CS 3630!

Lecture 18:

Deep Learning

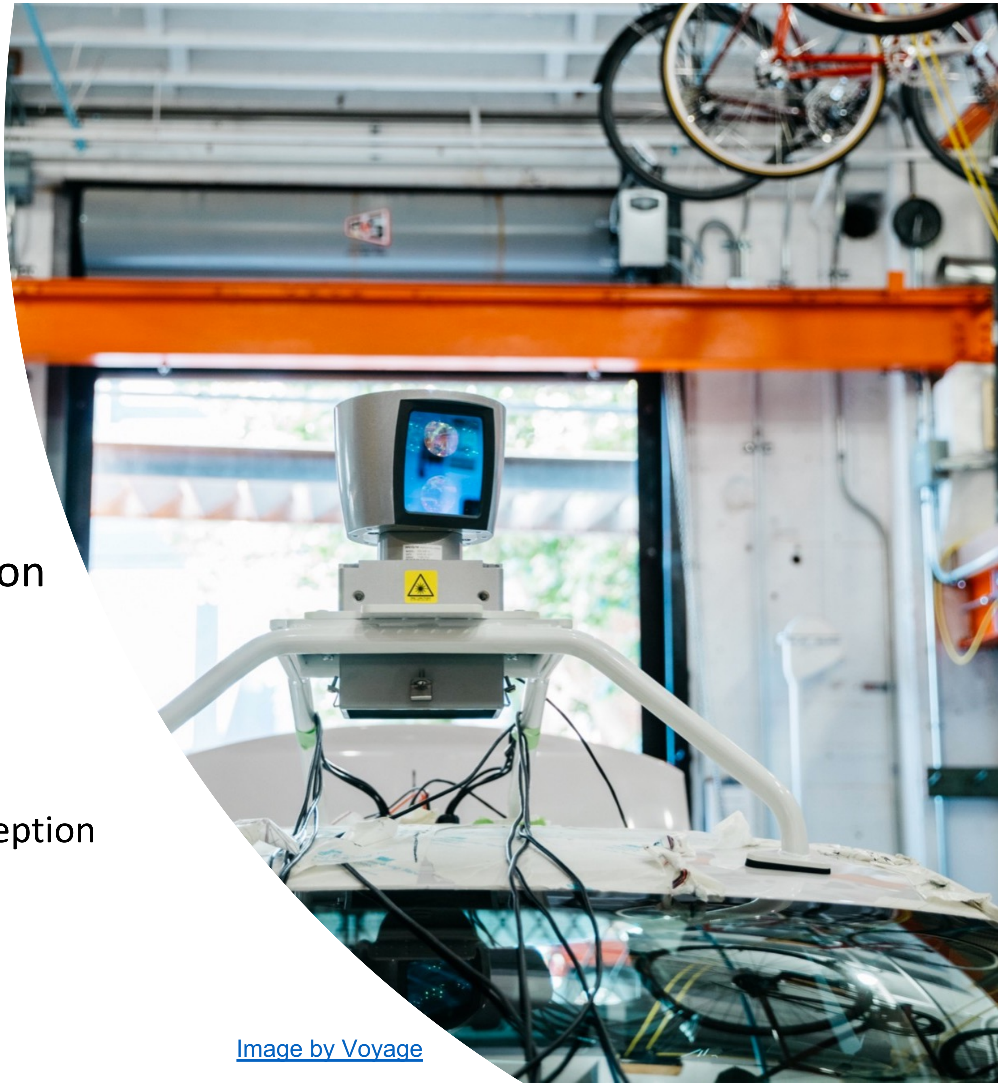
Many slides adapted from Stanford's CS231N by Fei-Fei Li, Justin Johnson, Serena Yeung, as well as Slides by Marc'Aurelio Ranzato (NYU), Dhruv Batra & Devi Parikh (Georgia Tech)

Topics

1. **Supervised Learning**
2. **Convolutional Neural Networks**
3. **Learning CNN Parameters**

Motivation

- Robotics:
  - Perception, thinking, acting
- Deep learning has revolutionized perception
- Getting increasingly important in thinking/acting
- This lecture:
  - High-level intro to CNNs and learning for perception
- Next lecture:
  - Applications in robotics



[Image by Voyage]()

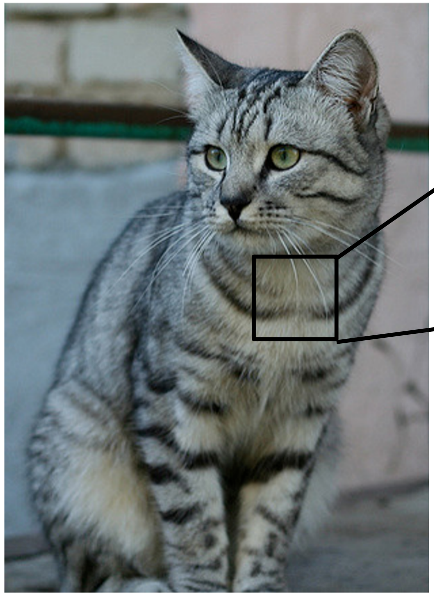
1. Supervised Learning

- Example: classification

(assume given set of discrete labels)
{dog, cat, truck, plane, ...}

cat

The Problem: Semantic Gap

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 [122 121 102  80  82  86  94 117 145 148 153 102  58  78  92 107]
 [122 164 148 103  71  56  78  83  93 103 119 139 102  61  69  84]]
```

What the computer sees

An image is just a big grid of numbers between [0, 255]:

e.g. 800 x 600 x 3
(3 channels RGB)

An image classifier

```python
def classify_image(image):
  # Some magic here?
  return class_label
```

Unlike e.g. sorting a list of numbers,

no obvious way to hard-code the algorithm for recognizing a cat, or other classes.

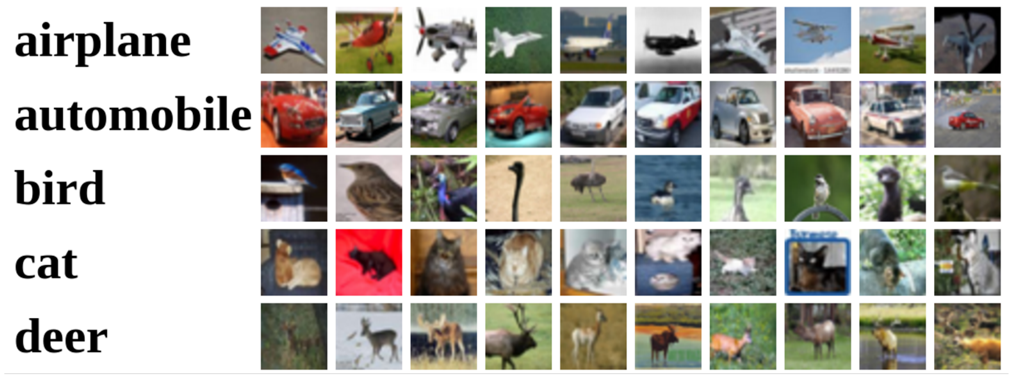
ML: A Data-Driven Approach

1. Collect a dataset of images and labels
2. Use Machine Learning to train a classifier
3. Evaluate the classifier on new images

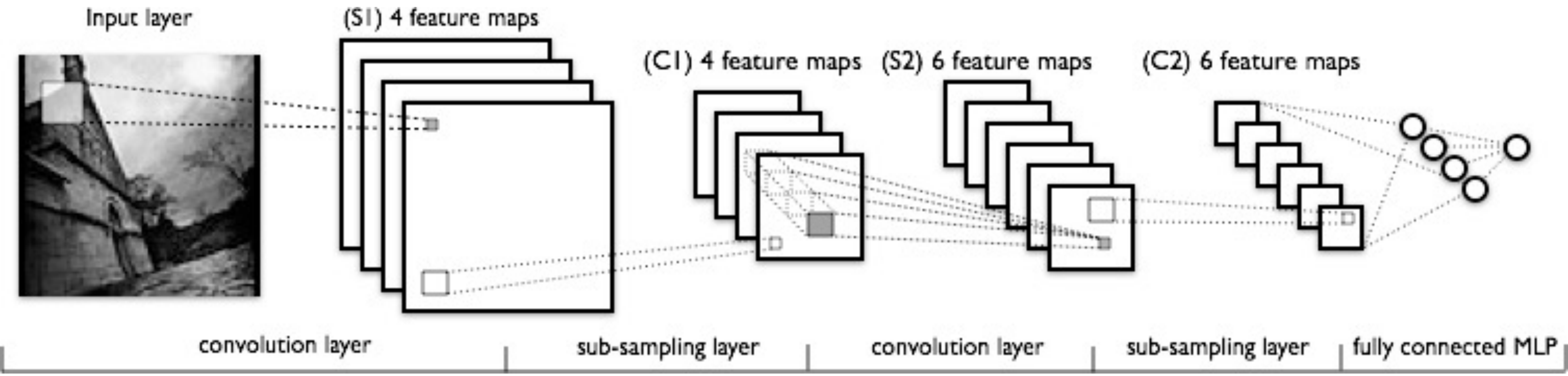
```python
def train(images, labels):
  # Machine learning!
  return model
```

```python
def predict(model, test_images):
  # Use model to predict labels
  return test_labels
```

Example training set



2. Convolutional Neural Networks



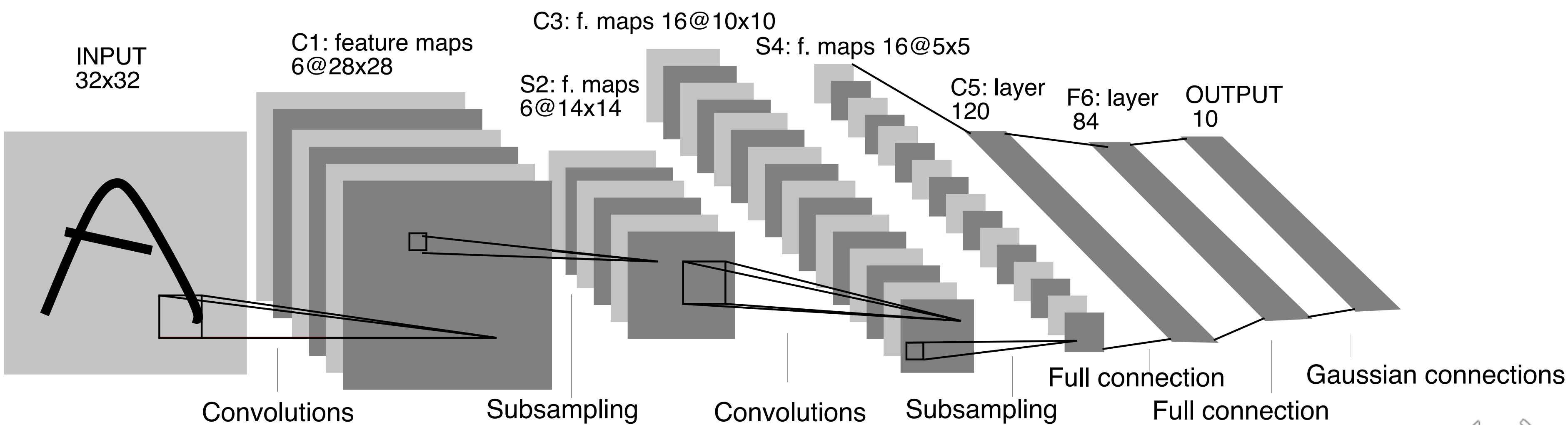
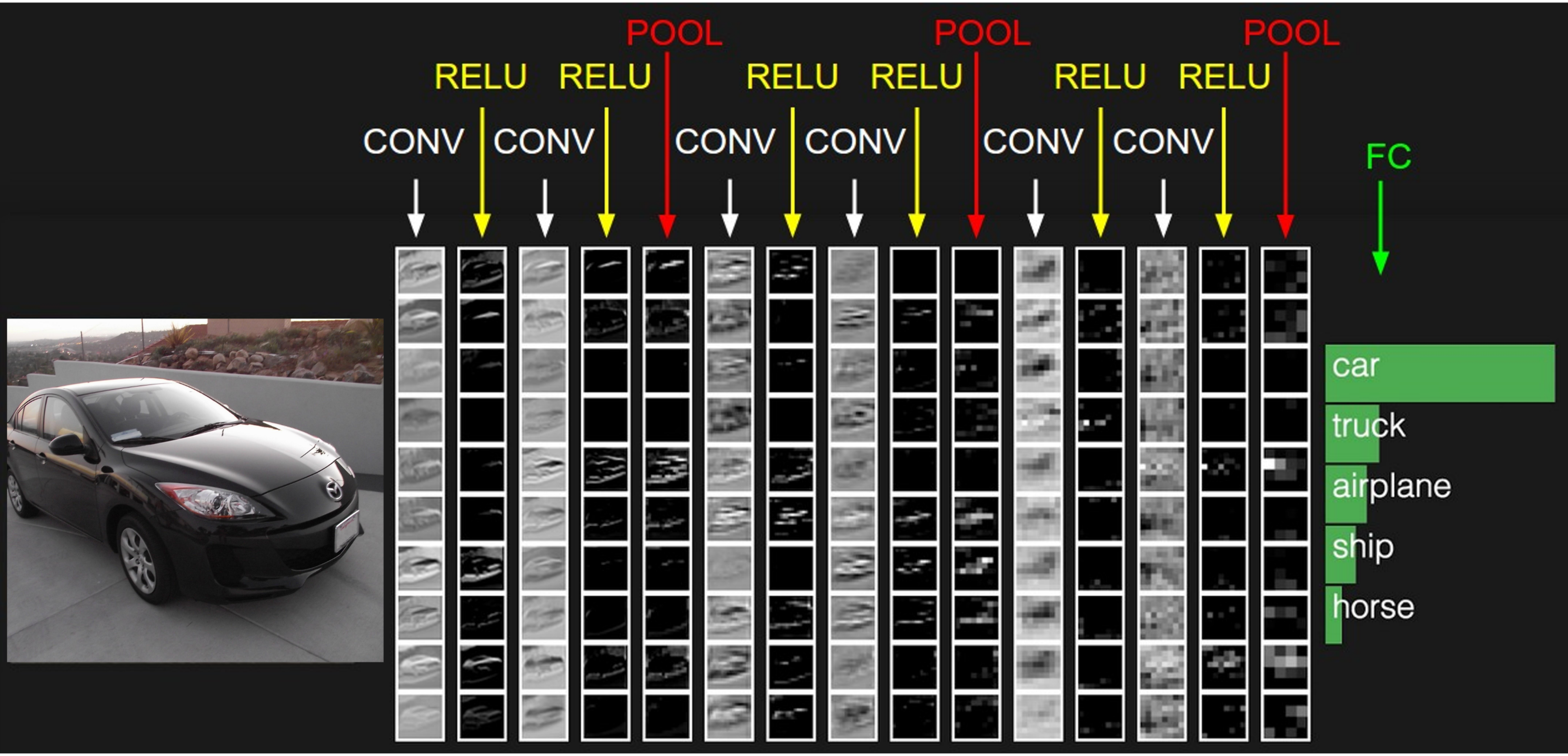


Image Credit: Yann LeCun, Kevin Murphy

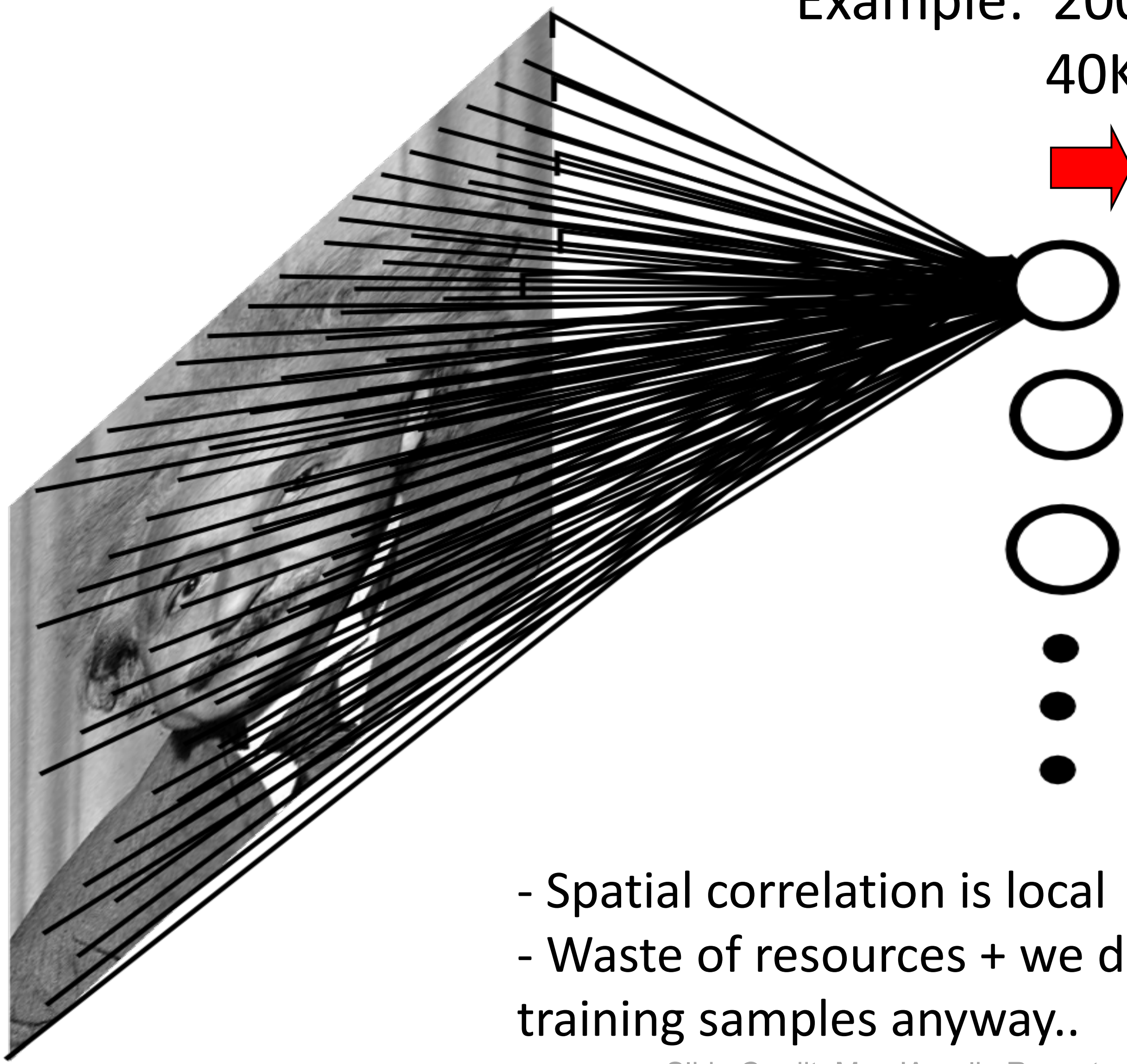
preview:



Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Fully Connected Layer

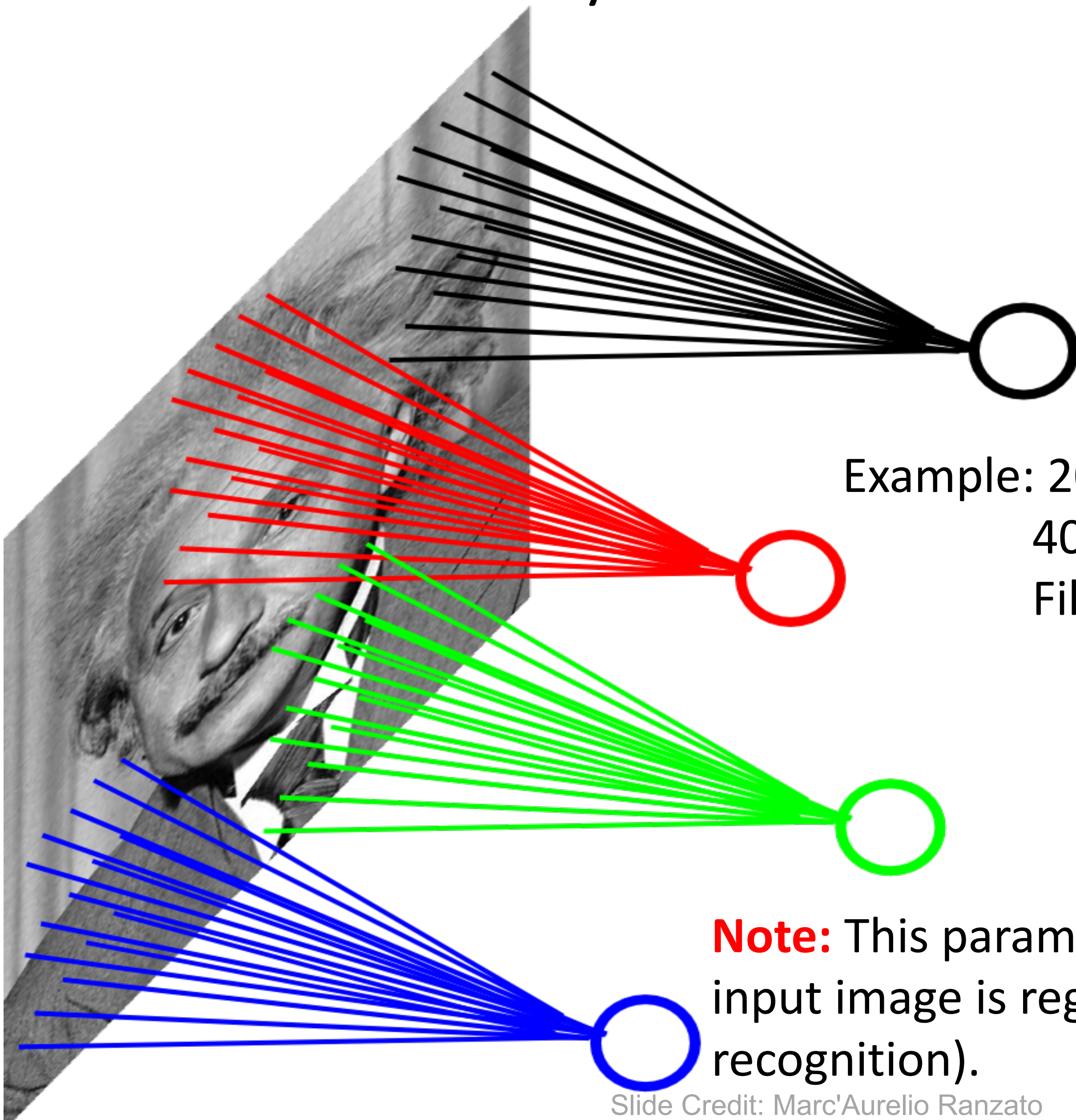
Example: 200x200 image
40K hidden units
~2.4B parameters!!!



- Spatial correlation is local
- Waste of resources + we do not have enough training samples anyway..

Slide Credit: Marc'Aurelio Ranzato

Locally Connected Layer

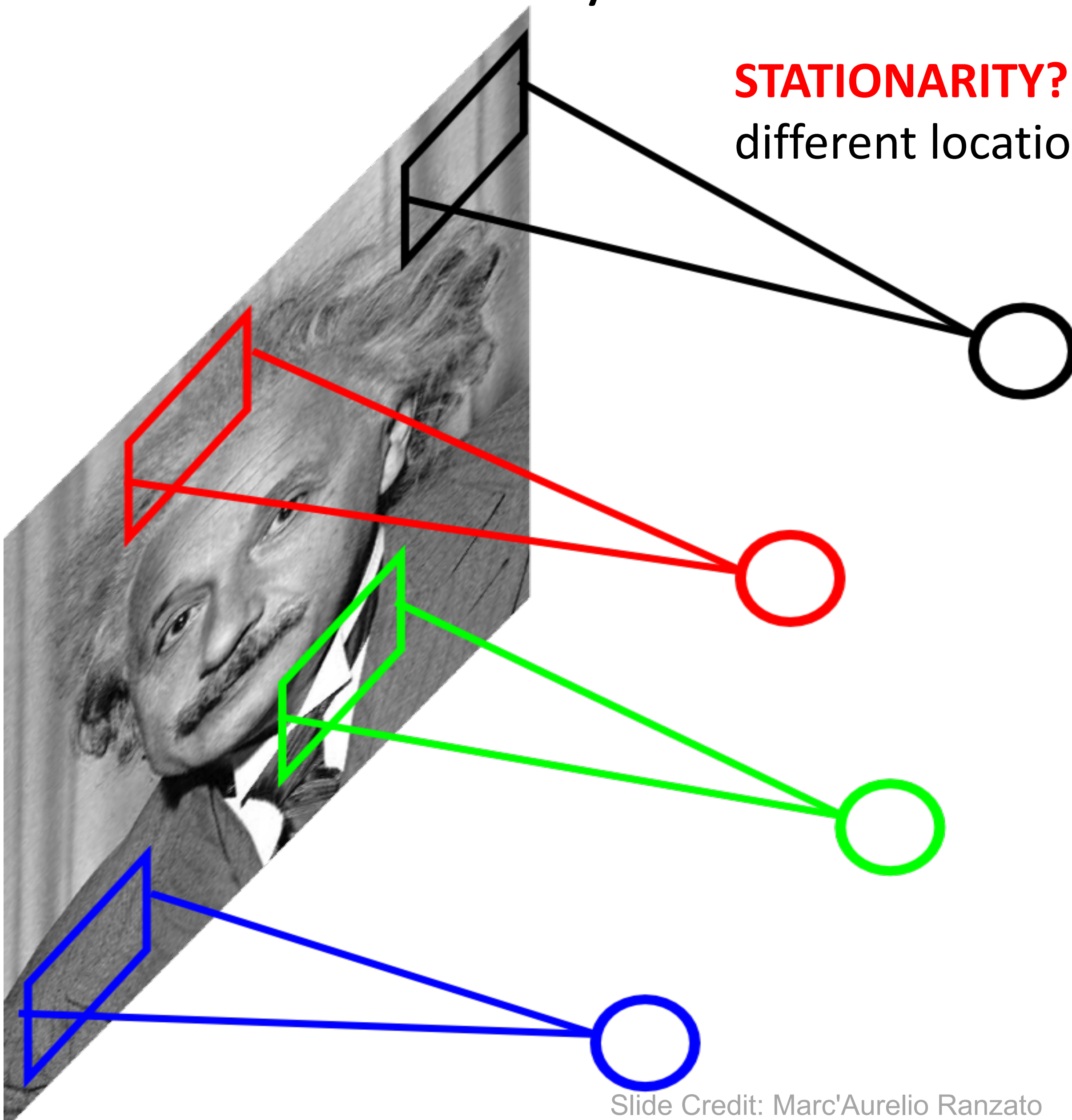


Example: 200x200 image
40K hidden units
Filter size: 10x10
4M parameters

Note: This parameterization is good when input image is registered (e.g., face recognition).

Slide Credit: Marc'Aurelio Ranzato

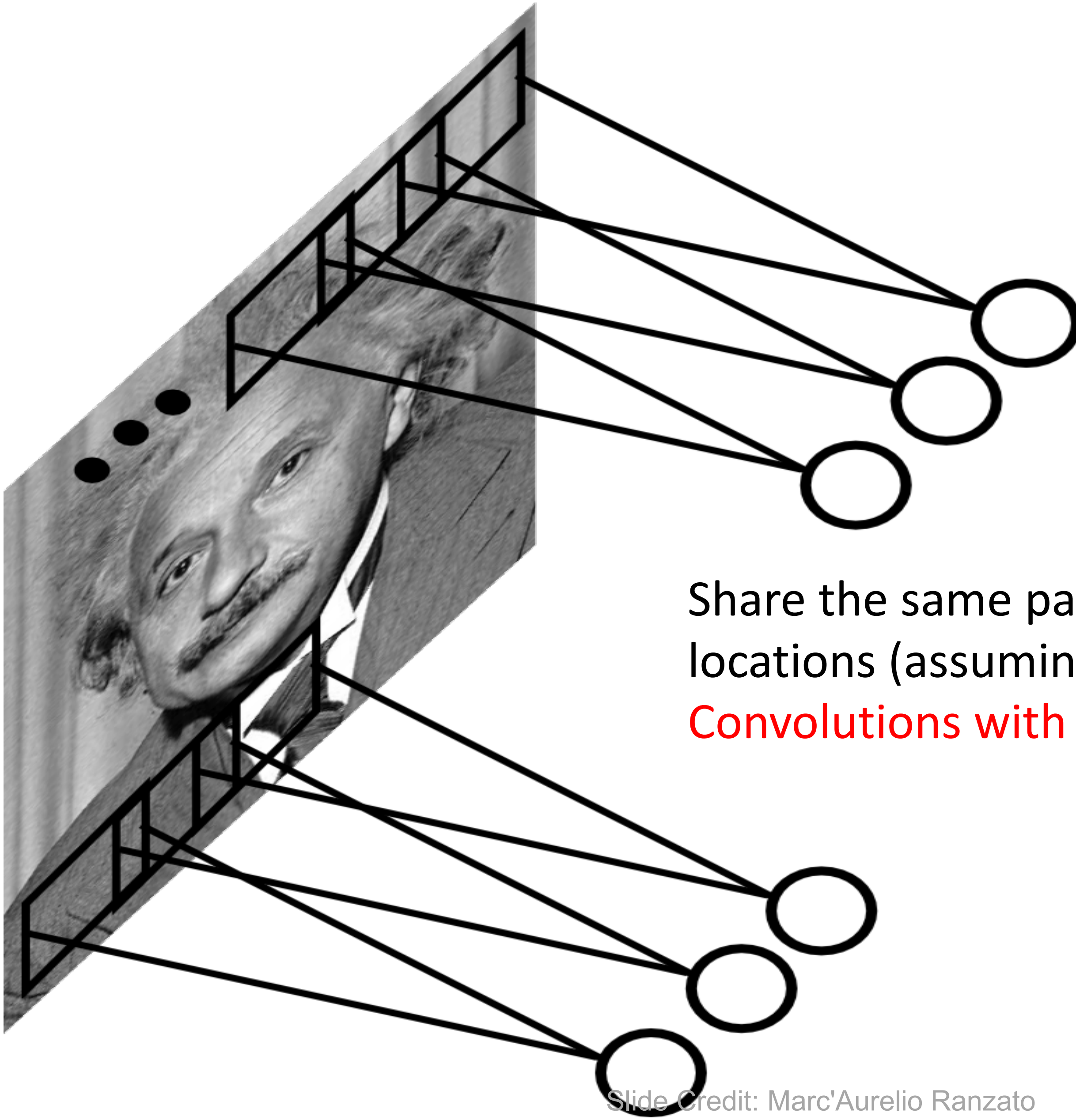
Locally Connected Layer



STATIONARITY? Statistics is similar at different locations

Slide Credit: Marc'Aurelio Ranzato

Convolutional Layer

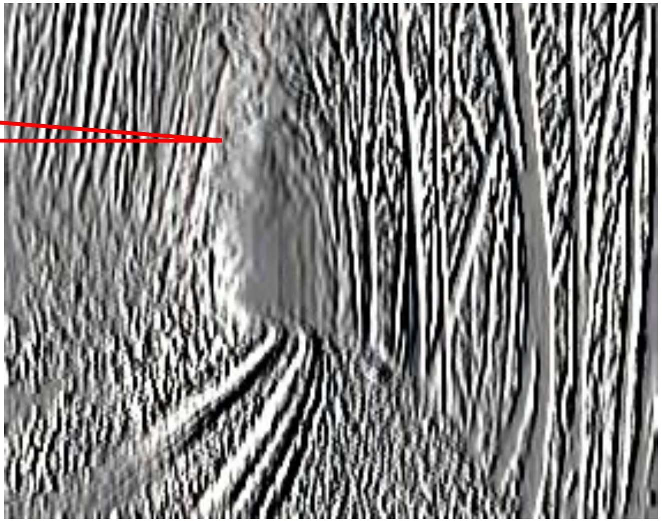


Share the same parameters across different locations (assuming input is stationary):
Convolutions with learned kernels

Slide Credit: Marc'Aurelio Ranzato

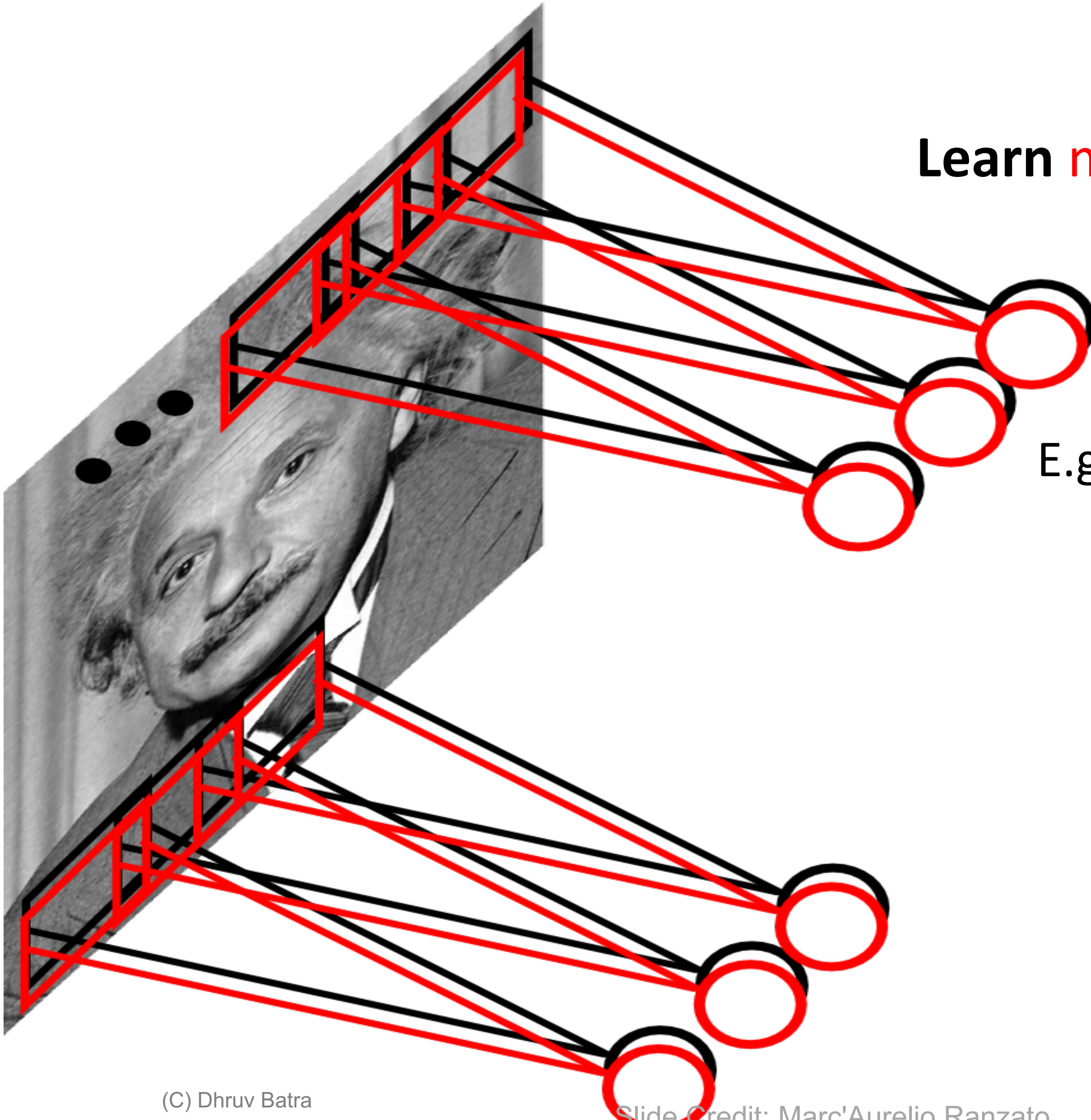
Convolutional Layer

$$* \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} =$$



Slide Credit: Marc'Aurelio Ranzato

Convolutional Layer

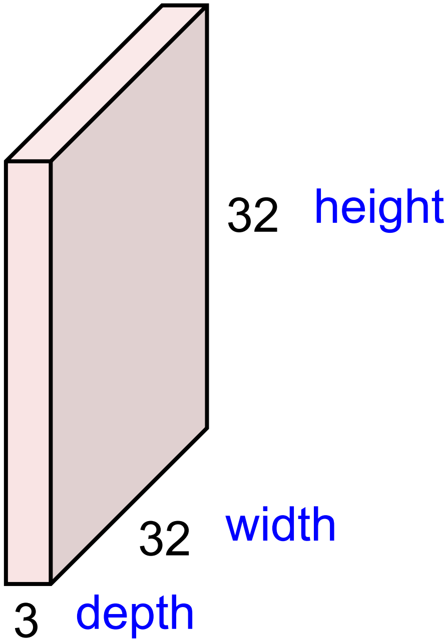


Learn multiple filters.

E.g.: 200x200 image
100 Filters
Filter size: 10x10
10K parameters

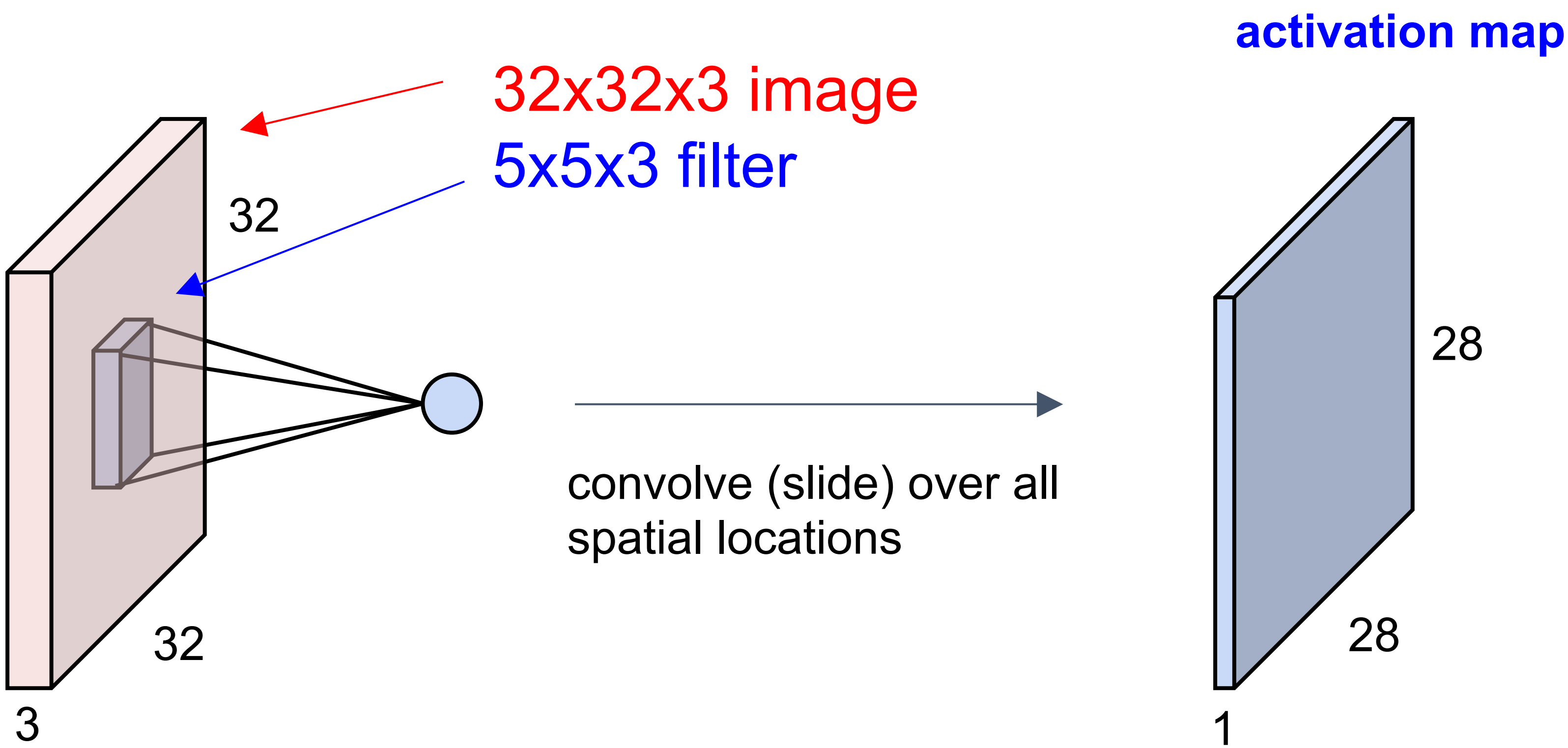
Convolution Layer

32x32x3 image -> preserve spatial structure

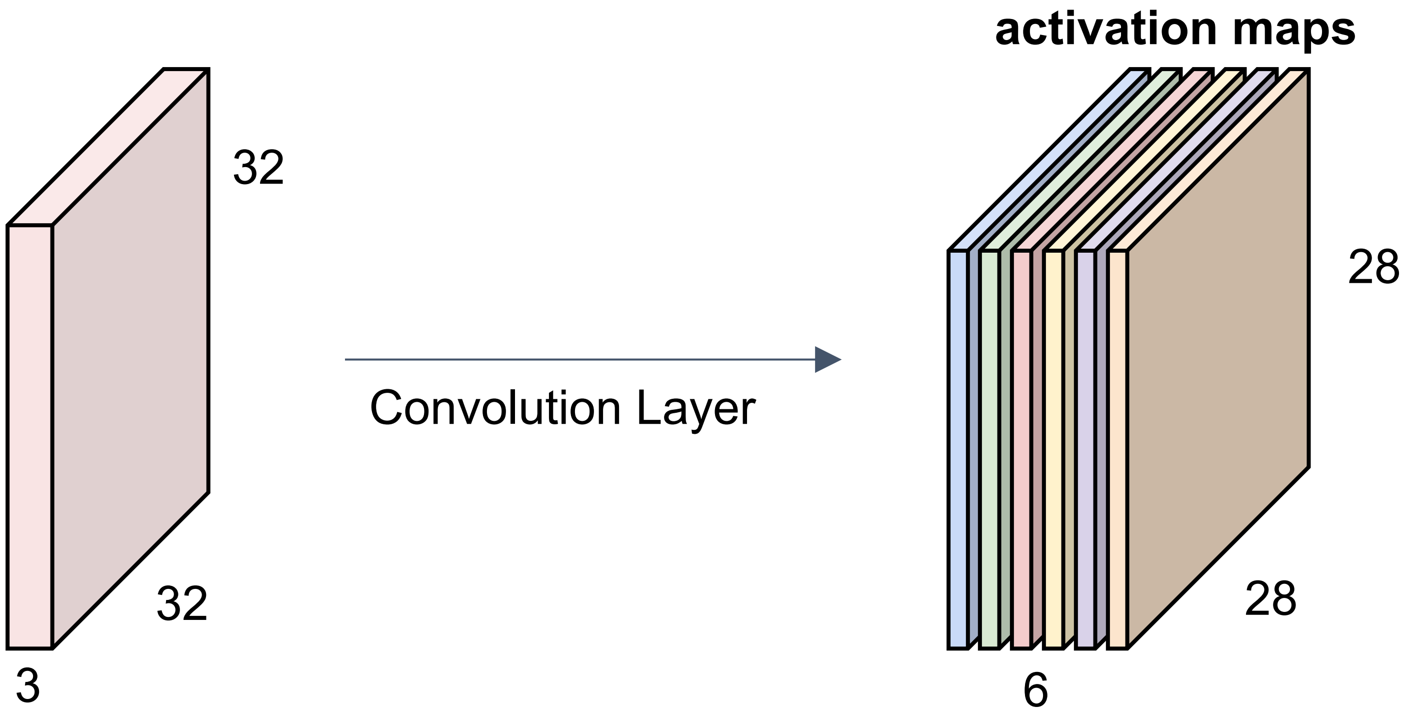


Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Convolution Layer

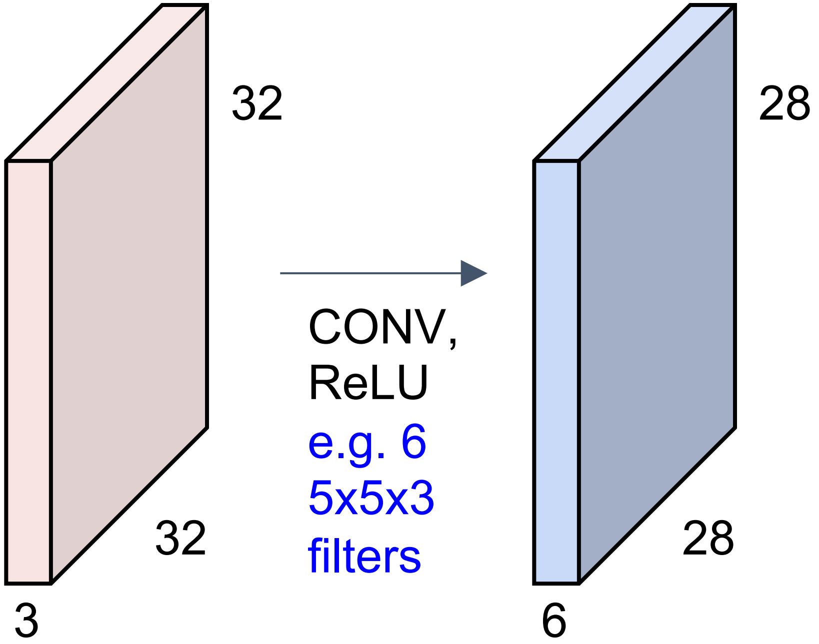


Multiple filters: if we have 6 5x5 filters, we'll get 6 separate activation maps:

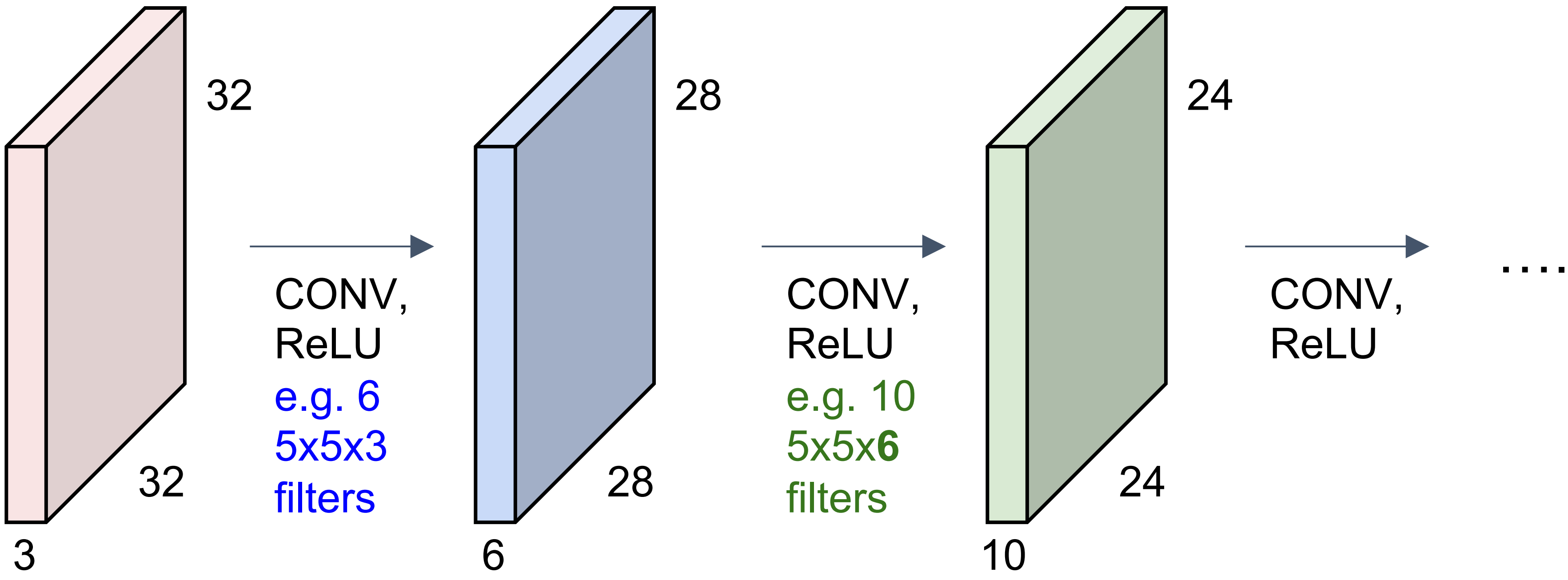


We stack these up to get a "new image" of size 28x28x6!

Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions

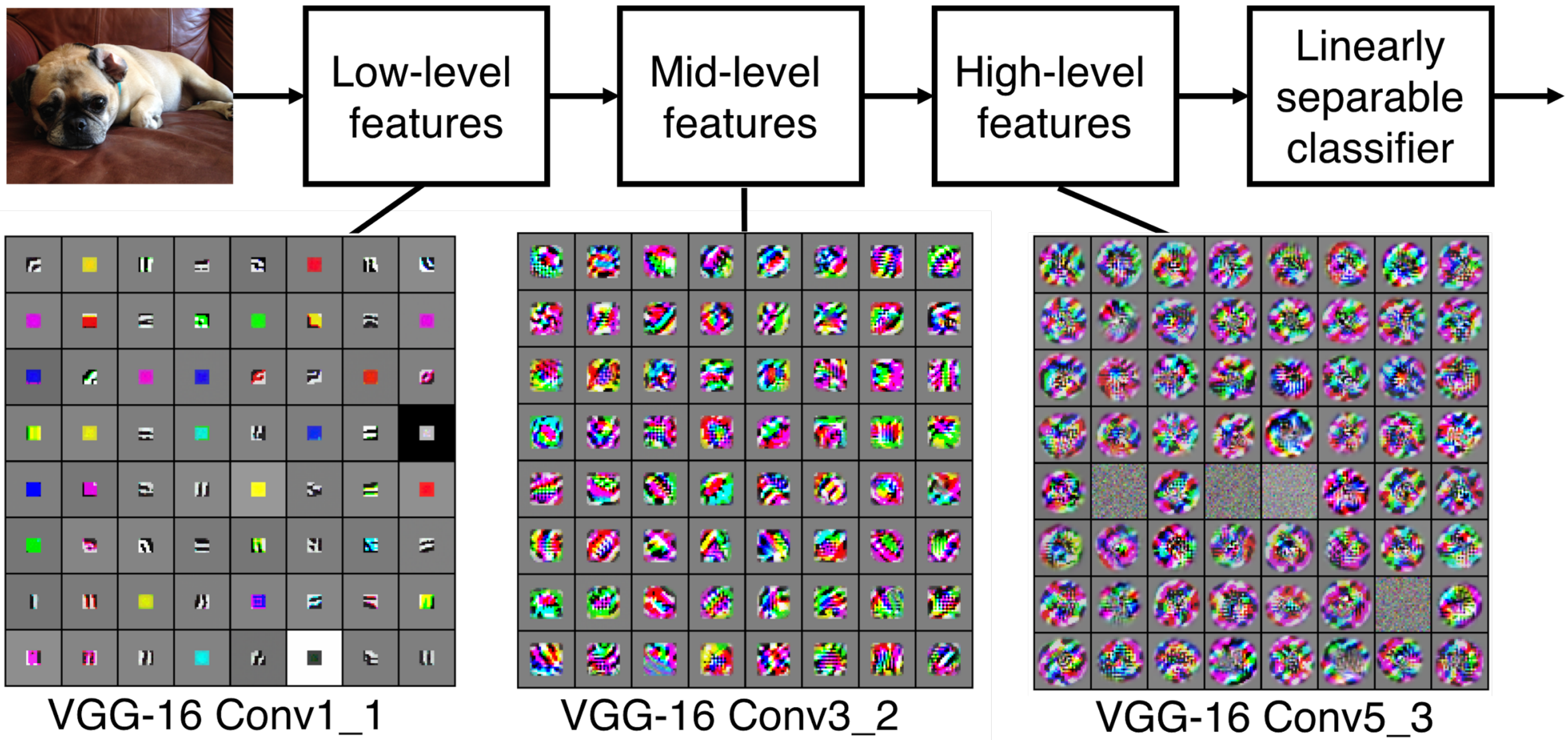


Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Preview

[Zeiler and Fergus 2013]

Visualization of VGG-16 by Lane McIntosh. VGG-16 architecture from [Simonyan and Zisserman 2014].



Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Visualizing Learned Filters

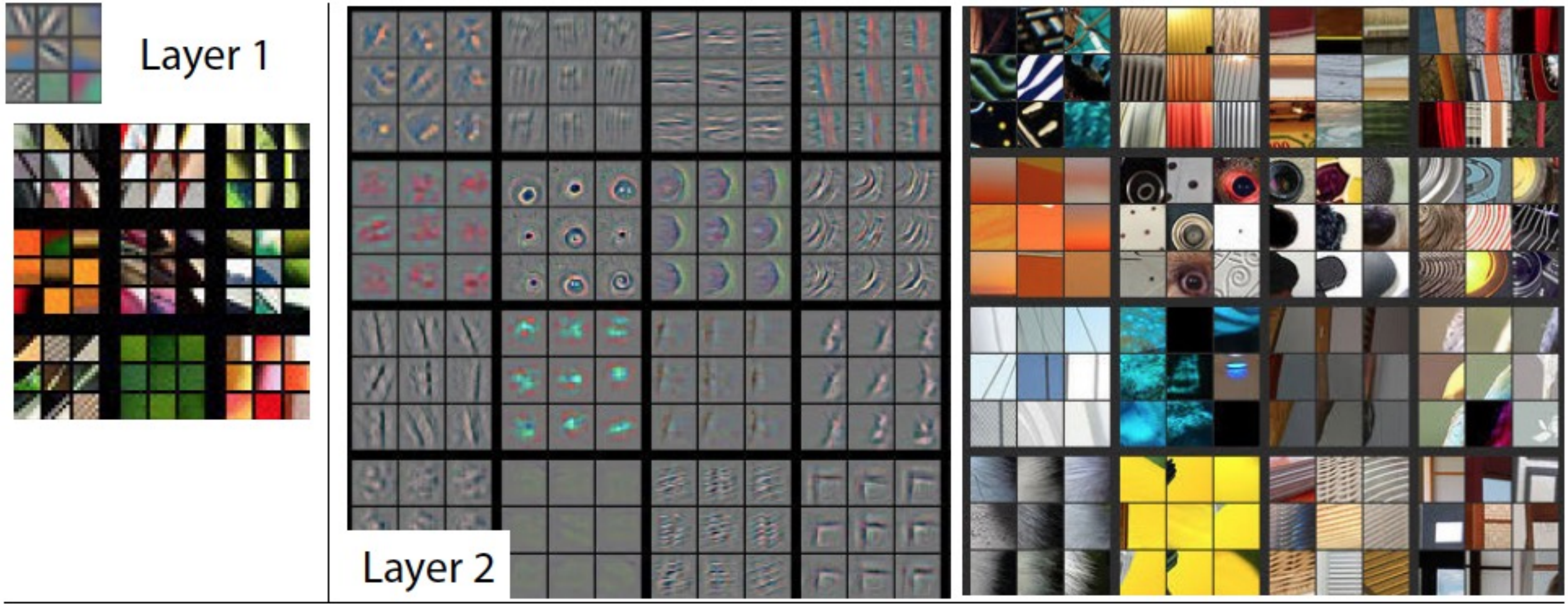
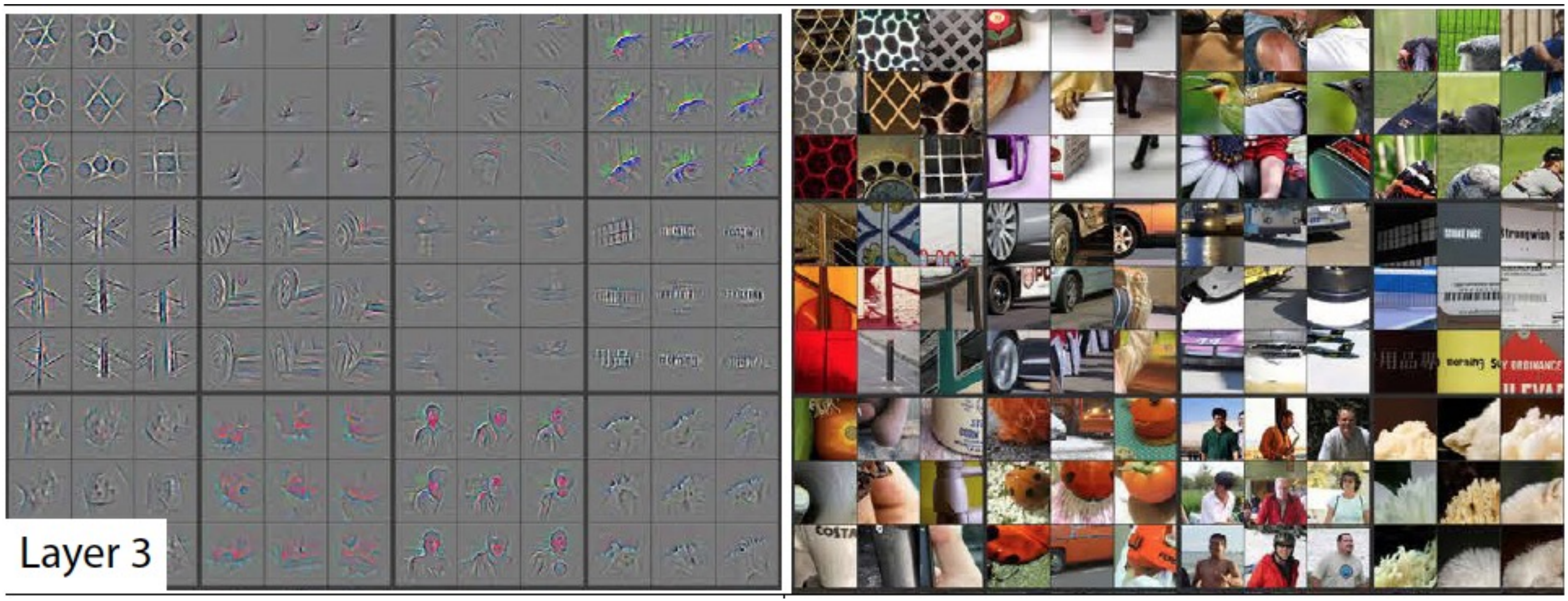


Figure Credit: [Zeiler & Fergus ECCV14]

Visualizing Learned Filters



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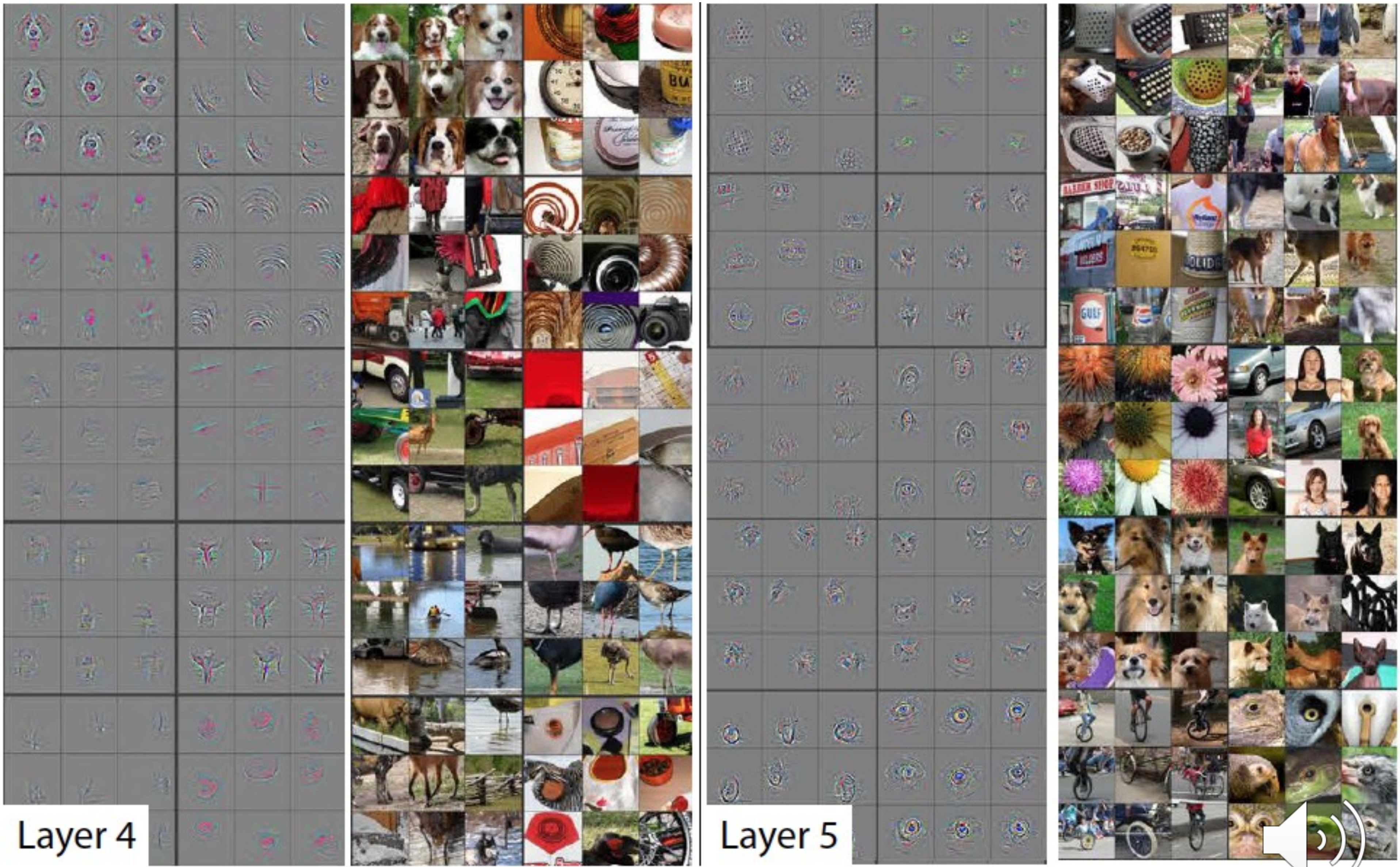
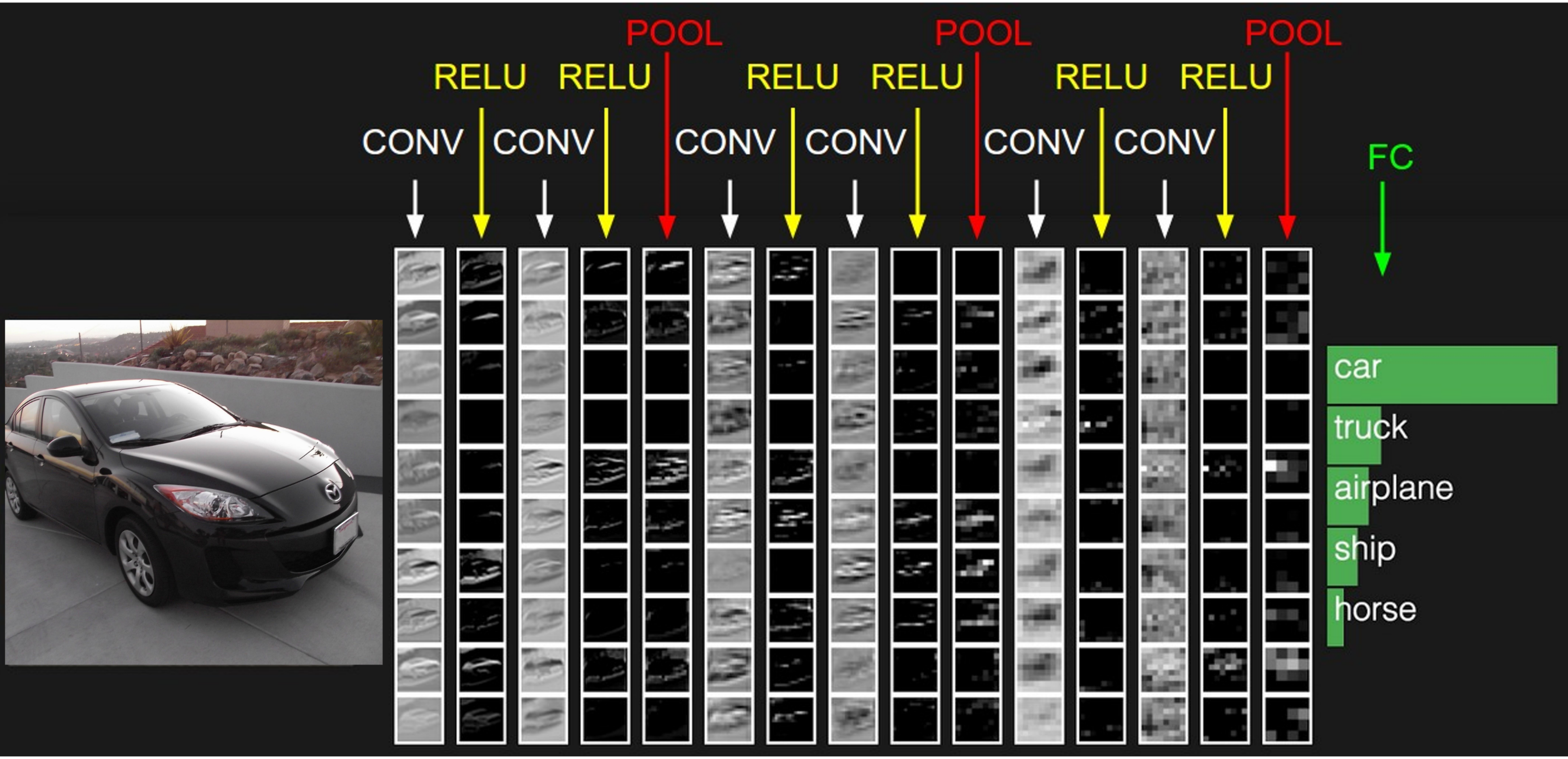


Figure Credit: [Zeiler & Fergus ECCV14]

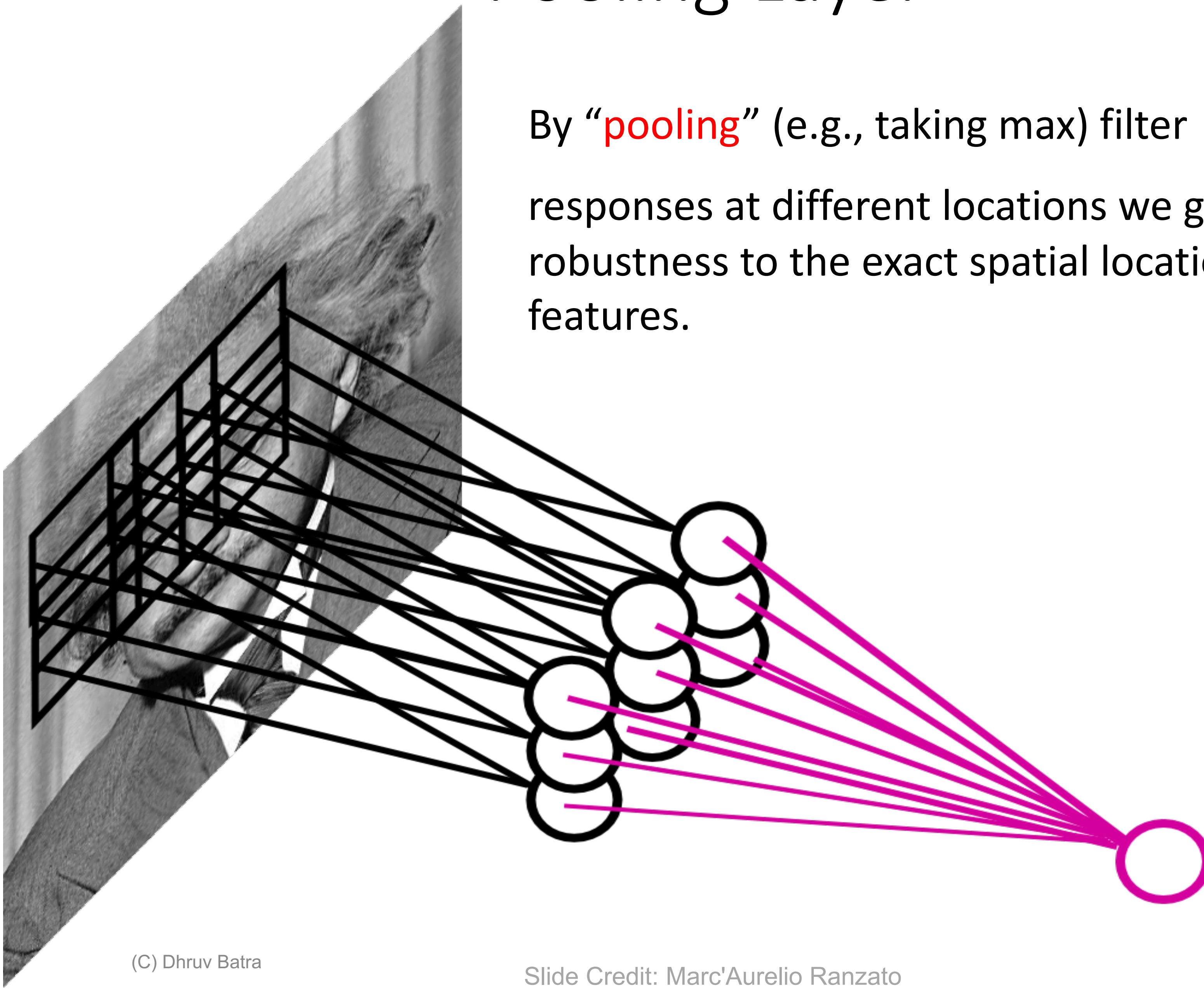
two more layers to go: POOL/FC



Pooling Layer

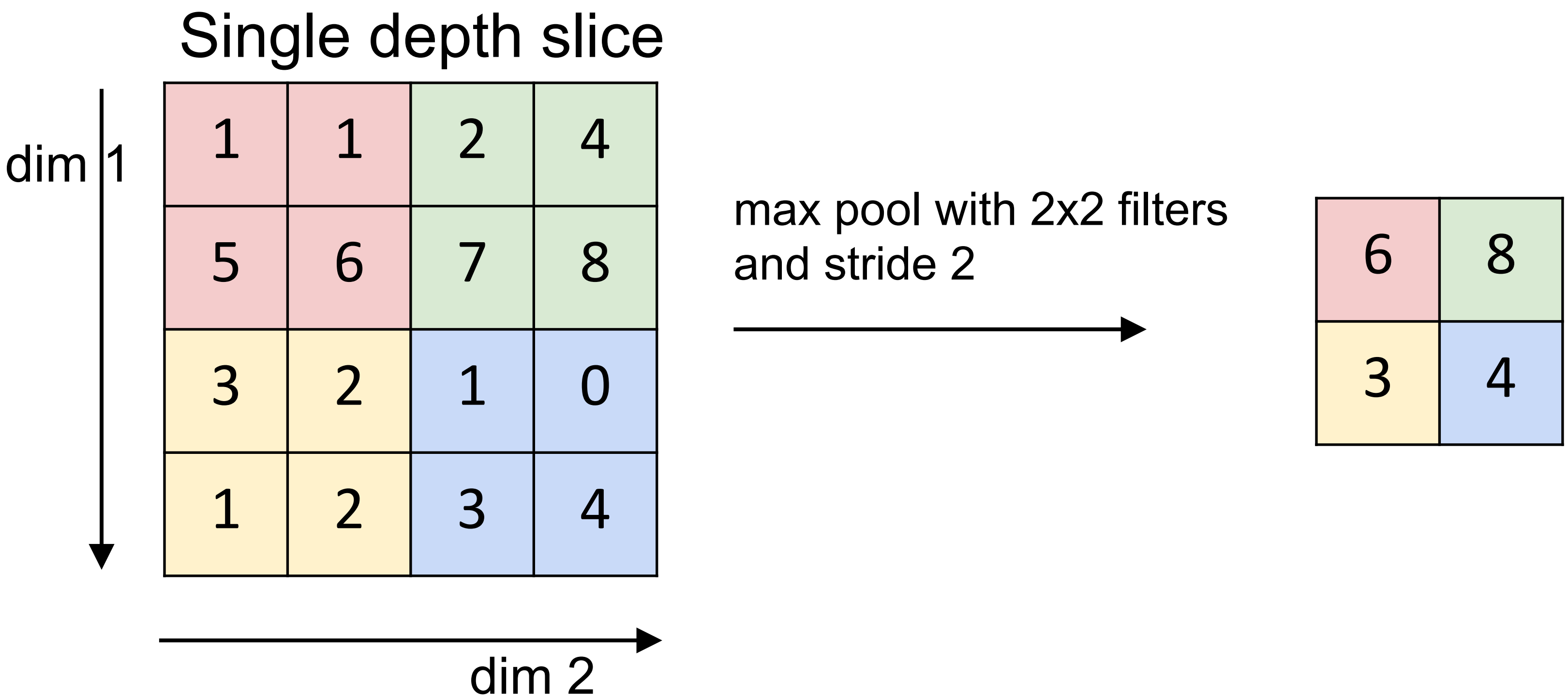
By "pooling" (e.g., taking max) filter

responses at different locations we gain robustness to the exact spatial location of features.



Slide Credit: Marc'Aurelio Ranzato

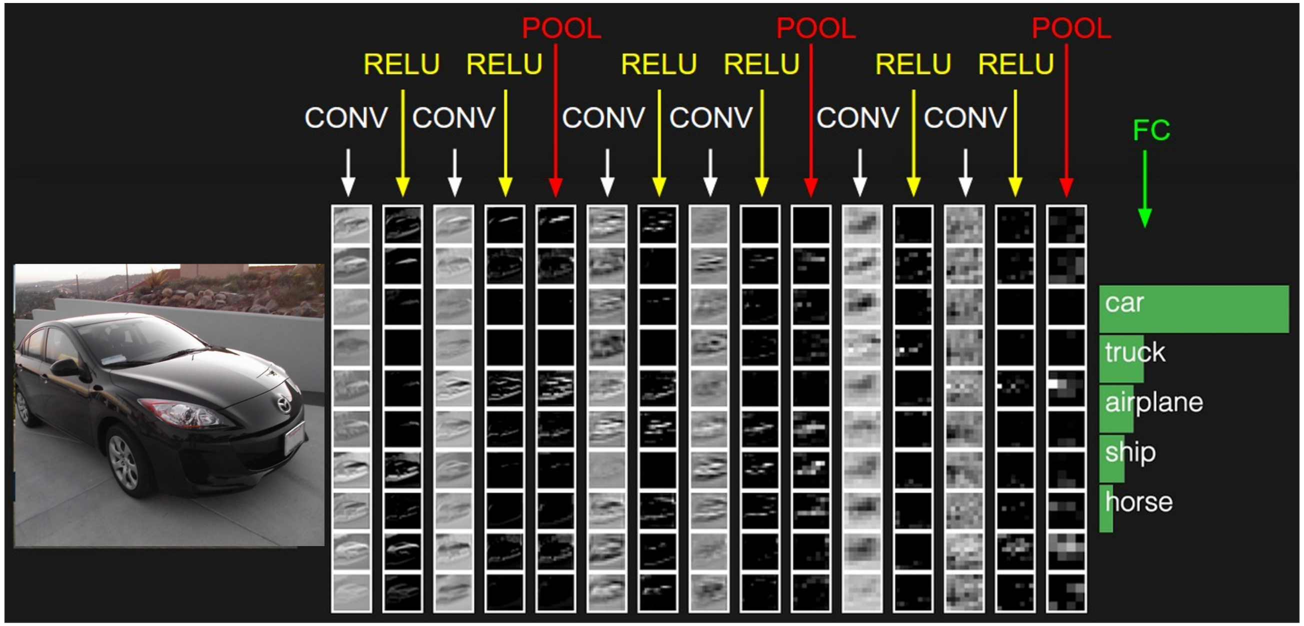
MAX POOLING



Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

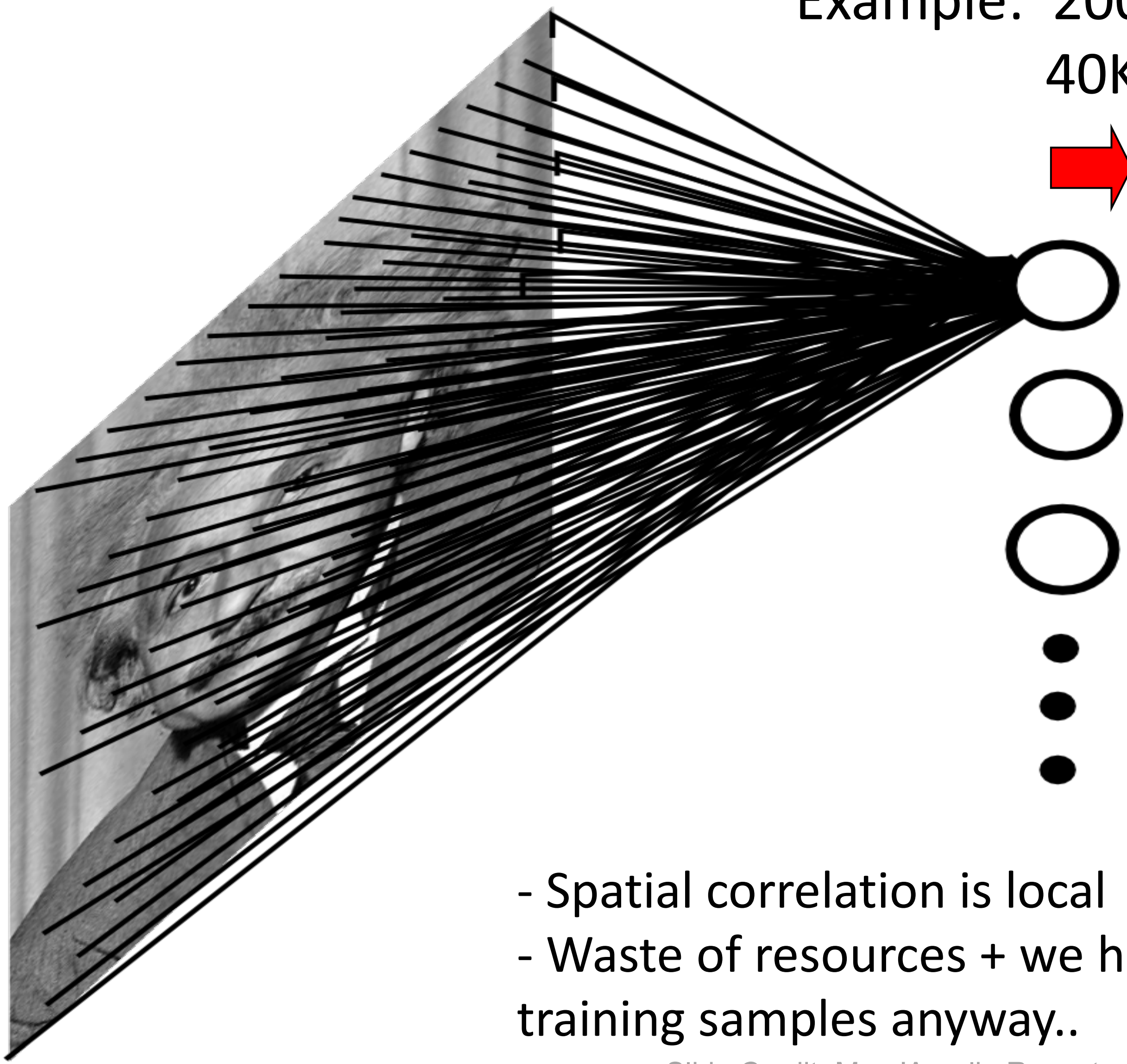
Fully Connected Layer (FC layer)

- Contains neurons that connect to the entire input volume, as in ordinary Neural Networks



Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Fully Connected Layer



Example: 200x200 image
40K hidden units
~2B parameters!!!

- Spatial correlation is local
- Waste of resources + we have not enough training samples anyway..

Slide Credit: Marc'Aurelio Ranzato

3. Learning CNN Parameters

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x,W) = Wx$ are:

cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**

A **loss function** tells how good our current classifier is

Given a dataset of examples

$$\{(x_i, y_i)\}_{i=1}^{N}$$

Where x_i is image and y_i is (integer) label

Loss over the dataset is a sum of loss over examples:

$$L = \frac{1}{N} \sum_i L_i(f(x_i, W), y_i)$$

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

How to minimize the loss by changing the weights?
Strategy: **Follow the slope of the loss function**

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Strategy: **Follow the slope**

In 1-dimension, the derivative of a function:

$$\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

In multiple dimensions, the **gradient** is the vector of (partial derivatives) along each dimension

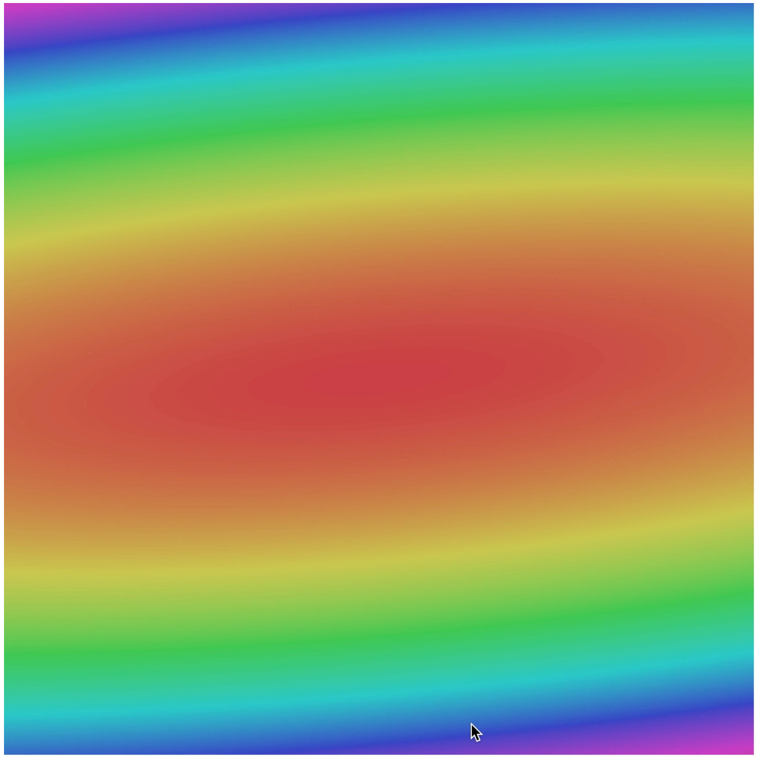
The slope in any direction is the **dot product** of the direction with the gradient

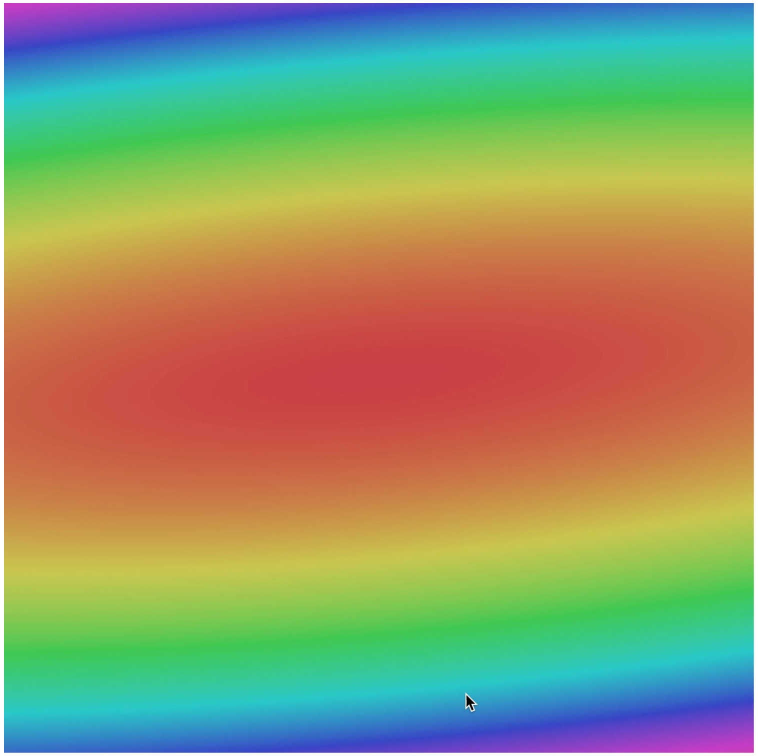
The direction of steepest descent is the **negative gradient**

Gradient Descent

```
# Vanilla Gradient Descent

while True:
  weights_grad = evaluate_gradient(loss_fun, data, weights)
  weights += - step_size * weights_grad # perform parameter update
```





Stochastic Gradient Descent (SGD)

$$L(W) = \frac{1}{N}\sum_{i=1}^{N} L_i(x_i, y_i, W) + \lambda R(W)$$

$$\nabla_W L(W) = \frac{1}{N}\sum_{i=1}^{N} \nabla_W L_i(x_i, y_i, W) + \lambda \nabla_W R(W)$$

Full sum expensive when N is large!

Approximate sum using a **minibatch** of examples
32 / 64 / 128 common

```
# Vanilla Minibatch Gradient Descent

while True:
  data_batch = sample_training_data(data, 256) # sample 256 examples
  weights_grad = evaluate_gradient(loss_fun, data_batch, weights)
  weights += - step_size * weights_grad # perform parameter update
```

How do we compute gradients?

- Analytic or “Manual” Differentiation
- Symbolic Differentiation
- Numerical Differentiation
- Automatic Differentiation!
  - Forward mode AD
  - Reverse mode AD
    - aka “backpropagation”
  - Implemented in specialized frameworks:
    - pytorch (Facebook)
    - TensorFlow (Google) frameworks
  - Main computation, mainly done on GPU (or TPU)