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Hybrid Recommendation from Cross Source Deep Learning Embeddings Based Rating Predictions

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ABSTRACT

Collaborative filtering based recommendation systems have data sparsity and cold start problems. Integrating other cues like latent factors in comments, user social profiles etc have been proposed as a solution to the problems in collaborative filtering. But current mechanisms for comments processing don't effectively process the aspects, sentence conflicts, sarcasm etc. Also they don't address the rating bias. The current approaches lack implicit finding of aspect orientation of users and fine tuning the recommendation based on aspect orientation. As the result, the accuracy of hybrid recommendation systems is reduced. As a solution to these problems, this work proposes a hybrid recommendation system integrating aspect based bias removal, matrix factorization with residual networks for rating prediction. The bias in rating is removed using a fuzzy Gaussian rating bias removal function. The bias removed rating matrix is converted to feature embedding using matrix factorization and residual network. The feature embeddings are then classified to ratings using softmax classifier. The performance of proposed solution is evaluated against Amazon product review dataset and the solution is found to increase recommendation accuracy by 3% compared to existing works.

KEYWORDS: Hybrid recommendation system, aspect orientation, deep residual network, features embeddings.

I. INTRODUCTION

Recommender algorithms are the important components of online shopping and E-commerce systems[1]. They help consumers to find their products of interest and highly relevant to their needs among a large cloud of products. The existing recommendation algorithms are in three categories of content based filtering, collaborative filtering and hybrid filtering. Content filtering algorithms group products by their similarity and recommend products similar to product previously purchased by active users. Collaborative filtering algorithms predict rating for the products not purchased by users based on similarity of products previously purchased with other users. Once after rating is predicted, top N highest ranked products not purchased by active users are recommended. Hybrid filtering algorithms combine both content and collaborative filtering algorithms [2]. Toward this they use various cues like latent factors in review comments, aspects preferences, social interest profiles etc. Many hybrid filtering recommendation algorithms have been proposed on above lines. Though these algorithms are able to solve the data sparsity and cold start, they affect the quality of recommendations due to failure in analysis of conflicts, sarcasm etc in reviews, aligning recommendation to aspect orientations etc. Reviews are quantized to rating without considering the sentence conflicts, sarcasm, review bias from users etc. Also fine grained aspect based polarization analysis and aligning recommendations according to aspect preferences is not explored much in existing literature. This work addresses these problems and proposes a hybrid recommendation algorithm. The algorithm combines the embedding learnt from reviews and ratings through a hybrid approach of matrix factorization and deep residual networks. The feature embedding is then classified to rating using softmax classifier. Following are the contributions of this work

(i) A novel fuzzy Gaussian rating bias removal function to remove bias in the rating matrix with consideration for conflicts, sarcasm, latent aspect and sentiments in the reviews.

(ii) A novel hybrid rating prediction algorithm combining feature embedding generated from matrix factorization and residual network and classifying the feature embedding to rating prediction. Linear relationship between user and products is learnt by matrix factorization and non linear relationship between user and products is learnt by residual networks. Rating prediction accuracy is increased with use of both linear and non linear relationship.

The rest of the paper is organized as follows. Section II provides the literature summary of existing works and their gaps. Section III details the proposed hybrid recommendation algorithm. Section IV provides the results of the proposed solution and its comparison to most recent existing works. Section V provides the concluding remarks and future scope of research.

II. RELATED WORK

Suresh et al [3] proposed a deep learning hashing based recommendation system to solve the problem of cold start and sparsity. The user to item matrix is reduced to hash code using deep learning convolutional neural network. The hash code distance computation is done to identify most similar users or active users. From the active users, the ratings for the items are predicted and highest ranked items are recommended to users. The problem in this solution is that the hash code needs to be computed every time when new batch of users are added. This increases the computational complexity. Also temporal variations in buying patterns are not considered during recommendation.

Jin et al [4] developed a hybrid recommendation algorithm to solve data sparsity problem. Authors modelled the content feature of items using fuzzy modelling and used it in the matrix factorization for similarity computation. Genetic algorithm is then used to predict the rating. Authors did matrix factorization on selected core users. The approach lacked recommendation diversity to satisfy different personality requirements. Elahi et al [5] proposed a hybrid recommendation system combining the ratings and sentiment scores derived from reviews. The reviews were classified to sentiment scores using BERT model. Review rating is then adjusted based on sentiment score. Recommendation is then performed using collaborative filtering. Authors observed that sentiment scores improved the quality of recommendation. But the sentiment score derivation did not consider sarcasm. Nassar et al [6] proposed a multi criteria recommender system. In this system, the criteria ratings are first predicted by combining matrix factorization with deep neural networks. From the criteria ratings, the final rating is then predicted using deep neural network. From the rating, recommendation is then found using collaborative filtering. The approach did not consider cold start problems. Hung le et al [7] proposed a multi criteria collaborative filtering based recommendation algorithm. Matrix factorization and deep learning are integrated to predict the ratings. Dempster's rule of combination is used to aggregate multi criteria ratings to overall rating. Authors also adopted data driven approach to determining criteria weights and their relative importance in prediction of overall rating. But the approach is not personalized to user preferences. Also approach lacks modelling the temporal variation in user interests. Ong et al [8] addressed the problem of cold start and data sparsity using a hybrid recommendation algorithm called Neural Matrix Factorization (NeuMF++). The algorithm has two important functionalities of feature extraction and neural collaborative filtering. Stacked Denoising Autoencoders are used to extract user item latent vectors from user item features. The user item latent vectors are fed to generalized matrix factorization and multi layer perceptron to predict the ratings. The approach lacks criteria based personalization in recommendation and also uses only ratings as base for recommendation. Ortega et al [9] added reliability to recommendation system using Bernoulli Matrix factorization(BMF). Different from regression based approach used in collaborative filtering systems, this work applied classification based approach. BMF returns pair of prediction and reliability to obtain the proper balance between quality and quantity of recommendations. Recommendations with higher reliability values are provided to users. This is the first innovative approach proposing reliability but lacked personalization based on criteria.

Kim et al [10] proposed a method to predict the representative score of a new item by utilizing the category information of the item. By this way, authors were able to solve the cold start problem. Authors used genre2vec to derive the predictions. But approach lacked personalization in deriving user preferences. Bobadilla et al [11] infused reliability concept using a deep learning architecture to increase the prediction accuracy of collaborative filtering. Different from usual process of obtaining prediction of non voted item, this method predictions are obtained for voted item and from it predictor error is calculated. A neural network is then trained in such way to minimize the prediction error and increase reliability. This neural network is then used to predict the rating for non voted item. By this way prediction accuracy was improved. But the approach lacked category and use interest wise personalization. Also the approach suffers from cold start problem. Yu et al [12] used gated recurrent unit (GRU)- generative adversarial network (GAN) to predict the ratings and use the rating to improve performance of collaborative recommender system. Use of GAN to predict rating is an innovation but the work did not consider preparing the training dataset for GAN with goal of minimization of rating prediction error.

Payandenick et al [13] integrated residual network and matrix factorization to improve the accuracy of recommendation. By capturing linear relations in data with matrix factorization and non linear relationship in data using deep residual network, authors fused them to improve the recommendation accuracy. Residual network predicted the errors in matrix factorization and improved the rating prediction accuracy. But the approach lacked personalization in recommendation and did not consider using latent information spread in reviews.

Shi et al [14] exploited the latent factors by proposing a neural network based aspect level collaborative filtering model. Authors extracted different aspect-level similarity matrices of users and items respectively through different meta-paths, and then feed an elaborately designed deep neural network with these matrices to learn aspect-level latent factors. Finally, the aspect-level latent factors are fused for the top-N recommendation. Authors also used self attention mechanism to fuse aspect level latent factors. Aspects were not weighted to user personalization requirement in this work. Gopalachari et al [15] proposed a method to measure the credibility of online reviews. It is based on aspect generation using word embedding process and then clustering based on aspect. The credible reviews can be filtered and used for rating score computation. Liang et al [16] proposed a deep latent recommendation system to provide high quality recommendations based on both rating and reviews. Authors used a auto encoder architecture to convert reviews to ratings. The review based rating and explicit rating are fused to get final rating. The auto encoder is not aspect based and not personalized to user interests based on aspects. Guo et al [17] proposed a hybrid recommendation system combining latent feature analysis (LFA) and autoencoder. Two different recommendation models are constructed using LFA and autoencoder. Their results are then integrated using self adaptive weighting strategy making best of both LFA and autoencoder. Both the recommendation models were constructed based on ratings. Aspects and personalization based on aspects were not considered. Hanafi et al [18] proposed a hybrid recommendation system integrating matrix factorization with novel models to convert reviews to ratings. Authors used word embedding with LSTM to convert reviews to ratings. By this way authors were able to solve the data sparsity problem. Contextual modelling technique to process reviews did not consider aspects and recommendation personalization based on user interests in aspects. Afoudi et al [19] proposed a hybrid recommendation system combining collaborative filtering with content based approach and self organizing map neural network technique. The results from collaborative filtering model and content based model are combined using weighted linear combination. From it, the best N recommendations are obtained by classification with self organizing map. But aspect based personalization and review filtering is not considered in this work. Guo et al [20] proposed a deep knowledge enhanced network to predict the probability of user selecting a item. Authors used deep neural networks to learn higher order feature interactions and integrated those features with knowledge graph embedding features. Item to item relationship is used to solve the data sparsity. But the approach is not customized to aspects and lacks personalization based on aspects. Wang et al [21] proposed a deep knowledge aware network for news recommendation. It is a multi-channel and word-entity-aligned knowledge-aware convolutional neural network that fuses semantic level and knowledge level representation of news. Matching with user history, news recommendations are made. The same idea can be explored for product recommendations. Walek et al [22] proposed a hybrid recommendation system combining collaborative filtering, content based system and expert system. The results from collaborative filtering found by SVD is passed to content based system where more relevant results based fetched by TF-IDF based meta data matching. Highly important items are then found applying expert system. The work did not address cold start and data sparsity problems

From the survey, it can seen that integrating content based feed back into collaborative filtering improves the performance of recommendation system against data sparsity and cold start problems. But current content based systems don't effectively process the conflicts, sarcasm expressed in review texts and rating bias. Due to this accuracy of hybrid recommendation system is affected leading to recommendation of irrelevant items to users. In addition many approaches lack implicit finding of aspect orientation of users and fine tuning the recommendation based on aspect orientation. They proposed a goal-aware fine-grained personalized learning framework that integrates learner knowledge, preferences, affective states, interaction behaviour, and learning objectives. The framework dynamically updates learner preferences to provide more suitable and personalized learning-resource recommendations [23]. This study developed a hybrid KNN–SVD, CNN, and RoBERTa framework for sentiment analysis of OTT film reviews. The study demonstrated effective extraction of contextual and sentiment information from user-generated reviews using machine-learning and transformer-based techniques [24].P. Thiruvenkatam et al. proposed an optimized deep-learning approach for human activity recognition using video surveillance data [25]. DKKK Atish Peshattiwar et al. presented an AI- and IoT-based predictive analytics approach for chronic disease prevention and patient monitoring [26].

III. PROPOSED SOLUTION

The architecture of the proposed hybrid recommendation algorithm is given in Figure 1. Like all collaborative filtering algorithms, rating matrix is used in this work for rating prediction. But the rating matrix is first processed to remove the bias or erroneous ratings. The sentiment polarity expressed in the reviews is used for this work. A novel fuzzy Gaussian bias removal technique is proposed to remove the rating bias by processing the aspect based sentiment polarity. Matrix factorization (MF) is the most used method for product recommendation. MF factorizes the user product rating matrix to new latent feature space in such a way, dot product of latent vectors of user and product is equal the rating given by user to the product. MF effectively handles the problem of data sparseness by mapping the high dimensional rating matrix to two low dimensional (user and product) matrix. But since its uses a linear fixed inner product to predict the rating, it is not able to estimate the complex user product interactions in the low dimensional latent space. This work proposes a hybrid strategy to solve this problem in MF. A residual network learns the non linear user product interactions and expresses it as embeddings. The MF learnt linear relationship is also expressed as embeddings. Both the embeddings are fused and used for rating prediction. The proposed solution has two stages of (i) Rating bias removal and (ii) Hybrid rating prediction. Each of the stages are detailed in below subsections.

A. Rating bias removal

Content based feedback like reviews has more implicit information which can compensate for erroneous and bias rating. Reviews are unstructured test with details on aspect latent factors and sentiment polarizations. The sentences in review are classified to one of aspect labels defined in SemEval datasets [23-25]. Glove feature vectors are extracted from SemEval dataset sentences and a convolutional neural network(CNN) is trained to classify the sentence to one of aspect labels defined in SemEval dataset. The configuration of the CNN to classify the sentences to aspects is given in

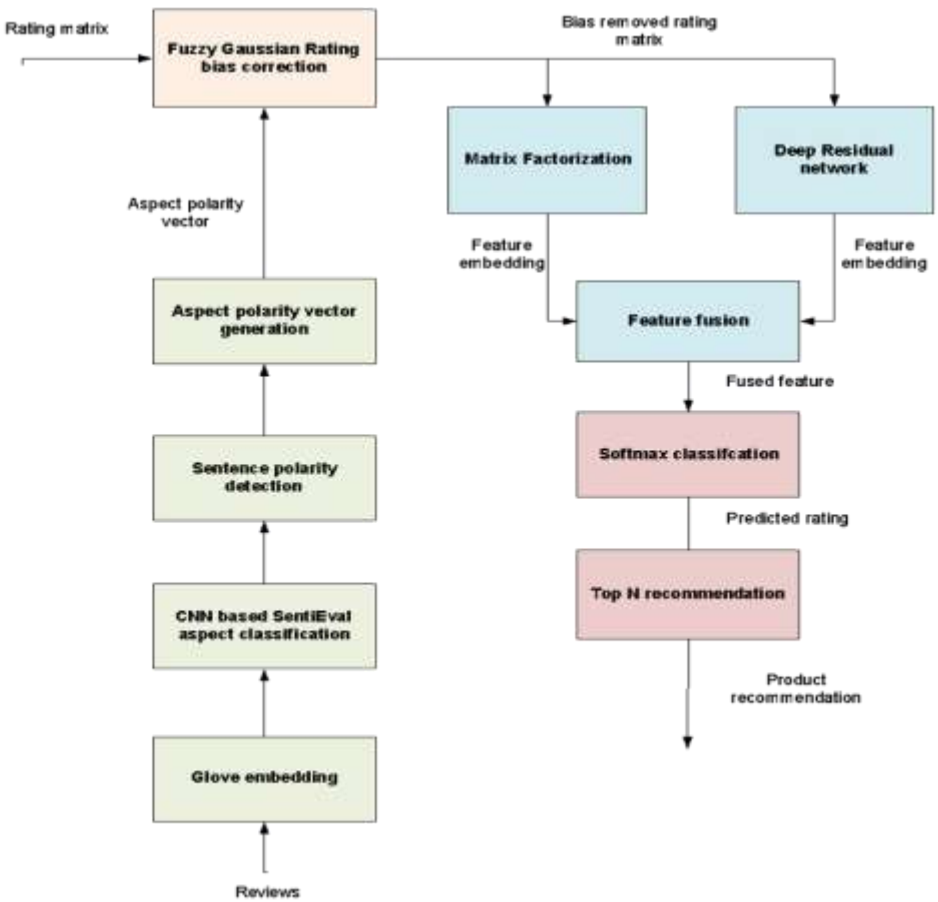

Figure 1 Hybrid recommendation architecture

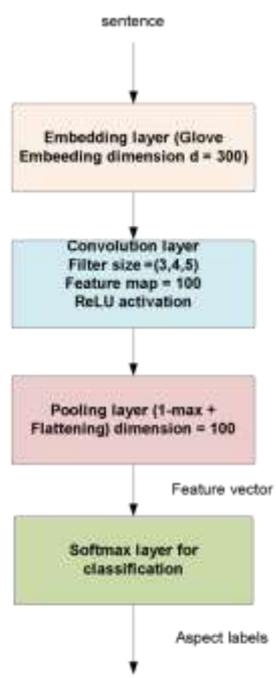

Figure 2 CNN for Aspect classification

with consideration for sarcasm is realized using the works of adversarial learning based sentiment Figure 2. For each sentence, the sentiment polarity detection proposed by Parvathi et al [26].
An aspect feature vector is constructed for each review with aspects polarity for all aspects in the review and their corresponding review rating. Training dataset of aspect vectors is constructed. The aspect vectors are then clustered based on polarity of aspects. The average rating is predicted for each cluster. The aspect vector row deviating from average rating is removed as bias from the cluster. From the remaining aspect vectors, a fuzzy Gaussian membership function is constructed for each rating (five ratings are considered). This is done by executing fuzzy c means clustering on the aspect vector training dataset C=5 (five ratings).
The cluster center after the fuzzy C means clustering is defined as

$$C = \left\{ C_{e,q}\ , e = 1,2,3\ and\ q = 1,2,3,4,5 \right\}$$

Where $C_{e,q}$ is the q[th] feature of the e[th] cluster.
The closeness of the q[th] feature of the rt[h] class $f_{r,q}$ with q[th] feature of e[th] cluster is defined using Gaussian function as

$$G\left(f_{r,q}, C_{e,q}, \sigma_{e,q}\right) = e^{\frac{(f_{r,q}-C_{e,q})^2}{\sigma_{e,p}{}^2}} \qquad (1)$$

Where,

$$\sigma_{e,q} = \frac{1}{N_e}\sum_{r=1}^{N_e} \quad (f_{r,q} - C_{e,q})^2 \qquad (2)$$

The closeness of features of r[th] link to the e[th] cluster is given as

$$\Psi_{r,e} = \prod_{q=1}^{P} \quad G\left(f_{r,q}, C_{e,q}, \sigma_{e,q}\right) \qquad (3)$$

The output label for e[th] cluster is found from the linear regression of input features $f_{r,q}$ as

$$\Phi_{r,e} = W_{e,0} + \sum_{q=1}^{P} \quad W_{e,q,f_{r,q}} \qquad (4)$$

Where W is the regression coefficient of the e[th] cluster. Since each of the r[th] link has membership value to all three clusters, final label of that particular link is given by weighting the label of the link with its membership value as

$$\underline{N}(r) = \sum_{e=1}^{3} \quad \Psi_{r,e}\Phi_{r,e} \qquad (5)$$

The value of $\underline{N}(r)$ calculated above may have a error with respect to $N(r)$ from training. The total error is calculated as

$$E = \sum_{r=1}^{N} \quad \left|\left|\underline{N}(r) - N(r)\right|\right|^2 \qquad (6)$$

The Gaussian parameters $C_{e,q}, \sigma_{e,q}$ and the regression coefficients $W_{e,p}$ are tuned to reduce the error defined above using gradient decent method.

$$C_{e,q}(t+1) = C_{e,q}(t) + \ \eta_C \frac{\partial E}{\partial C_{e,q}} \qquad (7)$$

$$\sigma_{e,q}(t+1) = \sigma_{e,q}(t) + \ \eta_\sigma \frac{\partial E}{\partial \sigma_{e,q}} \qquad (8)$$

$$W_{e,q}(t+1) = W_{e,q}(t) + \ \eta_W \frac{\partial E}{\partial W_{e,q}} \qquad (9)$$

Where t is the iteration number and $\eta_C, \eta_\sigma, \eta_W$ are the learning parameters. The iteration is stopped when error threshold is reached. The fuzzy Gaussian membership function $\Phi_{r,e}$ is constructed for rating. These function taking the aspect polarity as input, provides probability values for each rating.
The rating corresponding to highest probability value is decided as final rating and updated in the rating matrix. This also reduces the sparseness in rating matrix when review is available from user instead of rating.
The pseudo code for rating bias removal is given below

Algorithm: Rating bias removal
Input: Rating matrix M, Review S,user u, product p
Output: Bias removed rating matrix MB
1. for each sentence sk in S
2.   as[]⍰extract aspects(sk);
3.   for each a in as
4.   asp[a]=classify_polarity(sk);
5.   end
6. end
7. max⍰0
8. ra⍰0
9. for i=1:Num_rating
10.   rx⍰$\Phi_{r,i}$(asp)
11.   if rx>max
12.   max⍰rx
13.   ra⍰i
14.   end
15. end
16. M[u][p]⍰ra

B. Hybrid rating prediction

The bias corrected rating matrix is processed by MF and deep residual network to convert to feature embedding. Deep residual network is used to their exceptional performance in capturing non linear relationships between the user and product.

MF decomposes the rating matrix to two matrices of user and product. The two matrices are joined in row major order to generate the 1-D feature vector.

The deep residual network has three layers of: residual, transition and output. In the residual layer, sequence of convolution and cross aggregate is repeated to capture more intricate information in the rating matrix. The architecture of the residual layer is given in Figure 3. The figure shows the connections between the convolution (C1- C4) and the residual (R1,R2) operation. The output of each convolution layer is modeled as

$$C_l = f\left(K * \left(R_{i=1}^{l-1} C_i\right) + b\right) \qquad (10)$$

Where K is kernel weight, * is the convolution operation and b is convolution bias. R is the residual operation. The configuration for convolution operation in the residual layer is shown in Figure 4. The transition layer has convolution and max pooling operations to generate the user product latent representations. The transition layer reduces the dimensionality of feature representation at same time retains the representative features. The transition layer operation is represented as

$$t_m = f(K * C_l + b) \qquad (11)$$

$$o = max\{t_m\} \qquad (12)$$

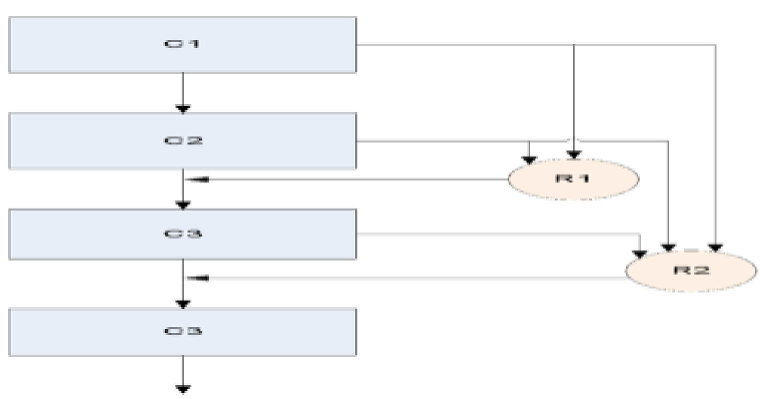

Figure 3 Residual network architecture

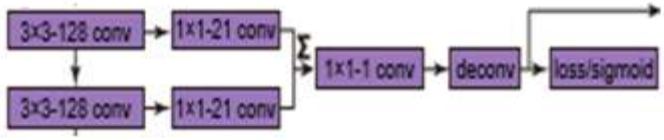

Figure 4 Convolution operation in Residual network

The output of tensor layer is flattened to 1-D feature vector at output layer.
The results (1-D feature vector) of MF and deep residual network are joined back to back and given as input to softmax classifier for rating prediction. The rating prediction is treated as classification problem and the softmax classifier is trained to provide rating as output for the results of MF and deep residual networks as input. The loss function of softmax classifier is based on computation of cross entropy loss between the predicted rating ($\underline{M}_{u,p}$) and ground truth ($M_{u,p}$).

$$L = \sum_{<u,p>} \sum_{r=1}^{R} - M_{u,p,r} . log \underline{M}_{u,p,r} \quad (13)$$

Where R is the number of choices for rating.
Once the ratings are predicted, the top N products with higher ratings are recommended to the user.

IV. RESULTS

The performance of the proposed hybrid recommendation algorithm is evaluated against Amazon product review dataset [28]. About 7 million reviews from 1.5 million users who review and ratings in categories of electronics are used for evaluation. The performance is measured in terms of Hit Ratio (HR), Normalized Discounted Cumulative Gain (NDCG) and root mean square error (RMSE). In addition standard metrics of accuracy, precision, recall and F-measure are calculated based on the number of relevant products in total products recommended.
HR is calculated as

$$HR = \frac{\#hits}{\#users} \quad (14)$$

Where #hits is the number of users whose test item appears in the recommended list and $\#users$ is the total number of users. NDCG is calculated as

$$NDCG = \frac{1}{\#users} \sum_{i=1}^{\#users} \frac{1}{log_2(p_i+1)} \quad (15)$$

Where p_i is the position of the test item in the
list for the i-th hit. In our experiments, we truncate the ranked list at K ϵ [5; 10; 15; 20] for both metrics of HR and $NDCG$.

$$RMSE = \sqrt{\frac{\sum_{(u,v)\epsilon T} (\check{r}_{uv} - r_{uv})^2}{|T|}} \quad (16)$$

Where r_{uv} is the actual rating of user u on product v and $\check{r}_{uv}$ is the predicted rating of user u on product v and $|T|$ is the number of user item pair in the test set.
The performance is compared against hybrid recommendation algorithm proposed by Afoudi et al [19], collaborative filtering with multi aspect information proposed by Shi et al [14] and sentiment based hybrid recommendation system proposed by Elahi et al [27].

The results for HR and NDCG across the solutions for various K values is given in Table 1

Table 1 Comparison of HR and NDCG

Solution	HR	NDCG
K=5		
Proposed	0.3771	0.2532
Afoudi et al [19]	0.2766	0.1800
Shi et al [14]	0.3429	0.2308
Elahi et al [27]	0.3055	0.1922
K=10		

Proposed	0.5426	0.3071
Afoudi et al [19]	0.4207	0.2267
Shi et al [14]	0.4933	0.2792
Elahi et al [27]	0.4133	0.2346
K=15		
Proposed	0.6048	0.3366
Afoudi et al [19]	0.5136	0.2513
Shi et al [14]	0.5498	0.3060
Elahi et al [27]	0.5056	0.2768
K=20		
Proposed	0.7372	0.3559
Afoudi et al [19]	0.5852	0.2683
Shi et al [14]	0.6702	0.3236
Elahi et al [27]	0.5607	0.2876

From the results, it can be seen that proposed solution has atleast 1.2% higher HR and NDCG compared to existing works. This is due to two factors of review bias removal using aspect based polarity and hybrid recommendation capturing both linear and non linear relations between users and product. Afoudi et al [19] used content and collaborative filtering but did not use any deep network to learn non linear characteristics. Also they did not consider aspect based rating revision. Shi et al [14] used multiple aspect information by rating prediction in their work did not consider linear and non linear characteristics between user and products. Elahi et al [27] used both rating and reviews but learning feature embedding from each and fusing them for rating prediction was not considered.
The results for RMSE between the ground truth and predicted ratings for top N recommendation (N=10) is shown below.

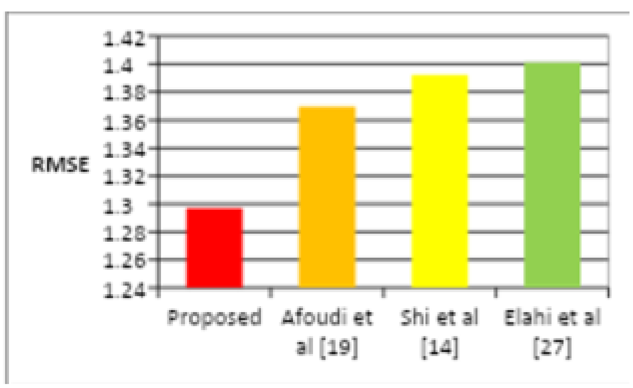

Figure 5 Comparison of RMSE

The RMSE is atleast 5.1% lower compared to existing works. The RMSE has reduced due to accurate prediction of ratings from a hybrid method combining both MF and deep residual network.
The accuracy, precision, recall and F-measure is calculated between ground truth and predicted top N recommendations and the results are given below

Table 2 Classification performance

Solution	Accuracy	Precision	Recall	F1-measure
Proposed	0.87	0.80	0.87	0.82
Afoudi et al [19]	0.82	0.76	0.82	0.77
Shi et al [14]	0.83	0.76	0.83	0.78
Elahi et al [27]	0.84	0.77	0.84	0.79

The proposed solution has atleast 3% higher accuracy compared to existing works. The accuracy has increased in proposed solution due to presence of more similar items to ground truth due to use of removal of rating bias and using the capturing of complete linear and non linear relationship between user and product.
Ablation study is conducted with different variants of proposed solution to demonstrate the value of each component. The ablation studies are conducted with five fold cross validation.

Ablation 1: The performance improvement due to rating bias removal is measured by testing the proposed solution with and without rating bias removal. The results are given in Figure 6.

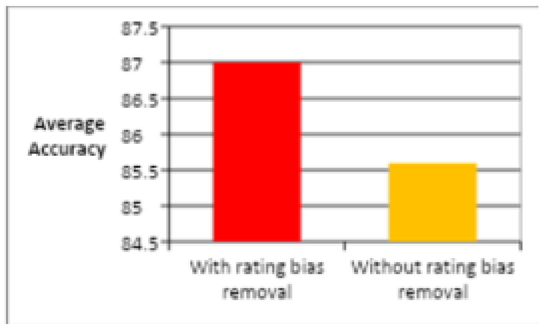

Figure 6 Impact of rating bias removal

The rating bias removal has increased the accuracy by atleast 1.4%. This emphasize that reviews provide more details on customer intentions compared to ratings. Thus correcting the rating based on latent aspect sentiments has contributed positively to the recommendation accuracy of proposed solution.

Ablation 2: The impact on accuracy of MF, Deep residual networks and their combination together is measured and the result is given in
The accuracy in proposed solution is compared under four conditions of (a) MF alone (b) Deep residual network alone and (c) Hybrid MF + Deep residual network.

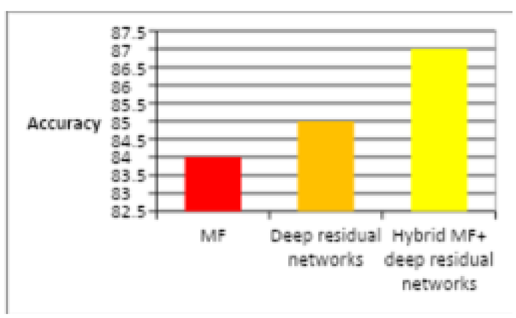

Figure 7 Impact of hybrid combination

Compared to MF and Deep residual networks in separation for rating prediction, their hybrid combination has increased the accuracy by atleast 2%. MF rating prediction is based only on linear relationship between users and product. Deep residual networks are able to learn intricate non linear relationships between user and product. Using both MF and deep residual network exploits both linear and non linear relationship and thus has increased the accuracy.

V. CONCLUSION

A hybrid recommendation algorithm combining matrix factorization and residual network is proposed in this work. A novel fuzzy Gaussian rating bias removal is proposed as part of work to remove the rating bias using the sentiment polarity expressed in aspect spread across reviews. The proposed work exploits both linear and non linear relationship between the user and product. This has increased the recommendation accuracy in the proposed solution. The proposed solution has increased accuracy by atleast 3%, reduced RMSE by 5.1%, increased hit ratio by 1.2% compared to existing works.

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