Modelling office workers' activity of eating out

会社員の勤務時における外食行動の分析

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Outline

- Background
- Objectives
- Data overview
- Modeling and estimating parameters
  - Setting
  - Estimation result and interpretation
- Scenario analysis

Background

Staying in office may results in…… 会社に引きこもっていると…

- Less communication between co-workers
  会社内でのコミュニケーション不足
- Less use of restaurants
  飲食店利用の減少

→ Quick meals are not beneficial for both workers nor the area.
"コンビニ飯"は会社員にとっても地域にとってもよくない？

Let's vitalize both areas and office workers with a city where people want to go out for eat!

外食しやすい町で、地域を・会社員を活気づけよう！

Objectives

Decision-making mechanism of office workers' eating out activity

会社員の勤務時外食の意思決定メカニズムの解明

★ Modelling workers' eating out actions

会社員の外食選択行動のモデル化

★ Analyzing the related promotion policies

外食促進政策の検討

Data

Toyosu PP (2019), Activity data of office workers

豊洲PP (2019), 会社員の活動データ

- Activity chain per day:

  Trips between “**通勤・通学**”(commute) and “**帰宅**”(going home)

  １日の活動チェーン：”通勤・通学”と”帰宅”に挟まれた活動

- Eating-out trip: “**食事**”(Eating out) trip made during certain time

  特定時間帯の”食事”を外食として扱う

Data overview

- Data
- Eating-out activity

使用データ
外食の分析

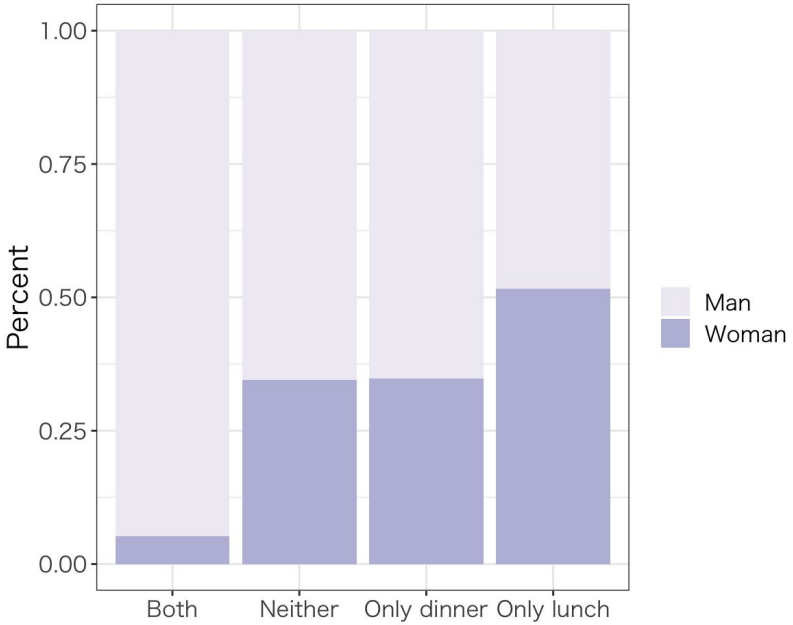
Data

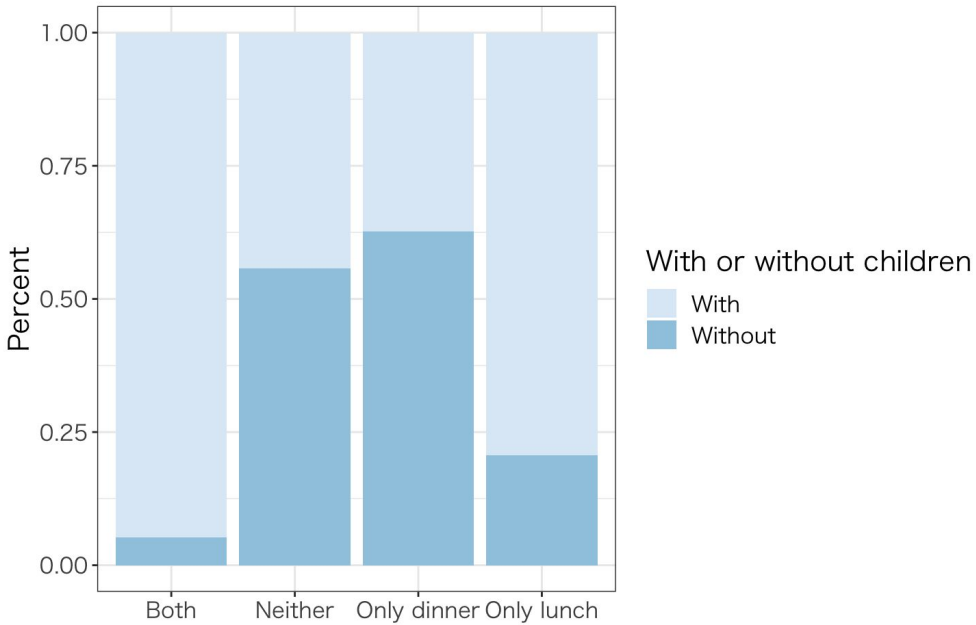
Toyosu PP (2019), Action data of workers

豊洲PP (2019), 会社員の活動データ

	Eating out for lunch	**Else**
Eating out for dinner	19 samples / 8 users	233 samples / 59 users
Else	126 samples / 30 users	2236 samples / 107 users

Attributes of monitors - gender and child

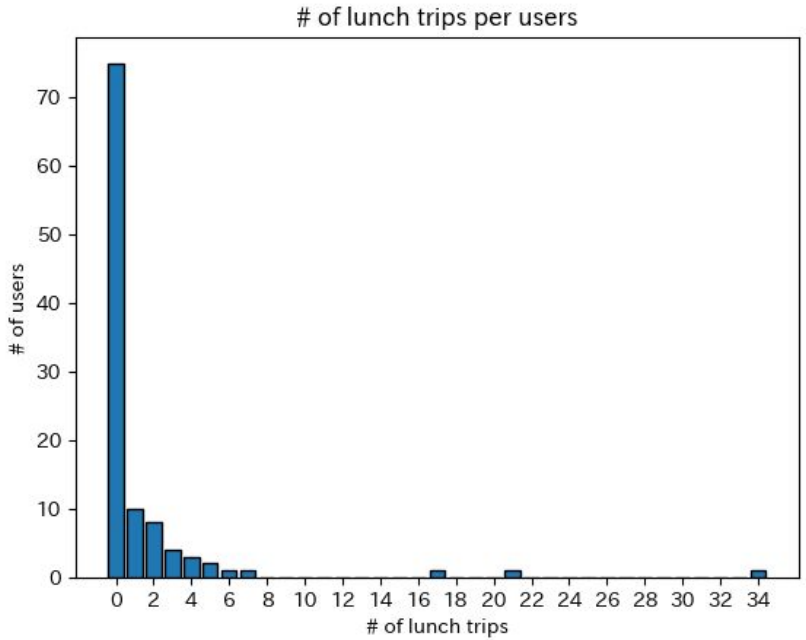


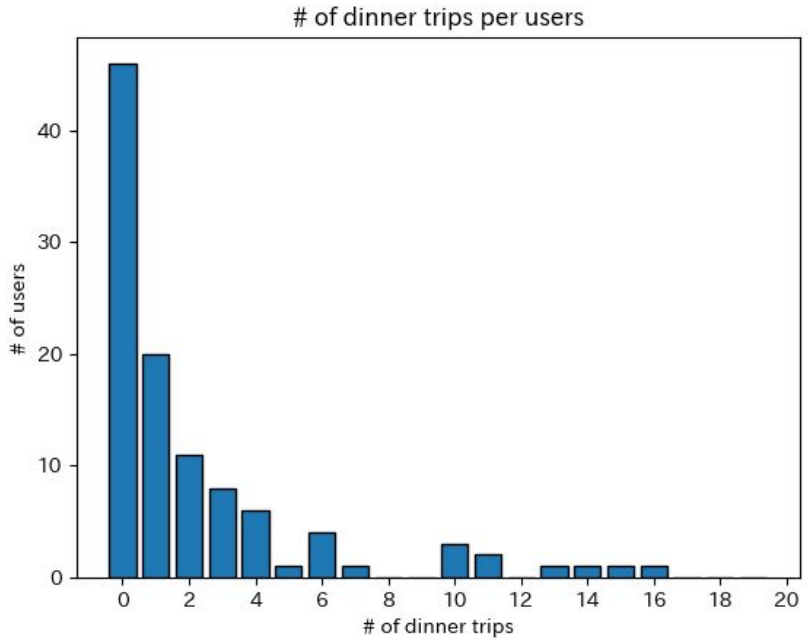


High percentage of men except for only lunch.

Those who eat out for dinner only and both activities without tend to be childless.

Eating-out activity - # of lunch / dinner trips per users



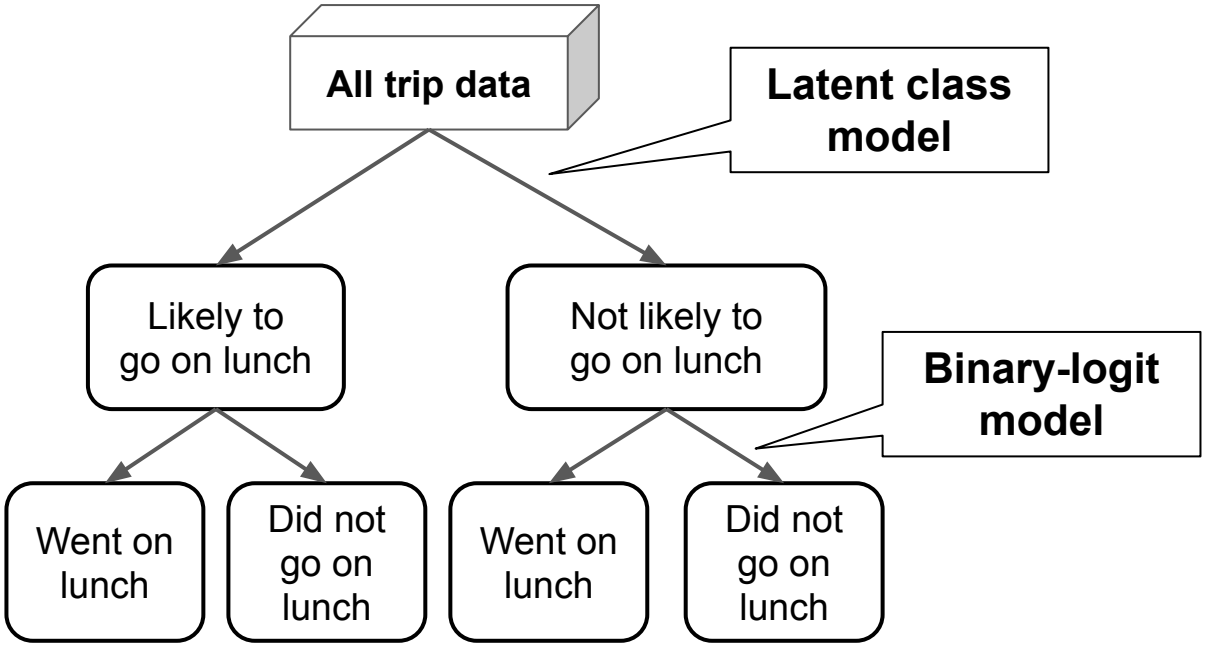


Presence of habitual users → Influence of endogenous factors

習慣的利用者の存在　　内生的な要素の影響

Modeling and estimating parameters

Overview of our model



1st step
modelling
Latent tendency

2nd step
modelling
decision making

Setting – variables

Latent class model

X_{gender}	Dummy variable (1: man)
X_{income}	Dummy variable (1: income > six million)
X_{partner}	Dummy variable (1: have a partner)
X_{child}	Dummy variable (1: have at least a child)
$X_{\text{supermarket}}$	Number of supermarkets near house

Binary-logit model

$X_{\text{time\_of\_commute}}$	Commuting time
$X_{\text{Friday}}/X_{\text{Thursday}}$	Dummy variable (1: Friday/Thursday)
$X_{\text{restaurant}}$	Number of restaurant near office

Setting - modelling latent tendency

Latent class model　潜在クラスモデル

- Represents individuals' heterogeneity of eating-out activity as a mixture of several typical choice behavior patterns**.**

  会社員の外食行動決定メカニズムの異質性を、いくつかの典型的な選択パターンの混ぜ合わせとして表現

$$M^{\text{lunch}}_{\text{class\_1}} = ASC^{\text{lunch}}_{\text{class}} + \beta^{\text{lunch}}_{\text{gender}} \times X_{\text{gender}} + \beta^{\text{lunch}}_{\text{income}} \times X_{\text{income}} + \beta^{\text{lunch}}_{\text{partner}} \times X_{\text{partner}} + \beta^{\text{lunch}}_{\text{child}} \times X_{\text{child}} + \beta^{\text{lunch}}_{\text{supermarket}} \times X_{\text{supermarket}}$$

$$M^{\text{lunch}}_{\text{class\_2}} = 0$$

$$P^{\text{lunch}}_{\text{class\_1}} = \frac{\exp\left(M^{\text{lunch}}_{\text{class}_1}\right)}{\exp\left(M^{\text{lunch}}_{\text{class}_1}\right) + \exp\left(M^{\text{lunch}}_{\text{class\_2}}\right)}$$

Setting - modelling decision-making

Binary-logit model　二項ロジットモデル

- Represents actual behavioral choices by exogenous factors
  外生的な要素に影響された、実際の行動選択
- Assume that lunch and dinner choices are independent of each other. 昼食・夕食の行動選択は、それぞれ独立のものとする

$$V^{\text{lunch}}_{\text{eating\_out\_class\_1}} = ASC^{\text{lunch}}_{\text{class\_1}} + \beta^{\text{lunch}}_{\text{time\_of\_commute\_class\_1}} \times X_{\text{time\_of\_commute}} + \beta_{\text{Friday\_class\_1}} \times X_{\text{Friday}} + \beta^{\text{lunch}}_{\text{restaurant\_class\_1}} \times X_{\text{restaurant}}$$

$$V^{\text{lunch}}_{\text{eating\_out\_class\_2}} = ASC^{\text{lunch}}_{\text{class\_2}} + \beta^{\text{lunch}}_{\text{time\_of\_commute\_class\_2}} \times X_{\text{time\_of\_commute}} + \beta_{\text{Friday\_class\_2}} \times X_{\text{Friday}} + \beta^{\text{lunch}}_{\text{restaurant\_class\_2}} \times X_{\text{restaurant}}$$

$$V^{\text{lunch}}_{\text{else\_class\_1}} = V^{\text{lunch}}_{\text{else\_class\_2}} = 0$$

$$P^{\text{lunch}}_{\text{eating\_out\_class\_1}} = \frac{\exp\left(V^{\text{lunch}}_{\text{class\_1}}\right)}{\exp\left(V^{\text{lunch}}_{\text{class\_1}}\right) + \exp\left(V^{\text{lunch}}_{\text{class\_1}}\right)}$$

Estimation result – Latent class model

⬇️ Membership function

	Lunch		Dinner	
Explanatory variables	estimate	t-value	estimate	t-value
ASC	1.86	7.4***	5.11	7.57***
Gender	-0.19	-1.19	2.09	6.59***
Income	-0.50	-3.12***	0.43	1.29
Partner	0.09	0.50	-0.32	-0.40
Child	0.36	2.08**	-4.07	-5.68***
No. of supermarket	-0.03	-0.21	-0.86	-1.74*

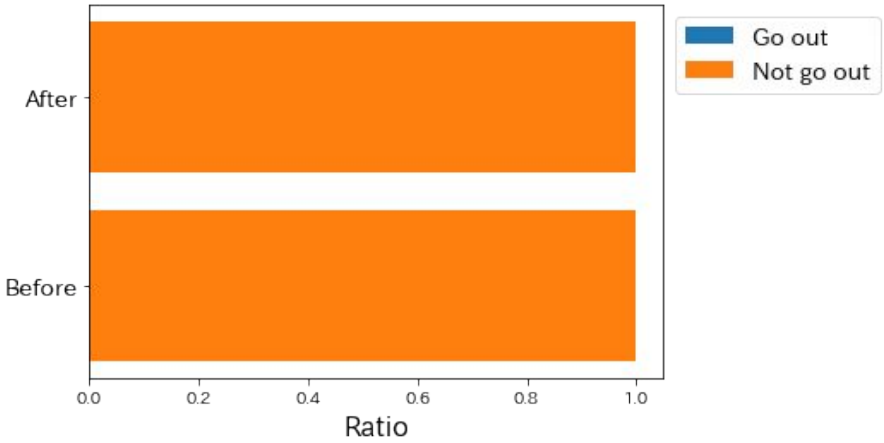
*: p < 0.1; **: p < 0.05; ***: p < 0.01.

⬇️ Utility function

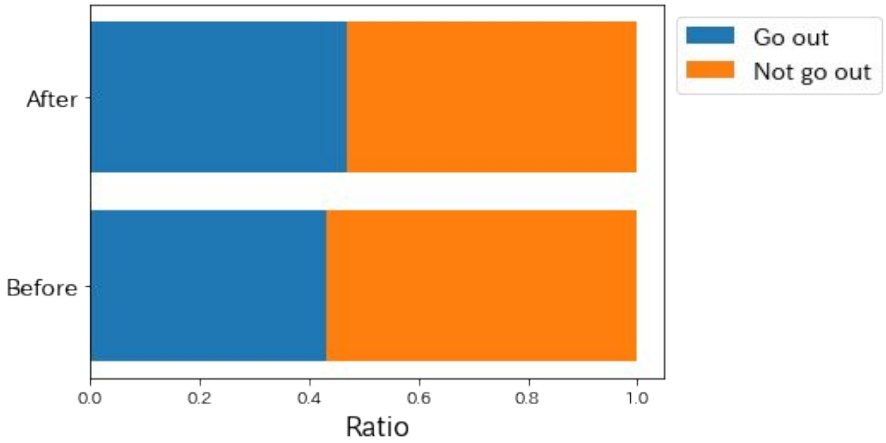
	Lunch		Dinner	
Explanatory variables	estimate	t-value	estimate	t-value
Class_1: ASC	0.66	6.92E-5	-2.87	-12.68***
Class_2: Constant	-0.43	-1.89*	-2.63	-13.55***
Class_1: Commute time	-1.09	-1.78E-3	-5.27E-3	-3.07***
Class_2: Commute time	4.72E-4	NaN	-0.01	NaN
Class1: Friday/Thursday	0.371	1.25E-4	-0.50	-1.04
Class2: Friday/Thursday	0.29	0.64	-1.00	NaN
Class1: No. of restaurant	-0.50	-1.44E-3	6.80E-3	NaN
Class2: No. of restaurant	7.14E-3	1.78*	0.04	NaN
Sample size	2614		2614	
Initial log likelihood	-1811.89		-1811.89	
Final log likelihood	-812.48		-457.09	
Corrected ρ^2	0.54		0.74	

Interpreting each class (lunch)

Class1



Class2



After: change in variables (commute time, # of restaurants around office)

Class1 is a class that **captures activity pattern without eating-out,**

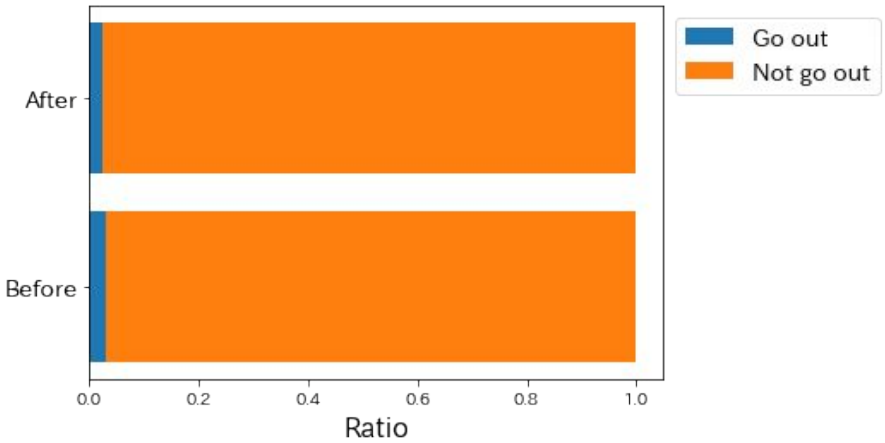
クラス1は“外食をしない”活動パターンを捉えたクラス

Class2 is a class that **captures decision-making.**

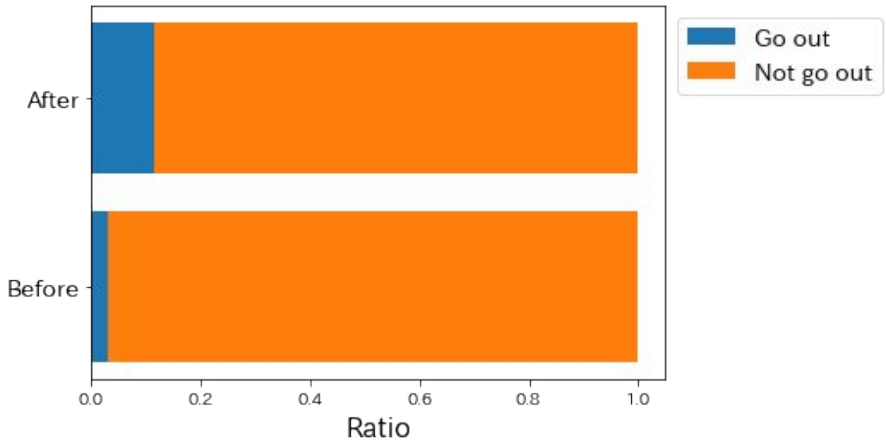
クラス2は意思決定を捉えたクラス

Interpreting each class (dinner)

Class1



Class2



After: change in a variable (# of restaurants around office)

Also in dinner, **Class1** is a class that **captures activity pattern without eating-out,**

“夕食”も同様、クラス1は“外食をしない”活動パターンを捉えたクラス

Class2 is a class that **captures decision-making.**

クラス2は意思決定を捉えたクラス

Interpreting membership function

Positive parameters

Lunch
Partner, Child

People who have the partner or a child tend to have **fixed activity patterns**.

Dinner
Gender, Income

Male or people with high incomes tend to have **fixed activity patterns**.

Negative parameters

Lunch
Gender, Income

Lunch activities of people who has the partner or a child is the result of choice behavior.

Dinner
Partner, Child

Male or people with high incomes tend not to go out on dinner latently

Scenario analysis

- Lunch trips
  - Increasing⬆️ # of restaurants by **50%** results in **0.9% increase⬆️** (9.6% → 10.5%) in lunch trips
  - Decreasing⬇️ commute time by **30%** results in **0.9% increase⬆️** (9.6% → 10.5%) in lunch trips
- Dinner trips
  - Increasing⬆️ # of restaurants by **50%** results in **0.8% decrease⬇️** (5.5% → 4.7%) in dinner trips
  - Decreasing⬇️ commute time by **30%** results in **0.3% increase⬆️** (5.5% → 5.8%) in dinner trips

Lunch/dinner activities are formed as living patterns rather than decision-making.

Summary

- Objectives:
  Modelling office-workers' decision-making of lunch/dinner trips
- Modelling:
  Latent class model and binary-logit model

Our analysis showed that lunch/dinner activities are formed as living patterns rather than decision-making.

外食行動は日々の意思決定ではなく、
生活パターンの結果として形成されことを示唆

Thank you for listening

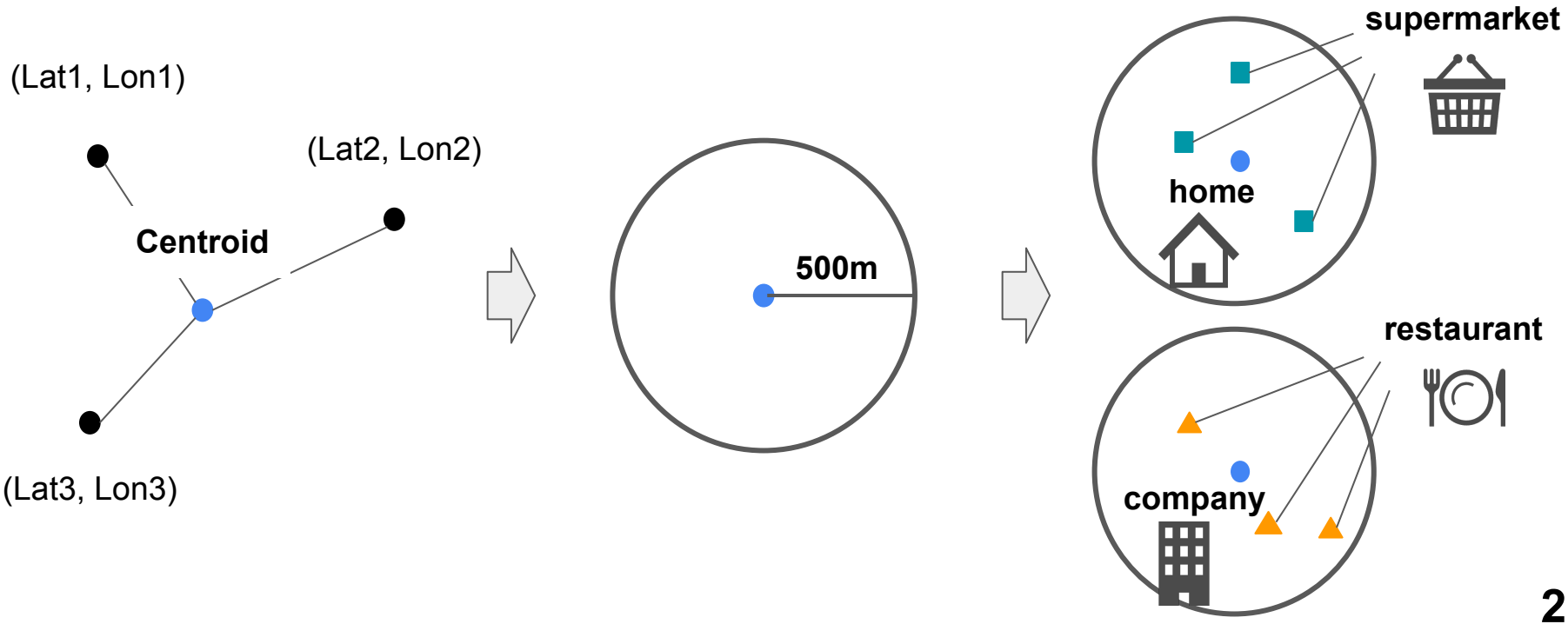
Appendix

Explanatory variables - # of supermarket and restaurant

Extracting centroid from GPS Data

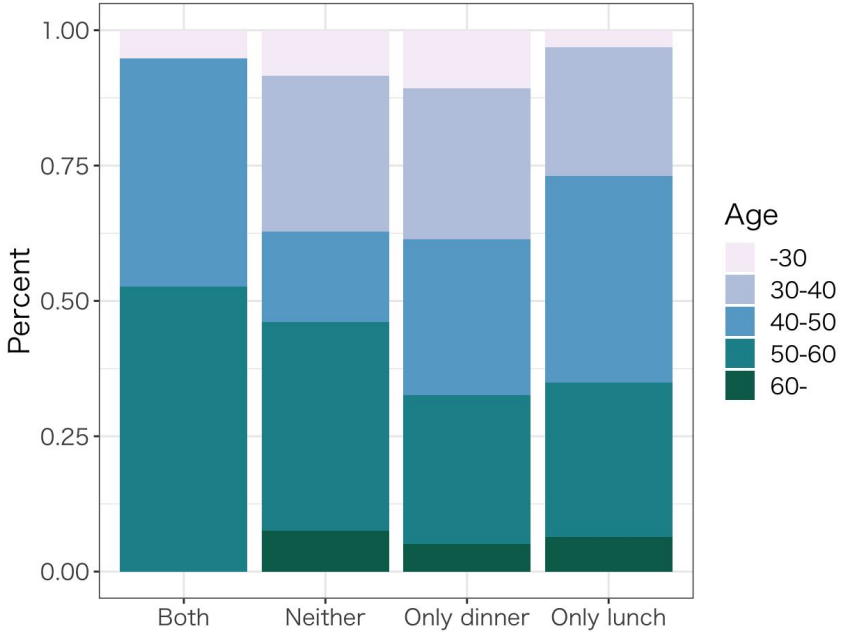
Identifying the area within a 500m radius

Acquiring retail information via Foursquare API



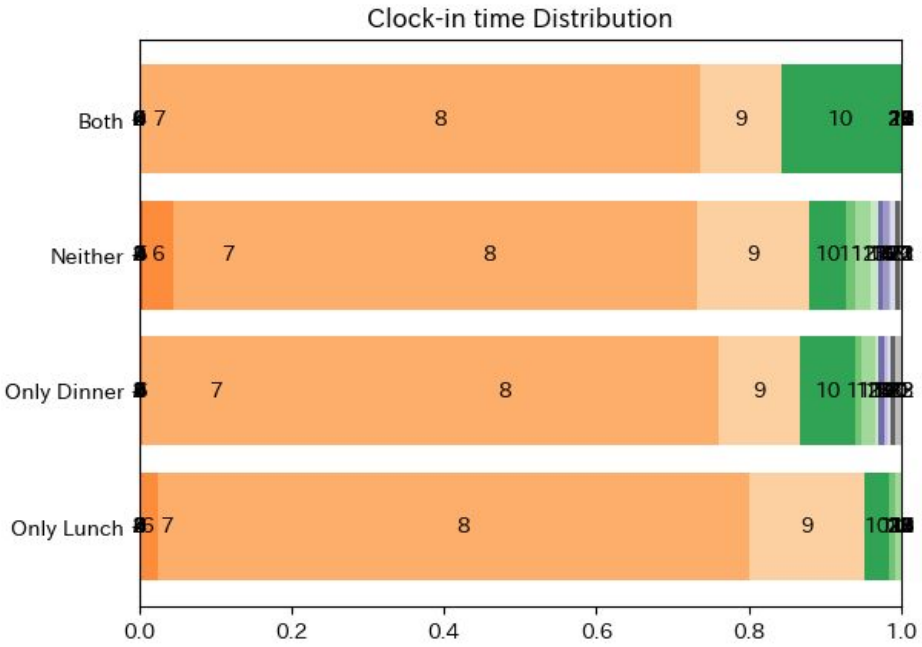
Attributes of monitors - Income and age

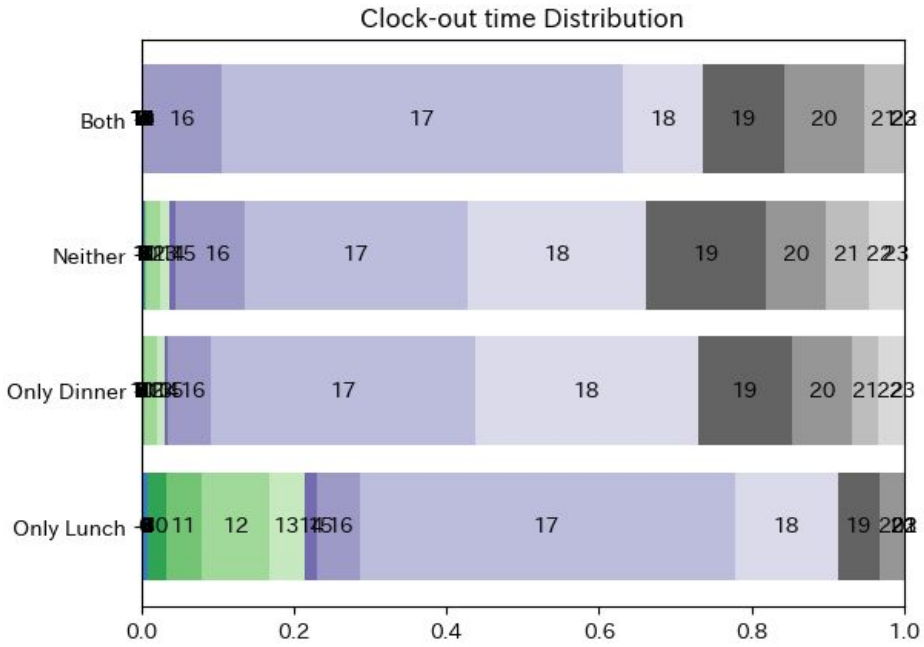
High percentage of people who eat only lunch have a higher income.



High percentage of over 40s in all types.

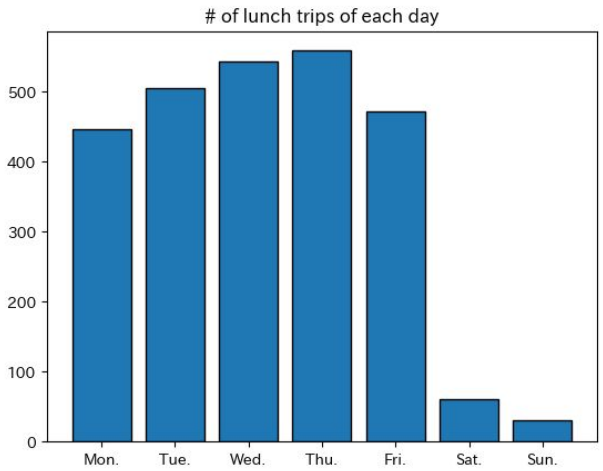
clock -in/out time Distribution

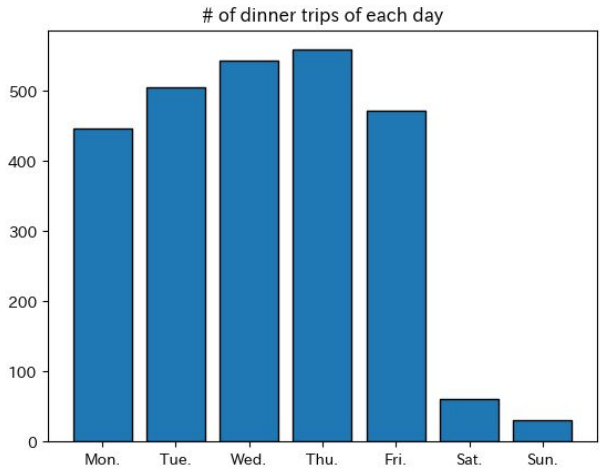


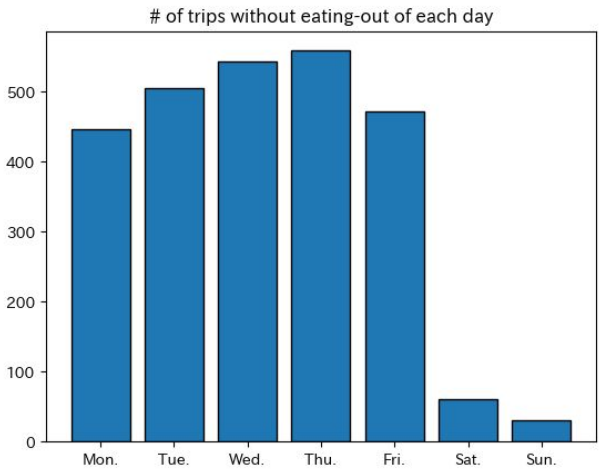


* Each numbers in the graph represent hour-part of clock-in / clock-out time

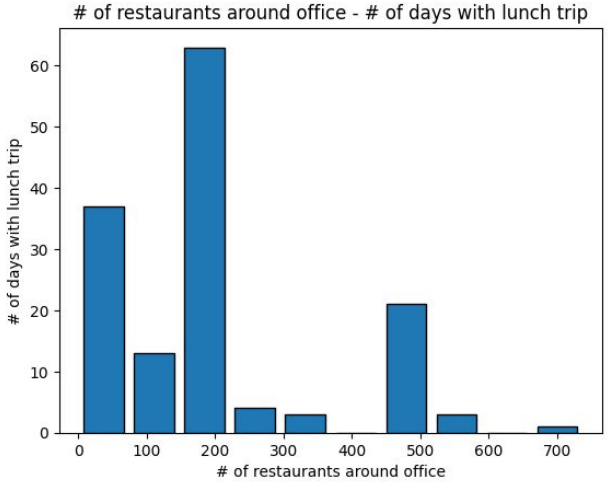
of trips of each day

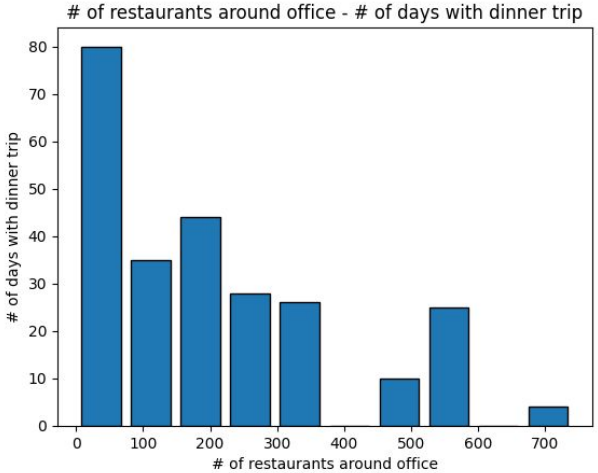


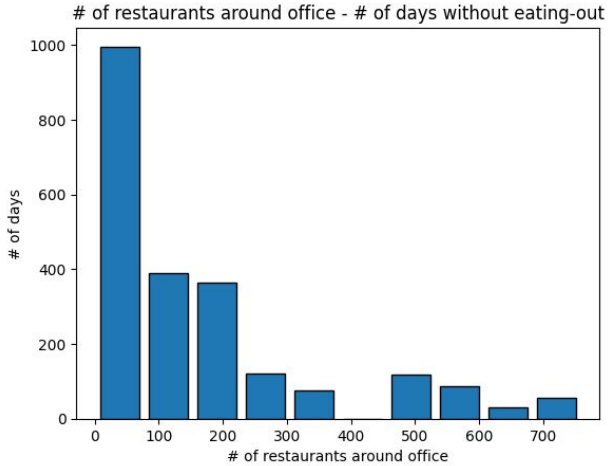




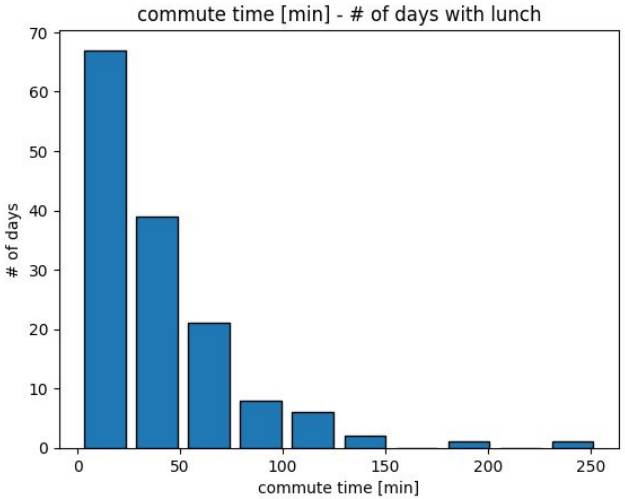
of restaurants around office

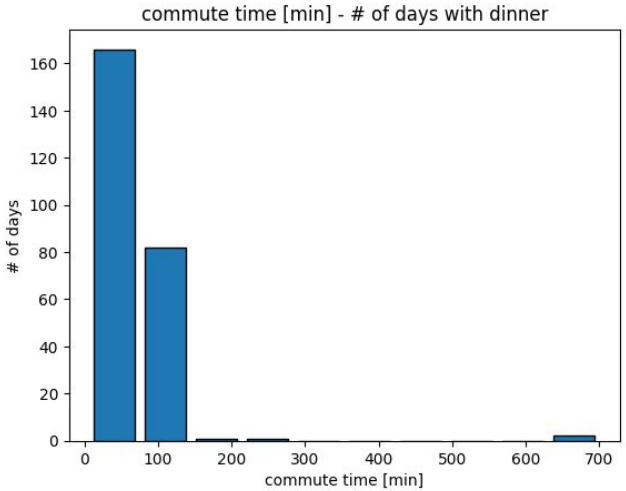


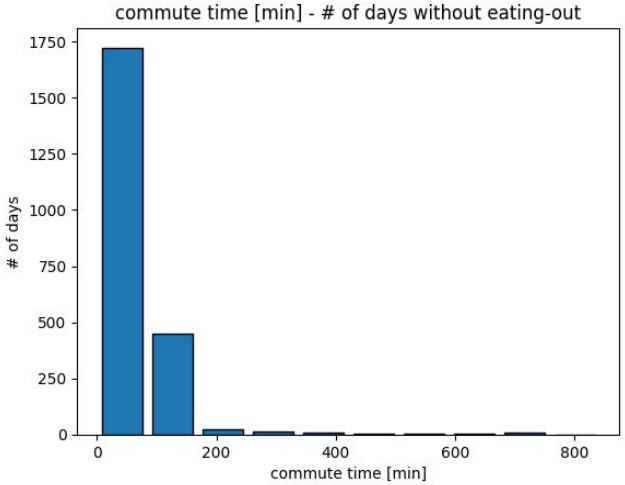




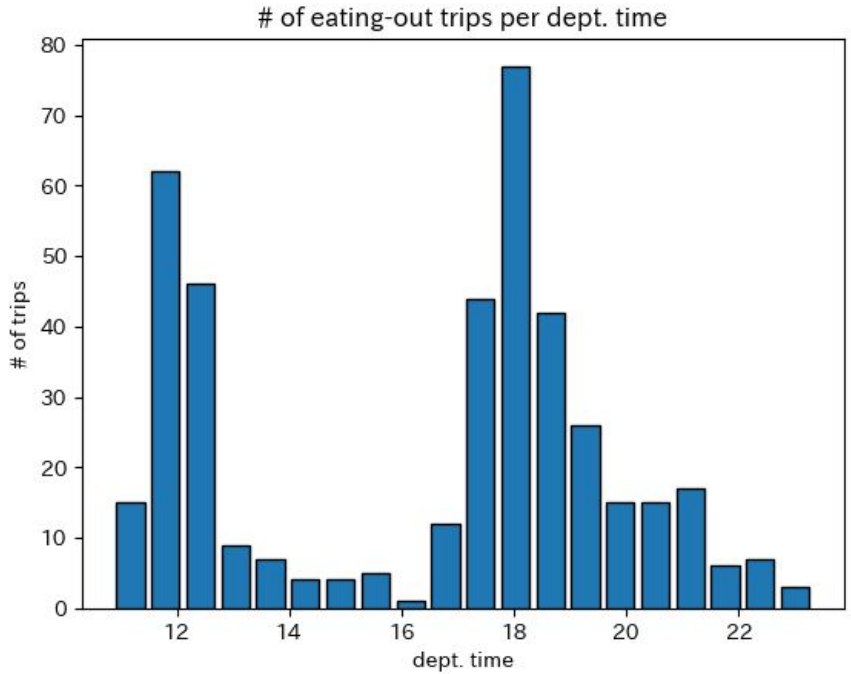
commute time







Eating-out activity - # of eating-out trips per dept. time



Eating-out trips has 2 peaks (12:00 for lunch, 18:00 for dinner)

Estimation result – Binary logit model

	Lunch		Dinner	
Explanatory variables	estimate	t-value	estimate	t-value
ASC	-3.616	-9.734***	-2.390	-17.553***
Commute time	-0.017	-5.519***	-	-
Friday / Thursday	0.713	3.470***	0.231	1.410
No. of restaurant	-	-	0.001	1.090
Gender	0.789	3.908***	-0.226	-1.524
Income	-1.324	-5.721***	0.498	3.336***
Partner	-	-	-0.115	-0.680
Child	2.646	10.029***	-0.349	-2.126**
No. of supermarket	0.544	2.081**	-	-
Sample size	2614		2614	
Initial log likelihood	-1811.887		-1811.887	
Final log likelihood	-458.841		-815.772	
Corrected ρ^2	0.743		0.546	

*: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.