Towards Understanding Mobility in Museums

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Abstract: Data mining techniques can provide valuable insight to understand mobility in museums. However, the results of such techniques might not be easily understood by the museum staff. In this paper, we propose a graph-based approach to model museum exhibitions, sensor locations, and guiding tasks. We further discuss how route-based trajectory mining can be adapted to work with this graph model and which challenges need to be addressed to cope with the graph dynamics and the continuous flow of sensor data. Based on the demands of two target groups, curators and visitors, three applications are proposed: a *museum graph editor*, a *mobile museum guide*, and a *curator decision support*. We propose an architecture for a platform that provides context information and data mining results to such applications. We claim that our proposed platform can cover many aspects and demands that arise in the museum environment today.

Keywords: mobility in museum, property graph model, museum knowledge management, incremental trajectory data mining

1 Introduction

Museum exhibitions are areas where mobility plays an important role. The museum staff designs the layout of exhibits so that an optimal visiting experience can be gained, often by assuming certain movement patterns or routes. In addition, they may offer audio guides, info boards, sign posts, and even mobile gaming apps [EM11, Va10] that should further help visitors to follow proposed routes or topics. Visitors may or may not be aware of such offers; they might only follow their interests and show a more or less predictable behavior. A case study analysis of an ambient intelligent museum guide [WE05] describes a museum as ecology: as an information ecology, it is a system of people, practices, values, and technologies in a local environment; and to understand that ecology, understanding visitor mobility is a key factor. Nowadays, a multitude of sensors could be used to automatically observe visitor mobility in a museum: light barriers at doors, cameras [Ru13], the usage of electronic guides [BF16], or dedicated sensors like in the work of Martella [Ma16]. Here, proximity sensors attached to visitors and exhibits were used to sense the fact that someone is close to an exhibit. All these data sources provide raw data of varying data quality. To gain information about the movement (represented as trajectories) and to derive useful knowledge out of such data, various trajectory mining techniques can be exploited. However, as has been demonstrated in [Ma16], the results of such techniques might not be easily understood by the museum staff. In addition, such techniques often work on maps

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and coordinates. However, it might be tedious to model exact floor plans, exhibit locations and sensor locations for a whole museum, in particular since many aspects of such digital maps will change with new exhibitions. Hence, we propose a graph-based approach to model museum exhibitions, sensor locations, and guiding tasks (either for navigation or for location-based games). We further discuss how route-based trajectory mining can be adapted to work with this graph model and which challenges need to be addressed to cope with the graph dynamics. Based on the demands of two target groups in the museum, curators and visitors, two types of application are needed. First, a *mobile museum guide* for the visitor to find their way easily and, secondary, a *curator decision support* and a *museum graph editor* that helps the curators organize the museums in an efficient way. The paper is organized as follows. In Section 2 we propose the main architecture of our platform. In Section 3, we describe the features of the museum graph model designed according to two main challenges: the dynamic environment and the public environment in a museum. We use museum graph model to provide context information for mobility model management which we present in Section 4. We show that different preprocessing and mining techniques take use of that context information. We conclude with Section 5 and give an outlook on future work.

2 Architecture Overview

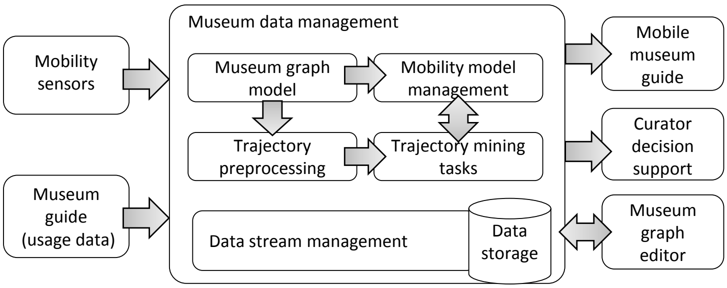

Fig. 1: Architecture overview

To manage mobility data we propose an architecture as depicted in Figure 1 to support three applications (right side): *Mobile museum guides* are mobile multi-media applications that inform visitors about exhibits, propose tours, and could contain scavenger-hunt-like games. In addition, by recognizing the mobility pattern and interests of the current user, such guide can individually recommend certain exhibits, topics, or tours ("'visitors who liked exhibits A and B also liked room C"'). The *Curator decision support* helps the museum staff to understand mobility. It is a domain-specific data analysis application that visualizes the results of various data analysis like popularity of exhibits, most popular paths, or classes of visitor behavior. Finally, we offer the *Museum graph editor* that provides an easy way for the museum staff to model exhibitions, game tasks, and room layouts. The *Museum data management* continuously processes incoming data from *Mobility Sensors* like cameras or WIFI trackers and from usage of the *Mobile museum guide*. Locations of visitors are *preprocessed* and mapped onto the *Museum graph model* (as provided by the corresponding editor) that represents the location of rooms, exhibits, and sensors. The results are semantic trajectories that are fed into various *Trajectory mining tasks* to produce mobility models like frequent mobility patterns or trajectory clusters. Since the museum graph model changes whenever new exhibits or game tasks occur, we need to manage these models so that they are compliant with the exhibition. For this, changes in the museum graph model are published to the *Mobility model management* which controls the mining tasks. In the following sections, we give more details on the Museum graph model and the Mobility model management.

3 Museum Graph Model

Based on previous evaluations on geometric and symbolic location models [BD05] we propose an attributed graph-based location model of the museum environment to represent the context information which is used in analysis of mobility inside the museum. We need to model exhibits, visitors, tasks, areas, sensor locations, routes and the spatial and non-spatial relationships between such assets and objects. Assets and objects are modelled as nodes. Relationships are represented as edges. Both, nodes and edges, can be further attributed. Relationships that express containment and connectedness are sufficient and necessary to answer common spatial queries [BD05] but to enable analysis that goes beyond spatial relationships, further properties like topics or temporal availability need to be included. We therefor chose the property graph approach [Su15, Da14] to design the model. For the implementation, Neo4j[4] will be used. Figure 2 shows an example graph that could be implemented as part of a bigger graph representing the whole museum. The graph consists of seven nodes: three are of type *POI* (point of interest), two of type *location*, one of type *passage* and one of type *activity*. Passage refers to objects connecting locations, like doors, stairs or elevators. Activity refers to different actions a visitor can take in the museum, like tasks related to exhibits. The nodes are attributed with subtypes, names and descriptions to ease the retrieval of individual nodes or sets of nodes. Each node has an unique ID and some human-readable values for each attribute. The nodes are connected through different kinds of relationships.

Figure 2 shows relationships that will be mainly used in our graph: *connected*, *inside* and *assigned*. In the example graph, two rooms – the entrance hall and the room named Vogelsaal – are *connected* by a door. One POI *inside* the entrance hall could be the cash desk, where visitors pay for their visit. In the Vogelsaal, two exhibits (vitrines) which show some birds and animals, are located. The *mobile museum guide* could offer some tasks to the visitors to increase their museum experience. Here, we *assigned* a task to the second vitrine, containing padded birds. For example, the visitor could be asked by the mobile museum guide to estimate the number of feathers as soon as she passes the vitrine.

The example shows that the graph model can be easily understood by humans. Curators and museum education officers should be able to understand the model as they might want to create and adapt it via the museum graph editor. A graph-based model provides a

[4] https://neo4j.com/

well suited representation and has a medium modelling effort compared to other location model approaches [BD05]. Furthermore the model can help to understand the reasons behind certain mobility patterns of visitors in the museum. A visitor might spent some time infront of the second vitrine to count the feathers.

Regarding museum data management, we face two main challenges: (i) the environment is dynamic, and (ii) the environment is public. Challenge (i) results in a variable frequency of updates, updates on different parts of the model (e.g. a property "‘accessible"’ is added for nodes of the type "‘room"’) and changing availability (e.g. a relationship exists only within a certain time interval). Because of challenge (ii), we need to deal with heterogeneous user groups and we need to integrate privacy-preserving methods into the data management platform [St16]. The graph model is scalable and adaptable to changes in the museum. Properties, nodes and relationships in the instantiated graph can be easily added or removed. However, such changes over time and within space must be considered in further processing steps. To control the knowledge that is stored in the graph, restricted relationships and unique nodes can be defined. Thus, the dynamics of the graph itself can be limited. In the future we will evaluate features of other graph variants and compare them to our property graph model. For improving the scalability of the graph and for enabling the organization of entities in subgraphs, we intend to use multiple relation-based layers [Bo12]. For investigating how fine-grained semantical information can be included into our model (e.g. exhibit B is between exhibit A and exhibit C) we will consider hypergraphs [ERV06].

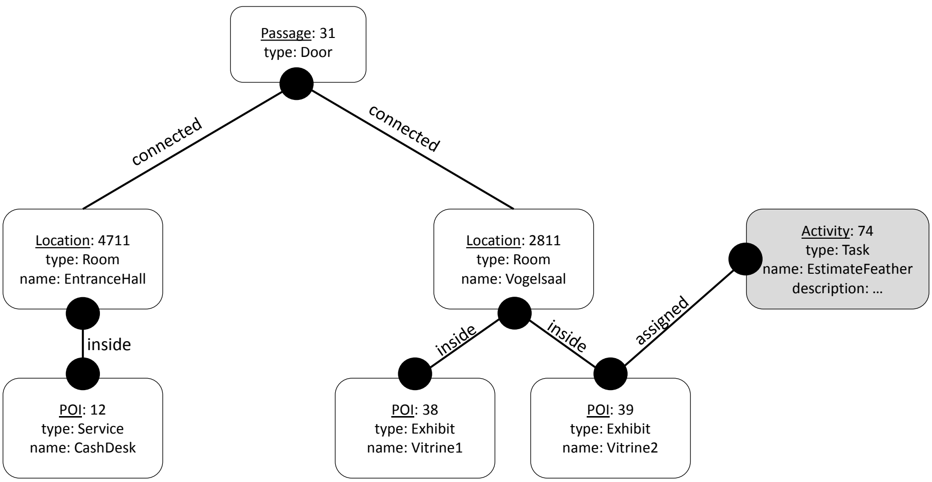

Fig. 2: Museum graph example

4 Mobility Model Management

In contrast to the museum graph model which represents the context information, mobility models represent the knowledge on movement of visitors. Examples for mobility model are frequent mobility patterns or trajectory clusters. The two main applications use such mobility models to provide their service. Curators can arrange their museum in a way to have a constant distribution of visitor population instead of some crowded area and some empty rooms. In addition, recommendations that are based on mobility models can help visitors find a specific exhibit in a shorter time and choose the best path based on their interests.

We use the information gained from Museum graph model as context information to preprocess the observations from mobility sensors and the usage data from the mobile museum guide. Therefor we can extract relations and points that build primary routes. For example, considering the attribute "'accessible"', we know that a potential route through a room is possible or not. Combining primary routes together with preprocessing techniques like stay point detection and map-matching lead to more accurate results [Kh08]. Additionally, we can use trajectory segmentation technique when we need to consider trajectories in some particular time or particular exhibition in the museum. We develop trajectory mining tasks such trajectory clustering and trajectory classification based on preprocessed semantic trajectories to produce several mobility models. Finally, we need to manage all the knowledge obtained from different mobility models to serve the applications.

Trajectory clustering in the museums is the process of finding frequent trajectory patterns shared by visitors and of grouping similar trajectories into clusters. Trajectory clustering has been presented for clustering the trajectories both in free space and in a route-based setting [Zh15]. As we mapped the information of the museum environment into a graph model, our clustering task is based on the trajectories in route-based setting. According to the fact that a museum is a changing environment and also the interests of visitors could change during time intervals, we need to implement incremental trajectory mining algorithms [Li10]. In such approaches, first a trajectory segmentation technique is applied on trajectories and then the last segment of trajectory in a time window can be considered. One of the benefits of this method is that if the visitors had different paths before the start of the time window, it does not affect the results of clustering within the time-window, and we can focus on analyzing recent movement patterns [SZM16]. For example, we can study the direct effects of some events or changes to the Museum graph model on the distribution of visitor population.

Based on the example mentioned in the previous section, we can apply stay point detection as preprocessing step and after extracting stay points from single trajectories we can apply clustering techniques to define different clusters of stay points based on duration or number of detected stay points. In addition, using points of interest defined in graph model can help us to find stay points easier. However, in stay point detection step we may find some other stay points which are not defined in the graph model as POI. For clustering the stay points incrementally, we define a window size and consider the stay points just within a time window. As described before, in the entrance hall there is a cash desk where all of the visitors should stop, even for few seconds, to buy a ticket for the museum. In this scenario, by applying stay point detection on single trajectories and clustering these points based on number on detected stay points we can extract three main stay points: a stay point in front of the cash in the entrance hall and two stay points in front of the vitrines in the Vogelsaal.

In incremental clustering, events can change the results of clustering during different time intervals. For example, a curator adds the activity of feather estimation at time t_2. Later, at time t_3, she is interested in the effects of this change in the mobility models.

As illustrated in Figure 3, we can define two time intervals based on the graph changes: one before t_2 and one from t_2 to now (which is t_3). After adding the activity, visitors become more interested in the birds in vitrine 2. Therefore, the number of detected stay points in the second time window increases. On the other hand, since there are no changes to the entrance hall, we do not define a new time window for this room. In the example, 20 visitors visit the museum within the time interval t_1 to t_3. We know all of the visitors stop at cash desk, so we can use this stay point to count the number of all visitors. From t_1 to t_2, 8 visitors are interested at vitrine 1 and 3 visitors are interested in vitrine 2. At time t_2 by changing the graph model of Vogelsaal the number of detected stay points for vitrine 2 changes. The number of detected stay points from t_1 to t_2 and from t_2 to t_3 is shown in table 1.

Based on the information obtained from preprocessed semantic trajectories we can classify different kinds of visitors based on their visiting style and time schedule. For the same reason mentioned for clustering techniques, like changes in museum environment and the interests of visitors, we use incremental classification [Le08]. The obtained knowledge helps curators to arrange the exhibits in a special order that makes visitors spend a shorter or longer time in the museum, and helps visitors by providing more accurate suggestions in order to have a more desirable path through the museum.

Location name	SPs $t_1 - t_2$	SPs $t_2 - t_3$
Cash desk	20	
Vitrine 1	8	8
Vitrine 2	3	12

Tab. 1: Detected number of stay points in different time windows

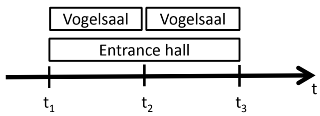

Fig. 3: Defined time windows

5 Conclusion and Outlook

We presented a platform that addresses many aspects and challenges regarding the museum environment. This platform can be deployed in any museum, regardless the focus of the exhibitions. The goal of this platform is to understand the mobility in the museums in order to support three applications that match different requirements. The platform contains a *museum graph editor* that can be used by museum staff to represent and update the graph model of the museum environment. The graph model further serves several data mining tasks which provide mobility models to a *mobile museum guide* and a *curator decision support*. Using different preprocessing and mining tasks on semantic trajectories can provide accurate mobility models that result in a deeper understanding of mobility in museums. However, for this we have to solve the challenge of a dynamic mobility model management that controls the time windows and data scopes of incremental trajectory mining algorithms so that it stays consistent with the real world, as it is represented by the

Museum graph model. Future works will cover investigations on requirements and therefore cooperation with museums. Throughout the development process we will evaluate the property graph model and decide on how it can be extended by further features to cover different application and mining use cases. The important aspect in developing a mobile museum guide application and a curator decision support application is that the applications should provide consistent information to the curators and visitors at the same time. For example, a new event like offering snack in buffet should provide new suggestion for visitors and help the curators to organize the event efficiently.

References

[BD05] Becker, Christian; Duerr, Frank: On Location Models for Ubiquitous Computing. Personal Ubiquitous Comput., 9(1):20–31, January 2005.

[BF16] Bay, Herbert; Fasel, Beat: , Interactive Museum Guide - Semantic Scholar, 2016.

[Bo12] Boden, Brigitte; Guennemann, Stephan; Hoffmann, Holger; Seidl, Thomas: Mining Coherent Subgraphs in Multi-layer Graphs with Edge Labels. In: Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. KDD '12, ACM, New York, NY, USA, pp. 1258–1266, 2012.

[Da14] Das, Souripriya; Srinivasan, Jagannathan; Perry, Matthew; Chong, Eugene; Banerjee, Jayanta: , A Tale of Two Graphs: Property Graphs as RDF in Oracle, 2014.

[EM11] Economou, Maria; Meintani, Elpiniki: Promising Beginning? Evaluating Museum Mobile Phone Apps. Limerick, 2011.

[ERV06] Estrada, Ernesto; Rodriguez-Velazquez, Juan A.: Complex Networks as Hypergraphs. Physica A: Statistical Mechanics and its Applications, 364:581–594, May 2006. arXiv: physics/0505137.

[Kh08] Kharrat, Ahmed; Popa, Iulian Sandu; Zeitouni, Karine; Faiz, Sami: Clustering Algorithm for Network Constraint Trajectories. In (Ruas, Anne; Gold, Christopher, eds): Headway in Spatial Data Handling, Lecture Notes in Geoinformation and Cartography, pp. 631–647. Springer Berlin Heidelberg, 2008. DOI: 10.1007/978-3-540-68566-1_36.

[Le08] Lee, Jae-Gil; Han, Jiawei; Li, Xiaolei; Gonzalez, Hector: TraClass: Trajectory Classification Using Hierarchical Region-based and Trajectory-based Clustering. Proc. VLDB Endow., 1(1):1081–1094, August 2008.

[Li10] Li, Zhenhui; Lee, Jae-Gil; Li, Xiaolei; Han, Jiawei: Incremental Clustering for Trajectories. In (Kitagawa, Hiroyuki; Ishikawa, Yoshiharu; Li, Qing; Watanabe, Chiemi, eds): Database Systems for Advanced Applications, Lecture Notes in Computer Science 5982, pp. 32–46. Springer Berlin Heidelberg, April 2010. DOI: 10.1007/978-3-642-12098-5_3.

[Ma16] Martella, Claudio; Miraglia, Armando; Cattani, Marco; Steen, Maarten van: Leveraging proximity sensing to mine the behavior of museum visitors. In: 2016 IEEE International Conference on Pervasive Computing and Communications, PerCom 2016, Sydney, Australia, March 14-19, 2016. pp. 1–9, 2016.

[Ru13] Rubino, Irene; Xhembulla, Jetmir; Martina, Andrea; Bottino, Andrea; Malnati, Giovanni: MusA: Using Indoor Positioning and Navigation to Enhance Cultural Experiences in a Museum. Sensors, 13(12):17445–17471, December 2013.

[St16] Steuer, Simon; Benabbas, Aboubakr; Kasrin, Nasr; Nicklas, Daniela: Challenges and Design Goals for an Architecture of a Privacy-preserving Smart City Lab. Datenbank-Spektrum, 16(2):147–156, July 2016.

[Su15] Sun, Wen; Fokoue, Achille; Srinivas, Kavitha; Kementsietsidis, Anastasios; Hu, Gang; Xie, Guotong: SQLGraph: An Efficient Relational-Based Property Graph Store. ACM Press, pp. 1887–1901, 2015.

[SZM16] Silva, Ticiana L. Coelho da; Zeitouni, Karine; Macedo, Jose A.F. de: Online Clustering of Trajectory Data Stream. IEEE, pp. 112–121, June 2016.

[Va10] Van Hage, Willem Robert; Stash, Natalia; Wang, Yiwen; Aroyo, Lora: Finding your way through the Rijksmuseum with an adaptive mobile museum guide. In: The Semantic Web: Research and Applications, pp. 46–59. Springer, 2010.

[WE05] Wakkary, Ron; Evernden, Dale: Museum as ecology: A case study analysis of an ambient intelligent museum guide. In: Museums and the Web. volume 2005, pp. 151–164, 2005.

[Zh15] Zheng, Yu: Trajectory Data Mining: An Overview. ACM Transaction on Intelligent Systems and Technology, September 2015.