Autoencoders

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

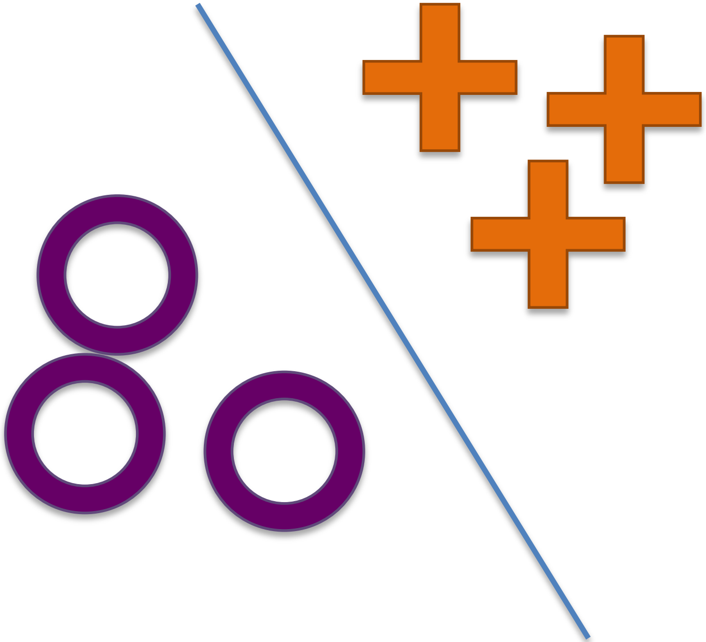
CAT

CAT

DOG

Machine learning

Unsupervised learning



Supervised learning

Machine learning

Unsupervised learning

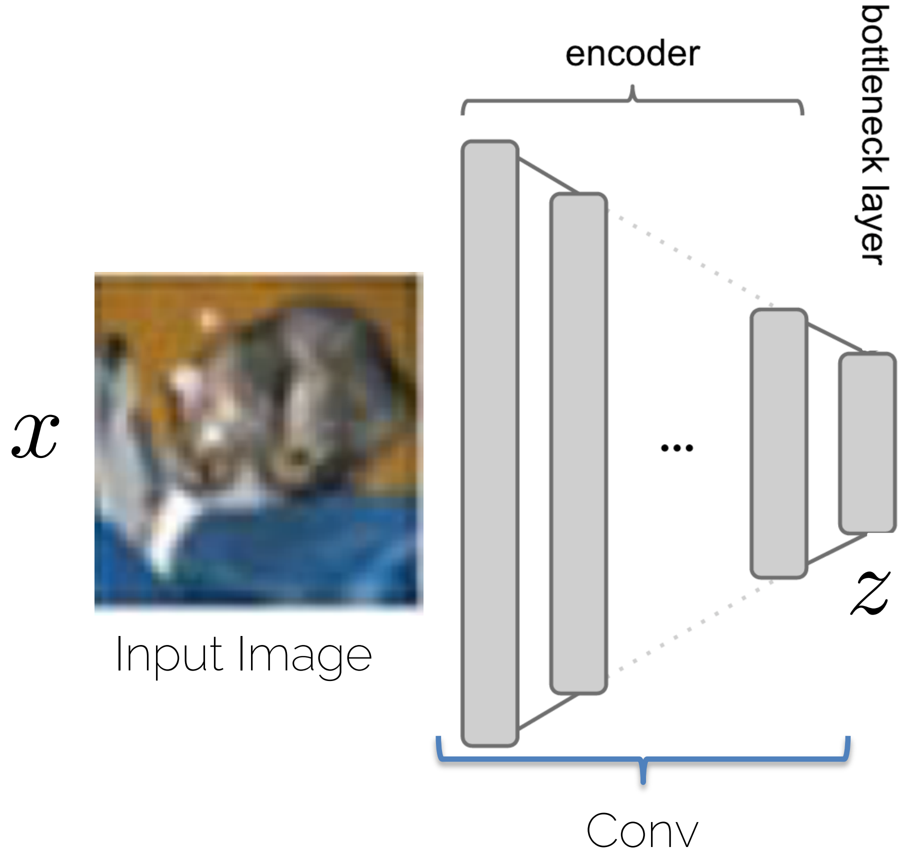
Supervised learning

Unsupervised learning with autoencoders

Autoencoders

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

Autoencoders

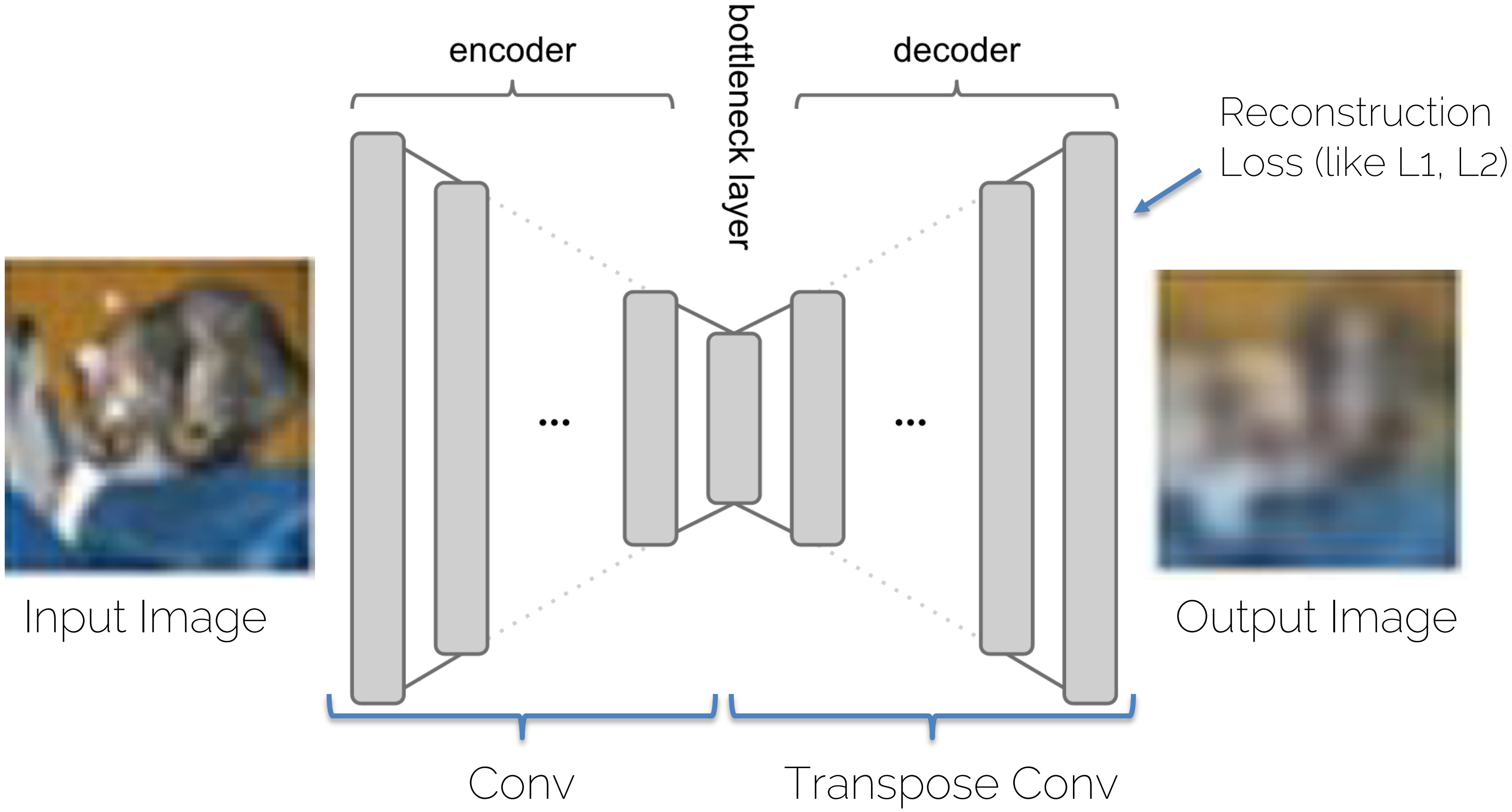


- From an input image to a feature representation (bottleneck layer)
- Encoder: a CNN in our case

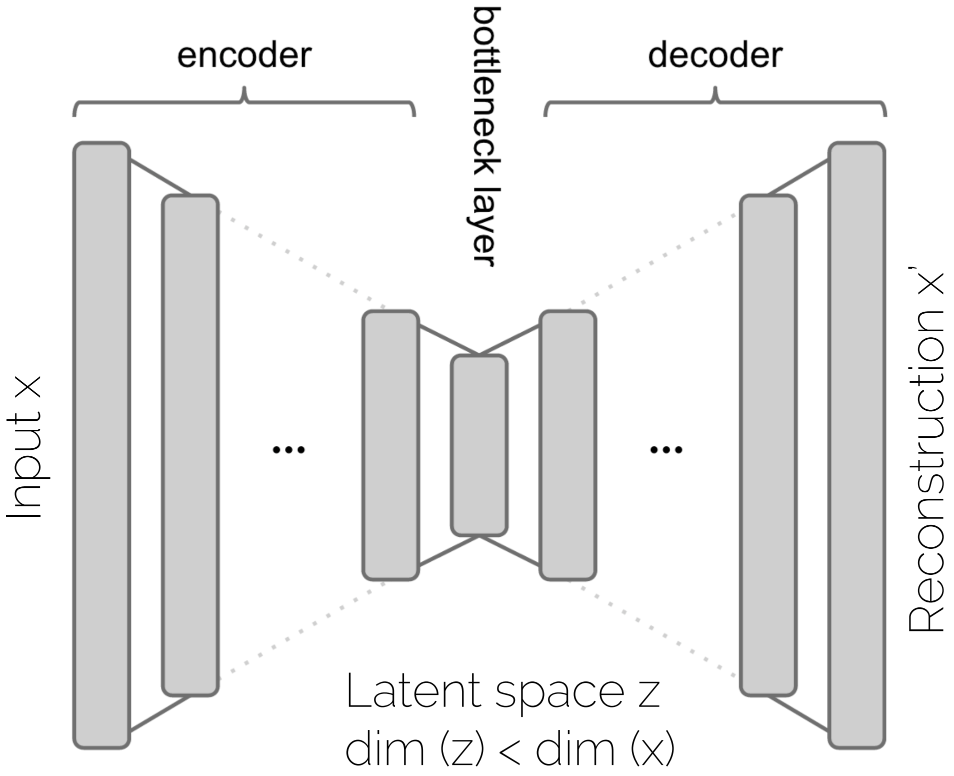
Autoencoders

- Why do we need this dimensionality reduction?
- To capture the patterns, the most meaningful factors of variation in our data
- Other dimensionality reduction methods?

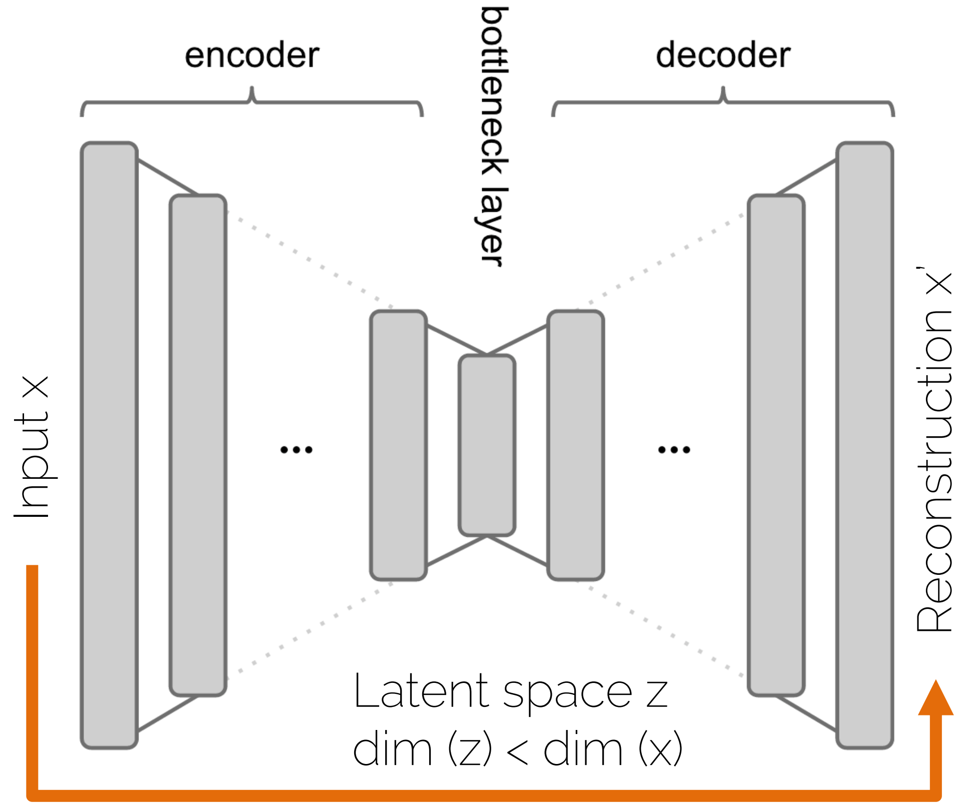
Autoencoder: training



Autoencoder: training



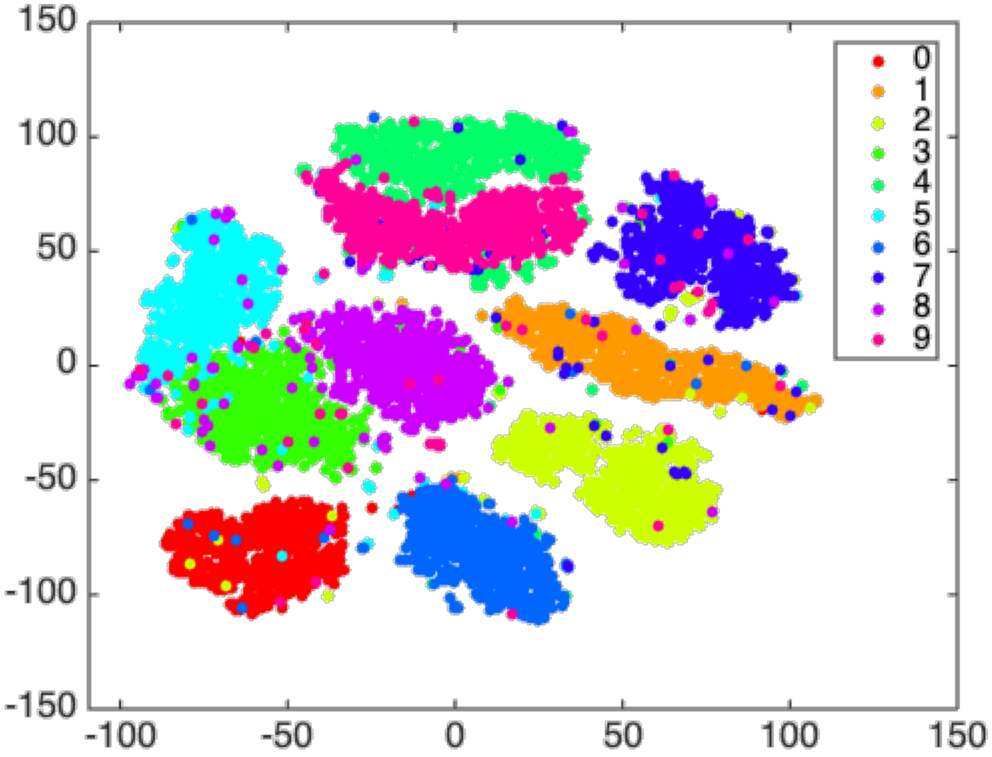
Autoencoder: training



- No labels required
- We can use unlabeled data to first get its structure

Autoencoder: Use Cases

Embedding of MNIST numbers



Autoencoder for pre-training

- 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?

- The image features are different CT vs natural images

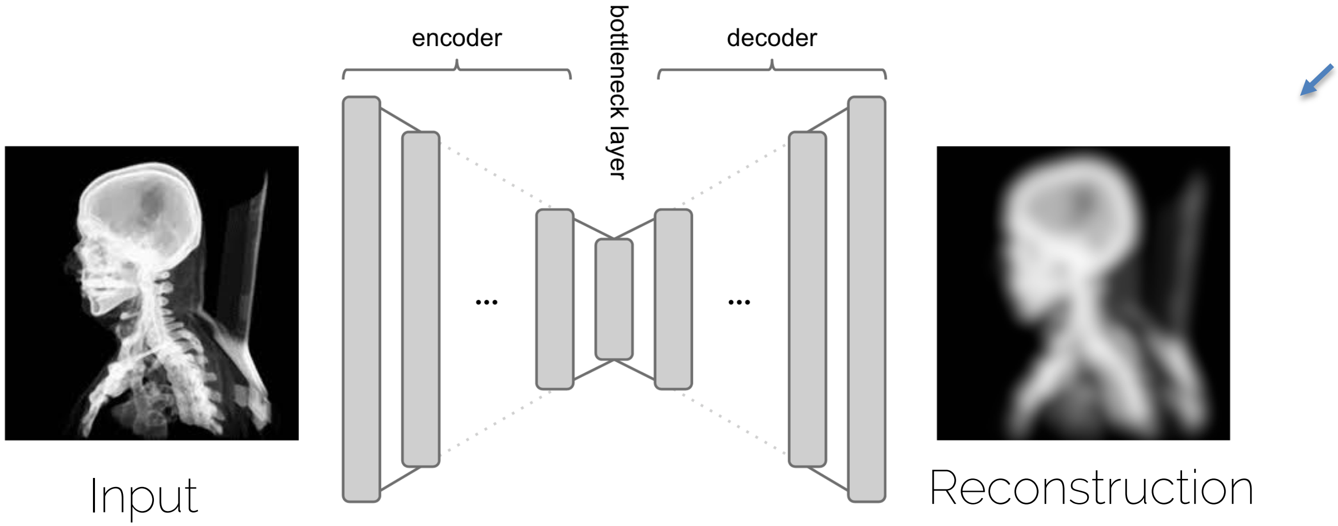
Autoencoder for pre-training

- 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

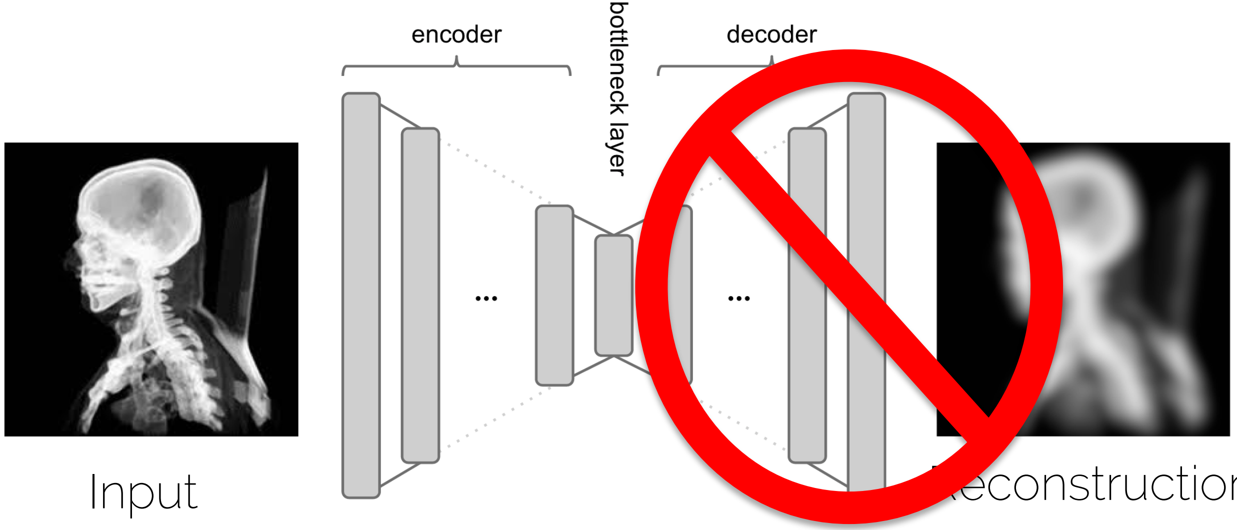
Autoencoder for pre-training

- Step 1: Unsupersived training with autoencoders



Autoencoder for pre-training

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



Input

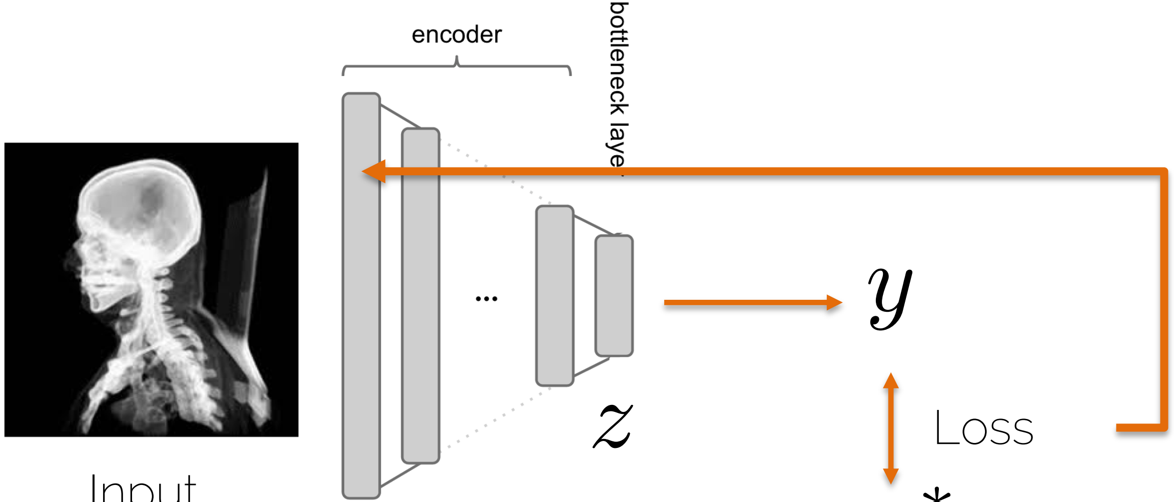
Reconstruction

Throw away the decoder

Autoencoder for pre-training

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

x



Input

z

y

Loss

y^*

Backprop as always

Ground truth labels for supervised learning

Why using autoencoders?

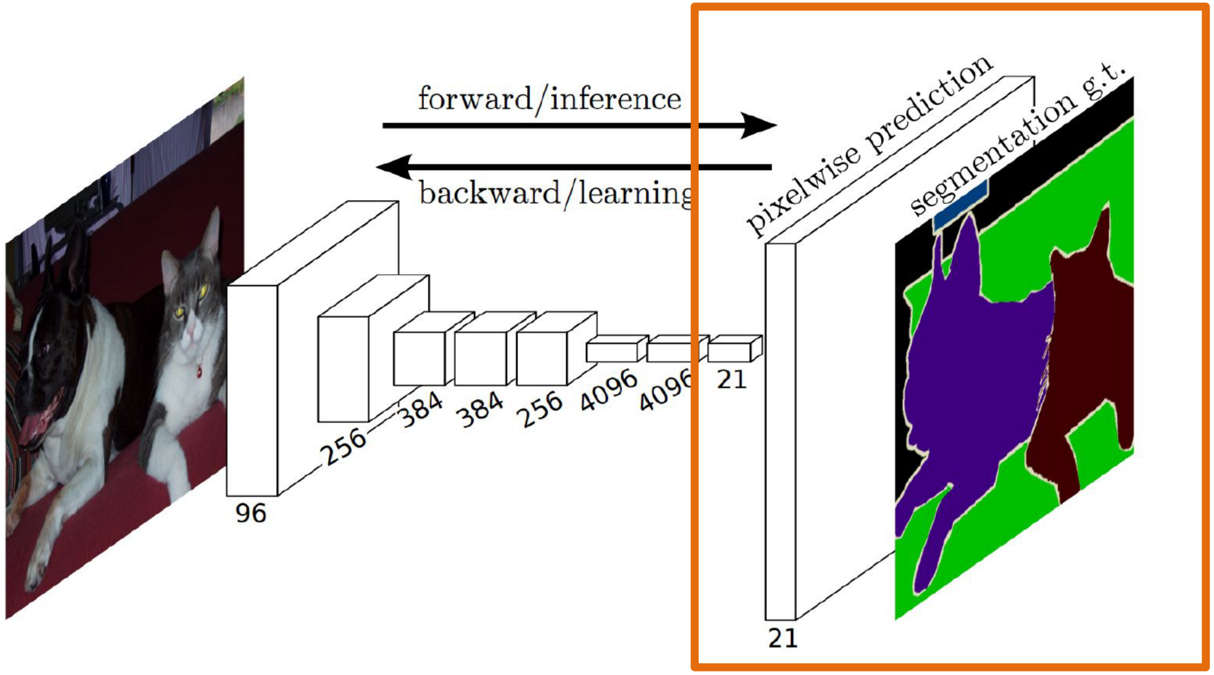
- Use 1: pre-training, as mentioned before
  - Image → same image reconstructed
  - Use the encoder as "feature extractor"

- 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)

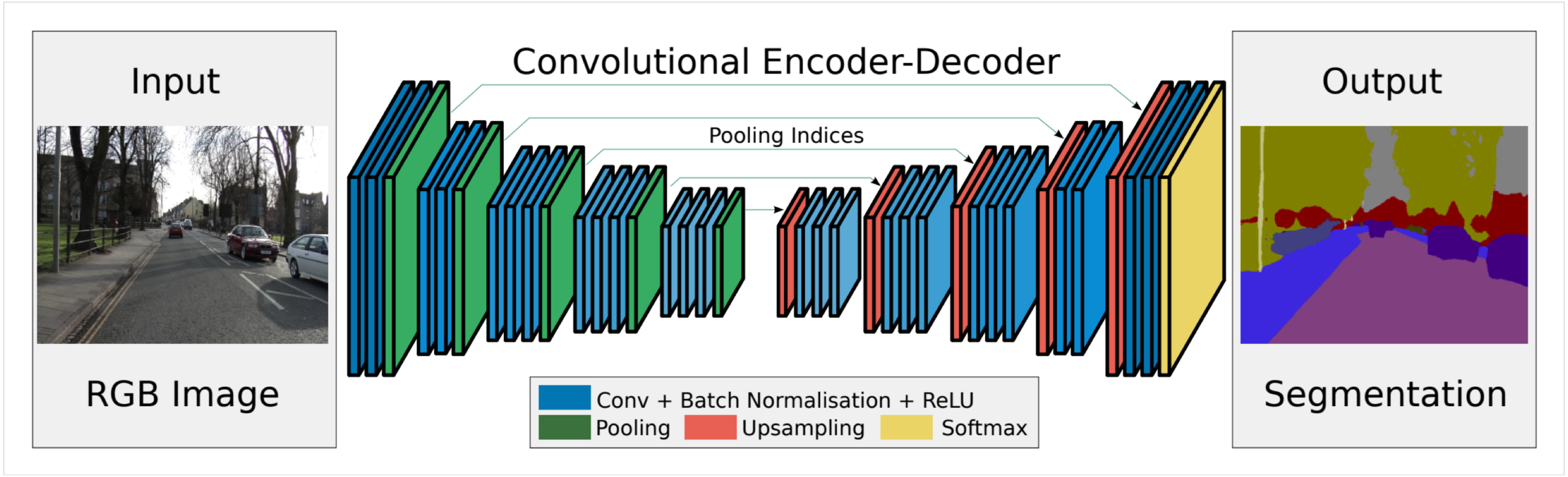
- Recall the Fully Convolutional Networks



Can we do better?

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

SegNet

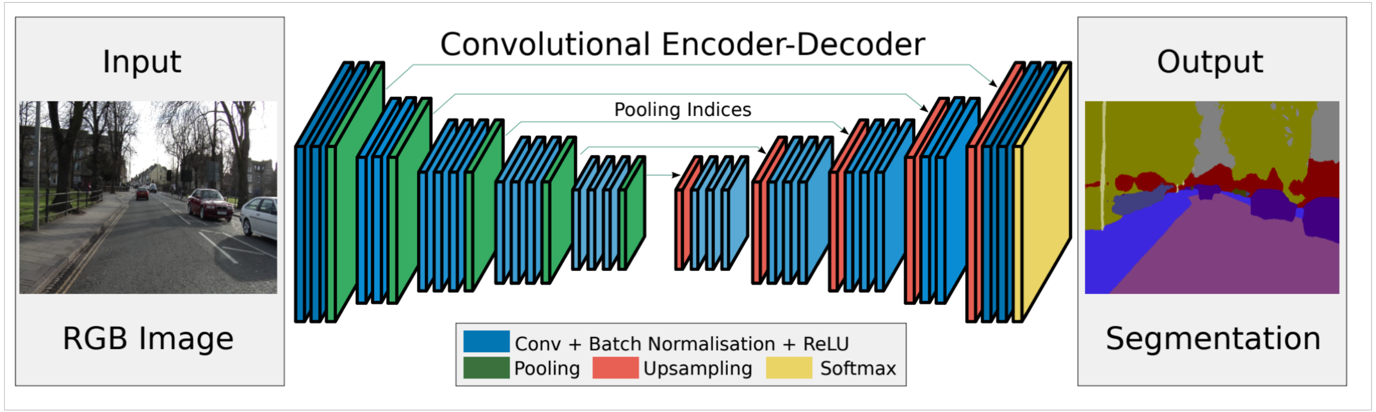


Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation". TPAMI 2016

SegNet

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

- **Decoder**: Upsampling + convolutional filters



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

SegNet

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

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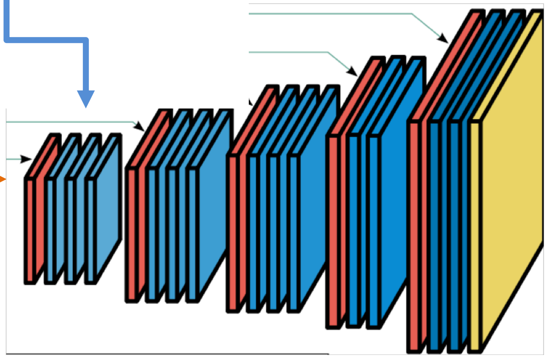


Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation". TPAMI 2016

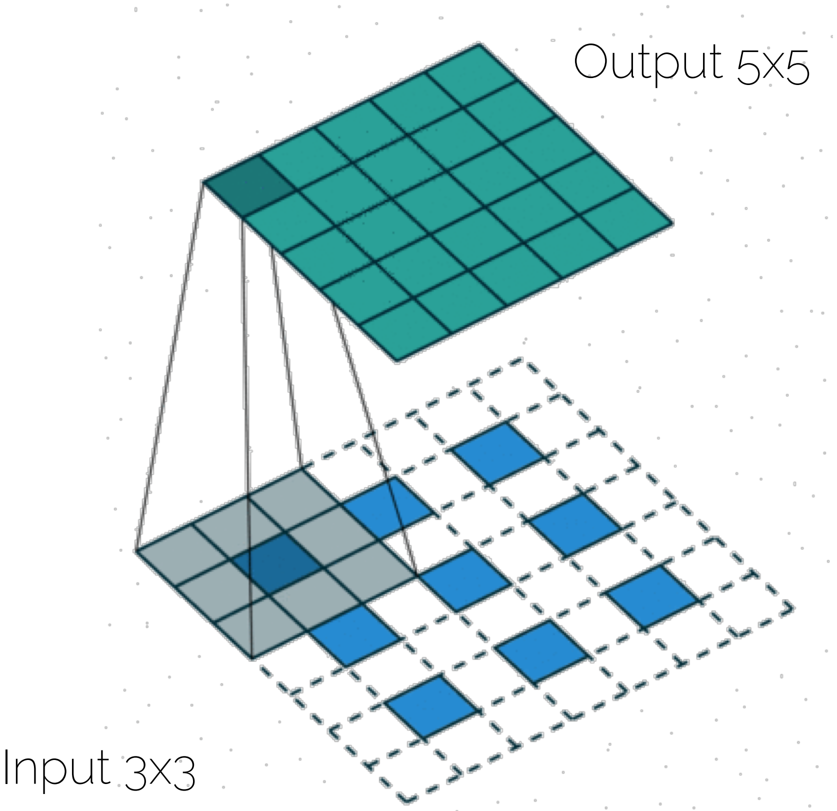
SegNet

- **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 (never deconvolution)



SegNet

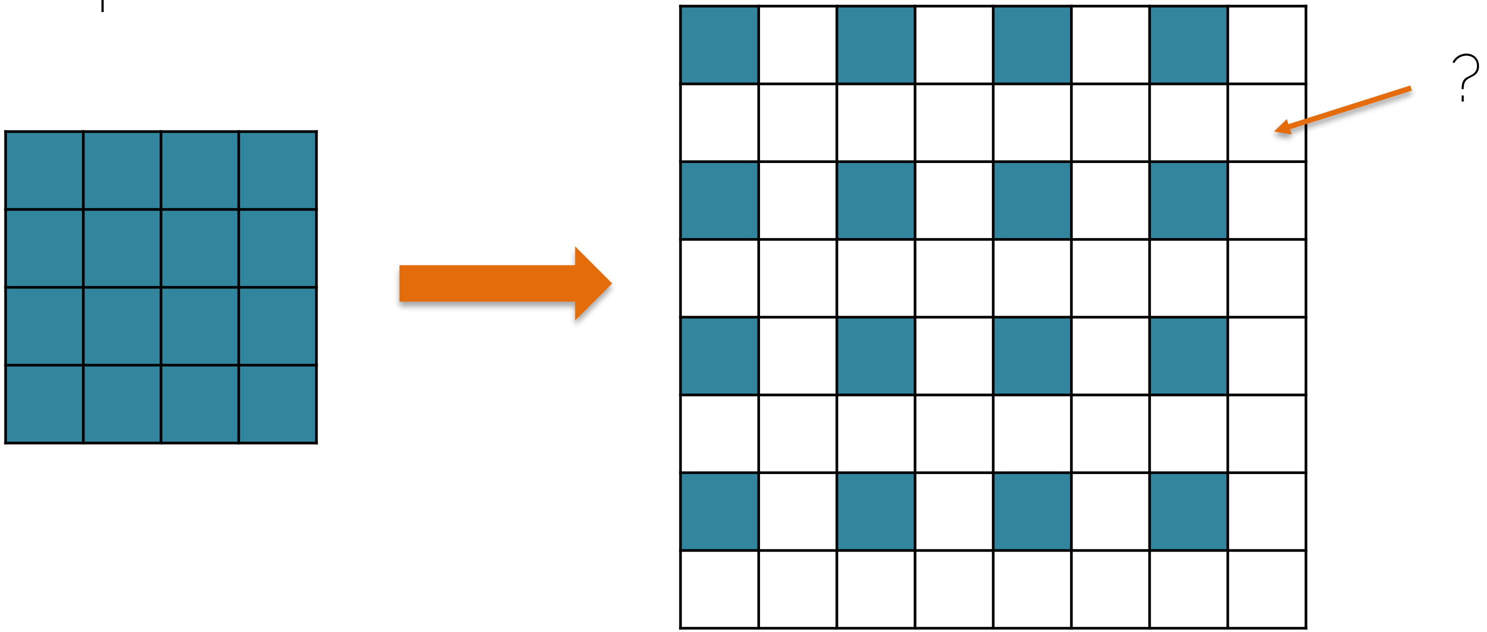
- **Encoder**: normal convolutional filters + pooling
- **Decoder**: $\boxed{\text{Upsampling}}$ + convolutional filters
- **Softmax** layer: The output of the soft-max classifier is a K channel image of probabilities where K is the number of classes.

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

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

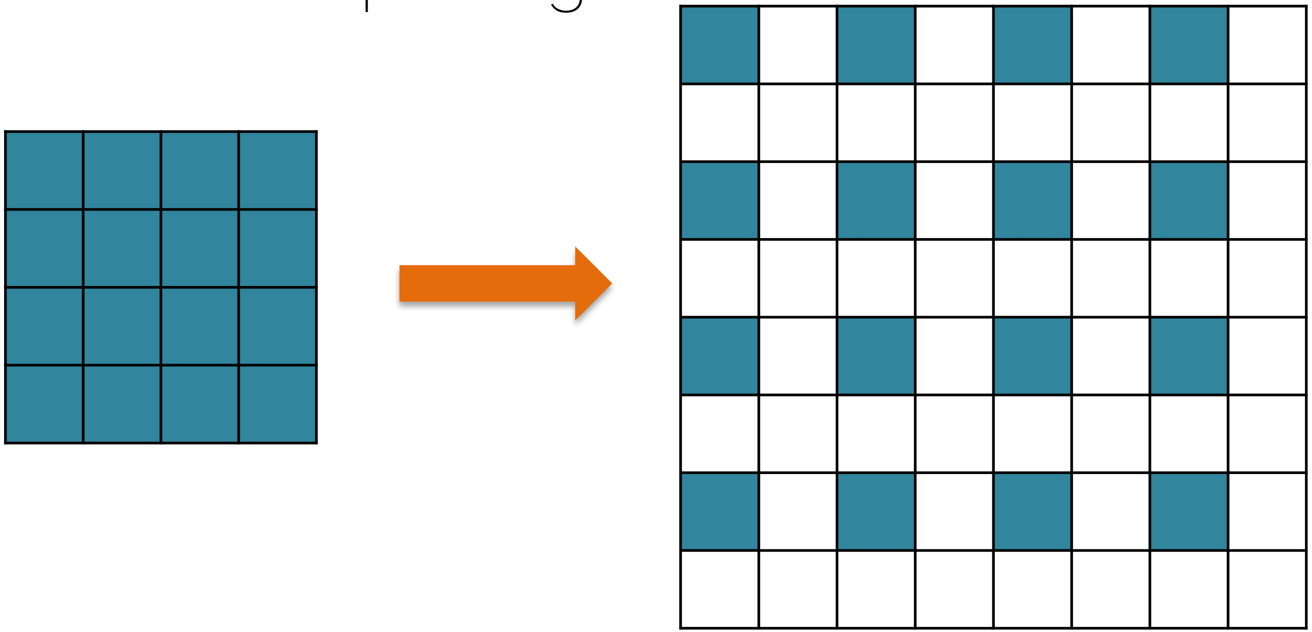
Few artifacts

Image: Michael Guerzhoy

Types of upsamplings

- 2. Fixed unpooling

efficient



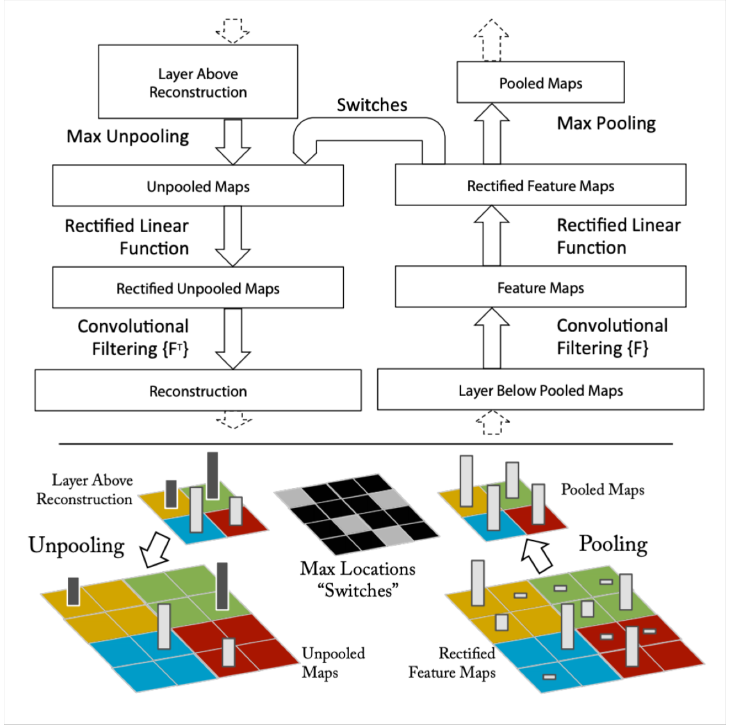
+ CONVS

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

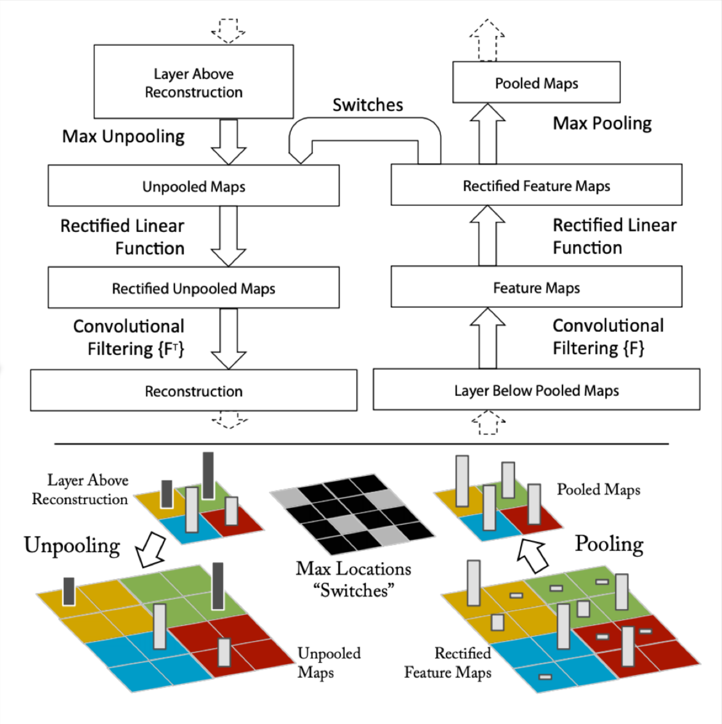


Types of upsamplings

- 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”

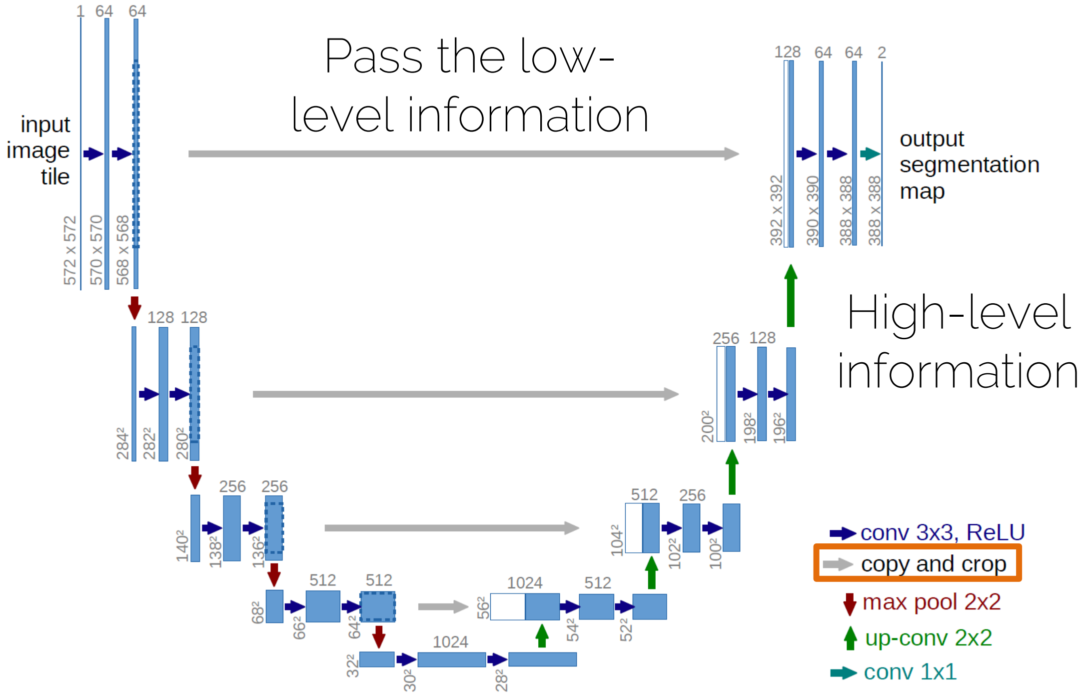
Keep the details of the structures

U-Net or skip connections in autoencoders

Skip Connections

- U-Net

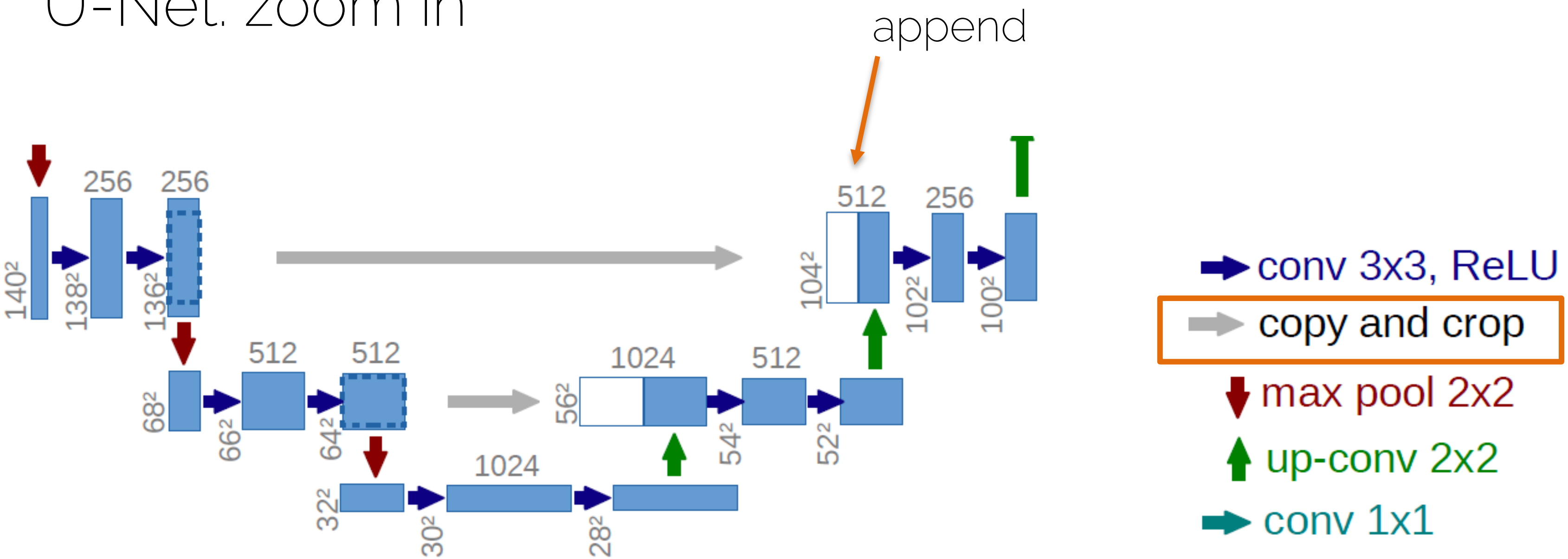
Recall ResNet



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

Skip Connections

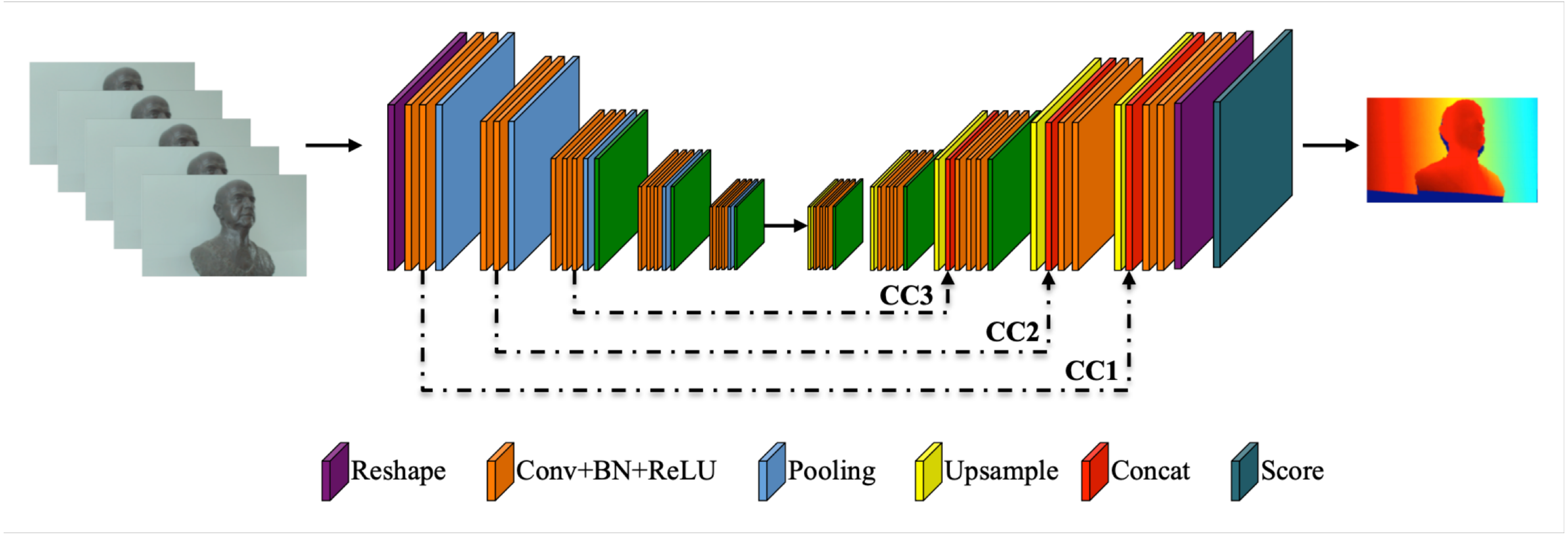
- U-Net: zoom in



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

Skip Connections

- Concatenation connections



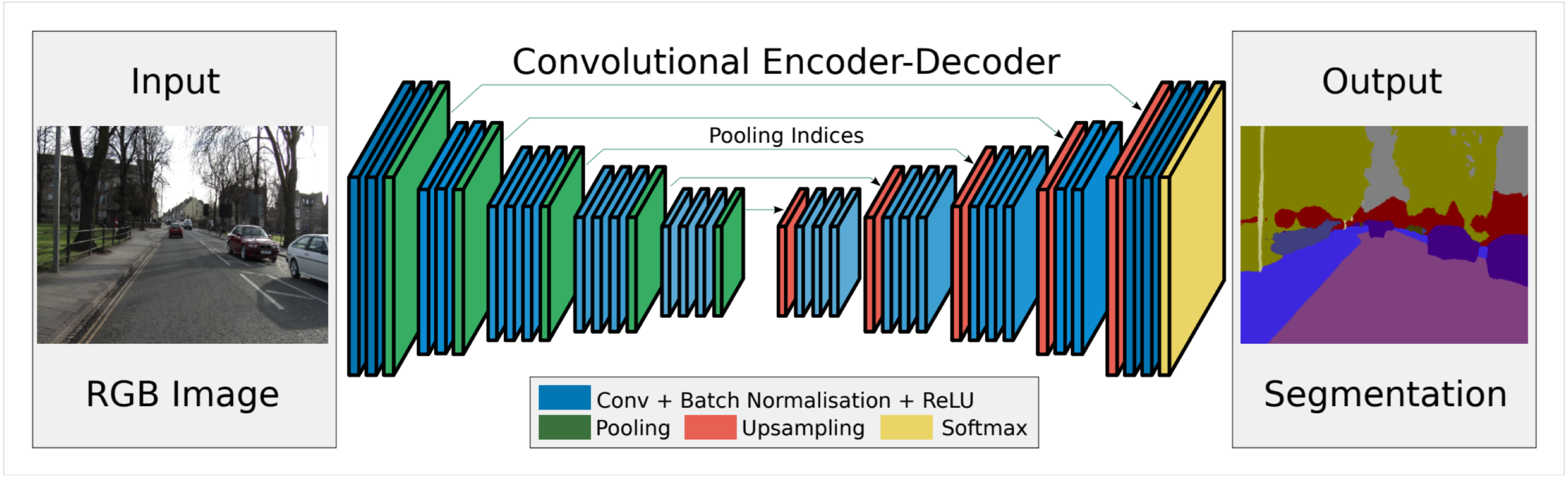
C. Hazirbas et al. "Deep depth from focus". ACCV 2018

Skip Connections

- Widely used in Autoencoders
- At what levels the skip connections are needed depends on your problem

Autoencoders in Vision

SegNet



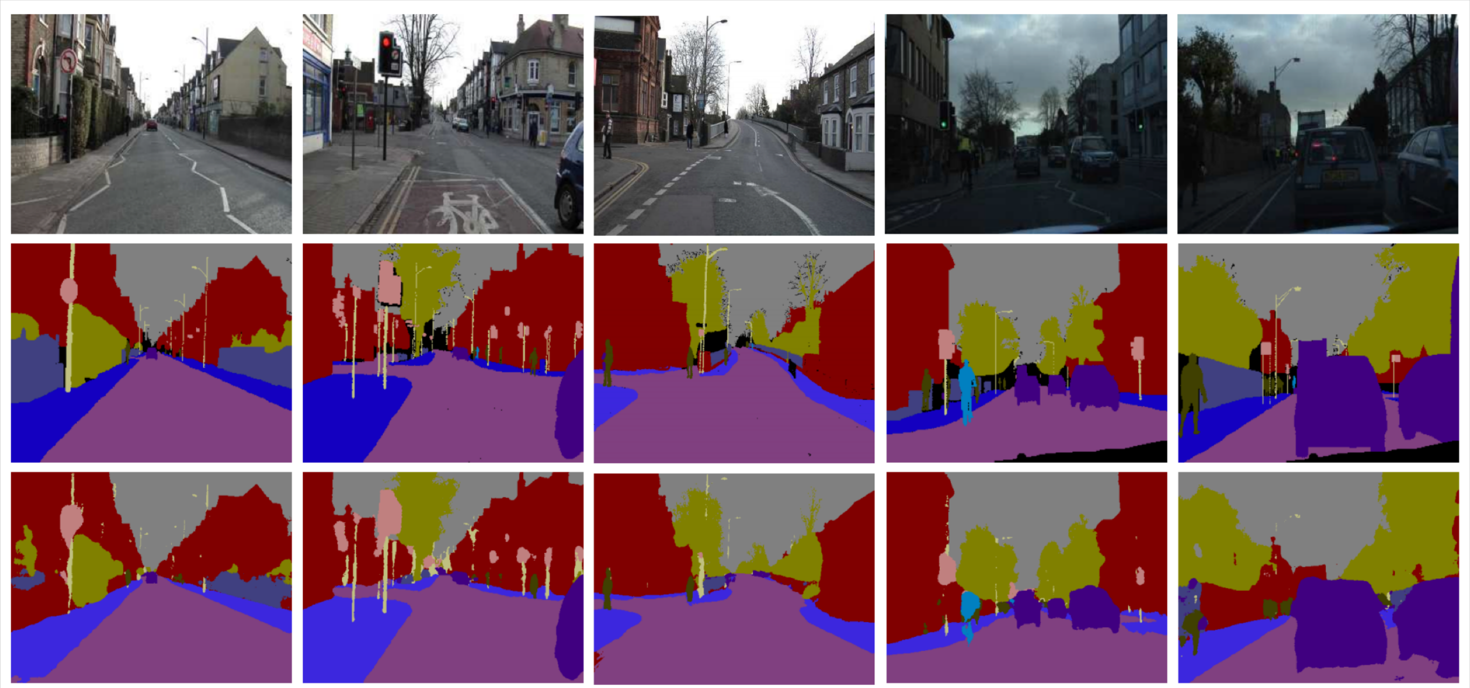
Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation". TPAMI 2016

SegNet

Input

Ground truth

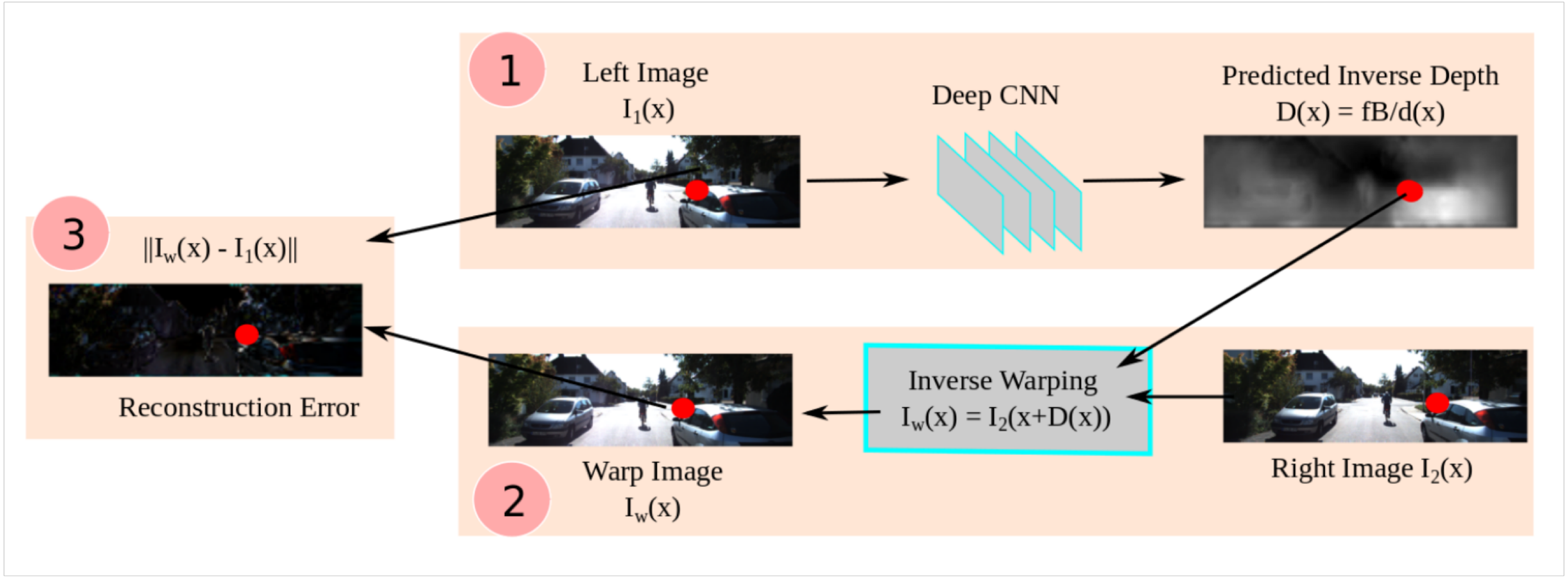
SegNet



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

Monocular depth

- Unsupervised monocular depth estimation



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

Image super resolution

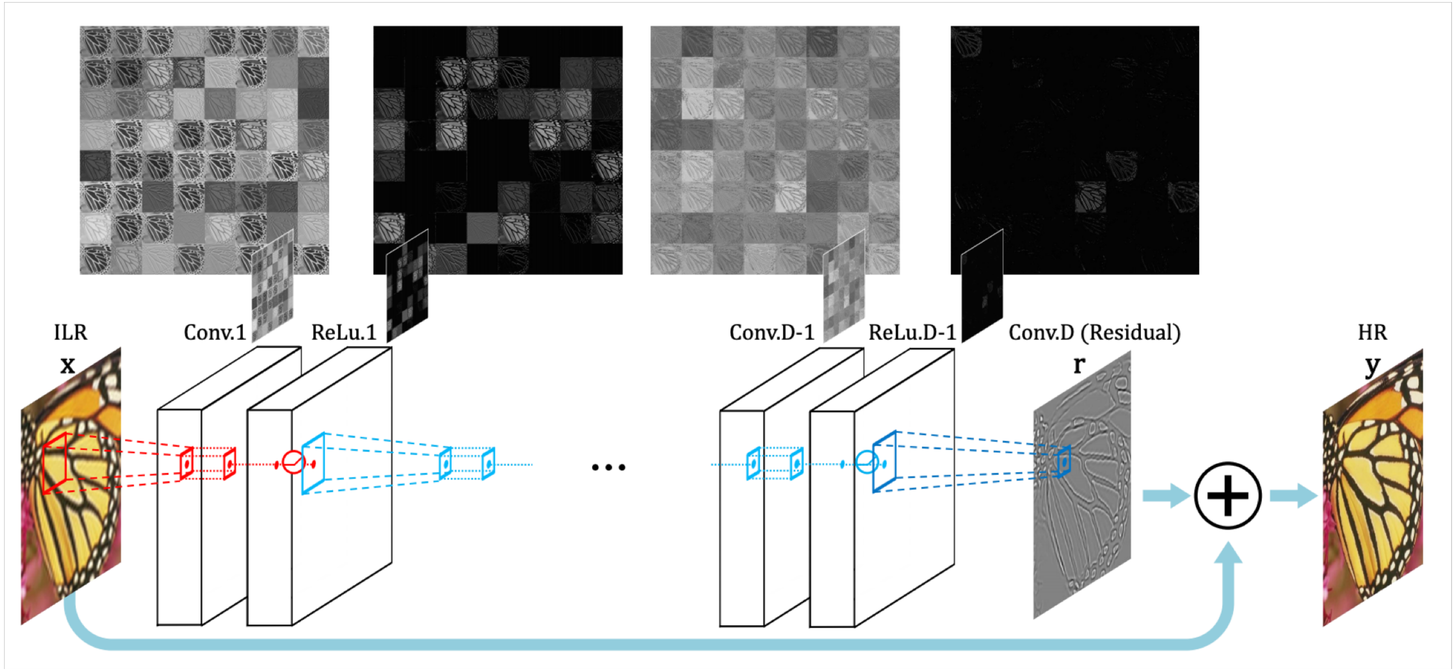
- Image in low resolution → Image in high resolution
- Problems:
  - The content of the image needs to pass through the network (skip connections [2] or other strategies [1]).

[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

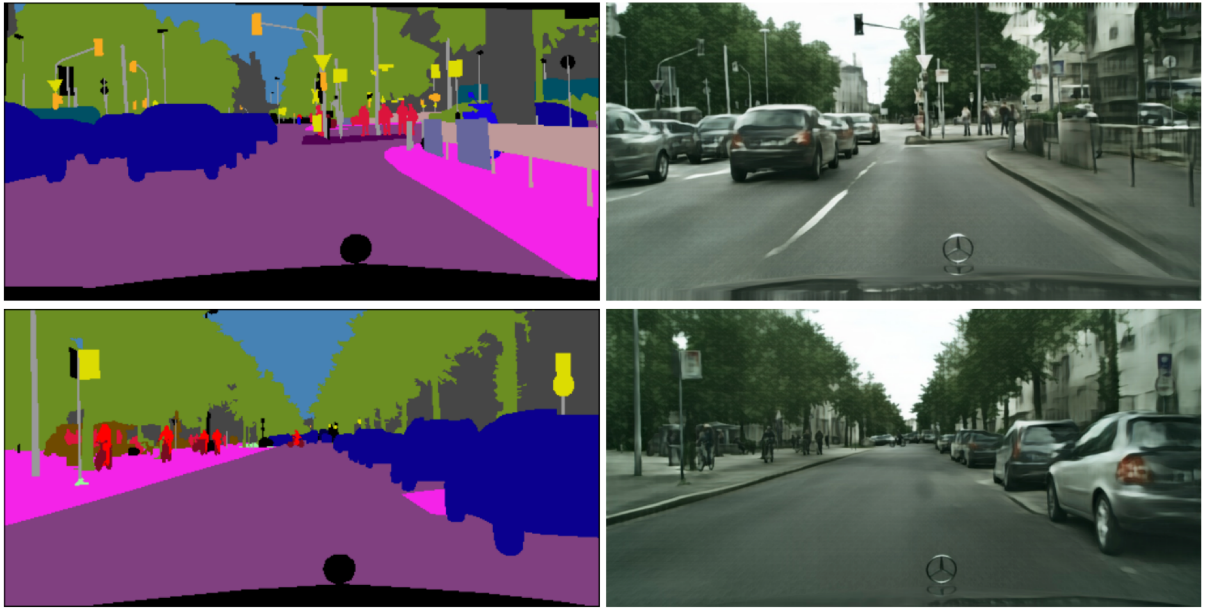
- Why not learning the residual only? → Much easier!



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

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)

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]

Image: J. Johnson

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


A
B
E
F

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

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

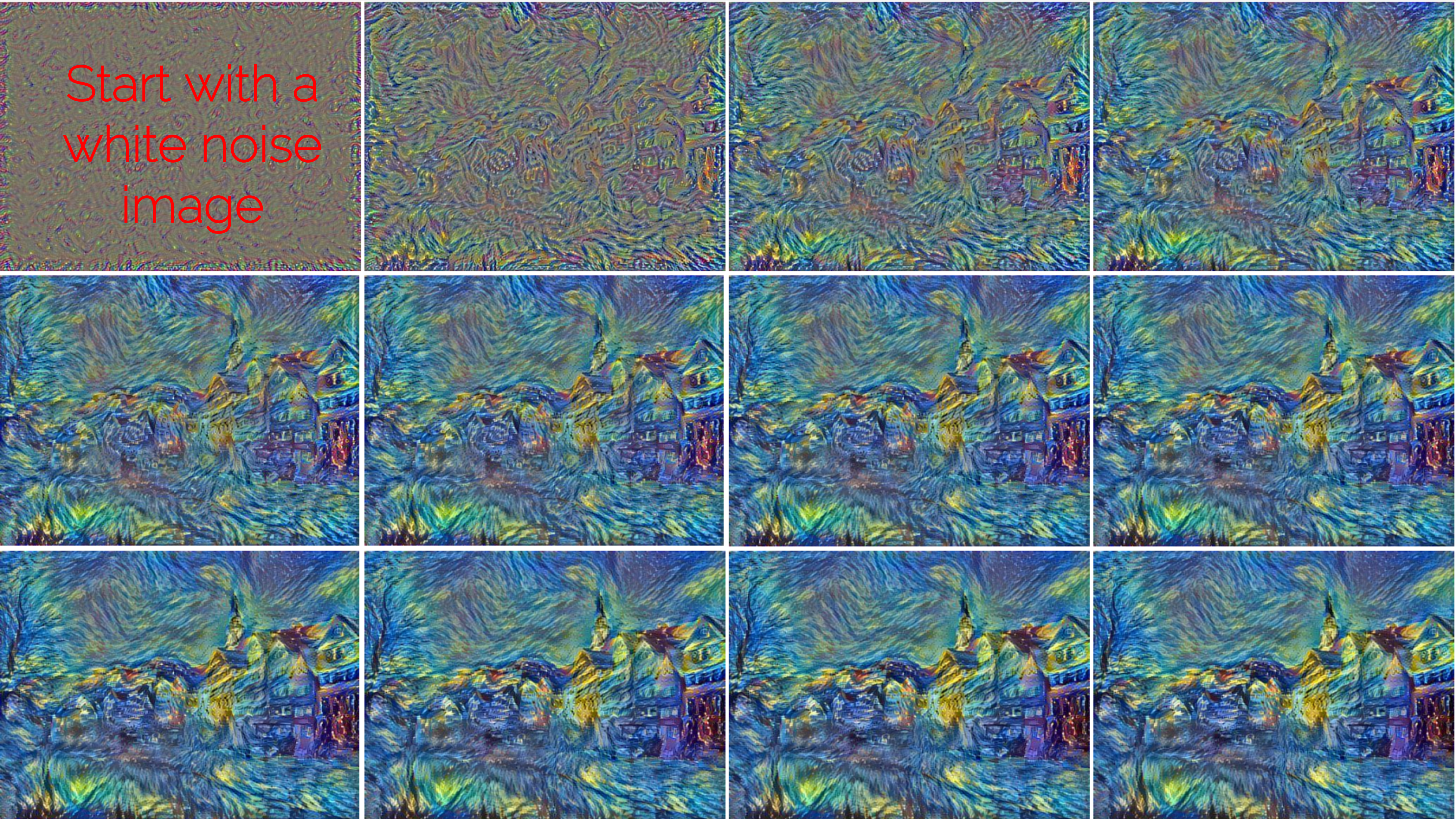
- Comparing channels c and c'

Style loss

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

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

- In practice: vectorize the feature maps to the size of C x (HW)
- 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

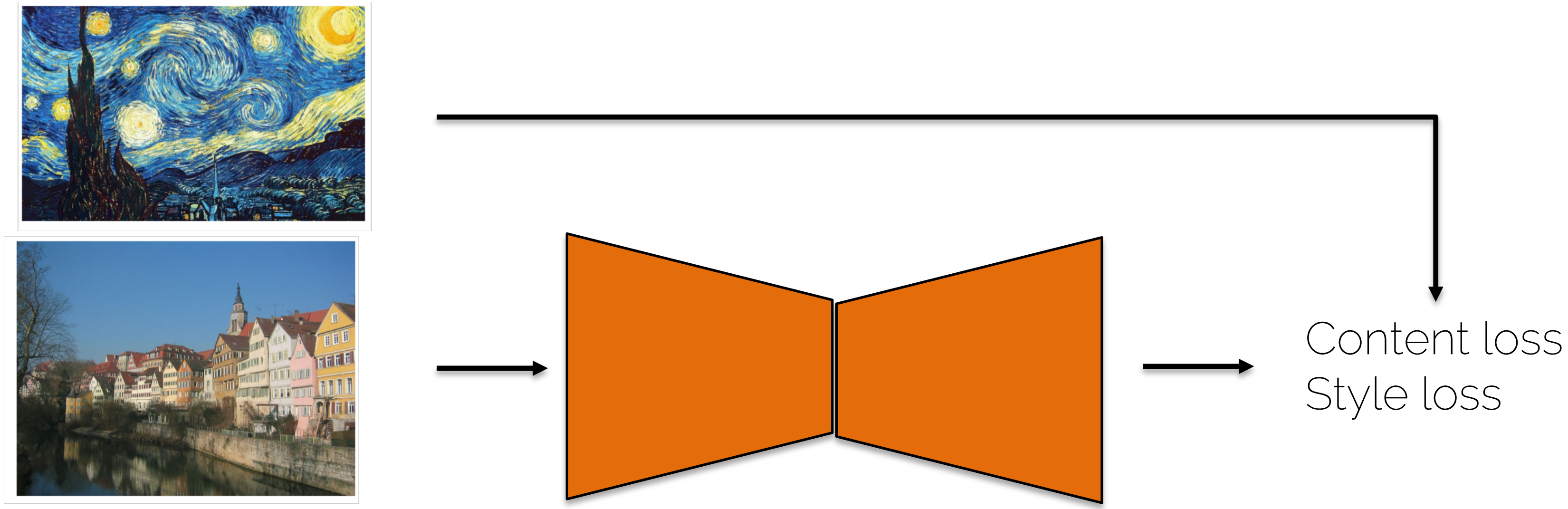
- The aforementioned method is slow, requires many forward/backward passes through VGG.

- 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

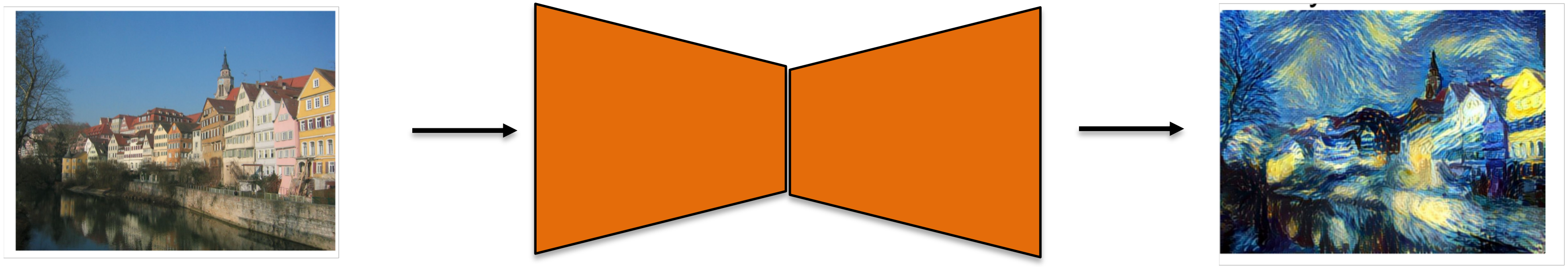
- Training: use multiple content images, use the style image to compute the loss



Fast style transfer

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

- Test: one forward pass is enough!



Other uses of autoencoders

- Anomaly detection. For example: C. Baur et al. „Deep Autoencoding Models for Unsupervised Anomaly Segmentation in Brain MR Images“ MICCAI 2018

- Deep multimodal autoencoders → to mix the representation of several sources (audio and video)

Next lecture

- Next lecture on Monday 3rd
- Make sure you are working on your projects!
- Group #2 presenting this Friday!