Deep learning

episode 2

Computer vision applications

Yandex Data Factory

LAMBDA

British Hedgehog Preservation Society

Image recognition

→ “Dog”

Image recognition

"Gray wall"

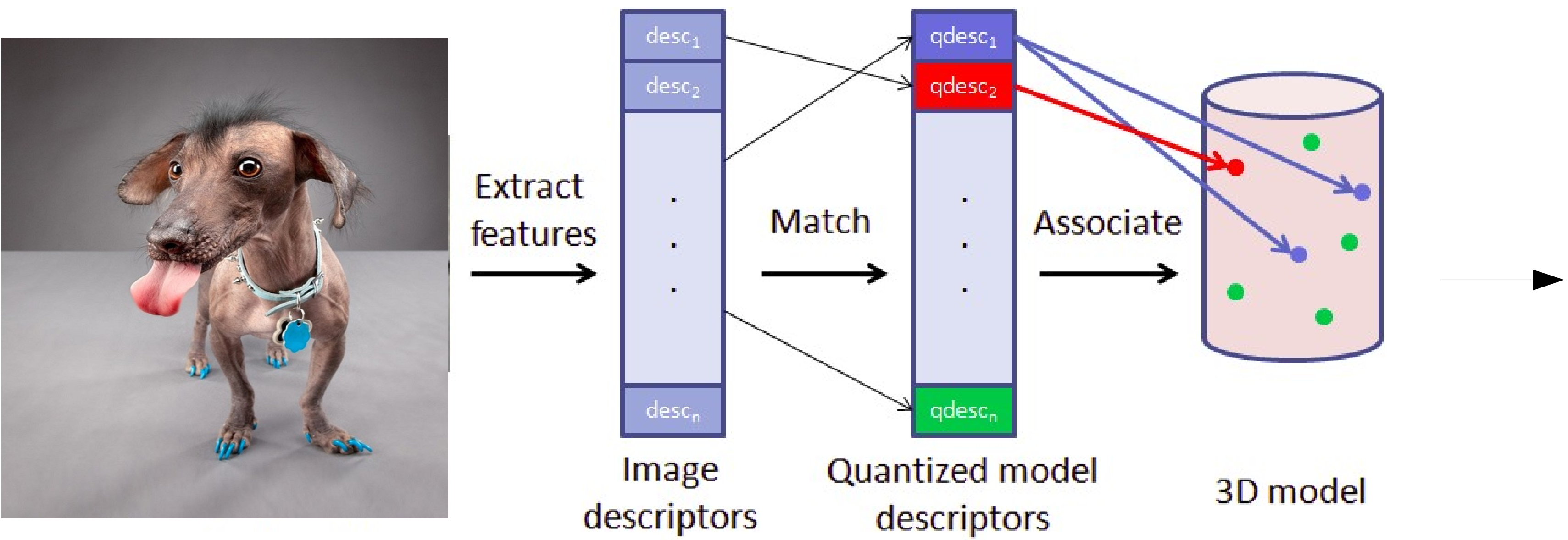
"Dog tongue"

"Dog"

<a particular kind of dog>

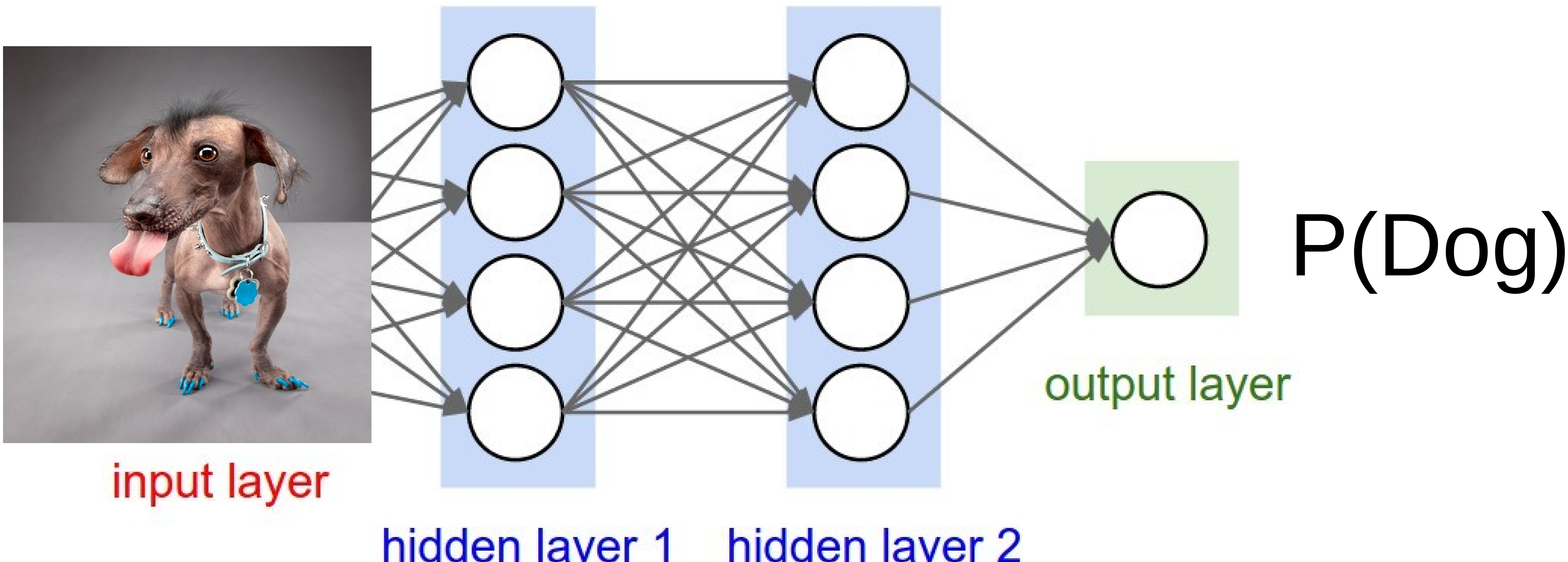
"Animal sadism"

Classical approach



“Dog”

NN approach



What features could NN learn this way?

Problem

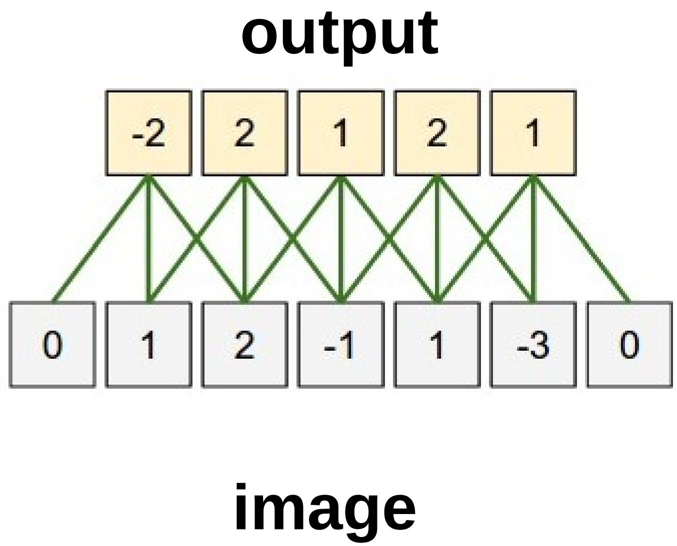
Should we require, say, “Dog ear” feature

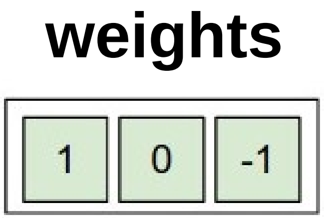
- Linear combination can only select dog ear at a one (or a few) positions.
- Need to learn independent features for each position
- Next layer needs to react on “dog ear 0,0 or dog ear 0,1 or … or dog ear 255,255”
- Introduce **a lot** of parameters and risk overfitting.

Idea: force all these “dog ear” features to use **exactly same weights**, shifting weight matrix each time.

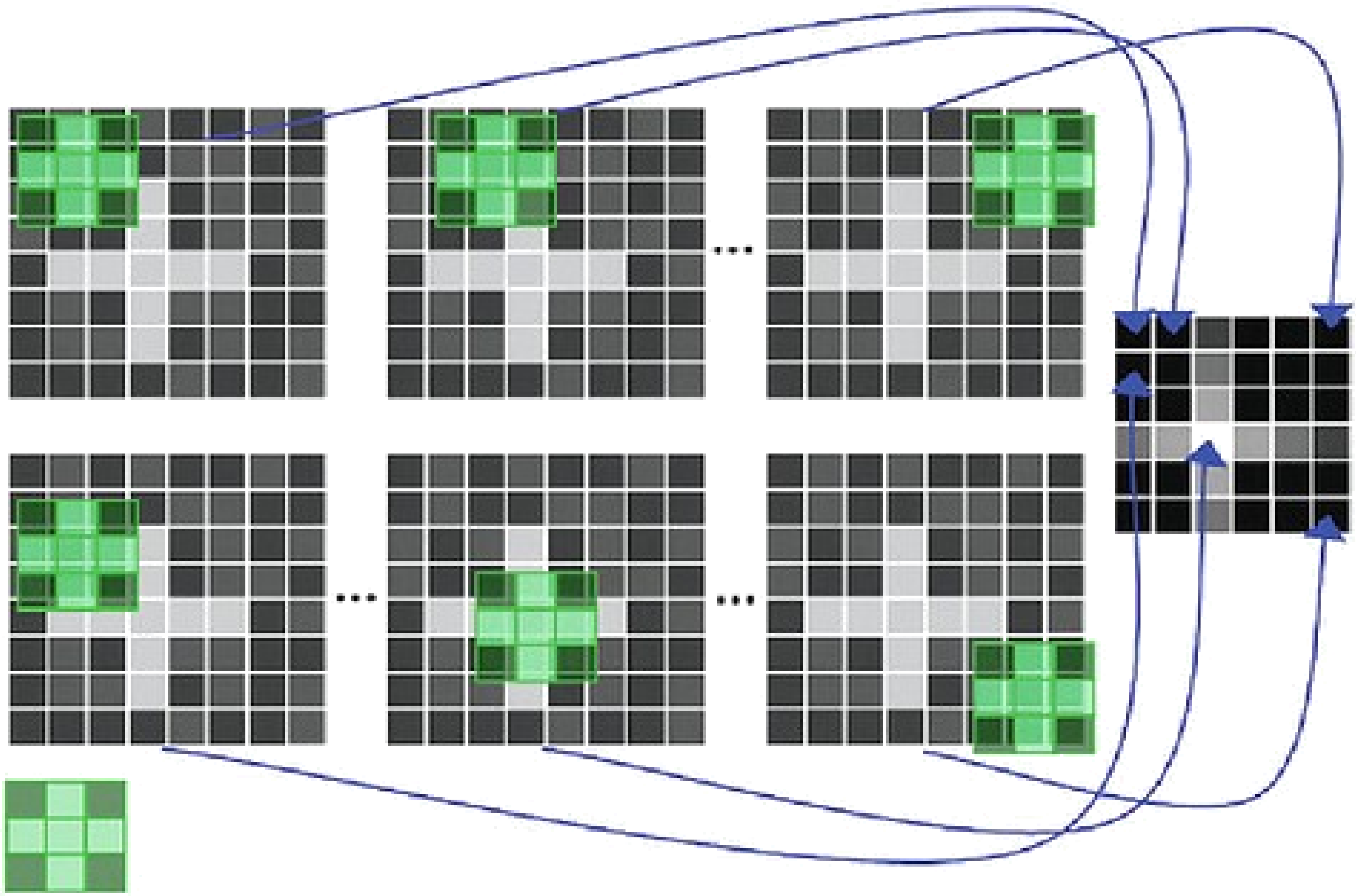
Convolution

- Apply same weights to all patches





Convolution

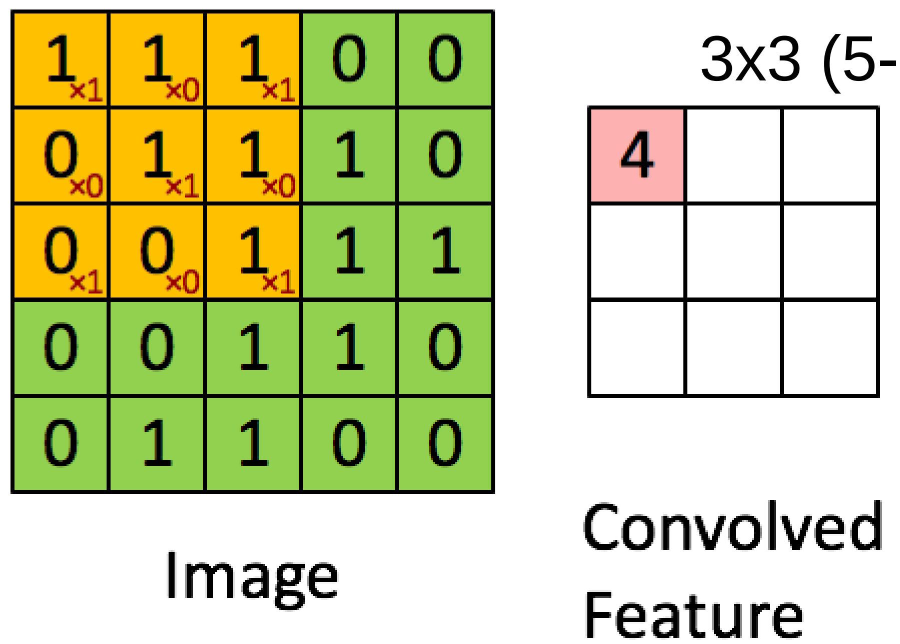


apply same filter to all patches

Convolution

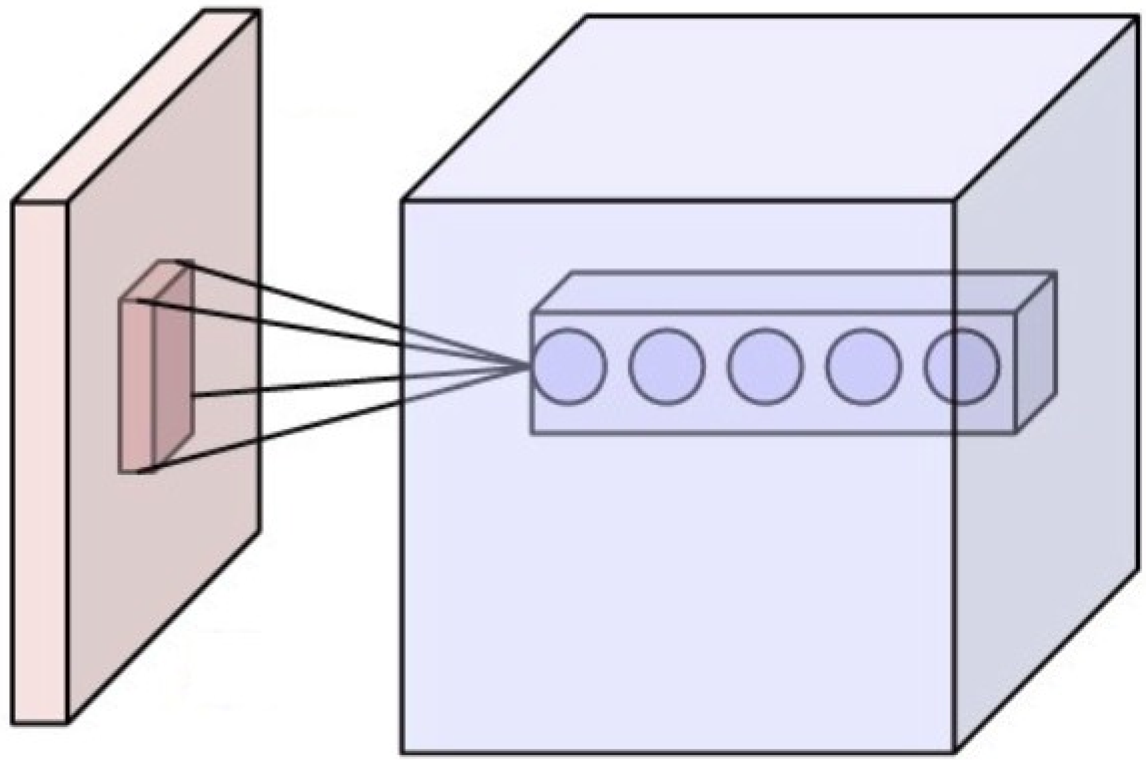
5x5

3x3 (5-3+1)



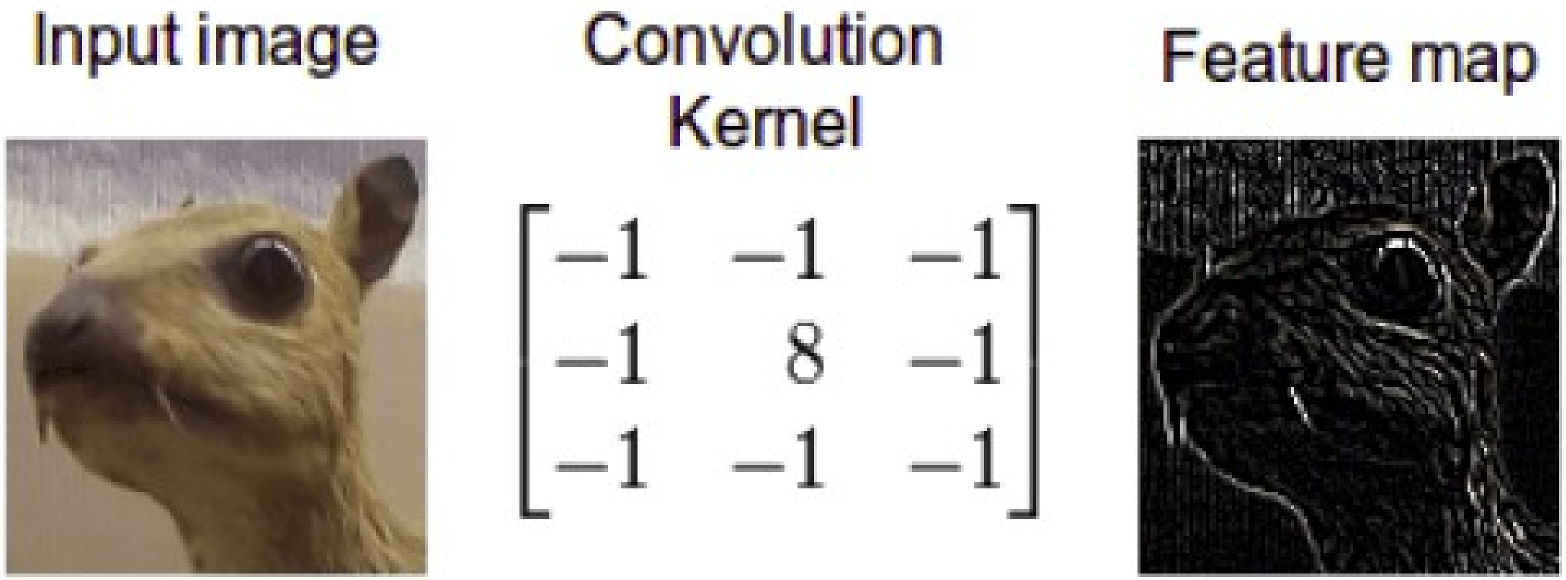
Intuition: how cat-like is this square?

Convolution



Intuition: how cat-like is this square?

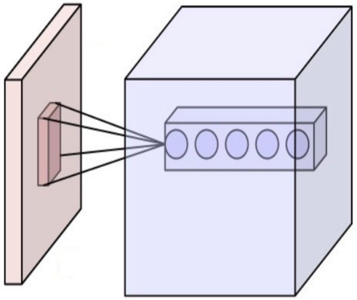
Convolution



$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Intuition: how **edge-like** is this square?

Convolution

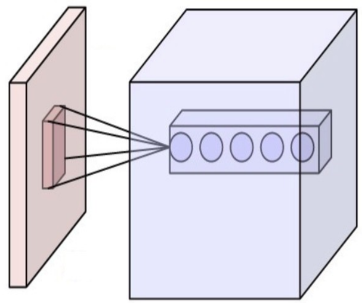


?!

Filters: 100x(3x5x5)

Image : 3 (RGB) x 100 px x 100 px

Convolution



100x96x96

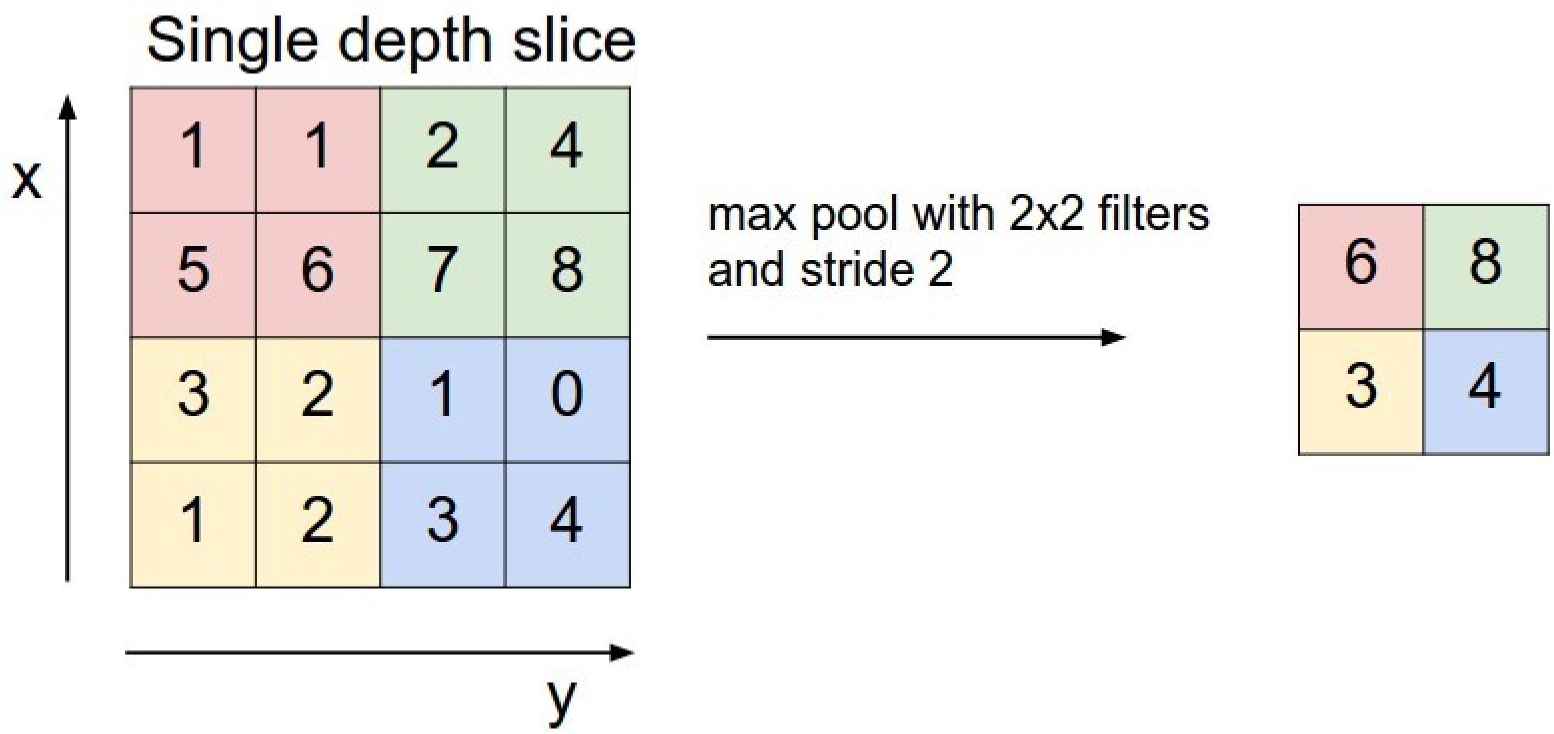
~10^6

Filters: 100x(3x5x5)

Image : 3 (RGB) x 100 px x 100 px

Somewhat too many!

Pooling



Intuition: What is the max cat-likelihood over this area?

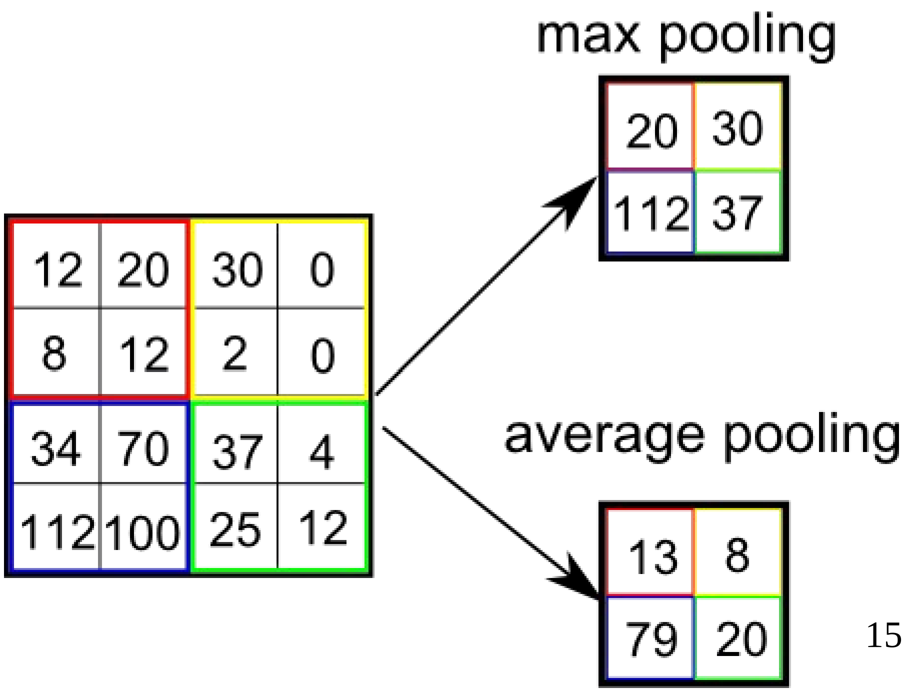
Pooling

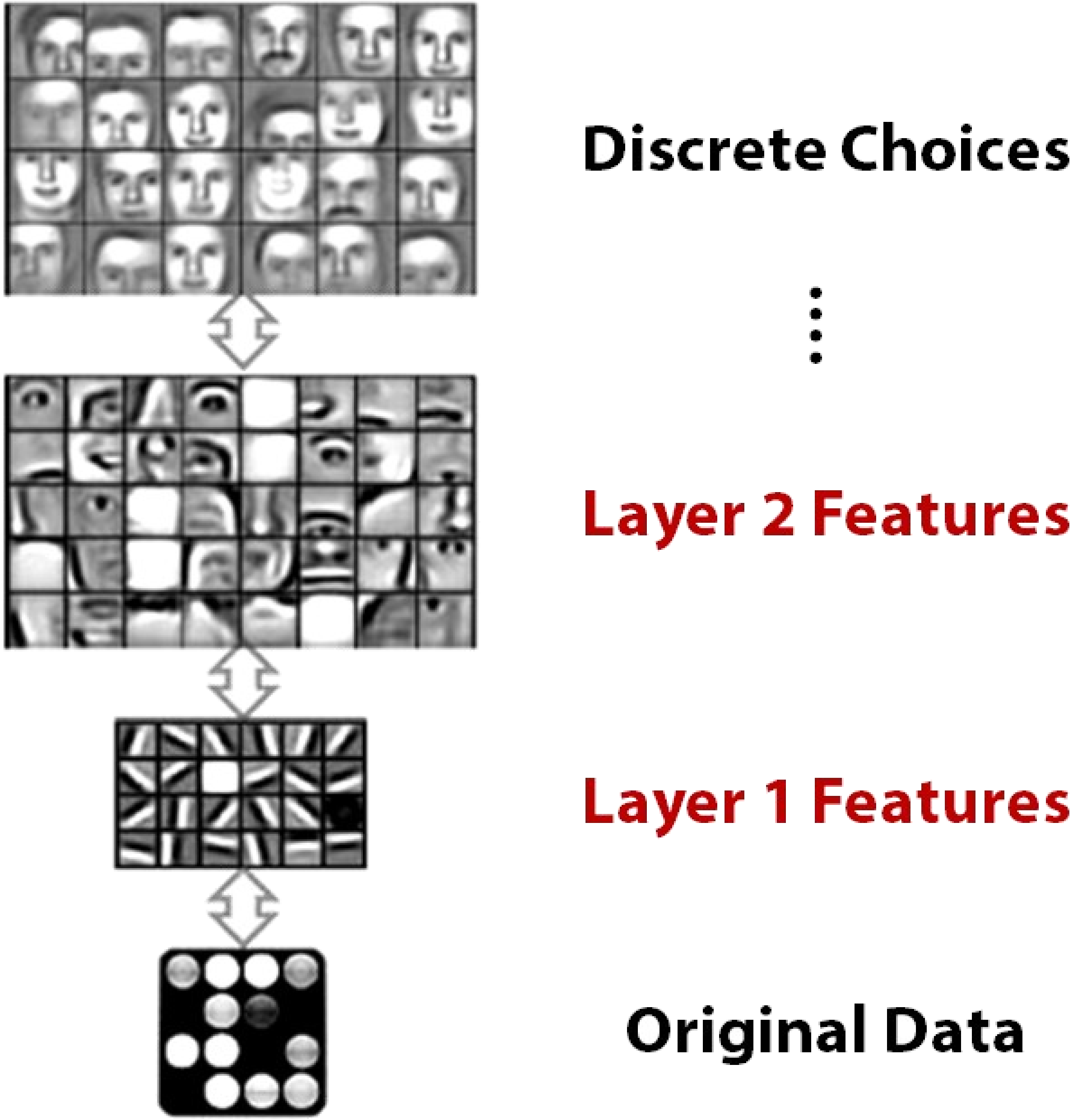
Motivation:

- Reduce layer size by a factor
- Make NN less sensitive to small image shifts

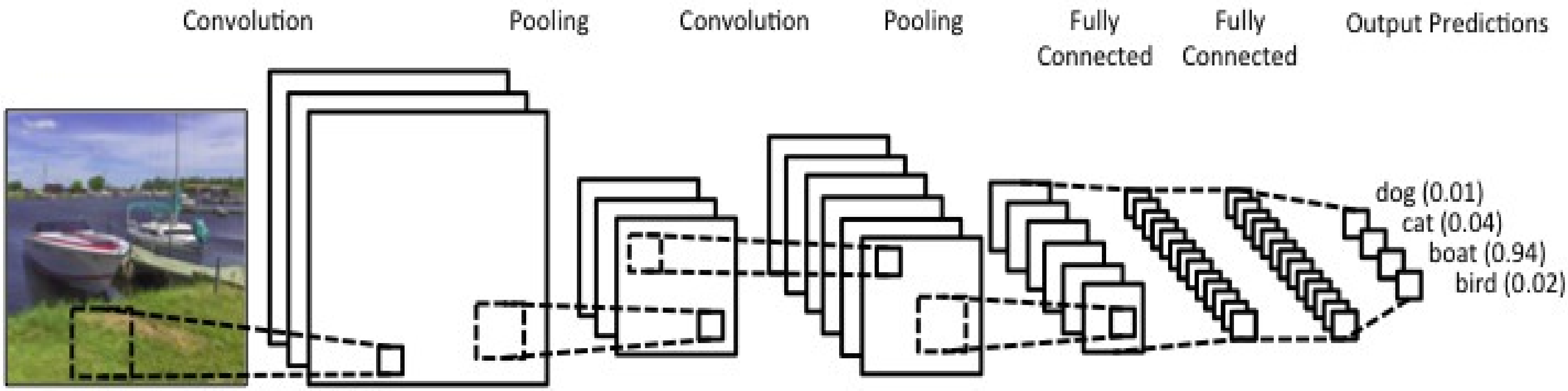
Popular types:

- Max
- Mean(average)

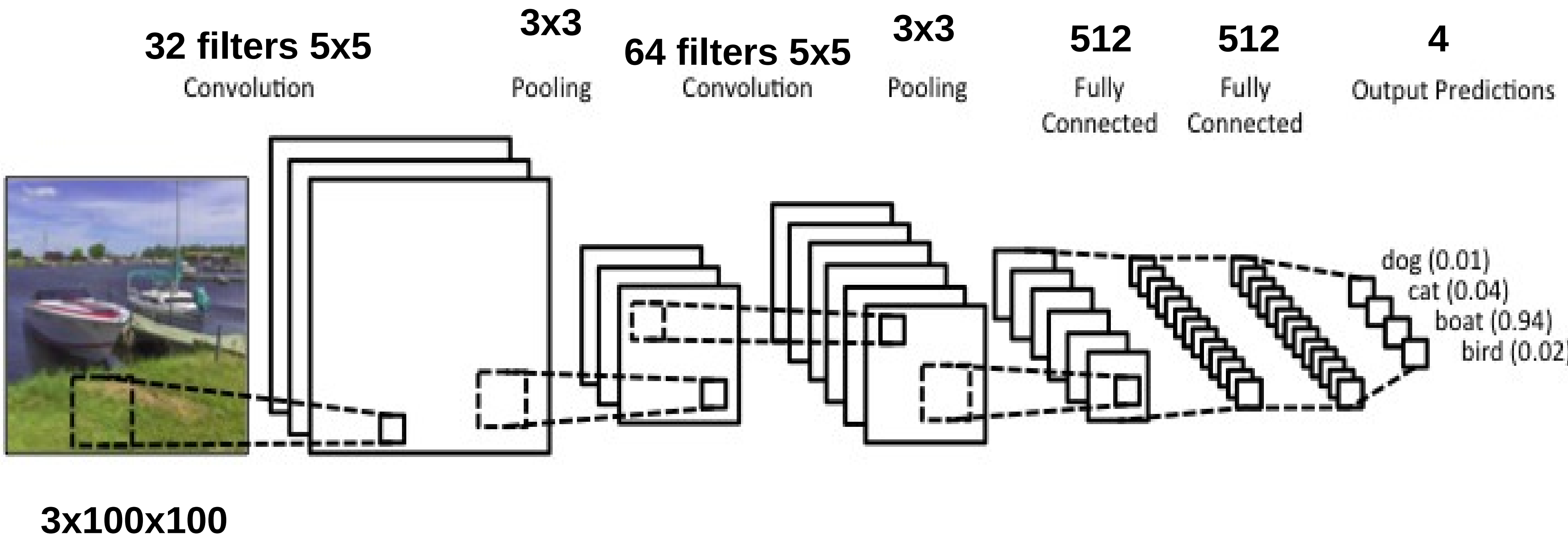



Discrete Choices
⋮
Layer 2 Features
Layer 1 Features
Original Data

Convolutional NNs



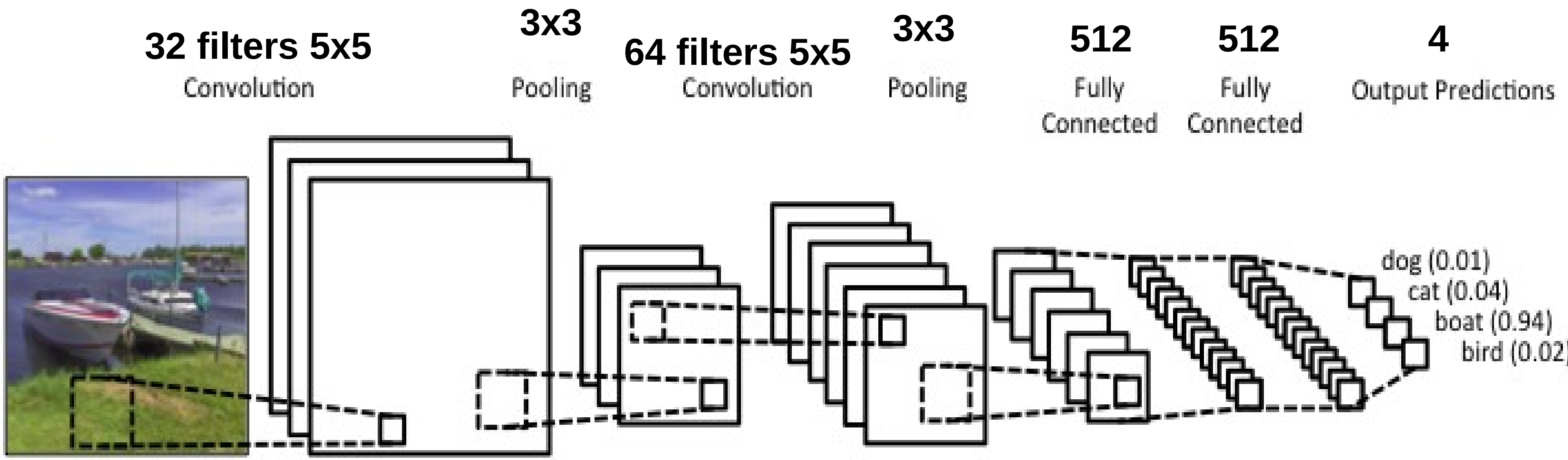
Convolutional NNs



Quiz:

1) What is the blob size **after second pooling**

Convolutional NNs

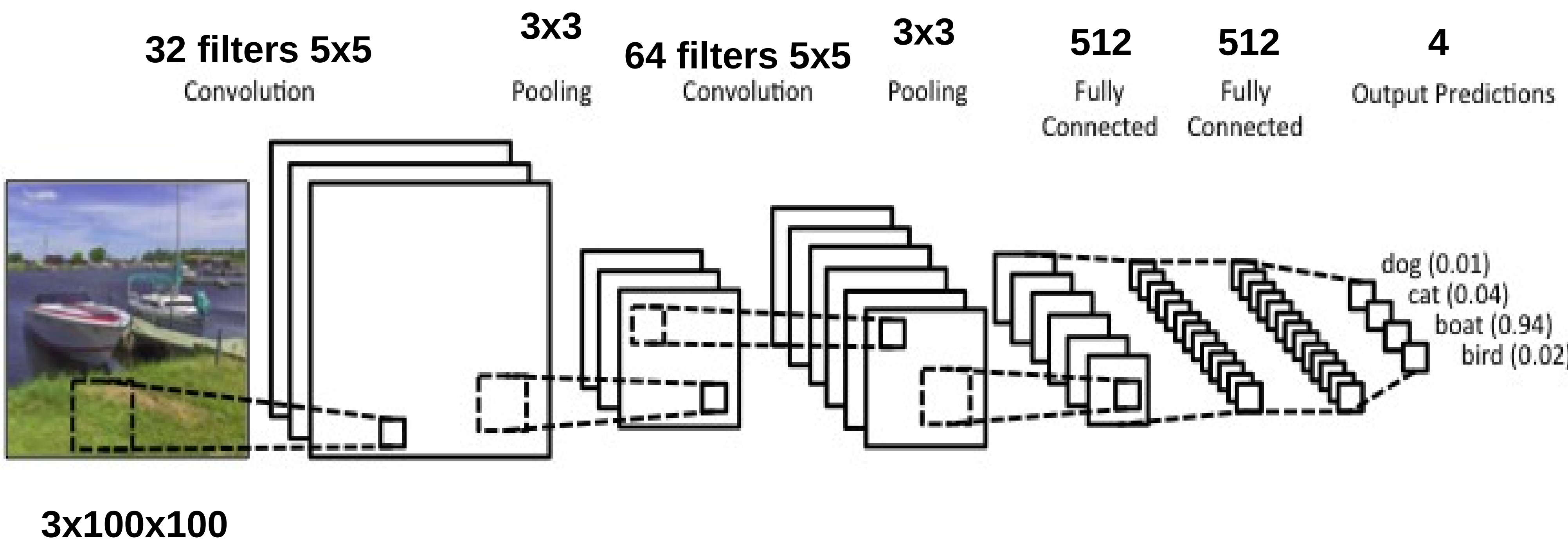


3x100x100

Quiz:

2) How many image pixels does **one cell** after **second convolution** depend on?

Convolutional NNs

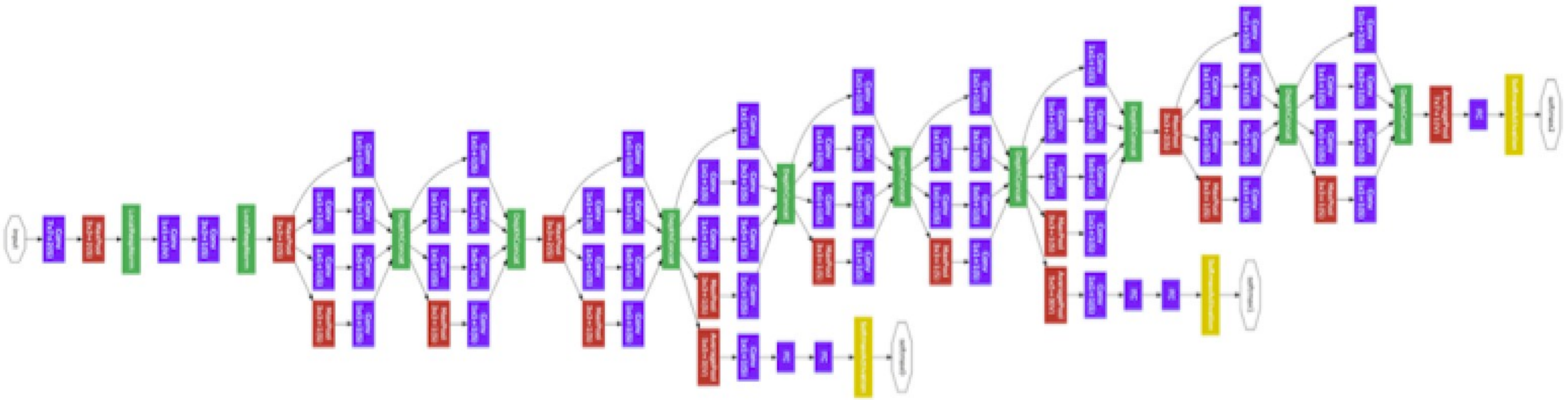


Quiz:

3) Which layer is hardest to compute?

4) Which layer has most independent parameters?

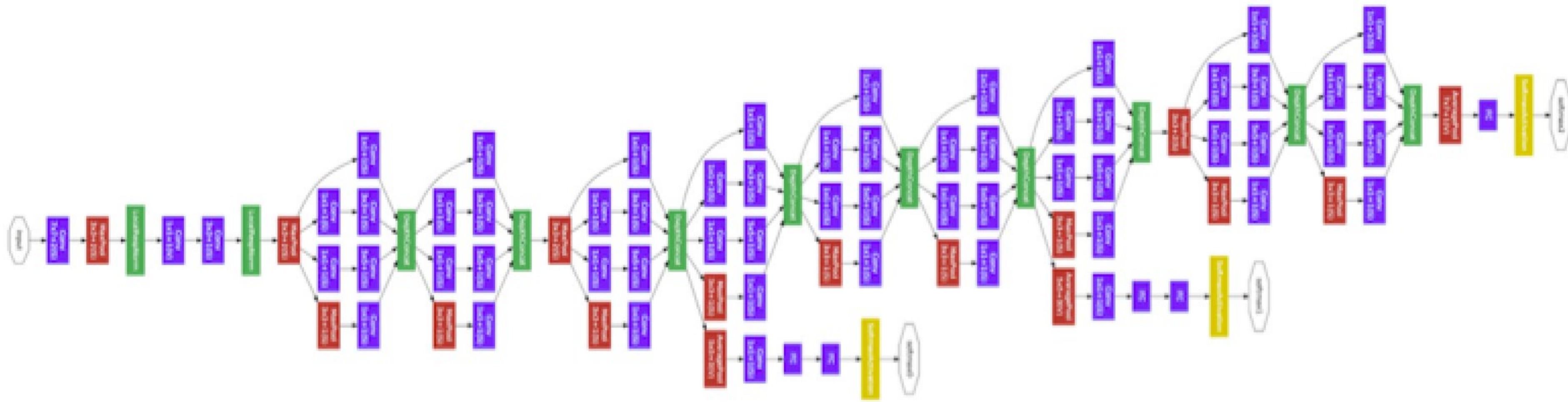
Inception-GoogleNet



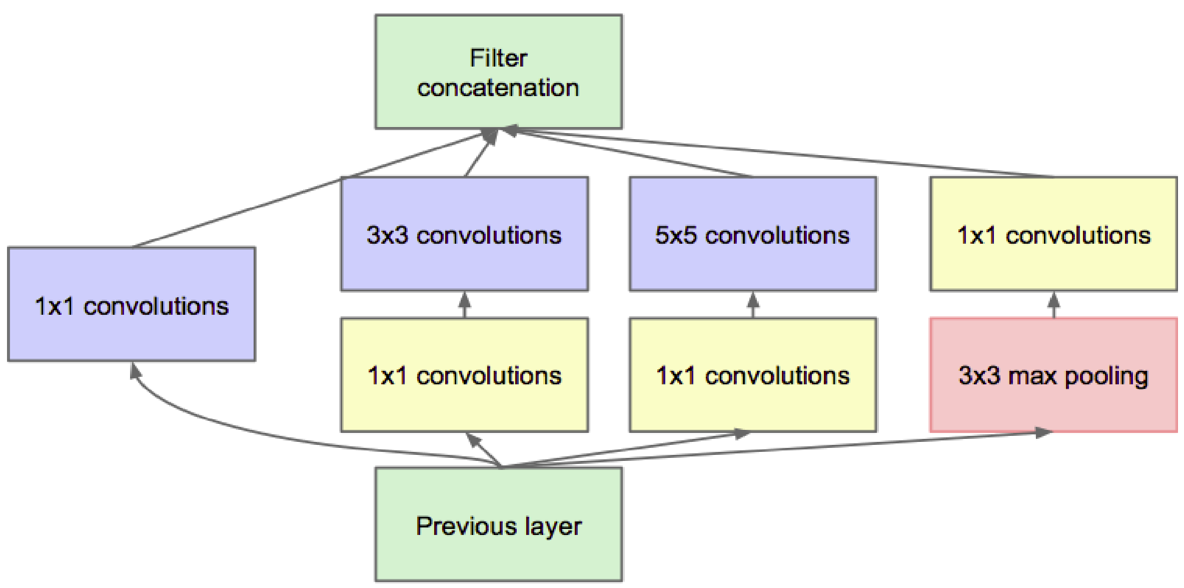
Convolution
Pooling
Softmax
Other

It is not a moon. It is a space station (c)

Inception-GoogleNet



Convolution
Pooling
Softmax
Other



Data augmentation

- Idea: we can get N times more data by tweaking images.
- If you rotate cat image by 15°, it's still a cat

- Rotate, crop, zoom, flip horizontally, add noize, etc.
- Sound data: add background noizes

Batch normalization

Problem:

- Consider a neuron in any layer beyond first
- At each iteration we tune it's weights towards better loss function
- But we also tune it's inputs. Some of them become larger, some – smaller
- Now the neuron needs to be re-tuned for it's new inputs

Batch normalization

TL;DR:

- It's usually a good idea to normalize linear model inputs

(c) Every machine learning lecturer, ever

Batch normalization

Idea:

- We normalize activation of a hidden layer

  (zero mean unit variance)

$$h_i = \frac{h_i - \mu_i}{\sqrt{\sigma_i^2}}$$

- Update μ_i, σ_i^2 with moving average while training

$$\mu_i := \alpha \cdot mean_{batch} + (1 - \alpha) \cdot \mu_i$$

$$\sigma_i^2 := \alpha \cdot variance_{batch} + (1 - \alpha) \cdot \sigma_i^2$$

Batch normalization

Idea:

– We normalize activation of a hidden layer

(zero mean unit variance)

$$h_i = \frac{h_i - \mu_i}{\sqrt{\sigma_i^2}}$$

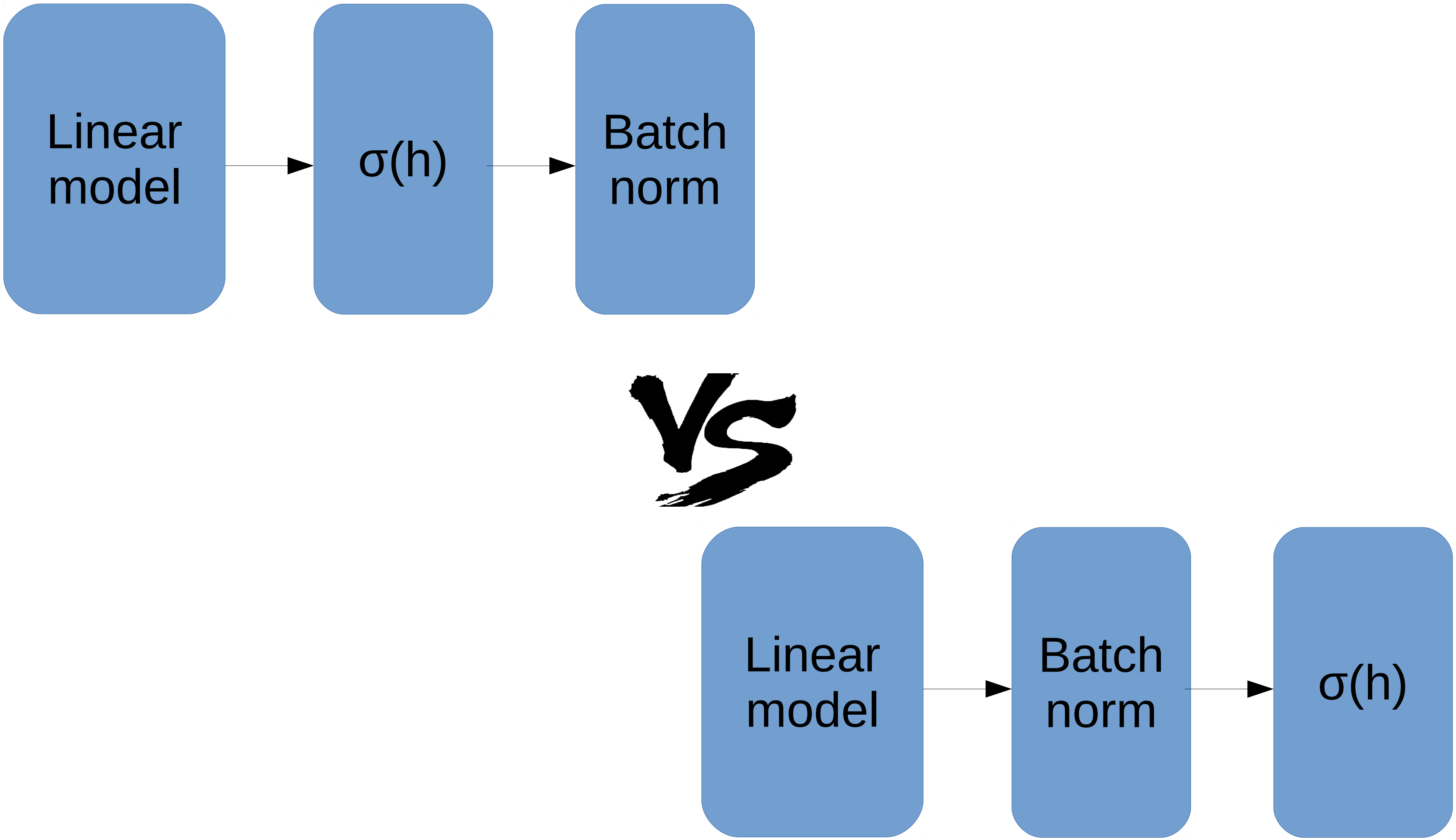
i stands for i-th neuron

– Update μ_i, σ_i^2 with moving average while training

$$\mu_i := \alpha \cdot mean_{batch} + (1 - \alpha) \cdot \mu_i$$

$$\sigma_i^2 := \alpha \cdot variance_{batch} + (1 - \alpha) \cdot \sigma_i^2$$

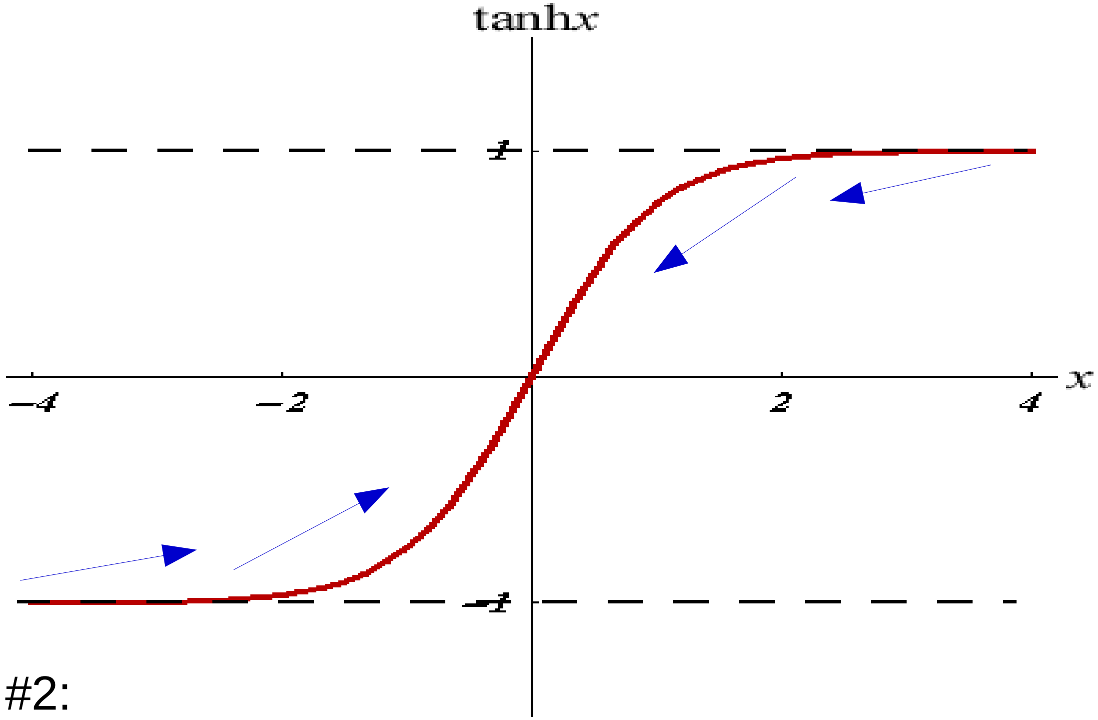
Batch normalization



Batch normalization

Good side effect #1:

– Vanishing gradient less a problem for sigmoid-like nonlinearities



Good side effect #2:

– We no longer need to train bias (+b term in Wx+b)

Other CV applications

Real computer vision starts when
image classification is no longer enough.

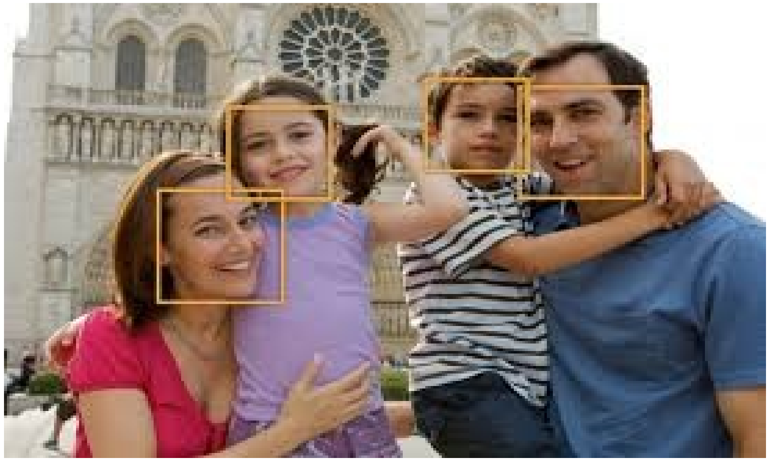
Bounding box regression

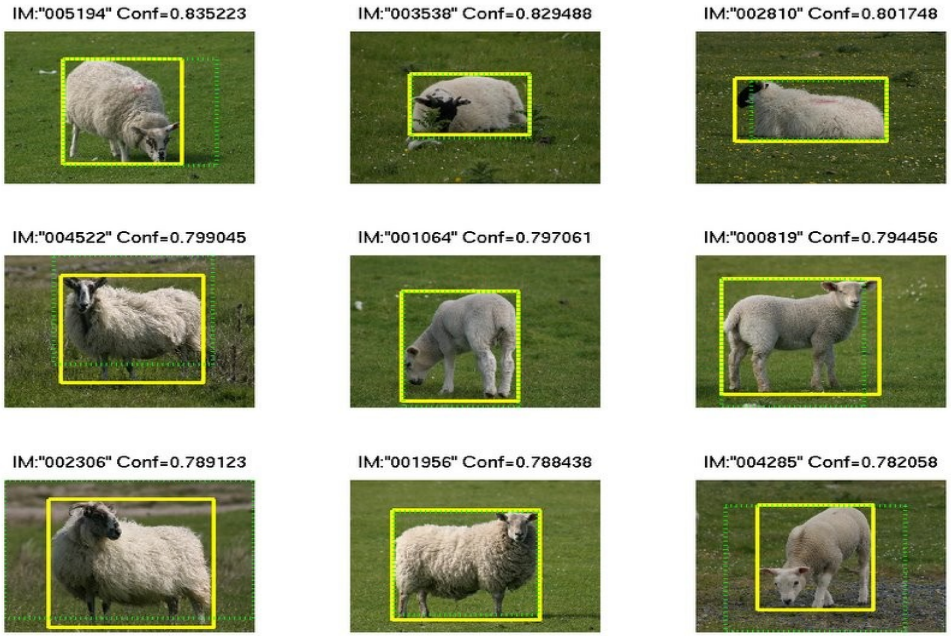
Predict object bounding box

(x0,y0,w,h)

or several bounding boxes for multiple objects.

Applications examples:
- Face detection @ cameras
- Surveillance cameras
- Self-driving cars

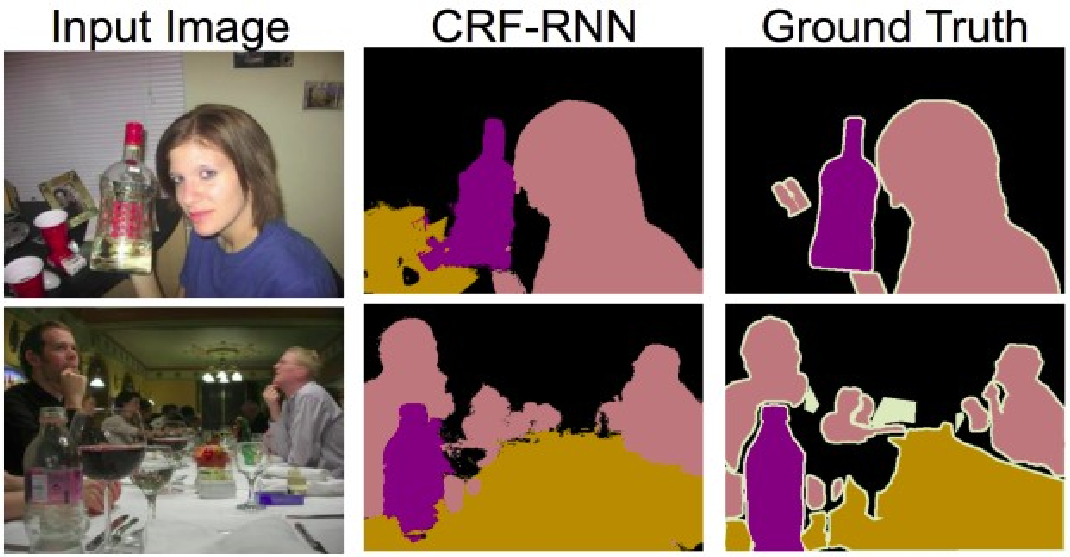




Segmentation

Predict class for each pixel

(fully-convolutional networks)



Applications examples:
- Moar surveillance
- Brain scan labeling
- Map labeling

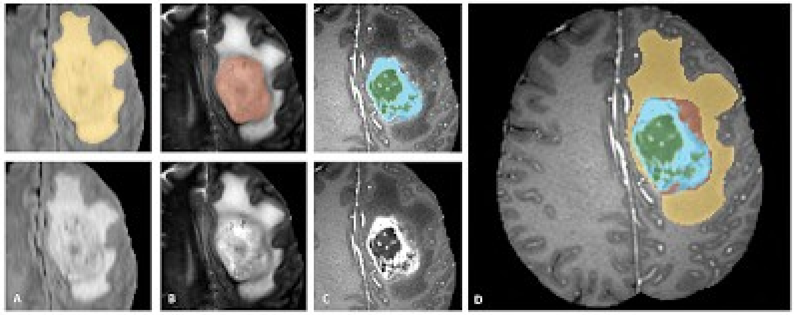
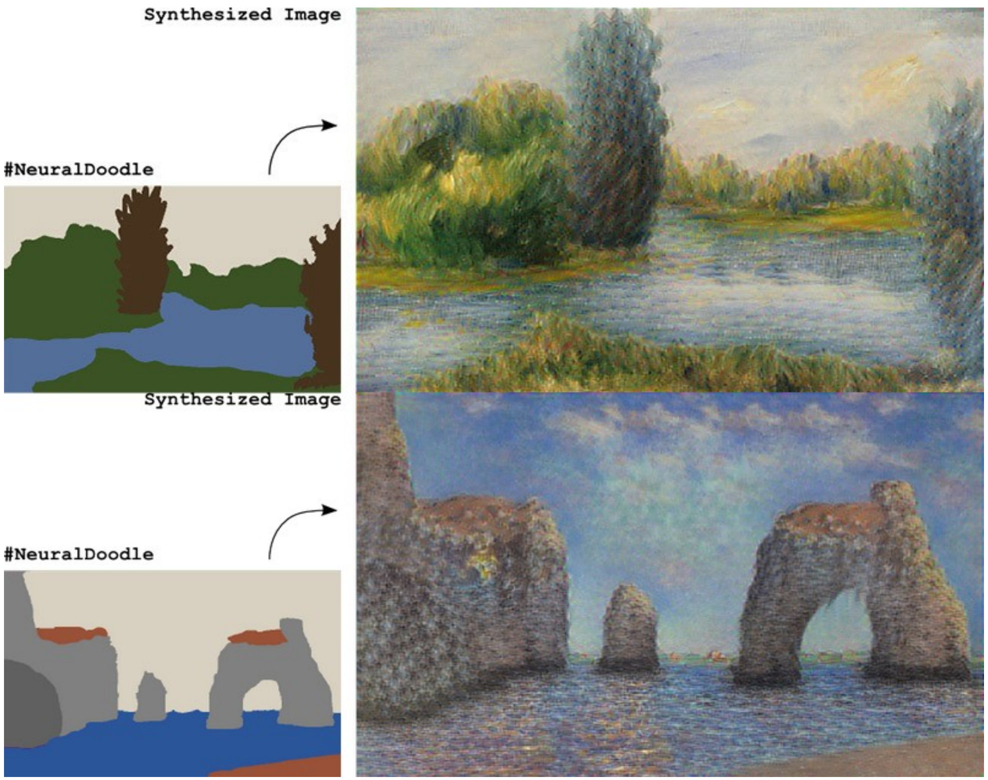


Image generation/transformation

- **Generation:** Given a set of reference images, learn to generate new images, resembling those you were given.
- **Transformation:** Given a set of reference images, learn to convert other images into ones resembling the reference set.



Neural Doodle
(D. Ulyanov et al.)

Image tagging
Image captioning
Image retrieval
Image encoding
Image morphing
Image encoding
Image upscaling
Object tracking on video
Video processing
Video interpolation

Fine-tuning
Adversarial Networks
Variational Autoencoders
Knowledge transfer
Domain adaptation
Online learning
Explaining predictions
Soft targets
Scene reconstruction
3D object retrieval
Classifier optimization

Nuff

Let's train some CNNs!