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Machine Learning for Imaging
Image Registration

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Inverse problems in imaging

- Observe:

$$y = Ax + n$$

Inverse problems in imaging

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- Goal:

Recover x from y

Inverse problems in imaging

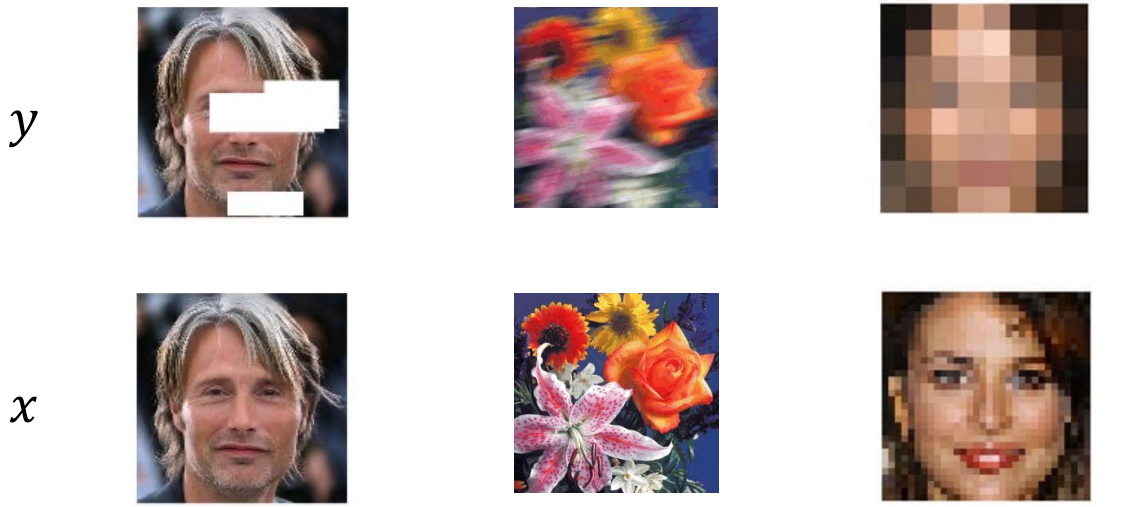
- Observe:

$$y = Ax + n$$

- Goal:

Recover x from y

- Inpainting
- Deblurring
- Denoising
- Super-resolution
- Image Reconstruction (Medical imaging)



Classical Approach

- Example: deblurring

Classical Approach

- Example: deblurring
- Least squares problem:

$$\arg\min_x \mathcal{D}(Ax, y)$$

$$\mathcal{D}(Ax, y) = \frac{1}{2}\|Ax - y\|_2^2$$

Operator A describes the forward map (here a linear operation)

Classical Approach

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- Least squares problem:

$$\arg\min_x \mathcal{D}(Ax, y)$$

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- Least squares solution:

$$\hat{x} = (A^T A)^{-1} A^T y$$

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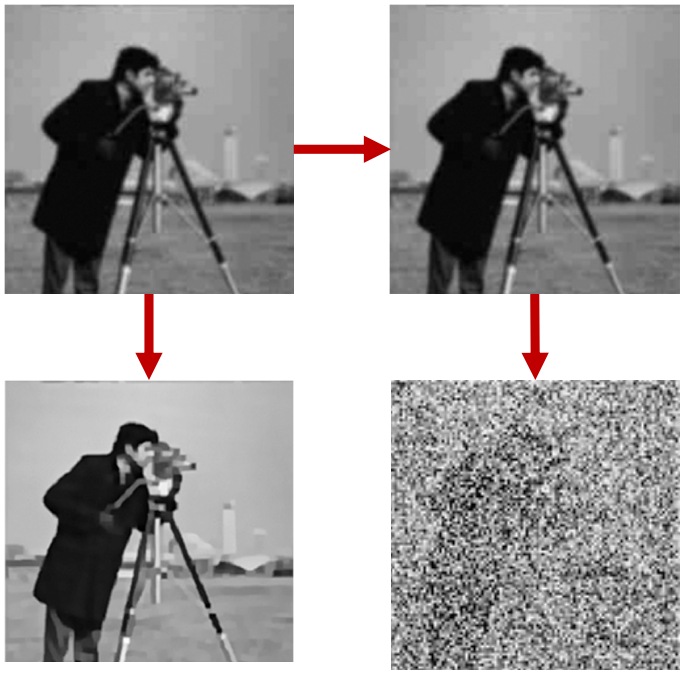

Wildly different solutions

Classical Approach

- Example: deblurring

- Least squares problem:

$$\arg\min_x \mathcal{D}(Ax, y) + \lambda \mathcal{R}(x)$$

Regularisation

$$\mathcal{D}(Ax, y) = \frac{1}{2}\|Ax - y\|_2^2 \quad \text{and} \quad \mathcal{R}(x) = \frac{1}{2}\|x\|_2^2$$

Classical Approach

- Example: deblurring

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$$\mathcal{D}(Ax, y) = \frac{1}{2}\|Ax - y\|_2^2 \quad \text{and} \quad \mathcal{R}(x) = \frac{1}{2}\|x\|_2^2$$

- Least squares solution with Tikhonov regularisation:

$$\hat{x} = \underbrace{(A^T A + \lambda I)^{-1}}_{\text{Better conditioned (and noise suppression)}} A^T y$$

General approach for images

$$\arg\min_x \mathcal{D}(Ax, y) + \lambda \mathcal{R}(x)$$

$\mathcal{D}(Ax, y)$	Data consistency term
$\mathcal{R}(x)$	Regularisation term (encoding prior knowledge on x)
λ	Regularisation parameter

General approach for images

$$\arg\min_x \mathcal{D}(Ax, y) + \lambda\mathcal{R}(x)$$

$\mathcal{D}(Ax, y)$	Data consistency term
$\mathcal{R}(x)$	Regularisation term (encoding prior knowledge on x)
λ	Regularisation parameter

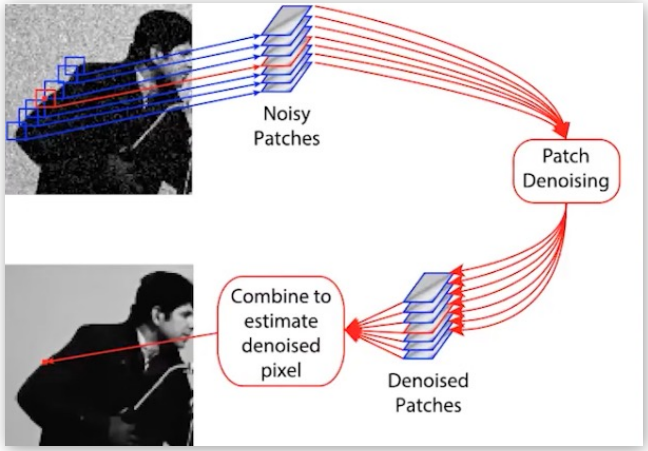
Common regularisers:

$\mathcal{R}(x) = \|\nabla x\|_2^2$	Tikhonov regularisation
$\mathcal{R}(x) = \|\nabla x\|_{2,1} = \sum_{i=0}^{n} \sqrt{\sum_d \left(\|\nabla x\|_i^{(d)}\right)^2}$	Total variation regularisation
$\mathcal{R}(x) = \|\Psi x\|_1$	Wavelet regularisation

General approaches for images

Total variation

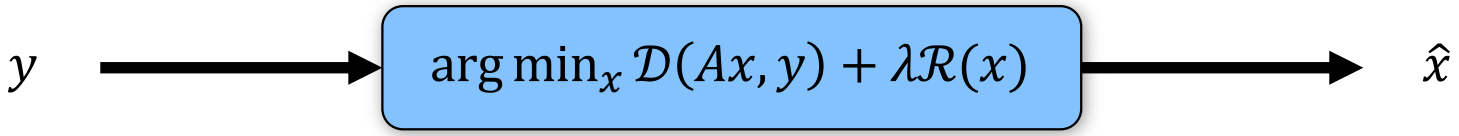
Wavelet decomposition



Patches and manifold

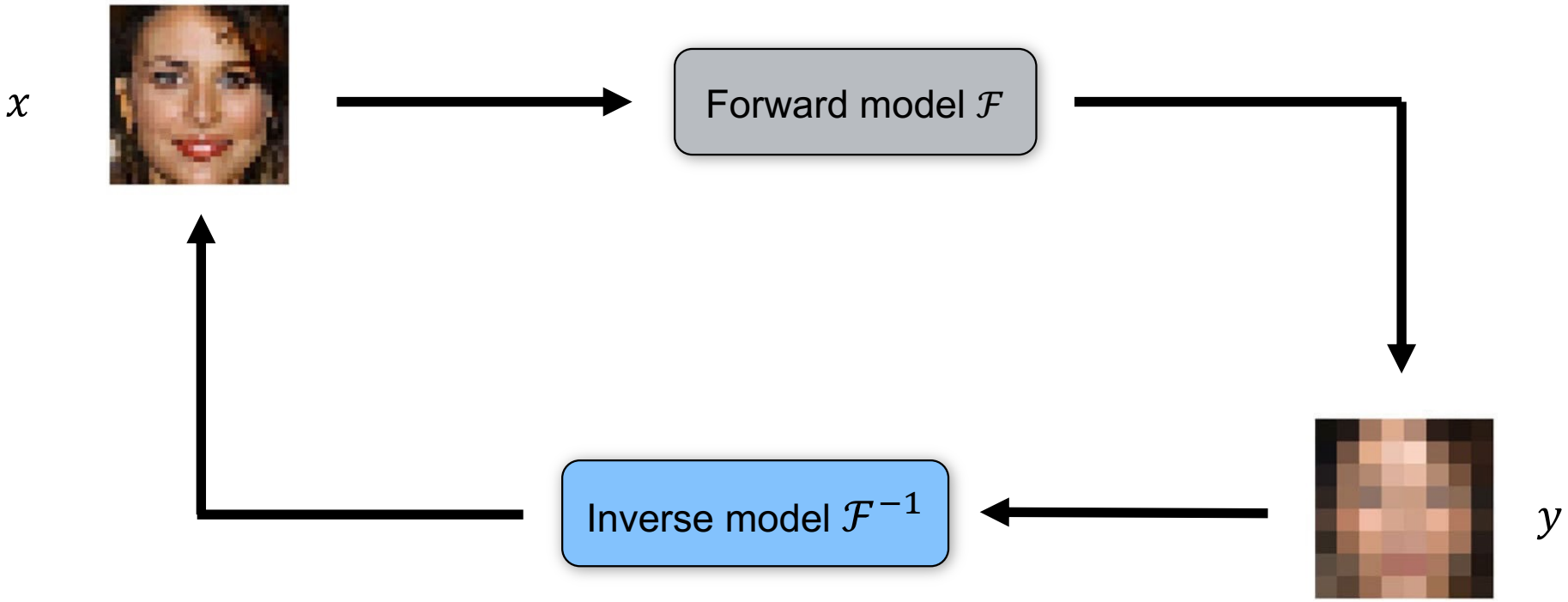
Figure adapted from Rebecca Willett

Regularisation in inverse problems

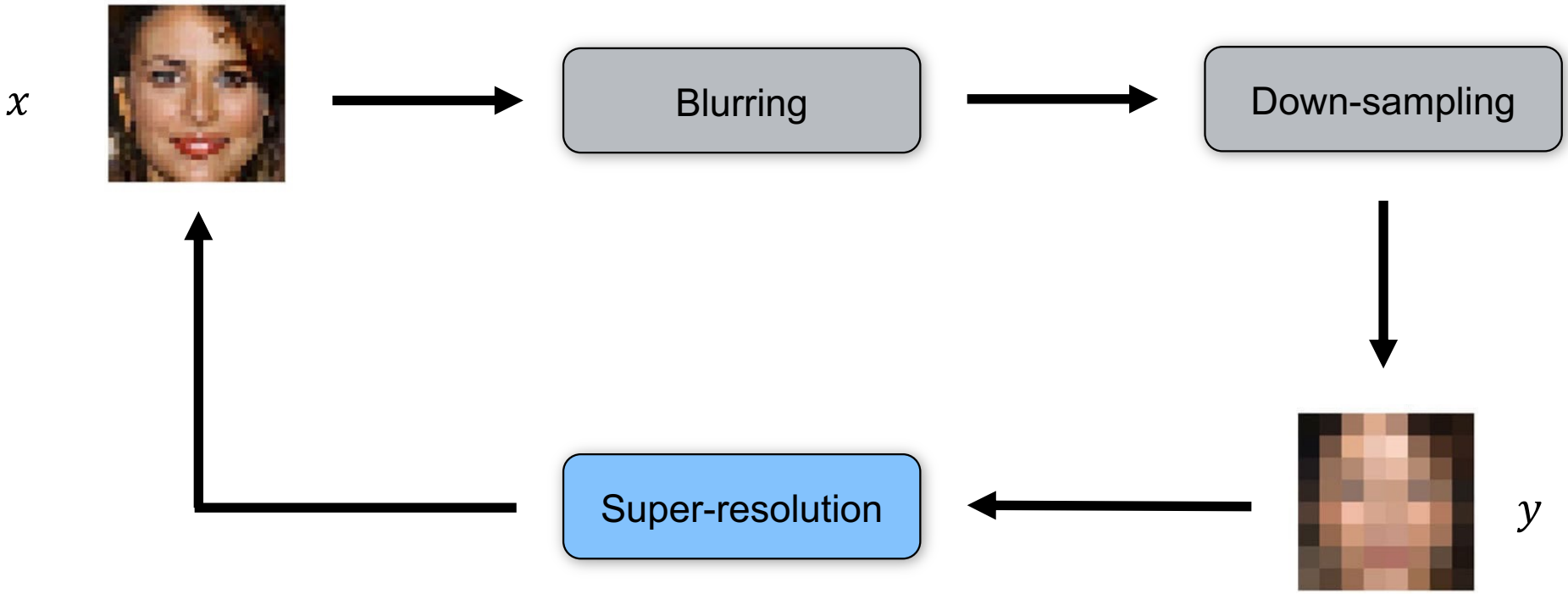


Instead of choosing $\mathcal{R}$ a-priori based on a simple (geometric or other) model of image, learn $\mathcal{R}$ from training data

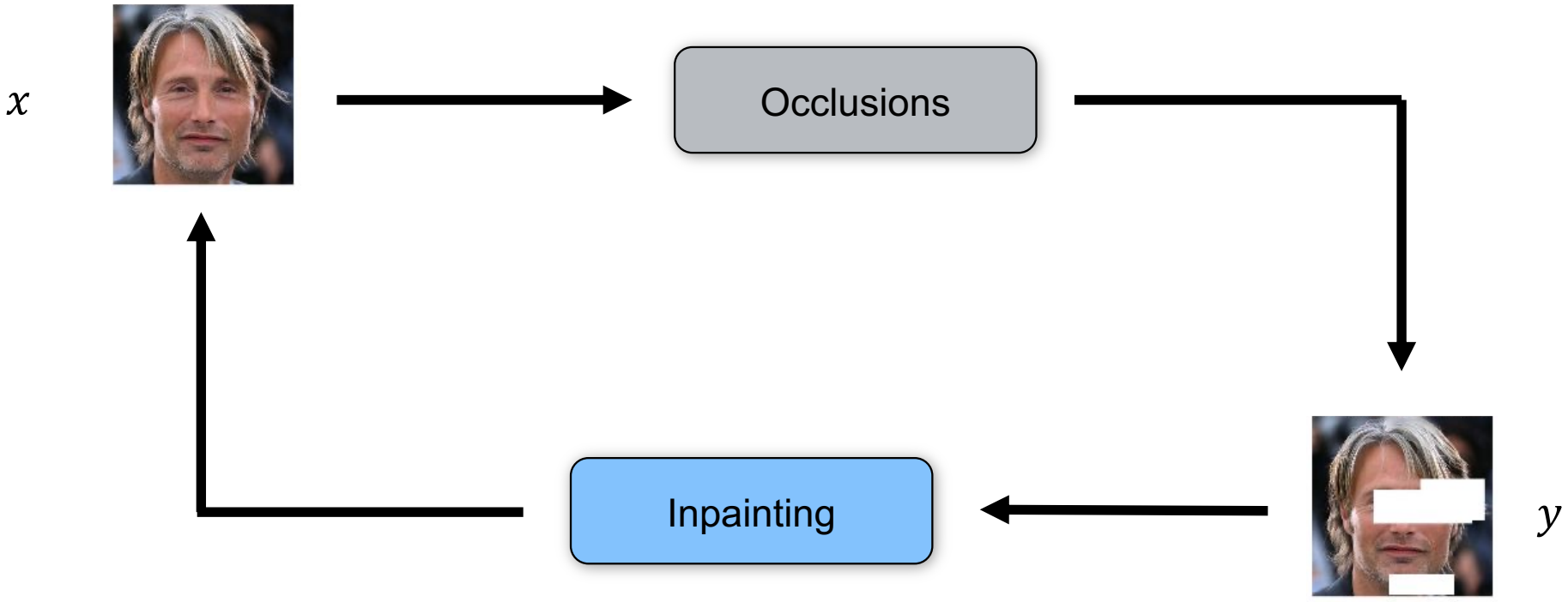
Forward model/Inverse model



Forward model/Inverse model



Forward model/Inverse model



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Solving Inverse Problems with Deep Learning

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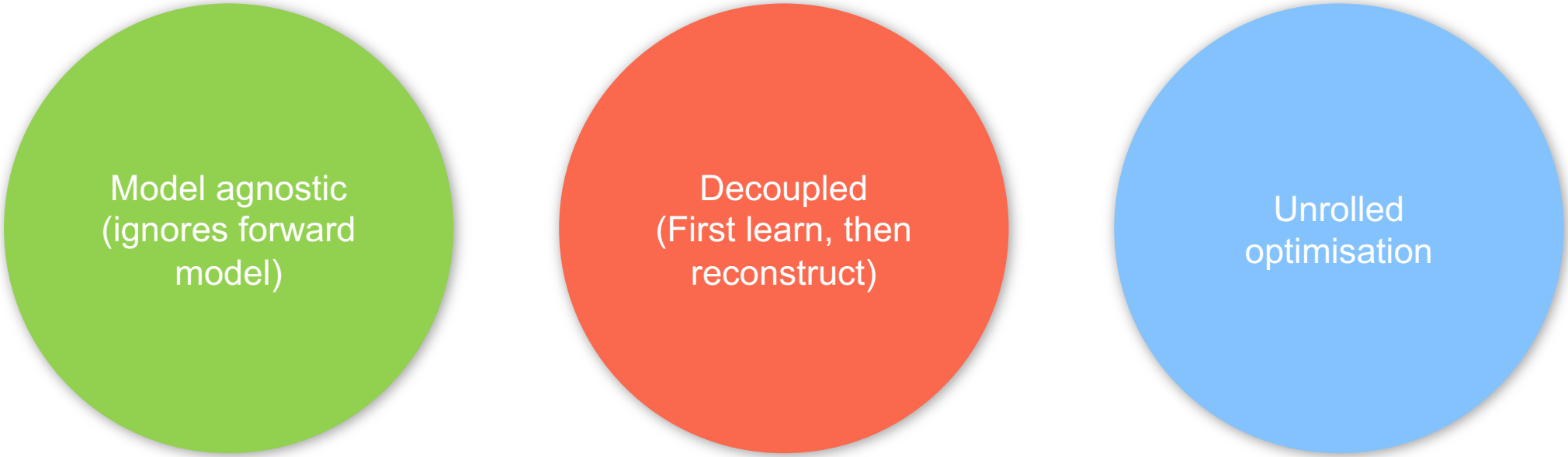
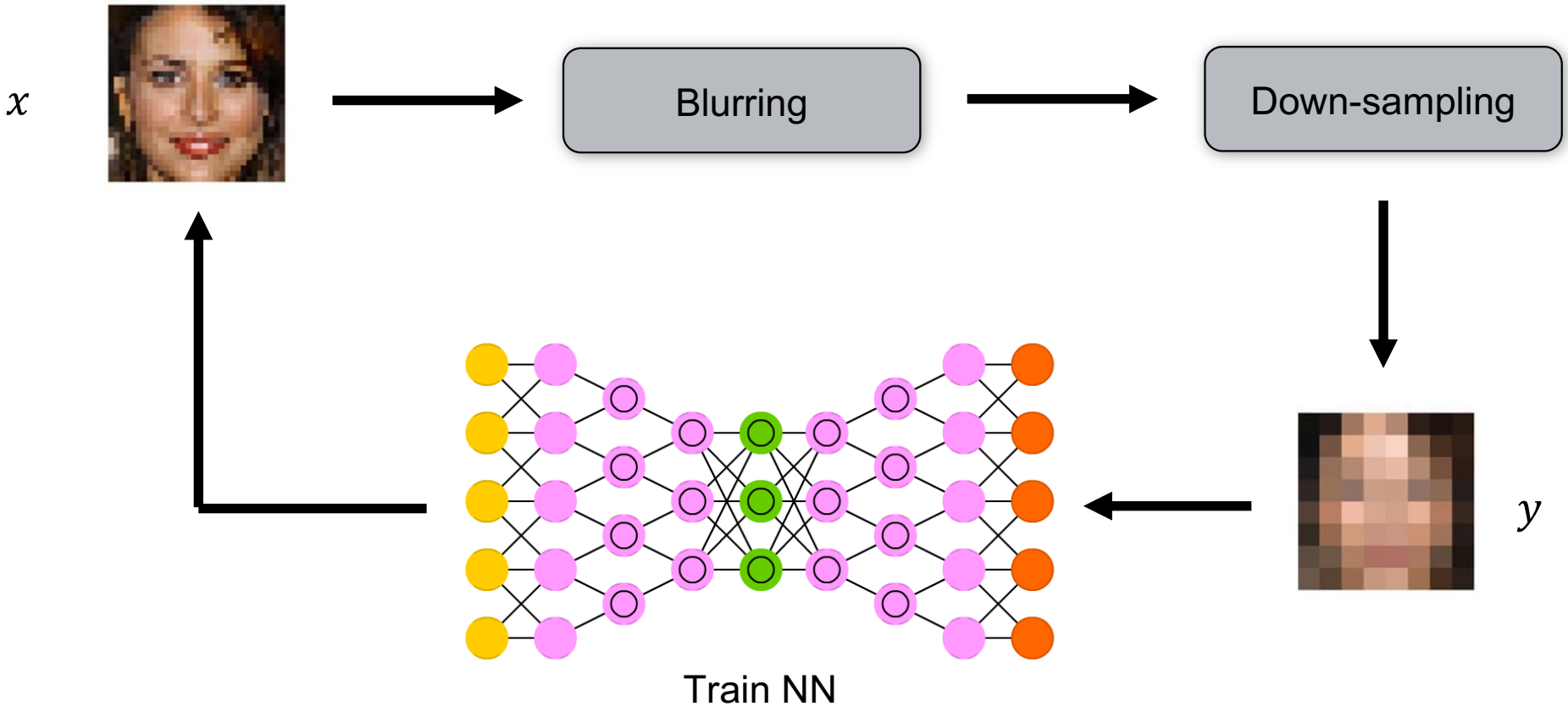
Imperial College London, UK

Classes of methods



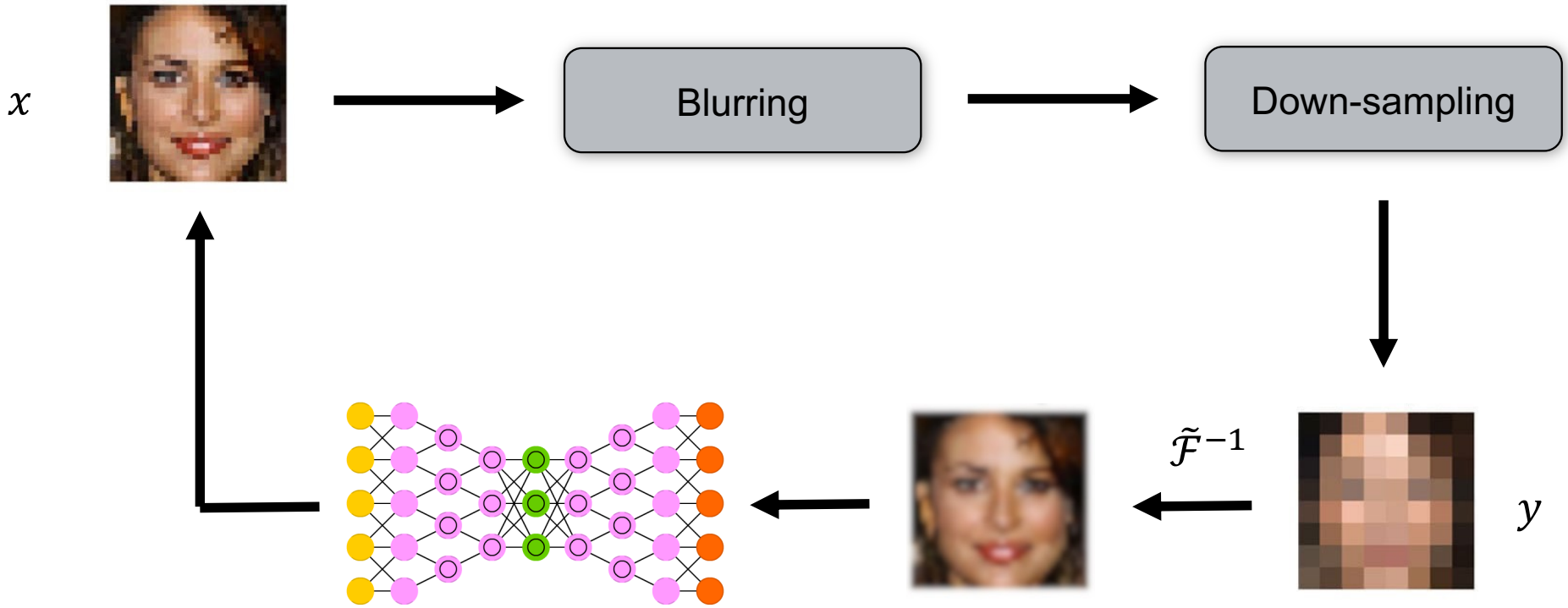
Solving the inverse problem

Model agnostic



Solving the inverse problem

(partly) model agnostic



Solving the inverse problem: Deep proximal gradient

Decoupled (First learn, then reconstruct)

$$y \longrightarrow \boxed{\arg\min_x \mathcal{D}(Ax, y) + \lambda \mathcal{R}(x)} \longrightarrow \hat{x}$$

set $\hat{x}^{(1)}$ and stepsize η

for $k = 1, 2, \cdots$

$$z^k = \hat{x}^{(k)} + \eta A^T \left(y - A\hat{x}^{(k)}\right)$$

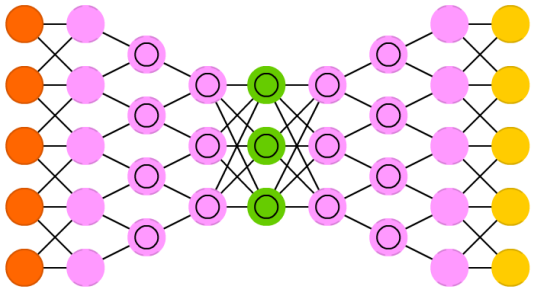
gradient descent (DC)

$$\hat{x}^{(k+1)} = \boxed{\arg\min_x \left\|z^k - x\right\|_2^2 + \eta\lambda\mathcal{R}(x)}$$

denoising

replace with learned NN

z^k



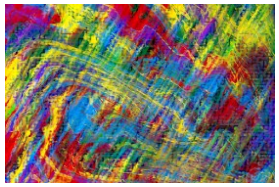
$\hat{x}^{k+1}$

Solving the inverse problem: GANs

Decoupled
(First learn, then reconstruct)

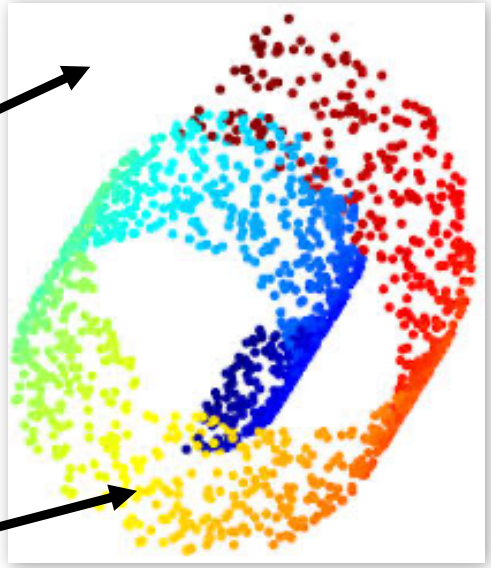
$$y \rightarrow \boxed{\arg\min_x \mathcal{D}(Ax, y) + \lambda \mathcal{R}(x)} \rightarrow \hat{x}$$

$$\mathcal{R}(x) = \begin{cases} 0 & x \text{ on image manifold} \\ \infty & \text{otherwise} \end{cases}$$

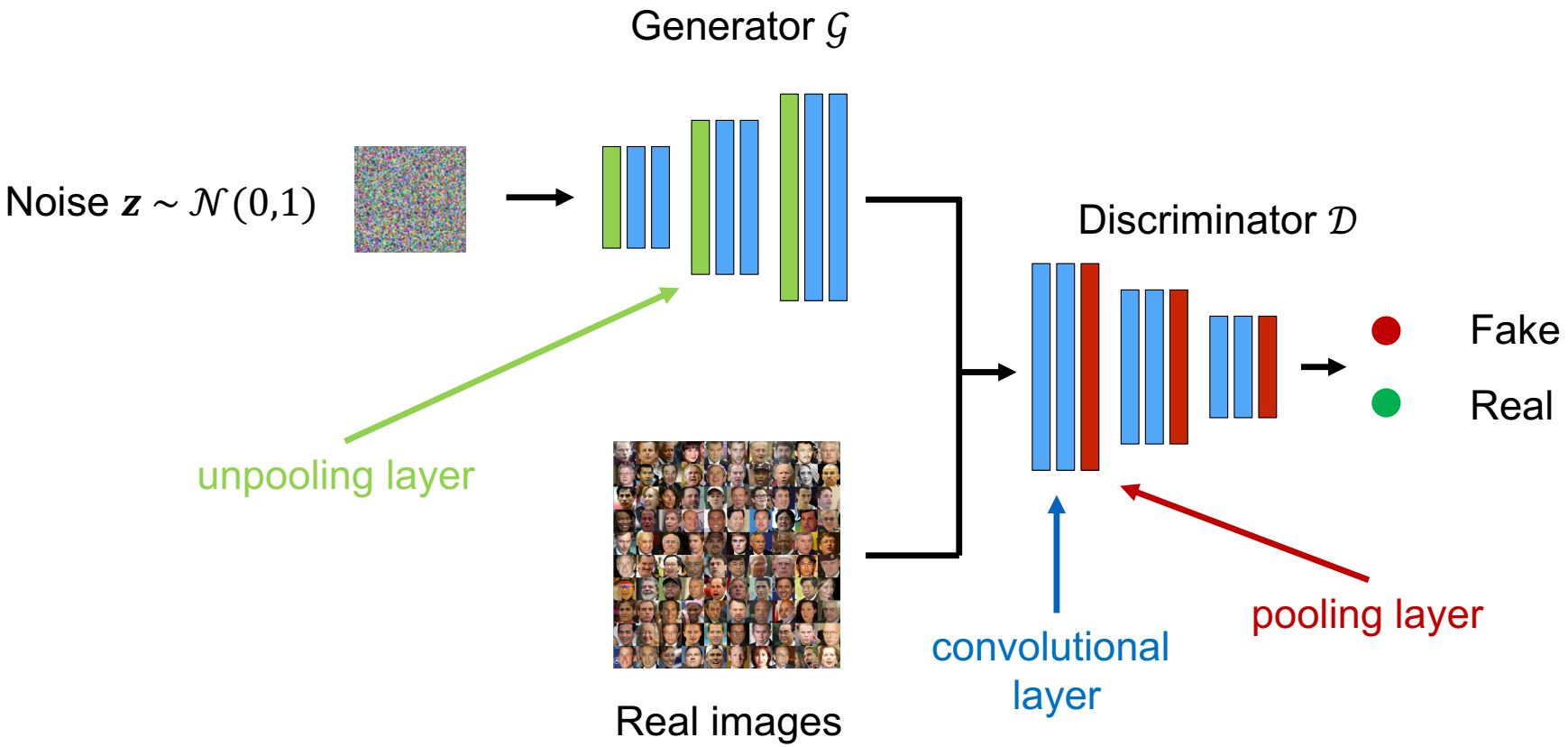


Non-natural image
(bad)

Natural image
(good)



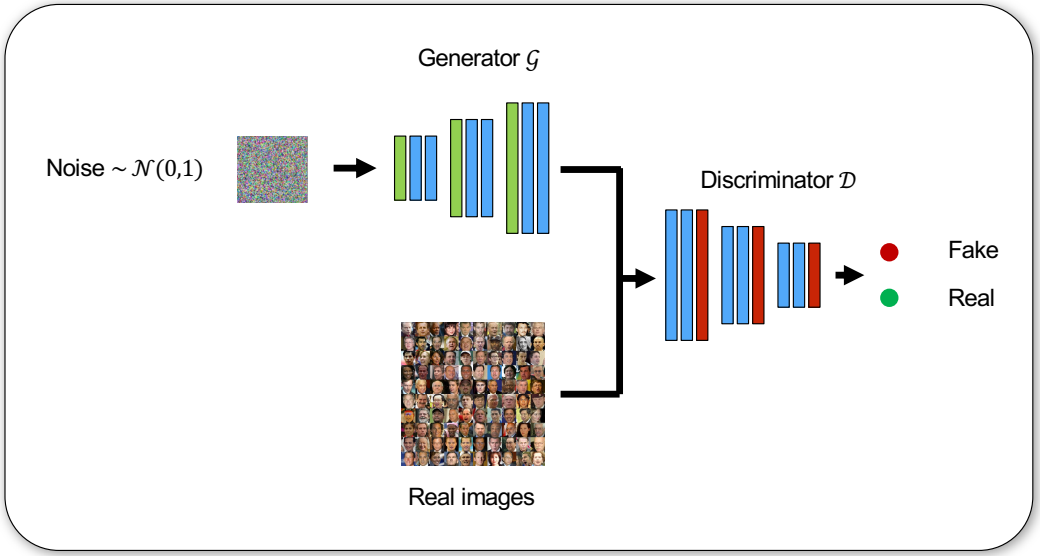
Generative adversarial networks (GANs)



I. Goodfellow, NIPS, 2014

Generative adversarial networks (GANs)

- $\mathcal{D}(x)$ represents the probability that x came from the real data rather than from $\mathcal{G}$.
- $\mathcal{D}$ is trained to maximize the probability of assigning the correct label to both real examples and samples from $\mathcal{G}$.



- Simultaneously train $\mathcal{G}$ to minimize $\log(1 - \mathcal{D}(\mathcal{G}(\boldsymbol{z}))$, e.g. $\mathcal{D}$ and $\mathcal{G}$ play a two-player minimax game with value function $V(\mathcal{G}, \mathcal{D})$:

$$\min_{\mathcal{G}} \max_{\mathcal{D}} V(\mathcal{G}, \mathcal{D}) = \underbrace{\mathbb{E}_{x \sim p_{data}(x)}[\log \mathcal{D}(x)]}_{\text{real}} + \underbrace{\mathbb{E}_{z \sim p_z(z)}[\log(1 - \mathcal{D}(\mathcal{G}(\boldsymbol{z}))]}_{\text{synthetic (aka “fake”)}}$$

Solving the inverse problem: GANs

Decoupled (First learn, then reconstruct)

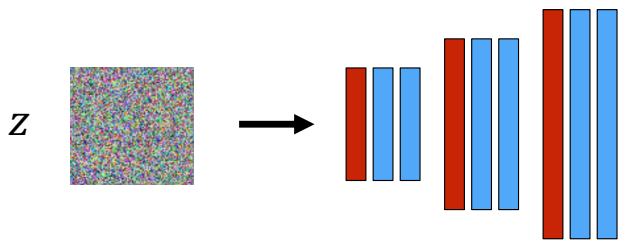
$$y \rightarrow \boxed{\arg\min_x \mathcal{D}(Ax, y) + \lambda \mathcal{R}(x)} \rightarrow \hat{x}$$

$$\mathcal{R}(x) = \begin{cases} 0 & x \text{ on image manifold} \\ \infty & \text{otherwise} \end{cases}$$

- Learn generator $\mathcal{G}$ that outputs $x \in \mathbb{R}^d$ given $x \in \mathbb{R}^{d'}$ for $d' < d$

$$\mathcal{R}(x) = \begin{cases} 0 & x \in \text{range}(\mathcal{G}) \\ \infty & \text{otherwise} \end{cases}$$

Generator $\mathcal{G}$



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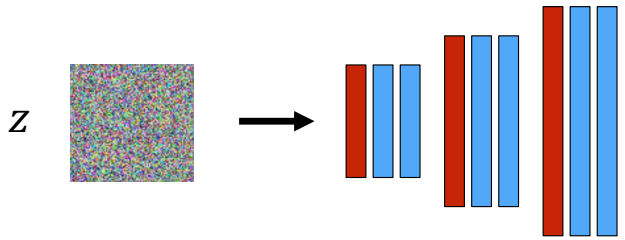
$$\mathcal{R}(x) = \begin{cases} 0 & x \in \text{range}(\mathcal{G}) \\ \infty & \text{otherwise} \end{cases}$$

- Chose $x \in \text{range}(\mathcal{G})$ that best fits the data

$$\hat{x} = \arg \min_{x \in \text{range}(\mathcal{G})} \|y - Ax\|_2^2 = \mathcal{G}(\text{z})$$

$$\hat{z} = \arg \min_z \|y - A\mathcal{G}(\text{z})\|_2^2$$

Generator $\mathcal{G}$



Solving the inverse problem: Gradient descent networks

Unrolled optimisation

Let's assume that $\mathcal{R}(x)$ is differentiable

$$\arg\min_x \mathcal{D}(Ax, y) + \lambda\mathcal{R}(x)$$

Solving the inverse problem: Gradient descent networks

Unrolled optimisation

Let's assume that $\mathcal{R}(x)$ is differentiable

$$\arg\min_x \|y - Ax\|_2^2 + \mathcal{R}(x)$$

set $\hat{x}^{(1)}$ and stepsize η

for $k = 1, 2, \cdots$

$$\hat{x}^{(k+1)} = \hat{x}^{(k)} + \eta A^T\left(y - A\hat{x}^{(k)}\right) - \boxed{\eta \nabla \mathcal{R}(\hat{x}^{(k)})}$$

replace with learned NN

Solving the inverse problem: Gradient descent networks

Unrolled optimisation

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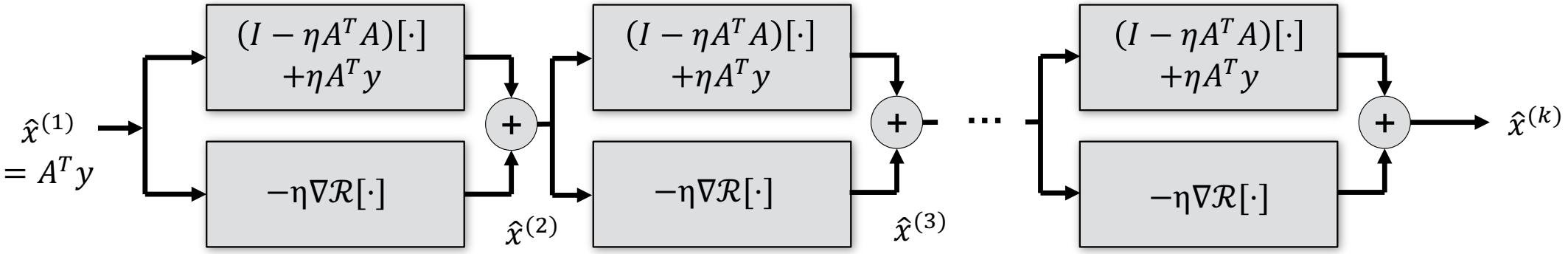

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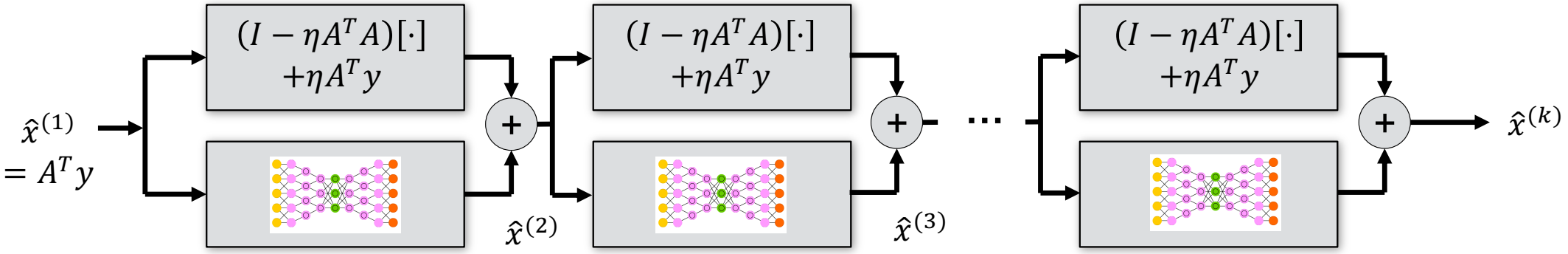
replace with learned NN



Unrolled optimization framework **trained end-to-end**

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Deep Learning for Image Super-Resolution

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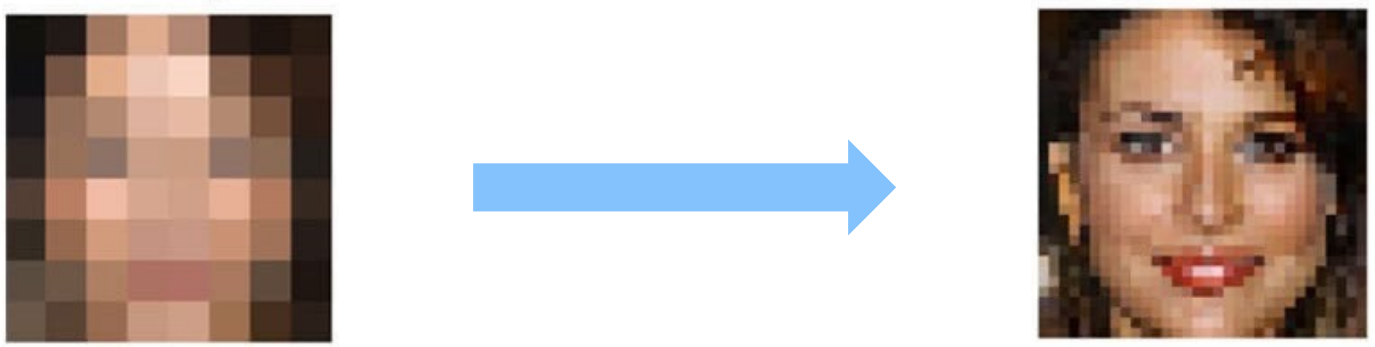
Problem formulation

- Upsample low-resolution (LR) image to high-resolution (HR or SR) image



- Forward model (going from high- to low-resolution) is straightforward and involves some image degradation followed by downsampling
- Inverse model: e.g. interpolation-based models

Super-resolution framework: Post-upsampling super-resolution

- Directly upsamples LR image into SR
- Requires learnable upsampling layers

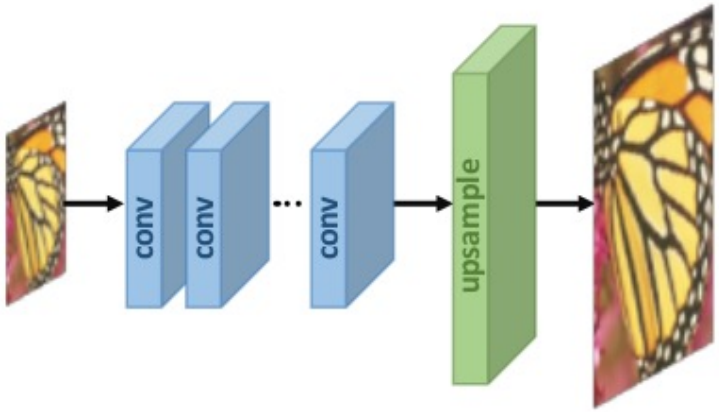
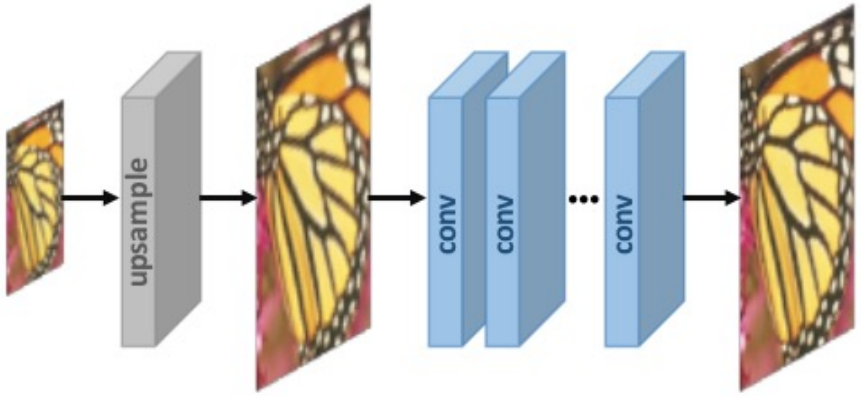


Figure from: Deep Learning for Image Super-resolution: A Survey
https://arxiv.org/abs/1902.06068

- Advantages:
  - Fast and low memory requirements
- Disadvantages:
  - Network has to learn entire upsampling pipeline
  - Network typically limited to a specific up-sampling factor

Super-resolution framework: Pre-upsampling super-resolution

- Two stage process:
  1. First use traditional upsampling algorithm (e.g. linear interpolation) to obtain SR images
  2. Then refining upsampled using a deep neural network (usually a CNN)



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- Advantages:
  - Upsampling operation is performed using interpolation, then correct smaller details
  - Can be applied to a range of upscaling factors and image sizes
- Disadvantages:
  - Operates on SR image, thus requires more computation and memory

Super-resolution framework: Progressive upsampling super-resolution

- Multi-stage process:
  - Use a cascade of CNNs to progressively reconstruct higher-resolution images.
  - At each stage, the images are upsampled to higher resolution and refined by CNNs

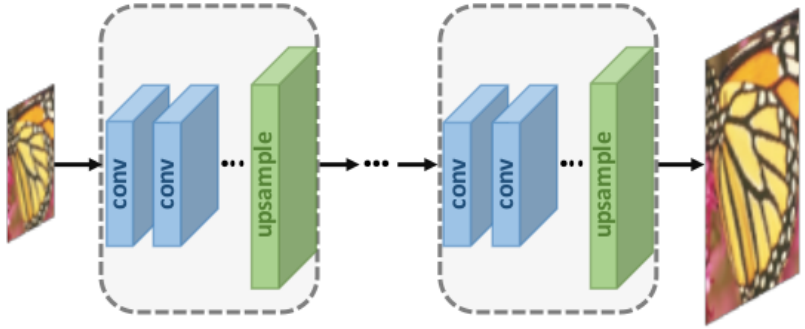

Figure from: Deep Learning for Image Super-resolution: A Survey
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- Advantages:
  - Decomposes complex task into simple tasks
  - Reasonable efficiency
- Disadvantages:
  - Sometimes difficult to train very deep models

Super-resolution framework: Iterative up-and-down sampling super-resolution

- Approach:
  - Alternate between upsampling and downsampling (back-projection) operations
  - Mutually connected up- and down-sampling stages

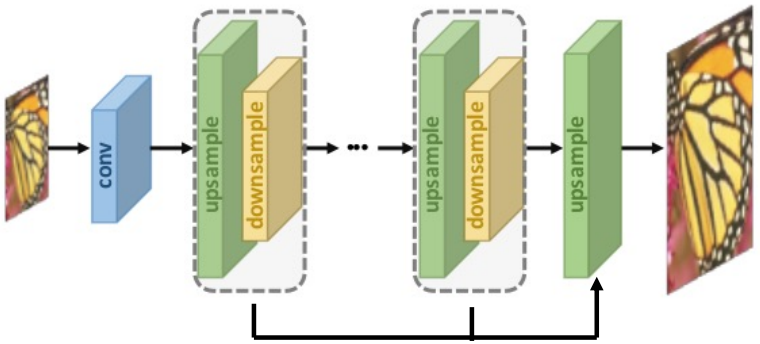

Figure from: Deep Learning for Image Super-resolution: A Survey
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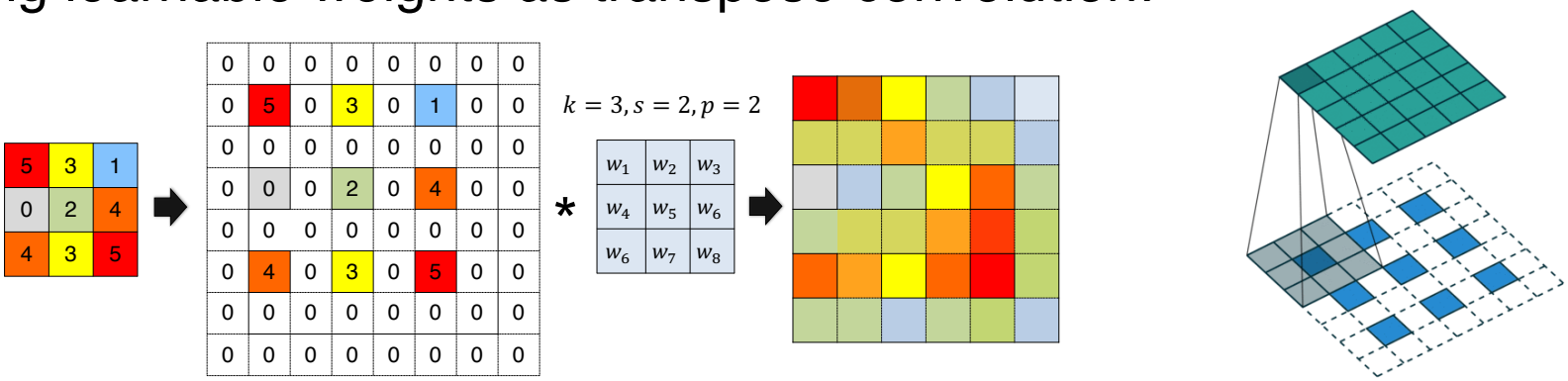
- Advantages:
  - Has shown superior performance as it allows error feedback
  - Easier training of deep networks

How to implement upsampling?

- Traditional interpolation-based upsampling (NN, bi-linear) can be implemented as a convolutional layer with fixed weights:

- Or using learnable weights as transpose convolution:



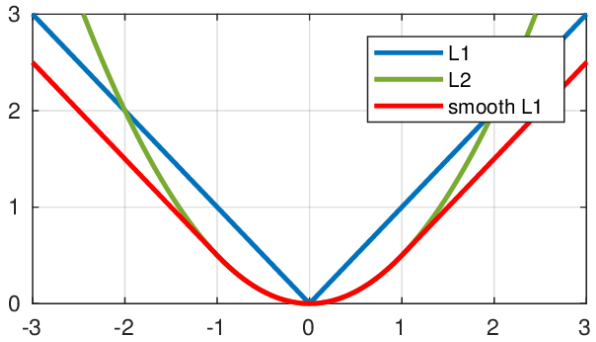
Loss functions for super-resolution

- Pixel-wise loss function (either L1 or L2)

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} |x_i - \hat{x}_i|^p$$

- Alternative: Huber loss function

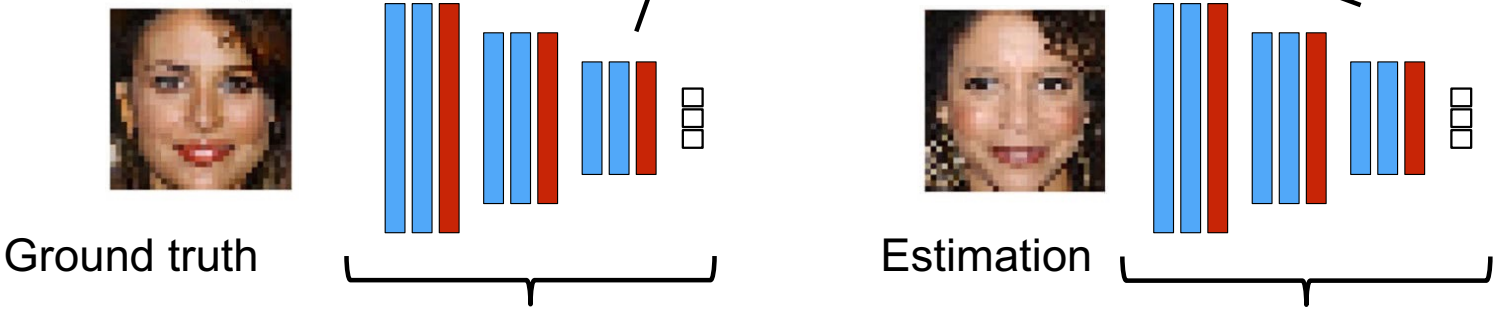
$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} \delta(x_i - \hat{x}_i) \qquad \delta(a) = \begin{cases} 0.5a^2 & \text{for } |a| \leq 1 \\ |a| - 0.5 & \text{otherwise} \end{cases}$$



Loss functions for super-resolution

- Perceptual loss: Computes loss on the output θ of an intermediate layer l of a pre-trained network:

$$\mathcal{L} = \frac{1}{M}\sum_{i=1}^{M}\left(\Theta_i^{(l)}(x) - \Theta_i^{(l)}(\hat{x})\right)^2$$



Loss functions for super-resolution

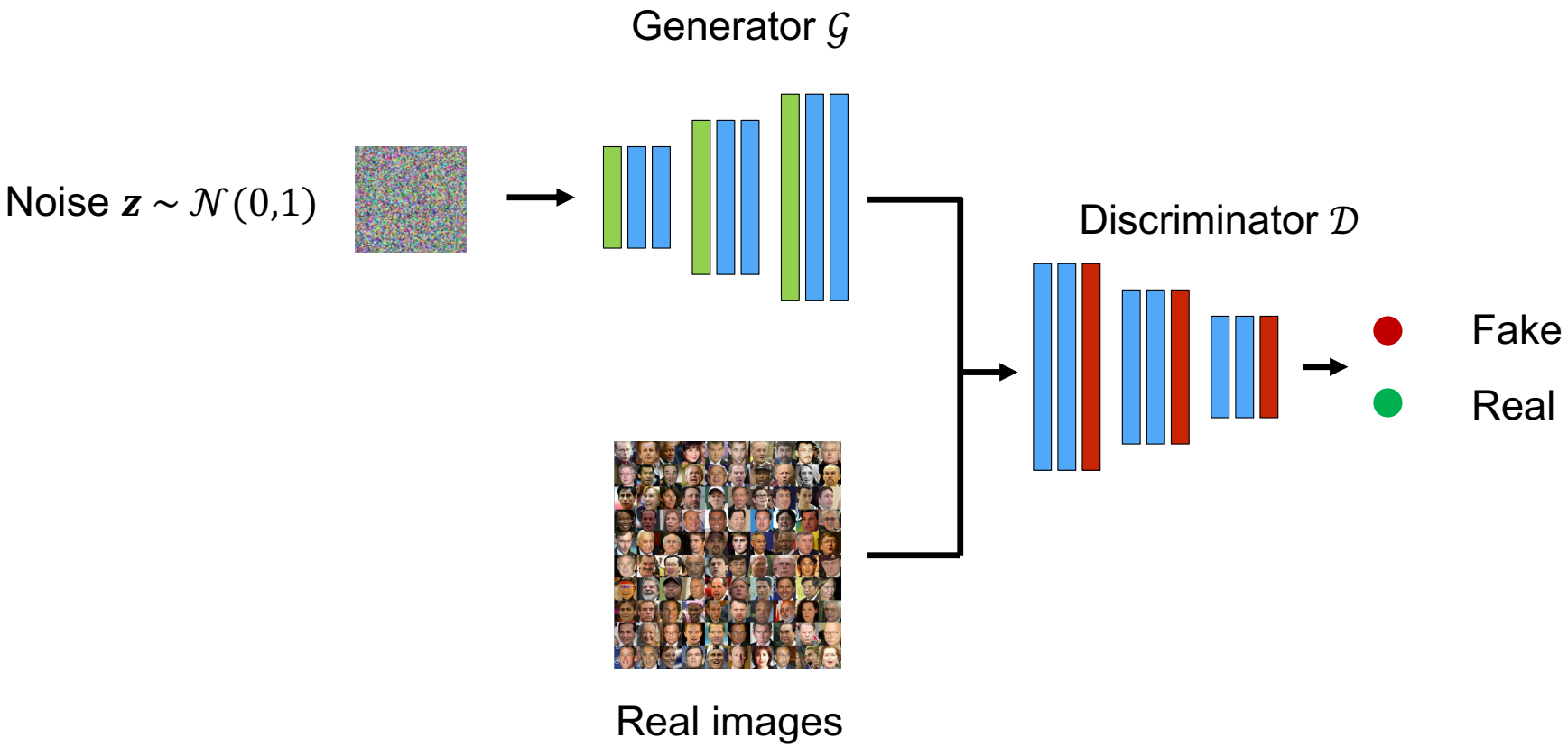
- Total variation

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}\sqrt{\sum_{d}\left(|\nabla x|_i^{(d)}\right)^2}$$

- Assumption: Absolute value of gradient of the image is low, e.g. image is piecewise constant
- Implementation for 2D image (using forward differences to approximate the gradient):

$$\mathcal{L} = \frac{1}{n_1 n_2}\sum_{i=1}^{n_1-1}\sum_{j=1}^{n_2-1}\sqrt{\left|x_{i-1,j} - x_{i,j}\right|^2 + \left|x_{i,j-1} - x_{i,j}\right|^2}$$

Generative adversarial networks (GANs)



I. Goodfellow, NIPS, 2014

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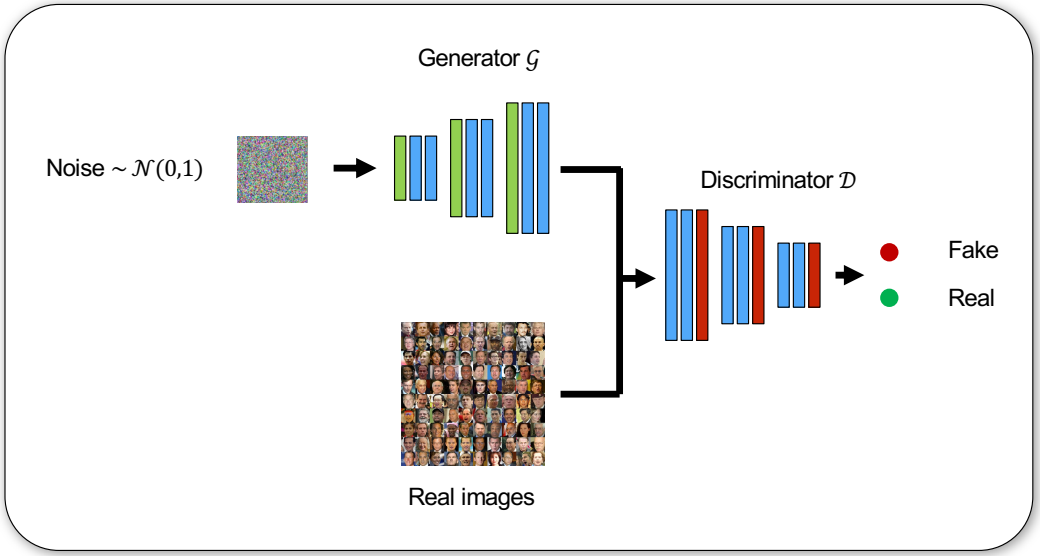
- $\mathcal{D}(x)$ represents the probability that x came from the real data rather than from $\mathcal{G}$.
- $\mathcal{D}$ is trained to maximize the probability of assigning the correct label to both real examples and samples from $\mathcal{G}$.



- Simultaneously train $\mathcal{G}$ to minimize $\log(1 - \mathcal{D}(\mathcal{G}(\boldsymbol{z}))$, e.g. $\mathcal{D}$ and $\mathcal{G}$ play a two-player minimax game with value function $V(\mathcal{G}, \mathcal{D})$:

$$\min_{\mathcal{G}} \max_{\mathcal{D}} V(\mathcal{G}, \mathcal{D}) = \underbrace{\mathbb{E}_{x \sim p_{data}(x)}[\log \mathcal{D}(x)]}_{\text{real}} + \underbrace{\mathbb{E}_{z \sim p_z(z)}[\log(1 - \mathcal{D}(\mathcal{G}(\boldsymbol{z}))]}_{\text{synthetic (aka “fake”)}}$$

Loss functions for super-resolution based on GANs

- Minimax game for super-resolution:

$$\min_{\mathcal{G}} \max_{\mathcal{D}} \mathbb{E}_{I_{HR} \sim p_{train}} [\log \mathcal{D}(I_{HR})] + \mathbb{E}_{I_{LR} \sim P_{\mathcal{G}}(I_{LR})} [\log(1 - \mathcal{D}(\mathcal{G}(I_{LR}))]$$

- Aim: To detect
  - Which images are (real) high-resolution?
  - Which images are super-resolved?

- Use discriminator output as loss function:

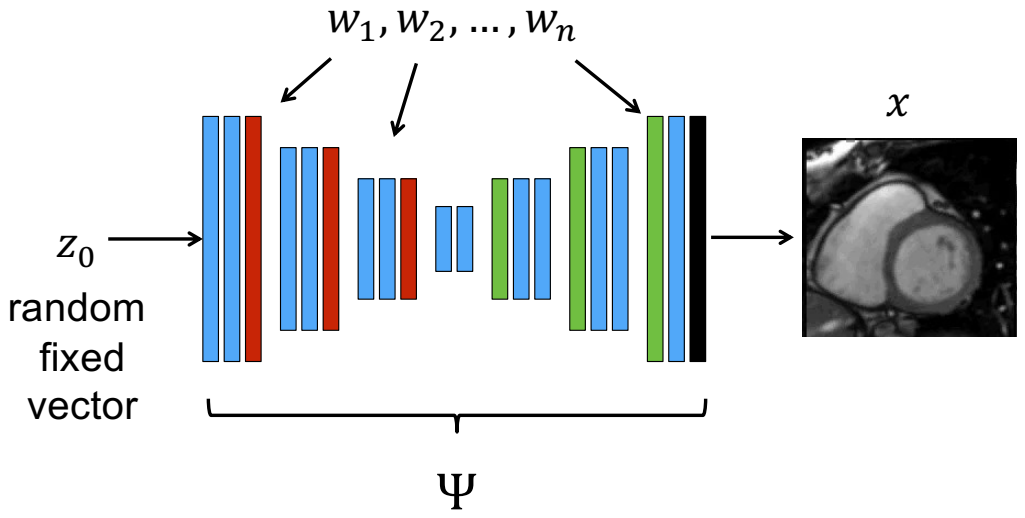
$$\mathcal{L} = -\log \mathcal{D}(\mathcal{G}(I_{LR}))$$

Parameterizing images via generative networks

- Consider a generator network Ψ with a fixed input z_0

- The network parameters w can be thought as a ***parameterization*** of images

$$w \longmapsto x = \Psi(z_0; w)$$



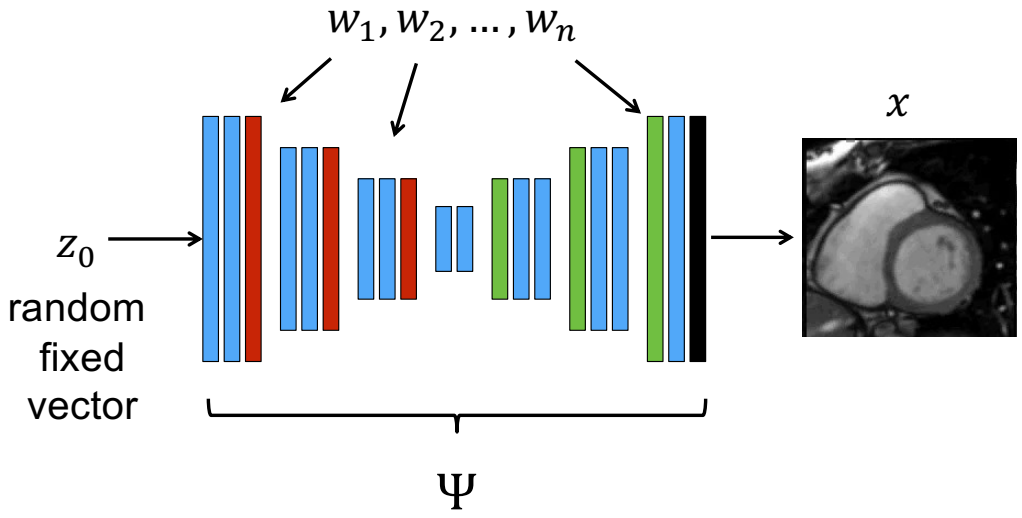
Parameterizing images via generative networks

Fit a network to a single image:

- Start with a random-initialised network
- Given an image x, its parameters w are recovered by solving the following optimization problem:

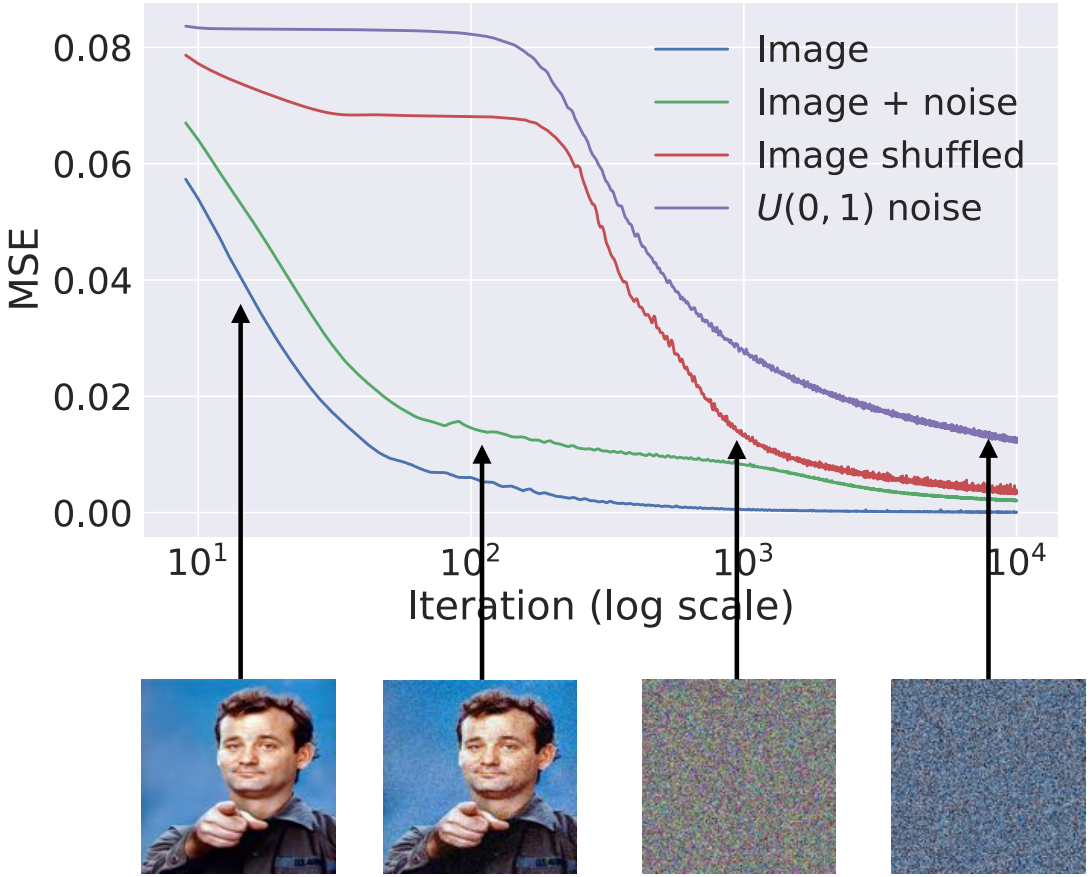
$$\min_{w} \|x - \Psi(z_0; w)\|^2$$

- This is similar to learning a network from a single image



Deep image prior

For most generative networks fitting naturally looking images is easier/faster than fitting others



Deep Image Prior. Ulyanov, Vedaldi & Lempistky, CVPR 2018

Deep image prior: Application to inpainting

For inpainting we only reconstruct the visible pixels, implicitly inferring the pixels that are masked out by mask m:

$$\min_{w} \left\| m \odot \left(x - \Psi(z_0; w) \right) \right\|^2$$

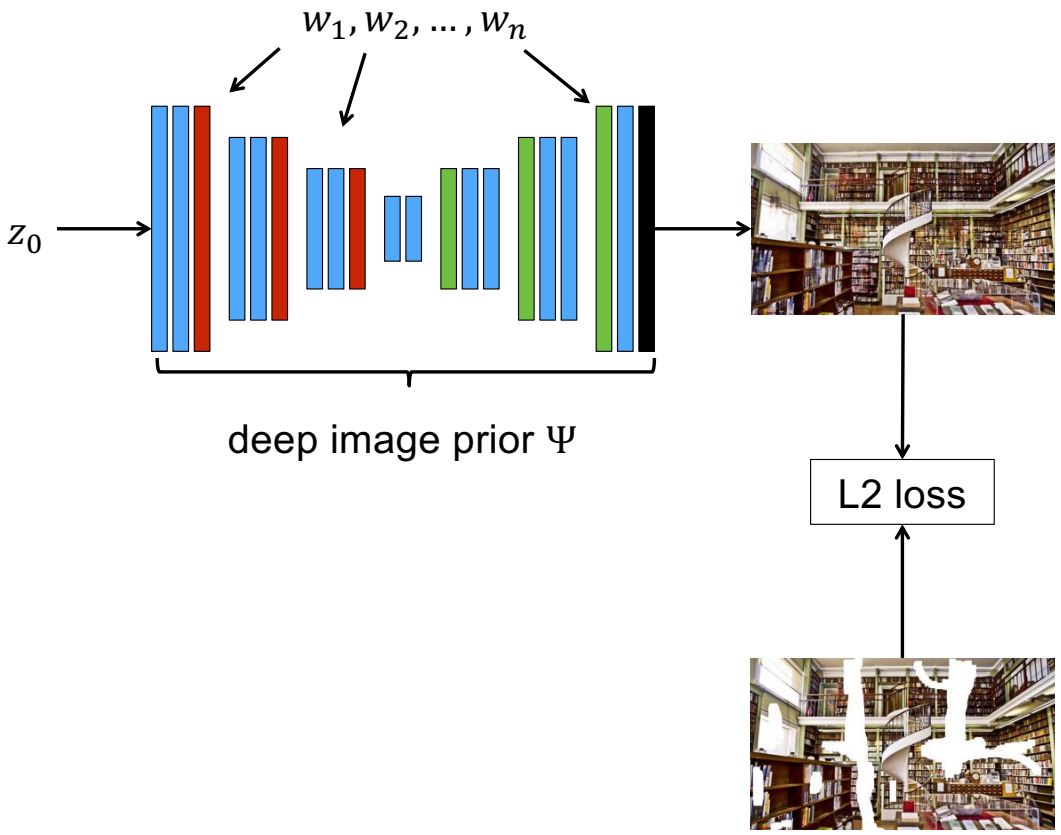
Conventional inpainting

Inpainting using deep image prior

Deep image prior: Application to inpainting

Deep Image Prior. Ulyanov, Vedaldi & Lempistky, CVPR 2018

Inpainting via deep image priors



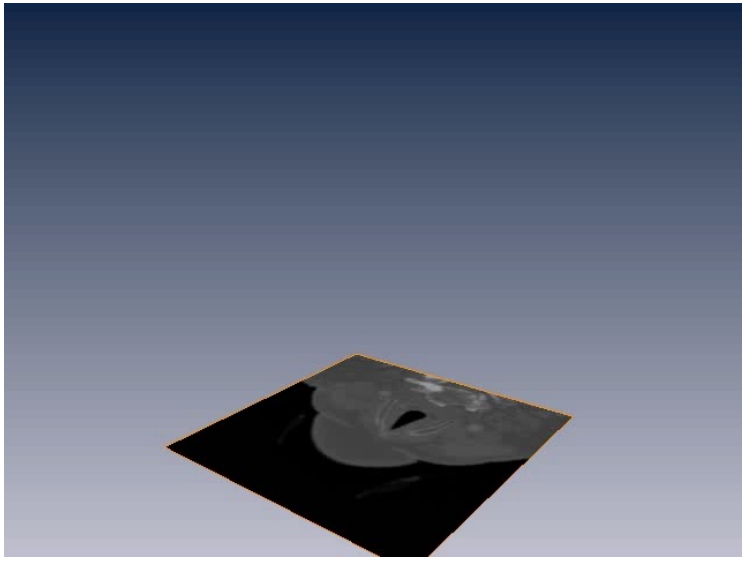
Imperial College London

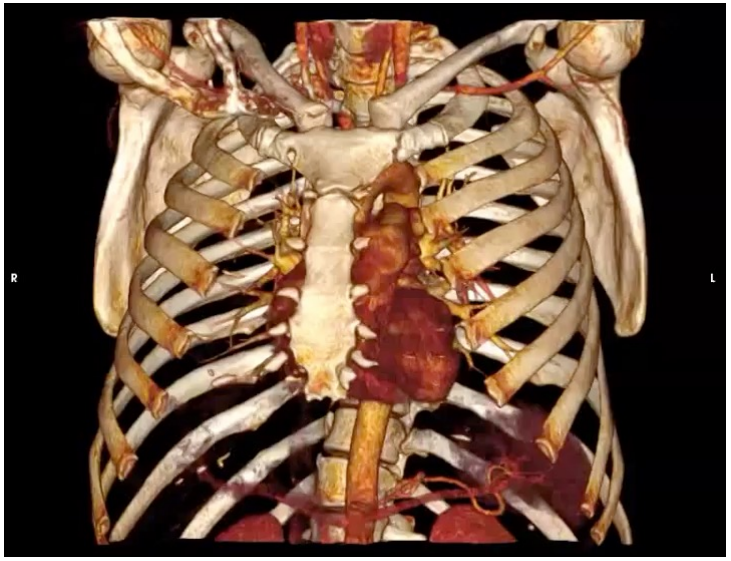
Imperial College London

Deep Learning for Image Reconstruction

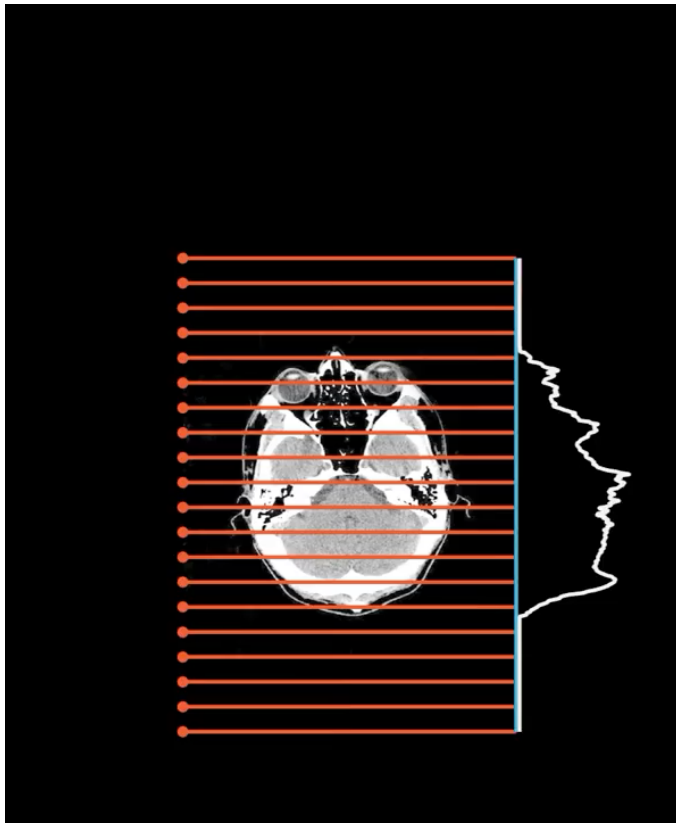
Daniel Rueckert
Department of Computing
Imperial College London, UK

Medical Imaging: X-ray computed tomography (CT)





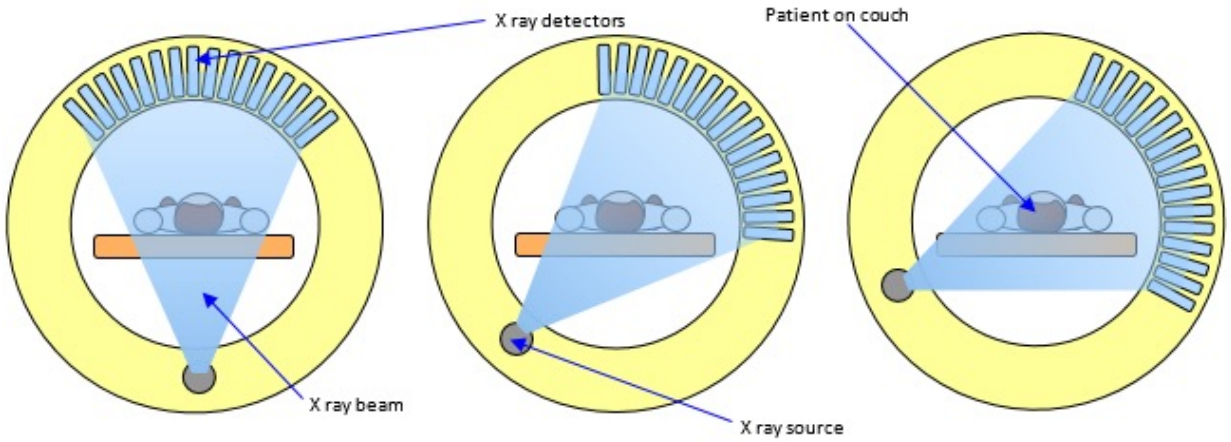
Medical Imaging: X-ray computed tomography (CT)



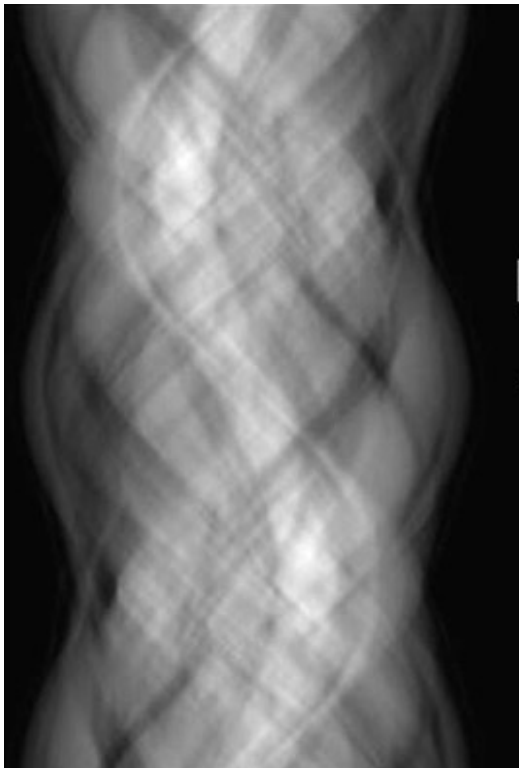
source: https://youtu.be/q7Rt_OY_7tU

Medical Imaging: X-ray computed tomography (CT)

- CT imaging
  - high contrast
  - high spatial resolution
  - fast acquisition
  - but ionising radiation



Medical Imaging: X-ray computed tomography (CT)

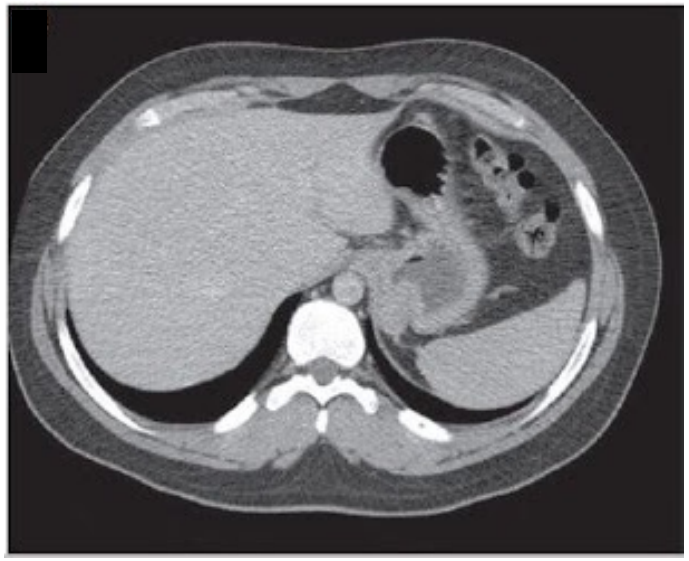


Sinogram

Forward problem
(Radon transform)

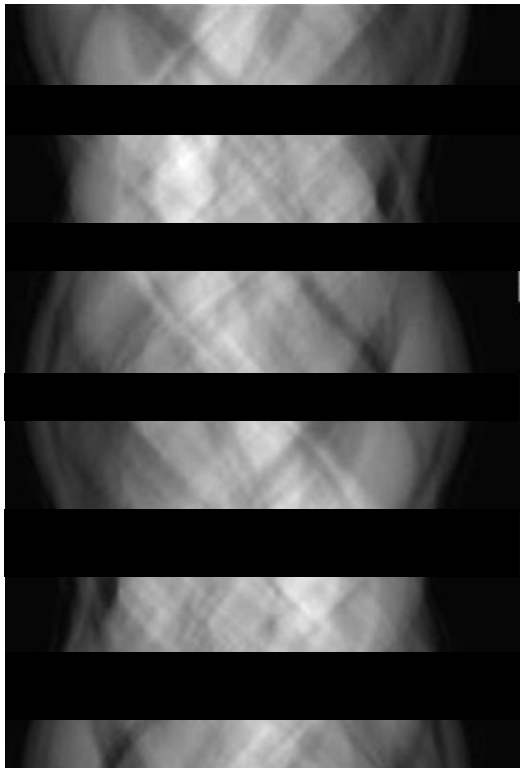
Inverse problem:

Fully sampled
reconstruction



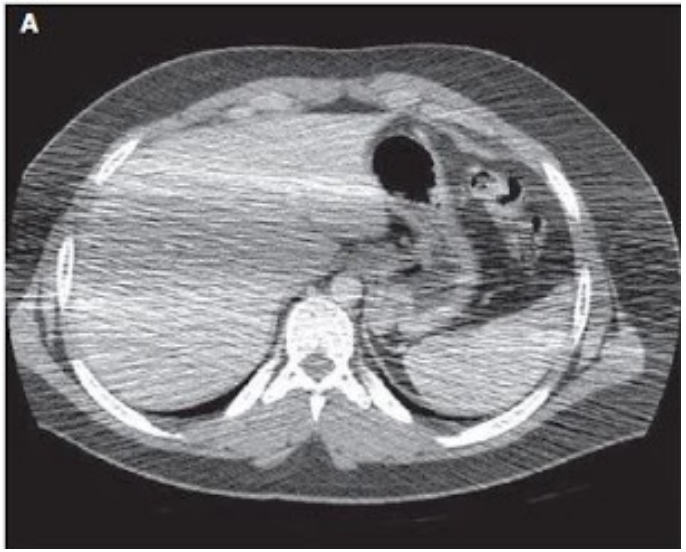
CT image

Medical Imaging: X-ray computed tomography (CT)



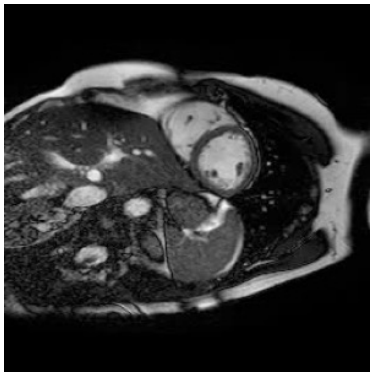
Sinogram

Under-sampled reconstruction

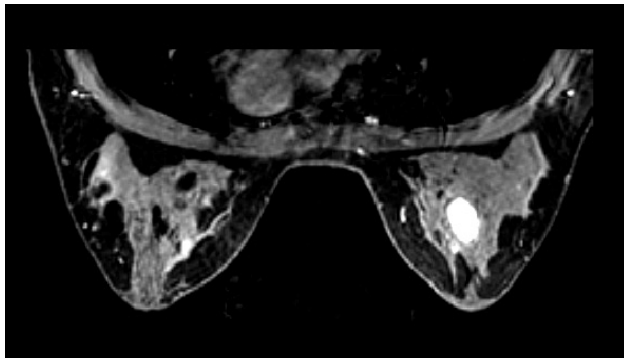


CT image

Medical Imaging: Magnetic Resonance (MR)

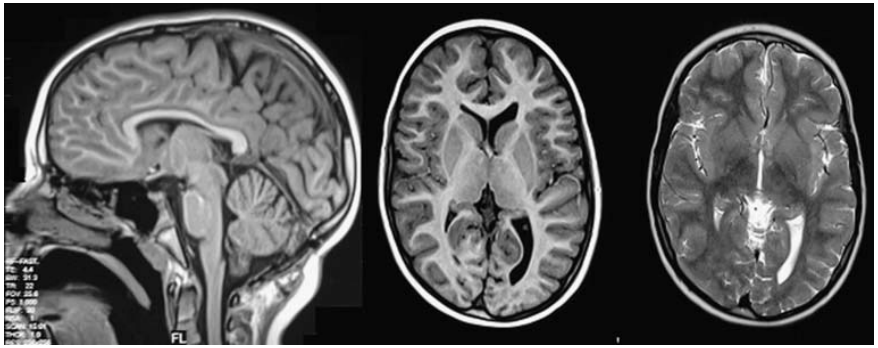


heart



cancer

Whole body



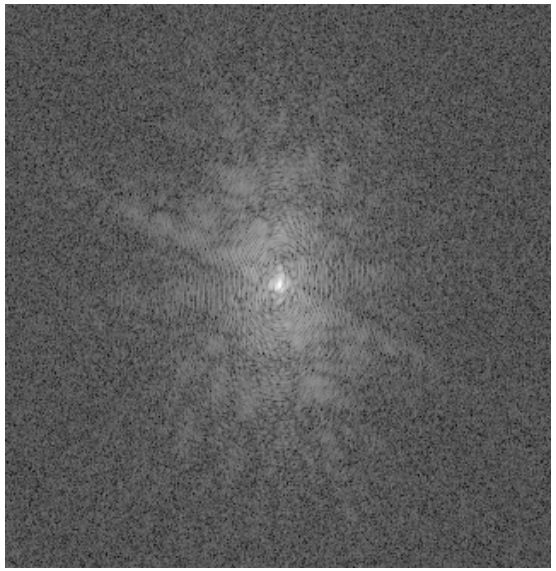
brain

lung

Medical Imaging: Magnetic Resonance (MR)

- MR imaging:
  - high contrast ✓
  - high spatial resolution ✓
  - no ionising radiation ✓
  - but slow acquisition process 👎
- Slow acquisition is
  - ok for static objects (e.g. brain, bones, etc)
  - problematic for moving objects (e.g. heart, liver, fetus)
- Options for MR acquisition:
  - real-time MR: fast, but 2D and relatively poor image quality
  - gated MRI fine for period motion, e.g. respiration or cardiac motion but requires gating (ECG or navigators) leading to long acquisition times (30-90 min).

Medical Imaging: Magnetic Resonance (MR)

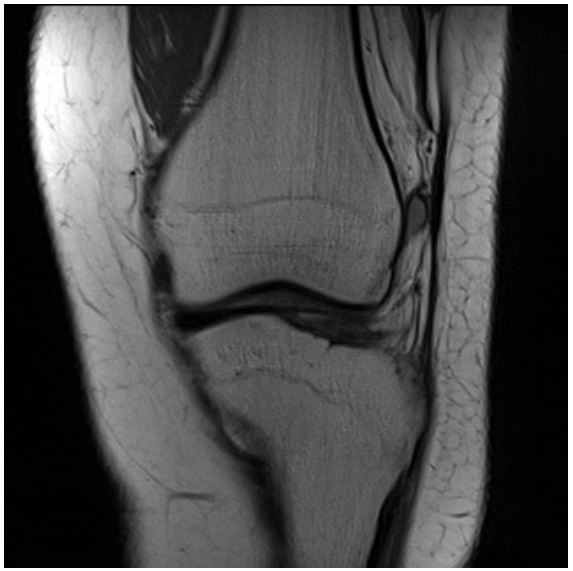


K-Space

Forward problem
(Fourier transform)

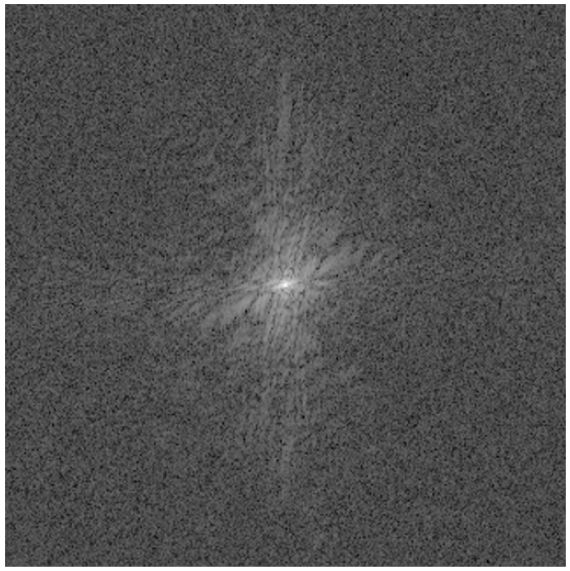
Inverse problem:

Fully sampled
reconstruction



MR image

Medical Imaging: Magnetic Resonance (MR)



Forward problem
(Fourier transform)

Inverse problem:

Fully sampled
reconstruction

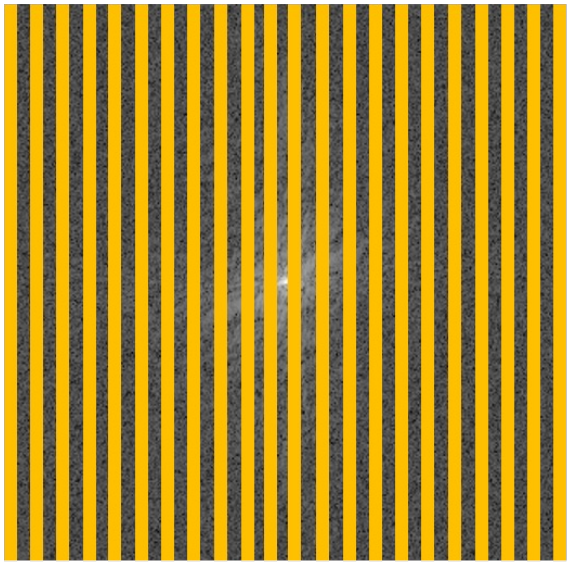
K-Space

MR image

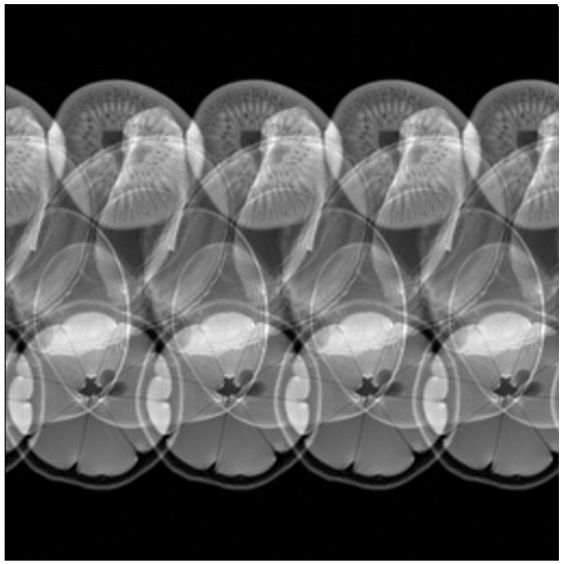
Recover an image $x \in \mathbb{K}^{N_x}$ from a set of observations $y \in \mathbb{K}^{N_y}$ which are corrupted by noise $n \in \mathbb{K}^{N_y}$, and A: $\mathbb{K}^{N_x} \to \mathbb{K}^{N_y}$ is a linear operator

$$y = Ax + n$$

Medical Imaging: Magnetic Resonance (MR)



Inverse problem



Undersampled K-Space

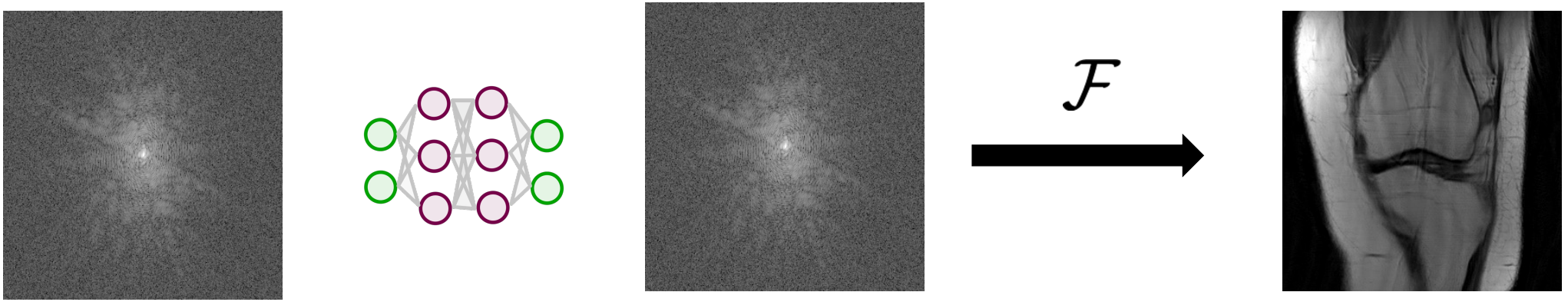
Aliased MR image

Recover an image $x \in \mathbb{K}^{N_x}$ from a set of observations $y \in \mathbb{K}^{N_y}$ which are corrupted by noise $n \in \mathbb{K}^{N_y}$, and A: $\mathbb{K}^{N_x} \rightarrow \mathbb{K}^{N_y}$ is a linear operator

$$y = Ax + n$$

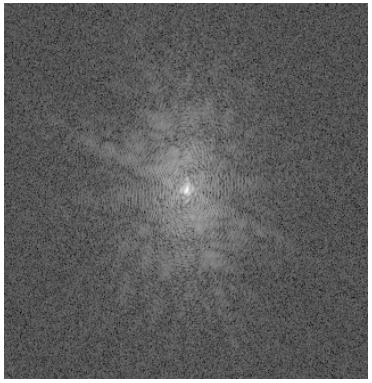
Possible reconstruction approaches: Image domain

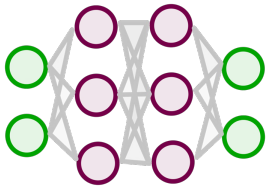
Possible reconstruction approaches: k-space domain

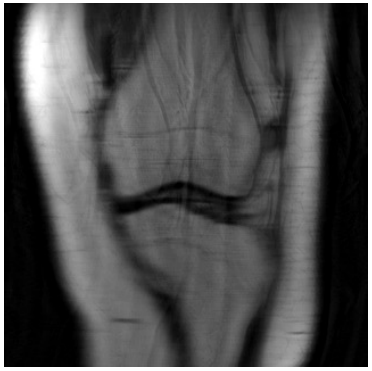


Training Phase

- Optimize θ of the model f_θ using the training set







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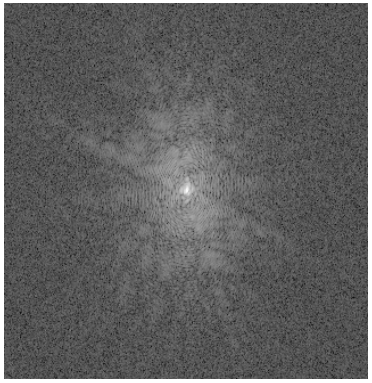
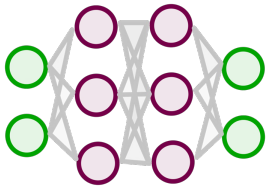
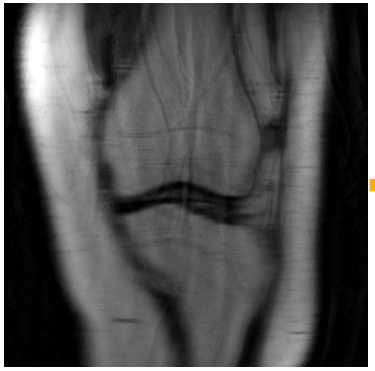


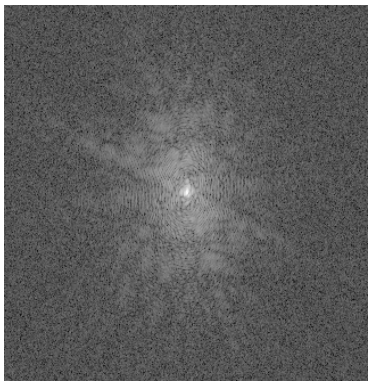


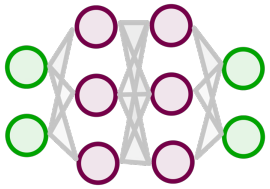


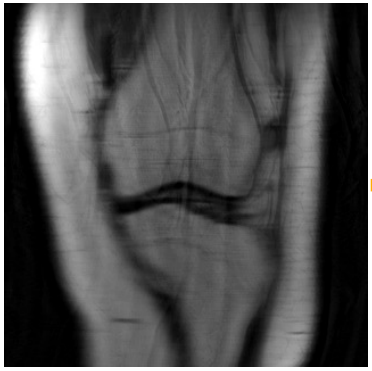
Cost Function

Training Phase

- Optimize θ of the model f_θ using the training set





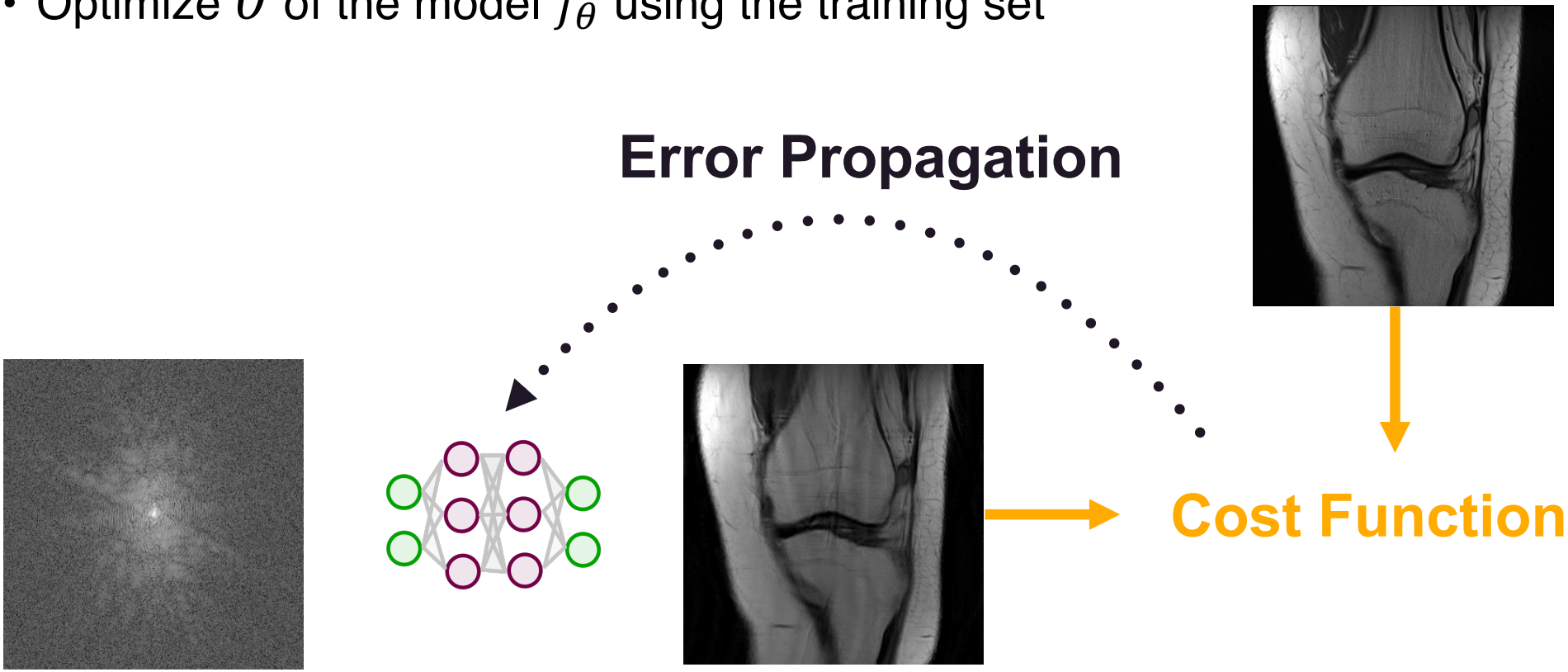


Error Propagation

Cost Function

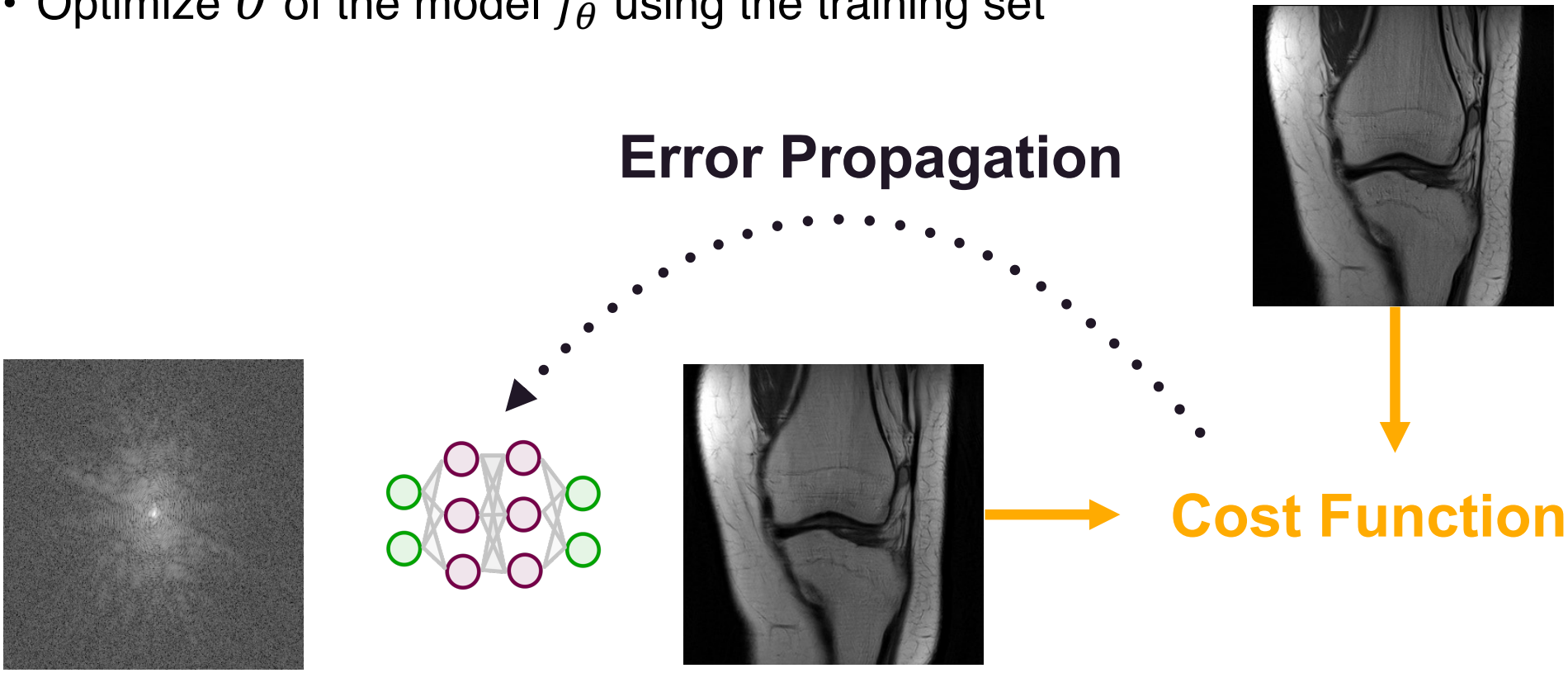
Training Phase

- Optimize θ of the model f_θ using the training set



Training Phase

- Optimize θ of the model f_θ using the training set



Cost Function

Synonym: Loss function, error function, similarity measure

- Quantifies how well the model prediction matches targets
- Needs to be selected according to the underlying task
- Is optimized during training → needs to be differentiable!

Cost Function

Synonym: Loss function, error function, similarity measure

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Example for image reconstruction: Mean Squared Error

$$MSE(y, \hat{y}) = \frac{1}{N_S} \sum_{n=1}^{N_S} \| y_n - \hat{y}_n \|_2^2$$

Training Phase

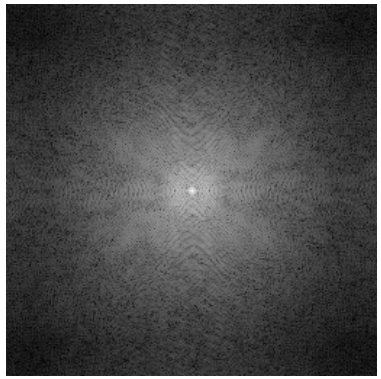
Learning model: $\widehat{\boldsymbol{y}}_{\boldsymbol{n}} = \boldsymbol{f}_{\boldsymbol{\theta}}(\boldsymbol{x}_{\boldsymbol{n}})$

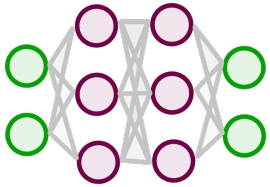
- The parameters θ of the mapping function f_θ are optimized under a cost function
- The cost function quantifies how well $\hat{y}_n = f_\theta(x_n)$ is predicted given x_n
- The parameters θ by minimizing the cost function $\mathcal{L}$ with learning rate τ

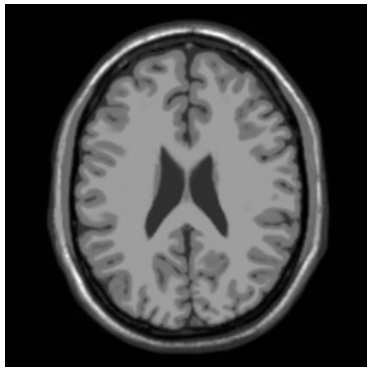
$$\theta^{(k+1)} = \theta^{(k)} - \tau \frac{\partial \mathcal{L}(\theta, x)}{\partial \theta}\Big|_{\theta=\theta^{(k)}}$$

Testing Phase (Inference)

- Apply f_θ using the optimized θ to the test set

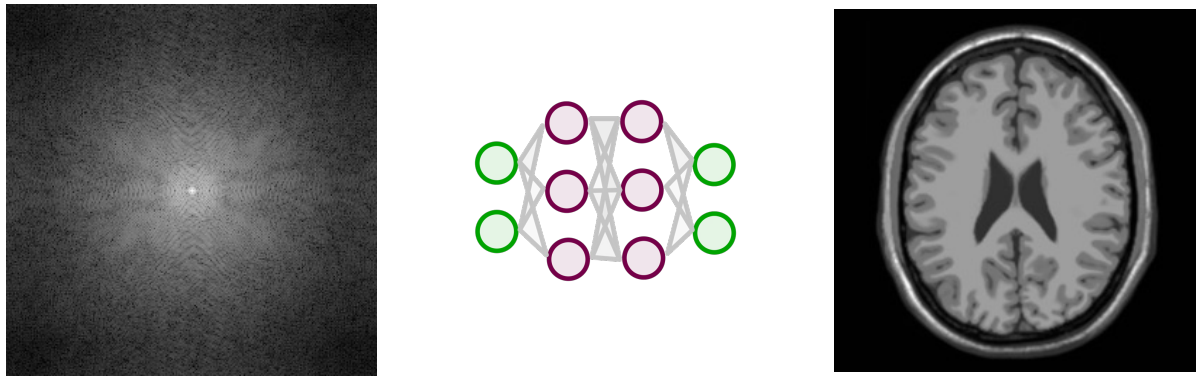






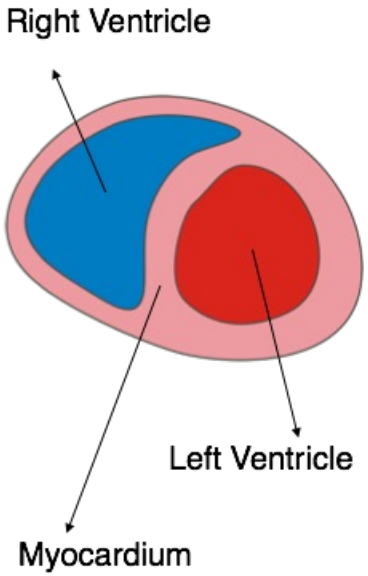
Testing Phase (Inference)

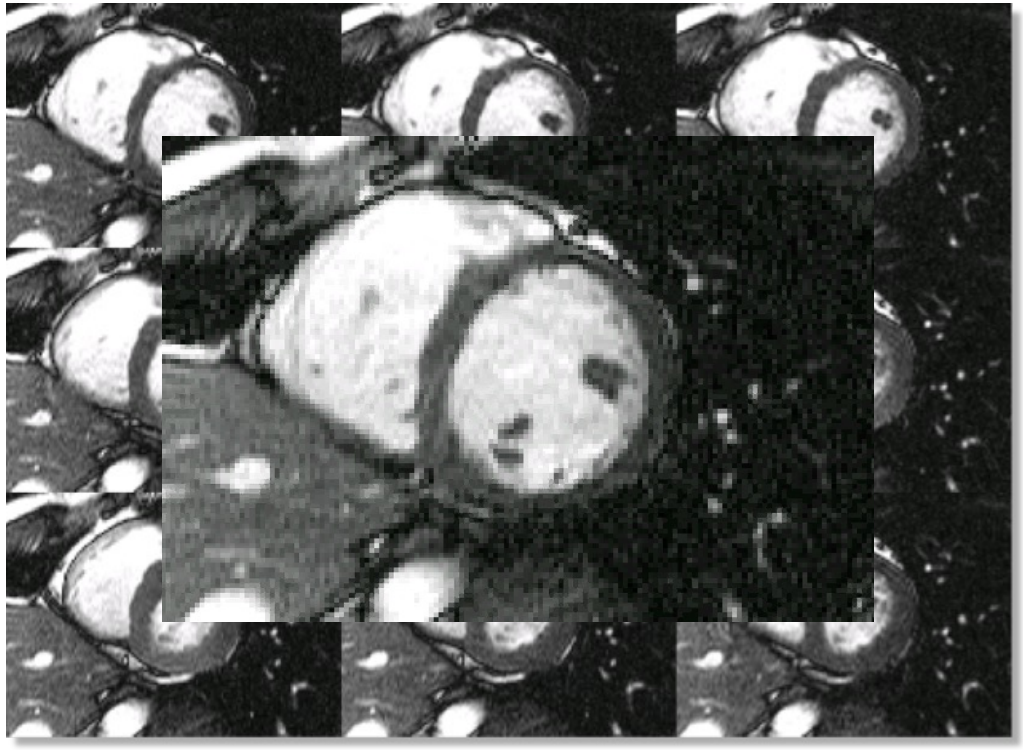
- Apply f_θ using the optimized θ to the test set



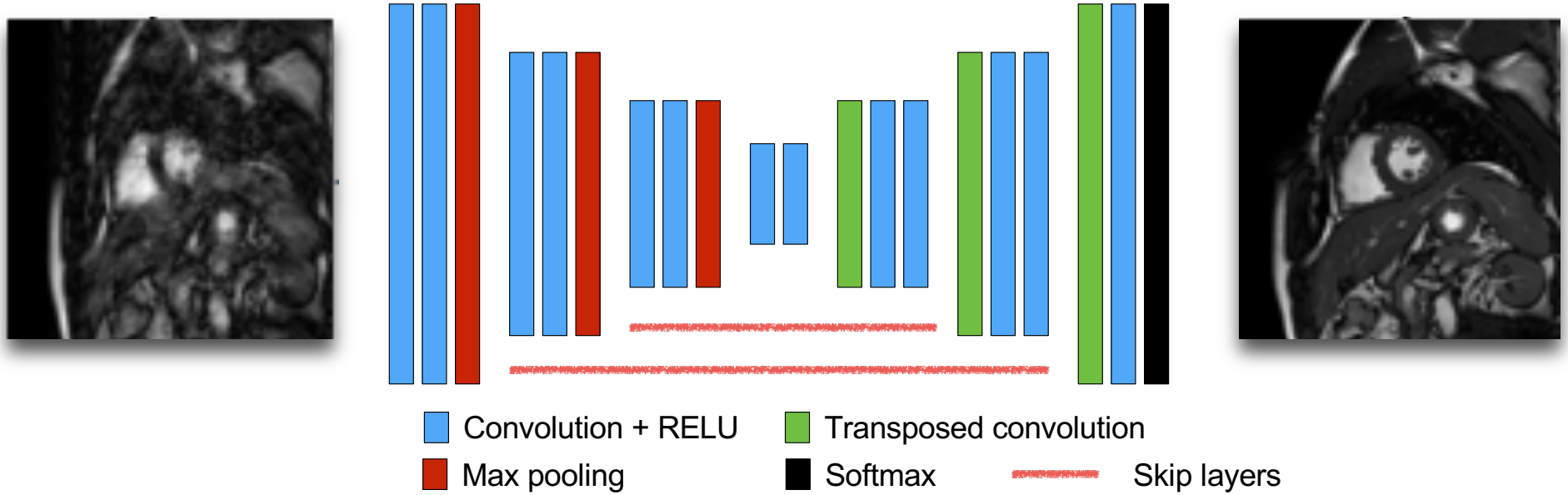
Generalization: Ability to correctly predict unseen examples

Magnetic Resonance (MR)

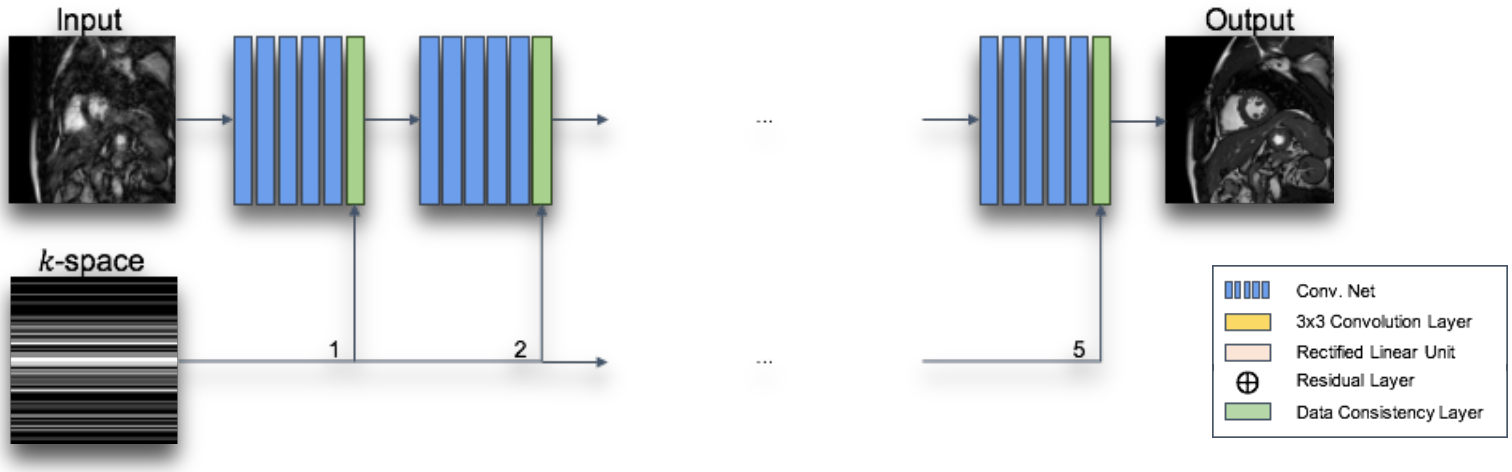




Deep learning for image reconstruction

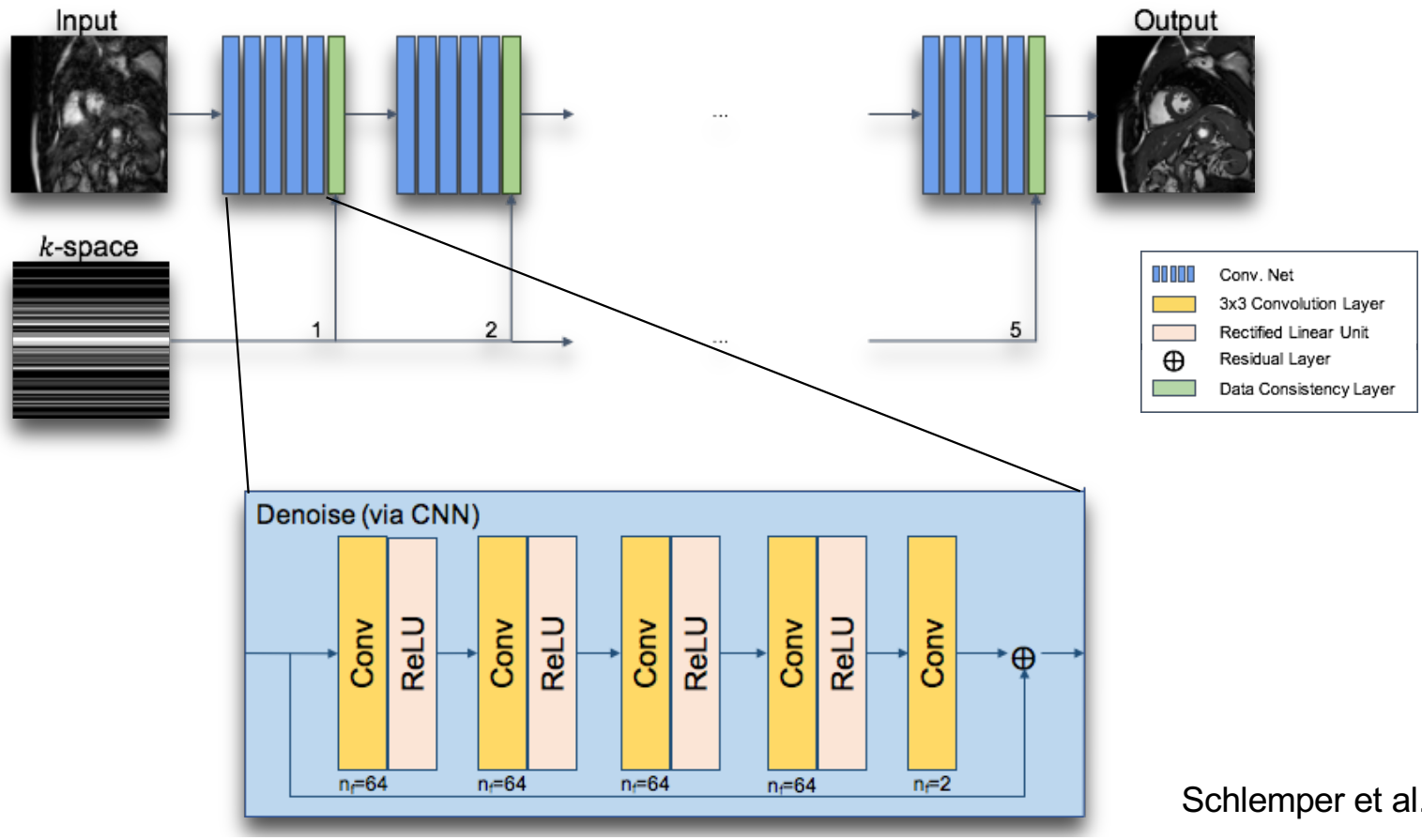


Deep learning for image reconstruction



Schlemper et al. IEEE TMI 2017

Deep learning for image reconstruction



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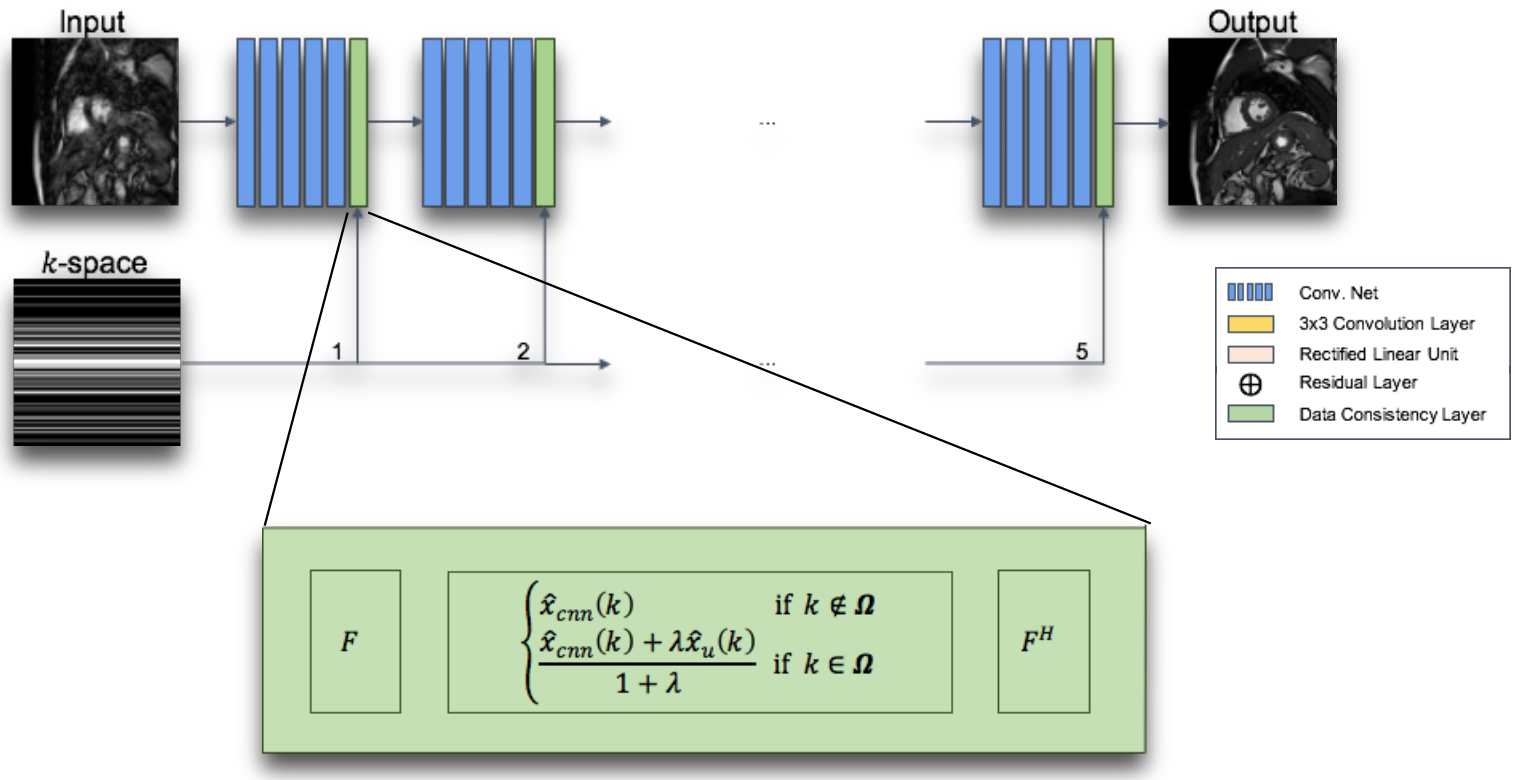
Deep learning for image reconstruction



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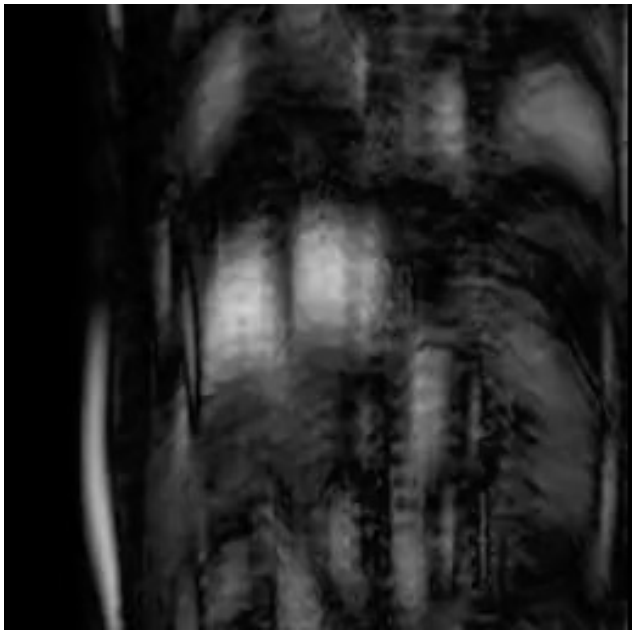
Magnitude reconstruction (6-fold)



(a) 6x Undersampled

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Magnitude reconstruction (11-fold)

(a) 11x Undersampled

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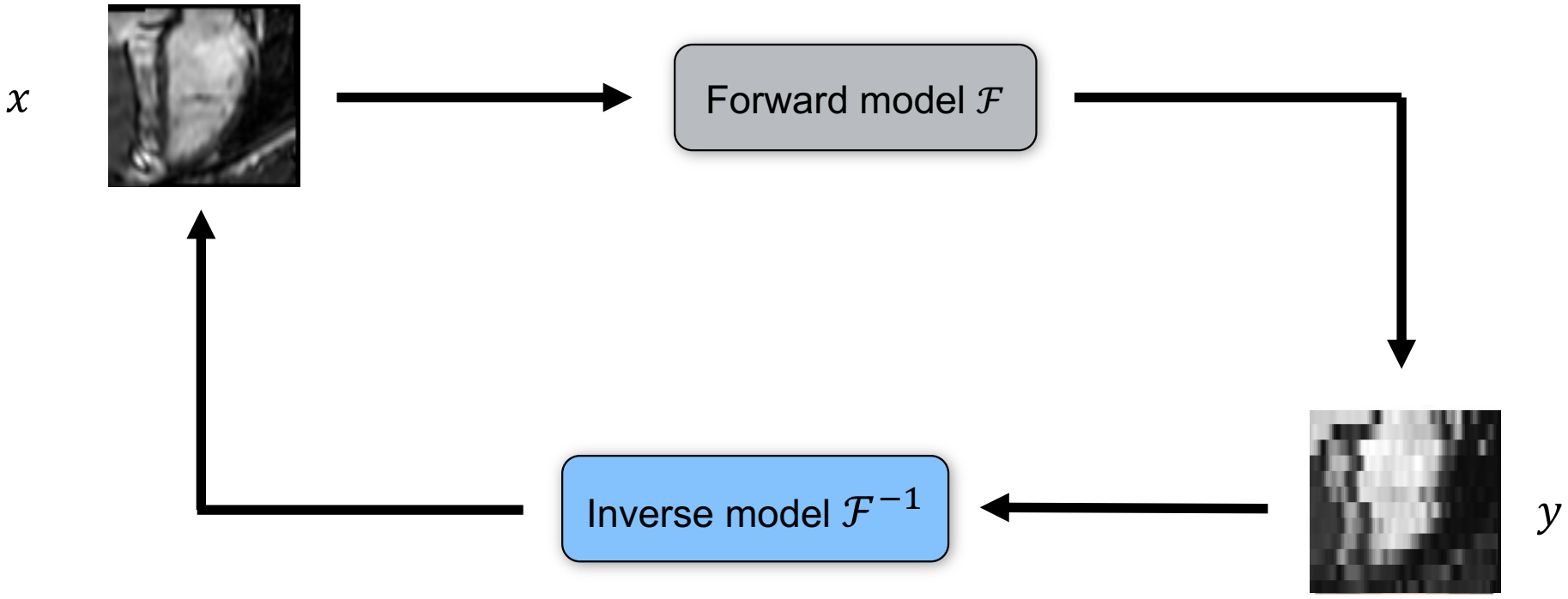
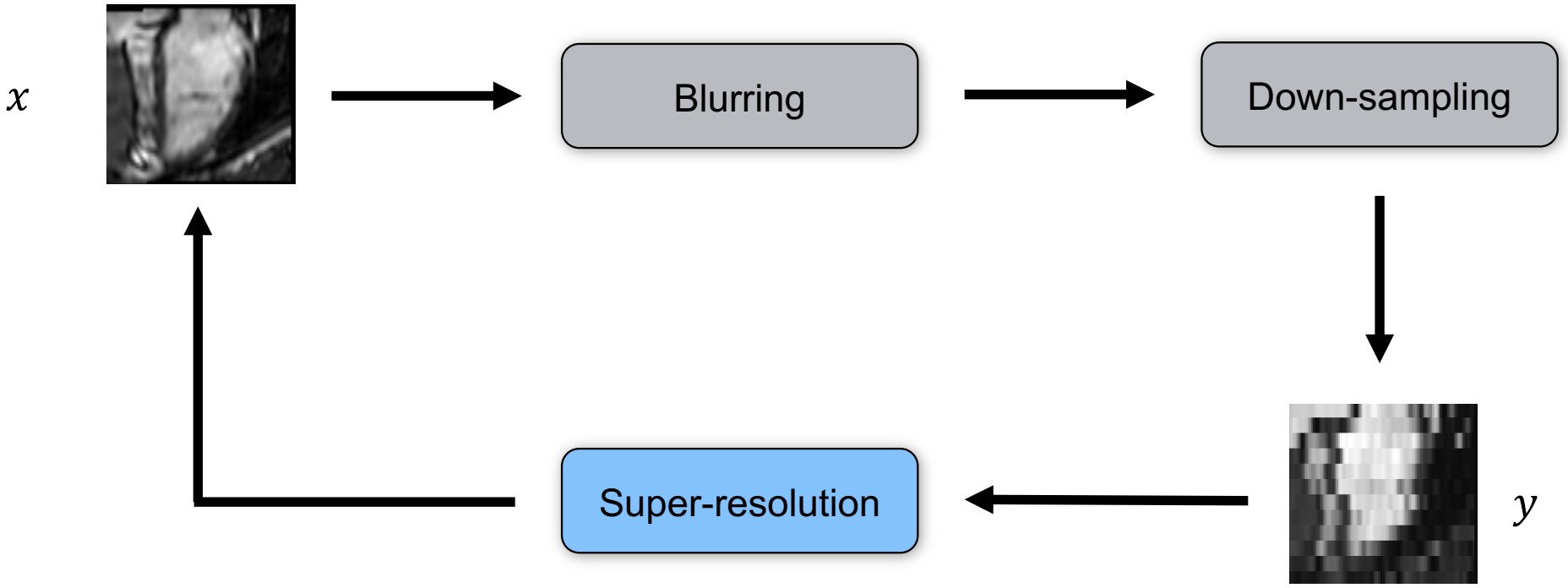
Forward model/Inverse model

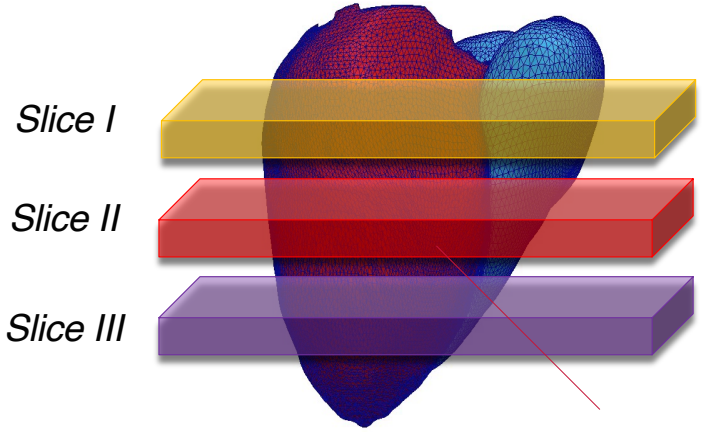


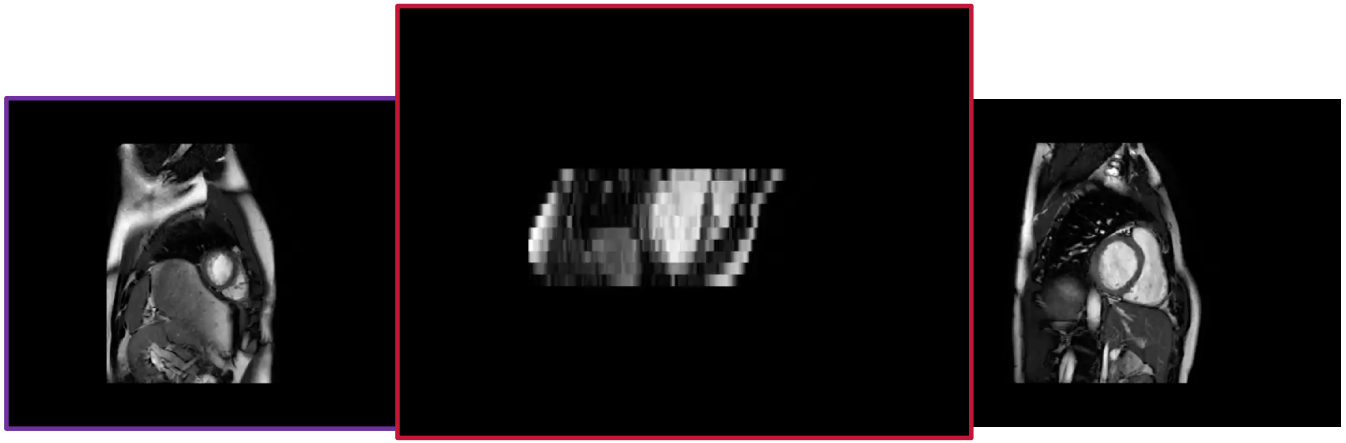
Forward model/Inverse model



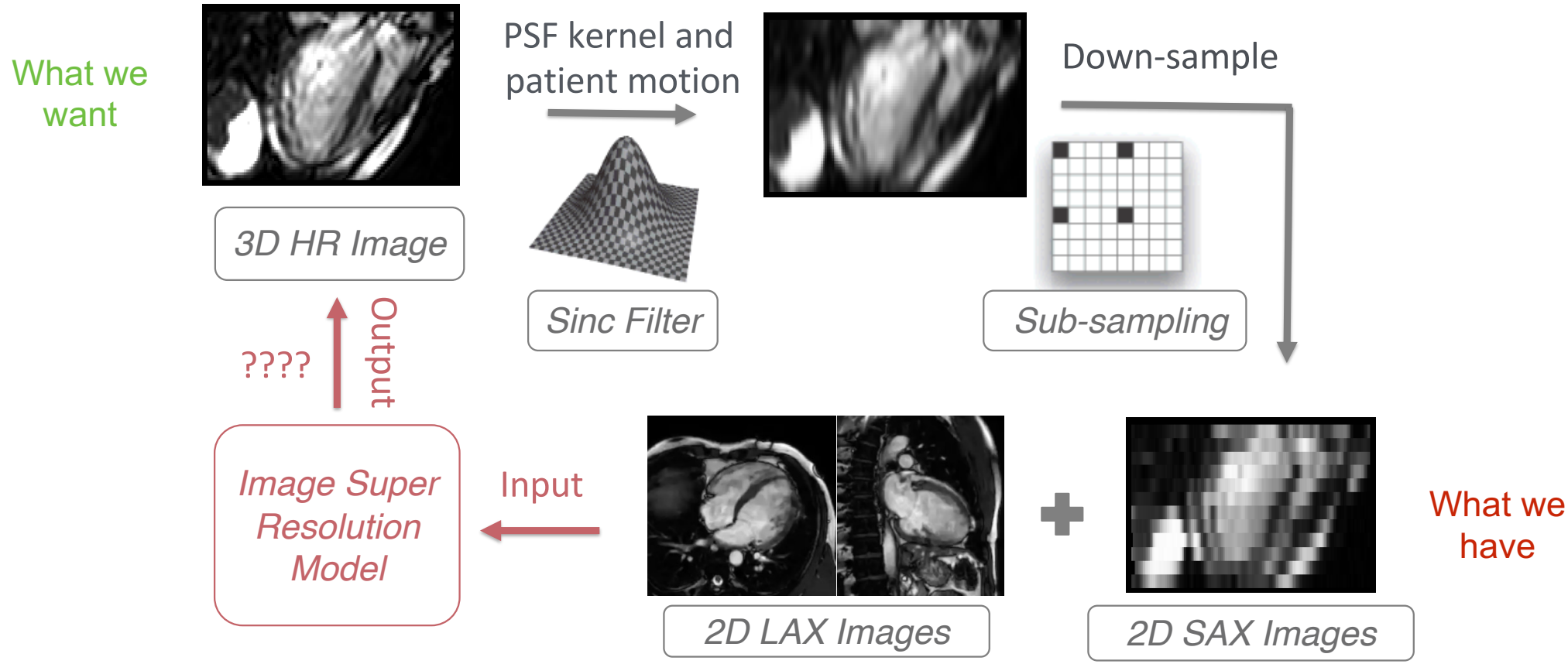
AI-enabled image super-resolution

- Acquisition of cardiac MRI typically consists of 2D multi-slice data due to
  - constraints on SNR
  - breath-hold time
  - total acquisition time
- This leads to thick slice data (thickness 8-10 mm per slice)

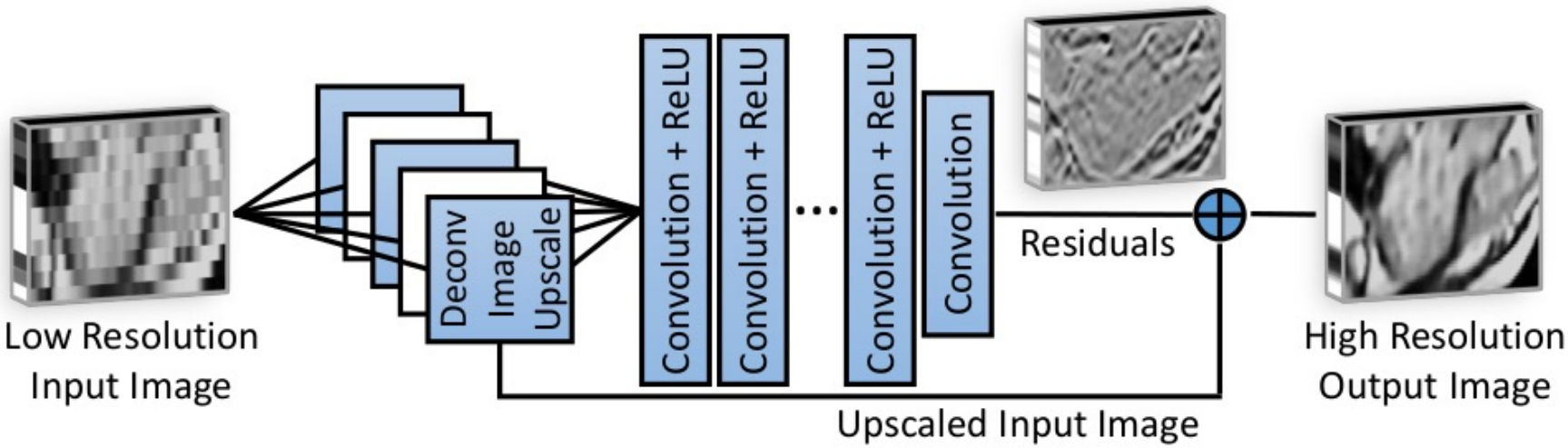




Deep learning for image super-resolution



Deep learning for image super-resolution



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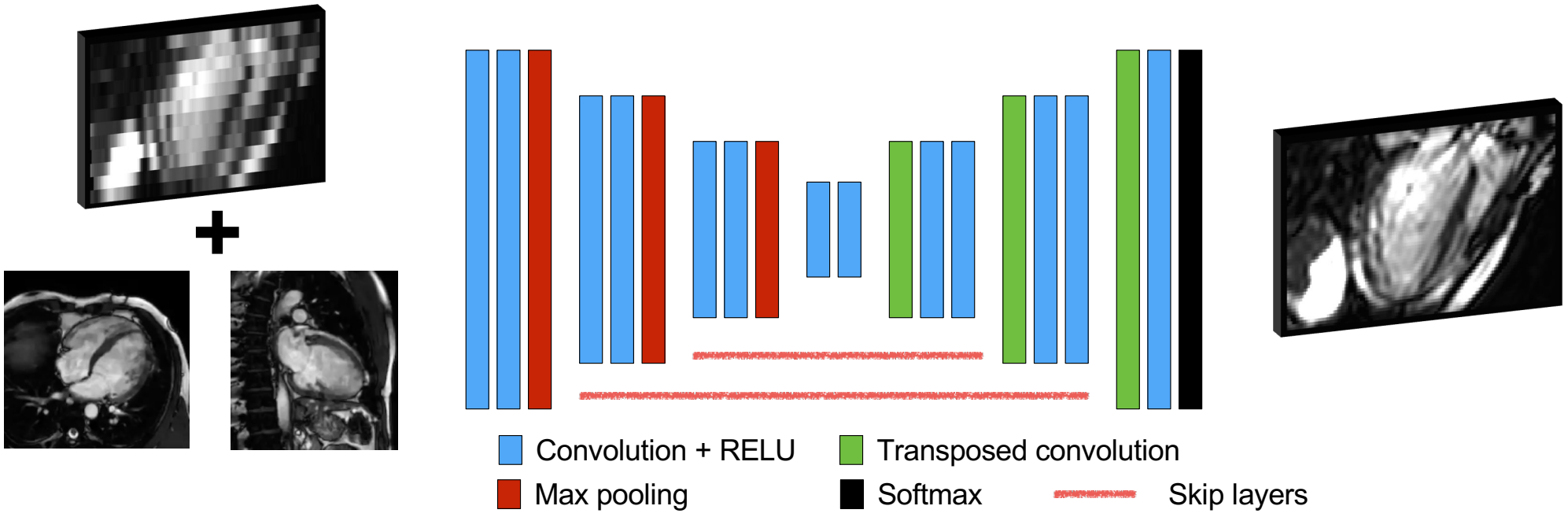
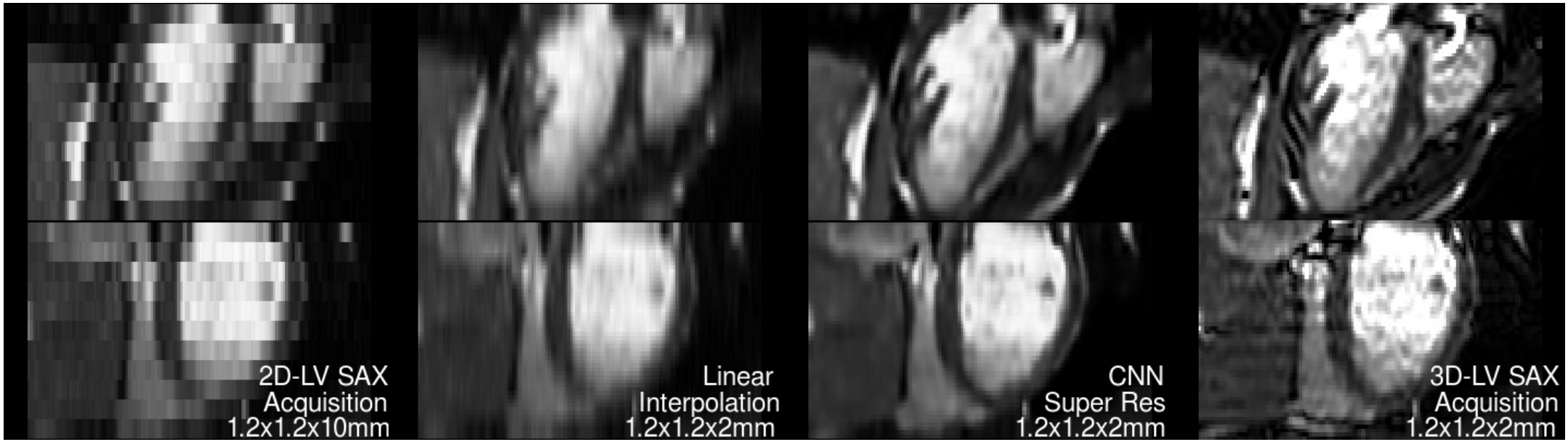
AI-enabled image super-resolution



AI-enabled image super-resolution



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That’s all for now…

References

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  – https://arxiv.org/abs/1902.06068
- Deep Learning Techniques for Inverse Problems in Imaging
  – https://arxiv.org/abs/2005.06001