International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-8, June 2020

Explanation Generation Mechanism for Black Box Recommendation Model

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Abstract**: *The recommender system is everywhere, and even streaming platform they have been looking for a maze of user available information handling products and services. Unfortunately, these black box systems do not have sufficient transparency, as they provide littlie description about the their prediction. In contrast, the white box system by its nature can produce a brief description. However, their predictions are less accurate than complex black box models. Recent research has shown that explanations are an important component in bringing powerful big data predictions and machine learning techniques to a mass audience without compromising trust.This paper proposes a new approach using semantic web technology to generate an explanation for the output of a black box recommender system. The developed model is trained to make predictions accompanied by explanations that are automatically extracted from the semantic network.***

Keywords:* *Recommender systems, Matrix factorization, Artificial intelligence, collaborative filtering, Explanation, Semantic network.

I. INTRODUCTION

Today, it is well recognized that a model-based approach to recommendations can recommend items of a very high level. Unfortunately, even if the model embeds content-based information, navigating to a potential space can result in a reference to the actual semantics of the suggested item and therefore this makes it non-trivial to interpret the recommendation process. On the other hand, in the next generation of recommendation algorithms, the transparency and interpretability of the predictive model is gaining momentum because the predictive model has been identified as a key factor. Interpretability can increase user awareness in the decision-making process and lead to rapid (efficiency), conscious, and correct decision-making. When the results of recommendations are interpreted, the system is no longer just a black box [1, 2, 3], and users are ready to make extensive use of the prediction [4, 5].In fact, transparency increases trust [6] (taking advantage of a certain semantic structure [7]) and satisfaction when using the system.

Revised Manuscript Received on June 30, 2020.
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The recommendation system is an increasingly used online platform that predicts preferences and recommends options for user. Matrix factorization (MF) [8] is strong recommendation model generate accurate recommendations, but unfortunately lacks transparency. The reason for its output cannot be explained and is therefore referred to as the black box recommendation system shows in the Fig 1. In addition, the explicit setting of the user may be unreasonable to think about the model of the proposed product. Since users may not have given the new elements any preference, these elements are discarded. This phenomenon is known as the cold start problem in the field of recommendation [9]. Linked open data (LOD) [10], structured and connect the data to internet. LOD is to semantically connect the information for machine process. The contribution of this paper is to solve the problem of non-transparent recommendation system of MF, as well as to build semantic representations of users, elements, and semantic attributes for the process of inference and explanation shown in Fig 3.

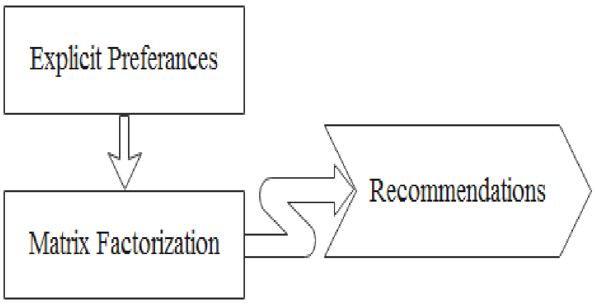


Fig 1: Without Explanation Black Box Matrix Factorization.

II. RELATED WORK

MF is technologies are uses to generate recommendation models [8]. The MF is learn the latent space vector M , N of each user and item. The Fig. 2 shows MF method flowchart. The idea is dot product of two latent spatial representations can be used to predict the evaluation of an invisible item, as well as to approximate the original evaluation of a given potential feature. The SGD is a Stochastic Gradient Descent.

The authors [11] take advantage of Koren work [8], including information like from customer side and product side. Contrary to the film's genre, size, color, and actors, details about the information to represent, and this data is almost always available. RippleNet [12] is an approach that provides Side information for the system using KGs in collaboration filtering.

In paper [13] the author focuses on uses a structured knowledge base and adding an explanation to the black box recommendation system. For users of structured bases of knowledge of the exact recommendations to historical user preferences for the system of preparation of the item grounds. After the model is recommended, the soft matching algorithm is used to make the best use of the knowledge base of nanoscience and nanotechnology for the explanation of recommendations. The author noted that in this model there is no existing baseline.

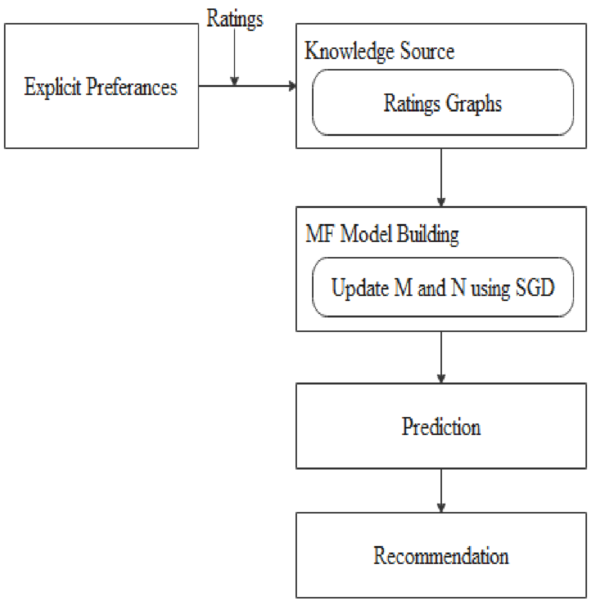


Fig 2: MF method flowchart [8]

In paper [14], Black box recommendation focuses on issues that explain the system's output. The SemAuto recommendation system utilizes the neural network technology of an automotive encoder to recognize the KG.The KGs are employed for the generation of description. The authors claim that the description increases user's satisfaction, loyalty, and confidence in the system. In [15], preparing explanations was proposed. A single heterogeneous information network (HIN) is created that provides explanation to recommended elements. Three ranking indicators are used to rank candidates for the path of explanation. In [16] [17] investigated produced explanation to inferring black box systems. As a result, it was found that the explicable matrix factorization (EMF) was more effective than the basic approach. The large data [18] structure conforms to resource description structure (RDF) standards. In a number of studies, LOD has been used to improve recommendation systems.

Passant [19] products use semantic web technology. The system generates a list of recommendation and utilizes LDSD algorithm [20]. In [21] proposes an explainable approach for recommending hybrids, white boxes, and movies. In this study, we will examine the items and users obtained from the additional information that collaborative research and content-type filtering techniques are used. The author stressed that the interpretation is important in gaining the trust and satisfaction of customers. Another in [22] describes the community tags used. In this study, the authors used the description style of KSE for a variety of tasks, such as 1) an item-based description was created based on similar items, 2) a user-based description of recommendations by similar users, and 3) the functional base that various functions used to explain output.

III. METHODOLOGY

A. Semantic Knowledge graphs (KG)

Network replete with information to collected and structured in the form of KG. The KGs is an extensive network of objects, which is the relationship between their properties, semantic types, and objects that represent actual information in a particular area [23]. Some examples of KG are DBpedia [24], Wikidata [25], NELL [26], YAGO [27], Freebase [28], and Google Knowledge Graph [29].The proposed system block diagram shows in Fig 3.

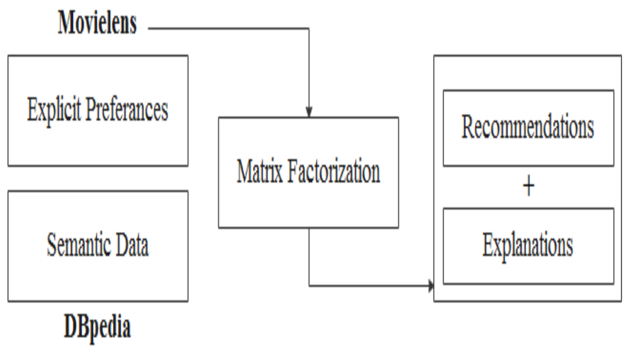


Fig 3: Block diagram of the proposed system.

DBpedia used to find KGs of approximately the user's items. In contrast to [30], when constructing KG, only one semantic attribute (actor) is taken into account, and therefore the model, the other semantic attribute like subject, director, and producer are considered. The LDSD algorithm [20] compares the similarities of items. To build the model uses the MF [8] [11]. Passant [31] proposed a method of building music recommendation system. The proposed algorithm takes incoming and outgoing, as well as direct and indirect relationships among the subjects.

B. Linked Data Semantic Distance Matrix Factorization (LDSD-MF)

The proposed techniques are described as follows by loss functions, related to Linked data semantic distance matrix Factorization (LDSDMF) [8][11]:

$$L = \sum_{u,i\in R}(R_{u,i} - M_u N_i^T)^2 + \frac{\gamma}{2}\sum_{i,j\in S^{ldsd}}(S_{i,j}^{ldsd} - NiN_j^T)^2 + \frac{\beta}{2}(||M_u||^2 + ||N_i||)^2 \quad (1)$$

Where, the rating represented by $R_{u,i}$ for item *i* and by user *u*.The low dimensional latent factor vectors of users represented by M_u, N_i. S^{ldsd} isthe semantic KG. The N_i and N_j indicate two items in S^{ldsd} and γ is a coefficient. The method in [32] is used to iteratively update M and N until J converges. The updated rules are:

$$M_u^{(t+1)} \leftarrow M_u^{(t)} + \alpha(2(R_{u,i} - M_u^t(N_i^{(t)})^T)N_i^{(t)} - \beta M_u^{(t)}) \quad (2)$$

$$N_i^{(t+1)} \leftarrow N_i^{(t)} + \alpha(2(R_{u,i} - M_u^{(t)}(N_i^{(t)})^T)M_u^{(t)} + 2\gamma(S_{i,j}^{ldsd} - N_i^{(t)}(N_j^{(t)})^T)N_j^{(t)} - \beta N_i^{(t)}) \quad (3)$$

KG used an approach that followed Alsham Marie (2018). To known evaluations update N_i, KG also contributes to the final predictive evaluation of item *i* by user *u*.

IV. RESULT AND DISCUSSION

The study uses the MovieLens100K benchmark dataset. The total number of users is 943, the total number of films is 1,862. The mapping process uses SPARQL, the semantic web query language,and the movie title for mapping.As a result 1,012 movies interact with two datasets, the reason for this decline is either the absence of a DBpedia movie or the absence of another spell.

This mapping also led to a decrease assessments to 60k. All ratings are normalized to 1. 90% of the evaluation is used to train the model, and 10% is used to test the model. The latent space of the user and the item randomly initialized by our method, an average of 10 experiments was observed. In Table 1, number of attributes selected in the test, with a unique Id, total number triples of the movies and total number triples of users.

TABLE 1: In experiment selected semantic attributes of numeric values

ATTRIBUTES	UNIQUE ID	TRIPLE (MOVIES)	TRIPLE (USERS)
Subject	3454	12454	818783
Actor	3156	5456	353432
Director	1675	1945	83456
Producer	1456	1867	102387
Writer	1564	1934	110645

Five different features extracted from KG DBpedia semantic databases.

The unique items displayed second column. The third column shows pre-existing film triple and attributes of DBpedia. For example, "Mel Gibson plays the title role in the film Braveheart".

The last column shows semantic size KG. The first metric is the error rate in Eq. (4), while the other metrics are the Mean explicability accuracy (MEP) in Eq. (5), Mean Explain ability Recall (MER) in Eq. (6), and the harmonic mean of accuracy and recall (XF-score) in Eq.(7).

$$RMSE = \sqrt{\frac{1}{|T|}\sum_{(u,i)\in T}(r_{ui}^{i} - r_{ui})^2}$$

(4)

The total number of prediction is represented by *T*, r_{ui}^{i} represents rating and r_{ui} is actual rating.

$$MEP = \frac{1}{|U|}\sum_{u\in U}\frac{|R \cap W|}{|R|} \quad (5)$$

$$MER = \frac{1}{|U|}\sum_{u\in U}\frac{|R \cap W|}{|W|} \quad (6)$$

$$XF - score = 2 * \frac{MEP*MER}{MEP+MER}$$

(7)

Where, the set of user represented by *U*, Recommended items is represented by *R*, and *W*is denoted by set of explainable items. The MEP calculates the ratio of recommended and explainable elements. The MER counts recommended and explicable element of explicable elements of whole customers. The XF report is a harmonious means and measures of MEP and MER. Our hypothesis is based on our metric model using a basic approach. The model runs 10 times for random initialization of the user and hidden element factors, calculates all metrics, and calculates the significance described in this paper.Table 2 shows the error rate for all methods. The best values is lower value, indicated in bold.

Table 2: RMSE, varying the number of hidden features, K.

K	MF	EMF	PMF	AMF	ASEMF _ UIB	LDSD-MF
10	0.205	0.205	0.667	0.235	0.205	**0.204**
20	0.212	0.208	0.667	0.25	0.204	0.204
30	0.213	0.211	0.667	0.308	0.204	0.205
40	0.214	0.213	0.7	0.335	0.203	0.205
50	0.215	0.216	0.7	0.367	0.203	0.206

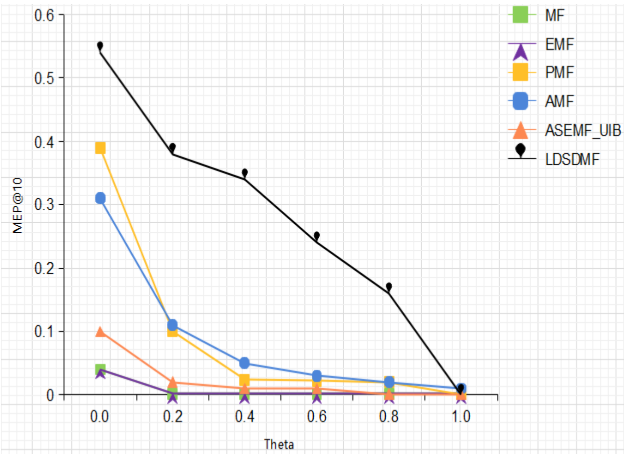
The Fig 4, shows the performance of all models, it varying θ^n . θ^n Specifies a barrier element that can be measured enables neighborhood method uses in EMF. The formula for generating a neighborhood-method in Eq. (8):

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

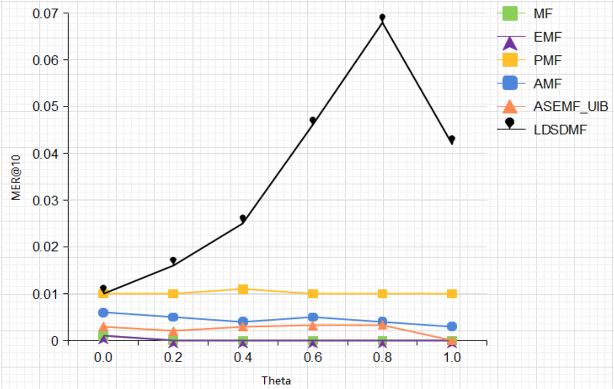
(8)

Where, set of neighbor's*u* is represented by $N'(u)$ who rate the item *I*, and$N_k(u)$represents the *k*nearest neighbors of *u*.

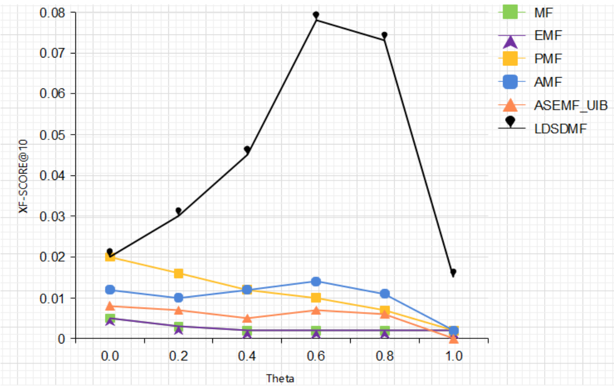
The graph in the fig. 4, the effectiveness of the model in measuring the explicability feasibility of recommended elements based on the neighborhood method is shown.Our model, LDSDMF, has significantly outperformed all the basic methods in all three metrics. This observation shows that our proposed system accurately recommends the explainable items, than other baseline method using the semantic KGs and neighborhood based techniques.



(a) MEP@10 Vs Theta



(b) MER@10 Vs Theta



(c) XF-Score@ 10 Vs Theta

Fig 4: Effectiveness of models in measuring the explicability of recommended elements based on the neighborhood method

V. CONCLUSION

As recommendation systems, large data and artificial intelligence (AI) systems is an essential component of and as this system of society, more and more sectors includes, it becomes more critical often turns into trust and transparency to machine learning algorithms without any loss of prediction power. We uses AI capabilities such as KGs and semantic inference to help build explicability in accurate black box forecasting systems so that it is modular and extensible for various forecasting tasks inside and outside of recommendation systems.

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