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Pedestrian Movement Modelling using Ubiquitous Data

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Introduction

The optimization of crowd movement in busy venues has for a long time been a focus of studies in building safety codes and event planning. However, predicting the flow and speed of pedestrians in public areas requires detailed insight that can be a challenge to obtain, due to the flexible and highly variable nature of the pedestrian. First, data must be obtained related to observed behaviours in the type of venue in question, either by staging or using actual events. Next the data can be processed and used for modeling purposes, which are the main tools of prediction used in behavioural studies.

UrbanFLUX, the pedestrian data collection system explored in (Farooq, 2015) is used to collect pedestrian data during a 4-month period on a pedestrian street in Montréal. Descriptive results of this case study are presented in (Beaulieu, 2017). Some of those results allow us to generate indicators and explanatory variables that are then used to elaborate a location choice model adapted to the study area. The nature of the data collected can be described as panel data, as individuals are identified over repeated visits. This is the basis for the elaborated model.

Methodology

The case study revolves around pedestrian movement along a pedestrianized street where 13 sensors are spread out among 14 intersections, as shown in figure 1. While knowing the current and previous locations of an individual, we are interested in developing a model that can determine their next location. The options are as follows: 1-stay at the current location, 2-move to another known location (east or west of the current location). The difficulty in this is not knowing the true objective of the detected individuals, and having to rely on general location characteristics. Previous work done on the subject hints at possible explanatory variables that can be tested.

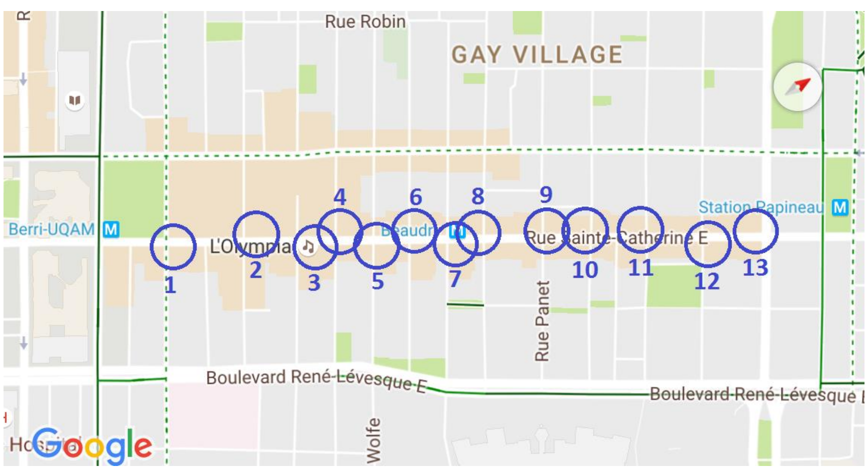

Figure 1: sensor locations

Danalet (2013) describes destination choice as a function of a location's activity potential, and Hoogendoorn (2005) points to utility maximization, where potential activities are weighed against ease of access to each option. Bhat (1999) notices a change in activity participation depending on time and day.

Danalet (2016) elaborates a model describing location choice using activity, travel and land use characteristics, time, and weather conditions. Following these ideas, potential indicators tested and presented in this paper are as follows: current time and day, time spent at current location, distance between current location and all other locations, previous location, location attractiveness, crowd density and direction of travel.

The data used is a subset of all the data collected. A single week of collections is chosen: August 15th to 21st 2016, due to having the largest number of active data collection devices (97%). After filtering, 1000 individuals are randomly selected for model definition and estimation. 200 more are retained for cross-verification. The type of model used is a dynamic mixed multinomial logit model with agent effect that determines if an individual will go East, West or remain at their current location. It is compared to both a dynamic mixed multinomial logit model and a dynamic multinomial logit model.

Application of explanatory variables

Previous location: This indicator describes if an individual has already been previously seen at a location or not. This is where the dynamics come in, as if an individual has been seen at a location it is more probable that they will be seen there again.

Time spent at current location: This indicator stems from the fact that the more time an individual spends at one location the more likely they are to stay there.

Distance matrix: The distance matrix is used to consider the distance between the individual's current location and all other locations. Due to the nature of the data and the linearity of the data collection area, all locations not immediately adjacent to the current location have their linear distance increased by a "detour" distance because they don't pass through the adjacent location first. Distance to the "home" location is not considered. This indicator has a significant effect on the model specification.

Location attractiveness: A specific location's attractiveness score increases with the presence of public transit hubs, restaurants, bars, etc. This indicator is enriched with the use of each business' opening hours.

Crowd density: As well as affecting walking speed, crowd density can be taken into consideration by an individual who might chose a destination that is less desirable over one that is more crowded.

Parameter estimation for all three models are presented in figure 2 below. Validation of the elaborated model is done using 200 individuals taken randomly from the original 1-week long subset of the data, different from the 1000 used in model development. Success rate is 60% including near-misses.

Conclusion

Pedestrian datasets obtained with UrbanFLUX systems can easily be converted to rich panel datasets. A model is developed that attempts to predict the next location an individual will be registered depending on certain indicators. Distance and land use are strong indicators that help determine the next location of an individual. The failure of many other potential indicators underlines the complex nature of pedestrians and the difficulties that arise when attempting to model their behaviours. To further this analysis, it might be possible to use a hazard-based model to determine the probability of leaving the area entirely instead of choosing another location.

	MNL		MMNL		MMNL-AE	
Constant	**Value**	**Std. err.**	**Value**	**Std. err.**	**Value**	**Std. err.**
ASC_1 (fixed)	0	-	0	-	0	-
ASC_2	-0.1110	0.1080	-0.0278	0.0925	0.1120	0.1210
ASC_3	0.1520	0.1010	0.2340	0.0695	0.4830	0.1130
ASC_4	-0.2120	0.1070	-0.1540	0.0733	0.1320	0.1210
ASC_5	0.1120	0.1040	0.1790	0.0727	0.4650	0.1170
ASC_6	0.1370	0.0788	0.0148	0.0677	0.3390	0.0882
ASC_7	-0.0524	0.0963	0.0379	0.0756	0.1910	0.1090
ASC_8	0.3060	0.1020	0.4450	0.0861	0.6090	0.1150
ASC_9	-0.2510	0.0996	-0.0957	0.0786	0.0478	0.1100
ASC_10	-1.3500	0.1250	-1.2500	0.1070	-1.0300	0.1370
ASC_11	-1.2100	0.1300	-1.1600	0.1070	-1.6400	0.1650
ASC_12	-0.0939	0.1180	-0.0706	0.0852	0.1930	0.1310
ASC_13	-0.0287	0.0845	-0.0819	0.0762	0.3200	0.0968
Parameter	**Value**	**Std. err.**	**Value**	**Std. err.**	**Value**	**Std. err.**
B_BB4	0.2050	0.0360	0.2090	0.0368	0.3270	0.0653
B_DENS	0.5420	0.0410	0.5460	0.0416	0.7440	0.0463
B_DIST	-0.0022	0.0001	-0.0023	0.0001	-0.0025	0.0001
B_LU_BAR	-0.0287	0.0249	-0.0335	0.0272	-	-
B_LU_GRO	-0.0951	0.0246	-0.0922	0.0248	-0.1480	0.0293
B_LU_RES	0.0368	0.0140	-	-	0.0315	0.0151
B_LU_TRA	-0.1000	0.0837	-	-	-	-
B_TSAC	1.1600	0.0258	1.2100	0.0296	0.8850	0.0410
Std. Dev.	**-**	**-**	**Value**	**Std. err.**	**Value**	**Std. err.**
B_BB4_S			-	-	-1.6000	0.0844
B_DENS_S			-	-	-	-
B_DIST_S			0.0003	0.0002	0.0009	0.0001
B_LU_BAR_S			0.2300	0.0686	-0.0538	0.0226
B_LU_GRO_S			-	-	-0.1770	0.0223
B_LU_RES_S			0.0264	0.0342	-	-
B_LU_TRA_S			0.8510	0.1240	-	-
B_TSAC_S			-	-	-0.7110	0.0641

Figure 2: Estimated parameter values

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