A Semantically Aware Explainable Recommender System using Asymmetric Matrix Factorization

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Abstract: Matrix factorization is an accurate collaborative filtering method for predicting user preferences. However, it is a black box system that lacks transparency, providing little information about both users and items in comparison with white box systems. White box systems can easily generate explanations, relying on the rich information foundation that these systems exploit in an explicit manner. However, the accuracy of recommendations is generally low. In this work, we take advantage of the Semantic Web in the process of building a black box model which can make recommendations that can be explained. Our experiments show that our proposed method succeeds in producing lower error rates and in explaining its outputs.

1 INTRODUCTION

Collaborative filtering (CF) uses only rating data to predict user preferences. Because it does not require content, CF is generally better able to handle complex domains where content is hard to collect or to encode. In addition, because it is based on users' collective activity or ratings, CF is better able to make serendipitous suggestions that share little content-based similarity with a user's past preferences. One well-known CF technique that has shown powerful predictive ability is Matrix Factorization (MF) (Koren et al., 2009). Like other black box models, MF is accurate; however, because the recommendations are not explainable, it is not transparent.

The Semantic Web (SW) is a platform for structured data that is considered a rich resource for extracting additional knowledge and meaning about users and items (Bizer et al., 2009), in addition to the explicit preference ratings available on hand. In this paper, we present a new MF recommendation strategy that exploits additional SW resources for explanation generation.

2 RELATED WORK

Building user models or profiles is a fundamental task in many recommender systems. For this reason, and because the SW is a platform of linked data, there have been many efforts using the SW in this area. The SW was has also been utilized to build meaning-aware user models and user profiles within the Web personalization and Web Mining fields (Stumme et al., 2002) (Berendt et al., 2002). Reference (Berendt et al., 2005) emphasized that the SW will play an important role in Web Mining because of its capability to make information on the Web machine-processable and understandable. The combination of SW and Web Mining was also studied in (Stumme et al., 2006) where SW technologies improved the Web Mining results. In addition, (Nasraoui et al., 2008) built user profiles by integrating semantics obtained from ontologies, website structures, and implicit user activity data (clicks).

Furthermore, (Achananuparp et al., 2007) used web page textual content data along with the WordNet ontology (Miller, 1995) to build a semantically enhanced user model that can help in personalization and understanding user needs in information retrieval. In the context of building MF models, (BenAbdallah et al., 2010) proposed an asymmetric factorization technique for leveraging more domains in building an MF model. This approach was later used by (Abdollahi and Nasraoui, 2014) to learn a MF recommendation system that can handle the cold start problem. The method is based on building the MF model using one domain and then using another domain to learn the final version of the model.

Explainability has been studied in the context of recommendations with several different methods. For instance, (Bilgic and Mooney, 2005) proposed several

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recommendation explanation styles, such as Neighbor Style Explanation (NSE), Influence Style Explanation (ISE), and Keyword Style Explanation (KSE), it has also been explored by (Symeonidis et al., 2008). Herlocher et al. (Herlocker et al., 2000) argued that explanations are needed to enhance the performance of CF recommender systems. In their work, they explored 21 explanation interfaces, where they eliminated the recommended items and kept only the explanations for users to choose from, They found that, from a promotion point of view, the best interface that users voted for was a histogram-like explanation interface. Other interfaces included past performance, table of neighbors' ratings, and similarity to other movies rated. Later, (Vig et al., 2009) used community tags to explain recommendations. The researchers categorized explanations into three types, as follows: item-based, where an explanation is created based on other similar items; user-based, where the system relies on other similar users to explain its recommendation; and feature-based, where features, such as genre, are used to justify the output. It is worth mentioning that this work used the KSE explanation style. An example of an explanation could be as follows: *This movie is being recommended to you because it is tagged with mystery which is present in the tags of movies you liked before*. Another study that used KSE as the explanation style is (McCarthy et al., 2004) in which the researchers designed a Content-based Filtering model for recommending digital cameras. This system explains recommendations by converting cameras' components, such as memory size and resolution, into sentences. Then, users can choose what set of the explained features meet their requirements. In (Zhang et al., 2014), the authors built a CF recommender system that relies on the Latent Factor Models technique to produce accurate recommendations with attached explanations that are generated using sentiment analysis of users' reviews. Moreover, a solution was proposed in (Abdollahi and Nasraoui, 2016) and (Abdollahi and Nasraoui, 2016b) for black box MF using the ratings in a user's neighborhood to generate explanations. An explanation is generated based on how neighbors rated the recommended item, and the explanation style is NSE.

3 PROPOSED METHOD

Semantic data represents a rich source of knowledge about both users and items. For instance, it is possible to identify users who clearly show an interest in movies where certain actors play leading roles. Such meaningful knowledge can be used to generate meaningful explanations for recommended movies. However, to maintain transparency, it is desired to have these explanations consistent with the actual MF model that is built from rating data. In other words, we would like to build a MF model that takes into account not only user preference ratings but also potentially meaningful explanations for these ratings. For this purpose, we propose including available semantic knowledge that could later be used for explanations, in the process of learning a low-dimensional latent space representation of users and items. This process will need to incorporate information from two different domains, namely the domain of semantic knowledge for the explanations, and the domain of ratings for recommendations. One approach for accomplishing this multi-domain task is using Asymmetric MF (BenAbdallah et al., 2010) (Abdollahi and Nasraoui, 2014) which is a two step, multi-domain process. In the first step, a semantic latent space model is built using the explanation semantics of either or both users and items. Then, the semantic latent space model vectors from the first step are transferred to the second MF step, where users' explicit preference, such as rating, are used to update the final recommendation model. In this way, the final latent space vectors will strive to reconstruct the ratings used as input data in the second step, while being anchored in the semantic explanation data used in the first step of the factorization.

The flowchart of the proposed method, namely Asymmetric Semantic Explainable MF with User-Item-based (ASEMF_UIB) semantic explainability graph, is shown in Figure 1. The method consists of two phases, as follows: the knowledge foundation phase and model-building phase. In the first phase (Knowledge Foundation), both the semantic explainability graph and known ratings are prepared to be used by the model-building algorithm in the second phase, which will be devoted to learning the MF model using these semantics. The first semantic explainability graph for all users relative to all items is constructed based on a specific semantic feature (such as the actor for movie items).

First, an item by a semantic feature matrix is built as follows:

$$S^{I}_{f,i} = \begin{cases} 1 & if\, f\, possessed\, by\, i, \\ 0 & otherwise. \end{cases} \tag{1}$$

where f represents a semantic feature, such as an actor; i denotes an item (in this paper, a movie); and I is the set of all items. We then compute a second matrix for each user and semantic feature as follows:

$$S^{U}_{f,u} = \begin{cases} N & f\, possessed\, by\, items\, liked\, by\, u, \\ 0 & otherwise. \end{cases} \tag{2}$$

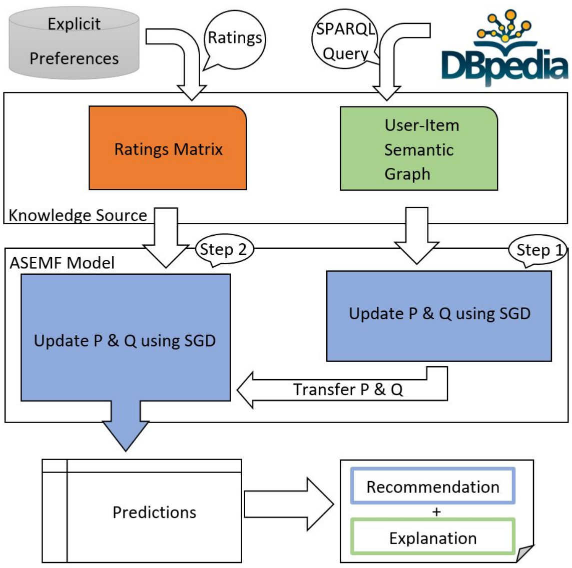

Figure 1: Flowchart for Asymmetric Semantic Explainable Matrix Factorization (ASEMF).

Here, U is set of all users and f is a semantic feature, as in the previous matrix. Moreover, u represents a user, and N is the number of times each semantic feature f was present in items that user u had rated in the past.

The previous two matrices can be combined into a score indicating how likely a user is to like an item based on how certain semantic features are preferred by the user and how likely those semantic features are to be present in the item. The combined score is computed using:

$$S^{UI}_{u,i} = \begin{cases} S^U_{f,u} \cdot S^I_{f,i} & if \;\; S^U_{f,u} \cdot S^I_{f,i} > \theta^s, \\ 0 & otherwise. \end{cases} \quad (3)$$

The resulting matrix contains explainable items. An explainable item is an item that has a certain probability of possessing a semantic property (such as having a certain starring actor) that seems to be possessed by many of the items liked by the target user based on previous ratings. Here, θ^s is a threshold for items to be considered explainable. In this study, we set θ^s to 0 when building the model, meaning that all items that have even a very small probability of being starred by actors who seem to be liked by the target user are considered explainable.

In this study, we focused on only the actors to illustrate our approach using the most widely employed public domain benchmark dataset which happens to be about movies. However, our technique applies to other properties, such as the director and writer which will be tested in the future. In fact, other domains have different properties and richer ontologies; however, the currently used public benchmark data are limited.

It is important to mention that the concept of explainability means explaining why a user would be interested in a recommended item (in the case of the example of the experimental data used in this paper, the item is a movie), and we propose to do this based on semantics underlying the item and domain while using MF to build the recommendation model. The idea of using a two-step MF approach to integrate two domains is called Asymmetric MF. The reason of choosing MF is because of its ability to handle big data and because it is one of the most commonly used and most powerful and versatile modeling methods for recommendations (Koren et al., 2009). In addition, it is chosen because it is a black box technique that lacks the power to explain its predictions.

In the next phase (model building), the model is built by going through two steps. The first step is learning the initial model's latent factors using the semantic explainability graph that was defined in equation 3. MF aims to perform the following factorization:

$$S^{UI}_{UxI} \simeq P_{UxK} Q^T_{IxK} \quad (4)$$

Here, K is the number of features, I denotes the number of items (e.g., movie), and U is the number of users. P_{uxk} represents the user lower rank dimensional space, where Q^T_{ixk} denotes the item lower rank dimensional space.
The objective function to be minimized over the semantic explainability graph is as follows:

$$J = \sum_{u,i \in \mathcal{S}} (S^{UI}_{u,i} - p_u q_i^T)^2 + \frac{\beta}{2}(\| p_u \|^2 + \| q_i \|^2) \quad (5)$$

where β is a coefficient for the regularization term and $\mathcal{S}$ is the set of user-item with non-zero explainability score $S^{UI}_{ui} > 0$. Since J is convex with respect to either p or q, stochastic gradient descent is used to update p and q in an alternating manner. The gradient of J with respect to p_u is

$$\frac{\partial J}{\partial p_u} = -2(S^{UI}_{u,i} - p_u q_i^T) q_i + \beta p_u \quad (6)$$

The gradient of J with respect to q_i is

$$\frac{\partial J}{\partial q_i} = -2(S^{UI}_{u,i} - p_u q_i^T) p_u + \beta q_i \quad (7)$$

Thus, the update rules are given by

$$p_u^{(t+1)} \leftarrow p_u^{(t)} + \alpha(2(S^{UI}_{u,i} - p_u^{(t)}(q_i^{(t)})^T) q_i^{(t)} - \beta p_u^{(t)}) \quad (8)$$

$$q_i^{(t+1)} \leftarrow q_i^{(t)} + \alpha(2(S^{UI}_{u,i} - p_u^{(t)}(q_i^{(t)})^T) p_u^{(t)} - \beta q_i^{(t)}) \quad (9)$$

In the second step of the model building phase, a MF model is built using the known ratings, as follows:

$$R_{UxI} \simeq P_{UxK} Q_{IxK}^{T} \tag{10}$$

where R_{UxI} represents the ratings matrix. The objective function to be minimized over known ratings is

$$J = \sum_{u,i \in \mathcal{R}} (R_{u,i} - p_u q_i^T)^2 + \frac{\beta}{2}(\| p_u \|^2 + \| q_i \|^2) \tag{11}$$

Where $\mathcal{R}$ is the set of user-rating pairs ui given ratings in R. The update rules can be shown to be:

$$p_u^{(t+1)} \leftarrow p_u^{(t)} + \alpha(2(R_{u,i} - p_u^{(t)}(q_i^{(t)})^T)q_i^{(t)} - \beta p_u^{(t)}) \tag{12}$$

$$q_i^{(t+1)} \leftarrow q_i^{(t)} + \alpha(2(R_{u,i} - p_u^{(t)}(q_i^{(t)})^T)p_u^{(t)} - \beta q_i^{(t)}) \tag{13}$$

In this study, we use two sources of knowledge to build the model: the explainability graph and the known ratings. In the second step, weak explainability scores will be taken over by the known ratings. However, if the explainability score is high in the first step, it will still be high in the second step and will take over the known ratings. It is likely that the number of iterations of MF updates in the second step will affect how likely the second domain (the ratings) will be to take over the first domain (semantics of items). In general, we can expect those users who show an interest in items with a semantic property (movies starring certain actors) to obtain better explainable recommendations using our proposed two-step model. Our method is not foolproof; it strives to optimize both explainability and predictive accuracy simultaneously, and hence, one of these criteria may weigh more heavily in the final optimum.

4 EXPERIMENTAL EVALUATION

We use the MovieLens 100K dataset. Movies from the MovieLens 100K and DBpedia [1] are first matched, resulting in a reduction of the total number of ratings to 60K. The ratings are normalized as follows:

$$R_{ui} = \frac{R_{ui} - min_i}{max_i - min_i} \tag{14}$$

where u and i are the user and item, respectively. The hyper parameters are $\alpha = 0.01$ and $\beta = 0.1$. They are tuned to their optimal values using cross-validation. The experiments are run 10 times, and the training portion of the dataset is 90%; the latest 10 % is allocated to the test set.

[1] small DBpedia.org

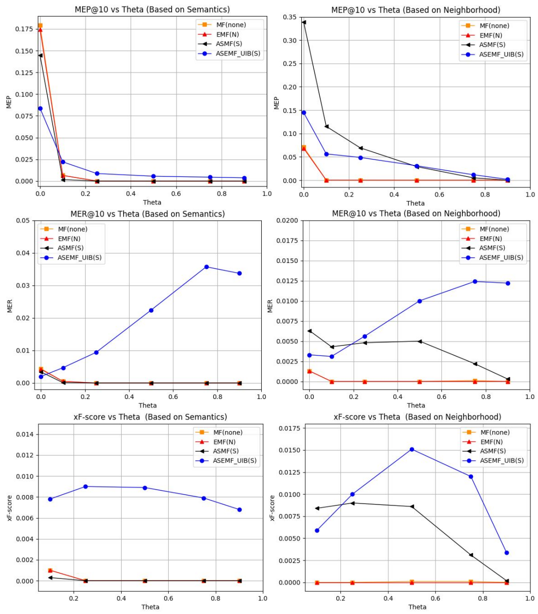

Figure 2: The left three graphs show a comparison of the MEP, MER, and xF-score between the methods using the semantic explainability graph versus θ^s. The three right graphs show a comparison of the MEP, MER, and xF-score between the methods using the neighborhood explainability graph versus θ^n.

We compared our model to three baseline approaches, as follows: basic MF (Koren et al., 2009), Explainable MF (EMF) (Abdollahi and Nasraoui, 2016), and basic Asymmetric MF (AMF) (Abdollahi and Nasraoui, 2014), which is a hybrid approach.

We first evaluate the prediction accuracy, and hence the error rate using the Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{|T|} \sum_{(u,i) \in T} \left(r'_{ui} - r_{ui}\right)^2} \tag{15}$$

where T represents the total number of predictions, r'_{ui} is the predicted rating of item i by user u, and r_{ui} is the real rating of item i by user u.

As illustrated in Table 1, we carried out a significance test to compare the RMSE of our approach with the baseline methods at K = 10. The p-value = 4.49e-15 between ASEMF_UIB and MF, 1.46e-13 between ASEMF_UIB and EMF, 1.77e-21 between ASEMF_UIB and AMF. This indicates that our method significantly outperforms other methods.

Since our approach aims to recommend explainable items, we also evaluated all the approaches using the explainability metrics MEP, MER, and xF-score (Abdollahi and Nasraoui, 2016) to show how much all the approaches recommend explainable items in the top 10. MEP is the Mean Explainability Preci-

Table 1: RMSE versus number of latent factors K. ASEMF_UIB denote our proposed method, namely Asymmetric Semantic Explainable Matrix Factorization augmented with User-Item based semantic explainability graphs.

K	MF	EMF	AMF	ASEMF_UIB
10	0.2221	0.2188	0.2386	0.2059
20	0.2503	0.2461	0.2756	0.2047
30	0.2866	0.2771	0.315	0.204
40	0.3283	0.3176	0.3508	0.2039
50	0.3844	0.3639	0.3833	0.2038

sion, the ratio of recommended and explainable items to the total number of recommended items. MER is the Mean Explainability Recall, the ratio of recommended and explainable items to the total number of explainable items. The xF-score is the harmonic mean of MEP and MER. The definitions of MEP, MER, and xF-score are (Abdollahi and Nasraoui, 2016):

$$MEP = \frac{1}{|U|}\sum_{u \in U}\frac{|R^{rec} \cap W|}{|R|} \quad (16)$$

$$MER = \frac{1}{|U|}\sum_{u \in U}\frac{|R^{rec} \cap W|}{|W|} \quad (17)$$

$$xF - score = 2 * \frac{MEP * MER}{MEP + MER} \quad (18)$$

Here, U represents the total number of users, R^{rec} is the set of recommended items, and W denotes the set of explainable items. In this type of evaluation, we compared our method with the baseline methods using MEP, MER, and xF-score, computed based on two different explainability graphs. The first graph is the semantic explainability graph S^{UI} that we constructed (see equation 3). The second graph is the neighborhood explainability graph (Abdollahi and Nasraoui, 2016), and it is defined as follows:

$$W_{ui} = \begin{cases} \frac{|N^{'}(u)|}{|N_k(u)|} & if \quad \frac{|N^{'}(u)|}{|N_k(u)|} > \theta^n \\ 0 & otherwise \end{cases} \quad (19)$$

where $N^{'}(u)$ is the set of neighbors of user u who rated item i, and $N_k(u)$ represents the list of k nearest neighbors of u. θ^n is a threshold for considering item i as an explainable item to user u or not.

The results are shown in the three left line charts in Figure 2 and they indicate that when comparing all methods based on using the explainability metrics that are computed based on the semantic explainability graph (see equation 3), the baseline methods EMF and MF perform better using MEP and MER metrics with $\theta^s = 0$. However, with increasing θ^s, which means putting more constraints on items for them to be considered semantically explainable, our proposed ASEMF_UIB method outperforms all three other methods, thus succeeding in producing more explainable items in the top 10 than the other methods do. The xF-score shows that our proposed method is the top performer.

We also compared all methods using the explainability metrics, based on the neighborhood explainability graph (see equation 19). The three line charts on the right in Figure 2 show that with $\theta^n = 0$ the baseline method Asymmetric MF (AMF) (Abdollahi and Nasraoui, 2014) is the best. This can be attributed to the fact that this method updates only the users' latent space in the second step of building the model, while leaving the items' latent space fixed, resulting in a bigger effect of neighbors in the recommendation process. Nevertheless, with increasing θ^n, our proposed ASEMF_UIB method performs better using all three metrics, namely the MEP, MER, xF-score.

5 CONCLUSIONS

MF is a powerful CF technique for predicting ratings for unseen items. However, it is unable to explain its output. We addressed this limitation by using the Semantic Web to provide a solution for increasing the transparency of MF while preserving its accuracy. The experimental results indicate that our proposed method, which leverages SW in building an explainable MF, outperformed the baseline approaches in terms of error rate and explainability metrics, MEP, MER, and xF-score, especially when placing more constraints on items to be considered semantically explainable. In the future, we plan to expand our explanations to richer semantics, and to perform more comprehensive experiments, including hybrid recommender baselines, and additional domains.

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