Politecnico di Torino

institute IMDEA networks

Uncovering Latent Patterns In Service-Level Spatiotemporal Mobile Traffic

Student: Prashant Kumar Ray (s271098)

Institute Supervisor: Prof. Marco Fiore

Academic Supervisor : Prof. Luca Vassio

Developing the Science of Networks

Agenda

- Introduction
- Objective
- Dataset
- Methodology
- Results
- Conclusion

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Introduction

- The widespread adoption of smartphones has led to a substantial presence of mobile subscribers within today's population.
- Operators log geo-referenced data for billing and resource management, purpose.
- The mobile traffic data analysis enable studies of diverse aspects of human behavior, facilitating research in multiple fields which includes land-use detection, mobility pattern analysis, and social interaction studies and others.

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Objective

Mobile Traffic Data Analysis

1. Uncover latent patterns (factors) along space, time and mobile services (apps)

2. Estimate the number of factors along each dimension

3. Explore the inter-relationship among the factors

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NetMob23 Dataset

- The dataset contains mobile traffic information of
  - 20 urban areas in France
  - 68 mobile services
  - 77 days continuous days
  - 15 minutes temporal resolution
  - 100 x 100 square meters spatial resolution

https://netmob2023challenge.networks.imdea.org/

- For this work, the mobile traffic data for Paris is analysed.

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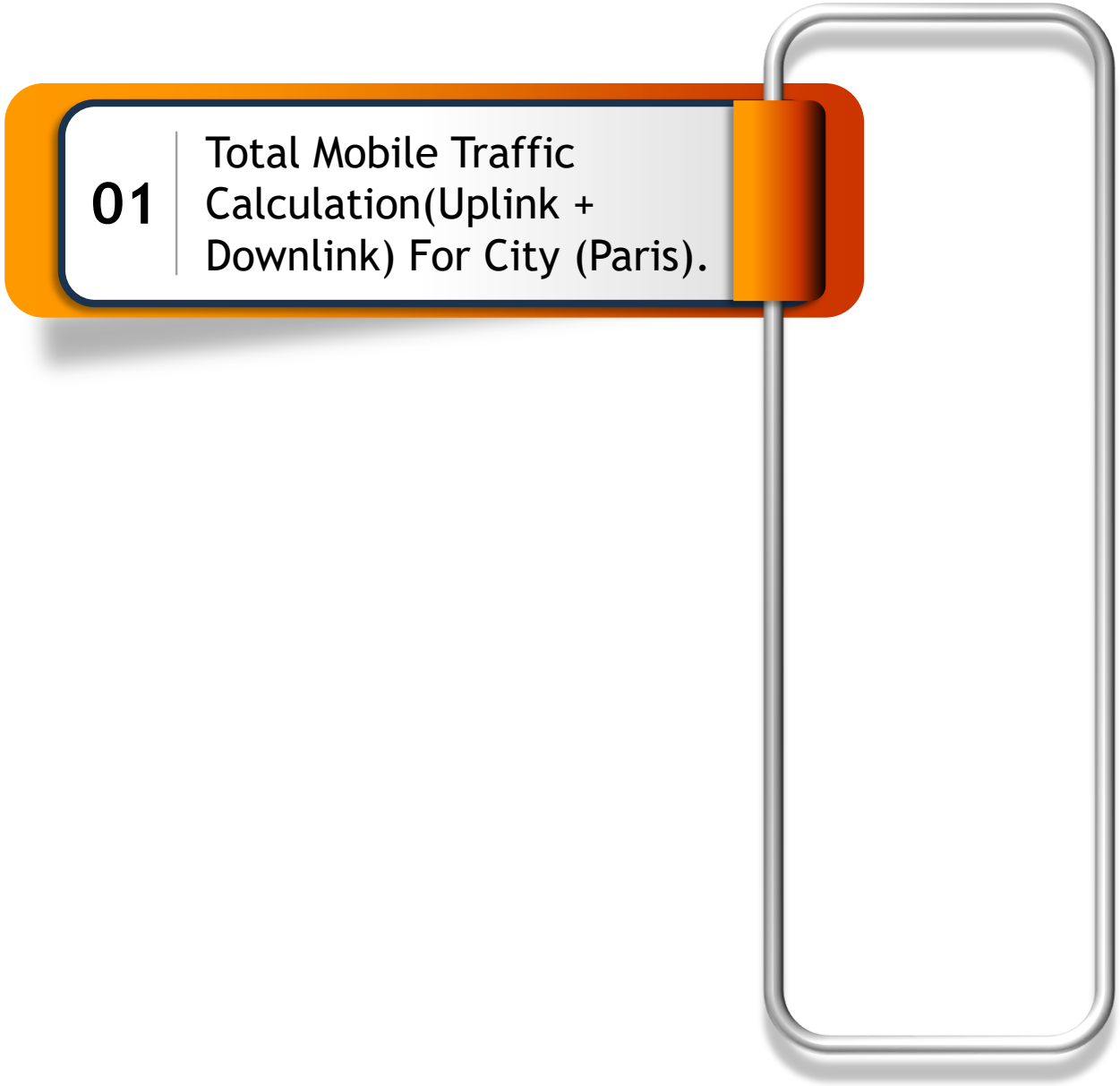
METHODOLOGY

01 Total Mobile Traffic Calculation(Uplink + Downlink) For City (Paris).

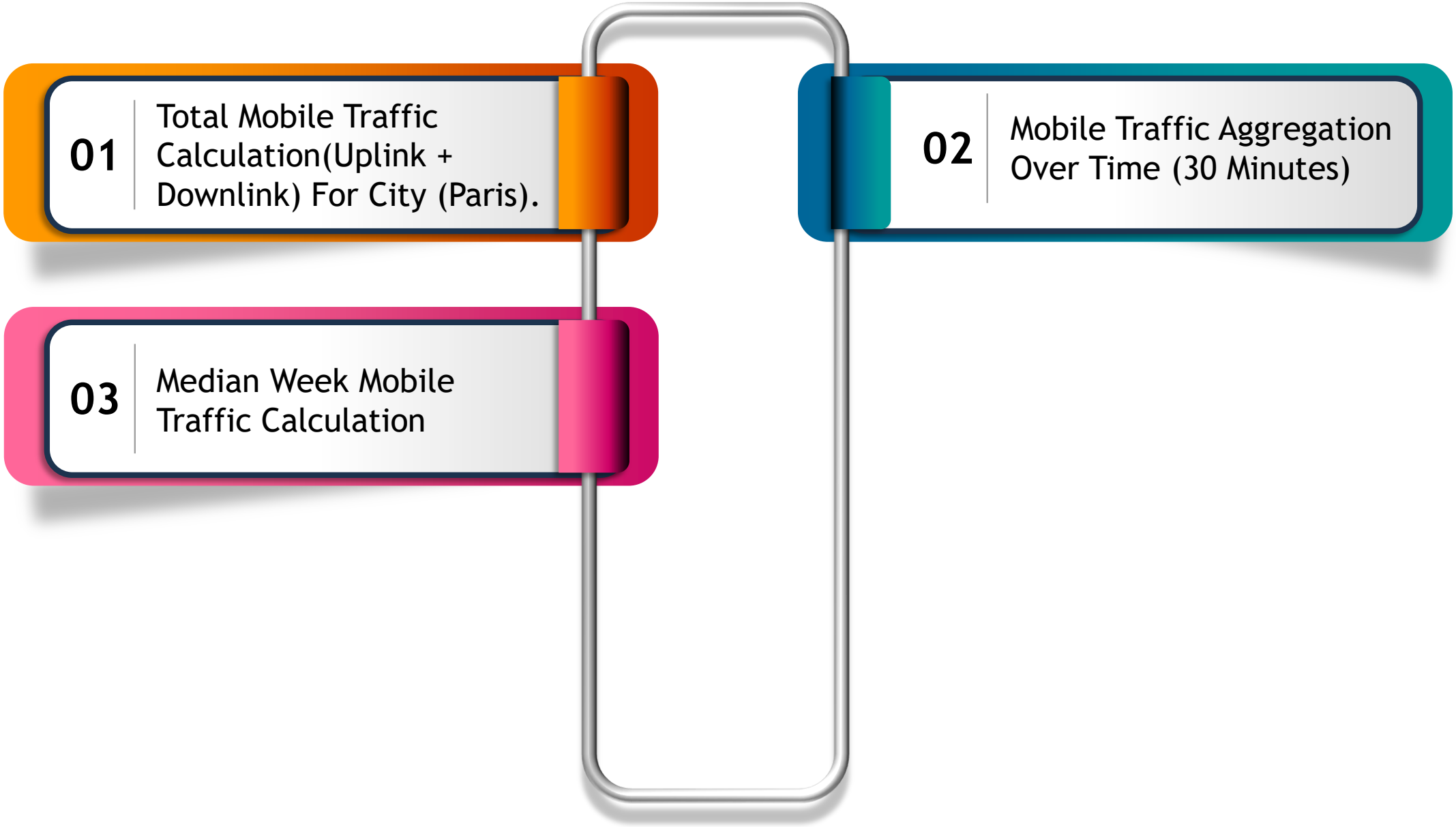


METHODOLOGY

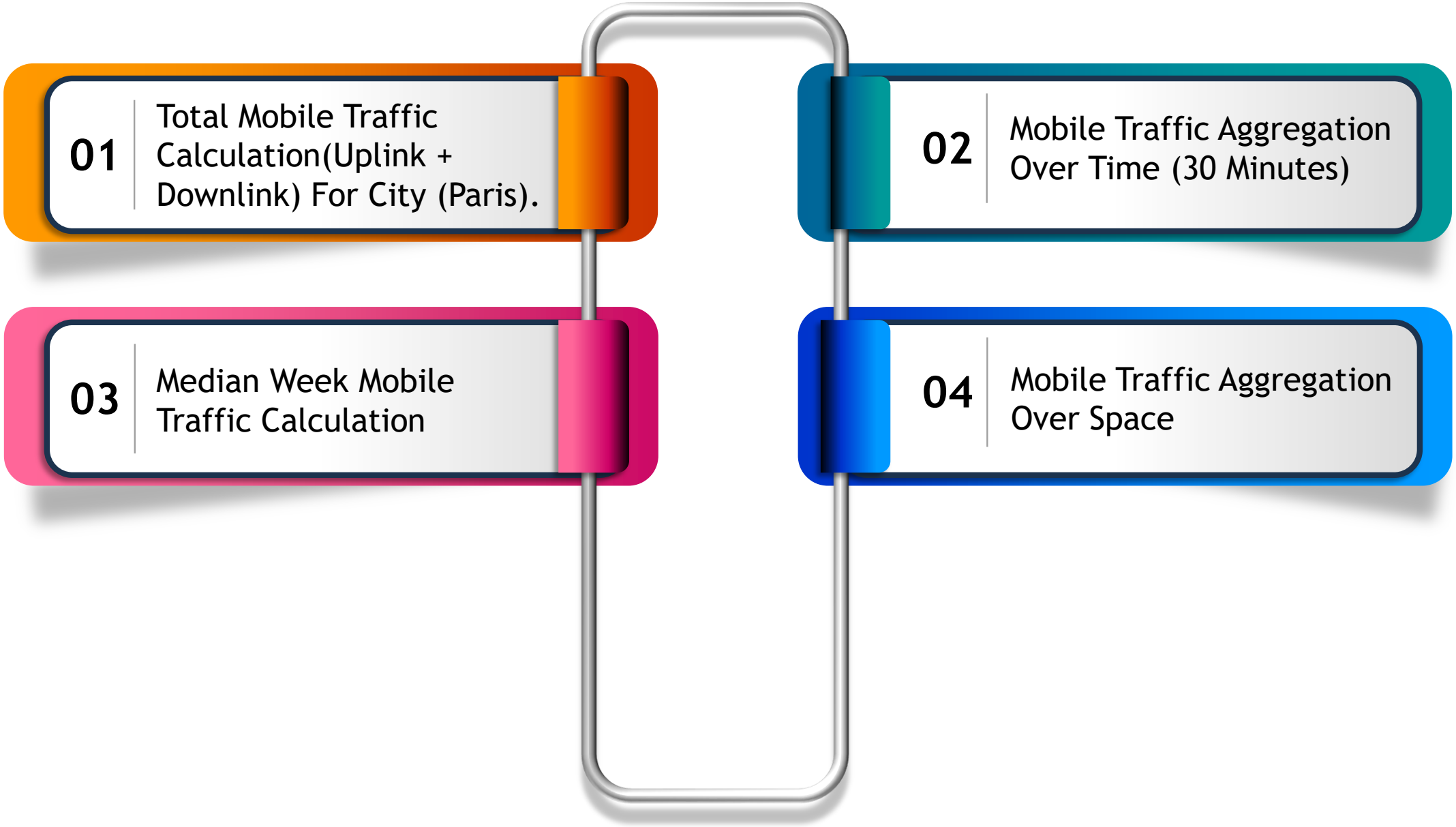
01 Total Mobile Traffic Calculation(Uplink + Downlink) For City (Paris).

02 Mobile Traffic Aggregation Over Time (30 Minutes)

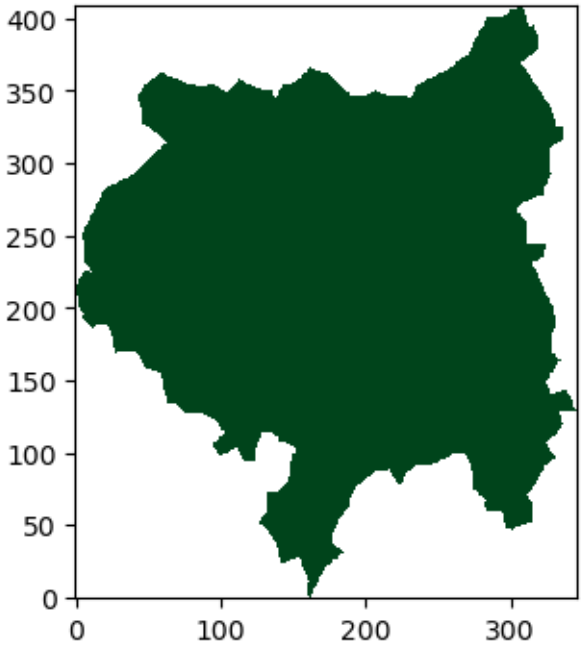
METHODOLOGY



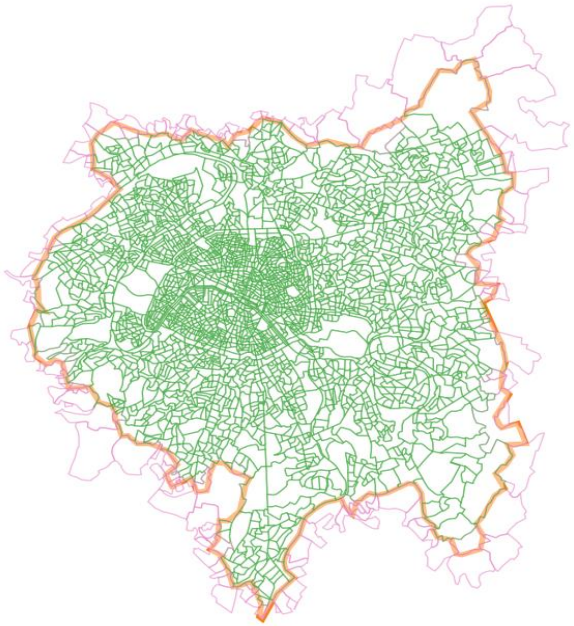
METHODOLOGY



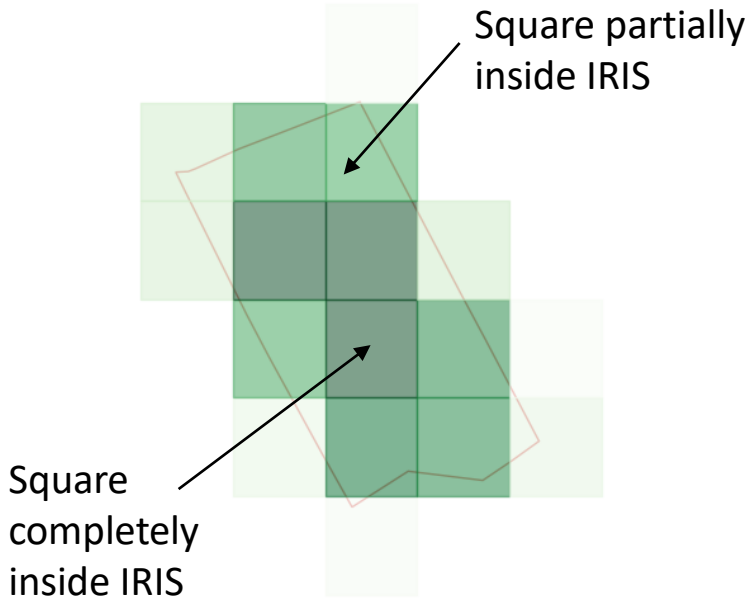
Mobile Traffic Aggregation Over Space



Square representation of Paris



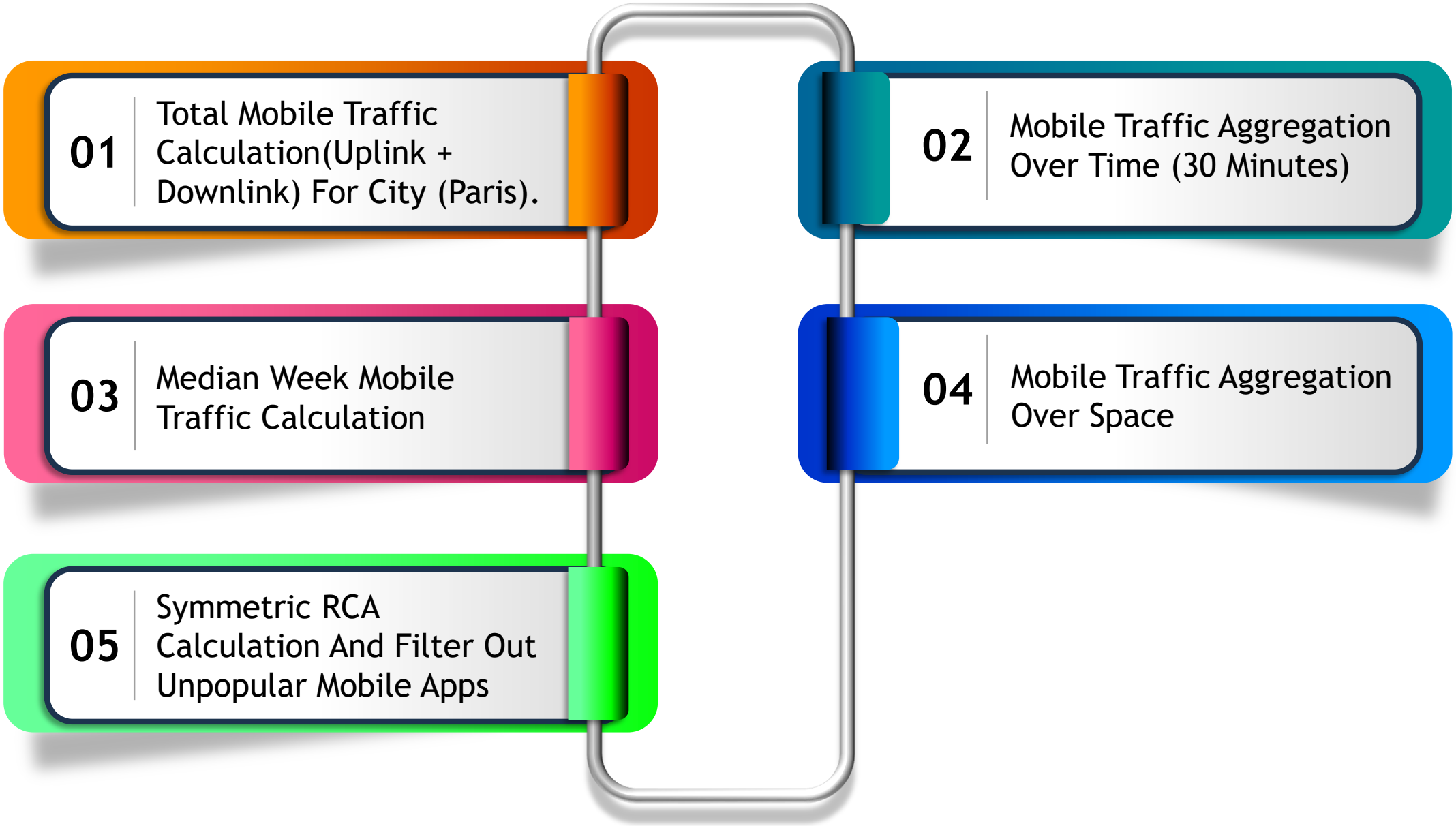
IRIS representation of Paris



Square and IRIS intercept example

- IRIS represents the fundamental unit that respects certain geographic and demographic criteria and have borders which are clearly identifiable and stable in the long term.

METHODOLOGY



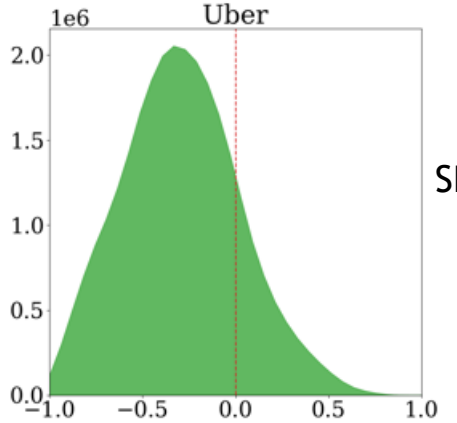
Revealed Comparative Advantage (RCA)

- Revealed Comparative Advantage (RCA) highlights the comparative aspect of different app usage and serves as an indicator of how various mobile apps are utilized within a geographical location and time frame.

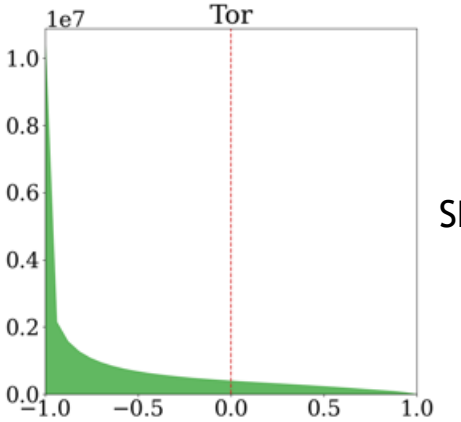
$$RCA = \frac{(T_{ij}/T_j)}{(T_i/T)}$$

T_{ij} = Mobile traffic generated by app i in location j
T_j = Total traffic generated by all apps in location j
T_i = total traffic generated by app i in all locations
T = total traffic generated by all apps in all locations

$$Symmetric\ RCA \quad (SRCA) = \frac{(RCA - 1)}{(RCA + 1)}$$

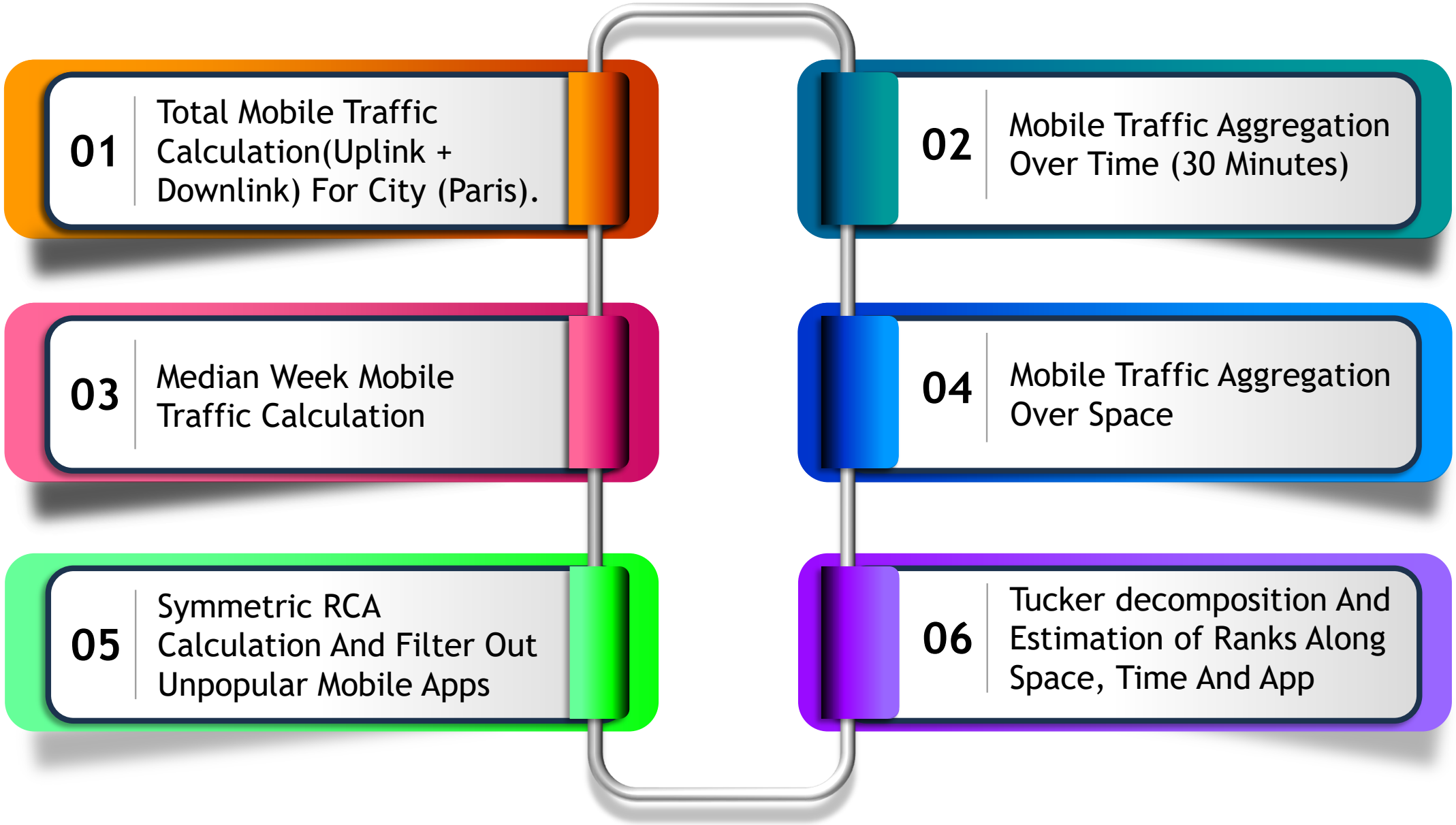


SRCA distribution Uber

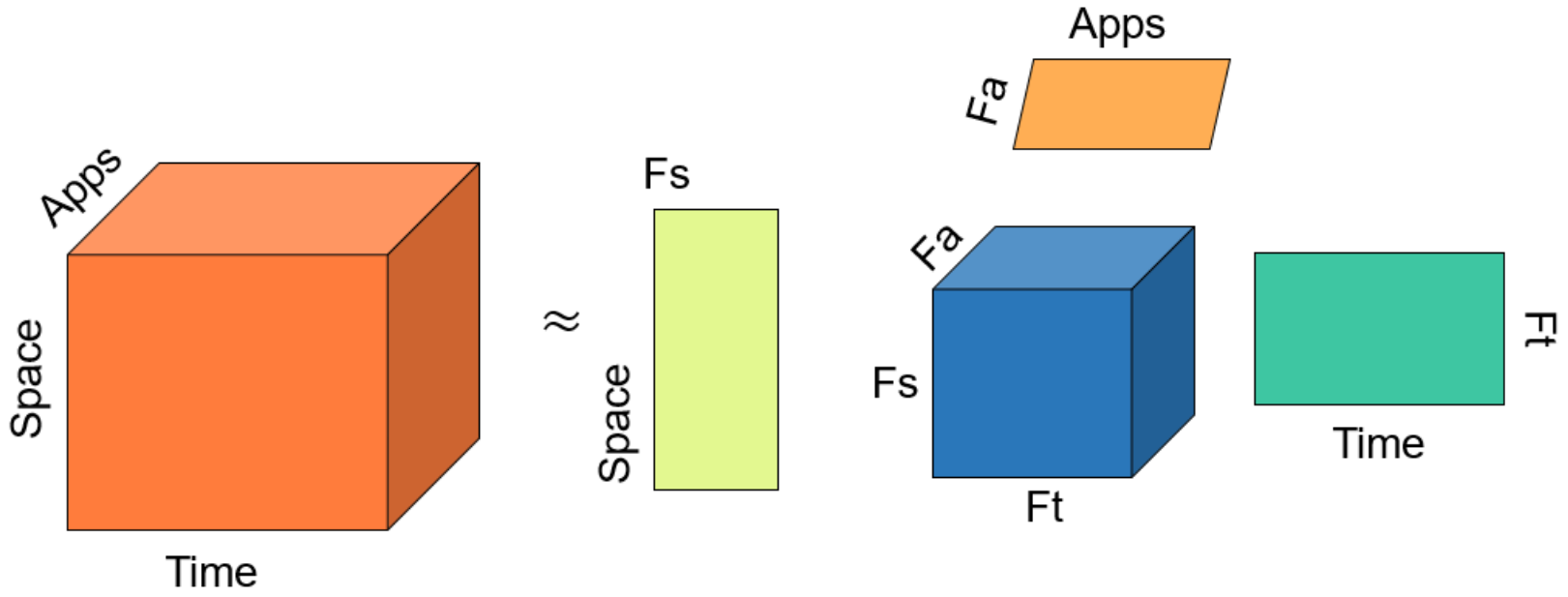


SRCA distribution Tor

METHODOLOGY



Tucker Decomposition



- Tucker decomposition decomposes a tensor into a set of matrices, with one matrix for each dimension, along with a core tensor.

- Tensor dimension (Space, App, Time) = (2800, 58, 336)

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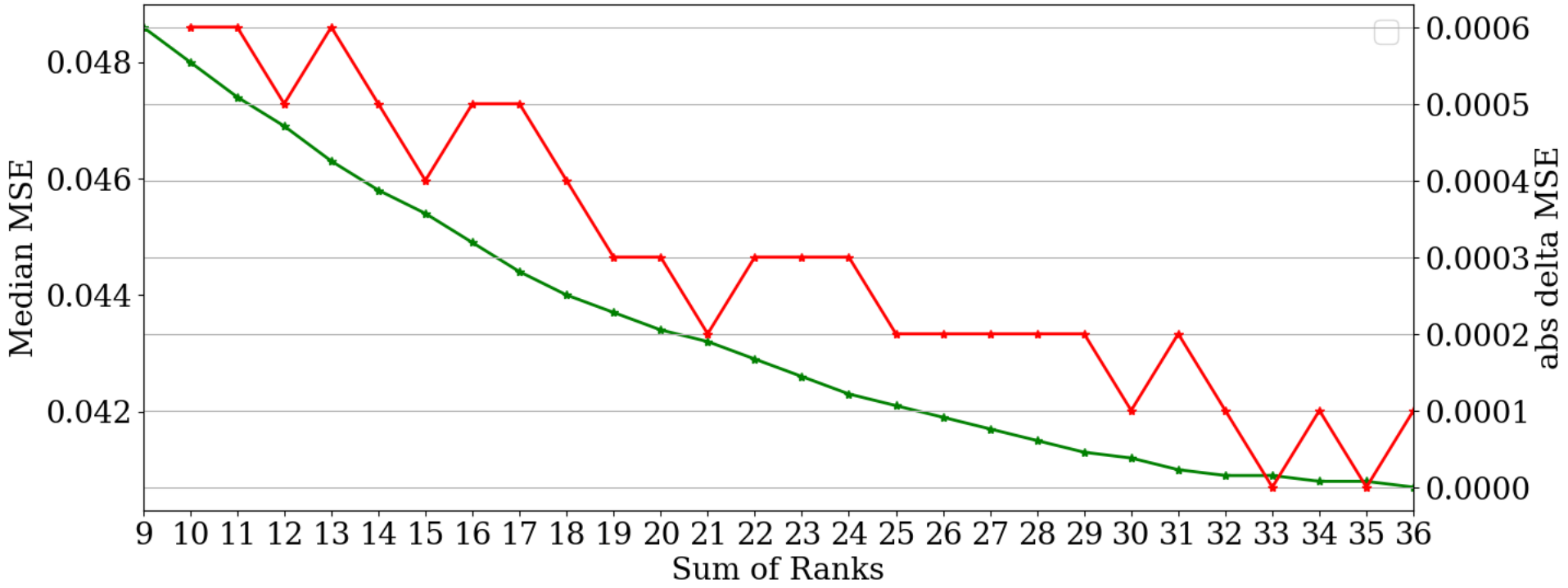
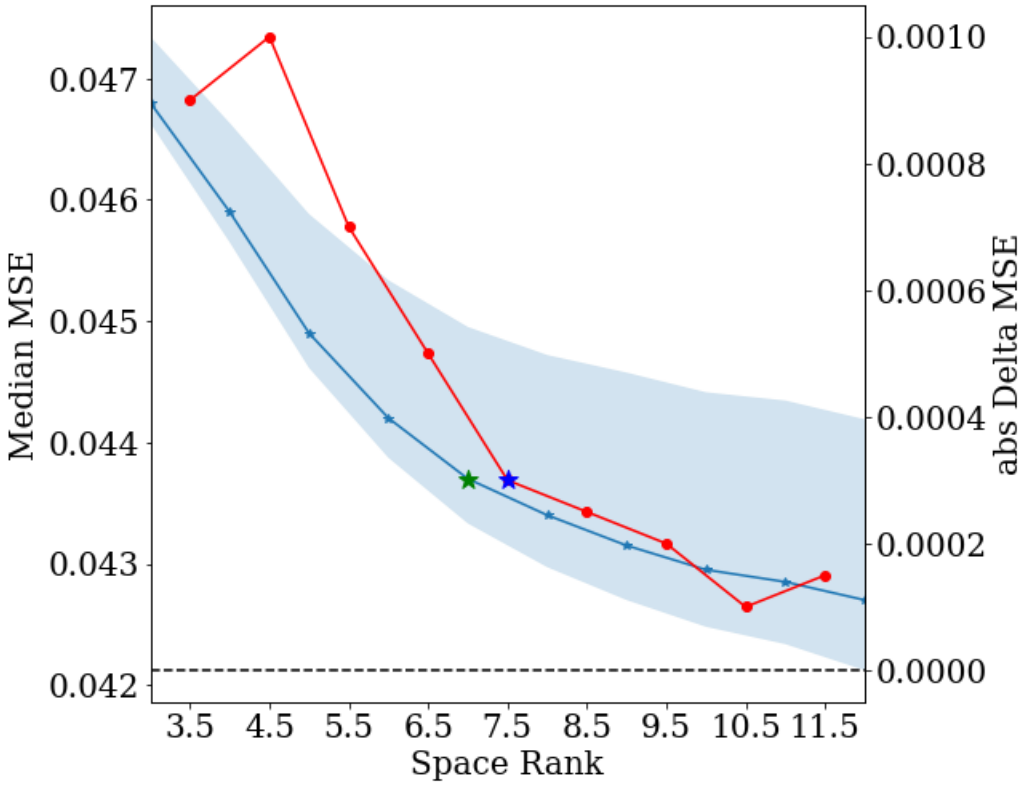
Determining Ranks For Tucker Decomposition

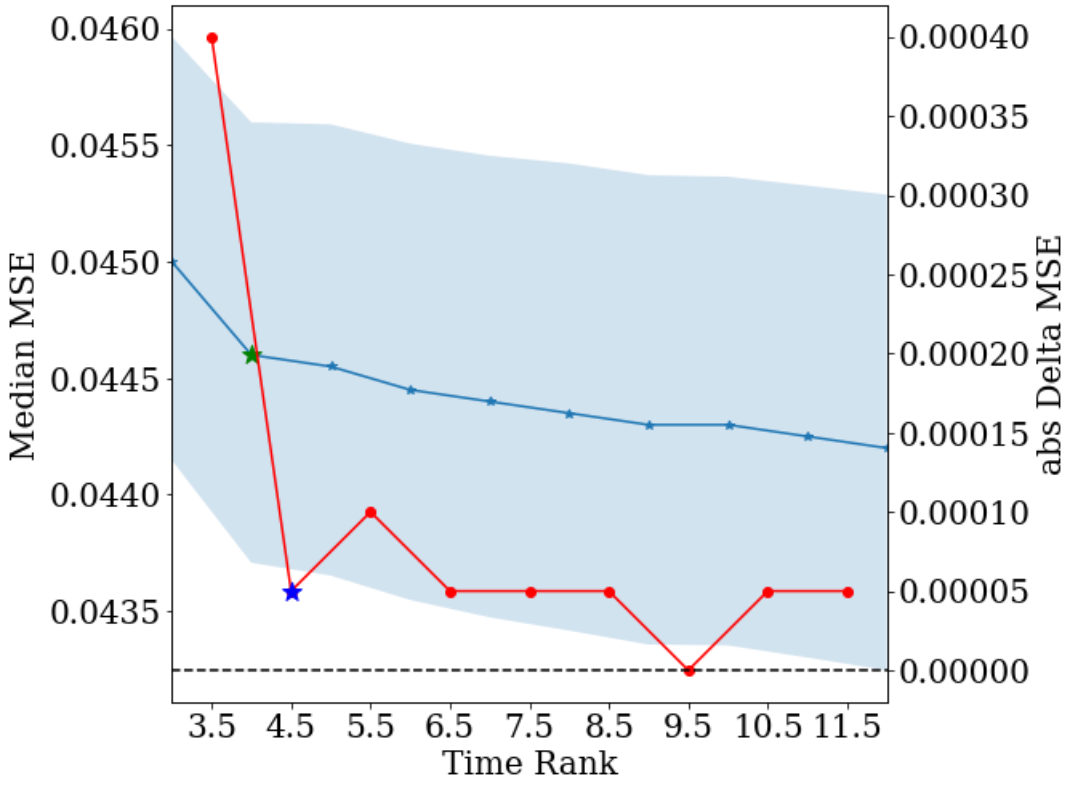


- MSE decreases as we increases number of ranks.
- It is important to have a balance between the number of factors along each dimension and the associated MSE.

Determining Ranks For Tucker Decomposition (contd..)

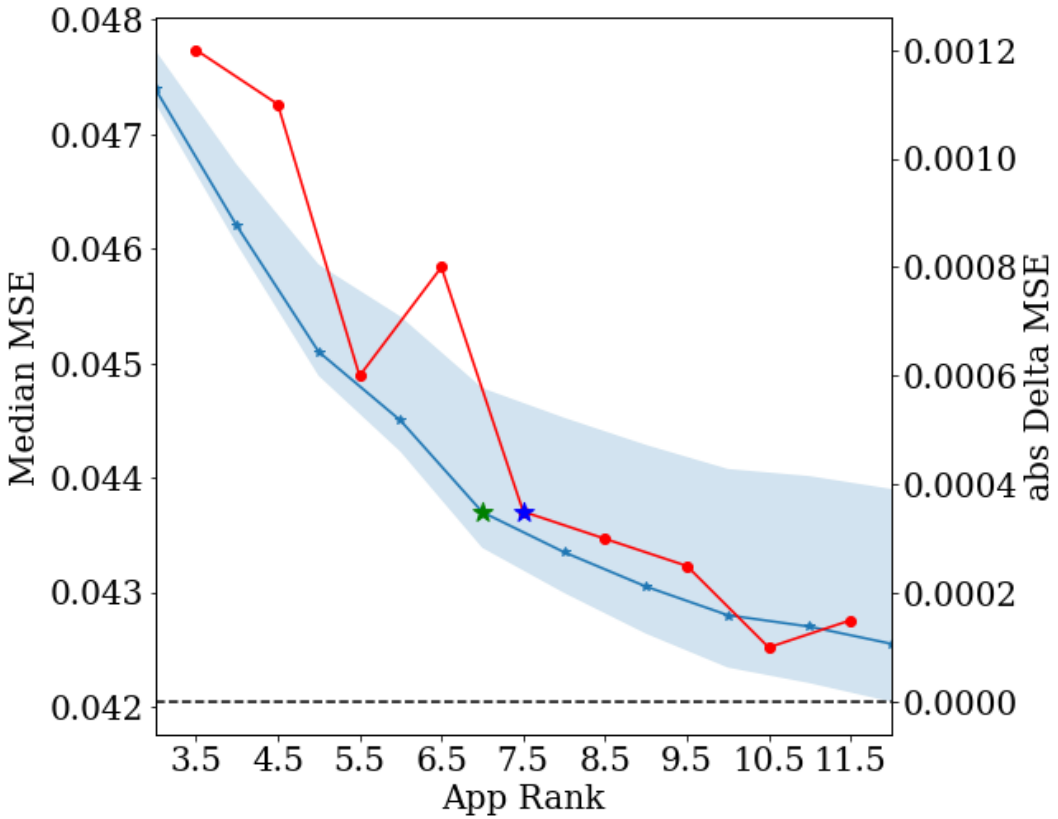


Space Rank = 7



Time Rank = 4

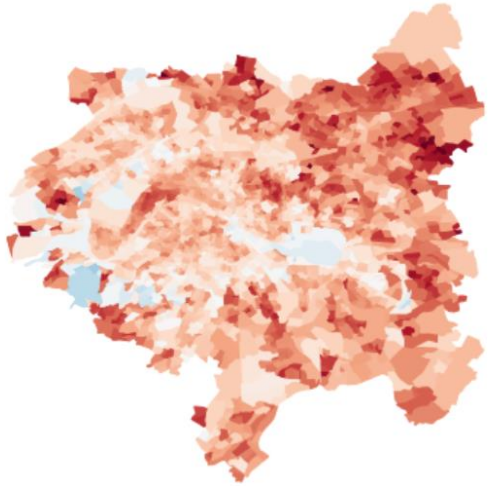
Determining Ranks For Tucker Decomposition (contd..)



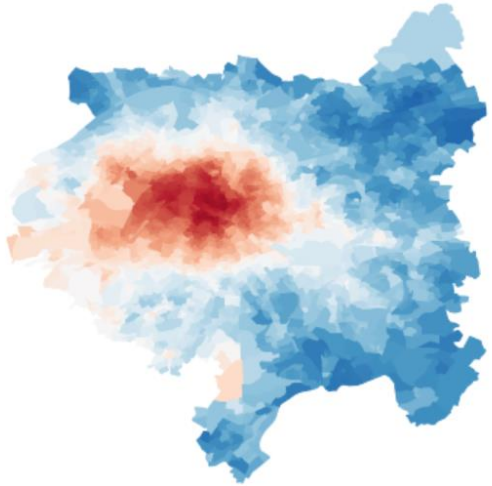
- App Rank = 7
- The rank combination used for the Tucker Decomposition

  [Space, App, Time] = [7 ,7 ,4]

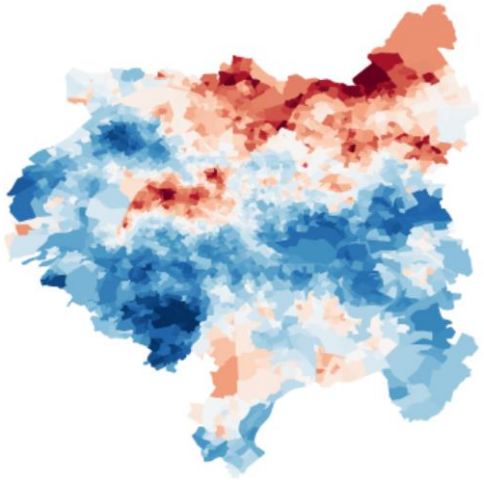
Space Factors



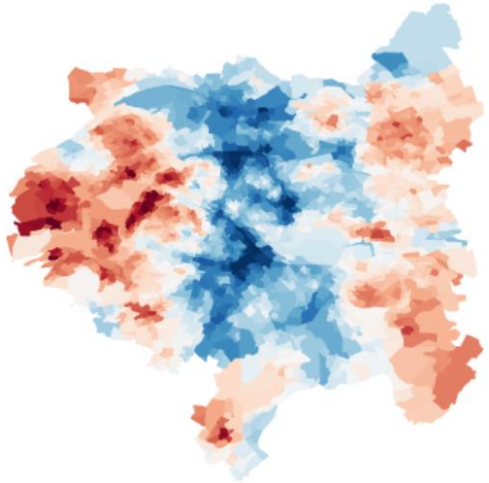
Space Factor 0



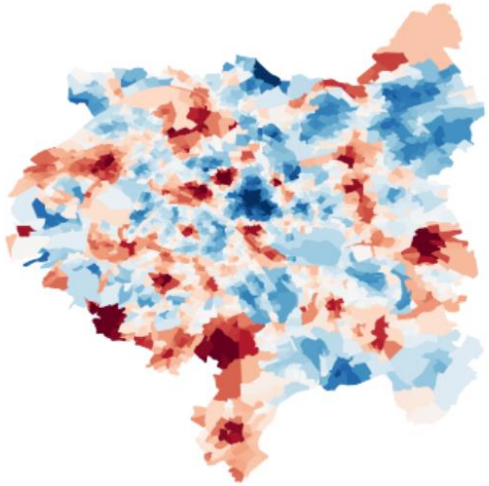
Space Factor 1



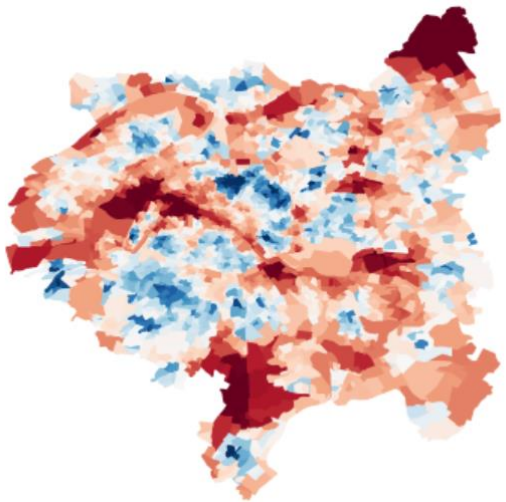
Space Factor 2



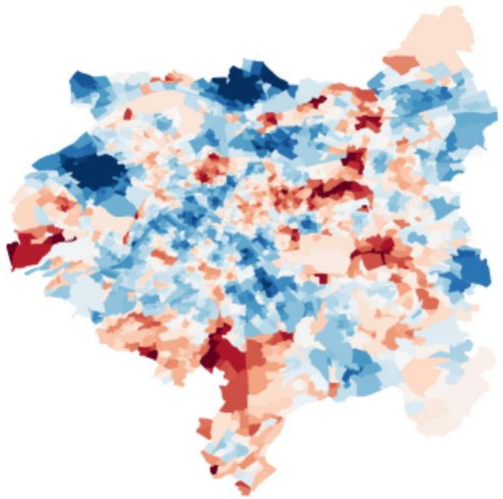
Space Factor 3



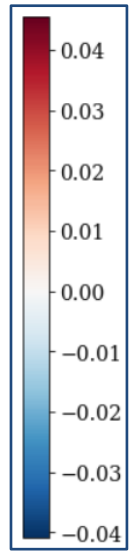
Space Factor 4



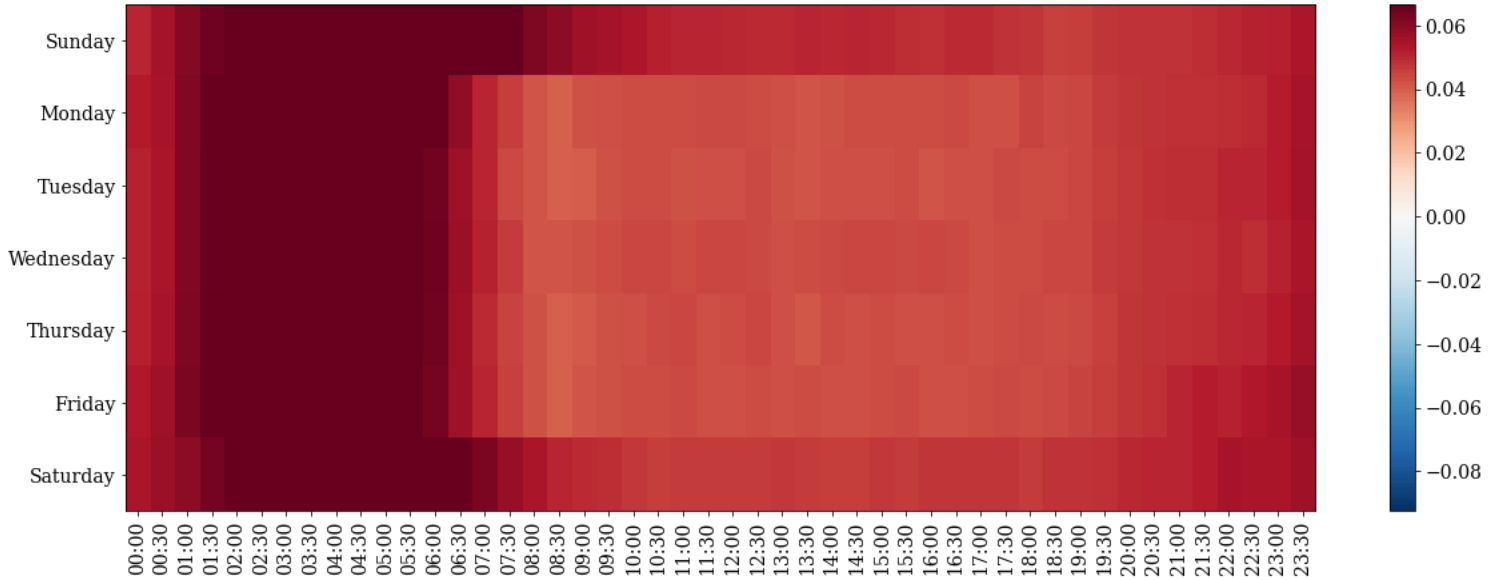
Space Factor 5



Space Factor 6

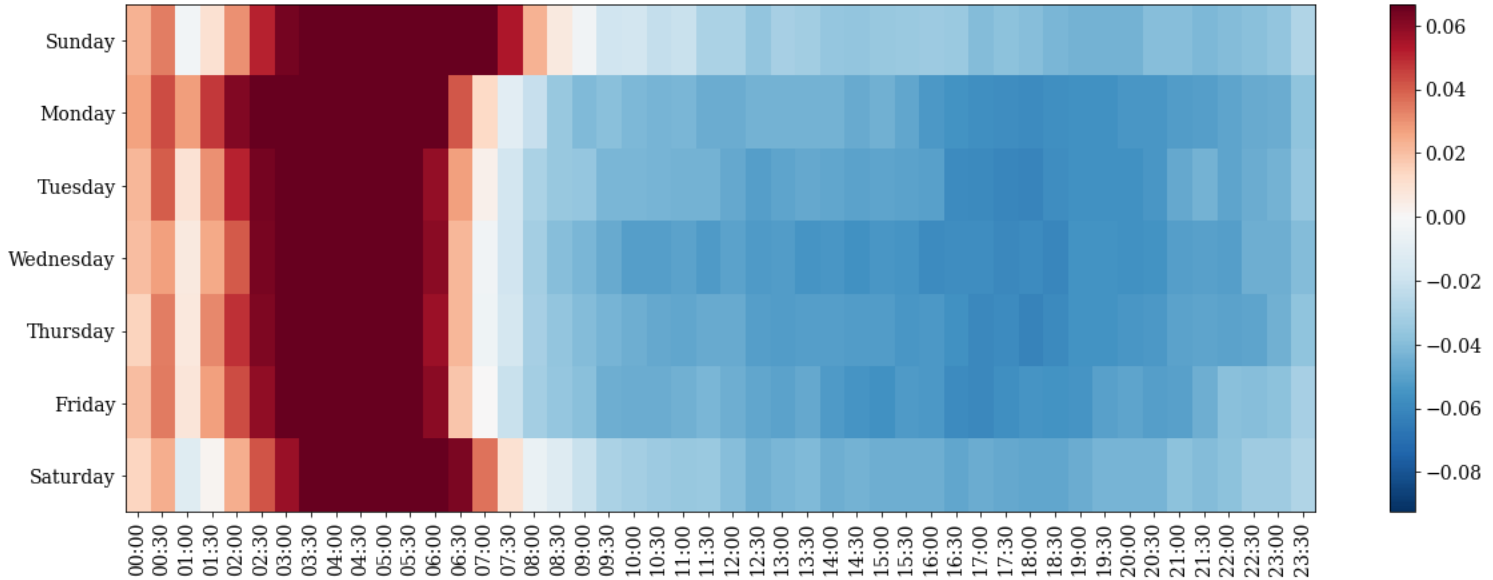


Time Factors



Time Factor 0:

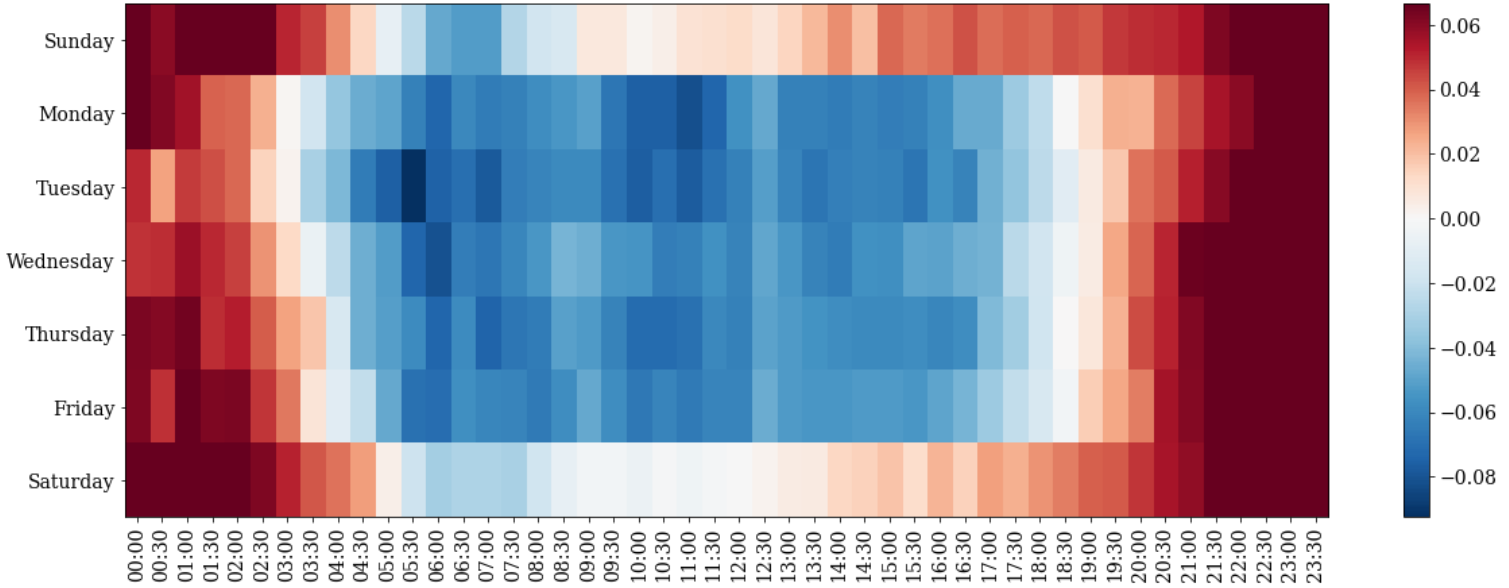
Day vs Night: Traffic slightly higher during night in comparison to day



Time Factor 1:

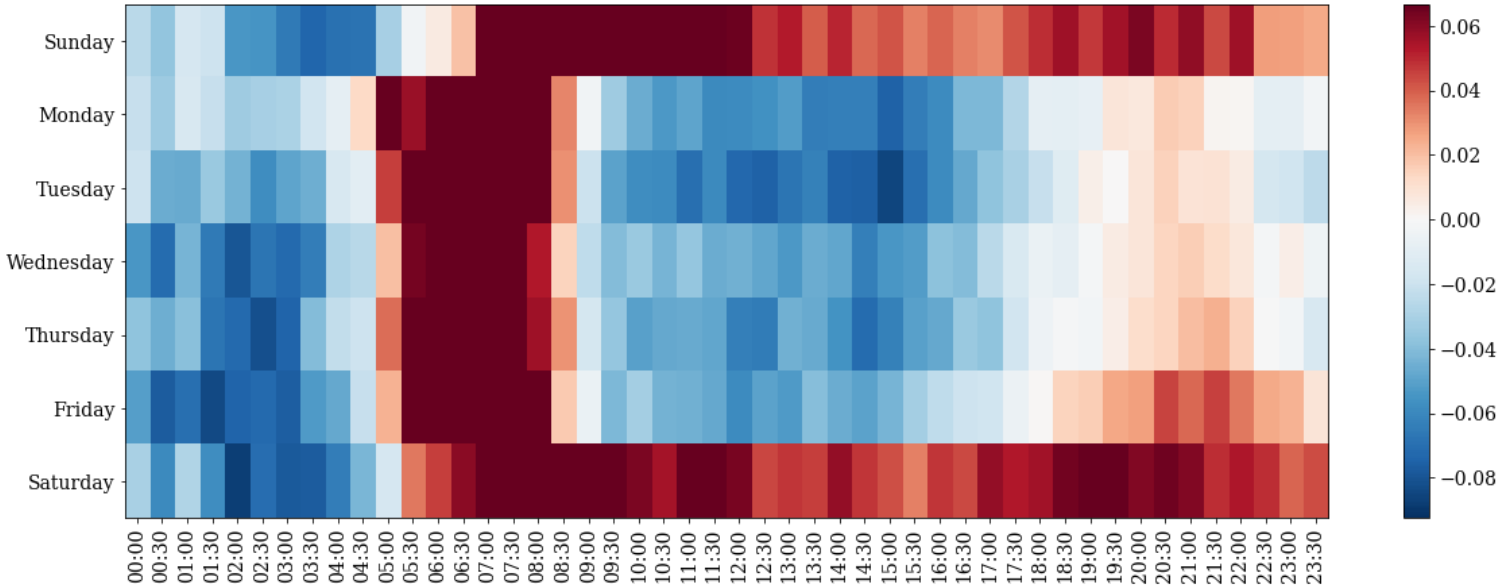
Day vs Night: Traffic significantly high during night than day

Time Factors (contd..)



Time Factor 2:

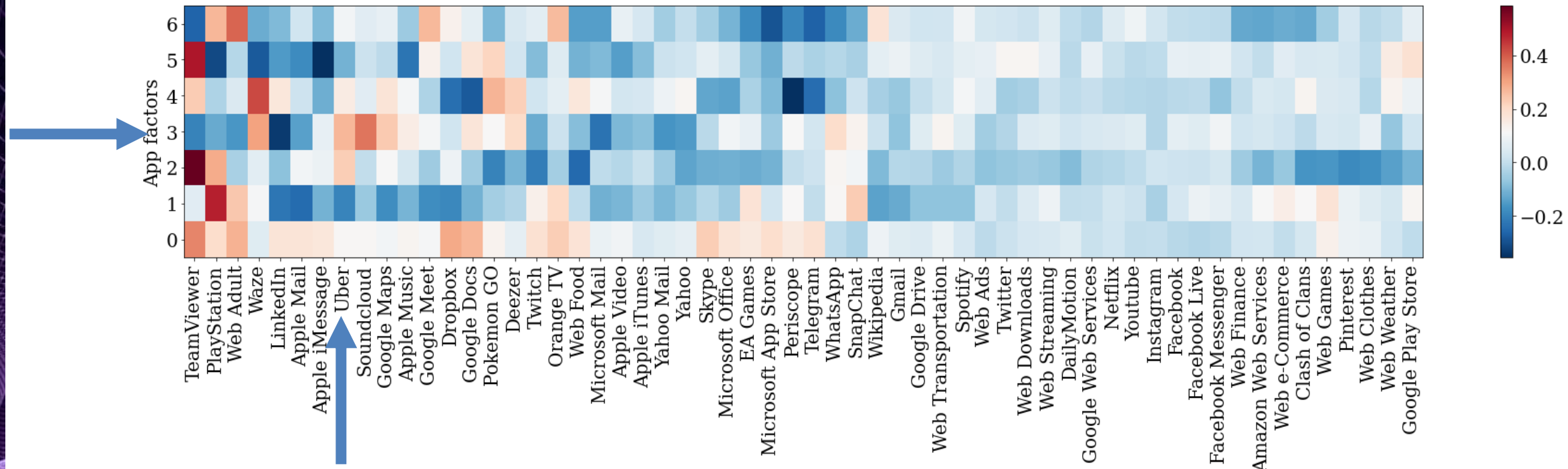
Early Morning and Working hours Vs rest of day



Time Factor 3:

Commuting and Weekend Patterns

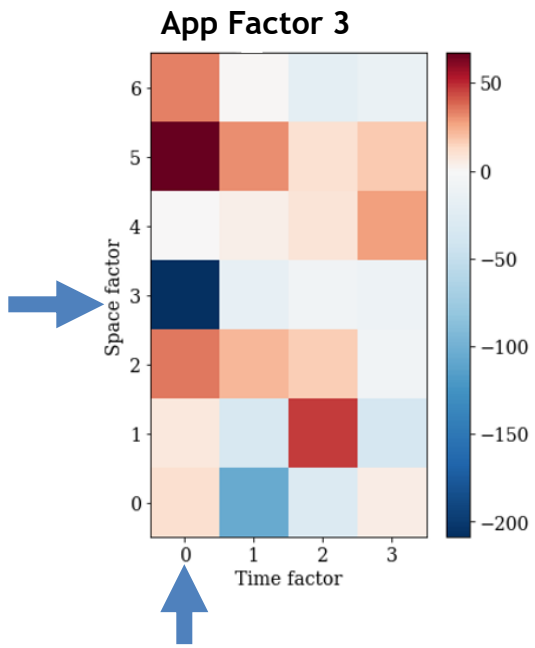
App Factors

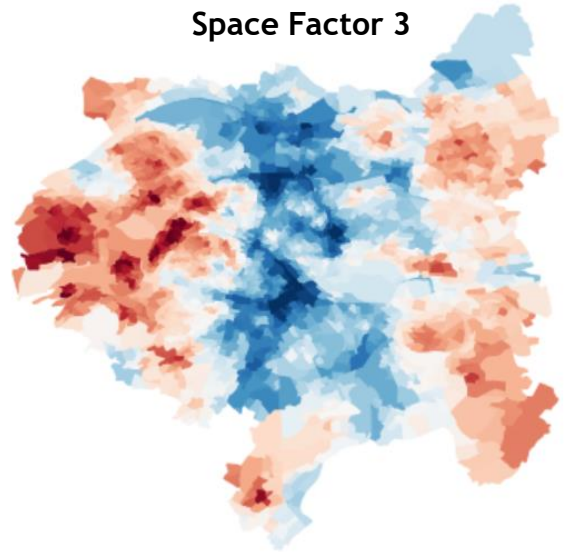


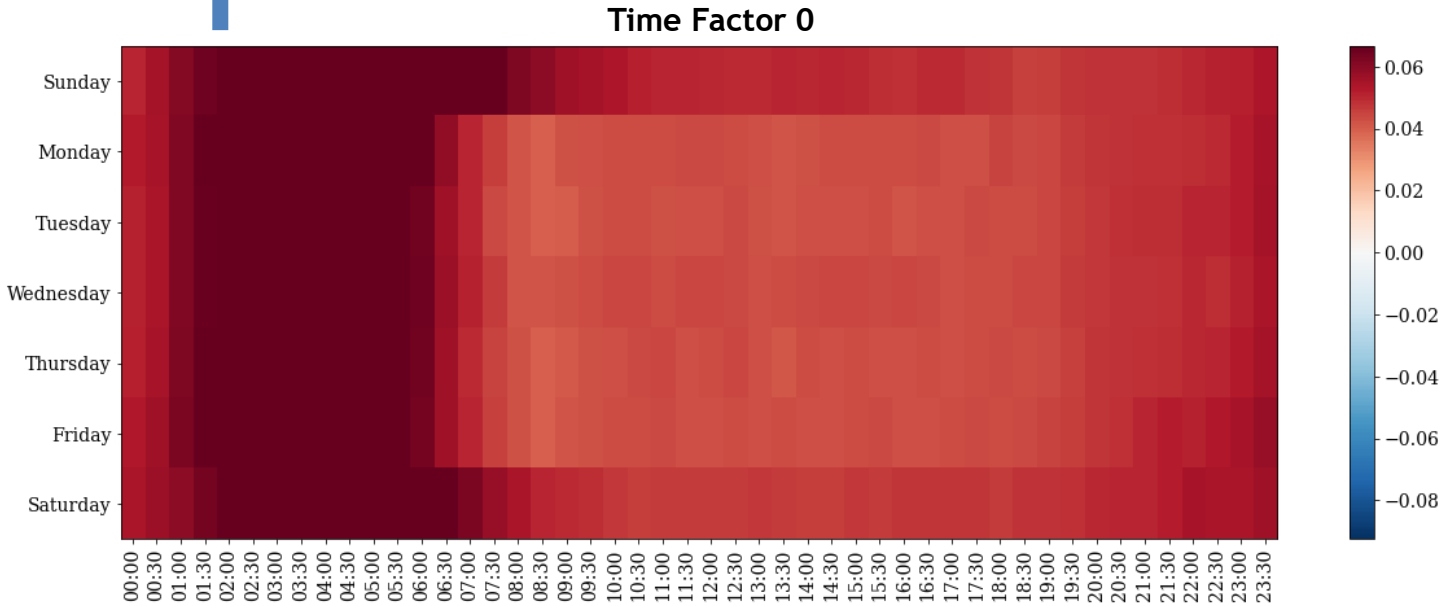
- The factor loadings represent the strength of the relationship between the app and the app factor.
- Uber has strongest relation with App Factor 3. It also shows good relationship with App factor 2.

Case Study : UBER

- Uber has the strongest relationship with App Factor 3.
- For App Factor 3, Space Factor 3 and Time Factor 0 has the highest magnitude with negative sign.
- Space Factor 3 represents mostly the sub-urban part of the Paris city.

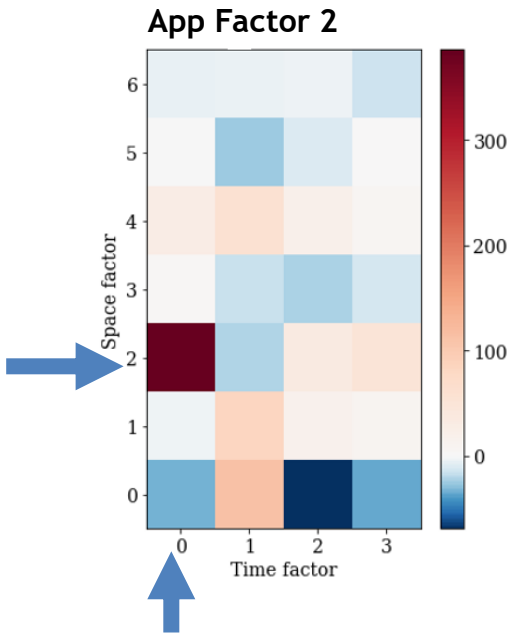


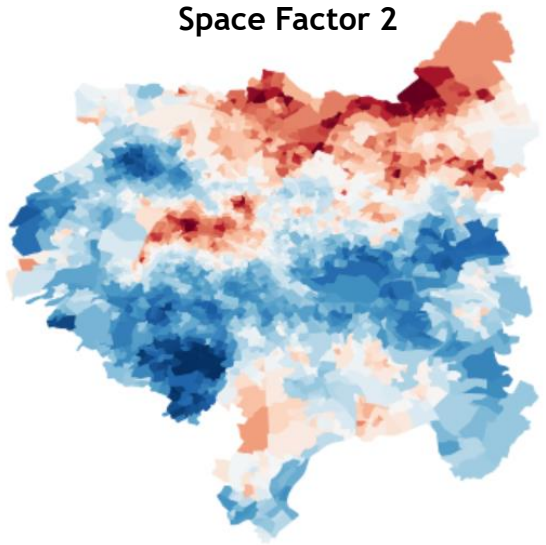


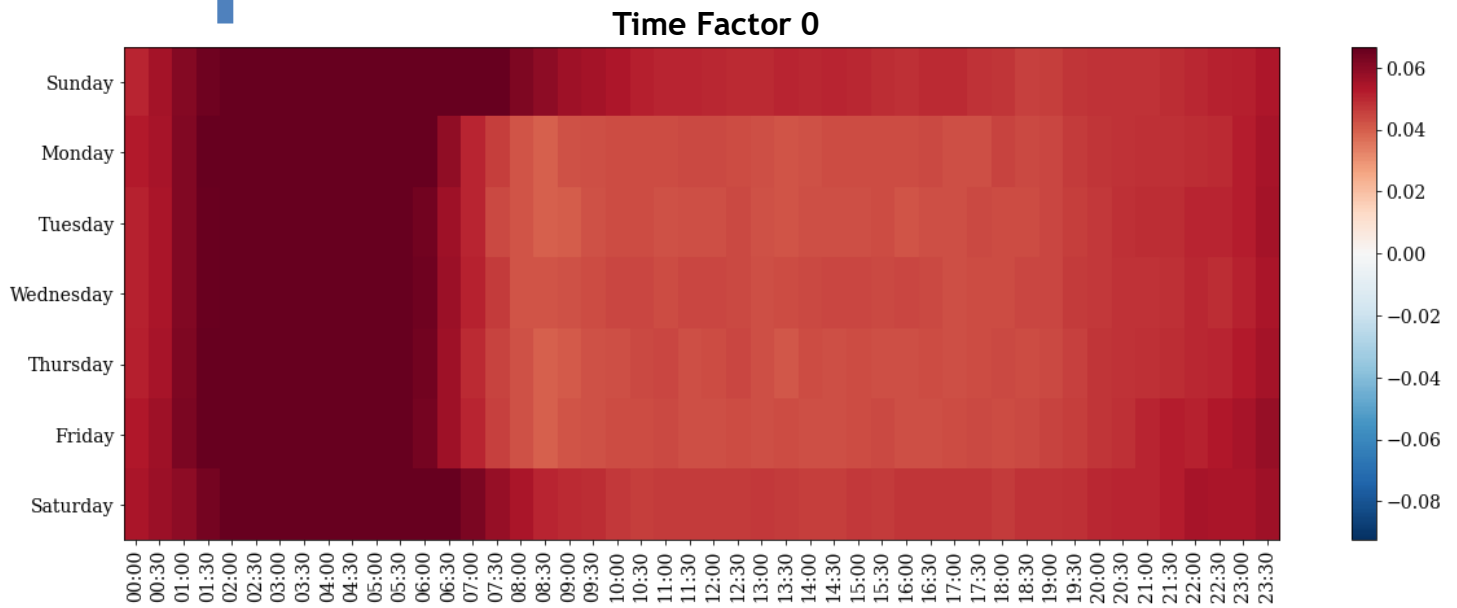


Case Study : UBER (contd..)

- Also, Uber show the good relationship with App Factor 2.
- For App Factor 2, Space Factor 2 and Time Factor 0 has the highest magnitude with positive sign.
- Space factor 3 highlights the areas including airports and some portion of city center of Paris city .







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Conclusion

- Uncovered latent patterns within each of the three dimensions: space, time, and mobile applications.
- Exploring interplay among latent factors with Core Tensor and gaining insights into mobile traffic dynamics.
- Time and resource consuming in determining the optimal ranks along each dimensions.
- Tucker decomposition leads to the merging of multiple patterns into a single factor.

Thank You