
A Bayesian Approach to Detect Pedestrian Destination-Sequences from WiFi Signatures

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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



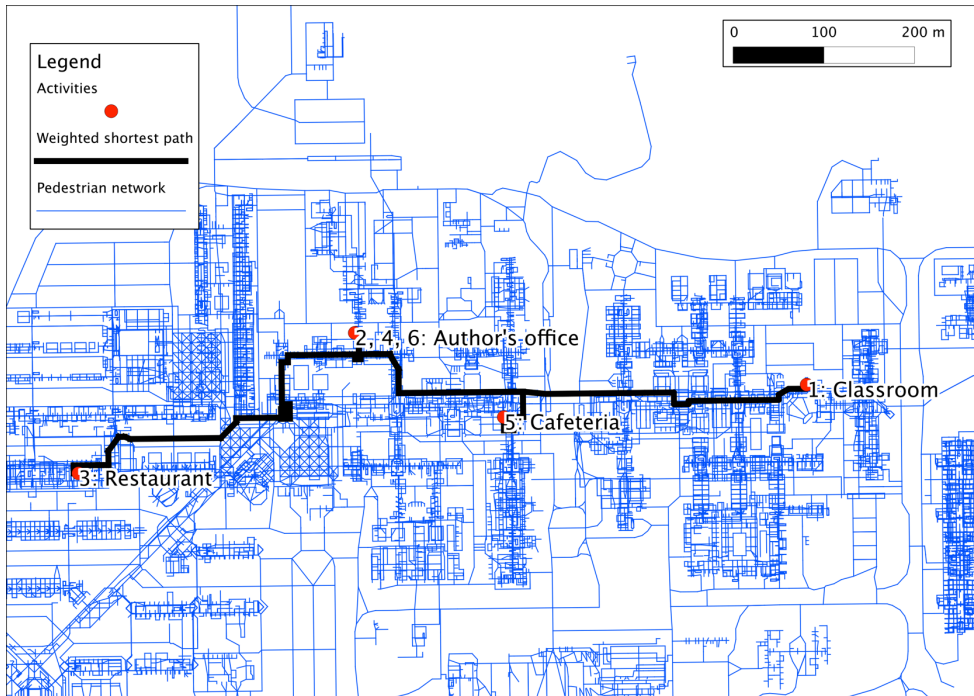
 = 2000 travelers/day

* Forecast by Swiss Railways for the maximum scenario

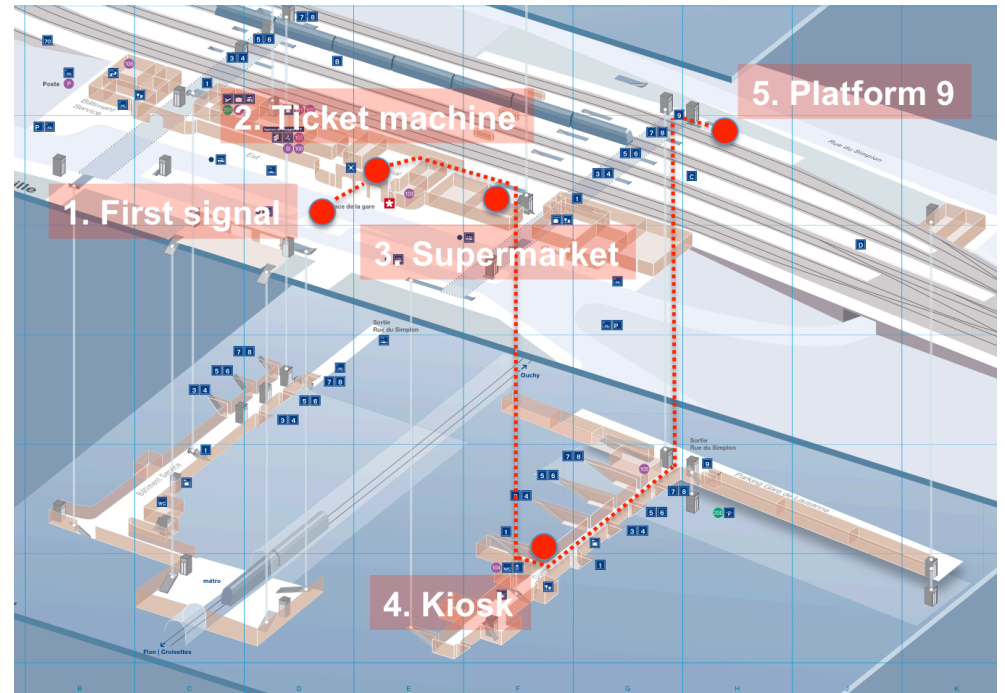


Understand pedestrian activities

What we are doing: Campus

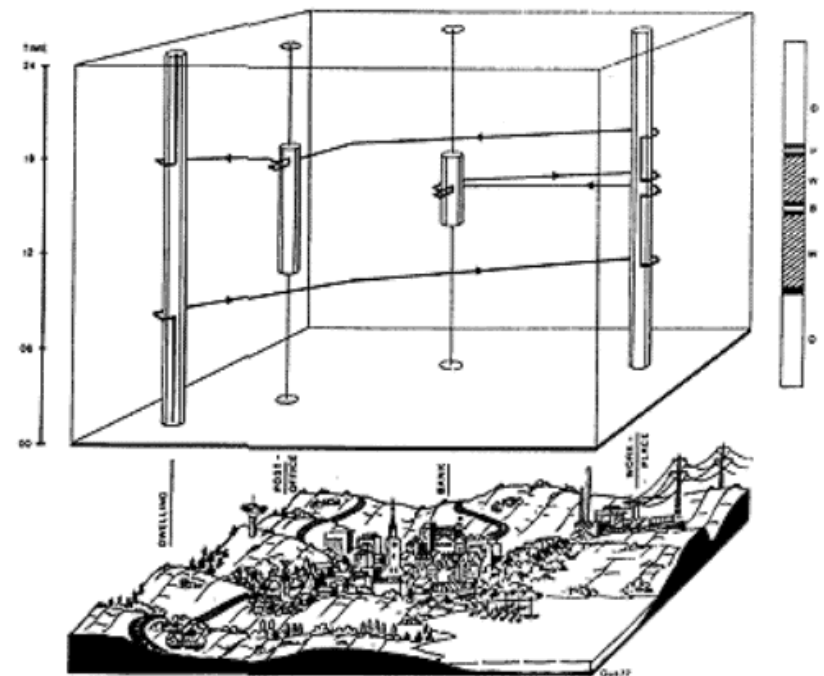


What we want to do: Station



Challenges

- Detect pedestrian destinations
- 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
 - Prior potential attractiveness

Data requirement: Localization

- Data from communication network infrastructure
 - GSM traces (Calabrese et al. 2011, Bekhor et al. 2011)
 - WiFi traces
- Data processing is needed (Rieser-Schüsseler 2012)
 - Detection of stop points
 - Activity purpose detection through land-use information and spatial matching

Data requirement: Pedestrian network

- We need maps
 - With **points of interests** (space)
 - With **shortest path** (time)
- More and more available in airports, malls, museums, campuses, hospitals
 - **Nokia**: 214 shopping malls in 2011, 4605 indoor maps in July 2012, 5100 in December 2012
 - **Microsoft**: 2700 indoor maps
 - **Google**: > 10'000 indoor maps
 - **Start-ups**: Wifarer, Meridian, Point Insider, ByteLight

Data requirement: Potential attractiveness

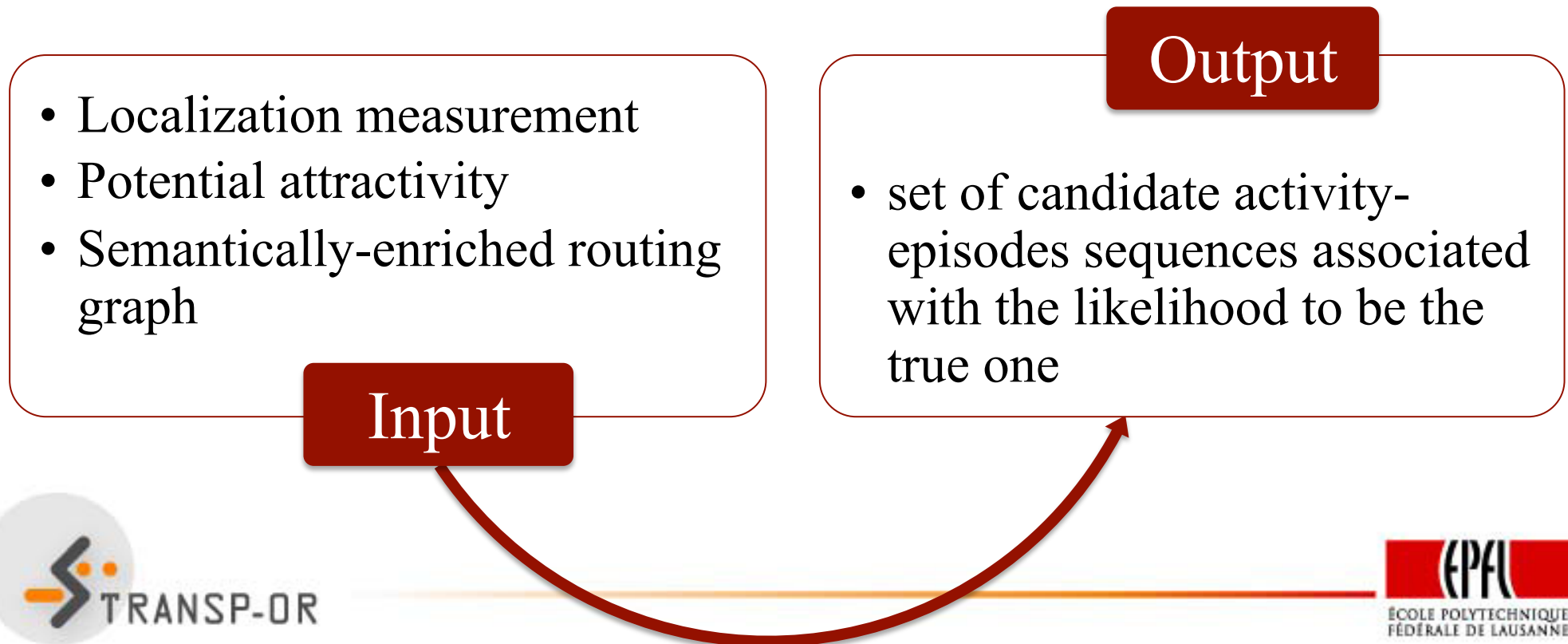
- **Potential attractiveness $C(x,t)$ depends on**
 - **destination x**
 - Classroom, platform, scene, ...
 - **time t**
 - class schedules, train schedules, opening hours, ...
- **Examples:**
 - 1500 passengers on platform 4 arriving at 16h04
 - 32 students in a classroom from 8h15 to 10h
 - 400 seats in a restaurant open from 11h to 14h30

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 model

Measurement error

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

Prior

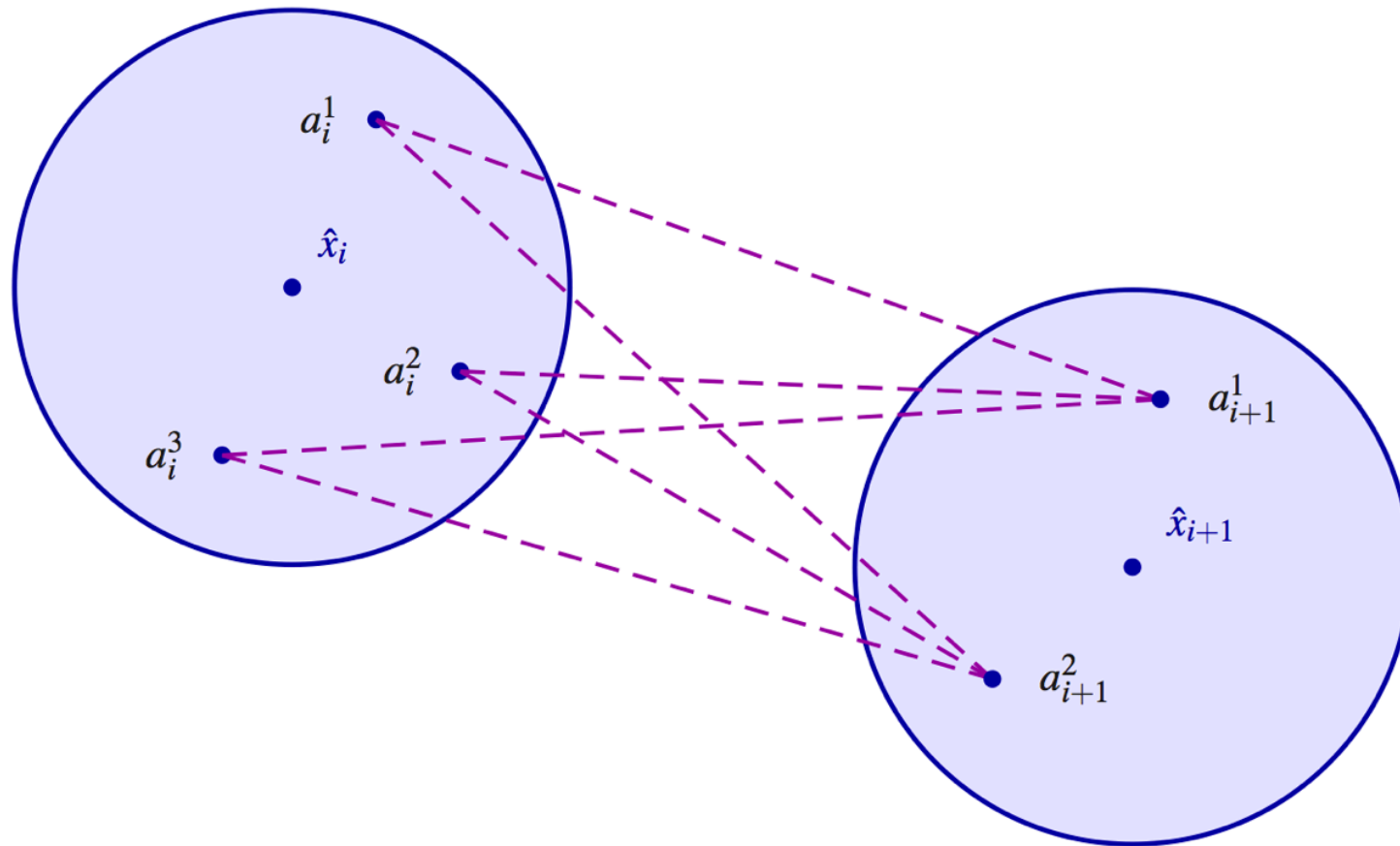
$$P(a_{1:m}) = \prod_{j=1}^m P(a_j) \quad (1)$$

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

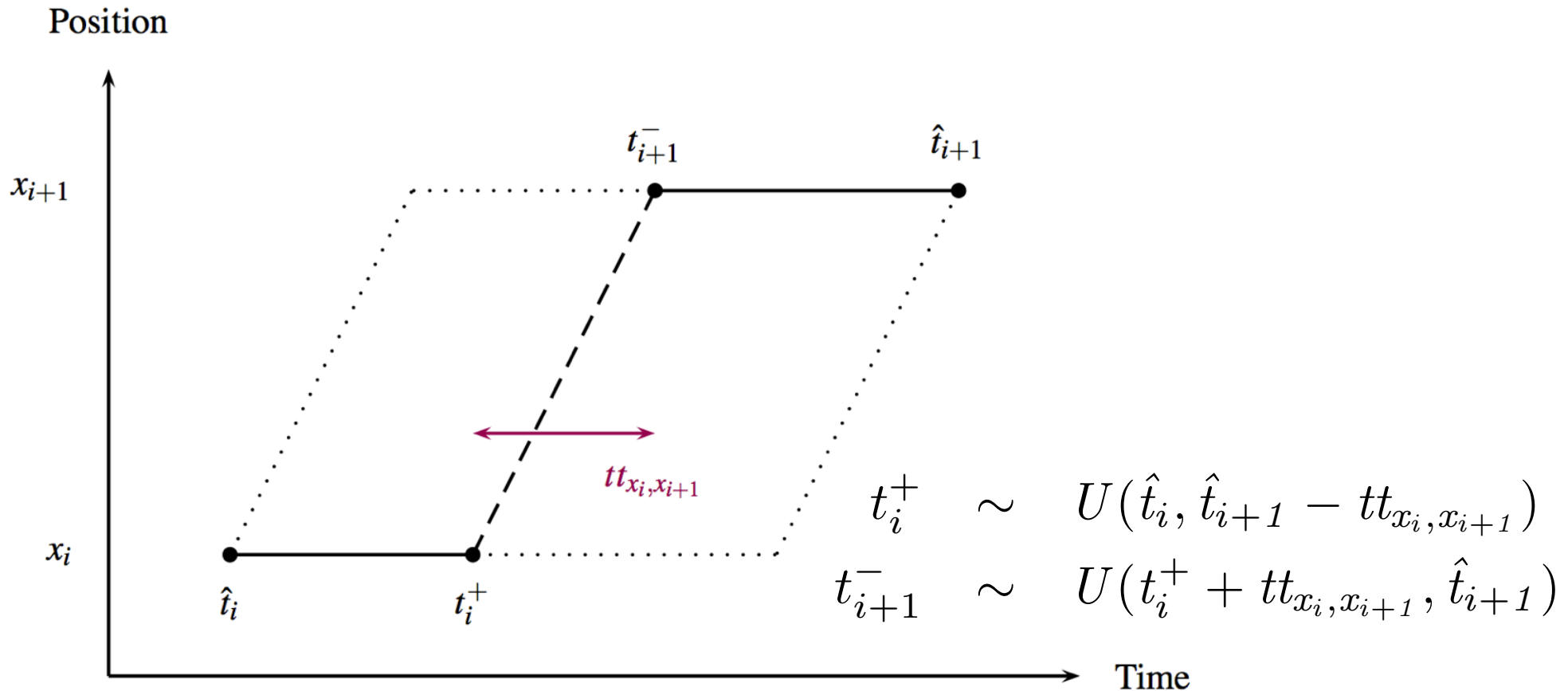
$$= \prod_{j=1}^m \frac{C_{x_j}(t_j^-, t_j^+)}{\sum_{x \in X} C_x(t_j^-, t_j^+)} \quad (3)$$

$$= \prod_{j=1}^m \int_{t_j^-}^{t_j^+} \frac{C_{x_j}(t_j)}{\sum_{x \in X} C_x(t_j)} dt \quad (4)$$

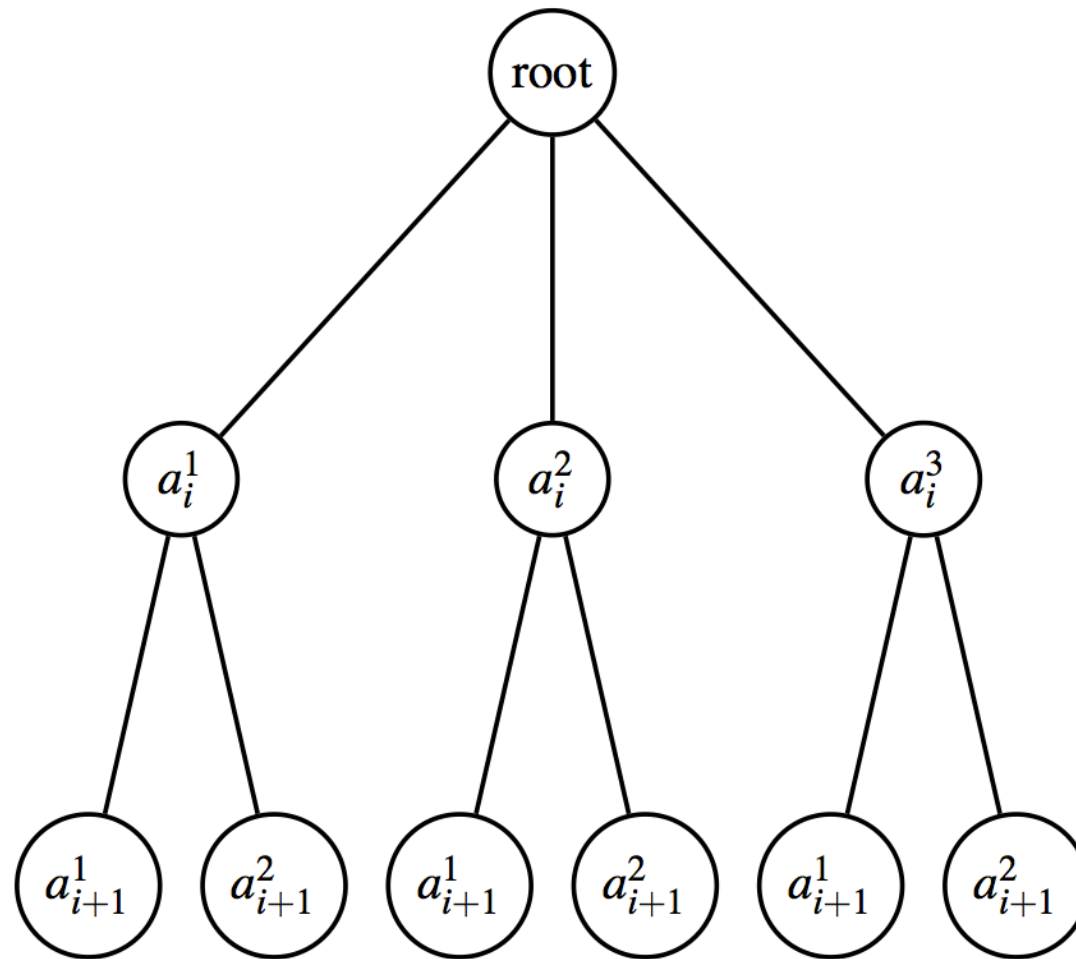
Generation of activity-episode sequences



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Generation of activity-episode sequences



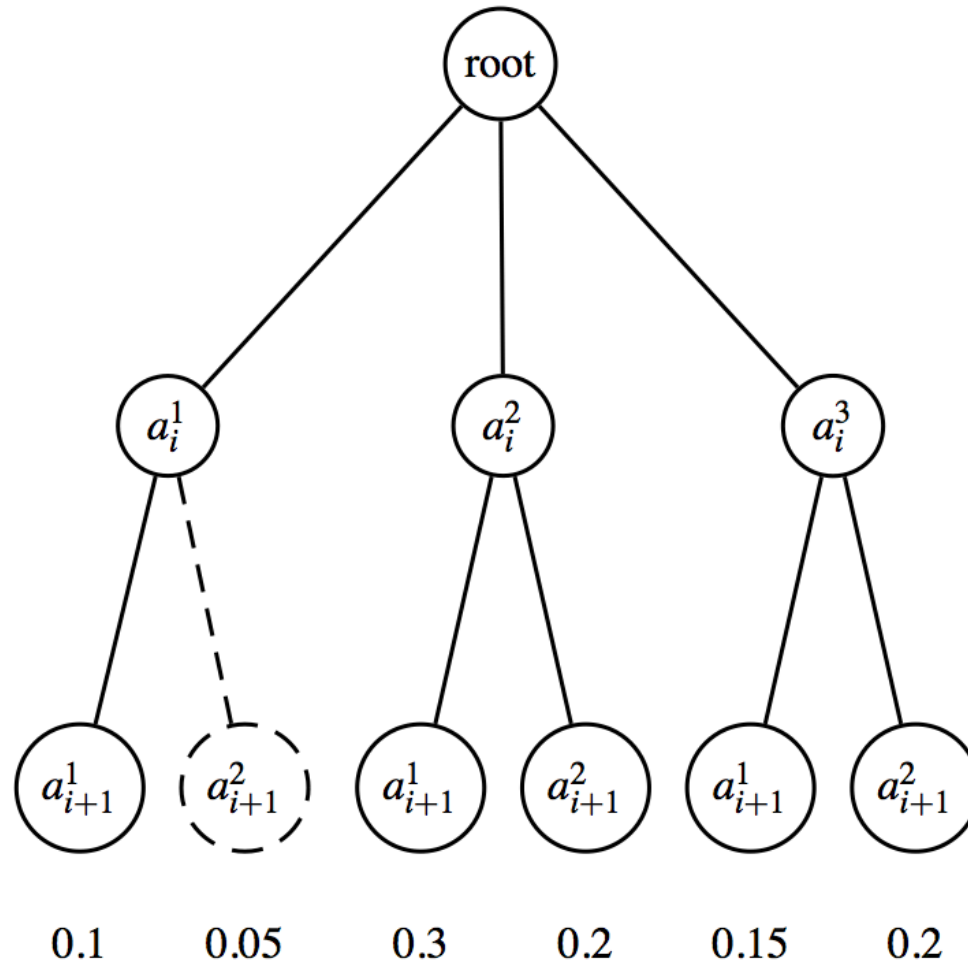
Intermediary signals

- 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



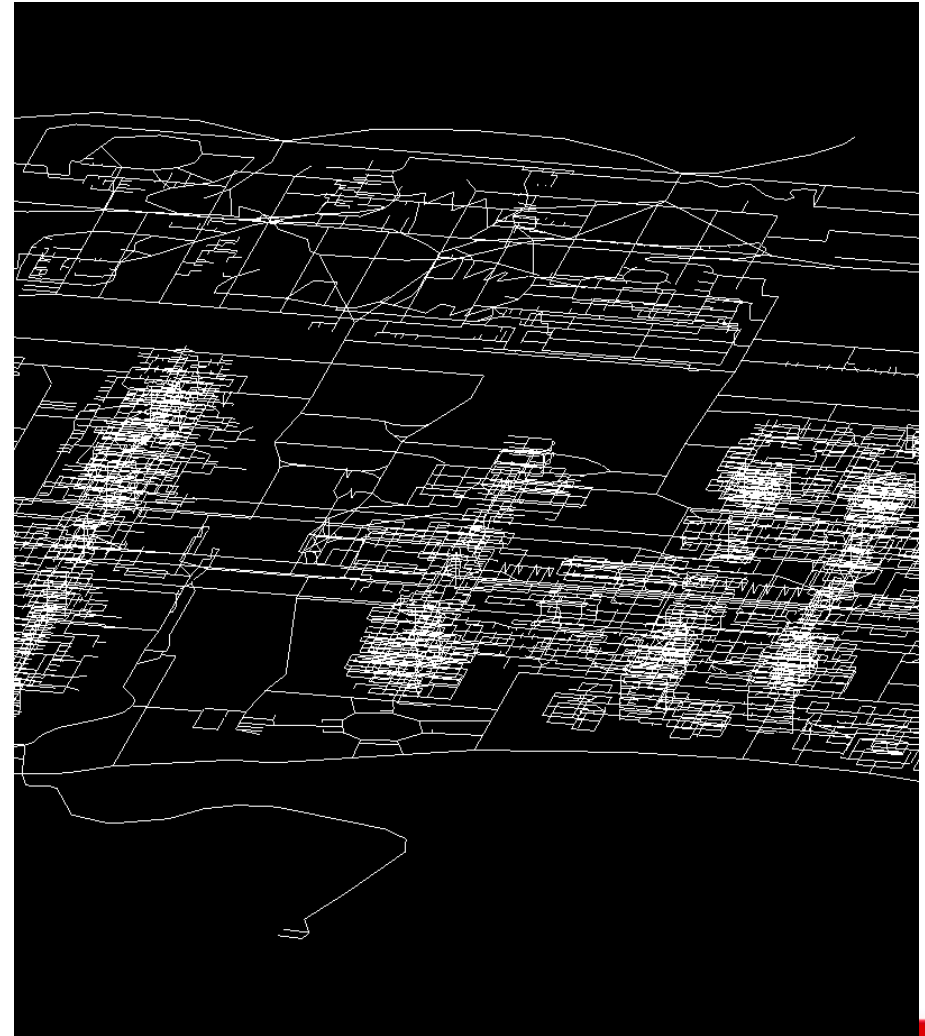
EPFL data: Localization

- 8 participants for 2 months with known ID
- Non-participants: 46 days, but only 10 with courses
 - 200 students in 6 different classes
 - 317 employees
 - 700 students from University of Lausanne
- For 151 CE students, 152'598 observations
- Precision: 191 meters



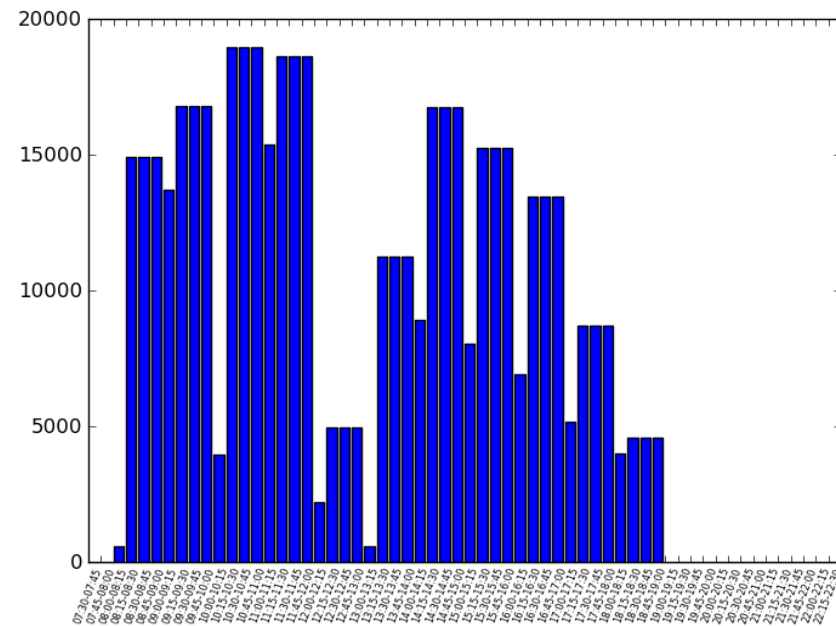
EPFL data: Pedestrian network

- Source: map.epfl.ch
- 56'655 edges
- 4 different levels of path
 - Major (« highway »)
 - Inter-building
 - Intra-building
 - Access to offices
- Shortest path
- All offices, restaurants, classrooms and other points of interest are coded: X



EPFL data: Potential attractivity $C(x,t)$

- Class schedules with
 - Number of students
 - Name of the classroom
- Number of employees per office
 - Name of the office
 - Sum of percent of work (e.g, 3 full times = 300%)
- Number of seats in restaurants
 - Localization
 - Opening hours
- Number of seats in library



Results

Model				Truth			Δx
<i>Arrival time</i>	<i>Departure time</i>	<i>Floor</i>	<i>Location</i>	<i>Time spent</i>	<i>Floor</i>	<i>Location</i>	<i>(in m.)</i>
8:33-8:33	10:38-10:38	1	Classroom	8.32am-10.30am	1	Classroom	0
10:40-10:40	11:51-11:51	3	Office	Until 11.47am	3	Author's office	7
11:54-11:54	12:47-12:53	1	Restaurant	From 11.55 am	1	Restaurant	0
12:51-12:58	13:03-13:44	3	Office	Around 1pm	3	Author's office	7
13:06-13:47	13:53-14:02	2	Cafeteria	Around 2pm	2	Cafeteria	0
13:55-14:04	19:45-19:45	3	Office	Until around 7.45pm	3	Author's office	7
19:47-19:47	19:52-19:52	3	Workshop	-	3	Metro stop	366

SENSITIVITY ANALYSIS

Sensitivity analysis: prior

- With flat prior
 - # destinations / Start and end time: OK
 - Distance / category of destination: Not OK
- Attractivity of visited destinations should be 3x bigger than of non-visited destinations
- Global capacity creates bias

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

- Robust for **low density data**

FUTURE WORK



Future work

- Binary choice model for attendance of scheduled activity
- Actual start and end times of scheduled activity-episodes
- Analysis of the access to the facility
 - First and last destination of the sequence
 - Arrival times, departure times
- Based on class attendance and on available time budget: activity scheduling

THANK YOU



References

- Bekhor, S., Cohen, Y. and Solomon, C. (2011), Evaluating long-distance travel patterns in Israel by tracking cellular phone positions. *J. Adv. Transp.*
doi: 10.1002/atr.170
- Calabrese, F.; Di Lorenzo, G.; Liang Liu; Ratti, C., "Estimating Origin-Destination Flows Using Mobile Phone Location Data," *Pervasive Computing, IEEE* , vol.10, no.4, pp.36,44, April 2011
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- Rieser-Schüssler, N. (2012). Capitalising Modern Data Sources for Observing and Modelling Transport Behaviour, *Transportation Letters: the International Journal of Transportation Research* (2): 115–128.
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