Semantic Trajectory and Recommender Systems in Cultural Spaces

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Semantic trajectories can efficiently model human movement for further analysis and pattern recognition, while personalised recommender systems can adapt to constantly changing user needs and provide meaningful and optimised suggestions.

Keywords: semantic trajectories ; recommender systems ; cultural space

1. Introduction

An already effective approach for discovering preferences and needs for moving users in cultural spaces is through the analysis of their trajectories (big movement data), as they contain rich explicit and implicit information and knowledge. Due to the evolution of mobile computing, wireless networking, and related technologies, such as GPS, mobile applications can monitor and share information about user position during movement, e.g., while the user is visiting a cultural space. The existing infrastructure enables applications to produce a vast amount of streaming data that include information not only about locations and places that users are visiting but also the paths/routes/trajectories the users are following, as an aggregation of connected spatial points in specific time-lapses [1][2][3][4].

Semantic Web technologies offer powerful representation tools for pervasive applications. The convergence of location-based services and Semantic Web standards allows easier interlinking and semantic annotation of trajectories, resulting in semantic trajectories. Trajectory-based operations, which involve spatiotemporal data of moving entities, are becoming increasingly important in related studies and applications, as they provide insights about human movement and the ability to extract patterns and predict future behaviours. As described in [5], a semantic trajectory-based recommender system (RS) is designed on the basis of the observation that users with similar trajectories would have similar preferences for the available objects, and outperform traditional recommendation methods that do not consider trajectory or environment information.

2. Preliminaries

2.1. Semantic Trajectories (STs)

A trajectory is defined as the composition of the sections of connected traces and points that express a meaningful movement in space and time by an object or entity of interest. The study of trajectories is fundamental for the comprehension of moving object/entity behaviour, as there is a plethora of useful information in the path/route the object/entity follows to navigate between start and end points. The behaviour of a trajectory is the sum of the characteristics that identify the essential details of a moving object/entity or a group of moving objects/entities. A set of such unique characteristics creates a short description of a group of trajectories which are called patterns [6][7]. Data analytics based on trajectories of moving objects/entities, such as trajectory clustering and construction, could provide advantages in the solutions of several common or more complex problems [8][9][10].

As stated by Dodge et al. [11], the movement behaviour depends on the general context in which it takes place, as every movement has a specific meaning in the moment and in the space/environment that it is happening. Semantic trajectories are the trajectories that have been enriched with semantic annotations and one or more complementary segmentations [7]. Annotations of segmented parts of a trajectory (episodes) could be “stop” or “move”, or, in other cases, could be points or regions of interest. An example semantic trajectory of a touristic walk is depicted in **Figure 1**.

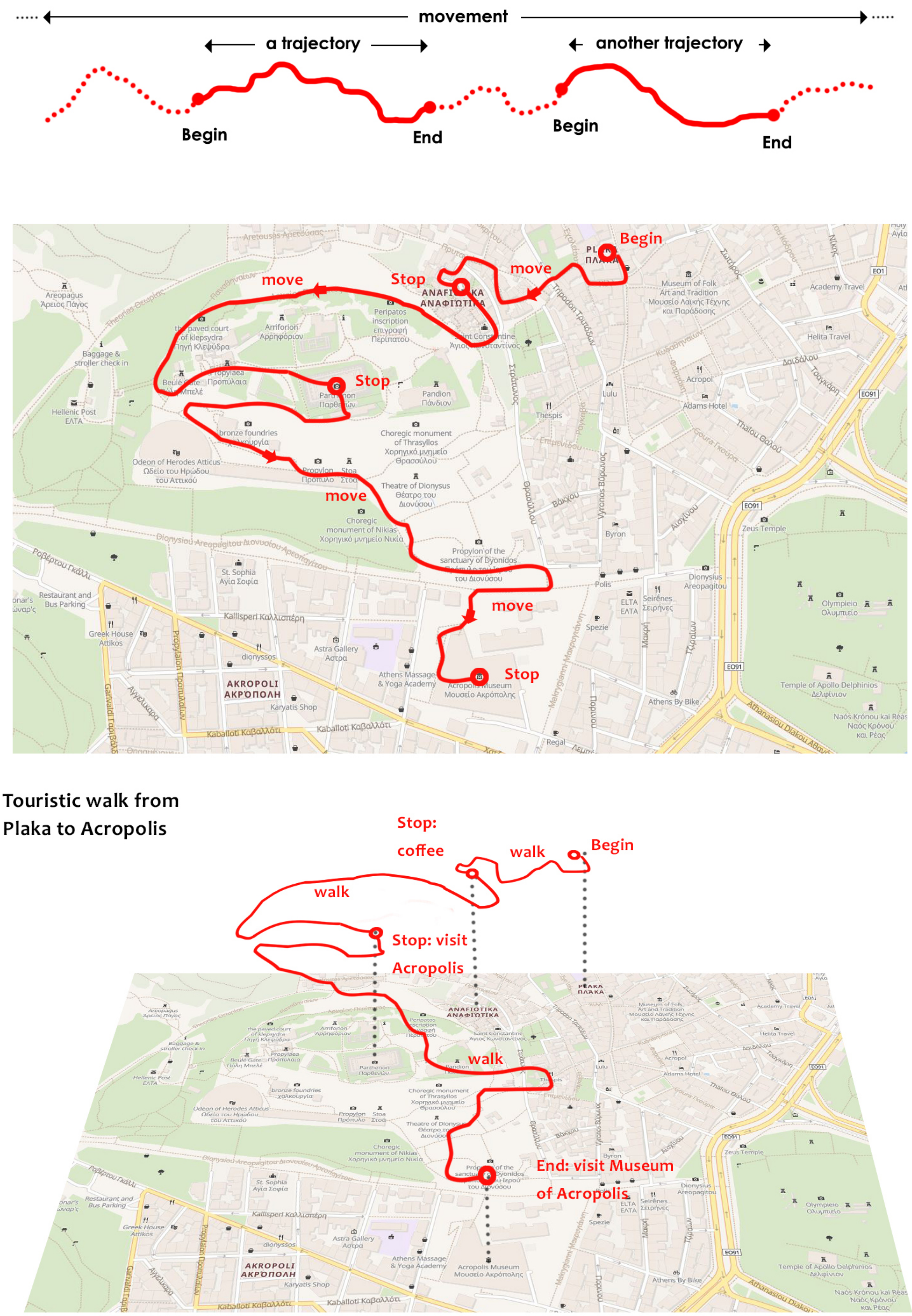

Figure 1. Example semantic trajectory depicting a tourist behaviour in Athens, starting from a simple trajectory, and resulting in a semantic trajectory.

2.2. Recommender Systems (RS)

RSs are software tools or AI applications that are designed to predict the user's interests and preferences based on statistics, data mining algorithms, and machine learning techniques, to suggest/recommend products, services, locations, routes, etc. RSs handle the problem of information overload that users normally encounter and affect the way users make decisions through the recommendation of suitable actions or objects of interest. An example of a Cultural Recommender System is depicted in **Figure 2**. The main tasks of a RS are to (a) gather and process data, (b) create models based on the available data, (c) apply the models to existing and future data, and (d) receive feedback and re-evaluate the models. Common characteristics that a RS should possess for it to be considered efficient are: accuracy, coverage, relevance, novelty, serendipity, and recommendation diversity [12]. Most recommendation strategies are defined based on three main relation types: (a) User–Item relation, (b) Item–Item relation and (c) User–User relation.

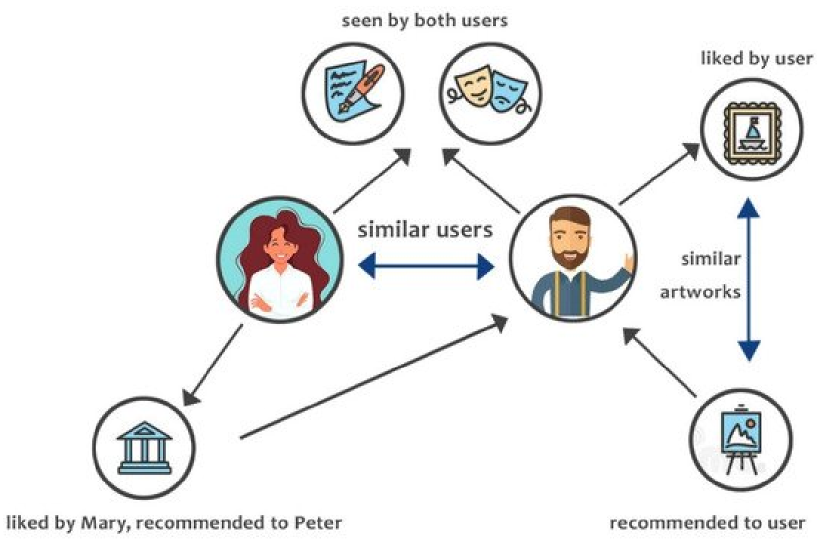

Figure 2. Example of a Cultural Recommender System.

- User–Item relation: This relation is based on the user profile and the explicitly documented preferences of the user towards a specific type of Item.
- Item–Item relation: This relation occurs based on the similarity or the complementarity of the attributes or descriptions of the Items.
- User–User relation: This relation describes the Users that possibly have similar tastes with respect to specific Items, such as mutual friends, age group, location, etc.

2.3. Knowledge Graphs

KGs are increasingly getting attention from academic and industry organisations as they provide several advantages compared to relational databases, regarding the representation and management of big and heterogeneous data. As defined by Hogan [13], a KG is a graph of data intended to accumulate and convey knowledge of the real world. The nodes represent entities of interest, and the edges represent relations between these entities. While there is a conceptual overlap between KGs and ontologies, because both are formed to be “an explicit specification of a conceptualisation”, KGs can be considered more as “a graph of data with the intent to compose knowledge” [14][15].

3. State of the Art in STs and RSs

3.1. Semantic Trajectories (ST)

3.1.1. Annotation of Trajectories

In de Graaff et al. [16], a novel algorithm for automating the detection of visited POIs is proposed. They describe a POI as “a location where goods and services are provided, geometrically described using a point, and semantically enriched with at least an interest category”. A Polygon of Interest (POLOI) has a similar definition to a POI, except that the location is described by a polygon. The proposed method tries to identify visited POIs both in outdoor and indoor trajectories from raw smartphone GPS data but is specifically designed for urban indoor trajectory analysis. It focuses on detecting stops that take place at known and predefined POIs. The challenges overcome by the proposed algorithm are the non-detection of indoor visited POIs and the false positive detection due to lack or instability of the GPS signal. Because of the unavailability of the GPS signal for the indoor segments of a trajectory, the proposed algorithm selects points before and after the users get into a building and projects them to a polygon. The POI visit extraction algorithm considers the accuracy of the location, reductions in speed, changes in direction, and projection of signals onto polygons to extract the staypoints (the centroids of stop sequences) from a trajectory. An experiment with students in the city of Hengelo was set up to validate the proposed approach and concluded that the algorithm outperformed several existing approaches.

3.1.2. Semantic Trajectory Management

The work of AL-Dohuki et al. [17] focuses on an approach to interact with trajectory data through visualisations, enriched with semantic information about the trajectories. The approach was designed and evaluated for taxi trajectories. The trajectories are converted to documents through a textualisation transformation process where the GPS points are mapped to street names or POIs, and the speed is described quantitatively. After the transformation, each document is described by a meta-summary and indexed to enable queries over a text-based search engine. The system is data-structure agnostic, and the results are integrated with visualisations and interactions to promote easy understanding. The evaluation of a prototype claimed to be successful, and its ease of use is demonstrated appropriately.

3.2. Recommender Systems (RS)

3.2.1. Cultural RS

In Amato et al. [18], a methodology that combines recommendation with agent-based planning techniques to implement a planner of routes within cultural spaces is proposed. The problem of finding a scheduled path of visitors in a cultural space or site is handled as a reachability problem and uses multi-agent models to achieve the goal of accessing POIs within certain deadlines. First, the approach analyses user preferences to provide an accurate list of cultural items. Then, the multi-agent planning methods calculate the paths that follow sequence steps to meet the goal of visiting the suggested items. For each pair of users and items, the recommender can compute a rank that measures the expected interest of the user in an item, using a knowledge base and a ranking algorithm. The ranking algorithm integrates information about preferences and past behaviours of the target user and the user community, user feedback, and contextual information, to create the list of suggested items. The browsing system is represented as a directed labelled graph and depicts the sequence of chosen items to increase the similarity measure between them. Finally, the agents compute and recommend the path that meets the requested goals or state that it is unreachable.

3.2.2. Semantic and Knowledge-Based Recommender Systems

Interactive RSs are modelled as a multistep decision-making process to capture the dynamic changes of user preferences. Zhou et al. [19] present a recommendation approach that utilises reinforcement learning methods and KG to provide semantic information to an Interactive RS. Reinforcement learning methods face an efficiency issue when provided with a small sample of data. To address the issue, they leverage prior knowledge of the item relations in the KG for better candidate item retrieval, enrich the representation of items and user states, and propagate user preferences among the correlated items. Interactions between the user and the system last for a defined time period. At each period, the system dynamically generates a list of items based on historical interaction data and item similarity from the KG, suggests them to the user, and receives feedback in order to update the recommendations. The introduced model consists of a graph convolution module, a state representation module, a candidate selection module, and the Q-learning network module. Evaluation experiments demonstrated that the proposed approach outperformed the state-of-the-art method.

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