

Prototype city generation for mobility simulation in urban typologies: a generalized framework

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1 Introduction

Household assignment and spatial allocation are two big issues we need to solve when facing the problem of population synthesis. Specifically, the first one addresses the problem of how to match individuals to the household where they belong, while the spatial allocation distributes households in geographical space. It is necessary because the ultimate goal of our work is to do transportation simulation, which can only be achieved by knowing the location of each agent.

2 Background

There has been lots of literature on population synthesis. The methods used varies from Iterative Proportional Fitting (IPF), MCMC-based sampling Farooq et al., 2013, to Bayesian network approach Sun and Erath, 2015. The original work in this field is presented in Beckman et al., 1996. It used a method called Iterative Proportional Fitting (IPF) to synthesize population based on data from two sources. What they do is iteratively fitting the cells of a multi-way contingency table expanded by attributes that characterize a household/individual so that it satisfies the constraints of marginal distribution of demographics and also preserves the correlation structure carried by sample data of the whole population. Here the marginals of demographics comes from census data in the level of census tract or block group while the correlation structure need to be derived from survey data of target population. In case of the absence of disaggregated sample data, IPF can still give a solution by iteratively adjust the cells in accordance only with the marginal constraints. However, lots of different joint distributions can share the same marginals and IPF may converge to anyone of them. This is certainly a downside of traditional IPF, and is also the reason why we need the correlation structure of sample data to make the solution captures the true population distribution. After the fitting of the table, a desired number of synthetic population is sampled according to individual or household weights in the table. And this is where the sensitivity of IPF to the quality of data and the sample size stems from. In this method, spatial allocation is solved concurrently with the population synthesis, since it generates the population for each zone and then adds up to the whole population. On contrary to this, one can also synthesize the total population first and then allocate them to different zones. However, this includes implementing a detailed matching method between households and zones, like what's developed in Ge et al., 2014, which is also very time-consuming.

Ever since Beckham et al. used IPF to do population synthesis, limitation of this method and the targeted modification has been published by other researchers. By IPF alone, one can only

separately generate a set of weights either for individual or household. According to Ye et al., 2009, the synthetic population generated based on the application of household weights can give a joint distribution of person attributes far from the given person marginal distribution. This is due to the fact that all persons are just simply selected from chosen households according to household weights. Ye et al. (2009) has improved this problem of IPF by a method called Iterative Proportional Updating (IPU), and they claim that the algorithm they proposed can match the person-level distribution and household-level attributes as closely as possible.

MCMC-based sampling is brought up by Farooq et al. (2013). The problem is defined as how to use partial views, including samples and conditional distributions, to estimate the true joint distribution of population attributes, where the attributes are defined as $X = (X^1, X^2, \dots, X^n)$. Here, they used Gibbs Sampling to generate certain amount of population based on prior knowledge of the joint distribution and proved that the sampled population is very much similar to the true simulation in the statistical sense. It has been pointed out that, since the task of getting full conditionals won't be trivial in reality, they replaced some of conditional distributions by marginal distributions. Thus, if one wants to implement MCMC, the sample data of the entire population is fundamental. Furthermore, the derivation of conditional distribution is not trivial especially when the number of attributes gets large.

The population synthesis method that used adapted ideas from probabilistic graphical models (PGM). In their graphical model, there are 7 socio-demographic attributes, which are Age, Gender, Employment, Income, Car ownership, Purpose of trip, and Who pay for the trip, to represent a person. Once the dependencies between variables are specified, we need to calculate or estimate conditional probability of one node given its parents. The flexibility of this method is that those conditional probabilities can be derived from different sources like census data or surveys on individuals. Nevertheless, compared to the high dependency of IPF on the quality of sample data, Bayesian method gives synthetic population more heterogeneity. Finally, the synthetic population is just random draws from the probabilistic graphical model. Though we can take marginal distributions of all variables as supplement for the graphical model, the population generated by Bayesian network model can only precisely match the marginals of mother nodes. This is because the distribution of a node is uniquely defined by its parent node and the conditional distribution based on PGM. And this point should be taken into consideration when choosing the population synthesis method.

3 Data

Most paper in population synthesis used Public Use Microdata Sample (PUMS) data, which is available both in individual level and household level. It includes multiple socio-economic parameters of a household or an individual in the region. The sample rate of this dataset is about 1% to 10% of the total population in the region. PUMS data is very complete in US cities and can be easily downloaded from government census website ¹, but the same data for cities in developing countries can be relatively outdated and harder to find. The sample data is used as seeds to initialize the contingency table in IPF methods. Another important part of data is called aggregate data ². They give marginal distribution for variables of our interests. It's worth noticing that the marginal distributions for subsets with more than 2 variables can be rarely found. An ideal format for aggregate data is that we have the marginal distributions in the level of geographical zone cause

¹<https://www.census.gov/programs-surveys/acs/data/pums.html>

²<https://factfinder.census.gov>

IPF is carried out separately in each zone. So when downloading the aggregate data, one should first choose a geographic type in corresponding to the zones in the virtual city, then specify the variables or tables you want.

The choice of algorithm should be based both on the data we have and the appearance of the final result we want. What is also important for us is the simplicity and novelty of methodology. We will start from a conventional IPF method using data from Houston city, then according to the execution time and the accuracy of the result we will make further extension to IPF method.

3.1 Network processing

4 Method

TABLE 1 List of symbols for variables and parameters

SN	Name	Supply candidate
1	Auto Sprawl	Baltimore
2	Innovative Heavyweights	Madrid
3	Sustainable Anchors	Vancouver
4	Congested Middleweights	Bandung
5	Boomers	Lagos
6	Emerging Green Anchors	Hiroshima
7	Dense Clique	Isfahan
8	Hybrid Congested	Mashdad
9	BRT- <i>STARs</i>	Sao Paulo
10	Metro-Bike Giants	Dalian

TABLE 2 Prototype city descriptions and candidates

City/Typology	Microdata	Aggregate data	Land use	Transit
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TABLE 3 Data availability for candidate cities

In summary, the following are steps involving in generating a synthetic population and preparing it for mesoscopic simulation.

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4.1 Supply

4.2 Demand

4.3 Geolocation and spatial assignment

Moekel et al. (2003) present an intuitive approach to assigning households to zones, which we propose to implement. First, they obtain land-use data, which they use to disaggregate zonal

characteristics (e.g. household location or firm location) into raster cells. The size of these cells are chosen based on computational tractability and desired resolution. Weights are then assigned to the cells based on the corresponding land-use category. For the household example, Moekel et al. (2003) aggregate land-use attributes into the following: high-density housing, low-density housing, industry and open space; to which weights of 10, 5, 1 and 1 are assigned, respectively. The weights are then normalized by zone, and households are randomly selected to populate each cell to fit each proportion. The address of each household is assumed to be the centroid of each cell, which each associated with its parent zone. The rasterization is performed by a so-called “point-in-polygon” algorithm. This approach presents a fast way for household assignment, assuming prior zonal assignment is available. Our implementation is outlined in the following subsections.

4.3.1 Households

- Aggregate land use categories into these: low residential (L), high residential (H), commercial (C), industrial (I), education (E), open land (O)
- Assign weights for households as follows:

$$HH(w_L, w_H, w_C, w_I, w_E, w_O) = (8, 10, 4, 1, 0, 0) \quad (4.1)$$

- Grid the map and assign weights to the cell w_c^{HH} given its prevailing land use category
- Normalize cell weights $p_{c(SAL)}^{HH}$ in each second administrative level (SAL)

$$p_{c(SAL)}^{HH} = \frac{w_c^{HH}}{\sum_{c \in SAL} w_c^{HH}} \quad (4.2)$$

- Number of households in each cell given by:

$$N_{HH}^{c(SAL)} = p_c^{SAL} \cdot N_{HH}^{SAL} \quad (4.3)$$

where N_{HH}^{SAL} is the number of households in each SAL .

- Randomly sample to locate households in cell centroids for all SAL

4.3.2 Firms and education zones

- We obtain numbers of firms and schools in each SAL
- Assign weights as follows:

$$WORK(w_L, w_H, w_C, w_I, w_E, w_O) = (1, 2, 10, 5, 3, 1) \quad (4.4)$$

$$EDU(w_L, w_H, w_C, w_I, w_E, w_O) = (0, 0, 0, 0, 1, 0) \quad (4.5)$$

- Assign weights to cells for work and education: w_c^{WORK} , w_c^{EDU}
- Find $p_{c(SAL)}^{WORK}$ and $p_{c(SAL)}^{EDU}$ as before
- Find $N_{WORK}^{c(SAL)}$ and $N_{EDU}^{c(SAL)}$ as before

- The final outputs here are the numbers of workplaces/schools in each TAZ:

$$N_{WORK}^{TAZ(SAL)} = \sum_{c(SAL) \in TAZ(SAL)} N_{WORK}^{c(SAL)} \quad (4.6)$$

$$N_{EDU}^{TAZ(SAL)} = \sum_{c(SAL) \in TAZ(SAL)} N_{EDU}^{c(SAL)} \quad (4.7)$$

4.4 Trip generation and population assignment

In this step, we estimate the number of home-based work trips and home-based education trips between zones in order to have a starting point from which to assign individuals to usual work and education zones. The result is an OD matrix of trips from TAZ to TAZ. From this, we then randomly assign each individual to a zone for work or education. The method is here is an entropy maximization model (analogous to the gravity model).

$$\max - \sum_{i=1}^K \sum_{j=1}^L x_{ij} \ln x_{ij} \quad (4.8)$$

$$\text{s.t. } \sum_{j=1}^L x_{ij} = O_i, \quad i = 1, 2, \dots, K \quad (4.9)$$

$$\sum_{i=1}^K x_{ij} = D_j, \quad i = 1, 2, \dots, L \quad (4.10)$$

$$\sum_{i=1}^K \sum_{j=1}^L c_{ij} x_{ij} = C \quad (4.11)$$

$$x_{ij} \geq 0, \quad i = 1, 2, \dots, K, \quad j = 1, 2, \dots, L \quad (4.12)$$

The reader is referred to Fang and Tsao (1995) for a more formal background of this problem. A fuzzy extension that accounts for uncertainty in cost estimates has also been proposed by Li et al. (2011). For now, however, we use the simple gravity approach outlined above. A quadratic cost constraint may also be introduced later:

$$\sum_{i=1}^K \sum_{j=1}^L d_{ij} x_{ij}^2 = D \quad (4.13)$$

We also solve a static traffic assignment problem in order to find congested zone-zone travel times. The input network is a graph in which the nodes are TAZes and the edges are generalized between each zone. An average link capacity is obtained from the limiting capacity of the union of shortest paths between the zones.

The congested travel time estimates for each TAZ OD is given by

$$tt^{OD} = tt_0^{OD} \left(1 + \left(\frac{f_{OD}}{Cap_{OD}} \right)^2 \right) \quad (4.14)$$

where tt_0^{OD} is the free-flow travel time for a given OD.

4.5 Zonal-level estimation

4.5.1 Estimation of origin-destination matrices

There are three key inputs at the zonal level required for running SimMobility preday: zonal attribute data, skim matrices, and zone-zone travel time data.

Parameters	Description	Notes
distance	Zone-zone distance (km)	
car_cost_erp	Road pricing cost (monetary units)	
car_ivt	Car in-vehicle time (hours)	
pub_ivt	Public transit in-vehicle time (hours)	
pub_walkt	Public transit access-egress walking time (hours)	
pub_wtt	Public transit waiting time (hours)	
pub_cost	Public transit cost between zones (monetary units)	
avg_transfer	Average number of public transit transfers between zones	
pub_out	Public transit out-of-vehicle travel time (hours)	Sum pub_walkt and pub_wtt

TABLE 4 Operating cost parameters (Skim matrix elements) in SimMobility

4.5.2 Initial estimates

1. The zone-zone distance can be readily estimated by averaging the shortest-path distances for all unique OD pairings within a pair of zones. Given $P_{n_{OD}}$ as the shortest path for a given node-node OD pair, n_{OD} , between two zones O and D , then we can write

$$d_{OD} = \frac{\sum_{n_{OD} \in V(O) \times V(D)} \|P_{n_{OD}}\|}{|V(O) \times V(D)|} \quad (4.15)$$

2. The road pricing cost can be zero for now, but these will be relevant for congestion pricing scenarios. Thus,

$$C_{OD}^{rp} = 0 \quad (4.16)$$

3. Car in-vehicle time $CIVT$ can be computed using free-flow speeds FFS_e along each edge e of the shortest-path ODs for each zone pair to travel times, which are then averaged to obtain the final estimate:

$$CIVT(P) = \sum_{e \in P} \frac{\|e\|}{FFS_e} \quad (4.17)$$

$$CIVT_{OD} = \frac{\sum_{n_{OD} \in V(O) \times V(D)} CIVT(P_{n_{OD}})}{|V(O) \times V(D)|} \quad (4.18)$$

4. Public transit in-vehicle time $PIVT$ is estimated using the procedure outlined in (iii) applied to the public transit graph
5. Public transit access-egress times are obtained by averaging the shortest edges connecting each road node to a public transit node in zone O and adding this to the corresponding value for zone D . We assume a walking speed of 5 km/h, and dividing the sum obtained by this value produces an estimate of the walking time for each zone OD pair.

6. To estimate the public transit waiting time, we consider the median headway of the train/bus route on the first edge of all the shortest paths connecting public transit nodes in each zone-zone pairing. If there is a transfer on a given path, then the headway of the train/bus on the edge incident on the transfer point is added to the headway for the beginning of that path.
7. The public transit cost between zone *ODs* is taken as the average fare scaled by the relative average length of the shortest paths between the nodes in a given pair of zones.
8. We can compute the average number of transfers for each zone *OD* by summing the number of transfers for the shortest paths in all node-node pairs between zones and dividing by the number of node-node pairings.

We assume morning peak period as 7-9am and evening peak period as 5-7 pm.

4.6 Summary of framework

In our first exploration, we have used 5 attributes to describe a households and they are household type, household size, household income in the last 12 months, number of vehicles and number of workers in the household. We not only find one dimensional marginal distribution for those variables but also two dimensional marginal distributions for household type \times household size, number of workers \times household size as well as number of vehicles \times number of workers in the household. Across the process of data retrieving and processing, we find the categories each variable can have is largely depends on the availability and format of aggregate data.

5 Results and discussion

6 Conclusion

7 References

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A Further notes on hierarchical iterative proportional fitting

Using IPF to synthesize population includes two major steps. In the first step, the disaggregate samples of population are used to initialize the contingency table expanded by attributes, and the fitting is carried out to meet marginal constraints from aggregated data. In the next step, the fitted contingency table is used to sample the population. To describe IPF, we need to define the contingency table it fits. Suppose a person or household is described by m attributes (or demographics), then we need to develop a m -way table. For each demographic i , there are n_i categories. Thus, a cell (i_1, i_2, \dots, i_m) represents a kind of person/household, where $i_j = 1, 2, \dots, n_j$ is the observed value of the j -th demographic with n_j categories it can choose from. From sample data like PUMS, n is the total number of observations while n_{i_1, i_2, \dots, i_m} is the counts for people/household of this type. Hence, the proportion of this type in the sample is denoted by

$$p_{i_1, i_2, \dots, i_m} = \frac{n_{i_1, i_2, \dots, i_m}}{n} \quad (\text{A.1})$$

The constraints is defined as T_k^j , which is the marginal totals for the k -th category of attribute i from census data. We can easily get the equation

$$\sum_i \sum_{k=1}^{n_i} T_k^j = n. \quad (\text{A.2})$$

Let $p_{i_1, i_2, \dots, i_m}^{(t)}$ denote estimated proportion of cell (i_1, i_2, \dots, i_m) in iteration t and

$$p_{\dots, i_j=k, \dots} = \sum_{i_1=1}^{n_1} \dots \sum_{i_m=1}^{n_m} p_{i_1, i_2, \dots, i_j=k, \dots, i_m}^{(t)} \quad (\text{A.3})$$

The IPF starts with initiating all weights in the contingency table by

$$p_{i_1, i_2, \dots, i_m}^{(0)} = p_{i_1, i_2, \dots, i_m} \quad (\text{A.4})$$

and in each iteration, the proportions are updated by the formula

$$p_{i_1, i_2, \dots, i_j=k, \dots, i_m}^{(new)} = p_{i_1, i_2, \dots, i_j=k, \dots, i_m}^{(old)} * \frac{T_k^j * p_{\dots, i_j=k, \dots}^{(new)}}{n} \quad (\text{A.5})$$

for all categories of each attribute, until it converges. Within an iteration, $p^{(old)}$ for the first marginal corresponds to $p^{(t-1)}$, which is the result from last iteration. And for marginals come next, $p^{(old)}$ should be set to proportions calculated from previous marginals. According to Beckman et al., 1996, the algorithm converges in 10 to 20 iterations.

In the next step, the synthetic population shall be constructed by selecting households from PUMS in proportion to the estimated weights in the multiway table. Or we can do Monte Carlo

sampling method to draw households from estimated weights from IPF. Specifically, the number of households of each demographic type in a census tract can be obtained by multiplying the total number of households by the probability in the cell representing this household type, or by drawing the numbers at random according to these probabilities. However, the household type represented by a cell in multiway table is not exactly that of PUMS data. The fitted multiway table can only be spanned by control variables, which is defined as variables which have marginal distribution in census data. However, households and individuals in disaggregate data are usually described by additional desired variables. So, the probability of a household type in PUMS data being chosen shall be assigned according to the distance between such a household p and a household type c in multi-way table. In Beckman et al., 1996, this probability is defined as

$$D(p, c) = w_p \prod_{i \in J} \left(1 - |(d_i^p - d_i^c)/r_i|^k\right) * \prod_{i \notin J} \left(1 - \Delta(d_i^p, d_i^c)\right) \quad (\text{A.6})$$