,h) = -\sum_{i=1}^{m} \sum_{j=1}^{F} \sum_{k=1}^{K} W_{ij}^k h_j v_i^k - \sum_{i=1}^{m} \sum_{k=1}^{K} v_i^k b_i^k - \sum_{j=1}^{F} h_j b_j \tag{3.4}$$

Movies that are missing rating cannot contribute to energy.

3.1.2 Learning

We made our machine-learned through "Contrastive Divergence". Where the weights of each layer are being continuously updated.

$$W_{ij}^k = \lambda((v_i^k h_i)_{fwd} - (v_i^k h_i)_{bwd}) \tag{3.5}$$

In the equation above, the $(v_i^k h_i)_{bwd}$ is a distribution of Gibbs Samplers of equation (3.1) and (3.2). In the beginning, the bwd is set up with learning rate and increase with learning convergence. When the value of bwd gets larger, the approximate maximum likelihood learning gets well at randomly but the large value of bwd is not required for this. We reconstructed the equation (3.1) for the non-missing ratings while running Gibbs sampler.

3.1.3 Prediction Making

Let us consider a movie t. We have to predict its rating. We can also predict its rating by our ratings V.

$$p(v_t^k = 1|V) \propto \sum_{h_1,h_2,..,h_n} e^{(-E(v_t^k,V,h))} \propto \Lambda_t^k \Pi_{j=1}^F \sum_{h_j \epsilon \{0,1\}} e^{(\sum_{il} v_i^l h_j W_{ij}^l + v_t^k h_j W_{qj}^k + h_j b_j)} \tag{3.6}$$

$$p(v_t^k = 1|V) = \Lambda_t^k \Pi_{j=1}^F (1 + e^{(\sum_{il} v_i^l W_{ij}^l + v_t^k W_{qj}^k + b_j)}) \tag{3.7}$$

Here, $\Lambda_t^k = e^{(v_t^k b_t^k)}$. We can either pick the rating with the maximum score as our prediction or perform normalization over K values to get probabilities $p(v_t = k|V)$ and take the expectation $E[v_t]$ as our prediction when we obtain unnormalized scores. The latter method works very well. When we will be asked to predict ratings for n movies t1, t2, ..., t3, we will able to compute

$$p(v_{t1}^{k1} = 1, v_{t2}^{k2} = 1, ..., v_{tn}^{kn} = 1|V) \tag{3.8}$$

For each user, it requires us to make K^n evaluations. Alternatively, we can perform one iteration of the mean-field updates to get the probability distribution over k ratings for a movie t.

$$S_j\prime = p(h_j = 1|V) = \sigma(b_j + \sum_{i=1}^{m} \sum_{k=1}^{K} v_i^k W_{ij}^k) \tag{3.9}$$

$$p(h_j = 1|S\prime) = \frac{e^{b_t^k + \sum_{j=1}^F S_j\prime W_{tj}^k}}{\sum_{l=1}^K e^{b_t^l + \sum_{j=1}^F S_j\prime W_{tj}^l}} \tag{3.10}$$

and take an expectation as our prediction. Although one iteration of the mean-field equations is considerably faster but in our experience, Eq.(3.6) makes slightly more accurate predictions.

3.2 Singular Value Decomposition

Singular Value Decomposition (SVD) is a matrix factorization method of a real or complex matrix. SVD is a built-in model for recommender system and its result is almost accurate. For this reason, it was widely used during the Netflix Prize. The SVD algorithm used in RS is an SVD inspired algorithm, not the pure SVD. Because pure SVD cannot be done on missing data.

3.2.1 Model

Let us consider R to be an $m \times n$ matrix whose m represents the row 'users' and n to be the column that represents the item or movies. We call R to be the rating matrix.
Now, let us consider a matrix U whose rows are users and columns are genres. Let's say that is a typical user matrix. Also, consider typical movie matrix M. This matrix has movies as rows and the genres of movies as columns.

$$R = M\Sigma U^T \tag{3.11}$$

Here, R is the multiplication of M, U and Σ (sigma) matrix. The Σ(sigma) is the diagonal matrix. R is the predicted rating of users' to items(Movies).

3.2.2 Learning

For recommendation system python has a built-in library called scikit-surprise. This library has a built-in framework for SVD algorithm. The algorithm SVD was trained by Stochastic Gradient Descent (SGD). It is quite straight forward and was iterated by 20 epochs by default.

$$b_u \longleftarrow b_u + \gamma(e_{ui} - \lambda b_u) \tag{3.12}$$

$$b_i \longleftarrow b_i + \gamma(e_{ui} - \lambda b_i) \tag{3.13}$$

$$p_u \longleftarrow p_u + \gamma(e_{ui}.q_i - \lambda p_u) \tag{3.14}$$

$$q_i \longleftarrow q_i + \gamma(e_{ui}.p_u - \lambda q_i) \tag{3.15}$$

In the equations above,

p_u = User Factor.

q_i = Item Factor.

b_u = User bias.

b_i = Item bias.

γ = learning rate

λ = regularization term

The error is reduced in learning that is denoted by e_{ui} which we will discuss in the next section.

3.2.3 Prediction

The rating is predicted by the following equation. The equation predicts missing rating by mean of ratings, users' bias, items' bias and multiplication of transpose of item factor and user factor.

$$\hat{r_{ui}} = \mu + b_u + b_i + q_i^T.p_u \tag{3.16}$$

Here, μ is the mean value or average of ratings and q_i^T is the transpose of q_i. If the user is unknown, the user bias and user factor will be zero. Same thing is applicable for item also. Item bias and item factor will be zero for unknown item. Mainly the error is calculated by $e_{ui} = r_{ui} - \hat{r_{ui}}$. In the framework, the following regularized squared error is reduced.

$$\sum_{r_{ui} \epsilon R_{train}} (r_{ui} - \hat{r_{ui}})^2 + \lambda(b_i^2 + b_u^2 + ||q_i||^2 + ||p_u||^2) \tag{3.17}$$

For this reason, this algorithm is most efficient and gives almost an accurate result.

3.3 Hybrid Approach

Finally, we have made a hybrid approach combining RBM and SVD. We have chosen these algorithms for their high accuracy and better performance over other existing algorithms. We have iterated RBM algorithm with several epochs to get a better result.
On the other hand, the SVD algorithm itself shows a better result. The error is very low in this algorithm. That is why we have chosen SVD for our approach.

Chapter 4

Result and Discussion

In this chapter, we have discussed our overall experimental setup. We discribe our dataset and experitmental results here.

4.1 Dataset

We have chosen movieLens data for our machine. This dataset has a low error. We downloaded the dataset from "https://grouplens.org/datasets/movielens/". From this link, we have downloaded "ml-latest-small.zip" file which is 1MB in size.

In our experiment, we used "rating.csv" and "movie.csv" files in most cases.

4.2 Evaluation Matrix

To evaluate our machine we use Mean Absolute Error(MAE) and Root Mean Square Error(RMSE). These parameters are quite efficient to improve the result of the algorithm.

4.2.1 MAE

In our case, we have tried to reduce MAE. Both of the matrics are built-in to the surprise library for Recommendation System.

$$M = \frac{\sum_{\hat{r_{ij}} \epsilon R} |r_{ui} - \hat{r_{ui}}|}{R} \tag{4.1}$$

Here M is the MAE. $\hat{r_{ij}}$ is the predicted rating, r_{ij} is the actual rating and R is the total ratings by user.

4.2.2 RMSE

We have also determined RMSE for our system. Following is the equation of RMSE

$$RS = \sqrt{\frac{\sum_{\hat{r_{ij}} \epsilon R} |r_{ui} - \hat{r_{ui}}|^2}{R}} \tag{4.2}$$

Here RS is the MAE. $\hat{r_{ij}}$ is the predicted rating, r_{ij} is the actual rating and R is the total ratings by user.

4.3 Graphical Analysis

Bellow is the graph of our model. From the graph above we represent the the total number of epochs in X-axis and the MAE values in Y axis. It represents that MAE is reducing with increasing values of epochs.

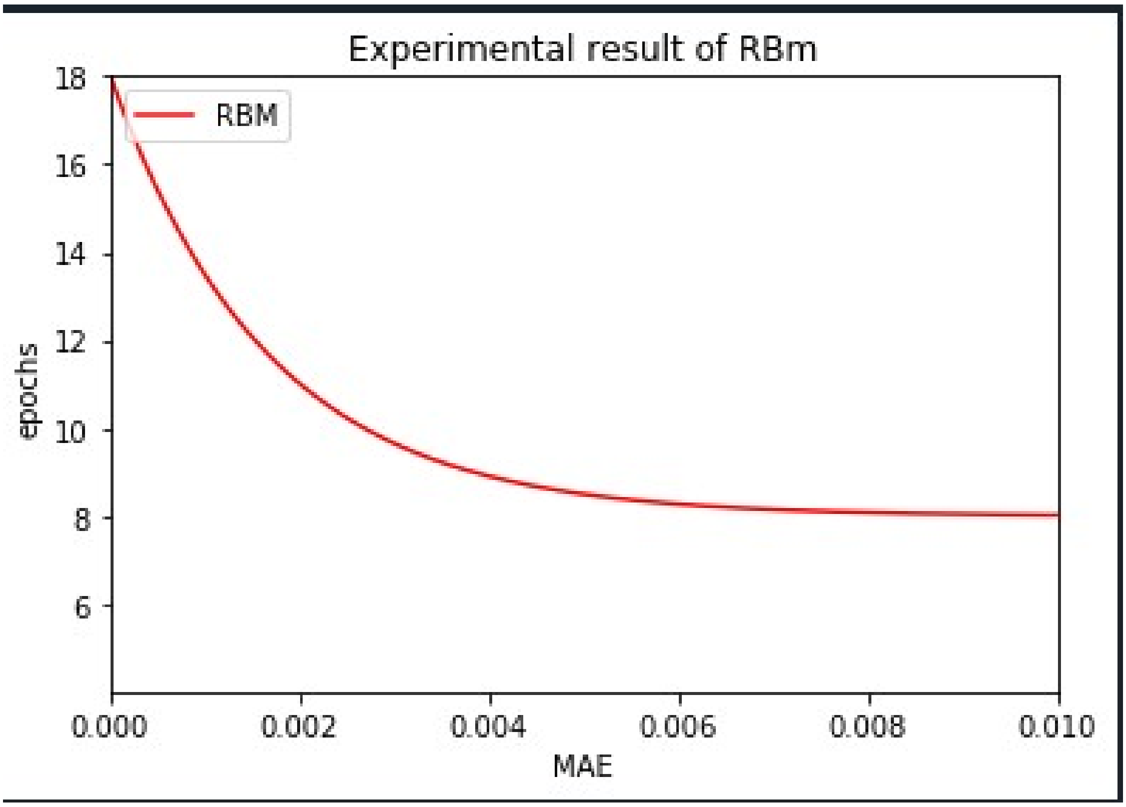

Figure 4.1: This graph represents the experimental result of our model

Chapter 5

Conclusion

We introduced a class of two-layer undirected graphical models (RBM's), suitable for modeling tabular or count data, and presented efficient learning and inference procedures for this class of models and Singular Value Decomposition (SVD) which finds low-rank approximations based on minimizing the sum-squared distance . We also demonstrated that RBM's can be successfully applied to a large dataset containing over 100 million user/movie ratings. A variety of models have recently been proposed for minimizing the loss corresponding to a specific probabilistic model [58, 59, 60]. All these probabilistic models can be viewed as graphical models in which hidden factor variables have directed connections to variables that represent user ratings. Their major drawback[60] is that exact inference is intractable due to explaining away, so they have to resort to slow or inaccurate approximations to compute the posterior distribution over hidden factors. Instead of constraining the rank or dimensionality of the factorization $X = UV$, i.e. the number of factors[61], proposed constraining the norms of U and V . This problem formulation termed "Maximum Margin Matrix Factorization" could be seen as constraining the overall "strength" of factors rather than their number. However, learning MMMF requires solving a sparse semi-definite program (SDP). Generic SDP solvers run into difficulties with more than about 10,000 observations (user/movie pairs), so direct gradient-based optimization methods have been proposed in an attempt to make MMMF scale up to larger problems. The Netflix data set, however, contains over 100 million observations and none of the above-mentioned approaches can easily deal with such large data sets.

5.1 Future Work

In future, we desire to develop our model with k medoid clustering, A novel hybrid algorithm in the field of recommendation system. For this approach, we will use RBM to design collaborative filtering. We have already made collaborative filtering with RBM. On the other hand, we will design the content-based filtering approach using K medoid algorithm in the near future. Each cluster will be each genre and movies having similar genres will be in the same cluster.

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Appendix A

List of Acronyms

3D	Three Dimensional Space
AWS	Amazon Web Services
VM	Virtual Machine

Appendix B

List of Notations

λ	This is Lambda
μ	This is mu
δ	This is Delta

Appendix C

List of Publications

International Journal Papers (SCI/SCIE-indexed)

1. Information of Journal Paper 1 (If Any).

2. Information of Journal Paper 2 (If Any).

3. Information of Journal Paper 3 (If Any).

International Conference Papers

4. Information of Conference Paper 1 (If Any).

5. Information of Conference Paper 2 (If Any).

6. Information of Conference Paper 3 (If Any).

7. Information of Conference Paper 4 (If Any).