Learning efficient data representation

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SimulaMet

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The Research Council of Norway

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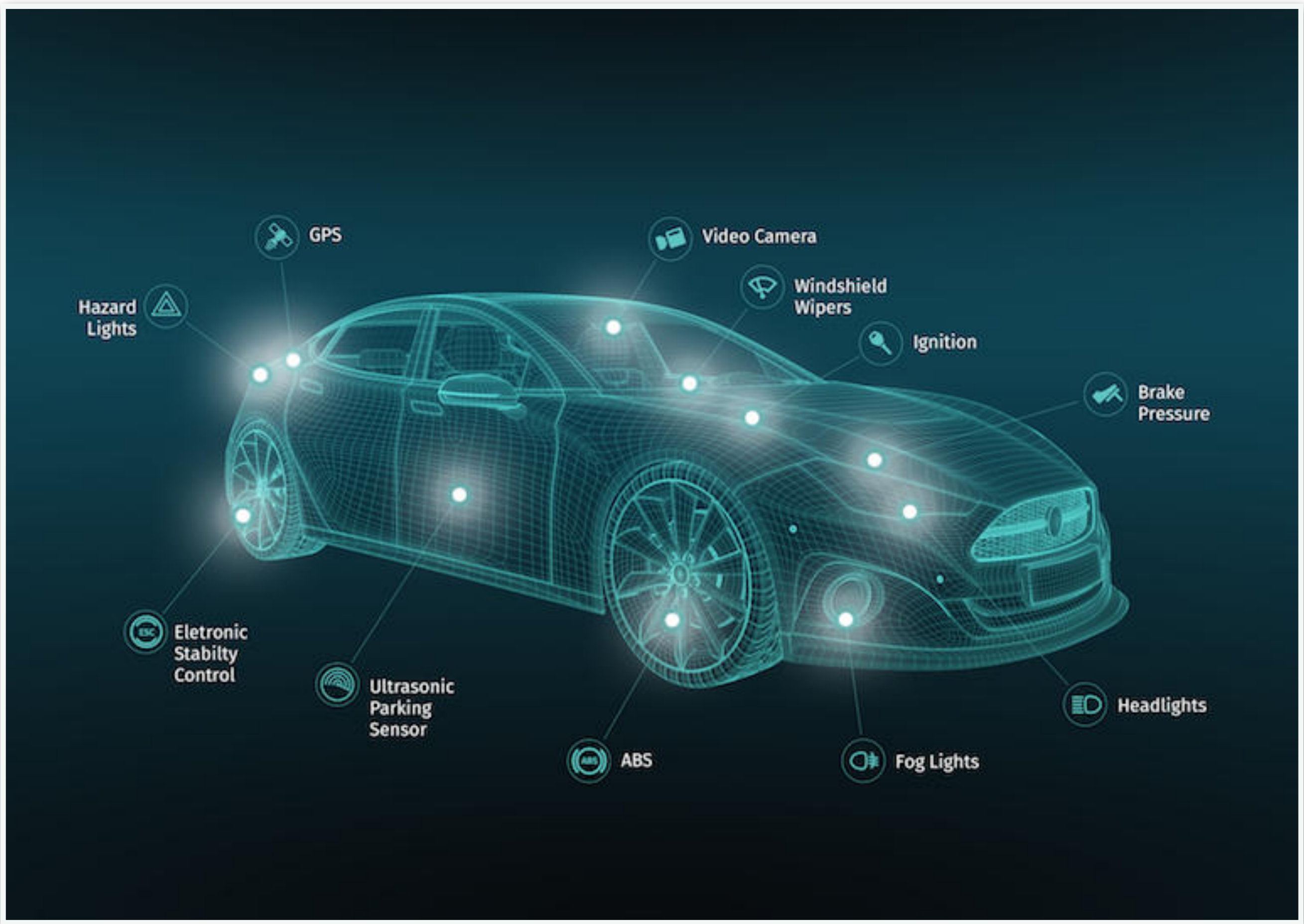

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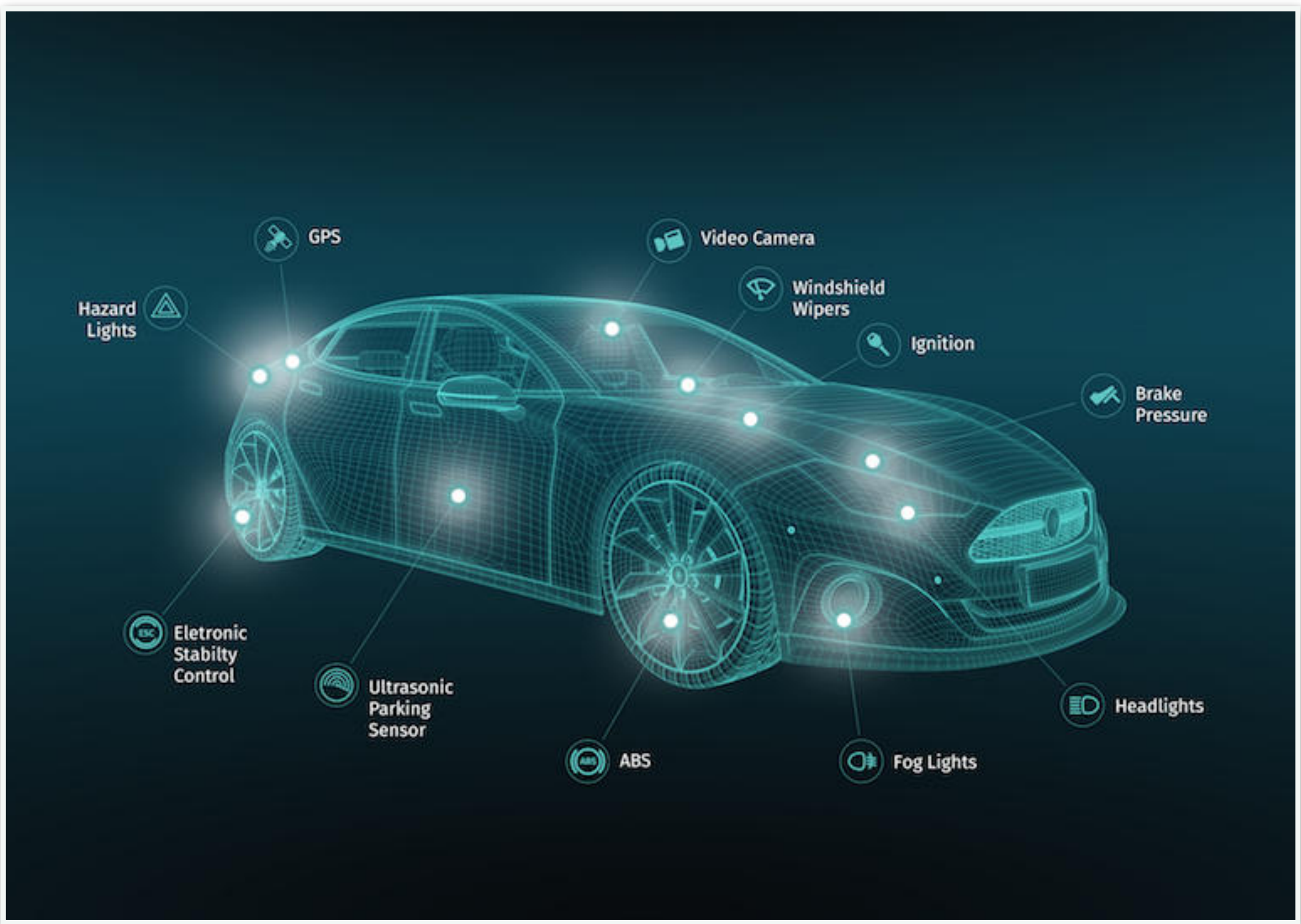

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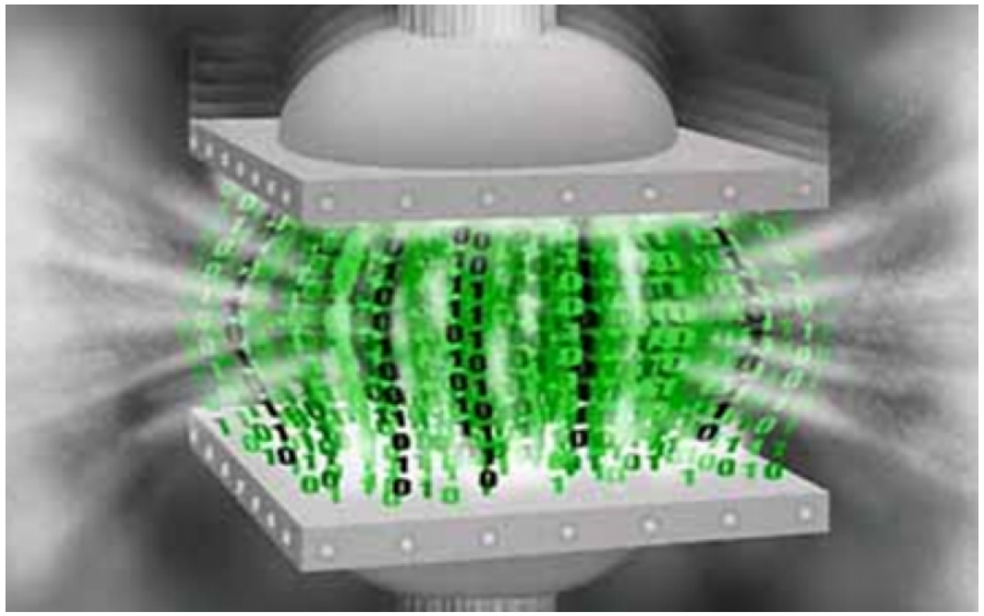

Compression

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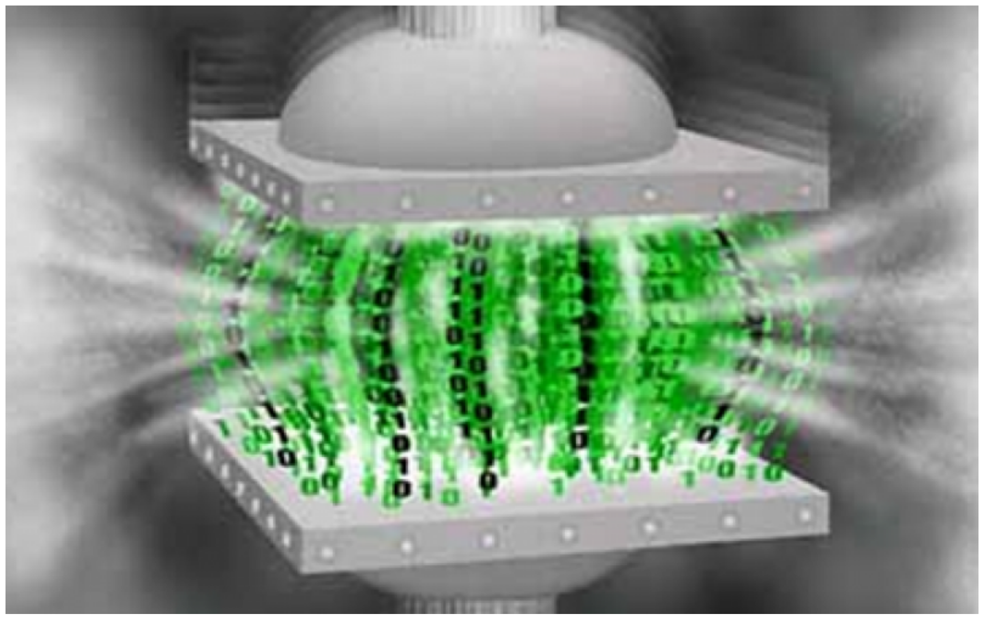

Compression

Segmentation

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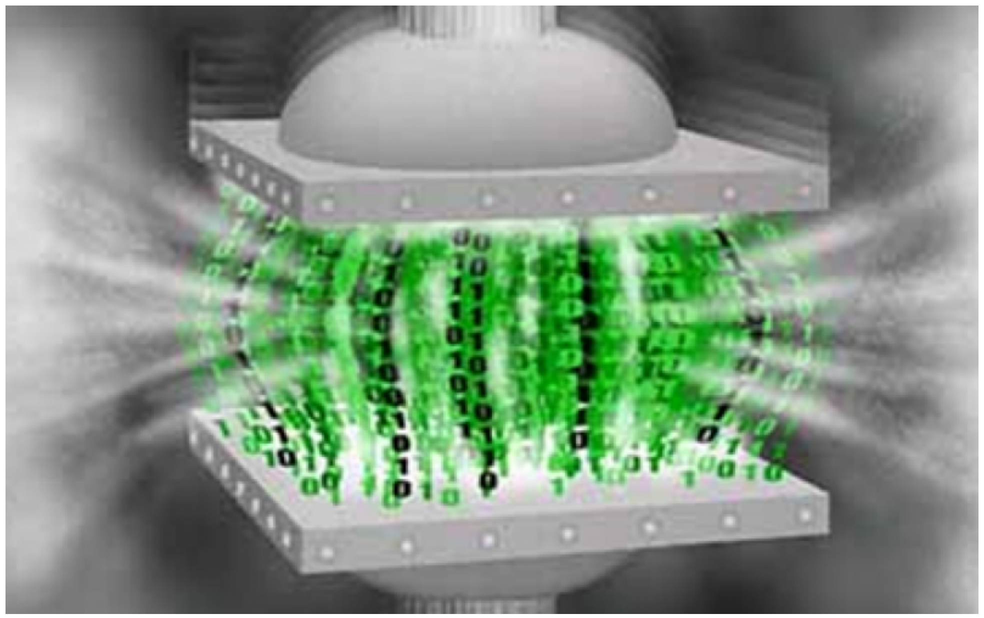

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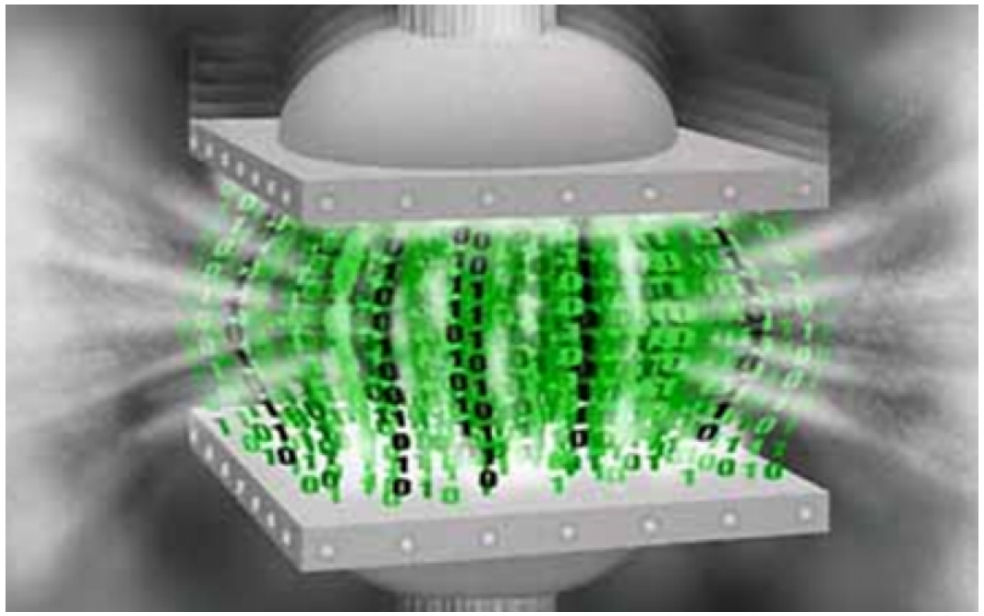

Compression

Segmentation

Prediction

Classification

Recent advances in modern signal processing are based on the fact that high-dimensional data follows a low complexity model

What is sparsity?

Sparsity implies many zeros in a vector or a matrix

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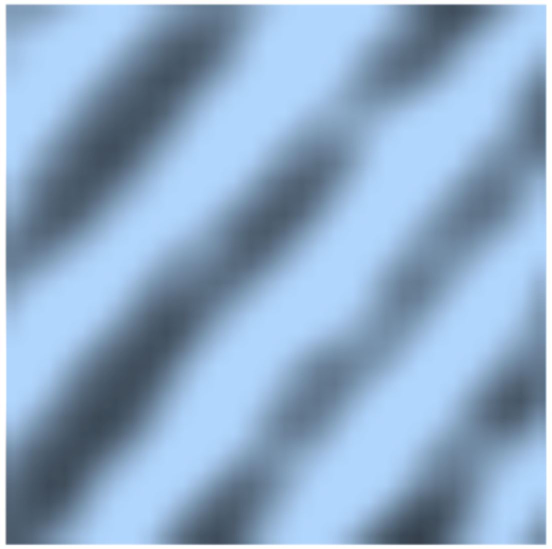

Fingerprint patch

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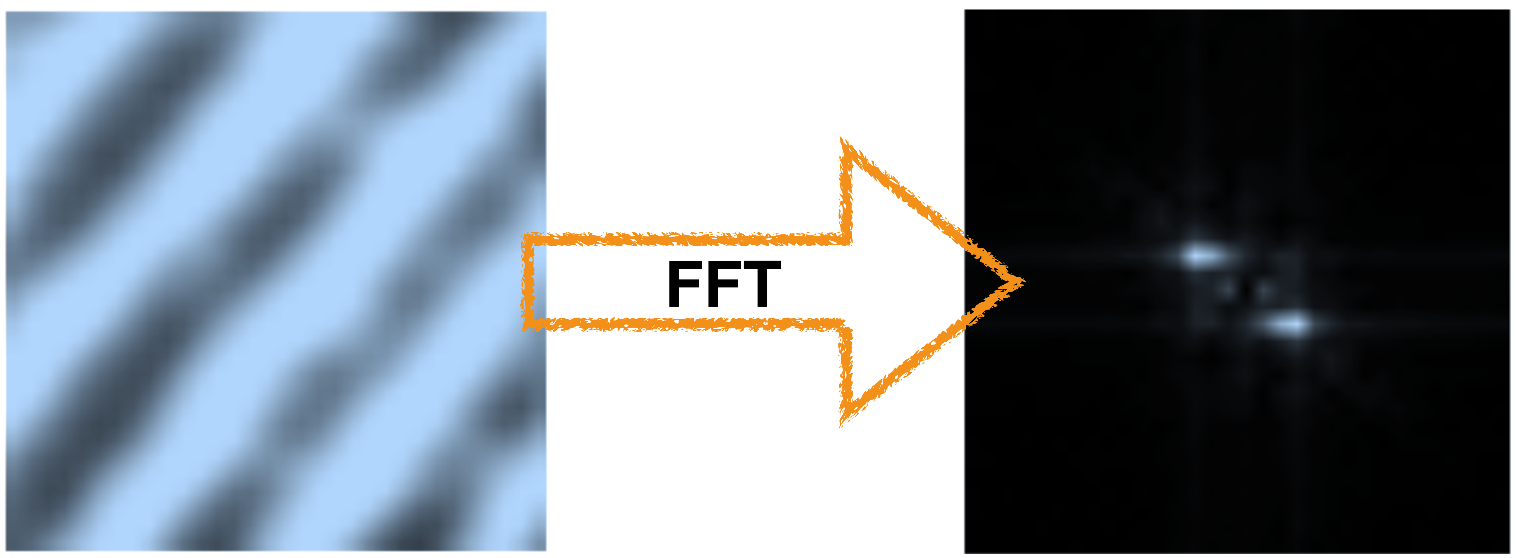

Fingerprint patch **FFT response**

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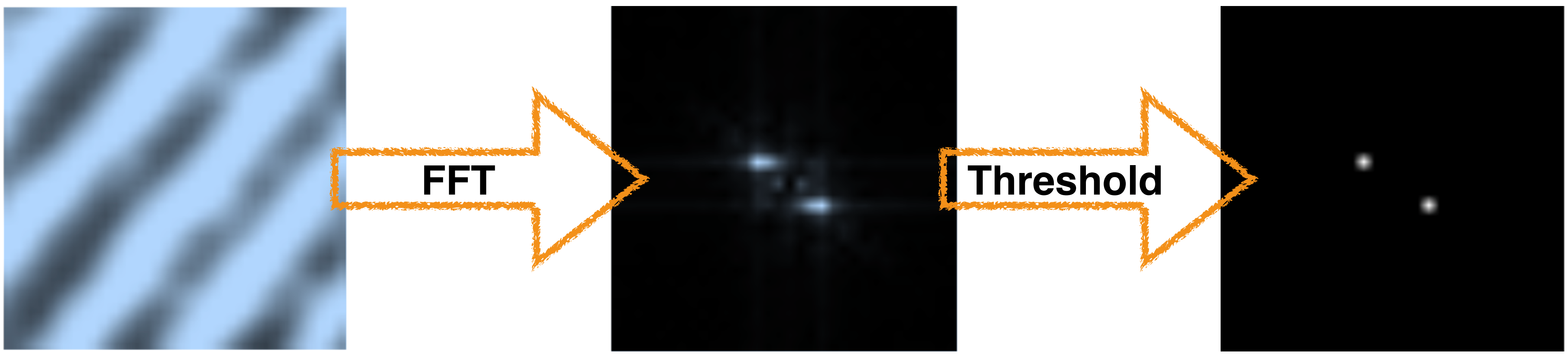

Fingerprint patch FFT response Sparse representation

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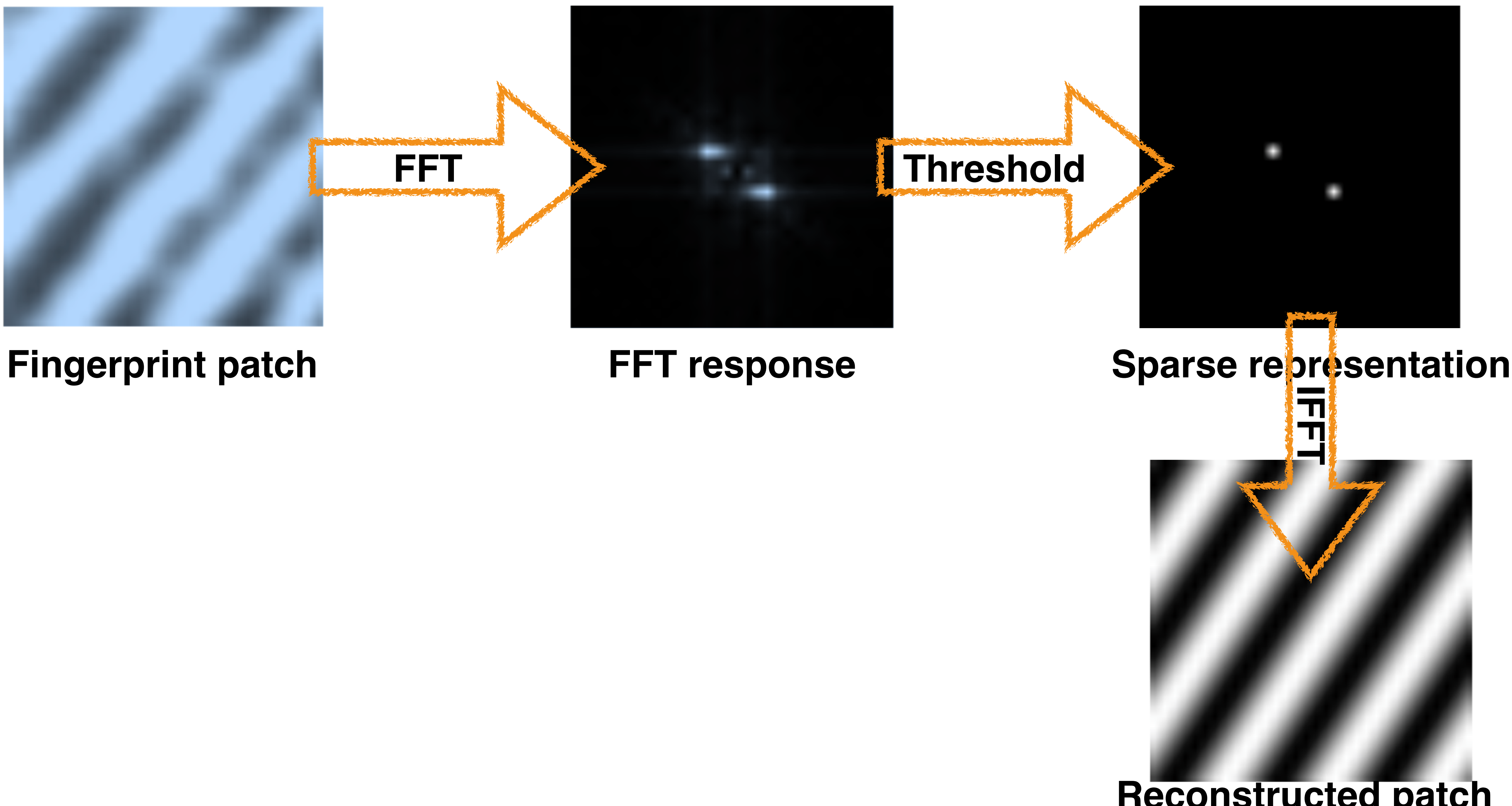

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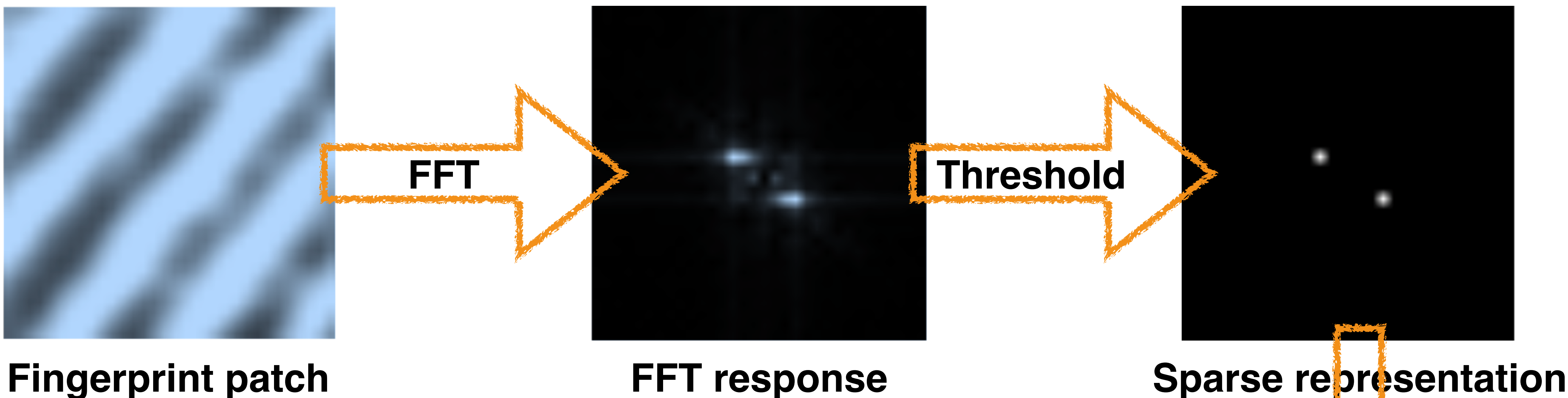

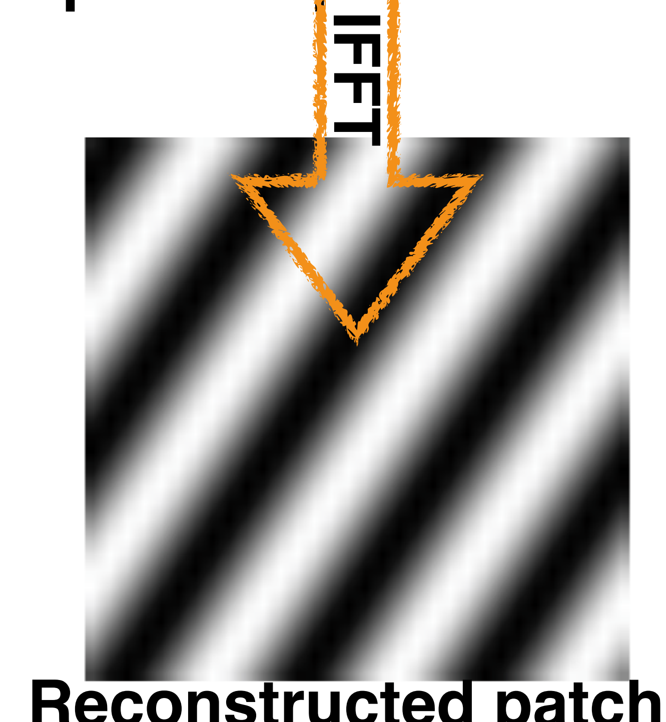

Main idea:
Sparse representation captures the essential information in a signal

Are images sparse?

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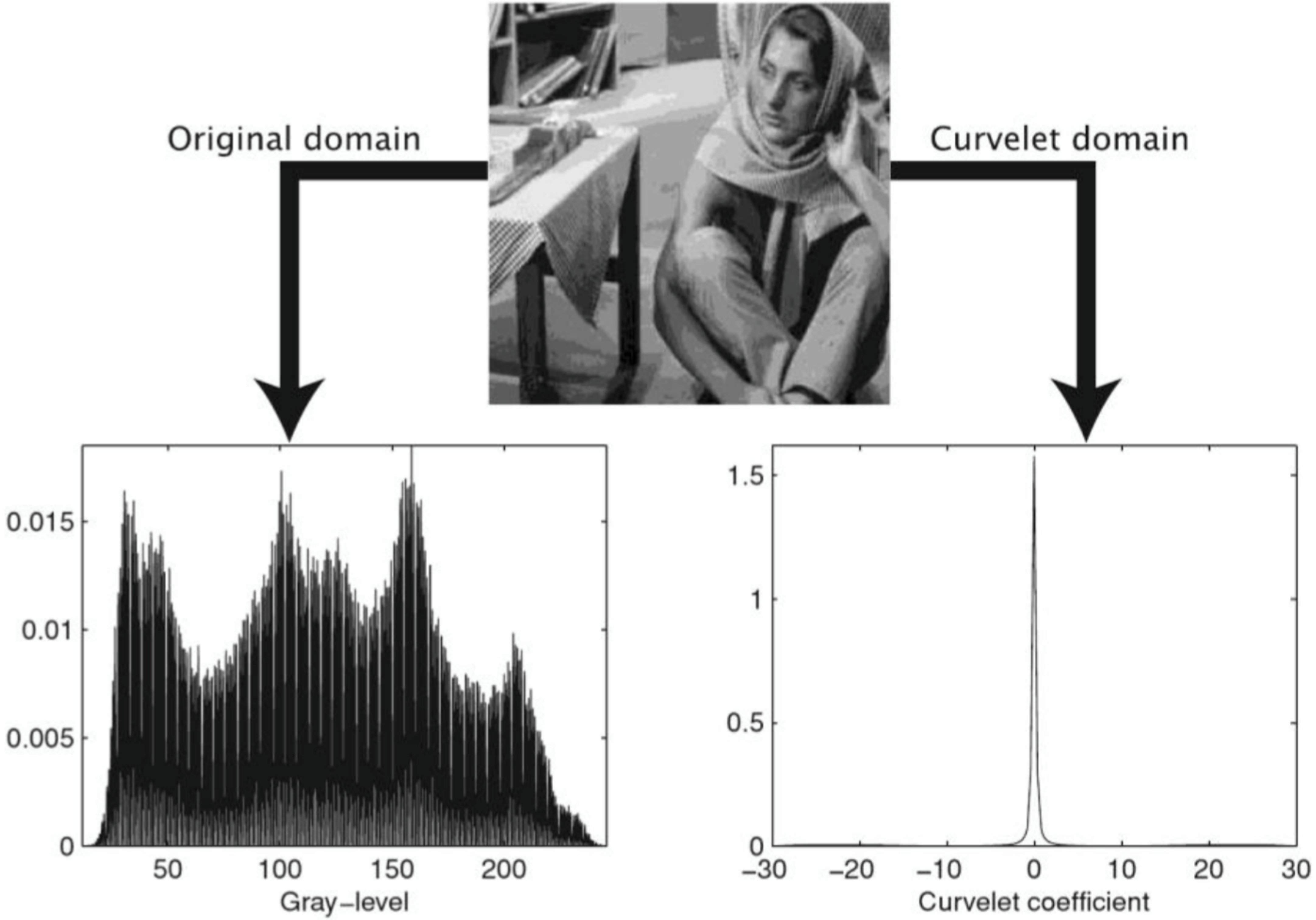
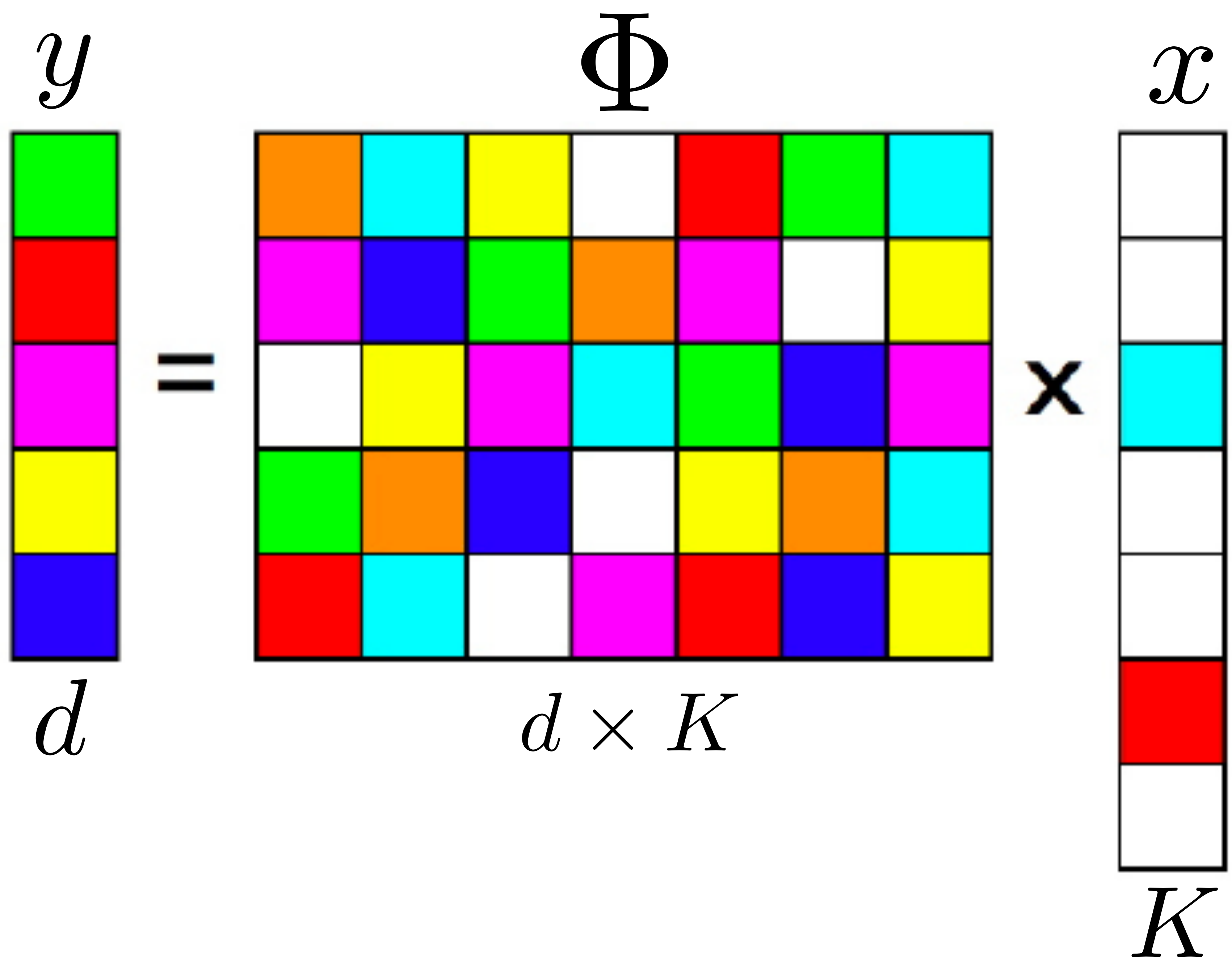


Natural signals are often high-dimensional that can be well represented by a small (sparse) number of elementary signals



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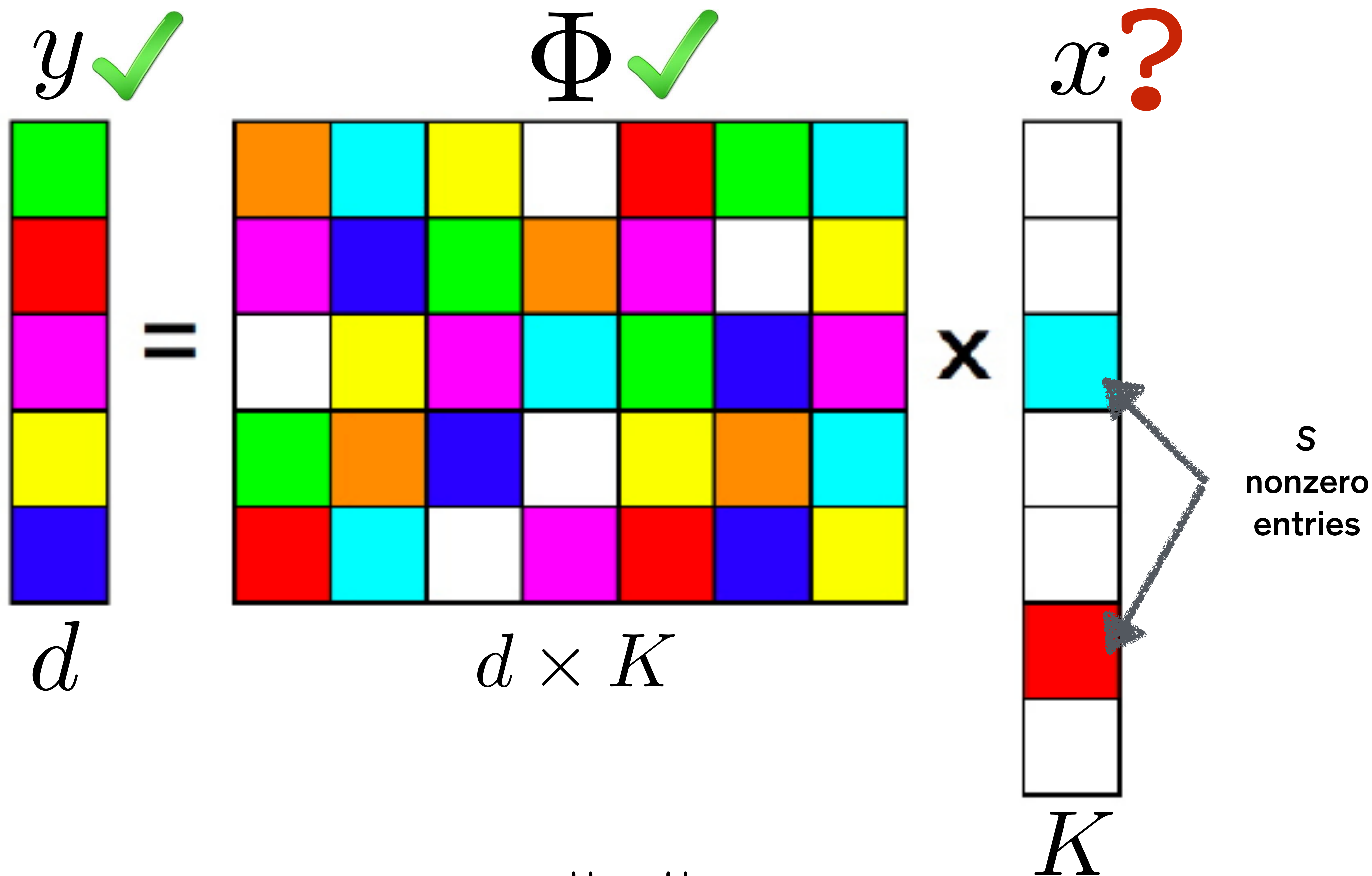
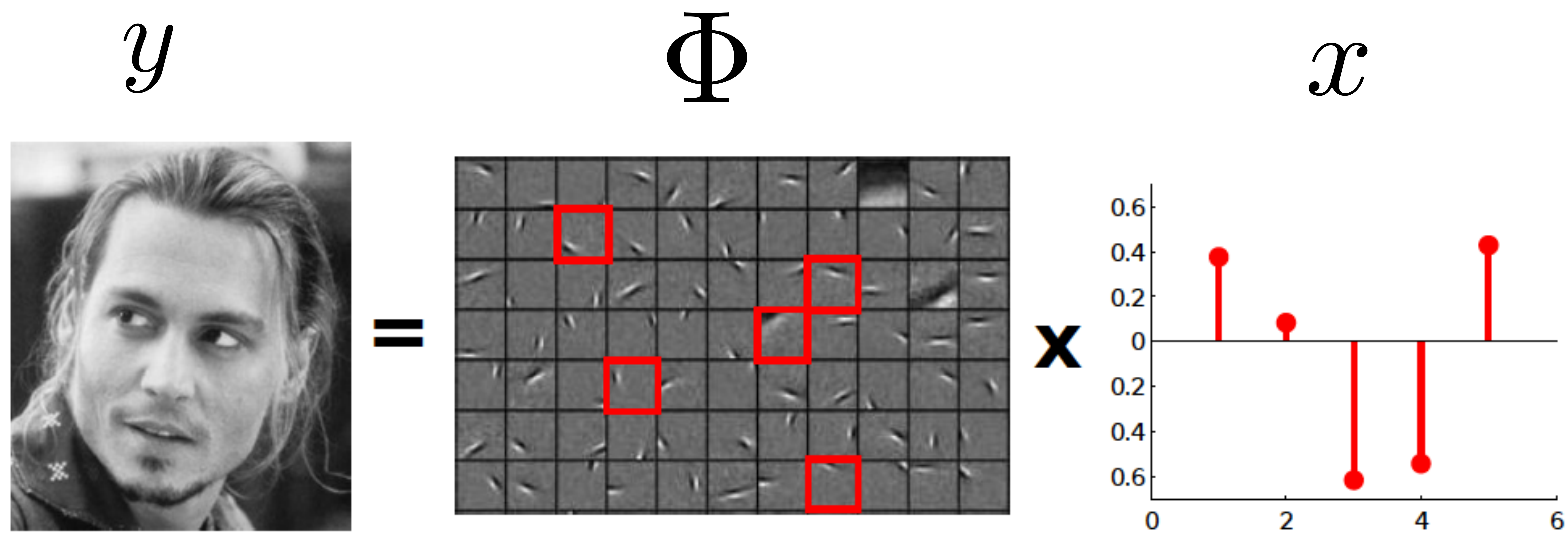


$$y = \Phi x, \|x\|_0 \ll d$$

A 'well-learned' dictionary allows to represent every signal of a class using only a small (sparse) number of atoms



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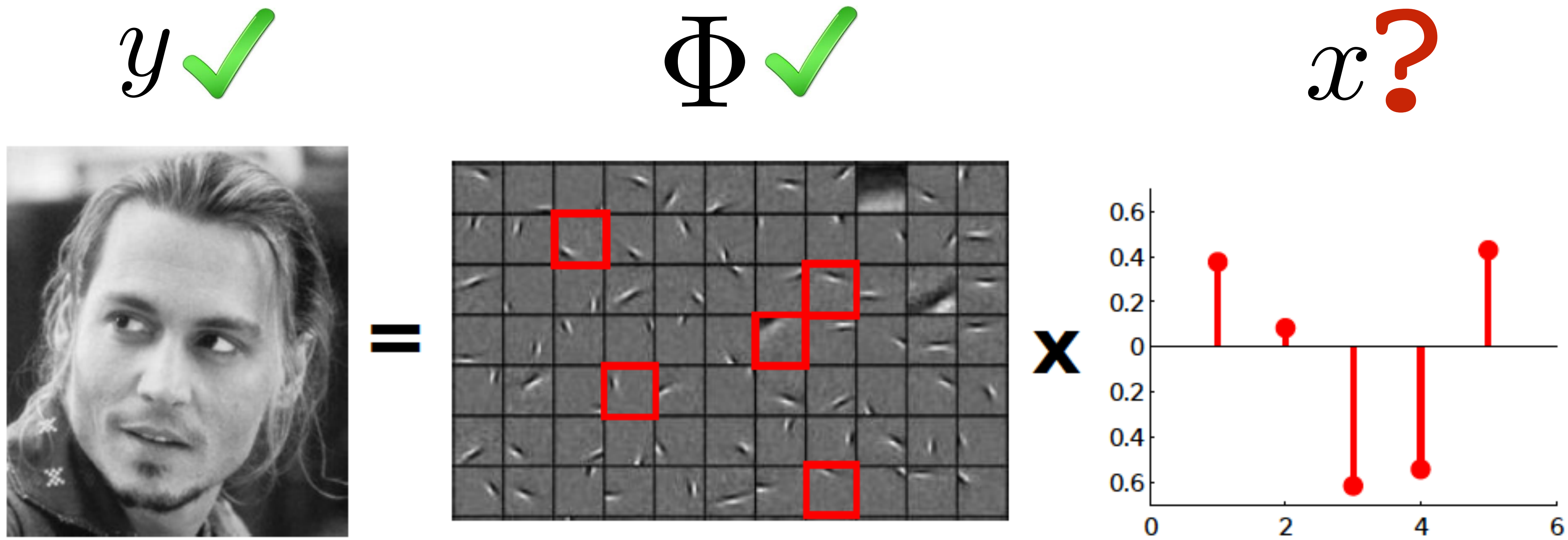

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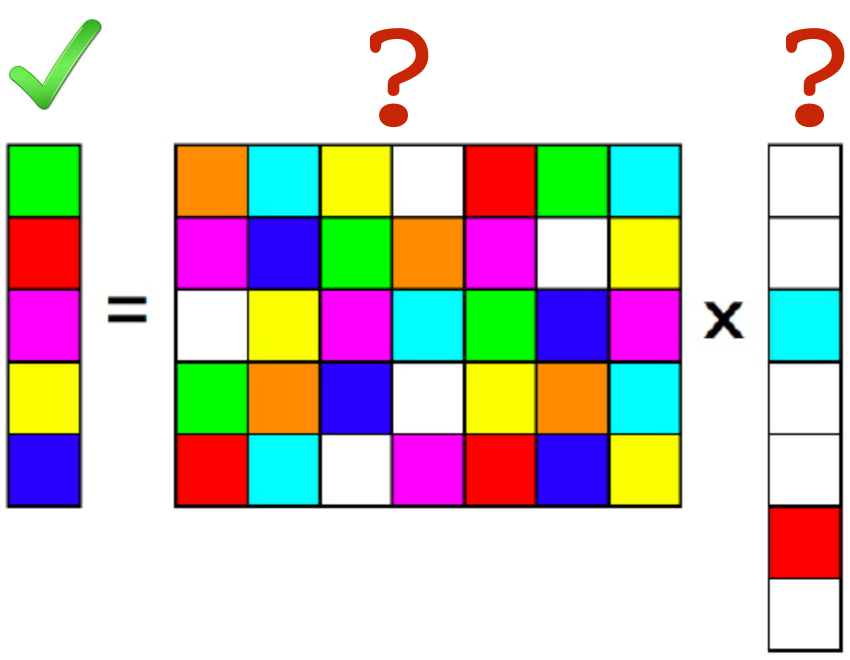
Data-driven dictionary learning:
[Olshausen and Field, 1997], [Engan et al., 1999], [Aharon et al., 2006] , [Roth and Black, 2005], [Lee et al., 2007], [Gribonval and Schnass, 2010], [Starck et al., 2013], [Schnass, 2015],....



$$\min_{x_n, \Phi \in \mathcal{C}} \sum_n \underbrace{\frac{1}{2}\|y_n - \Phi x_n\|^2}_{\text{reconstruction}} + \underbrace{\alpha\psi(x_n)}_{\text{sparsity}}$$

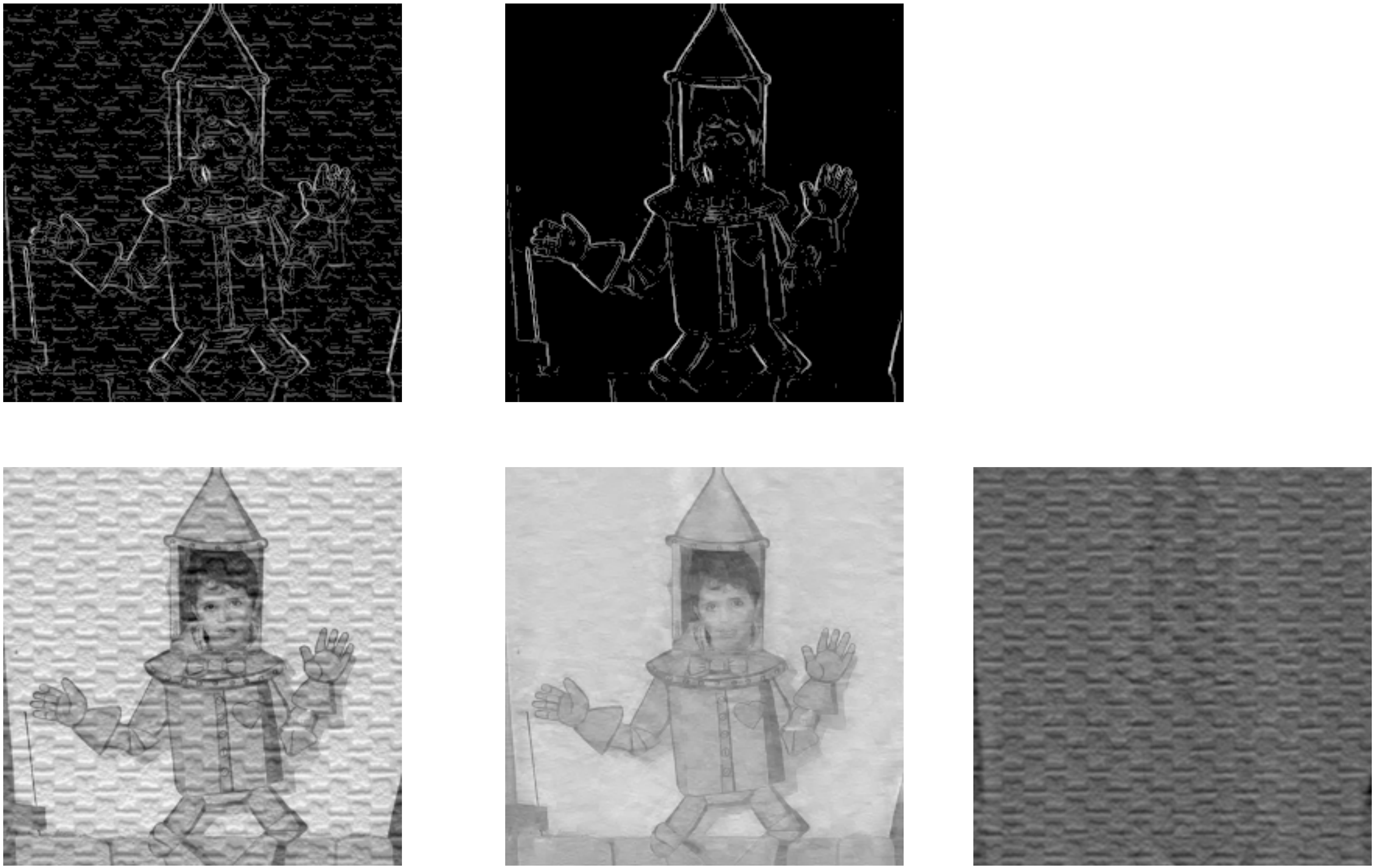
- $\psi(x) = \|x\|_0$
- $\psi(x) = \|x\|_1$

Dictionary learning has been successfully used in a number of applications like compression

RMSE is shown in brackets

[O. Bryt, M. Elad, 2008]

Dictionary learning has been successfully used in a number of applications like edge detection and texture separation

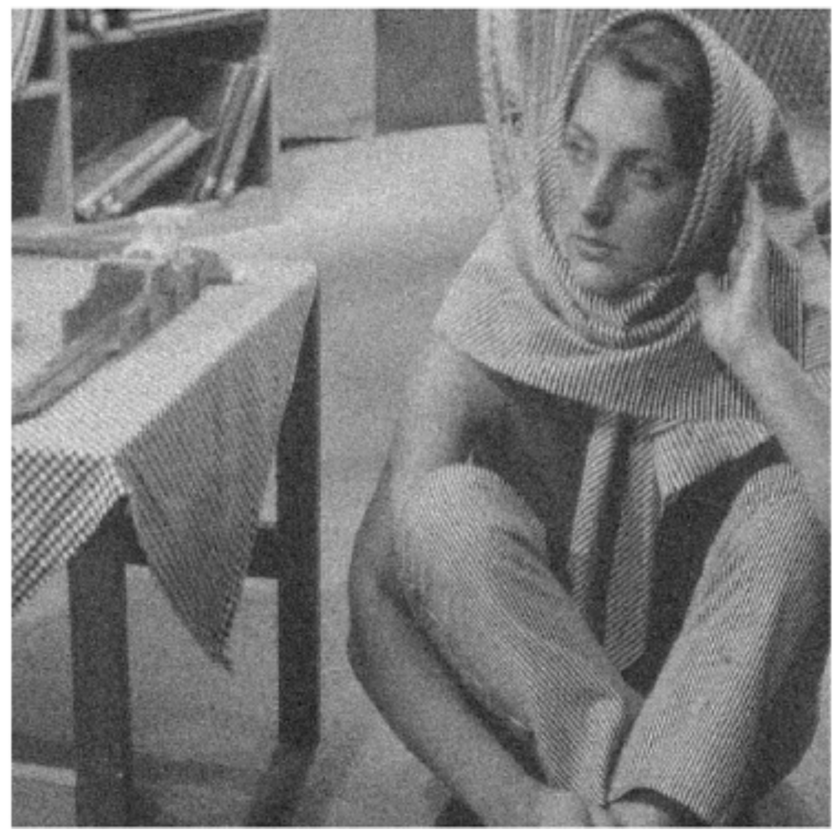


[JL Starck et al., 2010]

Dictionary learning has been successfully used in a number of applications like denoising

Original Image

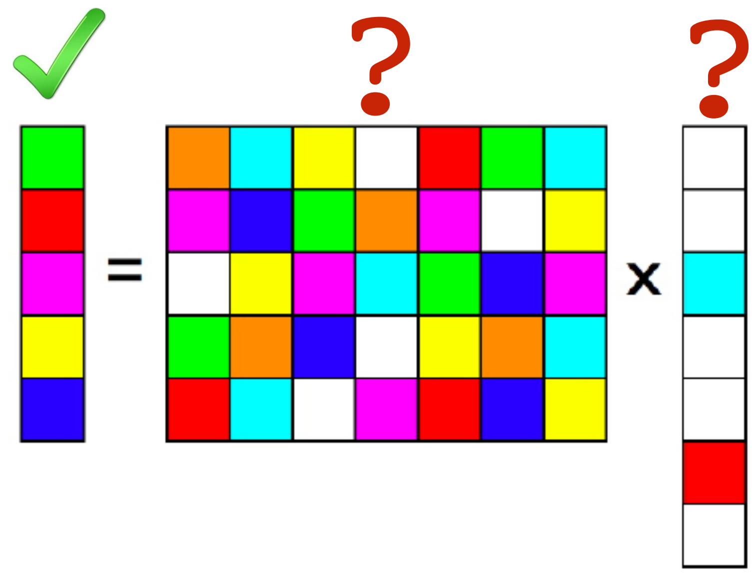
Noisy Image (22.1307 dB, σ=20)



Denoised image (30.83 dB)

[M. Elad, M. Aharon, 2006]

Dictionary learning delivers good results BUT only when a large number of clean high-quality signals is available



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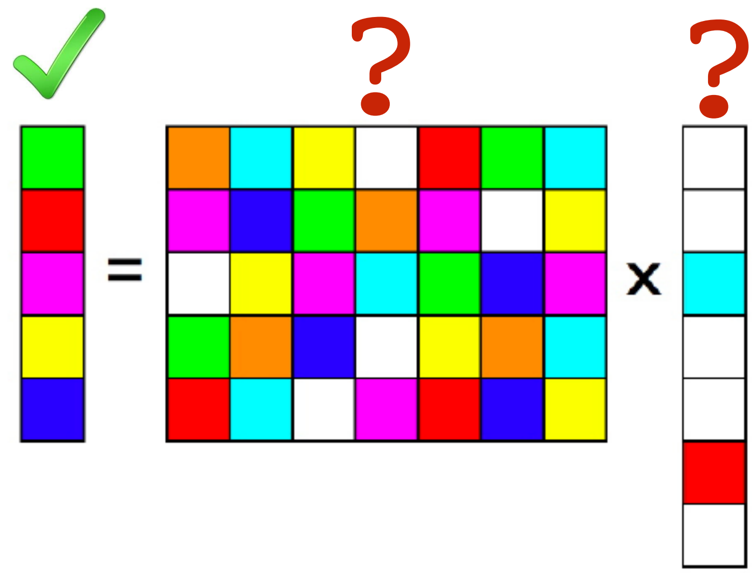

Dictionary learning:

☑ delivers state-of-the-art results for many image/video processing task.

☑ is well adapted to data that admits sparse representation.

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- are **computationally demanding.**

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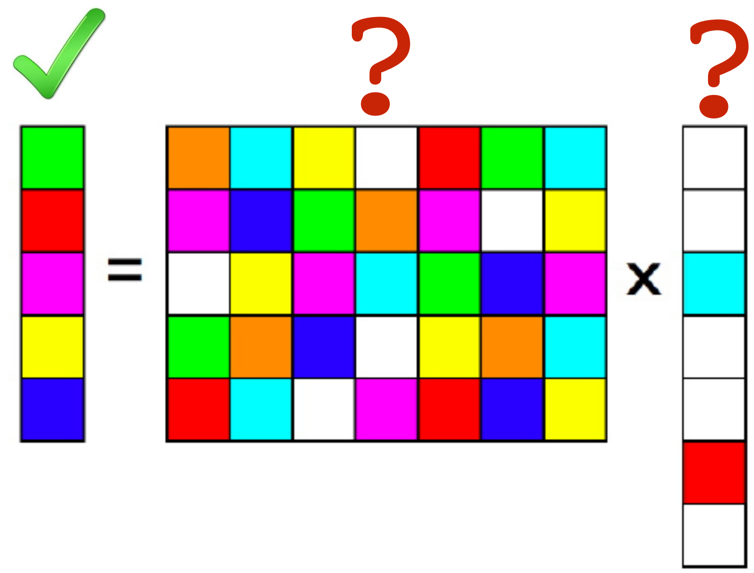

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Limited applicability for high-dimensional data.

Limited applicability for real-life sensor data.

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- ITKrMM algorithm demonstrates ***significant improvement in terms of computational complexity*** compared to the state-of-the-art methods.

ITKrMM algorithm has the same reconstruction quality as the state-of-the-art method

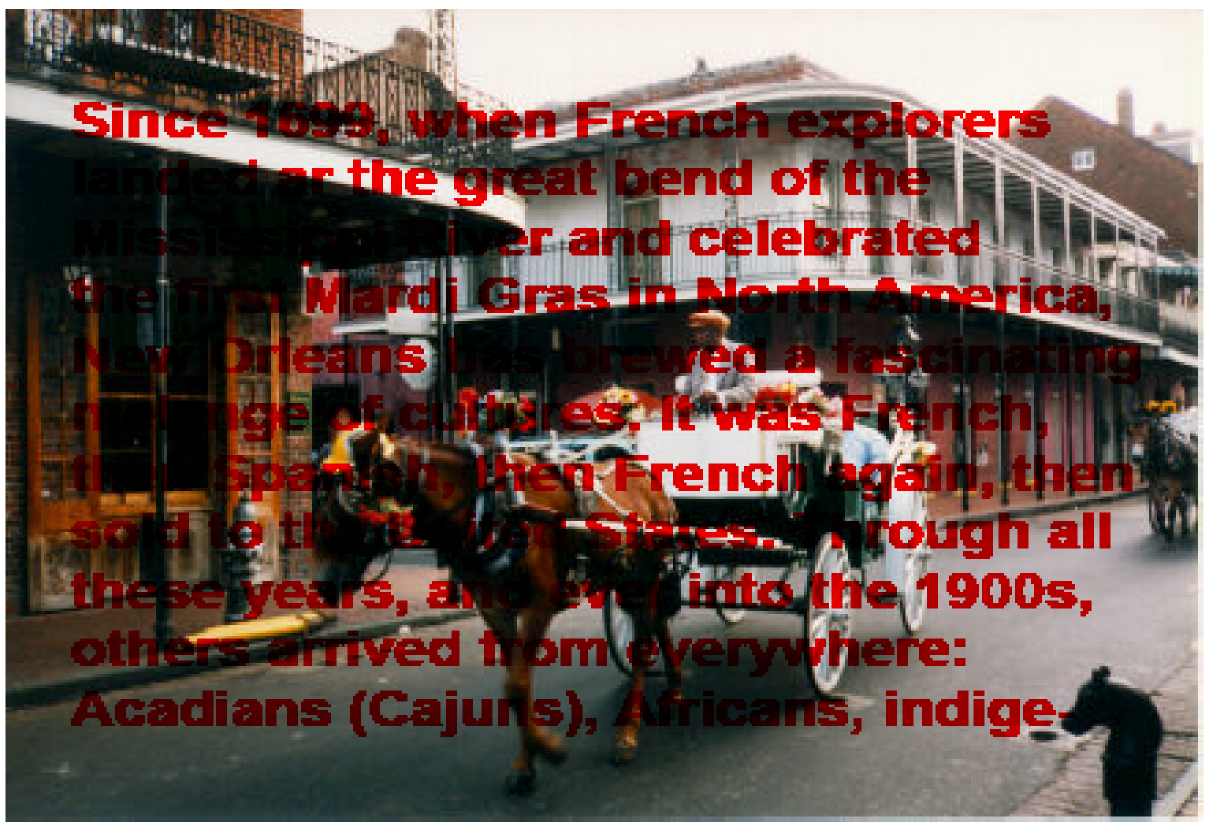

Image corrupted with the text

Recovered image with ITKrMM dictionary

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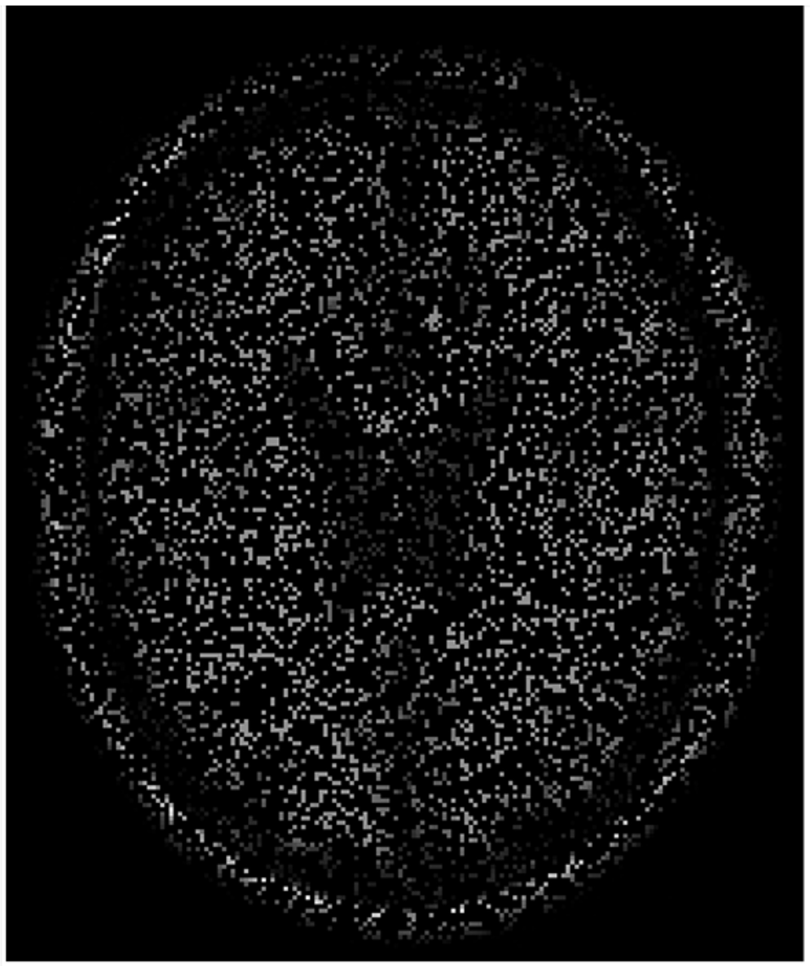
Corrupted image with 70 % missing data

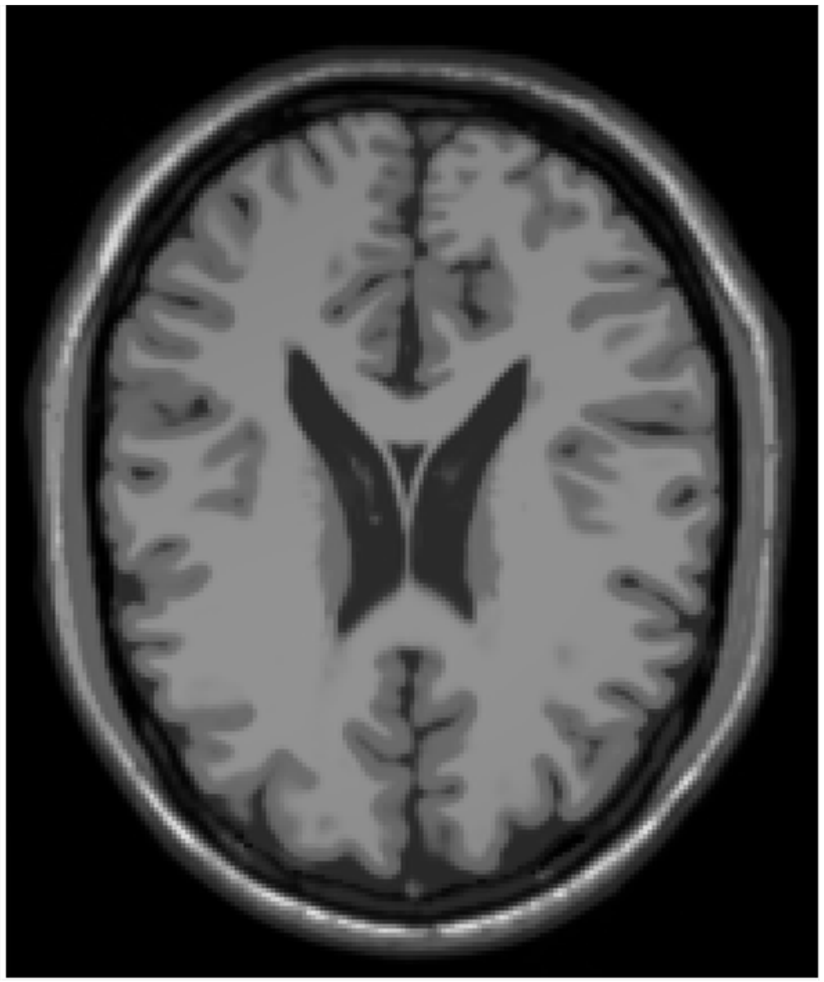
Ground truth

Recovered image with ITKrMM dictionary

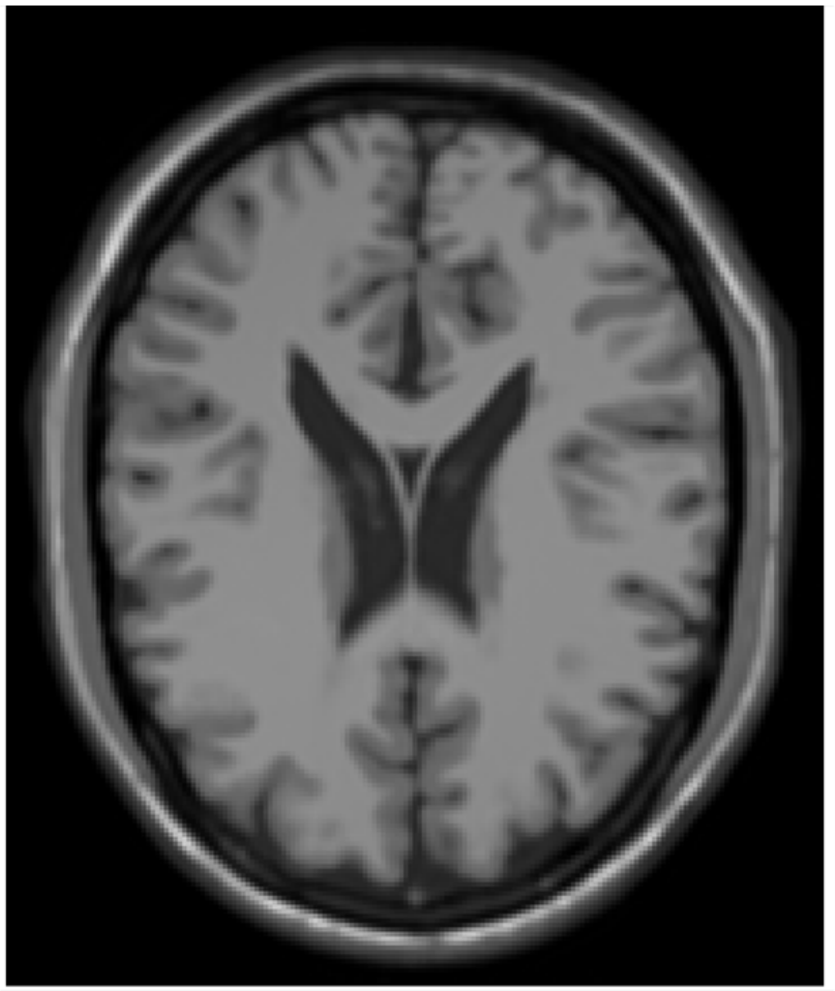
Good performance and reasonable complexity of ITKrMM also valid for 3D image inpainting



MRI volume with 80 % missing voxels



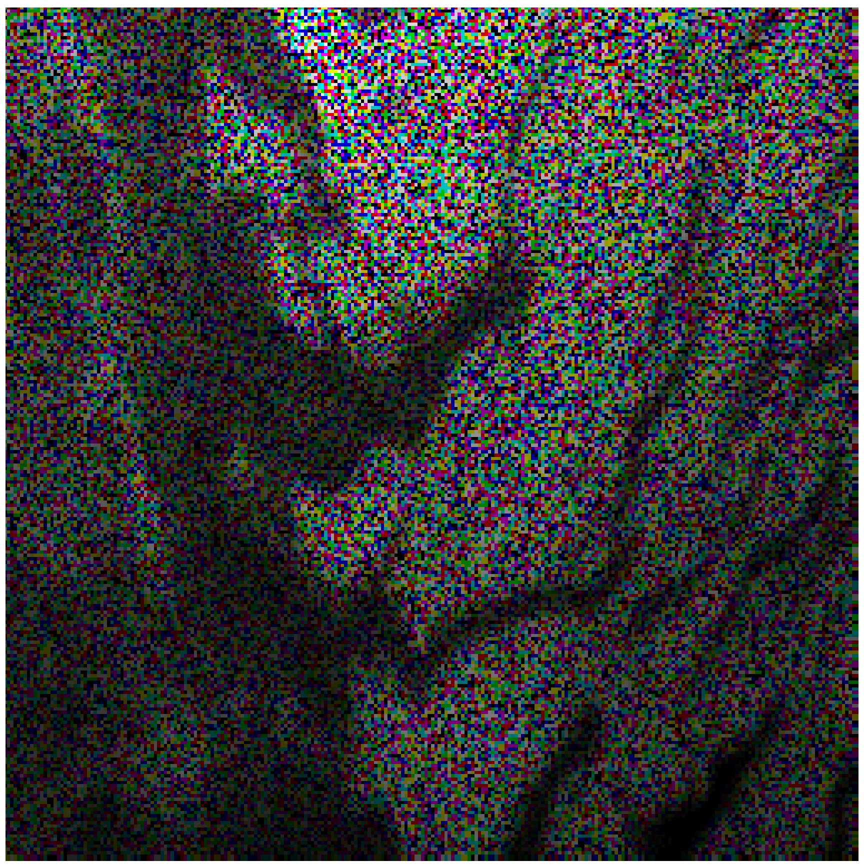
MRI volume of size 217×181×181



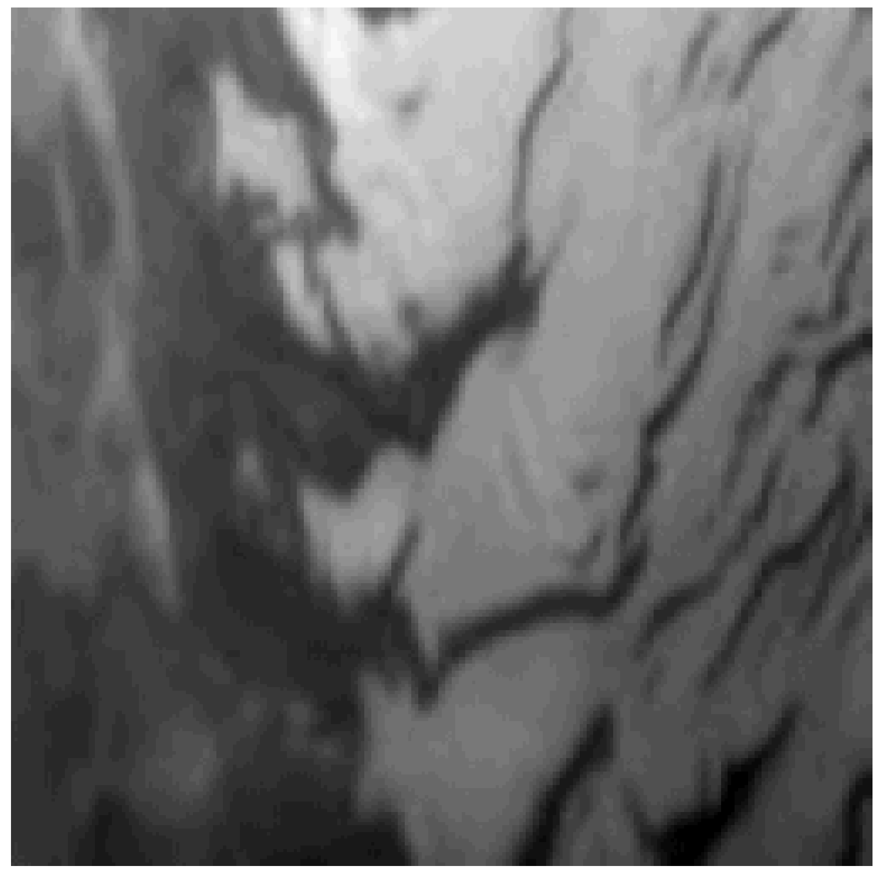
Recovered image with the ITKrMM dictionary

Synthetic cerebral MRI volumes available from BrainWeb

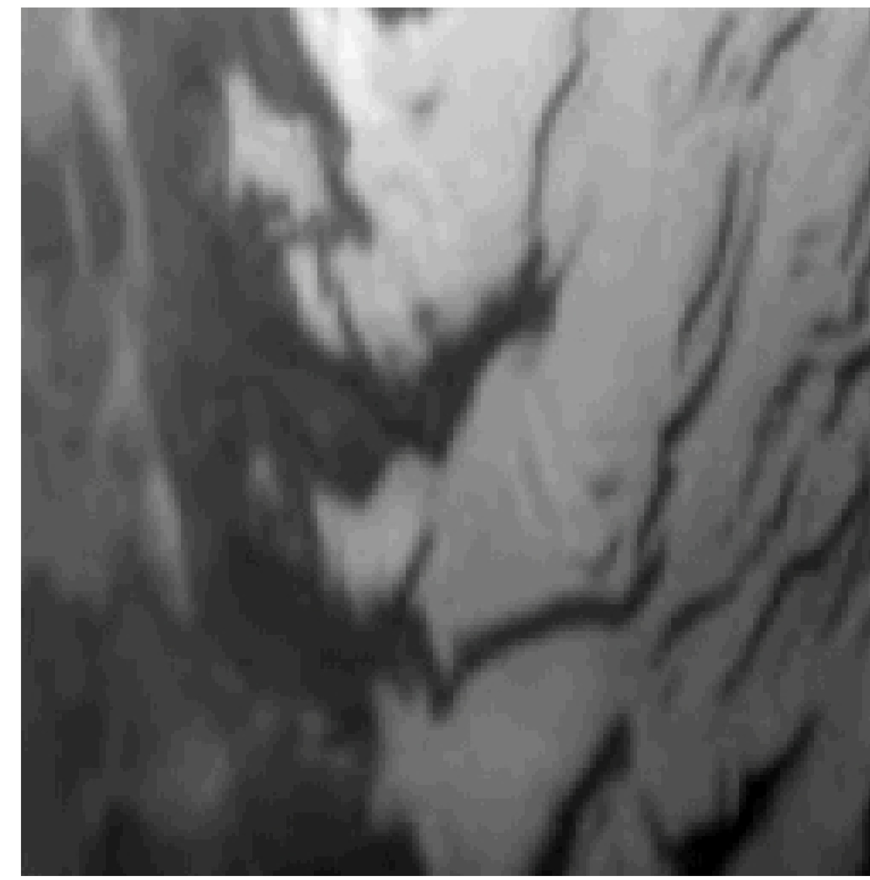
Good performance and reasonable complexity of ITKrMM also valid for hyperspectral image inpainting



Hyperspectral data with 50 % missing pixels



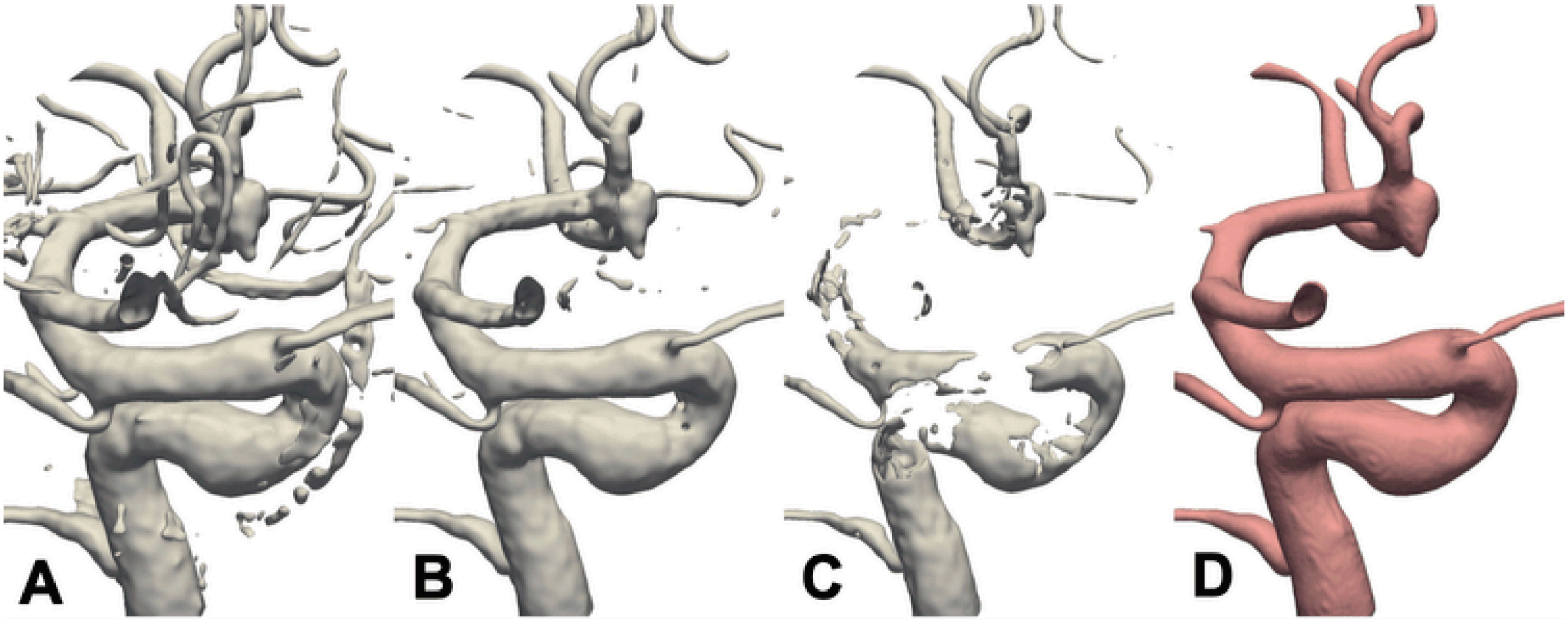
Hyperspectral data from Mars Observer, 128×128×64



Spatial recovery with the ITKrMM dictionary

Hyperspectral data available from Mars observer

Good performance of ITKrMM for medical image denoising and segmentation



Extracted brain blood vessels from the CT image with manual segmentation (A-C) and automatic ITKrMM-based segmentation (D)

Images from P.M. Florvaag Master Thesis, 2018

Thanks to

Karin Schnass, Uni Innsbruck

Jean-Luc Starck, CosmoStat CEA

Massimo Fornasier, TU Munich

Simula will contribute to the NORA activities with two PhD positions in AI