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Key Indicators 3.3- Number of Publications

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The Pleasure of Money Making And The American Dream in F. Scott Fitzgerald's *The Great Gatsby*

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Abstract

The American culture is a flamboyant and influential culture for many who want to live a high five rich and aristocratic life. The Jazz Age of 1920's was the age of America which saw a period of carefree hedonism, wealth, freedom and youthfulness in its society and popular culture. F. Scott Fitzgerald's *The Great Gatsby* concerns the life of Americans and their pleasure of money making and dream life to live as a millionaire. The novel *The Great Gatsby* is considered to be Fitzgerald's magnum opus, a masterpiece represented the American culture beautifully. The novel accords social upheavals of the protagonist Gatsby, creating a portrait of Roaring Twenties as said a cautionary tale known as The American Dream. In *The Great Gatsby* money makes world go around someone or something. It can buy you all the yellow Rolls-Royces, gas blue dresses, nice shirts and all those branded things a rich man have it or dream to have it. But in the end those things can't buy us real happiness. Apparently none of the characters in the novel are happy, either they are dissatisfied with marriage or with love or life and most of all with themselves. They are not only just dissatisfied but instead they cause the havoc of trying to make themselves happy which turns the table of a worse situation and end up even dead, of soul or of body.

Keywords: flamboyant, influential, aristocratic, youthfulness, dream.

America in the 1920s marked a time of great post-war economic growth and Fitzgerald captures the frenzy of the society well. The novel was set in a prosperous Long Island of 1922, *The Great Gatsby* provides a critical social history of Prohibition-era America during the Jazz Age. Known for its jazz music, economic prosperity, flapper culture, libertine mores, rebellious youth, and ubiquitous speakeasies is fully rendered in Fitzgerald's fictional narrative. Fitzgerald uses many of these 1920s societal developments to tell his story, from simple details such as petting in automobiles to broader themes such as Fitzgerald's discreet allusions to bootlegging as the source of Gatsby's fortune.

The life of aristocrats is a life of money making and pleasure driving happiness. That happens to be their dream as well. Scott Fitzgerald's *The Great Gatsby* talks chiefly about a rich guy named Gatsby whose dream is as significant as the American dream. He thinks as if with money all the world's pleasures could be accomplished. He lives in West Egg district of Long Island in a Gothic mansion with eighteen bedroom palace with wine cellar and hair salon. The palace is lit with thousands of lights where he organized lavish Saturday night parties which seemed as if wild forest in fire. All day and night people crowded his place like bees and were always busy in dancing and drinking wines. As a host Gatsby appeared once in a blue moon and conversed with a few selected people. On the whole he is an incredibly wealthy mysterious man. He comes from a humble origin and a desperate dream to win back his love of a rich woman Daisy and loses everything in his last attempt to win her over.

The impression of Gatsby we see through the eyes of Nick Carraway as a humble and less speaking introvert who is choosy with the words. He has a tan skinned and short hair. He is blank slate and expressionless and reads people's mind by their appearance. He understood people as they want them to be understood. "He smiled understandingly much more than understandingly. It was one of those rare smiles with a quality of eternal reassurance in it that you may come across four or five times in life. I was looking at an elegant young rough-neck, a year or two over thirty, whose elaborate formality of speech just missed being absurd" (Fitzgerald 61). His character shits from a mysterious party host to the military man madly in love with Daisy to the ambitious farm boy James Gatz.

Gatsby's money did not come from inheritance, as he would like people to believe, but it came from an organized crime. His rich life was produced by gambling and bootlegging, rife in America, with the help of a professional gambler Meyer Wolfshiem. Within three years Gatsby worked hard and accrued money to buy an extravagant mansion at West Egg and Rolls Royce cars to decorate his garage. He threw parties and balls to build a reputation and win Daisy. Throughout the novel he continues to do business with Wofshiem and runs his own bootlegging business through phone calls from mysterious people. Gatsby lives mysteriously with the rumors about him that makes him suspicious among people that from where he got all the money.

All these money making he did for Daisy because they loved each other in Louisville in 1916 when he was at military. Daisy thought Gatsby to be wealthy in a military uniform and promised to wait for him. Gatsby achieved Montenegro for valor and came to America only to learn that Daisy married. Thus the money making was an attempt to win the love of his lady Daisy which was never truly reciprocated to his satisfaction. Gatsby's love was an unrequited one as Daisy did not leave her husband Tom Buchanan even after so many attempts that he made to make her love him. He also tried to make her admit that she never loved her husband Tom, but the person she was in love with was Gatsby himself. But we all know that money cannot bring happiness and buy love. It can buy all sorts of material things but never love. This brought a character change in Gatsby and a lesson for us all who dream to live an American dream.

From the outside, Gatsby appears to be proof of the American dream, he is a man of humble origins who accumulated vast wealth. Gatsby's rags-to-riches success story makes him an embodiment of the American dream. However, Gatsby is miserable. His life is devoid of meaningful connection. And because of his humble background, he remains an outsider in the eyes of elite society. Through the rise and fall of Gatsby we come to know that anyone can work hard and achieve upward mobility in United States. But still class mobility is not so undemanding and wealth accumulation does not promise a good peaceful life. His entire pursuit of wealth and influence is carried out in hopes of making his dreams come true. His single-minded pursuit of those dreams particularly his pursuit of the idealized Daisy is the quality that ultimately destroyed him.

The idea of the American Dream, a notion was born when Dutch sailors first arrived in the place that would become New York. The American Dream to Gatsby's love for Daisy in that both are unattainable. He spent years hoping for a happy future with Daisy but this future always receded into the distance. The hopes for the future were elusive because they did not relate to the future at all. Instead these hopes actually bore him back ceaselessly into the past. His dream must have seemed so close that he could hardly fail to grasp it. Gatsby and America are tragic because they remain trapped in an old dream that has not and may never become a reality.

Everyone in this novel *The Great Gatsby* are money-obsessed whether they were born with money like Tom, Nick, Daisy or Jordan, whether they made a fortune like Gatsby or whether they are even for more like Myrtle and Wilson. Money and materialism mattered so much to them that they find a pleasure in making it. At the end all the old money whom are from inherited club still alive and new money are all dead.

The lifestyle of the Aristocrats and of West Egg people who live in Long Island are portrayed in the novel *The Great Gatsby.* They fashioned themselves with brands like branded coats and suits and ball gowns like gas blue dress of Cinderella model, vintage style cars like Rolls Royce that has a named to it. They lived in a Gothic mansion that had their own wine cellar and hair styling salon with number of bedrooms and bathroom suites. Gatsby's mansion was one such that produced thousands of lights in a fifteen storey building. The green light that Gatsby believed in was a symbol of love that he built for Daisy, to be with her and to dance under the dock of the shining light.

The novel takes a fairly cynical view of love. Even the central romance between Daisy and Gatsby is less a true love story and more a depiction of Gatsby's obsessive desire to relive or redo his own past. He loves the image of Daisy more than the woman in front of him. But Daisy on the other hand she never truly loved Gatsby. She is beautiful and mesmerizing. She represents the apex of sociability. She enraptures men, especially Gatsby, with her sheer nature and sultry voice. She is the object of Gatsby's desire, for good or ill.

The characters in the novel are connected with love affairs and deceitful relationships. First the extramarital affair between Myrtle Wilson and Tom Buchanan, second the love affair between Nick and Jordan, finally the famous love tale of Gatsby and Daisy. They were never true to themselves and in their relationships. The act of secrecy, lies and deceits goes on surrounds them. This even leads to the death of many characters. Myrtle Wilson was killed when she tried to run away from her husband George Wilson, the night she got collided with the yellow Rolls Royce car of Gatsby's that Daisy was driving. Gatsby saved Daisy from the crime and intend to take it upon himself.

Tom Buchanan put Gatsby into trouble by revealing Daisy about Gatsby's truth of Gambling and bootlegging. Daisy distanced herself from Gatsby. Tom wanted to finish of Gatsby's chapter so he informed George Wilson about the yellow car that killed his wife Myrtle belonged to Gatsby. Unknowing of the fact Myrtle's affair was with Tom himself, George thought it to be Gatsby and shot him dead at his swimming pool at night. Later he fatally shot himself with the same gun. Meanwhile Tom ran away with his wife Daisy to Fifth Avenue at the day of Gatsby's death form any troubles. Nick also ended his love affair with Jordan and left to his hometown Chicago.

Gatsby had a dream of concealing an incorruptible dream. The death of Gatsby is considered to be the death of the American Dream. Nick imagines Gatsby's final thoughts and pictures him disillusioned by the meaninglessness and emptiness of life without Daisy, without his dream. Gatsby has made Daisy a symbol of everything he values and made the green light on her dock a symbol of his destiny with her. Thinking about Gatsby's death, Nick suggests that all symbols are created by the mind

they do not possess any inherent meaning rather, people invest them with meaning. After the death of Gatsby, New York was haunted, the once shimmering golden mirage makes us feel sick. Let's not dwell on dreams and forget to live.

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REDUCTION OF RATING PREDICTION ERROR USING OPTIMIZATION OF LOG HYPERBOLIC COSINE ERROR LOSS FUNCTION

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Abstract
In recent years, Recommender systems shared or participated by the public: and functional in a variety of domains. Memory-based collaborative filtering algorithms present serious scalability problems given that the algorithm has to process all the data to compute a single prediction. Predicting rating from sparse rating matrix among different users or items is challenging. Latent factor matrix factorization model reduces the dimensionality of rating matrix. The root mean square error (RMSE) was applied to forecast predictions. This paper describes a study on reducing rating prediction error from a minimization of logarithmic hyperbolic cosine error loss (LHCEL) function approach. The LHCEL-BFGS algorithm is proposed which uses Broyden-Fletcher-Goldfarb-Shanno (BFGS) method to find user-item ratings. Experiments conducted on movie lens and real-world datasets. The result shows that the proposed algorithm gives remarkable results than existing work.

Introduction
The growth of internet, intranet and e-commerce share a large amount of information to the user. It is widely acknowledge today that E-commerce business is growing rapidly around the world. Every customer checks the product or service rating before purchasing the product or obtaining the service. Rating ranks higher among the factors impacting purchasing decisions just behind the price. Star rating is a rating by people to rate an item/product/service with number of stars. The star rating represented with stars instead of values ranges from 1-5. These star ratings of the item is collected and subset of samples used in collaborative filtering algorithms for predicting the future preference of the user. Collaborative Filtering is a technique to predict a user's taste and find the items that a user might prefer on the basis of information collected from other users having similar tastes or preferences. Predictions computed automatically from the past behavior. The collaborative filtering algorithms categorized into item-based and user based. Memory based model uses similarity measure to forecast rating. The issues of memory based model are the scalability and sparsity of data. The memory based model results in missing prediction due to data sparsity. The matrix factorization approximates the rating matrix by the product of two matrices of lower dimension. The scalability of data is resolved to perform matrix factorization with minimum latent factor. To overcome this problem, LHCE_BFGS algorithm is proposed to predict rating for the product that is not yet rated or product that is launched newly. The rating will show the positive or negative impact on buying the product. The validity of the algorithm is examined using RMSE. The algorithm implemented on Movielens 100k data set and concluded that the proposed model is better than existing study.

Literature Review
Zhang et.al, predicts a crime prediction deals with data sparsity. The Contextually Biased Matrix Factorization (CBMF) method applied on crimes data of San Francisco city. The results showed that 90% of future thefts using only 50% man-hour and 5% more than the gradient

prediction method [1]. Khishigsuren et.al compared two techniques such as MF and BMF using SGD. The experiment conducted on book crossing and movie lens 100k datasets. They found BMF using SGD can give better performance corresponds to RMSE by 25.78% and MAE by 19.69% for book crossing and RMSE by 19.69% and MAE by 14.08% for movie lens 100k dataset[2]. Ayangleima Laishram et.al, presented a combining different heuristics technique with gradient descent affects the accuracy metrics of RMSE and MAE. The framework experimented on Movielens and proved that PSO based MMMF model take less iterations and getting optimal solutions faster may lead to correct predictions [3]. Mohammed Fadhel et.al, assesses a parameter selection of Alternate Least Square (ALS) algorithm for movie recommender system engine using Apache spark. The model evaluation done using different metrics such as execution time, RMSE of rating prediction and rank in the best model was trained. Two best cases are chosen on best parameter selection from experimental results, which can lead to build good rating prediction for a movie recommender engine [4]. Shahjalal.M et.al,proposed a gradient descent algorithm of collaborative filtering based on courser course machine learning to minimize the squared error of the cost function. The cost function minimization ensured with visual representation of the cost minimization. A threshold value eliminated the outliers in prediction matrix. The proposed prototype implemented in Matlab[5].Charinya Wangwatcharakul and Sartra Wongthanavasu described dynamic collaborative filtering recommender system model to work under volatile condition. Captured the user preference dynamics in the rating matrix using decomposition method and combine latent factor together with associated topic evolution of text reviews by using topic modeling based on dynamic environment. The proposed model improved the accuracy on real dataset than existing one [6]. Letham.Bet.al, formulated a sequential event prediction algorithm to observe the sequence of events depends on user choices. The algorithm tailored the user's choice for optimization problem. This approach applied to an online grocery store recommender system, email recipient recommendation and in the health event prediction domain [7]. GuangxiaXu et.al demonstrated a new similarity measure method which considers user confidence and time context, to improve the similarity calculation between users. The experimental results show that the proposed algorithm is suitable for the sparse data and effectively improves the prediction accuracy and enhances the recommendation quality at the same time [8]. Nikolaos Polatidis and Christos K. Georgiadis proposed a Multi-level recommendation method to assist the users in making decision for better quality of recommendation. The method applied in different domains improves the overall user experience and compared the experiments on five real datasets to improve the accuracy [9].

Methodology

Prediction error (Pe) is central notion in recommender systems and it is defined as the difference between actual rating and predicted rating. Researcher's compute predicted rating by the minimization of the mean squared error value. The proposed models receive input in the form of numerical rating by the m user for the n product. However, assessing the performance of a forecasting algorithm is a big challenge. The rating matrix consists of mn rows and three column matrix whose first column is user id, second column is item id and third column is rating. The rating matrix are converted into a real rating matrix whose rows represent users, column represent item whose elements are real ratings. The objective of this work is to find the rating of the real rating matrix whose values are 0 that is to find the rating of the product that has not been rated by user. Predicted rating accuracy and prediction error are inversely proportional to each

other. In this work, the rating prediction error is defined as the logarithmic hyperbolic cosine of prediction error. The prediction error Pe is given by

$$Pe=RRM-PRM$$

where RRM is the real rating matrix, PRM is the predicted rating matrix

$$RRM = U_i . P_j^T$$

The matrix factorization reduces the dimensionality of rating vector space. The predicted rating for user-item matrix is decomposed into user-latent factor ($\boldsymbol{X_{ik}}$) and item-latent factor ($\boldsymbol{Y_{kj}}$)matrices, where k<m is the number of latent factors. The sparsity of the rating matrix is reduced with minimum latent factor representation.

$$PRM = X_{ik} . Y_{kj}$$

The problem is formulated as

$$\text{Minimize} \quad \mathbf{E = e_{ij} = \sum_i \sum_j log(cosh(Pe))}$$

In general, the prediction error E is complex consists of many local and global minima.BFGS method finds a (local) minimum of an objective function, making use of objective function values and the gradient of the objective function. The algorithm can be given an initial estimate of the Hessian (Identity matrix) for the optimization and it is possible to get the final approximation of the Hessian based on the series of BFGS updates. The BFGS algorithm is of quasi Newton type with updating of the inverse Hessian and soft line search. The method uses finite differences to approximate the gradient and Hessian. The gradients are $c(\tanh(Pe)*Y_{kj},t(\tanh(Pe))\%\%X_{ik})$. Figure.1 shows the process of LHCE-BFGS method recommendation.

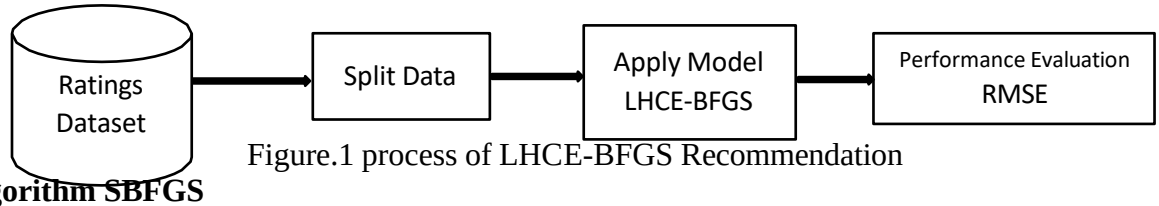

Figure.1 process of LHCE-BFGS Recommendation

Algorithm SBFGS

1. Given starting point $x^{(0)}$
2. Iteration Count t=0
3. $H_0=I_n$
4. Calculate gradient $g^{(t)} = - (H^{(t)})^{-1} c^{(t)}$
5. Return $x^{(t)}$ if $norm(g^{(t)})$<tolerance
6. $x^{(k+1)} = x^{(k)} + d^{(k)} g^{(k)}$
7. Calculate search direction
8. $y_k \leftarrow g_{k+1} - g_k$
9. Update H_{t+1} using H_t

$$H^{(t+1)} = \frac{y^t y^{t^T}}{y^t s^k} + \frac{g^t g^{t^T}}{g^t c^t}$$

10. Set t=t+1
11. Go to step 3

Algorithm LHCEL-BFGS

1. Gather the user rating for the item.
2. Construct user-item rating matrix
3. Transform to real rating matrix(RRM)
4. Assign random predicted matrix as vector x_0

5. Minimize E by calling subroutine SBFGS
6. Split X and Y from x
7. Calculate PRM=X*transpose(Y)
8. Compute VM=sqrt((Pe)^2/(m*n))

Dataset

The benchmark dataset Movie Lens is taken for study. It consists of 100,000 ratings for 1682 movies and 943 users [10]. The SMRR dataset constructed for a Samsung Mobile product. This dataset consists of User-Id, Product-Id and Ratings given by the users. It crawled from various websites sources like Amazon, Flip kart, Snapdeal, Mysmartprice and gadgets. The implementation carried out R language to simulate the model.

Results and Findings

The goal of LHCE-BFGS algorithm is to minimize difference between actual and predicted ratings. However, assessing the performance of a rating prediction is a big challenge. In order to improve the prediction accuracy, the validation measure RMSE (Root Mean Square Error) is used to evaluate the algorithm.

The RMSE is given by

$$\text{RMSE}=\text{VM}=\sqrt{\frac{Pe^2}{\text{Product}(\dim(PRM))}}$$

The proposed algorithms used to minimize the RMSE (Root Mean Square Error) and to find the missing or unknown ratings of the rating prediction problem (RPP). The rating matrix of user u_i and item $p_j$ofdot product converted into real rating matrix of size nxm. This converted matrix used to make predictions for the user u to item p. The latent factor k=2 is initialized to find the gradient descent. The iterative epoch is used for 50 iterations. Hessian matrix $H^{(t)}$ is initialized as identity matrix and multiplied with gradient $g^{(t)}$ until step length replaces the old gradient value. Update of new gradient with BFGS formula as in step4. The Hessian matrix $H^{(t+1)}$ is calculated for every iteration until the tolerance met or converges. The proposed LHCE-BFGS algorithm converge in less iterations. The Table.1 depicts the parameter for LHCE-BFGS algorithm and its validation measure of Movie Lens and SMRR datasets. Table 2. show the results of existing study of Movie lens dataset rating prediction.Figure.2 and Figure.3 shows the RMSE of the proposed LHCE-BFGS based latent factor model for Movie Lens dataset and SMRR dataset.

Table. 1. RMSE Value for Movie Lens and SMRR Dataset

Iterations	Movie Lens Dataset		SMRR Dataset	
	Sparsity	RMSE	Sparsity	RMSE
10	0.26087	0.2639376	0.733333	0.03635199
20	0.26087	0.2624460	0.733333	0.03533549
30	0.26087	0.2625894	0.733333	0.03405502
40	0.26087	0.2617392	0.733333	0.03405502
50	0.26087	0.2617392	0.733333	0.03405502

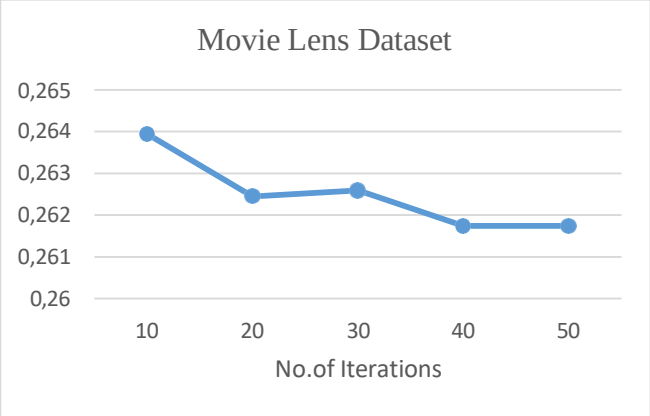

Figure.2 Plotting of RMSE value for Movie Lens Dataset

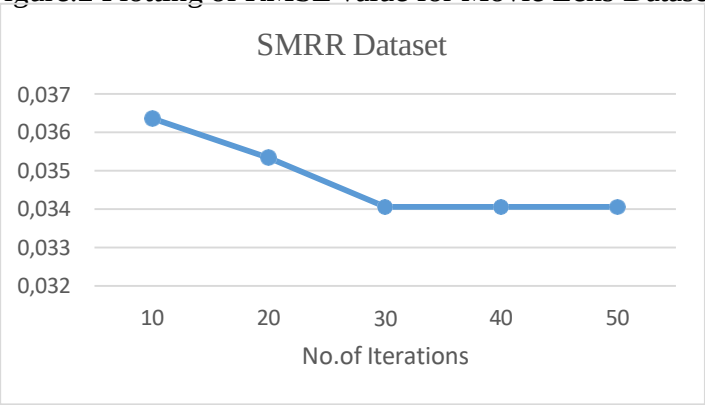

Figure.3 Plotting of RMSE value for SMRR Dataset

Table. 2. Existing Study of Movie Lens Dataset

Existing Literature	Iterations	Method	RMSE
Munafur Hussaina and Parimala[11]	1000	PSGD	0.785891
Waqar Ali et.al[12]	-	CBRP	0.773300
Zhipeng Wu et.al[13]	-	MFRC	0.898300
Xin Guan et.al[14]	-	ESVD	0.957000

Conclusion

Collaborative Filtering method are a very good well doing methods in rating prediction. This paper provides a high-level perspective on benchmarking of defining logarithmic hyperbolic cosine loss objective function for proposed rating prediction algorithms. This work introduces the concept of LHCE-BFGS based latent factor model which is a unique algorithm in itself. As noted in the experimental results, our models obtained significantly better Validation measure results compared to the benchmark methods.

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Strengthening Rating Prediction using Latent Factor Matrix factorization in Collaborative Filtering Algorithms

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Abstract

Businesses which are given no ratings must make urgent or major improvements to maintain a good online reputation for business. Businesses will now have to make a rapid transition from offline to online, which requires a completely new approach to business strategy. Recommender systems in online business generate a huge amount of income when they are efficient and stand out significantly from competitors. Collaborative Filtering uses matrix factorization technique that decomposes rating matrix into two entities. In this paper, a new objective function Log-Cosh Error Loss (LCHEL) is proposed to predict ratings. Steepest Gradient Descent (SGD) and projected Gradient Descent (PSGD) methods applies to loss minimization problems. The experiment conducted on Benchmark dataset Movie-Lens and collected real time SMRR dataset. The results show that LCHEL-PSGD algorithm bring out less prediction error compared to existing study.

Keyword: Collaborative Filtering, Log-Cosh, Gradient Descent, Ratings, Steepest Gradient Descent

Introduction

The main goal of any business is to generate revenue by providing a product or service. As consumers become more influential in the future, e-Commerce companies need to take advantage of ratings to start seeing the benefits. The growth of E-business would increase their profits and customer satisfaction through the ability of recommendation systems. Item ratings are the star ratings that users give to that item. Product ratings help influence customers' buyer behavior. Star rating can make or break the business. The rating prediction helps to recommend the not yet rated items to the user. The collaborative filtering technique is one of the widely used task of recommendation system which predicts the ratings for unknown items from the past behavior. The ratings classified into implicit and explicit ratings. The implicit ratings collected from feedback data of the user, where explicit ratings expressed in the form of ratings or votes. A collaborative filtering algorithm finds the similar users or similar items and calculates rating based on ratings of similar users. The rating prediction face several problems and challenges namely conversion of rating matrix, sparsity and high dimensionality of rating matrix [9]. The proposed work overcomes the challenges of scalability and efficiency of the process. The Matrix Factorization technique works with collaborative filtering algorithm, allows to discover the latent features from the rating matrix and to map the interactions between users and items against those factors. Steepest Gradient descent is an iterative optimization algorithm search in the direction which will minimize the prediction error.

Literature Review

[1] projected a novel machine language algorithm to predict a list of top-k items by optimizing the latent factors of users and items with the mapped scores from ratings. The scores predicted by using cosine based latent factors for the unseen items. Empirical evaluation

on benchmark dataset revealed that proposed model out performs recommending good items to a user.

[2] described an approach of generalized recommendation using content based filtering. The k-Nearest neighborhood algorithm implemented for Movielens with cosine similarity gives more accuracy than other distance metrics and gives low complexity.

[3]proposed cosine neighborhood similarity measure to calculate rating for items and recommend items to user. The recommender system performance evaluated exhibits the CNS similarity measure is more accurate and improves the quality of recommendation by reducing the error rates and latency.

[4] formularized a SynRec-Synergy score collaborative filtering technique based on trust factor extracted from user ratings to improve the quality of recommendation and given better predictions. Effectiveness justified with experimented on Film-trust dataset. Epinions and Movie Lens data sets compared for results

[5] recommended an approach that determined the best algorithm for accurate recommendations using statistical accuracy metrics. The user-based and item-based CF algorithms are compared with different similarity indexes for performance and accuracy. The experiment conducted on Movielens dataset and compared the similarity index of user based and item based algorithm.

[6] Proposed a framework of combinations of population based heuristics with gradient descent, affect the accuracy metrics like RMSE and MAE. The results shows extensive experiments on the large scale MovieLens dataset and demonstrated that approach provides better and more consistent solutions than gradient descent and lead to correct predictions.

[7]demonstrated Biased Matrix Factorization using SGD technique results in a substantial increase in recommendation accuracy for rating prediction. Compute with a regular Matrix Factorization technique, Biased Matrix Factorization produced reduction of the RMSE by 25.78% and MAE by 19.69% for Book Crossing dataset and RMSE by 19.69% and MAE by 14.08% for Movie Lens 100 K dataset. The result shows that for different datasets, Biased Matrix Factorization using SGD emerged less prediction error.

Methodology

Matrix factorization has become a predominant technique in recommender system. Matrix factorization technique works by decomposing the user-item interaction matrix. Consider actual rating matrix R=(r_{ij}) whose elements are ratings of n users for m items.

$$r_{ij} = U_i . P_j^T$$

The predicted ratings randomly chosen as user-item matrix r_{ij}decomposed into two entities namely user-latent factor (X_{ik})and item-latent factor matrices(Y_{kj}), where k is number of latent factors.

$$\hat{r_{iy}} = X_{ik} . Y_{kj}$$

A prediction error(e_{ij}) is defined as logarithmic hyperbolic cosine of difference between actual and predicted ratings. The objective of the study is to minimize the prediction error subject to no constraints or constraints on rating value.

$$e_{ij} = \sum\sum \log(\cosh(r_{ij} - \hat{r_{iy}})$$

where r_{ij} is the actual rating by user i for item j and $\hat{r_{iy}}$ is the predicted rating.

Steepest descent is typically defined as gradient descent in which the learning rate is chosen such that it yields maximal gain along the negative gradient direction. The gradient is the directional derivative of a function. The directional of steepest descent is the direction amongst all nearby directions that lowers the value of the objective function most. The algorithm LHC-GA-SGD is

presented. The predicted rating value is not in domain Ω, then "project" $\hat{r}_{iy}$ back into $\ell b \leq \hat{r}_{iy} \leq$ub before setting.

	i_1	i_2	i_3	i_4	i_5
u_1	5		4	1	
u_2		3		3	
u_3		2	4	4	1
u_4	4	4	5		
u_5	2	4		5	2

Figure.2 User-item Rating Matrix

The figure.2 shows the sample of rating matrix. The gradient is calculated iteratively until no more changes occur in the minimum function. The learning rate controls the rate of the update[9].The parameter X, Y are updated as

$$x_{ik} = x_{ik} + \alpha * tanh(e_{ij}) * y_{jk}$$
$$y_{jk} = y_{jk} + \alpha * tanh(e_{ij}) * x_{ik}$$

where α is the fixed learning rate. The initial value for X,Y is set as random vectors uniformly distributed in[0,1].There are two latent factor used in this study.

Algorithm LHCEL-SGD

Data: Training data contains user x∈ N, item y∈ N and rating r ∈ R.

Input: The latent vector K=2∈ n, X number of user ∈ N and Y number of item ∈ N.

1. Read actual rating matrix a_{ij}
2. r_{ij} ➛sample of 80% of a_{ij}
3. Randomly assign X as dim(nrow(r_{ij}),K),Y asdim(ncol(r_{ij}),K)
4. iterate epoch m no.of times (OR)while does not converge
   for each i,j
   calculate $e_{ij} = \sum\sum \log(\cosh(r_{ij} - \hat{r}_{ij}))$
5. update X and Y as

$x_{ik} = x_{ik} + \alpha * tanh(e_{ij}) * y_{jk}$

$y_{jk} = y_{jk} + \alpha * tanh(e_{ij}) * x_{ik}$

6. Return X and Y

Algorithm LHCEL-PSGD

Data: Training data contains user x∈ N, item y∈ N and rating r ∈ R.

Input: The latent vector K=2∈ n, X number of user ∈ N and Y number of item ∈ N.

1. Repeat step 1 to step 5 of Algorithm **LHCEL-PSGD**
2. For each update, Project $\hat{r}$ into the interval $\ell b \leq \hat{r}_{iy} \leq$ub
3. Return X and Y

Data Set used

The publically available Bench Mark dataset Movie Lens has 100,000 ratings by 943 users on 1682movies of scale rating 1-5 is considered for study[8]. Secondly, the ratings from real dataset Samsung Movie Review Ratings (SMRR) has 100 ratings by 4 users on 117 items extracted from different websites of amazon.com, mysmartprice.com, flipkart.com, snapdeal.com and gadget.com. The web crawling and proposed algorithms are implemented in R programming language. Samples of 80% are carried out for experiment.

Results and Findings

Sample of dataset are preprocessed and transformed into real rating matrix. The proposed algorithm runs for m iterations with fixed learning rate α=0.0002.The bounded rating projected into the interval[1, 5].Root Mean Square Error (RMSE) is a quadratic metric that measures the average magnitude of the error. It is the square root of the average of squared differences between prediction and actual ratings. The root mean square error value is recorded and presented in the Table1. Figure.3 and Figure.4 shows the diagrammatic representation of RMSE for both Movie Lens and SMRR dataset. The comparative results shows that LHCEL-SGD and LHCEL-PSGD have better RMSE error reduction when compared to existing study[7][9].

Table.1 RMSE value for Movie Lens Dataset

Iterations(m)	1	100	200	300	400	500	600	700	800	900	1000
LHCE-SGD	3.2224	2.1143	1.1507	0.9335	0.8996	0.8941	0.8920	0.8899	0.8874	0.8845	0.8811
LHCE-PSGD	3.3210	2.1567	1.1244	0.9062	0.8727	0.8680	0.8672	0.8667	0.8663	0.8658	0.8653

Table.2 RMSE value for SMRR Dataset

Iterations(m)	1	100	200	300	400	500	600	700	800	900	1000
LHCE-SGD	1.2099	1.1470	1.0745	0.9912	0.8958	0.7901	0.6794	0.5719	0.4745	0.3916	0.3241
LHCE-PSGD	1.1967	1.1174	1.0287	0.9293	0.8188	0.7007	0.5835	0.4773	0.3898	0.3215	0.2676

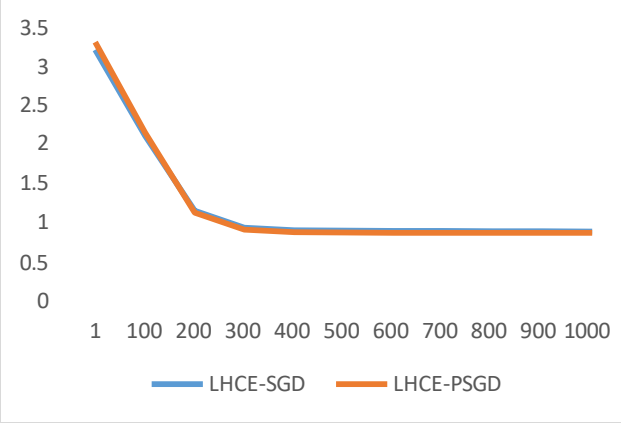

Figure 2. RMSE - Rating Prediction Error for Movie Lens Dataset

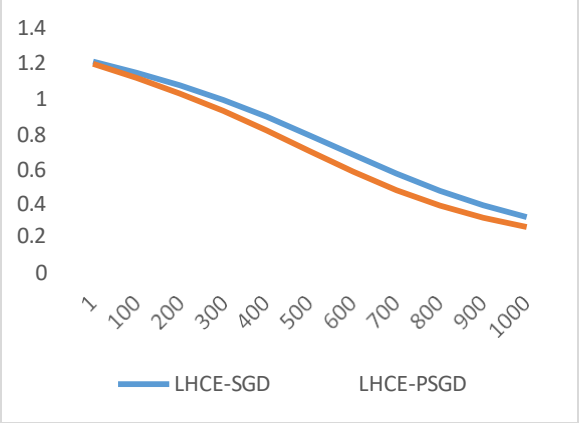

Figure 3. RMSE - Rating Prediction Error for SMRR Dataset

Conclusion

Internet online shopping and e-trading are necessary for today's life even during this covid'19 period. The recommender system helps the customer and e-commerce by targeting advertisement, personalized marketing and information retrieval. The predicted review ratings help the users to make a correct decision for choosing the items among many one. Similarity measures reserved the predicted ratings of the items / users from the past behavior. The proposed work using LHCEL-SGD and LHCEL-PSGD predicts ratings on Movie Lens and for real SMRR datasets. The experiment shows the LHCEL-PSGD provide lower RMSE value on both datasets. In future, the proposed work extends for other collaborative filtering algorithms and machine learning.

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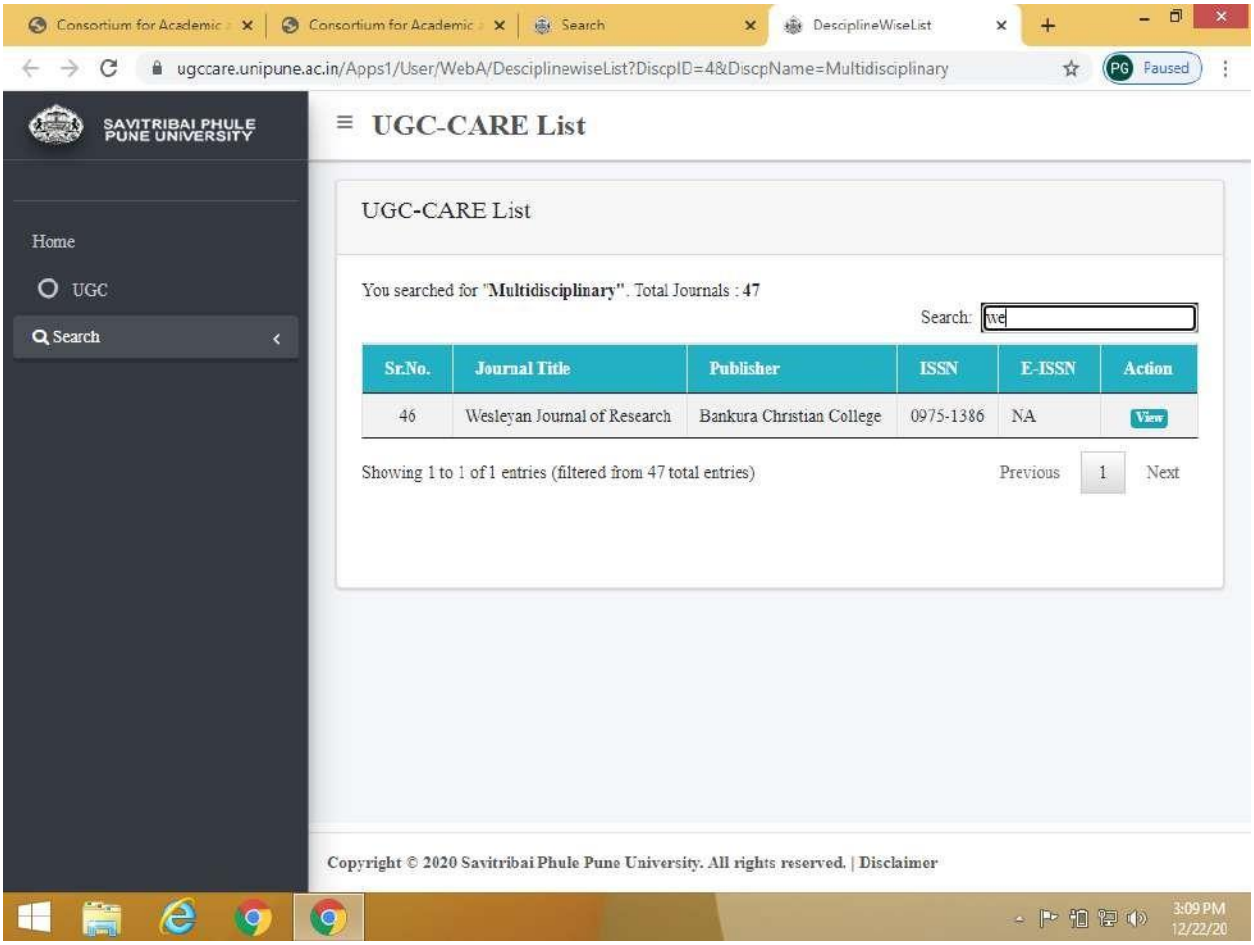

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Rating Prediction of Collaborative Filtering using Quasi-Newton Approach

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Abstract

Consumers search the product and its ratings rather than reviews to make purchasing decisions. Rating gives out different intention for different users and product. Collaborative Filtering models developed using Matrix factorization algorithm to predict user's rating of unrated items. There is a need for finding missing ratings for the products. A most popular latent factor Quasi-Newton method is applied to predict the unbounded missing ratings. And also in bounded rating prediction problem, the rating reviews are found using Projected Quasi-Newton algorithm. Experiments conducted on Movie Lens review dataset and real-world dataset. The result shows that the Projected Quasi-Newton algorithm gives better performance.

Keywords: Recommendation System, Newton Method, Hessian Matrix, Quasi-Newton, Rating Prediction Problem (RPP), Collaborative Filtering.

I. Introduction

In this decade, technologies play a major role in every sector, especially in consumer-oriented business. They try to bring any new mechanism on buying and selling environment to the user. World economy increases every year through online shopping. A person who likes shopping may want to look at hundreds of different items and read dozens of reviews before buying the products. E-Commerce Company needs to offer a reliable service based on customer's interest. Product recommendation helps the customer to make better buying decisions. Collaborative filtering is the technique used for recommendation system that constructs an intelligent recommenders' model to give better recommendations as information to the customers. The main categories of product recommendation system are Content-Based Filtering (CBF), Collaborative Filtering (CF), Complementary Filtering and Hybrid recommendation system which use a combination of CBF and CF. Researchers used the Collaborative Filtering as core part of their recommendation systems. The websites offer the recommendation information to the users based on likes and dislikes of similar users. Similarity measures used to determine the set of users having the same behaviour regard to selected items. Star rating is kind of reviewing in numeric scale based on quality and quantity that given by customers or viewers.

The rating prediction is a recommendation task aims to predict user's rating for those items which are similar or dissimilar or not yet rated. Predictions computed automatically from the user's feedback provided in the past [10]. Rating prediction is defined in terms of Root Mean Square Error (RMSE) and it is performed with rating based data. The Root Mean square error on rating prediction problem (RPP) is root mean square of observed and predicted ratings. Item-based approach recommends the items based on user ratings on those items. Item based filtering is faster and more stable than user based filtering. Collaborative filtering faces issues in data sparsity - user gives rating to a limited number of available items, especially when the catalogue is very large. This results in a sparse user-item rating matrix with insufficient data for identifying similar users or items. The issue scalability faces scalability of algorithms with large and real-world dataset. Some algorithms are computationally expensive to run the large datasets. Matrix Factorization (MF) recommendation algorithms emerge locally and produce results for scalability. Without comprising the precision of the system, the recommendation system finding ways in diversity increase. The issues overwhelmed by Latent Factor Model(LFM).The most frequently used algorithm in CF filtering is the K-

nearest neighbours' algorithm and factor analysis. Nearest neighbour method used to identify items with similar users like the inverted neighbourhood which occurs to identify less similar. The LFM measure does not require similarity computation to make inference or prediction. LFM technique projects the users and items by latent vectors in a low dimensional space to evaluate response values with the help of statistical model. In this paper, a proposed work focus on efficient optimization algorithm named Latent Factor Broyden-Fletcher-Goldfarb-Shanno (LF-BFGS) to predict unknown ratings of rating prediction problem. LF-BFGS is an optimization algorithm in the family of quasi-Newton methods which uses a limited amount of computer memory.

II. Literature review

[1] Wei-Sheng et.al developed an Alternating minimization algorithm based on Newton method and carry out factorization for training using MATLAB Package. Novel optimization techniques were used on large-scale training factorization to reduce the running time. The stochastic gradient algorithms are proposed and performed coordinate descent methods in multithreaded environment.

[2] Mahdi Nasiri et.al proposed matrix factorization with initial latent factor for preprocessing of users and items matrices. The method accuracy using optimization-based matrix factorization technique was improved and also increased the speed of convergence.

[3] Herlan et.al discussed the learning algorithm using BFGS Quasi-Newton method and updates the weight of back propagation (BP) using ANN. The BP with BFGS improves the convergences of learning process with optimal architecture and increased the accuracy for glass dataset.

[4] Jianke et.al offered a approach to social recommendation problem with graph Laplacian regularization to capture social relationship among users. The approach formulated a problem into a low-rank semi-definite problem using Quasi-Newton algorithm. The experiment conducted on Epinions dataset is more efficient and effective result for the social recommendation task.

[5] Liwei wu et.al proposed a Collaborative Ranking (CR) algorithm called Primal-CR and Primal-CR++ with Newton update. This reduces the time complexity for the items rated by the users. The results are compared and showed the same efficiency for both the algorithms with minimum loss in ranking.

[6] Ajit.P.Singh et.al projected a Collective matrix factorization, allows handling larger matrices using a sampled approximation to the gradient and Hessian. This method produces an efficient Newton update for the projection with fast rate of convergence.

[7] Fabio Sigrist presented tuning parameter for tree-based Newton boosting method for predicting accuracy. The results of unified framework of gradient, Newton boosting and hybrid variant algorithms are compared. The empirical results showed Newton boosting converged faster and achieves lower training loss.

[8] A.N.Nikolakopoulos and G Karypis et.al proposed uncoupled random walks based collaborative filtering method called as RecWalk, this method perform a novel random walk rely on customer weightage of past preferences on products via uncoupled Markov chain, which helps to find the past performances of customers.

[9] Agoritsa et.al conducted a random walk based model called as scholars walk, which caught the later relationships between the different courses in a university that recommended the courses to the students based on earlier knowledge and wisdom of the crowd. This framework considers as an important for educational institution to bring out the efficient in learning between students.

III. Proposed Methodology

This work resolves the product cold-start where a new product has been added to the database has not yet received enough rating. Matrix factorization is a common approach to CF represented as sparse user item/product

rating matrix. Gradient descent method follows iterative approaches that start from random feature vectors and gradually improves the solutions till there is no change in feature vectors, and/or convergence is reached. The stochastic gradient descent method is not feasible to find the solution in reasonable time. A Newton's method is used to replace the gradient descent, which has the advantages of fast convergence speed and less effort of tedious learning rate. The Quasi-Newton BFGS method is used for its effective, robustness and self-correcting properties, as well as for the super linear convergence approximation of the objective function. Quasi-Newton method is one of the unconstrained optimization techniques, substituting derivative computation using Hessian Matrix. Figure.1 shows the process of PLF-BFGS method to predict the unknown rating prediction. The size of |nxm| dimension of user-item real rating matrix is taken and converting into gradient vector. The inverse hessian matrix used with gradient vector for updating the rating value.

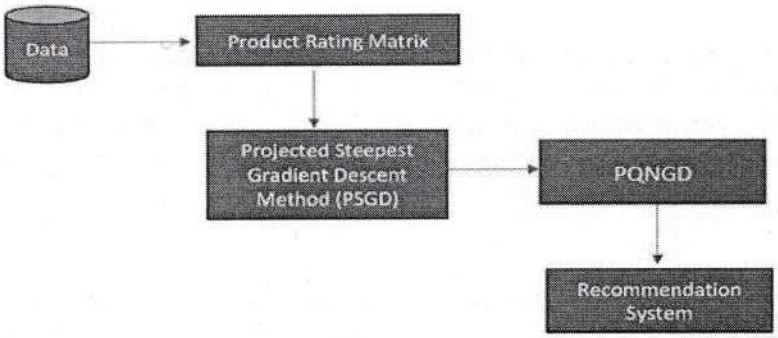

Figure 1. Process of Projected BFGS

The rating prediction is a task of recommender system to predict user ratings for the missing one's (items which are not rated by the user).The user-item rating matrix of a product j with a vector p_j and use i with a vector u_i is denoted as

$$\hat{r}_{ij} = u_i \cdot p_j^T \quad (1)$$

where u_i is of size n and p_j is of size m. A sample of the user-item rating matrix is shown in Figure.2.The squared prediction error MSE is defined as the difference between the actual and predicted ratings then

$$e_{ij}^2 = \sum_{ij}(r_{ij} - \hat{r}_{ij})^2 + \lambda[\|u\|_F^2 + \|p\|_F^2] \quad (2)$$

r_{ij} is the actual rating by user i for product j and $\hat{r}_{ij}$ is the ratings to predict. The objective function eij^2 is calculated with bias value λ=1 for rating prediction. The power of CF method projects users and items into latent vector space of reduced dimensionality to predict missing rating. The gradient descent is an optimization technique used to reduce the error rate. In rating prediction model, the objective is to minimize the root mean square error value.

		Items					
		1	*2*	...	*i*	...	*m*
Users	*1*	5	3		1	2	
	2		2				4
	:			5			
	u	3	4		2	1	
	:					4	
	n			3	2		

Figure 2: User-Item Rating Matrix

BFGS uses quadratic Taylor approximation of the objective function f(x) in x.

$$H_{k+1} = H_k - \frac{H_k S_k S_k{}^T H_k}{S_k{}^T H_k S_k} + \frac{Y_k Y_k{}^T}{Y_k{}^T S_k} \quad (4)$$

Where

$$s_k = x_{k+1} - x_k \quad (5)$$

$$y_k \leftarrow g_{k+1} - g_k \quad (6)$$

where initial Hessian H_0 is the identity matrix. Iterative Hessian saves a large amount of computation time when input data is in sparse. The loop is repeated with changes of gradient until the tolerance is met. The missing rating will be predicted and the root mean square error (RMSE) is recorded. The bound constrained rating prediction problem as in equation (2) $\min f(x), x \in R^n$ states that $l \leq x \leq u$ where l and u are bounded rating. The rating solution projects on to the set $\{l, u\}$. The PLF-BFGS algorithm predicts the unknown ratings or missing ratings with bounded constraints $l \leq r_{ij} \leq u$.

3.1 Algorithm

LF-BFGS

Input: Real Rating Matrix
Output: Predicting Missing ratings with fast convergence
Variables
$(c^{(0)})$ - as Gradient vector
$(H^{(0)})$ - as Hessian matrix
$z^{(0)}$ - as matrix
k – Number of iteration
Step 1: Read the real rating matrix
Step 2: Initialize the gradient vector($c^{(0)}$), tolerance, β, α and k.
Step 3: Compute the gradient matrix,
$g^{(k)} = -(H^{(k)})^{-1} c^{(k)}$
Step 4: Calculate the step length,
$d^{(k)} = f(z^{(k)} + dg^{(k)})$
Step 5: Find the rate of gradient $y^{(k)} = c^{(k+1)} - c^{(k)} \cdot y^{(k)}$.
Step 6: Compute $s^{(k)} = dg^{(k)}$
Step 7: Update Hessian Matrix as in (4)
Step 8:IF$\| g^{(k)} \| <$ tolerance then
Print "Converged"
Loop
Calculate the overall squared error,
$e_{ij}^2 = (r_{ij} - \hat{r}_{ij})^2$
End loop
Else // $\| c^{(k)} \| >$ error tolerance
go to Step 3.
Step 9: Stop.

a. Dataset

Bench mark Movie Lens is a web based recommender system dataset publically available from Group Lens Research, recommends movies for the users to watch [12]. The size of 1M (100k) has 943 users and 1682 movies with 100000 ratings in the dataset. Randomly selected 100 records from the database are taken for implementation.

The secondly Samsung Mobile real review (SMRR) datasets are crawled and collected from different websites like flipkart.com, amazon.com, mysmartprice.com, snapdeal.com and gadgets.com [11]. Dataset has information about

Product Name, ratings, price and text review information. The 5-star scale rating is deployed in movie lens and SMRR data set. A subset of review rating of size 100 is select for the study. The experimentation is conducted out in R language.

IV. Results and Findings

The proposed algorithms are used to minimize the RMSE (Root Mean Square Error) to find the missing rating of the rating prediction problem (RPP). The relationship between user u_i and item p_j of dot product of rating matrix converted into real rating matrix of size nxm. This conversion of rating matrix used to make prediction to rate from user u to item p. The learning factor k=2 is initialized in the algorithm to find the gradient descent. The epoch is used for 1000 iterations. Hessian matrix $H^{(k)}$ is initialized as identity matrix and multiplied with gradient $g^{(k)}$ until step length replaces the old gradient value. Update of new gradient with quasi-Newton formula as in (4). The Hessian Matrix as $H^{(k+1)}$ is calculated for every iteration until the tolerance met. The result reduces the error rate and predicts the new ratings for LF-BFGS method. A LF-BFGS algorithm extended to bound constraints. The proposed model uses the SMRR dataset that consist of variables namely UID, ITEM, PRICE, RATINGS as shown in Table.1. The implementation was written in R programming Language. Results are depicted in Figure.3. Table.2 shows the results of RMSE value for proposed method.

Table.1 A Sample of SMRR Dataset

UID	Name of the Product	Price	Ratings
1	Samsung On7 Pro (Gold)	7,990	3.8
1	Samsung On5 Pro (Gold)	7,490	4
1	Samsung Guru 1200 GT-E1200ZKYINS - Black	1,100	4
2	Samsung Guru Music 2 (Gold)	1,625	4
2	Samsung On7 Pro (Black)	7,990	3.8
3	Samsung Guru Music 2 (SM-B310E, Blue)	1,625	4
3	Samsung Galaxy J8 (Black, 64GB) with Offers	17,990	4
4	Samsung Guru Music 2 (SM-B310E, Black)	1,625	4
4	Samsung On5 Pro (Black)	7,490	4
4	Samsung Guru Music 2 SM-B310E (White)	1,625	4

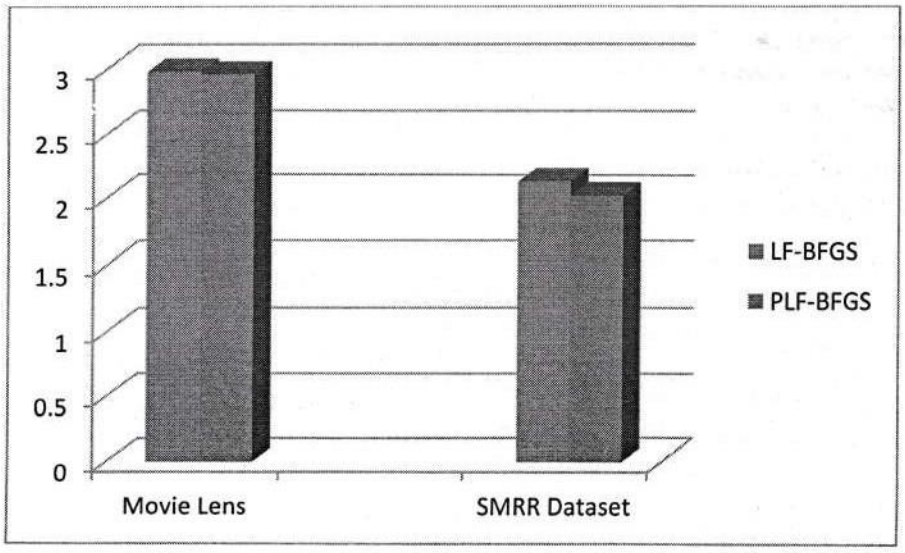

Figure 3. Comparison of Root Mean Square Error Value

Table 2.Error of RPP using LFBFGS and LFBFGS algorithms for Movie Lens & SMRR Dataset

	Algorithm	Movie Lens	SMRR Dataset
RMSE value	LFBFGS	2.97643	2.132463
	PLFBFGS	2.9546	2.024486

V. Conclusion

Algorithmic framework for solving unconstrained RPP and box constrained RPP using Quasi-Newton method. Two methods LF-BFGS and PLF-BFGS were presented. The empirical results of proposed method applied to movie lens rating prediction and SMRR rating prediction problem. The numerical results show that PLF-BFGS method performs substantially better than LF-BFGS method. An algorithmic improvement of rating prediction will be focused in future.

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A STUDY ON INDIA'S TRADE DEVELOPMENT THROUGH INDIA-SRI LANKA BILATERAL TRADE RELATIONS

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ABSTRACT

India and Sri Lanka enjoy a vibrant and growing economic and commercial partnership with bilateral trade growing rapidly in the last decade. Sri Lanka is one of the India's largest partners in SAARC. India is Sri Lanka's largest trade partner globally and also is one of the largest contributors to foreign Direct Investment in Sri Lanka. A bilateral trade agreement between India and Sri Lanka is promoting the highest possible volume of trade between the two countries and also taking into consideration the changing pattern of production or consumption of various commodities. The Trade Agreements provide better performance of trade, better foreign direct investment and tariff liberalization programme. Agricultural and industrial sectors had developed and quality of the products or services had also improved. This study aims at knowing the bilateral trade relationship between India and Sri Lanka and analyse the India's trade development through bi-lateral trade relation between India and Sri Lanka.

Key Words: Bilateral trade relations, Trade Development, SAFTA, ISFTA, CEPA, ETCA.

INTRODUCTION

India has entered into bilateral and regional trading agreements over the years. These agreements, besides offering preferential tariff rates on the trade of goods among member countries, also provide wider economic cooperation in the fields of trade in services, investment, and intellectual property. Some Trade Agreements provided tariff cuts in trade in goods and includes the liberalization in services and also the investment. India's first bilateral Trading Agreement, the India-Sri Lanka FTA (ISFTA) was signed in December 1998 and came into force in the year 2001. India's total trade in the last two decades with the world has increased substantially because of bilateral trade agreements. The trade between two nations increased from USD 0.7 billion in 2001 to USD 5 billion in 2017. India's exports to Sri Lanka grew from USD 0.6 billion in 2001 to USD 4.5 billion in 2017 whereas India's imports from Sri Lanka grew from 0.06 billion to 0.7 billion during the same period. This study aims at knowing the

bilateral trade relations between India and Sri Lanka and to analyse the India's trade development through this bilateral trade relations.

IMPORTANCE OF THE STUDY

As per the Doing Business 2019, World Bank, India ranks at 77th (an improvement of 23 places from 100th in 2017) among the 190 countries in the year 2018. India's improvement in the ranking is due to the better performance in the six indicators - starting a business, construction permits, getting electricity, getting credit, trade across borders and enforcing contracts. According to World Bank's assessment, India is among the top ten economies whose improvement in the ranking of ease of starting and doing business has been stable of late. India's trade improved gradually because it increases more exports. Bilateral trade relations are one of the reasons for development. From this point of view this research has become necessary, to understand the bilateral trade relationship and the trade development through trade relation between India and Sri Lanka.

AN OVERVIEW OF BILATERAL TRADE AGREEMENT

India and Sri Lanka have been connected by a legacy of cultural, religious and linguistic ties since the pre-colonial era. Over the years, this has evolved into a political and commercial bond through cooperation in the fields of development, education, culture and defense. Sri Lanka has always been one of the priority destinations for Indian trade and investment given its geographical proximity, strategic location in the Indian Ocean and natural resources. Economic ties particularly increased during 1990s with liberalization ushering in both the economies.

India-Sri Lanka Free Trade Agreement (ISFTA)

The India-Sri Lanka Free Trade Agreement (ISFTA) was signed with the objective of increasing investment flows from India with successful adoptable technology transfer to Sri Lanka. India has now emerged as the largest and the most balanced trading partner of Sri Lanka, with a high level of exports and imports taking place between the two countries. The ISFTA has made a substantial contribution in bringing this situation with over 70 percent of Sri Lankan exports to India moving under the FTA and below 30 percent of the Indian exports to Sri Lanka moving under the FTA.

Agreement on South Asian Free Trade Area (SAFTA)

The Agreement on South Asian Free Trade Area (SAFTA) came into force from 1st January, 2006. India, Pakistan and Sri Lanka are categorized as Non-Least Developed

Contracting States (NLDCS) and Bangladesh, Bhutan, Maldives, Afghanistan and Nepal are categorized as Least Developed Contracting States (LDCS). With SAFTA in force the concessions under SAPTA signed in 1995 ceased in respect of Sri Lanka and India as they are classified as NLDCSs. SAFTA Agreement provides for a phased tariff liberalization programme (TLP) under which, in two years, NLDC would bring down tariffs to 20 percent, while LDCS will bring them down to 30percent. Non-LDCS will then bring down tariffs from 20 percent to 0-5 percent in 5 years (Sri Lanka 6 years), while LDCS will do so in 8 years. NLDCs will reduce their tariffs for L.D.C. products to 0-5 percent in 3 years. This TLP would cover all tariff lines except those kept in the sensitive list (negative list) by the member states.

Comprehensive Economic Partnership Agreement (CEPA)

For taking incremental measures to reduce the negative lists of both countries and to deepen the tariff liberalization programme contained in FTA and provided additional concessions in garments and textiles sectors by India, the CEPA executed. The Agreement will also update the Bilateral Investment Protection and Promotion Agreement (BIPPA) which contain a schedule of commitment on investments which would larger for India than for Sri Lanka. Both countries have agreed to hold intensive consultations towards forging a special economic partnership for comprehensive and sustained economic cooperation.

Economic and Technology Co-operation Agreement (ETCA)

Presently ETCA agreed for both goods and services. The main aim of ETCA are to broaden the scope of FTA and to strengthen the economic, trade, investment and technology co-operation between India and Sri Lanka. With the help of ETCA, India and Sri Lanka can take advantage of the steady economic conditions prevailing globally and enhance bilateral cooperation in some key areas like agriculture, education, health, science and technology, tourism, telecom, automobiles, apparels, banking and financial services and space. This will also be beneficial for Indian producers as it will enable Indian manufacturers to set up factories in Sri Lanka to export their products to countries with which Sri Lanka has or is planning to have Free Trade Agreements.

REVIEW OF LITERATURE

Perera M.S.S (2008) had elaborated the impact of the Indo-Sri Lanka free trade agreement. The results indicated that both Sri Lanka and India got the welfare gains through

ILFTA. The industry analysis reflected that the industries, such as metal products, paper products and publishing, electronic equipment, chemical, rubber and plastic products, machinery and equipment got more benefit than agricultural sector due to the ILFTA. It showed that the quality of products in Sri Lanka had also enhanced in the market of India.

Nufile A.A.M (2014) examined the advantages of India-Sri Lanka Free Trade Agreement using the gravity model of trade. In that study the post-ISFTA scenario compared with pre-ISFTA scenario. This is evidenced that continuously increased post-ISFTA trade deficit. Hence, Sri Lanka should encourage investors from India to invest in Sri Lanka. Finally, the bilateral agreement was compared with SAARC and SAFTA and it was found that due to bilateral agreement there was a potential market seen for new products.

Hafa Wasim Akram et al. (2014) examined the India's trade relationship with SAFTA countries. The agreement between India and Sri Lanka is in operation since 1st March, 2000. Under this, both nations agreed to phase out trade tariffs from each other within a fixed time frame except for those items in the Negative List of each other. A Joint Study Group was set up in April, 2003 in order to widen the ambit of ISLFTA to go beyond trade in goods to include services and to facilitate greater investment flows between the two countries. They have agreed to take forward the process of signing a comprehensive agreement for economic cooperation.

OBJECTIVES OF THE STUDY

1. To know the Bilateral Trade Relation between India and Sri Lanka.
2. To analyse the development of **India's trade through Bilateral trade relation between** India and Sri Lanka

SCOPE OF THE STUDY

The scope of the study is limited to collecting data published in the reports of the High Commission of India, PHD Chamber of Commerce. The analysis is done to understand benefits of the bilateral trade relation and to interpret the information regarding the development of trade.

RESEARCH METHODOLOGY

In the present study, an attempt has been made to **assess the India's trade development** through bi-lateral trade relationship between India and Sri Lanka. The study is based on secondary data that has been collected from Hand Book on India-Sri Lanka Free Trade Agreement, published report by High Commission of India, PHD Chamber of Commerce and

Industry, magazines, journals, documents and other published information. Percentile Analysis and trend analysis was applied to analyze the trade development in India.

LIMITATIONS

1. The study is based on only secondary data.
2. The study is presented data only for nine years from 2010 to 2018.

INDIA AND SRI LANKA TRADE RELATION

The ISFTA has contributed towards more equitable and balanced growth of bilateral trade by narrowing the trade gap between the two countries in favour of Sri Lanka. Over 70 percent of Sri Lanka's exports have been undertaken under FTA preferences, compared to 30 percent of India's exports.

Table 1

Bilateral Trade result from 2010 – 2018 (US $ Million)

Year	Imports from India	Exports to India	Total Trade	Trade Deficit for Sri Lanka	EXIM Ratio for Sri Lanka
2010	2548	474	3022	-2074	5.4:1
2011	4351	525	4876	-3826	8.3:1
2012	3534	571	4105	-2963	6.2:1
2013	3186	544	3730	-2642	5.9:1
2014	3977	625	4602	-3352	6.4:1
2015	4061	645	4706	-3416	6.3:1
2016	3827	551	4378	-3276	6.2:1
2017	4543	690	5233	-3853	6.6:1
2018	4168	767	4935	-3401	5.4:1

Source: Sri Lanka customs report

Table 1 depicted the bilateral trade results from 2010 to 2018. In the year 2010 5.63 percent of products or services imported from India. It is increased by the year 2018 at the rate of 18.85 percent. Imports from India are gradually increased year by year but in the year 2012, 2013, 2016 had shown downward figure when compared to respective previous year.

Table 2

Percentage of Total Sri Lanka Trade with India

Year	Export Percentage	Import Percentage
2010	5.63	20.62
2011	5.16	22.08
2012	6.21	19.77

2013	5.44	17.77
2014	5.64	20.62
2015	21.37	6.31
2016	19.61	5.39
2017	21.08	5.96
2018	18.85	6.59

Source: Sri Lanka customs report

Table 2 indicated the Percentage of total Sri Lanka trade with India. In the year 2010, the export percentage is 5.63. The maximum rate of export (21.37) registered in the year 2015. The minimum rate of export(5.16) is founded in the year 2011. In the year 2010, the import percentage is 20.62. The maximum rate (22.08) of import registered in the year 2011. The minimum (5.39) rate of import is founded in the year 2016.

Chart 1
Trend of Percentage of Total Sri Lanka Trade with India

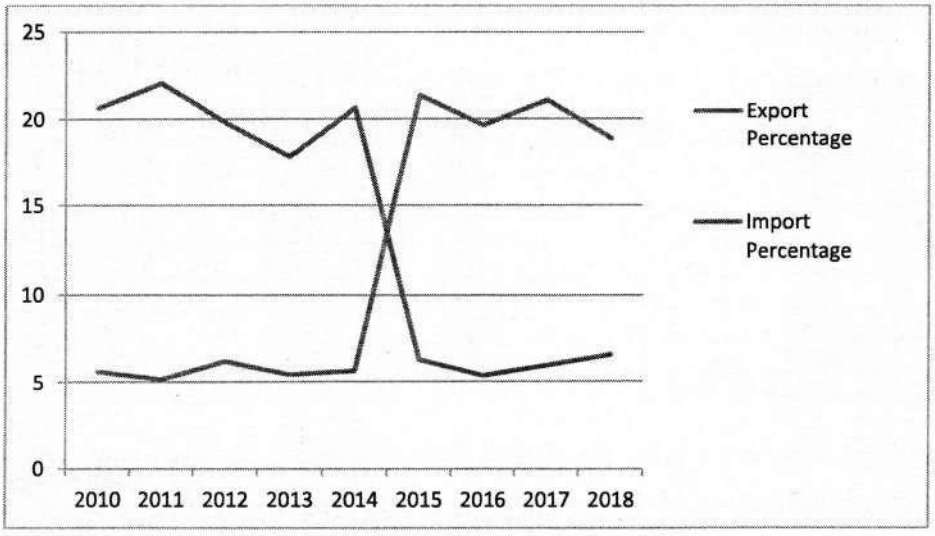

Chart 1 depicts the trend of export and import percentage of total Sri Lanka trade with India.

Table 3

Major articles (Top ten) exported from India to Sri Lanka-Year 2017

S.No.	Description	Percentage Share	US$ in Million
1	Gas oil/Diesel	28.39	**465.43**
2	Motorcycles	14.55	**238.52**
3	Pharmaceutical products	11.54	**189.15**
4	Portland cement	8.53	**139.8**
5	Semi-finished products of iron or non alloy steel	7.55	**123.74**
6	Military weapons, Artillery weapons	7.47	**122.5**
7	Fuel oil	6.63	**108.73**
8	Rice	5.36	**87.91**
9	Cement clinkers	5.17	**84.81**
10	Kerosene type jet fuel	4.82	**79.08**
	Total		**1639.67**

Source: Sri Lanka Customs

Table 3 shows that the major articles exported from India to Sri Lanka during the year 2017. Gas oil or diesel exported to Sri Lanka around 28.39 percent. The minimum value of Kerosene type jet oil exported from India to Sri Lanka.

Table 4

Major articles (Top ten) exported from Sri Lanka to India – Year 2017

S.No.	Description	Percentage Share	US$ in Million
1	Base oil	25.58	**77.76**
2	Poultry feed	16.28	**49.5**
3	Areca nuts	12.50	**38.0**
4	Unsorted waste and scrap (paper or paper board)	9.56	**9.07**
5	Matured berries of Pepper	7.68	**23.35**
6	Ignition wiring sets	6.88	**20.91**
7	Light berries of Pepper	6.45	**19.61**
8	Copper wire	5.69	**17.29**

9	Uncrushed and ungrounded Pepper	5.31	**16.15**
10	Marble, travertine and alabaster	4.07	**12.36**
	Total		**304.005**

Source: Sri Lanka Customs

Table 5 showed the major articles that is top ten as per value exported from Sri Lanka to India. India imported more (25.58%) quantity of base oil from Sri Lanka. It imported minimum (4.07%) value of marble, travertine and alabaster from Sri Lanka.

INDIA AND SRI LANKA INVESTMENT RELATION

India is among the top investors in Sri Lanka with cumulative investments of over USD 1.2 billion since 2003. The investments are in the areas of petroleum, retail, IT, financial services, real estate, telecommunication, hospitality & tourism, banking and food processing (tea & fruit juices) metal industries, tyre, cement, glass manufacturing, infrastructure development (railway, power, water supply) etc. According to the figures of BOI (Board of Investment) for the year 2017 Indian investment was amounted to USD 173.84 Million which is prominently higher than US$ 112.13 Million in year 2016.Total FDI inflow into Sri Lanka for the year 2017 was US$ 1,710.29 Million with India emerging as the third largest overall foreign director investor in Sri Lanka.

Table 5
FDI from India for the period 2010-2017(US$ in Million)

Year	FDI from India
2010	110
2011	147
2012	160
2013	51
2014	52
2015	68
2016	112
2017	174
Maximum	**174**
Minimum	**51**
Average	**109.25**

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Source: High Commission of India, Colombo

Chart 2
FDI from India

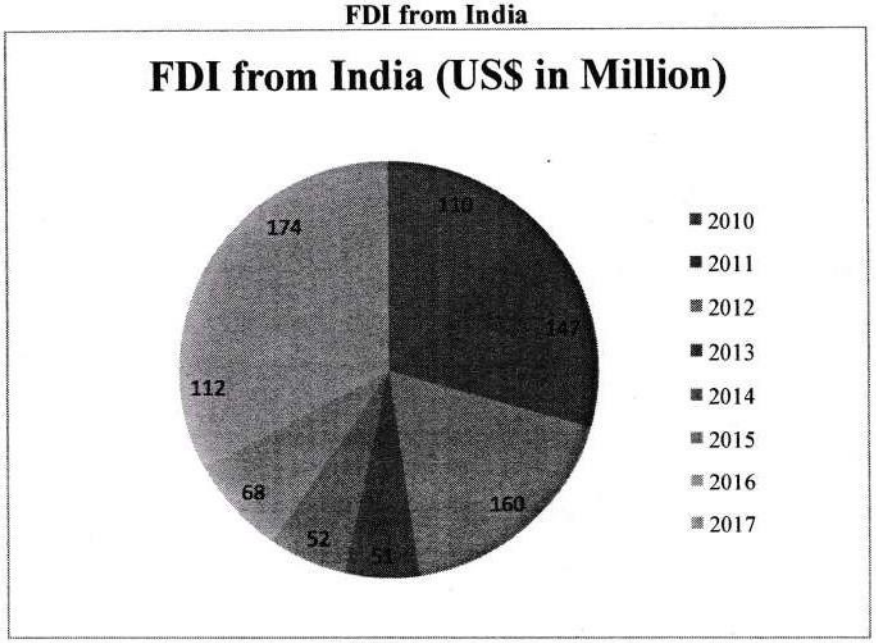

Table 5 and Chart 2 showed that the Foreign Direct Investment from India invested to Sri Lanka from the year 2010 to 2017. In the year 2013, India invested 51 US$ to Sri Lanka for the trade development of that country. Maximum value (174 US$) of investment had invested in the year 2017 from India.

CONCLUSION

The Bilateral trade relation between India and Sri Lanka is provided the Free Trade Agreements, Double Taxation Avoidance Agreement, Bilateral Investment Protection and Promotion Agreement. Both the countries increased their capabilities to develop the trade related activities and negotiated the incremental measures to reduce the negative lists and to deepen the tariff liberalization programme. India's trade with Sri Lanka that is imports from India has shown marked increased from 2548 US$ in millions in the year 2010 to 4168 US$ in millions in 2018. The number of products exported by Sri lanka to India also increased substantially during this period. The Foreign Direct Investment had increased from 110 US$ in millions in 2010 to 174 US$ in millions in 2017. According to FDI markets database, India has emerged as the

largest investor in Sri Lanka during 2010 to 2017. India definitely got considerable return reaped out of investment. So India's trade has been developing through the bilateral trade relation between India and Sri Lanka.

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