Optimization-based clustering of urban networks through snake segmentation

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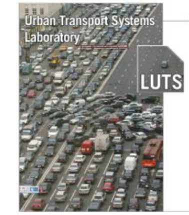
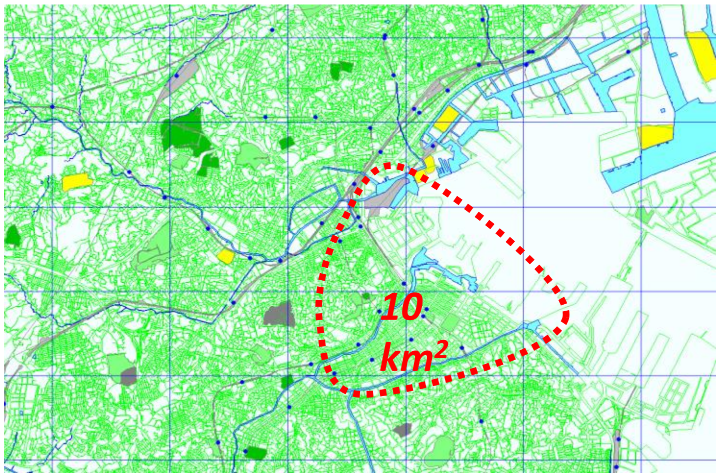
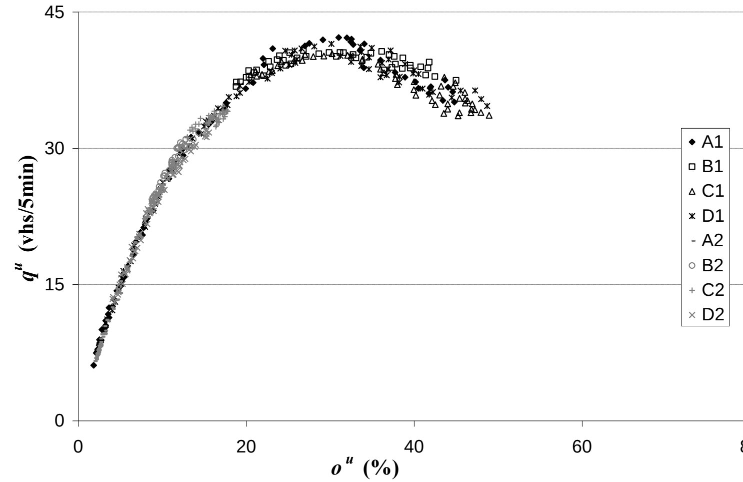


Macroscopic Fundamental Diagram (MFD)

Yokohama (Japan)

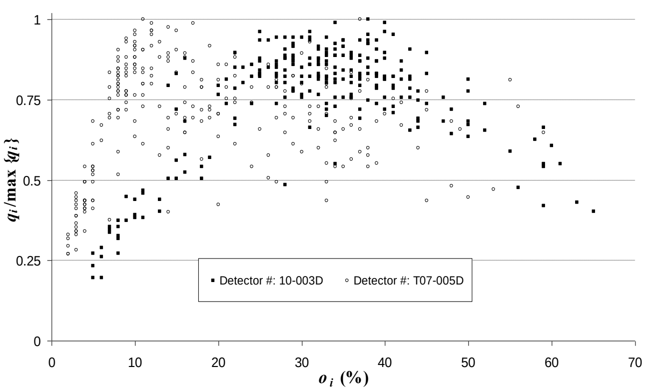


Average flow



Average occupancy

Individual flow



occupancy

Geroliminis and Daganzo (2008) – Tr. Res. Part B

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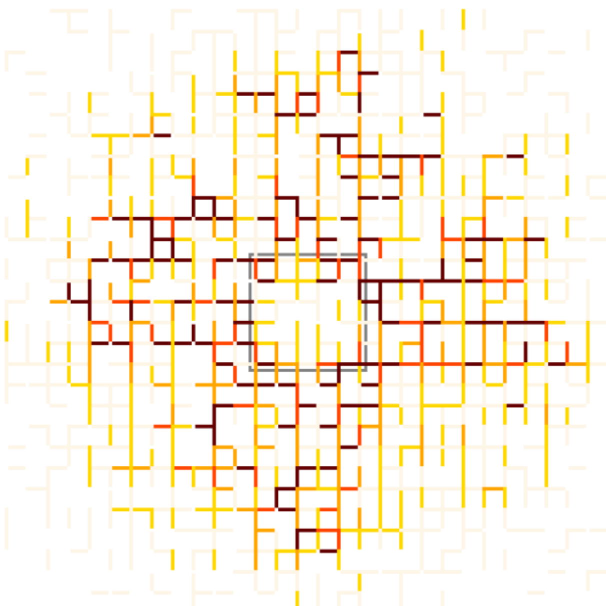
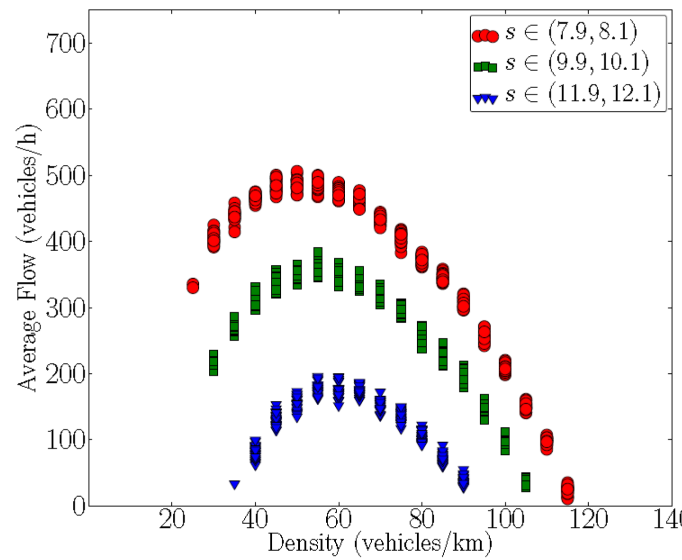
Macroscopic Fundamental Diagram (MFD)

- MFD is not a universal law
- Spatial distribution of congestion is crucial
  - Average flow is a function of both average and variance of link densities
  - Well-defined MFD exists in homogeneous regions





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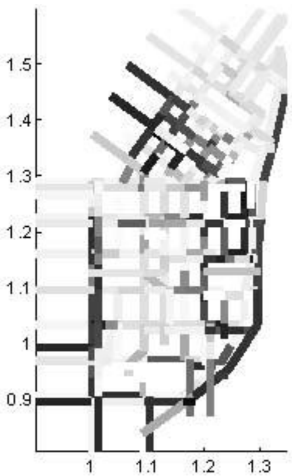
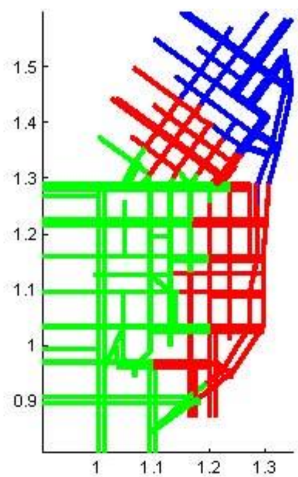
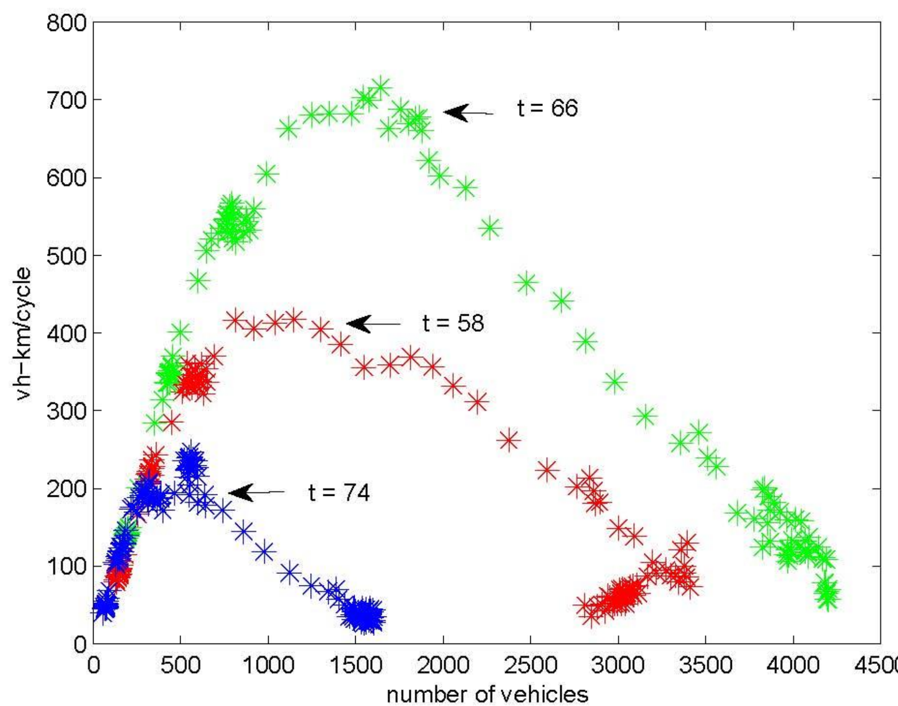
Mazloumian, Geroliminis and Helbing (2010) – Ph.Trans.Roy. Soc. A

Intro. to Clustering - Congestion Spreading

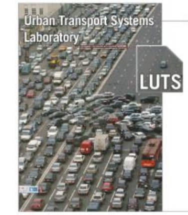
- Well-defined MFD
- Information about congestion time and location







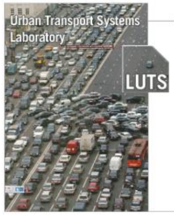
Ji and Geroliminis (2012) – Tr. Res. Part B:



Existing clustering approaches

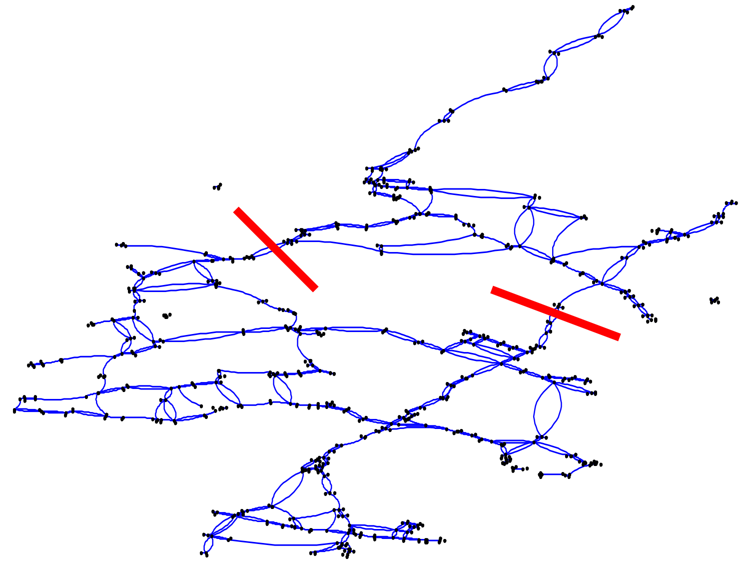
Goal: Find homogeneous compact clusters ⟶ Apply perimeter control

- Normal Clustering approaches
  - K-means
  - Fuzzy clustering
  - Artificial Neural networks
  - Spectral clustering
  - …
- Contiguity constrained clustering approaches
  - Penalized k-means
  - Hierarchical Agglomerative
  - NMB (Normalized cut + Merging + Boundary Adjustment)
  - …

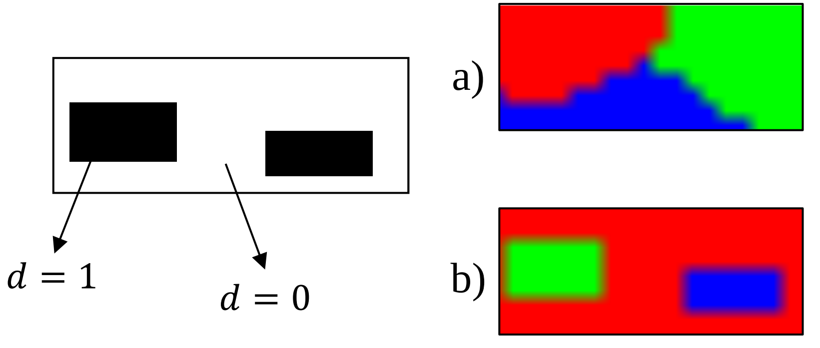


Issues of Existing Methods

- Sensitive to network structure
- Network is partially observable (Missing data)
- Sensitive to parameter calibration
- Incapable of finding directional congestion



Sydney (Australia)



Methodology

- Develop static clustering algorithm to find connected homogeneous regions in heterogeneous urban network
  - Detection of directional
  - Not sensitive to network structure (not perfect grid, well-connected)
  - Deal with missing data (partially observable networks)
  - Not sensitive to parameter calibration
- Three-step algorithm (Snake algorithm):
  - Running snakes
  - Defining similarities
  - Symmetric Nonnegative Matrix Factorization (SNMF)

Running Snakes

- Algorithm
  1) Start from point ‘i’ (link ‘i’) → ($S_i = [i]$)
  2) While snake covers all the network

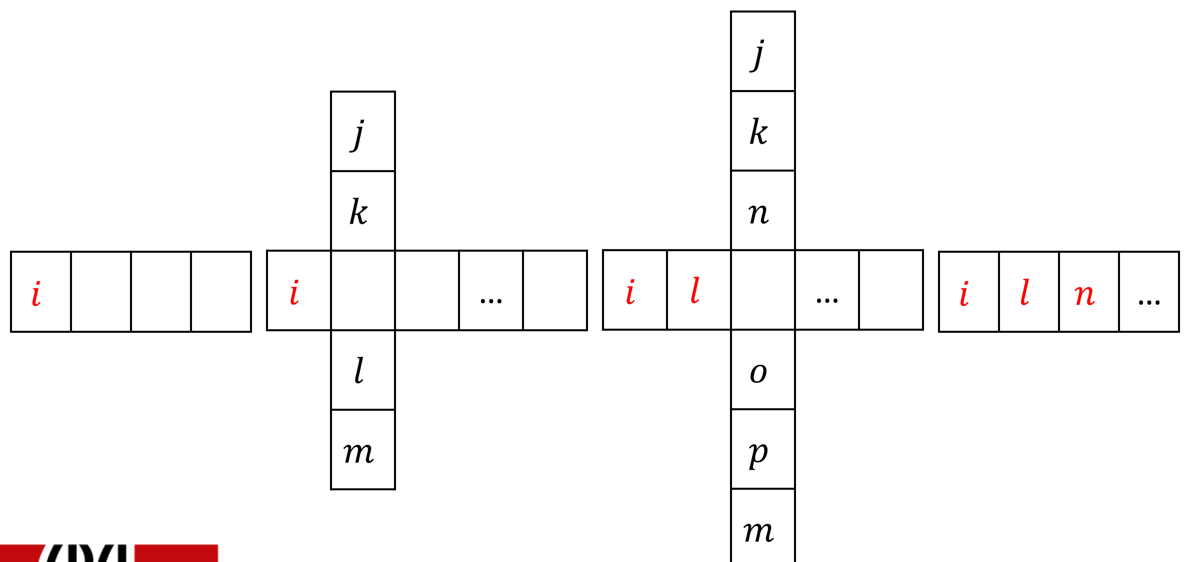
     {

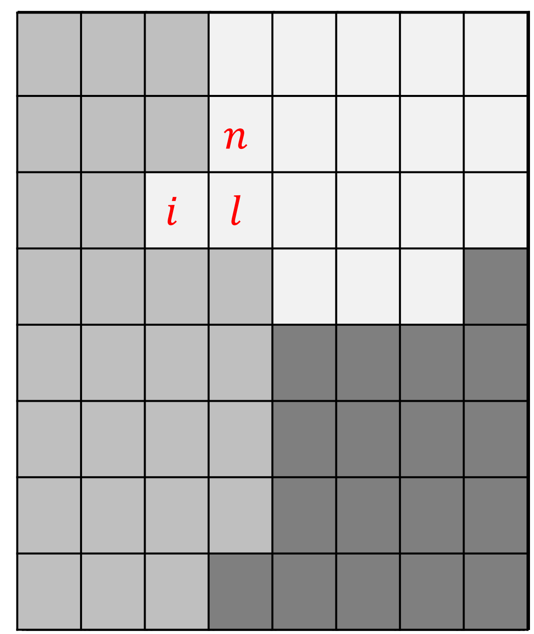
     i. Find all adjacent points → (S')

     ii. Compute the distance to the average

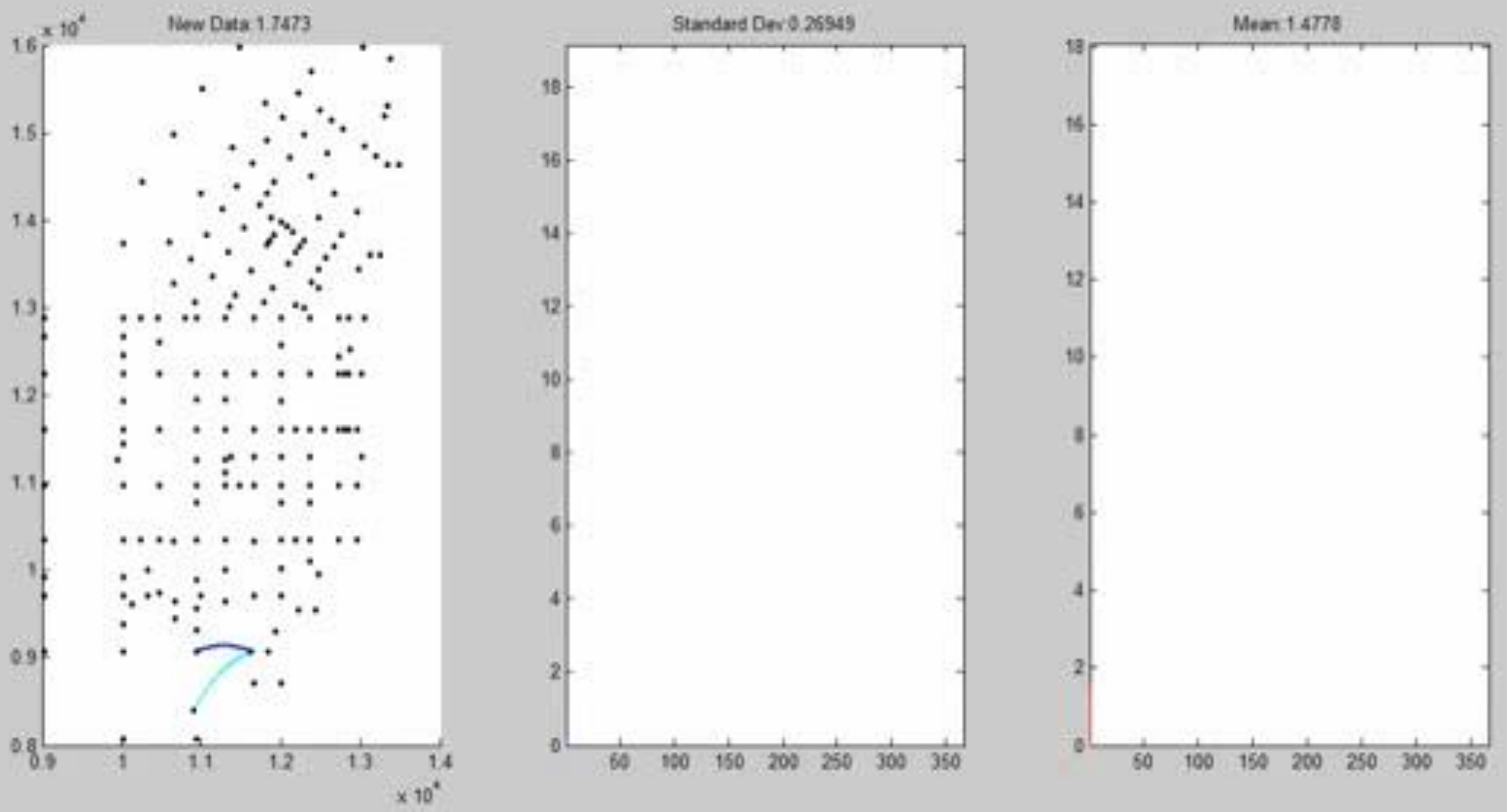
     iii. Pick the one with the closest value to the average and add it

     }





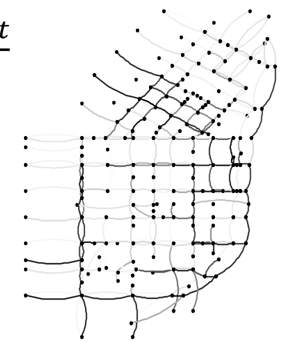
Running Snakes (step 1)

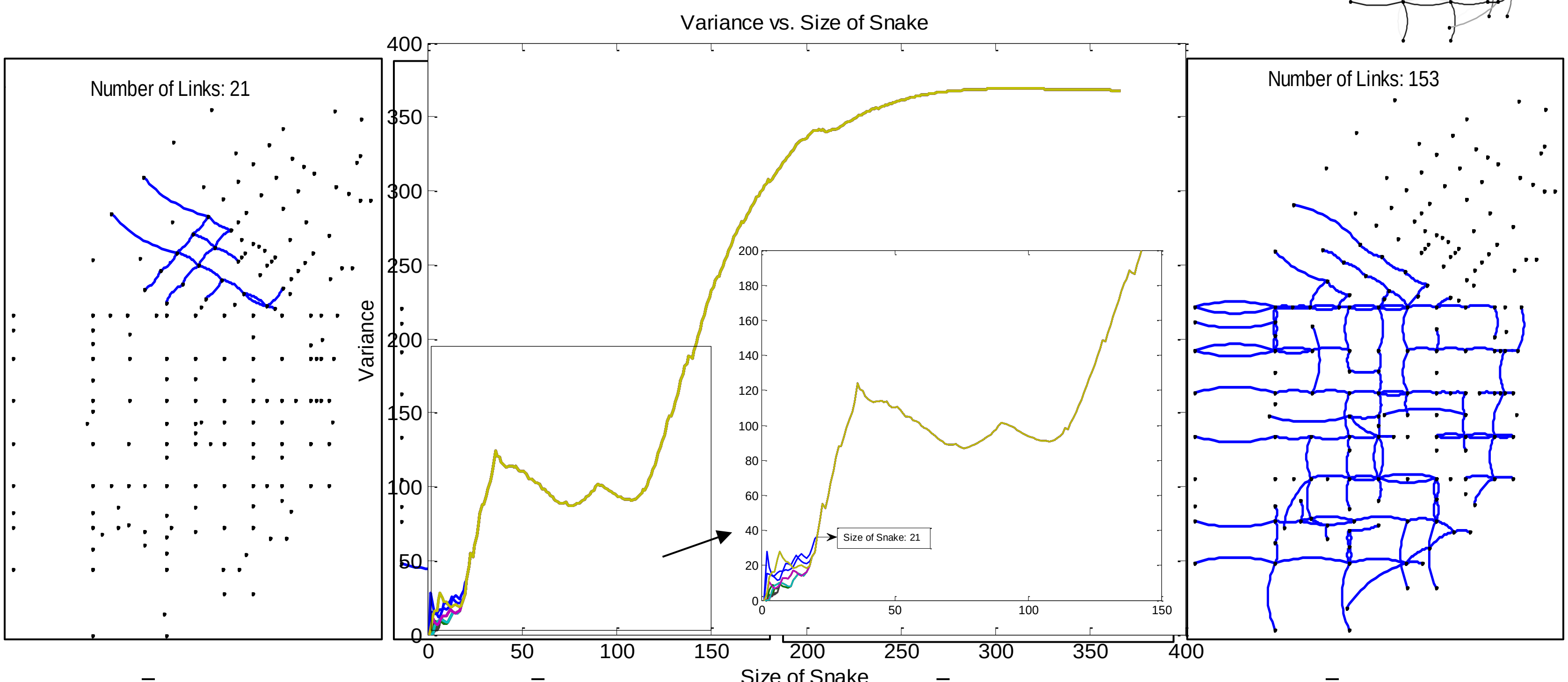


Running snakes

Robustness of the component: $\frac{Number\ of\ the\ snakes\ converge\ to\ the\ same\ component}{number\ of\ the\ links\ in\ the\ component}$

– Full robust components: Robustness = 1





$\bar{d}$: 48.51 $\bar{d}$: 51.63 $\bar{d}$: 5.36 $\bar{d}$: 4.86

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Defining similarities (step 2)

- Algorithm
  1) Set window size equal to one ($k = 1$)
  2) While (size of window $\leq$ size of network)

     {

     i. Calculate common points in first k elements of S_i and S_j arrays $\rightarrow$ (m)

     ii. $w_{ij} = w_{ij} + p^k \times m$

     iii. Increase the size of window $\rightarrow$ ($k = k + 1$)

     }

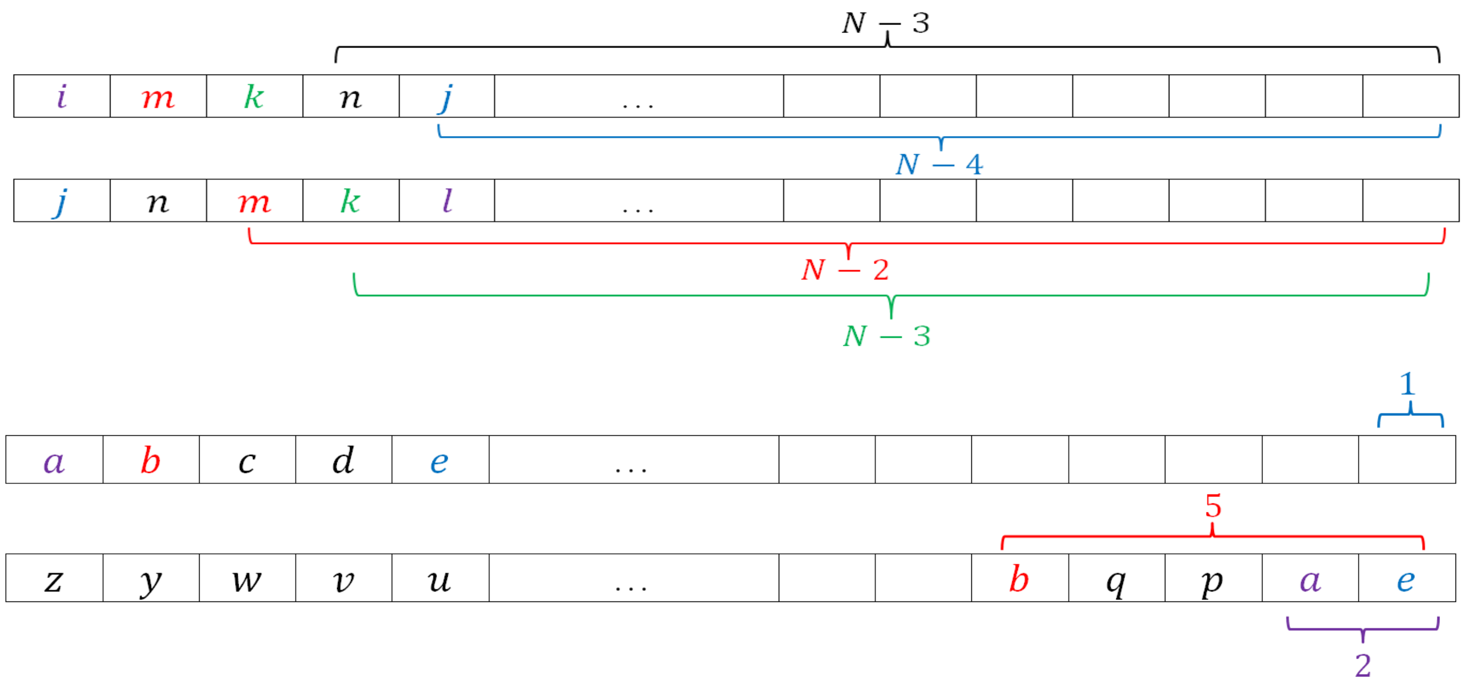
$k = 1$ $k = 2$ $k = 3$ $k = 4$

S_i	$\rightarrow$	i	b	c	d	…
S_j	$\rightarrow$	j	i	n	c	…

$m = 0$
$w_{ij} = 0 + m = 0$

Defining similarities

$$w(i,j) = \sum_{t \in links} \left\{ N - \max\left(L_{s_i}(t), L_{s_j}(t) \right) + 1 \right\}$$

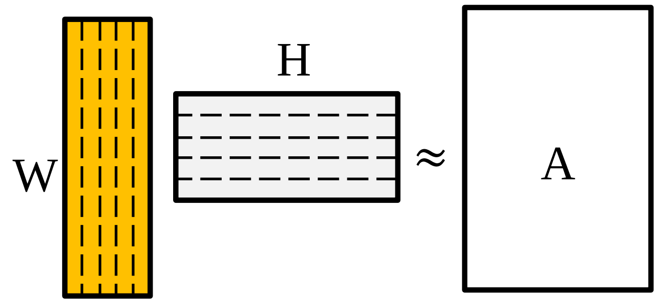


✓ Put more weight on adjacent links → (Connectivity, compact shape)

✓ Keep variance as lowest as possible → (Homogeneity)

Nonnegative Matrix Factorization (Step 3)

$$\left(\min_{W\geq 0, H\geq 0} \|A - WH\|_F^2\right)$$

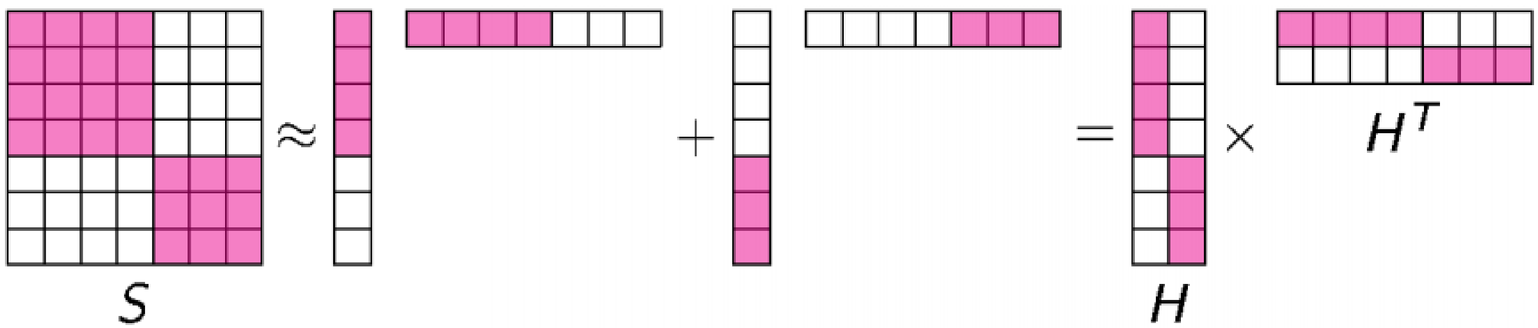


Given $A \in \mathcal{R}_+^{(m\times n)}$ and desired rank $k \ll \min(m,n)$, Find $W \in \mathcal{R}_+^{(n\times k)}$ and $H \in \mathcal{R}_+^{(k\times m)}$ such that $A \approx WH$

- Non-convex
- Lower rank approximation

Symmetric NMF

$$\min_{H \geq 0} \|S - HH^T\|^2$$

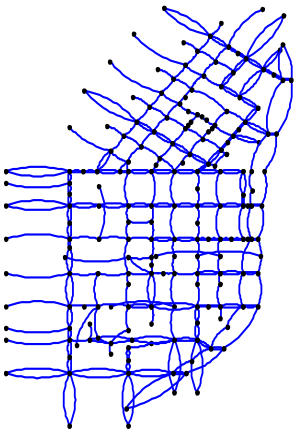


S: Similarity matrix

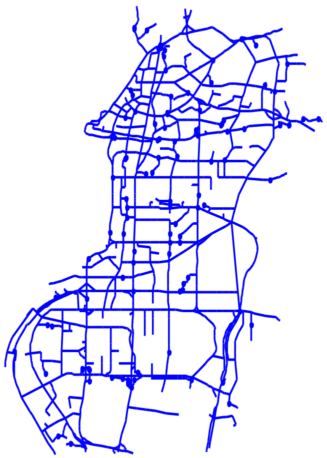
H: Clustering membership

Case Study

- San Francisco
  - About 100 intersections and 366 links
  - Average density for each 2 min time interval



- Shenzhen
  - About 600 intersections and 2000 links
  - Daily GPS data of taxis
  - Average speed of vehicles for each 5 min interval

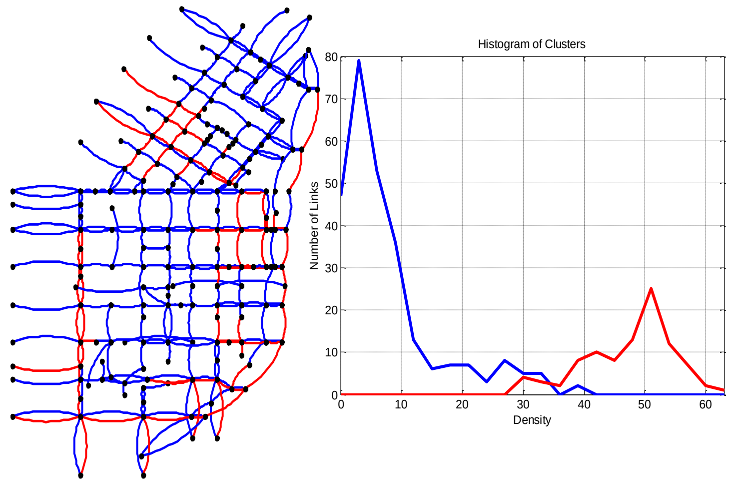


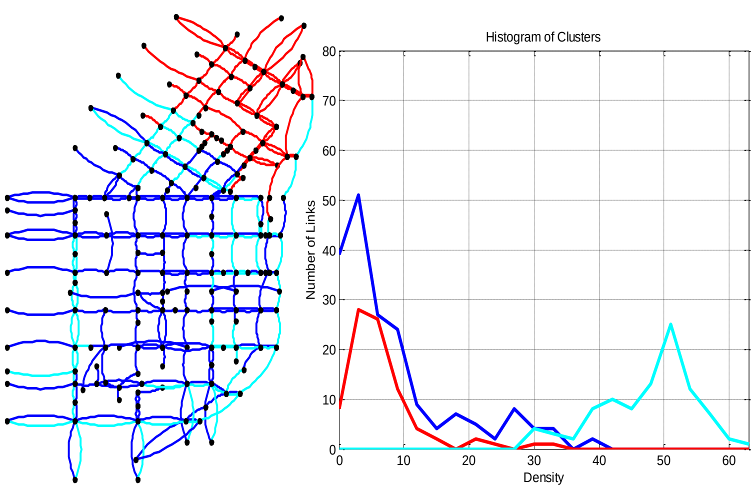
Case Study (San-Francisco)

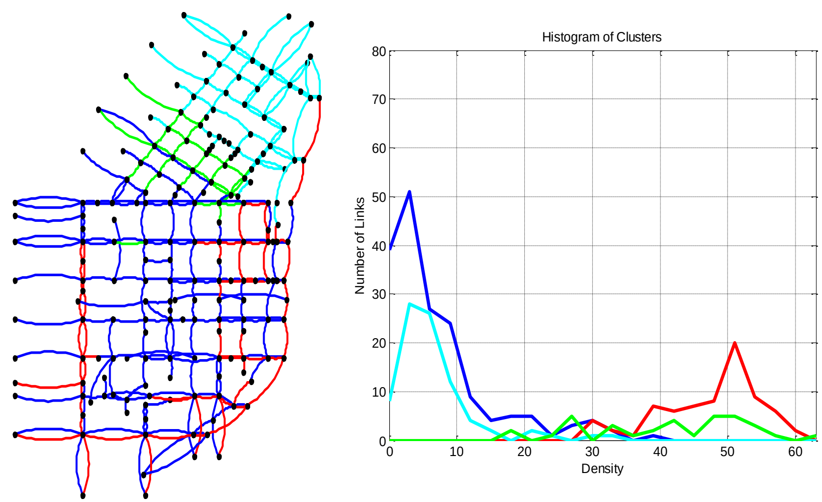
$$TV = \sum_{A \in C} N_A \times var(A)$$

Table 1: Average values and standard deviation of link densities for different clustering results [veh/(km.lane)]

(Mean/Standard deviation)	Blue	Red	Cyan	Green	Yellow	TV
2	7.73/8.28	47.43/7.22	-	-	-	2.36
3	8.30/9.16	6.48/5.71	47.43/7.22	-	-	2.34
4	7.11/7.94	47.32/7.38	6.48/5.71	41.15/11.5	-	2.22
5	9.57/9.64	6.48/5.71	47.80/6.68	47.32/7.38	3.36/4.33	2.23







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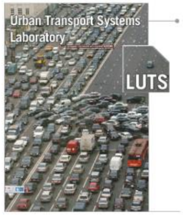
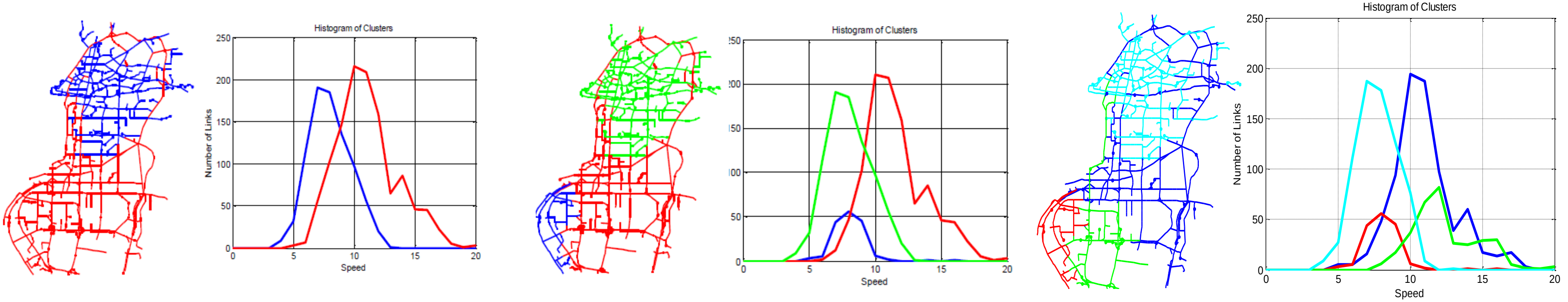


Case Study (Shenzhen)

Table 2: Average values and standard deviations of link speeds for different clustering results (2 -5 clusters) [m/s]						
(Mean/Standard deviation)	Blue	Red	Green	Cyan	Black	TV ($\times 10^4$)
2	8.05/1.69	11.03/2.49	-	-	-	0.97
3	8.07/1.30	11.51/2.30	8.05/1.69	-	-	0.80
4	10.95/2.17	8.07/1.30	12.40/2.26	7.71/1.40	-	0.71
5	10.87/2.86	7.32/1.24	12.40/2.26	8.07/1.30	10.28/1.40	0.74



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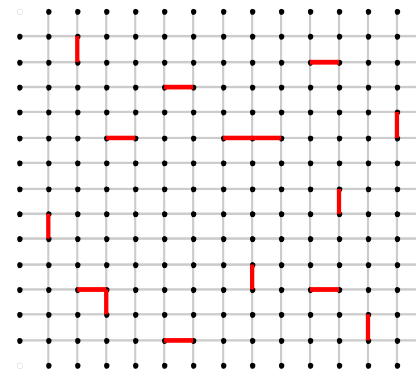
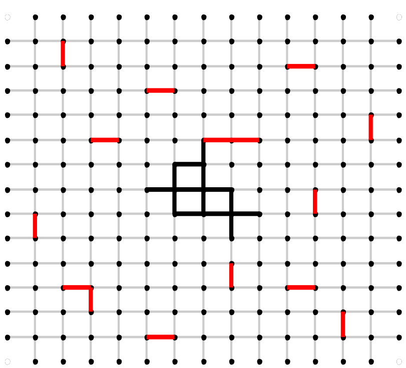
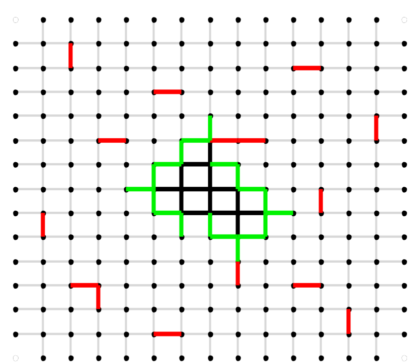
Algorithm Extension

- Investigate virtual connections through links with missing data
- Put a priority to the links that are closer
- Assign threshold to avoid bypassing heterogeneous parts

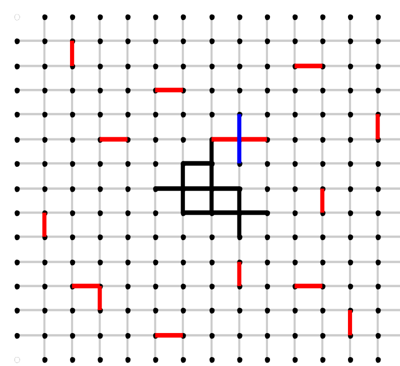


$$d_i = a^{r_i - 1} \times |D_i - \mu| \,, a \geq 1$$

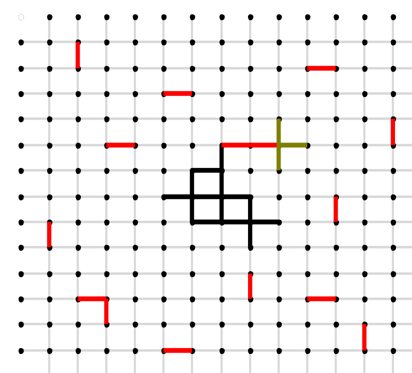




$d = |D_i - \mu|$



$d = a \times |D_i - \mu|$



$d = a^2 \times |D_i - \mu|$

Algorithm Extension

- Keep index of links with data in the arrays
- Define similarity matrix for links with data
- Finding symmetric lower rank approximation (Symmetric NMF)

Conclusion & Future work

- Conclusions
  - Congestion spreading
    - Congestion is spatially correlated in adjacent road
    - This correlation allows us define pocket of congestion
  - Partitioning algorithm
    - Independent of network structure
    - Capable of finding directional congestion
    - No need to parameter calibration
- Future work
  - Model the problem mathematically (size constraint – Contiguity constraints)
  - Dynamic clustering (Congestion evolution)

Thank you for your attention