Autoencoders & Variational AE

Machine learning

Unsupervised learning

Supervised learning

- Labels or target classes
- Goal: learn a mapping from input to label
- Classification, regression

Machine learning

Unsupervised learning

Supervised learning

CAT

DOG

DOG

CAT

CAT

DOG

Machine learning

Unsupervised learning

- No label or target class
- Find out properties of the structure of the data
- Clustering (k-means, PCA)

Supervised learning

CAT

DOG

DOG

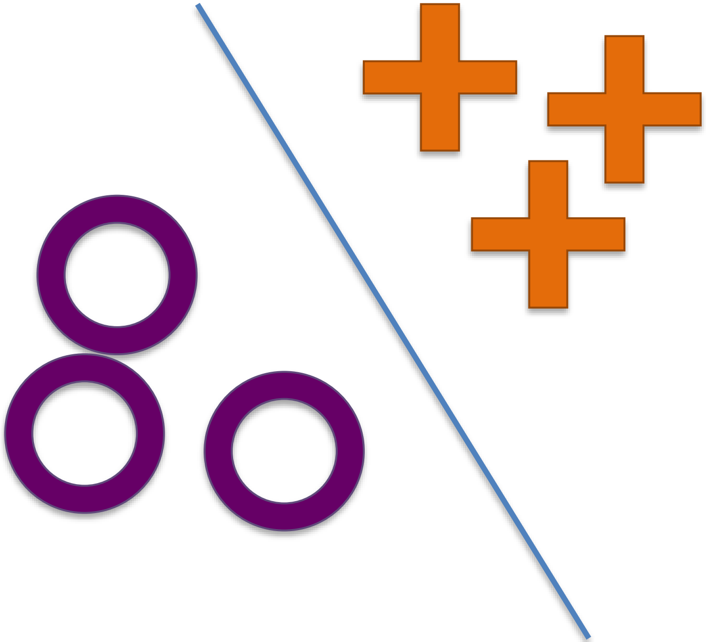
CAT

CAT

DOG

Machine learning

Unsupervised learning



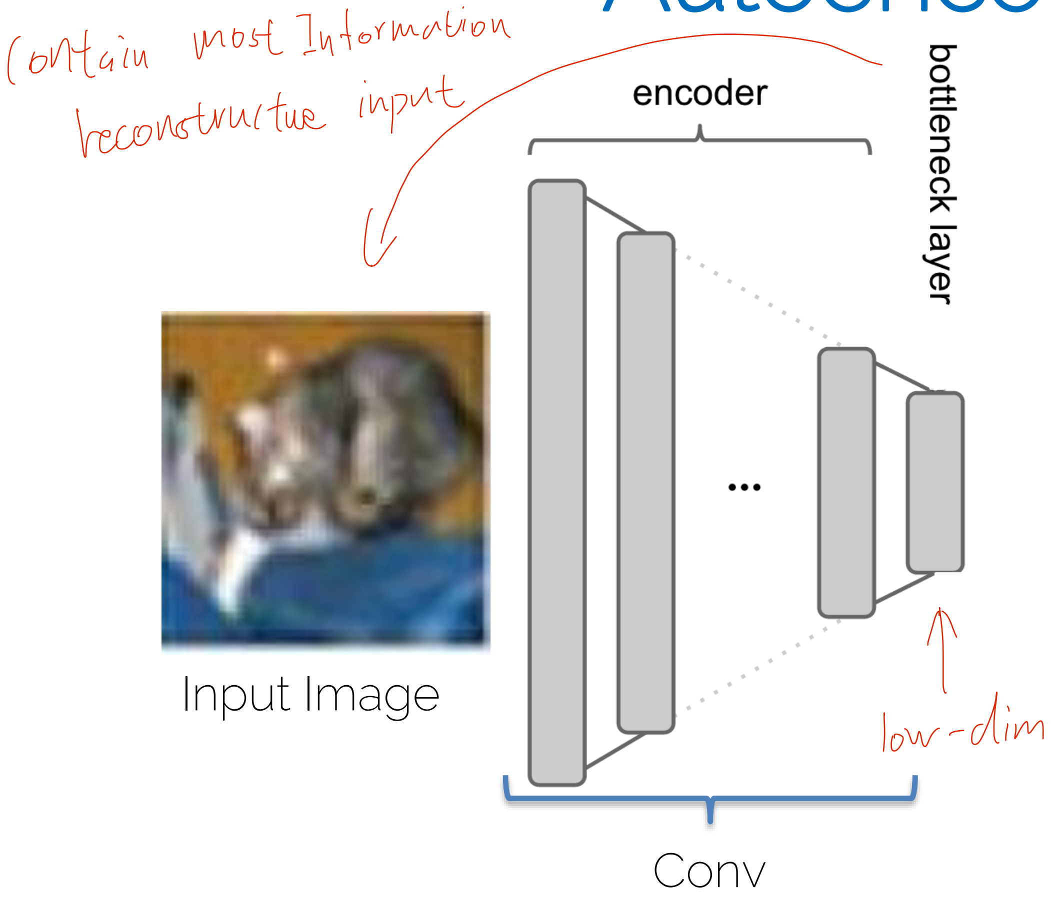
Supervised learning

Unsupervised learning with autoencoders

Autoencoders

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

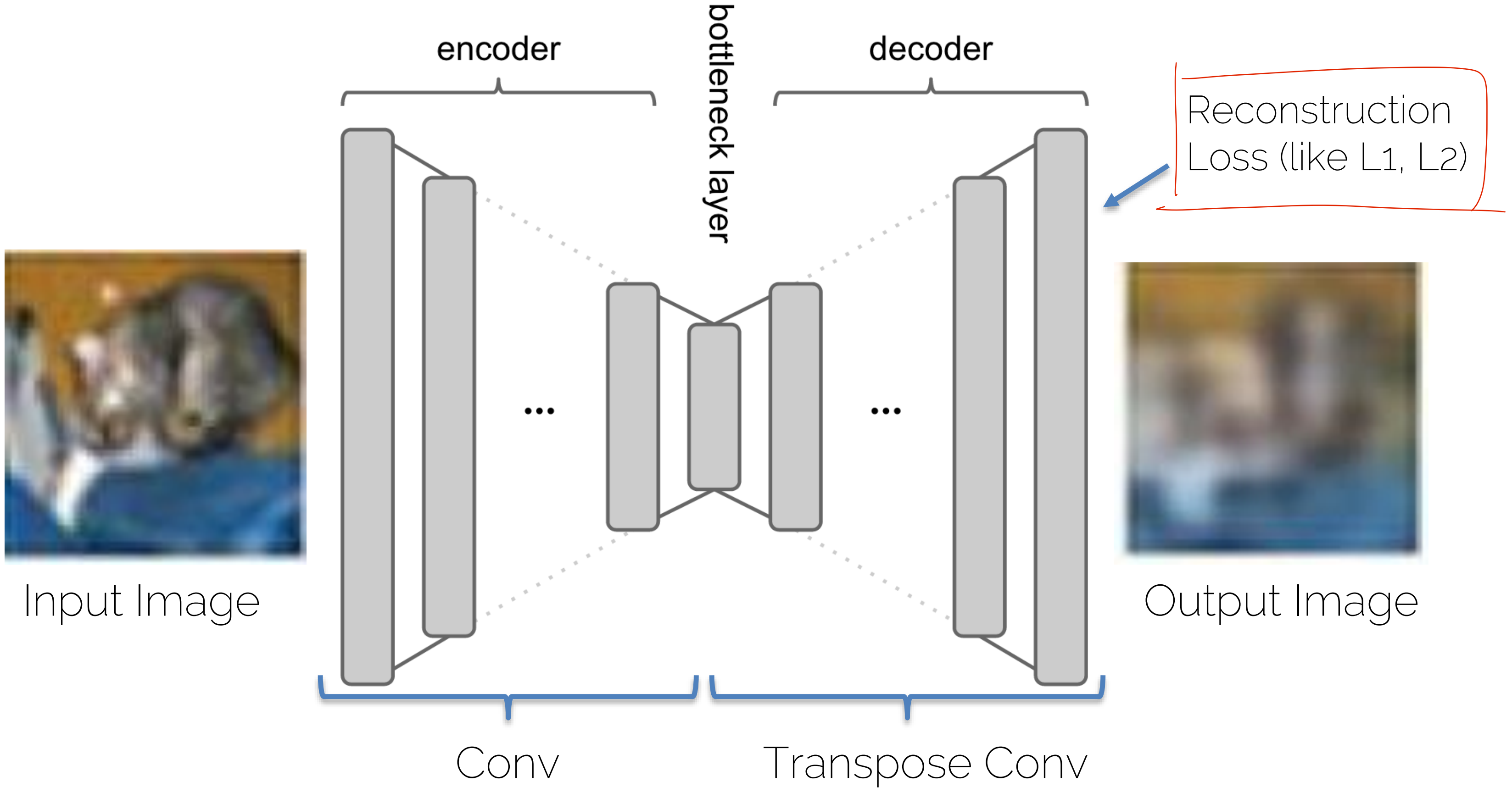
Autoencoders



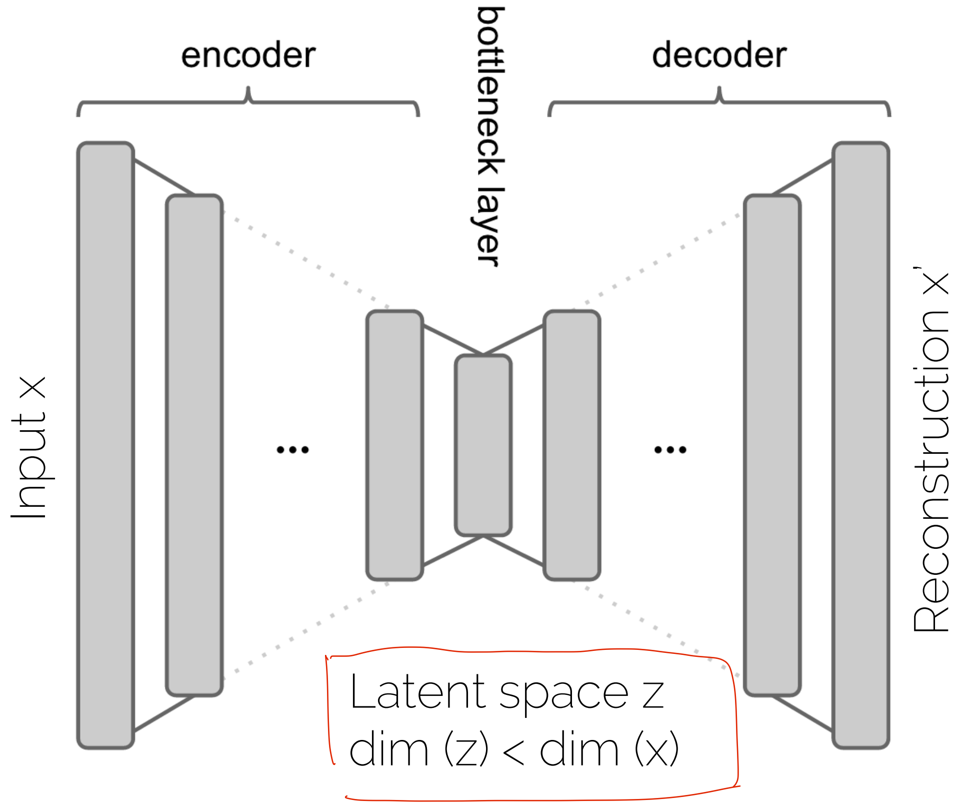
- From an input image to a feature representation (bottleneck layer)

- Encoder: a CNN in our case

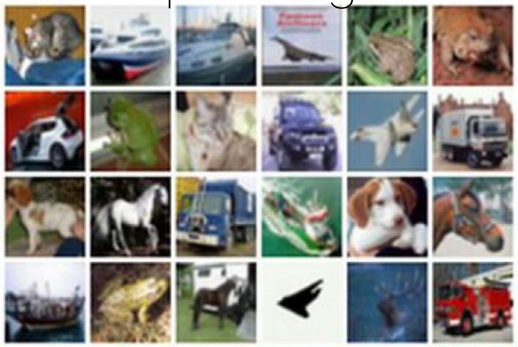
Autoencoder: training



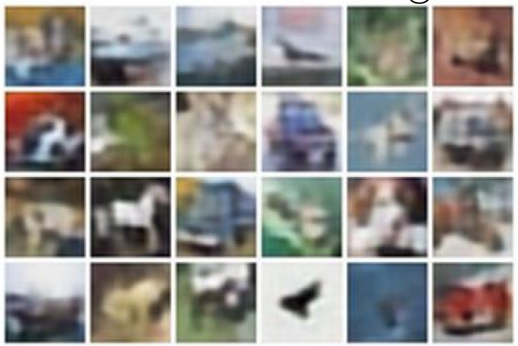
Autoencoder: training



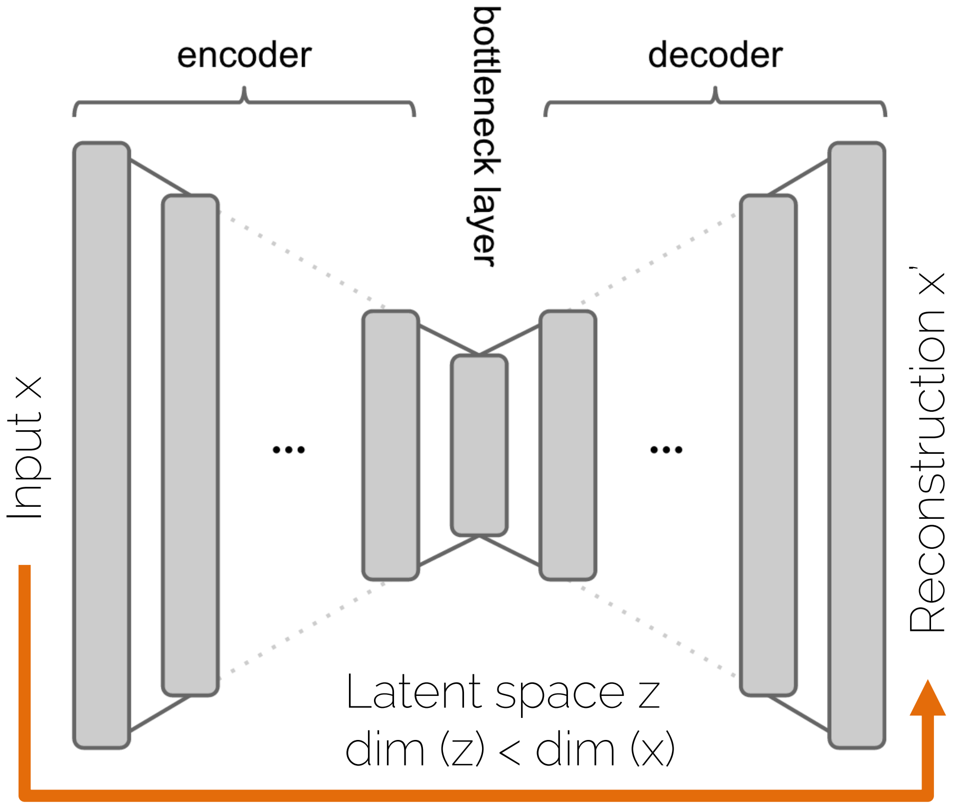
Input images



Reconstructed images



Autoencoder: training

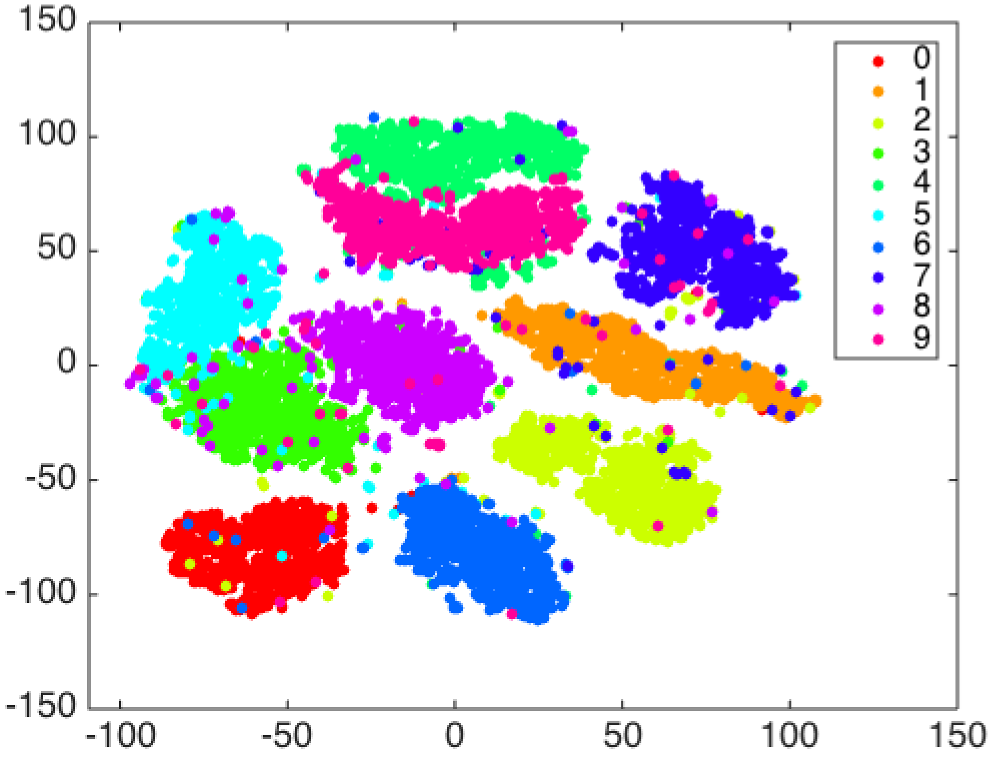


- No labels required

- We can use unlabeled data to first get its structure

Autoencoder: Use Cases

Embedding of
MNIST numbers



Autoencoder for pre-training

not so much label

- Test case: medical applications based on CT images
  - Large set of *unlabeled* data.
  - Small set of *labeled* data.

- We cannot do: take a network pre-trained on ImageNet. Why?

mismatch different data distrib

- The image features are different CT vs natural images

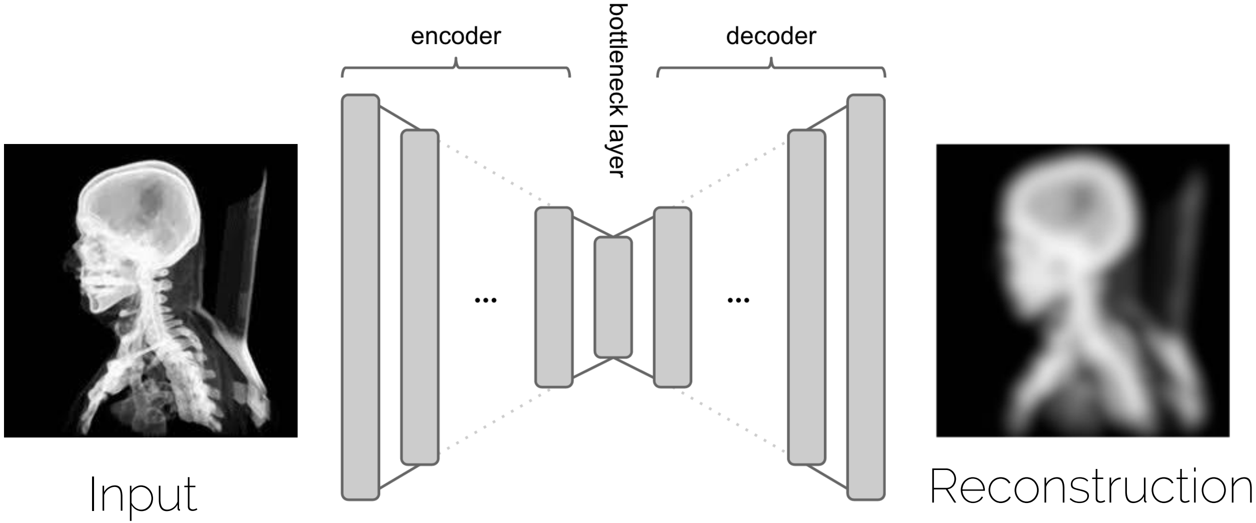
Autoencoder for pre-training

- Test case: medical applications based on CT images
  - Large set of *unlabeled* data.
  - Small set of *labeled* data.

- We can do: pre-train our network using an autoencoder to "learn" the type of features present in CT images

Autoencoder for pre-training

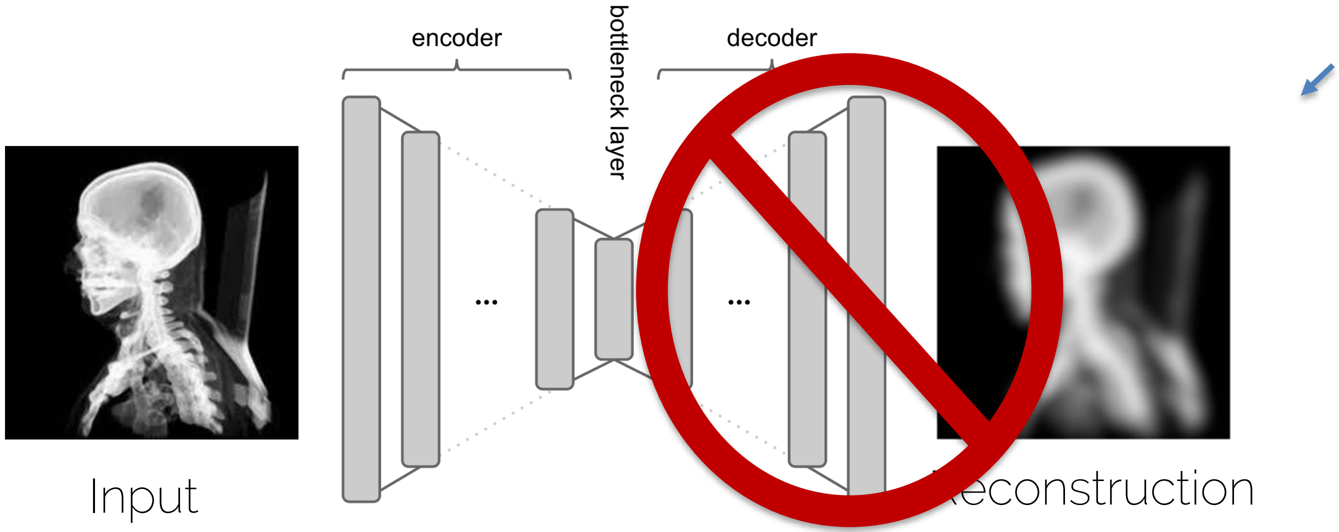
- Step 1: Unsupersived training with autoencoders



2x network size → 2x GPU
decoder don't use in test
⇒ waste

Autoencoder for pre-training

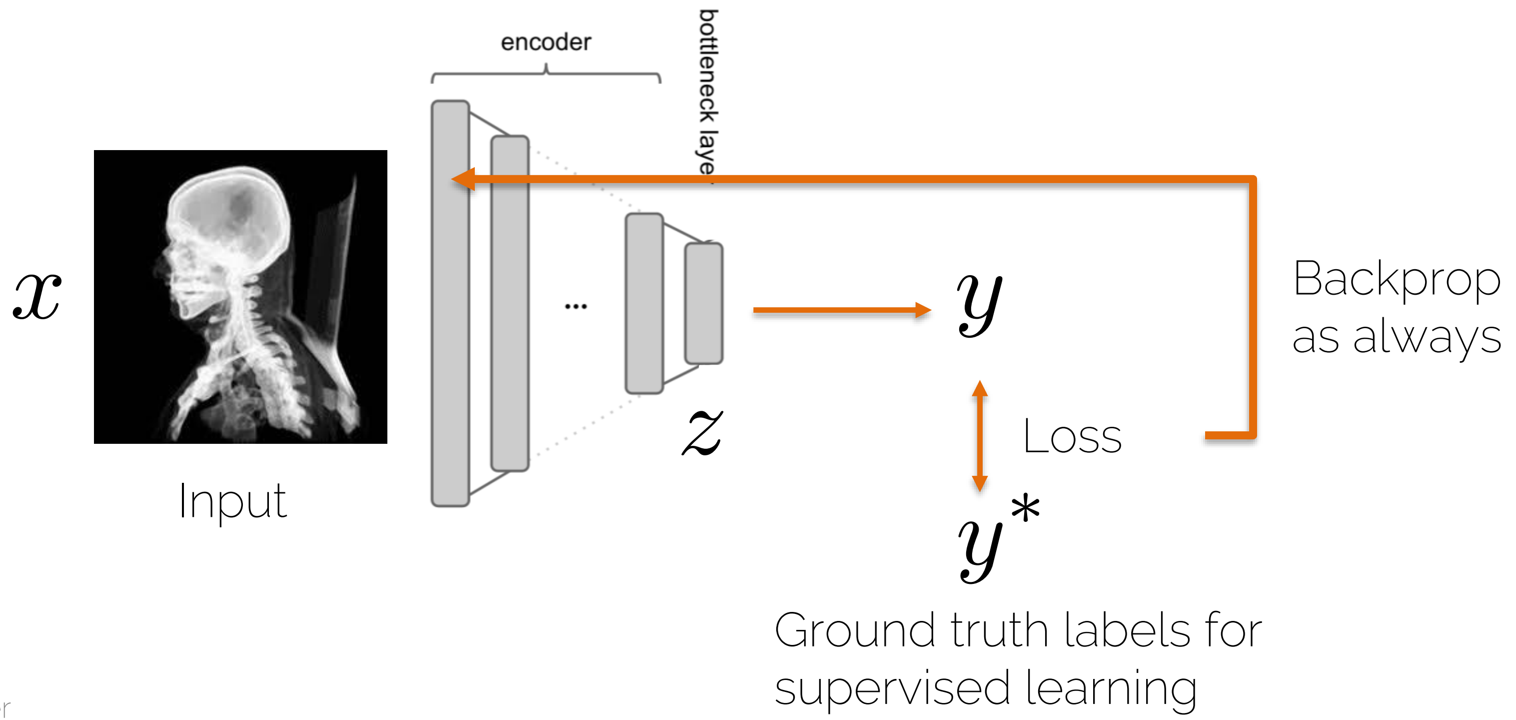
- Step 2: *Supervised* training with the labeled data



Throw away the decoder

Autoencoder for pre-training

- Step 2: *Supervised* training with the labeled data



Why using autoencoders?

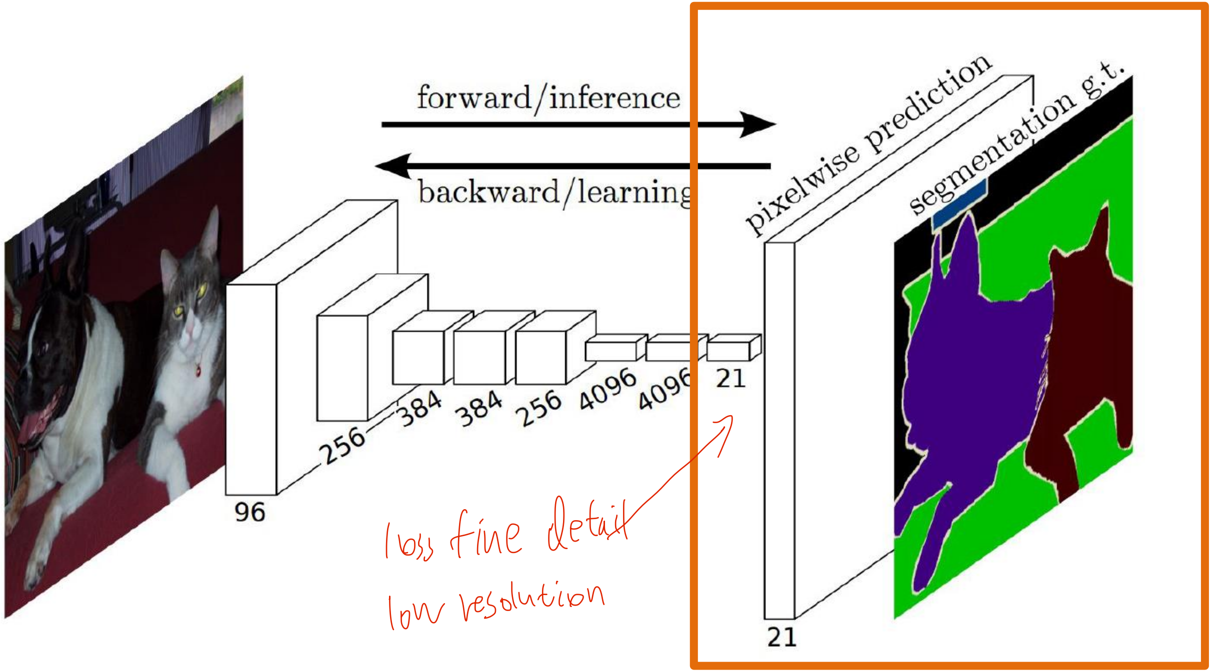
- Use 1: pre-training, as mentioned before
  - Image → same image reconstructed
  - Use the encoder as "feature extractor"

- Use 2: Use them to get pixel-wise predictions
  - Image → semantic segmentation
  - Low-resolution image → High-resolution image
  - Image → Depth map

Autoencoders for pixel-wise predictions

Semantic Segmentation (FCN)

- Recall the Fully Convolutional Networks

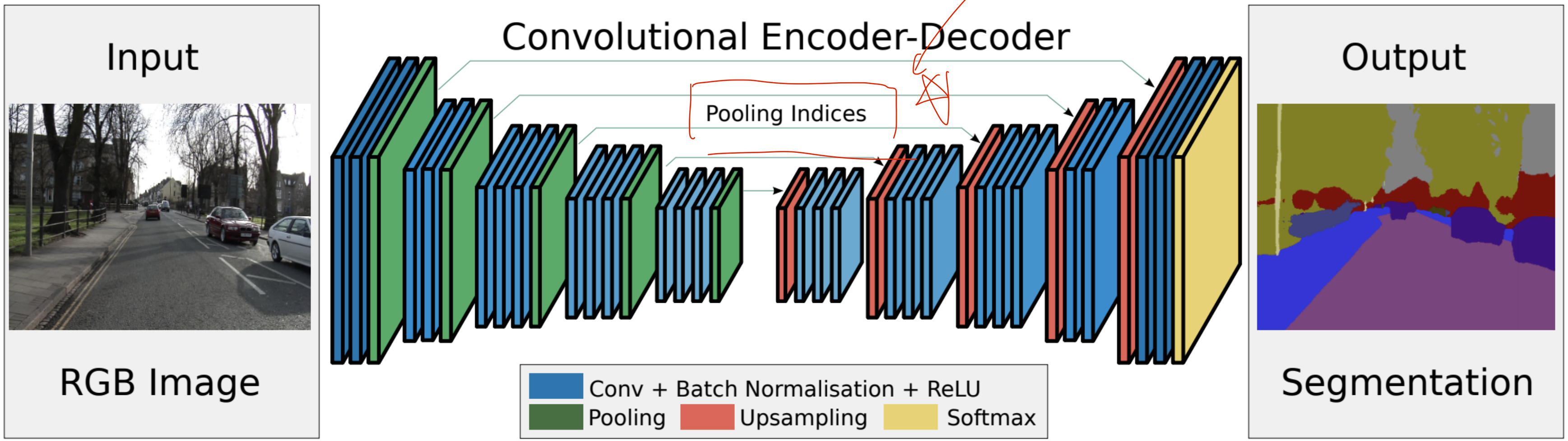


Can we do better?

[Long et al. 15] Fully Convolutional Networks for Semantic Segmentation (FCN)

SegNet

skipping connection

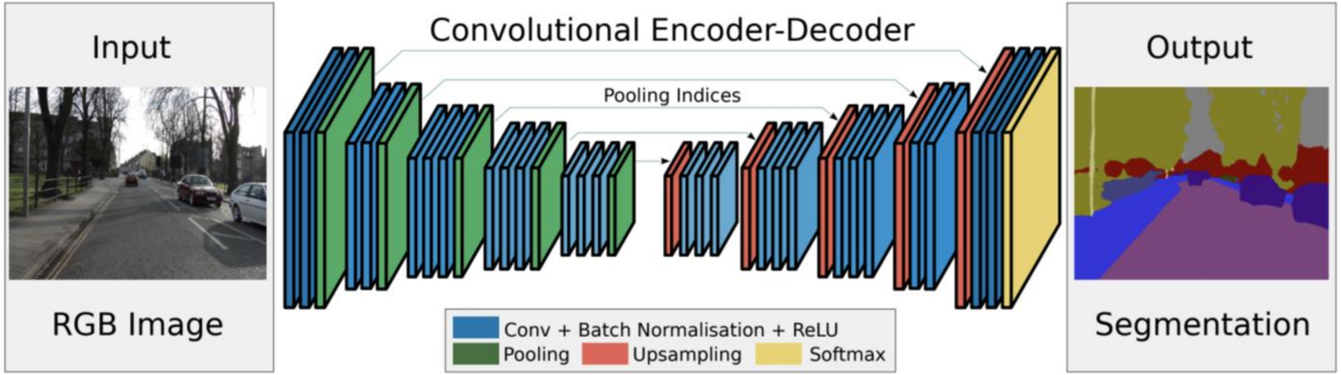


Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation". TPAMI 2016

SegNet

- **Encoder**: normal convolutional filters + pooling

- **Decoder**: Upsampling + convolutional filters



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SegNet

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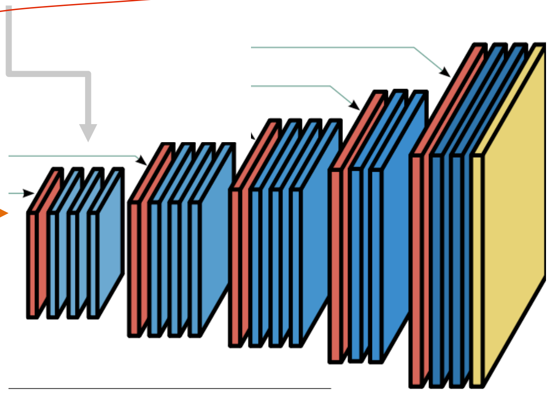


Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation". TPAMI 2016

SegNet

- **Encoder**: normal convolutional filters + pooling

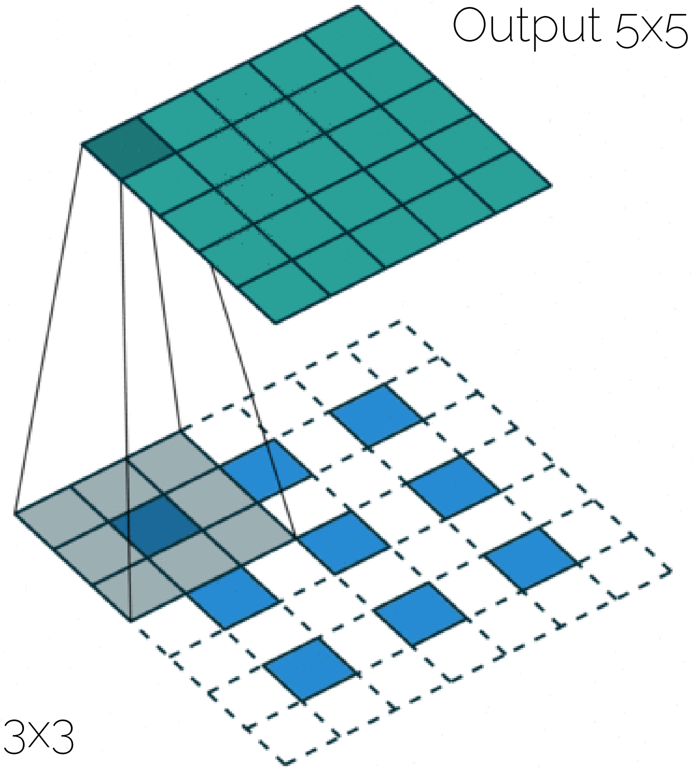
- **Decoder**: Upsampling + convolutional filters

- The convolutional filters in the decoder are learned using backprop and their goal is to refine the upsampling

Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation“. TPAMI 2016

Recall transposed convolution

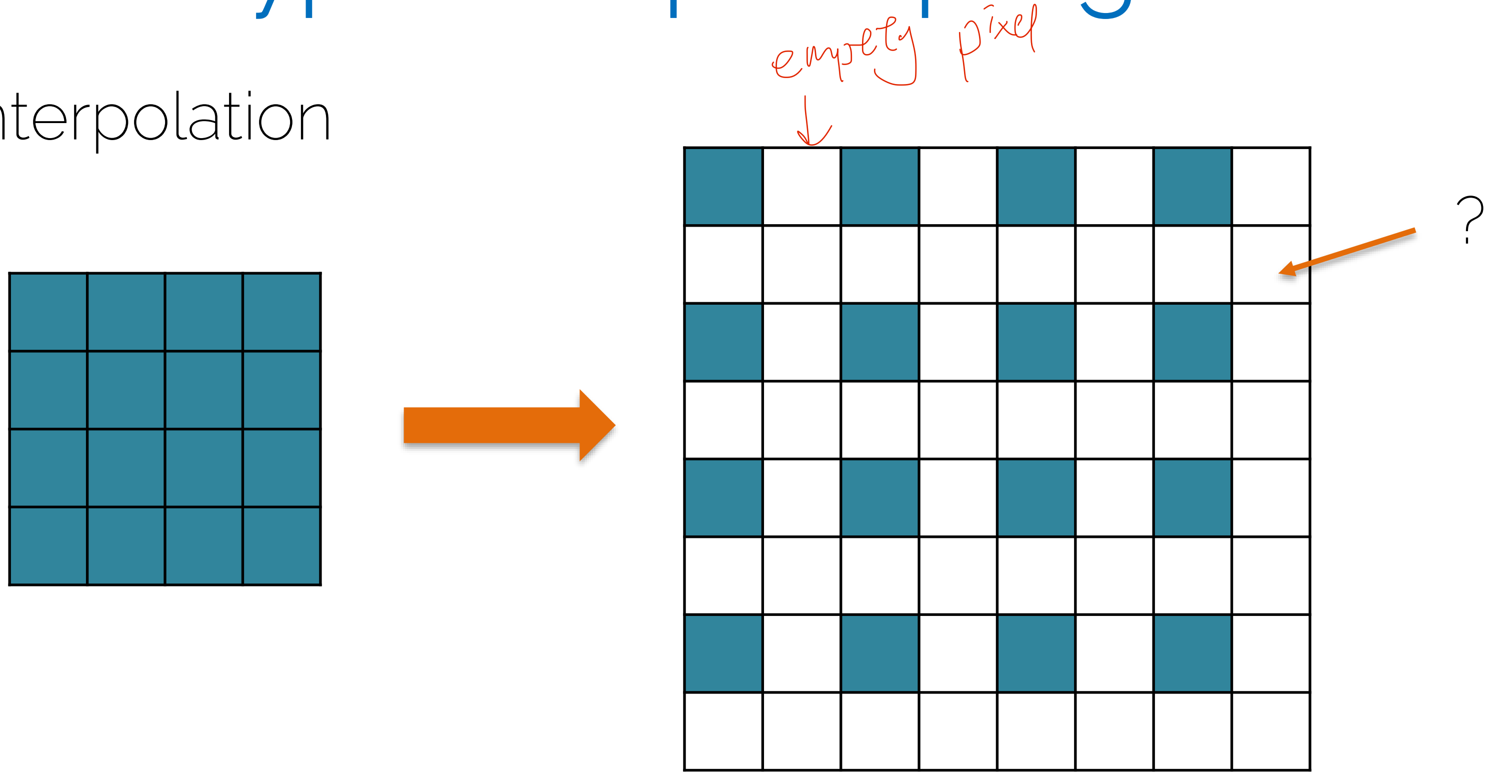
- Transposed convolution
  - Unpooling
  - Convolution filter (learned)
  - Also called up-convolution



Upsampling

Types of upsamplings

- 1. Interpolation



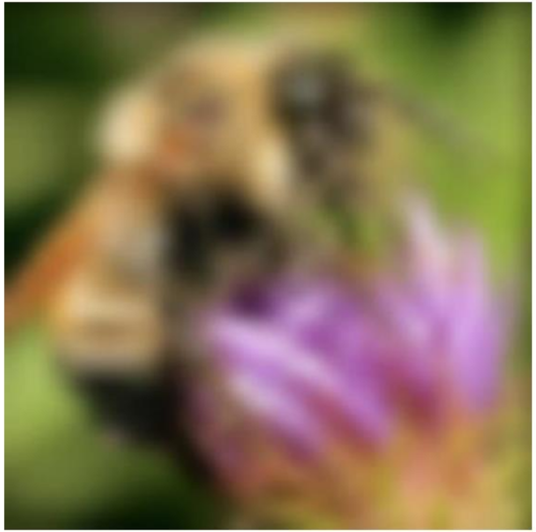
Types of upsamplings

- 1. Interpolation

Original image  x 10

Nearest neighbor interpolation

Bilinear interpolation



Bicubic interpolation

Image: Michael Guerzhoy

Types of upsamplings

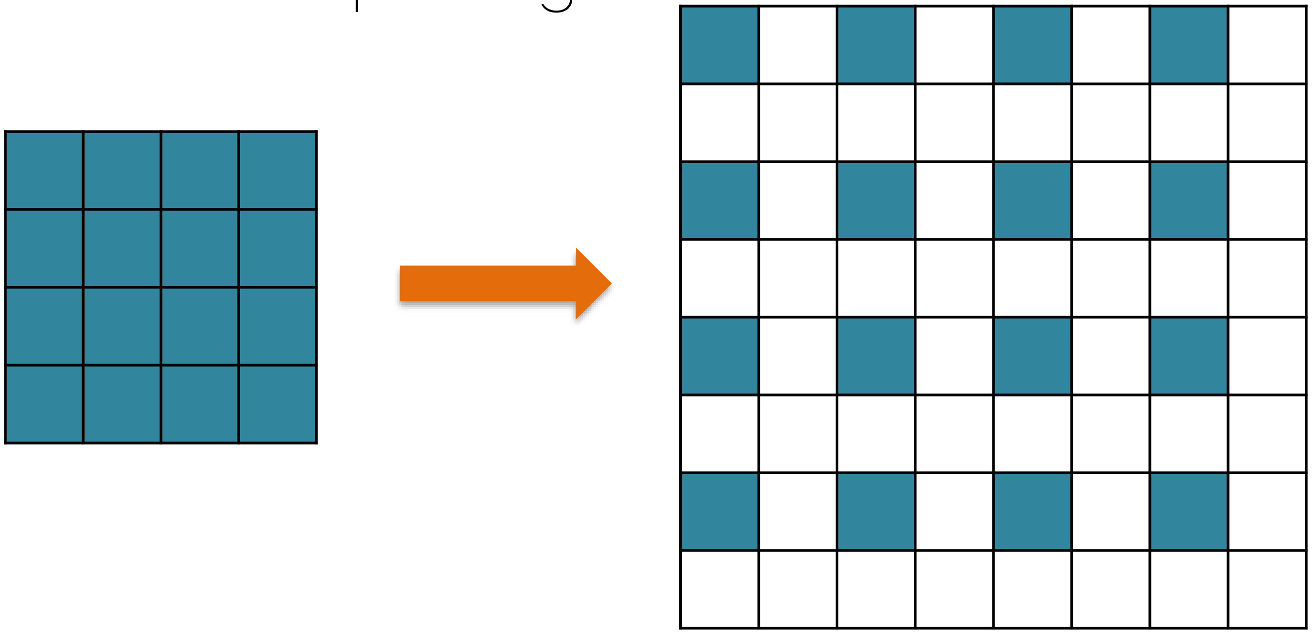
- 1. Interpolation

✓ Few artifacts

Image: Michael Guerzhoy

Types of upsamplings

- 2. Fixed unpooling



✓ efficient

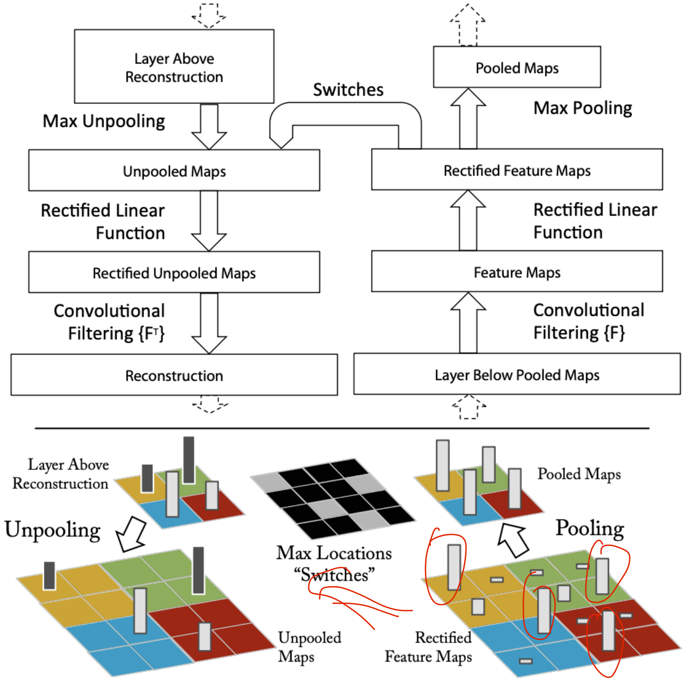
+ CONVS

A. Dosovitskiy, "Learning to Generate Chairs, Tables and Cars with Convolutional Networks". TPAMI 2017

Types of upsamplings

- 3. Unpooling: "à la DeconvNet"

Keep the locations where the max came from



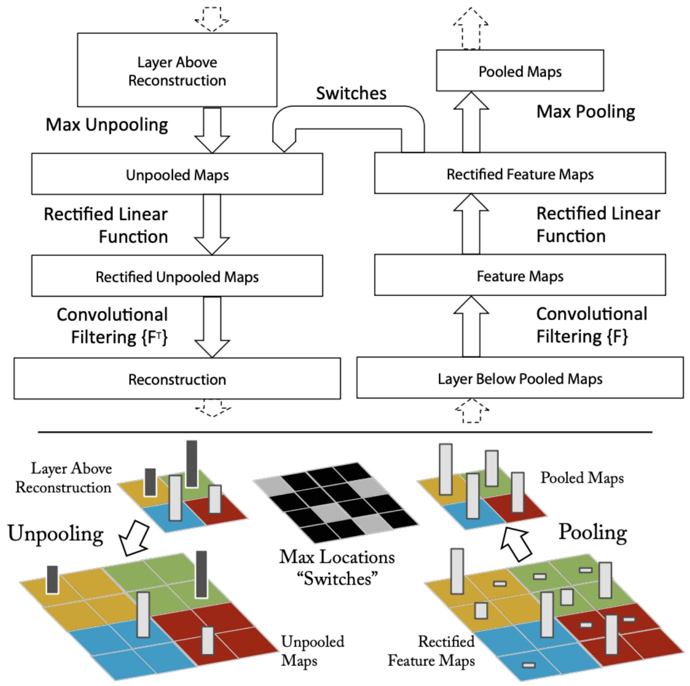
max pooling

Types of upsamplings

- 3. Unpooling: “à la DeconvNet”

Now: convolutional filters are LEARNED

In DeConvNet: we convolve with the transpose of the learned filter



Types of upsamplings

- 3. Unpooling: “à la DeconvNet”

✓ Keep the details of the structures

U-Net or skip connections in autoencoders

Skip Connections

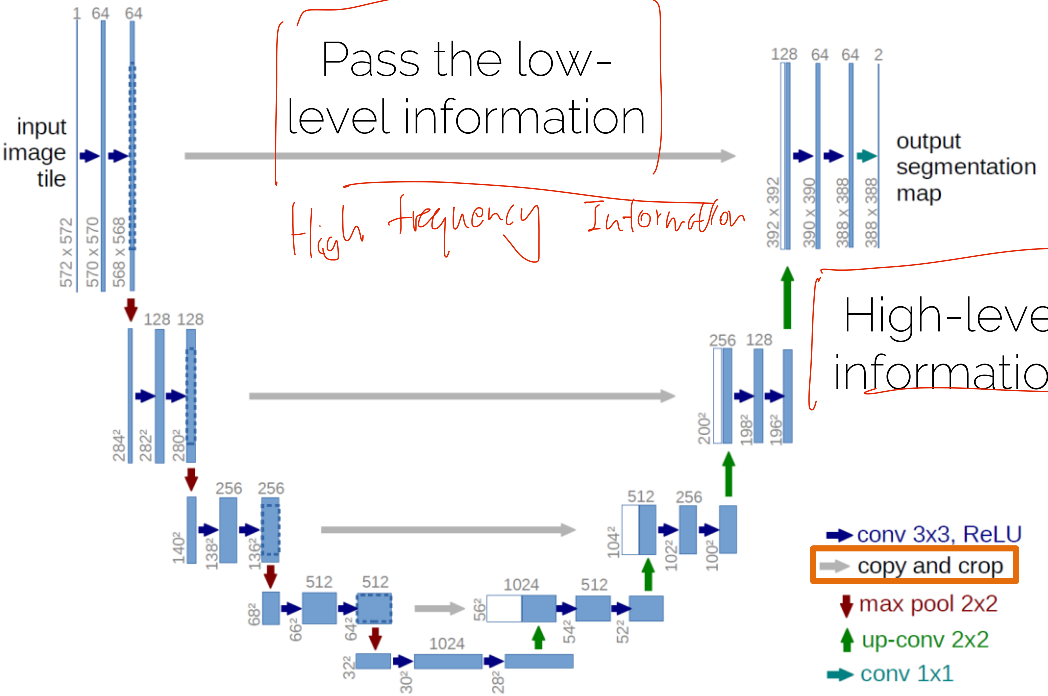
- U-Net

Pass the low-level information

High frequency Information

High-level information

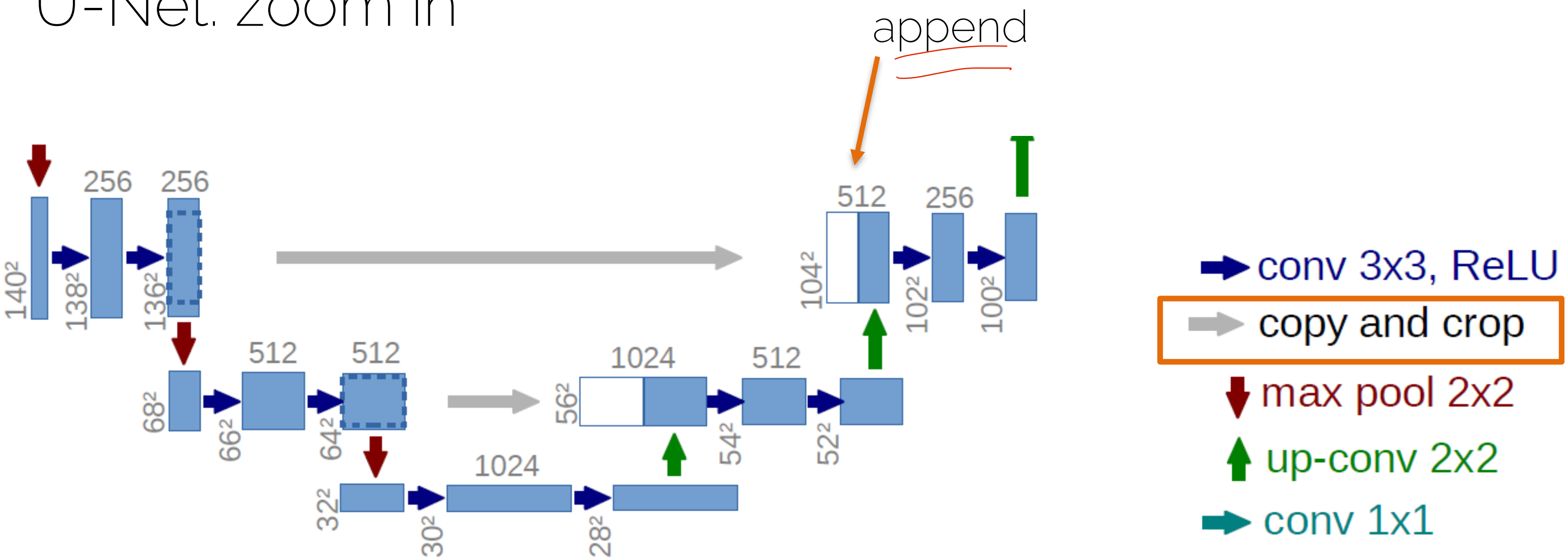
Recall ResNet



O. Ronneberger et al. "U-Net: Convolutional Networks for Biomedical Image Segmentation". MICCAI 2015

Skip Connections

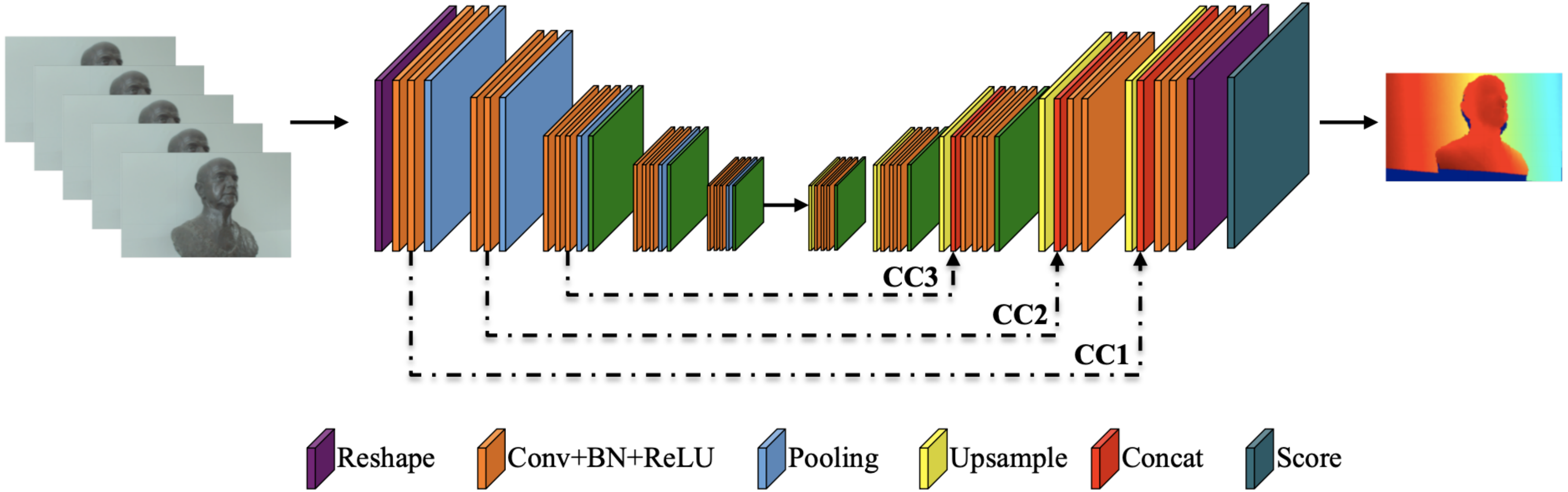
- U-Net: zoom in



O. Ronneberger et al. "U-Net: Convolutional Networks for Biomedical Image Segmentation". MICCAI 2015

Skip Connections

- Concatenation connections



C. Hazirbas et al. "Deep depth from focus". ACCV 2018

Skip Connections

- Widely used in Autoencoders

- At what levels the skip connections are needed depends on your problem

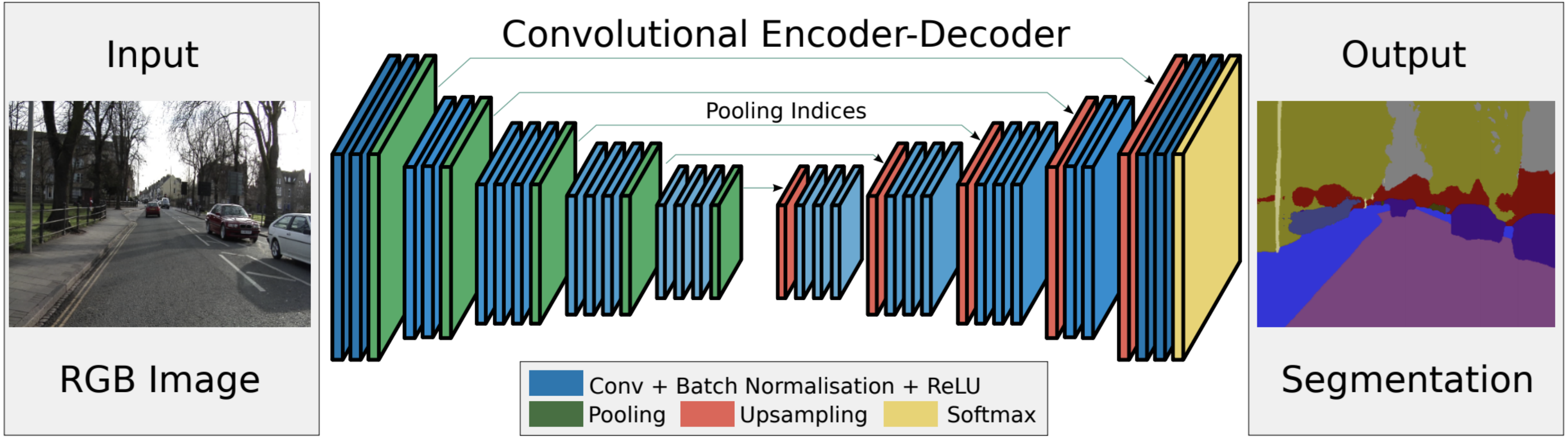
Autoencoders in Vision

Autoencoders in Vision

Examples of downstream tasks:

- Semantic segmentation
- Monocular depth estimation
- Image super resolution

SegNet



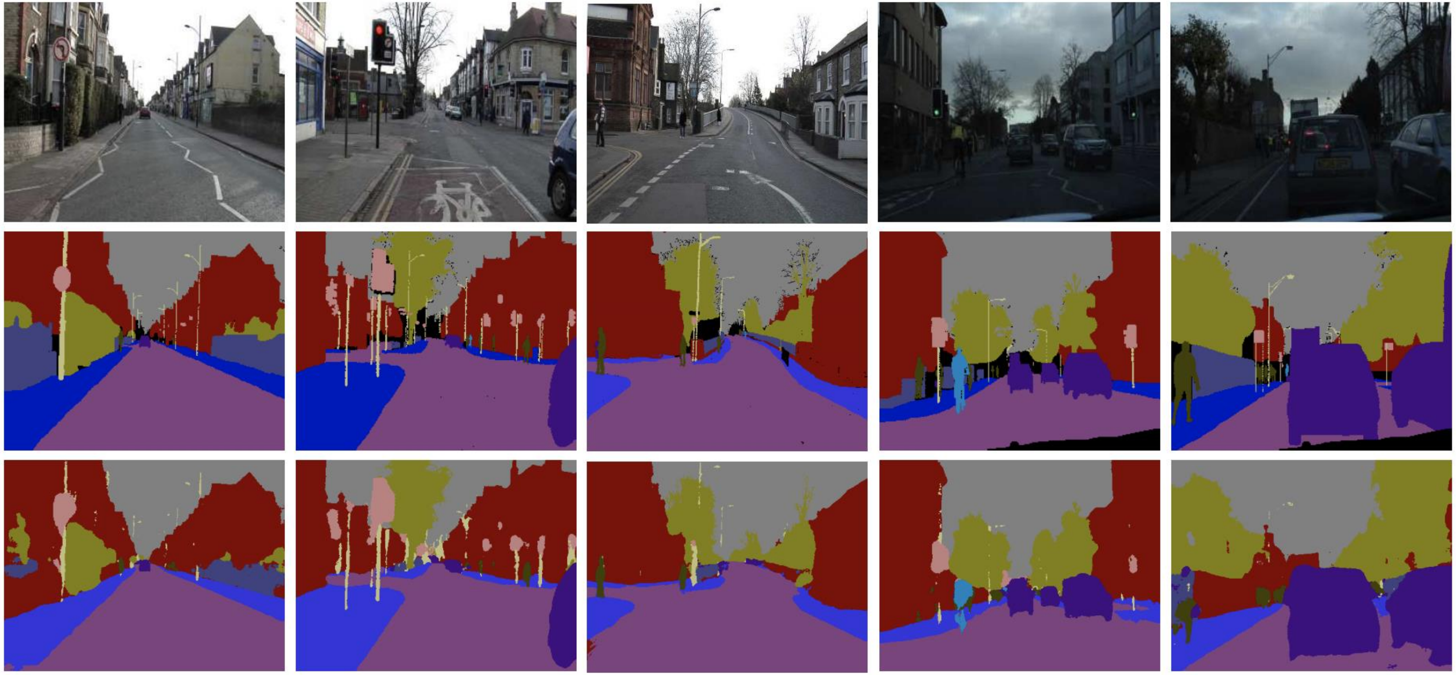
Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation". TPAMI 2016

SegNet

Input

Ground truth

SegNet

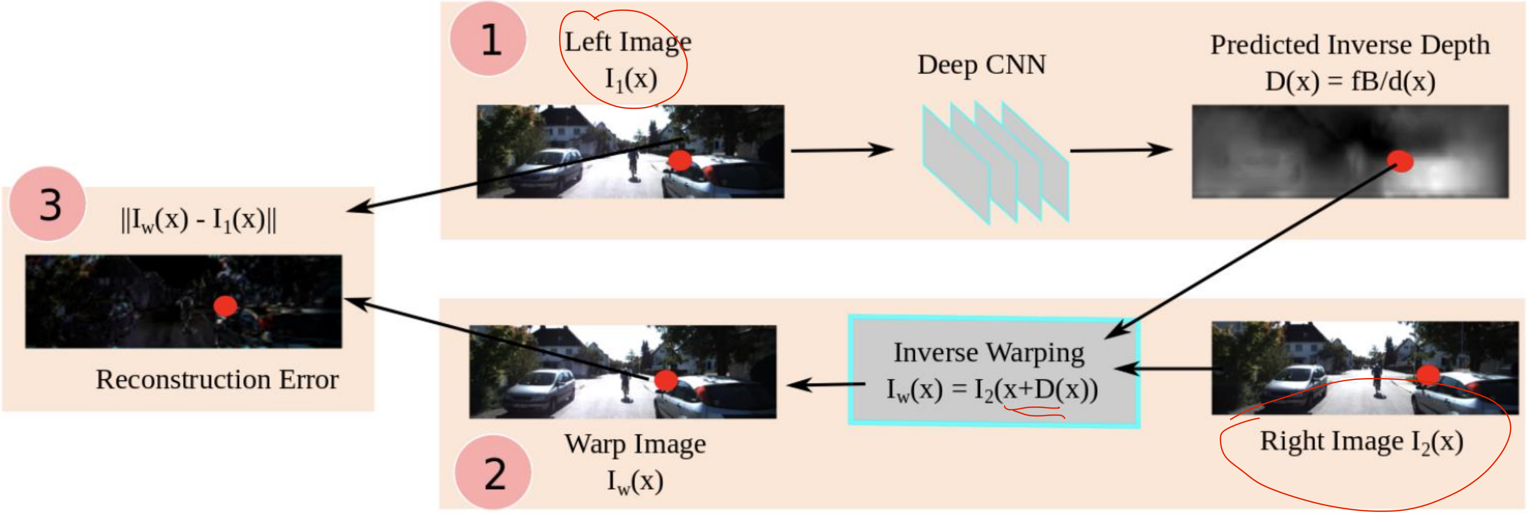


Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation“. TPAMI 2016

Monocular depth

- Unsupervised monocular depth estimation

Stero camera



R. Garg et al. „Unsupervised CNN for Single View Depth Estimation: Geometry to the Rescue" ECCV 2016

Image super resolution

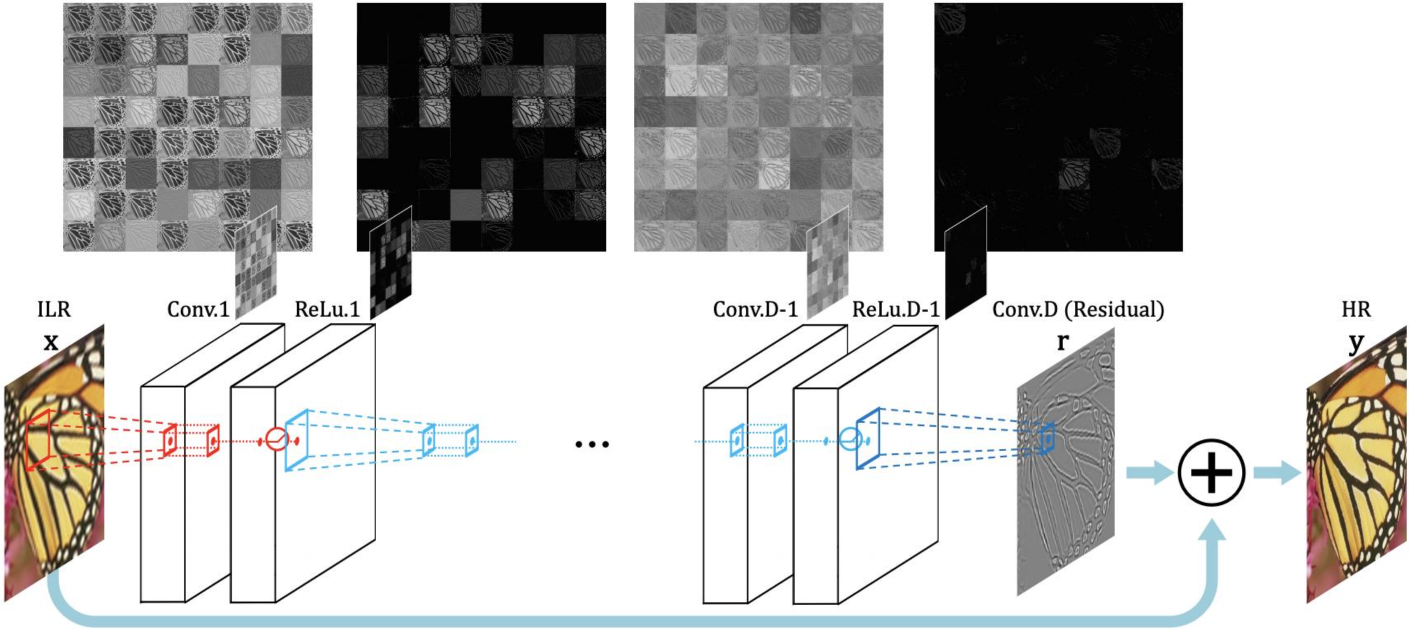
- Image in low resolution → Image in high resolution
- Problem:
  - The content of the image needs to pass through the network (skip connections [2] or other strategies [1]).

[1] C. Dong et al. „Image Super-Resolution Using Deep Convolutional Networks". TPAMI 2015

[2] XJ. Mao et al. "Image Restoration Using Very Deep Convolutional Encoder-Decoder Networks with Symmetric Skip Connections". NIPS 2016

Image super resolution

- Why not learning the residual only? → Much easier!

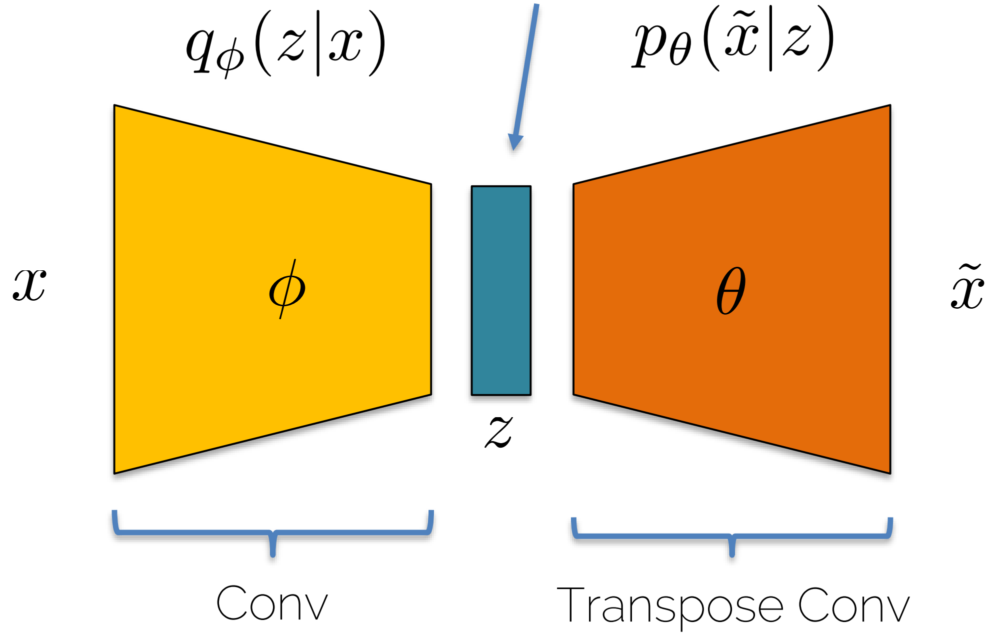


J. Kim et al. „Accurate Image Super-Resolution Using Very Deep Convolutional Networks". CVPR 2016

Variational Autoencoders

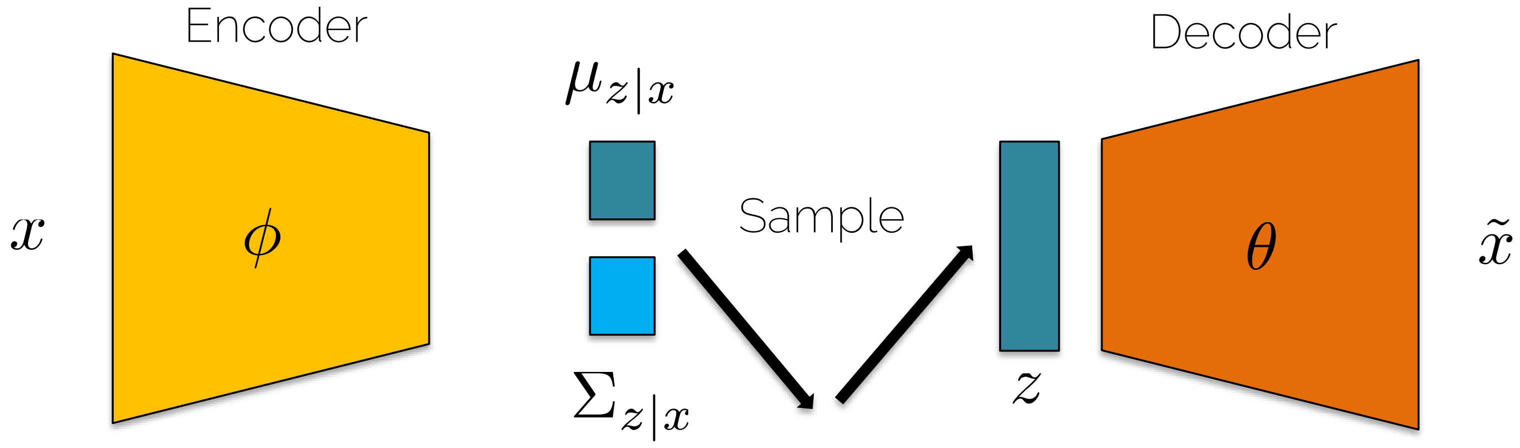
Variational Autoencoder

Goal: Sample from the latent distribution to generate new outputs!



Variational Autoencoder

- Latent space is now a distribution
- Specifically, it is a Gaussian



$$z|x \sim \mathcal{N}(\mu_{z|x}, \Sigma_{z|x})$$

Variational Autoencoder

- Latent space is now a distribution
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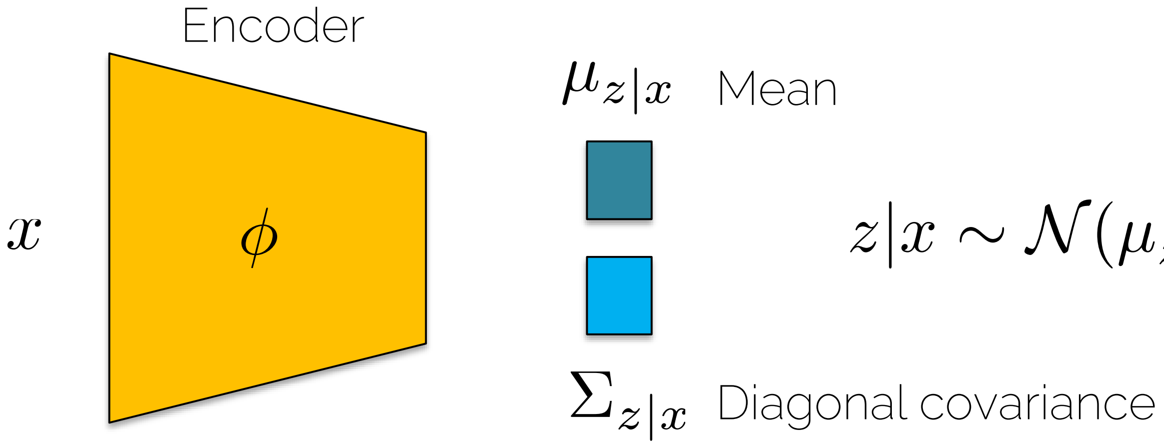
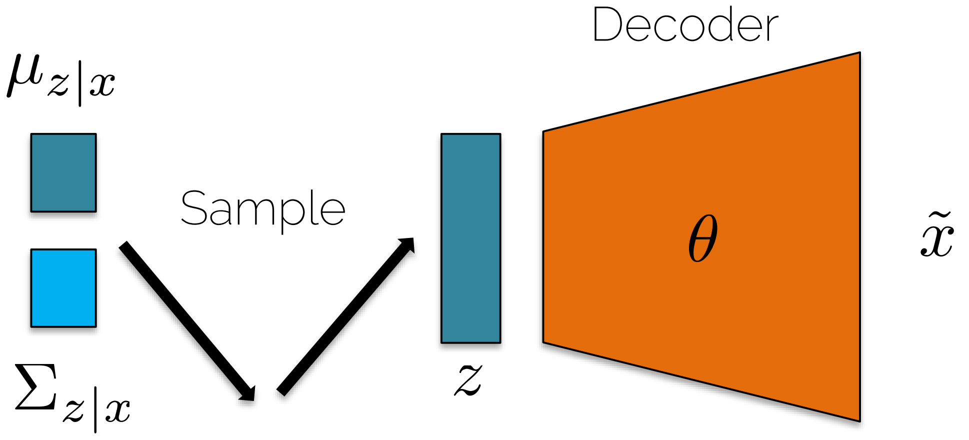


$$z|x \sim \mathcal{N}(\mu_{z|x}, \Sigma_{z|x})$$

VAE: testing

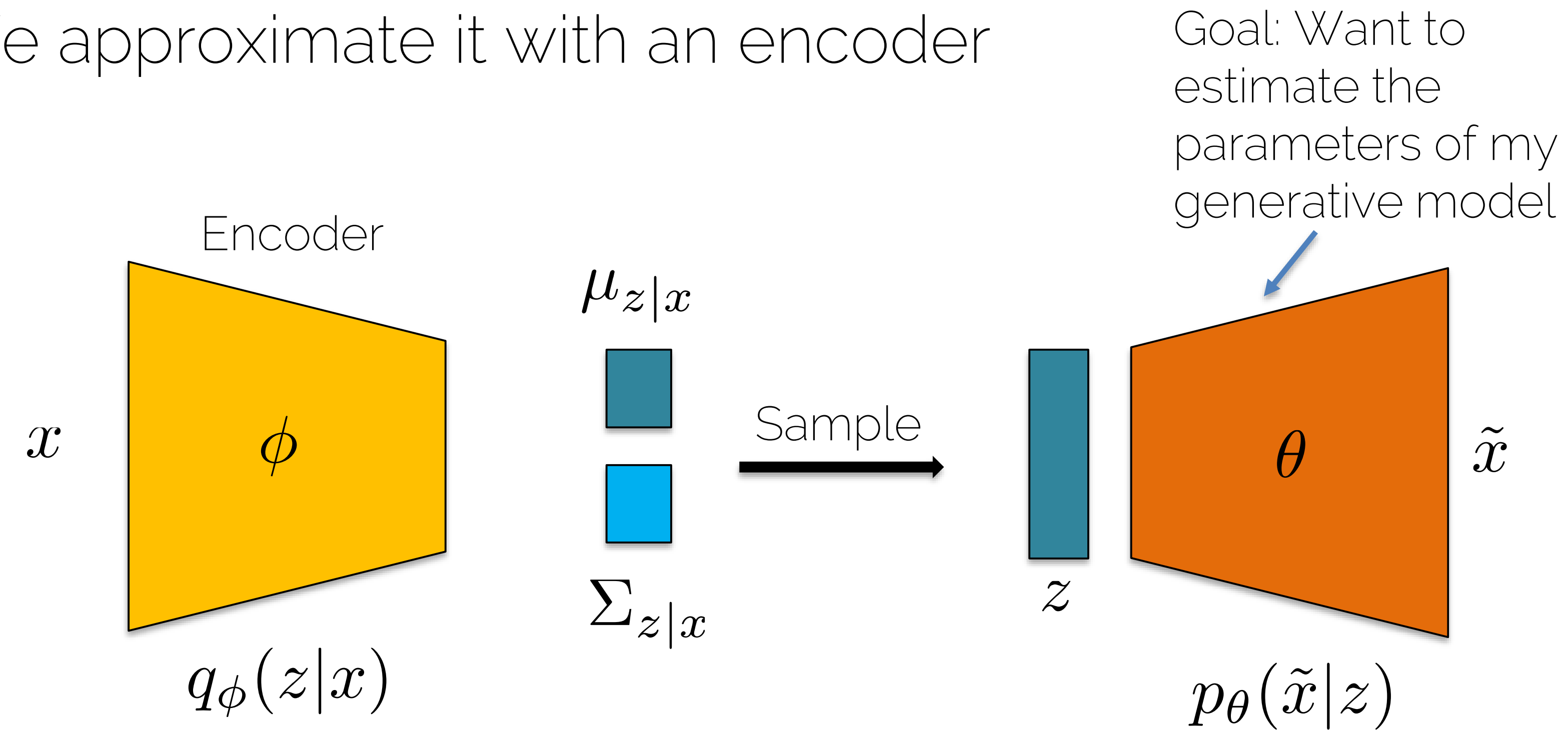
- Test: sampling from the latent space



$$z|x \sim \mathcal{N}(\mu_{z|x}, \Sigma_{z|x})$$

VAE: training

- We approximate it with an encoder



VAE: loss function

- Loss function for a data point x_i

$$\log(p_\theta(x_i)) = \boldsymbol{E}_{z \sim q_\phi(z|x_i)}[\log(p_\theta(x_i))]$$

I draw samples of the latent variable z from my encoder

decoder

VAE: loss function

- Loss function for a data point x_i

$$\log(p_\theta(x_i)) = \boldsymbol{E}_{z\sim q_\phi(z|x_i)}[\log(p_\theta(x_i))]$$

$$= \boldsymbol{E}_{z\sim q_\phi(z|x_i)}\left[\log \frac{p_\theta(x_i|z)p_\theta(z)}{p_\theta(z|x_i)}\right]$$

Bayes Rule

Inverse

Recall:

$$p_\theta(z|x) = \frac{p_\theta(x|z)p_\theta(z)}{p_\theta(x)}$$

Using the latent variable, which will become useful to simplify the expressions later according to our AE formulation

VAE: loss function

- Loss function for a data point x_i

$$
\begin{aligned}
\log(p_\theta(x_i)) &= \boldsymbol{E}_{z \sim q_\phi(z|x_i)}[\log(p_\theta(x_i))] \\
&= \boldsymbol{E}_{z \sim q_\phi(z|x_i)}\left[\log \frac{p_\theta(x_i|z)p_\theta(z)}{p_\theta(z|x_i)}\right] \\
&= \boldsymbol{E}_z\left[\log \frac{p_\theta(x_i|z)p_\theta(z)}{p_\theta(z|x_i)} \boxed{\frac{q_\phi(z|x_i)}{q_\phi(z|x_i)}}\right]
\end{aligned}
$$

Just a constant

VAE: loss function

- Loss function for a data point x_i

$$\log(p_\theta(x_i)) = \boldsymbol{E}_z\left[\log \frac{\boxed{p_\theta(x_i|z)}\boxed{p_\theta(z)}}{\boxed{p_\theta(z|x_i)}}\frac{\boxed{q_\phi(z|x_i)}}{\boxed{q_\phi(z|x_i)}}\right]$$

Encoder

$$= \underbrace{\boxed{\boldsymbol{E}_z\left[\log p_\theta(x_i|z)\right]}}_{\text{decoder}} - \boxed{\boldsymbol{E}_z\left[\log \frac{q_\phi(z|x_i)}{p_\theta(z)}\right]} + \boxed{\boldsymbol{E}_z\left[\log \frac{q_\phi(z|x_i)}{p_\theta(z|x_i)}\right]}$$

Decoder

Apply the logarithm and group as needed

VAE: loss function

- Loss function for a data point x_i

$$= \boxed{\boldsymbol{E}_z\left[\log p_\theta(x_i|z)\right]} - \boxed{\boldsymbol{E}_z\left[\log \frac{q_\phi(z|x_i)}{p_\theta(z)}\right]} + \boxed{\boldsymbol{E}_z\left[\log \frac{q_\phi(z|x_i)}{p_\theta(z|x_i)}\right]}$$

Kullback-Leibler Divergences to measure how similar two distributions are

VAE: loss function

- Loss function for a data point x_i

$$= \boxed{\boldsymbol{E}_z \left[\log p_\theta(x_i|z)\right]} - \boxed{\boldsymbol{E}_z \left[\log \frac{q_\phi(z|x_i)}{p_\theta(z)}\right]} + \boxed{\boldsymbol{E}_z \left[\log \frac{q_\phi(z|x_i)}{p_\theta(z|x_i)}\right]}$$

$$= \boxed{\boldsymbol{E}_z \left[\log p_\theta(x_i|z)\right]} - \boxed{KL(q_\phi(z|x_i)||p_\theta(z))} + \boxed{KL(q_\phi(z|x_i)||p_\theta(z|x_i))}$$

$KL \geq 0$

Kullback-Leibler Divergences

VAE: loss function

- Loss function for a data point x_i

$$= \boxed{\boldsymbol{E}_z \left[\log p_\theta(x_i|z)\right]} - \boxed{KL(q_\phi(z|x_i)||p_\theta(z))} + \boxed{KL(q_\phi(z|x_i)||p_\theta(z|x_i))}$$

Reconstruction loss (how well does my decoder reconstruct a data point given the latent vector z). We need to sample from z.

Measures how good my latent distribution is with respect to my Gaussian prior

match

I still cannot express the shape of the distribution. But I know

≥ 0

VAE: loss function

- Loss function for a data point x_i

$$\underbrace{\boxed{\boldsymbol{E}_z\left[\log p_\theta(x_i|z)\right]} - \boxed{KL(q_\phi(z|x_i)||p_\theta(z))}} + \underbrace{\boxed{KL(q_\phi(z|x_i)||p_\theta(z|x_i))}}_{\geq 0}$$

Lower bound of the loss function
= evidence lower bound (ELBO)

$$\mathcal{L}(x_i, \phi, \theta)$$

ignore

$$\log(p(x_i)) \geq \mathcal{L}(x_i, \phi, \theta)$$

VAE: loss function

- Loss function for a data point x_i

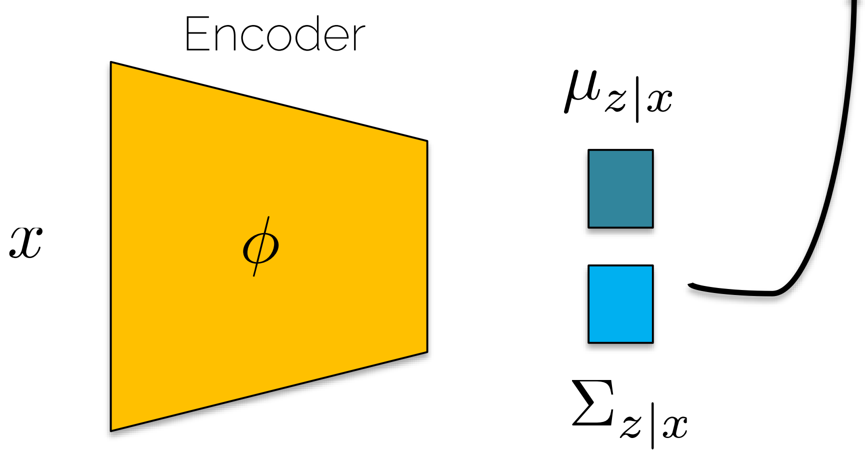
$$\underbrace{\boxed{\boldsymbol{E}_z\left[\log p_\theta(x_i|z)\right]} - \boxed{KL(q_\phi(z|x_i)||p_\theta(z))}}_{\substack{\text{Lower bound of the loss function} \\ \text{= evidence lower bound (ELBO)} \\ \mathcal{L}(x_i,\phi,\theta)}} + \underbrace{\boxed{KL(q_\phi(z|x_i)||p_\theta(z|x_i))}}_{\geq 0}$$

- Optimize $\phi^*, \theta^* = \arg\max \sum_{i=1}^{N} \mathcal{L}(x_i, \phi, \theta)$

Variational Autoencoder

- Training

$$\boxed{\boldsymbol{E}_z\left[\log p_\theta(x_i|z)\right]} - \boxed{KL(q_\phi(z|x_i)||p_\theta(z))} + \boxed{KL(q_\phi(z|x_i)||p_\theta(z|x_i))}$$

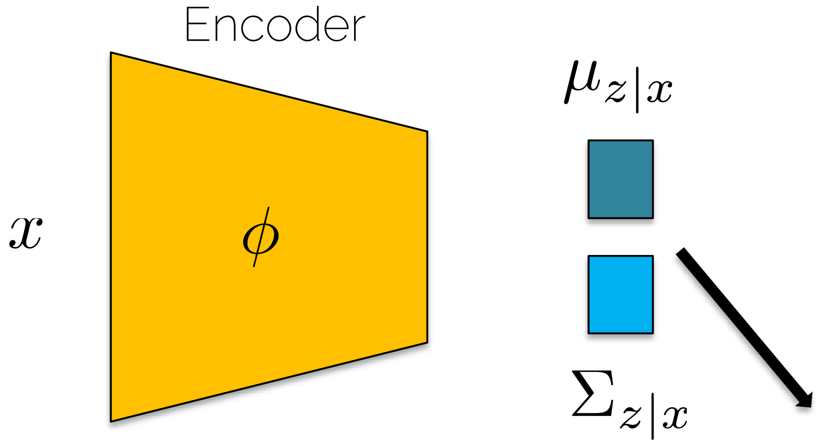


Make posterior distribution close to prior (close to unit Gaussian distribution)

Variational Autoencoder

- Training

$$\boxed{\boldsymbol{E}_z\left[\log p_\theta(x_i|z)\right]} - \boxed{KL(q_\phi(z|x_i)||p_\theta(z))} + \boxed{KL(q_\phi(z|x_i)||p_\theta(z|x_i))}$$

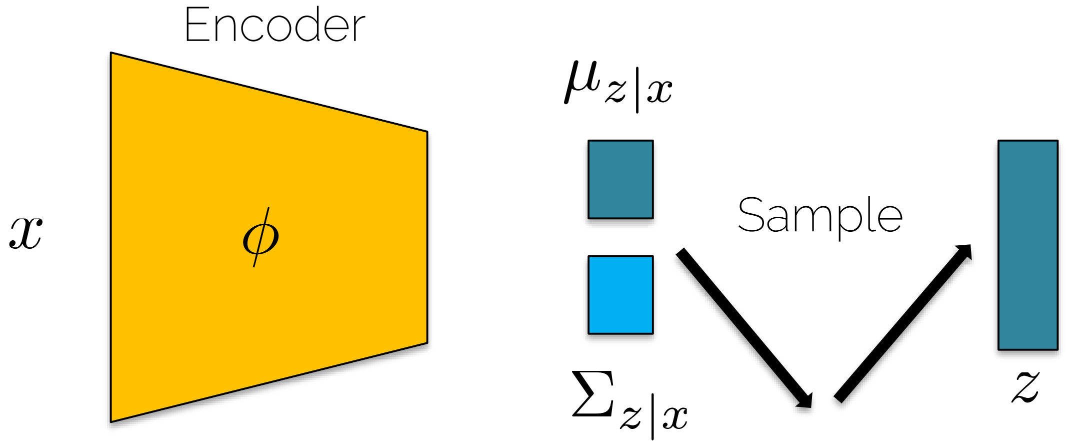


$$z|x \sim \mathcal{N}(\mu_{z|x}, \Sigma_{z|x})$$

Variational Autoencoder

- Training

$$\boxed{\boldsymbol{E}_z\left[\log p_\theta(x_i|z)\right]} - \boxed{KL(q_\phi(z|x_i)||p_\theta(z))} + \boxed{KL(q_\phi(z|x_i)||p_\theta(z|x_i))}$$



$$z|x \sim \mathcal{N}(\mu_{z|x}, \Sigma_{z|x})$$

! Monte Carlo based gradient estimation for $\boldsymbol{\phi}$ causes high variance.

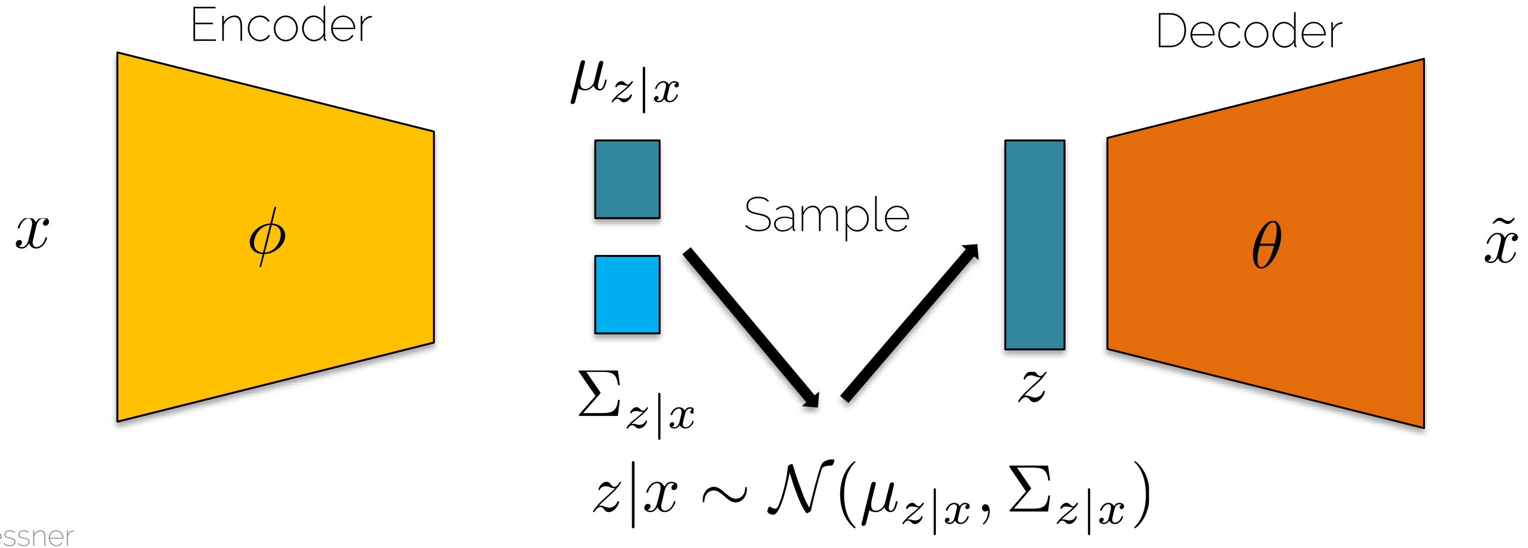
→ Reparameterization is needed to obtain low-variance gradients.

[Kingman and Welling 2014]
Auto-Encoding Variational Bayes

Variational Autoencoder

- Training

$$\boxed{\boldsymbol{E}_z\left[\log p_\theta(x_i|z)\right]} - \boxed{KL(q_\phi(z|x_i)||p_\theta(z))} + \boxed{KL(q_\phi(z|x_i)||p_\theta(z|x_i))}$$

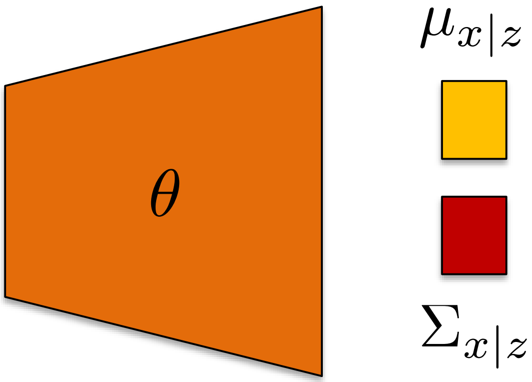


Variational Autoencoder

- Training

$$\boxed{\boldsymbol{E}_z\left[\log p_\theta(x_i|z)\right]} - \boxed{KL(q_\phi(z|x_i)||p_\theta(z))} + \boxed{KL(q_\phi(z|x_i)||p_\theta(z|x_i))}$$

Decoder



$$x|z \sim \mathcal{N}(\mu_{x|z}, \Sigma_{x|z}) \xrightarrow{\text{Sample}} \tilde{x}$$

Output is also parameterized

Variational Autoencoder

- Training

$$\boxed{\boldsymbol{E}_z\left[\log p_\theta(x_i|z)\right]} - \boxed{KL(q_\phi(z|x_i)||p_\theta(z))} + \boxed{KL(q_\phi(z|x_i)||p_\theta(z|x_i))}$$

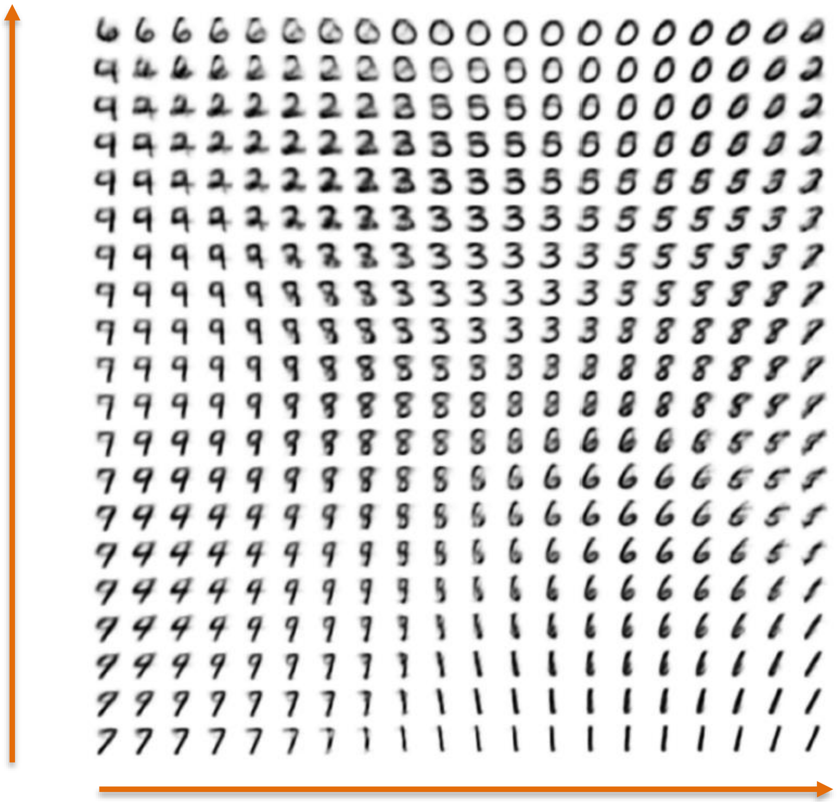
$\tilde{x}$

Maximize the likelihood of
reconstructing the input

Variational Autoencoder

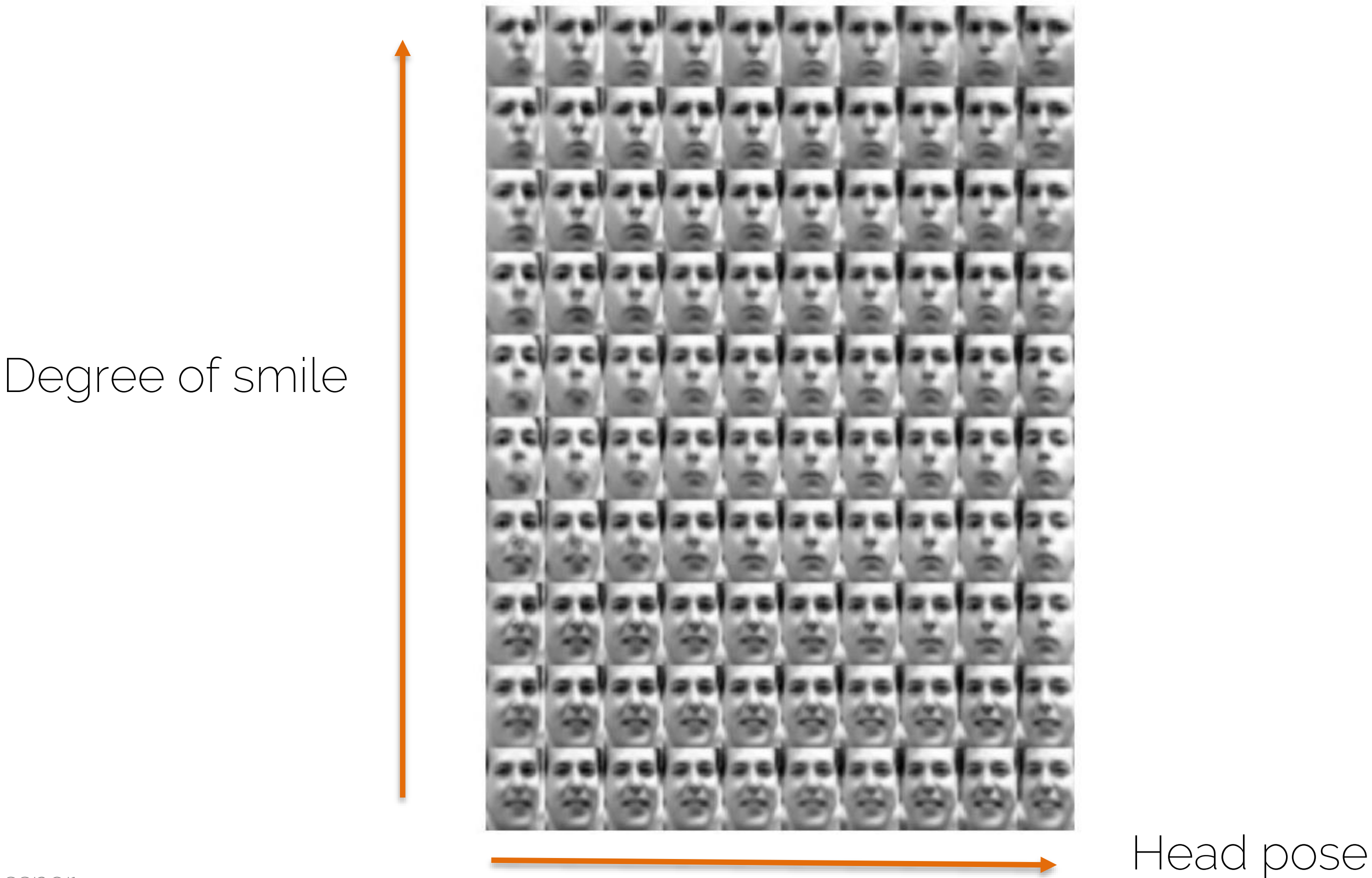
- Kingman and Welling. "Auto-Encoding Variational Bayes". ICLR 2014
  - Mathematical derivation
  - Reparameterization trick (expressing variables as Gaussians) that allows us to perform backpropagation

Generating data



Each element of z encodes a different feature

Generating data



Autoencoder vs VAE

Autoencoder

Variational Autoencoder

Ground Truth

https://github.com/kvfrans/variational-autoencoder

Autoencoder Overview

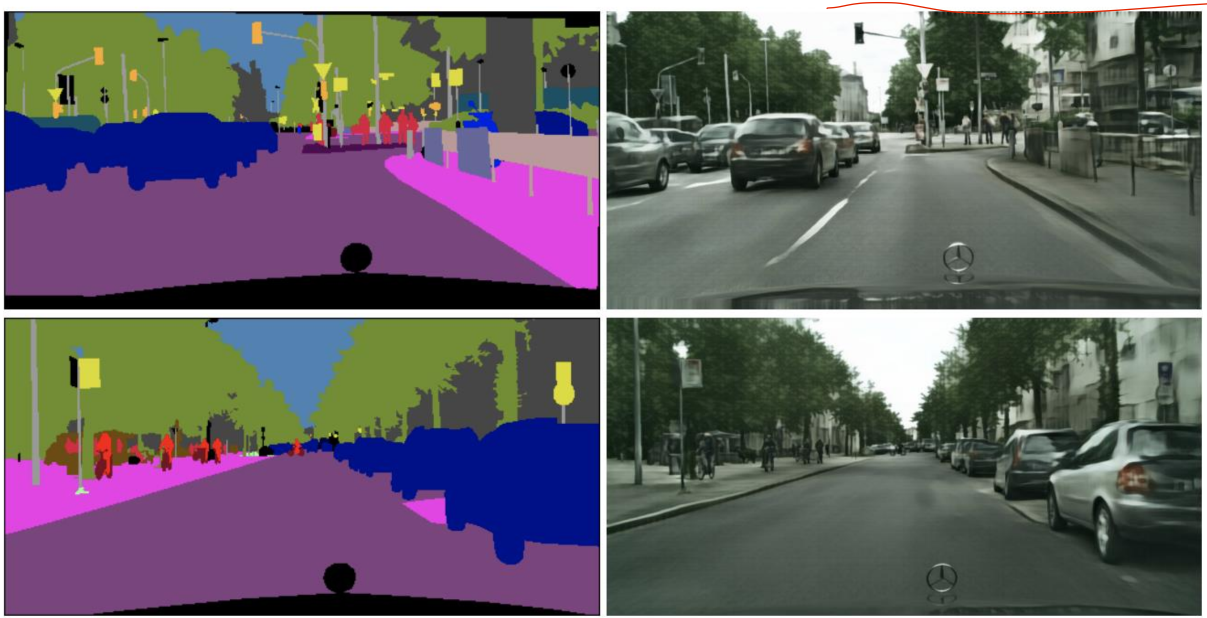
- Autoencoders (AE)
  - Reconstruct input
  - Unsupervised learning
  - Latent space features are useful

- Variational Autoencoders (VAE)
  - Probability distribution in latent space (e.g., Gaussian)
  - Interpretable latent space (head pose, smile)
  - Sample from model to generate output

Image synthesis (without GANs?)

Image synthesis

- Semantic segmentation image → Real image



(a) Input semantic layouts (b) Synthesized images

Q. Chen and V. Koltun „Photographic Image Synthesis with Cascaded Refinement Networks“. ICCV 2017

Image synthesis

- Semantic segmentation image → Real image
- No GANs?

Q. Chen and V. Koltun „Photographic Image Synthesis with Cascaded Refinement Networks". ICCV 2017

Image synthesis

- Several works show that one can use a *perceptual loss* to achieve high quality results
- Cannot use the L2 loss as this could penalize realistic results (black car vs white car)
- Perceptual loss measures the „content of the image"

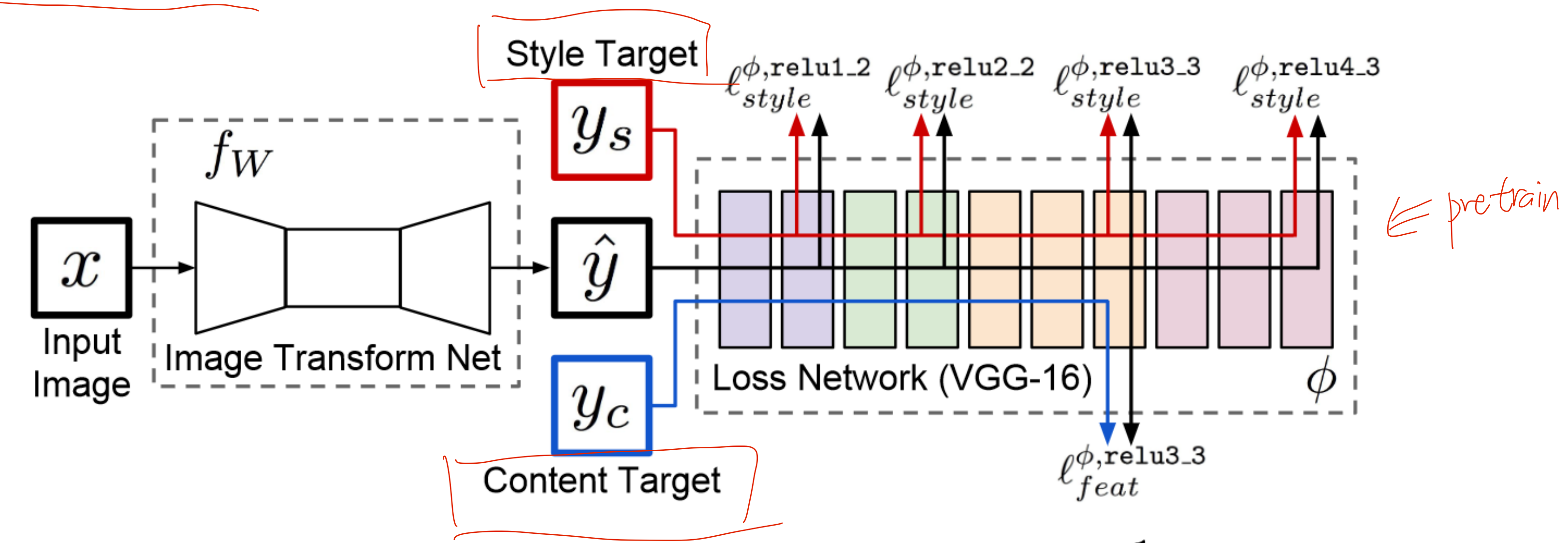
A. Dosovitskiy and T. Brox. „Generating Images with Perceptual Similarity Metrics based on Deep Networks". NIPS 2016

Q. Chen and V. Koltun „Photographic Image Synthesis with Cascaded Refinement Networks". ICCV 2017

Perceptual loss and style transfer

Content loss

- Content loss (or perceptual loss or feature reconstruction loss).



- Use a network to compute the loss: $\ell_{feat}^{\phi,j}(\hat{y}, y) = \frac{1}{C_j H_j W_j} \|\phi_j(\hat{y}) - \phi_j(y)\|_2^2$

Gatys et al „A neural algorithm of artistic style". arXiv preprint arXiv:1508.06576 (2015)
J. Johnson at al. „Perceptual losses for real-time style transfer and super-resolution" ECCV 2016

Content loss

- 1. Take a VGG network trained for image classification
- 2. Pass the generated image and the ground truth through the network
- 3. Compare the feature maps

Feature maps of the generated image at layer j

$$\ell_{feat}^{\phi,j}(\hat{y}, y) = \frac{1}{C_j H_j W_j} \|\phi_j(\hat{y}) - \phi_j(y)\|_2^2$$

Feature map size (channels, height, width)

Feature maps of the ground truth image at layer j

Content loss

- Intuition: if there was a car in the original image, we want to have “similar” features triggered for the generated image

- This means we want to “roughly see a car” in the generated image too (but, e.g., color does not matter)

Style Transfer

- The content loss was originally introduced for style transfer [1]

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Image: J. Johnson

[1] Gatys et al „A neural algorithm of artistic style“. arXiv preprint arXiv:1508.06576 (2015)

Prof.

Style Transfer

- Content loss: feature representation similarity

- Style loss:

Gram matrix of the features of layer j

$$\ell_{style}^{\phi,j}(\hat{y}, y) = \|G_j^\phi(\hat{y}) - G_j^\phi(y)\|_F^2$$

- Comparing Gram matrices

J. Johnson at al. „Perceptual losses for real-time style transfer and super-resolution" ECCV 2016

Gatys et al „A neural algorithm of artistic style". arXiv preprint arXiv:1508.06576 (2015)

Style loss

- 1. Take a VGG network trained for image classification
- 2. Pass the generated image and the ground truth through the network
- 3. Compute the Gram matrices at a certain layer

$$G_j^{\phi}(x)_{c,c'} = \frac{1}{C_j H_j W_j} \sum_{h=1}^{H_j} \sum_{w=1}^{W_j} \phi_j(x)_{h,w,c} \phi_j(x)_{h,w,c'}$$

feature vector

- Comparing channels c and c'

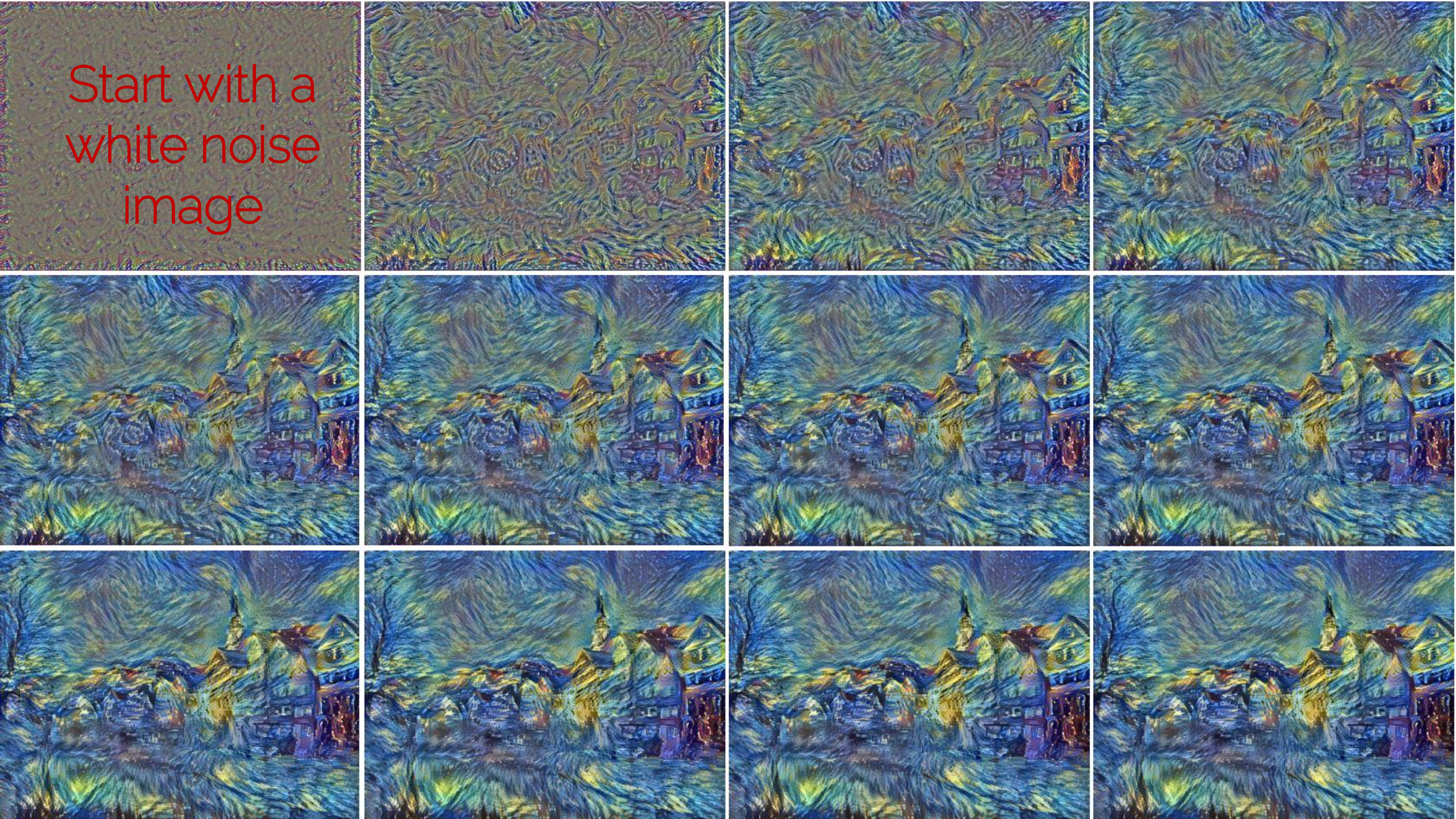
colour

Style loss

- Intuition: it captures information about which features tend to activate *together*.

$$G_j^{\phi}(x)_{c,c'} = \frac{1}{C_j H_j W_j} \sum_{h=1}^{H_j} \sum_{w=1}^{W_j} \phi_j(x)_{h,w,c} \phi_j(x)_{h,w,c'}$$

- This loss preserves the stylistic features but not the content


Start with a white noise image

Style Transfer

More weight to the content loss ⟷ More weight to the style loss

Image: Johnson/Fei-Fei/ Yeung

Style Transfer

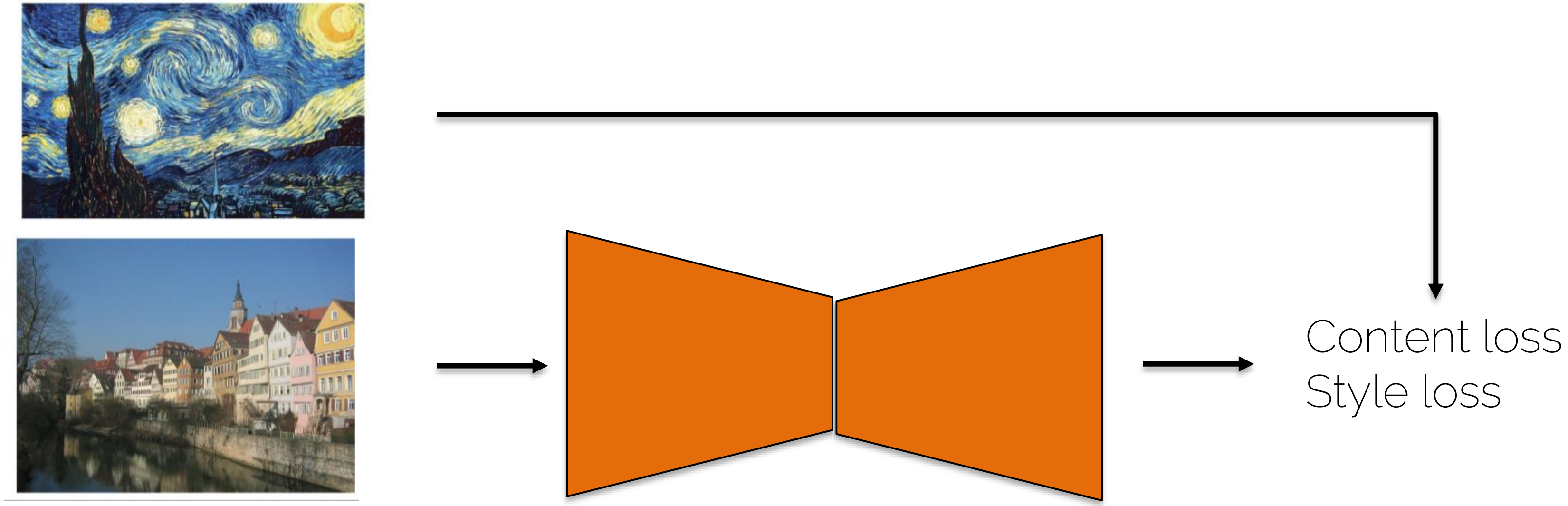
- The aforementioned method is slow, requires many forward/backward passes through VGG.

- Fast Neural style transfer → Train a Neural network to do the transfer (one network per style)

J. Johnson at al. „Perceptual losses for real-time style transfer and super-resolution“ ECCV 2016

Fast style transfer

- Training: use multiple content images, use the style image to compute the loss

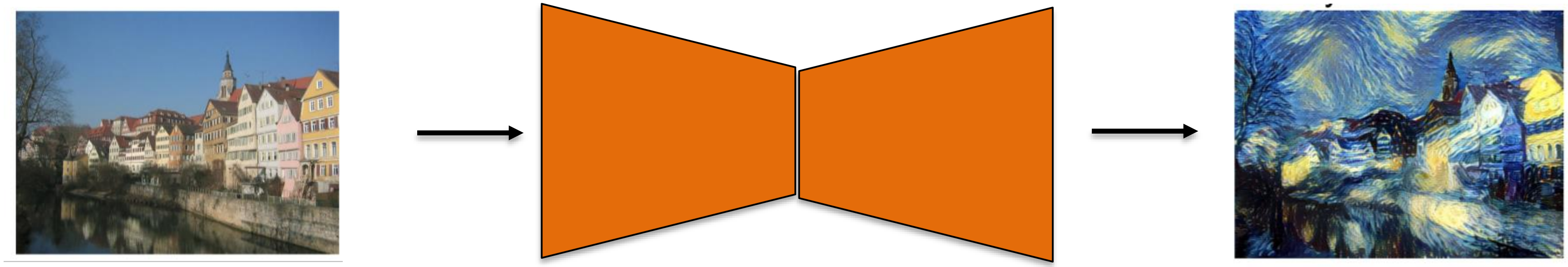


Fast style transfer

- Training: use multiple content images, use the style image to compute the loss

- Test: one forward pass is enough!

only for this style



any input image

Reading Homework

- [Kingman and Welling 2014] Auto-Encoding Variational Bayes
  – https://arxiv.org/pdf/1312.6114.pdf

- [Johnson at al. 2016] Perceptual losses for real-time style transfer and super-resolution
  – https://cs.stanford.edu/people/jcjohns/papers/eccv16/JohnsonECCV16.pdf

Literature

- Autoencoders
  - [Badrinarayanan et al. 2016] SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation
  - [Ronneberger et al. 2015] U-Net: Convolutional Networks for Biomedical Image Segmentation
  - [Garg et al. 2016] Unsupervised CNN for Single View Depth Estimation: Geometry to the Rescue
  - [Kim et al. 2016] Accurate Image Super-Resolution Using Very Deep Convolutional Networks

Literature

- Variational Autoencoders
  - [Kingman and Welling 2014] Auto-Encoding Variational Bayes
  - [Chen and Koltun 2017] Photographic Image Synthesis with Cascaded Refinement Networks
  - [Dosovitskiy and Brox 2016] Generating Images with Perceptual Similarity Metrics based on Deep Networks
- Style Transfer
  - [Johnson at al. 2016] Perceptual losses for real-time style transfer and super-resolution

Thanks for watching!