High-Quality Hyperspectral Reconstruction Using a Spectral Prior

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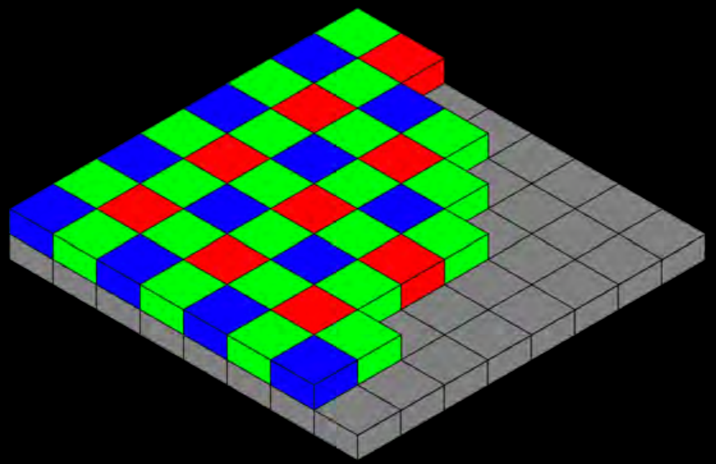
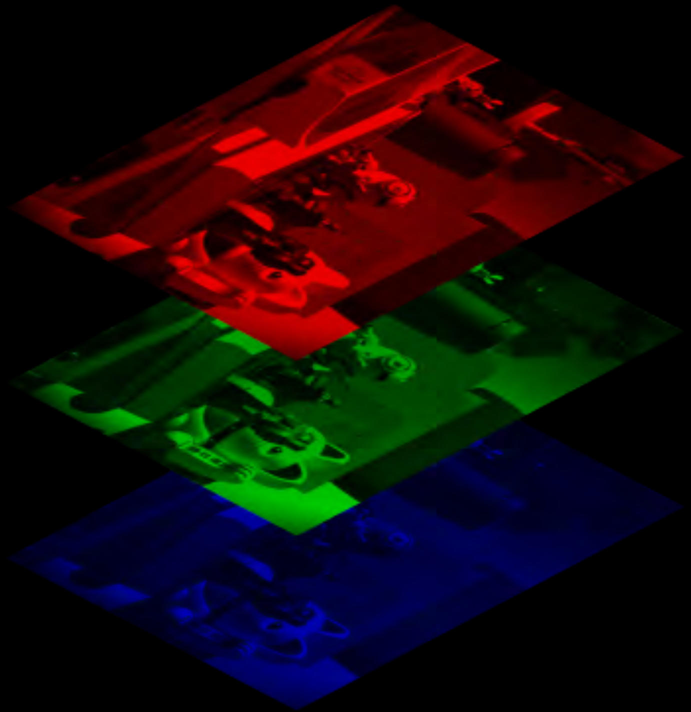
Light and Color Imaging

Continuous spectra of light

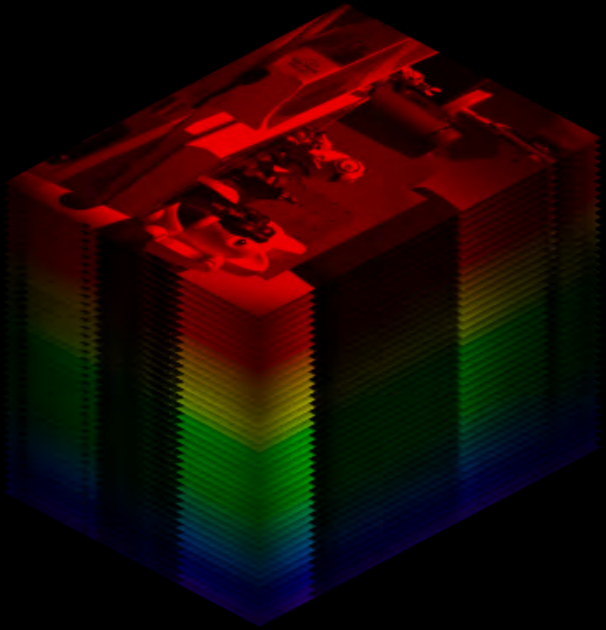


Bayer pattern

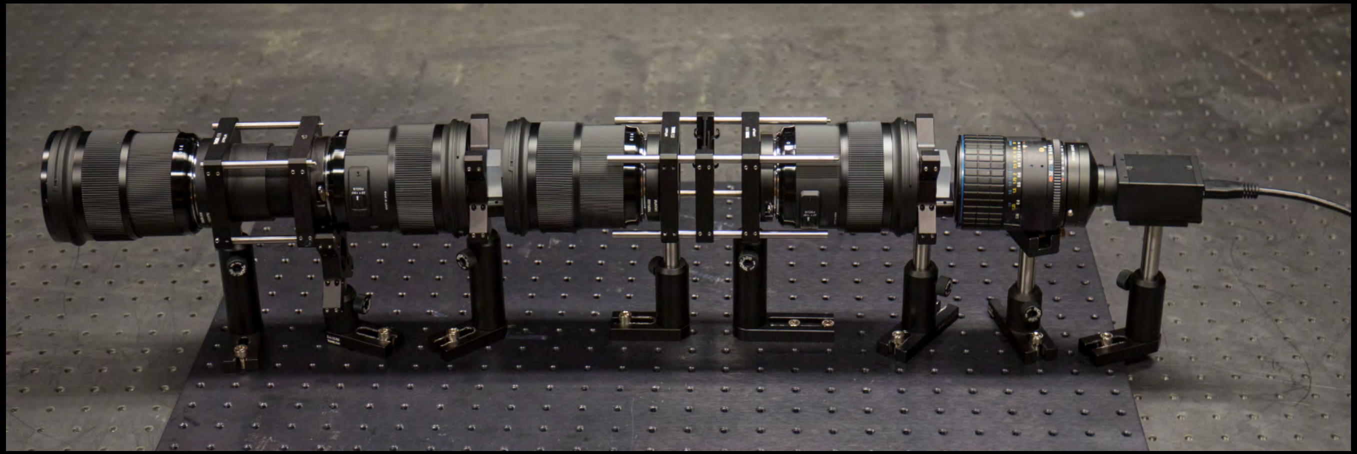


RGB imaging

Hyperspectral Imaging (HSI)

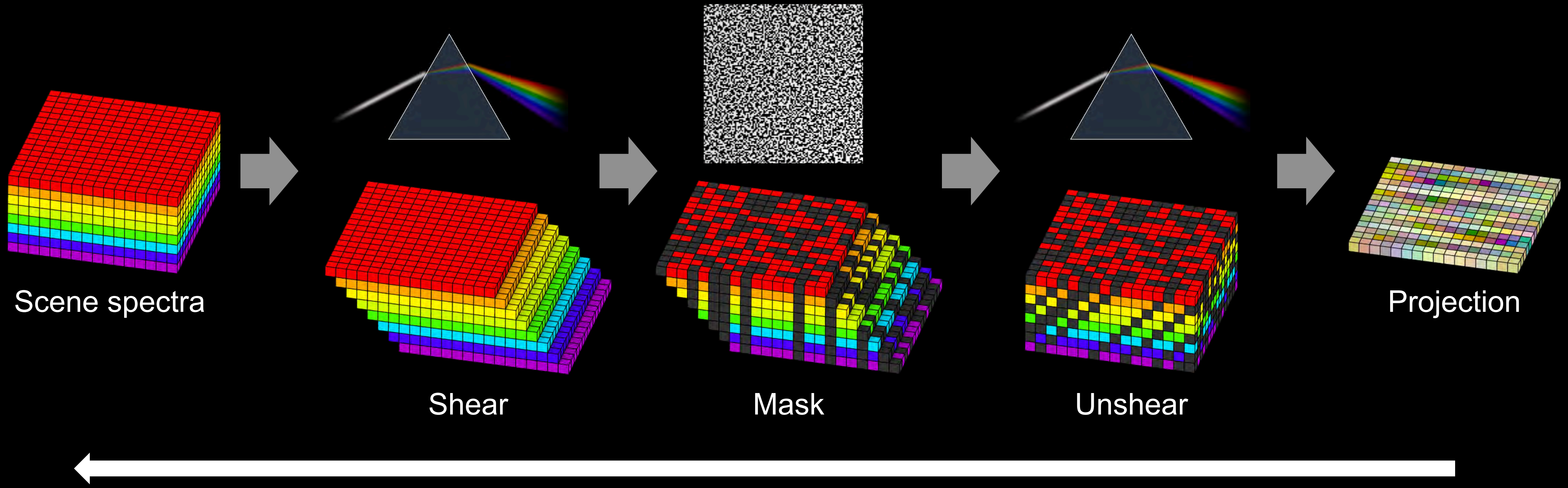


Hyperspectral imaging



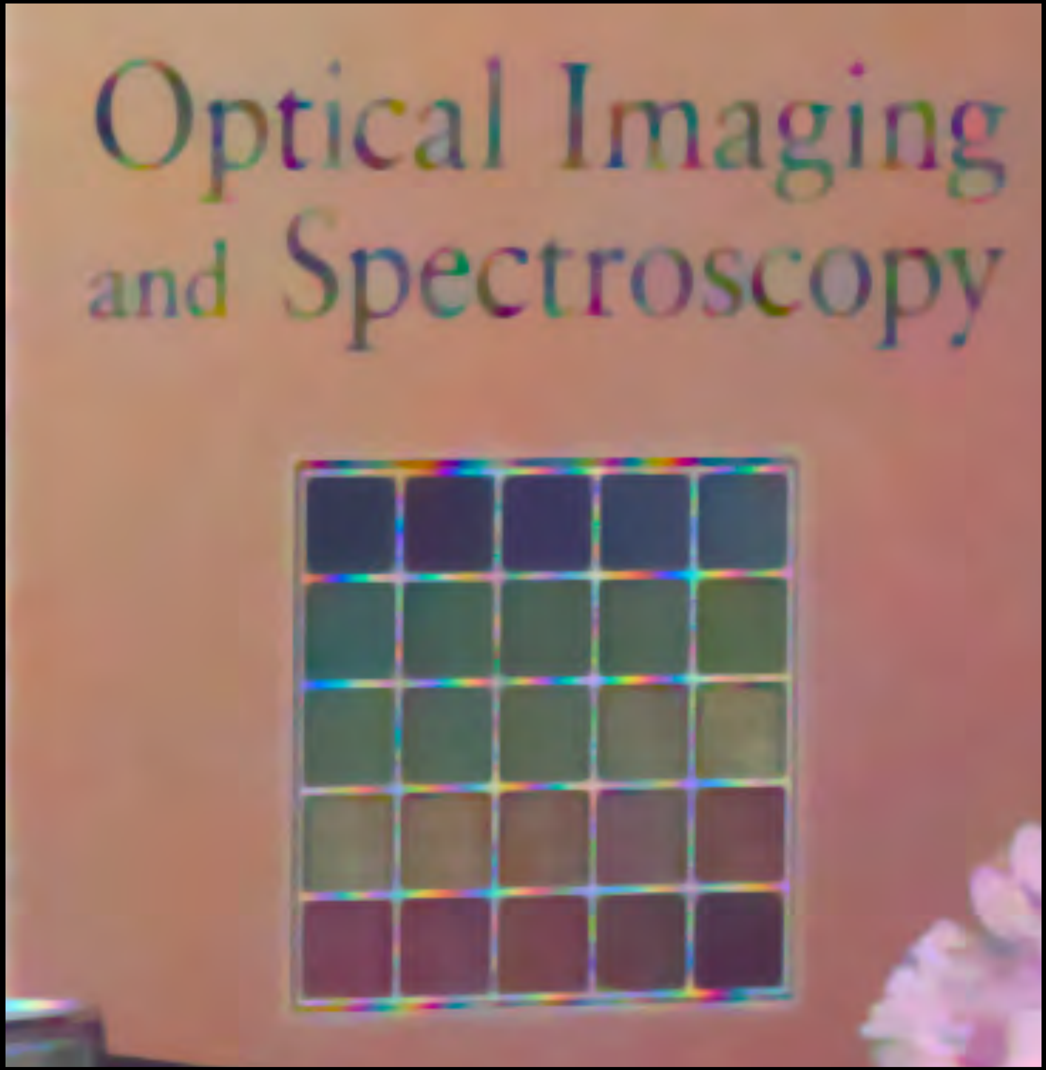
Compressive hyperspectral imaging

Compressive Hyperspectral Imaging

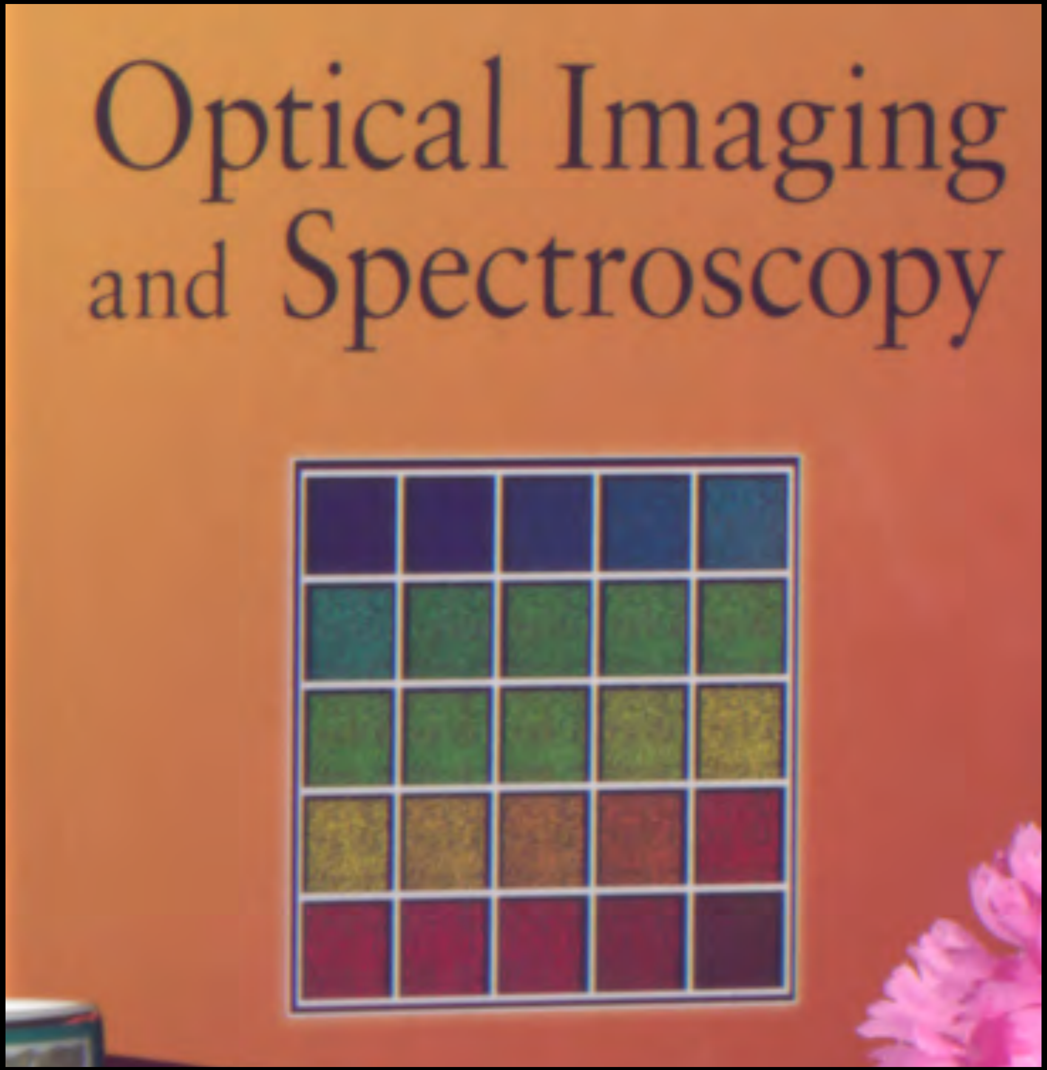


Reconstruction is an inverse problem of optical imaging

Total variation



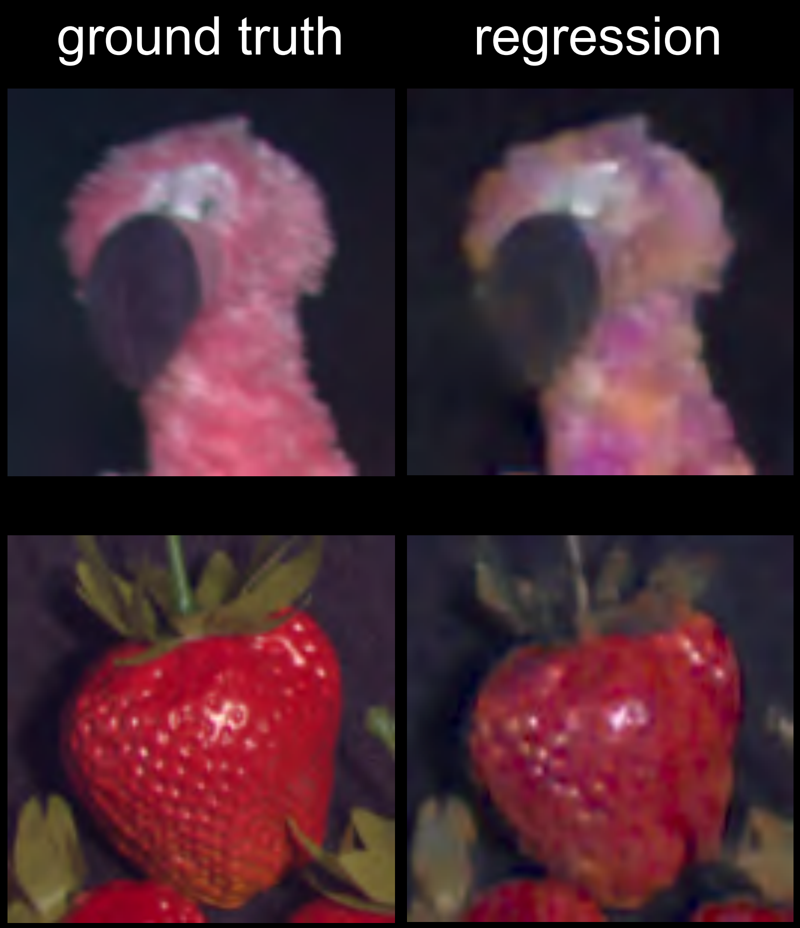
Ground truth



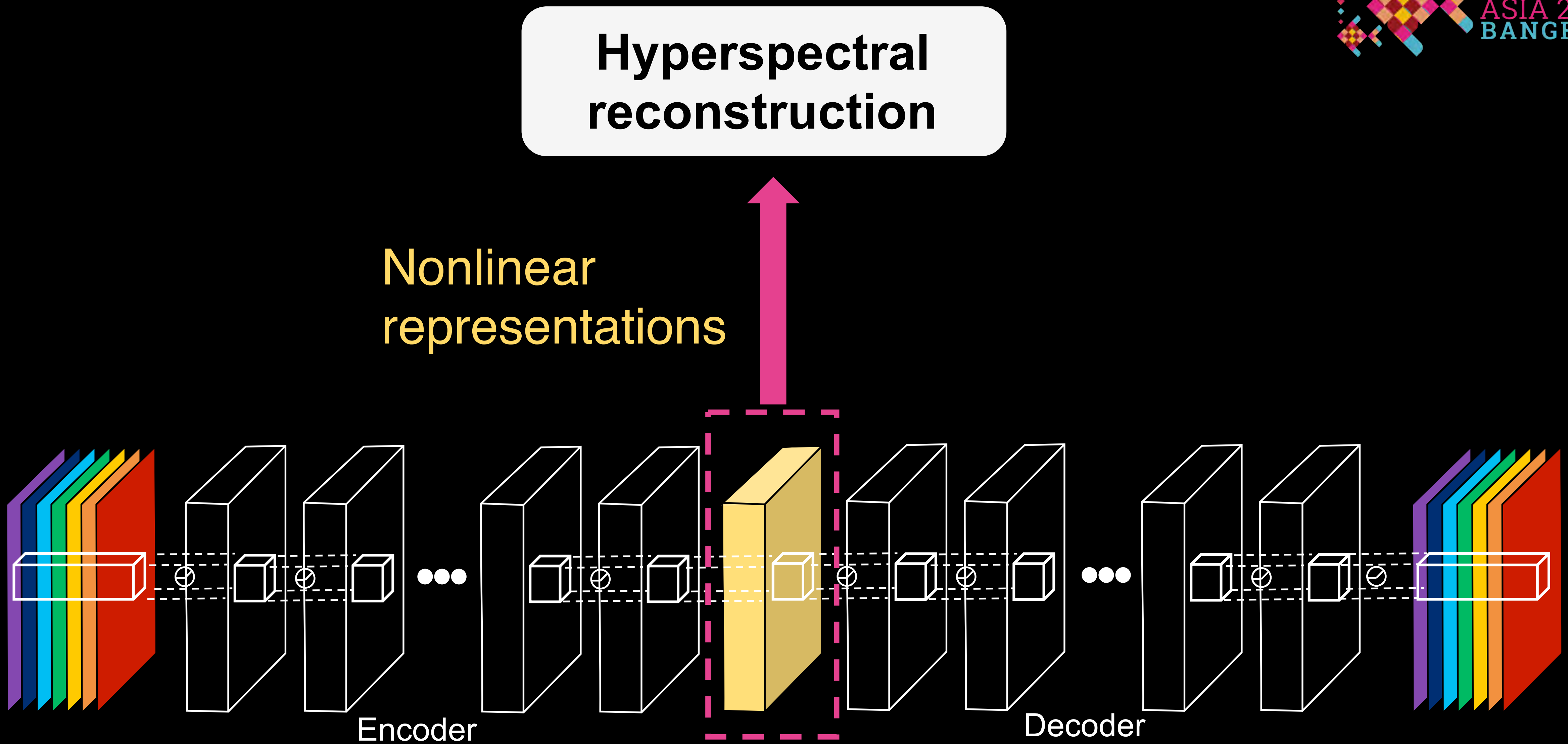
Straightforward Approach

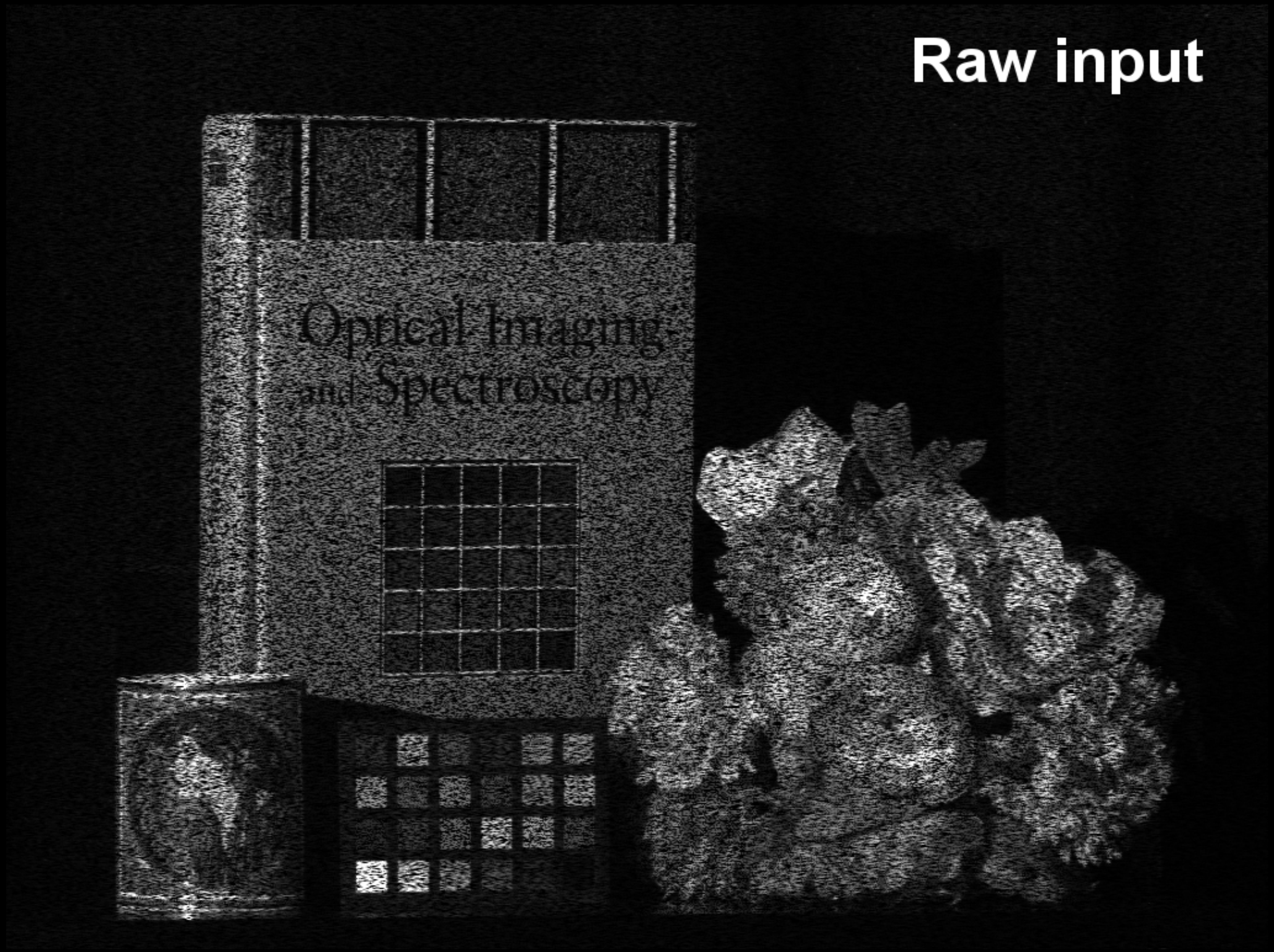
- Learning a regression function using a CNN

The Regression Network Fails

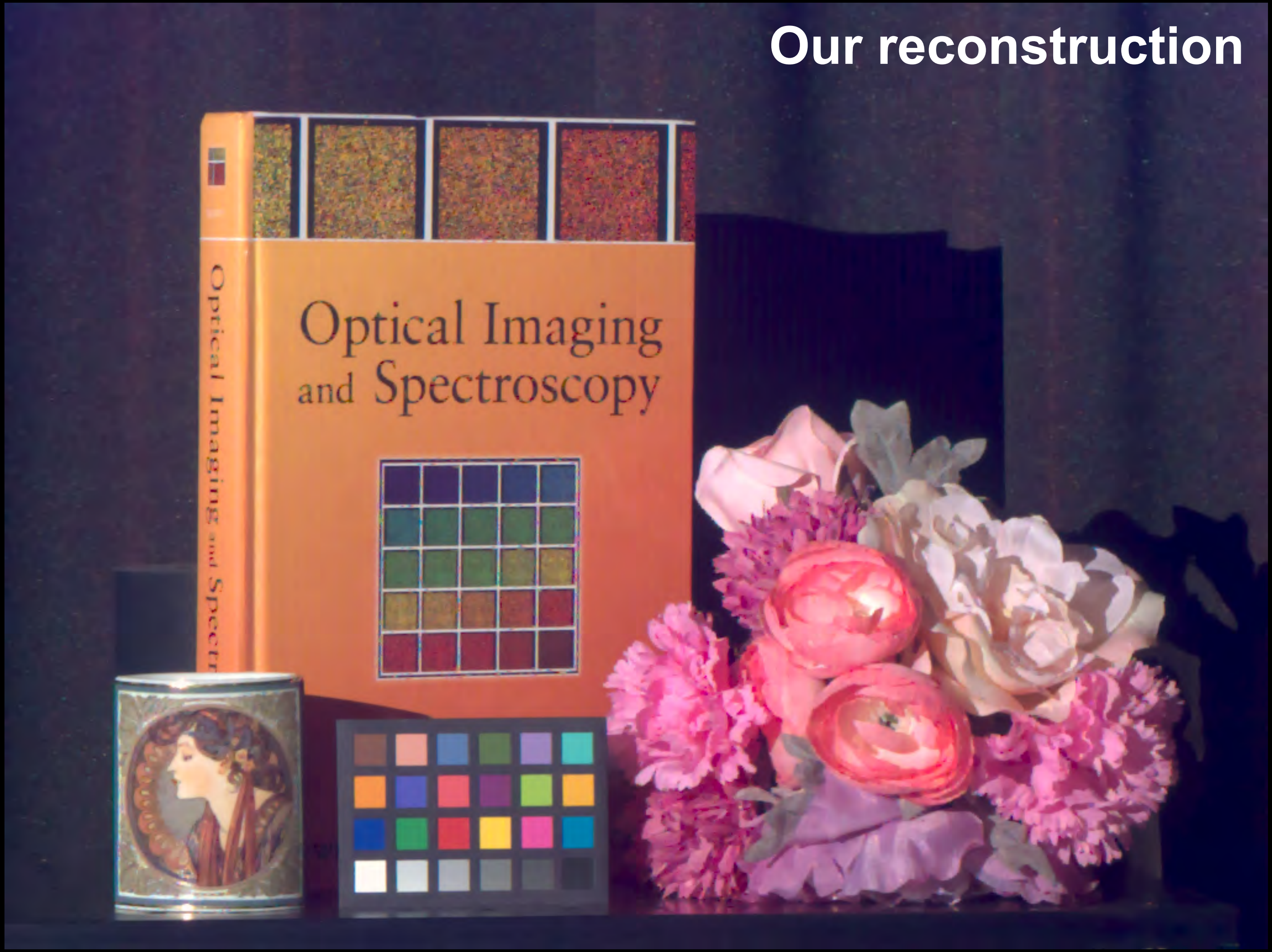


Our Approach




Raw input
Optical Imaging
and Spectroscopy


Our reconstruction

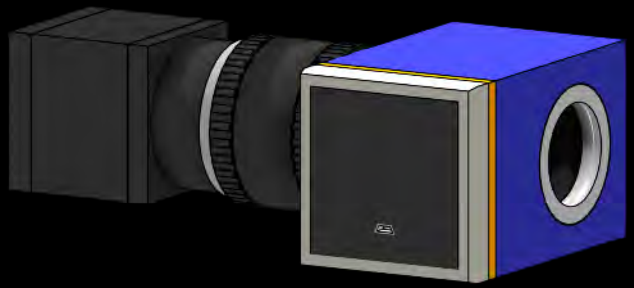

Our reconstruction
Optical Imaging
and Spectroscopy
Optical Imaging and Spectr

Related Work

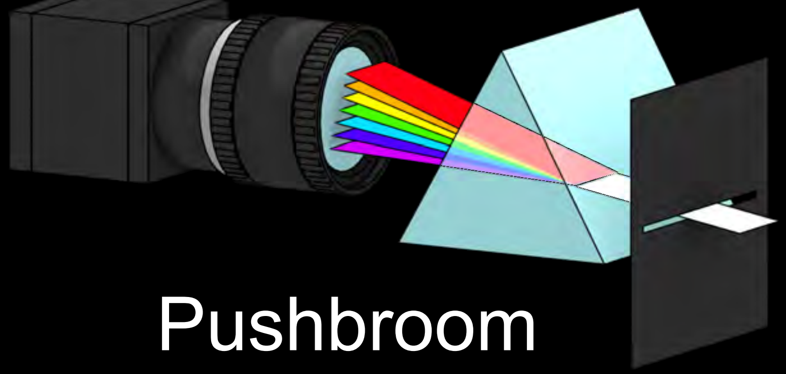
- Hyperspectral Imaging
- Compressive Hyperspectral Reconstruction

HSI without Reconstruction

Bandpass filter
[Mansouri et al. 2007]

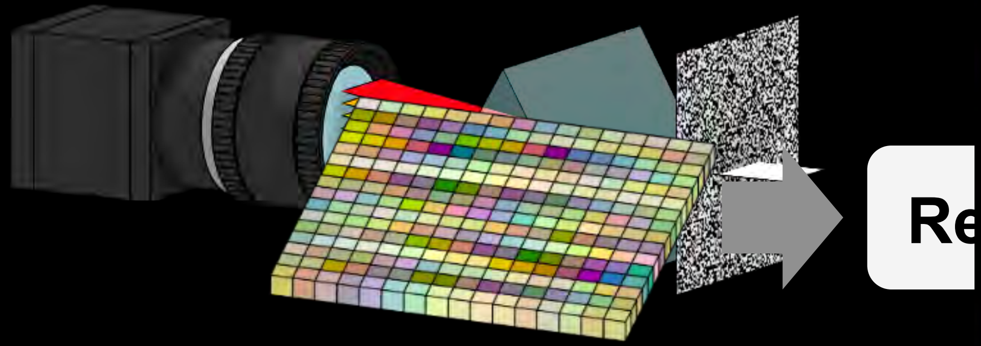


LCTF (liquid crystal tunable filter)
[Attas et al. 2003]



Pushbroom
[Brusco et al. 2006]

HSI with Reconstruction

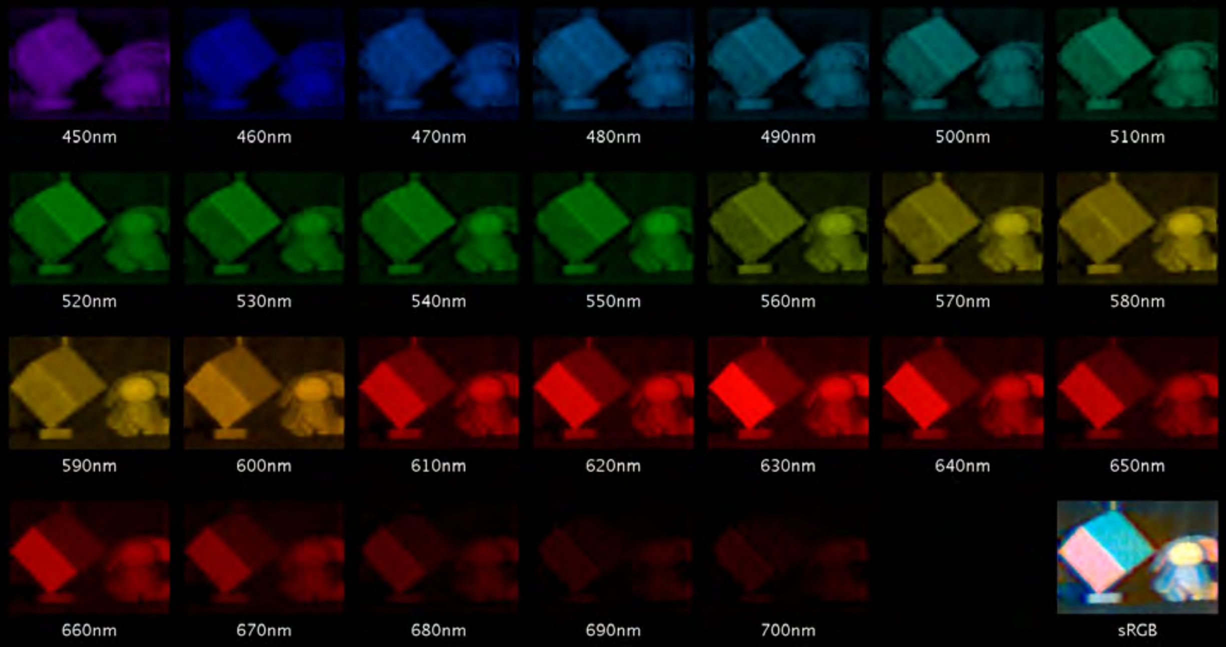


CASSI [Wagadarikar et al. 2008]

Compressive image

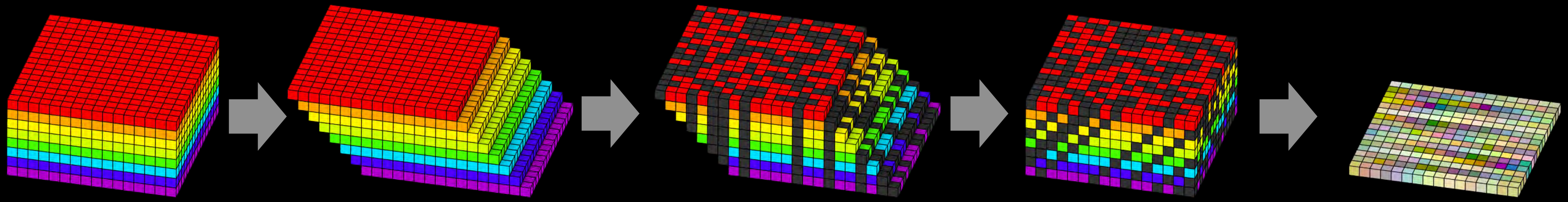
DD-CASSI [Gehm et al. 2007]

SS-CASSI [Lin et al. 2014]



[Jeon et al. 2016]

Image Formation



Spectra | Shear | Mask | Unshear and project | Observed image

$$\mathbf{i} = \Phi \mathbf{h}$$

Observation (2D)

Light modulation (3D to 2D)

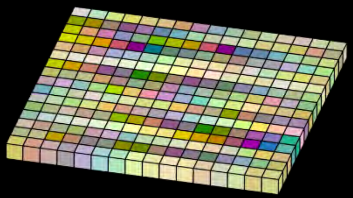
Spectra (3D)

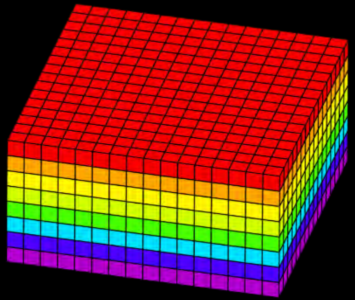
Hyperspectral Reconstruction

$$\min_{\mathbf{h}} \left\| \mathbf{i} - \boldsymbol{\Phi}\mathbf{h} \right\|_2^2$$

“Find a hyperspectral image $\mathbf{h}$ that satisfies the image formation”

\# equations $\ll$ # unknowns





underdetermined system

Reconstruction using TV-L1 Prior

- TV-L1 is very common in computational photography

$$\min_{h} \left\| i - \Phi h \right\|_2^2 + \left\| \quad\quad h \right\|_1$$

TwIST [Bioucas-Dias and Figueiredo 2007]

SpaRSA [Wright et al. 2009]

Reconstruction using Sparse Coding

- Use an overcomplete dictionary and a sparse code to represent a data

$$\mathbf{h} = \mathbf{D}\boldsymbol{\alpha}$$

D: a dictionary

α: a sparse code

For all overlapping image patches

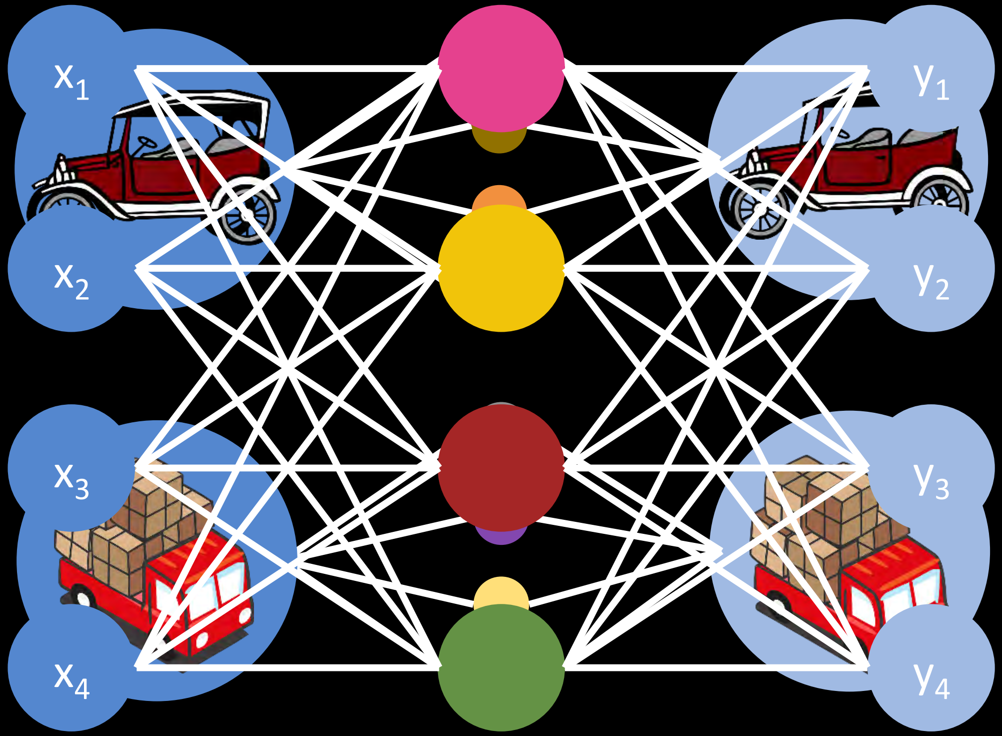
$$\min_{\alpha} \left\| \mathbf{i} - \boldsymbol{\phi}\mathbf{D}\boldsymbol{\alpha} \right\|_2^2 + \left\| \boldsymbol{\alpha} \right\|_1$$

[Lin et al. 2014]

Autoencoder

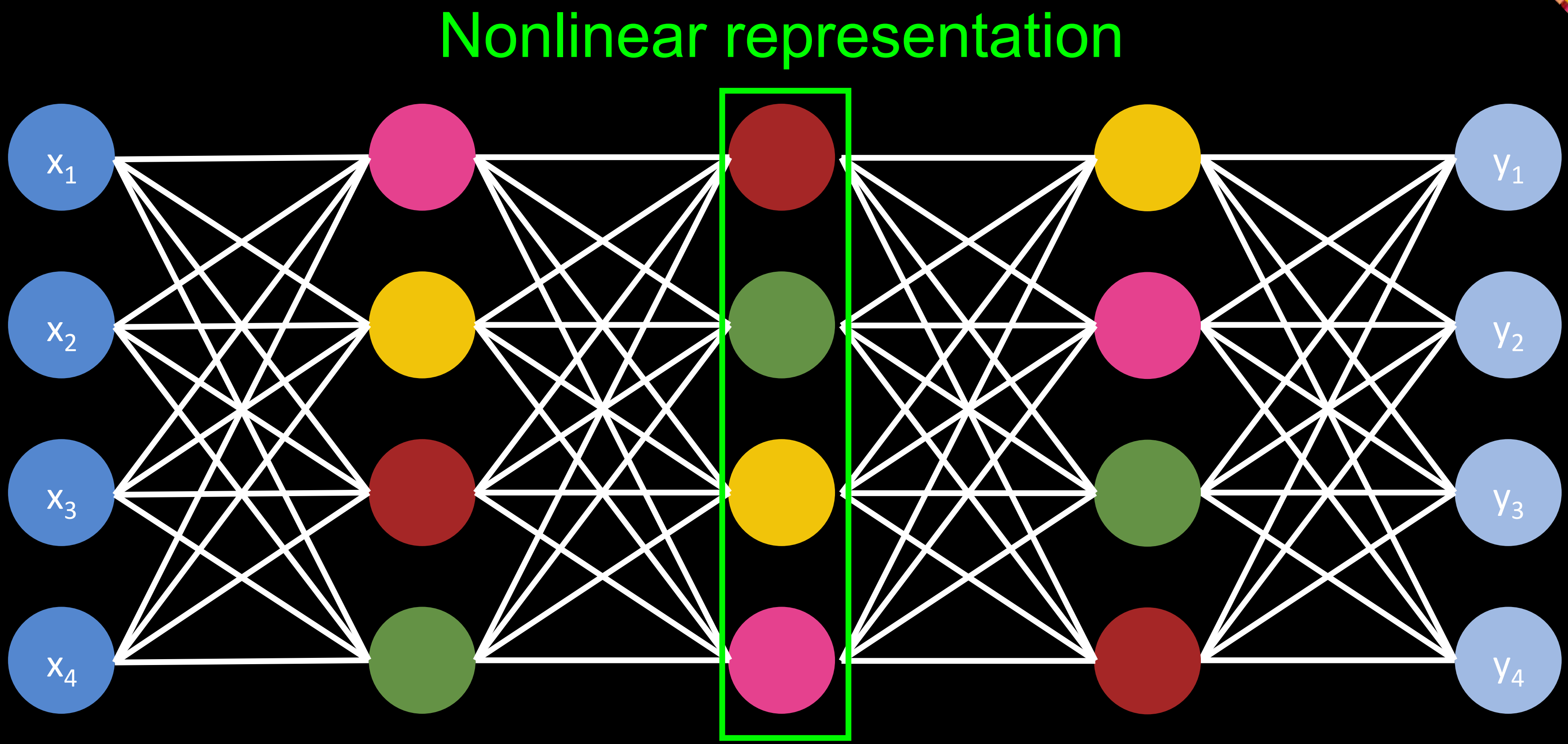
- For Our Deep Spectral Prior

Autoencoder



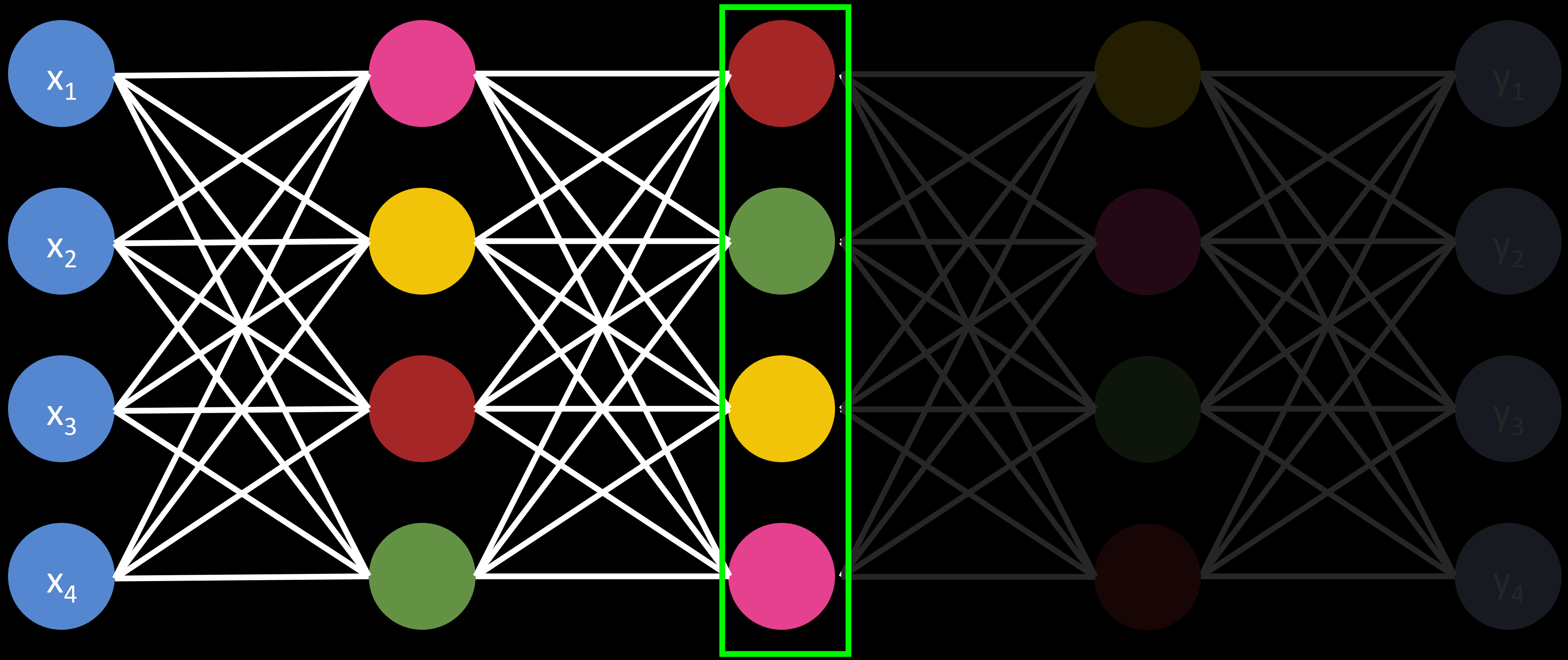
[Hinton and Salakhutdinov 2006]

Nonlinear Representation



Autoencoder: Encoder and Decoder

Nonlinear representation



Encoder

: generate nonlinear representation

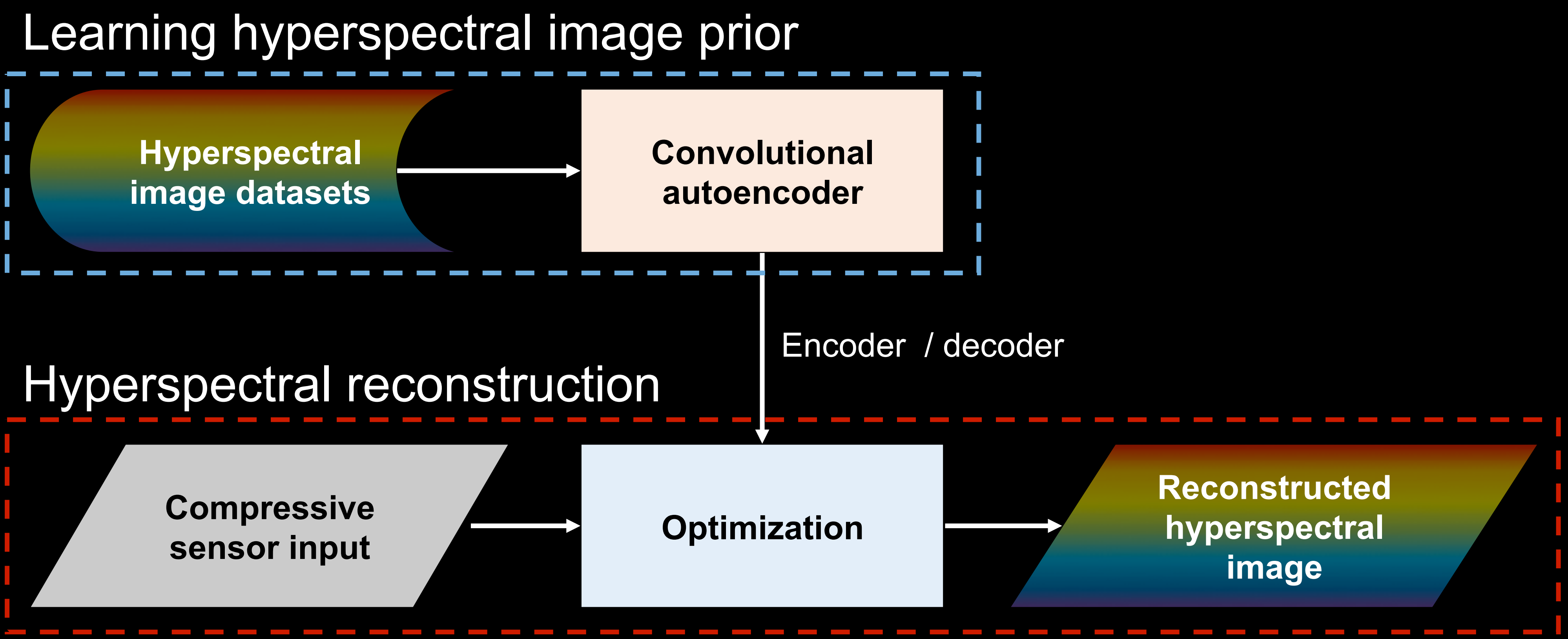
Decoder

: produce data from representations

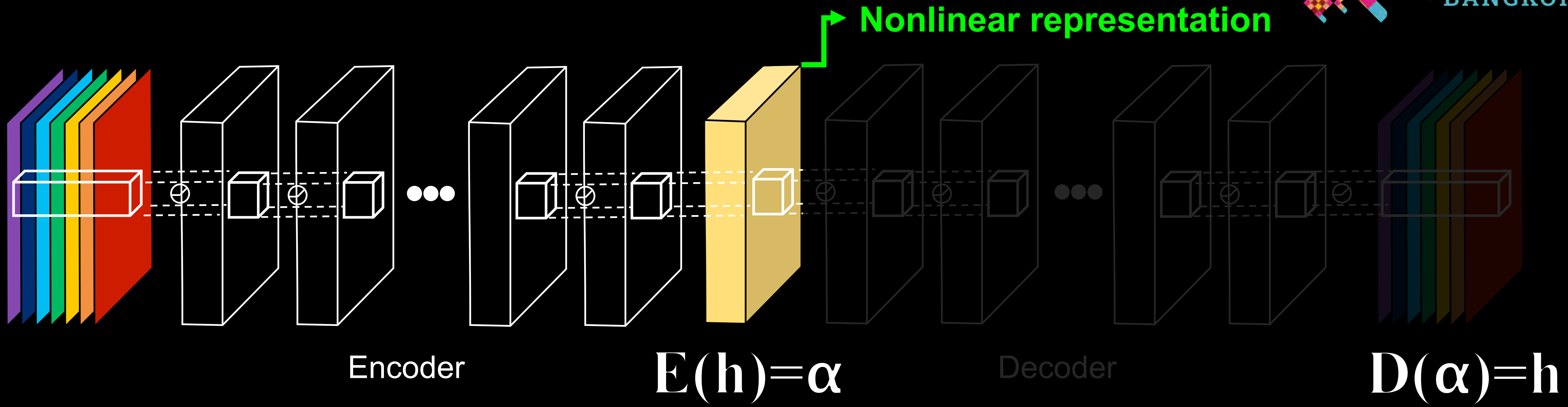
Hyperspectral Reconstruction

- Learning a Spectral Prior
- Reconstruction with Alpha-fidelity

Overview of Our Reconstruction



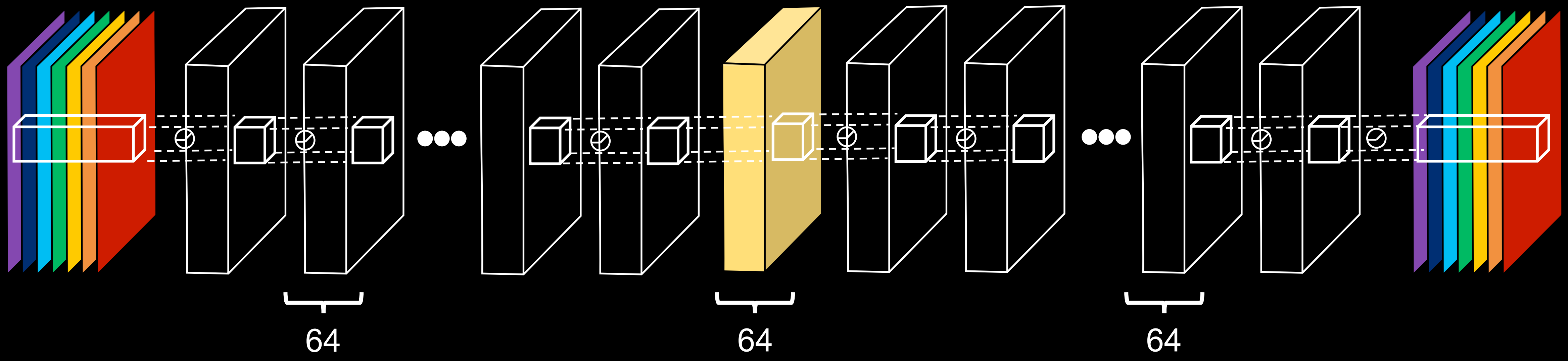
Autoencoder of Hyperspectral Images



$$\mathbf{A(h)=D(\,E(h)\,)\approx h}$$

Convolutional autoencoder of hyperspectral images — Decoder — Encoder

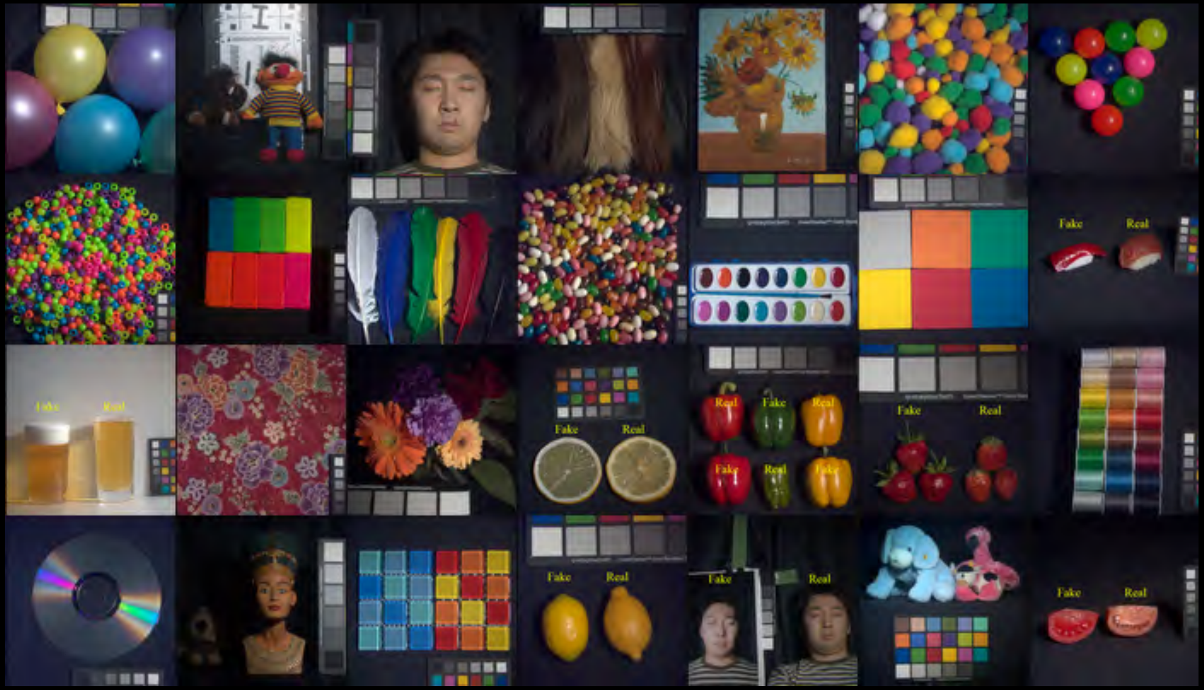
Autoencoder of Hyperspectral Images



- 3 x 3 convolution without pooling
- ReLU activation function
- 64 feature maps

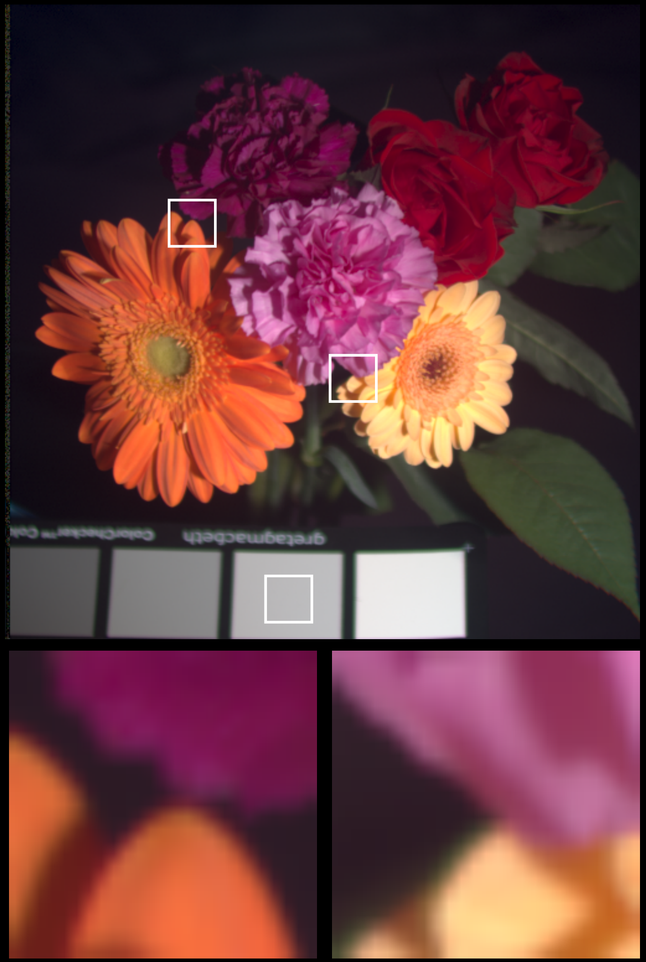
Training Data

Columbia dataset
[Yasuma et al. 2006]

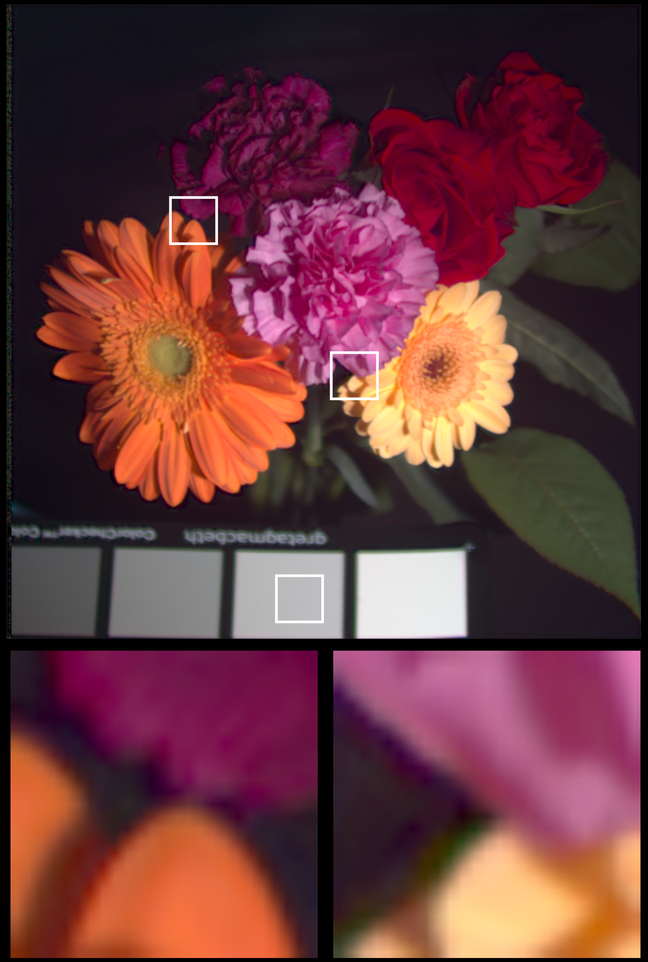


Harvard dataset
[Chakrabarti and Zickler 2011]

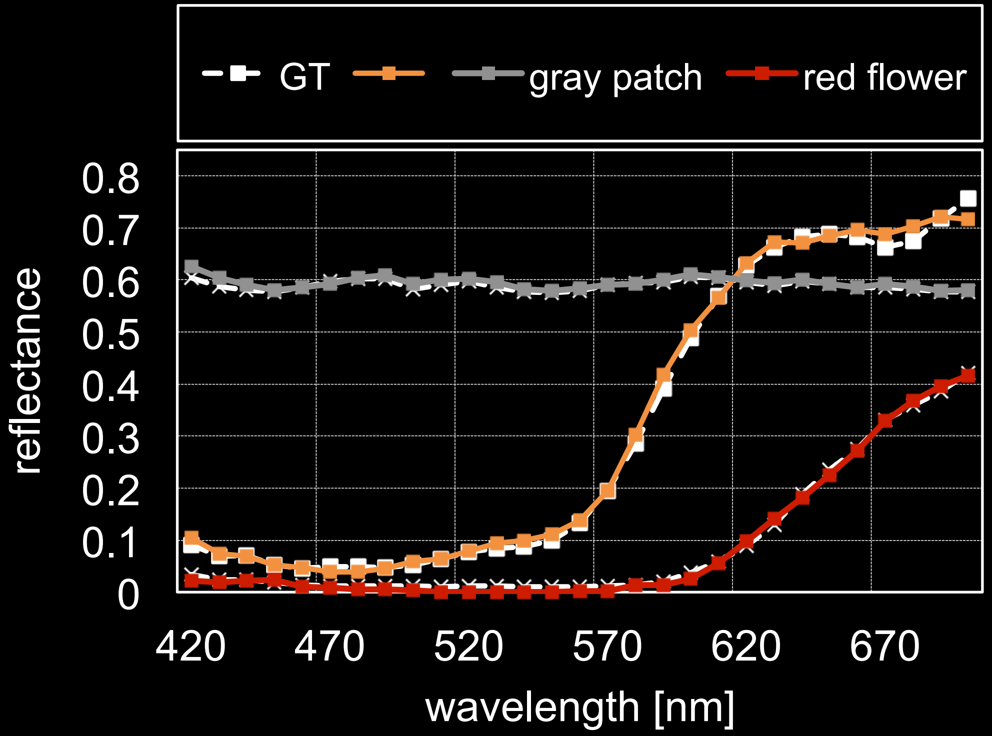
Validating Autoencoder



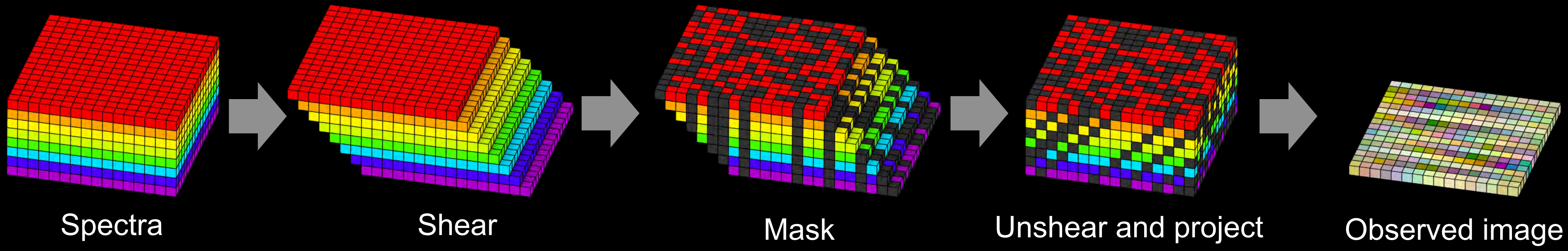
ground truth



reconstruction
(44.24 dB / 0.98)



Our Reconstruction - Data Term



$$\mathbf{i} = \Phi \mathbf{h}$$

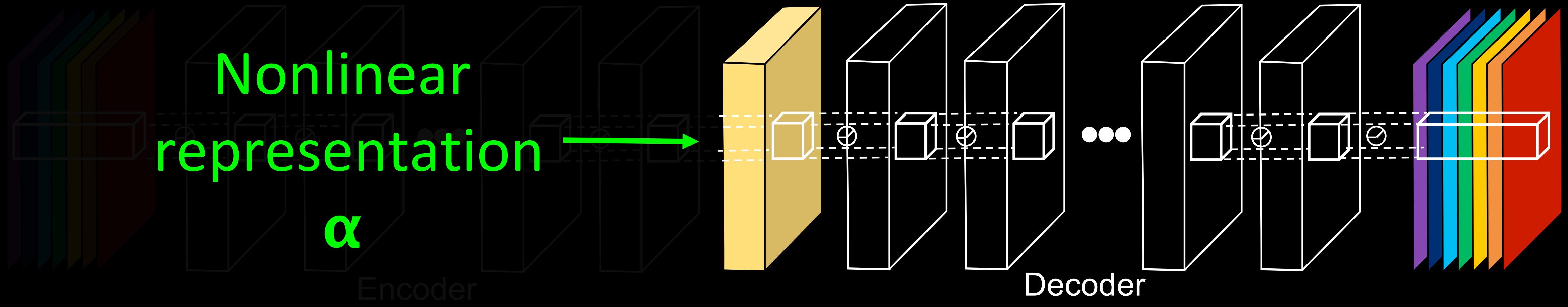
Spectra (3D)

Observation (2D)

Light modulation (3D to 2D)

Our Reconstruction - Data Term

$$\mathbf{i} = \Phi \mathbf{h}$$
$$= \Phi D(\alpha)$$



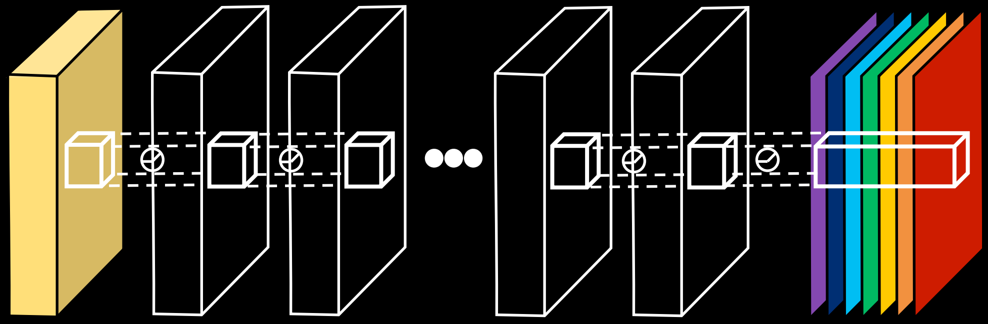
Our Reconstruction

$$\min_{\alpha} \left\| \mathbf{i} - \Phi \mathbf{D}(\alpha) \right\|_2^2 \quad \because \mathbf{h} = \mathbf{D}($$

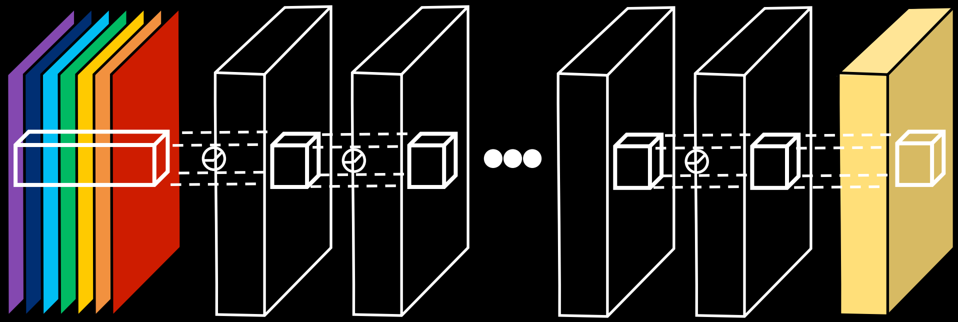
$$+ \quad \left\| \qquad \mathbf{D}(\alpha) \right\|_1$$

$$+ \quad \boxed{\qquad\qquad}$$

How can we utilize the encoder?



Decoder



Encoder

Decoder $\mathbf{D}(\alpha)$

- produce **h** (hyperspectral images)

  from (nonlinear representations)
- a prior on **h**
- know how **h** looks like

Encoder E(

- generate from **h**
- a prior on
- **know how looks like**

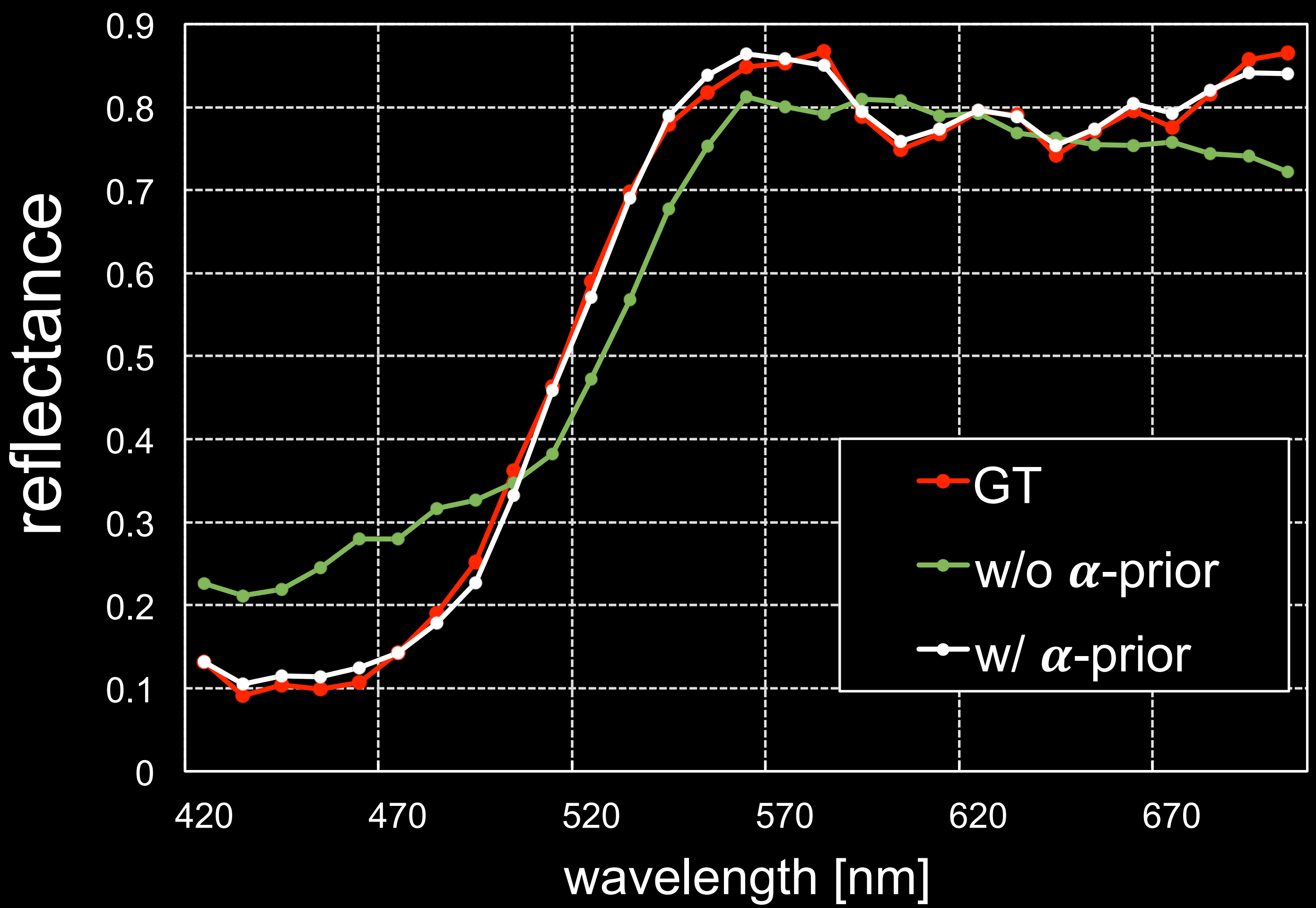
Our Reconstruction with fidelity Prior

$$\min_{\alpha} \left\| \mathbf{i} - \phi \mathbf{D}(\alpha) \right\|_2^2 + 2 \left\| \quad \mathbf{D}(\alpha) \right\|_1 + 1 \boxed{\left\| \alpha - \mathbf{E}(\mathbf{D}(\alpha)) \right\|_2^2}$$

"The nonlinear representation should be close to what the encoder knows."

Impact of fidelity Prior

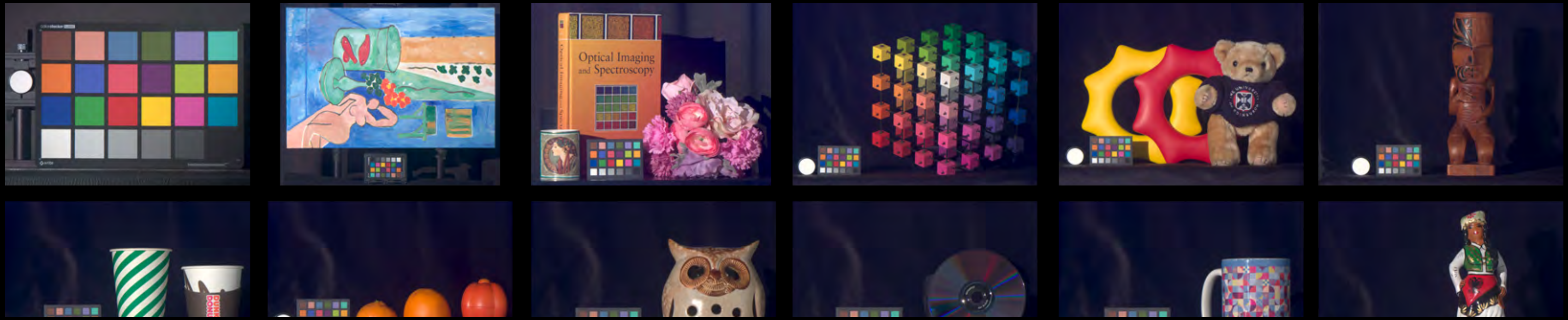
Yellow feather



Results

- Our Dataset
- Synthetic Results
- With a Real Compressive Imager

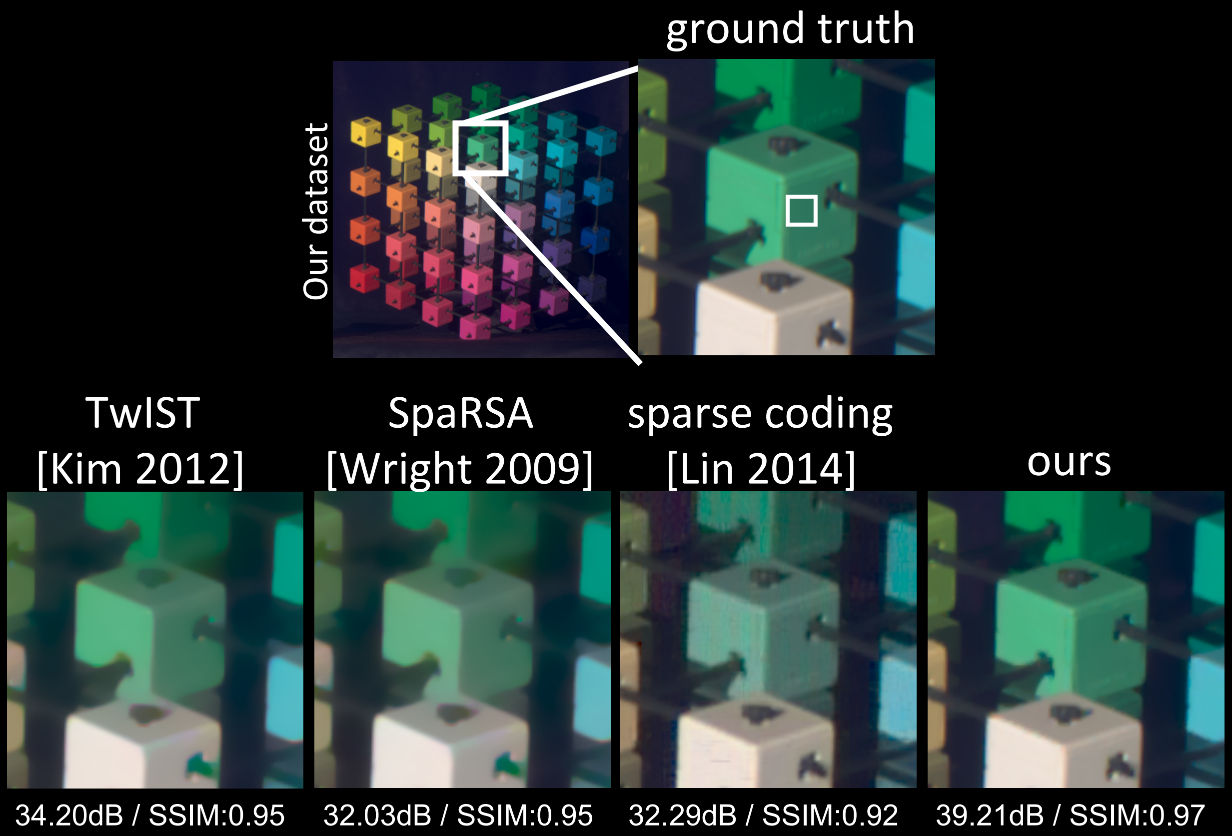
Our High-Quality Dataset

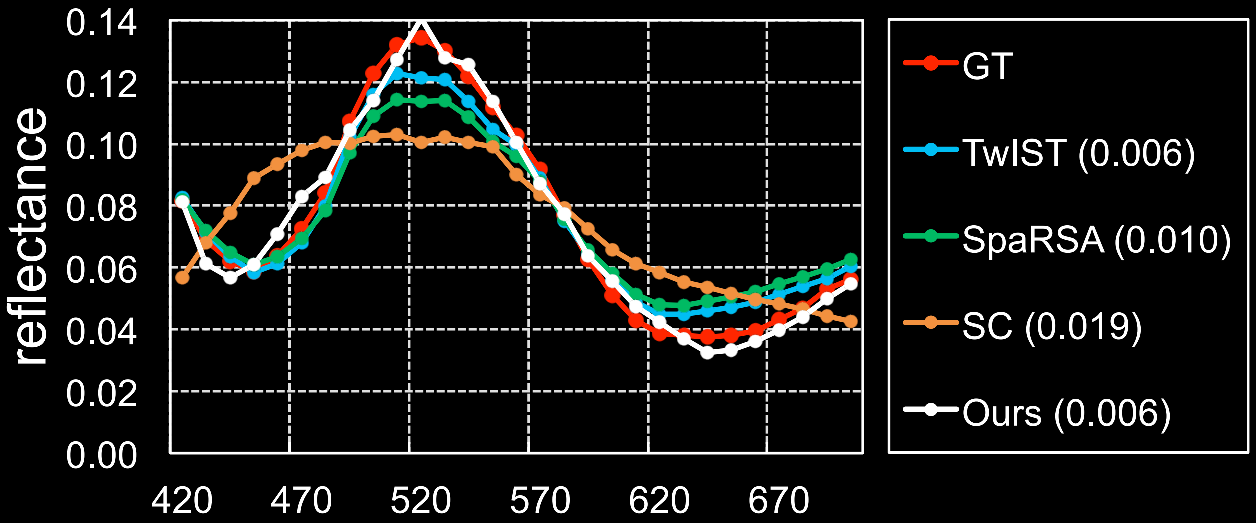


Download from

http://vclab.kaist.ac.kr

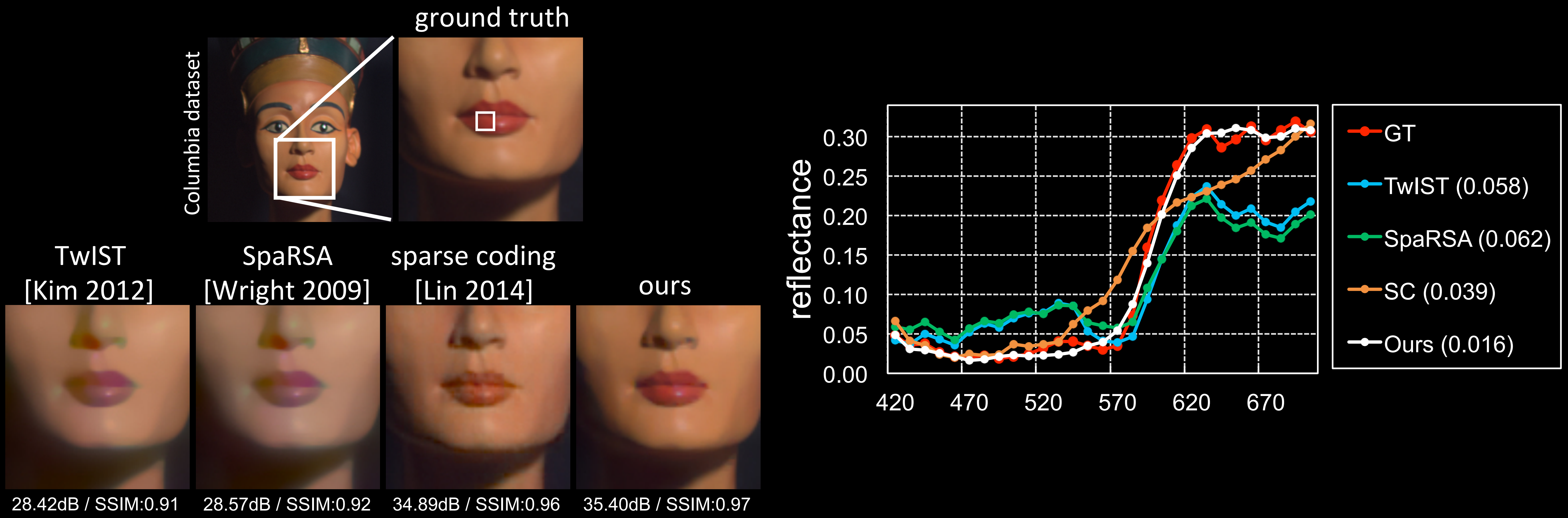
Synthetic Result with Our High Quality Dataset





Synthetic Result with Columbia Dataset

[Yasuma et al. 2010]

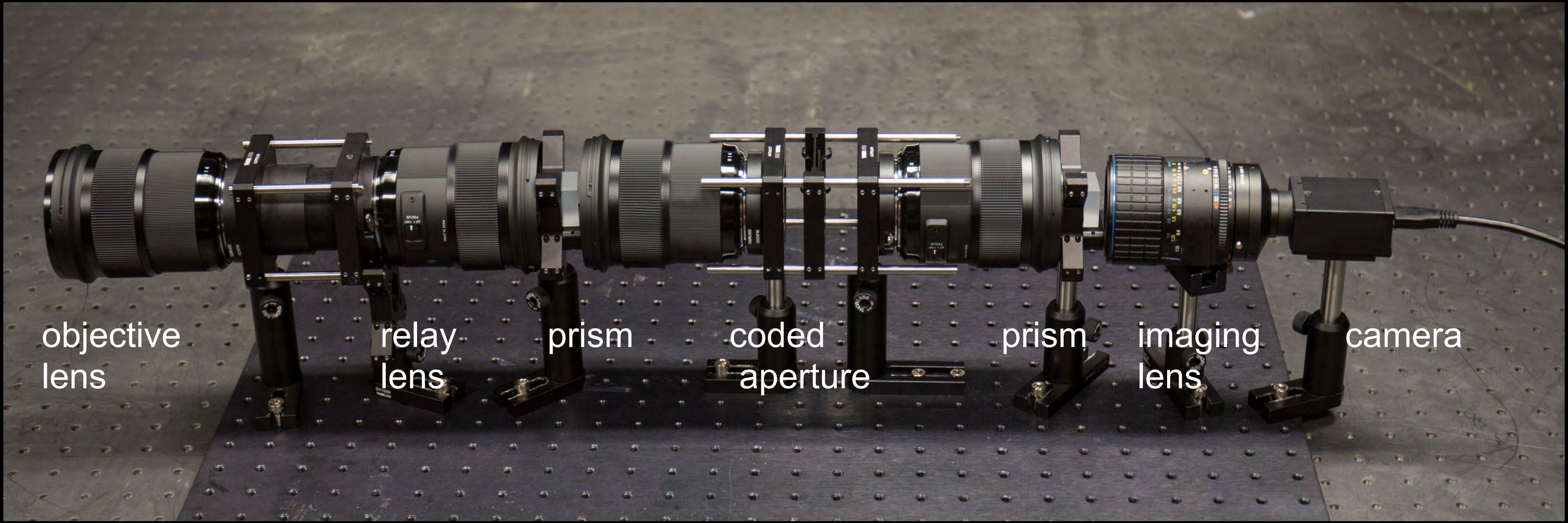


Synthetic Result with Our High Quality Dataset

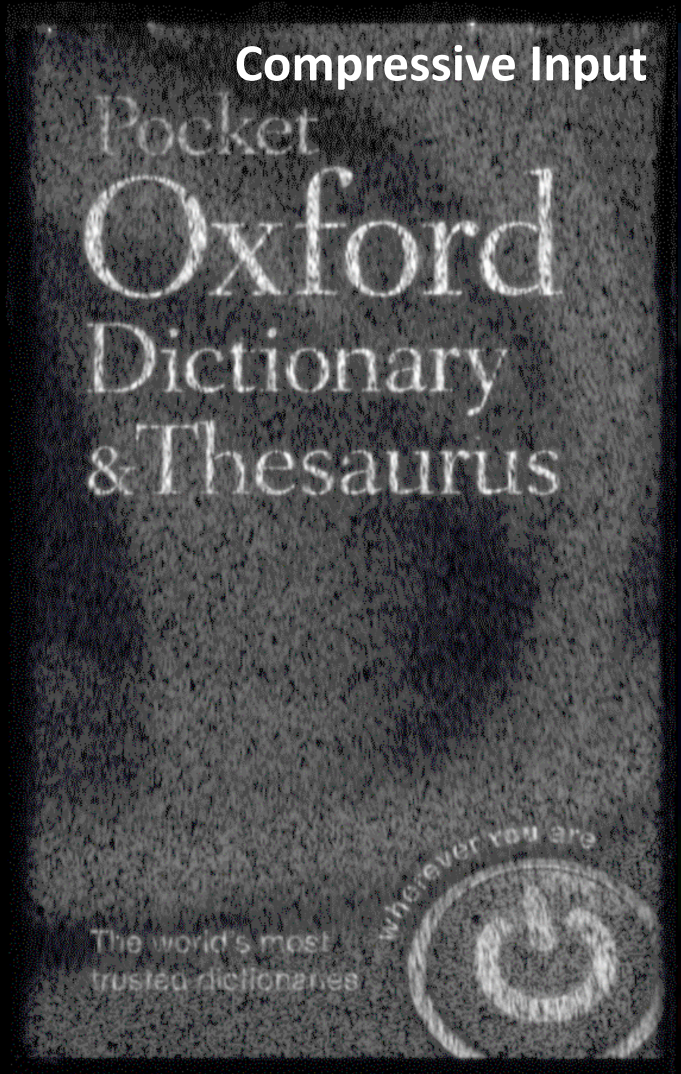
Synthetic Result with Our High Quality Dataset

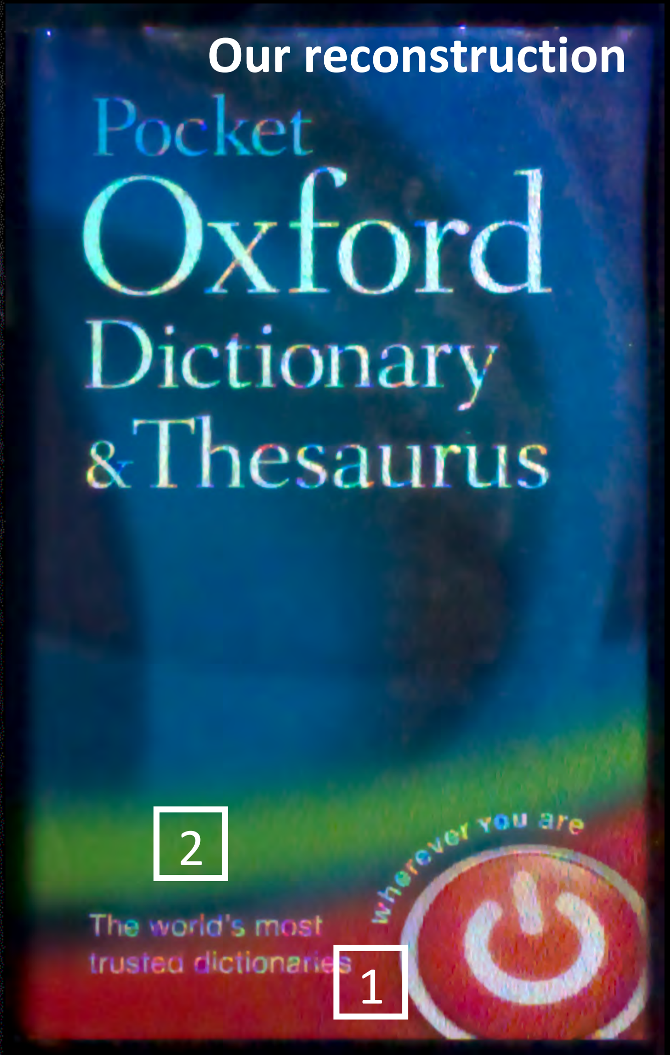
Our DD-CASSI Result

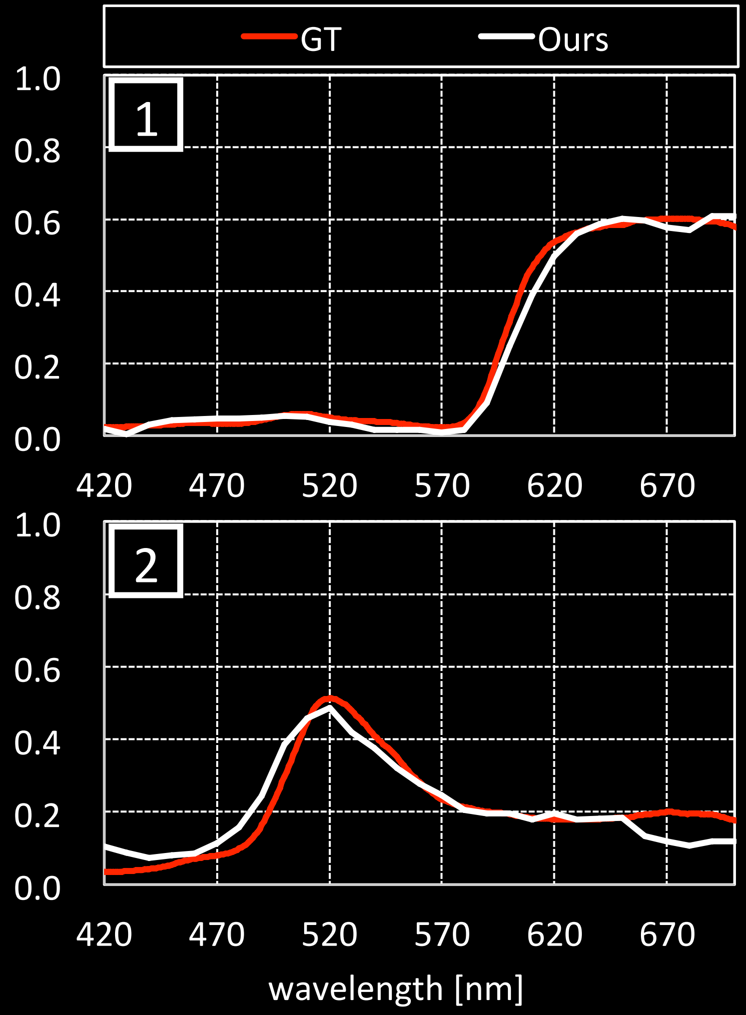
[Gehm et al. 2007]



Our DD-CASSI Result







Applications

- Spectral Interpolation
- Hyperspectral Demosaicing

Changing Modulation Matrix

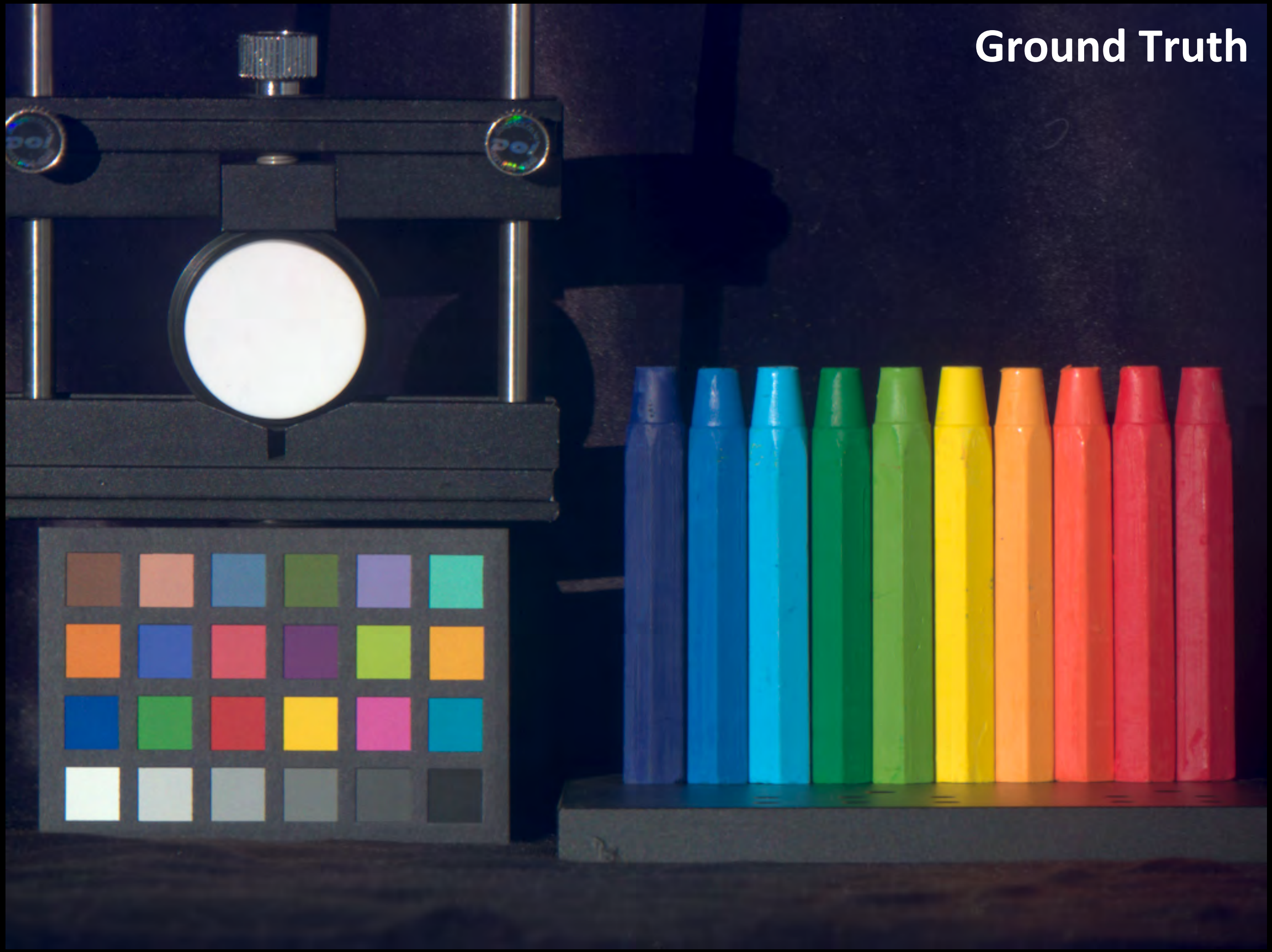
Our reconstruction:

$$\min_{\boldsymbol{\alpha}} \left\| \mathbf{i} - \boldsymbol{\phi} \mathbf{D}(\boldsymbol{\alpha}) \right\|_2^2 + \tau_1 \left\| \boldsymbol{\alpha} - \mathbf{E}(\mathbf{D}(\boldsymbol{\alpha})) \right\|_2^2 + \tau_2 \left\| \nabla_{xy} \mathbf{D}(\boldsymbol{\alpha}) \right\|_1$$

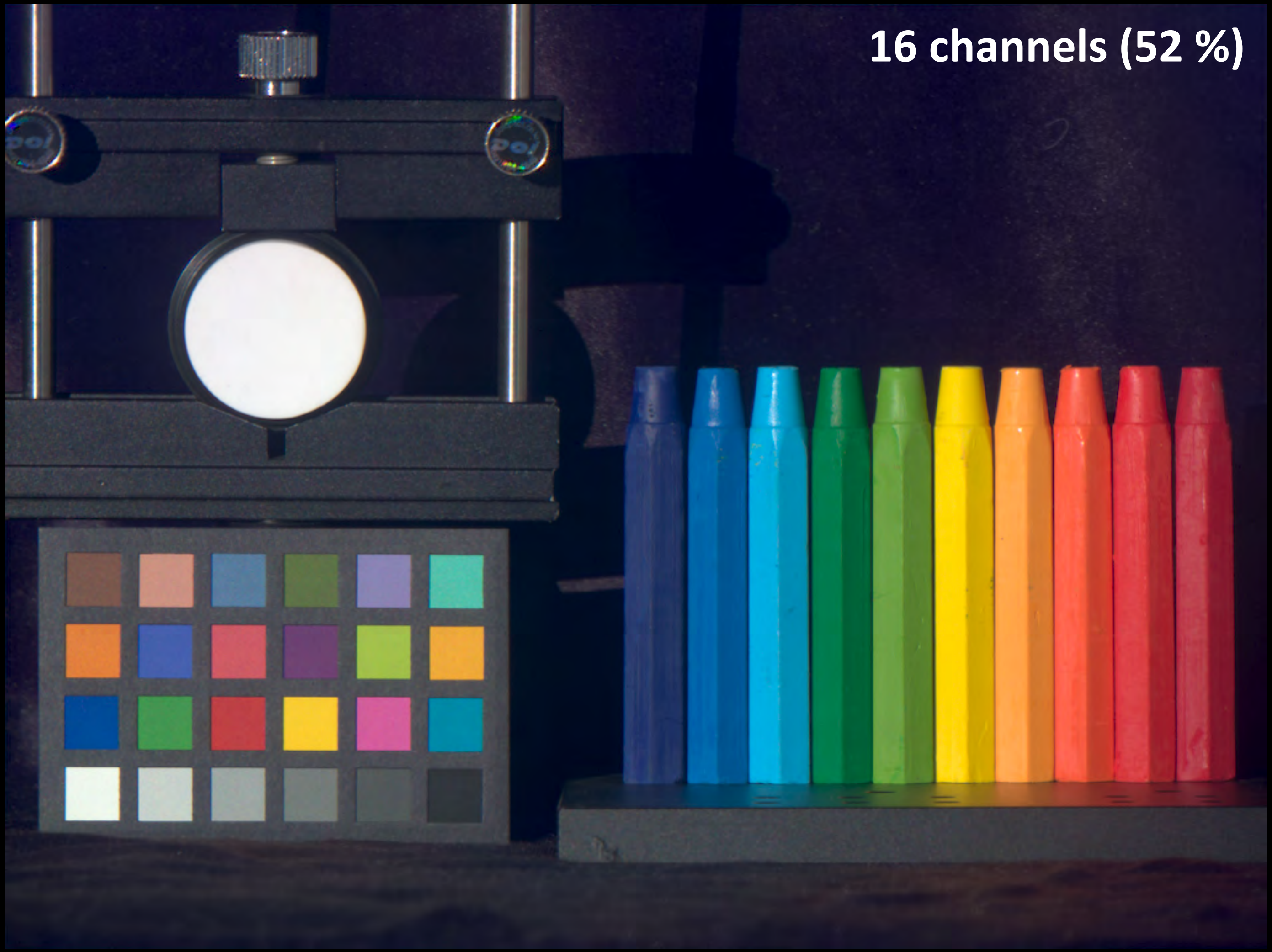
$\boldsymbol{\phi}$ for super-resolution: blurring + downsampling

Note: the observation i should be modified accordingly

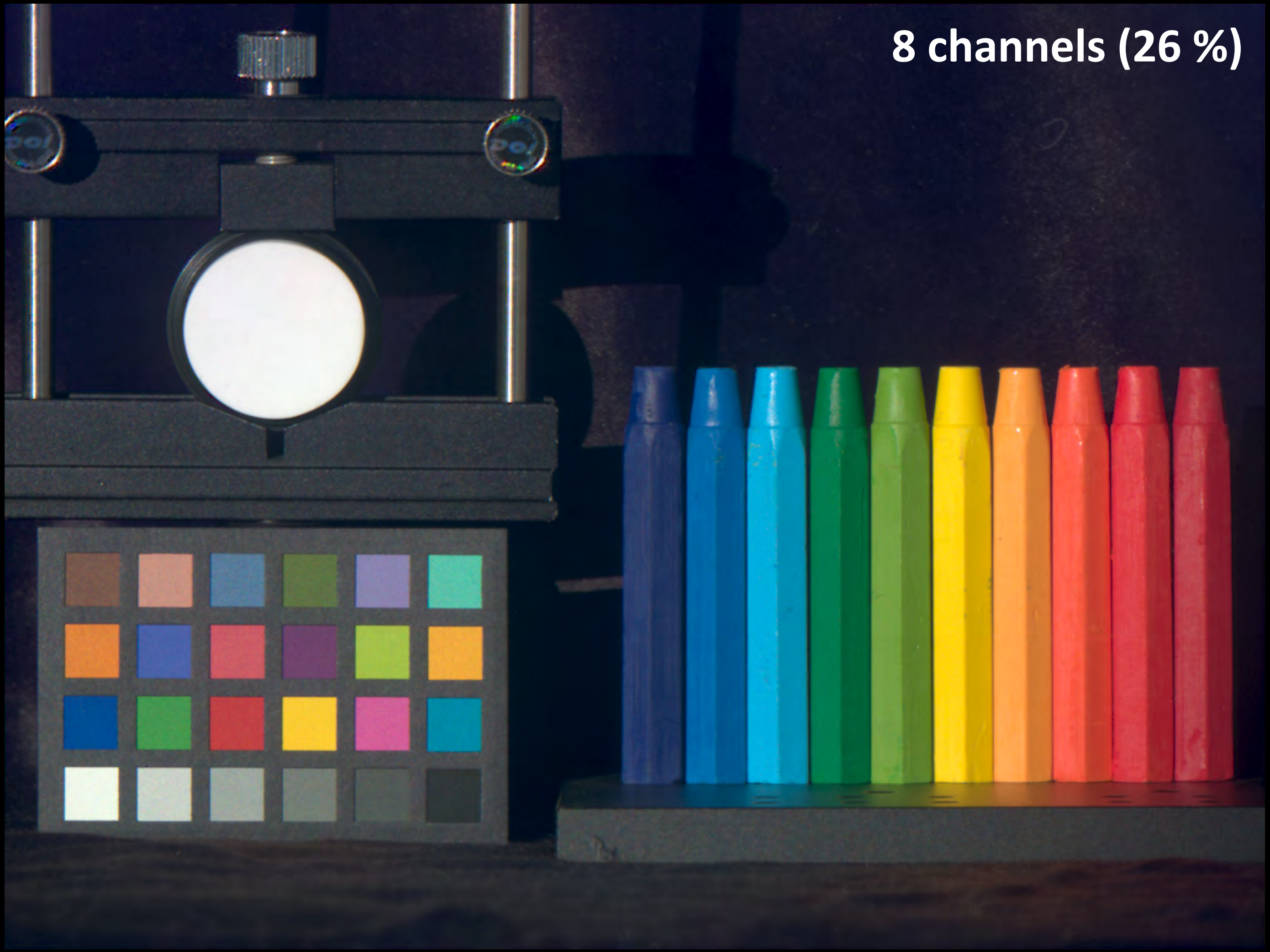
Spectral Interpolation



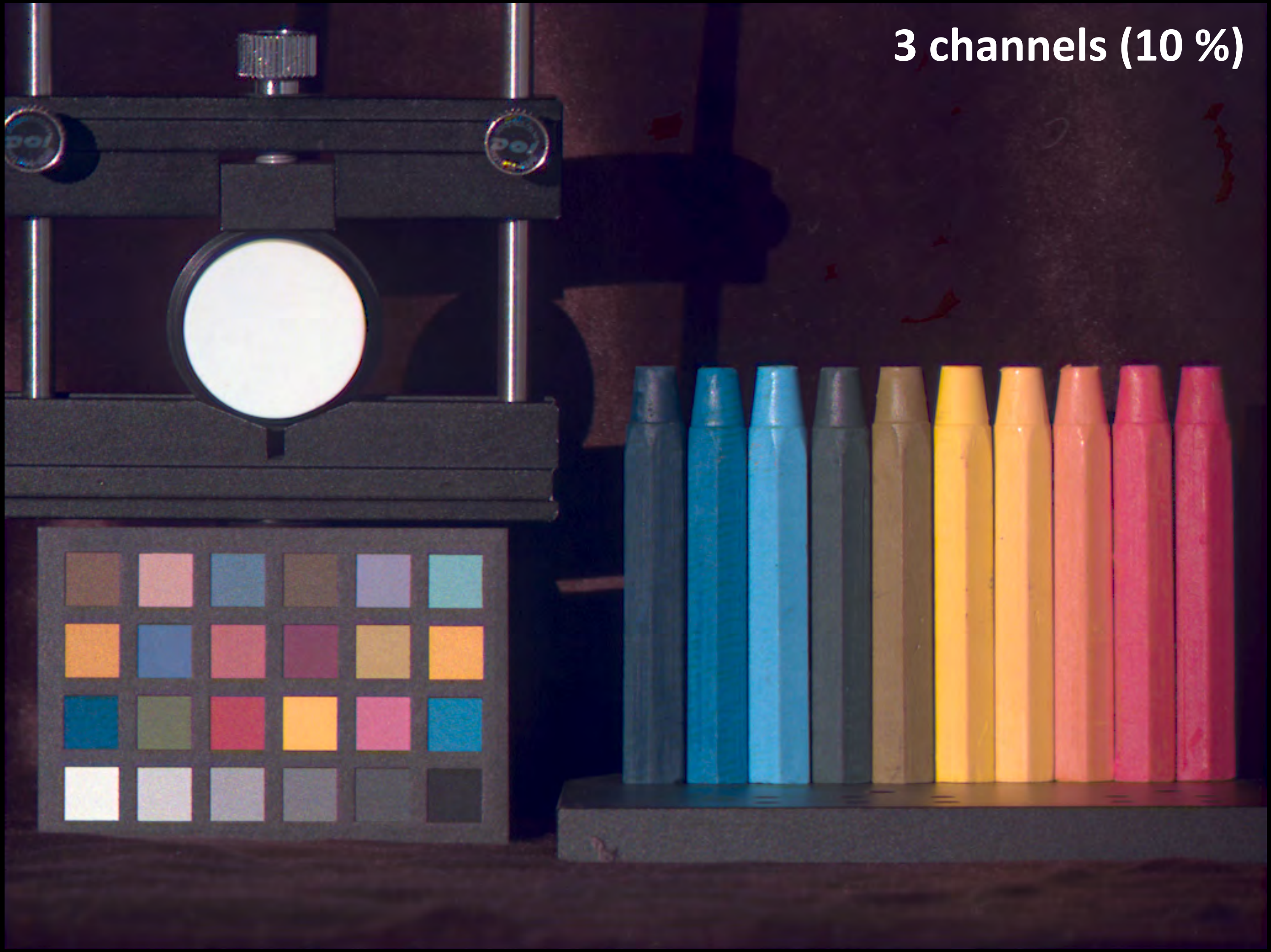
Spectral Interpolation



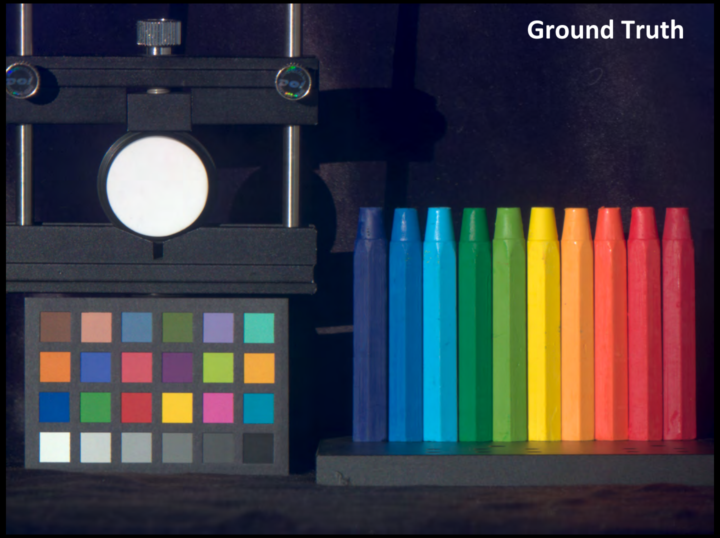
Spectral Interpolation

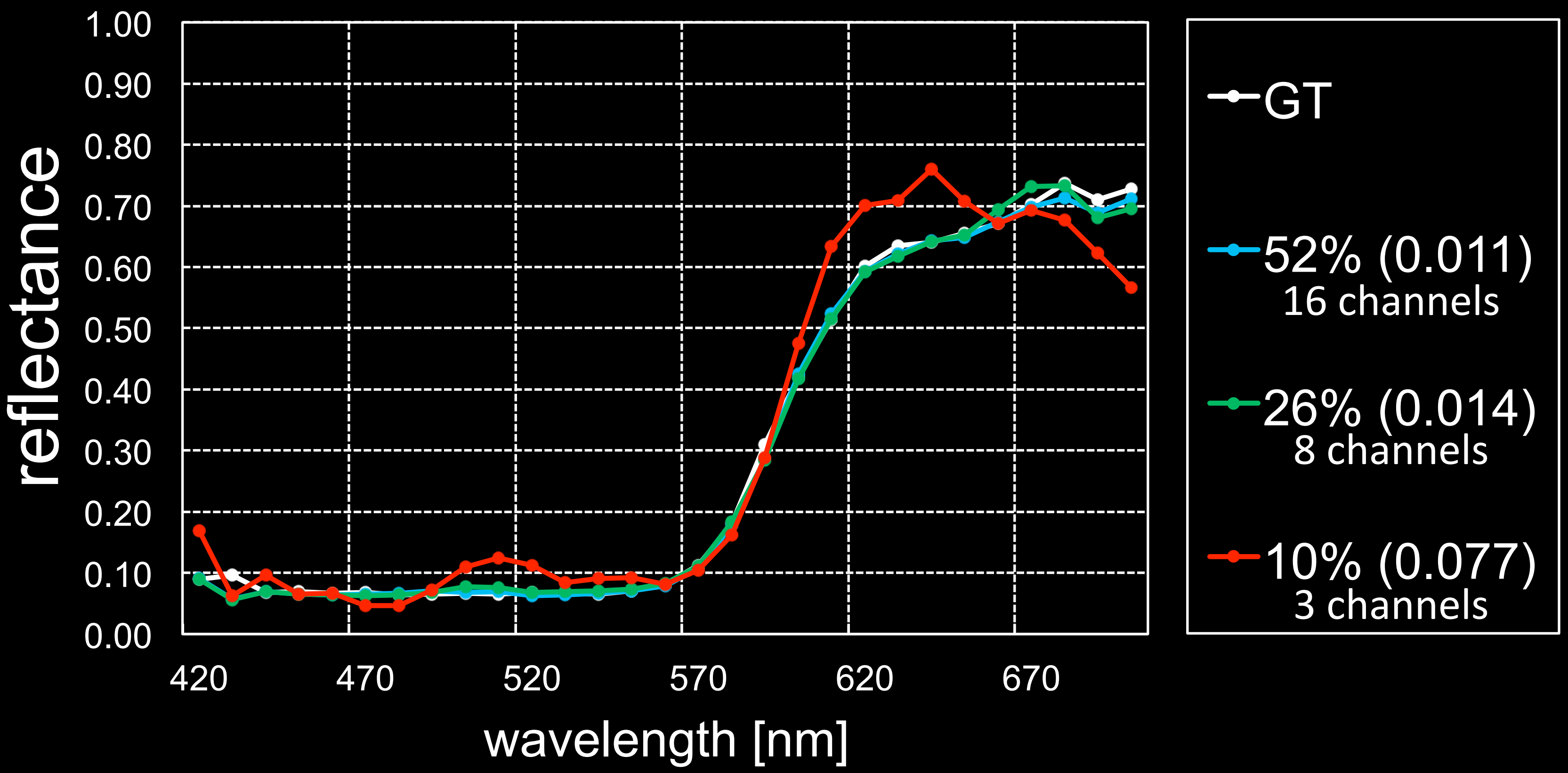


Spectral Interpolation



Spectral Interpolation



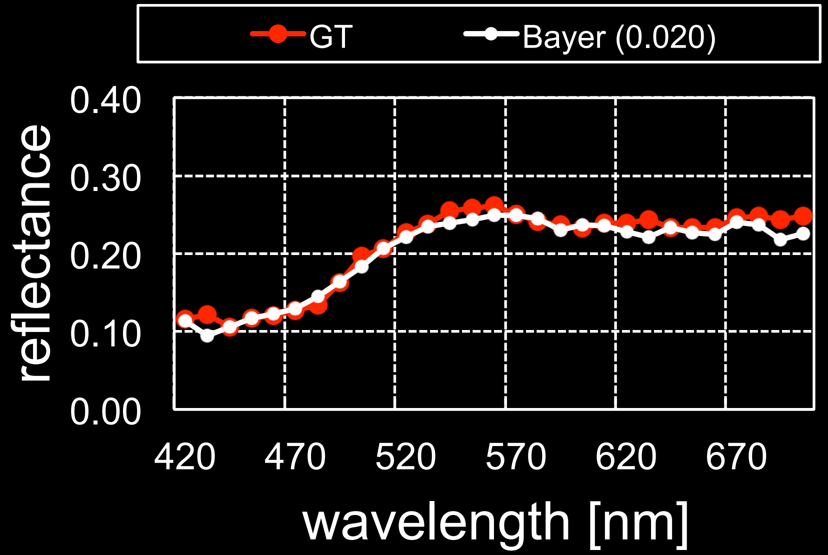


Hyperspectral Demosaicing

450 nm	520 nm
580 nm	650 nm

Hyperspectral Demosaicing

Hyperspectral Demosaicing



Conclusion

Conclusion

- Learned a spectral prior using a convolutional autoencoder
- Proposed a novel hyperspectral reconstruction using the learned prior
- Demonstrated interesting applications
- Published a high quality hyperspectral dataset

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