National Research
Council of Italy

Institute of
Electronics
Computer and
Telecommunication
Engineering

**WONS 2018**
Isola 2000, France
February 8, 2018

# Two ways you did not know mobile networks could be useful

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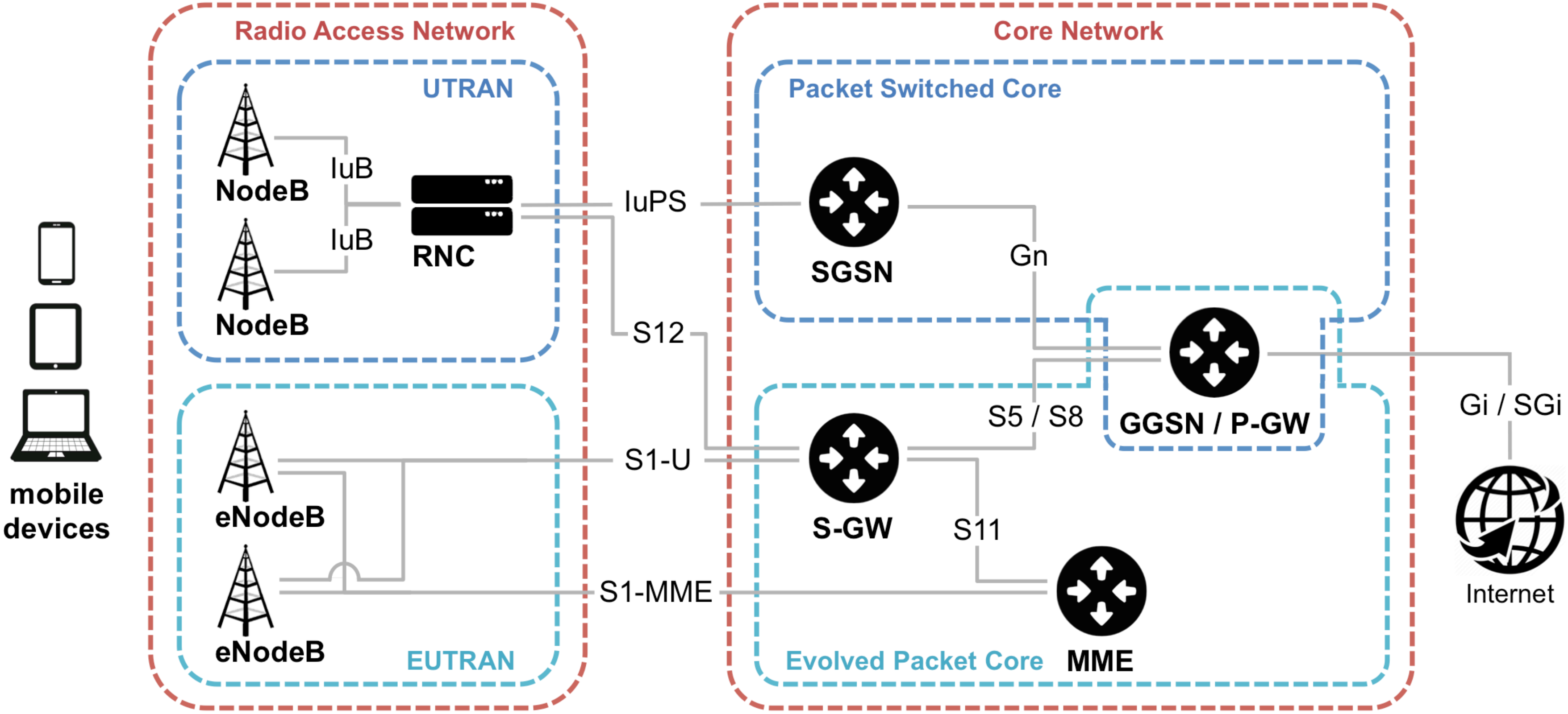
# What's a mobile network?

> *"A telecommunication system where the last link is wireless"*



# What's a mobile network for?

- **Evolution through generations**




| | | | | |
|---|---|---|---|---|
| 1G | 1980 | ***TACS*** | | Analog voice |
| 2G | 1991 | ***GSM*** | 9.6 kbps | Digital voice, text messages, minimum data |
| | | ***GPRS*** | 20-50 kbps | |
| | | ***EDGE*** | 100-130 kbps | |
| 3G | 2001 | ***UMTS*** | 384-400 kbps | Web browsing, social media, navigation, audio streaming |
| | | ***HSPA*** | 2-3 Mbps | |
| | | ***HSPA+*** | 5-8 Mbps | |
| 4G | 2010 | ***LTE*** | 10-20 Mbps | Video streaming, machine-type communication |
| | | ***LTE-A*** | 20-40 Mbps | |
| 5G | 2020 | | | Internet of things, automated vehicles, enhanced mobile broadband, augmented reality |

- **Can we go *beyond communication-based services*?**
  - A pervasive individual-level ***remote sensing platform***

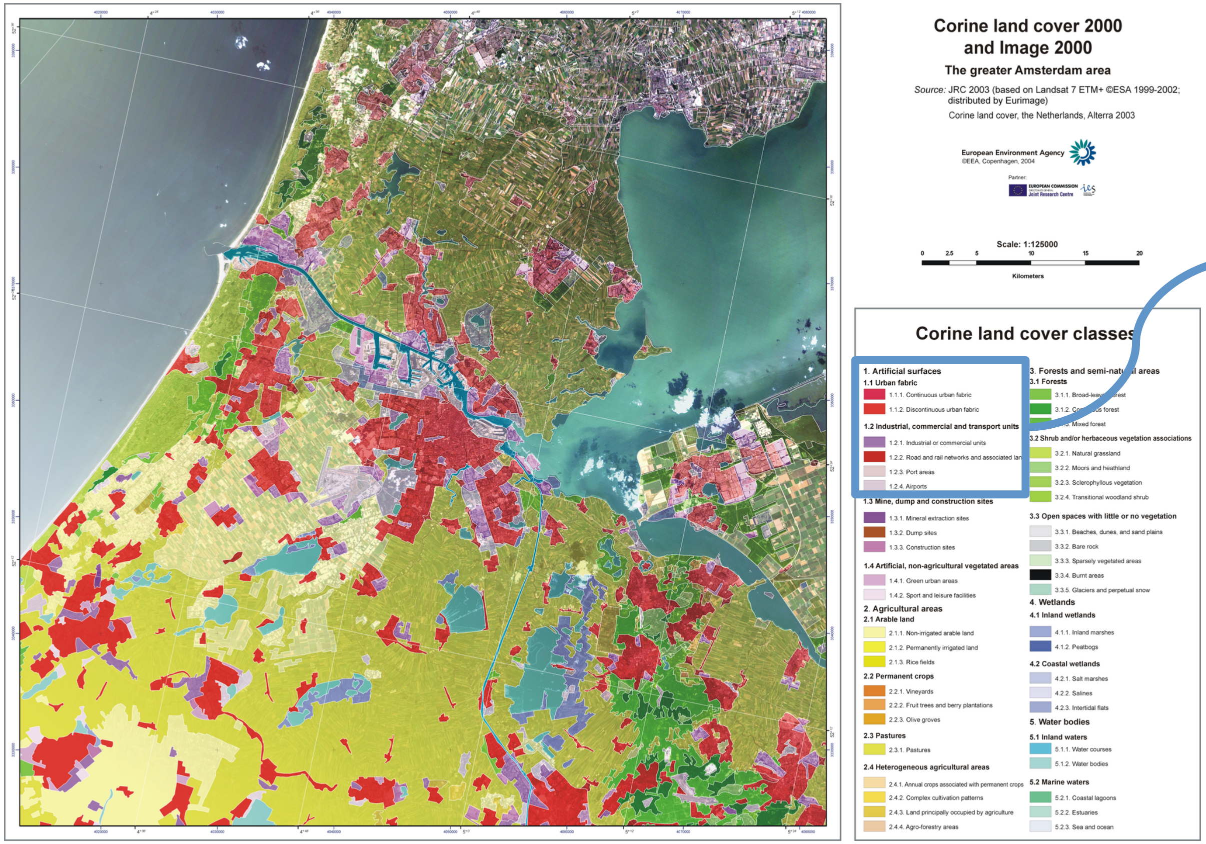
# I.1

## Land use

Context and mapmaking

# Land use

> *The total of arrangements, activities, and inputs that people undertake in a certain land cover type*



**1. Artificial surfaces**

**1.1 Urban fabric**

- 🟥 1.1.1. Continuous urban fabric
- 🟥 1.1.2. Discontinuous urban fabric

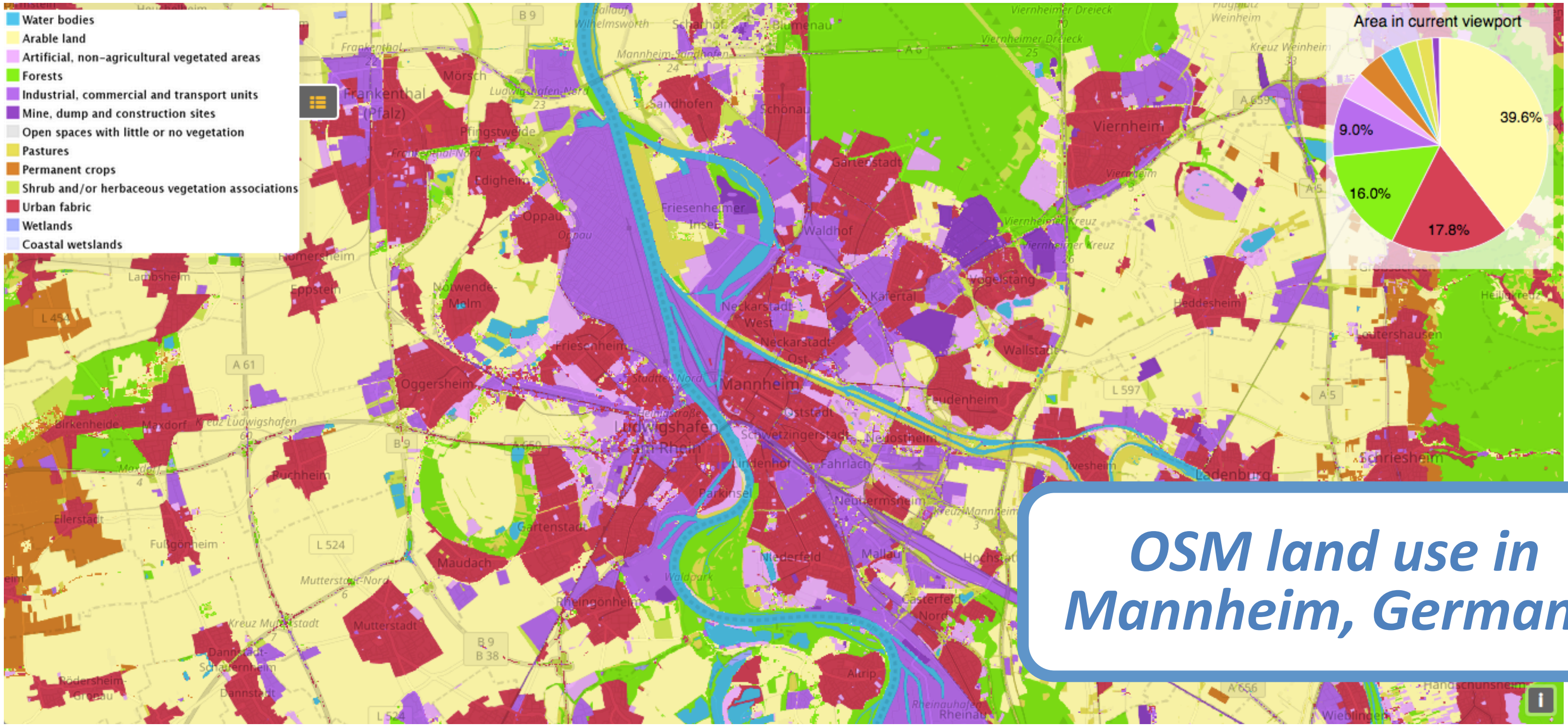
**1.2 Industrial, commercial and transport units**

- 🟪 1.2.1. Industrial or commercial units
- 🟥 1.2.2. Road and rail networks and associated land
- ⬜ 1.2.3. Port areas
- ⬜ 1.2.4. Airports

***Corine land use database in Amsterdam, The Netherlands***

# Urban land use

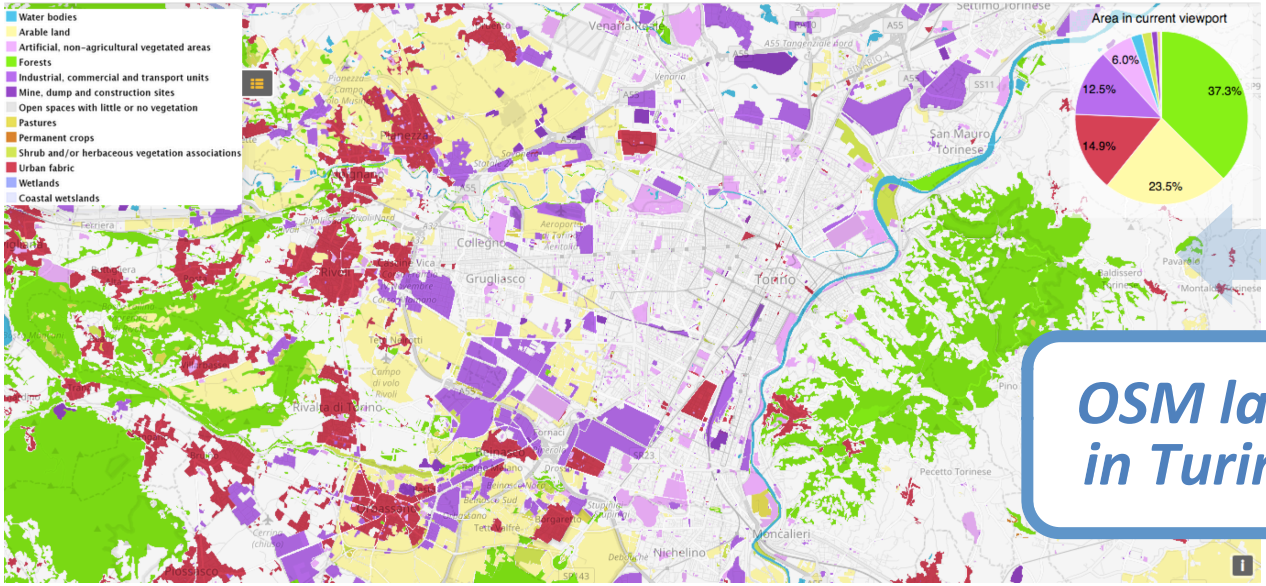
- **City land use has extensive applications**
  - Urban planning, ***zoning***, metropolitan ***transport system*** planning, demographics, social ***segregation***, etc.



*OSM land use in Mannheim, Germany*

# Land use mapmaking

- **Traditional approaches**
  - *Census* data, surveys, ***satellite imagery*** processing
  - An active research field in ***geoinformatics***
- **Current techniques have significant drawbacks**
  - Time-consuming, expensive, *easily* ***outdated***, incomplete



***OSM land use in Turin, Italy***

# I.2

# Using mobile network traffic to detect land use

## A simple hierarchical classification approach

# One-slide methodology

- **Intuition** – different land uses entail *diverse traffic dynamics*

**1.** Mobile traffic **signature** at one location

- metric
- temporal support
- (filtering)
- normalization

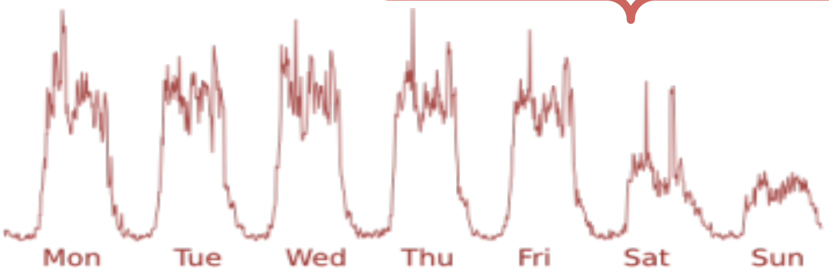
*aggregate mobile traffic volume*

*one* ***week*** [1,2]

*none*

***standard score***

***median*** *hourly volume*



**2.** Pairwise **signature distance** measure

$$p_{ab} = \frac{\sum_{t\in\mathcal{T}} (\mathbf{s_a}(t) - \mu_{\hat{a}}) \cdot (\mathbf{s_b}(t) - \mu_{\hat{b}})}{\sqrt{\sum_{t\in\mathcal{T}} (\mathbf{s_a}(t) - \mu_{\hat{a}})^2} \cdot \sqrt{\sum_{t\in\mathcal{T}} (\mathbf{s_b}(t) - \mu_{\hat{b}})^2}}$$

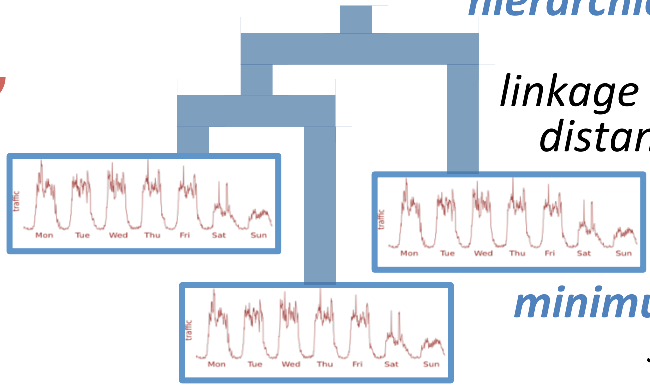
***correlation-based*** *distance*

**3.** Signature **clustering algorithm**

*agglomerative* ***hierarchical*** *clustering*

*linkage with average distance –* ***UPGMA***

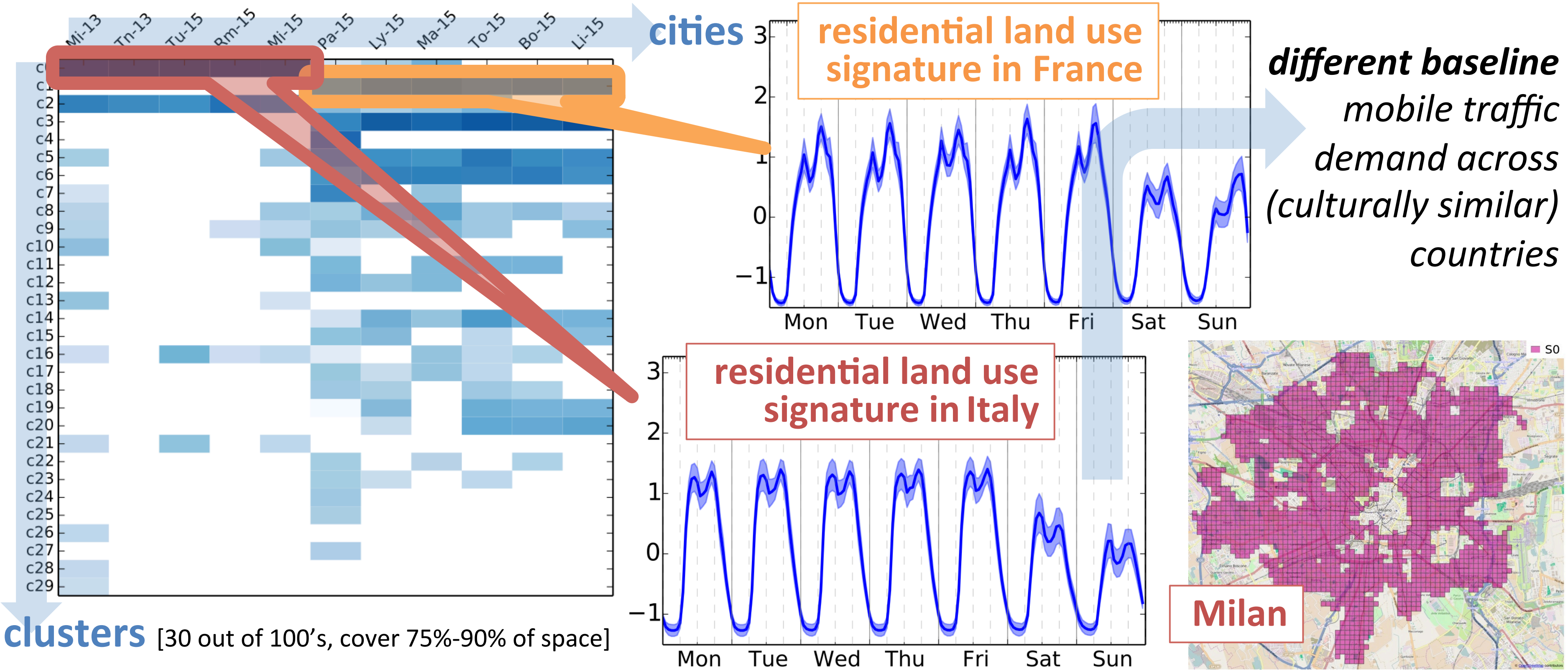
***minimum skewness*** *stopping rule*



[1] R. Keralapura et al., ACM MobiCom 2010; [2] M.Z. Shafiq et al., ACM SIGMETRICS 2011

# Case study

- **Real-world mobile network traffic datasets**
  - *Orange* 2014-15 [6 main cities in France, 4 months, antenna cells]
  - *TIM* BDC 2013-15 [4 main cities in Italy, 2 months, grid]



**clusters** [30 out of 100's, cover 75%-90% of space]

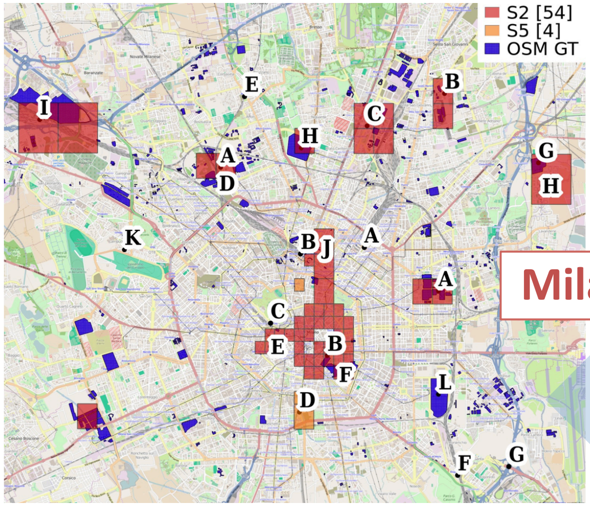
residential land use signature in France

residential land use signature in Italy

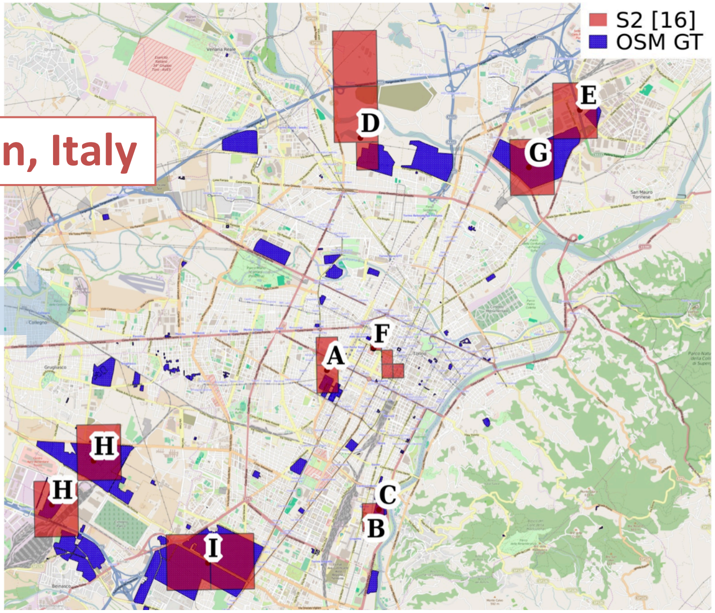
***different baseline*** *mobile traffic demand across (culturally similar) countries*

Milan

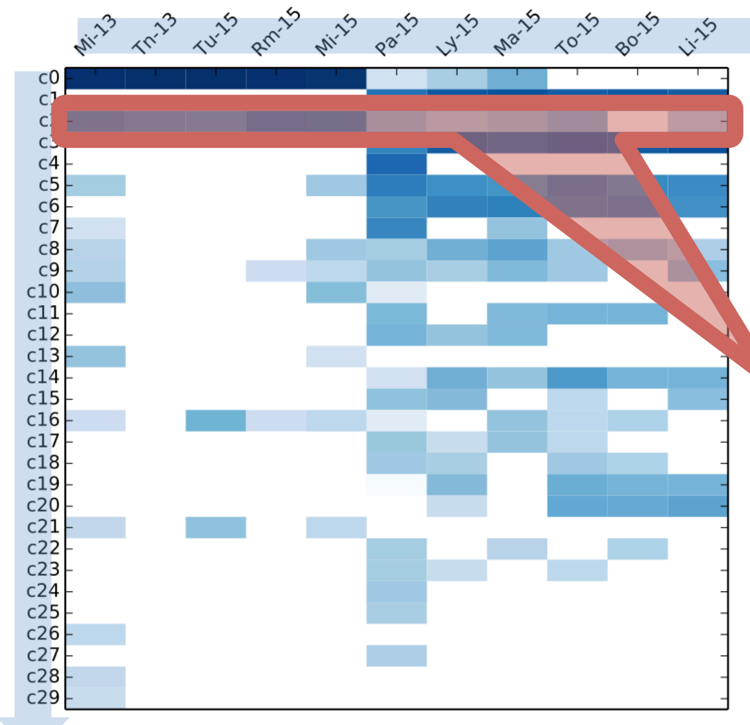
# Case study



**Milan, Italy**

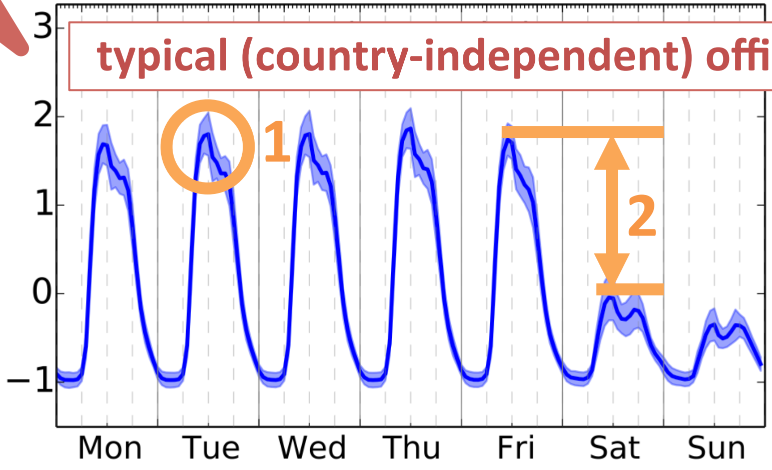


**Turin, Italy**



**cities**

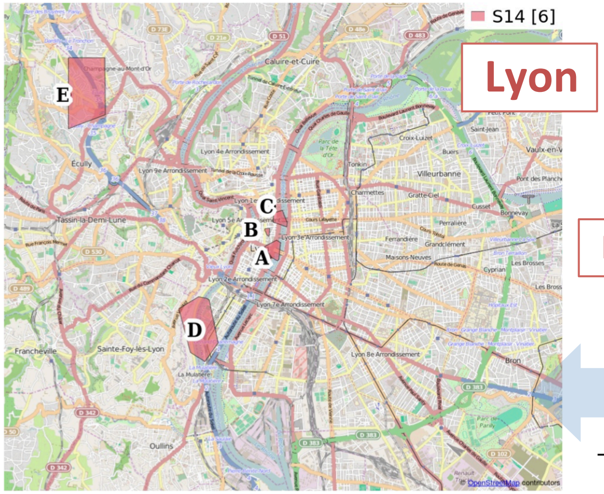
**profiles** [30 out of 100's, cover 75%-90% of space]



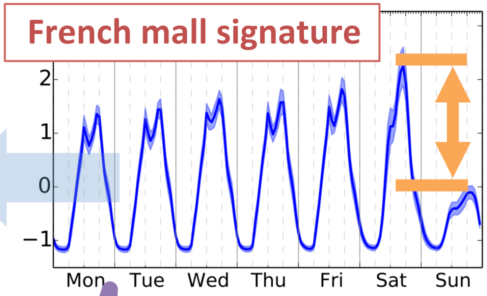
**typical (country-independent) office-area signature**

1. *morning peak*
2. *high workday to weekend ratio*

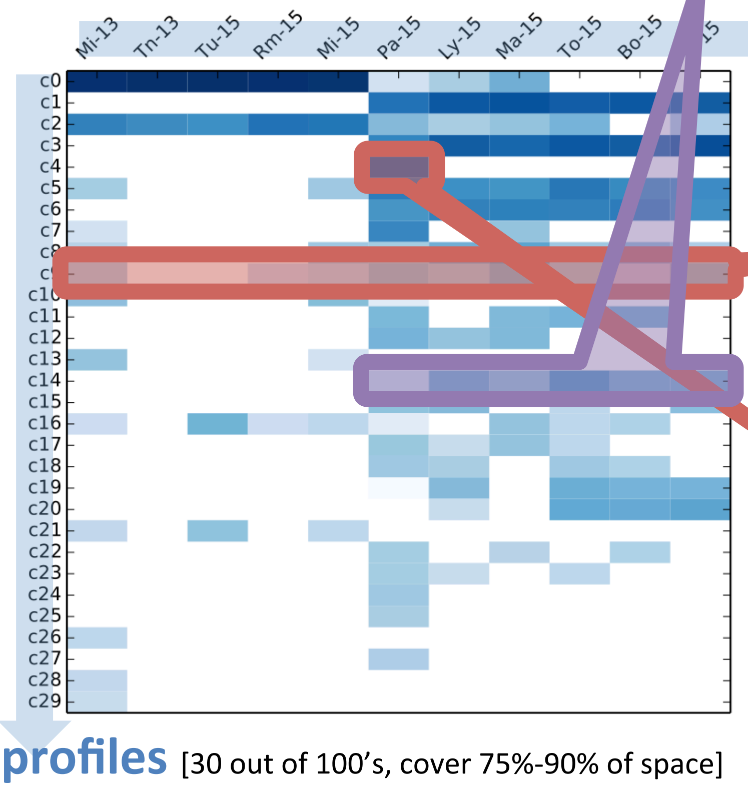
# Case study



Lyon

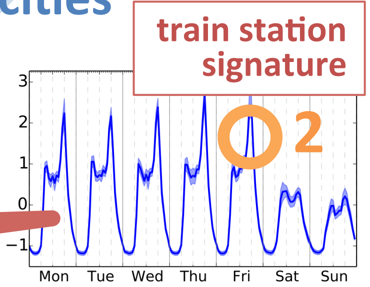


French mall signature

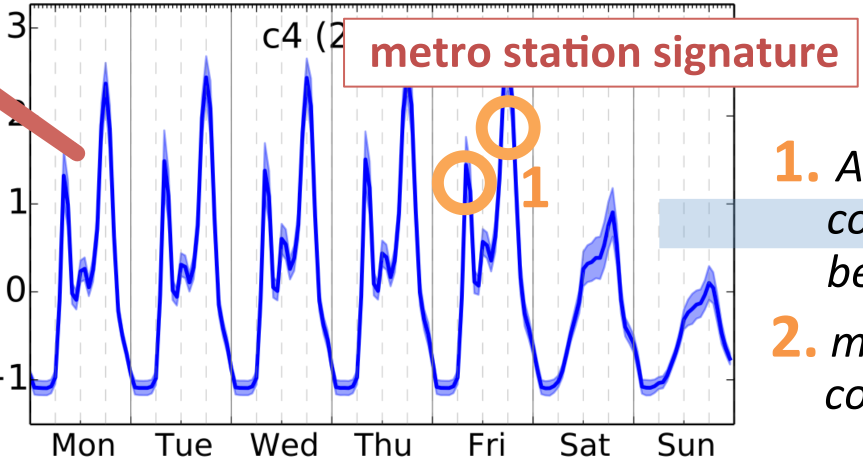


cities

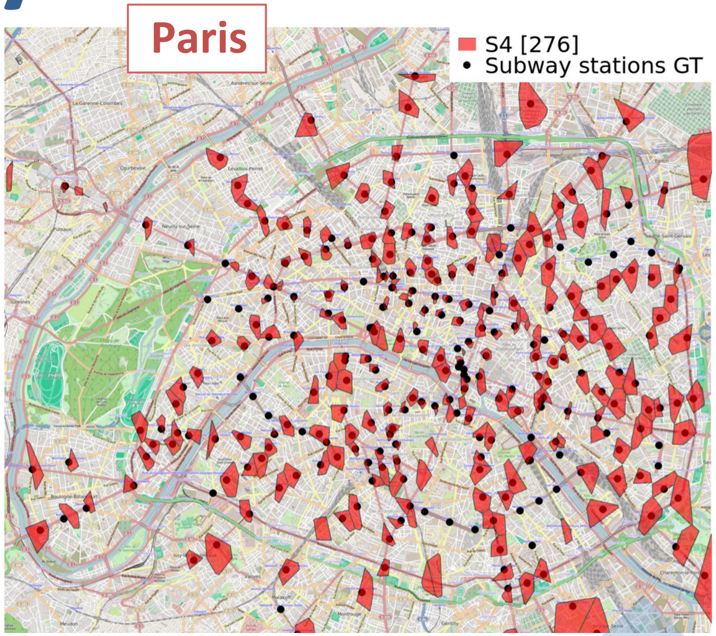
**profiles** [30 out of 100’s, cover 75%-90% of space]



train station signature



metro station signature



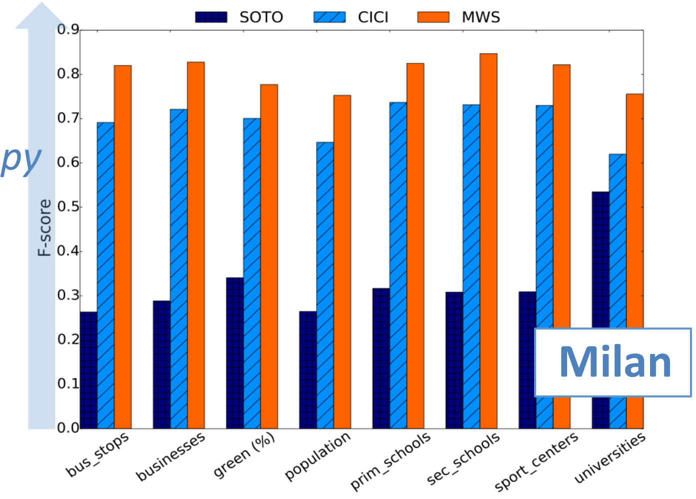
Paris

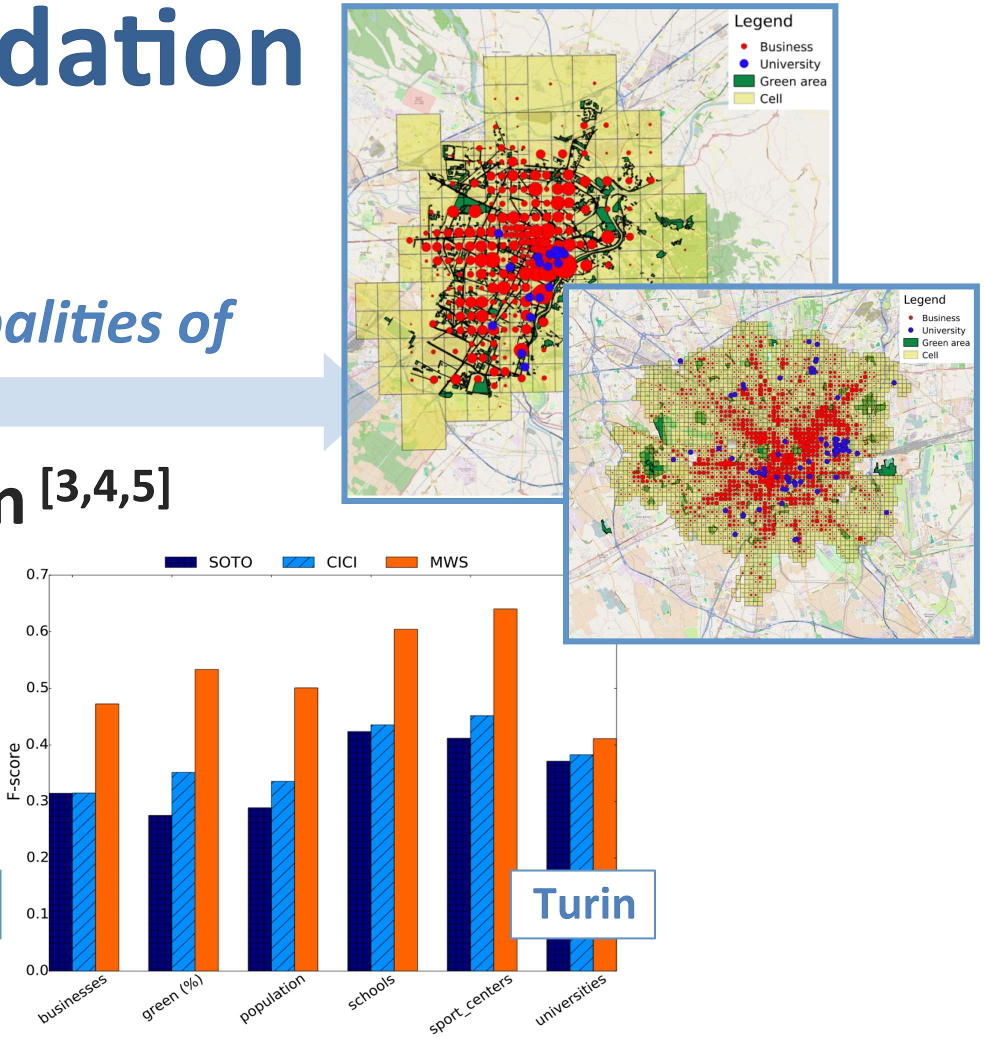
1. *AM-PM commuting behavior*
2. *mostly PM commuting*

# Validation

- **Ground truth land use**
  - Provided by the ***municipalities of Milan and Turin, Italy***
- **Comparative evaluation** [3,4,5]

*f-score* of coverage and entropy





  - A relevant ***complement*** to traditional land use mapmaking

[3] V. Soto et al., ACM HotPlanet 2011; [4] B. Cici et al., ACM MobiHoc 2015
[5] S. Grauwin et al., Geotechnologies and the Environment 2015

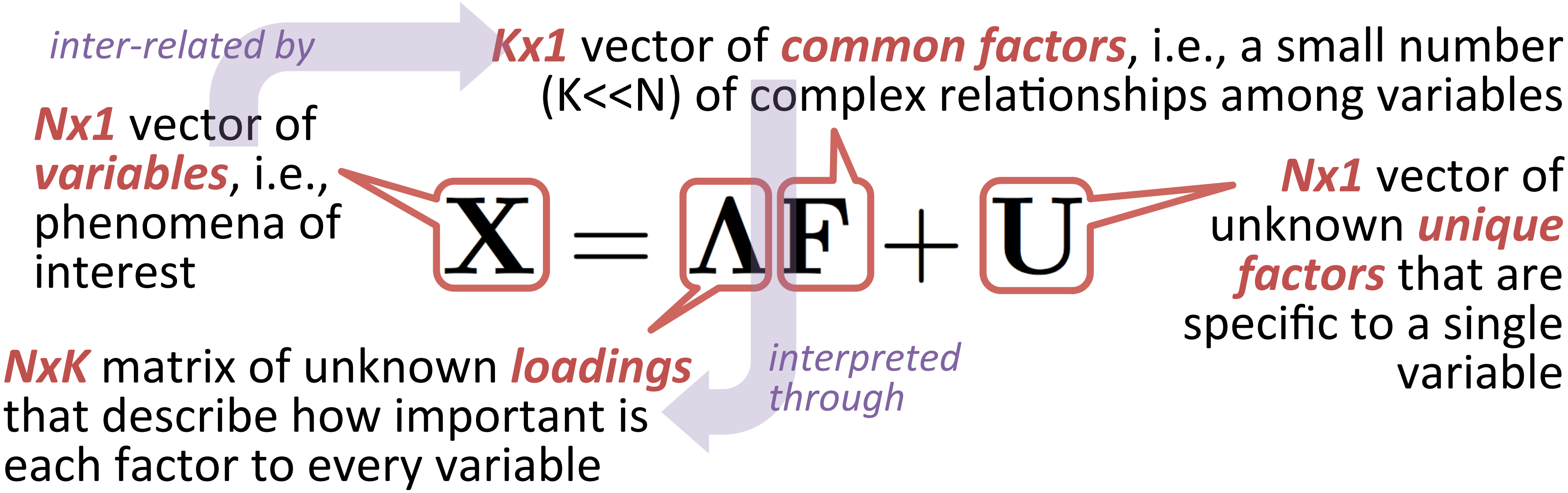
# I.3

# An alternative approach

## Exploratory Factor Analysis

# Methodology

- **Exploratory Factor Analysis (EFA)**



*inter-related by*

***Kx1*** vector of ***common factors***, i.e., a small number (K<<N) of complex relationships among variables

***Nx1*** vector of ***variables***, i.e., phenomena of interest

$$\mathbf{X} = \mathbf{\Lambda}\mathbf{F} + \mathbf{U}$$

***Nx1*** vector of unknown ***unique factors*** that are specific to a single variable

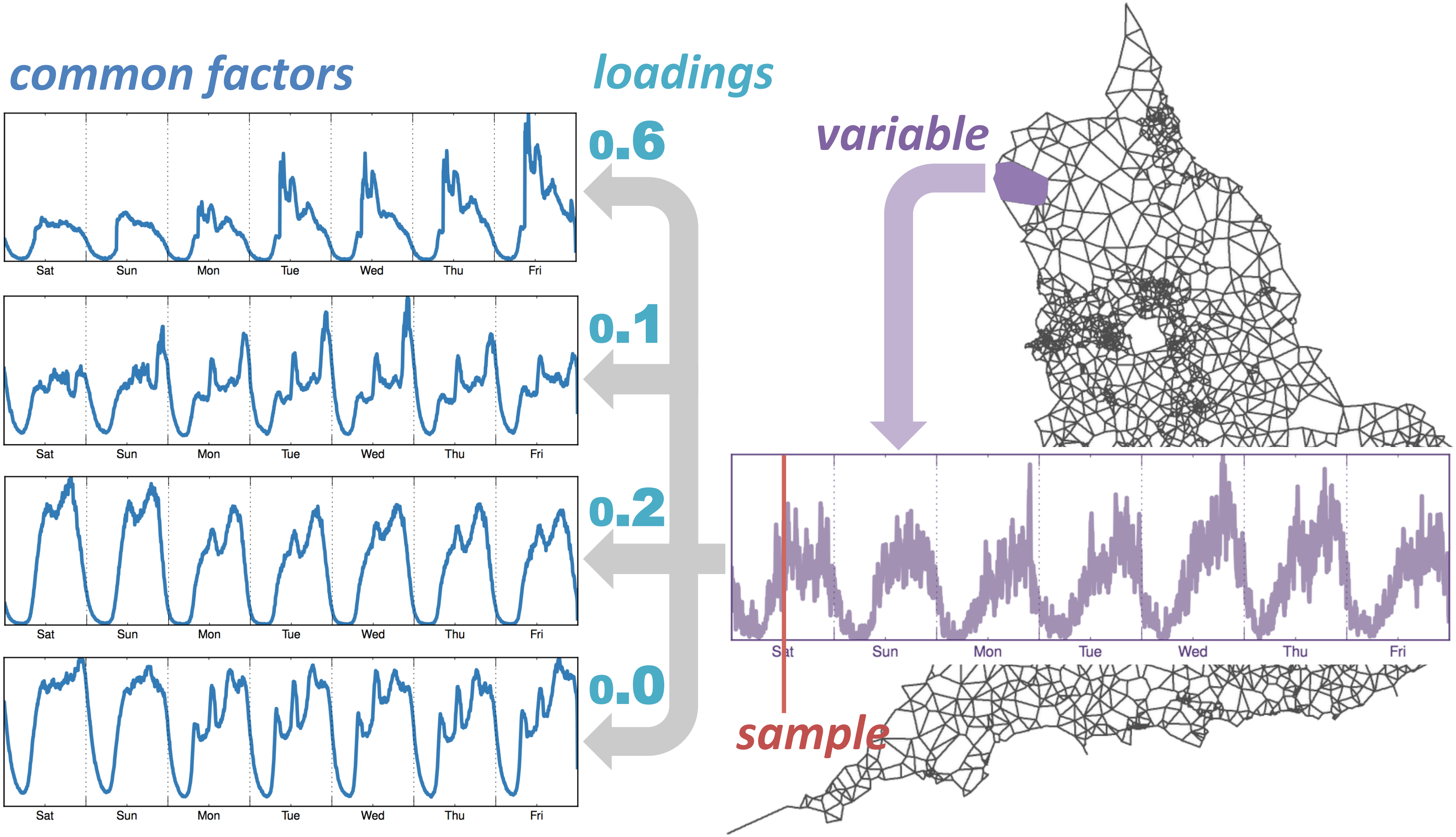
***NxK*** matrix of unknown ***loadings*** that describe how important is each factor to every variable

*interpreted through*

- **EFA solution**
  - By analyzing variable observations from a set of samples, ***EFA identifies common/unique factors, and loadings*** [6]

[6] S.A. Mulaik, Foundations of Factor Analysis, CRC Press, 2009

# Methodology



*common factors*

*loadings*

**0.6**

**0.1**

**0.2**

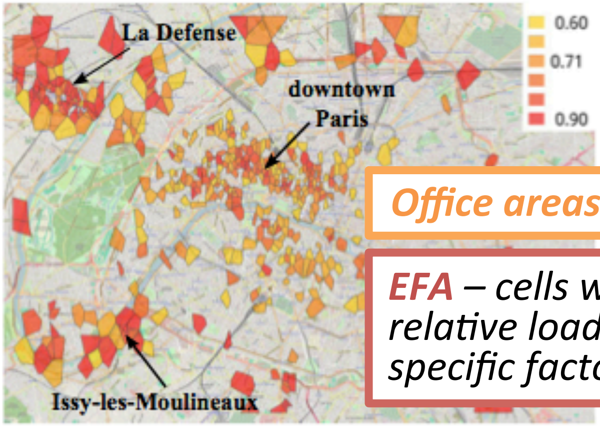
**0.0**

*variable*

*sample*

# Case study

- **Orange** 2014-15 [Paris, France, 4 months, antenna cells]
  - *14 EFA factors* are identified

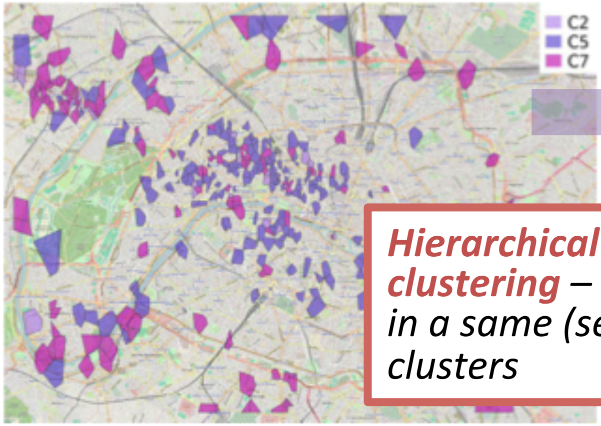


*Office areas*

*EFA – cells with high relative loading on a specific factor*

*Subway stations*

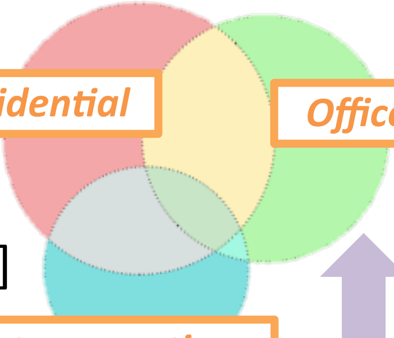
*Railway stations*



***Hierarchical clustering** – cells in a same (set of) clusters*

- 14 factors versus ***hundreds of clusters***
  - multiple signature clusters just capture ***different intensities of a same land use***
  - many clusters are ***unique factors***
  - traffic demands are in fact a ***mixture*** of actual common factors

***mixed land use detection***



*Residential*

*Office*

*Short commuting*

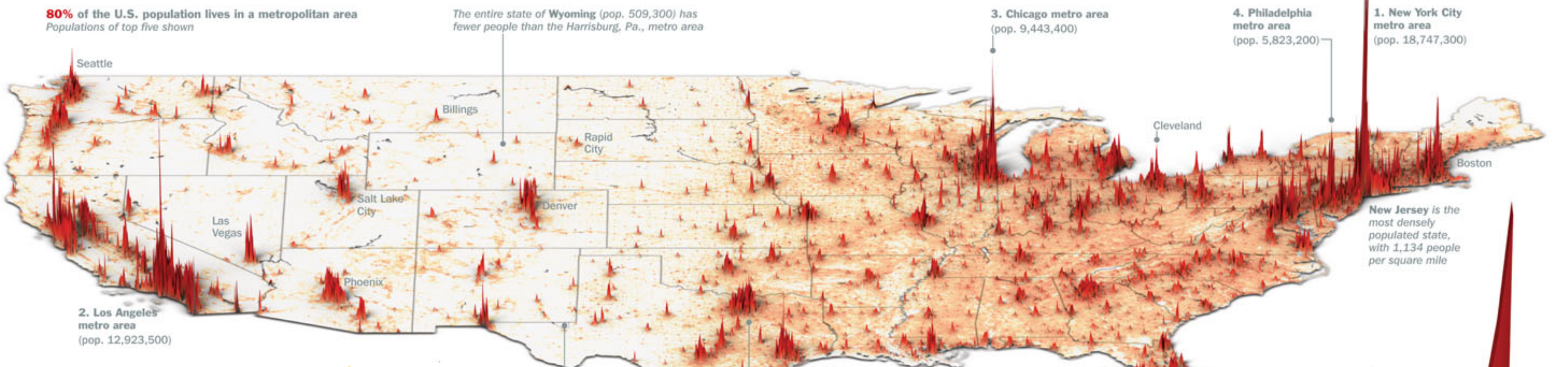
# II.1

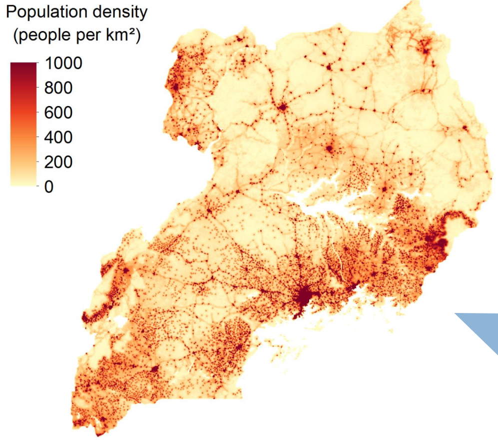
## Population density

Context and dynamic estimation

# Population density

> *A measurement of population per unit area or unit volume, frequently applied to humans*





***Uganda population density***

*[WorldPop]*

***USA population density***

*[Time magazine, Oct 30, 2006]*

# Urban population density

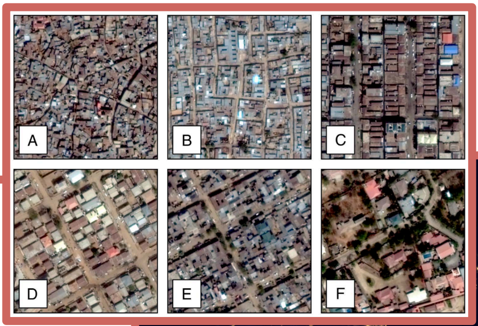
- **Urban population density has extensive applications**
  - Urban *planning*, transportations, *economics*, health, innovation, psychology, *geography*, sustainability

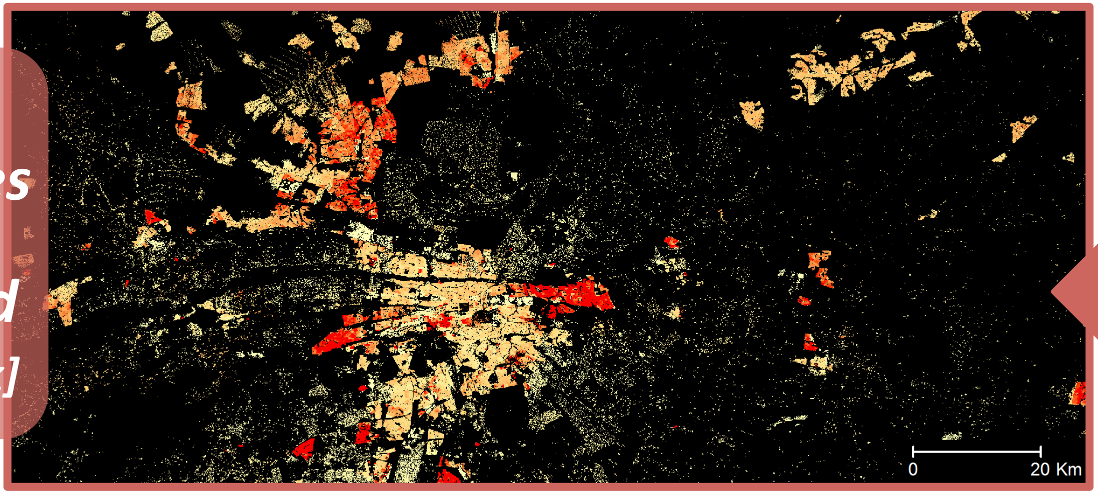
*Greater NYC tract level*

*[Social Explorer]*

# Population density estimation

- **Traditional and advanced approaches**
  - ***National censuses***, population ***registers***, local surveys
    - often outdated, unreliable, unavailable
  - An active research field in ***geoinformatics***
    - recent breakthrough form ***neural networks*** applied to high-definition satellite imagery





***23 countries fully mapped***

*[Facebook]*

  - Limited to ***static populations*** (dwelling units)

# II.2

## Using mobile network traffic to estimate population density

A regression model for static populations

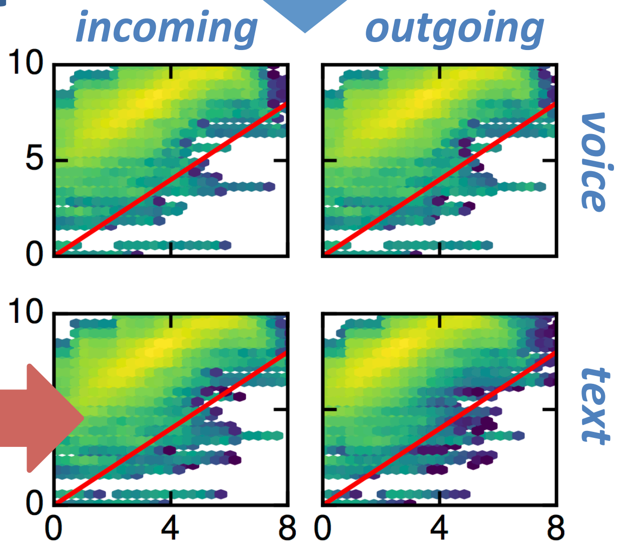
# Legacy model

*3 case studies: Milan, Rome, Turin*

- **A power-law relationship**
  - Mobile network traffic volume and census population density [7,8]

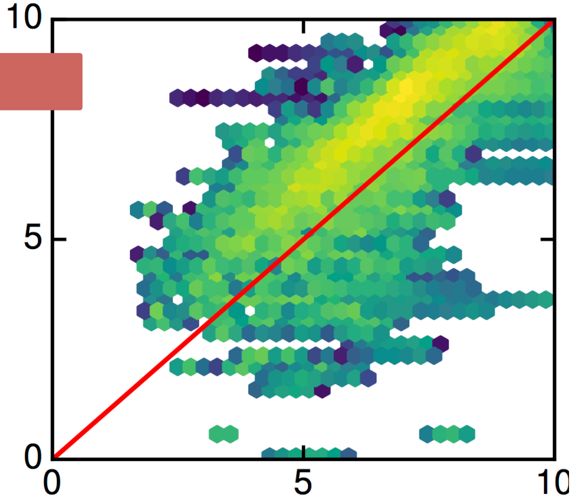
$$\rho_i = \alpha \, \sigma_i^{\beta}$$

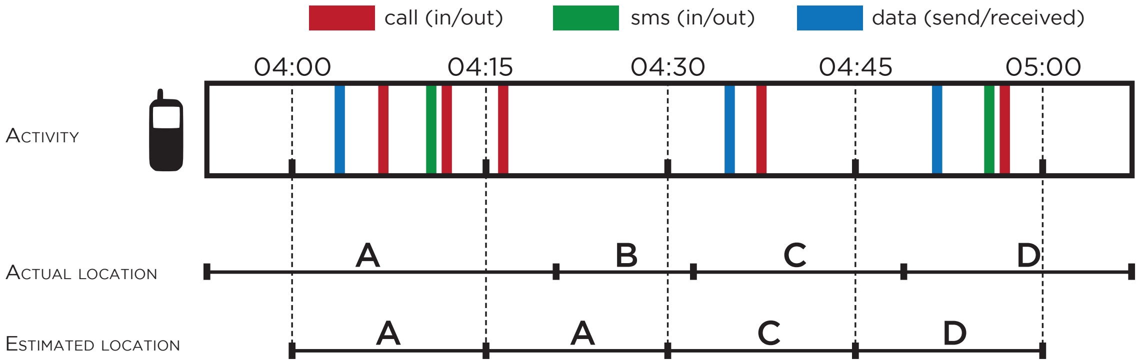
*correlation is very noisy*



- **Subscriber presence metadata**
  - Rough proxy for *users' location*

*best result*

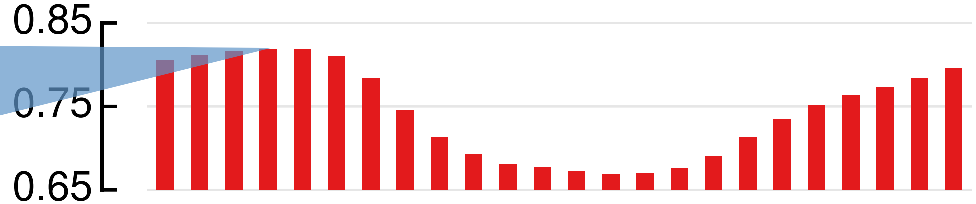




[7] Deville et al., PNAS, 2014; [8] Douglass et al., EPJ Data Science, 2015

# De-noising the correlation

- **Time filtering**
  - 4 to 5 am

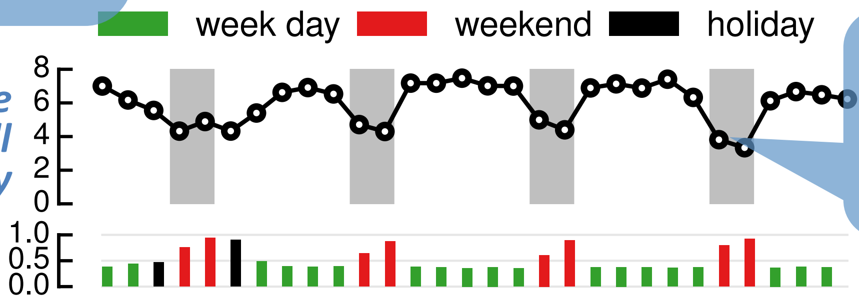


*maximum correlation overnight [0.8-0.9]*

- **Day filtering**
  - Working days

*average voice call density*

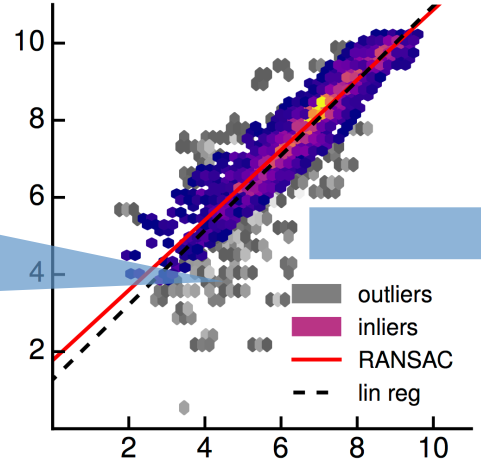
*zero-presence cells*

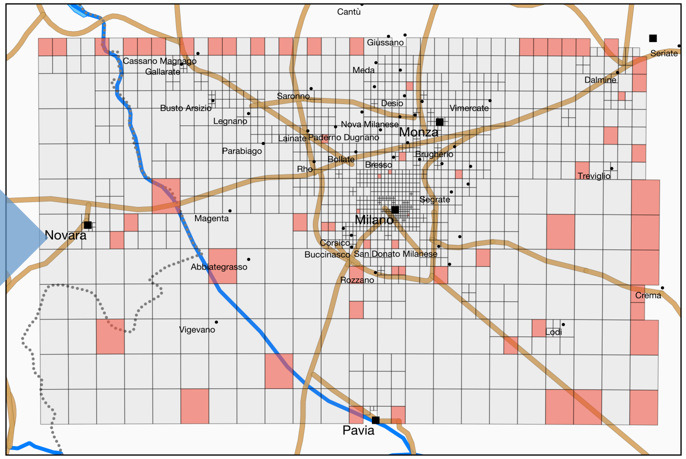


*abnormal weekend behavior*

- **Cell filtering**
  - Border effect

*non-correlated points belong to specific geographical cells*





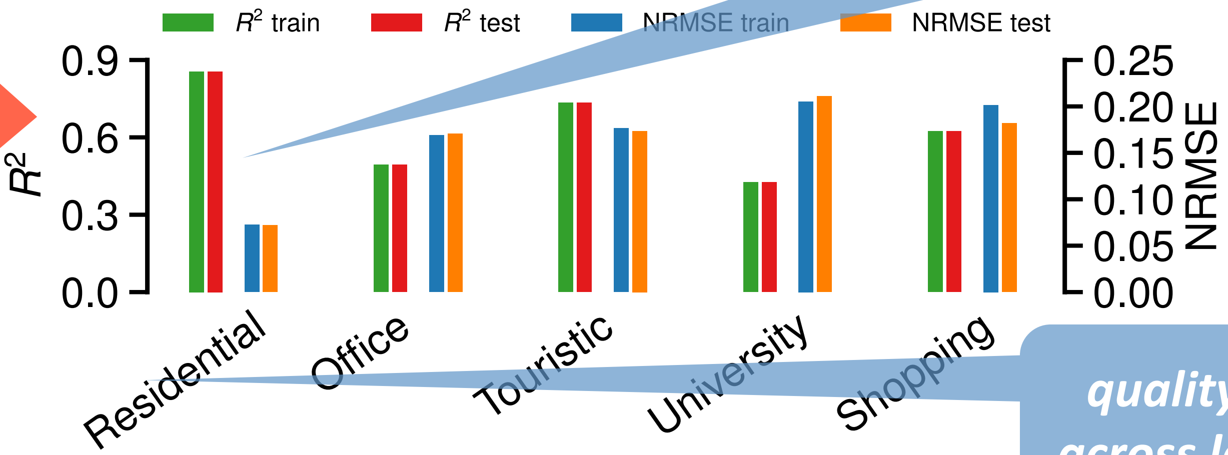
# A glance at results

- **Overall estimation quality**

*good result in residential areas (accounting for 70-80% of total)*

*$R^2$ = 0.8, 8.7% error*

*21% gain over state of art [8]*



*quality varies across land uses*

- **Model reuse across cities is possible**

*$R^2$ = 0.64–0.84, ~10% error*

*test* →

*training* ↓

| | $R^2$ | | | $NRMSE$ | | |
|---|---|---|---|---|---|---|
| | Milan | Rome | Turin | Milan | Rome | Turin |
| MILAN | 0.80 | 0.67 | 0.84 | 0.087 | 0.102 | 0.088 |
| ROME | 0.82 | 0.73 | 0.78 | 0.083 | 0.093 | 0.103 |
| TURIN | 0.77 | 0.64 | 0.84 | 0.094 | 0.108 | 0.087 |

[8] Douglass et al., EPJ Data Science, 2015

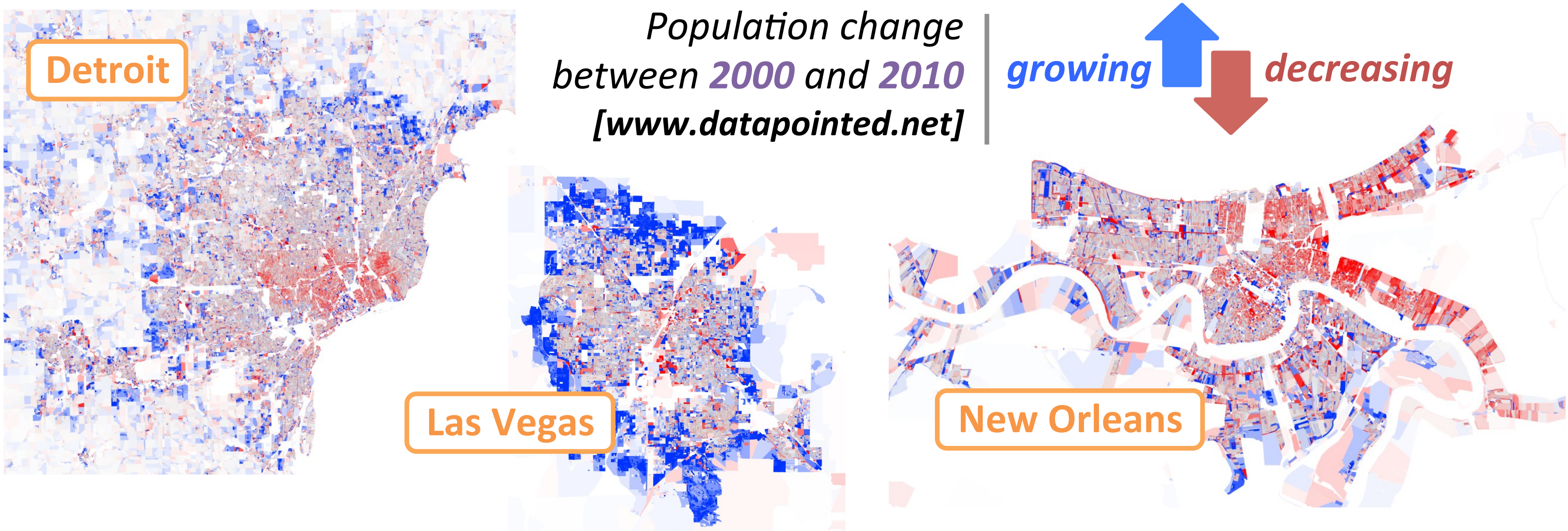
# II.3

# Towards dynamic urban population densities

## A multivariate model

# Dynamic population density

- **Population density is a time-varying phenomenon**
  - Current estimations capture *long-timescale* dynamics

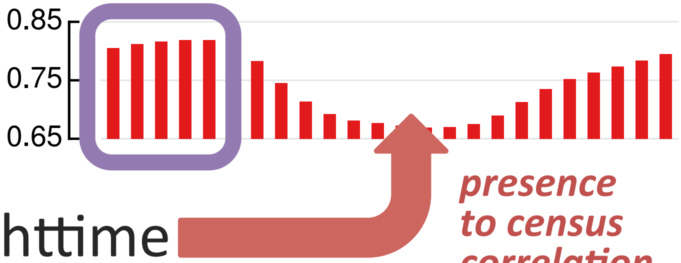


*Population change between **2000** and **2010***

***[www.datapointed.net]***

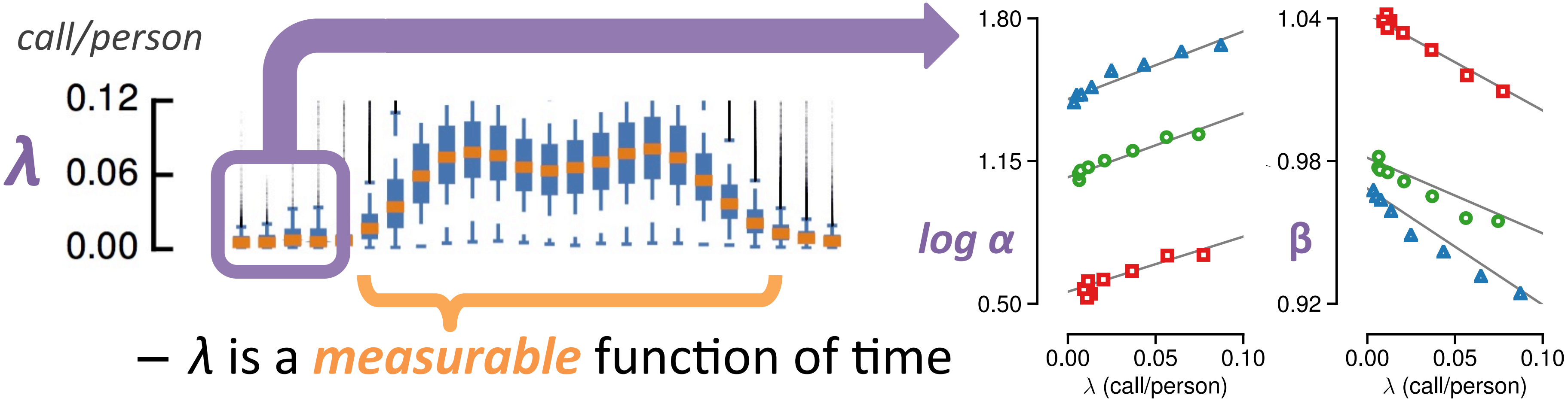
- **What about short-timescale fluctuations?**
  - People distributions in urban areas vary ***within minutes***
  - Mobile network metadata has ***suitable granularity***

# Estimating dynamic populations



*presence to census correlation*

- **Major problem: no ground truth**
  - *Cannot train* a regression model
  - *Cannot trust* a model trained on nighttime
- **A multivariate relationship**
  - $\alpha$ and β can be written as functions of the ***activity level λ***



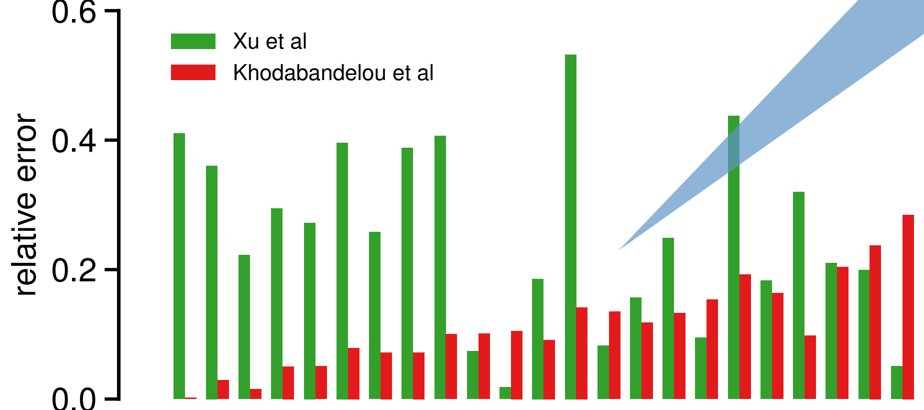
  - λ is a ***measurable*** function of time

$$\hat{\rho}_i(t) = e^{(\hat{a}_\alpha \underline{\lambda_i(t)} + \hat{b}_\alpha)} \cdot \sigma_i(t)^{(\hat{a}_\beta \underline{\lambda_i(t)} + \hat{b}_\beta)}$$

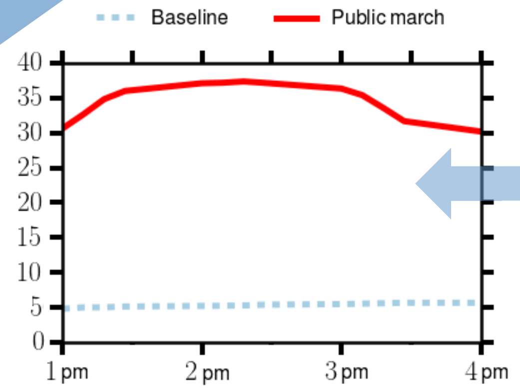
# Another glance at results

- **Validation**
  - Sports events ***attendance***
  - ***Ground truth*** by organizers

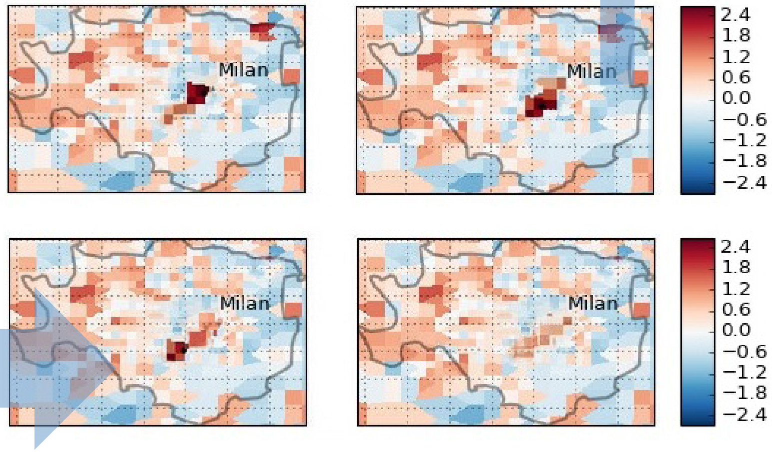
*10% error versus 25% of state of art [9]*



*football matches*



*public march participation estimated at 37,000 (peak)*



- **Model exploitation**
  - Morning/afternoon ***commuting***
  - Emergence of ***social events***

[9] Xu et al., ACM UbiComp, 2015

# III

# Outlook

And perspectives

# Outlook

- **Summary**
  - Mobile network data analysis can complement existing land use mapmaking, especially for ***up-to-date mixed land use***
  - Mobile network metadata analysis complements static and enables ***dynamic population density*** estimation

***Only two examples***

- **Takeaway message**

> *There is more to mobile networks than "plain" communication-based services*

  - Mobile network ***unique features***
    - *(i)* ***pervasiveness***, *(iI)* very low (additional) ***costs***, *(iii)* active/passive ***individual*** monitoring, *(iv)* decent level of ***spatiotemporal detail***

# Outlook

- **What is happening now**
  - A ***growing multidisciplinary*** research effort [10,11]
    - also fueled by ***open data challenges*** (e.g., D4D [12] and BDC [13])
  - Operators start understanding this ***added value***
    - increased ***CAPEX*** on monitoring/sensing facilities
    - development of dedicated solutions (e.g., Telefónica ***4th platform*** [14])
    - provisioning of data-driven services (e.g., Orange ***Flux Vision*** [15])
  - Unison with ***pure networking*** goals
    - consistency with a ***cognitive network management*** vision [16]

[10] D. Naboulsi et al., IEEE Communications Surveys and Tutorials, 2016

[11] V. Blondel et al., EPJ Data Science, 2015; [12] V. Blondel et al., arXiv:1210.0137 [cs.CY]

[13] Telecom Italia Big Data Challenge, http:/www.telecomitalia.com/bigdatachallenge

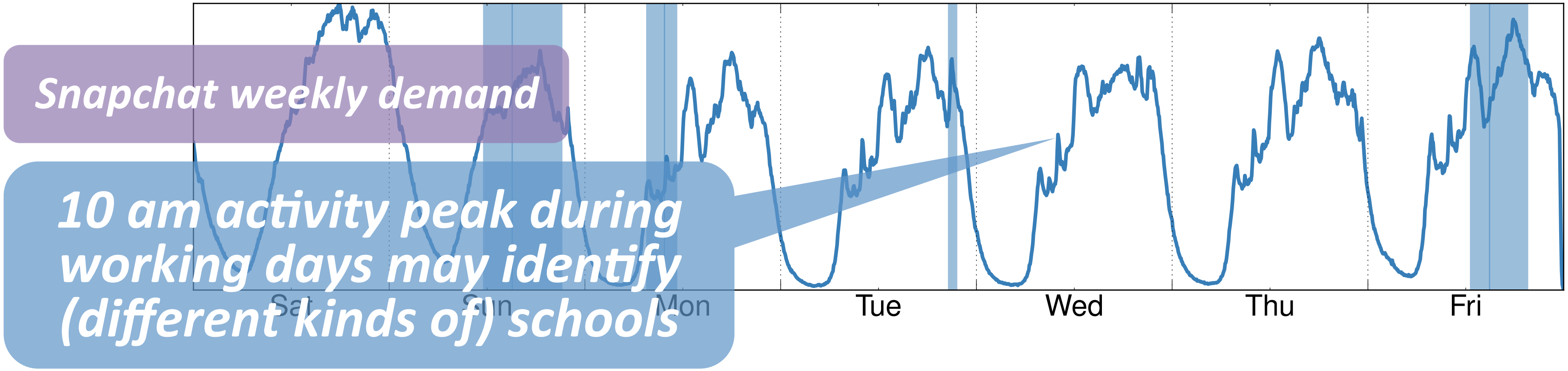
[14] Telefonica Smart Steps, http://dynamicinsights.telefonica.com/smart-steps/

[15] Orange Flux Vision, http://www.orange- business.com/fr/produits/flux-vision

[16] 5GPPP, https://5g-ppp.eu/cognative-network-management-for-5g/

# Perspectives

- **What will (possibly) happen next**
  - There is much ***unexploited (meta)data*** in 3G/4G networks
    - e.g., rich ***per-mobile service*** and ***per-user*** information



***Snapchat weekly demand***

***10 am activity peak during working days may identify (different kinds of) schools***

  - An opportunity for 5G and beyond-5G architectures to be ***"general-purpose systems"*** rather than just "networks"
    - fine-grained ***localization*** (e.g., via mmWave), high-frequency ***tracking*** (e.g., via edge passive probes), ***near-real-time*** provisioning

# ?

# Thanks!

🏠 http://perso.citi.insa-lyon.fr/mfiore/

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