



6.S191: Introduction to Deep Learning

Announcements

- I. Updates to Materials:
 1. Day 1 lecture slides posted
 2. Slides for Lecture 3: Computer Vision (now) posted
2. Lab Updates
 1. Solutions to Lab 1 and Lab 2 on website
 2. Office Hours after class 1:30-3pm (32-141)
3. T Shirts Tomorrow!



Deep Learning for Computer Vision

MIT 6.SI91

Ava Soleimany



Vision: Evolutionary Origins

Vision: 540 million years of data

vs.

Bipedal movement: 230+ million years of data

Human language: ~100 thousand years of data



Opabinia, 540 mil. years ago

Can we understand neural basis of vision?

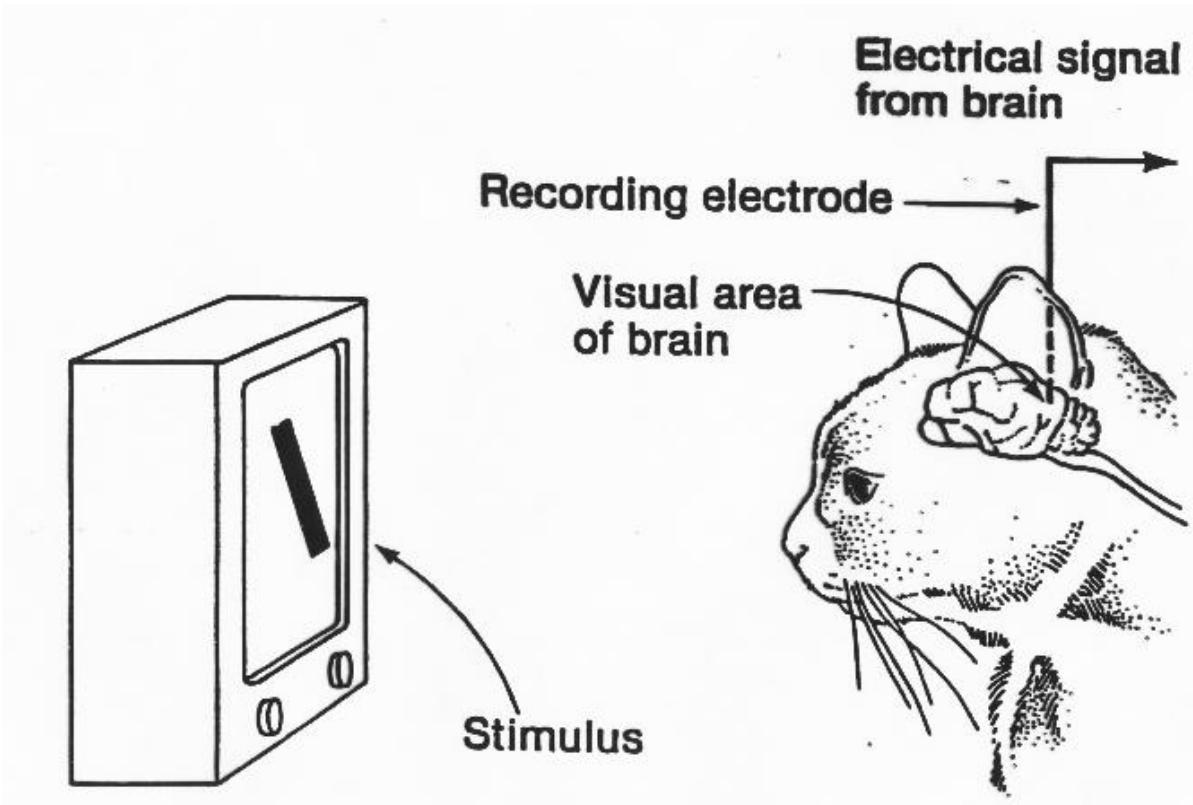
How is visual information processed?

Can we use that structure to inform computer vision?



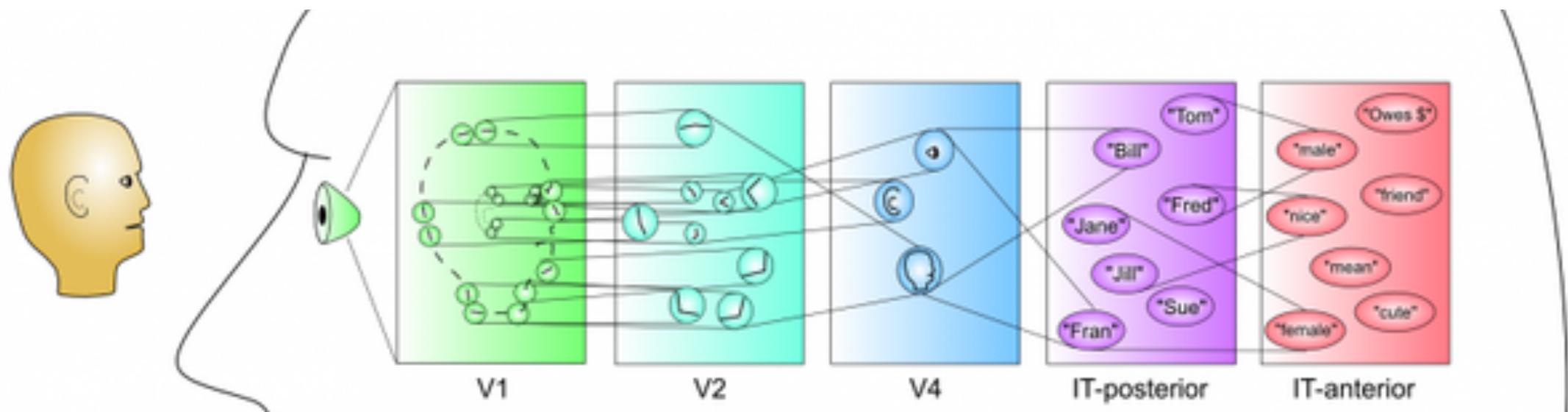
Hubel & Wiesel, Harvard. 1960s

The Visual Cortex



- 1) Spatial Invariance
- 2) Receptive Field
- 3) Hierarchy

The Visual Cortex



What Computers “See”

Images Are Numbers

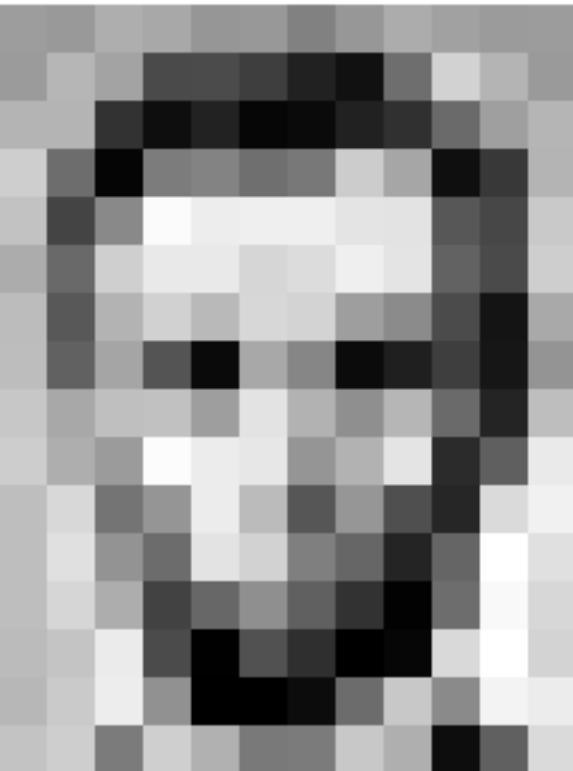


Images Are Numbers



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	84	6	10	33	48	106	159	181
206	109	5	124	191	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	105	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	296	187	85	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	95	59	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	209	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

Images are Numbers



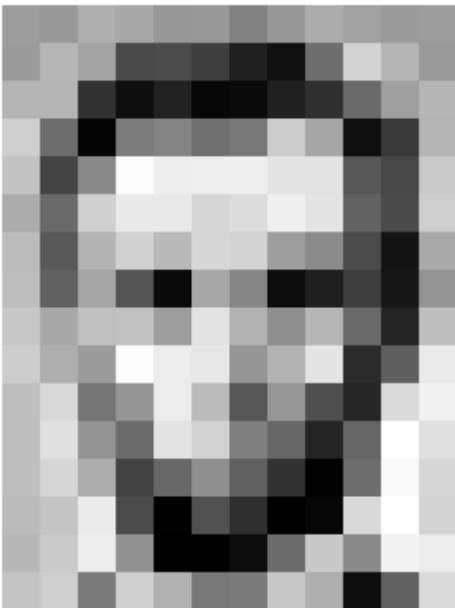
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155	182	163	74	75	62	33	17	110	210	180	154
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199	168	191	193	158	227	178	143	182	105	36	190
205	174	155	252	236	231	149	178	228	43	95	234
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190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	95	59	2	109	249	215
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183	202	237	145	0	0	12	108	209	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

What the computer sees

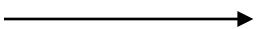
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155	182	163	74	75	62	33	17	110	210	180	154
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183	202	237	145	0	0	12	108	209	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

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

Tasks in Computer Vision



Input Image



157	153	174	168	160	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
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183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

Pixel Representation

classification

Lincoln

Washington

Jefferson

Obama



- **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

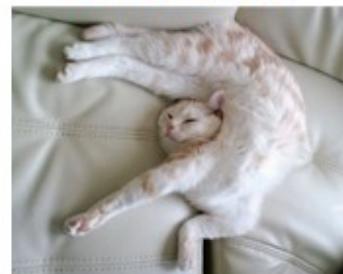
Viewpoint variation



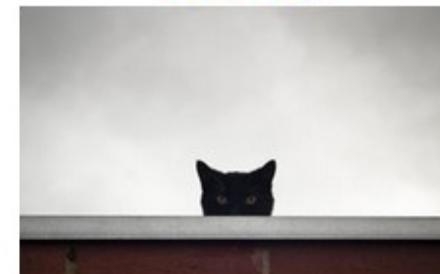
Scale variation



Deformation



Occlusion



Illumination conditions



Background clutter



Intra-class variation



Manual Feature Extraction

Domain knowledge

Define features

Detect features
to classify

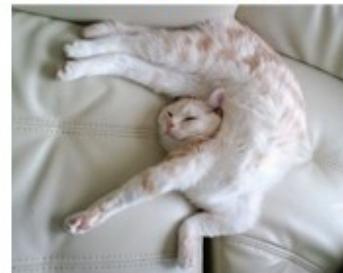
Viewpoint variation



Scale variation



Deformation



Occlusion



Illumination conditions



Background clutter



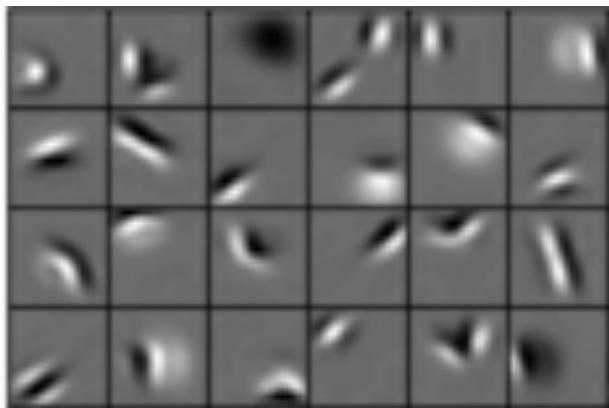
Intra-class variation



Learning Feature Representations

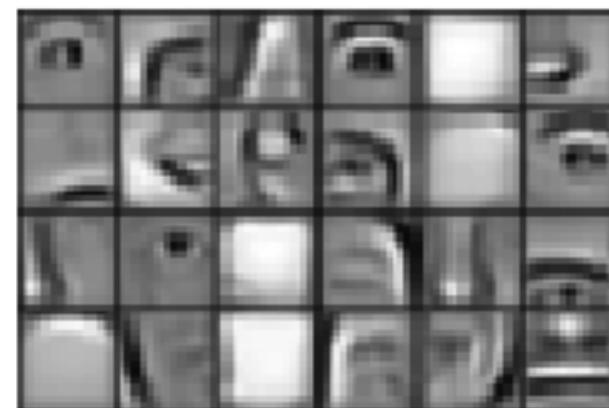
Can we **learn hierarchy of features** directly from the data instead of hand engineering?

Low level features



Edges, dark spots

Mid level features



Eyes, ears, nose

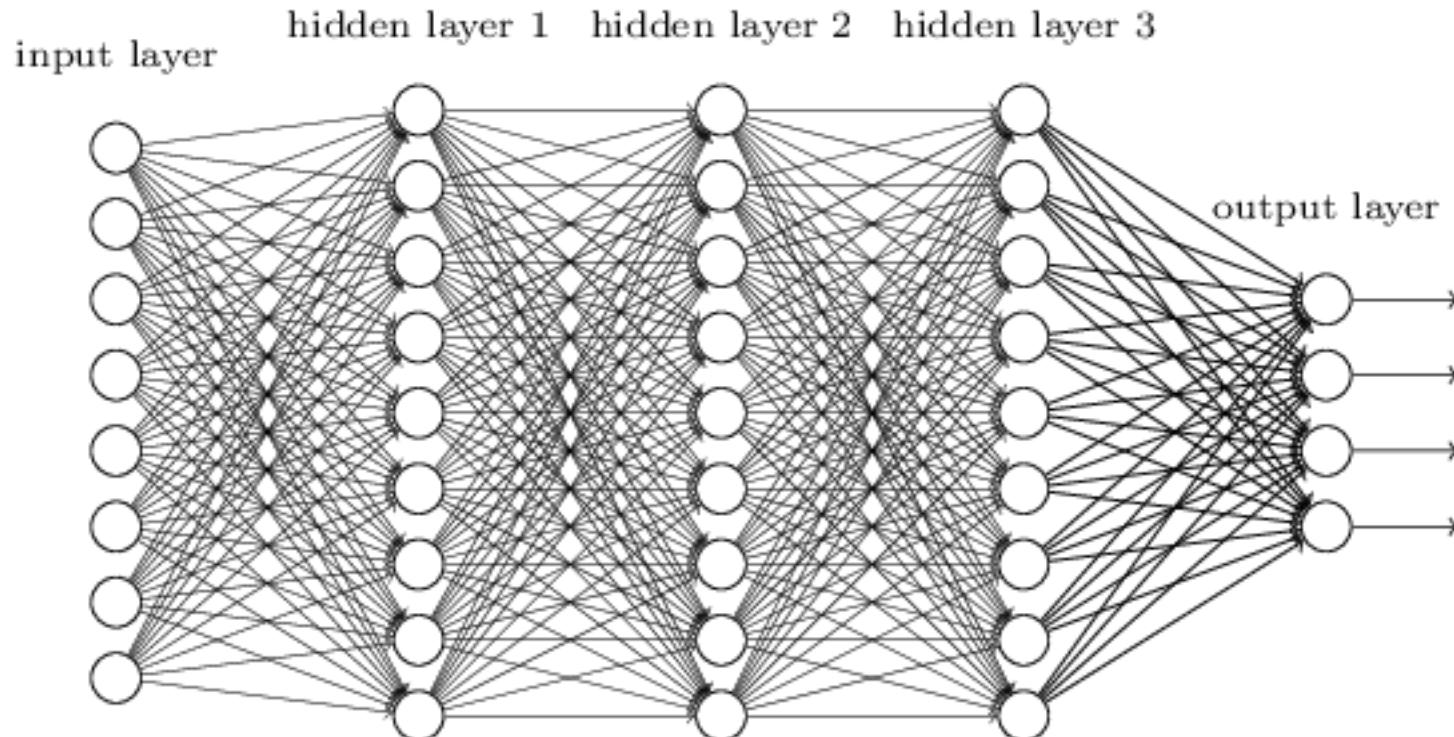
High level features



Facial structure

Learning Visual Features

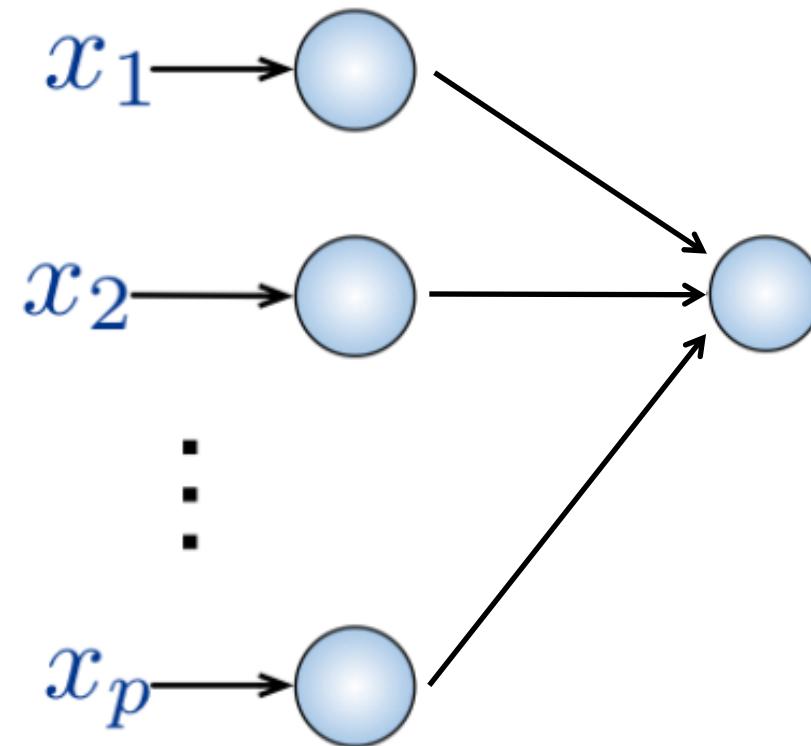
Fully Connected Neural Network



Fully Connected Neural Network

Input:

- 2D image
- Vector of pixel values



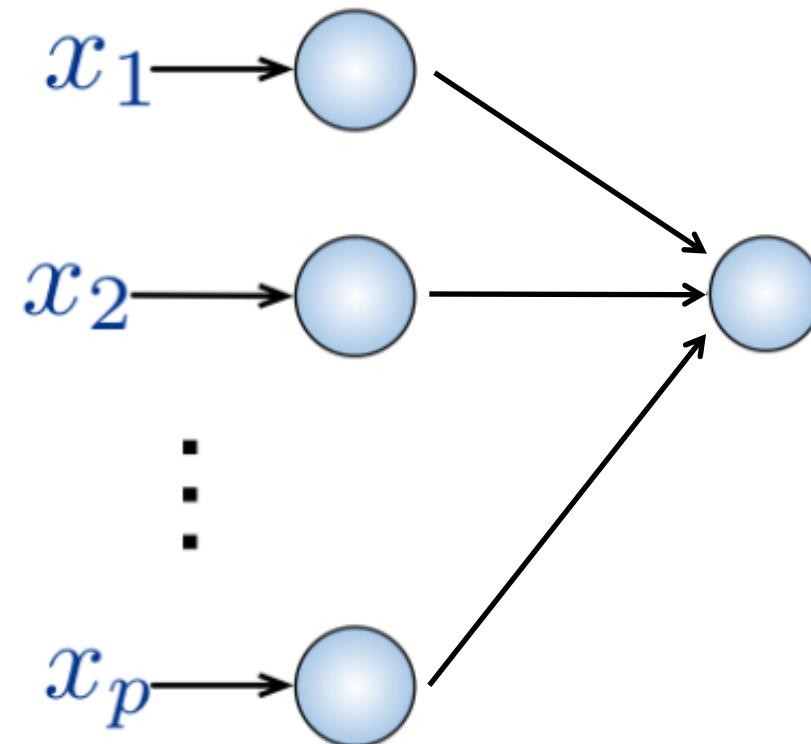
Fully connected:

- 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



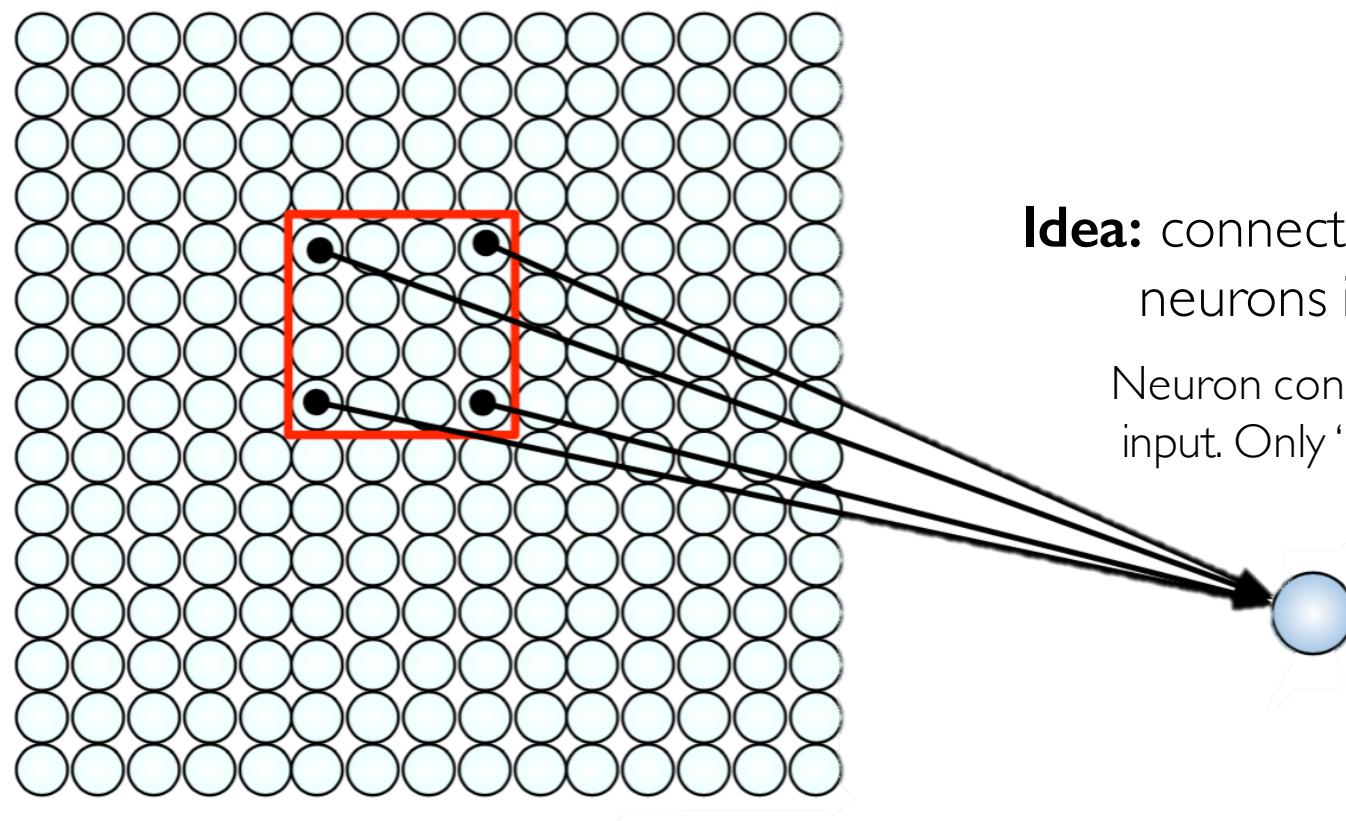
Fully connected:

- 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

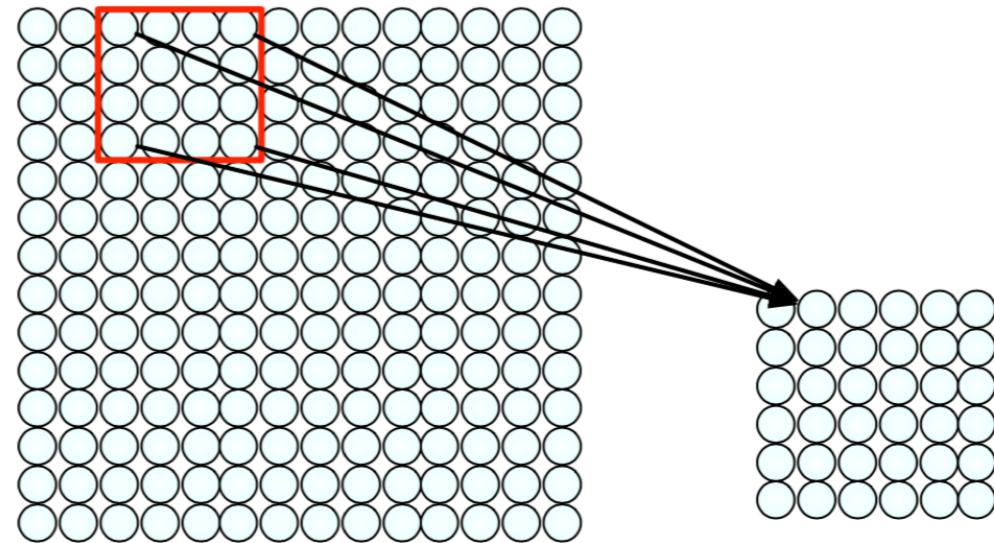
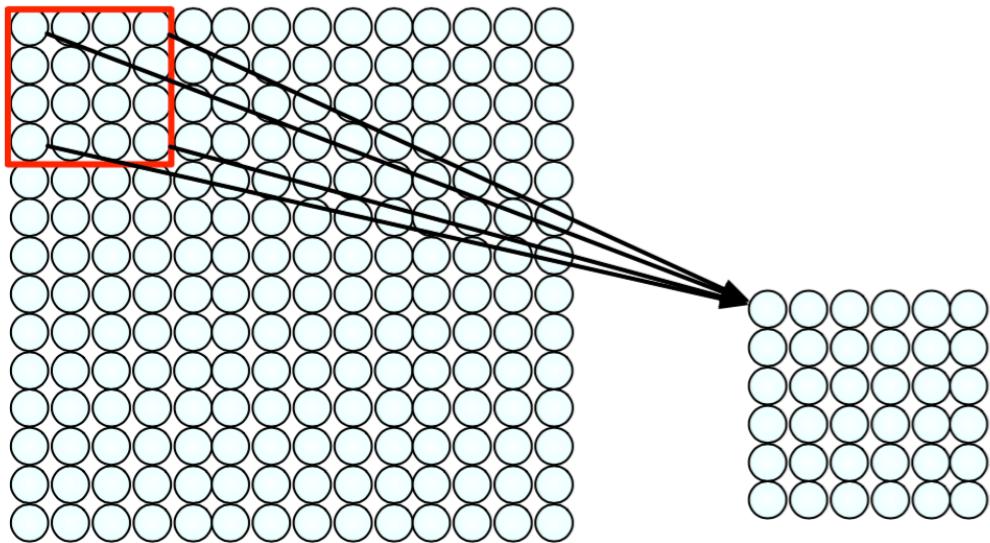
Input: 2D image.
Array of pixel values



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?

Applying Filters to Extract Features

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

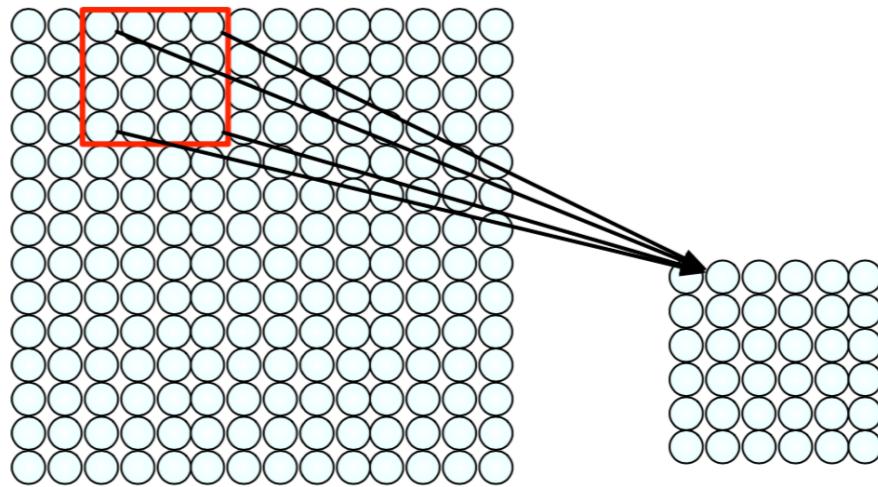
Applying Filters to Extract Features

- 1) Apply a set of weights – a filter – to extract **local features**
- 2) Use **multiple filters** to extract different features

Applying Filters to Extract Features

- 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
(features that matter in one part of the input should matter elsewhere)

Feature Extraction with Convolution



- Filter of size 4×4 : 16 different weights
- Apply this same filter to 4×4 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?

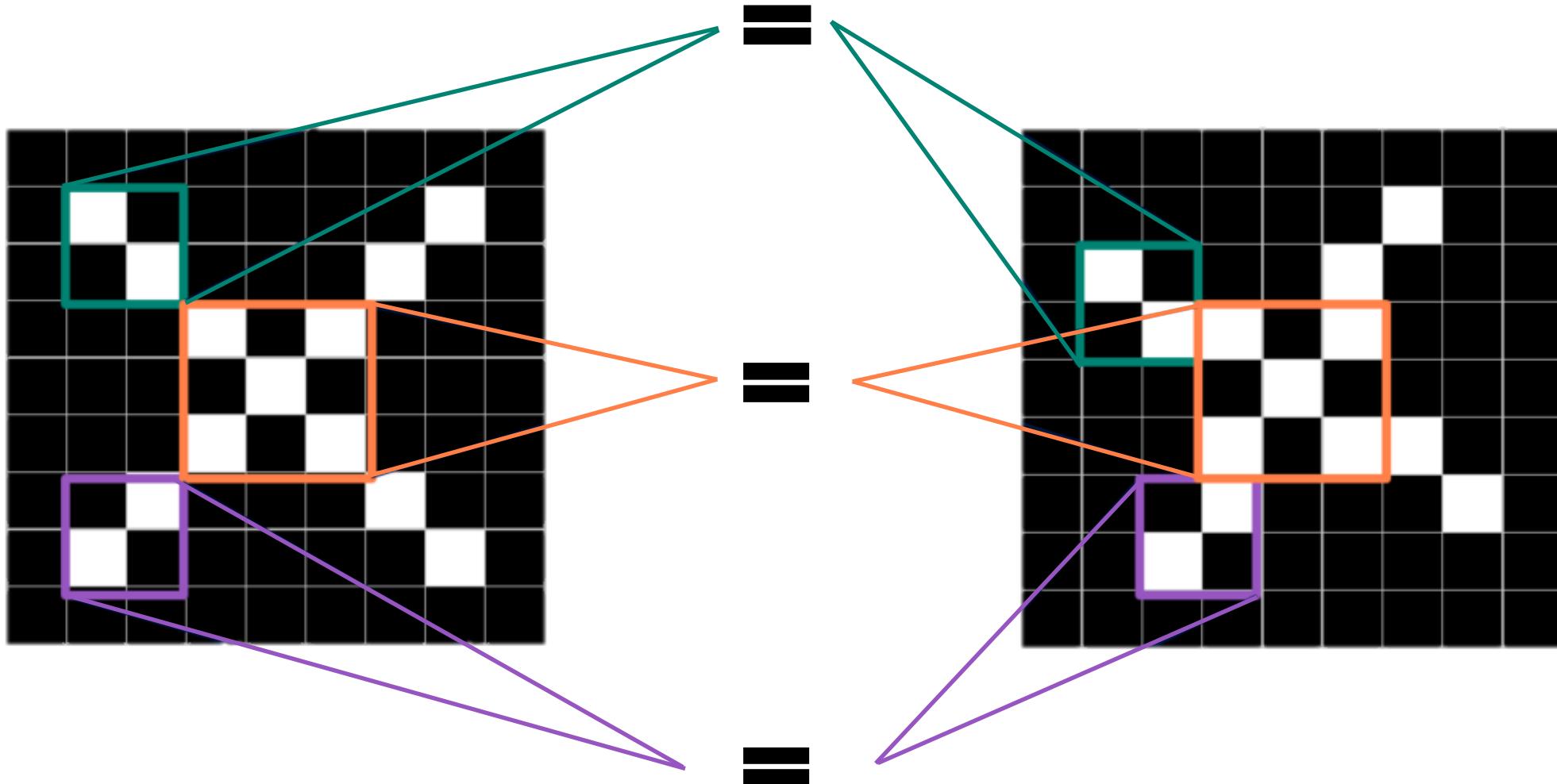
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1	
-1	-1	1	-1	-1	-1	1	-1	-1	
-1	-1	-1	1	-1	1	-1	-1	-1	
-1	-1	-1	-1	1	-1	-1	-1	-1	
-1	-1	-1	-1	1	-1	-1	-1	-1	
-1	-1	-1	1	-1	1	-1	-1	-1	
-1	1	-1	-1	-1	-1	1	-1	-1	
-1	-1	-1	-1	-1	-1	-1	-1	-1	



-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
-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



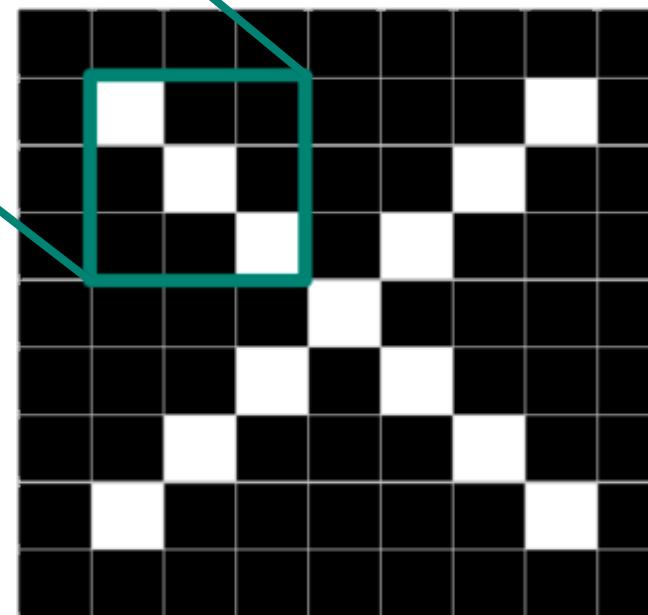
Filters to Detect X Features

filters

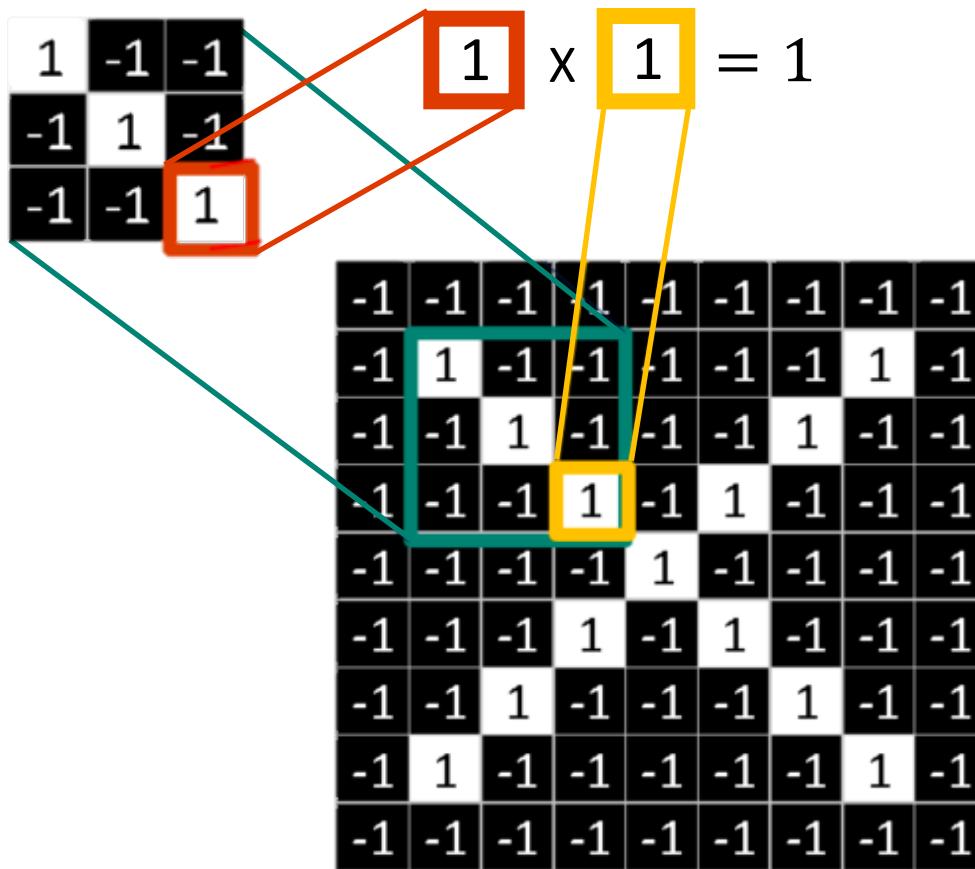
1	-1	-1
-1	1	-1
-1	-1	1

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

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



The Convolution Operation



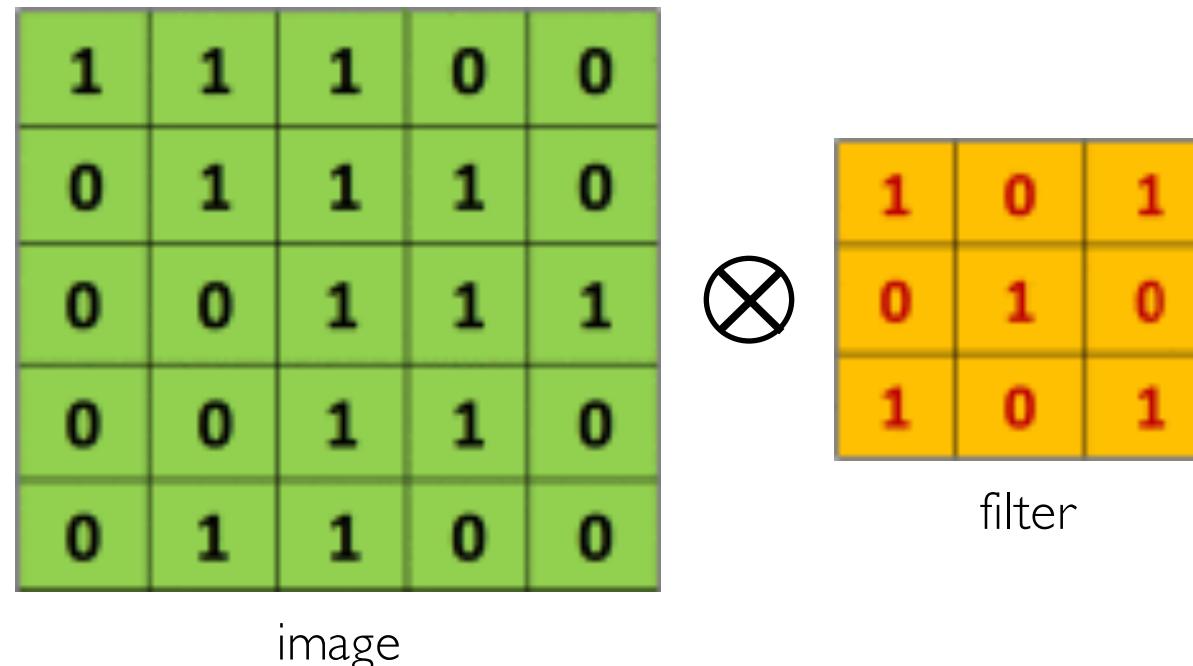
Element wise multiply

$$\odot \quad \begin{array}{|c|c|c|}\hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array} = 9$$

Add outputs

The Convolution Operation

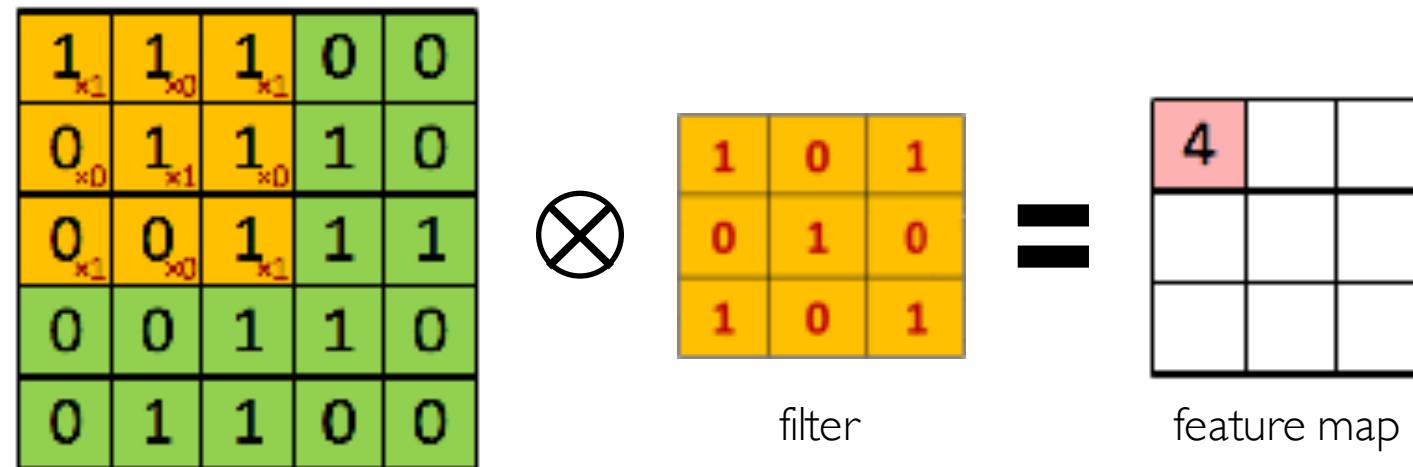
Suppose we want to compute the convolution of a 5x5 image and a 3x3 filter:



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

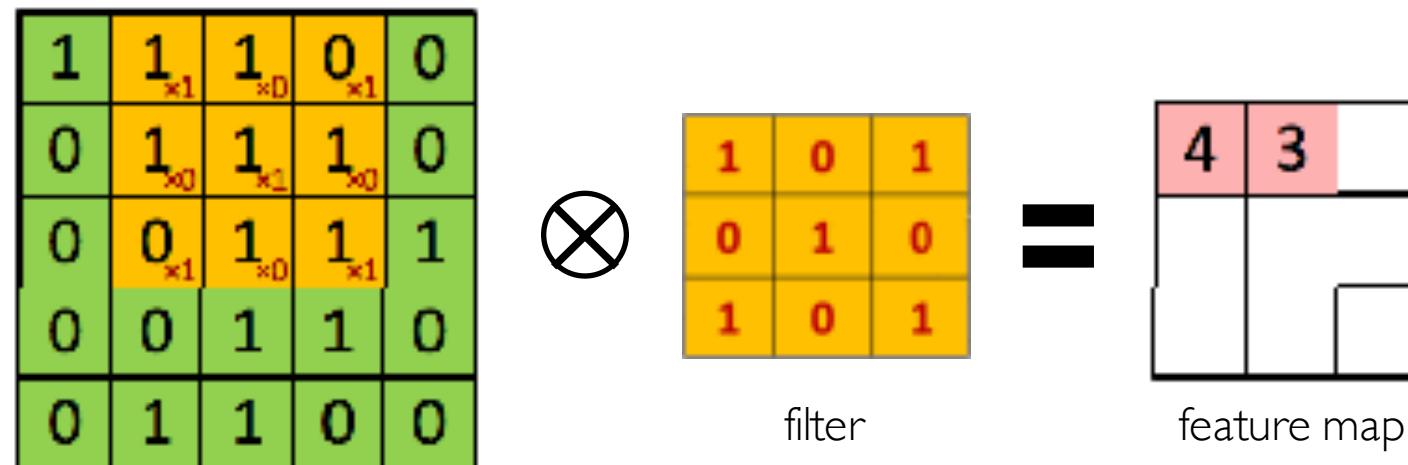
The Convolution Operation

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



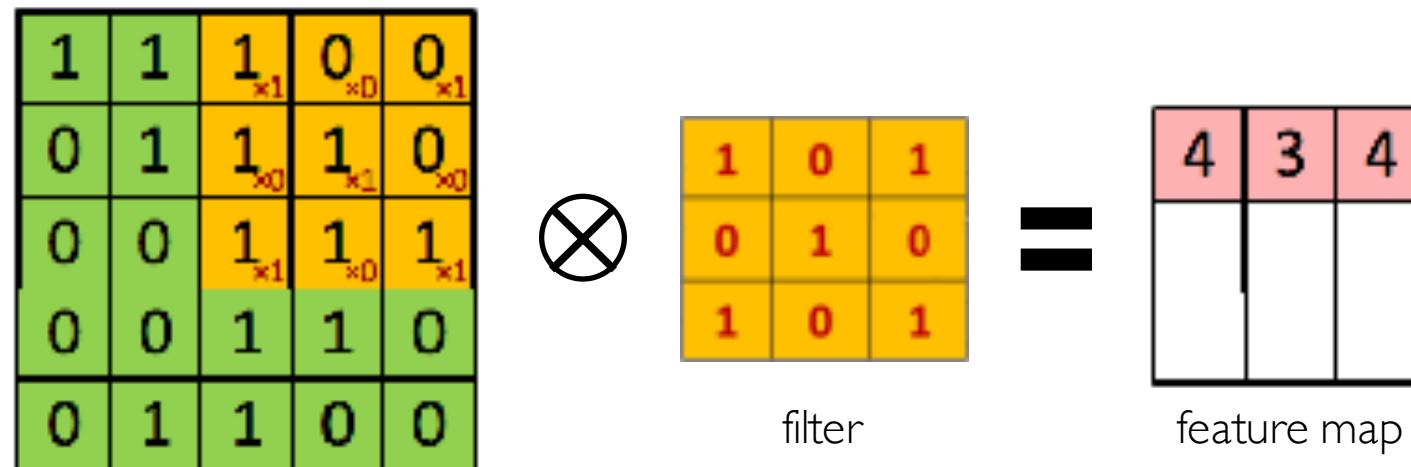
The Convolution Operation

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



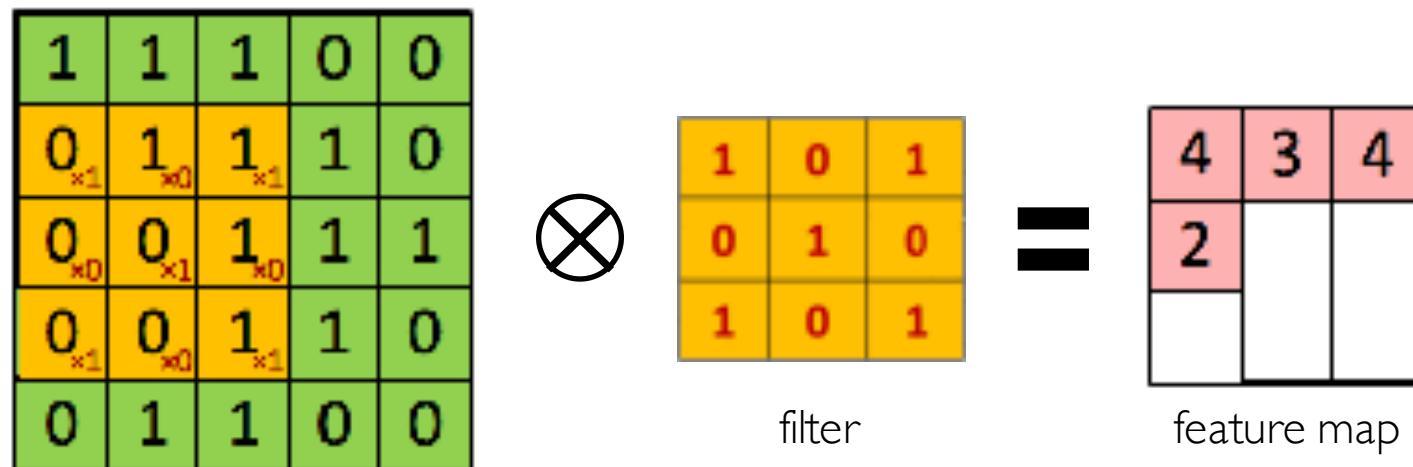
The Convolution Operation

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:



The Convolution Operation

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

The diagram illustrates the convolution operation. On the left is an input image represented as a 5x5 grid of green cells. The values in the grid are: Row 1: 1, 1, 1, 0, 0; Row 2: 0, 1 (with a red $\times 1$ below it), 1 (with a red $\times 0$ below it), 1 (with a red $\times 1$ below it), 0; Row 3: 0 (with a red $\times 0$ below it), 0 (with a red $\times 1$ below it), 1 (with a red $\times 1$ below it), 1 (with a red $\times 0$ below it), 1; Row 4: 0 (with a red $\times 1$ below it), 0 (with a red $\times 0$ below it), 1 (with a red $\times 0$ below it), 1 (with a red $\times 1$ below it), 0; Row 5: 0, 1, 1, 0, 0. In the middle, there is a multiplication symbol (\otimes) followed by the word "filter". To the right of the filter is an equals sign (=). On the far right is a feature map represented as a 3x3 grid of pink cells. The values in the grid are: Row 1: 4, 3, 4; Row 2: 2, 4. The bottom-right cell is empty.

The Convolution Operation

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

The diagram illustrates the convolution operation. On the left is an input image represented as a 5x5 grid of numbers. The middle part shows the multiplication of the input image with a 3x3 filter, indicated by a circled cross symbol. The result is an equals sign followed by a 3x3 feature map.

1	1	1	0	0
0	1	1 _{x1}	1 _{x0}	0 _{x1}
0	0	1 _{x0}	1 _{x1}	1 _{x0}
0	0	1 _{x1}	1 _{x0}	0 _{x1}
0	1	1	0	0

filter

1	0	1
0	1	0
1	0	1

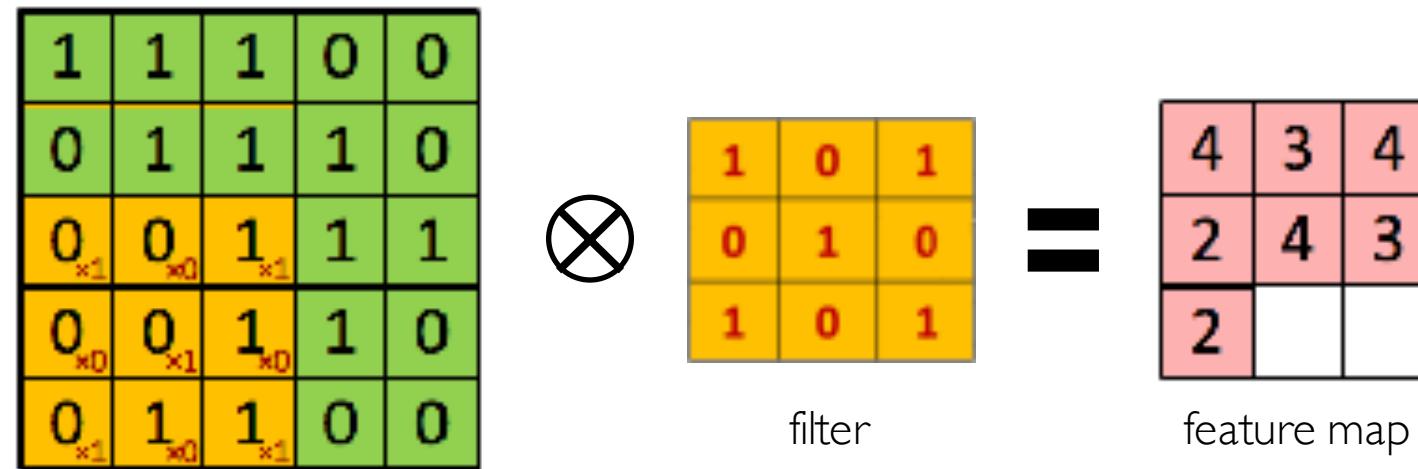
=

4	3	4
2	4	3

feature map

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 diagram illustrates the convolution operation. On the left, an input image of size 5x5 is shown. The elements are colored green, yellow, or orange, with some having small red multipliers (x0, x1) indicating which input channels are active for each output unit. In the center, a 3x3 filter is shown with red values. To the right, the result is shown as a feature map of size 3x3, with pink values representing the sum of the element-wise products.

1	1	1	0	0
0	1	1	1	0
0	0	1	1	x1
0	0	1	1	x0
0	1	1	0	x1

⊗

filter

1	0	1
0	1	0
1	0	1

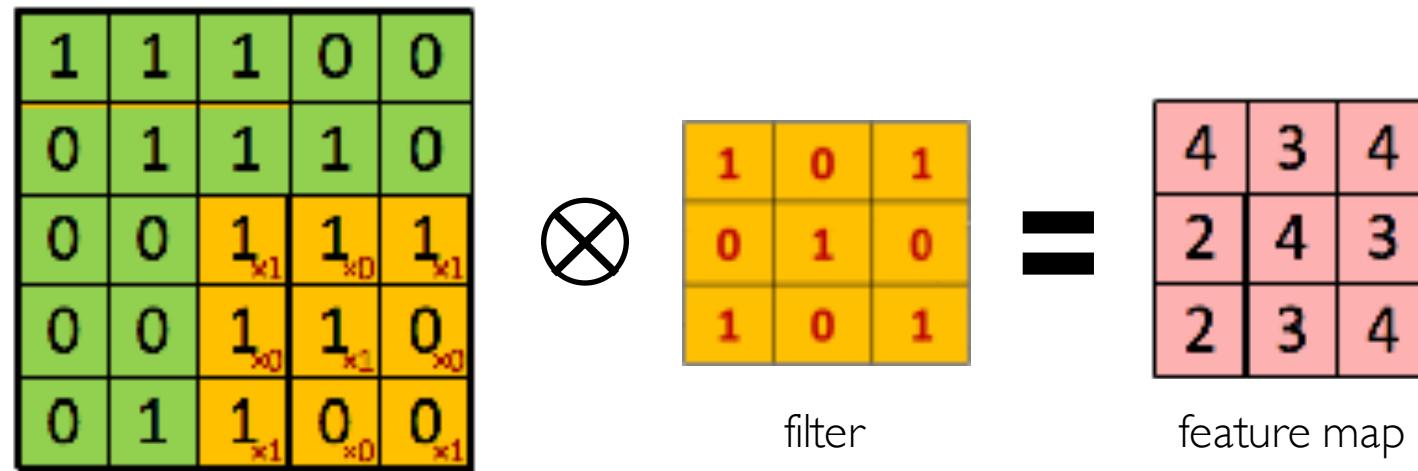
=

4	3	4
2	4	3
2	3	

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

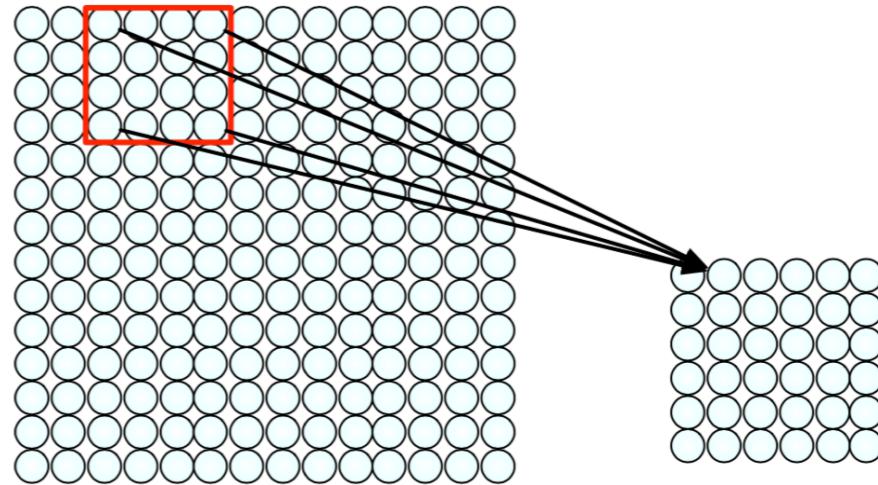


Edge Detect



“Strong” Edge
Detect

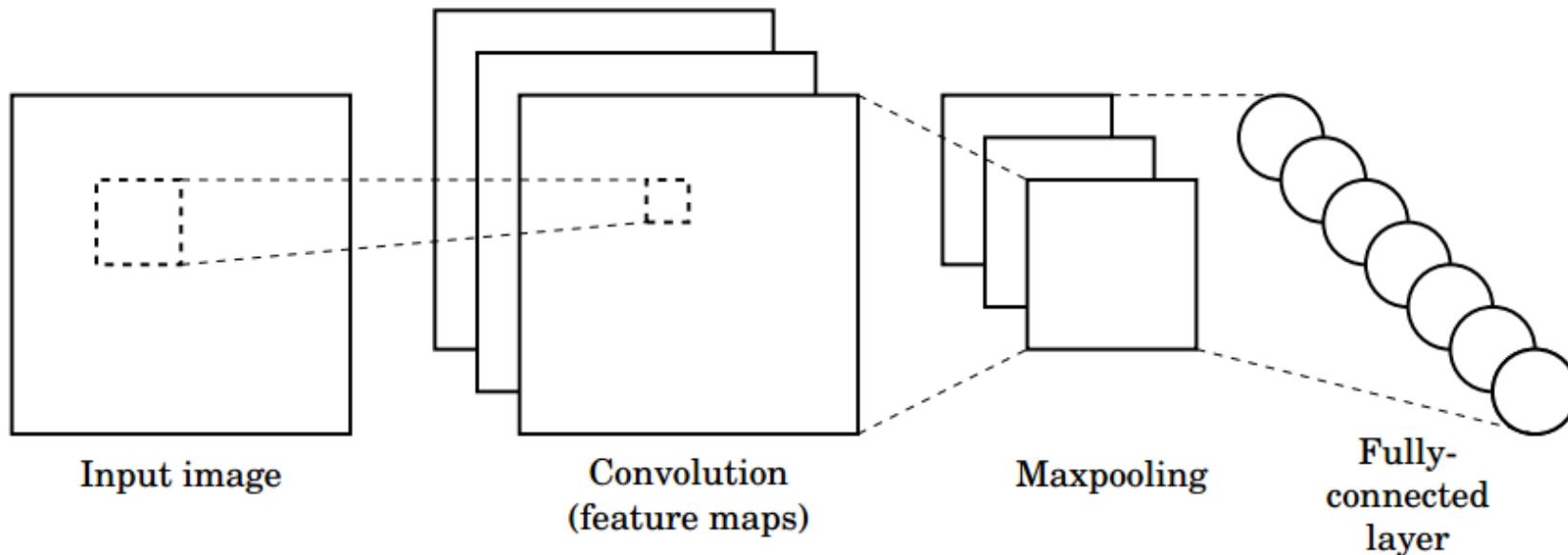
Feature Extraction with Convolution



- 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)

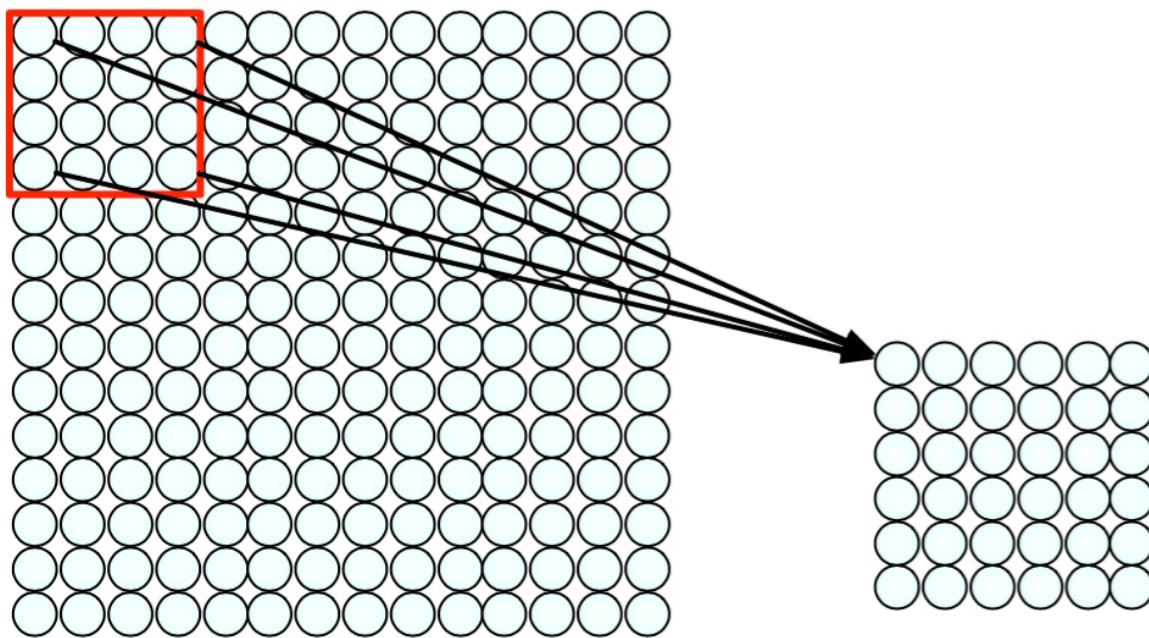
CNNs for Classification



1. **Convolution:** Apply filters with learned weights to generate feature maps.
2. **Non-linearity:** Often ReLU.
3. **Pooling:** Downsampling operation on each feature map.

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

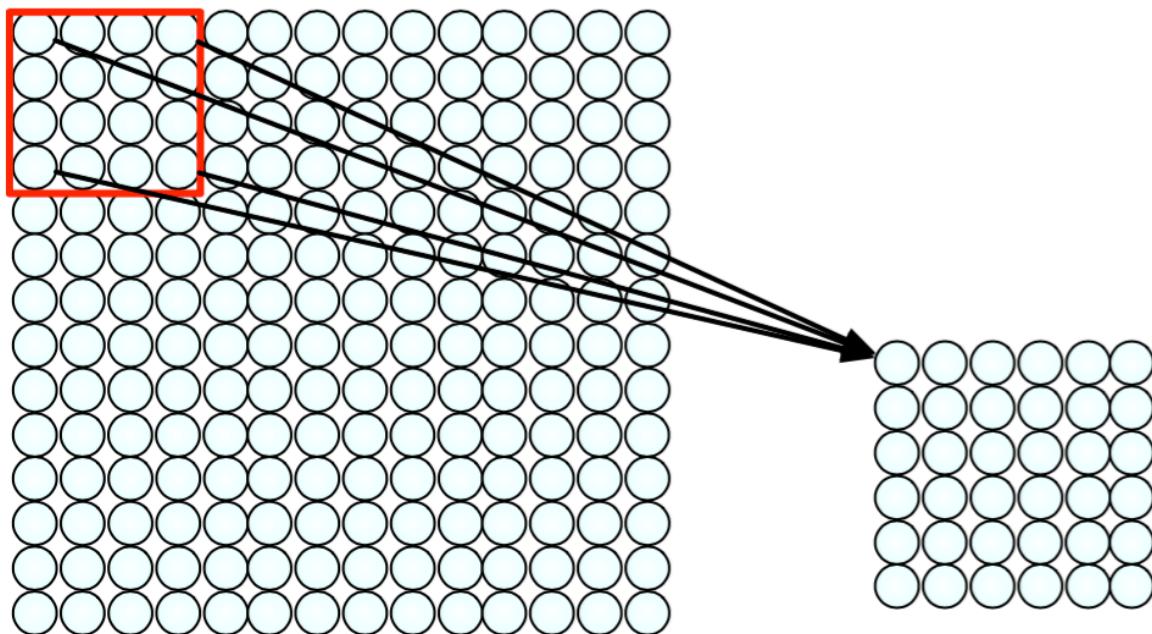
Convolutional Layers: Local Connectivity



For a neuron in hidden layer:

- Take inputs from patch the neuron “sees”
- Compute weighted sum
- Apply bias

Convolutional Layers: Local Connectivity



4x4 filter: matrix
of weights θ_{ij}

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

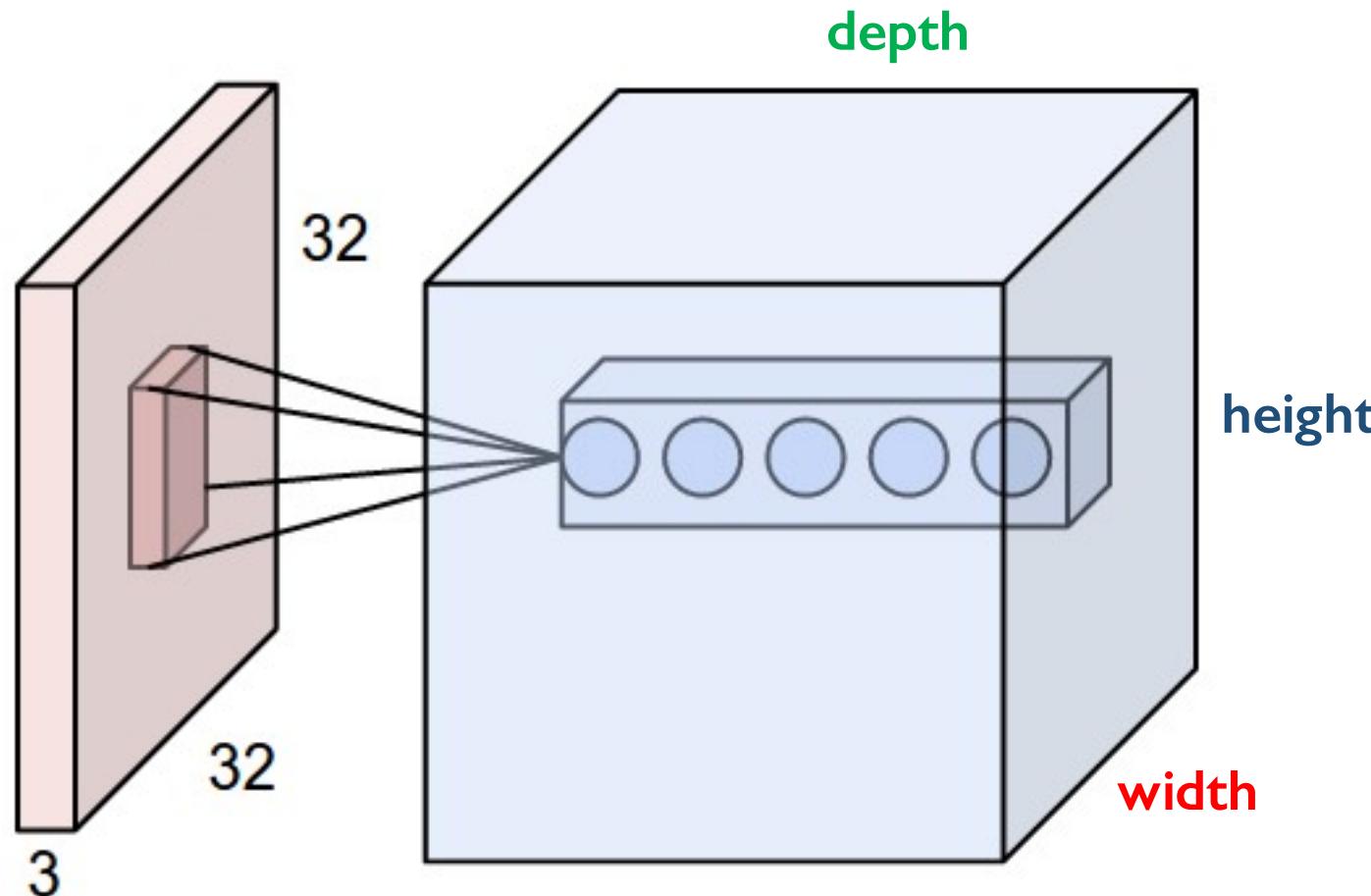
for neuron (p,q) in hidden layer

For a neuron in hidden layer:

- Take inputs from patch the neuron “sees”
- Compute weighted sum
- Apply bias

applying a window of weights
computing linear combinations
activating with non-linear function

CNNs: Spatial Arrangement of Output Volume



Layer Dimensions:

$$h \times w \times d$$

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

Stride:

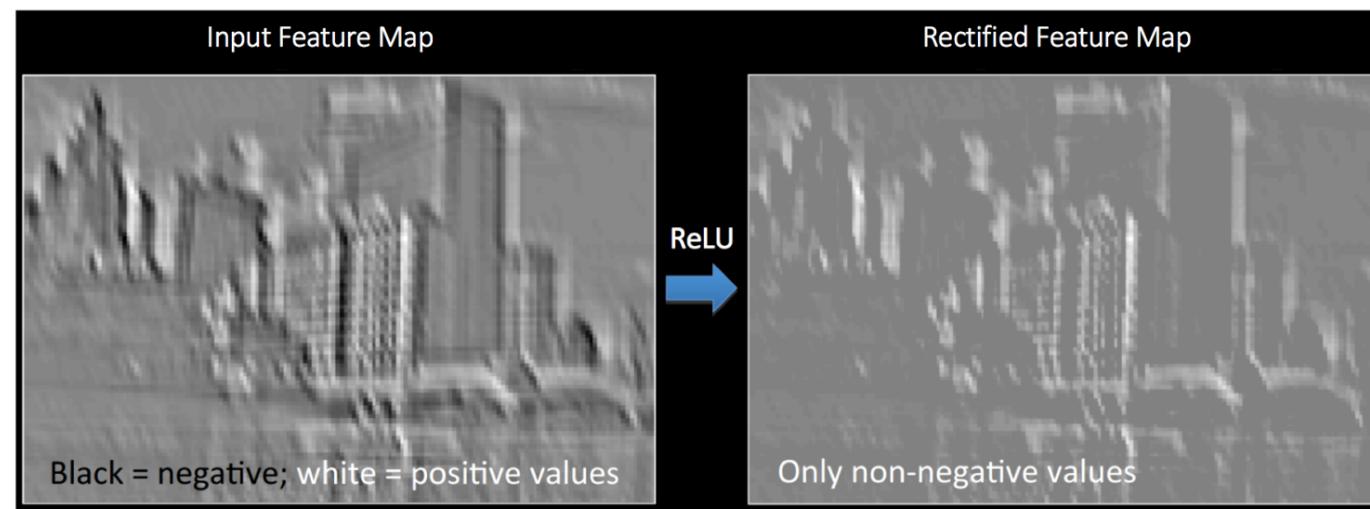
Filter step size

Receptive Field:

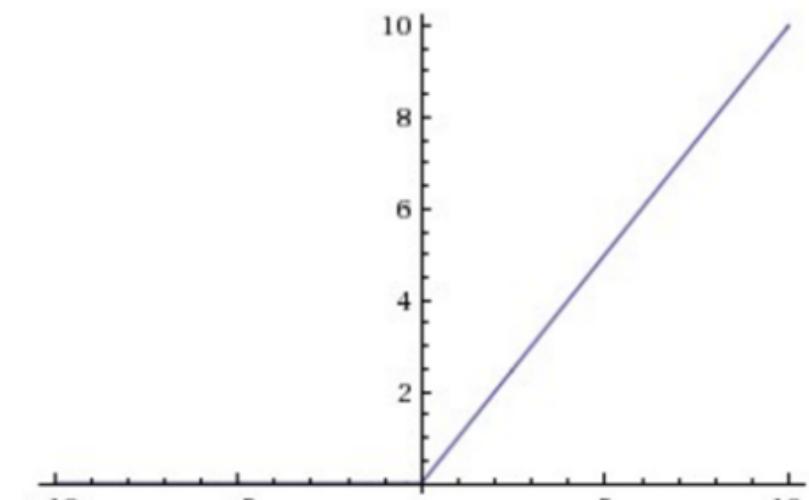
Locations in input image that
a node is path connected to

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**

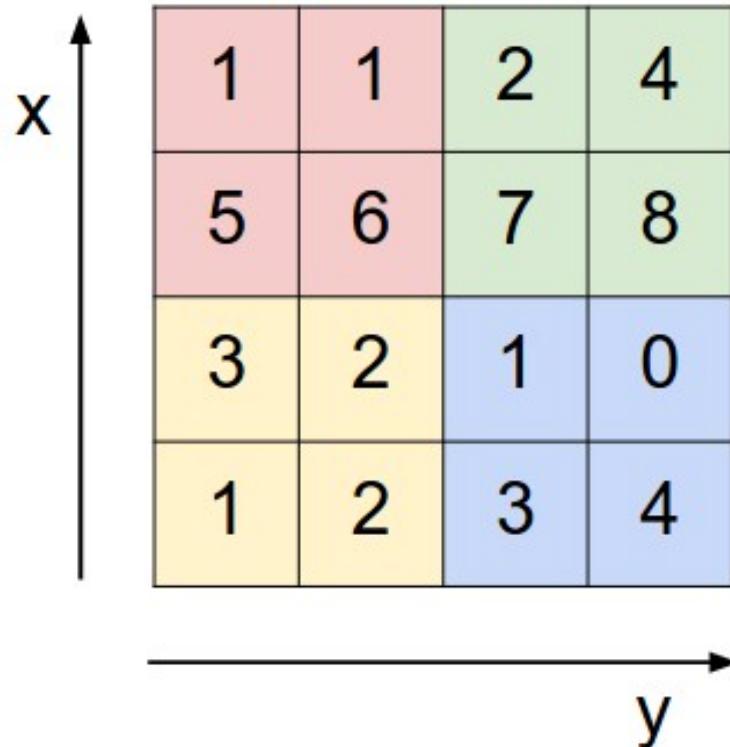


Rectified Linear Unit (ReLU)

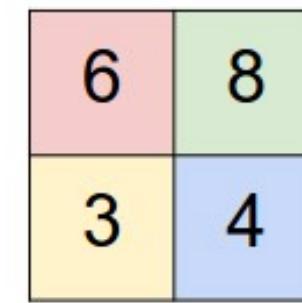


$$g(z) = \max(0, z)$$

Pooling



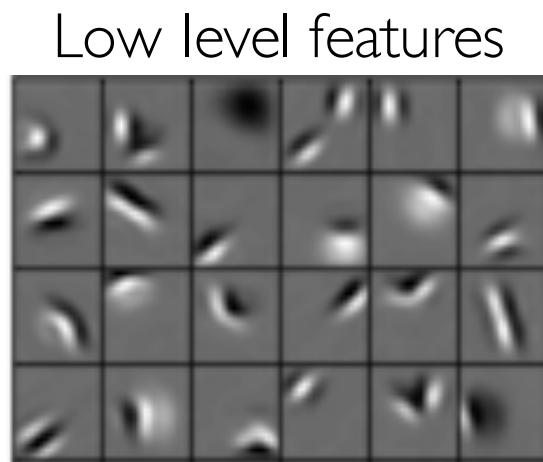
max pool with 2x2 filters
and stride 2



- 1) Reduced dimensionality
- 2) Spatial invariance

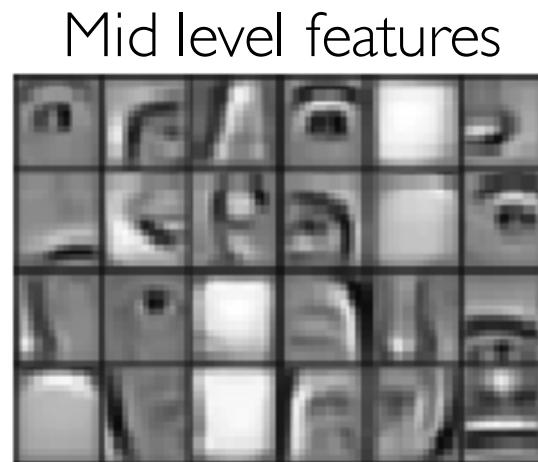
How else can we downsample and preserve spatial invariance?

Representation Learning in Deep CNNs



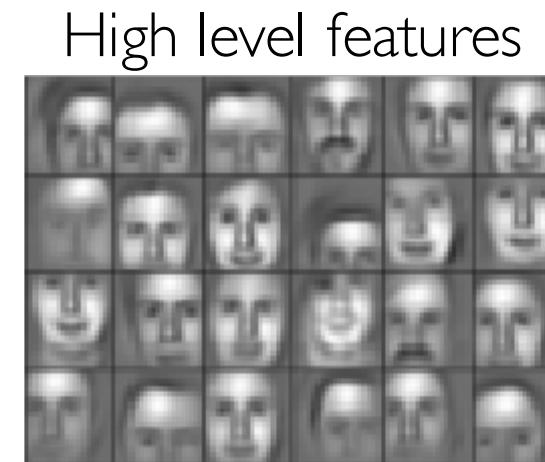
Edges, dark spots

Conv Layer 1



Eyes, ears, nose

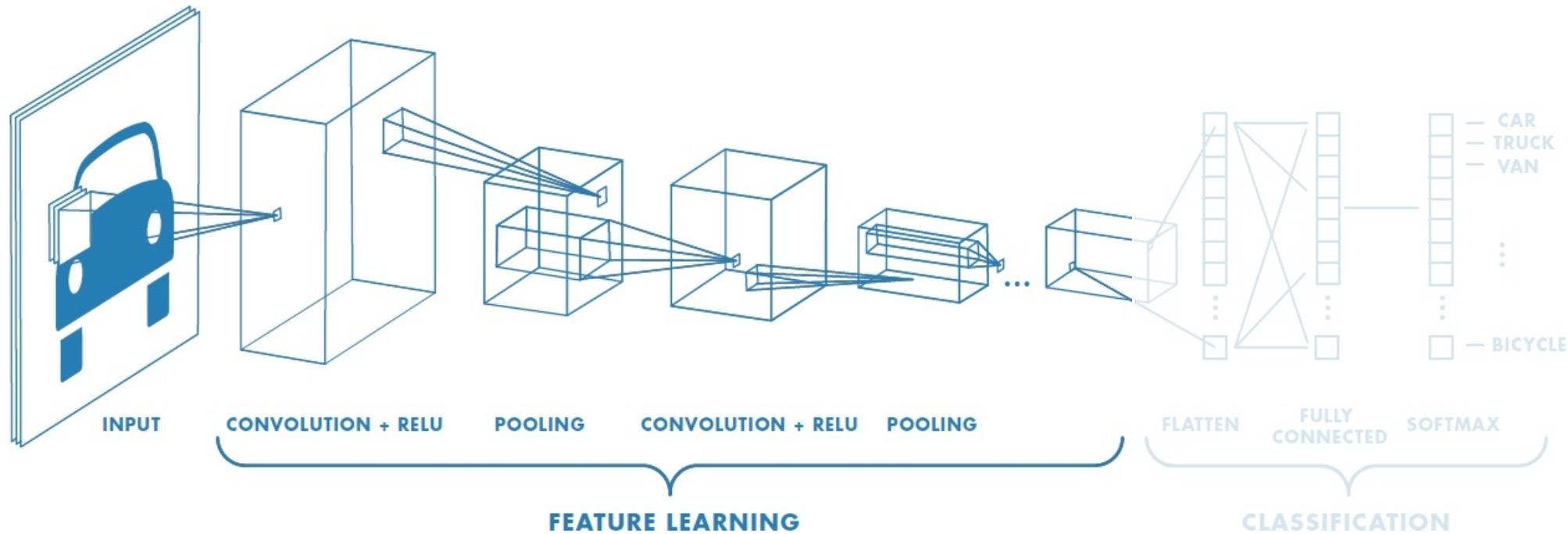
Conv Layer 2



Facial structure

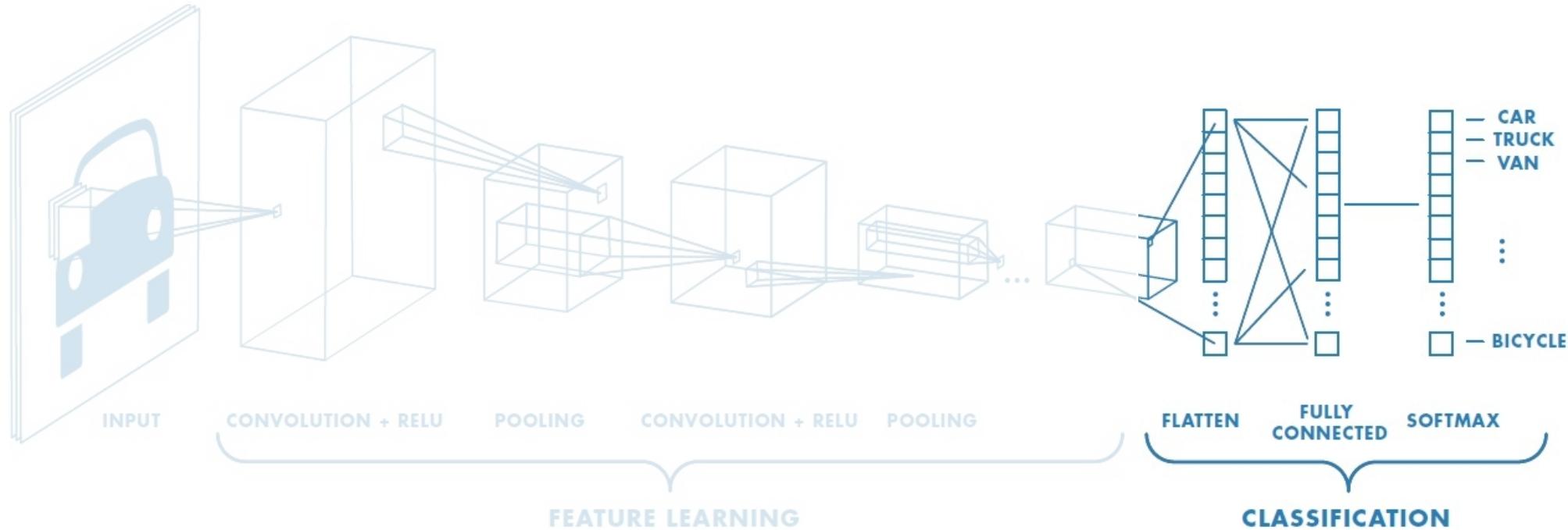
Conv Layer 3

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**

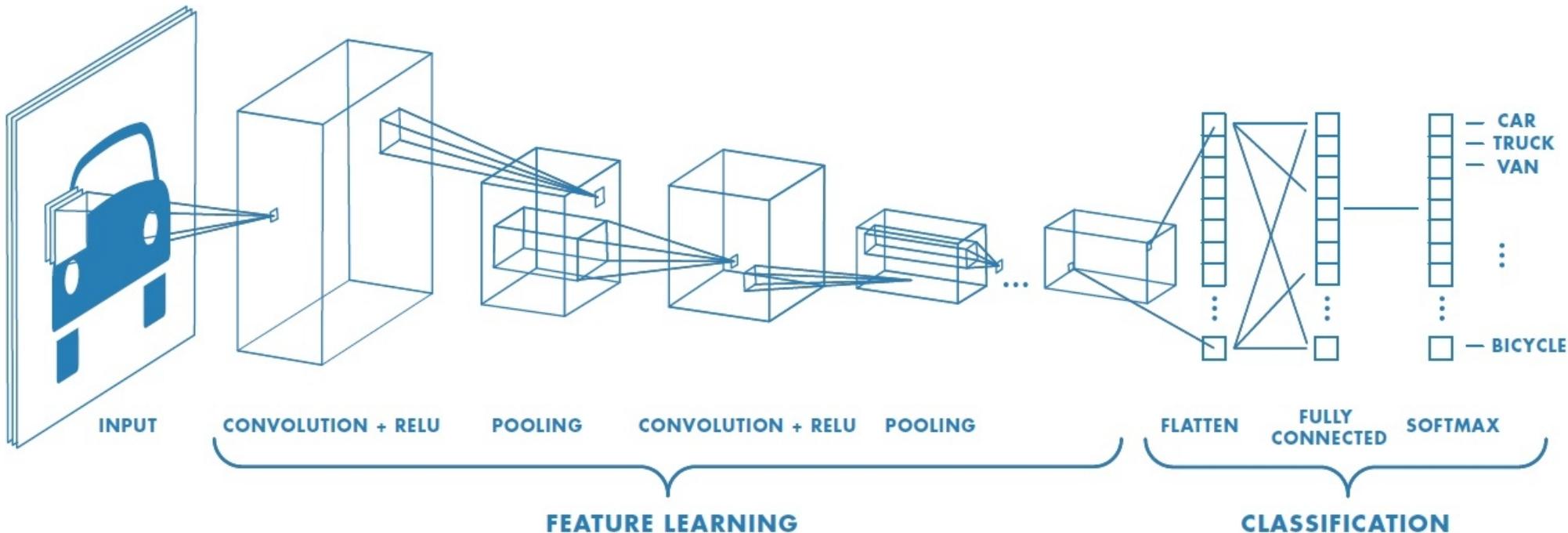
CNNs for Classification: Class Probabilities



- 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

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

CNNs: Training with Backpropagation



Learn weights for convolutional filters and fully connected layers

Backpropagation: cross-entropy loss

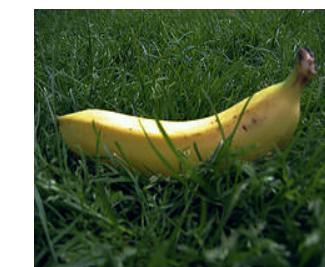
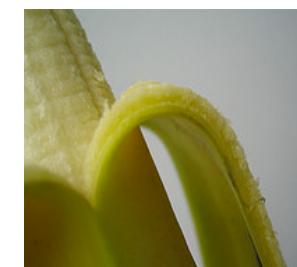
$$J(\theta) = \sum_i y^{(i)} \log(\hat{y}^{(i)})$$

CNNs for Classification: ImageNet

ImageNet Dataset

Dataset of over 14 million images across 21,841 categories

“Elongated crescent-shaped yellow fruit with soft sweet flesh”



| 409 pictures of bananas.

ImageNet Challenge



ImageNet Large Scale Visual Recognition Challenges

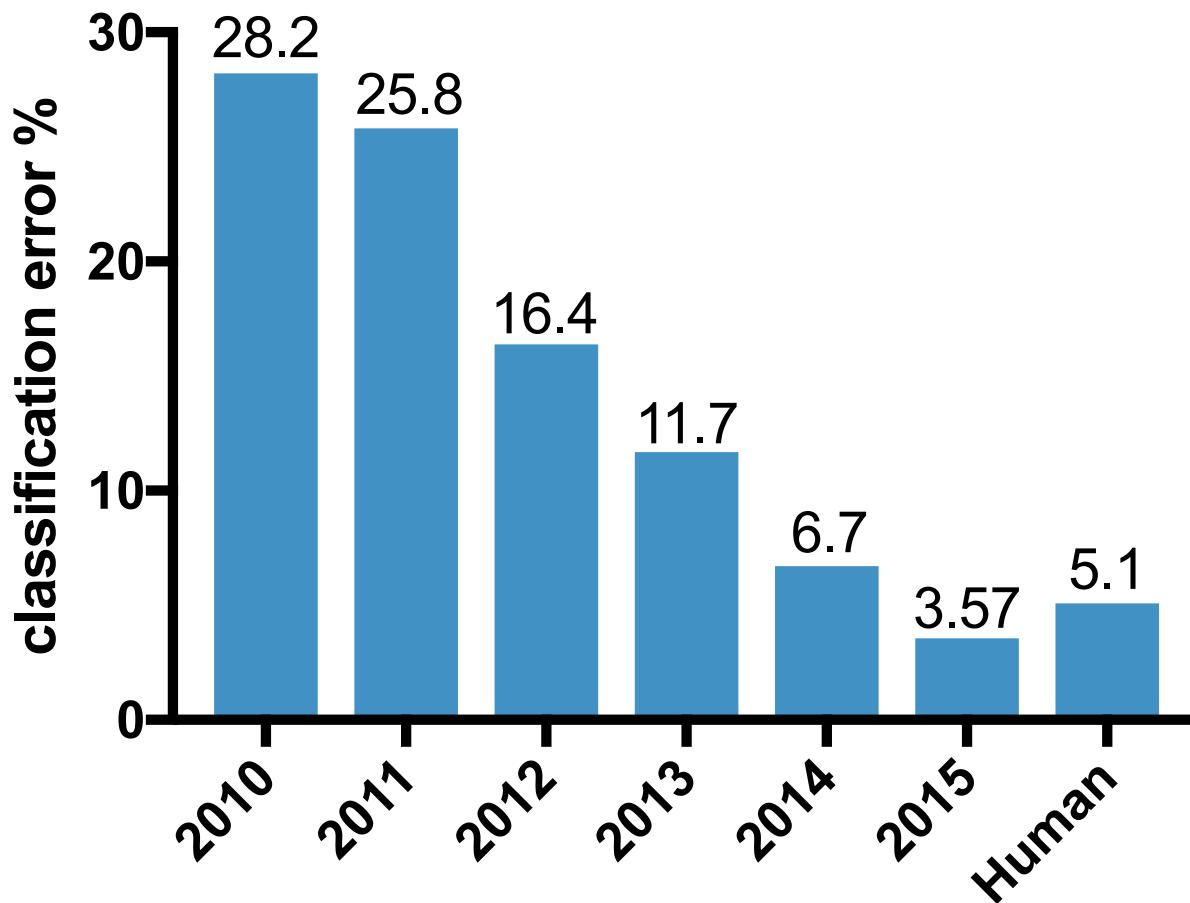


Classification task: produce a list of object categories present in image. 1000 categories.
“Top 5 error”: rate at which the model does not output correct label in top 5 predictions

Other tasks include:

single-object localization, object detection from video/image, scene classification, scene parsing

ImageNet Challenge: Classification Task



2012: AlexNet. First CNN to win.

- 8 layers, 61 million parameters

2013: ZFNet

- 8 layers, more filters

2014: VGG

- 19 layers

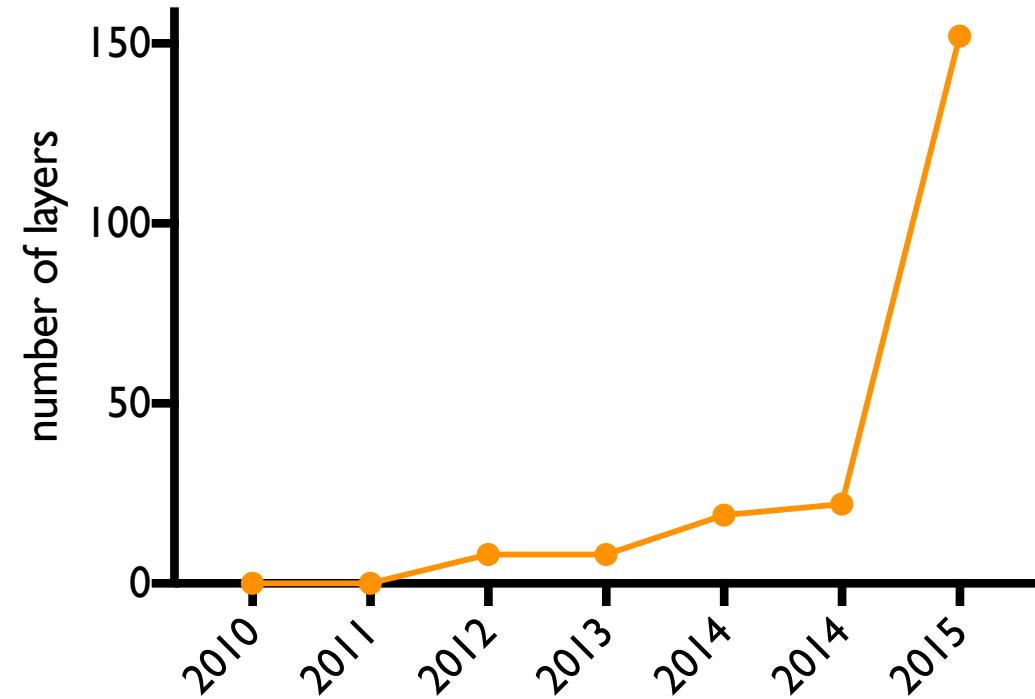
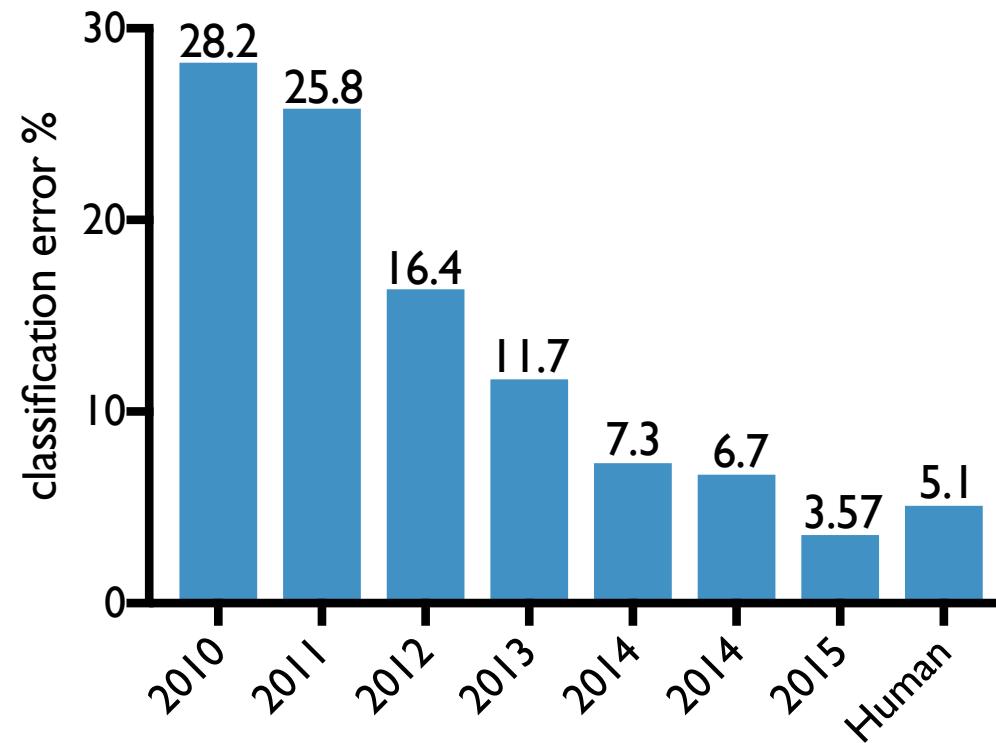
2014: GoogLeNet

- "Inception" modules
- 22 layers, 5 million parameters

2015: ResNet

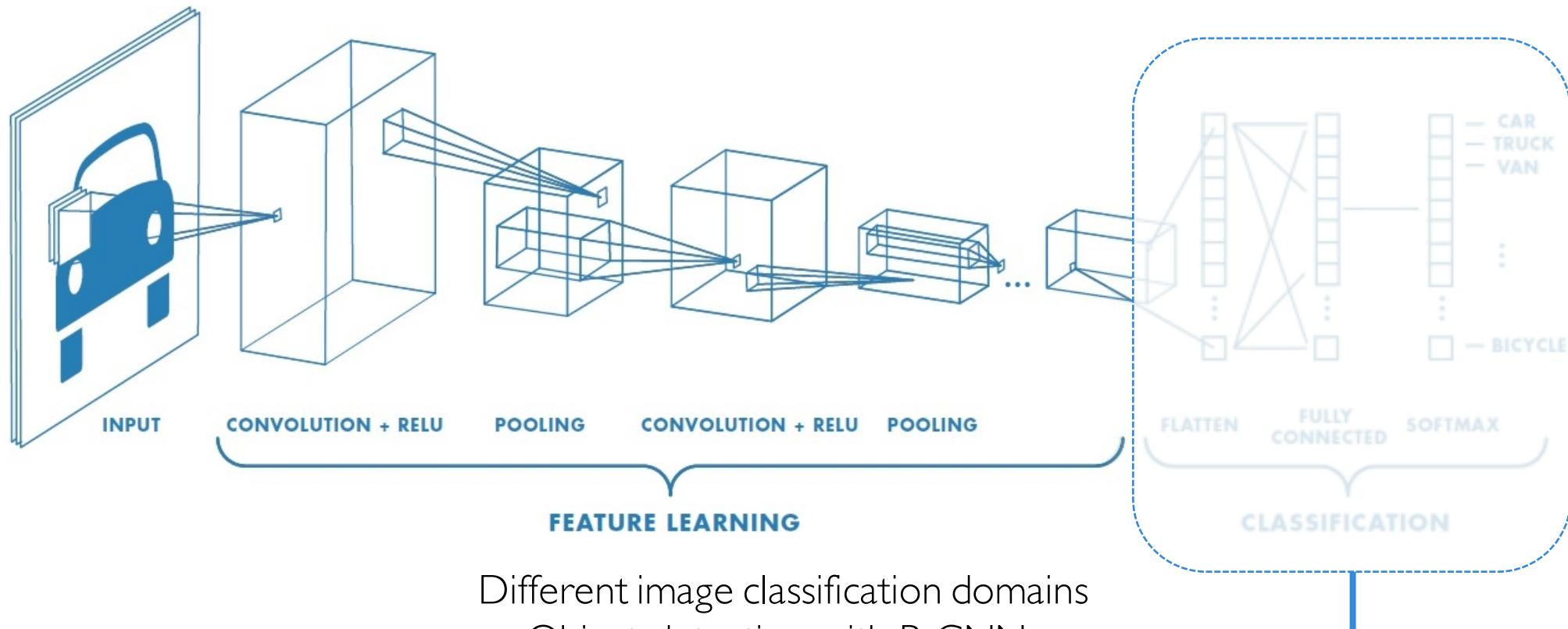
- 152 layers

ImageNet Challenge: Classification Task



An Architecture for Many Applications

An Architecture for Many Applications



Different image classification domains

Object detection with R-CNNs

Segmentation with fully convolutional networks

Image captioning with RNNs

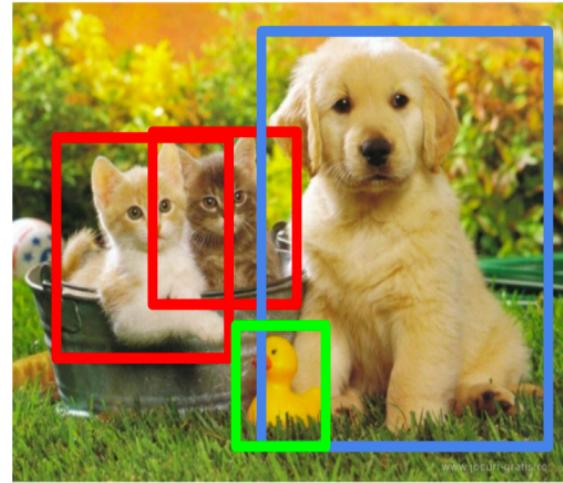
Beyond Classification

Semantic Segmentation



CAT

Object Detection



CAT, DOG, DUCK

Image Captioning



The cat is in the grass.

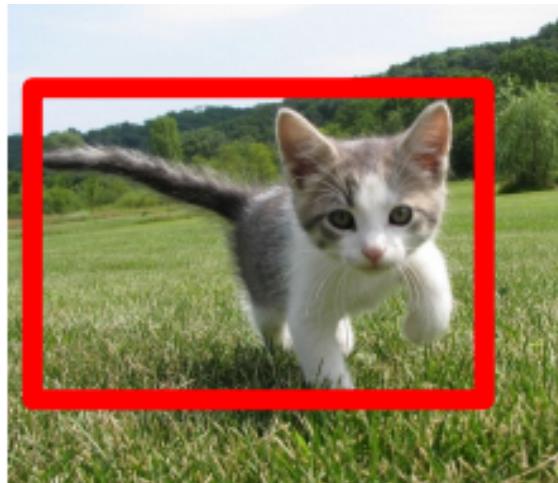
Beyond Classification

Semantic Segmentation



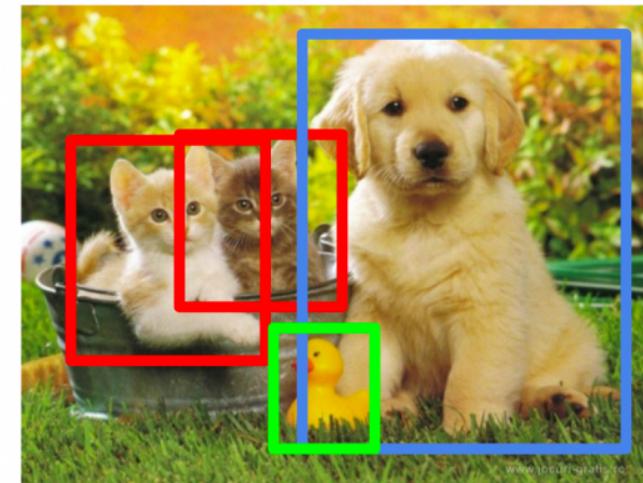
CAT

Classification + Localization



CAT

Object Detection



CAT, DOG, DUCK

Instance Segmentation



CAT, DOG, DUCK

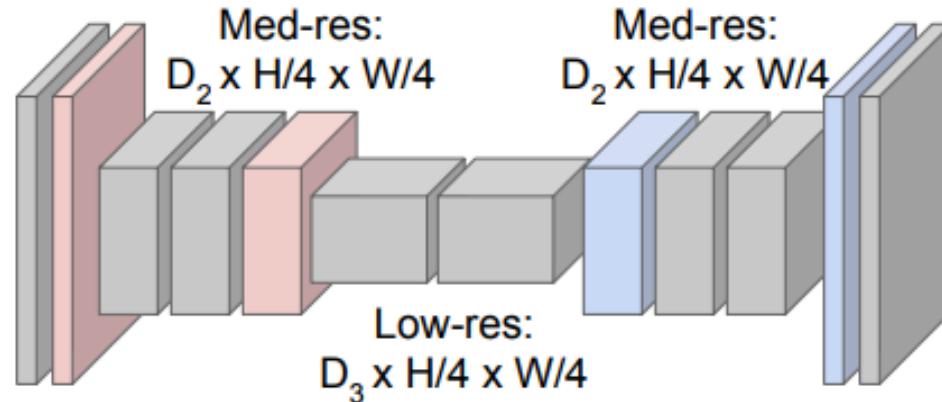
Semantic Segmentation: FCNs

FCN: Fully Convolutional Network

Network designed with all convolutional layers,
with **downsampling** and **upsampling** operations



Input:
 $3 \times H \times W$



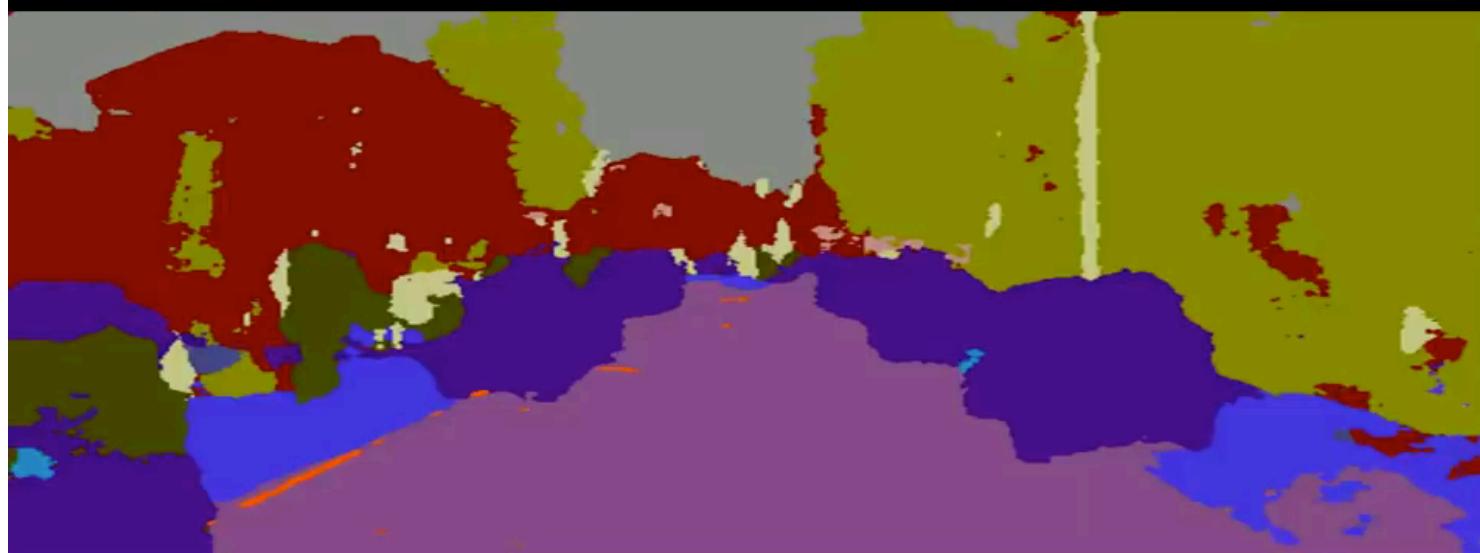
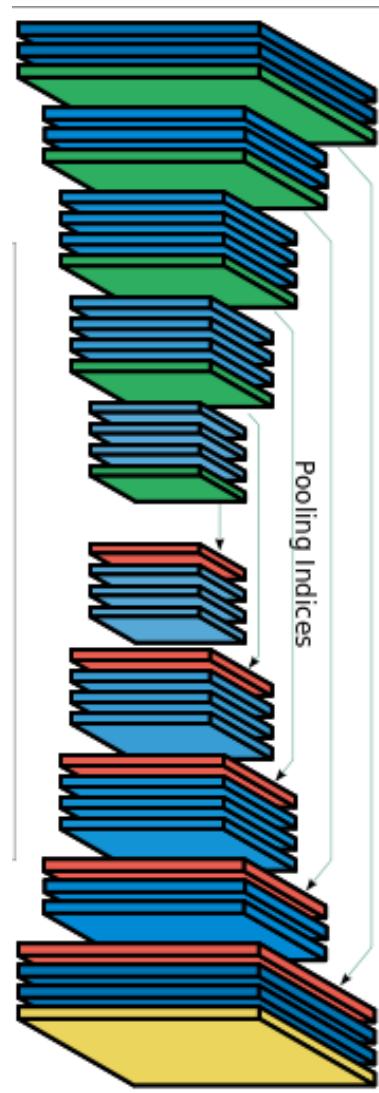
High-res:
 $D_1 \times H/2 \times W/2$

High-res:
 $D_1 \times H/2 \times W/2$



Predictions:
 $H \times W$

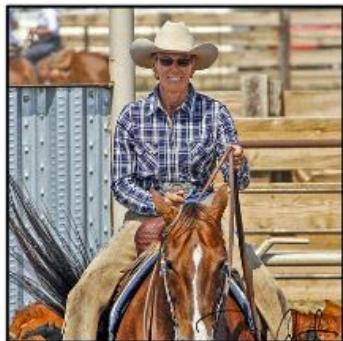
Driving Scene Segmentation



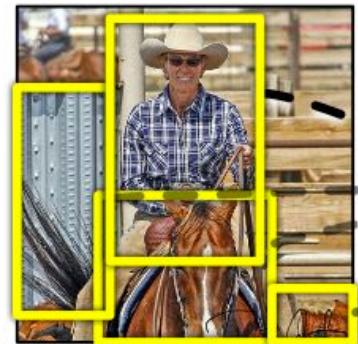
Light Gray	Sky
Red	Building
Yellow-Green	Pole
Orange	Road Marking
Purple	Road
Blue	Pavement
Green	Tree
Pink	Sign Symbol
Dark Purple	Fence
Dark Blue	Vehicle
Brown	Pedestrian
Cyan	Bike

Object Detection with R-CNNs

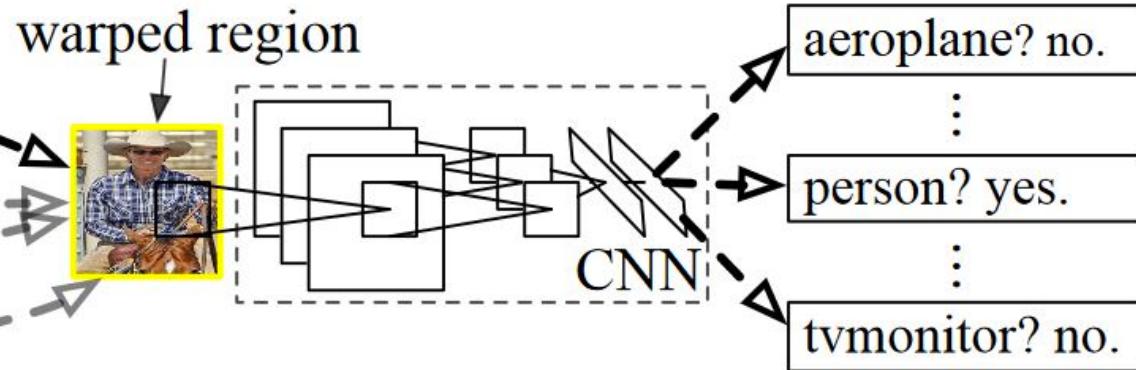
R-CNN: Find regions that we think have objects. Use CNN to classify.



1. Input image



2. Extract region proposals (~2k)



3. Compute CNN features

4. Classify regions

Image Captioning using RNNs

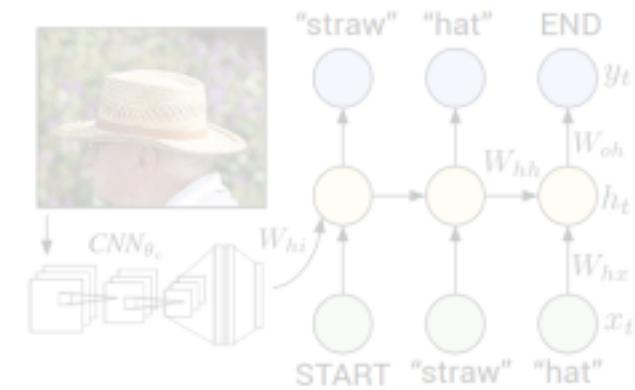
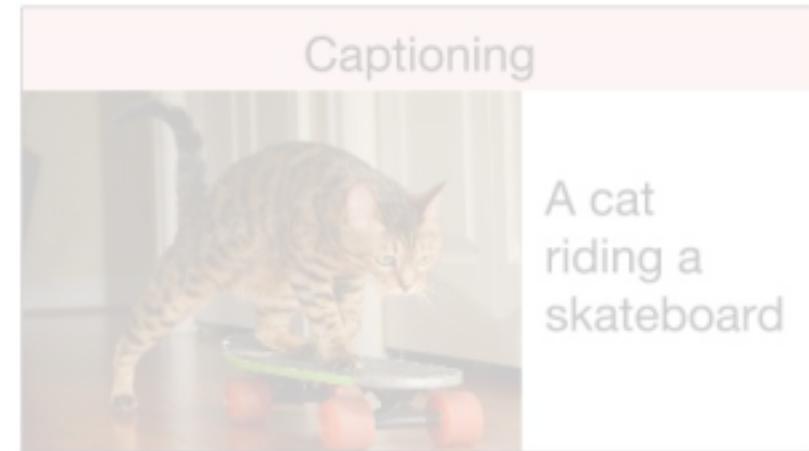
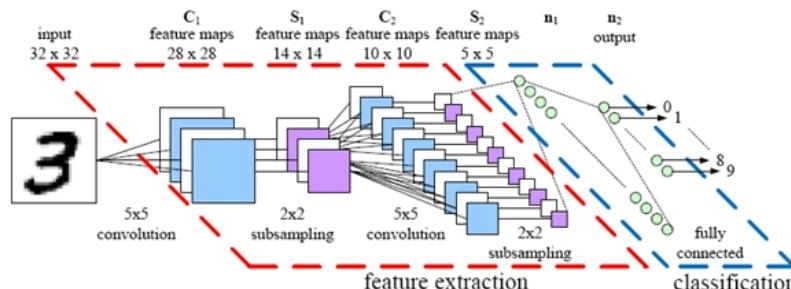
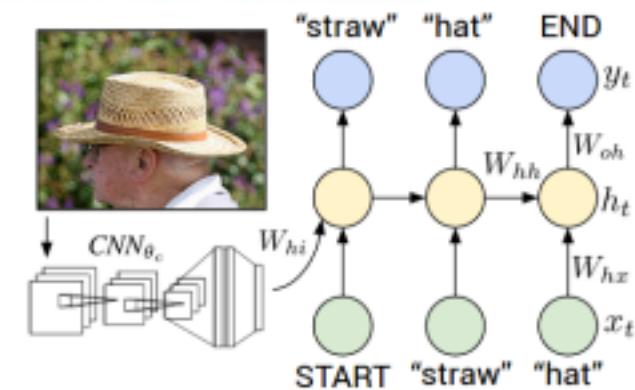
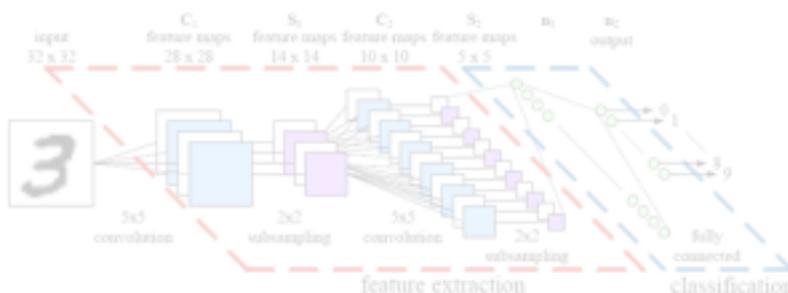
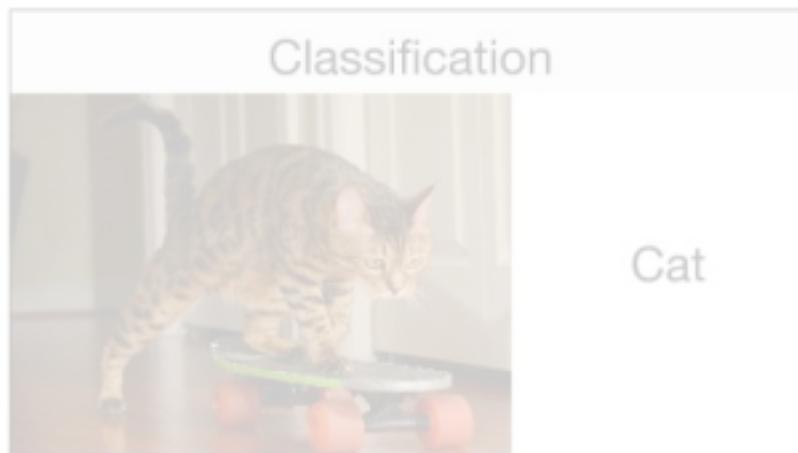


Image Captioning using RNNs



Visualizing Convolutional Neural Networks

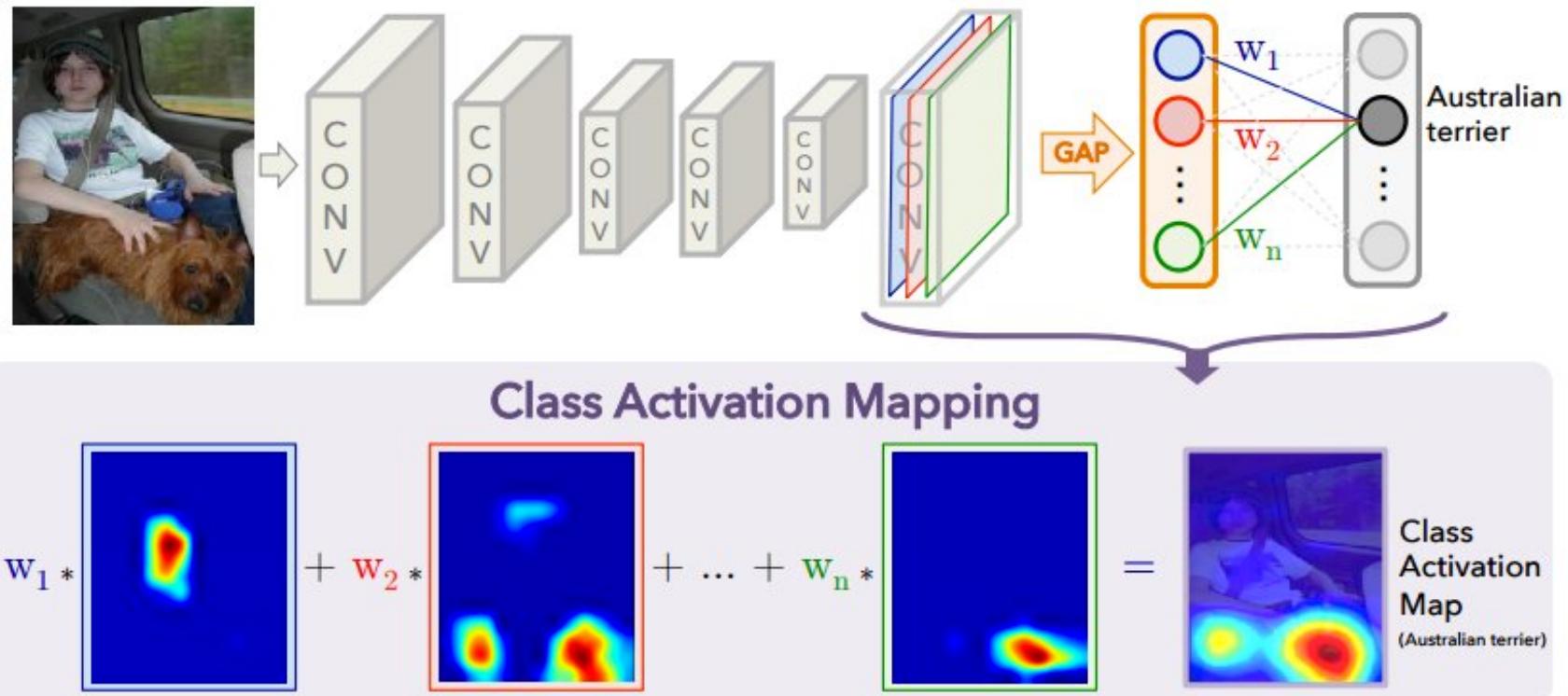
Peering Inside CNNs



Class Activation Maps (CAMs)



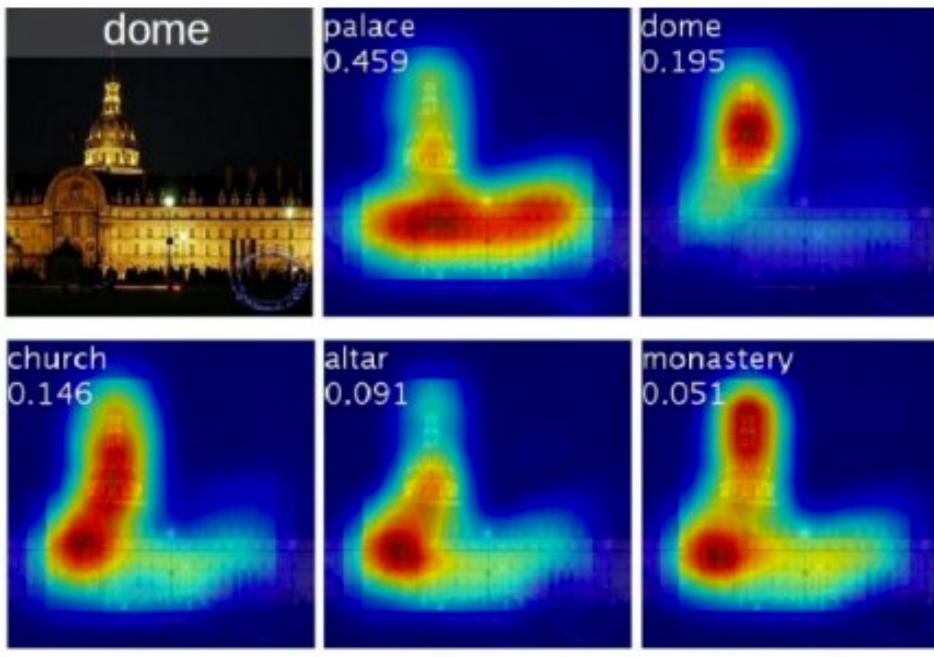
A **class activation map (CAM)** for a given class highlights the image regions used by the CNN to identify that class



Class Activation Maps (CAMs)



A **class activation map (CAM)** for a given class highlights the image regions used by the CNN to identify that class



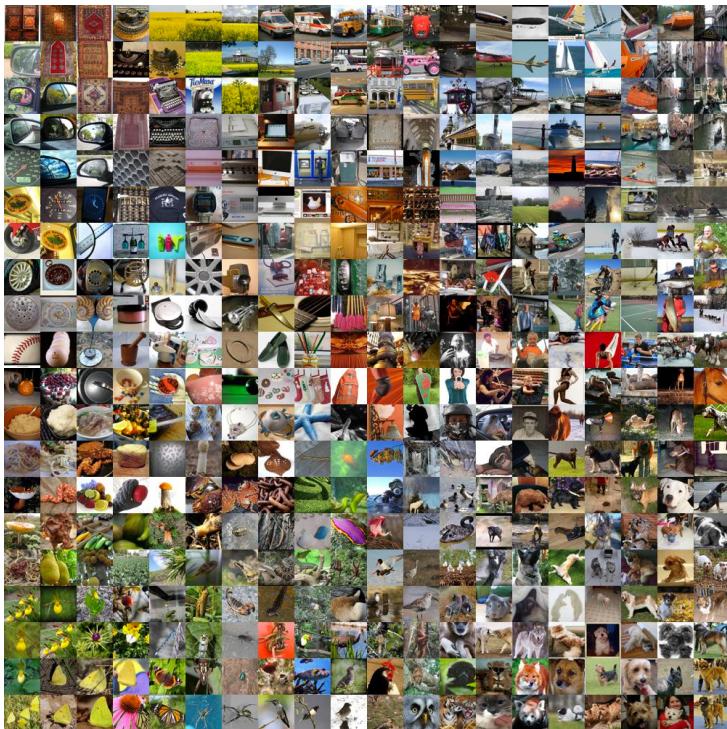
Class activation maps of top 5 predictions



Class activation maps for one object class

Deep Learning for Computer Vision: Impact and Summary

Data, Data, Data



ImageNet:
22K categories. 14M images.



MNIST: handwritten digits



places: natural scenes

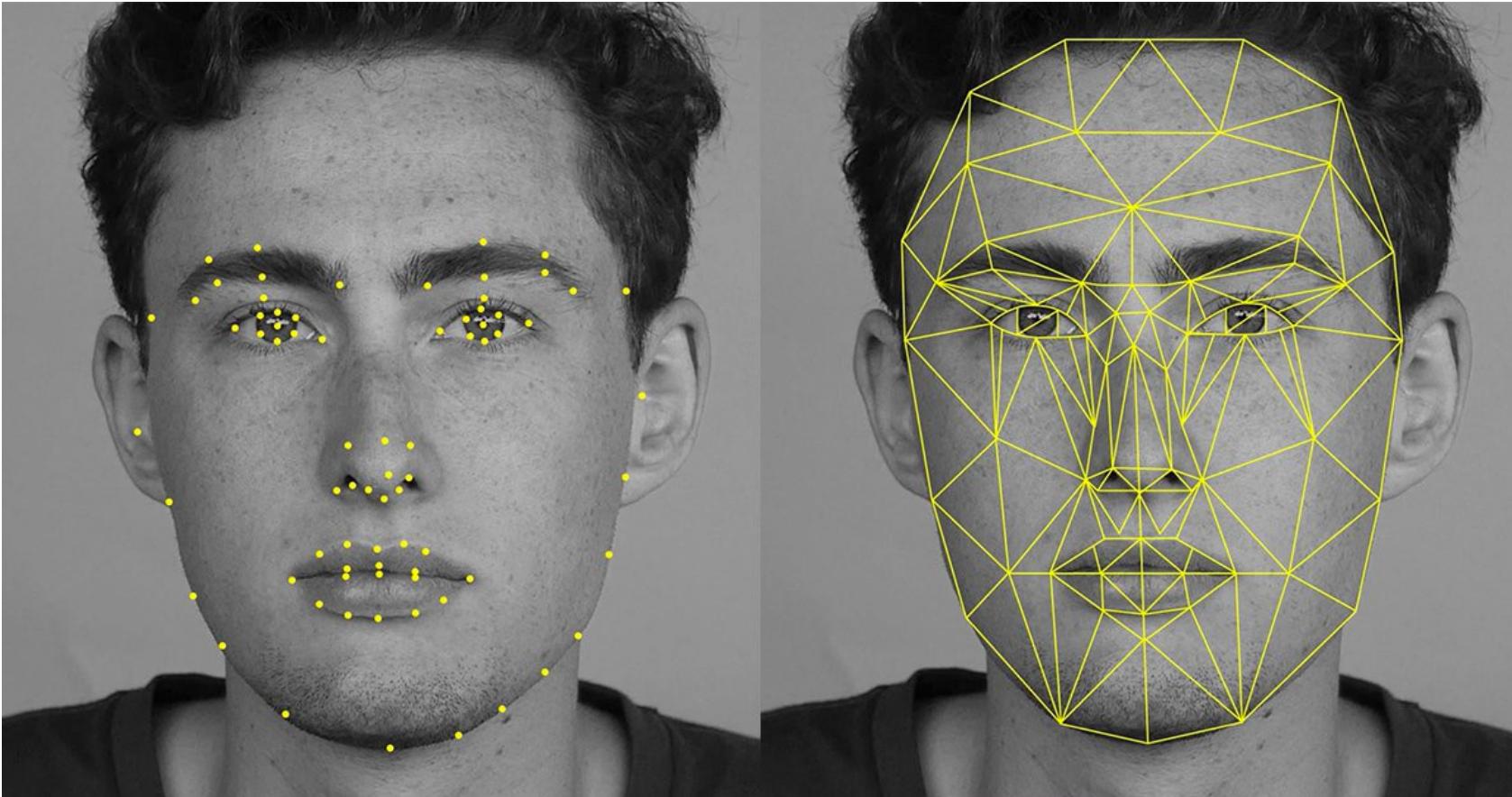
- Airplane**
- Automobile**
- Bird**
- Cat**
- Deer**
- Dog**
- Frog**
- Horse**
- Ship**
- Truck**

CIFAR-10

Deep Learning for Computer Vision: Impact



Impact: Face Recognition



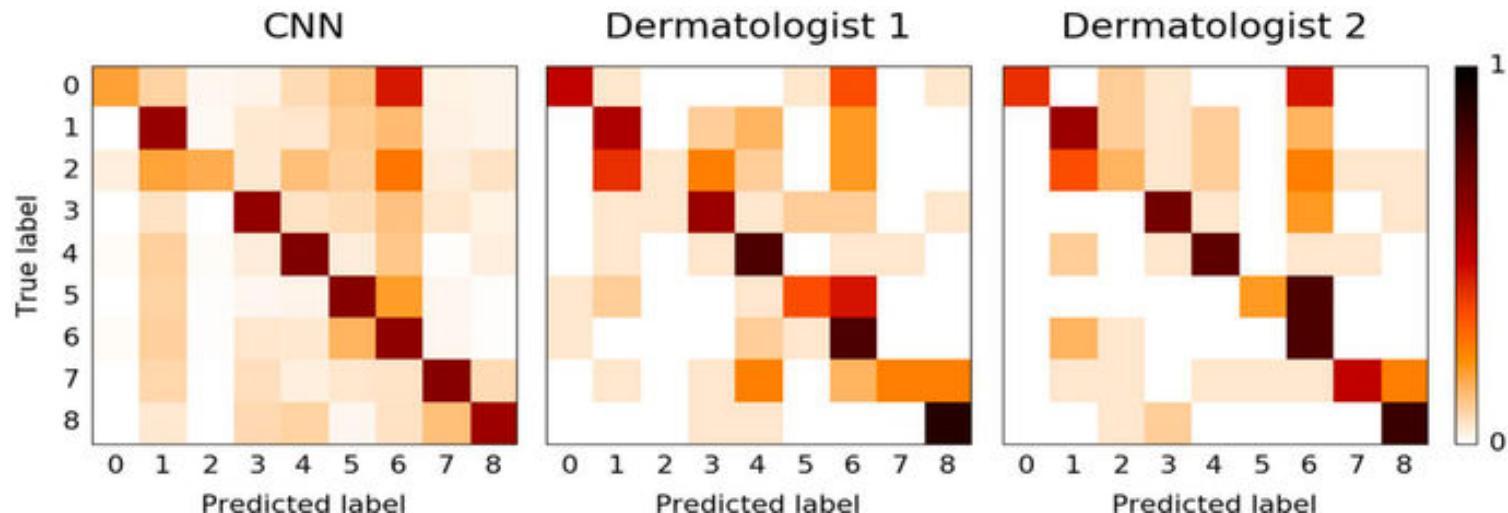
Impact: Self-Driving Cars



Impact: Medicine



Dermatologist-level classification of skin cancer with deep neural networks



Deep Learning for Computer Vision: Review

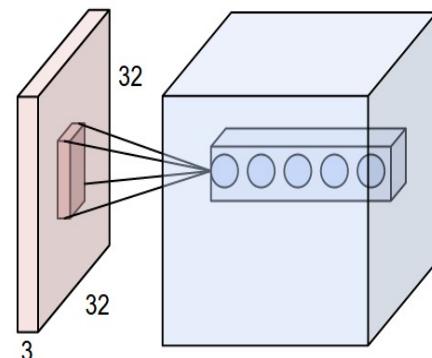
Foundations

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



CNNs

- CNN architecture
- Application to classification: ImageNet



Applications

- Segmentation, object detection, image captioning
- Visualization



Deep Generative Models

Prof. Aaron Courville