A random-utility-consistent machine learning method to estimate agents' joint activity scheduling behavior from ubiquitous data

Xiyuan Ren, Joseph Y. J. Chow*

C2SMART University Transportation Center, New York University Tandon School of Engineering, Brooklyn, USA
xr2006@nyu.edu, joseph.chow@nyu.edu
* Corresponding author

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1 INTRODUCTION

The scheduling of daily activities is a complicated process that covers multiple choice dimensions, including which activities to perform, as well as the timings, locations, durations, and mode-of-travel between activities. Existing studies postulate that individuals derive a utility from traveling and performing activities, and they schedule them to maximize the utility (Adler and Ben-Akiva, 1979). With such assumption, discrete choice models (DCM) are widely used to reveal the co-impact of various factors on individuals' choice behaviors. Despite their advantages, DCM tend to come short of activity scheduling applications, especially with large choice set and under big data context. Firstly, DCM require a likelihood function defined over finite alternatives, which is hard to formulate given huge choice set comprised of all possible schedule combinations (Pougala, et al., 2021). Secondly, DCM provide stochastic estimations based on assumed distributions of random utilities and coefficients (in the case of mixed logit models), which limits their performance on big datasets with large sample size while few personal information (Krueger, et al. 2021).

These limitations can be overcome under a ubiquitous data setting where attributes from a whole population can be obtained instead of just from a sample. In such a scenario, transferability of a model from a sample to a population is no longer necessary and we can eschew random parameters to infer individual, fixed parameters. We adopt a deterministic approach based on the inverse problem of random utility maximization as a hybrid machine learning/econometric method. The approach presents three key advantages compared to conventional DCM: (i) various choice dimensions (activity timings, locations, durations, and mode-of-travel) and corresponding parameters are modelled jointly; (ii) the model provides higher prediction accuracy compared to conventional DCM ; (iii) the model produces an empirical distribution of individual preference that can be integrated into optimization models more efficiently than relying only on simulation (e.g. Paneque et al., 2021).

2 METHODOLOGY

Our study focuses on the activity scheduling choices of commuters, which includes choices related to work activity, lunch activity, afterwork activity, and trips between them. There are five choice dimensions in total and 1,470 possible schedules for each individual (Table 1).

Table 1 – *Five choice dimensions and alternatives in choice sets*

Time to leave home	Commute mode	Time to have lunch	Lunch location	Time to leave workplace
6:30-7:00	Transit	11:00-11:30	Inside the CBD	17:30-18:00
7:00-7:30	Driving	11:30-12:00	Outside the CBD	18:00-18:30
7:30-8:00		12:00-12:30	In workplace	18:30-19:00
8:00-8:30		12:30-13:00		19:00-19:30
8:30-9:00		13:00-13:30		19:30-20:00
9:00-9:30				20:00-20:30
9:30-10:00				20:30-21:00

In line with the study of Ettema et al. (2007), we divide a whole-day activity schedule into a sequence of activities and trips with representative utility functions shown in Eq. (1) – (6), which differs from conventional DCM in that each parameter is indexed by individual, e.g. θ_i.

$$V_i = V^T_{commute,i} + V^A_{work,i} + V^T_{work-lunch,i} + V^A_{lunch,i} + V^A_{afterwork,i} \tag{1}$$

$$V^T_{commute,i} = \theta_{t,i} t_{commute} + \theta_{c,i} c_{commute} + \theta_{mode,i} M_{commute} \tag{2}$$

$$V^A_{work,i} = \theta^e_{work,i} SDE_{work} + \theta^d_{work,i} SDL_{work} + \theta_{pl,i} PL_{work} + \theta_{dwork,i}\, ln(d_{work}) \tag{3}$$

$$V^T_{work-lunch,i} = \theta_{t_l,i} t_{work-lunch} \tag{4}$$

$$V^A_{lunch,i} = \theta^e_{lunch,i} SDE_{lunch} + \theta^d_{lunch,i} SDL_{lunch} + \theta_{k1,i} K1_{lunch} + \theta_{k2,i} K2_{lunch} \tag{5}$$

$$V^A_{afterwork,i} = \theta_{dafterwork,i} \ln\left(d_{afterwork}\right) + \theta_{inter,i} \ln(d_{work}) \ln\left(d_{afterwork}\right) \tag{6}$$

where V_i is utility of individual I derived from the whole-day activity schedule; $V^T_{commute,i}$ is commute utility, depending on travel time $t_{commute}$, travel cost $c_{commute}$, and travel mode $M_{commute}$ (0 for driving; 1 for public transit); $V^A_{work,i}$ is work activity utility, depending on schedule deviation (schedule early SDE_{work} and schedule delay SDE_{work}), additional punishment for late for work PL_{work}, and log-formed work duration $ln(d_{work})$; $V^T_{work-lunch,i}$ is the utility of traveling between workplace and lunch spot, here we only consider the travel time $t_{work-lunch}$; $V^A_{lunch,i}$ is lunch activity utility, depending on schedule deviation (schedule early SDE_{lunch} and schedule delay SDE_{lunch}), and lunch spot ($K1_{lunch}$=1 denotes inside the CBD, $K2_{lunch}$=1 denotes outside the CBD, having lunch in workplace is the reference group); $V^A_{afterwork,i}$ is afterwork activity utility, here we only consider its total duration in log form, $\ln\left(d_{afterwork}\right)$, and an interaction item with work duration, $\ln(d_{work}) \ln\left(d_{afterwork}\right)$. All these variables can be observed from the data, and $\theta_{t,i}$, $\theta_{c,i}$, $\theta_{mode,i}$, $\theta^e_{work.i}$, $\theta^d_{work,i}$, $\theta_{pl,i}$, $\theta_{dwork,i}$, $\theta_{t_l,i}$, $\theta^e_{lunch,i}$, $\theta^d_{lunch,i}$, $\theta_{k1,i}$, $\theta_{k2,i}$, $\theta_{dafterwork,i}$, $\theta_{inter,i}$ are 14 parameters to be calibrated, as a mixed logit model with deterministic individual tastes. Let us call this an Agent-based Mixed Logit (AMXL) model.

Inverse optimization (IO) is initially used as a machine learning technique to update parameters from prior value in traffic assignment or schedule optimization problems (Chow and Recker, 2012; Xu, et al., 2018). We develop an original approach based on the concept to estimate the individual parameters of the AMXL model. For each schedule alternative j considered by individual I, we add a random utility ε_{ij}~G(0,1). Moreover, we add a safe boundary b ($b \geq 0$) to in case ε_{ij^*} is much larger than ε_{ij} (making most of the constraints useless). A proposed range of b is [1,3], which is between the 75% quantile and 95% quantile of $(\varepsilon_{ij^*} - \varepsilon_{ij})$. The IO problem is defined as follows: for a given prior θ_0 of a schedule utility's parameter and observed choice j^*, determine an updated θ such that j^* has the largest utility in the choice set J with a safe boundary b, while minimizing its squared L_2 norm from the prior, as shown in Equation (7).

$$\min \, \|\theta_0 - \theta\|_2^2 \, : V_{ij^*} + \varepsilon_{ij^*} \geq V_{ij} + \varepsilon_{ij} + b \, , \; \forall j \neq j^* \text{ in } J \tag{7}$$

An additional issue is that we have 1,470 whole-day schedules in the choice set, which is infeasible for DCM to converge and quite time-consuming for IO. Hence, we decompose the whole-day schedule choice into three inter-related IO problems: commute choice (time to leave home & commute mode), lunch choice (time to have lunch & lunch location), and afterwork choice (time to leave workplace). By doing this, we reduce the choice set from 1,470 ($7 \times 2 \times 5 \times 3 \times 7$) alternatives, to 14 ($7 \times 2$), 15 ($5 \times 3$), and 7 alternatives respectively, with an additional constraint ensuring that the shared parameter $\theta_{dwork,i}$ should be the same (and hence, jointly estimated). Finally, Method of Self-regulated Average (Liu, et al., 2007) is used to smooth the iterative convergence to provide stability without solutions flip-flopping. The IO approach is summarized in Algorithm 1.

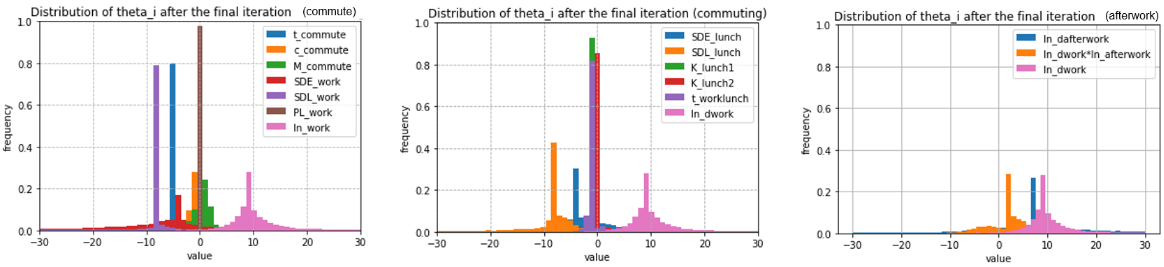
Algorithm 1. Inverse optimization with random utility for whole-day activity choice

1. Initialize with θ_0^1=[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0], n=1,b=1, and the stop criteria $\varepsilon > 0$
2. For each individual i,
   a. Get the priori parameter $\theta_{0\_c}^n$, $\theta_{0\_l}^n$, $\theta_{0\_a}^n$ from θ_0^n
   b. Solve IO problems: $min \left\| \theta_{0\_c}^n - \theta_{0\_c,i}^n \right\|_2^2$ s.t. $V_{ij^*} + \varepsilon_{nij^*} \geq V_{ij} + \varepsilon_{nij} + b$, $\forall j \neq j^*$ in J_c
   $min \left\| \theta_{0\_l}^n - \theta_{0\_l,i}^n \right\|_2^2$ s.t. $V_{ij^*} + \varepsilon_{nij^*} \geq V_{ij} + \varepsilon_{nij} + b$, $\forall j \neq j^*$ in J_l
   $min \left\| \theta_{0\_a}^n - \theta_{0\_a,i}^n \right\|_2^2$ s.t. $V_{ij^*} + \varepsilon_{nij^*} \geq V_{ij} + \varepsilon_{nij} + b$, $\forall j \neq j^*$ in J_a
   c. Calculate the mean value of shared parameter θ_{dwork} retrieved from three IO solutions
   d. Fixed θ_{dwork} and redo step 2b
   e. Combine $\theta_{0\_c,i}^n$, $\theta_{0\_l,i}^n$, $\theta_{0\_a,i}^n$ and output $\theta_{0,i}^n$
3. Self-regulated Average: set Γ=1.8, γ=0.3, calculate θ_0^{n+1} based on θ_0^n and $mean(\theta_{0,i}^n)$
4. If $\left\| \theta_0^{n+1} - \theta_0^n \right\|_2 \leq \varepsilon$, stop and output $\theta_{0,i}^n$, else let n = n+1 and go to step 2

3 SELECT RESULTS

3.1 Distribution of parameters

The dataset used in our study contains two-weekday activity information of 26,149 commuters working in the CBD of Shanghai (which we assume to be our population), which was collected using Shanghai mobile phone data in 2019 (considering data privacy, home location was aggregated into 500m*500m grids, workplace was aggregated into blocks). The IO algorithm took 28.9 hours to converge at the 60th iteration, resulting in calibrated parameters *per individual* that are not only similar with DCM results in signs, but the population distributions of those parameters are empirically derived, revealing them to be neither Gumbel nor Normal (Figure 1). This helps modelers capture inter-individual heterogeneities when detailed personal information is hard to obtain.



Commute choice   Lunch choice   Afterwork choice

Figure 1 – *Distribution of calibrated parameters*

3.2 Prediction accuracy

Figure 2 shows a comparison of prediction accuracy by the multinomial logit model (MNL) and the AMXL model. When we predict commuters' schedule choice on the weekday used to train the model, the AMXL model improves the individual-level accuracy greatly compared with MNL, from

1.37% to 47.18%. When we predict on a different weekday using the same population, though the individual-level accuracy of AMXL model decreases (since almost all commuters made small changes on their whole-day schedule), the aggregated-level accuracy is still high with 61.68% compared with 5.21% in MNL.

Prediction accuracy of the same weekday

	Commute choice (14 alternatives)	Lunch choice (15 alternatives)	Afterwork choice (7 alternatives)	Whole-day schedule (1470 alternatives)
Aggregated level (MNL)	81.40%	85.53%	92.88%	7.50%
Aggregated level (AMXL)	89.61%	86.71%	98.87%	80.89%
Individual level (MNL)	13.70%	31.16%	35.76%	1.37%
Individual level (AMXL)	74.67%	78.43%	80.93%	**47.18%**

Prediction accuracy of a different weekday

	Commute choice (14 alternatives)	Lunch choice (15 alternatives)	Afterwork choice (7 alternatives)	Whole-day schedule (1470 alternatives)
Aggregated level (MNL)	82.50%	89.92%	89.75%	5.21%
Aggregated level (AMXL)	75.79%	86.73%	96.07%	**61.68%**
Individual level (MNL)	13.53%	27.93%	28.99%	1.06%
Individual level (AMXL)	30.74%	24.25%	37.71%	4.33%

Figure 2 – *Comparison of prediction accuracy by MNL and AMXL*

4 DISCUSSION

The inverse optimization estimation method combined with the AMXL model is an agent-level machine learning method that is theoretically consistent with a utility-maximizing mixed logit model framework. It provides deterministic estimation at the individual level, which allows modelers to capture inter-individual heterogeneities given limited personal information and further integrated them into optimization models. The experimental results based on 26,149 samples show that an AMXL model can improve the individual-level in-sample accuracy, and the aggregated-level out-of-sample accuracy. This method is designed for a ubiquitous data set representing a whole population which is possible with big data. Further scenarios analyzing the trade-offs between congestion effects, work scheduling policy, and optimal incentives to attract workers to lunch locations are conducted.

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