Data-driven Mobility Analytics

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“ Good information helps make right decisions ”

Massive digital traces → Enhance mobility diagnosis

Mobility challenges

- Traffic congestion
- Energy concern
- Emissions and pollutions

Need insights for solutions

- Understand the needs
- Diagnose the problems
- Capture the trends

Massive Data

- Wide-coverage
- Up-to-date
- Rich info for obtainning knowledge of human movements

Modern Mobility Data

What is modern? (vs traditional surveys)

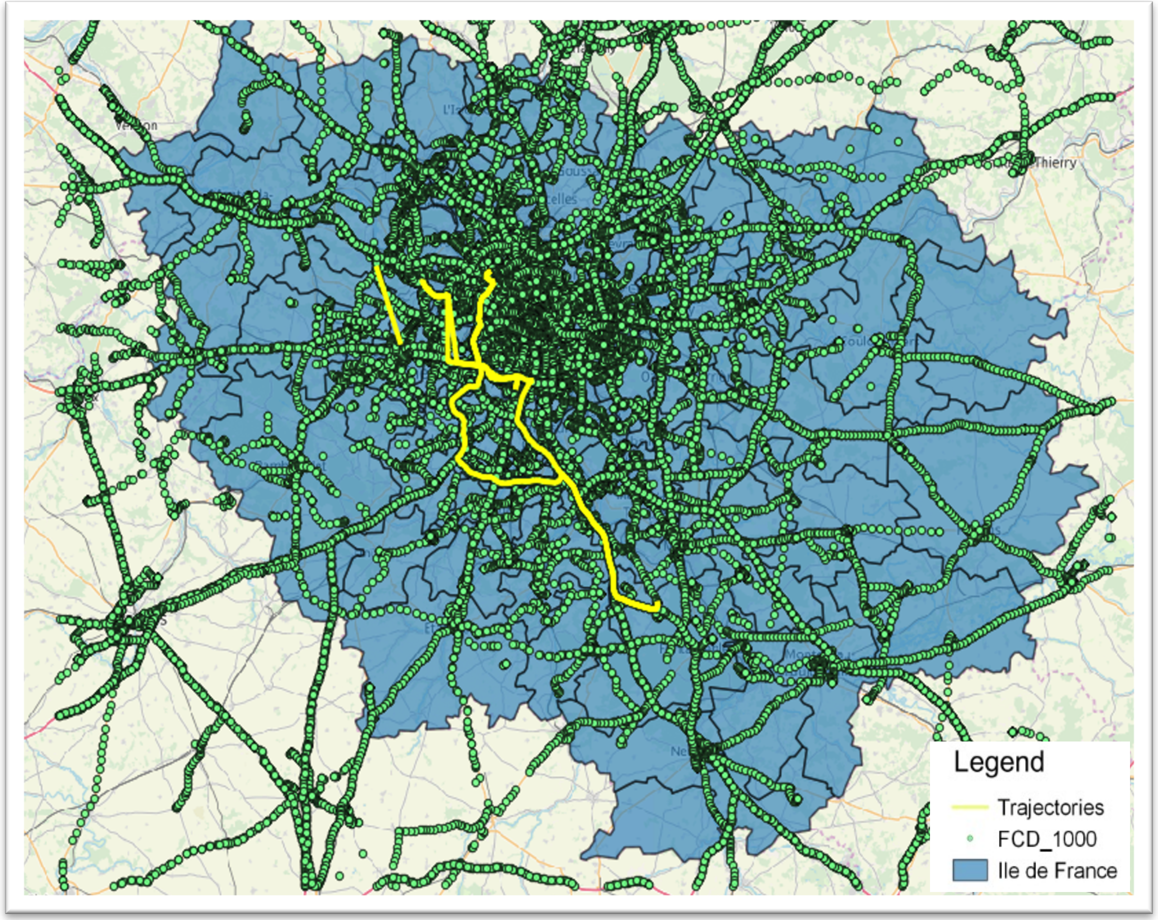
- By sensing technologies
- Mobility localization Info generated automatically

Digital trajectory data (as typical forms)

- GPS receivers (mobile phones, cars, etc.)
- Public transit records (ticket validations)
- Geo-tagged tweets etc.

Floating Car Data

- GPS traces of moving vehicles
- Per record per 30s~60s (sourced from Coyote)
- 3~5% penetration rate (160,000 observed vehicles in Île-de-France)



FCD examples over Île-de-France

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Research Topic

A Ph.D. thesis (2019.01-2021.12 @LVMT, ENPC, supervised by Fabien LEURENT and Xiaoyan XIE)

Objective

- Mobility pattern diagnosis by Trajectory data mining

Issues

Two levels of issues

Individual-Centered Mobility Patterns

- Vehicle usage type (trips)
  - User differentiation
- **Mobility regularities (stays)**
  - Anchor places (e.g. homes and work places)
- Travel time estimation (prediction)

Place-Based Mobility Patterns

- Functional zones (intra-)
  - Land occupations (e.g commercial vs residential)
- **Spatial organizations (inter-)**
  - Employment cores and their catchment areas
- Spatial interactions (inter-)
  - Origin – Destination trip flow

Case study:

Explore home-to-work spatial relations of Île-de-France

- Commuting situations
- Centers and catchment areas

Case Study:
"Explore home-to-work spatial relations of the IDF region"

Analytical steps

Individual analysis

Phase 1:
Trajectory processing → detect home and workplaces

Geographical analysis

Phase 2:
Spatial distribution analysis → identify employment centers

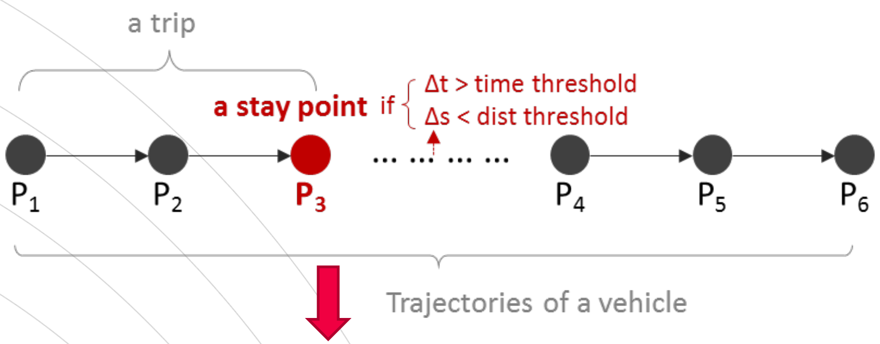
Phase 3:
Spatial relation analysis → discover bonded spatial communities

Phase 1: Home and workplace detection (anonymized)

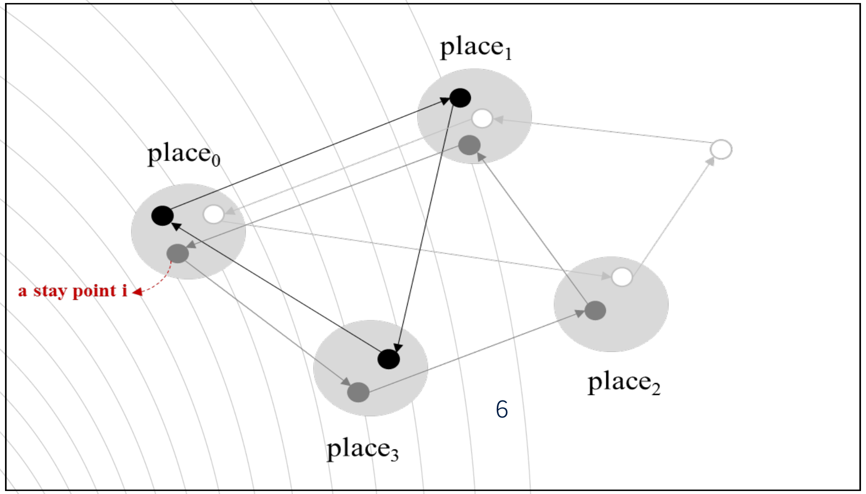
Aim: Recognize the home and workplaces

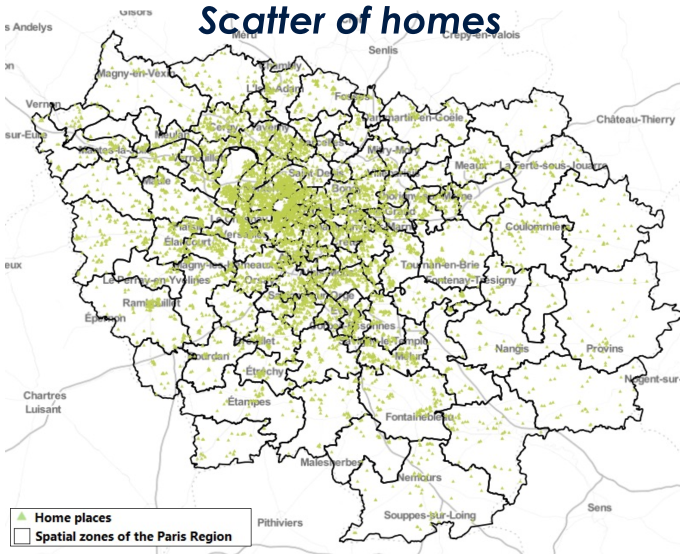
Approach: featuring mining + unsupervised learning -> Learn regularities

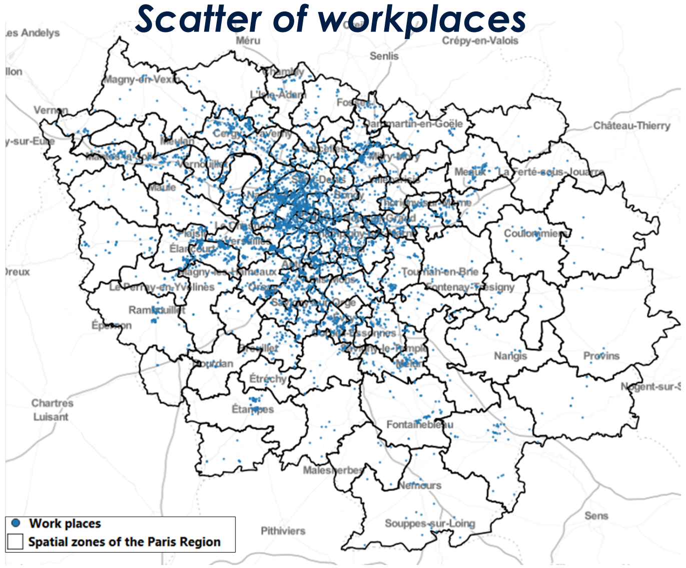
1) Trajectory → **stay points** (by sequencing algorithm)



2) Stay points → **functional places** (by DBSCAN)







3) Functional places → **homes, workplaces** (by Gaussian Mixture Model + Kmeans)

According to :

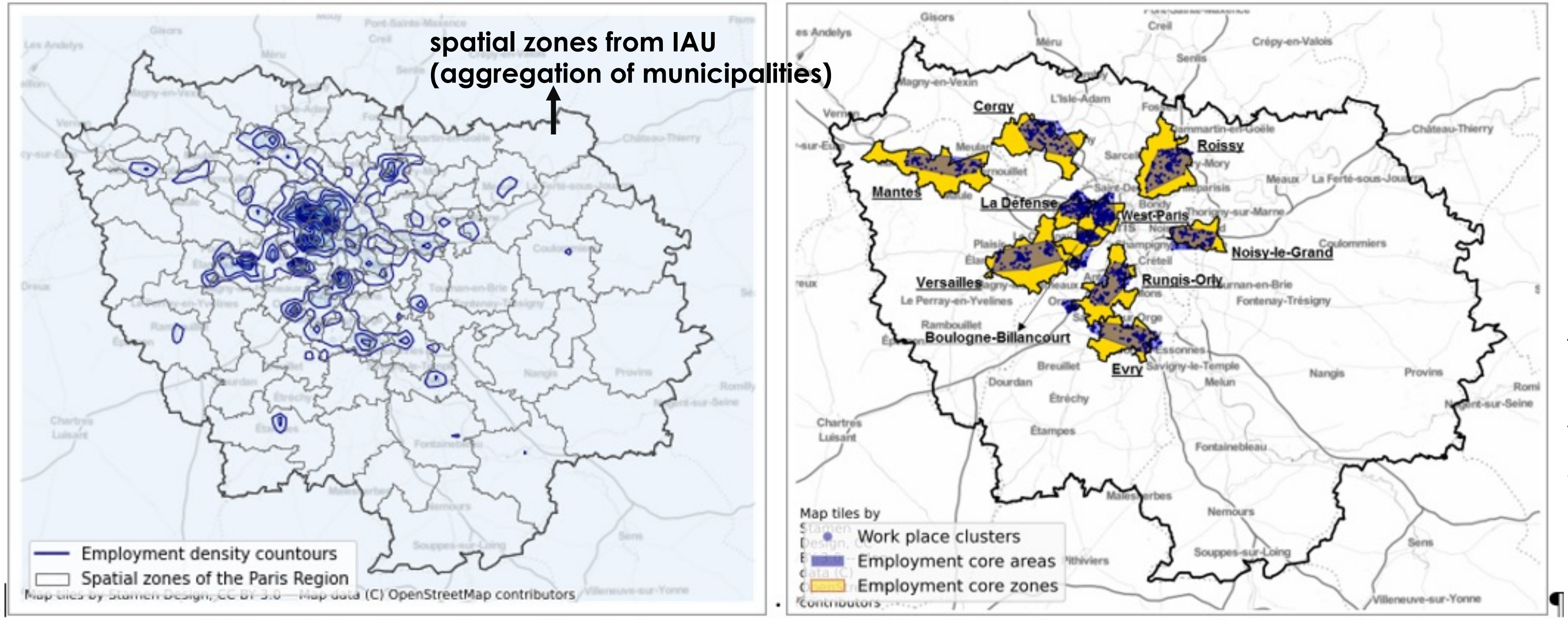
- Visit duration and frequentation
- E.g.: homes: more likely with patterns of visits at the end of day, on almost every day

Phase 2: Spatial distribution analysis

Aim: Identify employment core areas

Approach: density modeling + spatial clustering → delineate core areas based on workplaces

1) Kernel Density Estimation-> density contours **b) HDBSCAN (spatial clustering) -> core clusters -> core zones**



(a) Spatial density contours of work places (b) Employment core areas and core zones

Results:

10 employment core zones

- La-Défense
- Boulogne-Billancourt
- Versailles
- Noisy-le-grand
- Etc.

Account for 43% of total jobs

Notes:

Various-density clustering

- Finer-grained in dense areas and coarser in sparse areas

Results based on auto-mobilists only

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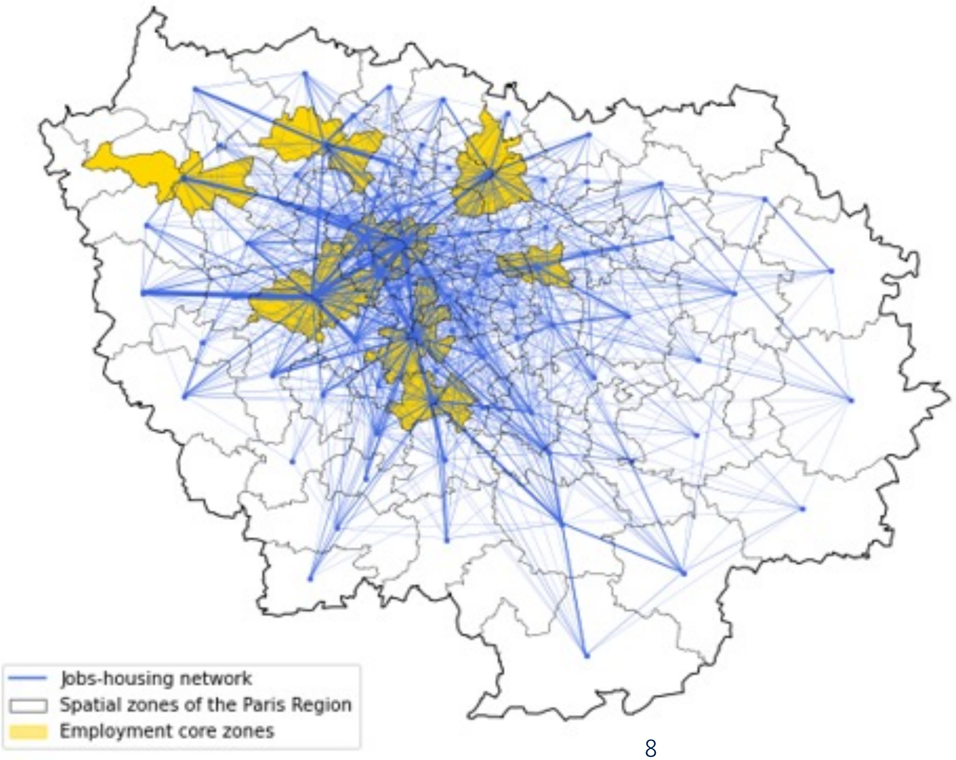
Phase 3: Spatial relation analysis (1)

Aim: Identify spatial communities

Approach: home-to-work flow + graph partition → detect bonded areas

1) Build jobs-housing graph network

- Based on home-to-work flow



2) Graph partition → find communities

- Method: find sub-networks with denser intra-connections and sparser inter-connections
- Output: communities, which are then used to interpret bonded territorial regions

e.g. Community detection by finding inner-dense sub-networks

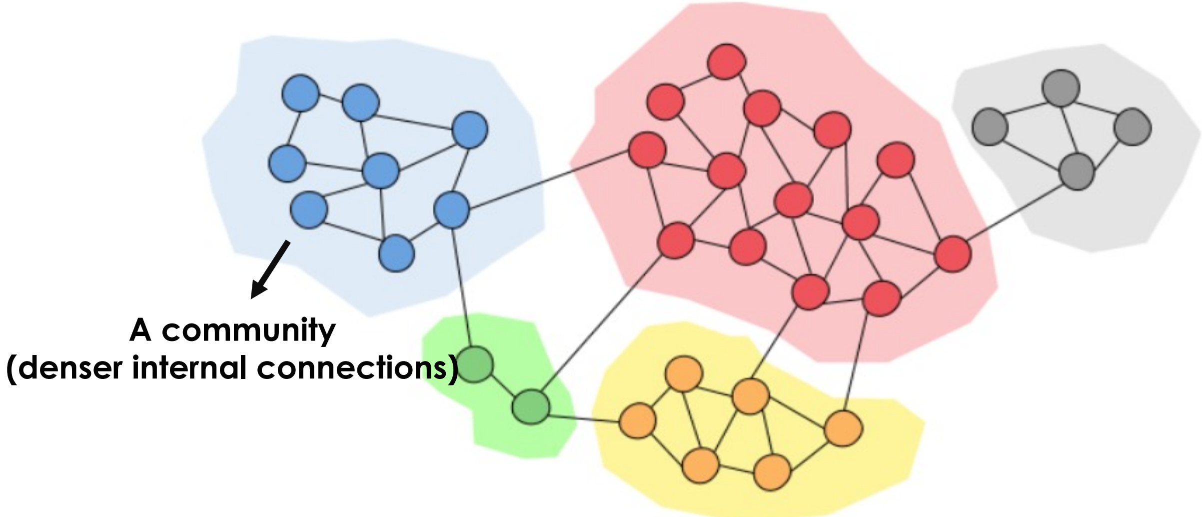
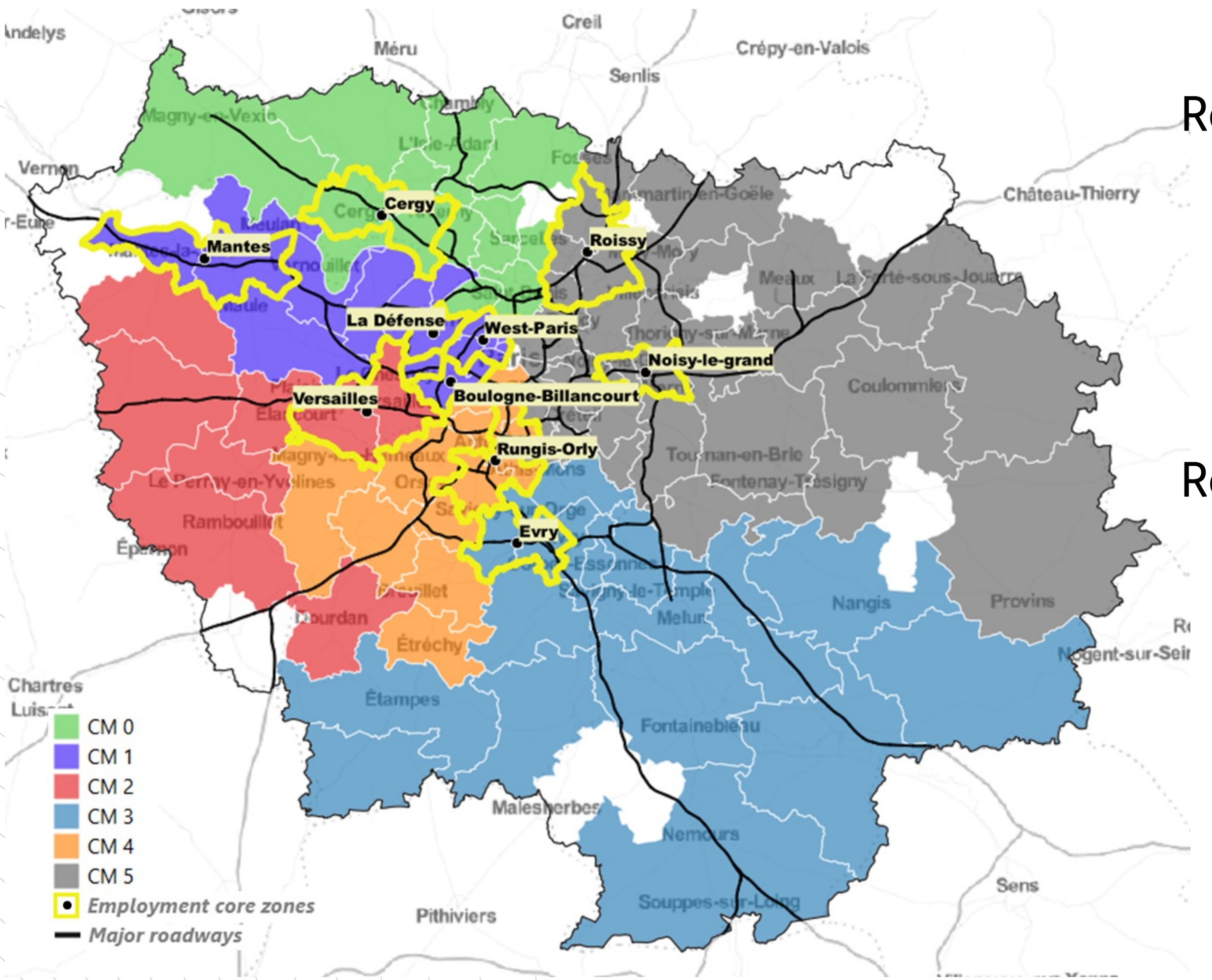


Figure source: by Thamindu Dilshan Jayawickrama @ towardsdatascience.com

Phase 3: Spatial relation analysis (2)

Results of detected spatial communities and their sub-centers



Results:

- 6 spatial communities
- Consistent with the layout of major highways

  (since results based on auto-mobilists from FCD)

Remarks

- Communities are mainly formed by adjacent zones

  → show the nature of spatial cohesion
- Employment cores are embedded in the communities

  → interpret the “catchment” property

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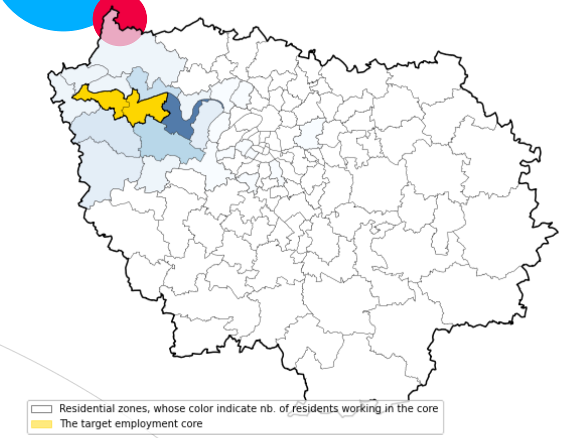
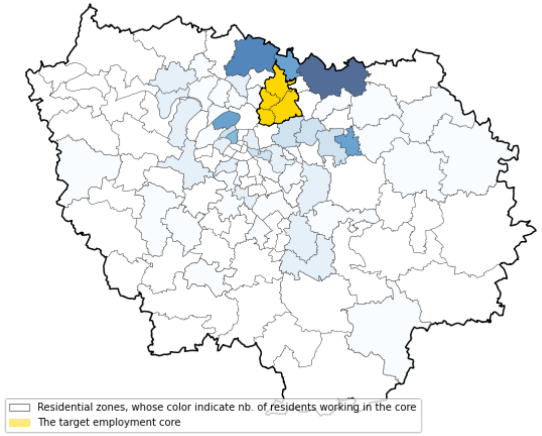
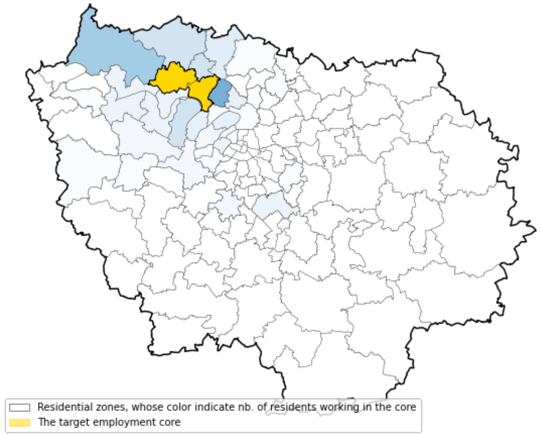
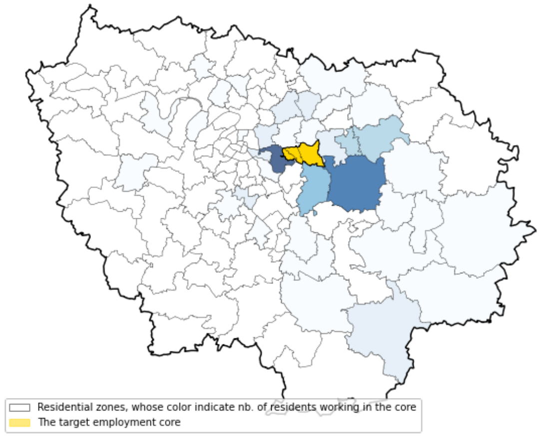
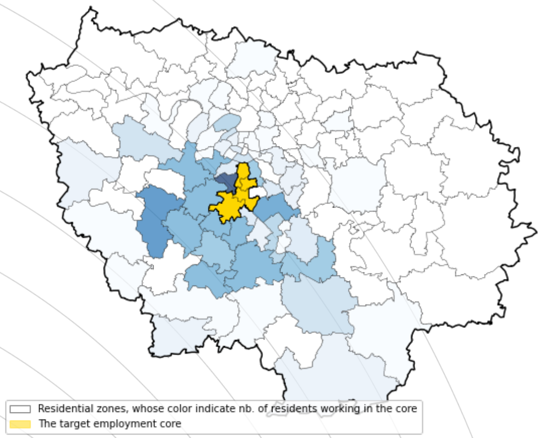
Core-periphery patterns: the "radiation" of cores

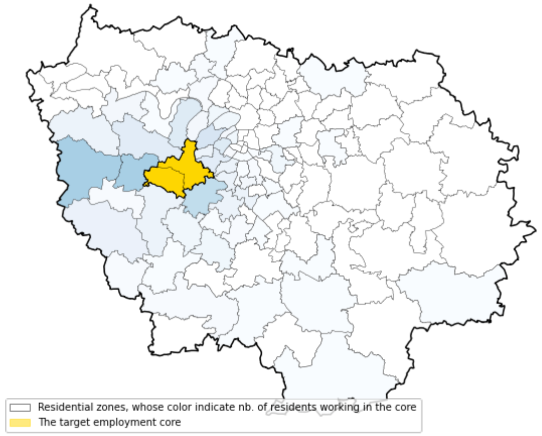


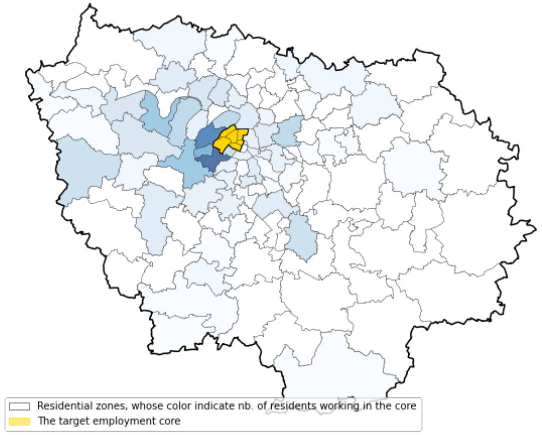


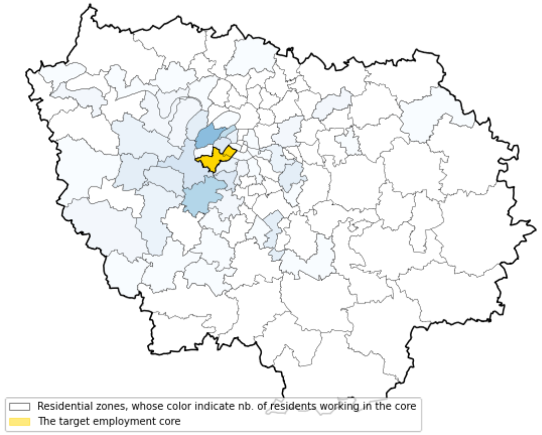




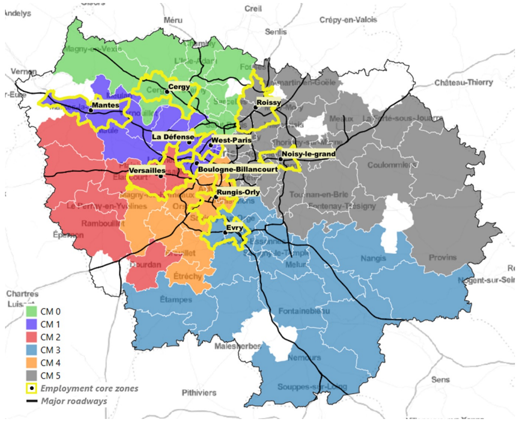


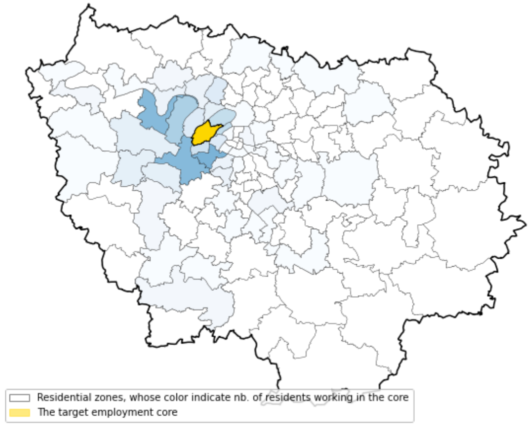


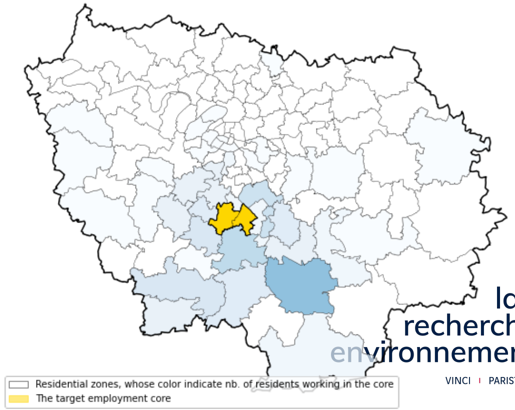




- The "blueness" indicates the number residents working in the core
- Confirm that the communities were not randomly aggregated







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Contribution

- Data-science driven method for automated mobility analytics
- Insights for facilitating network planning and land-use evaluation

Future expansion

- Currently only applied on car mode
- Replicable and scalable to multimodal analysis
  - by using a database involving multimodal trips

    (e.g. mobile phone data, fused datasets etc.)

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Des questions ?

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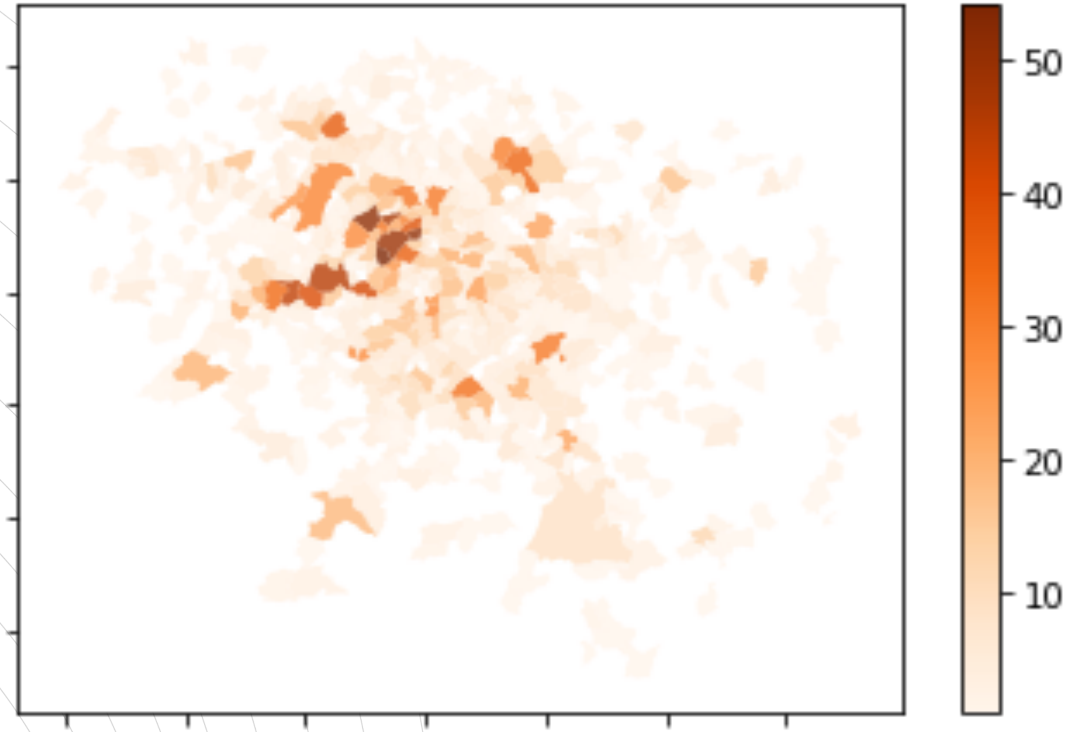
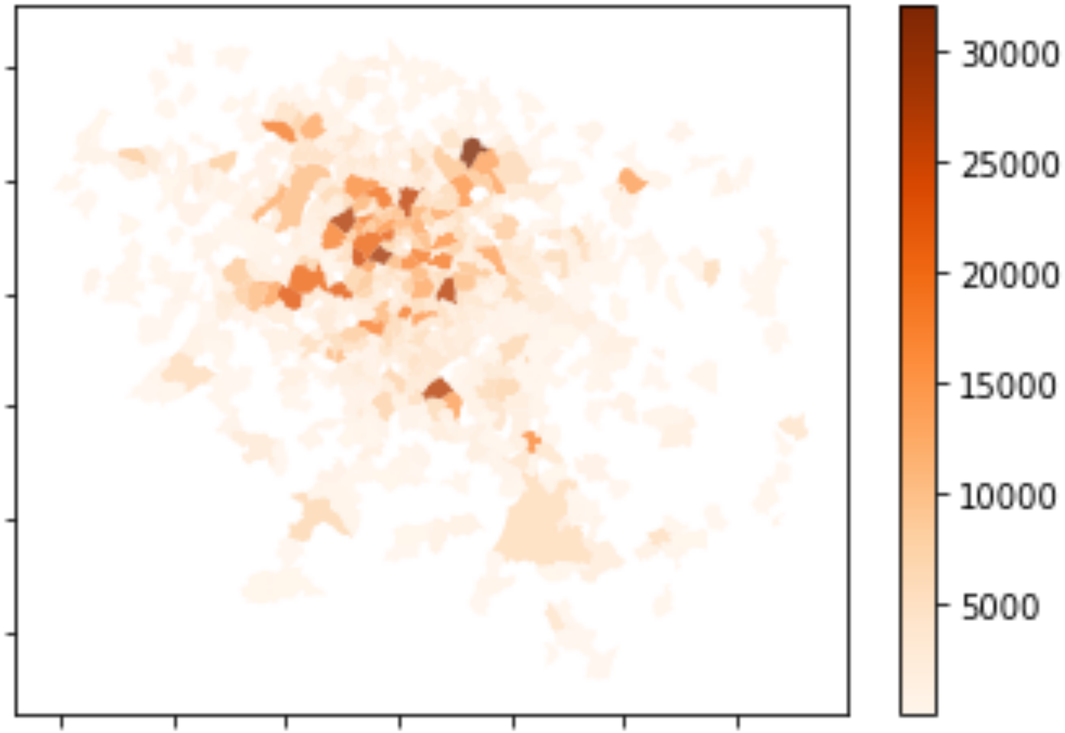
Appendix (1)

Result evaluation

- Comparing with census data (Insee, 2017)
  - ➢ Consistent → the dense areas of jobs in space can be well discovered based on FCD



Job numbers by municipalities from FCD (2019)



Job numbers by municipalities from census data (2017)

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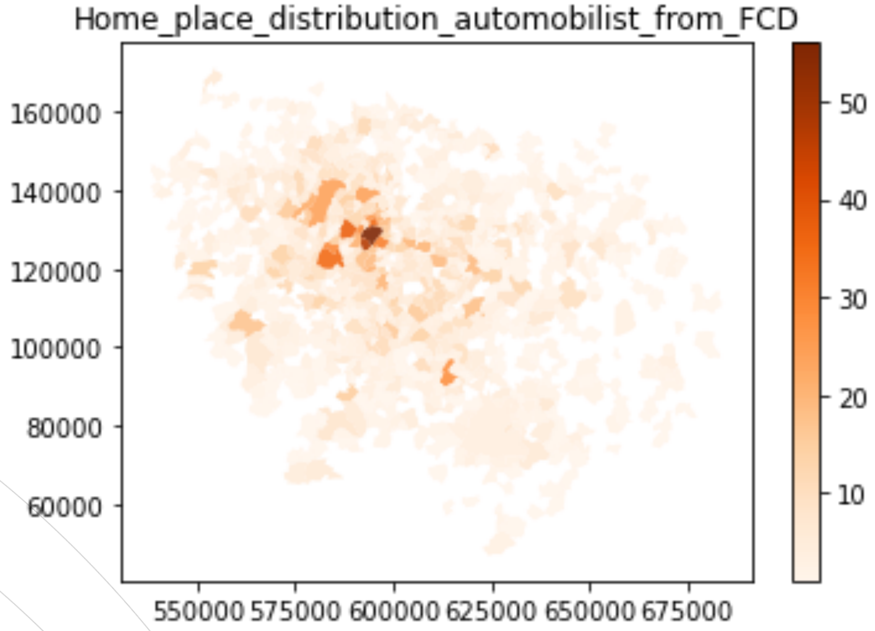
Appendix (2) - Data representativeness



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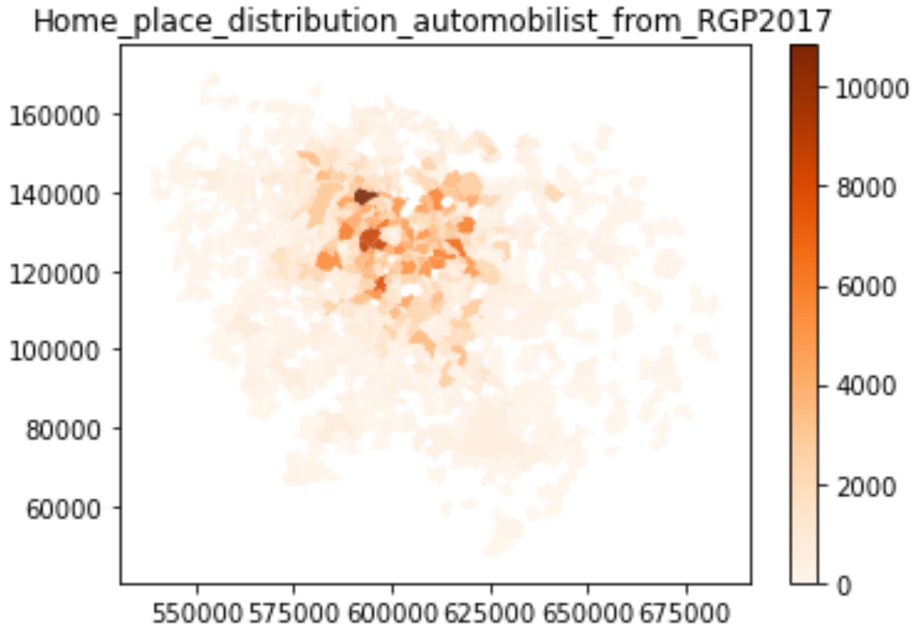

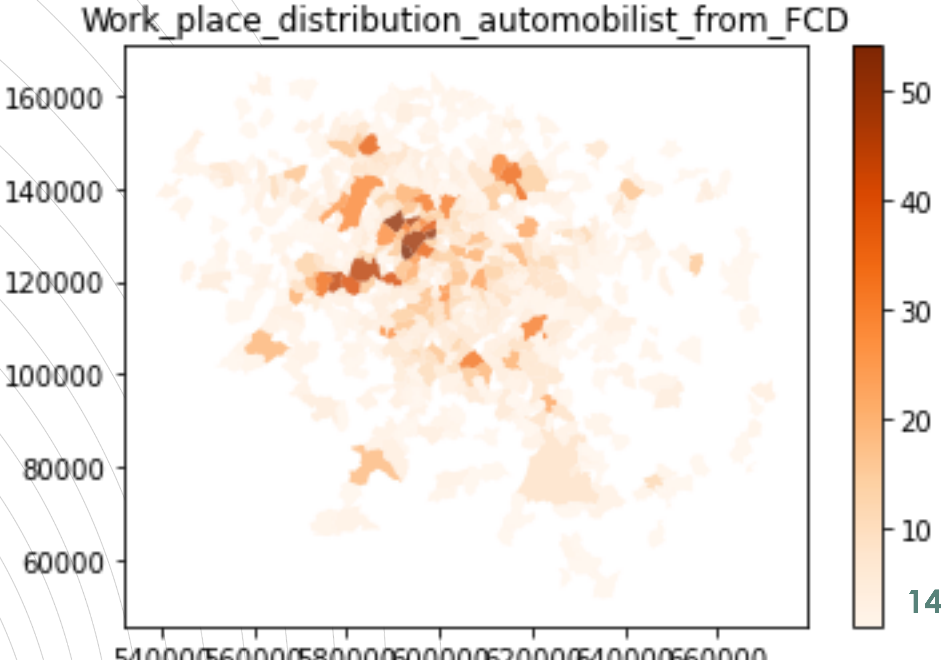

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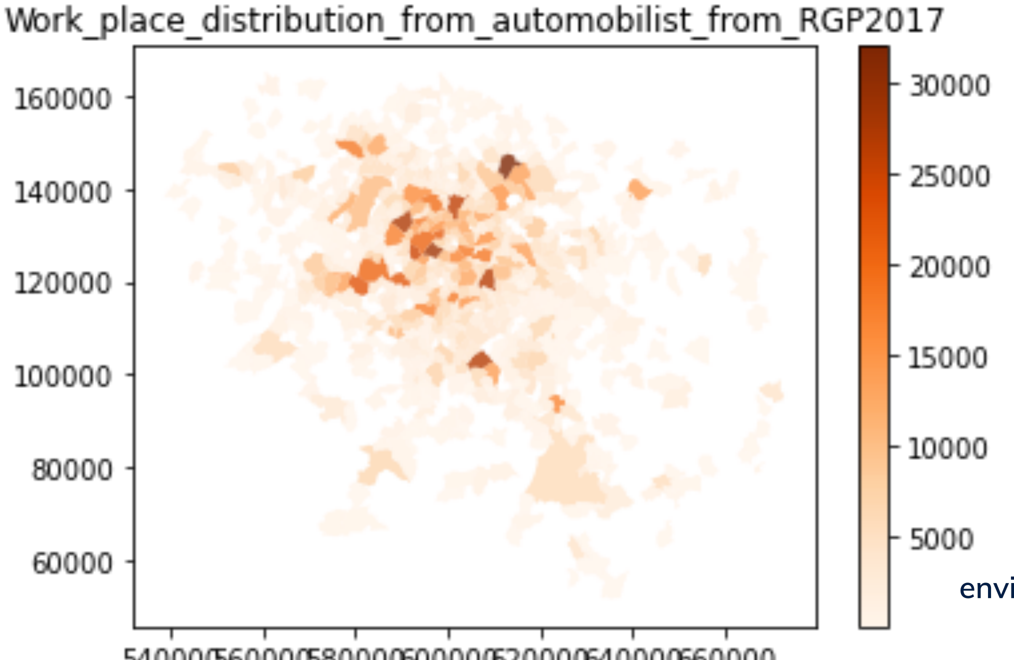
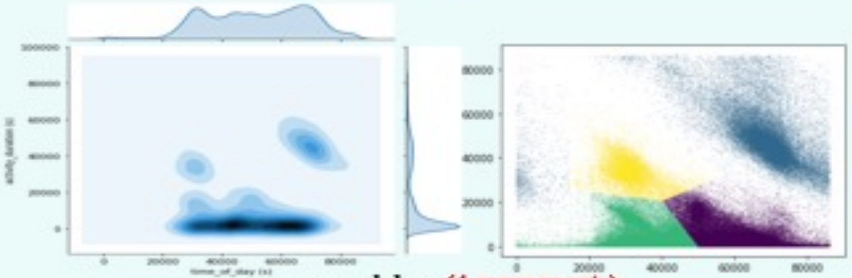


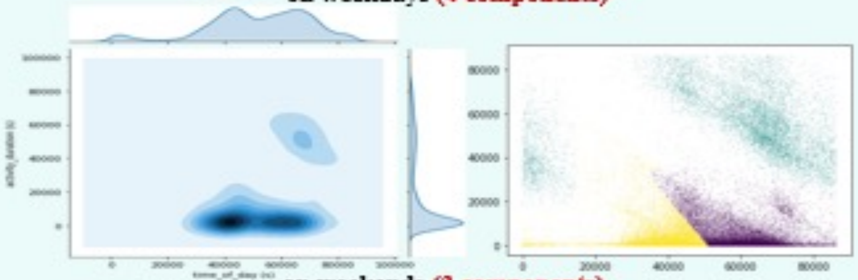
Appendix (3) - Two-level place type identification

Activity Type Identification

- **Features**: 1) time of day and 2) activity duration
- **Approach**: Gaussian Mixture Modeling
- **Results**:
  - Weekdays: 4 activity types
  - Weekends: 3 activity types



on weekdays (4 components)



on weekends (3 components)

Evaluation

Compare with Rule-Based Identification

- Rule-based identification are widely adopted on identifying home/work places
- A common lack of ground truth for such data
- Showed a highly consistent matching

Significant-Place Type Identification

- **Features**: Activity profiles of each place (conditional relative frequencies over each activity type)
- **Approach**: K-means clustering
- **Results**: 7 clusters -> 5 types by characterization
  - Home (c0 & c5): *significant late-day long activities*
  - Workplaces (c2 & c6): *significant early-day activities*
  - Secondary places etc.

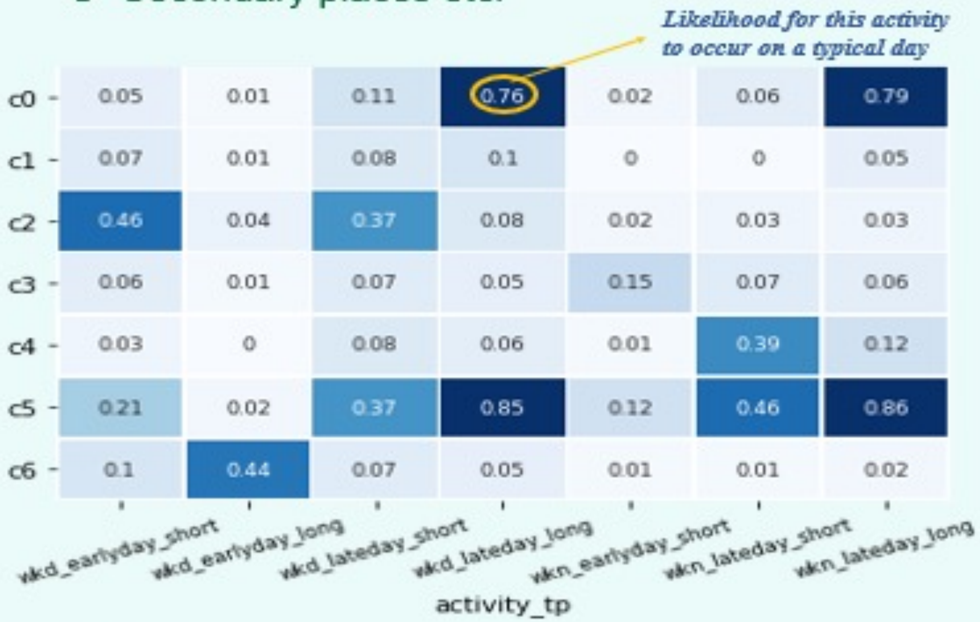


Table. Results of Evaluation

By our method	By rule-based identification (considered as base reference) Home	Work	Secondary	Consistency ratio
Home	5601	107	116	96.2%
Work	26	1254	108	90.3%
Secondary	188	2063	18282	89.0%