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Neural Networks

Deep Neural Networks & Convolution Neural Networks

Dr. Sharib Ali

Institute of Biomedical Engineering (IBME)
Big Data Institute (BDI)

EPSRC Engineering and Physical Sciences Research Council

MRC Medical Research Council

EPSRC & MRC Centre for Doctoral Training in Biomedical Imaging

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The University of Nottingham

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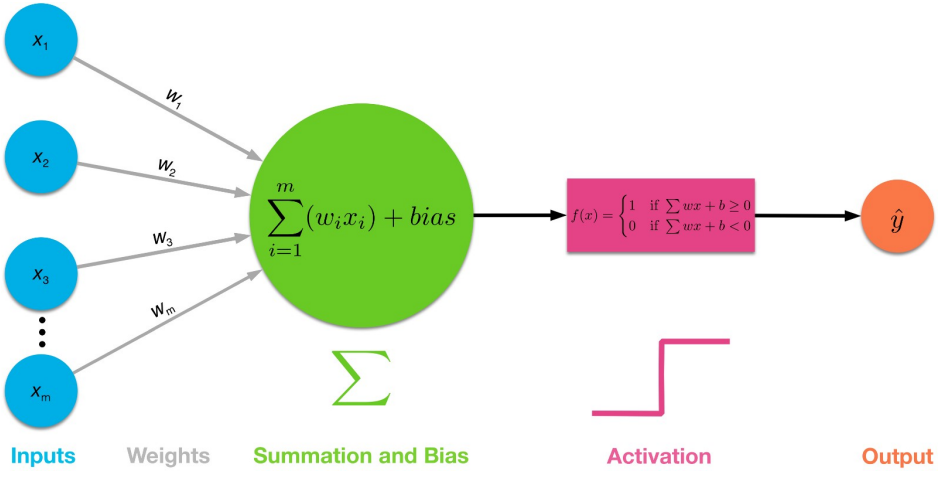
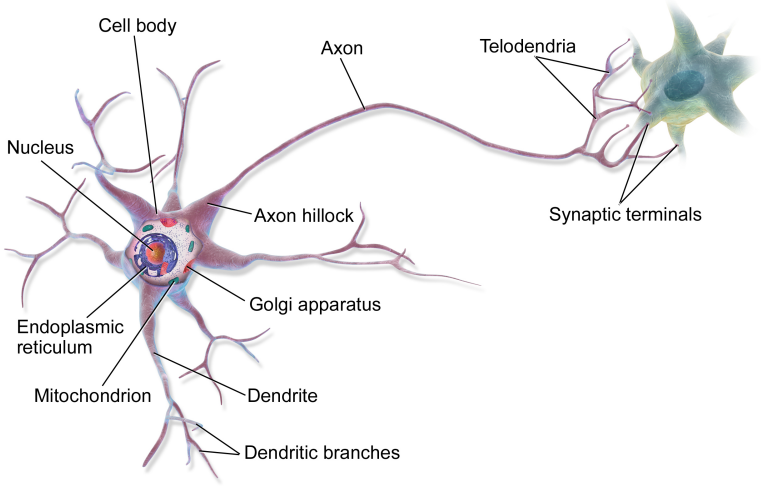
Perceptron

- Simple model of a neuron (1958, 1969, 80's…)
- Linear classifier
- Finds a hyperplane that separates 2 classes of points (if exists)



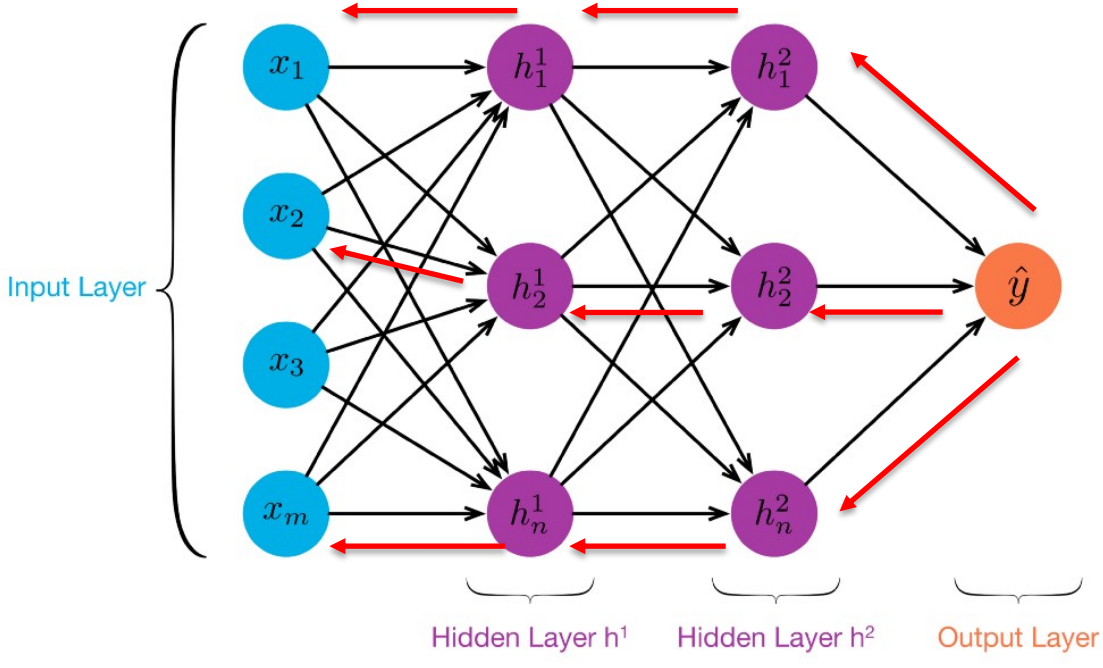
Single-layer Perceptron Network



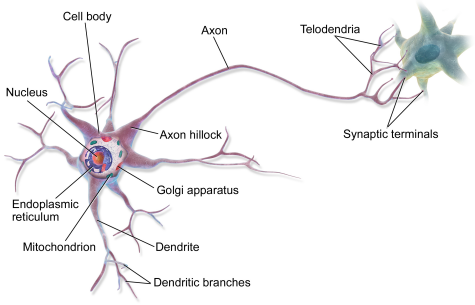
Source: wikipedia

Multi Layer Perceptron

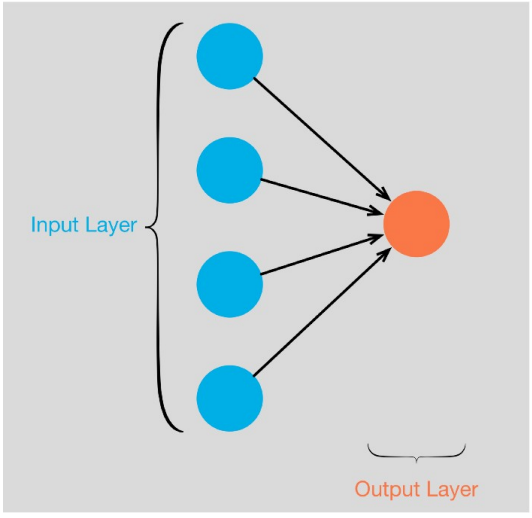
- Two main discoveries in 1960s
  - **Backpropagation**, a procedure to ***repeatedly adjust the weights***
  - **Hidden Layers**, which are ***neuron nodes stacked in between inputs and outputs***, allowing neural networks to learn more complicated features

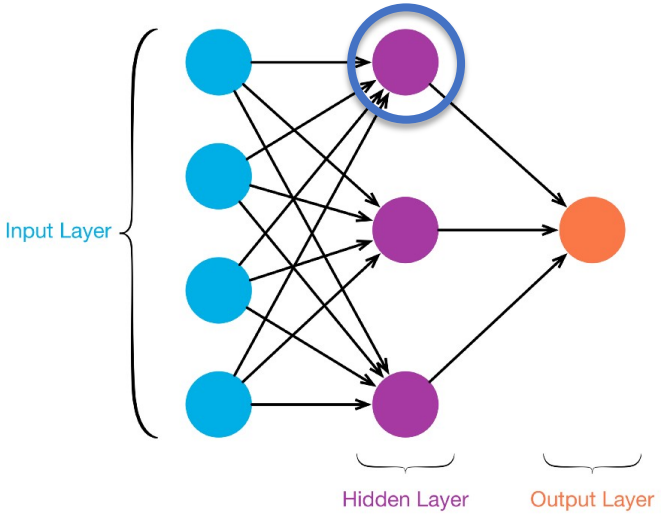


Effects of neurons



Source: wikipedia

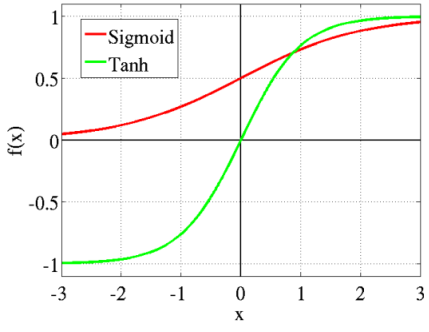


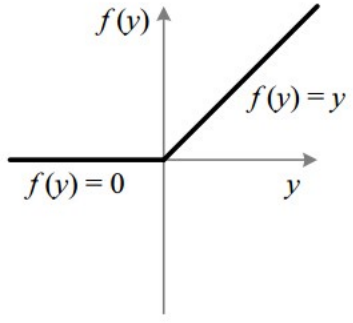


Multi-layer Perceptron Network

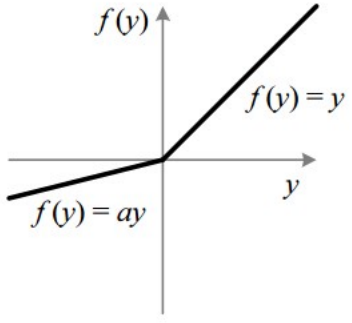
Live demo
Demo-NonLinearClassification

Activation functions





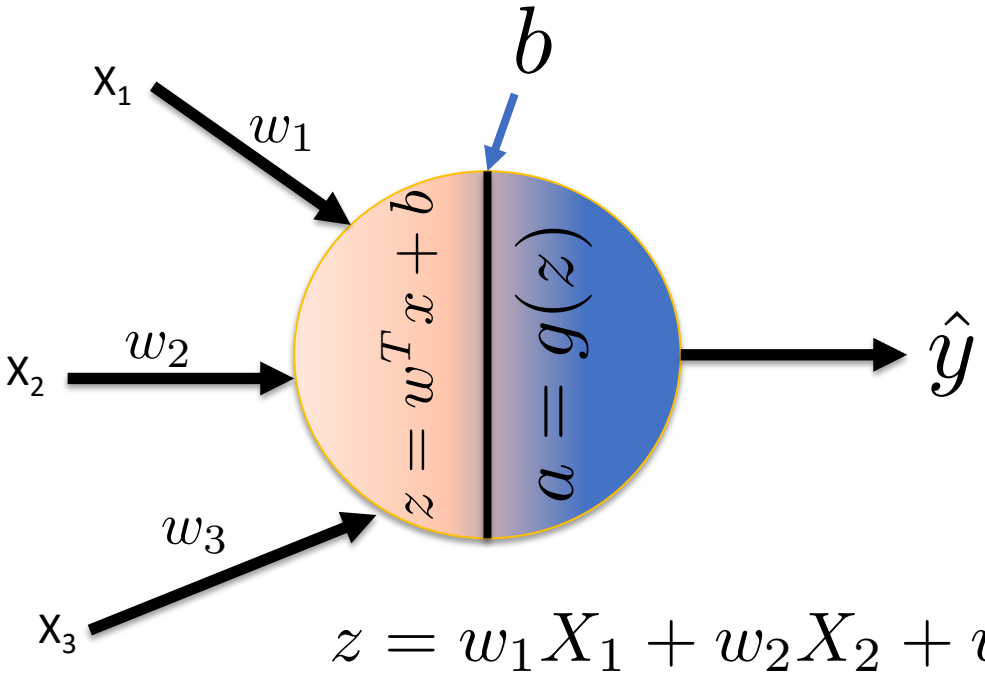
ReLU



Leaky ReLU

A single neuron

$label : y$



$$z = w_1 X_1 + w_2 X_2 + w_3 X_3 + b$$

Activations

$$g(z) = \frac{1}{1+e^{-z}} \qquad \text{(sigmoid)}$$

$$g(z) = \max(z, 0) \qquad \text{(ReLU)}$$

$$g(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \qquad \text{(tanh)}$$

2-layer neural network

Forward propagation

$$z^{[1]} = W^{[1]}x^{(i)} + b^{[1]}$$

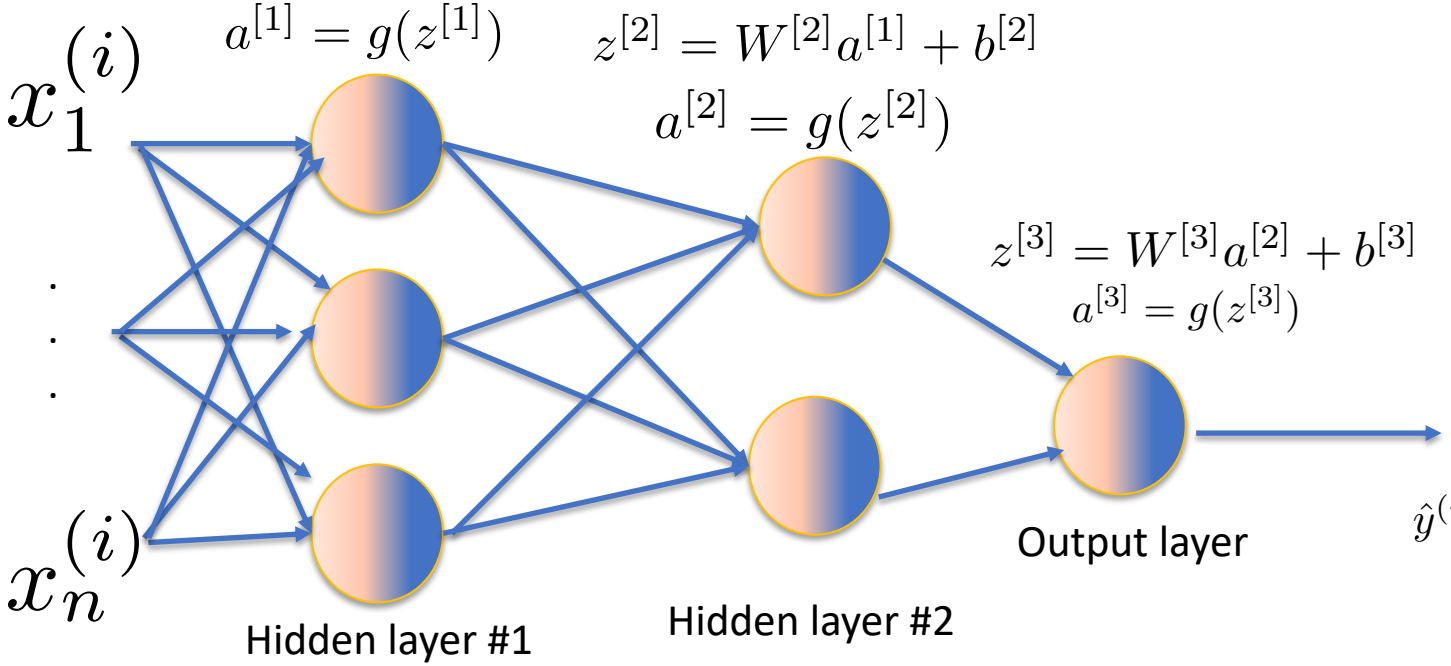
$$a^{[1]} = g(z^{[1]})$$

$$z^{[2]} = W^{[2]}a^{[1]} + b^{[2]}$$

$$a^{[2]} = g(z^{[2]})$$

$$z^{[3]} = W^{[3]}a^{[2]} + b^{[3]}$$

$$a^{[3]} = g(z^{[3]})$$



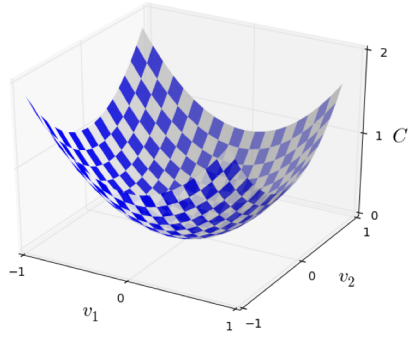
# parameters:	$3n + 3$	$2 * 3 + 2$	$2 + 1$
Sizes:	$W^{[1]} \in \mathbb{R}^{3\times n}$	$W^{[2]} \in \mathbb{R}^{2\times 3}$	$W^{[3]} \in \mathbb{R}^{1\times 2}$

$b?$

2-layer neural network

Loss function

$$L(\hat{y}, y) = -\left[(1-y)\log(1-\hat{y}) + y\log\hat{y}\right]$$



Cost function

$$J/\ C_0 = -\frac{1}{m}\sum_{i=1}^{m}(y^{(i)}\log\left(a^{[L](i)}\right) + (1-y^{(i)})\log\left(1-a^{[L](i)}\right))$$

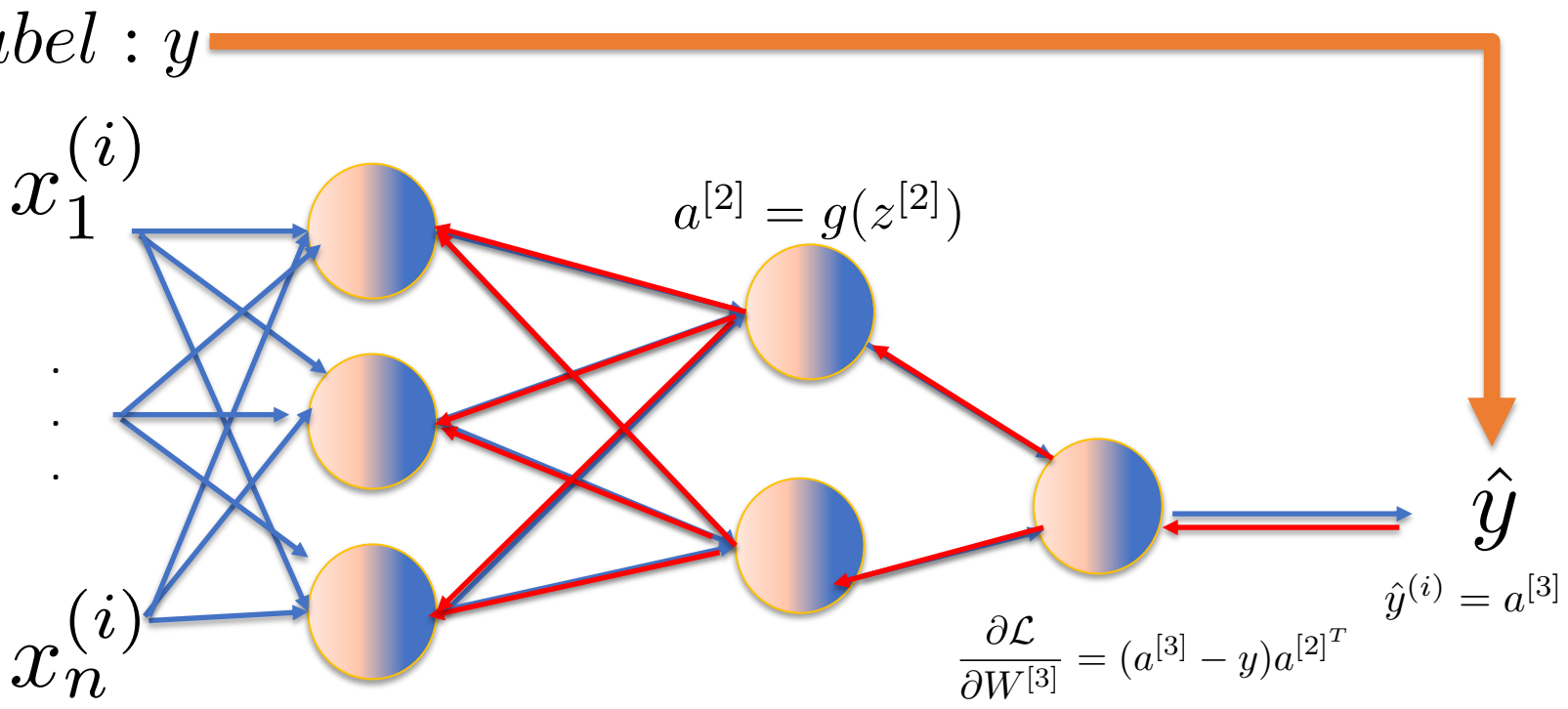
$$W^{[L]} := W^{[L]} - \alpha\frac{\partial J}{\partial W^{[L]}}$$

$$b^{[L]} := b^{[L]} - \alpha\frac{\partial J}{\partial b^{[L]}}$$

Backpropagation

2-layer neural network

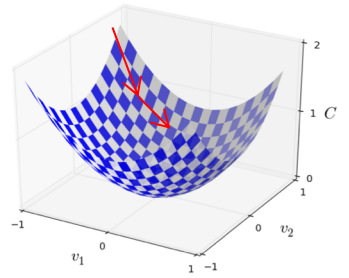
Backward propagation



*Here we assume Stochastic gradient descent.

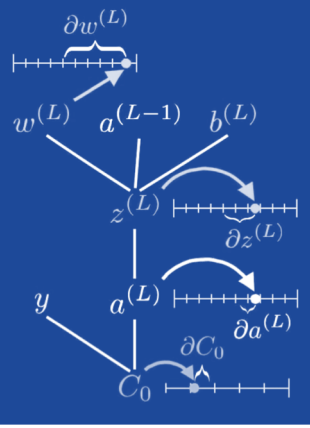
2-layer neural network

Backward propagation and updates



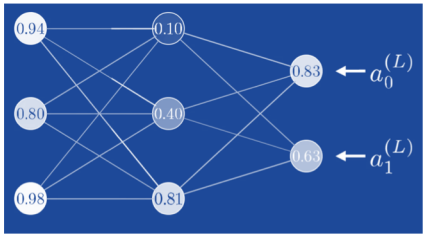
$$\frac{\partial C_0}{\partial w^{(L)}} = \frac{\partial z^{(L)}}{\partial w^{(L)}} \frac{\partial a^{(L)}}{\partial z^{(L)}} \frac{\partial C0}{\partial a^{(L)}}$$

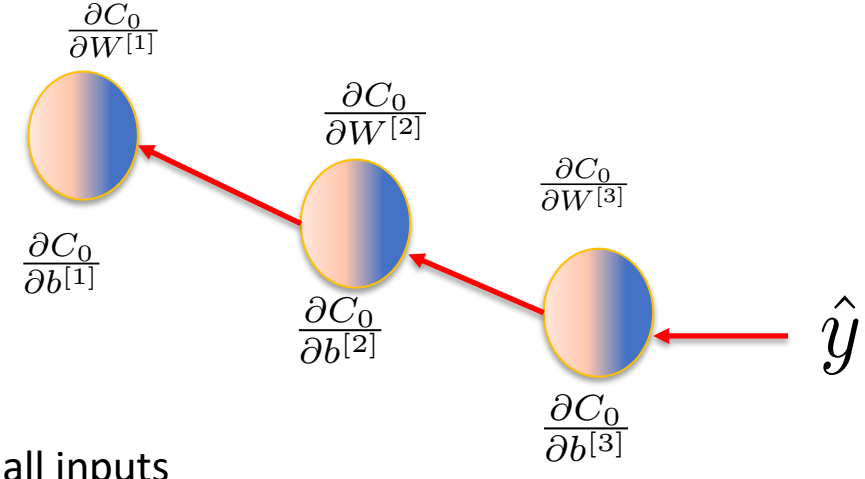
Chain rule



$$W^{[L]} := W^{[L]} - \alpha \frac{\partial J}{\partial W^{[L]}}$$

$$b^{[L]} := b^{[L]} - \alpha \frac{\partial J}{\partial b^{[L]}}$$

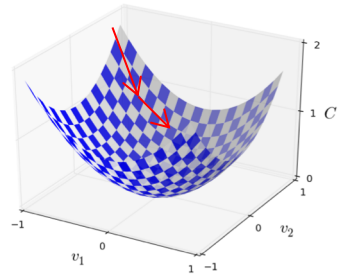


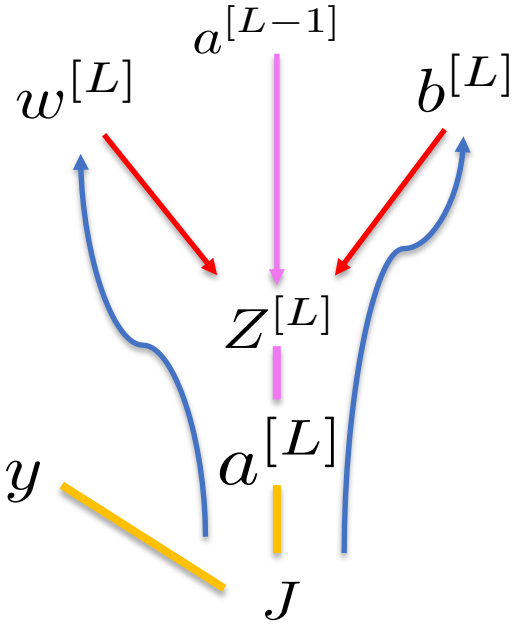


Assuming, gradient descent: do for all inputs

2-layer neural network

Backward propagation and updates





$$W^{[L]} := W^{[L]} - \alpha \frac{\partial J}{\partial W^{[L]}}$$

$$b^{[L]} := b^{[L]} - \alpha \frac{\partial J}{\partial b^{[L]}}$$

Assuming, gradient descent

2-layer neural network

Parameter initialization

- In practice, small random values are used to initialize ‘W’ and b is set to 0
- Best practice, use Xavier/He initialization

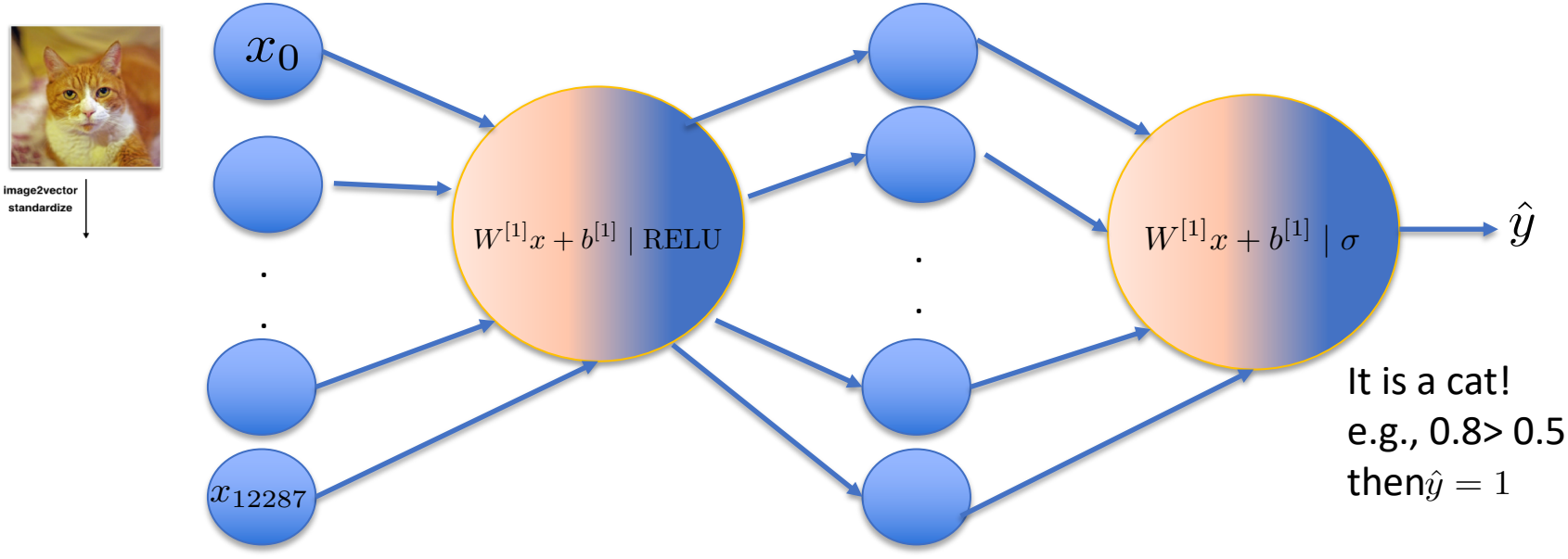
Optimization

- Gradient descent, Stochastic gradient descent (SGD) or Adam
- Other optimization techniques: momentum, RMSprop, minibatch gradient descent

2-layer neural network

Exercises

- First create a single neuron and perform logistic regression classification
- Design a 2-layer neural network to classify cat vs non-cat image



Convolutional neural network

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Drawbacks of DNN

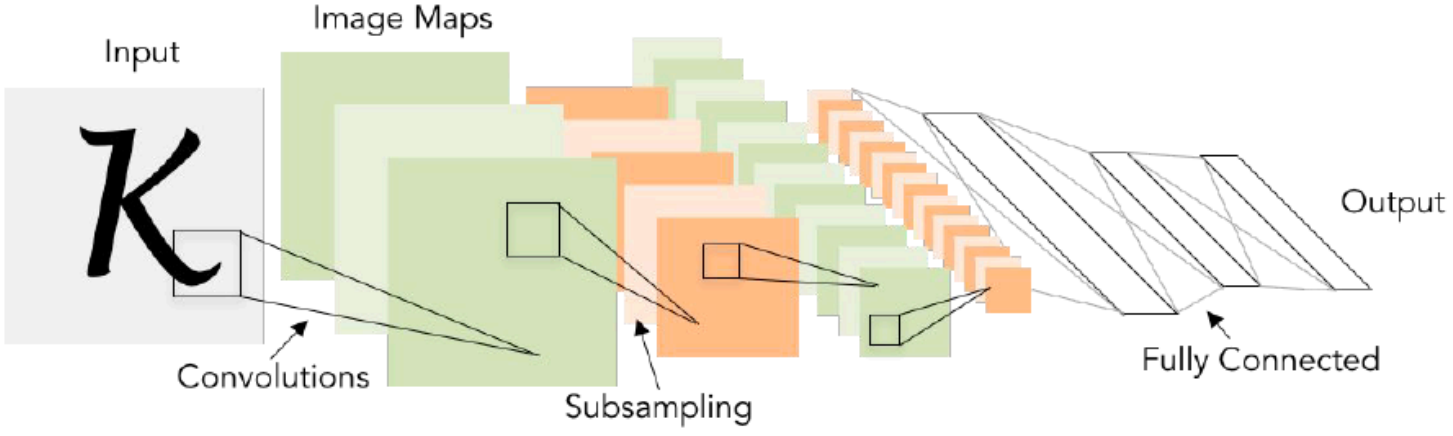
- Number of parameters are large (overfitting, computationally slower)
- Does not incorporate local information (like edges, corners in images)

Convolutions in NNs

- No. of parameters are reduced
- Incorporates local information
- Translation invariant

Concept: Use convolution filters to extract feature maps

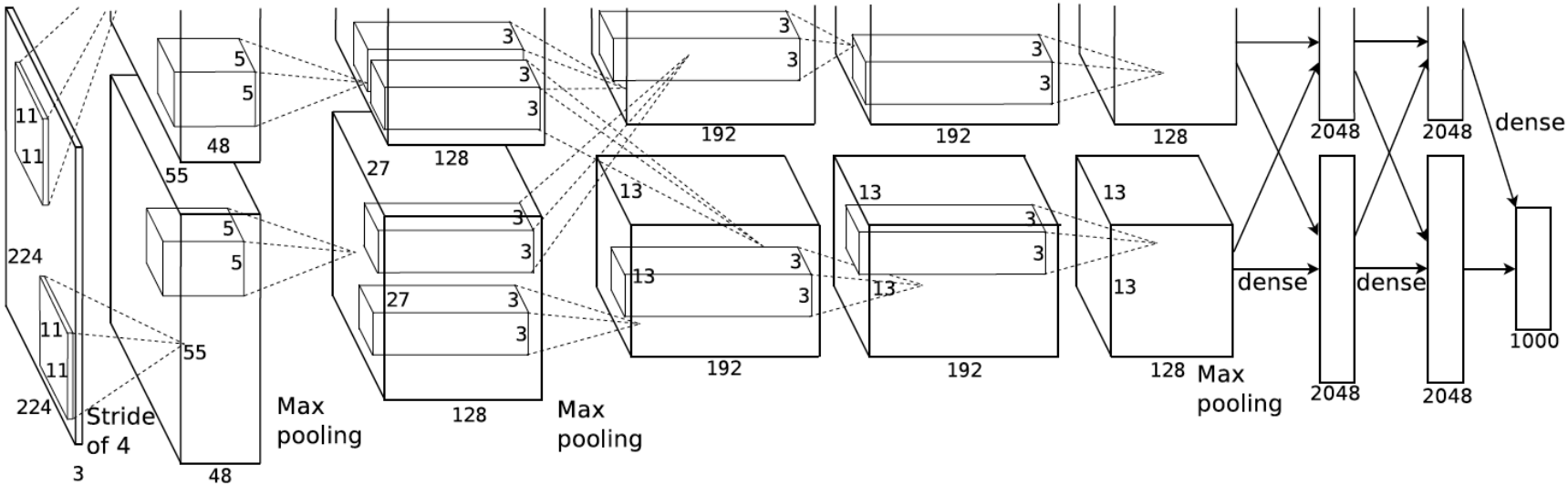
Brief history: CNN



LeNet-5

Gradient-based learning applied to document recognition, LeCun, Bottou, Bengio, Haffner, 1998

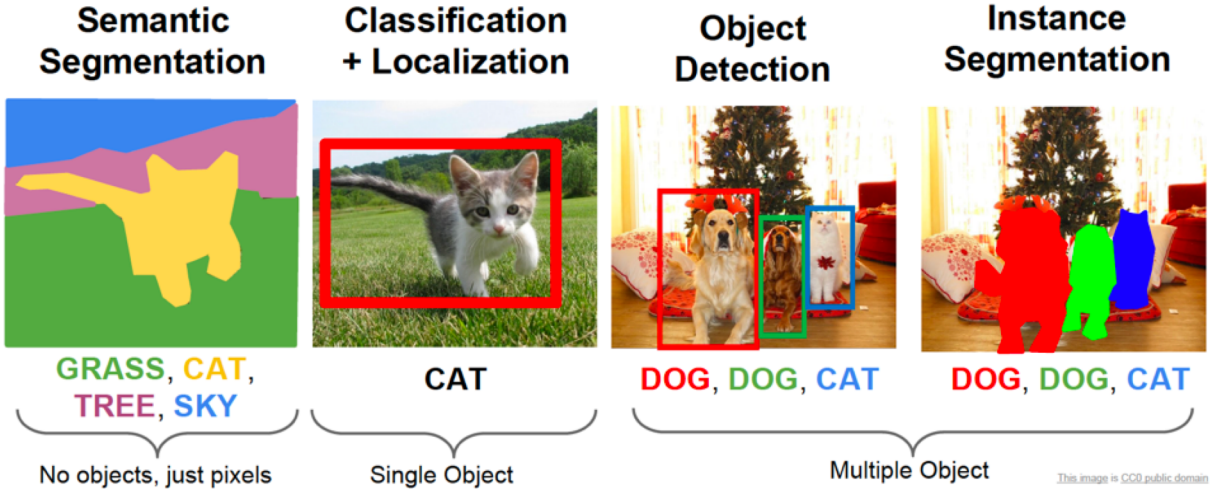
Brief history: CNN (Revolutionary)



ImageNet classification with Deep Convolutional Neural Networks, Krizhevsky, Sutskever, Hinton, 2012

Today: CNN

It's everywhere: from image classification and localization to image retrieval; from object detection to image segmentation; image generation; and many more…



This has to do a lot with advanced GPUs

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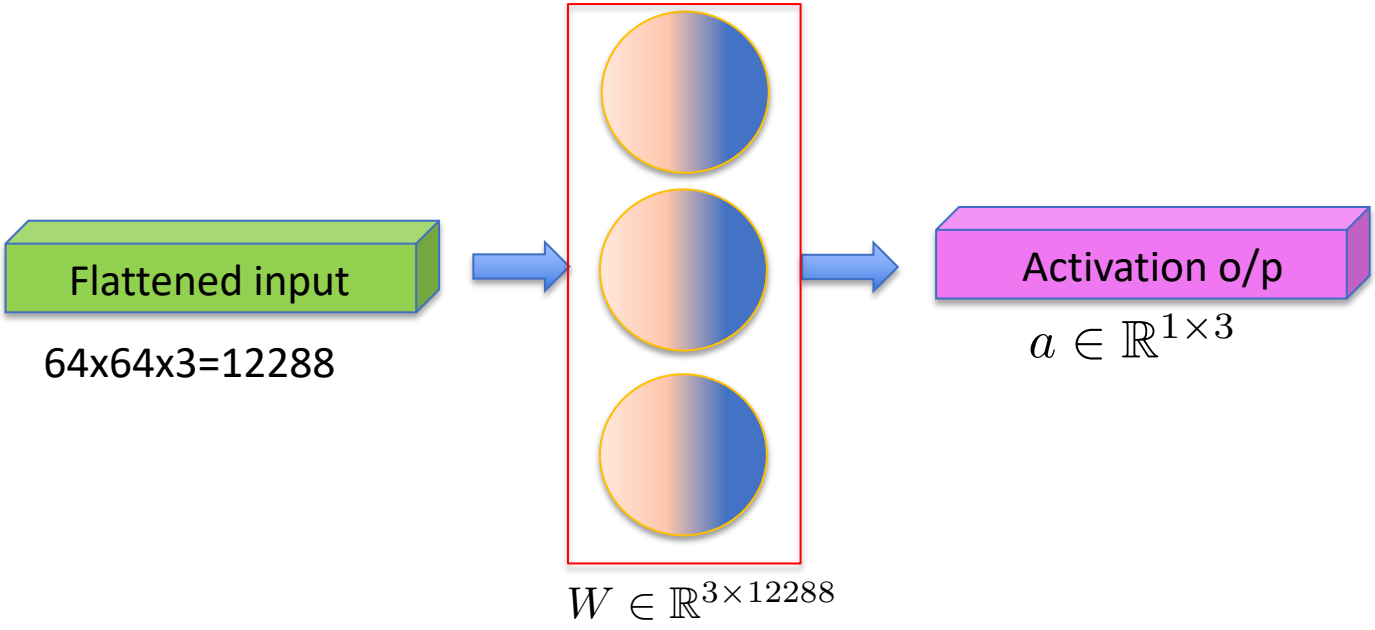
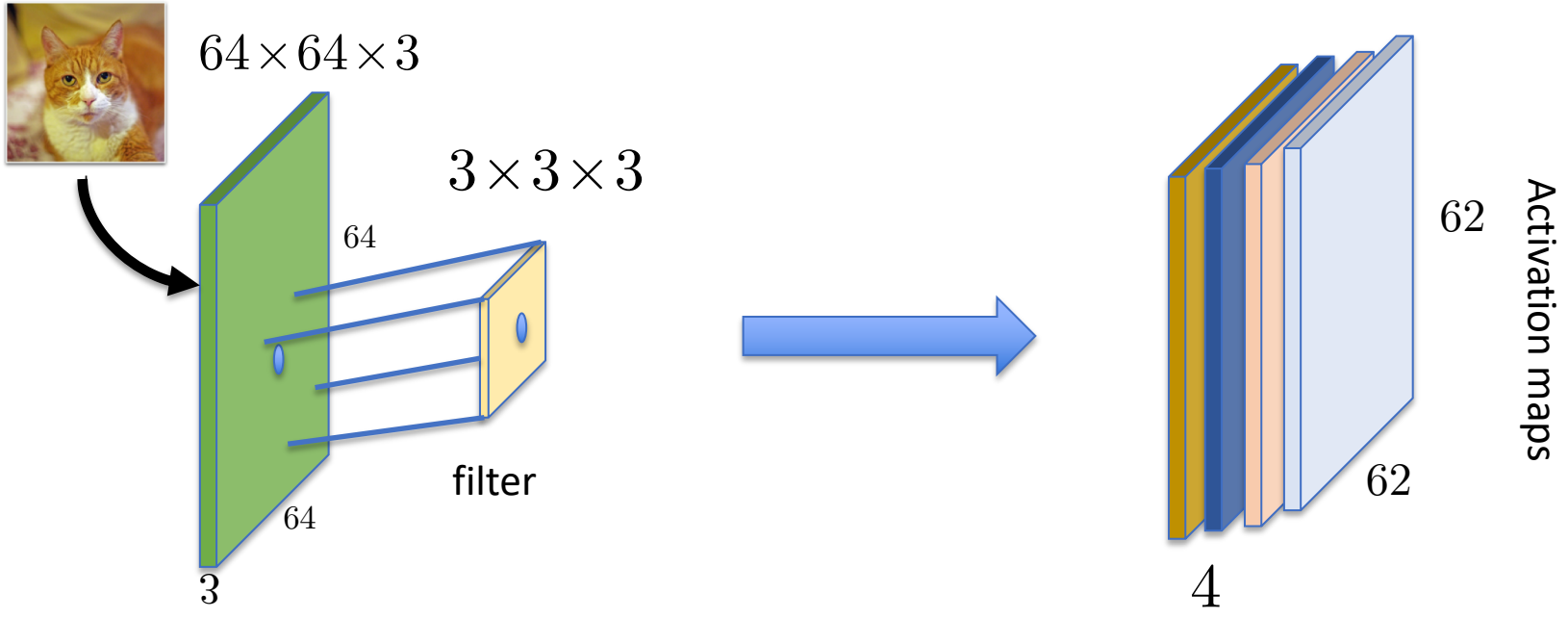
Recall, fully connected layer

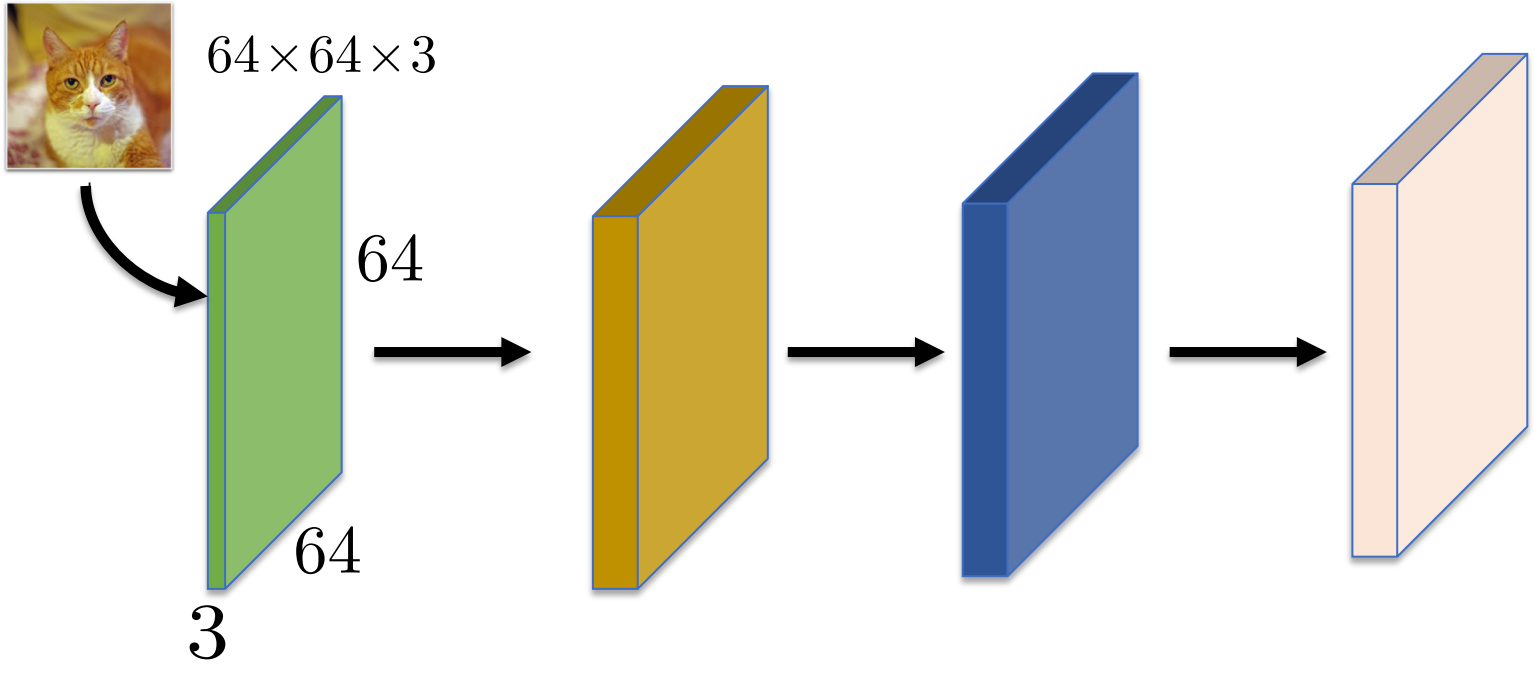


CNN



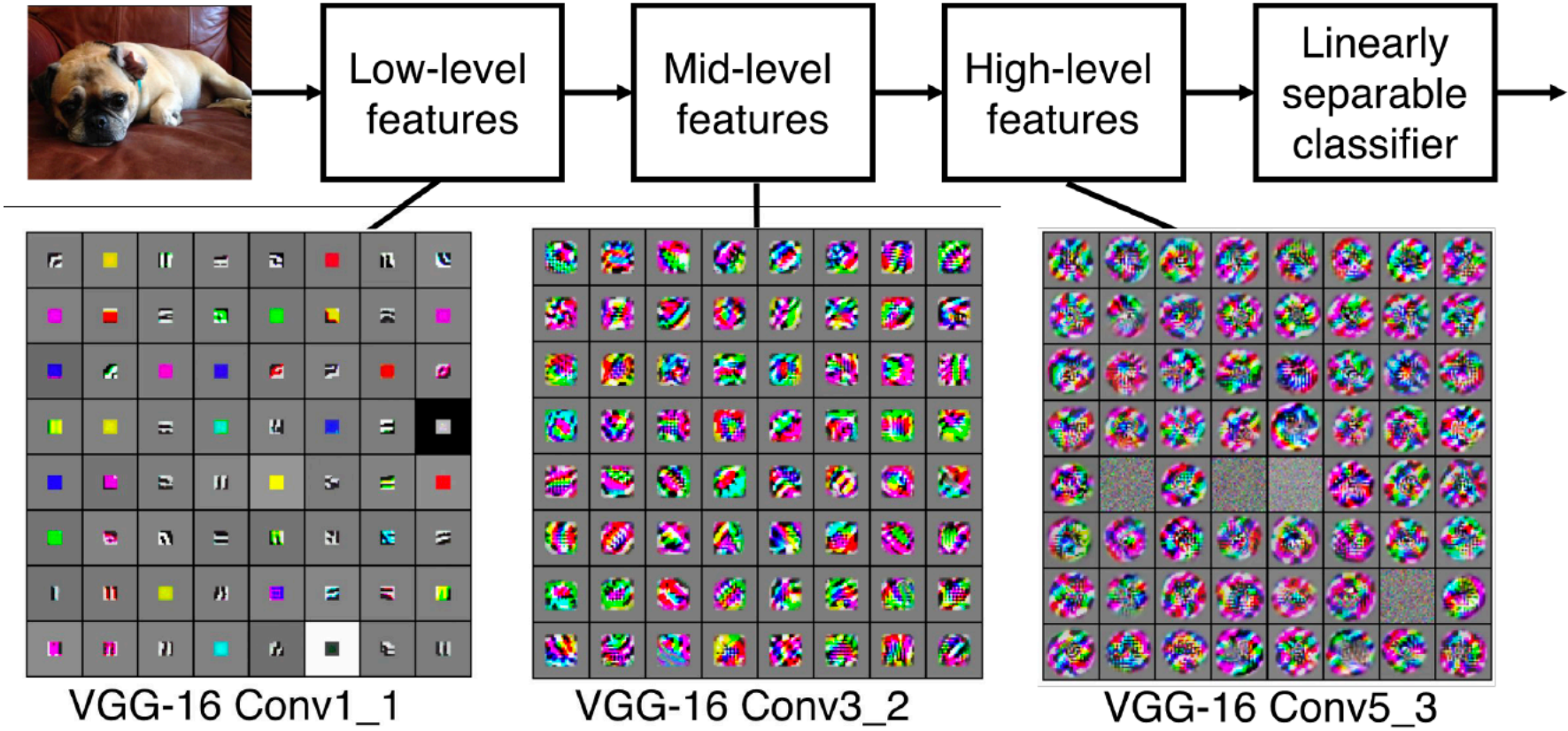
- Convolve the filter with the images, that is, slide your filter over the images spatially
- No. of parameters= #no. of filters * (27 + 1(bias)

CNN: Model?



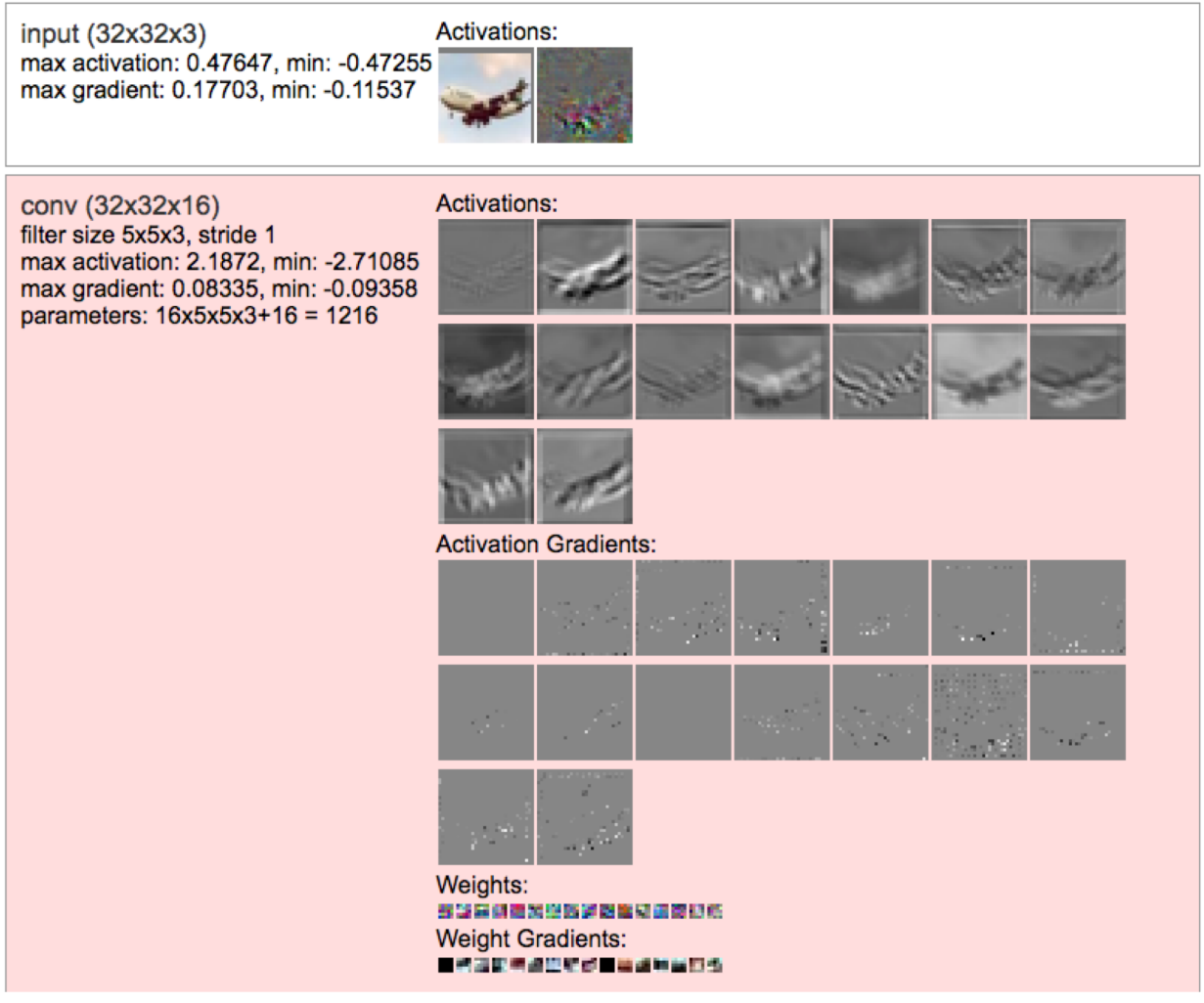
Suppose you want to convolve above image with **5x5x3** filters and you want to have **6-10-10** maps. Compute: a) No. of parameters and b) dimension of your activation maps

CNN: What do they learn?



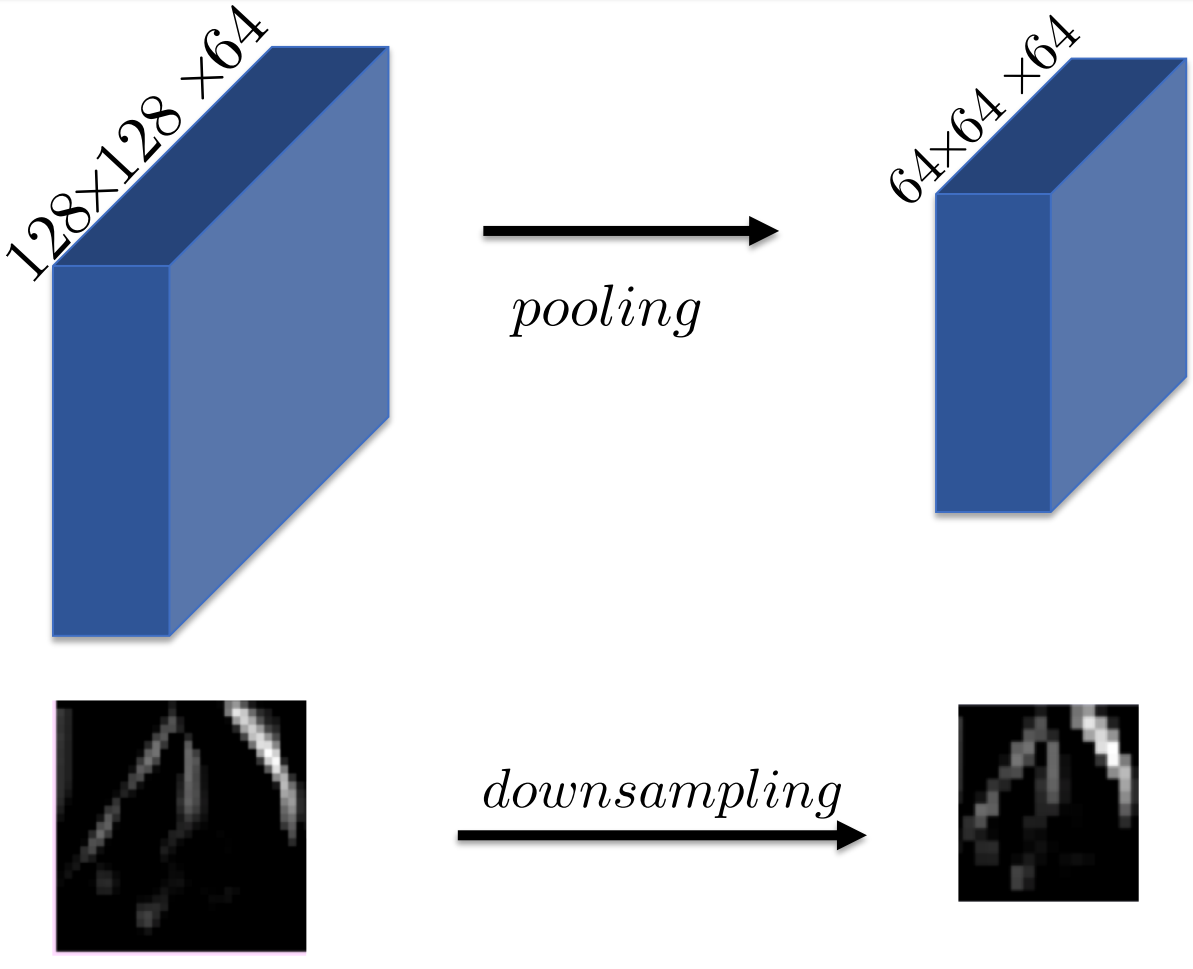
Visualization of VGG-16 by Lane Mcintosh. [Zeiler and Fergus 2013]

CNN: What do they learn?



Play here: [cnnsWithCifar10:onlineDemo_karpathy]

CNN: Pooling



Note: Each channel in activation map is down-sampled independently

CNN: Max pooling

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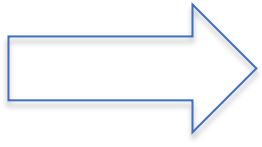
Concept

– Take maximum value in a given filter and stride e.g. 2x2 filter with stride 1

2	3	5	7
8	2	9	3
3	7	8	1
0	9	8	2



8	9	9
8	9	9
9	9	8

– Try with 2x2 filter with stride 2 and stride 3

CNN: FC layer

- Last layer always contains neurons that connect to the entire input volume
- Common practice is to add several pooling layers before the last layer
- Typical architecture is:
  - [(Conv-RELU)..(Conv-RELU)*POOLING]*--(FC-RELU)*K, Softmax
  - But, not only limited to above

CNN: Dropout

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Concept

- Randomly knocking out units in your neural network
- That is, using smaller network
- So, can't rely on any one feature so the weights get spread out
- This you can do it at a particular layer/vary your dropout differently at different layers
- This effect in regularization and avoid from over-fitting

CNN: Data augmentation

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Concept

- Increase your training data by performing transformations: e.g., color transformation, scaling, rotations, translations, shear etc
- You can do this on fly during your training (https://keras.io/preprocessing/image/)
- This allows regularization as well and you might get better accuracy

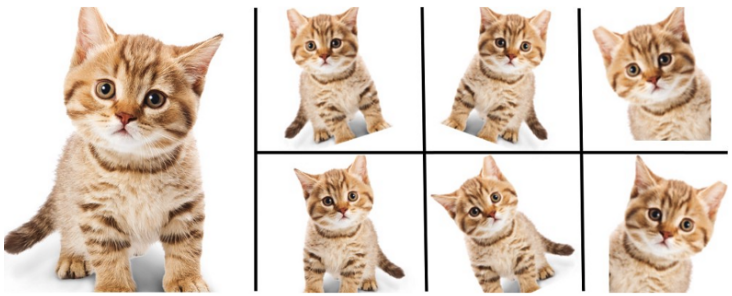

Image source: https://medium.com/nanonets

Keras

- Widely used (https://keras.io)
  - Easy to construct your network
  - Allows easy and fast prototyping
  - Runs both on CPU and GPU
  - High-level neural network API and tensorflow backend

Keras: How easy?

TensorFlow

Keras

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- Design your model

```
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),input_shape=input_shape))
model.add(BatchNormalization(momentum=0.95))
model.add(Activation('relu'))

model.add(Conv2D(64, kernel_size=(3, 3)))
model.add(BatchNormalization(momentum=0.95))
model.add(Activation('relu'))

model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(128, (3, 3)))
model.add(BatchNormalization(momentum=0.95))
model.add(Activation('relu'))

model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(256, (3, 3)))
model.add(BatchNormalization(momentum=0.95))
model.add(Activation('relu'))

model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
# model.add(Flatten()) # we can flatten or use a global pooling scheme.
model.add(GlobalAveragePooling2D())

model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))
```

- Compile your model

```
model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adadelta(), metrics=['accuracy'])
```

- Fit your model

```
model.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, verbose=1, validation_data=(x_test, y_test))
```

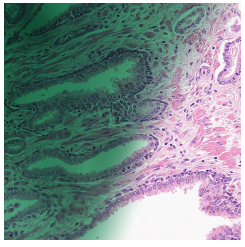
Tensorflow and PyTorch

- Worth learning for development
  - Both allows you to develop each component of your network
  - Tensorflow is better for deployment especially for real-time applications

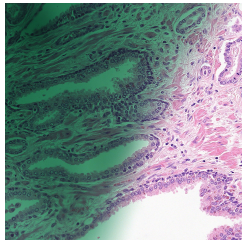
- We will show you how to get started with tensorflow as well

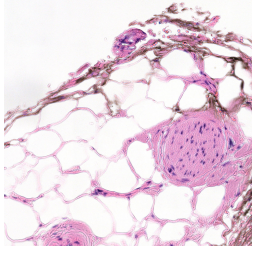
Example application

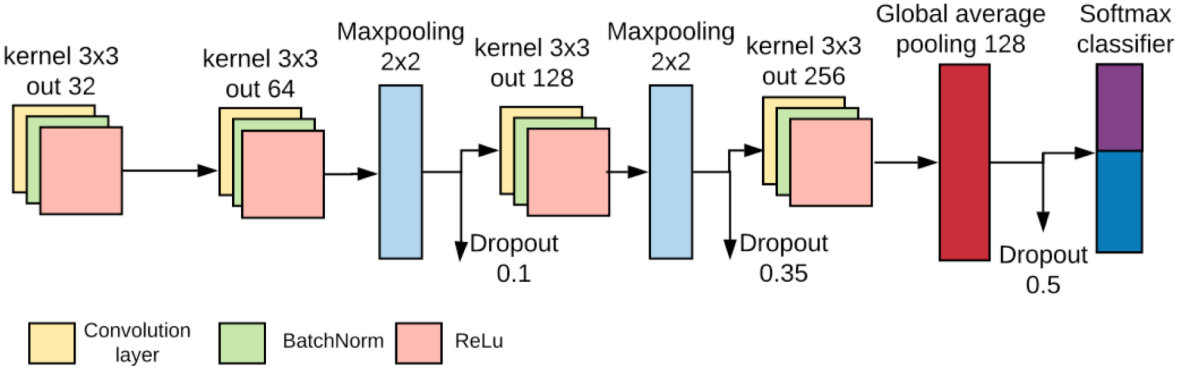
- Ink Removal in histopathology data

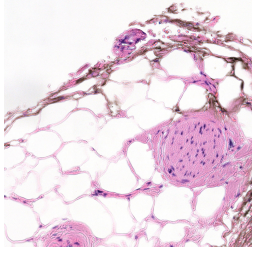


Ink:1









no-Ink:0

Summary

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- Perceptron
- Deep neural networks
- Convolutional neural networks
- Applications
  - Cat vs non-cat
  - MNIST digit dataset (classify 10 different digits)
  - Binary classification of marker ink vs non-ink in histopathology data

Practical

Exercises

- Now, lets look at L-layer neuron network and see how this improves test accuracy
- Lets implement using Keras and TensorFlow libraries
- Lets discover the limitation of small size data and see advantage of large size data

Datasets can be downloaded here:

https://s3.amazonaws.com/teachingv3.0/datasets.zip

You can also try ink-no-ink classification (complimentary)

https://s3.amazonaws.com/teachingv3.0/ink_removal_data.zip

Practical

Project: You will try to find publicly available medical dataset for multi-class or binary classification or use any one of below:

a) Grand-challenge datasets

https://grand-challenge.org/challenges/

https://ead2019.grand-challenge.org (multi-class problem and bounding box detection)

b) Kaggle datasets (you can even win cash prizes here!!!)

https://www.kaggle.com/c/histopathologic-cancer-detection

https://www.kaggle.com/c/diabetic-retinopathy-detection/data

https://www.kaggle.com/c/rsna-pneumonia-detection-challenge (multi-class problem and bounding box detection)

c) Malaria dataset released by Dr. Stefan Jaeger (https://ceb.nlm.nih.gov/repositories/malaria-datasets/). We have provided you data which contains downscaled 64x64x3 h5 compressed 27,558 images. Tasks are detailed in the provided ipython notebook.

*Note: Beware of computation power that you might need to work with these data. For learning, you will scale down all data that you intend to use.

Good reads!

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- *"Hands-On Machine Learning with Scikit-Learn and TensorFlow"* by Aurélien Géron
- *"Deep learning"* by Ian Goodfellow, Yoshua Bengio and Aaron Courville

You can look more lists here:

https://www.bonkersabouttech.com/ai/best-deep-learning-books/494