STRC

Importance sampling for activity path choice

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Outline

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Motivation

- **Activity-based approach**: modeling the activity participation patterns
- **Not tour-based** (no "home" location in pedestrian facilities)
- **No hierarchy** of dimensions or aggregation (high temporal precision)

Outline

Motivation: Activity-based model for pedestrian facilities

Literature review

A path choice approach to activity modeling

Choice set generation

Literature review

- Tour-based approach [BBA01, SBA11, AZBA12]
- Multiple discrete continuous nested extreme value model [PB10]
- Dynamic scheduling process [Hab11]

Literature review

Time representation in activity modeling:

- Time is decomposed in **tours** [BBA01, SBA11, AZBA12]
- Time is allocated to activity types (**no sequence**) [PB10]
- Time is allocated to activity types (**sequentially in time**) [Hab11]

Literature review

Problems

- **tours** [BBA01, SBA11, AZBA12]
- **no sequence** [PB10]
- **no pattern utility** [Hab11]

Outline

Motivation: Activity-based model for pedestrian facilities

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A path choice approach to activity modeling

Choice set generation

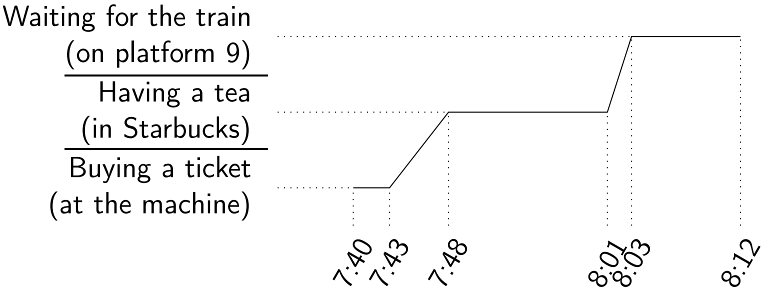
Modeling assumption

- Sequential choice:
  1. activity type, sequence, time of day and duration
  2. destination choice conditional on 1.
- Motivations:
  - Behavior: precedence of activity choice over destination choice
  - Dimensional: destinations $\times$ time $\times$ position in the sequence is not tractable

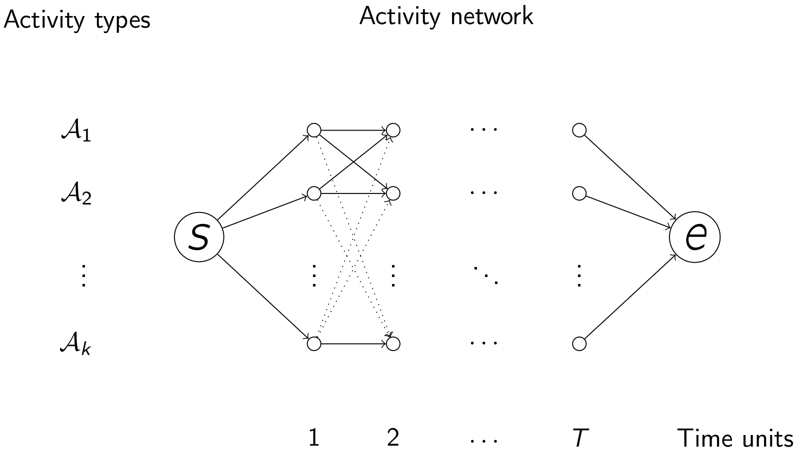
Today, we focus on 1. [DB15].
Tomorrow, 16:20, example of 2. on the same data [TDdLB15].

Observations: activity patterns in a transport hub

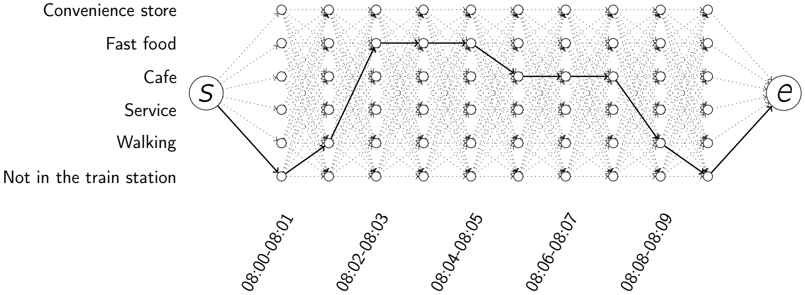
Activity types



Activity network



Activity path

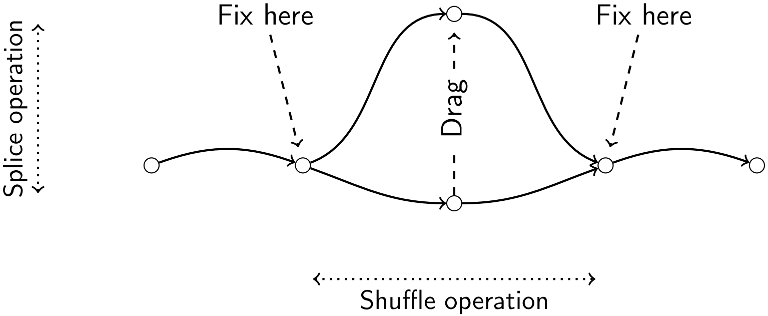


Outline

Sampling strategies

- Simple random sampling (SRS)
- Importance sampling
  using Metropolis-hastings algorithm [FB13]
  - Observation score [Che13]
  - Strategic sampling [LK12]

Metropolis-Hastings sampling of paths



[FB13]

Metropolis-Hastings sampling of paths

- Sample paths from given distribution, without full enumeration
- To be defined:
  - Target weight:
    $$b(i) = \exp\big(- \mu\delta(\Gamma)\big) \quad (1)$$
    Also with non-node-additive utility
  - Proposal distribution:
    $$P_{\text{insert}} = \frac{e^{-\tilde{\mu}\delta_{\boldsymbol{SP}}(\textit{origin},v)+\delta_{\boldsymbol{SP}}(v,\textit{destination})}}{\sum_w e^{-\tilde{\mu}\delta_{\boldsymbol{SP}}(\textit{origin},w)+\delta_{\boldsymbol{SP}}(w,\textit{destination})}} \quad (2)$$
    Relies on shortest paths, node-additive cost.

Utility structure

- Utility of activity pattern:
  - **time-of-day preferences**
  - **satiation effects: marginal utility decreases with increasing duration**

$$V(\mathit{duration}) = \eta \ln(\mathit{duration})$$

  - scheduling constraints: schedule delay

[EBPA07]

Observation score

- Node attractivity $\delta_v(v)$
- Activity-episode length attractivity $\delta_a(a)$
- Total attractivity:

$$\delta(\Gamma) = \sum_{v \in \Gamma} \delta_v(v) + r \sum_{a \in \Gamma} \delta_a(a) \tag{3}$$

- Scale and r estimated based on synthetic data [DB15].

Strategic sampling

- Target weight:
  utility from previously estimated model
- Proposal distribution:
  utility from previously estimated model using only time-of-day preferences (node-additive)

Case study

- Activity-episode sequences from WiFi traces on EPFL campus [DFB14]
- Activity network
  - 8 activity types
  - 24 time units (:00 - :15 / :15 - :59 between 7am and 7pm)

Results

- 100 elements in the choice set:
  SRS vs observation score.
- 10 elements in the choice set:
  SRS vs observation score vs strategic sampling.

Results: SRS, 100 el. in choice set

Attributes	Estimates	Std. error	t-stat
$\eta_{\text{Classroom, Shop, Library}}$	-0.492	0.168	-2.93
$\eta_{\text{Lab, Restaurant, Office, Other}}$	-0.638	0.167	-3.81
$\beta_{\text{3 lab episodes}}$	-0.998	0.265	-3.77
$\beta_{\text{4+ lab episodes}}$	-0.100	0.0243	-4.12
$\beta_{\text{3 office episodes}}$	-0.505	0.112	-4.49
$\beta_{\text{4+ office episodes}}$	-0.0494	0.0107	-4.62
$\beta_{\text{3 restaurant episodes}}$	-0.352	0.150	-2.34
$\beta_{\text{4+ restaurant episodes}}$	-0.0945	0.0270	-3.50
$\beta_{\text{3+ shop episodes}}$	-1.21	0.321	-3.77
$\beta_{\text{nb nodes NA afternoon, students}}$	-0.941	0.269	-3.50
$\beta_{\text{nb nodes NA before/after work, employees}}$	0.245	0.0726	3.38
$\beta_{\text{nb nodes NA work, employees}}$	-1.07	0.278	-3.86
$\beta_{\text{nb nodes classroom morning/afternoon, employees}}$	-0.132	0.0296	-4.46
$\beta_{\text{primary activity library, students}}$	0.0404	0.0108	3.73

Number of observations = 1734

Number of estimated parameters = 14

$$\begin{aligned} \mathcal{L}(\beta_0) &= -8002.619 \\ \mathcal{L}(\hat{\beta}) &= -10.234 \\ \rho^2 &= 0.999 \\ \bar{\rho}^2 &= 0.997 \end{aligned}$$

Results: observation score, 100 el. in choice set

Attributes	Estimates	Std. error	t-stat
$\eta_{\text{Classroom, Shop, Library}}$	-0.484	0.0877	-5.52
$\eta_{\text{Lab, Restaurant, Office, Other}}$	-0.687	0.137	-5.02
$\beta_{\text{3 lab episodes}}$	-0.710	0.146	-4.86
$\beta_{\text{4+ lab episodes}}$	-0.0735	0.0241	-3.05
$\beta_{\text{3 office episodes}}$	-0.427	0.139	-3.08
$\beta_{\text{4+ office episodes}}$	-0.0794	0.0265	-3.00
$\beta_{\text{3 restaurant episodes}}$	-0.0535	0.0122	-4.39
$\beta_{\text{4+ restaurant episodes}}$	-0.731	0.199	-3.67
$\beta_{\text{3+ shop episodes}}$	-0.740	0.250	-2.96
$\beta_{\text{nb nodes NA afternoon, students}}$	-1.10	0.347	-3.17
$\beta_{\text{nb nodes NA before/after work, employees}}$	0.231	0.0523	4.42
$\beta_{\text{nb nodes NA work, employees}}$	-0.0762	0.0199	-3.83
$\beta_{\text{nb nodes classroom morning/afternoon, employees}}$	-0.0908	0.0460	-1.97
$\beta_{\text{primary activity library, students}}$	0.0592	0.0260	2.28

Number of observations = 1734

Number of estimated parameters = 14

$$
\begin{aligned}
\mathcal{L}(\beta_0) &= -8002.619 \\
\mathcal{L}(\hat{\beta}) &= -13.293 \\
\rho^2 &= 0.998 \\
\bar{\rho}^2 &= 0.997
\end{aligned}
$$

Results: SRS, 10 el. in choice set

Attributes	Estimates	Std. error	t-stat
$\eta_{\text{Classroom, Shop, Library}}$	-2.48	0.00727	-341.00
$\eta_{\text{Lab, Restaurant, Office, Other}}$	-4.41	1.80e+308	-0.00
$\beta_{\text{3 lab episodes}}$	-3.42	0.00211	-1621.37
$\beta_{\text{4+ lab episodes}}$	-0.372	0.00406	-91.48
$\beta_{\text{3 office episodes}}$	-1.11	1.80e+308	-0.00
$\beta_{\text{4+ office episodes}}$	-0.598	0.00710	-84.27
$\beta_{\text{3 restaurant episodes}}$	-4.54	1.80e+308	-0.00
$\beta_{\text{4+ restaurant episodes}}$	-0.515	0.00418	-123.07
$\beta_{\text{3+ shop episodes}}$	-6.06	0.00167	-3637.41
$\beta_{\text{nb nodes NA afternoon, students}}$	-3.71	1.80e+308	-0.00
$\beta_{\text{nb nodes NA before/after work, employees}}$	0.886	0.00197	449.89
$\beta_{\text{nb nodes NA work, employees}}$	-0.922	0.00555	-166.01
$\beta_{\text{nb nodes classroom morning/afternoon, employees}}$	-0.856	0.00125	-685.45
$\beta_{\text{primary activity library, students}}$	0.267	0.00382	69.75

Number of observations = 1734

Number of estimated parameters = 14

$$\begin{aligned}
\mathcal{L}(\beta_0) &= -4157.950 \\
\mathcal{L}(\hat{\beta}) &= -0.000 \\
\rho^2 &= 1.000 \\
\bar{\rho}^2 &= 0.997
\end{aligned}$$

Results: observation score, 10 el. in choice set

Attributes	Estimates	Std. error	t-stat
$\eta_{\text{Classroom, Shop, Library}}$	-2.83	0.0400	-70.68
$\eta_{\text{Lab, Restaurant, Office, Other}}$	-4.47	1.80e+308	-0.00
$\beta_{\text{3 lab episodes}}$	-3.06	0.0404	-75.63
$\beta_{\text{4+ lab episodes}}$	-0.484	0.0256	-18.96
$\beta_{\text{3 office episodes}}$	-3.66	0.0772	-47.48
$\beta_{\text{4+ office episodes}}$	-0.575	0.00909	-63.30
$\beta_{\text{3 restaurant episodes}}$	-4.82	0.0462	-104.19
$\beta_{\text{4+ restaurant episodes}}$	-0.530	0.0175	-30.26
$\beta_{\text{3+ shop episodes}}$	-4.80	1.80e+308	-0.00
$\beta_{\text{nb nodes NA afternoon, students}}$	-6.06	0.0608	-99.70
$\beta_{\text{nb nodes NA before/after work, employees}}$	0.529	1.80e+308	0.00
$\beta_{\text{nb nodes NA work, employees}}$	-0.893	0.0129	-69.37
$\beta_{\text{nb nodes classroom morning/afternoon, employees}}$	-1.02	0.0129	-79.07
$\beta_{\text{primary activity library, students}}$	0.284	0.0120	23.67

Number of observations = 1734

Number of estimated parameters = 14

$$\mathcal{L}(\beta_0) = -4157.950$$
$$\mathcal{L}(\hat{\beta}) = -0.000$$
$$\rho^2 = 1.000$$
$$\bar{\rho}^2 = 0.997$$

Results: strategic sampling, 10 el. in choice set

Attributes	Estimates	Std. error	t-stat
$\eta_{\text{Classroom, Shop, Library}}$	-1.17	0.0469	-24.99
$\eta_{\text{Lab, Restaurant, Office, Other}}$	-1.64	0.0636	-25.86
$\beta_{\text{3 lab episodes}}$	-3.43	0.133	-25.74
$\beta_{\text{4+ lab episodes}}$	-0.188	0.0156	-12.05
$\beta_{\text{3 office episodes}}$	-1.71	0.0575	-29.80
$\beta_{\text{4+ office episodes}}$	-0.204	0.00723	-28.18
$\beta_{\text{3 restaurant episodes}}$	-1.19	0.0900	-13.17
$\beta_{\text{4+ restaurant episodes}}$	-0.135	0.00492	-27.41
$\beta_{\text{3+ shop episodes}}$	-3.20	0.0885	-36.10
$\beta_{\text{nb nodes NA afternoon, students}}$	-1.50	0.123	-12.23
$\beta_{\text{nb nodes NA before/after work, employees}}$	0.112	0.0185	6.09
$\beta_{\text{nb nodes NA work, employees}}$	-0.502	0.0163	-30.84
$\beta_{\text{nb nodes classroom morning/afternoon, employees}}$	-0.441	0.0193	-22.87
$\beta_{\text{primary activity library, students}}$	0.224	0.00725	30.87

Number of observations = 1734

Number of estimated parameters = 14

$$
\begin{aligned}
\mathcal{L}(\beta_0) &= -4157.950 \\
\mathcal{L}(\hat{\beta}) &= -0.000 \\
\rho^2 &= 1.000 \\
\bar{\rho}^2 &= 0.997
\end{aligned}
$$

Results

- 100 elements in the choice set:
  SRS vs observation score.
  - SRS gives similar results as observation score
- 10 elements in the choice set:
  SRS vs observation score vs strategic sampling.
  - preliminary: strategic sampling performs better than SRS, observation score

Conclusion and future work

- SRS and importance sampling with observation score generate dominated alternatives
- Strategic sampling gives the flexibility needed in activity path choice
- Activity path size for correlation between activity paths
  - Primary Activity Path Size (PAPS)
  - Activity Pattern Path Size (APPS)

Thank you

STRC:
Importance sampling
for activity path choice

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