Improve General Contextual SLIM Recommendation Algorithms By Factorizing Contexts

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Abstract

Context-aware recommender systems (CARS) emerged during recent years in order to adapt to users’ preferences in different contextual situations. For example, users may choose different movies if they are going to see movies with their partners rather than with kids. The motivation behind is that users’ preferences on items are always changing from contexts to contexts.

Contextual Sparse Linear Methods (CSLIM) were developed to offer a balance between effectiveness and explainability, and they have been demonstrated to be able to outperform the state-of-the-art CARS algorithms. Meantime, a simpler CSLIM, named general CSLIM (GCSLIM) was developed to reduce the computation cost in the original CSLIM. But GCSLIM still learns contextual preferences in different contextual situations. For example, users may choose different movies if they are going to see movies with their partners rather than with kids. The motivation behind is that users’ preferences on items are always changing from contexts to contexts.

Problem Statement and Proposed Solutions

There is an efficient context-aware recommendation algorithm proposed recently in ACM CIKM 2014, namely, the General Contextual SLIM (GCSLIM) algorithm which was demonstrated to be able to outperform the state-of-the-art contextual recommendation algorithms.

\[
\hat{S} = \mathbf{D} + \mathbf{X} \mathbf{W}
\]

In GCSLIM, we are going to estimate a ranking score to optimize the ranking of the recommendation list. All the contextual ratings in shape of \(<\text{UserID}, \text{ItemID}, \text{Rating}, \text{Contexts}>\) are stored in the space \(P\). Matrix \(W\) is a matrix estimating the rating deviations between any two contextual conditions. Matrix \(D\) is a matrix estimating the rating errors of any two conditions. GCSLIM aims to learn the values in matrices \(W\) and \(D\) to minimize the prediction error of the ranking score.

Contextual deviation in matrix \(D\) is estimated by pairs, e.g., \(\text{Dev} (c1, c2)\). Imagine we have split the data into training and testing set. And GCSLIM has learned \(\text{Dev} (c1, c2)\) and \(\text{Dev} (c2, c3)\). However, it is possible that we need \(\text{Dev} (c1, c3)\) in the testing set which was not learned in the training data set. -- It will introduce prediction errors! In other words, the design of GCSLIM shown above suffers from data sparsity problems in recommendation process.

Solution: Each context condition can be represent by a vector, such as a vector in size \(5\times 0.1, 0, 0.02, 0.06, 0.2\). The rating deviation is modeled as the Euclidean distance between each two vectors. In this way, the vector representing each context condition will be learnt by each iteration in the optimization algorithm.

For example, \(\text{Dev} (c1, c2)\) and \(\text{Dev} (c2, c3)\) have been learnt in the training data set. In this case, the vector representations for conditions \(c1, c2, c3\) were already learnt. \(\text{Dev} (c1, c3)\) can be calculated by Euclidean distance as a result, which solves the problem. In other words, this solution helps alleviate the data sparsity problem and gain the improvement.

Evalutations and Conclusions

We evaluated this solution over five different context-aware data sets. Due to limited space, we just present the results on the context-aware restaurant data set, where there are 50 users, 40 restaurants, and 2,314 ratings. There are only two context dimensions: time (weekend, weekday) and location (school, home, work).

Precision and Mean Average Precision (MAP) were chosen as the evaluation metrics over the 5-folds cross validation.

We choose CSLIM [7] and GCSLIM [8] as the baseline approaches, since they were demonstrated to be able to outperform the state-of-the-art context-aware recommendation algorithms in the previous research. We name our proposed solution as Improved General Contextual SLIM algorithm (IGCSLIM).

The blue curve is the CSLIM, and red curve is the GCSLIM algorithm. Our proposed solution is depicted by the dotted green line in the figures above. Generally, both precision and MAP were improved. The improvement is 16% on precision and 8% on MAP for this data set.

Conclusions and Future Work

In this paper, we propose to factorize contexts to improve the GCSLIM approaches, and experimental results demonstrate the solution is effective, but GCSLIM still cannot work well if the rating data is too sparse in contexts. It is able to alleviate the data sparsity problem but cannot totally solve the problem, especially when it comes to serious cold-start problems. Our future work will focus on the hybrid contextual models in order to handle the serious sparse situation – the cold start context problem in context-aware recommender systems.