Visualizing Recommendations for Points of Interest

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Abstract. Showing the results of a Recommender System in an friendly and understandable way is not an easy task. The platforms that use this kind of systems usually show to the final user a list of recommendations without indicating, in most of the cases, the order criteria and even less an explanation of why these items and not others. In this paper we propose a method to visualize tourist Point of Interest (POI) recommendations from a given user's image. Our method places this image in the center of a two-dimensional radial space and, orbiting around it, all the POIs recommended by our system. The final user can hover over each recommended POI and explore its representative image, which in fact explains the origin of the recommendation. In order to illustrate the behavior of our system, we collected a dataset from the platform TripAdvisor, containing the tourist POI data of the Principality of Asturias, Spain.

1 INTRODUCTION

A recommender system (RS) is a method that suggests new items to users [8]. We can typically find RS in well known platforms like Netflix or Spotify, which aim at making the best recommendations possible in order to boost the user satisfaction. The popularity of these webs have produced an increasing number of research works in this field [2], mostly focusing on enhancing the quality of the results. But improving other aspects like the explainability or the visualization of the results may also increment those values.

Explainable artificial intelligence (XAI) is a very important topic nowadays. The idea behind this concept is to create intelligent systems that not only return a result, but also are able to justify the origin of the final decision. If you can achieve that, the final users would stop seeing these systems like a *black box*, and they would start to understand and trust their recommendations.

As for the second aspect to be improved, following the saying *an image is worth a thousand words*, a good visualization technique can reduce enormously the task of understanding the results, particularly if you use a familiar or common way to represent those results.

In order to improve these aspects less explored in the RS world, in this paper we purpose a method that, given a POI image taken by a user, recommends multiple POIs allied to her tastes. Furthermore, our approach represents the results in a simple and explainable way.

There are several works related with the visualization of an RS output in an explainable way. Verbert et al. [9] and Mutlu et al.[7] research stands out due to its similarities with ours, but both of them takes little or no account of the simplicity, resulting in a complex and overloaded visualization. Another noteworthy work which, in this case, present a simple visualization, is the one of Hernando et al. [4]. In this paper, the authors are centered in explaining all the recommendations in the same graphic, whereas our target is to explain each individual recommendation only if the user want to know this information.

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2 DATASET

In order to create the dataset, we selected the locations that correspond to the most popular cities in the region of interest (Principality of Asturias), according to TripAdvisor. Each POI gathered is defined by means of a name, an address, and a set of categories.

The dataset includes a total of 36083 images corresponding to 311 POIs located in 29 different cities, and grouped into 76 categories. Analyzing the data, it can be observed that images follow a long tail distribution for POI and categories. In both cases, over 80% of the images are represented by less than 20% of these two variables (i.e., POIs and categories). This kind of distribution can also be seen when plotting POIs against cities.

3 METHODOLOGY

To achieve our goal we split the procedure into three different stages: encoding, recommendation and visualization.

Given a POI image, the first step aims at encoding it into an n-dimensional space. The following stage selects the POIs susceptible of being recommended, and the last one is in charge of visualizing all the recommended items in an understandable and explainable way.

3.1 Encoding

The objective here is to obtain a meaningful way to represent any POI image in a low dimensional space. To achieve this, the most common approach is to use the output of a pre-trained net without the top layer (i.e., base model) [3]. As we are interested on achieving a custom representation for our particular problem, we apply transfer-learning and fine-tune the base model (DenseNet [5] in our case).

A fully connected layer of dimension C, being C the number of categories considered, was appended to the base model aiming at obtain embeddings that represent the categories of the image, becoming a multilabel problem.

A dataset with n images was used to train this customized network. The training processing was carried out by using n pairs (i, c), where i represents the image reshaped into 224×224 (default in DenseNet), and c is a binarized array with the categories associated to the image. The set was then splitted into *train*, *dev* and *test* with proportions 0.8, 0.1, 0.1. F1 score is the metric computed in both *dev* and *test* sets, and Adam [6] is the optimizer used to minimize the binary cross-entropy, using a learning rate of 3e-4 and a batch size of 32. Once the final network was trained, achieving a $F1 = 0.835$ on *test*, we used the base model to generate the embedding of the images. In this manner, we generated a set E that includes all the embeddings e_i with $i = 1, ..., n$. Notice that these embeddings have a relevant meaning for our particular problem.

3.2 Recommendation

Given a POI image from the final user, we aim at obtaining a list of POI recommendations from a region (Asturias in our case). Note that this image represents, in some way, the user's tastes. Regarding the list, the idea is that the POIs are sorted by their closeness to the given image, calculated according to the following procedure:

1. Get the embedding f from the image with our encoding system.
2. Compute the euclidean distances d_i between f and the embeddings e_i.
3. Order (ascendingly) all the images in E by their distance d.
4. Obtain the POIs associated to these images, avoiding duplicates.

3.3 Visualization

The core of this work is to represent all the information in a understandable and explainable way. For this purpose, we use a two-dimensional radial space to place the user image along with the recommended POIs, locating the image in the center and the recommendations orbiting around it. Figure 1 depicts this space, which is splitted into three concentric regions. Note that each region represents the closeness or affinity respect to the user's tastes, depending of its distance to the center d. Once the maximum number of recommendations per region has been established ($k = 8, 12, 15$), a quality criterion is applied to prune them following the train distribution. This criterion is defined as $d < \alpha_k$, where α_k is the distance such that the train distribution contains k elements with a distance to the rest of elements is lower than α_k. Therefore, the smallest region contains the first 8 POIs from the list previously obtained (see Section 3.2), the second region the next 12, and the last one the next 15. Notice that the number of POIs per region increases with its size.

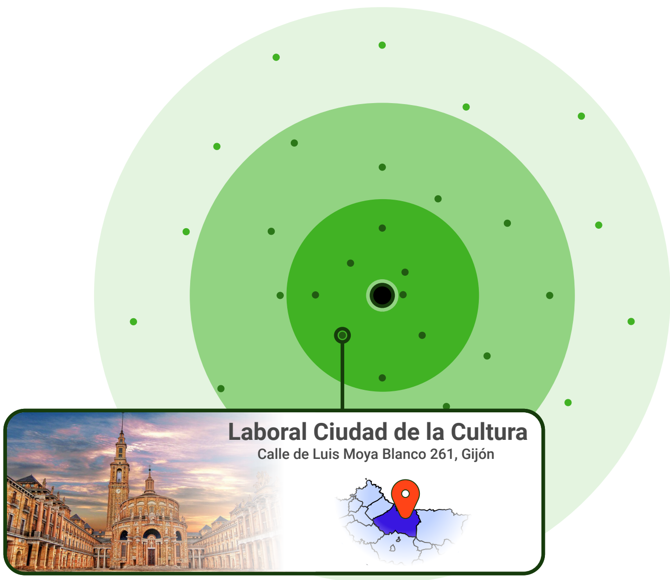

Figure 1. Radial visualization with three regions. The middle point represents the final user image and the other points each recommendation.

Each recommendation point can be hoverable, showing information about the POI and its corresponding image (i.e., the image with the lowest distance to the image of the final user). Bokeh [1] is the library used to achieve this interactive visualization.

4 CONCLUSION

The vast majority of the research works related to RS aim at improving the results, but few of them are focused on how to present the final recommendations to the users. The main objective of this paper is to present a method to visualize the results of an RS in an understandable and explainable way. For this purpose, we first downloaded an image dataset with POIs from a particular region, then we created an image encoding model, and finally we defined our custom RS. Regarding the visualization stage, we created an interactive and simple way to display the proposed POIs, showing each one an explanation in the shape of an image about why is recommended.

As future research, we plan to explore new encoding methods for the images in order to enhance the recommendation results. We also want to probe new visualization techniques aiming to improve, if its possible, the understandability of the final result.

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