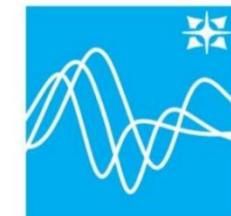
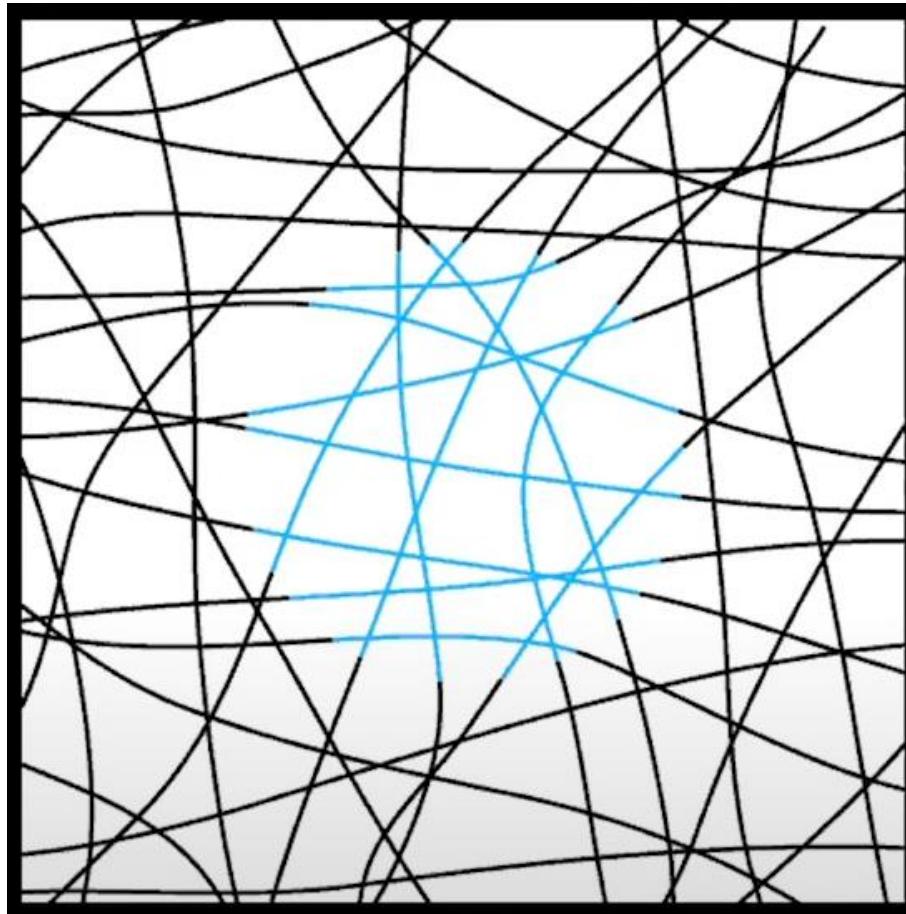


Генерация и обработка изображений с помощью нейросетей



Кафедра
технологий
проектирования
сложных
технических
систем

Идеи к генерации изображений



Superresolution



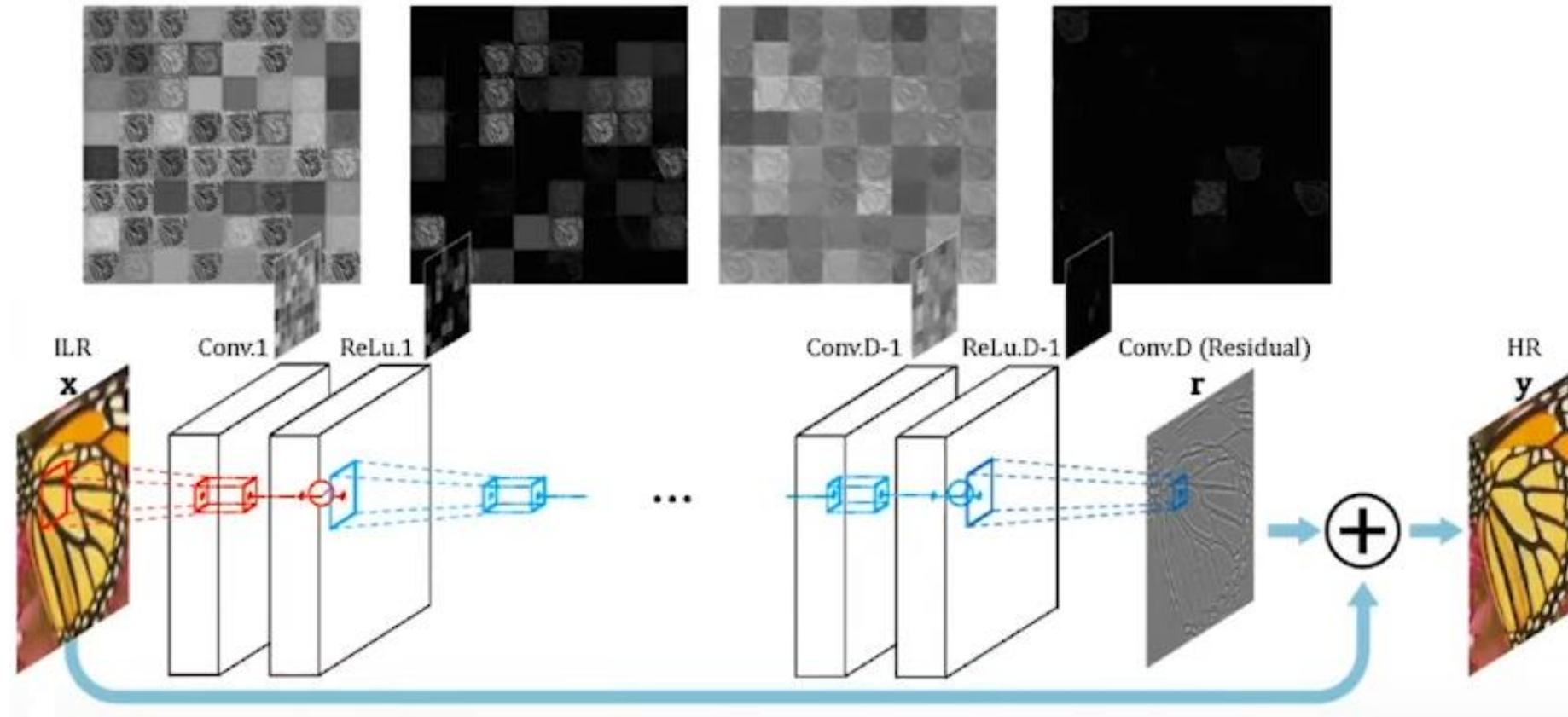
x_i



y_i

- CovNet, у которого вход – x , выход – y
- Есть возможность легко получить данные для обучения

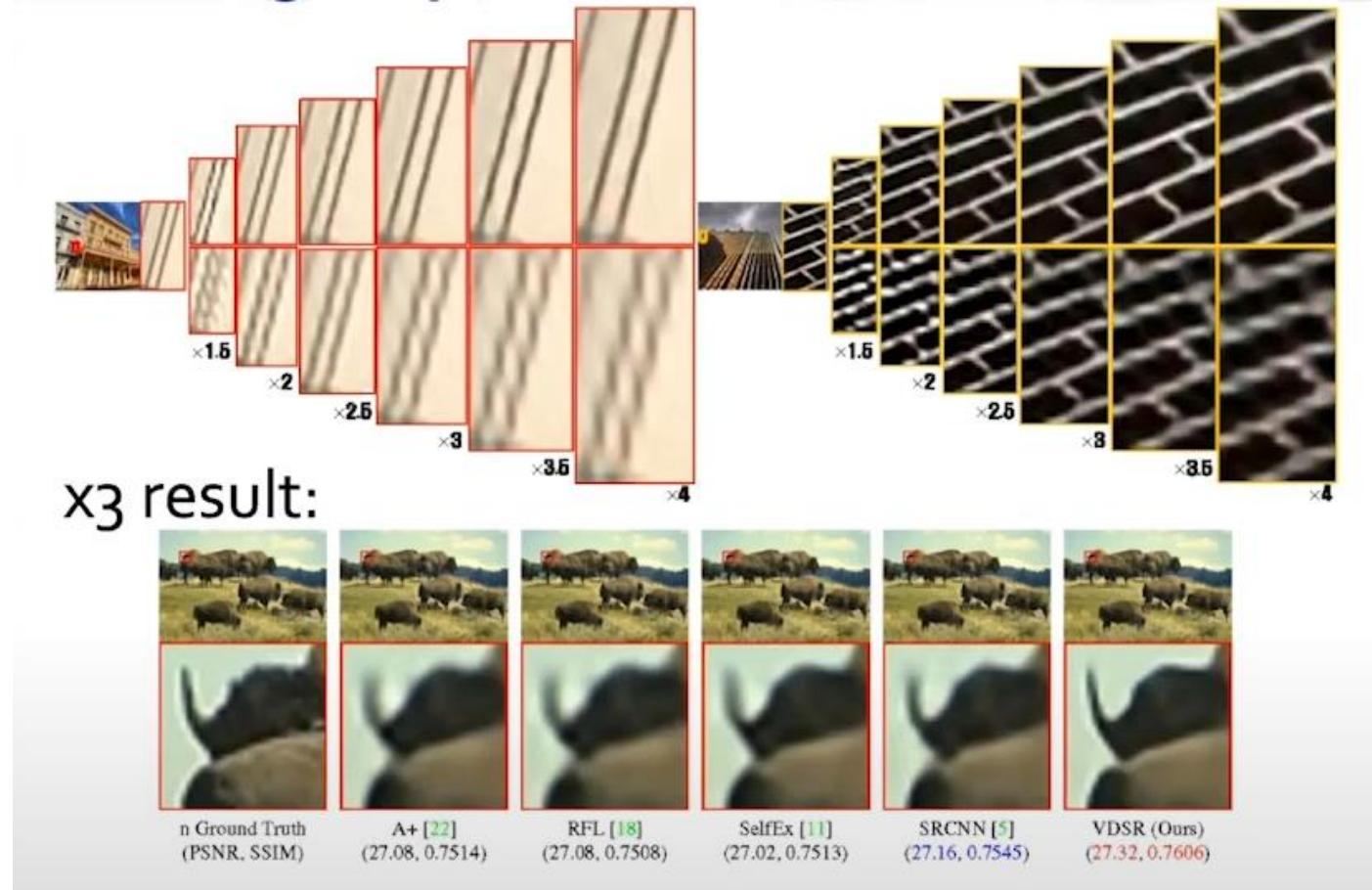
Image superresolution



[Kim, Lee, CVPR16]

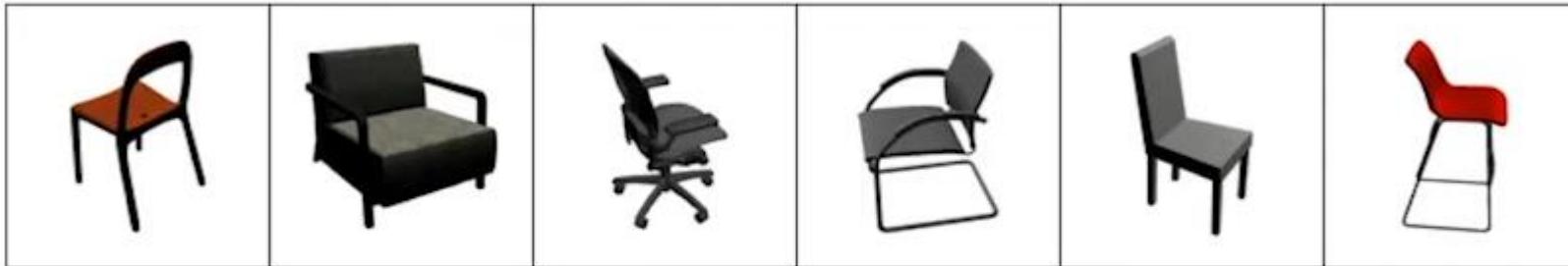
$$\hat{\theta} = \arg \min_{\theta} \sum_i \|f(x_i; \theta) - y_i\|^2$$

Image superresolution



[Kim, Lee, CVPR16]

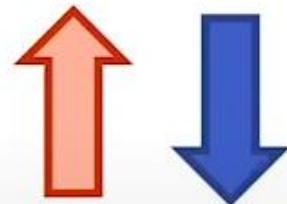
Neural rendering



x_i = chair ID and camera parameters

x_i = chair ID and camera parameters

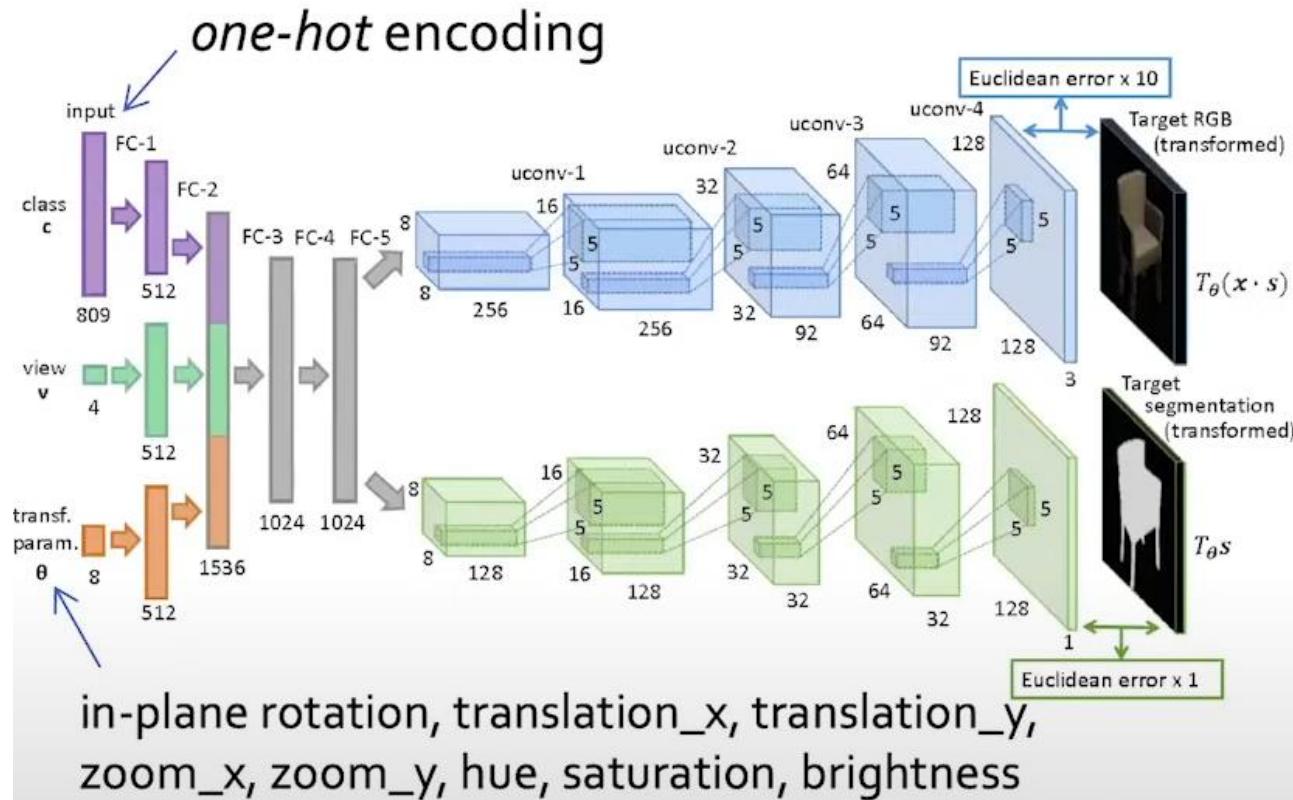
Recognition
(computer vision)



Rendering
(computer graphics)

y_i = RGB image + Binary foreground mask

Neural rendering



x_i = chair ID and camera parameters

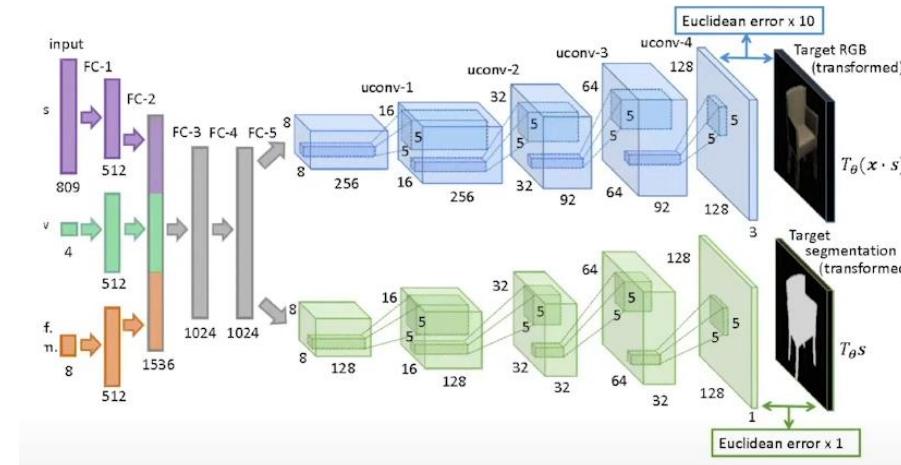
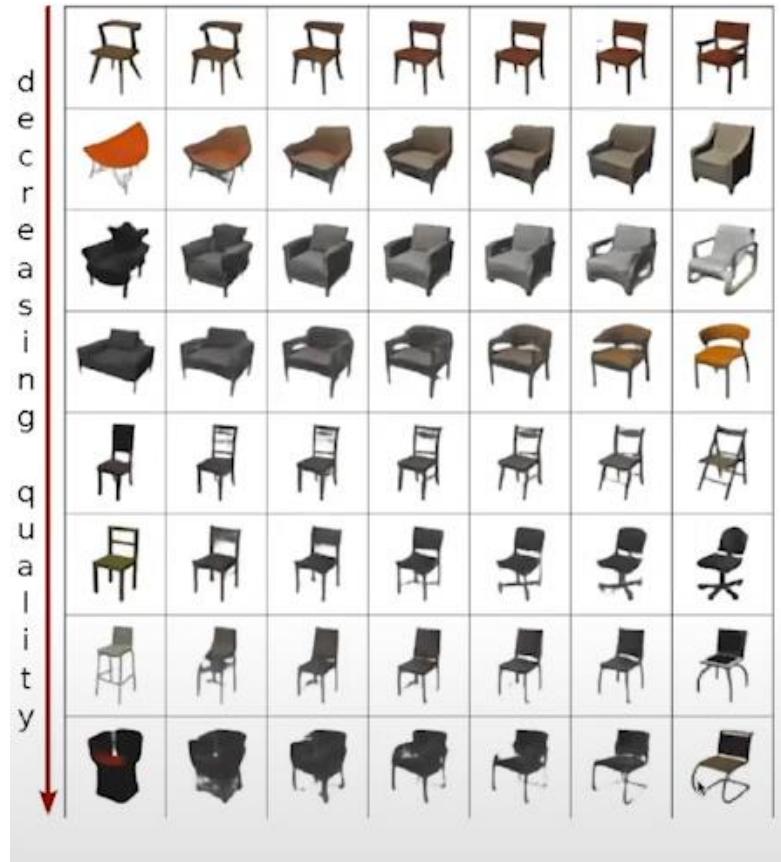
y_i = RGB image + Binary foreground mask

Training with MSE loss:

$$\hat{\theta} = \arg \min_{\theta} \sum \|f(x_i; \theta) - y_i\|^2$$

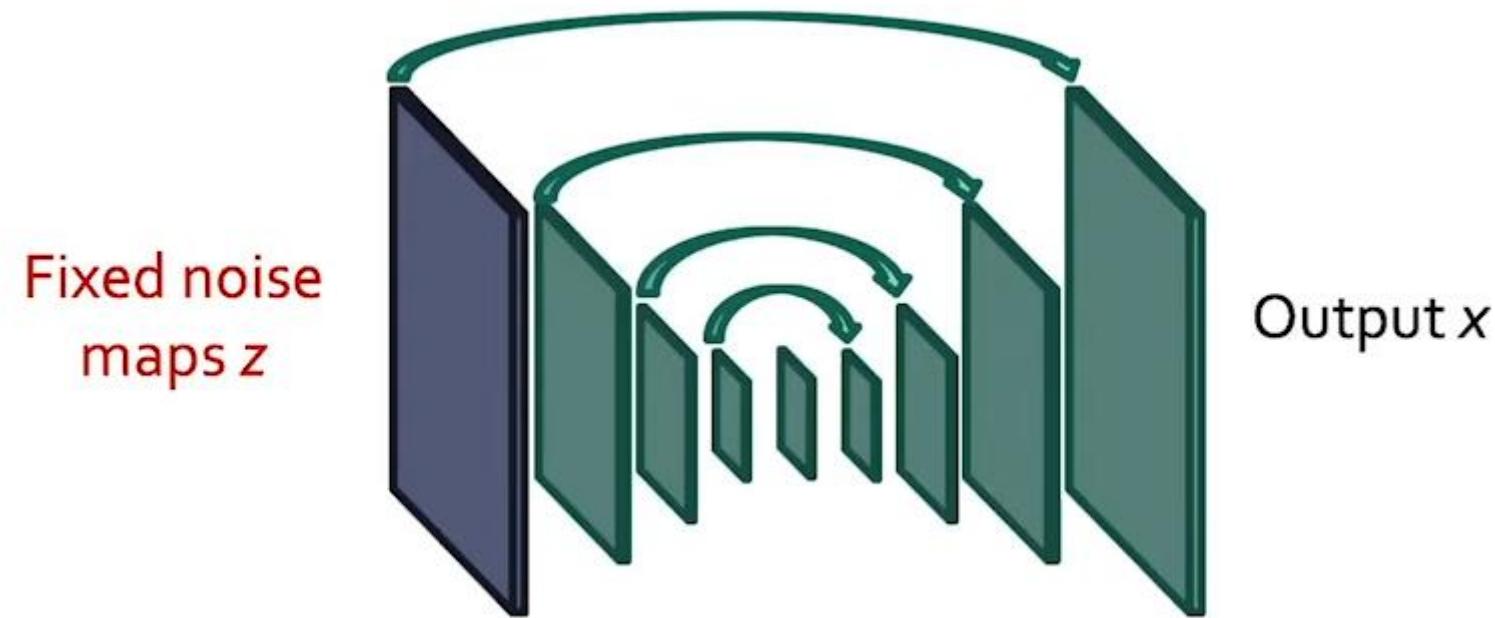
[Dosovitskiy, Springerber, CVPR15]

Neural rendering



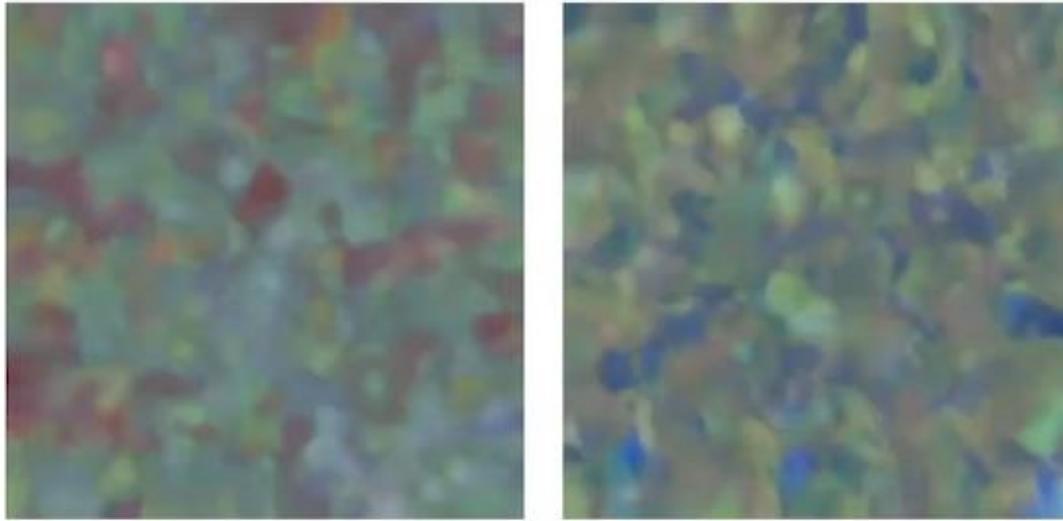
[Dosovitskiy, Springerber, CVPR15]

Почему это может работать?

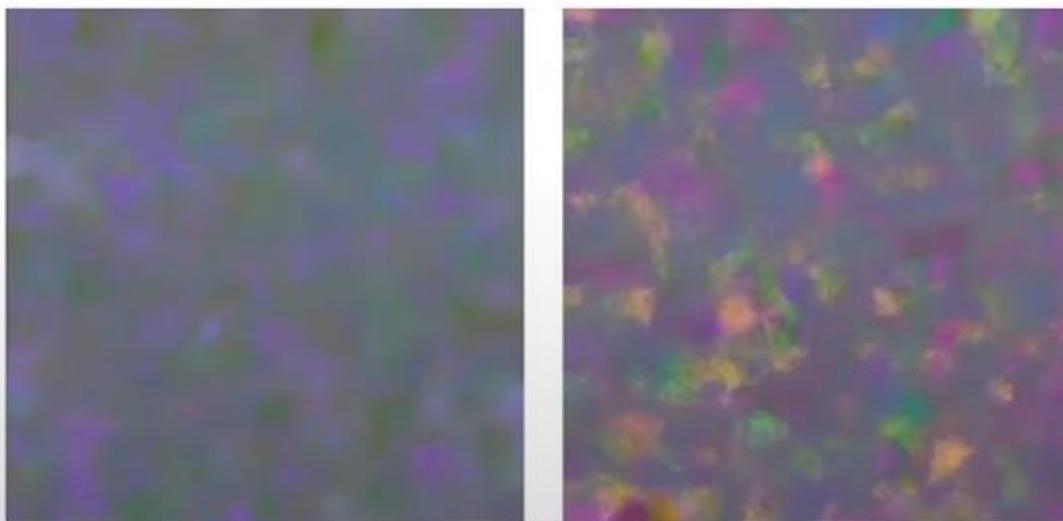


Почему это может работать?

Hourglass:

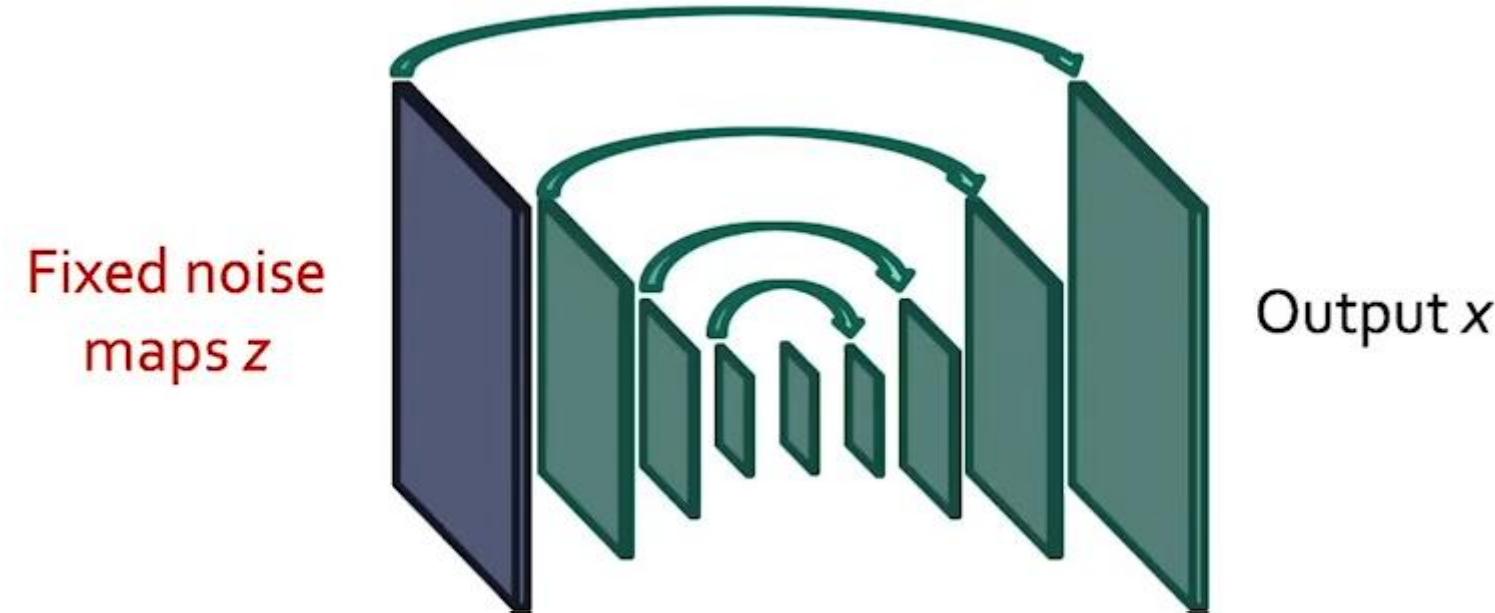


UNet:



[ШАД, 2021]

Deep inpainting



- U-net with thin skip connections (containing convolution blocks)
- Convolution block: conv + batch norm + leaky ReLU + (up/down-sample)
- ~2 millions of parameters
- Fit to known pixel values

[ШАД, 2021]

$$\min_{\theta} \|(f(z; \theta) - x_0) \odot m\|^2$$

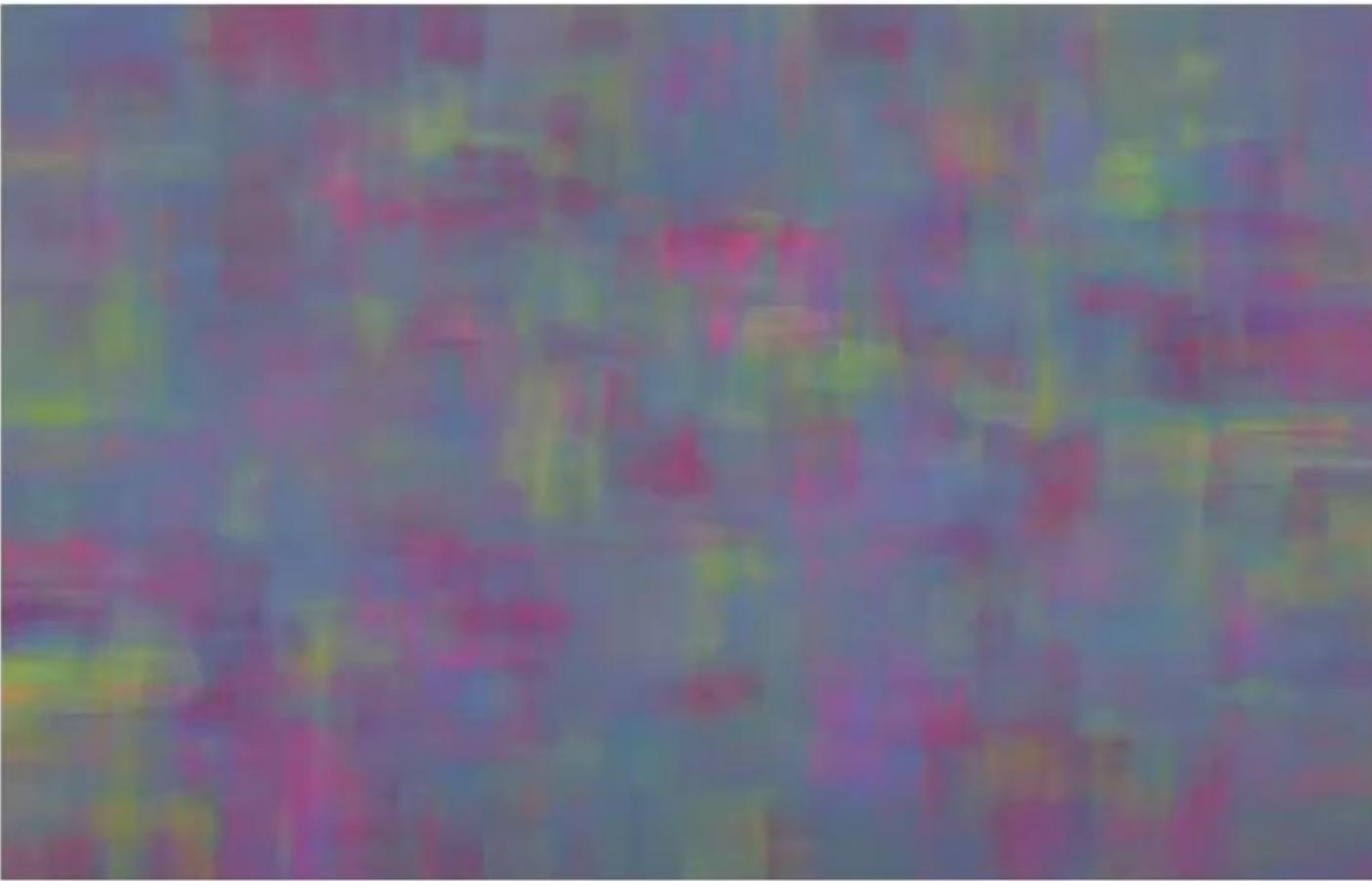


Deep inpainting



[Ulyanov, et.al CVPR2018]

Deep inpainting



[Ulyanov, et.al CVPR2018]

Deep inpainting



[Ulyanov, et.al CVPR2018]

Deep inpainting



[Ulyanov, et.al CVPR2018]

Deep inpainting



[Ulyanov, et.al CVPR2018]

Deep inpainting



[Ulyanov, et.al CVPR2018]

Deep inpainting



[Ulyanov, et.al CVPR2018]

Deep inpainting



[Ulyanov, et.al CVPR2018]

Deep inpainting



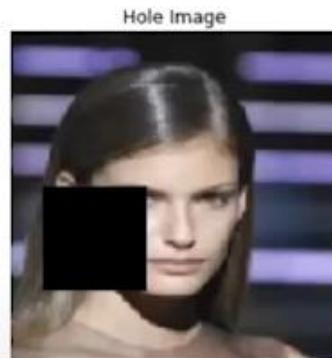
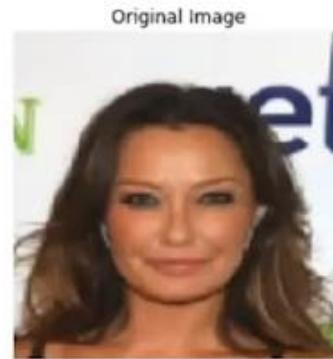
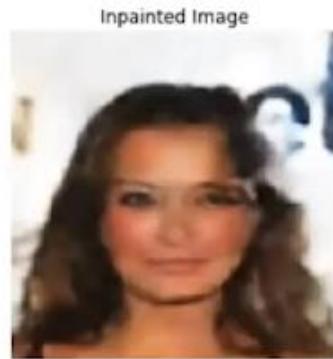
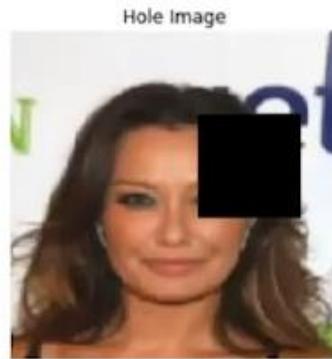
[Ulyanov, et.al CVPR2018]

Deep inpainting



[Ulyanov, et.al CVPR2018]

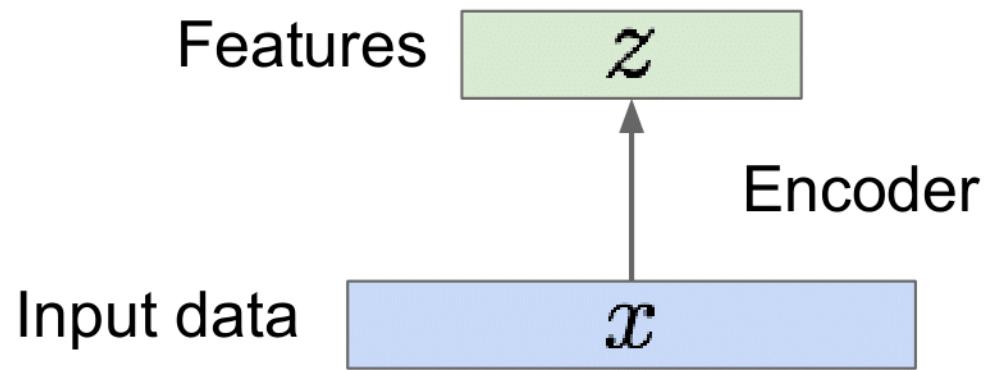
Deep inpainting



$$\min_{z \in \mathcal{Z}} \|(g_\theta(z) - x) \odot m\|$$

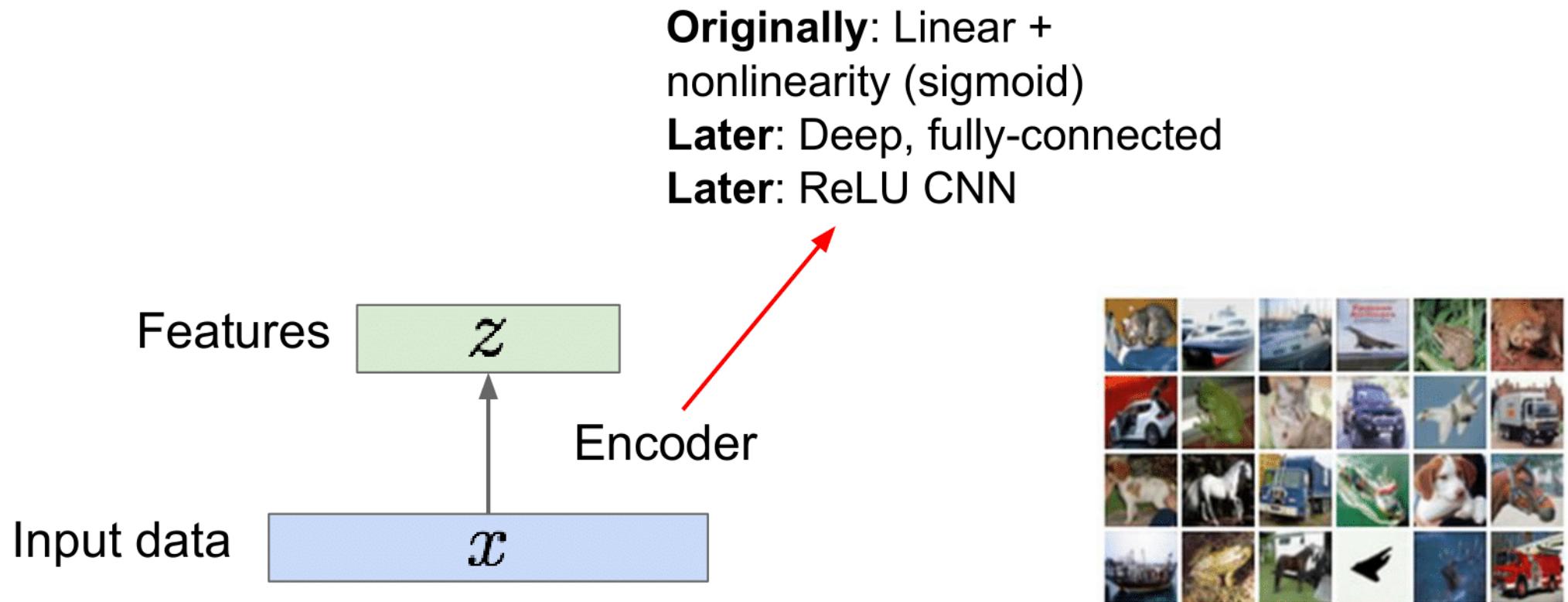
Some background first: Autoencoders

Unsupervised approach for learning a lower-dimensional feature representation from unlabeled training data



Some background first: Autoencoders

Unsupervised approach for learning a lower-dimensional feature representation from unlabeled training data



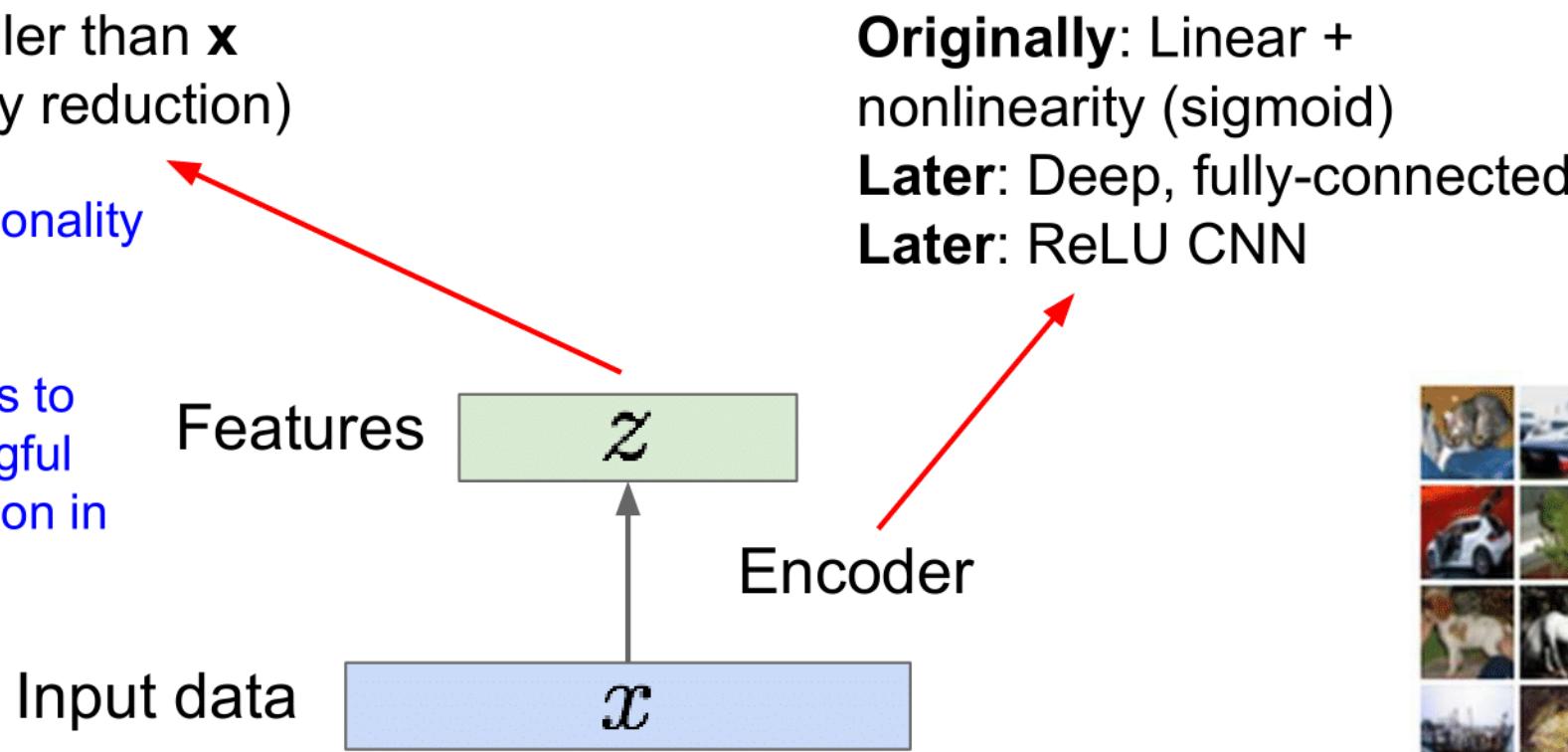
Some background first: Autoencoders

Unsupervised approach for learning a lower-dimensional feature representation from unlabeled training data

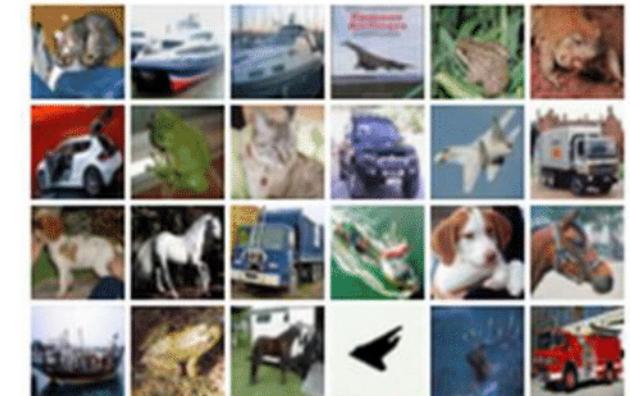
z usually smaller than x
(dimensionality reduction)

Q: Why dimensionality reduction?

A: Want features to capture meaningful factors of variation in data

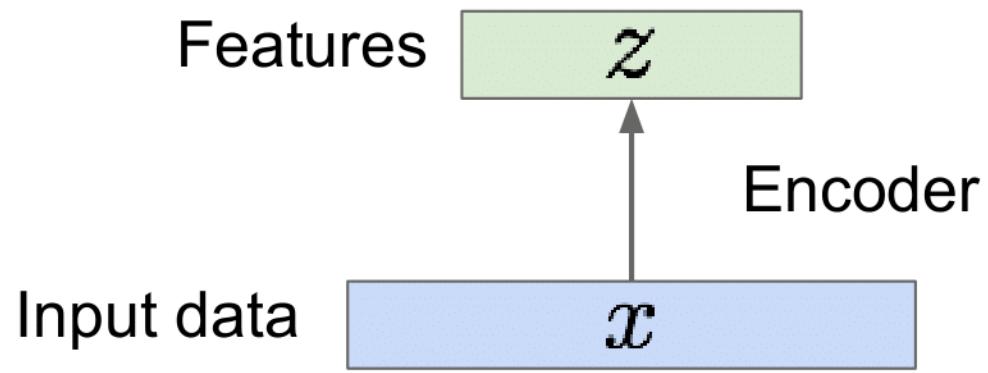


Originally: Linear + nonlinearity (sigmoid)
Later: Deep, fully-connected
Later: ReLU CNN



Some background first: Autoencoders

How to learn this feature representation?

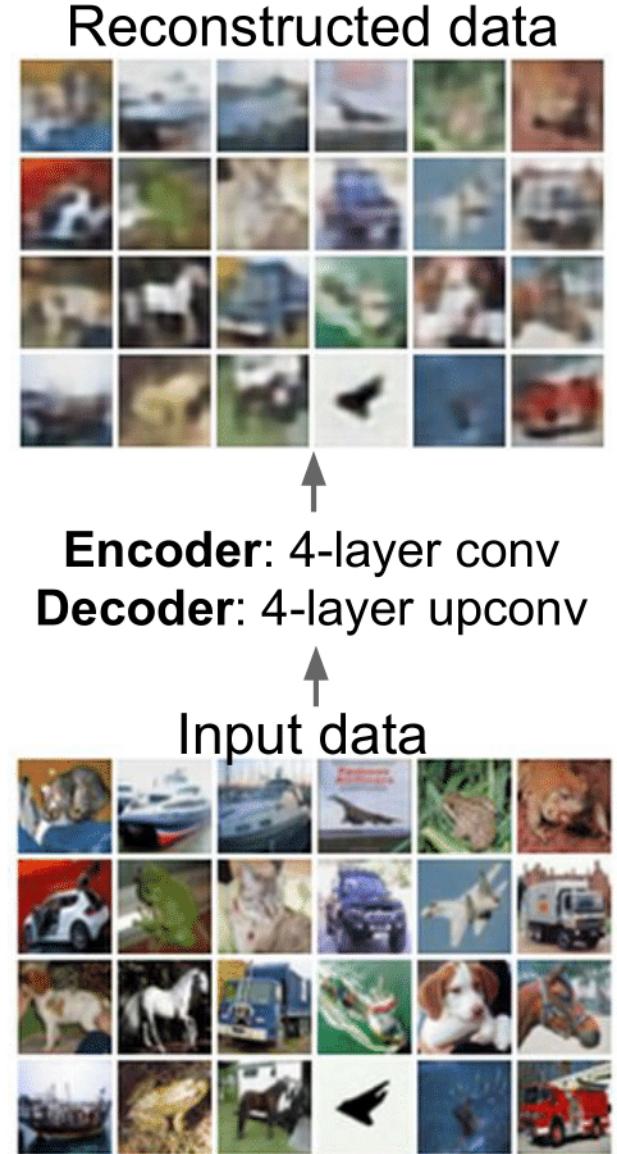
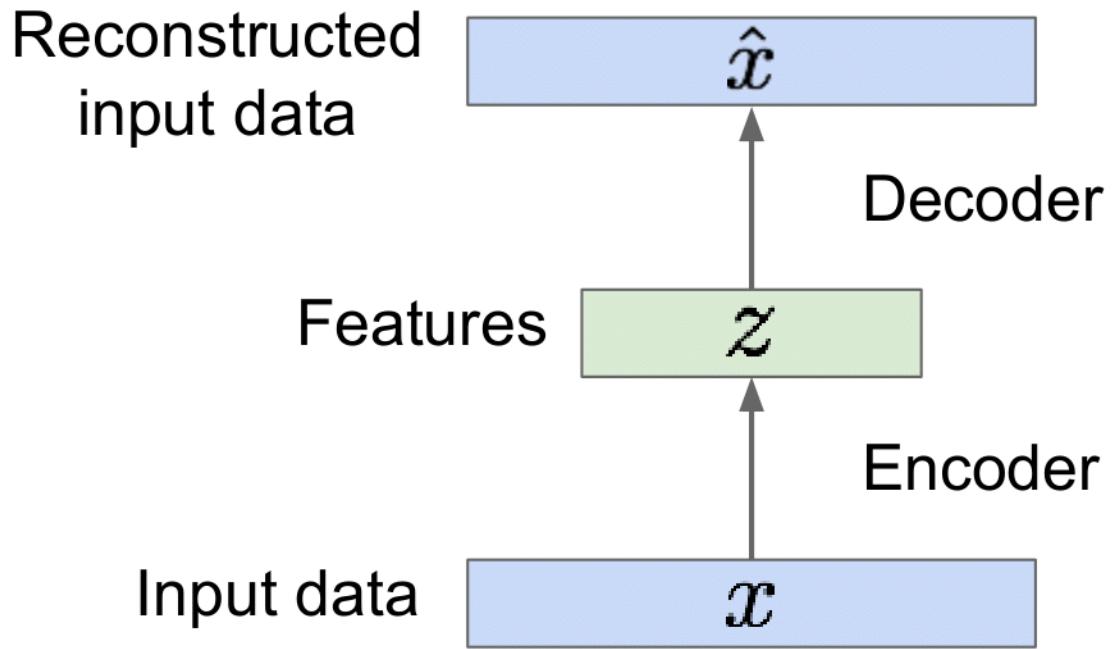


Some background first: Autoencoders

How to learn this feature representation?

Train such that features can be used to reconstruct original data

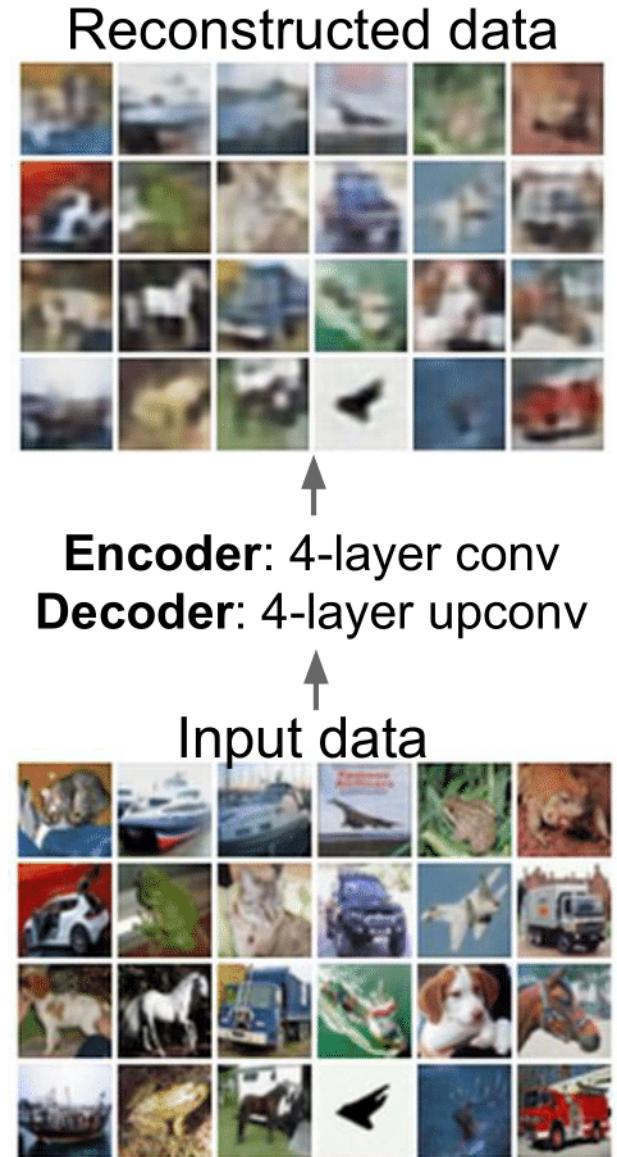
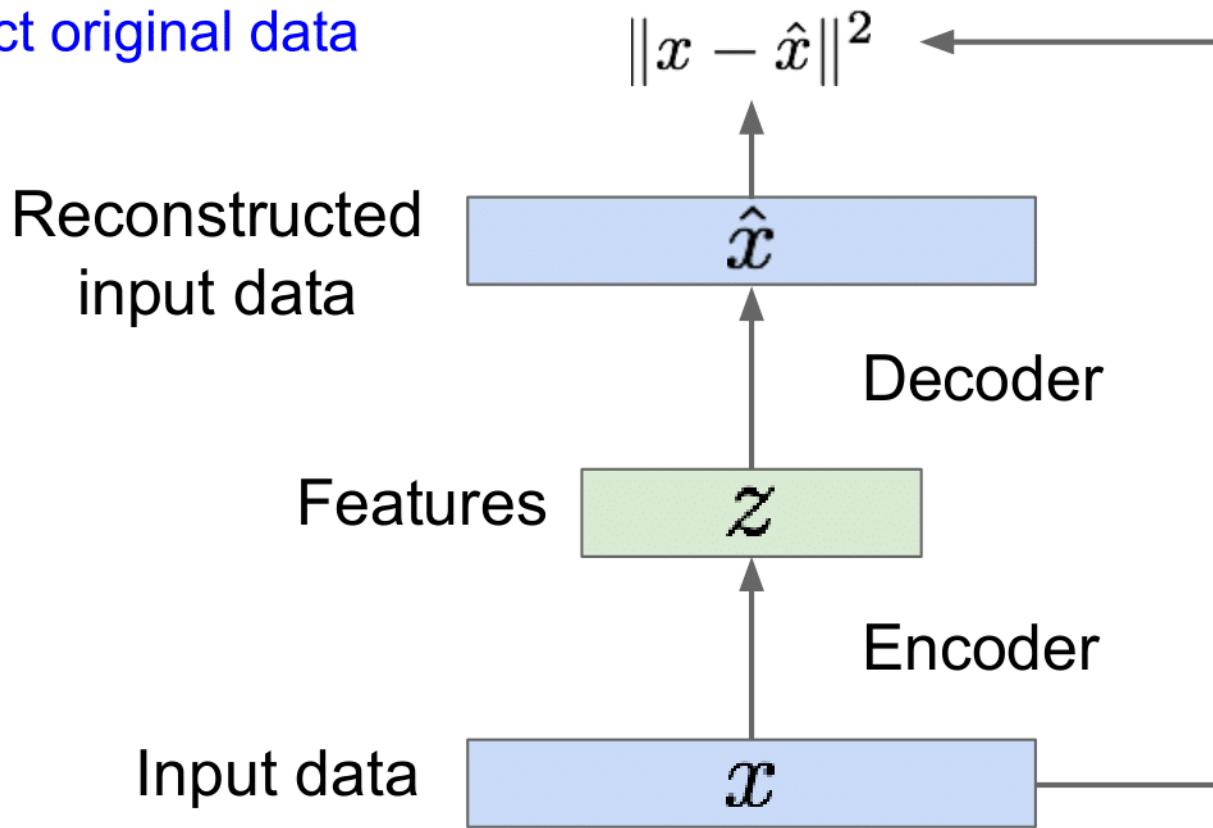
“Autoencoding” - encoding itself



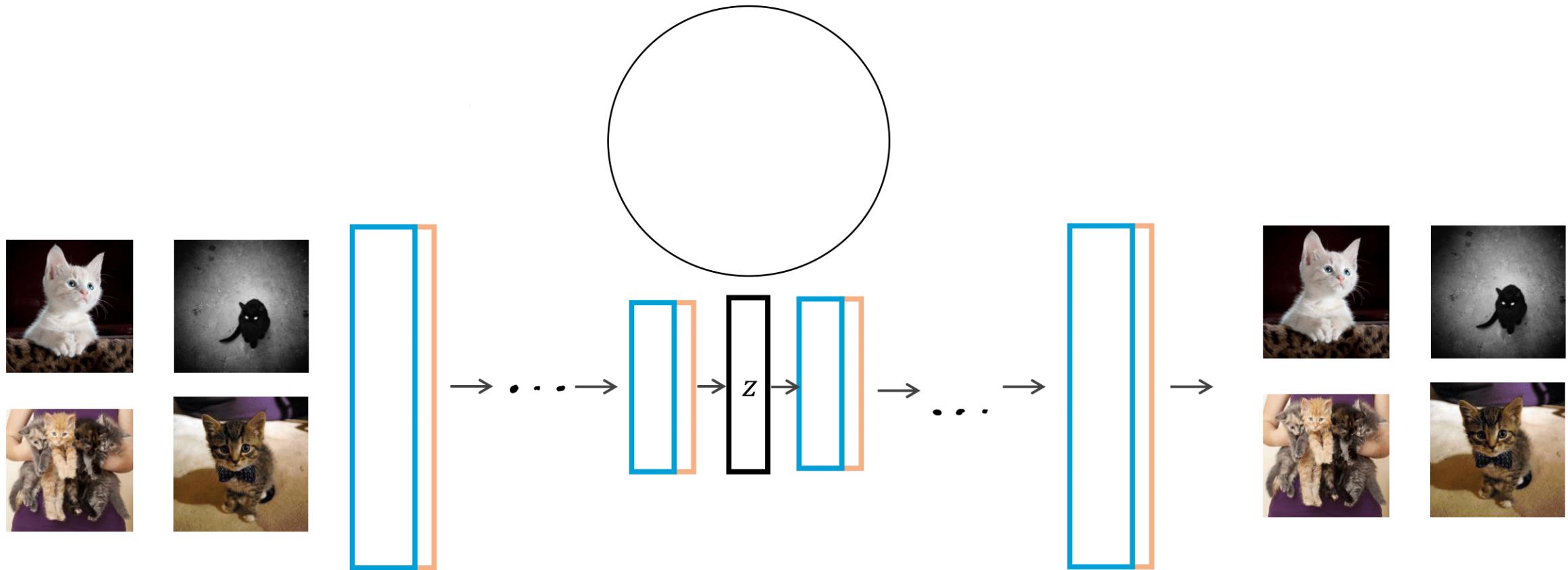
Some background first: Autoencoders

Train such that features
can be used to
reconstruct original data

L2 Loss function:

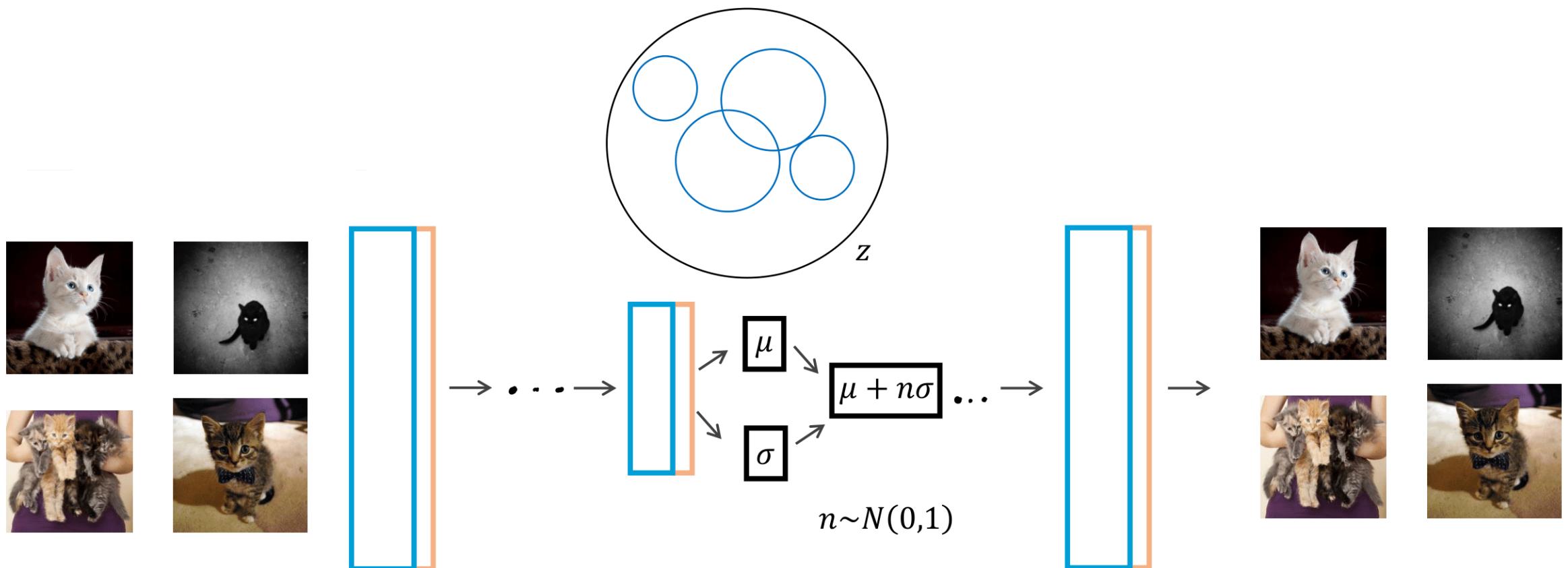


Some background first: Autoencoders



Source: slides by @sim0nsays

Variational Autoencoder



$$L_{\text{KL}} = D_{KL}(\mu, \sigma || N(0,1))$$

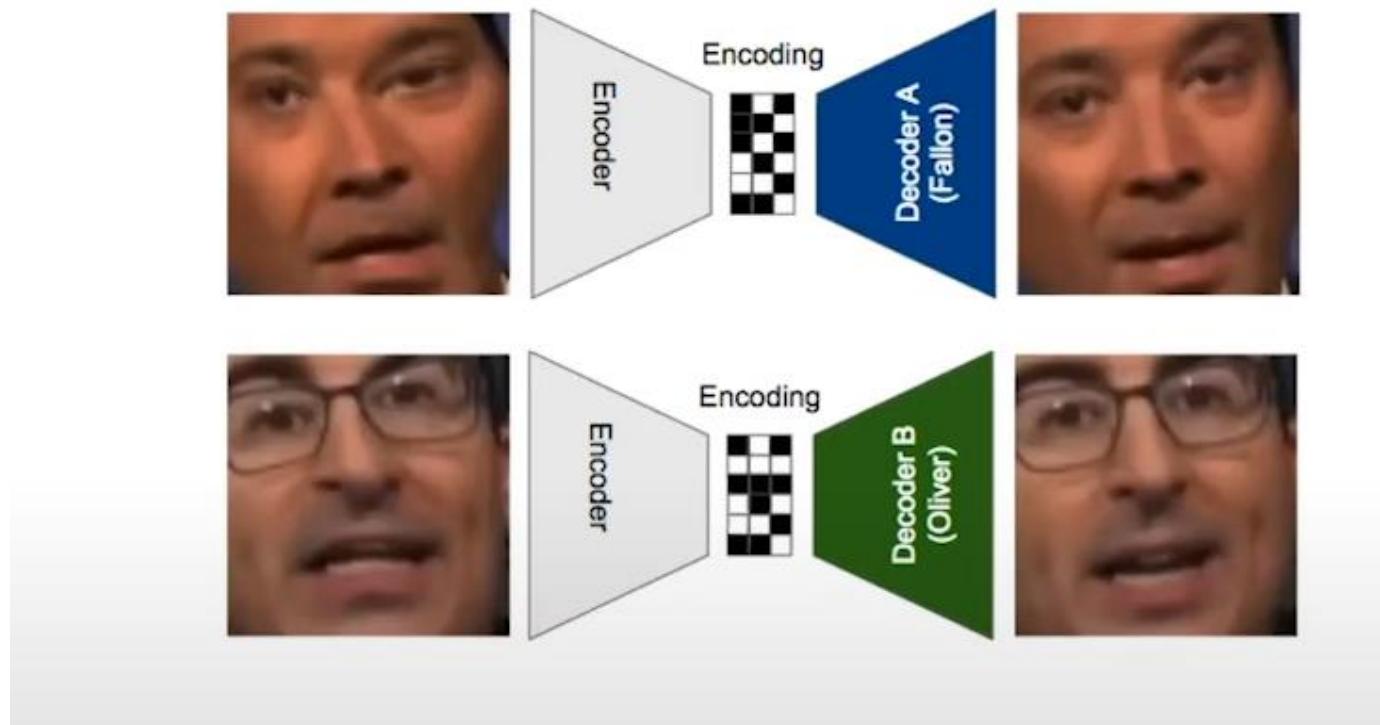
$$= \frac{1}{2} \sum_{j=0}^N (1 + \log \sigma_j^2 - \mu_j^2 - \sigma_j^2)$$

$$L_r = \|x_{\text{out}} - x_{\text{in}}\|^2$$

Source: slides by @sim0nsays

Deep Fake

Paired “dewarping” autoencoders:



[Gaurav Oberoi blog]

Generative Adversarial Networks

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Problem: Want to sample from complex, high-dimensional training distribution. No direct way to do this!

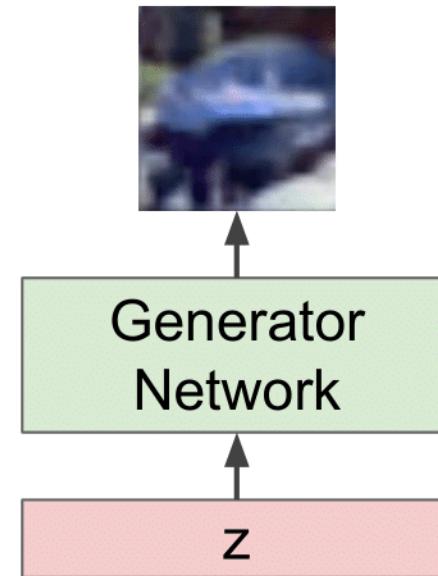
Solution: Sample from a simple distribution, e.g. random noise. Learn transformation to training distribution.

Q: What can we use to represent this complex transformation?

A: A neural network!

Output: Sample from training distribution

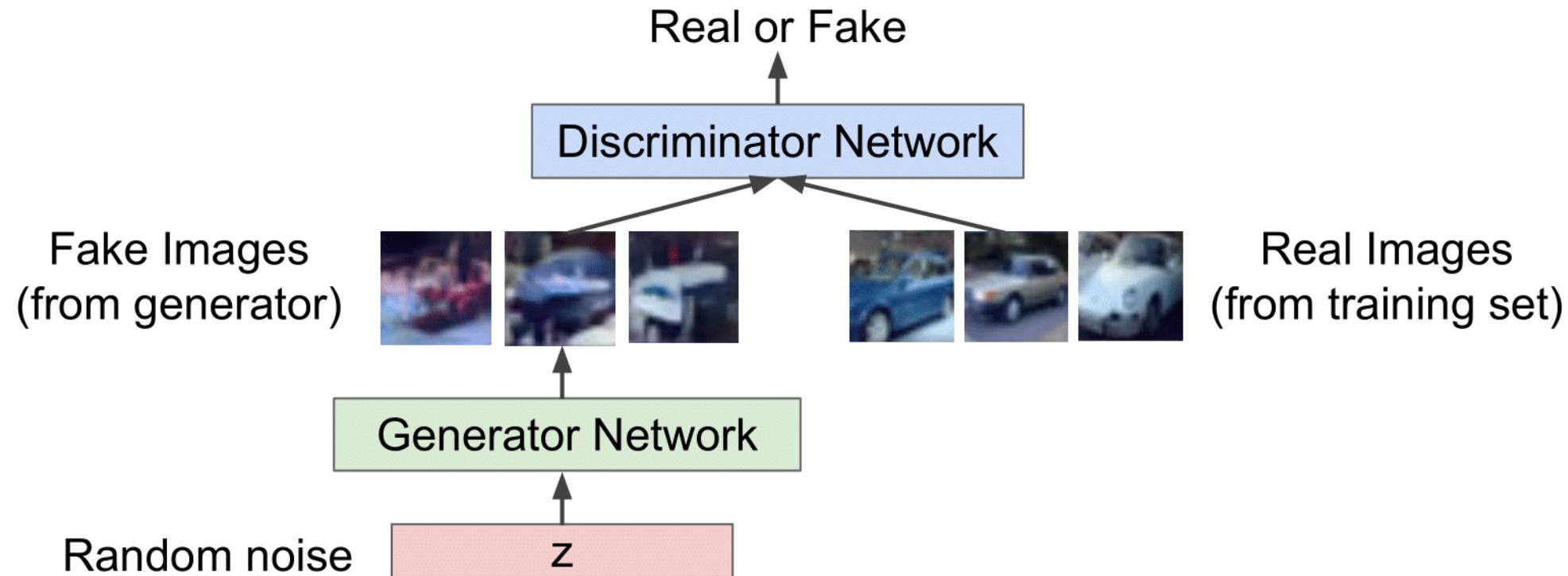
Input: Random noise



Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Generator network: try to fool the discriminator by generating real-looking images
Discriminator network: try to distinguish between real and fake images



Fake and real images copyright Emily Denton et al. 2015. Reproduced with permission.

Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Generator network: try to fool the discriminator by generating real-looking images

Discriminator network: try to distinguish between real and fake images

Train jointly in **minimax game**

Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

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Train jointly in **minimax game**

Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log \underbrace{D_{\theta_d}(x)}_{\text{Discriminator output for real data } x} + \mathbb{E}_{z \sim p(z)} \log(1 - \underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\text{Discriminator output for generated fake data } G(z)}) \right]$$

- Discriminator (θ_d) wants to **maximize objective** such that $D(x)$ is close to 1 (real) and $D(G(z))$ is close to 0 (fake)
- Generator (θ_g) wants to **minimize objective** such that $D(G(z))$ is close to 1 (discriminator is fooled into thinking generated $G(z)$ is real)

Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Putting it together: GAN training algorithm

```
for number of training iterations do
    for  $k$  steps do
        • Sample minibatch of  $m$  noise samples  $\{\mathbf{z}^{(1)}, \dots, \mathbf{z}^{(m)}\}$  from noise prior  $p_g(\mathbf{z})$ .
        • Sample minibatch of  $m$  examples  $\{\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(m)}\}$  from data generating distribution  $p_{\text{data}}(\mathbf{x})$ .
        • Update the discriminator by ascending its stochastic gradient:
            
$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^m \left[ \log D_{\theta_d}(\mathbf{x}^{(i)}) + \log(1 - D_{\theta_d}(G_{\theta_g}(\mathbf{z}^{(i)}))) \right]$$

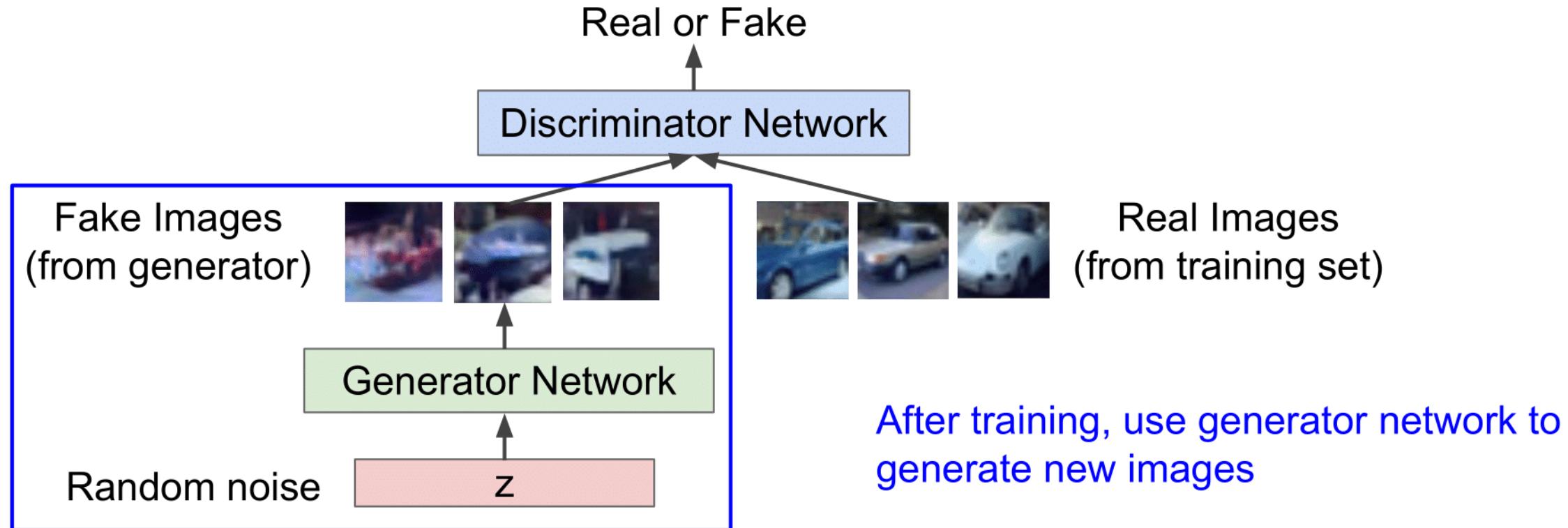
    end for
    • Sample minibatch of  $m$  noise samples  $\{\mathbf{z}^{(1)}, \dots, \mathbf{z}^{(m)}\}$  from noise prior  $p_g(\mathbf{z})$ .
    • Update the generator by ascending its stochastic gradient (improved objective):
        
$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^m \log(D_{\theta_d}(G_{\theta_g}(\mathbf{z}^{(i)})))$$

end for
```

Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

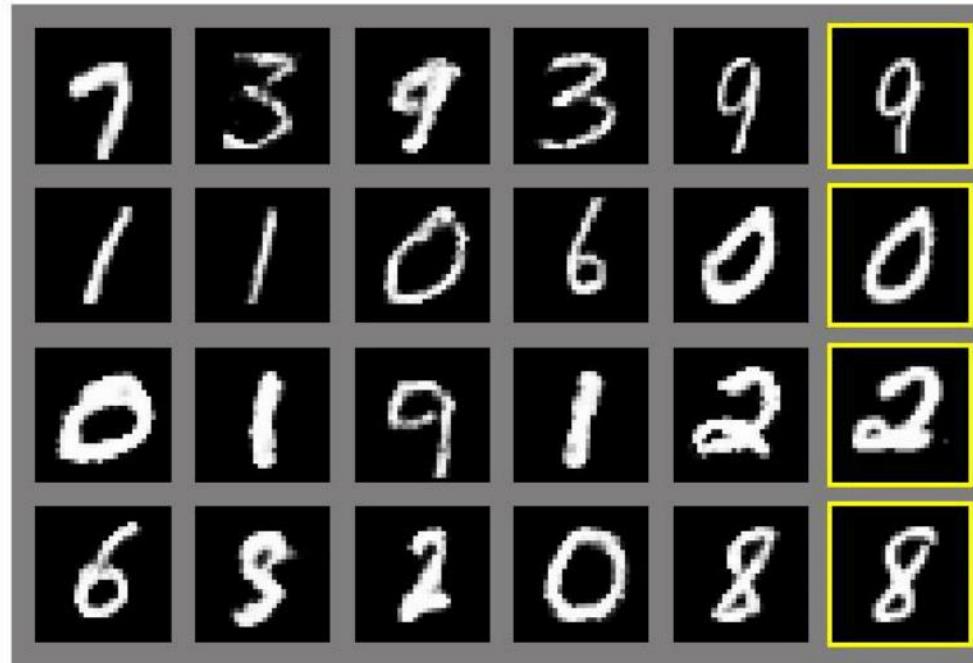
Generator network: try to fool the discriminator by generating real-looking images
Discriminator network: try to distinguish between real and fake images



Fake and real images copyright Emily Denton et al. 2015. Reproduced with permission.

Generative Adversarial Nets

Generated samples

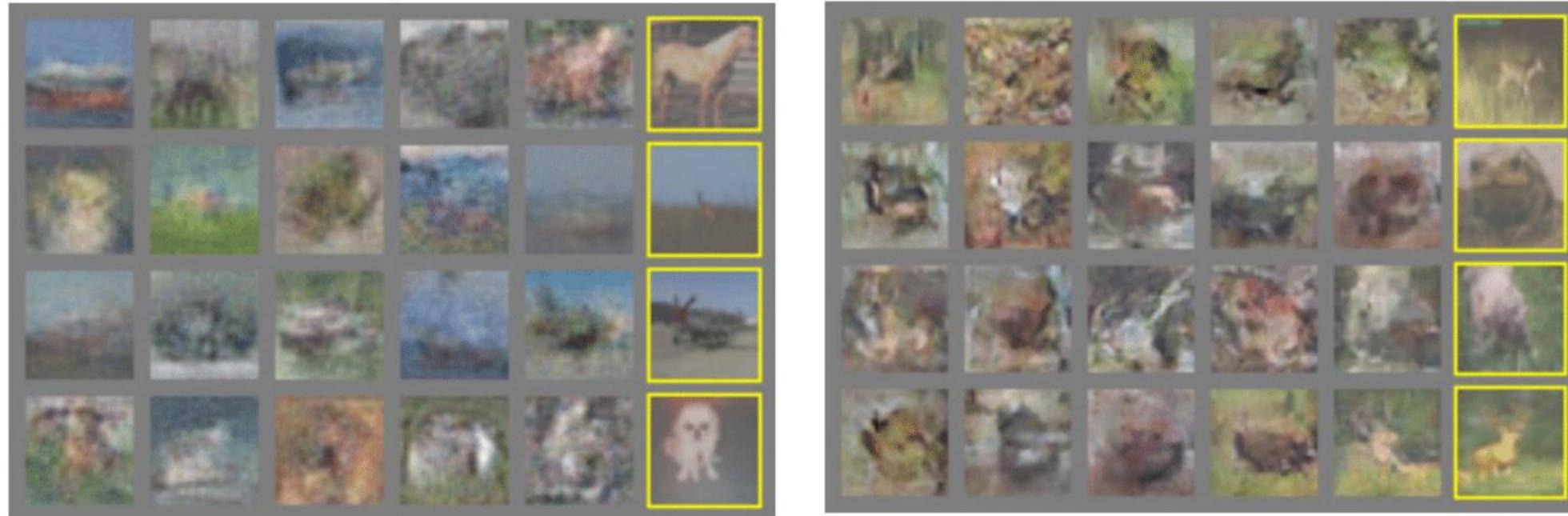


Nearest neighbor from training set

Figures copyright Ian Goodfellow et al., 2014. Reproduced with permission.

Generative Adversarial Nets

Generated samples (CIFAR-10)



Nearest neighbor from training set

Figures copyright Ian Goodfellow et al., 2014. Reproduced with permission.

Generative Adversarial Nets: Convolutional Architectures

Generator is an upsampling network with fractionally-strided convolutions
Discriminator is a convolutional network

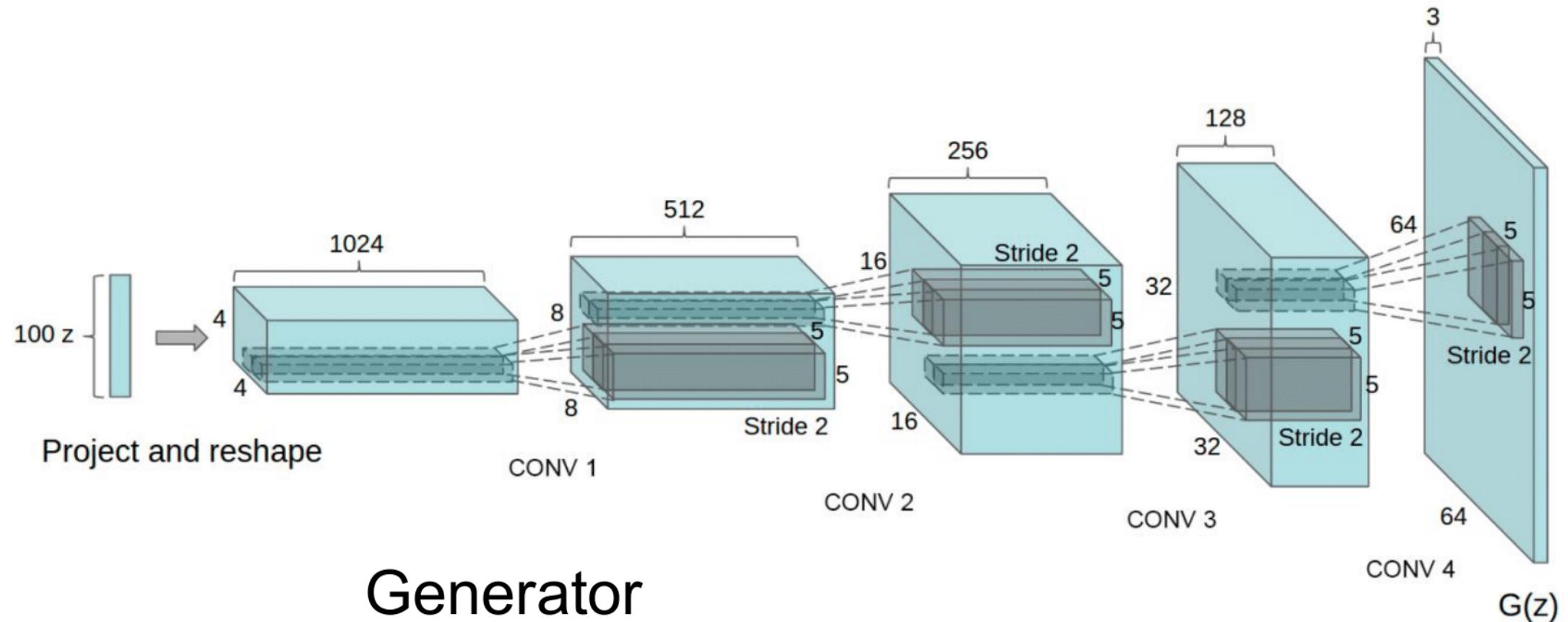
Architecture guidelines for stable Deep Convolutional GANs

- Replace any pooling layers with strided convolutions (discriminator) and fractional-strided convolutions (generator).
- Use batchnorm in both the generator and the discriminator.
- Remove fully connected hidden layers for deeper architectures.
- Use ReLU activation in generator for all layers except for the output, which uses Tanh.
- Use LeakyReLU activation in the discriminator for all layers.

Radford et al, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks", ICLR 2016

Source: Stanford CS231n Lecture 13 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Generative Adversarial Nets: Convolutional Architectures

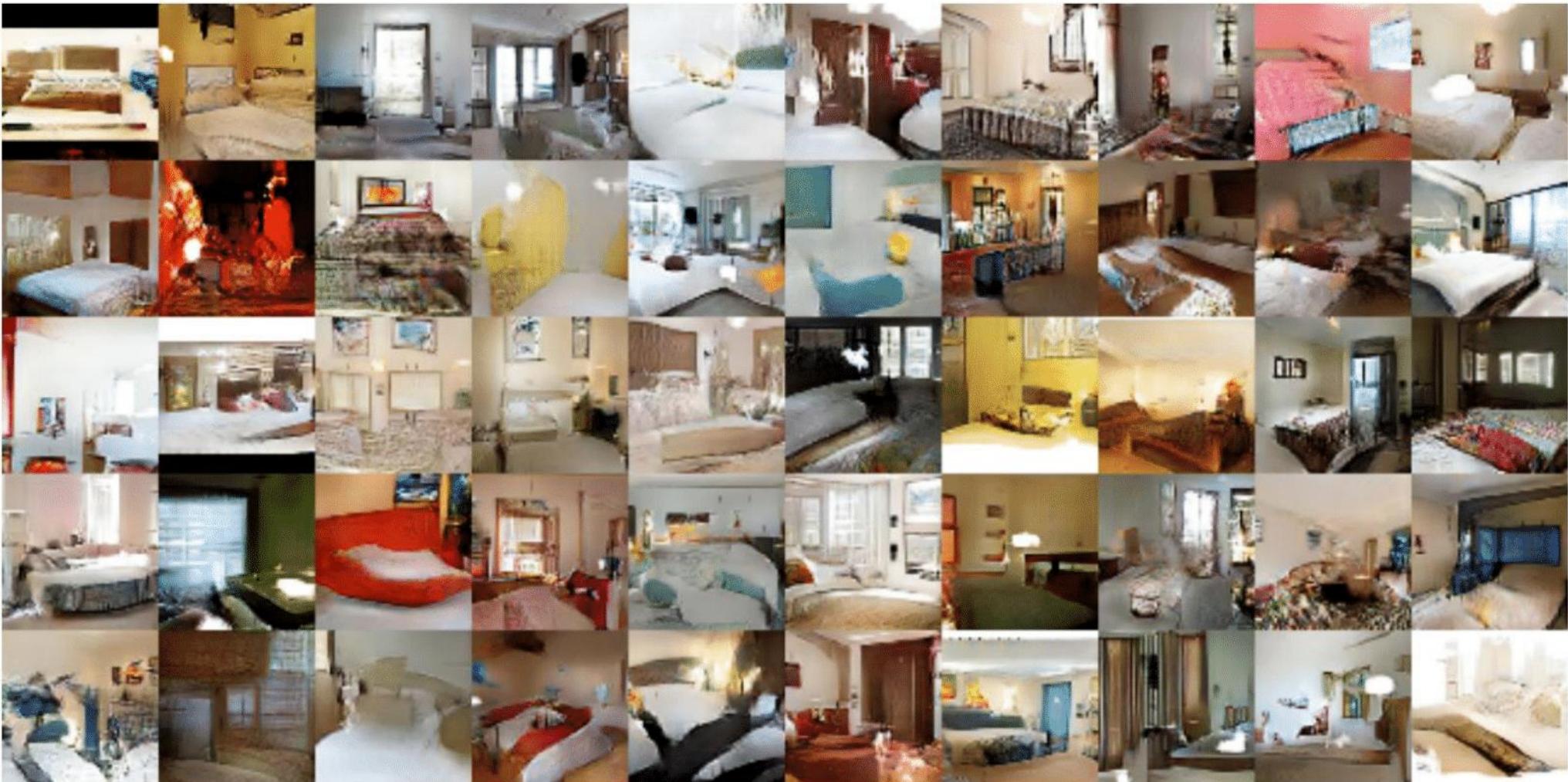


Radford et al, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks", ICLR 2016

Source: Stanford CS231n Lecture 13 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Generative Adversarial Nets: Convolutional Architectures

Samples
from the
model look
amazing!



Radford et al,
ICLR 2016

Source: Stanford CS231n Lecture 13 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Generative Adversarial Nets: Convolutional Architectures

Interpolating
between
random
points in latent
space



Radford et al,
ICLR 2016

Source: Stanford CS231n Lecture 13 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Generative Adversarial Nets: Interpretable Vector Math

Smiling woman



Neutral woman



Neutral man



Samples
from the
model

Radford et al, ICLR 2016

Generative Adversarial Nets: Interpretable Vector Math

Smiling woman Neutral woman Neutral man

Radford et al, ICLR 2016

Samples
from the
model



Average Z
vectors, do
arithmetic



Generative Adversarial Nets: Interpretable Vector Math

Smiling woman



Samples
from the
model

Neutral woman



Neutral man



Radford et al, ICLR 2016

Smiling Man



Average Z
vectors, do
arithmetic



Generative Adversarial Nets: Interpretable Vector Math

Glasses man



No glasses man



No glasses woman



Radford et al,
ICLR 2016



Source: Stanford CS231n Lecture 13 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Generative Adversarial Nets: Interpretable Vector Math

Glasses man



No glasses man

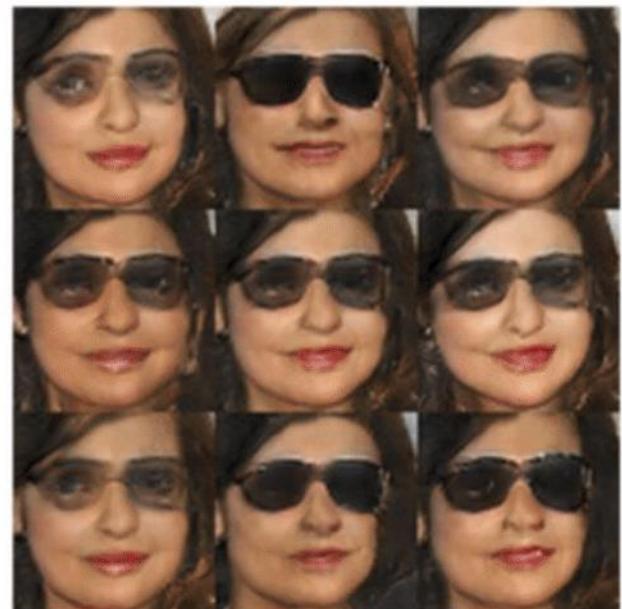


No glasses woman



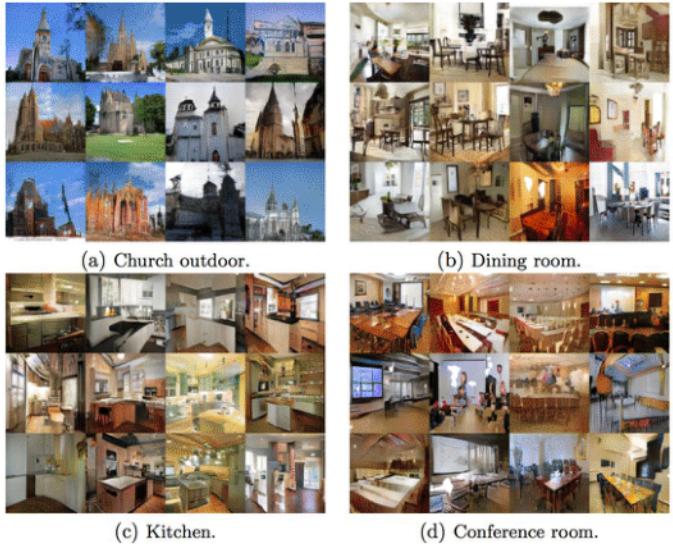
Radford et al,
ICLR 2016

Woman with glasses



2017: Year of the GAN

Better training and generation

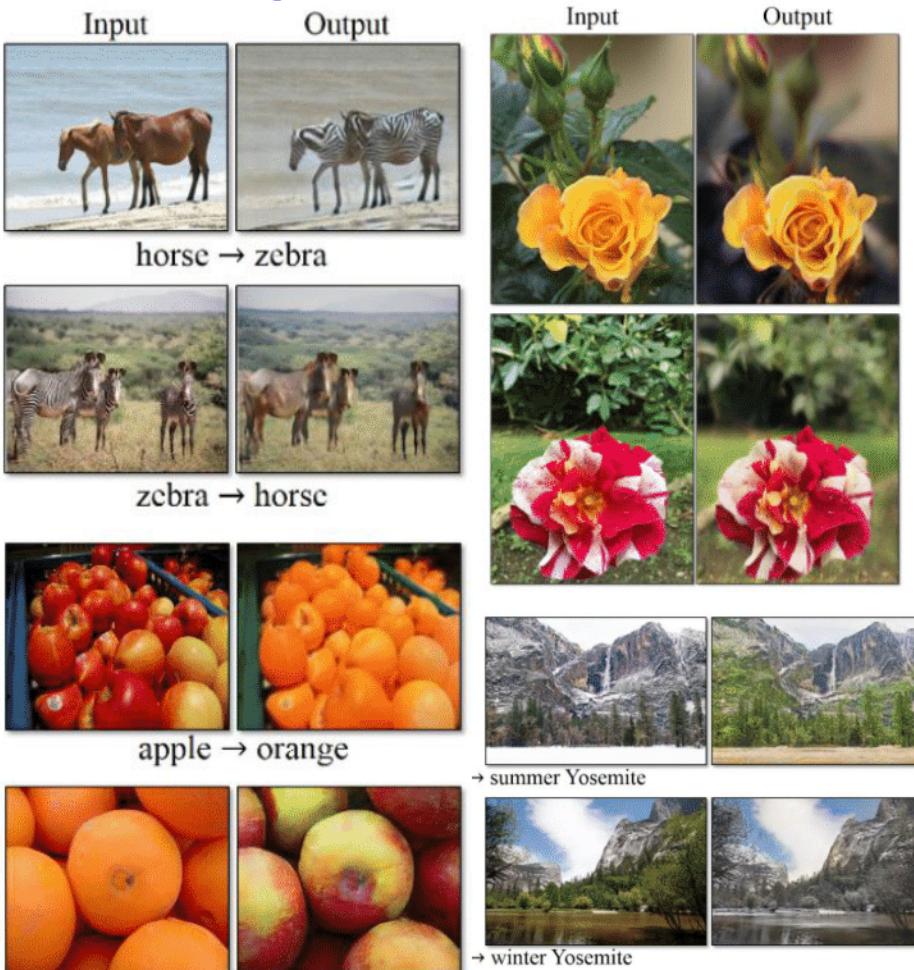


LSGAN. Mao et al. 2017.



BEGAN. Bertholet et al. 2017.

Source->Target domain transfer



CycleGAN. Zhu et al. 2017.

Text -> Image Synthesis

this small bird has a pink breast and crown, and black primaries and secondaries.



this magnificent fellow is almost all black with a red crest, and white cheek patch.



Reed et al. 2017.

Many GAN applications



Pix2pix. Isola 2017. Many examples at <https://phillipi.github.io/pix2pix/>

“The GAN Zoo”

- GAN - Generative Adversarial Networks
- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling
- acGAN - Face Aging With Conditional Generative Adversarial Networks
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- AdaGAN - AdaGAN: Boosting Generative Models
- AEGAN - Learning Inverse Mapping by Autoencoder based Generative Adversarial Nets
- AffGAN - Amortised MAP Inference for Image Super-resolution
- AL-CGAN - Learning to Generate Images of Outdoor Scenes from Attributes and Semantic Layouts
- ALI - Adversarially Learned Inference
- AM-GAN - Generative Adversarial Nets with Labeled Data by Activation Maximization
- AnoGAN - Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery
- ArtGAN - ArtGAN: Artwork Synthesis with Conditional Categorical GANs
- b-GAN - b-GAN: Unified Framework of Generative Adversarial Networks
- Bayesian GAN - Deep and Hierarchical Implicit Models
- BEGAN - BEGAN: Boundary Equilibrium Generative Adversarial Networks
- BiGAN - Adversarial Feature Learning
- BS-GAN - Boundary-Seeking Generative Adversarial Networks
- CGAN - Conditional Generative Adversarial Nets
- CaloGAN - CaloGAN: Simulating 3D High Energy Particle Showers in Multi-Layer Electromagnetic Calorimeters with Generative Adversarial Networks
- CCGAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks
- CatGAN - Unsupervised and Semi-supervised Learning with Categorical Generative Adversarial Networks
- CoGAN - Coupled Generative Adversarial Networks
- Context-RNN-GAN - Contextual RNN-GANs for Abstract Reasoning Diagram Generation
- C-RNN-GAN - C-RNN-GAN: Continuous recurrent neural networks with adversarial training
- CS-GAN - Improving Neural Machine Translation with Conditional Sequence Generative Adversarial Nets
- CVAE-GAN - CVAE-GAN: Fine-Grained Image Generation through Asymmetric Training
- CycleGAN - Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks
- DTN - Unsupervised Cross-Domain Image Generation
- DCGAN - Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks
- DiscGAN - Learning to Discover Cross-Domain Relations with Generative Adversarial Networks
- DR-GAN - Disentangled Representation Learning GAN for Pose-Invariant Face Recognition
- DualGAN - DualGAN: Unsupervised Dual Learning for Image-to-Image Translation
- EBGAN - Energy-based Generative Adversarial Network
- f-GAN - f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization
- FF-GAN - Towards Large-Pose Face Frontalization in the Wild
- GAWWN - Learning What and Where to Draw
- GeneGAN - GeneGAN: Learning Object Transfiguration and Attribute Subspace from Unpaired Data
- Geometric GAN - Geometric GAN
- GoGAN - Gang of GANs: Generative Adversarial Networks with Maximum Margin Ranking
- GP-GAN - GP-GAN: Towards Realistic High-Resolution Image Blending
- IAN - Neural Photo Editing with Introspective Adversarial Networks
- iGAN - Generative Visual Manipulation on the Natural Image Manifold
- IcGAN - Invertible Conditional GANs for image editing
- ID-CGAN - Image De-raining Using a Conditional Generative Adversarial Network
- Improved GAN - Improved Techniques for Training GANs
- InfoGAN - InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets
- LAGAN - Learning Particle Physics by Example: Location-Aware Generative Adversarial Networks for Physics Synthesis
- LAPGAN - Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks

<https://github.com/hindupuravinash/the-gan-zoo>