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Data-Driven Agent-Based Model of Intra-Urban Activities

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Abstract—We propose an agent-based model (ABM) to simulate city-scale intra-urban activities and movements. We calibrate the ABM for New York City, using NYC Open Data trip diaries and taxi journeys. Model validation demonstrates that the ABM is able to accurately predict activity demand across the city. Further, when a new hospital wing is opened in Queens, a central district of New York City, the ABM is shown to accurately predict increased shopping demand on Staten Island, an isolated area located at the edge of the city. This demonstrates the value of applying ABM to simulate intra-urban movements and activities, offering dynamic scenario testing that is not available in many other forms of modelling.

1. Introduction

With the recent proliferation of smart sensing technology, large volumes of GPS data with time resolved locations can be collected [1]. Such GPS data has been used to understand human mobility for urban planning [2], traffic forecasting [3], and location selection for new infrastructures [4].

Geographical and temporal movement of citizens in cities has been well studied, for example: Geographical Weighted Regression (GWR) has been used to calibrate the Huff model to discover shopping behaviours [5], [6]; ARIMA has been applied to shopping [3]; and social media check-in data has been used to model activities [7].

However, few studies systematically model citizens' daily movements on an individual basis. It has been shown that variations of human movements in different cities are mainly due to underlying differences in the distribution of activities across the urban environments [8]. Therefore, here we develop an activity destination model (ADM) to probabilistically map the state transitions between successive activities commonly found in large cities (e.g., work, shopping, school, medical, etc.). We incorporate the ADM into an agent-based model (ABM) to simulate individual behavioural activities across the city.

To test the validity of this approach, we perform a case study in New York City using the NYC Open Data [9], a collection of free public datasets published by New York City agencies and other partners. The NYC Open Data includes a full GPS record of taxi journeys across the city, and a sample of detailed trip diaries recorded by New York City residents. Together, these data enable us to calibrate and validate our model. We use taxi journey data and trip diaries to calibrate the activity state transitions of the ADM. Then, taxi data from a later time period are used to validate the simulation model. Validation results demonstrate the simulation has high accuracy for predicting temporal and geographical demands of activities across the city.

Further, and perhaps more importantly, the simulation model is able to accurately predict the consequence of a new hospital opening in Queens, a central district in New York City. Counter to intuition, real world taxi data shows that there is an increase in travel to Staten Island after the hospital opens, even though this area is far from the new hospital location. Yet, the simulation model is able to accurately predict this increase in demand. This validates the utility of ABM simulation for urban planning, offering dynamic *what if* scenario testing that other forms of modelling cannot incorporate.

While we present a case study for New York and use taxi trajectory data and trip diaries for model calibration, the method we propose is generally applicable for any city where individual travel data is available.

2. Background

Forecasting travel demand is a central issue for governments, especially public transport authorities and operators. As such, urban passenger travel demand is a hot topic in GIS research. A considerable number of studies have focused on using GPS data to understand urban mobility, with the majority aiming to discover passengers' habits, uncover traffic patterns, and predict passenger flows [10].

Figure 1. Agent-based activity-destination model.

Previously, both aggregate models (including traditional geographical models such as the gravity model) and disaggregate models (such as the logit model, and discrete choice model) have been used to predict passenger volumes in different time and locations [3], [11]. However, little research connects movement with purpose of travel (i.e. the intended activity associated with the journey) [7]. Yet, the intended activity at the destination of a journey is the key factor that influences travel demand [12]. For instance, it is clear that the location and opening time of a point of interest (POI) will directly influence travel behaviour.

A large body of literature on human mobility analysis exists, including, for example: weighted mobility networks to capture the flows between individual locations [13]; using social network check-in data to discover temporal activities [7], [14]; and inference modelling to estimate passengers' activities using taxi trajectory data [15], [16].

Yet, these works fail to consider the emergent consequences of interactions between decision behaviours of individuals. Classic, top-down modelling techniques fail to sufficiently represent these process interactions [17]. To truly model and understand mobility in urban environments, it is important to understand these interactions, since human behavioural interactions are the cause that produce second order effects such as traffic congestion.

A class of models that are especially popular in the computer science community is agent-based modelling (ABM) [18]. ABMs are bottom-up, such that individual behaviours are modelled at the micro-scale, and through the interactions of individual agents the macro-scale dynamics emerge [19]. These highly non-linear interaction dynamics can result in complex phenomena that are not immediately intuitive, and

also not possible to recreate in top-down models that are designed to be mathematically tractable. ABMs naturally translate well to modelling urban dynamics and have been used, for example, to simulate urban transportation [20], daily commuting routines [21], travel demand [22], impulsive purchasing behaviours [23], spatial epidemics [24], and temporal activity patterns [25].

In this paper, we utilise ABM methodology to simulate urban transportation by modelling individual activity behaviours. We calibrate the model using real-world trip diary data from New York City. We call this the activity-destination model (ADM).

3. Activity-Destination Model (ADM)

The ADM, which we implement using NetLogo, is presented in Fig. 1. First, we import unique information for each agent, which includes seven characteristics: (i) the number of trips, (ii) the current location, (iii) the current time, (iv) residential location, (v) work location, (vi) working hours, and (vii) working end time. Each agent has a unique residential location, work location, and work time, which are directly sampled from trip diary data. In the model, time is defined from 0 to 24 hours, with each time step representing 30 minutes in the real world.

Every time step, the ADM provides each agent with the next activity to undertake. If the agent's previous activity has not yet finished, status will not change, else the model checks whether the current time meets the agent's work schedule. If so, the agent heads to work, until work end time. Otherwise, a successor activity will be generated, based on the activity transition probabilities observed in the trip

Algorithm 1 Monte Carlo simulation

Input: set of potential activities
Output: selected activity

```

for each number do
    the probability to trip numbers  $N$  are  $p_1, p_2, \dots, p_N$   $\triangleright \sum_{n=1}^N p_n = 1$ 
    set  $p_0 = 0$ 
    generate random value,  $r \in [0, 1]$ 
    for  $n = 0$  to  $N - 1$  do  $\triangleright$  decide target number
        if  $\sum_{j=0}^n p_j \leq r < \sum_{j=0}^{n+1} p_j$  then
            result = number[n + 1]
        end if
    end for
end for
return result

```

diaries. The probability that the agent has the successor activity is calculated as:

$$P_n^{tripnum} = P_n + P_{n+1} + \dots + P_N \quad (1)$$

where n is the next trip number, N is the maximum trips in one day (taken directly from the trip diaries), $P_n^{tripnum}$ is the probability that the agent has at least n trips, and P_n is the probability that the agent has n trips in one day. Once $P_n^{tripnum}$ is calculated, Monte Carlo simulation is used to select the next activity (see Algorithm 1). Once all activities are completed, the agent heads home and remains there for the rest of the day.

The next activity is calculated using the transition probabilities observed in the trip diaries:

$$P(A_{pt}, A_{s(t+1)}) = \begin{cases} P(A_p, A_s), (t+1) \in A_s^{opentime} \\ 0, (t+1) \notin A_s^{opentime} \end{cases} \quad (2)$$

where t is the current time step, $P(A_p, A_s)$ is the transition probability between p and s , and $A_s^{opentime}$ is the open time range for activity s .

If there are more activities to complete (i.e., if the next destination is not home), the following equation is used to estimate the next geographic destination for an activity:

$$P(A_{pL_1}, A_{sL_2}) = P(A_p, A_s) \times \frac{d(L_1, L_2)^\beta}{\sum d(L_1, L)^\beta} \quad (3)$$

where $P(A_{pL_1}, A_{sL_2})$ is the probability of agent moving from activity p in location L_1 to successor activity s in location L_2 . $P(A_p, A_s)$ is the probability that the agent's next trip is activity s when previous activity is p . L is the location area containing activity s , $d(L_1, L_2)$ is the distance from location L_1 to L_2 , and β is the distance decay parameter.

The ADM simulates 48 time steps, equivalent to 24 hours.

4. ABM case study: New York City

4.1. Data

We calibrate the ADM using travel data for the city of New York, USA. To calibrate the model, we use 6,003 trip diaries for the month of June, 2017. The trip diaries include

Figure 2. Residential locations of agents (red dots) in New York.

trip information and personal information of participants. Trip information includes three features: (i) trip number, (ii) current activity (home, work, school, child daycare, park, shopping, social, restaurant, and medical activity), and (iii) next activity. Personal information includes: (i) resident's home location, which is denoted by neighbourhood tabulation area (NTA);¹ (ii) resident's work location, which is also denoted by NTA; (iii) time work begins; and (iv) time work ends.

We also collected New York taxi data for June 2017, which we use for model calibration (15–25 June) and validation (26–30 June). These taxi data includes: (i) pick-up NTA, (ii) drop-off NTA, (iii) trip length, (iv) pick-up time, and (v) drop-off time.

4.2. Calibration

We use the ADM with 3,590 agents to simulate one week-day in New York. The agents' residential distributions (per NTA) are shown in Fig. 2, with each red dot representing an agent. We can see, for example, that Manhattan is more residential than Queens. Taxi calibration data is used to fit the distance decay parameter, resulting in $\beta = -1.6$. This matches the value found in a previous study [7].

4.3. Simulation

4.3.1. Activity schedule analysis. Fig. 3 presents ABM simulation of new activity destinations across New York (i.e., the arrival locations of agents). We see activities vary across the day. At 9 am (Fig. 3(a)), the majority of activities are in Manhattan (trip diaries confirm that 48% of the New York citizens work in Manhattan). At noon (Fig. 3(b)), uptown Manhattan and Brooklyn have highest density (trip diaries confirm 57% of restaurants and 56% shopping malls

1. NTAs are aggregations of census tracts that are subsets of New York City's 55 Public Use Microdata Areas (PUMAs)

Figure 3. ABM simulation of new activity destinations during one day. Red indicates high density ($> 1\%$), orange indicates medium density ($0.5\% - 1\%$), yellow indicates low density ($0.1\% - 0.5\%$), and grey is very low density (below 0.1%).

TABLE 1. TRANSITION PROBABILITY FROM PREDECESSOR TO SUCCESSOR ACTIVITY IN TRIP DIARIES. LARGEST VALUES IN BOLD, SMALLEST VALUES UNDERLINED.

		successor activity							
		home	work	school	recreation	shopping	social	restaurant	doctor
predecessor activity	home	N/A	0.411	0.073	0.116	0.187	0.076	<u>0.065</u>	0.072
	work	0.742	N/A	<u>0.013</u>	0.035	0.103	0.012	<u>0.080</u>	0.016
	school	0.464	0.232	0.149	<u>0.006</u>	0.048	0.042	0.030	0.030
	recreation	0.700	0.048	0.011	<u>0.117</u>	0.073	0.007	0.040	<u>0.004</u>
	shopping	0.686	0.068	0.003	0.024	0.166	0.021	0.029	<u>0.002</u>
	social	0.712	0.017	<u>0.011</u>	0.017	0.051	0.130	0.051	<u>0.011</u>
	restaurant	0.569	0.234	<u>0.005</u>	0.023	0.037	0.041	0.083	0.009
	doctor	0.545	0.053	<u>0.023</u>	0.023	0.159	<u>0.008</u>	0.091	0.098

TABLE 2. TRANSITION PROBABILITY FROM PREDECESSOR TO SUCCESSOR ACTIVITY IN ABM. LARGEST VALUES IN BOLD, SMALLEST VALUES UNDERLINED.

		successor activity							
		home	work	school	recreation	shopping	social	restaurant	doctor
predecessor activity	home	N/A	0.598	0.053	0.096	0.058	<u>0.053</u>	0.062	0.078
	work	0.795	N/A	<u>0.010</u>	0.034	0.053	0.022	0.067	0.019
	school	0.406	0.251	0.078	<u>0.004</u>	0.058	0.078	0.057	0.069
	recreation	0.701	0.079	0.051	0.111	0.054	0.002	<u>0.001</u>	<u>0.001</u>
	shopping	0.761	0.068	0.021	0.031	0.064	0.027	0.026	<u>0.001</u>
	social	0.737	0.051	<u>0.029</u>	0.044	0.034	0.044	<u>0.029</u>	0.034
	restaurant	0.579	0.246	<u>0.001</u>	<u>0.001</u>	0.067	0.017	0.088	<u>0.001</u>
	doctor	0.550	0.304	<u>0.010</u>	0.022	0.031	<u>0.010</u>	0.017	0.056

(a) Home, work, other. (b) Breakdown of other activities.

Figure 4. ABM simulation of activities during one day.

are located in these areas). At 3 pm, (Fig. 3(c)), activities are relatively scattered (remember, that agents in work are not presented on these figures, so these activities are non-working agents). At 5 pm (Fig. 3(d)), agents head to uptown Manhattan, middle of Brooklyn, and south of Queens (these areas account for around 30% of all residential accommodation in the city). These figures indicate intuitively realistic mobility dynamics.

ABM temporal activities are presented in Figs. 4(a) and

TABLE 3. ADM VALIDATION.

Time	RMSE	MAE	ME
9am	0.024	0.010	2.089e-16
12pm	0.012	0.007	-5.722e-16
3pm	0.026	0.011	-3.112e-16
5pm	0.019	0.008	6.956e-16
8pm	0.020	0.009	6.813e-16

4(b). Since most people remain at home at night, we only analyse activities between 7 am and 10 pm. The distribution in Fig. 4(a) is intuitive (agents tend to be at home early morning and evening, and at work during the day), and acts as a sanity check for the model. Fig. 4(b) shows daily activities other than work. We see school, entertainment, and medical activities are prominent between 7 am to 9 am. The other four activities (shopping, restaurant, social, and entertainment) are most prominent after 5 pm, when work ends.

Figure 5. Ground truth taxi data: drop-off volumes across New York before (left) and after (middle) a new wing of Elmhurst Hospital is opened in QN29 (represented by black dot). Change presented on the right, showing increased demand (red) on Staten Island, a long way from the new hospital.

Figure 6. ABM simulation: activity volumes across New York before (left) and after (middle) a new wing of Elmhurst Hospital is opened in QN29 (represented by black dot). Change presented on the right, showing increased demand (red) on Staten Island, a long way from the new hospital.

Figure 7. ABM simulation: change in medical activities after the new wing of Elmhurst Hospital is opened in QN29 (black dot). Unsurprisingly, medical activity around the new hospital has increased dramatically (red).

4.3.2. Transition probability between activities. Tables 1 and 2 present transition probabilities between activities in trip diaries and ADM, respectively. Values in both are similar, indicating that the ABM accurately captures these transitions.

4.4. Validation

We use five days of taxi data to validate the ABM, by comparing the taxi drop-off density for each NTM simulated activity drop-off density per NTM (shown in Fig. 3) at 12 pm and 5 pm. Table 3 presents Root Mean Square

Error (RMSE), Mean Error (ME), and Mean Average Error (MAE). Low error values demonstrate high prediction accuracy.

4.5. Scenario testing

We have demonstrated the ABM model is capable of simulating realistic activity patterns, and have validated these against real-world taxi data. However, the real power of agent based modelling comes from the ability to scenario test, such that we are able to ask questions like “*what effect on urban transportation and mobility dynamics does a new hospital have?*” and “*where should a new hospital be located?*”.

A common charge levelled against ABM simulations is that they are “just-so” stories with no connection to reality. Without ground truth, it is difficult to argue against this. Fortunately, however, we have real-world data that enables us to scenario test and then validate. On June 12, 2017, a new wing of Elmhurst Hospital opened in Queens, QN29. We therefore have real world taxi data for the period immediately prior, and immediately after the hospital opened. We use the ABM to test the scenario: “*a new hospital is opened in QN29*”. We then validate the ABM simulation output by comparing outcomes with observed changes in activity patterns in the real world taxi data.

Fig. 5 shows real world taxi drop-off densities for New York, before (Fig. 5(a)) and after (Fig. 5(b)) the new Elmhurst hospital wing is opened. The difference in presented in Fig. 5(c). Output of the ABM simulation of this scenario is presented in Fig. 6. Clearly, the result is similar to reality. However, one feature is particularly compelling. In the real data (Fig. 5), we see that the opening of Elmhurst in Queens results in an increase in activity on Staten Island - an geographically isolated area located far from the hospital. Explaining this counterintuitive outcome is difficult. However, notice that the ABM simulation (Fig. 6) *also* predicts this increase in activity in Staten Island. This is compelling evidence of the value of the ABM.

Further, while the real world taxi data does not reveal *why* activities increase in Staten Island, the ABM enables us to query exactly this kind of detail. Fig. 7 shows ABM output for medical activities. We see (unsurprisingly) that medical activities increase dramatically (red) in the area of the new hospital (black dot). We also see that, overall, Staten Island has a fall in medical activities (green). This is to be expected, but it does not explain the increased demand in Staten Island for all activities that we see in the real world taxi data (Fig. 5) and ABM simulation (Fig. 6). Looking at ABM output in detail (not shown), we see that the overall increase in volume in Staten Island is caused by a doubling in shopping activities. There are shopping malls located across Staten Island, but also across much of the city. We are currently unable to explain *why* there is an increase in shopping on Staten Island after the new hospital wing opens in far-away Queens, but this kind of spatially dislocated effect is not unusual in complex real world systems. It could, perhaps, be a result of lower traffic and parking congestion around medical facilities in Staten Island leading to the area becoming more attractive for shoppers.

5. Conclusion

We have introduced an agent based model (ABM) to simulate activity destination modelling of populations living in urban environments. We calibrated the model for the city of New York, using trip diaries and taxi journey drop offs for the month of June 2017. Results demonstrate that the ABM can accurately simulate daily activity volumes across the city, with low prediction error. Further, a scenario test was performed, to simulate the impact of a new hospital development in Queens. The ABM predicted intuitive outputs, such as increased volume of medical activities in the area Queens near to the new hospital, but also counterintuitive outputs, such as increased volume of shopping activities on Staten Island, an area far away from Queens. We are unable to explain this outcome, but we were able to determine that it is an accurate prediction, by using real world taxi data covering the period immediately prior and immediately after the Elmhurst Hospital in Queens was opened. Given that the hospital opening caused an effect in a remote location and for a different activity, it is compelling to see that the ABM was able to accurately predict this. However,

since ABMs are designed to simulate complex interactions between individuals, perhaps we should not be too surprised.

Future work will consider extending the ABM presented here by utilising a coevolutionary framework (e.g., see [26] for optimisation using competitive coevolution) to optimise locations of buildings and infrastructure to minimise traffic congestion and reduce travel times across the city. The long-term aim is to develop a general-purpose ABM for urban simulation that can be calibrated for any city.

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