Correlation-Based Pre-Filtering for Context-Aware Recommendation

Zahra Vahidi Ferdousi [1 2], Elsa Negre [1] and Dario Colazzo [1]
[1]Paris-Dauphine University, LAMSADE, Data Science Team,
[2]Coheris

Abstract

With the increasing use of connected devices and IoT, users' contextual information is more and more available and used in different information systems. As a matter of fact, context-aware recommender systems have demonstrated that taking contextual information about users into account can improve the effectiveness of recommendation, by generating more relevant recommendations to the users in their specific contextual situation. In this paper we propose a new context representation and approach to integrate this kind of information into a recommender system. We make a strong representation of the context, based on the influence of context on ratings, calculated using the Pearson Correlation Coefficient. We do a pre-filtering recommendation based on this representation. Our evaluations demonstrate that our approach can outperforms the state of the art.

Context-Aware Recommender System (CARS)

Recommender Systems are software tools and techniques providing suggestions for items to be of use to a user [7]. But they do not take into account the fact that the contextual situation in which a user is in, at the moment she wants to use the item, can influence her preferences.

So the objective of CARSs is to integrate contextual information about users into their recommendation process ($user \times item \times context \rightarrow rating$), in order to propose more relevant recommendations [1].

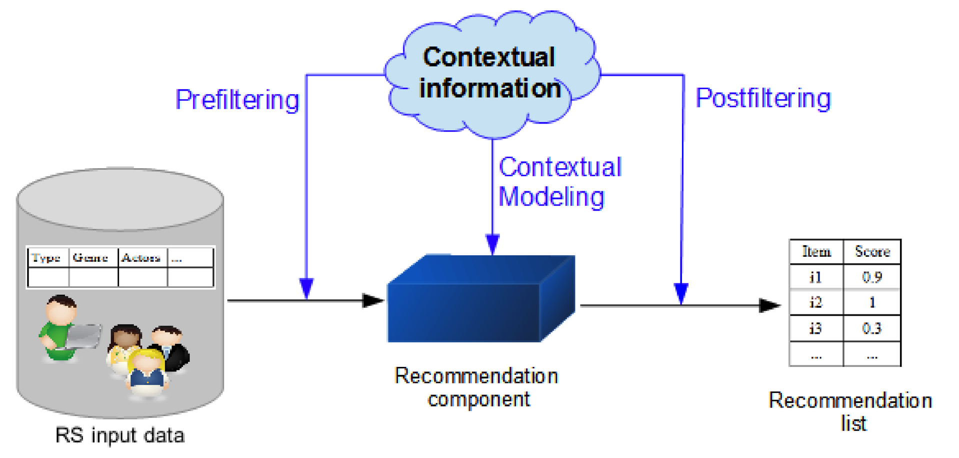

Figure 1: Three context integration approaches [2]

Correlation-Based Pre-Filtering (CBPF)

To recommend an item to a user in a specific context situation:

1. find similar context situations to the target user's one:
   (a) represent each context condition based on the item-based influence of context on ratings (computed by PCC),

$$w_{c_j i} = PCC_i(r, c_j) = \frac{\sum_{k \in K}(r_k - \overline{r_i})(c_{jk} - \overline{c_i})}{\sqrt{\sum_{k \in K}(r_k - \overline{r_i})^2}\sqrt{\sum_{k \in K}(c_{jk} - \overline{c_i})^2}} \quad (1)$$

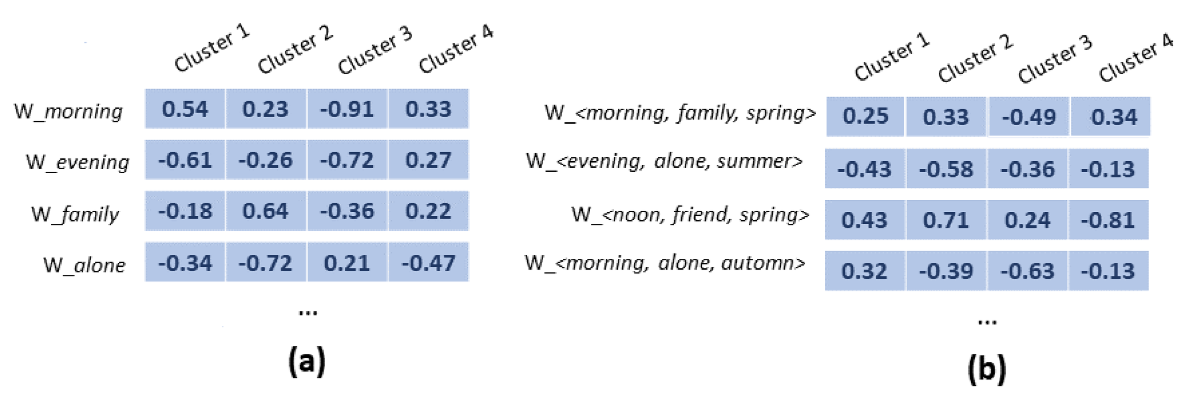

Figure 2: Context condition representation

   (b) represent each context,

Figure 3: Context situation representation

   (c) compute the similarity between each pair of context situation's vector.

$$sim(s, s^*) = cosine(\overrightarrow{w_s}, \overrightarrow{w_{s^*}}) = \frac{w_s^T w_{s^*}}{\sqrt{\sum_{i=0}^{d} w_{s,i}^2}\sqrt{\sum_{i=0}^{d} w_{s^*,i}^2}} \quad (2)$$

2. select the associated ratings (local dataset),
3. apply a traditional recommendation technique (matrix factorization) on this local dataset (local model).

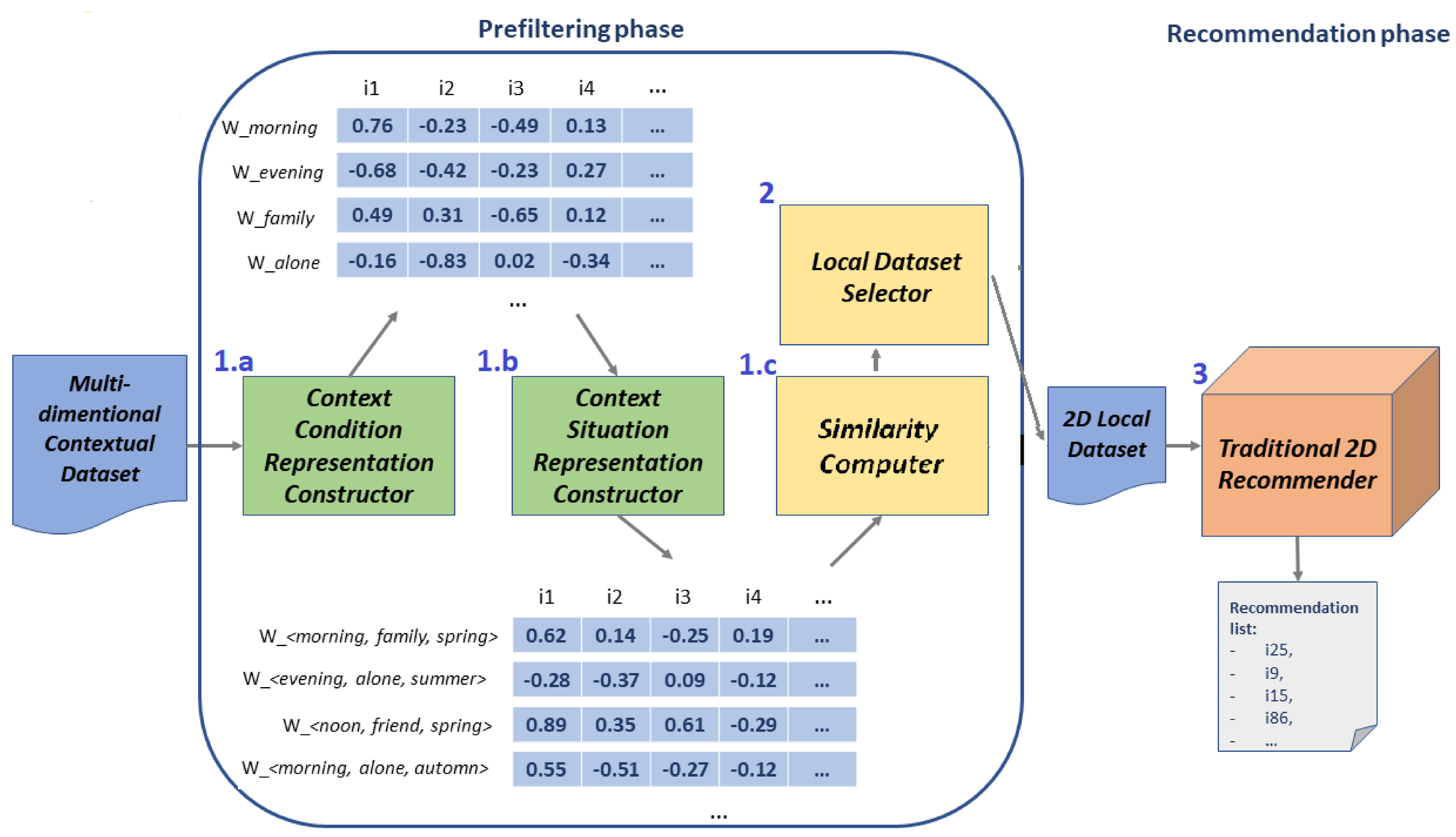

Figure 4: CBPF processing chain

Models	*MAE*	*RMSE*
CBPF	**0.733**	**0.945**
UI-Splitting [8]	0.826	1.035
DSPF [4]	0.867	1.089
CAMF [3]	0.737	0.966
TF [5]	0.869	1.114

Figure 5: Comparison with state of the art on CoMoDa dataset [6]

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Contact

zahra.vahidi-ferdousi@dauphine.fr / zvahidiferdousi@coheris.com