
A Pedestrian Destination-Chain Choice Model from Bayesian Estimation of Pedestrian Activities using Sensors Data

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Presentation outline

- Motivation
- Data requirement
- Methodology
- A case study on EPFL campus
- Conclusion
- Future work

MOTIVATION



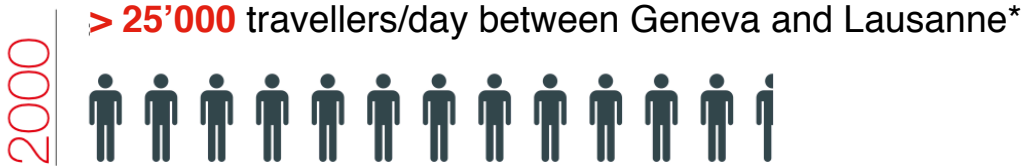
Walking is the key for efficient multimodal transport systems



Crowd in a railway station in Mumbai, India
Photo: National Geographic

Lake Geneva region

By 2030, 100'000 passengers per day between Geneva and Lausanne



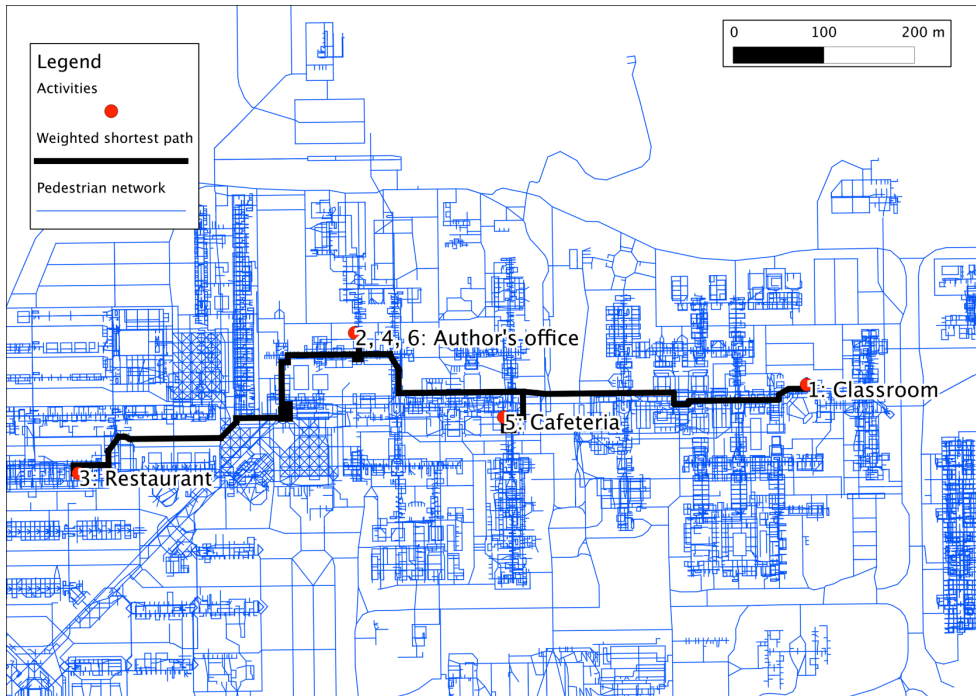
 = 2000 travelers/day

* Forecast by Swiss Railways for the maximum scenario

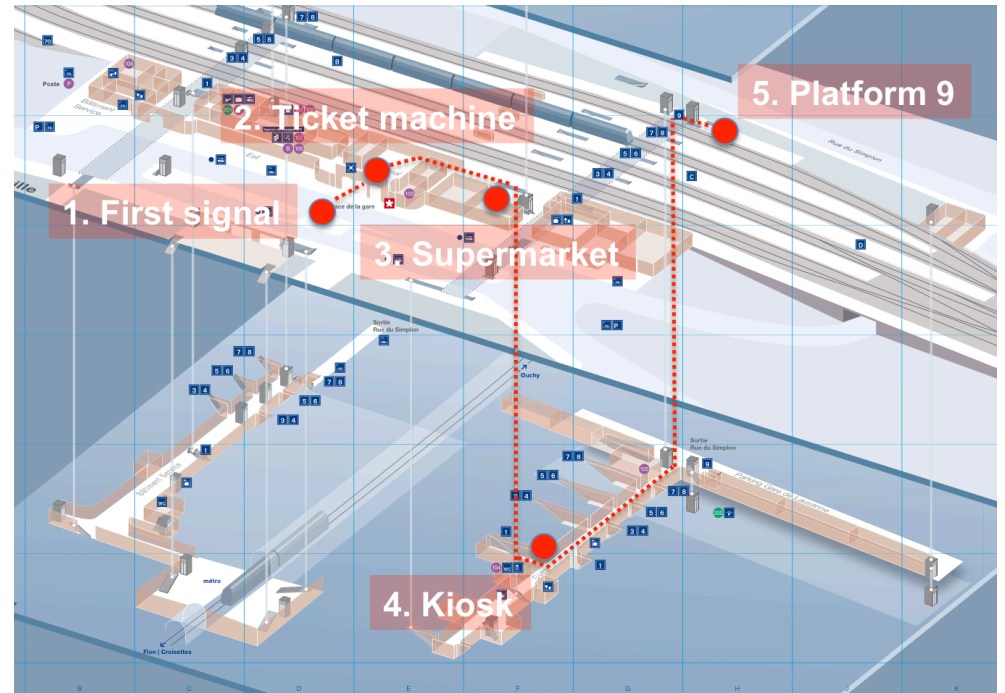


Understand pedestrian activities

What we are doing: Campus

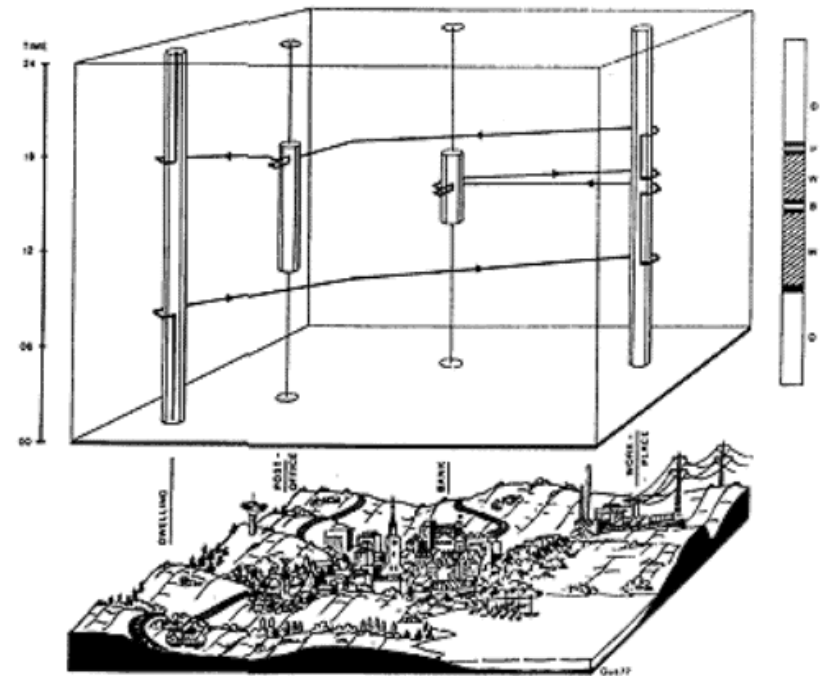


What we want to do: Station



Challenges

- Detect pedestrian activity-episode locations
- Model pedestrian activity scheduling behavior
- Forecast the impact of changes in the infrastructure



Carlstein, T. (1978)

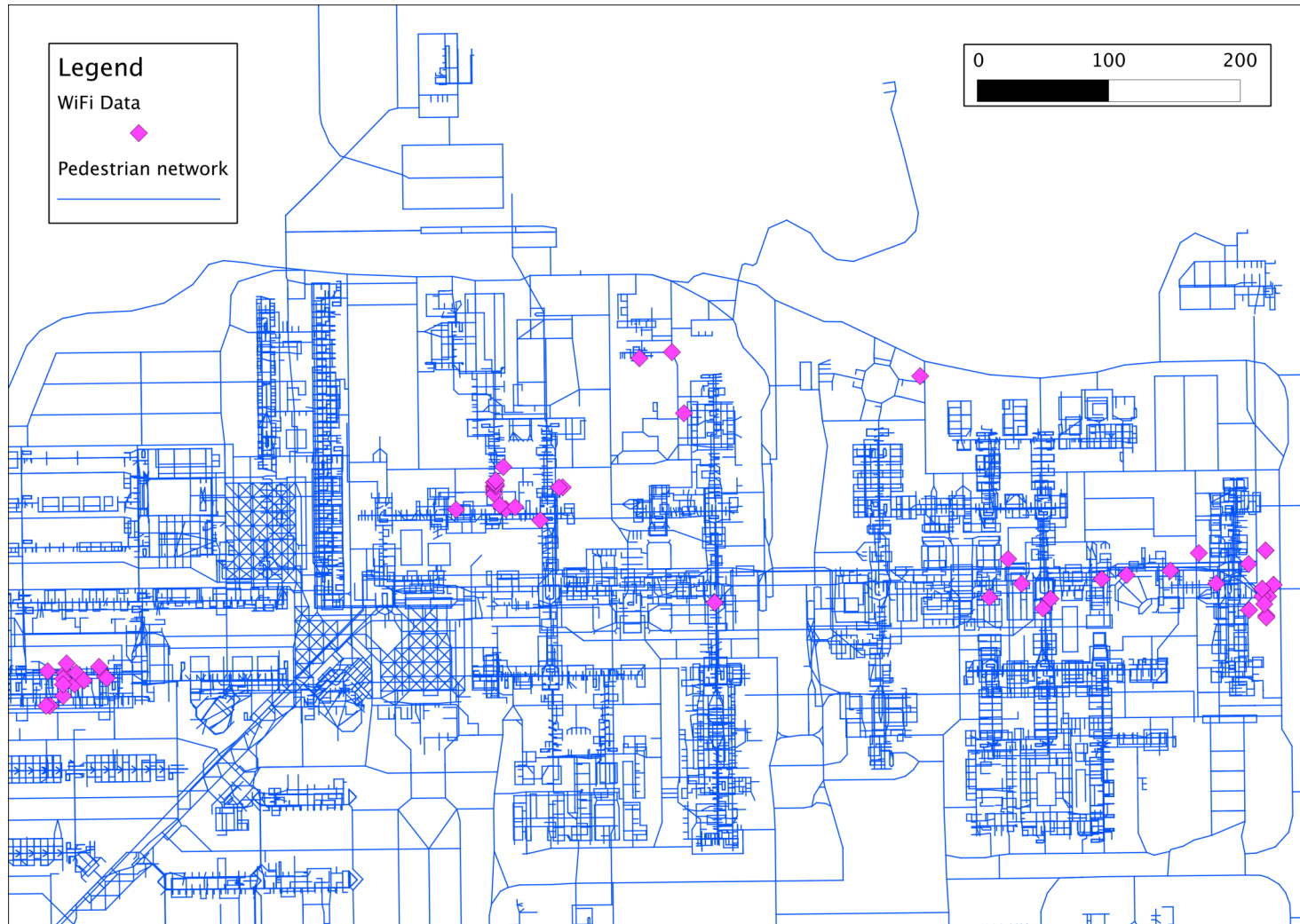
DATA REQUIREMENT



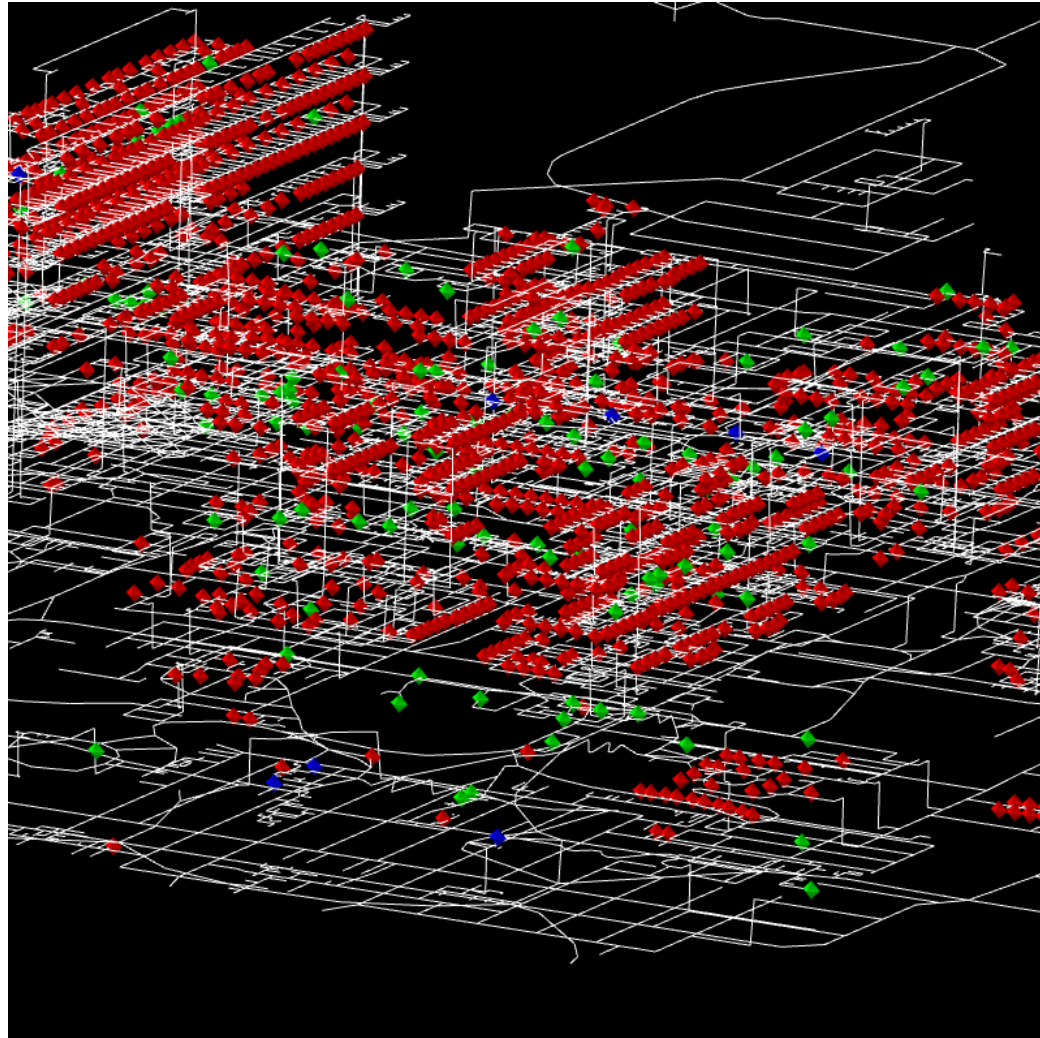
Data requirement

- Required
 - Localization data with full coverage of the facility
 - Semantically-enriched routing graph for pedestrians
- Not really required but often available information
 - Potential attractiveness measure

Data requirement: Localization



Data requirement: Pedestrian network



J. Lopez-Montenegro Ramil,
Antonin Danalet (Dir.), Michel
Bierlaire (Dir.), Visualization of
pedestrian demand in a 3D graph,
semester project, Spring semester,
2013

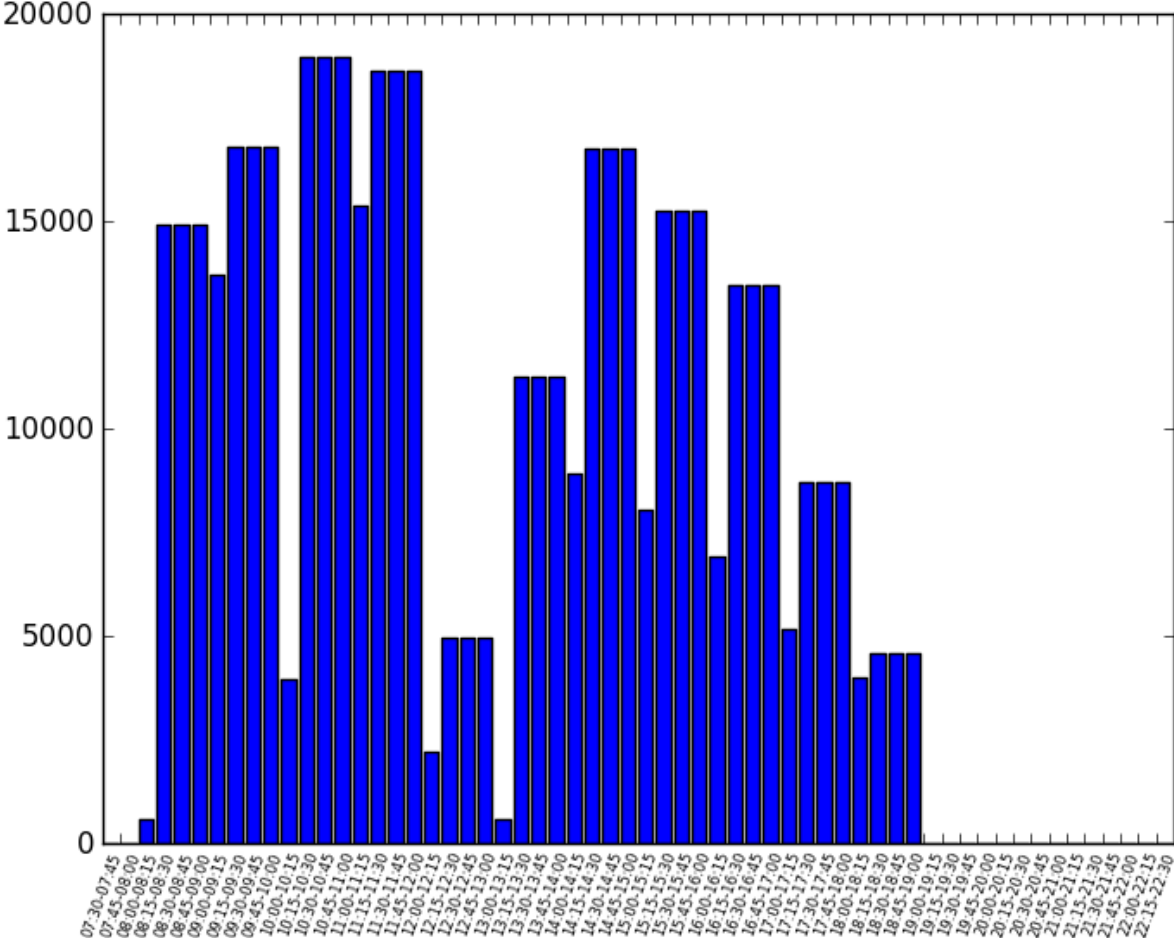
Data requirement: Potential attractivity

- **Potential attractivity measure (PAM)** depends on
 - **Destination attractivity** $att(x, t)$
 - Classroom, platform, scene, ...
 - **Time-constraints** $\delta_{x,i}(t)$
 - Class schedules, train schedules, opening hours, ...

$$PAM_{x,i}(t^-, t^+) = \int_{t=t^-}^{t^+} \delta_{x,i}(t) \cdot att(x, t)$$

- **Examples:**
 - 1500 passengers on platform 4 arriving at 16h04
 - 32 students in a classroom from 8h15 to 10h
 - 400 seats in a restaurant open from 11h to 14h30

Data requirement: Potential attractiveness

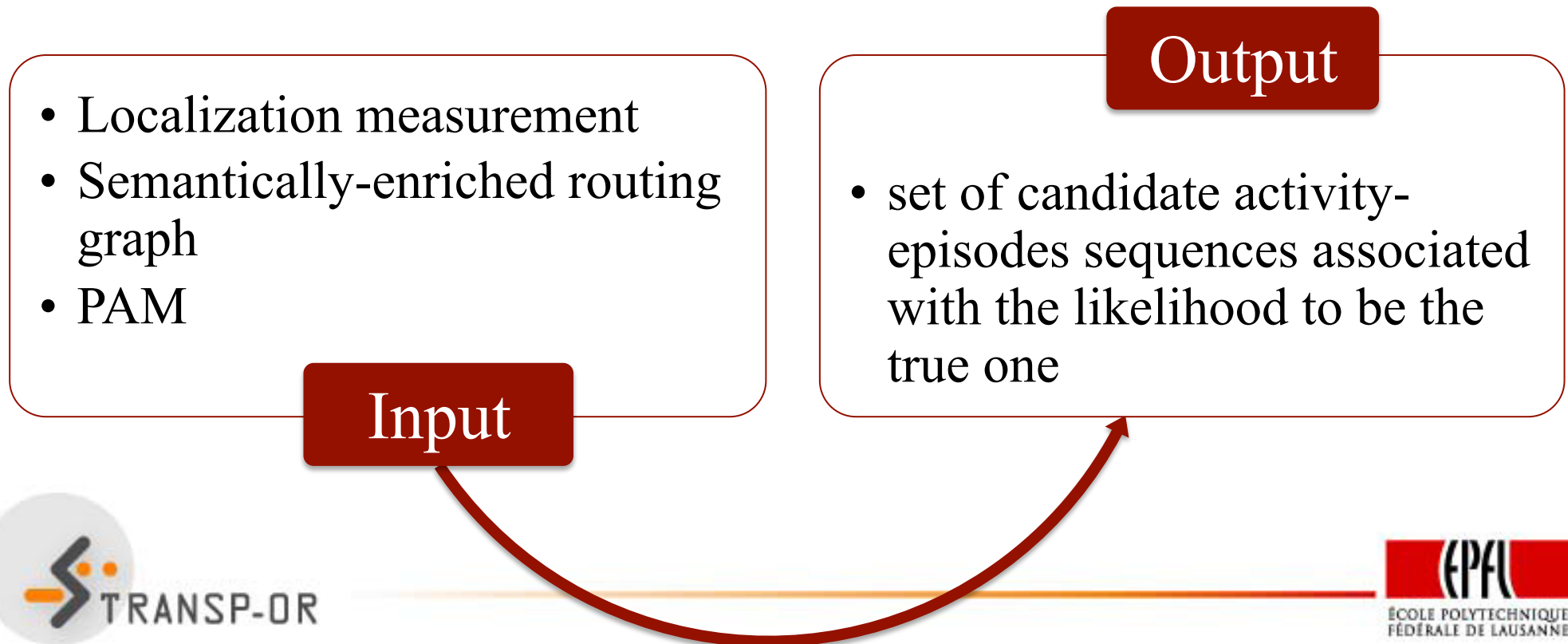


METHODOLOGY



Methodology

- **Goal:** extract the possible activity-episodes performed by pedestrians from digital traces from communication networks



Definitions / Notations

- Measurement: $\hat{s} = (\hat{x}, \hat{t})$
- Activity-episode: $a = (x, t^-, t^+)$
- Episode location, start time and end time
- Activity-episode sequence: $(a_1, \dots, a_m) = a_{1:m}$
- Activity: $A(a)$
- Activity pattern: $(A_1, \dots, A_m) = A_{1:m}$

Methodology

- Probabilistic measurement model:
 - A Bayesian approach
 - Measurement equation
 - Prior
- Generation of activity-episode sequences
 - Episode location
 - Episode start and end times

Probabilistic measurement model

Measurement likelihood

Prior

$$P(a_{1:m} | \hat{s}_{1:n}) \propto P(\hat{s}_{1:n} | a_{1:m}) \cdot P(a_{1:m})$$

Activity probability

Measurement error

$$\begin{aligned} P(\hat{s}_{1:n} | a_{1:m}) &= \prod_{j=1}^m P(\hat{s}_{1:n}^j | a_j) \quad \leftarrow \text{Independence between activities} \\ &= \prod_{j=1}^m \prod_{i=1}^n P(\hat{s}_i^j | a_j) \quad \leftarrow \text{Independence between signals} \\ &= \prod_{j=1}^m \prod_{i=1}^n P(\hat{x}_i^j | x_j) \quad \leftarrow \text{No time measurement error} \end{aligned}$$

Prior

$$P(a_{1:m}) = \prod_{j=1}^m P(a_j) \quad (1)$$

$$= \prod_{j=1}^m P(x_j, t_j^-, t_j^+) \quad (2)$$

$$= \prod_{j=1}^m \frac{PAM_{x_j, i}(t_j^-, t_j^+)}{\sum_{x \in POI} PAM_{x, i}(t_j^-, t_j^+)} \quad (3)$$

Probabilistic measurement model

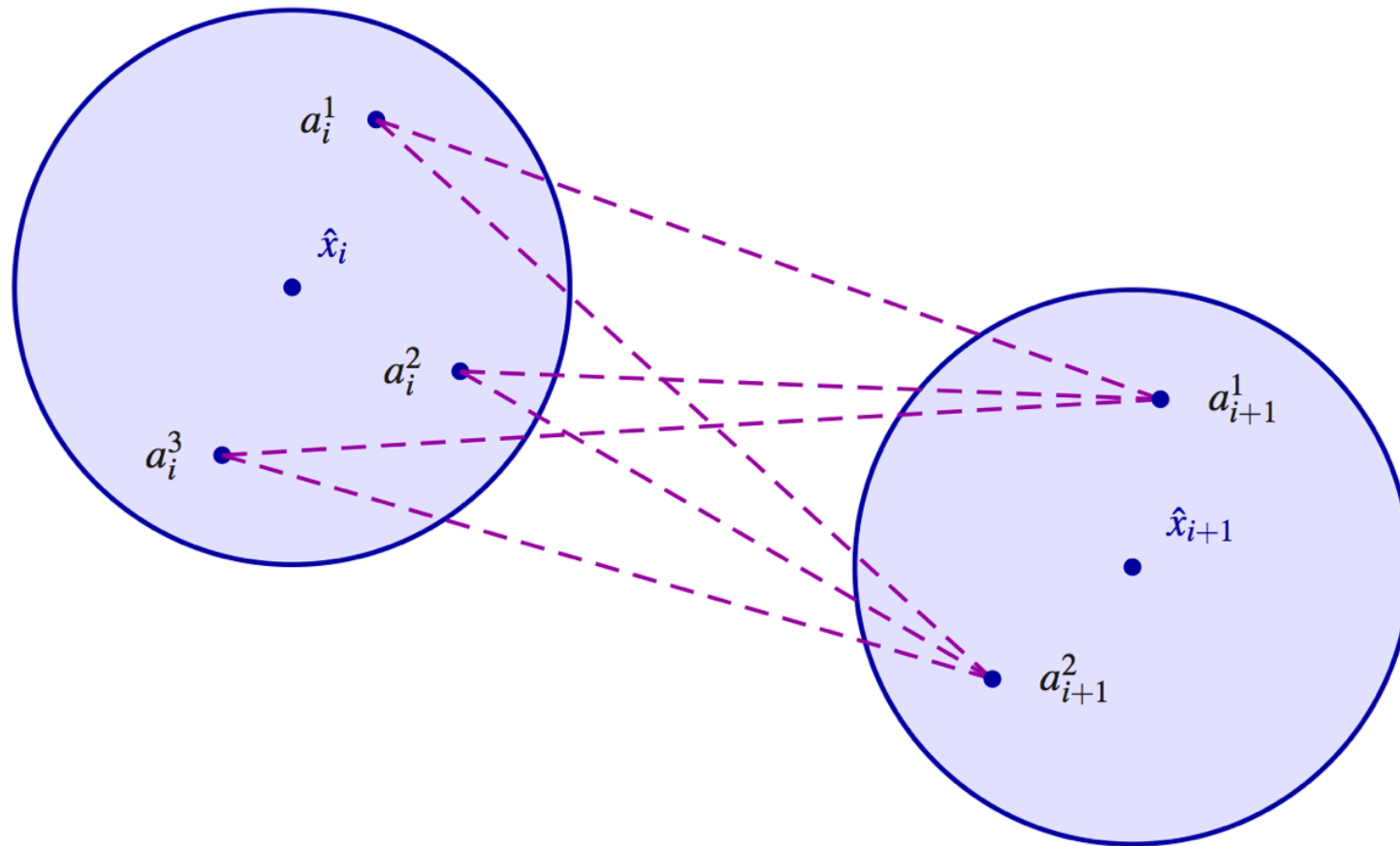
Measurement likelihood

Prior

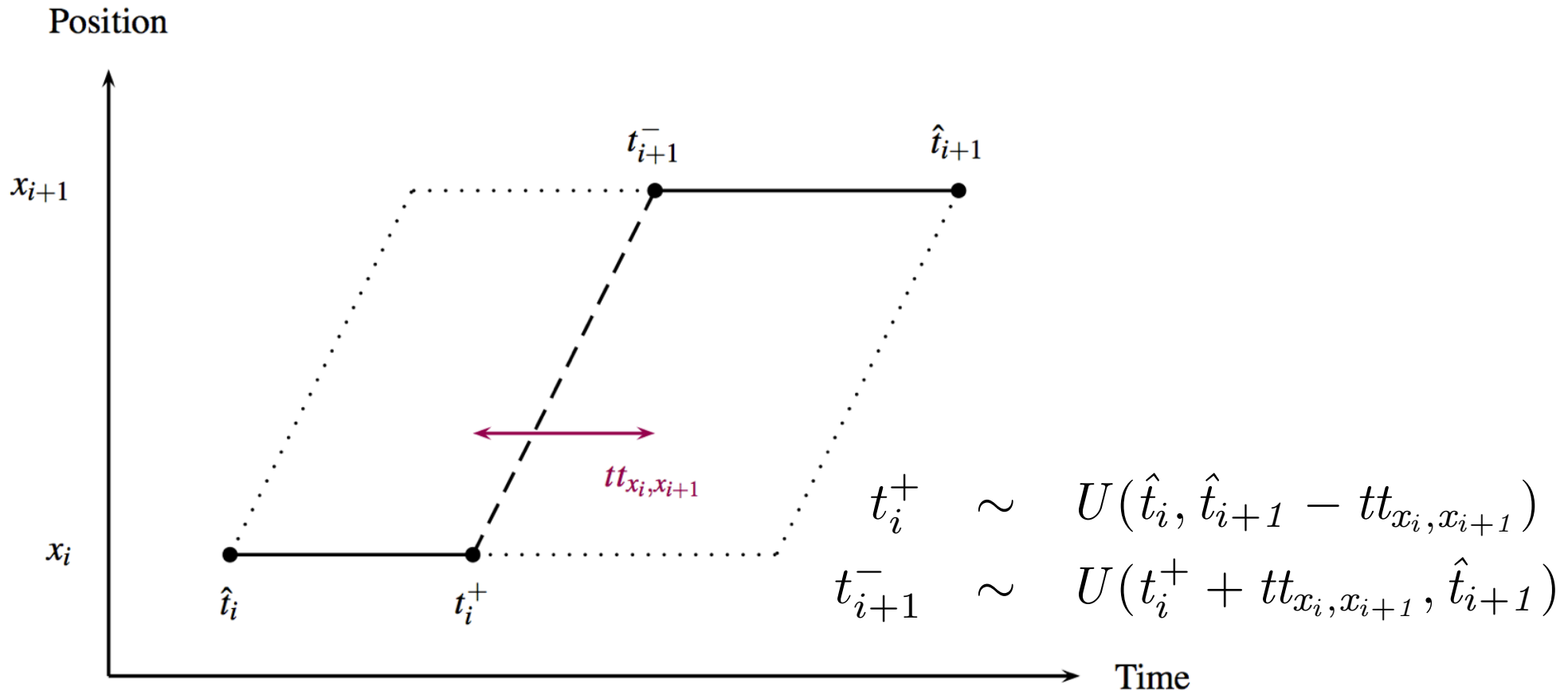
$$P(a_{1:m} | \hat{s}_{1:n}) \propto P(\hat{s}_{1:n} | a_{1:m}) \cdot P(a_{1:m})$$

Activity model

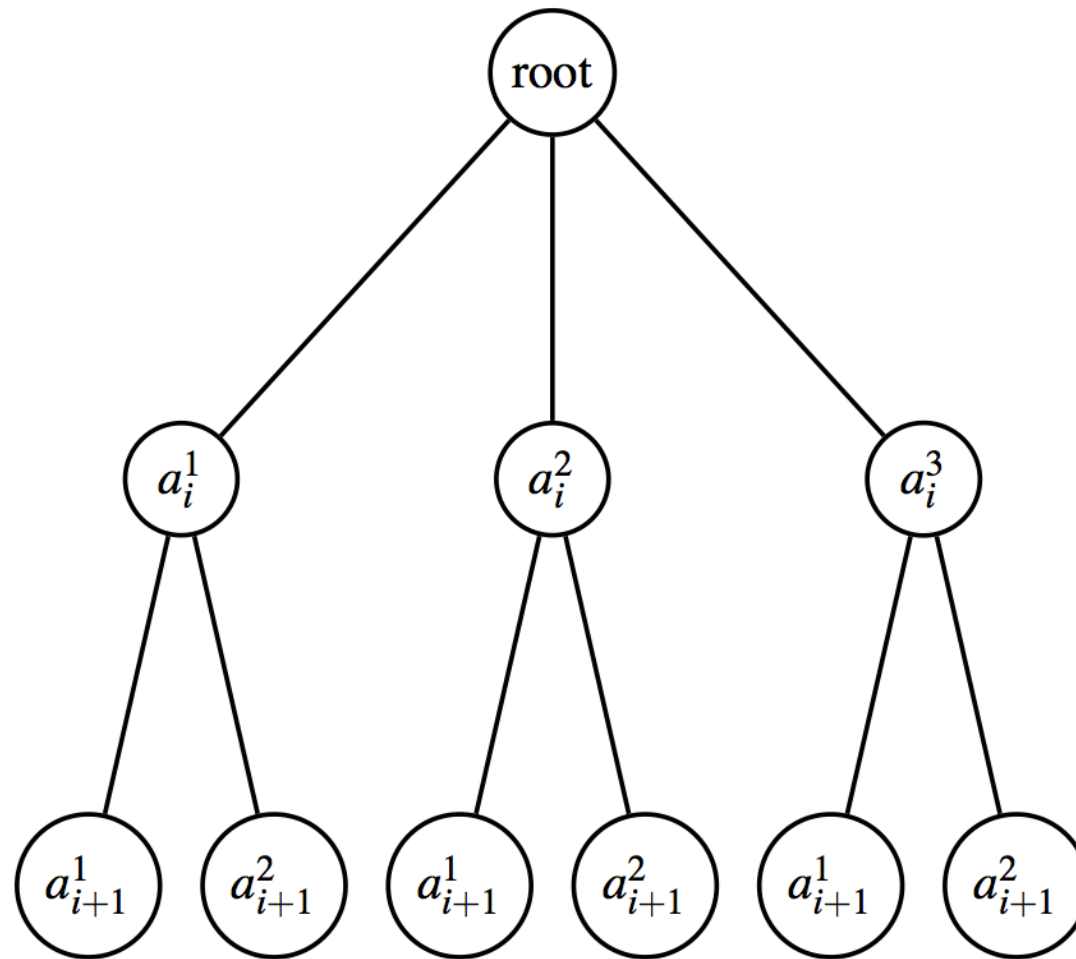
Generation of activity-episode sequences



Generation of activity-episode sequences



Generation of activity-episode sequences



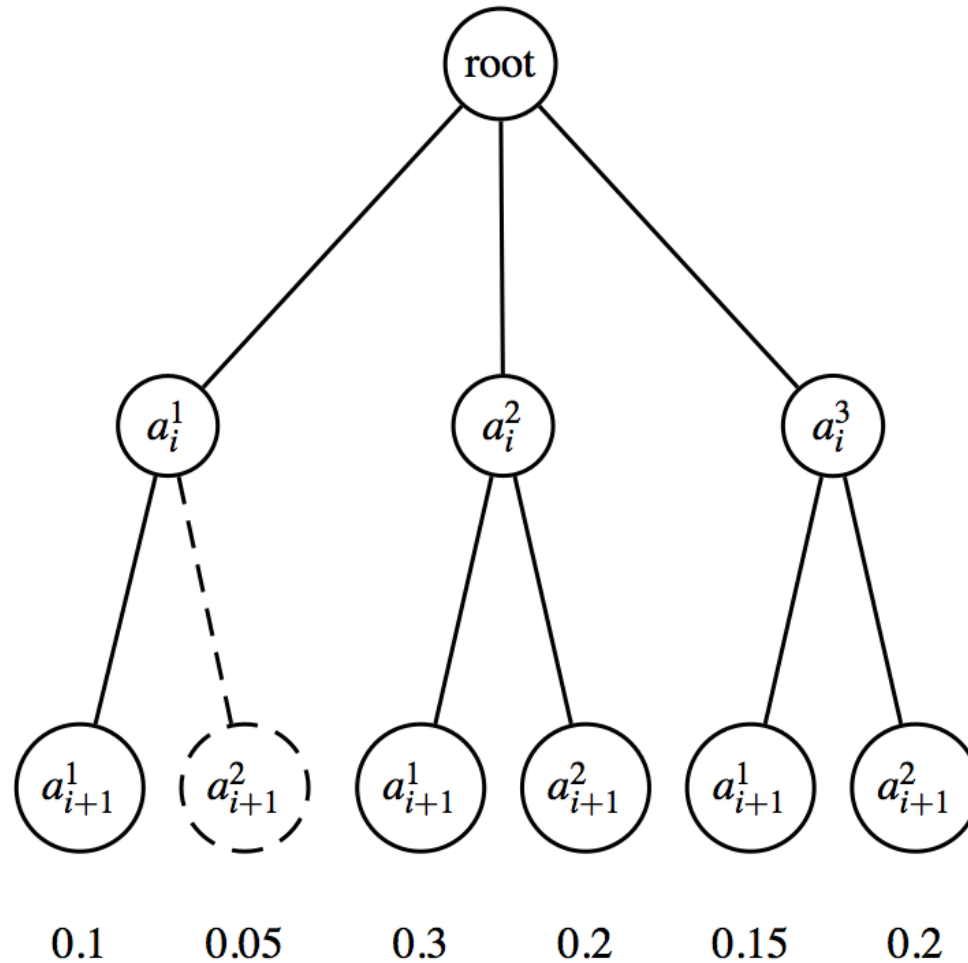
Intermediary signals

- Eliminate intermediary signal if

$$E(t^+) - E(t^-) < T_{min}$$

since we generate an activity episode at each signal.

Sequence elimination



A CASE STUDY ON EPFL CAMPUS



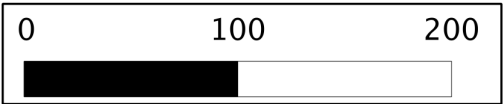
Legend

WiFi Data

◆

Pedestrian network

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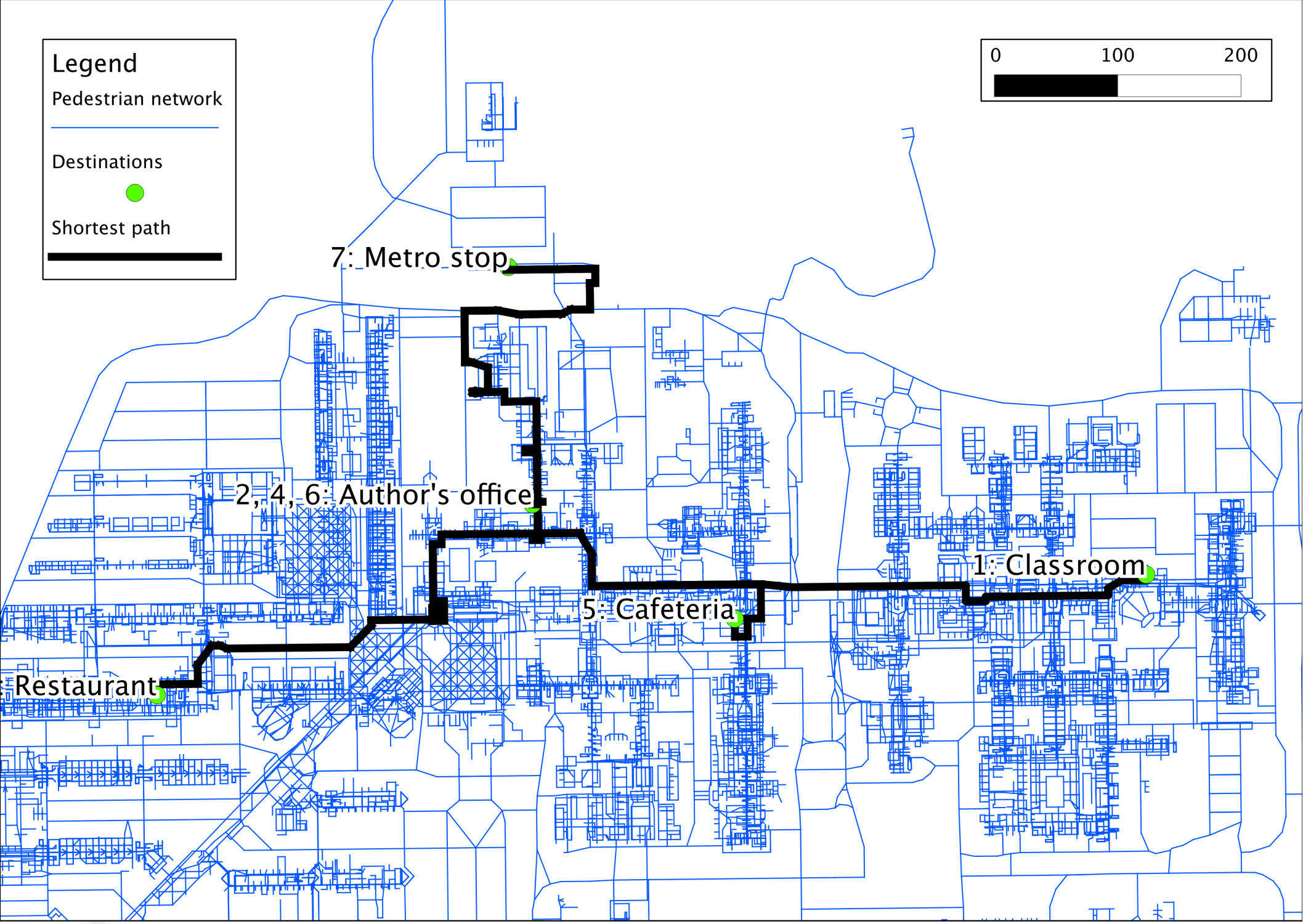
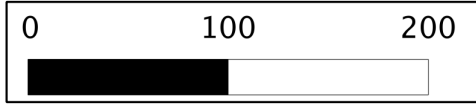
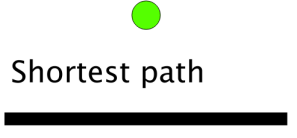


Legend

Pedestrian network

Destinations

Shortest path



7: Metro stop

2, 4, 6: Author's office

5: Cafeteria

1: Classroom

Restaurant

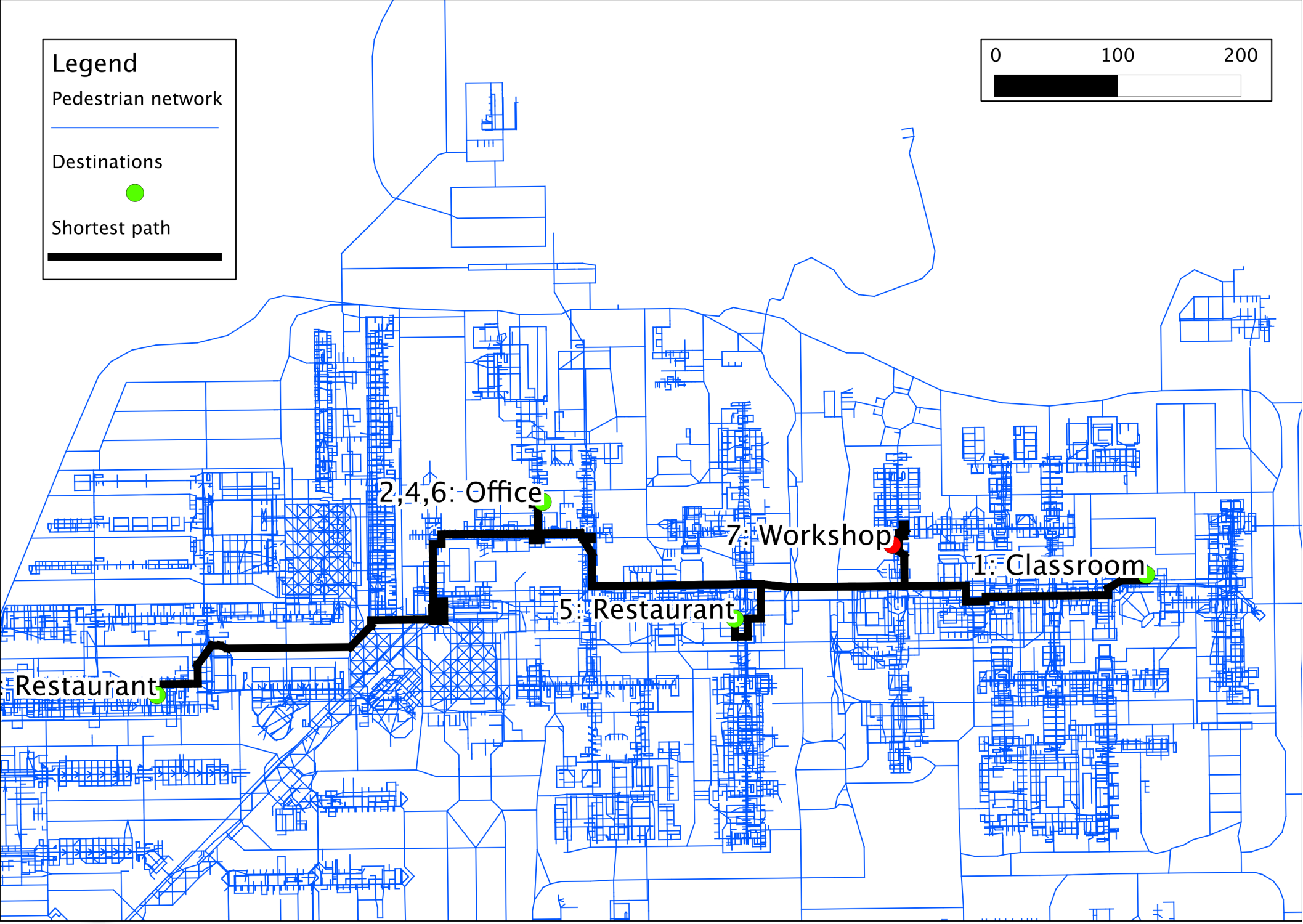
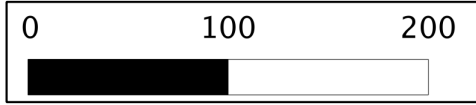
Legend

Pedestrian network

Destinations



Shortest path



Restaurant

2,4,6: Office

7: Workshop

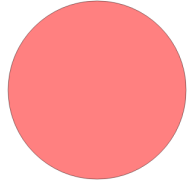
1: Classroom

5: Restaurant

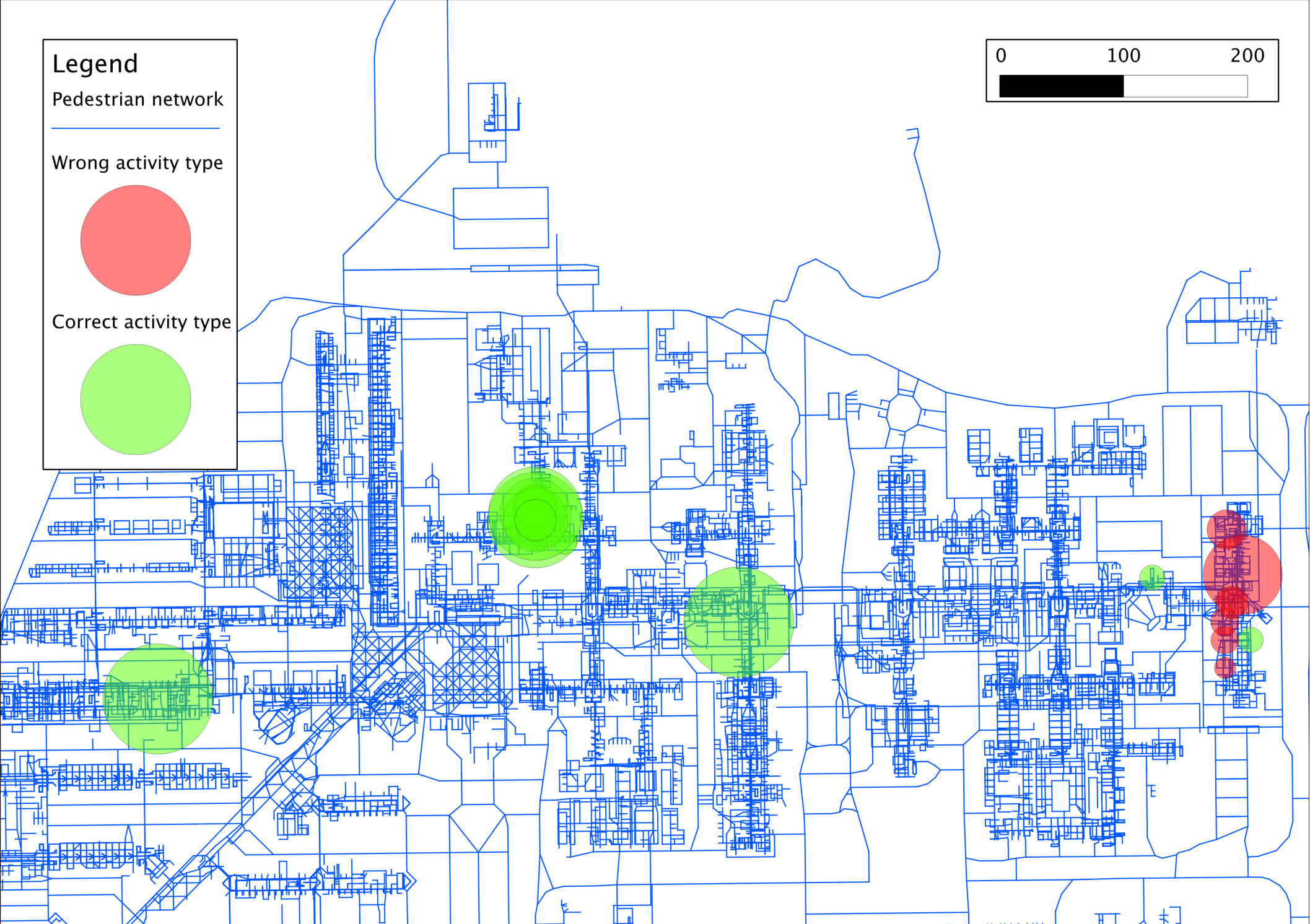
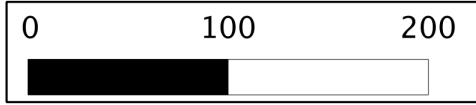
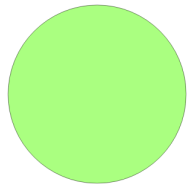
Legend

Pedestrian network

Wrong activity type



Correct activity type



SENSITIVITY ANALYSIS

Sensitivity analysis: prior

- Uniform PAM
 - # destinations / Start and end time: OK
 - Distance / category of destination: Not OK
- Aggregate PAM creates bias
- Disaggregate / individual PAM must be used

- PAM of visited destinations should be 3x bigger than of non-visited destinations

CONCLUSION



Conclusion

- Prior needed to **overcome low precision**
- **Localization data brings dynamics** in the model
- Pedestrian map gives:
 - Spatial information
 - Temporal information
- Our methodology is **merging** these different types of data
 - Explicitely showing the ambiguity of the signal
- Robust for **low density data**

FUTURE WORK



Future work

- Model of choice of activity sequence as a path in a decision network
 - Discretization of time
 - Including the ambiguity in the “chosen” path
 - Sampling path from PAM as sampling probabilities (Flötteröd and Bierlaire, 2013)
- Railway station case study
 - Shorter activity episodes

THANK YOU

