OD-Vis: A Map-based Dashboard for Insight Discovery of OD Data

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Abstract:

Understanding human mobility is crucial in addressing many urban challenges such as traffic congestion or air pollution problems. Urban and transport planners often rely on simulations to predict human trips in future scenarios. In addition, domain experts study mobility patterns from these trips and conduct further analysis. For example, adjusting the energy supply infrastructure according to electric vehicle charging demand (Bae and Kwasinski, 2012) and reshaping the urban functions to reach a sustainable future city (Ballo et al., 2023).

Visual analytical methods are increasingly adopted to reveal patterns in spatial data. For instance, the visualization methods, such as circular glyphs and flow maps, are designed to represent spatial patterns of Origin-Destination (OD) data Lu et al. (2015), Tennekes and Chen (2021). Furthermore, interactive analytical dashboards can facilitate human reasoning through a designed layout and coordinated views (Shin et al., 2023, Zuo et al., 2020). This preliminary study demonstrates that visualization can not only show the location of origins and destinations, but also guide people further to interpret the stops between ODs, the attributes like speed and modes attached to trips. This study can be reproduced with the Open Digital Twin Platform (Grübel et al., 2023) in three major steps, namely data generating, data transformation, and visual interface design.

In this study, Corsica, France was chosen as the test area. The OD data was generated by an agent-based model using MATSim (Horni et al., 2016) in ODTP. Figure 1 shows an example of the generated records, including 11 attributes. In this dataset, one trip means an agent travels from one place to another place for an activity, such as work or shopping. A trip could be composed of multiple modes, including *car*, *walk*, *public transport (pt)*, *car passenger*, and *bike*. The test data includes 10,815 records and 2,953 simulated agents, and covers 30 hours, from midnight to 6 o'clock of the next day. The data transformation includes four steps. First, the coordinates are converted from the local coordinates system RGF 93 to a common geodetic system WGS 84. Second, the location and duration of activity stops and transitional stops are calculated between the trips and legs, respectively. Third, the number of legs was aggregated by travel modes in each hour. Fourth, the statistics of the key parameters are calculated.

Table 1. An example of an OD record.

Item	Example
person_id	157709
trip_id	1
leg_id	4
origin_x	1209874.0925
origin_y	6148177.8233
destination_x	1210439.0621
destination_y	6147797.2159
departure_time	21763 (seconds)
travel_time	318 (seconds)
routed_distance	7979.2032 (metres)
mode	car

OD-Vis is an interactive coordinated map-based dashboard as Figure 1 shows. It supports insight discovery of OD data by showing data as visualizations and allowing users to interact. It is composed of six panels. From left to right, Panel A allows users to filter data by *departure time*, *travel duration*, *routed distance*, and *transport mode*. It allows users to download the filtered subset. Panel B is the title panel suggesting the OD-Vis is used for "Trip Data Analysis". It is important to bring the context to the users and understand the purpose of using OD-Vis. Panel C shows the key statistics of OD pairs. Panel D is the main view and shows the geographic information of OD data. It shows the location of the OD pairs in a flow map on the left, with green representing origin locations and red representing destinations. The activity stops and the transitional stops are represented in proportional symbol maps on the middle and right in Panel D. The height of the 3D symbols indicates the duration of stops. Users are allowed to zoom, rotate, and hover over the maps to retrieve more details of the data. In Panel E, an area chart is placed at the bottom to show the transport mode in each hour,

with each color representing one type of travel mode. Panel F is a table that allows users to read the filtered original OD data. The combination of statistics, maps, and charts in OD-Vis gives users an overview of OD data. It encourages users to correlate the statistics and the locations in reasoning. Moreover, each panel can be enlarged as a full-screen display for reading the visualizations in detail.
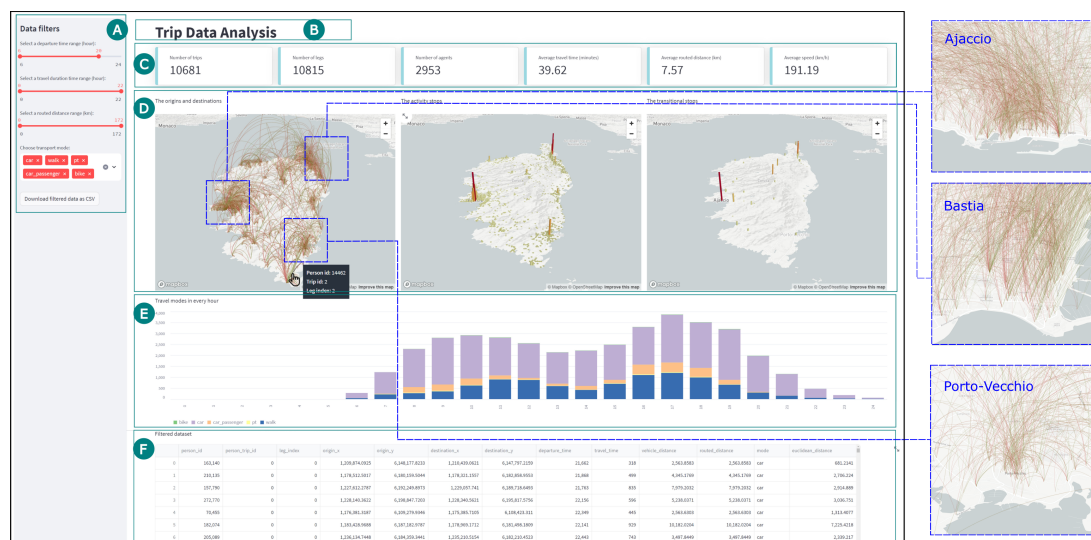

Figure 1. The visual interface of OD data analytical dashboard.

The hidden patterns of OD data can be found by viewing OD-Vis. For example, the blue-dashed maps are cropped from the flow map showing three harbor cities on Corsica, namely Ajaccio, Bastia, and Proto-Vecchio as enlarged in Figure 1 with the blue frames. The maps show that more trips took place in Ajaccio and Bastia than in Porto-Vecchio. The trips in Ajaccio and Bastia are closer to the harbors than in Porto-Vecchio. Moreover, cars are the dominant travel mode in the test data and walking is the second most adopted travel mode. Most of the stops are made in these three aforementioned cities. The maps confirmed that transitional stops are much fewer than stops for activities. In addition, the most popular travel time is from 17:00 to 18:00.

OD-Vis is designed as a self-explanatory visual interface to discover spatial and temporal patterns. It can be used to verify the knowledge of experts and support them in learning the deviations from expectations. This study describes the preliminary design of the OD-Vis. In the future, OD-Vis will integrate the OD data with domain experts' knowledge and highlight the patterns of interest in visualization design.

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