CHULA ENGINEERING Foundation toward Innovation COMPUTER

Data Mining Group
Machine Intelligence and Knowledge Discovery Lab
Chulalongkorn University

Introduction to Deep Learning

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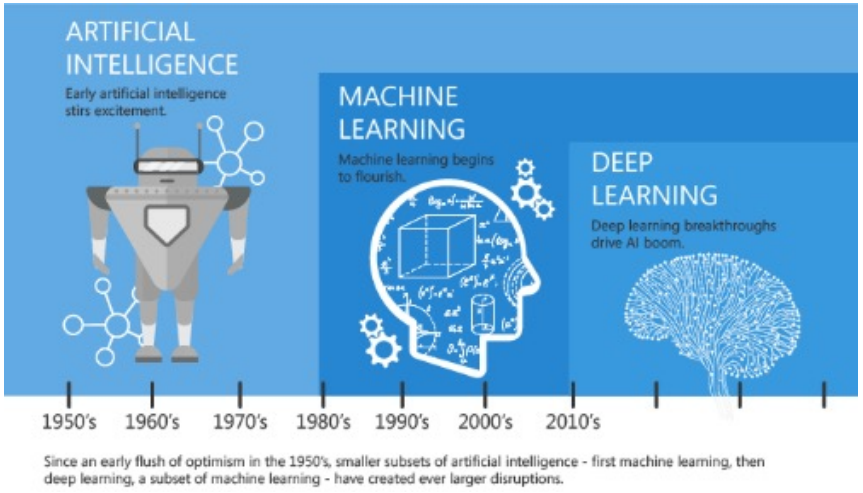
Outline

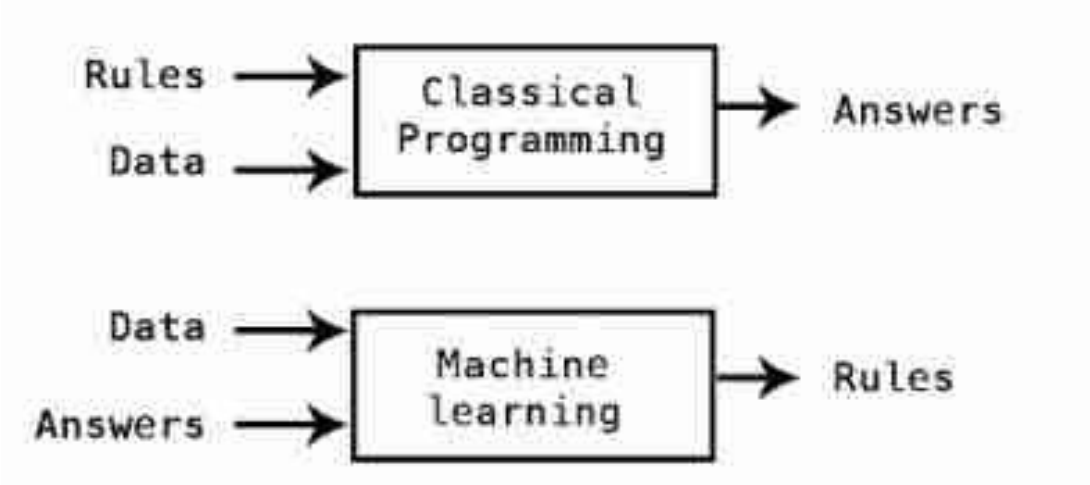
- Introduction to Deep Learning
- Convolutional Neural Networks (CNN) [Imaging Task]
- Recurrent Neural Networks (RNN) [Time Series Forecasting]
- Language Technologies

Introduction to Deep Learning

AI = Automation

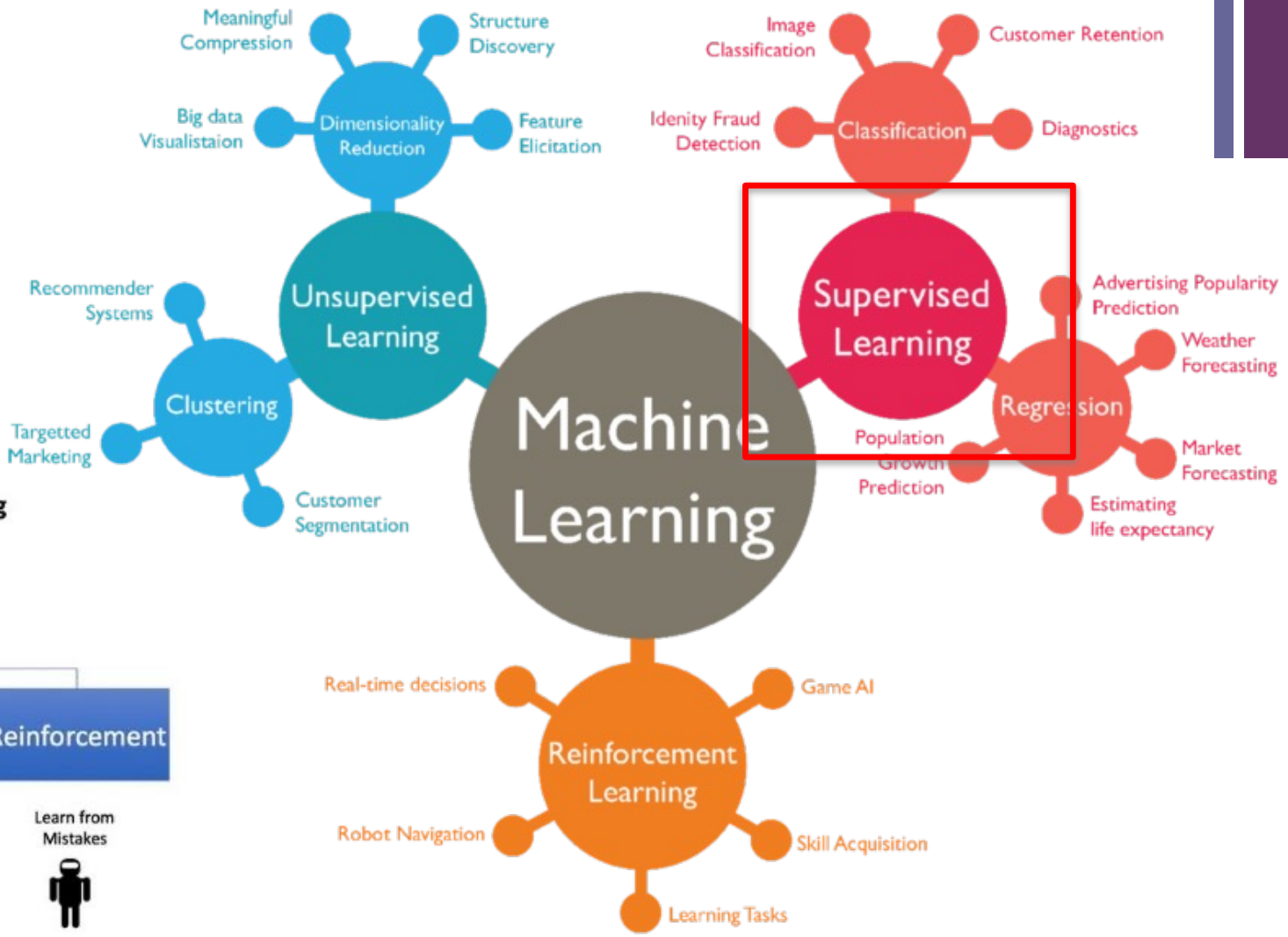
- 1) Rule-based AI (Symbolic AI)
- 2) Machine Learning



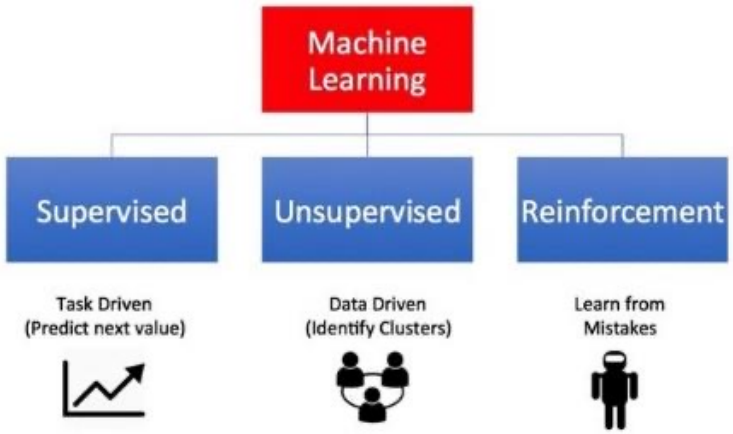


https://mc.ai/machine-learning-basics-artificial-intelligence-machine-learning-and-deep-learning/

Machine Learning



Types of Machine Learning



Task1: Supervised learning

Handcrafted features

Training Data

	inputs			target
Age	**Gender**	**BodyTemp**	**Cough**	**Corona**
12	Female	37	Yes	Yes
35	Female	39	No	Yes
32	Male	38	Yes	No

Testing Data

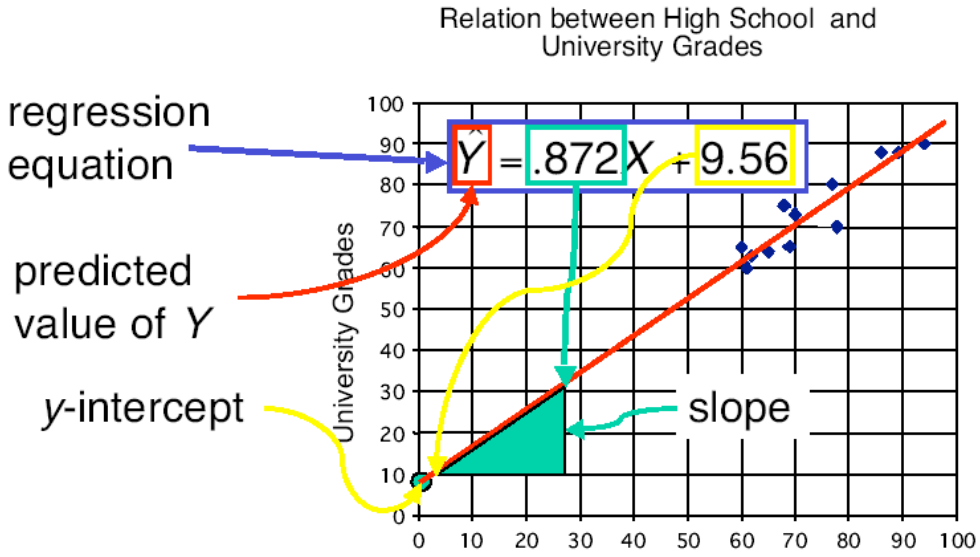
Age	**Gender**	**BodyTemp**	**Cough**	**Corona**
25	Male	40	No	?

Application: Corona Prediction

Prediction algorithms

- Decision Tree
- (Logistic) Regression
- kNN
- Support Vector Machine
- Neural Networks (NN)
- Deep Learning

Regression – Linear Relationship



weight, coefficient

$$\underset{\text{target}}{\hat{y}} = \underset{\text{intercept}}{\hat{w}_0} + \hat{w}_1 x_1 + \hat{w}_2 x_2 \quad \text{input}$$

- **The least square method** aims to minimize the following term

$$\sum_{\substack{training \\ data}} (y_i - \hat{y}_i)^2$$

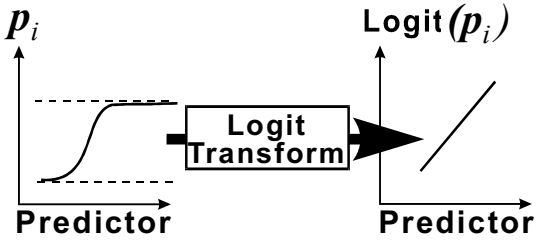
Logistic Regression (cont.)
Linear Relationship

Training Data

inputs				target
Age	**Gender**	**BodyTemp**	**Cough**	**Corona**
12	Female (0)	37	Yes (1)	Yes
35	Female (0)	39	No (0)	Yes
32	Male (1)	38	Yes (1)	No

Logit_score = w0 + w1*Age + w2*Gender + w3*Temp + w4*Cough
Logit_score = 0.01 – 0.3*Age +0.2*Gender + 0.2*Temp + 0.9*Cough

Example
Logit_score = 0.01 – 0.3*12 +0.2*0 + 0.2*37 + 0.9*1 = 4.71
prob = 0.9911 → "Yes"

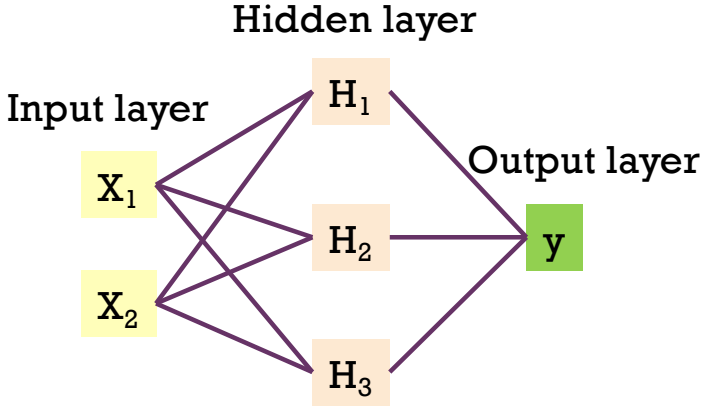


$$\hat{p} = \frac{1}{1 + e^{-\text{logit}(\hat{p})}}$$

Application: Corona Prediction

Neural Networks (universal approximator)

Non-linear relationship

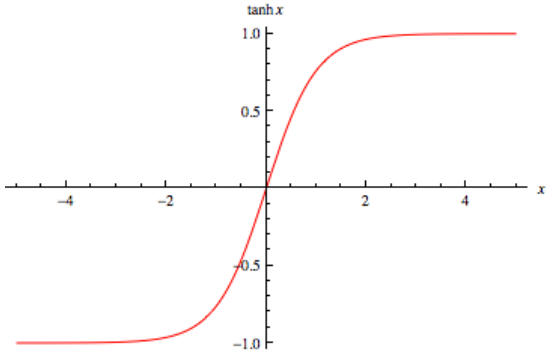


$$log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \hat{w}_0 + \hat{w}_1 H_1 + \hat{w}_2 H_2 + \hat{w}_3 H_3$$

$$H_1 = tanh(\hat{w}_{10} + \hat{w}_{11} x_1 + \hat{w}_{12} x_2)$$

$$H_2 = tanh(\hat{w}_{20} + \hat{w}_{21} x_1 + \hat{w}_{22} x_2)$$

$$H_3 = tanh(\hat{w}_{30} + \hat{w}_{31} x_1 + \hat{w}_{32} x_2)$$

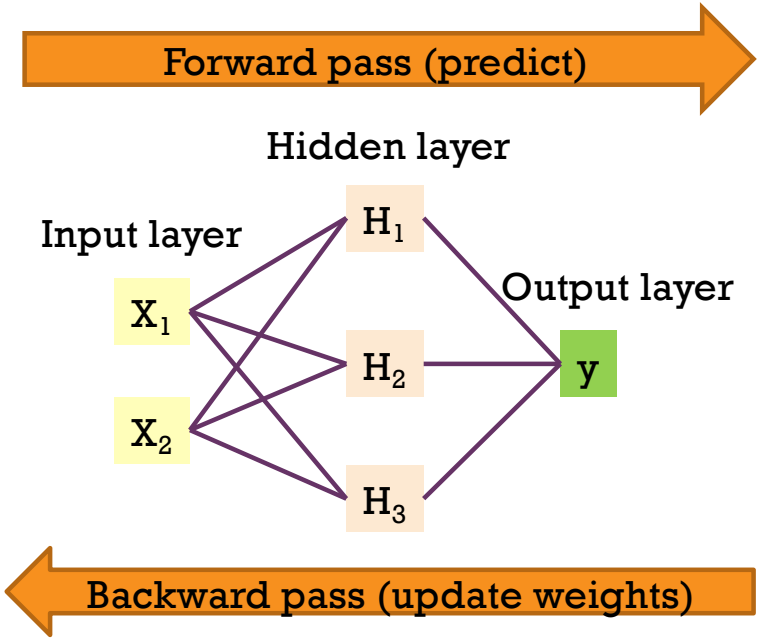


Stop when?
- Converge (no change in loss)
- Max epochs

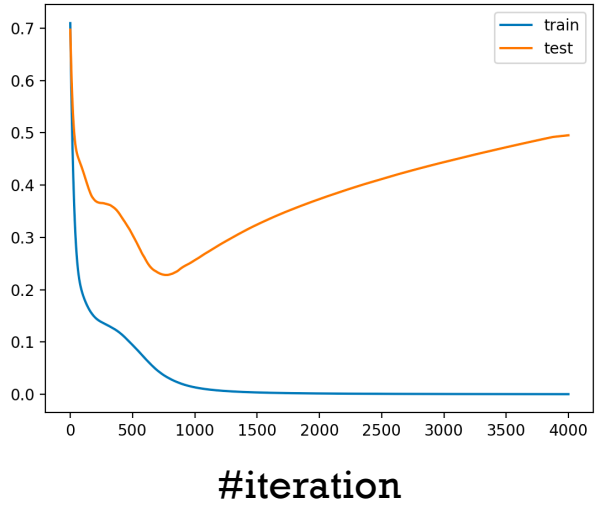
Important Params:
- #hidden units, #hidden layers
- Learning rate, Momentum, decay
- Seed number, etc.

Neural Networks (cont.): Training

Non-linear relationship



Age	Income	Gender	Province	Corona
25	25,000	Female	Bangkok	Yes
35	50,000	Female	Nontaburi	Yes
32	35,000	Male	Bangkok	No



$$log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \hat{w}_0 + \hat{w}_1 H_1 + \hat{w}_2 H_2 + \hat{w}_3 H_3$$

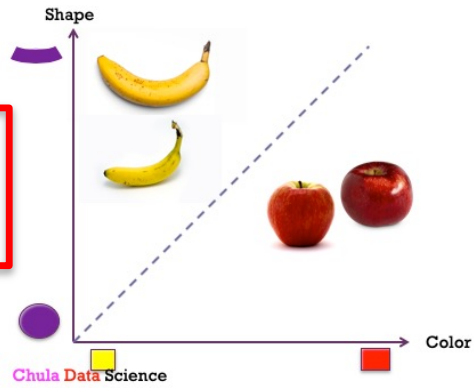
$$H_1 = tanh(\hat{w}_{10} + \hat{w}_{11} x_1 + \hat{w}_{12} x_2)$$

$$H_2 = tanh(\hat{w}_{20} + \hat{w}_{21} x_1 + \hat{w}_{22} x_2)$$

$$H_3 = tanh(\hat{w}_{30} + \hat{w}_{31} x_1 + \hat{w}_{32} x_2)$$

Handcrafted features

Age	Income	Gender	Province	Corona
25	25,000	Female	Bangkok	Yes
35	50,000	Female	Nontaburi	Yes
32	35,000	Male	Bangkok	No

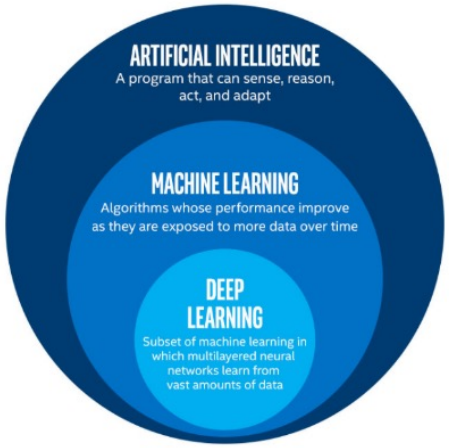


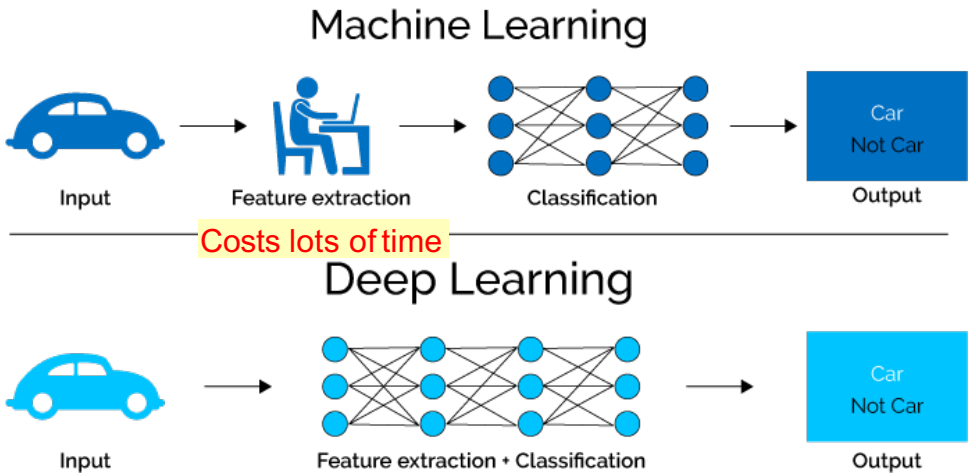
Can we still tell the features (columns)?

What is Deep Learning (DL)?

Part of the machine learning field of learning representations of data. Exceptional effective at learning patterns.

Utilizes learning algorithms that derive meaning out of data by using a hierarchy of multiple layers that mimic the neural networks of our brain.



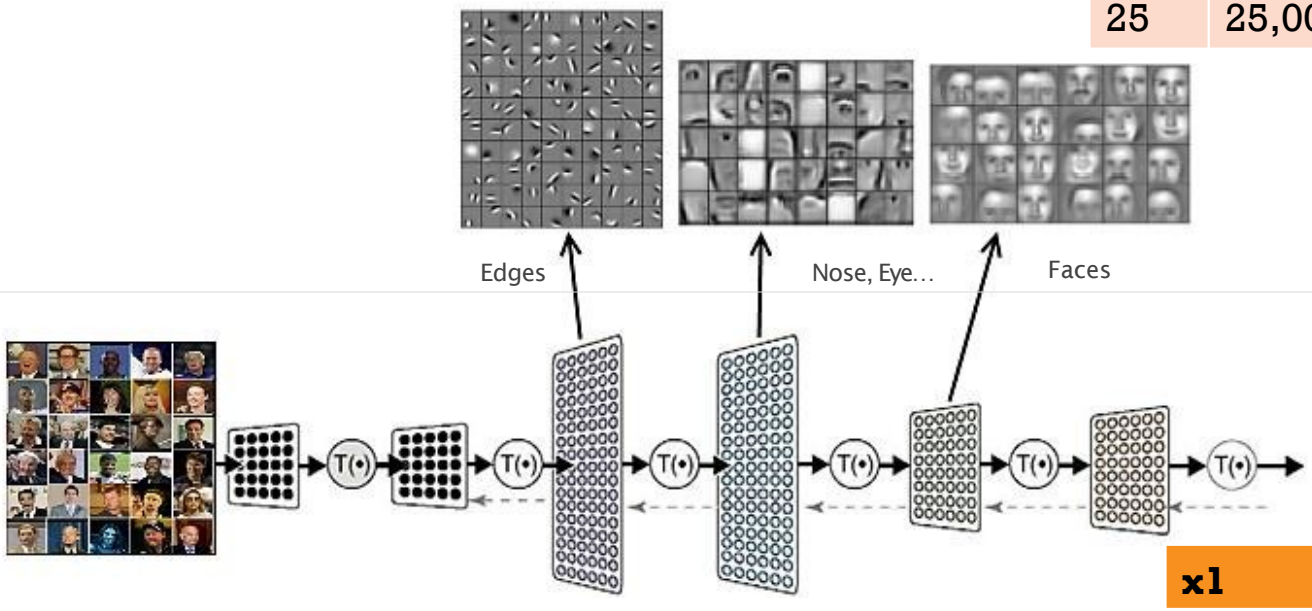


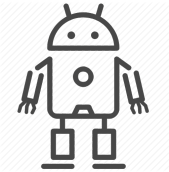
Deep Learning – Basics (cont.)

What did it learn?

A deep neural network consists of a hierarchy of layers, whereby each layer transforms the input data into more abstract representations (e.g., edge -> nose -> face). The output layer combines those features to make predictions.

Age	Income	Gender	Province	Corona
25	25,000	Female	Bangkok	Yes





x1	x2	x3	x4	Corona
0.7	0.2	-0.5	-0.1	Yes

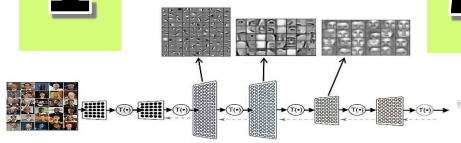
Deep Learning Application

Speech Recognition

Computer Vision

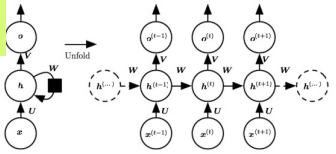
Natural Language Processing

1



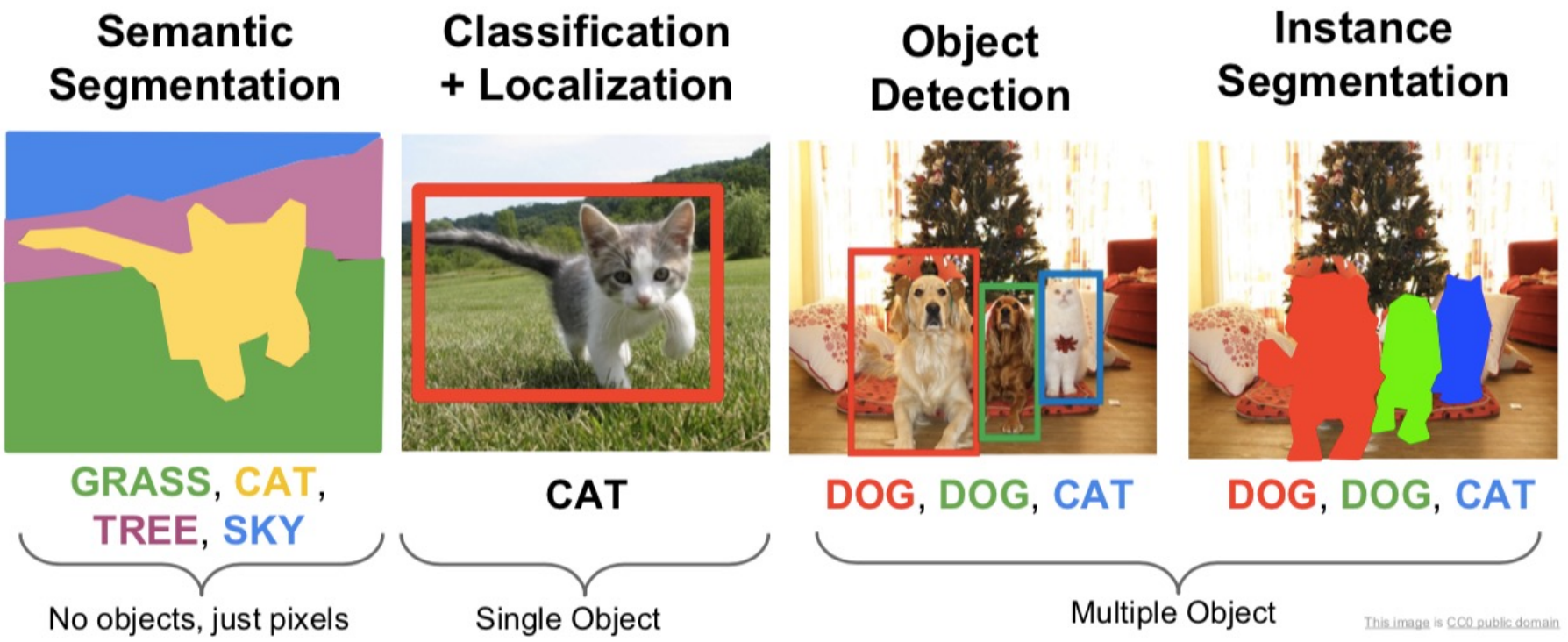
CNN

2



RNN (LSTM)

Type of image tasks



Face Recognition

Smart Medical Diagnosis

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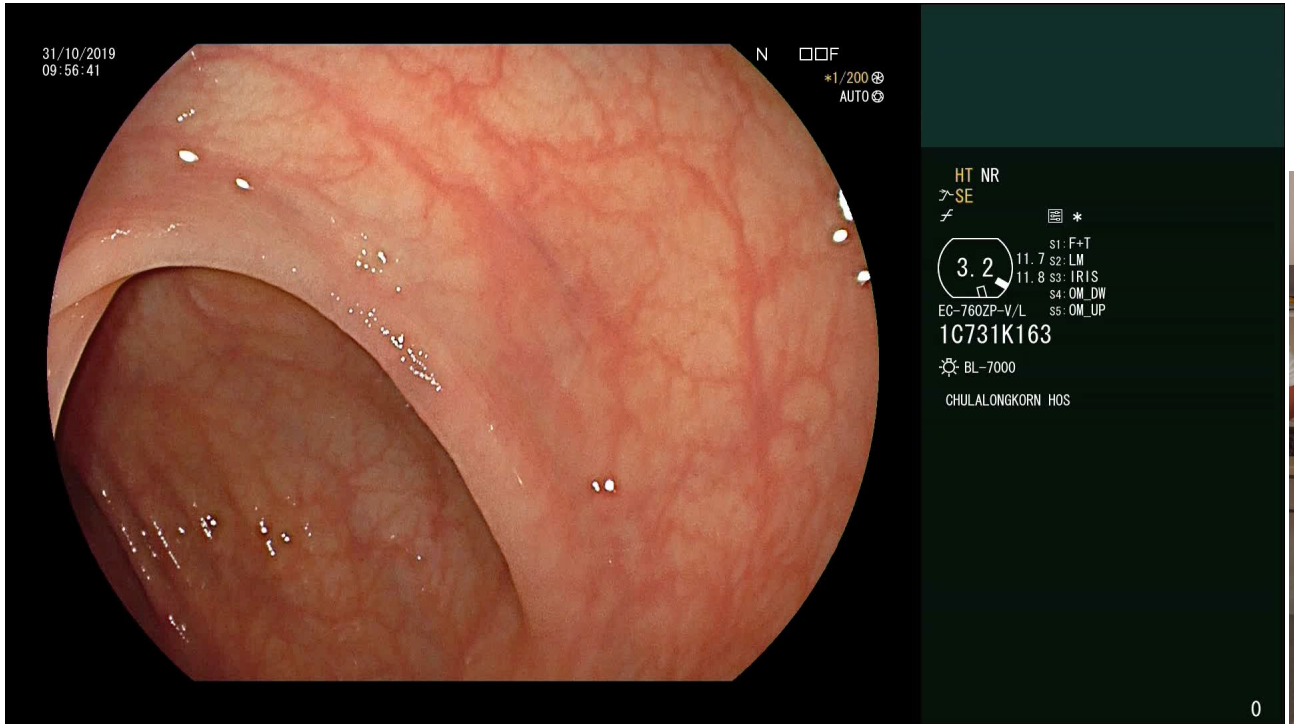
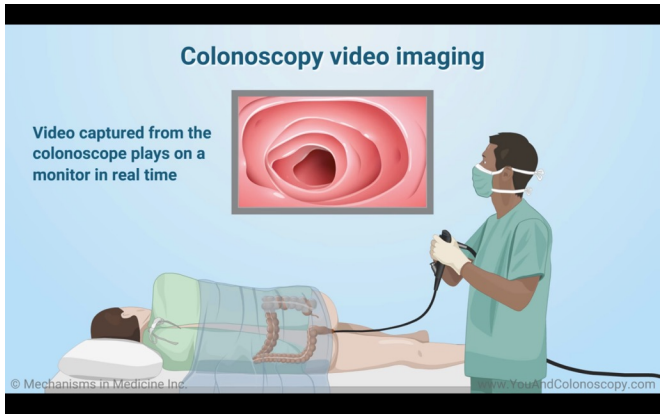
Foundation toward Innovation

King Chulalongkorn Memorial Hospital
The Thai Red Cross Society





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CNN

Outline

- Introduction
- Basic Image Processing
- Overview of CNN
- Image Processing Tasks with SOTA
- Case Study in Polyp Detection

IMAGENET www.image-net.org

The **ImageNet** project is a large visual database designed for use in visual object recognition software research. Over **14M** URLs of images have been hand-annotated by ImageNet to indicate what objects are pictured on **22K** categories.

IMAGENET Large Scale Visual Recognition Challenge

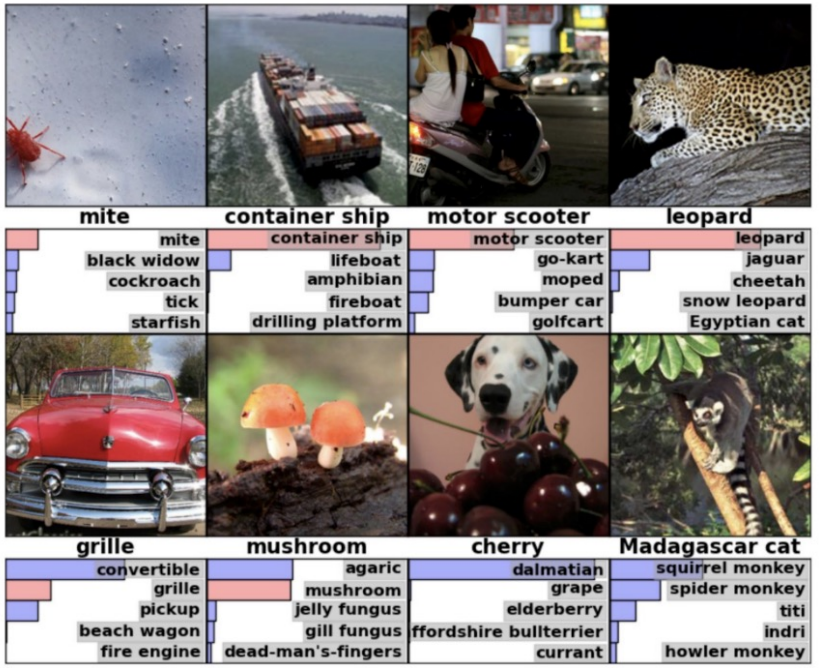
ILSVRC

The Image Classification Challenge:

1,000 object classes

1,431,167 images

ImageNet 2017 is the last challenge.



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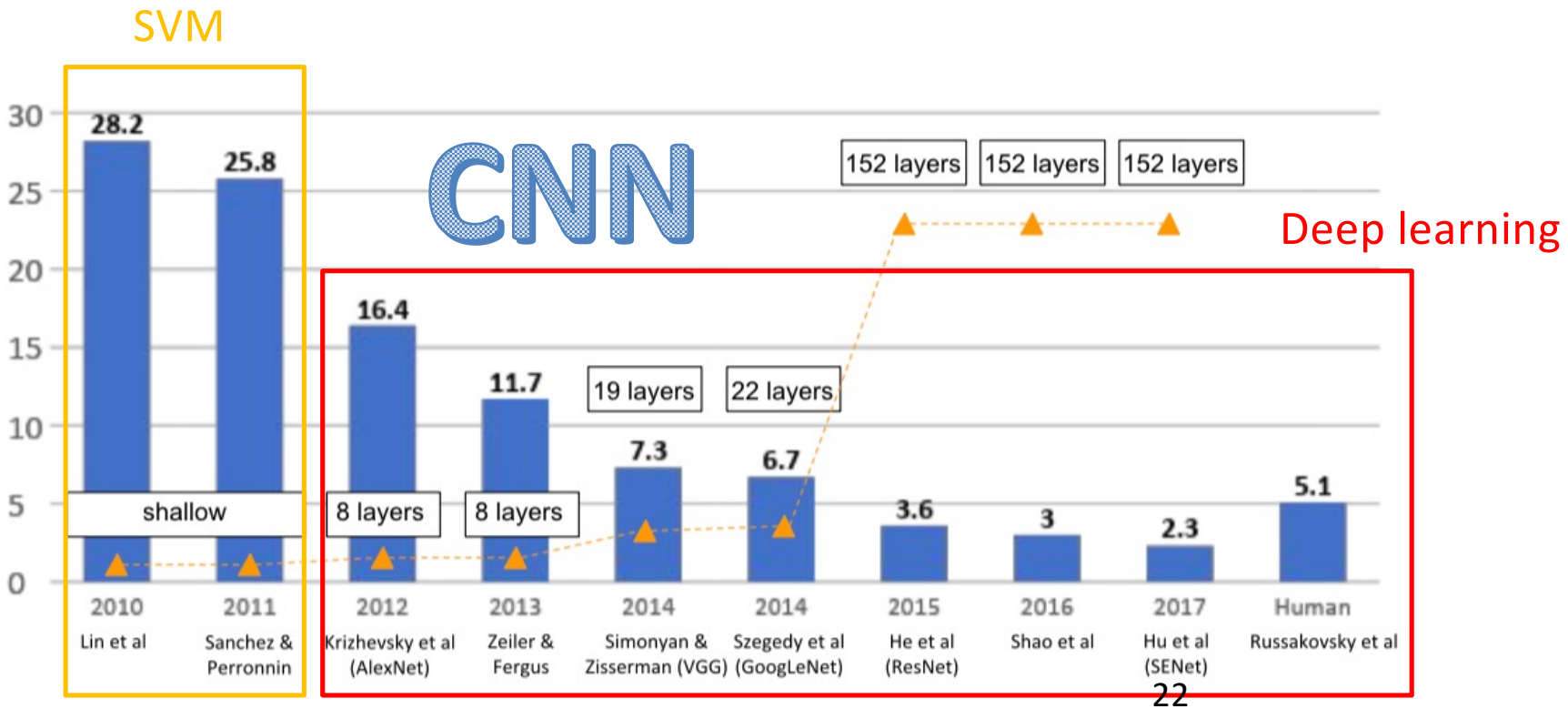
ImageNet Large Scale Visual Recognition Challenge (ILSVRC winners): From SVM to Deep Learning



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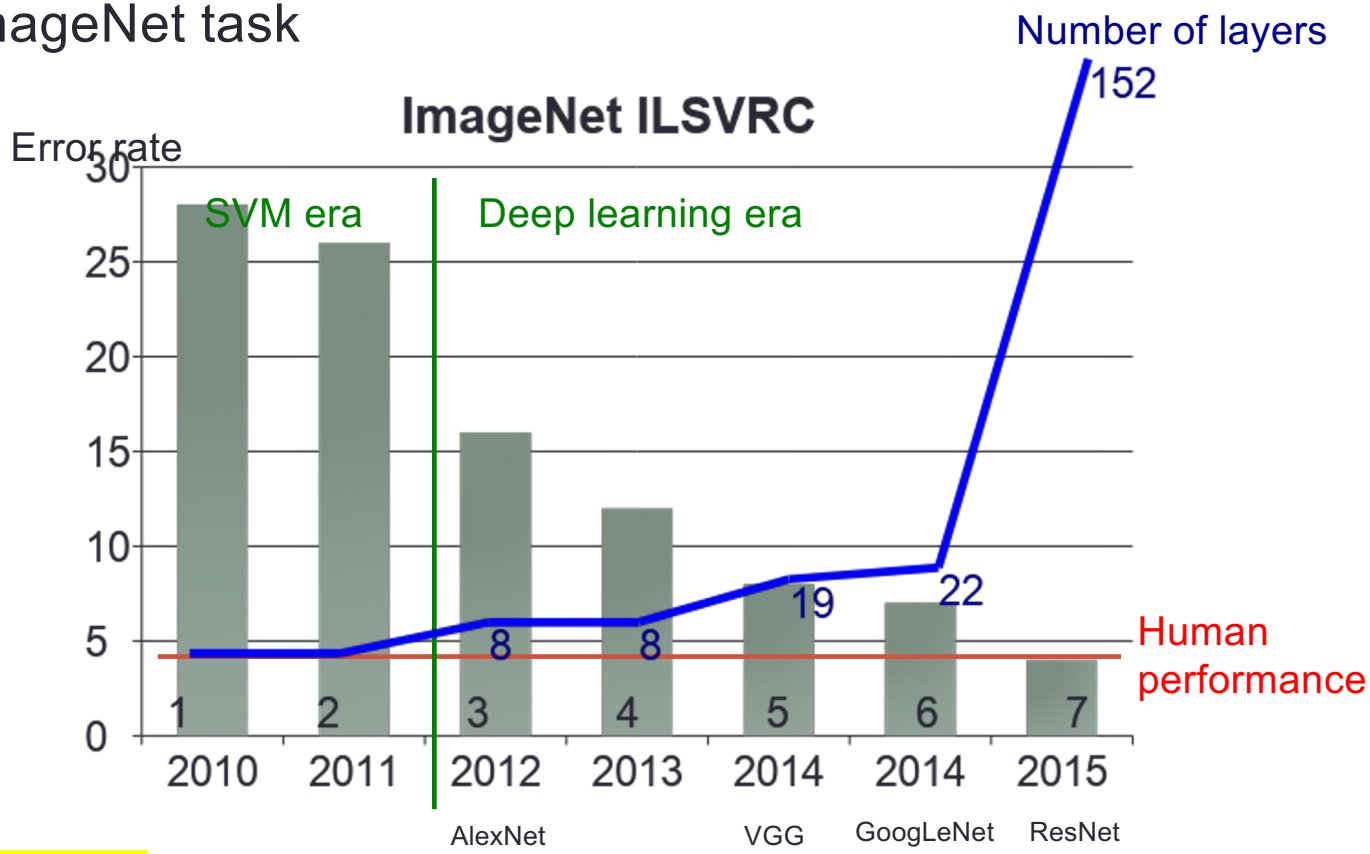
Wider and deeper networks (Beyond Human)

- ImageNet task

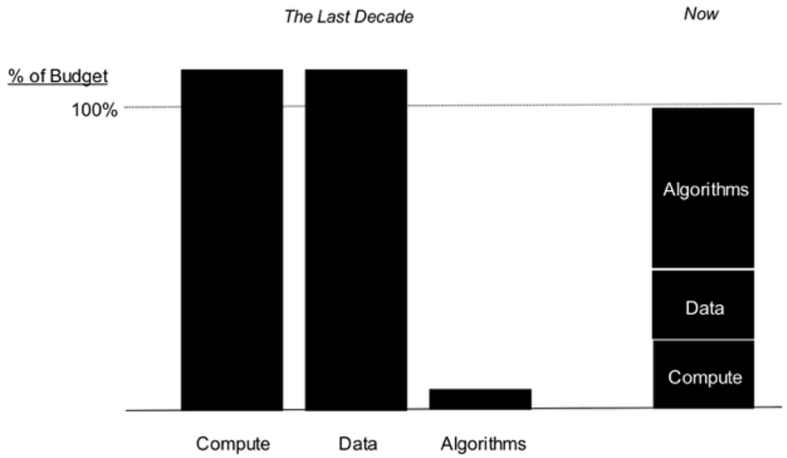


Based on the slide of Aj.Ekapol

Net Large Scale Visual Recognition Challenge, 2014 https://arxiv.org/abs/1409.0575

Why now

- Neural Networks has been around since 1990s
- Big data – DNN can take advantage of large amounts of data better than other models
- GPU – Enable training bigger models possible
- Deep – Easier to avoid bad local minima when the model is large



Based on the slide of Aj.Ekapol /www.kdnuggets.com/2017/06/practical-guide-machine-learning-understand-differentiate-apply.html

Application 1: Basic Image Processing

https://softwaredevelopmentperestroika.wordpress.com/2014/02/11/image-processing-with-python-numpy-scipy-image-convolution/

ภาควิชาวิศวกรรมคอมพิวเตอร์
จุฬาลงกรณ์มหาวิทยาลัย

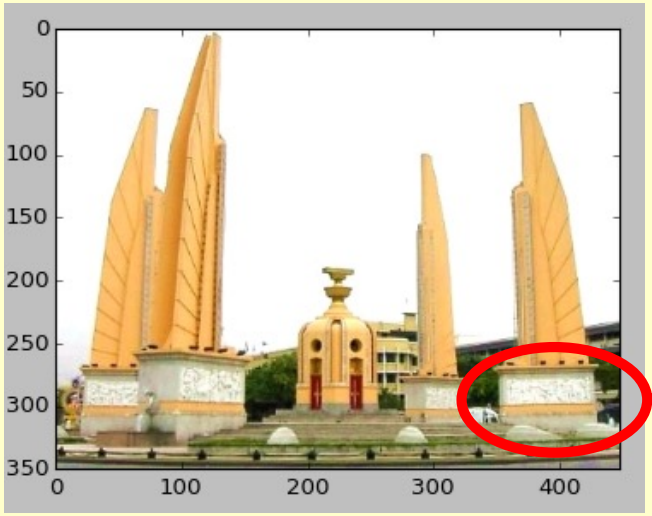
การแสดงรูปภาพใน python ด้วย matplotlib

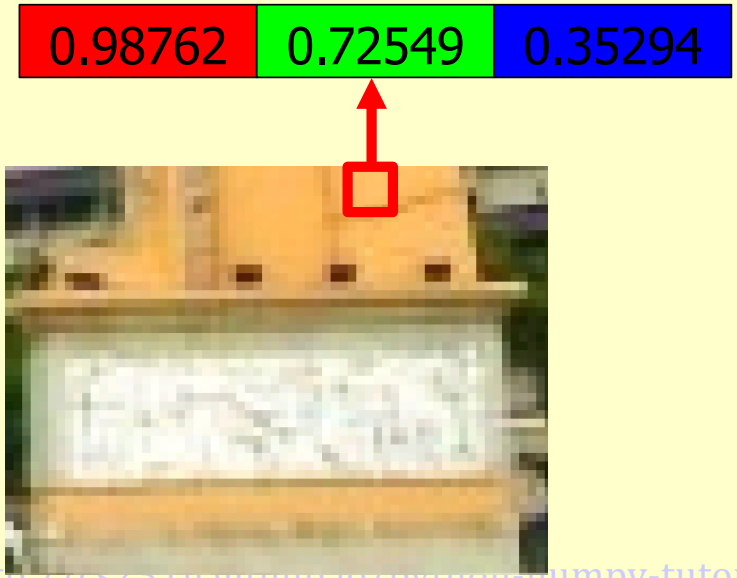
```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

image = mpimg.imread('monument.png')
plt.imshow(image)

plt.show()
```

เพื่อความง่ายโปรแกรมที่จะเขียนจากนี้ไปใช้กับแฟ้ม png เท่านั้น

image เป็นอาเรย์ที่แต่ละช่อง
มีค่า 0 ถึง 1 แทนความเข้มของสี

1 pixel = 1 จุดสี มี 3 สีย่อย

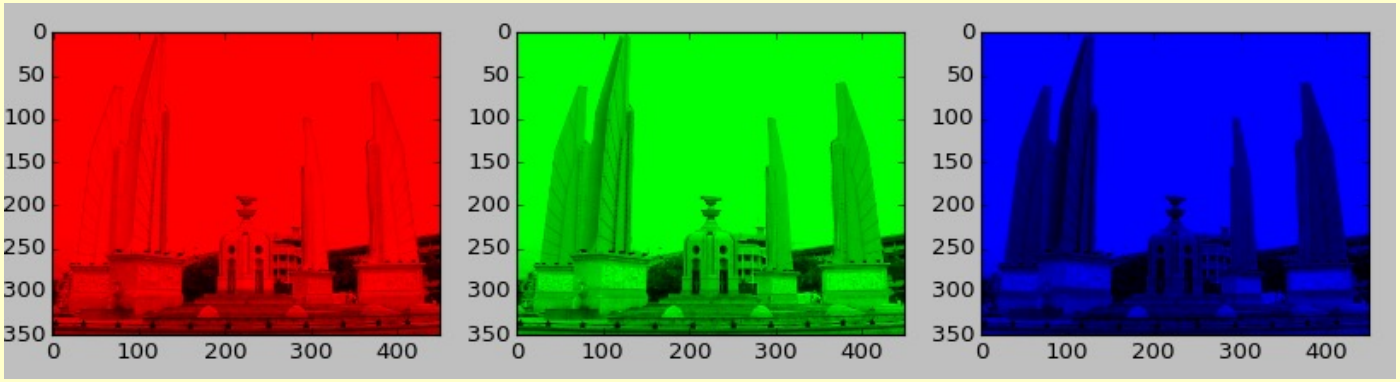




http://cs231n.github.io/python-numpy-tutorial/#numpy

1 ภาพ เป็นอาเรย์ 3 สามมิติเก็บค่าความเข้มของ R G B

```
>>> image.shape
(350, 449, 3)
```



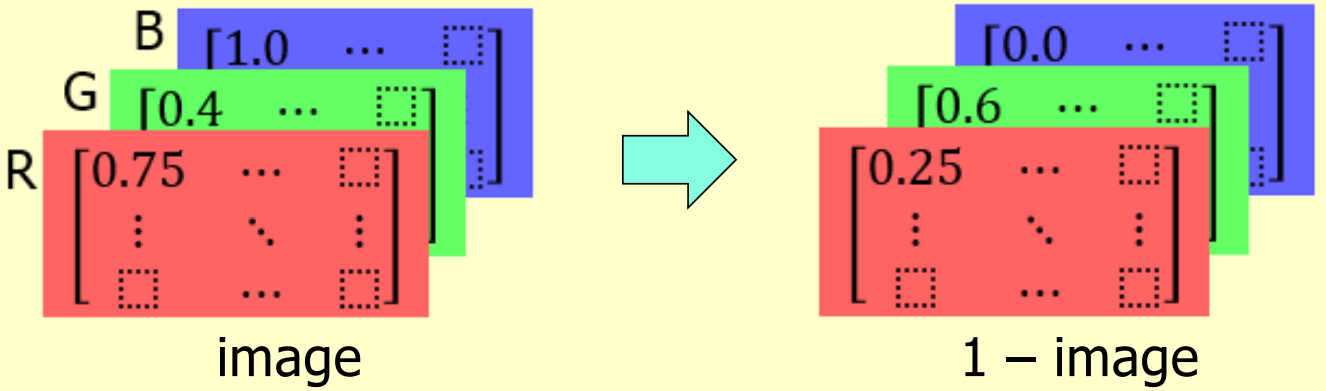
อาร์เรย์ 2 มิติสีแดง
image[:,:,0]

อาร์เรย์ 2 มิติสีเขียว
image[:,:,1]

อาร์เรย์ 2 มิติสีน้ำเงิน
image[:,:,2]

การประมวลผลภาพเบื้องต้น

- image = mpimg.imread('monument.png')
- image.shape → (350, 449, 3)
- image = 1 – image (broadcast & element-wise op.)

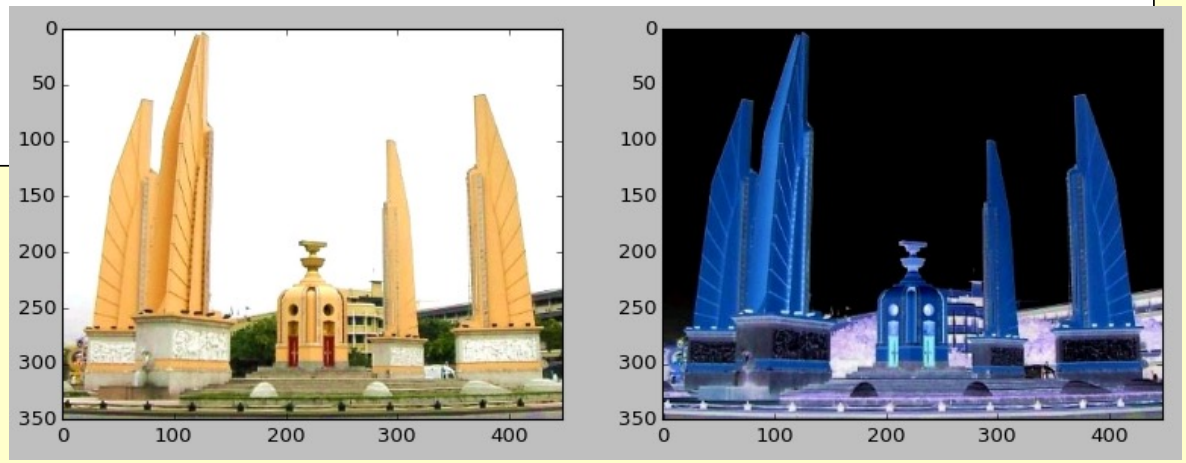


ทำแบบนี้แล้ว ภาพเปลี่ยนแปลงไปอย่างไร ?

การประมวลผลภาพเบื้องต้น : ภาพ Negative

```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

image = mpimg.imread('monument.png')
plt.subplot(1, 2, 1)
plt.imshow(image)

negative = 1 - image
plt.subplot(1, 2, 2)
plt.imshow(negative)

plt.show()
```

1 – image คือนำค่าทุกช่องไปลบออกจาก 1
ความเข้มสีเปลี่ยนเป็นตรงข้าม
(ขาว → ดำ, เหลือง → น้ำเงิน, ...)
broadcast & element-wise subtract

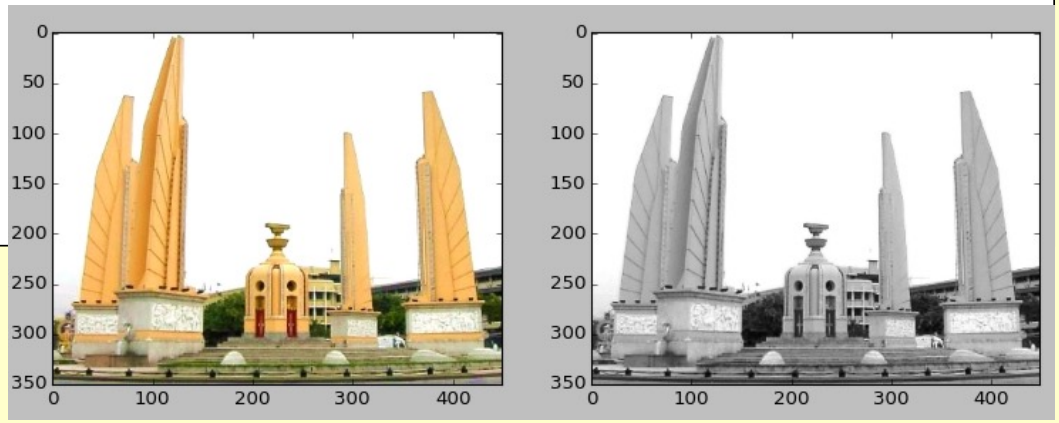


การประมวลผลภาพเบื้องต้น : ภาพสีเทา

```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

image = mpimg.imread('monument.png')
plt.subplot(1, 2, 1)
plt.imshow(image)
gray = np.ndarray(image.shape)
gray[:,:,0] = \
gray[:,:,1] = \
gray[:,:,2] = (image[:,:,0]+image[:,:,1]+image[:,:,2]) / 3
plt.subplot(1, 2, 2)
plt.imshow(gray)

plt.show()
```

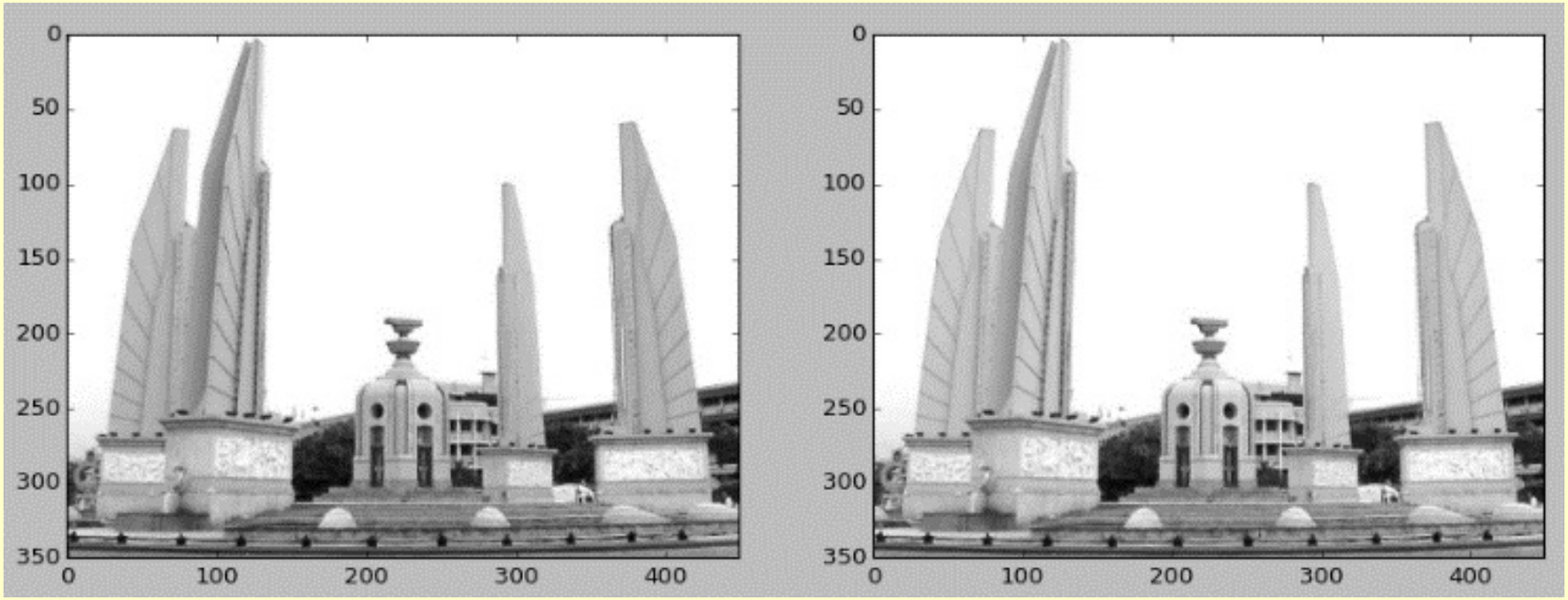
จุดสีที่ R G B มีค่าความเข้มเท่ากัน ได้จุดสีเทา

นำค่าความเข้มของ R G B มาหาค่าเฉลี่ย แล้วเปลี่ยน R G B ให้เป็นความเข้มระดับเดียวกัน

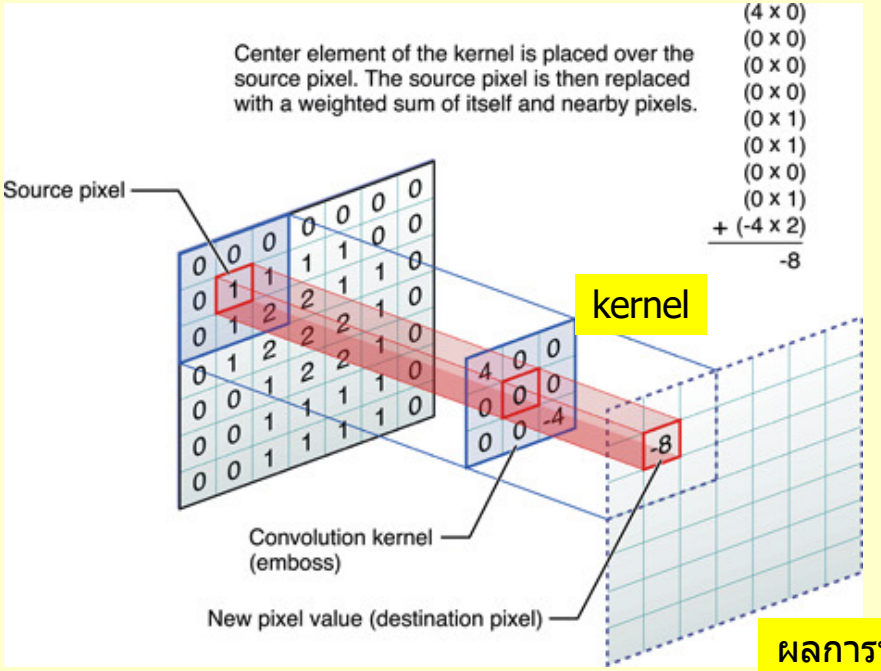


สีเทา เขาว่าสูตรนี้ดีกว่า 0.299*R + 0.587*G + 0.114*B

- CH08_6 จงเขียนโปรแกรมเพื่อแปลงรูปภาพจากรูปสีให้เป็นรูปสีเทา (gray scale) ด้วยสูตรข้างบนนี้ เทียบกับสูตร (R + G + B)/3



Convolution

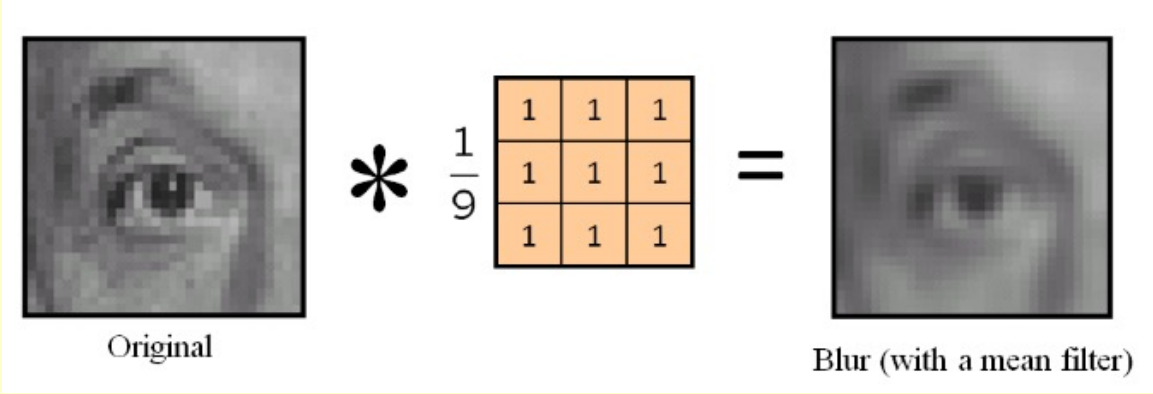


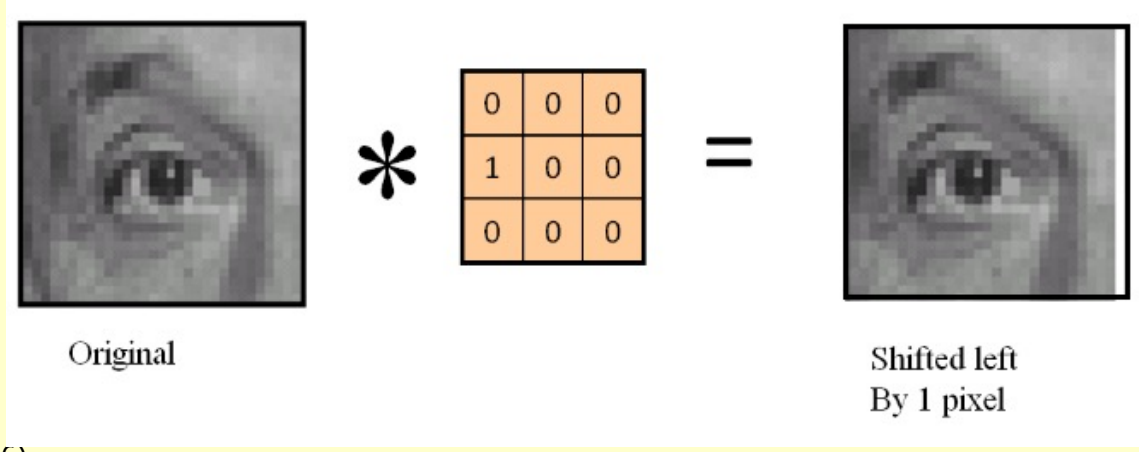
ผลการทำ convolute

เปลี่ยนค่าของเมทริกซ์ kernel
จะได้การประมวลผลภาพแบบอื่น ๆ

Image Convolution

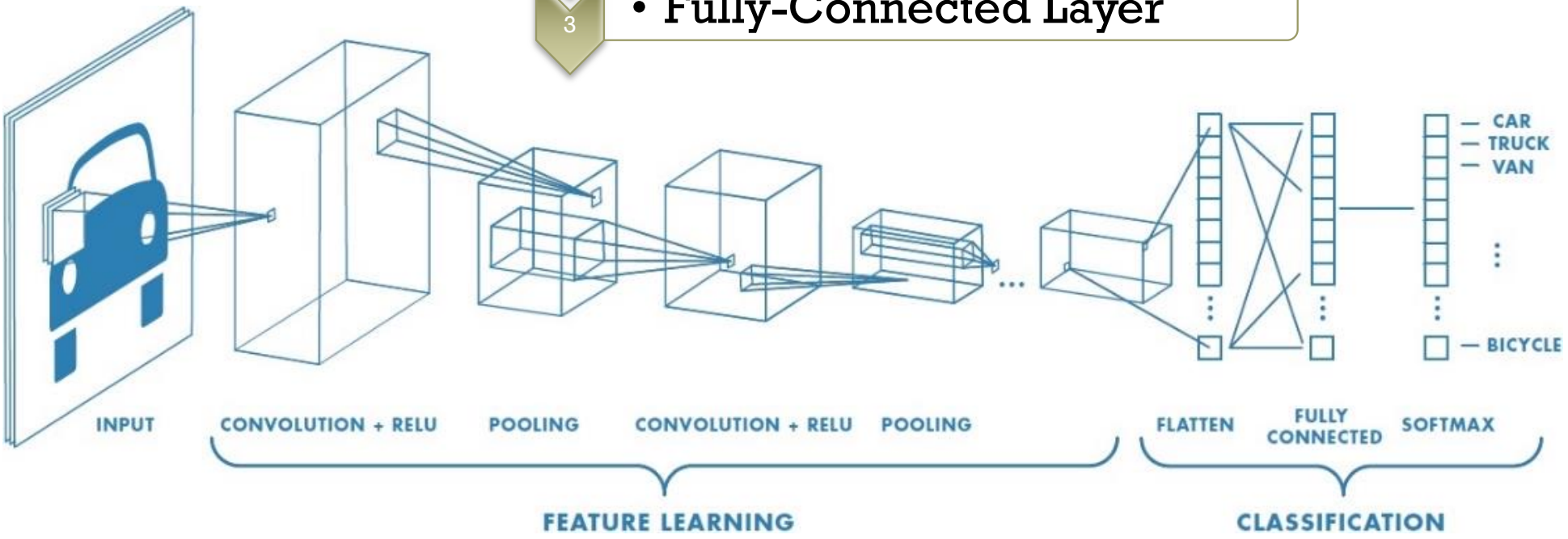
- Image Convolution คือการนำรูปภาพมาผ่านตัวกรอง (kernel) เพื่อให้ได้ผลลัพธ์ตามที่ต้องการ เช่น blur, ขยับรูป, จับขอบรูป เป็นต้น



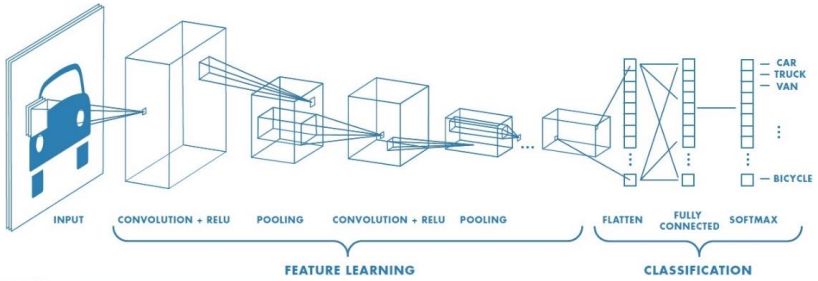


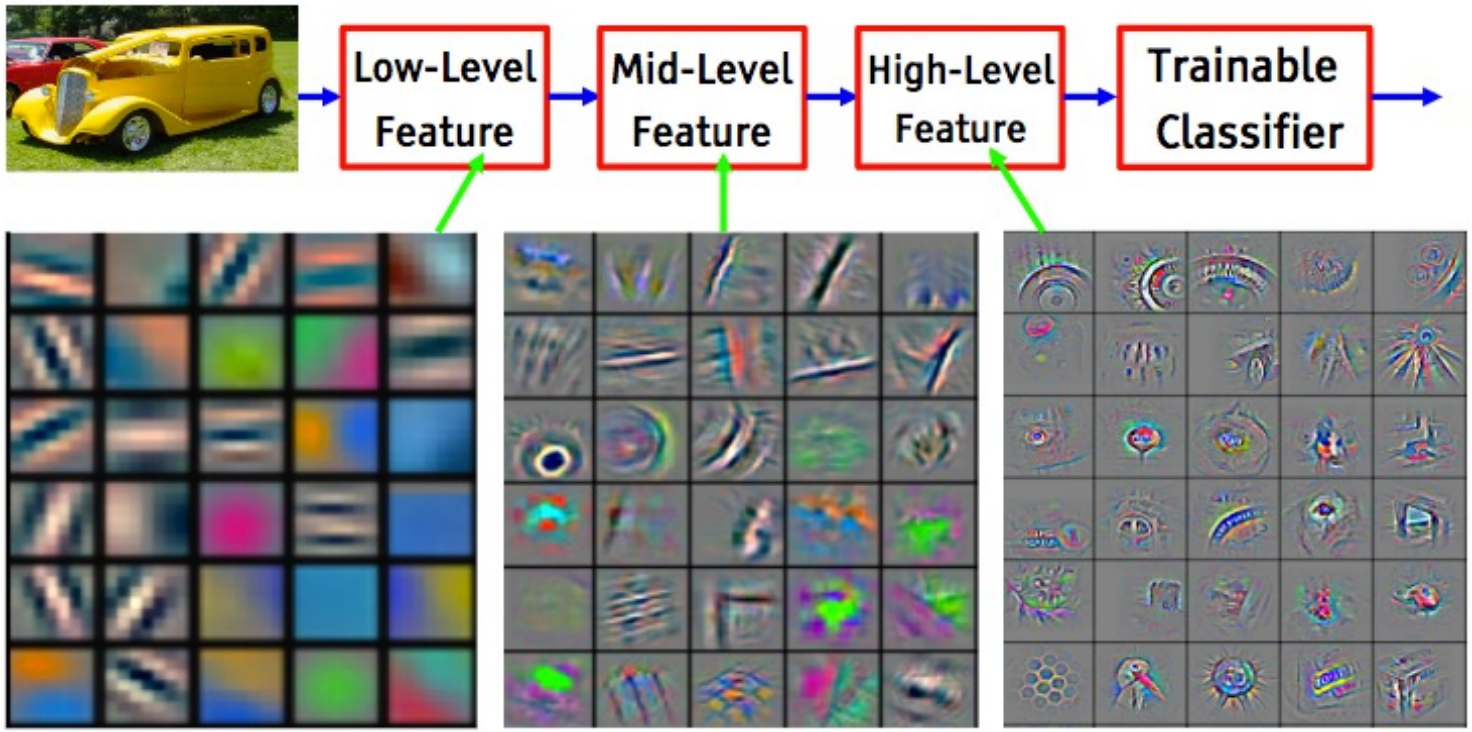
Convolutional Neural Networks (CNN)

1. Convolutional Layer
2. Pooling Layer
3. Fully-Connected Layer



CNN (cont.)

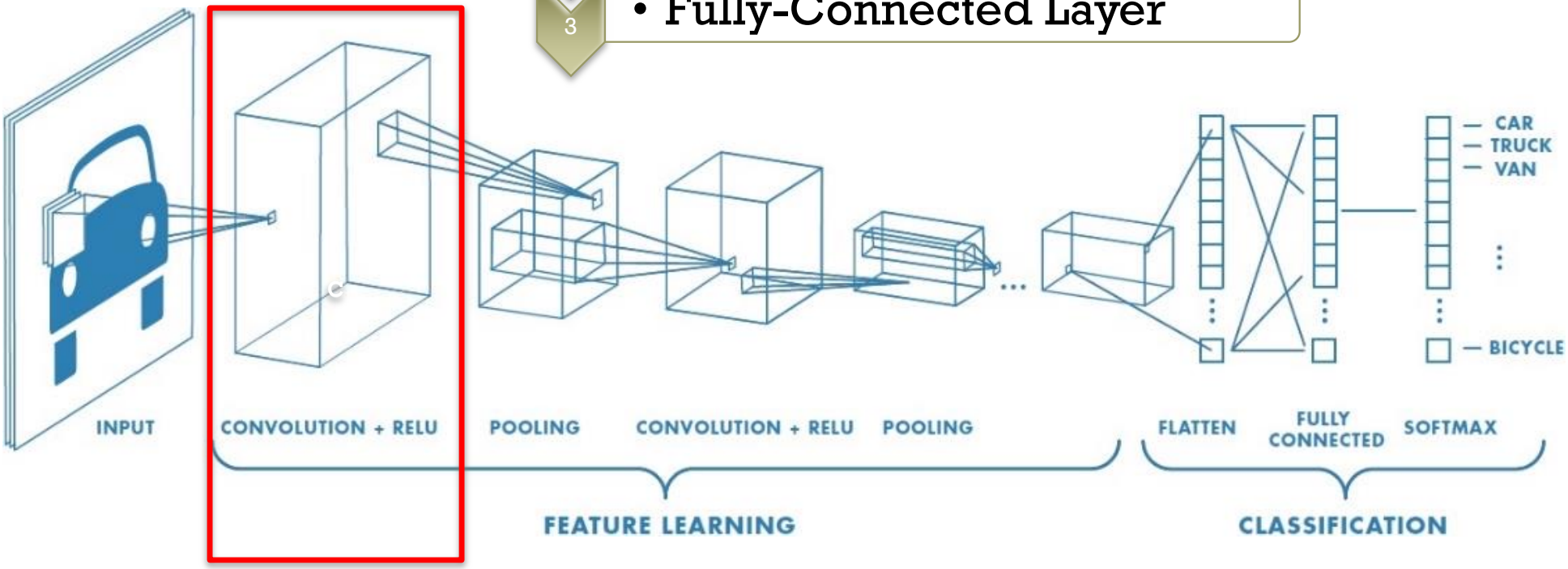

CAR
TRUCK
VAN
BICYCLE
INPUT
CONVOLUTION + RELU
POOLING
CONVOLUTION + RELU
POOLING
FLATTEN
FULLY CONNECTED
SOFTMAX
FEATURE LEARNING
CLASSIFICATION


Low-Level Feature
Mid-Level Feature
High-Level Feature
Trainable Classifier

Convolutional Neural Networks (CNN)

1) Convolutional Layer

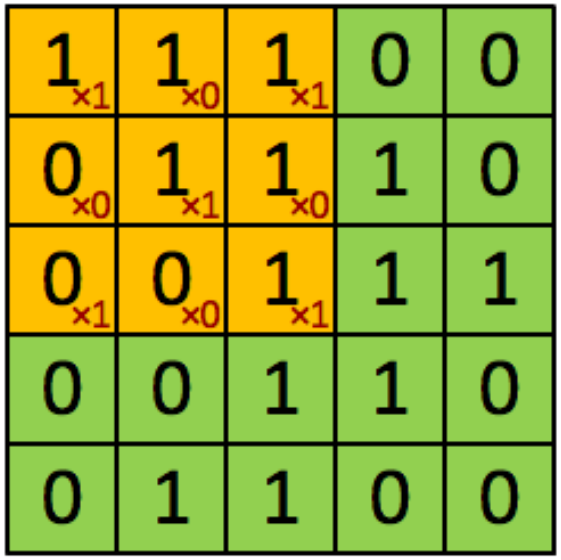
1. Convolutional Layer
2. Pooling Layer
3. Fully-Connected Layer



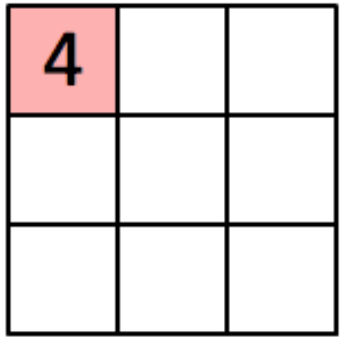
Layer 1: Convolutional Layer

(3*3 filter)

1	0	1
0	1	0
1	0	1

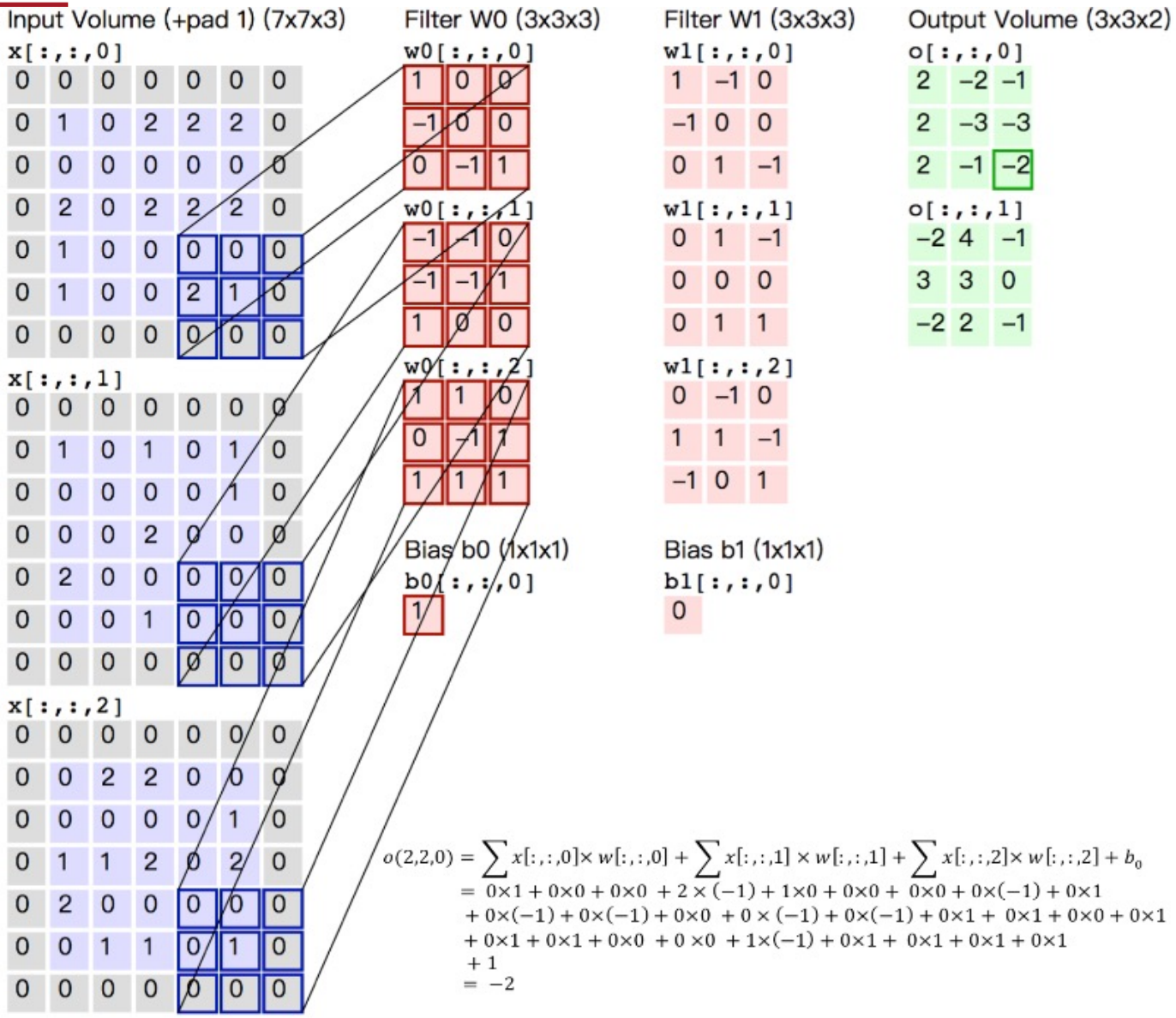


Image



Convolved Feature

1 • Convolutional Layer
2 • Pooling Layer
3 • Fully-Connected Layer



$$
\begin{aligned}
o(2,2,0) &= \sum x[:,:,0]\times w[:,:,0] + \sum x[:,:,1]\times w[:,:,1] + \sum x[:,:,2]\times w[:,:,2] + b_0 \\
&= 0\times1 + 0\times0 + 0\times0 \; + 2\times(-1) + 1\times0 + 0\times0 + \; 0\times0 + 0\times(-1) + 0\times1 \\
&\quad + 0\times(-1) + 0\times(-1) + 0\times0 \; + 0\times(-1) + 0\times(-1) + 0\times1 + \; 0\times1 + 0\times0 + 0\times1 \\
&\quad + 0\times1 + 0\times1 + 0\times0 \; + 0\times0 \; + 1\times(-1) + 0\times1 + \; 0\times1 + 0\times1 + 0\times1 \\
&\quad + 1 \\
&= -2
\end{aligned}
$$

CNNs: 1) Convolutional Layer

Feature Extraction

http://cs231n.github.io/convolutional-networks/

$$w^T x + b$$

(3*3 filter)

1	0	1
0	1	0
1	0	1

$1_{\times 1}$	$1_{\times 0}$	$1_{\times 1}$	0	0
$0_{\times 0}$	$1_{\times 1}$	$1_{\times 0}$	1	0
$0_{\times 1}$	$0_{\times 0}$	$1_{\times 1}$	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

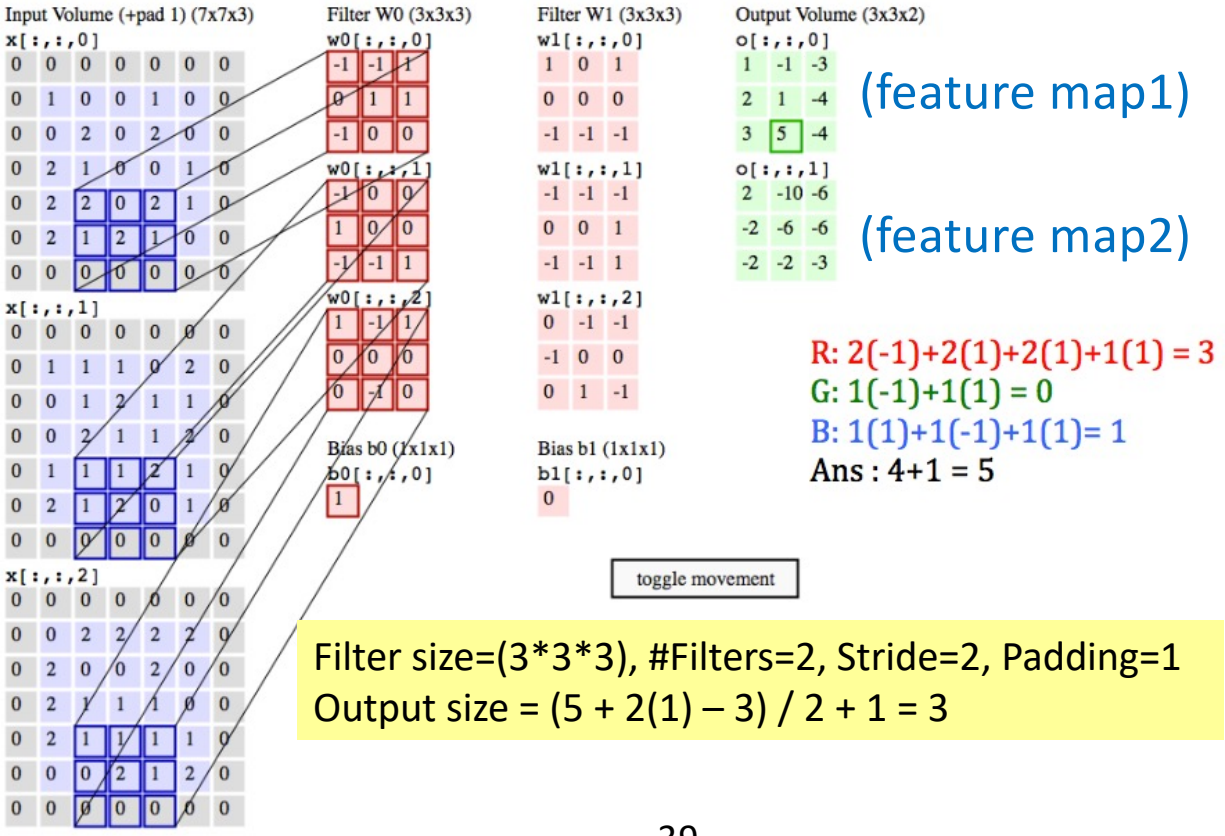
Convolved Feature (feature map)

Filter size=(3*3), #Filters=1, Stride=1, Padding=0
Output size = (5 +2(0) – 3) / 1 + 1 = 3

Summary: **4 parameters** for convolutional layer

- (1) Filter size, (2) #Filters, (3) Stride, (4) Padding

Output size = (N + 2*P – F) / S + 1



(feature map1)

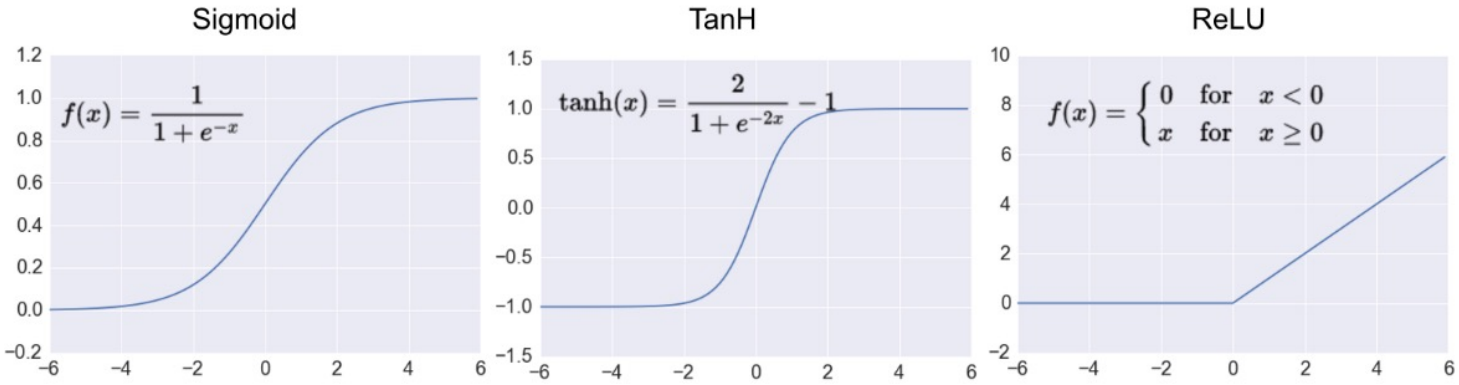
(feature map2)

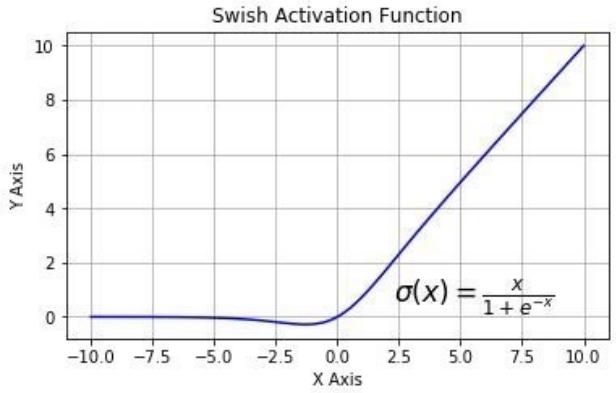
R: 2(-1)+2(1)+2(1)+1(1) = 3
G: 1(-1)+1(1) = 0
B: 1(1)+1(-1)+1(1)= 1
Ans : 4+1 = 5

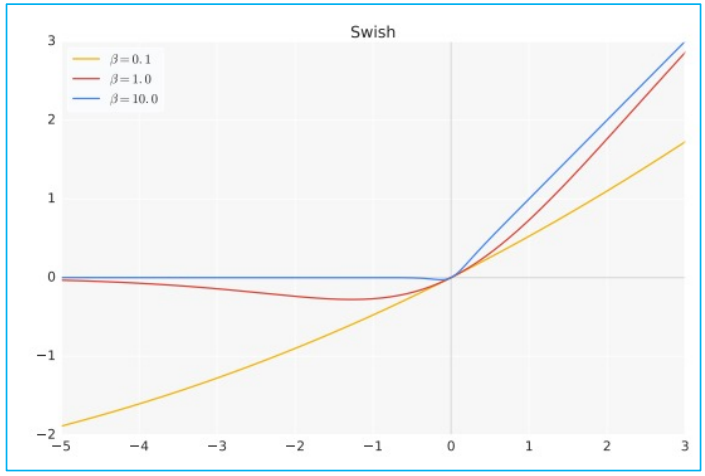
Filter size=(3*3*3), #Filters=2, Stride=2, Padding=1
Output size = (5 + 2(1) – 3) / 2 + 1 = 3

CNNs: 1) Convolutional Layer (cont.)

Non-Linear Activation Function



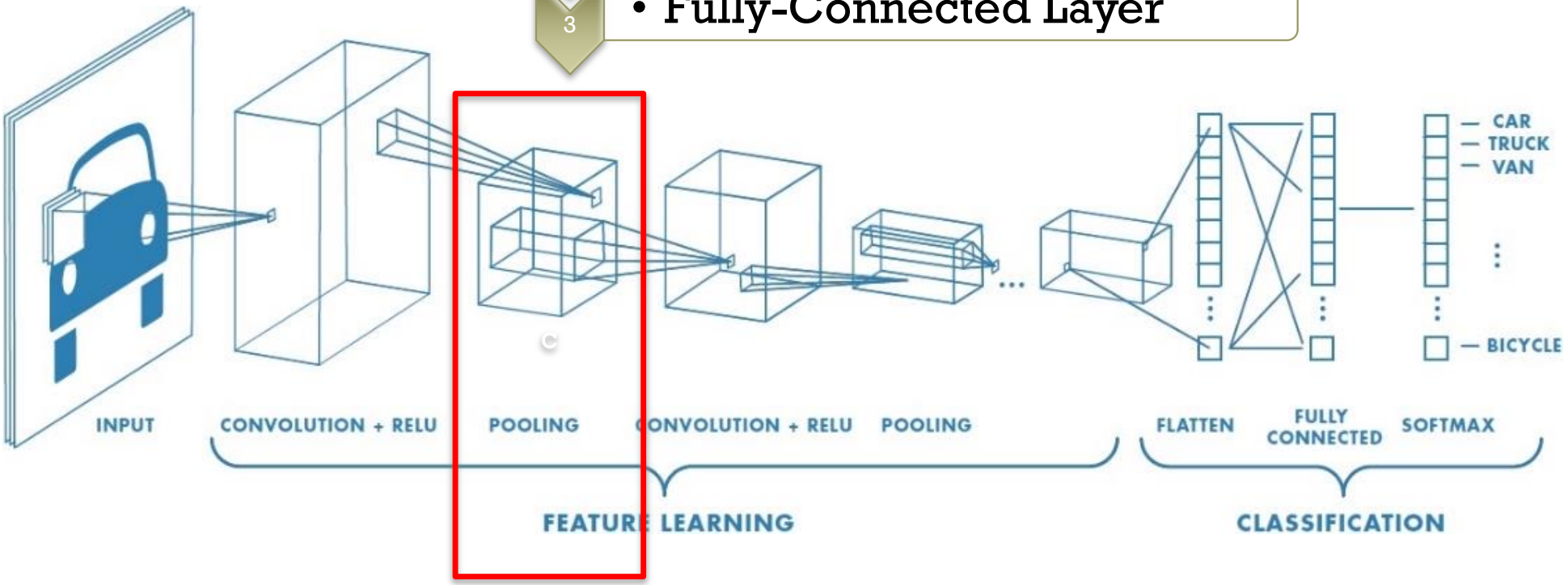




Convolutional Neural Networks (CNN)

2) Pooling Layer

1. Convolutional Layer
2. Pooling Layer
3. Fully-Connected Layer



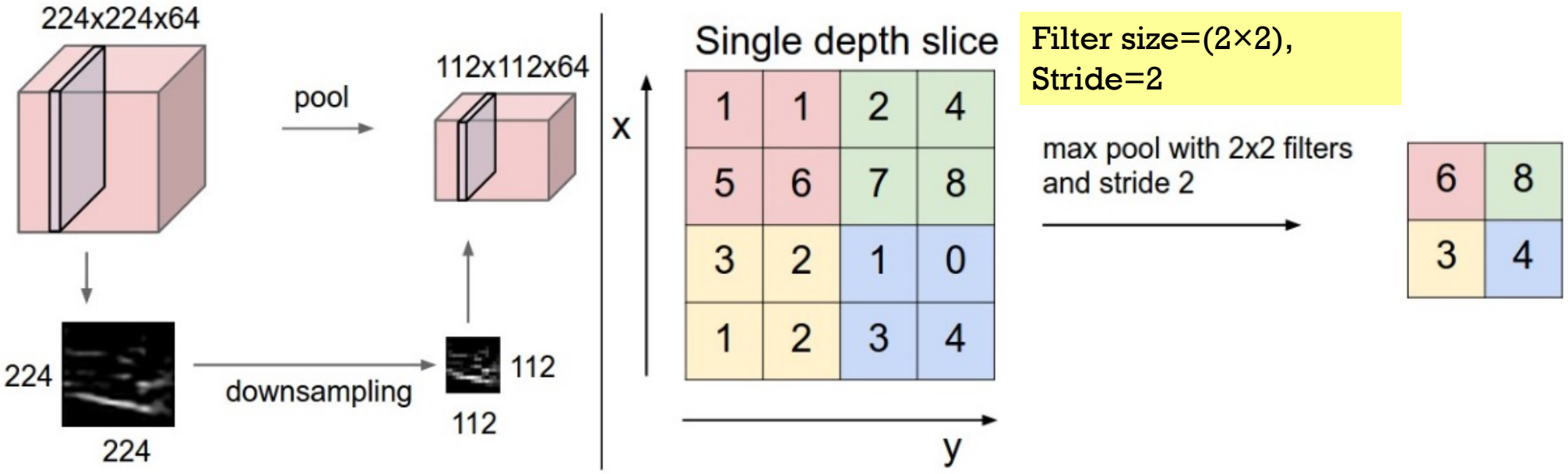
CNNs: 2) Pooling Layer

http://cs231n.github.io/convolutional-networks/

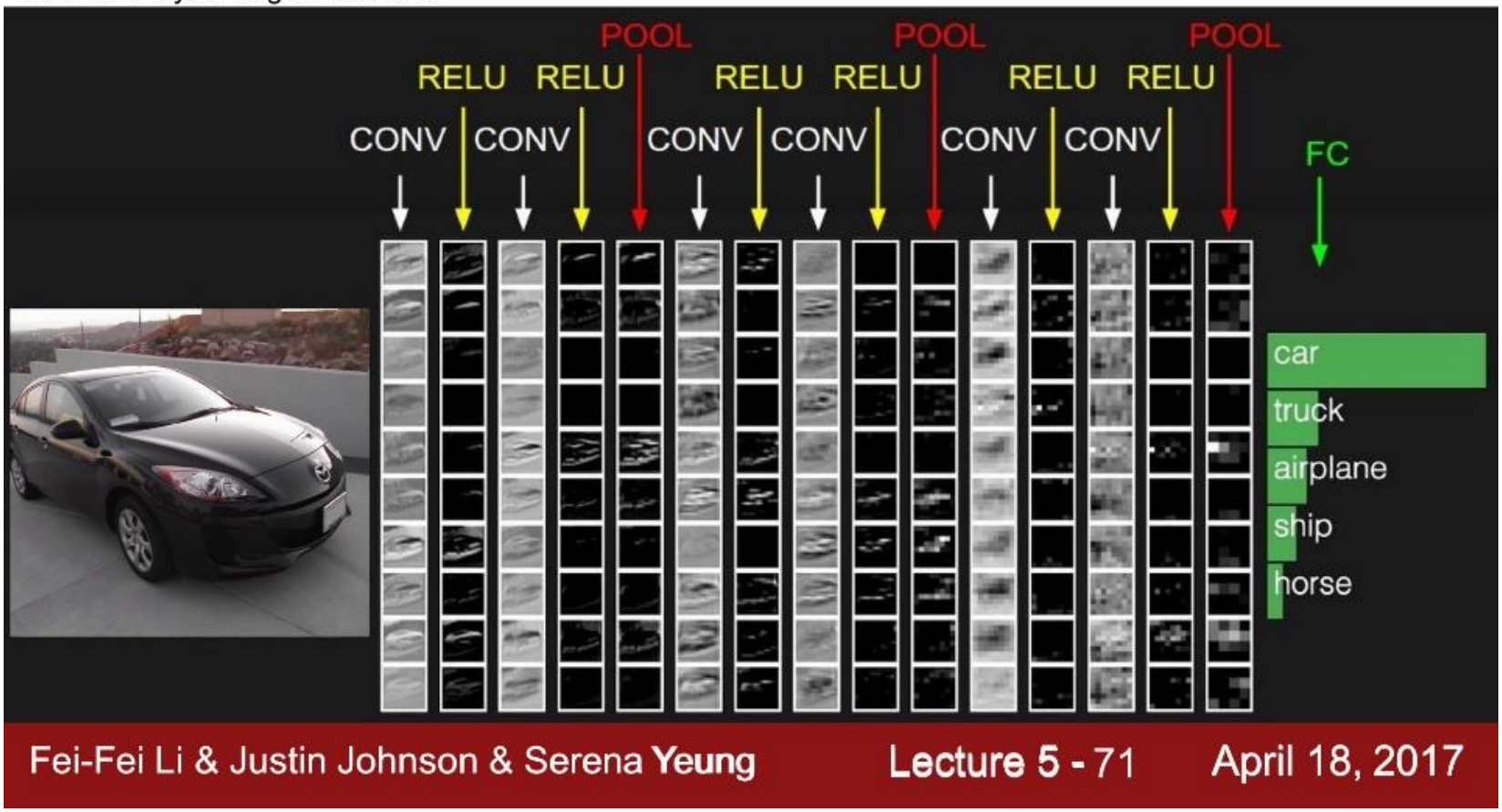
Summary: **2 parameters** for pooling layer

- Filter size, Stride

- Feature selection (reduction); downsampling



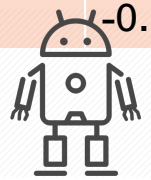
two more layers to go: POOL/FC



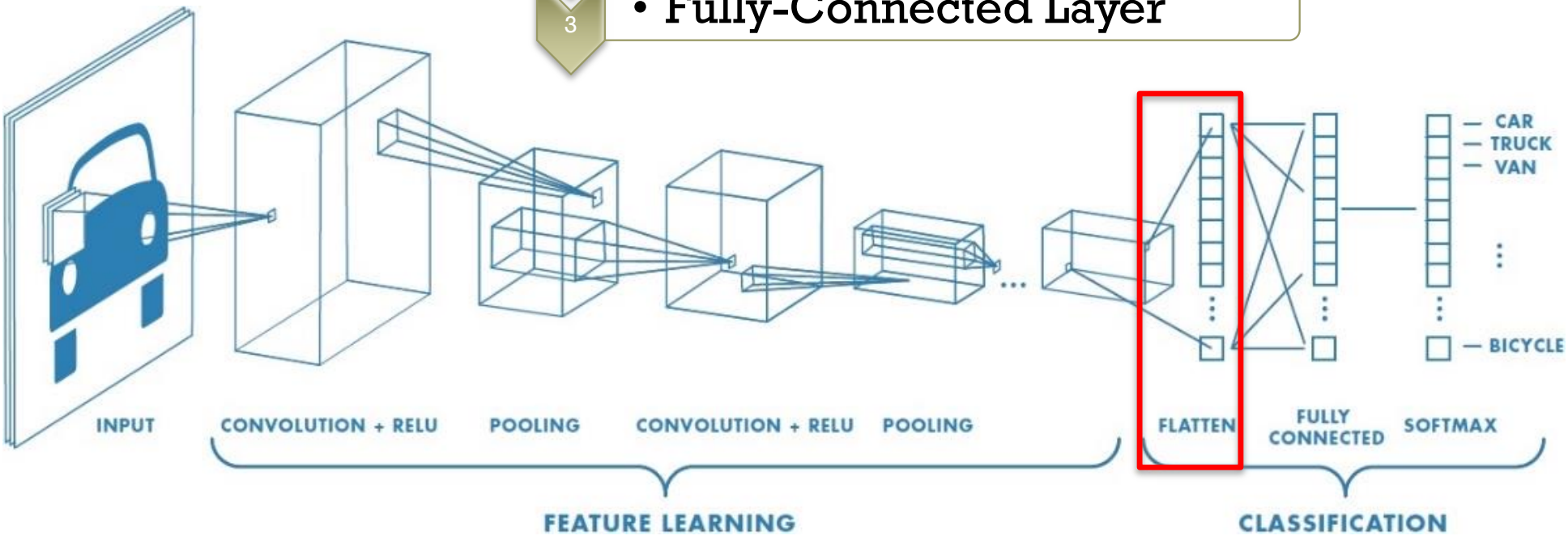
Convolutional Neural Networks

Embedding Vector

x1	x2	x3	x4	Corona
0.7	0.2	-0.5	-0.1	Yes



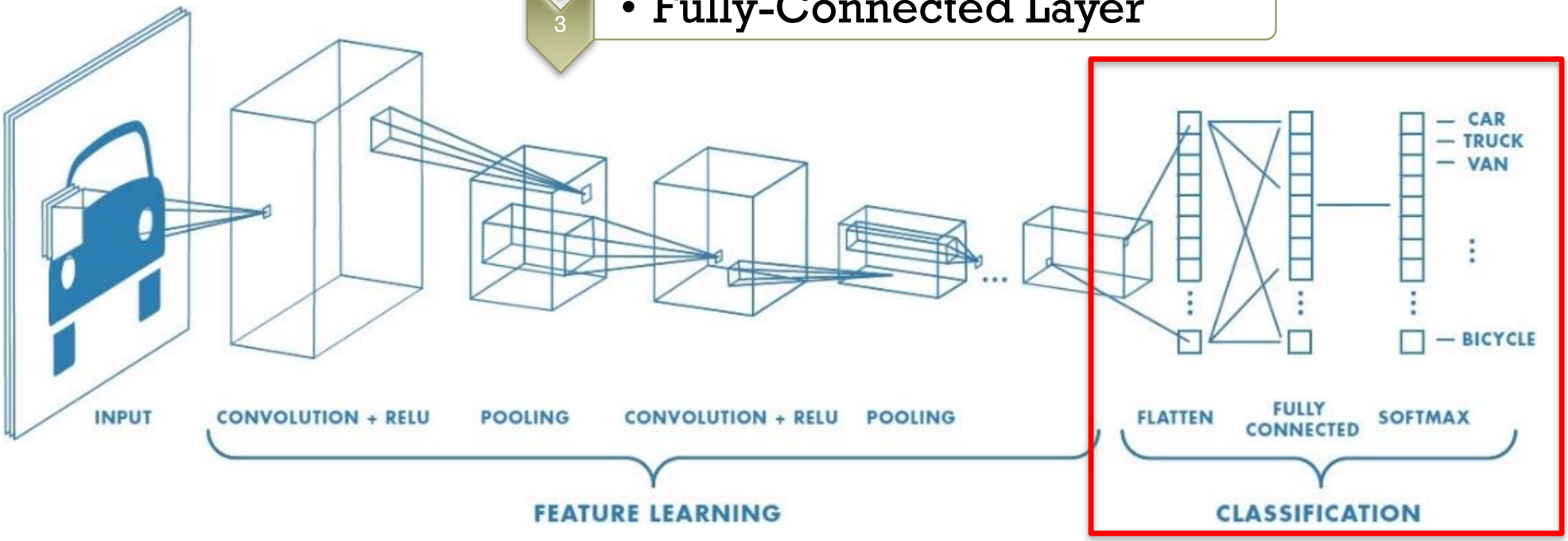
1. • Convolutional Layer
2. • Pooling Layer
3. • Fully-Connected Layer



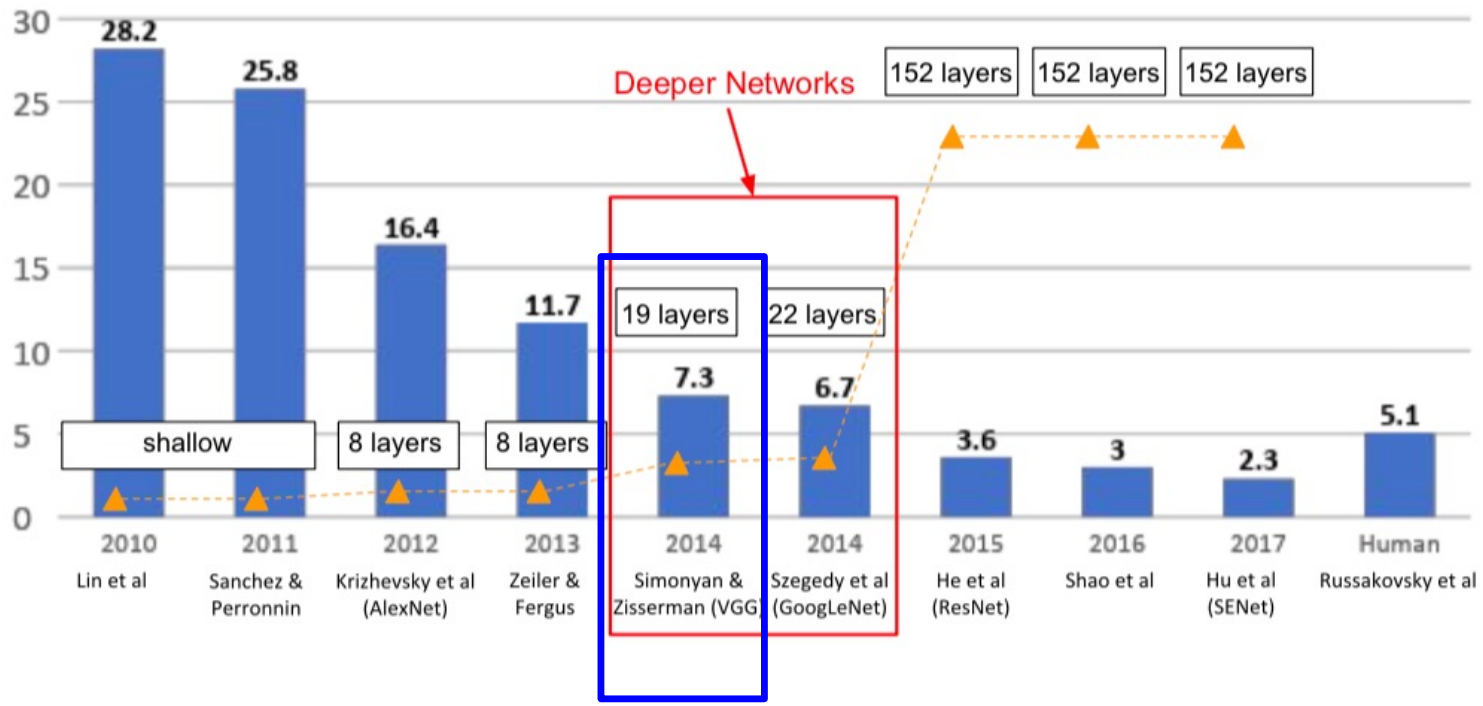
Convolutional Neural Networks (CNN)

3) Fully-Connected Layer (FC) = Neural Networks

1. Convolutional Layer
2. Pooling Layer
3. Fully-Connected Layer



ImageNet Large Scale Visual Recognition Challenge (ILSVRC 2nd runner-up in 2014): VGG19



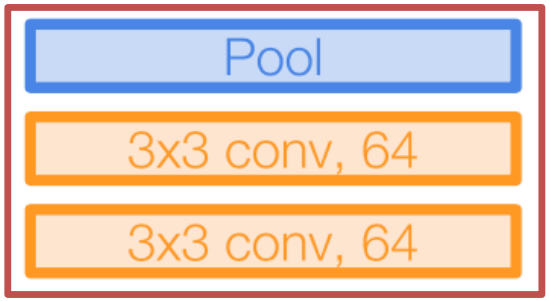
Case Study: VGGNet (2014)

[Simonyan and Zisserman, 2014]

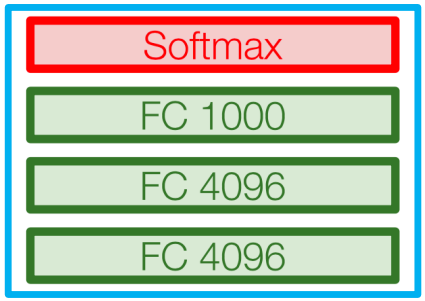
Small filters, Deeper networks

8 layers (AlexNet) → 16-19 layers (VGG16Net)

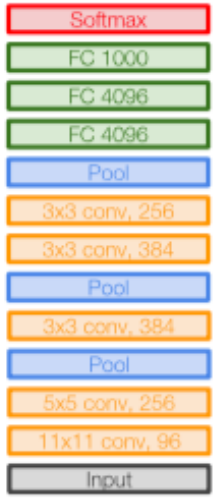
Only 3x3 CONV Stride 1, pad 1
And 2x2 MAX POOL stride 2



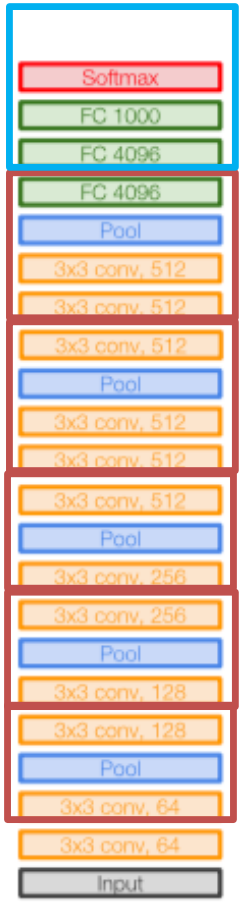
1) Feature extraction block



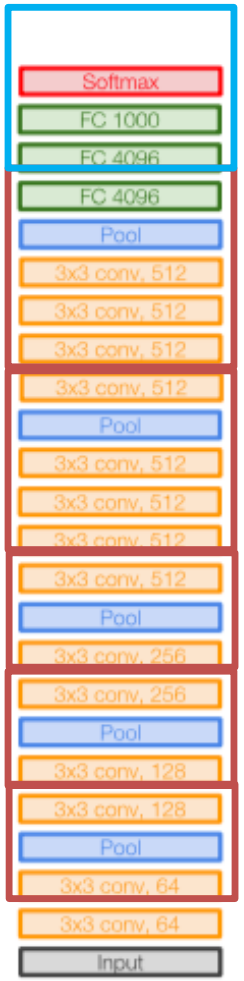
2) Classification block



AlexNet



VGG16



VGG19

Case Study: VGGNet (2014)

[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)

Stack of three 3×3 conv (stride 1) layers has same **effective receptive field** as one 7×7 conv layer in ZFNet

But deeper, more non-linearities

And fewer parameters: $3 \times (3^2C^2)$ vs. 7^2C^2 for C channels per layer

Keras

```
#VGG Block
conv1 = Conv2D(64, (3,3), strides=(1,1), padding='same', activation='ReLU')(x)
conv2 = Conv2D(64, (3,3), strides=(1,1), padding='same', activation='ReLU')(conv1)
maxpool1 = MaxPooling2D((2,2))(conv2)
```

Padding='valid'
No padding

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Variants of VGG

- **ConvNet configurations**
  - The depth of the configurations increases from the left (A) to the right (E), as more layers are added (the added layers are shown in bold)
- The convolutional layer parameters are denoted as "conv⟨receptive field size⟩-⟨number of channels⟩"

- ILSVRC'14 2nd in classification, 1st in localization
- Use VGG16 or VGG 19 (VGG19 only slightly better, more memory)

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

VGG16 VGG19

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Calculate the number of parameters on VGG Net

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 **conv3-256**
maxpool					
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Network	A	B	C	D	E
Number of parameters (Millions)	133	133	134	138	144

https://hoanglehaithanh.com/calculate-the-number-of-parameters-on-vgg-net/

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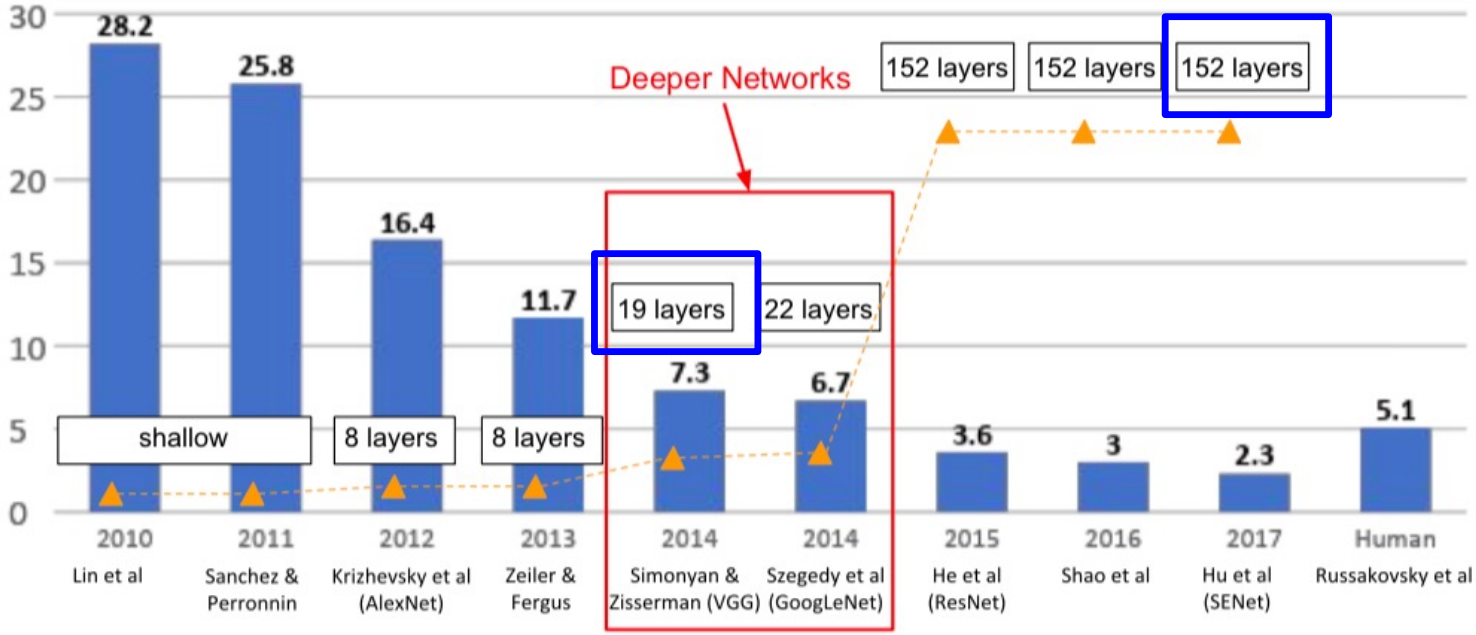
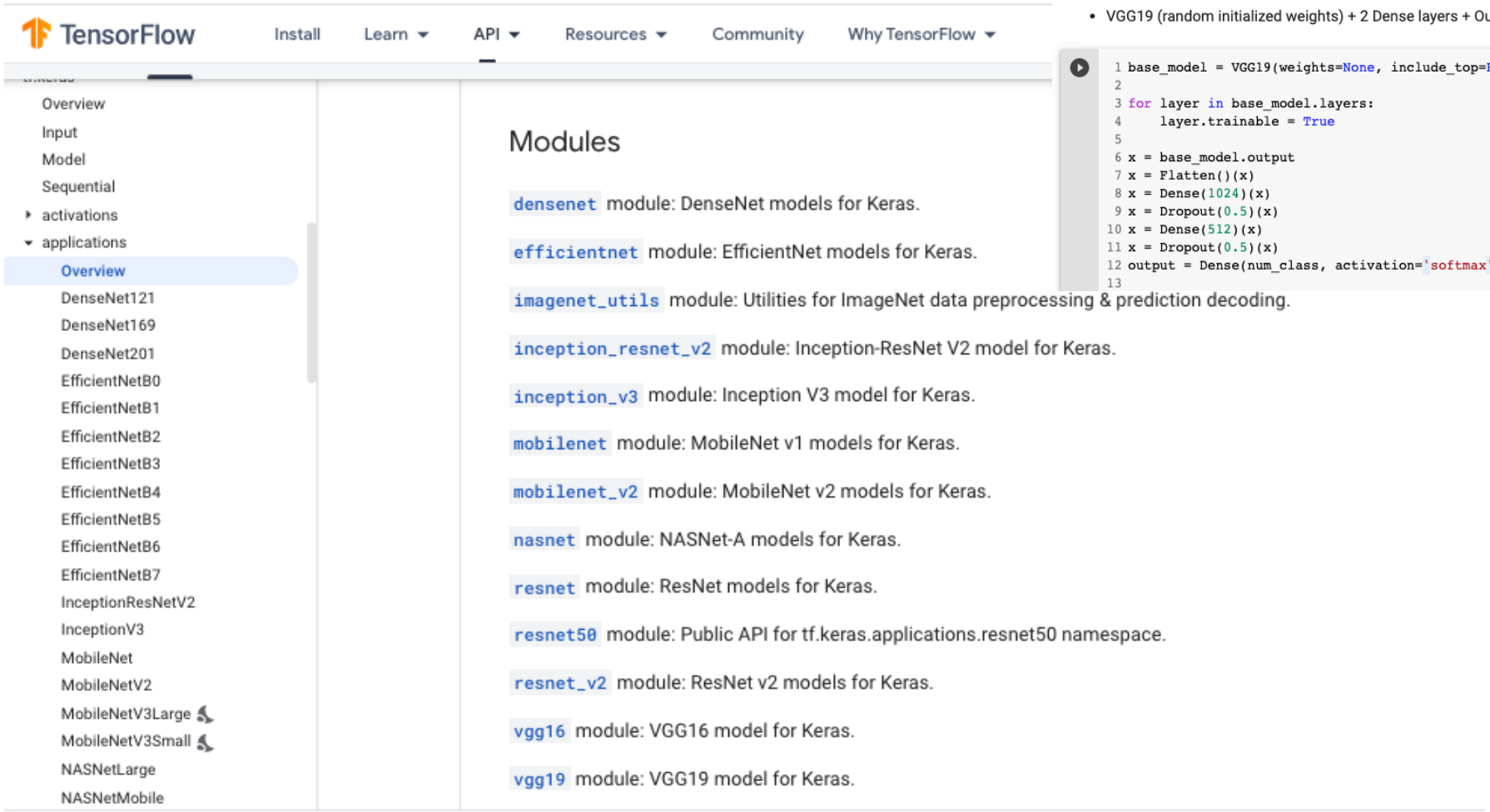
ImageNet Large Scale Visual Recognition Challenge (ILSVRC 2nd runner-up in 2014): Deeper than VGG19



51



Model 1

- VGG19 (random initialized weights) + 2 Dense layers + Output layer

```
base_model = VGG19(weights=None, include_top=False, input_shape=(224, 224, 3))

for layer in base_model.layers:
    layer.trainable = True

x = base_model.output
x = Flatten()(x)
x = Dense(1024)(x)
x = Dropout(0.5)(x)
x = Dense(512)(x)
x = Dropout(0.5)(x)
output = Dense(num_class, activation='softmax')(x)

```

https://www.tensorflow.org/api_docs/python/tf/keras/applications

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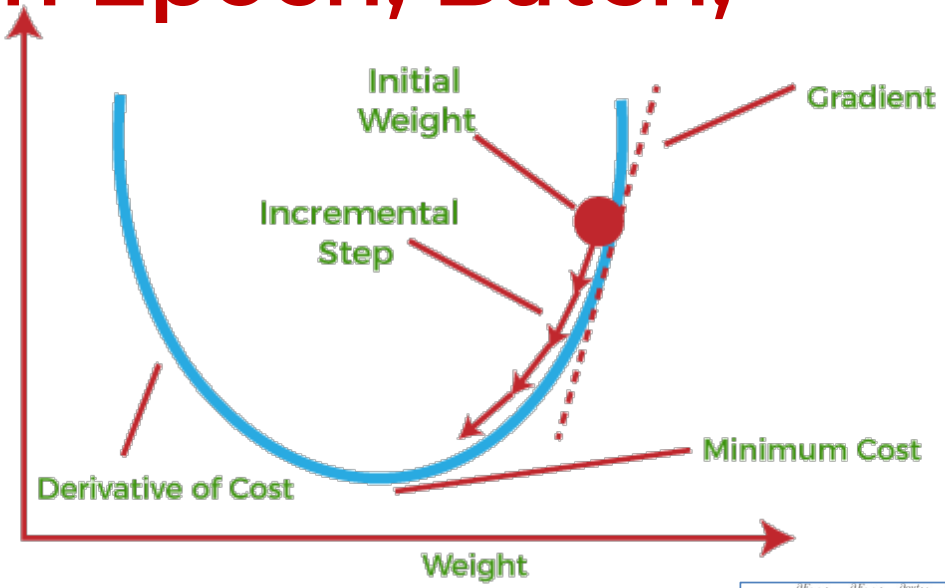
Differences Between Epoch, Batch, and Mini-batch

- The gradient descent algorithm works in two steps that are performed continuously for a specific number of iterations:
  - First, we compute the gradient, which is the first-order derivative of the objective function with respect to the variables.
  - Then, we update the variables in the opposite direction of the gradient
- Terms:
  - Epoch = use all training examples
  - Iteration = each round of updating weight

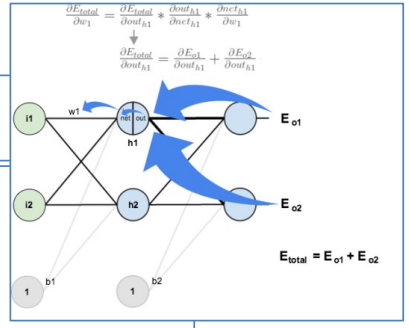


$$w_5^+ = w_5 - \eta * \frac{\partial E_{total}}{\partial w_5} = 0.4 - 0.5 * 0.082167041 = 0.35891648$$

Putting it all together:

$$\frac{\partial E_{total}}{\partial w_5} = \frac{\partial E_{total}}{\partial out_{o1}} * \frac{\partial out_{o1}}{\partial net_{o1}} * \frac{\partial net_{o1}}{\partial w_5}$$

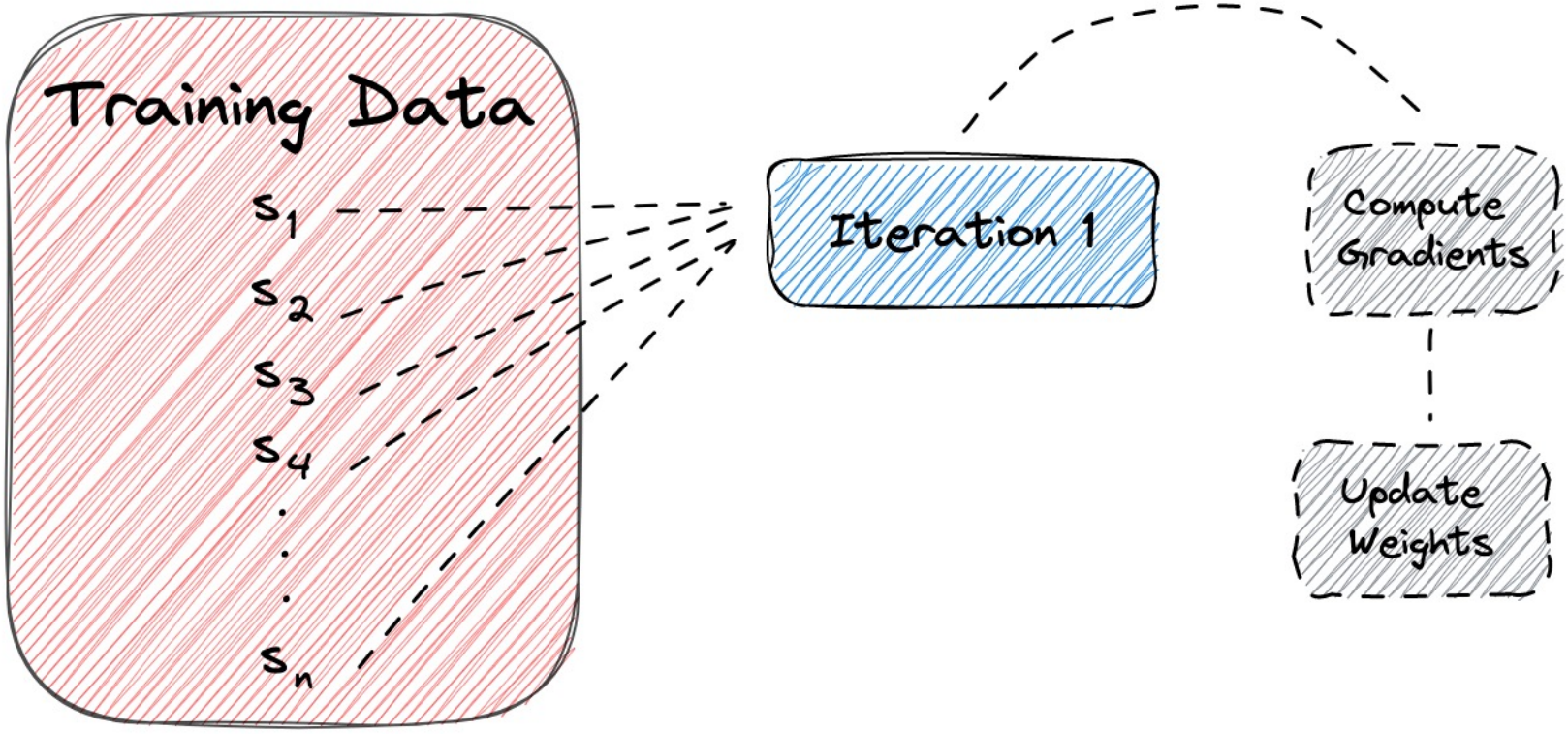
$$\frac{\partial E_{total}}{\partial w_5} = 0.74136507 * 0.186815602 * 0.593269992 = 0.082167041$$



https://www.baeldung.com/cs/epoch-vs-batch-vs-mini-batch#:~:text=So%2C%20a%20batch%20is%20equal,in%20mini%2Dbatch%20gradient%20descent.

1) Batch Gradient Descent

- In batch gradient descent, we use all our training data in a single iteration of the algorithm.



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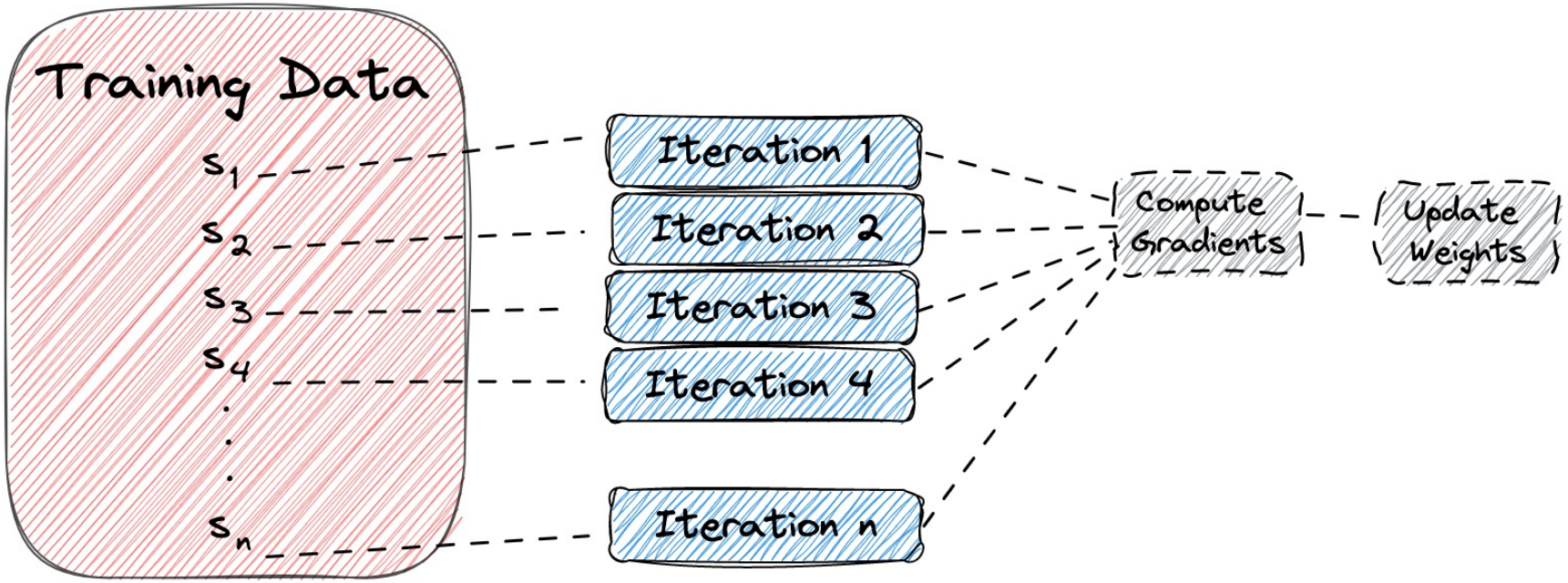
2) Stochastic Gradient Descent

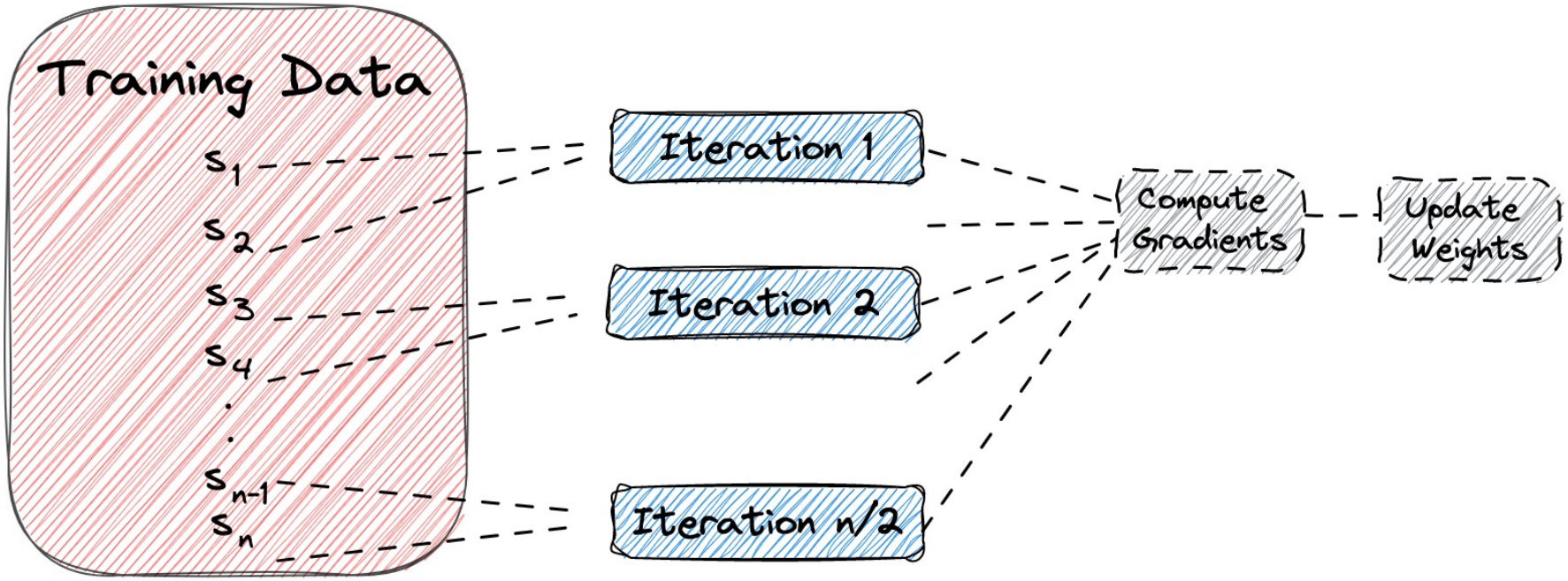
- The previous method can be very time-consuming and inefficient in case the size of the training dataset is large. To deal with this, we use stochastic gradient descent, where we use just one sample in a single iteration of the algorithm.



55

3) Mini-Batch Gradient Descent

- Mini-batch gradient descent is a combination of the previous methods where we use a group of samples called mini-batch in a single iteration of the training algorithm.
- The mini-batch is a fixed number of training examples that is less than the actual dataset. So, in each iteration, we train the network on a different group of samples until all samples of the dataset are used.



Conclusion about batch

An epoch means that we have passed each sample of the training set one time through the network to update the parameters. Generally, the number of epochs is a hyperparameter that defines the number of times that gradient descent will pass the entire dataset.

If we look at the previous methods, we can see that:

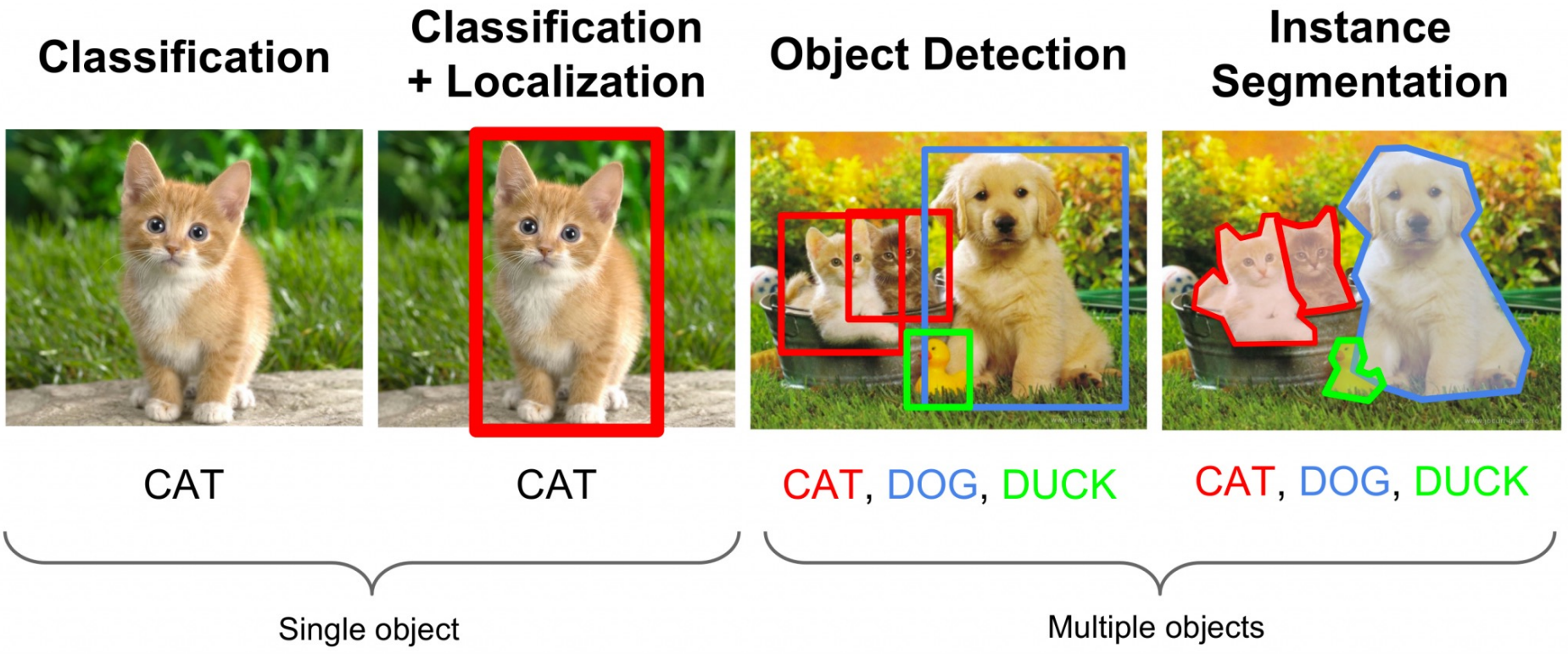
- In batch gradient descent, one epoch corresponds to a single iteration.
- In stochastic gradient descent, one epoch corresponds to n iterations where n is the number of training samples.
- In mini-batch gradient descent, one epoch corresponds to $\frac{n}{b}$ iterations where b is the size of the mini-batch.

Finally, let's present a simple example to better understand the three terms.

Let's assume that we have a dataset with $\mathbf{n = 2000}$ samples, and we want to train a deep learning model using gradient descent for $\mathbf{10}$ epochs and mini-batch size $\mathbf{b = 4}$:

- In batch gradient descent, we'll update the network's parameters (using all the data) 10 times which corresponds to 1 time for each epoch.
- In stochastic gradient descent, we'll update the network's parameters (using one sample each time) $2000 * 10 = 20000$ times which corresponds to 2000 times for each epoch.
- In mini-batch gradient descent, we'll update the network's parameters (using $b = 4$ samples each time) $\frac{2000}{4} * 10 = 5000$ times that corresponds to $\frac{2000}{4} = 500$ times for each epoch.

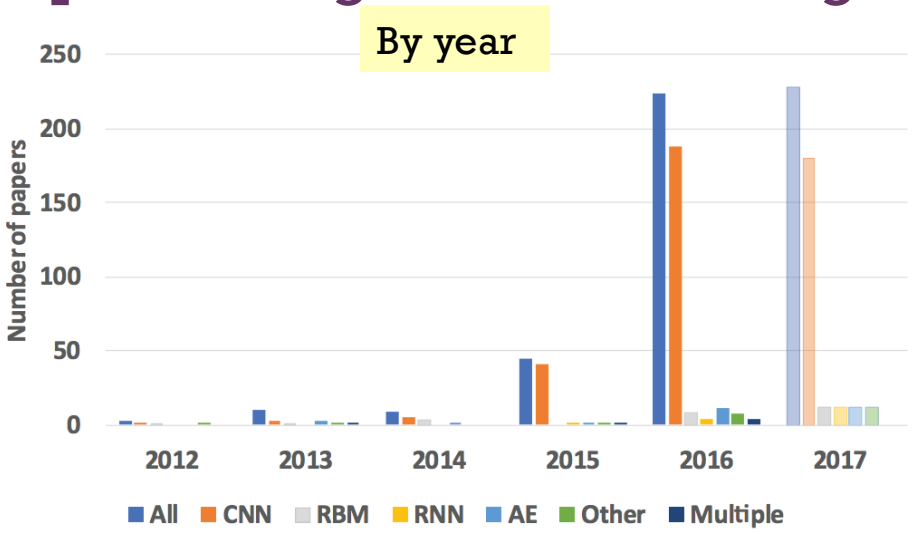
Image Classification Tasks

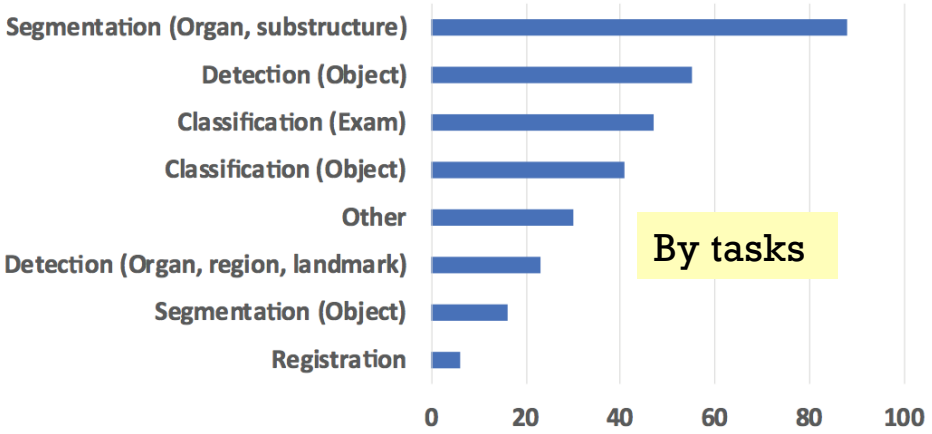


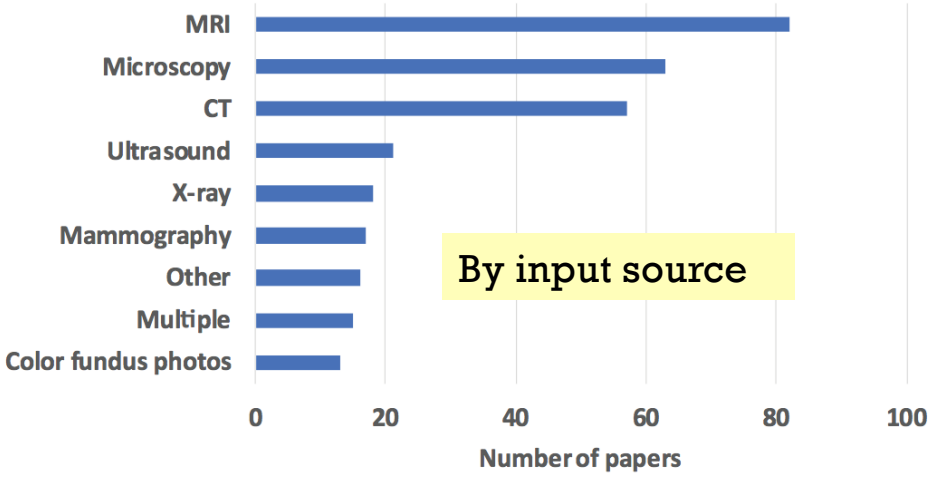
https://analyticsindiamag.com/top-5-image-classification-research-papers-every-data-scientist-should-know/

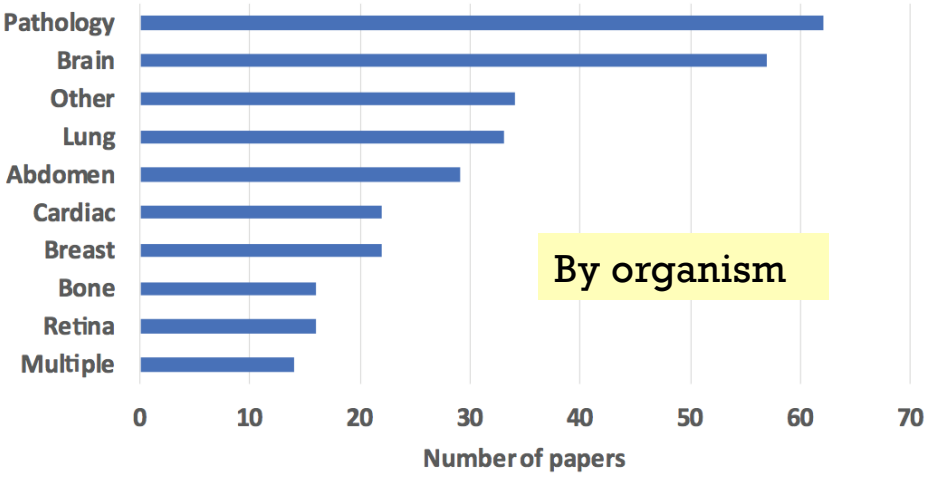
https://arxiv.org/pdf/1702.05747.pdf

Deep Learning in Medical Image Analysis [arXiv 2017]

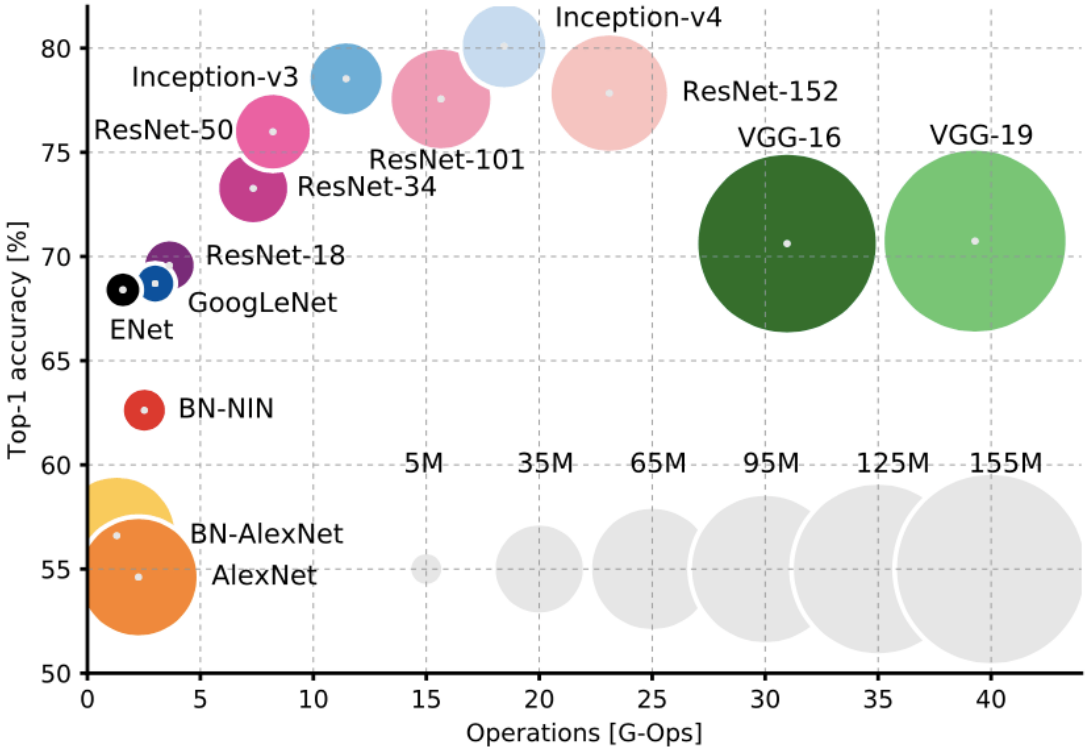




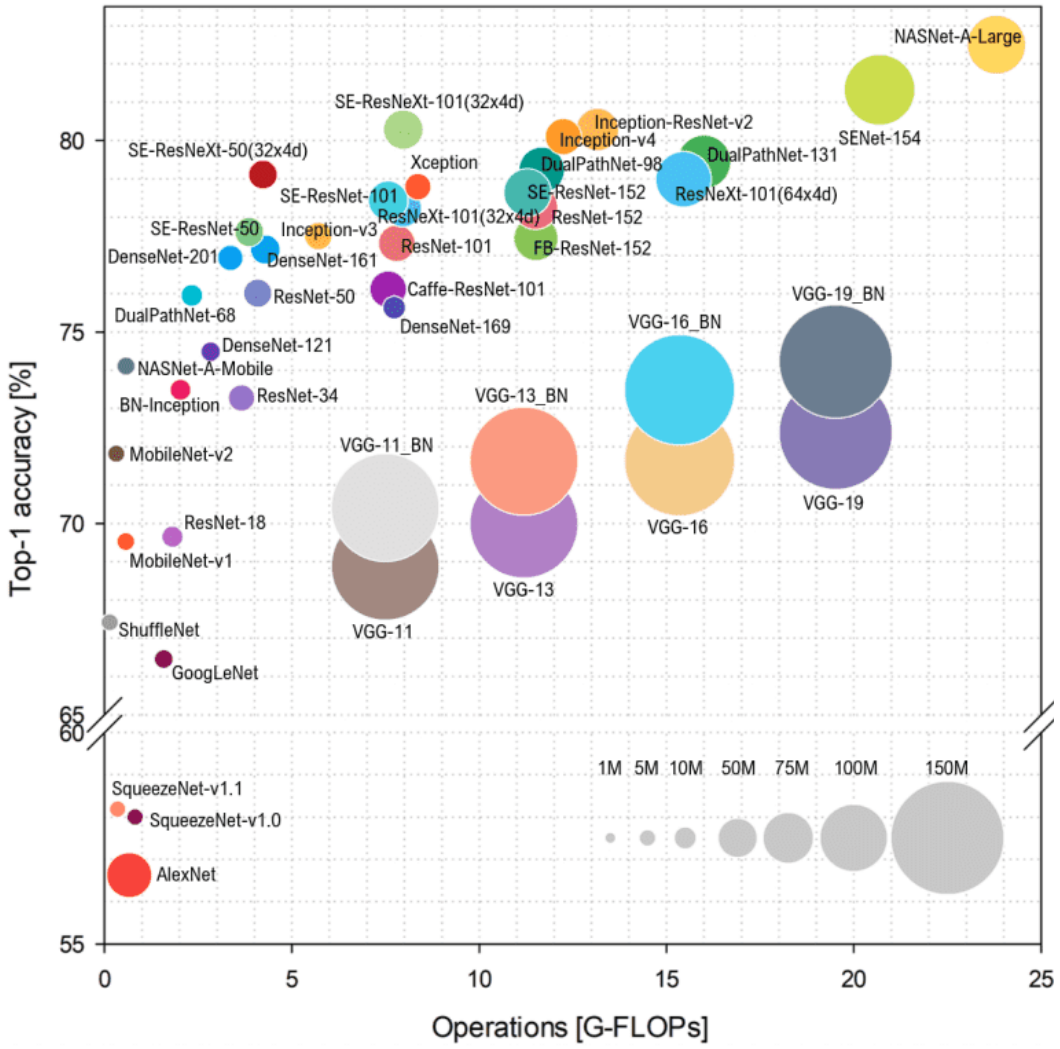




SOTA of Image Classification



https://blog.csdn.net/qq_34216467/article/details/83061692



https://theaisummer.com/cnn-architectures/

EfficientNet (May, 2019) → EffNetV2 (2021)

EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

Mingxing Tan [1] **Quoc V. Le** [1]

Abstract

Convolutional Neural Networks (ConvNets) are commonly developed at a fixed resource budget, and then scaled up for better accuracy if more resources are available. In this paper, we systematically study model scaling and identify that carefully balancing network depth, width, and resolution can lead to better performance. Based on this observation, we propose a new scaling method that uniformly scales all dimensions of depth/width/resolution using a simple yet highly effective *compound coefficient*. We demonstrate the effectiveness of this method on scaling up MobileNets and ResNet.

To go even further, we use neural architecture

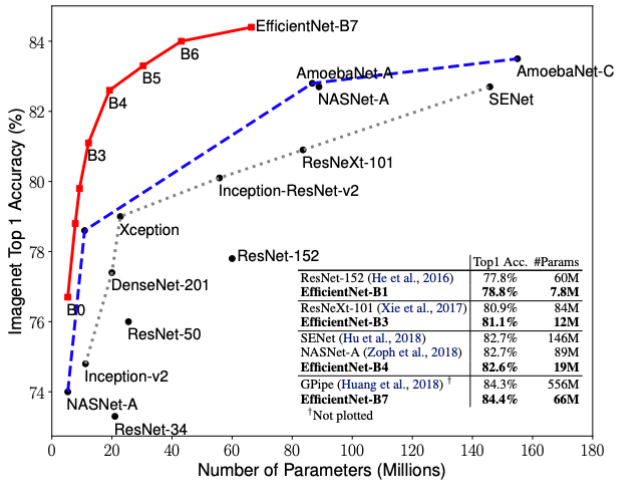
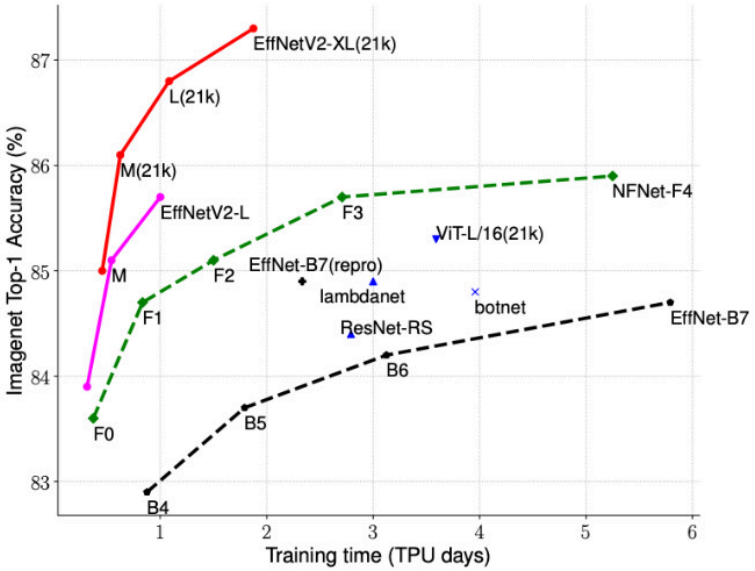


Figure 1. Model Size vs. ImageNet Accuracy. All numbers are



(a) Training efficiency.

	EfficientNet (2019)	ResNet-RS (2021)	DeiT/ViT (2021)	EfficientNetV2 (ours)
Top-1 Acc.	84.3%	84.0%	83.1%	83.9%
Parameters	43M	164M	86M	24M

(b) Parameter efficiency.

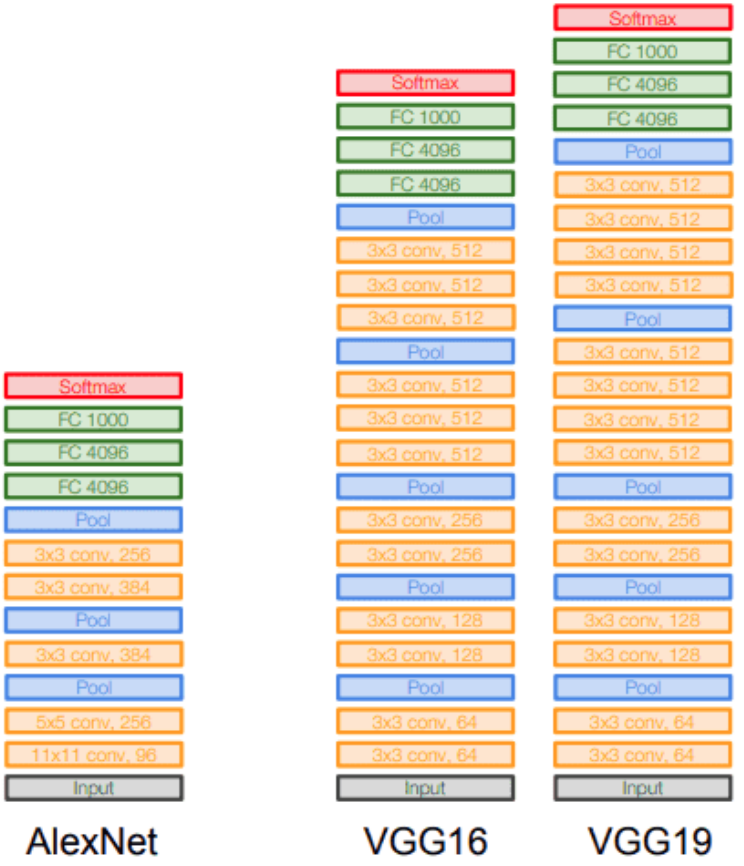
http://proceedings.mlr.press/v97/tan19a/tan19a.pdf

https://twitter.com/TensorFlow/status/1423359562724175873/photo/1

Network series

1. VGG (2014)
2. Inception/GoogleNet (2014)
3. Inception V2, V3
4. ResNet
5. DenseNet
6. Inception-V4 & Inception-ResNet
7. EfficientNet V1, V2

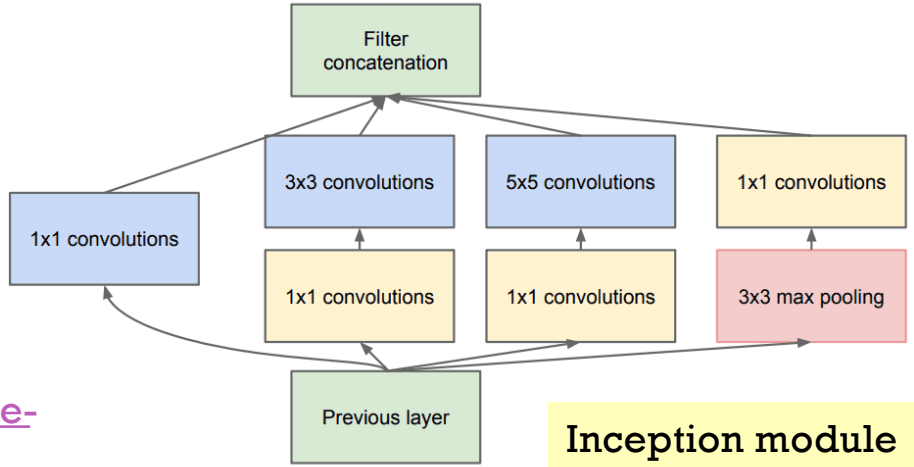
1) VGG (2014)



2) Inception V1/GoogLeNet (2014)

- After VGG, the paper "Going Deeper with Convolutions" [3] by Christian Szegedy et al. was a huge breakthrough. What about increasing both the depth (more layers) and width (more feature maps) of the network while keeping computations to a constant level?
- The answer is with 1×1 convolutions! The main purpose is dimension reduction, by reducing the output channels of each convolution block.
  - 1×1 convolutions are used to compute reductions before the computationally expensive convolutions (3×3 and 5×5).
- Moreover, it uses convolutions of different kernel sizes (5×5, 3×3, 1×1) to capture details at multiple scales.
- The InceptionNet/GoogLeNet architecture consists of 9 inception modules stacked together, with max-pooling layers between (to halve the spatial dimensions). It consists of 22 layers (27 with the pooling layers). It uses global average pooling after the last inception module.

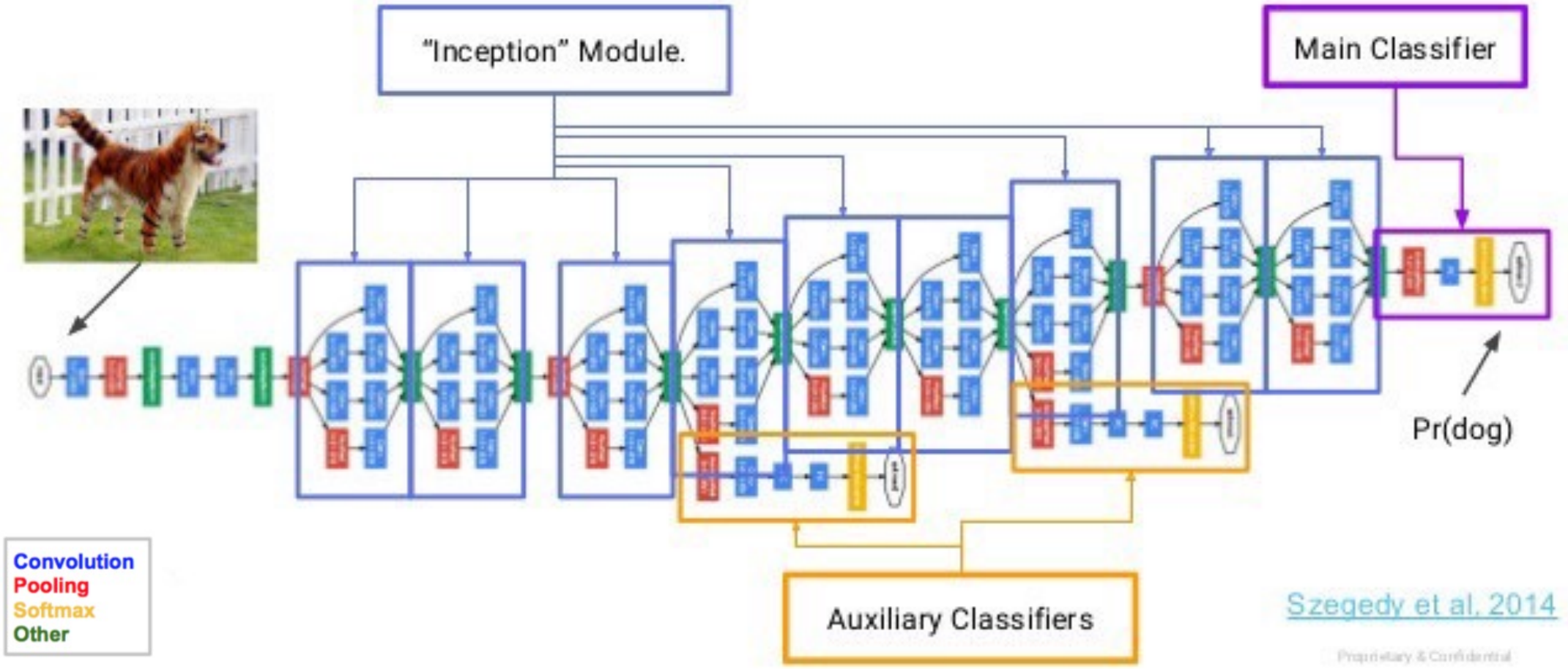
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202



Inception module

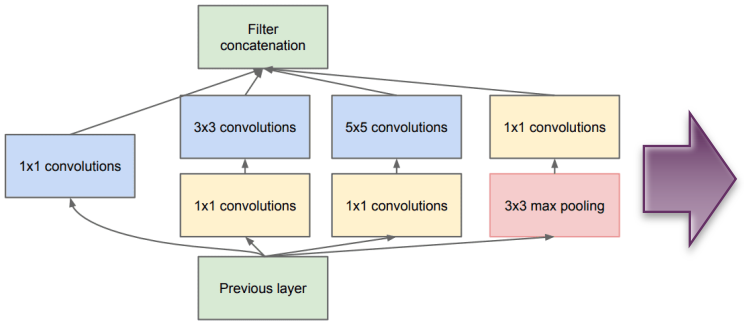
GoogLeNet (aka “Inception”) Architecture

Inception is a deep network, to prevent the **middle part** of the network from “**dying out**”(vanishing gradient problem), the authors introduced **two auxiliary classifiers.** Softmax is applied in each of them, and then **Auxiliary loss** is calculated on the same labels of the output classifier.

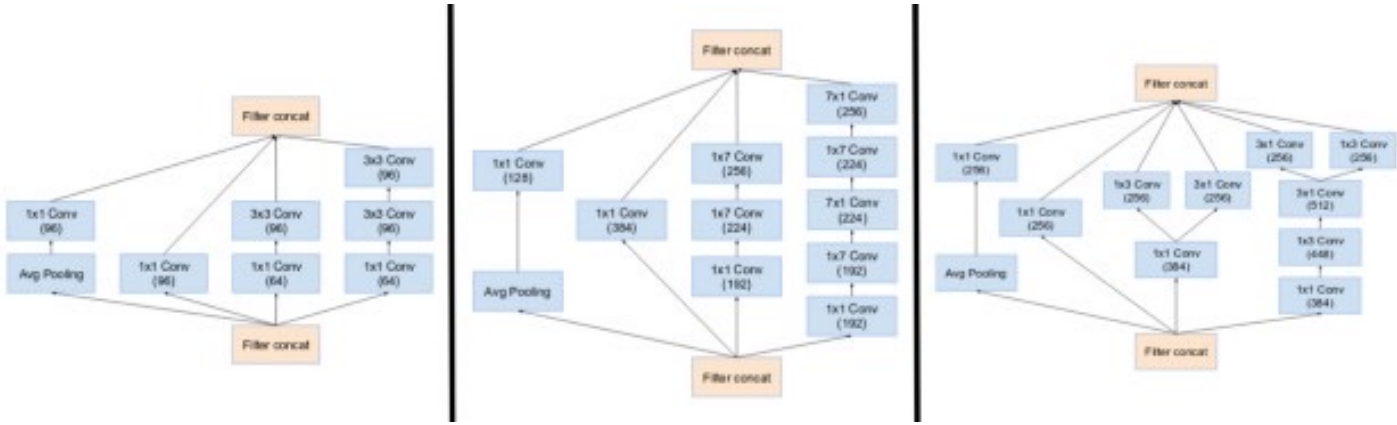


3) Inception V2, V3 (2015) – improve speed

- Factorize 5x5 and 7x7 (in InceptionV3) convolutions to two and three 3x3 sequential convolutions respectively. This improves computational speed. This is the same principle as VGG.
  (analogy: 5*5 = 25 parameters vs. 2*(3*3) = 18 parameters)
- Simply, a 3x3 kernel is decomposed into two smaller ones: a 1x3 and a 3x1 kernel, which are applied sequentially. (analogy: 3*3 = 9 parameters vs. (1*3) + (3*1) = 6 parameters)
- The inception modules became wider (more feature maps).
- They added batch normalization.



Inception-V1 module



Inception Module (A, B, C)
in Inception V2, V3

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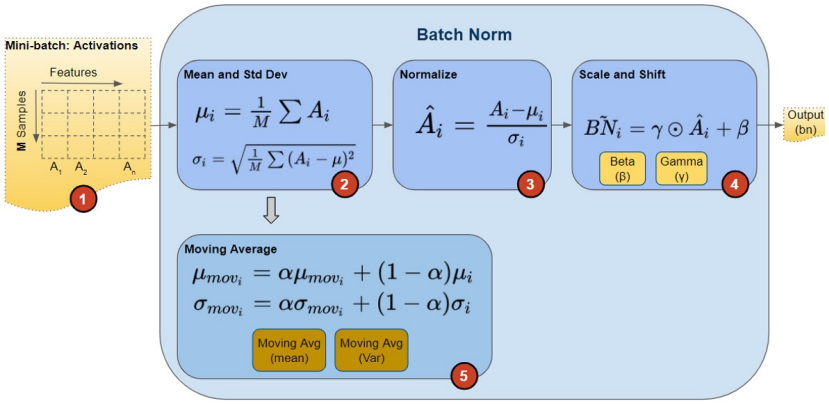
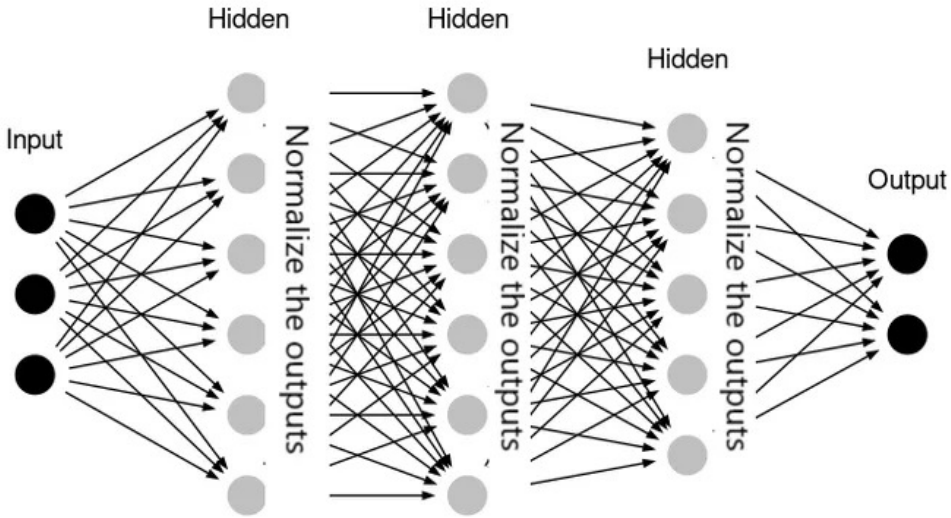
Batch normalization

$$\hat{x} = \frac{x - mean(\bar{x})}{std(\bar{x}))}$$



https://towardsdatascience.com/batch-norm-explained-visually-how-it-works-and-why-neural-networks-need-it-b18919692739

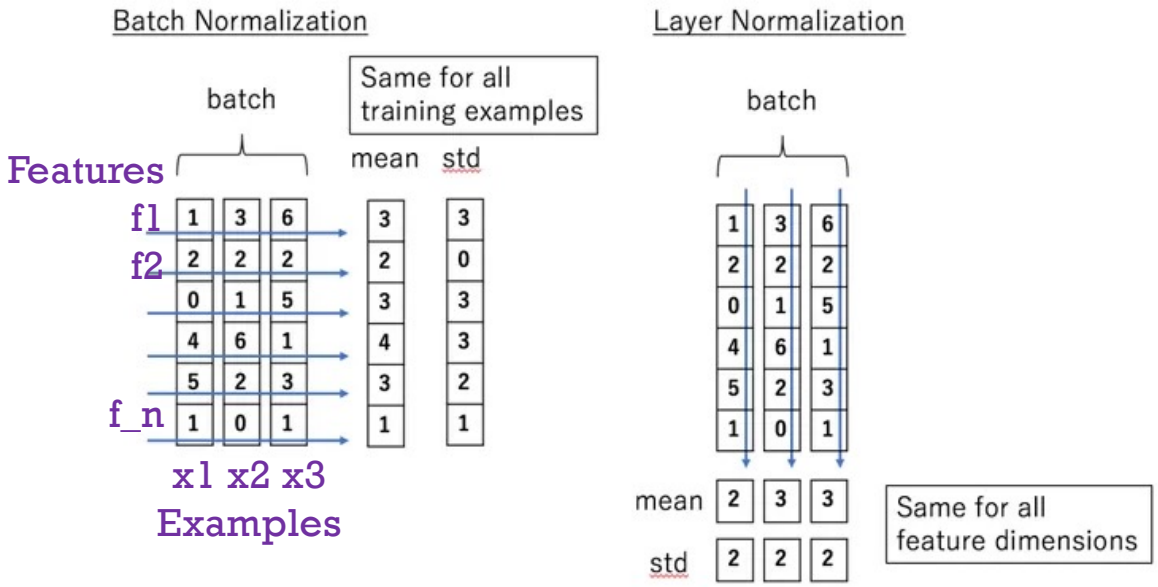
- Batch Normalization focuses on standardizing the inputs to **any particular layer** (i.e., activations from previous layers).
- **Advantages of Batch Normalization Layer**
- Batch normalization improves the training time and accuracy of the neural network.
- It decreases the effect of weight initialization.
- It also adds a regularization effect on the network.
- It works better with the fully Connected Neural Network (FCN) and Convolutional Neural Network.
- **Disadvantages of Batch Normalization Layer**
- Batch normalization is dependent on mini-batch size which means if the mini-batch size is small, it will have little to no effect
- Batch normalization does not work well with Recurrent Neural Networks (RNN)

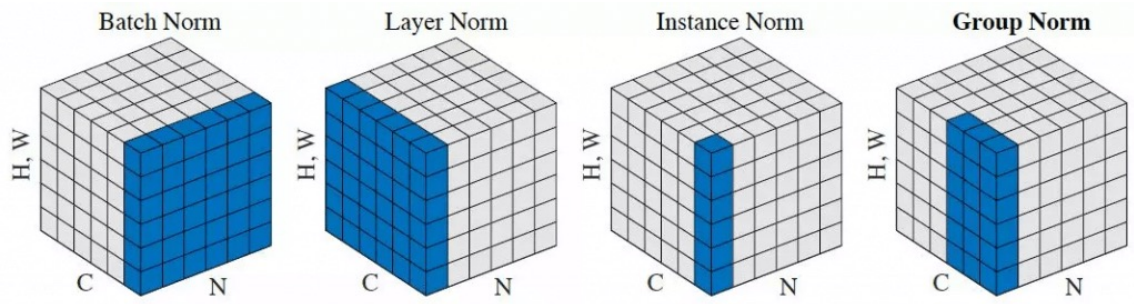


https://machinelearningknowledge.ai/keras-normalization-layers-explained-for-beginners-batch-normalization-vs-layer-normalization/#Layer_Normalization_Layer

Layer normalization

- Layer Normalization which addresses the drawbacks of batch normalization. This technique is not dependent on batches and the normalization is applied on the neuron for a single instance across all features.
- **Advantages of Layer Normalization**
- It is not dependent on any batch sizes during training.
- It works better with Recurrent Neural Network.
- **Disadvantages of Layer Normalization**
- It may not produce good results with Convolutional Neural Networks (CNN)



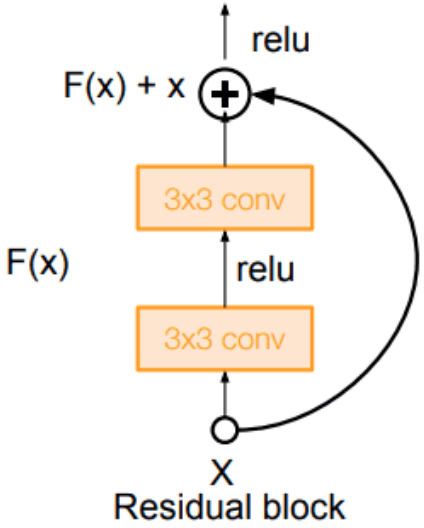


C = features (channels)
N = each mini-batch

https://machinelearningknowledge.ai/keras-normalization-layers-explained-for-beginners-batch-normalization-vs-layer-normalization/#Layer_Normalization_Layer

4) ResNet: Deep Residual Learning for Image Recognition (2015)

- All the predescribed issues such as vanishing gradients were addressed with two tricks:
  - batch normalization and
  - short skip connections - Instead of H(x) = F(x), we ask them model to learn the difference (residual) H'(x) = F(x) + x, which means H(x) - x = F(x) will be the residual part [4].
- Designed deeper architectures ranging from 18 (Resnet-18) to 150 (Resnet-150) layers.
- For the deepest models they adopted 1x1 convs, as illustrated on the right:



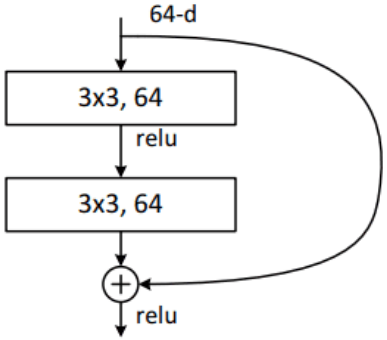
the layer followed by adding a bias term.

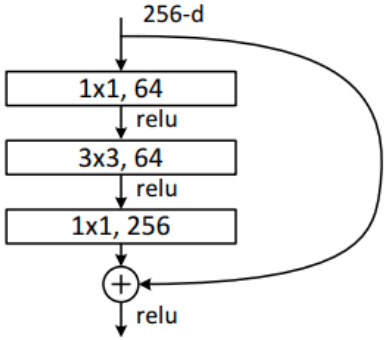
Then comes the activation function, f() and we get the output as H(x).

H(x)=f(wx + b) or H(x)=f(x)

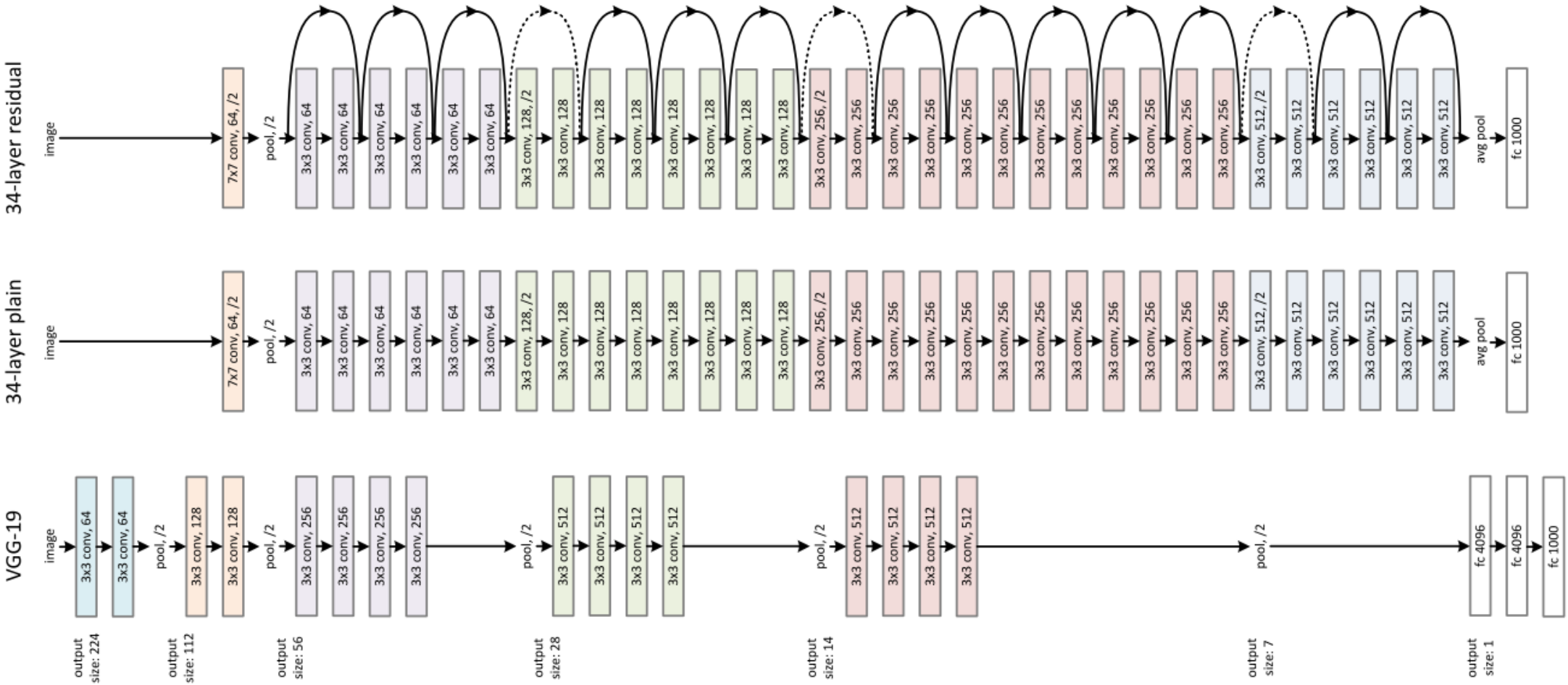
Now with the introduction of a new skip connection technique, the output is H(x) is changed to

H(x)=f(x)+x

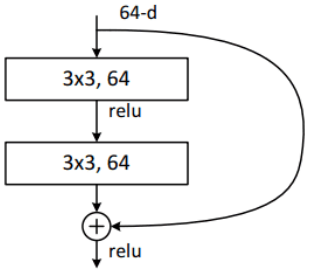


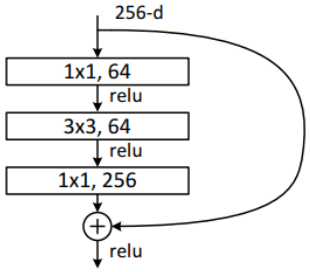


ResNet-34 vs. Plain Network (no skip connection)



ResNet (cont.)
ResNet-18, 34, 50, 101, 152



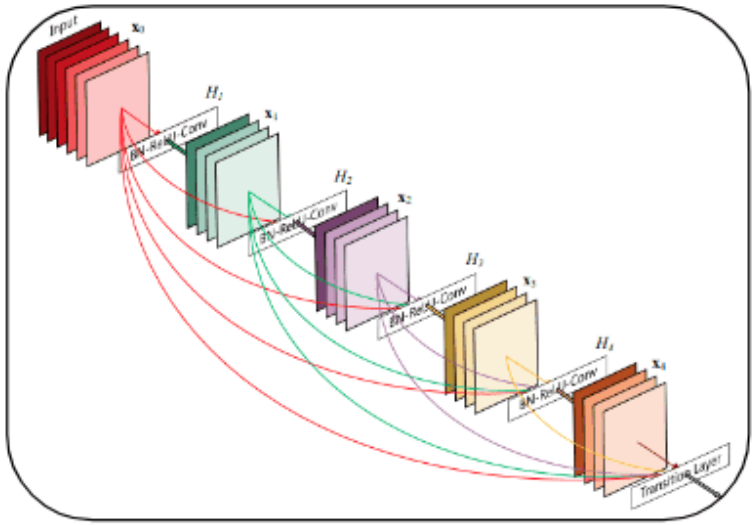


layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

5) DenseNet: Densely Connected Convolutional Networks (2017)

- Skip connections are a pretty cool idea. Why don't we just skip-connect everything?

Dense Block 1

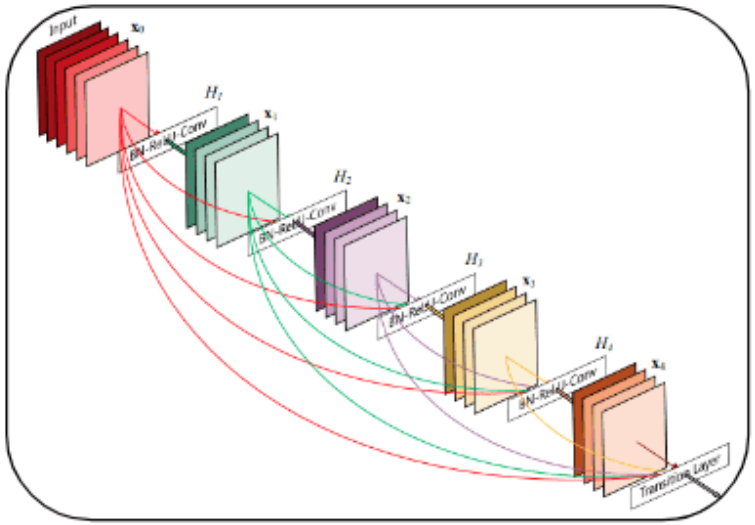


Spatial dims: 256x256
512 feature maps

Transition Layer

1×1×K convs
+
2×2 average pooling

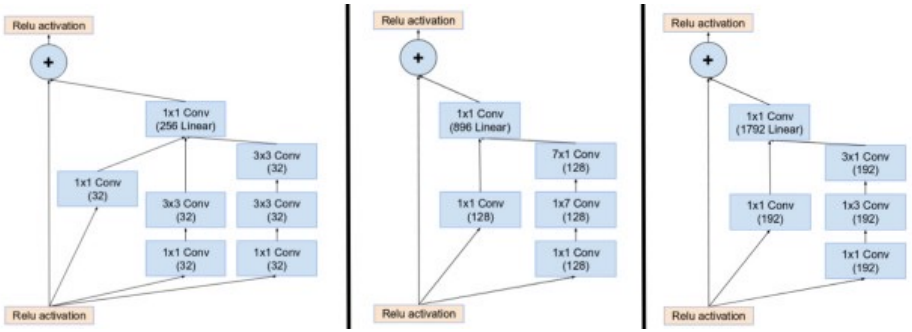
Dense Block 2



Spatial dims: 128x128
K feature maps < 512

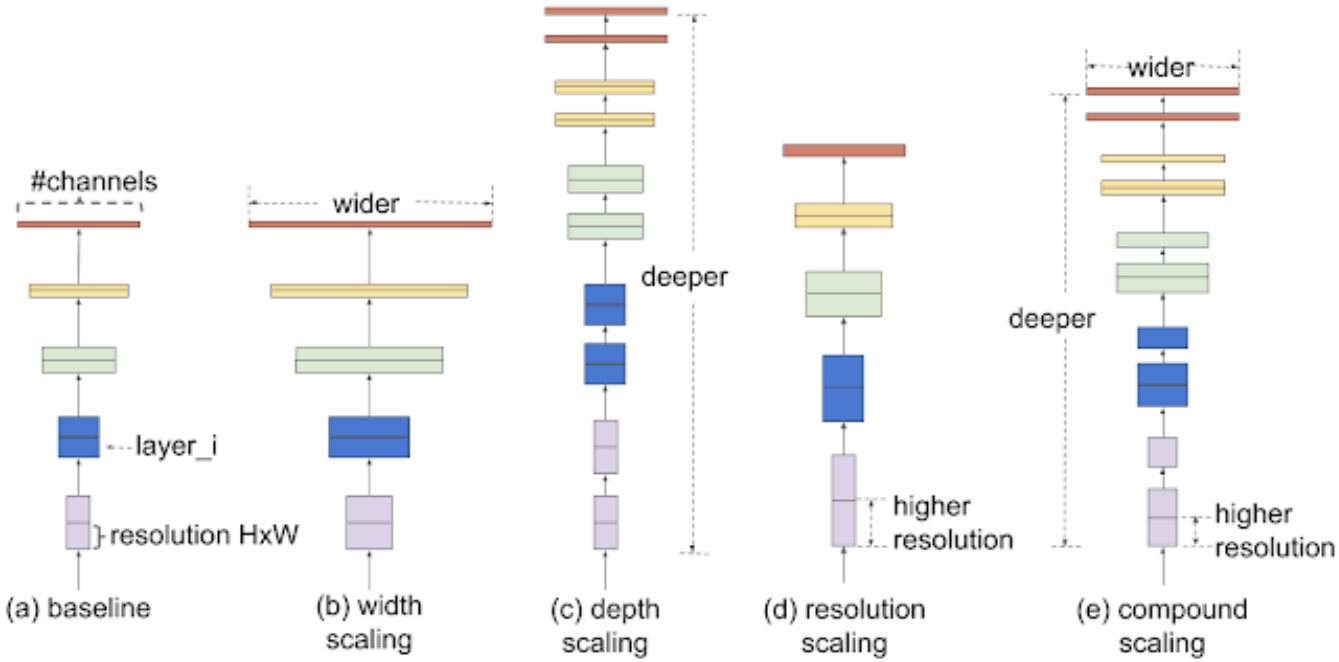
6) Inception-V4 & Inception-ResNet

- Inception v4 and Inception-ResNet were introduced in the same paper.
- Inception-V4 (simplified previous version)
  - Make the modules more uniform. The authors also noticed that some of the modules were more complicated than necessary. Thus; the "stem" of Inception v4 was modified (simplified).
  - Inception v4 introduced specialized "Reduction Blocks" (simplified) which are used to change the width and height of the grid.
- Inception-ResNet V1, V2
  - For residual addition to work, the input and output after convolution must have the same dimensions. Hence, we use 1x1 convolutions after the original convolutions, to match the depth sizes (Depth is increased after convolution).
  - Inception-ResNet v1 has a computational cost that is similar to that of Inception v3.
  - Inception-ResNet v2 has a computational cost that is similar to that of Inception v4.



7) EfficientNet (May, 2019)

- So, let's instead scale up network depth (more layers), width (more feature maps), resolution (various sizes of filters) simultaneously. This is known as compound scaling.



For B0 to B7 base models, the input shapes are different. Here is a list of input shape expected for each model:

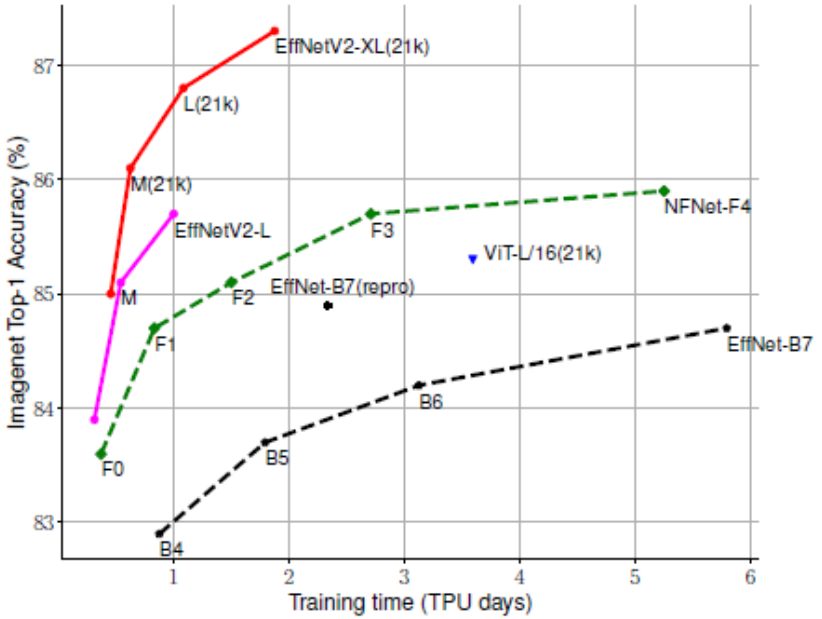
Base model	resolution
EfficientNetB0	224
EfficientNetB1	240
EfficientNetB2	260
EfficientNetB3	300
EfficientNetB4	380
EfficientNetB5	456
EfficientNetB6	528
EfficientNetB7	600

https://blog.roboflow.com/how-to-train-efficientnet/

7) EfficientNetV2 (2021)

Smaller models & faster training

- Our experiments show that EfficientNetV2 models train much faster than state-of-the-art models while being up to 6.8x smaller.
- There are many versions: small, medium, large, and extra-large (XL).



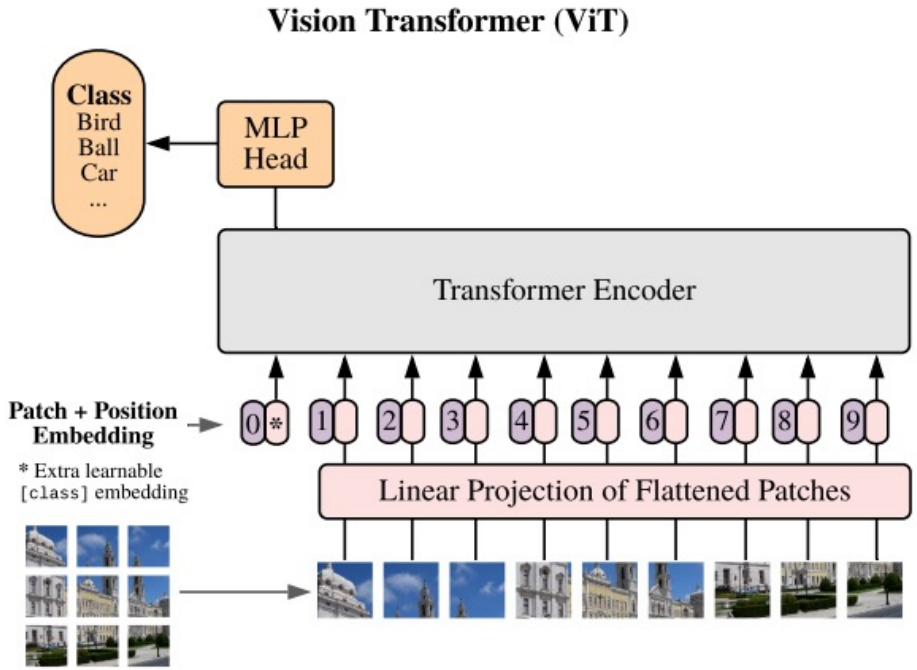
(a) Training efficiency.

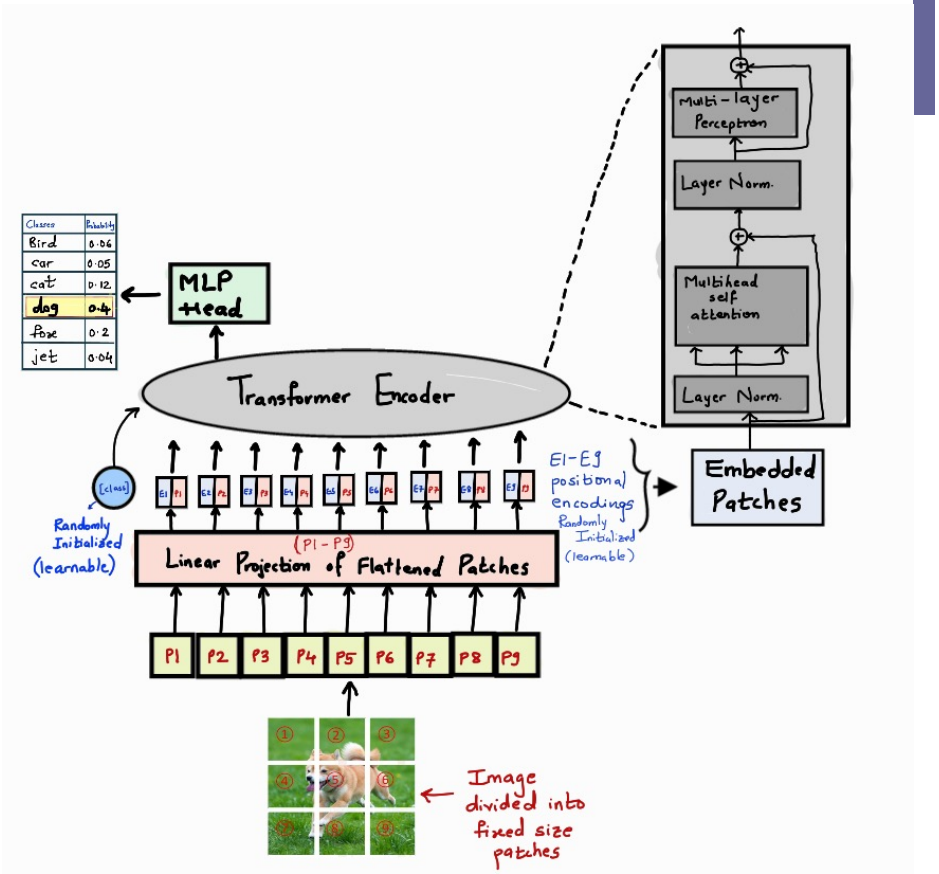
	EfficientNet (2019)	ResNet-RS (2021)	DeiT/ViT (2021)	EfficientNetV2 (ours)
Top-1 Acc.	84.3%	84.0%	83.1%	83.9%
Parameters	43M	164M	86M	24M

(b) Parameter efficiency.

8) Vision Transformer (ViT) (ICLR2021)

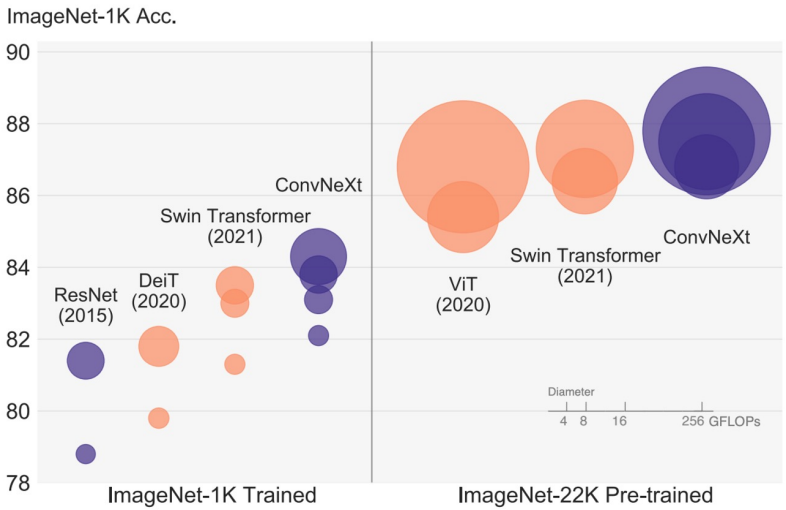
Hugging Face

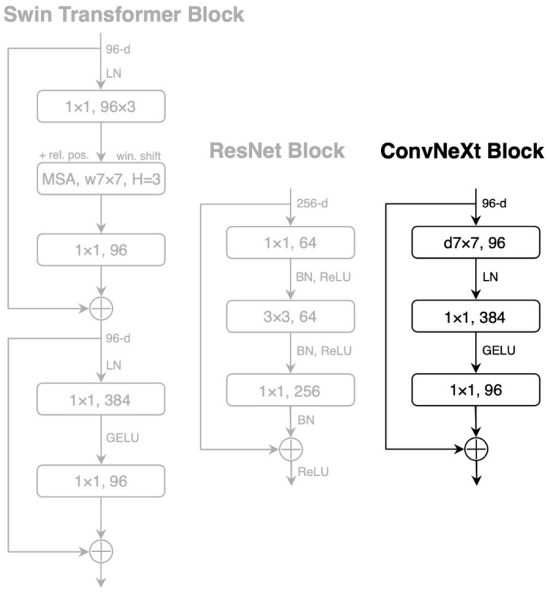


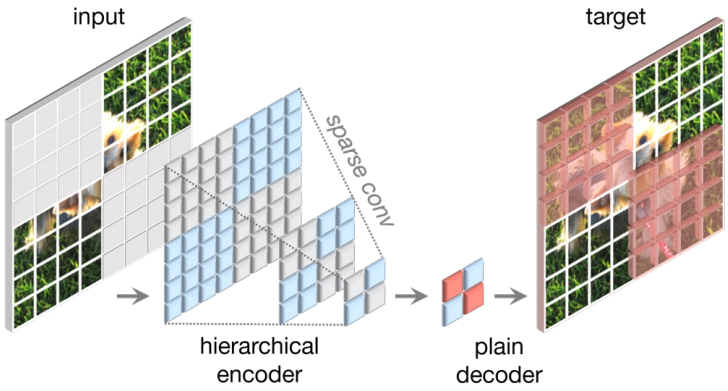


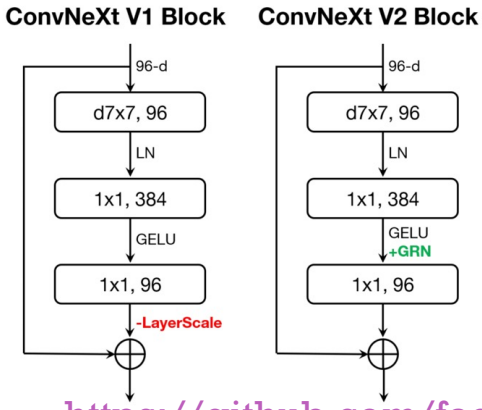
https://medium.com/machine-intelligence-and-deep-learning-lab/vit-vision-transformer-cc56c8071a20

9) ConvNeXt (CVPR2022) → ConvNeXt V2 (2023)





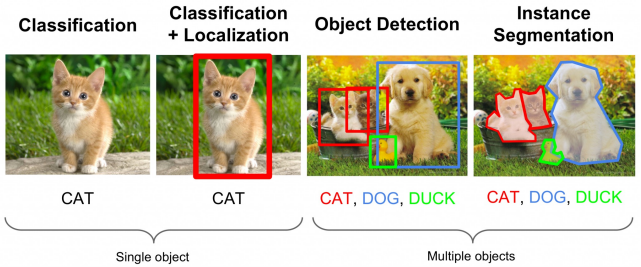




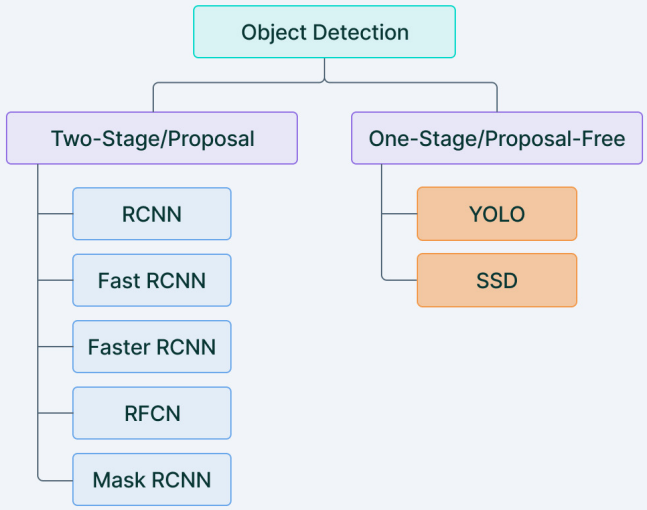
https://github.com/facebookresearch/ConvNeXt-V2

https://github.com/facebookresearch/ConvNeXt

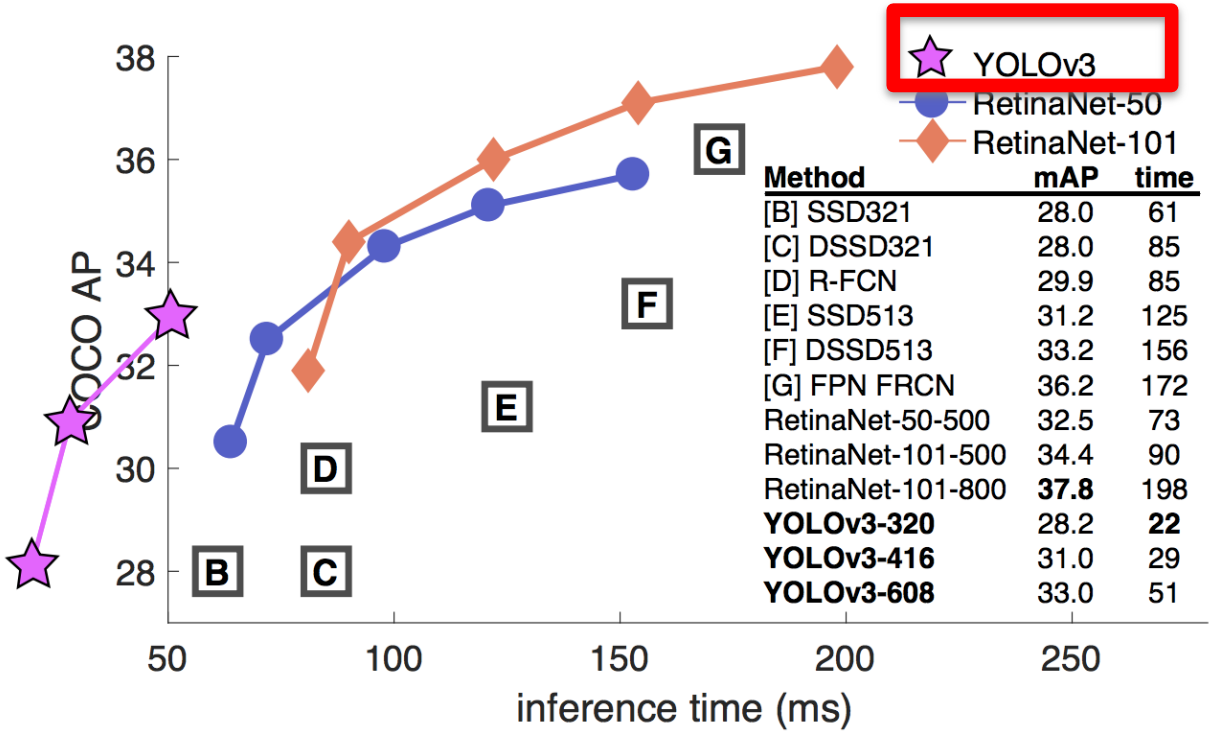
SOTA of Object Detection



One and two stage detectors



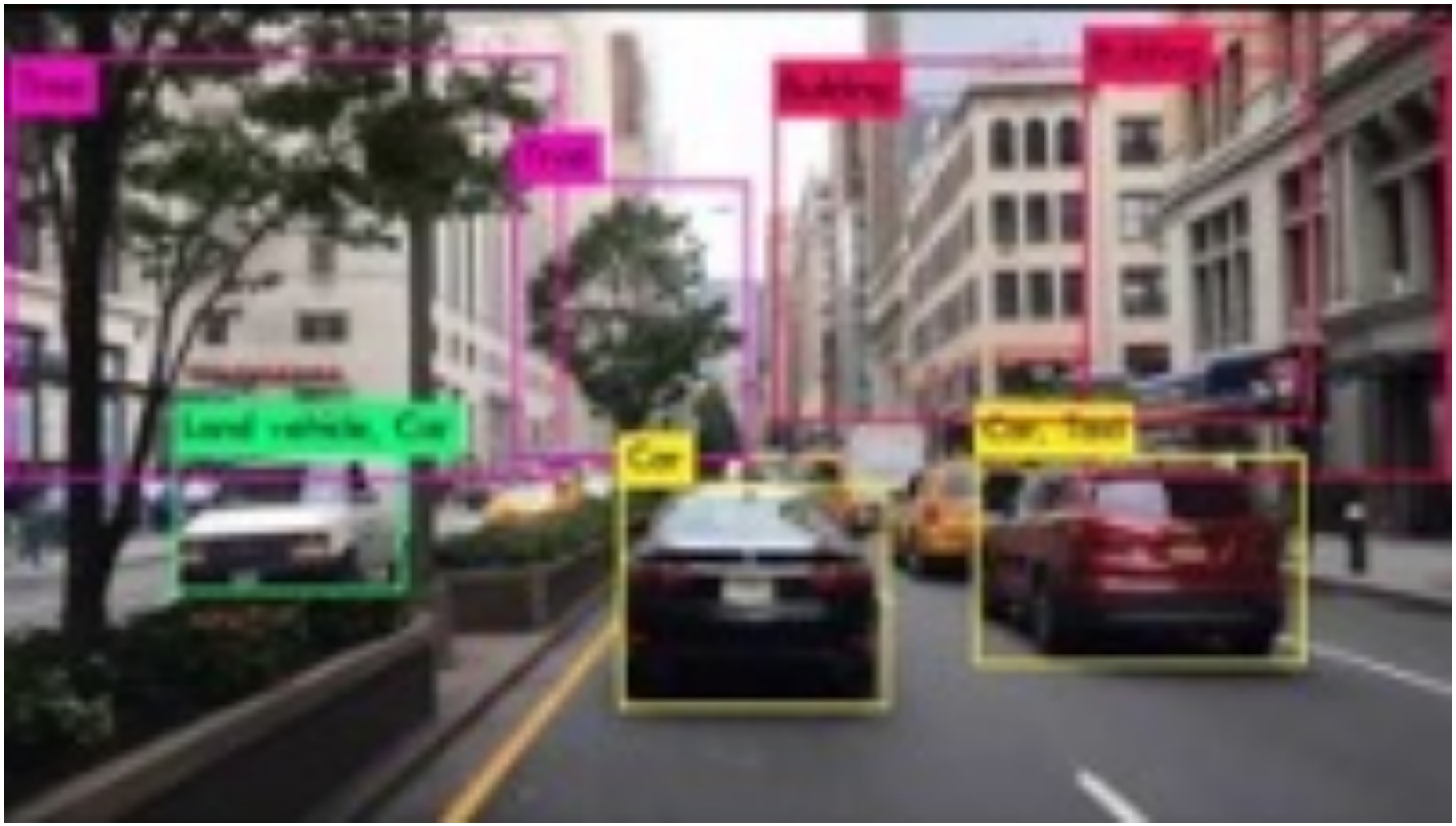
V7 Labs



Method	mAP	time
[B] SSD321	28.0	61
[C] DSSD321	28.0	85
[D] R-FCN	29.9	85
[E] SSD513	31.2	125
[F] DSSD513	33.2	156
[G] FPN FRCN	36.2	172
RetinaNet-50-500	32.5	73
RetinaNet-101-500	34.4	90
RetinaNet-101-800	**37.8**	198
YOLOv3-320	28.2	**22**
YOLOv3-416	31.0	29
YOLOv3-608	33.0	51

https://medium.com/@jonathan_hui/real-time-object-detection-with-yolo-yolov2-28b1b93e2088

YOLO Open Images in New York



YOLO's output

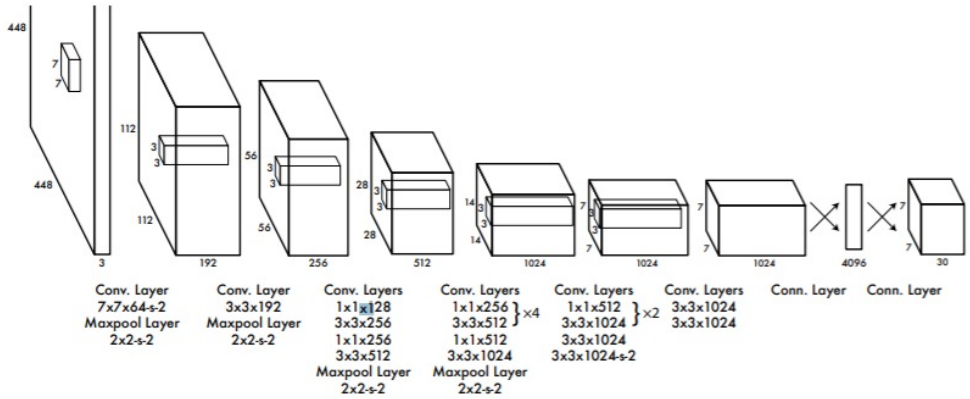
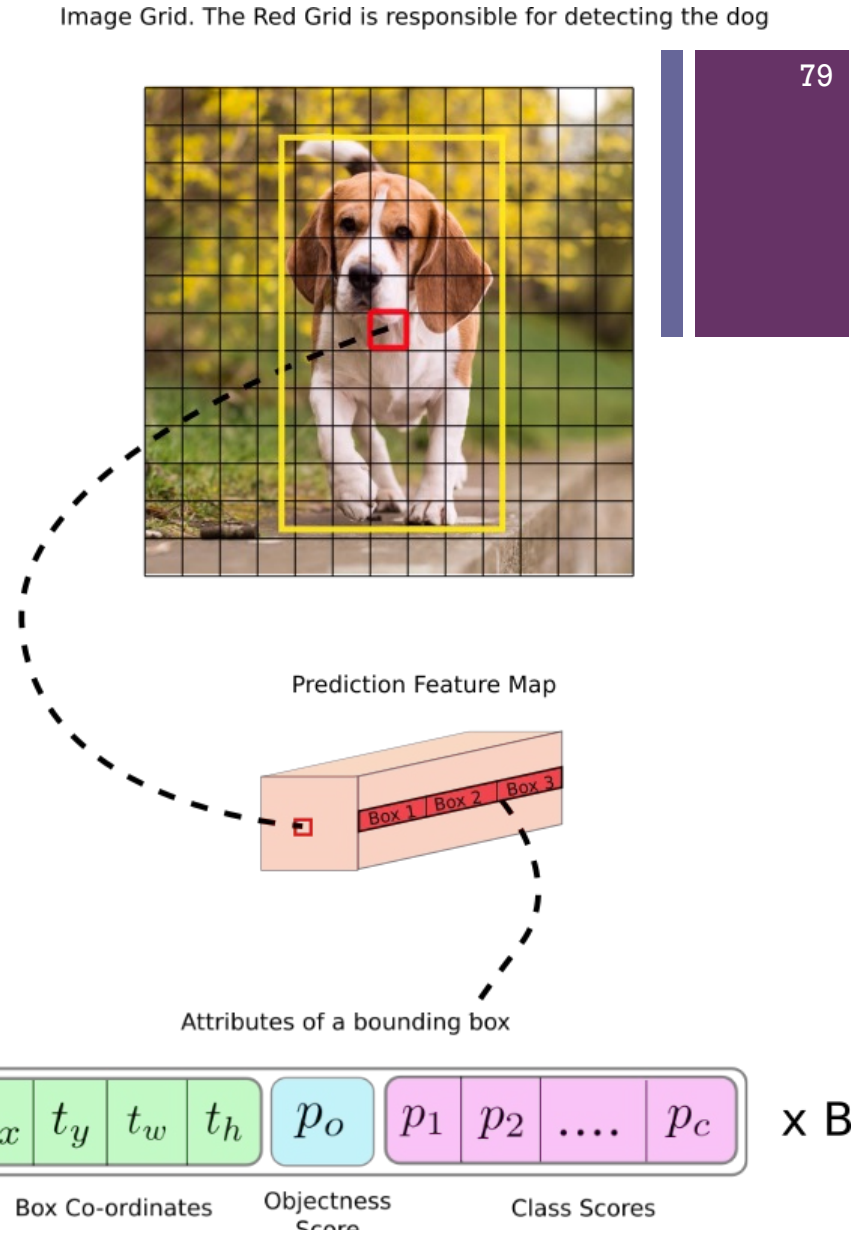
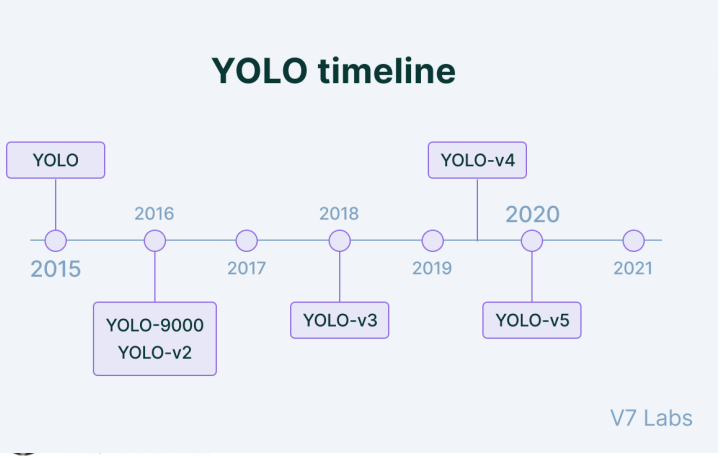


Figure 3: The Architecture. Our detection network has 24 convolutional layers followed by 2 fully connected layers. Alternating 1×1 convolutional layers reduce the features space from preceding layers. We pretrain the convolutional layers on the ImageNet classification task at half the resolution (224×224 input image) and then double the resolution for detection.



https://blog.paperspace.com/how-to-implement-a-yolo-object-detector-in-pytorch/

SOTA of Object Detection (cont.)



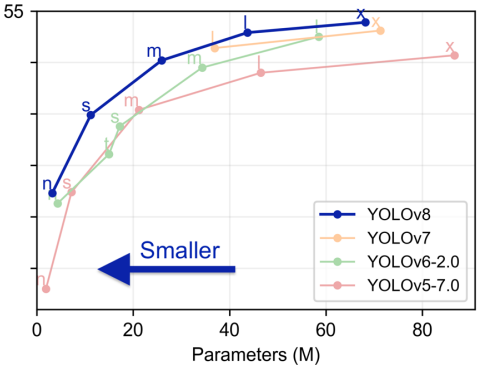
You can read more about YOLOP here.

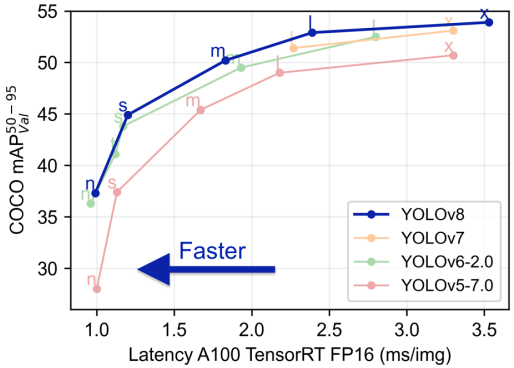
Rank	Model	box AP	AP50	AP75	APS	APM	APL	Extra Training Data	Paper	Code	Result	Year	Tags
1	YOLOR-D6 (1280, single-scale, 30 fps)	57.3	75.0	62.7	40.4	61.2	69.2	×	You Only Learn One Representation: Unified Network for Multiple Tasks			2021	single scale, YOLO
2	YOLOR-E6 (1280, single-scale, 37 fps)	56.4	74.1	61.6	39.1	60.1	68.2	×	You Only Learn One Representation: Unified Network for Multiple Tasks			2021	single scale, YOLO
3	YOLOv4-P7 with TTA	55.8	73.2	61.2				×	Scaled-YOLOv4: Scaling Cross Stage Partial Network			2020	multiscale, YOLO
4	YOLOR-W6 (1280, single-scale, 47 fps)	55.5	73.2	60.6	37.6	59.5	67.7	×	You Only Learn One Representation: Unified Network for Multiple Tasks			2021	single scale, YOLO
5	YOLOv4-P7 CSP-P7 (single-scale, 16 fps)	55.4	73.3	60.7	38.1	59.5	67.4	×	Scaled-YOLOv4: Scaling Cross Stage Partial Network			2020	single scale, YOLO

Top YOLO Variants Of 2021

https://medium.com/augmented-startups/top-yolo-variants-of-2021-19dddc23043c

YoloV5 (2020) → YoloV8 (2023)





English | 简体中文

Ultralytics CI passing | codecov 87% | DOI 10.5281/zenodo.7347926 | docker pulls 22k

Run on Gradient | Open in Colab | Open in Kaggle

Ultralytics YOLOv8 is a cutting-edge, state-of-the-art (SOTA) model that builds upon the success of previous YOLO versions and introduces new features and improvements to further boost performance and flexibility. YOLOv8 is designed to be fast, accurate, and easy to use, making it an excellent choice for a wide range of object detection and tracking, instance segmentation, image classification and pose estimation tasks.

We hope that the resources here will help you get the most out of YOLOv8. Please browse the YOLOv8 Docs for details, raise an issue on GitHub for support, and join our Discord community for questions and discussions!

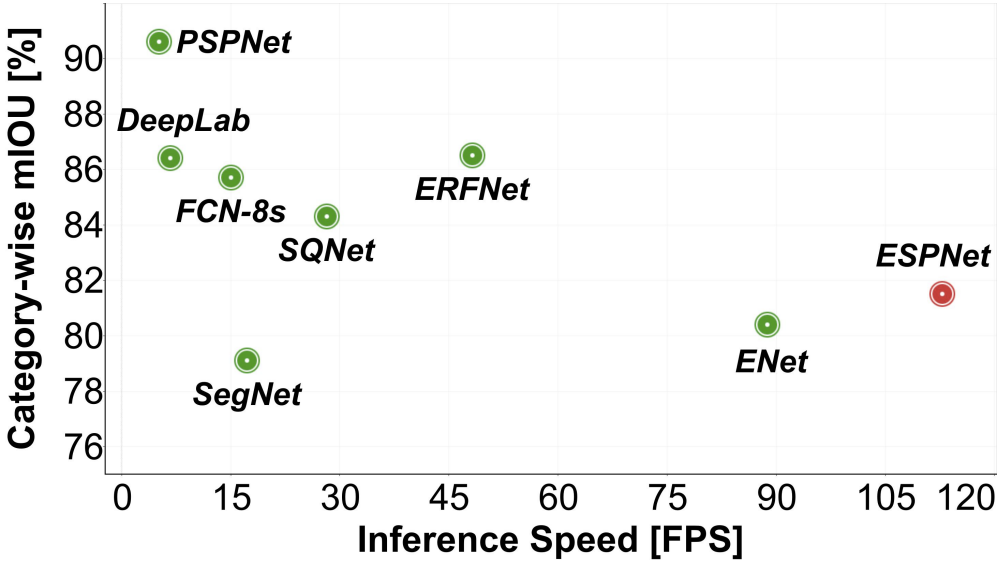
To request an Enterprise License please complete the form at Ultralytics Licensing.

Models

YOLOv8 Detect, Segment and Pose models pretrained on the COCO dataset are available here, as well as YOLOv8 Classify models pretrained on the ImageNet dataset. Track mode is available for all Detect, Segment and Pose models.

All Models download automatically from the latest Ultralytics release on first use.

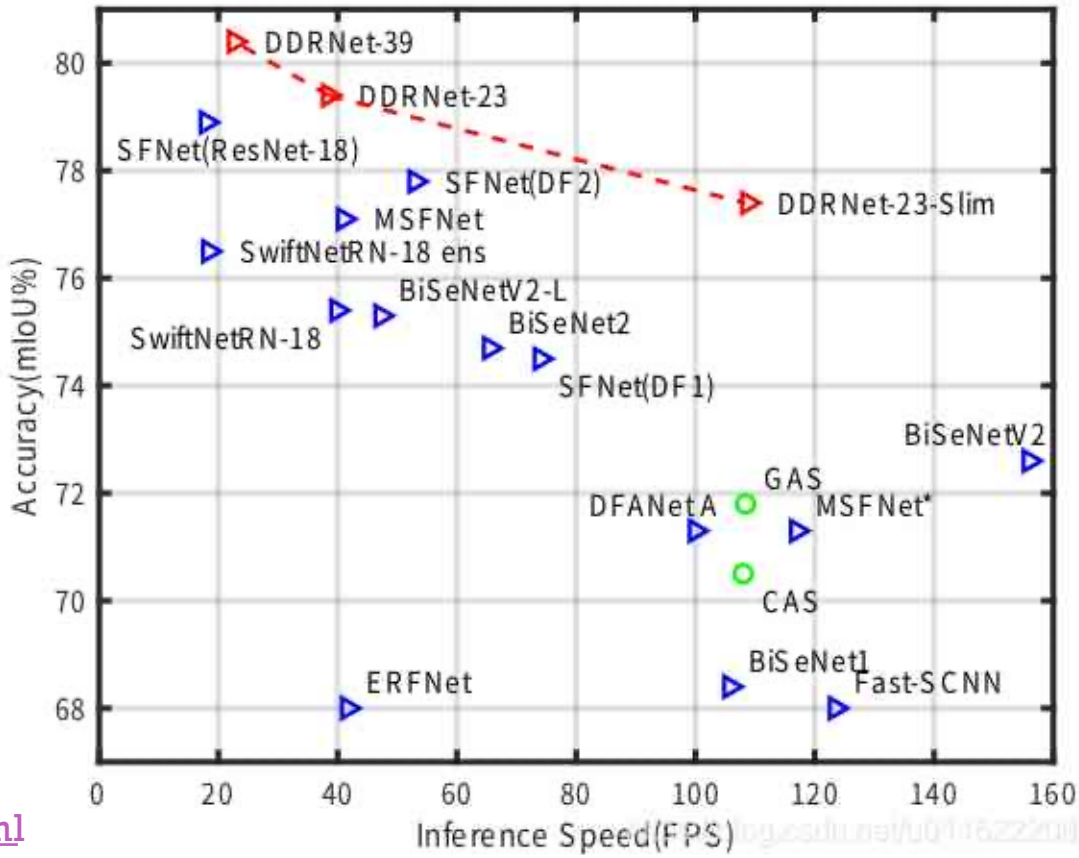
SOTA of Semantic Segmentation



- **Real-time semantic segmentation**
- BiSeNet V1,V2
- DDRNet

[Personal open source] - -
Real - time Semantic Segmentation ddrnet

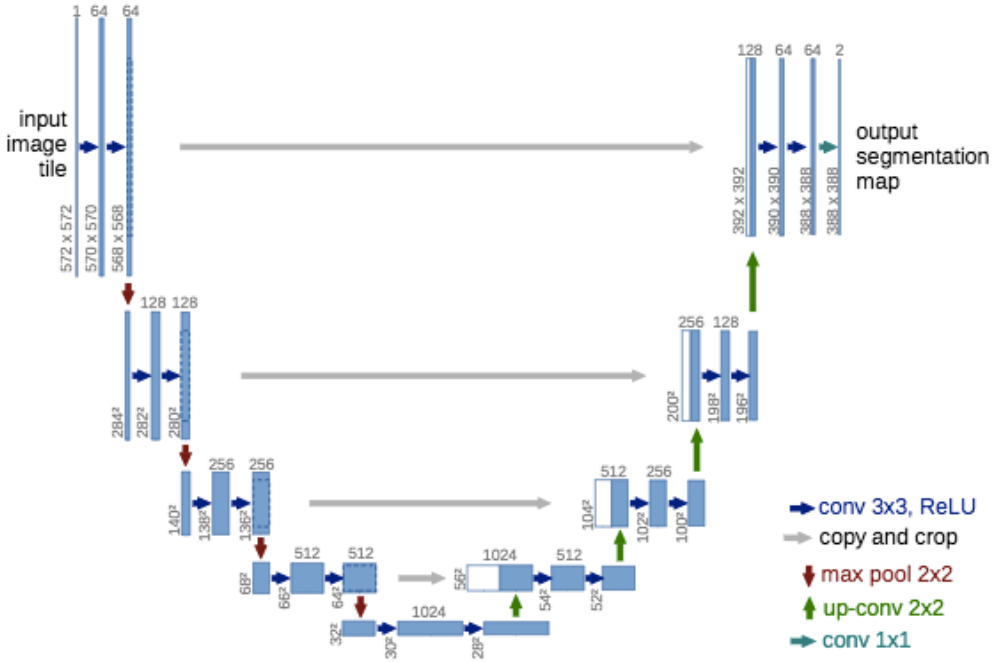
2021-11-09 04:24:01 【Nongfu Mountain Spring 2】

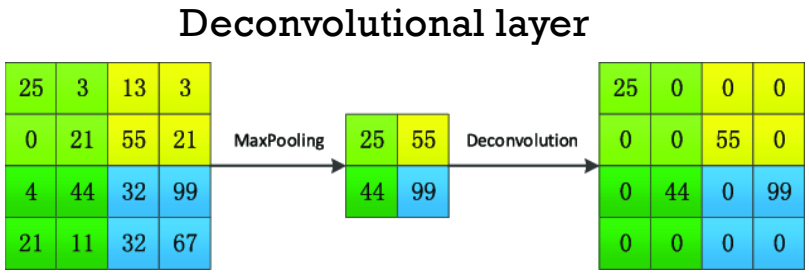


https://chowdera.com/2021/11/20211109042359120o.html

Review of Deep Learning Algorithms for Semantic Segmentation (cont.)

- **U-Net**





Architecture of the U-net for a given input image. The blue boxes correspond to feature maps blocks with their denoted shapes. The white boxes correspond to the copied and cropped feature maps.
Source: O. Ronneberger et al. (2015)

Semantic Segmentation

Easy to use and customizable SOTA Semantic Segmentation models with abundant datasets in PyTorch

Open in Colab

Supported Backbones:

- ResNet (CVPR 2016)
- ResNetD (ArXiv 2018)
- MobileNetV2 (CVPR 2018)
- MobileNetV3 (ICCV 2019)
- MiT (NeurIPS 2021)
- ResT (NeurIPS 2021)
- MicroNet (ICCV 2021)
- ResNet+ (ArXiv 2021)
- PVTv2 (CVMJ 2022)
- PoolFormer (CVPR 2022)
- ConvNeXt (CVPR 2022)
- UniFormer (ArXiv 2022)
- VAN (ArXiv 2022)
- DaViT (ArXiv 2022)

Supported Heads/Methods:

- FCN (CVPR 2015)
- UPerNet (ECCV 2018)
- BiSeNetv1 (ECCV 2018)
- FPN (CVPR 2019)
- SFNet (ECCV 2020)
- SegFormer (NeurIPS 2021)
- FaPN (ICCV 2021)
- CondNet (IEEE SPL 2021)
- Light-Ham (ICLR 2021)
- Lawin (ArXiv 2022)
- TopFormer (CVPR 2022)

Supported Standalone Models:

- BiSeNetv2 (IJCV 2021)
- DDRNet (ArXiv 2021)

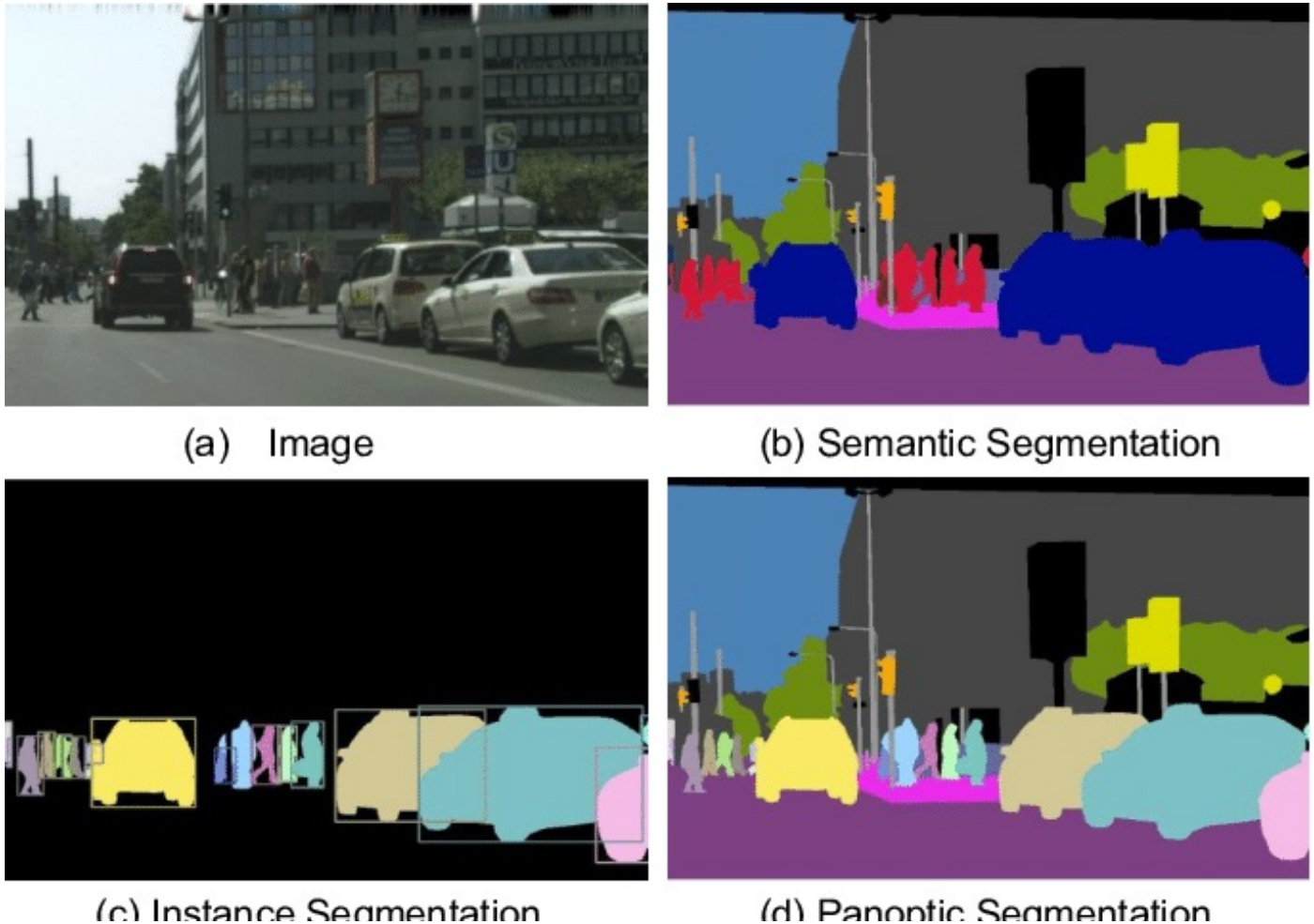
Supported Modules:

- PPM (CVPR 2017)
- PSA (ArXiv 2021)

Refer to MODELS for benchmarks and available pre-trained models.

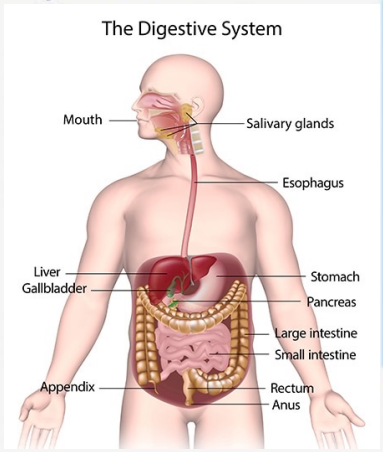
https://github.com/sithu31296/semantic-segmentation

Panoptic Segmentation



Real-Time Colonic Polyp Detection

An AI-assisted solution that aims to improve colonic polyp detection in real-time. It is compatible with all standard colonoscope systems.

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13:53:24
COLON
*1/200
Lv+2 AUTO
HT NR
SE
3.8
12.0
12.0
S1: F+T
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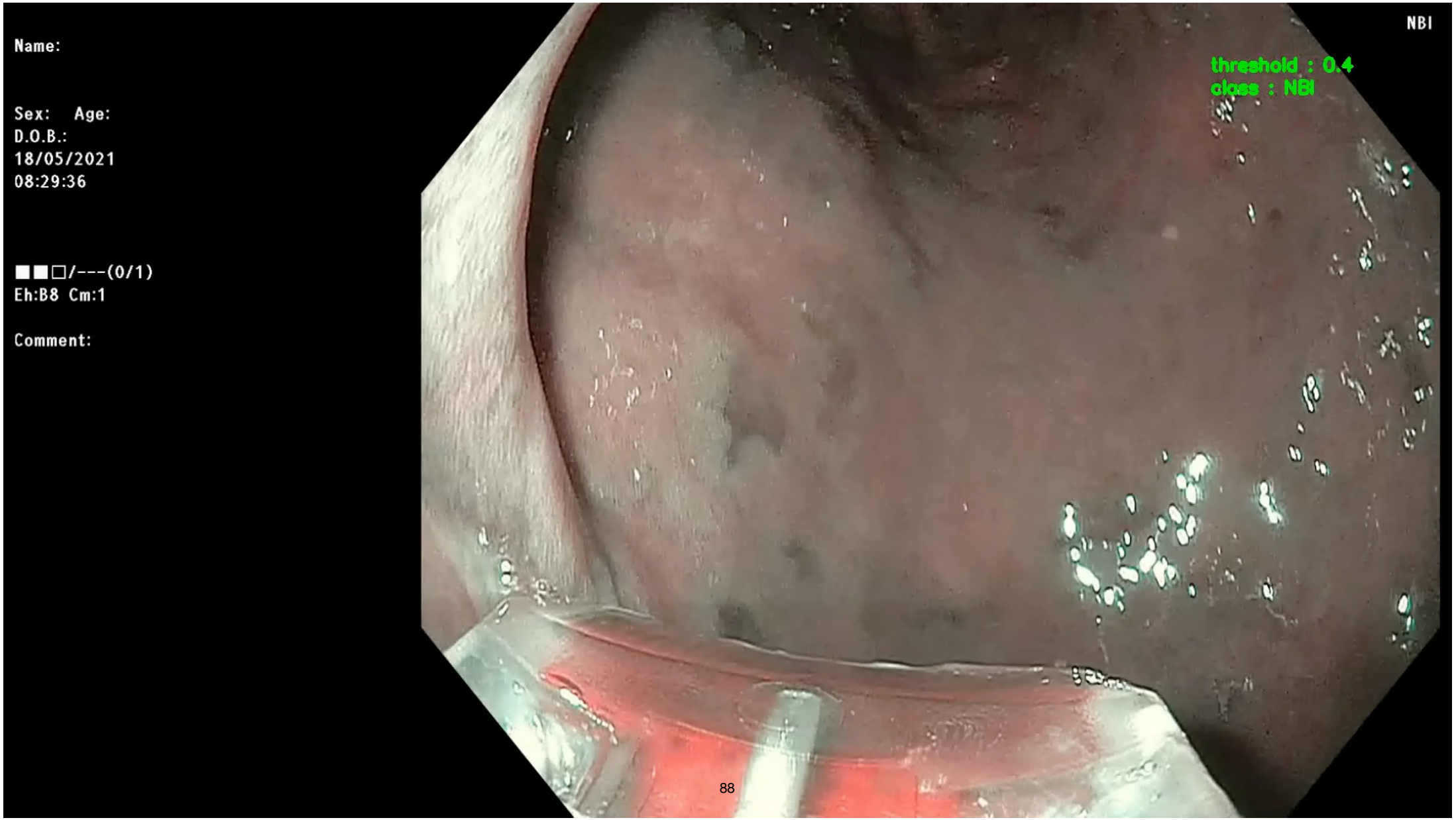
S3: CAD
S4:
EC-760R-V/L
3C729K035
BL-7000
CHULALONGKORN HOS
6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Eh:B8 Cm:1
Comment:
NBI
threshold : 0.4
class : NBI

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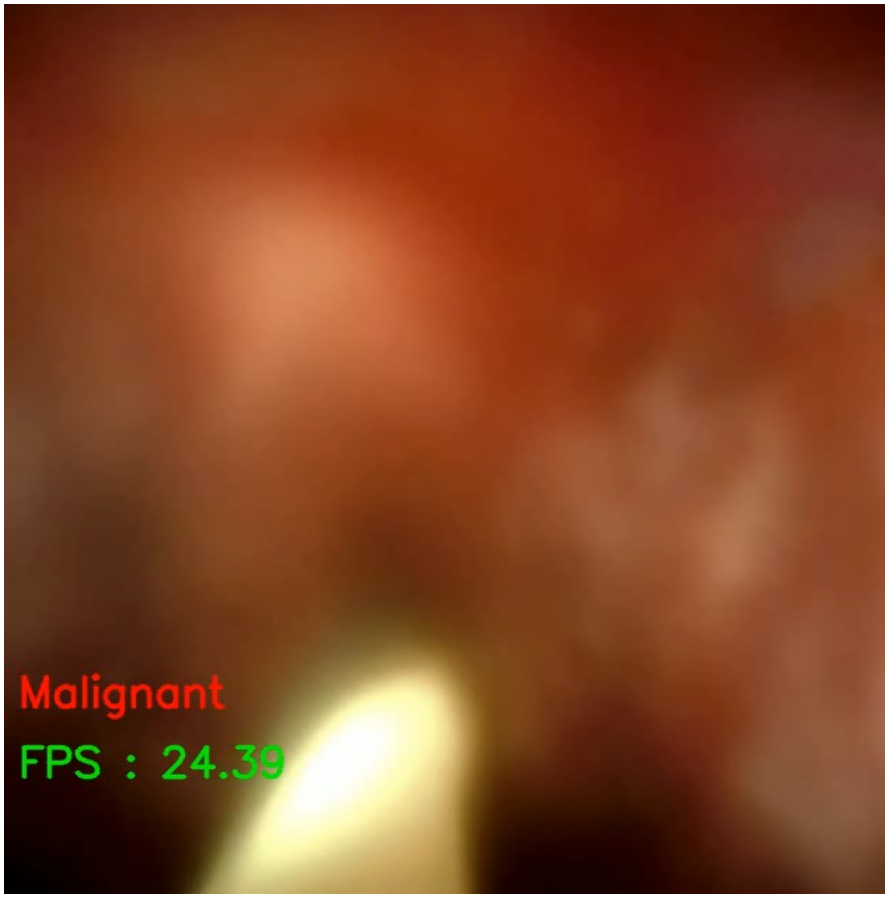
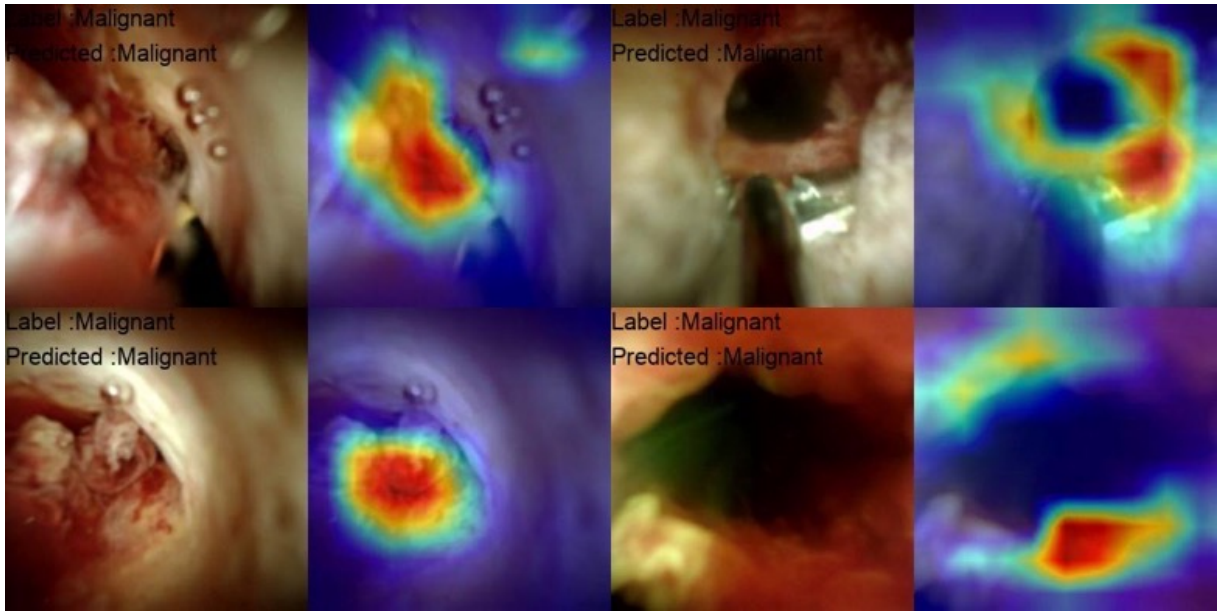


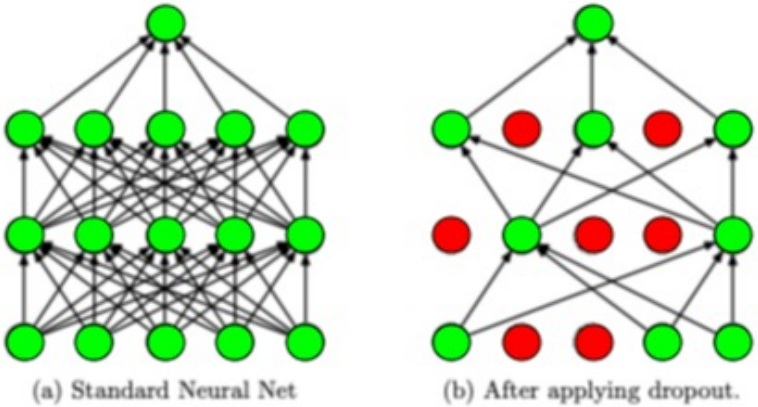


More techniques to prevent overfitting

- Dropout
- Augmentation
- Best validation loss

Droupout

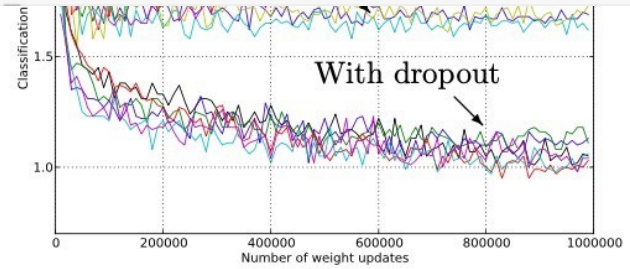
- The Dropout layer prevents overfitting the model during training. Notably, Dropout randomly deactivates some neurons of a layer, thus nullifying their contribution to the output.
- Dropout is only used in training, so we don't want these weights to be fixed at this high a number during testing.



(a) Standard Neural Net (b) After applying dropout.

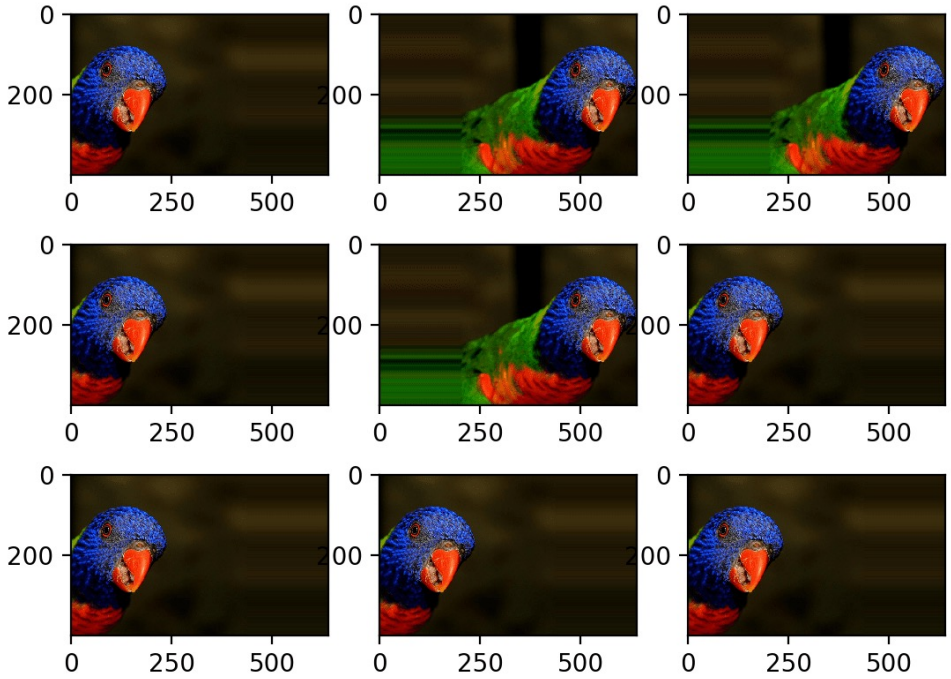
```
#create model
model = Sequential()
#add model layers
model.add(Conv2D(64, kernel_size=3, activation='relu', input_shape=(28,28,1)))
model.add(Conv2D(32, kernel_size=3, activation='relu'))
model.add(Dropout(.5, noise_shape=None, seed=None)) #dropout layer
model.add(Conv2D(32, kernel_size=3, activation='relu'))

model.add(Flatten())
model.add(Dense(10, activation='softmax'))
```

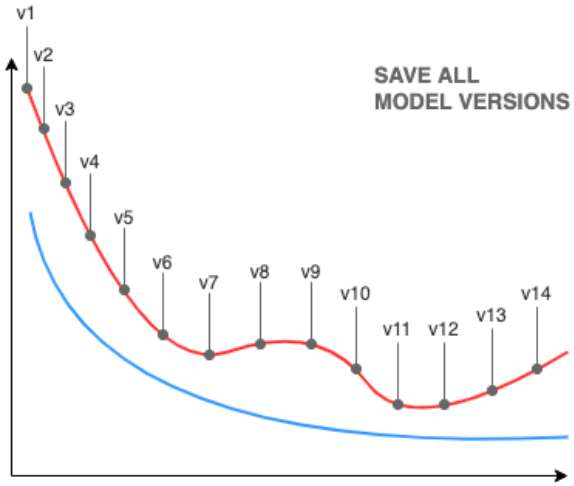


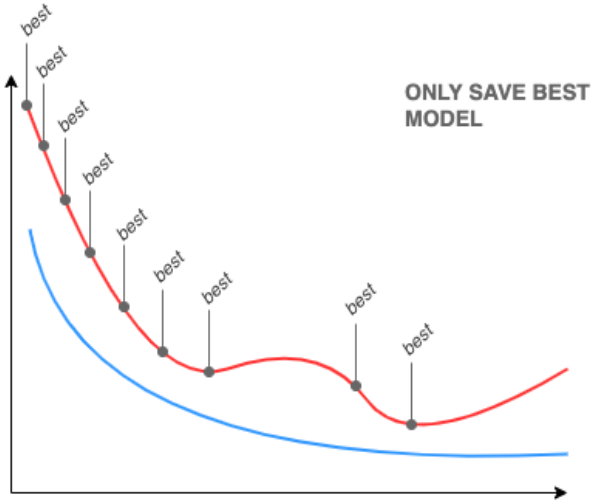
https://deepakbattini.medium.com/implementing-drop-out-regularization-in-neural-networks-ab2fc8d985e8

Augmentation



Best validation loss



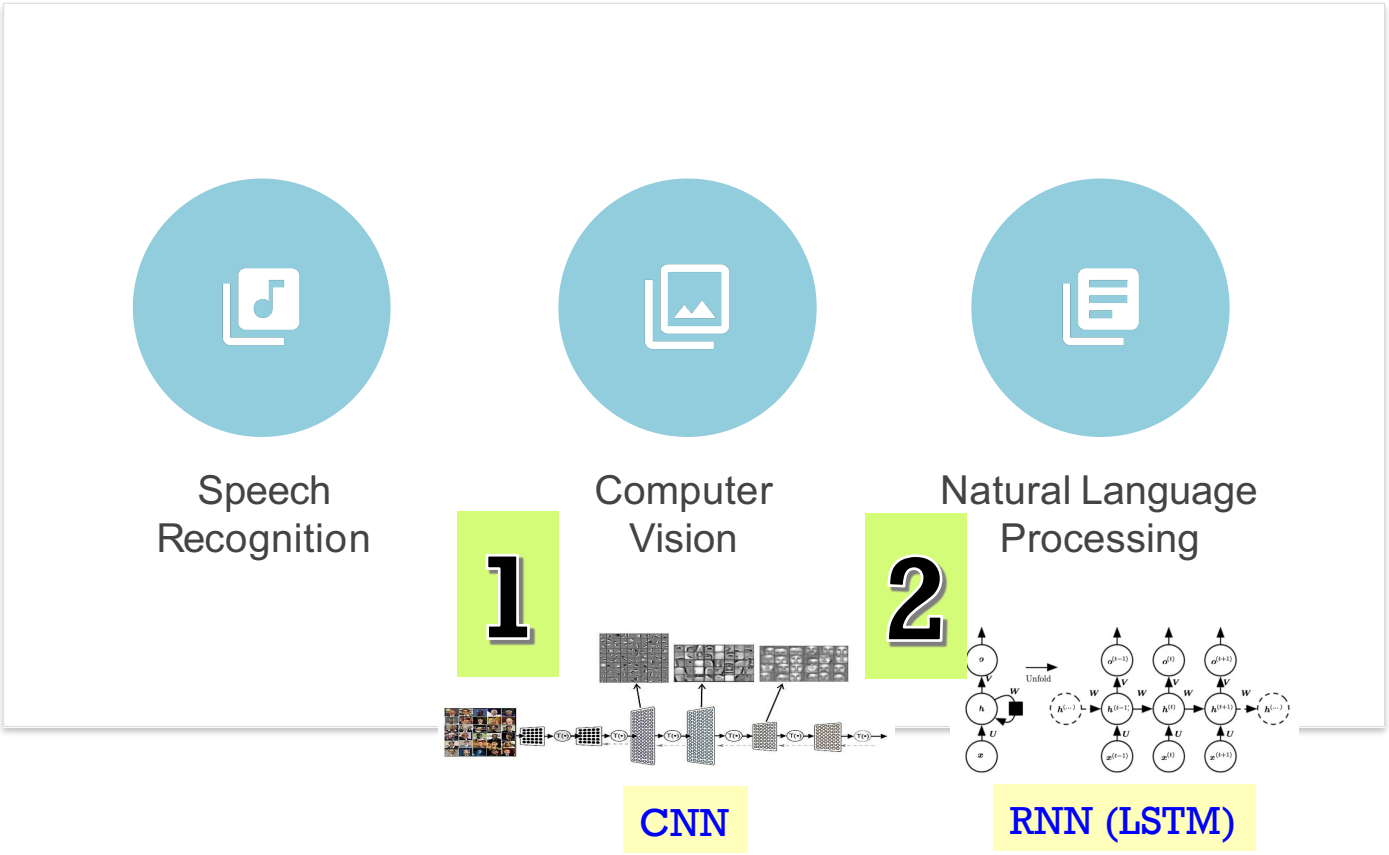


https://nicjac.dev/posts/identify-best-model/

+

RNN

Deep Learning Application



Top 10 Strategic Technology Trends for 2020

People-centric

- Hyperautomation
- Multiexperience
- Democratization
- Human Augmentation
- Transparency and Traceability

Smart spaces

- Empowered Edge
- Distributed Cloud
- Autonomous Things
- Practical Blockchain
- AI Security

gartner.com/SmarterWithGartner

Source: Gartner

Gartner

Gartner Top Strategic Technology Trends for 2021

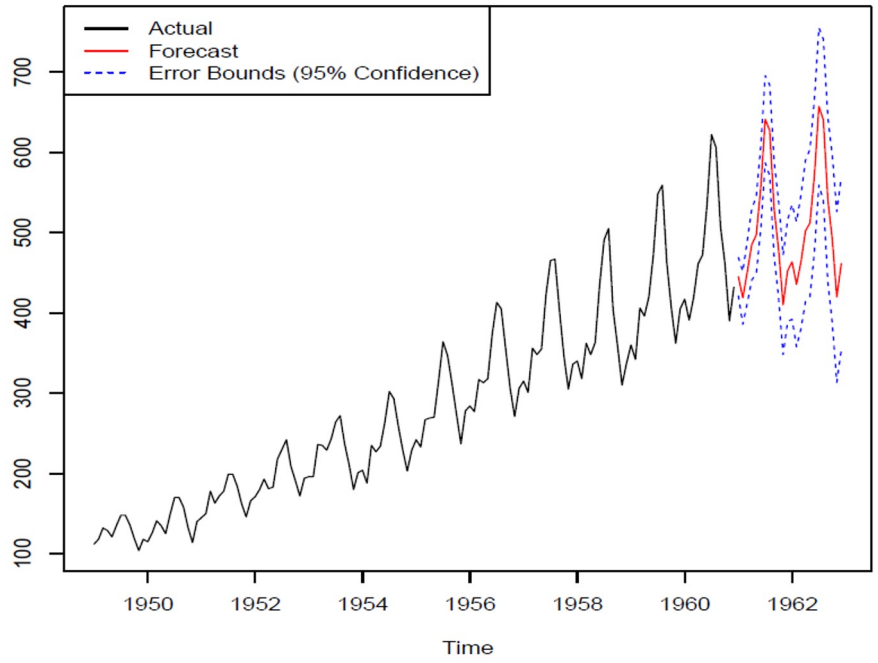
People centricity	Location independence	Resilient delivery
Internet of Behaviors	Distributed cloud	Intelligent composable business
Total experience strategy	Anywhere operations	AI engineering
Privacy-enhancing computing	Cybersecurity mesh	Hyperautomation

Combinatorial innovation

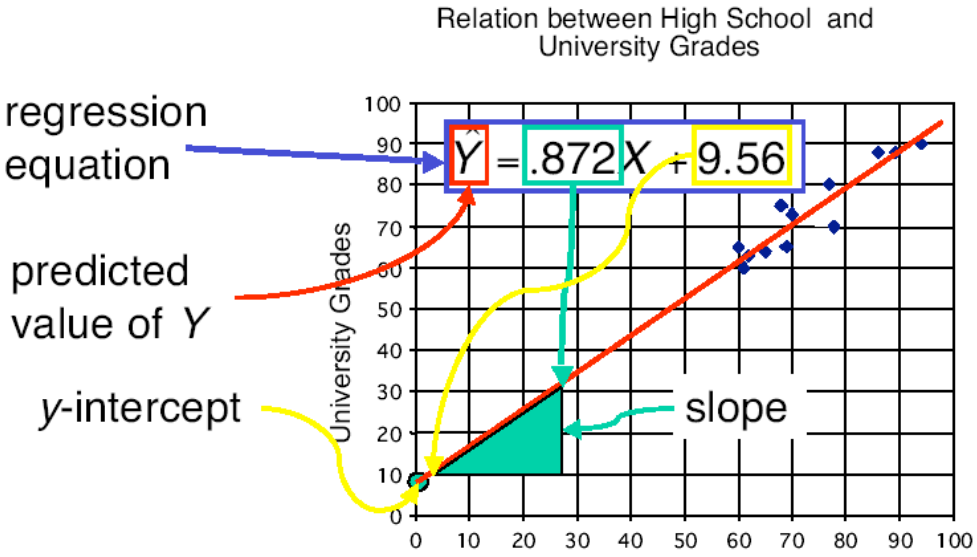
gartner.com/SmarterWithGartner

Source: Gartner

Gartner



Regression – Linear Relationship



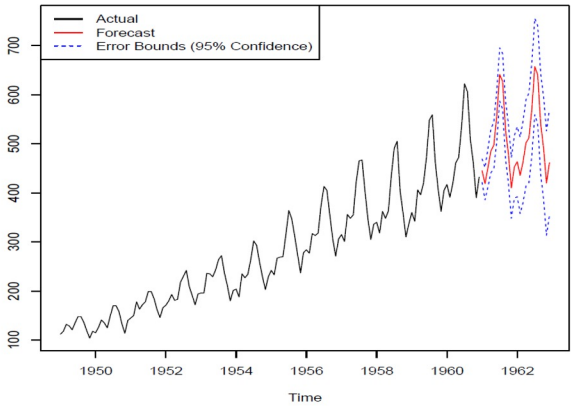
weight, coefficient

$$\underset{\text{target}}{\hat{y}} = \underset{\text{intercept}}{\hat{w}_0} + \hat{w}_1 x_1 + \hat{w}_2 x_2 \quad \text{input}$$

- **The least square method** aims to minimize the following term

$$\sum_{\substack{training \\ data}} (y_i - \hat{y}_i)^2$$

Autoregressive Model – Linear Relationship



- Based on linear regression, but using previous timestep data

$$X_t = c + \Sigma_{i=1}^{p} \varphi_i X_{t-i}$$

- Where X_t is data at timestep t, c is constant, and $\varphi_1, \varphi_2, \varphi_3, \ldots, \varphi_p$ are parameters for each timestep data

Example: When p = 2 (looking back two steps), the equation will be

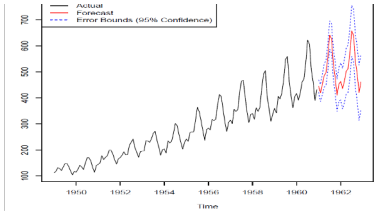
$$X_t = c + \varphi_1 X_{t-1} + \varphi_2 X_{t-2}$$

- Parameters are able to calculate using various method, such as ordinary least square procedure or Yule–Walker equations

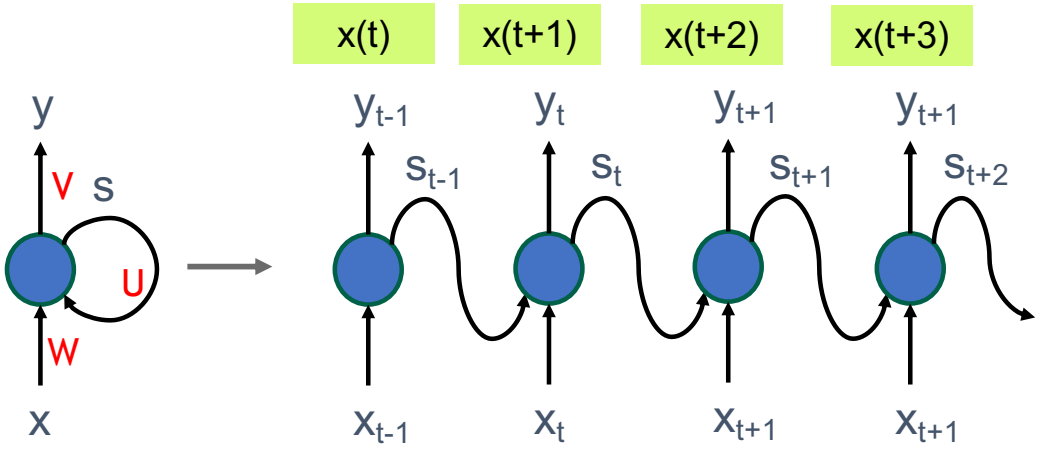
$$x(t+1) = \hat{w}_0 + \hat{w}_1 x(t) + \hat{w}_2 x(t-1)$$

RECURRENT NEURONS (RNN)

Non-Linear Relationship



Forward Pass



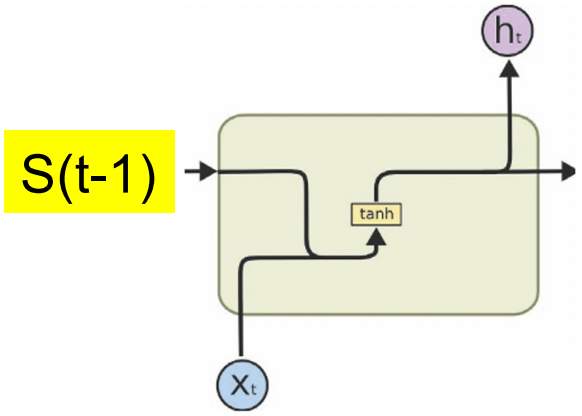
Unrolling in Time

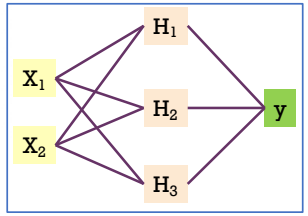
$$s_t = \tanh(Ux_t + Ws_{t-1})$$

x(t+1) $$\hat{y}_t = softmax(Vs_t)$$

x(t+1)

y(t)



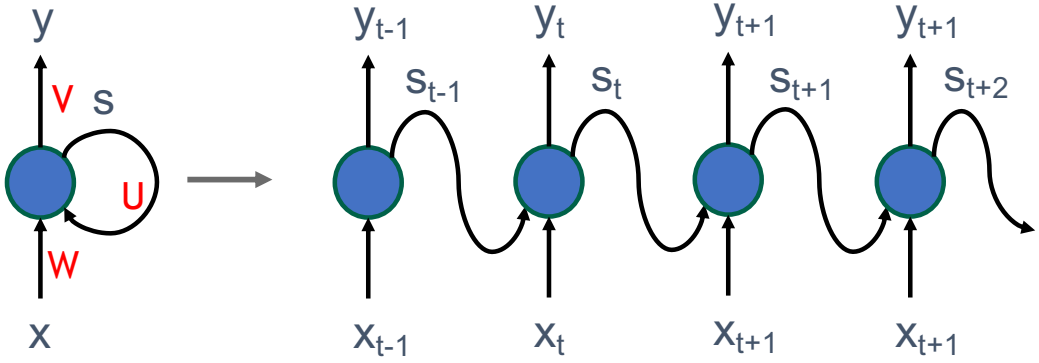


Reference: https://www.cse.iitk.ac.in/users/sigml/lec/Slides/LSTM.pdf

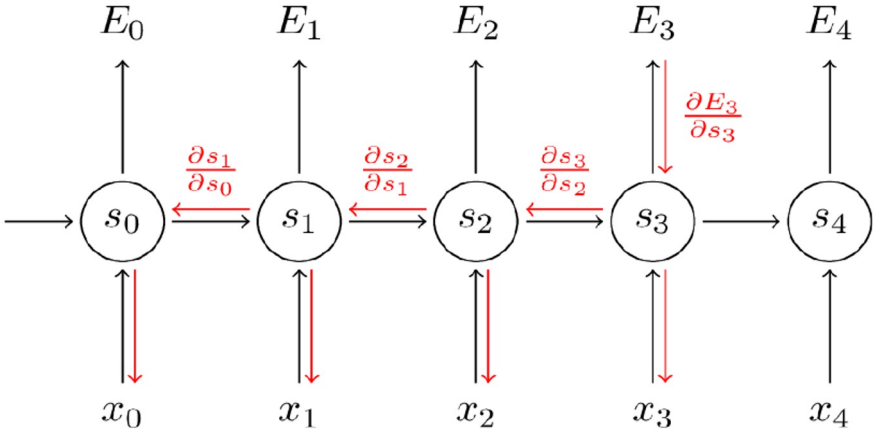
RECURRENT NEURONS (RNN)

Ggradient vanishing
= multiplication

Forward Pass



Backward Pass

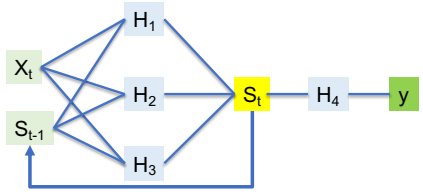


Unrolling in Time

Backpropagation-Through-Time (BPTT)

$$s_t = \tanh\left(Ux_t + Ws_{t-1}\right)$$

$$\hat{y}_t = softmax\left(Vs_t\right)$$

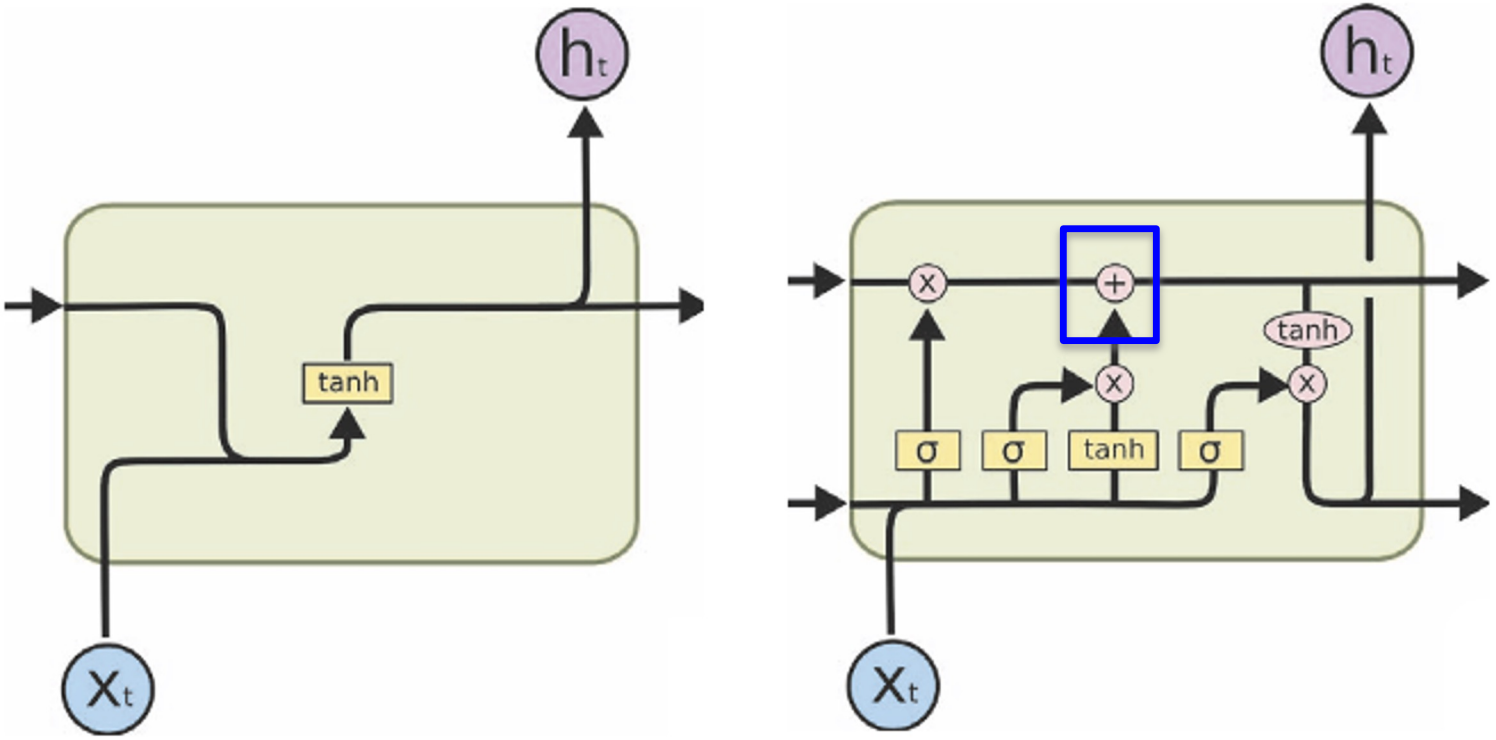


$$\frac{\partial E}{\partial W} = \sum_t \frac{\partial E_t}{\partial W}$$

$$\frac{\partial E_3}{\partial W} = \sum_{k=0}^{3} \frac{\partial E_3}{\partial \hat{y}_3} \frac{\partial \hat{y}_3}{\partial s_3} \frac{\partial s_3}{\partial s_k} \frac{\partial s_k}{\partial W}$$

Reference: https://www.cse.iitk.ac.in/users/sigml/lec/Slides/LSTM.pdf

RNN VS LSTM

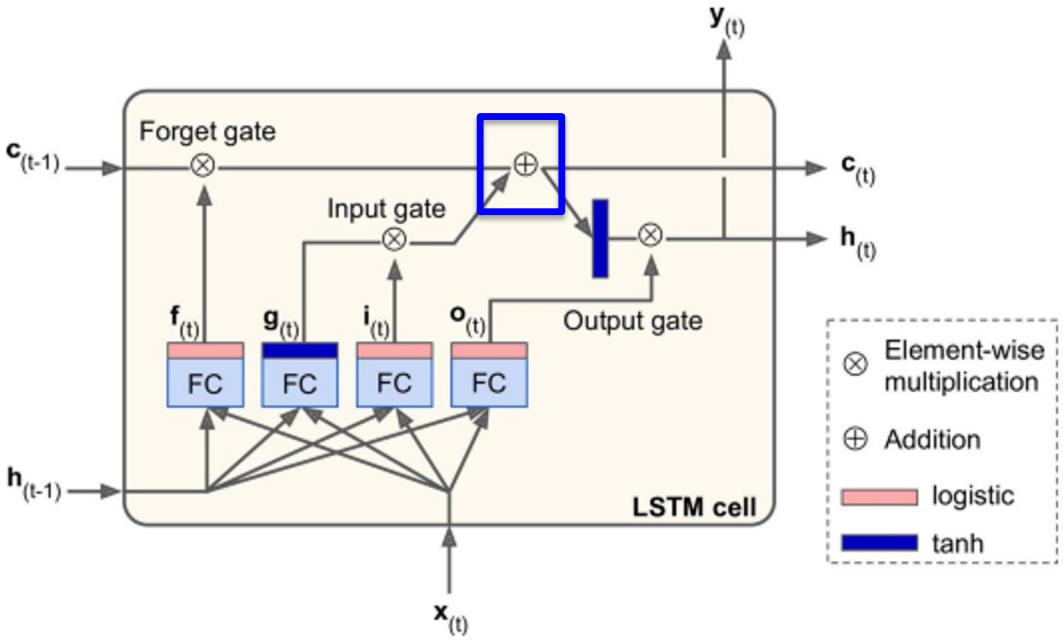


(a) RNN

(b) LSTM

Reference: https://cs.uwaterloo.ca/~mli/Deep-Learning-2017-Lecture6RNN.ppt

LONG SHORT TERM (LSTM) CELL



There are 3 gates with 2 outputs.

$$\mathbf{i}_{(t)} = \sigma(\mathbf{W}_{xi}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hi}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_i)$$

$$\mathbf{f}_{(t)} = \sigma(\mathbf{W}_{xf}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hf}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_f)$$

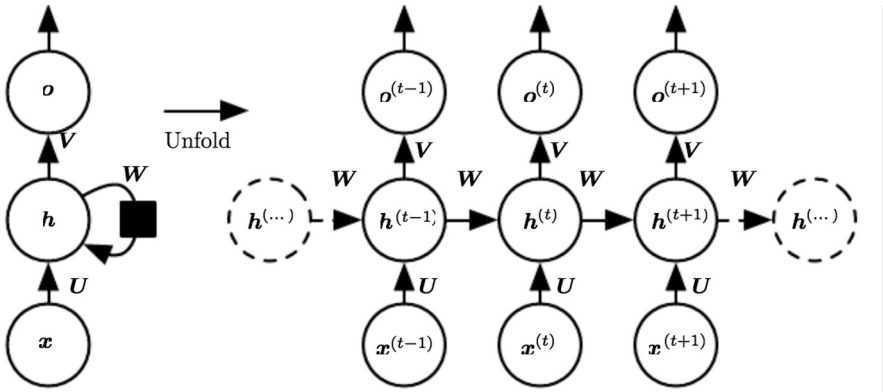
$$\mathbf{o}_{(t)} = \sigma(\mathbf{W}_{xo}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{ho}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_o)$$

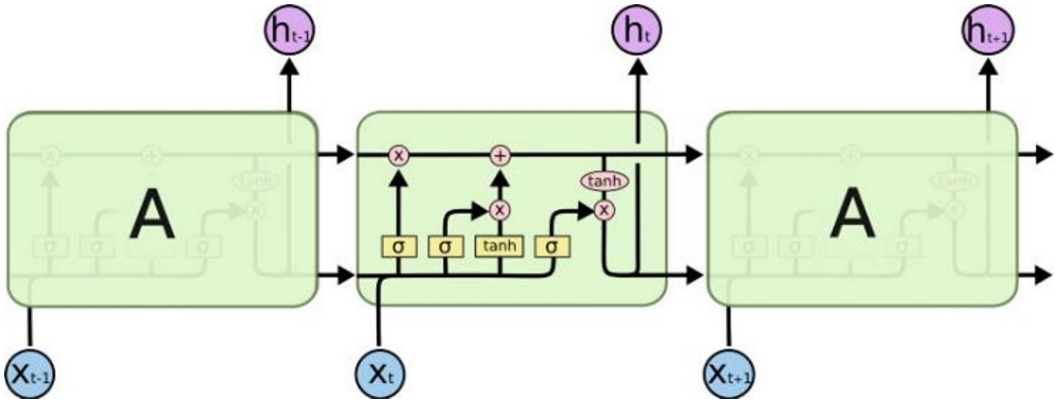
$$\mathbf{g}_{(t)} = \tanh(\mathbf{W}_{xg}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hg}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_g)$$

$$\mathbf{c}_{(t)} = \mathbf{f}_{(t)} \otimes \mathbf{c}_{(t-1)} + \mathbf{i}_{(t)} \otimes \mathbf{g}_{(t)}$$

$$\mathbf{y}_{(t)} = \mathbf{h}_{(t)} = \mathbf{o}_{(t)} \otimes \tanh(\mathbf{c}_{(t)})$$

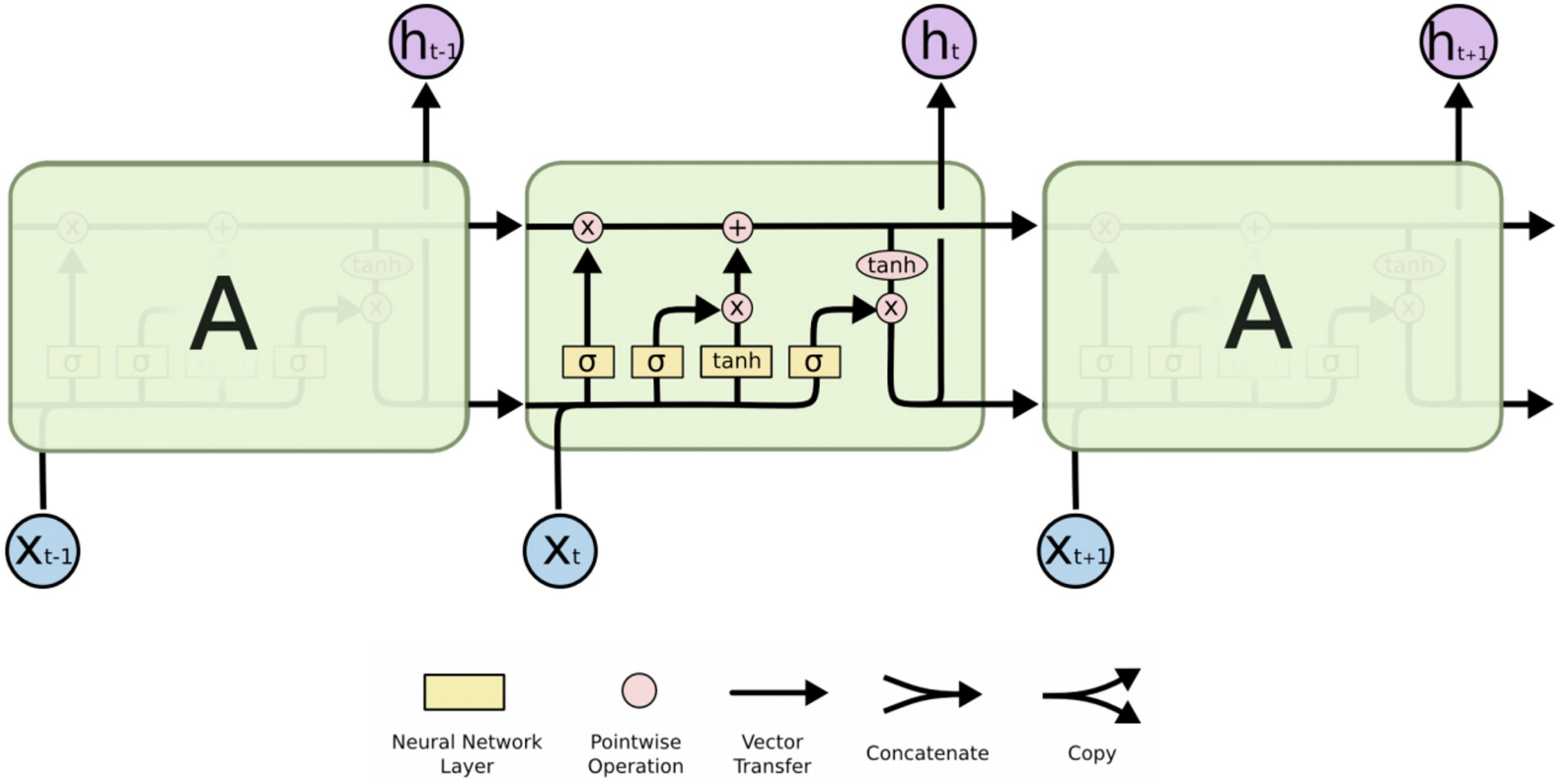
Deep Learning Approach: LSTM



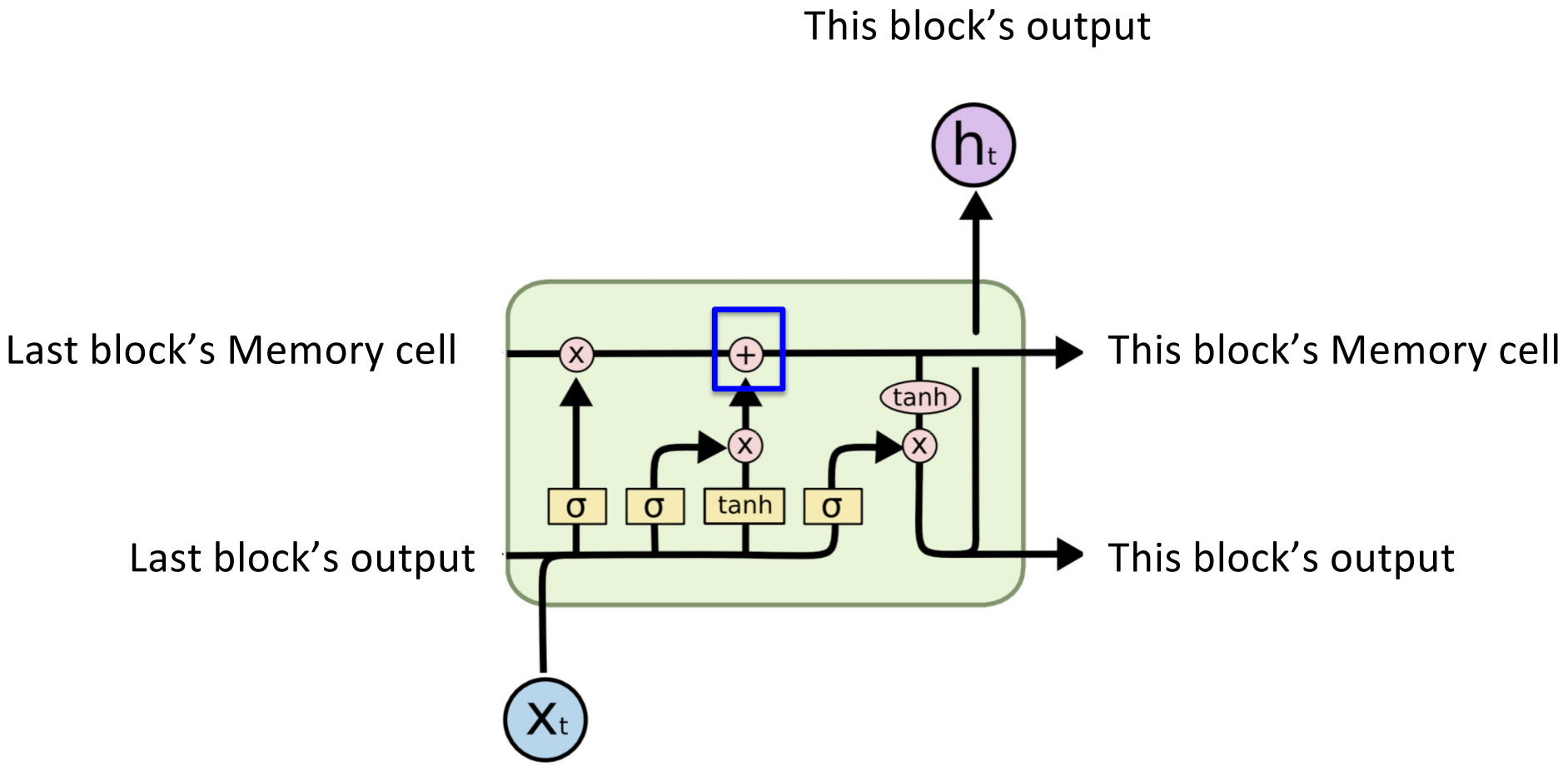


Reference: Ian Goodfellow, Yoshua Bengio, and Aaron Courville. 2016. Deep Learning. MIT Press.
http://www.deeplearningbook.org

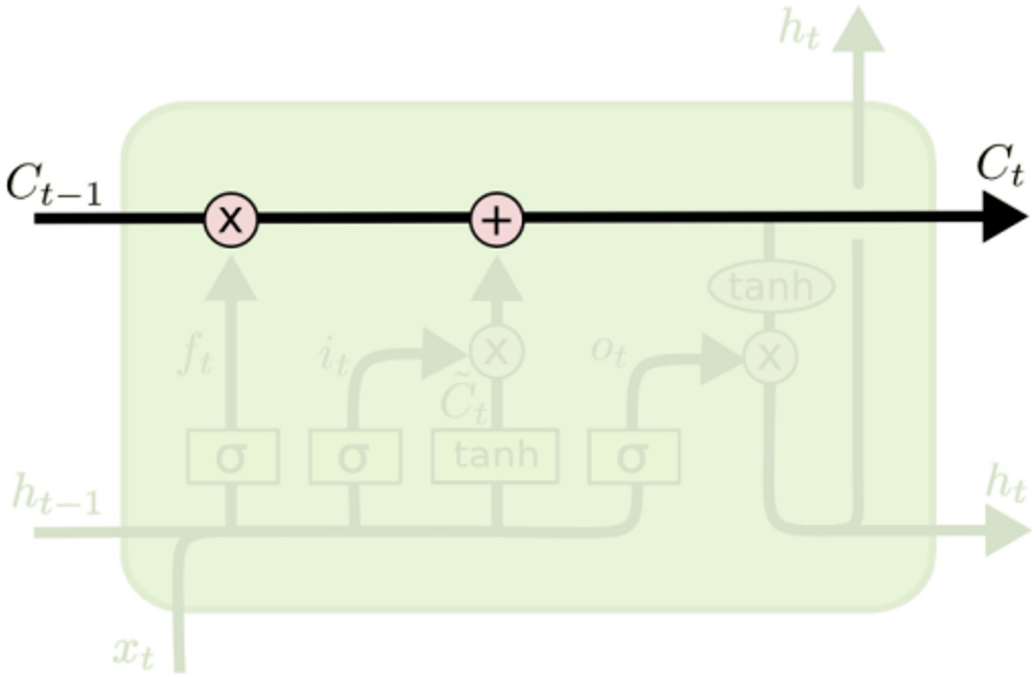
Inside LSTM

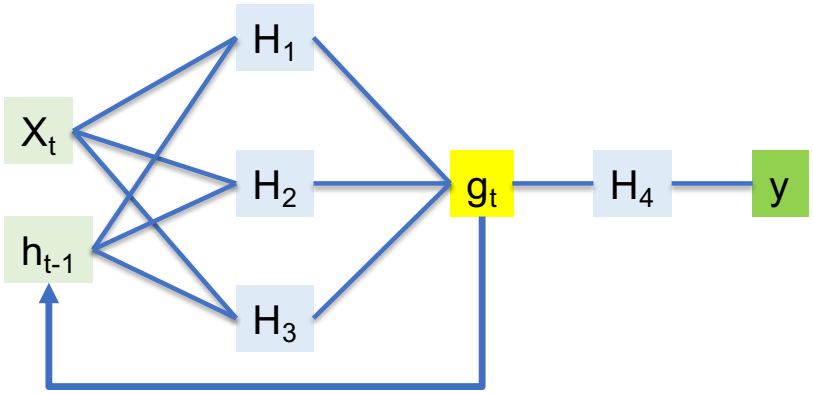

h_{t-1}
h_t
h_{t+1}
A
A
tanh
σ
σ
tanh
σ
X_{t-1}
X_t
X_{t+1}
Neural Network Layer
Pointwise Operation
Vector Transfer
Concatenate
Copy

Inside LSTM


This block's output
h_t
Last block's Memory cell
This block's Memory cell
tanh
σ
σ
tanh
σ
Last block's output
This block's output
X_t

Inside LSTM: (1) Cell Memory





There are 3 gates with 2 outputs.

$$\mathbf{i}_{(t)} = \sigma(\mathbf{W}_{xi}{}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hi}{}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_i)$$

$$\mathbf{f}_{(t)} = \sigma(\mathbf{W}_{xf}{}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hf}{}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_f)$$

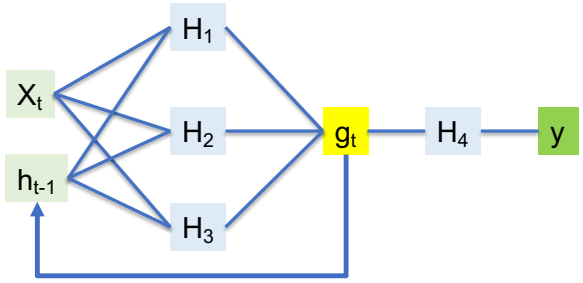
$$\mathbf{o}_{(t)} = \sigma(\mathbf{W}_{xo}{}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{ho}{}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_o)$$

$$\mathbf{g}_{(t)} = \tanh(\mathbf{W}_{xg}{}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hg}{}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_g)$$

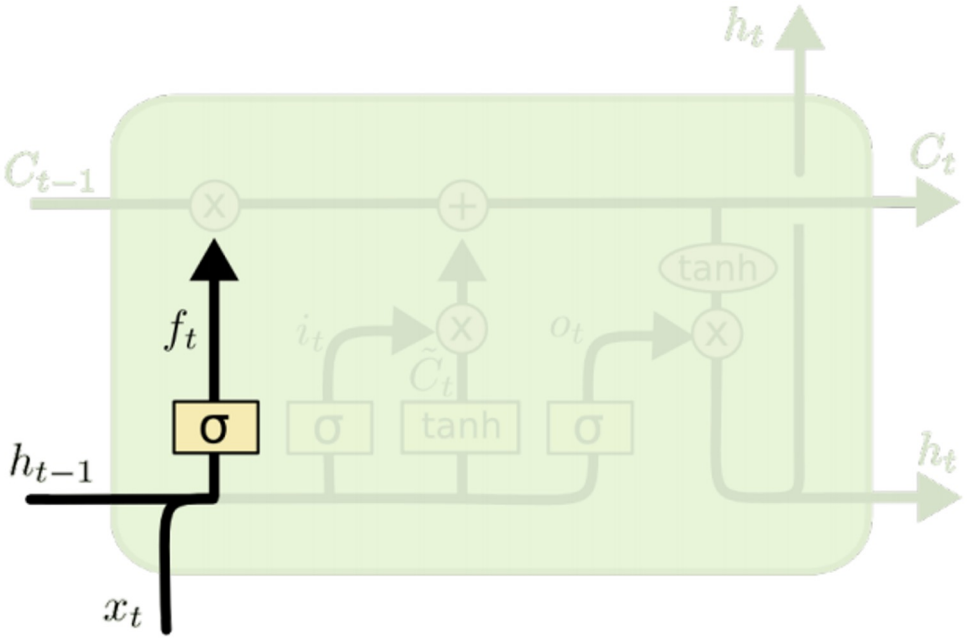
$$\mathbf{c}_{(t)} = \mathbf{f}_{(t)} \otimes \mathbf{c}_{(t-1)} + \mathbf{i}_{(t)} \otimes \mathbf{g}_{(t)}$$

$$\mathbf{y}_{(t)} = \mathbf{h}_{(t)} = \mathbf{o}_{(t)} \otimes \tanh(\mathbf{c}_{(t)})$$

Inside LSTM: (2) Forget Gate



Should we continue to remember this "bit" of information or not?



There are 3 gates with 2 outputs.

$$\mathbf{i}_{(t)} = \sigma(\mathbf{W}_{xi}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hi}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_i)$$

$$\mathbf{f}_{(t)} = \sigma(\mathbf{W}_{xf}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hf}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_f)$$

$$\mathbf{o}_{(t)} = \sigma(\mathbf{W}_{xo}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{ho}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_o)$$

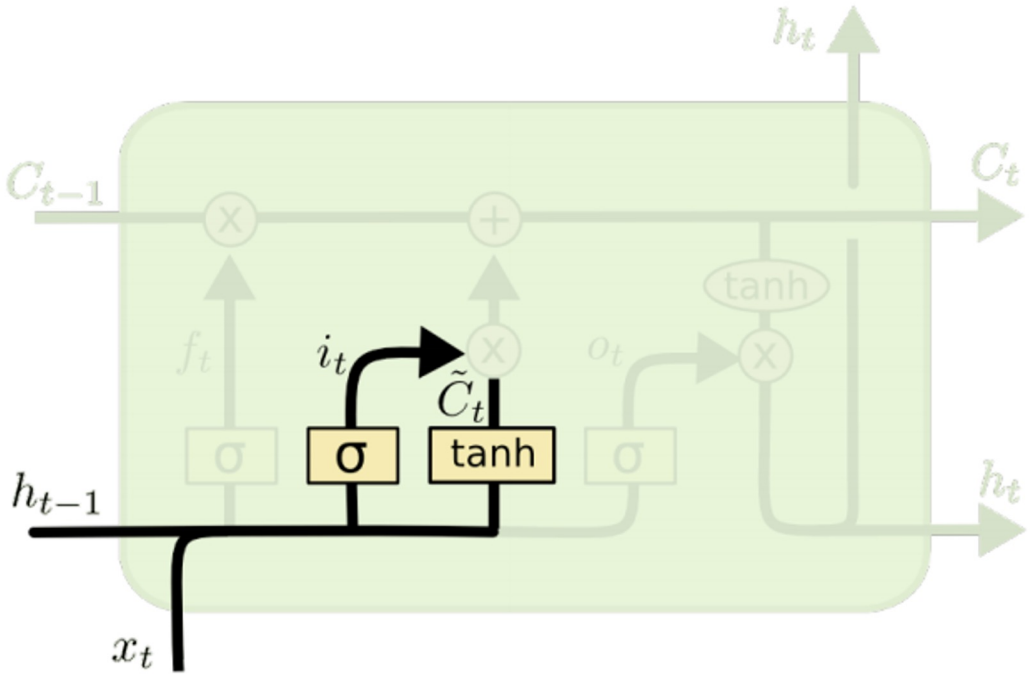
$$\mathbf{g}_{(t)} = \tanh(\mathbf{W}_{xg}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hg}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_g)$$

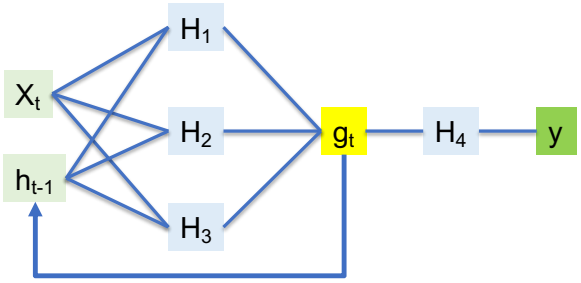
$$\mathbf{c}_{(t)} = \mathbf{f}_{(t)} \otimes \mathbf{c}_{(t-1)} + \mathbf{i}_{(t)} \otimes \mathbf{g}_{(t)}$$

$$\mathbf{y}_{(t)} = \mathbf{h}_{(t)} = \mathbf{o}_{(t)} \otimes \tanh(\mathbf{c}_{(t)})$$

Inside LSTM: (3) Input Gate

Should we update this “bit” of information or not?
If yes, then what should we remember?





There are 3 gates with 2 outputs.

$$\mathbf{i}_{(t)} = \sigma(\mathbf{W}_{xi}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hi}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_i)$$

$$\mathbf{f}_{(t)} = \sigma(\mathbf{W}_{xf}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hf}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_f)$$

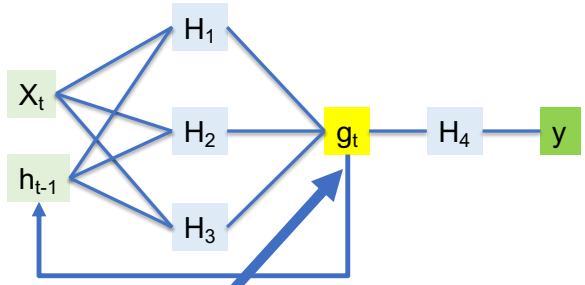
$$\mathbf{o}_{(t)} = \sigma(\mathbf{W}_{xo}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{ho}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_o)$$

$$\mathbf{g}_{(t)} = \tanh(\mathbf{W}_{xg}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hg}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_g)$$

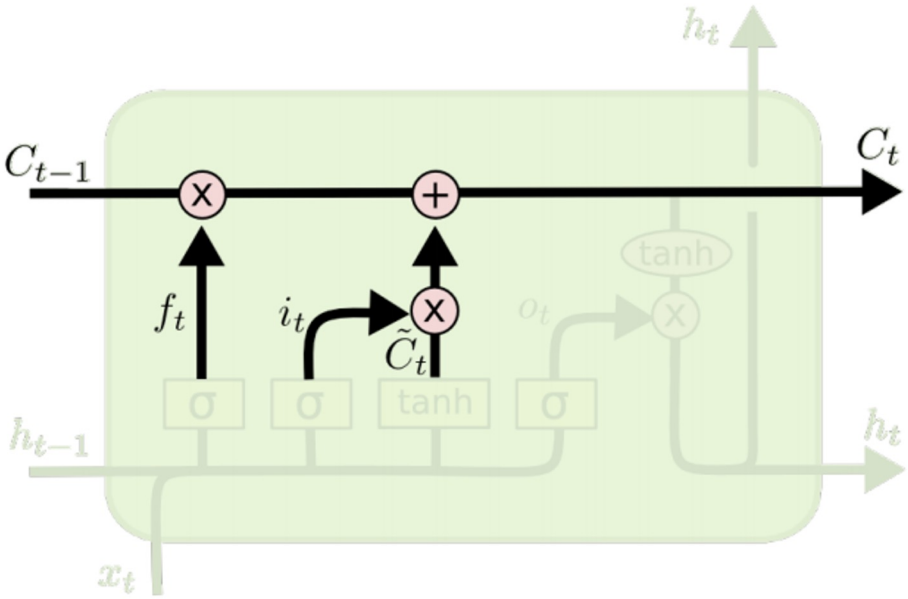
$$\mathbf{c}_{(t)} = \mathbf{f}_{(t)} \otimes \mathbf{c}_{(t-1)} + \mathbf{i}_{(t)} \otimes \mathbf{g}_{(t)}$$

$$\mathbf{y}_{(t)} = \mathbf{h}_{(t)} = \mathbf{o}_{(t)} \otimes \tanh(\mathbf{c}_{(t)})$$

Inside LSTM: (4) Memory Update



Forget what needs to be forgotten + memorize what needs to be remembered



There are 3 gates with 2 outputs.

$$\mathbf{i}_{(t)} = \sigma(\mathbf{W}_{xi}^T \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hi}^T \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_i)$$

$$\mathbf{f}_{(t)} = \sigma(\mathbf{W}_{xf}^T \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hf}^T \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_f)$$

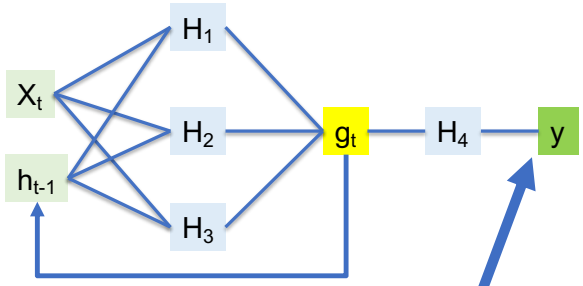
$$\mathbf{o}_{(t)} = \sigma(\mathbf{W}_{xo}^T \cdot \mathbf{x}_{(t)} + \mathbf{W}_{ho}^T \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_o)$$

$$\mathbf{g}_{(t)} = \tanh(\mathbf{W}_{xg}^T \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hg}^T \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_g)$$

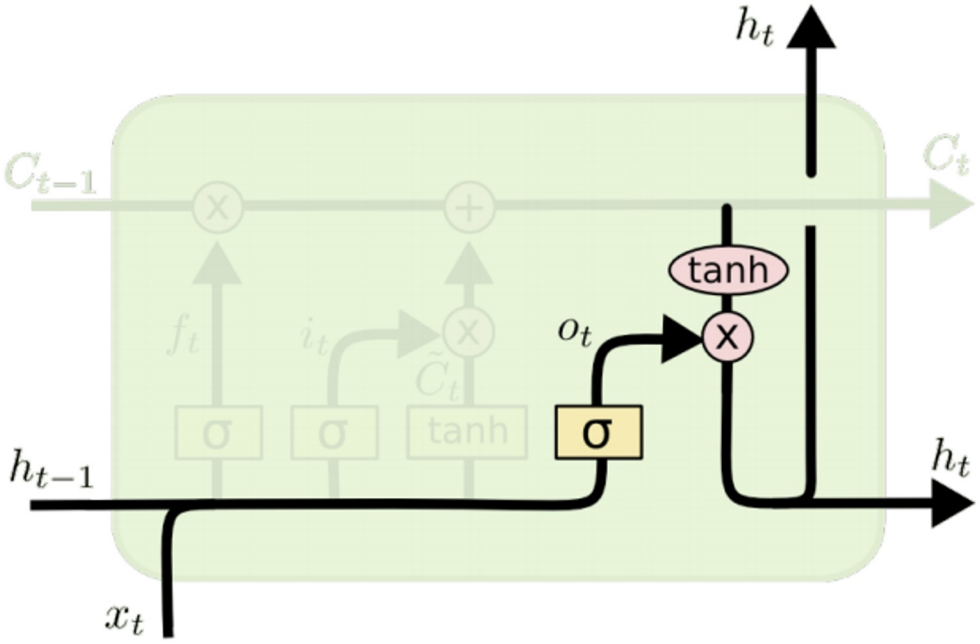
$$\mathbf{c}_{(t)} = \mathbf{f}_{(t)} \otimes \mathbf{c}_{(t-1)} + \mathbf{i}_{(t)} \otimes \mathbf{g}_{(t)}$$

$$\mathbf{y}_{(t)} = \mathbf{h}_{(t)} = \mathbf{o}_{(t)} \otimes \tanh(\mathbf{c}_{(t)})$$

Inside LSTM: Output Gate



Should we output this bit of information (e.g., to “deeper” LSTM layers)?



There are 3 gates with 2 outputs.

$$\mathbf{i}_{(t)} = \sigma(\mathbf{W}_{xi}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hi}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_i)$$

$$\mathbf{f}_{(t)} = \sigma(\mathbf{W}_{xf}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hf}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_f)$$

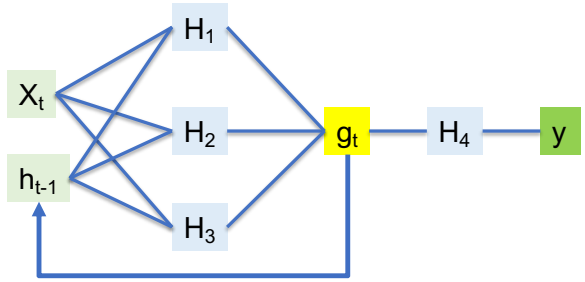
$$\mathbf{o}_{(t)} = \sigma(\mathbf{W}_{xo}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{ho}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_o)$$

$$\mathbf{g}_{(t)} = \tanh(\mathbf{W}_{xg}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hg}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_g)$$

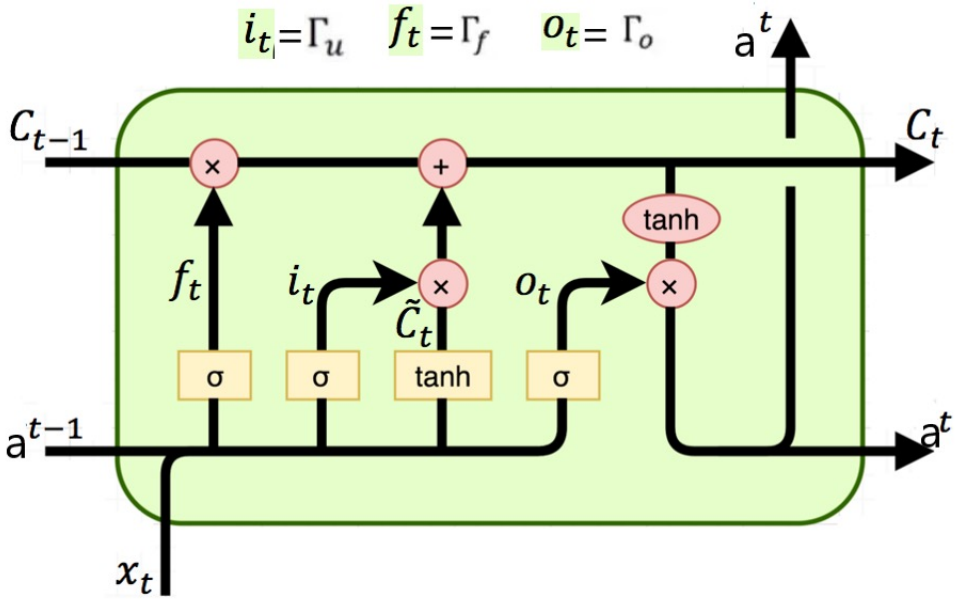
$$\mathbf{c}_{(t)} = \mathbf{f}_{(t)} \otimes \mathbf{c}_{(t-1)} + \mathbf{i}_{(t)} \otimes \mathbf{g}_{(t)}$$

$$\mathbf{y}_{(t)} = \mathbf{h}_{(t)} = \mathbf{o}_{(t)} \otimes \tanh(\mathbf{c}_{(t)})$$

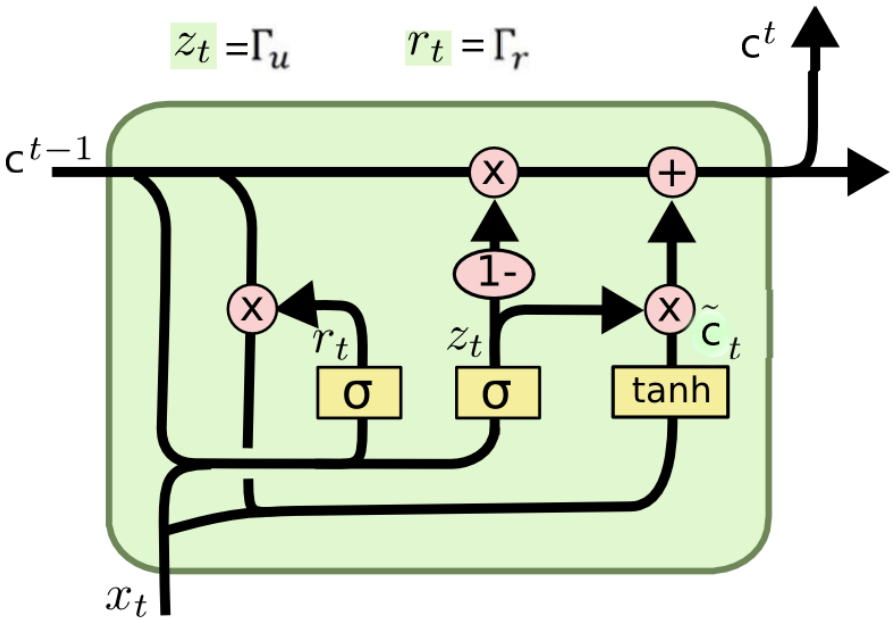
LSTM vs. Gated Recurrent Units (GRU)



There are 3 gates with 2 outputs.
3 inputs (x(t), C(t-1), a(t-1))

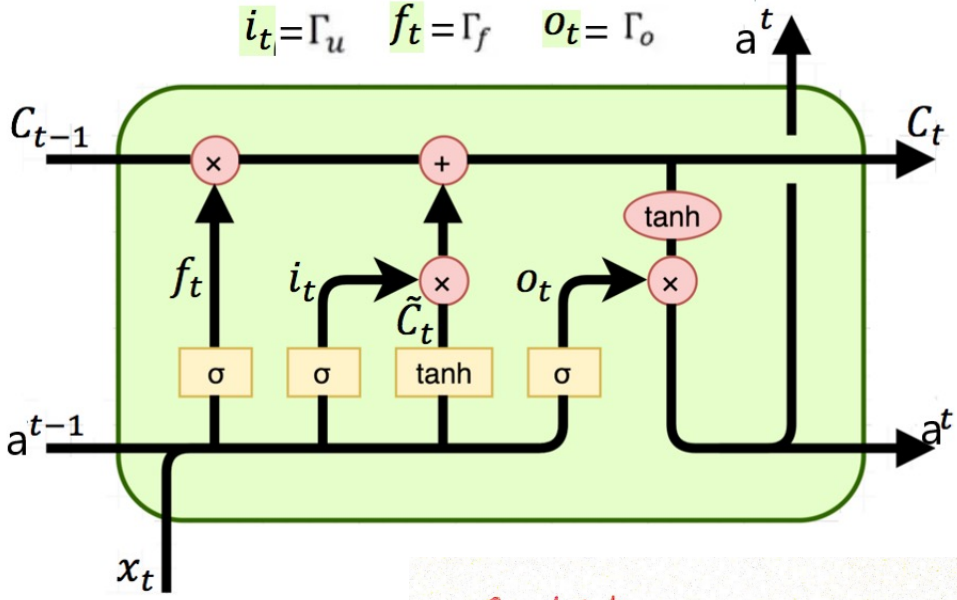


- There are 2 gates (update & reset gates)
- 1 output
- 2 inputs (x(t), C(t-1), ~~a(t-1)~~)



https://medium.com/analytics-vidhya/rnn-vs-gru-vs-lstm-863b0b7b1573

There are 3 gates with 2 outputs.



$$\mathbf{i}_{(t)} = \sigma(\mathbf{W}_{xi}{}^T \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hi}{}^T \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_i)$$
$$\mathbf{f}_{(t)} = \sigma(\mathbf{W}_{xf}{}^T \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hf}{}^T \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_f)$$
$$\mathbf{o}_{(t)} = \sigma(\mathbf{W}_{xo}{}^T \cdot \mathbf{x}_{(t)} + \mathbf{W}_{ho}{}^T \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_o)$$
$$\mathbf{g}_{(t)} = \tanh(\mathbf{W}_{xg}{}^T \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hg}{}^T \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_g)$$
$$\mathbf{c}_{(t)} = \mathbf{f}_{(t)} \otimes \mathbf{c}_{(t-1)} + \mathbf{i}_{(t)} \otimes \mathbf{g}_{(t)}$$
$$\mathbf{y}_{(t)} = \mathbf{h}_{(t)} = \mathbf{o}_{(t)} \otimes \tanh(\mathbf{c}_{(t)})$$

g(t) Candidate cell → $\tilde{c}^{\langle t \rangle} = \tanh(W_c[a^{\langle t-1 \rangle} + x^{\langle t \rangle}] + b_c)$

i(t) Update / Input gate → $\Gamma_u = \sigma(W_u[a^{\langle t-1 \rangle} + x^{\langle t \rangle}] + b_u)$

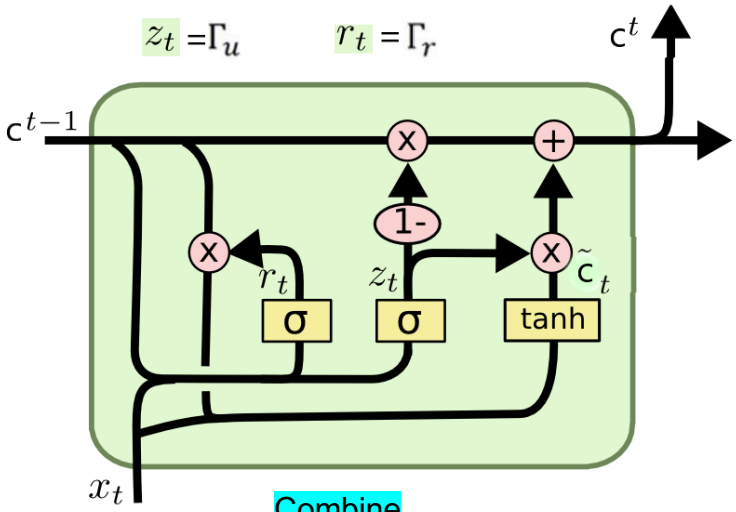
f(t) Forget gate → $\Gamma_f = \sigma(W_f[a^{\langle t-1 \rangle} + x^{\langle t \rangle}] + b_f)$

o(t) Output gate → $\Gamma_o = \sigma(W_o[a^{\langle t-1 \rangle} + x^{\langle t \rangle}] + b_o)$

C(t) Cell state → $c^{\langle t \rangle} = \Gamma_u * \tilde{c}^{\langle t \rangle} + \Gamma_f * c^{\langle t-1 \rangle}$

y(t) Activation → $a^{\langle t \rangle} = \Gamma_o * \tanh c^{\langle t \rangle}$

- There are 2 gates (update & reset gates)
- 1 output
- 2 inputs (x(t), C(t-1), ~~a(t-1)~~)



Combine
- Previous → how much to reset C(t-1)
- Current [x(t)]

g(t) Candidate cell → $\tilde{c}^{\langle t \rangle} = \tanh(W_c[\Gamma_r * c^{\langle t-1 \rangle} + x^{\langle t \rangle}] + b_c)$

i(t) Update gate → $\Gamma_u = \sigma(W_u[c^{\langle t-1 \rangle} + x^{\langle t \rangle}] + b_u)$

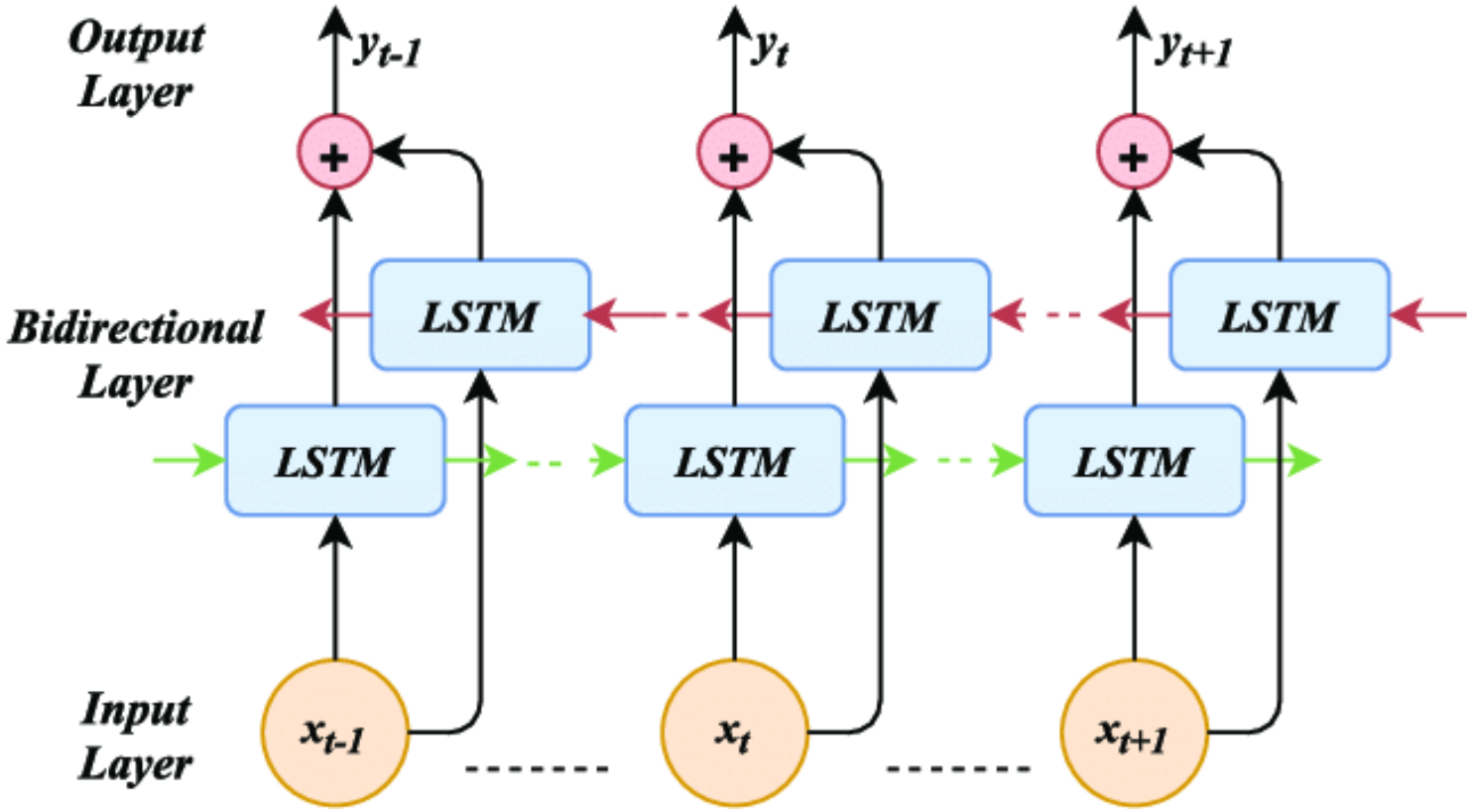
f(t) Reset gate → $\Gamma_r = \sigma(W_r[c^{\langle t-1 \rangle} + x^{\langle t \rangle}] + b_r)$

C(t) Cell state → $c^{\langle t \rangle} = \Gamma_u * \tilde{c}^{\langle t \rangle} + (1 - \Gamma_u) * c^{\langle t-1 \rangle}$

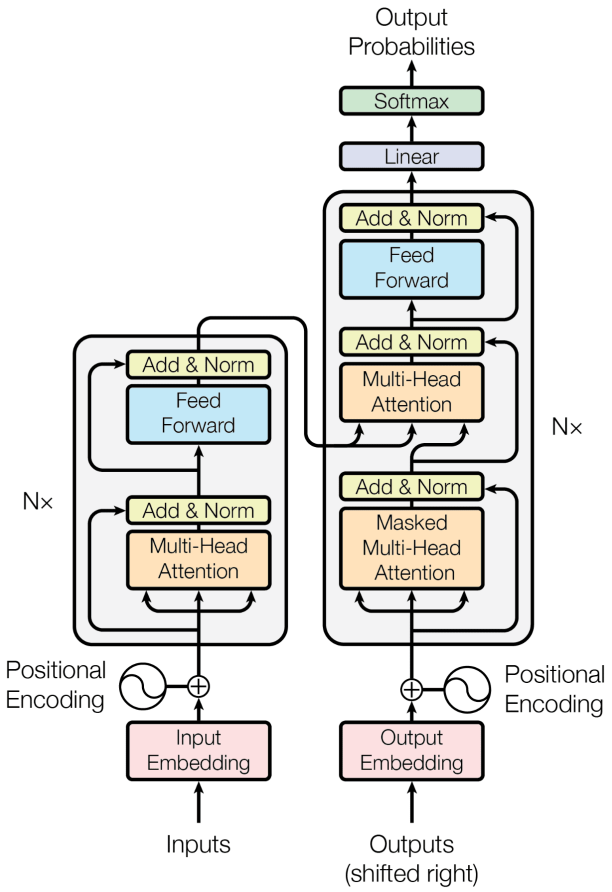
y(t) Activation / Output → $a^{\langle t \rangle} = c^{\langle t \rangle}$

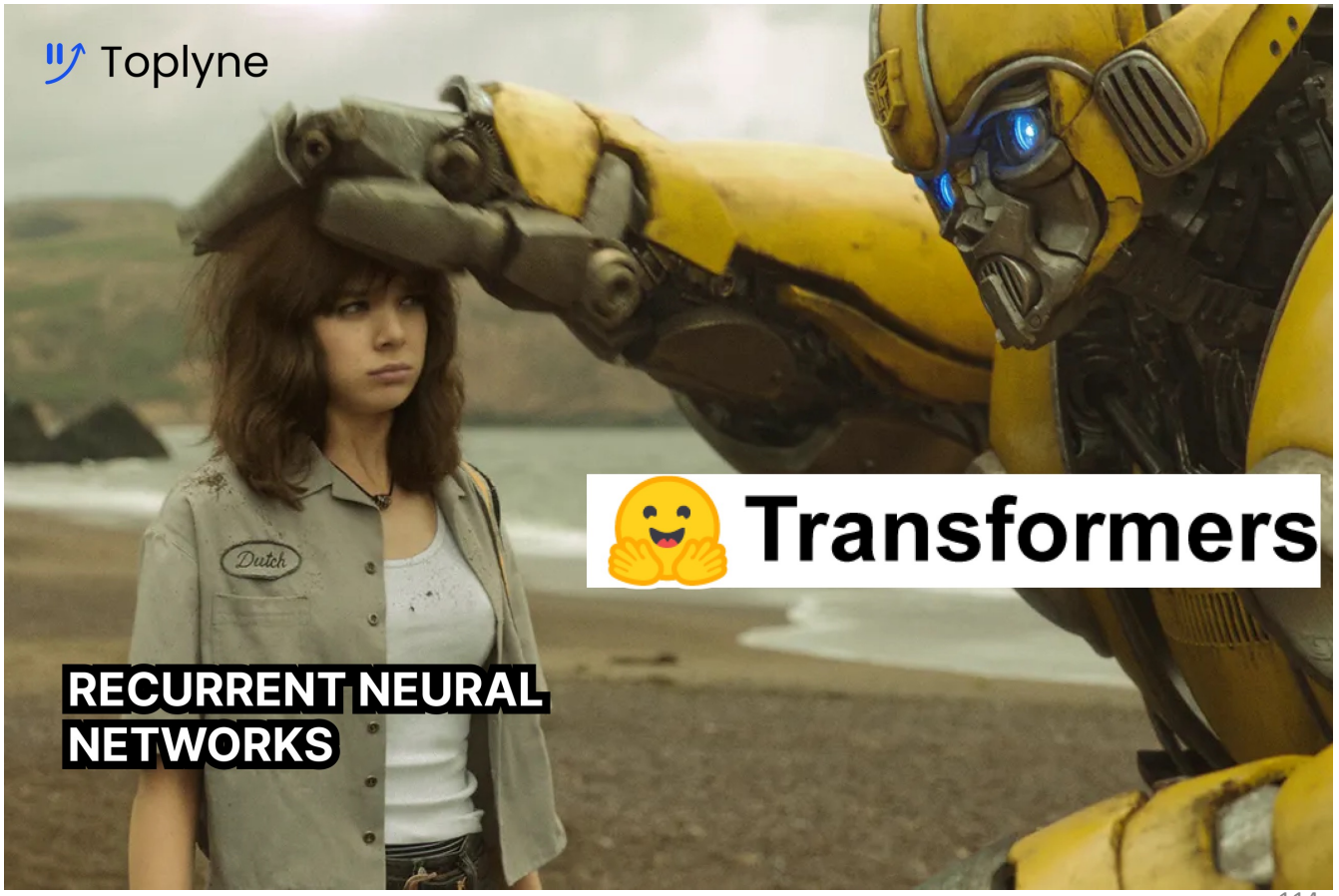
Update g(t) & C(t-1)

Bidirectional LSTM



Rise of Transformer (2017)



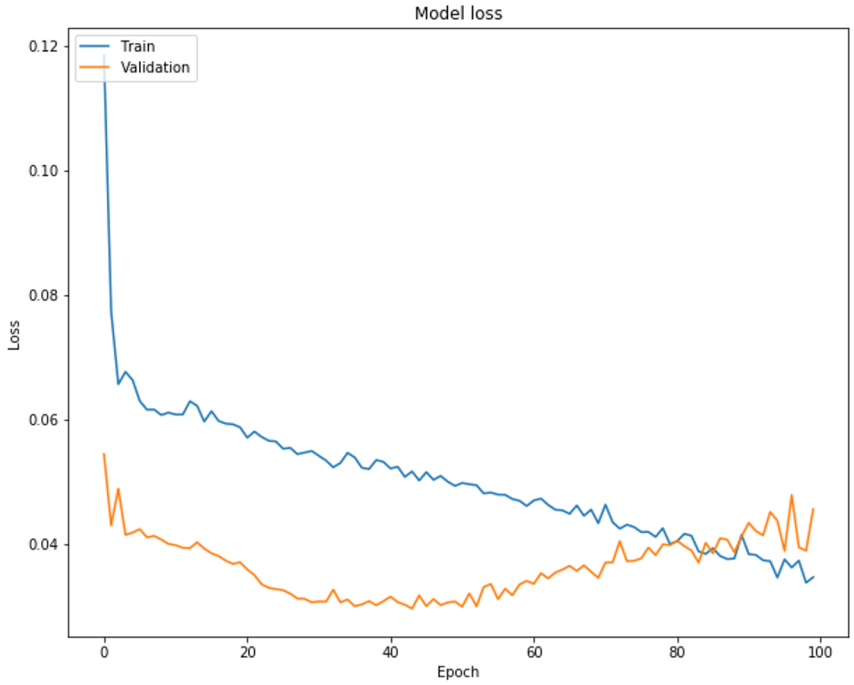


LSTM Parameters Tuning

- Epochs
- Learning Rate
- LSTM Parameters
  - Number of hidden Unit
  - Number of layers
- Loss function

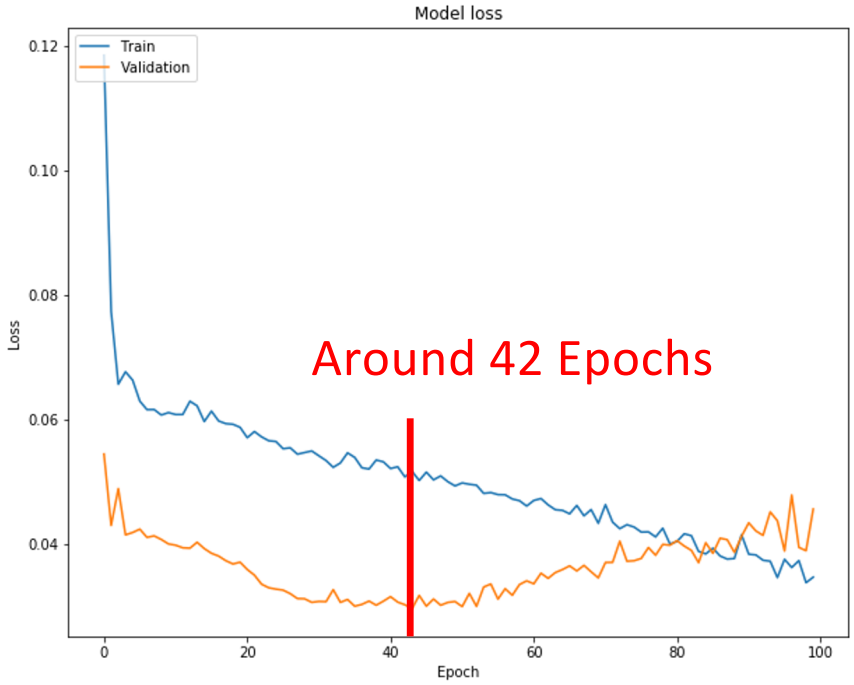
LSTM Parameters Tuning: Epoch

- The single time you see all examples in the dataset.
- Choosing by Plotting Train, Validation loss



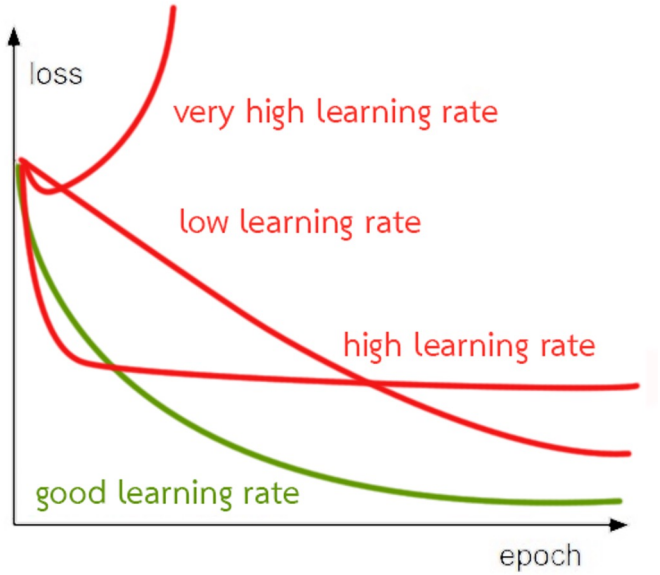
LSTM Parameters Tuning: Epoch (cont.)

- The single time you see all examples in the dataset.
- Choosing by Plotting Train, Validation loss



LSTM Parameters Tuning: Learning Rate

- The learning rate is a hyperparameter that controls how much to change the model in response to the estimated error each time the model weights are updated.



LSTM Parameters Tuning: Loss Function

- We are currently use Mean Square Error

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2$$

NLP Lecture2 (2020s2) by Aj.Ekapol
https://youtu.be/WxiO3wvKhCE