Graph-based Rating Prediction Using Eigenvector Centrality

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Abstract: The most of recommendation systems rely on the statistical correlations of the past explicitly given user rating for items (e.g. collaborative filtering). However, in conditions of insufficient data of past rating activities, these systems are facing difficulties in rating prediction, this situation is commonly known as the *cold-start problem*. This paper describes how graph-based represendation and Social Network Analysis can be used to help dealing with cold-start problem. We proposed a method to predict user rating based on the hypotesis that the rating of the node in the network corresponded to the rating of the most important nodes which are connected to it. The proposed method has been particularly applied to three MovieLens datasets to evaluate rating predition performance. Obtained results showed competitiveness of our method.

1 INTRODUCTION AND RELATED WORK

Rating prediction is an important and popular research topic in the area of recommendation systems. In a typical Collaborative filtering system user assigns ratings to already known items, so the system can predict ratings of unknown items based on the ratings that other similar users assigned to these items (Celma, 2010). Similarity among the users can be represented by the similarity of rows in user-item matrix where each row represents the rating given by user to the particular item (i.e. who rated the same items with similar scores). The most highly rated unknown items commonly are presented as recommendations to the user.

Despite the fact that Collaborative filtering is one of the most widely used recommendation methods it has several issues, such as the complexity of the finding the similar users in case of sparse user-item matrix (i.e. *cold-start problem*) and subjectivity and ambiguity of explicitly given rating (Ricci et al., 2011). Moreover, according to (Cena et al., 2010) and (Gena et al., 2011), users have different preferences with respect to the rating scales to use for the object they are evaluating i.e. rating scale are differently perceived by users.

Recommendation systems collect data for a significant period of time and emotional state of the user can vary greatly during this period, causing variation of the rating. As a consequence, the search for similar users may give false positive results.

Content-based filtering approach solves some of the issues of the Collaborative filtering by collecting information describing items. This approach relies on the similarity of items, which is defined as objective distance between items (e.g. the similarity of properties), without any influence by subjective factors. Items which are similar to the preferences given by user are typically presented as recommendations. Obvious problem of this approach is the need to extract, maintain and store a lot of relevant and reliable information about the items that can be a challenging task depending on the domain complexity. For instance, due to the vastness of the multimedia field, the user is often unable to describe his preferences correctly and fully. In addition, in a real world his preferences at the specific moment of time may be influenced by the other unknown factors such as various psychological effects or his friends' opinions. Besides, content-based filtering approach is limited by the type of content that can be recommended in that way.

Towards improving the results of recommendations, many researchers use so-called Hybrid methods to find the best combination of the abovementioned methods (Burke, 2002).

Nowadays, usage of graph-based structures and application graph theory to extract additional hid-

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den features is gaining popularity (Nuñez-Gonzalez and Graña, 2015; Tiroshi et al., 2014; Zeng et al., 2013). Graph-based representation allows to visualise and deeply understand semantic relations among items and users. Introduced in the beginning of the 20th century by sociologists, *Social Network Analysis (SNA)*(Scott, 2012) became widespread in recent years due to the advent of the social network websites such as *Facebook* and *Twitter*.

For example, the effective identification of important nodes and, in general, discovering of hidden network organization structure is a challenging task for current large-scale social networks (Sun et al., 2014). Like the most powerful people in the community, important nodes influence not only the nodes directly connected to them, but also the whole network. User's interests also have heterogeneous structure and they can be represented by the network of connected nodes (interests) which have varying degrees of importance. Typical for the Collaborative filtering methods user-items relationships can be easily represented as a bipartite graph and applying SNA to this network structure might discover some hidden features. Obtained additional information is capable to help to better understand the data that can be useful to improve the results of recommendation process.

The advantages of usage of SNA motivated us to examine rating prediction process from the other side. We have used the network structure to predict the user's given rating based only on user's personal preferences and his previous feedback. The proposed method has no limitations concerning the type of recommended items, which is typical for content-based systems, and also does not rely on the other users' feedback, as collaborative filtering algorithm does. This approach adapts to the user's behaviour and allows us to calculate recommendations independently for each user.

Summary of Contributions

The main contributions of the paper are the followings:

- Novel graph-based rating prediction method that is based on eigenvector centrality.
- Rating impact measuring process, which helps to deal with the variation of rating.
- Experiments on three well-known MovieLens datasets to show the comparison results in different data sparseness and measuring its performance with respect to well-known *MAE* and *RMSE* metrics.

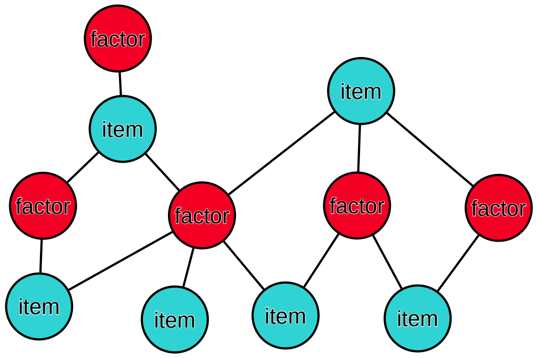

Figure 1: The example of created undirected bipartite item-factor graph.

2 METHODOLOGY

Our research was based on the hypothesis that *the rating of the node in the network corresponds to the rating of the most important nodes which are connected to it*.

We have focused on the item-item relationships inside users interests. This examination allowed us to look deeper into the preferences of each individual user, by identifying the underlying factors that influenced his choice. The item-item relationships are of little use to find hidden patterns, because they describe only the existence of a link (similarity) between objects, but do not explain the reason for this connection. To compensate it, we needed to add the intermediate objects in the relationships between items - *the factors*.

The factor is any object semantically defining the existence of connection between items. In other words, if there is a common factor between two or more items, these items are semantically connected. Genres (categories) of music, films or literature may be considered as the representative examples of factors.

As a result, we have created undirected bipartite graph $G = (I, F, E)$ where I is a set of items, F is a set of factors and E denoting the edges of the graph (Figure 1).

Following our aforementioned hypothesis, we require to determine the importance of each node in the network, before we can predict the rating. For this purpose, we have used the SNA *eigenvector centrality* measure. Based on the idea that the node importance in a network is increased by having connections to other nodes that are themselves important, eigenvector centrality computes the centrality of a node based on the centrality of its neighbours. Hence, the value of eigenvector centrality can be large not

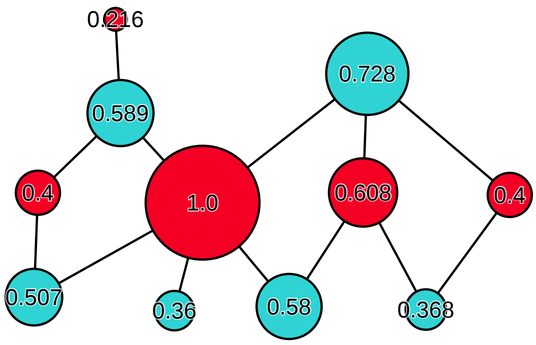

Figure 2: Nodes are ranked, based on the normalized value of eigenvector centrality.

only because a node has many neighbours, but also if it has important neighbours (or in both cases).

Definition 1 (Eigenvector Centrality)**.** *For given graph G the eigenvector centrality $c(i)$ of node i is proportional to the sum of the centralities of i's neighbours:*

$$c(i) = \sum_{t \in G} A_{it} c(t) \tag{1}$$

where A_{it} is an element of adjacency matrix (Newman, 2010). This measure was firstly proposed by Bonacich in 1987 (Bonacich, 1987). Figure 2 demonstrates the example of graph, where nodes are ranked, based on the value of centrality.

In the most of the practical cases a rating scale is discrete, not continuous. As we mentioned before, user's choice can be influenced by the unknown factors, so rating scale can be differently interpreted depending on user's current emotional state. As a result, we are dealing with *atypical* rating for this user. We elaborated rating impact measure using eigenvector centrality to deal with outliers. This measure allowed us to correctly approximate the rating of node, based on the rating of its neighbours.

Definition 2 (Rating Impact)**.** *Let R be predetermined numerical set of possible ratings (e.g. from 1 to 5), predicted rating r_i of the node i must be an element of predetermined set R. Based on the eigenvector centrality we can determine the impact of each possible rating in the subset of node neighbours.*

A rating impact I_r of rating $r \in R$ can be measured by:

$$I_r = \sum_{i \in N} c(i) \tag{2}$$

where N is a subset of node neighbours which have rated by rating r and $c(i)$ is a value of eigenvector centrality of node $i \in N$.

High-impact rating among node neighbours can be used as the predicted rating of node. In other words, neighbour nodes are *"voting"* for the best rating according to their importance. Similarly to eigenvector centrality, rating of node can be chosen not only because node has a lot of neighbours rated by some rating, but also if it has important neighbours.

3 EXPERIMENTAL EVALUATION

3.1 Datasets

To implement and evaluate the proposed algorithm, we have exploited three datasets provided by GroupLens Research group at University of Minnesota [1] to show the comparison results in different data sparseness. The first dataset is MovieLens 1M dataset, which contains 1,000,209 anonymous ratings of approximately 3,900 movies made by 6,040 users, ratings are made on a 1-to-5-star scale. The second dataset is MovieLens 10M dataset, which contains 10,000,054 ratings applied to 10,681 movies by 71,567 users, ratings are made on a 5-star scale, with half-star increments (from 0.5 to 5). The last dataset is MovieLens 20M dataset, which contains 20,000,263 ratings of 27,278 movies made by 138,493 users, ratings are made on a 5-star scale, with half-star increments (from 0.5 to 5) (Harper and Konstan, 2015). All of them provided genres and year of release as side information for each movie.

3.2 Evaluation Procedure

From the abovementioned datasets we produced small datasets consisted of ratings, given by randomly selected 1000 users. Each user's subset of ratings was randomly 80%-20% split to train-test subsubsets of the ratings data.

For our experiment, we developed the prediction script in Python programming language. For graph constructing, analysis and eigenvector centrality calculation we used NetworkX library (Hagberg et al., 2008).

Afterwards, for each user, prediction script constructed undirected bipartite (movie-factor) graph using training set and conducted calculating eigenvector centrality for each node in this graph. Genres and year of release were used as the factors.

At the initial stage all *factor nodes* are not rated. Obtained values of centrality were used by the script to predict rating for each *factor node* in the graph

[1] http://grouplens.org/

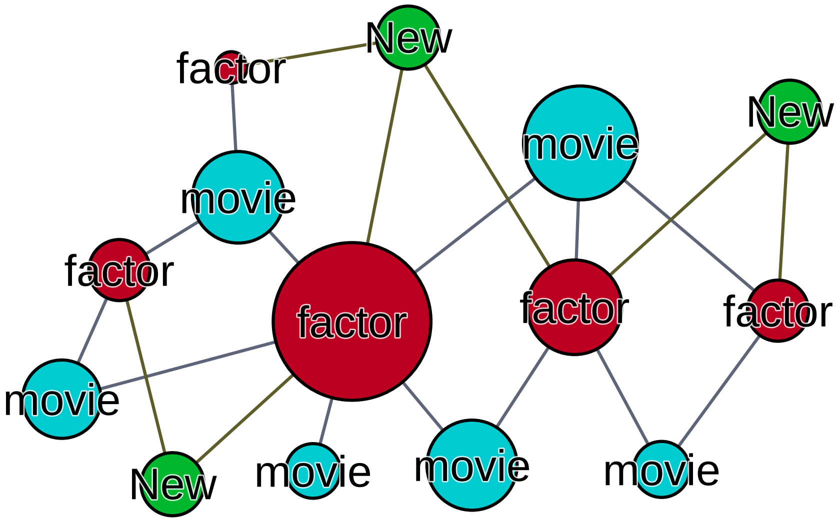

Figure 3: Rating prediction.

based on the rating impact measure proposed in section 2. After this step, all nodes in the graph were rated.

At the next step, to predict the rating of movies in the test set, our script created nodes for each of them and connected them to their *factor nodes* if they existed in the graph before (Figure 3). Thereafter the script performed the similar rating prediction process for new nodes based on the rating of *factor nodes* to which they were connected.

We repeated this process five times to reduce the variance caused by the random split selection.

3.3 Evaluation Metrics

In order to measure the accuracy of the system predicted ratings Mean Absolute Error (MAE) and the RMSE (Root Mean Square Error) were used. They are well-known metrics widely used for the evaluation of the accuracy of the predicted ratings (Sotelo and Juayek, 2015; Barjasteh et al., 2015; Gupta and Nagpal, 2015; Shi et al., 2015). MAE is defined as

$$MAE_u = \frac{\sum_{i \in U_{test}} |\hat{r}_i - r_i|}{|U_{test}|} \qquad (3)$$

where U_{test} is the test set of user's ratings, $\hat{r}_i$ and r_i are predicted and actual rating value respectively.

RMSE gives more weight to larger prediction errors and is defined as

$$RMSE_u = \sqrt{\frac{\sum_{i \in U_{test}} (\hat{r}_i - r_i)^2}{|U_{test}|}} \qquad (4)$$

For each metric, the results were also averaged over all users.

3.4 Results and Discussion

To reduce the variance, the results were averaged over 5 validation folds. Table 1 summarizes our results. A smaller value of metrics indicates better accuracy.

As can be seen from the results, our method showed better performance for the MovieLens 20M dataset. This is caused by the fact that this dataset not only contains more ratings data, but also a greater amount of side information about the movies. For example, the average number of genres per movie has increased from 1.65 to 2 in comparison with 1M dataset. The total number of movies has also increased, enabling users to evaluate their preferences in more detail. The results for datasets 10M and 20M do not differ so much due to the fact that they contain approximately the same amount of side information.

However, based on the fact that the number of users and ratings increased nearly two times, it can be assumed, that the proposed method shows stable results despite variability of users in the dataset.

The results indicate that this method is at the level of the performance of some recently introduced semantic-based and social-based methods (Qian et al., 2014; Sotelo and Juayek, 2015), but without requiring a large volume of metadata. Another benefit of our method is the possibility to calculate recommendations for each user independently, which can be useful in the case of parallel computations or in case of absence data about other users (e.g. new e-commerce website).

Table 1: The results of experiments using MovieLens dataset. A smaller value of metrics indicates better accuracy.

n	MovieLens 1M		MovieLens 10M		MovieLens 20M	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
1	0.8598	1.1719	0.8334	1.1207	0.8189	1.1026
2	0.8558	1.1719	0.8315	1.1198	0.8139	1.0916
3	0.8543	1.1568	0.8184	1.1068	0.8392	1.1169
4	0.8471	1.1601	0.8184	1.1064	0.8082	1.0891
5	0.8762	1.1504	0.8218	1.1114	0,8096	1.1002
Avg.	**0.8586**	**1.1845**	**0.8250**	**1.1130**	**0.8180**	**1.1001**

4 CONCLUSION AND FUTURE WORK

We have introduced a graph-based rating prediction method that is based on eigenvector centrality. The advantages of usage of eigenvector centrality let us create rating prediction method using items metadata as well as explicitly given rating. We also proposed rating impact measuring process to compensate the variation of rating, considering the individual rating behaviour of the particular user.

The proposed method can be useful to predict rating in conditions of insufficient data of past rating activities of other users that help dealing with the *cold-start problem*. This method can also be used in combination with Collaborative Filtering approaches to predict rating for untypical users.

We conducted our experiments on three well-known MovieLens datasets from the movie domain to evaluate the proposed method and to compare the results with existing methods. The results indicated that this method was at the level of the performance of the recently introduced content-based methods, but without requiring a large volume of metadata.

Furthermore, the presented method provides the the ability to calculate the recommendations for each user separately.

An important future work direction is investigating of alternative ways to adaptive recommendation process to the user's behaviour. We are also interested in exploiting additional data sources for online recommendations, for example Linked Open Data.

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