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Multi-class speed-density relationship for pedestrian traffic

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Outline

1. Introduction
2. Methodology
3. Case study
   - Model specification
   - Model estimation and performance analysis
4. Conclusion and future work

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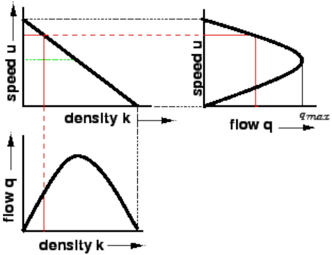
Fundamental relationships

- Play an important role in the filed: design and planing; model input or calibration criterion
- Modeling assumption: the traffic system is at equilibrium - homogenous and stationary



Speed-density relationships for pedestrian traffic

Deterministic approach

- Empirically derived models [Older, 1968; Tregenza, 1976; Weidmann, 1993; Rastogi et al., 2013]
- Simulation-based models [Blue and Adler, 1998]
- Theory-based models [Flötteröd and Lämmel, 2015]

Empirical observations

- Scatter: violation of the equilibrium assumptions

Probabilistic approach

- Data-driven PedProb-vk [Nikolić et al., 2016]
- Superior compared to deterministic approaches from the literature

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Behavioral approach

Assupmtions

- Pedestrian population is heterogeneous (e.g. trip purpose, age, gender, etc.)
- Heterogeneity leads to the existence of multiple pedestrian classes
- Classes are characterized by different types of behavior
- Latent class modeling approach to capture unobserved heterogeneity

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Multi-class speed-density relationship (MC-vk)

Model structure

$$P(v_i|k_i) = \sum_{c=1}^{C} P(v_i|k_i, c)P(c|X_i)$$

$P(v_i|k_i, c)$: class-specific model

$P(c|X_i)$: class membership model

i: pedestrian identifier, $i = 1, ..., N$

v_i: speed of pedestrian i

k_i: density for pedestrian i

c: class identifier, C - number of classes

X_i: characteristics associated to pedestrian i

Class-specific speed-density relationship

Social Force Model

$$\vec{a}_i = \frac{\vec{v}_i^f - \vec{v}_i}{\tau_i} - C_i \sum_j \exp(-\frac{R_{ij}}{B_i})\vec{n}_{ij}(\lambda_i + (1-\lambda_i)\frac{1+\cos(\phi_{ij})}{2})$$

[Helbing and Molnar, 1995]

Class-specific speed-density relationship

Isotropy ($\lambda_i = 1$)

$$a_i = \frac{v_i^f - v_i}{\tau_i} - C_i \sum_j \exp(-\frac{R_{ij}}{B_i}) = \frac{v_i^f - v_i}{\tau_i} - C_i k_i$$

Stationatity ($a_i = 0$)

$$v_i = v_i^f - \gamma_i k_i$$

Homogeneity (all pedestrians have the same movement parameters)

$$v_i = v = v_f - \gamma k_i$$

Class membership model

- It cannot be deterministically identified to which class a pedestrian belongs
- Probability that a pedestrian i, associated with characteristics X_i (e.g. trip purpose, age, gender, etc.), belong to a latent class c: for each pedestrian there is a utility associated to each class c

Specification of utilities

$$U_i^c = \underbrace{ASC^c + \beta^c X_i}_{V_i^c} + \xi_i^c$$

V_i^c: deterministic part of utilities
ξ_i^c: error term

Multi-class speed-density relationship (MC-vk)

Class-specific model: $P(v_i|k_i, c)$

$$v_i^c = v_f^c - \gamma^c k_i + \epsilon_i^c$$

$P(v_i|k_i, c)$ is determined by ϵ_i^c

Class membership model: $P(c|X_i)$

$$U_i^c = \underbrace{ASC^c + \beta^c X_i}_{V_i^c} + \xi_i^c$$

$P(c|X_i)$ is determined by ξ_i^c

Likelihood of the sample

$$\mathcal{L} = \prod_{i=1}^{N} P(v_i|k_i) = \prod_{i=1}^{N} \sum_{c=1}^{C} P(v_i|k_i, c) P(c|X_i)$$

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Lausanne railway station

Pedestrian underpass West

1: South entrance, 3: Coop Pronto Supermarket

2 - 4: Stairs (resp. ramp) to platform 9

5 - 6: Stairs (resp. ramp) to platform 7 and 8

7 - 8: Stairs (resp. ramp) to platform 5 and 6

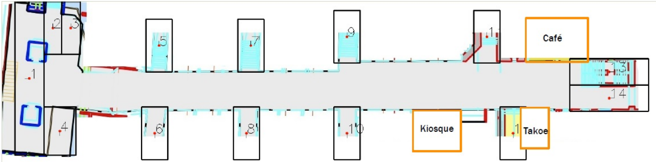
9 - 10: Stairs (resp. ramp) to platform 3 and 4

11: Stairs to platform 1 and out of the station

12: Access ramp

13: Stairs to or out of the train station and to buses

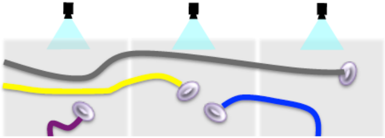
14: Pathway leading to buses and metro (M2)



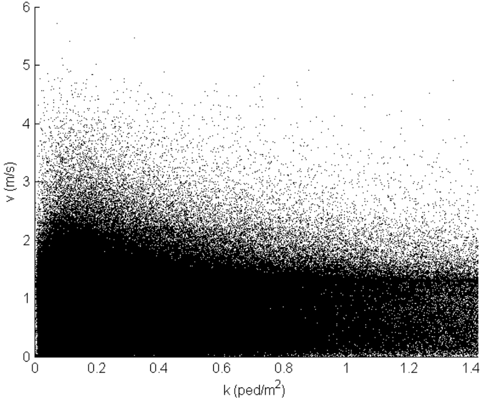
Data set

Pedestrian underpass

- A large-scale network of smart sensors: a sparsity driven tracking framework [Alahi et al., 2014]
- Dataset: 25,603 trajectories, collected between 07:00 and 08:00 on February 12, 13, 14, 15 and 18, 2013
- The average length of the trajectories: 78 meters
- The duration of a pedestrians' stay: from 15 seconds to 2.2 minutes



Speed-density relationship



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Specification issues

Panel data

- Data collected over multiple time periods for the same sample of individuals

Serial correlation

- The observations across time for a single pedestrian are likely to be correlated, due to the unobserved factors related to a pedestrian that exist over time
- $\epsilon^c_{i(t-1)}$ cannot be assumed independent from ϵ^c_{it}
- If ignored - consistent but not efficient estimators

Multi-class speed-density relationship (MC-vk)

Class-specific model: $P(v_i|k_i, c)$

$$v_{it}^c = v_f^c - \gamma^c k_{it} + \alpha_{\mathbf{i}}^{\mathbf{c}} + \epsilon_{it}^{\prime c}$$

$P(v_i|k_i, c)$ is determined by $\epsilon_{it}^{\prime c}$, α_i^c is an agent effect

Class membership model: $P(c|X_i)$

$$U_i^c = \underbrace{ASC^c + \beta^c X_i}_{V_i^c} + \xi_i^c$$

$P(c|X_i)$ is determined by ξ_i^c

Likelihood of the sample

$$\mathcal{L} = \prod_{i=1}^{N} \sum_{c=1}^{C} \{\frac{1}{R} \sum_{r}^{R} exp(\sum_{t=1}^{T} \log P(v_i|k_i, c, \alpha_r^c))\} P(c|X_i)$$

Assumptions

Number of classes

1. Pedestrians sensitive to congestion
2. Pedestrians non-sensitive to congestion

Class specific model

- The same functional form of v-k for each class
- $\epsilon_{it}^{\prime c} \sim$ Rayleigh distribution
- $\alpha_{i}^{\prime c} \sim$ Rayleigh distribution

Class membership model

- Logit model
- Explanatory variables: type of pedestrian, time to departure, OD distance, peak periods

Pedestrian types

Classification based on origins and destinations

1: Arriving passenger - pedestrians originating from a platform and exiting the station

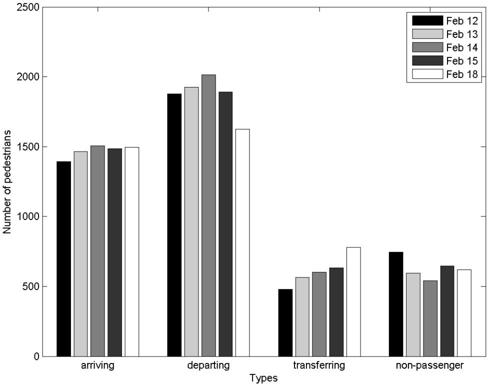
2: Departing passenger - pedestrians walking to a platform to embark on their trains

3: Transferring passenger - pedestrians whose origin and destination are different platforms

4: Non-passenger - pedestrians whose origin and destination are different from a platform (e.g. pedestrians that go shopping in the station)

Pedestrian types

Number of pedestrians per pedestrian type



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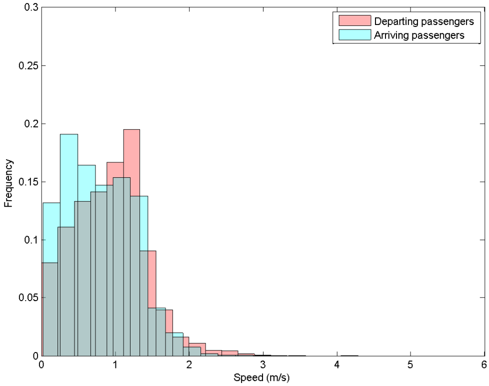
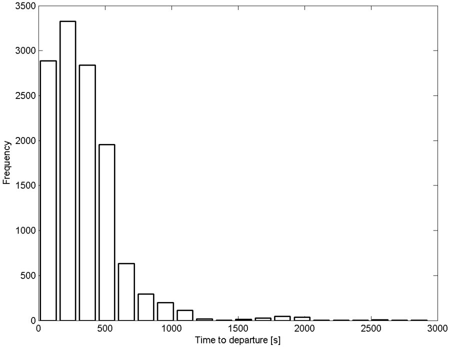
Pedestrian types

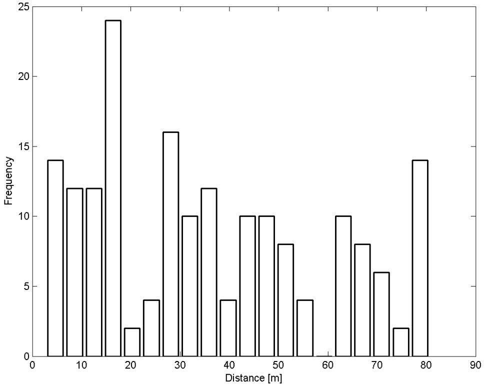
Speed distribution per pedestrian type



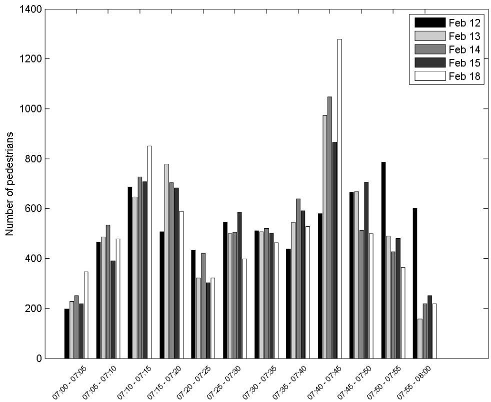
Time to departure



OD distance



Peak periods



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Estimation results

Class membership model

Parameter	Value	Std.err.
ASC^{NS}	-0.258	$5.18e^{-06}$
$\beta^{NS}_{\text{Arriving pass.}}$	-0.641	$1.03e^{-05}$
$\beta^{NS}_{\text{Departing pass.}}$	58.5	$2.11e^{-05}$
$\beta^{NS}_{\text{Transferring pass.}}$	63.5	$1.73e^{-05}$
$\beta^{S}_{\text{Time to departure}}$	0.236	$1.57e^{-05}$
$\beta^{S}_{\text{Peak period}}$	0.125	$1.54e^{-05}$
$\beta^{S}_{\text{OD distnce}}$	0.0328	$1.93e^{-05}$

Class specific model

Parameter	Value	Std.err.
v_f^{NS}	1.13	$1.32e^{-05}$
γ^{NS}	0.0812	$1.73e^{-05}$
v_f^{S}	0.949	$9.37e^{-05}$
γ^{S}	0.178	$1.28e^{-05}$
η^{NS}	0.0104	$2.67e^{-05}$
η^{S}	0.102	$1.66e^{-05}$

S - Pedestrians sensitive to congestion
NS - Pedestrians non-sensitive to congestion

How many classes?

Bayesian information criterion - *BIC*

Model	1 class	2 classes	3 classes
$\log \mathcal{L}$	-527491.289	-524094.577	-523726.125
#observations	747385	747385	747385
#parameters	3	13	23
BIC	1055023.152	1048364.971	1047763.309

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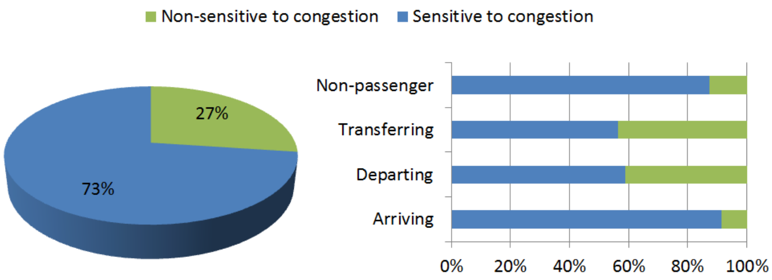
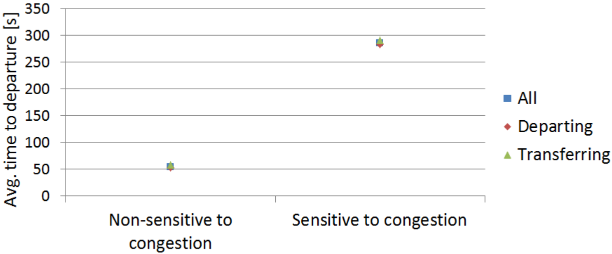
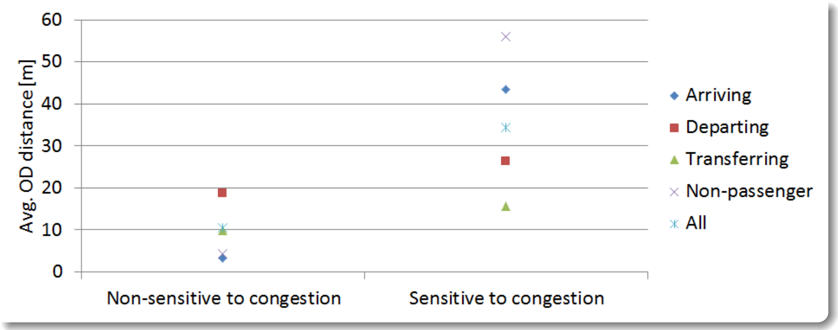
Shares


Non-sensitive to congestion
Sensitive to congestion
27%
73%
Non-passenger
Transferring
Departing
Arriving
0%
20%
40%
60%
80%
100%

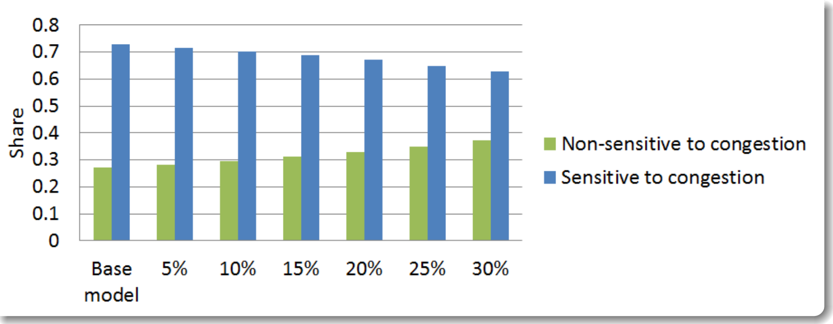
Average time to departure



Average OD distance



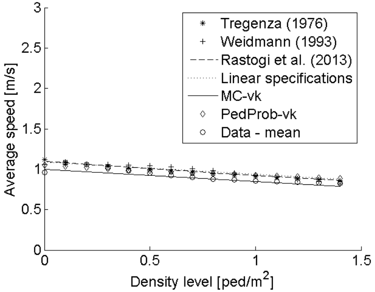
Scenario: time table change (decrease of the time to departure)



Model comparison

Average behavior

$$\bar{v}_{MC-vk} = \sum_{c=1}^{C} \left\{ \frac{1}{N} \sum_{i=1}^{N} P(c|X_i;\beta^c) v^c(k;\theta^c) \right\}$$



Model	Weidmann	Tregenza	Rastogi	Linear	*PedProb-vk*	*MC-vk*
MSE	$4.81e^{-03}$	$3.63e^{-03}$	$3.95e^{-03}$	$4.99e^{-03}$	$3.17e^{-03}$	$2.12e^{-03}$
$\bar{R}^2$	$2.64e^{-01}$	$4.45e^{-01}$	$3.96e^{-01}$	$2.37e^{-01}$	$5.16e^{-01}$	$6.76e^{-01}$

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Conclusion and future work

Conclusion

- MC-vk: latent class modeling approach to capture heterogeneity in pedestrian population
- Satisfying behavioral interpretation
- Good performance at the aggregate level

Future work

- Additional factors: walking in groups, attractiveness of origins/destinations
- Additional scenarios: train reallocation
- Accounting for dynamics

Thank you

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