Deep Computer Vision

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MIT Introduction to Deep Learning

January 6, 2026


"To know what is
where by looking."

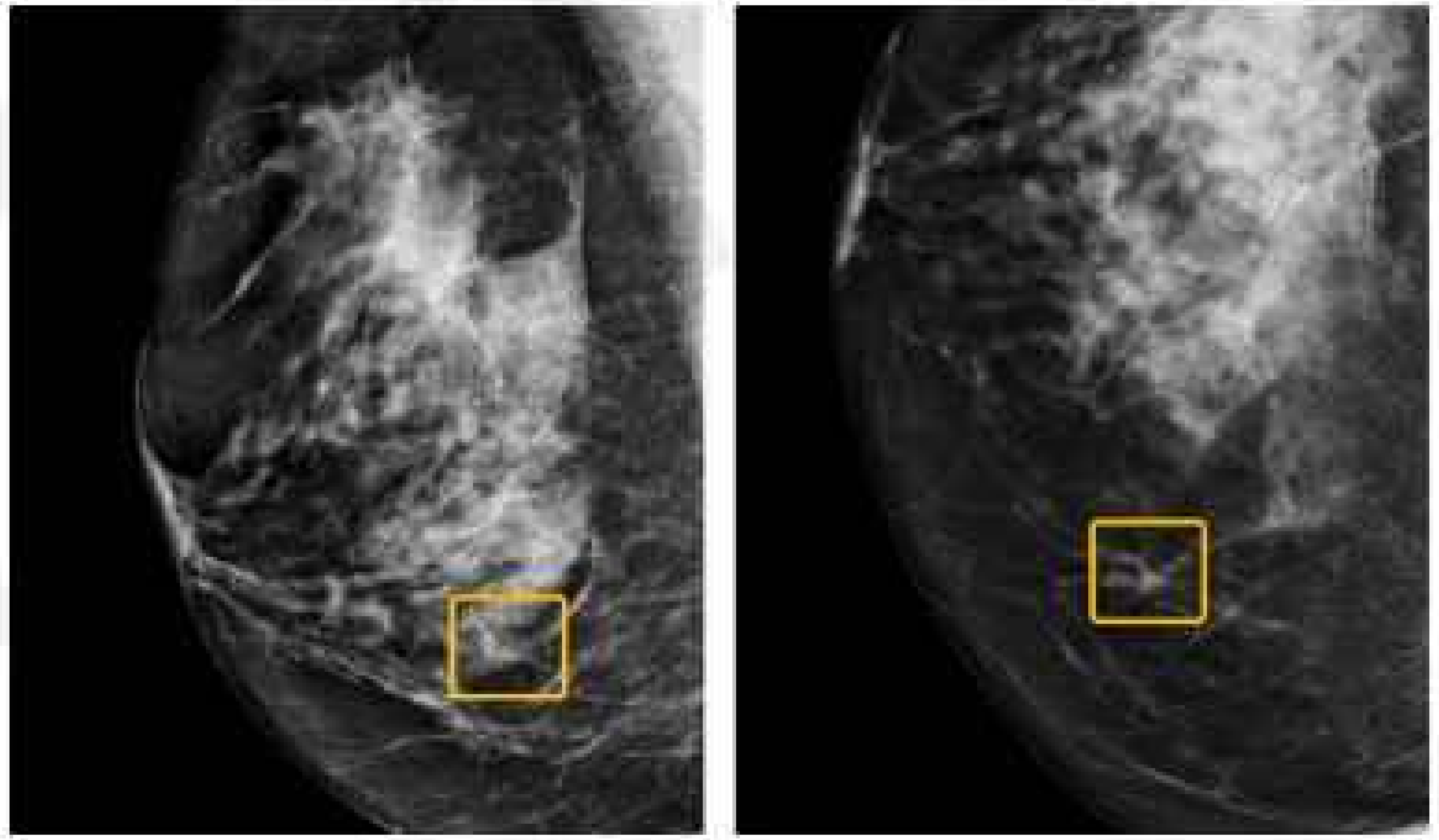
To discover from images what is present in the world, where things are, what actions are taking place, to predict and anticipate events in the world

The rise and impact of computer vision

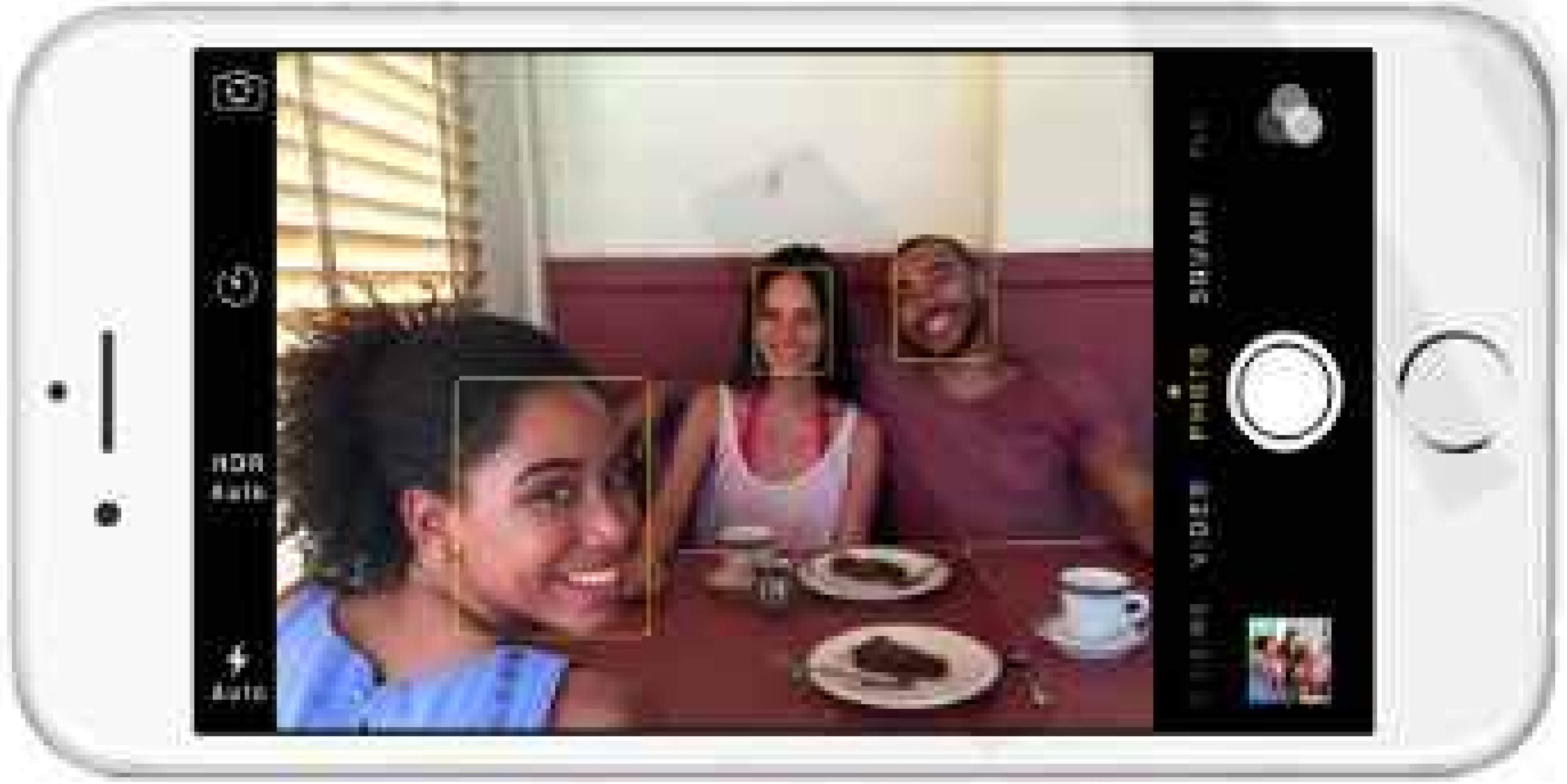
Robotics

Accessibility

Biology & Medicine

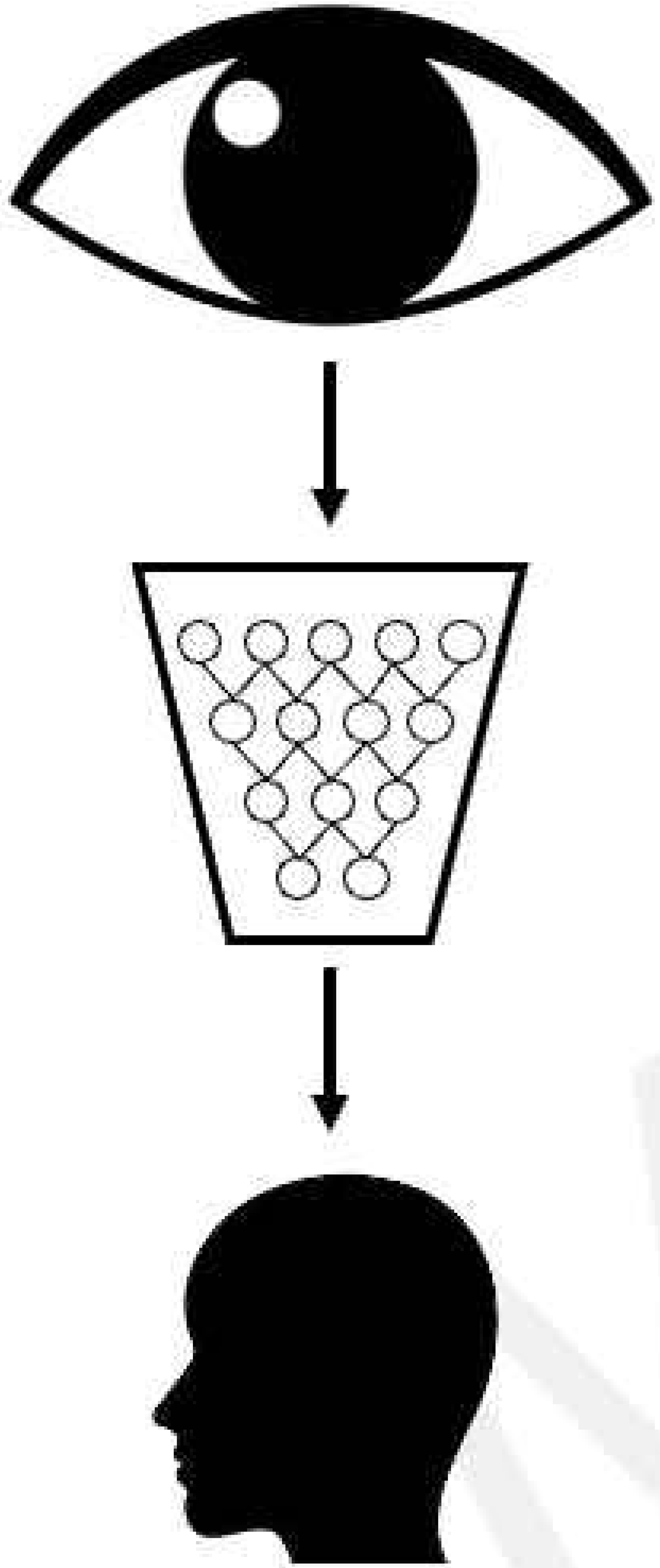


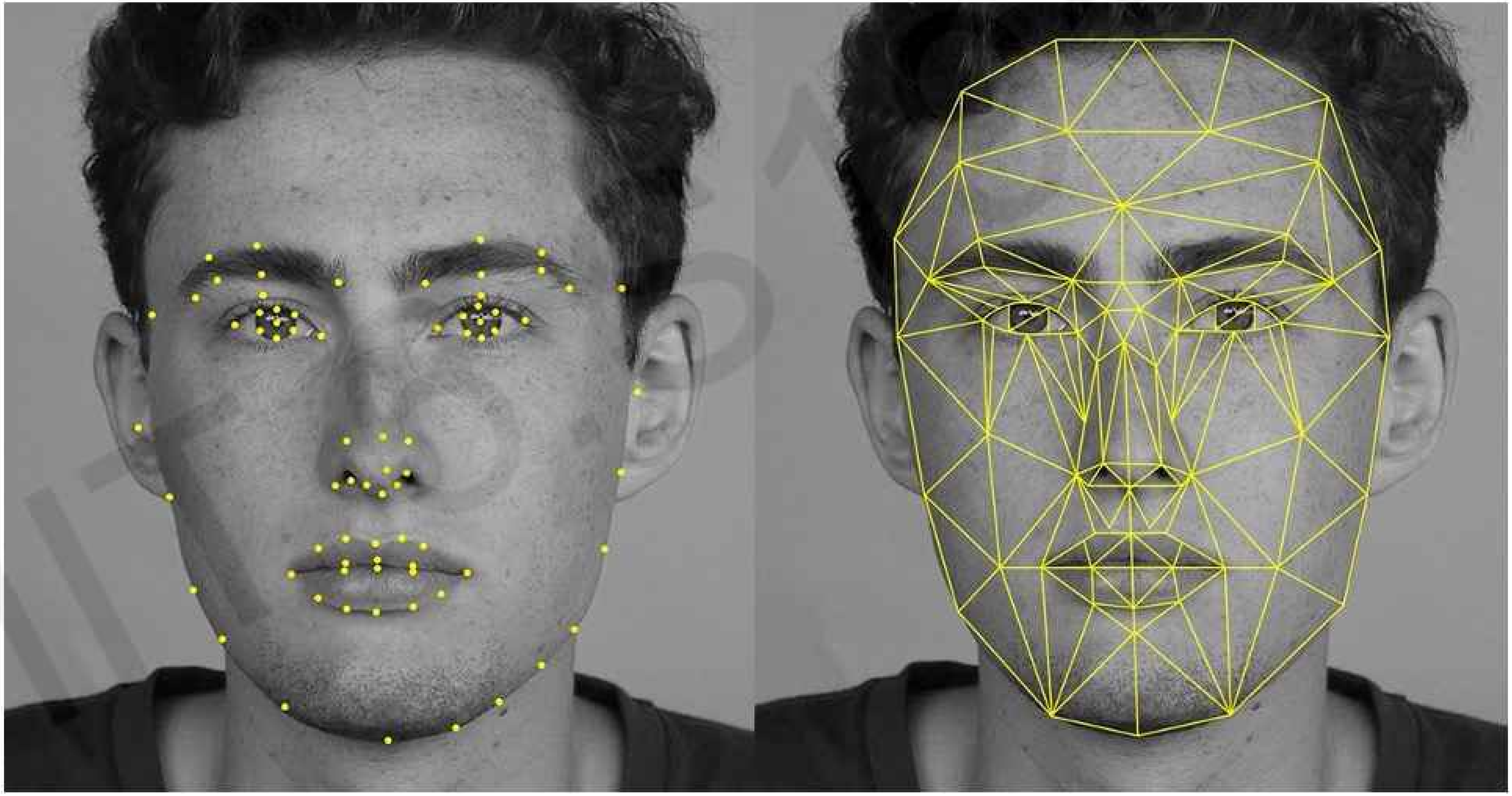
Autonomous driving



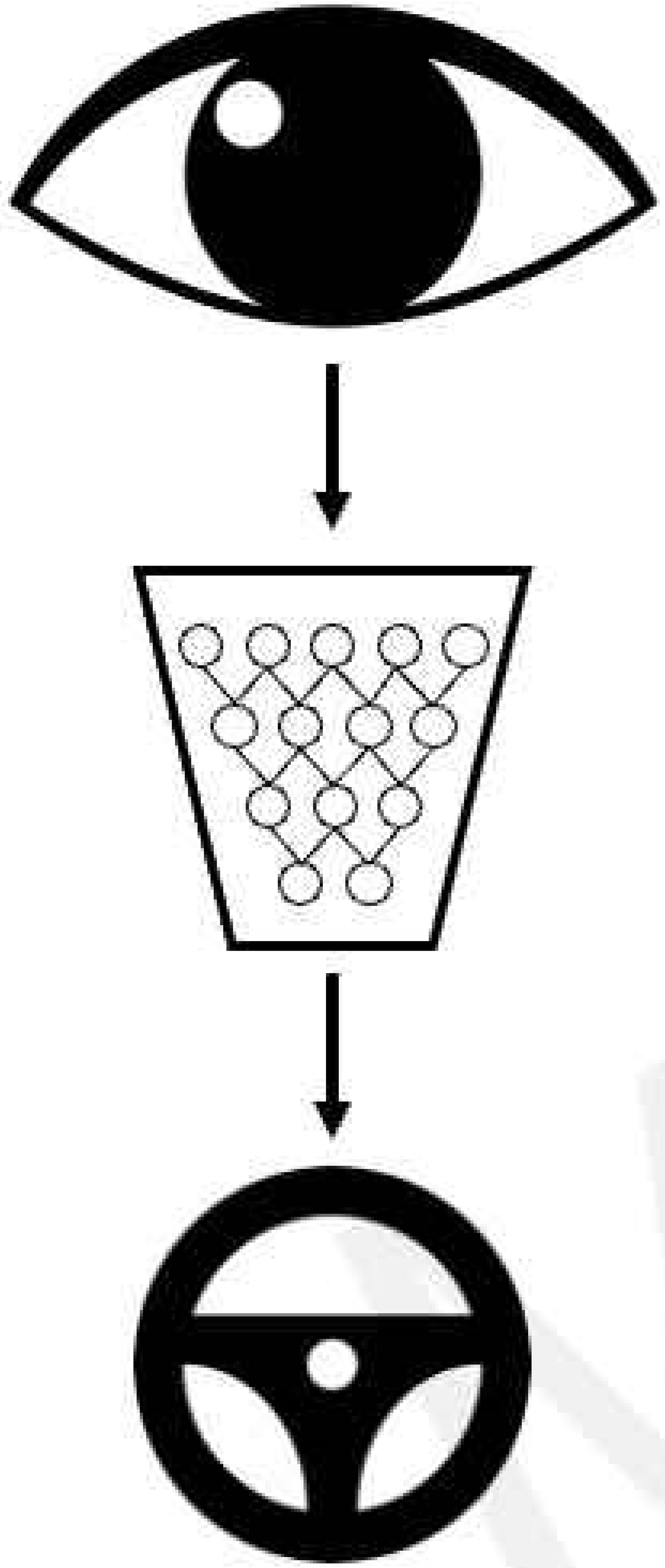
Mobile computing

Impact: Facial Detection & Recognition

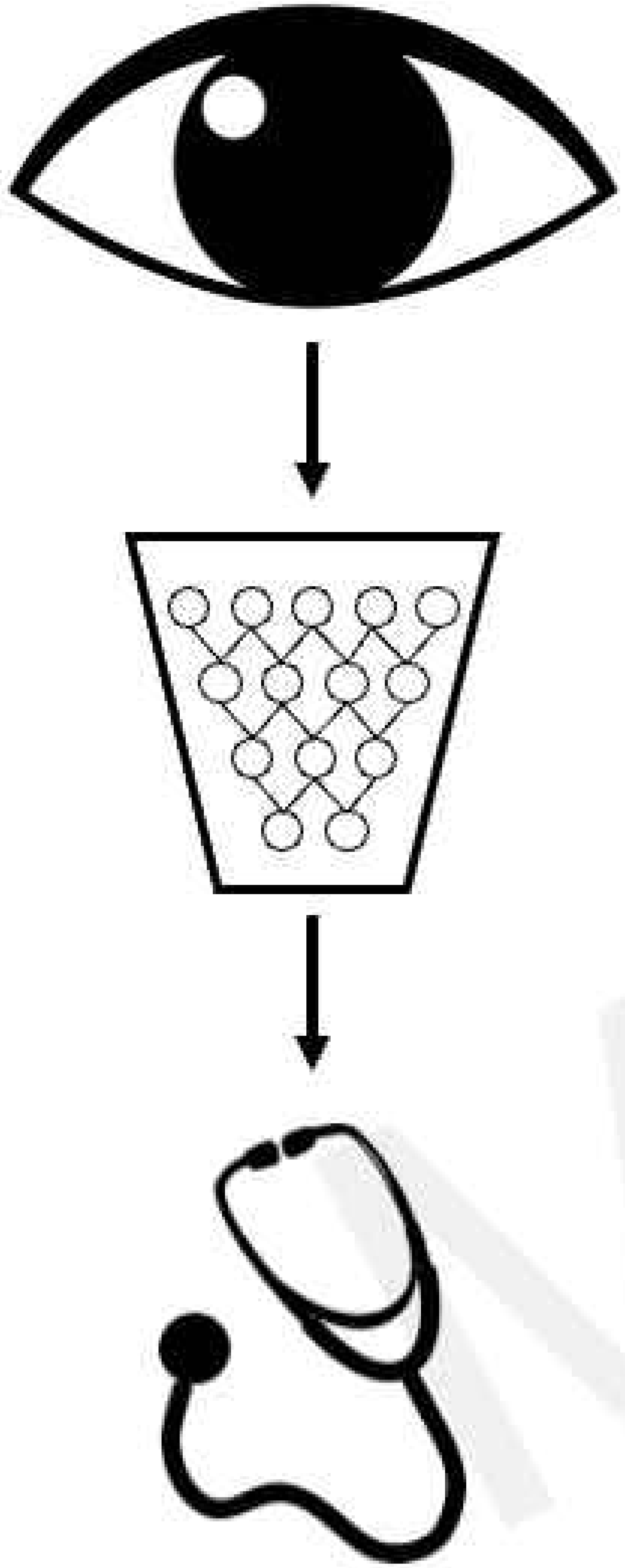




Impact: Self-Driving Cars



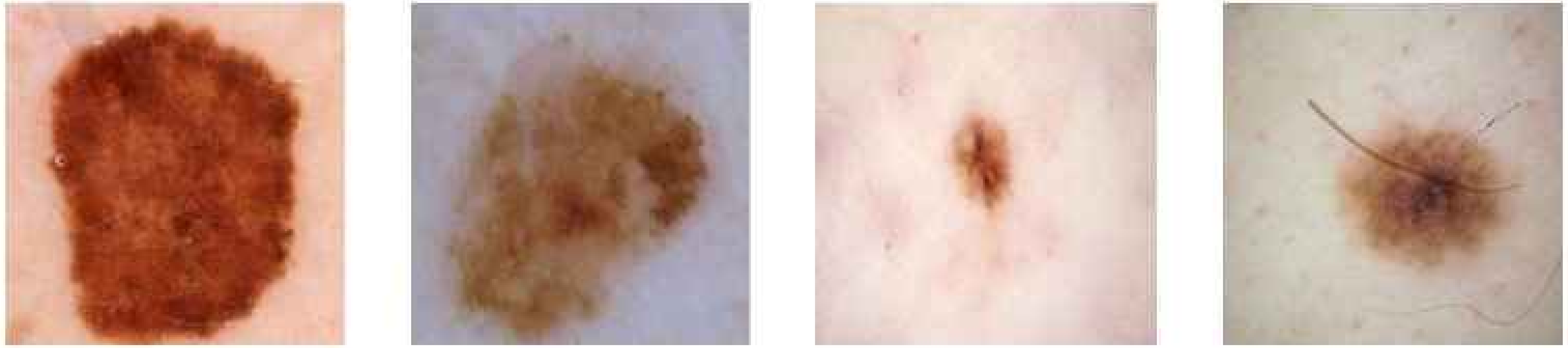
Impact: Medicine, Biology, Healthcare



Breast cancer

COVID-19

Skin cancer

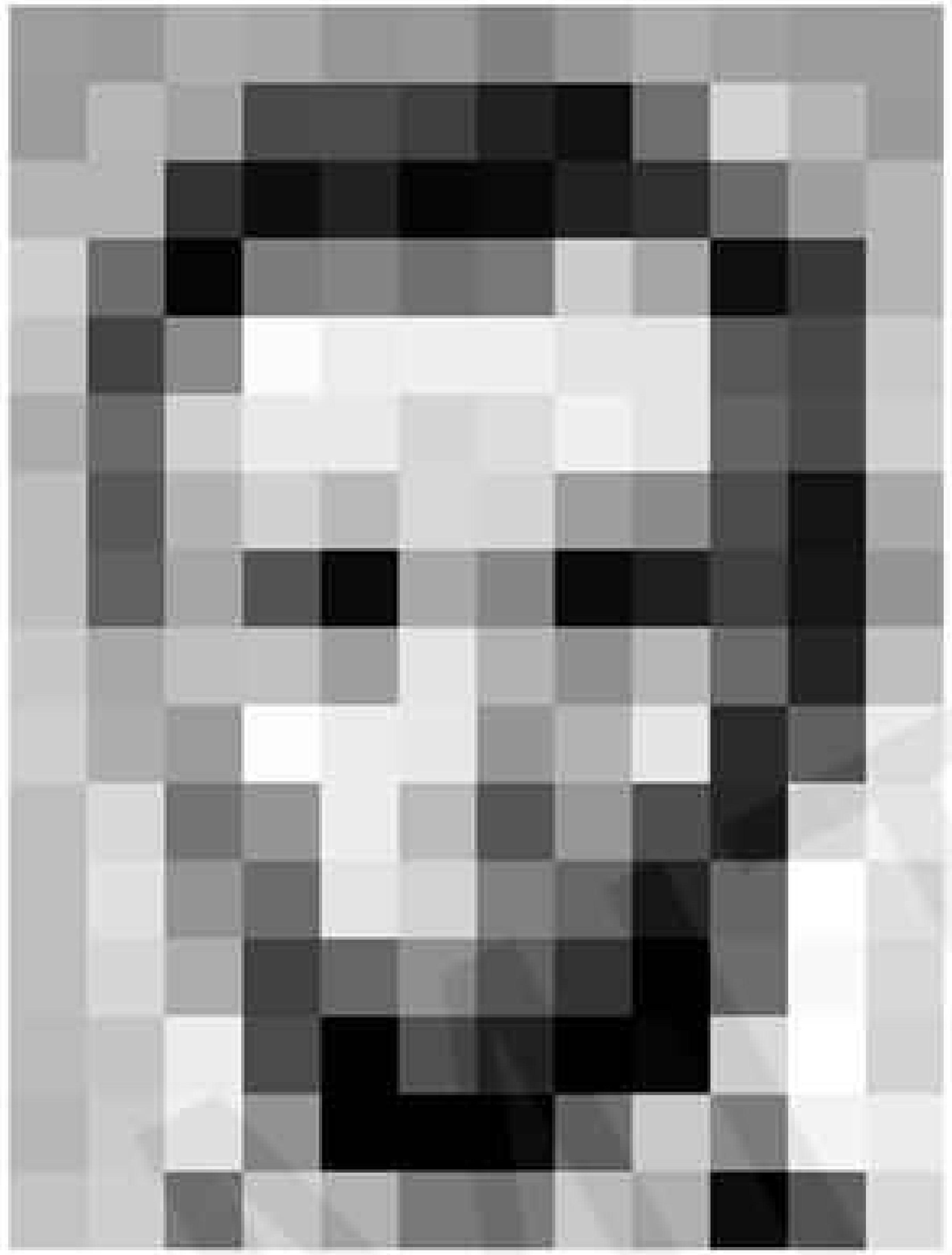


Esteva+ *Nature* 2017,
McKinney+ *Nature* 2020, Wang+ *Sci. Rep.* 2020.

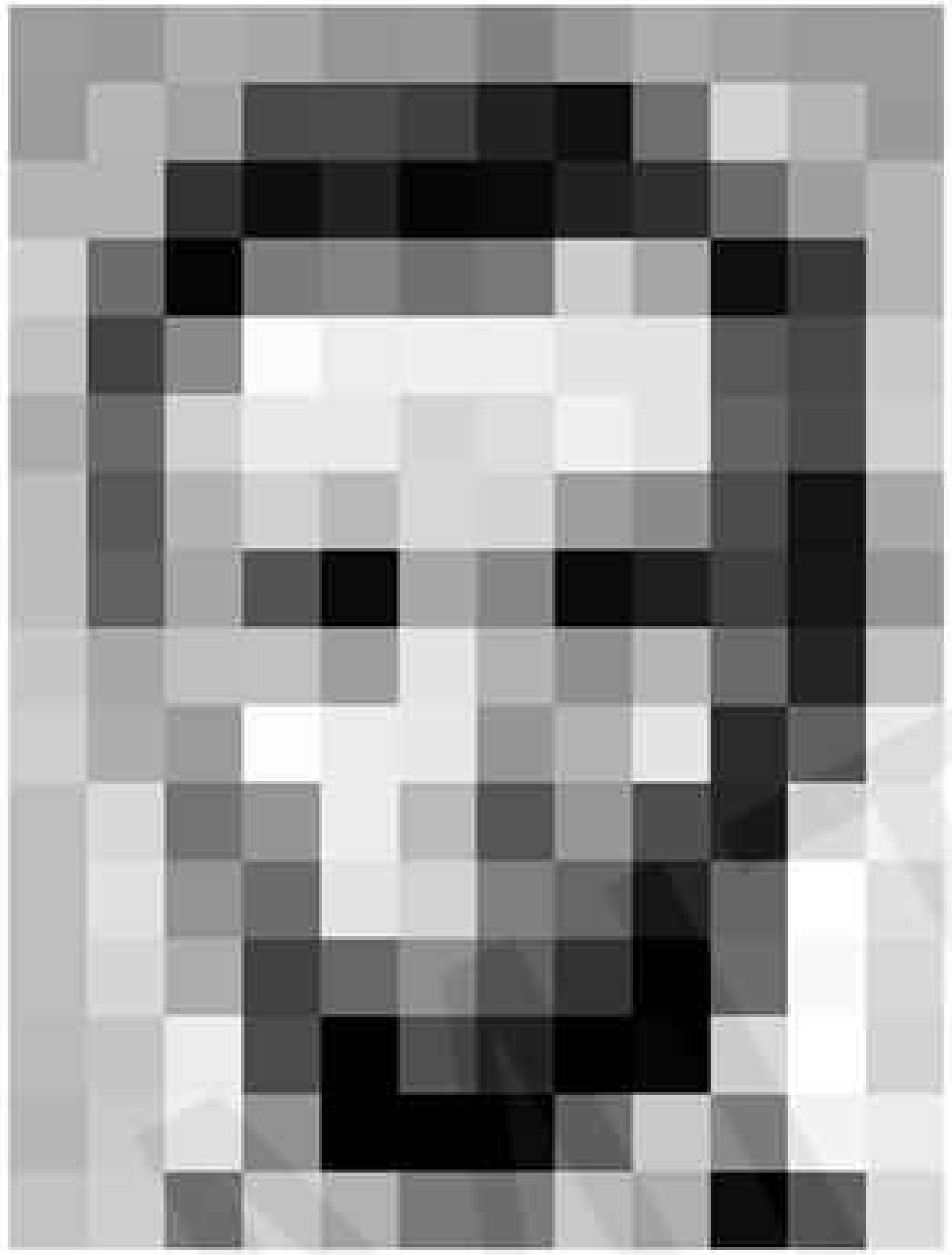
Impact: Accessibility

What Computers “See”

Images are Numbers

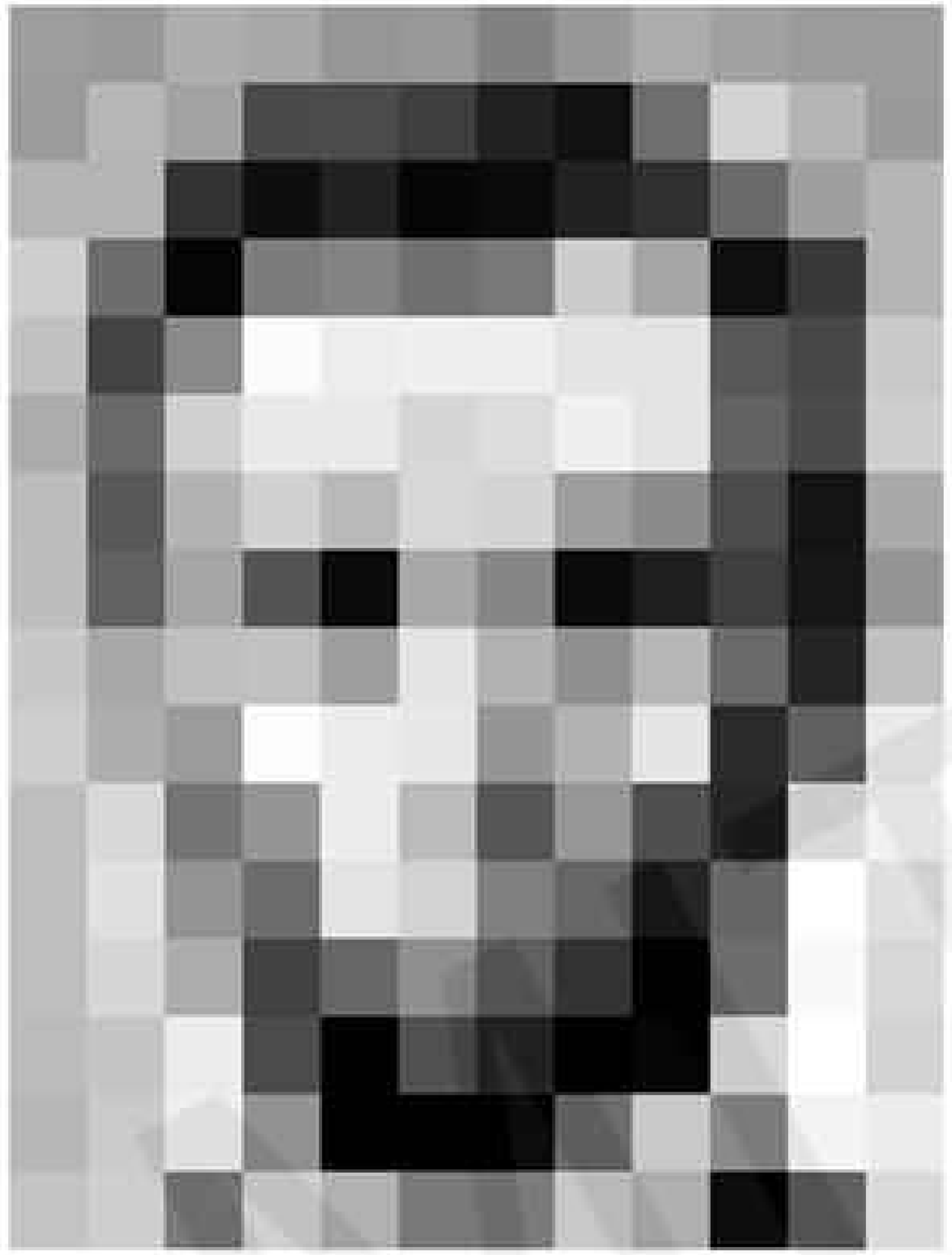


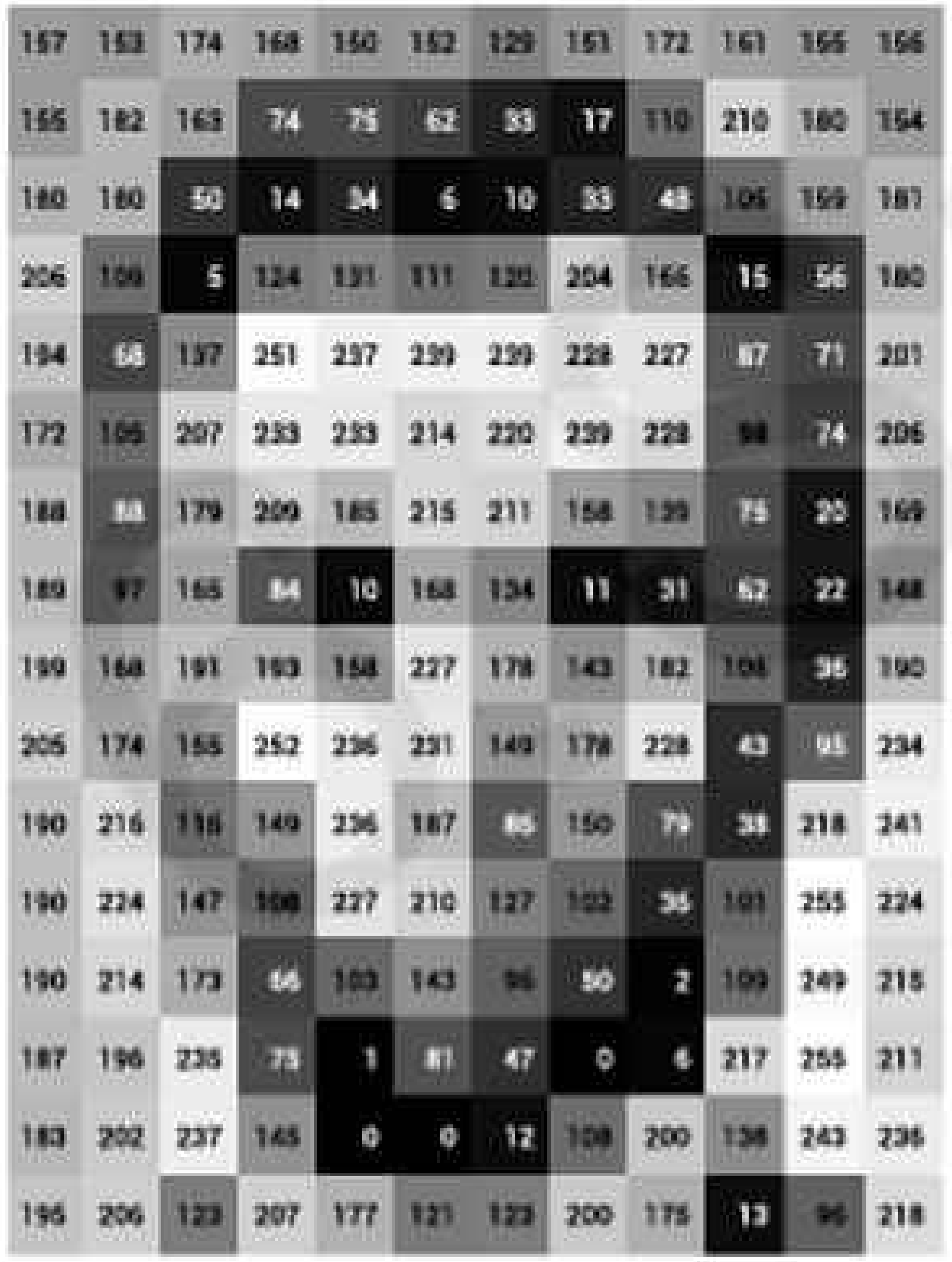
Images are Numbers



157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

Images are Numbers



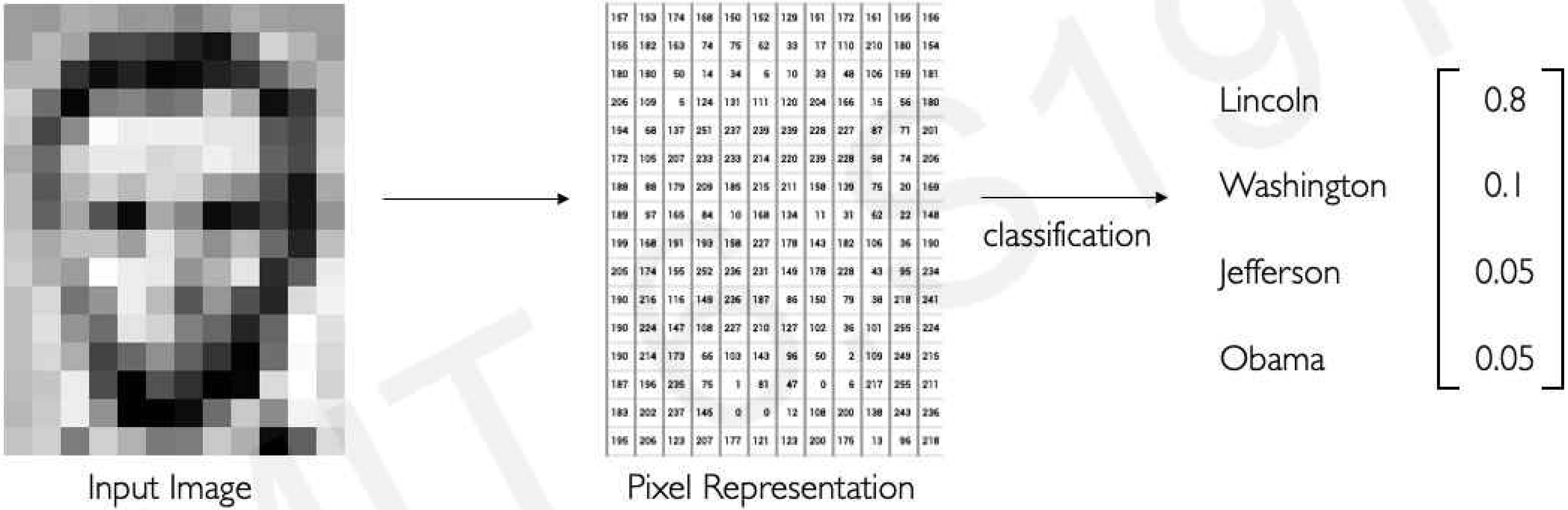


What the computer sees

157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

An image is just a matrix of numbers [0,255]!
i.e., 1080x1080x3 for an RGB image

Tasks in Computer Vision



- **Regression**: output variable takes continuous value
- **Classification**: output variable takes class label. Can produce probability of belonging to a particular class

High Level Feature Detection

Let's identify key features in each image category

Nose,
Eyes,
Mouth

Wheels,
License Plate,
Headlights

Door,
Windows,
Steps

Manual Feature Extraction

Domain knowledge → Define features → Detect features to classify

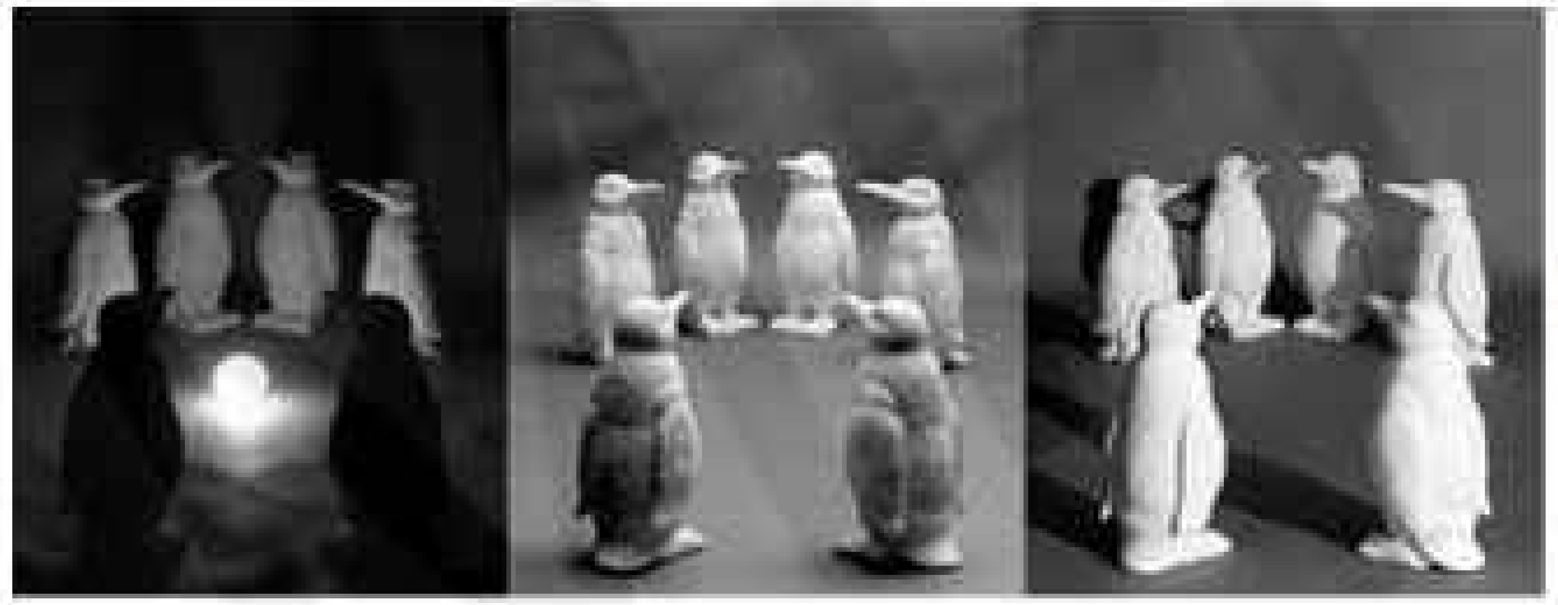
Problems?

Manual Feature Extraction

Domain knowledge → Define features → Detect features to classify

Viewpoint variation

Illumination conditions



Scale variation

Deformation

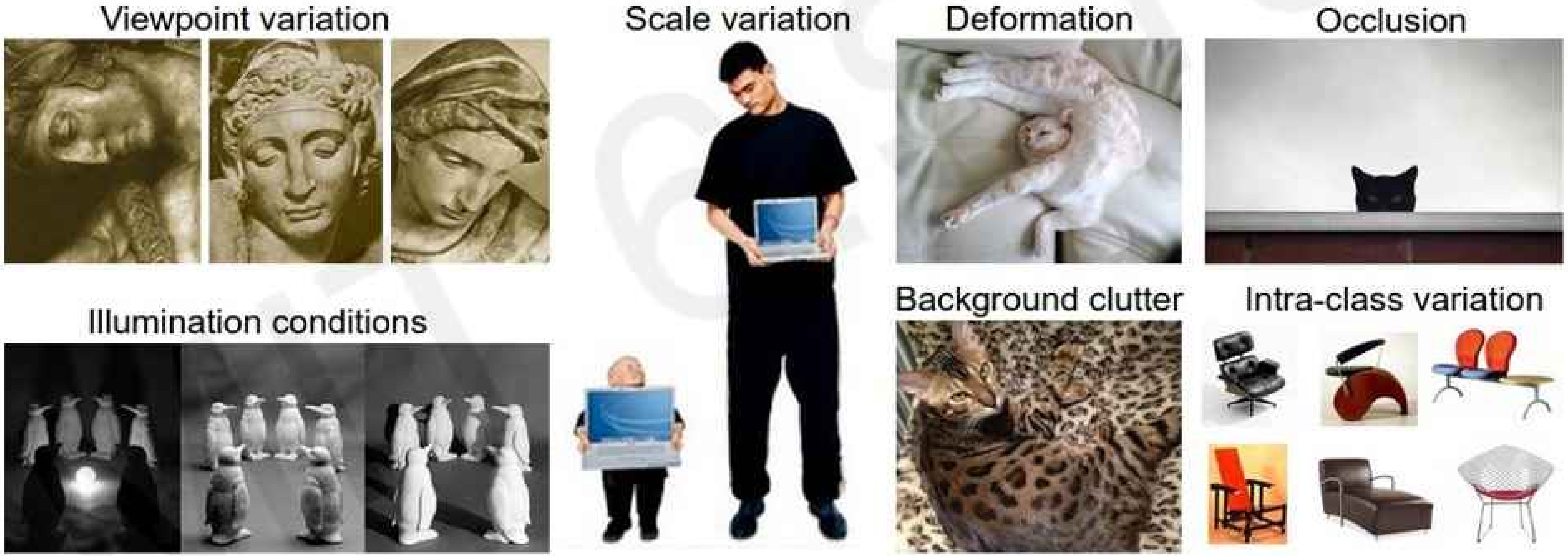
Background clutter

Occlusion

Intra-class variation

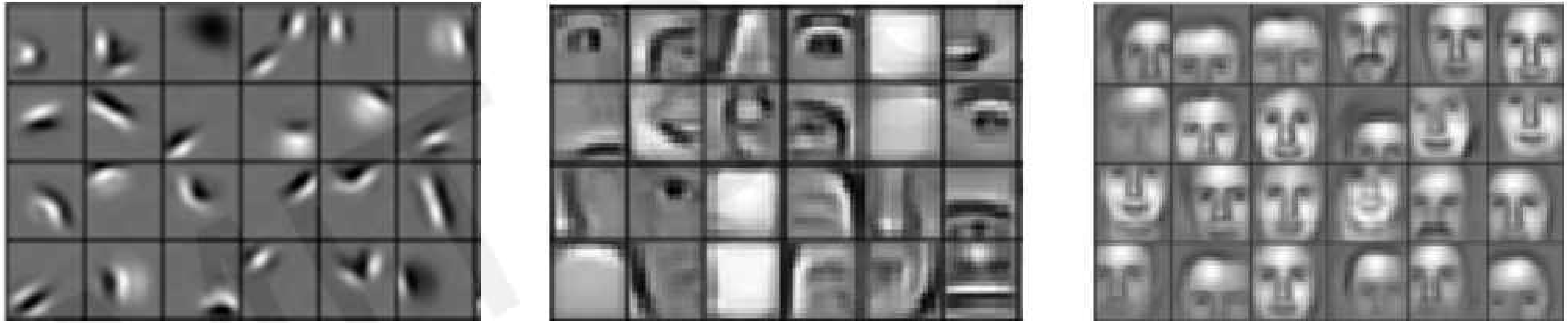
Manual Feature Extraction

Domain knowledge → Define features → **Detect features to classify**



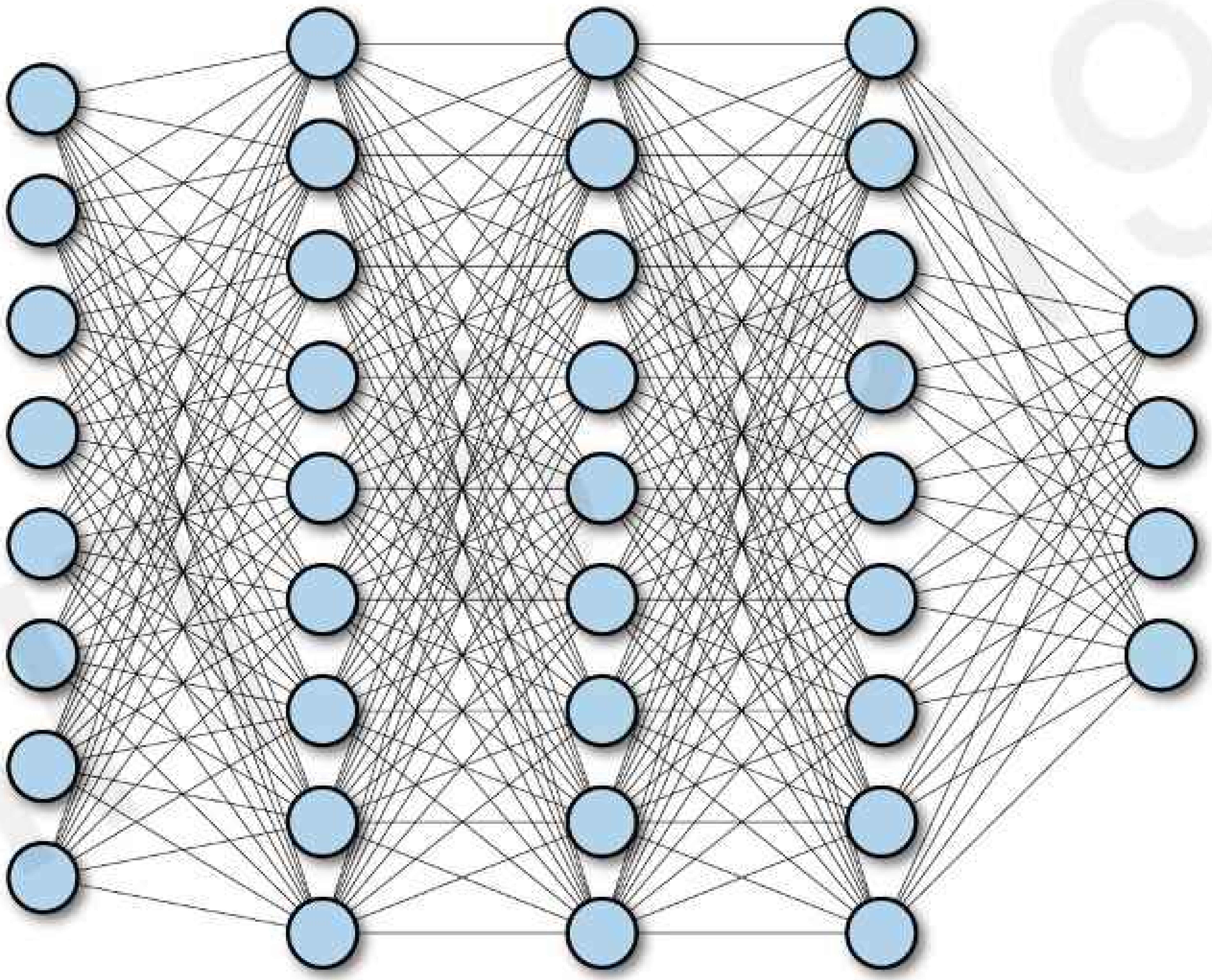
Learning Feature Representations

Can we learn a **hierarchy of features** directly from the data instead of hand engineering?



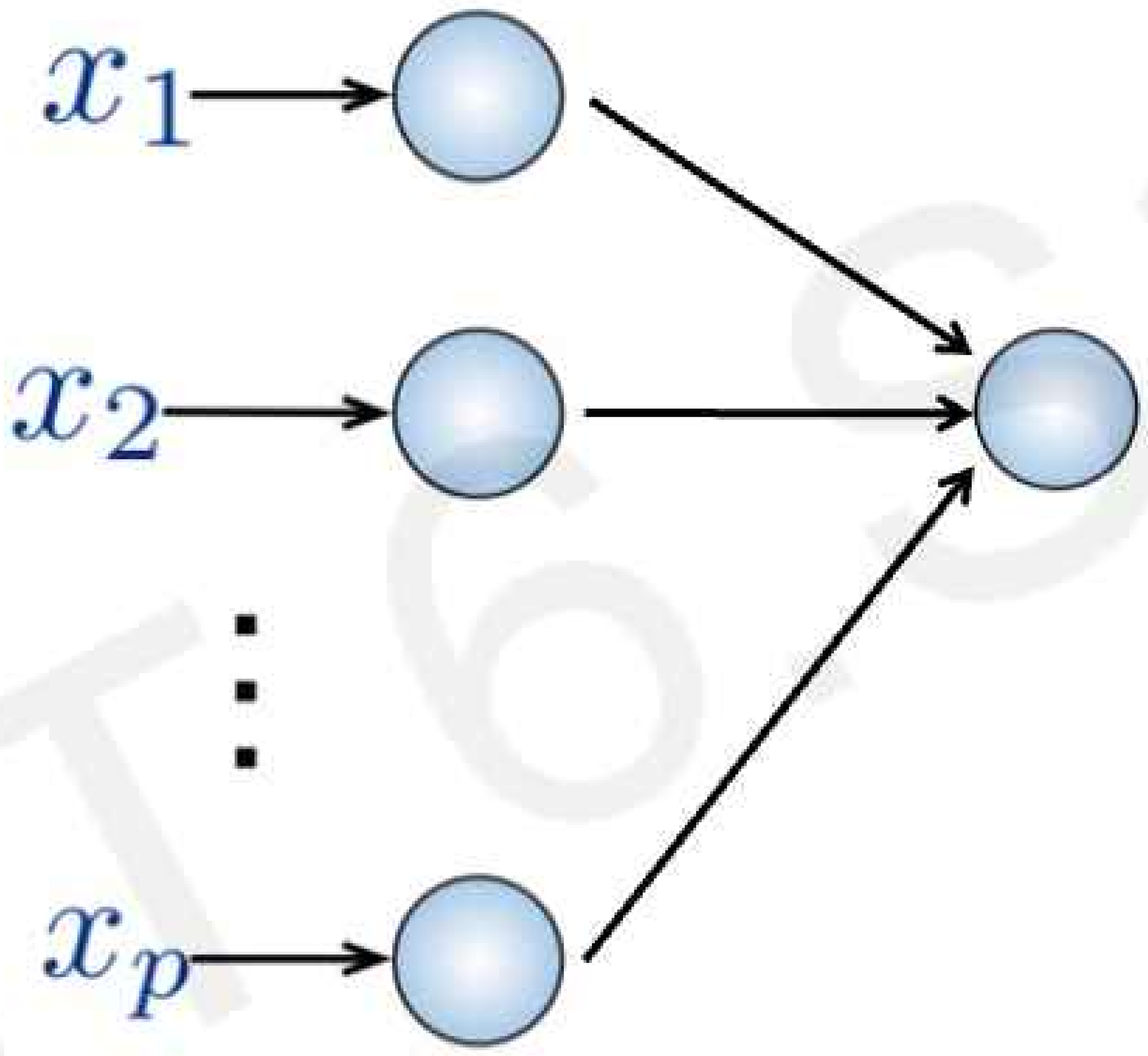
Learning Visual Features

Fully Connected Neural Network



Fully Connected Neural Network

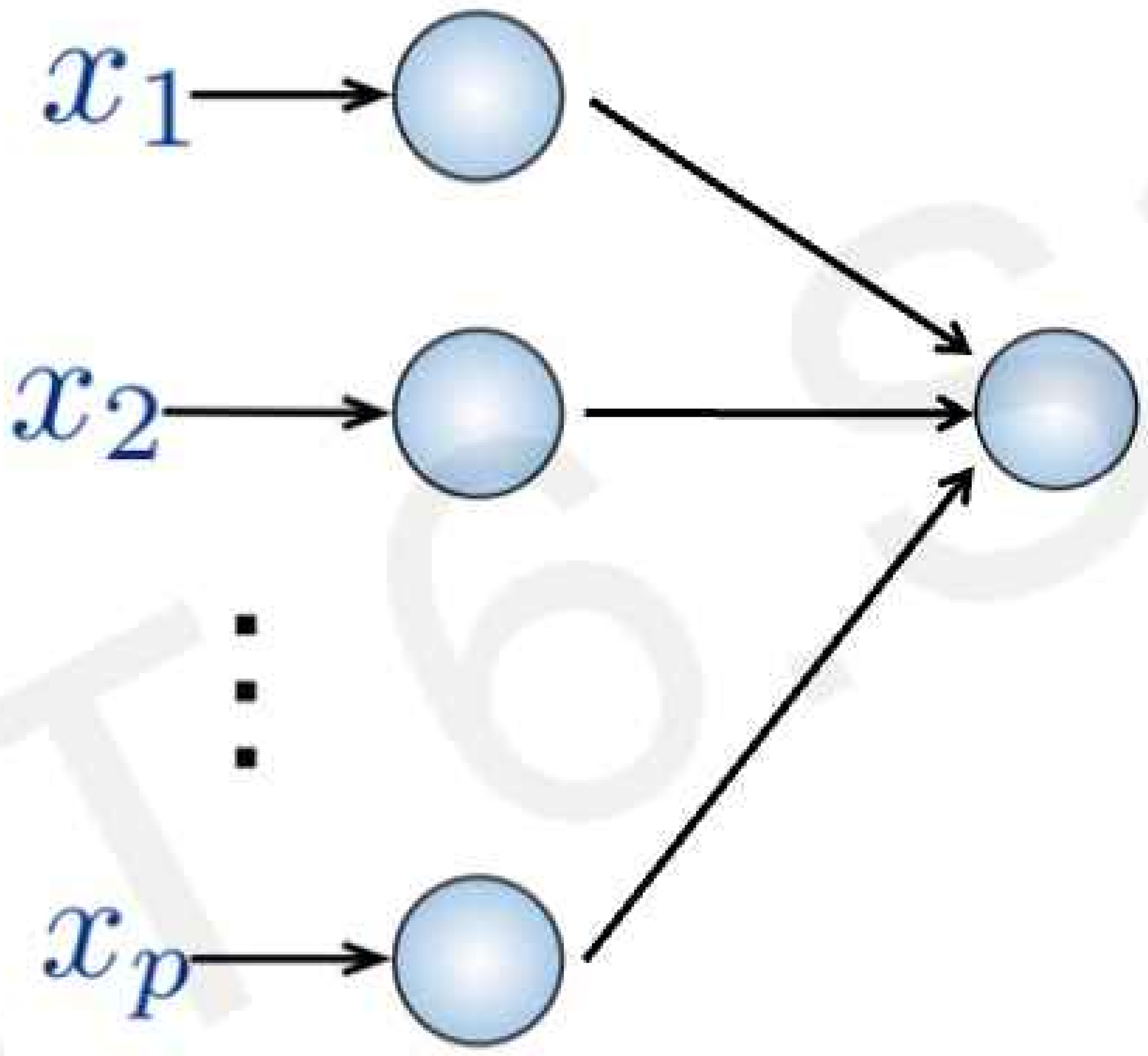
Input:
- 2D image
- Vector of pixel values



Fully Connected:
- Connect neuron in hidden layer to all neurons in input layer
- No spatial information!
- And many, many parameters!

Fully Connected Neural Network

Input:
- 2D image
- Vector of pixel values

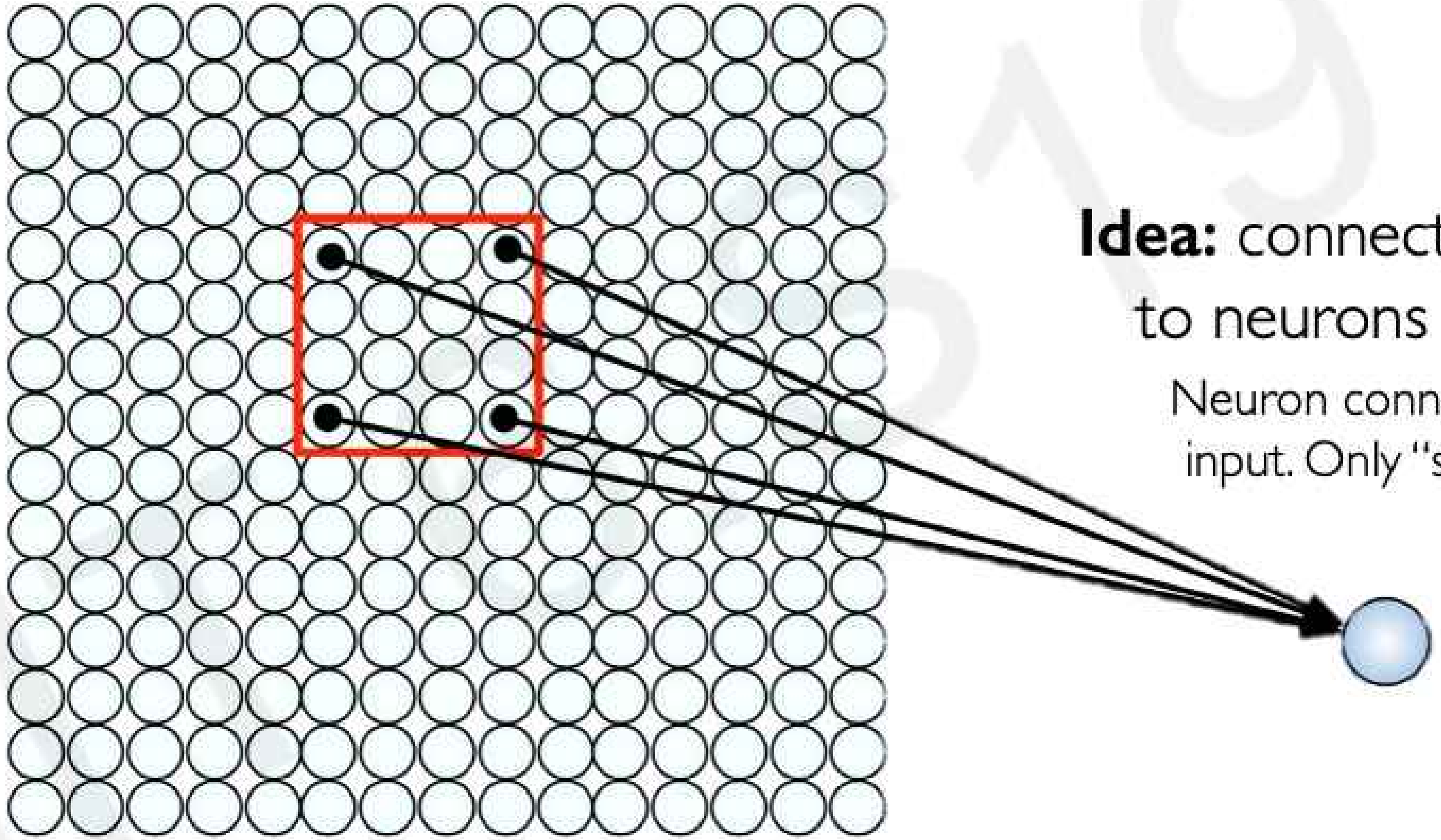


Fully Connected:
- Connect neuron in hidden layer to all neurons in input layer
- No spatial information!
- And many, many parameters!

How can we use **spatial structure** in the input to inform the architecture of the network?

Using Spatial Structure

Input: 2D image.
Array of pixel values



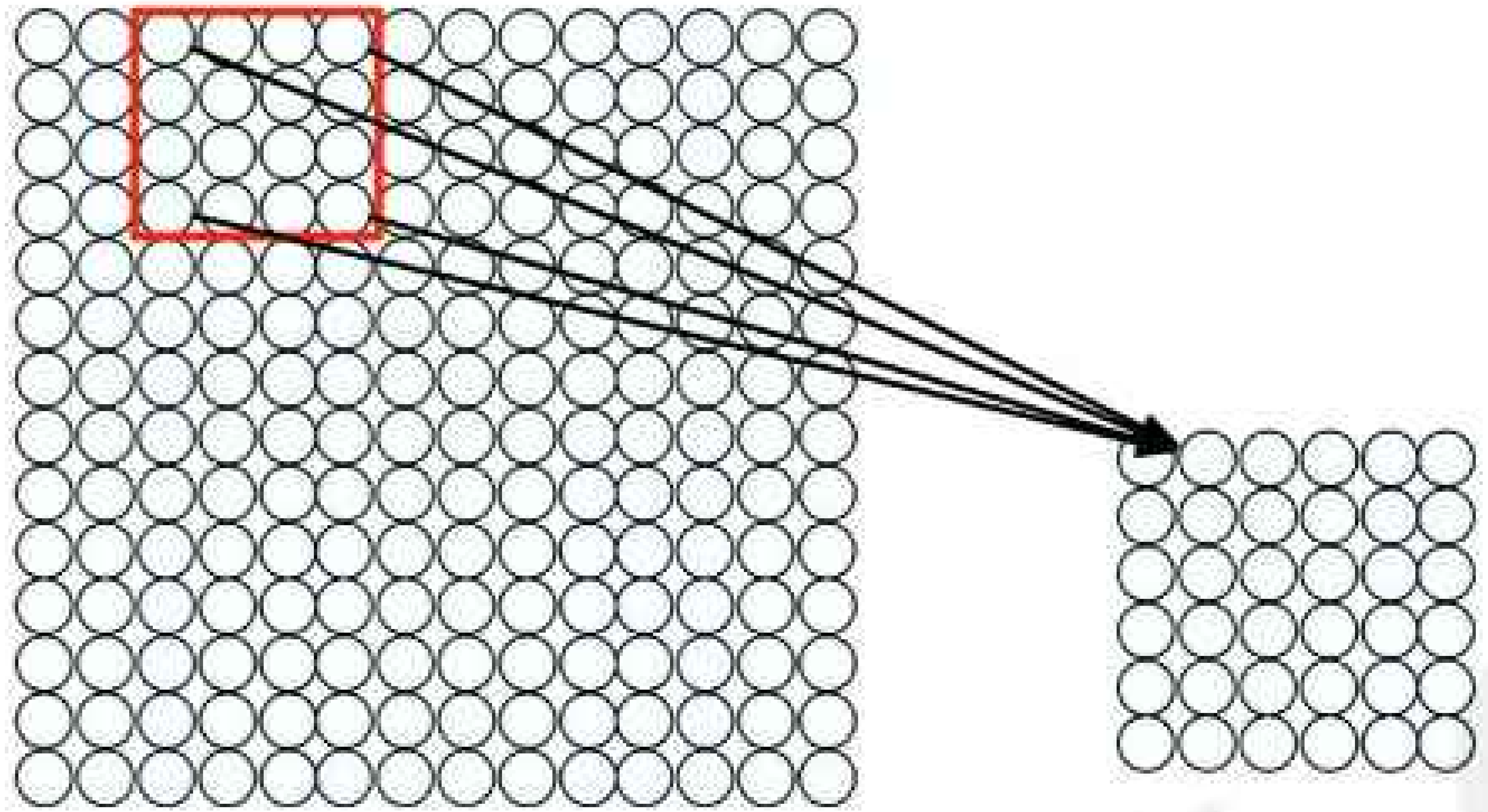
Idea: connect patches of input to neurons in hidden layer.

Neuron connected to region of input. Only "sees" these values.

Using Spatial Structure

Connect patch in input layer to a single neuron in subsequent layer.
Use a sliding window to define connections.
How can we ***weight*** *the patch to detect particular features?*

Feature Extraction with Convolution



- Filter of size 4x4 : 16 different weights
- Apply this same filter to 4x4 patches in input
- Shift by 2 pixels for next patch

This "patchy" operation is **convolution**

1) Apply a set of weights – a filter – to extract **local features**

2) Use **multiple filters** to extract different features

3) **Spatially share** parameters of each filter

Feature Extraction and Convolution
A Case Study

X or X?

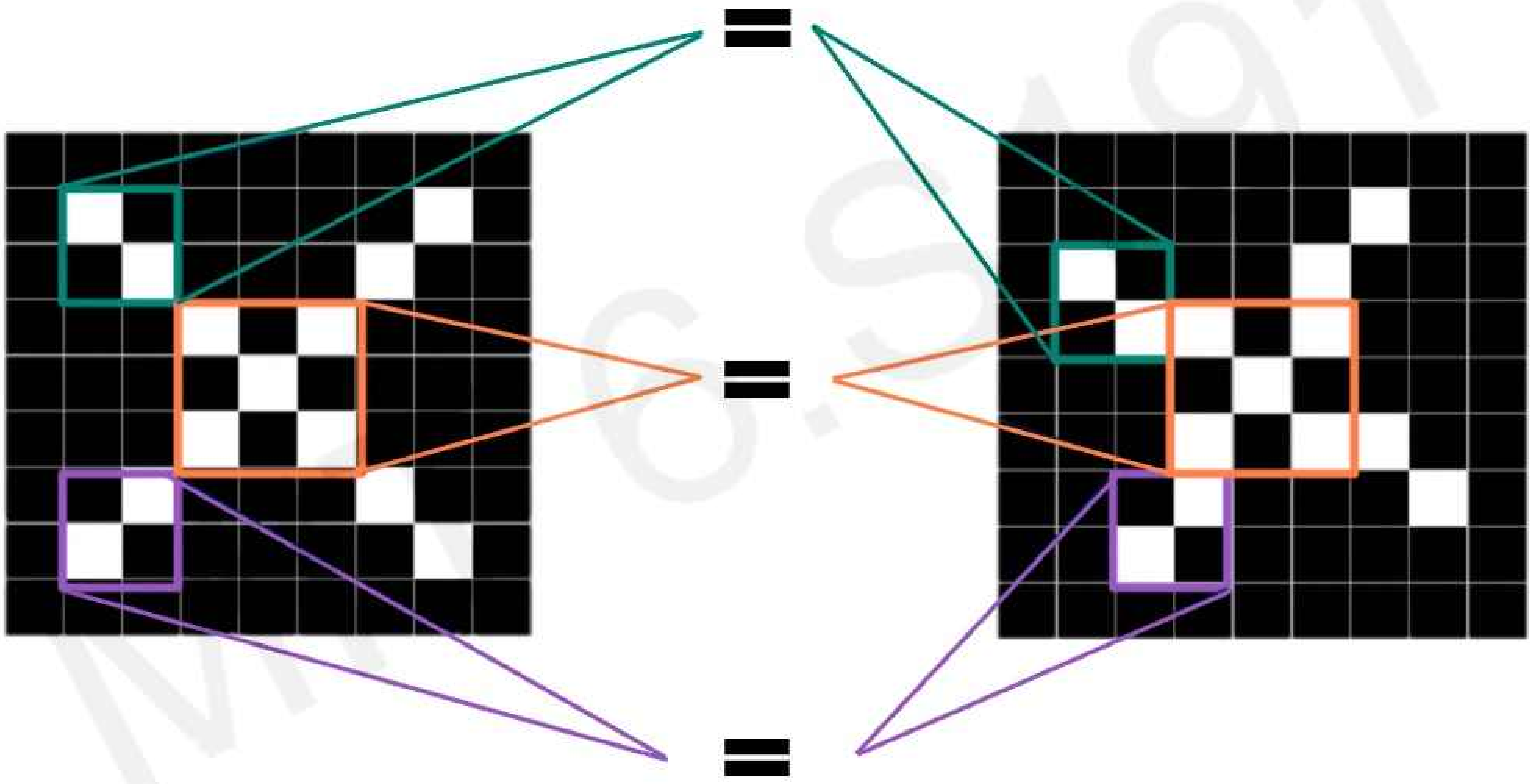
-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

$\stackrel{?}{=}$

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	1	-1	-1	-1
-1	-1	1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	1	-1	-1
-1	-1	-1	1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

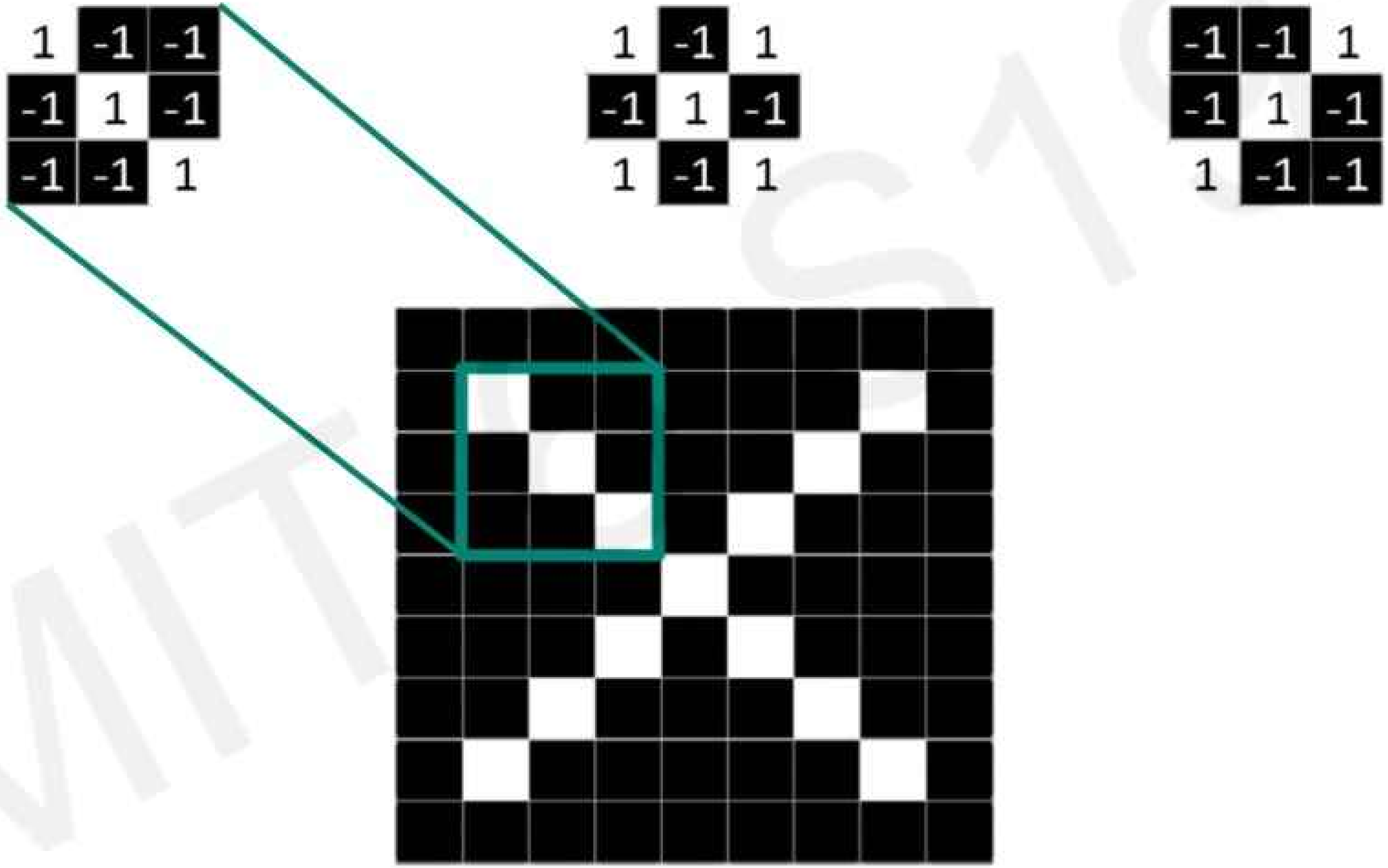
Image is represented as matrix of pixel values… and computers are literal!
We want to be able to classify an X as an X even if it's shifted, shrunk, rotated, deformed.

Features of X



Filters to Detect X Features

filters



The Convolution Operation

The Convolution Operation

Suppose we want to compute the convolution of a 5x5 image and a 3x3 filter:

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

image

$\otimes$

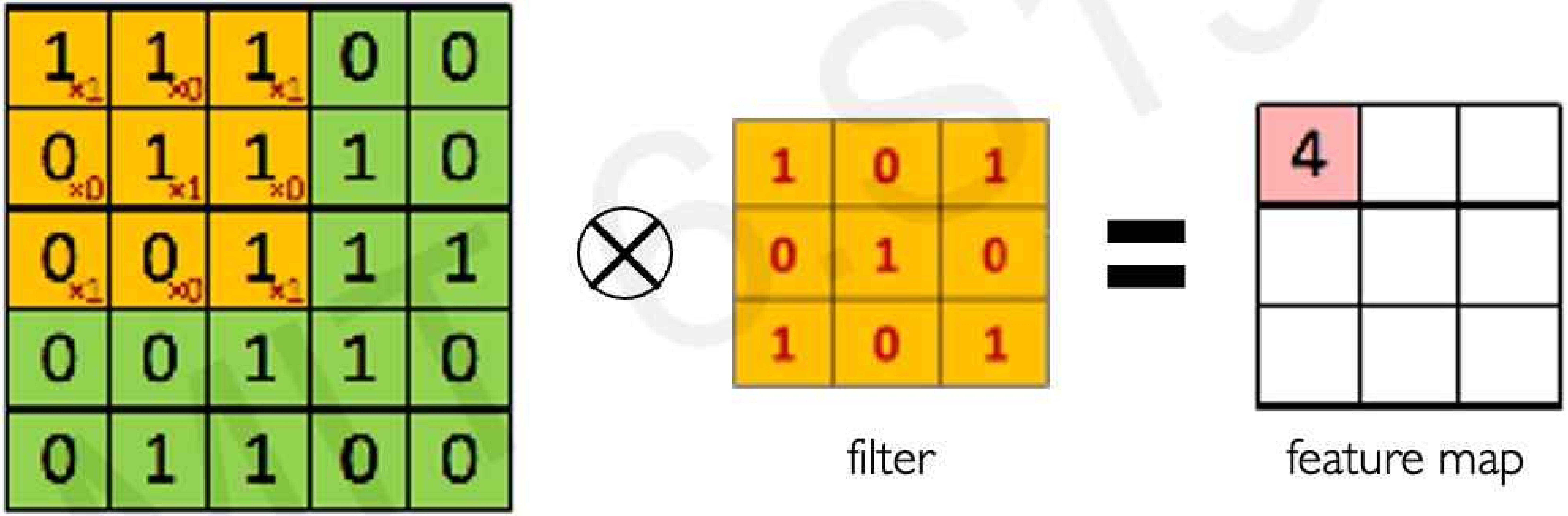
1	0	1
0	1	0
1	0	1

filter

We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs…

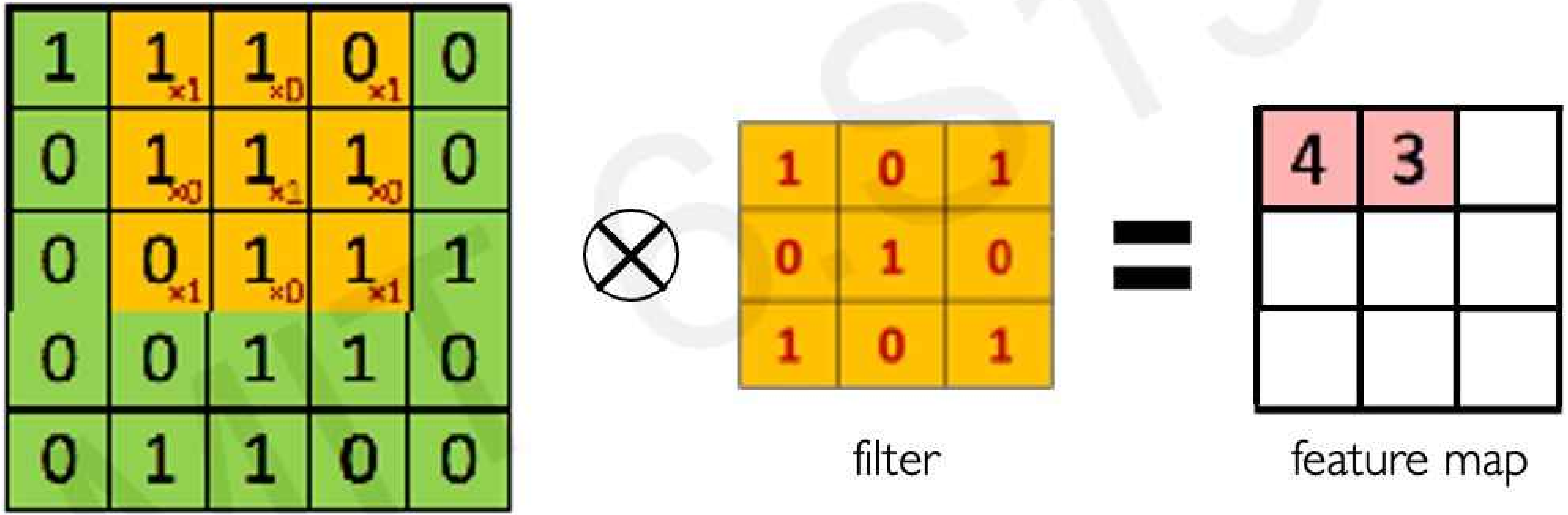
The Convolution Operation

We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs:



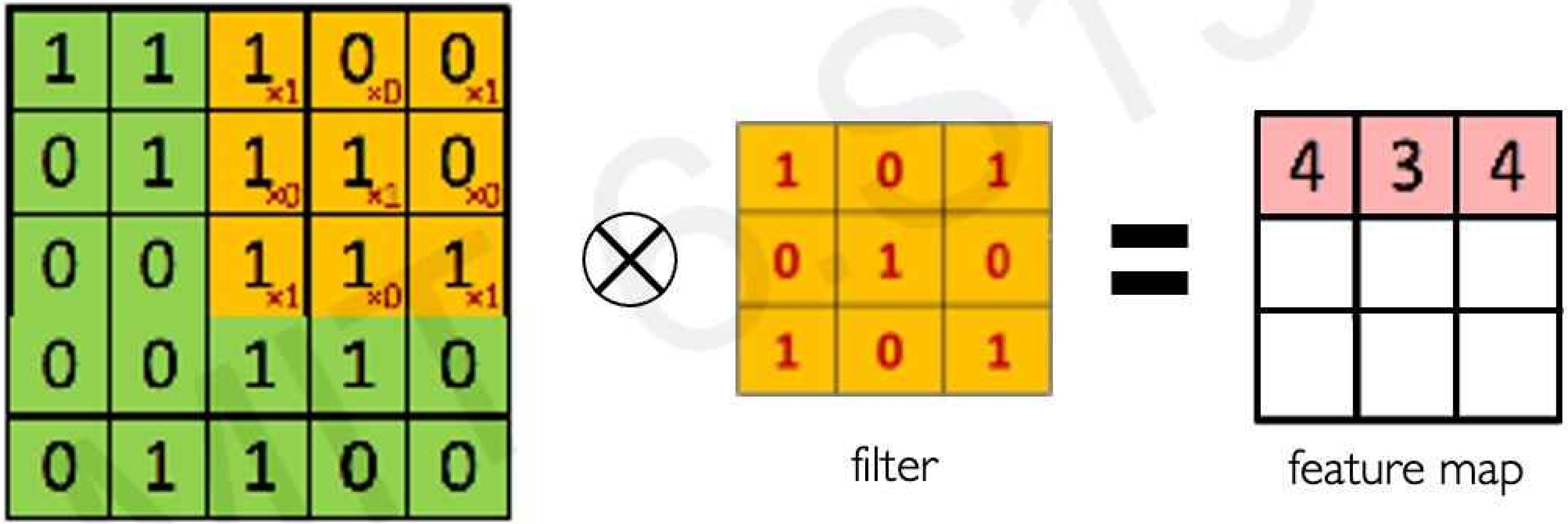
The Convolution Operation

We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs:



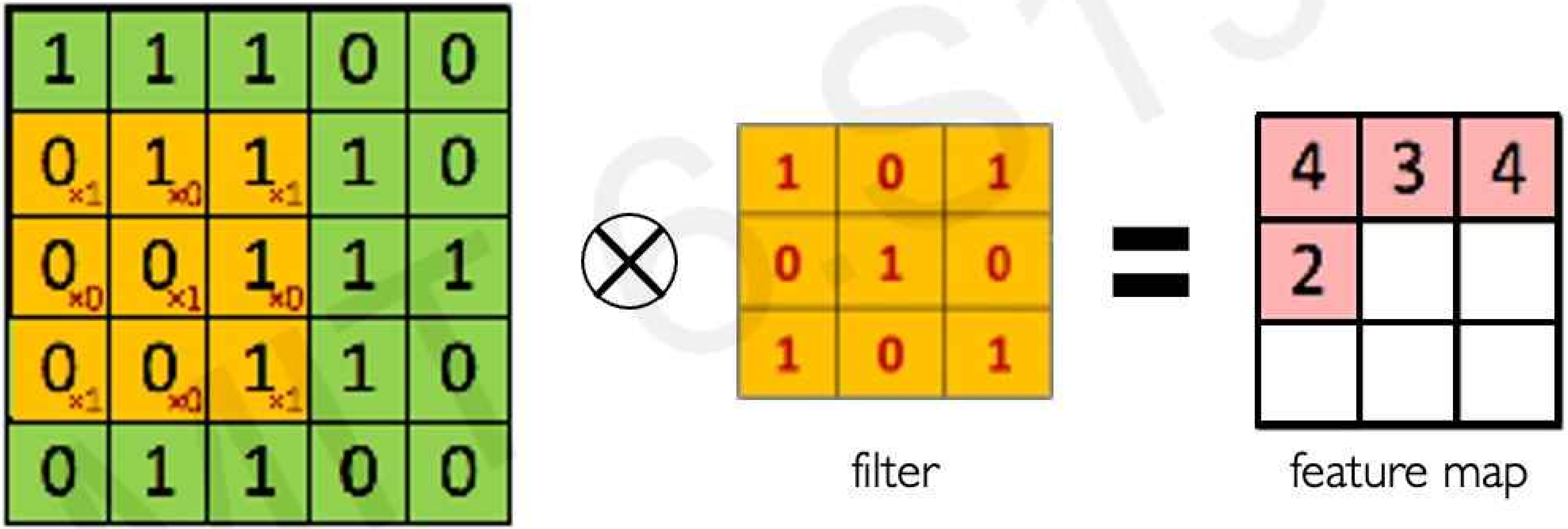
The Convolution Operation

We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs:



The Convolution Operation

We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs:



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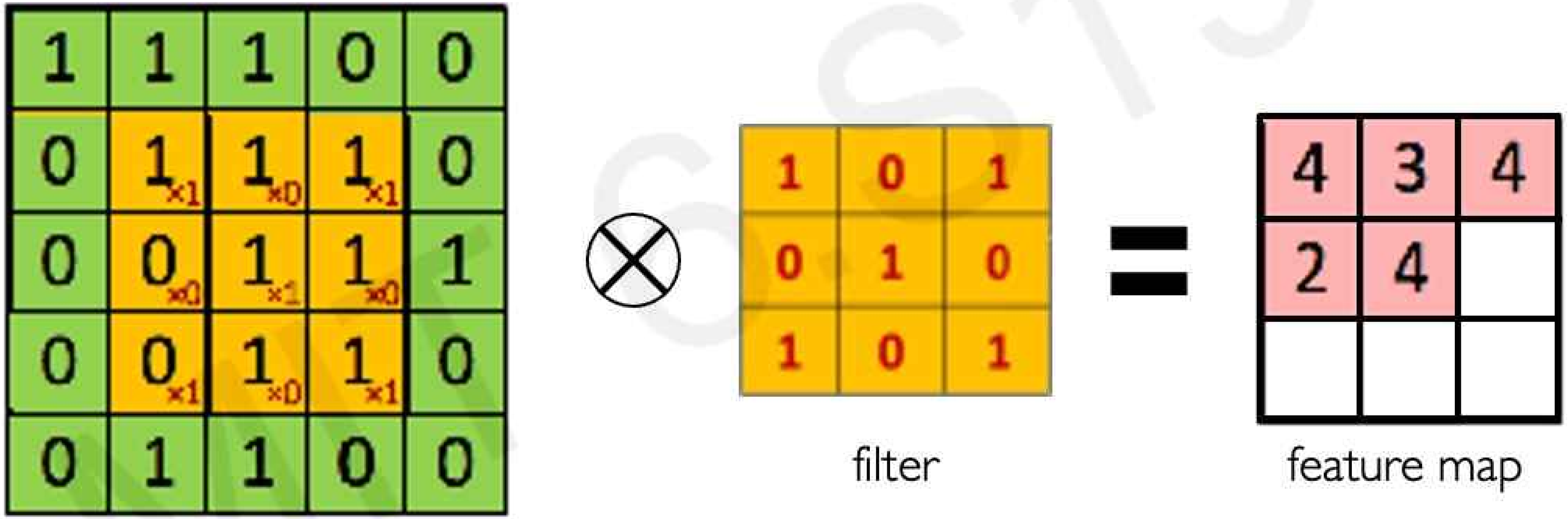
We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs:



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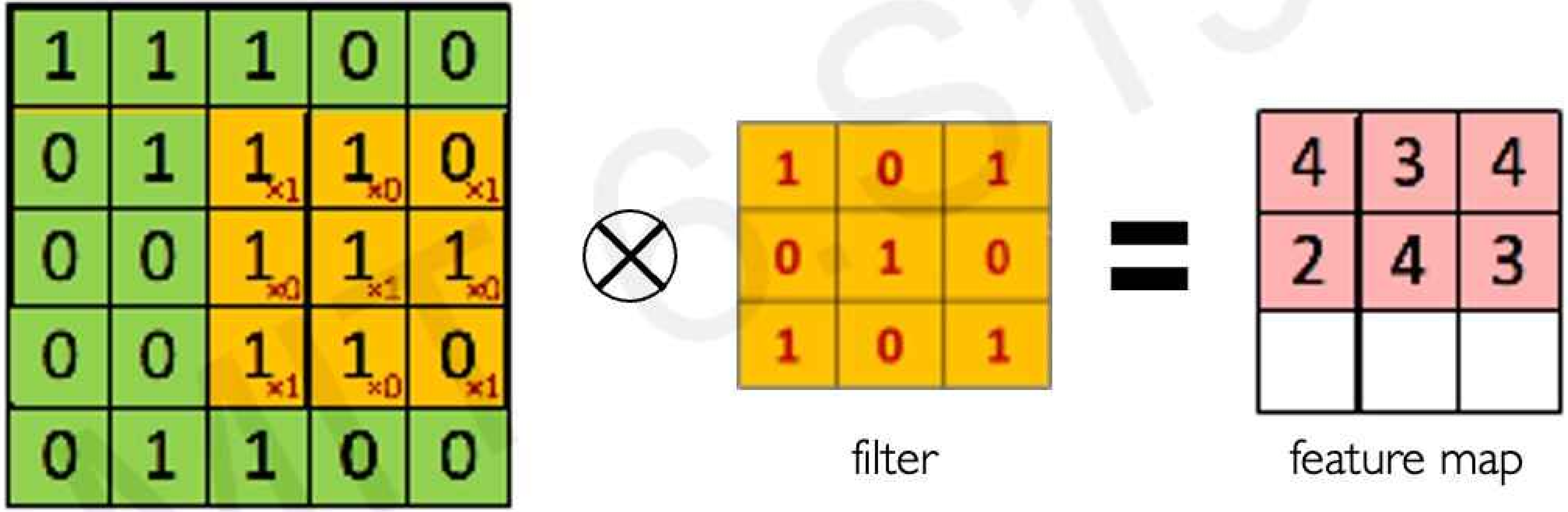
We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs:



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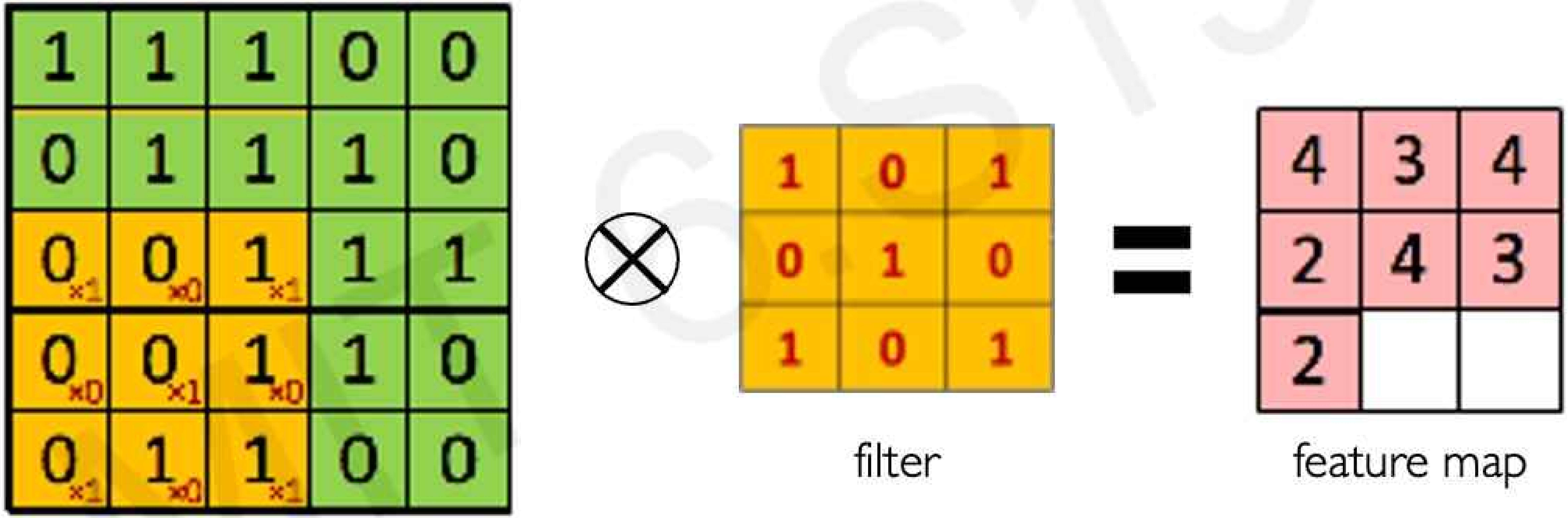

The Convolution Operation

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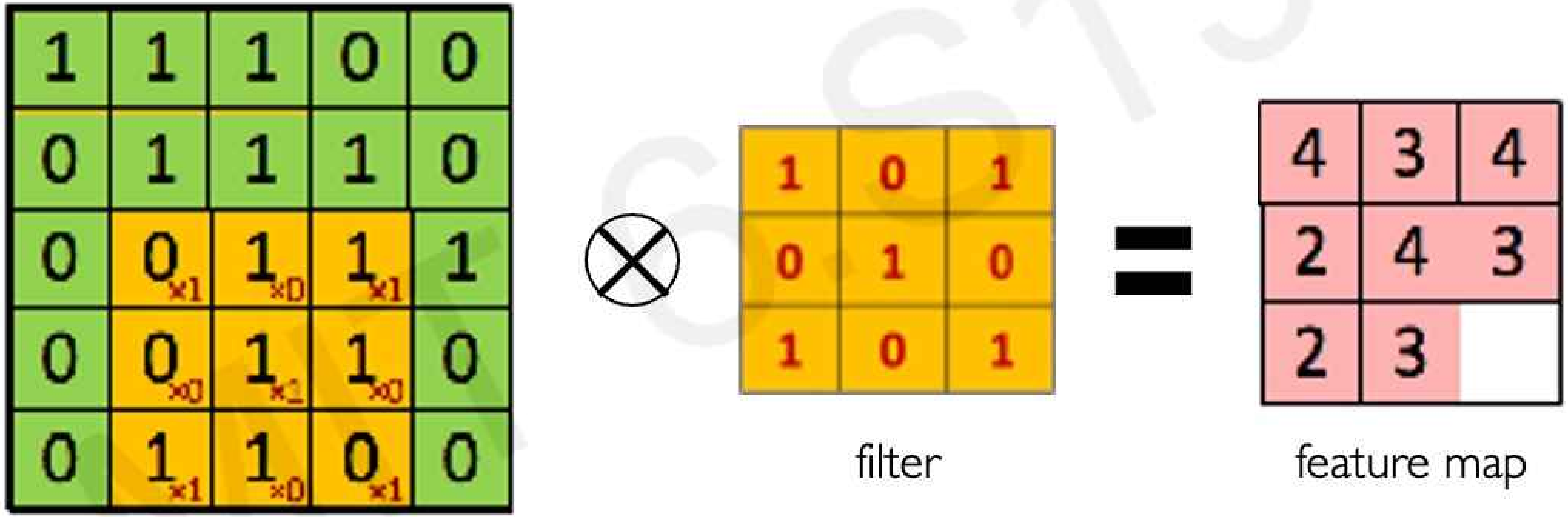
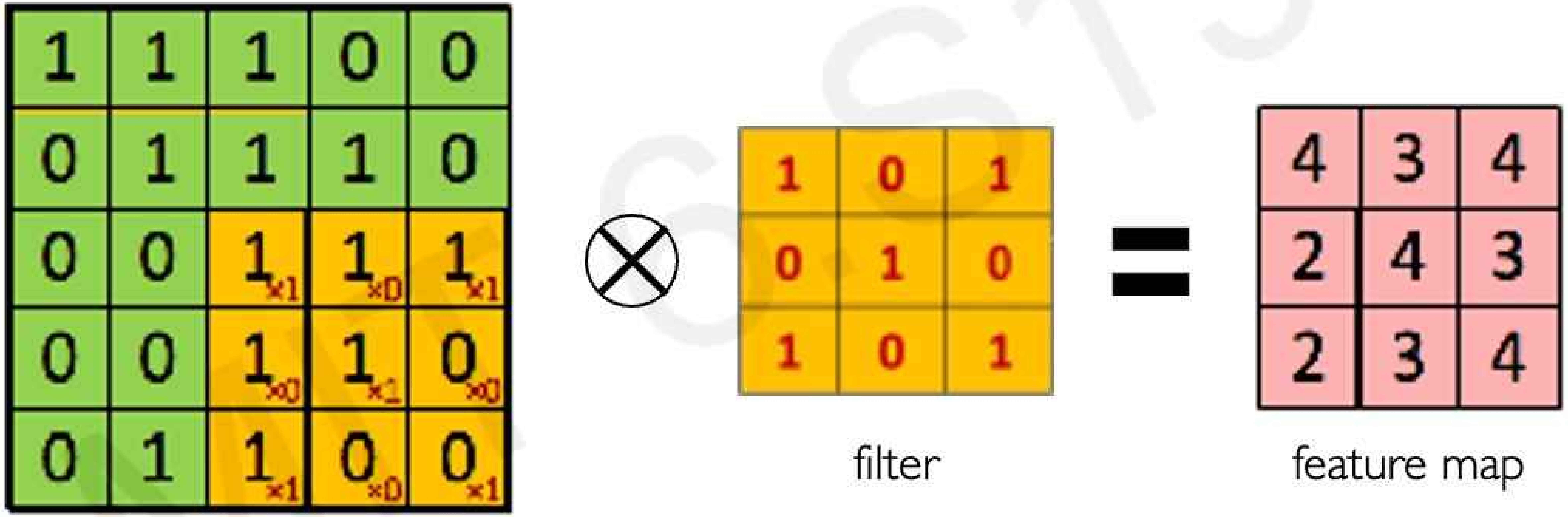


filter

feature map

The Convolution Operation

We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs:



Producing Feature Maps

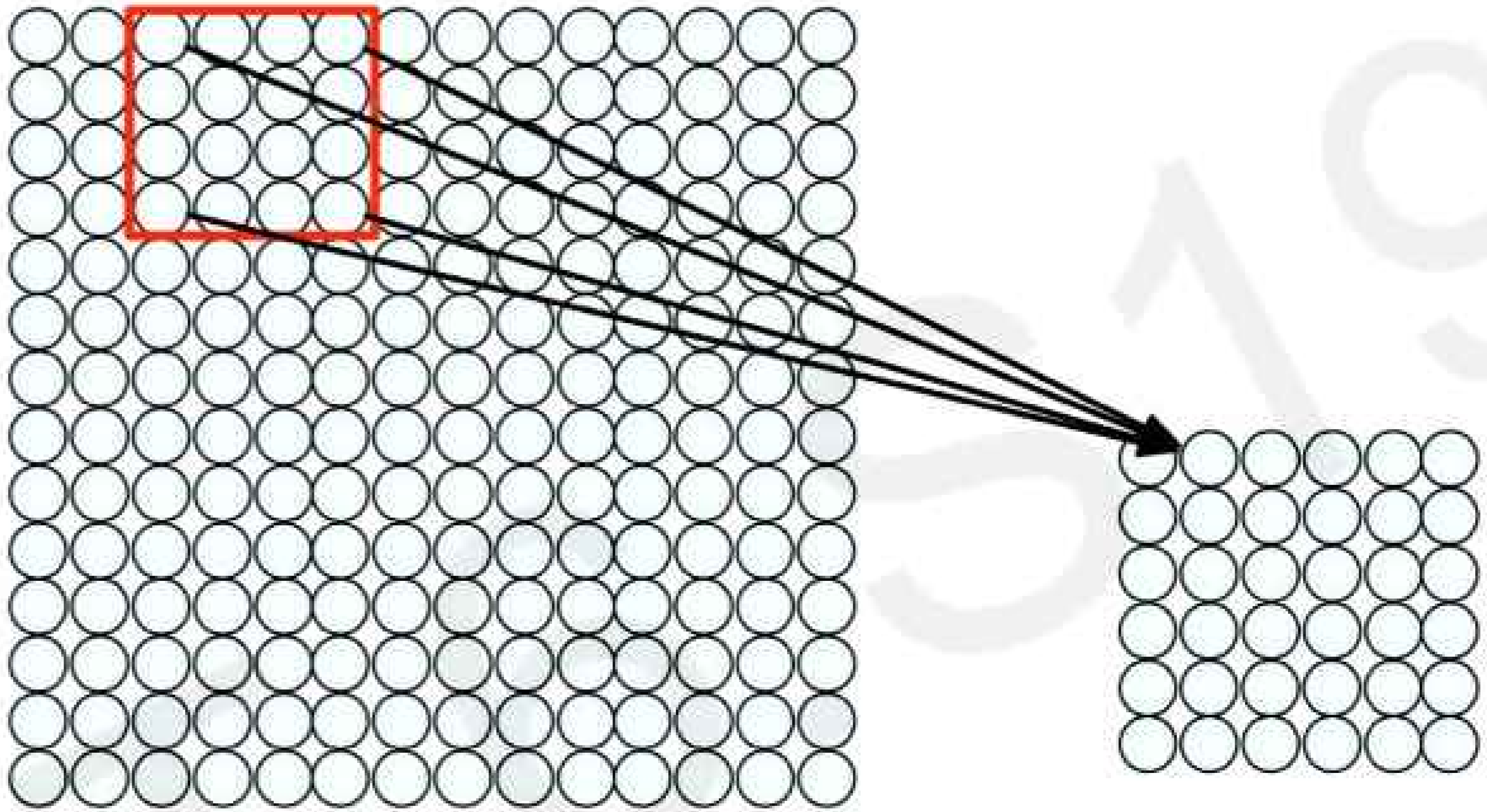
Original

Sharpen

Edge Detect

"Strong" Edge Detect

Feature Extraction with Convolution



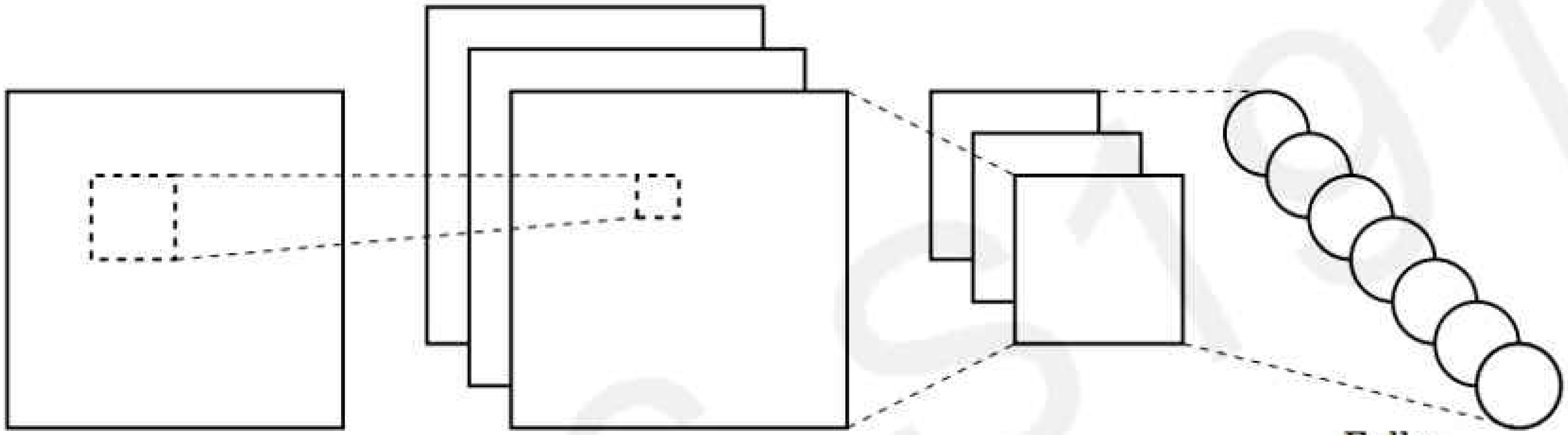
1) Apply a set of weights – a filter – to extract **local features**

2) Use **multiple filters** to extract different features

3) **Spatially share** parameters of each filter

Convolutional Neural Networks (CNNs)

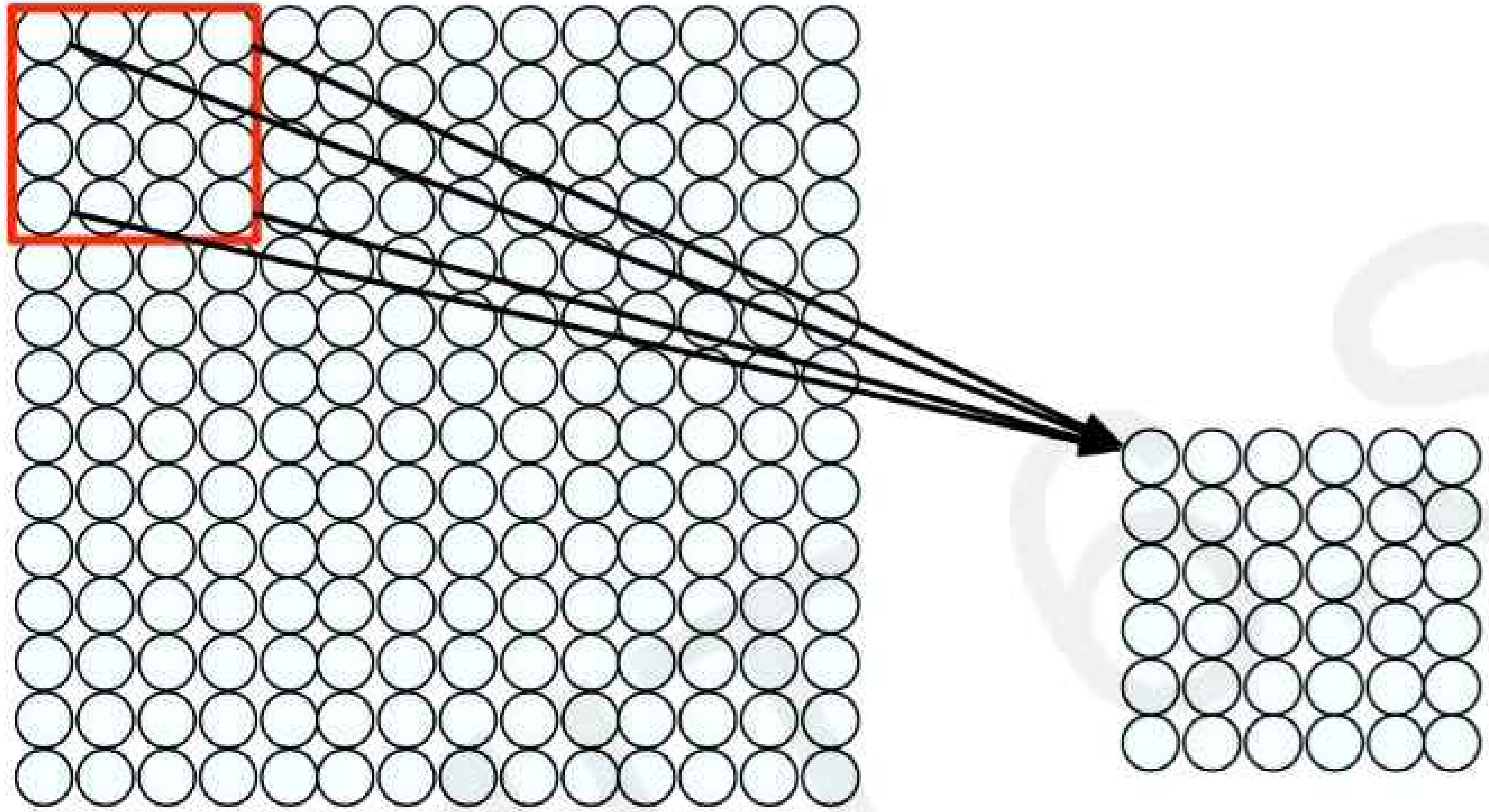
CNNs for Classification



TensorFlow		PyTorch
`tf.keras.layers.Conv2D`	1. **Convolution**: Apply filters to generate feature maps.	`torch.nn.Conv2d`
`tf.keras.activations.*`	2. **Non-linearity**: Often ReLU.	`torch.nn.ReLU,…`
`tf.keras.layers.MaxPool2D`	3. **Pooling**: Downsampling operation on each feature map.	`torch.nn.MaxPool2d`

Train model with image data.
Learn weights of filters in convolutional layers.

Convolutional Layers: Local Connectivity



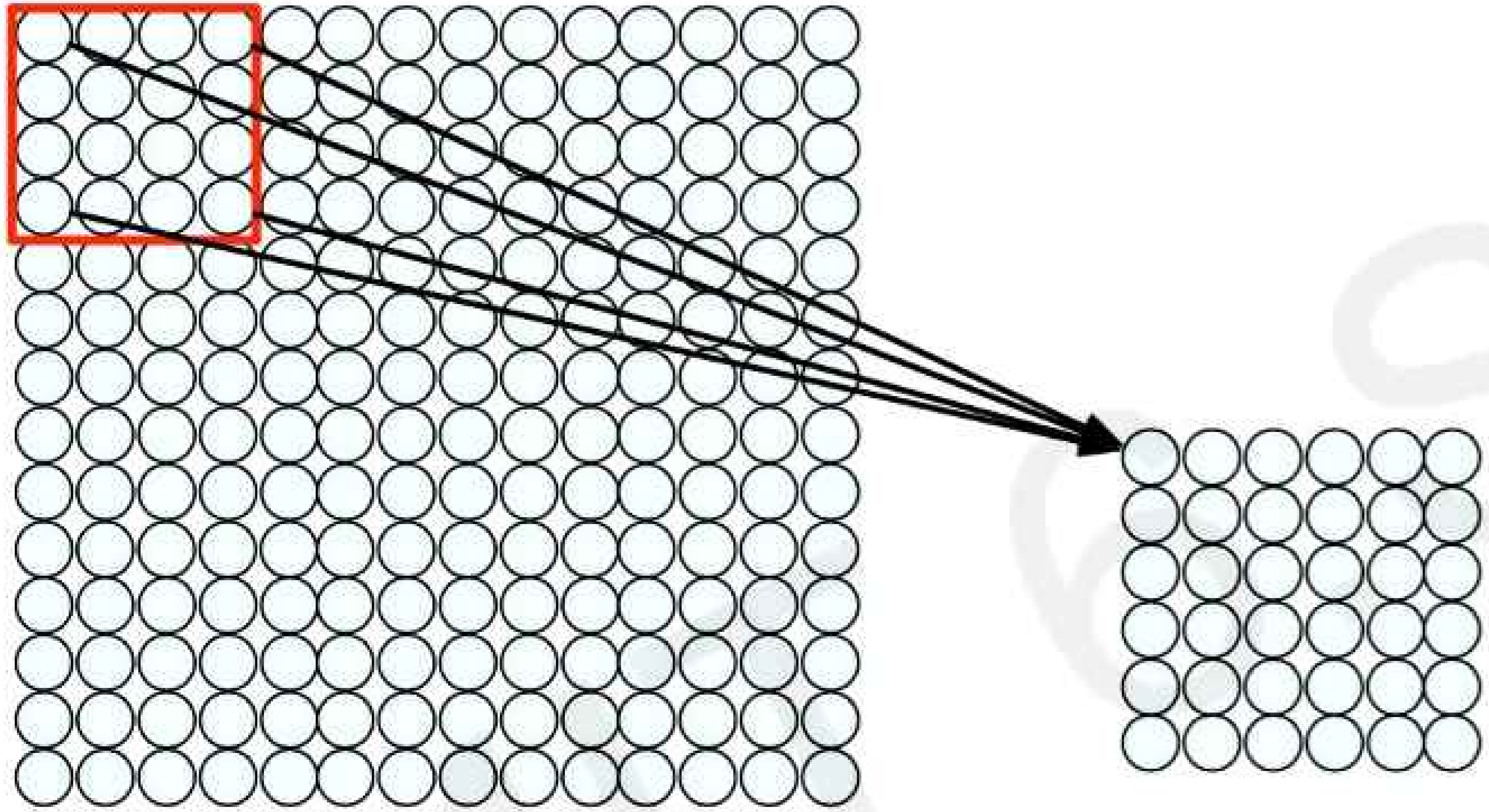
```
tf.keras.layers.Conv2D
```

```
torch.nn.Conv2d
```

For a neuron in hidden layer:

- Take inputs from patch
- Compute weighted sum
- Apply bias

Convolutional Layers: Local Connectivity



`tf.keras.layers.Conv2D`

`torch.nn.Conv2d`

For a neuron in hidden layer:

- Take inputs from patch
- Compute weighted sum
- Apply bias

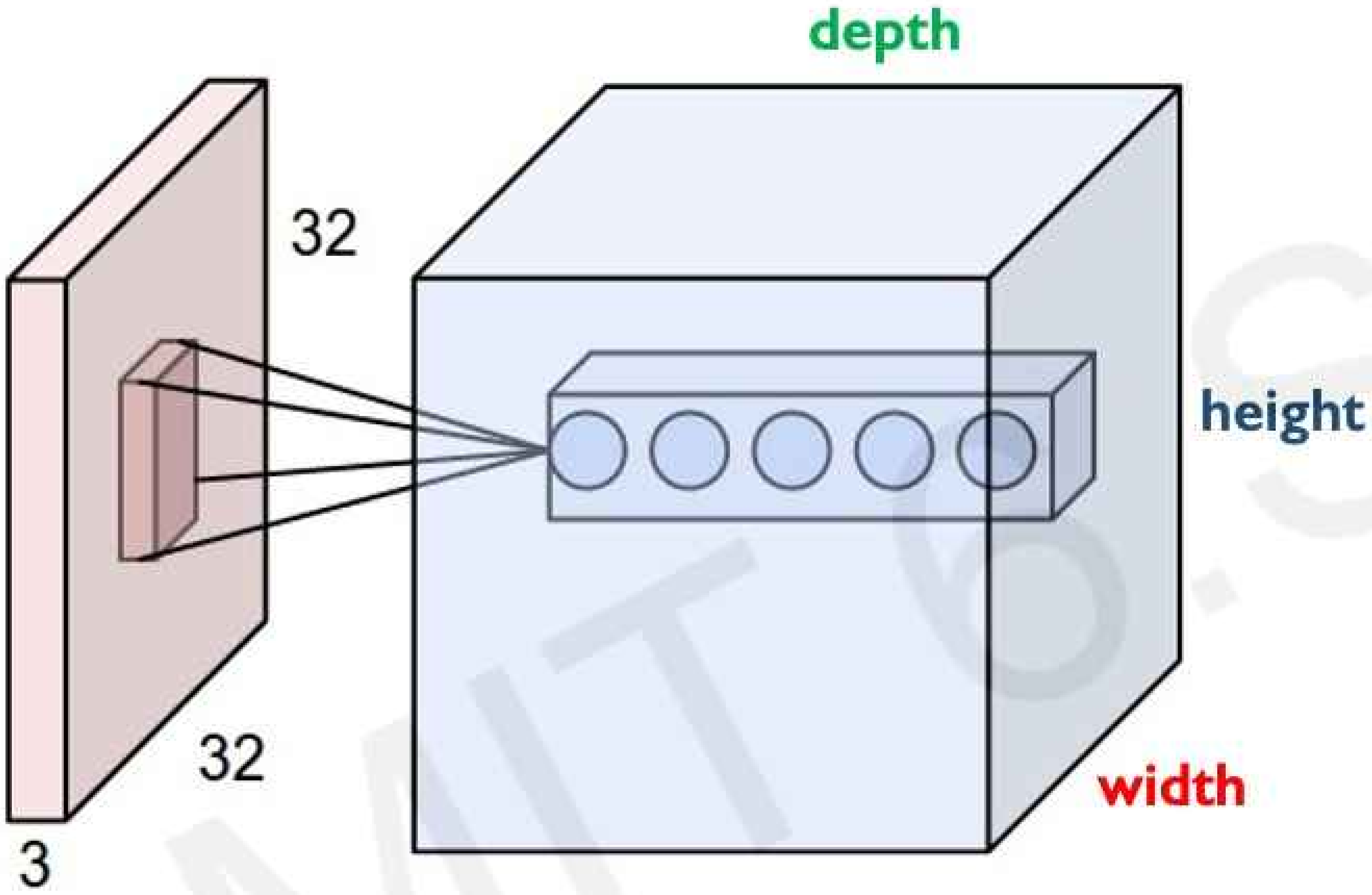
4x4 filter: matrix of weights w_{ij}

$$\sum_{i=1}^{4}\sum_{j=1}^{4} w_{ij}\, x_{i+p,j+q} + b$$

for neuron (p,q) in hidden layer

1) applying a window of weights
2) computing linear combinations
3) activating with non-linear function

CNNs: Spatial Arrangement of Output Volume



Layer Dimensions:

$h \ x \ w \ x \ d$

where h and w are spatial dimensions
d (depth) = number of filters

Stride:

Filter step size

Receptive Field:

Locations in input image that
a node is path connected to

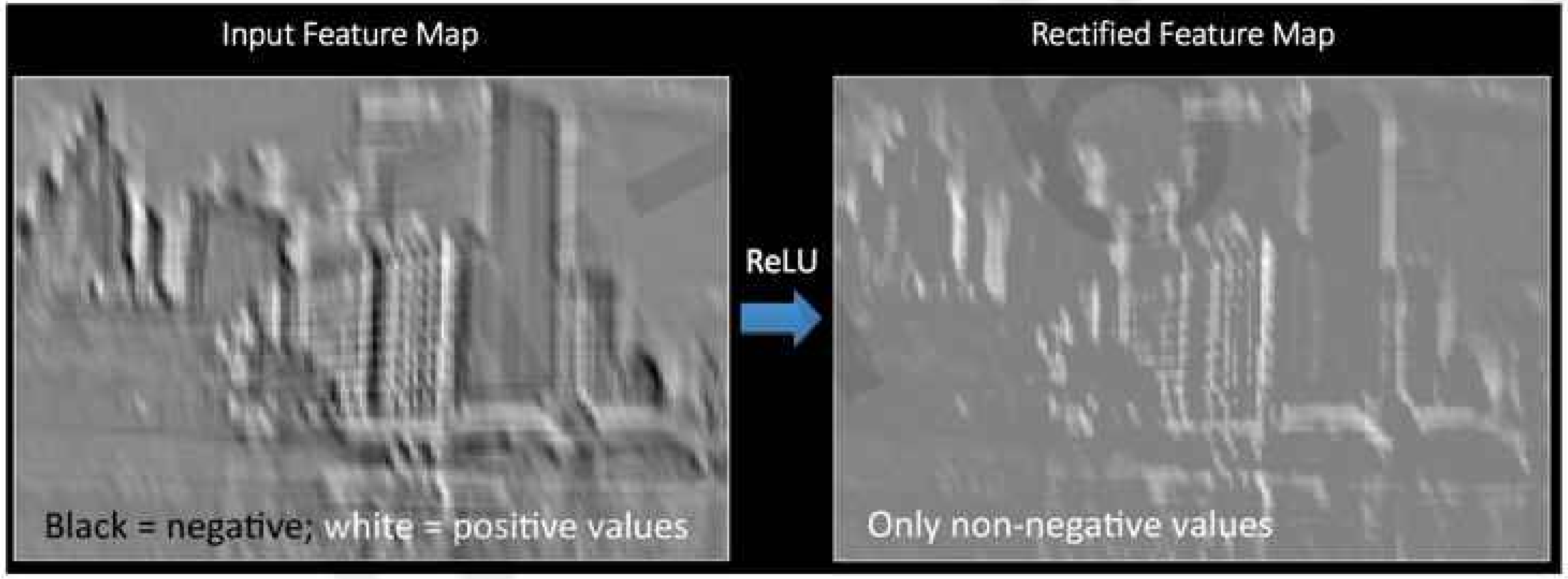
```
tf.keras.layers.Conv2D( filters=d, kernel_size=(h,w), strides=s )
```

```
torch.nn.Conv2d( in_channels=3, out_channels=d, kernel_size=(h,w), stride=s )
```

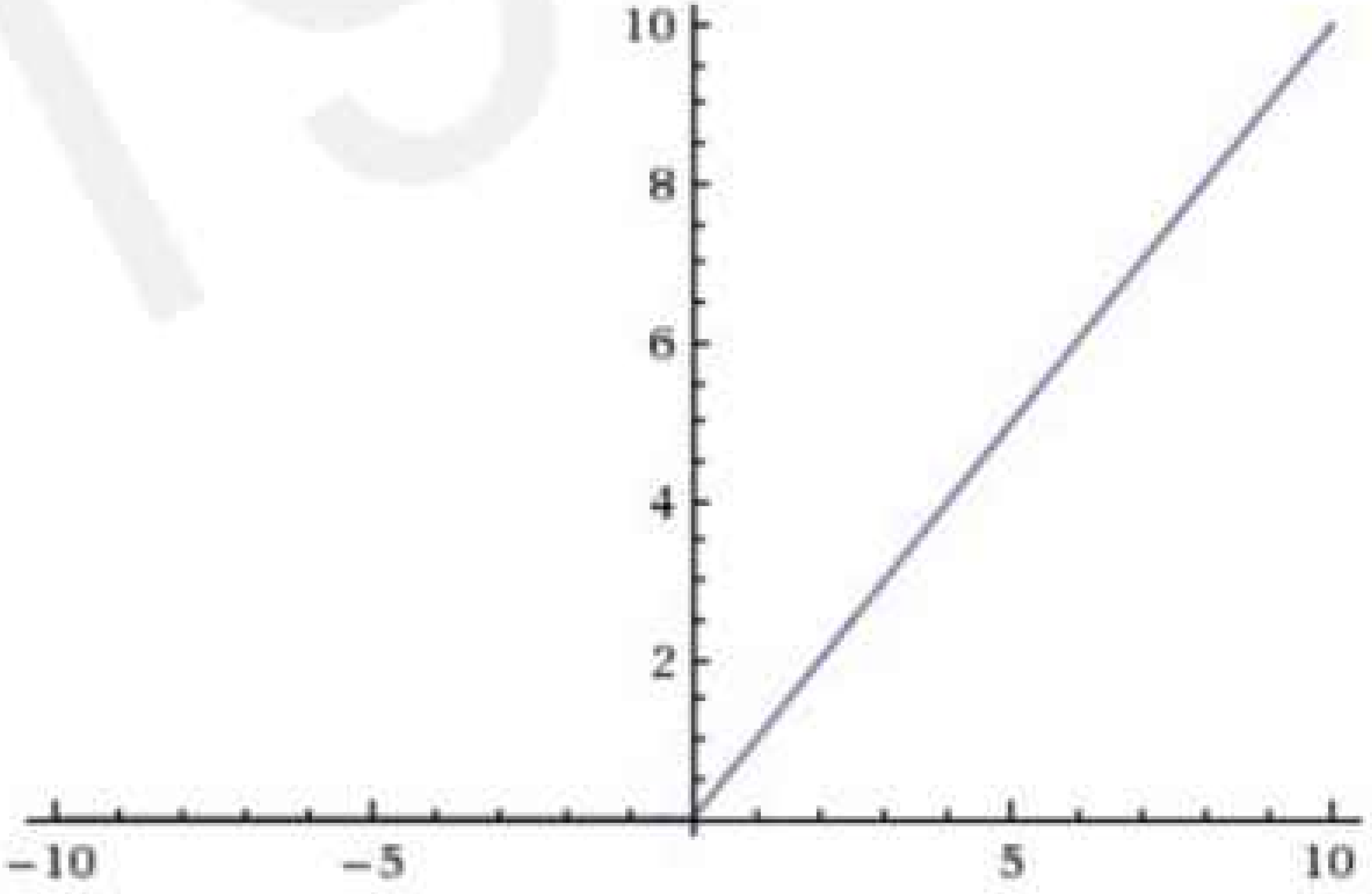
Need to specify input dimensionality!

Introducing Non-Linearity

- Apply after every convolution operation (i.e., after convolutional layers)
- ReLU: pixel-by-pixel operation that replaces all negative values by zero. **Non-linear operation!**



Rectified Linear Unit (ReLU)

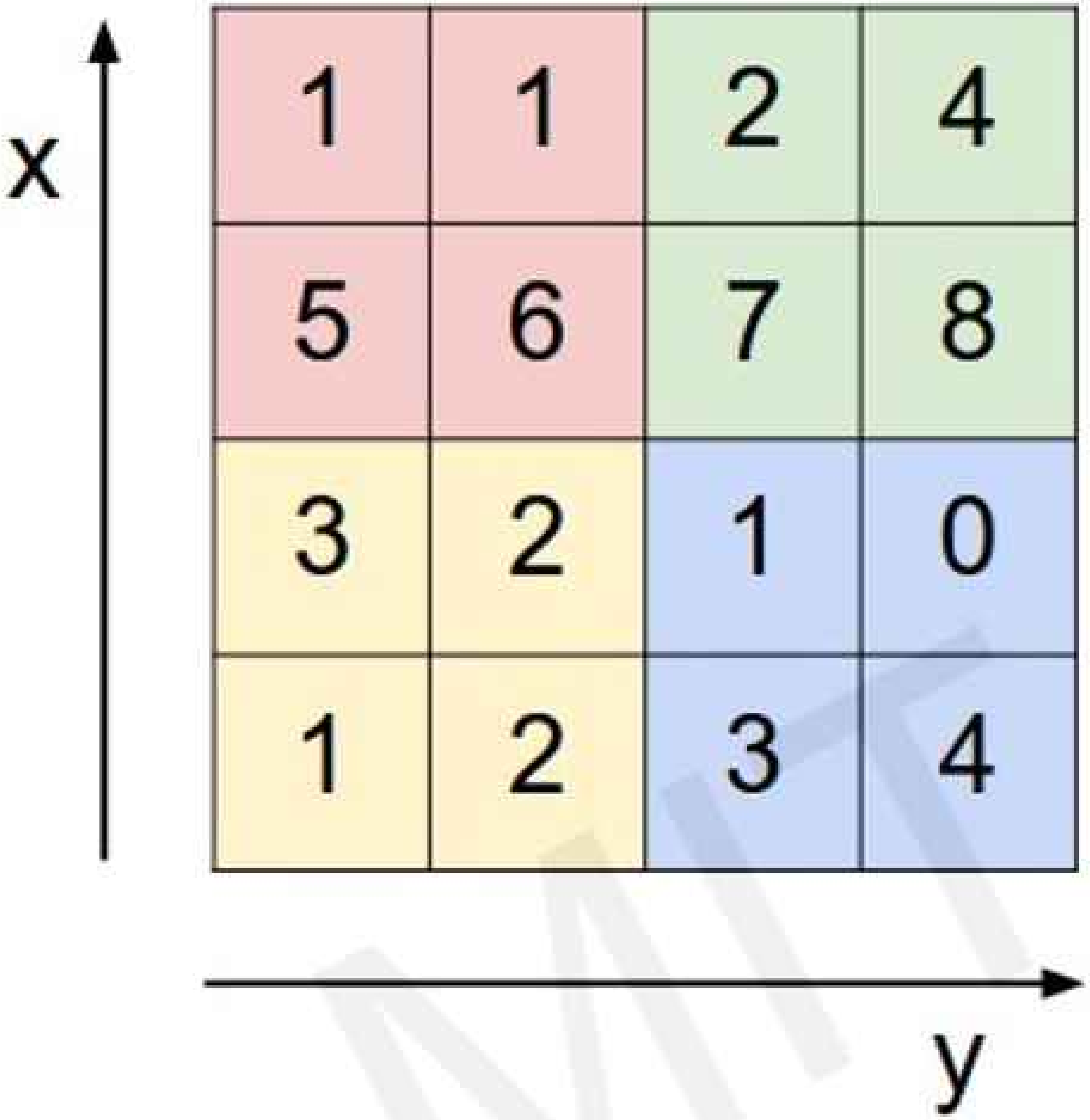


$$g(z) = \max(0, z)$$

```
tf.keras.layers.ReLU
```

```
torch.nn.ReLU
```

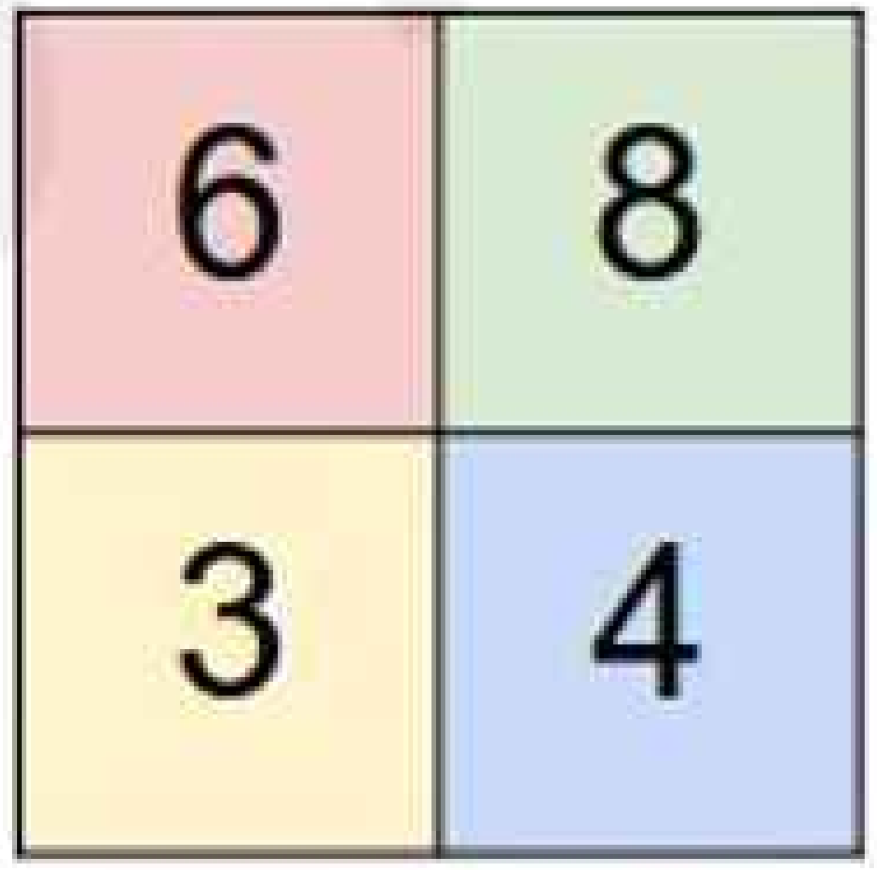
Pooling



max pool with 2x2 filters
and stride 2

```
tf.keras.layers.MaxPool2D(
    pool_size=(2,2),
    strides=2
)
```

```
torch.nn.MaxPool2d(
    kernel_size=(2,2),
    stride=2
)
```

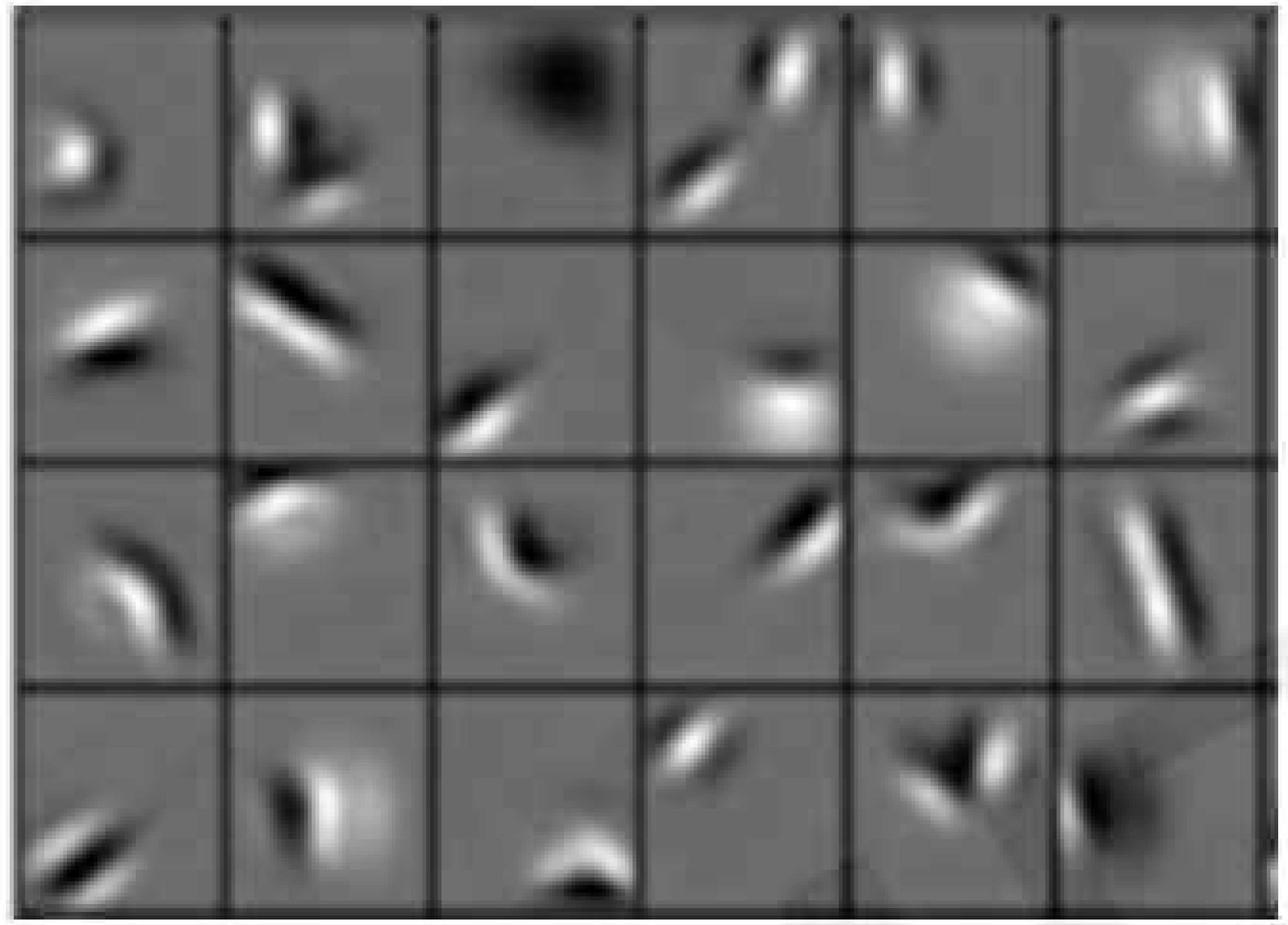


1) Reduced dimensionality
2) Spatial invariance

How else can we downsample and preserve spatial invariance?

Representation Learning in Deep CNNs

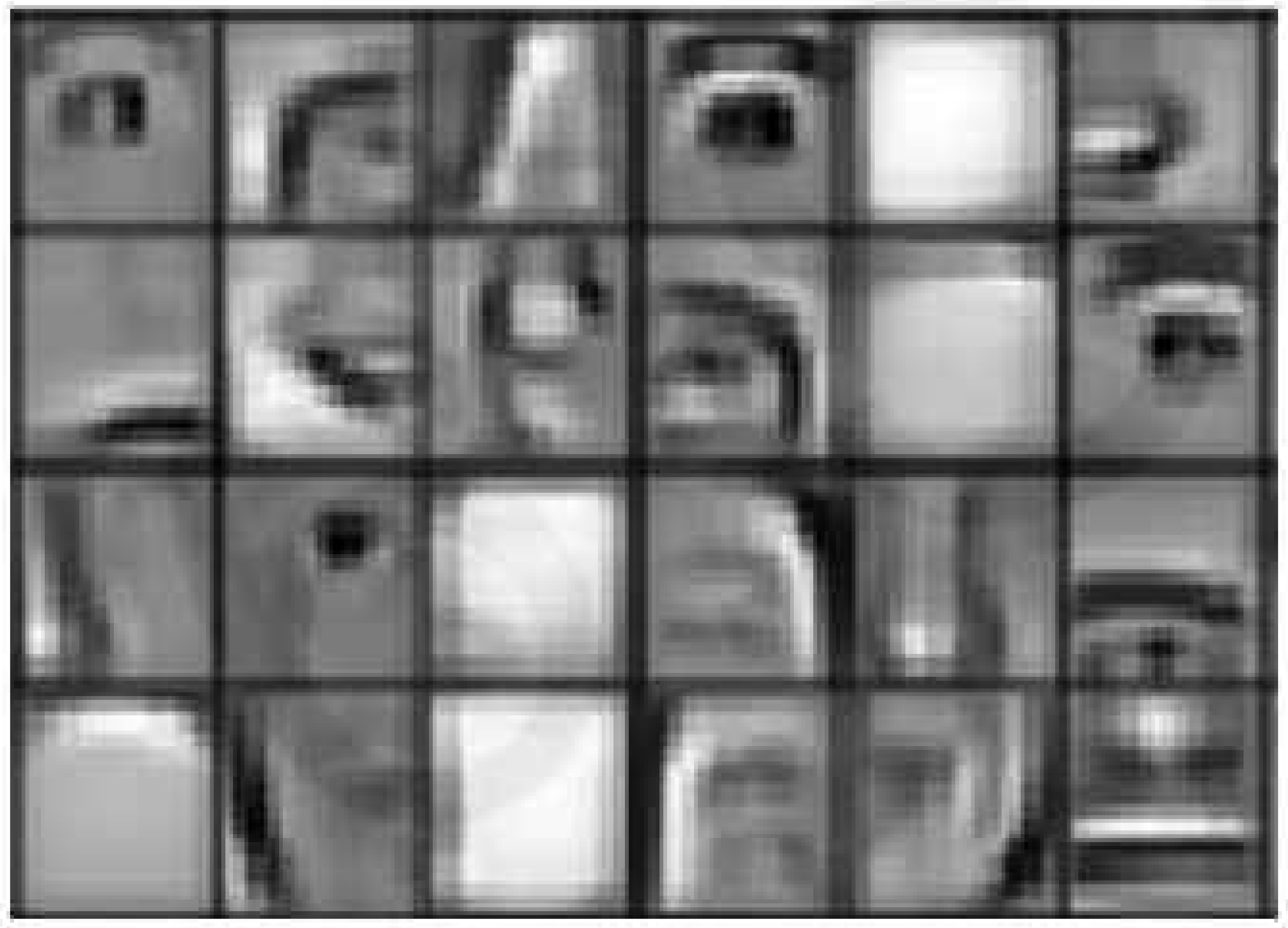
Low level features



Edges, dark spots

Conv Layer 1

Mid level features



Eyes, ears, nose

Conv Layer 2

High level features

Facial structure

Conv Layer 3

CNNs for Classification: Feature Learning

1. Learn features in input image through **convolution**
2. Introduce **non-linearity** through activation function (real-world data is non-linear!)
3. Reduce dimensionality and preserve spatial invariance with **pooling**

CNNs for Classification: Class Probabilities

- CONV and POOL layers output high-level features of input
- Fully connected layer uses these features for classifying input image
- Express output as **probability** of image belonging to a particular class

$$\text{softmax}(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}$$

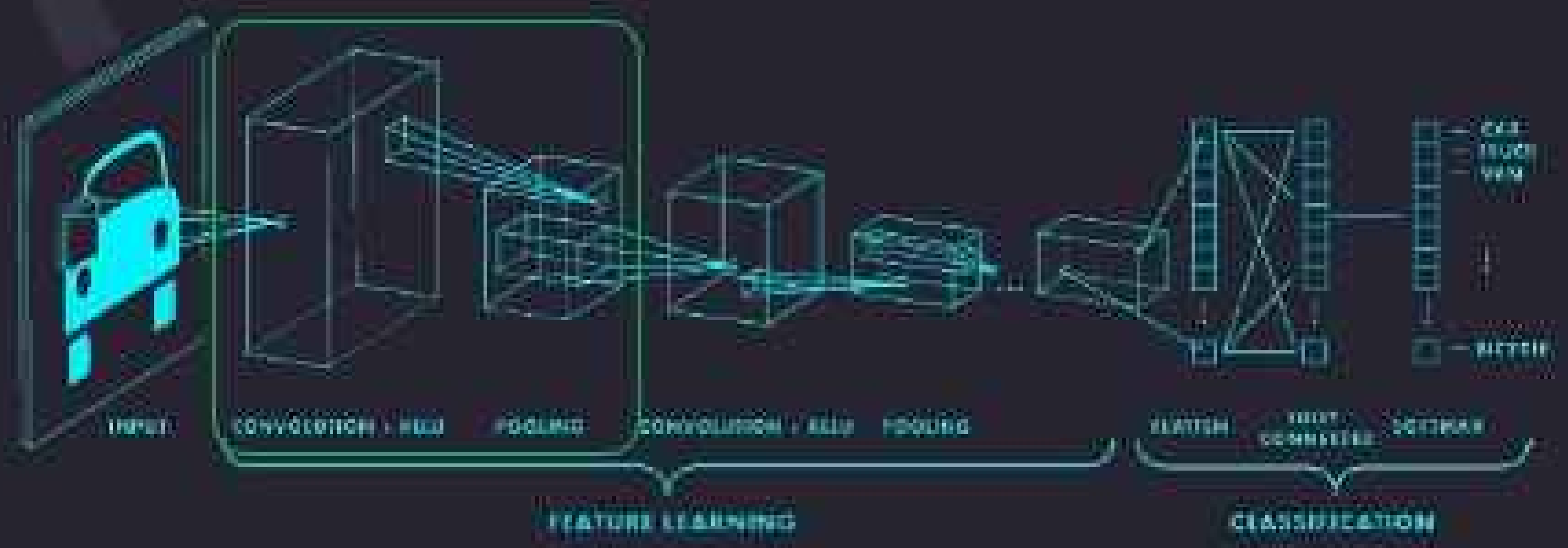
Putting it all together: CNN in TensorFlow

```python
import tensorflow as tf

def generate_model():
    model = tf.keras.Sequential([
        # first convolutional layer
        tf.keras.layers.Conv2D(32, filter_size=3, activation='relu'),
        tf.keras.layers.MaxPool2D(pool_size=2, strides=2),

        # second convolutional layer
        tf.keras.layers.Conv2D(64, filter_size=3, activation='relu'),
        tf.keras.layers.MaxPool2D(pool_size=2, strides=2),

        # fully connected classifier
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(1024, activation='relu'),
        tf.keras.layers.Dense(10, activation='softmax')  # 10 outputs
    ])
    return model
```



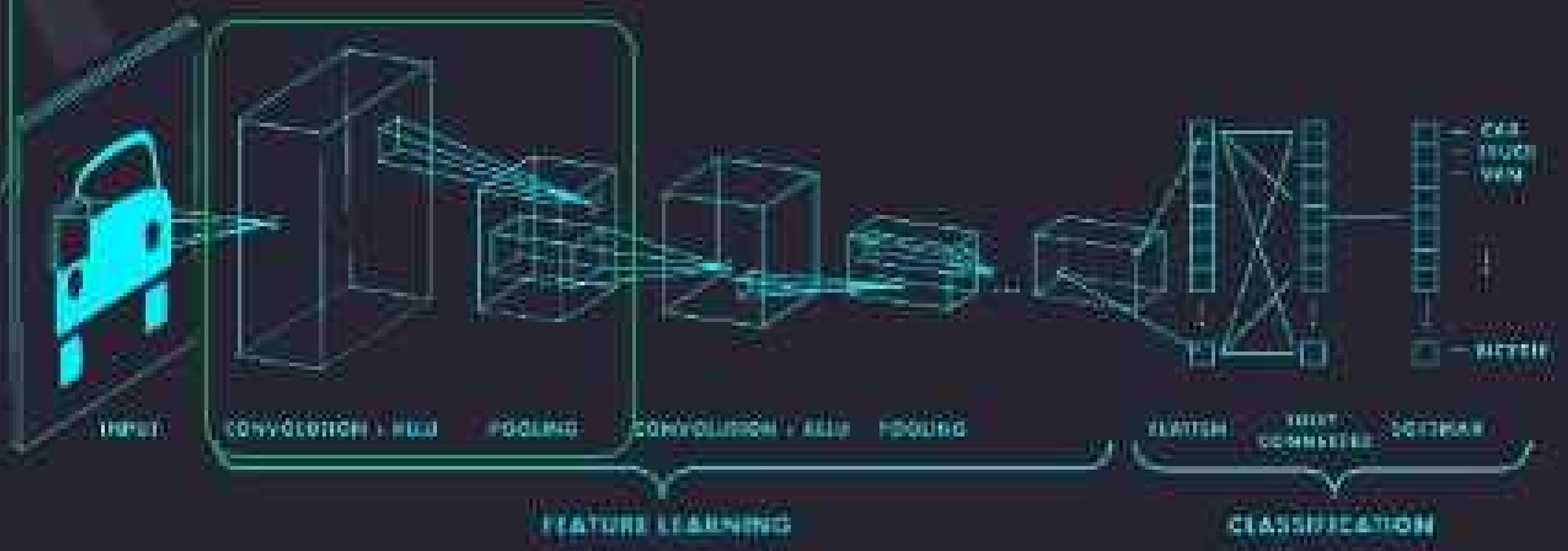
Putting it all together: CNN in PyTorch

```python
import torch

def generate_model():
    model = nn.Sequential([
        # first and second convolutional layer
        torch.nn.Conv2d(in_channels=3,out_channels=32, filter_size=3),
        torch.nn.ReLU(),
        torch.nn.MaxPool2d(kernel_size=2, stride=2),

        torch.nn.Conv2d(in_channels=32, out_channels=64, filter_size=3),
        torch.nn.ReLU(),
        torch.nn.MaxPool2d(kernel_size=2, stride=2),

        # fully connected classifier
        torch.nn.Flatten(),
        torch.nn.Linear(64*6*6, 1024), # flattened dim after 2 conv layers
        torch.nn.ReLU(),
        torch.nn.Linear(1024, 10),  # 10 outputs
    ])
    return model
```

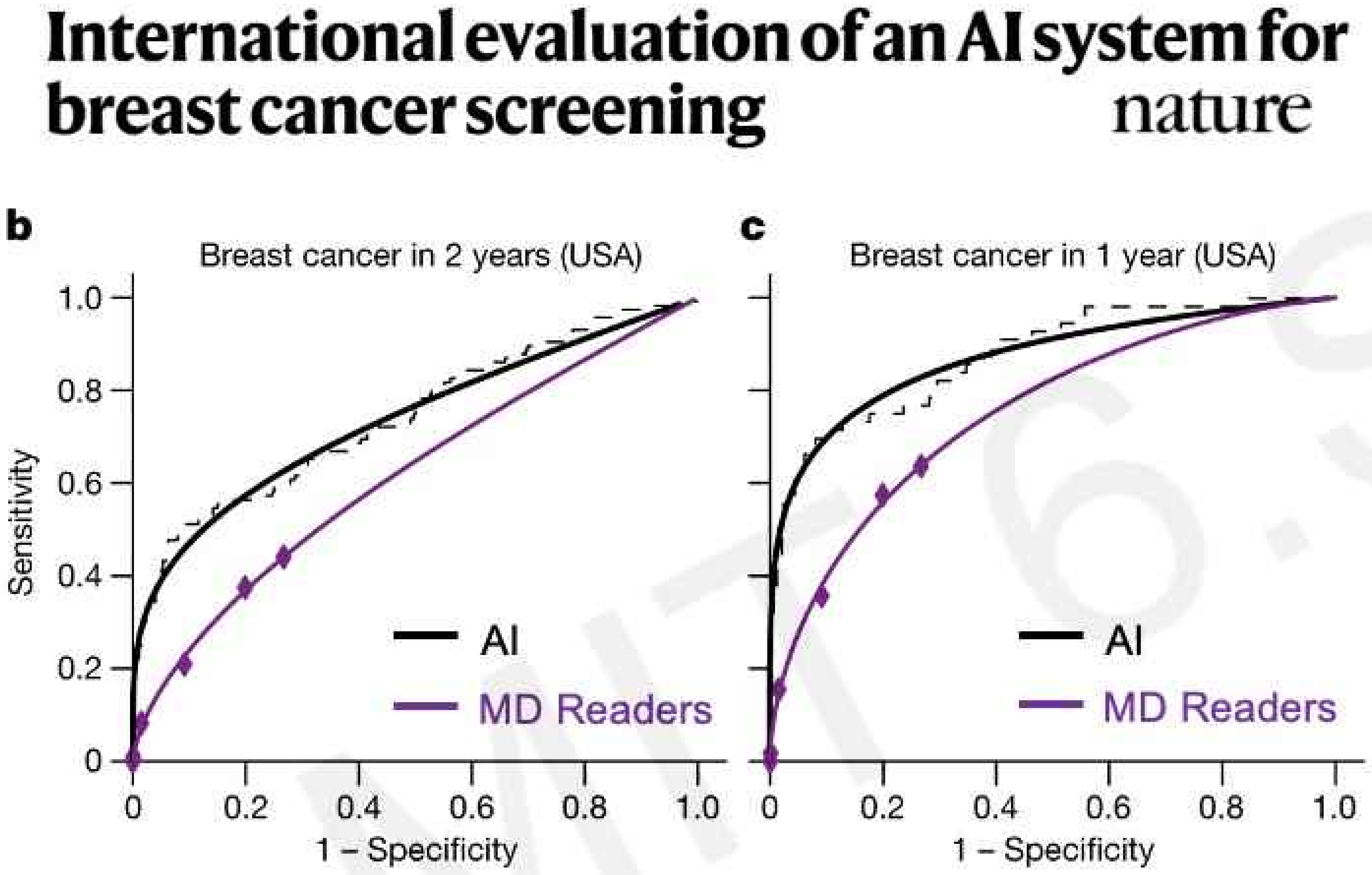


An Architecture for Many Applications

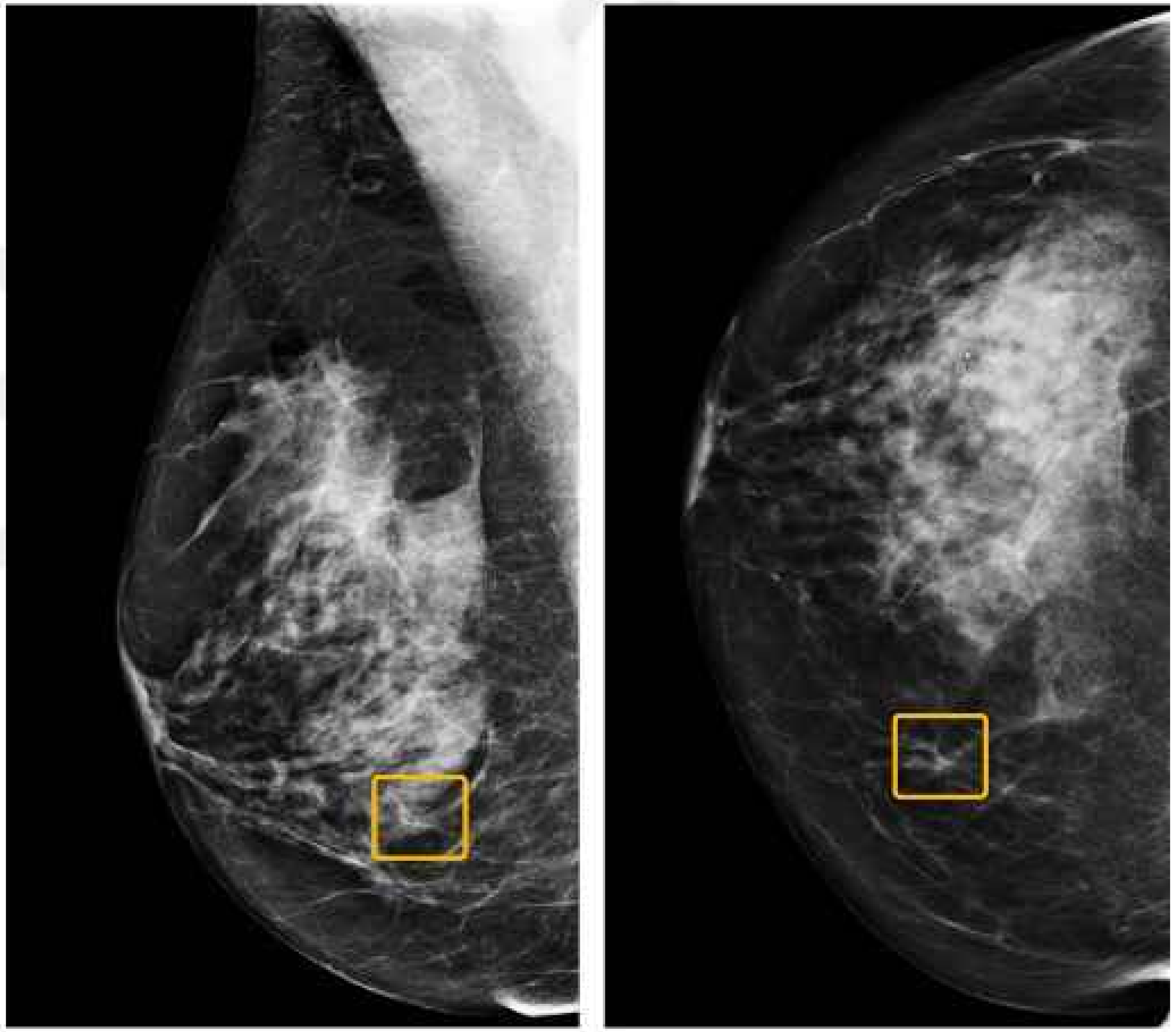
An Architecture for Many Applications

Classification
Object detection
Segmentation
Probabilistic control

Classification: Breast Cancer Screening

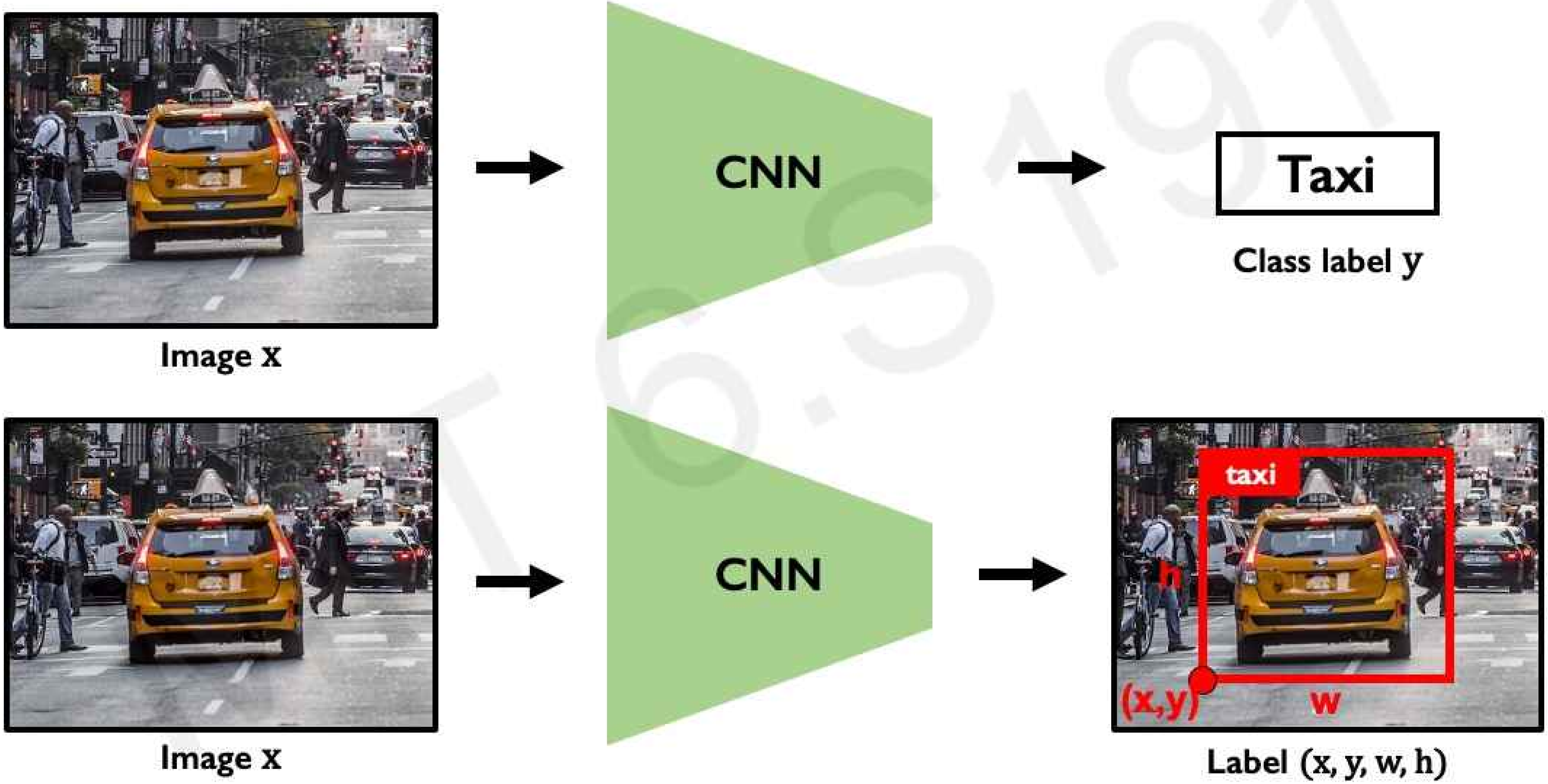


CNN-based system outperformed expert radiologists at detecting breast cancer from mammograms



Breast cancer case missed by radiologist but detected by AI

Object Detection

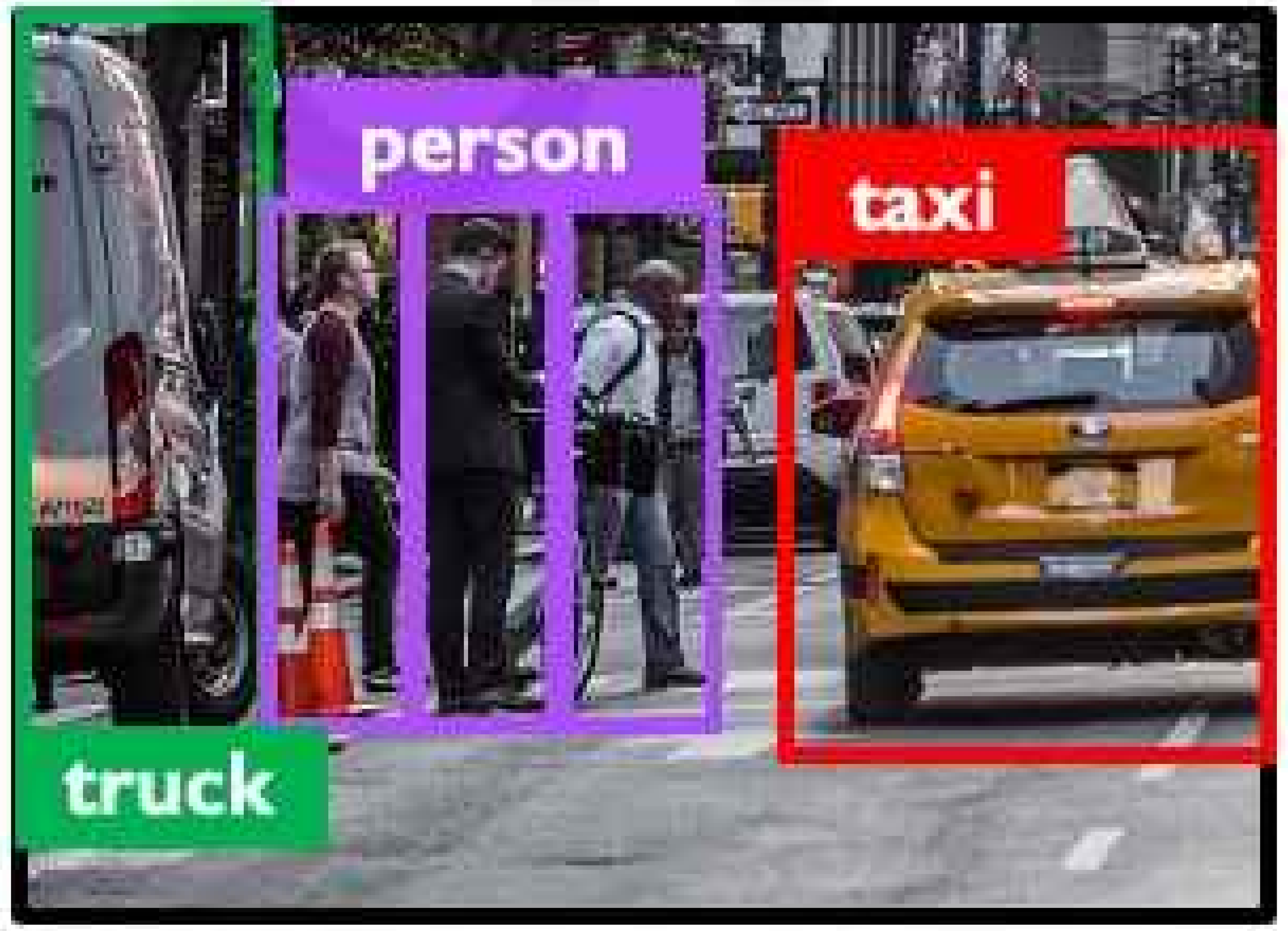


Object Detection

Image **x**

Output:
taxi: (x1, y1, w1, h1)

Image **x**



Output:
taxi: (x1, y1, w1, h1)
person: (x2, y2, w2, h2)
person: (x3, y3, w3, h3)
....

Naïve Solution to Object Detection

Problem: Way too many inputs! This results in too many scales, positions, sizes!

Object Detection with R-CNNs

R-CNN algorithm: Find regions that we think have objects. Use CNN to classify.

Problems: 1) Slow! Many regions; time intensive inference.
2) Brittle! Manually defined region proposals.

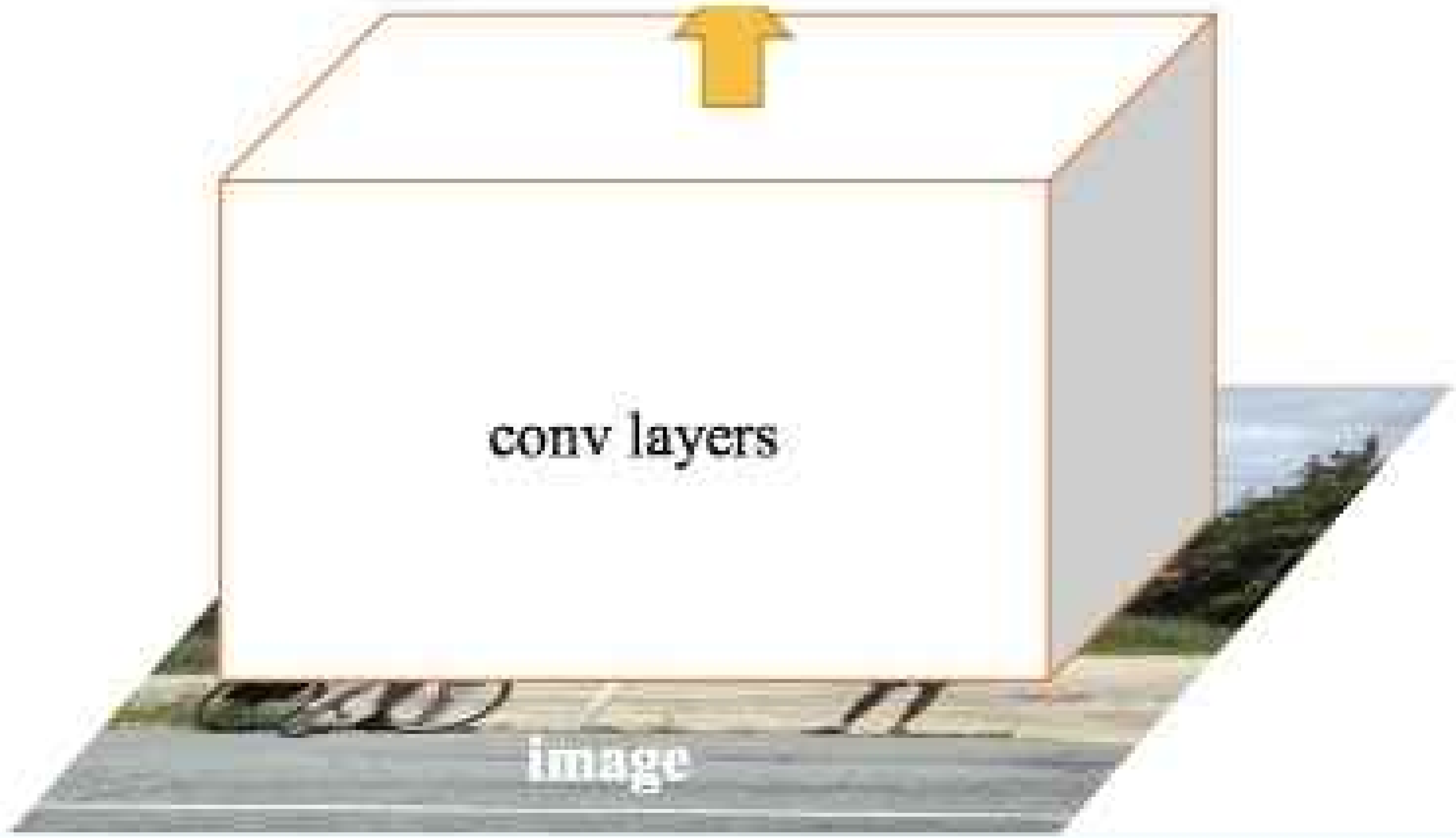
Faster R-CNN Learns Region Proposals

Classification of regions → object detection

Feature extraction over proposed regions

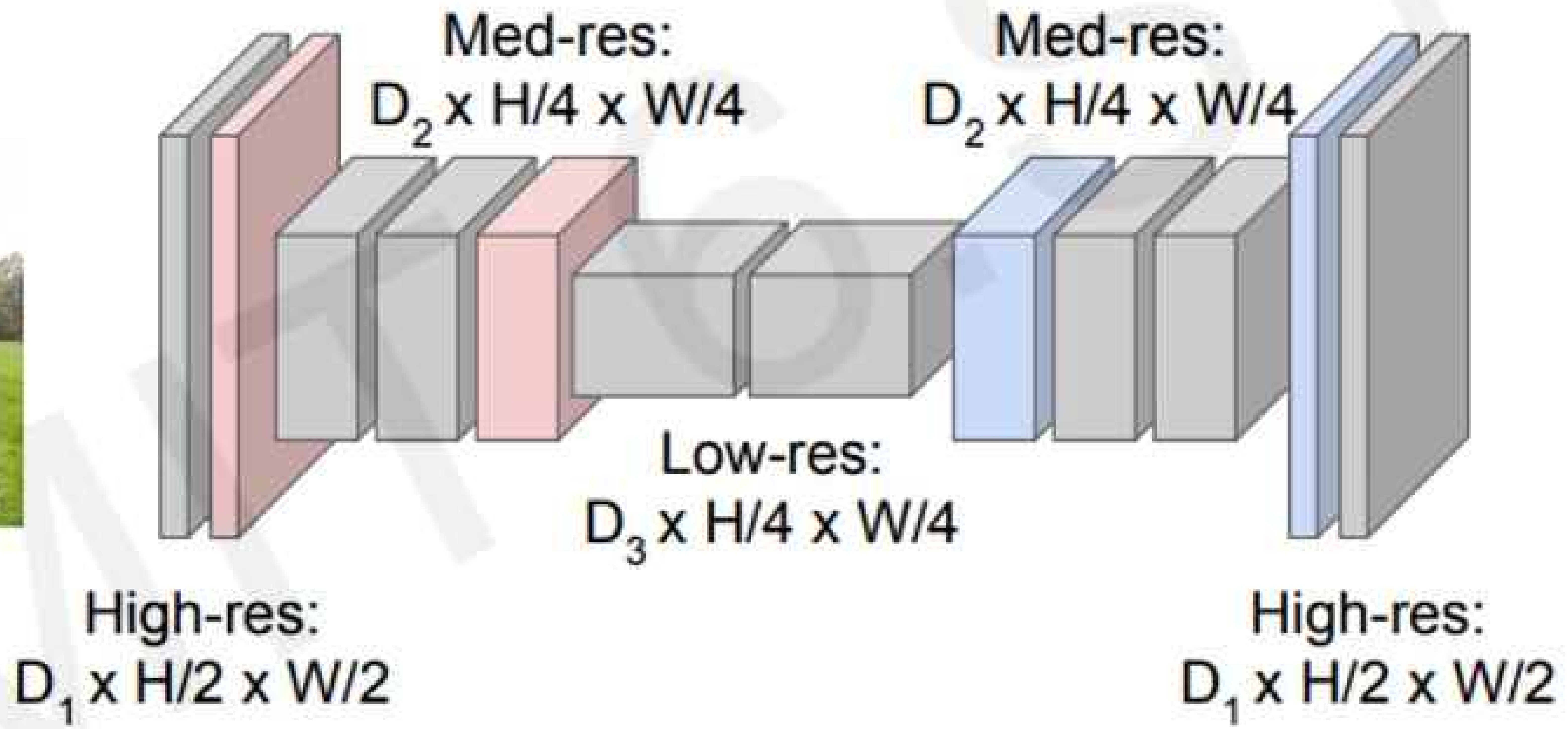
Region proposal network to learn candidate regions
Learned, data-driven

Image input directly into convolutional feature extractor
Fast! Only input image once!



Semantic Segmentation: Fully Convolutional Networks

FCN: Fully Convolutional Network.
Network designed with all convolutional layers,
with **downsampling** and **upsampling** operations



Input:
3 x H x W

Predictions:
H x W

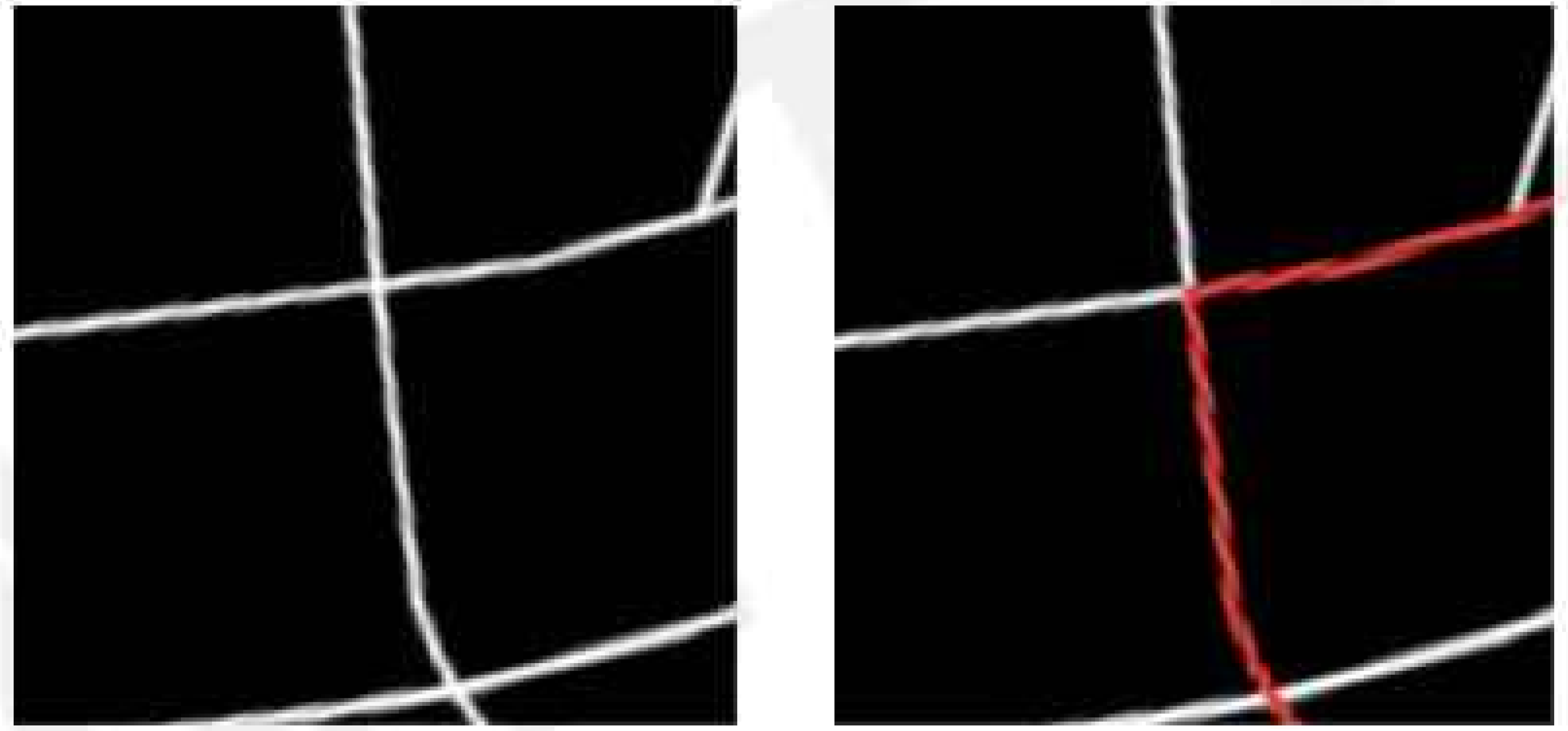
`tf.keras.layers.Conv2DTranspose`

`torch.nn.ConvTranspose2d`

Continuous Control: Navigation from Vision

Raw Perception
I
(ex. camera)

Coarse Maps
M
(ex. GPS)



Possible Control Commands

End-to-End Framework for Autonomous Navigation

Entire model is trained end-to-end **without any human labelling or annotations**

$$L = -\log(P(\theta|I,M))$$


Auto ON
Navigation and Localization
Amini+ ICRA 2019.

Deep Learning for Computer Vision: Impact

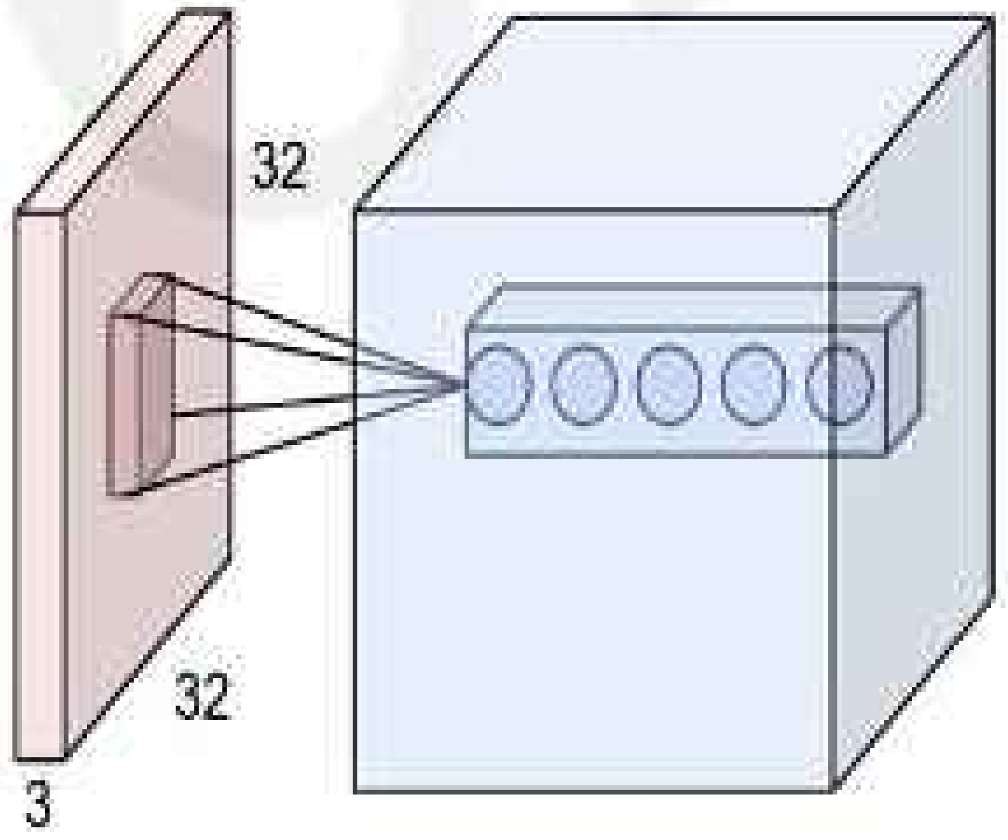
Deep Learning for Computer Vision: Summary

Foundations

- Why computer vision?
- Representing images
- Convolutions for feature extraction

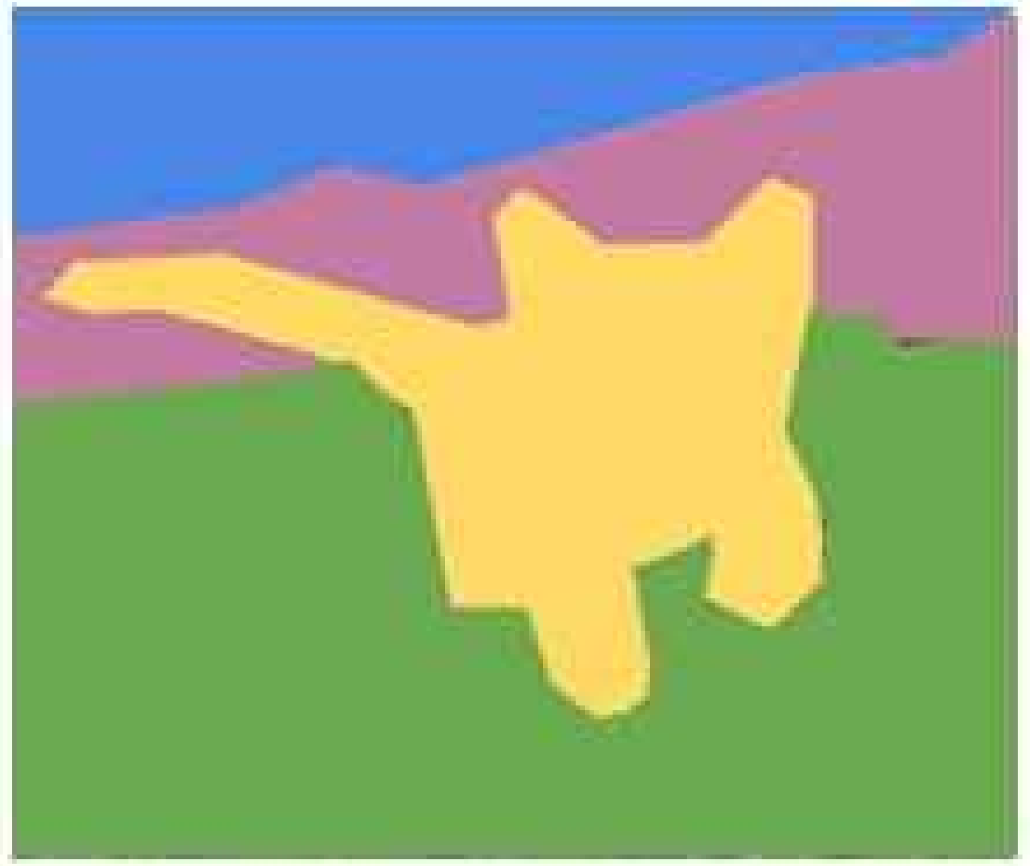
CNNs

- CNN architecture
- Application to classification
- ImageNet



Applications

- Segmentation, image captioning, control
- Security, medicine, robotics



MIT 6.S191
Introduction to Deep Learning

Lab 2: Facial Detection Systems

Link to download labs:

introtodeeplearning.com#schedule

github.com/MITDeepLearning/introtodeeplearning

1. Open the lab in Google Colab
2. Start executing code blocks and filling in the #TODOs
3. Need help? Come to 32-123!

Introduction to Deep Learning

Announcements and Reminders

Lecture 4: Generative Modeling starting soon!

Lab 2 begins today!
Prizes for participants!
Enter for a chance to win $$$!

Lots of swag will be available after class tomorrow!

Interested in cutting-edge AI jobs?
introtodeeplearning.com/jobs.html