CSLIM: Contextual SLIM Recommendation Algorithms

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Abstract

Context-aware recommender systems (CARS) take contextual conditions into account when providing item recommendations. In recent years, context-aware matrix factorization (CAMF) has emerged as an extension of the matrix factorization technique that also incorporates contextual conditions. In this paper, we introduce another matrix factorization approach for contextual recommendations, the contextual SLIM (CSLIM) recommendation approach. It is derived from the sparse linear method (SLIM) which was designed for Top-N recommendations in traditional recommender systems. Based on the experimental evaluations over several context-aware data, we demonstrate that CSLIM can be an effective approach for context-aware recommendations, in many cases outperforming state-of-the-art CARS algorithms in the Top-N recommendation task.

Introduction & Related Work

Context-aware Recommender Systems (CARS)

CARS additionally take contexts into consideration, where multiple contexts can be taken into account at the same time, which formulates a multidimensional rating space.

CARS Recommendation Algorithms

- Based on neighborhood-CF: DCM [9,10]
- Based on MF: CAMF [2] and TF [3].

DCM are explainable but they suffer from sparsity problems; TF and CAMF work well but it is difficult to interpret the latent factors in the models.

Preliminary: Sparse linear method (SLIM)

SLIM improves upon the ItemKNN CF by learning, directly from the data, a sparse matrix of aggregation coefficients that are analogous to the traditional item-item similarities [5]. The example of SLIM-1 model is shown as below.

Matrix R

\[
\hat{R}_{ui}^{ \text{SLIM-1} } = \sum_{j \in \text{items}} R_{uj} W_{ij} \cdot \text{diag}(W) = 0
\]

Rating score \( \hat{R}_{ui} \) is estimated by a sparse aggregation of the ratings on the other items (except item \( t \)) that have rated by user \( u \). Note: \( R \) is the user-item rating matrix and \( W \) is coefficient matrix analogous to item similarities.

A SLIM-U model similar to UserKNN can be built too.

Contextual SLIM (CSLIM) Recommendation Algorithms

To incorporate contexts into SLIM recommenders, we’d like to estimate the ranking score in specific contexts \( C \) by aggregation of contextual ratings in the same contexts \( C \). We use a binary vector \( c = [c_1, c_2, c_3, \ldots] \) to represent contexts.

However, users may not rate other items in the same contexts; in this case, users’ contextual ratings in \( C \) is estimated by users’ non-contextual rating plus contextual rating deviations (CRDs) in different contexts.

Estimation of Contextual Rating:

\[
\hat{R}_{ui}^{ \text{CSLIM}} = R_{ui}^{ \text{SLIM}} + \sum_{j \in \text{items}} D_{ij} c_i
\]

Afterwards, it is able to estimate the ranking score in contexts \( C \):

\[
\hat{S}_{i,j,(c)} = \sum_{h \in \text{contexts}} \hat{R}_{ih,c_h} W_{h,j} = \sum_{h \in \text{contexts}} (R_{ih} - \sum_{l \neq h} D_{ih} c_l) W_{h,j}
\]

This approach is named as CSLIM-C, because CRD is assumed for each \( C \), context condition-pair; accordingly, there could be CSLIM-I-C model, where CRD is assumed for each user, contextual condition-pair.

Similarly, CSLIM-L-C assumes CRD is associated with each contextual condition regardless who is the user and what item it is.

The same idea of incorporating contexts into SLIM-I can also be applied to SLIM-U models, thus we can build another three CSLIM models: CSLIM-U-C, CSLIM-I-U and CSLIM-I-C.

Experimental Evaluations

Data sets: we have evaluated CSLIM approaches over five context-aware data sets. URL: http://tiny.cc/contextdata

Experiments: 5-folds cross validation; Metrics: Precision, Recall and Mean Average Precision (MAP).

Baseline approaches: SLIM, Context-aware splitting approaches (CASA) [11], CAMF [2], TF [3].


Analyses and Findings

1). CSLIM models outperform the state-of-the-art CARS algorithms, including CASA, CAMF, TF;

2). Some SLIM models outperform the baseline CARS algorithms, but CSLIM always works better than SLIM algorithms;

3). The performance of CSLIM algorithms are associated with the density of contextual ratings in the data sets.

In this paper, we successfully incorporate contexts into SLIM and develop several CSLIM algorithms, where they estimate the ranking score by the intuition behind ItemKNN or UserKNN via the aggregation of users’ estimated contextual ratings on items. CSLIM models are demonstrated to outperform the state-of-the-art CARS algorithms for top-N recommendations. We also find that the performance of CSLIM is correlated with the density of multiple ratings in contexts. In our future work, we plan to incorporate the contexts into the coefficient matrix \( W \), which helps estimate the coefficients between each contextual conditions and discover more insights about the contextual effects.

References