A Completion Network for Reconstruction from Compressed Acquisition

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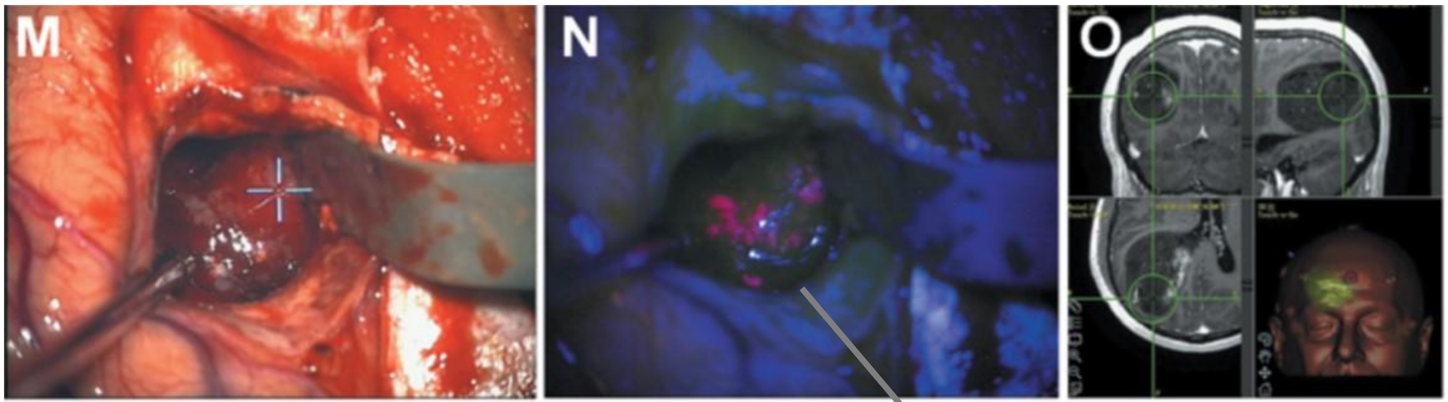
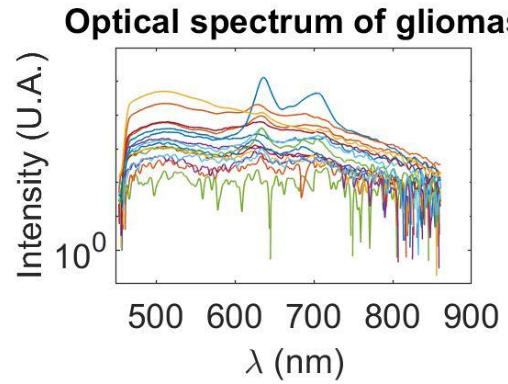
MEDICAL APPLICATION

- **Fluorescence-guided neurosurgery**
  - Protoporphyrin IX (PpIX) fluorescence

P. Valdés *et al.*, J. Neurosurgery, **123**(3), 2015



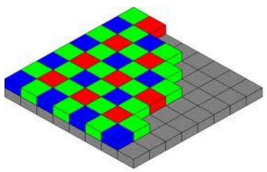


- **Full spectrum acquisition**
  - Better **detection** of tumor **margins**
    [P. Valdés et al., JNS, **123**(3), 2015]
    [P. Leclerc et al., Sci Reports **10**, 2020]

HYPERSPECTRAL IMAGING

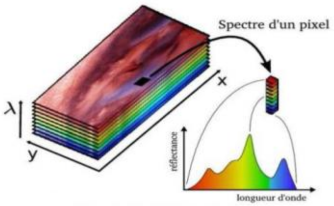
Array

Colour



Multi-spectral

Hyper-spectral



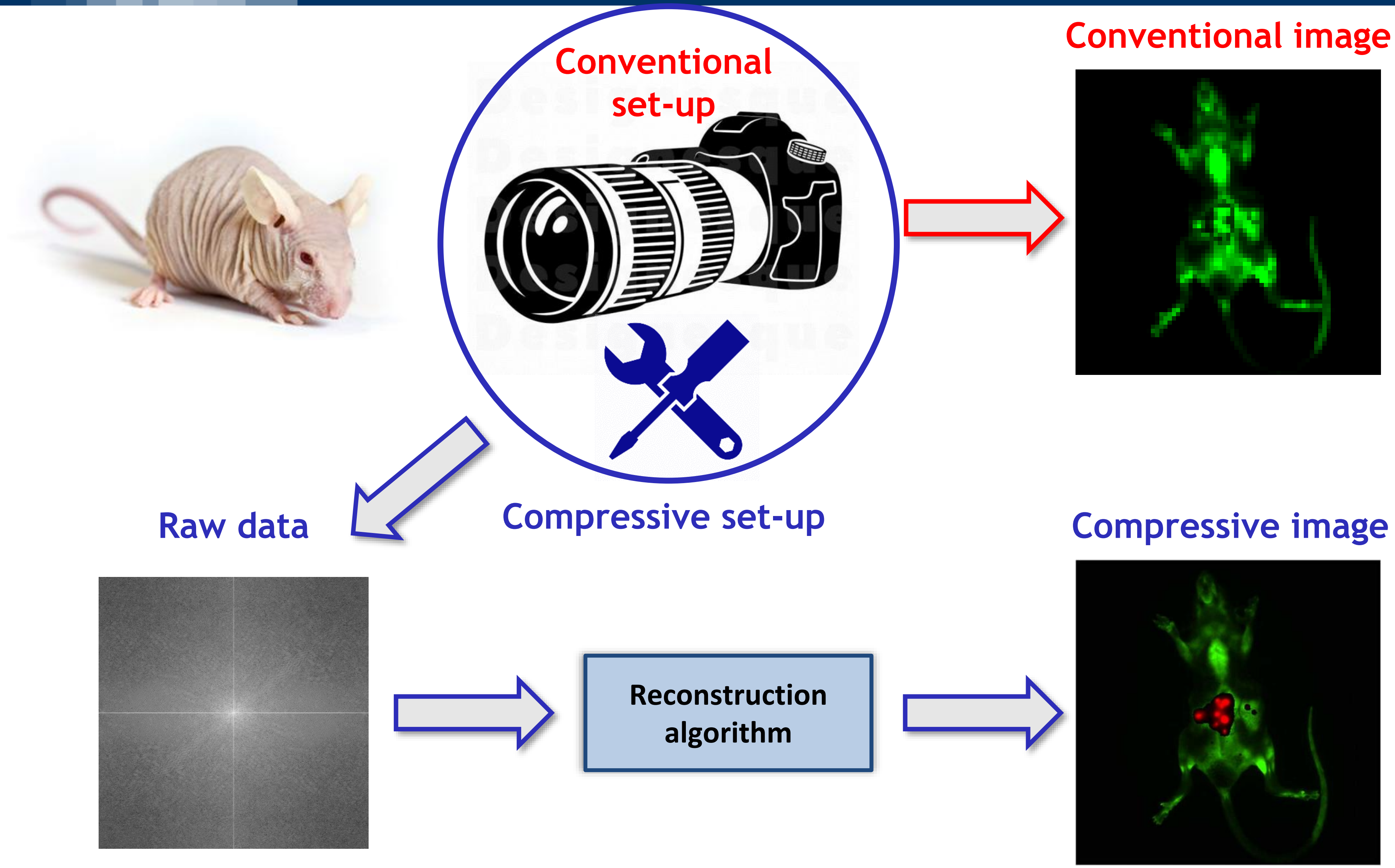
Point

Spectrometer

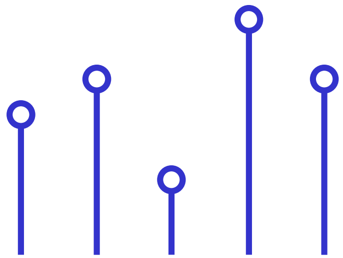
	Colour	Multi-spectral	Hyper-spectral	Spectrometer
Spatial resolution	yes	yes	yes	no
Number of spectral channels / *Spectral channels*	3	2—10	10—100	100—2,000
Cost	~€1k	~€10k	~€100k	~€1k

Need for **low-cost array** with **high spectral** resolution

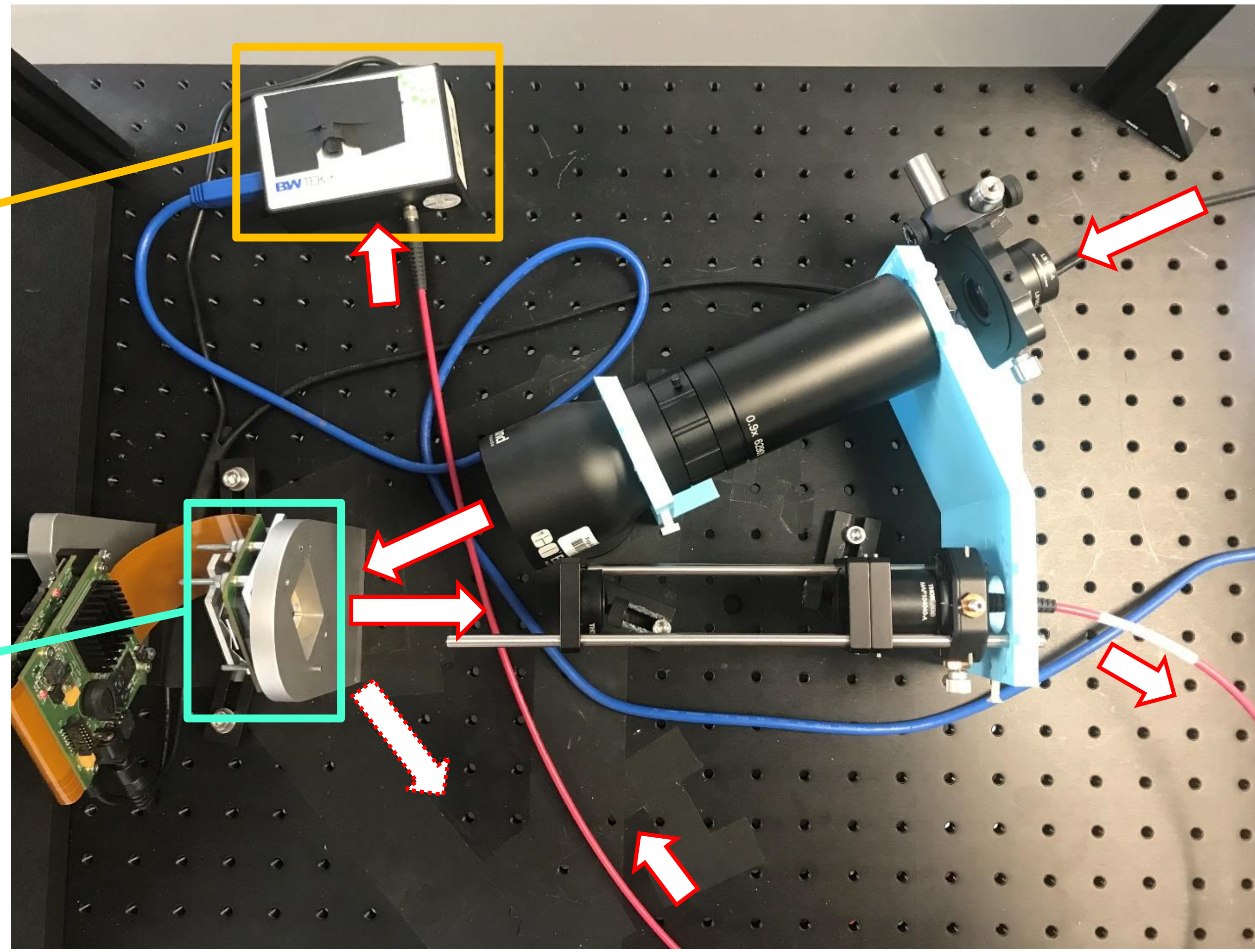
COMPRESSIVE OPTICS

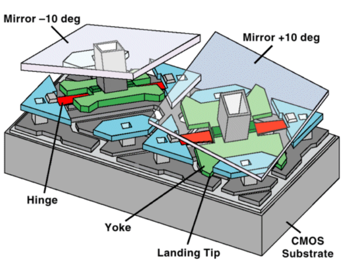


COMPRESSIVE (SINGLE-PIXEL) CAMERA

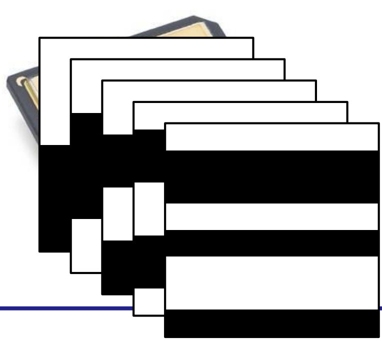


Point detector (spectrometer)

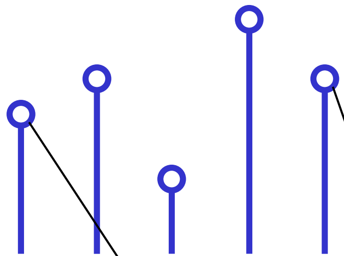




Spatial light modulator



ACQUISITION MODEL

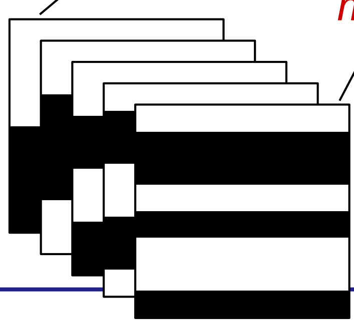


Point detector (spectrometer)

$$\boldsymbol{m} = [m_1, \ldots, m_M]^\top \in \mathbb{R}^M$$

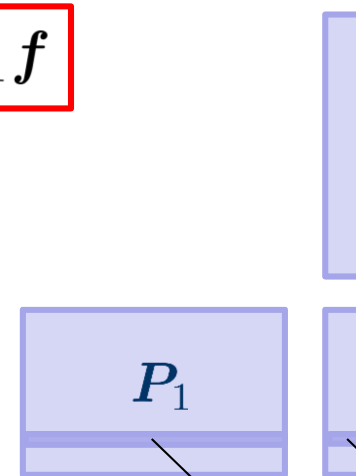
$$\boldsymbol{P}_1 = [\boldsymbol{p}_1^\top, \ldots, \boldsymbol{p}_M^\top]^\top \in \mathbb{R}^{M \times N}$$

Spatial light modulator



- **Linear model**

$$\boxed{\boldsymbol{m} = \boldsymbol{P}_1 \boldsymbol{f}}$$



$\boldsymbol{f} \in \mathbb{R}^N$

$M \ll N$ $\quad \boldsymbol{P}_1 \quad$ $\boldsymbol{m} \in \mathbb{R}^M$

$\boldsymbol{p}_k^\top$ $\quad m_k$

- **Challenge**
  - A small M limits the acquisition time
  - A small M limits the image resolution too!

RECONSTRUCTION

1. **Experiment design:** How to choose the patterns (codes) P?
   Not addressed here! We choose

$$\boxed{\boldsymbol{m} = \boldsymbol{P}_1 \boldsymbol{f}}$$

$$\text{orthogonal basis} \longrightarrow \boldsymbol{P} = \begin{bmatrix} \boldsymbol{P}_1 \\ \boldsymbol{P}_2 \end{bmatrix} \begin{matrix} \longleftarrow \textbf{acquired}\text{ patterns} \\ \longleftarrow \textbf{missing}\text{ patterns} \end{matrix}$$

2. **Reconstruction:** How to recover the image ***f*** from ***m***?

❖ Constrained optimization

$$\min_{\boldsymbol{f}} \mathcal{R}(\boldsymbol{f}) \quad \text{such that} \quad \boldsymbol{m} = \boldsymbol{P}_1 \boldsymbol{f}.$$

- Least squares: fast but low resolution [Rousset *et. al*, IEEE TCI, 2017]
- Total variation: higher resolution but time consuming [Duarte *et. al*, IEEE SPM, 2009]

❖ CNN: Learn a nonlinear reconstructor [Higham *et. al*, Sci. Rep., 2018]

$$\boldsymbol{f}^* = \mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{m}),$$

RECONSTRUCTION AS COMPLETION (proposed)

- **The least-squares problem**

$$\min_{\boldsymbol{f}} \|\boldsymbol{f}\|_2^2 \quad \text{such that} \quad \boldsymbol{m} = \boldsymbol{P}_1 \boldsymbol{f}.$$

…has the closed-form solution

$$\boldsymbol{f}^* = \boldsymbol{P}_1^\top \boldsymbol{m}$$

… equivalent to

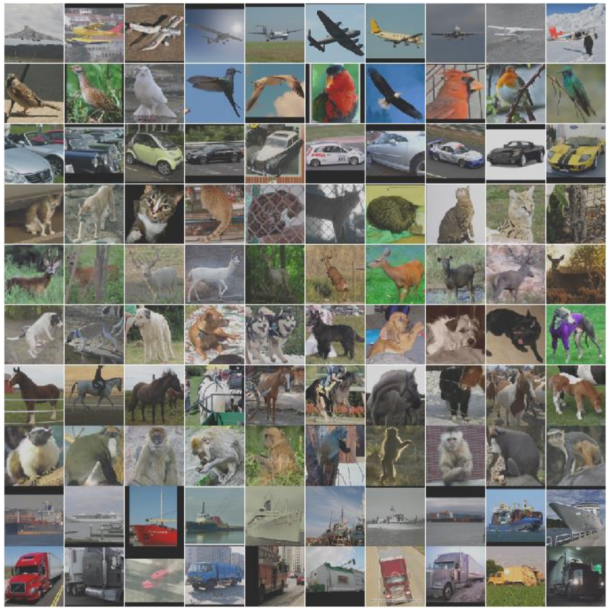
$$\boldsymbol{f}^* = \boldsymbol{P}^\top \boldsymbol{y}^*, \quad \text{with } \boldsymbol{y}^* = \begin{bmatrix} \boldsymbol{m} \\ \boldsymbol{0} \end{bmatrix} \in \mathbb{R}^N$$

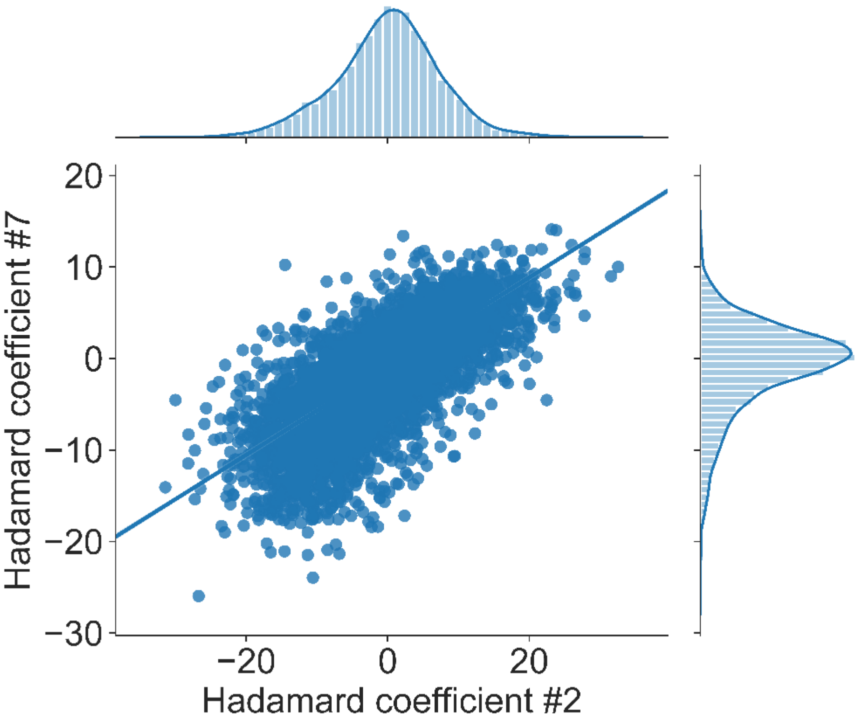
What about completing the missing measurements by relevant values?

RECONSTRUCTION AS COMPLETION (proposed)

➢ **How to complete?**

STL-10 dataset





→ Exploiting the correlation between the measured coefficients

RECONSTRUCTION AS COMPLETION (proposed)

Completion approach

$$\boxed{\boldsymbol{f}^* = \boldsymbol{P}^\top \boldsymbol{y}^*, \quad \text{with } \boldsymbol{y}^* = \begin{bmatrix} \boldsymbol{m} \\ \boldsymbol{y}_2^* \end{bmatrix},}$$

with

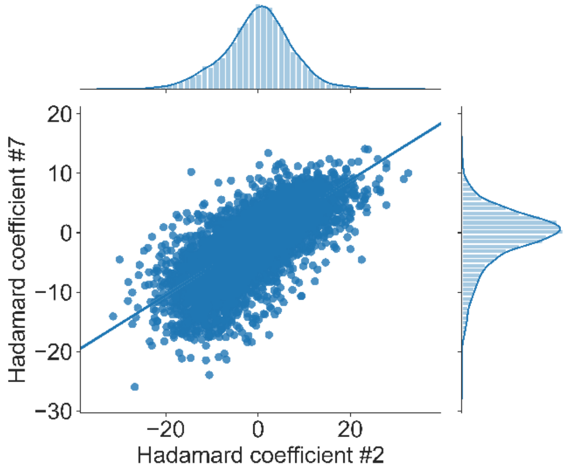
$$\boldsymbol{y}_2^*(\boldsymbol{m}) = \mathbb{E}\left(\mathbf{y}_2 \,|\, \mathbf{y}_1 = \boldsymbol{m}\right)$$

- **Under Gaussian assumptions**

$$\boldsymbol{y}_2^*(\boldsymbol{m}) = \boldsymbol{\mu}_2 + \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_1^{-1}(\boldsymbol{m} - \boldsymbol{\mu}_1)$$

Covariance between measured and missing

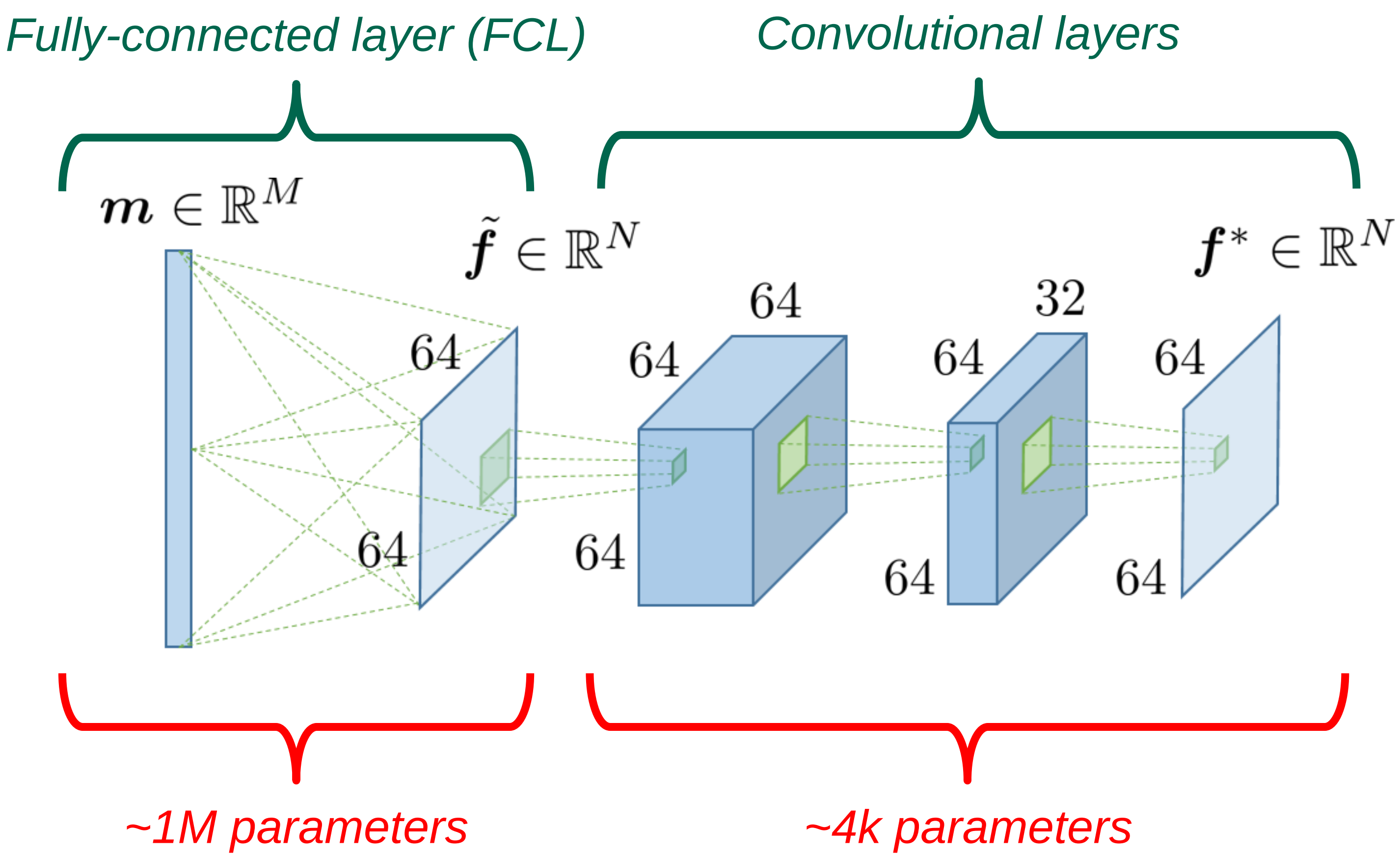
Covariance of measured



- **No assumption: This is the best linear solution!**

LEARNING-BASED RECONSTRUCTION

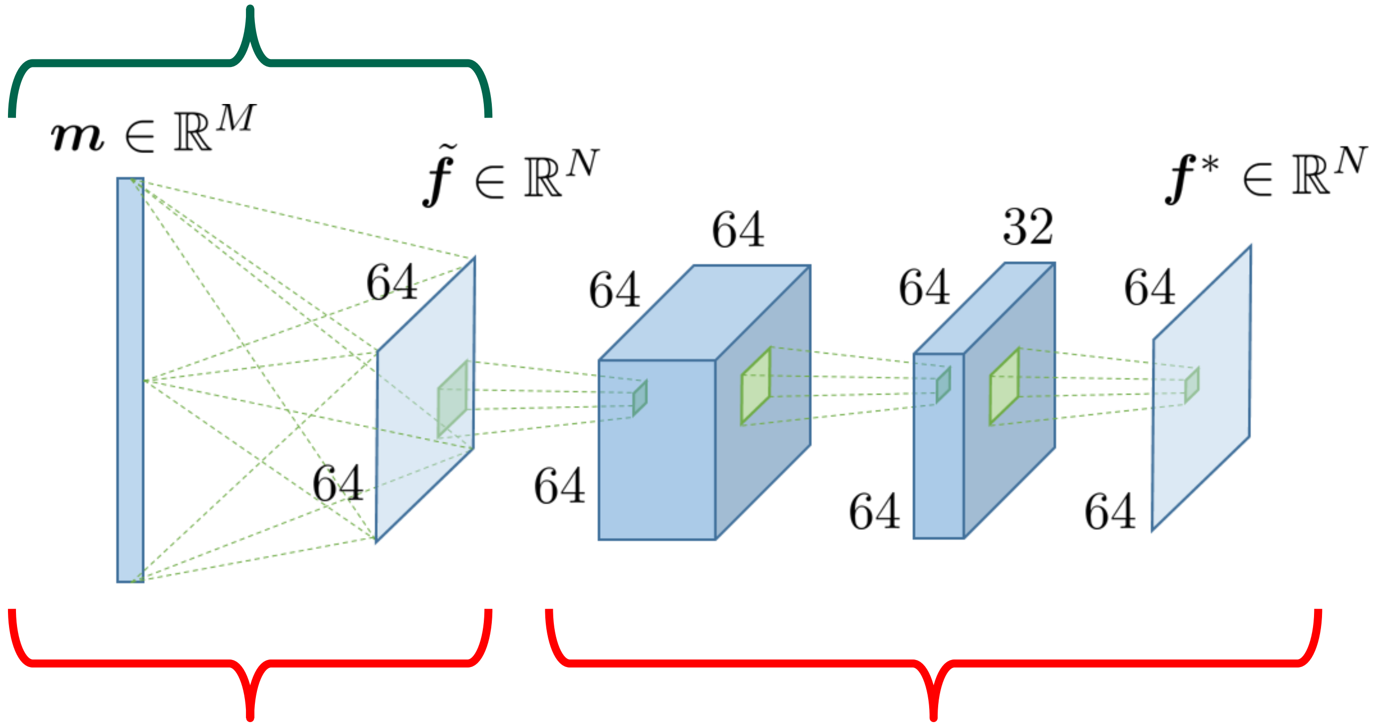
➢ CNN architecture



[Higham *et. al*, Sci. Rep., 2018]

- **CNN architecture**

Fully-connected layer (FCL)



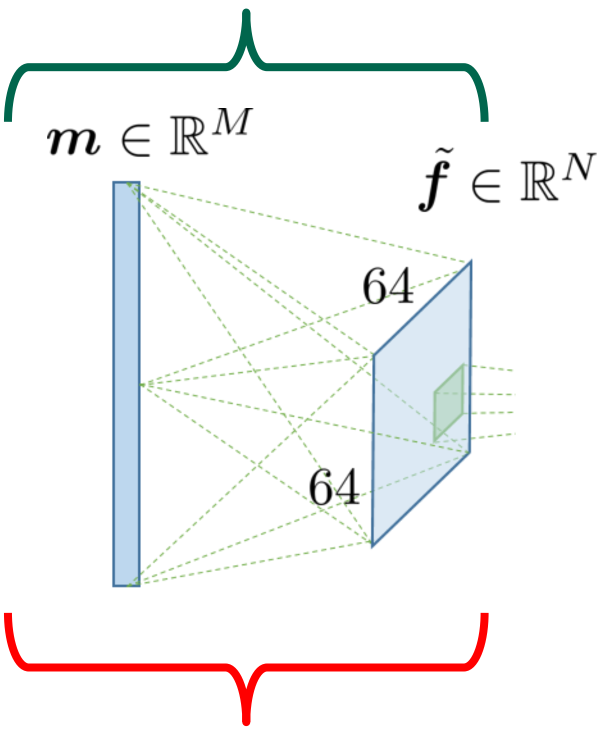
Gaussian completion recon

Learn to compensate for the non Gaussianities

LEARNING-BASED RECONSTRUCTION

➢ CNN architecture

Fully-connected layer (FCL)



measurement-to-image mapping

➢ Choices for the FCL

- Free [Higham *et. al*, Sci. Rep., 2018]

$$\tilde{\boldsymbol{f}} = \mathcal{H}_{\theta_1}(\boldsymbol{m})$$

- Pseudo inverse [Jin *et. al*, IEEE TIP, 2017, Ravishankar *et. al*, Proc. IEEE, 2020]

$$\tilde{\boldsymbol{f}} = \boldsymbol{P}_1^\top \boldsymbol{m}$$

- Bayesian completion

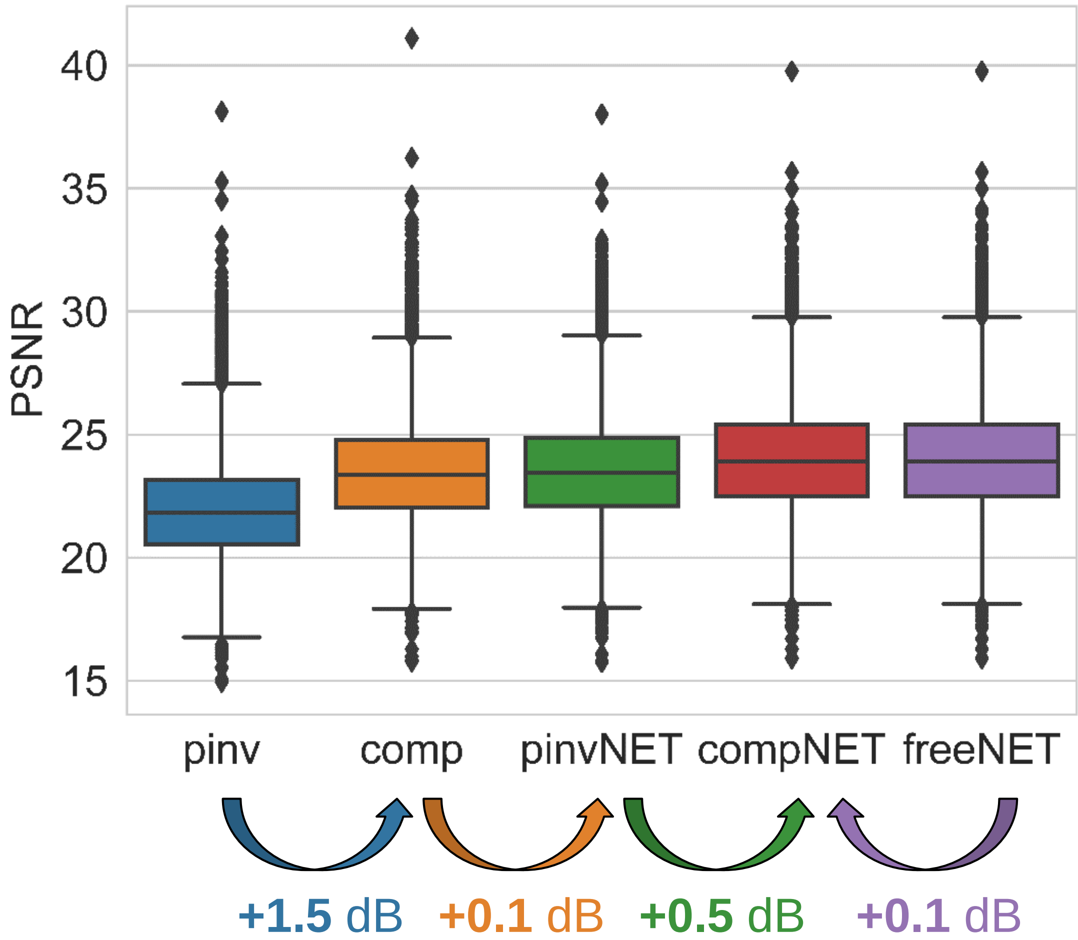
$$\tilde{\boldsymbol{f}} = \boldsymbol{P}^\top \boldsymbol{y}^*, \quad \text{with } \boldsymbol{y} = \begin{bmatrix} \boldsymbol{m} \\ \boldsymbol{y}_2^* \end{bmatrix}$$

➢ 3 network variants

- freeNet: (~1M parameters)
- pinvNet: (~4k parameters)
- compNet: (~4k parameters)

- **STL-10 (Training using ~100k images, test using 8k images)**

pinv: 22.0 ± 2.2 dB
comp: 23.5 ± 2.2 dB
pinvNET: 23.6 ± 2.2 dB
compNET: 24.1 ± 2.3 dB
freeNET: 24.0 ± 2.2 dB

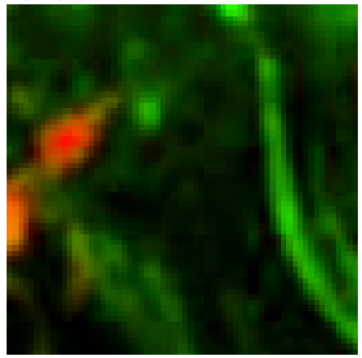


RESULTS

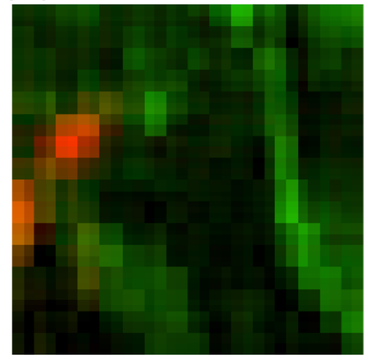
- **Fluorescence microscopy images (not from STL-10!)**

(a) Ground-Truth

$\boldsymbol{f}^{\text{true}}$



(b) Pseudo Inverse

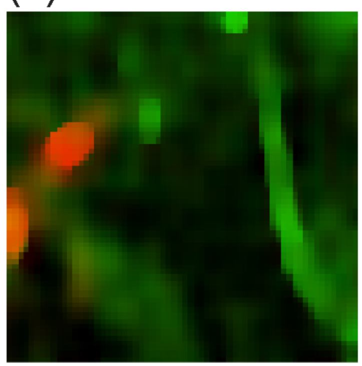


$$\boldsymbol{f}^* = \underset{\substack{\boldsymbol{f} \\ \text{s.t.}\ \boldsymbol{m}=\boldsymbol{P}\boldsymbol{f}}}{\arg\min} \|\boldsymbol{f}\|_2^2$$

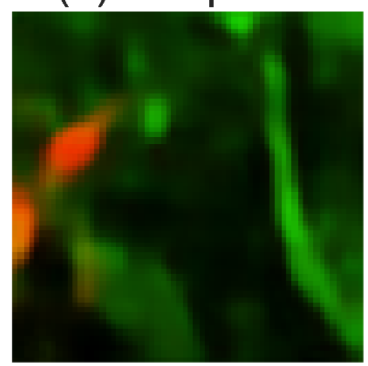
red: 27.15 dB
green: 24.27 dB

$$\boldsymbol{f}^* = \underset{\substack{\boldsymbol{f} \\ \text{s.t.}\ \boldsymbol{m}=\boldsymbol{P}\boldsymbol{f}}}{\arg\min} \|\boldsymbol{\nabla}\boldsymbol{f}\|_1$$

(c) Total Variation



(d) compNET



$$\boldsymbol{f}^* = \mathcal{H}_{\boldsymbol{\theta}^*}(\boldsymbol{m})$$

red: PINV + **3.52** dB
green: PINV + **2.41**dB

red: TV + **0.8** dB
green: TV + **1.16** dB

CONCLUSIONS & PERSPECTIVES

Conclusions

- Reconstruction as completion
- Simple **linear reconstruction** scheme based on **Bayesian completion**
- Simple **nonlinear convolutional network**
- **Code**
  - Bayesian completion (MATLAB): https://github.com/nducros/SPIRIT
  - Convolutional Network (Python): soon…

Perspectives

- Noise
- Experimental data
- Video imaging
  - Much higher compression rate
  - Still challenging…

Don't miss the talk by Antonio Lorente Mur Tomorrow morning!

Thanks for watching!