Model-Based Optimization Meets Deep Learning in Image Analysis

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Model-Based Optimization vs. Deep Learning

$$y \approx \mathcal{T}(x) \longrightarrow \boxed{\min_{x \in X} \mathcal{L}(\mathcal{T}(x), y) + \tau \phi(x)} \xrightarrow{x}$$

Model-Based Optimization vs. Deep Learning

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- ✓ We know what we do
- ✓ Have performance guarantees
- ✗ Tends to be slow
- ✗ Model is often simplified
- ✗ Parameters often hand tuned

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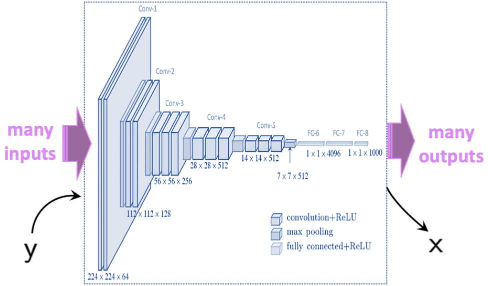
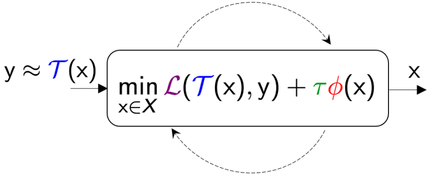


Model-Based Optimization vs. Deep Learning



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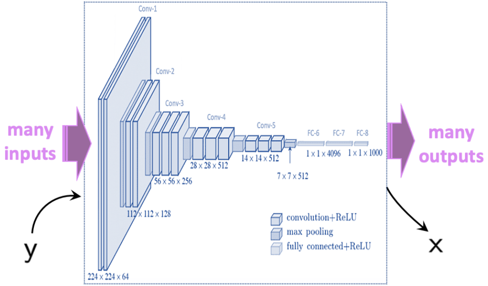
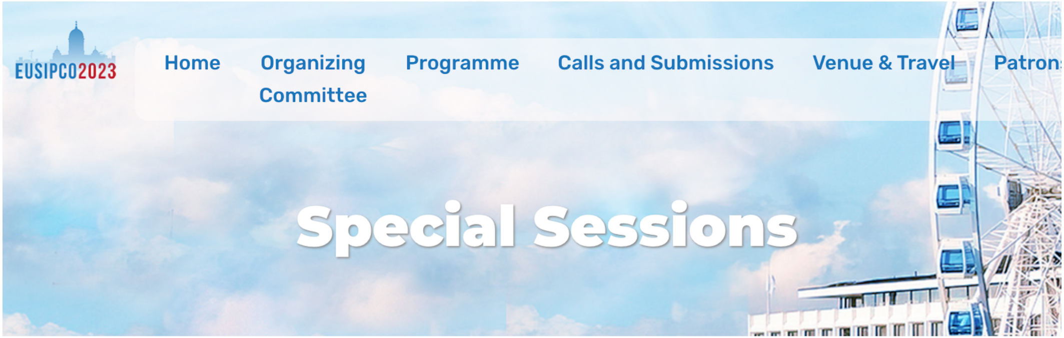


- ✓ Often works **much** better
- ✗ Success on new data not evident
- ✗ Often don't know why it fails

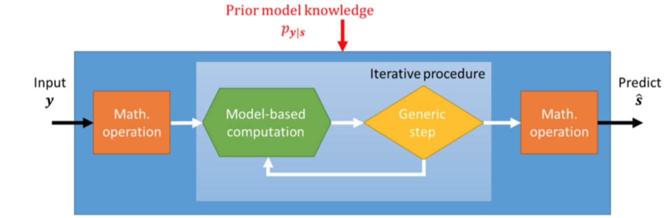
Huge interest in model-based deep learning

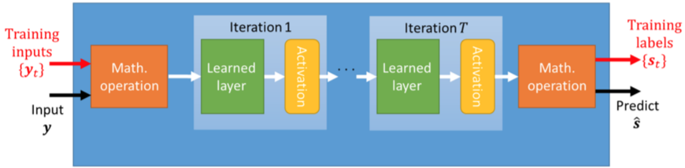


SS1 - Advances in Model-based Deep Learning

Organizers: Emilie Chouzenoux (University Paris Saclay, France), Nikos Deligiannis (Vrije Universiteit Brussel, Belgium), and Aleksandra Pizurica (Ghent University, Belgium)

Model-based deep learning: Unfolding/Unrolling

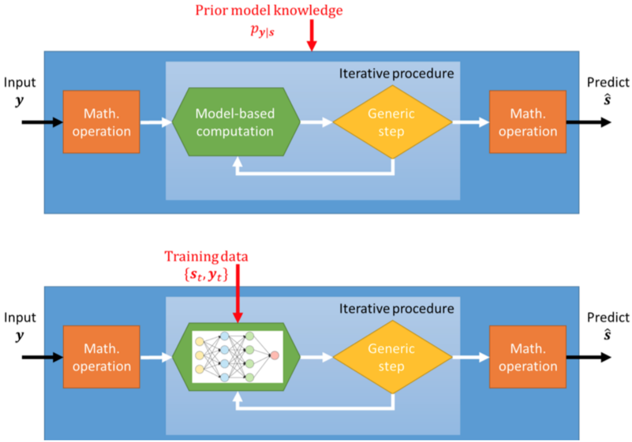




Picture credit: N. Shlezinger et al. Model-Based Machine Learning for Communications, 2021.

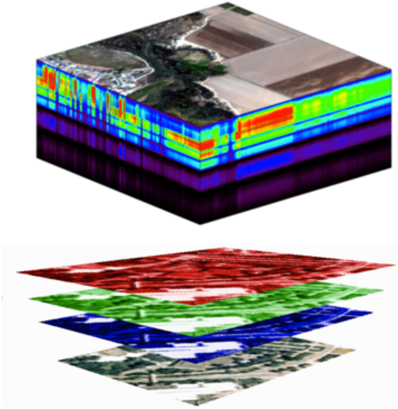
Going back to at least Learned ISTA (**LISTA**) [Gregor & LeCun, 2010].

Model-based deep learning: Hybrid models



Picture credit: N. Shlezinger et al. Model-Based Machine Learning for Communications, 2021.

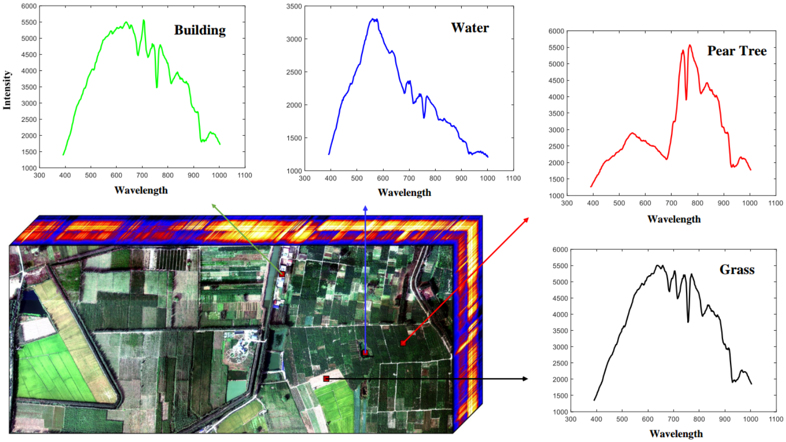
Focus of this talk: Analysis of high-dimensional and multimodal images



Remote sensing data (hyperspectral, visible, LiDAR,...)

Digitized paintings (infrared, X-Ray, visible)

Hyperspectral Images in Remote Sensing

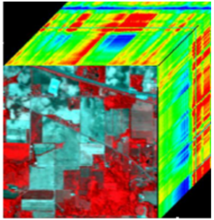


Matiwan Village, Hebei Province (China), 250 bands, spatial size 3750 × 1580

Many applications: agriculture, environment monitoring, urban planning ...

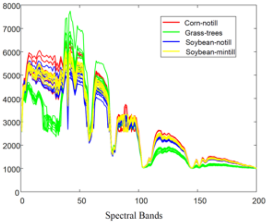
Hyperspectral Image (HSI) Classification and Clustering

- By classification we mean assigning **each pixel** to a given class
- **Clustering** is **unsupervised** classification (no labelled data to train the model)

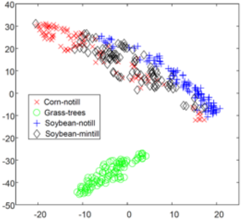


3D HSI data

clustering map



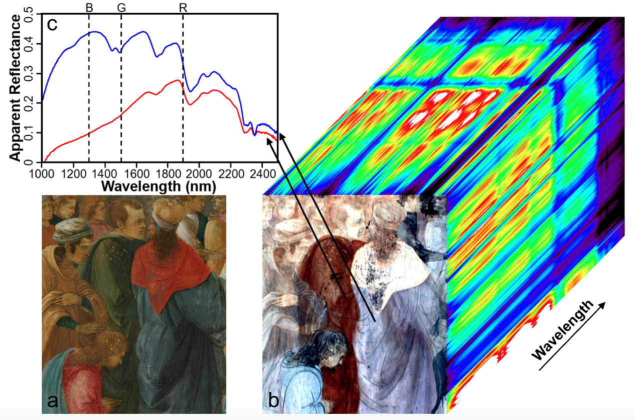
spectral signatures



t-SNE visualization

High variability of the spectral signatures within the same class makes both classification and clustering tasks very challenging!

Hyperspectral Images in Art Investigation

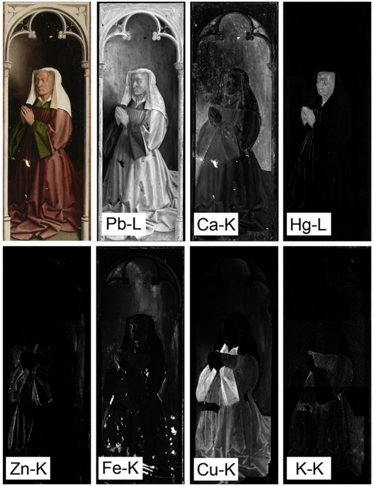


Sandro Botticelli and Filippino Lippi, Adoration of the Kings, about 1470, The National Gallery, London

B. Sober et al. Revealing and Reconstructing Hidden or Lost Features in Art Investigation. IEEE Bits, 2022.

Multimodal imaging of paintings

Detail from Fragonard's *Young Girl Reading*, National Gallery of Art, Washington
Picture credit: J.K. Delaney



MA-XRF imaging of the panel *Elisabeth Borluut*
Ghent Altarpiece, http://closertovaneyck.kikirpa.be/

The *Ghent Altarpiece*

Hubert and Jan Van Eyck, completed in 1432.

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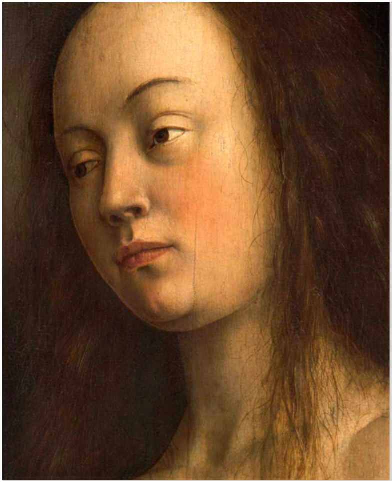
The *Ghent Altarpiece* - Some details



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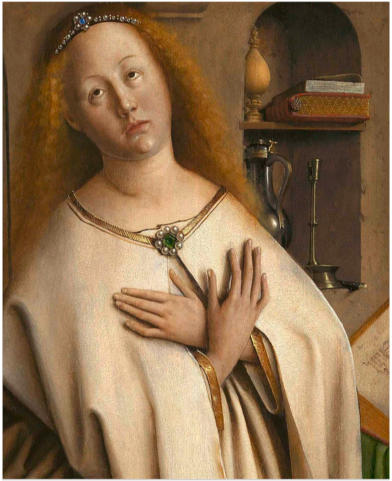


The *Ghent Altarpiece* - Some details

Recent restoration of the *Ghent Altarpiece*

The *Ghent Altarpiece* - Recent Restoration Campaign

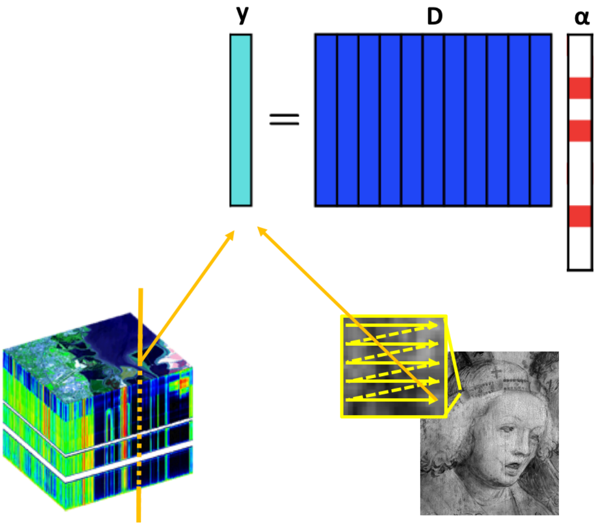
SCIENCE

The New York Times

A Master Work, the Ghent Altarpiece, Reawakens Stroke by Stroke

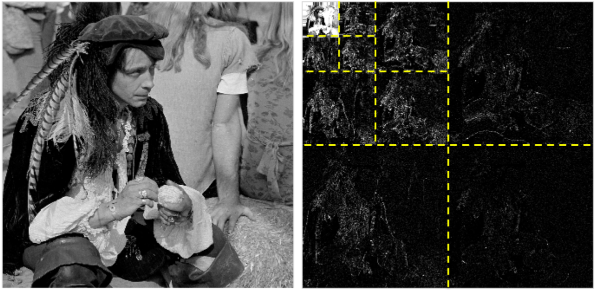
By MILAN SCHREUER DEC. 19, 2016

Sparse representation



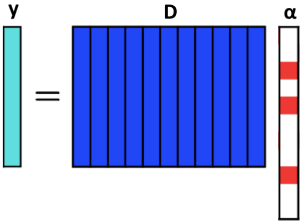
Designed vs. Learned Dictionaries

- **Designed dictionaries**: wavelets, curvelets, shearlets...
  - typically yield sparse representation of signals and images
  - advantages: generic, fast computation



- **Learned dictionaries**
  - trained on a set of representative examples
  - goal: optimally sparse representation for a given class of signals

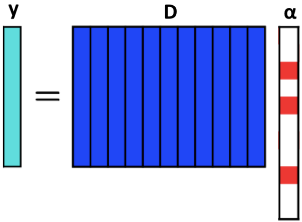
Sparse coding



$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\mathrm{y} - \mathrm{D}\boldsymbol{\alpha}\|_2^2 \quad \text{subject to} \quad \|\boldsymbol{\alpha}\|_0 \leq K$$

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\boldsymbol{\alpha}\|_0 \quad \text{subject to} \quad \|\mathrm{y} - \mathrm{D}\boldsymbol{\alpha}\|_2^2 \leq \epsilon$$

Sparse coding



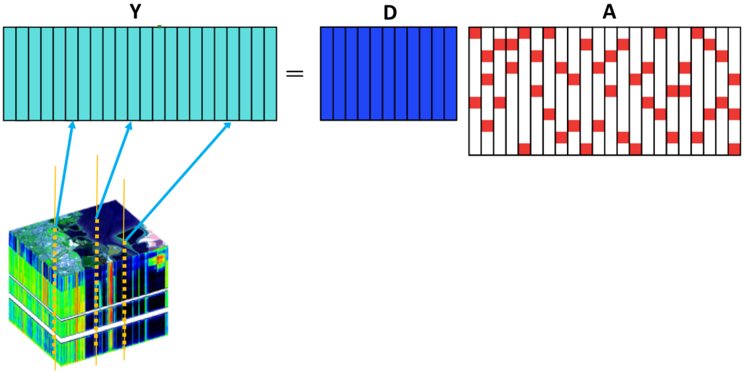
Convex relaxation:

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\boldsymbol{\alpha}\|_1 \quad \text{subject to} \quad \|\mathrm{y} - \mathrm{D}\boldsymbol{\alpha}\|_2^2 \leq \epsilon$$

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\mathrm{y} - \mathrm{D}\boldsymbol{\alpha}\|_2^2 + \lambda\|\boldsymbol{\alpha}\|_1$$

LASSO [Tibshirani, '96], BPDN [Chen et al, '01]

Sparse coding and dictionary learning

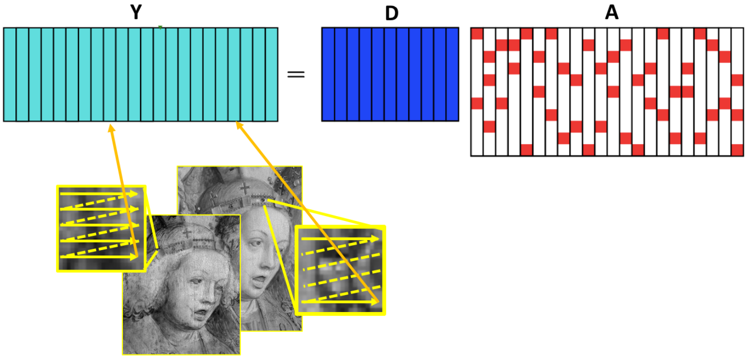


$$\{\hat{D}, \hat{A}\} = \arg\min_{D,A} \left\{ \|Y - DA\|_F^2 \right\} \quad \text{subject to} \quad \forall i, \|\boldsymbol{\alpha}_i\|_0 \le K$$

A similar objective:

$$\{\hat{D}, \hat{A}\} = \arg\min_{D,A} \sum_i \|\boldsymbol{\alpha}_i\|_0 \quad \text{subject to} \quad \|Y - DA\|_F^2 \le \epsilon$$

Sparse coding and dictionary learning



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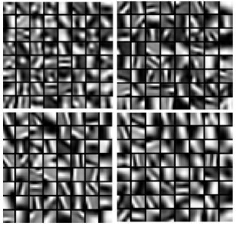
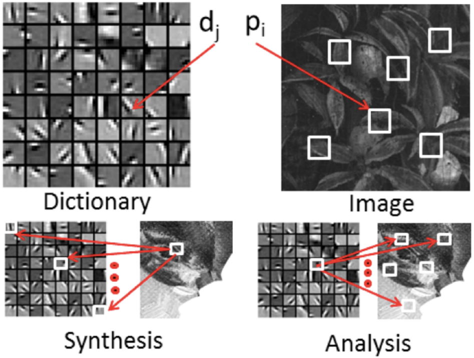
Application in Painter Style Characterization





[Hughes et al, 2009], [Latić and Pižurica, 2014]

Outline

1. Sparse Representation-based Classification (SRC)
   - Robust HSI classification
   - Sparse unmixing
   - Optimal target detection
2. Sparse subspace clustering (SSC)
   - Self-representation model
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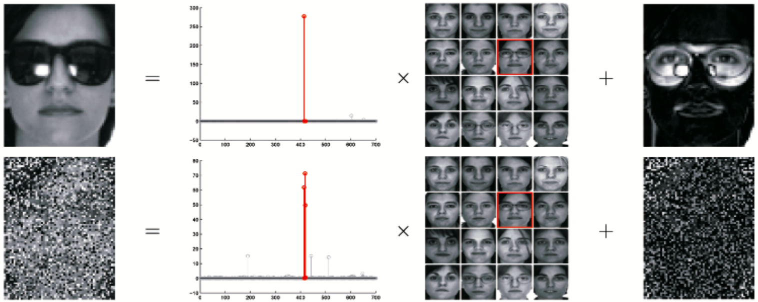
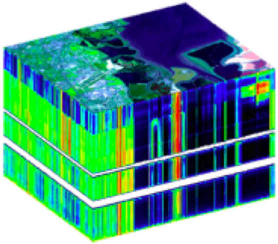
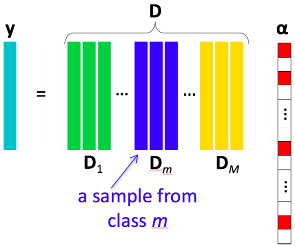
Sparse Representation-based Classification (SRC)



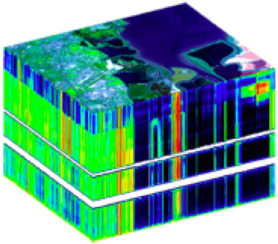
Wright, J., Yang, A. Y., Ganesh, A., Sastry, S. S., and Ma, Y. (2009). Robust face recognition via sparse representation. IEEE PAMI.

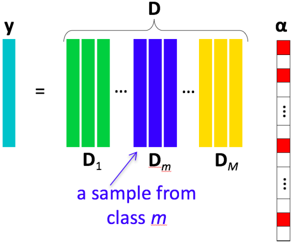
SRC in hyperspectral image classification





SRC in hyperspectral image classification





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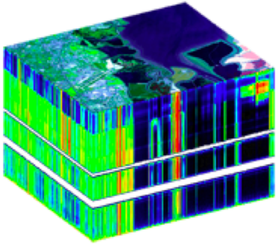
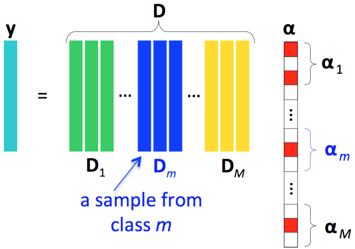
SRC in hyperspectral image classification



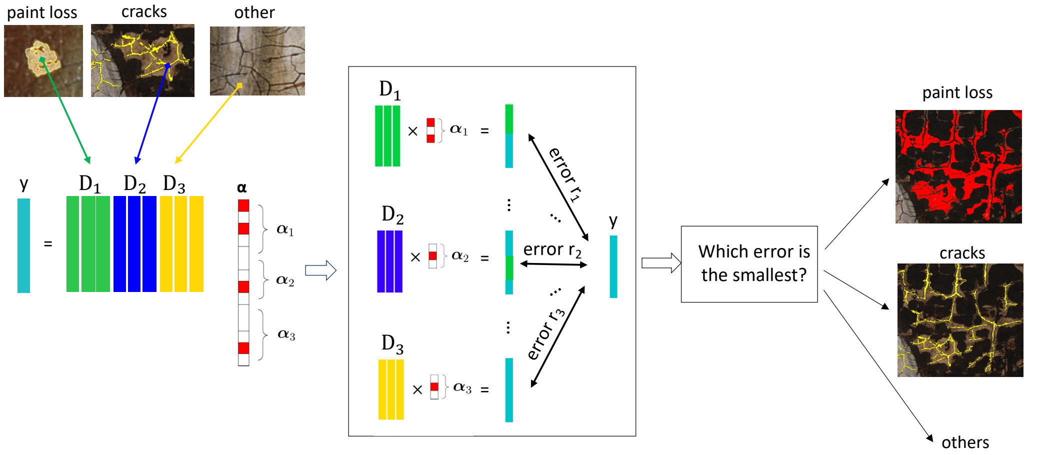


$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\mathrm{y} - \mathrm{D}\boldsymbol{\alpha}\|_2^2 \ \text{ subject to } \|\boldsymbol{\alpha}\|_0 \leq K$$

$$r_m(\mathrm{y}) = \|\mathrm{y} - \mathrm{D}_m\hat{\boldsymbol{\alpha}}_m\|_2, \qquad m = 1, \ldots, M$$

$$class(\mathrm{y}) = \arg\min_{m=1,\ldots,M} r_m(\mathrm{y})$$

SRC in digital painting analysis



S. Huang, B. Cornelis, B. Devolder, M. Martens and A. Pižurica. Multimodal Target Detection by Sparse Coding: Application to Paint Loss Detection in Paintings. IEEE TIP, 2020.

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Joint Sparsity Model

Collect pixels from a small neighbourhood $\mathcal{N}_\epsilon$ into $\mathrm{Y} = [\mathrm{y}_1, ..., \mathrm{y}_T] \in \mathbb{R}^{B \times T}$

$$\mathrm{Y} = \underbrace{[\mathrm{y}_1 \ \ \ldots \ \ \mathrm{y}_T]}_{\text{pixels from } \mathcal{N}_\epsilon} = [\mathrm{D}\boldsymbol{\alpha}_1 \ \ \ldots \ \ \mathrm{D}\boldsymbol{\alpha}_T] = \mathrm{D}\underbrace{[\boldsymbol{\alpha}_1 \ \ \ldots \ \ \boldsymbol{\alpha}_T]}_{\mathrm{A}} = \mathrm{DA}$$

Sparse codes $\{\boldsymbol{\alpha}_t\}_{t=1}^{T}$ share the same support $\implies$ A is sparse with only K non-zero rows, i.e., A is row sparse.

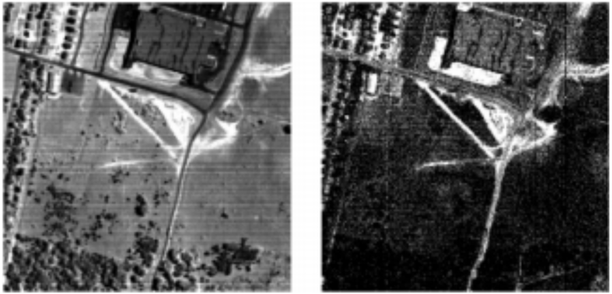
$$\hat{\mathrm{A}} = \arg\min_{\mathrm{A}} \|\mathrm{Y} - \mathrm{DA}\|_F^2 \ \ \text{subject to} \ \ \|\mathrm{A}\|_{row,0} \leq K$$

$$r_m(\mathrm{Y}) = \|\mathrm{Y} - \mathrm{D}_m\hat{\mathrm{A}}_m\|_F, \qquad m = 1, ..., M$$

$$class(\mathrm{y}_{central}) = \arg\min_{m=1,...,M} r_m(\mathrm{Y})$$

Robust SRC for Hyperspectral Image Classification

$$Y = \underbrace{X}_{\text{ideal image}} + \underbrace{N}_{\text{Gaussian noise}} + \underbrace{\color{red}{S}}_{\color{red}{\text{sparse noise}}}$$



Examples of stripe noise and mixed noise in a real hyperspectral image.

Huang, S., Zhang, H., Liao, W., and Pižurica, A. (2017). Robust joint sparsity model for hyperspectral image classification. In IEEE ICIP 2017.

Robust SRC for Hyperspectral Image Classification

$$\mathrm{Y} = \underbrace{\mathrm{X}}_{\text{ideal image}} + \underbrace{\mathrm{N}}_{\text{Gaussian noise}} + \underbrace{\mathrm{S}}_{\text{sparse noise}}$$

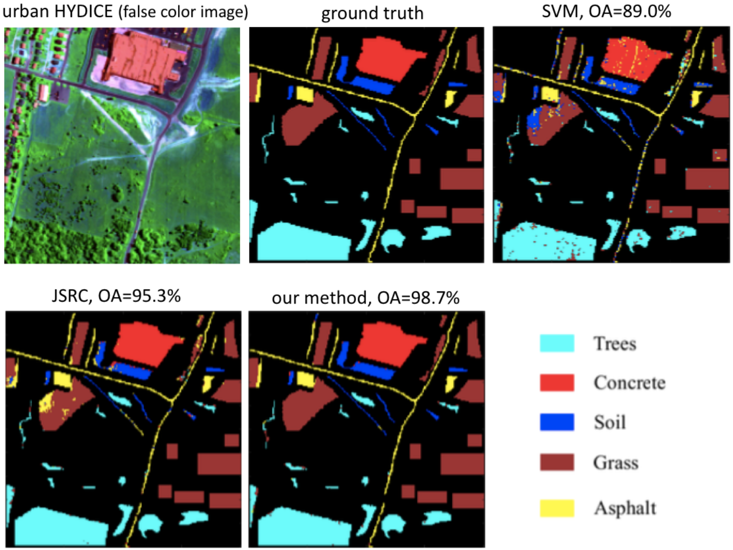
$$\{\hat{\mathrm{A}}, \hat{\mathrm{S}}\} = \arg\min_{\mathrm{A},\mathrm{S}} \|\mathrm{Y} - \mathrm{DA} - \mathrm{S}\|_F^2 + \lambda\|\mathrm{S}\|_1 \quad \text{subject to} \quad \|\mathrm{A}\|_{row,0} \leq K$$

$$r_m(\mathrm{Y}) = \|\mathrm{Y} - \mathrm{D}_m\hat{\mathrm{A}}_m - \hat{\mathrm{S}}\|_F, \qquad m = 1, \ldots, M$$

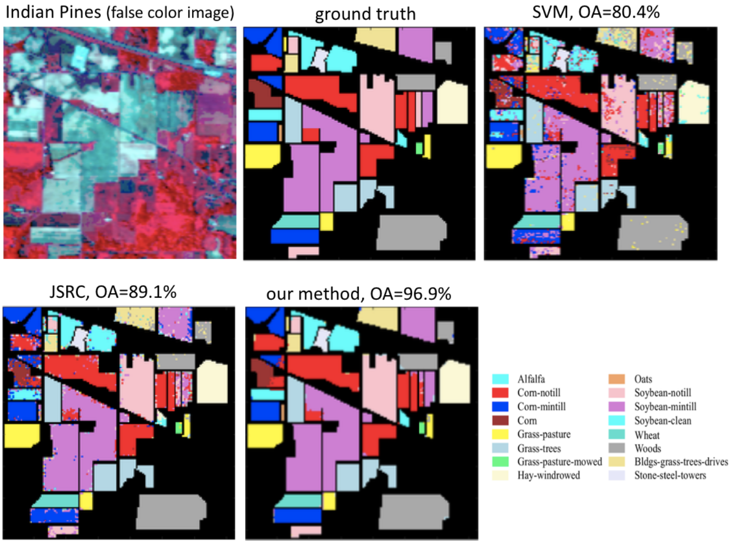
$$class(\mathrm{y}_{central}) = \arg\min_{m=1,\ldots,M} r_m(\mathrm{Y})$$

S. Huang, H. Zhang and A. Pižurica (2017). A Robust Sparse Representation Model for Hyperspectral Image Classification. Sensors.

Robust SRC for Hyperspectral Image Classification



Robust SRC for Hyperspectral Image Classification



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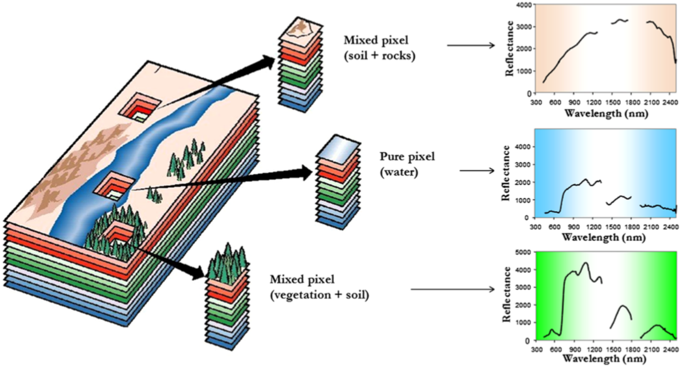
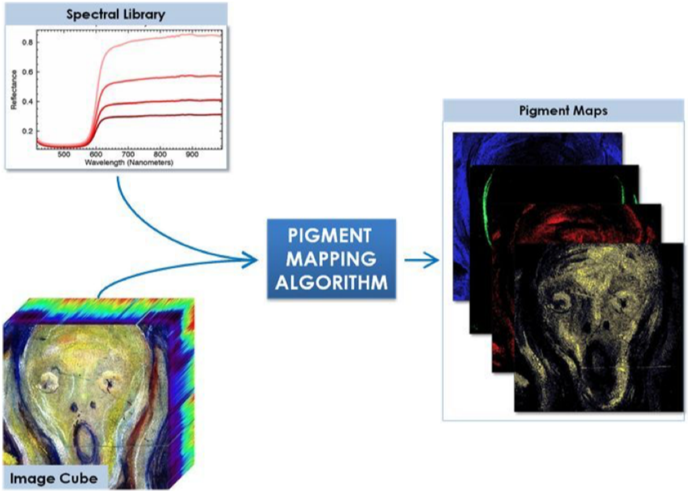
Why do we need spectral unmixing?



S.R Bijitha et al (2016). Performance Analysis and Comparative Study of Geometrical Approaches for Spectral Unmixing. Int. J. Sci. Eng. Research.

Pigment mapping



H. Deborah: Pigment Mapping of Cultural Heritage Paintings Based on Hyperspectral Imaging. Master thesis, Gjøvik University College, 2013. Supervisors: J.Y. Hardeberg and S. George.

Sparse Unmixing

Ideal hyperspectral image reordered as a matrix $X \in \mathbb{R}^{B \times MN}$

Linear mixing model:

$$X = EA$$

$E \in \mathbb{R}^{B \times K}$ – library of **endmembers**; $A \in \mathbb{R}^{K \times MN}$ – **abundance**

$$Y = \underbrace{E}_{\text{library}} \underbrace{A}_{\text{abundance}} + \underbrace{N}_{\text{Gaussian noise}} + \underbrace{S}_{\text{sparse noise}}$$

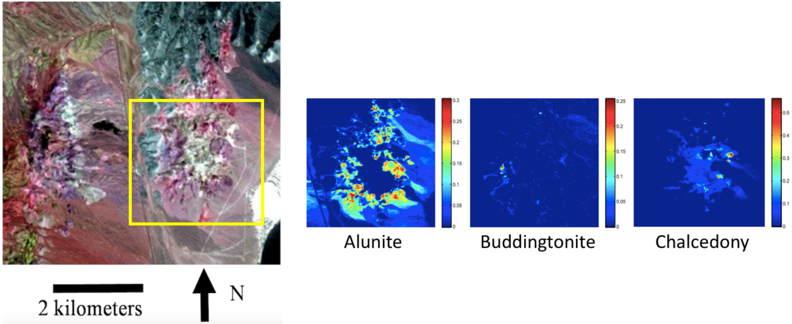
The approach of [Aggarval et al, 2016]:

$$\min_{A,S} \|Y - EA - S\|_F^2 + \lambda_1 \|A\|_{2,1} + \lambda_2 \|S\|_1$$

Many similar variants exist, also making use of low-rank assumption:

$$\min_{A} \operatorname{rank}\{A\} \quad \text{subject to} \quad \|Y - EA - S\|_F^2 \leq \epsilon$$

Sparse Unmixing



Estimated fractional abundance maps (AVIRIS Cuprite subscene, USGS library).

R. Wang, H.-C. Li, A. Pižurica, J. Li, A. Plaza, and W. J. Emery. Hyperspectral Unmixing Using Double Reweighted Sparse Regression and Total Variation. IEEE Geoscience and Remote Sensing Letters, 2017.

Outline

Sparse Representation-based Target Detectors

$H_0 : \mathrm{x} = \mathrm{D}_b \boldsymbol{\alpha}_b + \mathrm{n}_1, \quad \mathrm{x}$ is a background pixel
$H_1 : \mathrm{x} = \mathrm{D}_t \boldsymbol{\alpha}_t + \mathrm{n}_2, \quad \mathrm{x}$ is a target pixel

Input:

$$\mathrm{x} = \mathrm{D}_b \boldsymbol{\alpha}_b + \mathrm{D}_t \boldsymbol{\alpha}_t + \mathrm{n} \;=\; \mathrm{D}\boldsymbol{\alpha} + \mathrm{n}; \qquad \mathrm{D} = [\mathrm{D}_t, \mathrm{D}_b]$$

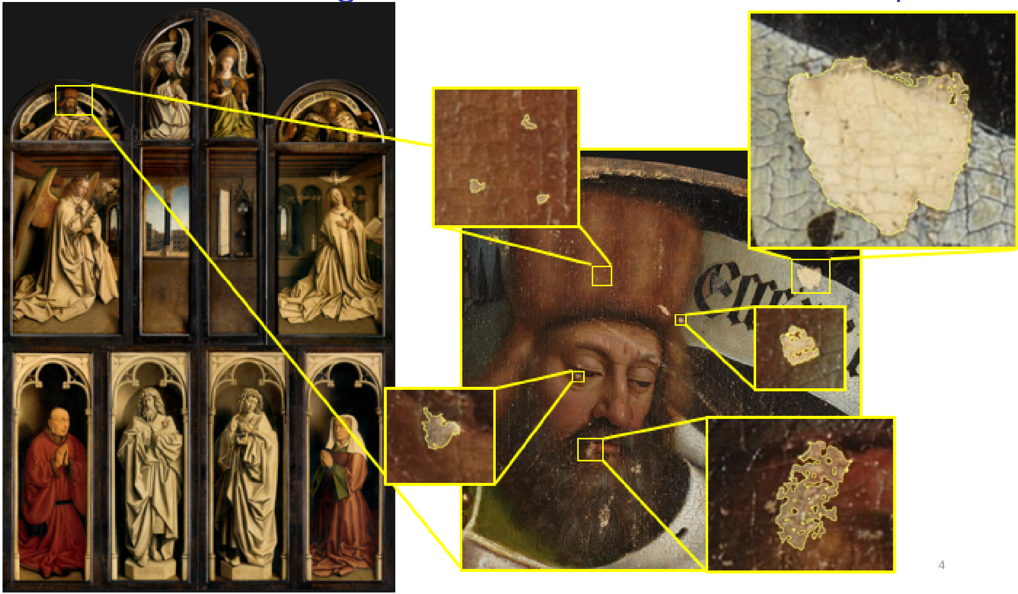
Solve: $$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\mathrm{x} - \mathrm{D}\boldsymbol{\alpha}\|^2 \quad s.t. \;\; \|\boldsymbol{\alpha}\|_0 < K_0$$

Find the residuals: $$r_b(\mathrm{x}) = \|\mathrm{x} - \mathrm{D}_b \hat{\boldsymbol{\alpha}}_b\|_2; \quad r_t(\mathrm{x}) = \|\mathrm{x} - \mathrm{D}_t \hat{\boldsymbol{\alpha}}_t\|_2$$

Detect as target if $$r_b(\mathrm{x}) - r_t(\mathrm{x}) > \delta; \qquad \delta \geq 0$$

S. Huang, B. Cornelis, B. Devolder, M. Martens and A. Pižurica. Multimodal Target Detection by Sparse Coding: Application to Paint Loss Detection in Paintings. IEEE TIP, 2020.

Paint losses revealed during the restoration of the *Ghent Altarpiece*



Why do we need automatic paint loss detection?

Paint loss detection is crucial for

- documenting purpose
- virtual restoration
- decision making in the actual restoration process

Currently done manually:

- labor intensive
- only rough indication
- prone to errors

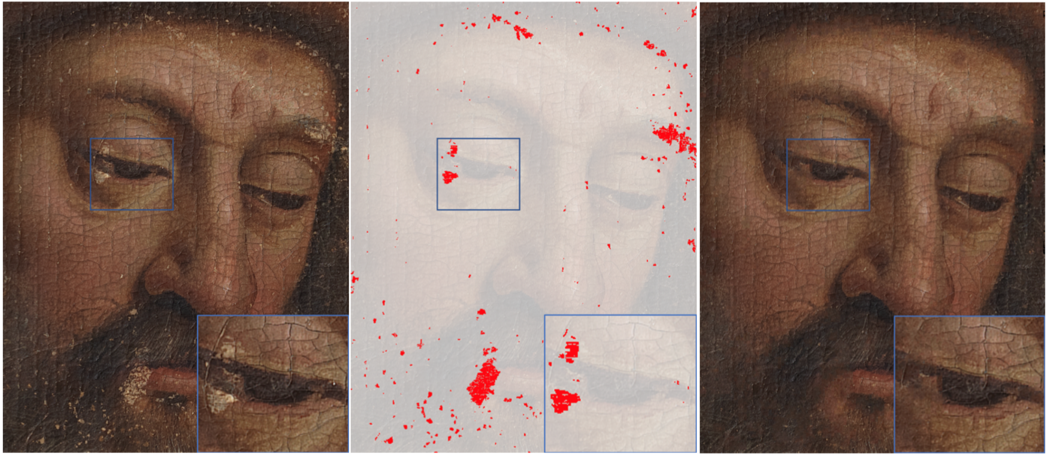
A multimodal approach

Macrophotography | X-radiography | Infrared macrophotography | Macrophotography | Infrared reflectography

Before treatment | During treatment

Paint loss detection data sets - *prophet Zachary*

Virtual Restoration



S. Huang, B. Cornelis, B. Devolder, M. Martens and A. Pižurica. Multimodal Target Detection by Sparse Coding: Application to Paint Loss Detection in Paintings. IEEE TIP, 2020.

Target detection in HSI images

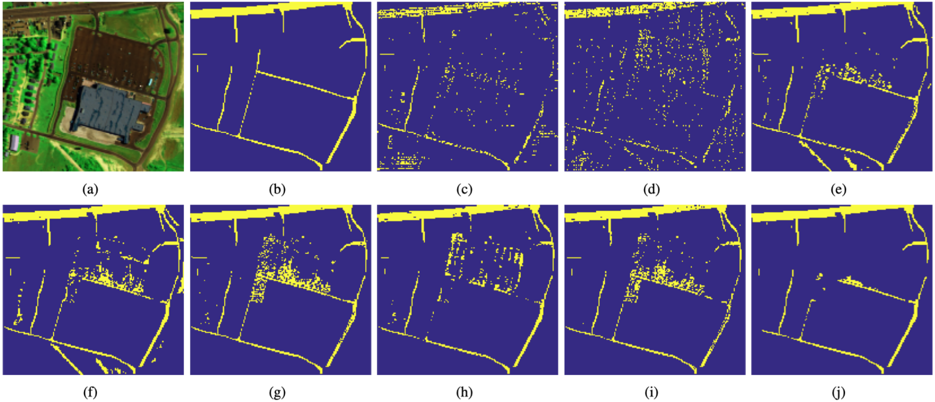


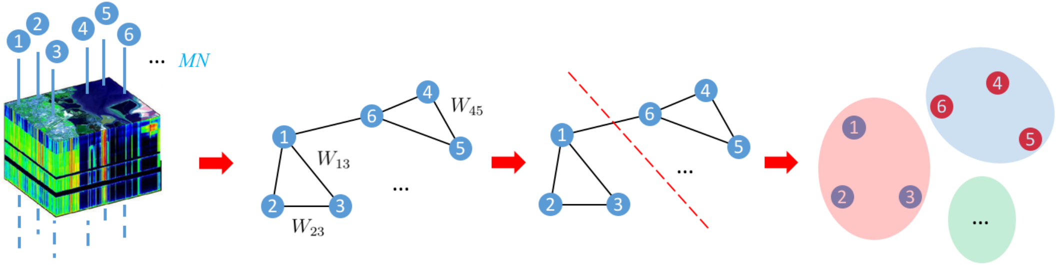
Fig. 14. Detection results on the *HYDICE Urban* image. (a) False color image (b) Ground truth of asphalt road and detection maps obtained by (c) MSD, (d) ACE, (e) STD, (f) SVM, (g) SRC, (h) MFL, (i) MSC and (j) SRC-KF.

S. Huang, B. Cornelis, B. Devolder, M. Martens and A. Pižurica. Multimodal Target Detection by Sparse Coding: Application to Paint Loss Detection in Paintings. IEEE TIP, 2020.

Outline

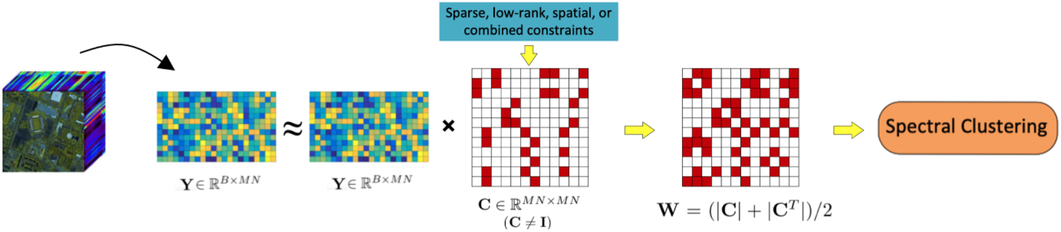
Spectral clustering

No labelled data available → no supervised classification but instead clustering



Similarity matrix: $\mathbf{W} \in \mathbb{R}^{MN \times MN}$

Self-representation model

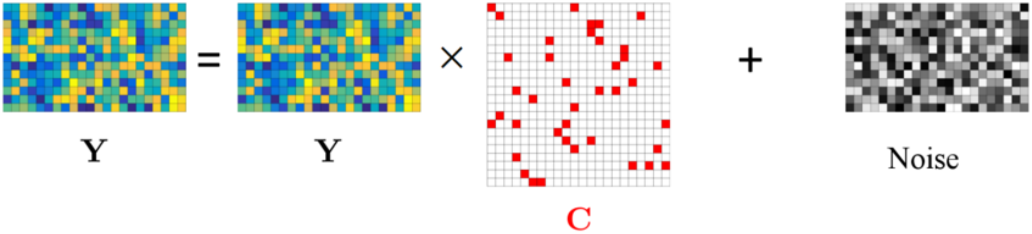


- Traditional approach: estimate the similarity matrix and apply spectral clustering.
- **Spectral clustering**: use the spectrum (eigenvalues) of the similarity matrix of the data to perform dimensionality reduction, then cluster in fewer dimensions.
- Main challenge: obtaining the similarity matrix. Many state-of-the-art methods use the self-representation model with sparsity or low-rank constraints.

Sparse Subspace Clustering

[Elhamifar and Vidal, 2013]

Self-representation model: $\mathrm{Y} = \mathrm{Y}{\color{red}\mathrm{C}} + \mathrm{N}$; $\quad \mathrm{Y} = [\mathrm{y}_1 \ldots \mathrm{y}_N] \in \mathbb{R}^{m \times N}$



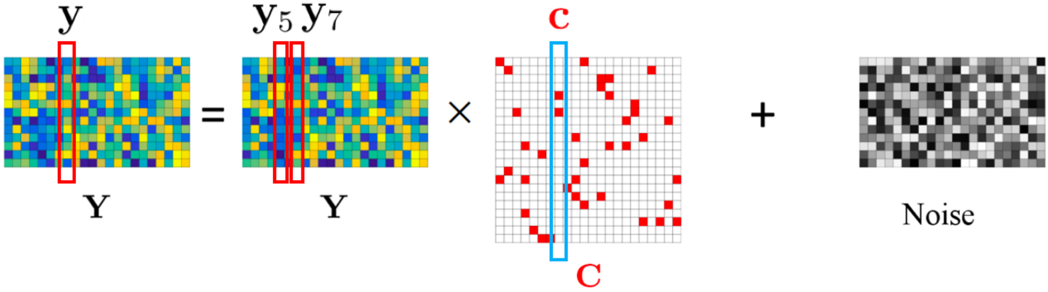
${\color{red}C_{i,j}} \neq 0 \rightarrow \mathrm{y}_i$ and y_j are in the same subspace.

Similarity matrix: $W = |{\color{red}C}| + |{\color{red}C}|^T$

Sparse Subspace Clustering

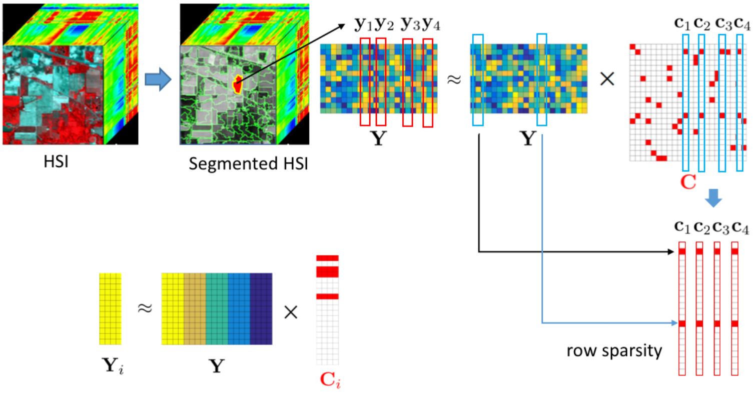
[Elhamifar and Vidal, 2013]

Self-representation model: $\mathsf{Y} = \mathsf{Y}\mathsf{C} + \mathsf{N}$; $\mathsf{Y} = [\mathsf{y}_1 \ldots \mathsf{y}_N] \in \mathbb{R}^{m \times N}$



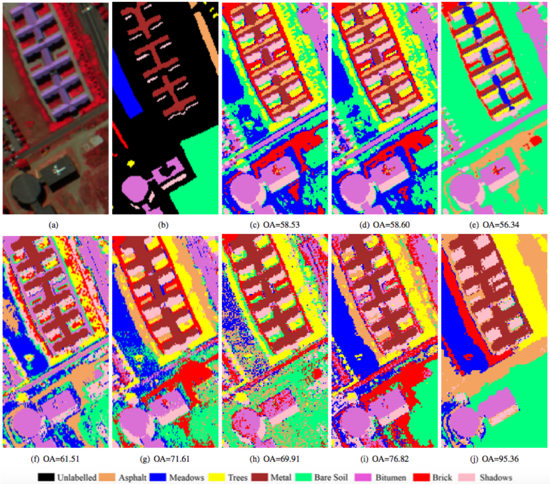
$\mathsf{y} \approx \mathsf{Y}c = \sum_i \mathsf{y}_i c_i = c_5 \mathsf{y}_5 + c_7 \mathsf{y}_7$

Joint Sparse Subspace Clustering - JSSC



S. Huang, H. Zhang and A. Pižurica (2018). Semi-supervised Sparse Subspace Clustering Method With a Joint Sparsity Constraint for Hyperspectral Remote Sensing Images. IEEE J. Sel. Topics in Earth Observation and Remote Sens.

Joint Sparse Subspace Clustering - JSSC



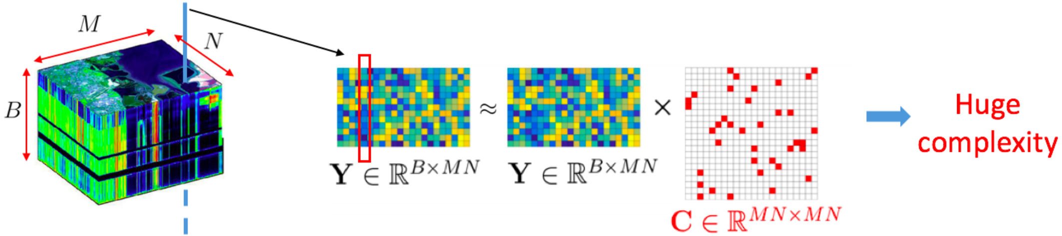
Pavia University image. (a) False color image, (b) Ground truth (c) FCM, (d) k-means, (e) CFSFDP, (f) SSC, (g) L2-SSC, (h) CPPSSC (1 % labelled samples), (i) JSSC and (j) JSSC-L (1% labelled samples)

S. Huang, H. Zhang and A. Pižurica (2018). IEEE JSTARS

Outline

1. Sparse Representation-based Classification (SRC)
   - Robust HSI classification
   - Sparse unmixing
   - Optimal target detection
2. Sparse subspace clustering (SSC)
   - Self-representation model
   - Scalable SSC models
3. Model-based Deep Learning
   - Some hybrid models
   - Deep clustering

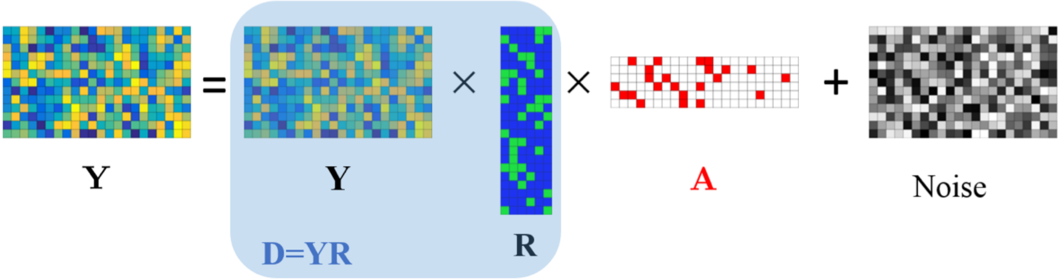
Nice, but ...



SSC becomes practically infeasible for very large scale data.

E.g. for the full **Pavia University** image 610×340, the size of C is 207400×207400
$\rightarrow$ 320,5 GB memory

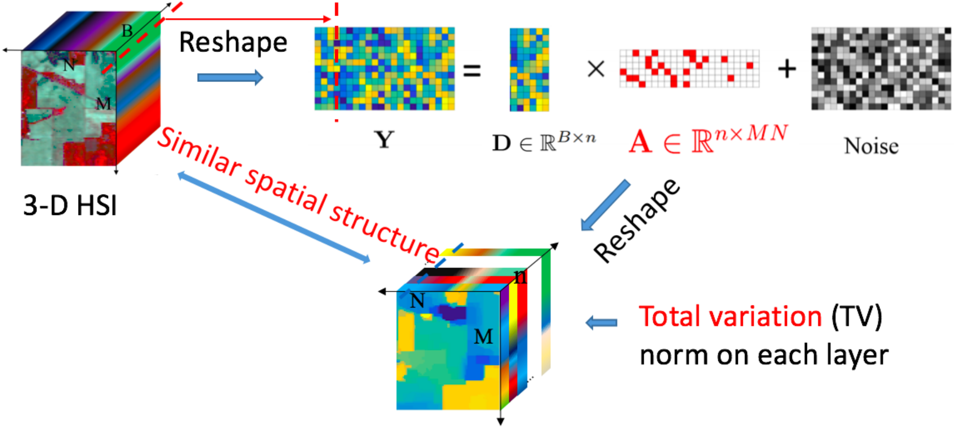
Sketching



Reduces greatly the size of the problem!

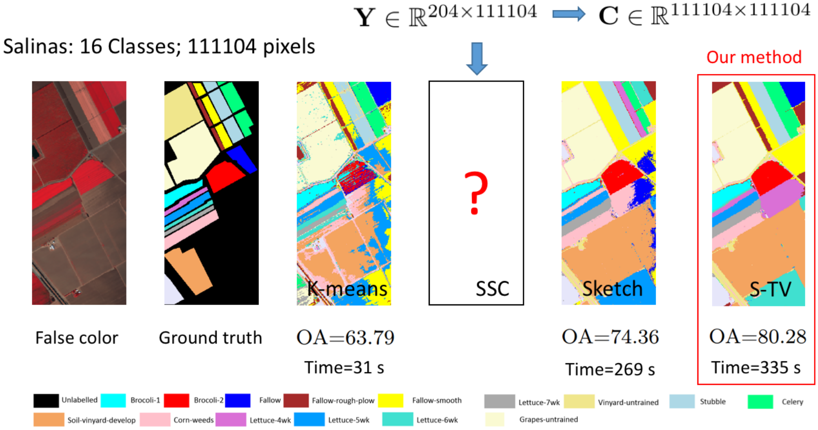
P. A. Traganitis and G. B. Giannakis. Sketched subspace clustering. IEEE Trans. Signal Process., vol. 66, no. 7, pp. 1663–1675, 2018.

Sketched Sparse Subspace Clustering for Hyperspectral Images



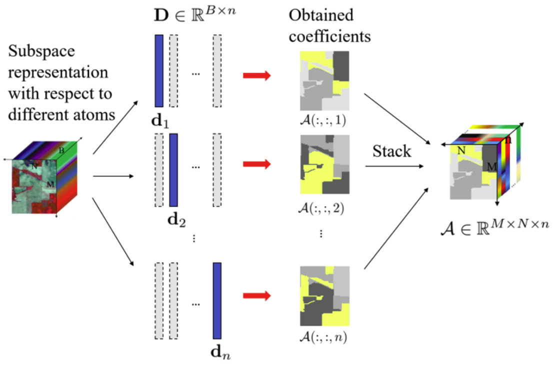
S. Huang, H. Zhang and A. Pižurica Sketched Sparse Subspace Clustering with Total Variation Constraint for Hyperspectral Images, submitted to Information Sciences (2019).

Sketched Sparse Subspace Clustering for Hyperspectral Images



S. Huang, H. Zhang and A. Pižurica Sketched Sparse Subspace Clustering with Total Variation Constraint for Hyperspectral Images, submitted to Information Sciences (2019).

Subspace clustering via dictionary learning



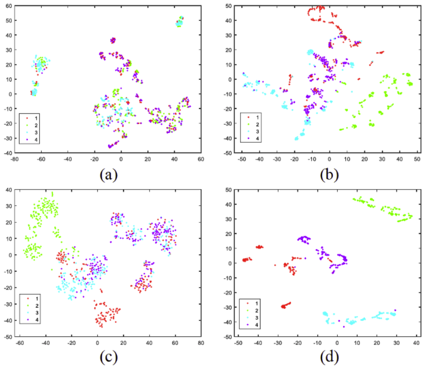
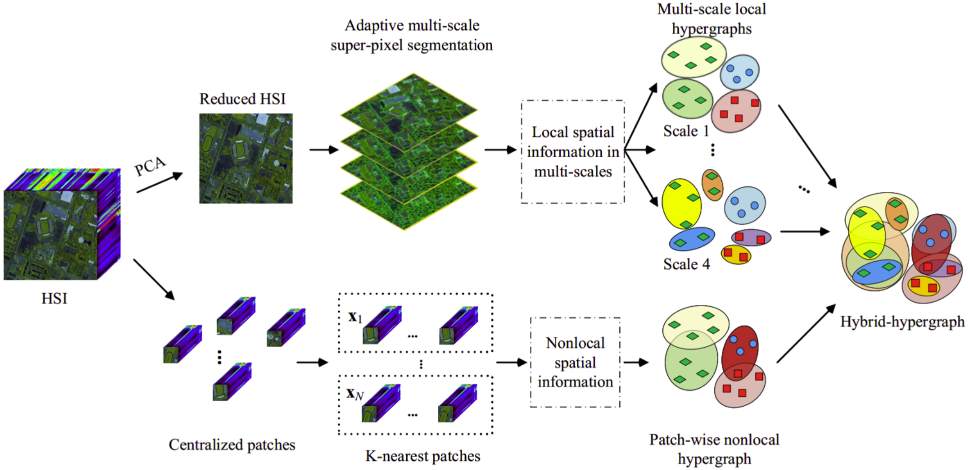


Fig. 12. Feature visualization by applying (a) raw data, (b) coefficients of SSC, (c) coefficients of DLSC and (d) coefficients of IDLSC in the dimension reduction algorithm t-SNE. The dimension of data is reduced to two.

S. Huang, H. Zhang, A. Pižurica. Subspace Clustering for Hyperspectral Images via Dictionary Learning with Adaptive Regularization. *IEEE Transactions on Geoscience and Remote Sensing*, 2022.

Multi-view clustering



S. Huang, H. Zhang, A. Pižurica. Hybrid-Hypergraph Regularized Multiview Subspace Clustering for Hyperspectral Images. *IEEE Transactions on Geoscience and Remote Sensing*, 2022

Band Selecton in HSI

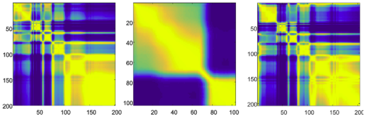


Fig. 1. Correlations of spectral bands in three typical HSIs: Indian (left), Pavia University (middle), and Salinas (right).

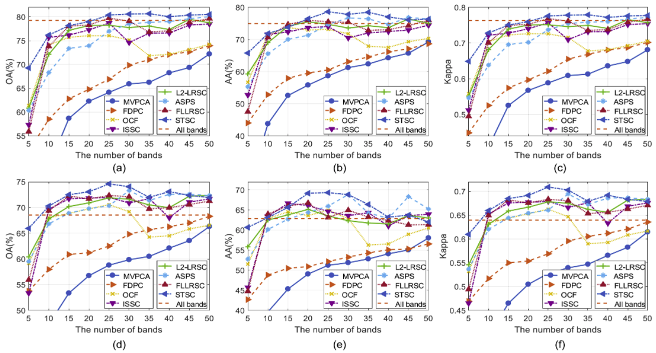


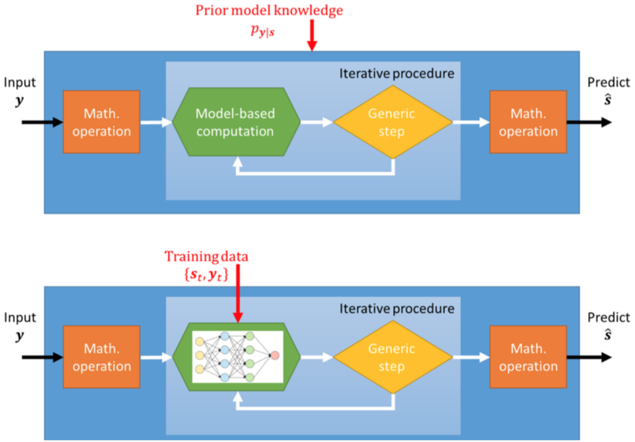
Fig. 5. Influence of band selection on the classification performance in classifiers SVM and KNN on the dataset IndianP. (a) OA in SVM, (b) AA in SVM (c) κ in SVM, (d) OA in KNN, (e) AA in KNN, and (f) κ in KNN.

S. Huang, H. Zhang, A. Pižurica. A Structural Subspace Clustering Approach for Hyperspectral Band Selection. *IEEE Transactions on Geoscience and Remote Sensing*, 2022.

S. Huang, H. Zhang, J.Xue, A. Pižurica. Heterogeneous regularization-based tensor subspace clustering for hyperspectral band selection. *IEEE Transactions on Neural Networks and Learning Systems*, 2022.

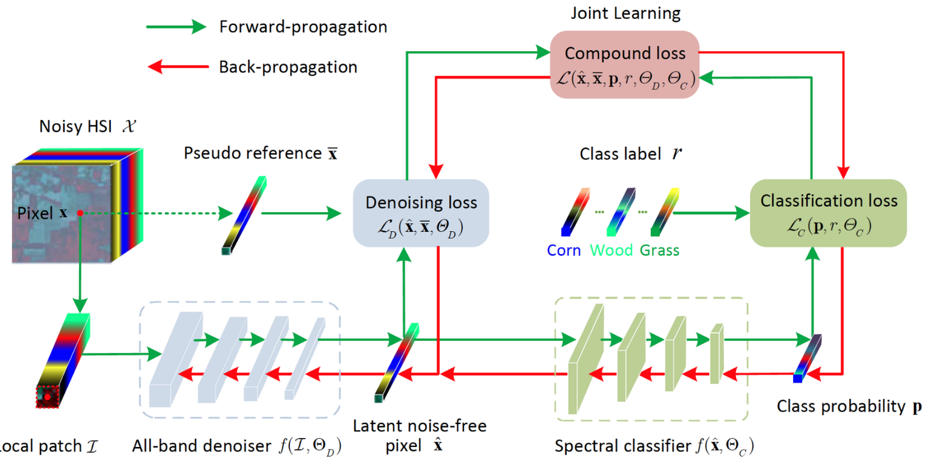
Outline

Model-based deep learning: Hybrid models



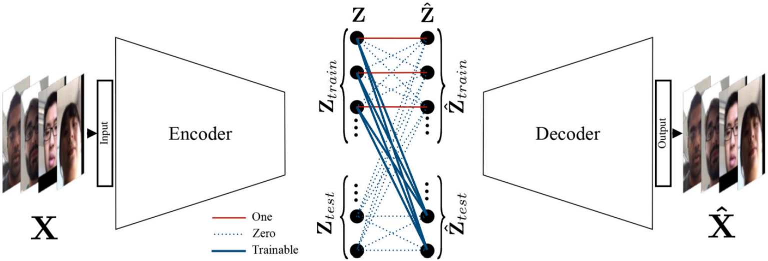
Picture credit: N. Shlezinger et al. Model-Based Machine Learning for Communications, 2021.

Joint denoising and classification



X. Li, M. Ding and A. Pižurica. [An End-to-End Framework for Joint Denoising and,Classification of Hyperspectral Images]. *IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS*, 2023.

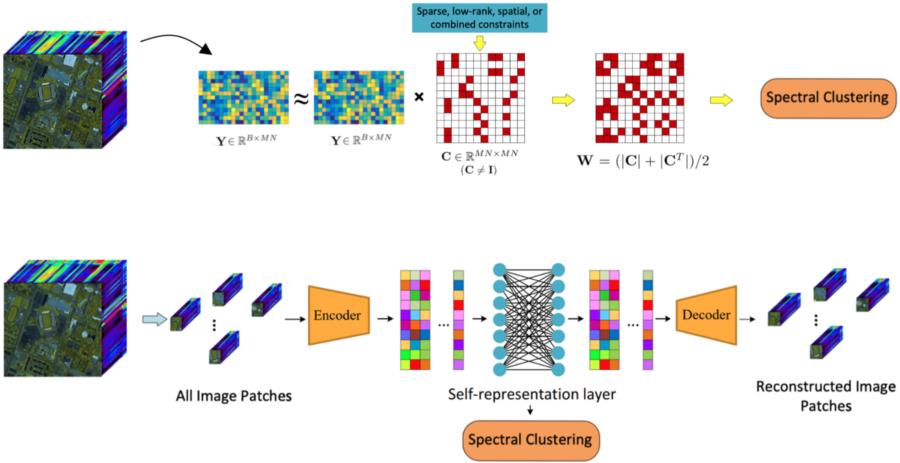
Deep SRC



M. Abavisani and V.M. Patel. Deep Sparse Representation-Based Classification. IEEE Sig. Proc. Lett., 2019.

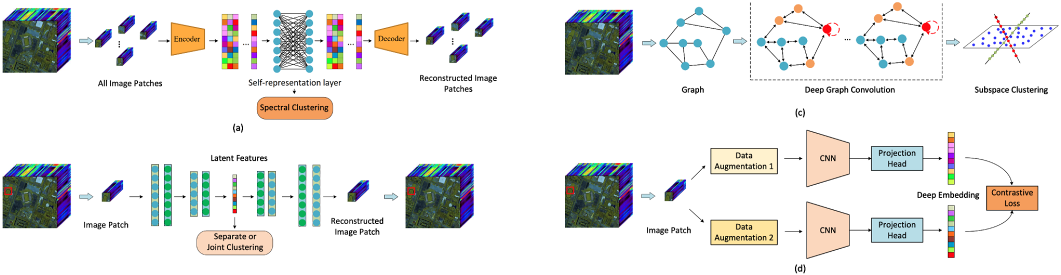
Outline

Model-based deep clustering



Deep Subspace Clustering Networks [Ji et al, 2017]. Instead of solving a sparse coding problem, a neural network outputs the data representation matrix.

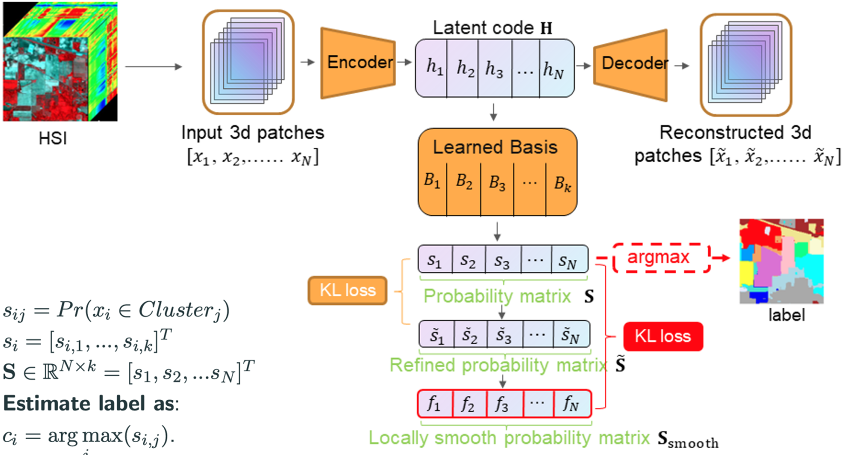
Model-based deep clustering



Four types of deep clustering models of HSI: (a) self-representation-based, (b) AEs-based, High-level Highly discriminative (c) intrinsic graph feature convolution-based and feature (d) self-supervision-based models.

S. Huang, H. Zhang, H. Zeng and A. Pižurica. From Model-Based Optimization Algorithms to Deep Learning Models for Clustering Hyperspectral Images. Remote Sensing, 2023.

Model-aware deep clustering



$s_{ij} = Pr(x_i \in Cluster_j)$

$s_i = [s_{i,1}, \ldots, s_{i,k}]^T$

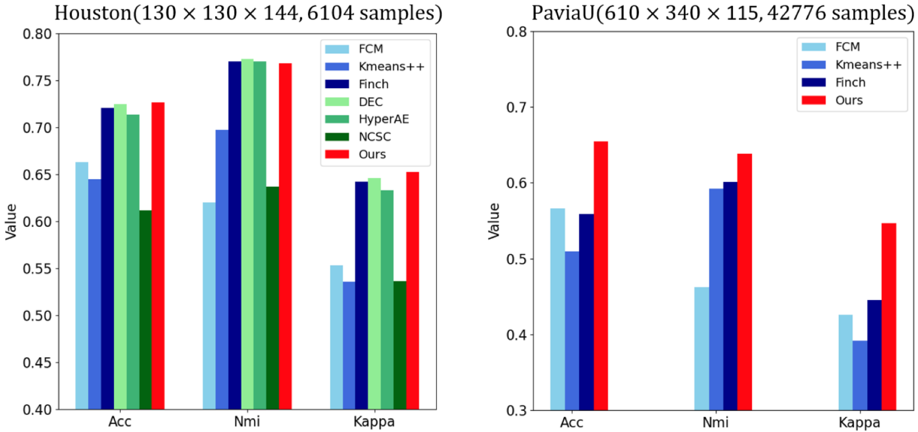
$\mathbf{S} \in \mathbb{R}^{N\times k} = [s_1, s_2, \ldots s_N]^T$

Estimate label as:

$$c_i = \arg\max_j (s_{i,j}).$$

X. Li, N. Nadisic, S. Huang, N. Deligiannis and A. Pižurica. Model-Aware Deep Learning for the Clustering of Hyperspectral Images with Context Preservation. EUSIPCO'23

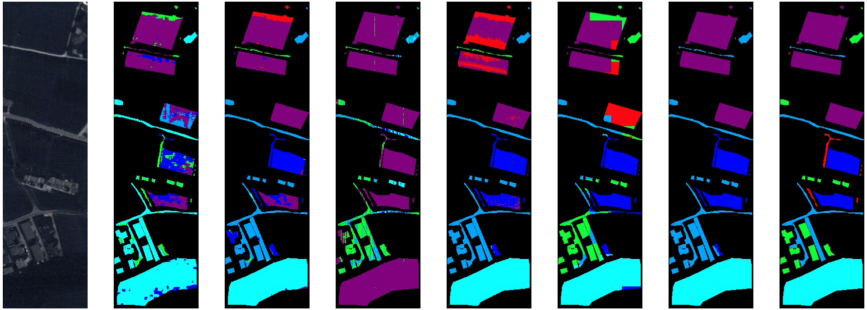
Comparison with other methods



Finch (Sarfraz et al. 2019): nearest neighbors based; DEC (Xie et al. 2016): data-driven deep learning;

HyperAE (Cai et al. 2021), NCSC (Cai et al. 2022): self-representation based deep learning;

Comparison with other methods



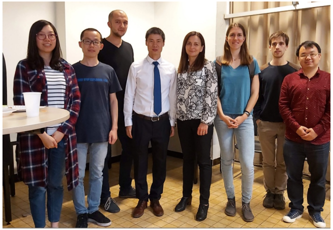
false color image	64.63% FCM	80.30% Kmeans++	48.50% DEC	76.22% Finch	75.92% NCSC	**88.80%** Ours	Ground truth	class color

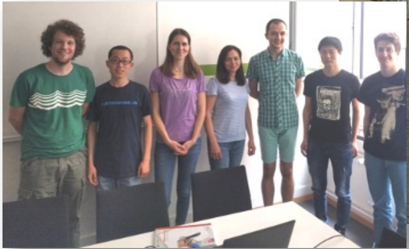
The numbers below each image are the clustering accuracies (ACC).

Summary and conclusions

- Sparse optimization finds many uses in image analysis
- Hybrid deep learning: replace intensive calculations by learned representations
- Current results show advantages over purely data-driven deep learning
- An emerging topic - much room for improvement!

Research Group Artificial Intelligence and Sparse Modelling – GAIM





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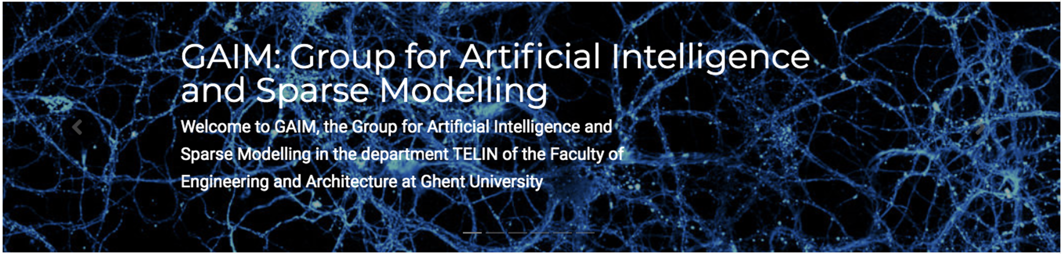
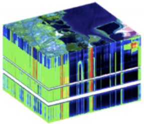
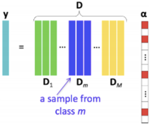
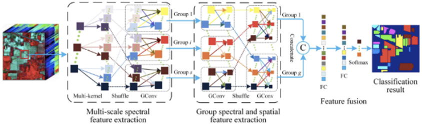


Sparse modelling in high-dimensional data analysis





Deep learning in sensor fusion and HSI analysis



Signal & image processing – machine learning – information theory