PhD thesis

Activity choice modeling for pedestrian facilities

Antonin Danalet
Outline

Motivation: Understanding pedestrian demand

Detecting activity-episode sequences

A path choice approach to activity modeling

Location choice with panel effect

Conclusion and future work
Outline

Motivation: Understanding pedestrian demand

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Conclusion and future work
New interest in pedestrian modeling

- Urban growth and its pressure on pedestrian facilities
- Availability of new tracking data
In airports...

- +38% air passengers (2008-2013)
- Surveying [LUS14], space syntax [KBM14]
In hospitals...

- US: Hospital-building and renovation boom [HCSL08]
- Time use of nurses using RFID [HCSL08]
In museums...

- Louvre: +35% visitors (2004-2014)
- Understanding congestion using Bluetooth [YSR⁺14]
In train stations...

- Utrecht Central Station: +14% visitors by 2020
- Activity location choice using WiFi and Bluetooth [Ton14]
Challenges of pedestrian facilities

- Knowing the number of visitors
- Determining the source of congestion
- Localizing points of interest
- Modifying/building new facilities
- Defining timetables
## Data from communication antennas

<table>
<thead>
<tr>
<th>+</th>
<th>-</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Large sample size</td>
<td>• No socioeconomics</td>
</tr>
<tr>
<td>• Low cost</td>
<td>• Not representative</td>
</tr>
<tr>
<td>• Low privacy risk</td>
<td>• Privacy risk</td>
</tr>
<tr>
<td>• No recall bias</td>
<td>• Low frequency</td>
</tr>
<tr>
<td>• No need to distribute devices</td>
<td>• Low precision</td>
</tr>
<tr>
<td>• Tracking non-travelers</td>
<td>• No stops</td>
</tr>
<tr>
<td>• Full coverage of the facility</td>
<td>• No activity purpose</td>
</tr>
</tbody>
</table>
Goal: Understanding pedestrian demand

• Where, when and for how long do pedestrians perform activities in pedestrian facilities?
• Based on communication network traces from existing antennas
Activity path approach

Pre-processing

Activity-episode sequence detection

Modeling

Activity path choice model

Location choice model
Activity-episode sequence detection

• Explicit modeling of the imprecision in the measure
• Usage of prior knowledge of the infrastructure
• Avoidance of the pingpong effect
Activity-path choice model

- No tours, no priorities
- Managing large choice sets
- Unique utility for activity type, time-of-day and duration choices
Location choice model

• Including panel data
• Correcting for serial correlation
More details

- Introduction: Chapter 1 in [Dan15b]
- Literature review: Chapter 2 in [Dan15b]
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Conclusion and future work
Data requirement

- Required
  - Localization data with full coverage of the facility
  - Semantically-enriched routing graph for pedestrians
- Not required but often available information
  - Potential attractiveness measure
Data requirement: Localization
Data requirement: Map (POI + network)
Potential attractivity measure

For individual $n$, point of interest $x$, start and end times $t^{-}$ and $t^{+}$:

$$S_{x,n}(t^{-}, t^{+}) = \int_{t=t^{-}}^{t=t^{+}} \delta_{x,n}(t) \cdot att_{n}(x, t) dt$$

with

- Time constraints $\delta_{x,n}$
  (e.g., train or class schedules, opening hours)
- Destination attractivity $att_{n}(x, t)$
  (e.g., classroom, platform, scene aggregate occupancy)
Data requirement: Potential attractiveness

Cumulative number of students in class by week based on class schedules
Methodology

Input
- Localization measurement
- Semantically-enriched routing graph
- Potential attractivity measure

Output
- Set of candidate activity-episode sequences associated with the likelihood to be the true one
Probabilistic measurement model: a Bayesian approach

\[
P(a_1:\psi | \hat{m}_{1:J}) \propto P(\hat{m}_{1:J} | a_1:\psi) \cdot P(a_1:\psi)
\]

with
- measurement \( \hat{m} = (\hat{x}, \hat{t}), (\hat{m}_1, \hat{m}_2, ..., \hat{m}_j, ..., \hat{m}_J) = \hat{m}_{1:J} \)
- activity episode \( a = (x, t^-, t^+), (a_1, a_2, ..., a_\psi, ..., a_\psi) = a_{1:\psi} \)
Measurement likelihood

\[
P(\hat{m}_{1:J} | a_{1:J}) = \prod_{\psi=1}^{\Psi} P(\hat{m}_{1:J}^{\psi} | a_{\psi}) \quad \Leftrightarrow \quad \text{Independence between activities}
\]

\[
= \prod_{\psi=1}^{\Psi} \prod_{j=1}^{J} P(\hat{m}_{j}^{\psi} | a_{\psi}) \quad \Leftrightarrow \quad \text{Independence between measurements}
\]

\[
= \prod_{\psi=1}^{\Psi} \prod_{j=1}^{J} P(\hat{x}_{j}^{\psi} | x_{\psi}) \quad \Leftrightarrow \quad \text{No time measurement error}
\]
Prior: Potential attractivity measure

\[ P(a_{1:\psi}) = \prod_{\psi=1}^{\psi} P(a_{\psi}) \]

\[ = \prod_{\psi=1}^{\psi} P(x_{\psi}, t_{\psi}^-, t_{\psi}^+) \]

\[ = \prod_{\psi=1}^{\psi} \frac{S_{x_{\psi}, n(t_{\psi}^-, t_{\psi}^+)}}{\sum_{x \in POI} S_{x, n(t_{\psi}^-, t_{\psi}^+)} } \]
Probabilistic measurement model: a Bayesian approach

$$P(a_1:\psi | \hat{m}_{1:J}) \propto P(\hat{m}_{1:J} | a_1:\psi) \cdot P(a_1:\psi)$$
Generation of activity-episode sequences
Generation of activity-episode sequences

with \( tt_{x_j, x_{j+1}} \) the travel time from \( x_j \) to \( x_{j+1} \)
Generation of activity-episode sequences

- $x_j^1$
- $x_j^2$
- $x_j^3$
- $x_{j+1}^1$
- $x_{j+1}^2$
- $x_{j+1}^3$
- $x_{j+1}^4$
Intermediary measurements

Eliminate intermediary measurements if

\[ E(t^+) - E(t^-) < T_{\text{min}} \]

since we generate an activity episode at each measurement.
We keep $L$ (here, $L = 5$) most likely activity-episode sequences.
Results: me on EPFL campus, raw data
Results: me on EPFL campus, truth

Legend
Pedestrian network
Destinations
Shortest path

1: Classroom
2, 4, 6: Author’s office
5: Cafeteria
7: Metro stop
Restaurant
Results: me on EPFL campus, model, $L = 1$
Results: me on EPFL campus, model, $L = 100$
Results: an employee on EPFL campus, $L = 20$
Results: an computer science student, $L = 20$
Results: an employees?, \( L = 20 \)
Detection: Results for full population

- 3 activity episodes on average
- 1h37 on each activity
- Devices detected in restaurant during lunch break (see figure)
More details

- Article: [DFB14]
- Chapter 3 in [Dan15b]
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Conclusion and future work
Modeling assumption

• Sequential choice:
  1. activity type, sequence, time of day and duration
  2. destination choice conditional on 1.
• Motivations:
  – Behavioral: precedence of activity choice over destination choice [BBA01, AT04, HB04, AZBA12, KR13]
  – Dimensional: destinations × time × position in the sequence is not tractable
Observations: activity patterns in a transport hub

Activity types

Waiting for the train
(on platform 9)

Having a tea
(in Starbucks)

Buying a ticket
(at the machine)

7:40 7:43 7:48 8:01 8:03 8:12
Activity network

Activity types

$A_1$

$A_2$

$\vdots$

$A_k$

Activity network

1 2 ... $T$  

Time units
Activity path

Convenience store
Fast food
Cafe
Service
Walking
Not in the train station
Sampling strategies for choice set generation

- Simple random sampling (SRS)
- Importance sampling using Metropolis-Hastings algorithm [FB13] and 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: Also with non-node-additive utility
  - Proposal distribution:

\[
P_{\text{insert}} = \frac{e^{-\tilde{\mu} \delta_{SP}(\text{origin}, v) + \delta_{SP}(v, \text{destination})}}{\sum_w e^{-\tilde{\mu} \delta_{SP}(\text{origin}, w) + \delta_{SP}(w, \text{destination})}}
\]

Relies on shortest paths, node-additive cost.
Strategic sampling

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

- Utility of activity pattern:
  - Node utility $V(A_k, t)$
    - time-of-day preferences
  - Activity-episode utility $V(a)$
    - satiation effects: decreasing marginal utility, $\eta \ln(\text{duration})$
    - scheduling constraints: schedule delay
  - Activity path utility $V(\Gamma)$
    - primary activity
    - number of episodes

- Sampling correction

$$\mu\left(\sum_{k=1}^{K} \sum_{\tau=1}^{T} V(A_{k,\tau}) + \sum_{a \in A_{1:T}} V(a) + V(\Gamma)\right) + \ln \frac{k_{\Gamma n}}{b(\Gamma)}$$
Case study: pedestrians on EPFL campus

• 13,000 people per day
• 8 activity types:
  – classrooms,
  – shops,
  – offices,
  – restaurant,
  – library,
  – lab,
  – other and
  – not being detected
• 12 time units in the activity network, from 7am to 7pm
## Proposal distribution (using simple random sampling)

<table>
<thead>
<tr>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Robust Asympt. std. error</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>β NA, 17-19, employees</td>
<td>0.263</td>
<td>0.0302</td>
<td>8.70</td>
</tr>
<tr>
<td>β NA, 14-17, students</td>
<td>-0.222</td>
<td>0.191</td>
<td>-1.16</td>
</tr>
<tr>
<td>β NA, 7-8, students</td>
<td>0.349</td>
<td>0.0281</td>
<td>12.44</td>
</tr>
<tr>
<td>β NA, 7-9, employees</td>
<td>0.326</td>
<td>0.0262</td>
<td>12.43</td>
</tr>
<tr>
<td>β NA, 17-19, students</td>
<td>1.14</td>
<td>0.187</td>
<td>6.09</td>
</tr>
<tr>
<td>β classroom, 12-14, students</td>
<td>-0.336</td>
<td>0.337</td>
<td>-1.00</td>
</tr>
<tr>
<td>β classroom, 7-12, employees</td>
<td>-0.723</td>
<td>0.397</td>
<td>-1.82</td>
</tr>
<tr>
<td>β classroom, 7-12, students</td>
<td>0.598</td>
<td>0.262</td>
<td>2.28</td>
</tr>
<tr>
<td>β library, 14-19, employees</td>
<td>-0.624</td>
<td>0.553</td>
<td>-1.13</td>
</tr>
<tr>
<td>β library, 12-14, employees</td>
<td>-0.575</td>
<td>0.481</td>
<td>-1.20</td>
</tr>
<tr>
<td>β library, 7-12, employees</td>
<td>-1.57</td>
<td>0.508</td>
<td>-3.09</td>
</tr>
<tr>
<td>β office, 14-19, employees</td>
<td>1.41</td>
<td>0.246</td>
<td>5.73</td>
</tr>
<tr>
<td>β office, 7-12, employees</td>
<td>1.12</td>
<td>0.228</td>
<td>4.92</td>
</tr>
<tr>
<td>β restaurant, 14-19, students</td>
<td>-0.410</td>
<td>0.185</td>
<td>-2.21</td>
</tr>
<tr>
<td>β restaurant, 12-14, employees</td>
<td>0.136</td>
<td>0.0259</td>
<td>5.26</td>
</tr>
<tr>
<td>β restaurant, 12-14, students</td>
<td>0.665</td>
<td>0.286</td>
<td>2.32</td>
</tr>
</tbody>
</table>

...  

Number of observations = 1087  
Number of estimated parameters = 43  
\( \mathcal{L}(\beta_0) = -5016.636 \)  
\( \mathcal{L}(\hat{\beta}) = -453.225 \)  
\( \rho^2 = 0.910 \)  
\( \overline{\rho}^2 = 0.901 \)
Target weight (using simple random sampling)

<table>
<thead>
<tr>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Robust Asympt. estimate std. error</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{\text{library 7-12, employees}}$</td>
<td>-2.08</td>
<td>0.422</td>
<td>-4.93</td>
</tr>
<tr>
<td>$\beta_{\text{office 7-12, 14-19, employees}}$</td>
<td>1.69</td>
<td>0.393</td>
<td>4.30</td>
</tr>
<tr>
<td>$\beta_{\text{restaurant 12-14, employees}}$</td>
<td>1.22</td>
<td>0.502</td>
<td>2.43</td>
</tr>
<tr>
<td>$\beta_{\text{shop 12-14, students}}$</td>
<td>-7.36</td>
<td>1.24</td>
<td>-5.92</td>
</tr>
<tr>
<td>$\beta_{\text{shop 7-12, 14-19, students}}$</td>
<td>-1.16</td>
<td>0.538</td>
<td>-2.16</td>
</tr>
<tr>
<td>$\beta_{\text{NA 7-8, students}}$</td>
<td>4.27</td>
<td>0.995</td>
<td>4.29</td>
</tr>
<tr>
<td>$\beta_{\text{NA 8-12, students}}$</td>
<td>1.40</td>
<td>0.498</td>
<td>2.82</td>
</tr>
<tr>
<td>$\beta_{\text{NA 17-19, students}}$</td>
<td>1.75</td>
<td>0.568</td>
<td>3.08</td>
</tr>
<tr>
<td>$\beta_{\text{NA 9-17, employees}}$</td>
<td>1.43</td>
<td>0.296</td>
<td>4.84</td>
</tr>
<tr>
<td>$\beta_{\text{NA 7-9, 17-19, employees}}$</td>
<td>3.34</td>
<td>0.554</td>
<td>6.02</td>
</tr>
<tr>
<td>$\eta_{\text{Office, Lab, Classroom}}$</td>
<td>5.22</td>
<td>0.764</td>
<td>6.83</td>
</tr>
<tr>
<td>$\eta_{\text{Restaurant, Library, Other}}$</td>
<td>7.85</td>
<td>1.11</td>
<td>7.10</td>
</tr>
<tr>
<td>$\eta_{\text{Shop}}$</td>
<td>7.33</td>
<td>0.894</td>
<td>8.20</td>
</tr>
<tr>
<td>$\eta_{\text{NA}}$</td>
<td>2.75</td>
<td>0.393</td>
<td>7.00</td>
</tr>
<tr>
<td>$\beta_{3+ \text{ lab episodes}}$</td>
<td>-5.03</td>
<td>0.952</td>
<td>-5.28</td>
</tr>
<tr>
<td>$\beta_{3+ \text{ resto episodes}}$</td>
<td>-2.50</td>
<td>0.759</td>
<td>-3.29</td>
</tr>
</tbody>
</table>

Number of observations = 1087
Number of estimated parameters = 22

$\mathcal{L}(\beta_0) = -5016.636$

$\mathcal{L}(\hat{\beta}) = -47.218$

$\rho^2 = 0.991$

$\bar{\rho}^2 = 0.986$
# Model using strategic sampling

<table>
<thead>
<tr>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Robust Asympt. std. error</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta \text{ classroom 7-12, students} )</td>
<td>0.478</td>
<td>0.238</td>
<td>2.01</td>
</tr>
<tr>
<td>( \beta \text{ restaurant 12, students} )</td>
<td>2.69</td>
<td>0.527</td>
<td>5.10</td>
</tr>
<tr>
<td>( \beta \text{ shop 14-19, students} )</td>
<td>1.46</td>
<td>0.343</td>
<td>4.27</td>
</tr>
<tr>
<td>( \beta \text{ NA 7-12, students} )</td>
<td>2.33</td>
<td>0.285</td>
<td>8.17</td>
</tr>
<tr>
<td>( \beta \text{ NA 17-19, students} )</td>
<td>2.83</td>
<td>0.343</td>
<td>8.24</td>
</tr>
<tr>
<td>( \beta \text{ NA 7-9, 17-19, employees} )</td>
<td>2.91</td>
<td>0.303</td>
<td>9.60</td>
</tr>
<tr>
<td>( \eta \text{ office, lab, classroom} )</td>
<td>-6.85</td>
<td>0.379</td>
<td>-18.09</td>
</tr>
<tr>
<td>( \eta \text{ restaurant, library, other} )</td>
<td>-6.58</td>
<td>0.360</td>
<td>-18.31</td>
</tr>
<tr>
<td>( \eta \text{ shop} )</td>
<td>-3.72</td>
<td>0.278</td>
<td>-13.40</td>
</tr>
<tr>
<td>( \eta \text{ NA} )</td>
<td>-7.63</td>
<td>0.541</td>
<td>-14.12</td>
</tr>
<tr>
<td>( \beta_0 \text{ restaurant episode} )</td>
<td>4.11</td>
<td>0.365</td>
<td>11.28</td>
</tr>
<tr>
<td>( \beta_0 \text{ classroom episodes, employees} )</td>
<td>10.3</td>
<td>0.887</td>
<td>11.65</td>
</tr>
<tr>
<td>( \beta_1 \text{ shop episodes} )</td>
<td>-3.87</td>
<td>0.573</td>
<td>-6.76</td>
</tr>
<tr>
<td>( \beta_2+ \text{ shop episodes} )</td>
<td>-3.49</td>
<td>1.08</td>
<td>-3.24</td>
</tr>
<tr>
<td>( \beta_0 \text{ library episode, employees} )</td>
<td>2.72</td>
<td>0.335</td>
<td>8.10</td>
</tr>
<tr>
<td>( \beta_0 \text{ library episode, students} )</td>
<td>4.77</td>
<td>0.495</td>
<td>9.64</td>
</tr>
<tr>
<td>( \beta_0 \text{ library episode, students} )</td>
<td>4.77</td>
<td>0.495</td>
<td>9.64</td>
</tr>
</tbody>
</table>

Number of observations = 1087
Number of estimated parameters = 39

\[ \mathcal{L}(\beta_0) = -5016.636 \]
\[ \mathcal{L}(\hat{\beta}) = -400.633 \]
\[ \rho^2 = 0.920 \]
\[ \bar{\rho}^2 = 0.912 \]
Validation

Predicted probabilities for the chosen alternative

Probabilities for the chosen alternative

Simple random sampling

Strategic sampling
More details

- Conference proceeding: [DB15]
- Chapter 4 in [Dan15b]
Outline

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Conclusion and future work
Goal

- Model location choice conditional on an activity type
- Adapted to panel data
Static model

\[ U_{int} = V_{int} + \varepsilon_{int} \]

Ignores two aspects:
- Dynamics
- Serial correlation
Dynamic model without agent effect

\[ U_{int} = V_{int} + \rho y_{in(t-1)} + \varepsilon_{int} \]

Assumes

- Dynamic process of order one
- Location-specific dependence
- Previous choice \( y_{in(t-1)} \) independent of error term \( \varepsilon_{int} \)
Relaxing the independence assumption of error terms

- Agent effect $\alpha_{in}$: time-invariant factor ("between" individuals variability)
- Unobserved heterogeneity $\varepsilon'_{int}$: short-term variation of probabilities ("within" an individual variability)

$$U_{int} = V_{int} + \rho y_{in(t-1)} + \alpha_{in} + \varepsilon'_{int}$$

Endogeneity issue:
- $y_{in(t-1)}$ and $\alpha_{in}$ are correlated
An approach by Wooldridge [Woo05]

For activity location $i$, individual $n$, at time $t$:

\[
U_{int} = V_{int} + \rho \gamma_{in}(t-1) + \alpha_{in} + \varepsilon_{int}
\]

\[
\alpha_{in} = a + b \gamma_{in0} + c' \bar{x}_n + \xi_{in}
\]

\[
\sim \mathcal{N}(0; \Sigma_{\alpha})
\]

Endogeneity issue solved [Woo05]
3 different models

<table>
<thead>
<tr>
<th>Static model</th>
<th>Dynamic model without agent effect</th>
<th>Dynamic model with agent effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho = 0$</td>
<td>$\rho \neq 0$</td>
<td>$\rho \neq 0$</td>
</tr>
<tr>
<td>$a, b, c, \sigma^2_\alpha = 0$</td>
<td>$a, b, c, \sigma^2_\alpha = 0$</td>
<td>$a, b, c, \sigma^2_\alpha \neq 0$</td>
</tr>
</tbody>
</table>
Case study: EPFL catering locations
Two specifications of the agent effect

- First choice
  \[ \alpha_{in} = a + by_{in0} + \xi_n \]

- First choice and frequency
  \[ \alpha_{in} = a + by_{in0} + cy_{int}^{count} + \xi_n \]
  \[ \sum_{t'=1}^{t-1} I(y_{int'}) \]
4 models estimated

<table>
<thead>
<tr>
<th>Static model</th>
<th>Dynamic model without agent effect</th>
<th>Dynamic model with agent effect correction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First choice</td>
<td>First choice and frequency</td>
</tr>
<tr>
<td>$\rho = 0$</td>
<td>$\rho \neq 0$</td>
<td>$\rho \neq 0$</td>
</tr>
<tr>
<td>$a = 0$</td>
<td>$a = 0$</td>
<td>$a \neq 0$</td>
</tr>
<tr>
<td>$b = 0$</td>
<td>$b = 0$</td>
<td>$b \neq 0$</td>
</tr>
<tr>
<td>$c = 0$</td>
<td>$c = 0$</td>
<td>$c \neq 0$</td>
</tr>
<tr>
<td>$\sigma_{\alpha} = 0$</td>
<td>$\sigma_{\alpha} = 0$</td>
<td>$\sigma_{\alpha} \neq 0$</td>
</tr>
</tbody>
</table>
Estimation results

- **Distance** has a **negative** impact
- **Yearly evaluation** has a **positive** impact
- **Beer after 14:00** has a **positive** impact
- **Cost** has a **negative** impact
- **Dinner** has a **positive** impact
- **Capacity** has a **positive** impact
## Likelihood ratio tests

<table>
<thead>
<tr>
<th>Static model</th>
<th>Dynamic model without agent effect</th>
<th>Dynamic model with agent effect correction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First choice</td>
<td>First choice and frequency</td>
</tr>
<tr>
<td>354.003 (&gt; 5.99)</td>
<td>920.354 (&gt; 58.12)</td>
<td>16.172 (&gt; 5.99)</td>
</tr>
</tbody>
</table>
Validation

<table>
<thead>
<tr>
<th></th>
<th>Predicting last observations based on past observations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Static model</td>
</tr>
<tr>
<td>Sum of the squares of the errors</td>
<td>232.95</td>
</tr>
</tbody>
</table>
Elasticities to price

- Static model
  - Employees
  - Students

- Dynamic model without agent effect
  - Employees
  - Students

- Dynamic model with agent effect correction: First choice
  - Employees
  - Students

- Dynamic model with agent effect correction: First choice and frequency
  - Employees
  - Students
Forecasting: opening a new catering location

Nesting structure with the most similar alternative

- Nesting parameter $\theta = 1$: logit model, independent error terms
- Nesting parameter $\theta \to \infty$: perfectly correlated error terms
Forecasting: opening a new catering location

Frequency of visits for the new catering destination

- $\theta = 1$
- $\theta = 2$
- $\theta = 5$
- $\theta = 10$
- Point-of-sale data

Graph showing the frequency of visits over different models and agent effect corrections.
Outline

Motivation: Understanding pedestrian demand

Detecting activity-episode sequences

A path choice approach to activity modeling

Location choice with panel effect

Conclusion and future work
Activity-episode sequence detection

- Explicit modeling of the imprecision in the measure
- Usage of prior knowledge of the infrastructure
- Avoidance of the pingpong effect
Activity-path choice model

- No tours, no priorities
- Managing large choice sets
- Unique utility for activity type, time-of-day and duration choices
Location choice model

- Including panel data
- Correcting for serial correlation
Limitations

• Activity purpose is extracted from map data
• No mode detection
• No congestion
Future work

- Congested case study
- Include the uncertainty from detection in modeling
- Metropolis-Hastings algorithm for the sampling of activity paths
- More complex correlation structure for the choice of an activity path
- Include other sources of endogeneity (group, queue)
Thank you

PhD thesis:
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Privacy issues in this thesis

• EPFL ethics committee:
  – “No personal identifier when sharing data”
• In practice:
  – We have no access to MAC addresses in our dataset
  – The dataset is public [Dan15a]