Only for your eyes: Visualizing the results of a personalized recommendation system

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Abstract. This paper presents a visual representation of the data obtained from a recommendation system, which uses the images uploaded by users to model their tastes in order to build a personalized recommendation. To increase user confidence and interest, results are presented by means of a graphic composition with the images of the five restaurants with the highest affinity, accompanied by additional information of interest.

1 INTRODUCTION

The success of personalized recommendation systems (RS) is beyond doubt. With the constant increase of the flow of available information within the reach of users, platforms such as Amazon, Netflix or YouTube reflect the benefit of adopting this model. Likewise, in recent years the focus of research has been not only on obtaining good recommendations, but also on offering systems that improve accessibility, transparency, and a good understanding of results. Several studies show how the success of an RS can be degraded if the presentation of the results does not please the user [2]. Although the suggestions provided by an RS are valuable, user perception may be poor due to aspects related to both the presentation of the information and the appearance of the system. Thus, convincing users that the system is trustworthy is essential, and both explaining and justifying the recommendations have a great influence on this issue.

Visualization takes advantage of visual representations to facilitate human perception seeking a correct interpretation. However, presentation of results, despite having a direct influence on the user's perception of the system, has received relatively low attention. Nanou et al. [6] explored the persuasive capacity that the different forms of visualization of recommended products have on users. Bookshelf et al. [1] demonstrated that the creation of browsing interfaces, specifically emulating a digital library, positively influenced the user by making them feel more integrated. Sagel et al. [7] proposed the use of narrative visualization for RS, generating a screen with the recommended items connected to each other at the initial query, with the intention of transmitting a sort of story to the user with their disposition. Finally, it is worth mentioning PeerChooser [5] and VizRec [3], two collaborative filtering recommendation systems that propose an interactive visualization of the recommendations through an interface.

This paper proposes a personalized visualization approach to show the output offered by an image-based RS, in order to present the results to the user in a more attractive and understandable way.

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2 METHODOLOGY

This work combines personalized recommendations with visualization of results. Our goal is to generate a personalized visual representation from the list of recommended items offered by an RS. In particular, to obtain this list we use the model proposed in [4], which provides gastronomic recommendations based on the users' images published along with their ratings. In general terms, the problem is formulated as a binary classification task in which each sample is defined by a triad $x = (u, r, i)$, where i is the image of restaurant r posted by user u. Regarding the labels $y = (0|1)$, where 0 means the user u does not like the restaurant r, and 1 that he/she does.

2.1 Data set

The data set used is composed of reviews posted by TripAdvisor users in the city of Santiago de Compostela. It includes 43627 reviews from 25456 users to 513 restaurants, but only 7003 of them contain images. In total, there are 16168 images: 13915 belong to positive reviews, and 2253 to negative reviews. The treatment of the data set, in relation to the split required for training and the image preprocessing, is exactly the same as the one followed in [4].

2.2 Recommender System

For training the system, users and restaurants are represented by a one-hot codification and images are represented through the deep features extracted by an autoencoder (CAE). Therefore, it is a two-part process, which includes both the training of CAE and the classifier. As mentioned above, the specific details of the models used in this research, both in relation with their architecture and their training specifications, are described in [4].

In short, the CAE was trained using the set of all available images and then used to extract the deep feature vector from each one. This vector, along with a number that uniquely identifies each user and restaurant, composes the feature vector that represents each of the input examples required by the classifier (see Figure 1). The classifier initially maps the three input features to their corresponding embedding representations of 512 features each, using embedding layers for the user and restaurant identifiers, and a fully connected layer (FC) for the image feature vector. Then, the output of these three layers is concatenated into a single vector, normalized by using a Batch Normalization layer. Following, a succession of FC layers and reduce blocks are used to finally map an input vector into an output vector of half size. Finally, there is an FC layer with a sigmoid activation function generating a probability output in the range $[0, 1]$.

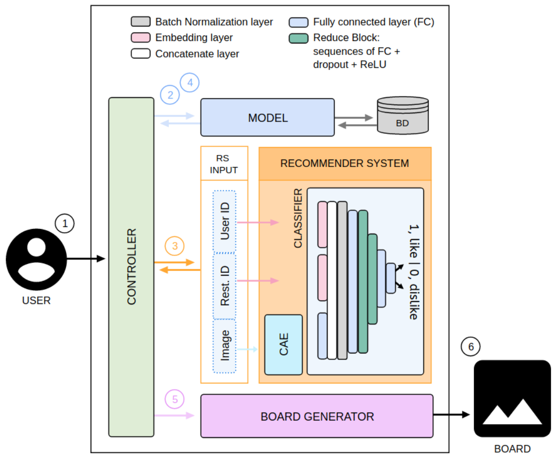

Figure 1. Proposed model for generate a personalized graphic composition for the recommendations obtained from an RS.

2.3 Visualization system

Once the RS training has been completed, it is possible to obtain the degree of affinity existing between all the users and restaurants in the data set. Since the user reviews are available, it is possible to know which restaurants they do not know yet. Therefore, the first step is to get the list of all the images of the restaurants not related to the target user (see Figure 1). The next step is to obtain the predictions given to each of them by the recommendation system, to later obtain the average per restaurant and select the five best ones. To generate the final output it is necessary to obtain for each of the five restaurants: original name, total score on TripAdvisor, price range, average of all the predictions and a list of images. Due to the great amount of images obtained from each restaurant, in order not to overwhelm the user and lose the essence of the recommendation, we decided to choose only those images that most represent him/her according to the prediction result of the RS, showing therefore those that have a higher probability of being liked by the user. To generate the final graphic composition, the information of each restaurant is placed on a small predefined background. For each restaurant it is possible to specify the color of the text and alignment of the images. Subsequently, each of these small backgrounds are placed on specific coordinates of a larger base background depending on the desired graphic design, also including a label with the user's name. The system was developed using Python and several basic libraries for large data sets and image processing, such as Numpy and PIL (Python Imaging Library).

3 RESULTS

To illustrate the performance of the system, we show the output offered for a particular user. As we have just mentioned, first it was necessary to obtain the images of all the restaurants with which the user had no relationship, their corresponding predictions and select the five restaurants with the highest average predictions, as well as the best images of each of them. Then, the list of restaurants is processed to create a figure with each one of them in a certain background, as we can see in Figure 2, we choose images that represent pieces of a notebook. They include related information extracted from TripAdvisor, as well as the images that the user likes most according to our RS. Finally, each of these images is placed in some specific coordinates of the general background, which will be defined according to the design of the final desired composition (a wooden background,

Figure 2. Final output generated by the system for a given user.

in our case). Our intention is to represent the wall that a user would build in his/her house based on his/her personal tastes.

4 CONCLUSION

We believe that the effectiveness of RSs can be increased if the presentation of results is attractive and easy to understand for the user. In this paper, we present a form of artistic visualization to show the list of recommended elements generated by an image-based recommendation system. The idea is to compress the information obtained into a personalized graphic composition, in which both the restaurants and the images shown are chosen according to a criterion of probability of being liked by the user.

As future work, our intention is to move this composition to a more interactive environment, allowing to display additional information of each restaurant.

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