

Deep Learning - Convolutional Neural Network (CNN)

Itthi Chatnuntawech

Fully connected layer (Dense)

Convolutional layer
Conv1D, 2D, 3D, ...
separable Conv

Optimizer
SGD
Adam
RMSprop

Evaluation metric
accuracy
F1-score
AUC
confusion matrix

Loss function
categorical crossentropy
binary crossentropy
mean squared error
mean absolute error

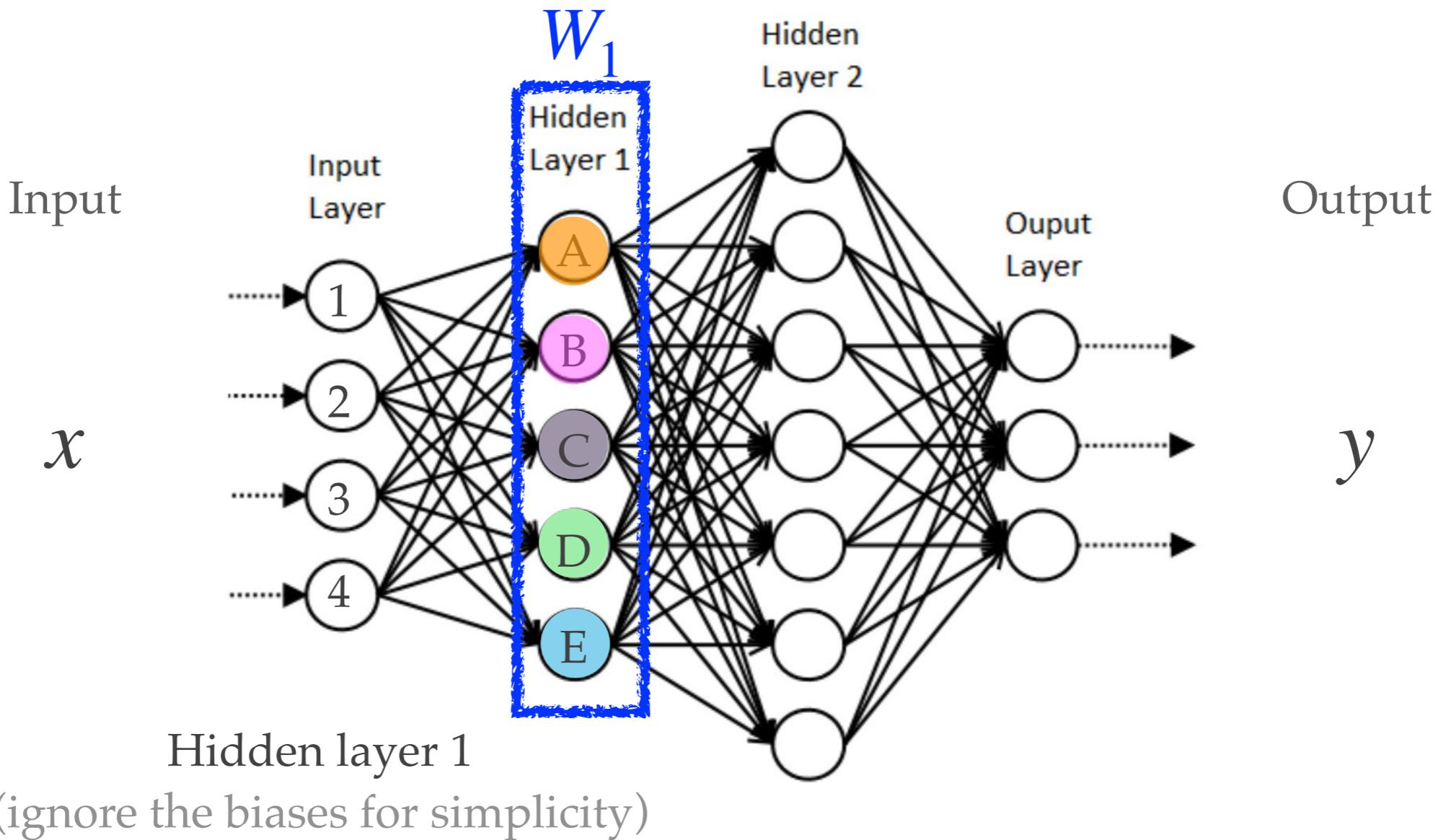
Regularization
Dropout
Data augmentation
 l_1, l_2 regularizations

Pooling layer
max-pooling
average-pooling

Activation function
sigmoid
softmax
ESP (swish)
ReLU



- ❖ **Combine basic components to build a neural network**
 - More components → “More” representative power



$$\begin{bmatrix} out_A \\ out_B \\ out_C \\ out_D \\ out_E \end{bmatrix} = a_1(W_1x) = a_1 \left(\begin{bmatrix} w_{A,1} & w_{A,2} & w_{A,3} & w_{A,4} \\ w_{B,1} & w_{B,2} & w_{B,3} & w_{B,4} \\ w_{C,1} & w_{C,2} & w_{C,3} & w_{C,4} \\ w_{D,1} & w_{D,2} & w_{D,3} & w_{D,4} \\ w_{E,1} & w_{E,2} & w_{E,3} & w_{E,4} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \right)$$

of weights for hidden layer 1
 $= 4 \times 5 = 20$

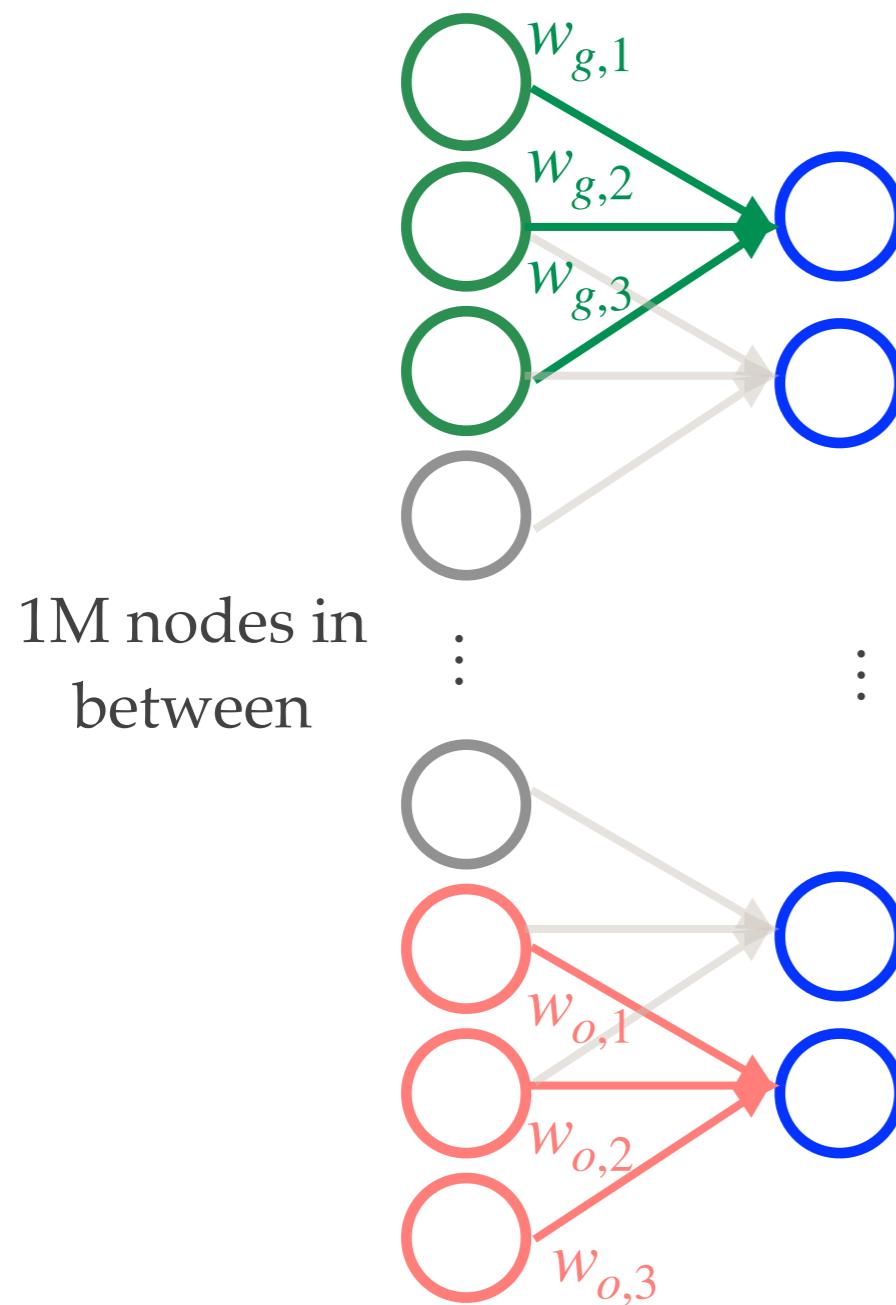
of weights per layer = # of incoming nodes x # of hidden nodes

What if our input dimension is $256 \times 256 = 65,536$ and we use 1024 hidden nodes?

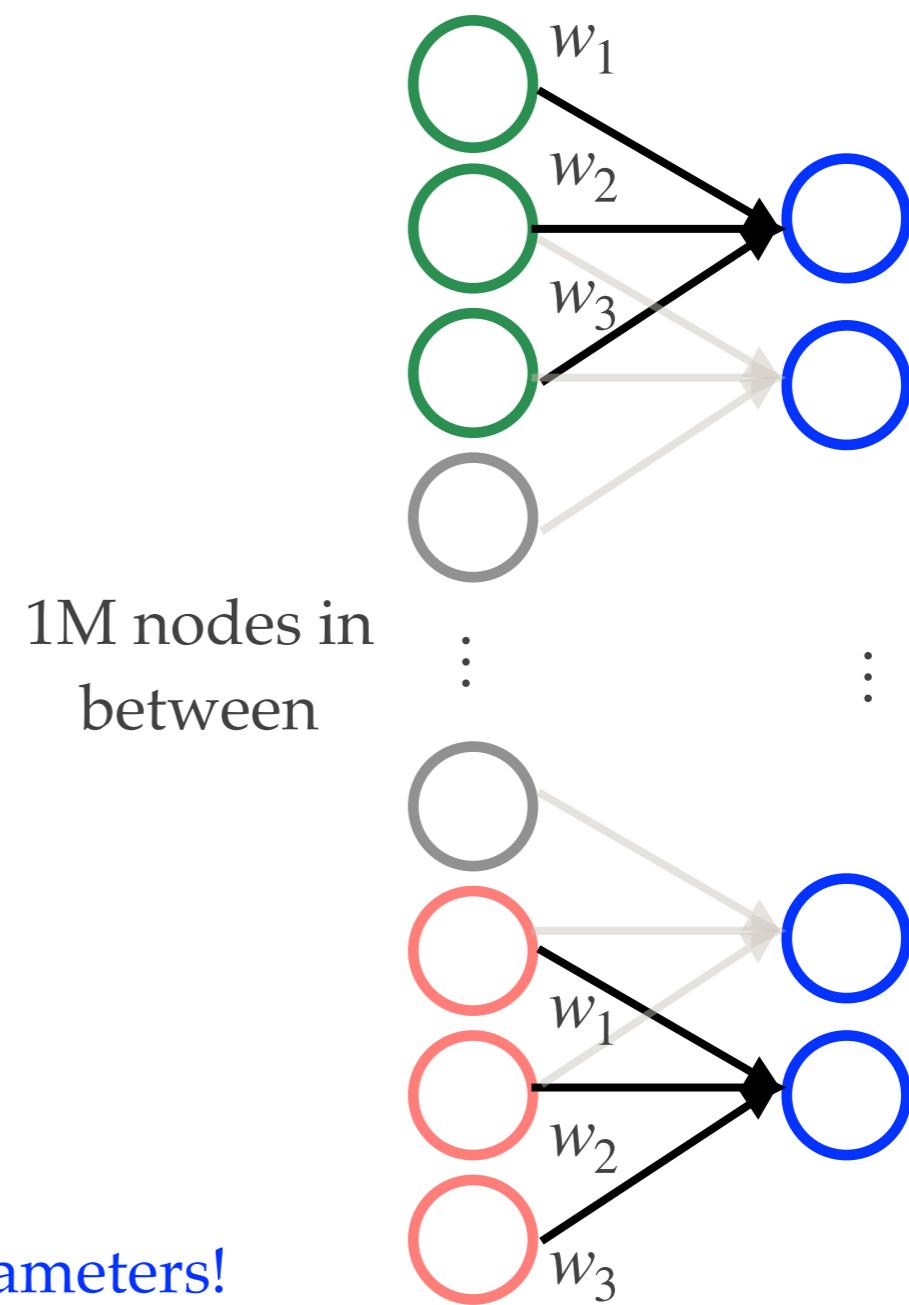
67 M trainable parameters for just one layer!

Do we need that many parameters?

- ❖ Would it be the case that
 - ❖ Only neighboring neurons talk to each other?
 - ❖ Furthermore, they talk to their neighbors in the same way?

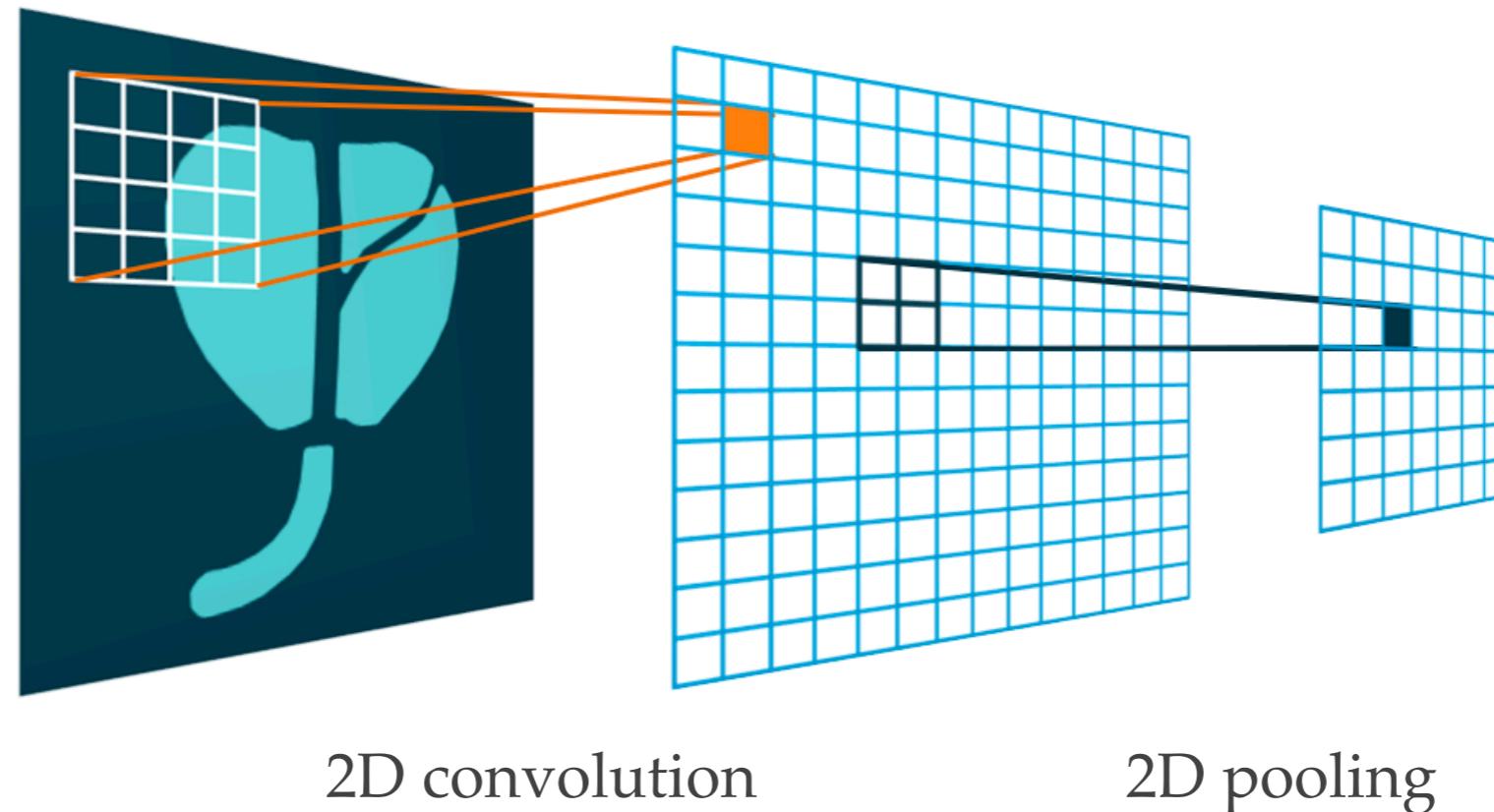


Much fewer parameters!



2D Convolution

- ❖ Similarly, for images, maybe only neighboring pixels talk to each other?



2D Convolution

$$y[n_1, n_2] = x[n_1, n_2] * h[n_1, n_2] = \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} x[k_1, k_2] h[n_1 - k_1, n_2 - k_2]$$

↑
2D Conv

$$0^*0 + 2^*1 + 1^*0 + 0^*1 + 1^*1 + 1^*1 + -3^*0 + -1^*1 + 1^*0$$

0	2	1	1	0
0	1	1	1	0
-3	-1	1	0	1
0	6	0	0	1
0	4	1	7	0

Input

x

0	1	0
1	1	1
0	1	0

h

Filter/kernel

defines the relationship
between neighboring pixels

		3		

y

2D Convolution

$$y[n_1, n_2] = x[n_1, n_2] * h[n_1, n_2] = \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} x[k_1, k_2] h[n_1 - k_1, n_2 - k_2]$$

↑
2D Conv

$$2*0 + 1*1 + 1*0 + 1*1 + 1*1 + 1*1 + -1*0 + 1*1 + 0*0$$

0	2	1	1	0
0	1	1	1	0
-3	-1	1	0	1
0	6	0	0	1
0	4	1	7	0

Input

x

0	1	0
1	1	1
0	1	0

h

Filter/kernel

defines the relationship
between neighboring pixels

3	5

y

2D Convolution

$$y[n_1, n_2] = x[n_1, n_2] * h[n_1, n_2] = \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} x[k_1, k_2] h[n_1 - k_1, n_2 - k_2]$$

↑
2D Conv

$$1^*0 + 1^*1 + 0^*0 + 1^*1 + 1^*1 + 0^*1 + 1^*0 + 0^*1 + 1^*0$$

0	2	1	1	0
0	1	1	1	0
-3	-1	1	0	1
0	6	0	0	1
0	4	1	7	0

Input

0	1	0
1	1	1
0	1	0

Filter / kernel

defines the relationship
between neighboring pixels

3	5	3

y

2D Convolution

$$y[n_1, n_2] = x[n_1, n_2] * h[n_1, n_2] = \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} x[k_1, k_2] h[n_1 - k_1, n_2 - k_2]$$

↑
2D Conv

0	2	1	1	0
0	1	1	1	0
-3	-1	1	0	1
0	6	0	0	1
0	4	1	7	0

Input

x

0	1	0
1	1	1
0	1	0

h

Filter / kernel

defines the relationship
between neighboring pixels

	3	5	3
	4	1	3
	9	8	8

smaller output

y

2D Convolution

Zero-padding

0	0	0	0	0	0	0
0	0	2	1	1	0	0
0	0	1	1	1	0	0
0	-3	-1	1	0	1	0
0	0	6	0	0	1	0
0	0	4	1	7	0	0
0	0	0	0	0	0	0

Input

x

0	1	0
1	1	1
0	1	0

h

Filter/kernel

defines the relationship
between neighboring pixels

3	5	3
4	1	3
9	8	8

smaller output

y

2D Convolution

Zero-padding

x	0	0	0	0	0	0	0
0	0	0	2	1	1	0	0
0	0	1	1	1	0	0	0
0	-3	-1	1	0	1	0	0
0	0	6	0	0	1	0	0
0	0	4	1	7	0	0	0
0	0	0	0	0	0	0	0

0	1	0
1	1	1
0	1	0

h

Filter/kernel

defines the relationship
between neighboring pixels

2	4	5	3	1
-2	3	5	3	2
-4	4	1	3	2
3	9	8	8	2
4	11	12	8	8

y

output of the same size

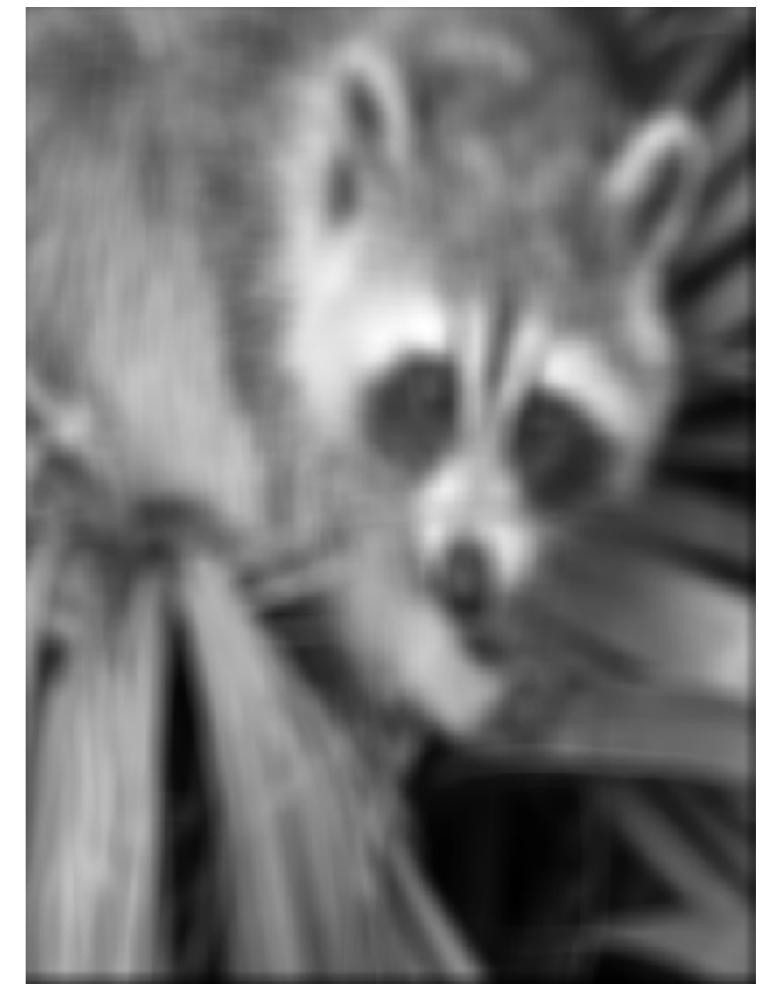
2D Convolution

- ❖ Low-pass Filter



$$\text{Input} * \begin{array}{|c|c|c|c|c|c|c|c|} \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline \end{array} = \text{Output}$$

The diagram illustrates a 2D convolution operation. On the left is the input image of a raccoon. In the center is a 7x7 filter kernel filled with the value 1. An asterisk (*) indicates the convolution operation, followed by an equals sign (=). Below the filter is the label "Filter / kernel". To the right is the resulting output image, which is a blurred, low-pass filtered version of the original raccoon face.

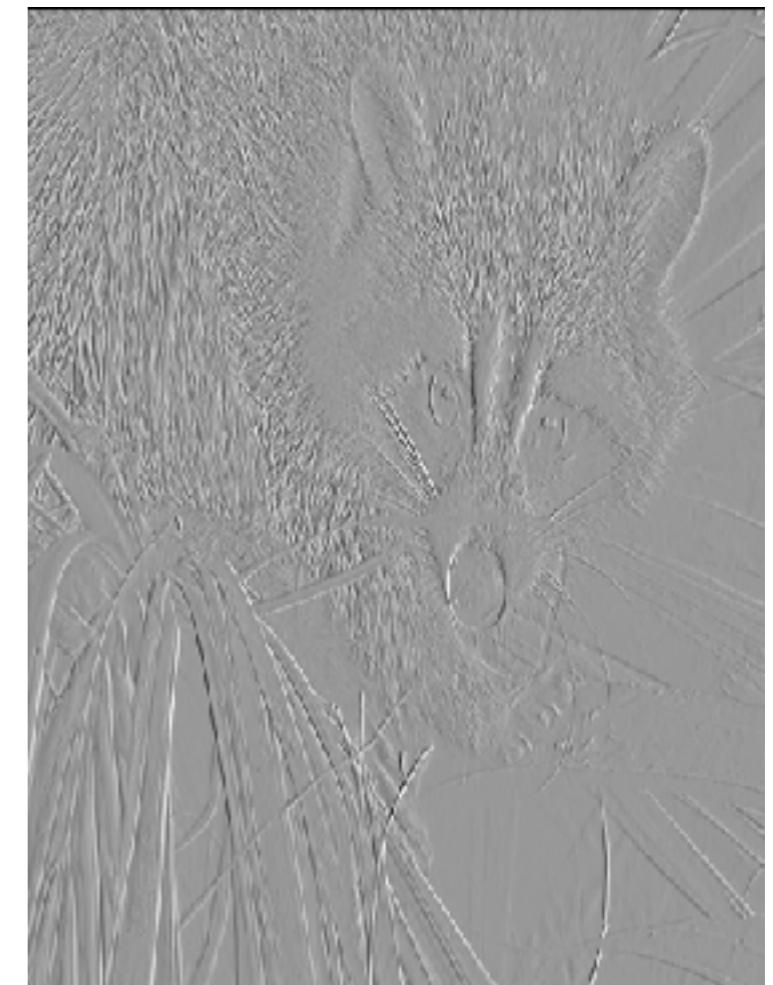


2D Convolution

- ❖ “Gradient image”



$$\ast \quad \begin{array}{|c|c|} \hline -1 & 1 \\ \hline -1 & 1 \\ \hline \end{array} = \quad \text{Filter/kernel}$$

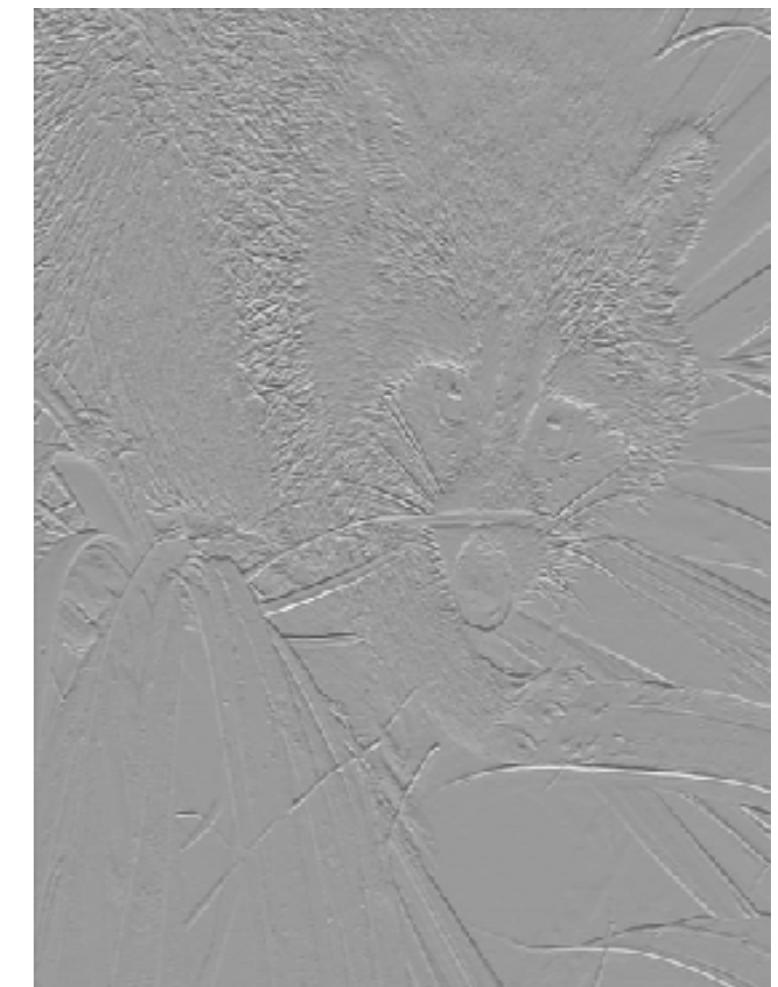


2D Convolution

- ❖ “Gradient image”

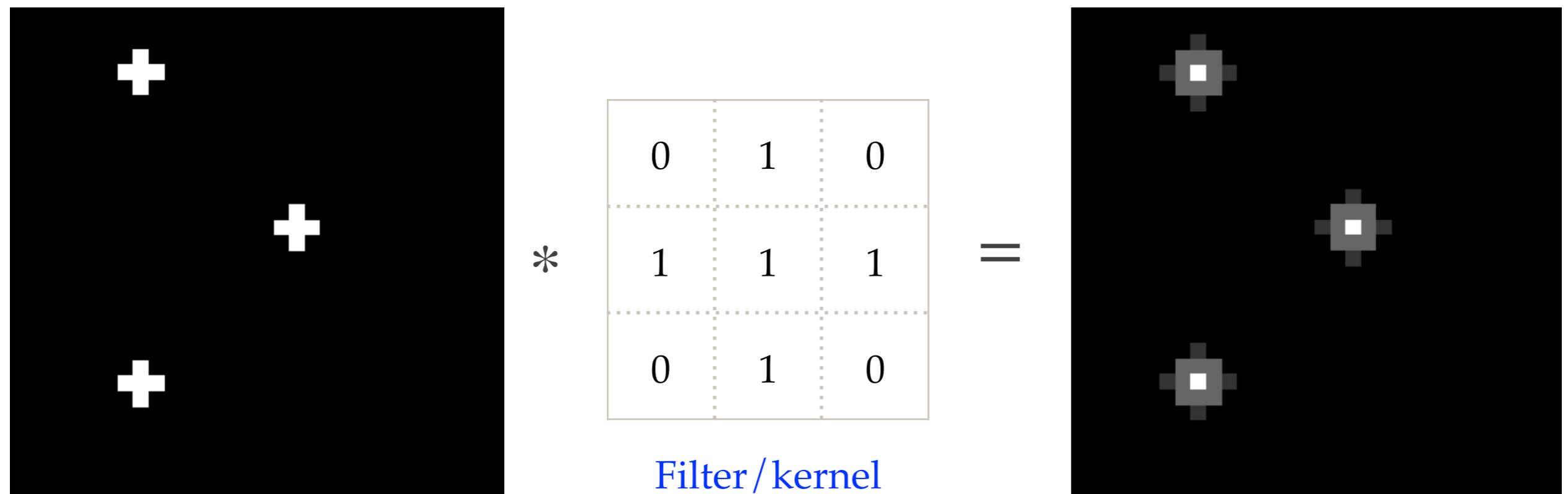


$$\text{Image} * \begin{bmatrix} -1 & -1 \\ 1 & 1 \end{bmatrix} = \text{Filter / kernel}$$



2D Convolution

- ❖ “Plus-sign Detector”



2D Convolution

- ❖ Different filters/kernels process images differently
 - ❖ Low-pass filter (blurring/denoising)
 - ❖ High-pass filter (sharpening)
 - ❖ Shape detector
 - ❖ Refer to [Image Kernels](#) for a good demo
- ❖ Instead of defining the filter ourselves, we let neural network come up with good ones for us

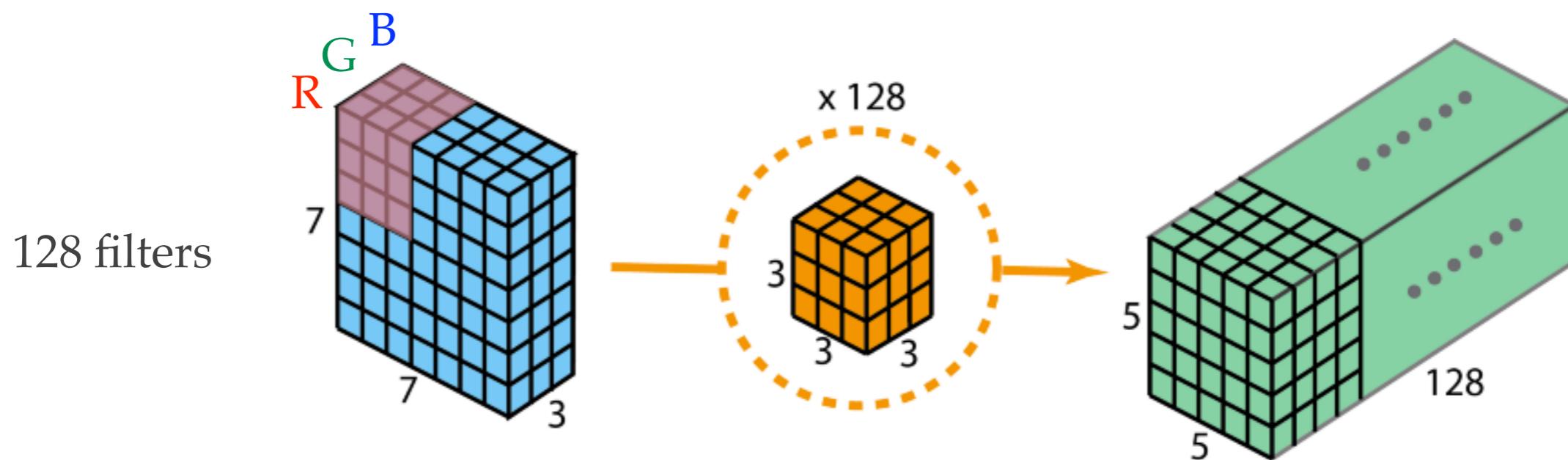
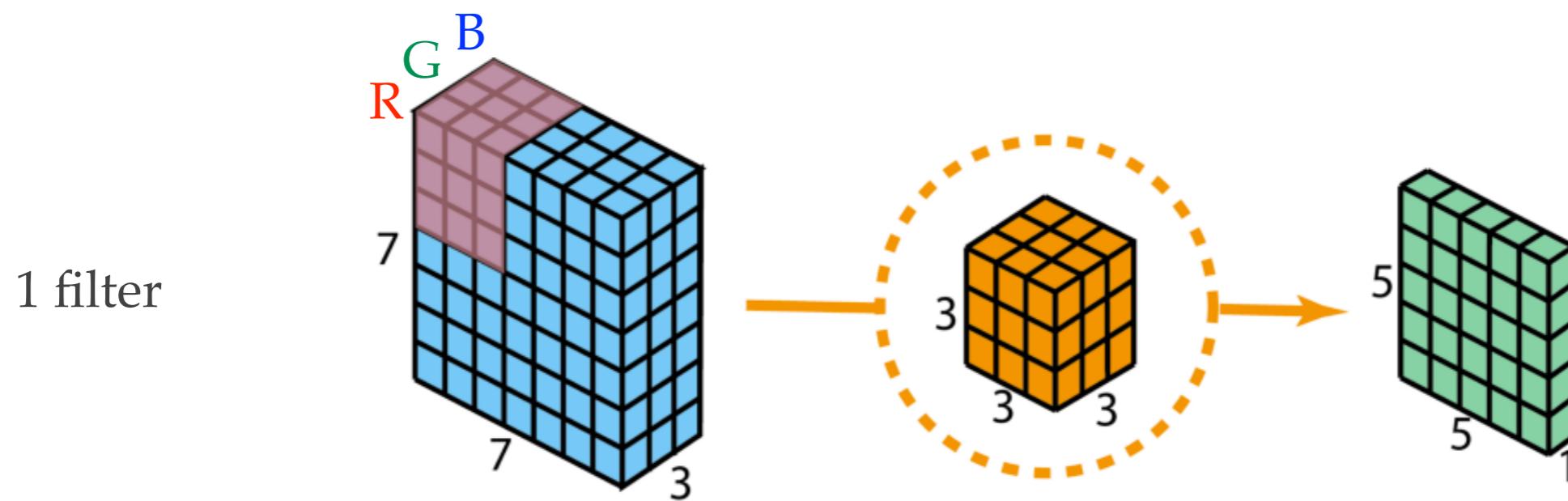


Filter/kernel
defines the relationship
between neighboring pixels

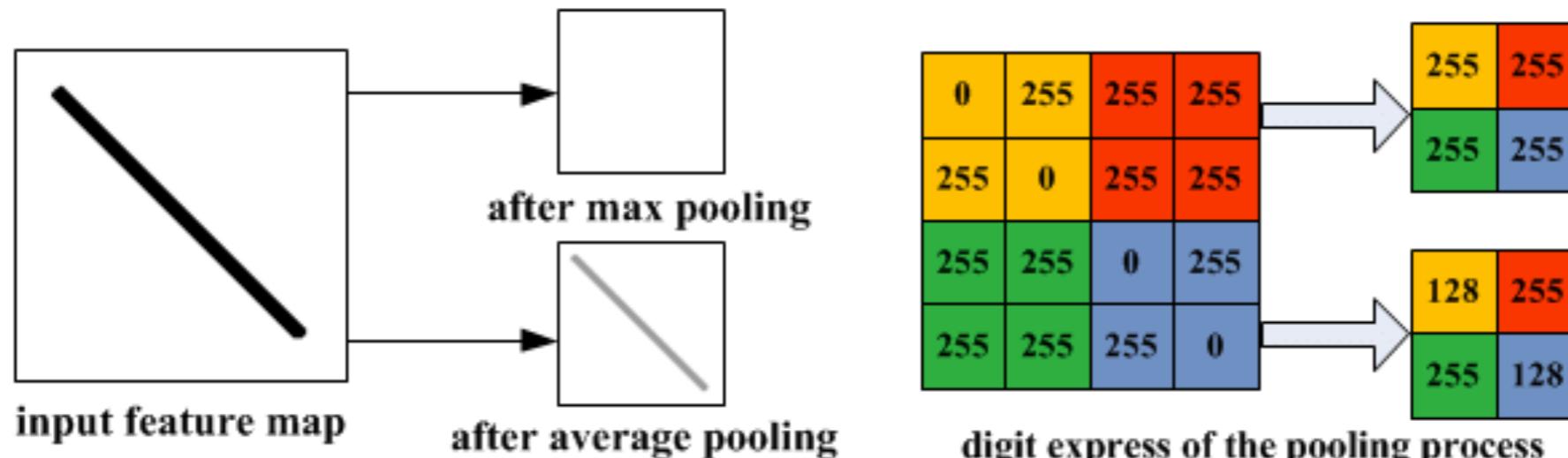
```
model.add(Conv2D(32, (3, 3), padding="same", activation="relu"))  
# of filters      filter size
```

2D Convolution

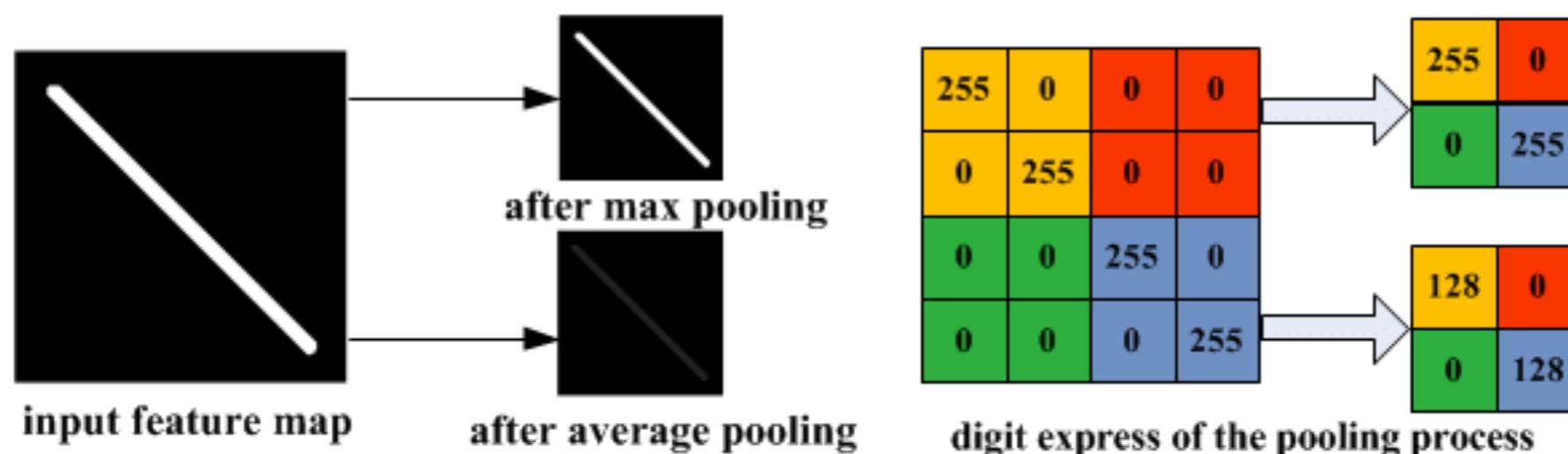
- ❖ 2D convolution with more than one channels



Pooling Layers



(a) Illustration of max pooling drawback

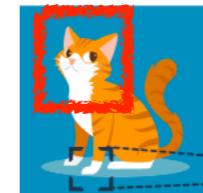
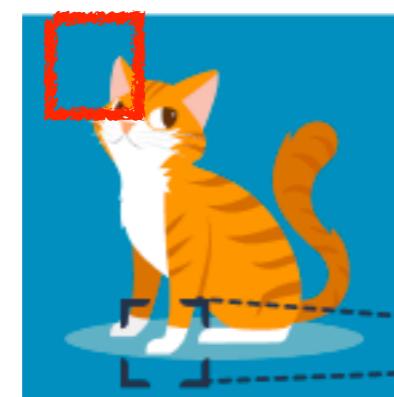
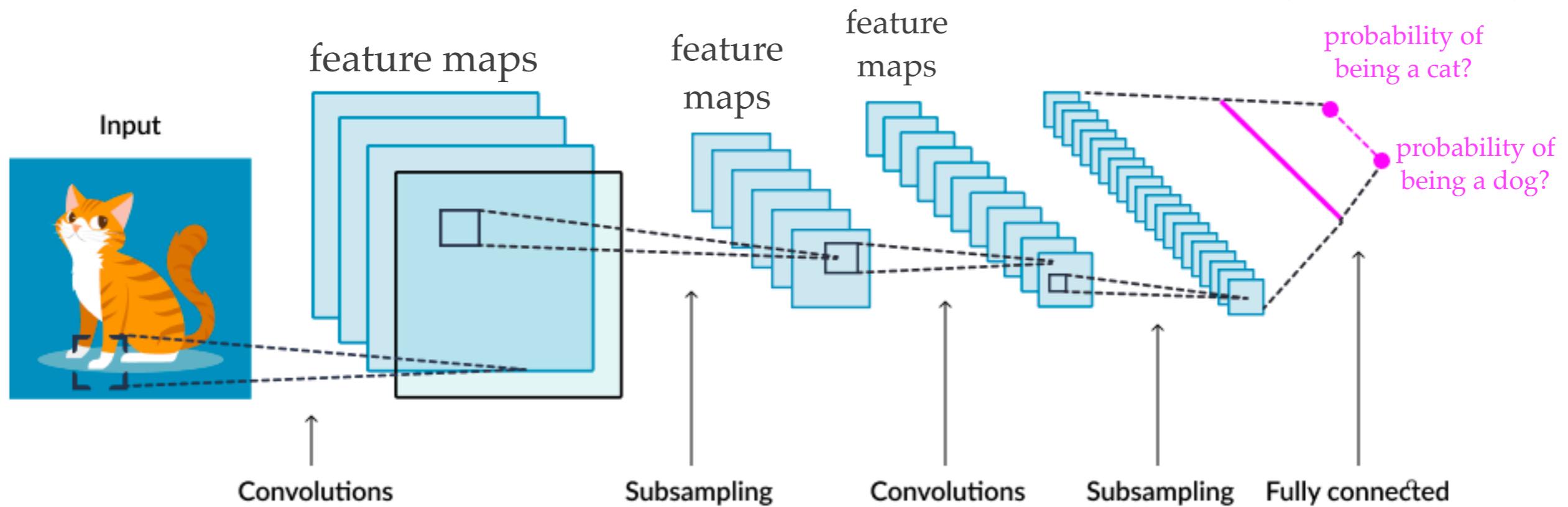


(b) Illustration of average pooling drawback

```
model.add(layers.MaxPooling2D((2,2)))
```

keywords: feature maps, activation maps, receptive field, backbone

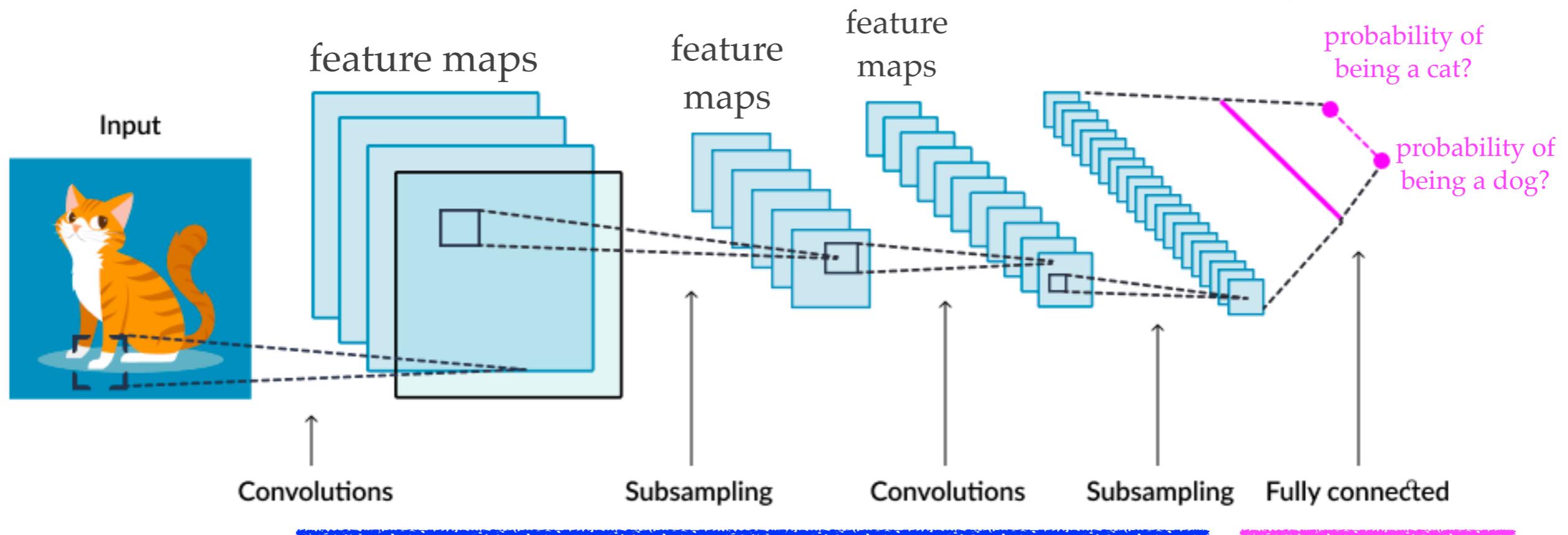
Convolutional Neural Network (CNN)



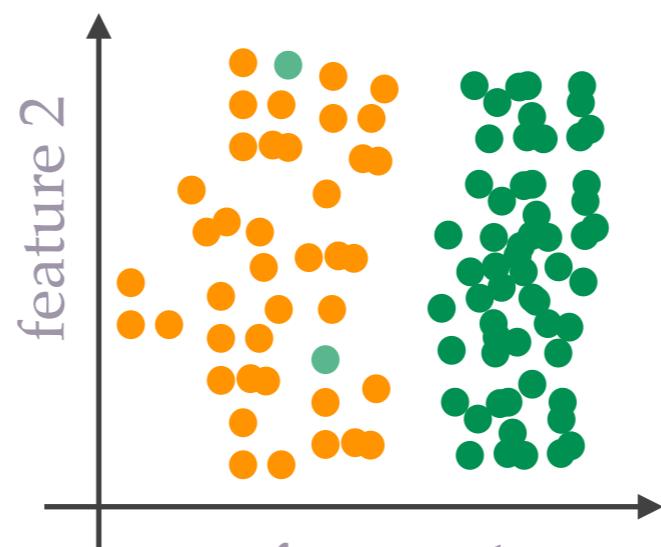
Same filter size (e.g., 3 x 3 filter), but different coverages for different “resolutions”

keywords: feature maps, activation maps, receptive field, backbone

Convolutional Neural Network (CNN)

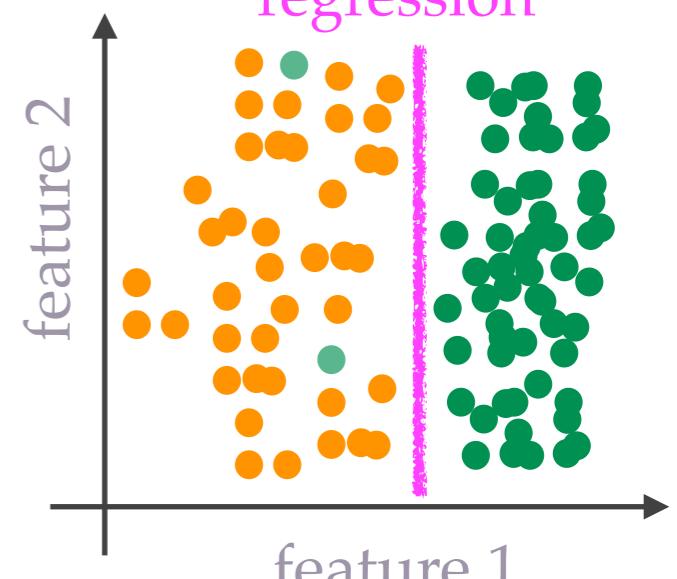


Feature extraction



Disadvantages of CNN models

Classification / regression



Fully connected layer
(Dense)

Convolutional layer
Conv1D, 2D, 3D, ...
separable Conv

Optimizer
SGD
Adam
RMSprop

Evaluation metric
accuracy
F1-score
AUC
confusion matrix

Loss function
categorical crossentropy
binary crossentropy
mean squared error
mean absolute error

Regularization
Dropout
Data augmentation
 l_1, l_2 regularizations

Pooling layer
max-pooling
average-pooling

Activation function
sigmoid
softmax
ESP (swish)
ReLU



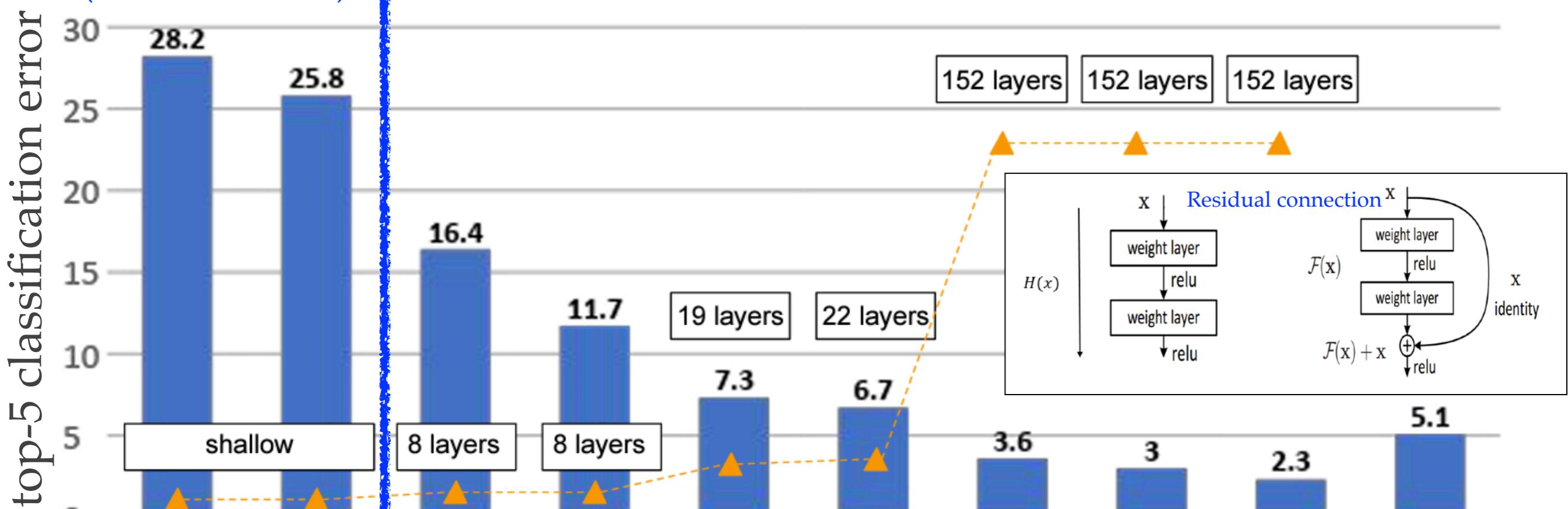
- ❖ **Combine basic components to build a neural network**
 - More components → “More” representative power

More networks: Xception, ResNeXt, DenseNet, MobileNet, NASNet, EfficientNet, SqueezeNet, Feature Pyramid Network

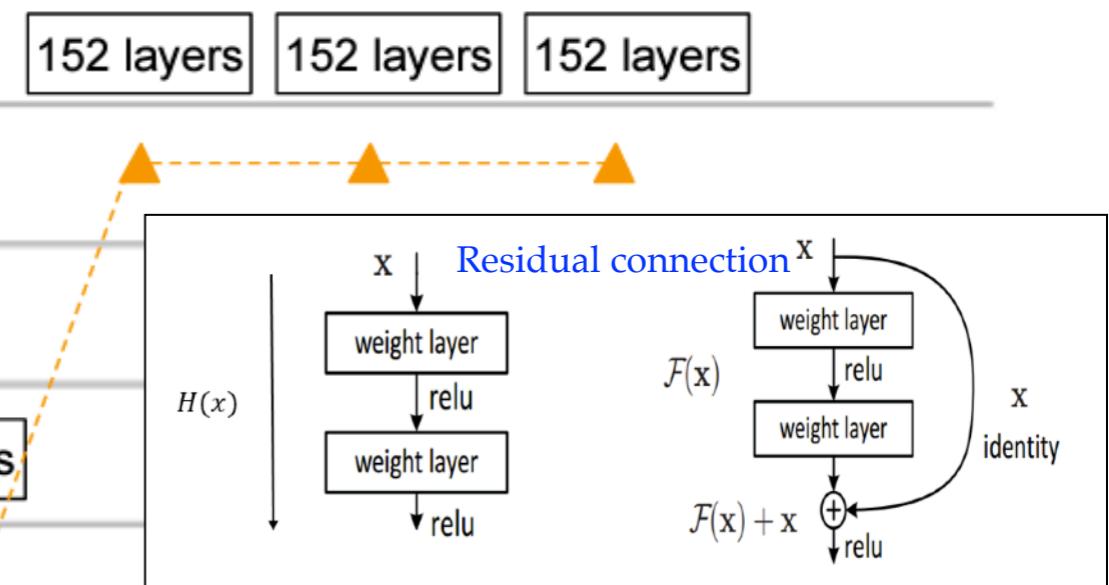
ImageNet

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

The SVM era
(traditional ML)



The deep learning era



- Conv
- Pooling
- Dense
- Dropout
- ReLU
- SGD with momentum

- Optimized "AlexNet" in terms of # filter, kernel sizes etc.

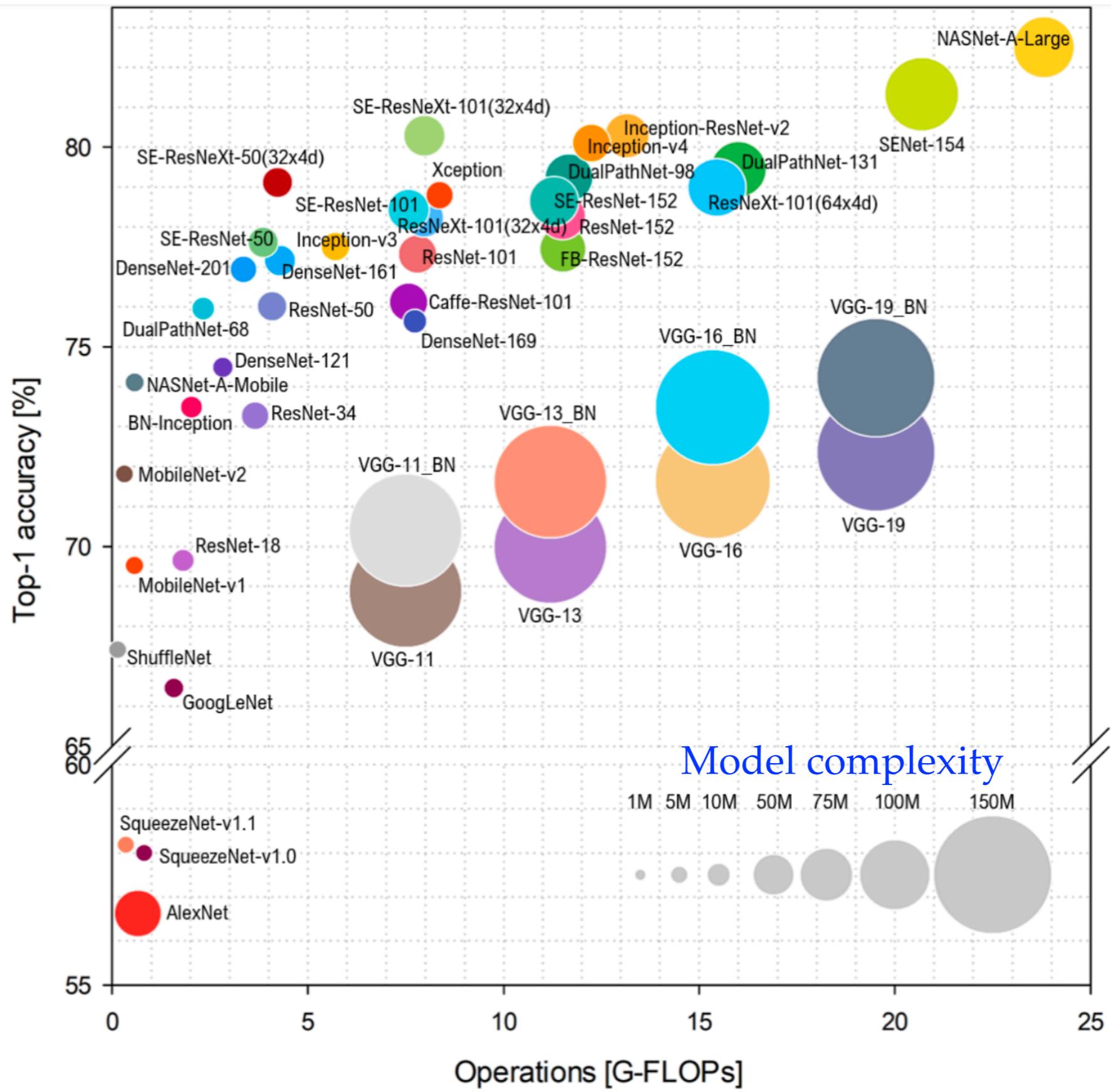
- 19 layers with filter size = 3x3

- Introduce 1x1 Conv to reduce the dimensions
- Multiple losses to help with gradients
- Inception module

- Skip connection to help with the vanishing gradient problem
- Batch normalization
- Network ensemble

- Squeeze-and-Excitation (SE) block
- Adaptive feature map reweighting

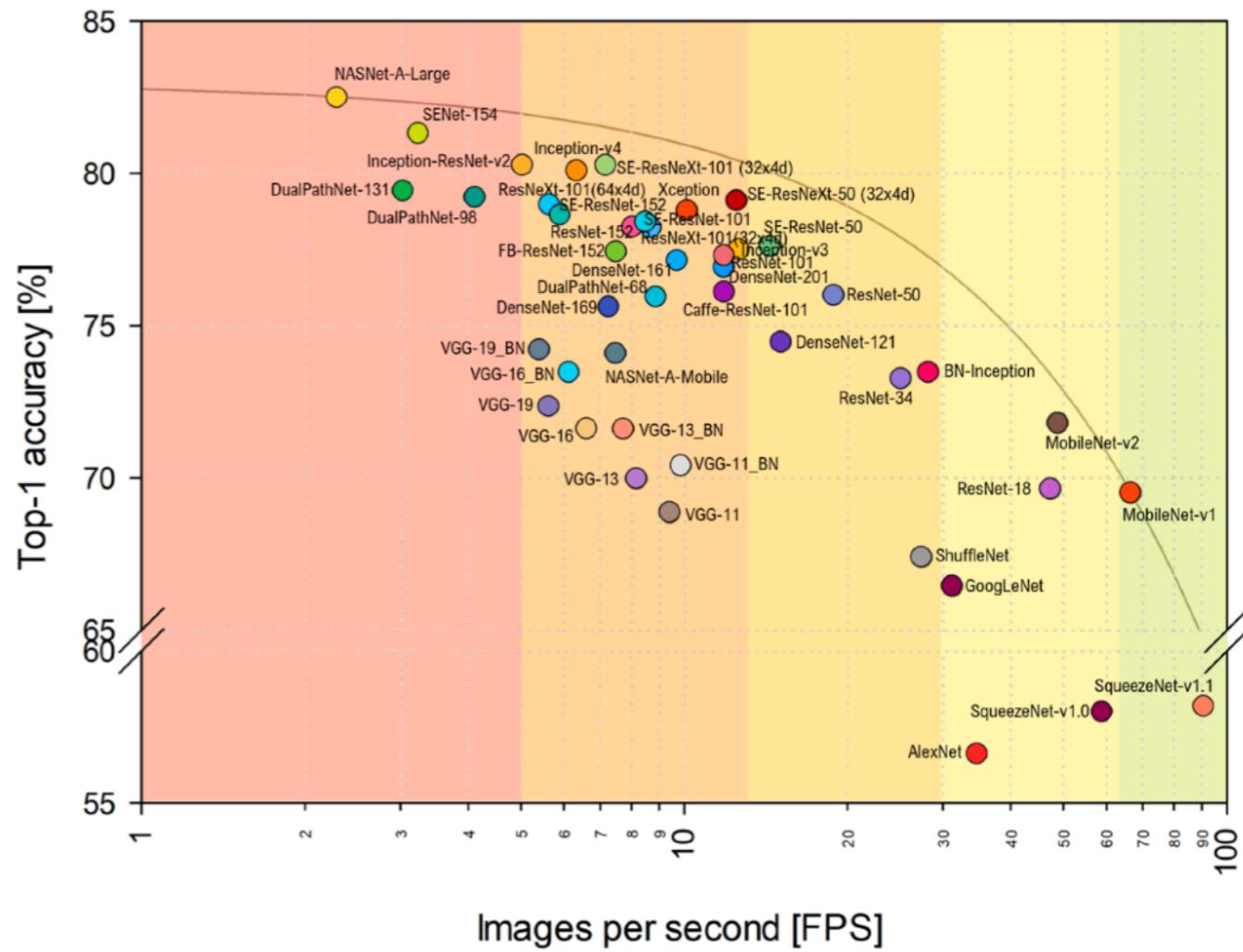
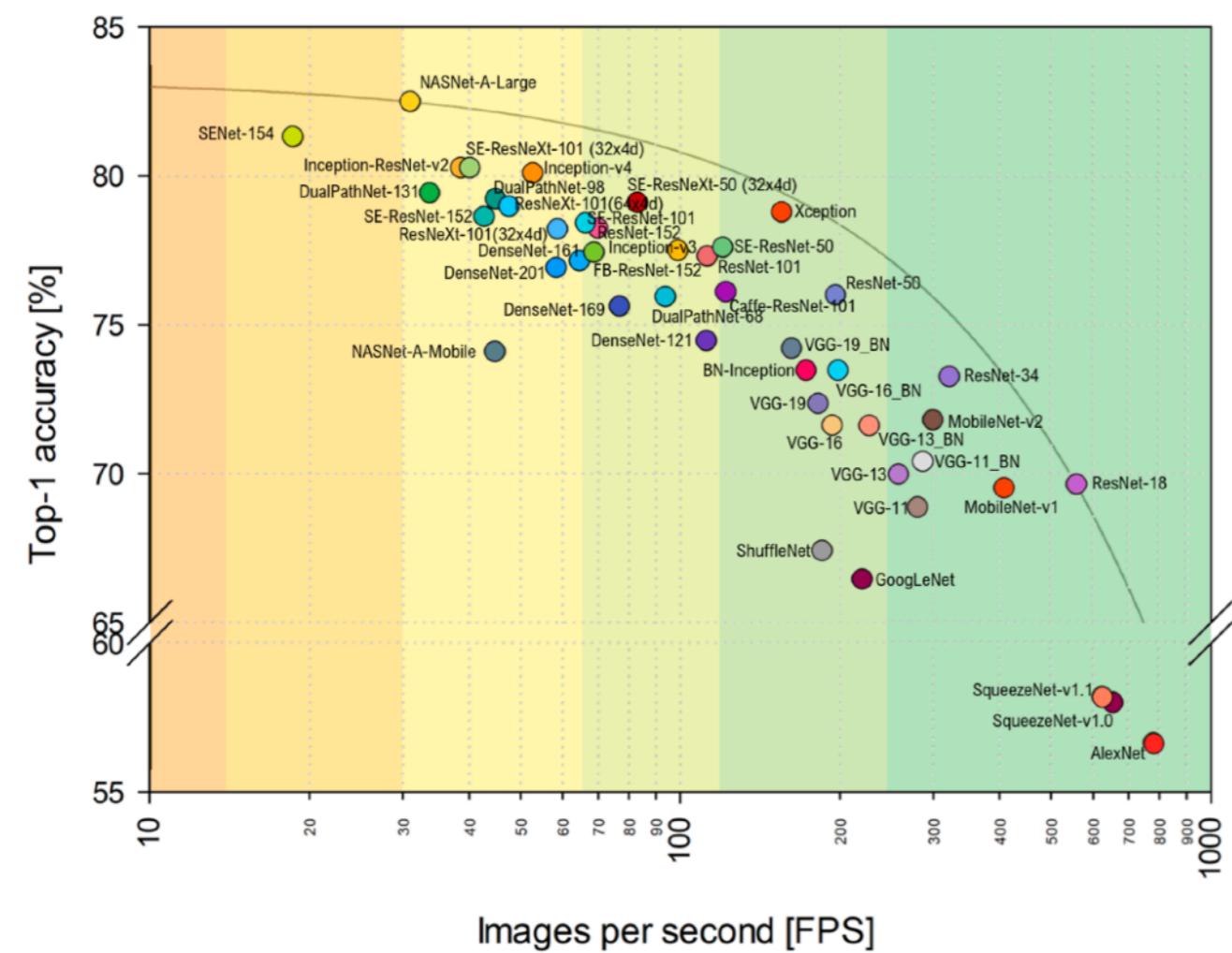
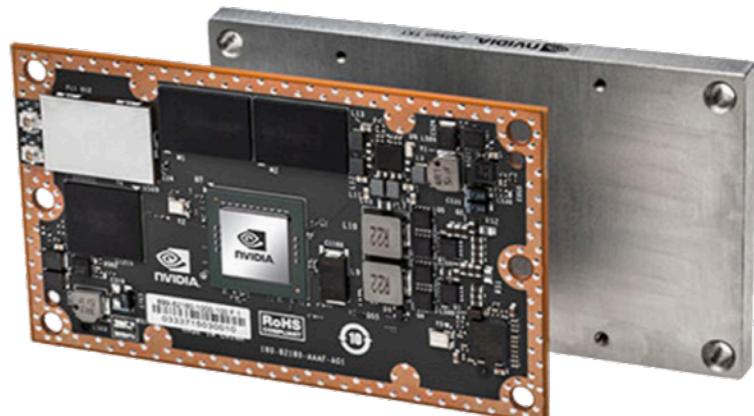
The last annual ImageNet competition was held in 2017



Titan Xp

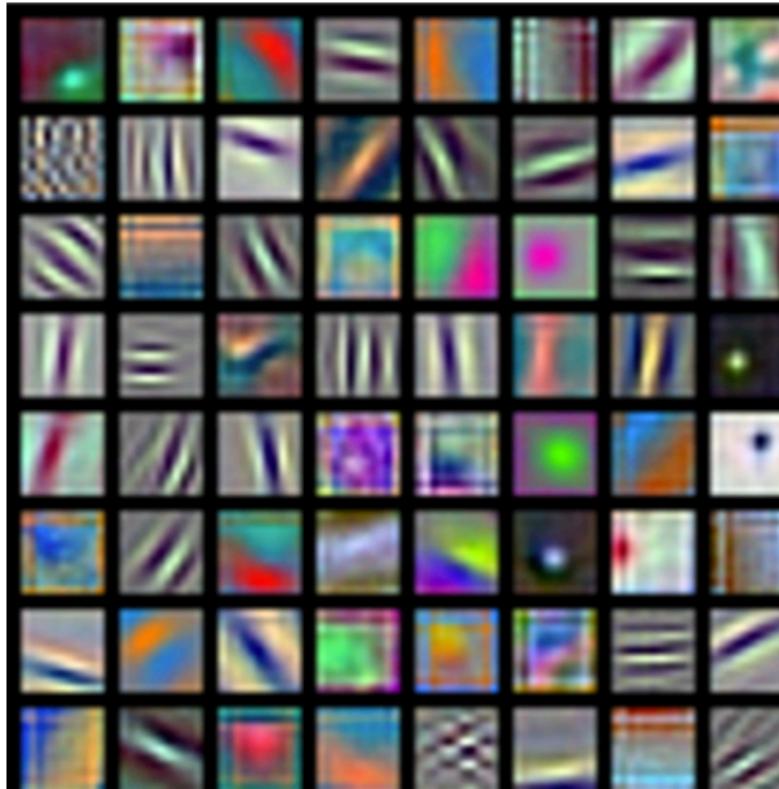


Jetson TX1



Understanding CNN - Filter Visualization

Learned weights of the filters at the first layer



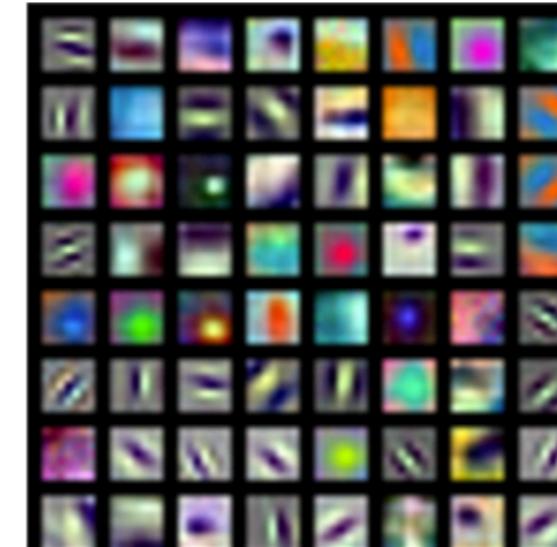
AlexNet:
64 x 3 x 11 x 11

64 filters filter size = 11 x 11
with 3 channels

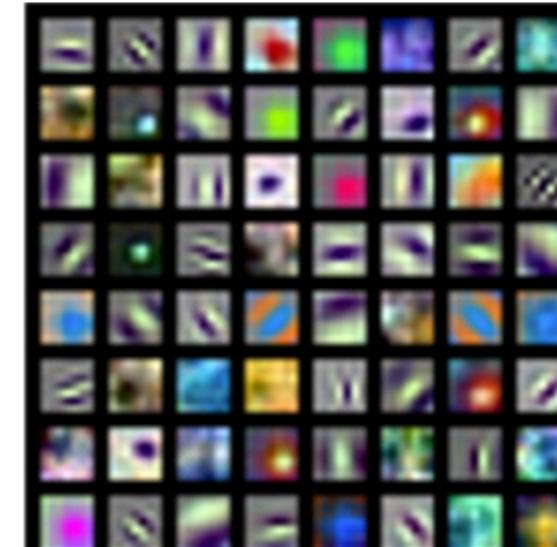
What these filters look for (through template matching/inner product)

- oriented edges
- opposing colors

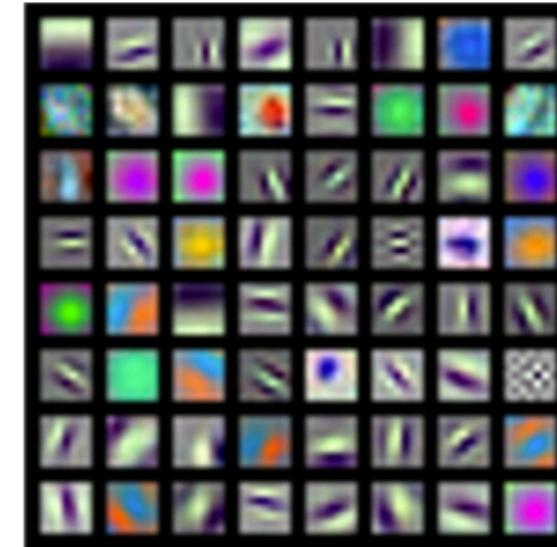
Similar to human visual system!



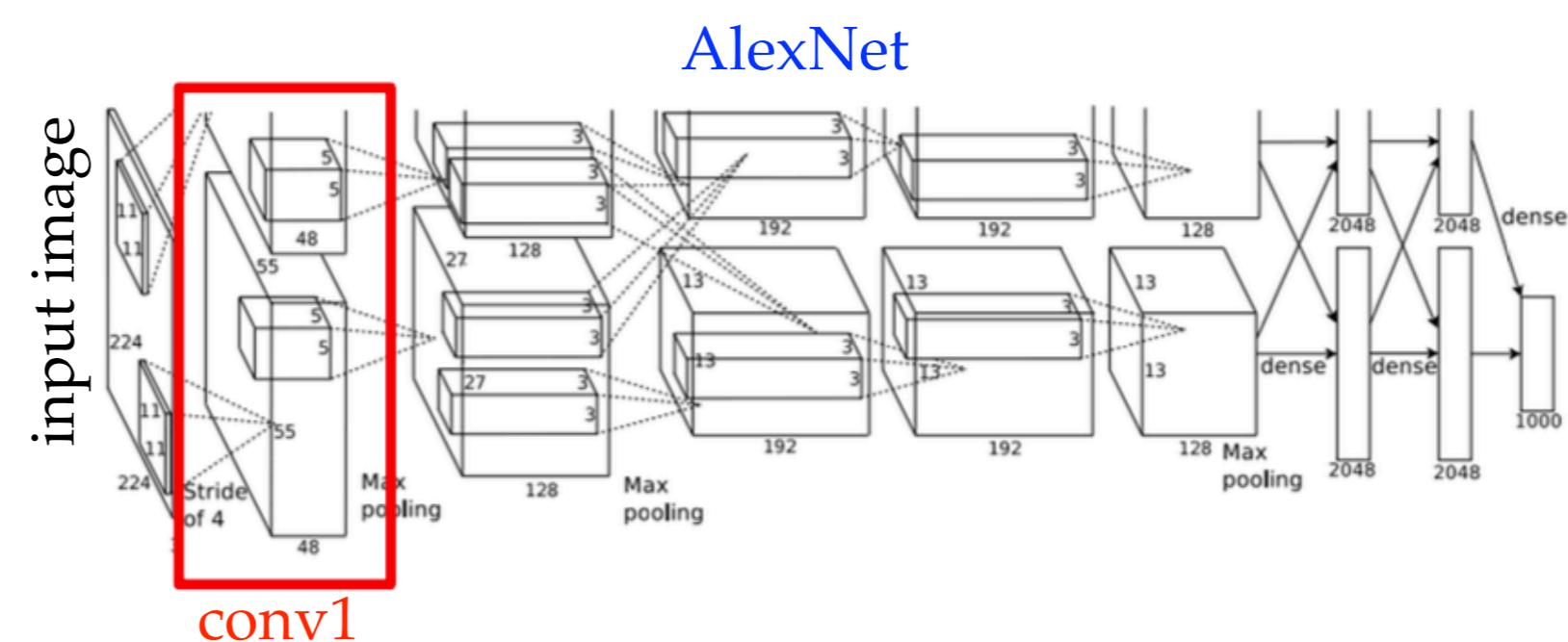
ResNet-18:
64 x 3 x 7 x 7



ResNet-101:
64 x 3 x 7 x 7



DenseNet-121:
64 x 3 x 7 x 7



Understanding CNN - Filter Visualization

Visualize the filters/kernels (raw weights)

We can visualize filters at higher layers, but not that interesting

(these are taken from ConvNetJS CIFAR-10 demo)



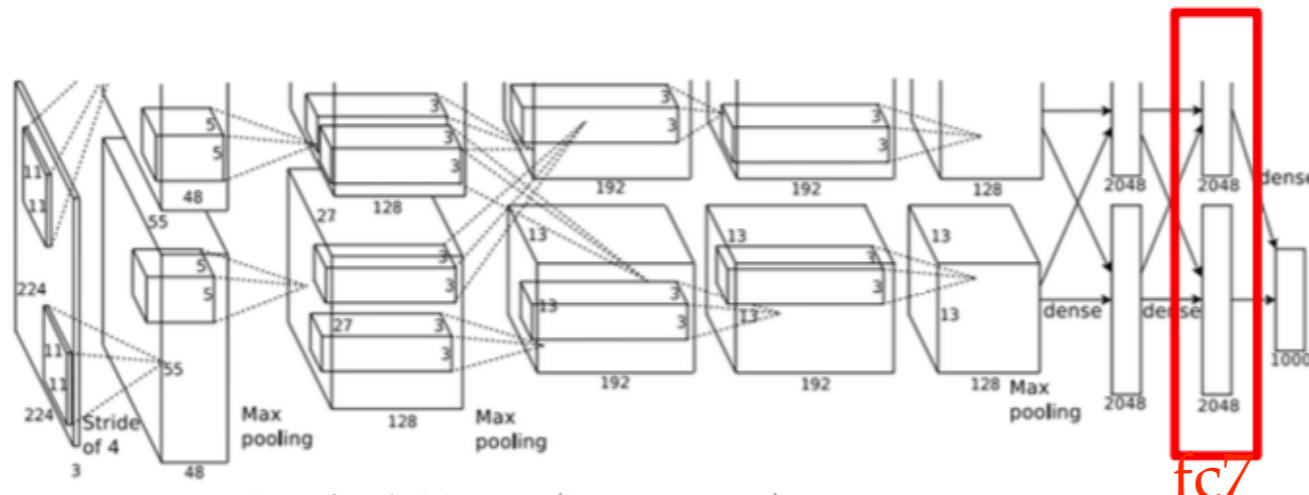
Stanford CS231n (Spring 2022): Lecture 8.

The weights of conv2 tell us what type of the activation patterns after conv1 that would cause conv2 to maximally activate. These filters are not connected directly to the input image, so it is not directly interpretable.

We need more complicated techniques to get a sense of what is going on.

Understanding CNN - Last Layer

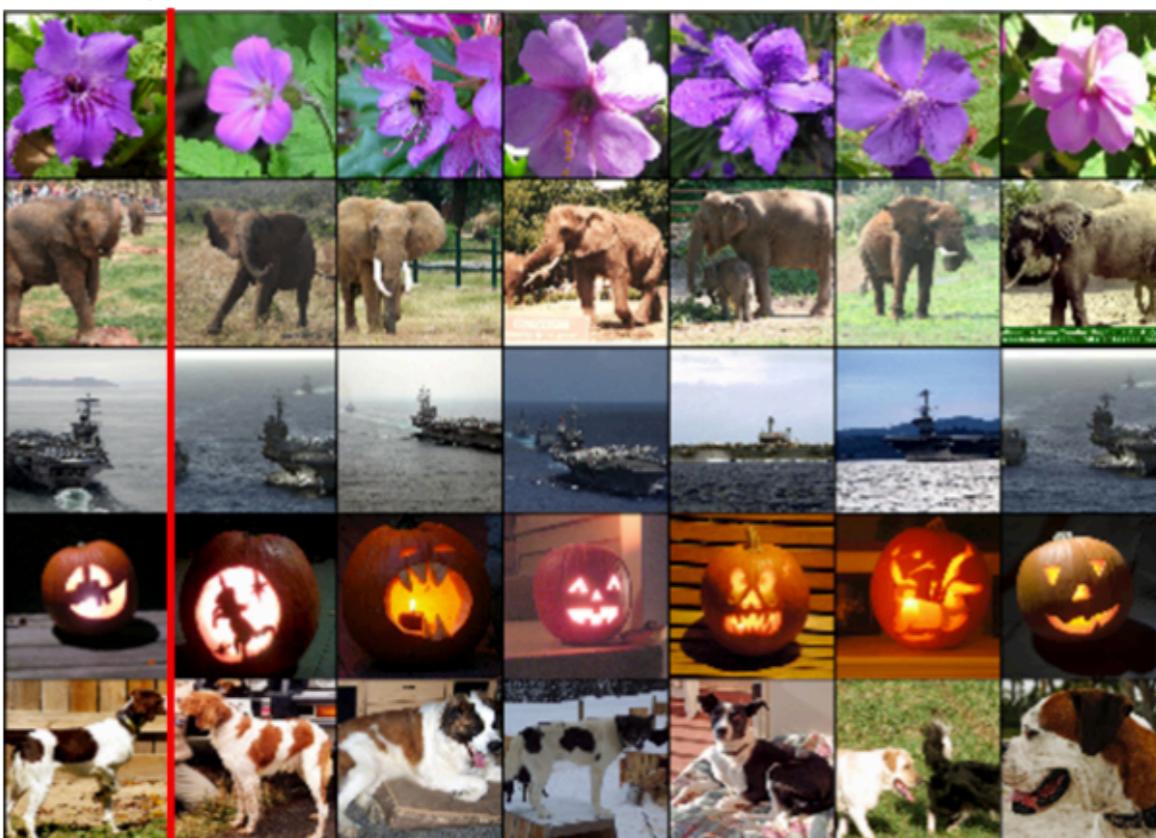
input image



Stanford CS231n (Spring 2022): Lecture 8.

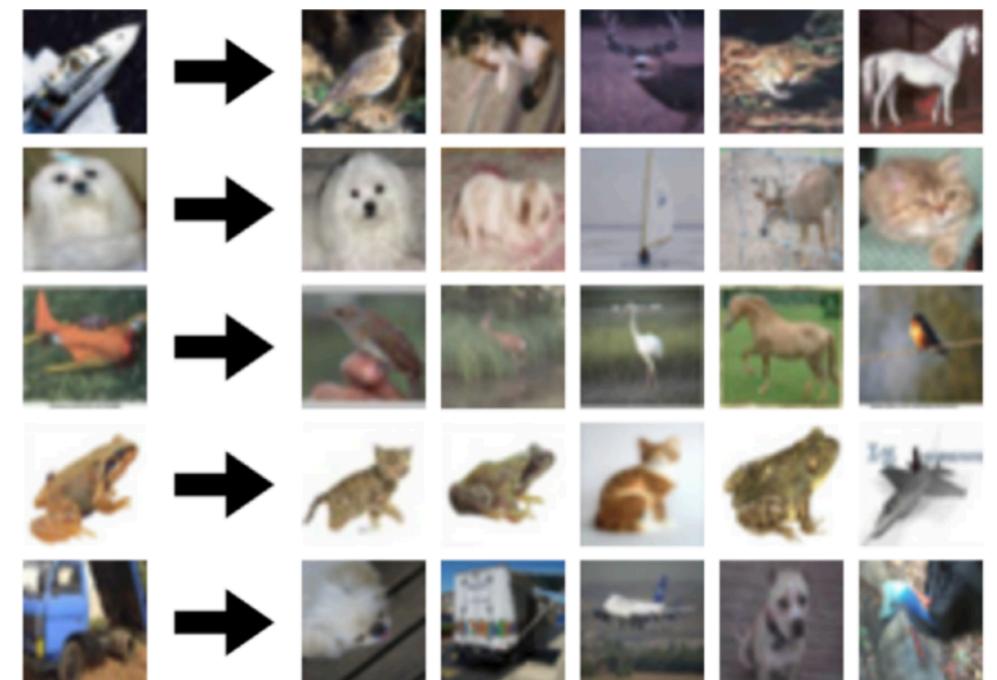
output of fc 7 = feature vector (last layer)
of size 4096

Test image L2 Nearest neighbors in feature space



Test
image

L2 Nearest neighbors in pixel space

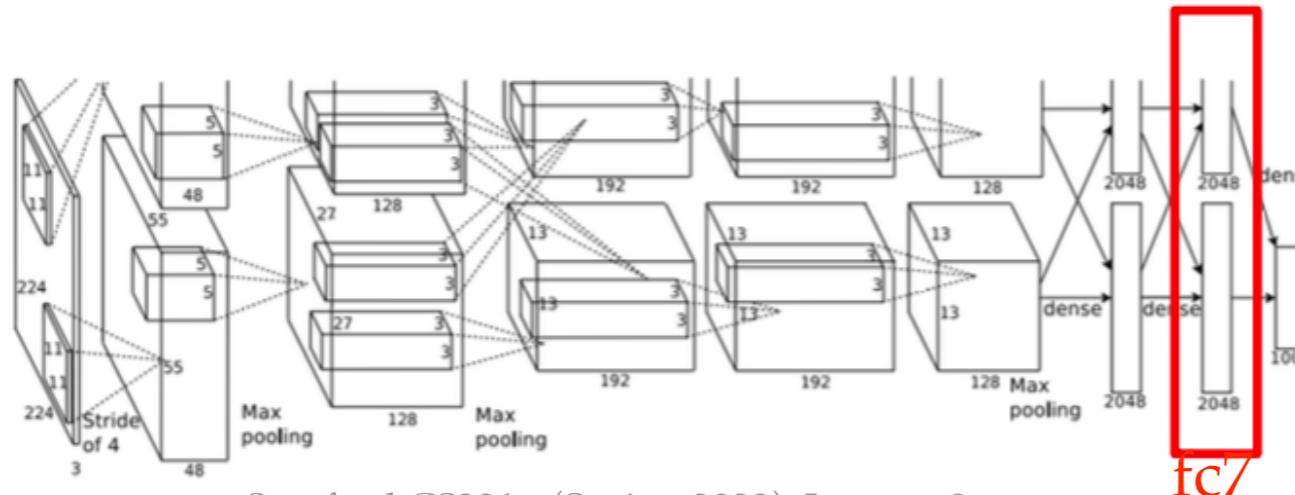


Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *Advances in neural information processing systems* 25 (2012).

Stanford CS231n (Spring 2022): Lecture 8.

Understanding CNN - Last Layer

input image



output of fc 7 = feature vector (last layer)
of size 4096

Stanford CS231n (Spring 2022): Lecture 8.

Perform a machine learning algorithm to the output of fc7

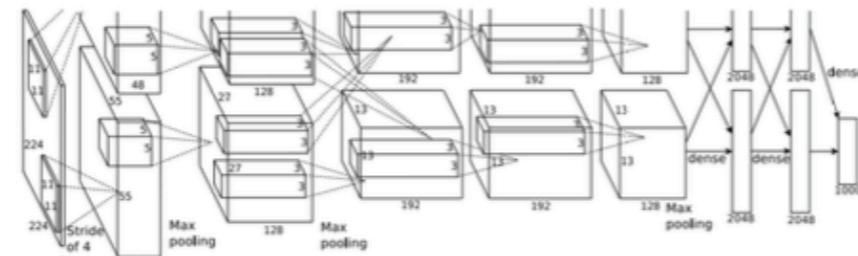
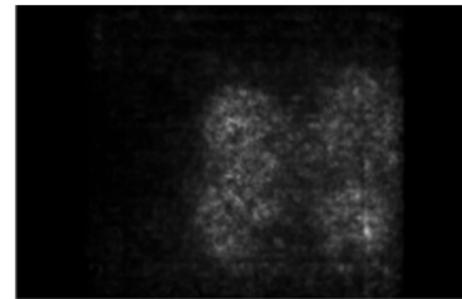
Barnes-Hut t-SNE



Understanding CNN - Other Techniques

Saliency Maps

Forward pass: Compute probabilities



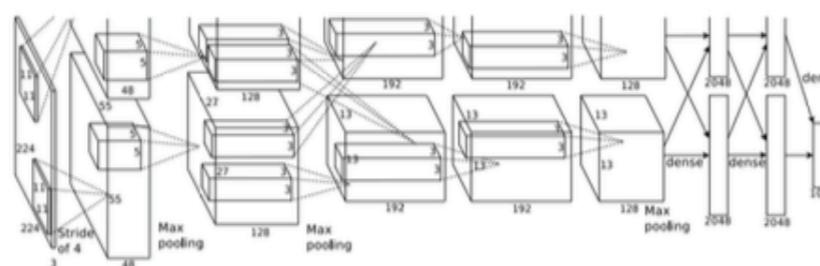
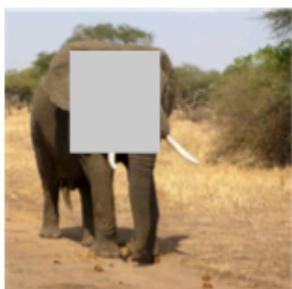
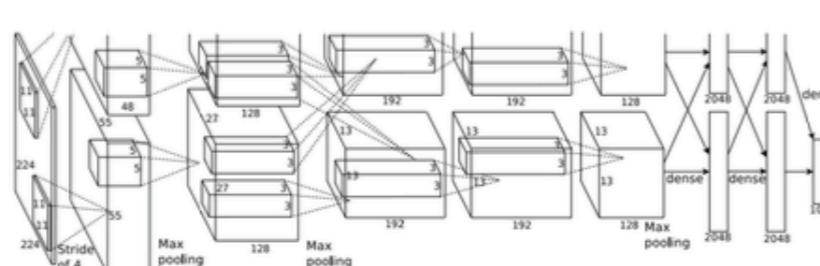
Dog

gradient of class score w.r.t. image pixels

Simonyan, Karen, Andrea Vedaldi, and Andrew Zisserman. "Deep inside convolutional networks: Visualising image classification models and saliency maps." arXiv preprint arXiv:1312.6034 (2013).

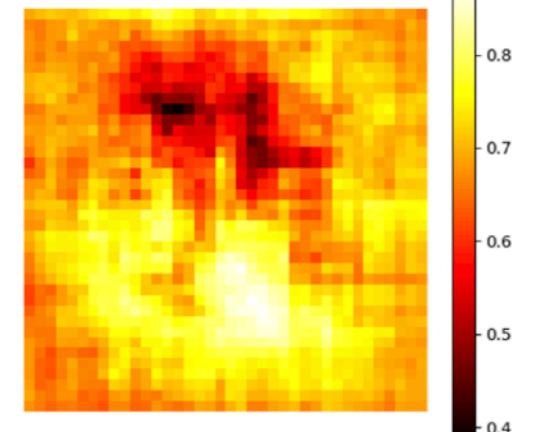
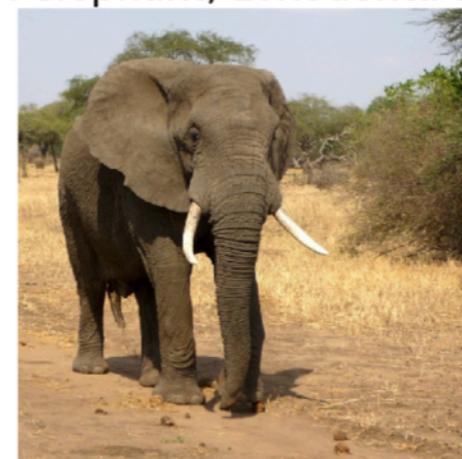
Occlusion Experiments

Mask part of the image before feeding to CNN, check how much predicted probabilities change



Zeiler, Matthew D., and Rob Fergus. "Visualizing and understanding convolutional networks." European conference on computer vision. Springer, Cham, 2014.

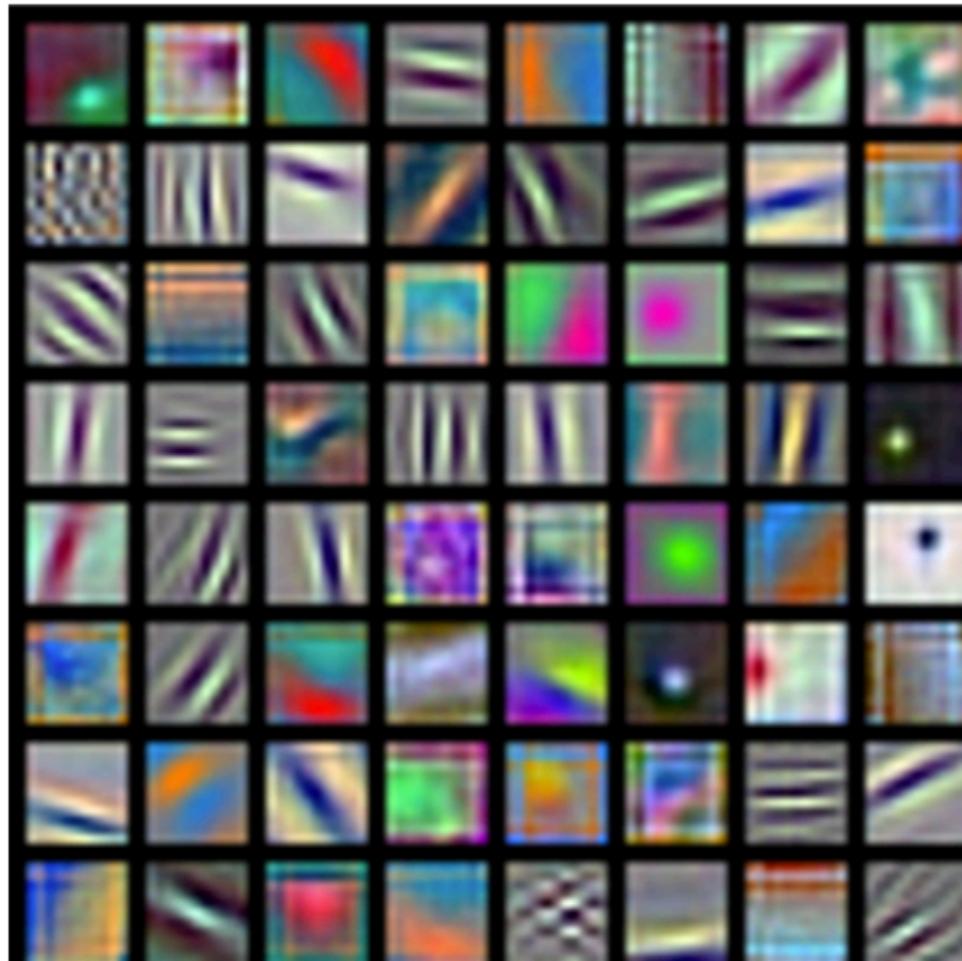
African elephant, Loxodonta africana



...and many more such as

- ❖ Guided Backpropagation
- ❖ Grad-CAM, Score-CAM, HiResCAM
- ❖ Attention map visualization

Trained CNN as a Feature Extractor



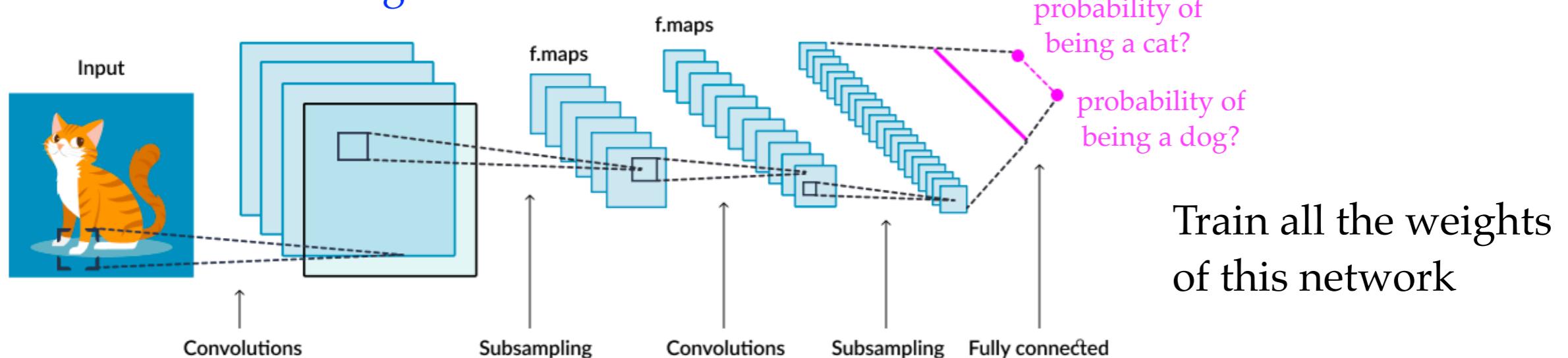
What these filters look for (through template matching/inner product)

- oriented edges
- opposing colors

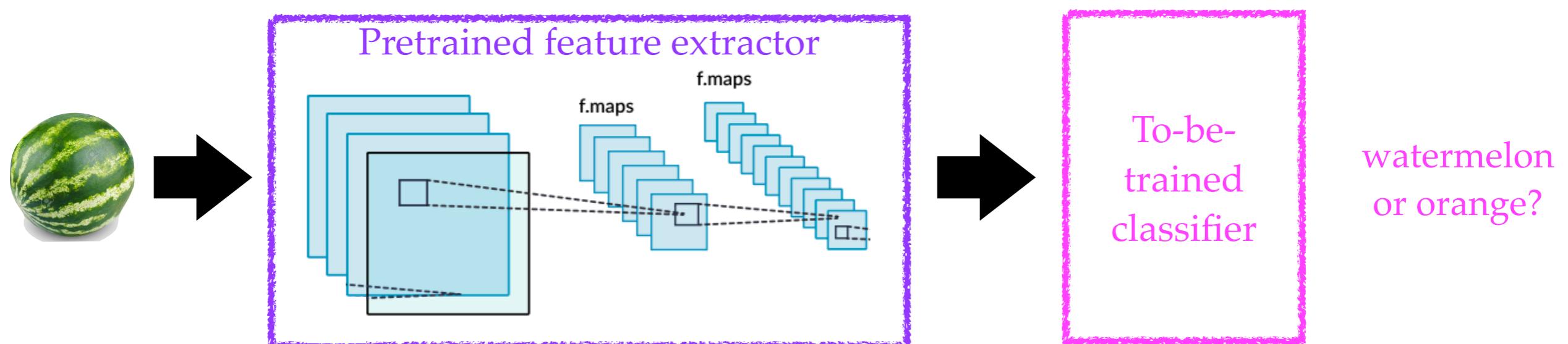
These patterns are important for processing other types of images as well, so we can reuse trained weights when we encounter a related task or the same task but with a different dataset

Trained CNN as a Feature Extractor

Previous Task: Cat-vs-dog classification



New Task: Watermelon-vs-orange classification



Take parts of the trained network
and use them as a feature extractor

Only train the
weights here

Transfer Learning and Fine-Tuning

ImageNet (1000 classes)

14M images

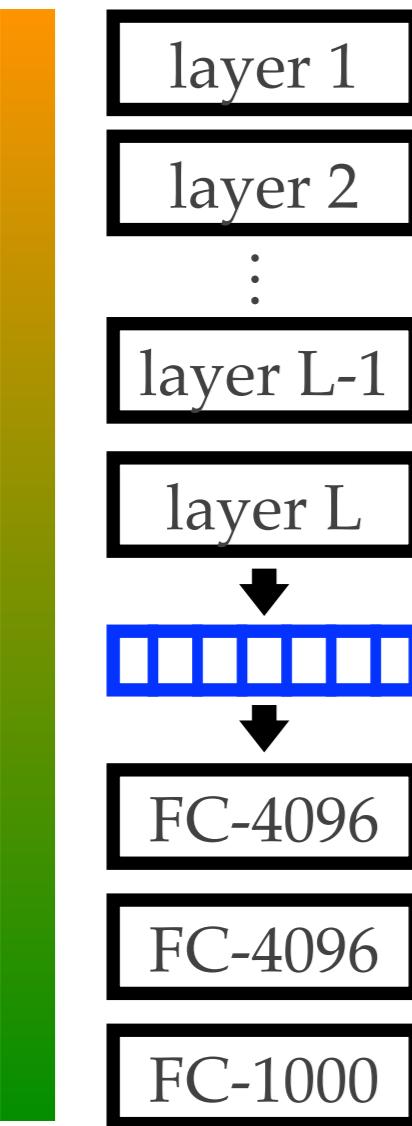


AI-vs-Artists (2 classes)

Assume small dataset

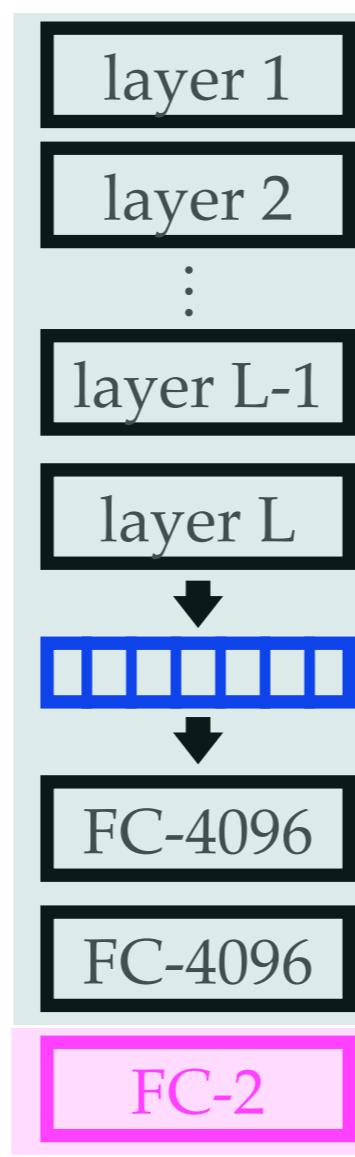


More
“reusable”



Clone these layers
along with their
weights and do not
modify the weights

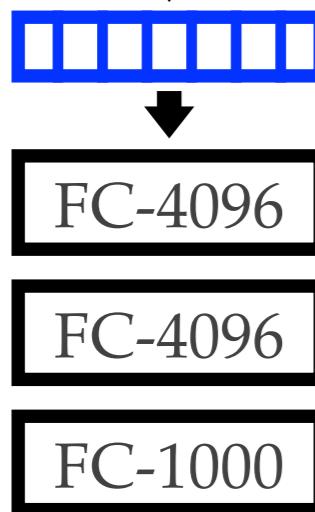
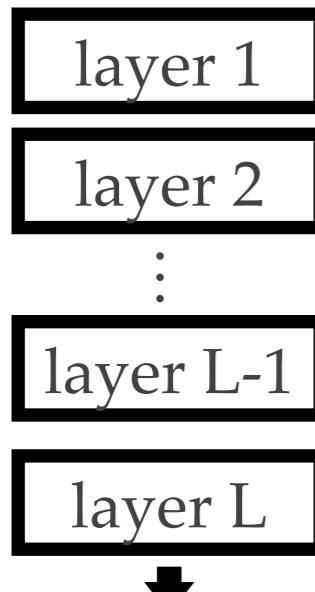
Replace the
classification layer
and train it



Transfer Learning and Fine-Tuning

ImageNet (1000 classes)

14M images

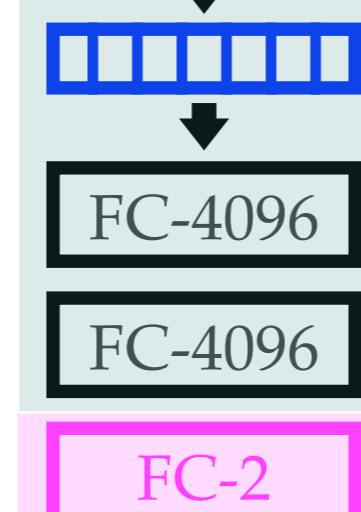
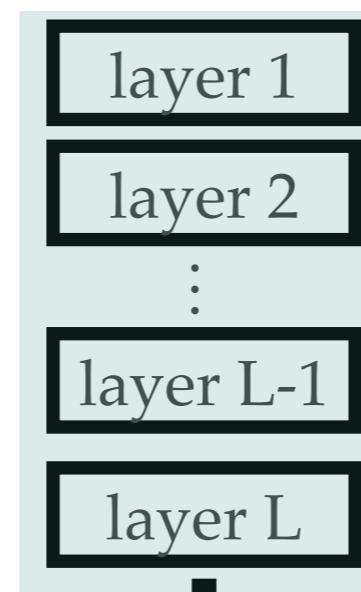


Clone these layers along with their weights and do not modify the weights

Replace the classification layer and train it

AI-vs-Artists (2 classes)

Assume small dataset



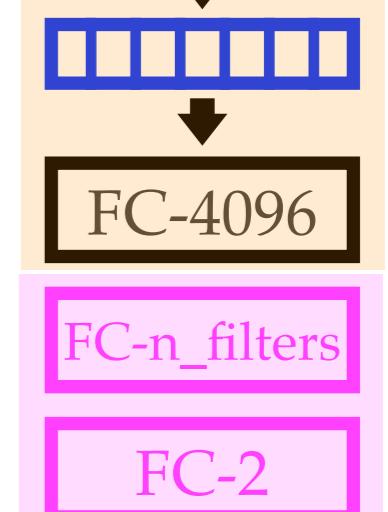
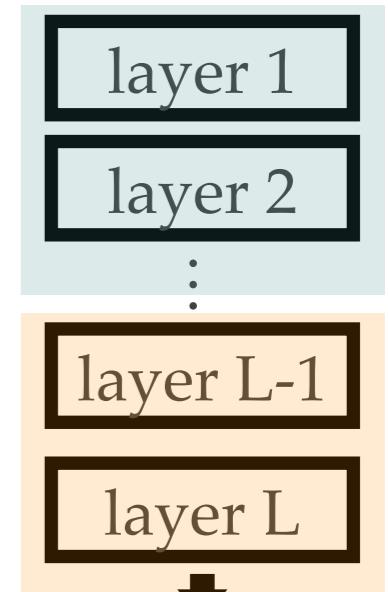
Clone these layers along with their weights and do not modify the weights

Clone these layers along with their weights and retrain them with an initially low learning rate

Replace these layers and train them

Dog-vs-cat (2 classes)

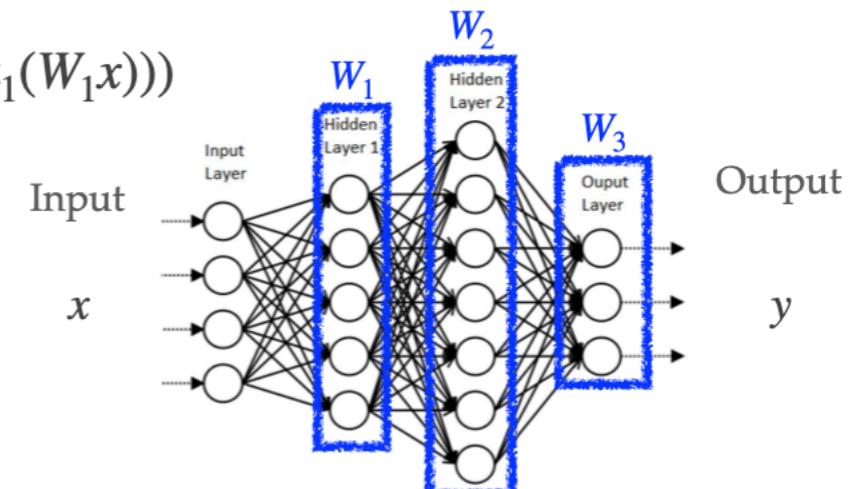
Assume dataset of moderate size



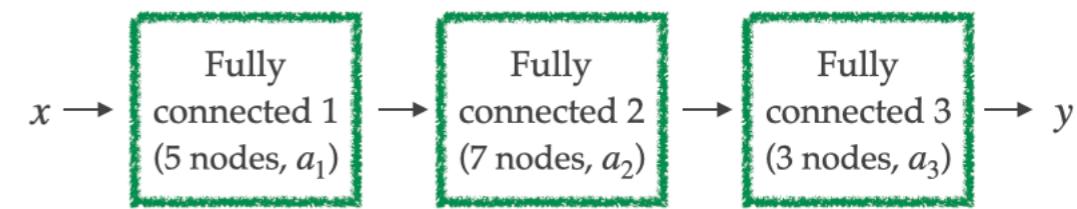
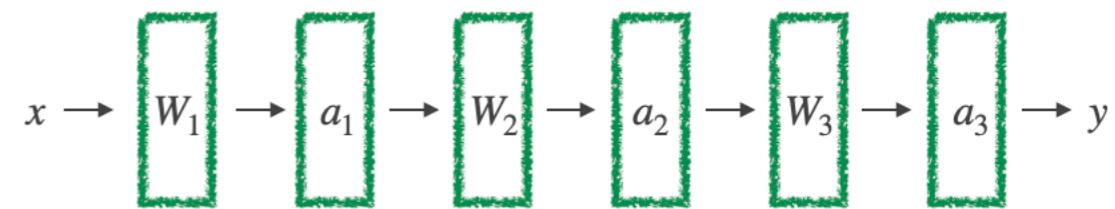
Outline

- ❖ Deep Learning Components
 - ❖ Fully connected layer
 - ❖ Computation graph
 - ❖ Activation functions
 - ❖ Loss function
 - ❖ Model optimization
 - ❖ Gradient descent
 - ❖ Backpropagation
 - ❖ Stochastic gradient descent (SGD)
 - ❖ Regularization
 - ❖ ℓ_2 and ℓ_1 regularization
 - ❖ Dropout
 - ❖ Batch normalization
 - ❖ Convolutional layer
 - ❖ Pooling layer
- ❖ Convolutional Neural Network (CNN)

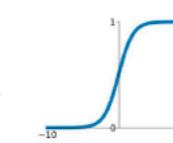
$$y = a_3(W_3 a_2(W_2 a_1(W_1 x)))$$



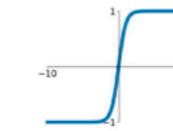
Computation graph



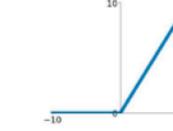
Sigmoid
 $\sigma(x) = \frac{1}{1+e^{-x}}$



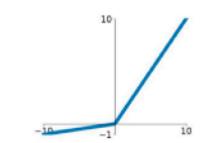
tanh
 $\tanh(x)$



ReLU
 $\max(0, x)$

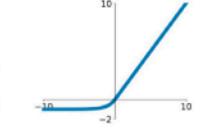


Leaky ReLU
 $\max(0.1x, x)$



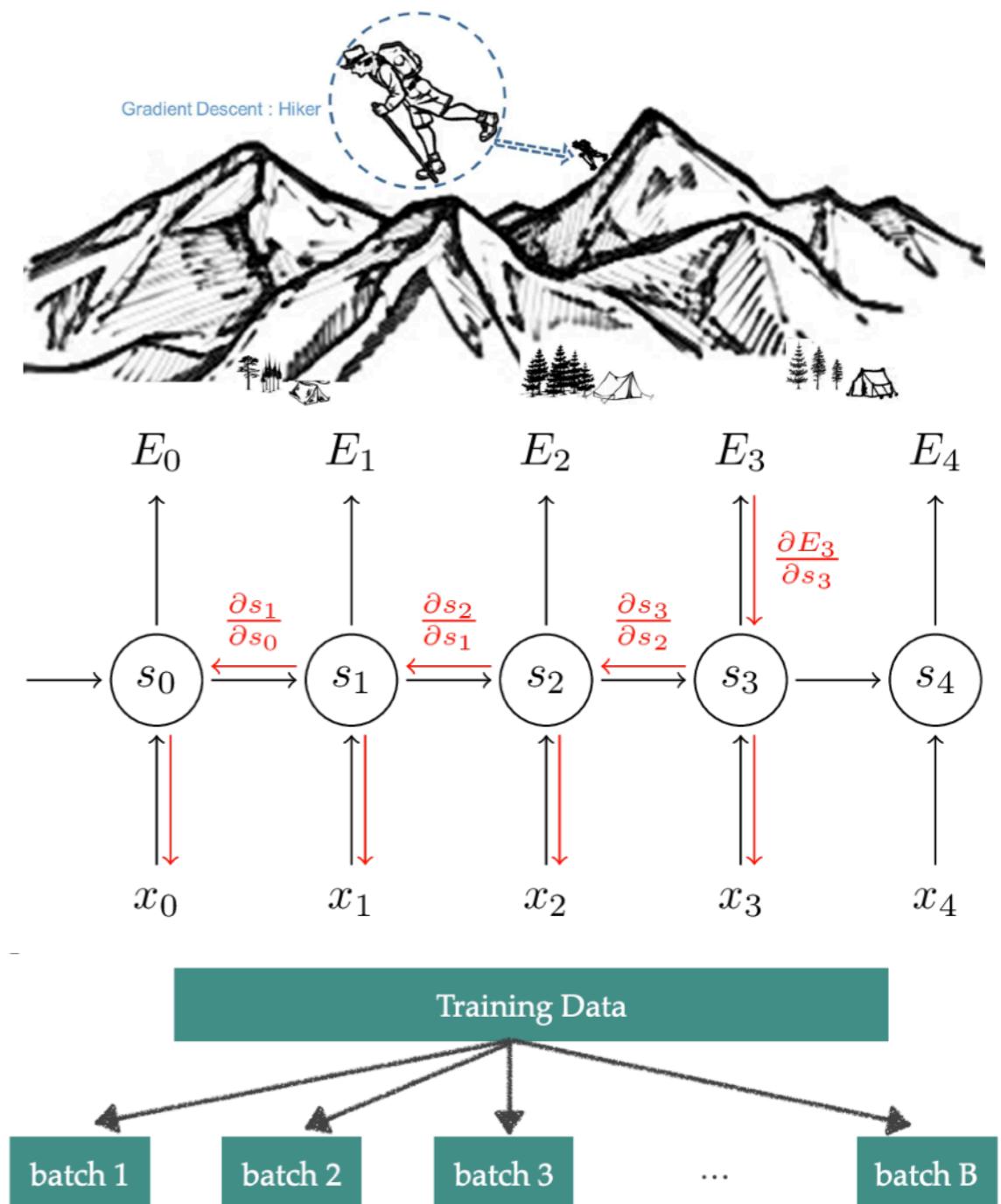
Maxout
 $\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU
 $\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$



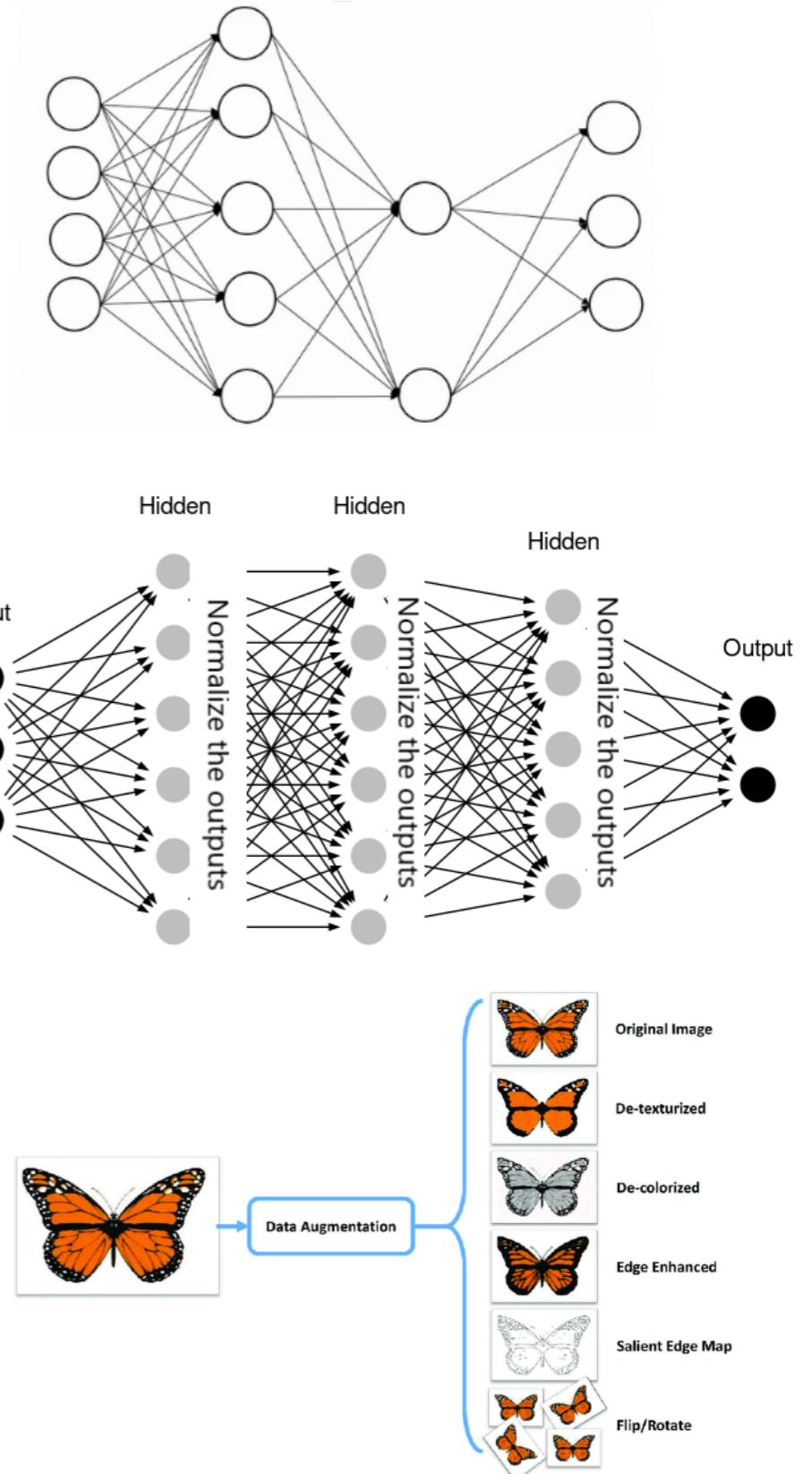
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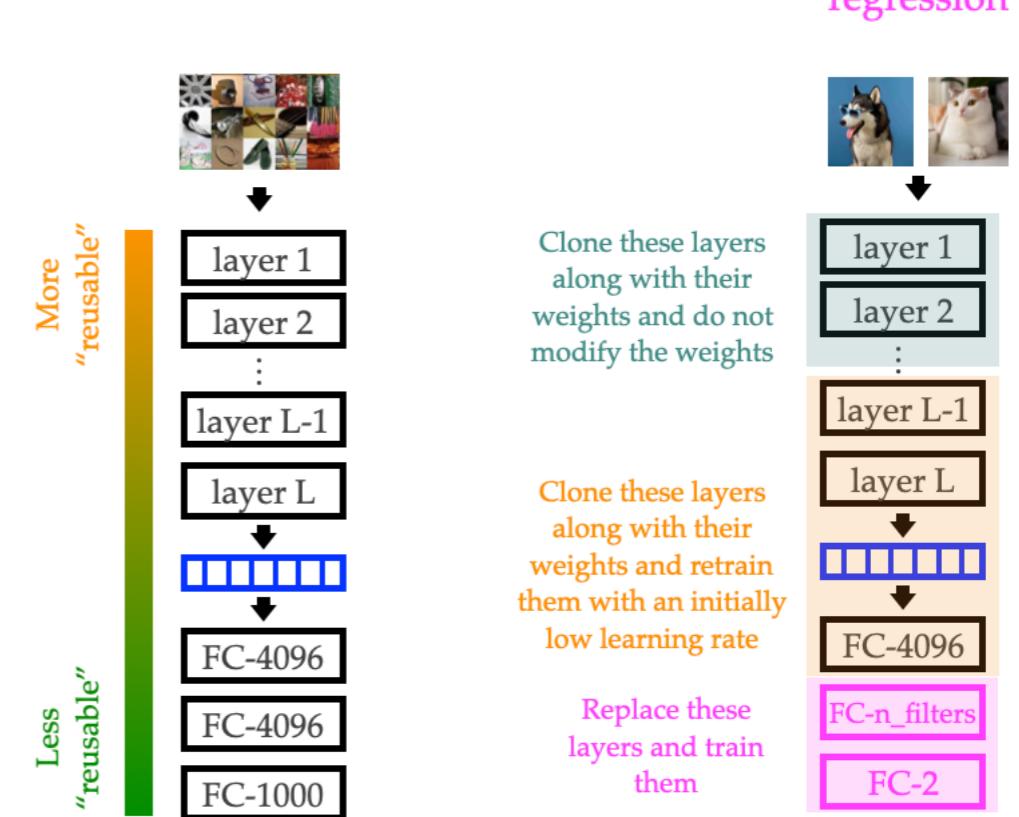
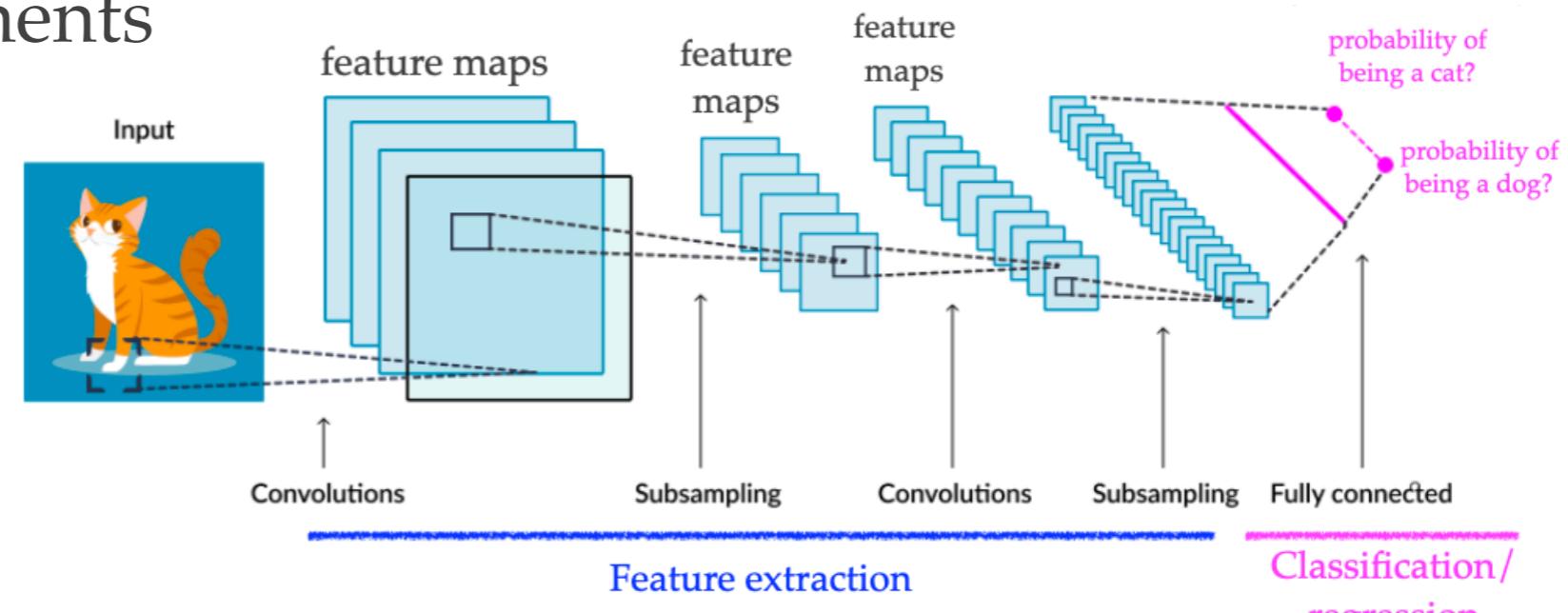


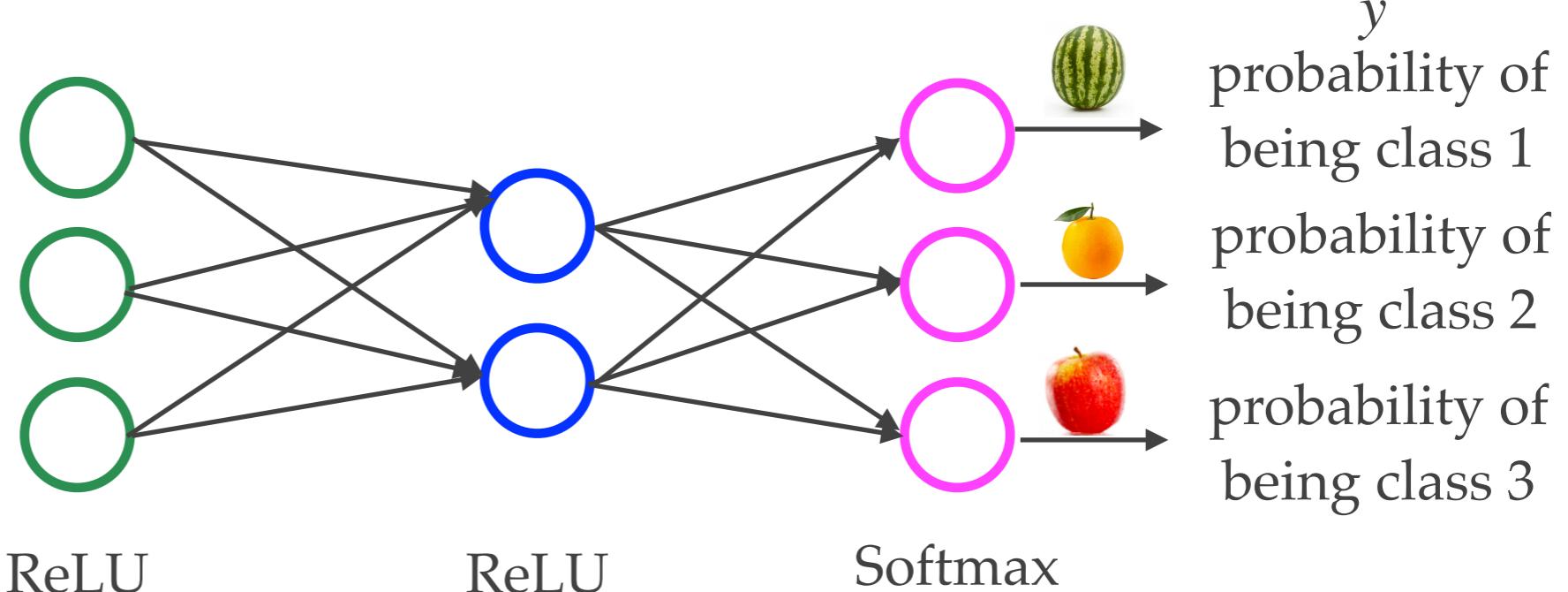
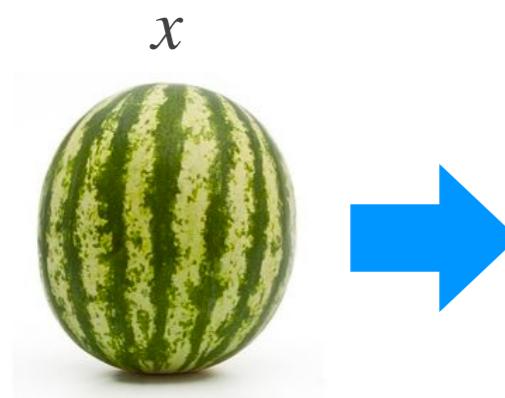
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activation functions

ReLU

ReLU

Softmax

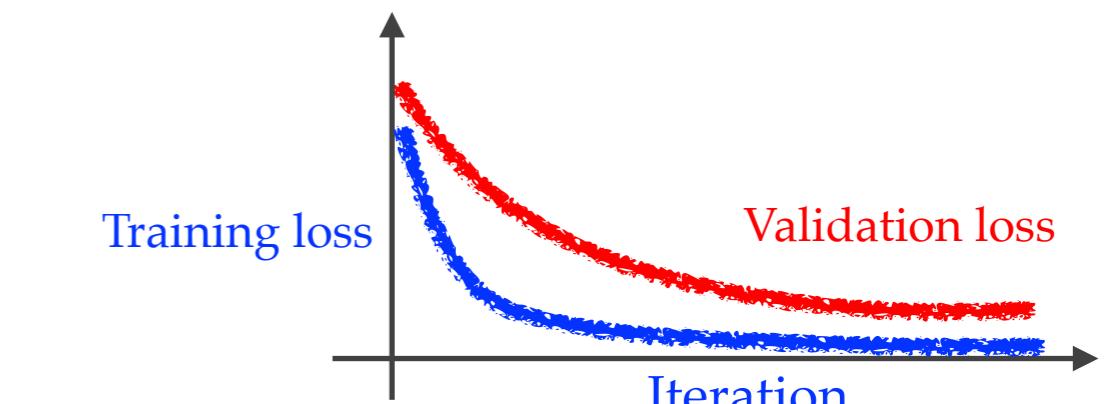
y
probability of
being class 1
probability of
being class 2
probability of
being class 3

```
# Import necessary modules
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

# Create the model
model = keras.Sequential()
model.add(layers.Dense(3, activation="relu"))
model.add(layers.Dense(2, activation="relu"))
model.add(layers.Dense(3, activation="softmax"))

# Compile the model
model.compile(
    optimizer='adam',
    loss=tf.keras.losses.CategoricalCrossentropy(),
)

# Train the model for 100 epochs with a batch size of 32
model.fit(x_train, y_train, batch_size=32, epochs=100, validation_data=(x_val,y_val))
```



Model

Loss function
and optimizer