Caltech

MACHINE LEARNING & DATA MINING

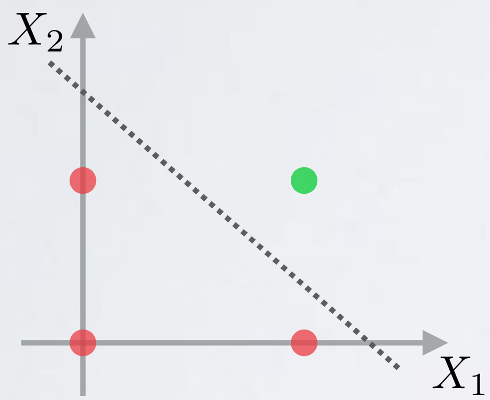
CS/CNS/EE 155

Deep Learning
Part II

recap of last lecture

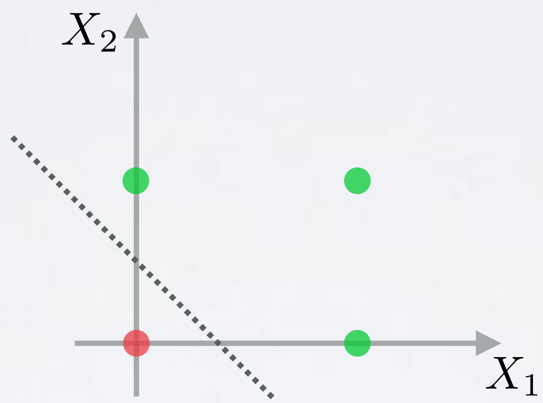
logistic regression can't handle non-linear data distributions

AND



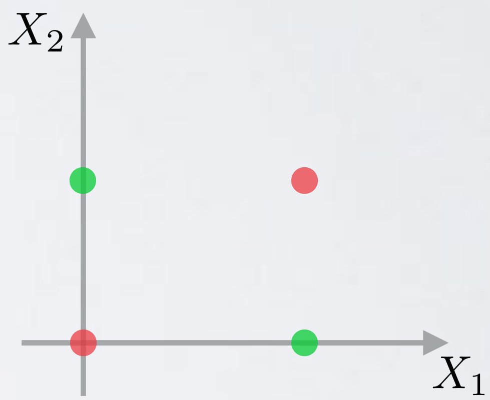
linearly separable

OR



linearly separable

XOR



not linearly separable

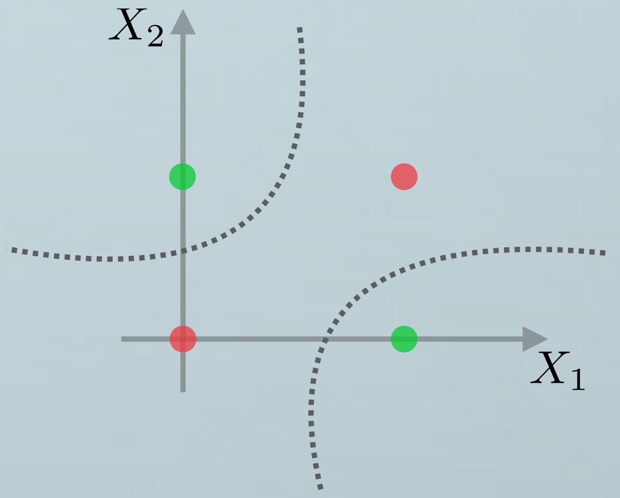
recap of last lecture

let's use non-linear features to linearize the problem!

one approach: use a set of ***hand-crafted*** non-linear transformations

$$X_1, X_2 \rightarrow X_1, X_2, X_1 X_2$$

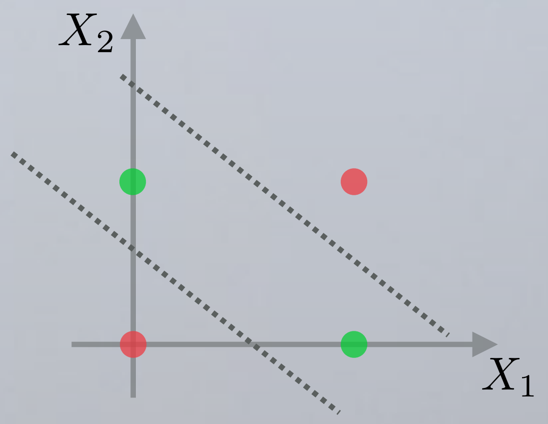
linear decision boundary — hyperbolic decision boundary



another approach: use a set of ***learned*** non-linear transformations

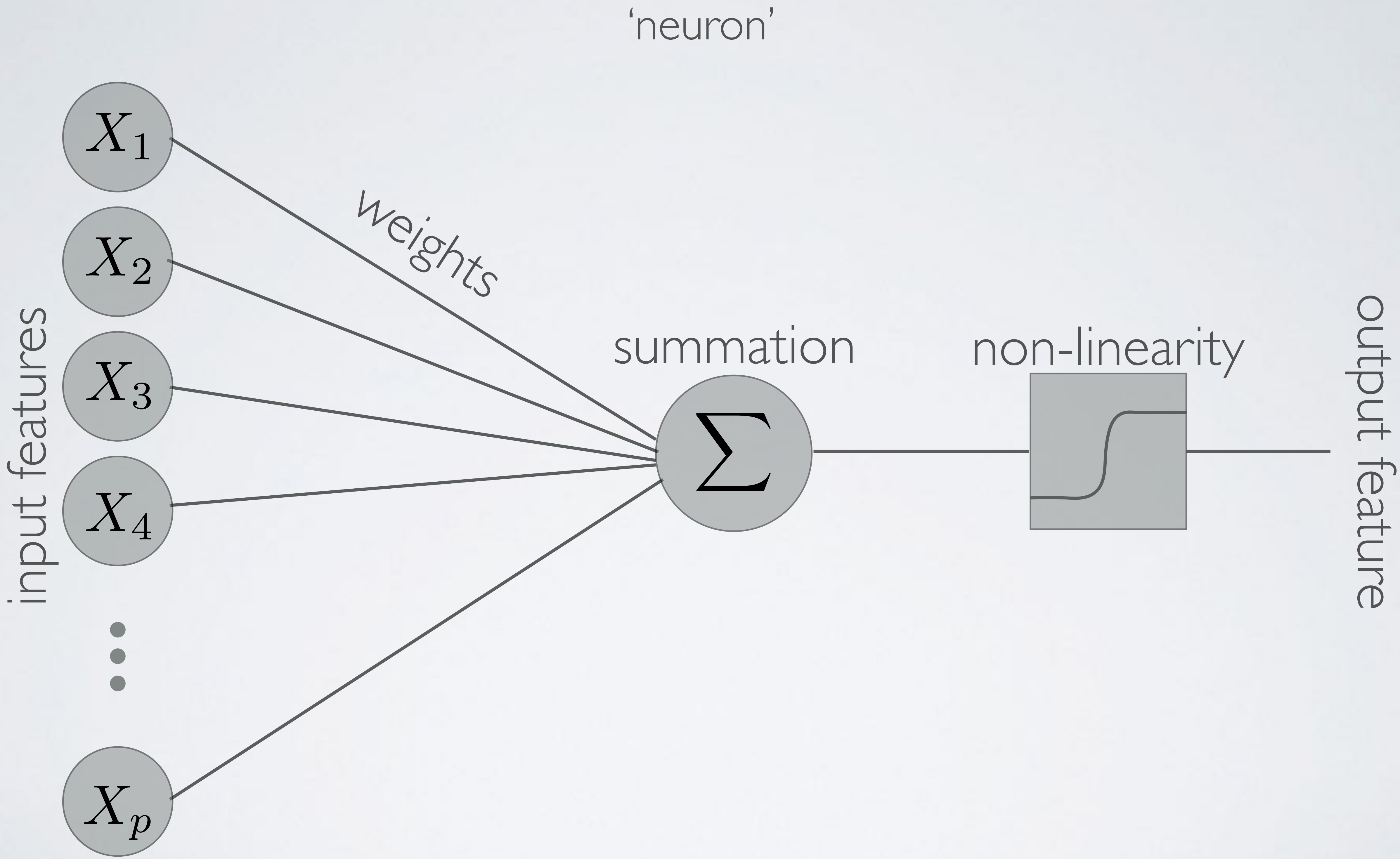
$$X_1, X_2 \rightarrow X_1 \wedge X_2, X_1 \vee X_2$$

linear decision boundary — multiple linear decision boundaries



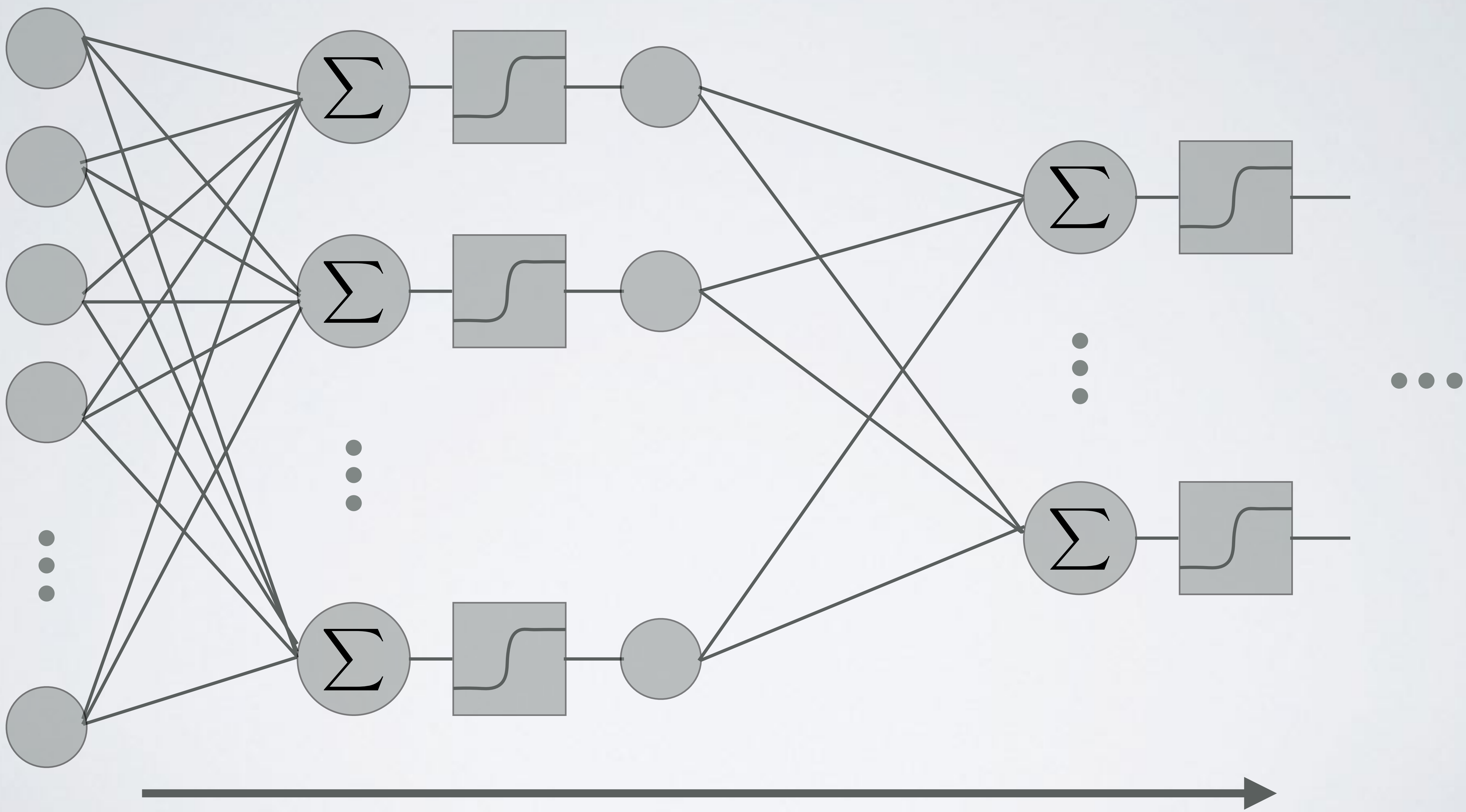
$$\longrightarrow \neg(X_1 \wedge X_2) \wedge (X_1 \vee X_2)$$

recap of last lecture



recap of last lecture

'neural network'



big picture

neural networks are function approximators that can be trained to match the data's label distribution

f(data) ~ P(label | data)

more parameters, depth → more expressive, better approximation

(as long as you don't overfit)

when is this useful?

Q: who is in this picture?

A: Yisong

Q: why? / how do you know?

A: umm…

environment | **observation** | **inference**

Yisong

pose, facial expression

jacket, collared shirt, jeans, watch

red chair, wood wall

lighting

laws of nature

black box

your brain

black box

Yisong

pose, facial expression

jacket, collared shirt, jeans, watch

red chair, wood wall

lighting

environment

Yisong

pose, facial expression

jacket, collared shirt, jeans, watch

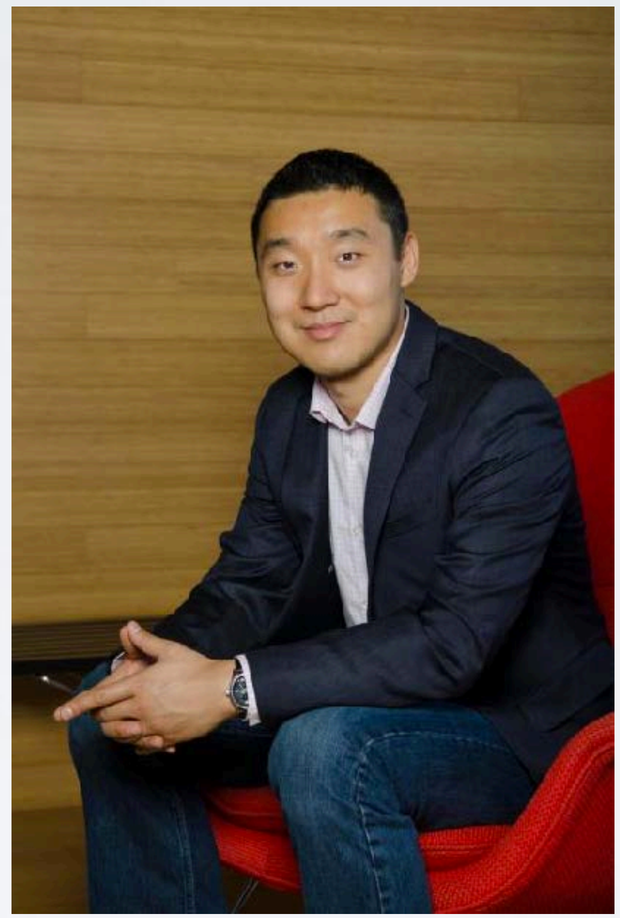
red chair, wood wall

lighting

laws of nature

black box

observation



your brain

black box

'who is this?'

inference

Yisong

pose, facial expression

jacket, collared shirt, jeans, watch

red chair, wood wall

lighting

two sides of the same coin

<u>generation</u>

there are latent properties that result in specific patterns in images

Yisong →

<u>discrimination</u>

there are patterns in images that allow us to infer latent properties

→ Yisong

the mappings between properties and images are too complicated to define manually

deep learning to the rescue!

task:

train a deep neural network to discriminate whether or not an image contains Yisong

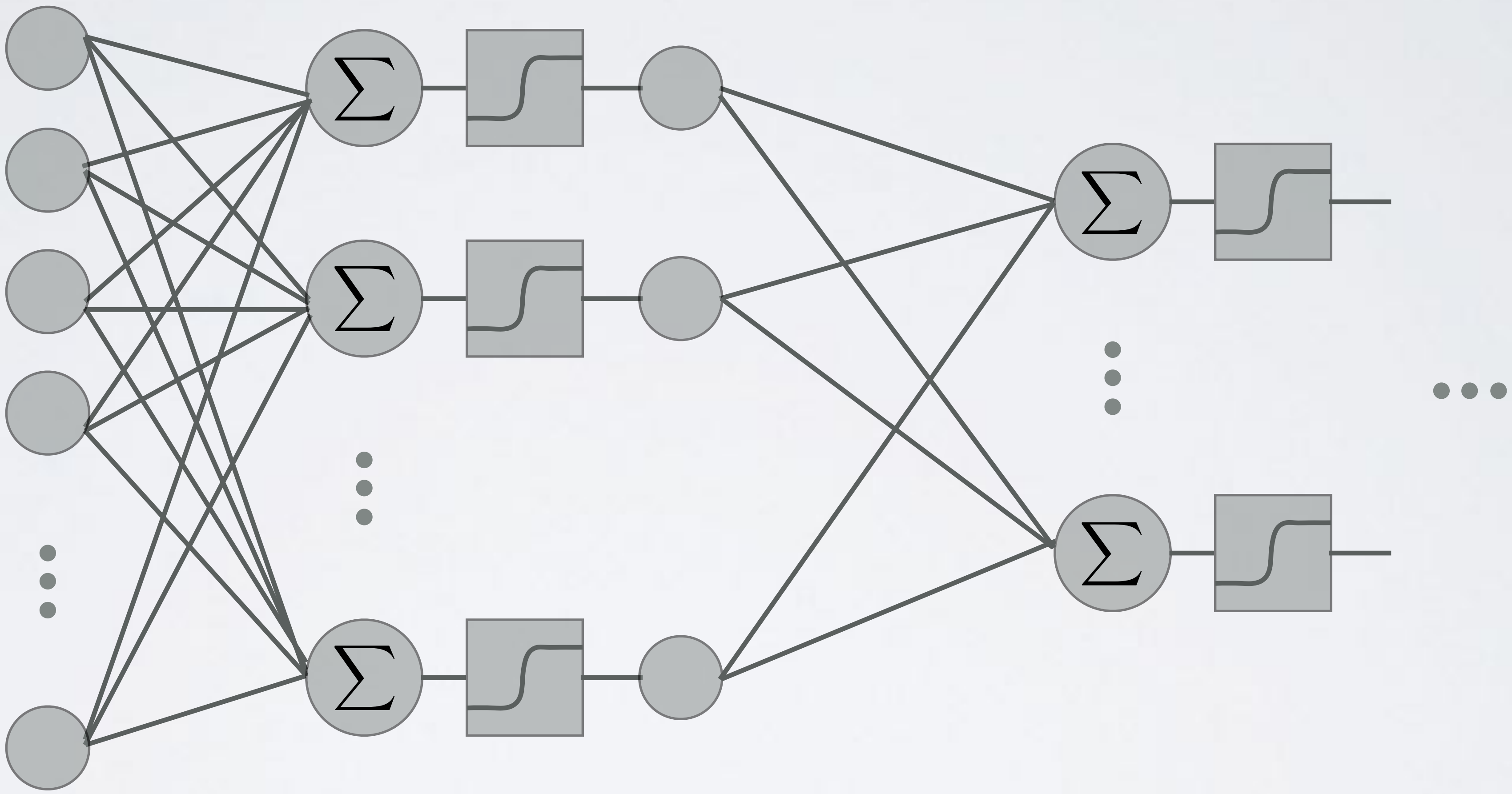
data

Yisong

not Yisong

labels

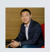
network architecture?



decide on an input size

larger input:
more parameters
clearer patterns

15 × 15 × 3

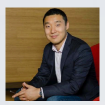


675

25 × 25 × 3

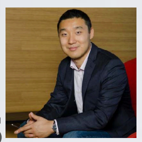
1,875

35 × 35 × 3



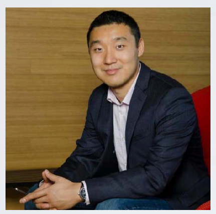
3,675

50 × 50 × 3



7,500

75 × 75 × 3



16,875

100 × 100 × 3

30,000

150 × 150 × 3

67,500

205 × 205 × 3

126,075

280 × 280 × 3

235,200

smaller input:
fewer parameters
noisier patterns

decide on an input size

larger input:
more parameters
clearer patterns

smaller input:
fewer parameters
noisier patterns

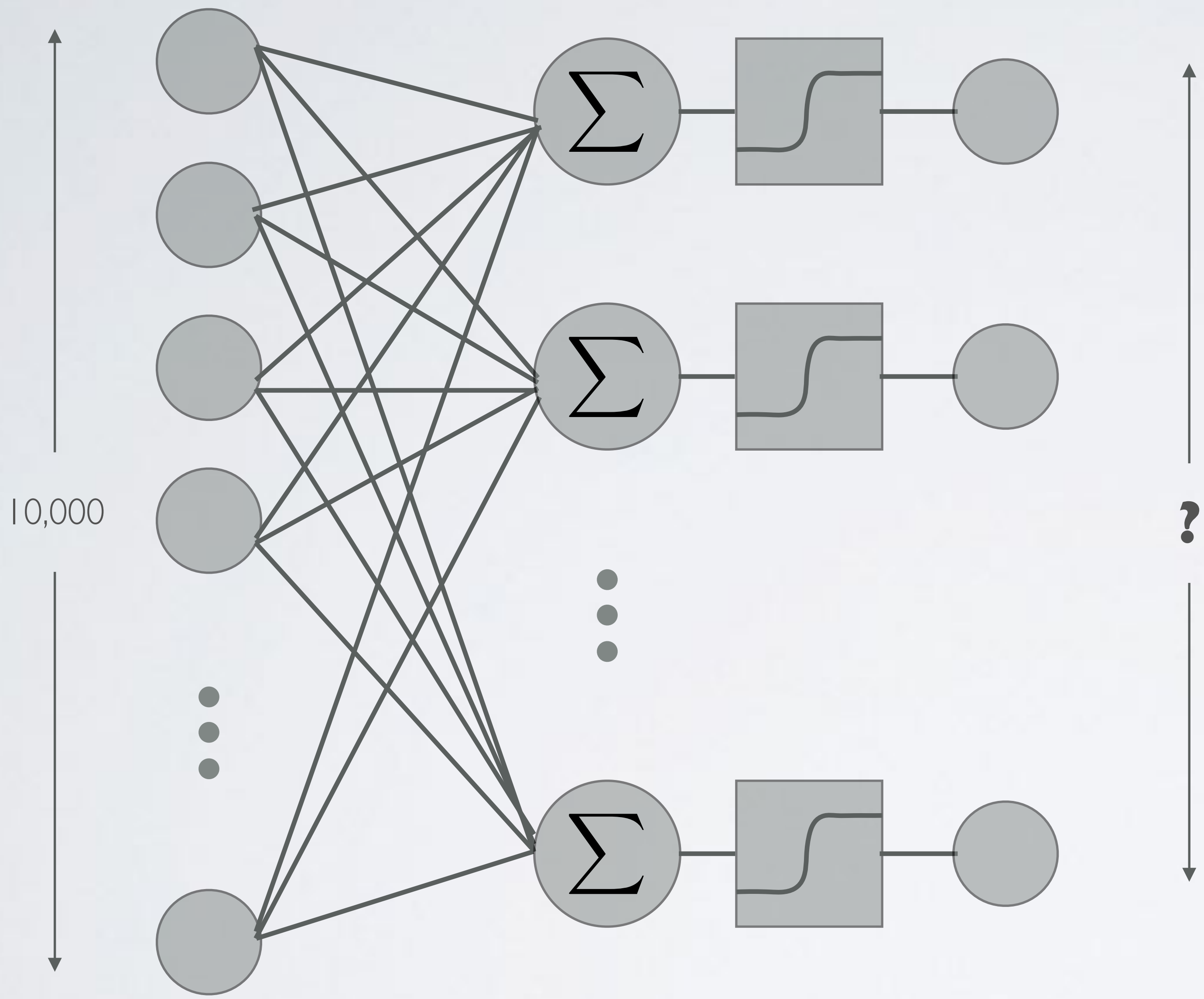
reshape the image into a vector

100 × 100 × 1

10,000

reshape

what about the rest of the architecture?



how many units can we afford?

10,000 × 100 = 1 million weights

10,000 × 1,000 = 10 million weights

10,000 × 10,000 = 100 million weights

10,000 × 100,000 = 1 billion weights

⋮

how many basic patterns do we expect to find in the image?

how many patterns can the image contain?

100 × 100 × 1

10,000

upper bound

if we consider all values (1 - 256) of all 10,000 pixels, there are $\mathbf{256^{10,000}}$ possible patterns

this is more than the number of atoms in the known, observable universe.
in reality, the actual number will be much less

lower bound

if we want to recognize *multiple* basic, low-level patterns (e.g. edges, gradients, etc.) *anywhere in the image*, I estimate there will be a total of *at least* **10,000** of these.

the actual number may be far more

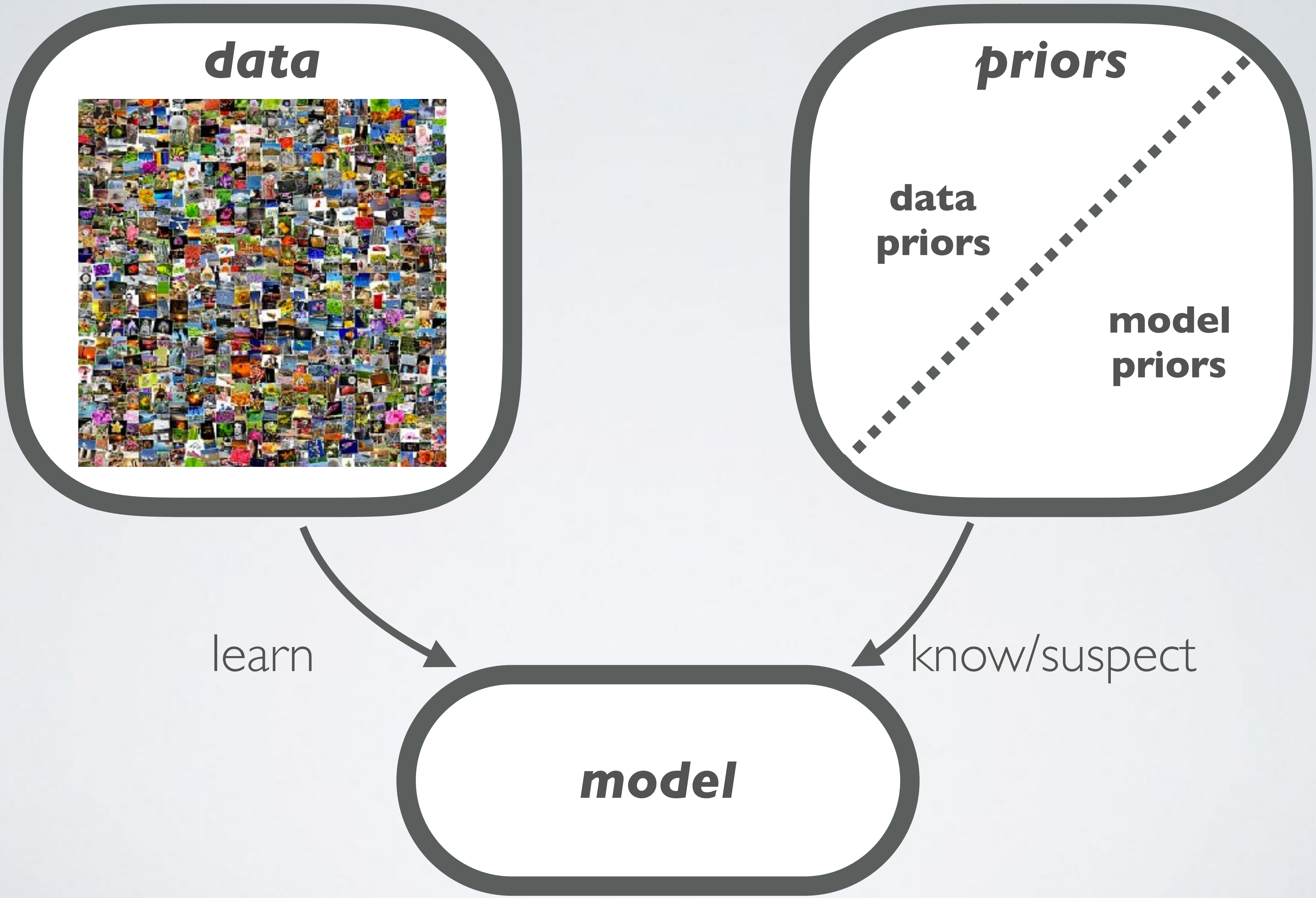
→ at least 100 million weights in the first layer alone *our approach requires a huge number of weights (parameters)*

this dramatically increases the amount of data/labels we need to collect

as well as the amount of computation required for training

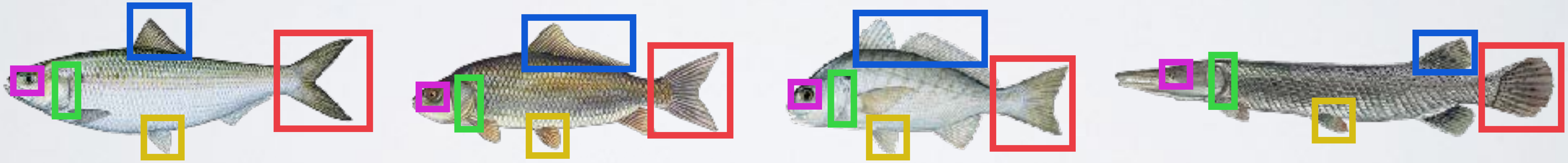
we need to re-evaluate our approach

two sources for improving a model



two sources for improving a model

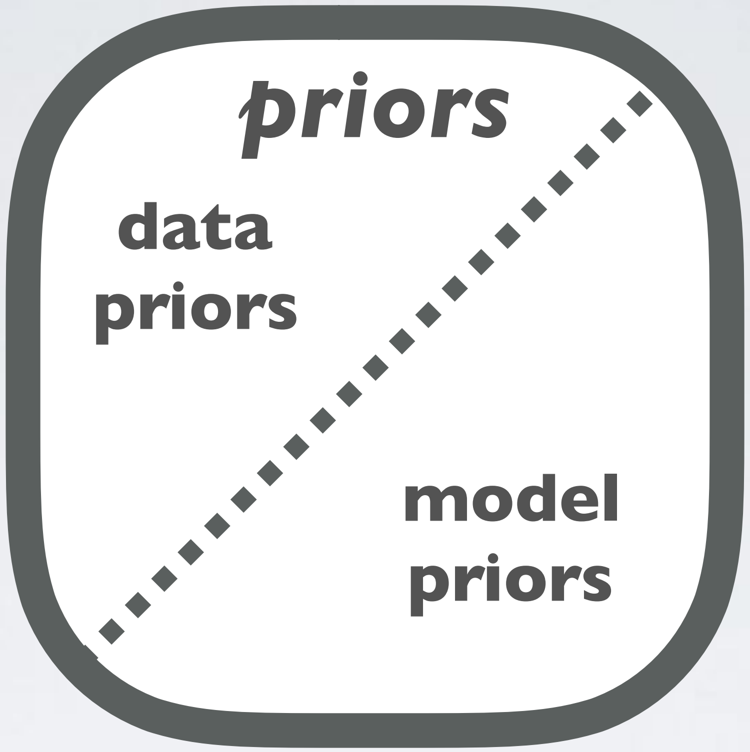
by observing data samples, we can learn about the data distribution



e.g. learn features common to fish and differences between them

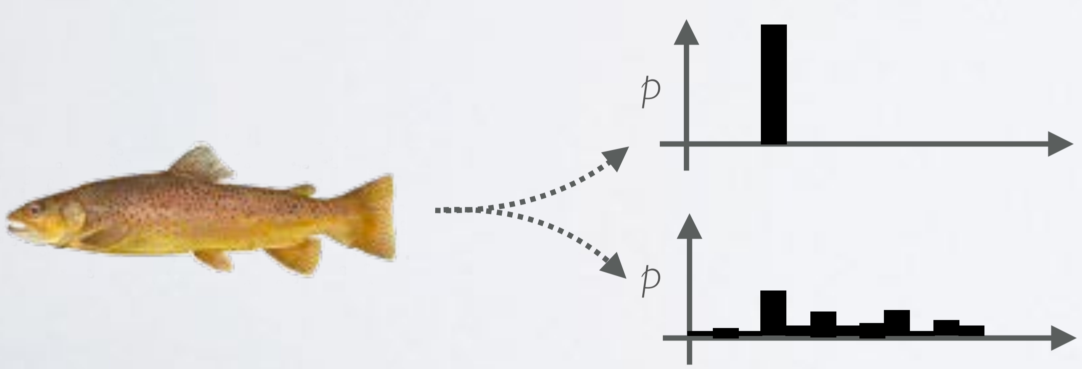
with this knowledge, we can more easily learn mappings
to/from the data to latent quantities of interest
(transfer learning from unsupervised features)

two sources for improving a model

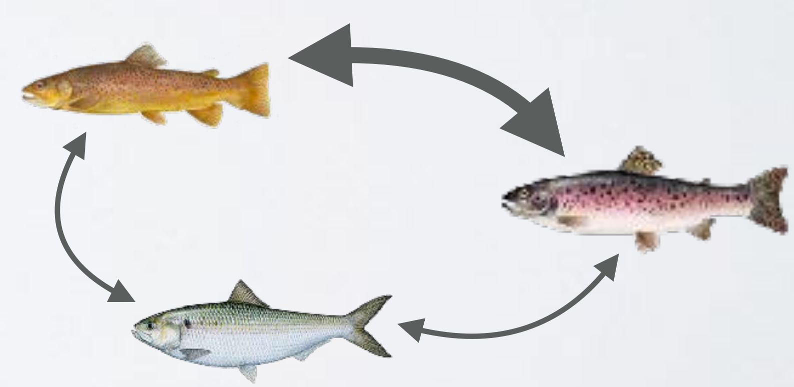


priors correspond to knowledge (or suspicions) that we already have about the task

a ***data prior*** is additional relevant information about a data example

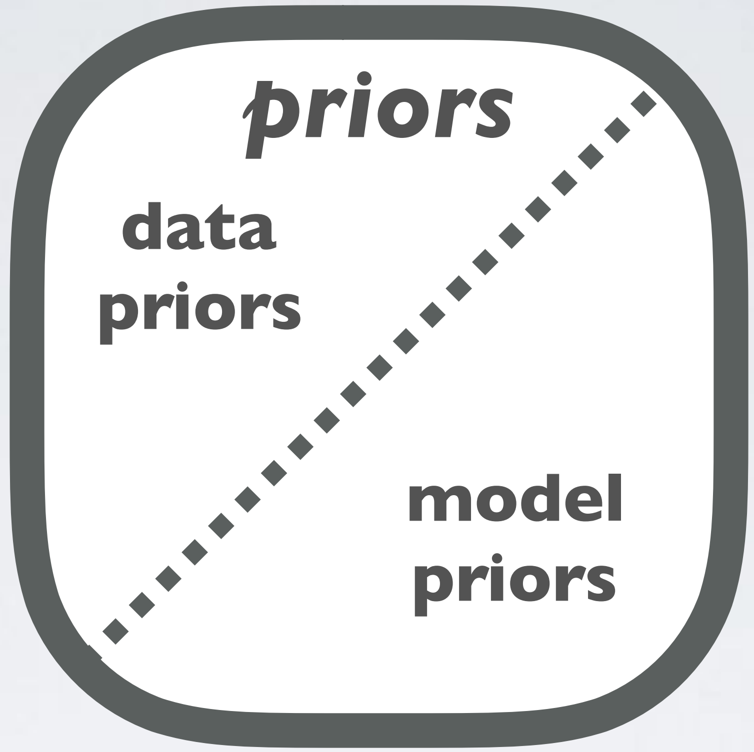


label or label distribution



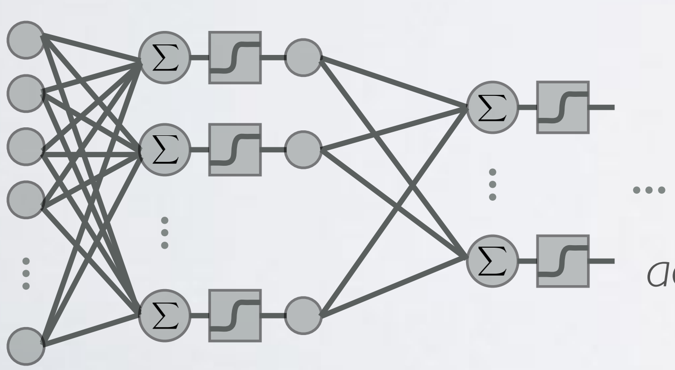
example/class similarity

two sources for improving a model



priors correspond to knowledge (or suspicions) that we already have about the task

a ***model prior*** is relevant information about the model/task



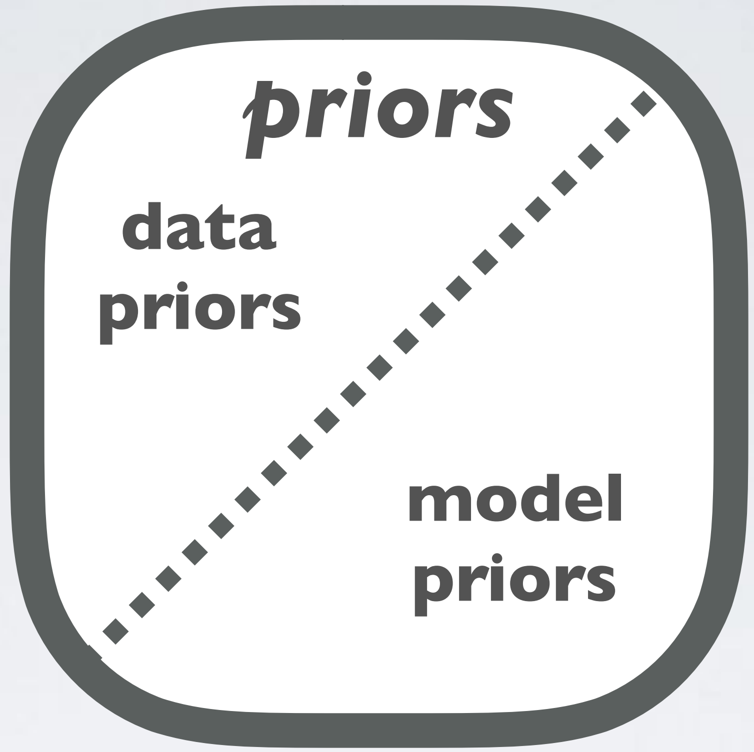
depth
layer sizes
non-linearities
output distribution
activity constraints (e.g. dropout)
etc.

model class/architecture

weight magnitude constraints (L1/L2)
transfer learning from a similar task
hand-crafted features
etc.

parameter constraints/values

two sources for improving a model



priors are necessary for any task

without them, we would have no way of knowing what/how to learn

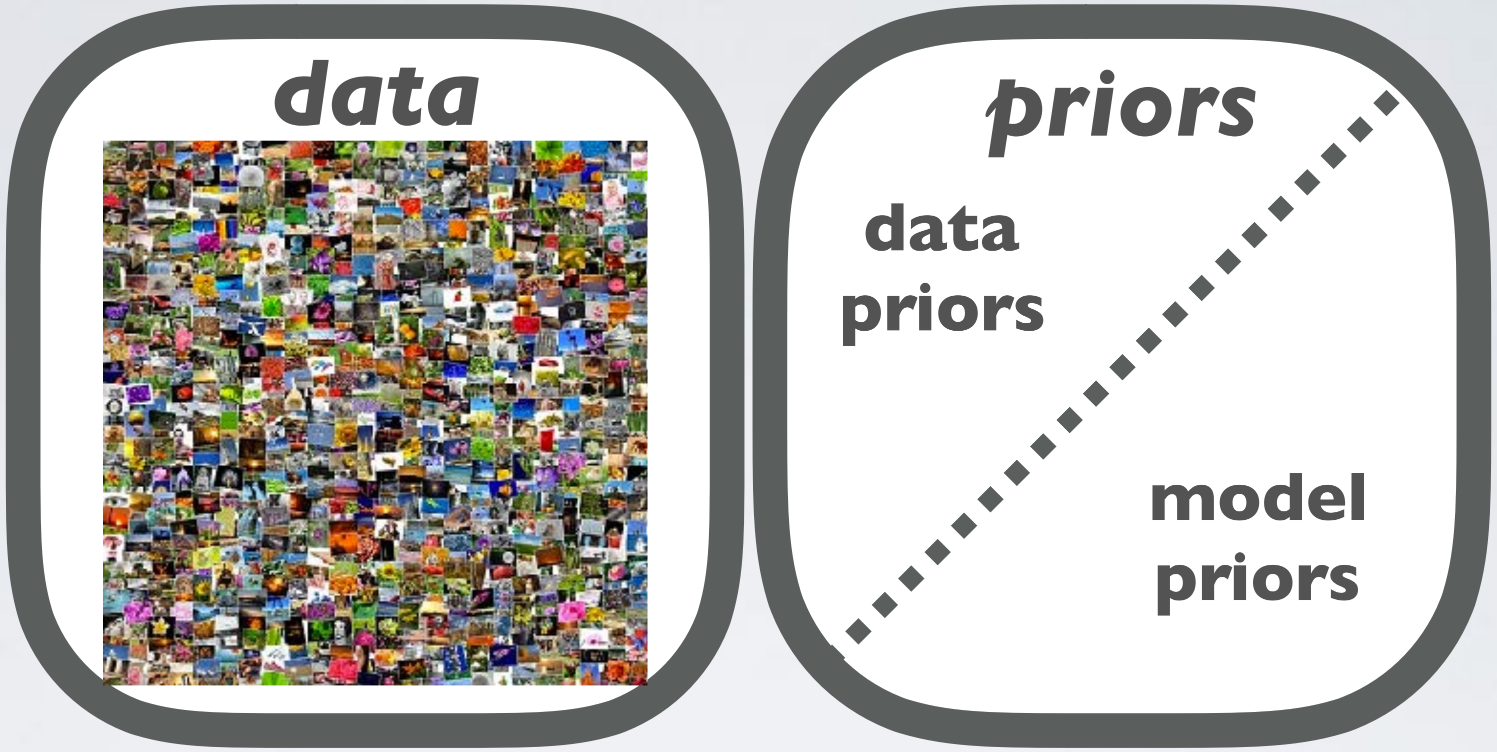
priors can vary in strength

with *strong* priors, we don't need data (we already *know* the solution)
with *weak* priors, we need a lot of data (we mostly *learn* the solution)

priors can be good or bad

good/correct priors make learning easier
bad/incorrect priors make learning more difficult or impossible

two sources for improving a model



our current approach to visual object recognition relies too heavily on data

need to impose additional/stronger priors to simplify learning

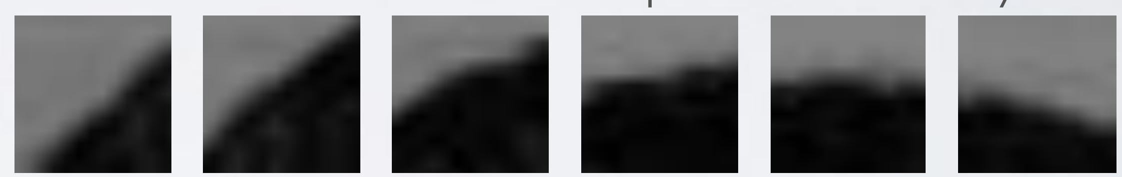
we'll impose model priors to restrict the model class for this task

properties of images

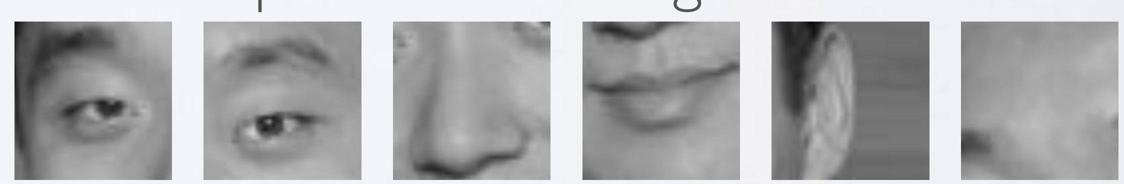
images have a notion of ***locality***, which operates at *multiple scales:*

neighboring *pixels* tend to be similar and vary in particular ways

nearby *patches* tend to share characteristics and are combined in particular ways



nearby *regions* (of objects) tend to be found in particular arrangements



properties of images

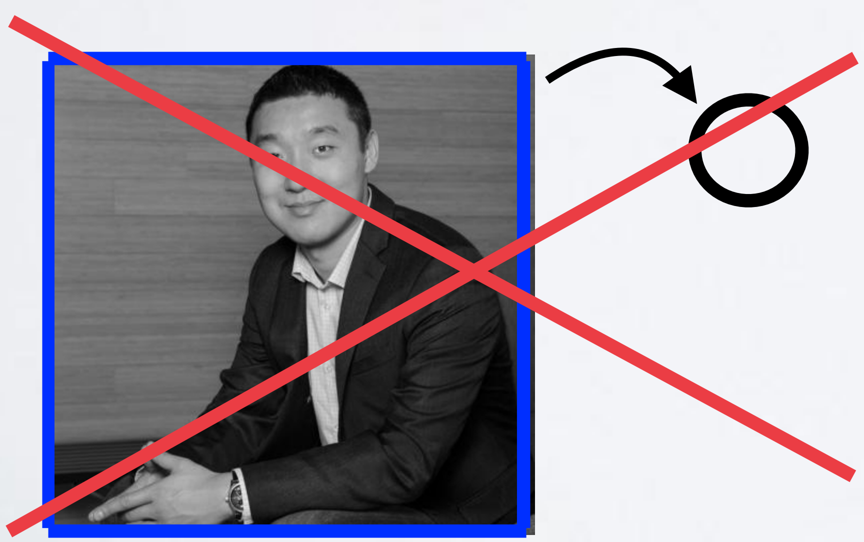
what does ***locality*** imply for our model?

more meaningful to work in image space than with reshaped vectors

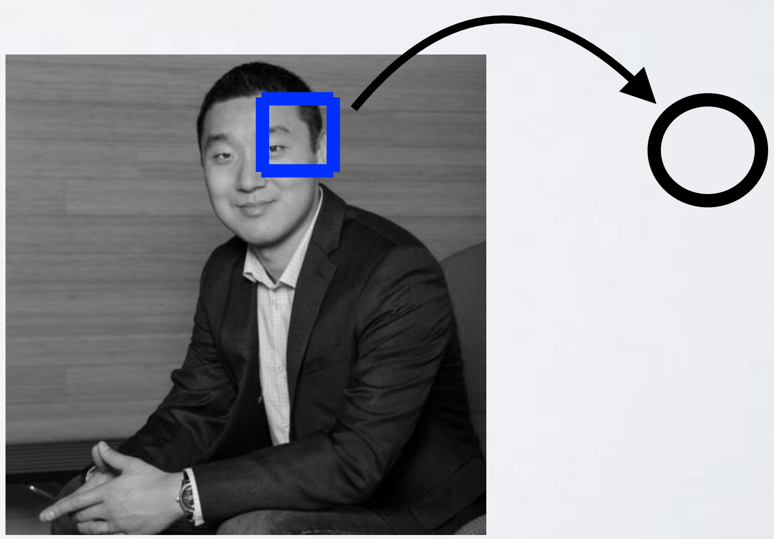
vector-space is less meaningful

image-space is more meaningful

units should restrict their inputs to areas of nearby units in the previous layer



entire input



input patch

properties of images

objects have a notion of ***translation invariance***

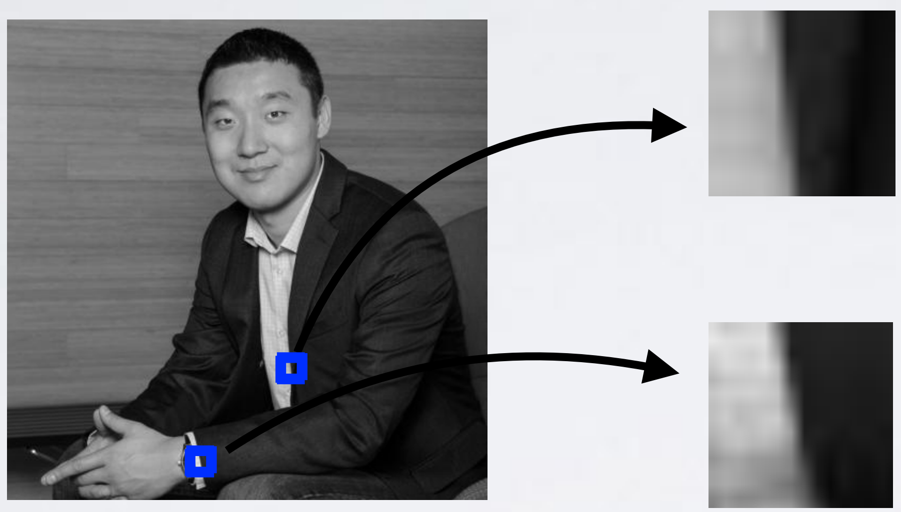
Yisong's identity is independent of his spatial location

similar statistics apply throughout the image

properties of images

what does ***translation invariance*** imply for our model?

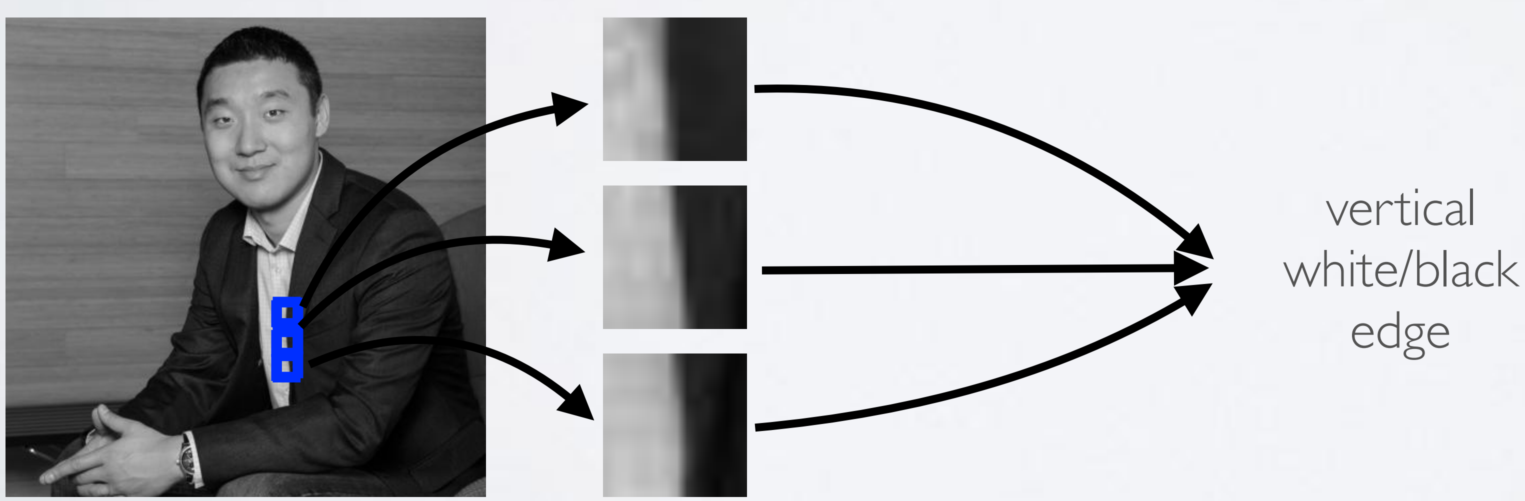
the same weights should apply throughout the input



can use the same weights
to detect both edges

only need a single
vertical edge detector
to find all vertical edges

we can aggregate (*pool*) over a feature to detect whether or not it is present



decrease the spatial size
by 'summarizing' the lower-level
activations

keep only a relevant summary

builds translation invariance

additional model priors - summary

work in the image-space

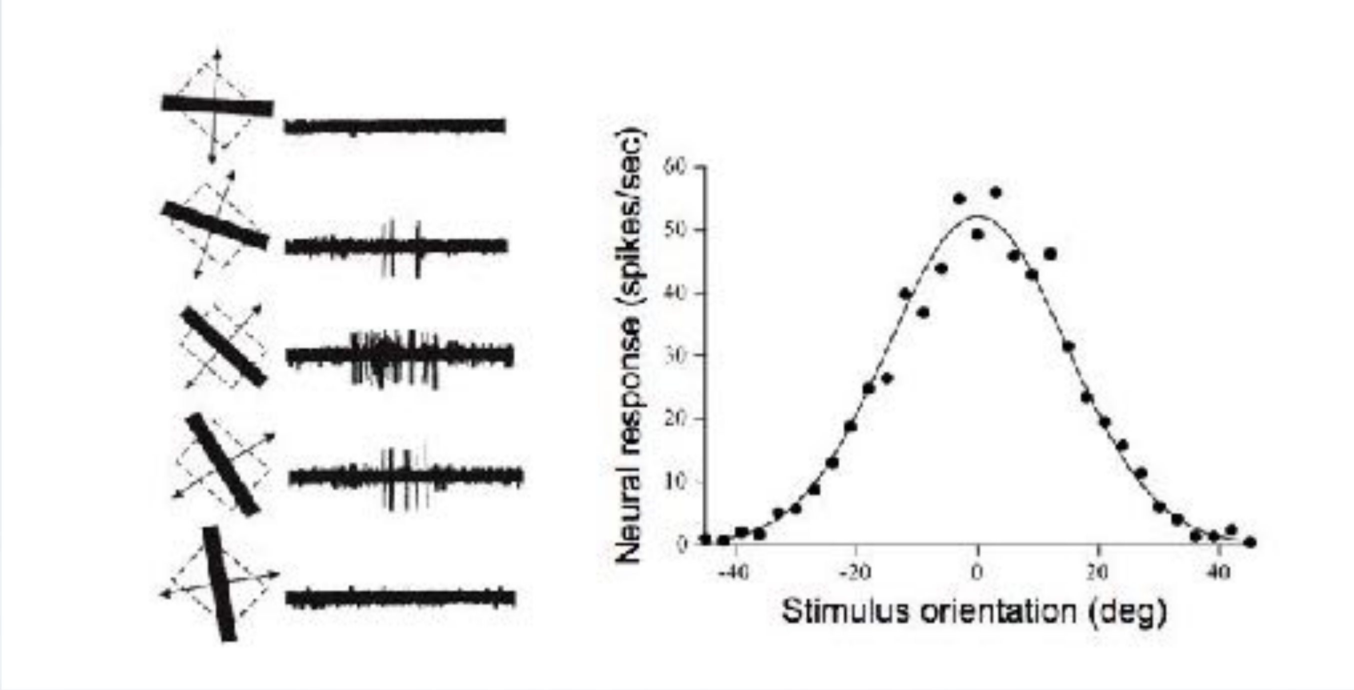
units only take a small window of inputs

weights will be shared across multiple units

pool each feature to create translation invariance

biological inspiration

how do animals recognize visual stimuli?



Hubel & Wiesel - 1950s

recorded responses of neurons in primarily visual cortex (V1) to simple visual stimuli

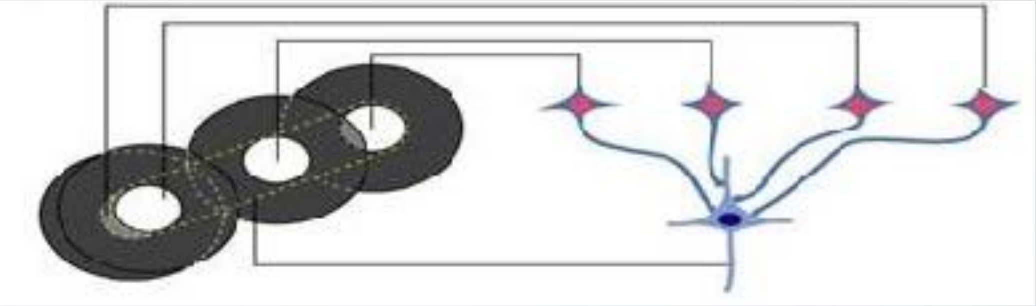
found neurons selective for bars at a specific orientation at specific locations

Hubel & Wiesel, 1959

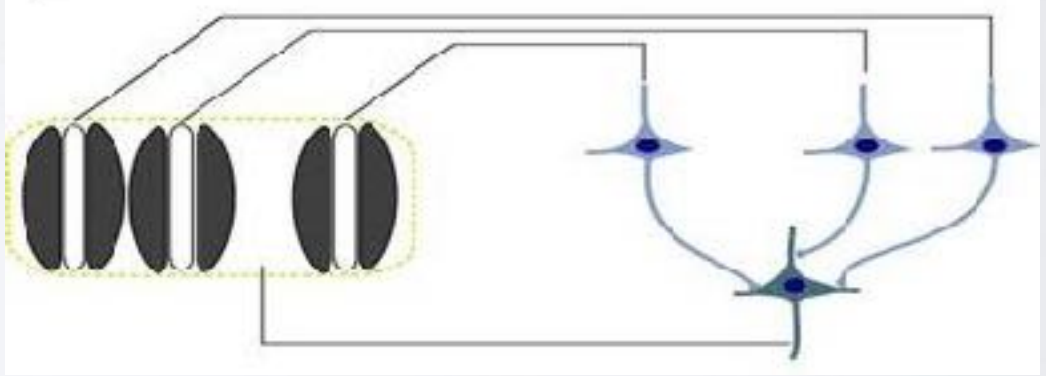
biological inspiration

how do animals recognize visual stimuli?

simple cells combine lower level features (on/off ganglion responses) within a receptive field to select for more complex features

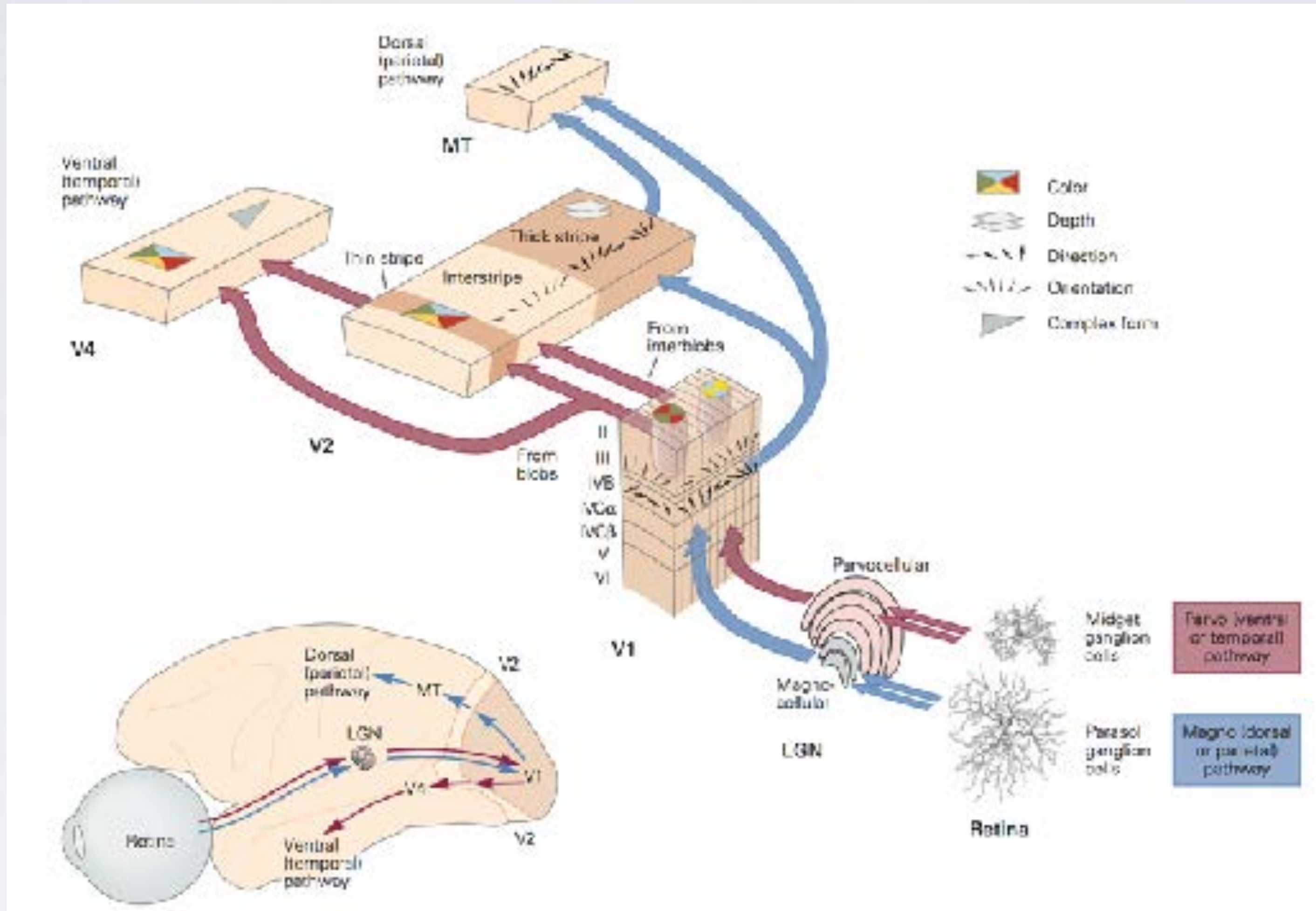


complex cells combine responses from simple cells within a larger receptive field to develop translation invariance



biological inspiration

how do animals recognize visual stimuli?



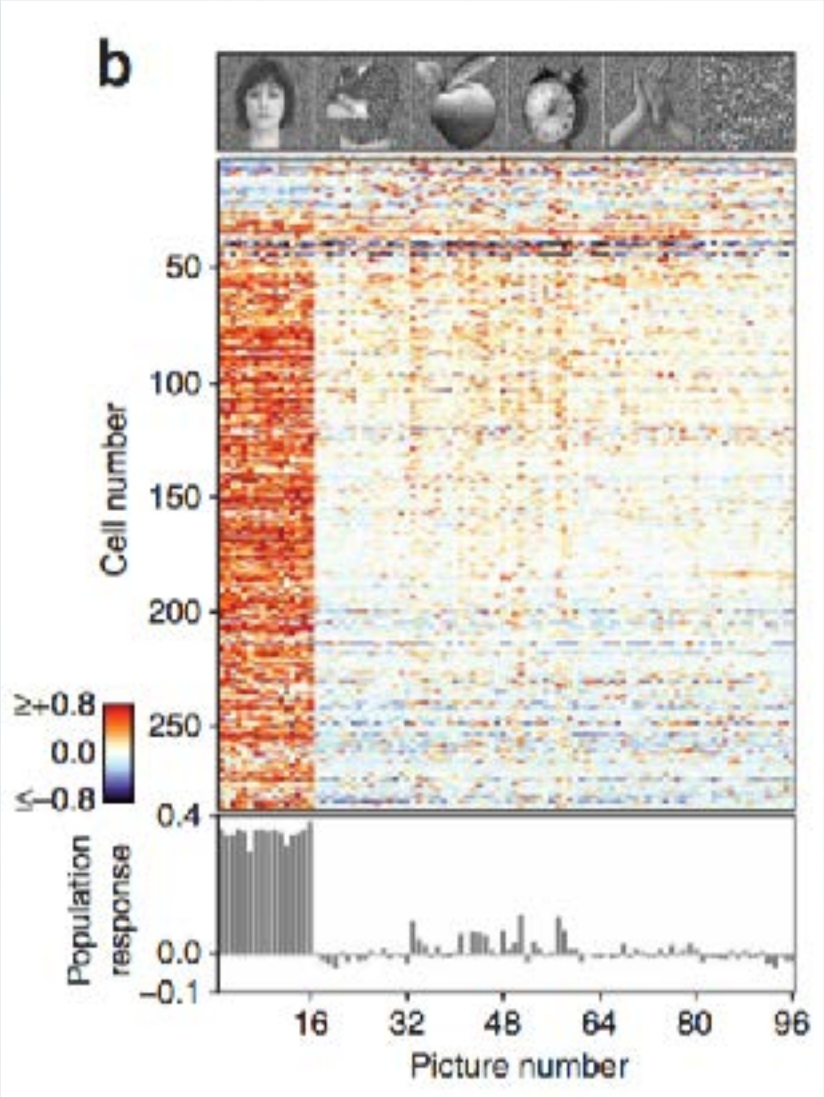
two main pathways:
<u>recognition/what (ventral) pathway</u> & location/where (dorsal) pathway

simple visual features are combined hierarchically to select for more complicated visual features

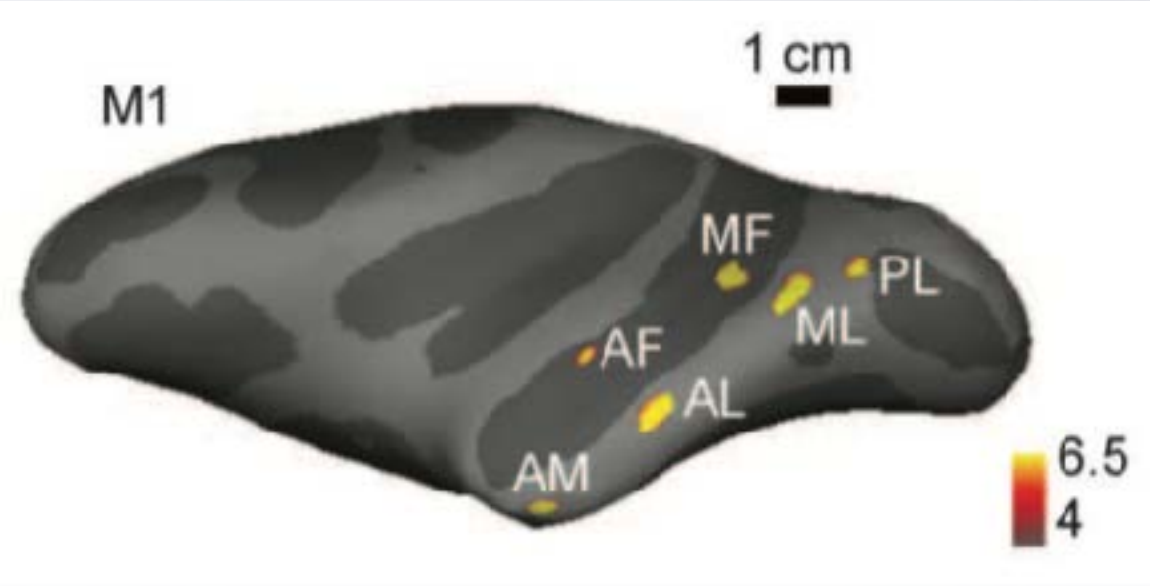
Kandel et al., 2012

biological inspiration

how do animals recognize visual stimuli?



face 'patches'



areas higher in the recognition hierarchy are selective for highly specific features

these areas tend to be densely interconnected
and relatively invariant to spatial location

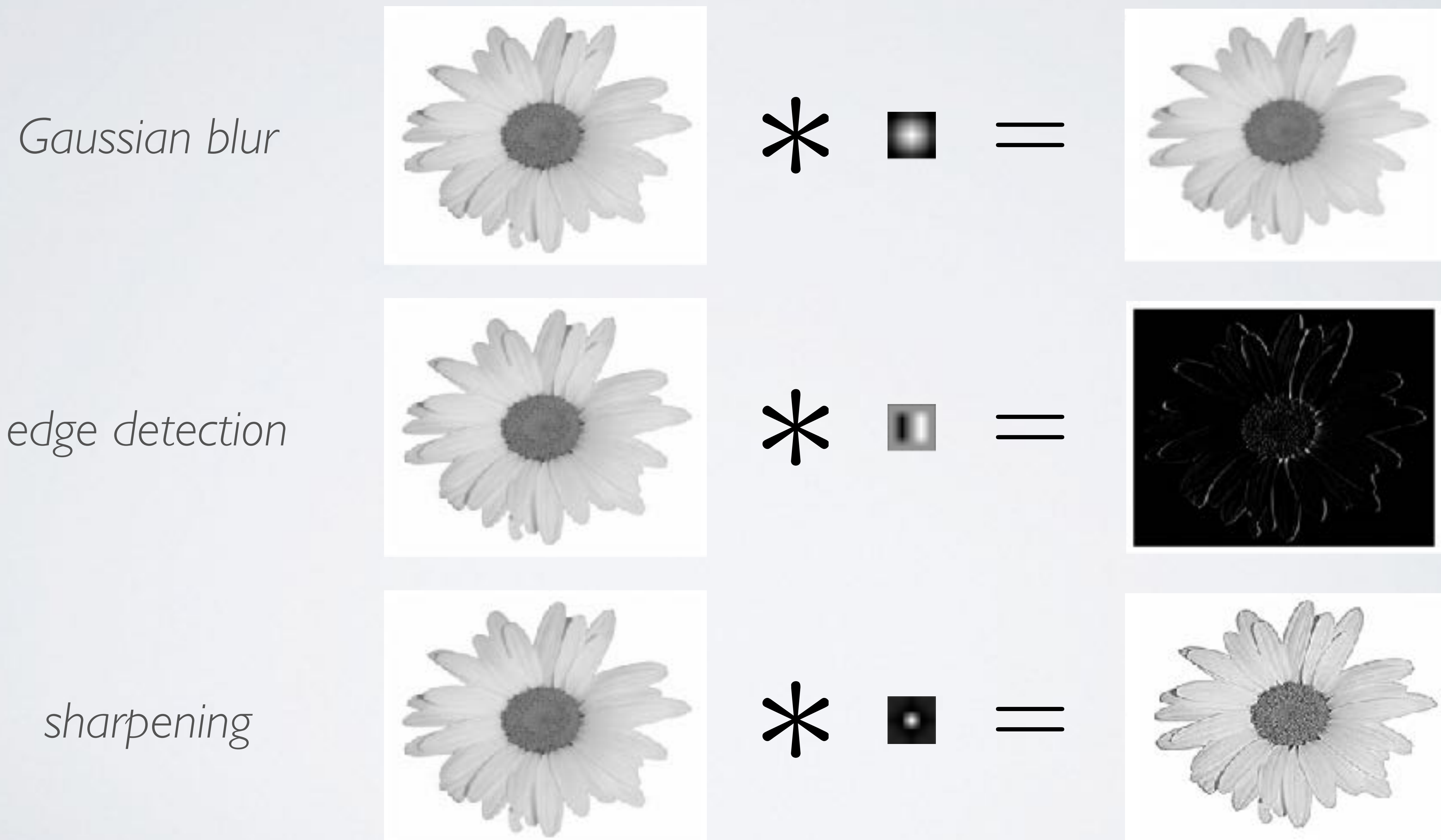
Friewald et al., 2009, 2010

CONVOLUTIONAL NEURAL NETWORKS

(discrete) convolution

convolution is a filtering operation

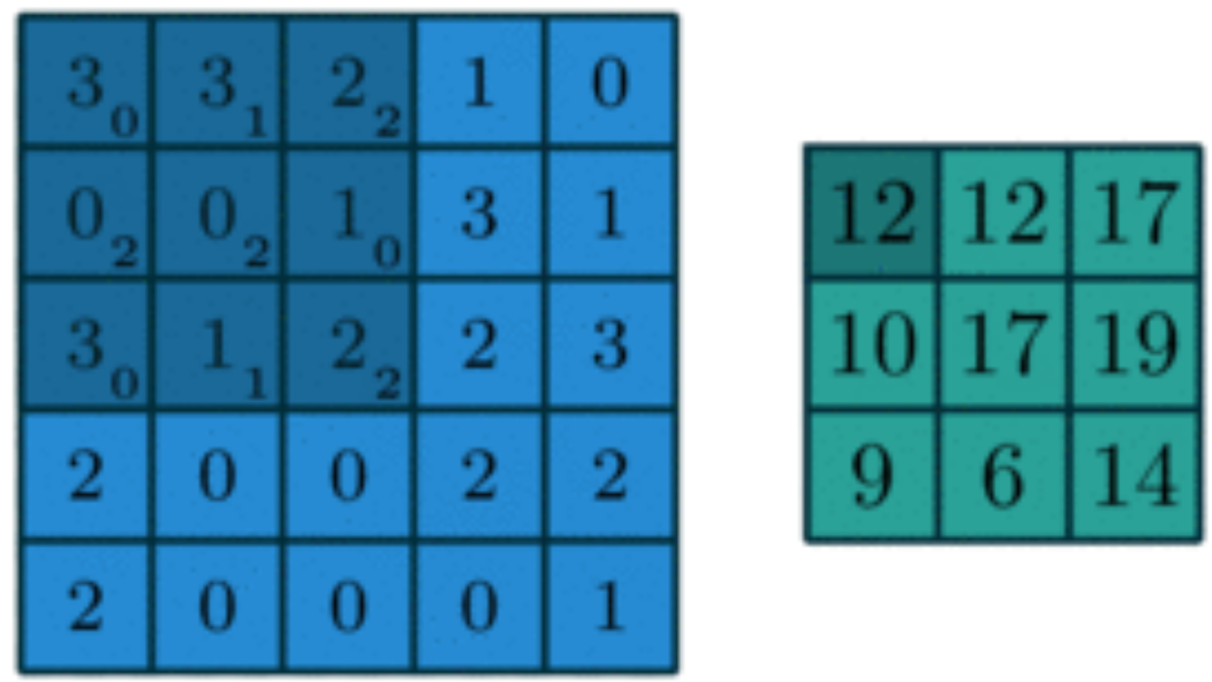
convolve a filter/kernel with the input



(discrete) convolution

example:

$$\text{filter weights} = \begin{pmatrix} 0 & 1 & 2 \\ 2 & 2 & 0 \\ 0 & 1 & 2 \end{pmatrix}$$



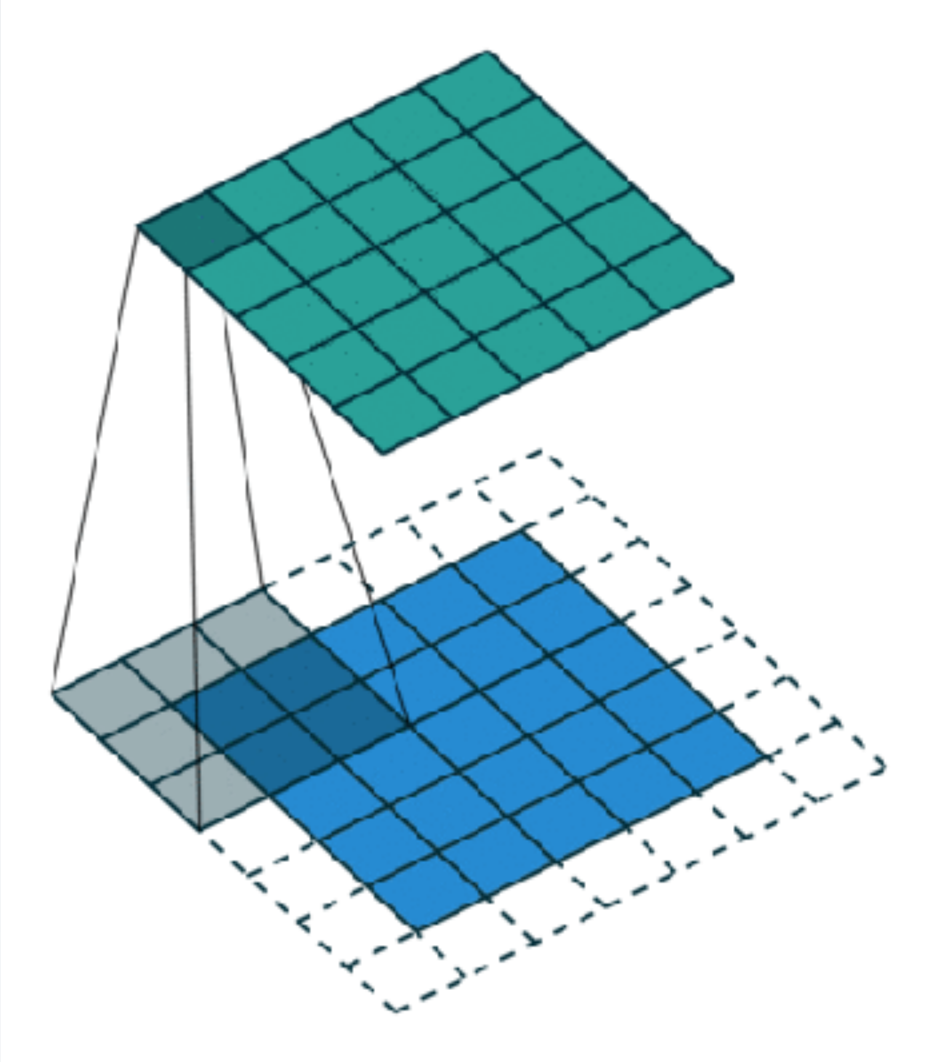
take the *inner-product* of filter weights and input patches across entire input

the output is a measure of the degree of the filter feature's presence at each location in the input, known as a ***feature map***

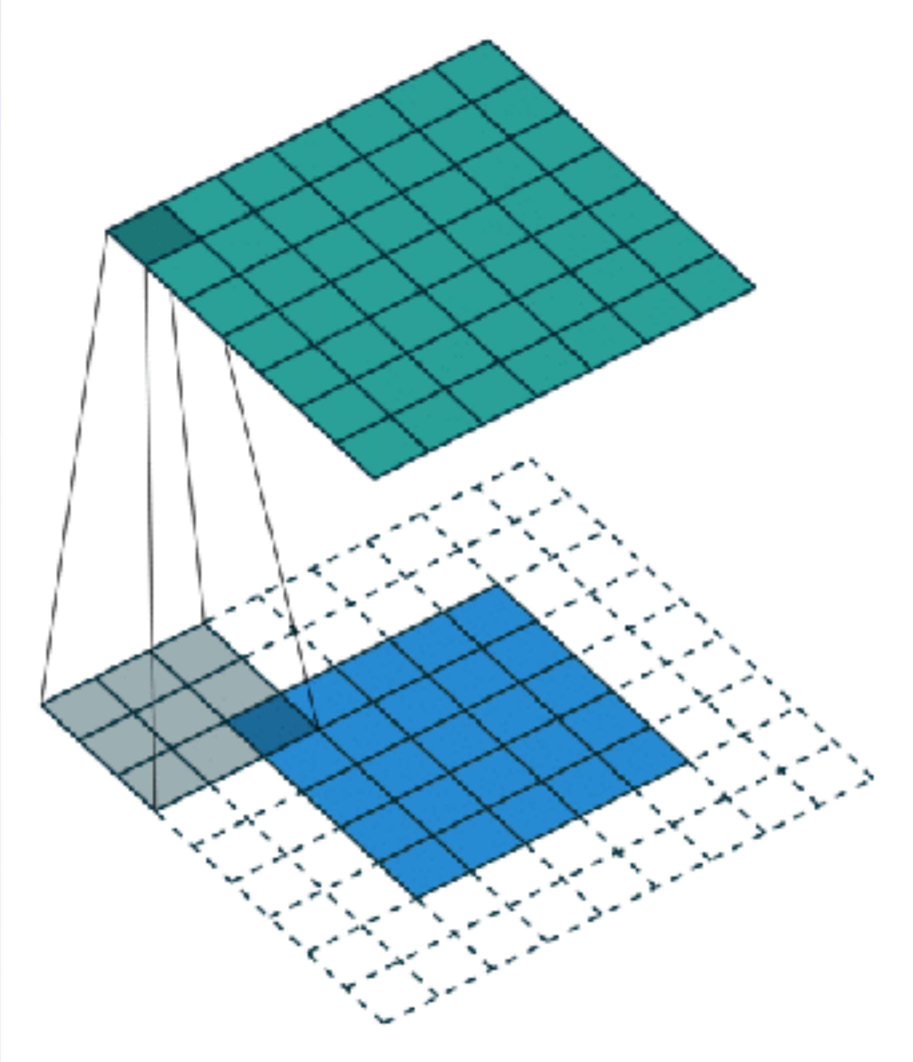
http://deeplearning.net/software/theano_versions/dev/tutorial/conv_arithmetic.html

padding

half (same) padding



full padding



we can ***pad*** the input with additional values (typically zeros) around the perimeter

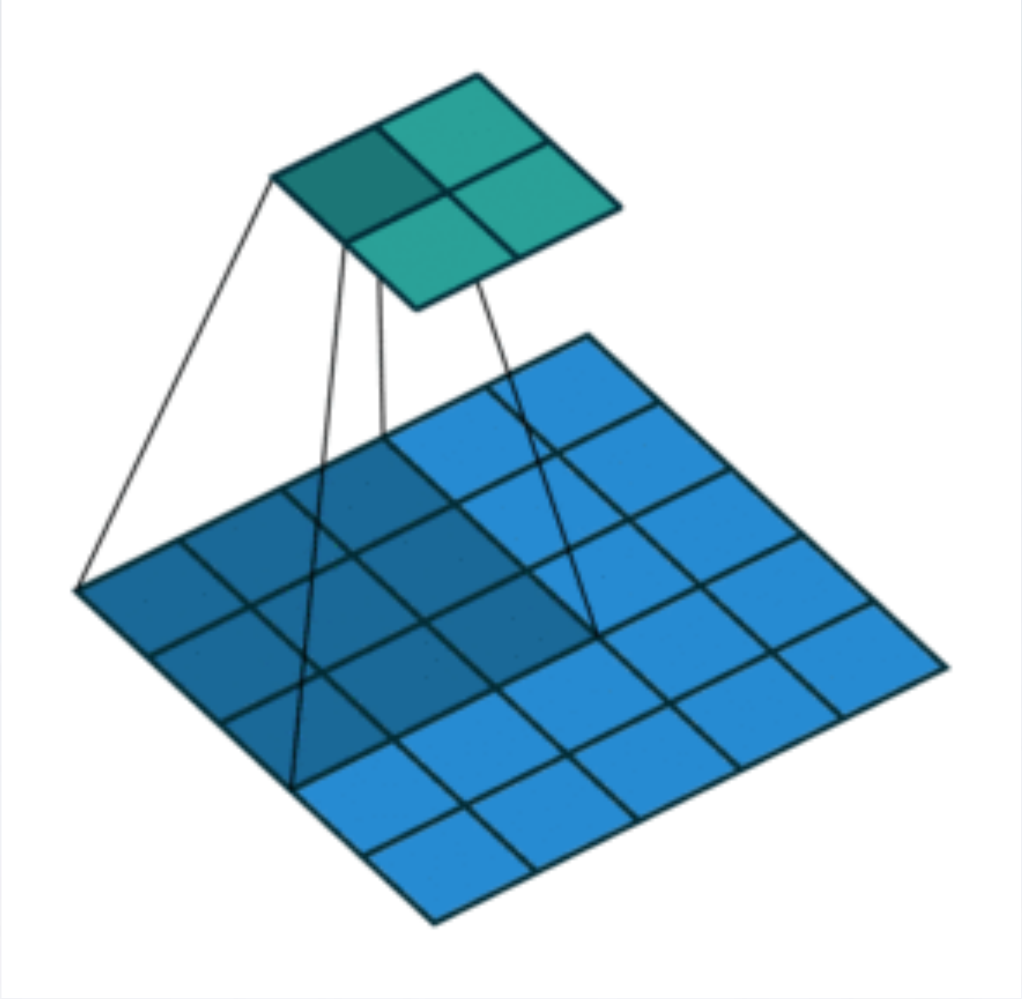
this increases the output spatial size in comparison with non-padded convolutions

'same' padding maintains the input size
note that *'valid'* padding refers to no padding

http://deeplearning.net/software/theano_versions/dev/tutorial/conv_arithmetic.html

stride

vertical stride = horizontal stride = 2

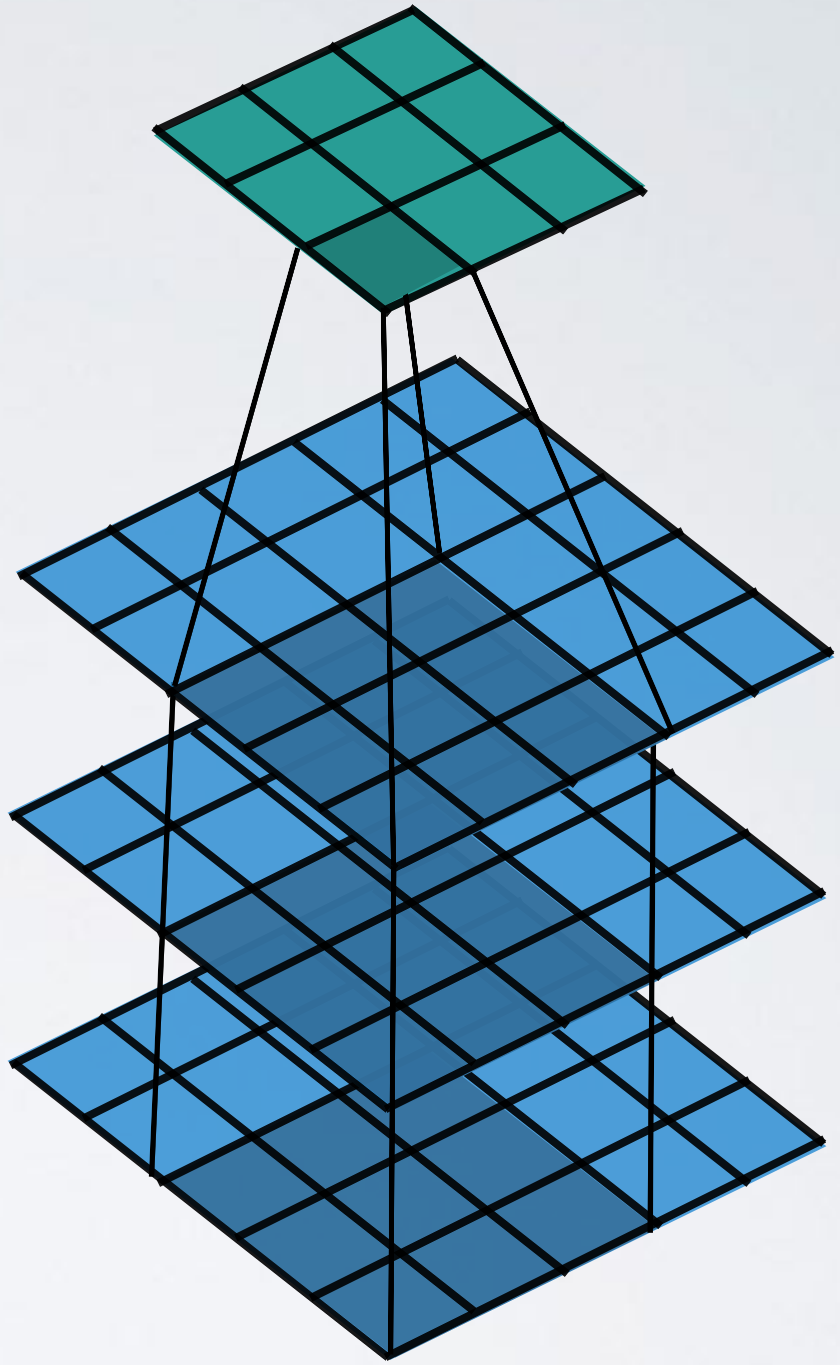


we can apply the kernel with a ***stride***, only computing the output at certain integer intervals

this <u>decreases</u> the output spatial size in comparison with non-strided convolutions, where the stride is one

http://deeplearning.net/software/theano_versions/dev/tutorial/conv_arithmetic.html

(discrete) convolutions



3 x 3 x 3 filter tensor

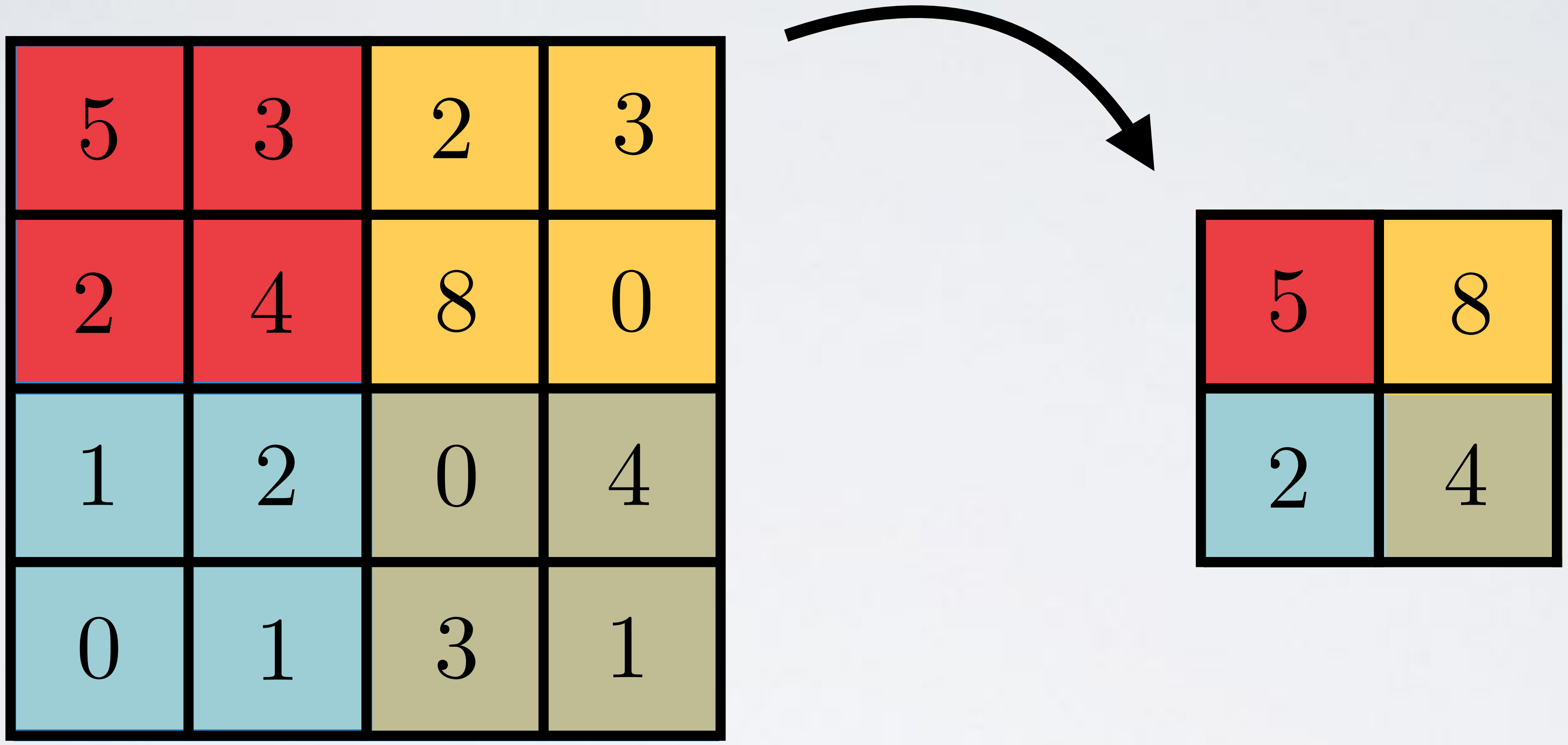
convolutions can be applied over *multiple* input feature maps

in this case, instead of being a matrix, *the kernel/filter is a tensor*

can handle RGB images

pooling

example: *max pooling, 2 x 2 window, stride 2, no padding*



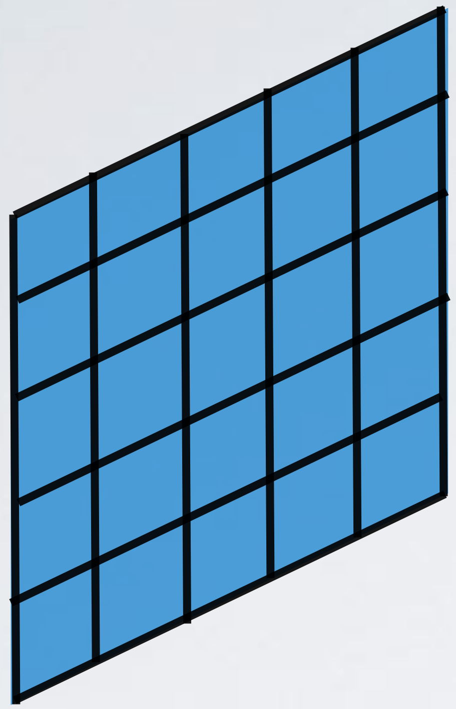
aggregate (pool) over each feature map

pooling is performed over a window

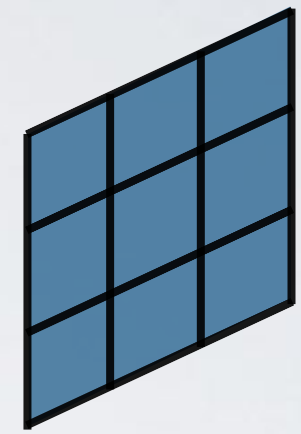
pad and *stride* can also be applied

can use different operations, e.g. max, average, etc.

convolutional pop quiz



5 x 5 input feature map



3 x 3 filter

a 3 x 3 filter is convolved with a 5 x 5 input feature map

if we use *unit strides* and *no padding ('valid')*, what is the output spatial size? 3 x 3

if we use a *stride of 2* and *no padding ('valid')*, what is the output spatial size? 2 x 2

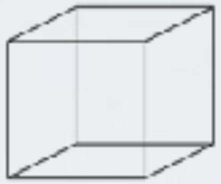
if we use *unit strides* and *half padding ('same')*, what is the output spatial size? 5 x 5

if we use a *stride of 2* and *half padding ('same')*, what is the output spatial size? 3 x 3

fully-connected vs. convolutional

example calculation

convolutional layer with 64 3 x 3 filters operating on 3 input channels

64 x  + 64

→ 64 filters x 3 x 3 x 3 + 64 biases = <u>1792 parameters</u>

note that the number of parameters is independent of the spatial size

if the input dimension is 128 x 128 and the convolution is applied with unit strides and 'same' padding, the convolutional layer will have an output size of 64 x 128 x 128 = <u>1,048,576 units</u>

to get the same number of output units from a **fully-connected layer** would require (128 x 128 x 3) x 1,048,576 + 1,048,576 = <u>51,540,656,128 parameters</u>

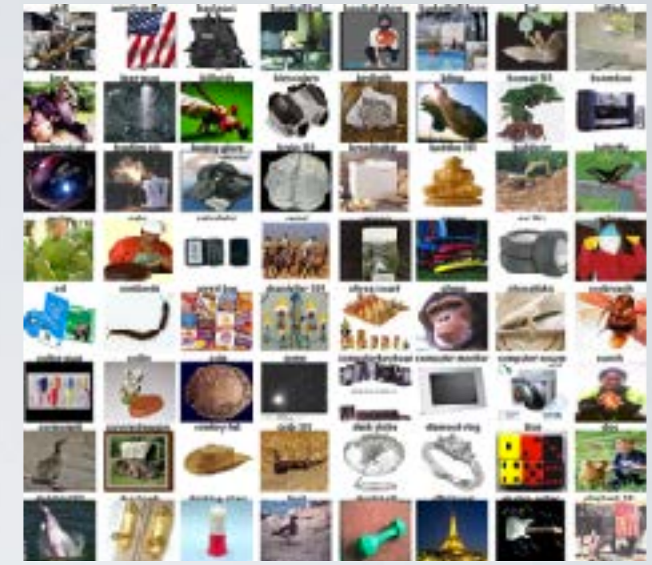
if the assumptions we made about images (locality, translation invariance) are valid, then we have <u>reduced the number of parameters by a factor of over *10 million*</u>

convolutional layers allow us to trade off *flexibility* for an *increased representation size*

image datasets

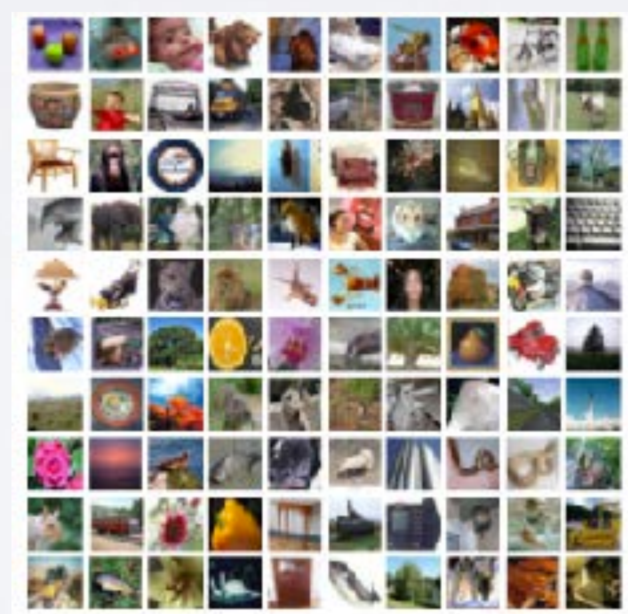
MNIST
10 classes,
60,000 images

Caltech-101
101 classes,
9,146 images



Caltech-256
256 classes,
30,607 images

PASCAL VOC
20 classes,
9,963 images



CIFAR 10
10 classes,
60,000 images

CIFAR 100
100 classes,
60,000 images

image datasets

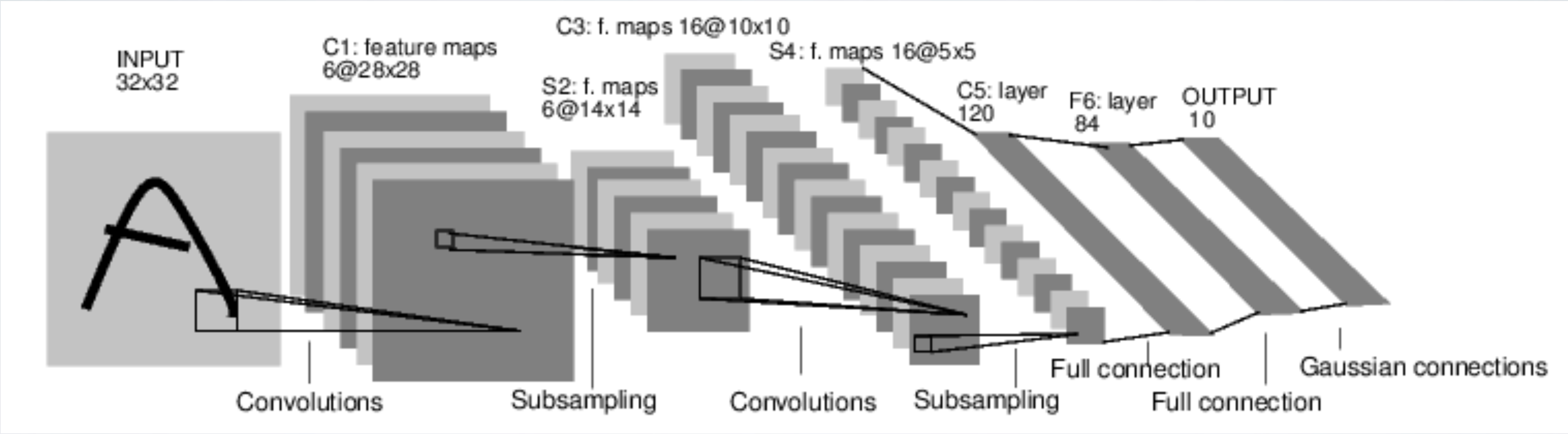
ImageNet

Competition (ILSVRC) Dataset
1,000 classes,
1.2 million images

Full Dataset
21,841 classes,
14 million images

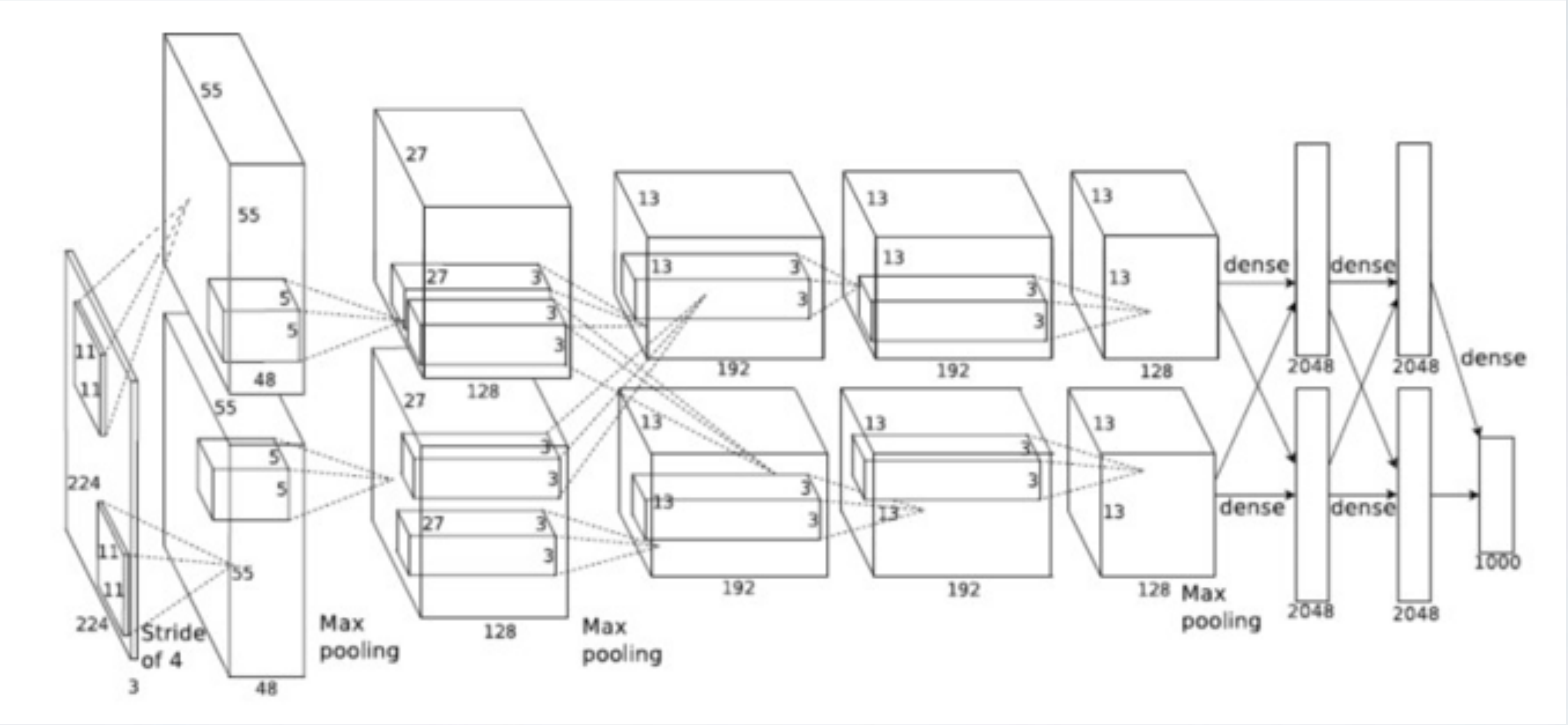
karpathy.github.io

models



LeNet - 1998

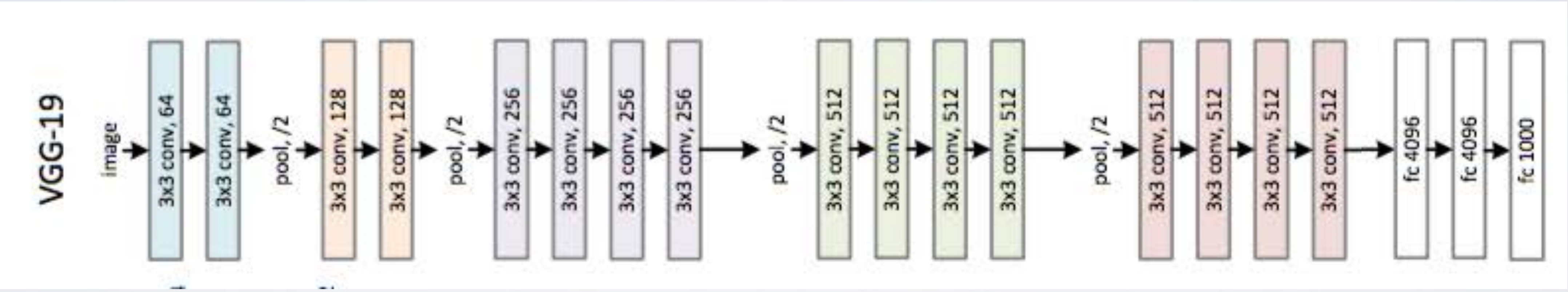
LeCun et. al, 1998



AlexNet - 2012

Krizhevsky et. al, 2012

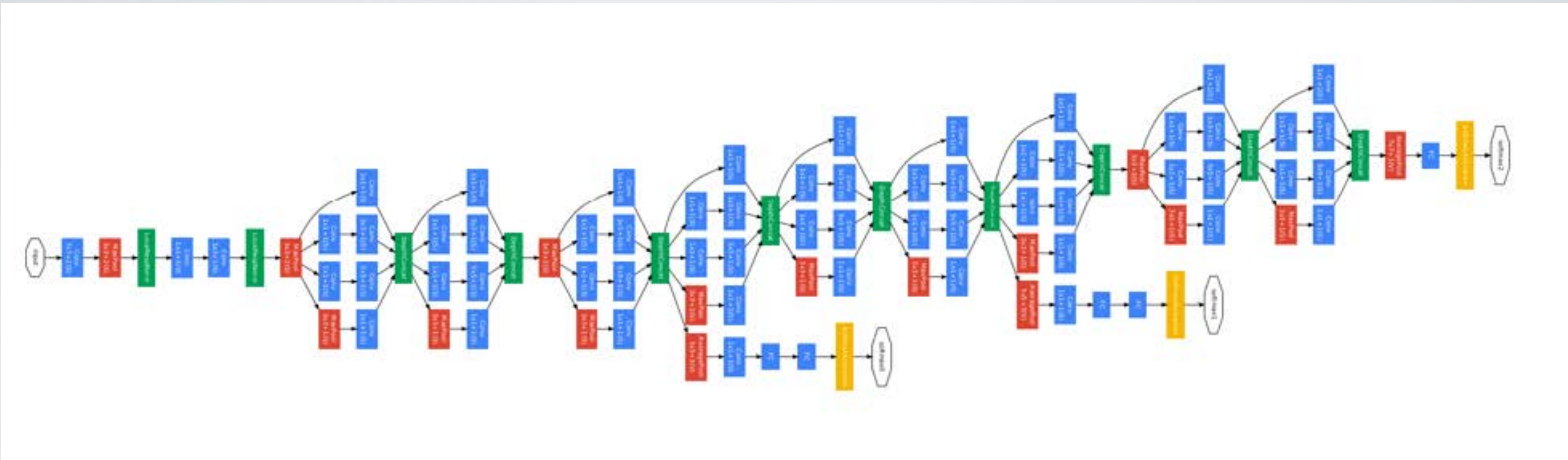
models



VGG - 2014

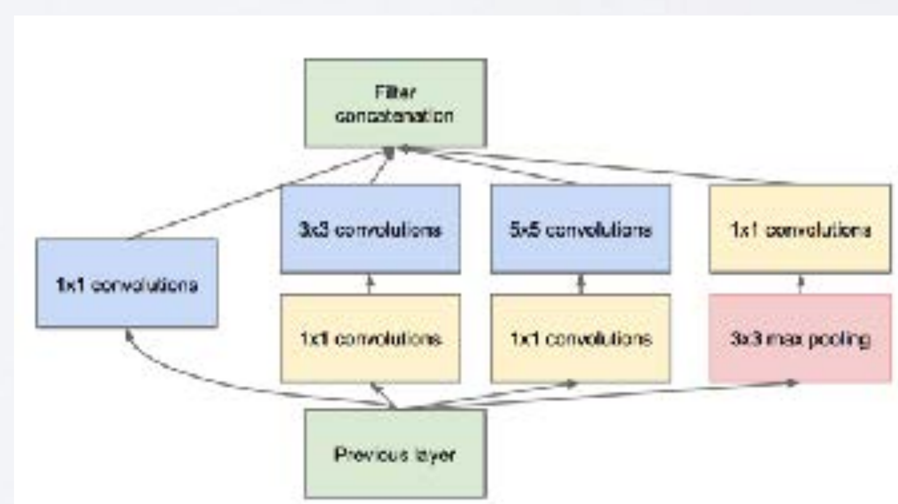
Simonyan et. al, 2014

models



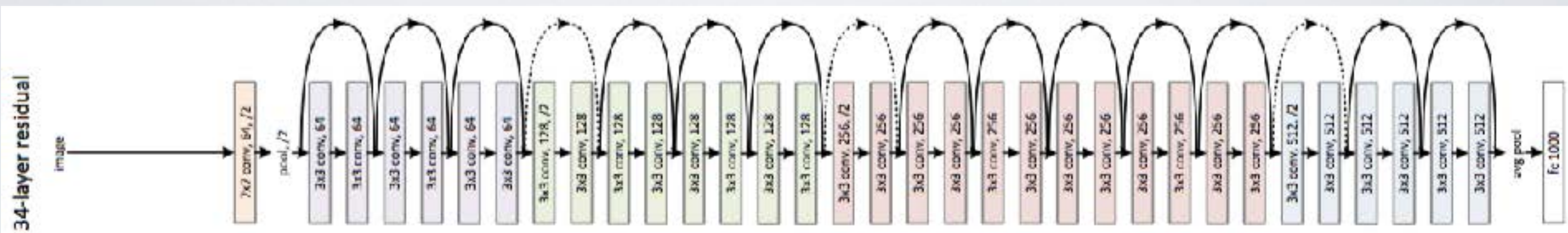
GoogLeNet - 2014

Inception Block:



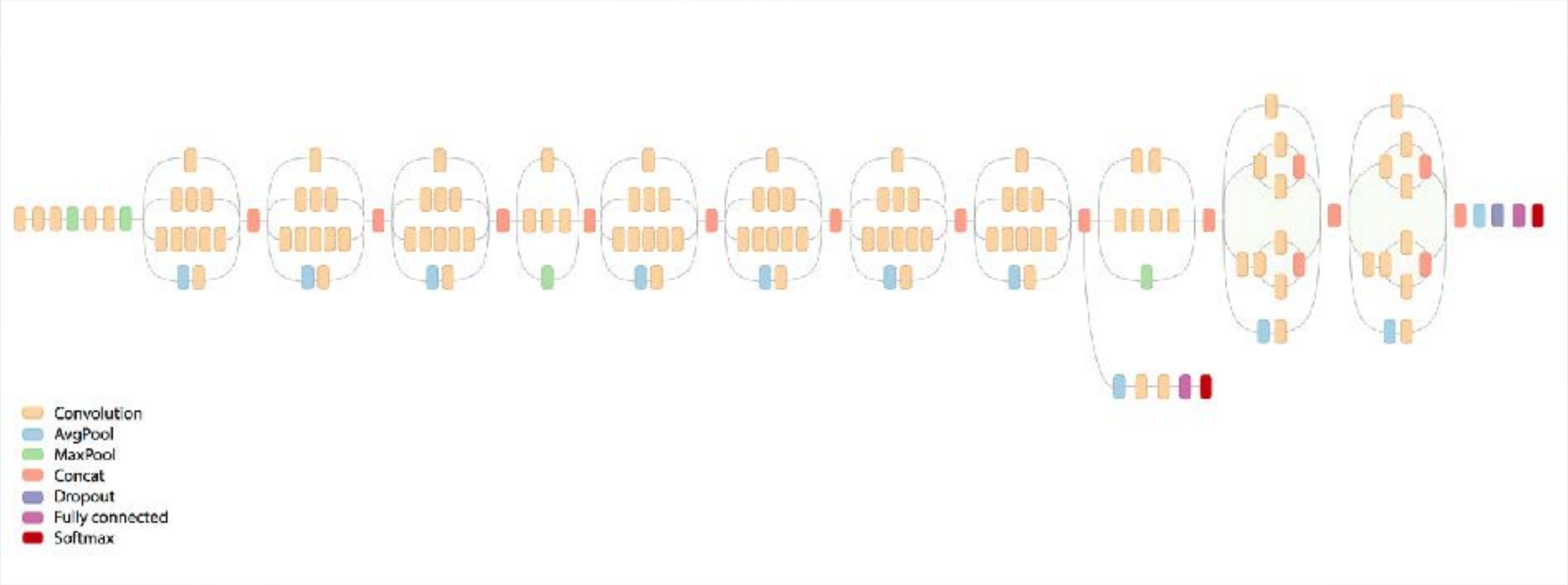
Szegedy et. al, 2014

models



ResNet - 2015

He et. al, 2015



Inception v4 - 2016

Szegedy et. al, 2016

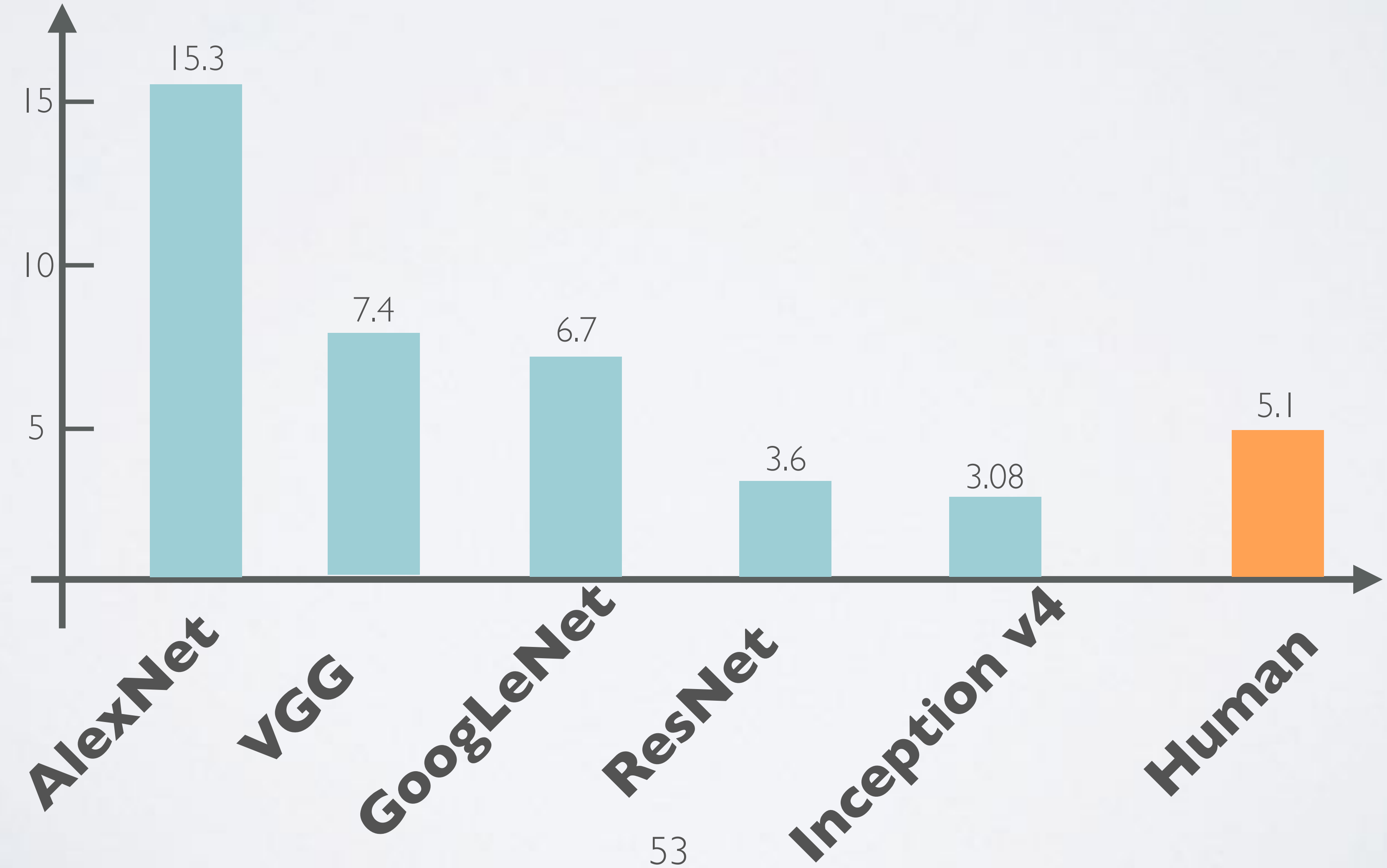
top-5 error on ILSVRC

top-5 error denotes the percentage of examples for which the ground truth label is not in the model's top 5 predictions

1. television
2. radio
3. walkie talkie
4. pager
5. **cell phone**

→ correct top-5 prediction

top-5 error (%)

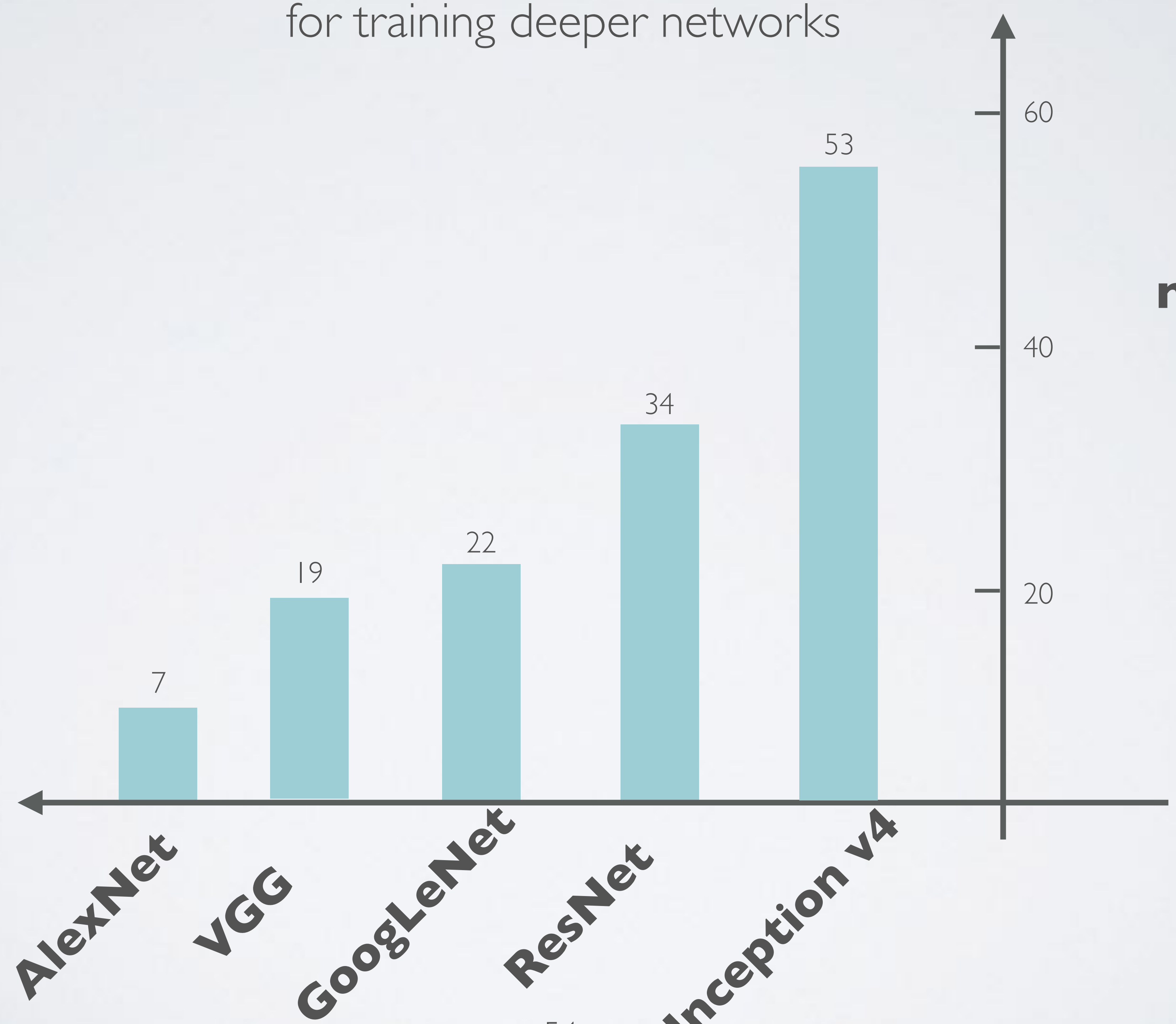


Karpathy, 2014

number of layers

the number of layers with weights in state-of-the-art networks has grown

this is primarily due to new tricks that have been developed for training deeper networks

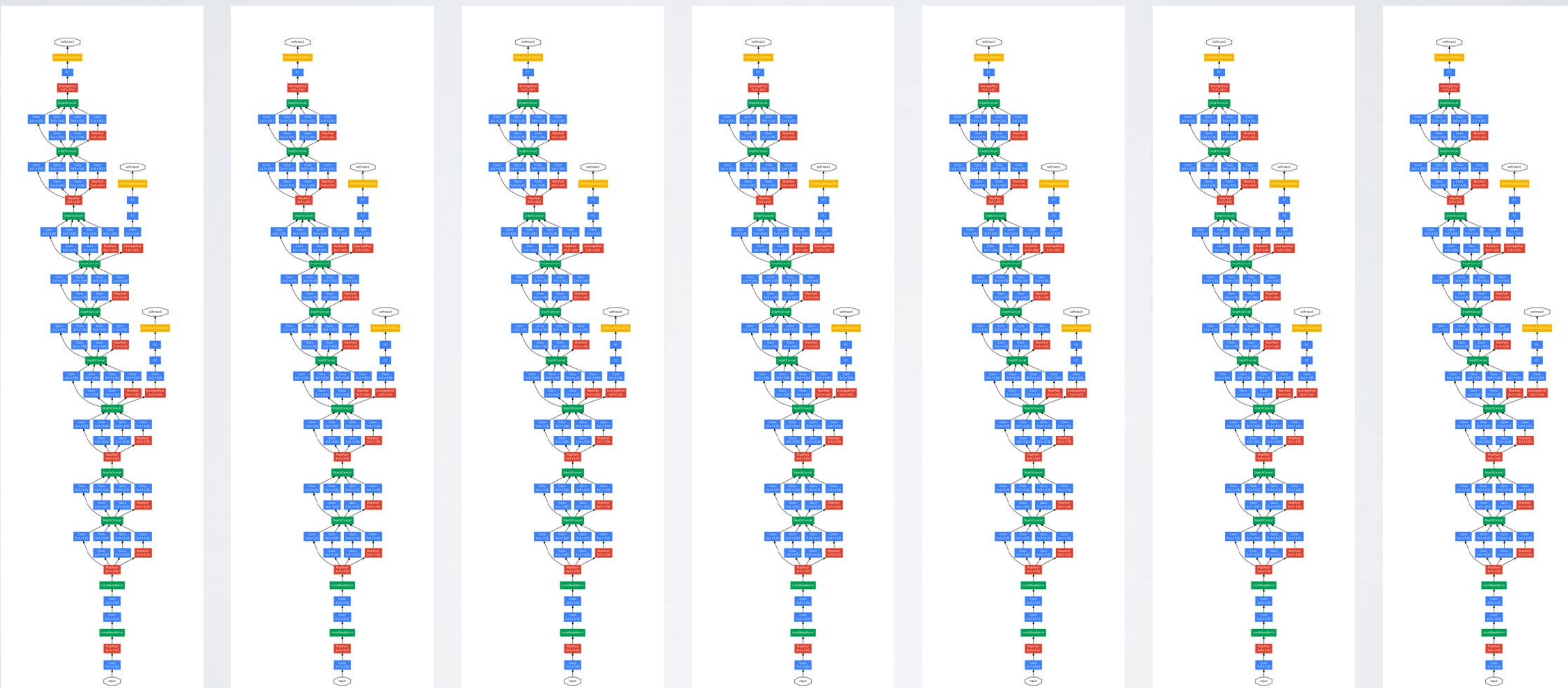


number of layers

ensembles

as a side note:
the winning entries are typically *ensembles* of networks

since each network likely converges to a different local minimum,
averaging their predictions helps in generalization



data augmentation

in training these networks, people often use *data augmentation* to effectively boost the number of examples in the training set

we use priors on the nature of the data to create additional examples

original image

<u>*example data augmentation:*</u>

crops

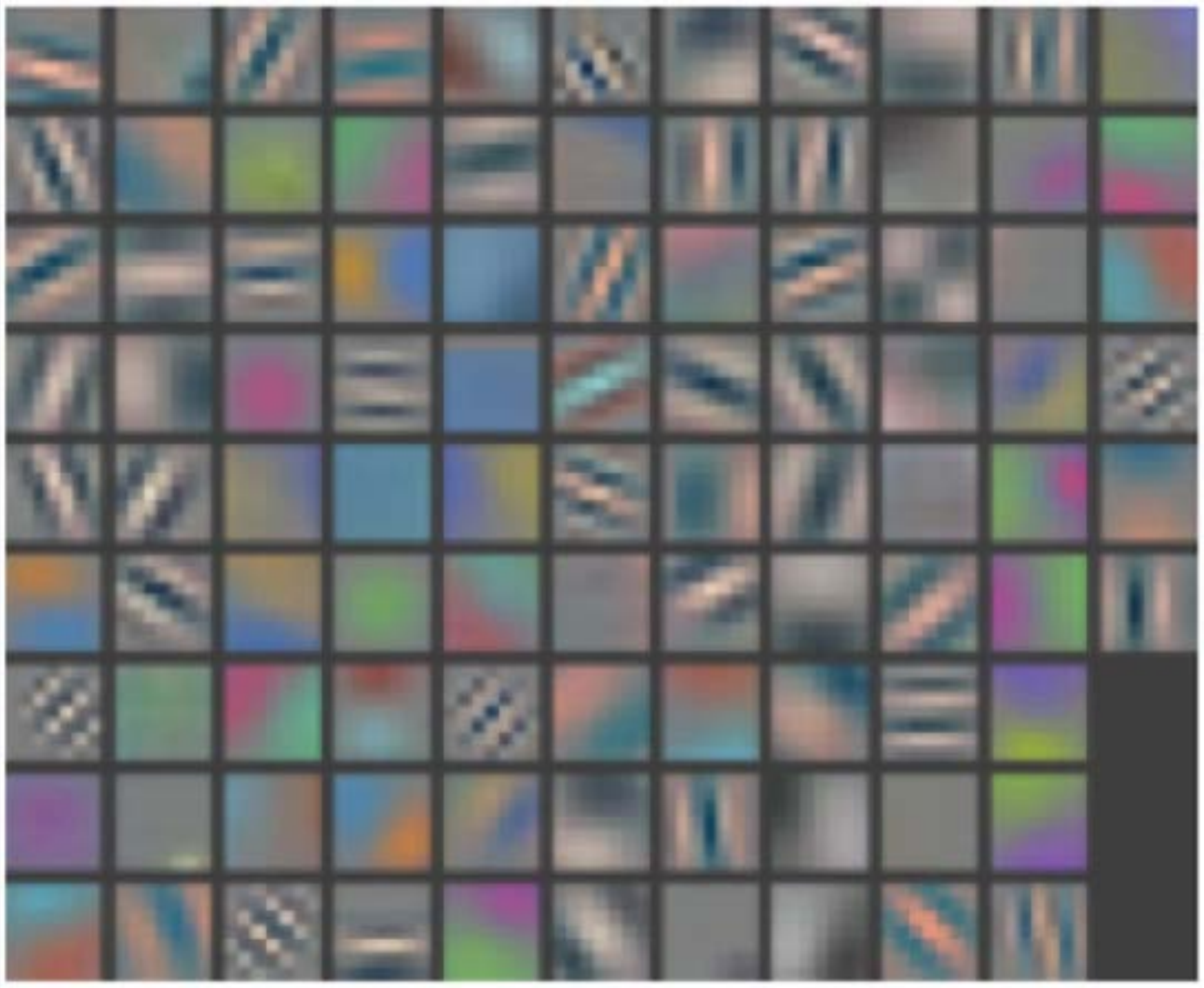
left-right flip

rotations

what are these models learning?

filter visualization

at the first layer, we can visualize the filters as RGB images



Zeiler, 2013

filter visualization

for later layers, we can no longer visualize them directly in the image domain

there are three main ways in which to visualize them:

maximal images from dataset

- feed in all images from the dataset and see which images make the filter activate maximally

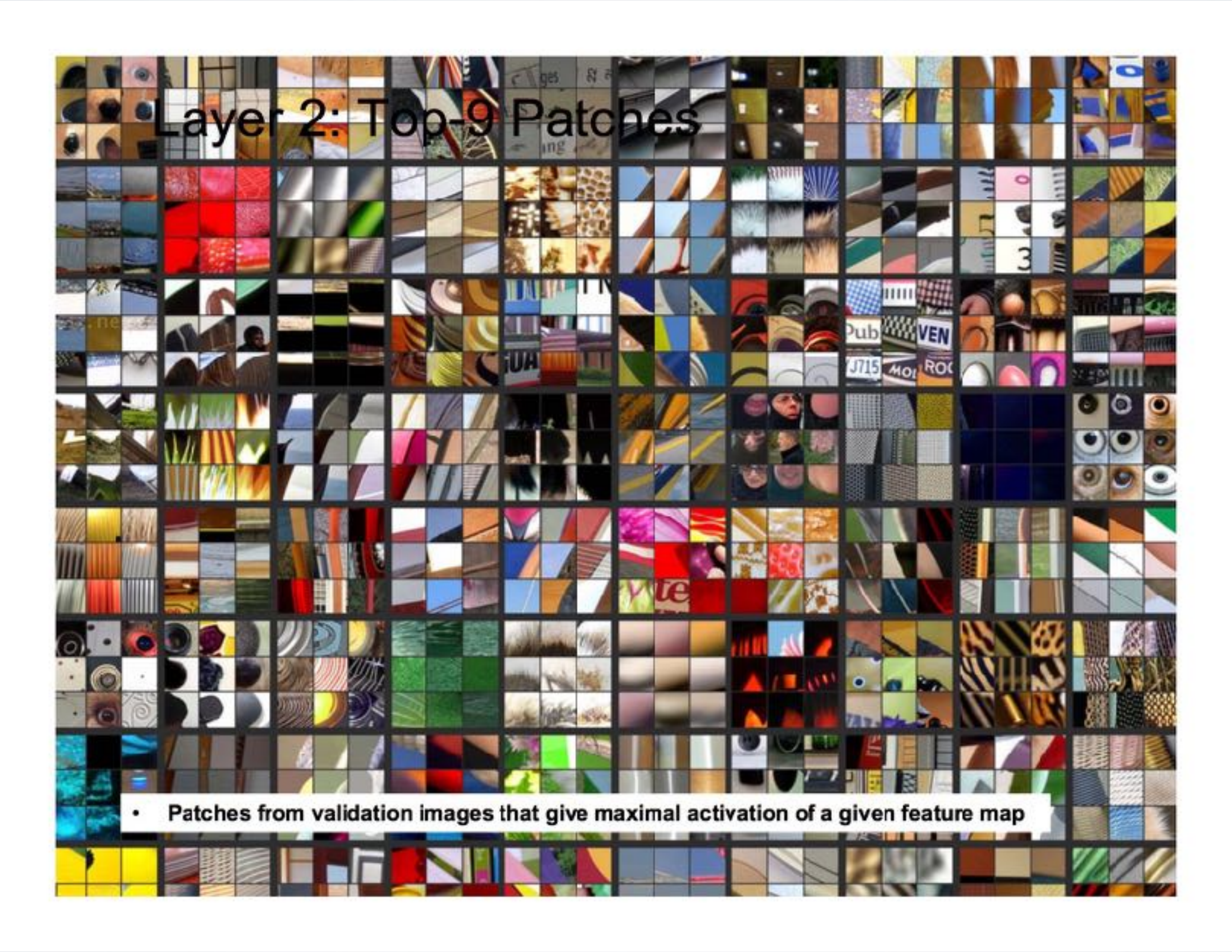
deconvolution

- run the network in reverse from an intermediate layer to try to convert its activation back to the image domain

optimized image

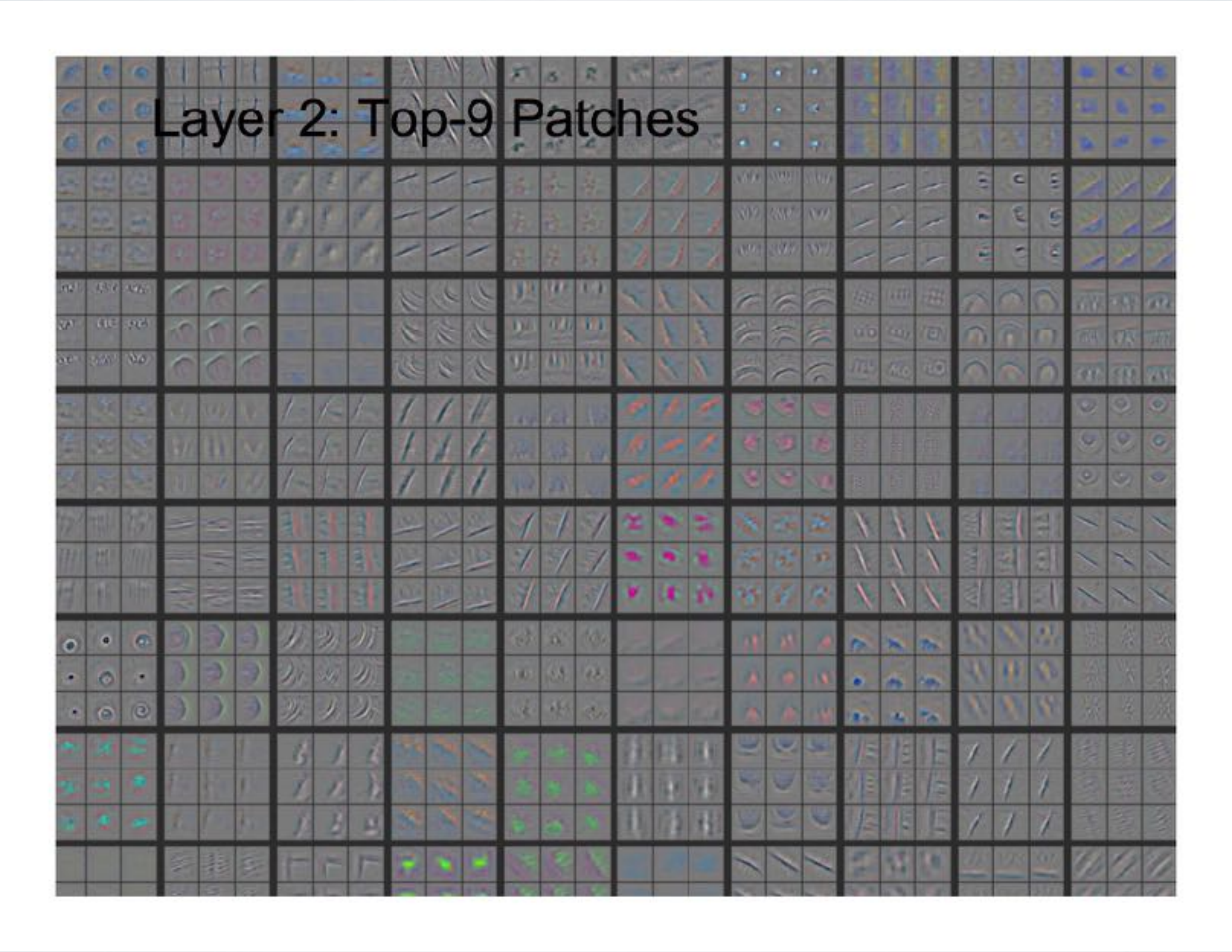
- backpropagate from a filter to the image itself to find an image that would make it fire maximally

filter visualization



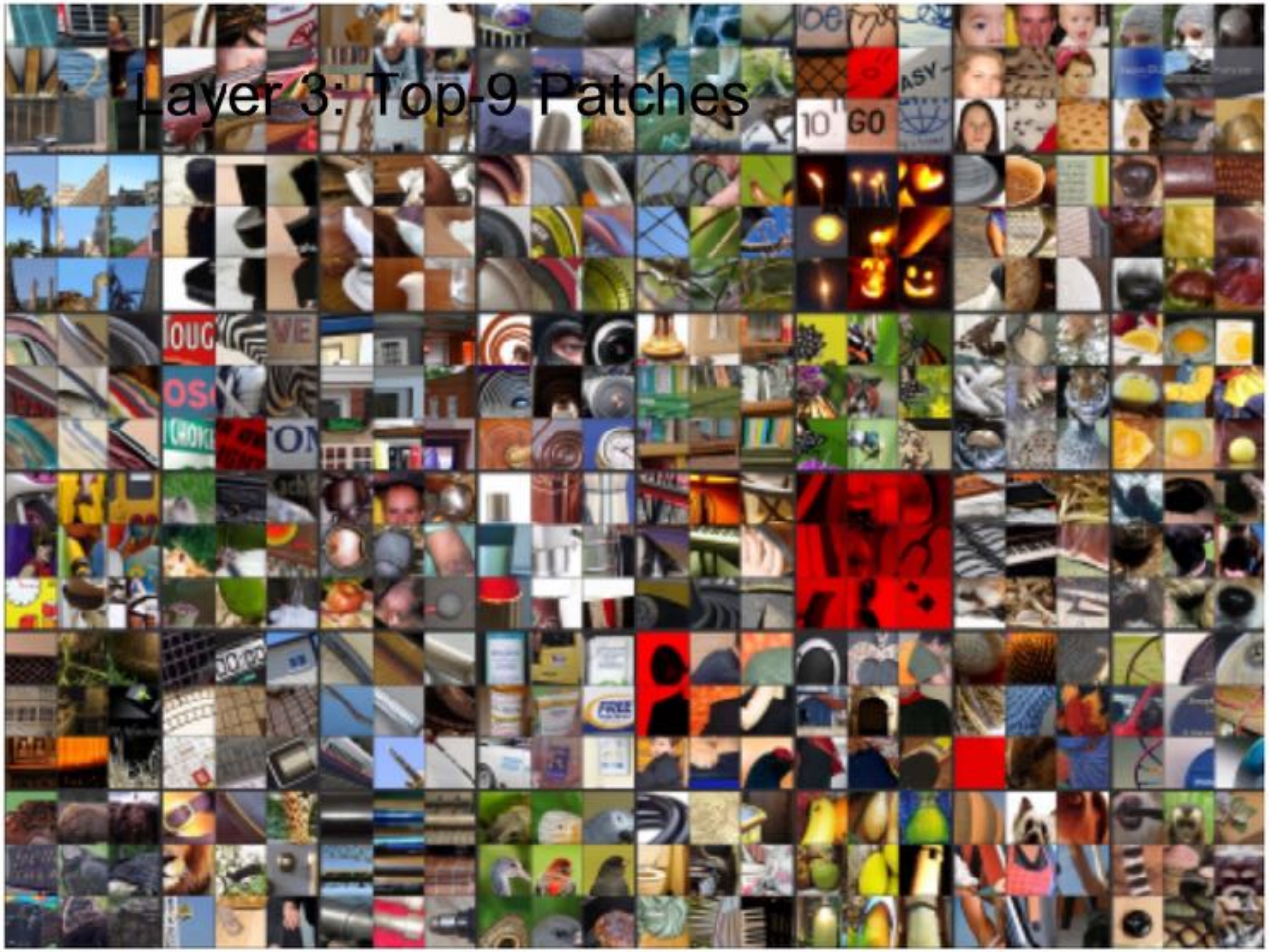
Zeiler, 2013

filter visualization



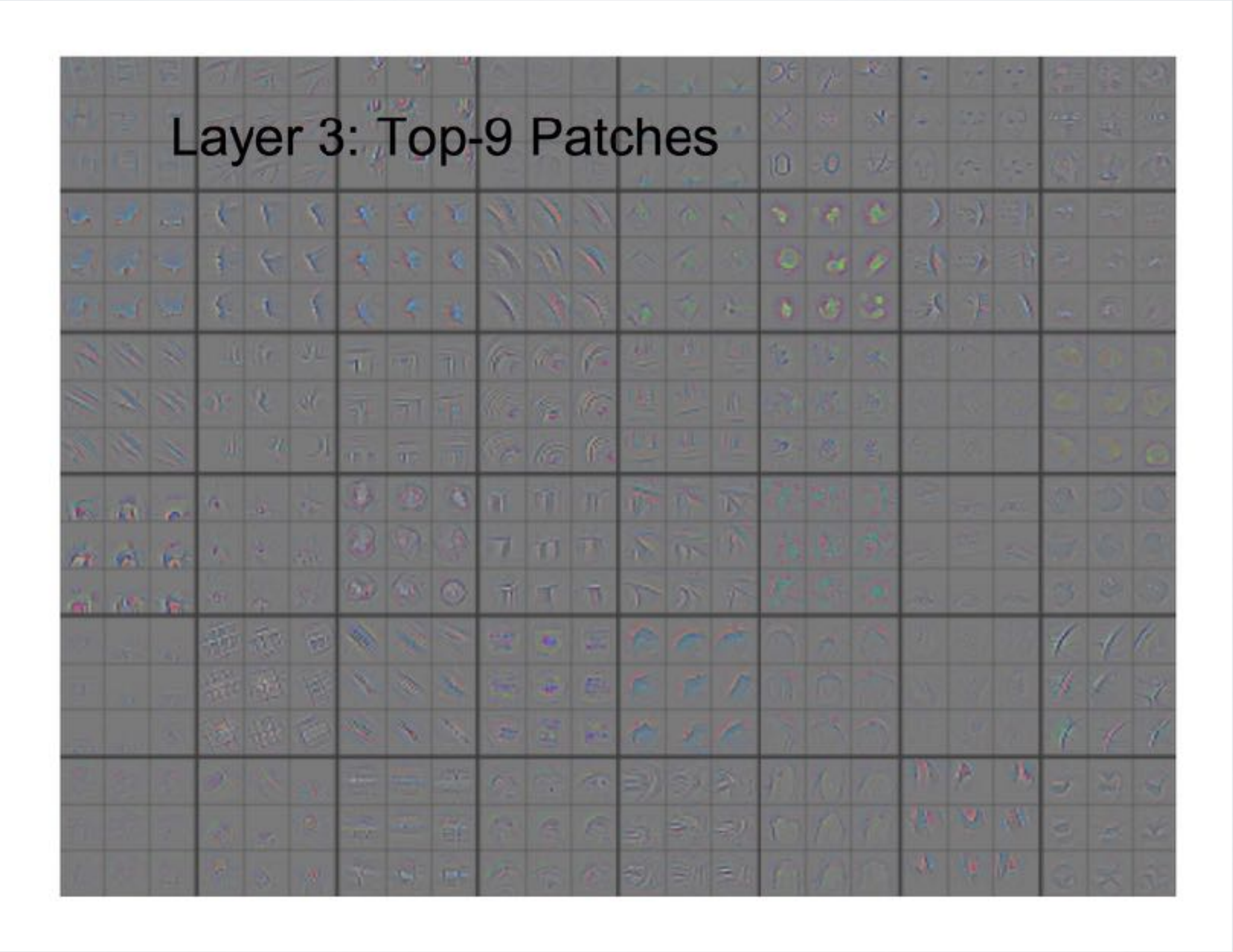
Zeiler, 2013

filter visualization



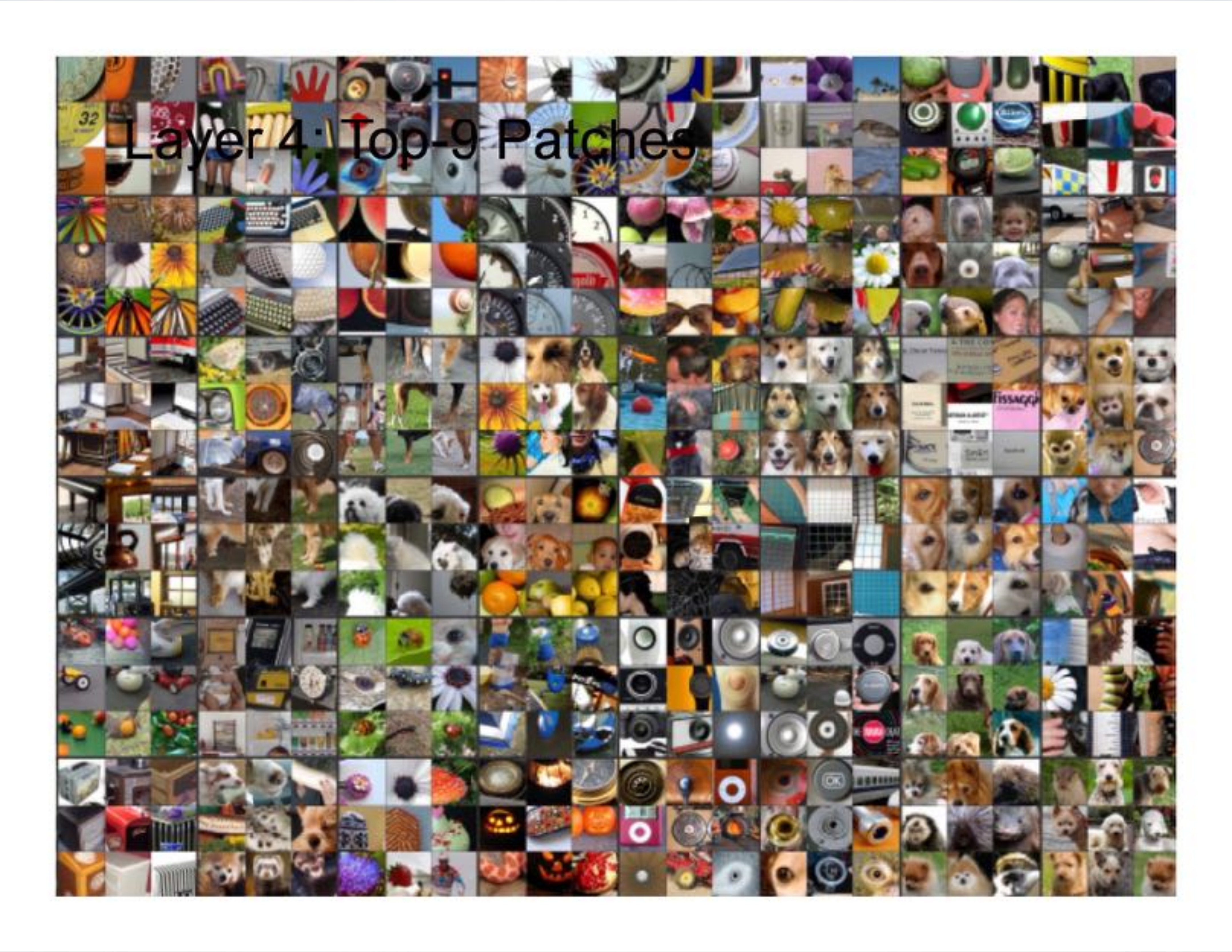
Zeiler, 2013

filter visualization



Zeiler, 2013

filter visualization

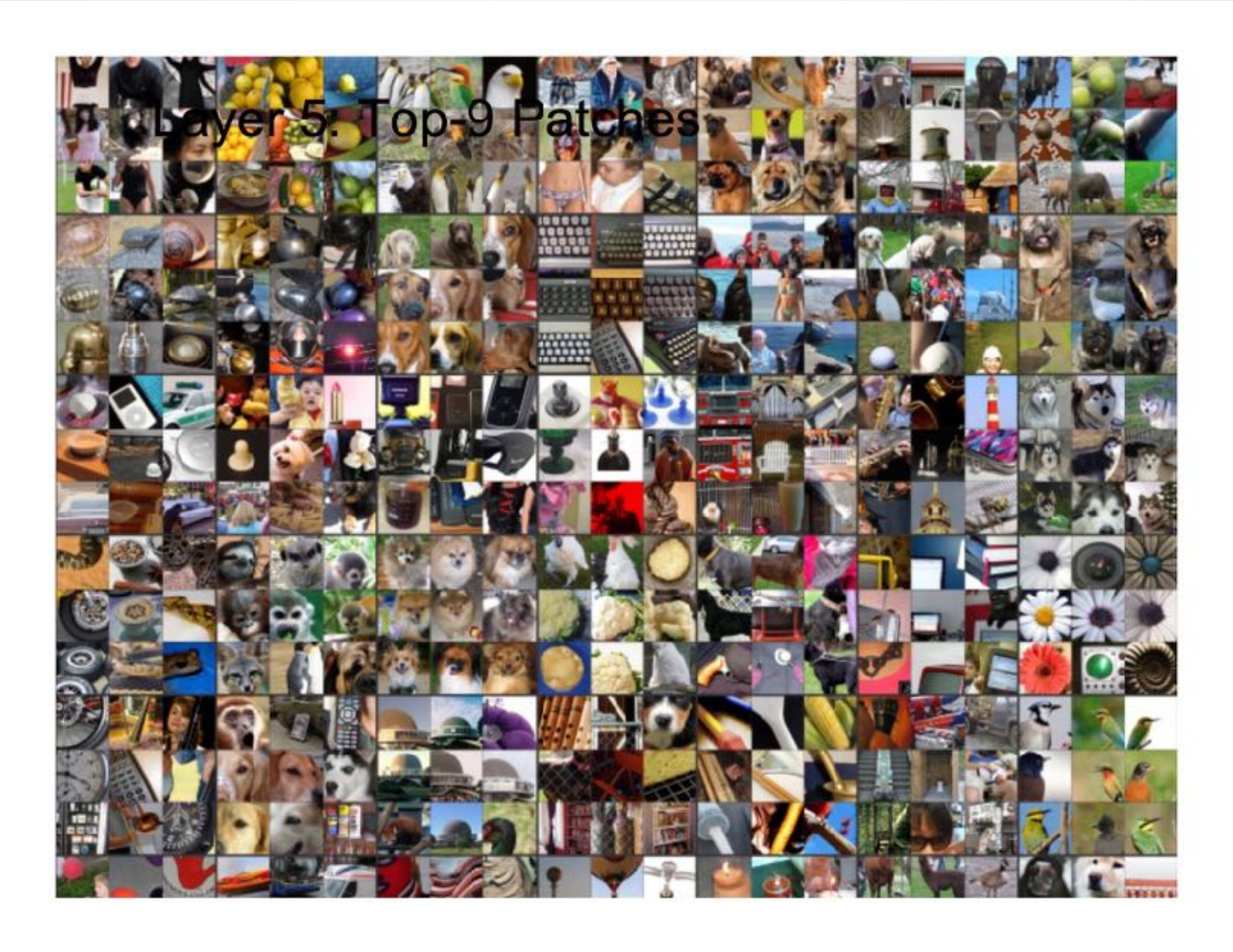


Zeiler, 2013

filter visualization

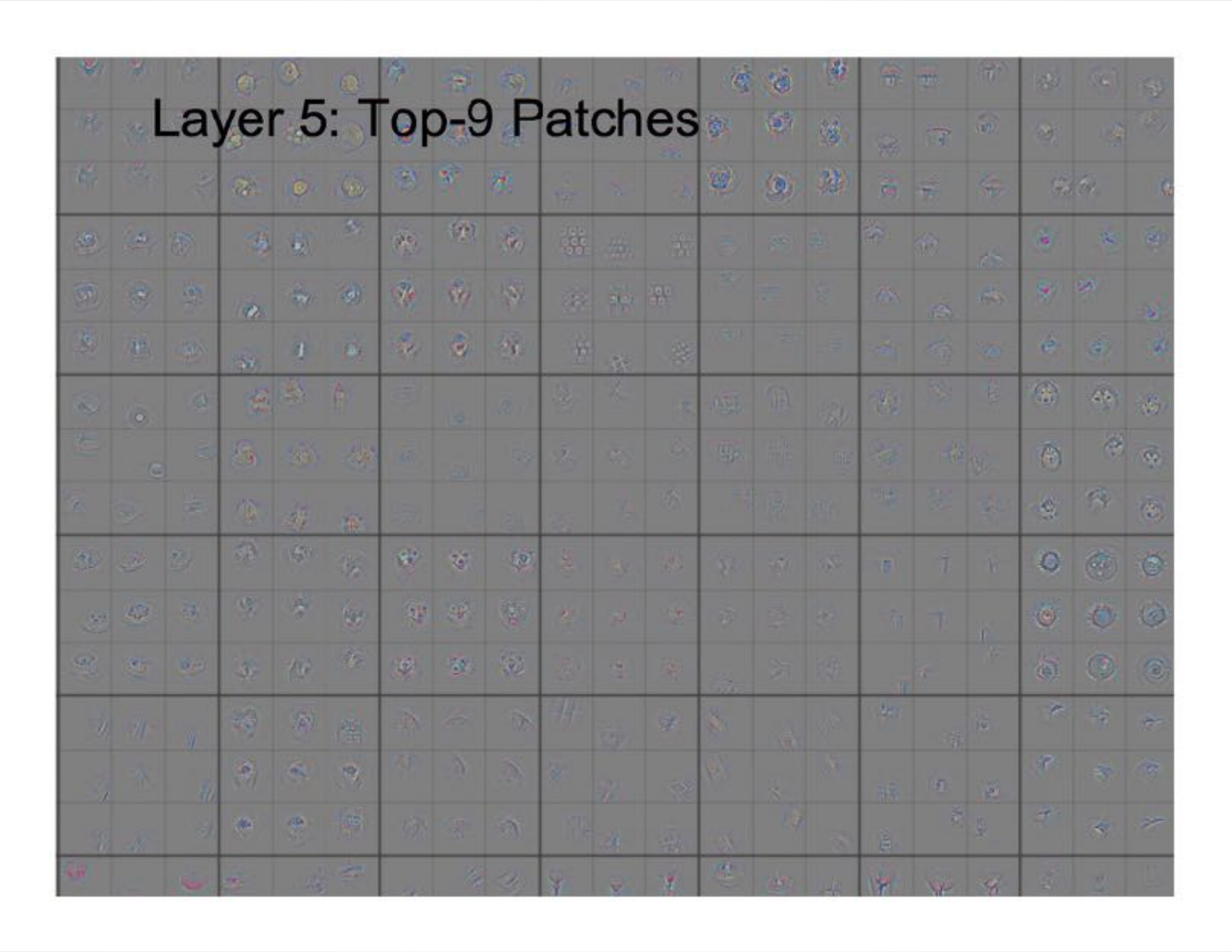
Zeiler, 2013

filter visualization



Zeiler, 2013

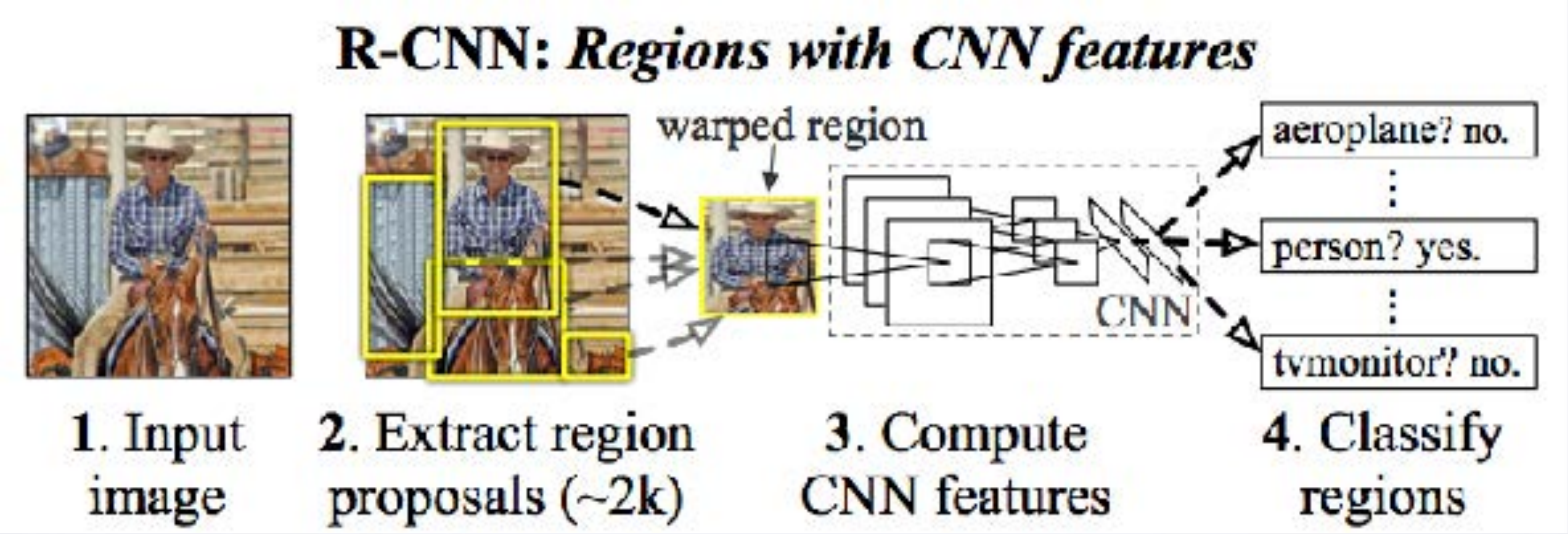
filter visualization



Zeiler, 2013

moving beyond object recognition

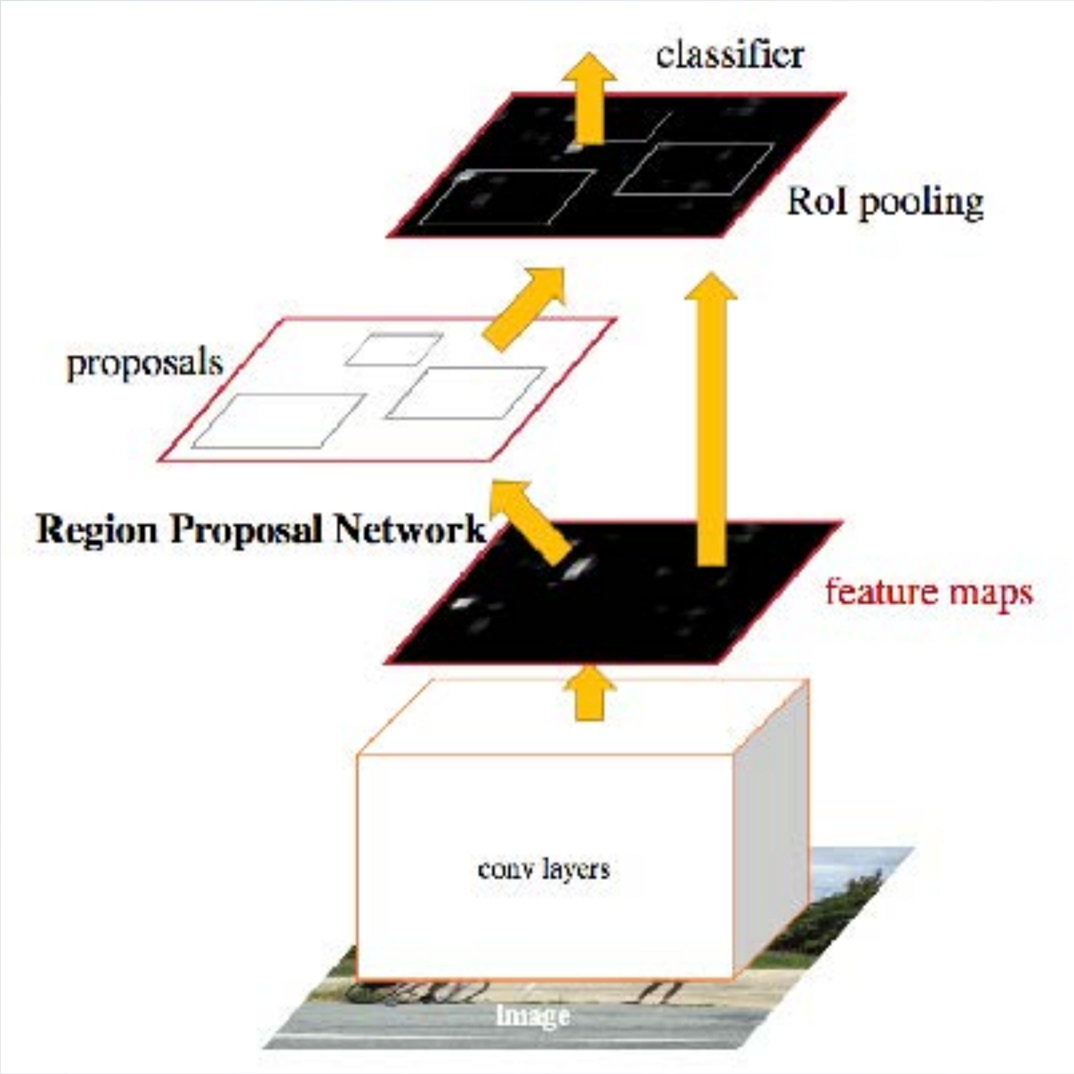
object detection

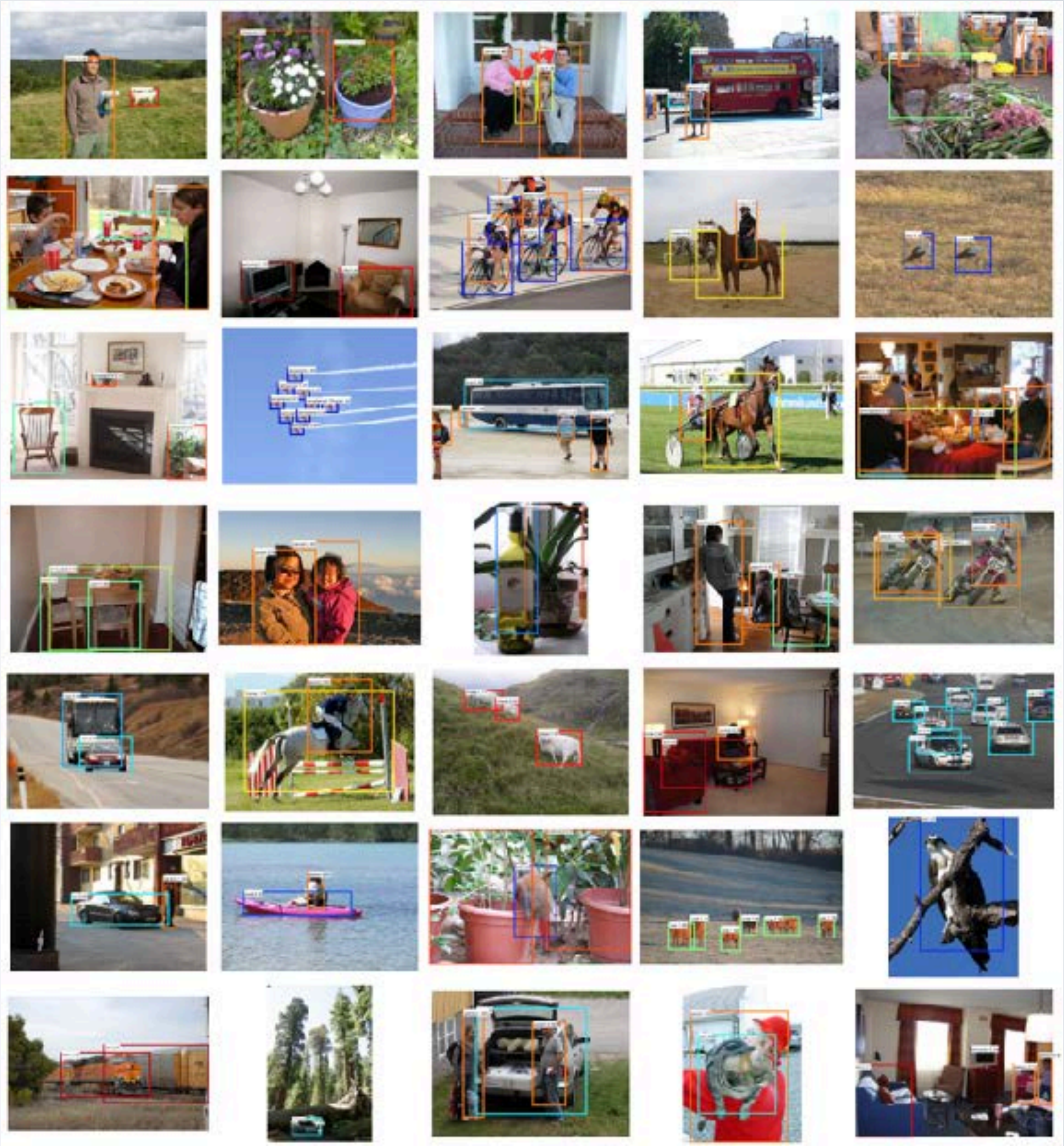


Girshick, 2013

object detection

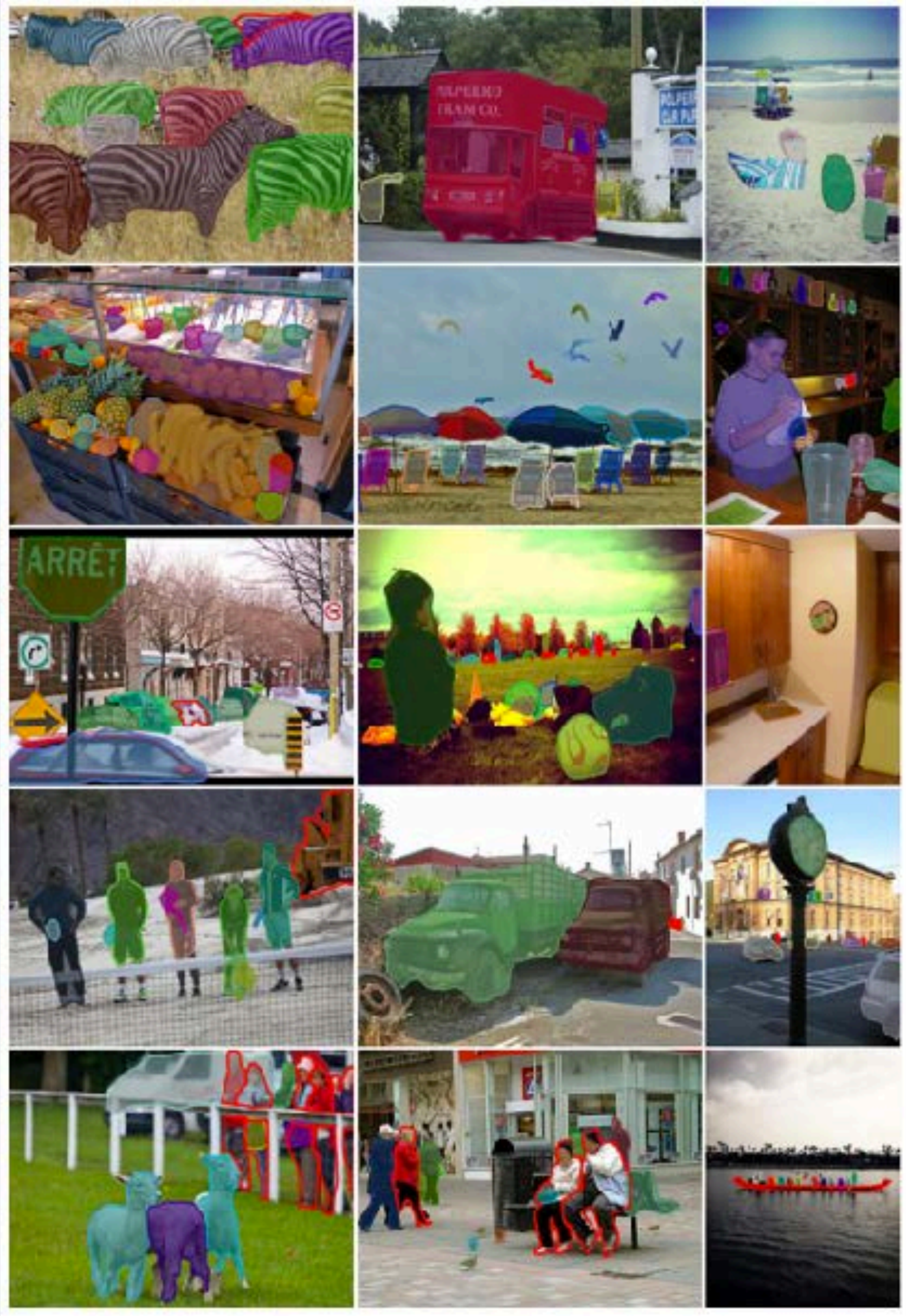
Faster R-CNN

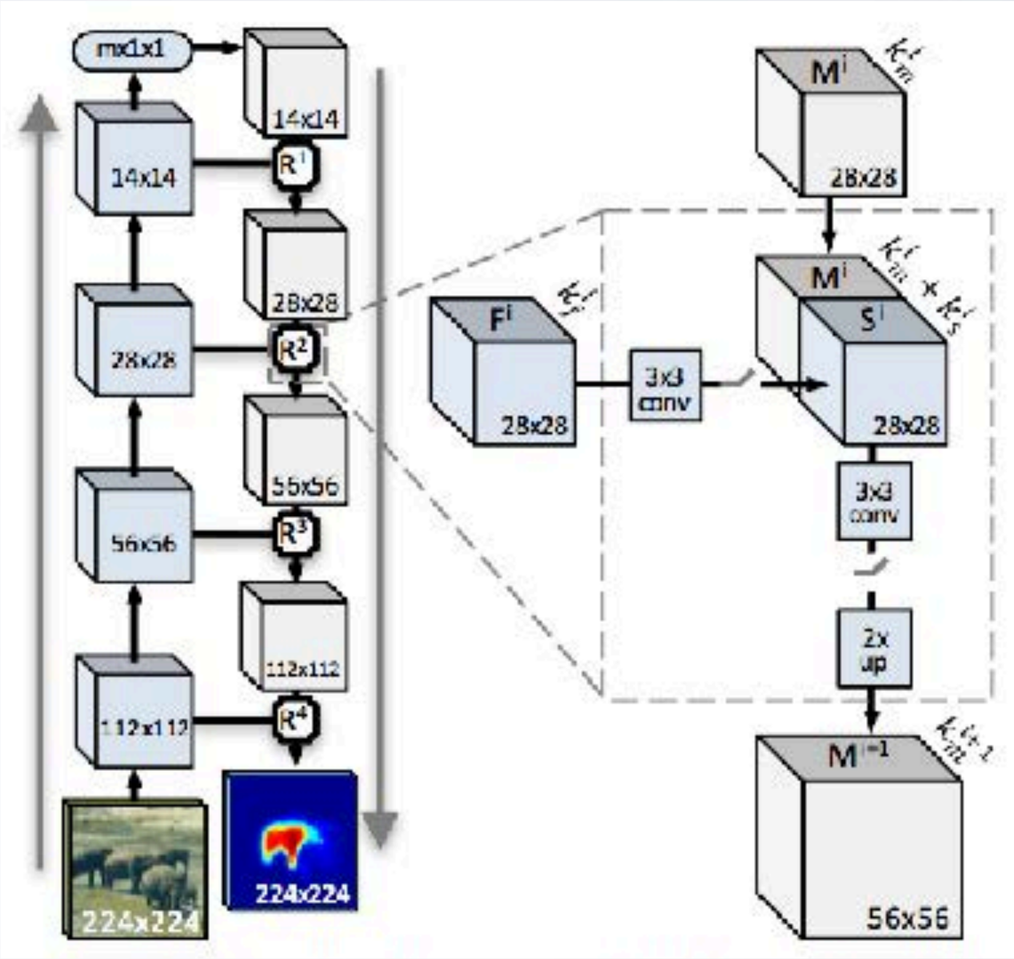




He, 2015

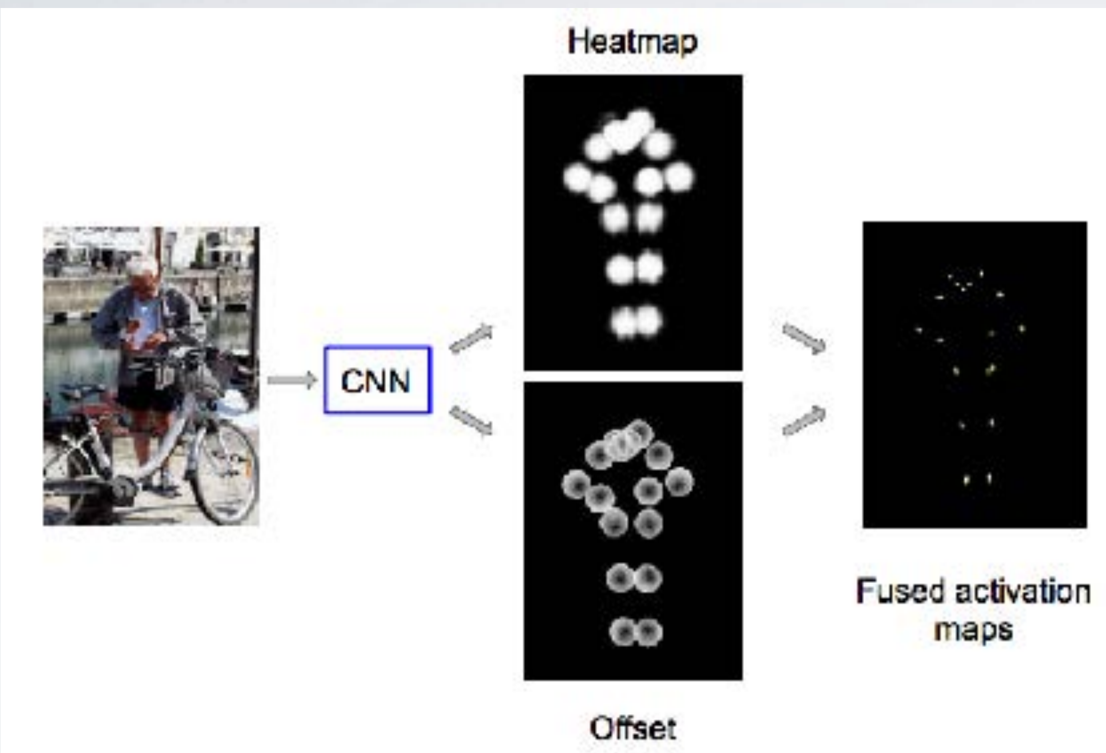
object segmentation





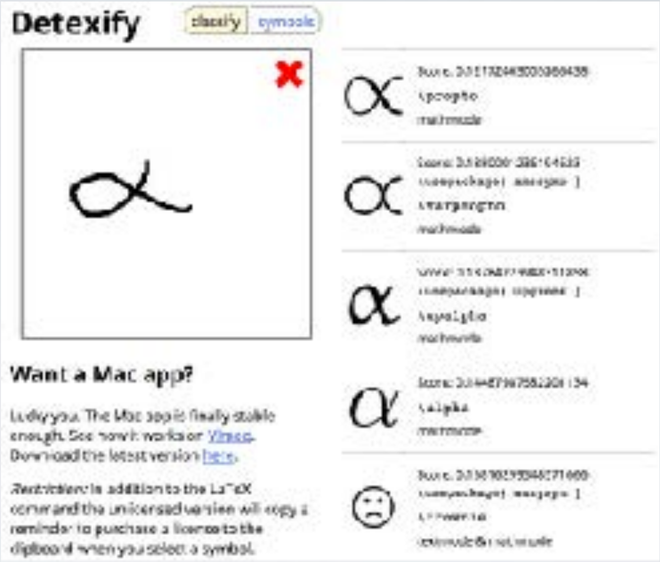
Pinheiro, 2016

key point estimation



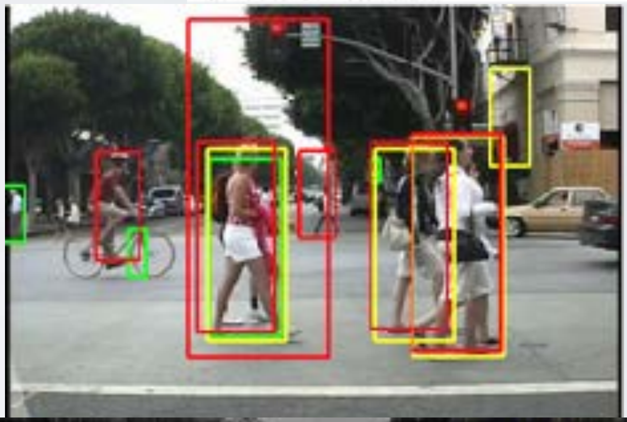
Papandreou, 2017

applications



handwriting recognition

- ATM
- note taking



pedestrian/object detection for self-driving cars

face detection/recognition

- Facebook
- Microsoft
- Snapchat

search by image

- Google image search
- search by image for products on Amazon

applications

fine-grained object recognition

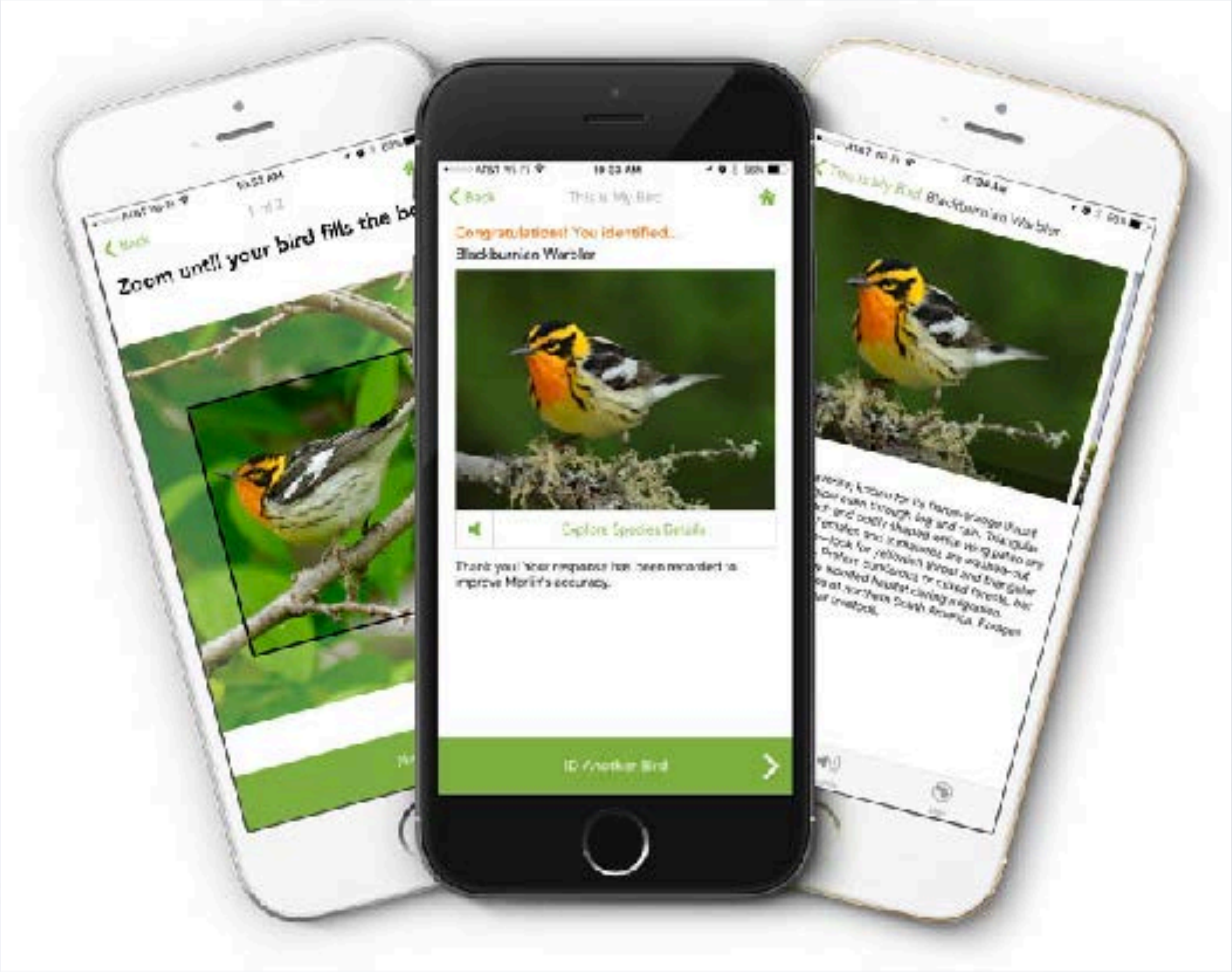
e.g. recognizing any bird species

applications

fine-grained object recognition

an expert birder on your phone

Merlin

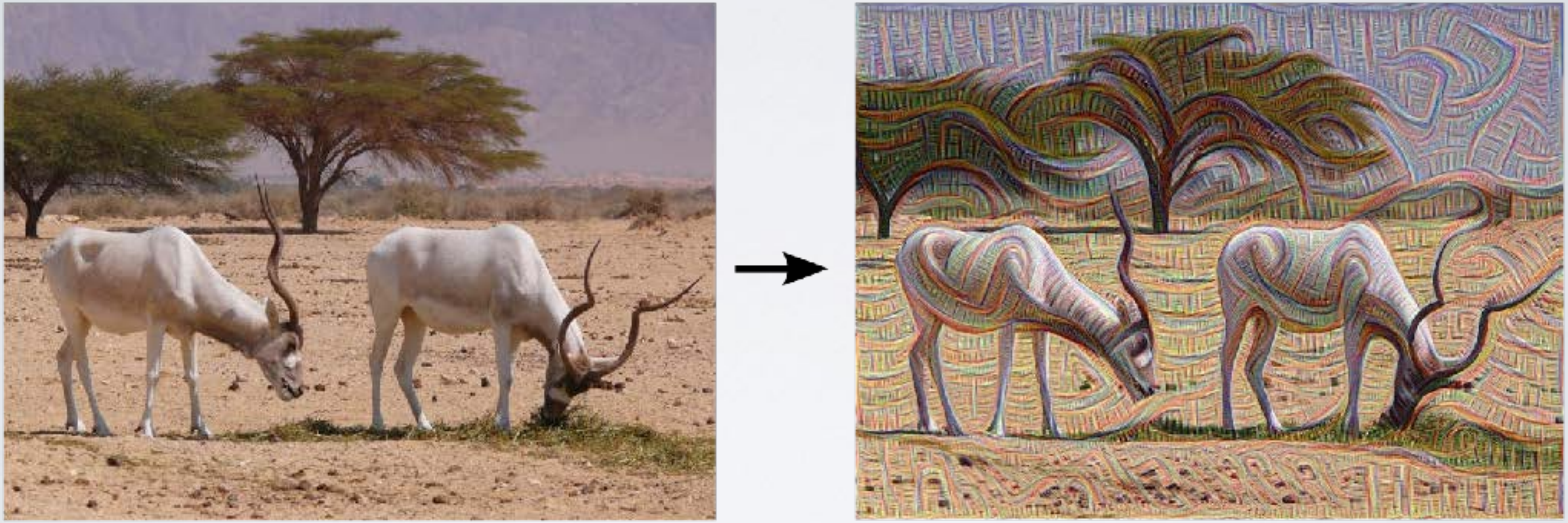


recognition component developed at Caltech

other cool stuff

start with an input image or random noise

randomly activate filters within the network, backpropagate to the image



depending on which filters are chosen, has different interesting effects

it's as though the network is dreaming, hence, *deep dream*

https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

other cool stuff

deep dream masterpieces

https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

other cool stuff

neural style transfer

start with a 'content image' and a 'style image'

backpropagate the style image's high-level statistics to the content image

Gatys et al., 2015
Johnson et al., 2016

other cool stuff

colorization

learn a mapping from black and white images to color images based on visual features

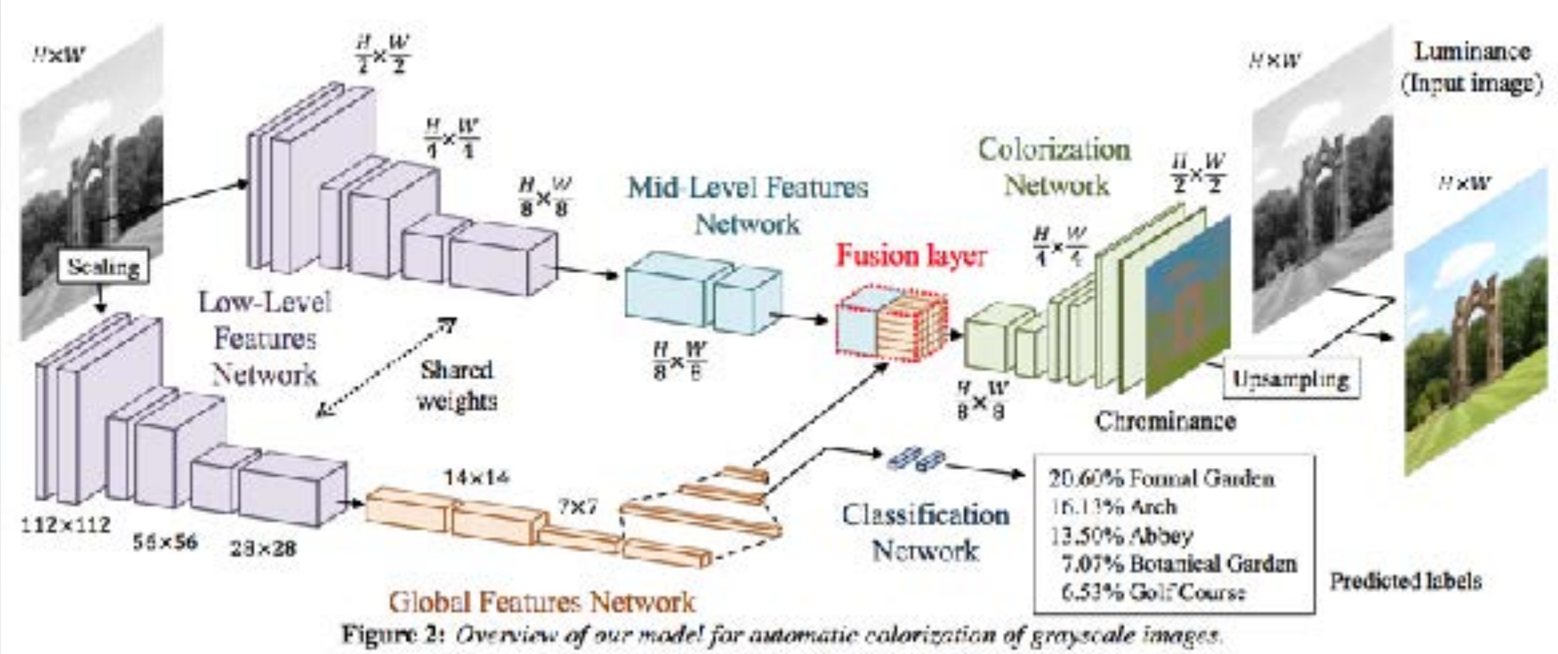


Figure 2: *Overview of our model for automatic colorization of grayscale images.*

(a) Cranberry Picking, Sep. 1911 (b) Burns Basement, May 1910 (c) Miner, Sep. 1937 (d) Scott's Run, Mar. 1937

Iizuka et al., 2016

discrimination

there are patterns in images that allow us to infer latent properties

→ Yisong

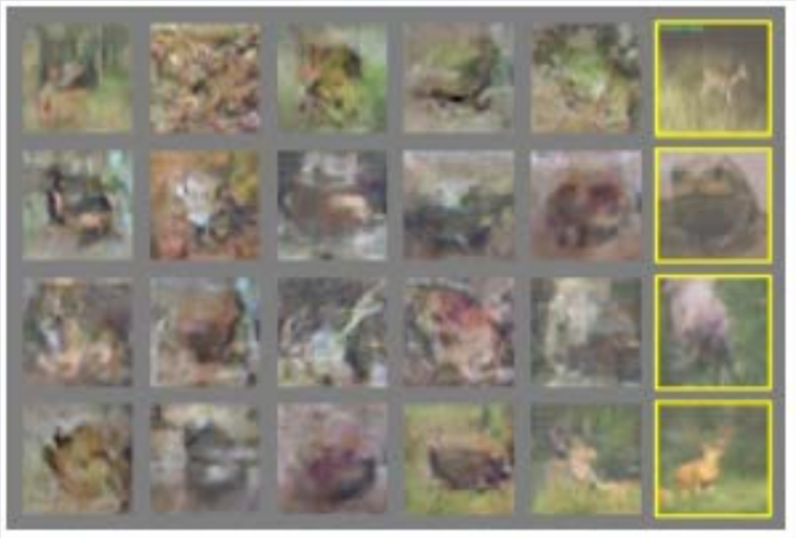
generation

there are latent properties that result in specific patterns in images

Yisong → 

other cool stuff

generative modeling of images

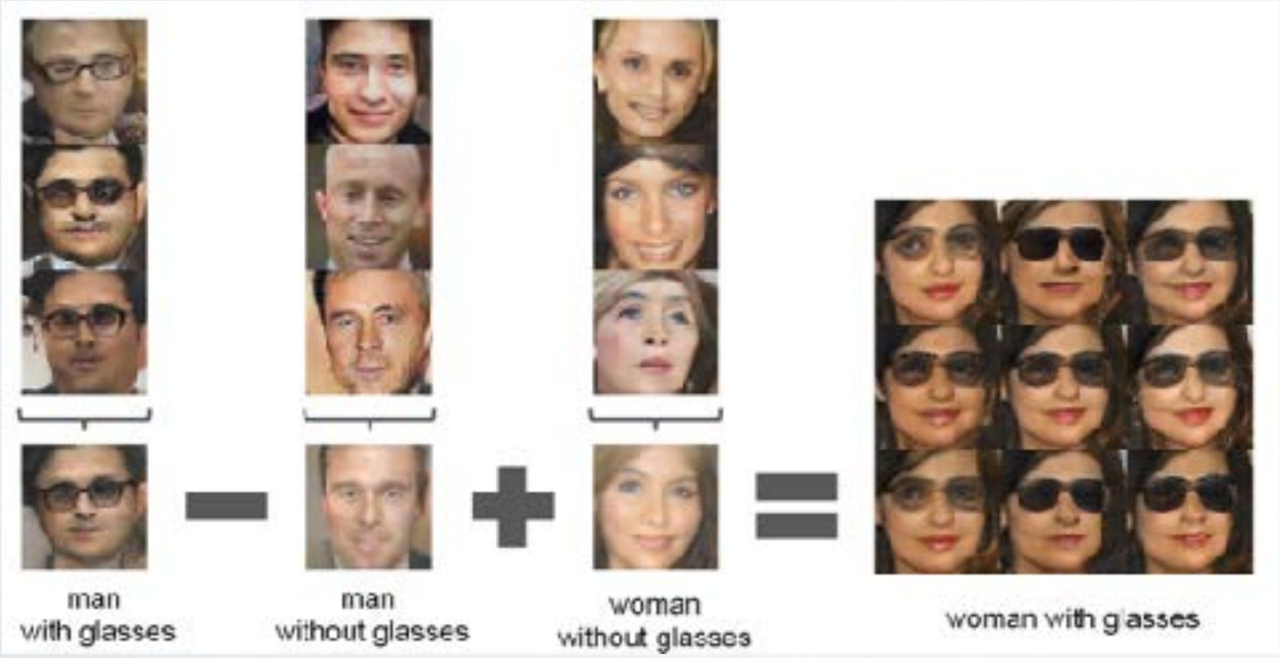


Goodfellow et al., 2014

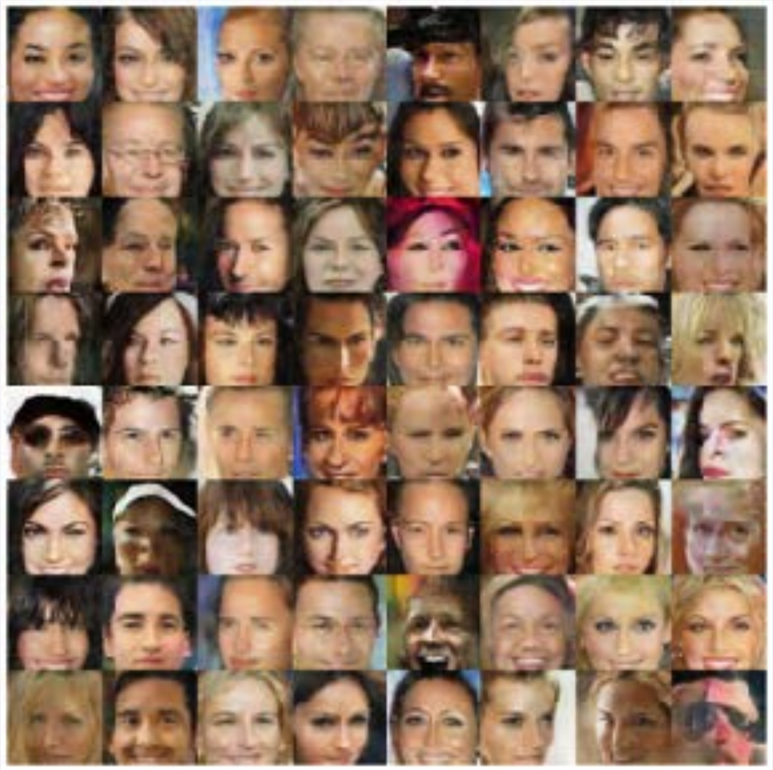
Goodfellow et al., 2016

Kingma et al., 2016

Radford et al., 2015



Volkhonskiy et al., 2017



conclusion

convolutions are an ideal choice when working with data with invariances

- increases parameter efficiency through model priors
- can also be applied to 1-D and 3-D data

convolutional neural networks have enabled rapid gains in nearly all areas of computer vision and other fields

- object recognition/detection/segmentation
- success depends heavily on *data* and *hardware*

many interesting new areas to explore

- work with images at multiple levels of abstraction, not just pixel level

open problems

- choosing network architecture
- limited reasoning abilities, just an input-output mapping
- learning from few examples
- understanding what/how these networks are learning, improving training
- etc.