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# Contextual-Aware Hybrid Recommender System for Mixed Cold-Start Problems in Privacy Protection

Vicky Na Zhao, Melody Moh*, and Teng-Sheng Moh
Department of Computer Science
San Jose State University
San Jose, CA, USA
*Contact author. Email: Melody.Moh@SJSU.EDU

***Abstract*—With the rapid growth of web services, more and more users elect to hide their information settings. While this practice protects users' privacy, it also creates highly sparse dataset, which in turn causes cold start problems in Recommender Systems (RS) and leads to poor prediction results. Contextual-aware recommender system (CARS) has been recognized as an efficient solution to address either a new user or a new item cold start scenario. It outperforms traditional collaborative filtering recommender systems. Most existing CARS solutions however have not provided efficient solutions for mixed cold start scenarios, in which two or more cold start problems co-exist. In this work, we introduce a Weighted Switching Hybrid Context-Aware (W-SHCA) Recommender System. It is based on two algorithms: Content-based CAMF-CC (Context-Aware Matrix Factorization) and Demographics-based CAMF-CC, and utilizes their weighted sum to perform the prediction when a mixed cold start problem is detected. We exploit the W-SHCA model in three recommendation applications: places of interest (STS), music (Music), and movie (CoMoDa). We illustrate some significant performance differences among these three datasets under various mixed cold start situations, and deduced a stable weight selection pattern for W-SHCA associating with dataset characteristics. We believe that this work is a pioneer in dealing with mixed cold-start problems, and would provide a vital reference point for their future research.**

***Keywords*: *content-based recommender systems, context-aware recommender systems (CARS), cold-start problems, demographic-based recommender systems, matrix factorization algorithms, and weighted scheme.***

## I. INTRODUCTION

A RECOMMENDER System (RS) produces a list of rating recommendations. It is usually based on a variety of known sources related to both users and items. This reduces the effort spent on searching interested items while at the same time improves the applications' usability. Most existing solutions focused on utilizing historical rating records that include only user- and item-related information; they rarely combine them with contextual situations.

Unlike traditional recommendation solutions, CARS, or Contextual-Aware Recommender System takes the contextual information into its model while modeling and predicting user tastes and preferences. For example, a CARS algorithm may recommend the most relevant items to users by taking into account some contextual information, such as occurrence time, weather, or user's mood.

The ratings predicted by CARS can be defined as the rating function *R* shown below:

$$R: User \times Item \times Context,$$

where *R* is the domain of ratings, *User* and *Item* are the domains of users and items, respectively, and *Context* specifies the contextual situation associates with the recommender system.

Cold start problem arises when a dataset does not contain sufficient resource to reference a user's preference or an item's review. It often causes poor prediction results for a recommended system (RS). To address three basic cold start problems (new user, new item, and new context), Braunhofer, Codina, and Ricci proposed the Switching Hybrid Content-Aware (SHCA) algorithm [1]. It is a hybrid combination of two CARS algorithms: demographics- based CAMF-CC (Context-Aware Matrix Factorisation for item categories) and content-based CAMF-CC [2]. While it is effective in dealing with basic cold-start problems, it did not consider, and does not perform well when dealing with mixed cold start problems, as demonstrated in Section V.

In this paper we proposed W-SHCA, or Weighted SHCA, to address mixed cold start scenarios when two or more cold start problems co-exist. W-SHCA is a weighted hybrid context-aware recommender system solution, it applies the weighted scheme on demographics-based CAMF-CC and content-based CAMF-CC. Unlike SHCA which either takes one or averages the results of the two, W-SHCA takes the weighted sum of the prediction results of two algorithms.

In addition to the three basic cold start problems, in this paper the following mixed cold start problems are also dealt with by W-SHCA:

1. Mixture of new user and new item problem, which refers to the situation where prediction is made without any useful information to the user and the item;
2. Mixture of new item and new contextual situation problem, in which both the item and contextual situation are new to the recommender system;
3. Mixture of new user, new item and new contextual situation problem, in which all information needed in recommendation, are new and nothing can be referred to predict.

The paper is organized as follows: In Sections II and III we introduce related work and describe the SHCA model [1].

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Section IV describes the proposed W-SHCA algorithm. The experiment setup and evaluation results are presented in Section V. Finally Section VI concludes the paper by pointing to some future research work. This is our on-going work in applying machine learning on recommender systems [21, 23] and on security and privacy [22].

## II. RELATED WORK

Although most the work on the Recommender Systems (RS) focused on the traditional two-dimensional user/item matrix, recently there has been an increased interest in adding contextual information to rating prediction models.

Adomavicius and TuzhilinShi [5] did a thorough review of the current approaches to contextual recommendations in their book. They categorized context-aware recommender systems (CARS) into three types based on in which the contextual information used. They proved that regardless of the contextual information used in the prediction model, the contextual information does improve the recommender system's accuracy.

Karatzoglou, Amatriain, Baltrunas, and Oliver proposed a solution that Multiverse Recommendation [3] based on Tensor Factorization technology. This method allowed for a flexible and generic integration of contextual information by modeling the data as a User-Item-Context n-dimensional tensor instead of the traditional 2D User-Item matrix.

Braunhofer, Codina and Ricci [1] found an effective solution for cold-start CARSs. They tackled the cold-start problems with a switching hybrid solution, SHCA, which exploited a custom selection of two CARS algorithms, each one suited for a particular cold-start situation. The switching between these two algorithms is depending on the three detected situations (new user, new item or new context information).

Domingues and Marcos [10] incorporated available contextual information from topic hierarchies into the recommendation process and indeed improved the accuracy of the outcomes.

Zhang, Lau and Tao [13] proposed a novel text mining method that was applied to automatically extract the domain-specific knowledge for the context-aware recommendations. It can be for-seen that integrating text-mining methods into the recommender model will is a promising new research direction in the CARS domain.

## III. SWITCHING HYBRID CONTEXTUAL-AWARE (SHCA)

Since the proposed W-SHCA is based on SHCA [1], for ease of understanding we describe SHCA in this section. It is a switching hybrid algorithm that combines content-based CAMF-CC and demographics-based CAMF-CC algorithms. Each of these two algorithms has a particular usage that can tackle a special cold-start problem. For example, SHCA uses content-based CAMF-CC method when it predicts the rating for a new item case. It switches to the demographics-based CAMF-CC method to calculate the prediction in a new user or a new contextual cold-start situation. We conjecture that SHCA may fail or may not be accurate enough to provide meaningful recommendations for a mixture cold-start problem because SHCA uses the average sum of those two based methods when a mixture of cold-start situations are detected.

### *A. Content-based CAMF-CC*

The content-based CAMF-CC method is an extension of the context-aware matrix factorization (CAMF) [6] approach. It takes into account the item's category information in the rating prediction model. In this way, items are grouped in categories first. Then the algorithm uses a distinct factor vector $x_a$ for each item $i$ with attribute $a \in A(i)$ where $A(i)$ is the attribute set for item $i$. The algorithm models how an item's attribute influences the item's rating $\sum_{a \in A(i)} x_a$:

$$\hat{r}_{u_i c_{1,\dots,} c_k} = (q_i + \sum_{a \in A(i)} x_a)^{\mathrm{T}} p_u + \mu + b_i + b_u + \sum_{t \in T(i)} \sum_{j=1}^{k} b_{tc_j} \quad (1)$$

where $\hat{r}_{u_i c_{1,\dots,} c_k}$ is the rating that provides the evaluation of user $u$ for item $i$ made in the context $c_1,\dots,c_k$. $c_j$ may take the value of $0, 1,\dots,z_j$ where $c_j = 0$ means that the $j^{th}$ contextual factor is unknown, while the other index values refer to possible values for the $j^{th}$ contextual factor. $p_u$ and $q_i$ are the latent factor vectors associated to item i and user $u$. $\mu$ is the average rating of the item $i$ in the data set. $b_u$ and $b_i$ are the baseline parameters for user $u$ and item $i$. $T(i)$ is the set of categories associated to item $i$. $b_{tc_j}$ is the parameter models the interaction of the contextual conditions and the item categories.

### *B. Demographic-based CAMF-CC*

To address the new user and/or new contextual cold-start cases, demographics-based CAMF-CC method profiles users through known user attributes and introduces a new factor vector $y_a$ to describe a new user $i$ via the set of user-associated attributes $\sum_{a \in A(i)} y_a$. The demographics-based CAMF-CC predicts ratings using the following formula:

$$\hat{r}_{u_i c_{1,\dots,} c_k} = q_i^{\mathrm{T}} (p_u + \sum_{a \in A(i)} y_a) + \mu + b_i + b_u + \sum_{t \in T(i)} \sum_{j=1}^{k} b_{tc_j} \quad (2)$$

where all the parameters are similar to those of Equation (1), as described above.

## IV. WEIGHTED-SHCA ALGORITHM

We propose the Weighted Switching Hybrid Content-Aware (W-SHCA) recommender system, which exploits a weighted sum of two novel CARS algorithms: Content-based CAMF-CC method and Demographics-based CAMF-CC method. Depending on to the detected *User × Item × Context* situation, W-SHCA switches the optimal solution between the two base CAMF-CC methods, and takes the best weighted sum of these two accordingly. For example, W-SHCA switches to the content-based CAMF-CC method to do the rating prediction when a basic new item cold-start case is detected, and uses the demographics-based CAMF-CC method to do the rating prediction when a new user or a new contextual situation is detected. When a mixed cold-start situation is detected, W-SHCA assigns the best weight combination to those two-based CAMF-CC algorithms based on the estimated characteristics of the dataset.

The procedure of W-SHCA algorithm is summarized in Algorithm 1.

**Algorithm 1 W-SHCA**

**Input** Dataset D
**If** (new item situation) **then**
$R = R_1$: Content-based CAMF-CC
**Elseif** (new user or new contextual situation) **then**
$R = R_2$: Demographics-based CAMF-CC
**Else** {
**If** (sufficient item attributes found) **then**
$R= w_1 * R_1 + w_2 * R_2$ ($w_1$: $w_2$ = 0.9: 0.1 && $w_1 + w_2 = 1.0$)
**Elseif** (new user) **then**
$R= w_1 * R_1 + w_2 * R_2$ ($w_1$: $w_2$ = 0.1: 0.9 && $w_1 + w_2 = 1.0$)
**Else**
Weight combination changes based on the detected number of item attributes
**Output** Ratings $R$

According to Algorithm 1, the detailed procedure of our proposal is described as follows:

1) Check whether content-based CAMF-CC can provide an accurate rating to the detected situation. If so, use it;
2) Check whether demographics-based CAMF-CC can provide an accurate rating. If so, use it;
3) Otherwise, make a prediction by performing the W-SHCA algorithm:
   a. If sufficient number of item attributes are detected, assign the weight ratio between content-based CAMF-CC and demographics- based CAMF-CC as $w_1$: $w_2$ = 0.9: 0.1.
   b. If the user is unknown, assign the weight ratio between those two algorithms as $w_1$: $w_2$ = 0.1:0.9.
   c. Otherwise, only a few item attributes are detected, so assign the proper weight ratio based on the training model's results.

In order to find the optimal and stable weight ratio between those two-based algorithms, we conduct many offline experiments using three different contextually tagged datasets. The weight ratio between these two novel algorithms depends on whether sufficient item attributes exist. For example, the demographics-based CAMF-CC algorithm is highly preferred in a dataset that only a few item attributes are available; on the other hand the content-based CAMF-CC algorithm is highly preferred when a dataset provides sufficient number of item attributes. According to a series of experiments, we find the W-SHCA algorithm always outperforms the average scheme SHCA solution when the detected rating case is mixed cold-start. However, how to decide the weights is very important and deserved to be discussed more next.

## V. EXPERIMENTAL EVALUATION

Our study consists of comparing W-SHCA and the baseline SHCA algorithm [1], while obtaining the best weights for mixed cold start problems for data sets of different characteristics. We first describe the datasets used in the evaluation step, then the experimental design idea, the obtained results, and then finally we demonstrate how much the results are influenced if we change the number of item attributes and the number of user attributes.

### *A. Data Set*

To keep the experiment results consistent between the W-SHCA and SHCA algorithm, we use the three contextually tagged rating datasets that were also used in the SHCA algorithm's experiments. These three datasets are *STS* [7], *Music* [9], and *CoMoDa* [8]. The detailed characteristics of these three datasets are summarized in Table I.

TABLE I
DATASET CHARACTERISTICS

| Dataset | STS | Music | CoMoDa |
|---|---|---|---|
| Domain | POIs | Music | Movies |
| Rating scale | [1-5] | [1-5] | [1-5] |
| Ratings | 2534 | 4012 | 2296 |
| Users | 325 | 42 | 121 |
| Items | 249 | 139 | 1232 |
| Contextual factors | 14 | 8 | 12 |
| Contextual conditions | 57 | 26 | 49 |
| User attributes | 7 | 1 | 4 |
| Item attributes | 1 | 2 | 7 |
| Sparsity | 96.87% | 32.87% | 98.45% |

From Table I (Dataset Characteristics), we can see that the STS dataset has 14 contextual factors, 7 user attributes and 1 item attribute. Music dataset has 8 contextual factors, only 1 user attribute and 2 item attributes. CoMoDa dataset has 12 contextual factors, 4 user attributes and 7 item attributes. The difference among those three datasets will be shown in the experiment result section in the report later.

### *B. Creating Cold Start Problems*

To measure the predictive ability of the proposed W-SHCA algorithm, we use the 10-fold cross validation method and calculate the measure metrics Mean Absolute Error (MAE) to compare with the original SHCA method. To do this, the datasets are randomly partitioned into ten subsets. For each fold, we use nine of those subsets of data for training and the remaining one fold for testing.

To obtain three simple cold-start situations mentioned before, we perform the special 10-fold cross validation as follows. First, we split the whole dataset into ten equally sized subsets based on the user ID. Then in each of the cross-validation iteration, we use those nine merged user subsets as training set to build the models and the remaining one as the testing set. In this manner, the testing set contains users without any rating histories in the training set. Finally, after the ten iterations, we computed the MAE of the model. The MAE is calculated by averaging the results from ten experiments. In the same way, we build new items and new contextual situation experiment and perform the 10-fold cross validation on the set of items and contextual situations instead of the set of users.

For building three mixture cold-start situations, the experimental procedures are much more complex In the mixture of new user and new item case, first we choose one user from the set of users and one item from the set of items, and then we remove all rating data related to that specific user and item pair.

In this way, the remaining dataset can be used as the training set, and those for the specific user and item pair can be used as the testing set to do the prediction. This is how the new user and new item mixture cold-start situation is created. Similarly the other two mixed cold start problems are created.

### C. Evaluation Results

#### 1) Overview of Results of Best Weights

The best weights of W-SHCA results are summarized in Table II. In order to obtain these results, a large number of experiments are preformed to decide optimal values of the weight to be assigned to content-based CAMF-CC ($w_1$) and demographics-based CAMF-CC ($w_2$) in the W-SHCA model. Results for the experiments for finding the optimal weights are shown in Tables III - VII. Note that for each of these tables, the result of SHCA, where weights are both 0.5, and the result of the best weights, are both shown. The tables are: Table III (for STS dataset), Table IV (for Music dataset), and Table V (for CoMoDa dataset) for basic cold-start problems. Table VI (Estimation on MAE for mixture of "new user + new item + new context"), Table VII (Estimation on MAE for mixture of "new user + new item"), and Table VIII (Estimation on MAE for mixture of "new item + new context") for mixed cold start problems.

From Table II, we can see that the demographics-based CAMF-CC algorithm is highly preferred in both STS and Music datasets, and the content-based CAMF-CC algorithm always has a heavy weight in CoMoDa dataset.

Although the weight ratio between those two CAMF-CC methods in Music dataset are not as obvious as much as the weight ratio in STS dataset, W-SHCA still highly prefers demographics-based CAMF-CC to content-based CAMF-CC. The reason for that phenomenon is that two item attributes are available in the Music dataset and its sparsity is only 32.87%, which is much lower than the other two datasets. In another word, the Music dataset does not use the weighted sum of two-based CAMF-CC methods very often because the demographics-based algorithm and content-based algorithm can perform a very good prediction solely in this situation due to the characteristics of the dataset.

TABLE II
BEST WEIGHTS IN TERMS OF MAE I W-SHCA

| The Cold-Start Cases | Best Results in Terms of MAE with Optimal Weight Selection | | | | | |
|---|---|---|---|---|---|---|
| | STS | | Music | | CoMoDa | |
| | Content-based CAMF-CC | Demographics based CAMF-CC | Content-based CAMF-CC | Demographics based CAMF-CC | Content-based CAMF-CC | Demographics based CAMF-CC |
| New User | 0.1 | 0.9 | 0 | 1 | 0.9 | 0.1 |
| New Item | 0.2 | 0.8 | 0.3 | 0.7 | 0.9 | 0.1 |
| New Contextual * | 0.4 | 0.6 | 0 | 1 | 0.9 | 0.1 |
| New User + New Item | 0.1 | 0.9 | 0.1 | 0.9 | 0.9 | 0.1 |
| New Item + New Contextual | 0.2 | 0.8 | 0.4 | 0.6 | 0.9 | 0.1 |
| New User + New Item + New Contextual | 0.1 | 0.9 | 0.1 | 0.9 | 0.9 | 0.1 |

*Notes: Only the reviews have contextual information that is 1260 out of 2534 are used in the new contextual case of STS dataset.

#### 2) Basic Cold-Start Problems

The tables are: Table III (for STS dataset), Table IV (for Music dataset), and Table V (for CoMoDa dataset) for basic cold-start problems. From Table III (Estimation on MAE for Different sets of weights (STS)), we see that all three situations prefer demographics-based CAMF-CC to content-based CAMF-CC algorithm. Similarly, from Table IV (Estimation on MAE for Different sets of weights (Music)), it is clear that both new user and new contextual situation cases do not use the weighted sum method and they directly use demographics-based CAMF-CC algorithm only. Finally from Table V (Estimation on MAE for Different sets of weights (CoMoDa)), all three cold-start cases highly prefer content-based CAMF-CC algorithm, which are consistent with our conjectures.

Based on all three tables, we see that W-SHCA does provide some improvement in basic cold-start problems, but not in a significant amount, since the algorithm is proposed mainly for mixed cold-start problems, to be presented below.

TABLE III
ESTIMATION ON MAE FOR DIFFERENT SETS OF WEIGHTS (STS)

| Cold - Start Case | Content based CAMFCC | Demographics based CAMFCC | MAE (W-SHCA) | Improve ment |
|---|---|---|---|---|
| New User | 0.5 | 0.5 | 0.995 | |
| | **0.1** | **0.9** | **0.994** | **0.064%** |
| New Item | 0.5 | 0.5 | 0.999 | |
| | **0.2** | **0.8** | **0.996** | **0.207%** |
| New Context | 0.5 | 0.5 | 0.872 | |
| | **0.4** | **0.6** | **0.871** | **0.008%** |

TABLE IV
ESTIMATION ON MAE FOR DIFFERENT SETS OF WEIGHTS (MUSIC)

| Cold - Start Case | Content based CAMFCC | Demographics based CAMFCC | MAE (W-SHCA) | Improve ment |
|---|---|---|---|---|
| New User | 0 | 1 | 1.323 | |
| New Item | 0.5 | 0.5 | 1.184 | |
| | **0.3** | **0.7** | **1.183** | **0.056%** |
| New Context | 0 | 1 | 0.836 | |

TABLE V
ESTIMATION ON MAE FOR DIFFERENT SETS OF WEIGHTS (COMODA)

| Cold - Start Case | Content based CAMFCC | Demographics based CAMFCC | MAE (W-SHCA) | Improvement |
|---|---|---|---|---|
| New user | 0.5 | 0.5 | 0.876 | |
| | **0.9** | **0.1** | **0.868** | **0.876%** |
| New Item | 0.5 | 0.5 | 0.829 | |
| | **0.9** | **0.1** | **0.820** | **1.176%** |
| New Context | 0.5 | 0.5 | 0.819 | |
| | **0.9** | **0.1** | **0.815** | **0.436%** |

*3) Mixed Cold-Start Problems*

The three mixture cold-start experiment results are shown in Table VI (Estimation on MAE for mixture of "new user + new item + new context"), Table VII (Estimation on MAE for mixture of "new user + new item"), Table VIII (Estimation on MAE for mixture of "new item + new context"). Most significantly, W-SHCA has obtained results that are significantly better than using SHCA, specifically for the Music dataset. Overall, the improvements are more than those in the basic cold start problems.

The results are also consistent with our conjectures. From Table VI (Estimation on MAE for mixture of "new user + new item + new context") and Table VII (Estimation on MAE for mixture of "new user + new item), both STS and Music datasets use the weight ratio $w_1: w_2$ = 0.1:0.9 between content-based CAMF-CC and demographics-based CAMF-CC, while in the meantime CoMoDa still highly prefers content-based CAMF-CC algorithm. From Table VIII (Estimation on MAE for mixture of "new item + new context"), both STS and Music datasets change the weight ratio between content-based CAMF-CC and Demographics-based CAMF-CC from $w_1: w_2$ = 0.1:0.9 to $w_1: w_2$ = 0.2:0.8 and $w_1: w_2$ = 0.4:0.6 because only half of the reviews have contextual information. In other words, we believe that if the dataset is large enough, the weight ratio between those two CAMF-CC algorithms should be as same as other experiment results ($w_1: w_2$ = 0.1:0.9).

The CoMoDa dataset highly prefers content-based CAMF-CC algorithm because seven item attributes are available for its rating prediction, whereas the other two datasets do not have enough item attributes in the rating prediction system. Therefore, both STS and Music datasets prefer a large weight parameter on the demographics-based CAMF-CC approach when the mixture cold-start case is detected.

TABLE VI
ESTIMATION ON MAE FOR MIXTURE OF "NEW USER + NEW ITEM + NEW CONTEXT" (FOR THREE DATASETS)

| Dataset | Content based CAMF-CC | Demographics based CAMF-CC | MAE (W-SHCA) | Improvement |
|---|---|---|---|---|
| STS | 0.5 | 0.5 | 1.045 | |
| | **0.1** | **0.9** | **1.025** | **1.934%** |
| Music | 0.5 | 0.5 | 1.718 | |
| | **0.1** | **0.9** | **1.316** | **23.432%** |
| CoMoDa | 0.5 | 0.5 | 0.866 | |
| | **0.9** | **0.1** | **0.836** | **3.492%** |

TABLE VII
ESTIMATION ON MAE FOR MIXTURE OF "NEW USER + NEW ITEM" (FOR THREE DATASETS)

| Dataset | Content based CAMF-CC | Demographics based CAMF-CC | MAE (W-SHCA) | Improvement |
|---|---|---|---|---|
| STS | 0.5 | 0.5 | 1.043 | |
| | **0.1** | **0.9** | **1.023** | **1.97%** |
| Music | 0.5 | 0.5 | 1.746 | |
| | **0.1** | **0.9** | **1.307** | **25.157%** |
| CoMoDa | 0.5 | 0.5 | 0.865 | |
| | **0.9** | **0.1** | **0.835** | **3.496%** |

TABLE VIII
ESTIMATION ON MAE FOR MIXTURE OF "NEW ITEM + NEW CONTEXT" (FOR THREE DATASETS)

| Dataset | Content based CAMF-CC | Demographics based CAMF-CC | MAE (W-SHCA) | Improvement |
|---|---|---|---|---|
| STS | 0.5 | 0.5 | 0.947 | |
| | **0.2** | **0.8** | **0.943** | **3.947%** |
| Music | 0.5 | 0.5 | 1.203 | |
| | **0.4** | **0.6** | **1.203** | **0.017%** |
| CoMoDa | 0.5 | 0.5 | 0.830 | |
| | **0.9** | **0.1** | **0.817** | **1.52%** |

*4) Effect of Item Attributes*

To better understand the relationship between weight selection and item attributes, we conduct another set of experiments where we reduce the item attributes of CoMoDa dataset from seven to one. From the result in Table IX (Estimation on MAE for one Item Attribute (CoMoDa)), the weight combination for content-based CAMF-CC algorithm and demographics-based CAMF-CC is changed from $w_1: w_2$ = 0.9: 0.1 to $w_1: w_2$ = 0.1: 0.9 in both new user and new item cases. These changes have demonstrated that the number of item attributes is significant in deciding weight ratios in W-SHCA.

TABLE IX
ESTIMATION ON MAE FOR ONE ITEM ATTRIBUTE (COMODA)

| Cold - Start Case | Content based CAMFCC | Demographics based CAMFCC | MAE (W-SHCA One Item Attribute) | Improvement |
|---|---|---|---|---|
| New User | 0.5 | 0.5 | 0.888 | |
| | **0.1** | **0.9** | **0.879** | **0.994%** |
| New Item | 0.5 | 0.5 | 0.877 | |
| | **0.1** | **0.9** | **0.867** | **0.004%** |

*5) Effect of User Attributes*

To understand the relationship between weight selectioin and the number of user attributes, we combine three genre attributes to one genre attribute and three actor attributes to one actor attribute in CoMoDa's new contextual situation. From Table X (Estimation on MAE for reduced User Attribute), when the number of user attributes changes from 4 to 2, the weight selection does not change but the rating prediction accuracy is worse than the prediction using all user attributes (comparing with Table V). We can conclude that the number of user attributes is important for improving the prediction accuracy in W-SHCA.

TABLE X
ESTIMATION ON MAE FOR REDUCED USER ATTRIBUTE (COMODA)

| Cold-Start Case | C-based | D-based | MAE (4 User Attributes) | Improvement |
|---|---|---|---|---|
| New Context | 0.5 | 0.5 | 0.830 | |
| | **<u>0.9</u>** | **<u>0.1</u>** | **<u>0.816</u>** | **<u>1.77%</u>** |
| | **C-based** | **D-based** | **MAE (2 User Attributes)** | |
| | 0.5 | 0.5 | 0.846 | |
| | **<u>0.9</u>** | **<u>0.1</u>** | **<u>0.835</u>** | **<u>1.3%</u>** |

## VI. CONCLUSION AND FUTURE WORK

In this paper a new algorithm W-SHCA is presented. The algorithm provides a relatively stable weighted mechanism to utilize both the content-based CAMF-CC and demographics-based CAMF-CC methods to cope with different mixed cold-start problems. The W-SHCA algorithm has been clearly described, and is easy to follow, implement and further improve. The experiment evaluation is performed for three simple cold-start problems and three mixed cold-start problems. A large set of experiment results has shown that the W-SHCA method can effectively cope with different types of mixed cold-start problems, and outperforms the average sum scheme SHCA solution. We have derived stable weight patterns for W-SHCA based on the characteristics of different datasets. We have also demonstrated that the number of item attributes in the dataset affects the weighted selection, and the accuracy of W-SHCA prediction is improved by incorporating more user attributes. Future work may include further analysis of weight selections in W-SHCA for different data sets, deriving a general guideline of weight selection based on the number of users, items and contextual attributes, performing a comprehensive experimental evaluation on a large contextually tagged datasets, and using real user data to verify if rating predictions match users' actual decisions.

## VII. ACKNOWLEDGMENT

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