Location Choice Equilibrium - pedestrian demand analysis at EPFL

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Project Overview

Discrete choice models have always been a very useful tool in analyzing and predicting people's travel behavior and demand. Thus they are important for transportation planning and policy making.

This project aims at:

- derive a pedestrian location choice model on EPFL campus about catering places
- compute the aggregated demand at each location
- \bullet extend the model by taking congestion effect into consideration.

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Data Description

The original data are WiFi traces collected in 2012. It is then cleaned by Antonin Danalet et al. using a Bayesian procedure to detect activity-episode sequence.

The data used for modelling contains 1868 observations of 211 individuals.

Each observation corresponds to a catering location choice, including:

- choice results: chosen location, duration, ...
- attributes of alternatives: evaluation, capacity, ...
- socio-economic characteristics: employee or student, ...

Basic Model

$$\begin{split} V_{i} = ASC_{i} + \beta_{PRICE_STUDENT} \cdot lunch_min_price_student_{i} \\ + \beta_{PRICE_EMPLOYEE} \cdot lunch_min_price_employee_{i} \\ + \beta_{DISTANCE} \cdot distance_{i} + \beta_{EVA} \cdot eva_{i} \\ + \beta_{DISTANCE_NO_AV} \cdot distance_no_av_{i} \\ i = 1, 2, ..., 21 \end{split}$$

 $\begin{array}{c} \textbf{Variable} \\ \textbf{lunch_min_price_student}_i \\ \textbf{lunch_min_price_employee}_i \\ \textbf{distance}_i \\ \textbf{distance_no_av}_i \end{array}$

 eva_i

Definition

 MIN_PRICE_i if student and lunch MIN_PRICE_i if employee and lunch $DISTANCE_i/100$ if $DISTANCE_i > 0$ 1 if $DISTANCE_i = -1$ $EVALUATION_2013_i$ if > 0, lunch and the chosen alternative is not 3 or 7

Main Results

| | Coeff. | | |
|---------------------|----------|--------------------------|----------------|
| Description | estimate | Std err | <i>t</i> -stat |
| BETA_DISTANCE | -0.73 | 0.0256 | -28.5 |
| BETA_EVA | 1.85 | 0.0175 | 10.6 |
| BETA_NO_DISTANCE_AV | -5.16 | 0.364 | -14.2 |
| BETA_PRICE_EMPLOYEE | -0.286 | 0.0331 | -8.64 |
| BETA_PRICE_STUDENT | -0.456 | 0.0434 | -10.5 |

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Aggregation

Based on the sample size, the population is divided into two groups: student and employee.

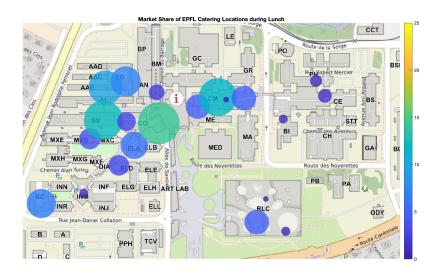
In our data, there are 649 student observations and 1219 employee observations.

According to the figures of 2012, there are 7117 students and 5493 employees.

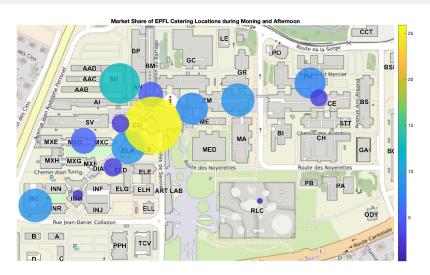
Each group is associated with a weight: $\omega_g = \frac{N_g}{N} \frac{S}{S_g}$

The predicted share can be expressed as: $\hat{W}(i) = \frac{1}{S} \sum_{n=1}^{S} \omega_n P(i|\beta)$ where $\omega_n = \sum_g \omega_g \delta_{ng}$ $\delta_{ng} = 1$ if individual n belongs to group g

Market Share of EPFL Catering Locations during Lunch



Market Share of EPFL Catering Locations during morning and afternoon



Congestion Condition

When computing the congestion, the capacity of each catering location is taken into consideration.

T: total time during lunch.

 \bar{t}_i : average time individuals spent at each location.

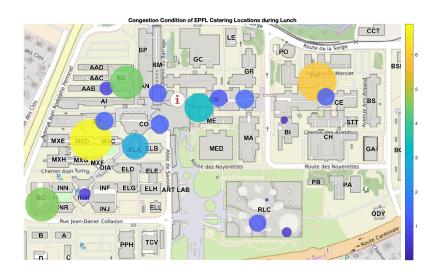
 c_i : indoor capacity at location i.

 $d_i(\hat{W}_i)$: demand at location i, it can be computed using the predicted market share and the size of the population on campus.

$$congestion_i = \frac{t_i d_i}{Tc_i}$$

For those locations with $congestion_i > 1$, demand is larger than the capacity, leading to over congestion.

Congestion Condition



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Discrete Game

In reality, individuals are not independent when making choices. They will be affected by other members in the population.

Brock and Durlauf described the general framework of binary choice model with social interactions in 2001. They later extend the model to a multinomial choice model.

Turning to the field of game theory, static discrete games are used to analyze individuals' catering choice on campus.

Critical assumption: incomplete information. Individuals are uncertain about other members' choice in the group.

Model with Congestion Effect

$$U_{n.i} = V_{n,i} + \alpha f(\bar{p}_{n,i}) + \epsilon_{n,i}$$

N individuals, I alternatives:1, ..., I

 $V_{n,i}$: deterministic part $\epsilon_{n,i}$: error term.

 $\alpha f(\bar{p}_{n,i})$: social utility.

 $\bar{p}_{n,i}$: individual n's expected percentage of people choosing the same location i.

 α : parameter to be estimated.

Under Logit model:

$$\mathbb{P}_{n}(i|V_{n,i}, \bar{p}_{n,i}, \forall i) = \frac{\exp(V_{n,i} + \alpha f(\bar{p}_{n,i}))}{\sum_{i=1}^{I} \exp(V_{n,i} + \alpha f(\bar{p}_{n,i}))}$$

Suppose that all individuals make rational expectations:

$$\bar{p}_{n,i} = \bar{p}_i = \hat{W}(i)$$

In our case: the social utility can be written as $f(d_i(\hat{W}_i)) = congestion_i$

Estimation

We estimate the model when it reaches a Bayesian Nash equilibrium, which means all individuals choice strategy is a best response to his expectations regarding other members.

In our case, the Bayesian Nash equilibrium coincides with our assumption: individuals' expected demand of each location is exactly the true demand(an equilibrium), and their choices maximize the utility.

When the distribution of error term is continuous, Brouwer's fixed point THM guarantees the existence of a solution.

Estimation Methods

Different approaches have been used to estimate the model:

- Nested Fixed Point(Rust, 1985)
- 2-step Pseudo Maximum Likelihood Estimation(Aguirregabiria and Mira, 2007)
- Nested Pseudo Likelihood Estimation(NPL)(Aguirregabiria and Mira, 2007)
- Mathematical program with equilibrium constraints(Su and Judd, 2007)

NPL estimation is used, which iteratively compute the demand from the model and then use the computed result in the estimation of model again.

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Conclusion

So far, the work finished:

- estimation of basic model
- aggregation of demand
- design of model with congestion effect

The following step:

• estimate the model with congestion effect using the NPL estimation

Model Development

Begin with the base model i = 1, 2, ..., 21:

$$V_i = ASC_i + \beta_{PRICE} \cdot MIN_PRICE_i + \beta_{DISTANCE} \cdot DISTANCE_i$$

Improve the model gradually by adding new terms and nonlinear specifications, e. g. $TAP_BEER_AV_i$ $DINNER_HOT_MEAL_AV_i$ $EVALUATION_2013_i$ interaction of $HOT_MEAL_AV_i$ and MIN_PRICE_i interaction of $LUNCH_i$ and MIN_PRICE_i alternative specific parameters, ...