Choice set generation for activity-based models

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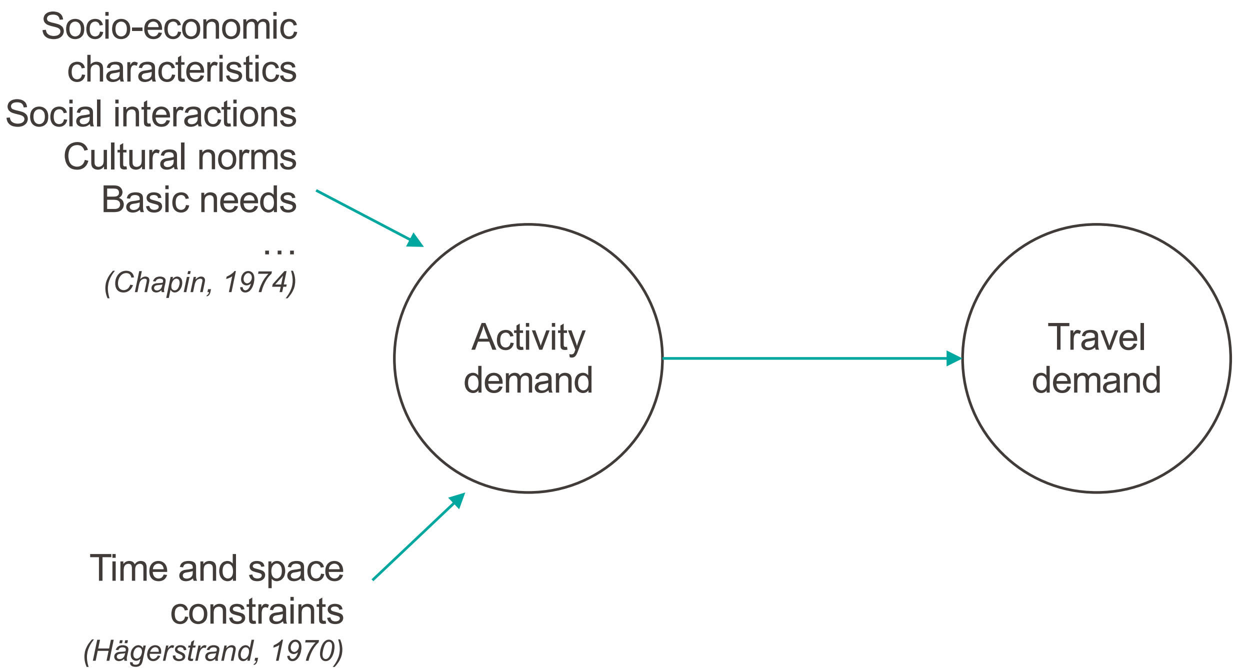
Introduction



Introduction

Utility-based models

Decision is made by maximizing utility derived from activities

e.g.

Bowman & Ben-Akiva, 2001
Bhat et al, 2004
Pougala et al, 2022

Rule-based models

Decision is made by considering context-dependent rules

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Gollegde et al., 1994
Arentze & Timmermans 2000

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Parameter estimation

- Maximum likelihood estimation (MLE) of parameters in discrete choice models:

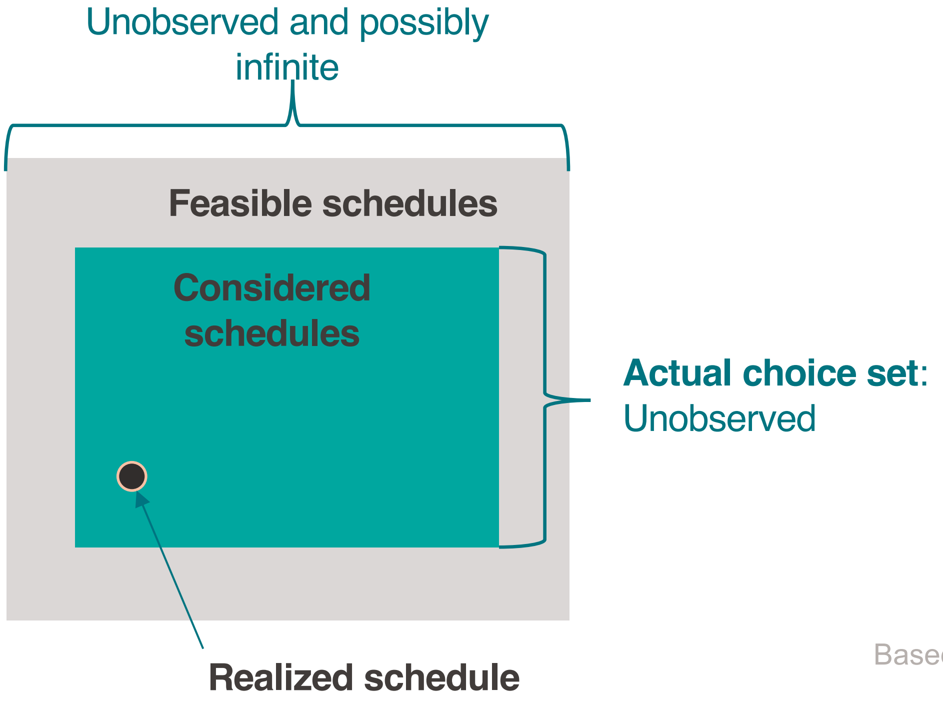
$$\hat{\theta} = \arg\max L_n(\theta)$$

$$L_n = \prod_{n=1}^{N} \prod_{i \in C_n} P_n(i)^{y_{in}}$$

Enumeration over choice set C_n

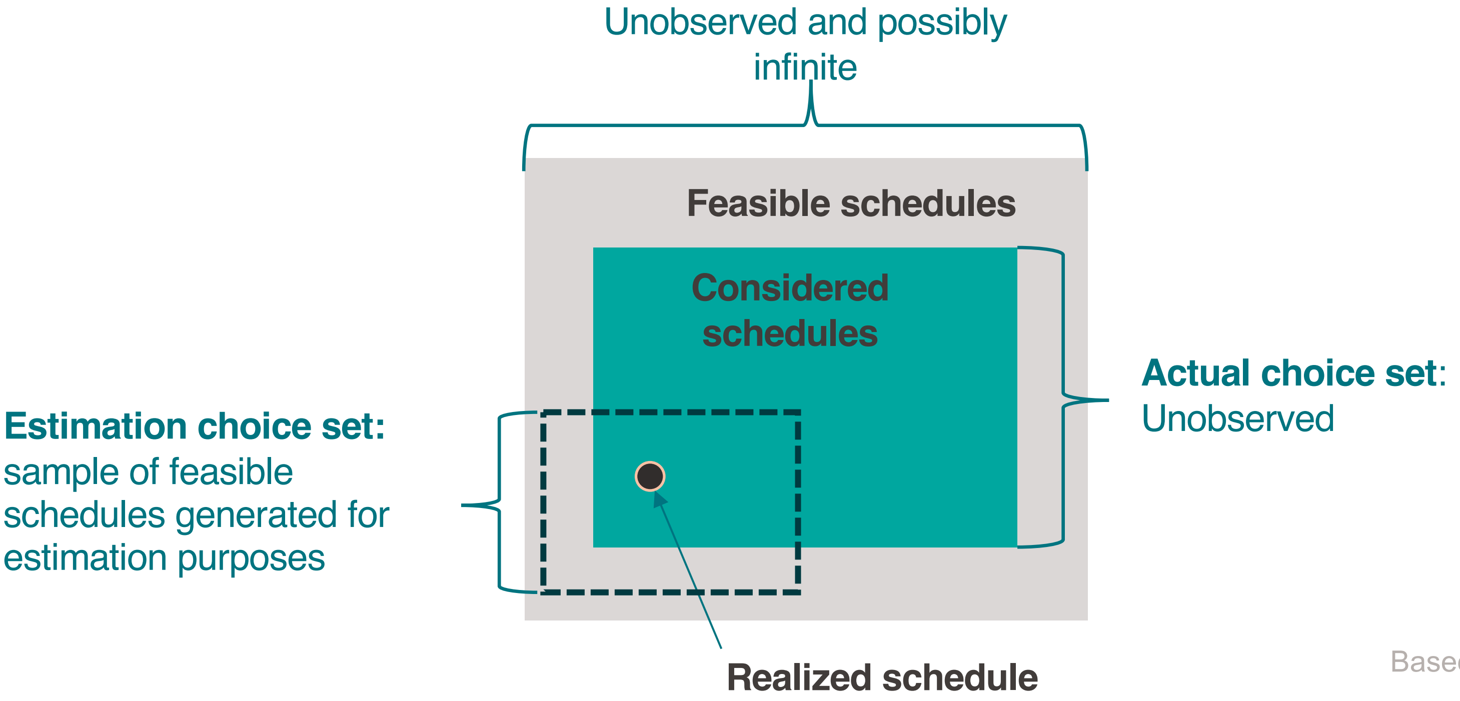
- Common assumptions on choice set:
  - Universal across population
  - Fully observed or observable

Choice set



Based on Shocker (1991)

Choice set



Based on Shocker (1991)

Objective

- Generate choice set of **considered** schedules for **estimation** purposes
- Efficient exploration of solution space:
  - High probability alternatives to ensure **robust parameters estimates** (Frejinger & Bierlaire, 2009)
  - Low probability alternatives to **reduce parameter bias** (Krüger & Bierlaire, 2020)
- Avoid full enumeration of alternatives

Background

○ **Flötterod & Bierlaire 2013:**

- Importance sampling in route choice context
- Metropolis-Hastings algorithm used to draw fom a distribution of path
- Candidate states generated with operators (shuffle, splice)

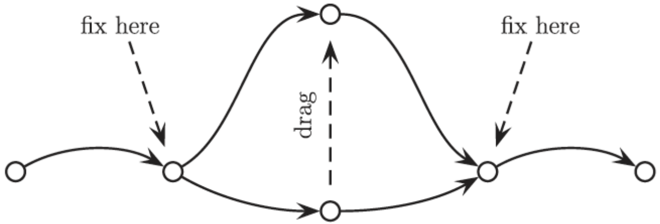
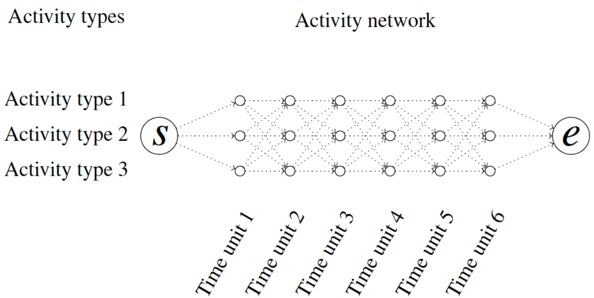


Fig. 1. "Rubber band"-like variation of a path.

G. Flötterod and M. Bierlaire, "Metropolis-Hastings sampling of paths," *Transportation Research Part B*, 2013.

Background

- **Danalet & Bierlaire 2015:**
  - Importance sampling in the activity-based modelling context
  - Activity schedules represented as paths in spatio-temporal network
  - Shuffle/splice operators to generate new candidates



A. Danalet and M. Bierlaire, “Importance sampling for activity path choice,” in *15th Swiss Transport Research Conference*, 2015.

Proposed methodology

- Extend previous works to include **multiple choice dimensions**:
    - Activity participation
    - Activity scheduling
    - Location
    - Mode of transportation

Proposed methodology

$n \leftarrow 0$, initialise state with random schedule $X_n \leftarrow S_0$

while $n \leq n_{iter}$ **do**

Choose operator ω

With probability P_ω, $X^* \leftarrow \textbf{Operator}(X_n)$

Compute acceptance probability $\alpha(X_n, X^*) = \min\left(\frac{b(X^*)q(X_n|X^*)}{b(X_n)q(X^*|X_n)}\right)$

With probability $\alpha(X_n, X^*)$, $X_{n+1} \leftarrow X^*$, else $X_{n+1} \leftarrow X_n$

end while

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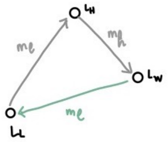
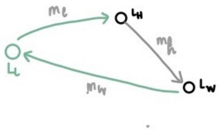
Operators

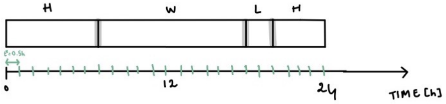
Mode



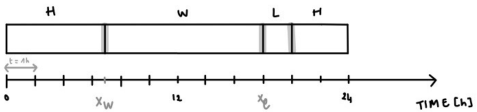
Location

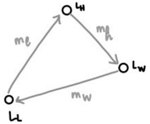


Block

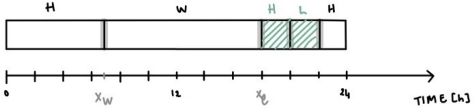


Initial state

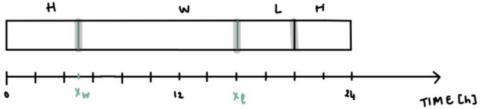




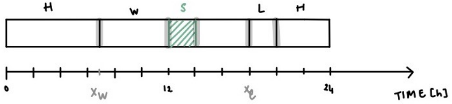
Swap



Inflate/Deflate



Assign



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Target distribution

- Unnormalized target weights: $\boldsymbol{b}(\boldsymbol{X_t}) = \boldsymbol{U}(\boldsymbol{X_t}) = \sum_{a \in A_{X_t}} \boldsymbol{U_a}$

- E.g. Utility function of a schedule (Pougala et al, 2022)
  - For an individual n considering an activity a with a flexibility k:

$$U_{an} = U_{const} + \boxed{U_{early} + U_{late}} + \boxed{U_{long} + U_{short}} + U_{travel} + \varepsilon_{an}$$

Start time deviations:

$$U_{early} = \boldsymbol{\theta_{ek}} \max(0, \boldsymbol{x_a^*} - x_a)$$
$$U_{late} = \boldsymbol{\theta_{lk}} \max(0, x_a - \boldsymbol{x_a^*})$$

Duration deviations:

$$U_{short} = \boldsymbol{\theta_{dsk}} \max(0, \boldsymbol{\tau_a^*} - \tau_a)$$
$$U_{long} = \boldsymbol{\theta_{dlk}} \max(0, \tau_a - \boldsymbol{\tau_a^*})$$

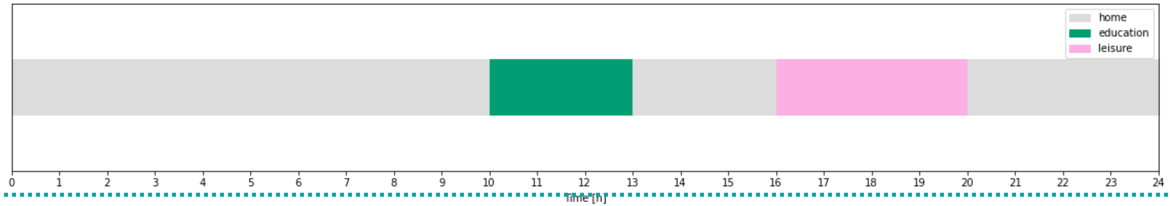
Example

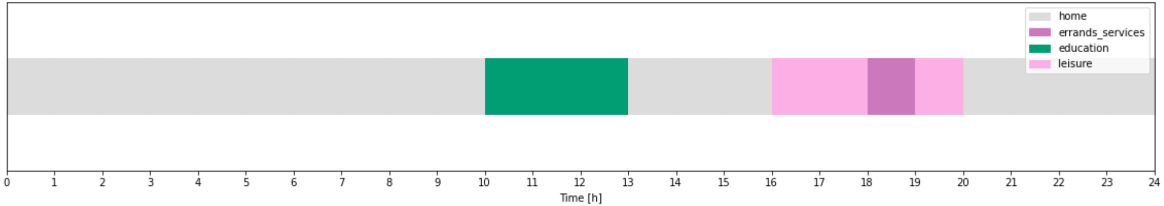
- Sample data:
  - 2015 Mobility and Transport microcensus (BFS & ARE)
  - Student population of Lausanne (236 individuals)

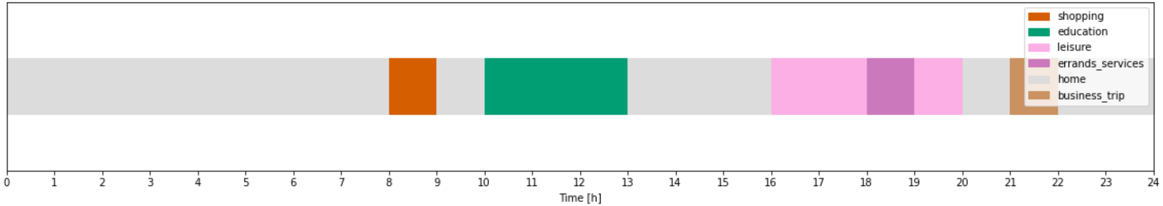
- MH set-up:
  - 10’000 iterations (5’000 warm-up)
  - Initial state: observed schedule from dataset
  - Operators: block, assign, swap, inflate/deflate, combo
  - Initial parameters for target weights: estimated on random choice set

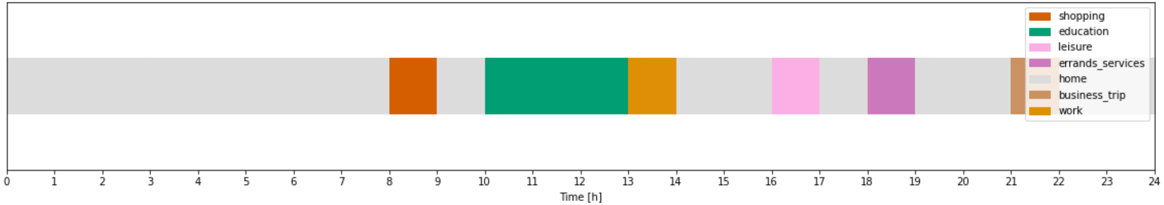
Example

Initial schedule

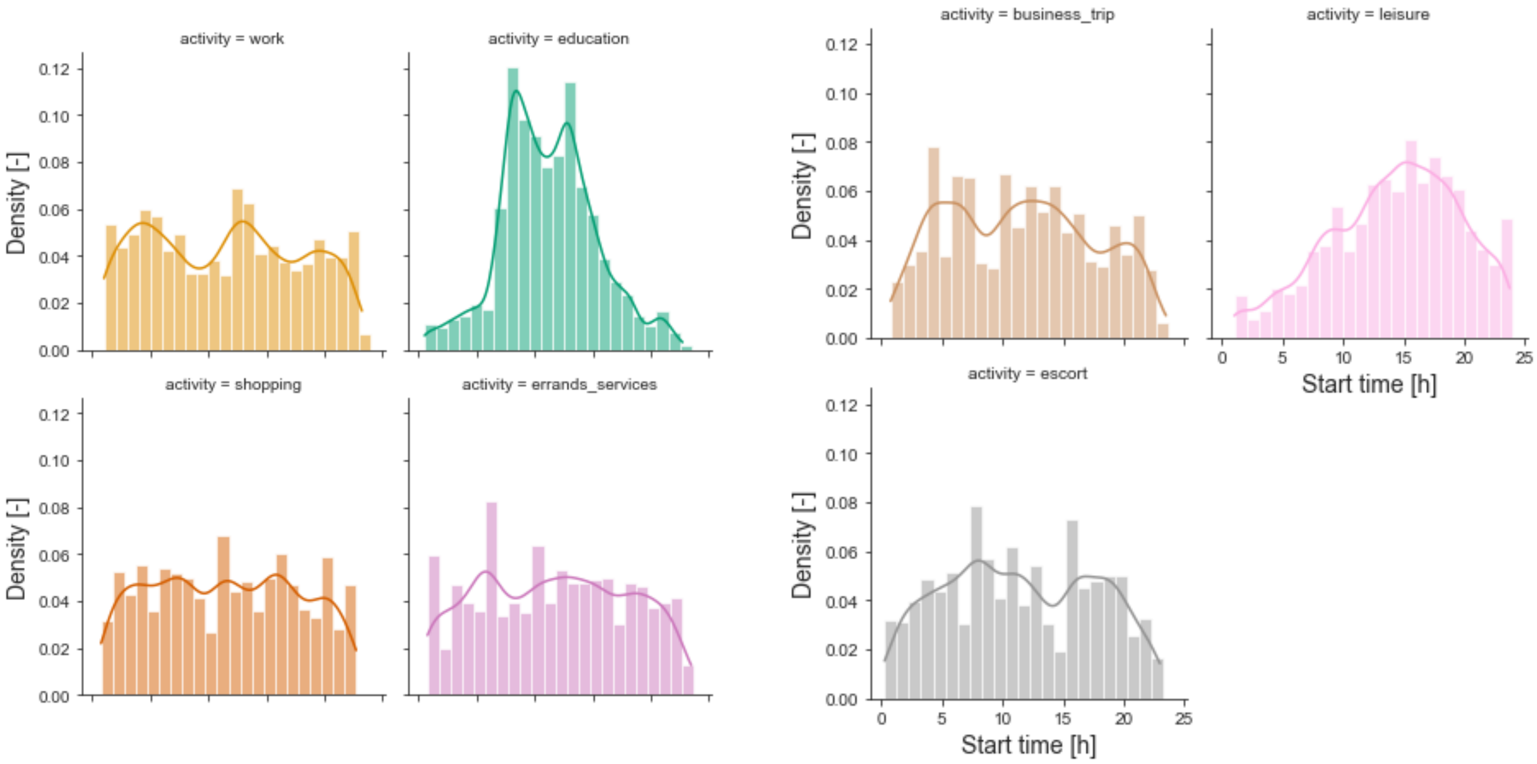






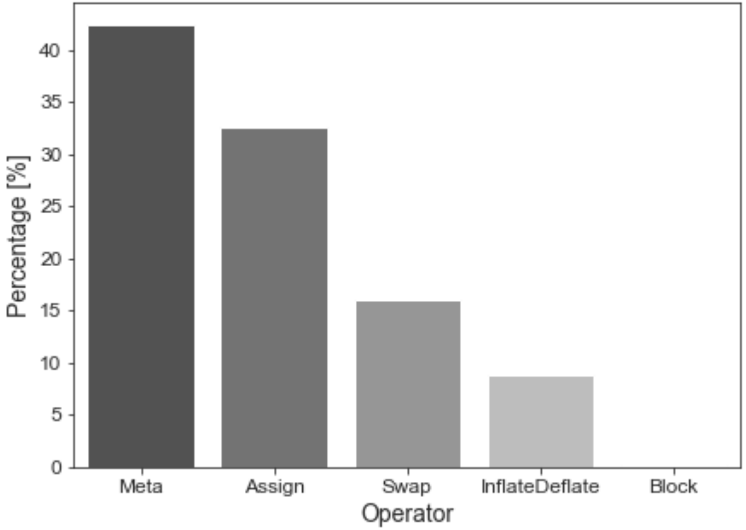


Example

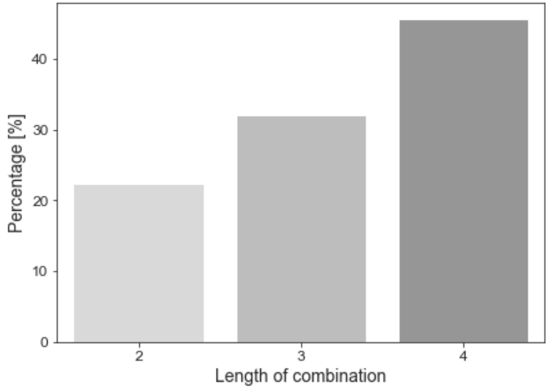


Activity start times across choice set

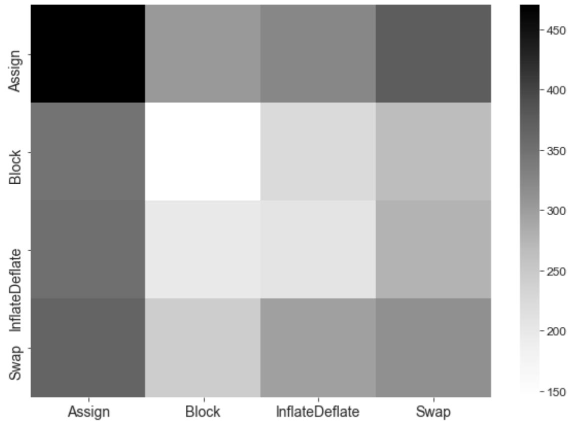
Example



Frequency of accepted operator changes



Typology of accepted combinations



Discussion & future work

- Validation:
  - Compare estimated parameters with MH sampled and random choice set
  - Use synthetic population to evaluate param. with control values
- Sensitivity analysis:
  - Probability of selecting operators
  - Different utility specifications for target weights
- Performance:
  - Convergence analysis
  - Optimal size of choice set

Thank you!

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