TOWARDS UNDERSTANDING OF GLOBAL TRAFFIC STATES IN LARGE-SCALE TRANSPORTATION NETWORKS

Yufei HAN, CAOR MINES-ParisTech & IMARA INRIA

Collaborate with Jean-Marc LASGOUTTES, IMARA, INRIA

Cyril FURTLEHNER, TAO, INRIA Saclay

Fabien MOUTARDE, CAOR, MINES-ParisTech

Victorin MARTIN, IMARA, INRIA

Paris, 12 June 2012

MINES ParisTech

INVENTEURS DU MONDE NUMÉRIQUE

OUTLINE

- Context: Global traffic state analysis
- Motivation: Compact feature representation of global traffic states for mining and prediction
- Data source: Traffic scene simulations and real traffic data
- Methodology: Non-negative Matrix for mining global traffic state patterns
- Methodology: Tensor Factorization for mining/predicting dynamical patterns of global traffic states
- Summary

CONTEXT

- Intelligent Vehicles: Sensing scenes and controlling itself without / with less drivers' intervention

Background sensing

Laser, GPS, camera, RFID…..

Control/ Optimization

Network-level traffic state information

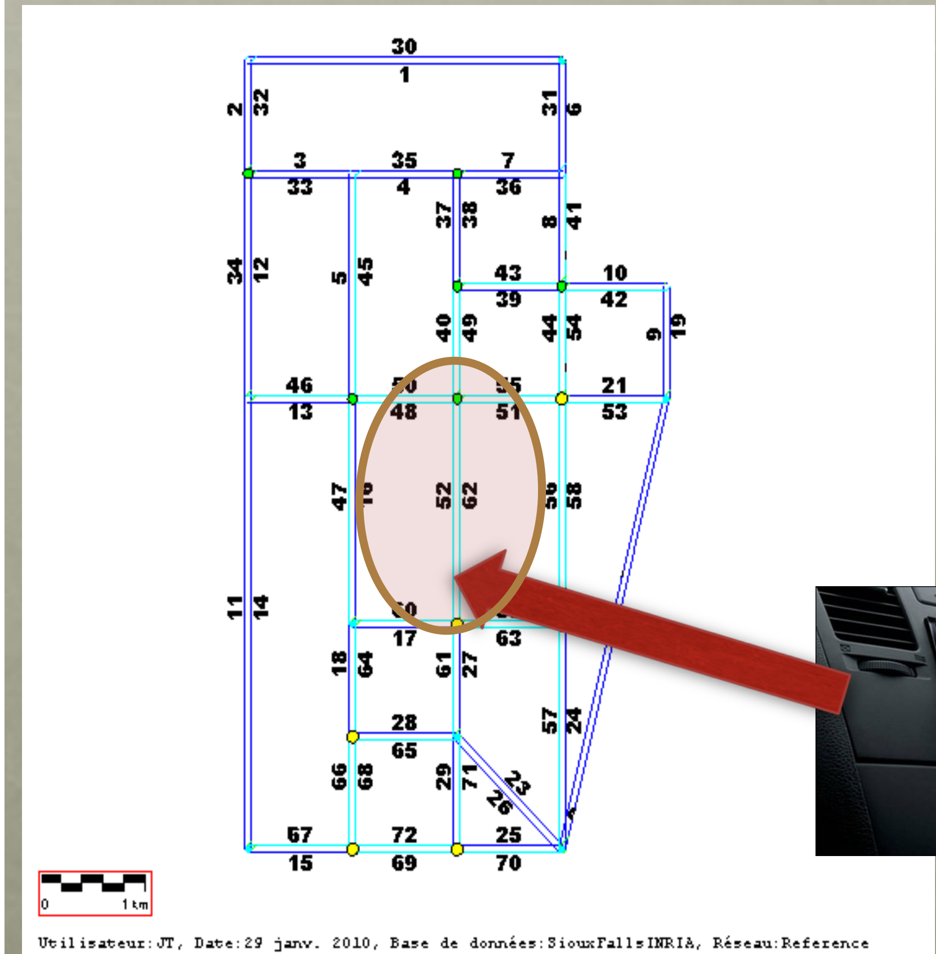
Floating car, loop detector, wifi, 3G (maybe), GPS…

Copy image from cybercars.org

OUTLINE

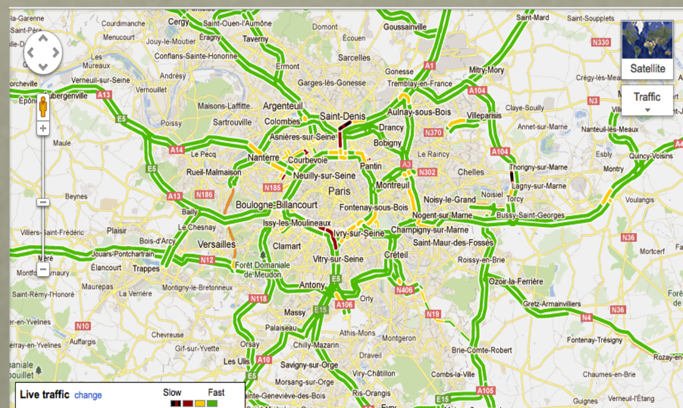
- Context: Global traffic state reconstruction, mining and prediction
- ***Motivation: Compact feature representation of global traffic states for mining and prediction***
- Data source: Traffic scene simulations and real traffic data
- Methodology: Non-negative Matrix for mining global traffic state patterns
- Methodology: Tensor Factorization for mining/predicting dynamical patterns of global traffic states
- Experimental results

MOTIVATION



Traffic state collected from distributed sensors : free-flowing or congestion in individual roads/intersections

Global traffic state information over the whole transportation network



MOTIVATION

Some global information about traffic state patterns:

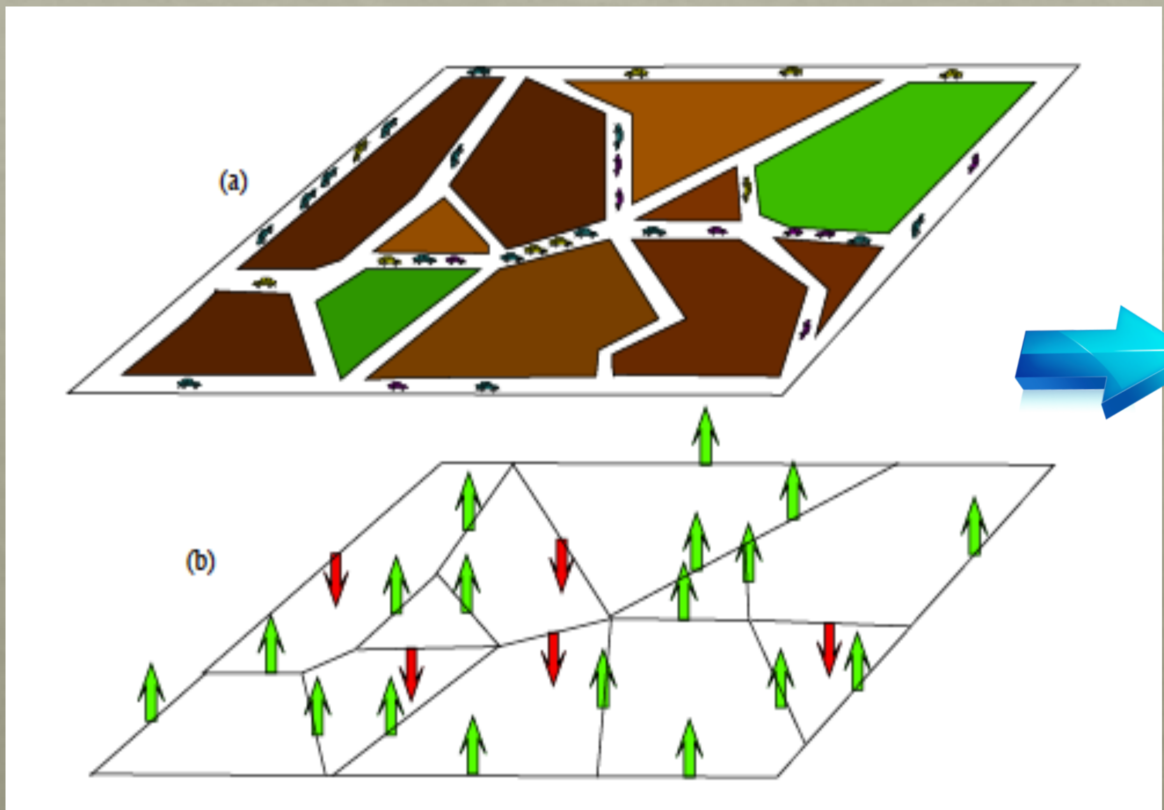
- Spatial configurations of local traffic states over the whole network

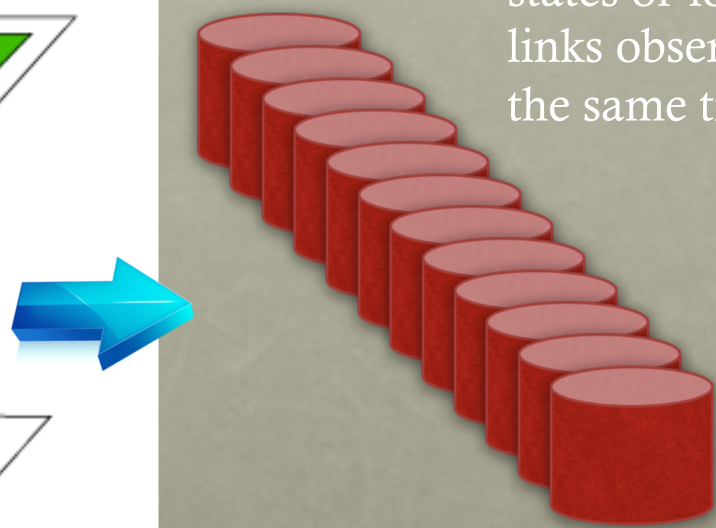
Benefits from the global information……

- Prediction of traveling time for drivers ever since they left their home
- Adjusting the overall transportation management strategy
- Suggestions to drivers automatically for choosing proper paths

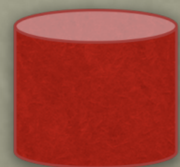
MOTIVATION

- Very high-dimensionality of the global traffic states





Listing traffic states of local links observed at the same time



The traffic state of one specific link observed at one specific time step

MOTIVATION

- Analysis of the high-dimensional global traffic states
- Feature dimension reduction, subspace learning ….
- Objective: Low-dimensional representation of global traffic states
  - The low-dimensional representation is feasible to perform data analysis tools, such as temporal regression
  - Clustering in the low-dimensional space is helpful in finding typical spatial configuration pattern of the local traffic states
  - Avoid the issue of curse-of-dimensionality

OUTLINE

- Context: Global traffic state reconstruction, mining and prediction
- Motivation: Compact feature representation of global traffic states for mining and prediction
- ***Data source: Traffic scene simulations and real traffic data***
- Methodology: Non-negative Matrix for mining global traffic state patterns
- Methodology: Tensor Factorization for mining/predicting dynamical patterns of global traffic states
- Experimental results

SIMULATED TRAFFIC DATA: IAURIF DATABASE

- Simulation of traffic scenes in the transportation network inside Ile-de-France
- Data setting:
  - Recording traveling paths and traveling time of simulated floating vehicles in an integrated simulation software
  - Covering totally 13,627 links and 146-day simulated scenes.
  - 8-hour simulation in each scene, with 10-mintue time interval between each neighboring pair of time sampling steps

Real Traffic Data: Mobile Millennium Project

- Real traffic data: Traveling time observations in the San-Francisco transportation network
- Mobile Millennium Project: UC Berkeley, NOKIA Research Center and NAVTEQ launched from November 10, 2008
- Objective:
  - Collecting floating-car data from GPS devices equipped with taxis, mobile phones and so on
  - Traveling time estimation in the network
  - Data fusion (cellular phones, radar, loop detectors and so on)
  - Covering over 4000 roads and over 3000 joints in the network
  - Covering totally 24-hours daily traffic dynamics

http://traffic.berkeley.edu

OUTLINE

- Context: Global traffic state reconstruction, mining and prediction
- Motivation: Compact feature representation of global traffic states for mining and prediction
- Data source: Traffic scene simulations and real traffic data
- ***Methodology: Non-negative Matrix for mining global traffic state patterns***
- Methodology: Tensor Factorization for mining/predicting dynamical patterns of global traffic states
- Experimental results

METHODOLOGY

- Feature dimension reduction: Non-negative Matrix Factorization

$$O = \|X - MV\|_F^2 \quad V_{i,j} \geq 0 \;\; M_{i,j} \geq 0$$

- The matrix X with non-negative entries, with n rows and k columns, is decomposed as the product of a non-negative loading matrix M (with n rows and s columns) and a non-negative scoring matrix V (with s columns and k columns)

- Cost function: Minimizing the Frobenius norm, element-wise reconstruction error between X and the production of M and V

- $$\|A\|_F^2 = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{k} A_{ij}}$$

METHODOLOGY

X_j • The j-th column in X

M_k • The k-th column in M

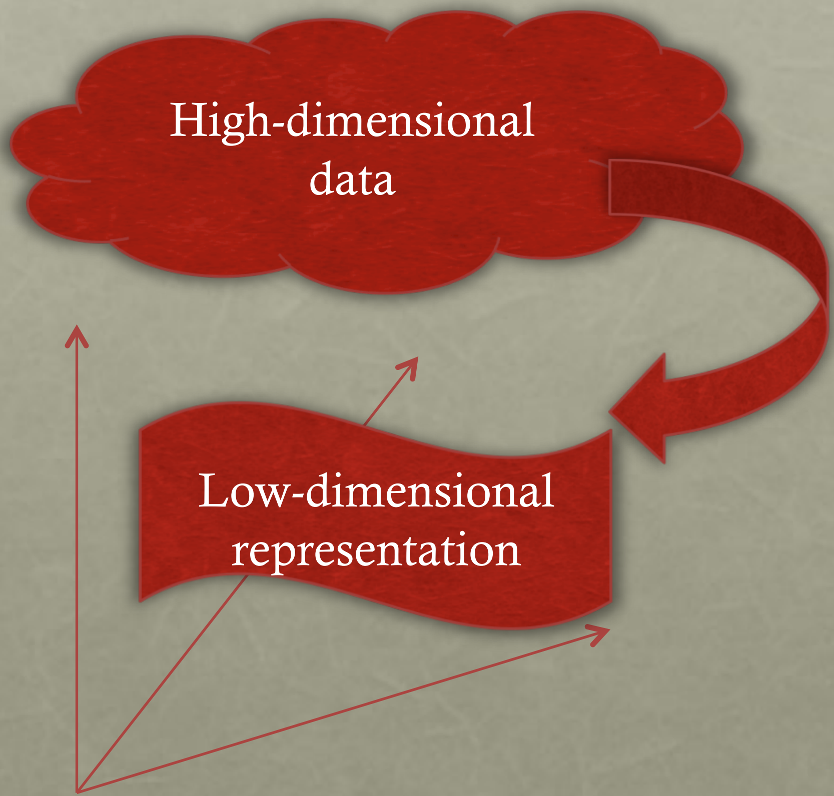
V_{kj} • The entry of V locating at the k-th row and j-th column

$$X_j = \sum_{k=1}^{S} M_k V_{kj}$$

Considering the column space of X as high-dimensional data:

Columns of M are the expanding basis of the low-dimensional projection space

Columns of V represent the projections of the high-dimensional data in the projection space



METHODOLOGY

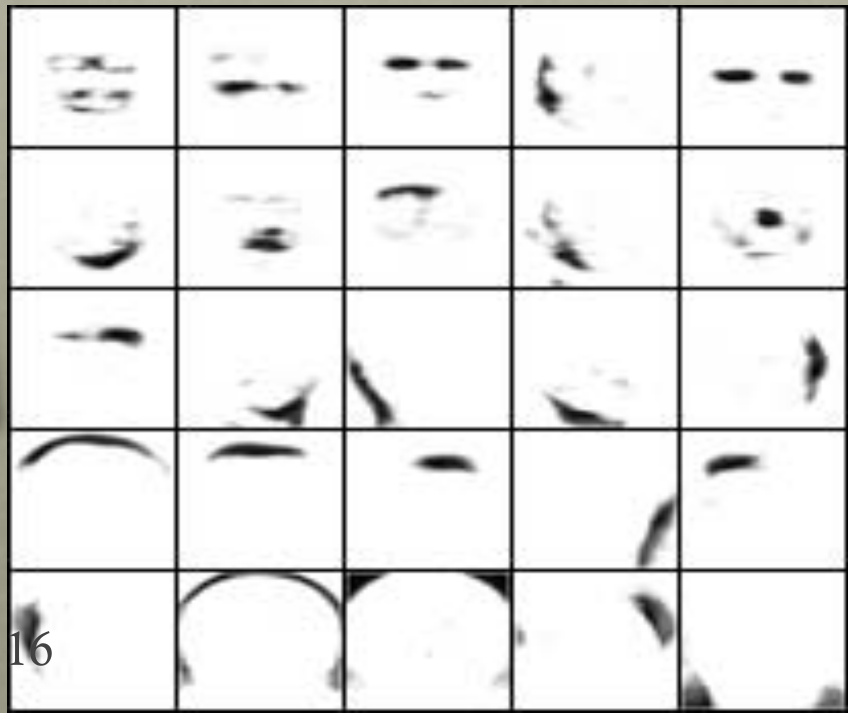
- Characteristics of NMF, compared with PCA

$$X_j = \sum_{k=1}^{S} M_k V_{kj} \quad V \geq 0 \quad M \geq 0$$

- Non-negativity constraints: decomposing the high-dimensional data as a linear additional superposition of the decomposition bases

- Part-based representation of the high-dimensional data: each decomposing basis represents a localized component in the data, just like we have done in blind source separation and image processing

Global components represented by the PCA bases



Localized components represented by the NMF bases

Graph Laplacian Constraint in NMF

Insert an additional constraint on topological structures of the derived subspace [1]

$$O = \|X - MV\|_F^2 + \boxed{\lambda Tr(VLV^T)}$$

$L = D - W$ L: Graph Laplacian, which is used to describe topological structures of the data distribution

D is a diagonal matrix whose entries are column-wise sum of W $D_{ii} = \sum_j w_{ij}$

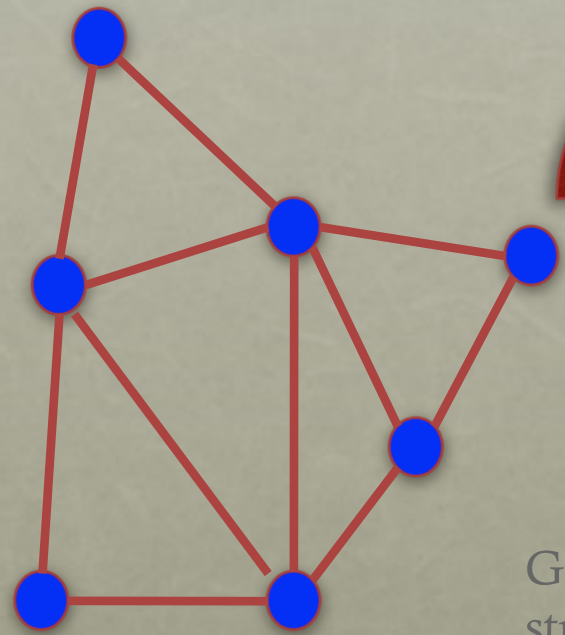
W Similarity matrix of data X

w_{ij} is the pair-wise similarity measure between the i-th and j-th column of data X

[1] Cai, X.Fei He, X.H.Wang, H.J.Bao and J.W.Han, "Locality Preserving Nonnegative Matrix Factorization", In Proceedings of International Joint Conference on Artificial Intelligence 2009)

Graph Laplacian Constrain

Graph Laplacian Constrained NMF

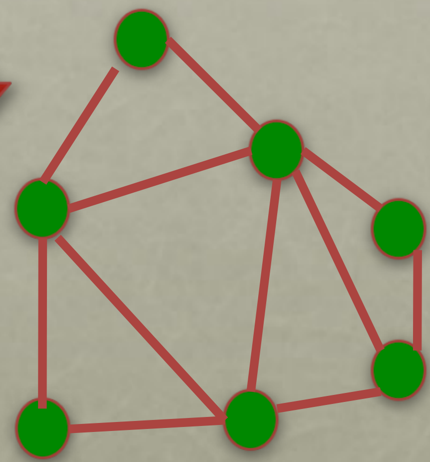


Data points in the original high-dimensional data space

Global smoothness of the projected space

$$L = D - W$$

Graph Laplacian: the structural information structure of the data distribution



Corresponding data points in the low-dimensional NMF projection space: keep the similarity relationship between data points in the projected space

METHODOLOGY

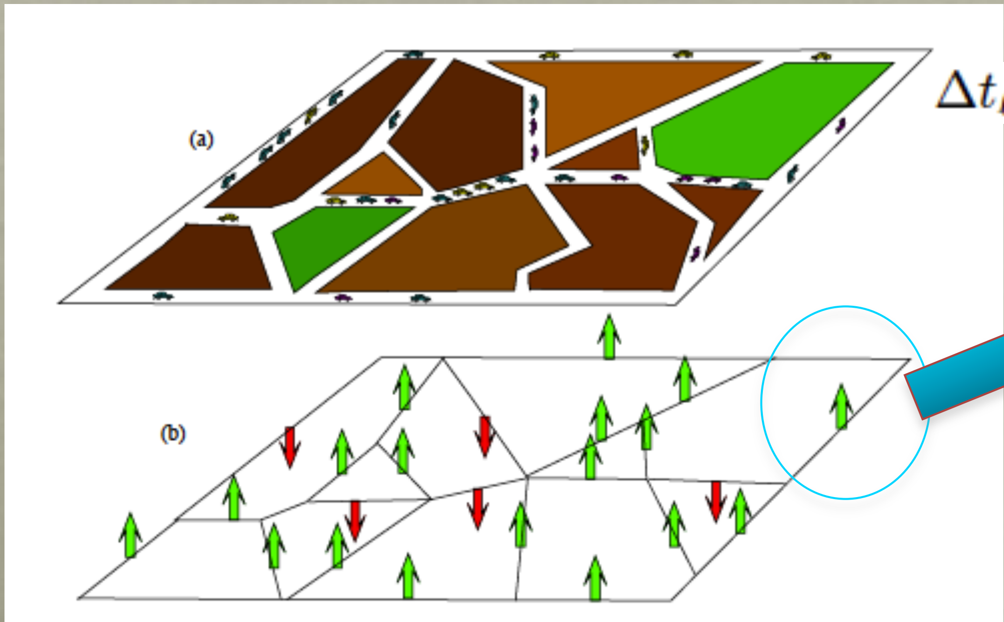
- Analysis of global traffic states using the NMF method
  - Low-dimensional representation of the global traffic states derived using the Graph Laplacian Constrained NMF
  - Clustering of the global traffic states using the proposed NMF method
  - Localized segments of the transportation network derived by the NMF decomposition

IAURIF DATABASE

Data structure for traffic state evaluation: traffic index value

Δt_ℓ^0 is the free-flow travel time on segment ℓ / link ℓ

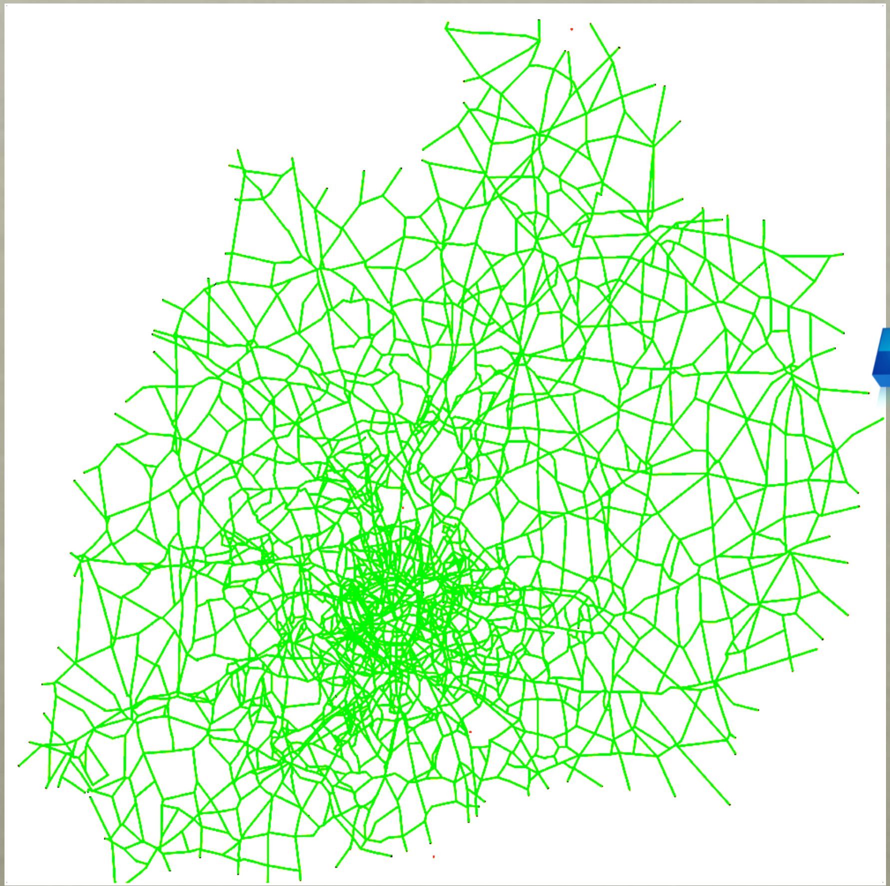
$\Delta t_{\ell t}$ is the travel time on segment ℓ at the time t



$$x_{\ell t} \stackrel{\text{def}}{=} \frac{\Delta t_\ell^0}{\Delta t_{\ell t}} \in [0, 1]$$

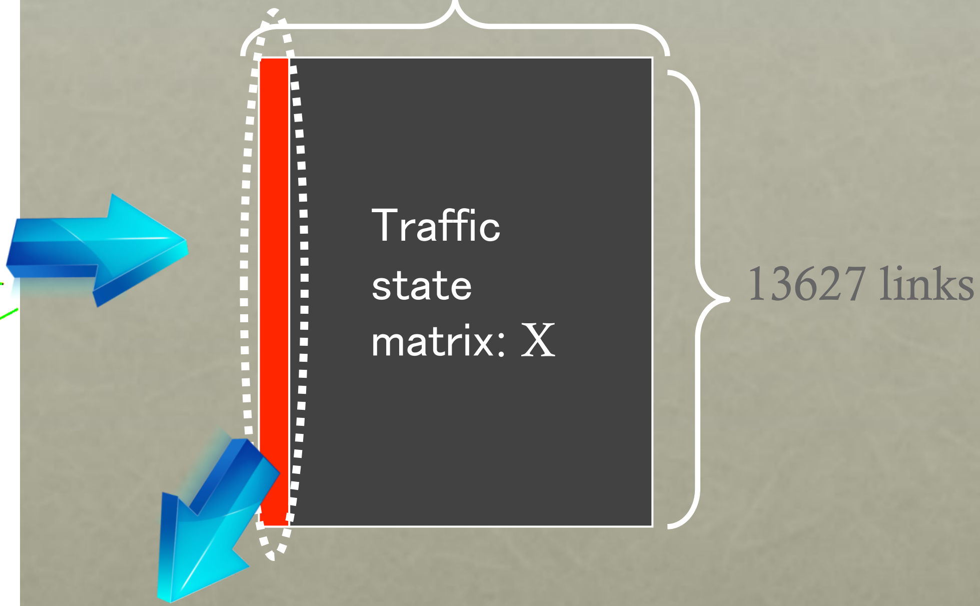
$x_{\ell t} = 1$ corresponds to the free-flow state while lower value indicate congestion in the segment

IAURIF DATABASE



Transportation network
around and inside Paris

48 (daily time sampling steps)*146 (simulations) = 7008 time sampling steps

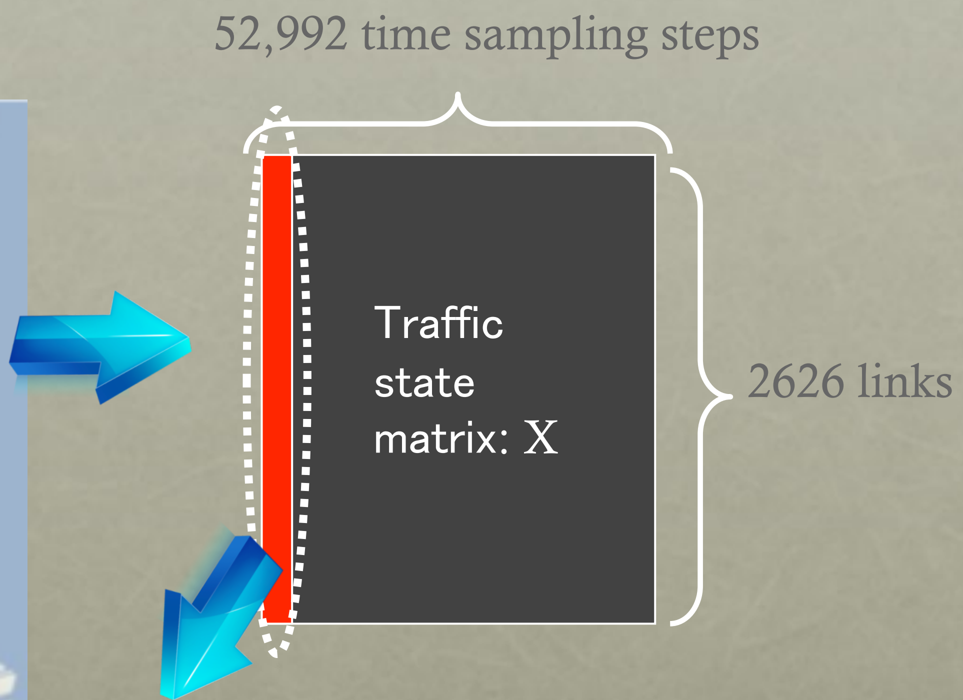


Network-level traffic state: the global traffic state observed at the specific time sampling step

A 13627*7008 matrix. Each column corresponds to a network-level traffic state obtained at each time step, which is a 13627-dimensional vectors.

Real Traffic Data: Mobile Millennium Project

2626 roads and 52,992 time sampling steps



Network-level traffic state: the global traffic state observed at the specific time sampling step

Transportation network in San-Francisco

A 2626*52992 matrix. Each column corresponds to a network-level traffic state obtained at each time step, which is a 2626-dimensional vectors.

The Flow Chart of Data Processing

Feature dimension reduction

High-dimensional network-level traffic state X

Graph Laplacian constrained NMF projection

$$X \approx MV$$

Low-dimensional representation based on matrix factorization V

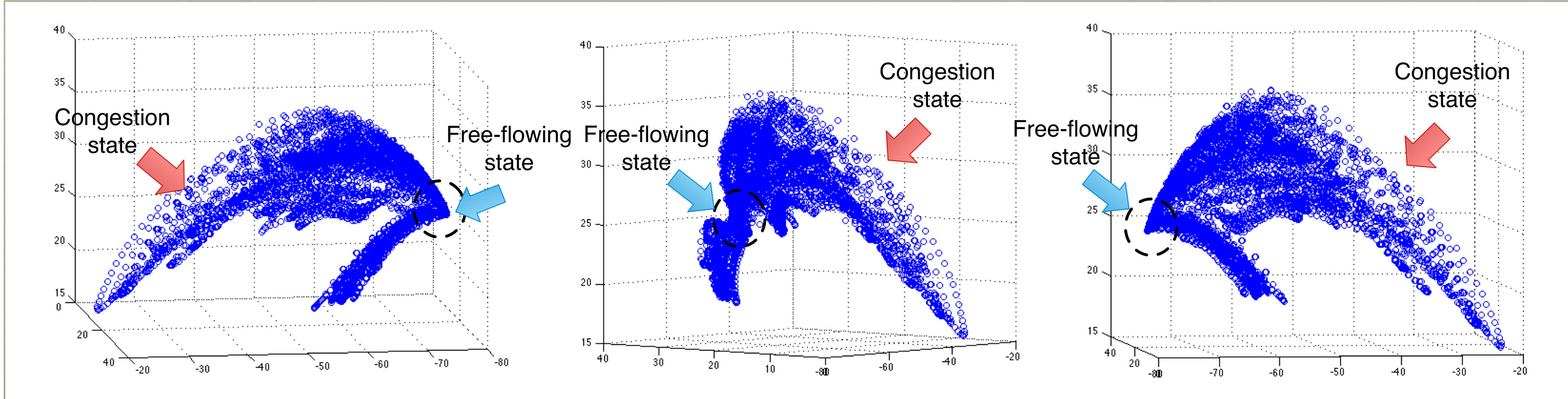
Clustering and prediction of the global traffic configurations in the projected space

Experimental Results

- Clustering of the network-level traffic state
- <u>Find out typical spatial configurations of local traffic states over the whole large-scale network</u>
- Correlated links groups found in the learned NMF decomposing bases

Clustering results on IAU-Paris database

We project the 13627D global traffic states into the 3D PCA space, as shown in three different viewpoints as follows:



The samples corresponding to the free-flowing network level states are concentrated within a small region

Samples corresponding to network-level congestion are distributed sparsely and far from the region of the free-flowing state.

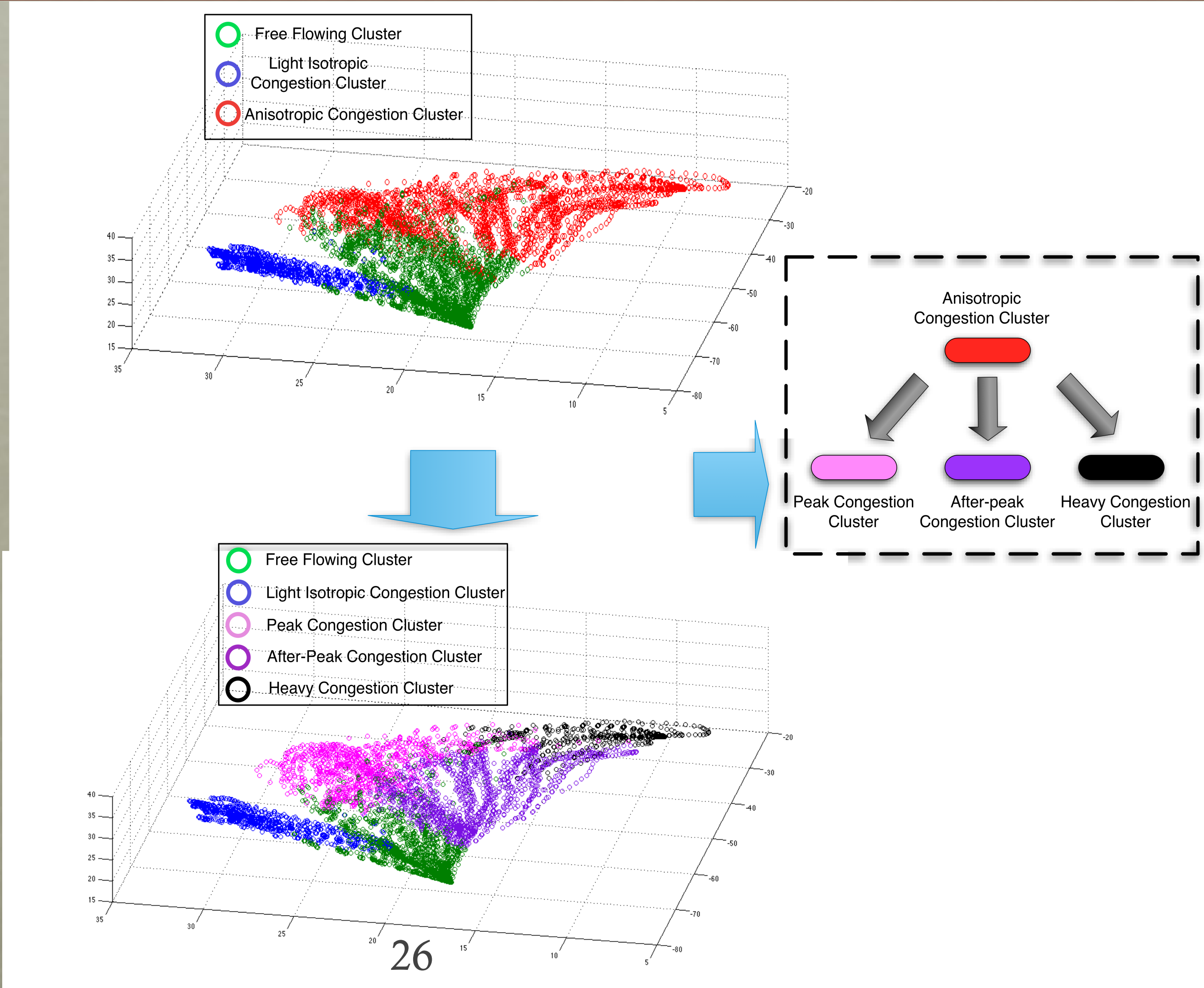
PCA is only used for visualization. For analysis, we use the NMF based projection !

Clustering results on IAURIF database

3 main state types (free-flow, light congestion, heavy congestion)

Increasing the number of cluster to 5

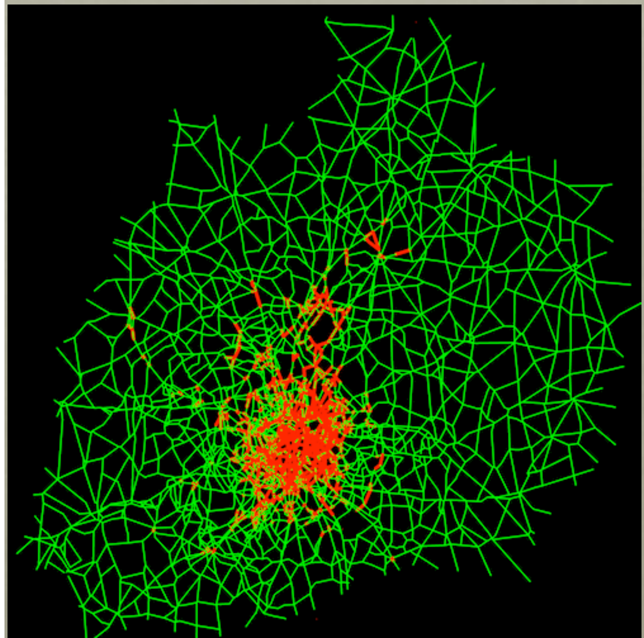
5 typical spatial patterns of the global state types



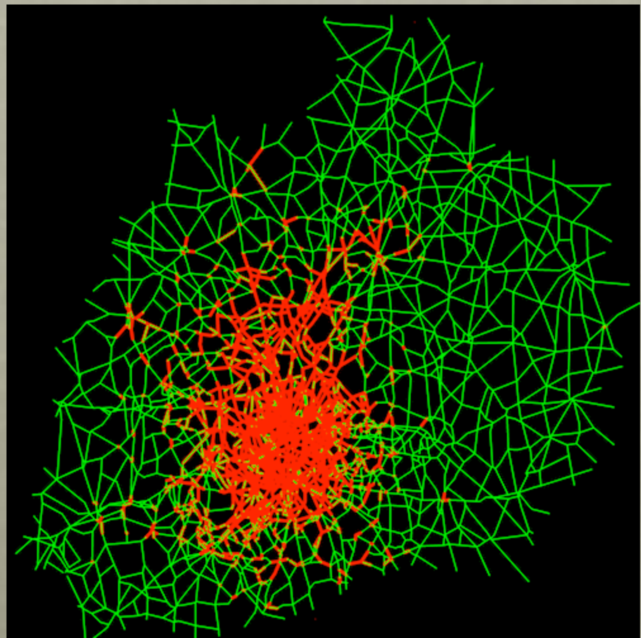
SPATIAL CONFIGURATION PATTERNS OF LOCAL TRAFFIC STATES

Visualization of *peak congestion* global state for each cluster

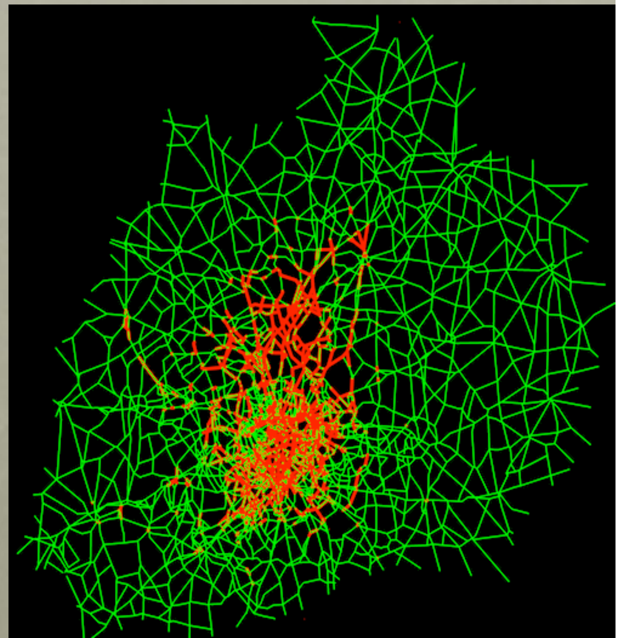
Light congestion before peak hour



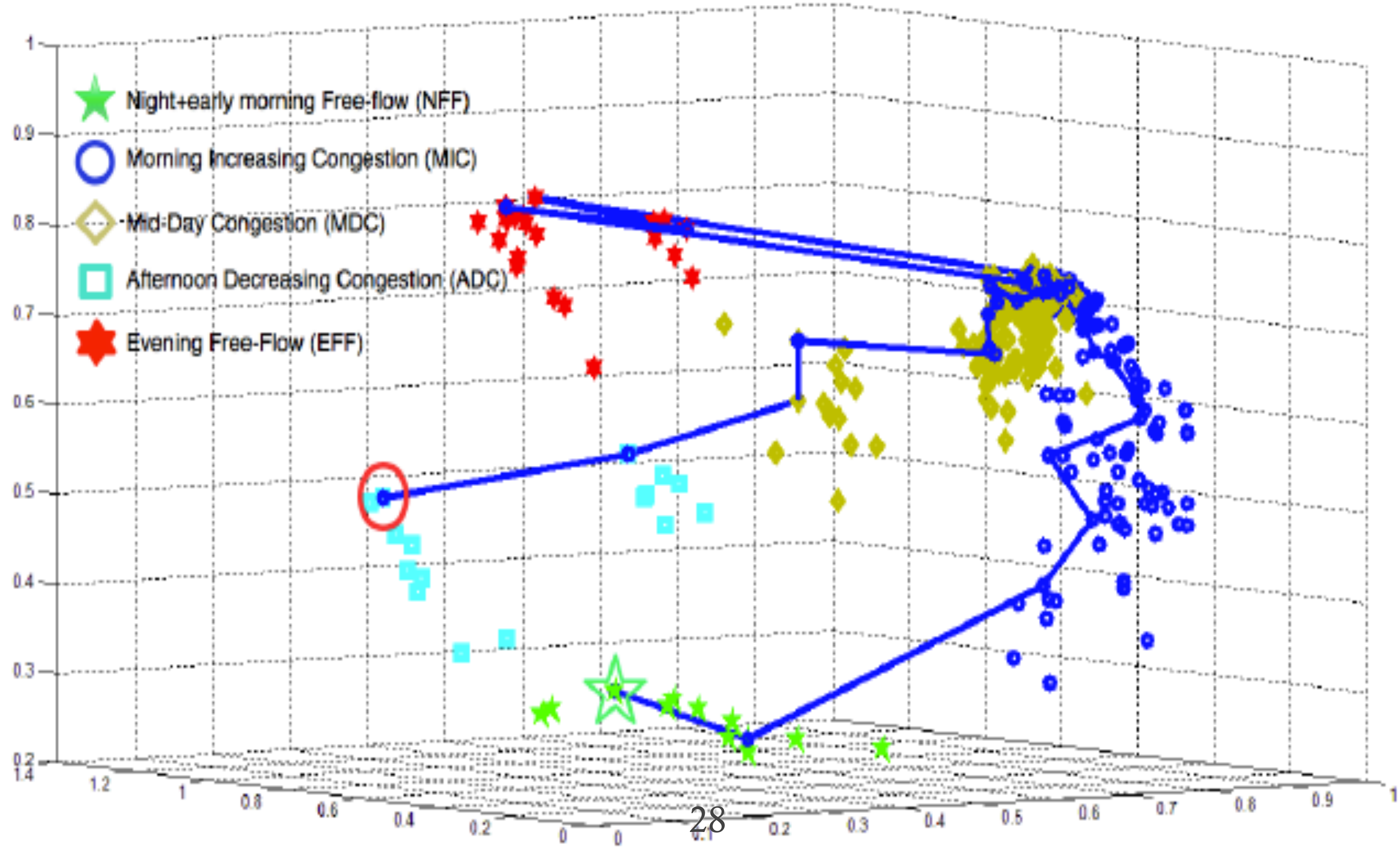
Heavy congestion of peak hour



Light congestion after peak-hour



Clustering Results on Real Traffic Data




(a) Night Free-Flow (NFF)


(b) Morning Increasing Congestion (MIC)


(c) Evening Free-Flow cluster (EFF)


(d) Afternoon Decreasing Congestion (ADC)


(e) Mid Day Congestion (MDC)

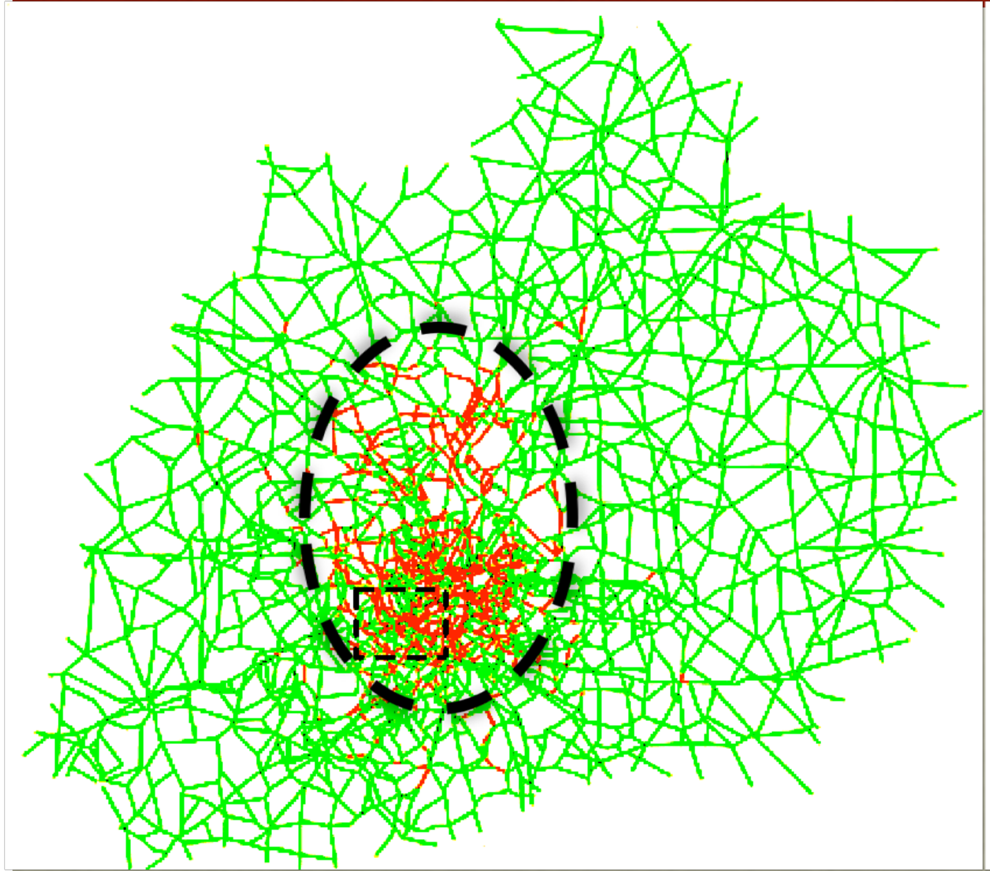
Experimental Results

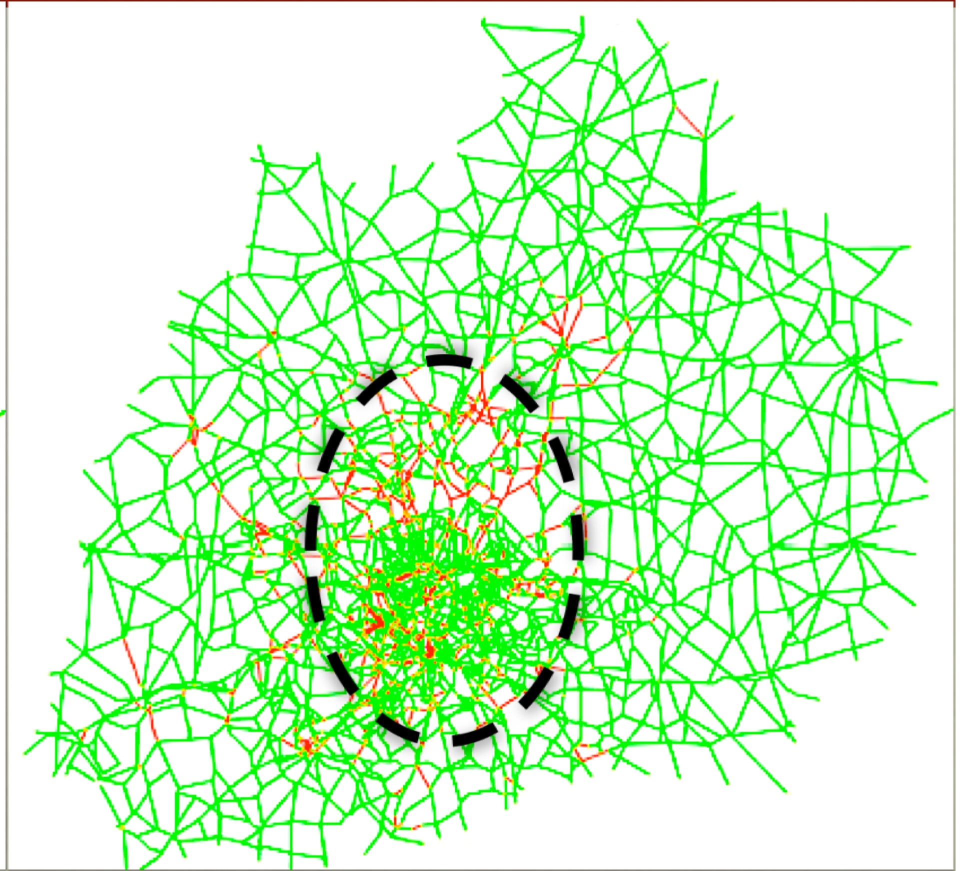
- Clustering of the network-level traffic state
- Find out typical spatial configurations of local traffic states over the whole large-scale network
- Correlated links groups found in the learned NMF decomposing bases

Correlated Link Group in the Network

- We label the localized links with the top 20% largest entries in each NMF basis and illustrate their spatial locations using red legends.
- The labeled links with distinctively large magnitudes correspond to the local links in the network are highly correlated in terms of traffic dynamics

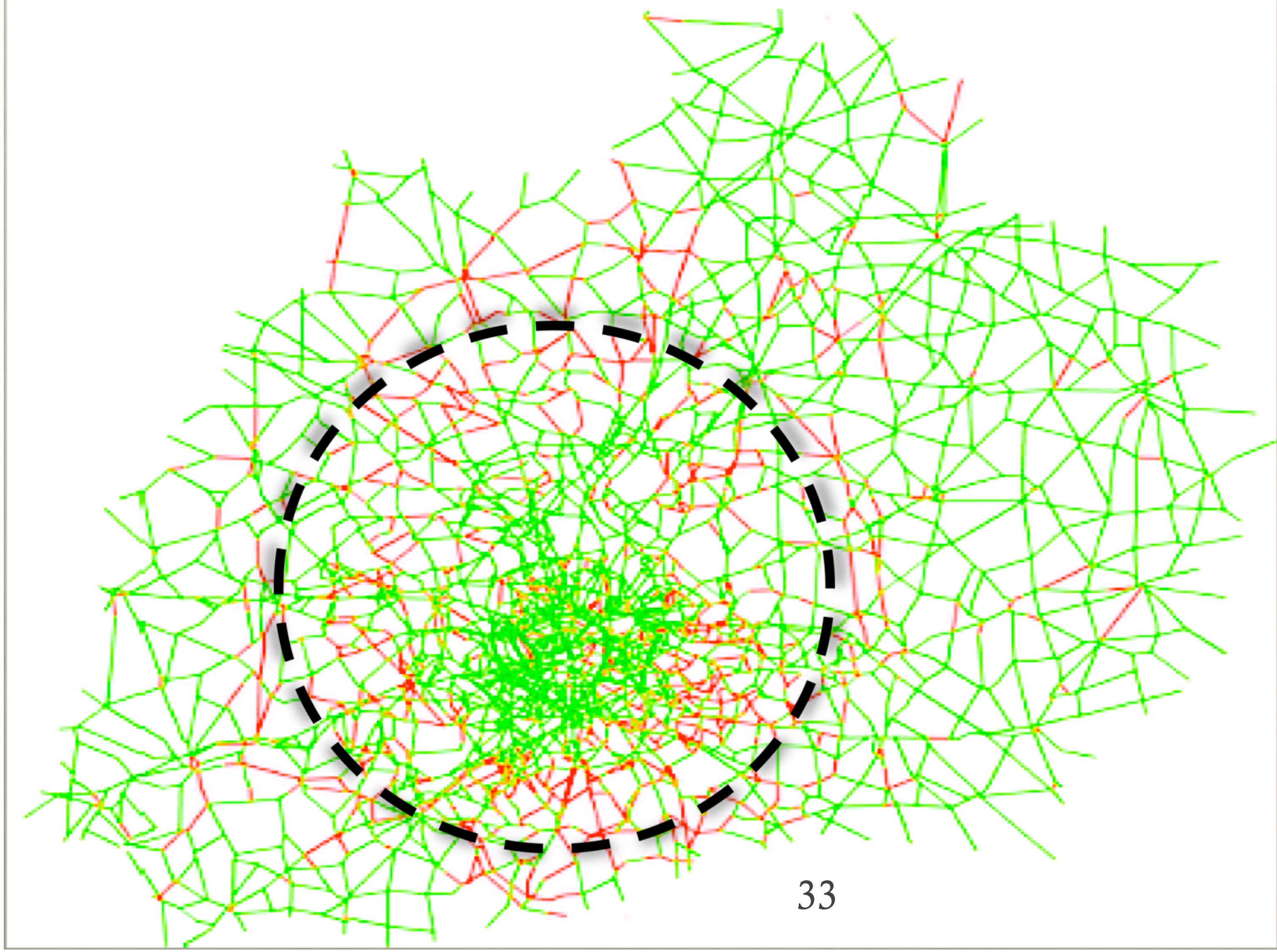
Part-based representation of the network: Grouping of links in three circular regions





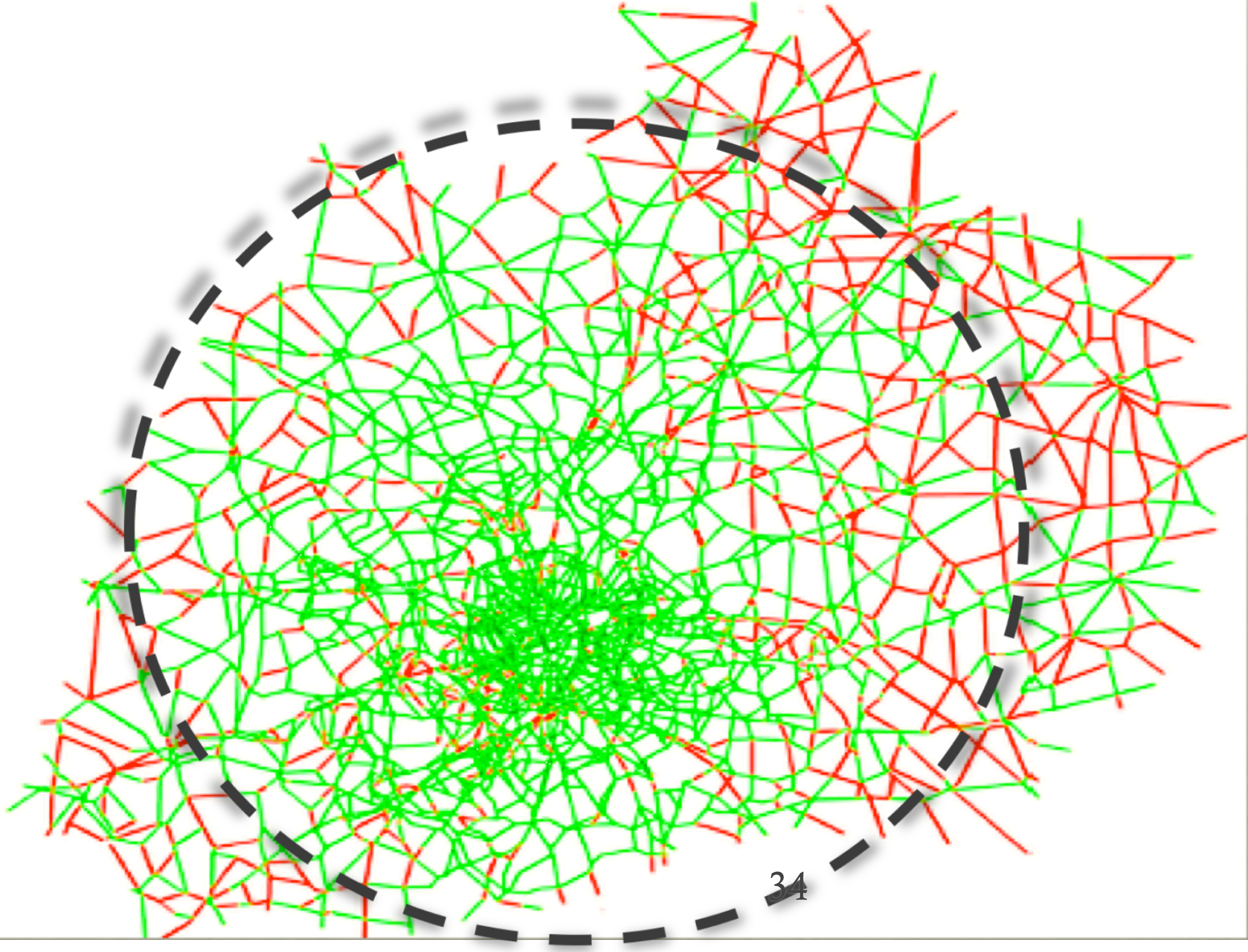
The circular region surrounding the center

Part-based representation of the network: Grouping of links in three circular regions



The circular region a little far from the center

Part-based representation of the network: Grouping of links in three circular regions



The circular region further away from the center: the outskirt region

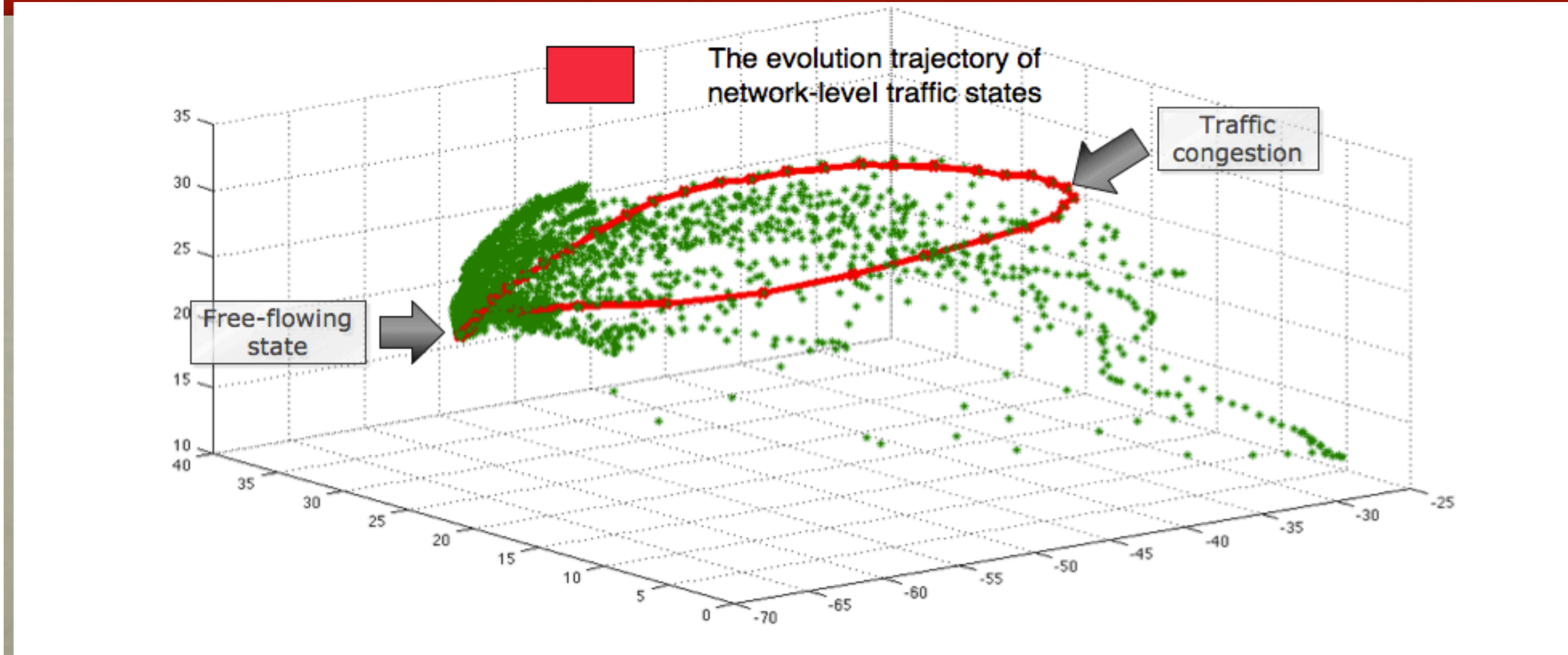
CONCLUSION

- Low-dimensional representation of the global traffic states based on the Graph Laplacian constrained NMF
- Clustering in order to find out typical spatial configuration patterns of the local traffic states
- Correlated link groups arranged in three different circular regions: segmentation of the correlated links in the network

OUTLINE

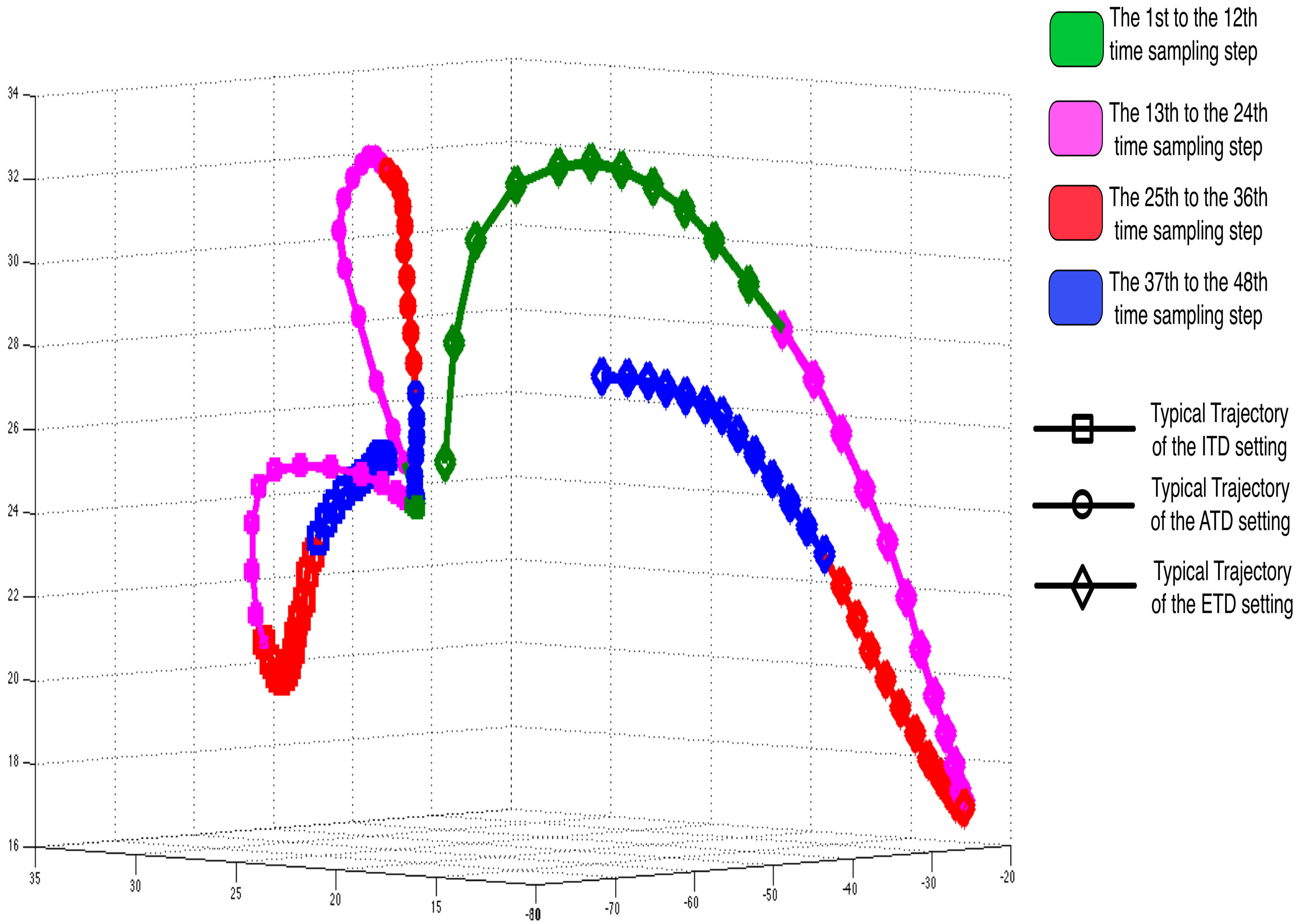
- Context: Global traffic state reconstruction, mining and prediction
- Motivation: Compact feature representation of global traffic states for mining and prediction
- Data source: Traffic scene simulations and real traffic data
- Methodology: Non-negative Matrix for mining global traffic state patterns
- ***Methodology: Tensor Factorization for mining/predicting dynamical patterns of global traffic states***
- Experimental results

GLOBAL TRAFFIC DYNAMICS

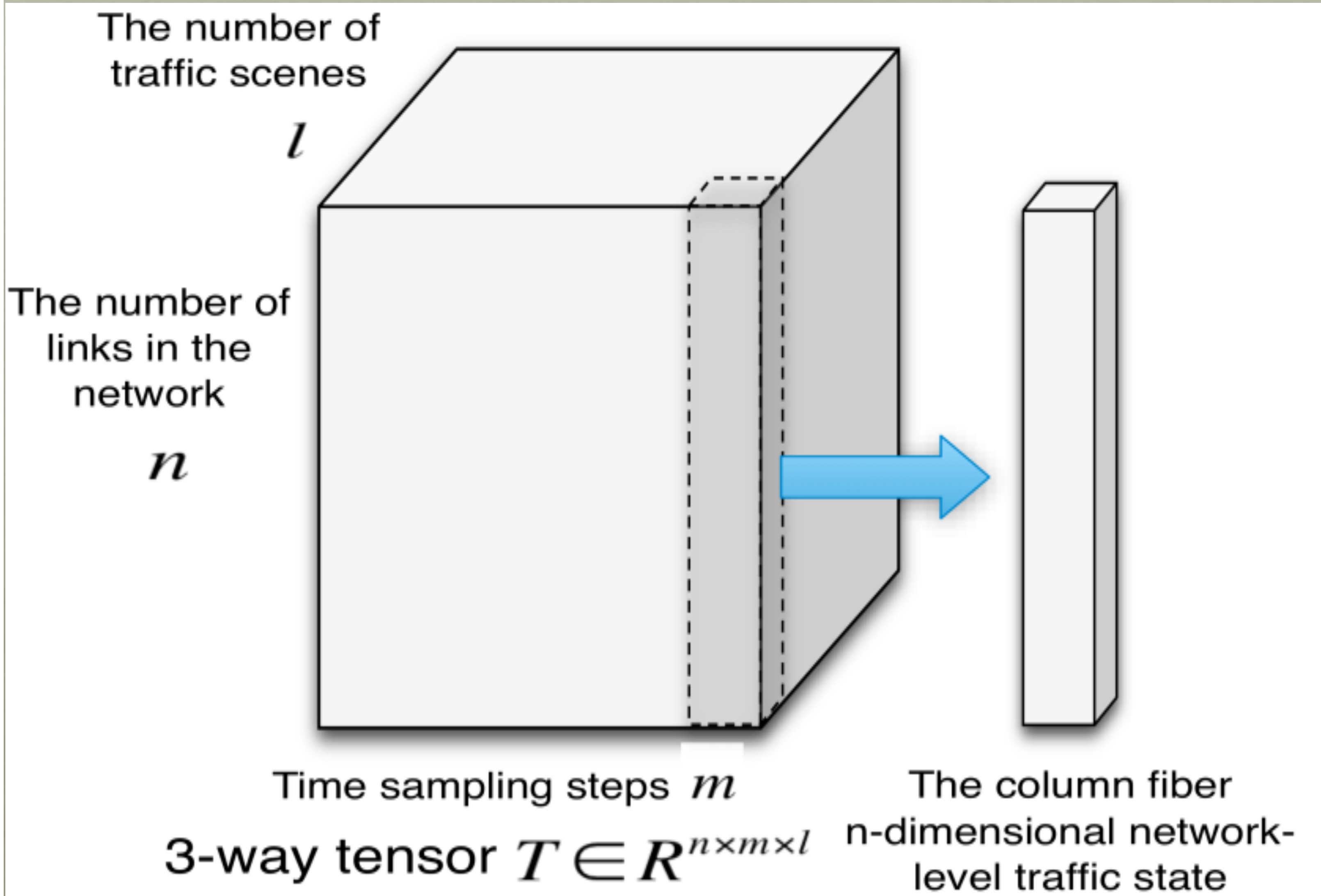


Typical daily evolution of traffic (a circular trajectory in 3D PCA space)

Iaurif Database


The 1st to the 12th time sampling step
The 13th to the 24th time sampling step
The 25th to the 36th time sampling step
The 37th to the 48th time sampling step
Typical Trajectory of the ITD setting
Typical Trajectory of the ATD setting
Typical Trajectory of the ETD setting
34
32
30
28
26
24
22
20
18
16
35
30
25
20
15
-80
-70
-60
-50
-40
-30
-20

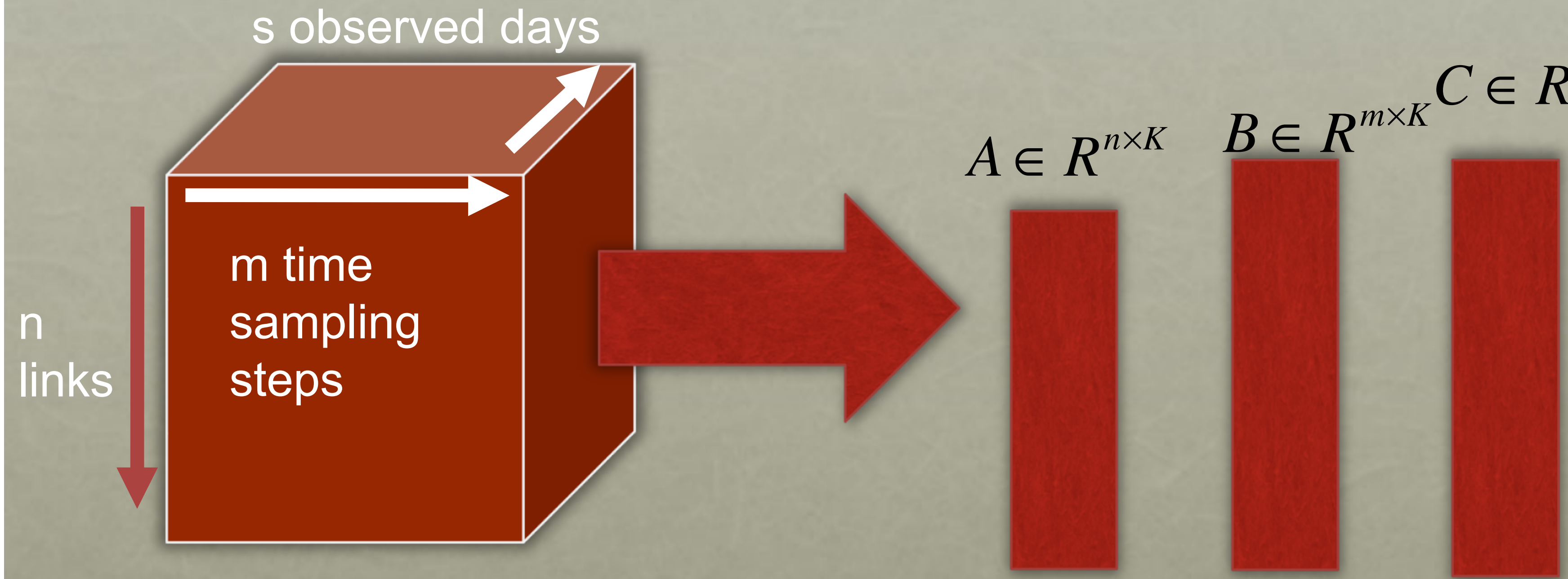
3-way Tensor



3-way tensor structure for storing traffic state data

Non-negative Tensor Factorization

Factorized into the outer product of three ***non-negative*** matrices



$A \in R^{n \times K}$ $B \in R^{m \times K}$ $C \in R^{s \times K}$

The n*m*s tensor T storing the traffic observations

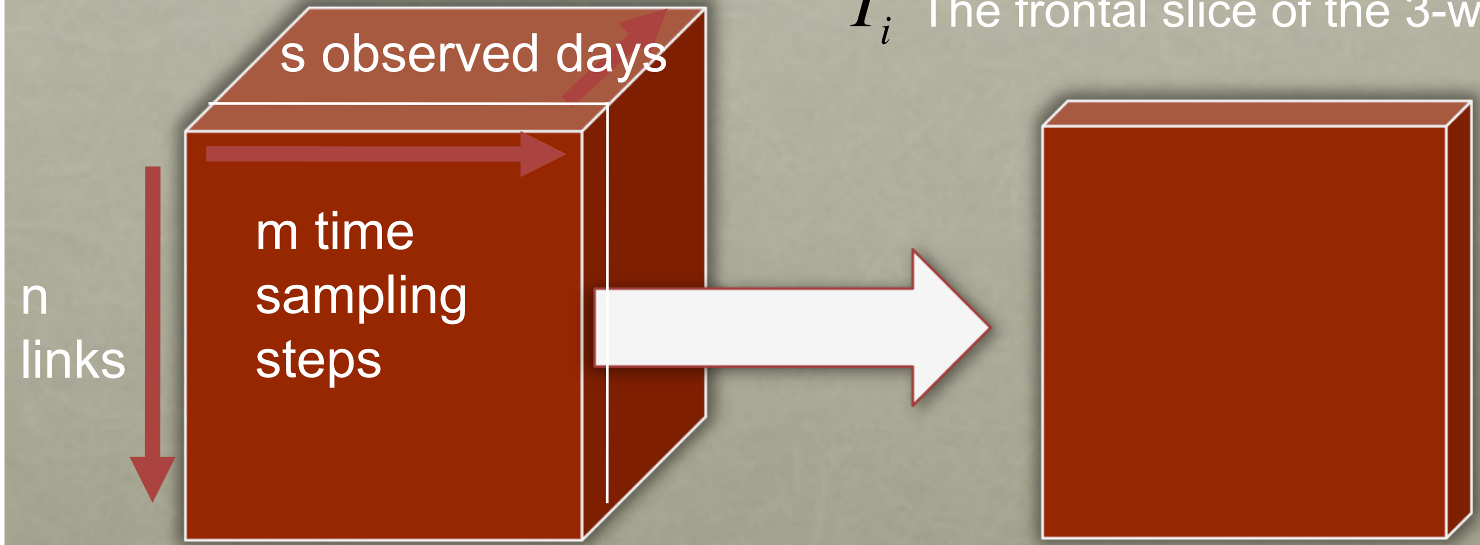
A_r, B_r, C_r are the r-th column of non-negative A, B and C respectively

$\otimes$ Outer-product

$$T = \sum_{r=1}^{K} (A_r \otimes B_r \otimes C_r)$$

Non-negative Tensor Factorization

T_i The frontal slice of the 3-way tensor



Temporal dynamics of all links in the network

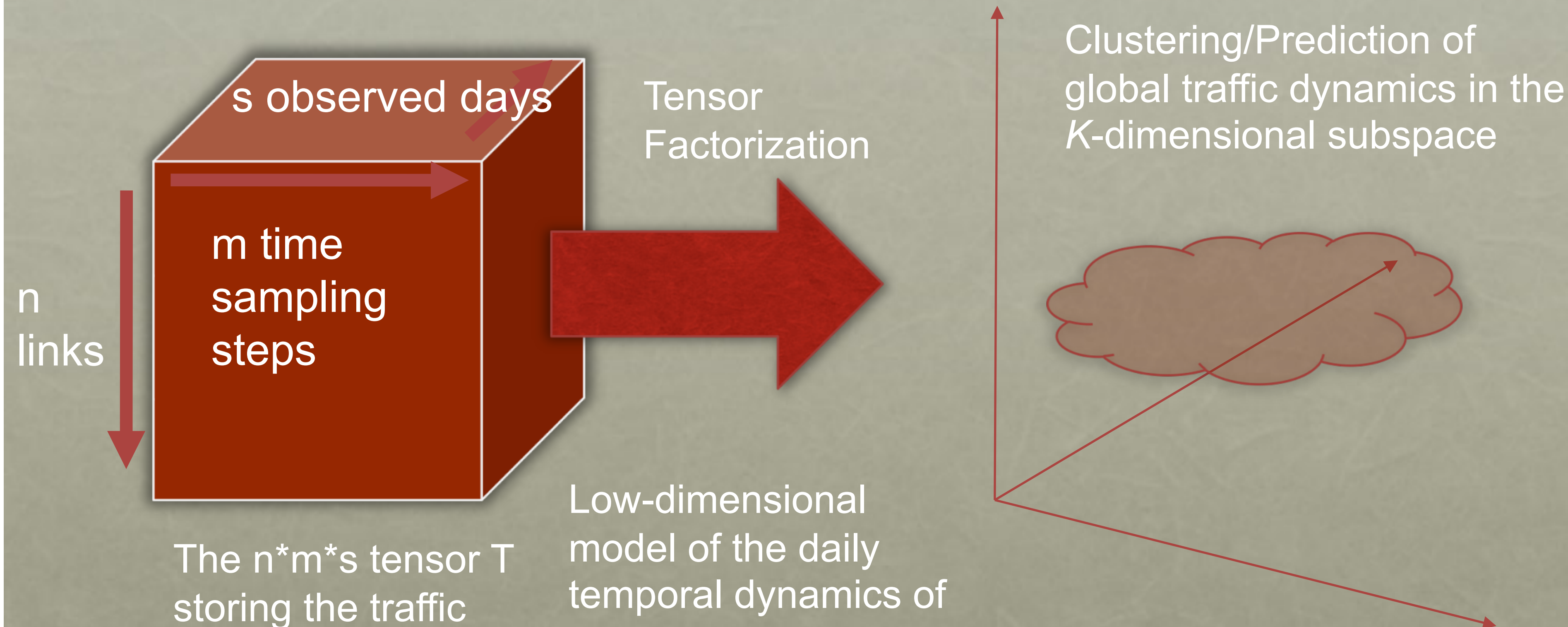
The n*m*k tensor T storing the traffic observations

$$T_i = \sum_{r=1}^{K} C_{i,r}(A_r B_r^T)$$

Fixing A and B ("projection basis"), each row vector of C can be treated as a *K*-dimensional representation for the corresponding frontal slice

$\{C_{i,r}\}(r = 1,2..K)$ The i-th row vector in C

NON-NEGATIVE TENSOR FACTORIZATION



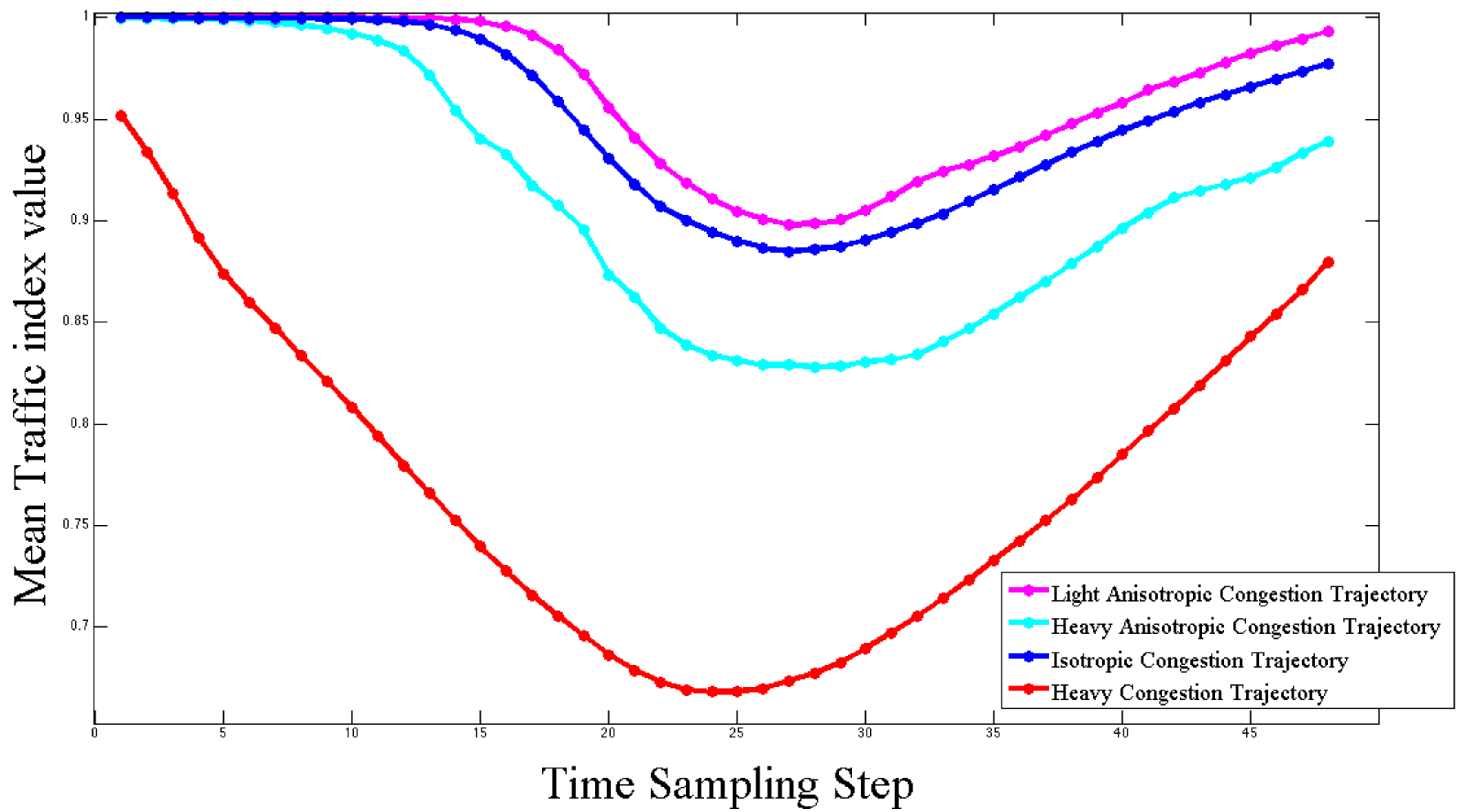
The n*m*s tensor T storing the traffic observations

Low-dimensional model of the daily temporal dynamics of global traffic state patterns

Project the each daily temporal sequence of the global traffic states (each frontal slice in the tensor) into a *K*-dimensional subspace

CLUSTERING OF GLOBAL TRAFFIC STATE DYNAMICS

- K-means clustering to the row space of the factorization



PREDICTION OF GLOBAL TRAFFIC STATE DYNAMICS

- Problem definition:
- Given: All historic traffic data observations for l traffic scenes $T^{historic} \in R^{n*m*l}$
- Target: A partially observed traffic scene, with only the first m_1 time sampling steps observed $M \in R^{n \times m}$
- Task: We aim to predict traffic dynamics of the whole network from the $m_1 + 1$ step until the end of the scene

PREDICTION OF GLOBAL TRAFFIC STATE DYNAMICS

- Solution: Tensor reconstruction

- **Step.1 : Non-negative Tensor Factorization on the historic traffic data**

$$T^{historic} = \sum_{r=1}^{K} (A_r^{historic} \otimes B_r^{historic} \otimes C_r^{historic})$$

- **Step.2 : Treating** $\{A_r^{historic}(B_r^{historic})^T\}(r=1,2..K)$ **as the expansion basis matrices,** $M \in R^{n\times m}$ **as a projected point lying on the manifold expanded by the basis matrices, its projection coordinates** C_r^M **is estimated as :**

$$C_r^M = \arg\min_{C_r^M} \left\| M - \sum_{r=1}^{K} C_r^M (A_r^{historic} \otimes B_r^{historic}) \right\|_{Fro}^{Obs} + \lambda \sum_{j=1}^{p} s_{h_j} \left\| C_r^M - C_{h_j}^{historic} \right\|_{L2} (C_r^M \geq 0)$$

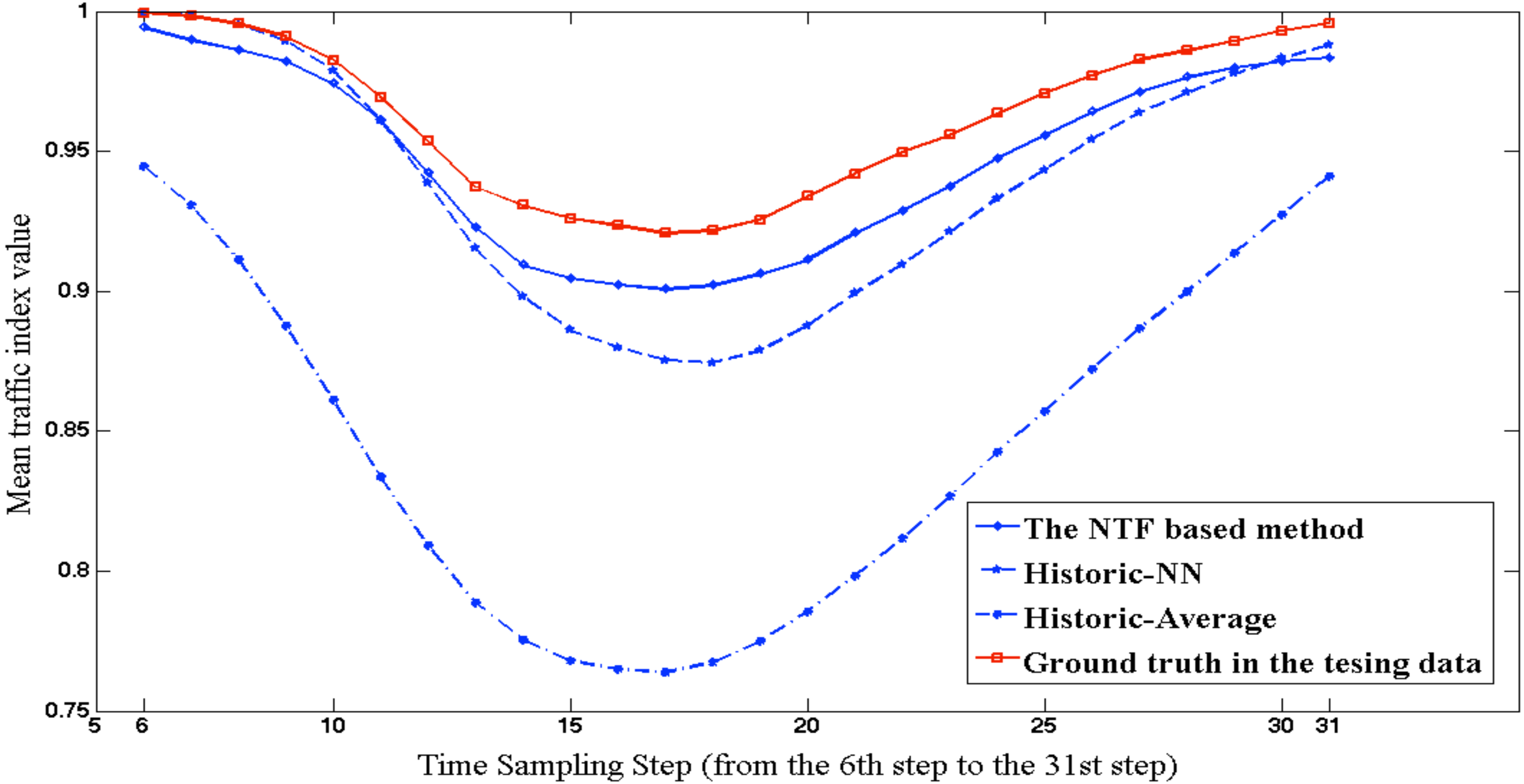
Prediction of Global Traffic State Dynamics

- Final step: Reconstruction of the missing entries in M is given as

$$M^{reconstruct} = \sum_{r=1}^{K} C_r^M \left(A_r^{historic} (B_r^{historic})^T\right)$$

- Basic scheme:
    - Manifold learning / reconstruction of missing entries
    - Nearest-neighboring constraint to smooth the obtained manifold structure

Prediction of Global Traffic State Dynamics



SUMMARY

- Manifold embedding of very high dimensional feature space
- Potential use of Matrix/Tensor Completion in traffic research
- Prior knowledge about correlation between links, time sampling steps, or even simulated scenes will do some help in our method ?
- Estimated global traffic state configuration as a spatial consistency constraint to Markov Random Fields based network model

Thanks for attention !