An Unsupervised Material Learning Method for Imaging Spectroscopy

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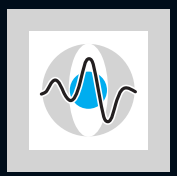
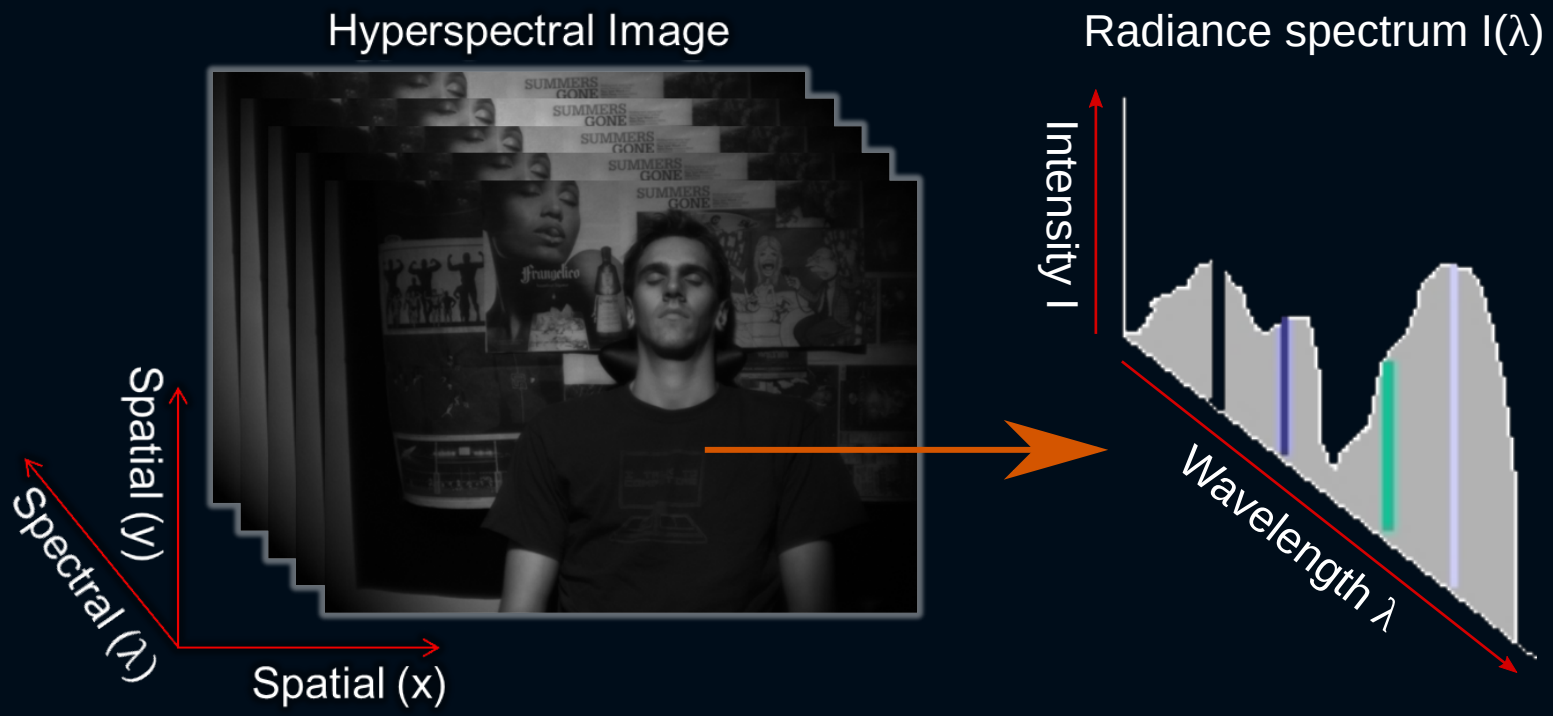


Multispectral Imaging / Imaging Spectroscopy



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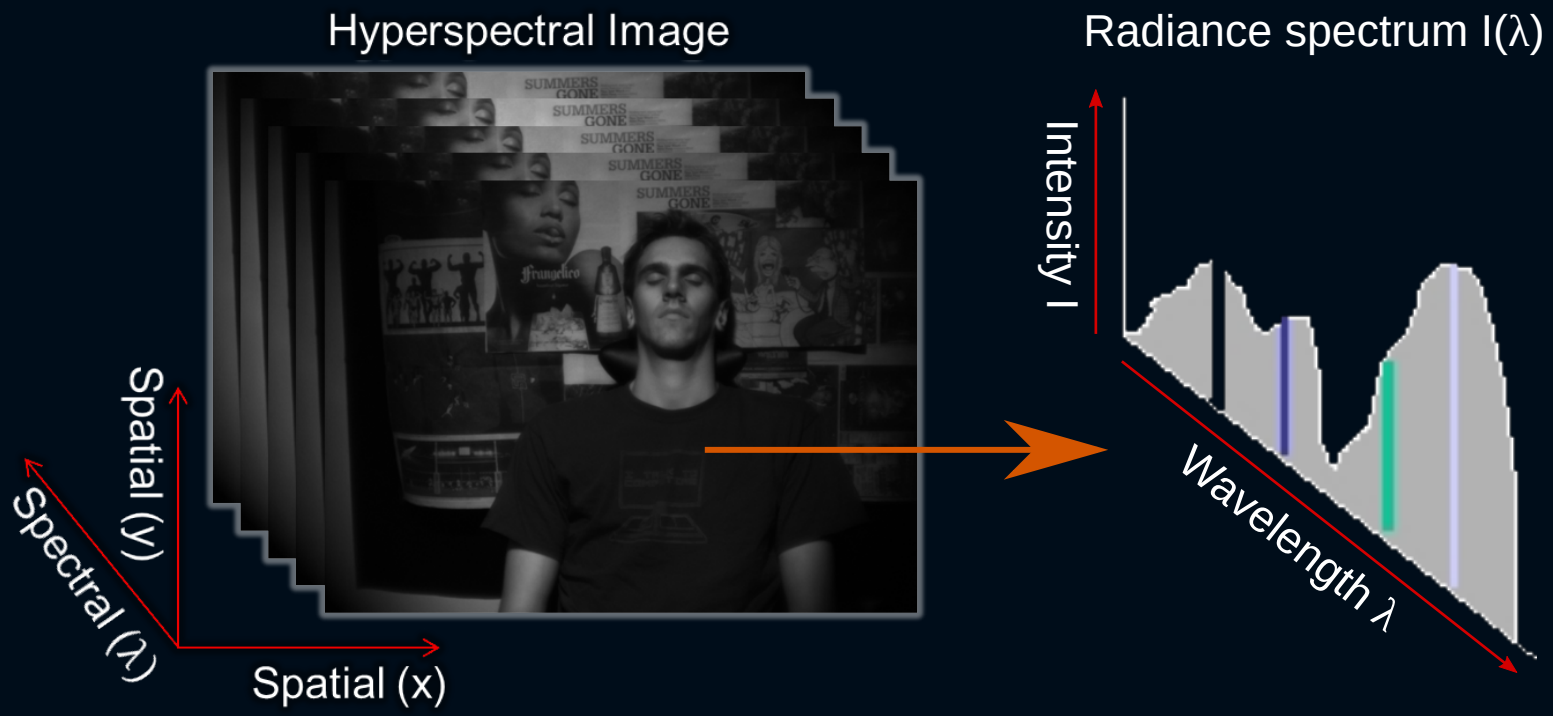

Benefits:

- feature-rich
- high accuracy possible

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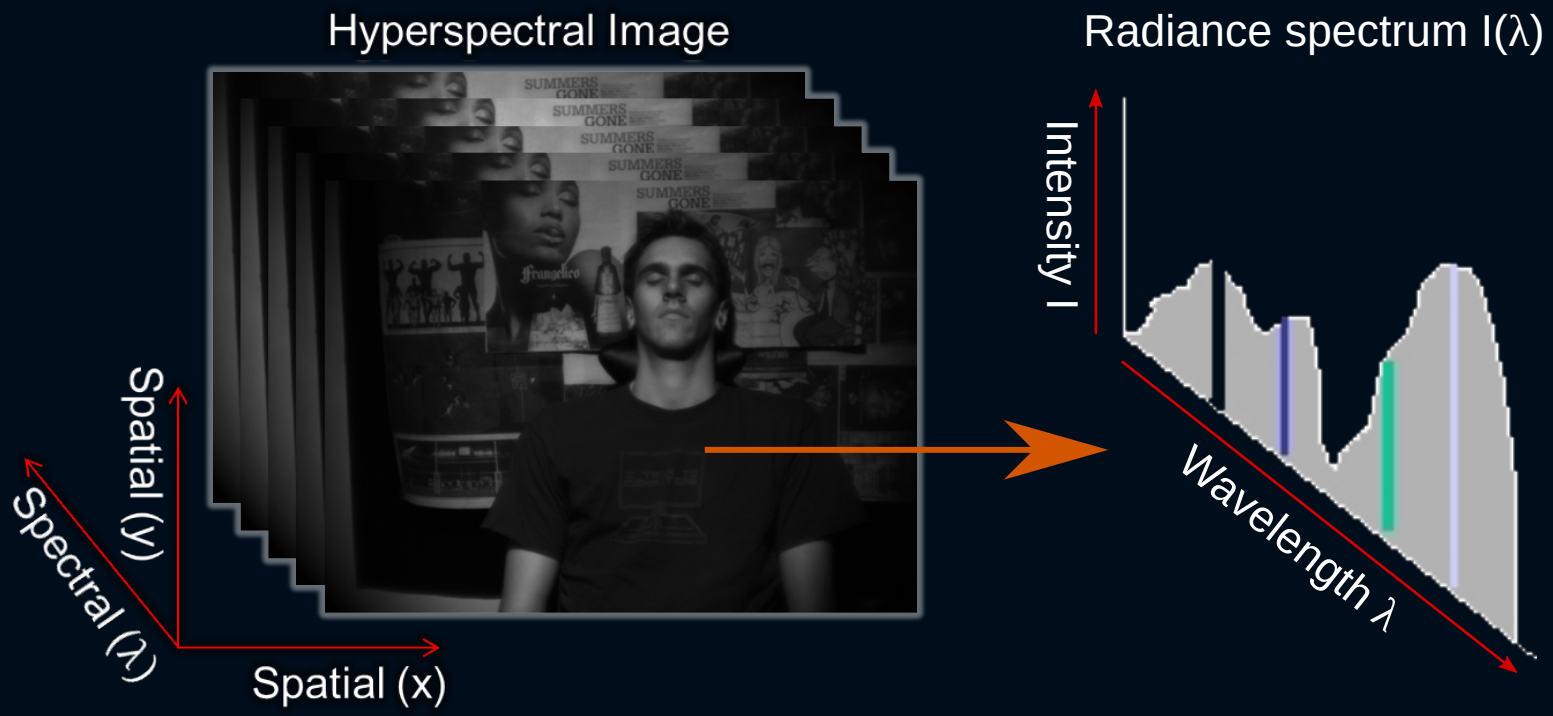

Benefits:

- feature-rich
- high accuracy possible

Challenges:

- high-dimensional
- highly correlated, but noisy

Contribution

Application: Material Learning

- False-colour visualisation of scene materials
- Extraction of material prototypes
    - Common application in remote sensing: Spectral unmixing

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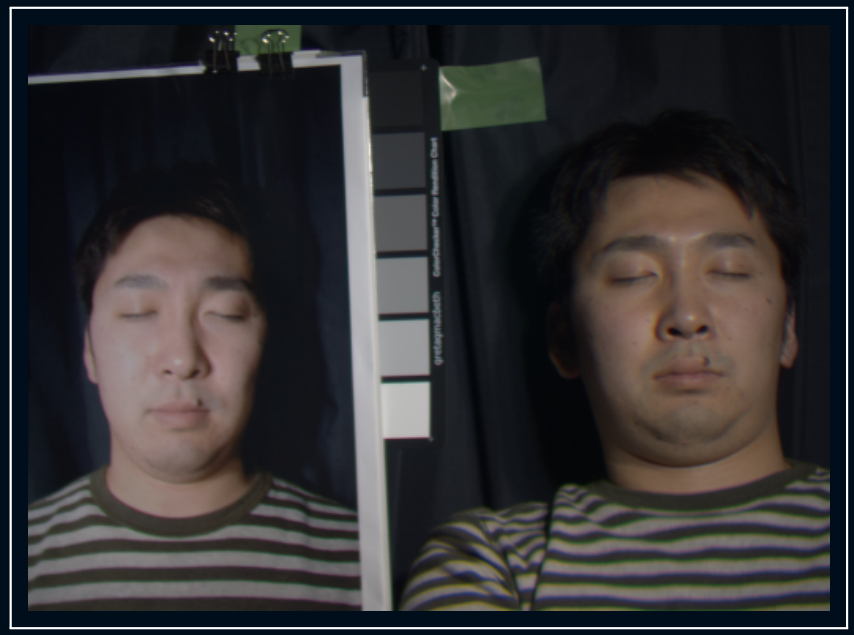
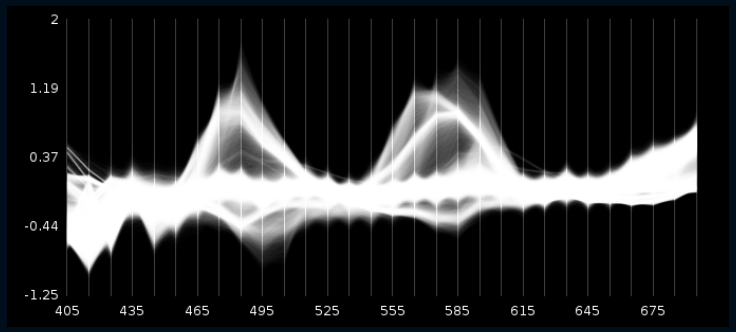
Methodology:

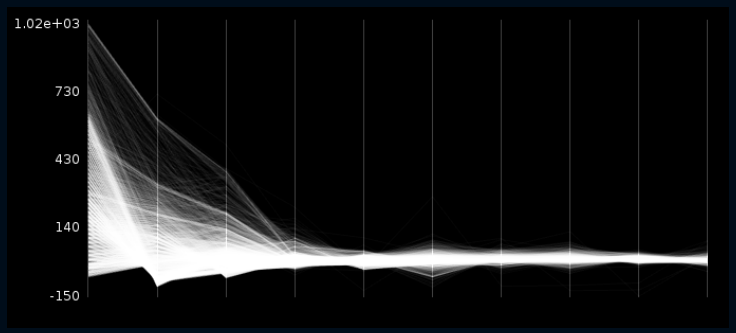
- Unsupervised manifold learning
- Fast clustering using established methods



Manifold Learning vs Dimensionality Reduction

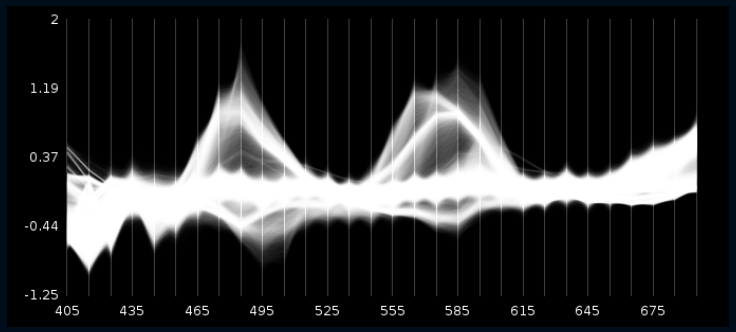


Original data (image spectral gradient)



Principal Component Analysis

Manifold Learning vs Dimensionality Reduction



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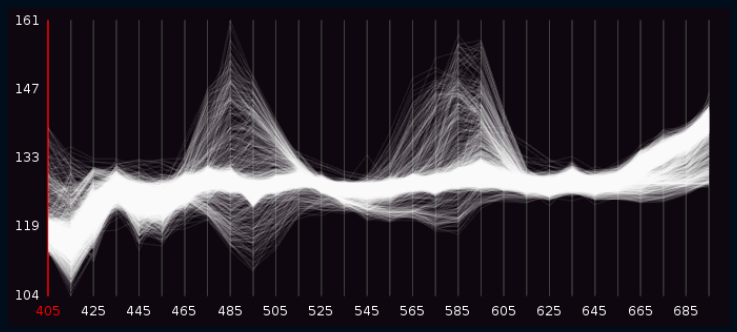
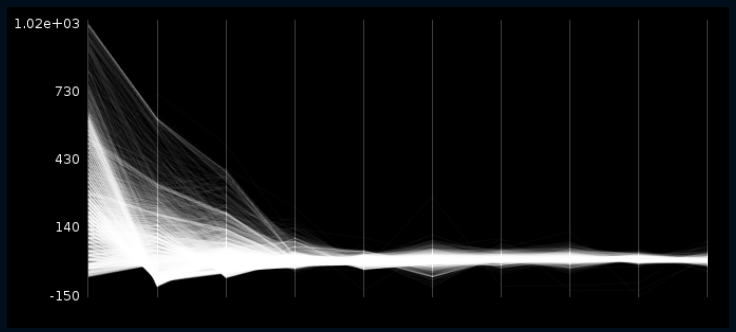


Sparse representation



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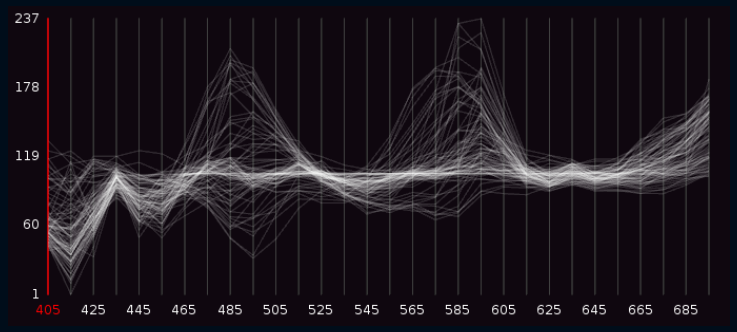
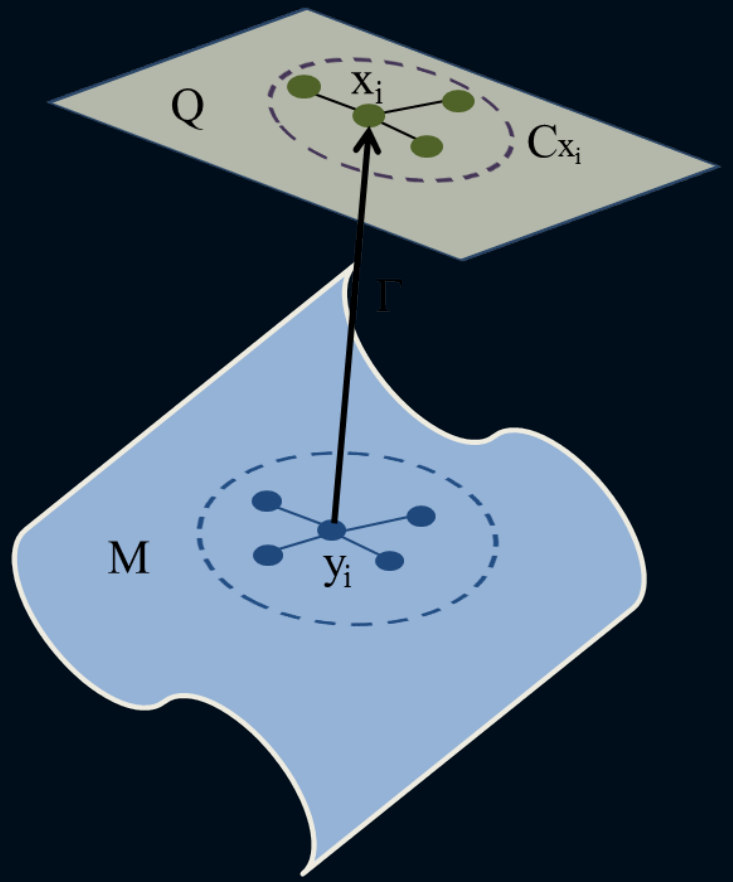


Material prototypes

Concept

- graph $G_M = (Y, E_M)$,
  node set Y comprises of $y_i \in \mathbb{R}^m$
- determining E_M is a hard problem
- graph $G_Q = (X, E_Q)$,
  constructed to help derive the manifold topology



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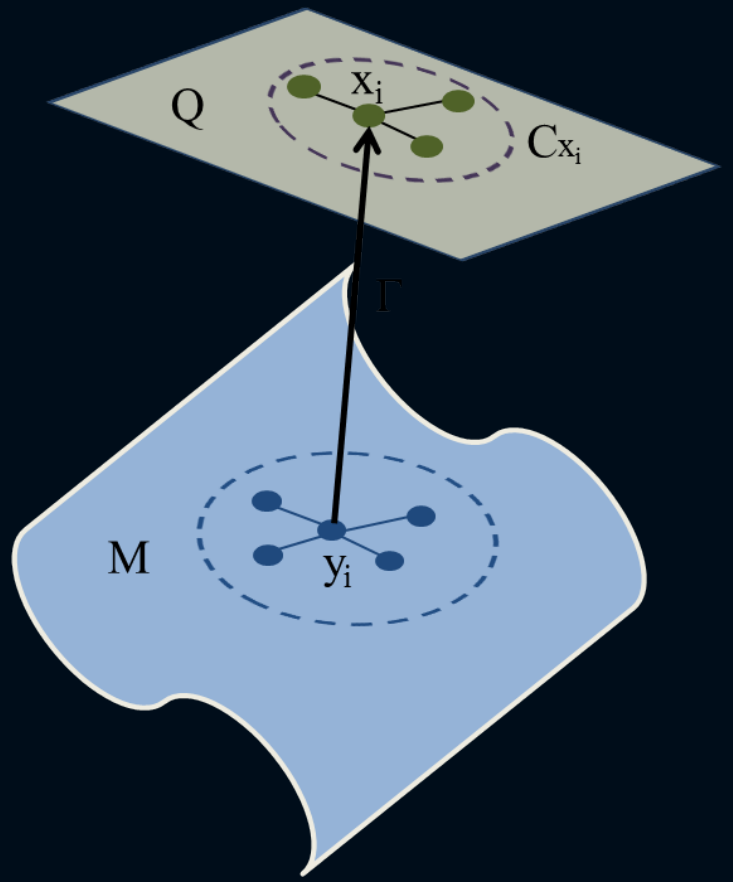
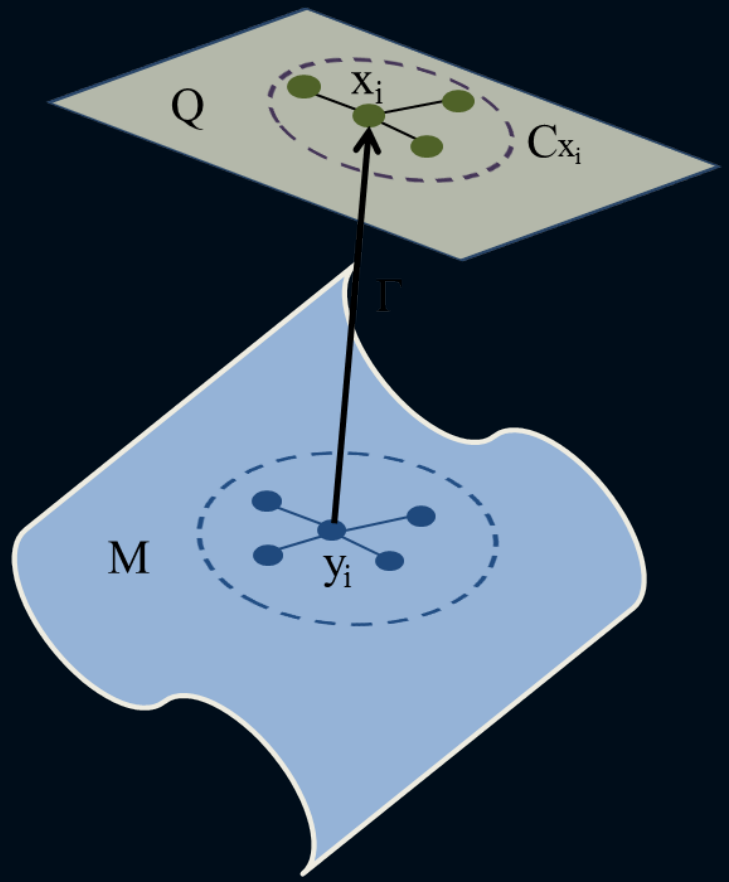
- determining E_M is a hard problem
- graph $G_Q = (X, E_Q)$,
  constructed to help derive the manifold topology
- X, Y are linked via
  $x_j = \sum_{y_k \in Y} \mathbb{I}(x_j \sim y_k)\Gamma(y_k)$
- $\Gamma : \mathbb{R}^m \mapsto \mathbb{R}^q$,
  $\mathbb{I}(x_j \sim y_k)$ indicator function for adjacency



Concept (1)

- G_Q is a **Gibbs Field**
- conditional probability of vertex x_i:
  $P(x_i \mid \mathcal{C}_{x_i}) = \frac{1}{Z_Q} \prod_{x_j \in \mathcal{C}_{x_i}} f_Q(x_j, x_i)$
- $\mathcal{C}_{x_i}$ clique centered at x_i
- Z_Q partition function,
  $f_Q(x_j, x_i)$ potential function, also
  edge weight between x_j and x_i



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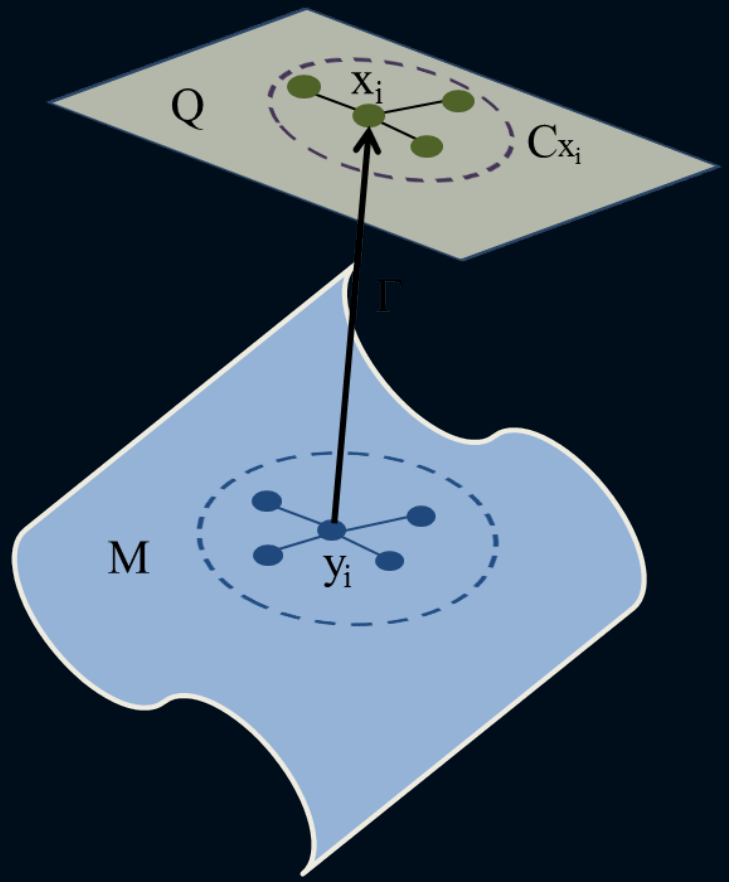
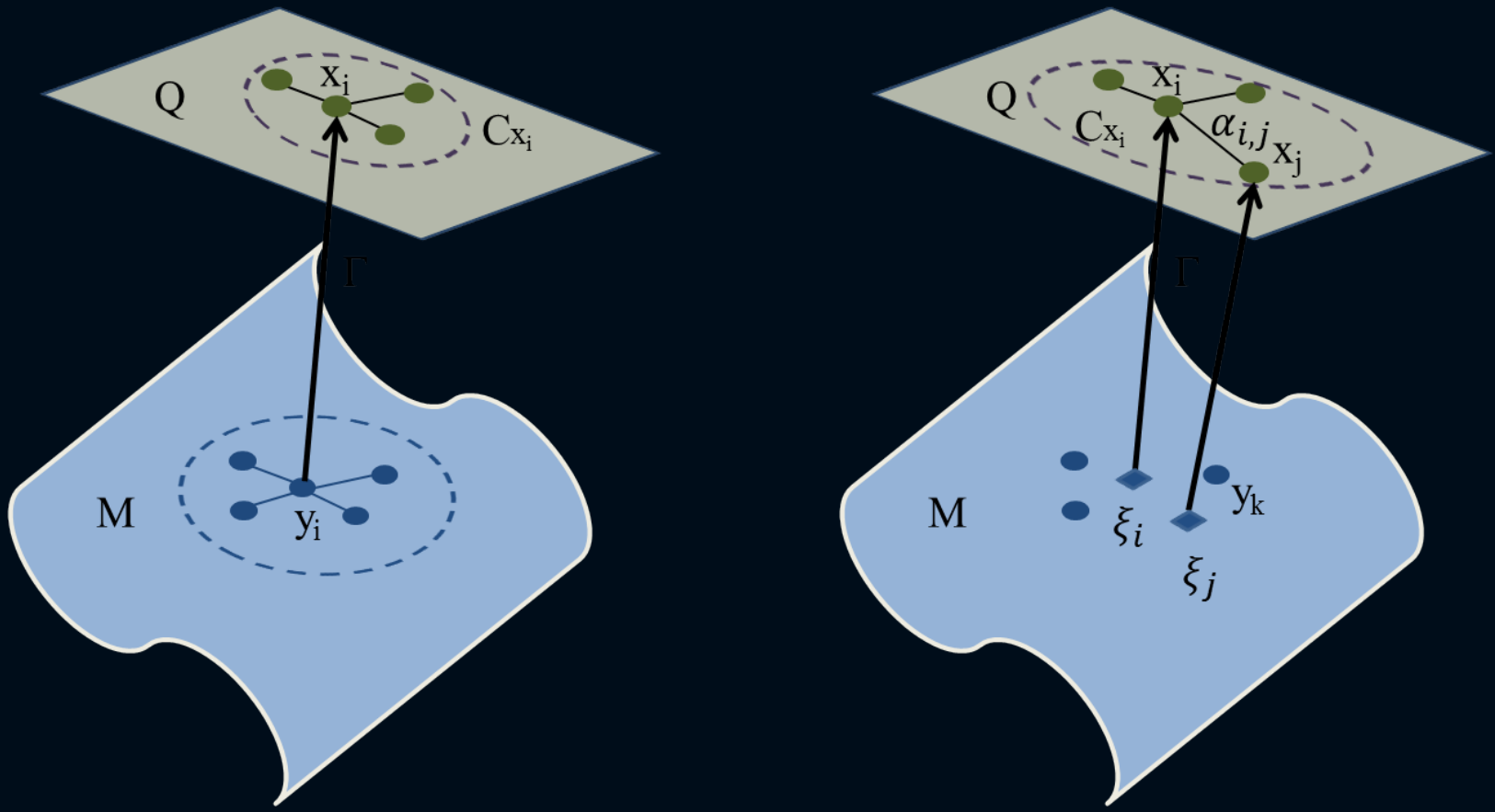
  edge weight between x_j and x_i
- maximum-likelihood estimation
  (MLE) on the vertex-set $Y \in G_M$
  based upon the vertices $X \in G_Q$



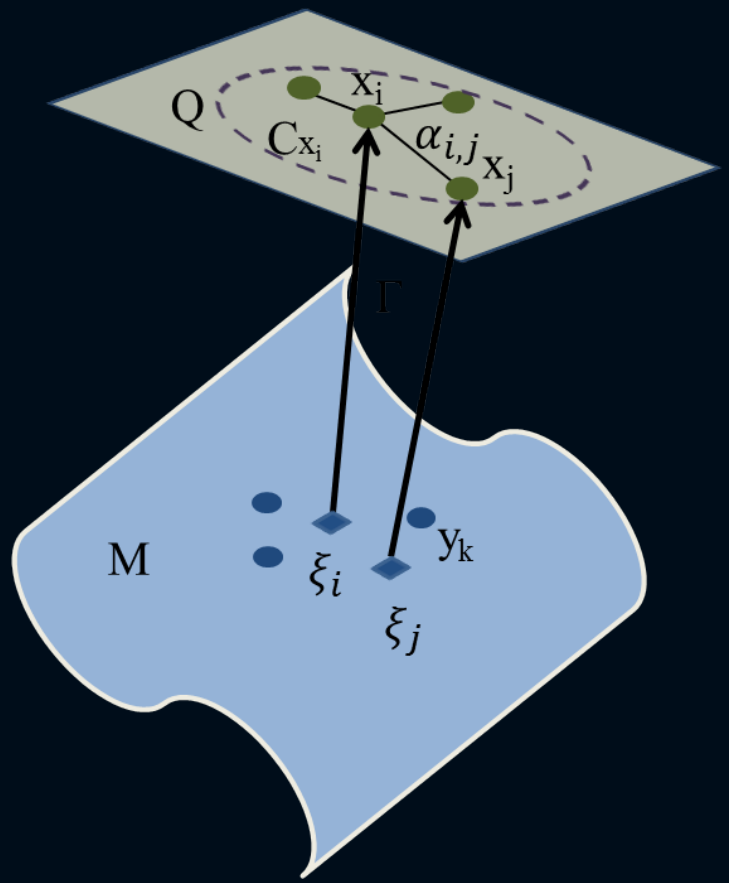
Concept (2)



We introduce the parameter set ξ_j with correspondence to x_j.

Concept (3)

- $x_j = \sum_{y_k \in Y} \eta_j \mathcal{K}(y_k, \xi_j)$
- prior η_j, kernel function $\mathcal{K}(\cdot)$
- vertex x_j in G_Q corresponds to parameter vector ξ_j



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- conditional probability of vertex x_i:
  $P(x_i \mid \mathcal{C}_{x_i}, Y) =$
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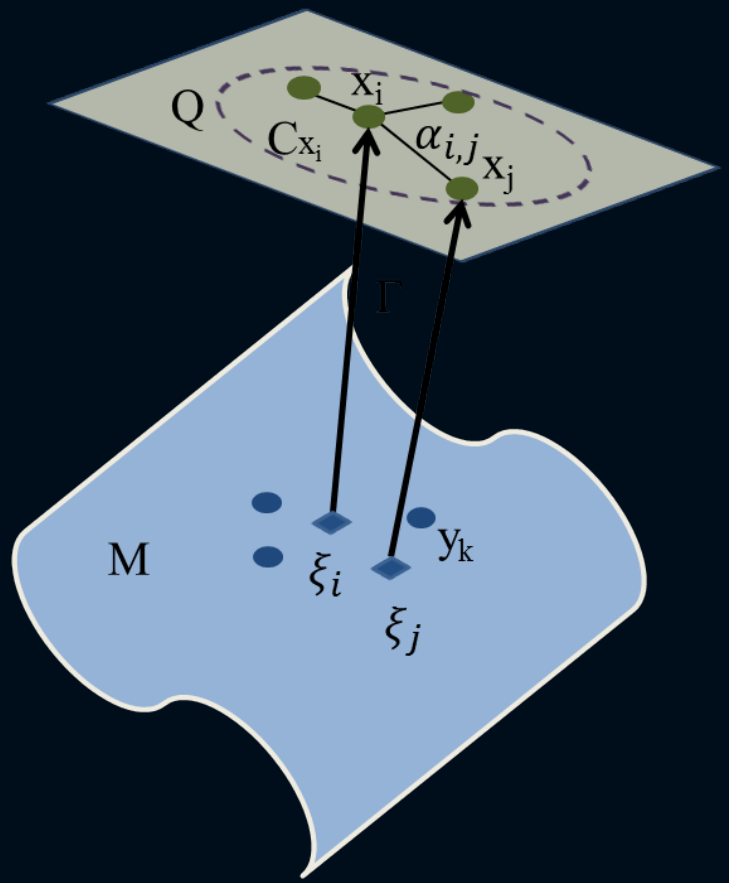

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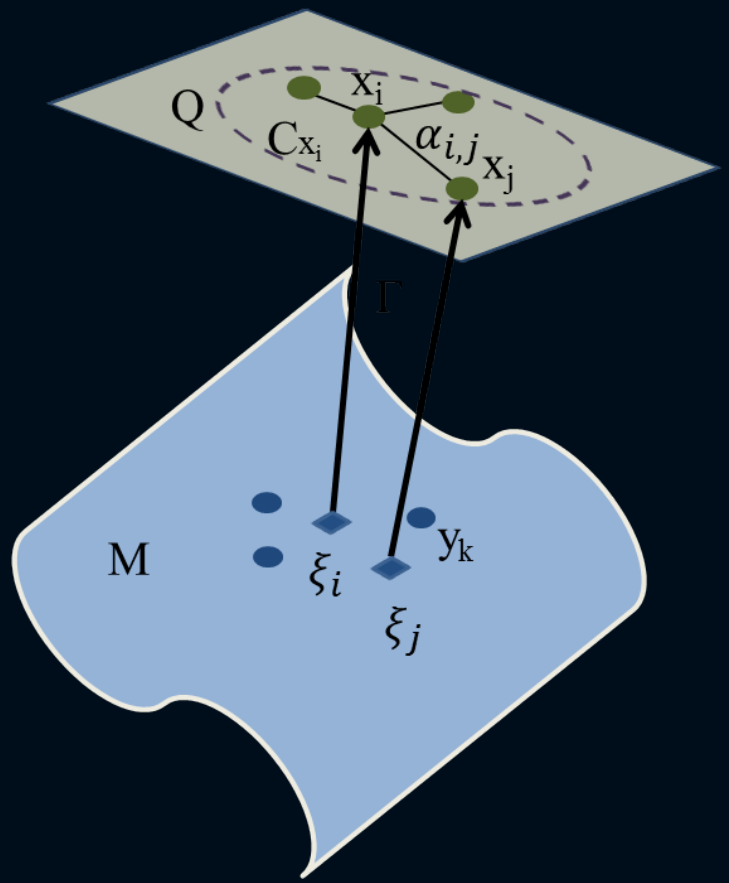
- **Choose $f_Q(\cdot)$, $\mathcal{K}(\cdot)$, obtain MLE estimate of parameter ξ_j.**



Parameter Learning

Potential function:

- Gibbs distribution:

$$f_Q(x_j, x_i) = \sum_{y_k \in Y} \alpha_{i,j} \exp\left\{ -\frac{1}{T} d_M(y_k, \xi_j)^2 \right\}$$

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- Rewrite using kernel:

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Algorithm: Expectation-Maximization on ξ_j, $\alpha_{i,j}$

Relation to Self-Organizing Maps

Consider a sampling process in M,

- $\alpha_{i,j} = \mathbb{I}(x_j \sim \rho) h\left(\frac{1}{T} d_Q(x_i, x_j)^2\right)$
- ρ resembles the *best-matching unit* in a SOM
- $\mathbb{I}(x_j \sim \rho)$ indicates the vertex x_j connected to ξ_j with minimum distance to the input sample

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Observations:

- Clique size eq. SOM neighborhood size
- Gibbs temperature T eq. SOM learning rate
- More general formulation, but binary neighborhood function

Experiments

Input: publicly available test images

- 1020 x 1340 pixels, 33 bands (400*nm* - 720*nm*)

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Visualization:

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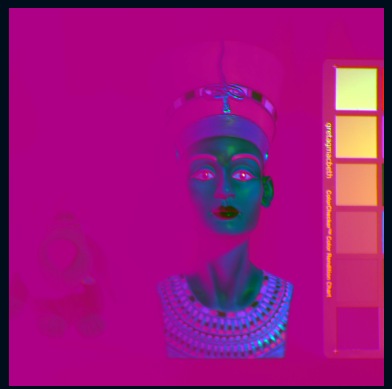
Material clustering:

- cluster on parameters ξ_j
- fast-adaptive mean shift algorithm
- hill-climbing to find material prototypes

Results: Learning process

Input

Pseudocolor



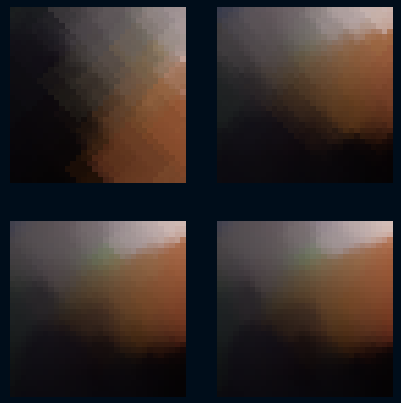
PCA

SOM-Euclidean

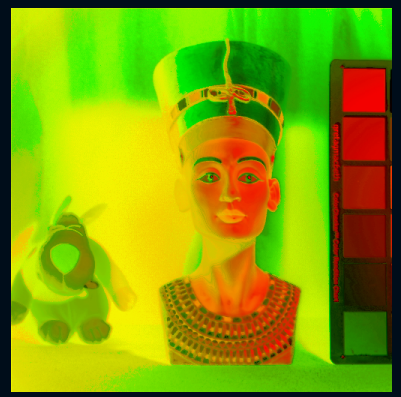
Parameter map

Visualisation

SOM-Constant

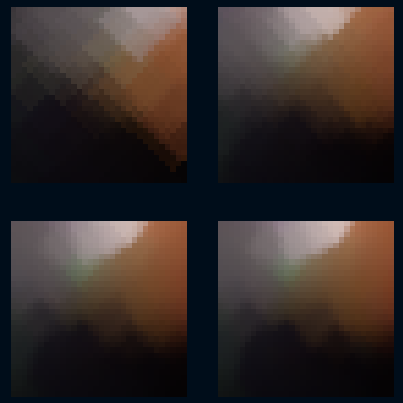


Parameter map



Visualisation

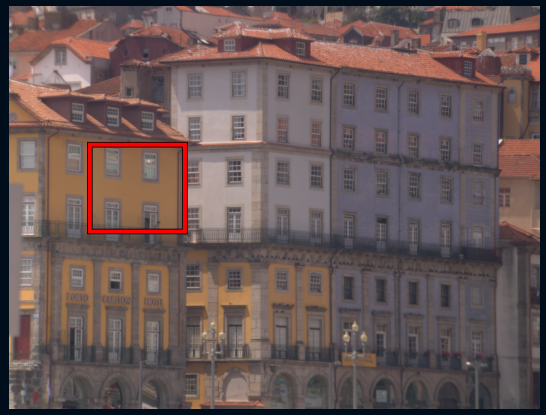
Our method

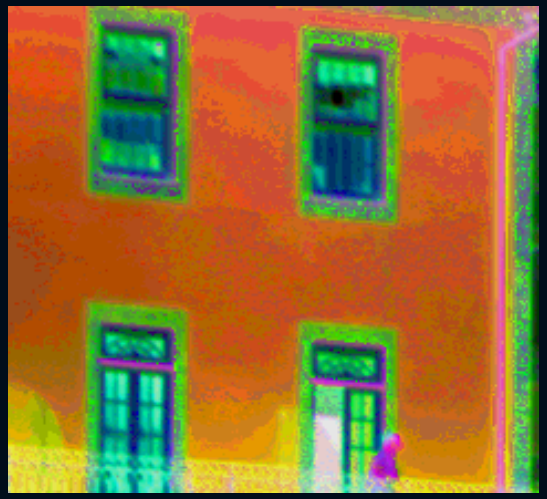


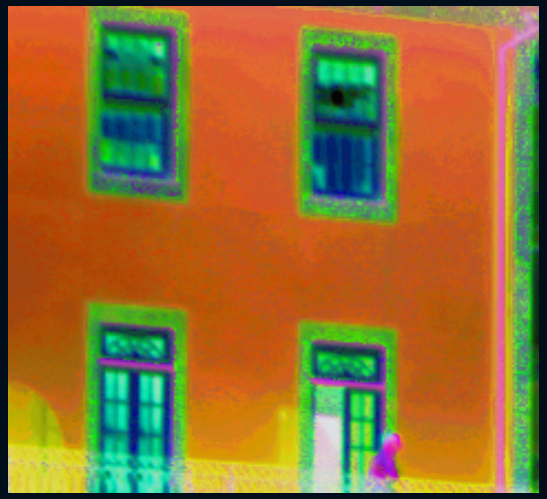
Parameter map

Visualisation

Results: Visualisation





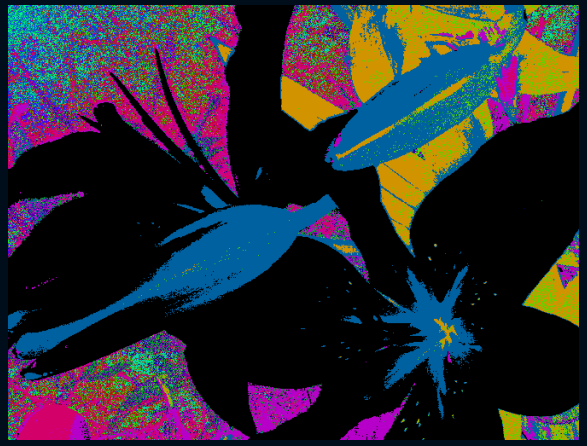


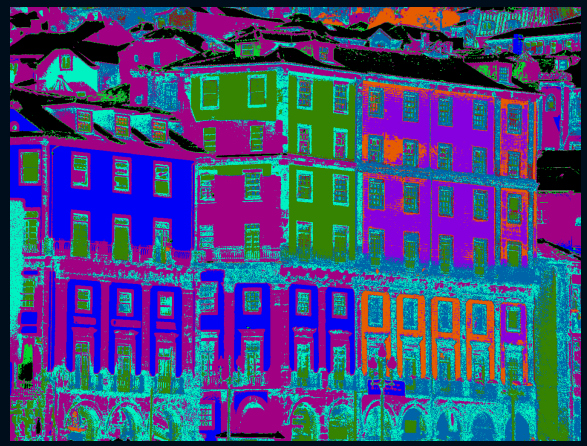
Input in pseudocolour

Visualisation using only the best matching unit

Visualisation recovered using clique information

Results: Material clustering



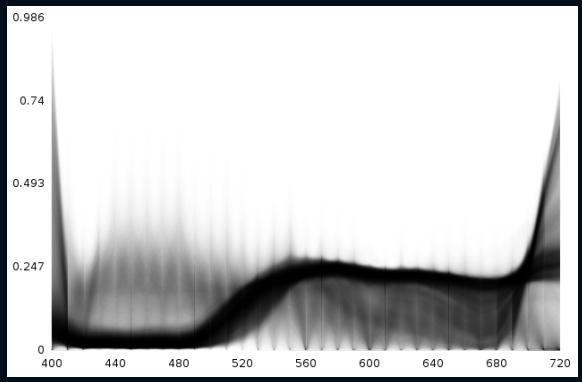


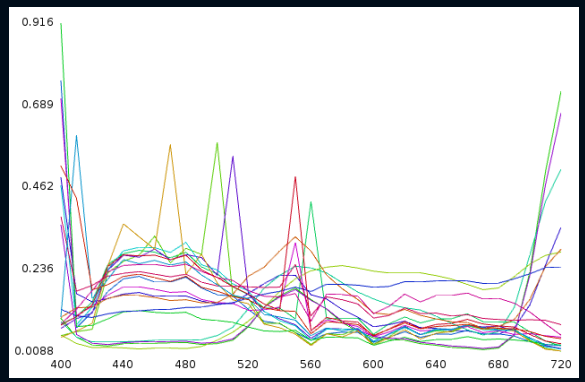
Input in pseudocolour

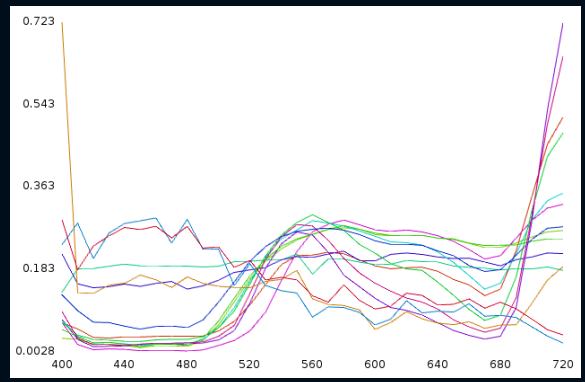
Huynh and Robles-Kelly

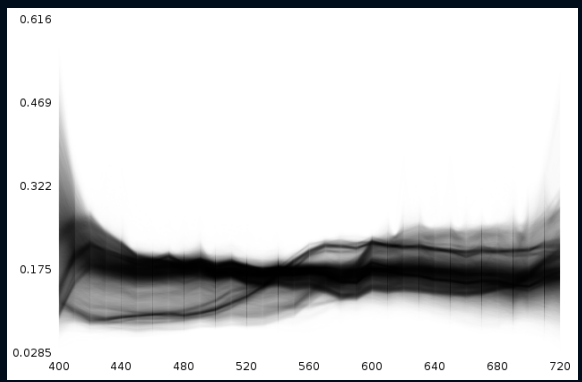
Our method

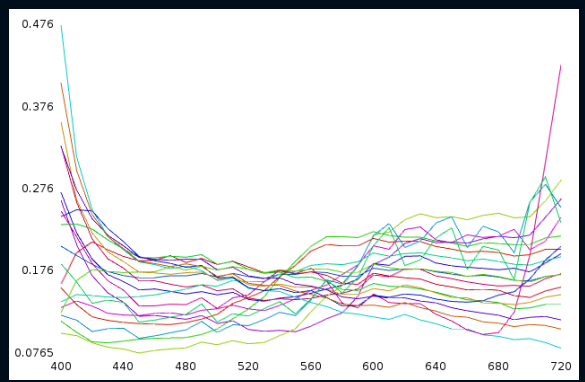
Results: Material clustering (2)











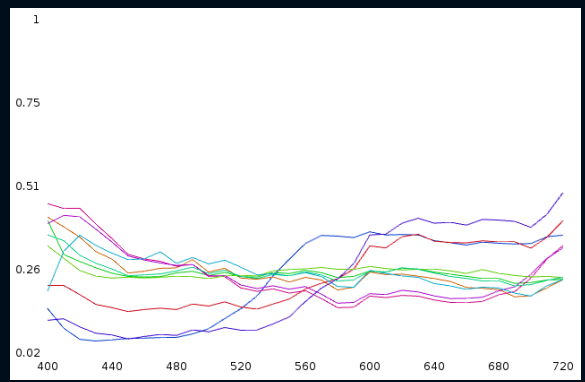
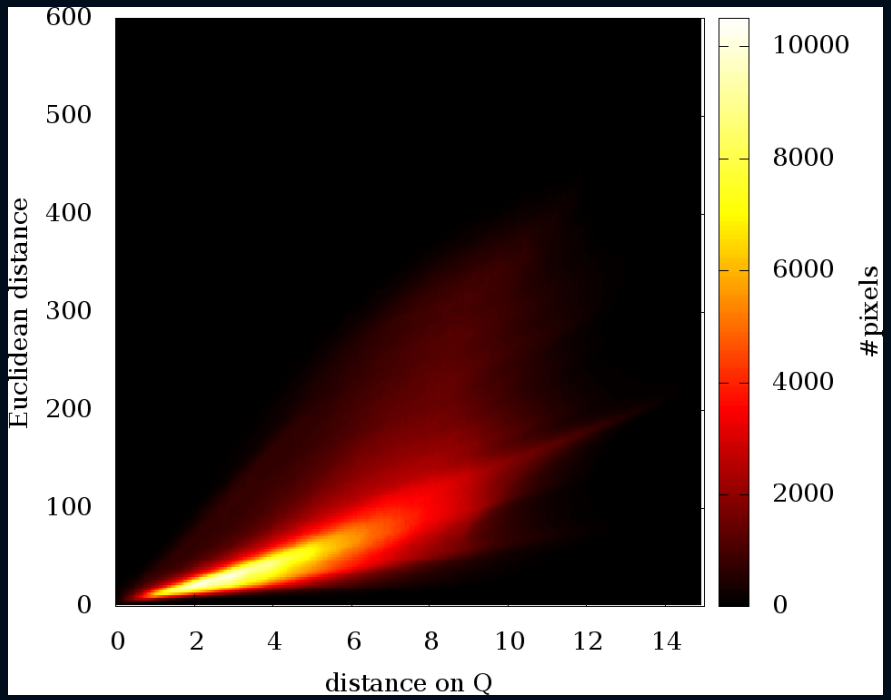
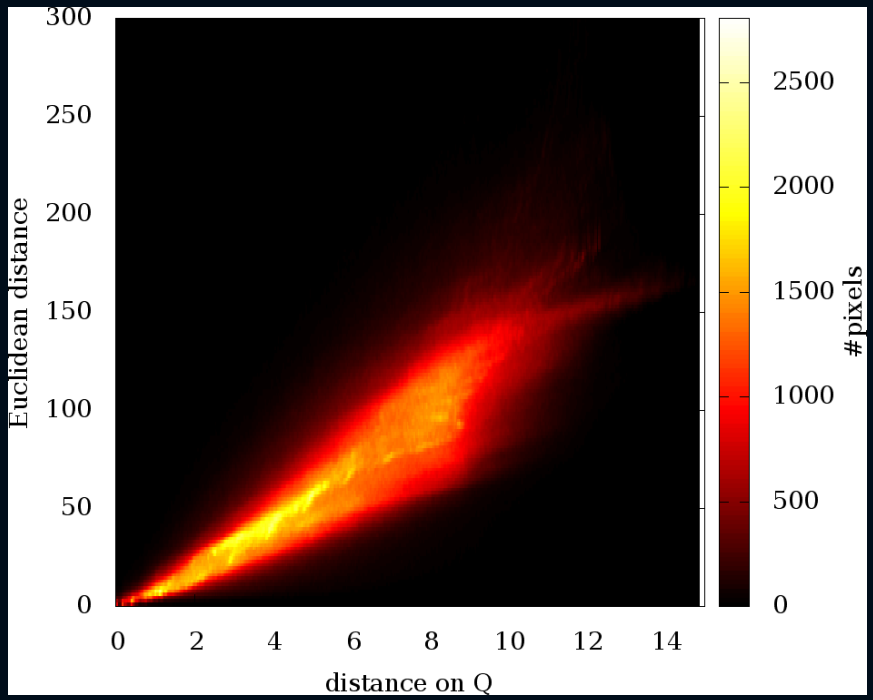


Image spectra | Huynh and Robles-Kelly | Our method

Results: Dimensionality Reduction



`Cbrufefields` (Foster dataset)



`D.C. Mall` (Remote sensing)

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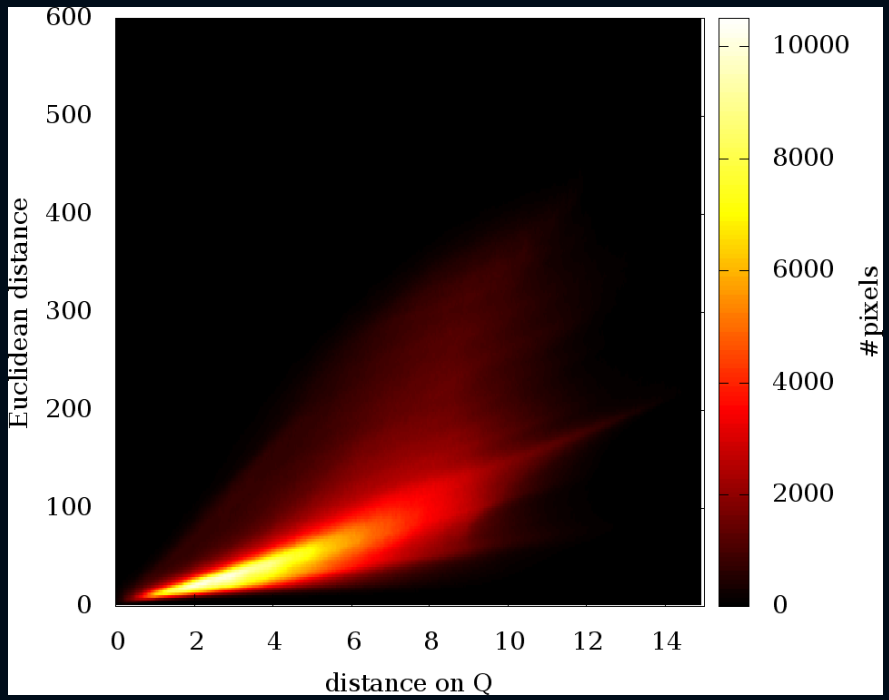

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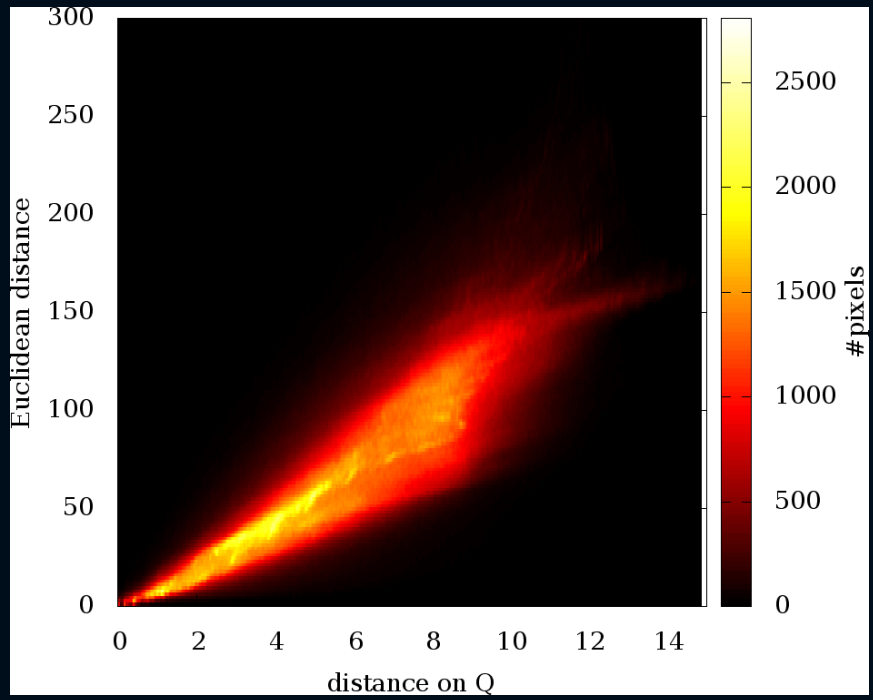

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Timing Results

Training: **3 s**, mapping: **12 s**, clustering: **3 s**, total **17.7 s**

Conclusions

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- We propose a new unsupervised statistical learning method
- We model the problem of manifold learning with two linked graphs
  1. G_M represents data samples, supports parameters ξ_j
  2. G_Q is a constructed Gibbs field, enables ξ_j inference

Conclusions

- We propose a new unsupervised statistical learning method
- We model the problem of manifold learning with two linked graphs
  1. G_M represents data samples, supports parameters ξ_j
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- Our method is shown to be effective for:
  1. material prototype recovery
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- Our method is computationally efficient in terms of computing power and memory use
- We improve over state-of-the-art in speed and performance