Attacking inverse problems with deep learning

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Inverse problems

High level formulation

- Forward process $\mathbf{y} \to \mathbf{x} = g(\mathbf{y})$

  to "invert" $\hat{\mathbf{y}}(\mathbf{x}) \in g^{-1}(\mathbf{x})$?

- Optimization-based inversion, with prior to make it well-posed

$$\forall \mathbf{x},\ \hat{\mathbf{y}}(\mathbf{x}) \in \arg\min_{\mathbf{y}} \underbrace{\left(\mathrm{Loss}(\mathbf{x}, g(\mathbf{y})) + \mathrm{Prior}(\mathbf{y})\right)}_{E(\mathbf{x},\mathbf{y};\boldsymbol{\theta})}$$

- Model bricks: given (e.g., *physics*), engineered, and/or *learned*

Classic examples

Signal enhancement or completion

- Forward process: degradation and/or masking
- Prior: spatial/temporal regularity

$$\min_{\mathbf{y}} \left(\|\mathbf{x} - g(\mathbf{y})\|_2^2 + \mu \|\nabla \mathbf{y}\|_p^q \right) \text{ s.t. } \mathbf{y}|_{\partial D} = \mathbf{y}^*$$

Signal recovery

- Linear forward process: atom composition, random measurements
- Prior: sparsity

$$\min_{\mathbf{y}} \left(\|\mathbf{x} - A\mathbf{y}\|_2^2 + \mu \|\mathbf{y}\|_1 \right)$$

Less classic examples

Inverse graphics

- CGI: from scene model to photoreal images
- *Inverse rendering*: from real images to scene model ("graphic code")
- Application: understanding, editing, AR/VR, personalized models

[Tewari 2017]

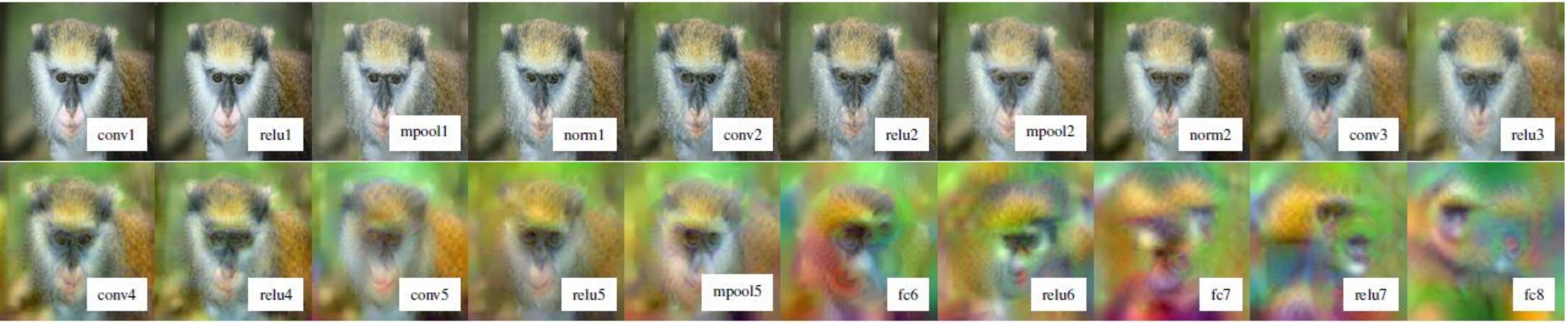
Less classic examples

"Neural" inverse problems

- Deep features: from signal to representations through feedforward neural net
- *Inverting*: from neural activations to NN input

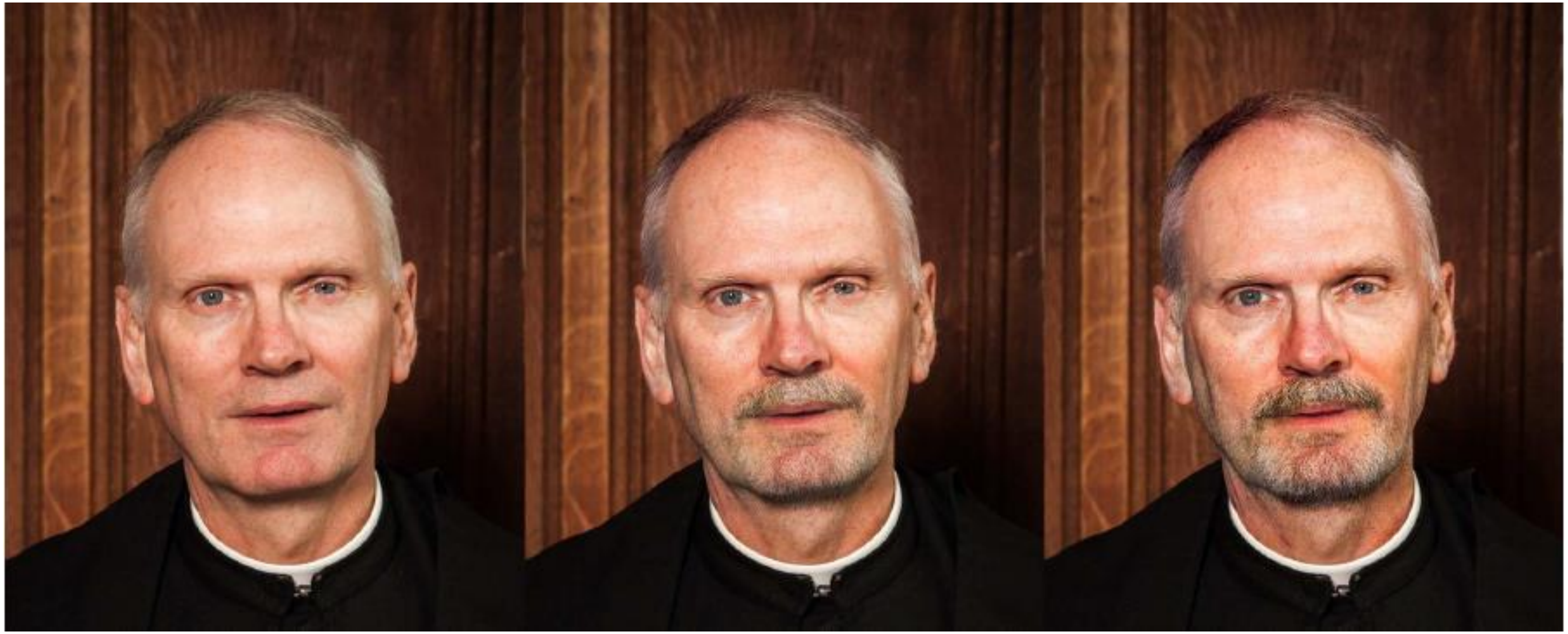
$$\min_{\mathbf{y}} \left(\|\mathbf{x} - \phi_{\ell_0}(\mathbf{y})\|_F^2 + \mu \|\nabla \mathbf{y}\|_1 \right)$$

- Application: visualization, inspection, editing in feature domain



Less classic examples

"Neural" inverse problems



[Upchich 2017]

Learning and inverse problems?

Learn the model, solve by optimization

- Forward process, prior and loss can be (partly) learned
- Examples: blind deconvolution, trained MRFs
- Inference with a classic solver, *iterative* and *generic*

$$\forall \mathbf{x},\ \mathrm{Solver}(\mathbf{x}) = \mathrm{Iter}^{\infty}(\mathbf{x}; \mathbf{y}^0) \approx \hat{\mathbf{y}}(\mathbf{x})$$

Train a direct solver

- From $\forall \mathbf{x},\ \hat{\mathbf{y}}(\mathbf{x}) \in \arg\min_{\mathbf{y}} E(\mathbf{x}, \mathbf{y})$

- To $\forall \mathbf{x} \sim \mathbb{P}_X,\ f(\mathbf{x}; \mathcal{W}) \approx \hat{\mathbf{y}}(\mathbf{x})$ or $\approx g^{-1}(\mathbf{x})$

Neural inversion

Train a DNN to regress solution/inverse *for plausible inputs*

$$\forall \mathbf{x} \sim \mathbb{P}_X,\ \text{DNN}(\mathbf{x}; \mathcal{W}) \approx \hat{\mathbf{y}}(\mathbf{x}) \text{ or } \approx g^{-1}(\mathbf{x})$$

- Fixed complexity
- Possibly way faster
- Flexible in various ways
- Differentiable and reusable

Architecture?

Training?

Architectures

Your favorite DNN

- Exploit popular architectures, possibly pre-trained
- Popular convolutional and recurrent neural nets

Unrolling

- Mimic (possibly loosely) structure of iterative solver
- Each [non-linear $\circ$ linear] iteration becomes a trainable neural layer
- Fixed, smaller number of "iterations"
- But, way more freedom exploited through training

Training

Fully-supervised – Using Solver, reconstruction loss

$$\mathbf{x}^{(n)} \sim \mathbb{P}_X, \ \min_{\mathcal{W}} \sum_{n=1}^{N} \|\mathrm{Solver}(\mathbf{x}^{(n)}) - \mathrm{DNN}(\mathbf{x}^{(n)}; \mathcal{W})\|_2^2$$

Self-supervised – Possibly only synthetic data, reconstruction loss

$$\mathbf{y}^{(n)} \sim \mathbb{P}_Y, \ \min_{\mathcal{W}} \sum_{n=1}^{N} \|\mathbf{y}^{(n)} - \mathrm{DNN}(g(\mathbf{y}^{(n)}); \mathcal{W})\|_2^2$$

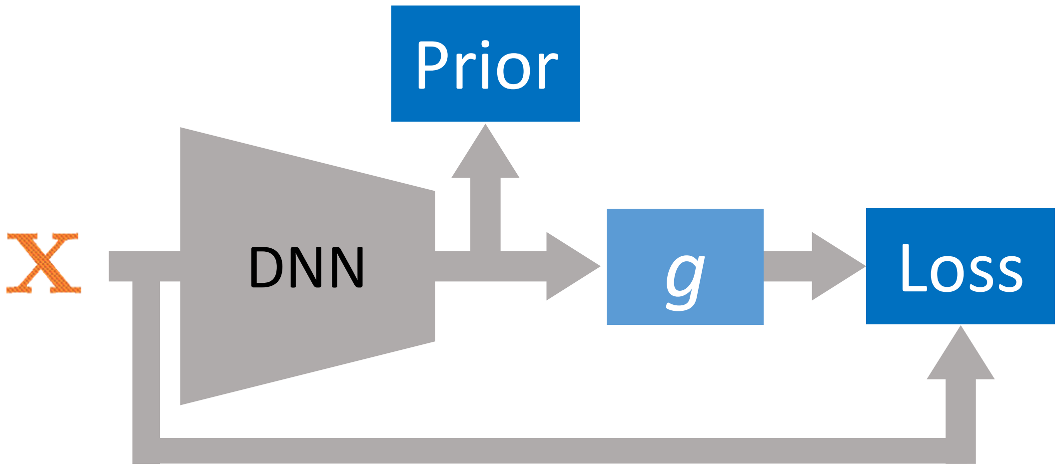
Unsupervised – Original objective function as training loss

$$\mathbf{x}^{(n)} \sim \mathbb{P}_X, \ \min_{\mathcal{W}} \sum_{n=1}^{N} E(\mathbf{x}^{(n)}, \mathrm{DNN}(\mathbf{x}^{(n)}; \mathcal{W}); \boldsymbol{\theta})$$

Unsupervised training

Unsupervised – Original objective function as training loss

$$\mathbf{x}^{(n)} \sim \mathbb{P}_X, \quad \min_{\mathcal{W}} \sum_{n=1}^{N} \mathsf{Loss}\Big(\mathbf{x}^{(n)}, g \circ \mathsf{DNN}(\mathbf{x}^{(n)}, \mathcal{W})\Big) + \mathsf{Prior}\Big(\mathsf{DNN}(\mathbf{x}^{(n)}, \mathcal{W})\Big)$$



Unrolling example

Sparse coding: LISTA [Gregor 2010]

$$\min_{\mathbf{y}} \left(0.5\|\mathbf{x} - A\mathbf{y}\|_2^2 + \mu\|\mathbf{y}\|_1\right)$$

Iterative solver: Iterative Soft Thersholding Alg. (ISTA)

$$\mathrm{Iter}(\mathbf{y}) = \sigma_{2\mu\alpha}\left((\mathrm{Id} - \alpha A^\top A)\mathbf{y} + \alpha A^\top \mathbf{x}\right)$$

Learned neural layer (residual block and skip connection)

$$f_k(\mathbf{y}) = \sigma\left((\mathrm{Id} - V_k)\mathbf{y} + W_k^\top \mathbf{x}\right), \ \mathcal{W} = \{(W_k, V_k)\}_k$$

- Fully supervised training
- The deeper, the better the approximation
- Modest speed-up

Unsupervised neural inversion

Personalized 3D face model: Tewari *et al.* 2017

Encoder-decoder with differentiable rendering layer

Artistic style transfer: Ulyanov *et al*. 2016, Johnson *et al*. 2016

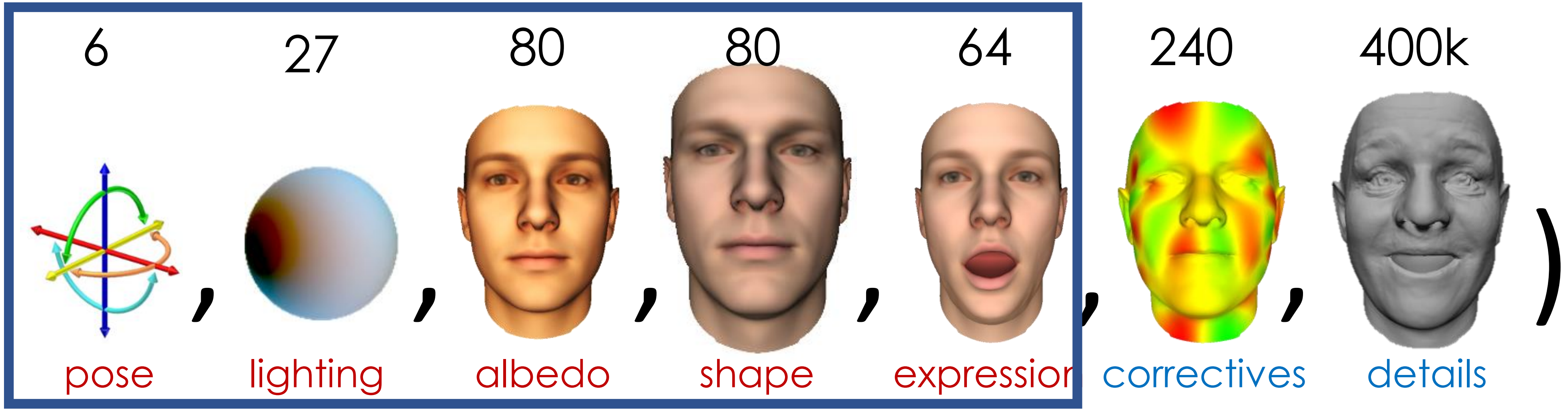
Encoder-decoder with “perceptual loss”

Flexible style transfer: Puy & Pérez 2019

Unrolling descent, run time flexibility

Photo-real face rendering

$\mathbf{y} = ($



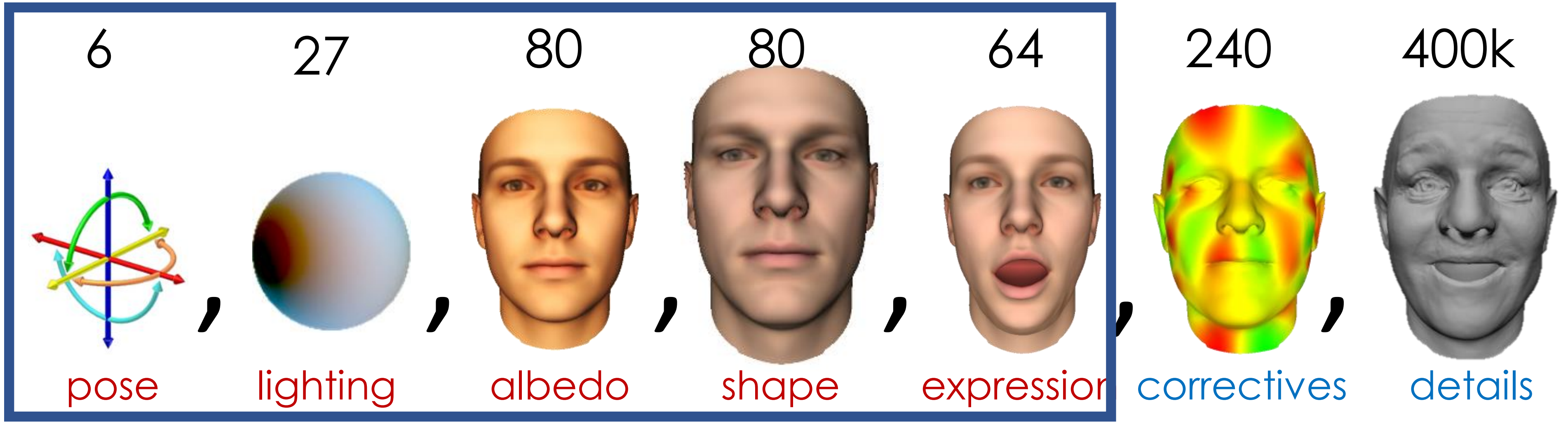
$)$

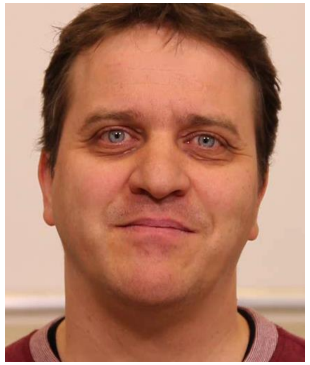
$\mathbf{y} \in \mathbb{R}^{257} \rightarrow g(\mathbf{y}) =$

[Garrido 2016]

Invert rendering

to obtain animatable personnalized 3D rig

$\mathbf{y} = ($  $)$

$\mathbf{x} =$  $\rightarrow \mathbf{y} \in \mathbb{R}^{257}?$

[Garrido 2016]

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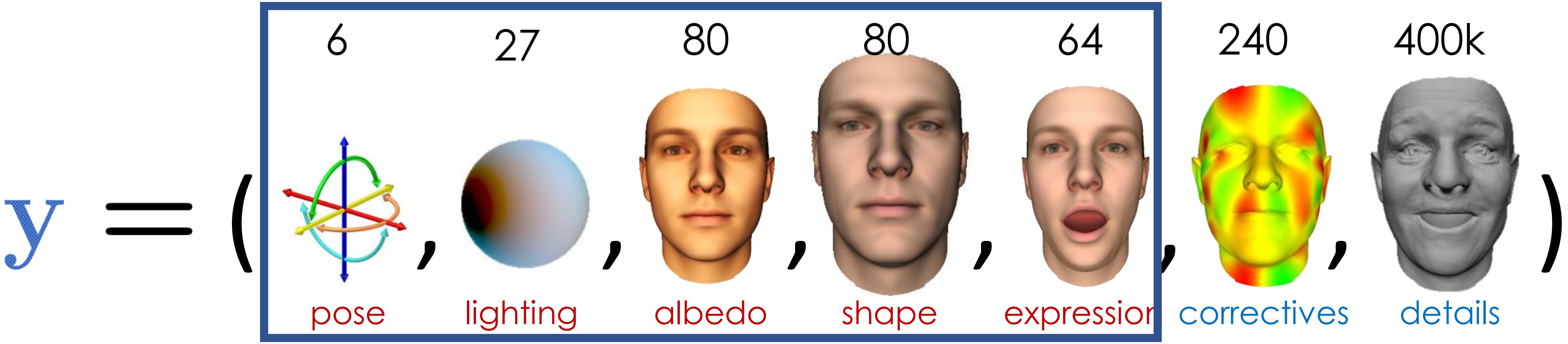
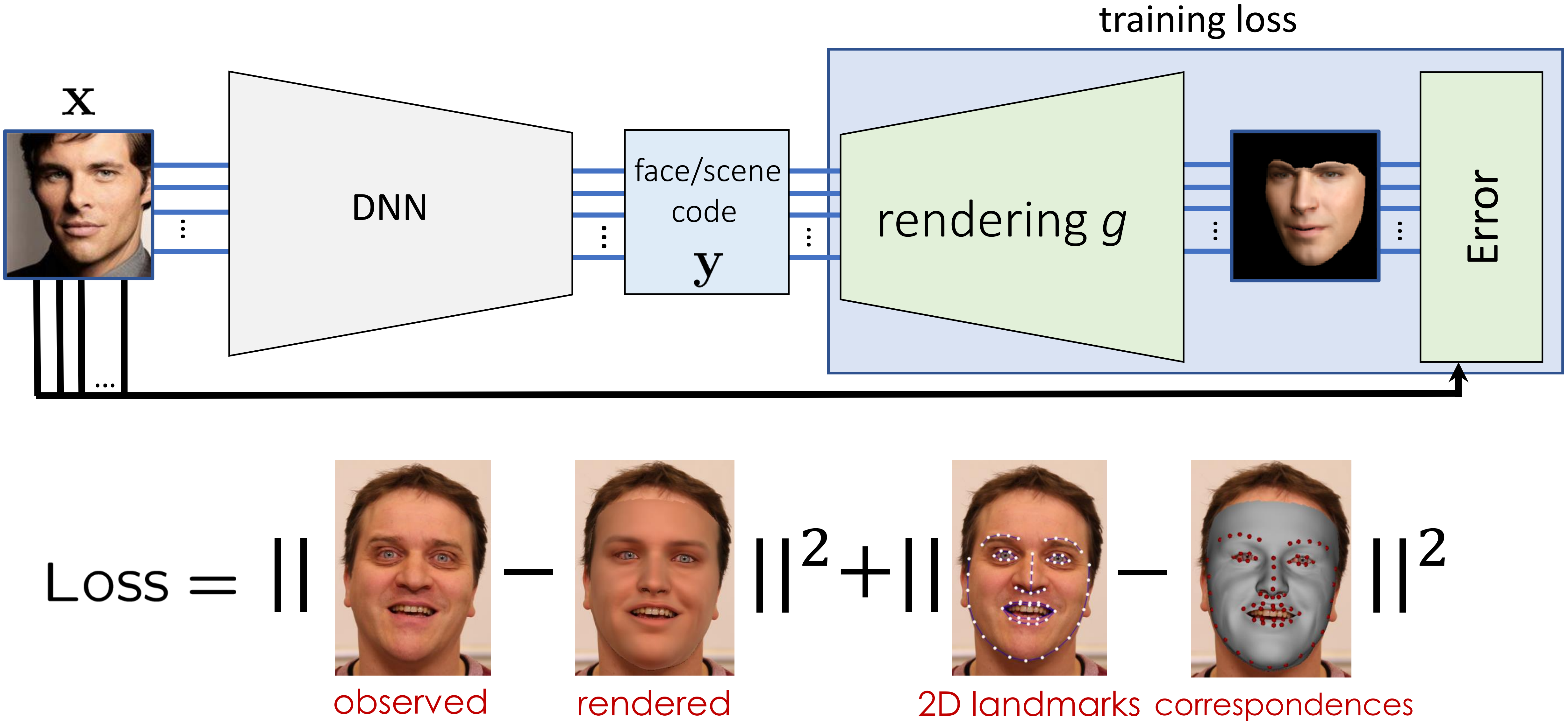


[Garrido 2016]

Fast DNN solver

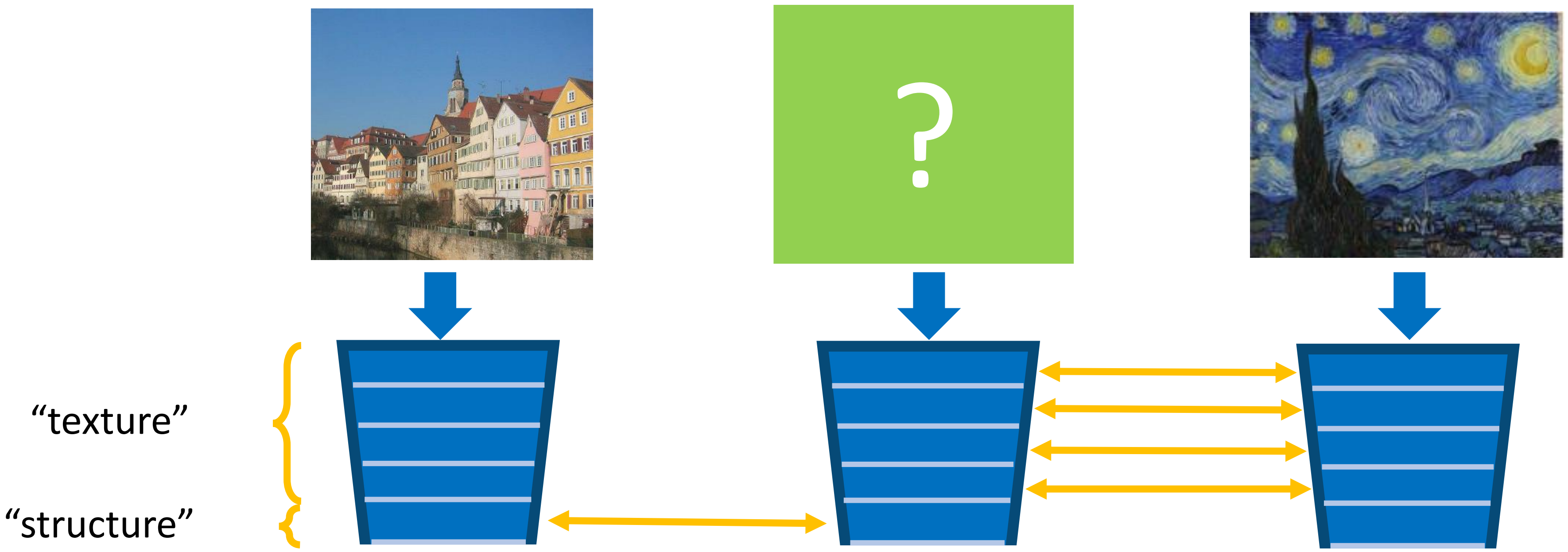


[Tewari 2017-2018]

“Artistic” style transfer

retain structure, imitate texture

$$\min_{\mathbf{y}} \left(\|\mathbf{x} - \phi_{\ell_0}(\mathbf{y})\|_{\mathsf{F}}^2 + \lambda \sum_{\ell \in \mathcal{L}_{\mathsf{sty}}} \|G_\ell - \phi_\ell(\mathbf{y})^\top \phi_\ell(\mathbf{y})\|_{\mathsf{F}}^2 \right)$$



[Gatys 2015-2016]

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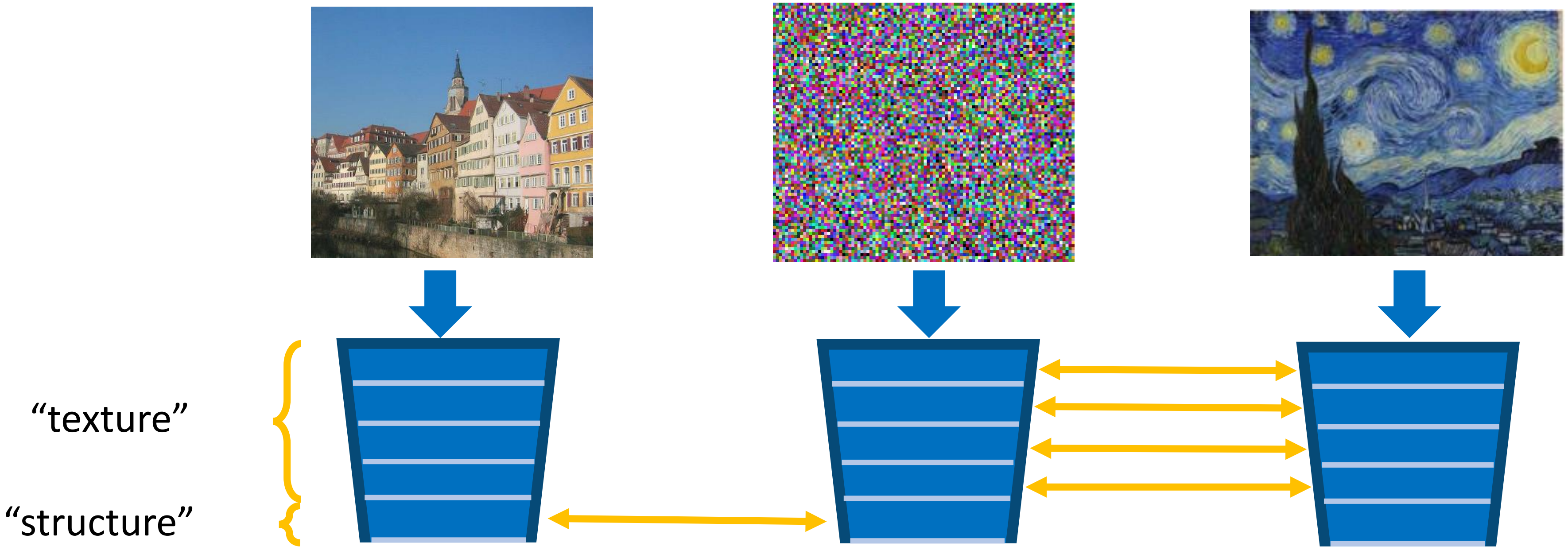

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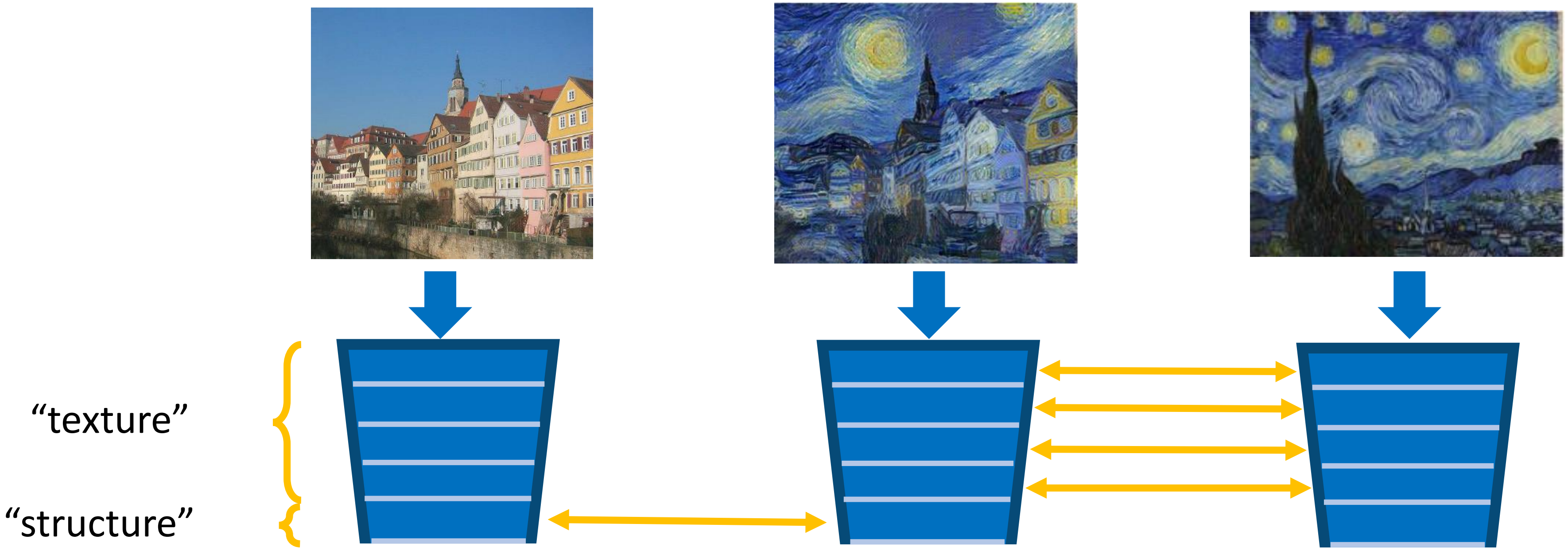

[Gatys 2015-2016]

Fast artistic style transfer

[Ulyanov 2016, Johnson 2016] and successors

- Convolutional encoder-decoder architectures
- Unsupervised training *for specified paintings*

[Ulyanov 2017]

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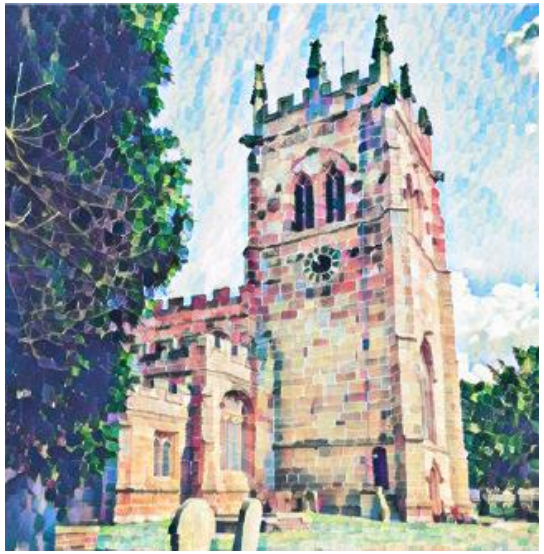

[Ulyanov 2017]

Fast flexible style transfer [Puy 2019]

Unrolling (part of) gradient descent

$$E(\mathbf{x},\mathbf{y}) = \|\mathbf{x} - \phi_{\ell_0}(\mathbf{y})\|_{\mathsf{F}}^2 + \mu\|\nabla\mathbf{y}\|_1 + \sum_{\ell\in\mathcal{L}_{\mathsf{sty}}} \lambda_\ell \|G_\ell - \phi_\ell(\mathbf{y})^\top \phi_\ell(\mathbf{y})\|_{\mathsf{F}}^2$$

- One layer mimics one step $\mathbf{y} \leftarrow \mathbf{y} - \alpha\nabla E_{\mathsf{sty}}(\mathbf{x},\mathbf{y})$

$$\mathbf{y}_k = \mathbf{y}_{k-1} - f_k\Big(\mathbf{x},\mathbf{y}_{k-1}; \mathcal{W}_k, \{\lambda_\ell, G_\ell\}_{\ell\in\mathcal{L}_{\mathsf{sty}}}\Big)$$

modifiable at *run time*

- Unsupervised training

Runtime restructuring

Choose style, mix styles, tune stylization intensity or scale

Runtime restructuring

Add new regularizers via proximal operator, e.g. for photorealism

$$\mathbf{y}_k = \mathbf{y}_{k-1} - \mathsf{Prox}_{\Omega}\Big[f_k(\mathbf{x}, \mathbf{y}_{k-1})\Big]$$

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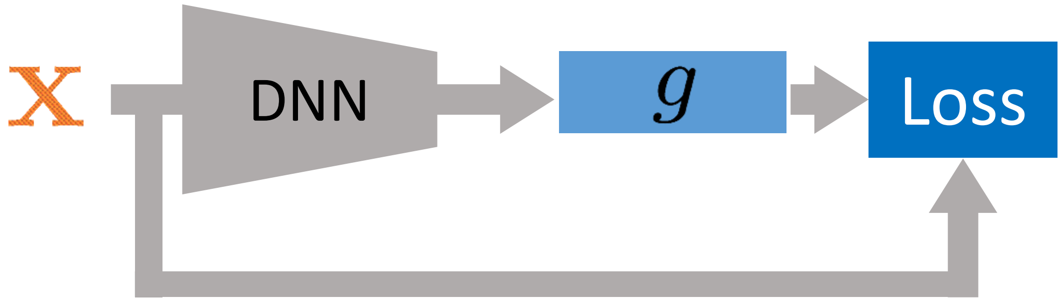
Perspectives

- Encoder-decoder view of unsupervised inversion: make forward process (partly) trainable, e.g. [Tewari 2018]



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- Multiple pre-images?
- Inversion of state-of-art GAN?

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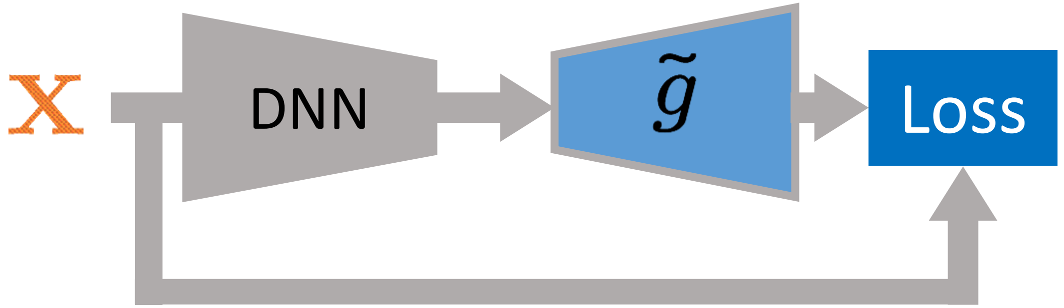

- *Invertible* NN [Ardizzone 2019] trained to mimic *g*, inversion for free
- Multiple pre-images?
- Inversion of state-of-art GAN?
- Mathematical properties of neural solver? Robustness, generability

Using invertible neural nets? [Ardizzone 2019]

Learn an *invertible* neural net (INN) to mimic forward process

$$\forall \mathbf{y} \sim \mathbb{P}_Y,\ h(\mathbf{y};\mathcal{W}) = [\underbrace{h_x(\mathbf{y};\mathcal{W})}_{\approx g(\mathbf{y})}, \underbrace{h_z(\mathbf{y};\mathcal{W})}_{\mathbf{z},\ \text{latent}}]$$

Invert it to get a *posterior distribution*

$$\forall \mathbf{x},\ \mathbf{z} \sim N(0, I) \to h^{-1}([\mathbf{x}, \mathbf{z}];\mathcal{W}) \approx \mathbf{y}|\mathbf{x}$$

Bi-directional supervised/unsupervised training

- Self-supervised training of forward mimicking using simulation
- Unsupervised on distributions of **y** and **z**, and independence of **x** vs. **z**

Conclusion

Neural solvers for inverse problems

- fast, specialized, differentiable, possibly unsupervised, flexible
- can go beyond original model by learning
- applies to other optimization-based/variational problems

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