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Towards Trajectory-Based Recommendations in Museums: Evaluation of Strategies Using Mixed Synthetic and Real Data

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Abstract

Recommendation systems, which suggest items that are of potential interest to the user (e.g., regarding which books to read, which movies to watch, etc.) have grown in popularity due to the ever-increasing amount of data available, that can lead to significant user's overload. In particular, in recent years, extensive research has focused on the so-called Context-Aware Recommender Systems (CARS), which exploit context data to offer more relevant recommendations.

In this paper, we study this problem with a use case scenario: recommending items to observe in a museum. We propose a trajectory-based and user-based collaborative filtering approach, that considers context data such as the location of the user and his/her trajectory to offer personalized recommendations. Besides, we exploit DataGenCARS, a dataset synthetic generator designed to construct datasets for the evaluation of context-aware recommendation systems, to build a mixed scenario based on both real and synthetic data. The experimental results show the advantages of the proposed approach and the usefulness of DataGenCARS for practical evaluation with a real use-case scenario.

Keywords: mobile recommendations, context-aware recommendation systems, dataset generation, evaluation

1. Introduction

In the last years, the so-called Context-Aware Recommender Systems (CARS)[1,2,3] have shown their suitability for domains where the context appears as a fundamental part of the recommendation process to take into account to enhance the user's experience. Motivated by the idea that more relevant recommendations can be provided to the user if context data are considered, many works have started to make progress in this direction. The increasing interest in

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the topic has also been fostered by the worldwide spreading and use of mobile smart devices as tools to facilitate our social engagement. An important feature of these devices lies in the possibility to obtain data from the environment by using multiple built-in sensors, such as a GPS receiver, accelerometers, light sensors, etc., which enables capturing context information unobtrusively.

As an example of recommendation scenario, museums represent one of the main leisure and cultural activities for individuals and groups, especially when visiting cities with touristic purposes. With the advance of technology, many museums have tried to implement new solutions to leverage the quality of experience of visitors by using, for example, new sources of interaction. Many tourist attractions offer visitors an audio-guide or some sort of multimedia device that guides the visitor by showing explanations about the works exhibited. However, we claim that these attempts are still in initial phases and do not constitute a robust solution, taking into account the possibilities offered by the current technology. Actually, in most of the cases the interaction is merely passive, since the visitor has to access the information explicitly by entering a numerical label or scanning a QR code. Besides, the visiting experience is not personalized for each individual user, as the electronic guides are passive elements that behave in the same way independently of the preferences and background of each user. As opposed to the existing work related to recommendations in museums (e.g., MusA[4], SmARTweet[5], UbiCicero[6]), our goal in this paper is to show the potential benefits of a context-aware trajectory-based recommendation approach, in the context of a museum, that exploits ratings provided by other visitors in real-time.

In this paper, we present the design and evaluation of a context-aware recommender system able to provide the visitor with accurate guided tours through a museum, taking into account different aspects of the context, such as opinions of other visitors, time constraints, his/her current location and trajectory, and his/her tastes, among others. We design the system in a push-based manner, which means that recommendations are automatically provided and updated whenever it is considered relevant, without the explicit user's intervention. The exchange of opinions among visitors relies on a central information service that allows to feed the recommendation process with data to pro-actively suggest changes in the recommended route in the museum.

Another important issue that emerges when working on CARS is how to correctly evaluate an approach. Existing datasets are scarce, and most of them are usually incomplete, since many users prefer not to disclose their context when rating items or they may just be lazy to do it. Furthermore, existing datasets do not cover a significant set of possible scenarios to prove the suitability of recommender systems. With that in mind, we use the DataGenCARS generator[7] in order to construct different datasets to test recommendation approaches. This tool can be used to obtain the required datasets for any type of scenario desired, allowing a high flexibility in the obtention of appropriate data that can be used to evaluate CARS. This generator presents some important advantages, such as a flexible definition of user schemas, user profiles, types of items, and types of contexts, a realistic generation of ratings and attributes of items, the possibility to mix real and synthetic datasets, and functionalities to analyze existing datasets as a basis for synthetic data generation. Specifically, in this paper, we use real data about the Museum of Modern Art (MoMa) in New York, including information about paintings and sculptures as well as the map layout of the museum, and we complete the real dataset with other synthetic data needed to evaluate different CARS algorithms.

Summing up, the novel contribution of this paper is twofold:

- We present a design and implementation of a recommender system for museum visitors, which is able to exploit context-awareness for mobile devices. The system collects information from other users (i.e., their opinions about the works of art visited), by means of an information exchange service, and offers personalized recommendations about the next works of art to visit, taking into account context factors such as the location and trajectory of the user.
- We contribute to filling the gap between the design and evaluation in CARS, by exploiting the DataGenCARS tool in a mixed scenario built using both real data (data about works of arts and map information) and synthetic data (ratings provided by the users about the works of arts). Up to our knowledge, this is the first experience of using a tool like this one to generate a mixed scenario for the evaluation of a recommendation approach for a real use-case scenario. This is particularly valuable because, especially for indoor environments, there is a lack of rich datasets that can be used to evaluate these kinds of systems.

The structure of the rest of this paper is as follows. In Section 2, we present the strategy used to define the experimental environment and the proposed recommendation approach. In Section 3, we show the experimental results, that show the interest of the proposal. Finally, in Section 4, we present our conclusions and some prospective lines of future work.

2. Methodology and Proposal

In this section, we first present the scenario that we consider as a use case. Then, we present the recommendation approach that will be evaluated.

2.1. Works of Art

Our use case scenario is that of the visit to a museum, being the goal of the recommendation system to maximize the user's satisfaction with the visit. For that purpose, we use a real dataset corresponding to the works of art in the Museum of Modern Art (MoMa) in New York, available at `https://github.com/MuseumofModernArt/collection`. This collection contains information about 129024 works of art, characterized by 29 attributes (such as the title, artist, nationality, dimensions, classification, and department, among others). Over this dataset, we performed some preprocessing tasks, to facilitate its management. For example, we discretized some attributes, like the date of acquisition by the museum, which was classified into "recent" and "no recent" (as some frequent visitors may feel attracted towards works of art that have been acquired recently), and binarized others (like the nationality of the work of art).

Unfortunately, the precise location of each work of art is not available in the original dataset. However, the location of each item is important for the evaluation of CARS. Therefore, we used the Java-based synthetic data generator DataGenCARS[7], which we have designed and implemented previously, to create a random location for each work of art, subject to some rules to ensure a feasible real-world distribution: the works of art are distributed among the floors and rooms of the museum, and then positioned equitably along the walls and interiors of the rooms, in order to avoid overcrowded areas or situating two works of art with very little separation between them. For that purpose, a class *ItemLocationAttributeGenerator* was defined to extend the DataGenCARS framework.

2.2. Layout of the Museum

According to the documentation available at the time of writing this paper, the MoMa museum is composed by six floors: the first floor hosts the hall and a garden with sculptures; the second floor contains contemporary works of art; the third floor is devoted to architecture, design, drawings and photographs; the fourth and fifth floor include paintings and sculptures; and, finally, the sixth floor is the place of special exhibitions. Without loss of generality, for simplicity, we focused on floors fourth and fifth and restricted the types of works of art considered to paintings and sculptures (a total of 240 items were considered). From map images available on the Web, we reproduced the layout of those floors by converting the images to graph structures, by using the tool WebPlotDigitizer (`http://arohatgi.info/WebPlotDigitizer/app/`) to capture the locations of key elements (rooms, doors, and stairs).

Then, we developed a museum simulation application that loads and displays the layout of the selected floors as well as the paintings and sculptures in the area. This desktop application has been implemented in Java using the library JGraphX (`https://github.com/jgraph/jgraphx`), that facilitates the management and visualization of graph structures, Sqlite-jdbc (`https://bitbucket.org/xerial/sqlite-jdbc`), to manage SQLite databases from Java, and the general recommendation framework that we presented in[8].

2.3. Generation of Ratings

Moreover, we also used DataGenCARS to generate a rating collection, that is, a set of ratings (opinions) provided by users about the works of art that they observe. For this purpose, we defined different user profiles and assigned a specific user profile to each user. Regarding the user profiles, several context attributes were considered as factors that could potentially affect the ratings provided: the mood of the user (happy, sad, or neutral), the current temperature of the room (warm, hot, or cold), the number of people in the room (large, medium, or small), and the noise level (high,

medium, or low). Then, for each user, and based on his/her profile, we generated a rating for each work of art in the museum, in each possible context. Besides, for each piece of art, we generated a synthetic attribute representing the emotion transmitted by that piece (happiness, sadness, or neutrality) and defined a simple rating adjustment function that can slightly modify the rating generated depending on the relation between the current mood of the user and the emotion transmitted by that work of art. Finally, random trajectories were assigned to each user. When a user's trajectory stops at a certain work of art, the user observes it for a certain time interval and releases a vote/rating corresponding to his/her satisfaction with that piece and according to his/her specific context at that time. That vote is stored in a centralized information service at the museum and communicated to all the visitors inside that are equipped with the recommendation application, in such a way that the knowledge base of each recommendation application is enhanced along time, thanks to the votes released by the visitors during their stay in the museum.

2.4. Recommendation Process

We propose a context-aware user-based collaborative filtering approach that consists of the following steps:

- Through user-based collaborative filtering (UBCF), other visitors with similar preferences to the user are found.
- The known ratings provided by them are considered to estimate the potential ratings that the user could provide for different items in the museum.
- If an estimated rating exceeds a predefined *recommendation threshold* (e.g., 2.5 given an evaluation scale from 0 to 5), then the corresponding item is added to the list of potential recommendations.
- The proposed approach initially determines the top-k items that could be recommended to the visitor, that is, the k items with the highest estimated rating.
- Then, those k items are re-ordered, if necessary, in order to minimize the distance traversed. For that purpose, the shortest path traversing all those k items is computed and that path is the one recommended to the user. In case the list of recommendations obtained is empty (due to the absence of enough data for the collaborative filtering to provide results –cold start problem–), then the closest POI (work of art or exit) is recommended to the user.

An appropriate and up-to-date list of recommendations is automatically maintained in a suitable way. More specifically, the recommendation is updated if any of the following conditions hold: 1) the recommender application has new information regarding at least a certain number of ratings (*knowledge base increase threshold*), including ratings provided by the user himself/herself or received from other visitors; 2) the user is about to leave a room (and therefore the recommender is activated to verify if there is any work of art in that room worth visiting at that moment); or 3) the user has deviated from the recommended trajectory significantly (e.g., because something not recommended attracted his/her attention). Besides, in order to avoid recommendation instability, a *minimum time interval between successive recommendation updates* is required. Independently of the previous conditions, the recommended list of items is updated if the list becomes empty because the visitor already observed all the items previously recommended.

3. Experimental Evaluation

In this section, we present an experimental evaluation performed to show the feasibility of our proposal and the benefits that it can offer over other recommendation strategies. The experimental settings are shown in Table 1.

We identify our proposed approach as *Trajectory and User-Based Collaborative Filtering* (T&UBCF). As baselines for comparison, we also consider the following recommendation alternatives:

- *Random recommender* (RAND): the user visits works of art that are recommended in a completely random manner, room by room. This is expected to be the worst approach possible, as the user could potentially have to traverse large distances to go from one item to the next.
- *Exhaustive visit recommender* (ALL): the user is recommended to visit all the works of art in his/her current room, then an exit (the stairs, that allow to change from one floor to another, or a door) is recommended randomly, guiding the user to a different room, and so on.

Table 1: Experimental settings.

Parameter	Default value
Number of visitors in the museum & visiting time in the museum	100 visitors & 1 hour
Visitor's average speed & observation time (of a painting or sculpture)	3 Km/h & 30 seconds
Time needed to change to another floor (take the stairs or the elevator)	60 seconds
Number of recommended items to keep in the result list (K)	10 items
Similarity threshold for the UBCF algorithm	0.1 (Pearson correlation)
Recommendation threshold (0-5)	2.5
Knowledge base increase threshold	40 new ratings
Minimum time interval between successive recommendation updates	30 seconds

- *Nearest Point Of Interest recommender* (NPOI): the user is recommended to go to the nearest POI (a work of art or an exit) in the museum. If the nearest POI is an exit/door, then the user leaves the current room.
- *Know-It-All recommender* (Know-It-All): the trajectory and user-based collaborative filtering strategy T&UBCF is applied, but assuming complete knowledge about all the real ratings that the other visitors would provide.
- *K-Ideal recommender* (K-Ideal): the real ratings are considered and the k items with the best real ratings (not seen yet by the user) are recommended, after re-ordering them according to the shortest trajectory passing through those items.

The last two strategies assume complete knowledge about the real ratings that the other visitors would provide for each work of art in the museum. Obviously, it is unrealistic to assume that this information could be available (it includes knowledge about votes that have not been released), and therefore the performance of these last two approaches could be considered as a top-level performance that could be potentially obtained if complete knowledge about the other visitors was available.

Figure 1a shows the average satisfaction of the user with each of the recommendation strategies, computed as the average of the ratings provided by the user for the items observed in the museum (in a scale of 0 –which represents the minimum score– to 5 –which would correspond to an item that the user liked very much–). Our proposed approach (T&UBCF) provides the best average satisfaction, with the exception of the two unrealistic ideal alternatives.

(a) Average satisfaction with the items observed.
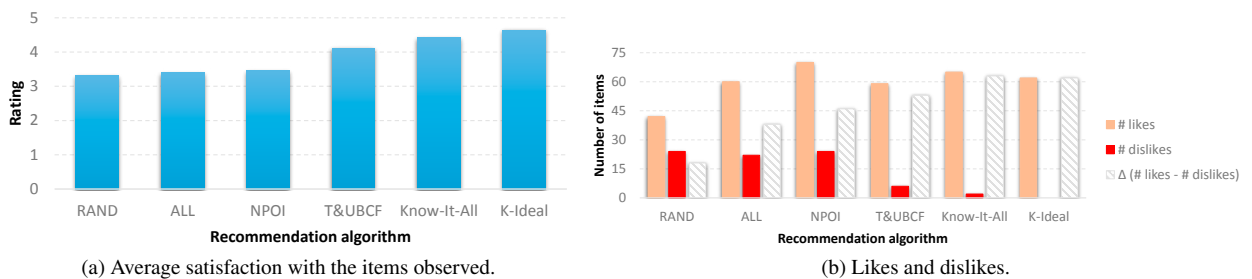
(b) Likes and dislikes.

Fig. 1: Performance evaluation: comparison of strategies.

Figure 1b shows the number of items observed by the user with each strategy, classifying them into likes (items rated by the user with a score above the recommendation threshold) and dislikes (items rated by the user with a score below the recommendation threshold). T&UBCF minimizes the number of dislikes (only outperformed by the ideal and unrealistic strategies). Although NPOI achieves a higher number of likes, it does it in exchange of a considerable higher number of dislikes. Besides, as it was shown in Figure 1a, the average satisfaction (average rating) obtained with NPOI is considerably lower than the one obtained with T&UBCF. Therefore, T&UBCF is the practical approach that offers the best results.

With the proposed approach, the recommendation system starts with an empty knowledge base and starts learning along the way, as time goes by and other visitors in the museum (and the user himself/herself) release votes about the items they observe. Figure 2a shows the evolution of the number of votes released along time and Figure 2b focuses on the evolution of the *MAE* (Mean Absolute Error) in the predicted rating of the items visited by the user along time.

As the dashed trend line depicted in Figure 2b shows, the recommendation system improves along time, as the MAE decreases as the knowledge base stored on the user's mobile device (initially empty) increases its size.
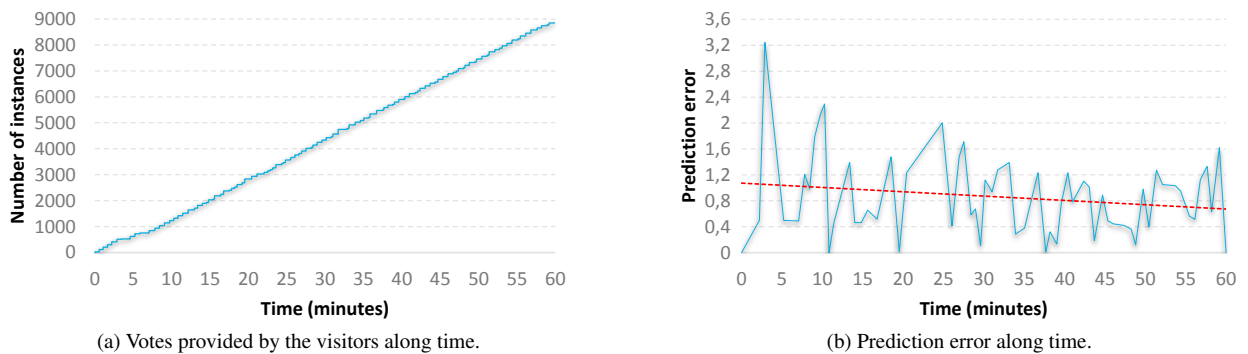

(a) Votes provided by the visitors along time.

(b) Prediction error along time.

Fig. 2: Incremental learning of user preferences along time.

4. Conclusions and Future Work

In this paper, we have presented a trajectory-based and user-based collaborative filtering approach for museum visitors, that tries to optimize their visiting time by offering them appropriate recommendations about the items to observe. The system proactively pushes new up-to-date recommendations to the user, when appropriate, and learns along time as new votes are released by other visitors in the museum and as the user's feedback (his/her own ratings) is collected. Our experimental evaluation shows the interest of the proposal. Besides, it represents a contribution to fill the gap between the design and evaluation in CARS, as we exploit the DataGenCARS tool in a mixed scenario built using both real data and synthetic data, to evaluate a recommendation approach for an indoors scenario. As far as we know, this is a relevant novelty in the literature. As future work, we intend to propose and evaluate other more sophisticated trajectory-based recommendation approaches. Besides, we are exploring alternative mobile ad hoc data sharing solutions to exchange directly data among the mobile devices of visitors located nearby.

Acknowledgments

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