Specification, estimation and validation of a pedestrian walking behavior model

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Motivation

- Model the pedestrian behaviour
Motivation

- Model of the pedestrian behaviour
  - incorporate the model in more global models

- Use of econometric models
  - visibility and control of the specification

- Calibration on real data
  - estimated parameters values
State of the art

pedestrian modelling

limited estimation data set

huge estimation data set

aggregate level

disaggregate behaviour

Flow problems

discrete models

- flexible
- lot of parameters

continuous models

- postulate equations
- few number of parameters

use of machine learning methods
Objectives

- Model the pedestrian behaviour at operational level
- Develop a specification with ‘constrained’ and ‘unconstrained’ parameters
- Estimate the model
- Validate the model
- Implement the model in a simulator
Outline

- Introduction
- Discrete choice models
- Model specification
- Model estimation
- Model validation
- Simulator
- Conclusion
Introduction

- **Microscopic** model: capture the behavior of each pedestrian
  - Discrete choice model

- Different **behavioral levels**:
  - Strategical: destination
  - Tactical: route choice
  - **Operational** level: short range behavior, instantaneous decisions
    
    - Fixed

- Concept of **personal space**: interactions with other pedestrians
  - Leader follower
  - Collision avoidance
• Introduction

• **Discrete choice models**
  
  • Model specification
  
  • Model estimation
  
  • Model validation
  
  • Simulator
  
  • Conclusion
Discrete choice models: introduction

- **Econometric** models developed since the 50’s
- **Disaggregate** model
- A choice theory defines:
  - a decision maker: each pedestrian
  - alternatives: possible immediate future steps
  - attributes of alternatives: characteristics
  - decision rule: utility maximisation theory
Discrete choice model: our context

- At **each step** the pedestrian has to choose the next step in a choice set
- **Example**: only considering distance toward destination

Which alternative will he choose?
Discrete choice model: decision rule

- Utility maximisation theory
- Association of a function, called utility to each alternative
- It depends on the alternative \( i \), and on the decision maker \( n \)

\[
\begin{align*}
\text{Alt. 1} & \quad \quad \quad \quad \quad \quad \quad \quad \quad U_{1n} \\
\text{Alt. 2} & \quad \quad \quad \quad \quad \quad \quad \quad \quad U_{2n} \\
\text{Alt. 3} & \quad \quad \quad \quad \quad \quad \quad \quad \quad U_{3n}
\end{align*}
\]

The decision maker \( n \) will choose the alternative \( i \) which has the higher utility
Discrete choice model: utility function

- Utility is a latent concept
- It can not be directly observed
- Decision maker: stochastic decision rules
- Analyst: Lack of information

\[ U_{in} = V_{in} + \epsilon_{in} \]

\( V_{in} \): deterministic part of the utility of alternative \( i \) for individual \( n \)
\( \epsilon_{in} \): error term, different assumptions can be made on its distribution

Uncertainty
Discrete choice model: utility specification

- Example: $V_{in}$ depends only on the distance toward the destination

$$V_{in} = \beta dist_i$$

$\beta$: unknown parameter, has to be estimated from the data

$dist_i$: distance between alternative $i$ and the final destination

How do we estimate $\beta$?
Discrete choice model: error term

- **Example**: suppose $\epsilon_{in}$ independent and identically distributed (iid) with an extreme value distribution

Multinomial Logit model

$$P_n(i|C_n): \text{probability for the individual } n \text{ to choose the alternative } i$$

$$P_n(i|C_n) = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{V_{jn}}}$$

$C_n$: Choice set, depends on the individual $n$
Discrete choice model: estimation data

Pedestrian trajectories

Data set

<table>
<thead>
<tr>
<th>Observation</th>
<th>Choice</th>
<th>dist.1</th>
<th>dist.2</th>
<th>dist.3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td></td>
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<tr>
<td>3</td>
<td>2</td>
<td></td>
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<tr>
<td>4</td>
<td>2</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>5</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Discrete choice model: likelihood

- Maximisation of the likelihood function

\[ l(\beta) = \prod_{n \in N} \prod_{i \in C_n} (P_n(i|C_n))^{y_{in}} = \prod_{n \in N} \prod_{i \in C_n} \left( \frac{e^{\beta_{dist_i}}}{\sum_{j \in C_n} e^{\beta_{dist_j}}} \right)^{y_{in}} \]

\( y_{in} \): indicator equals to 1, if individual \( n \) has chosen alternative \( i \), 0 otherwise

\( N \): set of individuals in the population

- In practice use of the log-likelihood (numerical reasons)

\[ L(\beta) = \sum_{n \in N} \sum_{i \in C_n} y_{in} \log \left( \frac{e^{\beta_{dist_i}}}{\sum_{j \in C_n} e^{\beta_{dist_j}}} \right) \]

\( \beta \) estimated from the data
Why using a discrete choice model?

- **Disaggregate**
  - capture the behaviour of each pedestrian

- **Flexible**
  - easy to add behavioural modules
  - easy to add pedestrians characteristics

- **Estimation**
  - estimation on a real data set by likelihood maximisation
- Introduction
- Discrete choice models
- **Model specification**
- Model estimation
- Model validation
- Simulator
- Conclusion
Model specification: the space discretization

At each step the choice set depends on the pedestrian speed and direction
Model specification: the choice set

3 speed regimes

11 directions

33 alternatives
Model specification: cross nested structure

- **Hypothesis**: alternatives correlated along speed regimes and directions
  
  Cross Nested Logit model

- **Cross Nested structure**: each alternative belongs to 2 nests

![Diagram](image)
Model specification: cross nested structure

Decision maker

non central  central  decelerate  constant  accelerate

alt. 1  alt. 17  alt. 33
Model specification: cross nested structure

- Probability of choosing the alternative i:

\[ P(i|C) = \sum_{m=1}^{M} \frac{\left( \sum_{j \in C} \alpha_{jm}^{\mu_m} \mu_i \right)^{\mu_m}}{\sum_{n=1}^{M} \left( \sum_{j \in C} \alpha_{jn}^{\mu_n} \mu_i \right)^{\mu_n}} \frac{\alpha_{im}^{\mu_m} \mu_i}{\sum_{j \in C} \alpha_{jm}^{\mu_m} \mu_j^{\mu_m}} \]

- \( C \): choice set
- \( M \): number of nests
- \( \nu_i \): utility of alternative i
- \( \alpha_{jm} \): membership degree of alternative j in the nest n
- \( \mu_m \): parameter of the nest m
- \( y_i = e^{\nu_i} \)
Model specification: utility specification

Pedestrian walking behavior

Unconstrained
- Keep direction
- Toward destination
- Free flow acc/dec

Constrained
- Collision avoidance
- Leader follower
Model specification: utility specification

\[ V_{vdn} = \beta_{dir\_central} \text{dir\_dn} I_{central} + \left\{ \begin{array}{l} \beta_{dir\_side} \text{dir\_dn} I_{side} + \beta_{dir\_extreme} \text{dir\_dn} I_{extreme} + \\
\beta_{ddist} \text{ddist\_vdn} + \beta_{ddir} \text{ddir\_dn} \end{array} \right\} \]

- keep direction

\[ \beta_{dec} I_{v,dec} \left( v_n / v_{max} \right)^{\lambda_{dec}} \]

- free flow acceleration

\[ \beta_{accLS} I_{LS} I_{v,acc} \left( v_n / v_{maxLS} \right)^{\lambda_{accLS}} \]

\[ \beta_{accHS} I_{HS} I_{v,acc} \left( v_n / v_{max} \right)^{\lambda_{accHS}} \]

- leader-follower

\[ I_{v,acc} I_{acc} \alpha_{acc} D_{L,acc}^{L} \Delta v_{L,acc} \Delta \theta_{L,acc}^{L} \]

\[ I_{v,dec} I_{dec} \alpha_{dec} D_{L,dec}^{L} \Delta v_{L,dec} \Delta \theta_{L,dec}^{L} \]

- collision avoidance

\[ I_{d,d_{n}} I_{C} \alpha_{C} e^{-\rho_{C} D_{C}} \Delta v_{C} \Delta \theta_{C}^{c} \]
Model specification: utility specification

- Keep direction (unconstrained):

\[
\beta_{\text{dir}_{\text{central}}} \text{dir}_{dn} I_{\text{central}} + \beta_{\text{dir}_{\text{side}}} \text{dir}_{dn} I_{\text{side}} + \beta_{\text{dir}_{\text{extreme}}} \text{dir}_{dn} I_{\text{extreme}}
\]
Model specification: utility specification

- Toward destination (unconstrained)
  \[ \beta_{ddist} \cdot ddist_{vdn} + \beta_{ddir} \cdot ddir_{dn} \]

\[ \begin{align*}
-1.55 &< 0 \\
-0.0790 &< 0
\end{align*} \]

- Distance
- Direction
Model specification : utility specification

- Free flow acceleration (unconstrained):

  Acceleration:

\[ \beta_{accLS} I_{LS} I_{v,acc} \left( \frac{v_n}{v_{maxLS}} \right)^{\lambda_{accLS}} + \beta_{accHS} I_{HS} I_{v,acc} \left( \frac{v_n}{v_{max}} \right)^{\lambda_{accHS}} \]

\[ \begin{align*}
\text{Low speed} & : 4.16 & \text{High speed} & : 0.358 \\
-4.97 & \quad & -7.47 & \\
\end{align*} \]
Model specification : utility specification

- Free flow acceleration (unconstrained) :
  - Deceleration : 
    
    $\beta_{\text{dec}} I_{v,\text{dec}} (v_n/v_{\text{max}})^{\lambda_{\text{dec}}}$

\[ \beta_{\text{dec}} \quad \text{and} \quad v_n \text{ to } v_{\text{max}} \]
Model specification : utility specification

- Leader follower (constrained):

\[ I_{v,acc} I_{acc}^L \alpha_{acc}^L D_{L}^{\rho_{acc}} \Delta \nu_{acc}^L \Delta \theta_{acc}^L + I_{v,dec} I_{dec}^L \alpha_{dec}^L D_{L}^{\rho_{dec}} \Delta \nu_{dec}^L \]

Sensitivity | Stimulus
---|---
0.942 | -0.489 | 0.625 | -0.171 | 3.69 | -0.663 | 0.652

- Potential leaders

- Leader

- \( D_k = 5D_{max} \)

- \( \theta_k \)

- \( \theta_d \)

- \( d \)

- \( d_k \)
Model specification : utility specification

- Collision avoidance (constrained) : $I_{d_a,d_n} I_C \alpha_C e^{-\rho_C D_C} \Delta \nu_C \Delta \theta_C$

- $-0.00639 \quad 0.239 \quad$ non significative

- sensitivity

- stimulus

Diagram showing potential colliders and a collider.
- Introduction
- Discrete choice models
- Model specification
- **Model estimation**
- Model validation
- Simulator
- Conclusion
The Japanese data set: video sequence

- Collected in Sendai, Japan, on August 2000, large pedestrian crossing road
The Japanese data set: data processing

- Tracking from video sequence: **2 observations per second**
- Pedestrians trajectories extracted using 3D-calibration (DLT algorithm)
- For each pedestrian trajectory:

![Diagram with frames and observations]

190 pedestrians, 9281 observations
The Japanese data set: pedestrian trajectory

- 4 alternatives are never chosen: 1, 12, 23, 33
Model estimation: general diagnosis

- Estimation made using the free Biogeme package (biogeme.epfl.ch)
- Estimation results:
  
  - Number of estimated parameters: 24
  - Init log-likelihood: -32451
  - Final log-likelihood: -13997.27
  - Likelihood ratio test: 36907
  - $\bar{\rho}^2 = 0.568$

- Parameters values consistent with hypothesis
Model estimation : parameters values

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Coefficient estimate</th>
<th>$t$ test 0</th>
<th>$t$ test 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{\text{dir}}$</td>
<td>-0.0790</td>
<td>-24.53</td>
<td></td>
</tr>
<tr>
<td>$\beta_{\text{dist}}$</td>
<td>-1.55</td>
<td>-11.66</td>
<td></td>
</tr>
<tr>
<td>$\beta_{\text{dir, extreme}}$</td>
<td>-0.0326</td>
<td>-9.30</td>
<td></td>
</tr>
<tr>
<td>$\beta_{\text{dir, side}}$</td>
<td>-0.0621</td>
<td>-21.87</td>
<td></td>
</tr>
<tr>
<td>$\beta_{\text{dir, central}}$</td>
<td>-0.0252</td>
<td>-8.74</td>
<td></td>
</tr>
<tr>
<td>$\lambda_{\text{acc,LS}}$</td>
<td>4.16</td>
<td>15.94</td>
<td></td>
</tr>
<tr>
<td>$\lambda_{\text{acc,HS}}$</td>
<td>0.358</td>
<td>2.09</td>
<td></td>
</tr>
<tr>
<td>$\lambda_{\text{dec}}$</td>
<td>-2.41</td>
<td>-8.43</td>
<td></td>
</tr>
<tr>
<td>$\alpha_{\text{acc}}$</td>
<td>0.942</td>
<td>2.28</td>
<td></td>
</tr>
<tr>
<td>$\rho_{\text{acc}}$</td>
<td>-0.489</td>
<td>-2.19</td>
<td></td>
</tr>
<tr>
<td>$\gamma_{\text{acc}}$</td>
<td>0.625</td>
<td>2.87</td>
<td></td>
</tr>
<tr>
<td>$\alpha_{\text{dec}}$</td>
<td>3.69</td>
<td>6.90</td>
<td></td>
</tr>
<tr>
<td>$\rho_{\text{dec}}$</td>
<td>-0.663</td>
<td>-7.11</td>
<td></td>
</tr>
<tr>
<td>$\gamma_{\text{dec}}$</td>
<td>0.652</td>
<td>6.19</td>
<td></td>
</tr>
<tr>
<td>$\delta_{\text{acc}}$</td>
<td>-0.171</td>
<td>-2.33</td>
<td></td>
</tr>
<tr>
<td>$\alpha_{\text{C}}$</td>
<td>-0.00639</td>
<td>-9.82</td>
<td></td>
</tr>
<tr>
<td>$\rho_{\text{C}}$</td>
<td>0.239</td>
<td>-8.28</td>
<td></td>
</tr>
<tr>
<td>$\mu_{\text{acc}}$</td>
<td>1.66</td>
<td>9.73</td>
<td>3.88</td>
</tr>
<tr>
<td>$\mu_{\text{const}}$</td>
<td>1.50</td>
<td>13.46</td>
<td>4.48</td>
</tr>
<tr>
<td>$\mu_{\text{central}}$</td>
<td>2.35</td>
<td>1.93</td>
<td>1.11</td>
</tr>
<tr>
<td>$\mu_{\text{not central}}$</td>
<td>1.75</td>
<td>9.46</td>
<td>4.04</td>
</tr>
</tbody>
</table>
• Introduction
• Discrete choice models
• Model specification
• Model estimation
• **Model validation**
• Simulator
• Conclusion
Model validation: methodology

- Validation of the specification:
  - Development of a model with constants only (ASC model)
  - Simulation on the Japanese data set
  - Cross validation on the Japanese data set

- Validation of the model:
  - Simulation on an experimental Dutch data set, not used for model estimation
  - Comparison of the proposed model with the ASC model
Model validation : model constants-only

- The simplest model: utility of each alternative represented only by an alternative specific constant (ASC)

- This model with only constants (ASC model) estimated on the Japanese data set.

  28 parameters (33, minus 4 never chosen, minus 1 for normalization)

- It reproduces the aggregated observations proportions of the Japanese data set

- The ASC model used for comparison (for example the number of outliers)
Model validation: simulation on the Japanese data set (Aggregate level)

- The proposed model is applied to the Japanese data set (used for estimation)

<table>
<thead>
<tr>
<th>Cone</th>
<th>$\Gamma$</th>
<th>$M_\Gamma$</th>
<th>$R_\Gamma$</th>
<th>$(M_\Gamma - R_\Gamma)/R_\Gamma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Front</td>
<td>5 – 7, 16 – 18, 27 – 29</td>
<td>8489.27</td>
<td>8481</td>
<td>0.10%</td>
</tr>
<tr>
<td>Left</td>
<td>3, 4, 14, 15, 25, 26</td>
<td>349.67</td>
<td>367</td>
<td>-4.72%</td>
</tr>
<tr>
<td>Right</td>
<td>8, 9, 19, 20, 30, 31</td>
<td>415.41</td>
<td>407</td>
<td>2.08%</td>
</tr>
<tr>
<td>Extreme left</td>
<td>1, 2, 12, 13, 23, 24</td>
<td>12.29</td>
<td>10</td>
<td>22.96%</td>
</tr>
<tr>
<td>Extreme right</td>
<td>10, 11, 21, 22, 32, 33</td>
<td>14.30</td>
<td>16</td>
<td>-10.59%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Area</th>
<th>$\Gamma$</th>
<th>$M_\Gamma$</th>
<th>$R_\Gamma$</th>
<th>$(M_\Gamma - R_\Gamma)/R_\Gamma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>acceleration</td>
<td>1 – 11</td>
<td>1041.50</td>
<td>1065</td>
<td>-2.21%</td>
</tr>
<tr>
<td>constant speed</td>
<td>12 – 22</td>
<td>7606.49</td>
<td>7565</td>
<td>0.55%</td>
</tr>
<tr>
<td>deceleration</td>
<td>23 – 33</td>
<td>633.02</td>
<td>651</td>
<td>-2.76%</td>
</tr>
</tbody>
</table>
Model validation: simulation on the Japanese data set (Disaggregate level)

- **Outlier**: Observation with predicted probability less than 1/33 (hazard)

![Graph showing predicted probabilities for Japanese data]

Number of outliers:
- **7.13%** for proposed model
- **19.90%** for ASC model
Model validation: Cross-validation on the Japanese data set

- Japanese data split into 5 subsets, each containing 20% of the observations

  5 experiments:
  - 1 subset saved for validation
  - estimation of the model on the 4 remaining

- Number of outliers (compared with the ASC model cross validation)

<table>
<thead>
<tr>
<th>Model</th>
<th>Exp. 1</th>
<th>Exp. 2</th>
<th>Exp. 3</th>
<th>Exp. 4</th>
<th>Exp. 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed spec.</td>
<td>8.78%</td>
<td>6.36%</td>
<td>7.60%</td>
<td>7.87%</td>
<td>5.87%</td>
</tr>
<tr>
<td>Constant only</td>
<td>20.79%</td>
<td>20.70%</td>
<td>17.13%</td>
<td>19.88%</td>
<td>18.64%</td>
</tr>
</tbody>
</table>

Robust specification
The Dutch data set: video sequence

- Collected at Delft university, in 2000-2001, 2 pedestrians crossing flows
The Dutch data set: general information

- **Experimental** data set
- Video sequence recorded at **10 frames per second**
- Pedestrians trajectories extracted from the video sequence
- For each pedestrian trajectory:

  - Frame used to calculate speed and direction:
    - Current frame: \( f \)
    - Observed choice: \( f+10 \)
    - Duration:
      - 0.1s
      - 1s

  - **724 pedestrians, 47481 observations**
The Dutch data set: comparison with the Japanese data set

- Normalized observations distribution among alternatives

- Observations repartitions inside the nest (Japanese / Dutch)

<table>
<thead>
<tr>
<th>Nest</th>
<th># steps</th>
<th>% of total</th>
</tr>
</thead>
<tbody>
<tr>
<td>acceleration</td>
<td>1065</td>
<td>11.48%</td>
</tr>
<tr>
<td>constant speed</td>
<td>7565</td>
<td>81.51%</td>
</tr>
<tr>
<td>deceleration</td>
<td>651</td>
<td>7.01%</td>
</tr>
<tr>
<td>central</td>
<td>4297</td>
<td>46.30%</td>
</tr>
<tr>
<td>not central</td>
<td>4984</td>
<td>53.70%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Nest</th>
<th># steps</th>
<th>% of total</th>
</tr>
</thead>
<tbody>
<tr>
<td>acceleration</td>
<td>1273</td>
<td>2.68%</td>
</tr>
<tr>
<td>constant speed</td>
<td>45869</td>
<td>96.61%</td>
</tr>
<tr>
<td>deceleration</td>
<td>339</td>
<td>0.71%</td>
</tr>
<tr>
<td>central</td>
<td>20950</td>
<td>44.12%</td>
</tr>
<tr>
<td>not central</td>
<td>26531</td>
<td>55.88%</td>
</tr>
</tbody>
</table>
The Dutch data set : comparison with the Japanese data set

- Quite similar observations proportions in the direction’s cones (not for speed regime)

<table>
<thead>
<tr>
<th>Dataset</th>
<th>extremeleft</th>
<th>left</th>
<th>front</th>
<th>right</th>
<th>extremeright</th>
</tr>
</thead>
<tbody>
<tr>
<td>Japanese</td>
<td>0.11%</td>
<td>3.95%</td>
<td>91.38%</td>
<td>4.39%</td>
<td>0.17%</td>
</tr>
<tr>
<td>Dutch</td>
<td>0.06%</td>
<td>4.40%</td>
<td>91.35%</td>
<td>4.15%</td>
<td>0.04%</td>
</tr>
</tbody>
</table>

- Speed distributions have different shapes (experimental design of Dutch data set)
Model validation: simulation on the Dutch data set (Aggregate level)

- The proposed model is applied to the Dutch data set (NOT used for estimation)

<table>
<thead>
<tr>
<th>Cone</th>
<th>$\Gamma$</th>
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<th>$(M_\Gamma - R_\Gamma)/R_\Gamma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Front</td>
<td>5 – 7, 16 – 18, 27 – 29</td>
<td>43619.98</td>
<td>43374</td>
<td>0.57%</td>
</tr>
<tr>
<td>Left</td>
<td>3, 4, 14, 15, 25, 26</td>
<td>1968.79</td>
<td>2089</td>
<td>−5.75%</td>
</tr>
<tr>
<td>Right</td>
<td>8, 9, 19, 20, 30, 31</td>
<td>1764.39</td>
<td>1972</td>
<td>−10.53%</td>
</tr>
<tr>
<td>Extreme left</td>
<td>1, 2, 12, 13, 23, 24</td>
<td>45.86</td>
<td>27</td>
<td>69.85%</td>
</tr>
<tr>
<td>Extreme right</td>
<td>10, 11, 21, 22, 32, 33</td>
<td>81.97</td>
<td>19</td>
<td>331.44%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Area</th>
<th>$\Gamma$</th>
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<th>$R_\Gamma$</th>
<th>$(M_\Gamma - R_\Gamma)/R_\Gamma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>acceleration</td>
<td>1 – 11</td>
<td>3892.35</td>
<td>1273</td>
<td>205.76%</td>
</tr>
<tr>
<td>constant speed</td>
<td>12 – 22</td>
<td>40733.53</td>
<td>45869</td>
<td>−11.20%</td>
</tr>
<tr>
<td>deceleration</td>
<td>23 – 33</td>
<td>2855.12</td>
<td>339</td>
<td>742.22%</td>
</tr>
</tbody>
</table>

Overprediction of acceleration and deceleration
Model validation: simulation on the Dutch data set (Disaggregate level)

- **Outlier**: Observation with predicted probability less than 1/33 (hazard)

Number of outliers: **2.48%**
Model validation: Comparison with the ASC model on the Dutch data set (Aggregate level)

- The ASC model is applied to the Dutch data set and compared to the proposed model.

<table>
<thead>
<tr>
<th>Cone</th>
<th>$\Gamma$</th>
<th>$M_\Gamma$</th>
<th>$R_\Gamma$</th>
<th>$(M_\Gamma - R_\Gamma)/R_\Gamma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Front</td>
<td>5 – 7, 16 – 18, 27 – 29</td>
<td>43386.42</td>
<td>43374</td>
<td>0.03%</td>
</tr>
<tr>
<td>Left</td>
<td>3, 4, 14, 15, 25, 26</td>
<td>1877.47</td>
<td>2089</td>
<td>−10.13%</td>
</tr>
<tr>
<td>Right</td>
<td>8, 9, 19, 20, 30, 31</td>
<td>2082.10</td>
<td>1972</td>
<td>5.58%</td>
</tr>
<tr>
<td>Extreme left</td>
<td>1, 2, 12, 13, 23, 24</td>
<td>51.16</td>
<td>27</td>
<td>89.47%</td>
</tr>
<tr>
<td>Extreme right</td>
<td>10, 11, 21, 22, 32, 33</td>
<td>81.85</td>
<td>19</td>
<td>330.80%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Cone</th>
<th>$\Gamma$</th>
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<th>$R_\Gamma$</th>
<th>$(M_\Gamma - R_\Gamma)/R_\Gamma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Front</td>
<td>5 – 7, 16 – 18, 27 – 29</td>
<td>43619.98</td>
<td>43374</td>
<td>0.57%</td>
</tr>
<tr>
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<td>3, 4, 14, 15, 25, 26</td>
<td>1968.79</td>
<td>2089</td>
<td>−5.75%</td>
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<tr>
<td>Right</td>
<td>8, 9, 19, 20, 30, 31</td>
<td>1764.39</td>
<td>1972</td>
<td>−10.53%</td>
</tr>
<tr>
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<td>1, 2, 12, 13, 23, 24</td>
<td>45.86</td>
<td>27</td>
<td>69.85%</td>
</tr>
<tr>
<td>Extreme right</td>
<td>10, 11, 21, 22, 32, 33</td>
<td>81.97</td>
<td>19</td>
<td>331.44%</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Area</th>
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<th>$R_\Gamma$</th>
<th>$(M_\Gamma - R_\Gamma)/R_\Gamma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>acceleration</td>
<td>1 – 11</td>
<td>5448.24</td>
<td>1273</td>
<td>327.98%</td>
</tr>
<tr>
<td>constant speed</td>
<td>12 – 22</td>
<td>38700.42</td>
<td>45869</td>
<td>−15.63%</td>
</tr>
<tr>
<td>deceleration</td>
<td>23 – 33</td>
<td>3330.34</td>
<td>339</td>
<td>882.40%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Area</th>
<th>$\Gamma$</th>
<th>$M_\Gamma$</th>
<th>$R_\Gamma$</th>
<th>$(M_\Gamma - R_\Gamma)/R_\Gamma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>acceleration</td>
<td>1 – 11</td>
<td>3892.35</td>
<td>1273</td>
<td>205.76%</td>
</tr>
<tr>
<td>constant speed</td>
<td>12 – 22</td>
<td>40733.53</td>
<td>45869</td>
<td>−11.20%</td>
</tr>
<tr>
<td>deceleration</td>
<td>23 – 33</td>
<td>2855.12</td>
<td>339</td>
<td>742.22%</td>
</tr>
</tbody>
</table>

Equivalent for direction (logical, due to proportions)
Model validation: simulation on the Japanese data set (Disaggregate level)

- **Outlier**: Observation with predicted probability less than 1/33 (hazard)

Number of outliers:
- **2.48%** for proposed model
- **10.31%** for ASC model

Superiority of the proposed model
- Introduction
- Discrete choice models
- Model specification
- Model estimation
- Model validation
- **Simulator**
- Conclusion
Simulator

- Implementation of the developed specification in a simulator
- Simulation of 2 pedestrian crossing flows with the model

Examples:
- Simulation of 300s
  - Start: random speed and direction
  - Finish: random destination

- Ex1: low density, 2 pedestrians per second entering
- Ex2: high density, 5 pedestrians per second entering
Simulator

- Low density:
Simulator

- High density:
Conclusions and Perspectives

● **Conclusions:**
  - Discrete choice model for pedestrian walking behavior with ‘**unconstrained**‘ and ‘**constrained**’ parameters
  - Model **estimated** on a real data set, parameters values consistent with hypothesis
  - Model validated on a real data set, **not used for estimation**
  - Operating **Simulator**

● **Perspectives:**
  - Improve the **acceleration** and **deceleration** patterns
  - Incorporate **physical characteristics** of the pedestrians
  - Model the **strategical** and **tactical** behavioural levels
Thanks for your attention

http://transp-or2.epfl.ch/publications.php#techrep