Multidimensional and time varying data visualization at ICMC-USP

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Instituto de Ciências Matemáticas e de Computação

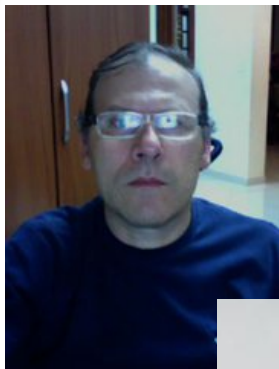Universidade de São Paulo - Brasil

Visual and Geometry Processing Group

Visualization and Imaging Group

Afonso Paiva

Antônio Castelo

Luis Gustavo Nonato

Marcio Gameiro

Paulovich

João Batista

Maria Cristiana

Rosane Minghim

Moacir Ponti

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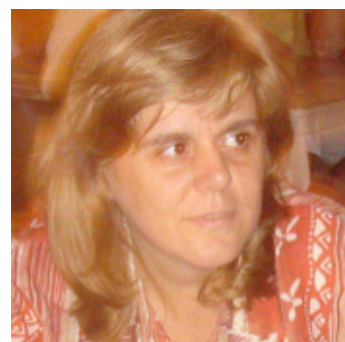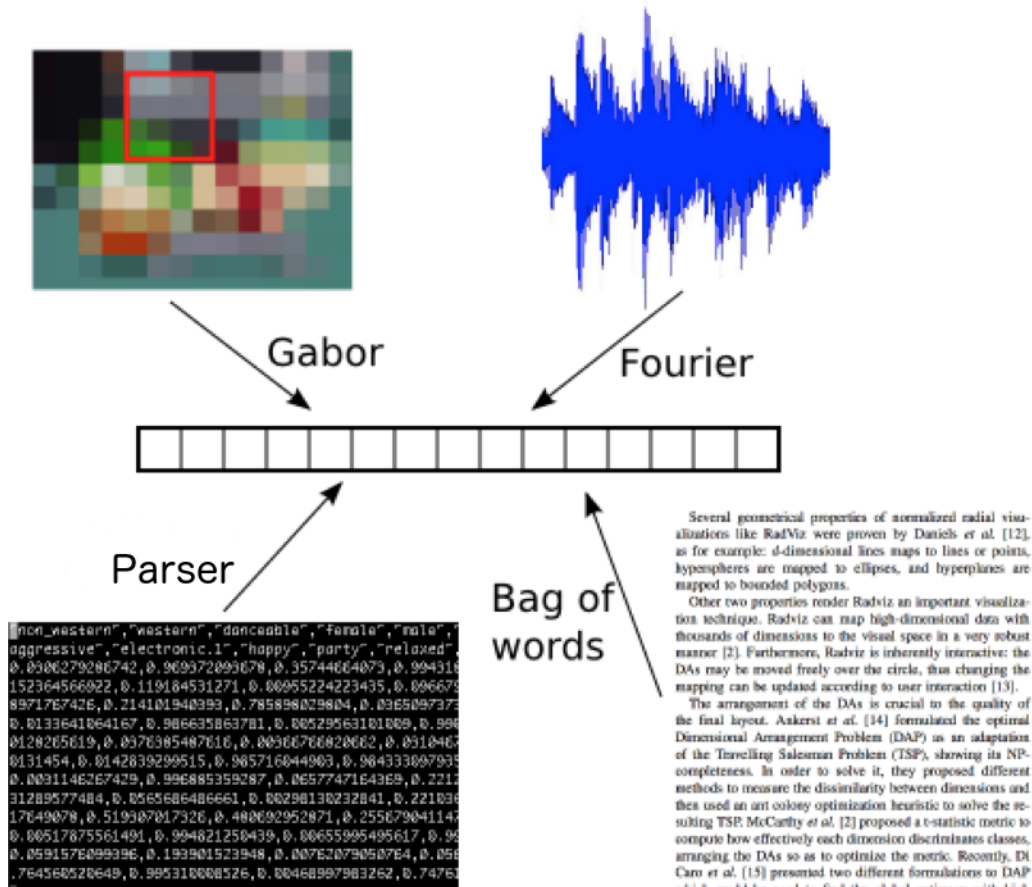
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Researches are focused mainly on

multidimensional data visualization

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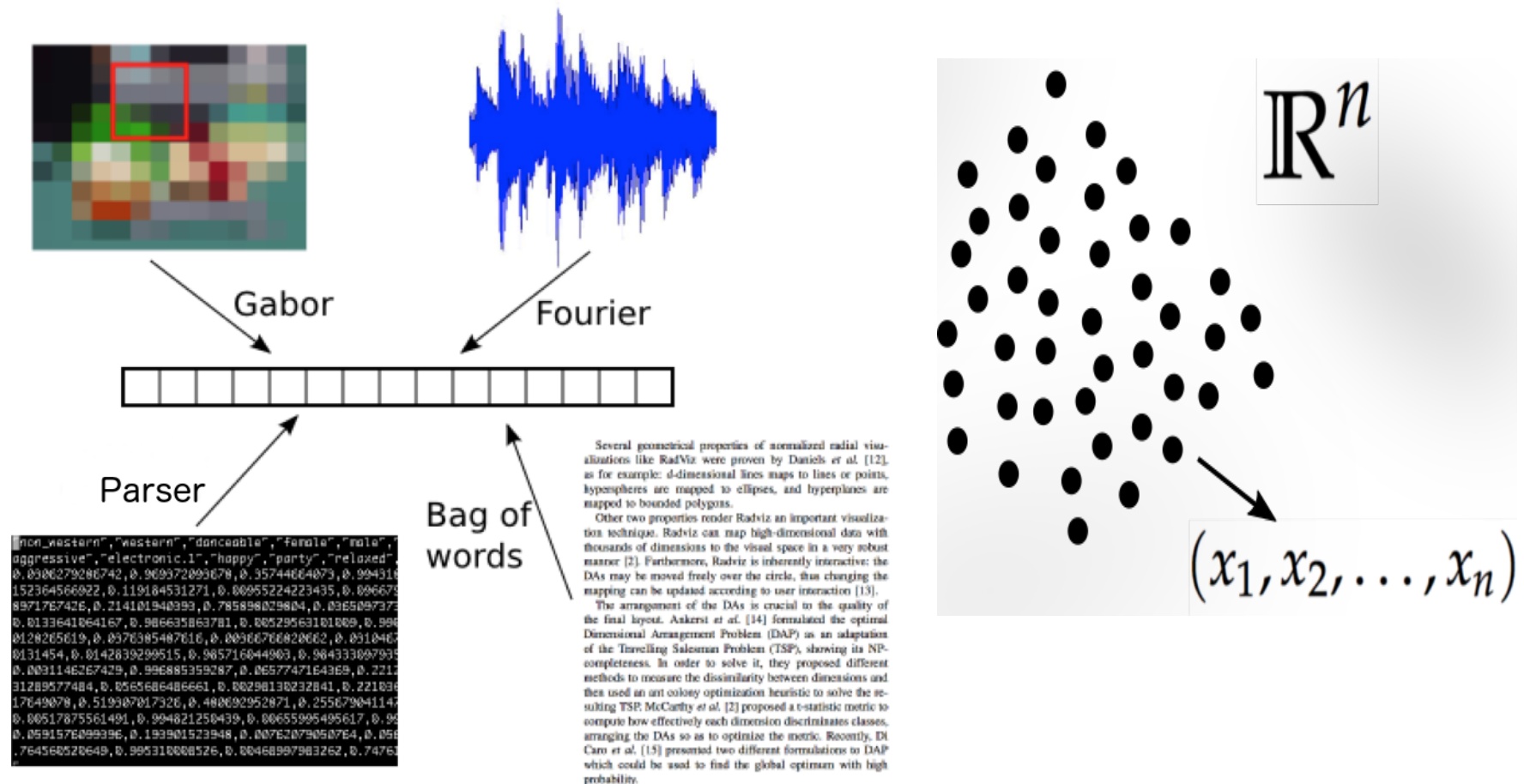# multidimensional data visualization

Researches are focused mainly on multidimensional data visualization

Two main topics:

- Multidimensional Projection based Visual Analytics

- Graph based Time-Varying data Visual Analytics

Two main topics:

- **Multidimensional Projection based Visual Analytics**
  - ✓ Supervised Projection Methods
  - ✓ Distortion Analysis
  - ✓ Enriched MP Layout

- Graph based Time-Varying data Visual Analytics

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- Multidimensional Projection based Visual Analytics
  - ✓ Supervised Projection Methods
  - ✓ Distortion Analysis
  - ✓ Enriched MP Layout

- Graph based Time-Varying data Visual Analytics
  - ✓ Graph-Wavelets
  - ✓ Multi-way Arrays (tensor decomposition)

Multidimensional Projection

Multidimensional Projection

Multidimensional Projection techniques aim to embed instances of data in a Cartesian k-dimensional space assuming that a (dis)similarity measure between pairs of instances is known.

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d(,)

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d(,)

Multidimensional Projection
@ ICMC

- Pioneered supervised MP methods

- First to propose a local MP method

Multidimensional Projection
@ ICMC

- Pioneered user driven MP methods

- First to propose a local MP method

  ✓ Least Square Projection (LSP)

  ✓ Local Affine Multidimensional Projection (LAMP)

Least Square Projection - LSP

Least Square Projection - LSP

LSP has been tailored to be interactive (supervised), enabling users to steer the projection process.

Multidimensional Space
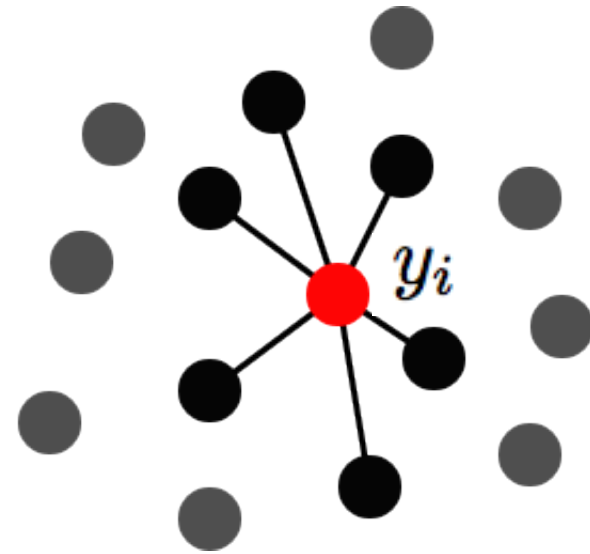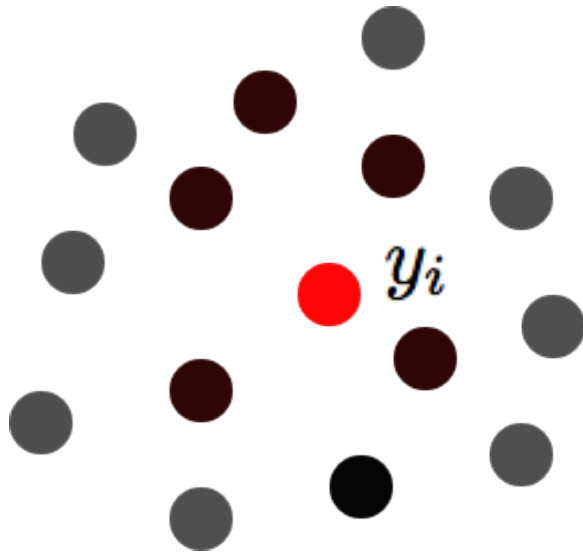
$$y_i = \sum_{j \in N_i} \alpha_{ij} y_j \qquad \alpha_{ij} = \frac{1}{|N_i|}$$

A tenable assumption is that neighborhoods should

be preserved in the visual space:

$$x_i = \sum_{j \in N_i} \alpha_{ij} x_j \quad \longrightarrow \quad x_i - \sum_{j \in N_i} \alpha_{ij} x_j = 0$$

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$$Lx^1 = 0 \qquad Lx^2 = 0$$

$$L_{ij} = \begin{cases} 1 & i = j, \\ -\alpha_{ij} & x_j \in N_i, \\ 0 & \text{otherwise} \end{cases}$$

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$$\boxed{Lx^1 = 0 \qquad Lx^2 = 0}$$

Laplace systems:
constraints are need to
ensure non-trivial solution

$$L_{ij} = \begin{cases} 1 & i = j, \\ -\alpha_{ij} & x_j \in N_i, \\ 0 & \text{otherwise} \end{cases}$$

Constraints for the homogeneous systems are given by control points in the visual, which can be interactively displaced to steer the projection process.

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control points

Multidimensional Space

Visual Space
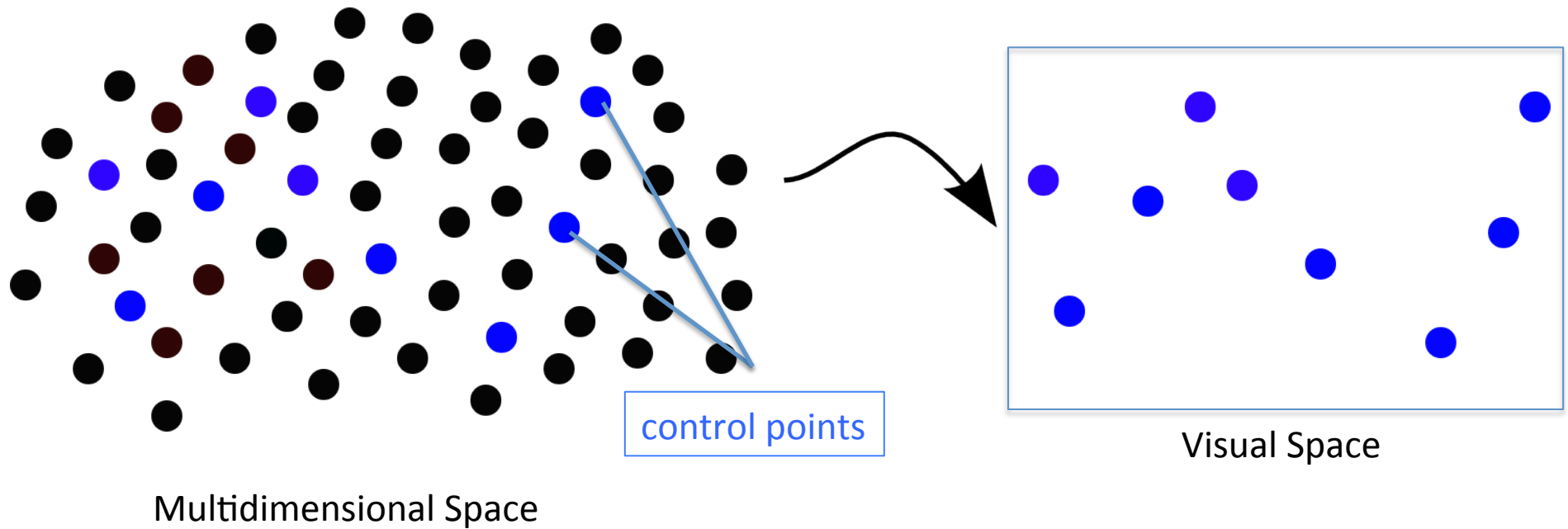
Unsupervised
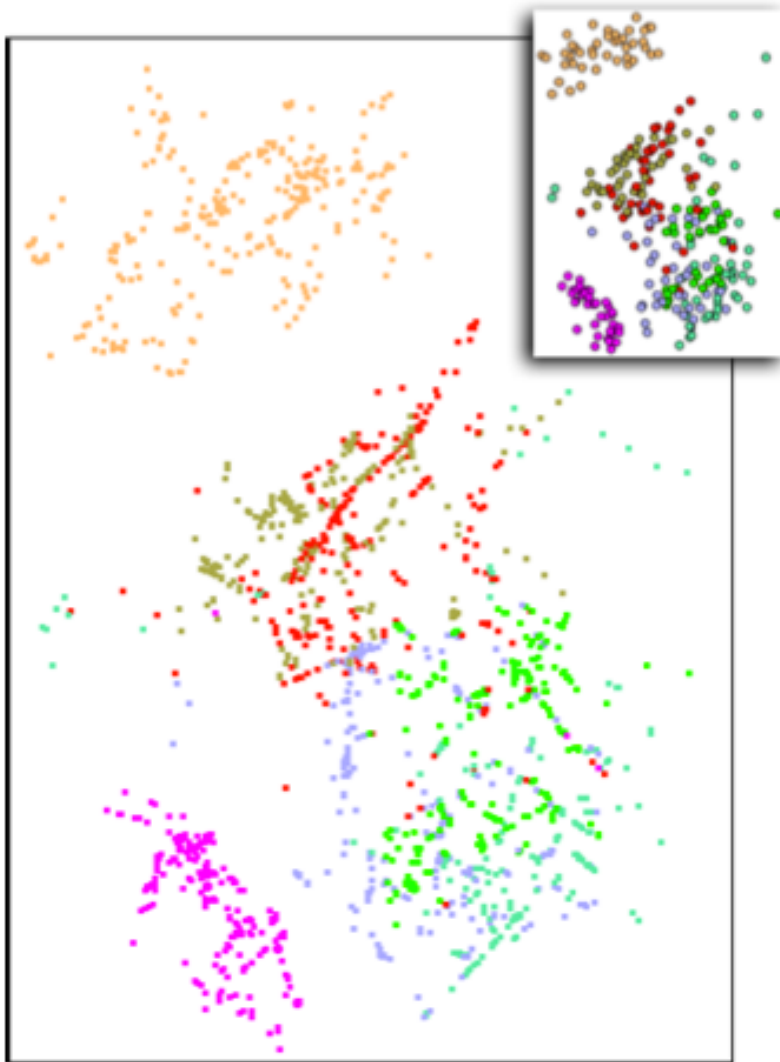
User Driven
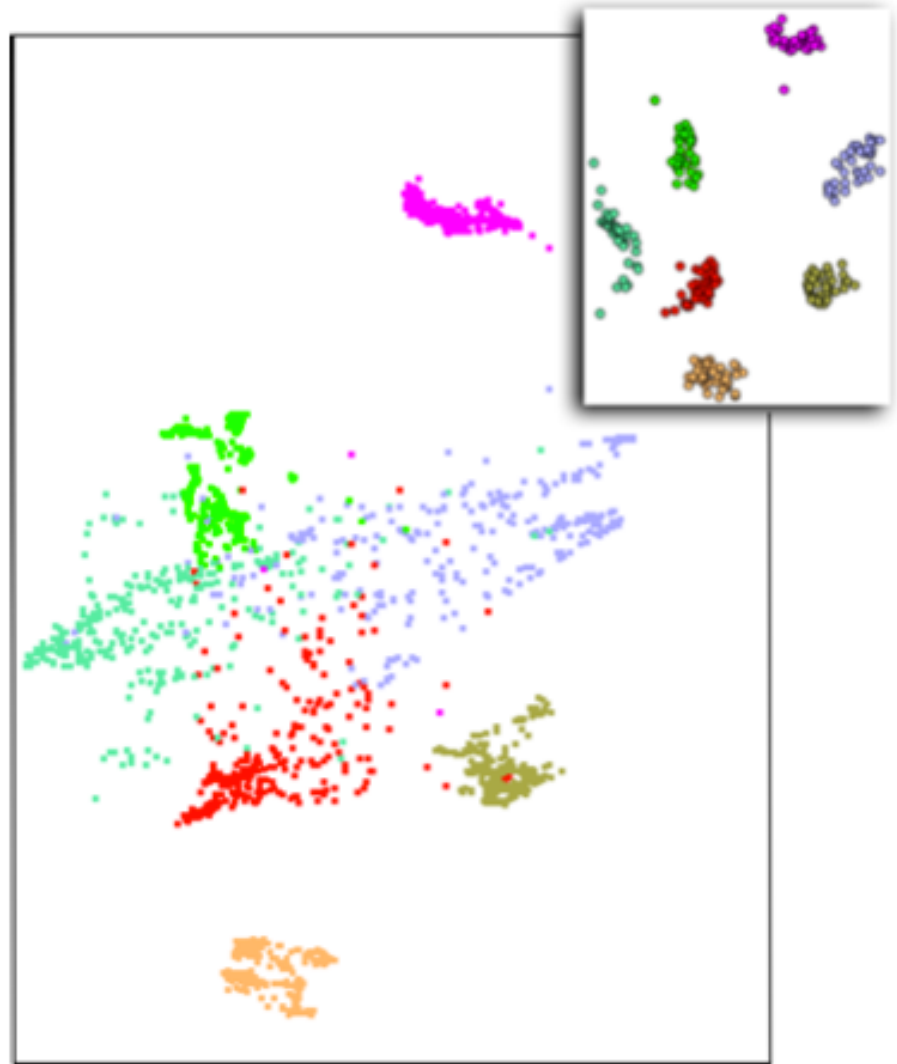
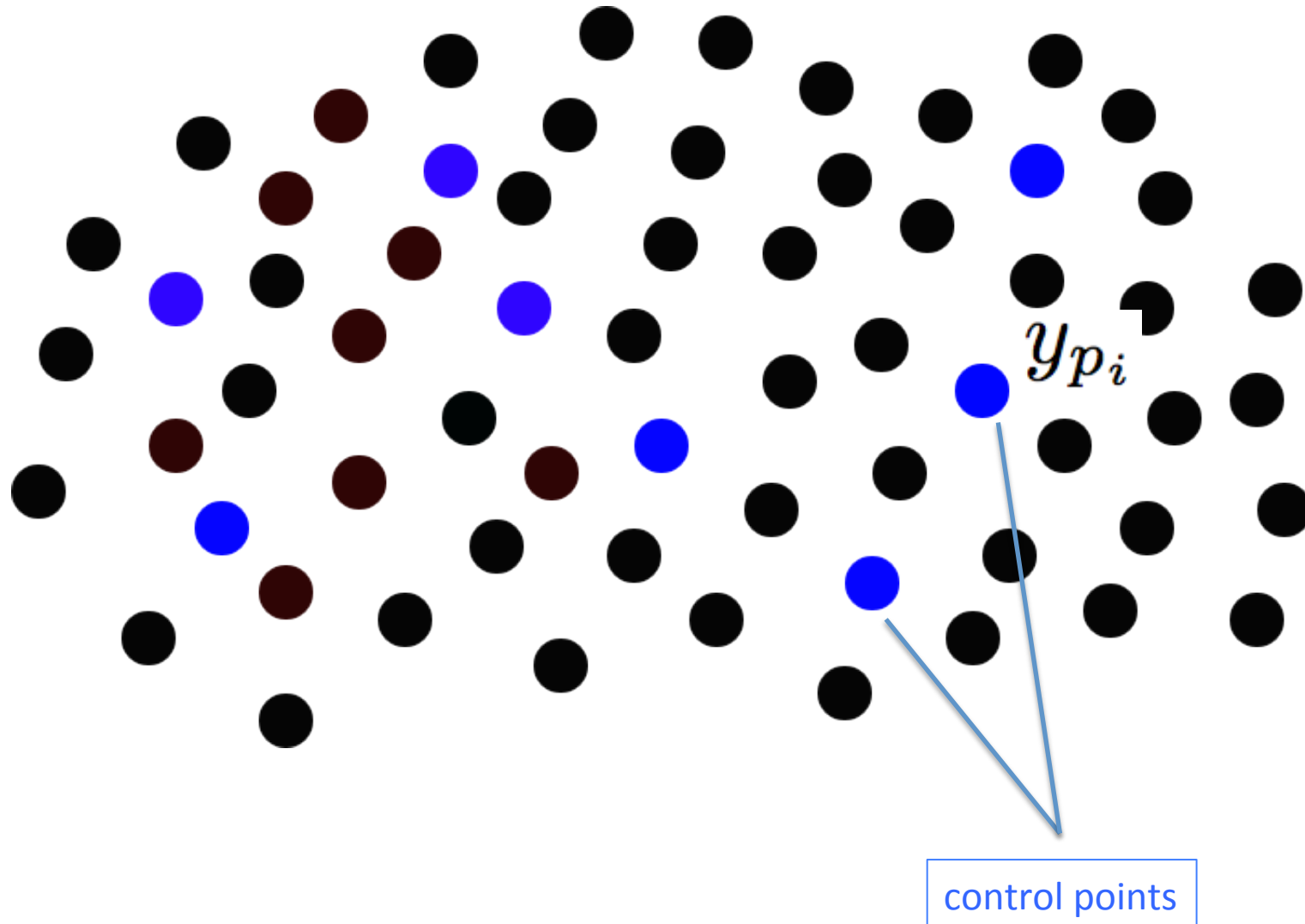Although LSP allows for user interaction it has two main drawbacks:

1. LSP is not super fast

   can not handle massive data sets

2. LSP mapping is global

   small changes in the control points affects the whole layout

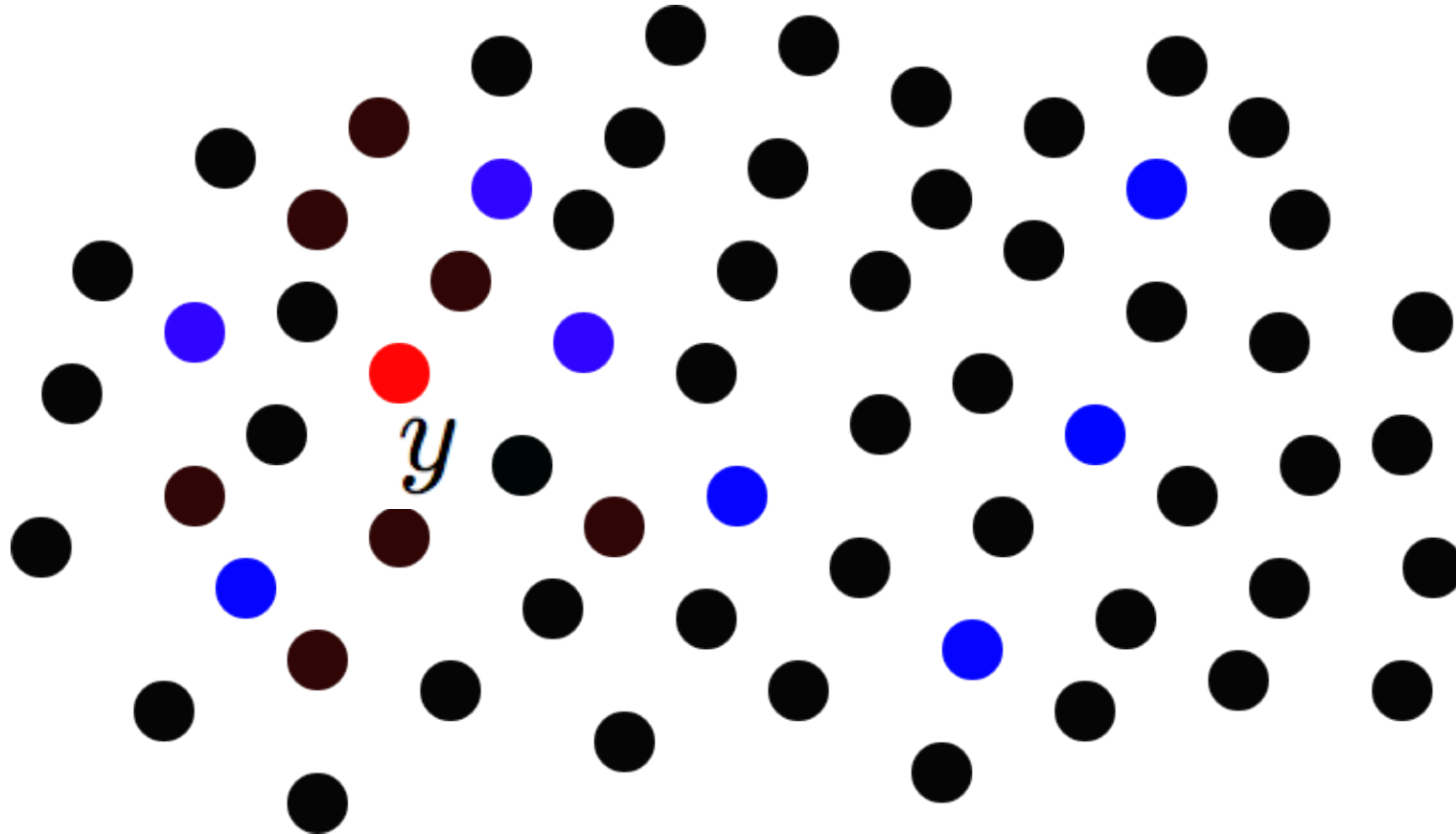# Local Affine Multidimensional Projection (LAMP)

Local Affine Multidimensional Projection (LAMP)

LAMP has been designed to be local,

interactive, and computationally efficient.
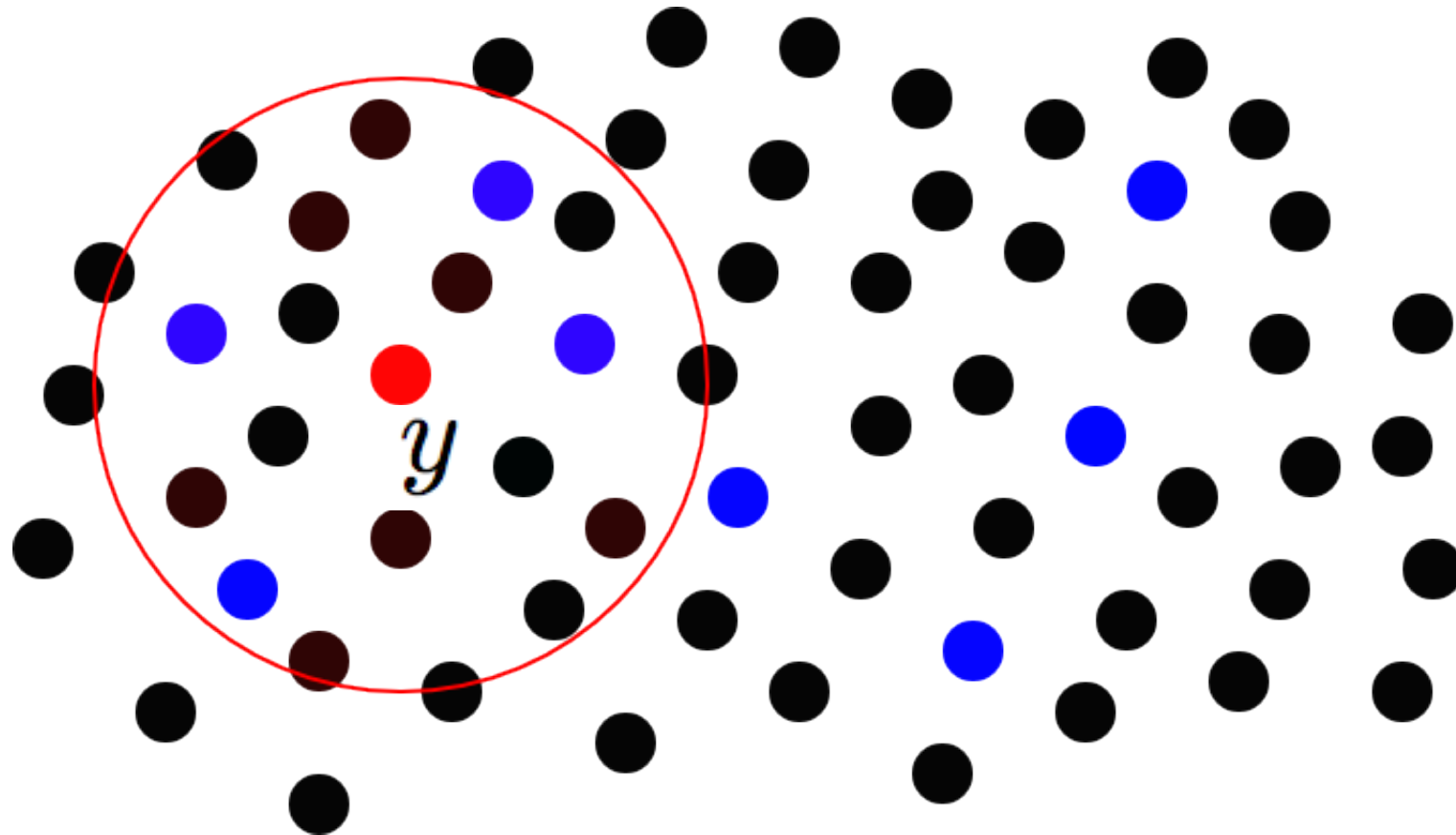
Multidimensional space

y_{p_i}

control points

Multidimensional space

y

Each point is mapped to the visual
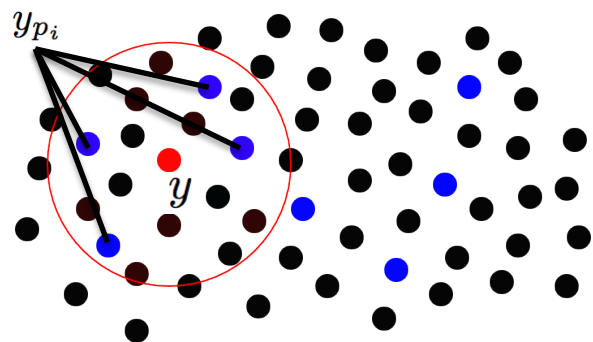space using its own affine transformation

$$f_y(y_i) = y_i M + t$$

Multidimensional space

Each point is mapped to the visual
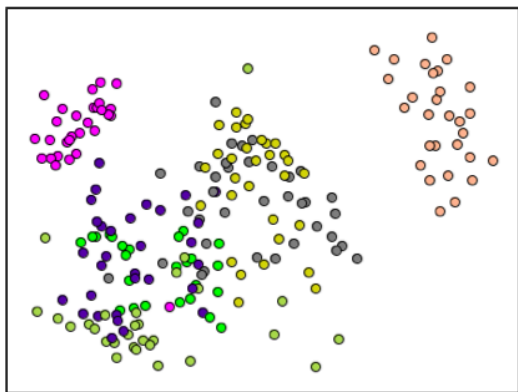space using its own affine transformation
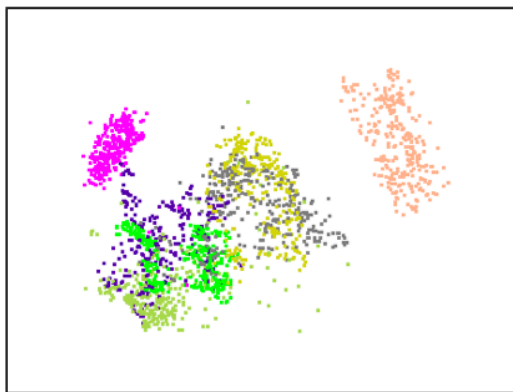
$$f_y(y_i) = y_i M + t$$

$$\sum_i w_i \|\hat{y}_{p_i} M - \hat{x}_{p_i}\|^2 \qquad \text{subject to } M^\top M = I$$

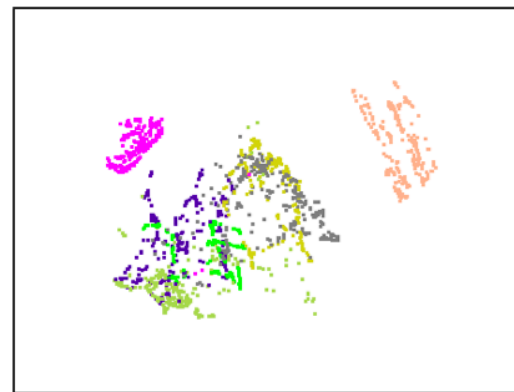$$\|AM - B\|_F, \qquad \text{subject to } M^\top M = I$$

$$A = \begin{bmatrix} \sqrt{w_1}\hat{y}_{p_1} \\ \sqrt{w_2}\hat{y}_{p_2} \\ \vdots \\ \sqrt{w_s}\hat{y}_{p_s} \end{bmatrix} \qquad B = \begin{bmatrix} \sqrt{w_1}\hat{x}_{p_1} \\ \sqrt{w_2}\hat{x}_{p_2} \\ \vdots \\ \sqrt{w_s}\hat{x}_{p_s} \end{bmatrix}$$
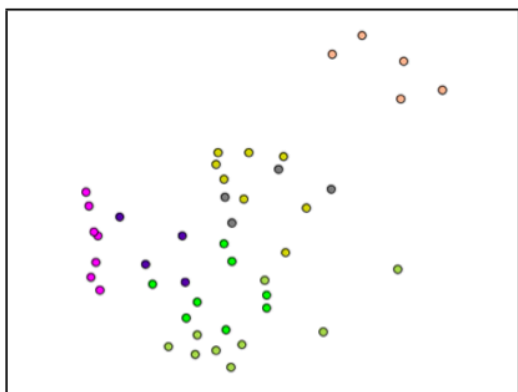
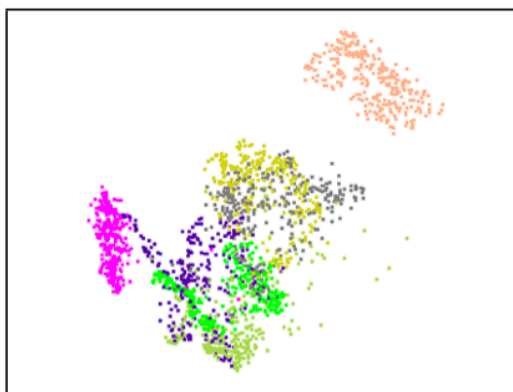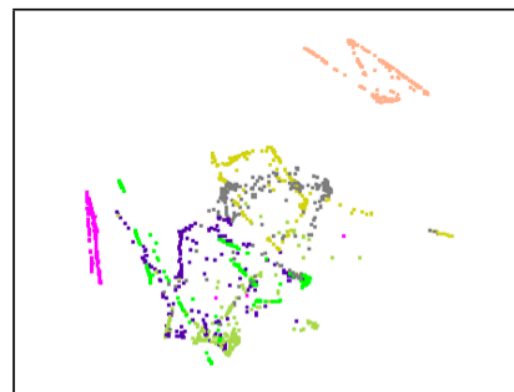(a) 10%.   (b) LAMP.   (c) LSP.

(e) $\sqrt{n}$.   (f) LAMP.   (g) LSP.
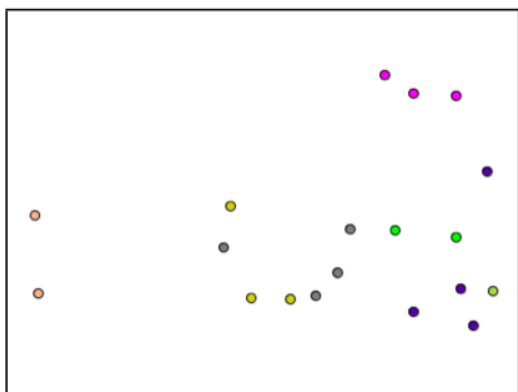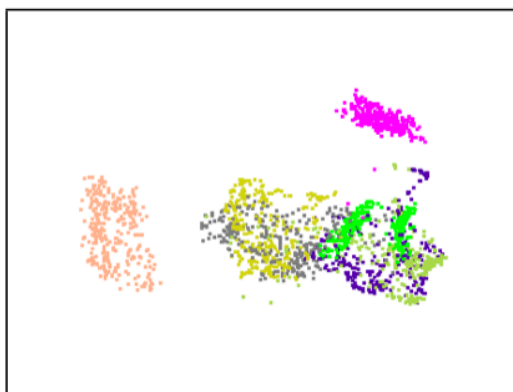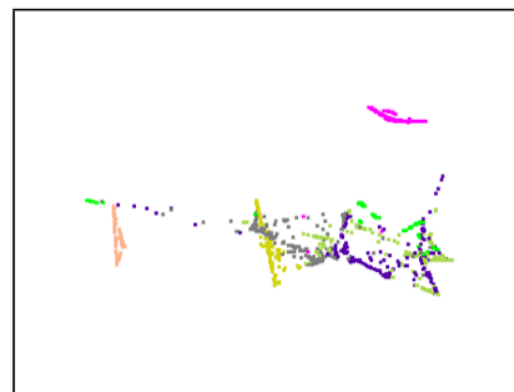
(i) 19.   (j) LAMP.   (k) LSP.

Point-based layouts allow to visualize neighborhood relation and well defined clusters.

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However, information such as:

- which are the content of the data in each region?
- which are the most relevant attributes in each region?

can not directly be obtained from the layout.

Layout Enrichment

Layout Enrichment: Semantic Wordification

Layout Enrichment: Web Search Visualization

Jaguars, Jaguar Pictures, Jaguar Facts - National Geographic
animals.nationalgeographic.com/animals/mammals/jaguar/
Learn all you wanted to know about **jaguars** with pictures, videos, photos, facts, and **...**
Photo: A young female **jaguar** stopped in its tracks **...** Big Cats **Features ...**

Jaguar International - XF Models and Features
www.jaguar.com › Home › XF
Jaguar XF: A sporting saloon with a choice of four trim levels and six engines including
3.0 Litre V6 Diesel S. Find out more about the XF, XF Portfolio and XFR.

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www.**jaguar**.com/us/en/**features**_disclaimer
These **features** are not a substitute for driving safely with due care and attention and will
not function under all circumstances, speeds, weather and road **...**

Jaguar USA - EXTERNAL FEATURES
www.jaguar.com › ... › XJ › MODELS & PRICING › FEATURES
Elegant design **features** enhance the bold, sporting profile of the XJ. **...** All XJ models
feature a dramatic full-width glass roof, sweeping back from the top of the **...**

Jaguar International - XK Models and Features
www.jaguar.com › Home › XK
Available in coupe or convertible bodystyles, the XK is available with a choice of two
performance engines. Find out more about XK, XK Portfolio and XKR.

Jaguar Specifications | Engine Performance & **Jaguar Features ...**
www.motortrend.com/used_cars/01/**jaguar**/specifications/
The Motor Trend used car buyer's guide has detailed used **Jaguar** specifications,
performance, standard equipment and comprehensive **Jaguar** data.

Atari **Jaguar** - Wikipedia, the free encyclopedia
en.wikipedia.org/wiki/Atari_**Jaguar**
Jump to Other **Jaguar features**: RAM: 2 MB on a 64-bit bus using 4 16-bit fast page mode
DRAMs; Storage: Cartridge – up to 6 MB; DSP-port (JagLink) **...**

Used Jaguar Specifications, Options, & **Jaguar Features** at **...**
www.automobilemag.com/used_car.../01/**jaguar**/index.html
View comprehensive used **Jaguar** specifications and car data at Automobile Magazine.

Pear-Shaped Tripod Vessel with Modeled **Jaguar Features** | Michael **...**
carlos.emory.edu/pataky_**jaguar** - United States
Pear-Shaped Tripod Vessel with Modeled **Jaguar Features**. Central America, Costa
Rica/Nicaragua, Greater Nicoya, Pataky Polychrome, Pataky Variety. Period **...**

Xclusively **Jaguar** - **Features** - For all your Jaguar needs.... Jaguar **...**
www.xclusively-**jaguar**.co.uk/xj06_**features**.php
Esta-jane Mace was nominated by her employer, **Jaguar** Land Rover, as a potential
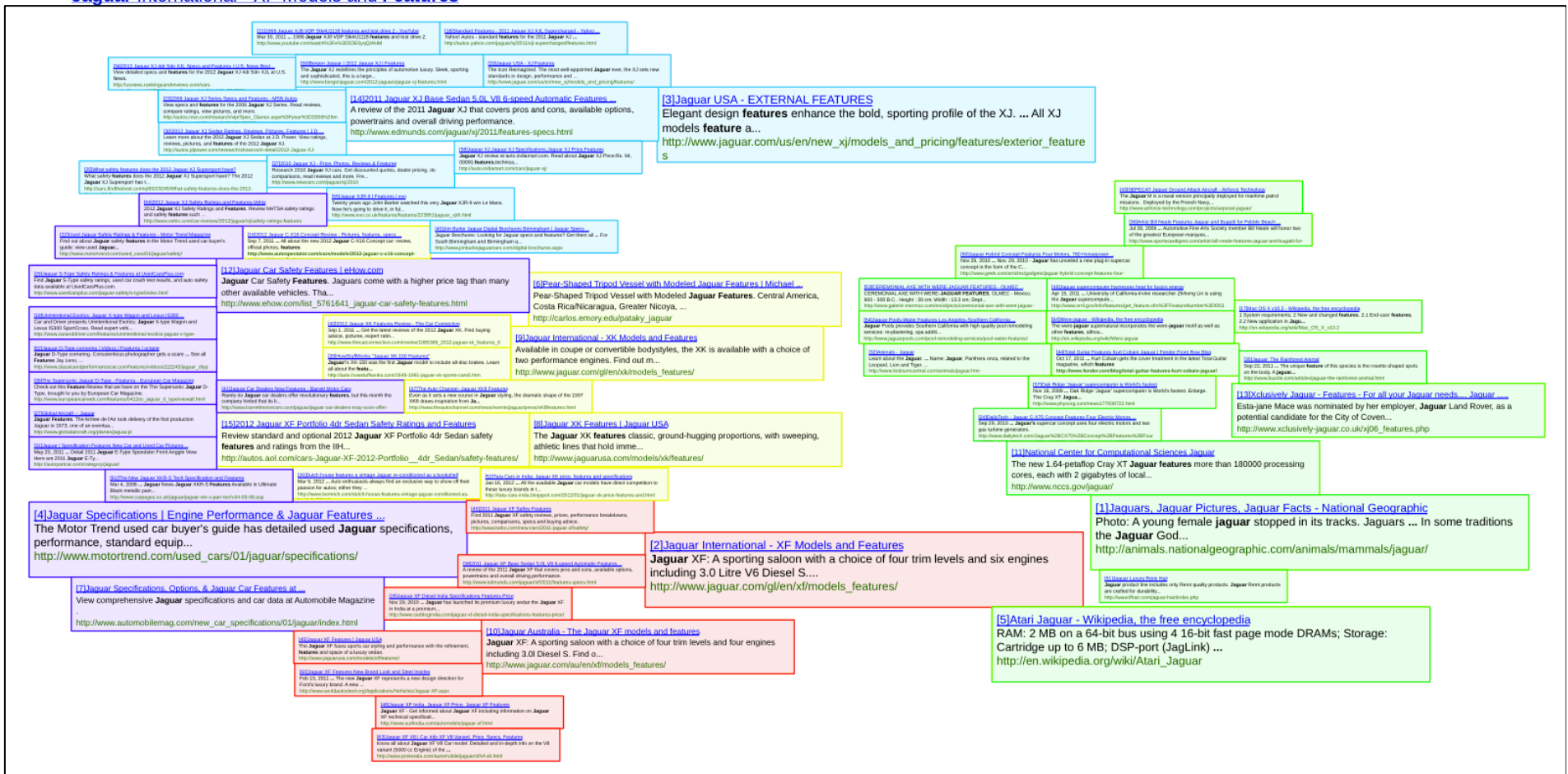candidate for the City of Coventry Freemen's Guild Apprentice of the Year **...**

Layout Enrichment: Web Search Visualization

Jaguars, Jaguar Pictures, Jaguar Facts - National Geographic
animals.nationalgeographic.com/animals/mammals/**jaguar**/
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Photo: A young female **jaguar** stopped in its tracks **...** Big Cats **Features ...**

Jaguar International - XF Models and **Features**

Xclusively Jaguar - Features - For all your Jaguar needs.... Jaguar ...
www.xclusively-**jaguar**.co.uk/xj06_**features**.php
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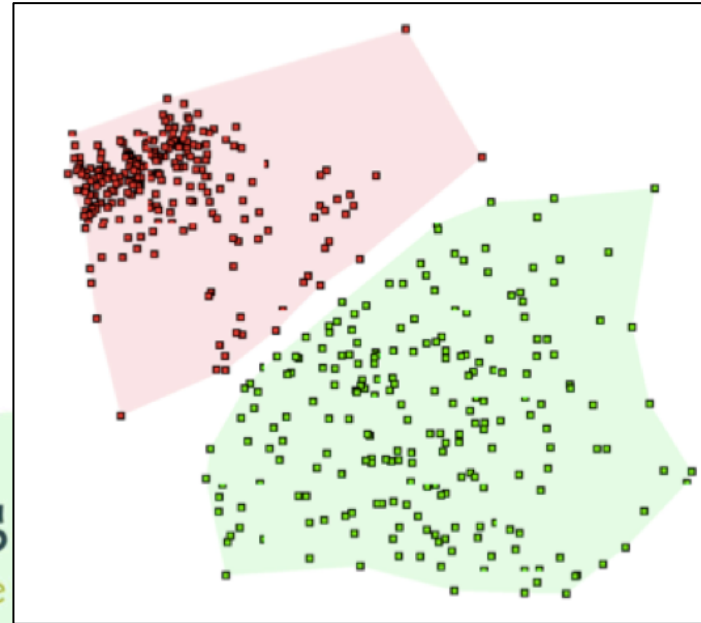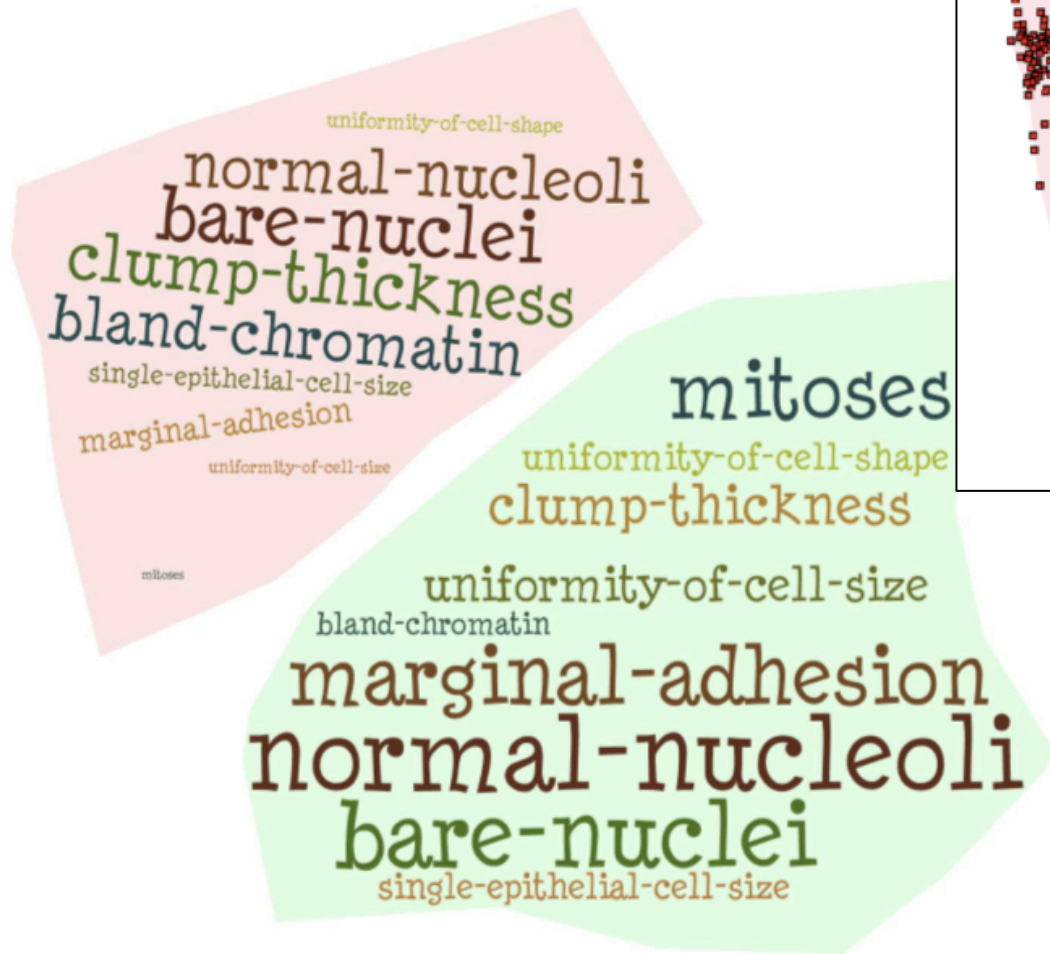# Layout Enrichment: Attribute Relevance

(a) Representative instances
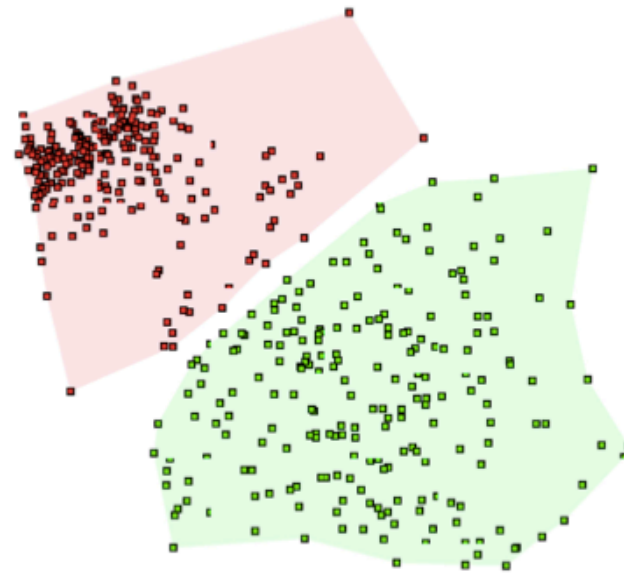
(b) Groups

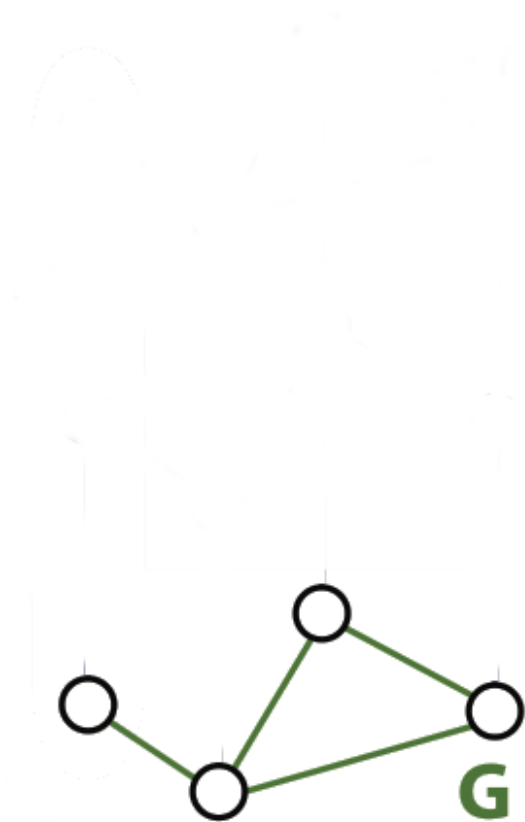# Layout Enrichment: Attribute Relevance

Graph based Time Varying Data:

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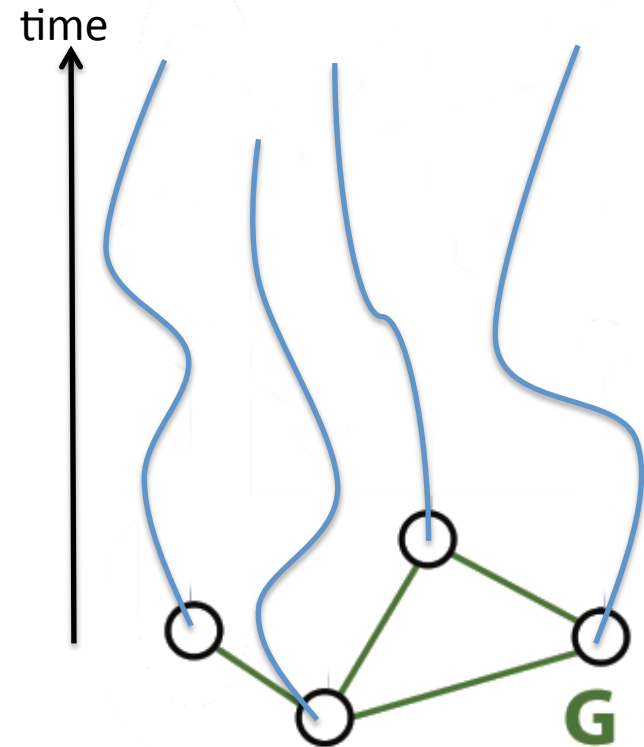
Graph Signal Processing

Graph based Time Varying Data: Graph-Wavelets

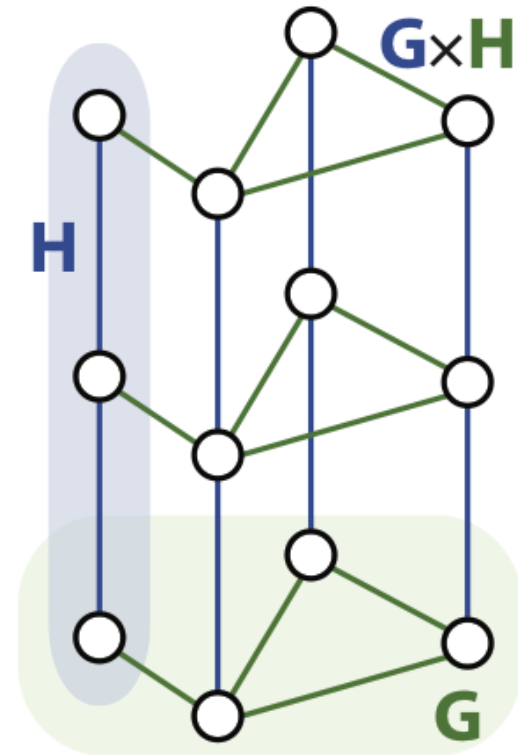$$G = (V, E)$$

Graph based Time Varying Data: Graph-Wavelets

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Graph based Time Varying Data: Graph-Wavelets
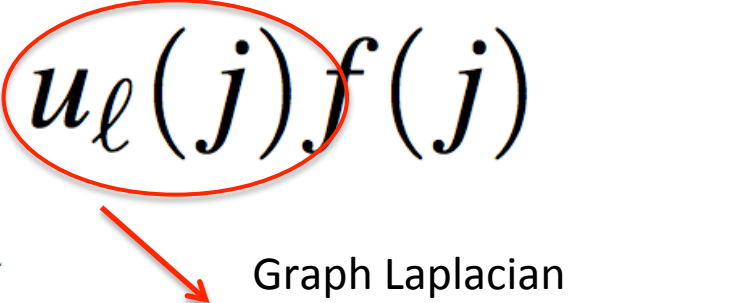
$$G = (V, E)$$

$$f : G \times H \to \mathbb{R}$$

Graph based Time Varying Data: Graph-Wavelets

$$\widehat{f}(\ell) = u_\ell^\top \cdot f = \sum_{j=1}^{n} u_\ell(j) f(j)$$

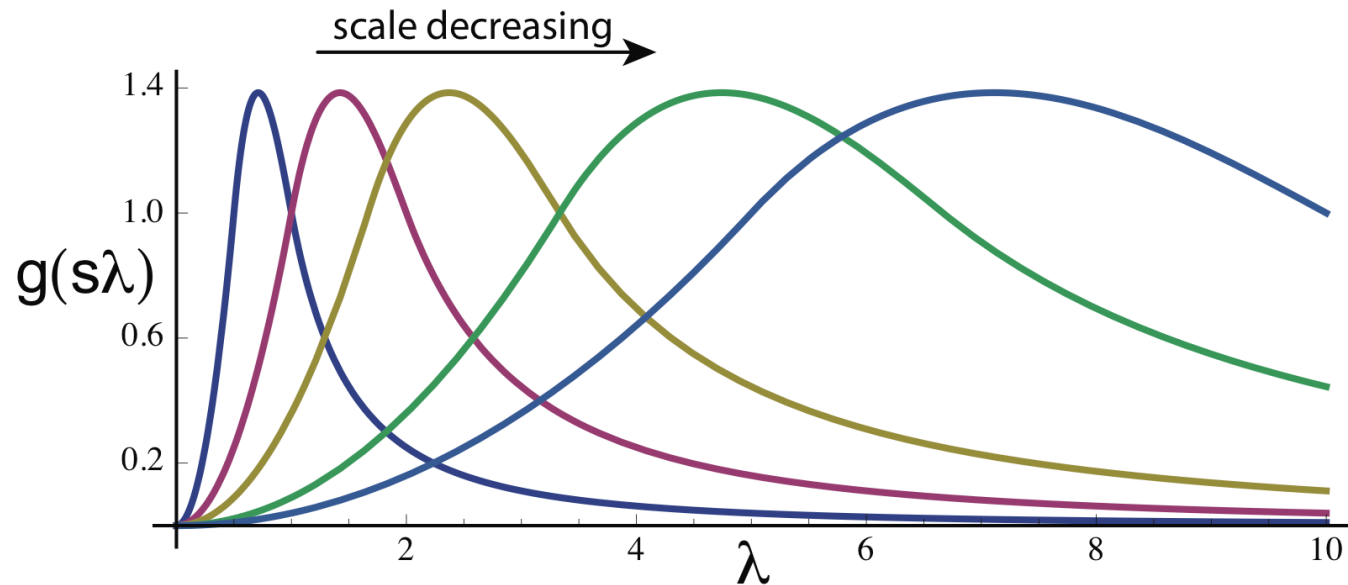$$\omega(s, j) = \sum_{\ell=1}^{n} g(s\lambda_\ell) \widehat{f}(\ell) u_\ell(j)$$

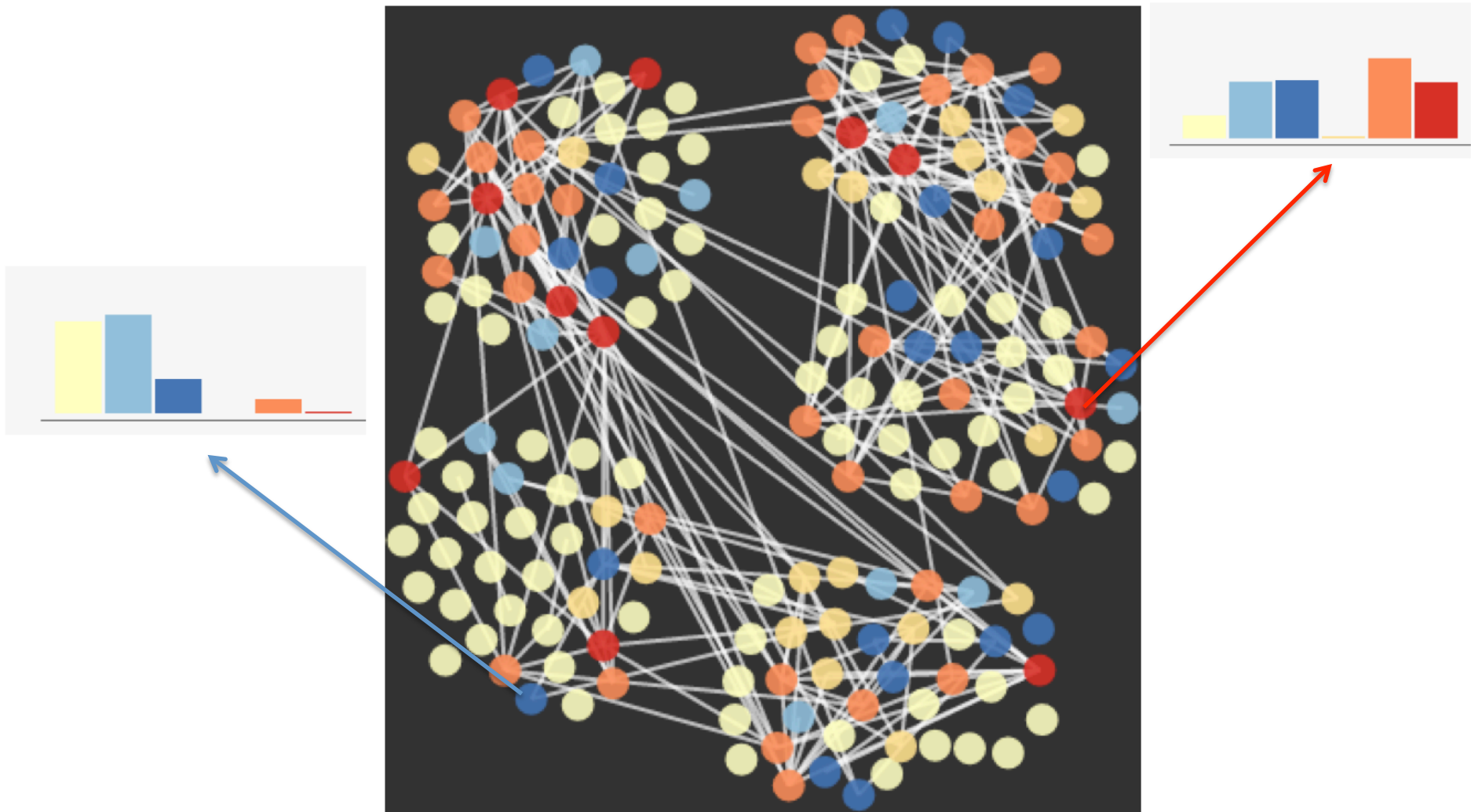# Graph based Time Varying Data: Graph-Wavelets

$$\widehat{f}(\ell) = u_\ell^\top \cdot f = \sum_{j=1}^{n} u_\ell(j) f(j)$$

Graph Laplacian

eigenvectors and eigenvalues

$$\omega(s,j) = \sum_{\ell=1}^{n} g(s\lambda_\ell) \widehat{f}(\ell) u_\ell(j)$$

Graph based Time Varying Data: Graph-Wavelets

scale decreasing →

$g(s\lambda)$

$$\omega(s,j) = \sum_{\ell=1}^{n} g(s\lambda_{\ell})\widehat{f}(\ell)u_{\ell}(j)$$

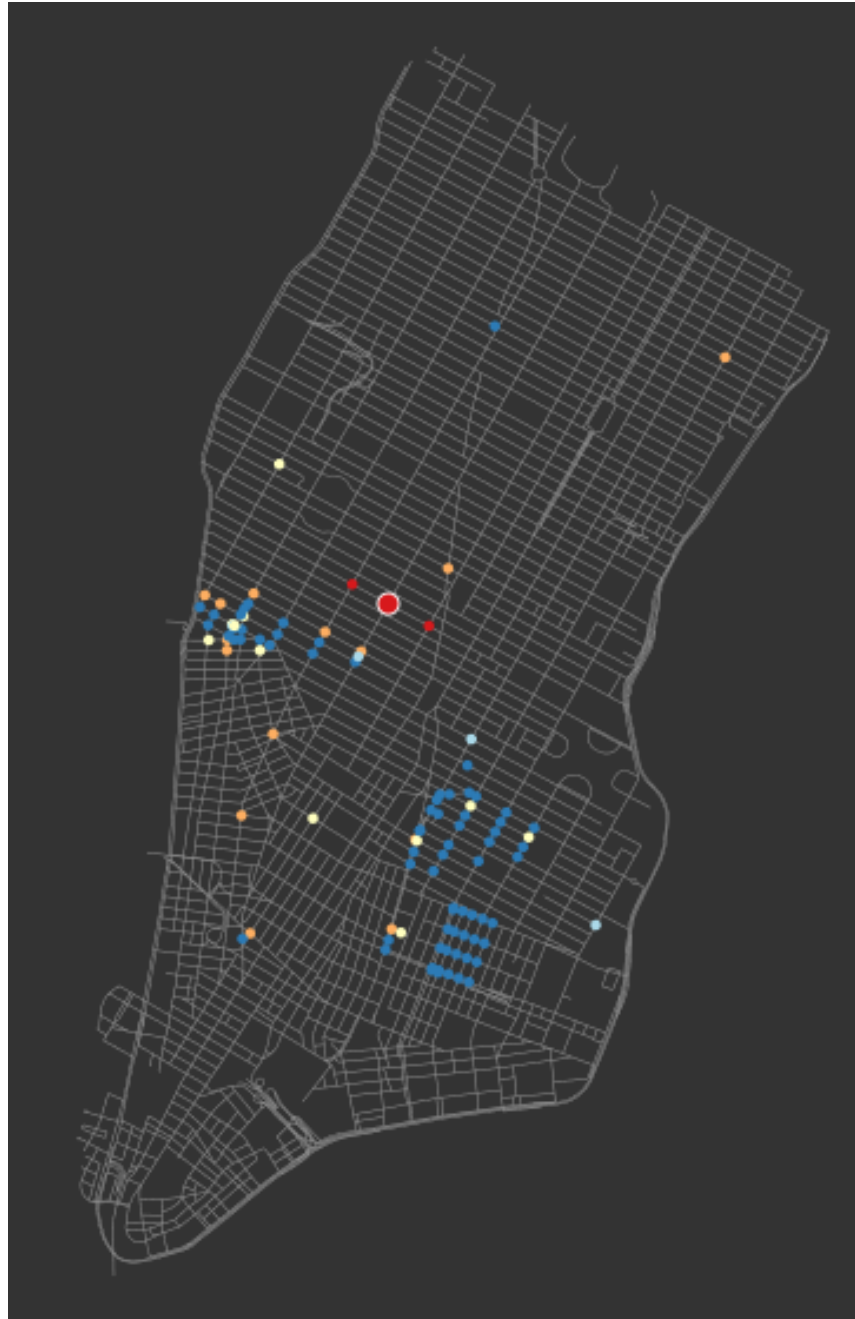# Graph based Time Varying Data: Graph-Wavelets

Graph based Time Varying Data:
Graph-Wavelets

Taxi Data

Taxi Data

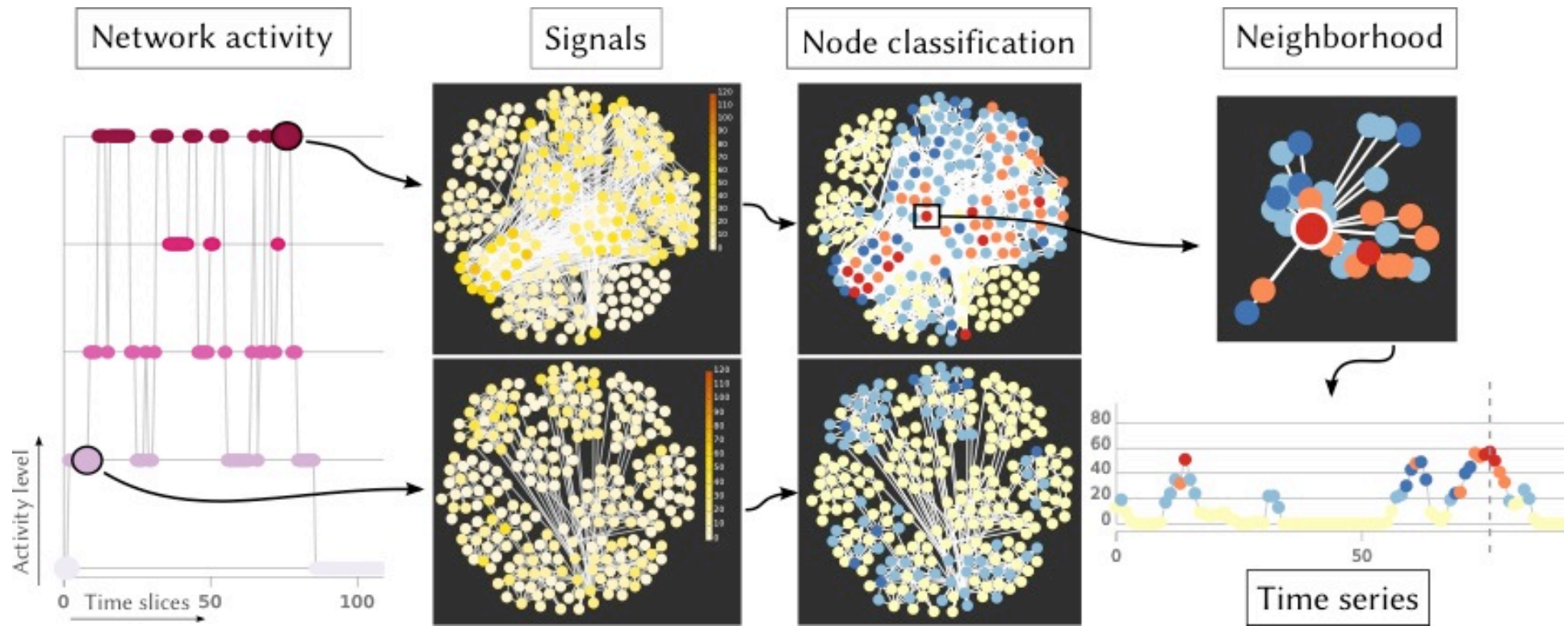# Graph based Time Varying Data:
Graph-Wavelets

Dynamic Networks

Thanks for your attention !!