# User Behaviour Analysis in a Simulated IoT Augmented Space*

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## ABSTRACT
In this paper we present a demo application aimed at supporting the research in the field of tourism and mobility support in IoT augmented areas. The application collects tourists' choices while browsing Points of Interest (POIs) descriptions through a map-based interface that simulates user movement between POIs. Collected observations serve two purposes: the computation and testing of recommendation strategies for POIs (both for on-line and off-line studies); the generation of simulated users' behaviour under alternative scenario and context conditions (e.g., weather, or the presence of a novel POI).

## Author Keywords
Simulation Environment; IoT; Recommender Systems.

## INTRODUCTION
Internet of Things (IoT) enables novel types of interactions with wireless sensor networks. It is now becoming a mainstream approach to the development of tourism and mobility applications [2]. In this demo we present an environment for simulating interactions with an IoT enabled area. By using the system, users can move in a virtual space that represents the real world. The system has been developed to: (1) overcome the lack of available and suitable datasets for studying decision making in such scenarios and (2) perform early testing before the actual deployment of an IoT network, such as that composed by a collection of beacons signalling the user proximity to a POI.

More precisely, the goals of the designed system are to:

- Register context-dependent decisions taken by users in a simulated IoT enabled area.
- Collect user's feedback (e.g., like/dislike) on POIs in order to compute and evaluate recommendation strategies in both on-line and off-line settings.
- Evaluate the usability and effectiveness of a mobile app that supports the user (tourist) in the navigation of a real physical space augmented with IoT devices.
- Simulate users' decisions in a range of alternative and possibly new contextual settings.

The designed system supports the research on user behaviour learning in IoT enabled areas by providing a controlled environment that allows conducting large scale simulations. Studies on user behaviour learning in IoT augmented spaces have been recently proposed [6, 3]. They have focused on indoor environments with a limited set of IoT augmented POIs. Conversely, the proposed system makes possible to deal with a larger and outdoor area where several IoT devices are located. In addition, external factors that may influence user behaviour (e.g., weather conditions) have not been previously considered. In [5] we discussed the expected benefits of the exploitation of context in user behaviour learning and simulation as well as in the generation of recommendations.

## USER BEHAVIOUR OBSERVATIONS AND FEEDBACK
The interaction process with the proposed simulation environment unfolds as follows. A user starts a simulated visit to a city by providing demographic information (e.g., his age and gender), his POI preferences (e.g., specific museums) and topic preferences (e.g., culture or relax). Then, the system proposes an itinerary, which is visualised over an interactive map, in the form of a path optimised according to the stated preferences. From now on the user can simulate movements along the proposed itinerary. He can decide to visit the next POI in the itinerary or deviate from it and visit other POIs located in the proximity of his virtual location. To let the user perceive the cost/time required for moving from a place to another place, the system animates the movement of a map placeholder. During the user decision making process (to visit a POI) the system notifies him the current simulated contextual conditions (e.g., weather, daytime, crowdedness), so that he can take them into account when deciding to visit a POI. As soon as the user reaches a POI, a pop-up window, which emulates the GUI of a mobile app, illustrates the reached place with information and media as it would happen when the visitor approaches the beacon associated to the POI (Figure

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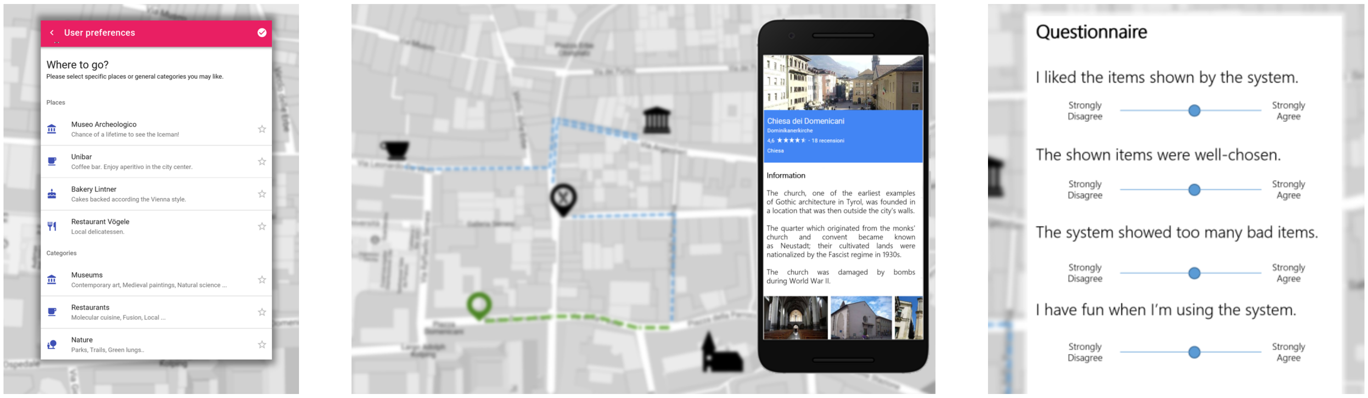


(a) (b) (c)

**Figure 1. System interface details. (a) Initial preference elecitation. (b) Interactive map and mobile app pop-up. (c) Evaluation questionnaire pop-up.**

1.b). Once the user has browsed the provided content, he is asked whether he would have liked to stop and visit the POI. While transitioning from place to place the user is also notified, depending on the observed choices and stated preferences, about the presence of nearby POIs that could be interesting for him (recommendations). The user can evaluate the usefulness of the suggestions (e.g., like/dislike feedback). The system records the user behaviour in the virtual space, which is supposed to approximate the real world one. In fact, the system simulates IoT sensors tracing user movements, records the dwell time in places, and stores the user's provided feedback on the visited POIs. In Figure 1 some screens of the system are shown.

## USER BEHAVIOUR LEARNING AND SIMULATION

The system collected user behaviour is stored per session and it is associated to the user id. That allows the retrieval of user's demographic information and the identification of the ordered list of visited POIs along with the associated contextual conditions (i.e., daytime, weather, temperature and crowdedness level). In order to produce an explainable user behaviour, i.e., a richer data structure that could then be used for simulations and recommendations generation, we rely on Inverse Reinforcement Learning (IRL) as discussed in [6, 5]. IRL allows to express the user behaviour in terms of an action selection policy (e.g., the sequential selection of POIs) as well as of preferences over the features of the visited POIs and the context conditions (e.g., POI category and weather). User behaviour model is learned by exploiting grouped observations of users who share common traits, such as preferred topics, or who visited similar places. From the learnt behaviour model the system can also generate simulated users' trajectories that depend on the contextual variables. This could be beneficial, e.g., for a mobility policy maker to assess the effect of novel contextual conditions and to design improved public transportation policies when events, like fairs, take place in a city. The system GUI allows the modification of the context variables through a set of sliders.

## RECOMMENDATION GENERATION AND EVALUATION

POI recommendations to users can be generated on the base of the observed behaviour, the current context situation and the user's set of preferences (see [5]). The proposed system allows to test the effectiveness of a recommendation strategy both on-line (e.g., A/B testing) and off-line (e.g., algorithms performance). In fact, during the simulated POIs visit supported by the system the user fills a questionnaire aimed at evaluating the system recommendations. Its questions ground on [4] and aim at measuring: (1) perceived recommendation quality, (2) choice satisfaction and (3) choice difficulty. In addition to the evaluation of recommendations, the system can be used to assess the effectiveness and usability of a prospective mobile app for tourism and mobility support in IoT scenarios. In fact, also the perceived app effectiveness [4] and usability [1] are measured.

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