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A Restaurant Recommendation Engine Using Feature-based Explainable Matrix Factorization

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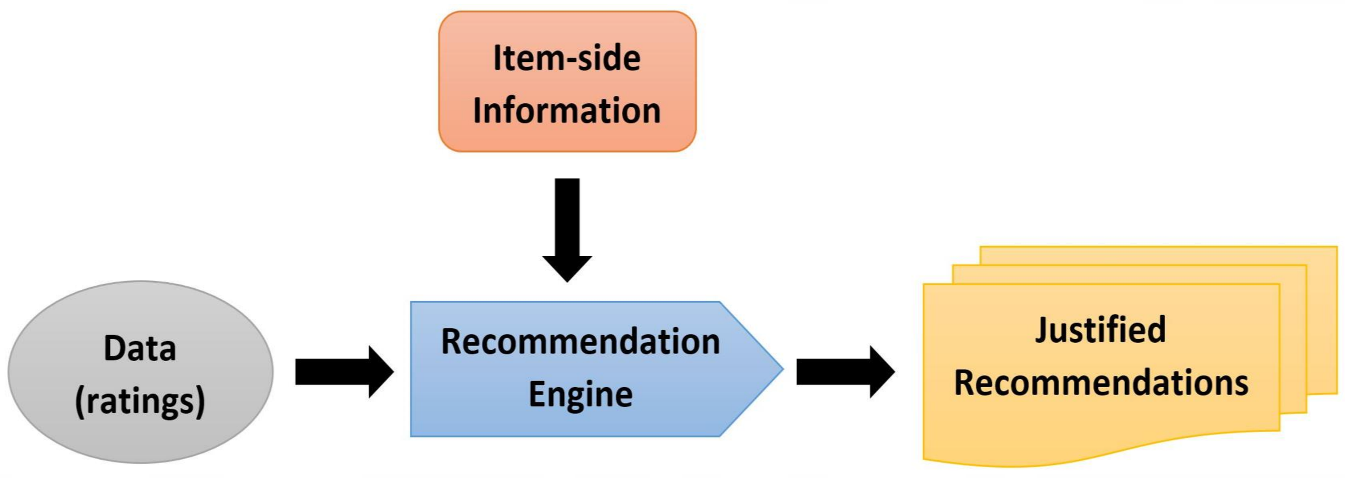
Introduction

Recommender Systems (RS) have been evolving in recent years. In the early years, recommendation engines were able to handle only simple data with straightforward suggestions like if the user sees an action movie, then the RS will recommend another action movie to watch next. In today's information-rich Internet, users explicitly and regularly express their interests and desires one way or the other through websites such as Amazon, Netflix, YouTube, and social media platforms. As a result, RS researchers and developers had to take advantage of this and create more robust and trustworthy recommendation engines. Moreover, the sparsity of data has increased and linking data together became a challenge. Therefore, the need for systems that can handle this issue arises.



Related Work

Collaborative filtering is designed to collaboratively build a list of items that target user's similar users have liked in the past [1]. In the other hand, Content-based Filtering is designed to take advantage of item-side information in building the recommendation list for the target user [2], [3], [4].
Recent work by [5] spots the light on the signification of explanation in hybrid RS. In this paper, they emphasize the need for more transparency in today's recommendation world. Therefore, the need for personalized and visualized recommendation justifications arises.
Abdollahi et al [6] proposed a novel method for extracting explainability scores for recommended items out of the black-box model. The idea is to calculate the cosine similarity of items similar to the rated ones. The experiment results showed more accurate recommendations yet explainable using only ratings as a source.

Proposed Method

In our proposed work we built the explainability score using users' cuisine interest in the restaurant dataset we used to experiment within this paper. We called our model FBEMF which stands for Feature-Based Explainable Matrix Factorization. We experiment using Restaurant Data with Consumer Ratings
The used dataset provide 1162 ratings of 138 users to 130 restaurants, in addition to 59 different cuisines names.
We constructed the feature-based explainability graph as follows:

$$E^I_{f,i} = \begin{cases} 1 & if\ f\ provided\ by\ i, \\ 0 & otherwise. \end{cases}$$

E denote the explainability matrix of items by features, whereas *f* is the selected feature to capture the explainability of the item which is in this case the cuisine type; *i* is the item or the restaurant name, *I* denotes the set of all restaurants or items in general.

$$E^U_{f,u} = \begin{cases} N & f\ provided\ by\ items\ rated\ by\ u, \\ 0 & otherwise. \end{cases}$$

f is the selected feature. *u* denotes a user whereas the total number of times each feature *f* (e.g., cuisine) is provided by items (e.g., restaurants) that the user *u* had interacted with previously. *U* is the set of all users.

$$E^{UI}_{u,i} = \begin{cases} E^U_{f,u} \cdot E^I_{f,i} & if\ \ E^U_{f,u} \cdot E^I_{f,i} > \theta^e, \\ 0 & otherwise. \end{cases}$$

A dot product of two equations will result in the explainability score for each user to each item based on the likeability of users to the selected feature which is the cuisine type in this case. ϑ^2 represents a threshold for items to be considered explainable to the user. We set it to 0 in this work causing all items even with a small explainability score to be in consideration.

$$\min J = \sum_{u,i \in R} (R_{u,i} - p_u q_i^T)^2 + \frac{\beta}{2}(\| p_u \|^2 + \| q_i \|^2) + \frac{\sigma}{2} \| p_u - q_i \|^2 E^{UI}_{u,i}$$

Koren et al [7] introduced the objective function of MF that factorizes the original matrix of known ratings into two matrices incorporating hidden features. The goal is to predict all ratings for all items by all users. Hidden features help MF understand both users and items better. The equation comprises a regularization term for overfitting avoidance. *β* is a regularization coefficient to ensure the addition of the new term is smooth. The next regularization term is for the explainability matrix calculated in previous equation with *σ* learning parameter to control the smoothness of the new term. *R* is the known ratings for item *i* by user *u*. *p_u* is the user latent space and *q_u* is the item latent space. *E* represents the feature-based explainability matrix for user *u* to item *i*. *U* and *I* are the set of all users and all items, respectively. Following are updating rules for *p_u* and *q_u* respectively:

$$p_u^{(t+1)} \leftarrow p_u^{(t)} + \alpha(2(R_{u,i} - p_u^{(t)}(q_i^{(t)})^T)q_i^{(t)} - \beta p_u^{(t)} + \sigma(p_u^{(t)} - q_i^{(t)})S^{UI}_{u,i})$$

$$q_i^{(t+1)} \leftarrow q_i^{(t)} + \alpha(2(R_{u,i} - p_u^{(t)}(q_i^{(t)})^T)p_u^{(t)} - \beta q_i^{(t)} + \sigma(p_u^{(t)} - q_i^{(t)})S^{UI}_{u,i})$$

Evaluation

- Explanation Style:

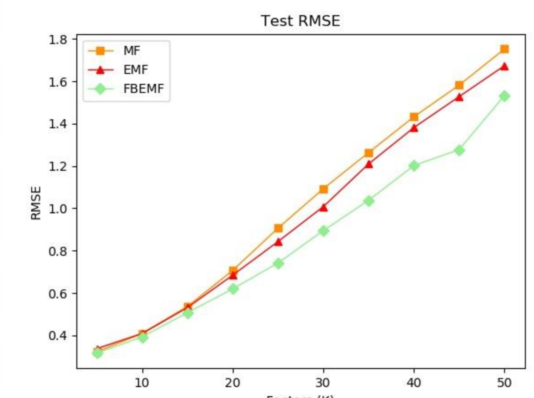
We are using Influence Style Explanation (ISE) explanation style:
We recommend restaurant X to you because it provides cuisine types A and B that you have liked in the past in other restaurants.

- Experimental Setting:

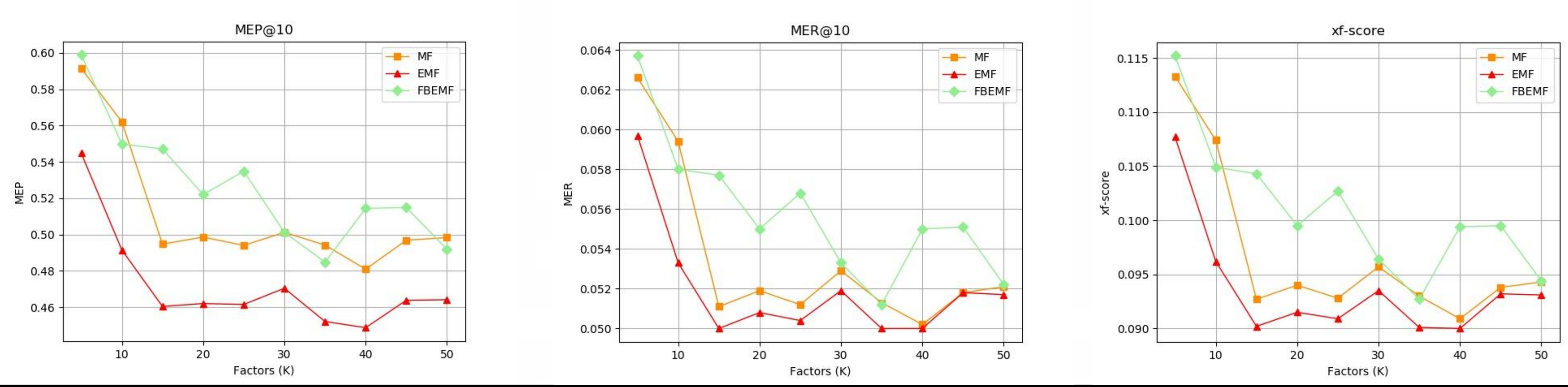
We tested out theory with Restaurant Data with Consumer Ratings dataset:
https://archive.ics.uci.edu/ml/datasets/Restaurant+\%26+consumer+data
Train dataset size is 90\% and the remaining 10\% is allocated for testing purpose. We tuned the hyper parameters with cross validation. We compared our model to state-of-the-art models EMF [6] and MF [7].

- Evaluation Metrics:

$$RMSE = \sqrt{\frac{1}{|T|} \sum_{(u,i) \in T} (r'_{ui} - r_{ui})^2}$$



$$MEP = \frac{1}{|U|} \sum_{u \in U} \frac{|R^{rec} \cap E|}{|R|} \quad \Big| \quad MER = \frac{1}{|U|} \sum_{u \in U} \frac{|R^{rec} \cap E|}{|E|} \quad \Big| \quad xF-score = 2 * \frac{MEP * MER}{MEP + MER}$$



Conclusion and References

Explanation in black box systems has been proven to be enormously beneficial in terms of improving the performance of the system and increasing the transparency, hence the trust, of the system.

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