Modelling Daily Mobility Patterns in the Era of Big Data

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Overview of main research directions

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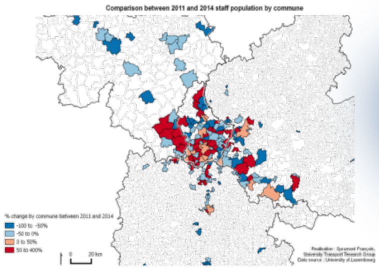

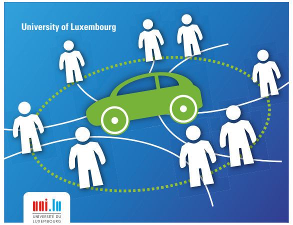

Travel to campus with
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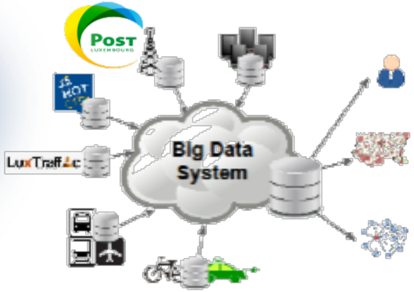

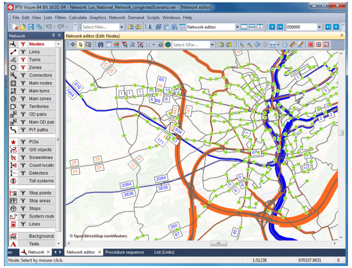

Data Scale

aggregate

Mobility patterns

Big Data

Transport planning & mobility management

Network modelling & design

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Modelling scale

Micro (Movements)

Macro (Flows)

Activity-travel behavior analysis

Optimal scheduling & complex systems control

Mobile sensor networks

ITS for Public Transport

Individual

The MobiLab Transport Research Group

- Head: Ass. Prof. dr. Ing. Francesco Viti
  - MSc – Univ. of Naples 'Federico II', Civil Engineering degree; PhD – TU Delft, transport planning
  - Post-doc – TU Delft (2007-2008) & Ku Leuven (2007 – 2012)
- Post docs
  - **Marco Rinaldi**, Computer scientist, automation and control
  - **François Sprumont**, Spatial planner, mobility management (0.4)
  - **Open position** (at partners Luxembourg Institute of Science and Technology)
- 6 PhD students
  - **Guido Cantelmo**, Civil engineer, network modelling
  - **Bogdan Toader**, Computer scientist, data science
  - **Giorgos Laskaris**, Transport and Geoinformation engineer, PT control
  - **Giulio Giorgione**, Civil engineer, smart mobility & agent-based simulation
  - **Xavier Mazur**, Operations Research, complex network analysis
  - **Ariane Scheffer**, Civil Engineer, Transport modelling

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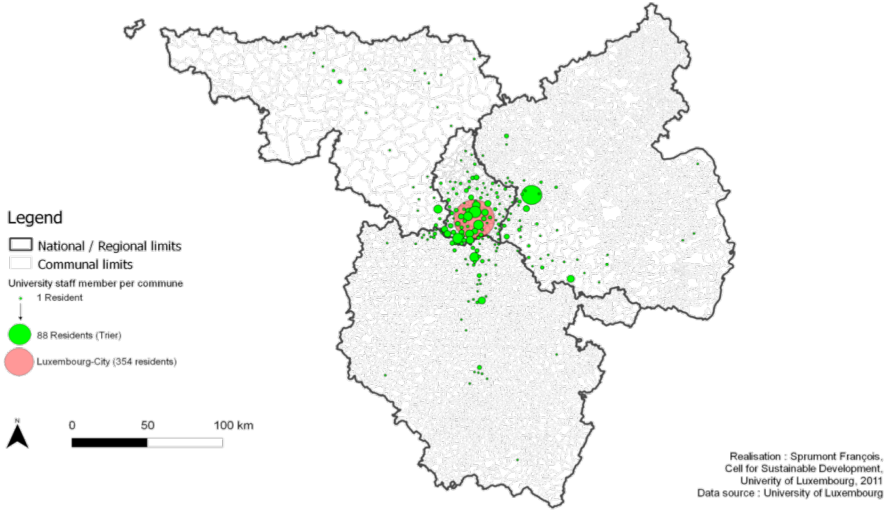
Modelling Daily Demand Flows

And some ingredients
for reliable estimation

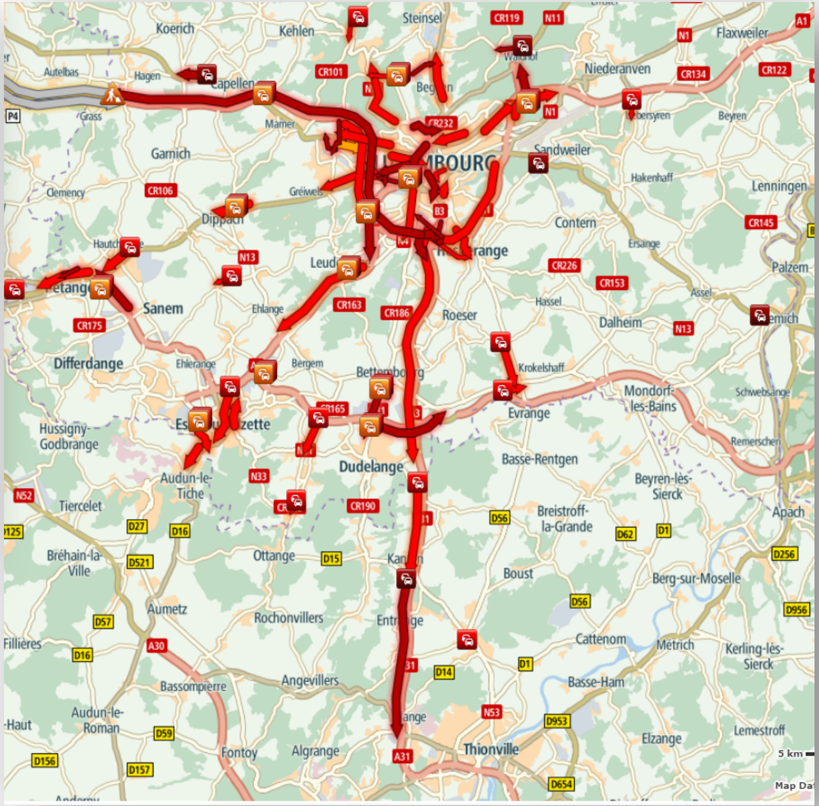
Mobility in Luxembourg

- Luxembourg strong monocentric country, financial and EU-institutional capital
- 76% car users (89% from outside); #1 car ownership rate in EU
- High car-dependency, heavy through traffic flows, truck tourism,…
- 360 000 daily commuters; 180 000 cross-border workers;

Communes of residence of the University staff living in the Greater Region



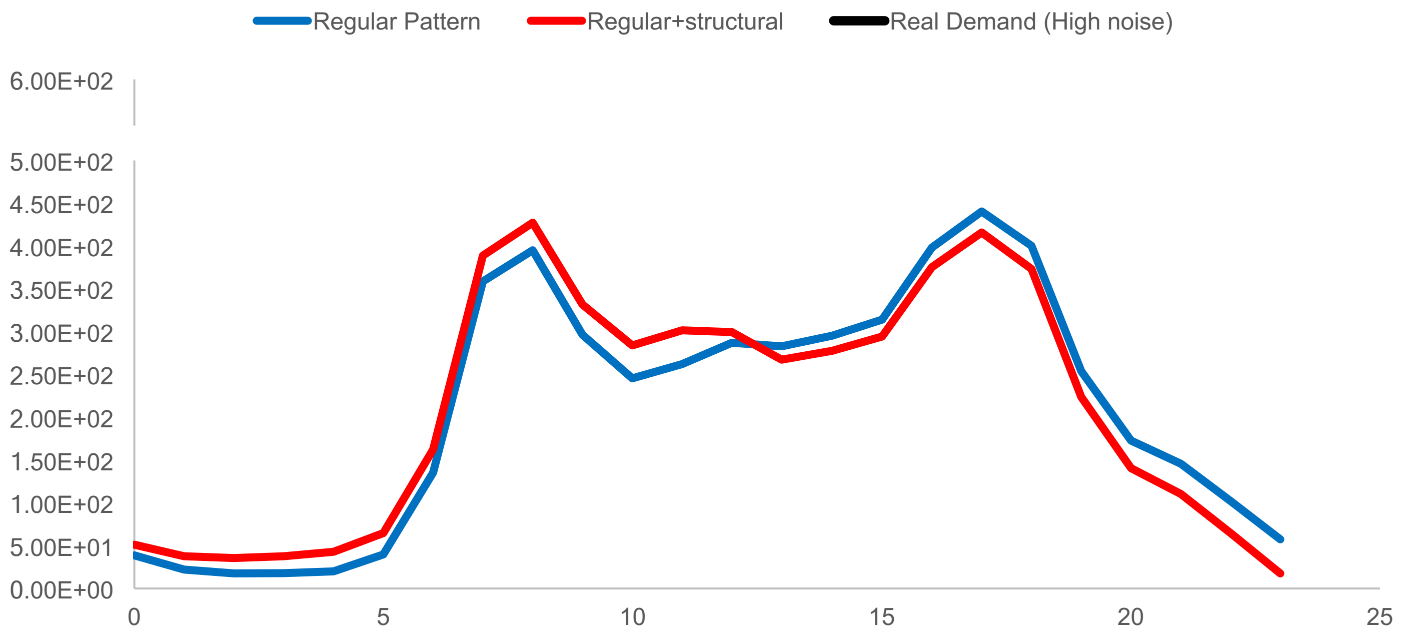
The complexity of daily mobility patterns



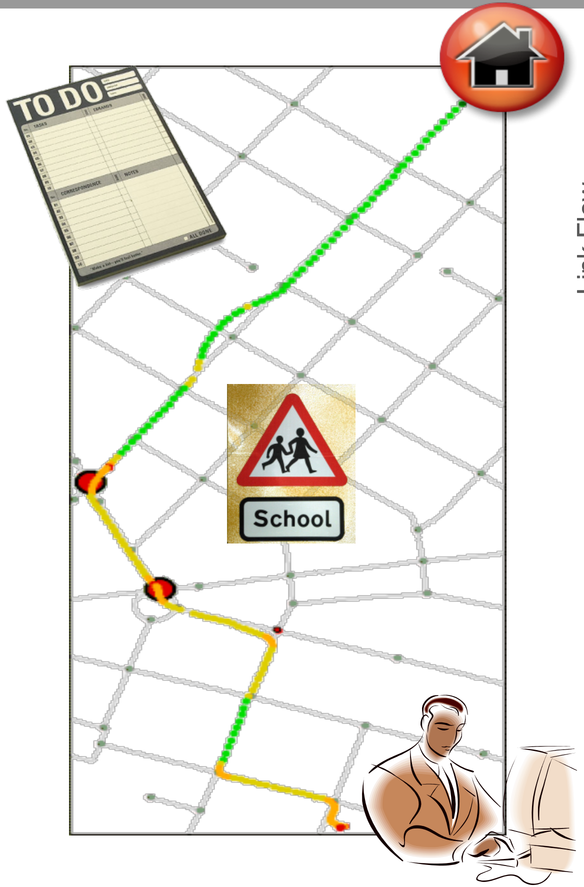
H W H	19%
H W A H	14%
H W H A H	9%
H W A A H	5%
H A W H	5%

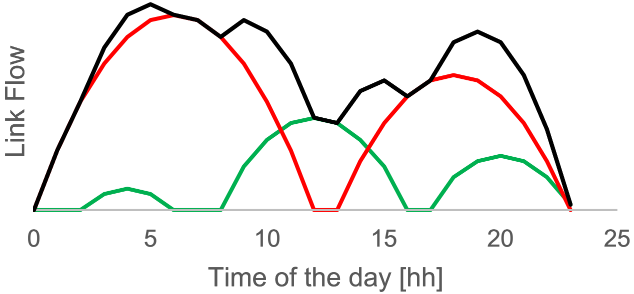
Distinguishing regular daily demand patterns

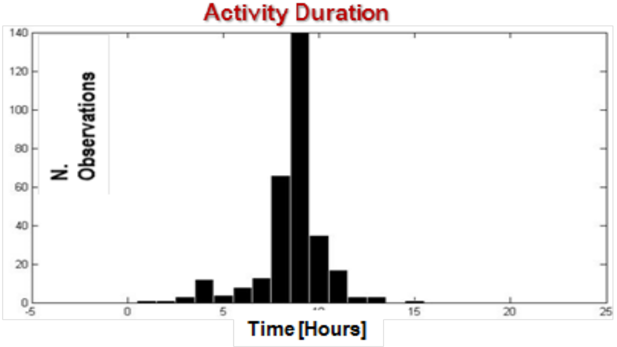
True Demand = regular pattern + structural deviations + random fluctuations

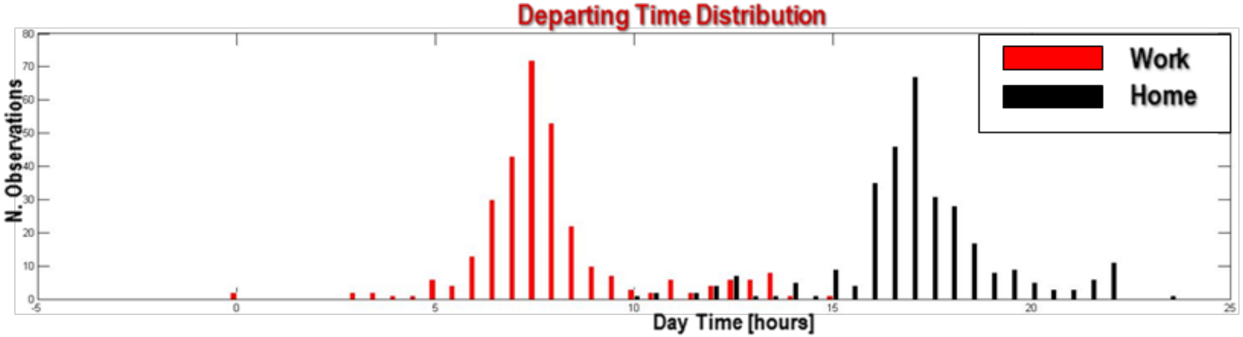


The complexity of daily mobility patterns



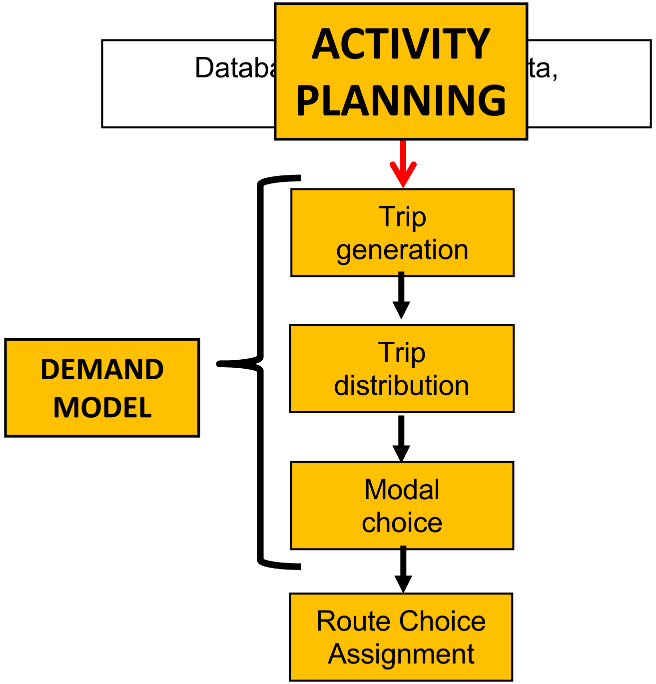






The traditional transport modelling approach

- The 'traditional' 4-stage model
  - Socio-demographic data
  - Travel surveys
  - Trip-based, busiest peak hour
  - Generally not suited for dynamic demand modeling
- Activity-based models
  - Schedule-based
  - Able to capture complex daily activity chains
  - Hard to calibrate and to get suitable data
  - Difficult to get consistent aggregated demand flows
  - Currently not much used for estimating daily flows



Traffic models, data collection and estimation methods

Infrastructure Planning

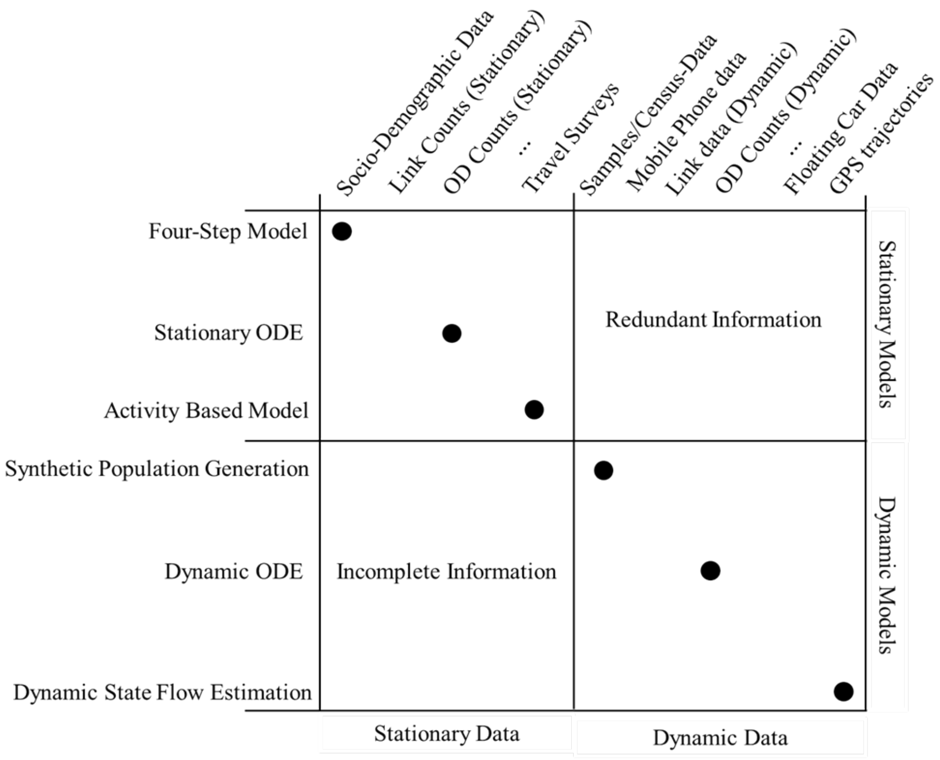
- Travel demand forecasting (static, quasi-static)
  - 4-step models, activity-based models
  - OD matrix correction / adjustments from traffic data

Dynamic Traffic Management

- Dynamic demand estimation (dynamic, offline)
  - Quasi-dynamic / sequential / simultaneous
  - Simulation DTA-based

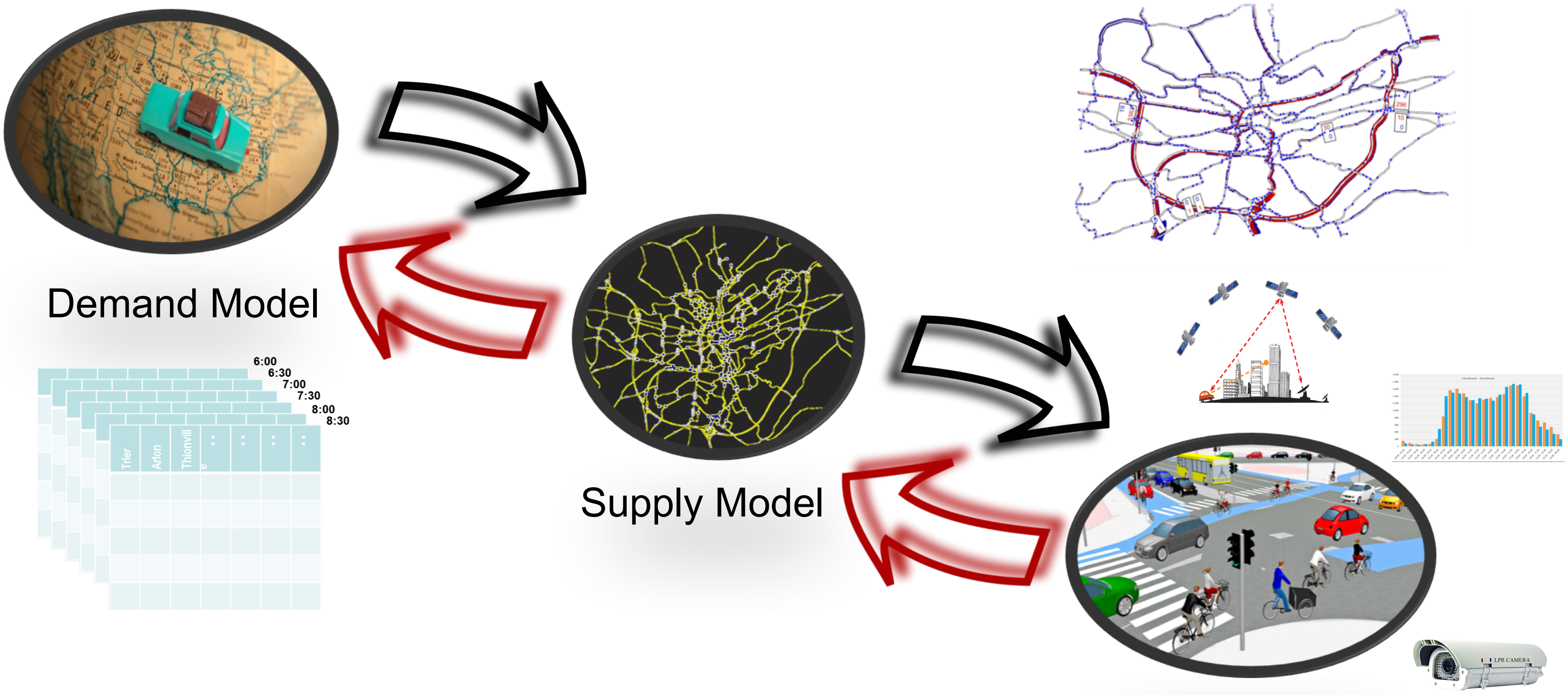
Real-time information & management

- Dynamic state flow estimation (dynamic, online)
  - Data-driven
  - Model-driven



Acknowledgment: Guido Cantelmo (UL)

The current state of the practice for calibrating transportation models



General bi-level dynamic demand estimation problem framework

Goal: find most likely demand and supply characteristics that reproduce the data

$$\mathbf{x} = \arg\min_{x} \left[\underbrace{\sum_t \sum_j f_1(x_j, \hat{x}_j)}_{\text{Distance btw estimated and prior matrix}} + \underbrace{\sum_t \sum_i f_2(y_i, \hat{y}_i)}_{\text{Distance btw simulated and observed traffic states}} \right]$$

x = demand flows
y = traffic flows

$$\text{s.t.} \quad y_i = \sum_{j \in J_i} A x_j = \sum_{j \in J_i} B(x) P(x) x_j$$

Traffic propagation functions (DNL)

Travel behavior functions (DTA)

- Some (well-known) issues
  - Complex dynamics caused by travel behavior
  - Traffic models (DNL/DTA) course representation of real traffic propagation
  - Highly combinatorial & non-linear problem

The under-determinedness problem

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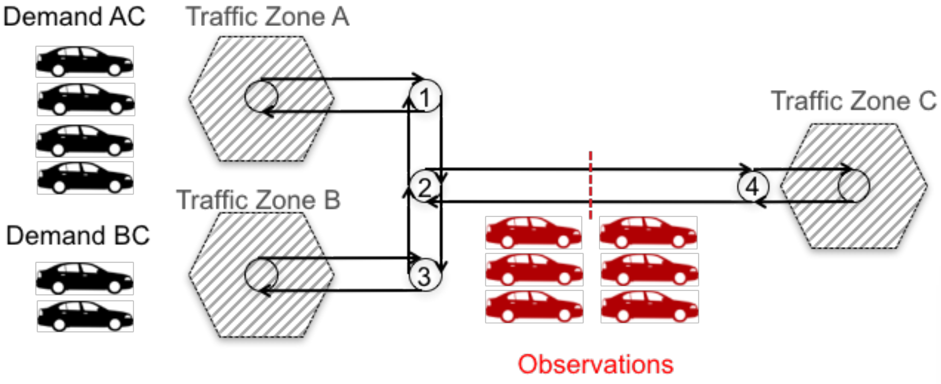
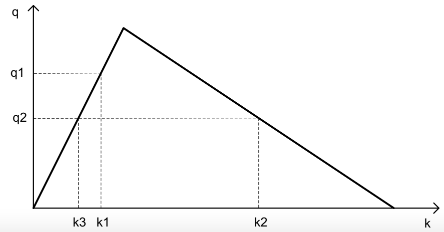
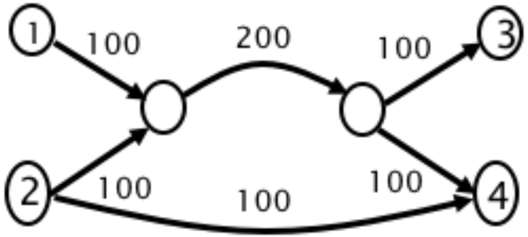
Spatial under-determinedness



Non-linear mapping link-OD flows



Non-unique link-path-OD relations



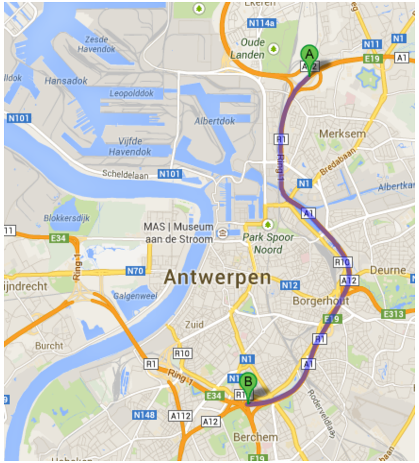
O\D	3	4
1	0	100
2	100	100

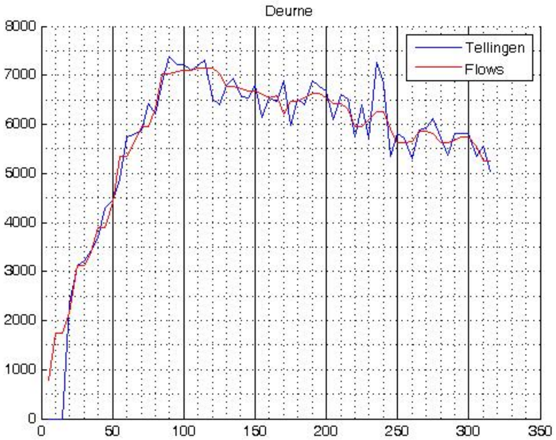
O\D	3	4
1	50	50
2	50	150

A simple example: Antwerp network

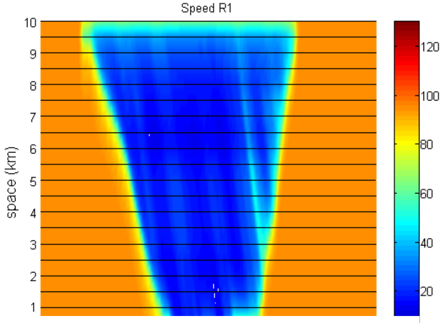
- Few route choice options
- Only traffic counts used for calibration
- Wrong structure of the demand matrix

- Spoiler: Better data and better models will solve the issue

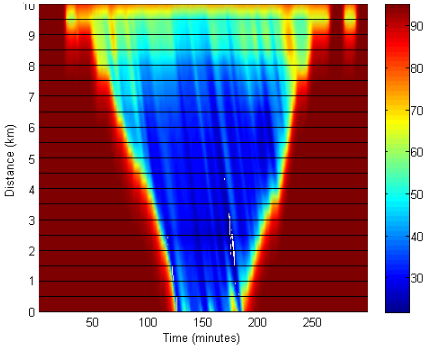




Measured speeds



Estimated speeds

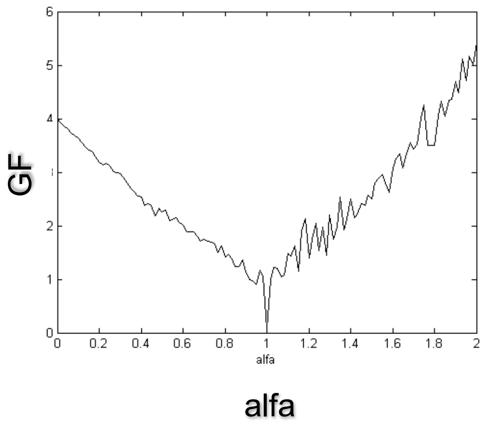


Acknowledgments: Rodric Frederix Chris Tampere (KU Leuven)

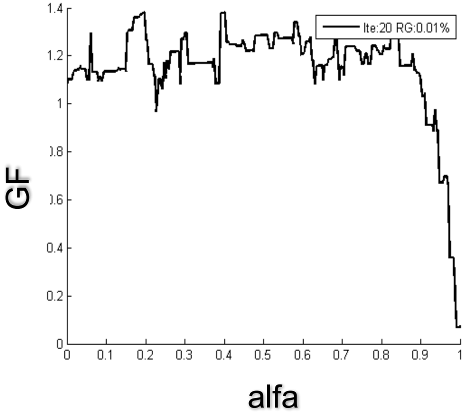
A bit more complex example

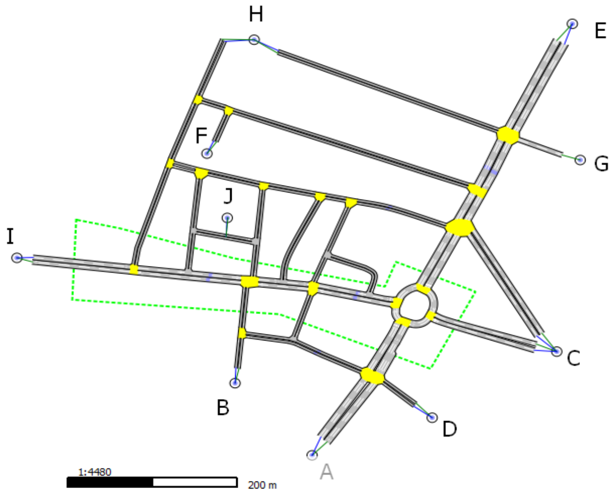
- Goal function unavoidably non-linear
  - Different heuristics to escape from local optima exist
  - Large part of the issue due to the structure of the OD matrix
  - Solution: two-step approach

Incremental Demand



Convex Combination





Some ingredients for reliable dynamic demand estimation

1. **Demand information**
    1. Mobility data
    2. Travel Demand models
2. **Data quality**
    1. Sensor locations
    2. Different data types
3. **Dynamic traffic flow models**
    1. Simulation of traffic flow propagation
    2. Reproduction of congestion dynamics
4. **Travel behavior models**
    1. Travel choice models
    2. Traffic assignment and equilibrium
5. **Optimisation algorithms**
    1. Structure of the estimator
    2. Gradient vs. gradient-free methods

Reduce solution search space and information reliability

Reduce the mismatch between model and reality

Helps for orientating in the solution space in the right direction

The era of Big Data

And how it can help
demand modelling


2005
Luca Bruno / AP

NBC/

The era of Big (mobility) Data

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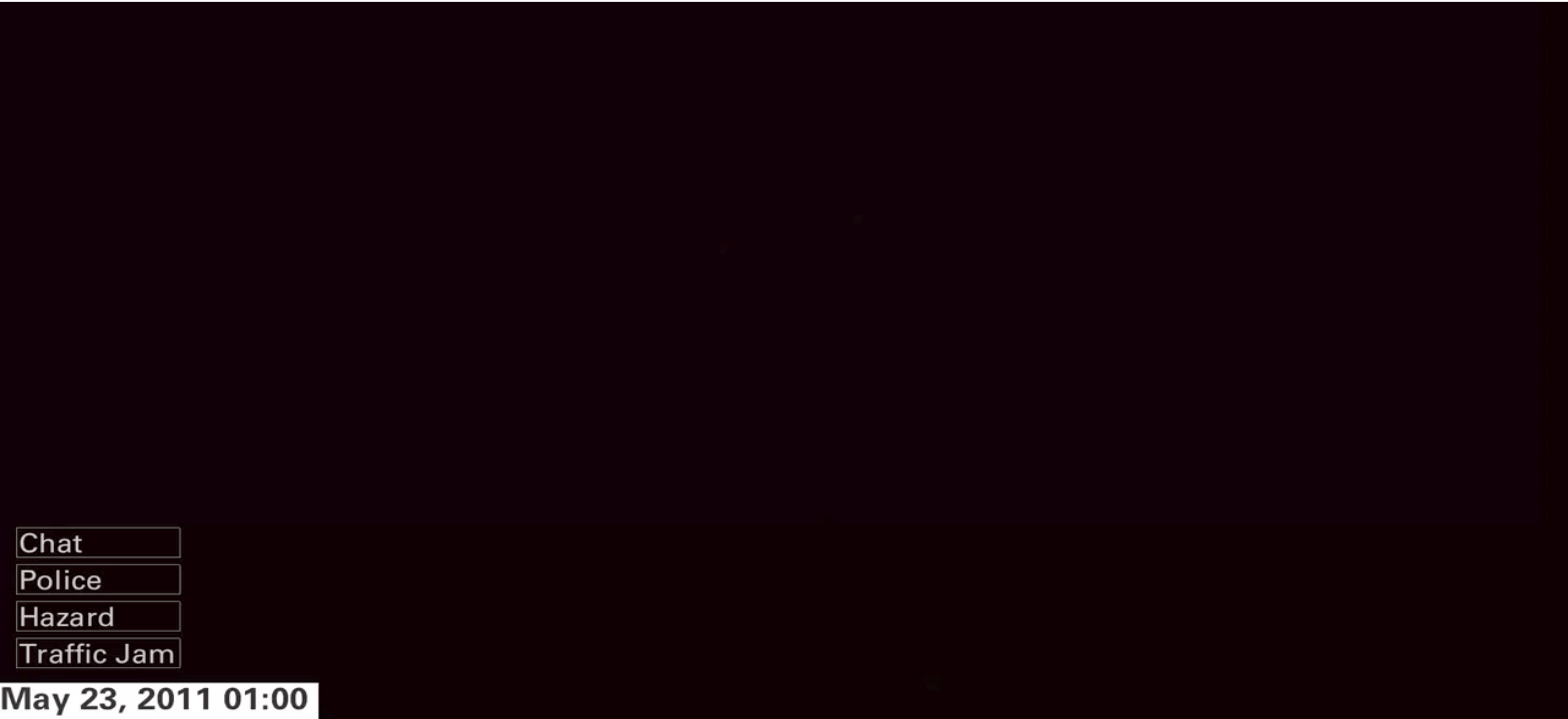
Big Data fireworks from Waze users



Using mobile phone data for daily demand production and spatial-temporal distribution

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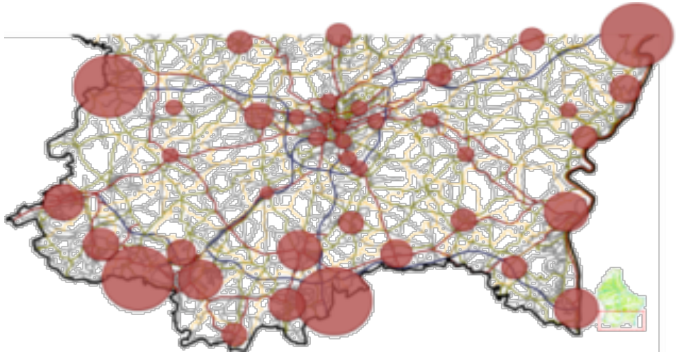
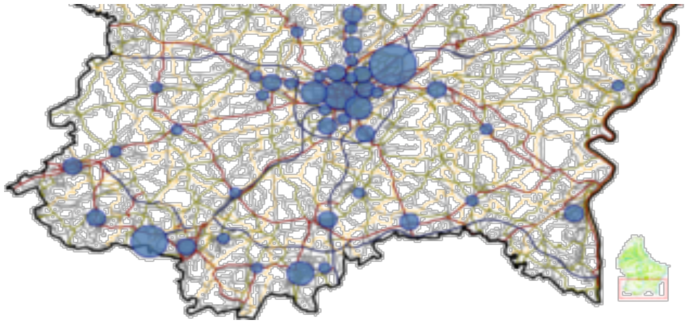
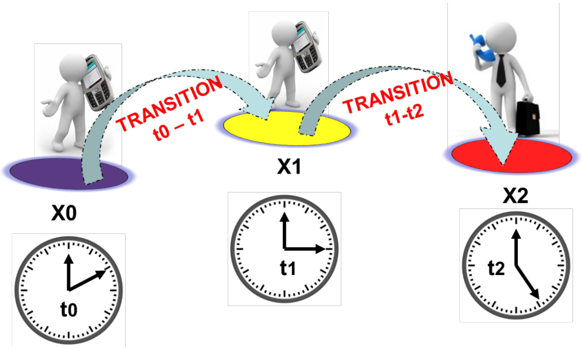
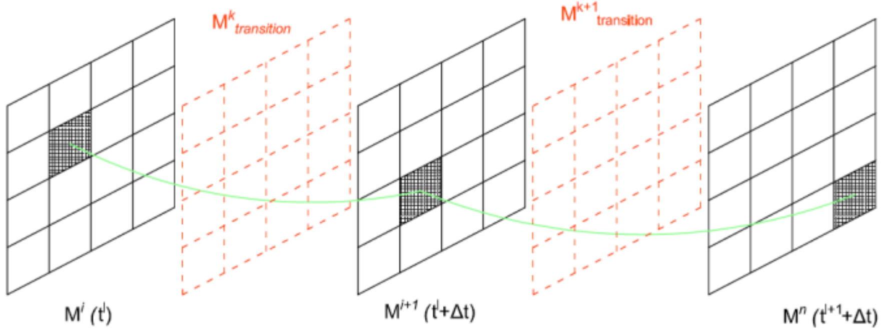


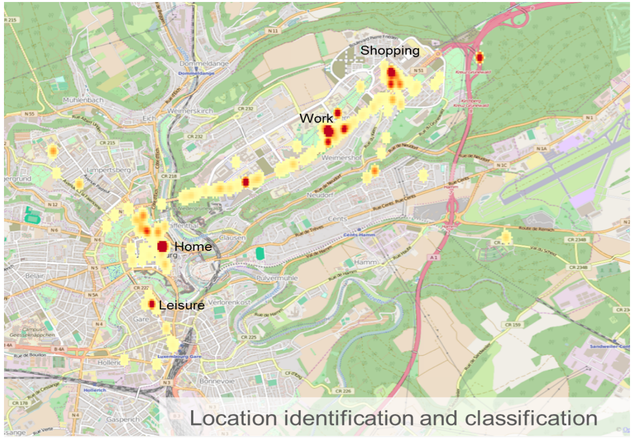


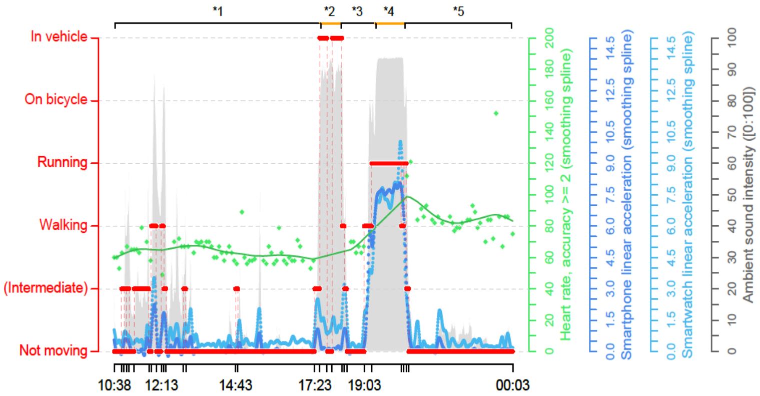




Acknowledgments: Simone Di Donna & Guido Cantelmo (UL)

Using smartphone (and smartwatch) data for capturing activity patterns and modes





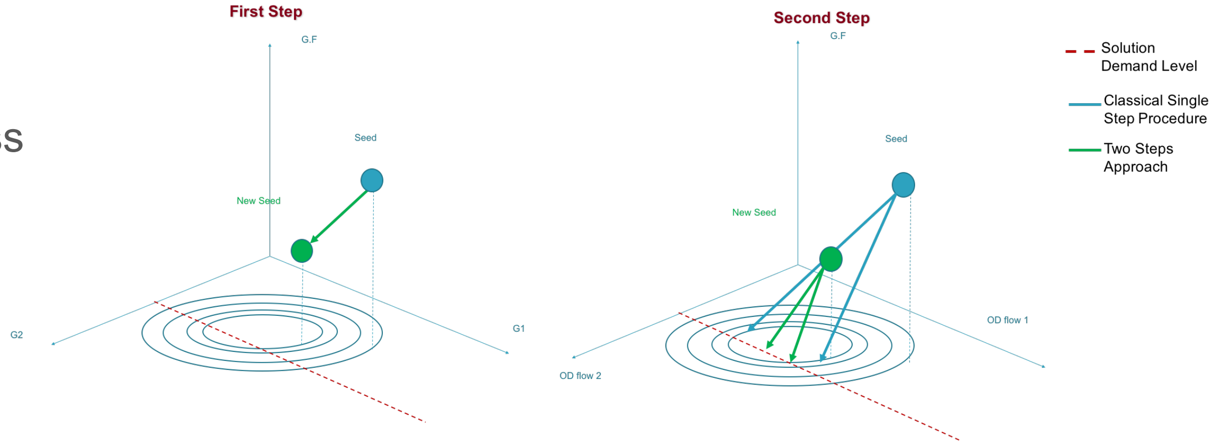
Acknowledgments: Bogdan Toader, Sebastien Faye (UL)

A new demand estimation framework

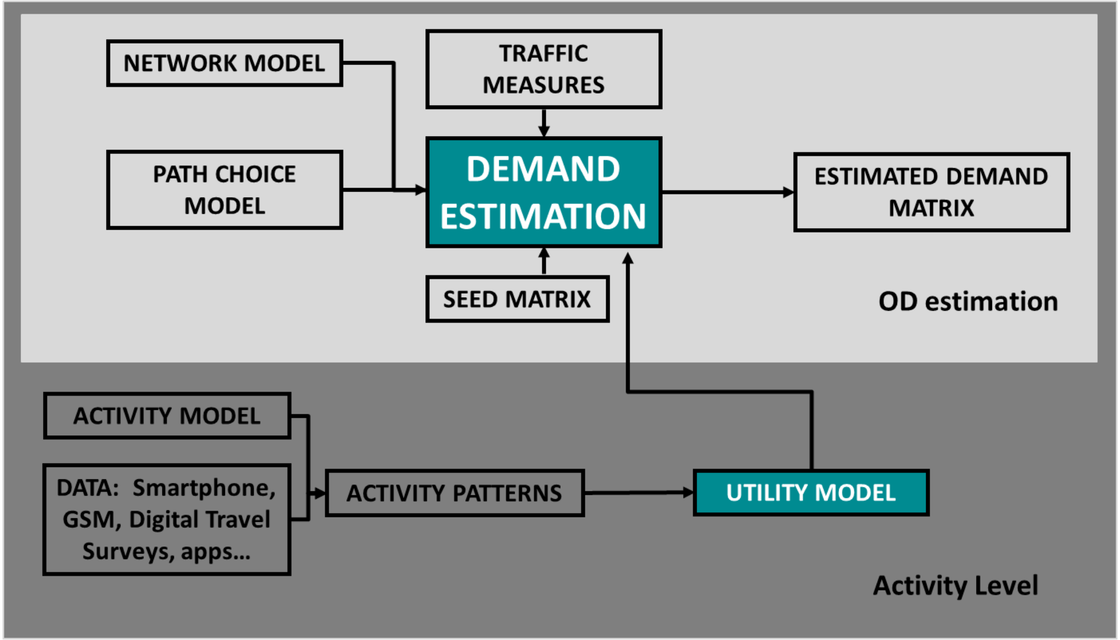
that uses (big) data
where it matters

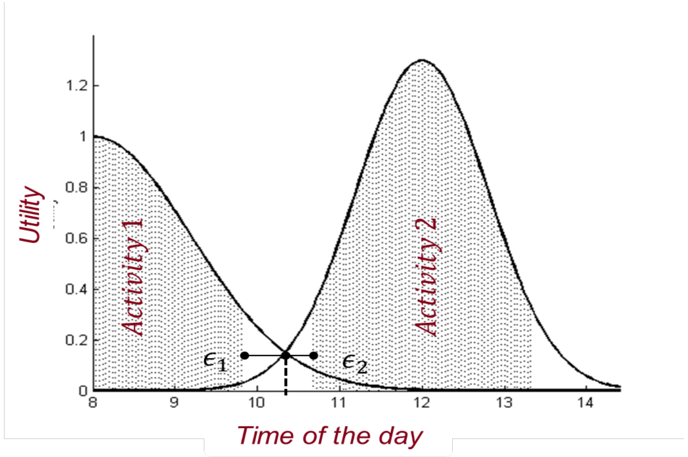
A new generic demand estimation framework

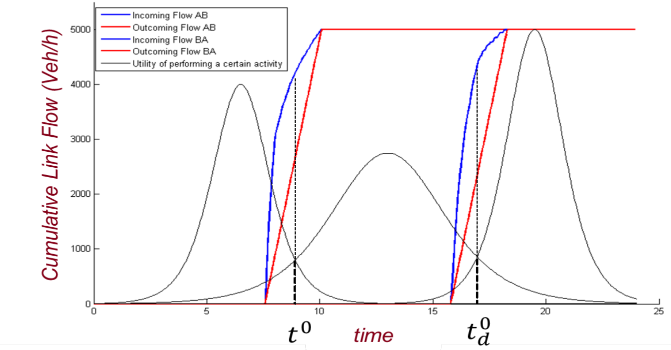
- 1. Estimating the demand production & attraction
  - Data driven: GSM, smartphone data
  - Output: total activity-specific trips originating and ending in each zone
- 2. Estimating the spatio-temporal distribution
  - Model driven: Utility-based model
  - Output: OD matrix structure
- 3. Demand adjustment process
  - Data: loop detectors
  - Classical approach



Including activity scheduling in daily demand estimation part 1: utility-based modelling







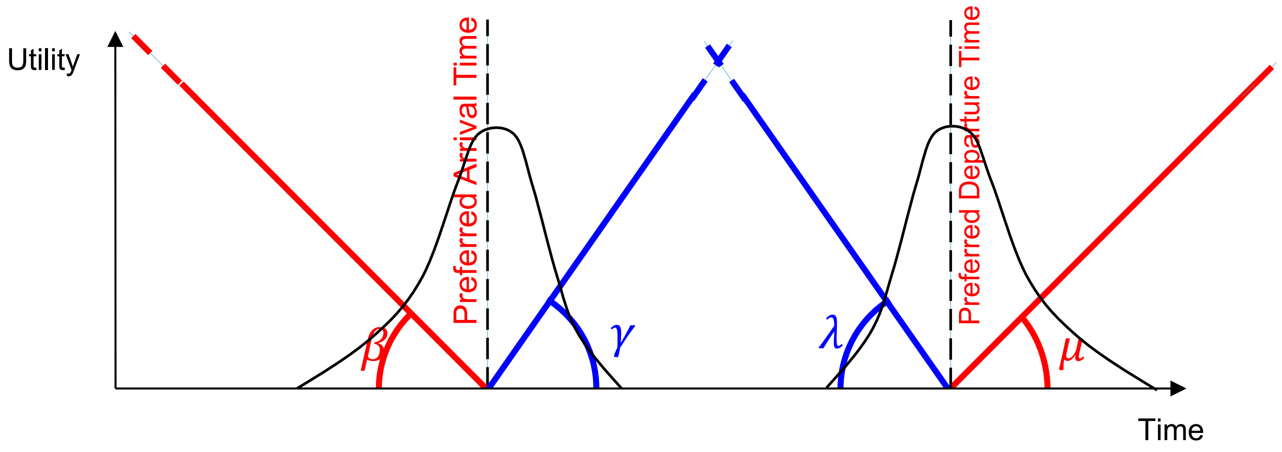
Acknowledgments: Guido Cantelmo (UL)

Utility-Based OD Estimation: lower level

The lower level: Utility Based Departure Time Choice Model

$$U = \underbrace{\alpha\left(T^M(t_h^d)\right)}_{\text{Travel Time}} + \underbrace{\beta \cdot max\left(0; t_w^{a^0} - t_h^d - T^M(t_h^d)\right)}_{\text{Late Arrival Time}} + \underbrace{\gamma \cdot max\left(0; t_h^d + T^M(t_h^d) + t_w^{a^0}\right)}_{\text{Early Arrival Time}}$$

$$U_n(t,r) = \max_{t,r}\left(U_n^A(t,r) - U_n^T(t,r)\right);$$



Utility-Based OD Estimation: upper level

The "classical" Bi-level Demand

$$\left(\mathbf{d}^*{}_1,\ldots,\mathbf{d}^*{}_n\right)=\underset{\cancel{(d_1,\ldots,d_n)\geq 0}}{\arg\min}\ z_1\left(\mathbf{v}_1,\ldots,\mathbf{v}_n,\hat{\mathbf{f}}_1,\ldots,\hat{\mathbf{f}}_n\right)$$

S.t.

$$\cancel{(\hat{\mathbf{f}}_1,\ldots,\hat{\mathbf{f}}_n)=DTA(\mathbf{d}_1,\ldots,\mathbf{d}_n)}$$

The Utility-Based Demand Estimation

$$\left(\mathbf{d}^*{}_1(\boldsymbol{\omega},\mathbf{n}),\ldots,\mathbf{d}^*{}_n(\boldsymbol{\omega},\mathbf{n})\right)=\underset{\boldsymbol{\omega},\mathbf{n}}{\arg\min}\ z_1\left(\mathbf{v}_1,\ldots,\mathbf{v}_n,\hat{\mathbf{f}}_1,\ldots,\hat{\mathbf{f}}_n\right)$$

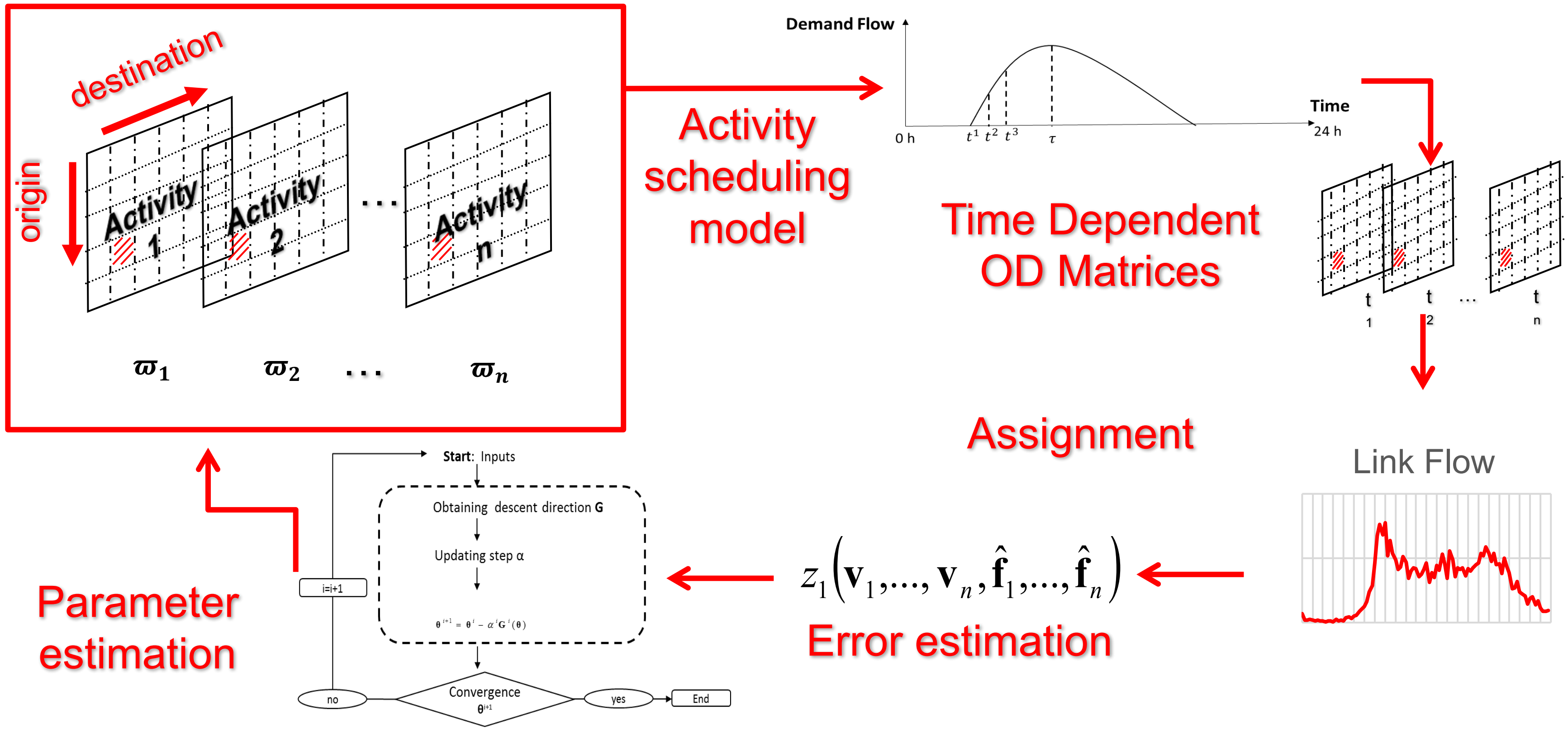
S.t.

$$\left(\widehat{\mathbf{f}_1},\ldots,\widehat{\mathbf{f}_n}\right)=\max_{\boldsymbol{t}}\left(U^s\left(\boldsymbol{t}(\boldsymbol{\varpi},\boldsymbol{r},\boldsymbol{n})\right)\right);$$

Where:

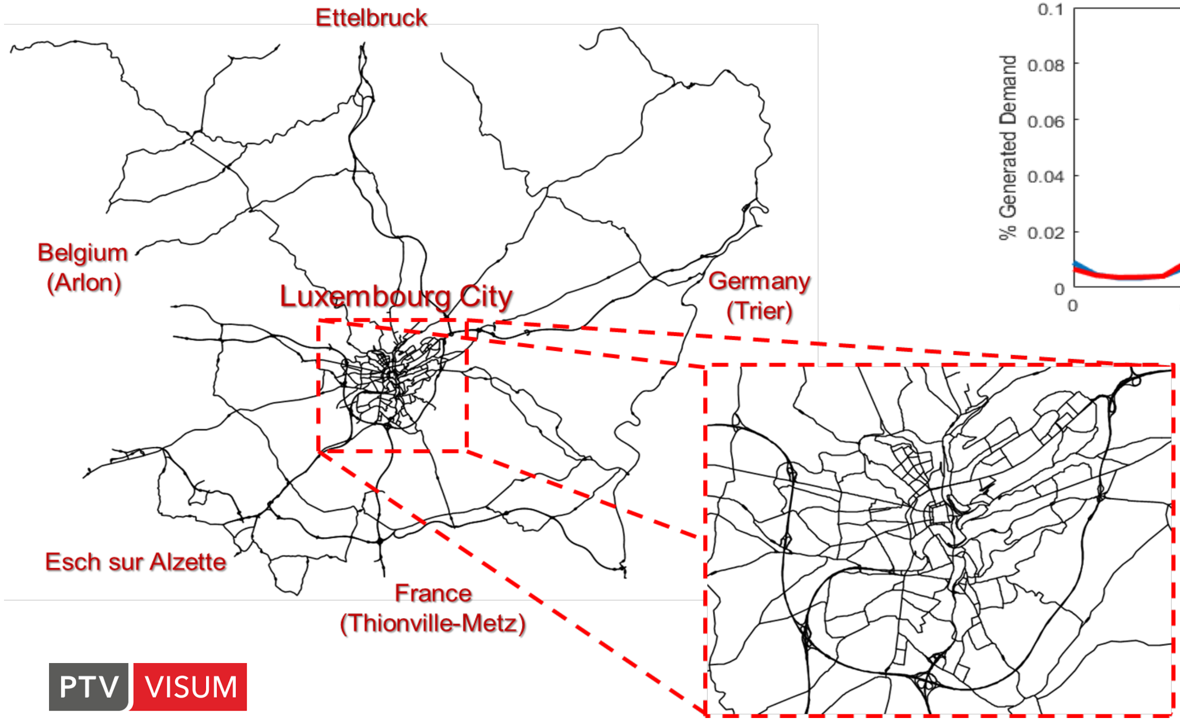
$$\boldsymbol{\varpi}=\{\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma},\boldsymbol{\tau}\}=$$

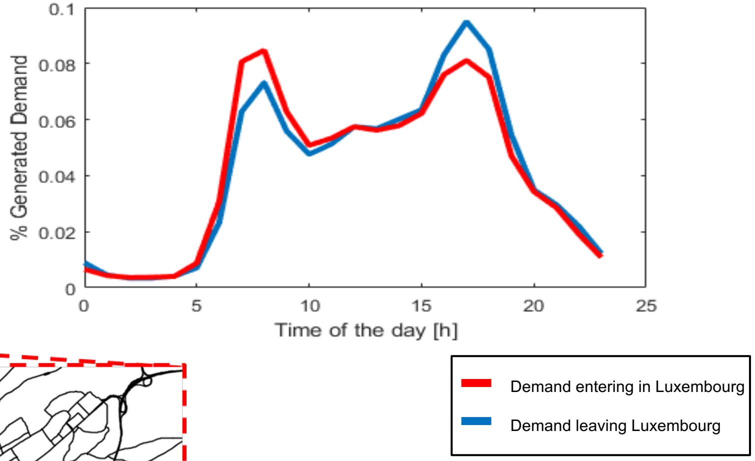
Including activity scheduling in daily demand estimation (3): adjustment process



Acknowledgments: Guido Cantelmo (UL)

Application on a real sized network: Luxembourg

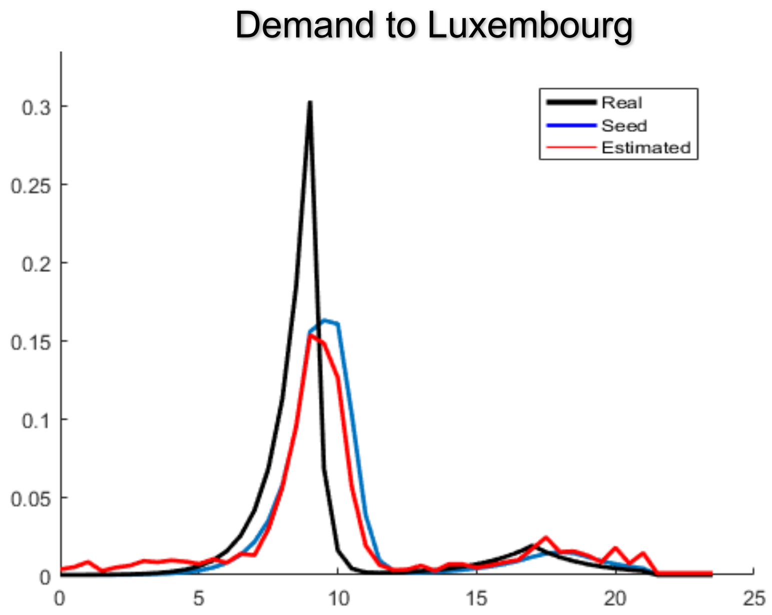


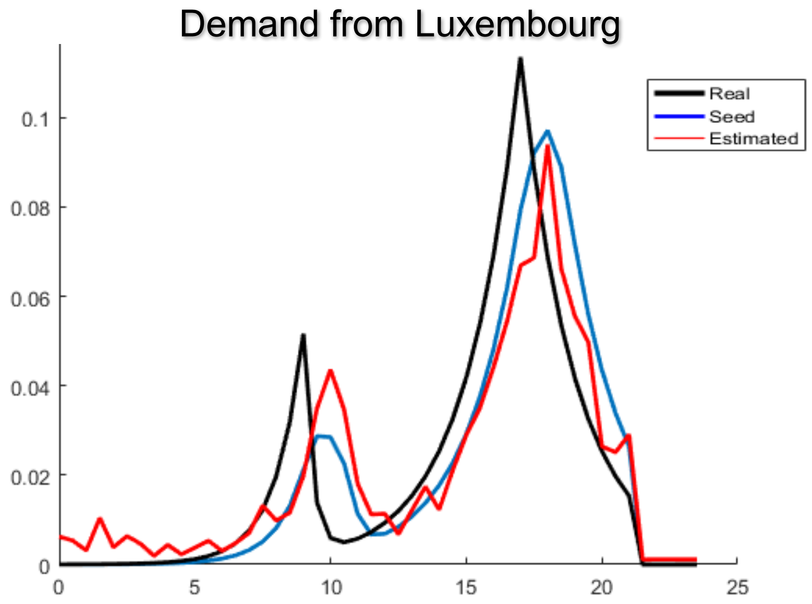


PTV VISUM
the mind of movement

Data provided by POST Luxembourg

Benchmarking scenario: Demand in/out of Lux City

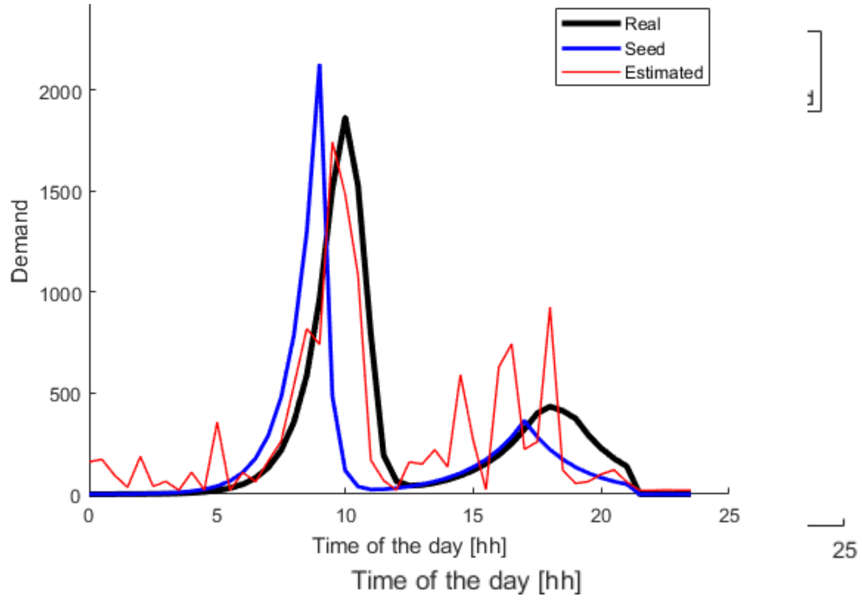




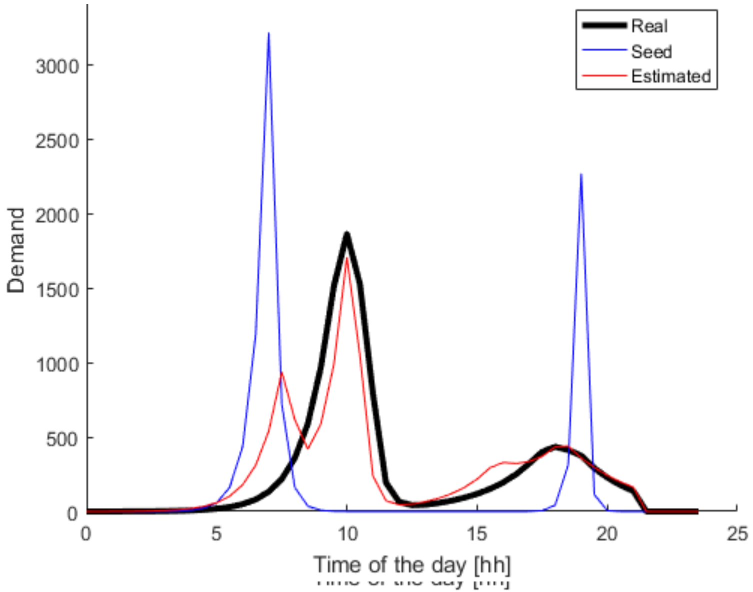
Acknowledgments: Guido Cantelmo (UL)

Results of daily demand flows on some OD pair

Trip-Based scenario: Classical approach

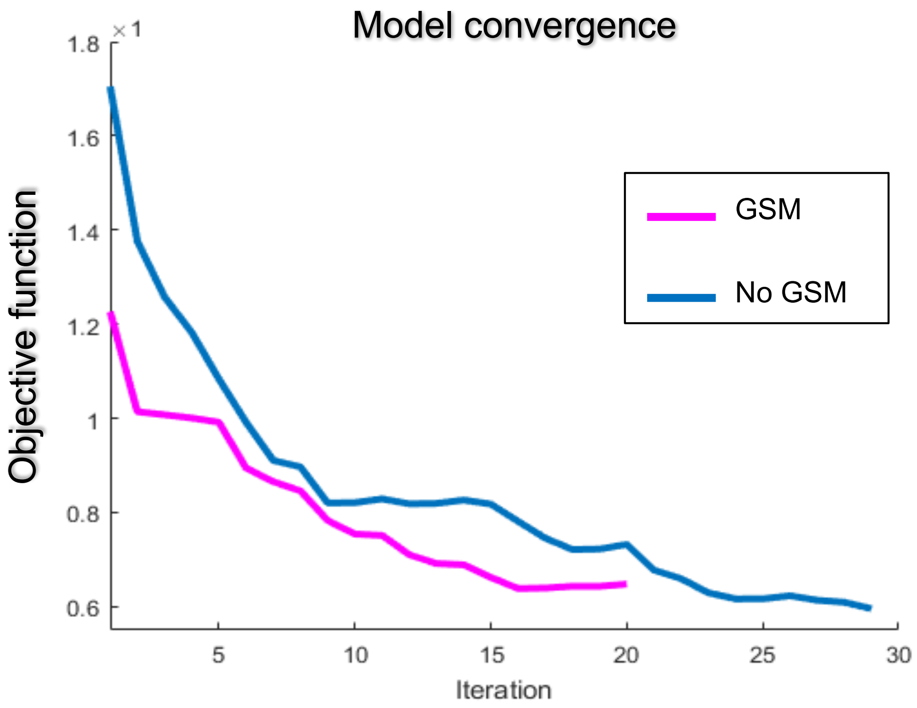


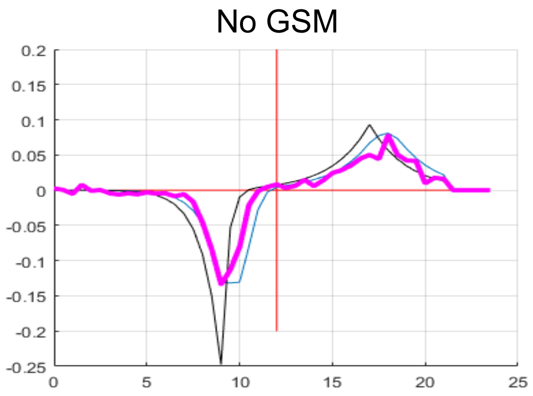
Utility-based formulation

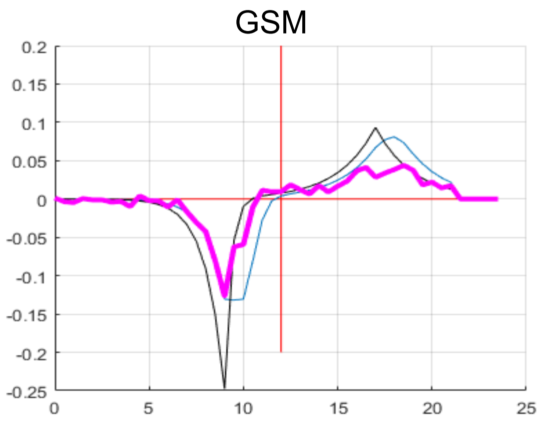


Acknowledgments: Guido Cantelmo (UL)

including mobile phone data for demand flow production



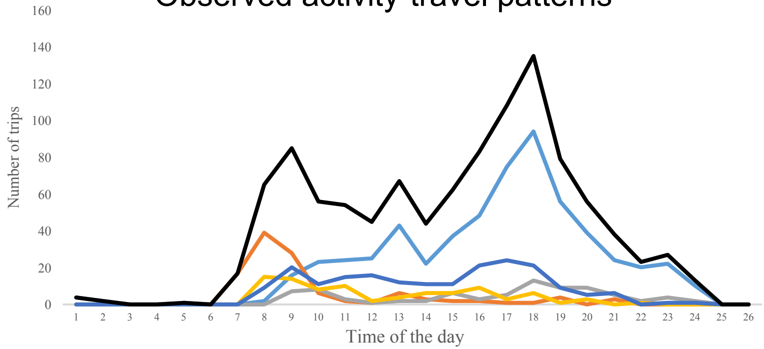


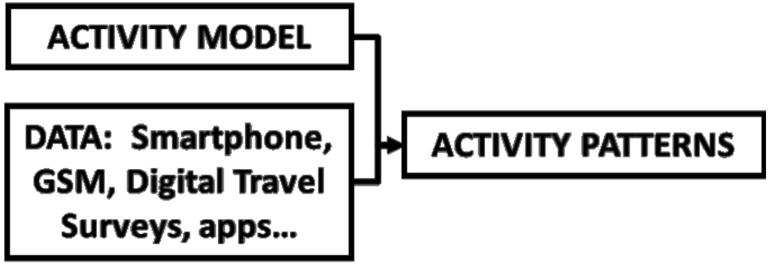


Acknowledgments: Guido Cantelmo (UL)

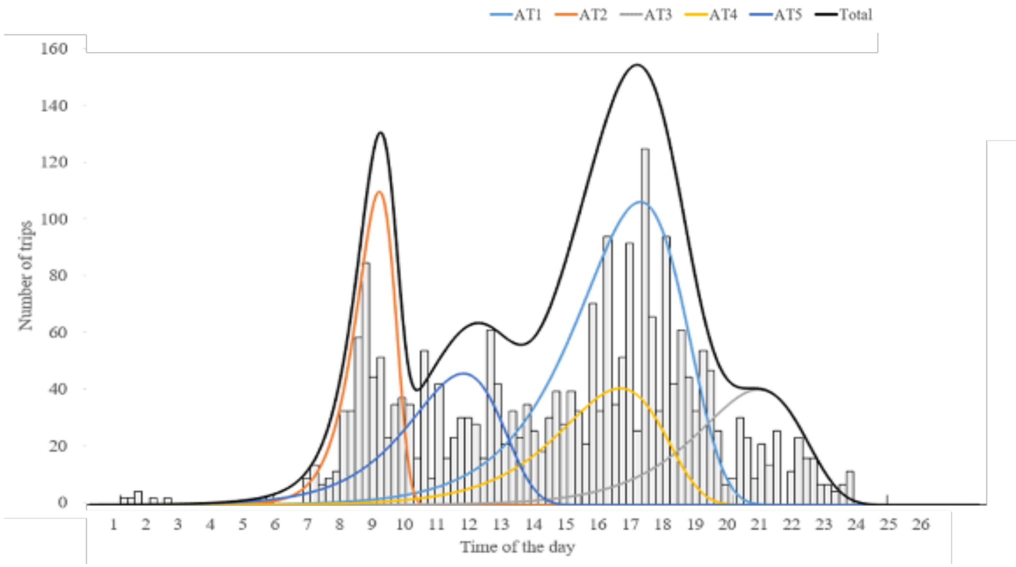
Including activity scheduling in daily demand estimation part 2: estimating activity primitives

Observed activity-travel patterns





Generated demand



Acknowledgments: Ariane Scheffer (UL)

Examples of possible Mobility Data available

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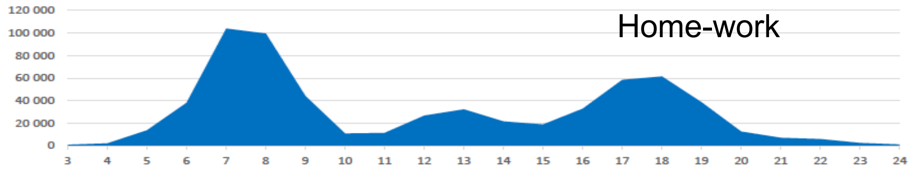
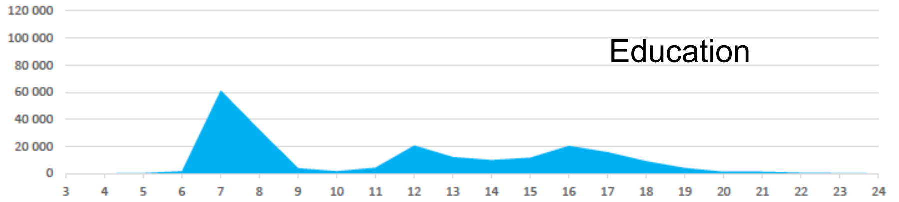
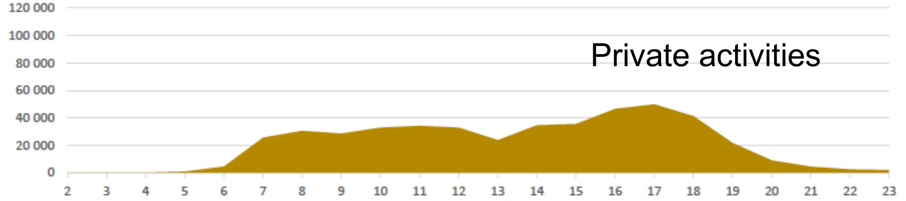
- Travel Diaries
  - Location and time of activities
  - Mode of transport
  - Per household

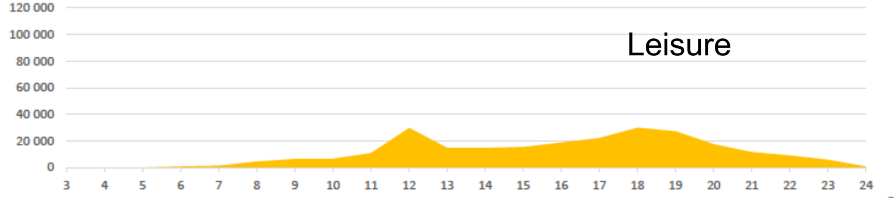
- Trajectories + semantic interpretation
  - Floating Car Data
  - Smartphones sensors

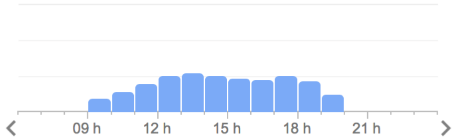
- Big Data analytics
  - Frequency of activities
  - Social media





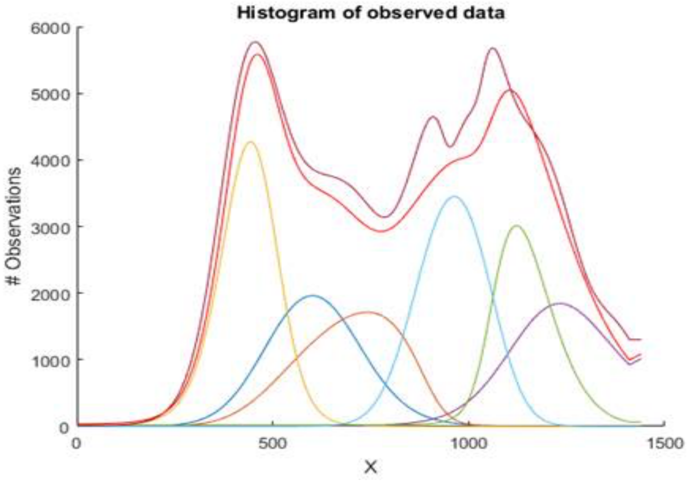


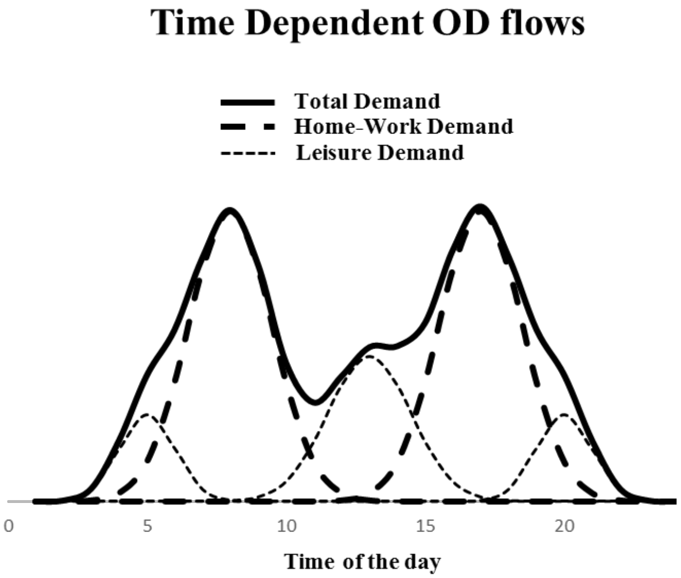




Next step: from offline to online

- Extending the utility-based DODE for real time applications
  - Collaboration with TUM (Antoniou) & MIT (Prakhash, Ben-Akiva)
  - Activity-related primitives used to construct daily patterns
  - Utility-based Kalman Filter
  - Testing on Singapore & Luxembourg networks





Outlook and closing remarks

- New Big Data gives opportunities for improving our demand models
  - Understanding mobility needs
  - Forecast future activity-travel patterns
  - Enable users with enhanced information
  - Improve our understanding of traffic dynamics

- A unified model-data-driven modelling approach needed
  - Travel demand models with dynamic flow estimation models
  - Behavioural and data science approaches
  - Interdisciplinary effort
    - Engineering
    - Computer Science
    - Social sciences
    - Geography
    - …

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