Kernel-based Attribute-aware Self adaptation and Multi thresholding for Rating Prediction

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Abstract. In recommender systems, our main task is to predict the rating of a new product from the authorized user and then return the best rating for the particular item and this technique reduced the existing prediction error rate. Our proposed system is user-item rating matrix prediction based on Synergetic filtering techniques and this technique is more efficiency compared to other technique. Proposed System are providing personalized recommendation for help the users accord with information overburden problem. However, the techniques are the data insufficiency of the user-item rating matrix underlying for brand-new items and users are severely affected by Synergetic filtering technique. Since the character of common links and items between more accessible by the users in the Internet and this paper exploits the common links of users and the character of items to overcome the existing problems and to ease the rating insufficient effect. However they may need excessive computational moment, and they often accost the insufficient problem which negatively modify the ability of the system. Specifically, we initially propose a Kernel-based Attribute-aware Self adaptation and multi thresholding model to blend the character information of items into matrix factorization and then introduce self-adaptation and multi thresholding. KASM can find the indefinite interactions among characters, users, and items, which reduce the rating insufficient effect for brand-new items by nature. In this paper we suggest a quick recommendation algorithm based on self-adaptation and multi thresholding. Self-adaptation in its genuine meaning is a state-of-the-art method to alter the setting of control specification. It is called self-adaptive because the algorithm controls the setting of these specification itself sink them into a distinctive genome and emerging them. It is construct to deal with the specified drawbacks and enhance the prediction quality. Extended analysis on two real world data sets establish that our proposed method can attain necessarily improve performance than other state-of the-art-methods. In this method we get the accuracy rate of predicting user rating will be 95%

Index Terms—Rating prediction, matrix factorization, attribute aware, self-adaptation, multi thresholding.

1. Introduction
In present different applications including e-commerce websites, entry websites, social media and GPS based social networks have been entirely developed in the Internet, which considerably changes the method we live and think. Common business requirement and user attitude create overwhelming data, which contains precious information. However, the development of a big amount of data leads to information weigh down, the difficulty for a user to search a favorite items in an e-commerce website. To beat this problem, recommender systems which provide custom-fit items for users by sorting useful information in the data, have been suggested and widely studied in college. The aim of recommender systems is to as in regularly recognize user first choice within group of data, then
use those option to make guidance that help with decisions. However, recommender systems be affected from data inadequate problem, which is specifically widespread in newly launched systems that have not still had adequate time to a mass required data. As a result, cross-domain recommender systems transmission know-how from a origin domain with comparably rich data to help recommendations in the destination domain.

In our proposed systems to anticipate the rating of a user is essential task to a brand-new item that the user has not been rating. To forward this task, synergetic filtering models utilize the synergetic power of the ratings provided by multiple users to make recommendation. Matrix factorization is one of the standard Synergetic filtering methods, which anticipate ratings over a user-item rating matrix. The major problem in matrix factorization is data inadequate that means the number of available ratings is relatively small and the rating matrix is extremely sparse. Therefore, it is not simple for matrix factorization to achieve adequate performance by simply using numeric rating data. When the predictions of multiple PMF models are precisely joined with the predictions of Restricted Boltzmann Machines models, we attain an error rate of 0.88 that is nearly 6.9% better than the result of Netflix’s own system. The regression model is suggested by the kernel trick to definite model turn into a indefinite model and kernel trick act as a support vector machine[3]. In our analysis, we display that by combine geological neighborhood authority, lower prediction fault is achieved than the state-of-the-art models containing Biased MF, SVD++, and Social MF.

2. Related work

This related work reviews shortly the advances on predicting rating in our proposed systems. The proposed systems finding techniques implement to the ratings prediction of items on user or to make materialized suggestion services for the users. The techniques for predicting rating can be classified into three categories: Framework-aware technique, Synergetic filtering technique, Contented based technique. The Framework-aware techniques with the SF including context, context information and framework changed to attach event for rating [5]. However, they three major limitations endure generally including scope up to inefficiency of high measure of two-attribute interaction, attribute interaction and definite interaction between the attributes. The designs display rating prediction be a better performance for social networks based on location, but to predict the ratings is to be a place. Among these categories, Synergetic filtering technique is the famous approach for rating prediction is used, because it need only a rating matrix user-item as the input raw and the indefinite or definite ratings are available extensively in our proposed systems. Here to estimate the main task of correspondence of each pairs of items or user using the rating matrix user-item with correspondence of some determination such as Pearson correlation [3]. The hidden components of MF models on data large be through gained distributed multiplicative update or SGD. This is simple techniques based on the associate information. The user of a rating of an item in terms of anticipated the correspondence in between the item contents the user profile. This techniques are applied generally in suggestions of social media, in which the attributes can be product with absorbed from website pages, user rating reviews and item content.

3. Kernel-based attribute-aware self-adaptation and multi thresholding

![Figure 1. Design of the proposed system](image)

The Figure 1 is briefly explained in the following section. In this section, we define the problem in Section 3.1, data collection and pre-processing in Section 3.2 and the matrix factorization in Section
3.3. Explain the attribute-aware, in Sections 3.4, we introduce the self-adaptation and in Section 3.5 describes the multi thresholding.

3.1 Problem statement
The primary task in a proposed System is rating of a user to predict a authorized rating of item and then return the top rating prediction of a new item to the user. In big data era, classical Matrix Factorization using only ratings suffer a serious drawback for not being able to exploit other accessible information such as the attributes of users/items/ratings [1]. Due to the data inadequate problem the user rating prediction efficiency would be decrease. To overcome this problem we introduce a self-adaptation and multi thresholding technique.

3.2 Data collection and pre-processing
The most initial component for any system is the input. Here the input is the data that is utilized in the user review details such as username, ratings, user-id, movie-id, genre. Then the data must be processed to table content discarding any false data. Dataset might contain noisy and missing values. Data Pre-processing techniques such as single imputation methods are used to change the missing and noisy data into a clean dataset. Single imputation methods are implemented using maximum occurrence attribute value substitution. This systems have become an integral part of e-commerce sites and other businesses like social networking, movie/music rendering sites. They have a big changes on the income earned by these businesses and also benefit users by decreasing the cognitive load of finding and sifting through an heavy load of data set collected from Amazon dataset.

3.3 Matrix factorization
Matrix factorization is one of most frequently used Synergetic filtering for producing recommendations to users. A main constraint of SF is that it entirely depends on noticed ratings and may abort if these noticed ratings are in definite amount called inadequate problem. Identifying this issues, cross-domain suggestion came into survival where transfer gaining mechanism is applied to ease inadequate problem and increase performance of the objective domain using other related origin domains. Matrix factorization (MF) has shown to be a superior ML idea for many problems such as dimensionality reduction, classification, latent topic modeling and manifold learning. In general, MF is a linear modeling method, so similar strategies, many of them based on kernel methods, have been recommended to extend it to non-linear modeling. Firstly, we lay on traditional matrix factorization (MF) method in origin domain to learn hidden factors of users and items through target function of MF[1]. After that, learned hidden factors of users are straightly transferred to destination domain. Modify target function of MF and learn users/items hidden factors of the objective domain. Finally, prediction on unobserved ratings in the objective domain is made using interior items of respective user and item hidden factors. Analysis results explained that our suggested method substantially work good from other without and with transmitting learning methods in terms of MAE and RMSE metrics.

3.4 Attribute awareness
Matrix factorization depend on the method of rating matrix user item with an amount of unknown user from undefined rating and generally data endure from the inadequate problem[2].A few users to check in restaurants while others choose to for different dishes for fun on the geological location to visit tourist attractions, indoors persons like visiting items in residential areas while choose travelling outdoors persons around to explore the world for new items. Therefore, the attribute-aware items on user complement the ratings of insufficient and more benefit bring for predicting rating[4]. In this technique, we using the attributes of products mainly focus because the attributes of users are more extensively, but our technique exploit the users of attribute in the identical way.

3.5 Self-adaptation
Self-adaptation in its natural meaning is a state-of-the-art method to adapt the setting of control framework. Self-adaptation is called self-adaptive because the algorithm controls the setting of these framework itself sink them into an exclusive genome and emerging them [5]. Self-adaptation technique
analysis the user rating and predict the rating by SGD (Stochastic Gradient Descent) algorithm. Stochastic Gradient Descent algorithm is based on user id and movie id. Final output will be predicted by highest Stochastic Gradient Descent value based on the user input. In self adaptation input will be acclimatization individually will help the result should be more fast and accuracy.

3.6 Multi thresholding

Multi-thresholding is a technique to predict the user rating with the help of training samples. This will help us to reduce the execution time for predicting the user rating. This threshold is persistent by diminishing intra-class intensity variance, or equivalently, by expanding inter-class variance. Otsu's technique is a 1-Dimensional individual companion of Fisher's Discriminant Analysis, is associated to Jenks optimize technique, and is similar to a globally optimize k-means accomplished on the intensity histogram.

Algorithm 1 Incremental learning process for KASM

**Input:** Inadequate rating matrix R and characteristic matrix X

**Output:**
- ui - user
- vi - item
- bi - bias for user ui
- \( \alpha_{ij} \) - Explicit coefficient associated user ui and item vi
- \( n_{ui} \) - Number of training samples of each user ui

1: The initializing phase
2: Set Dynamic arguments \( \{ u_i, v_j, b_i \} \) from (0,1) for each user ui and item vj
3: Initialize \( \alpha_{ij} \leftarrow 0 \) for each item vj and user ui
4: Initialize \( n_i \leftarrow 0 \) for the count of samples of user ui
5: For each iteration repeat the following steps until convergence do
6: For each randomly selected known rating \( r_{ij} \in R \) perform the following steps
7: Terminate the process if arrived at convergence
9: end for

**Algorithm 2 Stochastic Gradient Descent: SGD(u_i,v_j,r_{ij})**

**Input:** User ui, item vj, and rating r_{ij}

**Output:**
- ui - user
- vi - item
- bi - bias for user ui
- \( \alpha_{ij} \) - Explicit coefficient associated user ui and item vi
- \( n_{ui} \) - Number of training samples of user ui

1: Predict rating \( \hat{r}_{ij} \) based on Equation

\[
\hat{r}_{ij} = u_i^T v_j + \eta_1 (1-\lambda_3 \eta_3) \sum_j (f_j = 1)^N a_{ij} \phi(x_j') \phi(x_j) + b_i = u_i^T v_j + \eta_3 (1-\lambda_2 \eta_2) \]

2: Compute error \( e_{ij} \) based on \( e_{ij} = r_{ij} - \hat{r}_{ij} \)
3: Update parameter \( u_i \) based on the equation

\[
u_i \leftarrow u_i + \eta_1 (e_{ij} \cdot v_j - \lambda_1 \cdot u_i) \]
4: Update parameter \( v_j \) based on the equation

\[
v_j \leftarrow v_j + \eta_2 (e_{ij} \cdot u_i - \lambda_2 \cdot v_j) \]
5: Update parameter \( b_i \) based on equation

\[
b_i \leftarrow b_i + \eta_3 \cdot c_{ij} \]
6: \( n_{ui} \leftarrow n_{ui} + 1 \)
7: \( \alpha_{ij} \leftarrow \alpha_{ij} + (1 - \lambda \cdot \eta) - n_{ui}w_{ij} \)

4. Simulation Results

The proposed algorithm is implemented by taking a user data set as an input that contains some static and dynamic attributes. The static attributes are used as the base for calculation whereas the dynamic attributes changes with the training of the model in the incremental learning phase. The dynamic attributes plays a key role in this algorithm because they are used to induce the self-adaptation technique. When the dynamic values are changed by the self-adaptation methodology the Multi-threshold are varied, which is used to predict the values with high accuracy. Using Multiple thresholds in the experiment makes the system prone to more error rate as there are multiple attributes in place that is in need of tuning in the incremental learning phase. In the incremental phase the SGD algorithm performs the prediction and updates the value with attribute values in accordance with the self-adaptation technique. The SGD algorithm is comparatively faster than a normal Gradient Descent algorithm as it introduces a certain degree of randomness when it comes to picking up the points in the progress of the algorithm. After the prediction in the first iteration the error rate is computed, the dynamic parameters are updated for the next iteration to be performed. At the end, the algorithm generates the required user-item interaction matrix from which the output for recommendation is derived.

The data set shows the processed data based on the SGD value. The rating prediction error for our proposed system is 0.93

![Figure 2. Existing System rating prediction error rate](image)

Figure 2 shows that the prediction error rate using the existing methods, it is inferred from this graph that the prediction error rate of all the existing methods vary distinctively and the error rate is fluctuating to some extent starting from a minimal value of 0.8. It cannot be assured that the system always delivers an optimal performance. It can be seen that the KAMF is the most efficient among the already existing system.
Figure 3. Proposed System of rating prediction error rate

Figure 3 also shows the comparison of the prediction error rate of different methods in addition with the proposed technique. It is evident from this graph that the proposed KASM technique is having the most minimalistic error rate of all the available methods.

Figure 4. Comparison between KAMF vs KASM

Figure 4 provides a detailed comparison between the two methods KAMF (which is considered as the most efficient among the already existing methods) and KASM (the proposed method). The prediction error rates is considered as the metrics to measure the efficiency of the system. From this comparison it evident that the error rate of the proposed technique (KASM) is lesser than that of the already existing KAMF. The error is more stable than other techniques. It is even noted that the maximum error rate of KASM is lesser than that of the minimal error rate produced by the KAMF technique under the same circumstances.

This above graph shows the error rate of each technique based on the number of rating of a user. In Fig 2. show the error rate of existing system. In existing system KAMF produced minimum error rate.
In Fig 3. show the error rate of our proposed system KASM with the existing system. This will clearly show the error rate reduced in KASM and also produce a accurate rating for an new item. In Fig.4 show the comparison of existing system vs proposed system. In this graph error rate produced in KAMF minimum is 0.933 and our Proposed System of KASM produced error rate minimum is 0.5 and maximum is 0.9.

5. CONCLUSION

In this paper, Kernel-Based Attribute-aware Self-adaptation and Multi thresholding is a proposed model (KASM) to implement the items of attribute details into matrix factorization and self-adaptation. Kernel-based attribute-aware self-adaptation and multi thresholding to uncover the nonlinear interactions exploits the attributes of items among items, attribute, user, which the data sparsity effect of the rating matrix user rating on prediction rating. We used incremental algorithm to the model parameters estimate of KASM. KASM can find the indefinite interactions among characters, users, and items, which reduce the rating insufficient effect for brand-new items by nature. The major problem in matrix factorization is data inadequate was overcome using this self-adaptation and multi thresholding. In this technique we reduce the prediction error rate compared with matrix factorization. Our maximum error rate is 0.9% but existing system minimum error rate would be 1.0%. In this this technique we have reduced the data sparsity problem while predicting the user rating.

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