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SEMESTER PROJECT

Location Choice Equilibrium pedestrian demand analysis at EPFL

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ABSTRACT

Many types of human decision choice behaviors involve the influence of other individuals and this effect should be taken into consideration when modelling the behaviors. In this study, we propose and estimate a discrete location choice model with congestion effect when it reaches an equilibrium. The model is applied to a case study on EPFL campus about the catering place choice. The data used for estimating the model is collected in 2012, including the cateirng location choice behaviors of both students and employees on campus. A multinomial discrete choice model without congestion effect is first derived and used for predicting aggregated market share. Then we extend the model with congestion effect. To estimate this model when an equilibrium is reached, Nested Pseudo Likelihood method is used. Compared with the 2-step Pseudo Maximum Likelihood method which requires an efficient and consistent nonparametric estimator of the congestion effect, this Nested Pseudo Likelihood method eliminates the requirement for a nonparametric estimator by iteratively solving the problem.

1. INTRODUCTION

Discrete choice models are useful tools in analyzing and predicting people's decision process. Among various choice models, location choice models are often built on the discrete choice framework. They allow analysts to understand why people choose to travel in a certain way and predict to which place (and when) an individual travels. The location choice behaviors are often studied in a city scale. Viauroux (2007) [1] studies number of trips the household members decide to take in the greater Montpellier area in France, while Stern (1993) [2] researches the demand of different transportation mode of elderly and disabled people in rural areas of Virginia. However, literature in pedestrian facilities is relatively limited.

Over the past years, a considerable number of studies begin to take the influence of social interaction into consideration when studying human behaviors. This idea comes from the fact that nobody lives in vacuum, so people's behavior will more or less be influenced by others. Here social interaction is defined as "the utility or payoff an individual receives from a given action depends directly on the choices of others in that individual's reference group" (Brock et al., 2001) [3]. There are both negative and positive social interactions in real world. Positive social interaction leads to a tendency to conform to the majority, e.g. the expected fraction of truants rises when a girl who will definitely truant is added to a class (Soetevent, 2007) [4]. Negative social interaction reduces the probability of others making the same choice. Brock and Durlauf (2001) [3] described the general framework of a binary discrete choice model with social interactions, later they extended the model to a multinomial choice model (2002) [5]. Based on their general model, many empirical models are derived, e.g. Fukuda et al. (2007) [6] modelled the conformity effect among bicycle users in the choice model of bicycle parking location. When an individual's behavior stays unchanged under the influence of social interaction, we say that this is an equilibrium. To estimate the models when they reach equilibrium, different approaches have been developed, e.g. Nested Fixed Point Method (Rust, 1987) [7], 2-step Pseudo Maximum Likelihood Estimation (PML), Nested Pseudo Likelihood Estimation (NPL) (Mira et al., 2007)[8] and so on.

In this project, we develop a pedestrian location choice model incorporating social interactions to investigate the influence of congestion on individuals' decision. The structure of our model is derived from Brock et al. (2002) [3]. It is then applied to a case study of catering location choice on EPFL campus during lunch. There are 21 places located around different buildings offering lunch to students, and what factors impact on them becomes an interesting topic. The findings may help managers of catering locations analyze what aspects should be improved to provide better service, especially give suggestion on whether the capacity should be augmented or not.

The main contents of the project are organized as the following: In Section 2, the general model framework and theoretical basis of the estimation methods are provided. In Section 3, a brief introduction of the dataset collected on EPFL campus is given. In Section4, empirical results and findings of the case study of EPFL are presented. The last section will conclude all the work of this project and propose some suggestions about work that could be done in the future.

2. METHODOLOGY

2.1. MODEL

A base model without social interaction is first designed. There is a choice set C containing all the available choices. Assume that each individual can have access to the same choice set C. And for individual i, each alternative $i \in C$ is associated with a utility function U_{ni}:

$$U_{ni} = V_{ni} + \epsilon_{ni}$$

V_{ni} is the deterministic part involving the explanatory variables. ϵ_{ni} is the error term capturing all the unobserved characteristics. Under a logit model, the error term $\epsilon_{ni} \sim EV(0,\mu)$ i.i.d. For convenience, the scale parameter μ is normalized to 1. The probability that individual n chooses alternative i can be expressed as:

$$P_n(i|\beta) = \frac{\exp(V_{ni})}{\sum_{i=1}^{|C|} \exp(V_{n,i})}$$

β refers to all the parameters to be evaluated in V_{ni}. With the model derived, now the probability of people choosing each alternative can be computed. The whole population is divided into groups where there is no intersection between any two groups. Each group is associated with a weight:

$$\omega_g = \frac{N_g}{N} \frac{S}{S_g}$$

N is the size of the whole population, S is the size of the sample used for aggregation, N_g is the size of group g in the population, S_g is the size of group g in the sample. Then the predicted percentage of peopel choosing i can be expressed as:

$$\hat{W}(i) = \frac{1}{S} \sum_{n=1}^{S} \omega_n P_n(i|\beta)$$

where $\omega_n = \sum_g \omega_g \delta_{ng}$, $\delta_{ng} = 1$ if individual n belongs to group g.

In reality, individuals are not independent when making choices. They will be affected by other members in the same reference group. A model in the presence of social interaction is designed, according to the model Brock and Durlauf (2002) [3] derived:

$$U_{ni} = V_{ni} + \alpha f(\bar{p}_{ni}) + \epsilon_{ni}$$

$f(\bar{p}_{ni})$ is the social utility term, $\bar{p}_{ni}$ is individual n's expected value of the percentage of people choosing location i, and α is a scalar parameter representing the intensity of social interactions between an individual and his reference group. When lots of people choose the same catering place, for example, the place will get crowded and people will need to wait for a long time in queue. This of course will make people less willing to go to the place again. People choosing the same location can be defined as a reference group. Under a logit model, the probability that individual n chooses alternative i is:

$$P_n(i|\alpha,\beta,\bar{p}_{ni}) = \frac{\exp(V_{ni} + \alpha f(\bar{p}_{ni}))}{\sum_{i=1}^{|C|}\exp(V_{ni} + \alpha f(\bar{p}_{ni}))}$$

The work left to be done is how to compute people's expected choice proportion of alternative i. A rational expectation assumption is made that all individuals' expectation $\bar{p}_{ni}$ is equal to the mathematically predicted choice proportion: $\bar{p}_{n,i} = \bar{p}_i = \hat{W}(i)$. This is also referred to as self-consistency conditions (Brock et al., 2001) [3]: the values of the expected percentage for each individual must be equal to the average choice proportion of the population. We can write the equilibrium as:

$$\bar{p}_i = \hat{W}(i) = \frac{1}{S}\sum_{n=1}^{S}\omega_n P_n(i|\alpha,\beta,\bar{p}_i) \tag{2.1}$$

Multinomial discrete choice models with social interactions almost always have multiple equilibriums (Brock et al., 2002) [5]. This means there are multiple solutions to equation (2.1). To find an equilibrium, we can incorporate the framework of static discrete games in the field of game theory. Based on the assumptions we made above, the model with social interaction can be explained as a static discrete game with incomplete information. Static means individuals involved make their decisions simultaneously. Incomplete information is referred to as that individuals are uncertain about other members' choice. The game with incomplete games are also called Bayesian game. So the equilibrium that we are interested in is a *Bayesian Nash equilibrium* (BNE). Nash equilibrium is defined as all individuals choice strategy is a best response to his expectations regarding other members (Ellickson et al., 2011) [9]. BNE is the Nash equilibrium of a Bayesian game. The maximum likelihood problem under BNE can be expressed as:

$$\bar{p}_i = \hat{W}(i), \qquad \forall i \tag{2.2}$$

$$\alpha,\beta = \arg\max_{\alpha,\beta}\sum_{n,i} y_{ni}\ln P_n(i|\alpha,\beta,\bar{p}_i) \tag{2.3}$$

where $y_{ni} = 1$ if individual n chooses alternative i. If there are multiple equilibriums, the solution to (2.3) is not unique. Under this circumstance, the maximimum likelihood problem can be redefined as:

$$\alpha,\beta = \arg\max_{\alpha,\beta}\{\sup_{\bar{p}_i}\sum_{n,i} y_{ni}\ln P_n(i|\alpha,\beta,\bar{p}_i) \text{ subject to } \bar{p}_i = \hat{W}(i), \quad \forall i\}$$

2.2. Estimation

Several approaches have been developed to estimate the equilibriums, e.g. Nested Fixed Point (NFXP) (Rust, 1987) [7], 2-step PML, NPL and Mathematical program with equilibrium constraints (MPEC) (Ellickson et al., 2011) [9]. NFXP starts from candidate values of α and β, and repeat the following steps until convergence is gained: iteratively solves the equation (2.1) to get a solution $\bar{p}_i$, then plugs $\bar{p}_i$ in equation (2.3) to update the values of α and β. MPEC formulates (2.3) as a constrained optimization problem maximizing the likelihood function subject to the equilibrium constraint (Su et al., 2012) [10]. In this project, we implement NPL to estimate the model with social interaction when it reaches a BNE state.

Since NPL method is an extension of the 2-step PML, here we introduce the 2-step PML first. The *pseudo likelihood function* in 2-step PML, following the notations of (Aguirregabiria et al., 2007) [8], is defined as:

$$L(\alpha,\beta,\bar{p}_i)=\sum_{n,i} y_{ni}\ln P_n(i|\alpha,\beta,\bar{p}_i)$$

This function is called pseudo likelihood since the choice probabilities are not necessarily the probabilities associated with α and β when an equilibrium is reached. It is just a response to the choice proportion $\bar{p}_i$. The parameters α and β in (2.3) aims at maximizing the likelihood of the model reproducing the observed choice behavior. These parameters are denoted as *PML estimator.* However, the PML estimator is infeasible because $\bar{p}_i$ is unknown. If we can get a consisitent non parametric estimator of $\bar{p}_i$, then we are able to define two step PML estimators $\hat{\alpha}$ and $\hat{\beta}$. Asymptotic properties of the PML estimator are presented in (Aguirregabiria et al., 2007) [8]. The consistency and asymptotic normality of $\bar{p}_i$, together with regularity conditions, are sufficient to guarantee the consistency and asymptotic normality of PML estimator $\hat{\alpha}$ and $\hat{\beta}$. These PML estimators have several advantages. They eliminate the need to compute a fixed point problem, which is an improvement compared with NFXP. Besides, this method is easy to implement, with very few computation demand. However, as mentioned by Aguirregabiria et al. (2007) [8], there are a few drawbacks of 2-step PML estimation: First, the method may be asymptotically insufficient because the final result's asymptotic variance depends on the variance of the initial non-parametric estimator. Second, initial estimator may be imprecise in the small samples. This can generate serious finite sample biases. Third, under certain circumstances, a consistent estimator is not feasible.

The drawbakcs of 2-step PML leads to another method. Aguirregabiria and Mira (2007) [8] derived the iterative NPL method, which can be seen as an recursive extension of the two-step PML by iterating on predicting the potential values of $\bar{p}_i$ and estimating the parameters α and β. This method does not require a consistent initial estimator for $\bar{p}_i$, and at the same time keeps a low computation cost. Let $\hat{p}_i^0$ be an initial guess of $\bar{p}_i$, note that the guess need not to be consistent. This NPL method returns a sequence of estimators $\{\hat{\alpha}^k,\hat{\beta}^k\}$, where the k-stage estimator is given by:

$$\hat{\alpha}^k,\hat{\beta}^k=\arg\max_{\alpha,\beta} L(\alpha,\beta,\hat{p}_i^{k-1}) \tag{2.4}$$

$$\hat{p}_i^k=\frac{1}{S}\sum_{n=1}^{S}\omega_n P_n(i|\hat{\alpha}^k,\hat{\beta}^k,\hat{p}_i^{k-1}):=\phi_i(\hat{\alpha}^k,\hat{\beta}^k,\hat{p}_i^{k-1}) \qquad \forall i \tag{2.5}$$

If the initial guess $\hat{p}_i^0$ is consistent, followed from the properties of 2-step PML estimator, the sequence of estimators $\{\hat{\alpha}^k,\hat{\beta}^k,\{\hat{p}_i^k\}_i\}$ are all consistent. When the initial guess is a not consistent one, if the sequence $\{\hat{\alpha}^k,\hat{\beta}^k,\{\hat{p}_i^k\}_i\}$ converges to $\{\hat{\alpha},\hat{\beta},\{\hat{p}_i\}_i\}$, the limit $\{\hat{\alpha},\hat{\beta},\{\hat{p}_i\}_i\}$ maximizes $L(\alpha,\beta,\hat{p}_i)$ and satisfies the equation $\hat{p}_i=\phi_i(\hat{\alpha},\hat{\beta},\hat{p}_i)$. Such a triple is called a *NPL fixed point.* Aguirregabiria and Mira (2007) [8] proved that a NPL fixed point exists in every dataset and that if more than one exists, the one with the highest value of the pseudo likelihood is a consistent estimator. However, there is no enough sufficient conditions to guarantee that the NPL algorithm returns a consistent estimator. Comparing the values of pseudo likelihood among all the NPL fixed points is need. When applying NPL in practice, different initial values of $\hat{p}_i^0$ should be tested, and the returned estimators $\{\hat{\alpha},\hat{\beta},\{\hat{p}_i\}_i\}$ should be compared and the one with maximum likelihood is selected. Note that multiple NPL fixed points and multiple equilibriums are totally different, since NPL fixed points satisfies an additional constriant (2.4).

There are drawbacks of the NPL method, of course. One significant drawback is that its convergence is not guaranteed to exist under all circumstances. According to Aguirregabiria et al.

(2002) [11], under the assumption that the utility function U_{ni}, the distribution of error term p_ϵ, the choice probability $P_n(i|\alpha, \beta, \bar{p}_{ni})$ is continuous and twice differentiable, the probability that NPL converges locally goes to 1 as the sample size increases. This is a weak convergence theorem, because only local convergence is promised in a large dataset.

3. DATA

The original data are WiFi traces merged with map information, attractivity and time constraints. It is then cleaned by Danalet et al. (2014) [12] using a Bayesian procedure to detect activity-episode sequence. The dataset used for modelling consists of 715 observations of people's catering location choice during lunch. For each observation, the dataset (Danalet et al., 2016) [13] contains information about the results of choice (e.g. the chosen location, the length of duration stayed at the location), attributes of alternatives (e.g. evaluation of the location, minimum price for a meal,) and some socio-economic characteristics of the individuals (e.g. student or employee, department).

There are generally 21 catering locations available during lunch, which are spread over the whole campus. These places can be categorized into 5 groups: Self-Service, Cafeteria, Caravan, Restaurant and Other. The names and categories of places are available in Table. B.1. Alternative 3 and 7 belong to the category Other, because these places do not serve formal meals. Only sandwiches and coffee are provided by 3 and 7.

4. ESTIMATION

4.1. BASE MODEL

The model framework is generally a multinomial logit model. $i \in C = \{1,2,4,5,6,8,9,...,21,OPTOUT\}$ is the choice set of all available locations. Since alternative 3 and 7 do not serve meals during lunch, these two alternatives are taken as an OPTOUT choice. So the number of alternatives $|C|$ is $21-2+1=20$. After different attempts, the deterministic part V_{ni} for $i \in C \backslash \{OPTOUT\}$ is written as:

$$\begin{aligned} V_{ni} = ASC_i &+ \beta_{PRICE\_STUDENT} \cdot lunch\_min\_price\_student_{ni} \\ &+ \beta_{DISTANCE} \cdot distance_{ni} + \beta_{EVA\_X} \cdot eva_i \\ &+ \beta_{DISTANCE\_NO\_AV} \cdot distance\_no\_av_{ni} \end{aligned}$$

In this model, the influence of distance to the alternatives, minimum price of a meal for student, evaluation of the alternatives are captured. Based on people's common knowledge, these three variables are key elements when people make a decision about where to have lunch. In some of the observations, distance to several alternatives is missing. If $distance_{ni}$ is simply set to be 0 under such circumstance, the alternatives to which distance is missing become more attractive since they are close to the individuals, which is not the case. So $distance\_no\_av_{ni}$ is used. β_{EVA_X} is a parameter specified according to the category to which the alternative belongs to, so there are four parameters used for evaluation: $\beta_{EVA\_SELF}, \beta_{EVA\_CAFE}, \beta_{EVA\_CARA}, \beta_{EVA\_REST}$. The utility function for OPTOUT choice is special, since no meal is offered:

$$V_{n,OPTOUT} = ASC_{OPT}$$

The specifications and estimation results of the variables are displayed in Table A.1, Table A.2. All the parameters have expected signs. It can be seen that $\beta_{DISTANCE}$ and β_{PRICE} have negative signs. People are less willing to go to distant and expensive catering places. Evaluation has positive impact on the propensity to visiting a catering location, and among all the parameters related to evaluation, β_{EVA_SELF} has largest value. This can be explained by the fact that there are 9 self-services places on campus. People have more choices among this kind of catering location so we could capture the statistical property because of the sufficient number of observations.

4.2. Building-based Aggregation

Since the original dataset is rather small and biased, we collect additional information about the distribution of population on campus in each building and aggregate the demand building by building (building-based aggregation). A few assumptions are made:

- everyone of EPFL will have lunch on campus. According to the figures of 2012, there are 7117 students and 5493 employees.
- when leaving for a lunch, people in the same building leaves from the same location. This is for the ease of computation.
- the number of students leaving from one building is proportional to number of students subscribed to the courses whose classrooms are in the building.
- the number of employees leaving from one building is proportional to the capacity of offices in the building.

The prices and evaluation of each location are already given in the dataset. The path from each building to the alternatives is approximated through shortest path given by EPFL Map. The shortest path algorithm can return a path balancing between the shortest path and the simplest path, including floor change and preferring the main walkways on campus. The length of the path is calculated using EPFL Géoportail, see Fig. 4.1. The computed proportional distribution of population of each building is displayed in Table. B.2.

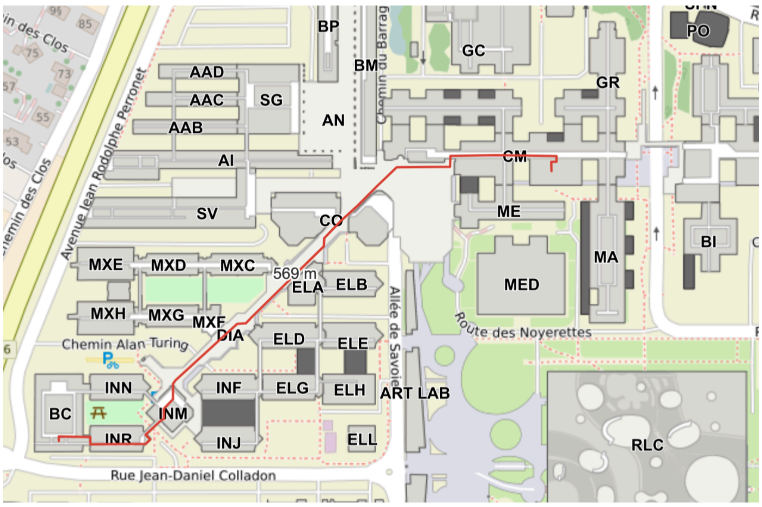

Figure 4.1: Calculate distance using Géoportail

Note that the building-based aggregation does not use the dataset which is used for estimating the model, so the alternative specific constants (ASC) should be calibrated. These constants are indeed expectations of the error terms, which are responsible for capturing unobserved effects.

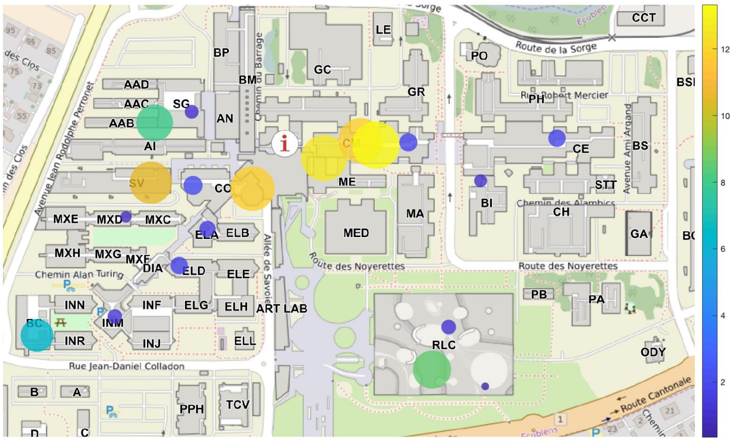

Figure 4.2: Market share during lunch

For each dataset, the ASCs should be different and it is not appropriate to use the same ASCs for different datasets. However, it is impossible for us to calibrate the ASCs for aggregation because to calibrate them we need to know the true market share, which is exactly what we are trying to aggregate. A way to cope with this problem that is a bit extreme is to remove ASCs from the utility function:

$$V'_{ni} = V_{ni} - ASC_i$$

The aggregated market share of catering locations during lunch is shown graphically in Fig. 4.2. The exact market share and the types of the catering places are displayed in the Appendix, see Table. B.1, Fig. B.1. The OPTOUT choice is not shown in the graph. We can see that self-service locations are the most popular one of the four categories. Most lectures' classrooms locate in building CM, CE and CO, thus we can expect that a large number of students will gather around these buildings during lunch hour. That is why the main demand concentrates on catering places in CM and CO. Self-Service places in SV and SG (L'Ornithorynque and Le Corbusier) are also popular since they are not far away from where students gather. The popularity of Self-Service BC is understandable because it is far away from most of the catering places, thus Self-Service BC becomes a good choice for people nearby because of the short distance.

Since each location has a limited capacity, when the demand is more than the capacity, the catering place is over congested. Define T as the total time during lunch (150min), $\bar{t}_i$ as average time individuals spent at each location, c_i as indoor capacity at location i, $d_i(\hat{W}_i)$ as demand at location i, which can be computed using the predicted market share $\hat{W}_i$ and the size of the population on campus. Then

$$congestion_i = \frac{t_i d_i(\hat{W}_i)}{T c_i}$$

For those locations with $congestion_i > 1$, demand is larger than the capacity, leading to over congestion. The congestion condition of all the locations is shown in Fig. 4.3. Note that Roulotte Diagonale and Roulotte Esplanade are caravans, so capacity is not available for these two alternatives, so does congestion. Popularity does not necessarily lead to congestion. There are three popular catering places in CM and they have similar market share, yet only one of them is significantly over-congested. Fig. 4.3 suggests that perhaps for some catering places the capacity should be increased, and for places that are not congested, they might need to improve their service quality (food flavor, environment, etc) to attract more customers.

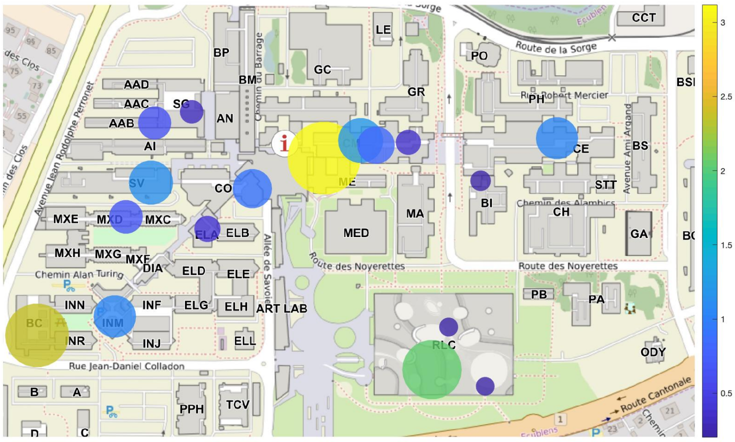

Figure 4.3: Congestion condition of catering places

4.3. Model with congestion effect

With the aggregated market share computed in Section 4.2, we can first estimate the congestion parameter by maximizing the likelihood function. Our two step estimation can be described as:

1. Estimate the base model without congestion effect. Predict the market share using building-based aggregation.
2. Plug the market share in the model with congestion effect and estimate the parameters while maximizing the likelihood, as (2.3).

As mentioned before, we will use NPL method to estimate the parameters when the model reaches a BNE. In this way, we can compare this simple two step estimation result with NPL's result to see the properties of BNE.

We use the market share aggregated in Section 4.2 to compute the congestion of each alternative, $f(\bar{p}_{ni}) = congestion_i$. For OUTPUT alternative, $congestion_{OPTOUT} = 0$. For those alternatives whose capacity values are not available: Roulotte Diagonale (i=17), Roulotte Esplanade (i=18), $congestion_i$ is set to be the average congestion level of other alternatives:

$$congestion_i = \frac{1}{|C|-3}\sum_j congestion_j$$

where $i = 17, 18$, $j \in C \backslash \{17, 18, OPTOUT\}$

The estimation result is shown in Table. C.1. The congestion parameter $\alpha = -0.541$, coincides with our expectation that the more crowded a location is, the less likely people are to choose the location. Yet we do not know whether this predicted market share is accurate enough or not. Also, we are not sure whether the BNE is reached or not. To estimate the parameters when a BNE is reached, we can use the NPL estimation.

Denote $\hat{p}_i^k$ as location i's market share at iteration k. $\delta = 1e-3$ is a given convergence threshold. The NPL method in our case can be written as:

1. Start from $k = 0$, set random initial values to the market share $\hat{p}_i^0$.
2. Update values of the parameters $\hat{\alpha}^k$ and $\hat{\beta}^k$ by maximizing the log-likelihood function, as (2.4)

Description	Value	t-stat
ASC_VIN	-2.74	-4.31
ASC_ARC	-1.41	7.28
ASC_ATL	-1.48	-5.1
ASC_GIA	0.866	4.82

Table 4.1: Values of some ASCs

3. Compute $\hat{p}_i^k$ using new values of the parameters $\hat{\alpha}^k$ and $\hat{\beta}^k$, as (2.5)
4. If not converge, $\sum_i |\hat{p}_i^{k+1} - \hat{p}_i^k| > \delta$, go to step 2.

First, we compute $\hat{p}_i^k$ using sample-based aggregation. Here sample-based aggregation is referred to as aggregating the market share using the dataset which we used for estimation. Since we are using the same dataset for both estimation and aggregation, the ASCs do not need to be calibrated. The estimation result is shown in Table. D.1. Different initial values of $\hat{p}_i$ are tried and the congerved NPL fixed point is the same.

The parameter of congestion effect is 1.1, opposed to our expectation. Potential reasons leading to this result are: first, the dataset we used is small and biased. As mentioned before there are only 700 observations and they are not perfectly randomly drawn from the population. Second, the congestion we defined above may actually indicate the popularity of a catering place. Congestion, thinking from a different direction, is also the popularity of the place.

To further investigate the congestion effect, we collect some additional information for market share prediction, leading to using building-based aggregation to compute the market share. Note that with a new dataset the ASCs should be calibrated. Since this is not possible, two different attempts are made. First, when doing aggregation, we use the ASCs computed from estimation process. The results are displayed in Table. D.2. $\alpha = 0.986$ is almost the same with the result gained using sample-based aggregation. Also, the predicted market share is still somehow biased. (Market share of Le Vinci is 0.4%, opposed to our knowledge). Potential reason leading to this problem may be that some of the ASCs have dominant influence in the utility function, compared with other parameters estimated. For example, as shown in Table. 4.1, the difference between ASC_VIN and ASC_GIA is 3.606, which is rather huge compared with $BETA\_PRICE\_STUDENT = -0.0494$ and $BETA\_EVA\_CAFE = 0.282$ (All the variables are rescaled to the interval $[0, 10]$).

A second attempt is to not use the ASCs when aggregating, which is described in Section 4.2. Nevertheless, NPL estimation does not converge in this case, see Table. 4.2. The value of α oscillates between -0.5 and 0 and there is no significant sign of convergence after 10 iterations.

Iteration	1	2	3	4	5	6
α	-0.541	-0.0865	-0.554	-0.0591	-0.55	-0.066
Iteration	7	8	9	10	11	...
α	-0.532	-0.0136	-0.538	-0.0269	-0.539	...

Table 4.2: α's value in the iterations

Because of the huge influence exerted by ASCs, a different way to reduce the influence of ASCs is tried: fix the ASCs gained from the base model, and estimate other parameters during the NPL iterations. The fixed ASCs push the parameters left to capture more features in the dataset. The results are shown in Table. D.3. α's value is small and insignificant, validating the fact that ASCs are way too influential in the utility function.

5. CONCLUSION

Many kinds of human behavior can be estimated using a discrete choice model incorporating social interaction. This project designs and estimates such a model based on a case study of catering location choice behavior on EPFL campus. More importantly, the BNE state is derived from the assumption that people do not know the choice of other people and thus make rational expectation of others' choice. An empirical analysis to analyze the BNE state of the dataset is done by implementing the NPL method. By our simple two step estimation, we draw the conclusion that congestion has negative influence on people's willingness to choose a catering place. Yet this conclusion is not validated by the NPL estimation method.

The advantages and disadvantages of 2-step PML and NPL are also discussed. 2-step PML allows estimating with a small amount of computation and can be easily implemented. The simple form of PML leads to a high demand of the accuracy of the initial non parametric estimator. To assure the consistency and sufficiency of the estimation method, the estimator should not only be available, but also be precise and has a rather low variance. NPL frees 2-step PML from the requirement of initial estimator by extending it recursively. For NPL, the initial value of estimator can be set randomly. However, when the sample size is small, NPL will not necessarily converge.

At present the estimation results of model with congestion effect are not consistent, there are still something we can do in the future. As mentioned above, the small and somehow biased dataset brings problem into estimation. An available larger dataset can help better understand the effect of congestion. Besides, the base model is rather simple, only capturing several features of the observations. A more complicate model, e.g. a nested logit model which learns the common characteristic of four categories of catering locations, can be derived.

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APPENDIX

A. SPECIFICATION AND ESTIMATION OF BASE MODEL

Number of estimated parameters	26
Sample size	715
Excluded observations	0
Init log likelihood	-2141.949
Final log likelihood	-1600.269

Variable	Value	Std err	t-test	p-value
ASC_ARC	0.604	0.263	2.29	0.0219
ASC_ATL	-2.22	0.286	-7.78	7.11e-15
ASC_BC	-0.216	0.176	-1.23	0.22
ASC_COP	-0.267	0.287	-0.928	0.353
ASC_COR	-0.305	0.152	-2.0	0.0451
ASC_ELA	1.06	0.211	5.01	5.52e-07
ASC_GIA	1.32	0.204	6.46	1.04e-10
ASC_HOD	-0.614	0.227	-2.7	0.00692
ASC_INM	-1.06	0.447	-2.37	0.0176
ASC_KEB	-0.555	0.168	-3.3	0.000964
ASC_KLE	-2.3	0.888	-2.59	0.00955
ASC_MX	0.343	0.266	1.29	0.197
ASC_OPT	-0.467	0.134	-3.5	0.00047
ASC_ORN	-0.324	0.145	-2.24	0.025
ASC_PAR	-0.301	0.148	-2.03	0.042
ASC_PIZ	0.63	0.166	3.79	0.00015
ASC_SAT	-0.124	0.296	-0.419	0.675
ASC_VAL	0.309	0.285	1.09	0.277
ASC_VIN	-4.01	0.715	-5.61	2.07e-08
BETA_DISTANCE	-0.617	0.0334	-18.5	0.0
BETA_EVA_CAFET	0.306	0.0536	5.7	1.17e-08
BETA_EVA_CARA	0.367	0.0628	5.85	4.84e-09
BETA_EVA_REST	0.245	0.0789	3.1	0.00195
BETA_EVA_SELF	0.762	0.0601	12.7	0.0
BETA_NO_DISTANCE_AV	-3.49	0.278	-12.5	0.0
BETA_PRICE_STUDENT	-0.0494	0.0253	-1.95	0.0507

Table A.1: Estimation results of base model

Variable	Definition
$lunch\_min\_price\_student_{ni}$	MIN_PRICE_i if student
$distance_{ni}$	$DISTANCE_{ni}/100$ if $DISTANCE_{ni} > 0$
$distance\_no\_av_{ni}$	1 if $DISTANCE_{ni} = -1$
eva_i	$EVALUATION\_2013_i$ if > 0

Table A.2: Specification of base model

B. AGGRREGATED MARKET SAHRE OF CATERING PLACES DURING LUNCH

Place	Type	Marketshare(%)
Cafe Le Klee	Cafeteria	1.285
BC	Self-service	6.395
ELA	Cafeteria	1.558
INM	Cafeteria	1.234
MX	Cafeteria	0.758
LArcadie	Cafeteria	1.8
LAtlantide	Self-service	12.551
Le Copernic	Restaurant	0.989
Le Corbusier	Self-service	7.975
Le Giacometti	Cafeteria	1.135
Le Parmentier	Self-service	11.91
Le Vinci	Self-service	13.331
LEsplanade	Self-service	11.712
LOrnithorynque	Self-service	10.576
Pizza	Caravan	1.803
Kebab	Caravan	2.149
Satellite	Cafeteria	1.953
Le Hodler	Self-service	8.596
Table de Vallotton	Restaurant	0.350
OPTOUT	Other	1.940

Table B.1: Market share of catering places

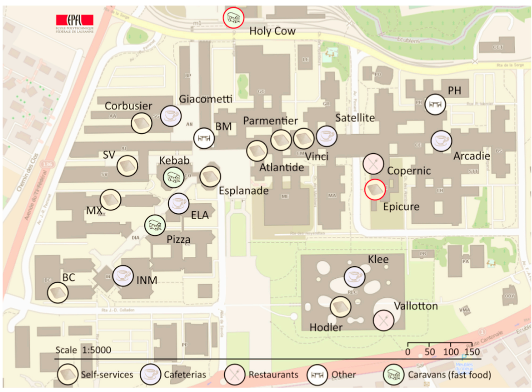

Figure B.1: Types of catering places

Building	Student(%)	Employee (%)
CM	10.67	0.91
CE	9.61	0.76
AAC/SG	4.21	1.45
BC	0.96	1.93
BM	0.21	2.75
BS	1.67	0.87
CO	8.48	0.05
BSP/Cub	0.55	1.23
EL	2.10	3.53
GC	1.25	2.78
GR	1.16	1.75
IN	2.42	3.40
MA	1.67	2.75
MX	0.32	2.43
ME/MED	0.19	1.85
PH	0	2.32
PA/PB	0	0.30
LE	0	0.24
CH	0	3.40
RLC	10.98	0.70
AI/SV	0	5.82
BP	0	2.34

Table B.2: Computed proportional distribution of the population in each building

C. Estimation Results using two step simple estimation

Number of estimated parameters	27
Sample size	715
Excluded observations	0
Init log likelihood	-2141.949
Final log likelihood	-1600.269

Variable	Value	Std err	t-test	p-value
ALPHA	-0.541	0.0933	-5.79	6.91e-09
ASC_ARC	0.842	0.256	3.29	0.00101
ASC_ATL	-1.04	0.192	-5.41	6.32e-08
ASC_BC	0.572	0.168	3.41	0.000654
ASC_COP	-0.262	0.287	-0.912	0.362
ASC_COR	-0.445	0.16	-2.77	0.00553
ASC_ELA	0.955	0.213	4.48	7.32e-06
ASC_GIA	1.17	0.208	5.63	1.81e-08
ASC_HOD	0.0151	0.204	0.0742	0.941
ASC_INM	-0.813	0.434	-1.87	0.0614
ASC_KEB	-0.551	0.168	-3.28	0.00104
ASC_KLE	-2.5	0.869	-2.88	0.00401
ASC_MX	0.385	0.265	1.46	0.146
ASC_OPT	-0.28	0.118	-2.38	0.0175
ASC_ORN	-0.205	0.139	-1.47	0.141
ASC_PAR	-0.149	0.141	-1.06	0.291
ASC_PIZ	0.634	0.166	3.81	0.000137
ASC_SAT	-0.245	0.297	-0.825	0.41
ASC_VAL	0.297	0.285	1.04	0.297
ASC_VIN	-4.05	0.714	-5.68	1.38e-08
BETA_DISTANCE	-0.617	0.0334	-18.5	0.0
BETA_EVA_CAFET	0.301	0.0537	5.6	2.18e-08
BETA_EVA_CARA	0.404	0.0619	6.54	6.22e-11
BETA_EVA_REST	0.203	0.0806	2.52	0.0117
BETA_EVA_SELF	0.793	0.06	13.2	0.0
BETA_NO_DISTANCE_AV	-3.49	0.278	-12.5	0.0
BETA_PRICE_STUDENT	-0.0494	0.0253	-1.95	0.0506

Table C.1: Estimation results of two step simple estimation

D. Estimation Results using NPL

Number of estimated parameters	27
Sample size	715
Excluded observations	0
Init log likelihood	-2141.949
Final log likelihood	-1600.269

Variable	Value	Std err	t-test	p-value
ALPHA	1.1	0.127	8.64	0.0
ASC_ARC	0.179	0.248	0.719	0.472
ASC_ATL	-1.15	0.287	-4.02	5.74e-05
ASC_BC	-2.37	0.291	-8.12	4.44e-16
ASC_COP	-0.0863	0.287	-0.301	0.763
ASC_COR	0.273	0.162	1.69	0.091
ASC_ELA	0.565	0.189	2.99	0.0028
ASC_GIA	0.341	0.175	1.95	0.0511
ASC_HOD	-0.601	0.227	-2.64	0.00826
ASC_INM	-0.282	0.453	-0.622	0.534
ASC_KEB	-0.576	0.168	-3.43	0.000603
ASC_KLE	-1.23	0.813	-1.52	0.13
ASC_MX	-0.424	0.235	-1.8	0.0713
ASC_OPT	-0.434	0.135	-3.22	0.00128
ASC_ORN	-0.327	0.145	-2.26	0.024
ASC_PAR	-0.0374	0.149	-0.251	0.802
ASC_PIZ	0.605	0.166	3.64	0.000269
ASC_SAT	0.765	0.327	2.33	0.0196
ASC_VAL	0.118	0.284	0.416	0.678
ASC_VIN	-2.51	0.615	-4.07	4.65e-05
BETA_DISTANCE	-0.617	0.0334	-18.5	0.0
BETA_EVA_CAFET	0.063	0.0635	0.993	0.321
BETA_EVA_CARA	0.138	0.0629	2.19	0.0285
BETA_EVA_REST	0.176	0.0782	2.25	0.0247
BETA_EVA_SELF	0.449	0.0618	7.27	3.55e-13
BETA_NO_DISTANCE_AV	-3.49	0.278	-12.5	0.0
BETA_PRICE_STUDENT	-0.0494	0.0253	-1.95	0.0509

Table D.1: Estimation results of NPL with sample-based aggregation

Number of estimated parameters	27
Sample size	715
Excluded observations	0
Init log likelihood	-2141.949
Final log likelihood	-1600.269

Variable	Value	Std err	t-test	p-value
ALPHA	0.986	0.137	7.18	6.74e-13
ASC_ARC	-1.38	0.227	-6.07	1.3e-09
ASC_ATL	-1.49	0.289	-5.14	2.68e-07
ASC_BC	-1.29	0.23	-5.62	1.87e-08
ASC_COP	-0.409	0.287	-1.42	0.154
ASC_COR	0.318	0.17	1.87	0.0609
ASC_ELA	0.784	0.194	4.03	5.47e-05
ASC_GIA	0.872	0.18	4.85	1.23e-06
ASC_HOD	-1.24	0.24	-5.14	2.69e-07
ASC_INM	-0.283	0.457	-0.619	0.536
ASC_KEB	-0.554	0.168	-3.3	0.000971
ASC_KLE	-1.12	0.779	-1.44	0.156
ASC_MX	0.425	0.27	1.57	0.116
ASC_OPT	-0.458	0.134	-3.42	0.000627
ASC_ORN	-0.135	0.145	-0.936	0.349
ASC_PAR	-0.461	0.151	-3.06	0.00222
ASC_PIZ	0.63	0.166	3.79	0.00015
ASC_SAT	0.549	0.33	1.66	0.0962
ASC_VAL	0.482	0.285	1.69	0.0904
ASC_VIN	-2.77	0.639	-4.33	1.48e-05
BETA_DISTANCE	-0.617	0.0334	-18.5	0.0
BETA_EVA_CAFET	0.281	0.0542	5.19	2.16e-07
BETA_EVA_CARA	0.369	0.0628	5.88	4.15e-09
BETA_EVA_REST	0.418	0.0863	4.84	1.3e-06
BETA_EVA_SELF	0.727	0.059	12.3	0.0
BETA_NO_DISTANCE_AV	-3.49	0.278	-12.5	0.0
BETA_PRICE_STUDENT	-0.0494	0.0253	-1.95	0.0508

Table D.2: Estimation results of NPL with building-based aggregation using ASCs computed from estimation process

Number of estimated parameters	8
Sample size	715
Excluded observations	0
Init log likelihood	-2212.942
Final log likelihood	-1600.27

Variable	Value	Std err	t-test	p-value
ALPHA	-0.000463	0.0785	-0.00589	0.995
BETA_DISTANCE	-0.617	0.0332	-18.6	0.0
BETA_EVA_CAFET	0.306	0.0572	5.34	9.34e-08
BETA_EVA_CARA	0.368	0.0647	5.68	1.32e-08
BETA_EVA_REST	0.245	0.0813	3.01	0.00264
BETA_EVA_SELF	0.762	0.0598	12.7	0.0
BETA_NO_DISTANCE_AV	-3.49	0.275	-12.7	0.0
BETA_PRICE_STUDENT	-0.0494	0.0231	-2.14	0.0326

Table D.3: Estimation results of NPL with building-based aggregation using fixed ASCs computed from base model