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第23回行動モデル夏の学校

観光客の宿泊場所選択に着目した L-RLモデルによる滞在遷移表現と混雑課金制御

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▼ Background

■ 観光客によるオーバーツーリズムは世界的な課題

Over-tourism caused by tourists is a worldwide problem

→ **混雑制御** / congestion control

■ 近年、観光客数の増加に伴う外部不経済への対策として**宿泊税を導入**する自治体が見られるようになった

External diseconomies due to an increase in the number of tourists

→ Introducing an accommodation tax



宿泊税による混雑制御に着目する

In our estimation, we focus on congestion control through accommodation taxes.

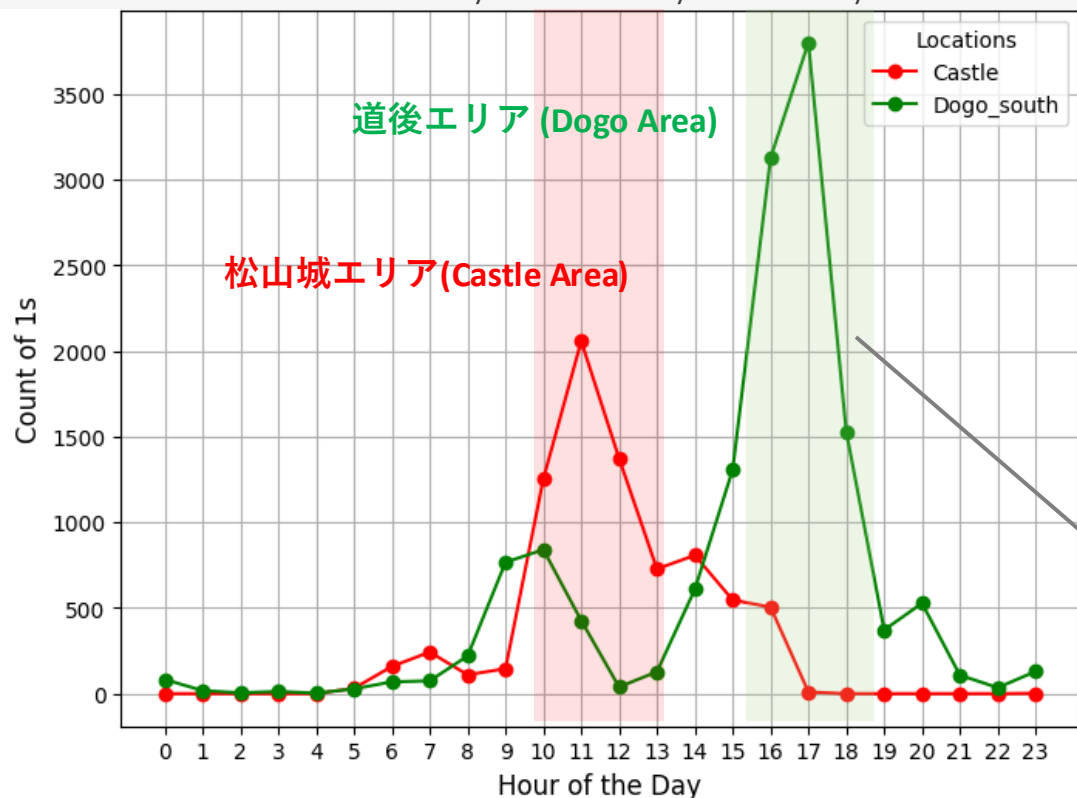
▼ Basic Analysis

観光地の混雑分布は動的で、かつ場所によって異なる

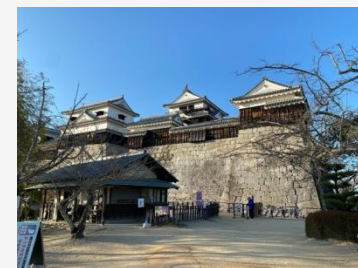
The level of crowding varies by time of day, making it important to address peak times.

松山における時間帯別滞在者数

Number of visitors by time of day in Matsuyama



Dogo Onsen



Matsuyama castle

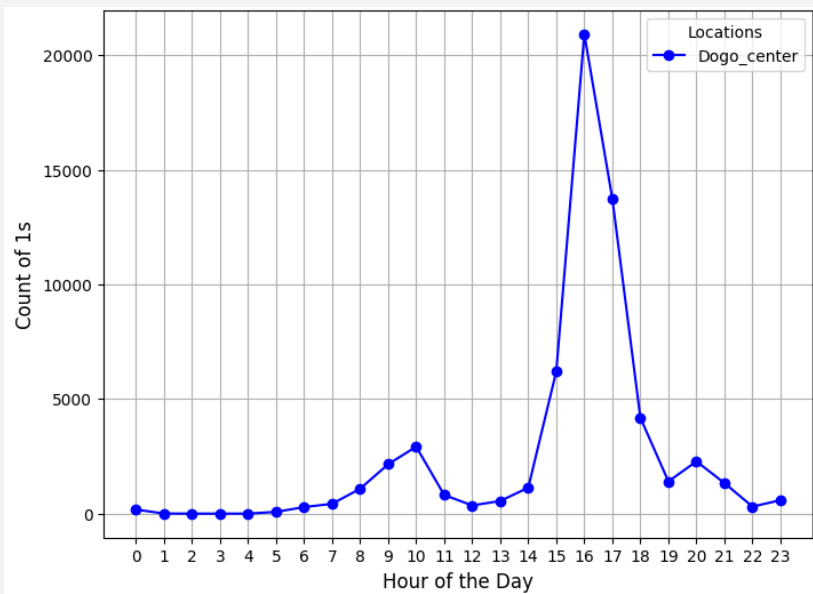
温泉は夕方に、
城は日中にピーク

Peak is in the evening in the area of hot spring, though that of castle is around the noon

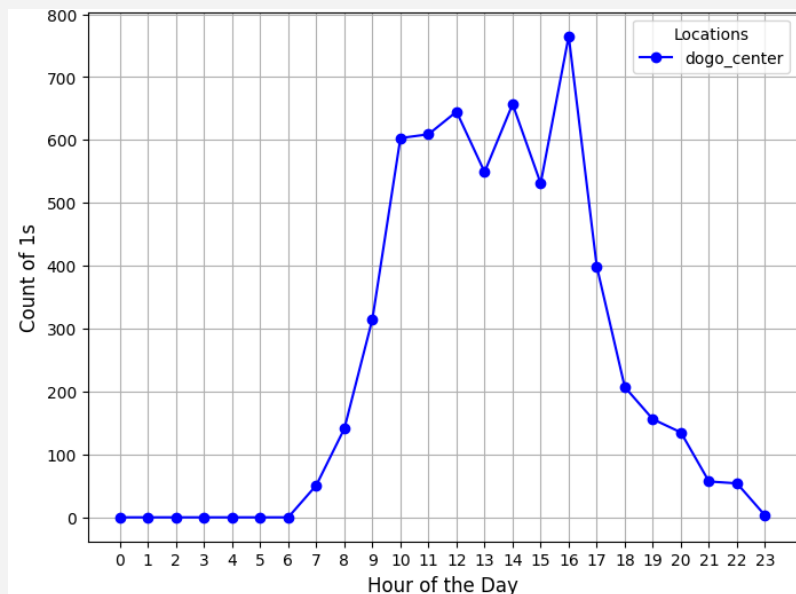
▼ Basic Analysis

同じエリアでも **宿泊場所により時間帯別の滞在行动が異なる**
Number of tourists by time differs depending on the hotel.

道後エリアの時間帯別滞在者数 Hourly Distribution of Dogo Area



道後内宿泊者のみ
Only tourists staying
in Dogo Area



松山全体宿泊者
Tourists staying in all areas
in Matsuyama

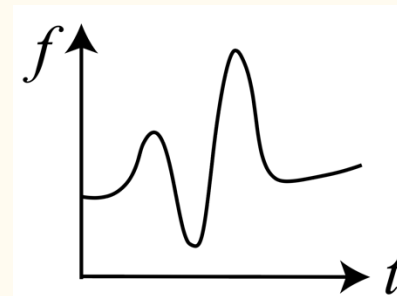
▼ Hypothesis

①各エリアの効用は時間に応じて非線形な挙動を示すのではないか

The utility of each area may exhibit nonlinear behavior depending on the time of day.

→温泉には朝夕に入りたい、城は日中に行く、など

People may want to visit hot springs in the morning or evening, while visiting the castle during the day, etc.

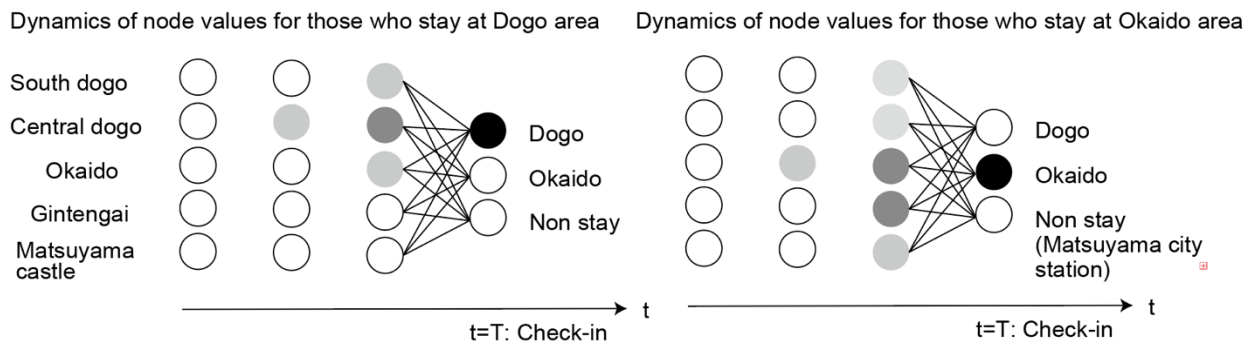


②1日の観光行動は宿泊場所による時間制約を受けるのではないか

The daily sightseeing activities may be constrained by the location of the hotel.

→ホテルチェックイン・夕食に向けて観光行動を切り上げて移動する、など

Tourists may cut short their sightseeing activities to move toward their hotel for check-in or dinner, etc.



▼ Purpose

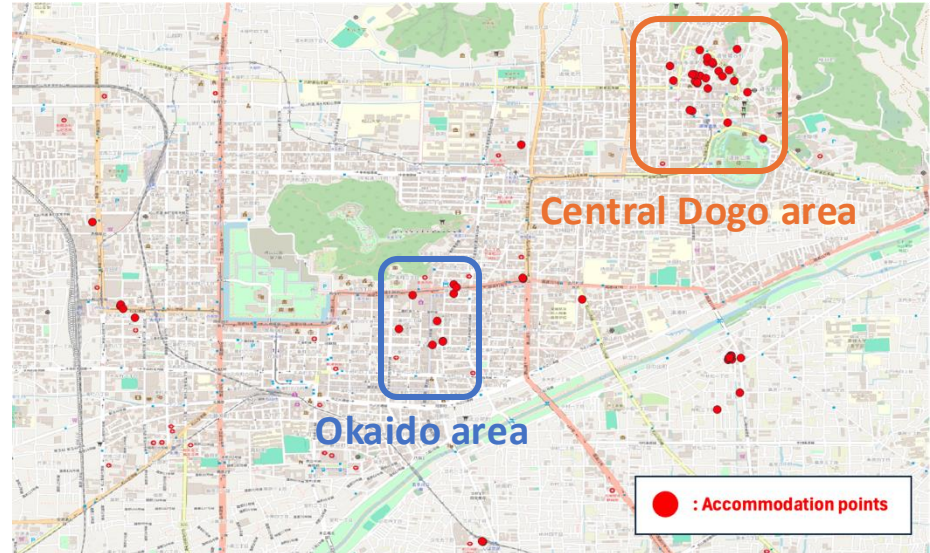
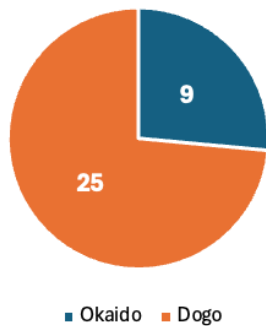
✓ エリア別ホテル課金により各エリアの混雑の時間帯による平準化を目指す

We aim to balance peak-hour congestion in each area by applying area-specific hotel pricing.

→ 宿泊地分布を操作することで1日の回遊行動の多様化・分散を促したい

We aim to encourage more diverse and dispersed visitor behavior by applying appropriate dynamic pricing.

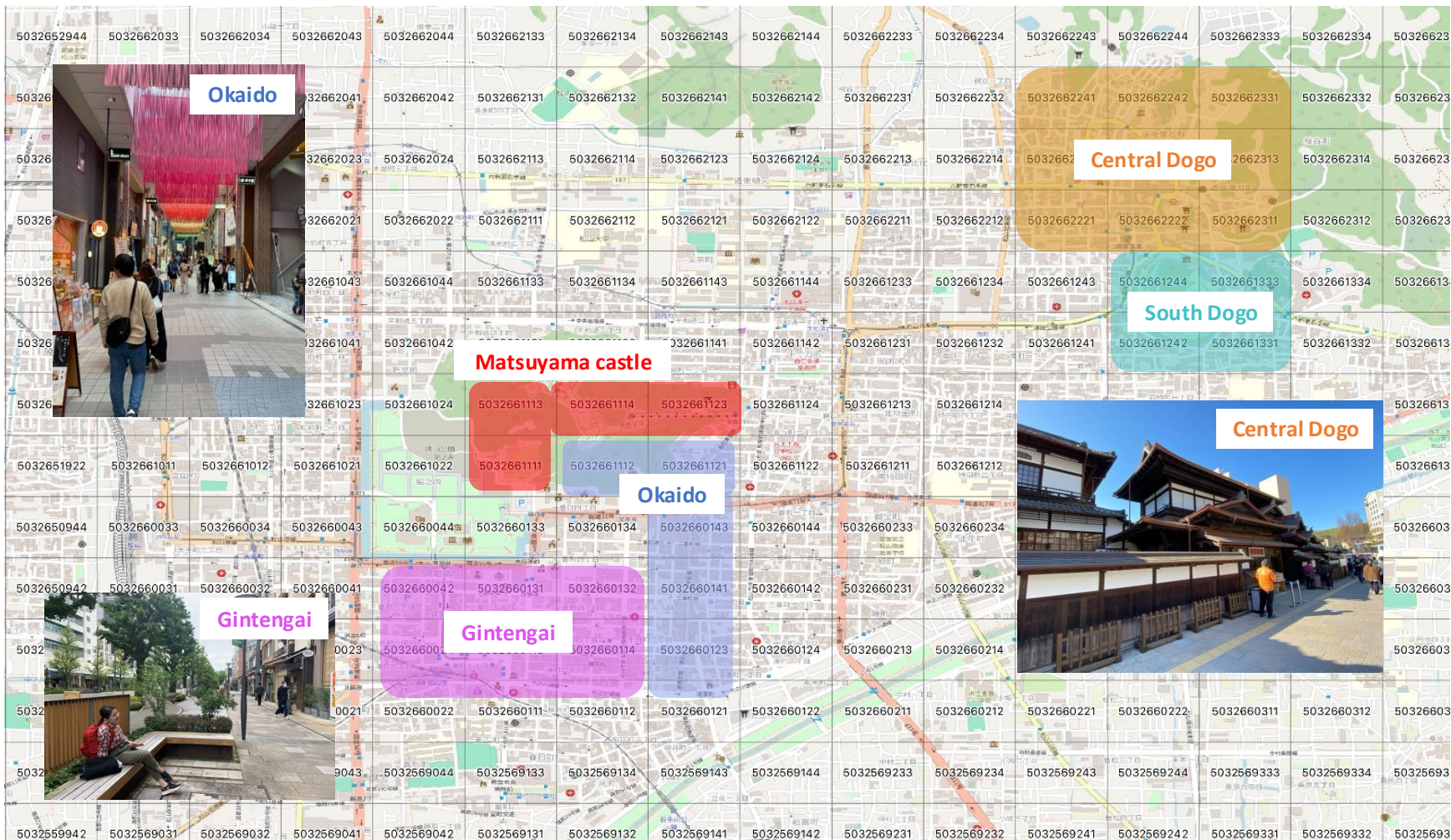
Number of overnight visitors in the Okaido and Dogo areas (2022 PP survey)



Accommodation locations of people who stayed in Matsuyama in the 2022 PP survey

▼ Framework

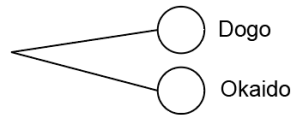
選択滞在場所として5つのエリアを設定
Five areas are set as the choice of areas to stay.



Area classification

▼ Framework

binary Logit Model for accommodation site choice

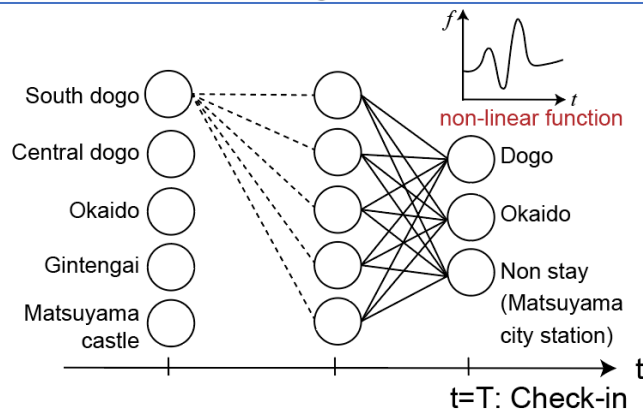


$$V_{dogo} = \beta_{fee} \frac{x_{fee}}{1000} + \beta_{time} x_{time}$$

$$V_{okaido} = \beta_{fee} \frac{x_{fee}}{1000} + \beta_{time} x_{time}$$

Learning-Recursive Logit Model for sightseeing scheduling

$$v(a_t | a_{t-1}) = \underbrace{\theta_{dist} d(a_t | a_{t-1})}_{\text{knowledge driven}} + \underbrace{f^{a_t}(t, c)}_{\text{data driven}}$$



➤ 観光地での滞在エリア遷移をRLで記述

Describing the transition of stay areas in tourist destinations using Recursive Logit model.

- 各観光エリアの時系列での効用（魅力度）を、NNを用いて非線形で非明示的な即時効用式として導入し機械学習で推定

Introduce the time-series attractiveness of each tourist area as a nonlinear utility function using a neural network and estimate it with machine learning.

→ Learning-Recursive Logit model

(Sifringer 2020, Han, Yafei, et al., 2022など)

➤ 宿泊地選択モデル(BL)を組み込み課金政策評価可能に

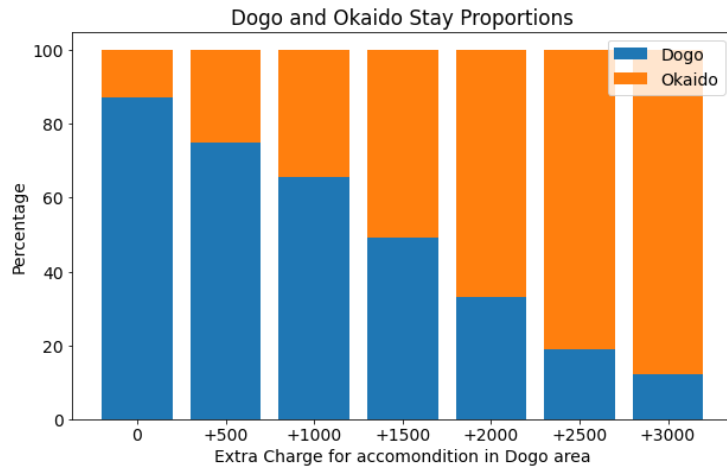
Integrate the accommodation choice model for the final destination.

Result

Estimation results of BL model
for accomodation site choice

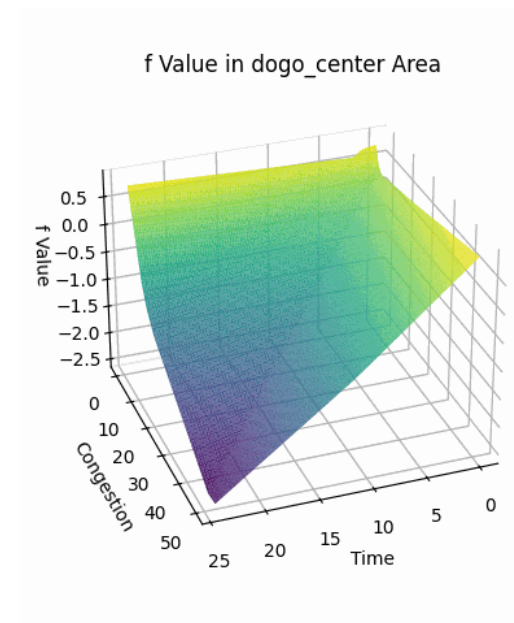
parameter	estimate	t-value
Hotel Fee [JPY]	-1.31	-101.9***
Time [min.]	-0.504	-27.0***
sample		120
Log-likelihood at 0		-1833.1
Final Log-likelihood		-400.9
ρ^2		0.781
Adjusted ρ^2		0.780

1% significant ***



Estimation results of L-RL model
for sightseeing scheduling

parameter	estimate
θ_{dist} [km]	-0.55
sample	1141
Log-Likelihood at 0	-1364.69
Final Log-likelihood	-616.24
ρ^2	0.55
Adjusted ρ^2	0.55



▼ Result?

Timestep = 00

Dogo Cente

Dogo Sout

Matsuyama Castle

Okaido

Sintengai

課金なし

Timestep = 00

Dogo Cente

Dogo Sout

Matsuyama Castle

Okaido

Sintengai

3000円課金

▼ Conclusion

①各エリアの効用は時間に応じて一定程度**非線形**な挙動を示す

The utility of each area exhibits a certain degree of **nonlinear** behavior over time.

②1日の観光行動は**宿泊場所による時間制約**を受ける

Tourist behavior is subject to time constraints **depending on accommodation location.**

→宿泊税の導入で**混雑を一定程度抑制**できた

Succeeded in controlling congestion with pricing for accommodation fee

✓ **オーバーツーリズムへの宿泊税の効果を現実的なモデルで示唆**

Indicating the impact of pricing for accommodation fee on over-tourism

< Future Work >

- Utilizing more data ex.) Personal Attribute
- To maintain the interpretability of NN
- The way of congestion control ex.) Dynamic Programming

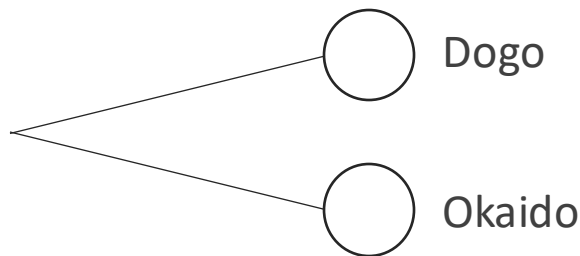
▼ Appendix. Binary Logit model

宿泊場所選択モデル(二項ロジット)の推定結果

- 宿泊客は道後温泉エリアと大街道商店街エリアから選択する
- 説明変数はホテル宿泊料金(円)と道後温泉へのアクセス時間(分)

This is the result of BL for accommodation site choice. In this model, guests choose Dogo or Okaido as their accommodation site. The explanatory variables are Hotel Price(JPY) and Time to Dogo(min.).

$$V_{dogo} = \beta_{price} \frac{x_{price}}{1000} + \beta_{time} x_{time}$$
$$V_{okaido} = \beta_{price} \frac{x_{price}}{1000} + \beta_{time} x_{time}$$



Estimation results of BL model
for accommodation site choice

parameter	estimate	t-value
Hotel Fee [JPY]	-1.31	-101.9***
Time [min.]	-0.504	-27.0***
sample		120
Log-likelihood at 0		-1833.1
Final Log-likelihood		-400.9
ρ^2		0.781
Adjusted ρ^2		0.780

1% significant ***

▼ Appendix. Learning-Recursive Logit model

$$v(a_t|a_{t-1}) = \theta_{dist}d(a_t|a_{t-1}) + f^{a_t}(t, c)$$

効用関数の非線型項にNeural Netを加えることで、非線型かつ柔軟な入力が可能

- 観光地の滞在効用や混雑による効用などの表現に有効だと考えられる
- 今回は関数形状分析のため、時間・時間ごとの混雑のみを入力とした

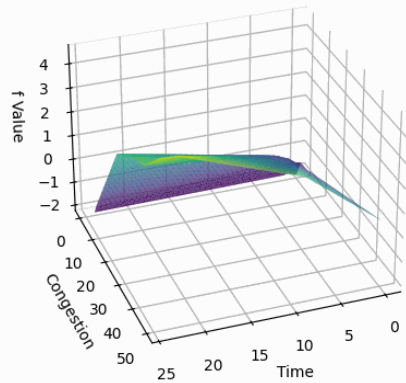
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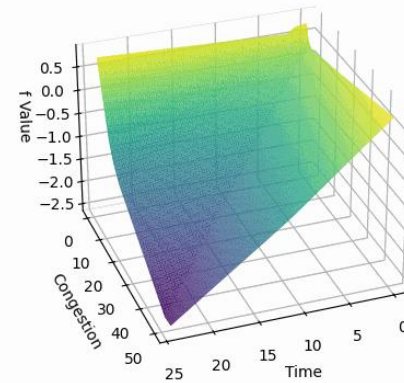
▼ Appendix. Learning-Recursive Logit

関数 $f^{at}(t, c)$ の関数形状を以下に示す。

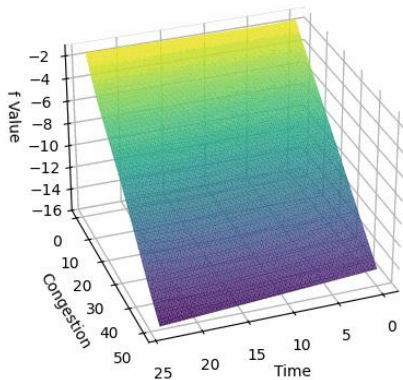
f Value in okaido_shopping_street Area



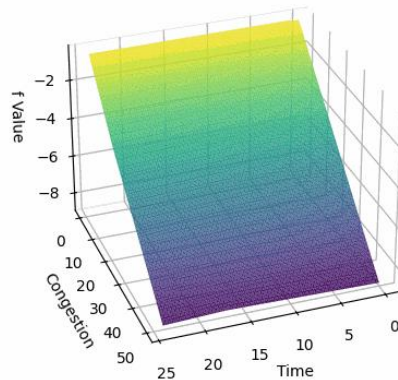
f Value in dogo_center Area



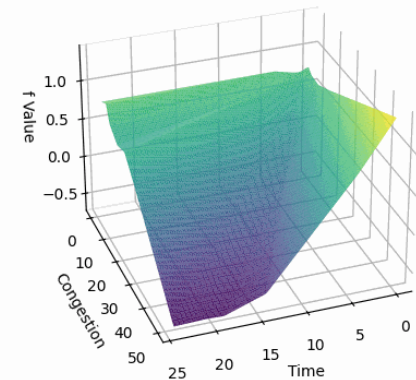
f Value in dogo_south Area



f Value in matsuyama_castle Area



f Value in gintengai_shopping_street Area



▼ Formulation

観光地での滞在場所遷移L-RLモデル

- 非線形で非明示的な即時効用式を導入し機械学習で推定 (Sifringer 2020など)

$$v_t(a|k) = \theta_a \underbrace{D(a, k)}_{\text{リンク長}} + \underbrace{f(a, t)}_{\text{時変のノード属性(NN: 非線形近似)}}$$

- NWの終ノードを**宿泊場所**に設定