Improving Recommendations by Using a Heterogeneous Network and User's Reviews

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***Abstract*—A recommendation system is an information filtering technology that seeks to predict and recommend items to its users through an analysis of their history of interactions with the system. An important point to consider is the analysis of user's reviews, which allows the aggregation of valuable information in the recommendation process. However, commom data representations for recommender systems usually are not enough to capture all the relationships between the entities of the problem. Therefore, in this work, we propose a heterogeneous network that aggregates information of users, items and reviews in a single representation for the recommendation task. Using the proposed network, recommendations were generated by a network regularization method. The experiments showed that the proposed method is very promising.**

***Index Terms*—recommender systems, heterogeneous network, user's reviews**

I. Introduction

The amount of data and information available on the Web is abundant, which makes it difficult for users to identify and choose the products or services that best meet their needs. In this context, a recommendation system is an information filtering technology that seeks to provide product and service suggestions to its users, through an analysis of its history of interactions with the system [1]. The advantages of using such systems are numerous from both the sellers and the users perspectives. For users, the idea is to predict and recommend items that may interest them, reducing the number of options available and providing higher quality results. When users can easily find what they are looking for, there is an increase in profit, which is the seller's ultimate goal for using a recommendation system.

In general, recommendation systems are classified into two main categories [1]: collaborative filtering and content-based filtering. Collaborative filtering seeks to identify patterns of relationship between items and/or users for generating recommendations based on this information. On the other hand, content-based filtering considers user data or items' features to create the user and/or items profiles, and then uses these profiles to find similar items to recommend.

These systems can use structured and unstructured data to generate recommendations. In the case of structured data, user interaction data (display time, purchase information, etc.) may be considered, as well as the numerical evaluations that they have provided to items. As for unstructured data, user's reviews can be used. These reviews are texts in natural language containing users' opinions on different aspects or characteristics of the items, which can aggregate important information to the process and enrich the recommendation generation [2].

Since these texts are sources of unstructured information, it is important to structure them adequately, making it feasible to use them in recommendation systems. There are several techniques that may be considered in this process, such as representing these texts as bag-of-words and/or extracting relevant information from them. In this sense, one possibility is to extract features of the items being reviewed, such as aspects [3], [4].

All of this information, gathered from structured and unstructured data, can be aggregated into a single representation and then used in recommendation systems. These systems have different entities (users, items and extracted information from texts, for example) that relate to each other. Therefore, it is necessary to understand the influence that each of them exerts on the others and on the recommendation process as a whole. It is important to choose such a representation that considers explicitly all of the interactions that exists among these entities [5]–[7]. A heterogeneous network is a representation that may bring higher quality recommendations and that may add semantics to the recommendation process [6].

Given this scenario, our goal is to propose and create a heterogeneous network to combine three different entities: which are users, items and extracted information from user's reviews. Although we could extract aspects from these reviews and they could enrich the recommendation process, most aspect extraction methods are very complex, as they analyse dependencies among words. Our goal is to simplify this process by extracting only the nouns of the reviews, since most words that represent aspects are nouns [8], and clustering them to obtain a reduced number of elements to be used in our network. Based on this proposed network, we applied a state-of-the-art network-based recommendation algorithm to generate recommendations. Our hypothesis is that the aggregation of these different entities into a heterogeneous network representation can lead to better recommendations (higher accuracy), compared to traditional methods, such as

Item-Based Collaborative Filtering (IBCF) and *Content-Based Filtering with K Nearest Neighbors (FBC-KNN)*. In summary, the main contributions of this work are: (i) the proposition of using clusters of nouns, represented as word embeddings, to incorporate information from reviews into the recommendation system; and (ii) the proposal of a heterogeneous network that relates users, items, and groups of reviews' nouns, with promising results for the recommendation task.

We carried out an experimental evaluation using the MovieLens benchmark dataset enriched with reviews collected from IMDBb. An analysis of the results revealed that our proposal statistically outperformed the traditional methods IBCF and FBC-KNN. In addition, the use of more semantic representations such as the heterogeneous networks of our proposal raises a variety of future research regarding the interpretability of the models, as well as explanaible recommendations.

The remainder of this article is organized as follows. In Section II, we present other works found in the literature that sought to create network representations; in Section III we present our proposal, which consists in the creation of a heterogeneous network of users, items and user's reviews. In addition, in Section IV, we show the experimental evaluation we performed and, finally, in Section V we draw our main conclusions from this work, as well as some perspectives of future works.

II. Related Work

According to [6], heterogeneous networks are very promising for recommendation systems because they make it feasible to exploit the interactions between users, items, and other entities in a semantically and visually appealing representation. Thus, the recommendation algorithm may exploit patterns in the network interactions to recommend items to users, which may bring interpretability to the system. Therefore, several recent studies have been exploring the use of heterogeneous networks in recommendation systems [3]–[5], [9], [10].

In [5], a generic recommendation model was proposed using heterogeneous networks, in which its main purpose was to allow the recommendation of items in different application domains. For this end, [5] proposed a method to create a heterogeneous network from any input data. Given this network, the recommendation consisted of identifyng the closest item-nodes with respect to a given user-node, which was the target of the recommendation. Experiments were carried out in databases of different domains, such as events, films and music, and according to [5], their results were better than all of the considered baselines.

[9] proposed a heterogeneous network, called *Aspect-Aware Geo-Social Influence Graph* (AGSG), which combines in a single representation information from users, points of interest and aspects, extracted from user's reviews. The recommendation task was considered as a problem of ranking the nodes of the constructed network. For this, in order to generate the recommendations, they proposed an approach that combined meta-paths with personalized PageRank (PPR), which obtained promising results.

[10] represented the recommendation data as a heterogeneous network, in a similar way as the other previously presented works. Their proposal was to use the Generalized Random Walk Model to generate the recommendations. In general, their main contribution was a method that learns, from the training data, the matrix of transitions probabilities, wich is an essential part of the Random Walks Models.

[3] extracted points of interest and their related aspects from user's reviews. Given this data, they applied a Factorization Machine (FM) [11] to generate the recommendations. An important part of their proposal was to generate explanations for the produced recommendations. In order to do so, they constructed a bipartite network, considering points of interest and the related aspects. Using several network mining algorithms, they identified the most relevant aspects and used them to explain the recommended points of interest. According to them, their results showed that the proposed method improved the performance of the recommendations and also brought interpretability to the recommendations.

In [4], a tripartite network was constructed considering three types of nodes: users, items and aspects extracted from user's reviews. For creating the network and defining the relationships among the network nodes, the authors considered user's interaction data; that is, if a user visualized an item whose review had a certain aspect, they created an edge between this user and item, an edge between this item and aspect, and also an edge between this user and aspect. For making the recommendations, they proposed a network regularization algorithm, called *TriRank*, which is, up to today, considered one of the state-of-the-art algorithms for network recommendations.

All of these research modeled the recommendation task using heteregeneous networks, which allows the aggregation of several entities in a single representation. We consider that our proposal is more related to [3], [4], [9], because, in a similar way, we consider user's reviews to enrich the recommendation process, unlike [5] and [10]. Moreover, like [4], we used a regularization algorithm to generate the recommendations. However, one main difference is that we want to explore the potential of representing texts with only the nouns of the reviews. We believe this strategy in simpler than most approaches of extracting relevant information from texts, and still could enrich the recommendation process. With this in mind, in the next section, we present our proposal for constructing a heterogeneous network using the nouns of the reviews, along with user and item data.

III. Constructing a heterogeneous network representing users, items and user's reviews

Our goal was to construct a heterogeneous network representing users, items and user's reviews relations. As shown in Section II, most works that uses reviews in the recommendation process considers aspects, which are features of items, as the most relevant information that could be extracted from these review texts. However, methods for extracting aspects from reviews normally involves analysing dependencies among words [8], which can overload the recommendation process.

Motivated by this, to avoid the need of extracting aspects, the first idea would be to use the whole texts in the process of constructing the network. However, the number of words in a review may be high and some words does not provide meaningful representations (such as articles, pronouns, etc). On the other hand, aspects are normally nouns. Thus, to alleviate the dimentionality problem of the bag-of-words model and, at the same time, to aggregate the notion of aspects to our representation, we decided to select only the nouns of a review and then to cluster them in a small set of groups.

In Fig. 1, we present our proposal for constructing the heterogeneous network, which has three major steps: **Extraction and Clustering of Nouns**, in which we extract the nouns of a review and apply a clustering algorithm to have a more compact representation; **Definition of the Network Structure**, in which we define how the nodes would relate to each other; and **Generation of the Recommendations**, in which we apply a regularization network algorithm to generate the recommendations. These steps are described in Sections III-A, III-B e III-C, respectively.

A. *Extraction and Clustering of Nouns*

The main purpose of this step is extracting relevant information from user's reviews in order to create the heterogeneous network, which is the focus of our work. As mentioned earlier, because of the high number of words in the reviews and the inability to create meaningful representations to some of them, such as articles and pronouns, we considered only the nouns as relevant terms of these reviews.

Thus, we apply the Part-Of-Speech Tagging [12] to these reviews, which assigs tags to the text words, indicating to which part of speech (nouns, adjectives, verbs, etc) they belong. With this information, we filter out from the reviews the words that are not nouns. Even with this filtering, a high number of words could be mantained, which could impact our recommendation system performance. In order to alleviate this problem and to reduce the dimentionality of our representation, we cluster the nouns into a small set of groups and use them instead of the whole set of nouns.

Most clustering algorithms in the literature work with vector representations. One possible way to create such representations from textual data is to use word embeddings, which consists of high-quality word vectors trained in large datasets. The main advantage of using such embeddings is that words with similar meaning tend to have closer representations in the resulting embedded space, bringing text semantics to the created representations [13].

Therefore, we cluster the nouns identified in the reviews based on these word embeddings. In this work, we used the embeddings from FastText library[1], which made avaible several pre-trained vectors for words in English. Using these embeddings, we applied the K-Means algorithm given its simplicity and good results, thus, selecting K groups of nouns, that were later used to create the network.

[1] https://fasttext.cc/

B. *Definition of the Network Structure*

The main purpose of this step is defining the structure of our network, using the information of users, items and nouns, extracted from user's reviews. In Fig. 2, we present a schematic of our network, which has three types of nodes: users, items and groups of nouns.

In order to define how these different nodes would relate to each other, we considered the user/item interaction data, such as viewing and rating information, and the nouns that occurs in each item review. Next, we describe how we defined these relations.

1) **User-user relations**: two users are connected (green lines in Fig. 2) if they are somehow similar. To calculate this similarity, we considered which items these users have rated and the value of these ratings; that is, if two users have rated simmilary the same set of items, they are considered similar. The weight of this relation (between users, u_i and u_j), is given by the similarity between them ($sim(u_i, u_j)$), which is calculated by the cosine distance:

$$sim(u_i, u_j) = \cos(p_{u_i}, p_{u_j}) = \frac{\vec{p}_{u_i} \times \vec{p}_{u_j}}{||\vec{p}_{u_i}|| \times ||\vec{p}_{u_j}||}$$

such that p_{u_i} represents the ratings of user u_i.

2) **User-item relations**: a user is connected to an item (orange lines) if the user has rated the item. The weight of this relation is given by the rating value that the user assigned to such item.

3) **Item-group relations**: this relation considers the frequency in which nouns appear in the item's review. For example, let's assume the following review of item i_1 (the terms that are not nouns were crossed out):

"~~*The*~~ *actor* ~~*of*~~ *saturday's movie* ~~*was terrible*~~"

Let's also assume that, given the clustering results of the step III-A, the nouns "*actor*" and "*movie*" were clustered into group g_1 and that "*saturday*" was clustered into g_2. In our proposal, we defined that exists an edge between an item i_k and a group g_m if we identifed a noun belonging to group g_m in an item's i_k review. The edge weight is given by the relative frequency of nouns in each group. For the given example, item i_1 and group g_1 and the item i_1 and group g_2 are connected, because we identified nouns of these groups in the review of item i_1. Since there were two nouns of group g_1 and only one noun of group g_2, the weight of the edge between item i_1 and group g_1 is $\frac{2}{3}$, whereas the weight of i_1 and g_2 relation is $\frac{1}{3}$.

4) **Item-item relation**: exists a relation between two items if they are connected simmilarly to the same set of groups of nouns (given the relations defined in (3)). We

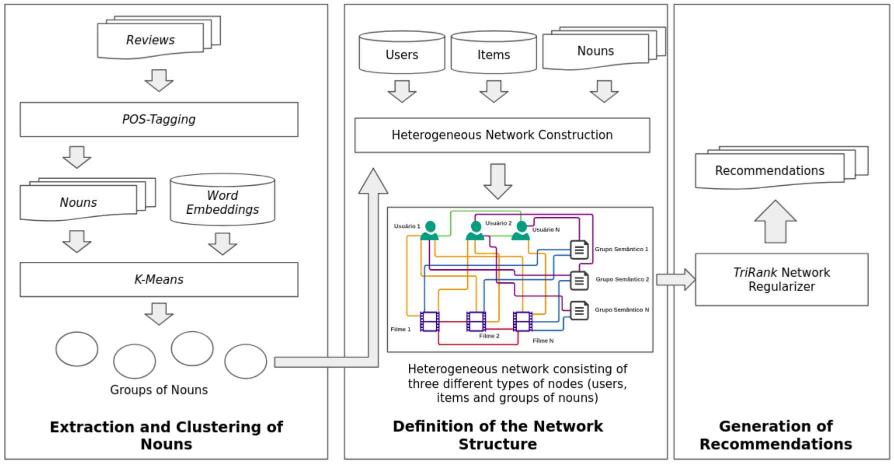

Fig. 1: Our proposal for constructing the heterogeneous network of users, items and groups of nouns from user's reviews

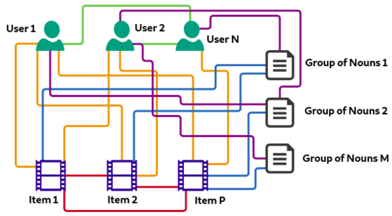

Fig. 2: Schematic of the proposed heterogeneous network

considered the cosine distance to measure the similarity between these items.

5) **Group-user relations**: if an user u_i has rated an item i_j, then u_i is connected to the same groups of nouns that i_j is connected. For the example given in (3), if user u_1 has rated item i_1, which is connected to groups g_1 and g_2, then u_1 is also connected to g_1 and g_2. We do not defined weights for these relations.

In the following section, we describe how to generate recommendations from the heterogenous network we proposed.

C. Generation of the recommendations using the proposed heterogeneous network

As presented in Section III-A, the heterogeneous network was constructed considering information from users, items and groups of nouns, extracted from the reviews. In order to generate recommendations using this network, we applied the *TriRank* network regularization method, proposed by [4]. While in [4] the network was constructed using aspects from reviews, in our work we used groups of nouns to do so. Thus, some modifications in the recommendation process have become necessary. Next, the *TriRank* will be detailed with such modifications.

In general, the regularization method proposed by [4] seeks to induce numerical scores for each one of the vertices in the network, focusing on a given user at a time. Therefore, three types of scores are inferred: for users' vertices, items and groups of nouns. As the process is performed with the focus on a given user at a time, these scores indicate the degree of similarity of this user to other users, the degree of preference of this user to the items and to the considered groups of nouns. Thus, from these scores, specially with the item scores, it is possible to generate the recommendations for the user in hand.

More specifically, the *TriRank* method considers three matrices, extracted from the weights of the edges of the constructed network: matrix R, which represents the weight of the relations between users and items; matrix Y, the weight between users and groups of nouns; and X matrix, the weight between items and groups of nouns. As we can see, this method considers only the relations between nodes of different types, so we are only using one subgraph of our proposed heterogeneous network.

The goal of *TriRank* is to estimate numerical values for three vectors, $f(u)$, $f(p)$ and $f(g)$, which indicates the previously mentioned score for nodes. For this, besides considering the structure of the network, *TriRank* also uses previous data from the target user: u^0, which indicates which users are similar to him; p^0, the items evaluated by him; and g^0, the groups of nouns he has preferred in the past. The process consists of minimizing the following equation, using Alternating Least Squares:

$$\begin{aligned} Q(f) = {} & \alpha \sum_{i,j} r_{ij} \Big(\frac{f(u_i)}{\sqrt{d_i^u}} - \frac{f(p_j)}{\sqrt{d_j^p}}\Big)^2 \\ & + \beta \sum_{j,k} x_{jk} \Big(\frac{f(p_j)}{\sqrt{d_j^p}} - \frac{f(g_k)}{\sqrt{d_k^g}}\Big)^2 \\ & + \gamma \sum_{i,k} y_{ik} \Big(\frac{f(u_i)}{\sqrt{d_i^u}} - \frac{f(g_k)}{\sqrt{d_k^g}}\Big)^2 + \eta_U \sum_i (f(u_i) - u_i^0)^2 \\ & + \eta_P \sum_j (f(p_j) - p_j^0)^2 + \eta_G \sum_k (f(g_k) - g_h^0)^2 \end{aligned} \tag{1}$$

such that $f(u_i)$ represents the degree of similarity of the target user to user i (similarly, for $f(p_j)$ and $f(g_k)$); $\sqrt{d_i^u}$ represents the weighted sum of the degree of u_i; α, β and γ represent the weight of user-item, item-group, and user-group matrices in regularization; and the parameters n_U, n_P and n_G represent the weight of the previous data of user, item, and groups of nouns (u^0, p^0 and g^0).

Using the induced scores for item nodes ($f(p)$), we select the top-N highest values, which corresponds to the N items the target user will probably like the most, thus, generating his N recommendations.

IV. Experimental Evaluation

In this work, our goal was to verify if a more complete representation, such as heterogeneous networks, could improve the accuracy of recommendations. In order to do so, we constructed a network from user's interaction data and written reviews, applying *TriRank* to generate the recommendations, which is considered a state-of-the-art network recommendation algorithm. In this section, we present the experiments we made to validate our hypothesis and the results we obtained.

A. Experimental Settings

In our experiments, we used an extension of the *MovieLens*[2] dataset. The original dataset, which consisted of ratings made by users to movies, was enriched using IMDb[3] reviews. These reviews are natural language texts, written by users, and contain their opnions about the different features of the movies. The dataset consists of 535,784 ratings, 3,564 movies, 3,974 users and 24,880 reviews.

According to [1], the recommendation task may be of two types: rating prediction, in which our goal is to predict a rating value for some user and item; and item prediction, in which our goal is to generate a list of recommendations. In this work, we considered the item prediction task. In order to evaluate our proposal, we used the Mean Average Precision (MAP) metric [14] to measure the quality of our list of recommendations. The main idea of such metric is to give higher importance to hits that occur in the beginning of the list. This metric ranges between 0 and 1, and the higher its value, the higher the quality of the recommendations. We compared the MAP metric obtained by our method to those obtained by two other recommendation algorithms, commonly used in the literature:

- **Collaborative-Filtering based on neighborhood of items (IBCF)**: we used the ratings data to calculate the similarities among items and then we predicted the ratings for unseen items based on their K most similar items;
- **Content-Based filtering with K Nearest Neighboors (FBC-KNN)**: the reviews were used to create item profiles, using a bag-of-words model. These profiles are then used to calculate the similarities among items. The predicted rating of a user for an item is given by the weighted average of the ratings this user made on similar items.

We selected these algorithms as baselines to our approach, since they are good representativies of the two classes of algorithms in recommendation systems literature, which are colaborative filtering and content-based filtering. In addition, we want to compare if our proposal: (i) is capable of generating better recommendations than an algorithm that does not use user's reviews (IBCF); and (ii) generates better recommendations than an algorithm that uses only the bag-of-words model to represent the textual data. In order to do so, we performed 10-fold cross validation and the wilcoxon statistical test to verify if the differences between the results have statistical significance. Details of the experimental evaluation, such as the formalization of the MAP metric, and the results of every experiment we performed are available at http://sites.labic.icmc.usp.br/vtonon/nouns-reviews/.

B. Results and Discussion

As mentioned in Section III-C, *TriRank* considers the network structure and previous known information in order to generate the recommendations. While the parameters α, β and γ control the degree in which the network structure influences the recommendations, the parameters η_U, η_P and η_G control the influence of previous known information.

We perfomed four experiments using our proposed heterogeneous network and the *TriRank* recommendation algorithm. In these experiments, in order to analyse the impact of the network structure and the previous known information onto the recommendations, we considered different sets of values for these parameters. In Table I, we present the mean and standard deviation of the MAP metric we obtained for these experiments, considering the results obtained in each fold.

TABLE I: MAP metric for the recommendations using our proposed network

Experiments	E_1	E_2	E_3	E_4
Parameters	$\alpha = 0.5$	$\alpha = 0.5$	$\alpha = 0.9$	$\alpha = 0.1$
	$\beta = 0.5$	$\beta = 0.5$	$\beta = 0.9$	$\beta = 0.1$
	$\gamma = 0.5$	$\gamma = 0.5$	$\gamma = 0.9$	$\gamma = 0.1$
	$\eta_U = 0.5$	$\eta_U = 0.1$	$\eta_U = 0.1$	$\eta_U = 0.9$
	$\eta_P = 0.5$	$\eta_P = 0.1$	$\eta_P = 0.1$	$\eta_P = 0.9$
	$\eta_G = 0.5$	$\eta_G = 0.1$	$\eta_G = 0.1$	$\eta_G = 0.9$
Mean	0.01048	0.03482	**0.14016**	0.00485
Standard Deviation	0.00127	0.00492	**0.00645**	0.00176

While in experiment E_1 we assigned the same importance for all parameters, in experiments E_2 and E_3 we assigned higher importance for the network structure in the recommendations, specially in experiment E_3. As we can see, the best results were obtained in experiments E_3 and E_2, which indicates that the network structure heavily impact the quality of recommendations. Moreover, in experiment E_4, in which we assigned the greatest importance for the previous known information, we obtained the worst results between all

[2]https://grouplens.org/datasets/movielens/
[3]https://www.imdb.com/

experiments. This also confirms the greater importance of the network structure in the recommendations.

We compare our best result, which was experiment E_3, to the considered baselines, which are IBCF and FBC-KNN. In Table II, we present the mean and standard deviation of the MAP metric of these experiments, considering the individual results obtained in each fold.

TABLE II: MAP metric for the considered baselines and our approach

Algorithms	IBCF	FBC-KNN	Our Proposal
Mean	0.01717	0.00158	**0.14016**
Standard Deviation	0.00066	0.00050	**0.00645**

As we can see, our proposal obtained the best results between all of the considered baselines. We also perfomed a wilcoxon statistical significance test, which showed that our proposal increased the quality of recommendations with statistical significance from both baselines. Moreover, our proposal performing better than IBCF indicates that using a heterogeneous network to represent the recommendation task is indeed a better representation than the traditional ones, used by IBCF.

From our results, we may also observe that FBC-KNN, which considers user's reviews, obtained a result worse than IBCF, which does not. Since our proposal also considers these reviews and obtained the best results, this may indicate that using the whole set of words of a review may impair the recommendations. This may show us that selecting the nouns and clustering them was indeed a good strategy to alleviate the dimensionality problem of representing texts as bag-of-words.

V. Conclusions

Recommendation systems seek to predict and recommend personalized products and services to users, maximizing their satisfaction with the system. In general, the recommendation is considered a success when the user accepts the recommendation and uses/purchases the recommended product or service. Thus, most recent works have been trying to generate higher quality recommendations. In order to do so, many researchers [3]–[5], [9], [10] have been using heterogeneous networks to model all the interactions and relationships between users, items and other revelant information, such as user's reviews.

Therefore, in this work, our goal was to define and create a heterogeneous network representing users, items and groups of nouns, which were extracted from user's reviews. Our hypothesis was that the aggregation of these different entities into this heterogeneous network representation could lead to better recommendations (higher accuracy).

The experimental evaluation we performed has showed that our heterogeneous network proposal could indeed improve the quality of recommendations, since our method performed statistically better than all of the considered baselines, regarding the Mean Average Precision metric. We also brought higher explainability to the process, since it's possibile to use the network relations as explanations to our recommendations.

As future work, we intend to explore other network-based recommendation algorithms, since *TriRank* considered only a subset of our original heterogeneous network. We believe that our recommendations could be even better when using the whole network. In addition, we also aim to consider other baselines, such as matrix factorization algorithms, and also compare the performance of our approach, which considers groups of nouns from users reviews, to approaches that consider aspects in this process. Finally, we intend to explore the computational complexity, scalability and adaptability of our proposal.

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