Convolutional Networks (ConvNets): Part I

April 27, 2021

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http://cross-entropy.net/ml530/Deep_Learning_2.pdf

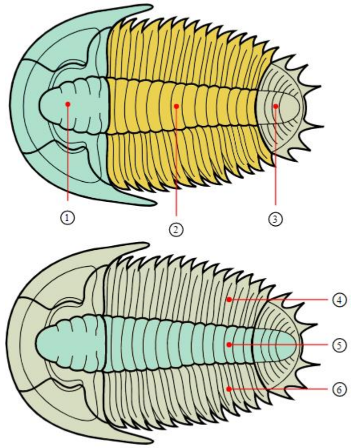
Agenda for Tonight

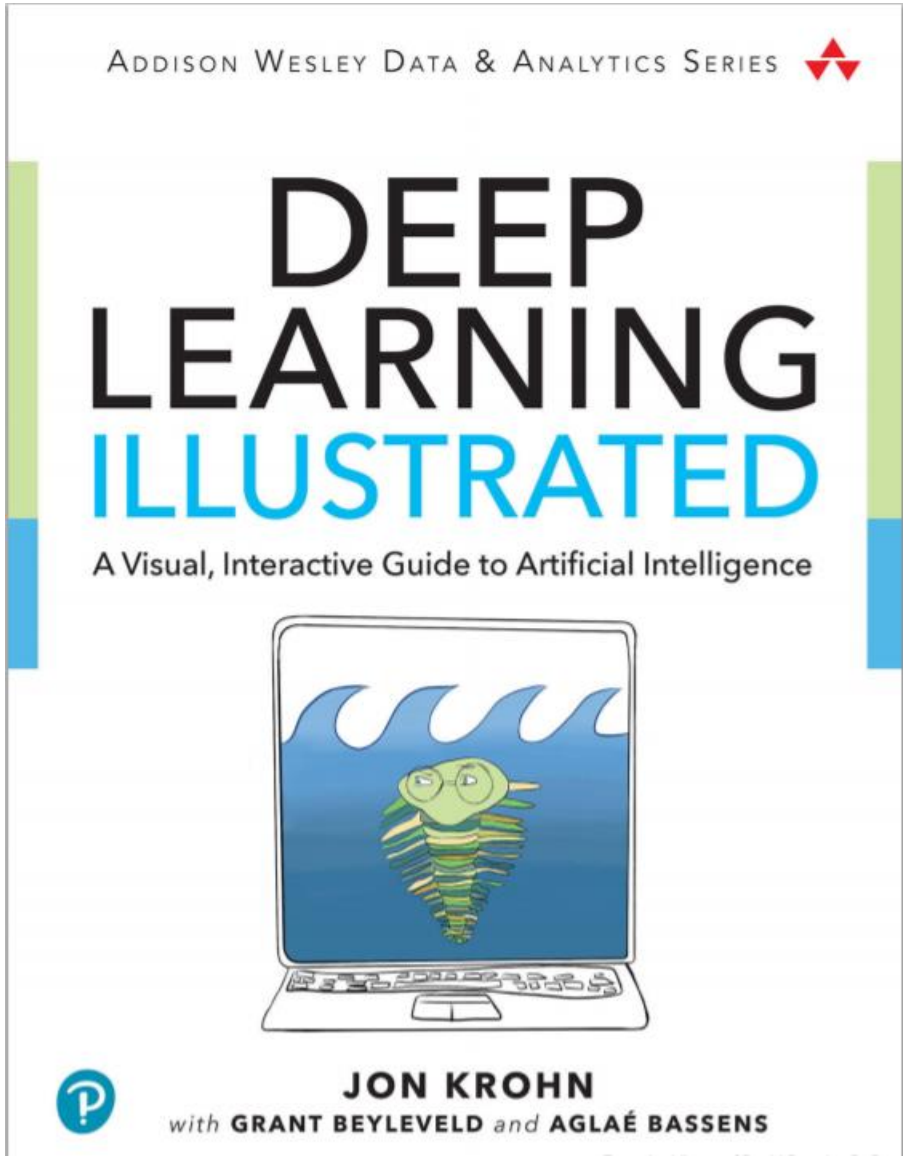
- Homework Review
- [DLI] Chapter 1: Biological and Machine Vision
- [DLI] Chapter 10: Machine Vision

Textbook #1

The cover of our textbook contains the unofficial mascot of the book, a trilobite in deep waters ☺

The trilobite is a 3-section, 3-lobe marine arthropod that went extinct 250 million years ago





https://en.wikipedia.org/wiki/Trilobite

[DLI] Chapter 1: Biological and Machine Vision

- Biological Vision
- Machine Vision
  - The Neocognitron
  - LeNet-5
  - The Traditional Machine Learning Approach
  - ImageNet and the ILSVRC
  - AlexNet
- TensorFlow Playground
- Quick, Draw!
- Summary

Authors

- Jon Krohn: chief data scientist at untapt.com

- Grant Beyleveld: data scientist at untapt.com

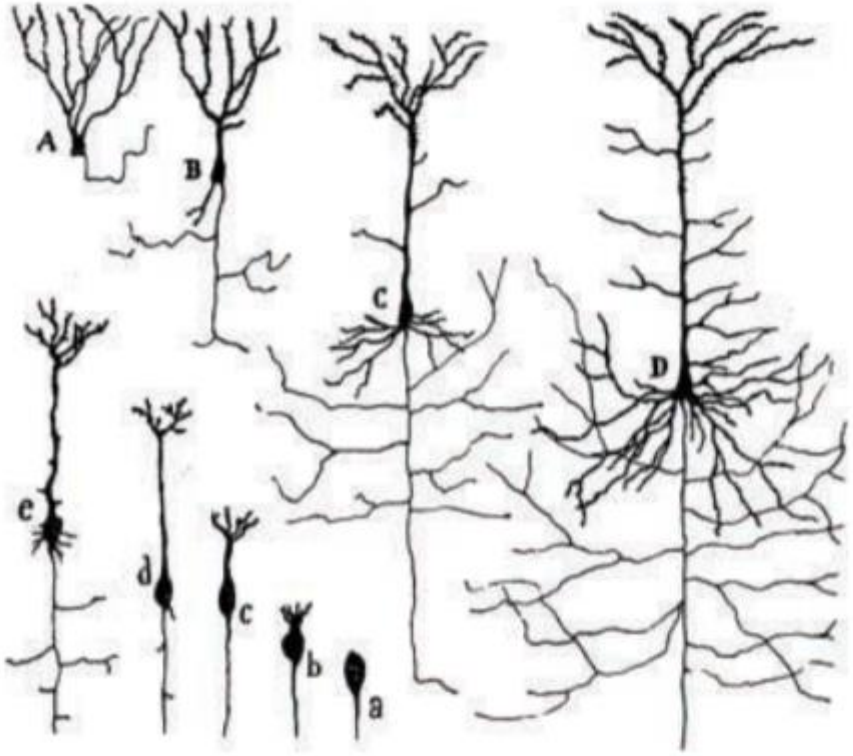
- Aglae Bassens: Belgian artist based in Paris

Santiago Cajal: 1852 - 1934

Spanish physician who was the first to identify neurons, by examining thin slices of brain tissue

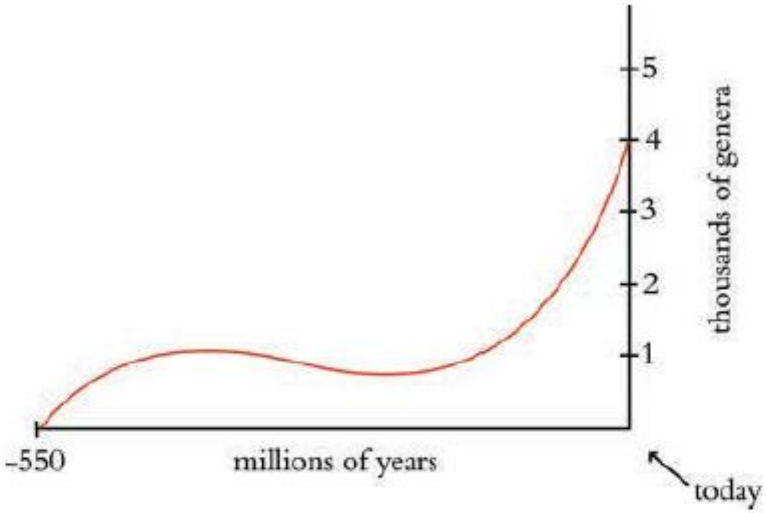
Hand-Drawn Neurons from Cajal (1894)

- (a)-(e) illustrates the growth of a neuron
- (A)-(D) contrasts the neurons of a frog, lizard, rat, and human respectively



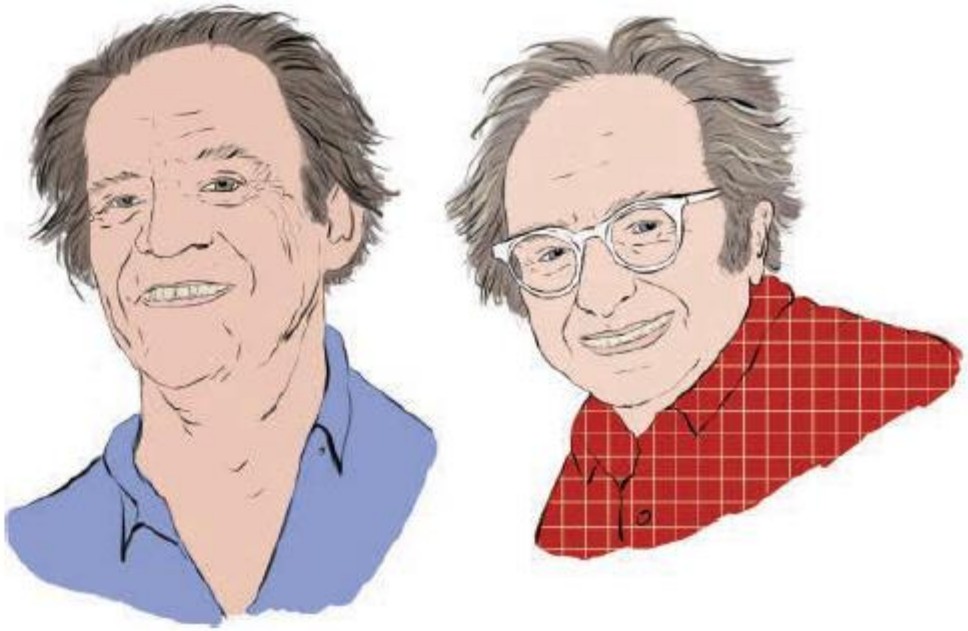
Surge in the Number of Species

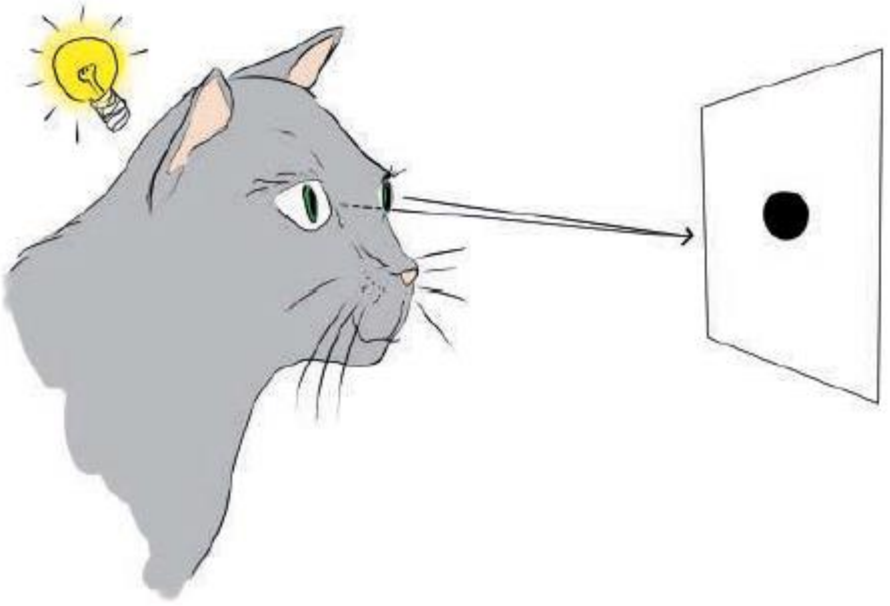
Evidence suggests this surge was driven by the development of light detectors in the trilobyte



Torsten Wiesel and David Hubel

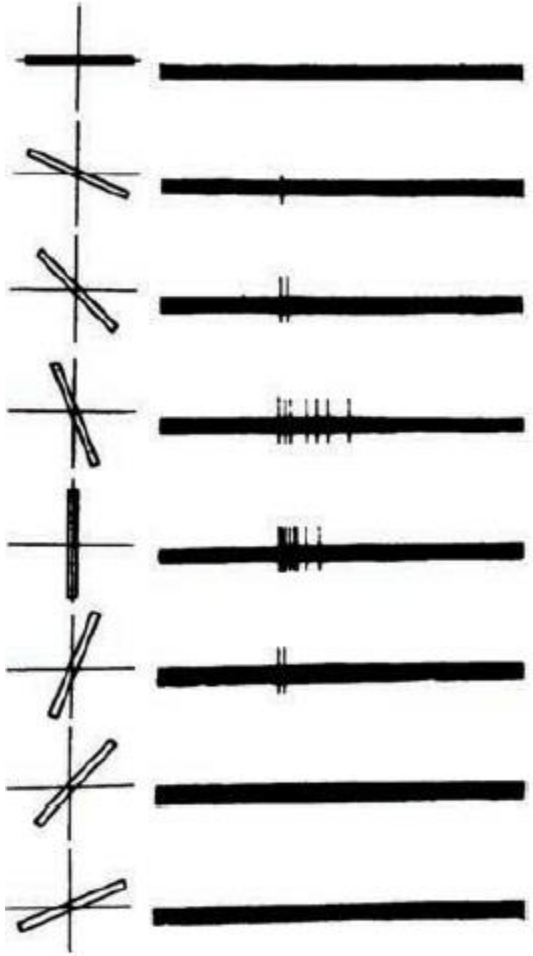
- Nobel prize-winning neurophysiologists
- Implanted electrical recording equipment within cat skulls, to measure activity in the primary visual cortex when projected presenting slides to anesthetized cats (slide edges elicited response)





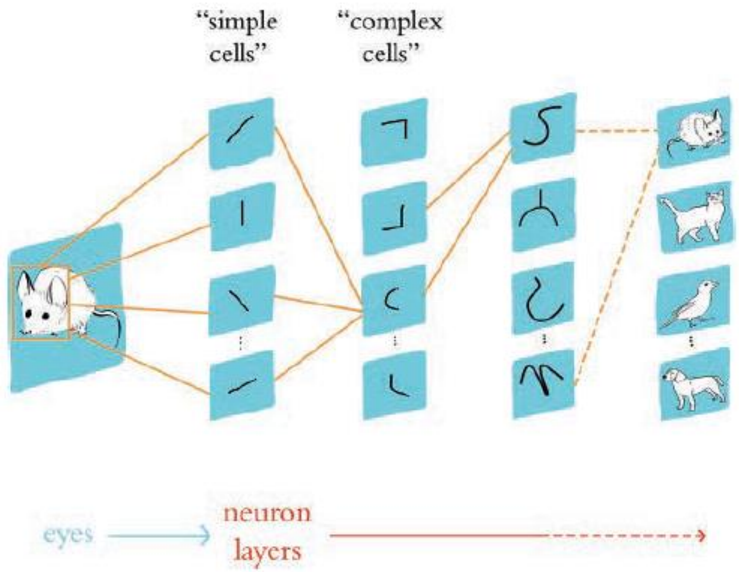
Cell Responding to Line Orientation

- Orientation of the line on the left
- Electrical activity over a second on the right
- Vertical line (5th row) generates the largest response



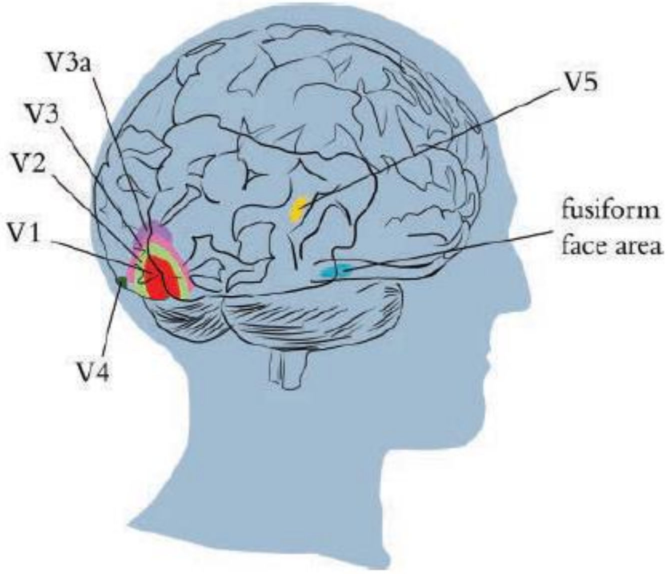
Consecutive Layers of Biological Neurons

- Cartoon has 5 layers: an input layer, 3 hidden layers, and an output layer
- First hidden layer neurons "fire" in response to simple concepts; e.g. edges
- Second and third layer neurons fire in response to successively more complex concepts; e.g. shapes and textures



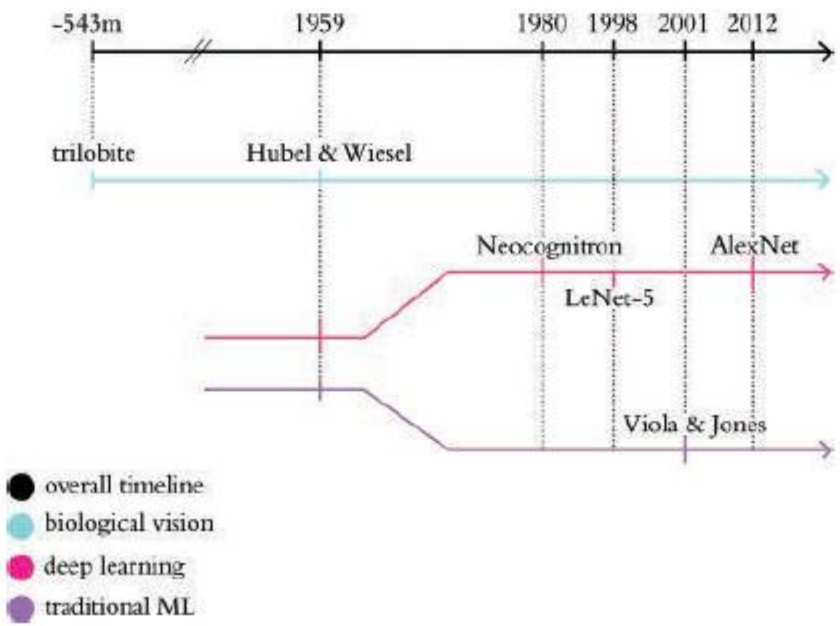
Regions of the Visual Cortex

- V1: contains simple cells that receive input from the eyes and detect edge orientations
- V2, V3, and V3a: increasingly complex, abstract concepts detected
- V4 specializes in detection of color
- V5 specializes in detection of motion
- Fusiform (spindle shaped) face area specializes in detection of faces



Computer Vision Timeline

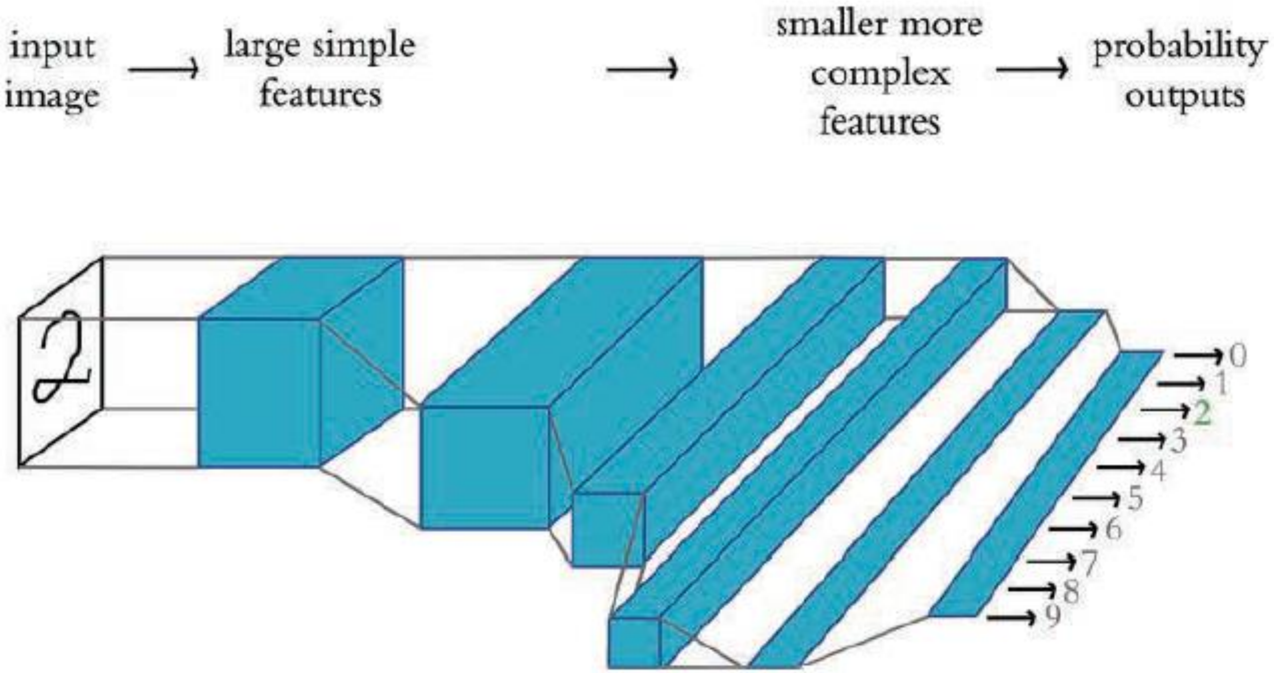
Light detectors; experiments on cats; handwritten digit detection (simple and complex cells; convolution and pooling); face detection (Haar features and adaptive boosting); image classification … something for everyone



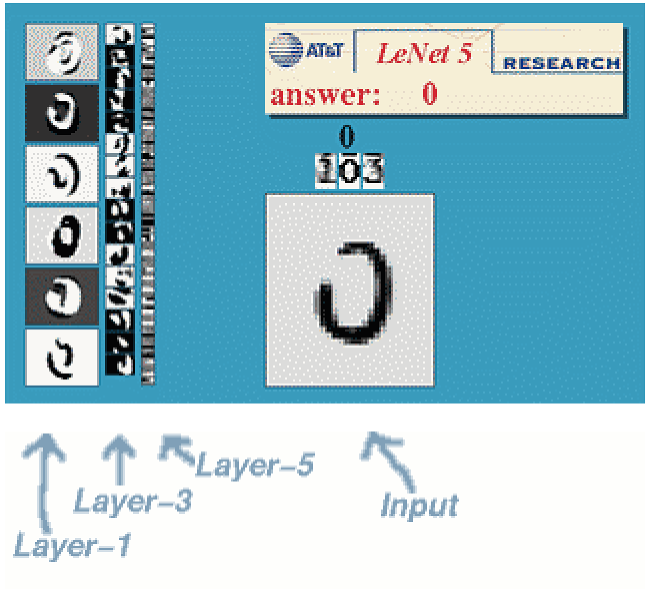
Yann LeCun and Yoshua Bengio

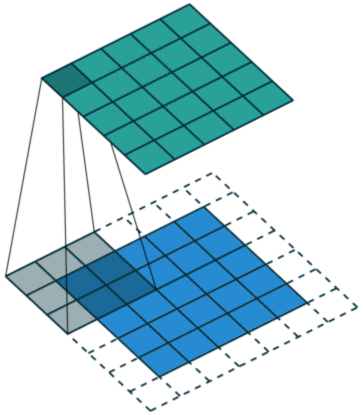
- Developed LeNet-5: first convolutional neural network; more accurate and more efficient for handwritten digit detection, compared to the Neocognitron
- Yann is Chief AI Scientist at Facebook
- Yoshua is a professor at the University of Montreal [Theano]

LeNet-5



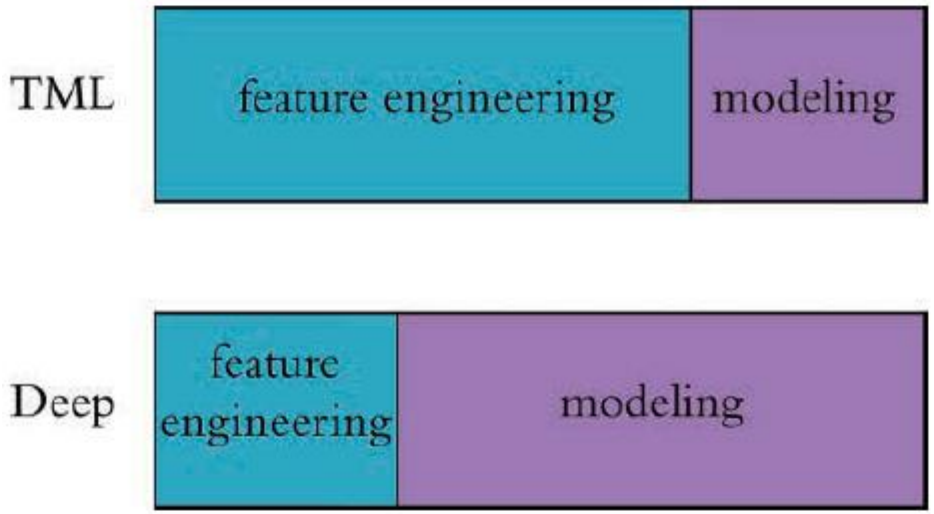
http://yann.lecun.com/exdb/lenet/





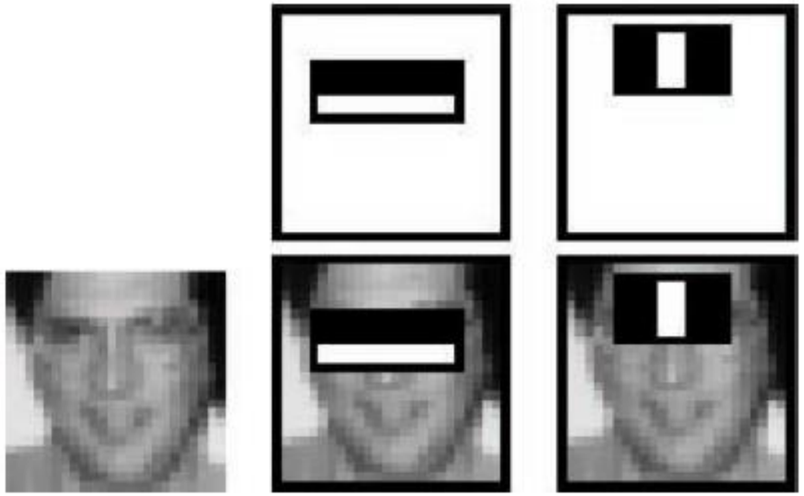
http://deeplearning.net/software/theano/tutorial/conv_arithmetic.html

Traditional Machine Learning versus Deep Learning



Viola Jones Face Detection

- Haar features used to detect regions, such as the eyes or the bridge of the nose
  - Eye region darker than the upper cheeks
  - Nose bridge region is brighter than the eyes
- Adaptive Boosting (AdaBoost) used for classification

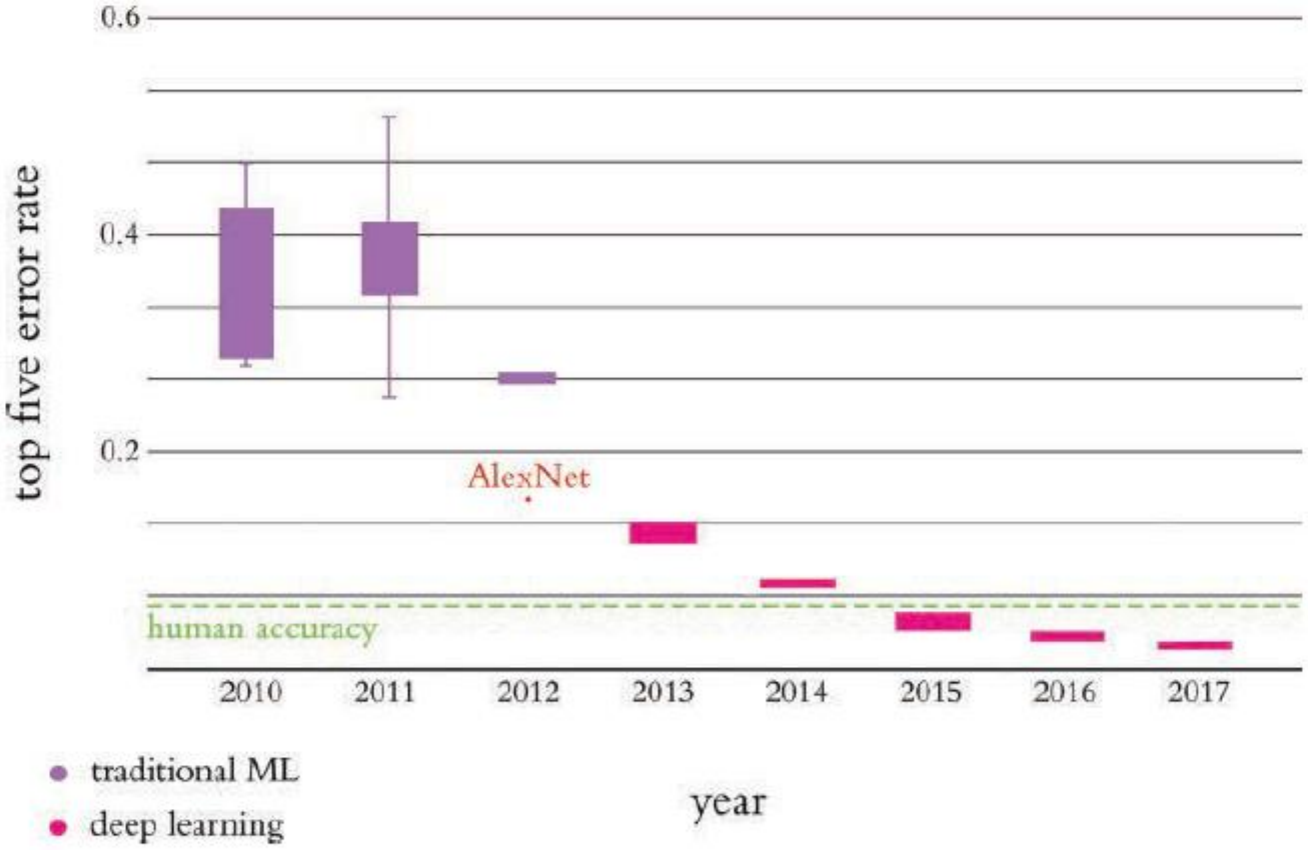


ILSVRC

- ImageNet dataset
  - Collected by Fei Fei Li and her colleagues at Princeton
  - 14 million images; 22,000 classes
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC) dataset
  - 1.4 million images
  - 1,000 classes
  - Used for both image classification (image contains a person) and object detection (bounding box contains a person)

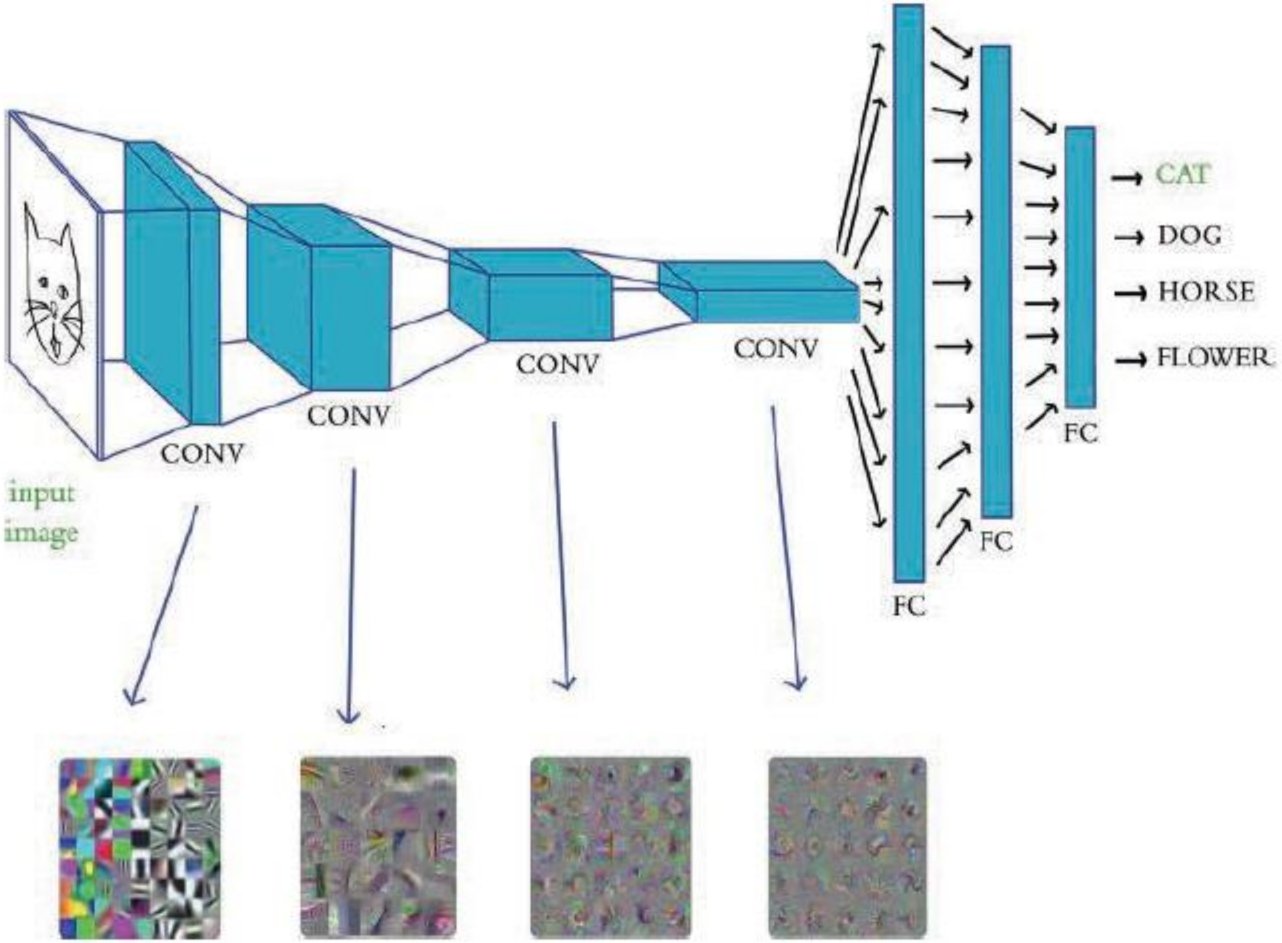
ILSVRC Performance

AlexNet (a convolutional neural network trained by Alex Krizhevsky, a student of Geoff Hinton) achieved a top-5 error rate of 15.3%



AlexNet Architecture

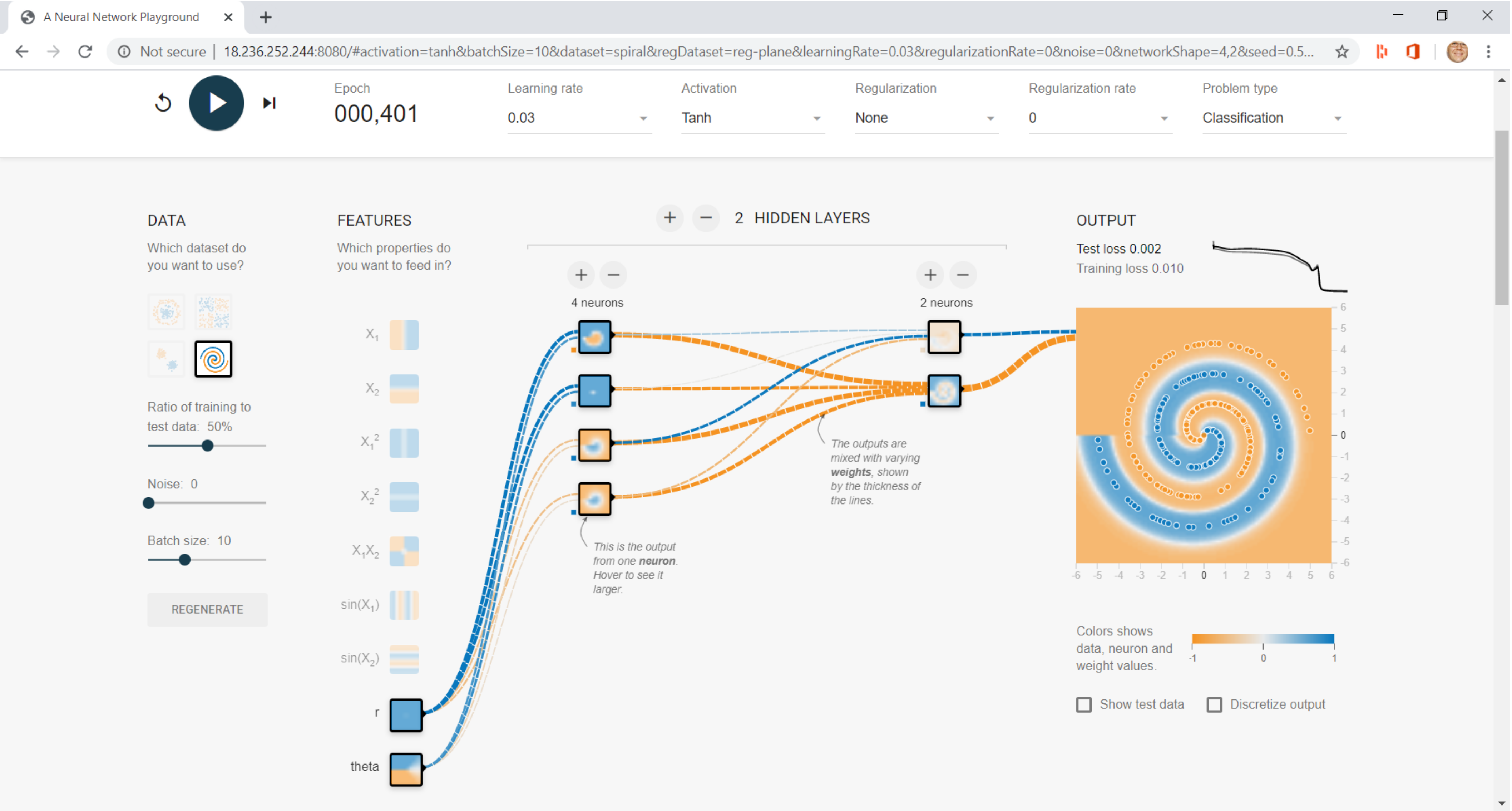
Convolution blocks followed by fully connected (dense) layers



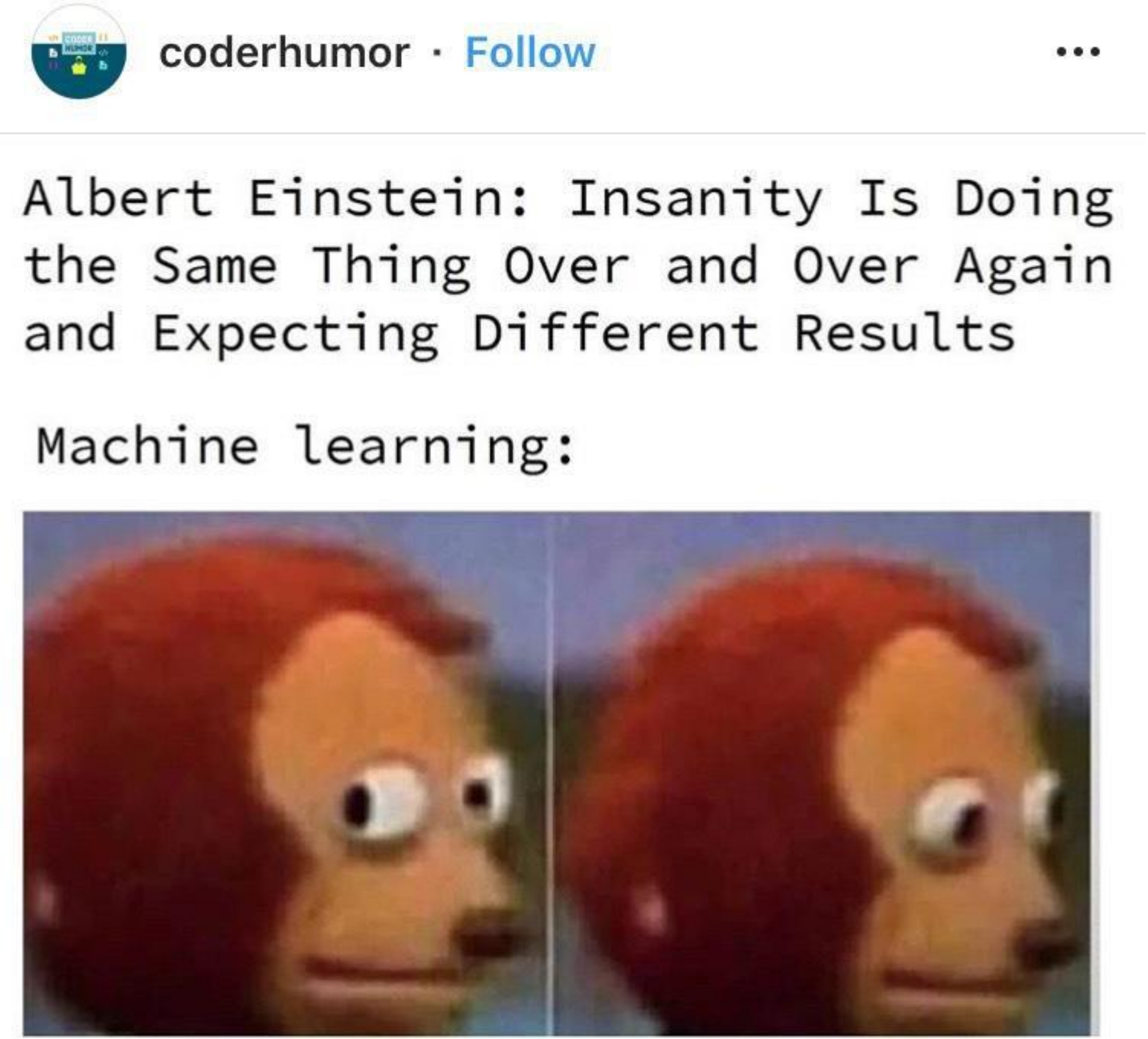
Customizing Tensorflow Playground

```
git clone https://github.com/tensorflow/playground
cd playground/src
nano plaground.ts
# add below sinY
  "r": {f: (x, y) => Math.sqrt(x * x + y * y), label: "r"},
  "theta": {f: (x, y) => Math.atan2(y, x), label: "theta"},
nano state.ts
# add below first occurrence of sinY
    {name: "r", type: Type.BOOLEAN},
    {name: "theta", type: Type.BOOLEAN},
# add below second occurrence of sinY
  r = false;
  theta=false;
cd ..
sudo apt install npm
npm i
npm run build
npm run serve
```

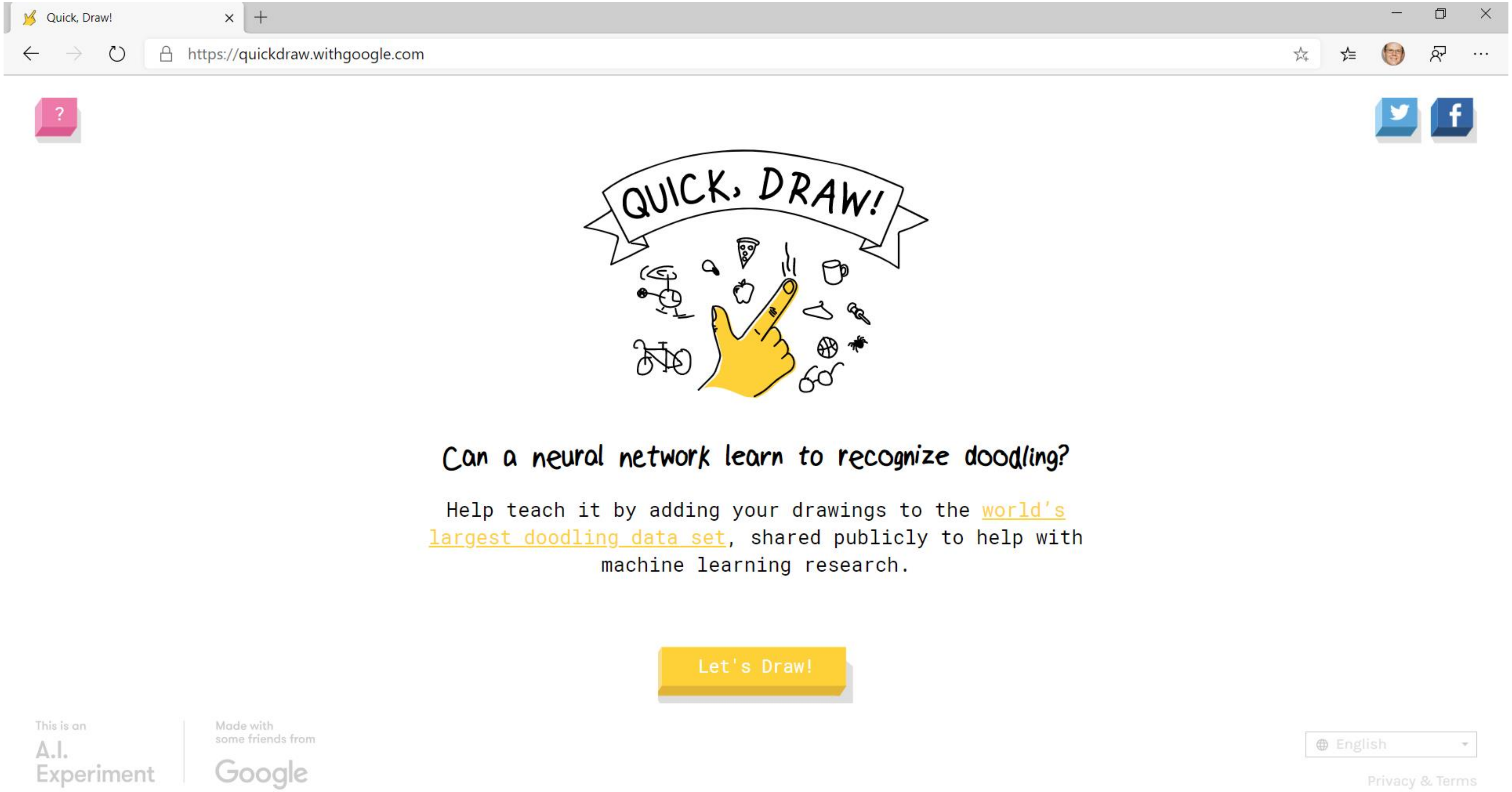
Spiral Classification with Polar Coordinates



Reminder About Repeatability



Fun with https://quickdraw.withgoogle.com/



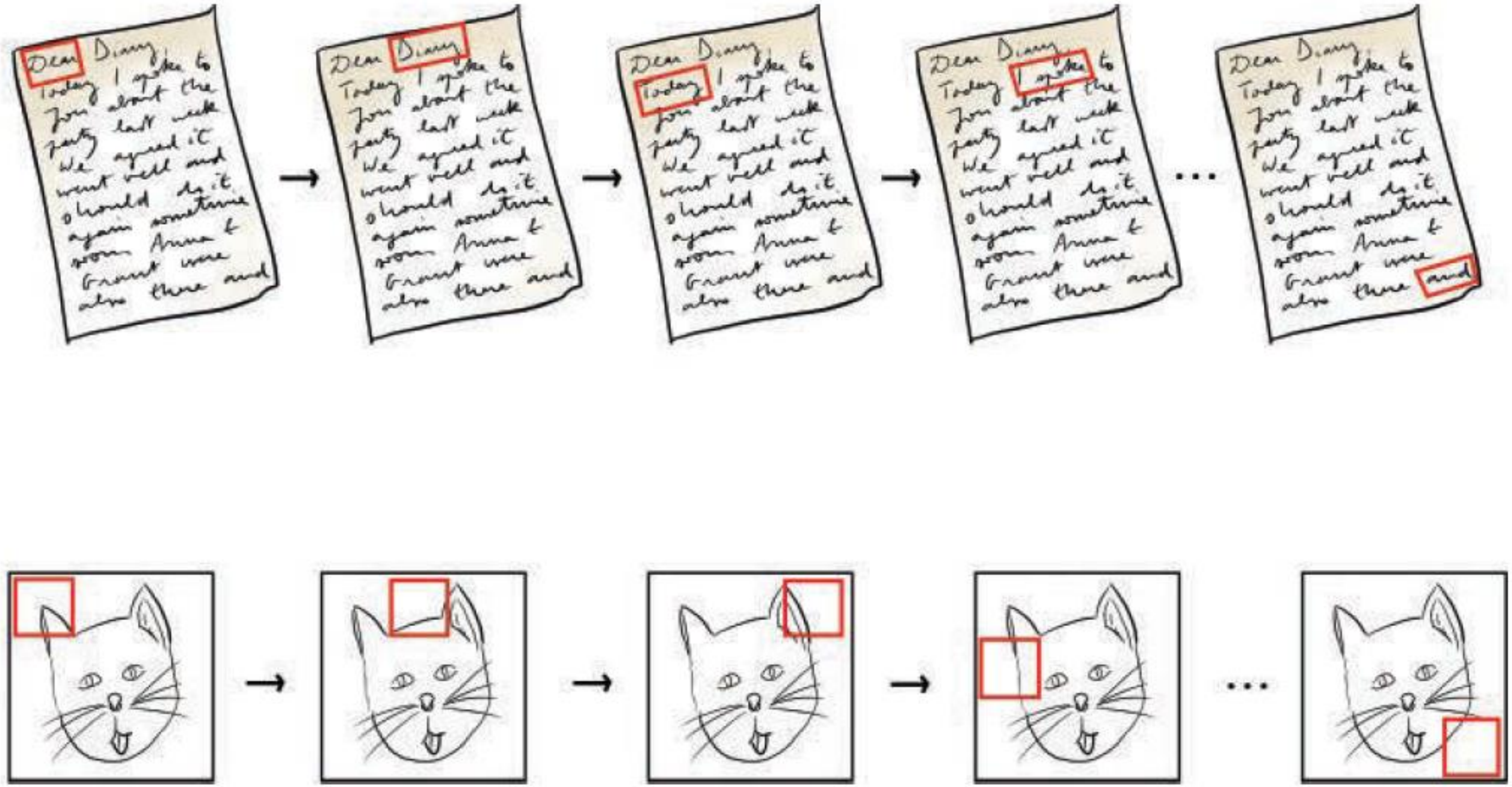
Summary

In this chapter, we traced the history of deep learning from its biological inspiration through to the AlexNet triumph in 2012 that brought the technique to the fore. All the while, we reiterated that the hierarchical architecture of deep learning models enables them to encode increasingly complex representations. To concretize this concept, we concluded with an interactive demonstration of hierarchical representations in action by training an artificial neural network in the TensorFlow Playground. In Chapter 2, we will expand on the ideas introduced in this chapter by moving from vision applications to language applications.

[DLI] Machine Vision

- Convolutional Neural Networks
- Pooling Layers
- LeNet-5 in Keras
- AlexNet and VGGNet in Keras
- Residual Networks
- Applications of Machine Vision

Motion of Convolution Filter



Convolution Filter Output Example

$$\begin{bmatrix} .01 & .09 & .22 \\ -1.36 & .34 & -1.59 \\ .13 & -.69 & 1.02 \end{bmatrix} \bullet \begin{bmatrix} .53 & .34 & .06 \\ .37 & .82 & .01 \\ .62 & .91 & .34 \end{bmatrix}$$

kernel weights

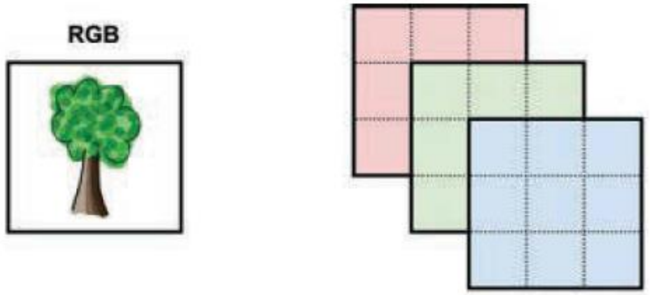
pixel input

$$\begin{aligned} w \cdot x &= .01 \times .53 + .09 \times .34 + .22 \times .06 \\ &+ -1.36 \times .37 + .34 \times .82 + -1.59 \times .01 \\ &+ .13 \times .62 + -.69 \times .91 + 1.02 \times .34 \\ &= -0.3917 \end{aligned}$$

$$\begin{aligned} z &= w \cdot x + b \\ &= -0.39 + b \\ &= -0.39 + 0.20 \\ &= -0.19 \end{aligned}$$

Convolution Filter Output Example: Same Padding

A filter will have weights for each input channel …



Images:

Red

0.00	0.00	0.00	0.00	0.00
0.00	0.20	0.40	0.30	0.00
0.00	0.30	0.90	0.60	0.00
0.00	0.90	0.10	0.20	0.00
0.00	0.00	0.00	0.00	0.00

Green

0.00	0.00	0.00	0.00	0.00
0.00	0.60	0.60	0.90	0.00
0.00	0.40	0.70	0.40	0.00
0.00	0.70	0.50	0.30	0.00
0.00	0.00	0.00	0.00	0.00

Blue

0.00	0.00	0.00	0.00	0.00
0.00	0.80	0.40	0.90	0.00
0.00	0.30	0.10	0.60	0.00
0.00	0.80	0.60	0.40	0.00
0.00	0.00	0.00	0.00	0.00

Weights:

0.10	0.20	0.60
0.60	0.80	0.70
0.50	0.40	0.30

0.60	0.60	0.90
0.40	0.70	0.40
0.70	0.50	0.30

0.80	0.40	0.90
0.30	0.10	0.60
0.80	0.60	0.40

Bias: 0.20

z value:

$$\sum\left(\begin{matrix}0.00 & 0.00 & 0.00\\ 0.00 & 0.16 & 0.28\\ 0.00 & 0.12 & 0.27\end{matrix} + \begin{matrix}0.00 & 0.00 & 0.00\\ 0.00 & 0.42 & 0.24\\ 0.00 & 0.20 & 0.21\end{matrix} + \begin{matrix}0.00 & 0.00 & 0.00\\ 0.00 & 0.08 & 0.24\\ 0.00 & 0.18 & 0.04\end{matrix}\right) + 0.2 = \begin{matrix}\boxed{2.64} & & \\ & & \\ & & \end{matrix}$$

Same Filter, Different Position

Images:

Red

0.00	0.00	0.00	0.00	0.00
0.00	0.20	0.40	0.30	0.00
0.00	0.30	0.90	0.60	0.00
0.00	0.90	0.10	0.20	0.00
0.00	0.00	0.00	0.00	0.00

Green

0.00	0.00	0.00	0.00	0.00
0.00	0.60	0.60	0.90	0.00
0.00	0.40	0.70	0.40	0.00
0.00	0.70	0.50	0.30	0.00
0.00	0.00	0.00	0.00	0.00

Blue

0.00	0.00	0.00	0.00	0.00
0.00	0.80	0.40	0.90	0.00
0.00	0.30	0.10	0.60	0.00
0.00	0.80	0.60	0.40	0.00
0.00	0.00	0.00	0.00	0.00

Weights:

0.10	0.20	0.60
0.60	0.80	0.70
0.50	0.40	0.30

0.60	0.60	0.90
0.40	0.70	0.40
0.70	0.50	0.30

0.80	0.40	0.90
0.30	0.10	0.60
0.80	0.60	0.40

Bias: 0.20

z values:

$$\sum\left(\begin{bmatrix}0.00 & 0.00 & 0.00\\ 0.12 & 0.32 & 0.21\\ 0.15 & 0.36 & 0.18\end{bmatrix} + \begin{bmatrix}0.00 & 0.00 & 0.00\\ 0.24 & 0.42 & 0.36\\ 0.28 & 0.35 & 0.12\end{bmatrix} + \begin{bmatrix}0.00 & 0.00 & 0.00\\ 0.24 & 0.04 & 0.54\\ 0.24 & 0.06 & 0.24\end{bmatrix}\right) + 0.2 = \begin{bmatrix}2.64 & \boxed{4.67} & \\ & & \\ & & \end{bmatrix}$$

Same Filter, Last Position

Images:

Red

0.00	0.00	0.00	0.00	0.00
0.00	0.20	0.40	0.30	0.00
0.00	0.30	0.90	0.60	0.00
0.00	0.90	0.10	0.20	0.00
0.00	0.00	0.00	0.00	0.00

Green

0.00	0.00	0.00	0.00	0.00
0.00	0.60	0.60	0.90	0.00
0.00	0.40	0.70	0.40	0.00
0.00	0.70	0.50	0.30	0.00
0.00	0.00	0.00	0.00	0.00

Blue

0.00	0.00	0.00	0.00	0.00
0.00	0.80	0.40	0.90	0.00
0.00	0.30	0.10	0.60	0.00
0.00	0.80	0.60	0.40	0.00
0.00	0.00	0.00	0.00	0.00

Weights:

0.10	0.20	0.60
0.60	0.80	0.70
0.50	0.40	0.30

0.60	0.60	0.90
0.40	0.70	0.40
0.70	0.50	0.30

0.80	0.40	0.90
0.30	0.10	0.60
0.80	0.60	0.40

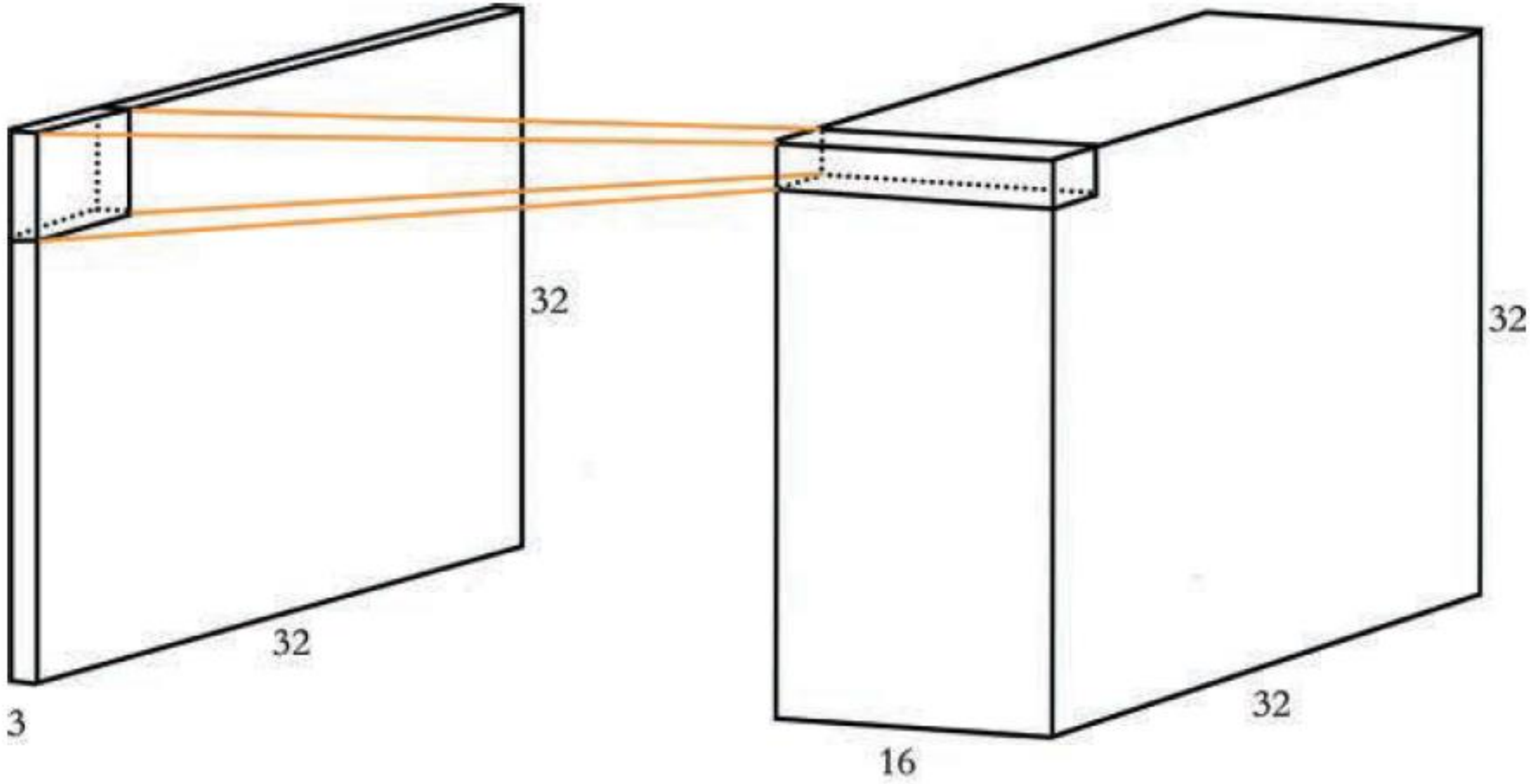
Bias: 0.20

z values:

$$\sum\left(\begin{bmatrix}0.09 & 0.12 & 0.00\\0.06 & 0.16 & 0.00\\0.00 & 0.00 & 0.00\end{bmatrix} + \begin{bmatrix}0.42 & 0.24 & 0.00\\0.20 & 0.21 & 0.00\\0.00 & 0.00 & 0.00\end{bmatrix} + \begin{bmatrix}0.08 & 0.24 & 0.00\\0.18 & 0.04 & 0.00\\0.00 & 0.00 & 0.00\end{bmatrix}\right) + 0.2 = \begin{bmatrix}2.64 & 4.67 & 3.58\\5.19 & 8.75 & 4.90\\3.80 & 4.66 & \boxed{2.24}\end{bmatrix}$$

3 Channel Input to 16 Channel Output

- 16 convolution filters: same padding



Basic Convolution Filters

- They allow deep learning models to learn to recognize features in a position invariant manner; a single kernel can identify its cognate feature anywhere in the input data.
- They remain faithful to the two-dimensional structure of images, allowing features to be identified within their spacial context.
- They significantly reduce the number of parameters required for modeling image data, yielding higher computational efficiency.
- Ultimately, they perform machine vision tasks (e.g., image classification) more accurately.

Careful with the “higher computational efficiency” talk: for example, for “same” padding a single convolution filter will be applied once for every output position

Nice review of convolutional features: http://bit.ly/DeepViz

Activation Map Dimensions

This corresponds to the number of activations per filter

$$\text{Activation map} = \frac{D - F + 2P}{S} + 1$$

- D is the size of the image (either width or height, depending on whether you're calculating the width or height of the activation map).
- F is the size of the filter.
- P is the amount of padding.
- S is the stride length.

$$\text{Activation map} = \frac{D - F + 2P}{S} + 1$$

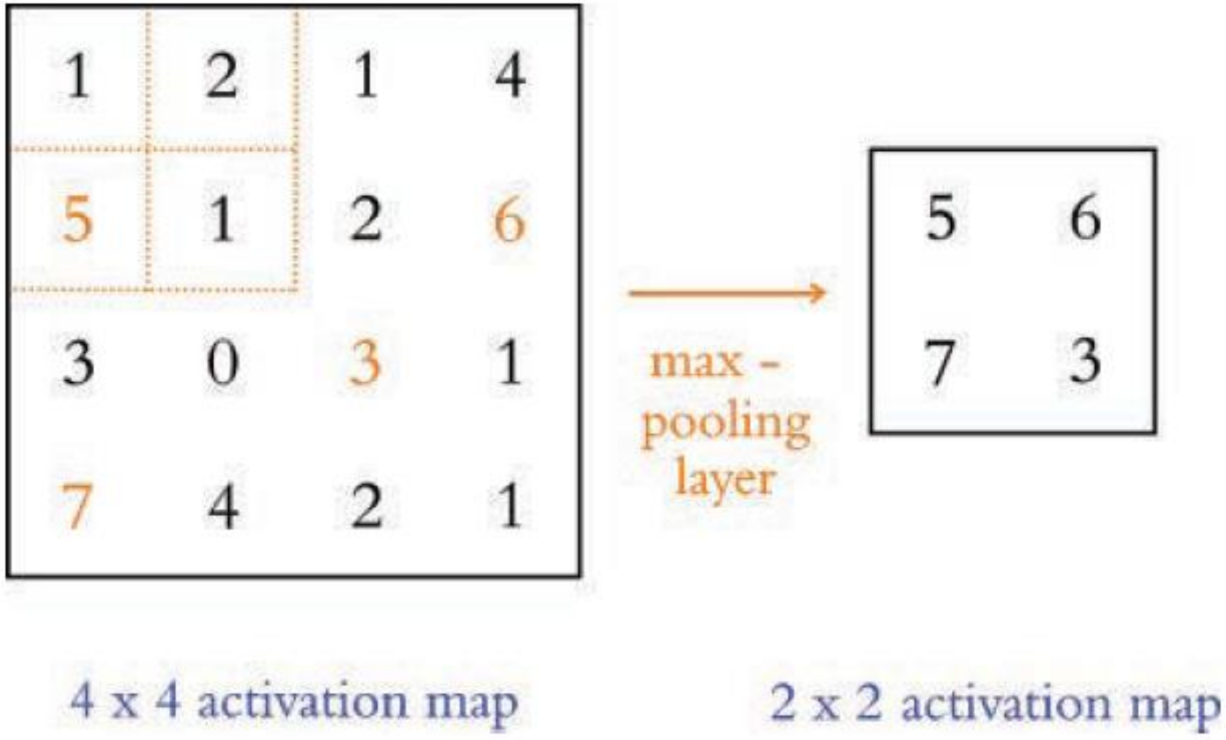
$$\text{Activation map} = \frac{28 - 5 + 2 \times 2}{1} + 1$$

… for MNIST, with a 5x5 filter, "same" padding, and stride 1

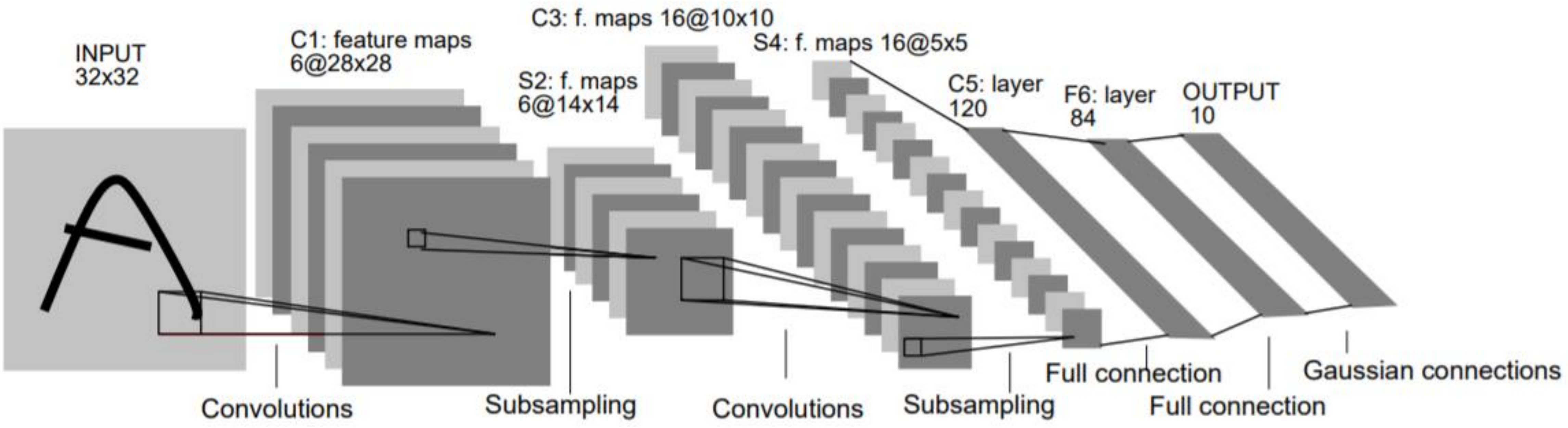
$$\text{Activation map} = 28$$

Max Pooling Example

pool_size = (2, 2) with stride = (2, 2)



LeNet-5



5x5 convolution filters in layers C1, C3, and C5 [“valid” padding]
2x2 subsampling in layers S2 and S4

http://yann.lecun.com/exdb/publis/pdf/lecun-99.pdf

Twists for LeNet-5 in Keras

- Because computation is much cheaper today, we opt to use more kernels in our convolutional layers. More specifically, we include 32 and 64 filters in the first and second convolutional layers, respectively, whereas the original LeNet-5 had only 6 and 16 in each.
- Also thanks to cheap compute, we are subsampling activations only once (with a max-pooling layer), whereas LeNet-5 did twice.[16]
- We leverage innovations like ReLU activations and dropout, which had not yet been invented at the time of LeNet-5.

CNN Inspired by LeNet-5

Example 10.3 CNN model inspired by LeNet-5

```
model = Sequential()

# first convolutional layer:
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu',
                 input_shape=(28, 28, 1)))

# second conv layer, with pooling and dropout:
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())

# dense hidden layer, with dropout:
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))

# output layer:
model.add(Dense(n_classes, activation='softmax'))
```

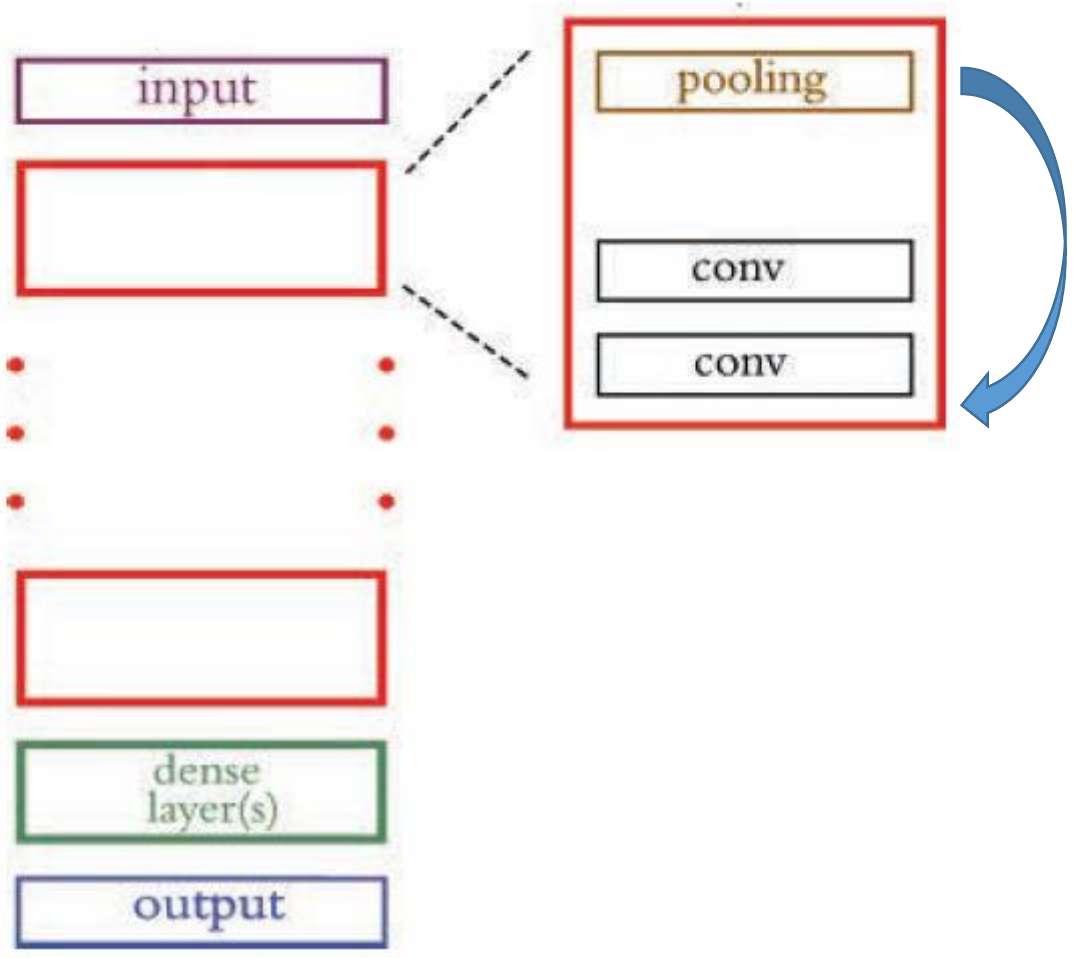
CNN Inspired by LeNet-5

```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 24, 24, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 12, 12, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 12, 12, 64)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 9216)              0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               1179776
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 10)                1290
=================================================================
Total params: 1,199,882
Trainable params: 1,199,882
Non-trainable params: 0
```

```
Epoch 9/10
60000/60000 [==============================] - 39s 654us/step - loss: 0.0276 - acc: 0.9911 - val_loss: 0.0260 - val_acc: 0.9927
```

General Approach to CNN Design

“conv > conv > pooling” rather than “pooling > conv > conv”



CNN Inspired by Alex Net

```
model = Sequential()

# first conv-pool block:
model.add(Conv2D(96, kernel_size=(11, 11),
   strides=(4, 4), activation='relu',
   input_shape=(224, 224, 3)))

model.add(MaxPooling2D(pool_size=(3, 3), strides=(2, 2)))
model.add(BatchNormalization())

# second conv-pool block:
model.add(Conv2D(256, kernel_size=(5, 5), activation='relu'))
model.add(MaxPooling2D(pool_size=(3, 3), strides=(2, 2)))
model.add(BatchNormalization())

# third conv-pool block:
model.add(Conv2D(256, kernel_size=(3, 3), activation='relu'))
model.add(Conv2D(384, kernel_size=(3, 3), activation='relu'))
model.add(Conv2D(384, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(3, 3), strides=(2, 2)))
model.add(BatchNormalization())

# dense layers:
model.add(Flatten())
model.add(Dense(4096, activation='tanh'))
model.add(Dropout(0.5))
model.add(Dense(4096, activation='tanh'))
model.add(Dropout(0.5))

# output layer:
model.add(Dense(17, activation='softmax'))
```

The Oxford Flowers dataset has 17 classes:
https://www.robots.ox.ac.uk/~vgg/data/flowers/17/

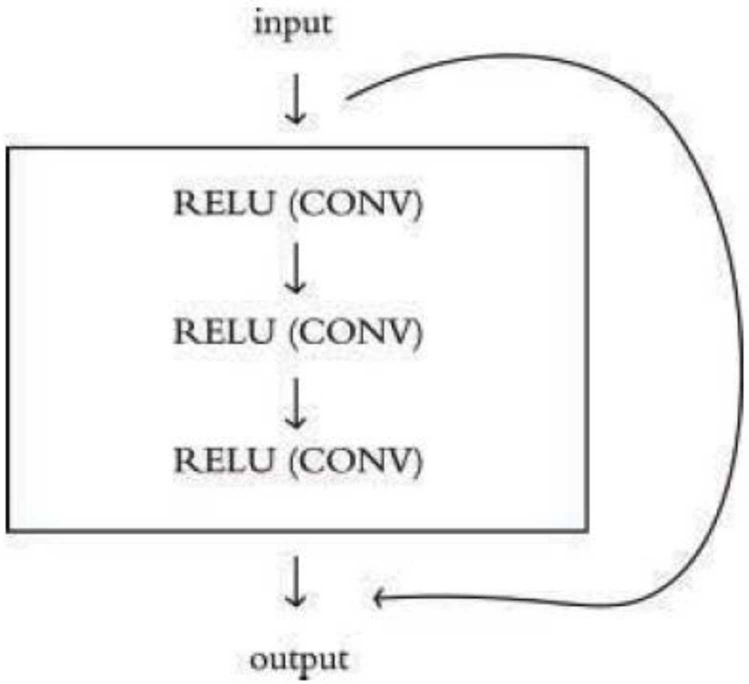
CNN Inspired by VGGNet

```
model = Sequential()

model.add(Conv2D(64, 3, activation='relu',
   input_shape=(224, 224, 3)))

model.add(Conv2D(64, 3, activation='relu'))
model.add(MaxPooling2D(2, 2))
model.add(BatchNormalization())

model.add(Conv2D(128, 3, activation='relu'))
model.add(Conv2D(128, 3, activation='relu'))
model.add(MaxPooling2D(2, 2))
model.add(BatchNormalization())

model.add(Conv2D(256, 3, activation='relu'))
model.add(Conv2D(256, 3, activation='relu'))
model.add(Conv2D(256, 3, activation='relu'))
model.add(MaxPooling2D(2, 2))
model.add(BatchNormalization())

model.add(Conv2D(512, 3, activation='relu'))
model.add(Conv2D(512, 3, activation='relu'))
model.add(Conv2D(512, 3, activation='relu'))
model.add(MaxPooling2D(2, 2))
model.add(BatchNormalization())

model.add(Conv2D(512, 3, activation='relu'))
model.add(Conv2D(512, 3, activation='relu'))
model.add(Conv2D(512, 3, activation='relu'))
model.add(MaxPooling2D(2, 2))
model.add(BatchNormalization())

model.add(Flatten())
model.add(Dense(4096, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(4096, activation='relu'))
model.add(Dropout(0.5))

model.add(Dense(17, activation='softmax'))
```

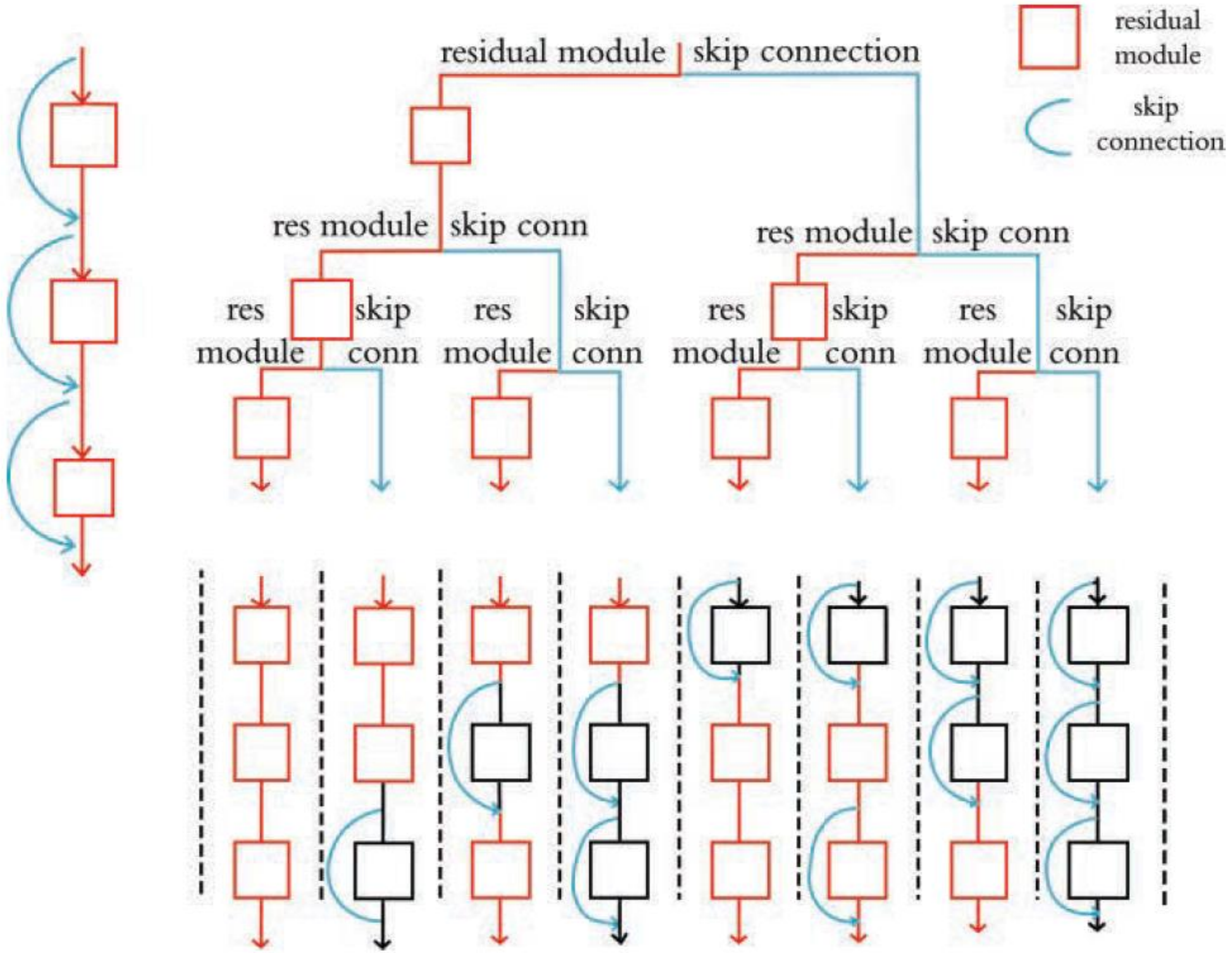
Computing Residuals

Residual = Desired – Current [Rearranging: Desired = Current + Residual]

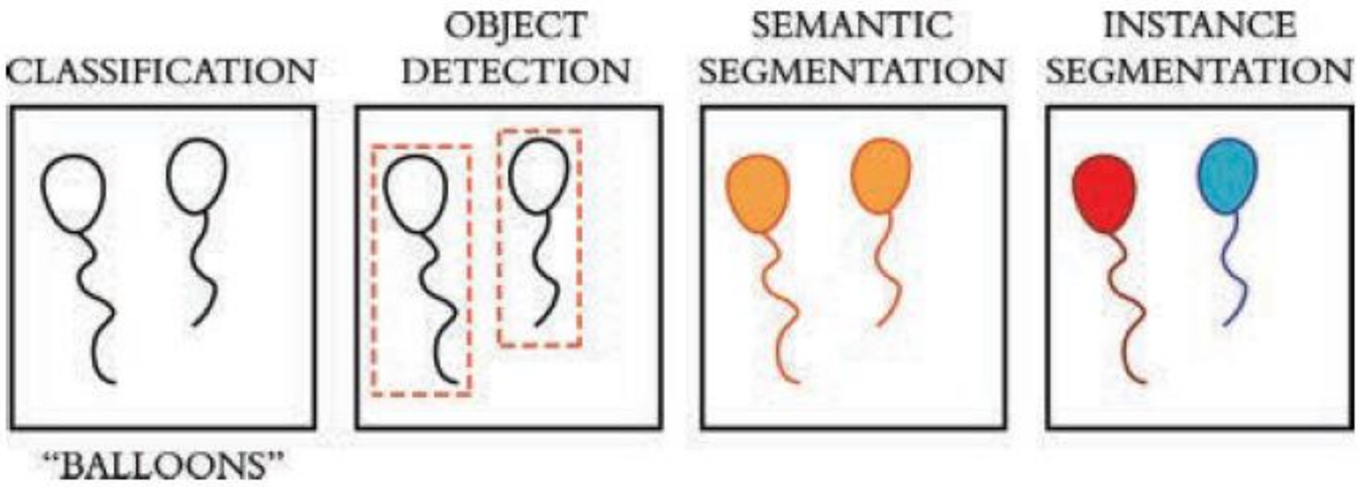
- What do we need to add to Current to get Desired
- Shortcut helps reduce vanishing gradients [shortens gradient path]



Skip Connections [residual module outputs 0]



Computer Vision Applications



Object Detection Pipeline

- A Region Of Interest (ROI) must be identified
- Automatic feature extraction is performed on this region
- The region is classified

R-CNN

Region-based Convolutional Neural Network [Berkeley, Girshick et al]:

1. Perform a selective search for regions of interest (ROIs) within the image
2. Extract features from these ROIs by using a CNN
3. Combine two “traditional” machine learning approaches—called linear regression and support vector machines—to, respectively, refine the locations of bounding boxes and classify objects within each of those boxes

Limitations:

- It was inflexible: The input size was fixed to a single specific image shape
- It was slow and computationally expensive: Both training and inference are multistage processes involving CNNs, linear regression models, and support vector machines

Fast R-CNN

- The chief innovation here was the realization that during step 2 of the R-CNN algorithm, the CNN was unnecessarily being run multiple times, once for each region of interest
- The Fast R-CNN model has to perform feature extraction using a CNN only once for a given image (thereby reducing computational complexity), and then the ROI search and dense layers work together to finish the object-detection task

Faster R-CNN

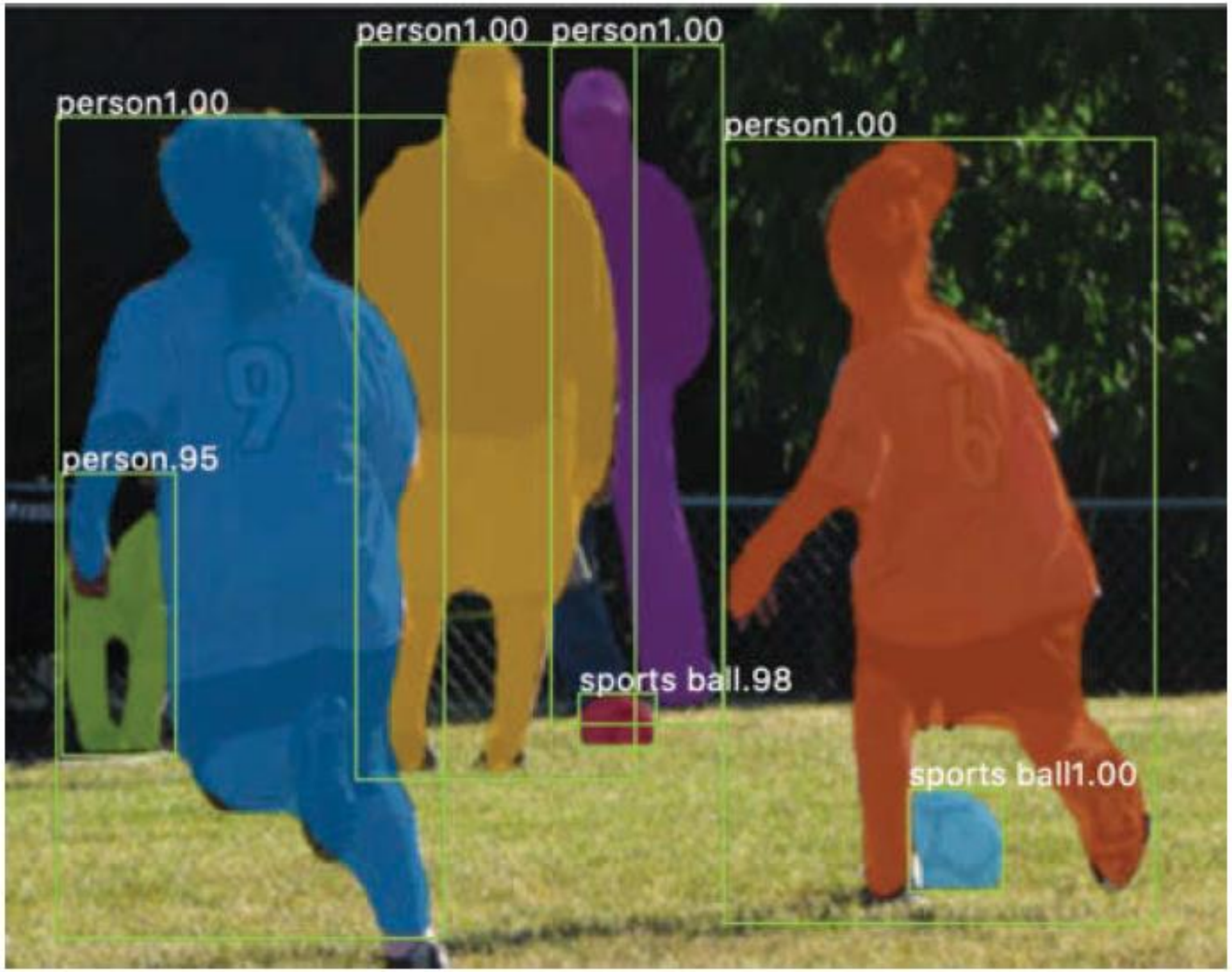
To overcome the ROI-search bottleneck of R-CNN and Fast R-CNN, Ren and his colleagues [at Microsoft research] had the cunning insight to leverage the feature activation maps from the model's CNN for this step, too

Object Detection Output from Faster R-CNN

YOLO: You Only Look Once

- YOLO begins with a pretrained CNN for feature extraction
- Next, the image is divided into a series of cells, and, for each cell, a number of bounding boxes and object-classification probabilities are predicted
- Bounding boxes with class probabilities above a threshold value are selected, and these combine to locate an object within an image
- You can think of the YOLO method as aggregating many smaller bounding boxes, but only if they have a reasonably good probability of containing any given object class

Instance Segmentation



Mask R-CNN

Facebook AI Research (FAIR):

1. Using the existing Faster R-CNN architecture to propose ROIs within the image that are likely to contain objects
2. An ROI classifier predicting what kind of object exists in the bounding box while also refining the location and size of the bounding box
3. Using the bounding box to grab the parts of the feature maps from the underlying CNN that correspond to that part of the image
4. Feeding the feature maps for each ROI into a fully convolutional network that outputs a mask indicating which pixels correspond to the object in the image

U-Net

- The U-Net model consists of a fully convolutional architecture, which begins with a contracting path that produces successively smaller and deeper activation maps through multiple convolution and max-pooling steps
- Subsequently, an expanding path restores these deep activation maps back to full resolution through multiple upsampling and convolution steps
- These two paths—the contracting and expanding paths—are symmetrical (forming a “U” shape), and because of this symmetry the activation maps from the contracting path can be concatenated onto those of the expanding path

Transfer Learning

- Oxford University's Visual Geometry Group's 19-layer CNN used as a pretrained network (pretrained on ImageNet data) to predict whether an image contains a hot dog or not

- model.add(Dense(2, activation='softmax', name='predictions'))

Capsule Networks

Unlike a CNN, a Capsule Network takes positional information into consideration

Summary

In this chapter, you learned about convolutional layers, which are specialized to detect spatial patterns, making them particularly useful for machine vision tasks. You incorporated these layers into a CNN inspired by the classic LeNet-5 architecture, enabling you to surpass the handwritten-digit recognition accuracy of the dense networks you designed in Part II. The chapter concluded by discussing best practices for building CNNs and surveying the most noteworthy applications of machine vision algorithms. In the coming chapter, you'll discover that the spatial-pattern recognition capabilities of convolutional layers are well suited not only to machine vision but also to other tasks.

Concepts

- parameters:
  - weight w
  - bias b
- activation a
- artificial neurons:
  - sigmoid
  - tanh
  - ReLU
  - linear
- input layer
- hidden layer
- output layer
- layer types:
  - dense (fully connected)
  - softmax
  - convolutional
  - max-pooling
  - flatten
- cost (loss) functions:
  - quadratic (mean squared error)
  - cross-entropy
- forward propagation
- backpropagation
- unstable (especially vanishing) gradients
- Glorot weight initialization
- batch normalization
- dropout
- optimizers:
  - stochastic gradient descent
  - Adam
- optimizer hyperparameters:
  - learning rate η
  - batch size

Bonus Topics

- Keras Applications
- ResNet: Version 1 versus Version 2
- Batch Normalization
- Inception vs Xception modules
- Common Objects in Context (COCO) Dataset
- RetinaNet: Single-Stage Object Detection Model

Keras Applications

- This is a Computer Vision Model Zoo; i.e. a collection of pretrained models
- "The top-1 and top-5 accuracy refers to the model's performance on the ImageNet validation dataset. "
- " Depth refers to the topological depth of the network. This includes activation layers, batch normalization layers etc. "

https://keras.io/api/applications/

Model	Size	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth
Xception	88 MB	0.790	0.945	22,910,480	126
VGG16	528 MB	0.713	0.901	138,357,544	23
VGG19	549 MB	0.713	0.900	143,667,240	26
ResNet50	98 MB	0.749	0.921	25,636,712	-
ResNet101	171 MB	0.764	0.928	44,707,176	-
ResNet152	232 MB	0.766	0.931	60,419,944	-
ResNet50V2	98 MB	0.760	0.930	25,613,800	-
ResNet101V2	171 MB	0.772	0.938	44,675,560	-
ResNet152V2	232 MB	0.780	0.942	60,380,648	-
InceptionV3	92 MB	0.779	0.937	23,851,784	159
InceptionResNetV2	215 MB	0.803	0.953	55,873,736	572
MobileNet	16 MB	0.704	0.895	4,253,864	88
MobileNetV2	14 MB	0.713	0.901	3,538,984	88
DenseNet121	33 MB	0.750	0.923	8,062,504	121
DenseNet169	57 MB	0.762	0.932	14,307,880	169
DenseNet201	80 MB	0.773	0.936	20,242,984	201
NASNetMobile	23 MB	0.744	0.919	5,326,716	-
NASNetLarge	343 MB	0.825	0.960	88,949,818	-
EfficientNetB0	29 MB	-	-	5,330,571	-
EfficientNetB1	31 MB	-	-	7,856,239	-
EfficientNetB2	36 MB	-	-	9,177,569	-
EfficientNetB3	48 MB	-	-	12,320,535	-
EfficientNetB4	75 MB	-	-	19,466,823	-
EfficientNetB5	118 MB	-	-	30,562,527	-
EfficientNetB6	166 MB	-	-	43,265,143	-
EfficientNetB7	256 MB	-	-	66,658,687	-

Example Network Depths

- VGG16 Network Depth is 16 (https://www.cross-entropy.net/ML530/vgg16.png):
  - 2 blocks * 2 conv
  - 3 blocks * 3 conv
  - 3 dense
- ResNet50 Network Depth is 50 (https://www.cross-entropy.net/ML530/resnet50_v1.png):
  - conv1: 1 conv
  - conv2: 3 blocks * 3 conv
  - conv3: 4 blocks * 3 conv
  - conv4: 6 blocks * 3 conv
  - conv5: 3 blocks * 3 conv
  - dense: 1 dense
- Default CIFAR10 Homework Network Depth is 27 (https://www.cross-entropy.net/ML530/cifar10.png):
  - 1 conv
  - 3 stages * 3 blocks * 3 conv
  - 1 dense

https://arxiv.org/abs/1603.05027

ResNet: Version 1 versus Version 2

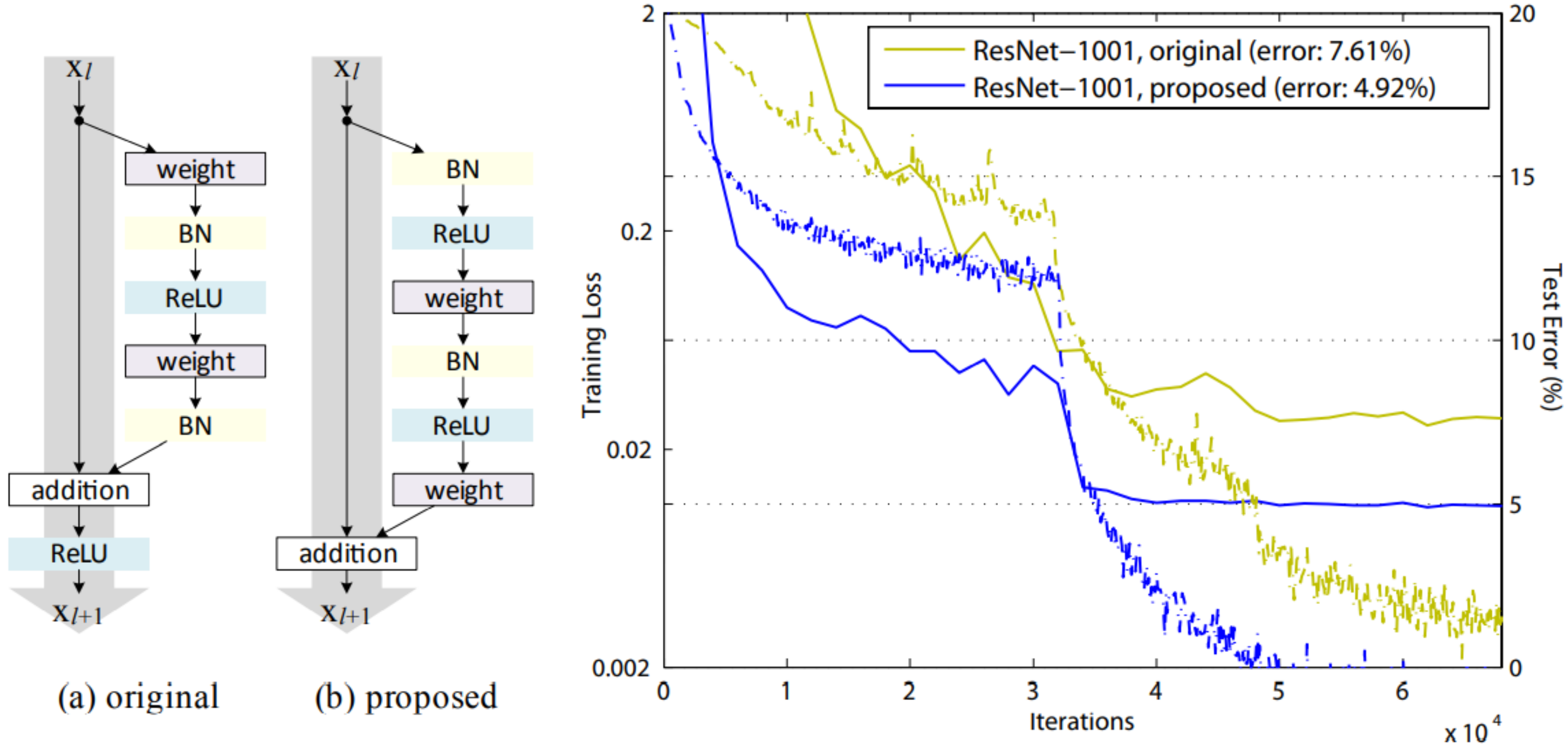


Figure 1. Left: (a) original Residual Unit in [1]; (b) proposed Residual Unit. The grey arrows indicate the easiest paths for the information to propagate, corresponding to the additive term "$\mathbf{x}_l$" in Eqn.(4) (forward propagation) and the additive term "1" in Eqn.(5) (backward propagation). **Right**: training curves on CIFAR-10 of **1001-layer** ResNets. Solid lines denote test error (y-axis on the right), and dashed lines denote training loss (y-axis on the left). The proposed unit makes ResNet-1001 easier to train.

https://arxiv.org/abs/1502.03167

Batch Normalization

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift

International Conference on Machine Learning (ICML) 2015

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

https://arxiv.org/abs/1610.02357

Inception and eXtreme inception (Xception)

- Think of 1x1 convolution as addressing cross-channel correlations, and 3x3 convolution as addressing spatial correlations
- Xception uses depthwise separable (per channel) 3x3 convolution followed by 1x1 convolution

Figure 1. A canonical Inception module (Inception V3).

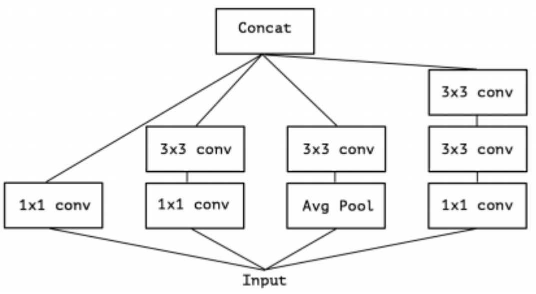


Figure 2. A simplified Inception module.

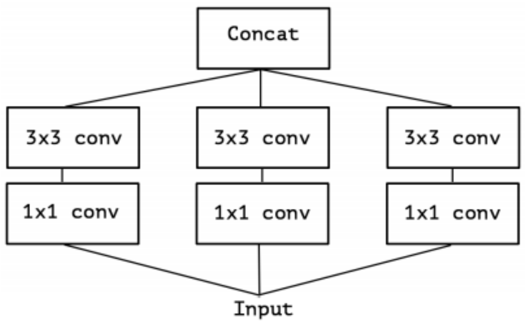


Figure 3. A strictly equivalent reformulation of the simplified Inception module.

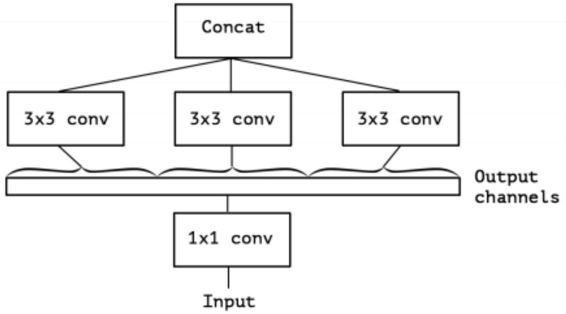
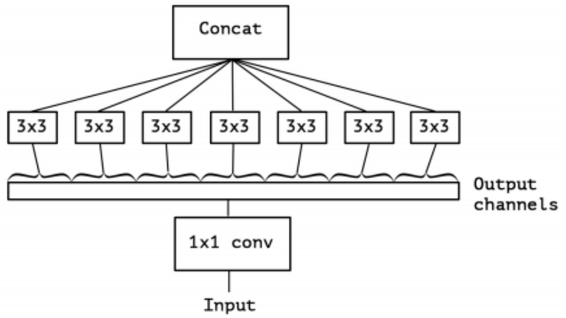


Figure 4. An "extreme" version of our Inception module, with one spatial convolution per output channel of the 1x1 convolution.



Common Objects in Context (COCO) Dataset

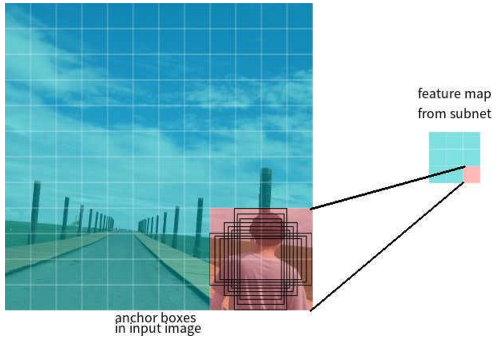
COCO is a frequently used dataset for object detection:

https://cocodataset.org/#download [Trn: 118K (18GB); Val: 5K (1GB); Tst: 41K (6GB)]

```
# $unzip annotations_trainval2017.zip annotations/instances_train2017.json
# import json
# annotations = json.load(open("annotations/instances_train2017.json", "r"))
# print([ category["name"] for category in annotations["categories"] ])
['person', 'bicycle', 'car', 'motorcycle', 'airplane', 'bus', 'train', 'truck', 'boat', 'traffic light',
'fire hydrant', 'stop sign', 'parking meter', 'bench', 'bird', 'cat', 'dog', 'horse', 'sheep', 'cow',
'elephant', 'bear', 'zebra', 'giraffe', 'backpack', 'umbrella', 'handbag', 'tie', 'suitcase',
'frisbee', 'skis', 'snowboard', 'sports ball', 'kite', 'baseball bat', 'baseball glove', 'skateboard',
'surfboard', 'tennis racket', 'bottle', 'wine glass', 'cup', 'fork', 'knife', 'spoon', 'bowl',
'banana', 'apple', 'sandwich', 'orange', 'broccoli', 'carrot', 'hot dog', 'pizza', 'donut', 'cake',
'chair', 'couch', 'potted plant', 'bed', 'dining table', 'toilet', 'tv', 'laptop', 'mouse', 'remote',
'keyboard', 'cell phone', 'microwave', 'oven', 'toaster', 'sink', 'refrigerator', 'book', 'clock',
'vase', 'scissors', 'teddy bear', 'hair drier', 'toothbrush']
```

https://blog.zenggyu.com/en/post/2018-12-05/retinanet-explained-and-demystified/

Object Detection with RetinaNet

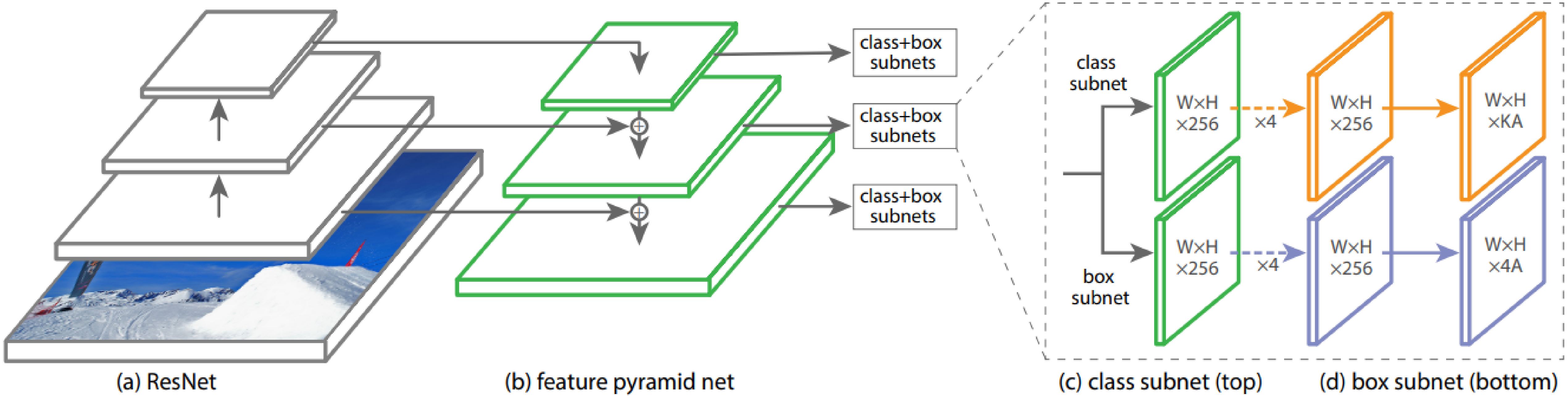


- https://keras.io/examples/vision/retinanet/
- Images are resized so that the shorter side is equal to "min_side": if the longer side is greater than "max_side", then the longer side is resized to "max_side"
- ResNet50 “backbone” pretrained on ImageNet data
  - 50 is the number of layers with parameters [excluding BatchNormalization] along the longest path from input to output [when the head is included]
  - 5 “pyramid” layers created from the output of layers "conv3_block4_out", "conv4_block6_out", and "conv5_block3_out“: https://github.com/keras-team/keras-io/blob/master/examples/vision/retinanet.py#L579-L590
- For each position, there are 9 “anchor” boxes being evaluated
  - 3 aspect ratios (width / height): { 0.5, 1.0, 2.0 }
  - 3 scales: $\{1, 1.2599, 1.5874\} = \{1,\ \sqrt[3]{2},\ \sqrt[3]{4}\}$
- Customized version of crossentropy (focal loss) used for classification heads
- Smooth l_1 loss used for bounding box regression: [x, y, width, height]
- Intersection Over Union [IOU] used to determine matches between ground truth and “anchor” boxes, as well as non-max suppression for predictions

RetinaNet Architecture

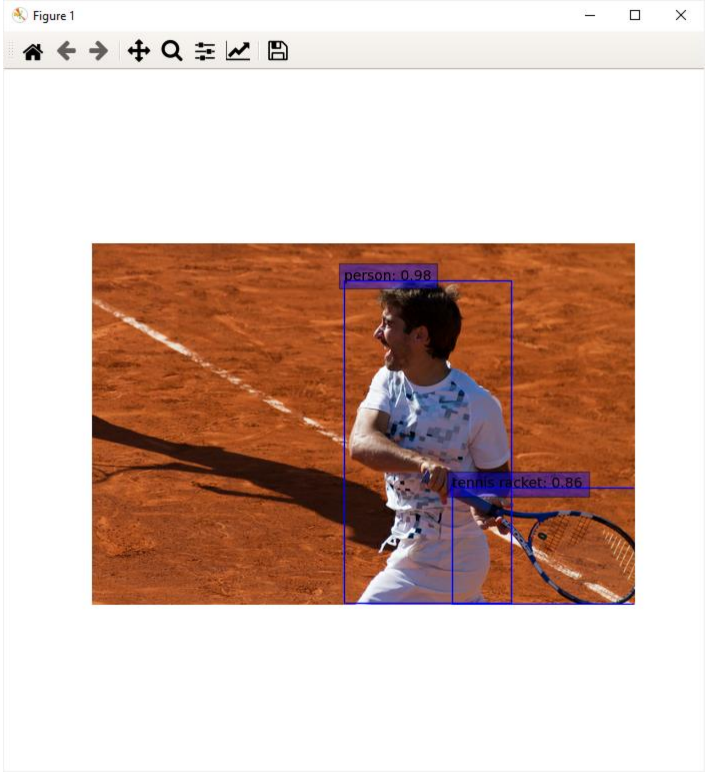
https://arxiv.org/abs/1708.02002

[K is the number of classes; A is the number of anchor boxes]

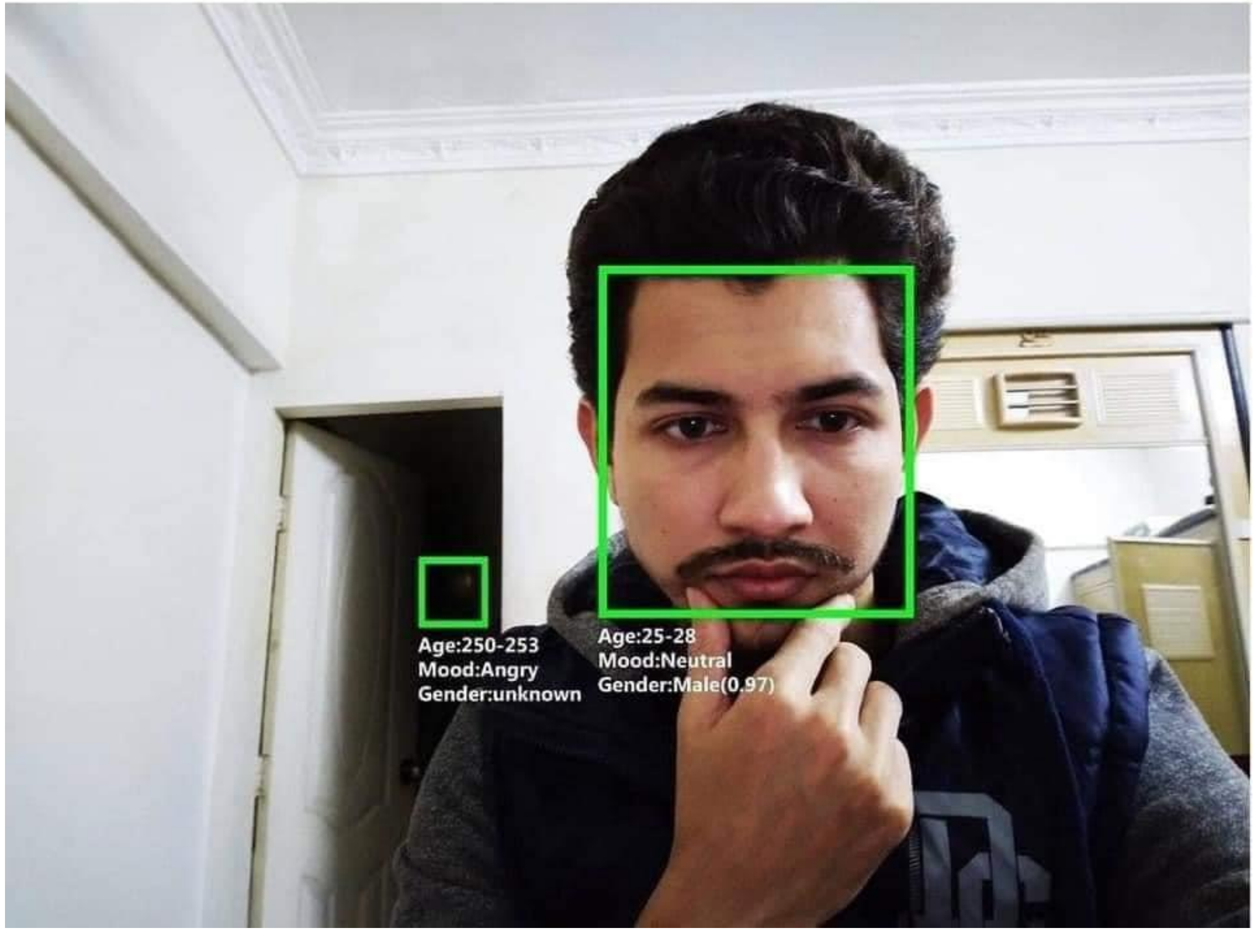


Example RetinaNet Outputs

- https://sourceforge.net/projects/vcxsrv/
- wget https://raw.githubusercontent.com/keras-team/keras-io/master/examples/vision/retinanet.py
- python retinanet.py



When your face recognition system detects something you don't want to know about



https://www.facebook.com/PittsburghParanormal/photos/a.585043914871130/4898410216867790/?type=3