INVESTIGATION OF HUMAN TRAVEL AND ACTIVITY PATTERNS BY LEVERAGING FOURSQUARE LOCATION-BASED SOCIAL NETWORK DATA

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INTRODUCTION: A description of the problem and a discussion of the background.

Researchers are interested to understand human activity patterns and travel behaviors. Conventionally, such information was in format of travel diaries, but the data is not highly available and difficult to gather by such methods. Also information about users gender, age, are available on Foursquare and can be correlated with the traffic and activity patterns in order to further understand gender differences in travel and activity which is a popular research topic. Diaries are used to record human daily movements, places visited, activities, time of day, duration of time spent at each place (venue). A diary is “a record of information in relation to the passage of time”

Information on the movement of people in the city can be used for: location management, transportation management, etc thus being of interest also for local authorities and companies.

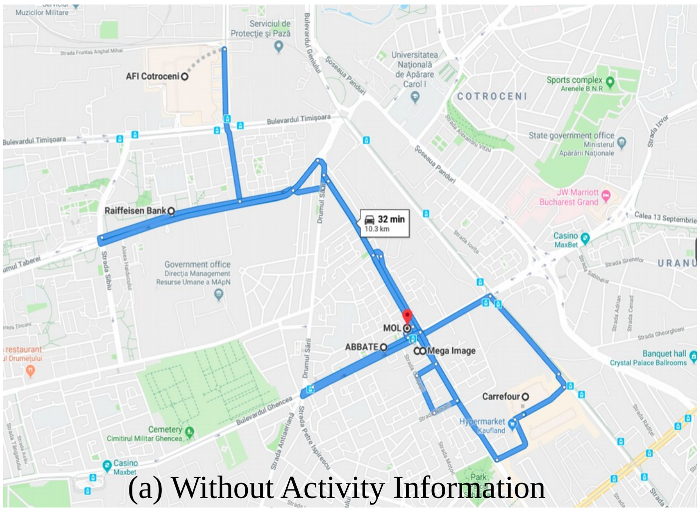
In my project, I will present an approach to understand the human activity and pattern behaviors in my town: *Bucharest, Romania*, using Foursquare’s location API (the GET NextVenue method).

Online social media, like geotagged travel photos, can be used as an alternative source of travel data. However, it is seriously limited because they cannot provide detailed contextual information on the activities for further analysis.

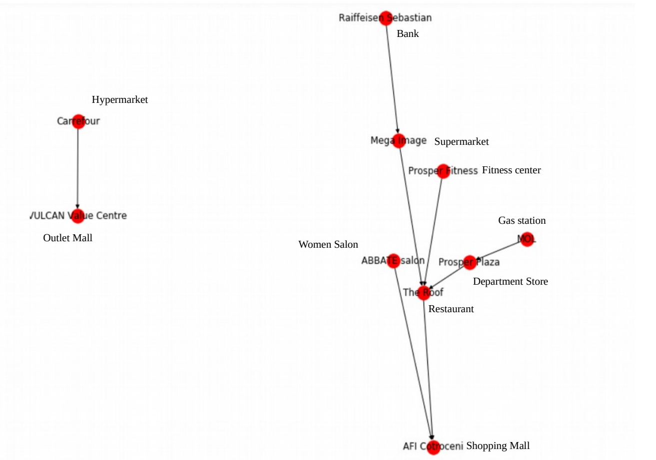
Suppose a group of people, report often visits to several locations in Bucharest, Romania. Figure 1a shows people visited several locations as pinpointed on the map. However *Figure 1b* provides much richer information such as traveling to gas station (‘MOL’), eating at the restaurant (‘The Roof’), shopping in the malls (‘Carrefour’, ‘AFI Cotroceni’), going to fitness, etc shown on a *directed graph*.

Travel Representation:

In LBSNs such as Foursquare, each venue represents a physical location (see Figure 1). Common types of venues include banks, restaurants, offices, apartments, hotels, bus stops, shops and gyms. In Figure 1, for instance, there is a pattern of users checks in at venue A (Prosper – Fitness Center) and venue B (‘The Roof’ restaurant) and venue C (‘AFI Cotroceni’ - shopping mall), consecutively. We can, therefore, deduce that people often moves from venue Fitness to venue Restaurant than to C Shopping Mall, irrespective of the specific route taken by the user between the two venues. A series of consecutive check-ins can record the user’s travel diary. Of note is that unlike GPS traces, check-ins seldom reflect the precise travel routes of users between distinct locations.



(a) Without Activity Information



(b) With Activity Information (directed graph)

Figure 1: Visited locations in Bucharest Romania, neighborhood: ‘13 Septembrie’

The availability of location-aware mobile social applications like Foursquare changed the way people indicate their activity information. Users can now share their location in the form of venue check-in, with meta-data such as venue name, category, *next venue* from which they traveled from the current venue. Therefore, accurate identification of activity is possible.

From the Foursquare API, I used: *Get Next Venues* which returns venues that people often check in to after the current venue. Up to 5 venues are returned in each query, and results are sorted by how many people have visited that venue after the current one.