Deep Learning for Vision & Language

Computer Vision I: The Convolutional Operator, Image Filtering and Convolutional Neural Networks

RICE UNIVERSITY

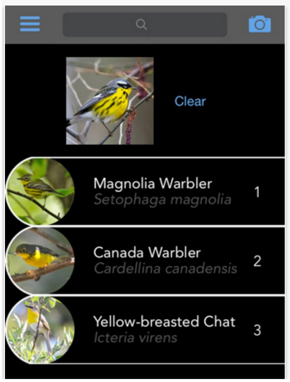
Assignment 1

- Assignment 1 is released and is available on the class website and to be submitted via Canvas.

- Due: Monday January 29th, midnight (you can and should submit early but not late – do not wait until finishing the whole assignment to have a version uploaded on canvas) kaggle

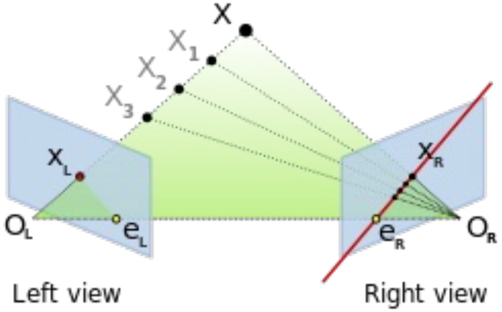
Create an algorithm to distinguish dogs from cats

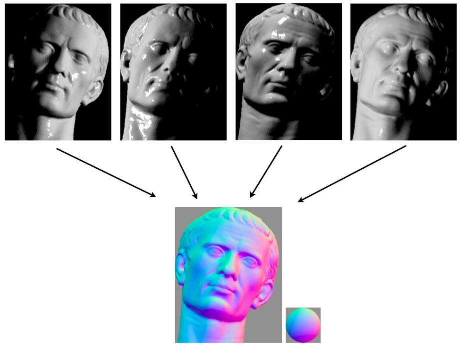
Birdsnap

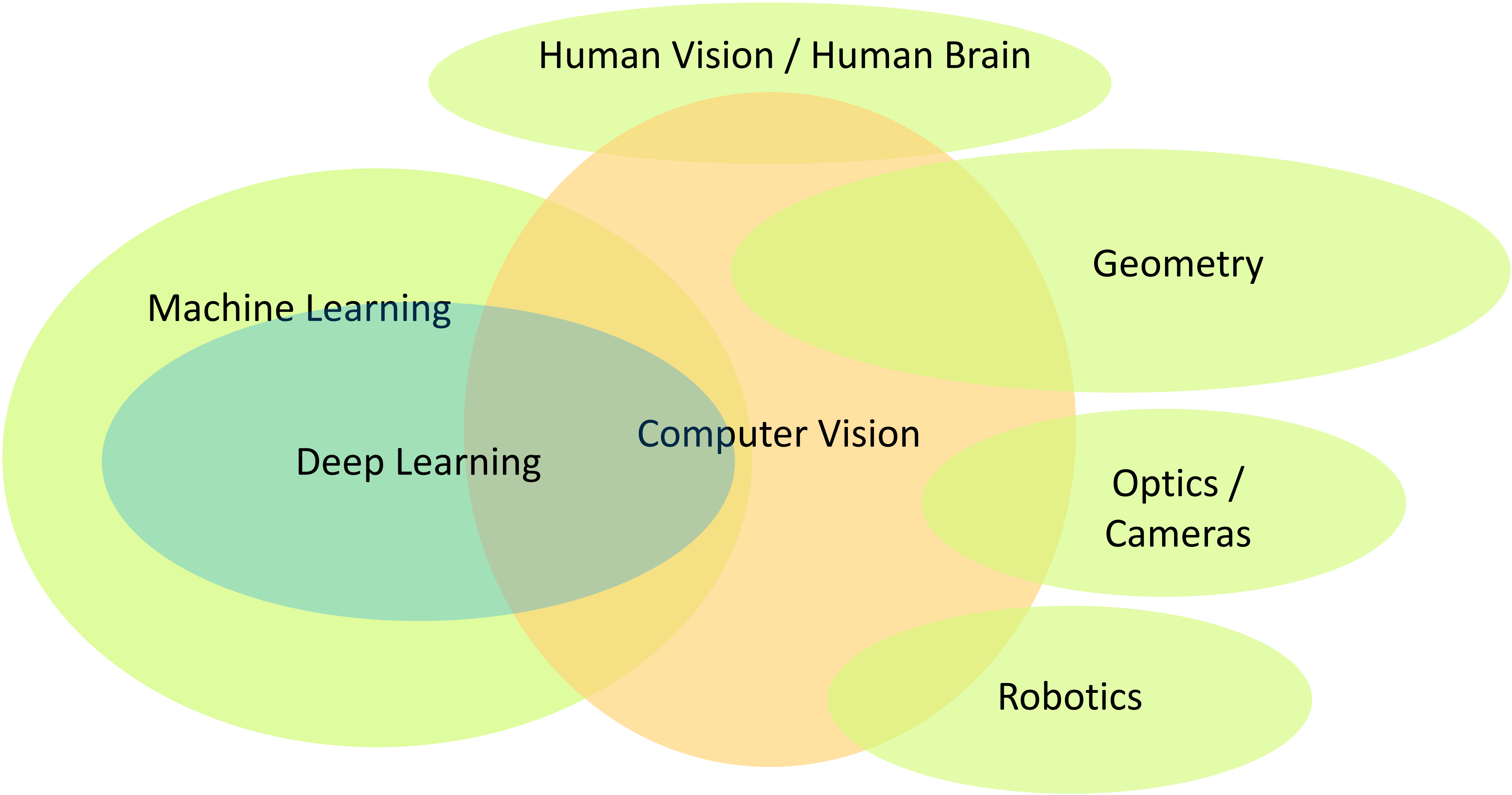


Face Detection in Cameras

Computer Vision

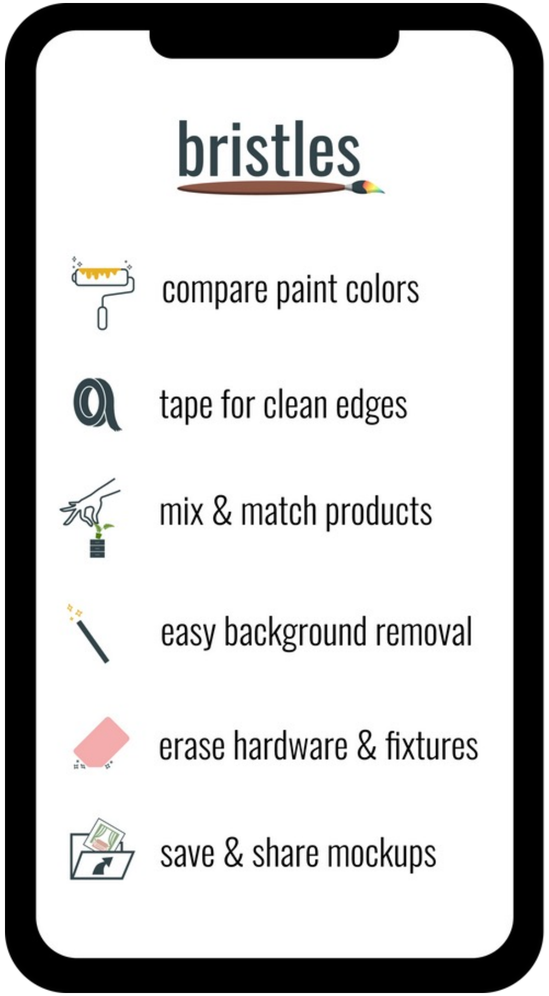


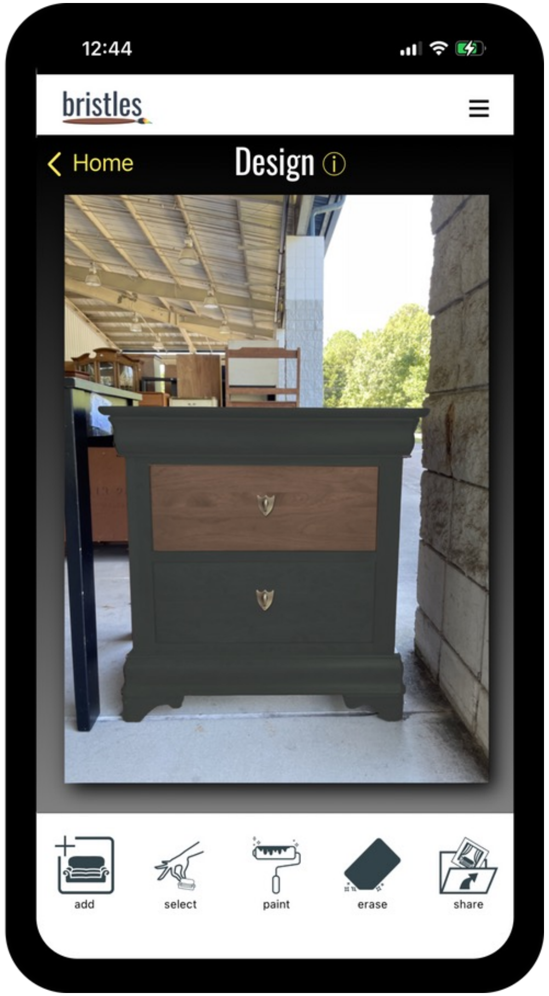



Human Vision / Human Brain
Geometry
Machine Learning
Computer Vision
Deep Learning
Optics /
Cameras
Robotics

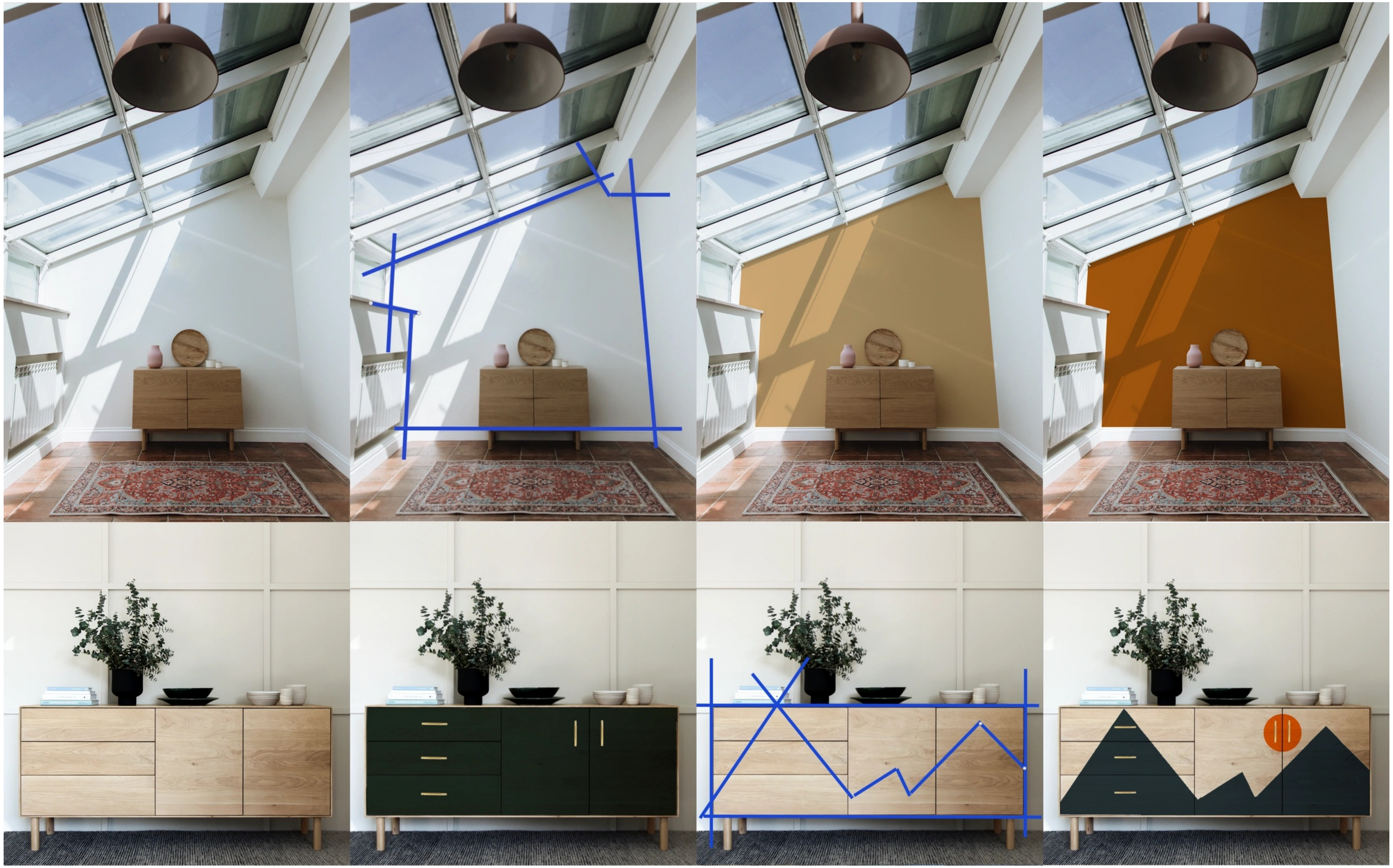
Who is using Computer Vision?

- Facebook – Oculus VR, Image Search, Image tagging, Content filtering, Instagram, etc.
- Google/Alphabet – Waymo, DeepMind, Image Search, Google Earth/Maps, Street View, Google Photos, etc.
- Adobe – Photoshop, Premiere, Lightroom, etc.
- Snap Inc – Snapchat, Smart Goggles, Filters, Face Detection, Style Transfer, etc.
- eBay Inc – Product Search, Product Matching, Content Filtering, Duplicate Removal, etc.
- Amazon – Warehouse robotics, Smart Stores, Product Search.
- IBM – Image Retrieval, Medical Applications, Product Quality.
- Microsoft – Hololens, Optical Character Recognition (OCR), Face Detection, Cloud Services.
- Apple – Face Verification, Enhanced cameras and chips for image processing.



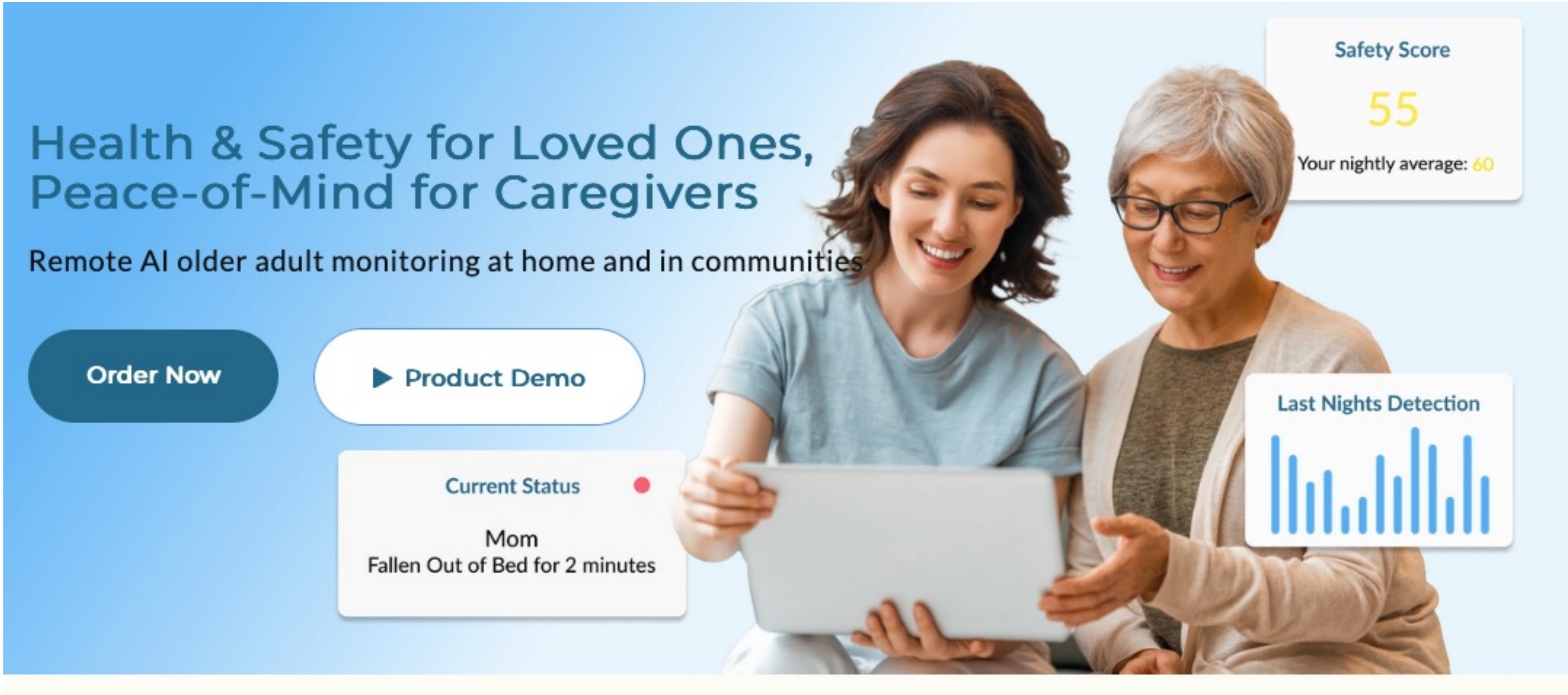


https://bristles.ai/



https://bristles.ai/

MercuryAlert



https://www.mercuryalert.ai/

PHIAR

Phiar.ai (now part of Google)

Images

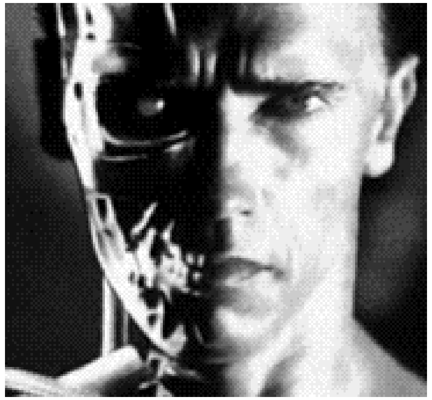
- Can be viewed as a matrix with pixel values

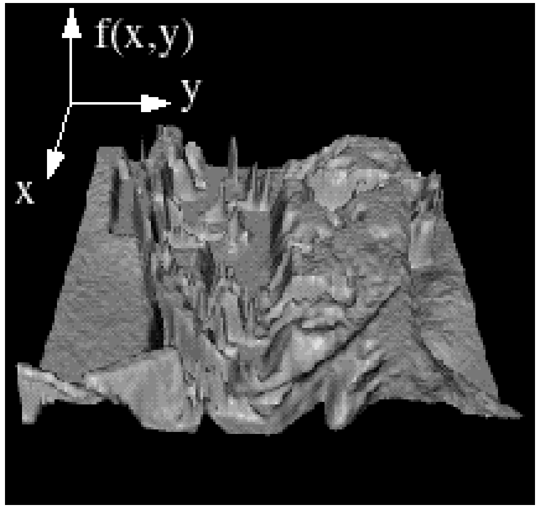
0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0

Images

- Or as a function in a 2D domain

$$z = f(x, y)$$

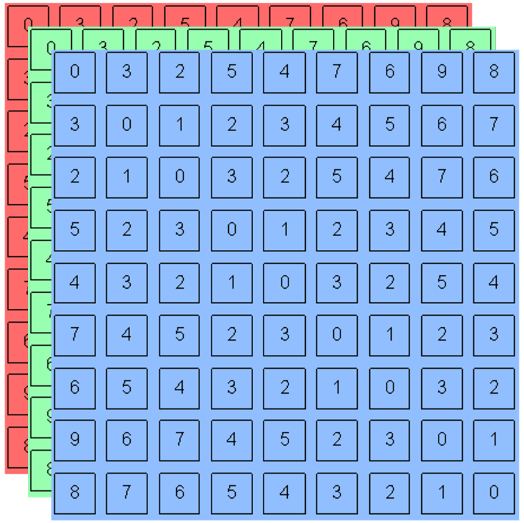




Color Images

- Can be viewed as tensors (3-dimensional arrays)

T =

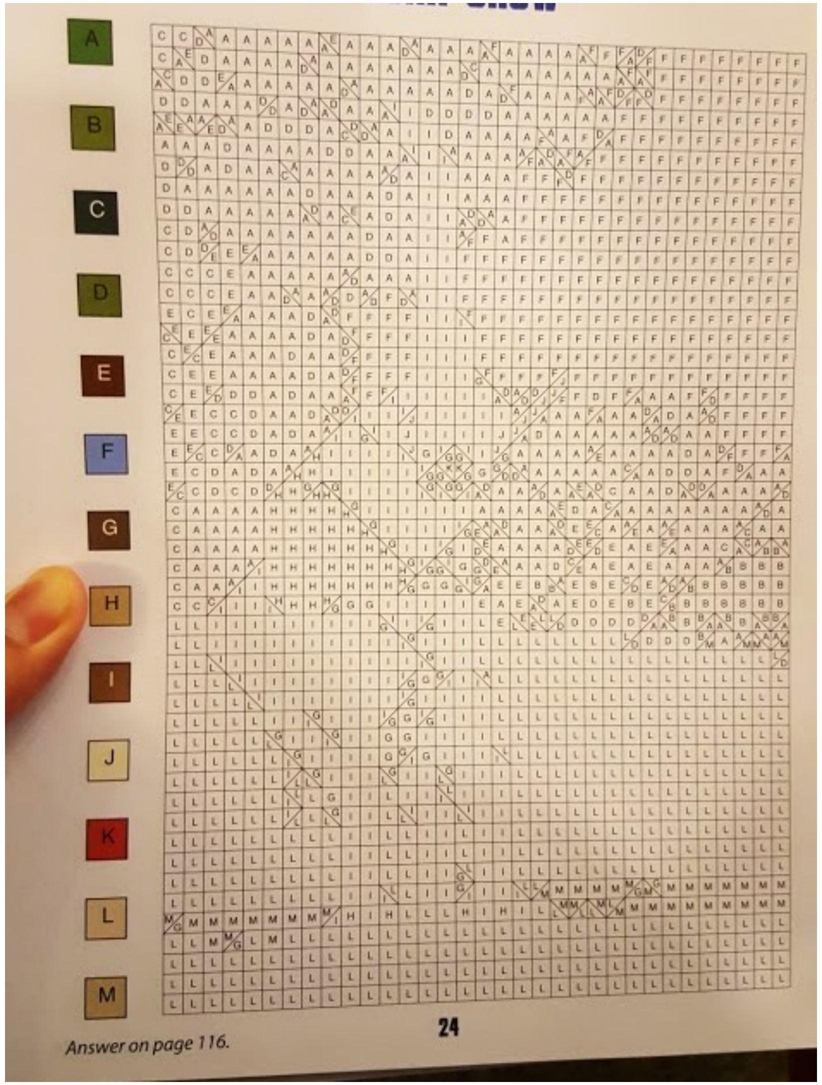


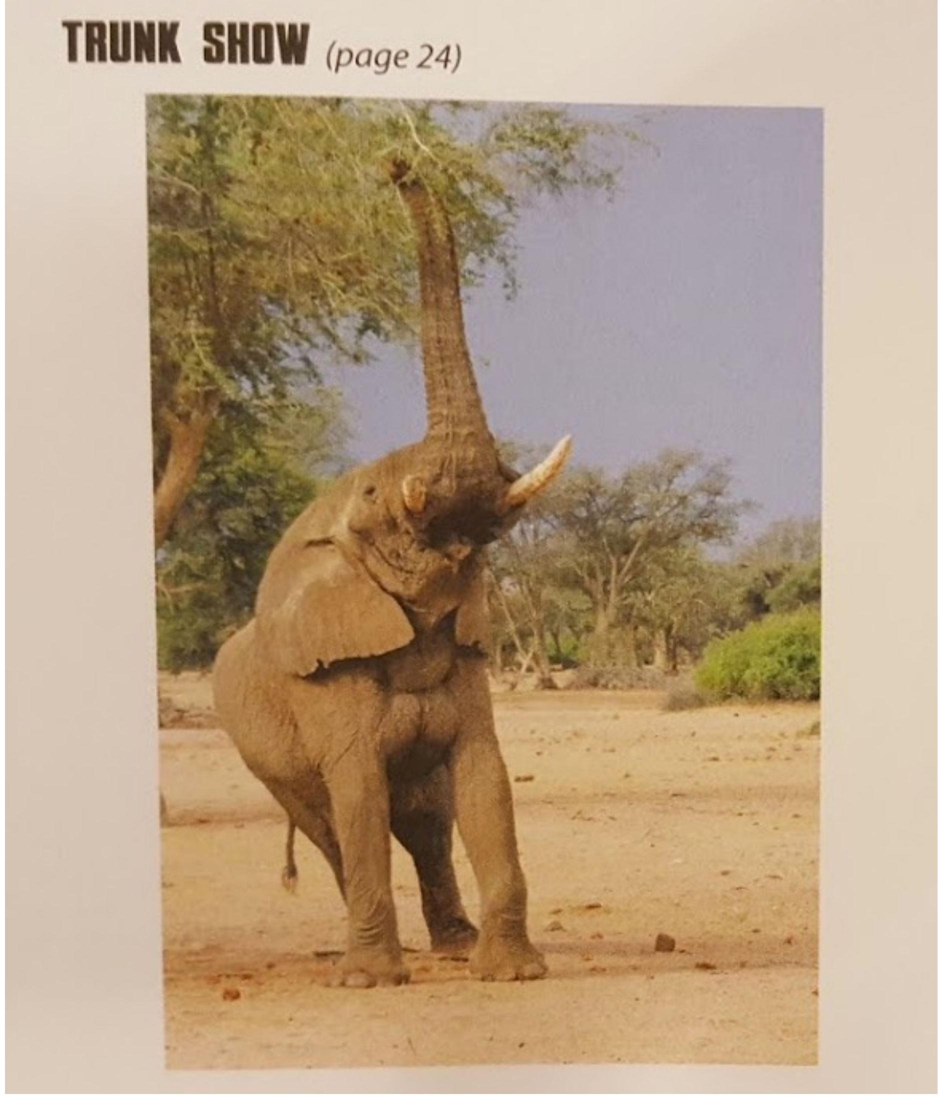
sizeof(T) = 3 x height x width

Channels are usually RGB: Red, Green, and Blue

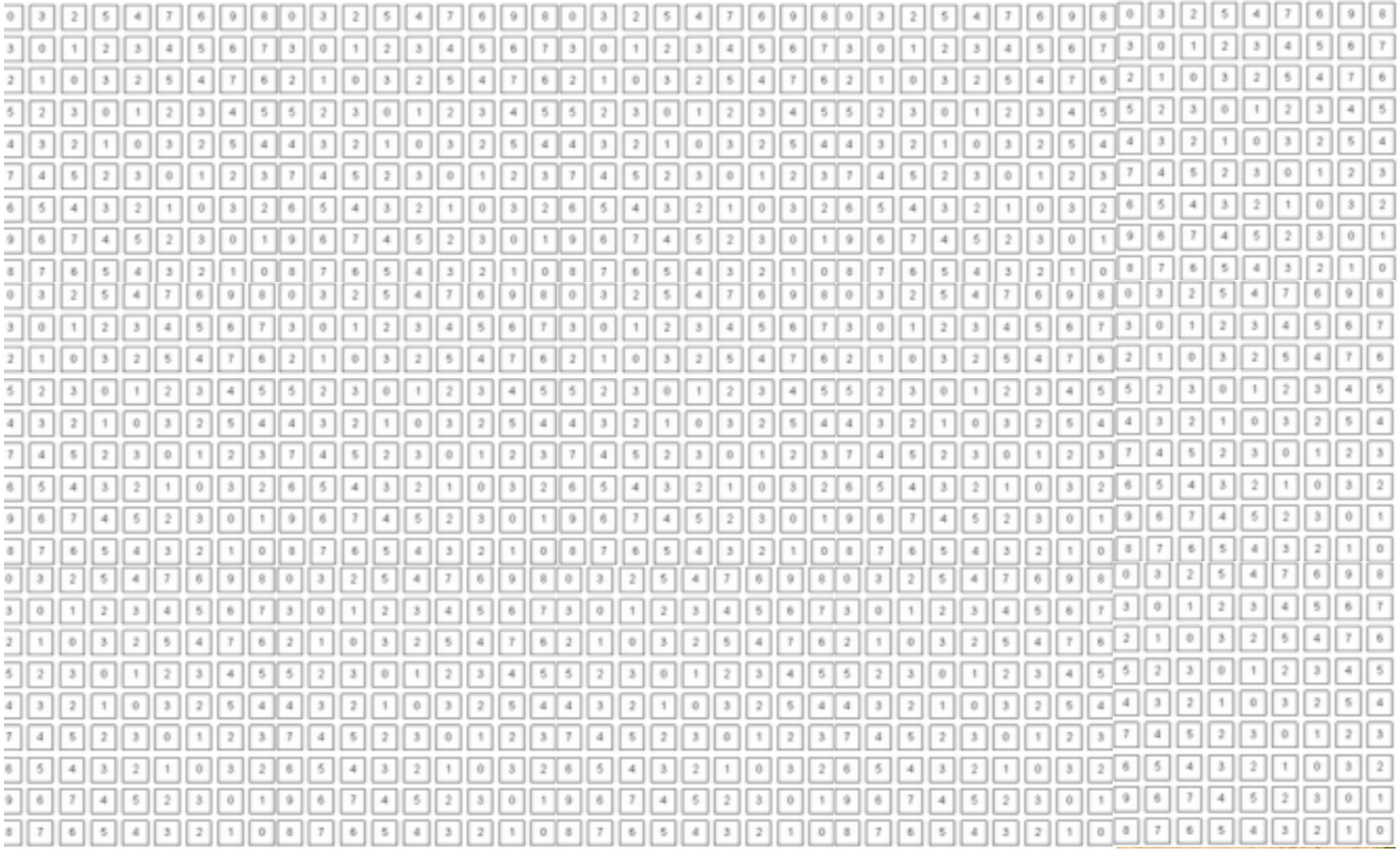
Other color spaces: HSV, HSL, LUV, XYZ, Lab, CMYK, etc

Why is it hard?



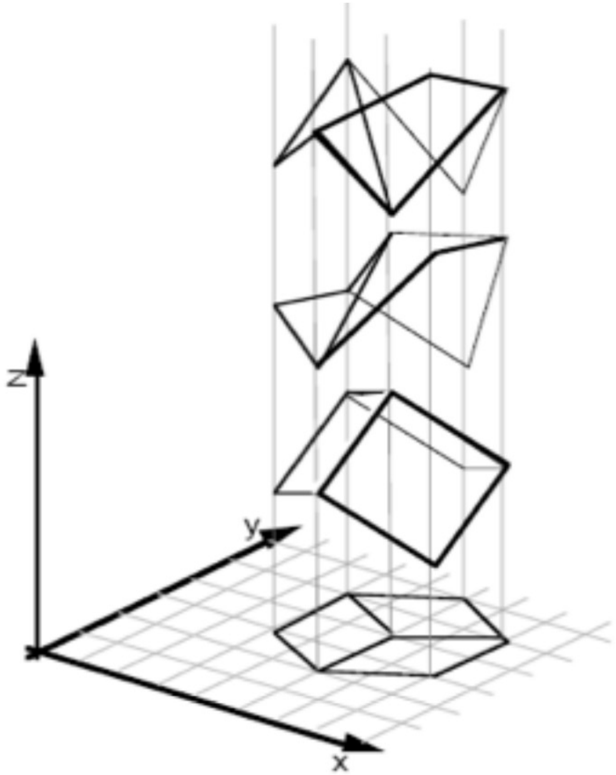


This is just as hard for computers



Why is Computer Vision hard?

Ambiguities due to viewpoints



[Sinha and Adelson 1993]

Why is Computer Vision hard?

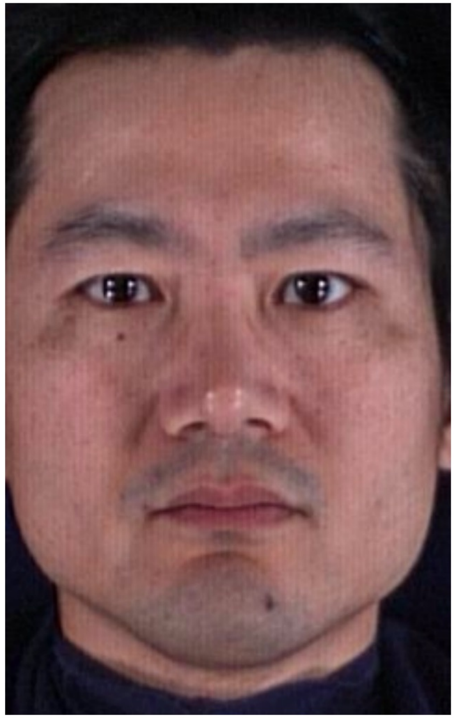
Ambiguities due to viewpoints

Michelangelo 1475-1564

slide by Fei Fei, Fergus & Torralba

Why is Computer Vision hard?

Issues with Illumination



slide credit: S. Ullman

Why is Computer Vision hard?

Background clutter

Why is Computer Vision hard?

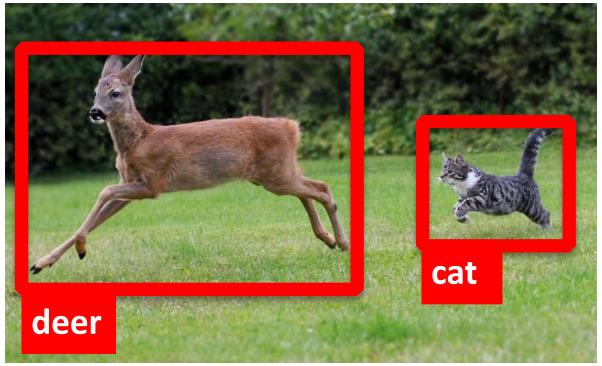
Intra-class variation

slide by Fei-Fei, Fergus & Torralba

Computer Vision vs Image Processing

- Computer Vision: Image ⟶ Knowledge

⟶

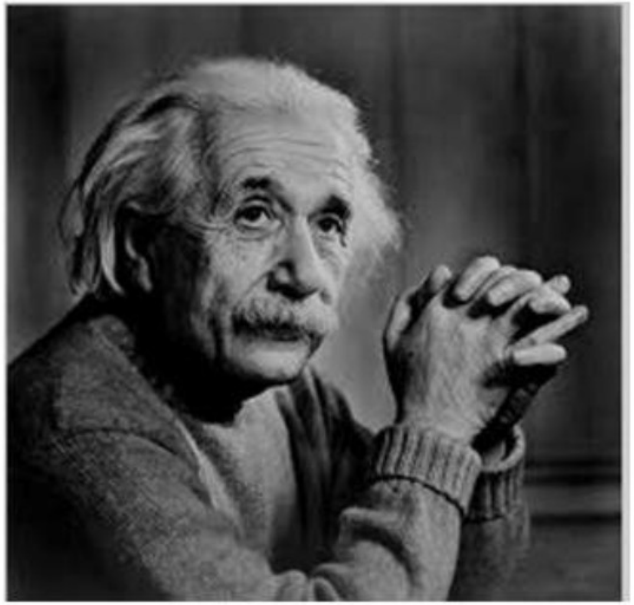


Computer Vision vs Image Processing

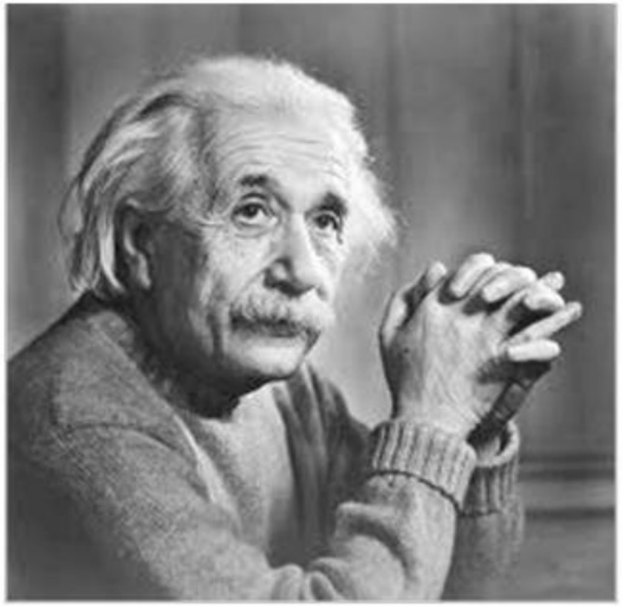
- Image Processing: Image $\longrightarrow$ Image

Basic Image Processing

I



αI



$\alpha > 1$

Primer on Image Processing: https://bit.ly/3lGEdwv

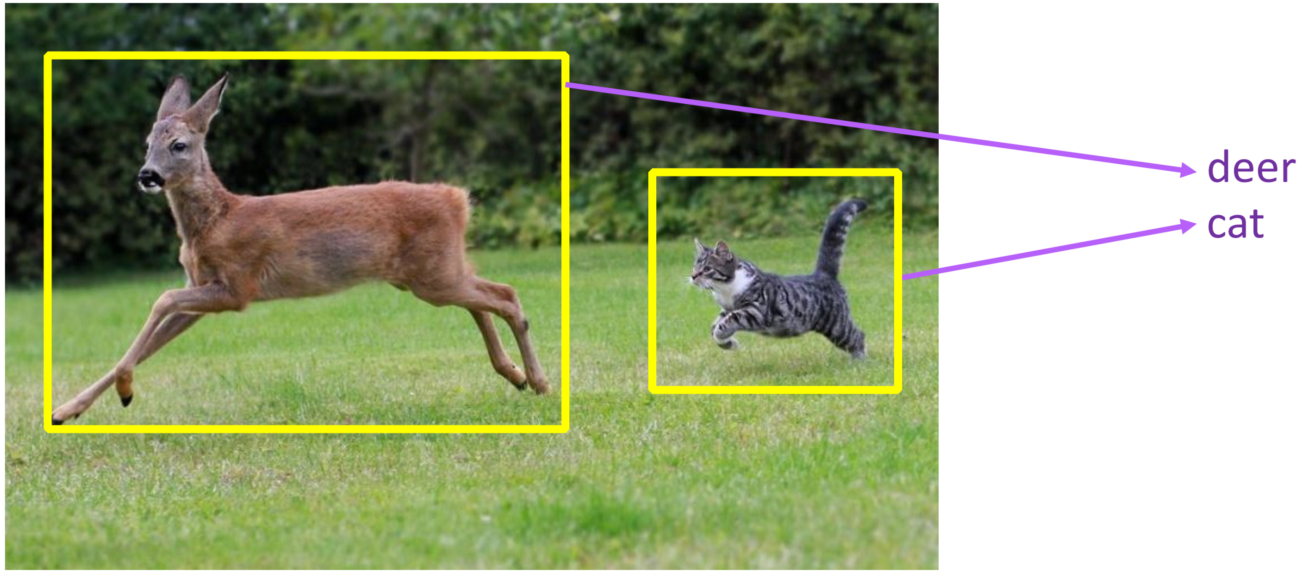
Common tasks in Computer Vision

Image tagging

deer
cat
trees
grass

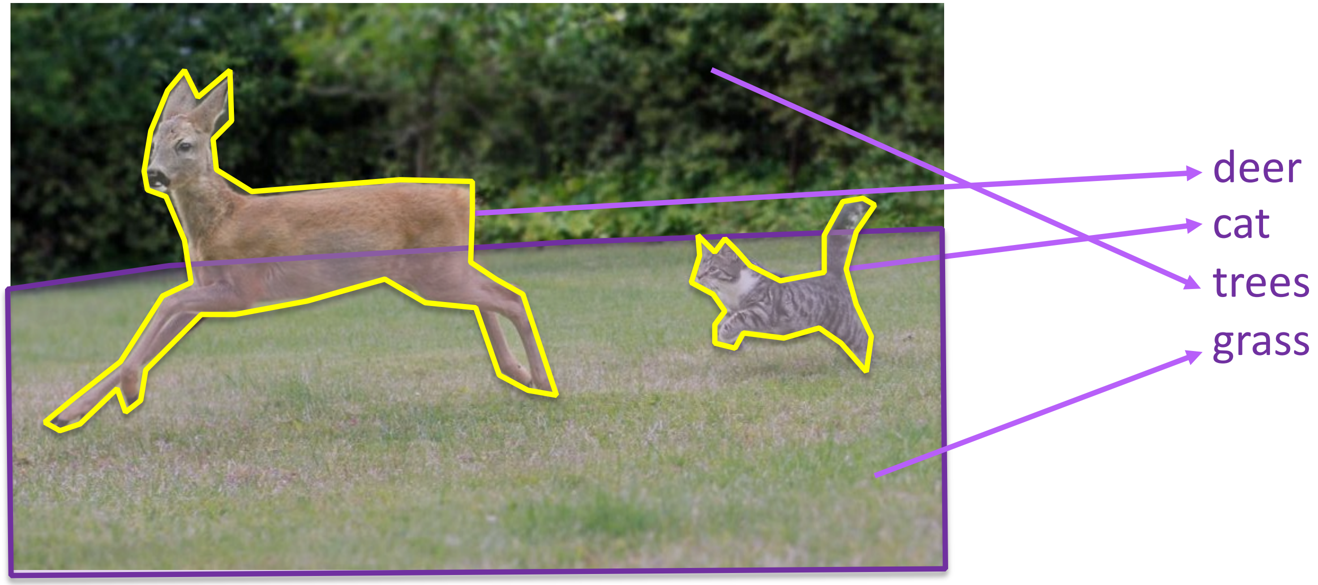
Common tasks in Computer Vision

Object detection



Common tasks in Computer Vision

Semantic segmentation



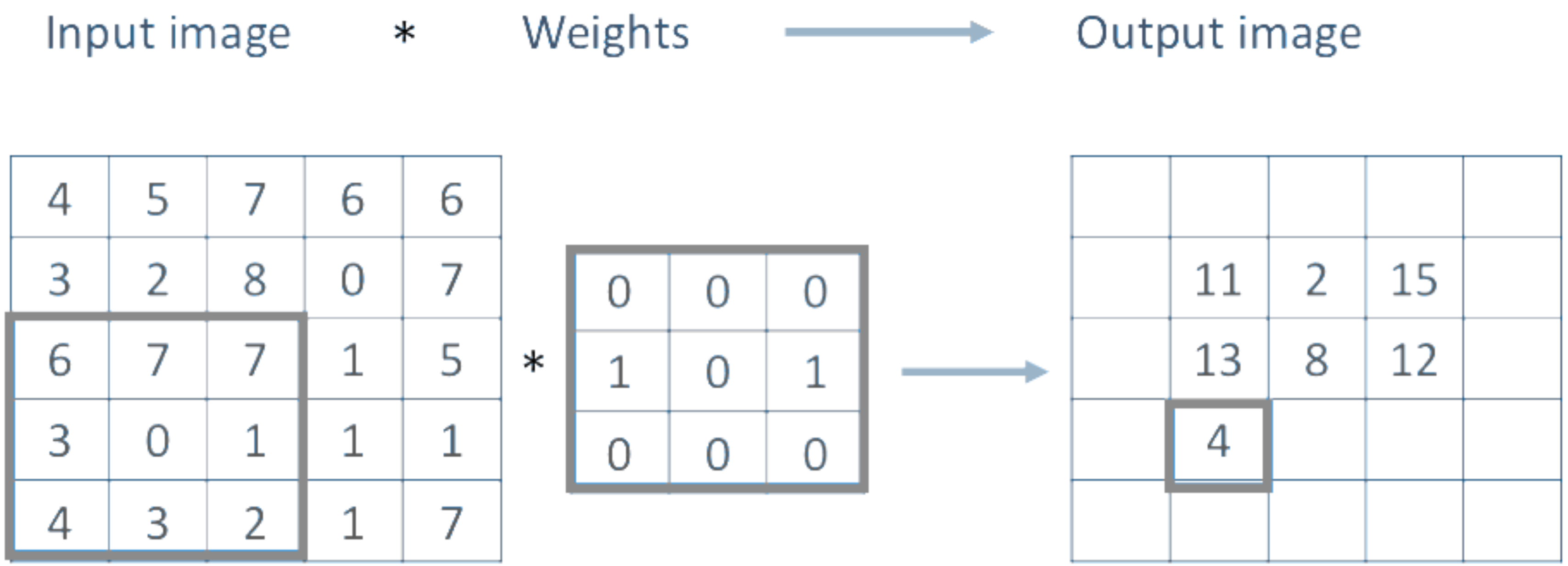
This class -> Vision and Language Tasks!

Reasoning about Language!

a cat is chasing a young deer

Most important operation for Computer Vision (*)

- The Convolution Operation



http://www.cs.virginia.edu/~vicente/recognition/animation.gif

(*) Maybe

Most important operation for Computer Vision (*)

- The Convolution Operation

Input image * Weights Output image

4	5	7	6	6
3	2	8	0	7
6	7	7	1	5
3	0	1	1	1
4	3	2	1	7

*

0	0	0
1	0	1
0	0	0

→

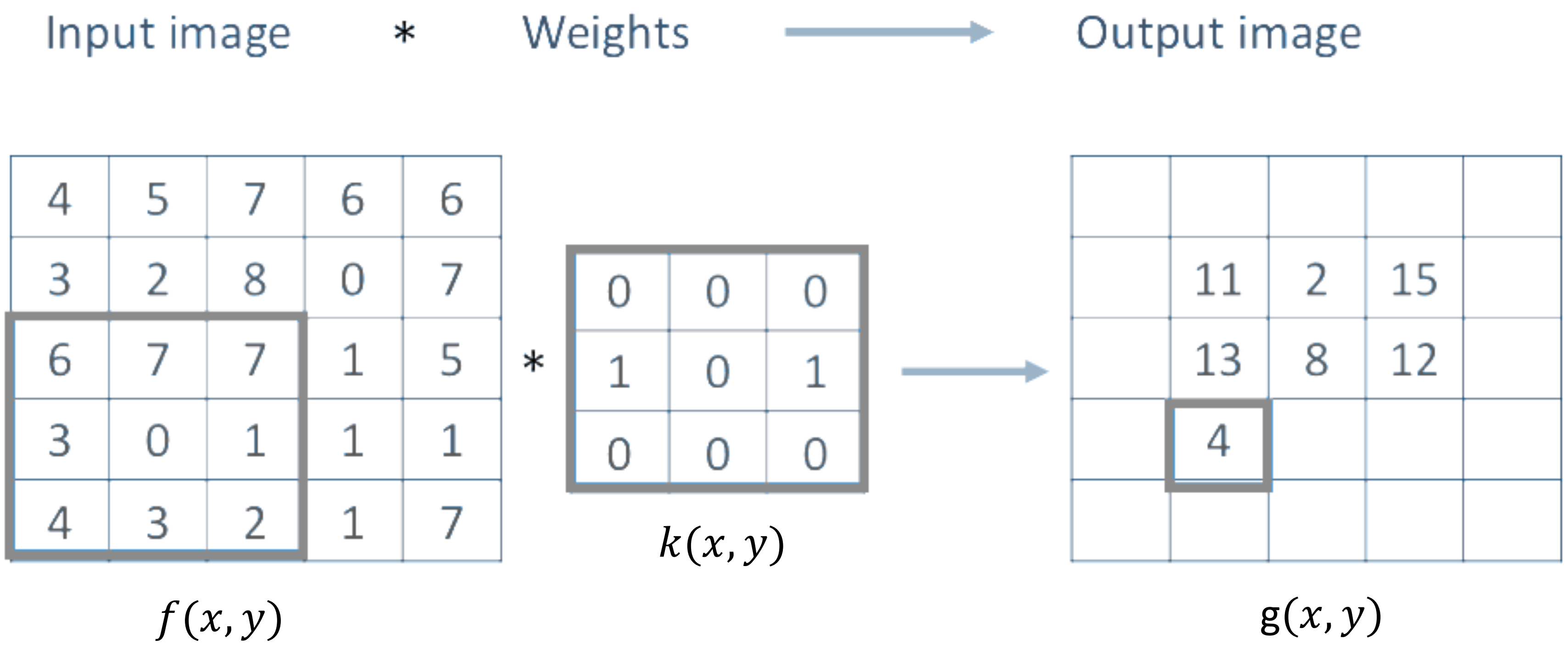
	11	2	15	
	13	8	12	
	4			

Convolutional filter
Convolutional kernel
Filter
Kernel

(*) Maybe

Most important operation for Computer Vision (*)

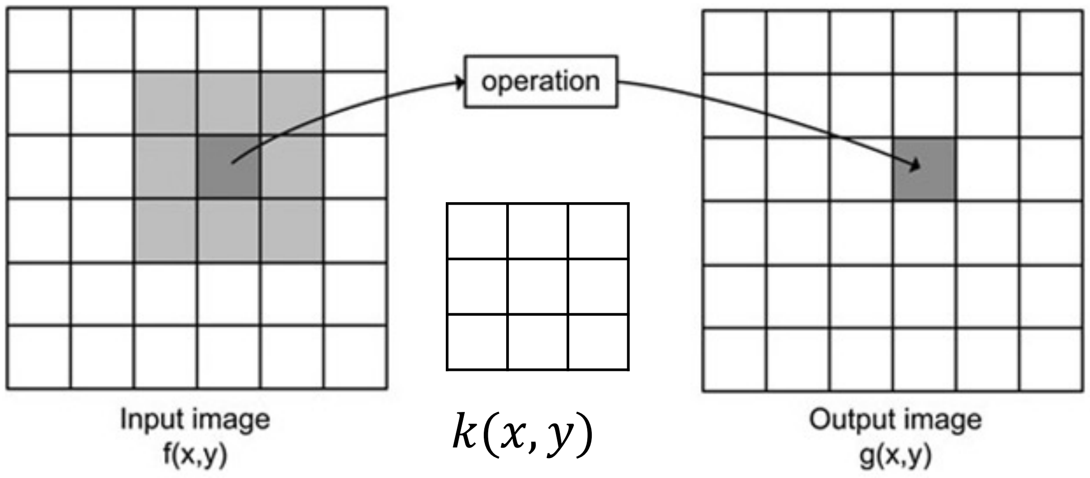
- The Convolution Operation



$$g(x, y) = \sum_{v} \sum_{u} k(u, v) f(x - u, y - v)$$

(*) Maybe

Image filtering: Convolution operator
e.g. mean filter

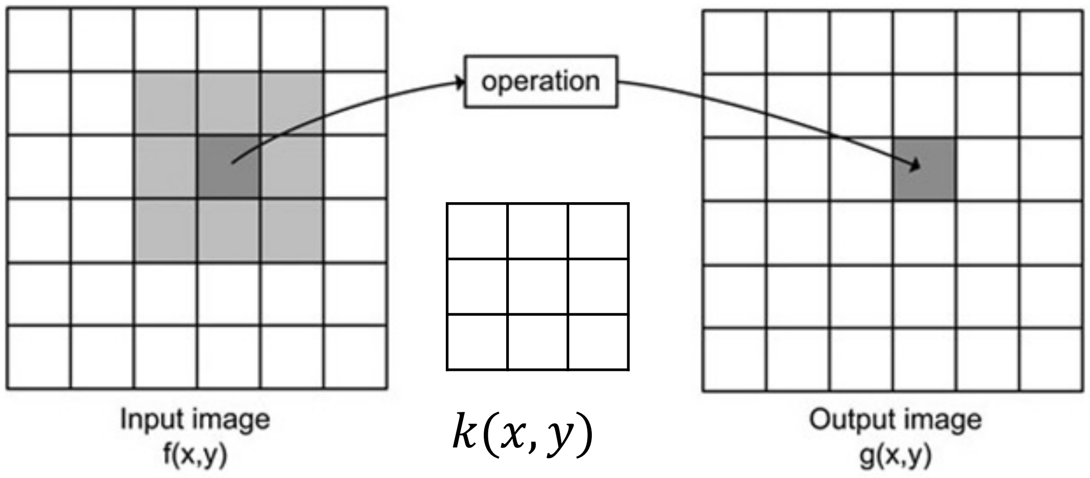


$k(x,y)$ =

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

Image Credit: http://what-when-how.com/introduction-to-video-and-image-processing/neighborhood-processing-introduction-to-video-and-image-processing-part-1/

Image filtering: Convolution operator
e.g. mean filter



$$k(x, y) = \begin{bmatrix} 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \end{bmatrix}$$

Image Credit: http://what-when-how.com/introduction-to-video-and-image-processing/neighborhood-processing-introduction-to-video-and-image-processing-part-1/

Example: box filter

$$g[\cdot\,,\cdot\,]$$

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Slide credit: David Lowe (UBC)

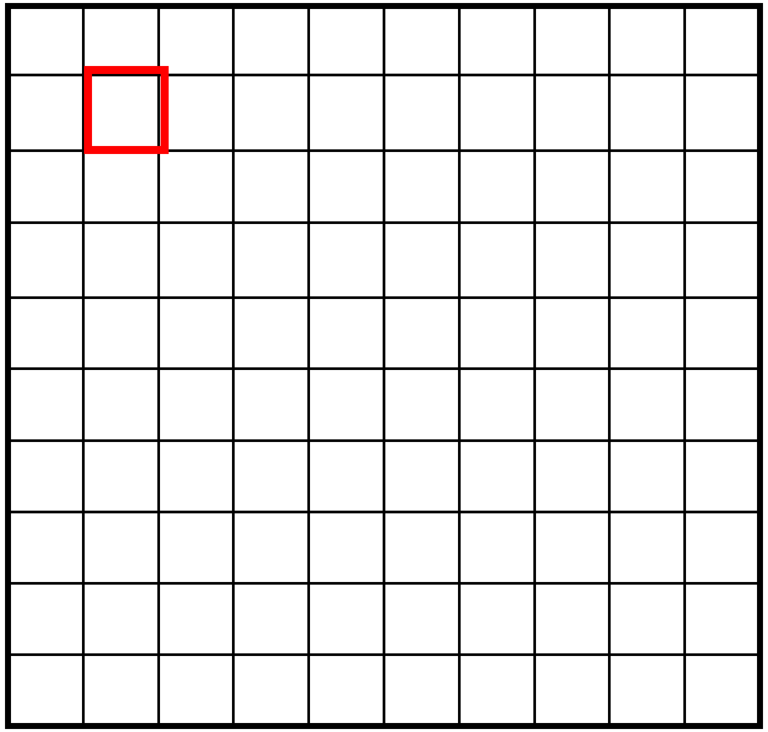
Image filtering

$$g[\cdot\,,\cdot\,]\ \frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$



$$h[m,n]=\sum_{k,l} g[k,l]\,f[m+k,n+l]$$

Credit: S. Seitz

Image filtering

$g[\cdot,\cdot]\ \frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10							

$$h[m,n]=\sum_{k,l} g[k,l]\, f[m+k,n+l]$$

Credit: S. Seitz

Image filtering

$g[\cdot\,,\cdot\,]\ \frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20						

$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k, n+l]$$

Credit: S. Seitz

Image filtering

$g[\cdot\,,\cdot\,]\ \frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20	30					

$$h[m,n]=\sum_{k,l} g[k,l]\, f[m+k,n+l]$$

Credit: S. Seitz

Image filtering

$$g[\cdot,\cdot]\ \frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}$$

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20	30	30				

$$h[m,n]=\sum_{k,l} g[k,l]\, f[m+k,n+l]$$

Credit: S. Seitz

Image filtering

$g[\cdot,\cdot]\ \frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20	30	30				
				?					

$$h[m,n]=\sum_{k,l} g[k,l]\, f[m+k,n+l]$$

Credit: S. Seitz

Image filtering

$$g[\cdot\,,\cdot\,]\ \frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20	30	30				
						?			
				50					

$$h[m,n]=\sum_{k,l} g[k,l]\, f[m+k,n+l]$$

Credit: S. Seitz

Image filtering

$$g[\cdot\,,\cdot\,] \quad \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20	30	30	30	20	10	
	0	20	40	60	60	60	40	20	
	0	30	60	90	90	90	60	30	
	0	30	50	80	80	90	60	30	
	0	30	50	80	80	90	60	30	
	0	20	30	50	50	60	40	20	
	10	20	30	30	30	30	20	10	
	10	10	10	0	0	0	0	0	

$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k, n+l]$$

Credit: S. Seitz

Box Filter

What does it do?

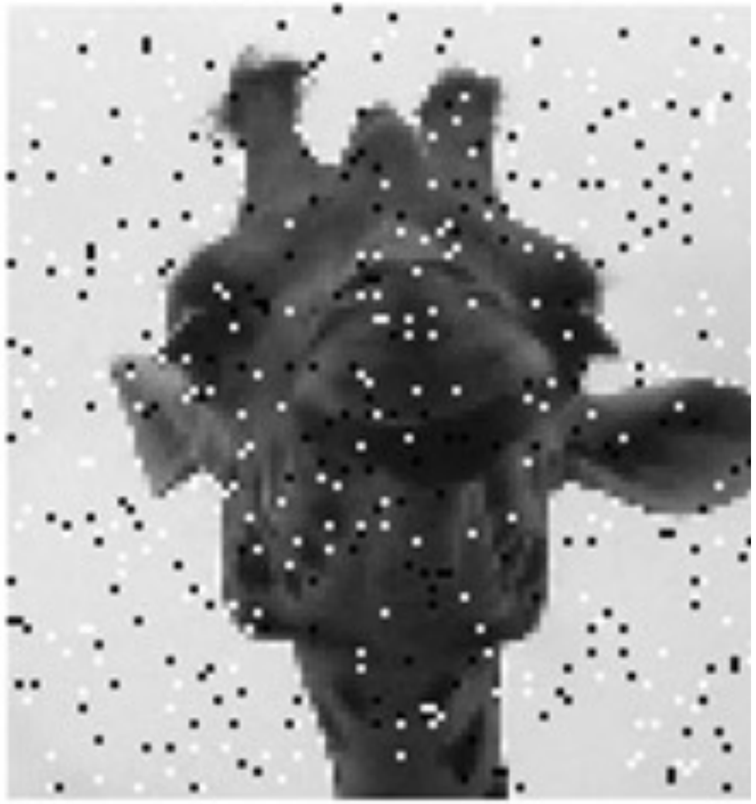
- Replaces each pixel with an average of its neighborhood
- Achieve smoothing effect (remove sharp features)

$$g[\cdot\,,\cdot\,]$$

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Slide credit: David Lowe (UBC)

Image filtering: e.g. Mean Filter



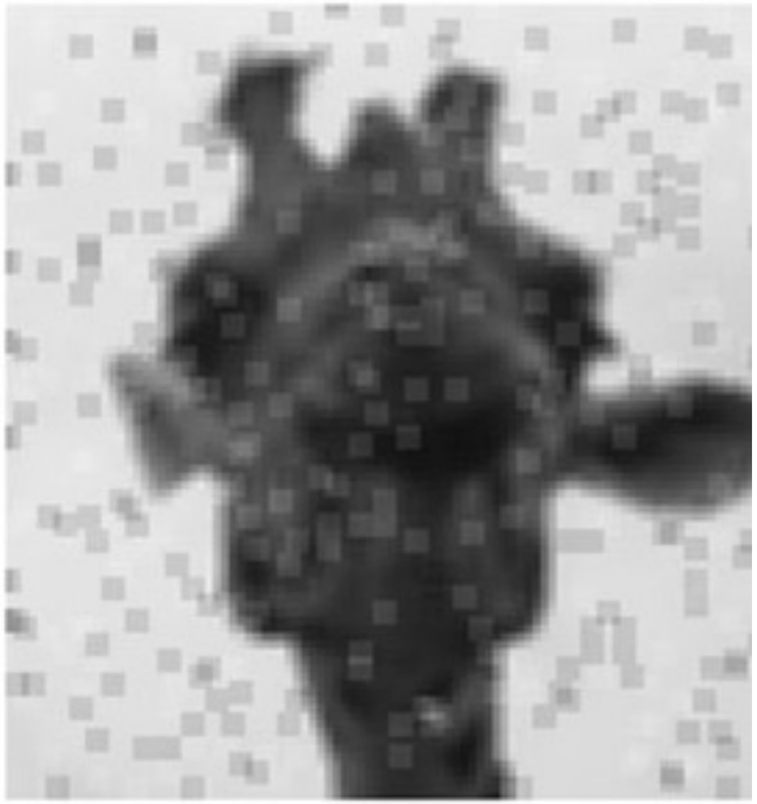
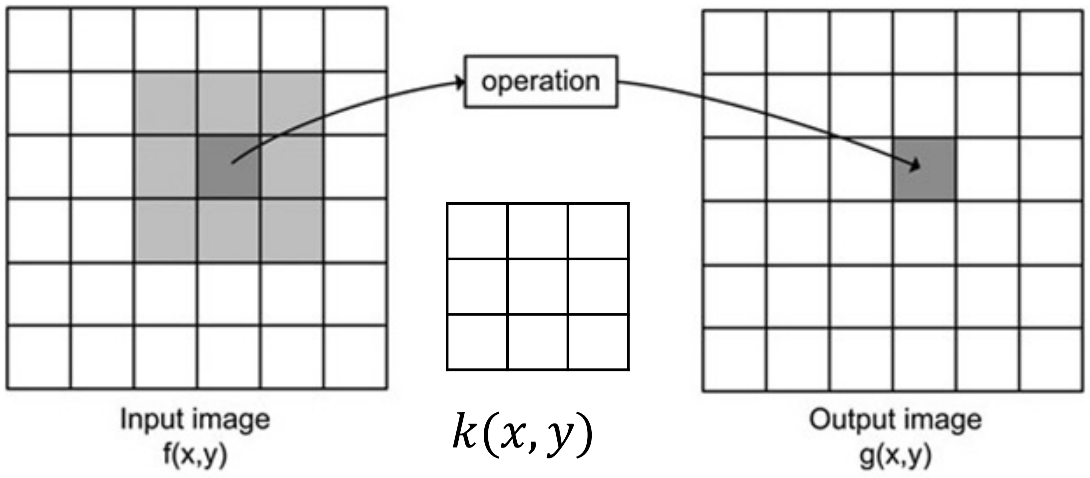


Image filtering: Convolution operator
Important filter: gaussian filter (gaussian blur)



$$k(x,y) = \begin{bmatrix} 1/16 & 1/8 & 1/16 \\ 1/8 & 1/4 & 1/8 \\ 1/16 & 1/8 & 1/16 \end{bmatrix}$$

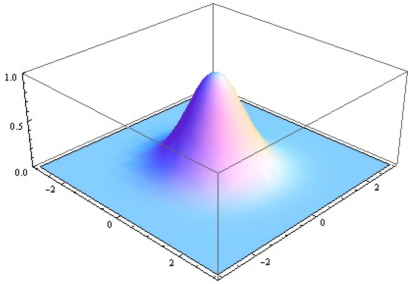
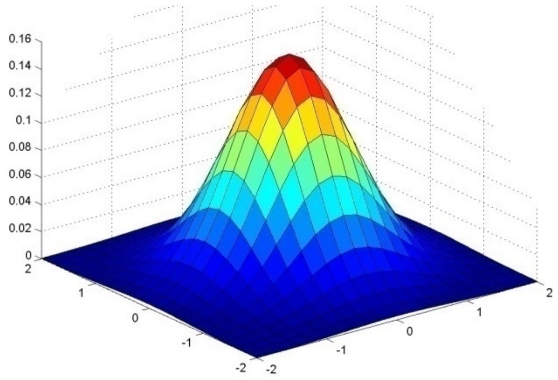
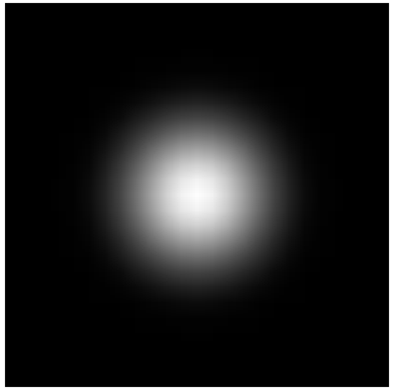


Image Credit: http://what-when-how.com/introduction-to-video-and-image-processing/neighborhood-processing-introduction-to-video-and-image-processing-part-1/

Important filter: Gaussian

- Weight contributions of neighboring pixels by nearness





0.003	0.013	0.022	0.013	0.003
0.013	0.059	0.097	0.059	0.013
0.022	0.097	0.159	0.097	0.022
0.013	0.059	0.097	0.059	0.013
0.003	0.013	0.022	0.013	0.003

5 x 5, $\sigma = 1$

$$G_\sigma = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

Slide credit: Christopher Rasmussen

Image filtering: Convolution operator
e.g. gaussian filter (gaussian blur)

Image Credit: http://what-when-how.com/introduction-to-video-and-image-processing/neighborhood-processing-introduction-to-video-and-image-processing-part-1/

Practical matters

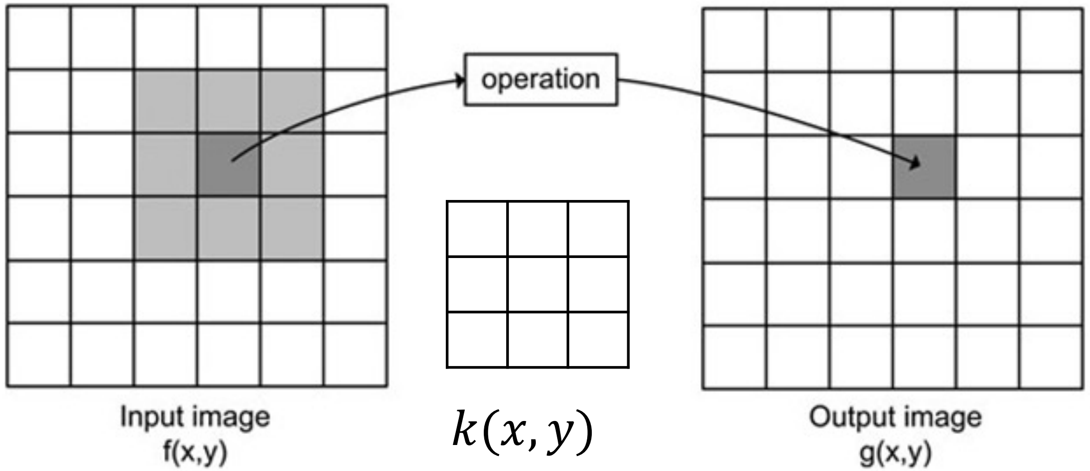
- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - clip filter (black)
    - wrap around
    - copy edge
    - reflect across edge

Source: S. Marschner

Convolution: Useful Operator for Image Processing

- Not all image filtering – region neighborhood operators can be expressed as convolutions.
- They also can be used to extract information about edges and shapes .e.g. for image recognition
- Convolutional operations are at the basis of convolutional neural networks.

Image filtering: Convolution operator
Important Filter: Sobel operator

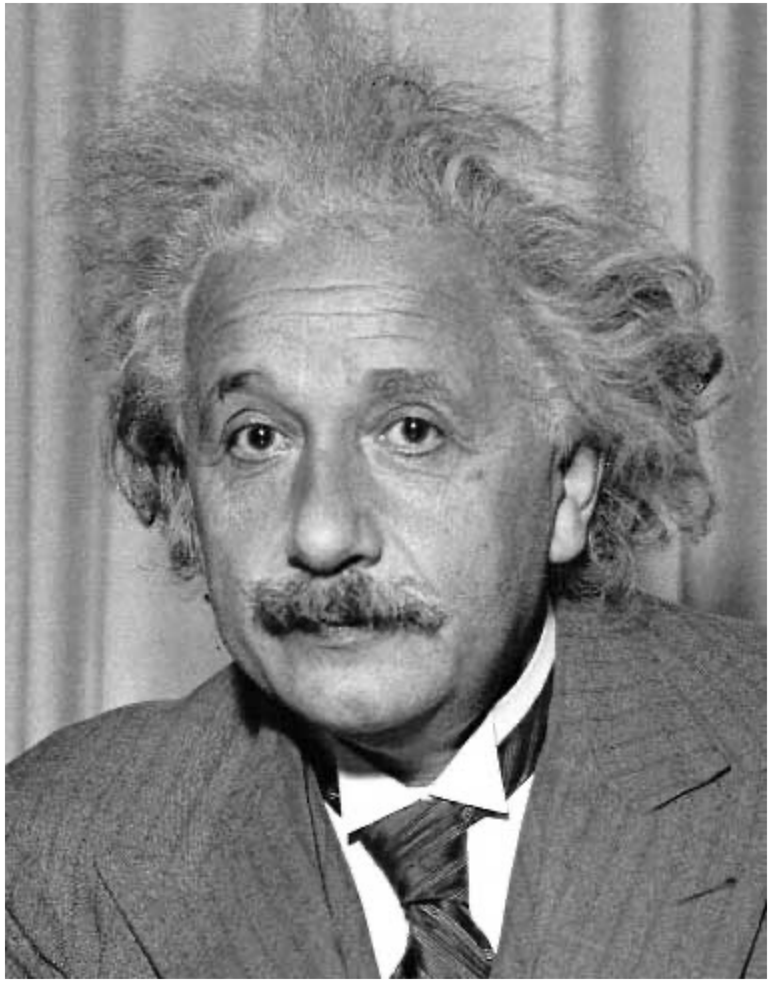


$k(x, y)$ =

1	0	-1
2	0	-2
1	0	-1

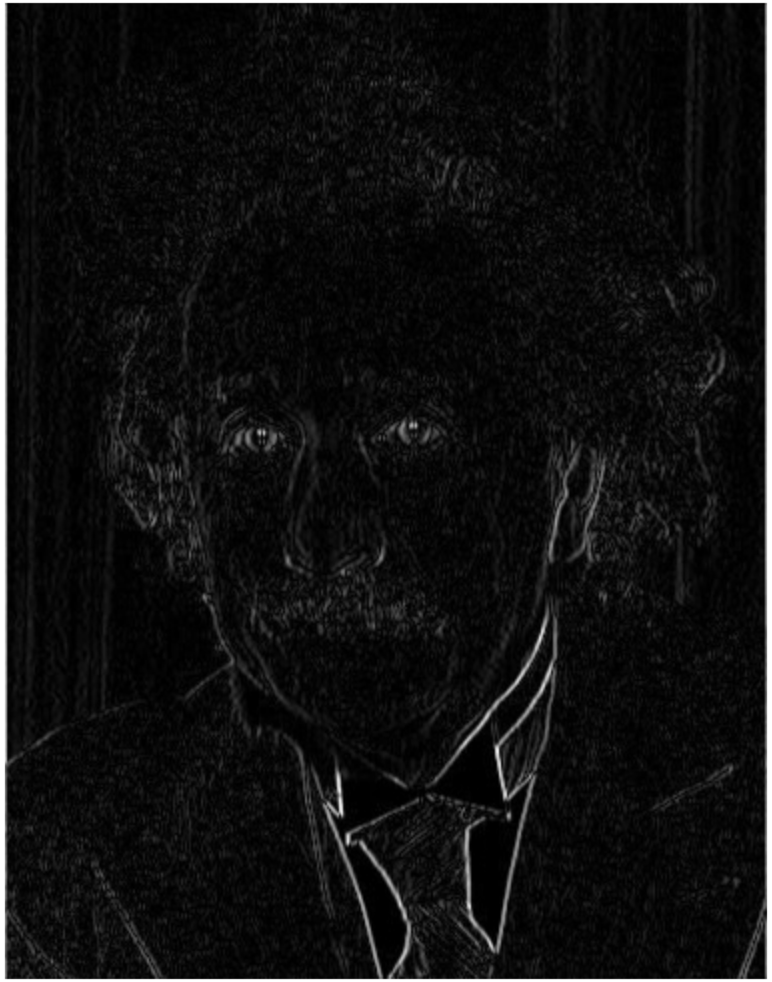
Image Credit: http://what-when-how.com/introduction-to-video-and-image-processing/neighborhood-processing-introduction-to-video-and-image-processing-part-1/

Other filters



1	0	-1
2	0	-2
1	0	-1

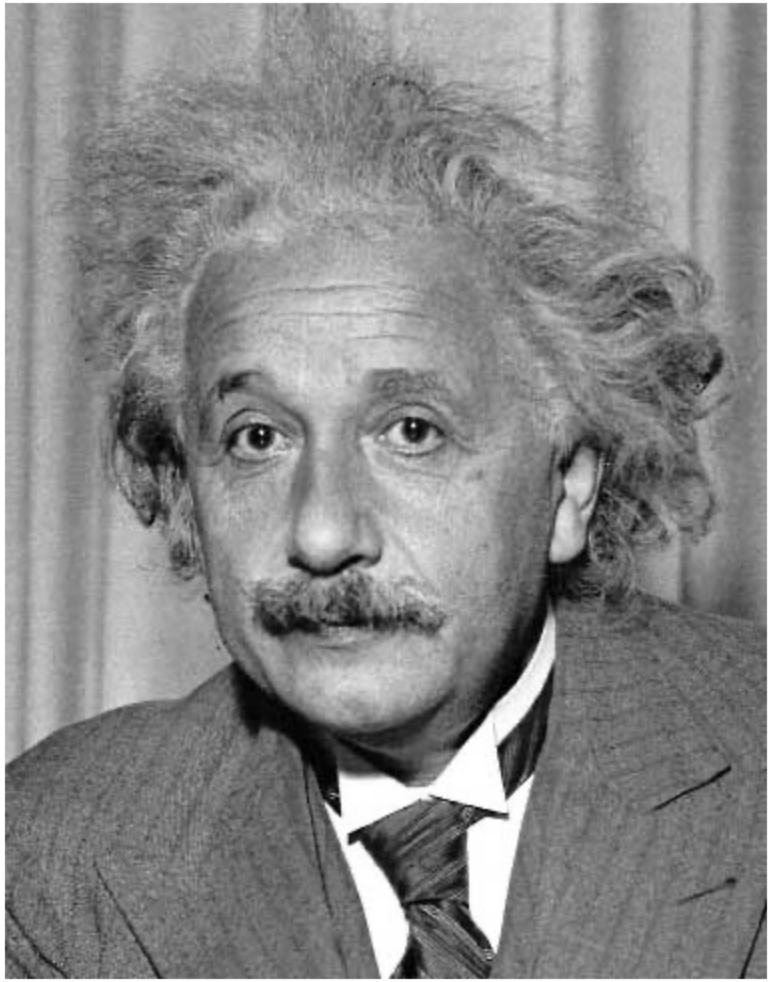
Sobel



Vertical Edge
(absolute value)

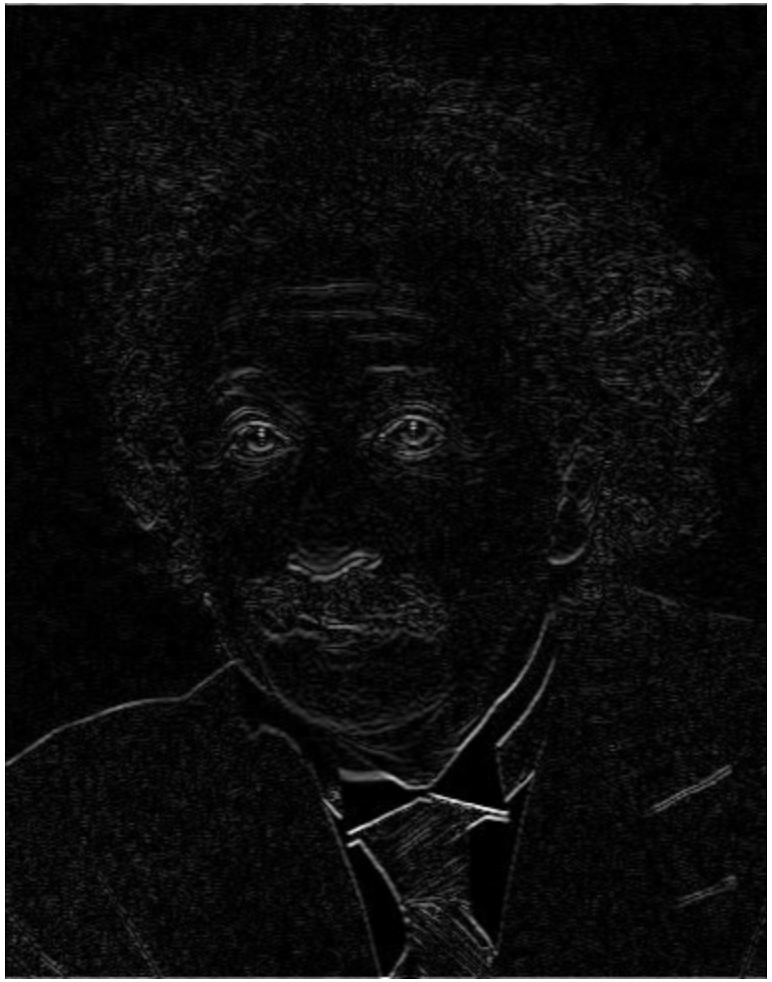
Slide by James Hays

Other filters



1	2	1
0	0	0
-1	-2	-1

Sobel



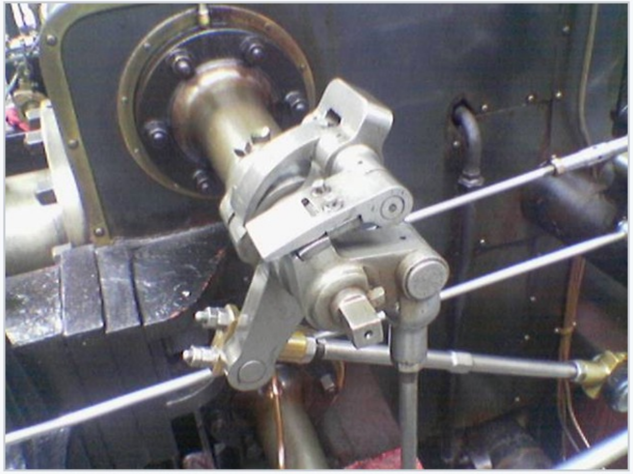
Horizontal Edge
(absolute value)

Slide by James Hays

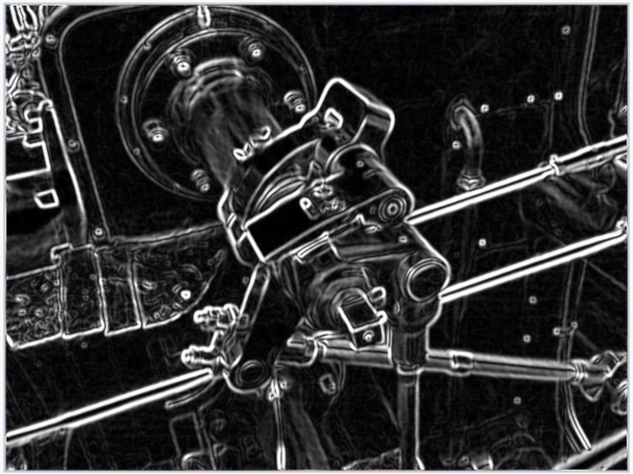
Sobel operators are equivalent to 2D partial derivatives of the image

- Vertical sobel operator – Partial derivative in X (width)
- Horizontal sobel operator – Partial derivative in Y (height)
- Can compute magnitude and phase at each location.
- Useful for detecting edges

https://en.wikipedia.org/wiki/Sobel_operator



A color picture of a steam engine



The Sobel operator applied to that image

Sobel filters are (approximate) partial derivatives of the image

Let $f(x, y)$ be your input image, then the partial derivative is:

$$\frac{\partial f(x,y)}{\partial x} = \lim_{h \to 0} \frac{f(x+h, y) - f(x,y)}{h}$$

Also:

$$\frac{\partial f(x,y)}{\partial x} = \lim_{h \to 0} \frac{f(x+h, y) - f(x-h,y)}{2h}$$

But digital images are not continuous, they are discrete

Let $f[x, y]$ be your input image, then the partial derivative is:

$$\Delta_x f[x, y] = f[x+1, y] - f[x, y]$$

Also: $$\Delta_x f[x, y] = f[x+1, y] - f[x-1, y]$$

But digital images are not continuous, they are discrete

Let $f[x, y]$ be your input image, then the partial derivative is:

$$\Delta_x f[x, y] = f[x+1, y] - f[x, y]$$

k(x, y) =

-1	1

Also: $$\Delta_x f[x, y] = f[x+1, y] - f[x-1, y]$$

k(x, y) =

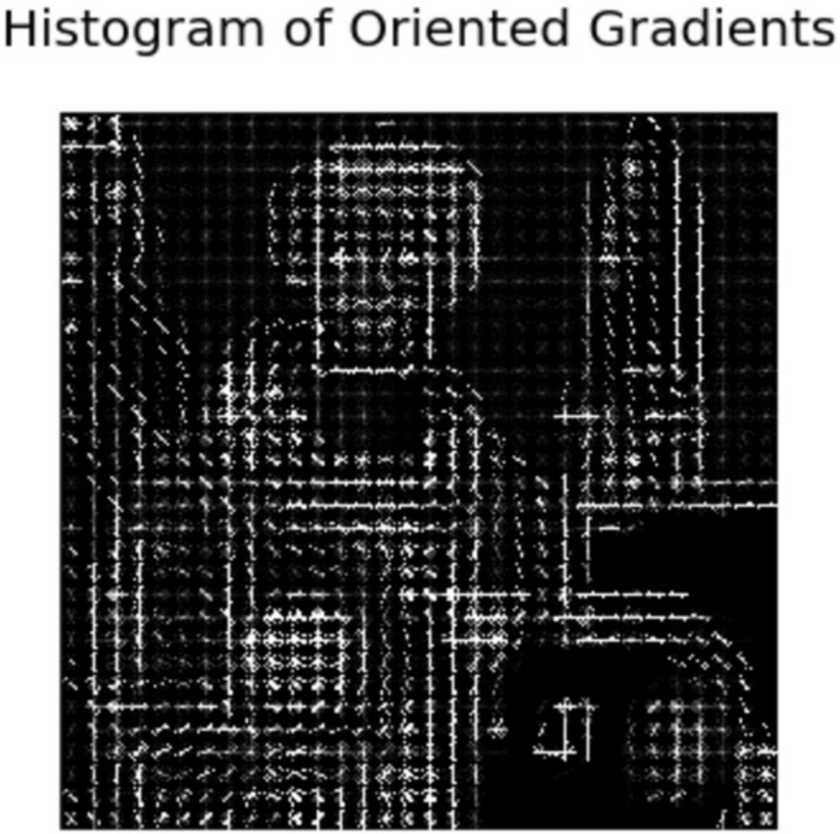
-1	0	1

Sobel Operators Smooth in Y and then Differentiate in X

$$k(x, y) = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} * \begin{bmatrix} 1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

Similarly to differentiate in Y

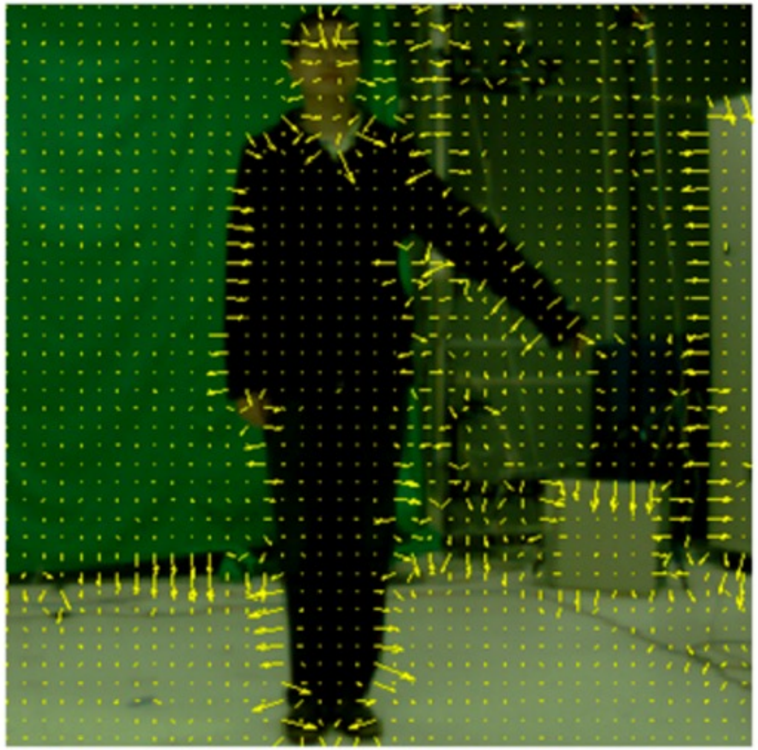
Image Features: HoG

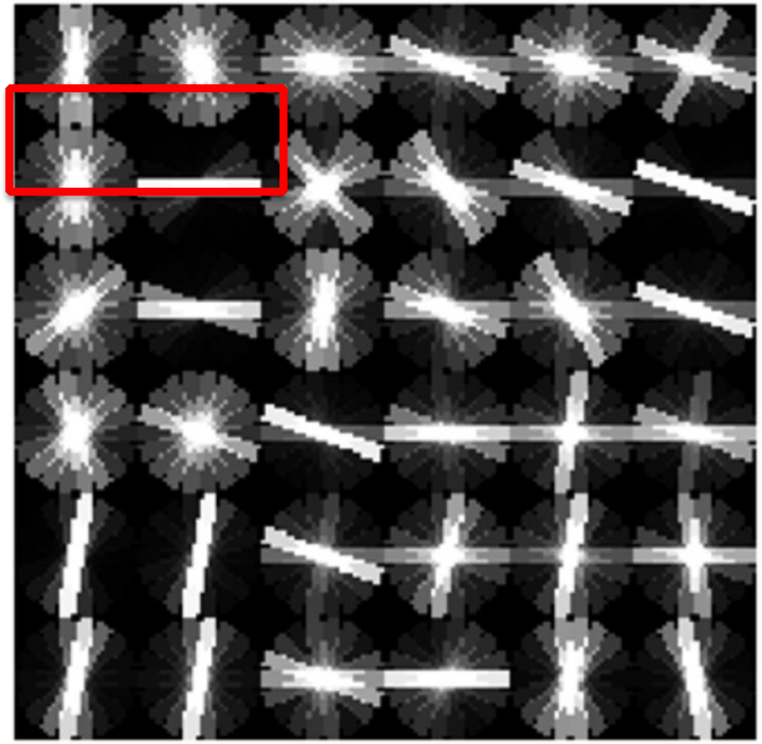


Paper by Navneet Dalal & Bill Triggs presented at CVPR 2005 for detecting people.

Scikit-image implementation

Image Features: HoG

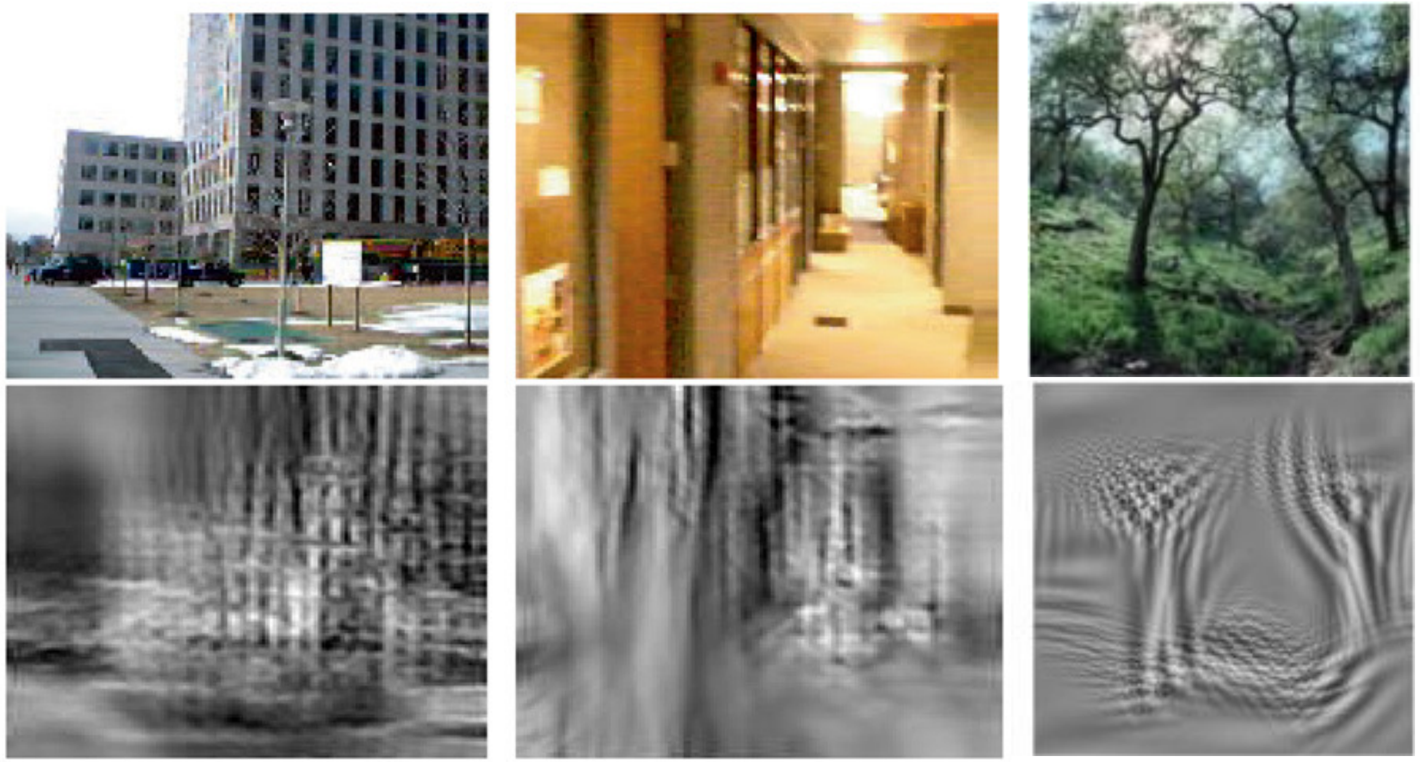




+ Block Normalization

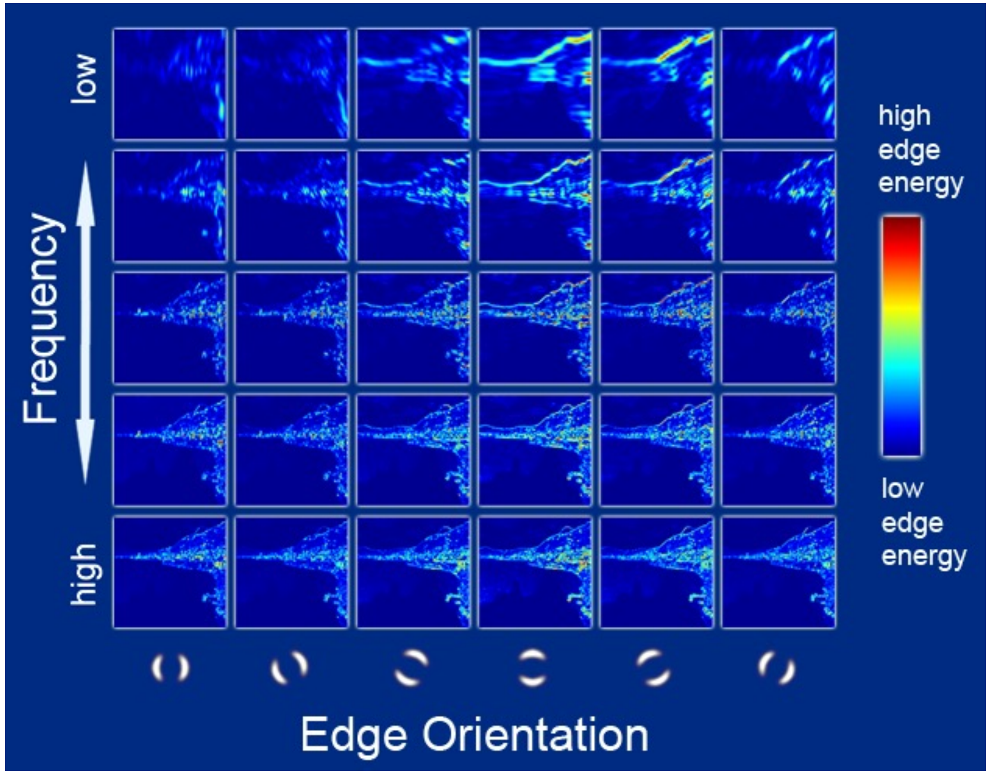
Paper by Navneet Dalal & Bill Triggs presented at CVPR 2005 for detecting people.
Figure from Zhuolin Jiang, Zhe Lin, Larry S. Davis, ICCV 2009 for human action recognition.

Image Features: GIST



The “gist” of a scene: Oliva & Torralba, 2001

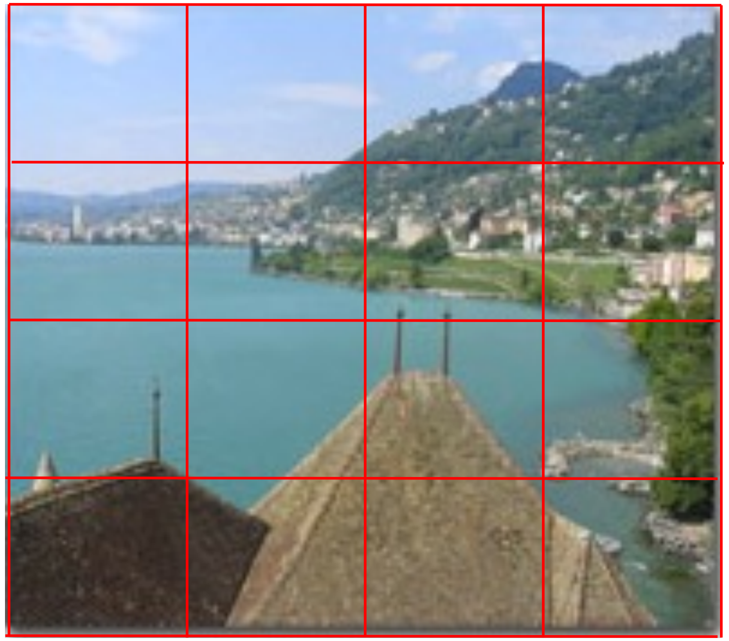
Image Features: GIST

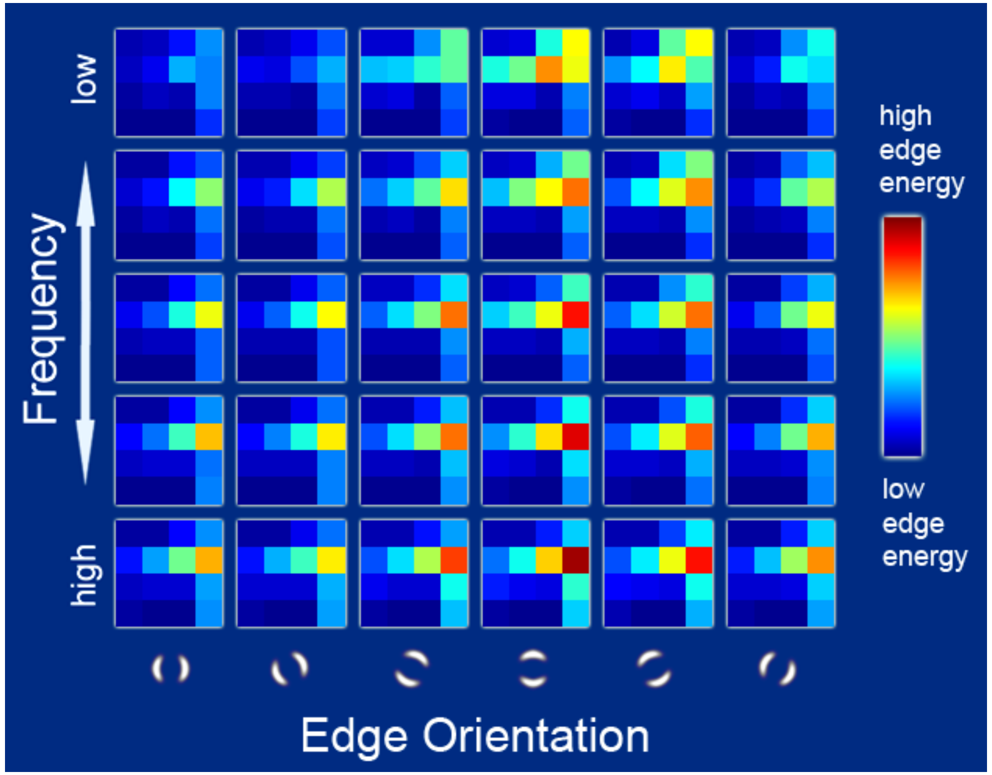


Oriented edge response at multiple scales (5 spatial scales, 6 edge orientations)

Hays and Efros, SIG
2007

Image Features: GIST





Aggregated edge responses over 4x4 windows

Hays and Efros, SIG
2007

The 2D Convolutional Layer in a Neural Network

Input image * Weights → Output image

4	5	7	6	6
3	2	8	0	7
6	7	7	1	5
3	0	1	1	1
4	3	2	1	7

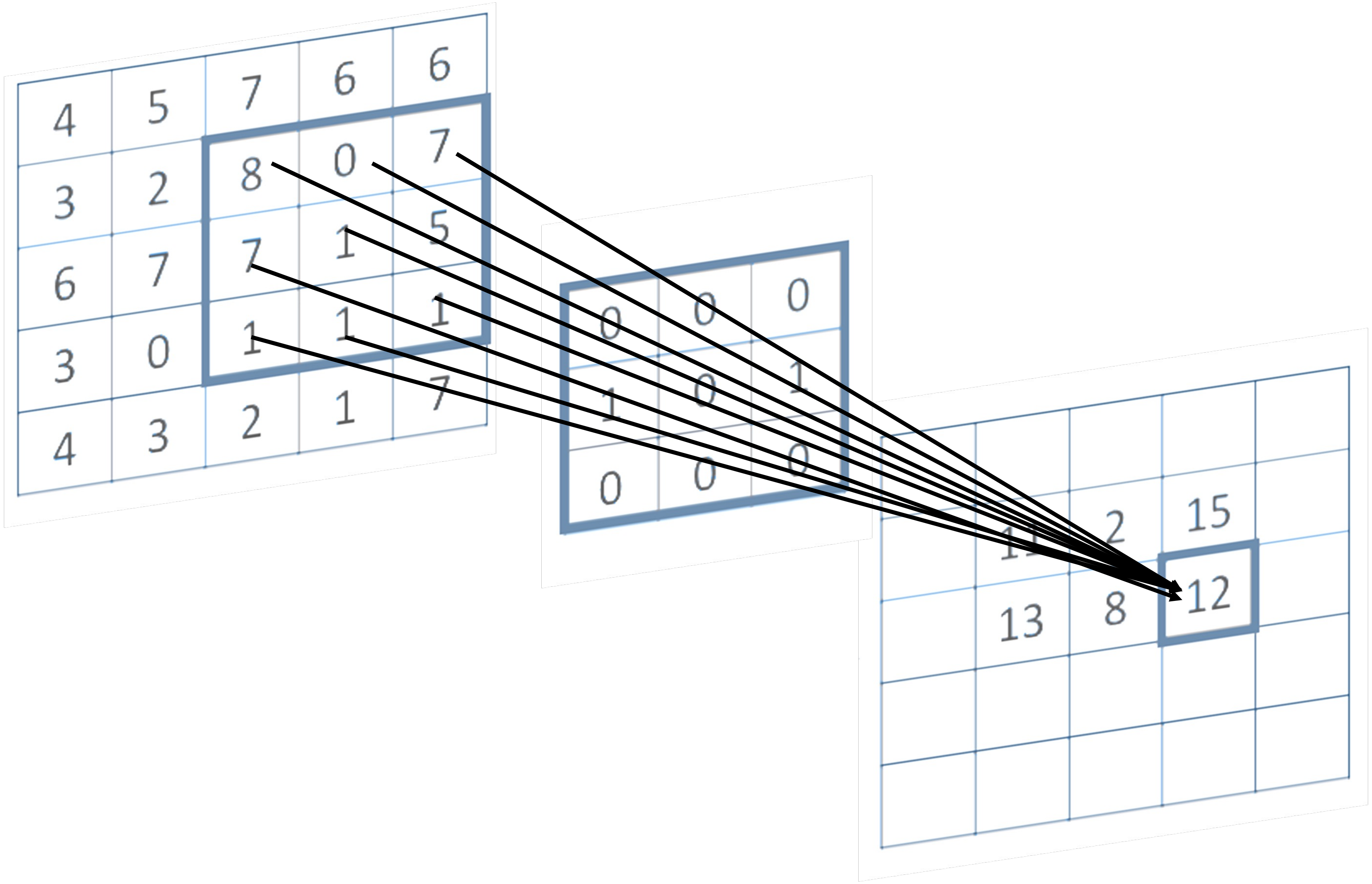
*

0	0	0
1	0	1
0	0	0

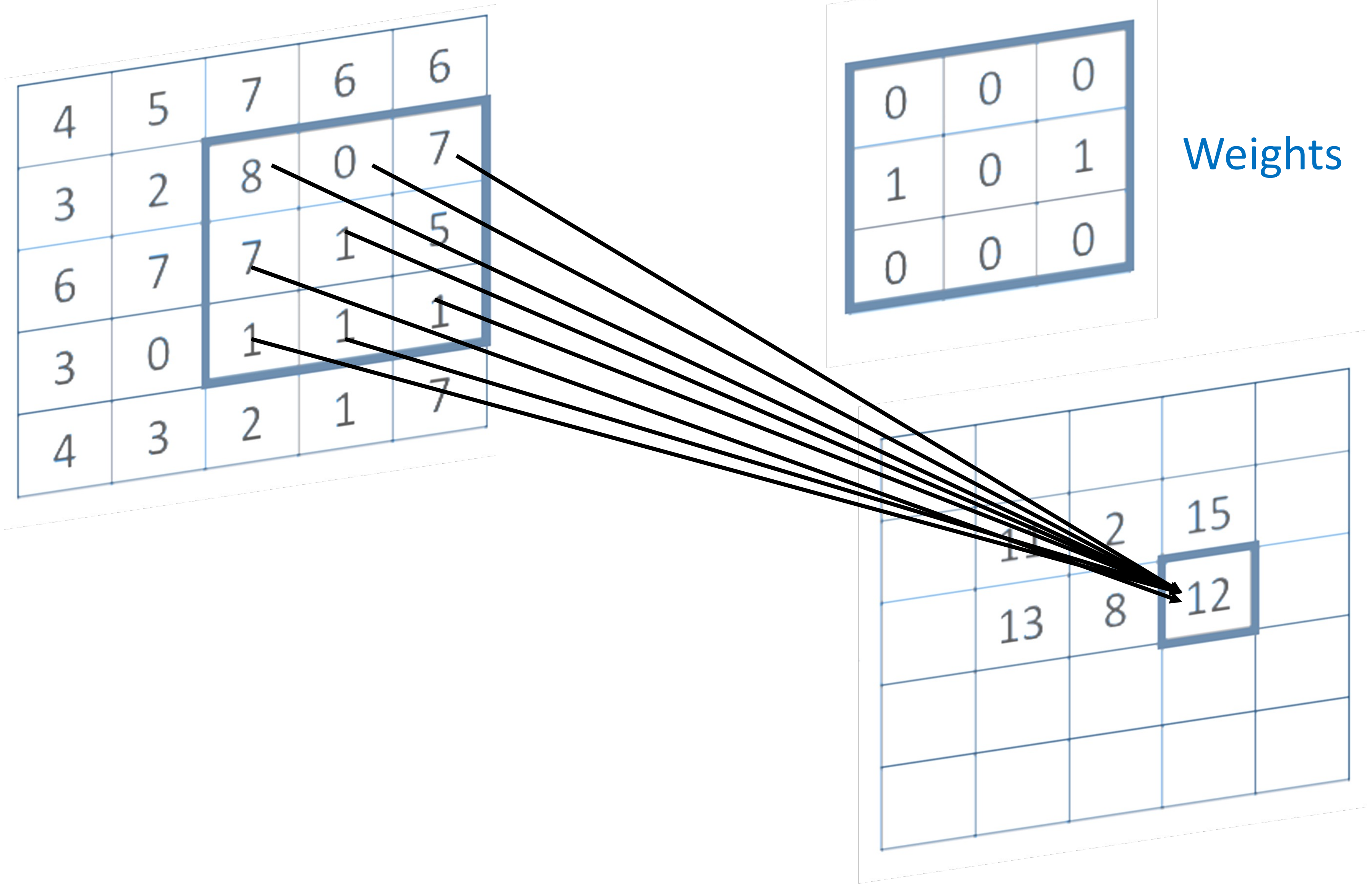
→

	11	2	15	
	13	8	12	

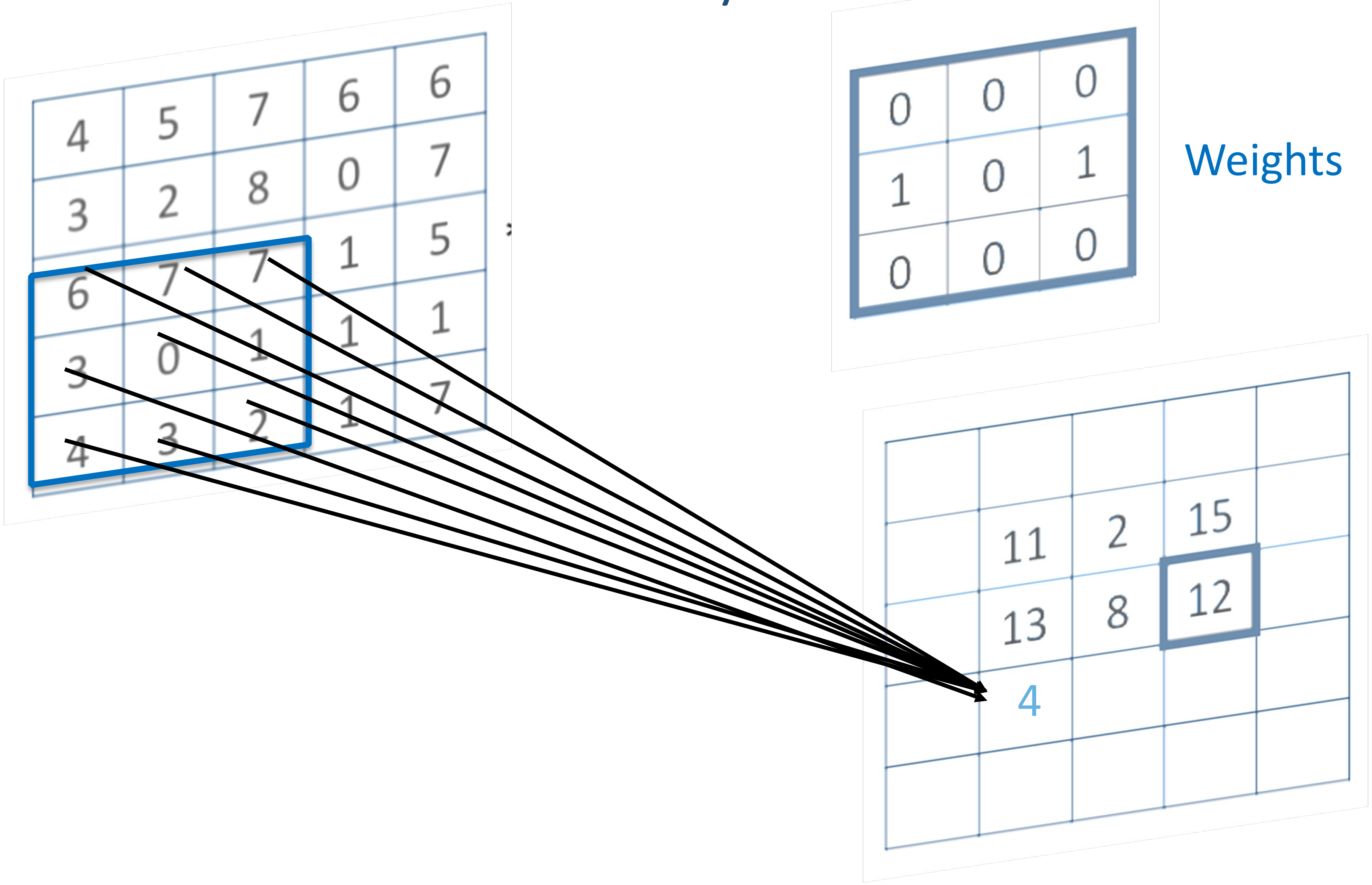
The 2D Convolutional Layer in a Neural Network



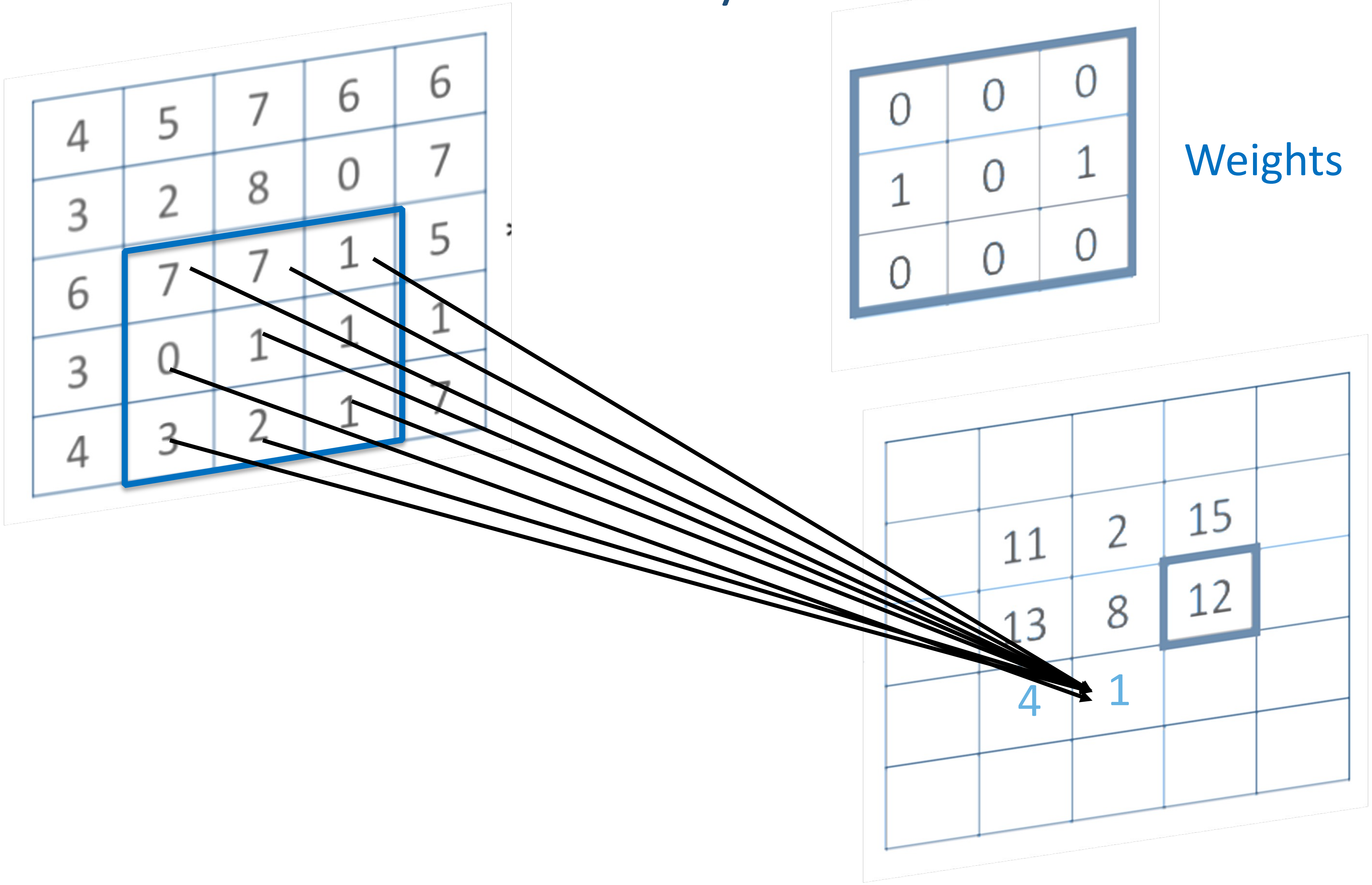
The 2D Convolutional Layer in a Neural Network



The 2D Convolutional Layer in a Neural Network



The 2D Convolutional Layer in a Neural Network



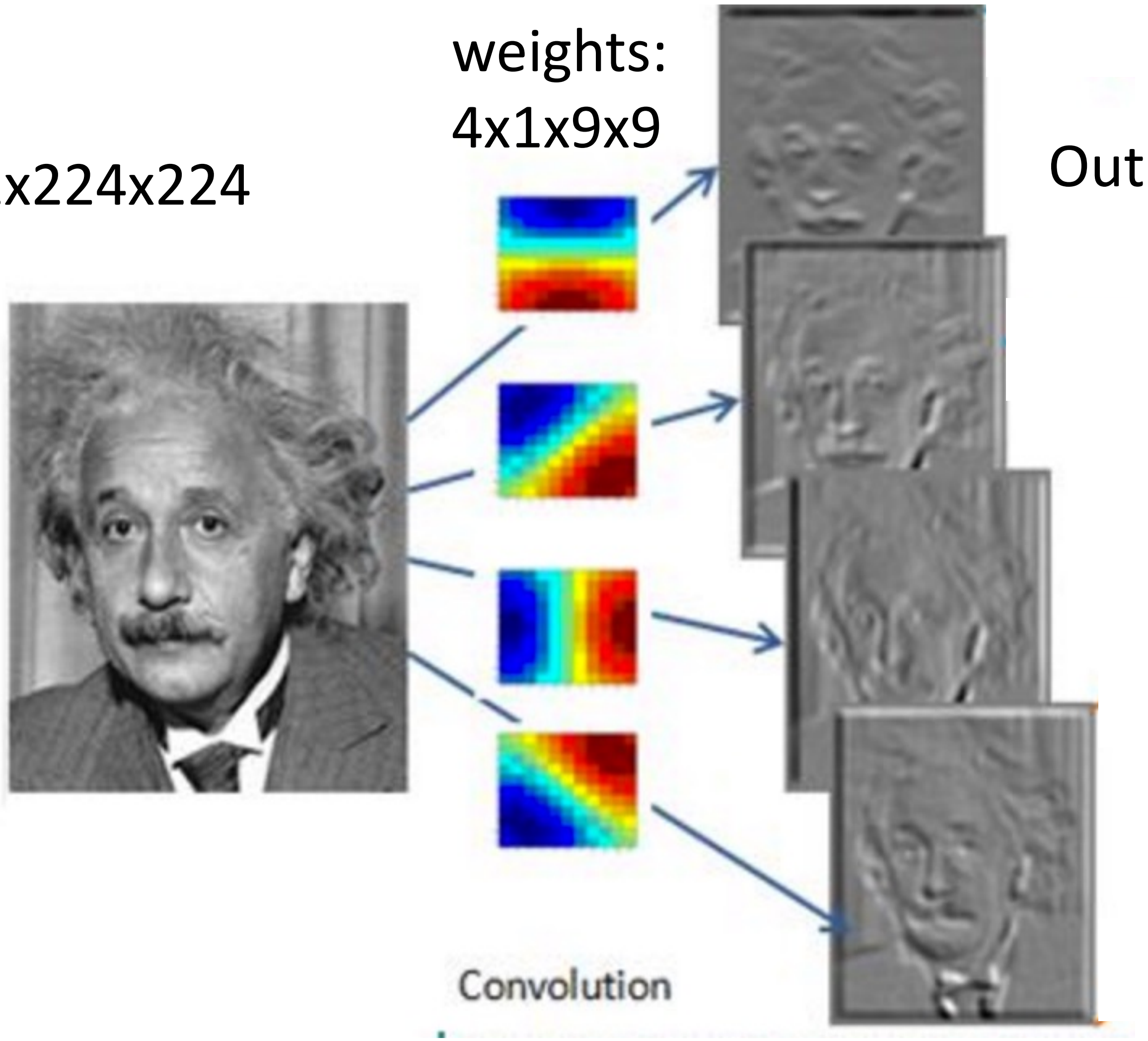
Convolutional Layer (with 4 filters)

weights:
4x1x9x9

Input: 1x224x224

Output: 4x224x224

if zero padding,
and stride = 1



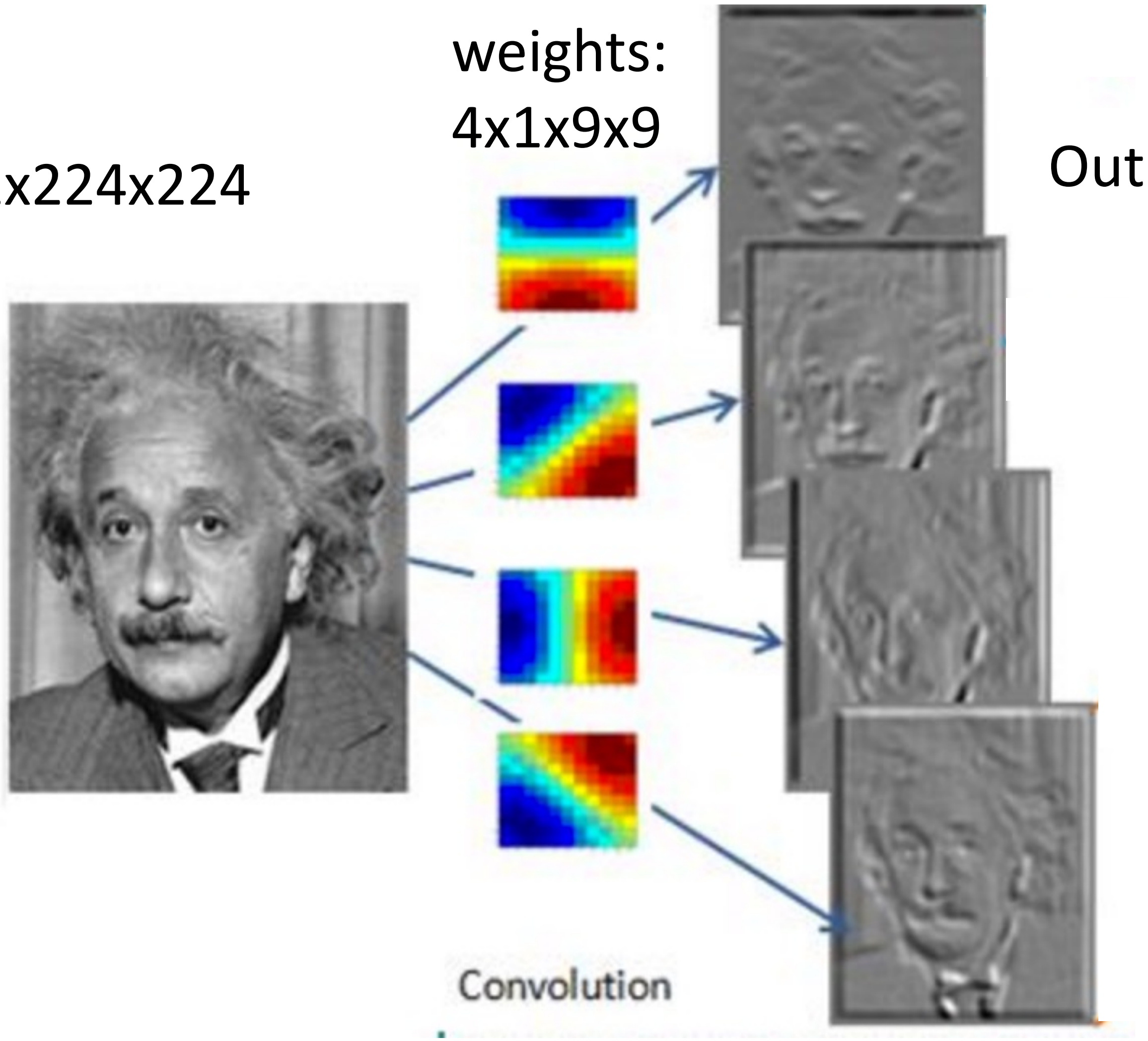
Convolutional Layer (with 4 filters)

weights:
4x1x9x9

Input: 1x224x224

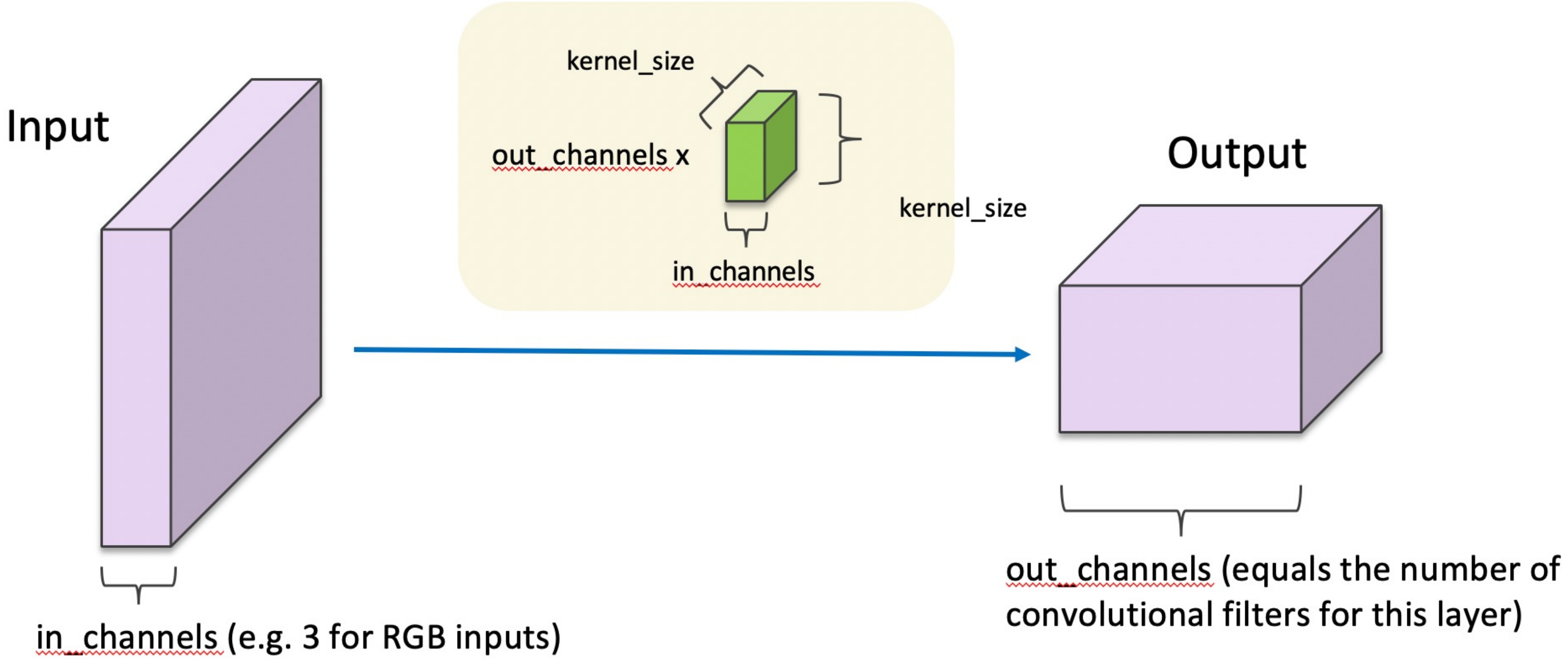
Output: 4x112x112

if zero padding,
but stride = 2

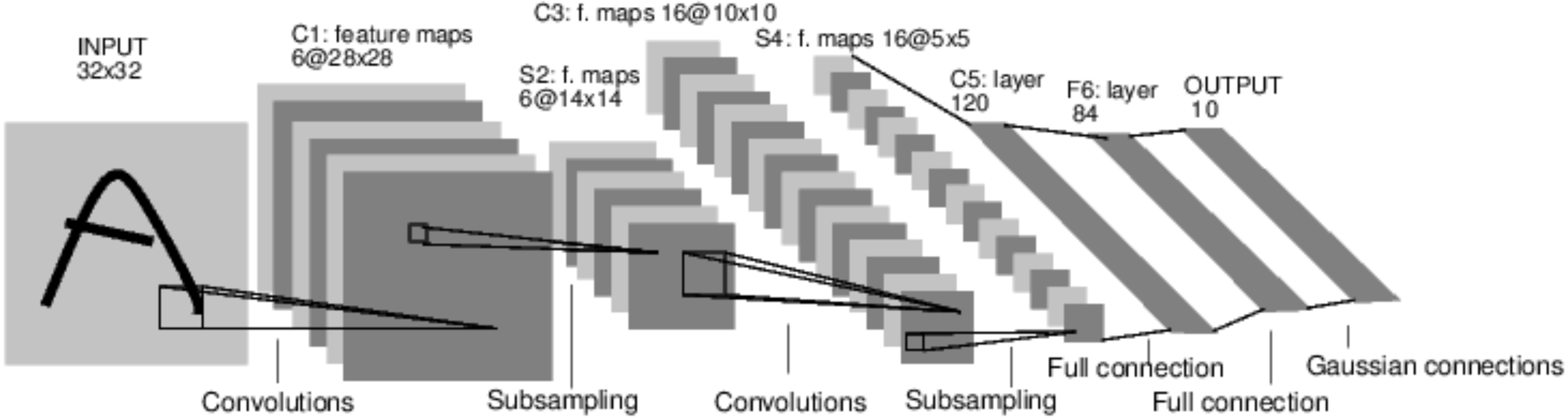


Convolutional Layer in pytorch

class `torch.nn.Conv2d`*(in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True)* [source]



Convolutional Network: LeNet



Yann LeCun

TITLE	CITED BY	YEAR
Gradient-based learning applied to document recognition Y LeCun, L Bottou, Y Bengio, P Haffner Proceedings of the IEEE 86 (11), 2278-2324	61889	1998

LeNet in Pytorch

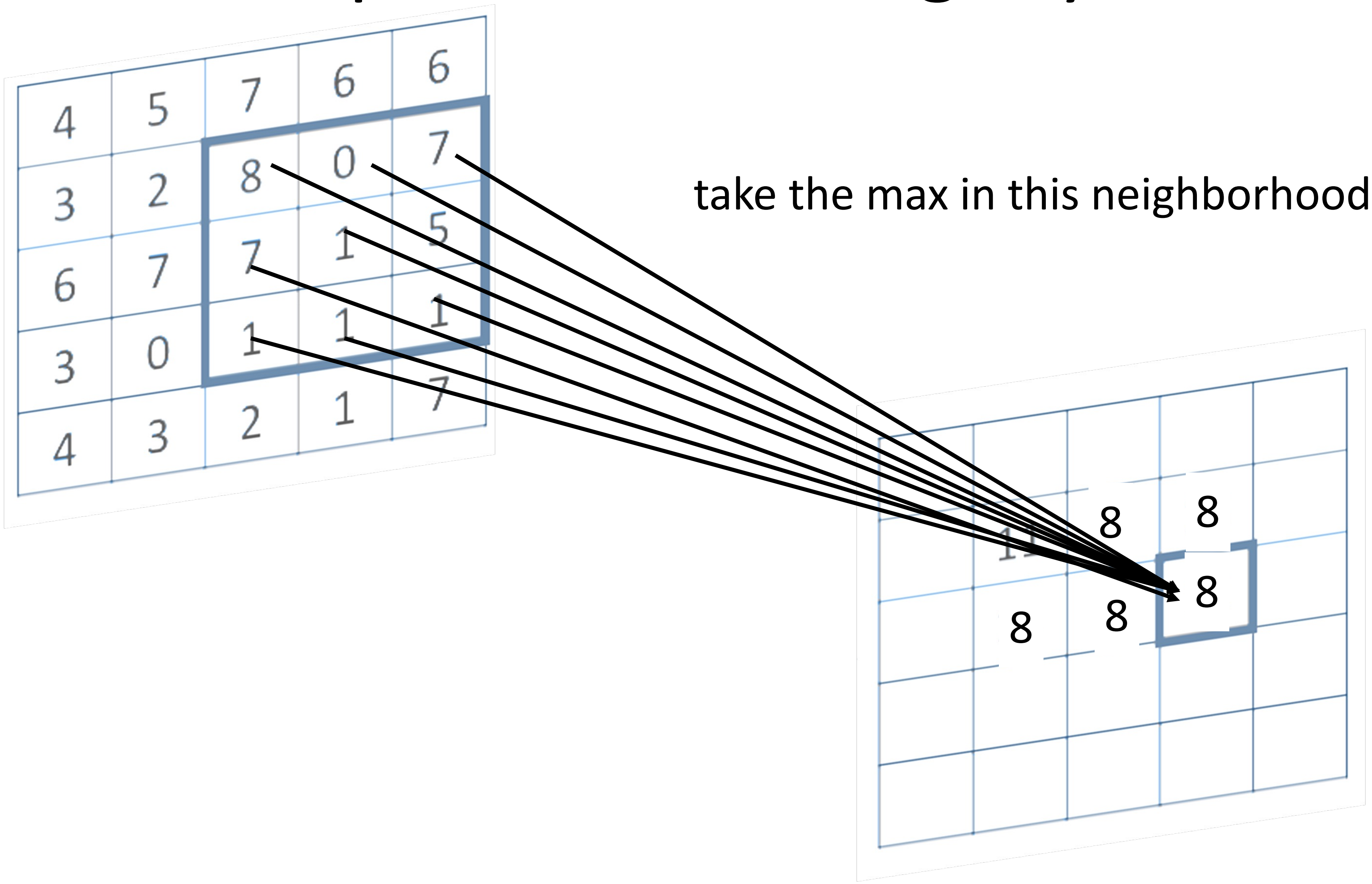
```python
# LeNet is French for The Network, and is taken from Yann Lecun's 98 paper
# on digit classification http://yann.lecun.com/exdb/lenet/
# This was also a network with just two convolutional layers.
class LeNet(nn.Module):
    def __init__(self):
        super(LeNet, self).__init__()
        # Convolutional layers.
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.conv2 = nn.Conv2d(6, 16, 5)

        # Linear layers.
        self.fc1 = nn.Linear(16*5*5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        out = F.relu(self.conv1(x))
        out = F.max_pool2d(out, 2)
        out = F.relu(self.conv2(out))
        out = F.max_pool2d(out, 2)

        # This flattens the output of the previous layer into a vector.
        out = out.view(out.size(0), -1)
        out = F.relu(self.fc1(out))
        out = F.relu(self.fc2(out))
        out = self.fc3(out)
        return out
```

SpatialMaxPooling Layer



LeNet Summary

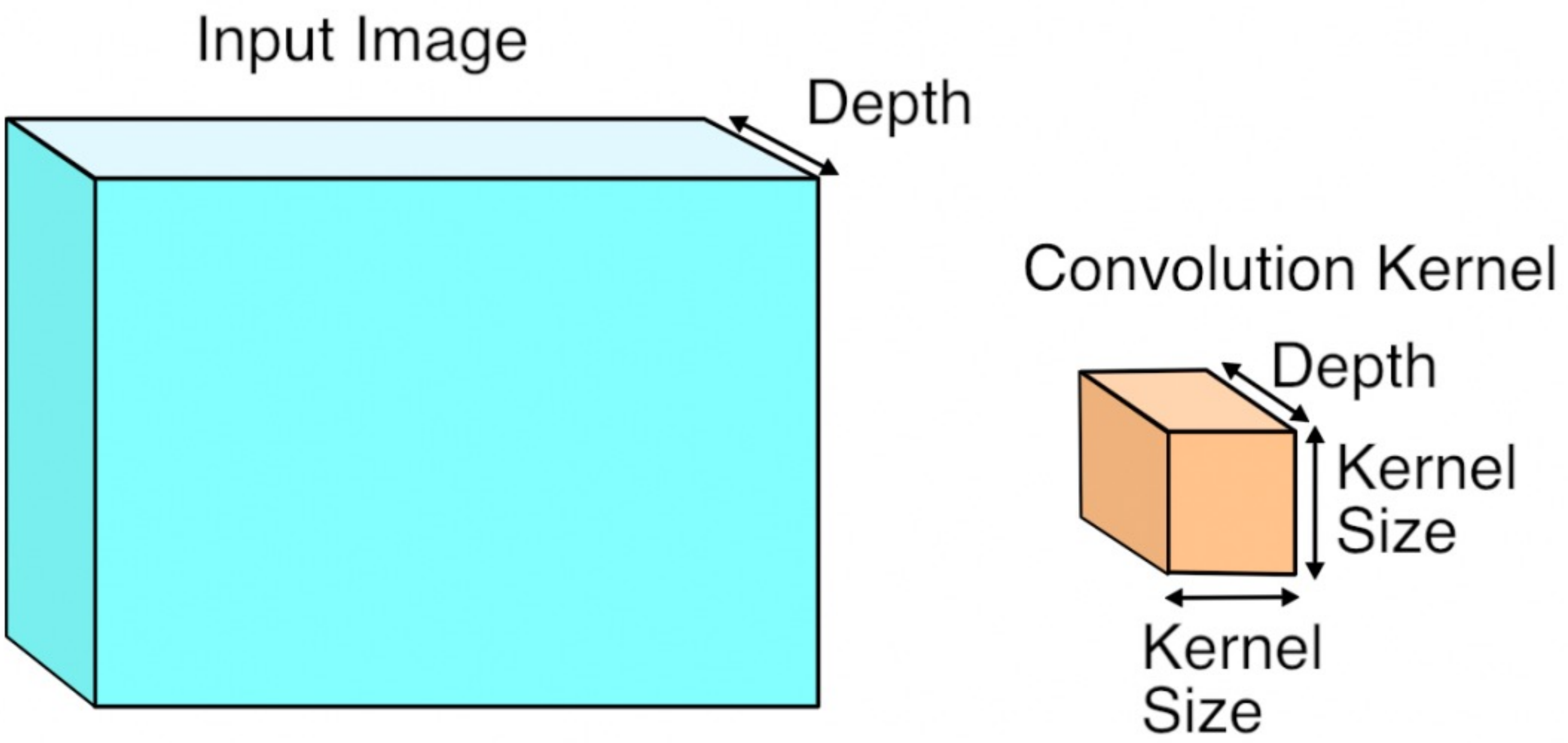
- 2 Convolutional Layers + 3 Linear Layers

- + Non-linear functions: ReLUs or Sigmoids
  + Max-pooling operations

New Architectures Proposed

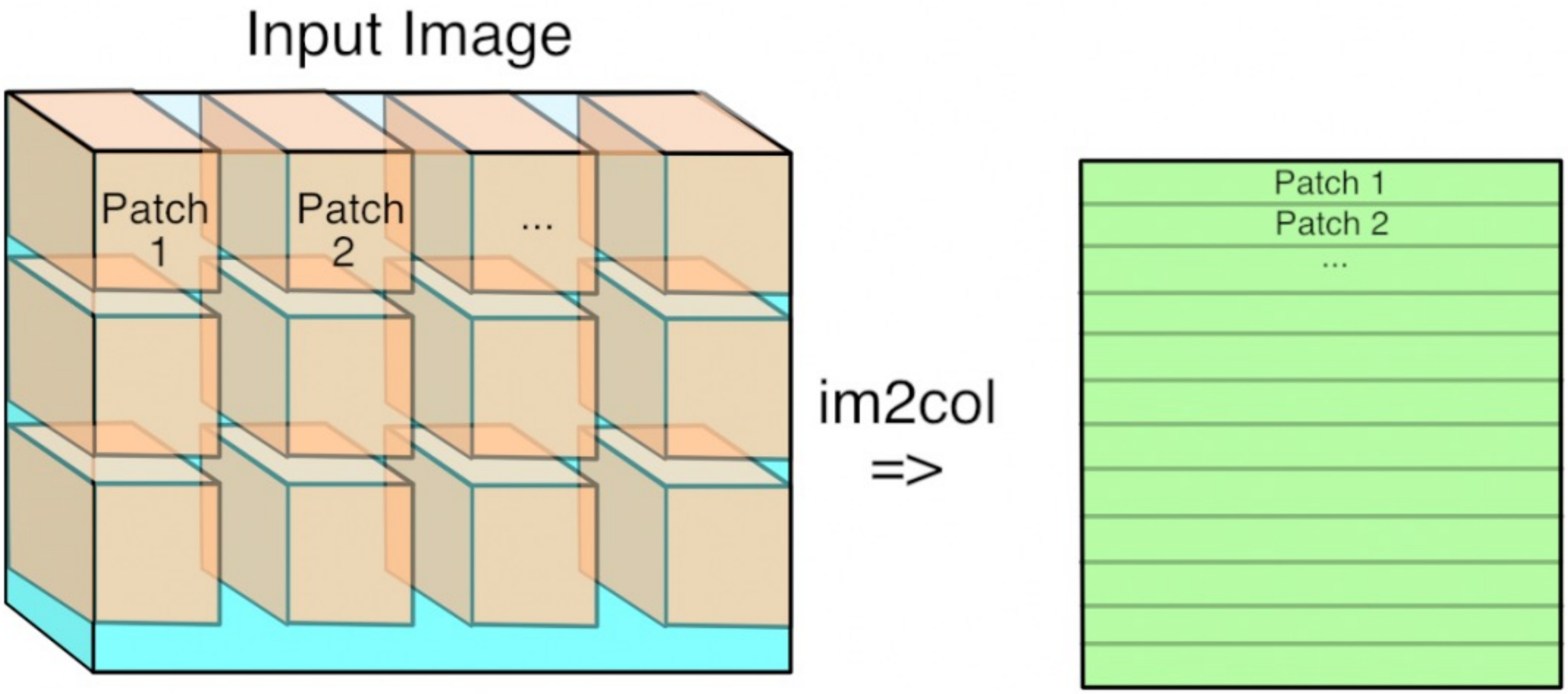
- Alexnet (Kriszhevsky et al NIPS 2012) **[Required Reading]**
- VGG (Simonyan and Zisserman 2014)
- GoogLeNet (Szegedy et al CVPR 2015)
- ResNet (He et al CVPR 2016)
- DenseNet (Huang et al CVPR 2017)

Convolutional Layers as Matrix Multiplication



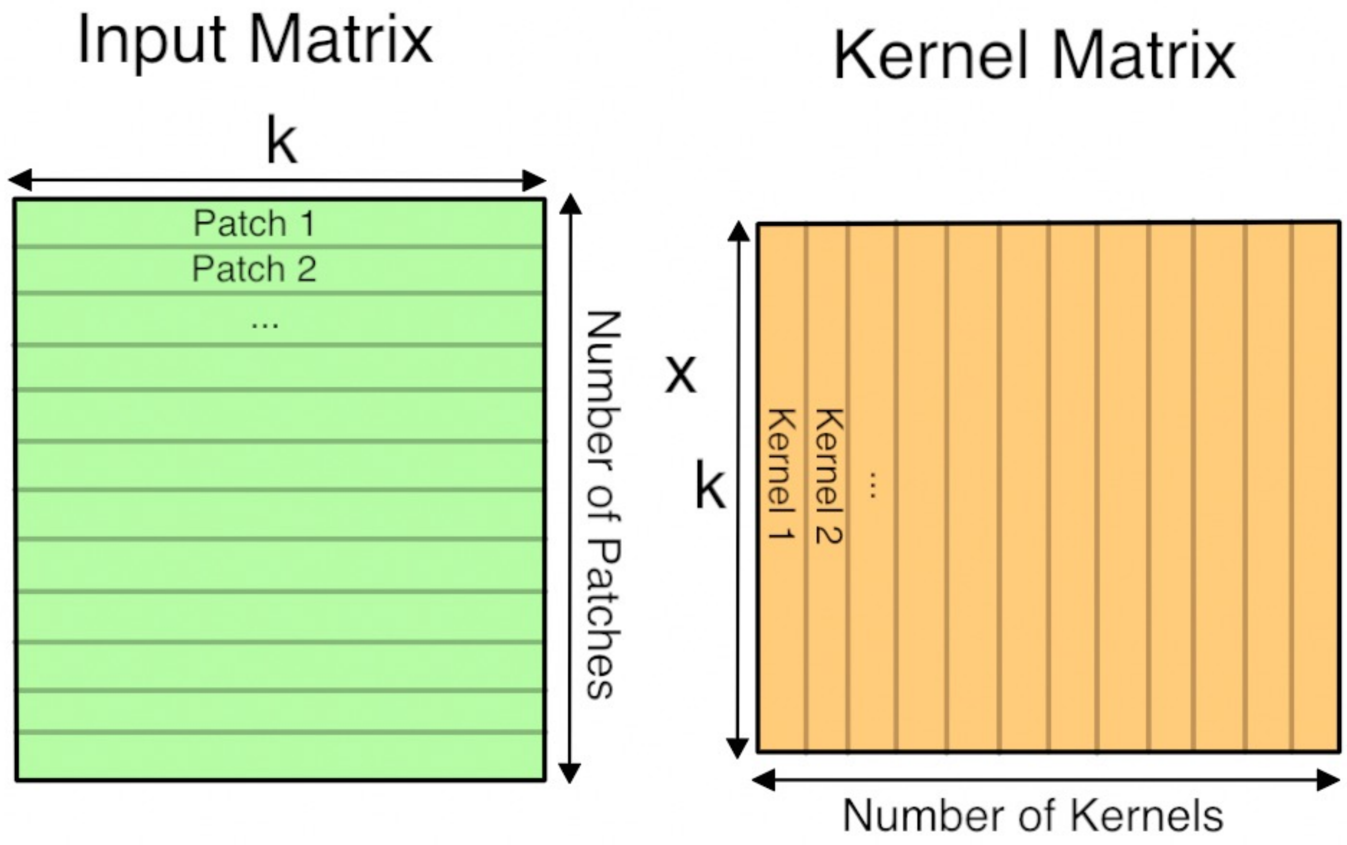
https://petewarden.com/2015/04/20/why-gemm-is-at-the-heart-of-deep-learning/

Convolutional Layers as Matrix Multiplication



https://petewarden.com/2015/04/20/why-gemm-is-at-the-heart-of-deep-learning/

Convolutional Layers as Matrix Multiplication



Pros?
Cons?

https://petewarden.com/2015/04/20/why-gemm-is-at-the-heart-of-deep-learning/

CNN Computations are Computationally Expensive

- However highly parallelizable
- GPU Computing is used in practice
- CPU Computing in fact is prohibitive for training these models

The Alexnet network (Krizhevsky et al NIPS 2012)

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
University of Toronto
kriz@cs.utoronto.ca

Ilya Sutskever
University of Toronto
ilya@cs.utoronto.ca

Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

The Problem: Classification

Classify an image into 1000 possible classes:
e.g. Abyssinian cat, Bulldog, French Terrier, Cormorant, Chickadee, red fox, banjo, barbell, hourglass, knot, maze, viaduct, etc.

→

cat, tabby cat (0.71)
Egyptian cat (0.22)
red fox (0.11)
.....

The Data: ILSVRC

Imagenet Large Scale Visual Recognition Challenge (ILSVRC): Annual Competition

1000 Categories

~1000 training images per Category

~1 million images in total for training

~50k images for validation

Only images released for the test set but no annotations,
evaluation is performed centrally by the organizers (max 2 per week)

The Evaluation Metric: Top K-error

True label: Abyssinian cat

Top-1 error: 1.0 Top-1 accuracy: 0.0

Top-2 error: 1.0 Top-2 accuracy: 0.0

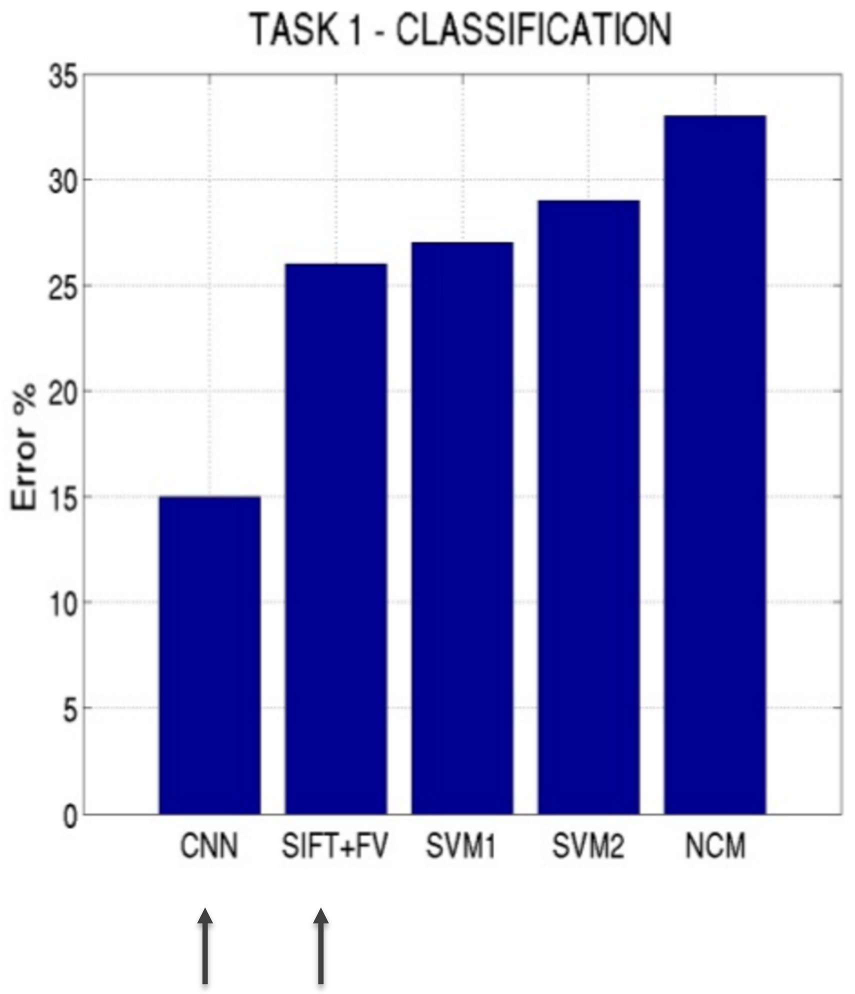
Top-3 error: 1.0 Top-3 accuracy: 0.0

Top-4 error: 0.0 Top-4 accuracy: 1.0

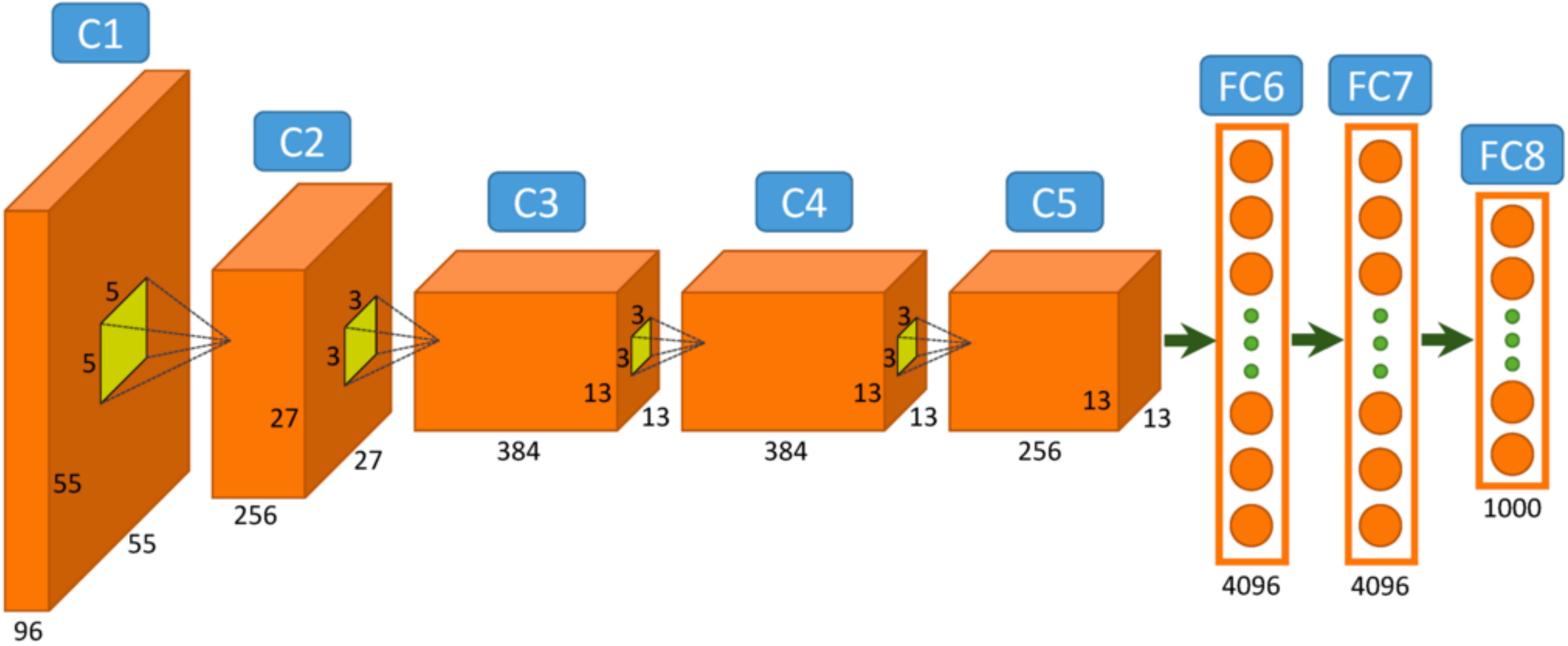
Top-5 error: 0.0 Top-5 accuracy: 1.0

cat, tabby cat (0.61)
Egyptian cat (0.22)
red fox (0.11)
Abyssinian cat (0.10)
French terrier (0.03)
.....

Top-5 error on this competition (2012)



Alexnet



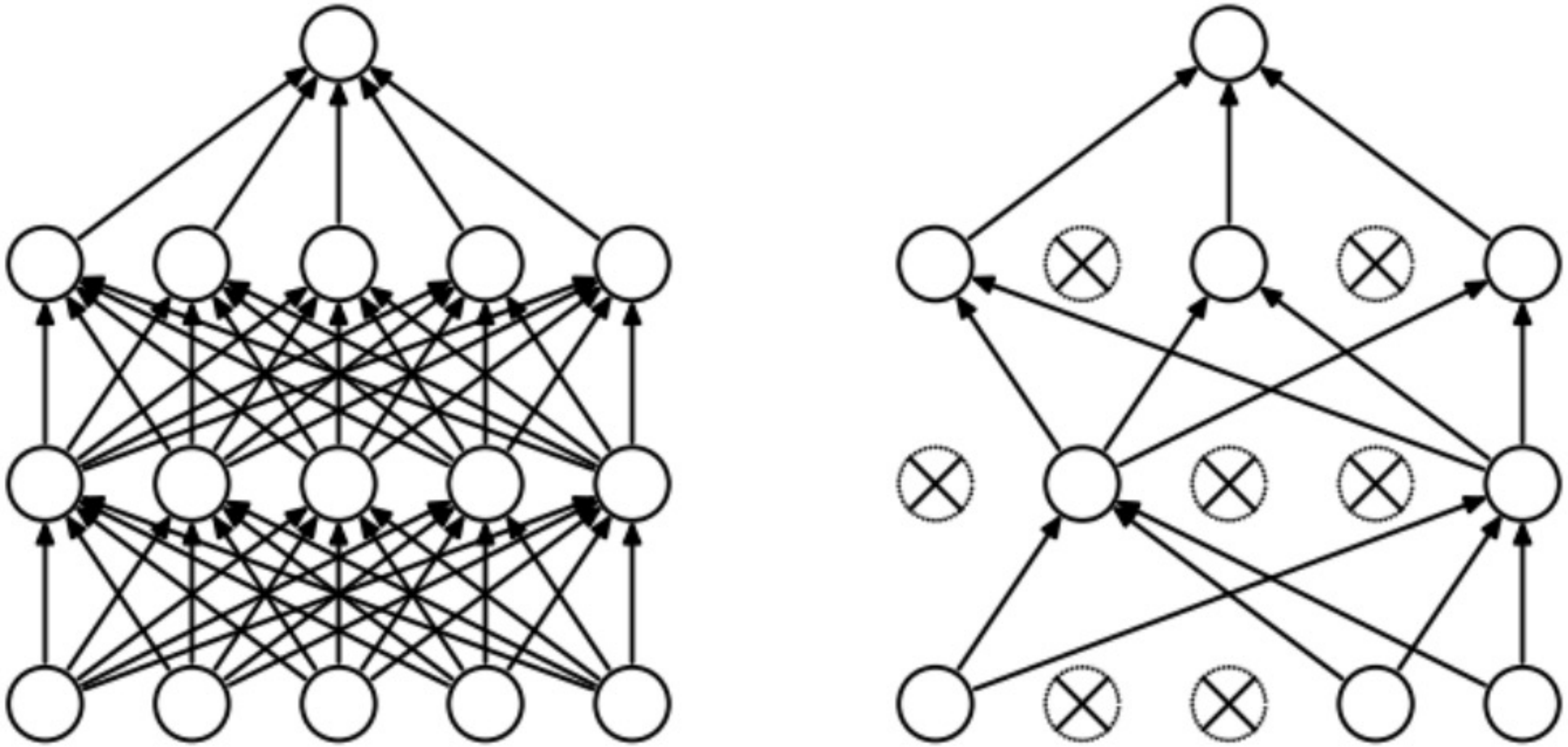
https://www.saagie.com/fr/blog/object-detection-part1

Pytorch Code for Alexnet

- In-class analysis

  https://github.com/pytorch/vision/blob/master/torchvision/models/alexnet.py

Dropout Layer

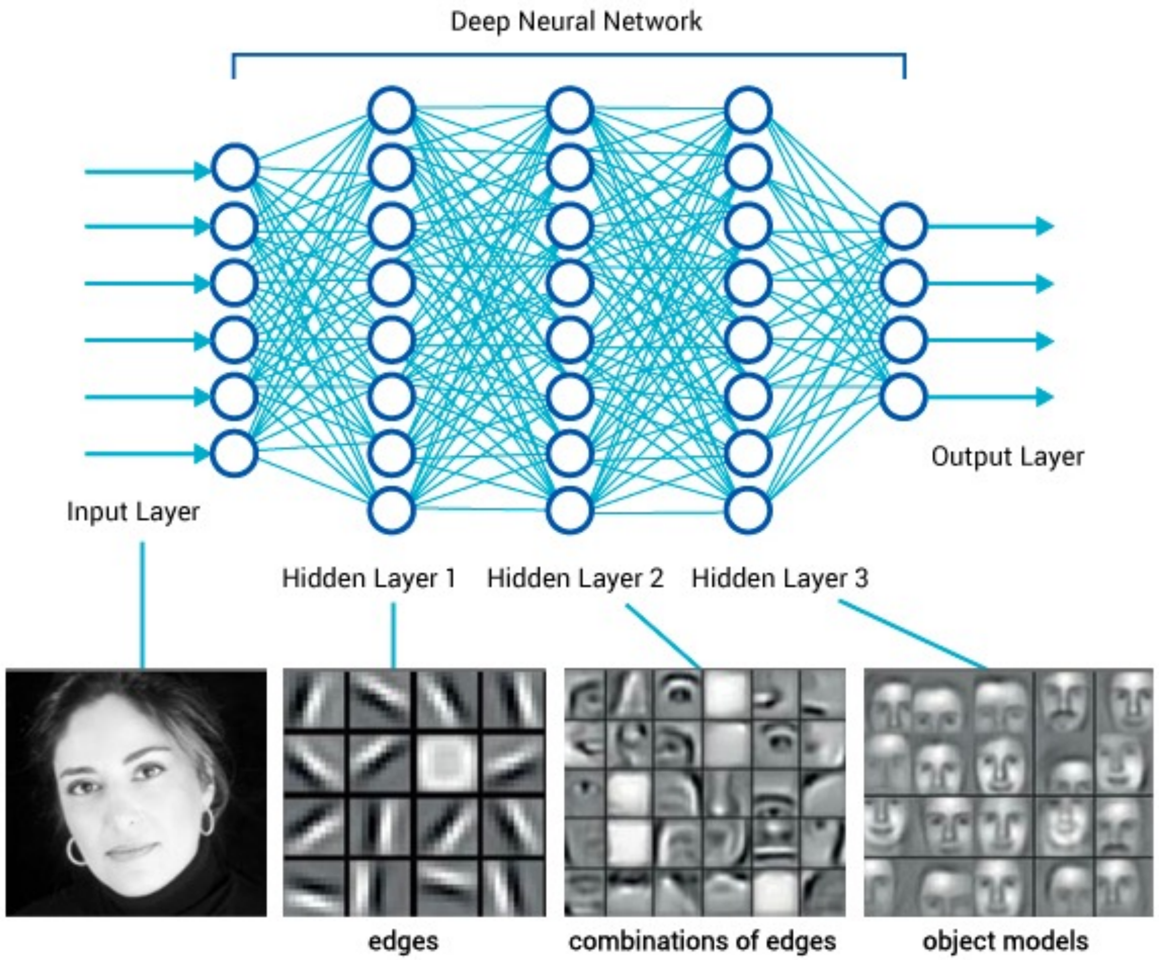


(a) Standard Neural Net

(b) After applying dropout.

Srivastava et al 2014

What is happening?



https://www.saagie.com/fr/blog/object-detection-part1

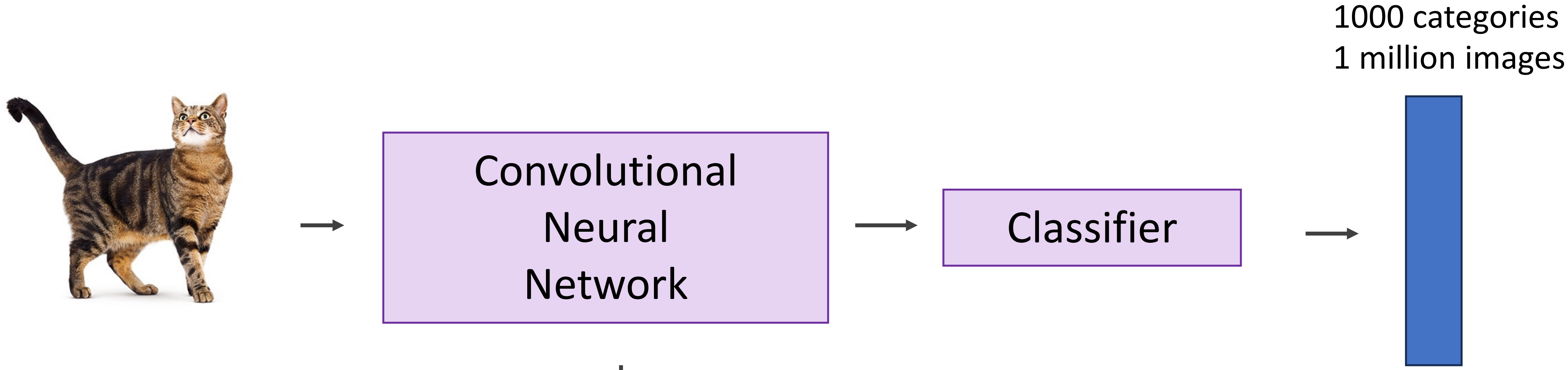
SIFT + FV + SVM (or softmax)

Feature extraction (SIFT) → Feature encoding (Bag of words) → Classification (SVM or softmax) →

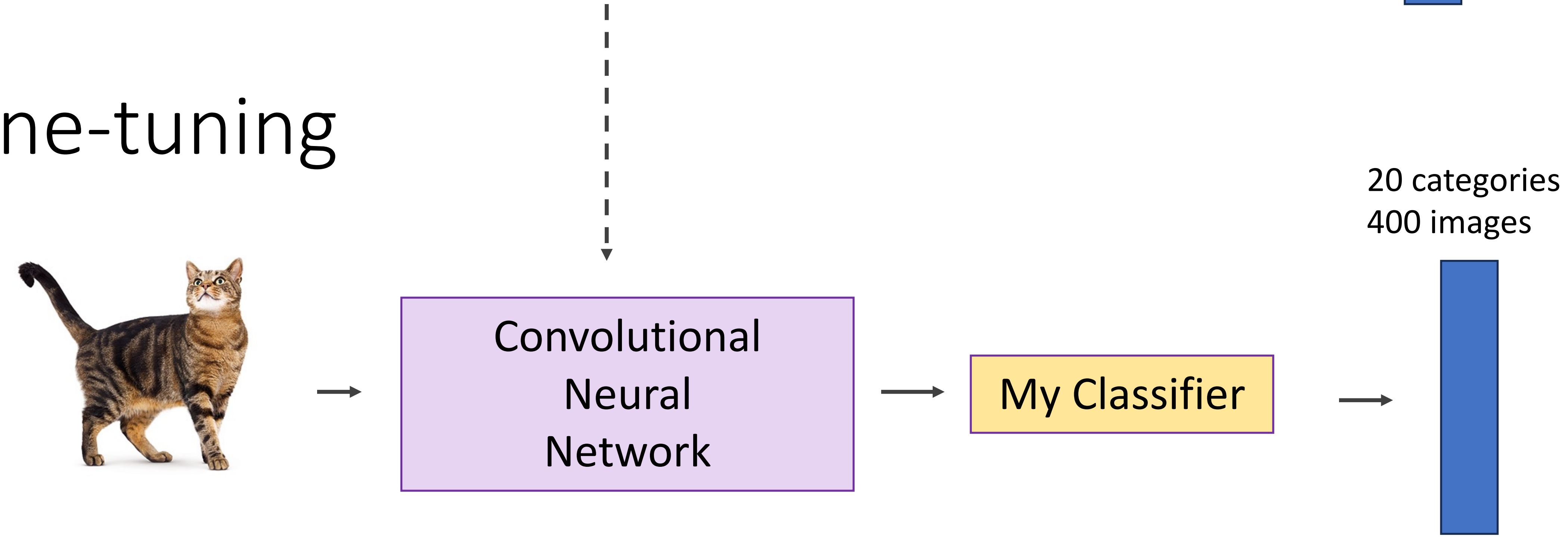
Deep Learning

Convolutional Neural Network → Classifier (SVM or softmax) →

Pre-training



Fine-tuning



Preprocessing and Data Augmentation

Preprocessing and Data Augmentation

256

256

Preprocessing and Data Augmentation

224x224

Preprocessing and Data Augmentation

224x224





True label: Abyssinian cat

Other Important Aspects

- Using ReLUs instead of Sigmoid or Tanh
- Momentum + Weight Decay
- Dropout (Randomly sets Unit outputs to zero during training)
- GPU Computation!

Model	**Top-1**	**Top-5**
Sparse coding [2]	*47.1%*	*28.2%*
SIFT + FVs [24]	*45.7%*	*25.7%*
CNN	**37.5%**	**17.0%**

Questions?