Machine Learning for Design

Lecture 4

Machine Learning for Images. *Part 2*

How do humans see?

Hubel and Wiesel, 1959

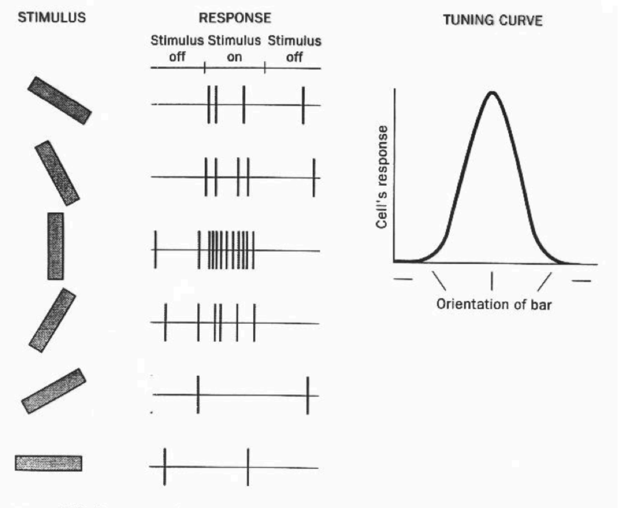
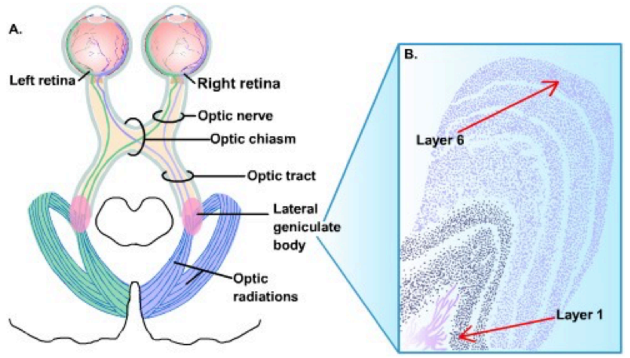


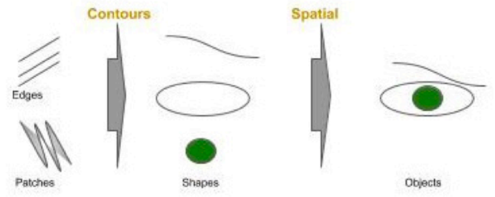
FIGURE 4.8 Response of a single cortical cell to bars presented at various orientations.

Neural Pathways



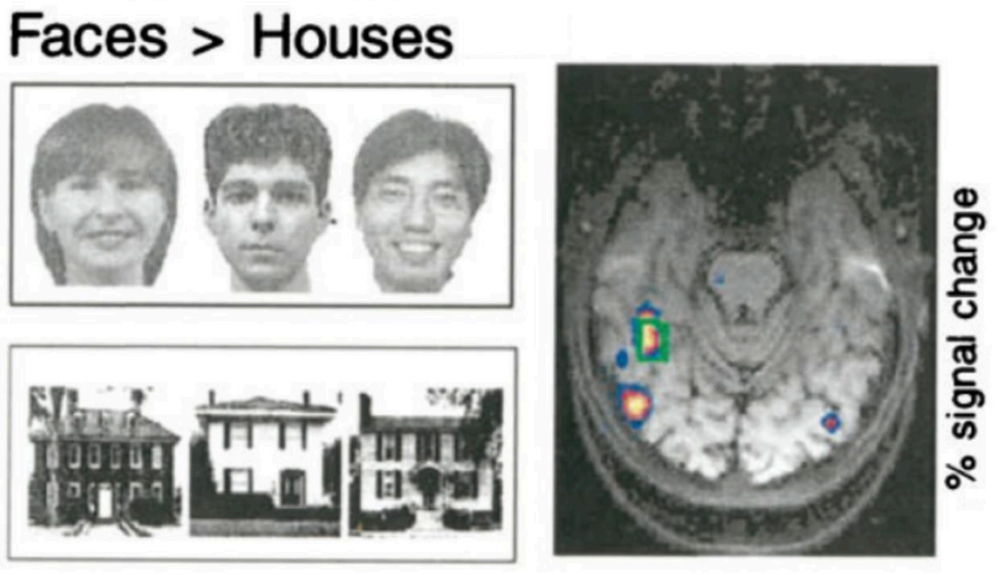
$$\begin{tikzcd}
\text{Edges} \arrow[r] & \text{Simple Shapes} \arrow[r] & \text{Complex Shapes} \arrow[r] & \text{Faces and Objects}
\end{tikzcd}$$

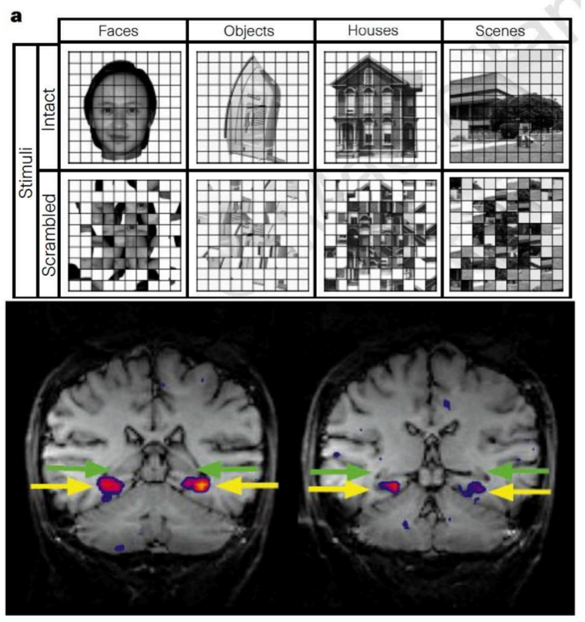
← Lower layers Upper layers →



Neural Correlation

of Objects & Scene Recognition





Kanwisher et al. J. Neuro. 1997

Epstein & Kanwisher, Nature, 1998

Why is machine vision hard?

The deformable and truncated cat

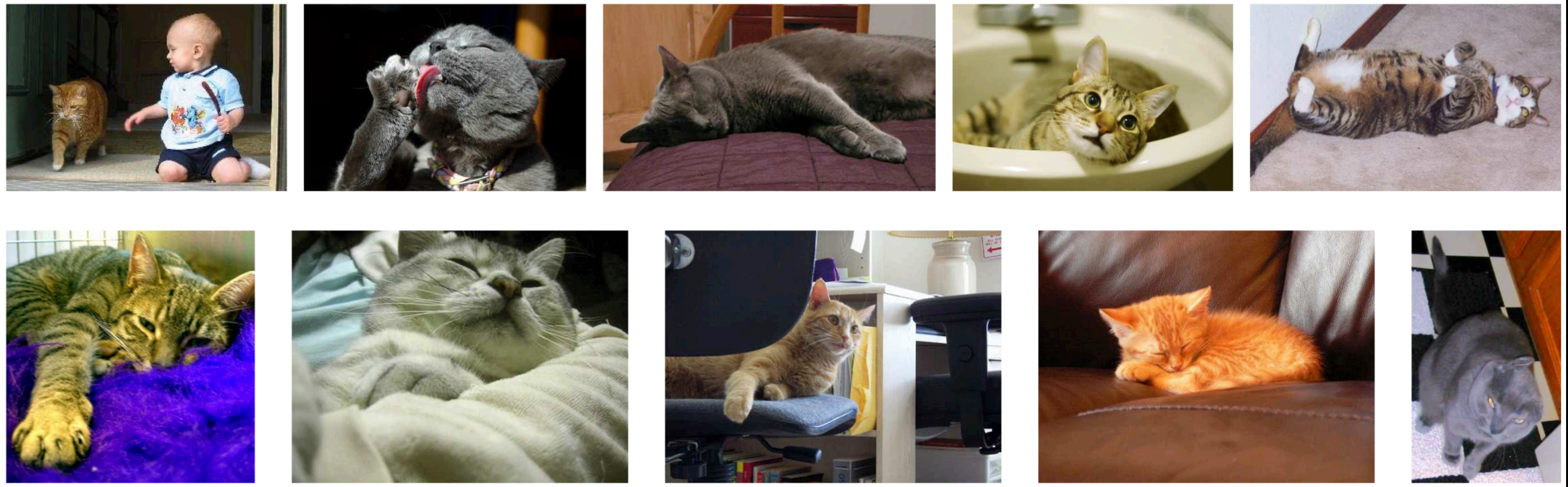
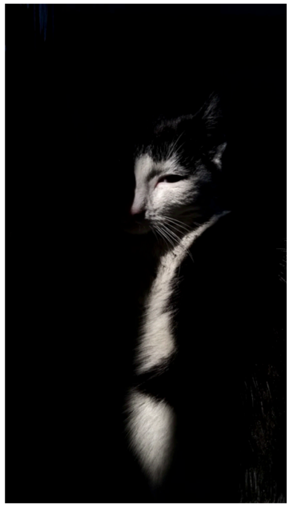
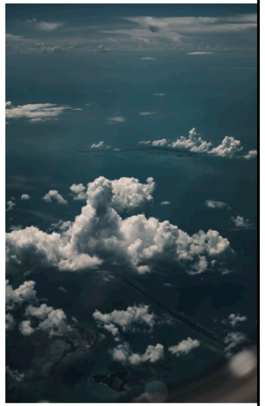
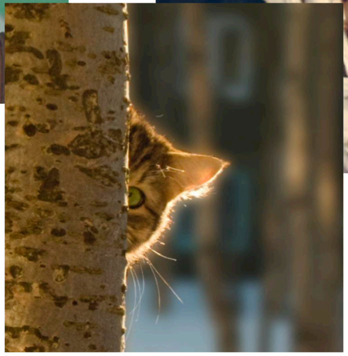
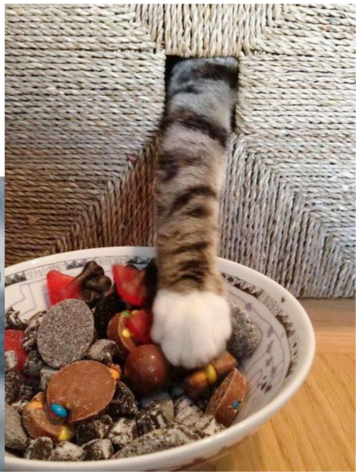


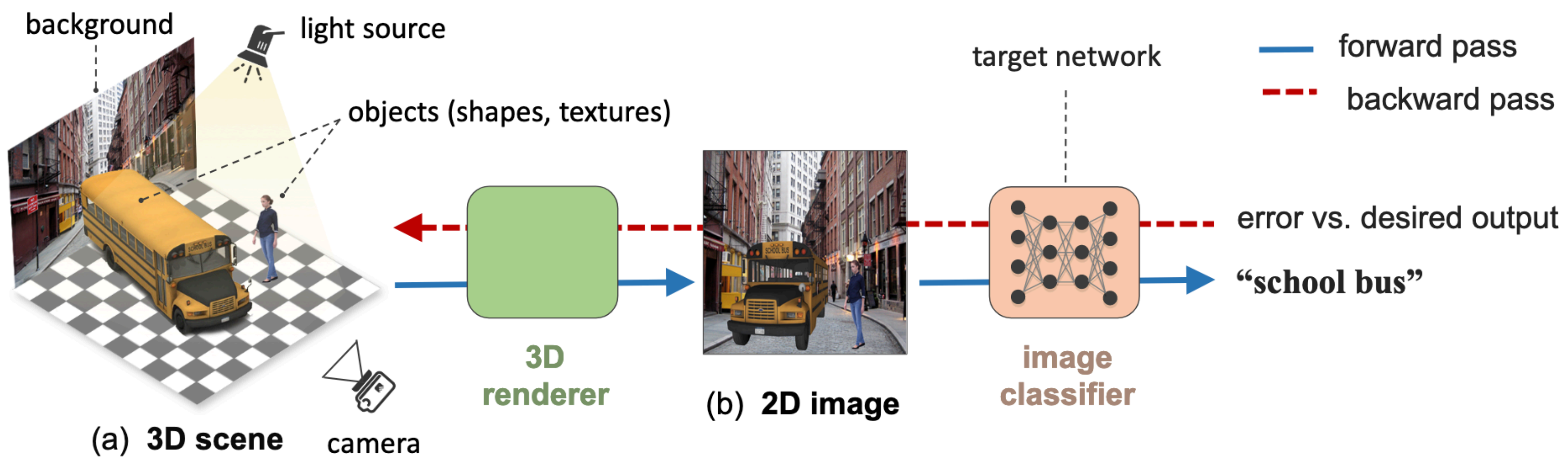
Figure 1. **The deformable and truncated cat.** Cats exhibit (almost) unconstrained variations in shape and layout.

Parkhi et al. *The truth about cats and dogs*. 2011



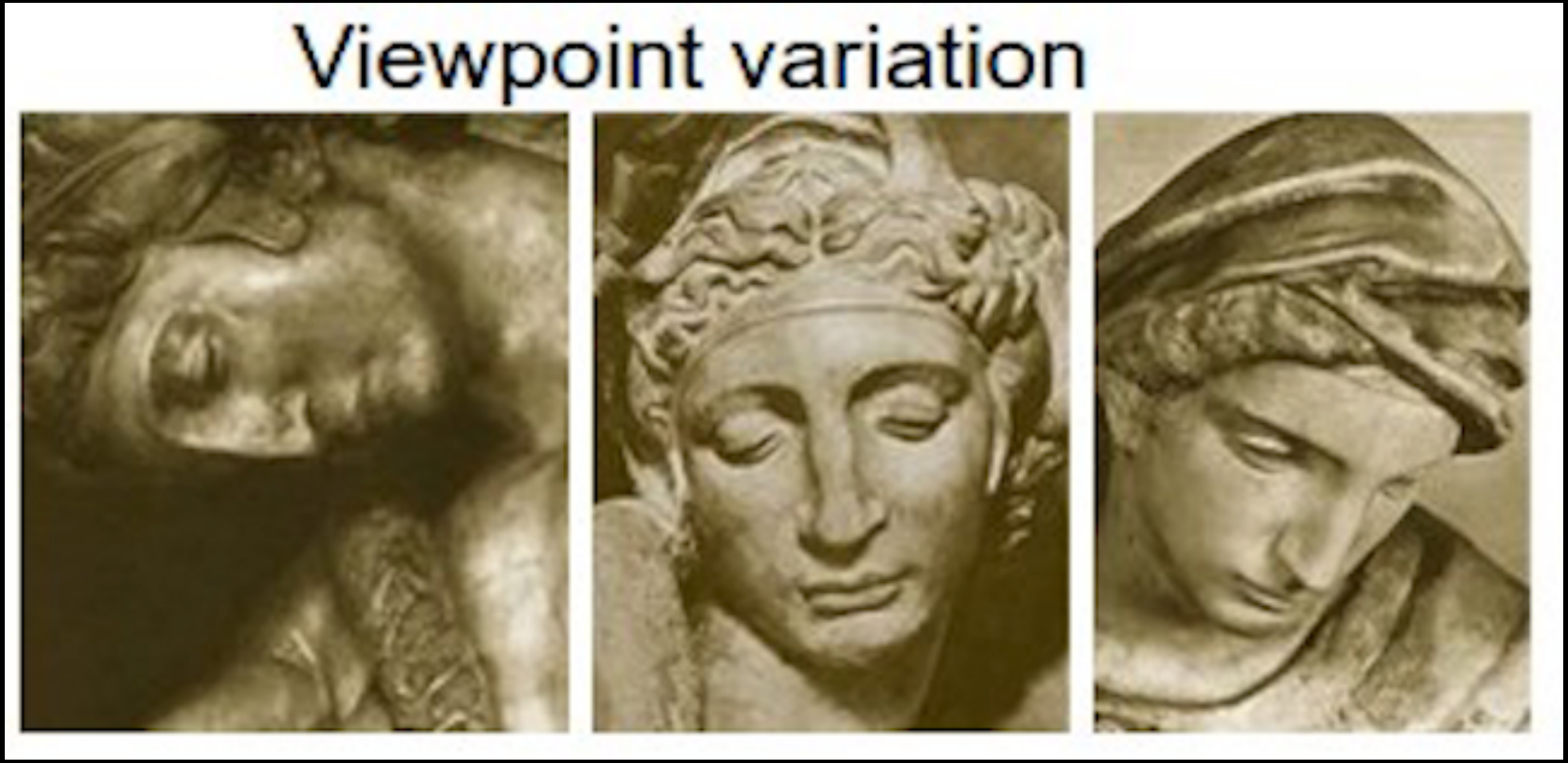



background
light source
objects (shapes, textures)
target network
forward pass
backward pass
error vs. desired output
"school bus"
3D renderer
(b) 2D image
image classifier
(a) 3D scene
camera

Computer Vision Challenges

Viewpoint Variation

A single instance of an object can be oriented in many ways to the camera.



Deformation

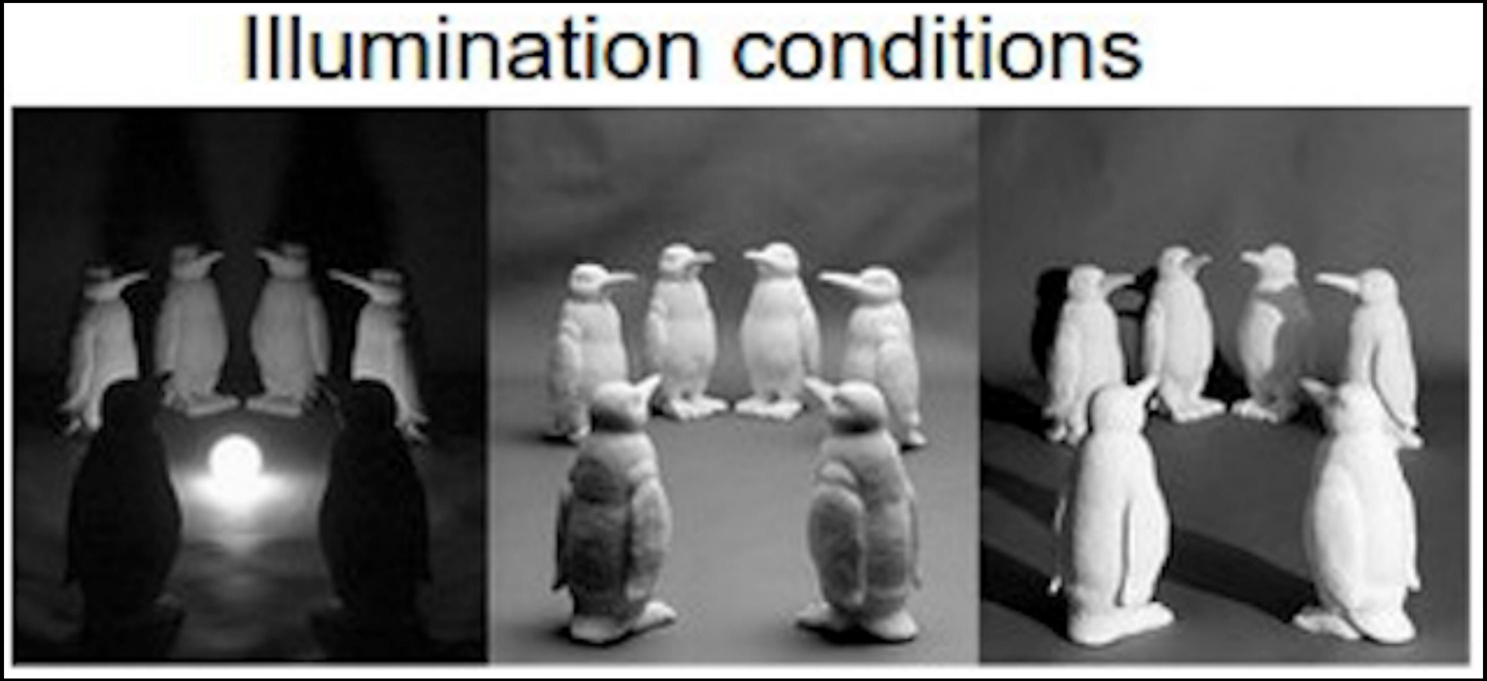
Many objects of interest are not rigid bodies and can be deformed in extreme ways.

Occlusion

The objects of interest can be occluded. Sometimes only a tiny portion of an object (as few pixels) could be visible.

Illumination Condition

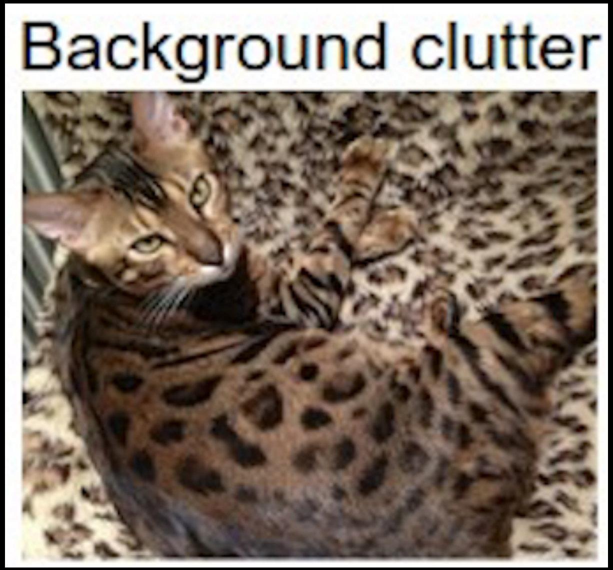
The effects of illumination can be drastic on the pixel level.



Scale variation

- Visual classes often exhibit variation in their size
    - Size in the real world
    - Size in the image

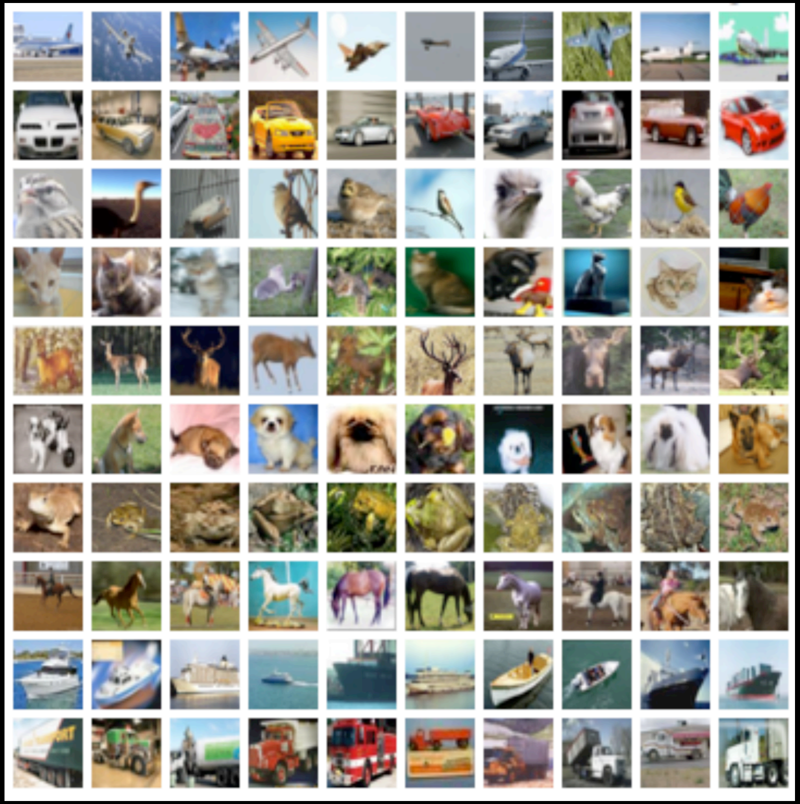
Background clutter



The objects of interest may blend into their environment, making them hard to identify.

Intra-class variation

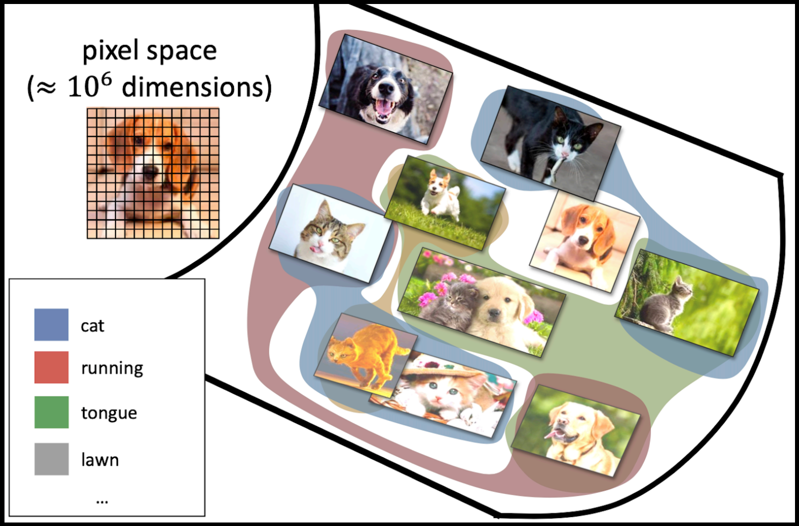
- The classes of interest can often be relatively broad, such as chairs.
- There are many different types of these objects, each with their appearance.



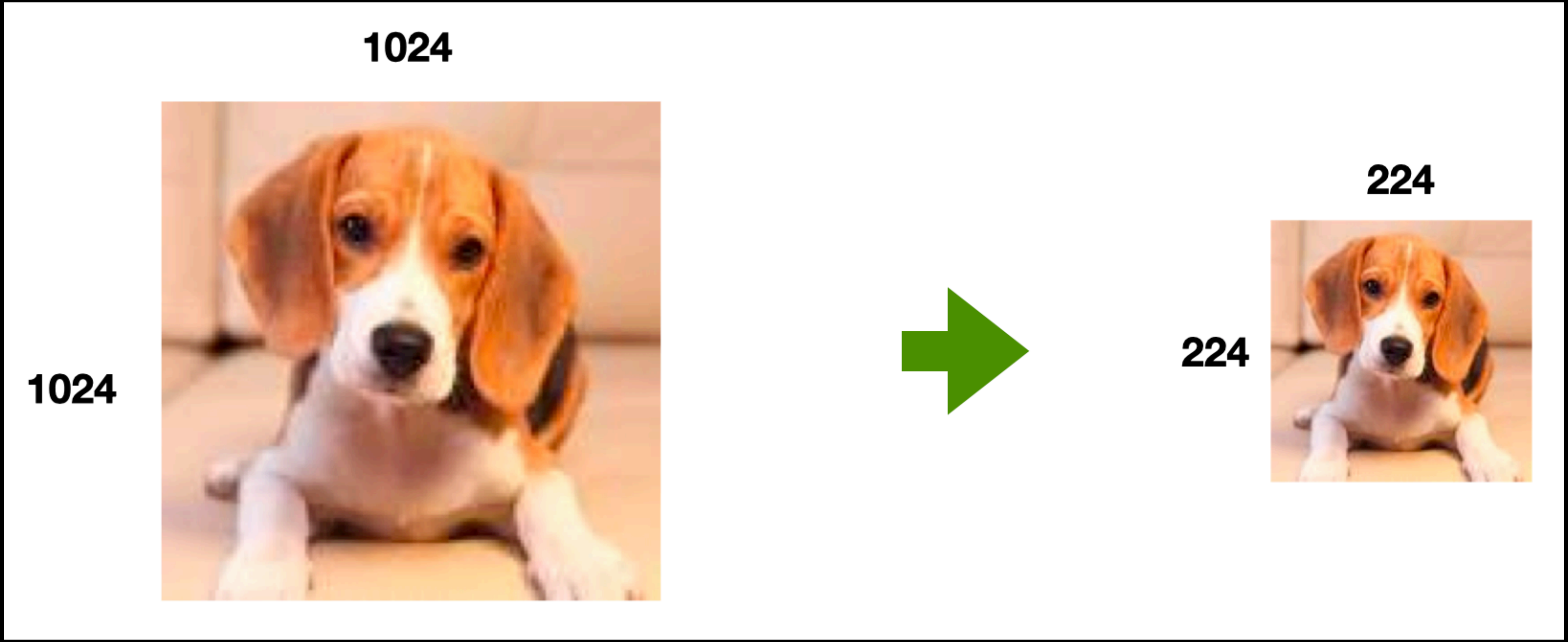
How Computer Vision models work?

Course of dimensionality

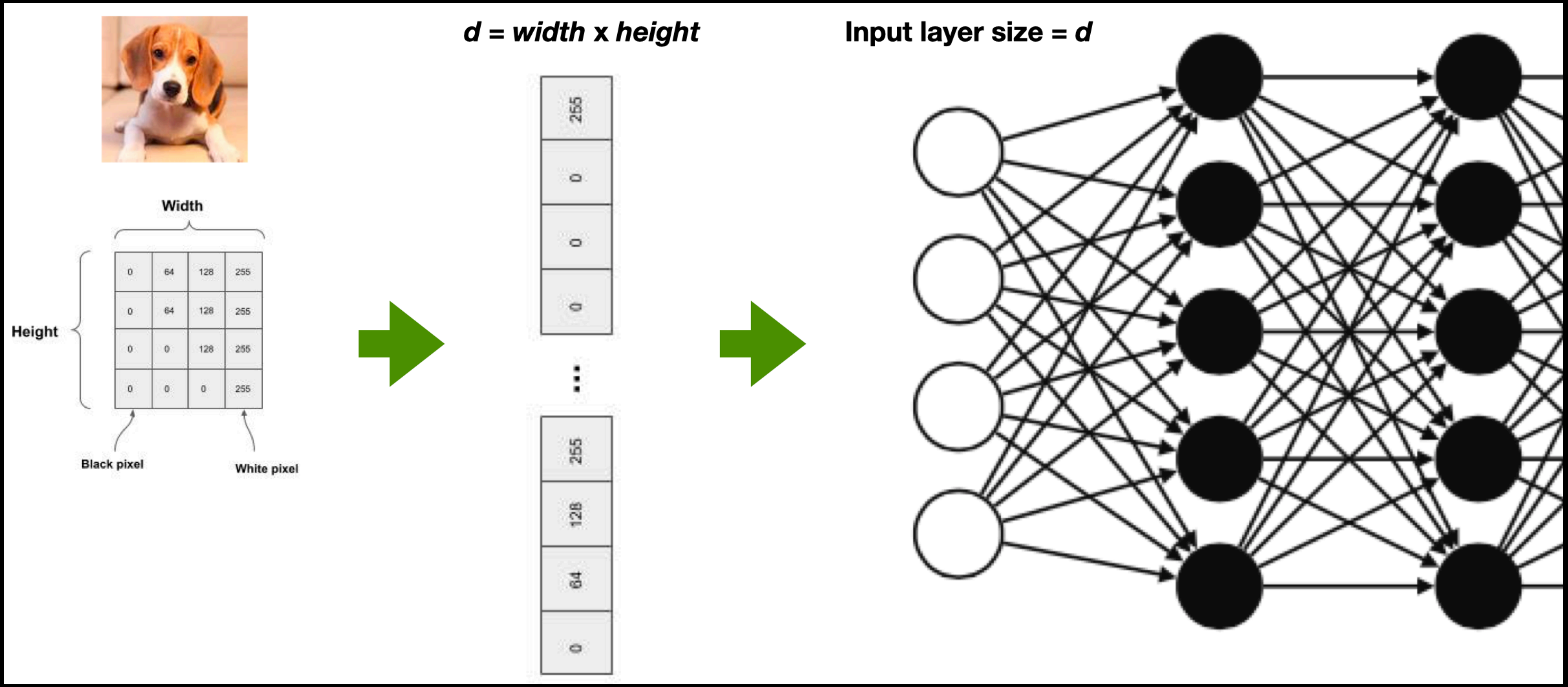
- High dimensionality
  - A 1024×768 image has d = 786432!
  - A tiny 32×32 image has d = 1024
- Decision boundaries in pixel space are extremely complex
- We will need “big” ML models with lots of parameters
  - For example, linear regressors need d parameters



Downsampling



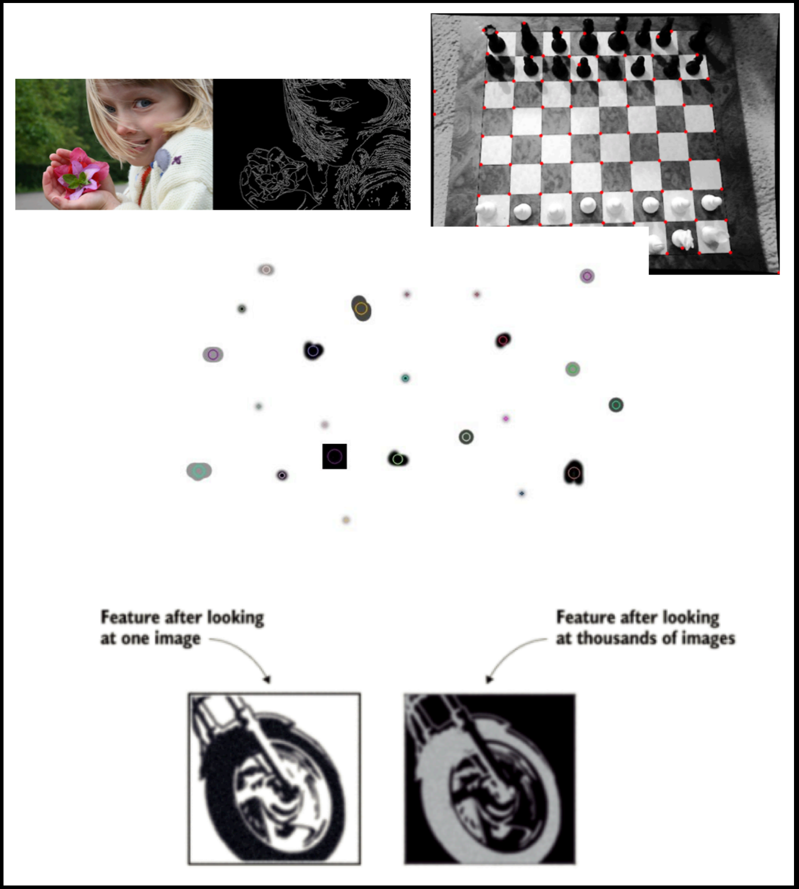
Flattening


Width
Height
0 64 128 255
0 64 128 255
0 0 128 255
0 0 0 255
Black pixel
White pixel
d = width x height
255
0
0
0
...
255
128
64
0
Input layer size = d

The "old days": Feature Extraction

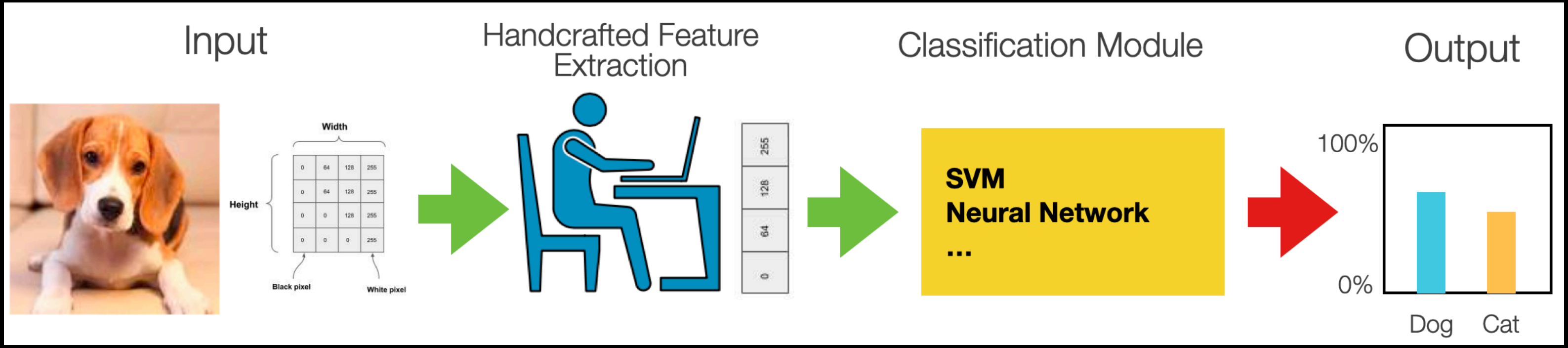
- **Feature**
  - A relevant piece of information about the content of an image

    -e.g., edges, corners, blobs (regions), ridges
- **A good feature**
  - Repeatable
  - Identifiable
  - Can be easily tracked and compared
  - Consistent across different scales, lighting conditions, and viewing angles
  - Visible in noisy images or when only part of an object is visible
  - Can distinguish objects from one another

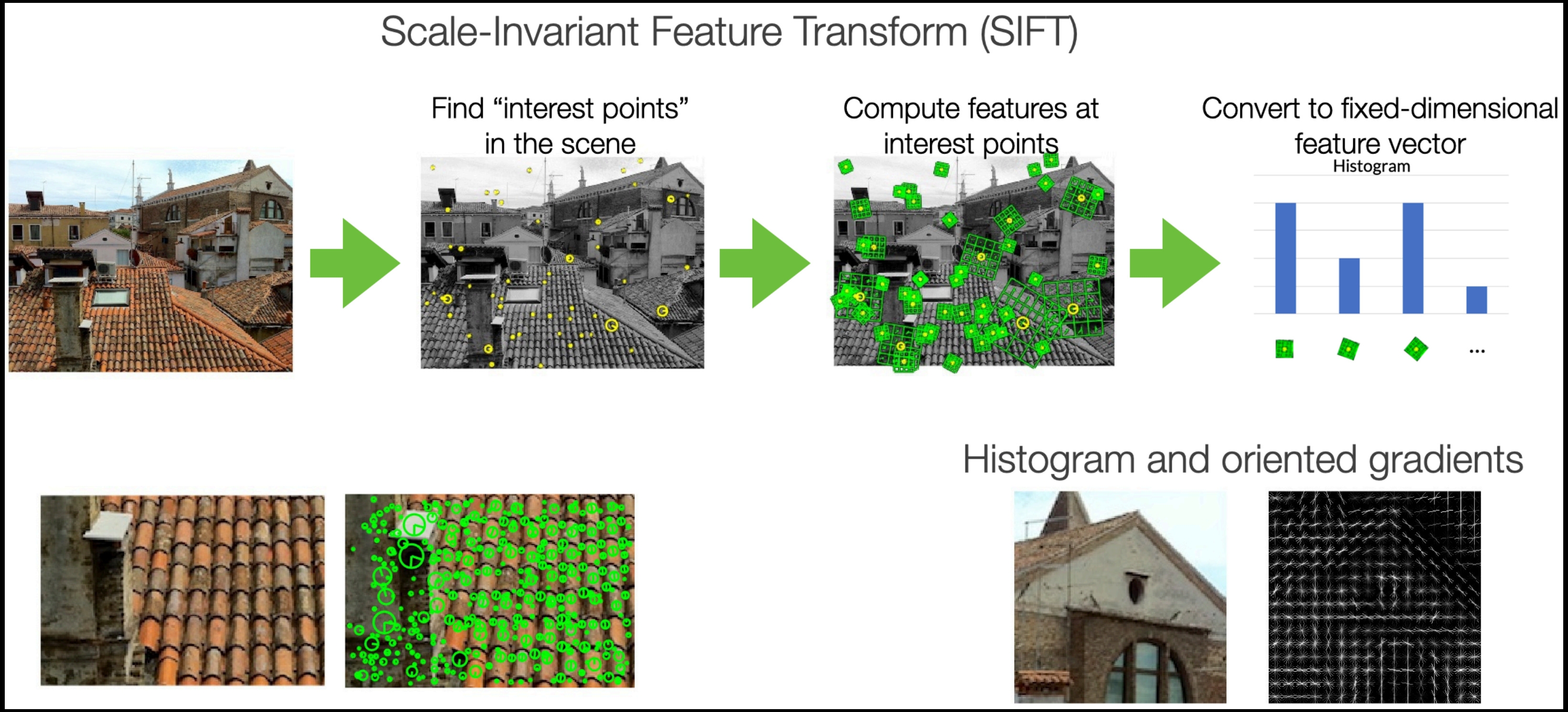

Feature after looking at one image
Feature after looking at thousands of images

The "old days": Feature Engineering

- Machine learning models are only as good as the features you provide
- To figure out which features you should use for a specific problem
- Rely on domain knowledge (or partner with domain experts)
- Experiment to create features that make machine learning algorithms work better

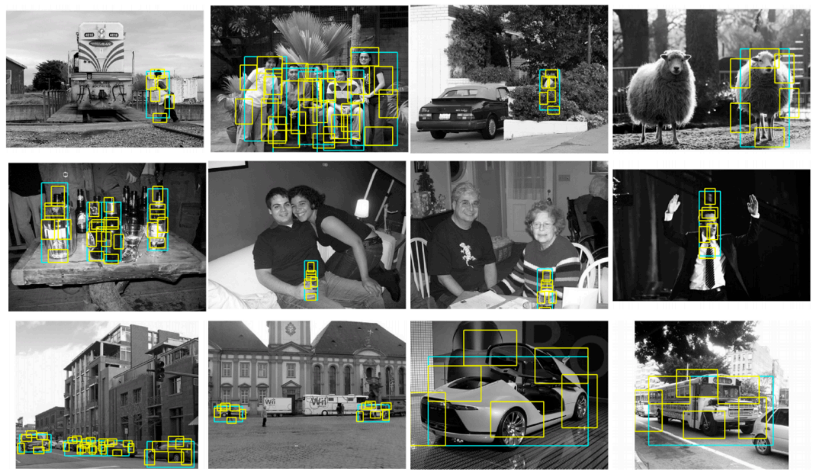


Feature Extraction Techniques


Scale-Invariant Feature Transform (SIFT)
Find “interest points” in the scene
Compute features at interest points
Convert to fixed-dimensional feature vector
Histogram
...
Histogram and oriented gradients

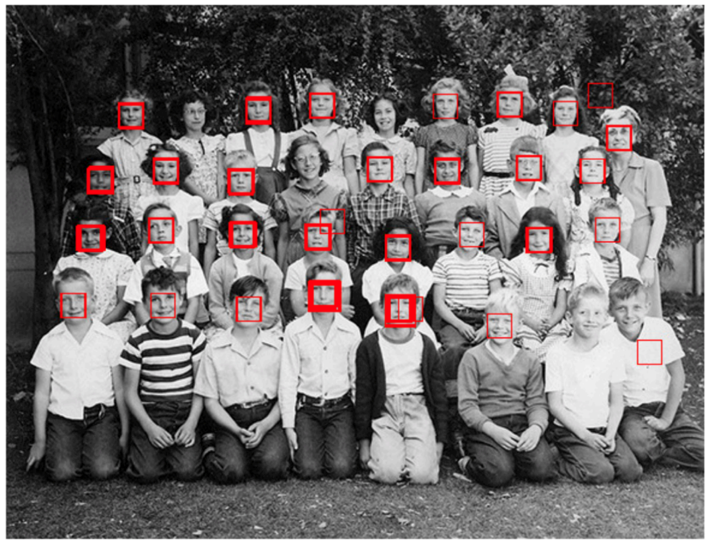
Performance

Object Detection (~2007)



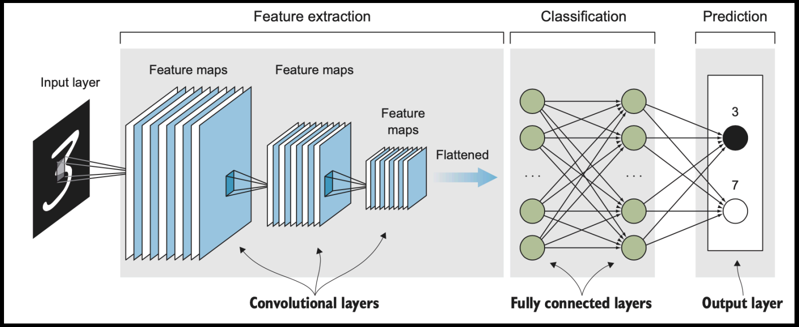
Felzenszwalb, Ramanan, McAllester. A Discriminatively Trained, Multiscale, Deformable Part Model. CVPR 2008 (DPM v1)

Face Detection (~2013)



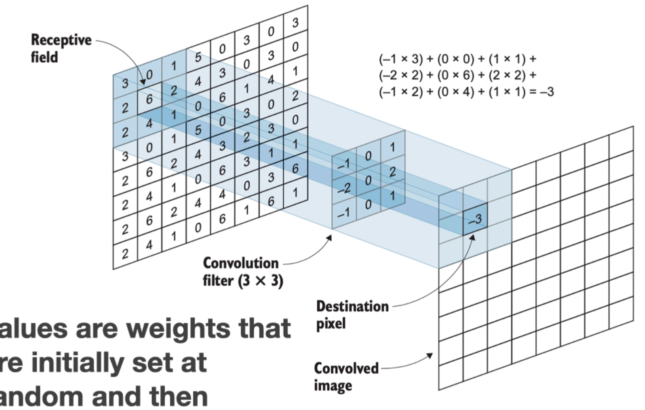
https://github.com/alexdemartos/ViolaAndJones

Convolutional Neural Networks

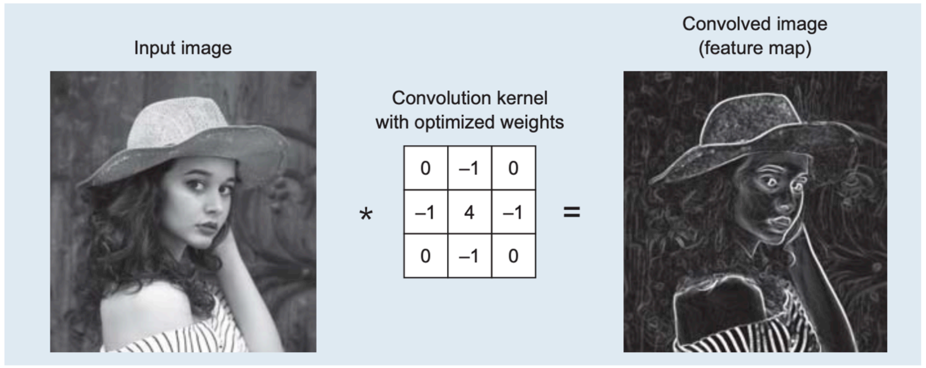


- CNNs exploit image properties to reduce the number of model parameters drastically
- Feature maps
  - Automatically extracted hierarchical
  - Retain spatial association between pixels
- Local interactions
  - all processing happens within tiny image windows
  - within each layer, far-away pixels cannot influence nearby pixels
- Translation invariance
  - a dog is a dog even if its image is shifted by a few pixels

Convolution & Feature Maps

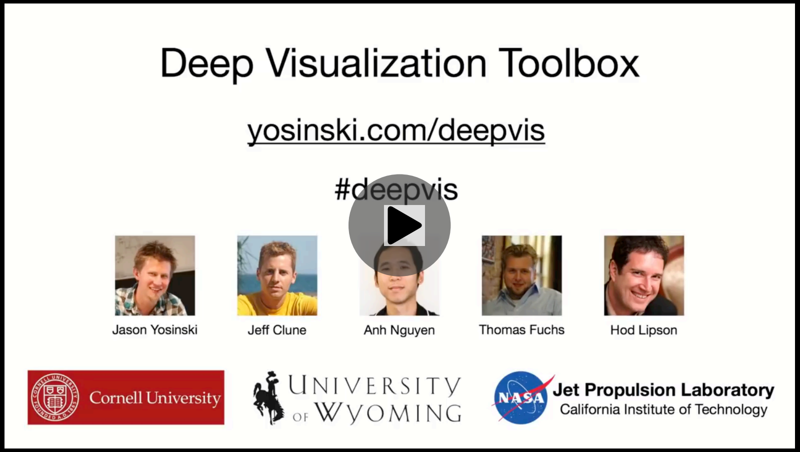


Values are weights that are initially set at random and then learned


Input image
Convolution kernel with optimized weights
0 –1 0
–1 4 –1
0 –1 0
*
=
Convolved image (feature map)

What CNNs learn?

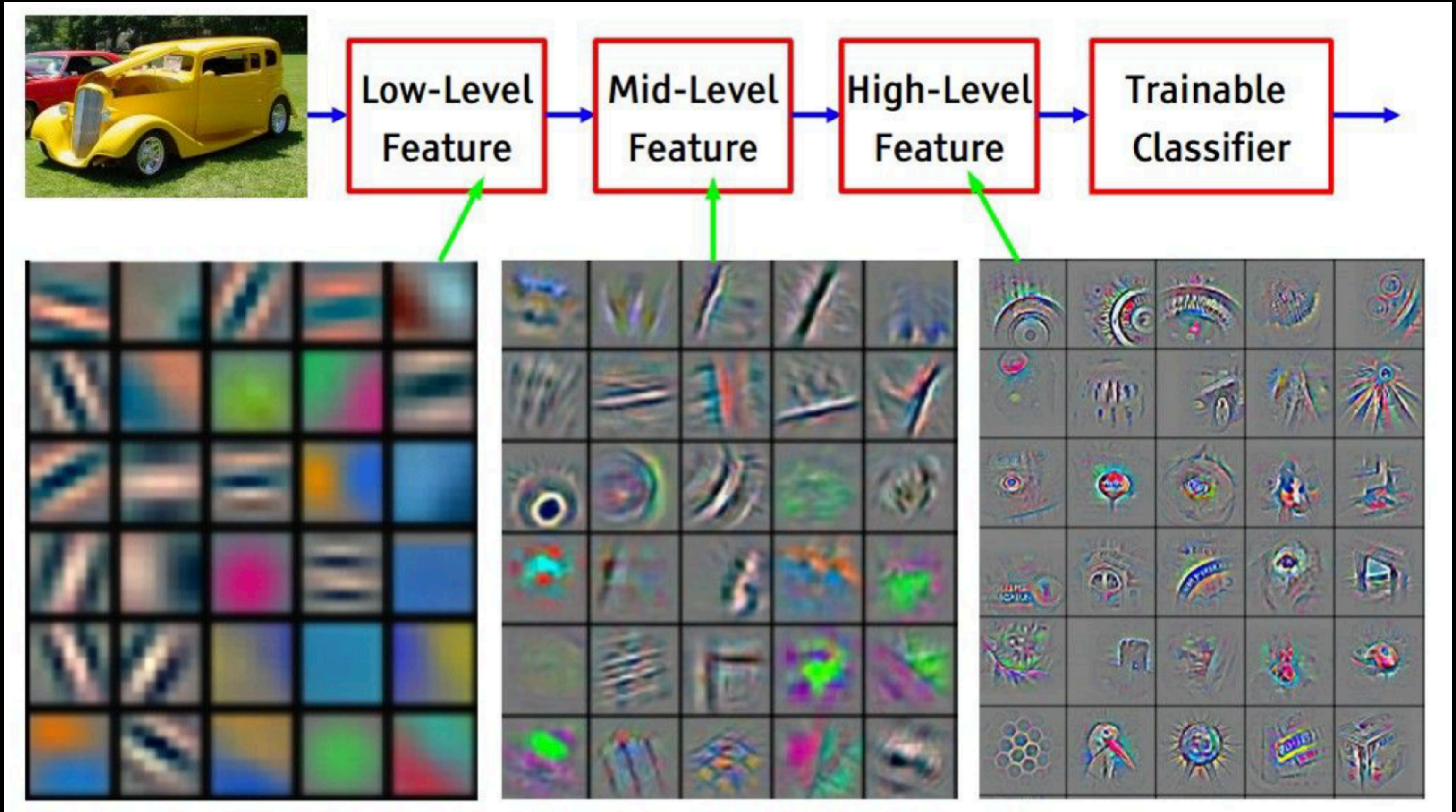
Deep Visualization Toolbox


Deep Visualization Toolbox

yosinski.com/deepvis

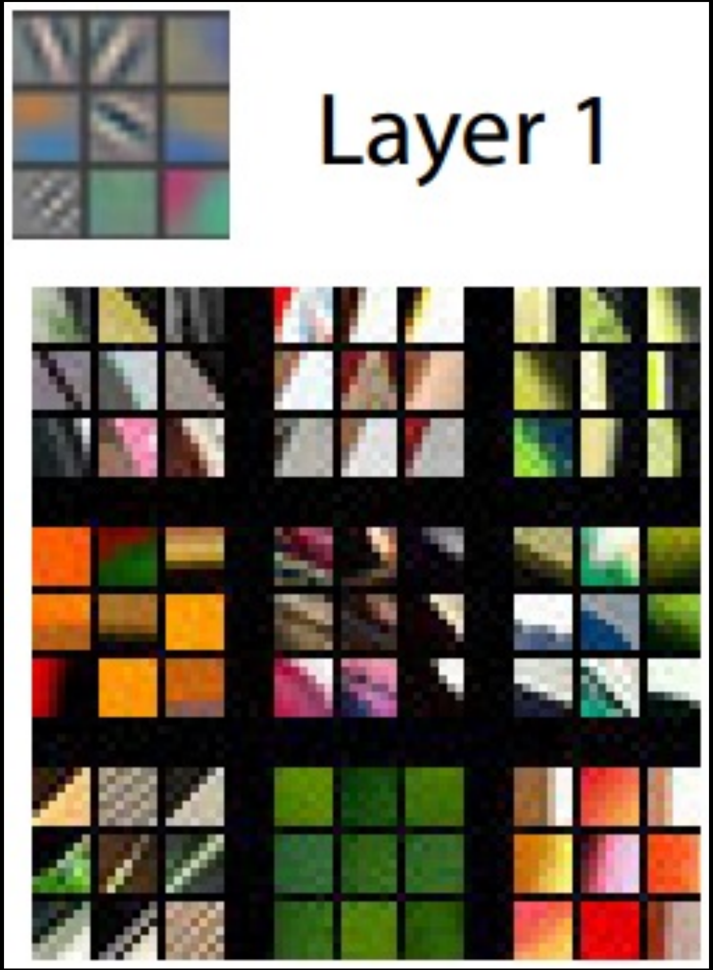
#deepvis

Feature Visualisation

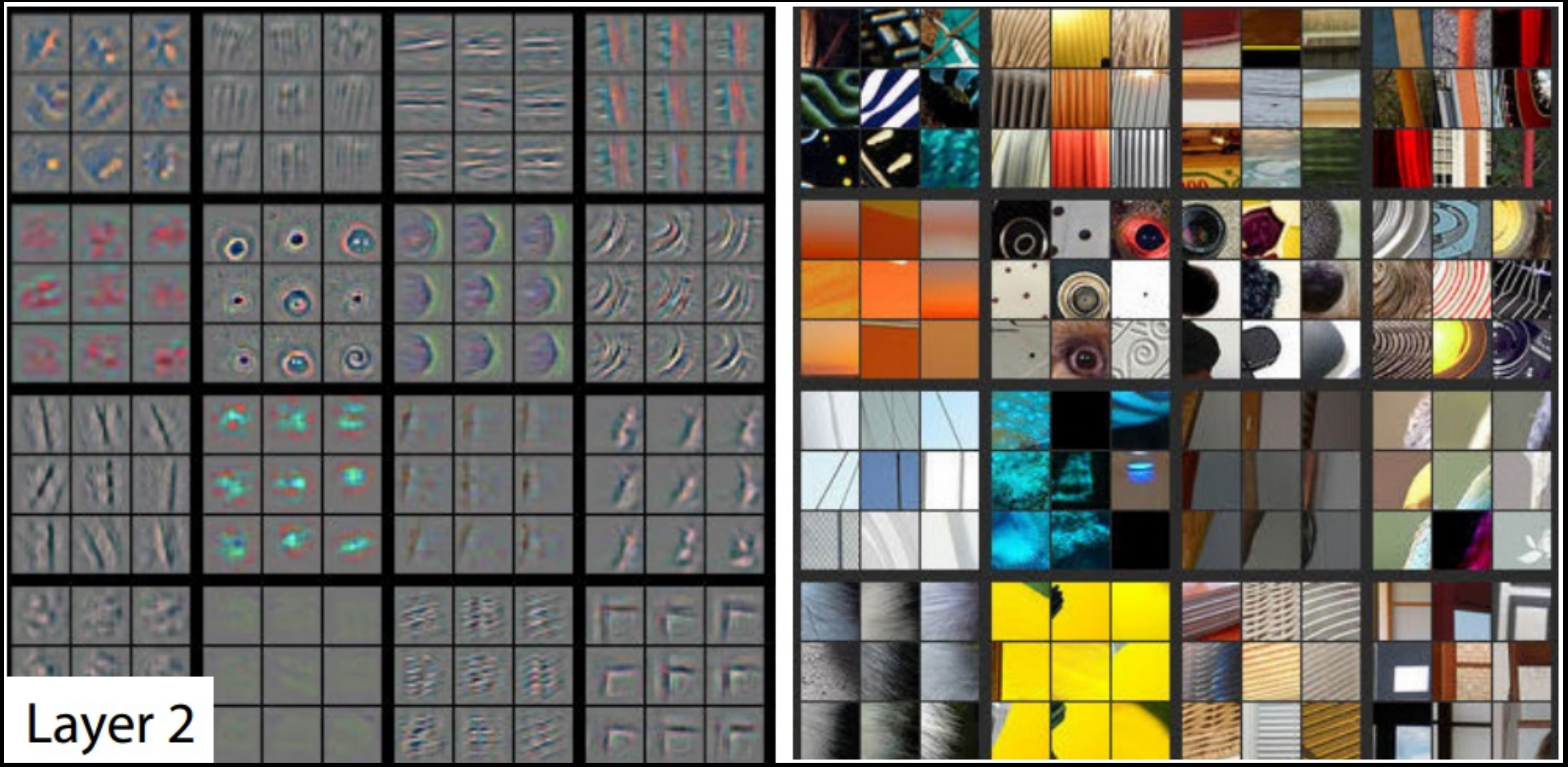


eature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

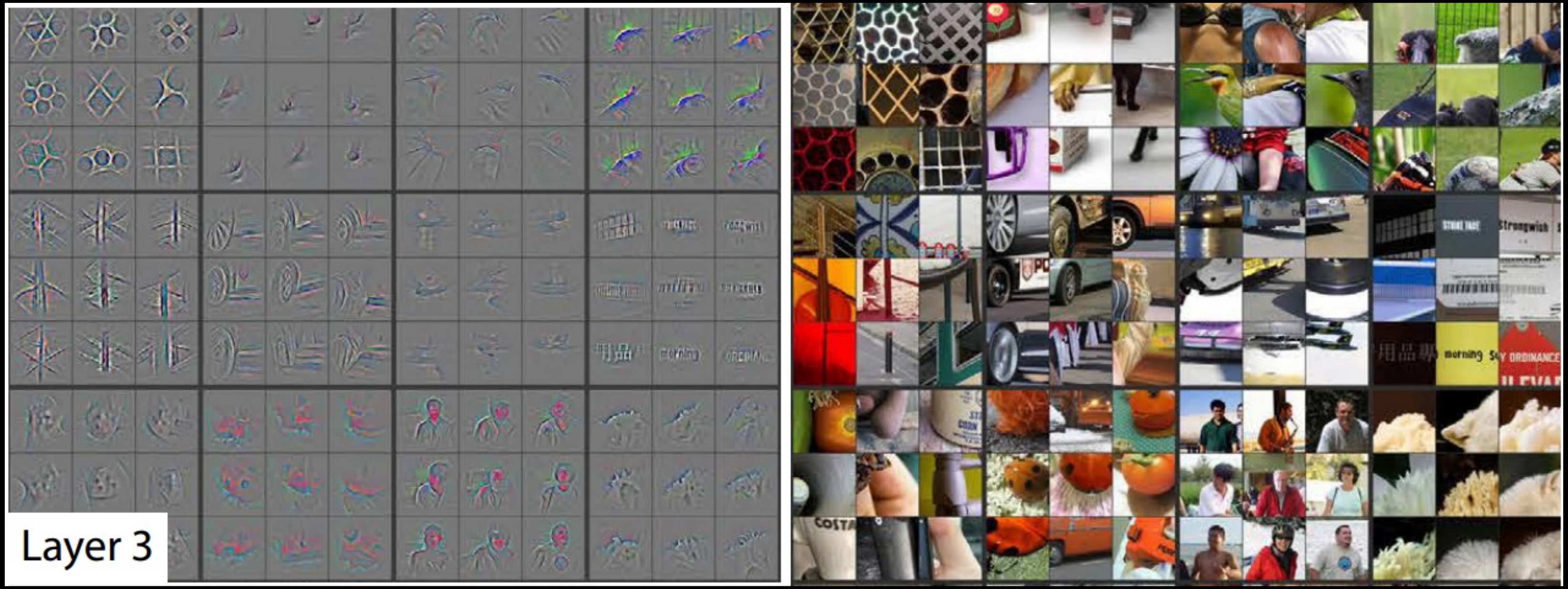
Layer 1



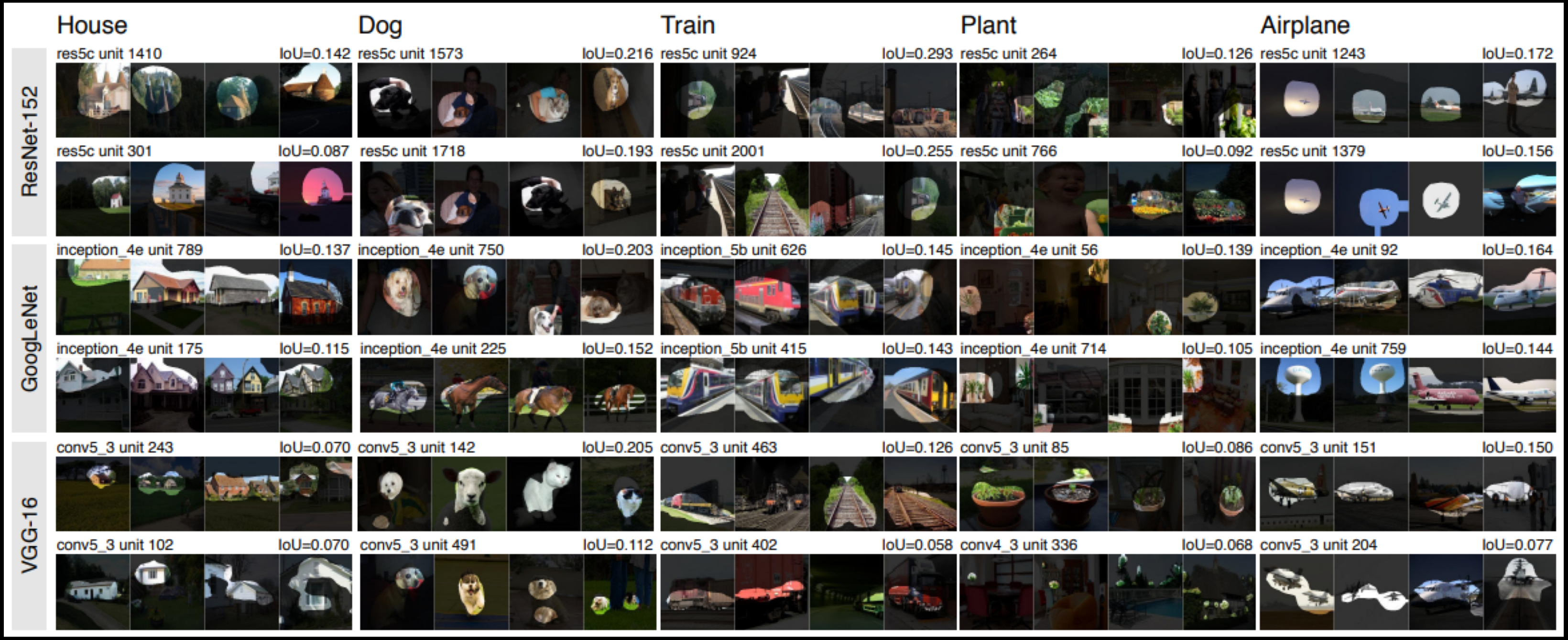
Layer 2



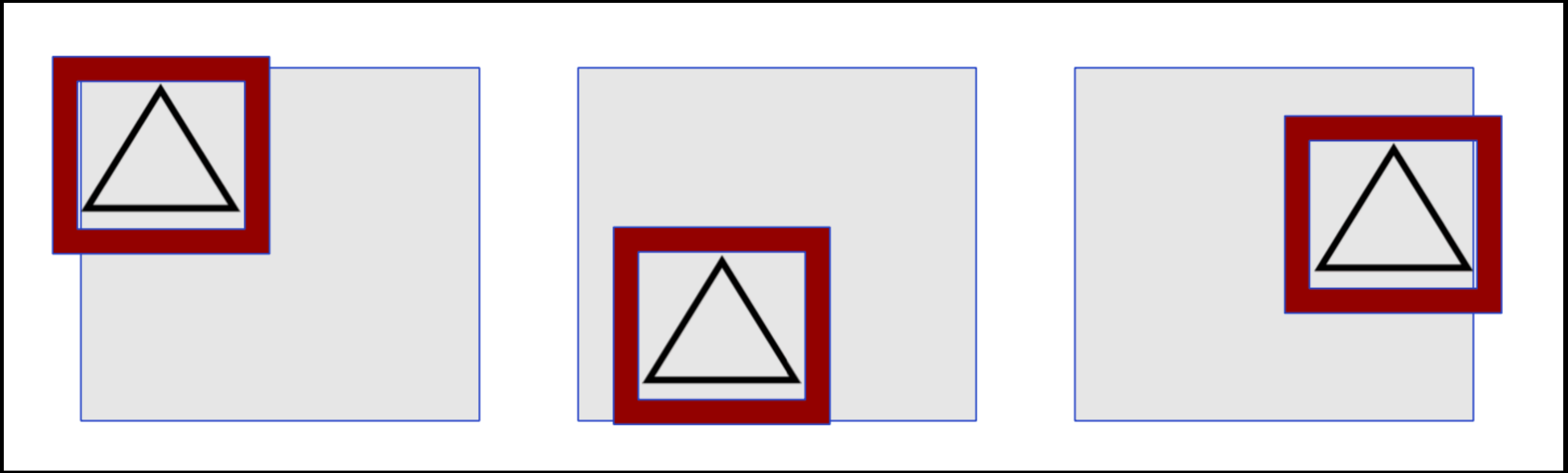
Layer 3



Network Dissection

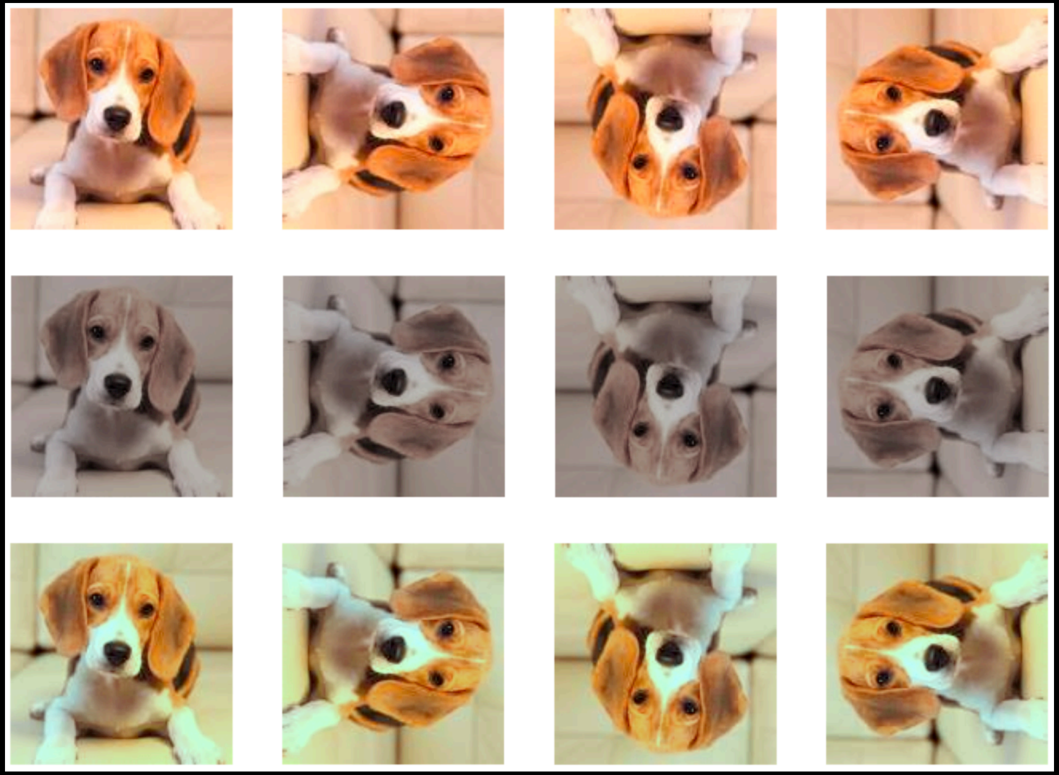

House
Dog
Train
Plant
Airplane
ResNet-152
GoogLeNet
VGG-16
res5c unit 1410 IoU=0.142
res5c unit 1573 IoU=0.216
res5c unit 924 IoU=0.293
res5c unit 264 IoU=0.126
res5c unit 1243 IoU=0.172
res5c unit 301 IoU=0.087
res5c unit 1718 IoU=0.193
res5c unit 2001 IoU=0.255
res5c unit 766 IoU=0.092
res5c unit 1379 IoU=0.156
inception_4e unit 789 IoU=0.137
inception_4e unit 750 IoU=0.203
inception_5b unit 626 IoU=0.145
inception_4e unit 56 IoU=0.139
inception_4e unit 92 IoU=0.164
inception_4e unit 175 IoU=0.115
inception_4e unit 225 IoU=0.152
inception_5b unit 415 IoU=0.143
inception_4e unit 714 IoU=0.105
inception_4e unit 759 IoU=0.144
conv5_3 unit 243 IoU=0.070
conv5_3 unit 142 IoU=0.205
conv5_3 unit 463 IoU=0.126
conv5_3 unit 85 IoU=0.086
conv5_3 unit 151 IoU=0.150
conv5_3 unit 102 IoU=0.070
conv5_3 unit 491 IoU=0.112
conv5_3 unit 402 IoU=0.058
conv4_3 unit 336 IoU=0.068
conv5_3 unit 204 IoU=0.077

Translation Invariance

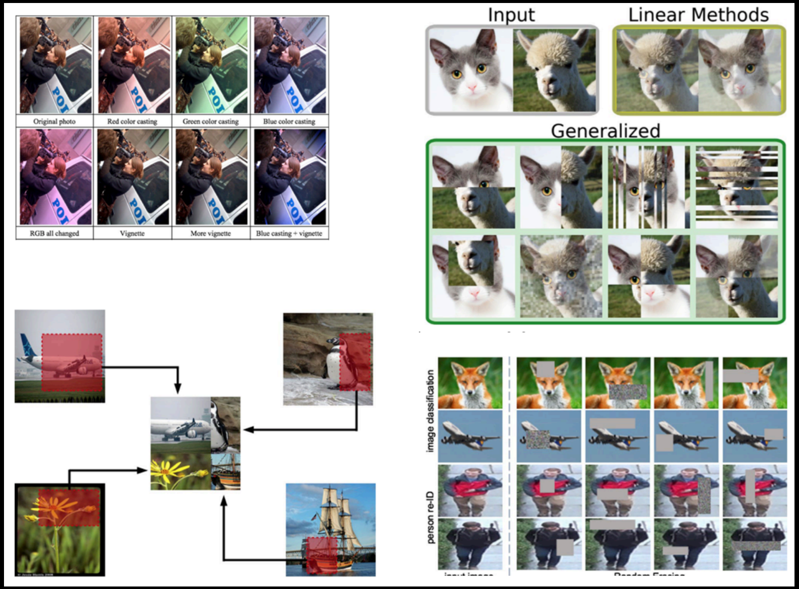


But not rotation and scaling invariance!

What about generalisation?

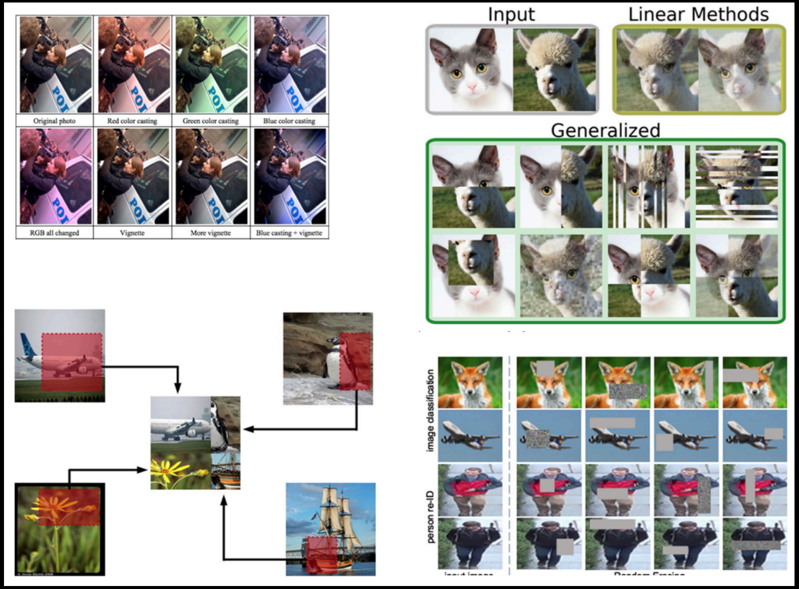


Data Augmentation



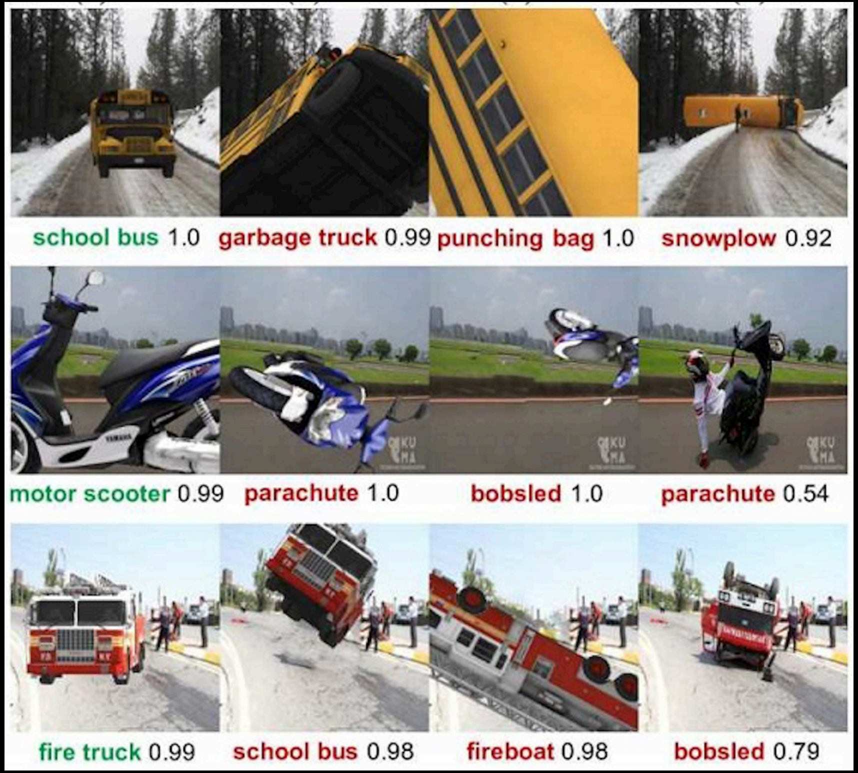
- Generate variations of the input data
  - To improve generalisability (out-of-distribution inputs)
  - Improve invariance (rotation, scaling, distortion)

Data Augmentation

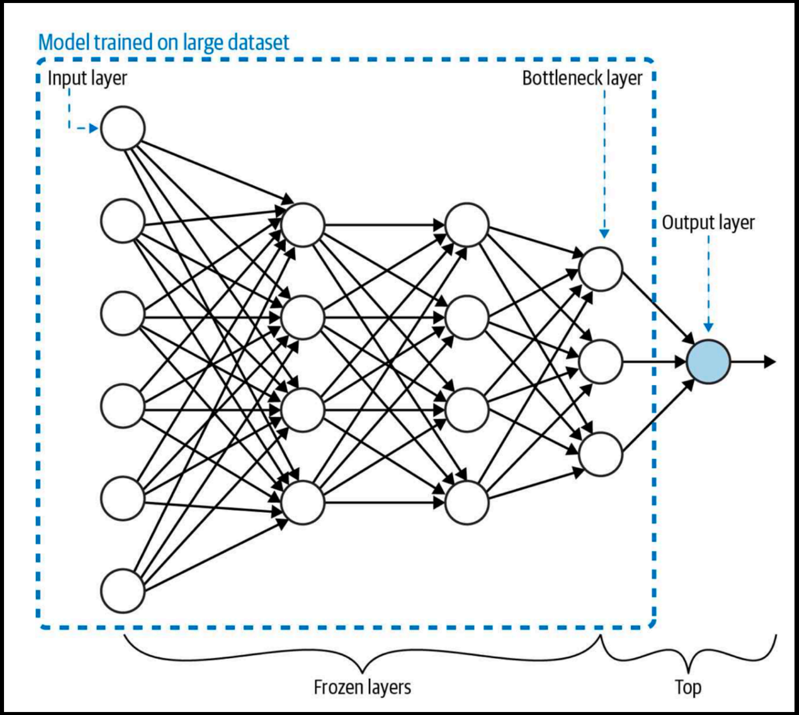


- Geometric
  - Flipping, Cropping, Rotation, Translation,
- Noise Injection
- Color space transformation
- Mixing Images
- Random erasing
- Adversarial training
- GAN-based image generation

Robustness to input variation



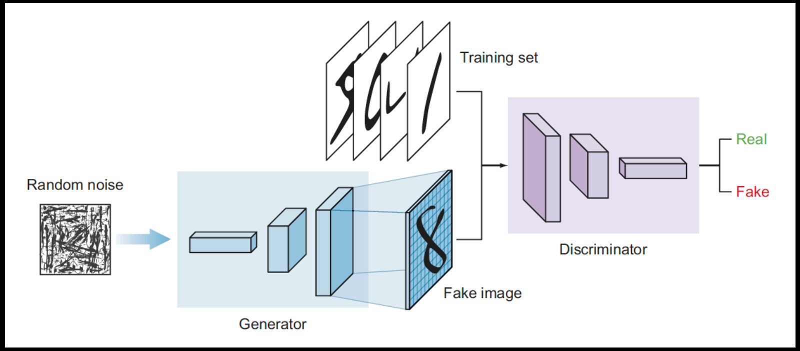
Transfer Learning



- **Problem**: training custom ML models requires huge datasets
- **Transfer learning**: take a model trained on the same data type for a similar task and apply it to a specialised task using our custom data.
  - **Same data**: same data modality. same types of images (e.g., professional pictures vs. Social media pictures)
  - **Similar tasks**: if you need a new object classification model, use a model pre-trained for object classification

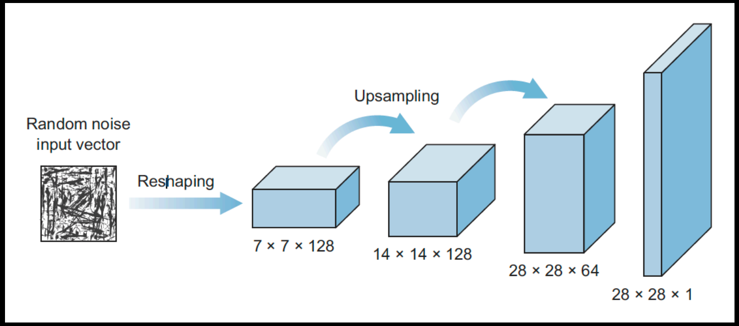
Advanced Computer Vision Techniques

Generative Adversarial Networks



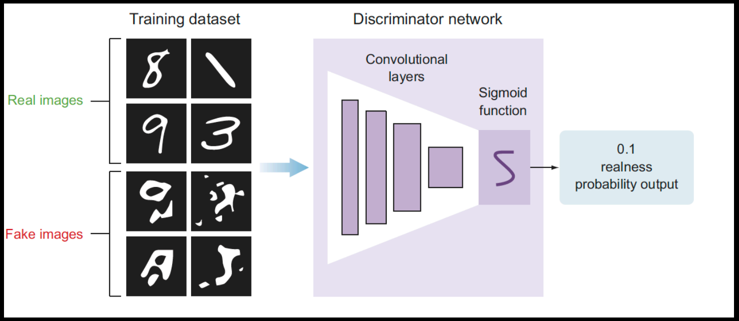
- Learn patterns from the training dataset and create new images that have a similar distribution of the training set
- Two deep neural networks that compete with each other
  - The **generator** tries to convert random noise into observations that look as if they have been sampled from the original dataset
  - The **discriminator** tries to predict whether an observation comes from the original dataset or is one of the generator's forgeries

- The **generator**’s architecture looks like an inverted CNN that starts with a narrow input and is upsampled a few times until it reaches the desired size

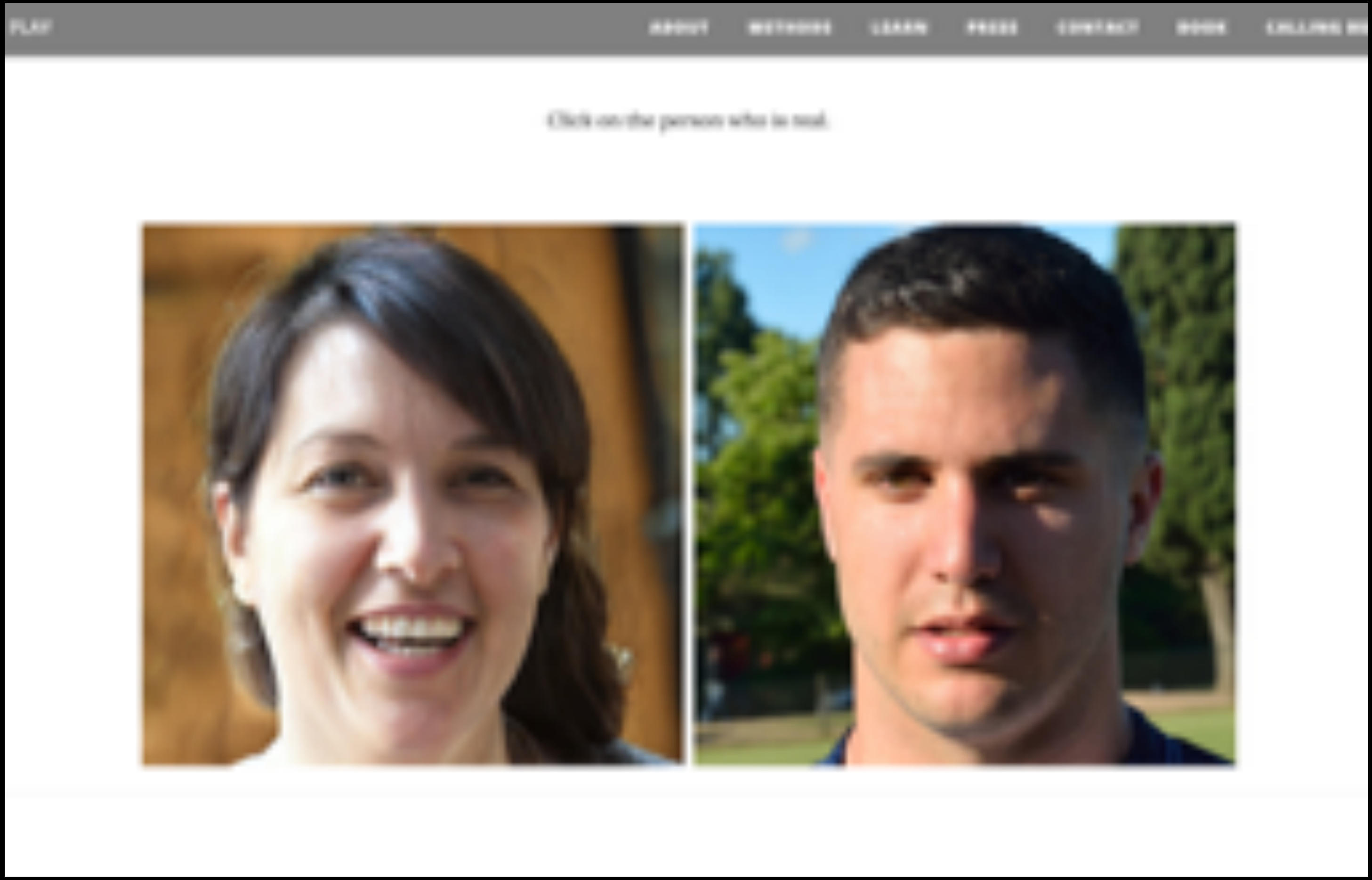


- The **discriminator**

  ’s model is a typical classification neural network that aims to classify images generated by the generator as real or fake

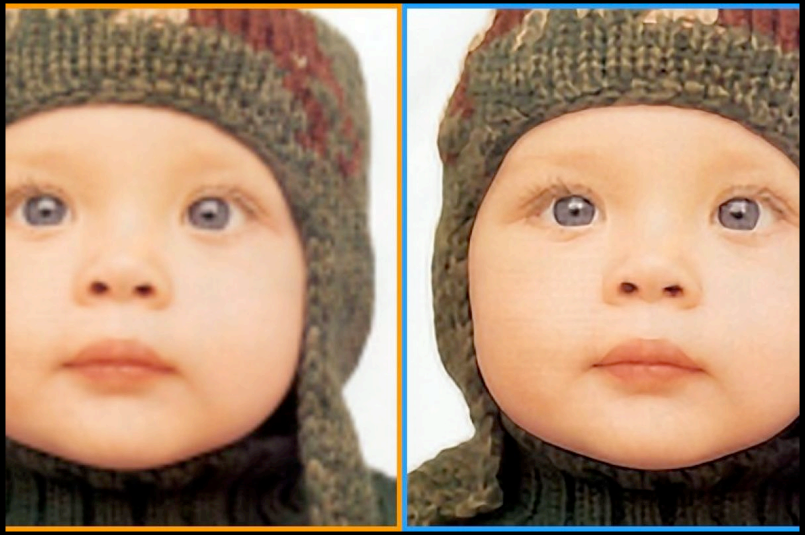


Which face is real?

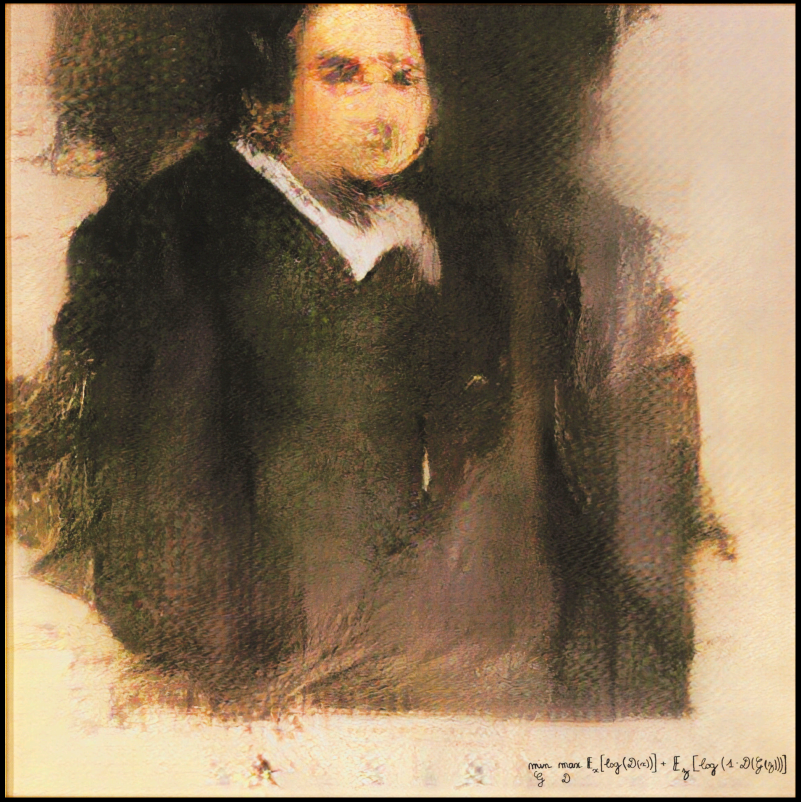


Click on the person who is real.

Image super-resolution GAN

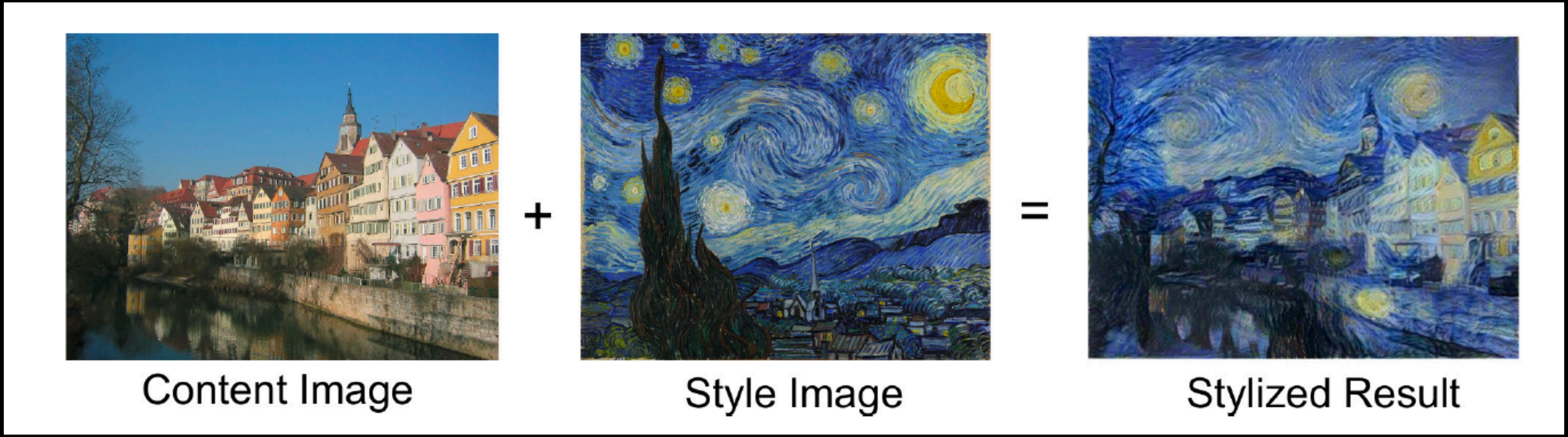


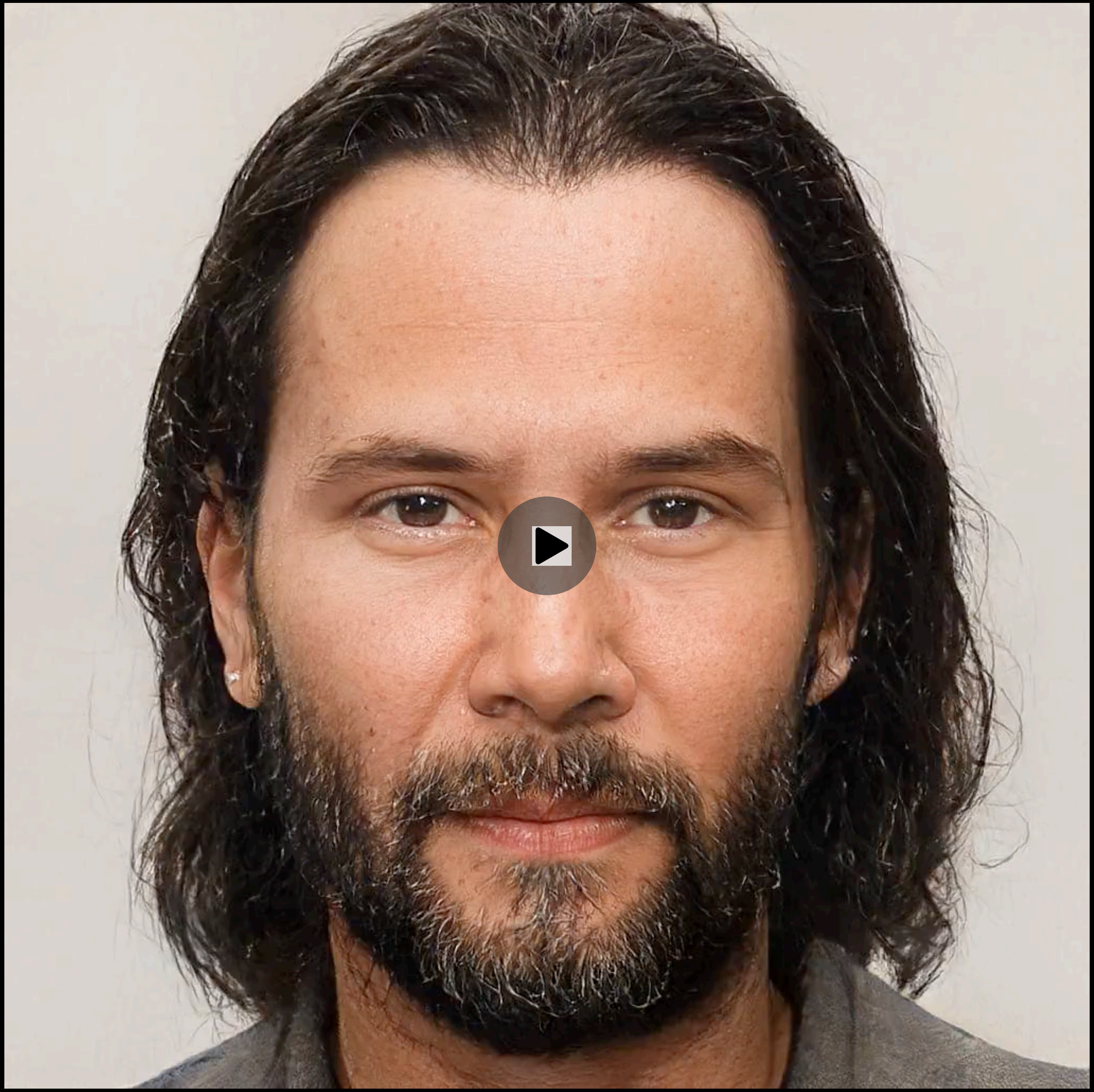
– A good technical summary


$\min_{\mathcal{G}} \max_{\mathcal{D}} \mathbb{E}_x[\log(\mathcal{D}(x))] + \mathbb{E}_z[\log(1-\mathcal{D}(\mathcal{G}(z)))]$

- ML-generated painting sold for $432,500
- The network trained on a dataset of 15,000 portraits painted between the fourteenth and twentieth centuries
- Network “learned” the style and generated a new painting

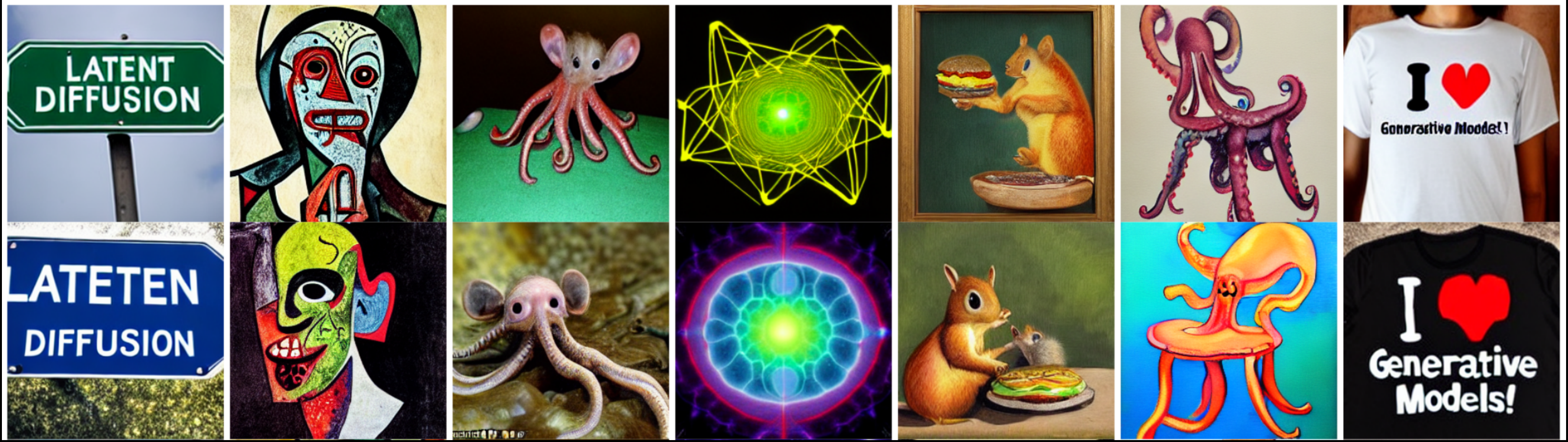
Neural Style Transfer





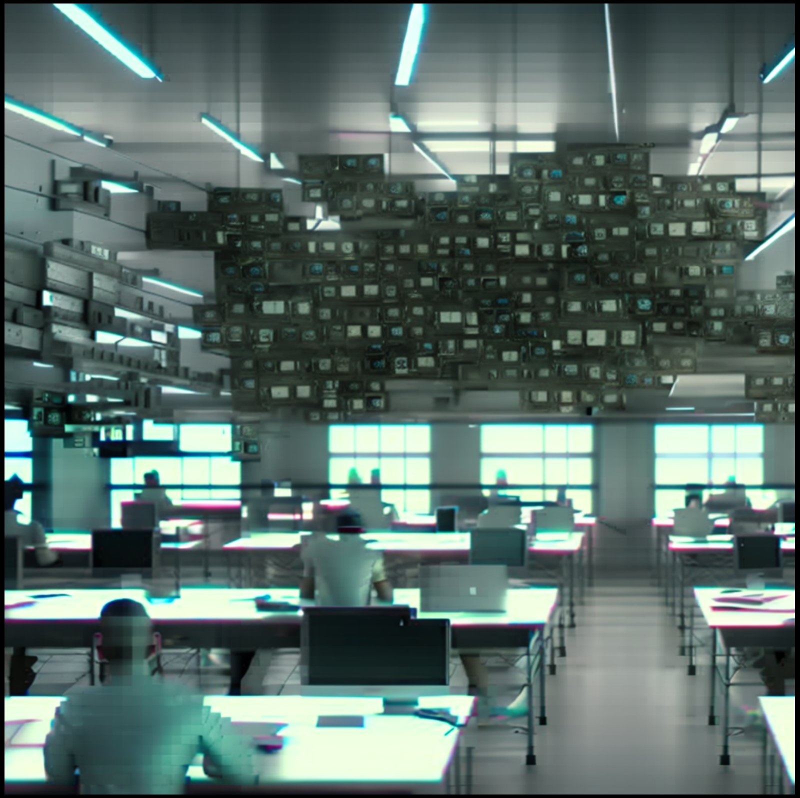
Text-To-Image Generation

’A street sign that reads “Latent Diffusion” ’	’A zombie in the style of Picasso’	’An image of an animal half mouse half octopus’	’An illustration of a slightly conscious neural network’	’A painting of a squirrel eating a burger’	’A watercolor painting of a chair that looks like an octopus’	’A shirt with the inscription: “I love generative models!” ’



Design

Computer Science



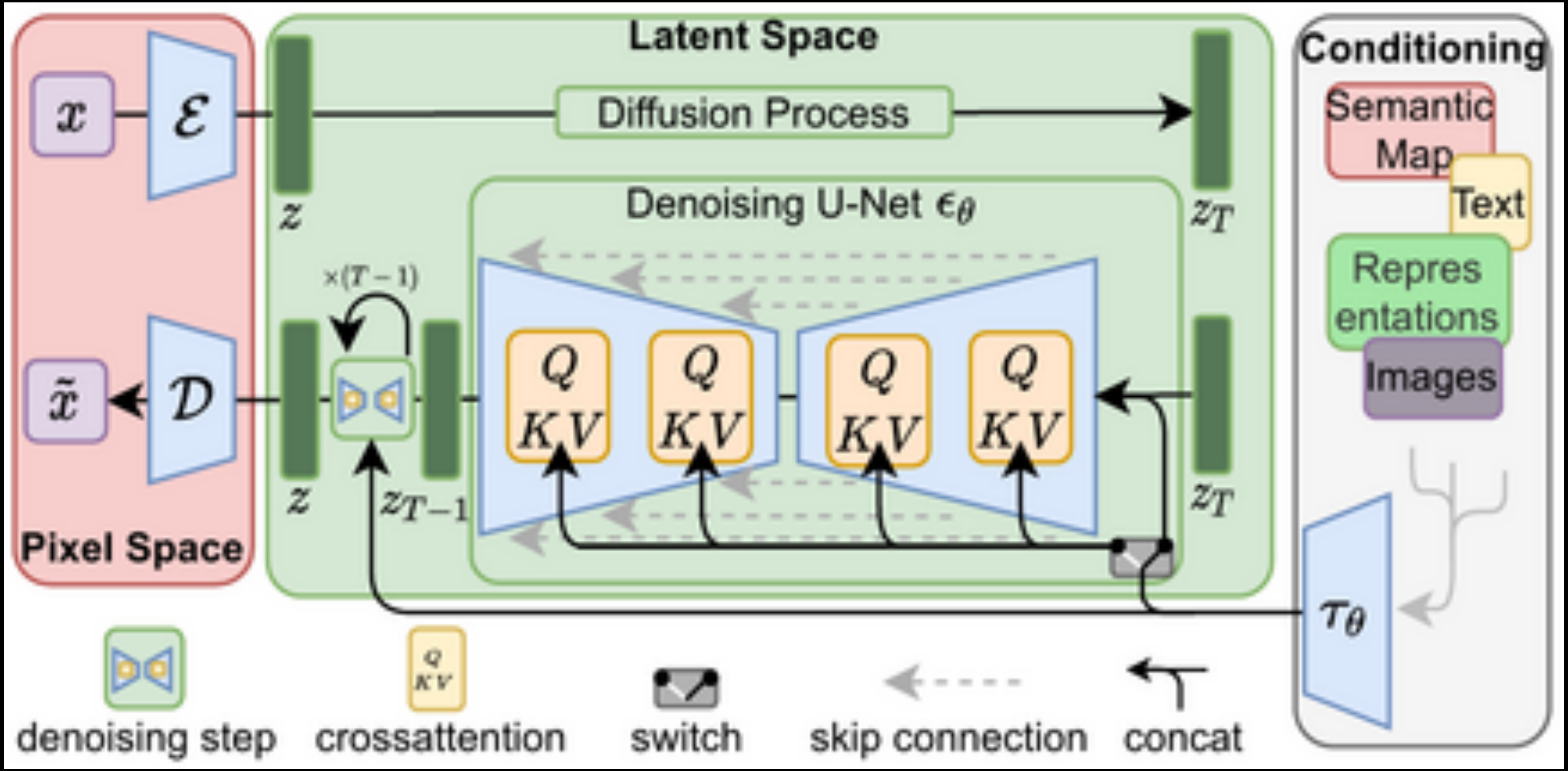
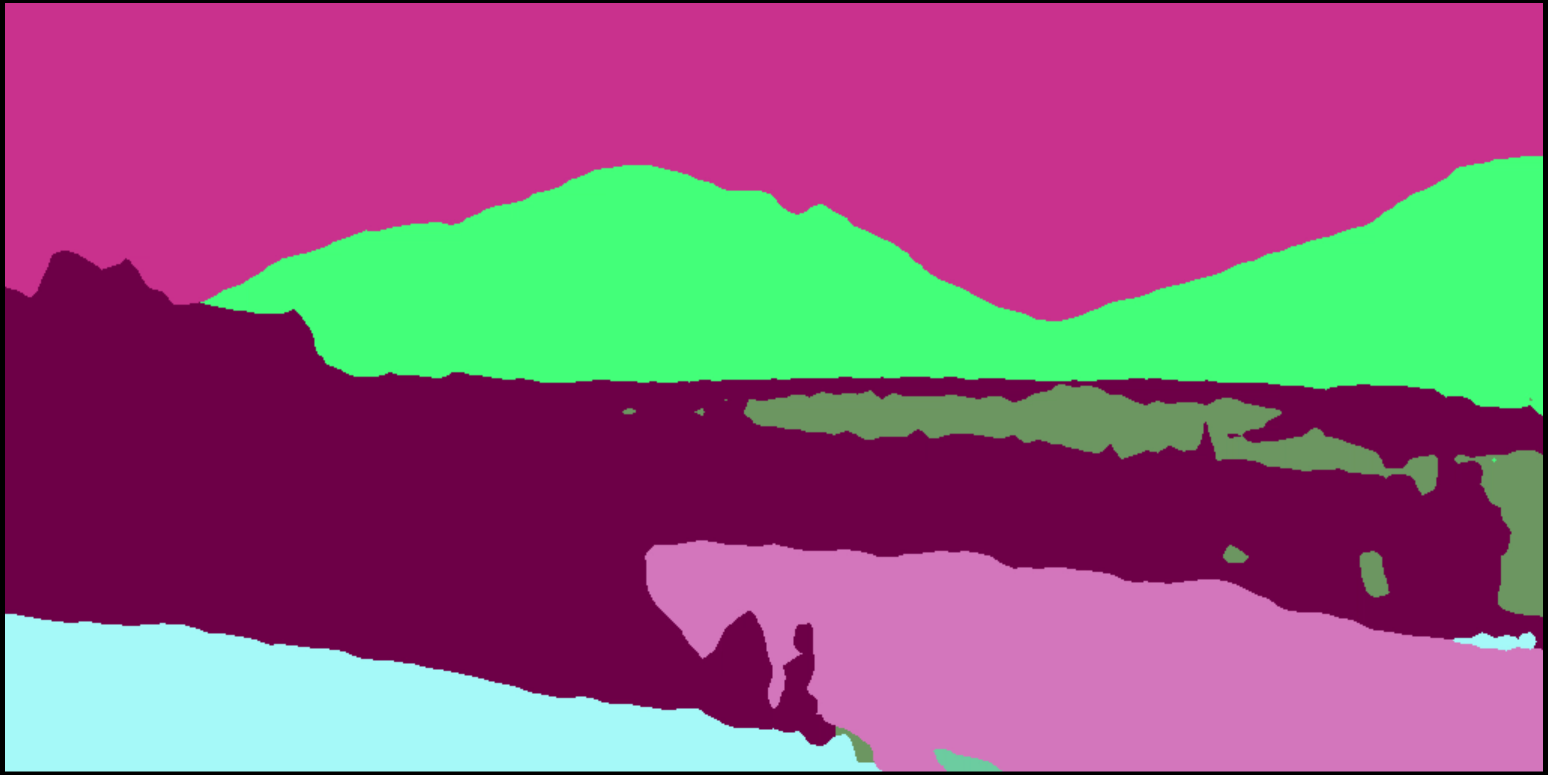
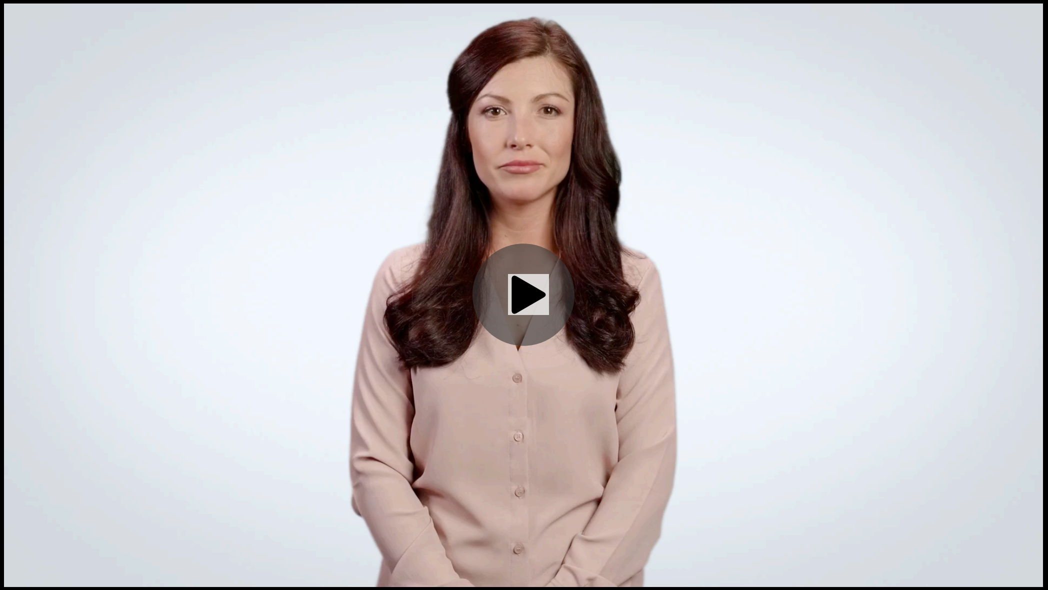

Latent Space
Pixel Space
Conditioning
x
$\mathcal{E}$
z
Diffusion Process
z_T
Semantic Map
Text
Repres entations
Images
Denoising U-Net ϵ_θ
$\times(T-1)$
$\tilde{x}$
$\mathcal{D}$
z
z_{T-1}
Q K V
z_T
τ_θ
denoising step
crossattention
switch
skip connection
concat

Image-to-Image Generation



Synthetic Video Generation



Generated from Synthesia.io

Deep Fakes

Very realistic Tom Cruise Deepfake

Machine Learning for Design

Lecture 4

Machine Learning for Images. *Part 2*

Credits

CMU Computer Vision course - Matthew O'Toole.

Grokking Machine Learning. Luis G. Serrano. Manning, 2021

[CIS 419/519 Applied Machine Learning]. Eric Eaton, Dinesh Jayaraman.

Deep Learning Patterns and Practices - Andrew Ferlitsch, Maanning, 2021

Machine Learning Design Patterns - Lakshmanan, Robinson, Munn, 2020

Deep Learning for Vision Systems. Mohamed Elgendy. Manning, 2020