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Matrix Factorization Methods Are Utilized For Context-Aware Recommendation Systems

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ABSTRACT

Context-aware recommender systems adapt recommendations according to the context in which the products will be used. We introduce an innovative Matrix Factorization recommendation algorithm with extended features. We incorporate contextual elements into our model by introducing extra parameters. The suggested method, as demonstrated by the experiments, As per with the most sophisticated techniques. This approach reduces computational requirements while allowing for more nuanced object-context connections. We applied the given methodology to both subject preference and research URL selection in our recommendation system.

Keyword: *Collaborative filtering, matrix factorization, context-based reasoning, recommender systems*

INTRODUCTION

Recommender systems (RS), as software tools, help online consumers deal with information overload by suggesting personalized choices from a broad selection of goods and services. Traditional recommender systems neglect the specific context of item consumption. To overcome this, Context Aware Recommender Systems (CARS) have been developed recently. CARS was demonstrated to offer more relevant recommendations [5] and more accurate rating predictions [7, 10, 6,] when it utilized more pertinent information (context).

CARS (Contextual Adaptive Routing Systems) techniques are classified into three categories: contextual pre-filtering, contextual post-filtering, and contextual modelling [2]. Earlier research centered on developing pre-filtering techniques. In reduction based CACF techniques [1], the context for determining target ratings is first established, followed by the selection of pertinent ratings gathered in that context (or a broader one). To enhance the accuracy of rating prediction beyond a generic baseline method, contextual data segments must be identified by the reduction strategy. The expense of searching for these distinctions is substantial. item-splitting [6] is an effective pre-filtering technique that reduces computational cost by dynamically identifying the relevant contextual elements for each item. If a statistically significant difference exists in this item's ratings between two contextual conditions, it is separated into two virtual items. Item-splitting produces more precise rating predictions than reduction techniques. In more recent CARS techniques, regression models are preferred for rating data matching [7, 10]. The current most precise CARS method is Tensor Factorization (TF) [7]. The two dimensional matrix factorization problem in TF is generalized into an n-dimensional version called tensor factorization. The multi-dimensional matrix lower dimensional representation utilizes a feature vector of reduced dimensions to depict the user, item, and contextual aspects.

Regression models, including Tensor Factorization, introduce several parameters that need to be learned from the training data set. The number of contextual elements exponentially increases with the number of model parameters. (Note: In the original text, "[7]" is a citation.) TF improves heuristic-based methods rating prediction accuracy with large training datasets [7]. Despite having fewer parameters, simpler models can perform effectively with smaller data sets. Including unhelpful modelling elements can negatively impact the precision of rating predictions. A contextual component that does not impact the rating is considered noise within the system. Considering both the accessibility of training data and the domain's specific features, including the type of dependency between contextual elements and ratings, we suggest that CARS should balance model complexity.

We test three Matrix Factorization-based CARS models in this study, with empirical evidence, to explore the trade-offs between their complexity and performance compared to TF models. Each model assumes unique ways in which ratings and context impact one another. The ratings are consistently influenced by a contextual component, no matter the specific object. Each contextual circumstance has a distinct impact on every item, as per the intricacy of its ratings. Considering equal influence of contextual factors, a third complex level option exists for items within the same category. Applying data sets from tourism and music industries, we prove that the third model outperforms others during testing.

In the subsequent sections, we present the suggested models and compare their assessment findings to those of TF and heuristic approaches on two previously used data sets, followed by showcasing the outcomes of these models on two new data sets, highlighting their significant impact on enhancing traditional matrix factorization's prediction accuracy. The study concludes with recommendations for future research.

CONTEXT AWARE MATRIX FACTORIZATION

We present an advanced Matrix Factorization (MF) method, Context-Aware Matrix Factorization (CAMF), that integrates contextual data within an RS's rating prediction process. Originally introduced in [9], CAMF enhances rating representation by handling an increased number of contextual elements. Our method enables us to manage varying degrees of interaction between ratings and context. In this study, we focus on a three-tiered version of the comprehensive model.

This model assumes that all contextual factors, apart from the object, collectively influence the evaluations. The contextual factor significantly influences places of interest (POIs) ratings, regardless of their specificity. Therefore, we incorporate a single parameter for each contextual condition in our CAMF-C model. This context-specific deviation from traditional personalized predictions is represented by the mentioned parameter.

Each contextual condition and item pair in the second model receives an additional parameter. It has a finer grain and more parameters than the original, necessitating additional learning. This model excels at predicting ratings when the context exhibits varied effects. Students can choose a study website, irrespective of future aspirations. CAMF-CI is the name given to this model.

The third model incorporates a separate parameter for each contextual condition and item category. In this scenario, the domain expert categorizes POIs as subjects and groups study websites and future goals under distinct genres. CAMF-CC is the name of this model.

We can denote user u's rating for item i as r_{ui}. In scenario c, the rating i receives from u is denoted as r_{uic}, influenced by contextual factors. The rating $r_{uic1...ck}$ reflects the user's evaluation of the item in the context of $c_1,..., c_k$. The other index values represent potential contextual factors and their respective conditions, while a zero for c_j signifies an unknown contextual factor. The data set $R = \{(u, i, c_1,..., c_k)|r_{uic1...ck}$ is known$\}$ contains the tuples $(u, i, c_1,..., c_k)$ for which the rating $r_{uic1...ck}$ is known.

$\vec{v}_u$ user in V and item i represented by column vector $\vec{q}_i$ in Q. Adjusting the dimension d in MF allows for a balance between the predictive model's capacity and generalization ability.

For individualized context-dependent ratings, it would be appropriate to model them using a modified version of the MF algorithm.

$$\hat{r}_{uic_1 \dots c_k} = \vec{v}_u \vec{q}_i + \bar{\iota} + b_u + \sum_{j=1}^{k} B_{ijc_j}$$

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Let b_u denote the user u baseline parameter, R_i the average rating of item i, and u_i, r_i two d-dimensional real vectors representing the user u and item i respectively. The interaction between items and contextual conditions is modelled by the B_{ijcj} parameters. We write K as the sum of z_1 to z_k, where each z_i is the count of alternative values for the corresponding contextual component and k represents the number of contextual factors. Each contextual condition in CAMF-CI's finest-grain model has an assigned parameter B_{ijcj} for item combinations. K_n represents the total number of B_{ijcj} parameters for n items. In the coarser CAMF-CC model, there exists only one parameter for every contextual condition and item category pair. If items i and f belong to the same category, then B_{ijcj} equals B_{fjcj} and the total number of parameters is K_t, where t is the number of distinct categories (our data sets contain five and 10 categories, respectively). For each contextual condition in CAMF-C, there is just one parameter, B_{ijcj}, and it is set to zero when the condition is unknown.

The suggested model has the potential for further expansion to include relationships among contextual elements. Additional circumstances (c_j and c_l) can be incorporated. The added complexity of this model may improve its accuracy, but a lack of sufficient training data could negatively impact its precision. Due to the small dataset size in our study, we opted for simpler models without considering the interplay of contextual factors. The relationship between users and context can also be modelled. Although expanding the data might enhance rating prediction, it would not change users' product rankings.

The model parameters should be learned using the training data for generating rating predictions. We treat the learning process as an optimization problem.

$$\min_{v*,q*,b*,B*} \sum_{r \in R} [(r_{uic1\ldots ck} - \vec{v}.\vec{q} - \bar{\imath} - b_u - \sum_{j=1}^{k} B_{ijcj})^2 + \lambda\,(b_u{}^2 + \|\vec{v}_u\|^2 + \|\vec{q}_i\|^2 + \sum_{j=1}^{k} \sum_{c_j=1}^{z_j} B_{ijcj}{}^2)]$$

For each rating r in R, it consists of user u, item i, and contexts $c_1,\ldots, c_k$. To enhance generalization performance, a regularization term is added to these model types. λ meta-parameter controls regularization. λ increase makes the model less adaptable to the training set. This issue has been addressed using stochastic gradient descent. This strategy has been proven effective [8]. This technique updates parameters one at a time, adjusting each in the reverse direction indicated by the gradient. γ, set to 0.005, governs the learning rate in our experiments.

The suggested models can be trained in a linear relationship with the quantity of data points and contextual variables. The wide range of contextual parameters the method can be used with is a significant advantage. 14 contextual elements, totalling 52 contextual situations, were utilized in our testing. The CACF approach based on Tensor Factorization comes with an exponential training and prediction time complexity, given the number of contextual dimensions.

EXPERIMENTAL EVALUATION

We have validated the proposed methods using artificial and authentic datasets, as detailed in Table 2. We will begin by showing that CAMF matches the performance of top Tensor Factorization (TF)-based CARS methods [7]. Using two sets of real data, we will provide a detailed analysis of CAMF at a later stage. CAMF and TF were compared using three semi-artificial and one real world data sets. The study used Yahoo Web scope movie data to construct semi-artificial data sets [11]. Tα value determines the impact of the artificial feature on the simulated contextual component in the data sets. For further details on these data sets, see reference [6]. We have also collected real-world data on the liking of subjects. In this comparison, we applied the CAMF-CI method. We did not use CAMF-CC and CAMF-C because the dataset generated from the artificial feature on the study websites was not correlated with item categories.

Through repeated random subsampling, we have estimated the models performance. The seventy two training-testing sets have been formed with 90% of the original data. The Mean Absolute Error (MAE) for each approach has been calculated. The findings are summarized in Table 1. In the context-reduced cases, including semi-artificial data sets and the small real world data set (Liking of Subjects), CAMF shows superior performance compared to TF.

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TABLE 1 : MAE for TF and CAMF

Data Set	CAMF-CI	TF
Liking of subjects	5.88	6.05
Liking of Study websites(α=0.1, β=0.9)	2.15	2.18
Liking of Study website (α = 0=0.5, β=0.9)	2.16	1.98
Liking of Study websites(α=0.9, β=0.9)	1.94	1.87

For small data sets, the simpler model with fewer parameters outperforms the more complex one. This is evident in The Liking of Subjects dataset. When context has minimal impact, such as liking of websites, CAMF using item and user baselines returns a lower generalization error than TF. However, TF outperforms CAMF when context significantly influences preferences, like in the liking of study websites with ample data. Pre-filtering strategies, such as reduction based approach [1] and item-splitting [6], underperform both TF and CAMF models on these datasets.

We employed two genuine datasets from the Liking of participants and Liking of study websites recommendation services for further investigations into the connection between model complexity and context. This data set was collected using two web applications. Users rated study websites based on contextual variables are imagined. Table 2 outlines the data collection process, featuring demonstrations of the particulars in [5] and [4].

Figure 1 shows the Mean Absolute Error (MAE) of the considered models. The comparison involves CAMF, regular MF, and the AVG model. The complexity of the model increases from left to right, as indicated by the rising number of model parameters. Among all the databases, CAMF-CI is the most complex and AVG is the simplest. In the tourism domain's dataset, the items' averages serve as model parameters, with AVG at 124 parameters, MF at 72 parameters, CAMF-C at 216 parameters, CAMF-CC at 86 parameters, and CAMF-CI at 72 parameters. Using the classical MF approach achieves the greatest improvement in AVG. Using traditional MF yields the greatest increase in AVG. The improvement in Liking of Subjects and Liking of Websites domain statistics amounts to 3% and 5%, respectively. These gains align with earlier research (e.g., [3]) reporting higher accuracy with personalized rating predictions. Contextualization can more effectively personalize the individualized model. The three context-aware MF models outperform AVG by 6% and 7% and 8% and 9% in the Liking of Study websites and subjects domain data, respectively.

The most effective context-aware machine learning technique isn't necessarily the most complex one. According to both datasets, CAMPF-CC outperforms other methods. Utilizing CAMF-CI enhances the model's complexity, thereby improving its rating prediction accuracy.

TABLE 2 : Data Set

Data set	users	Item	item categories	contextual factors	contextual conditions
Liking of Subjects	72	216	10	5	5
Study Website	72	86	31	10	10
Future goal	72	72	3	2	2

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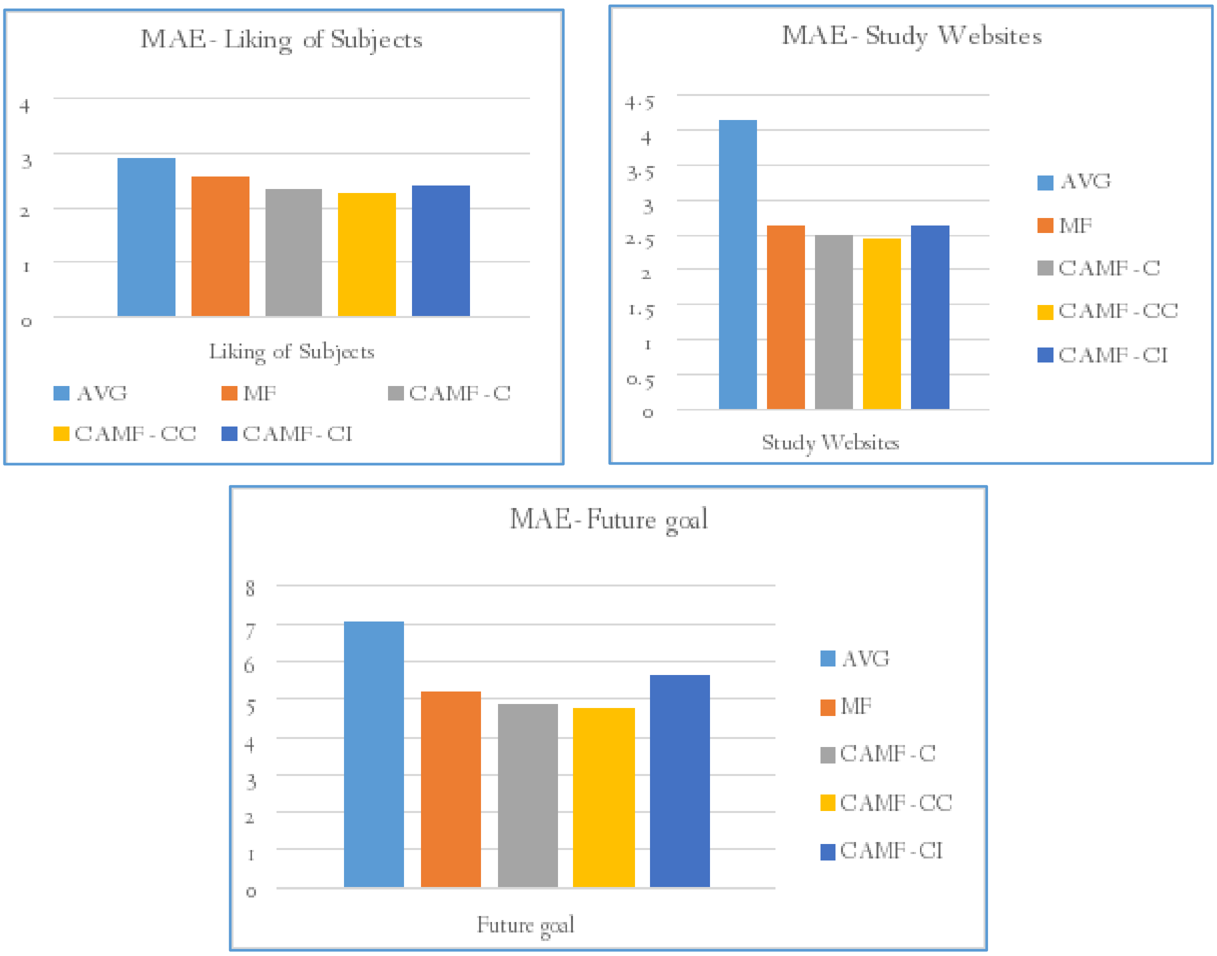

Figure 1: Mean Absolute Error of the compared methods

Following our research, we reached these conclusions with future scope

Using contextual information can significantly enhance rating prediction accuracy. The optimal model granularity for the interaction between context and items is determined by the size and scope of accessible data. Effectively organizing data by item category has been demonstrated for accessible datasets.

Further experimentation of different data set for user and item by using proposed method. It is essential to evaluate the sensitivity of the data to context model granularities while recognizing context-awareness limited usefulness. We will do deeper comparison of Tensor Factorization and Context Aware Matrix Factorization for the different data set.

Future research will examine multiple measures with varying accuracy to assess the effectiveness of the recommendation system.

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