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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]

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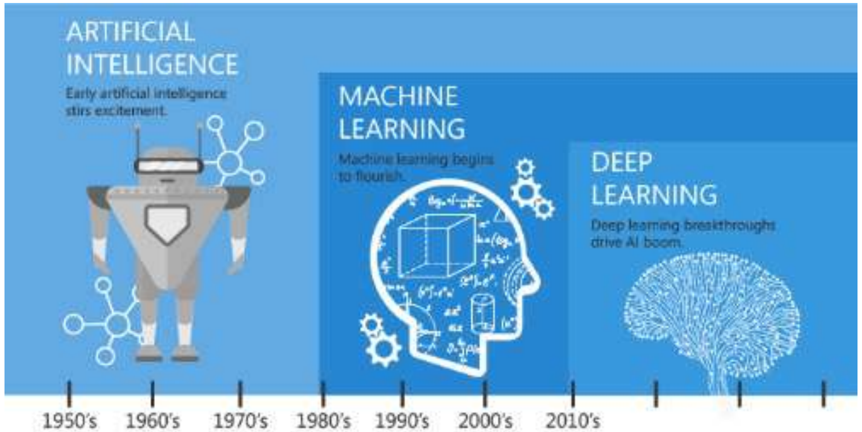
Introduction to Deep Learning

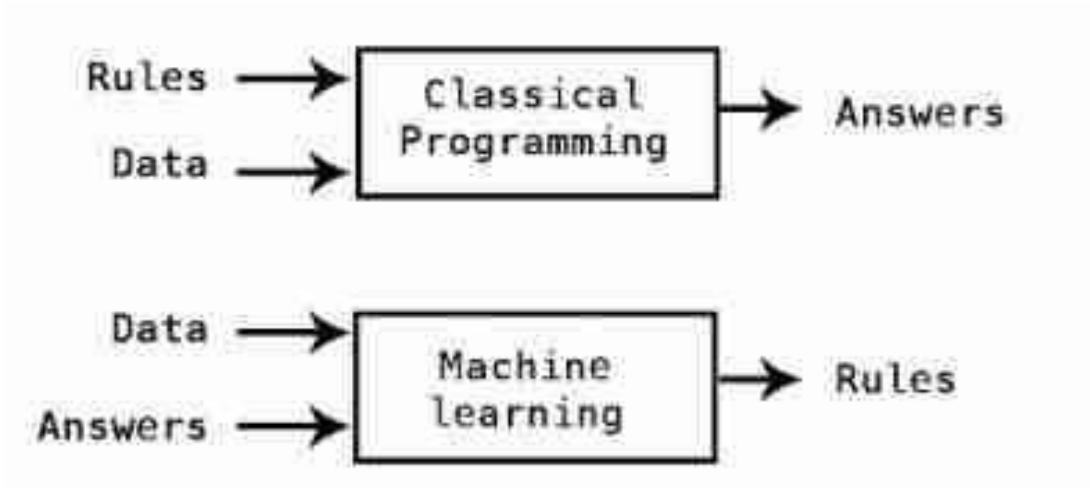
AI = Automation

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



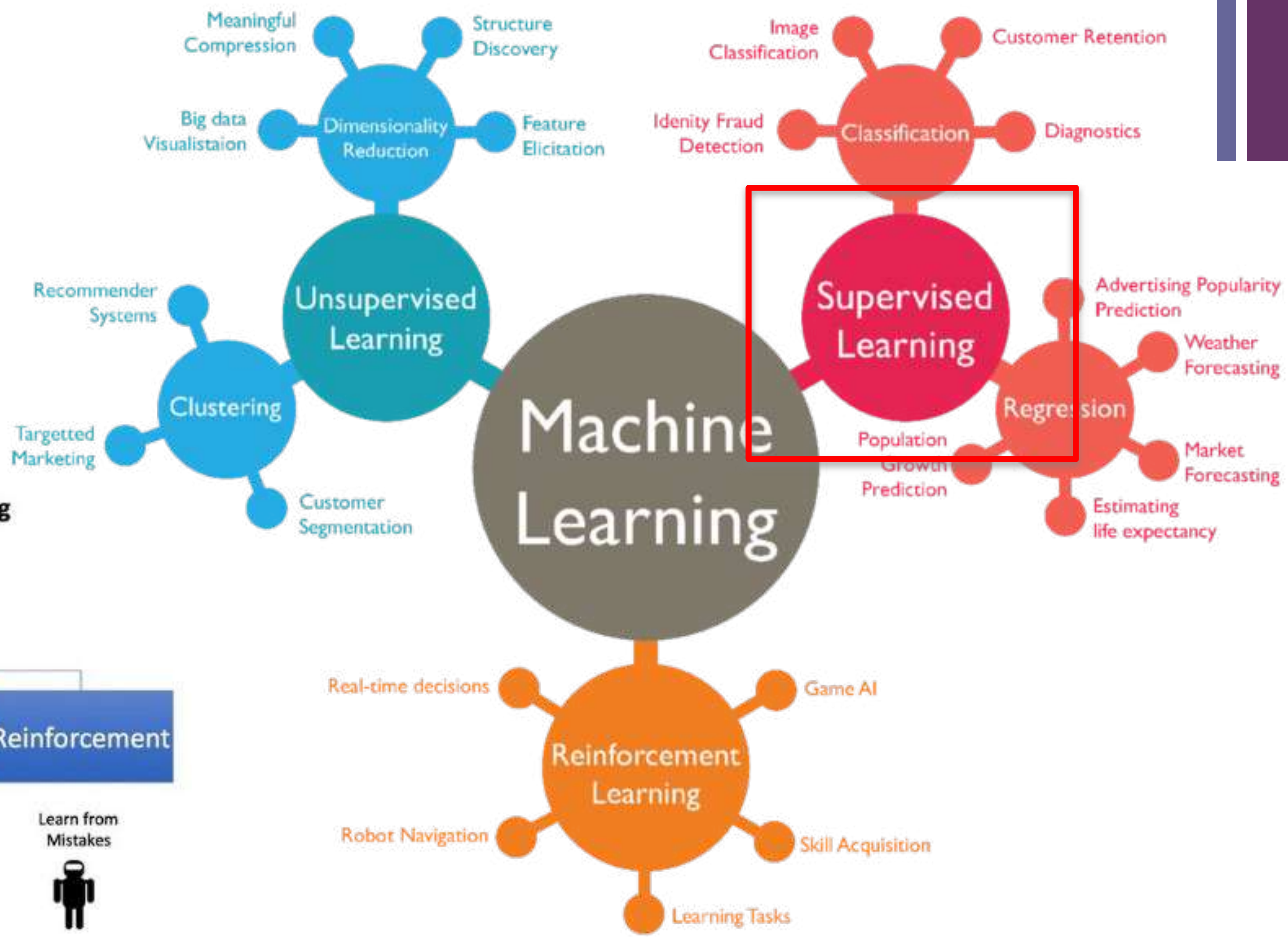
Since an early flush of optimism in the 1950's, smaller subsets of artificial intelligence - first machine learning, then deep learning, a subset of machine learning - have created ever larger disruptions.

1
2

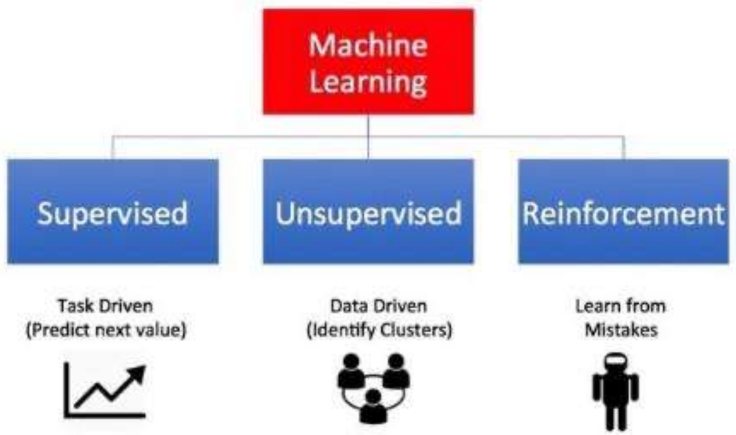


https://mc.ai/machine-learning-basics-artificial-intelligence-machine-learning-and-deep-learning/

+ 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

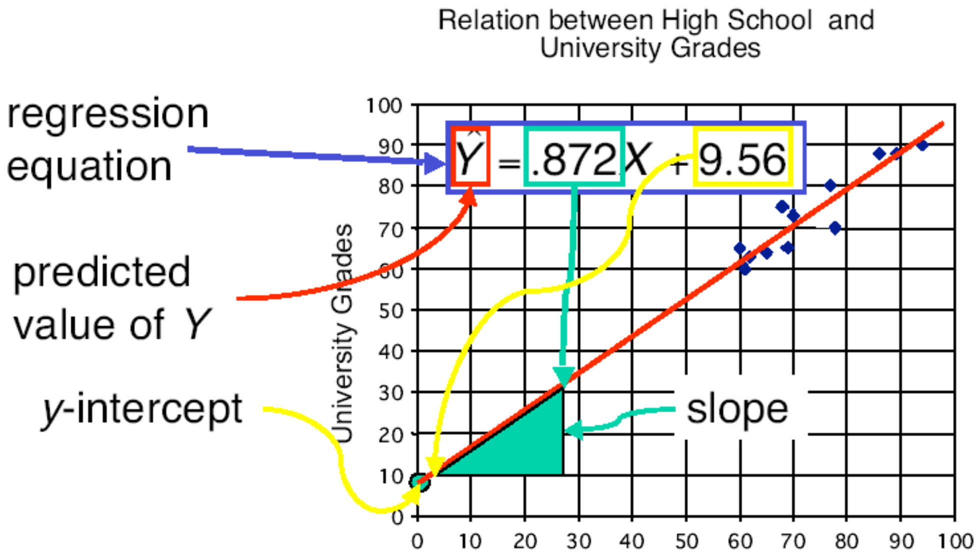
Age	Gender	BodyTemp	Cough	Corona
25	Male	40	No	?

Application: Corona Prediction

+ Prediction algorithms

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

Regression – Linear Relationship



weight, coefficient

$$\hat{y} = \hat{w}_0 + \hat{w}_1 x_1 + \hat{w}_2 x_2$$

target intercept input

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

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

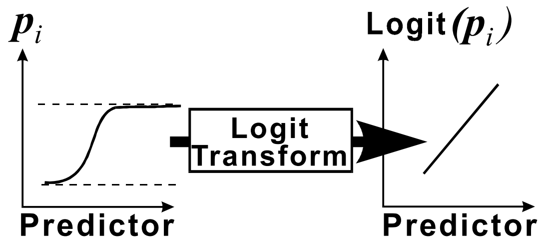
Logistic Regression (cont.)

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



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

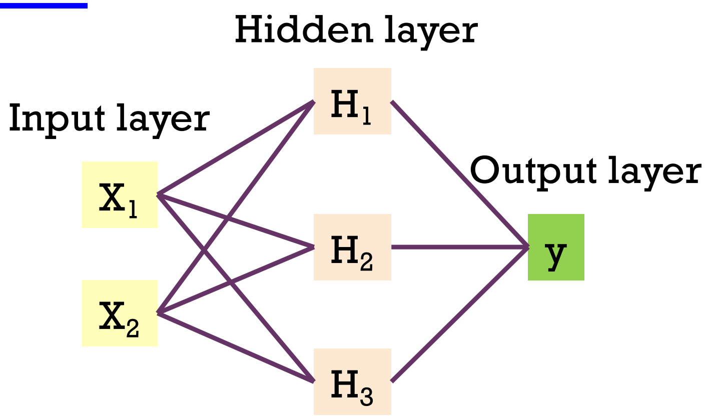
Example

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

Application: Corona Prediction

Neural Networks (universal approximator)

Non-linear relationship

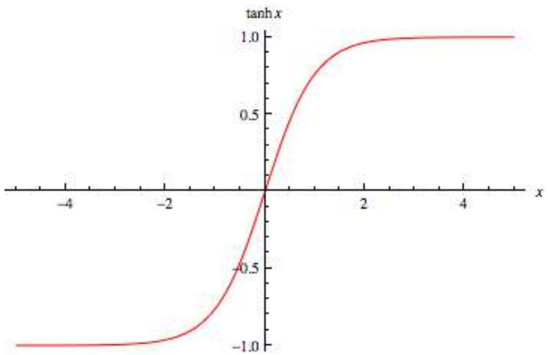


$$log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \hat{w}_0 + \hat{w}_1 H_1 + \hat{w}_2 H_2 + \hat{w}_3 H_3$$

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

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

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

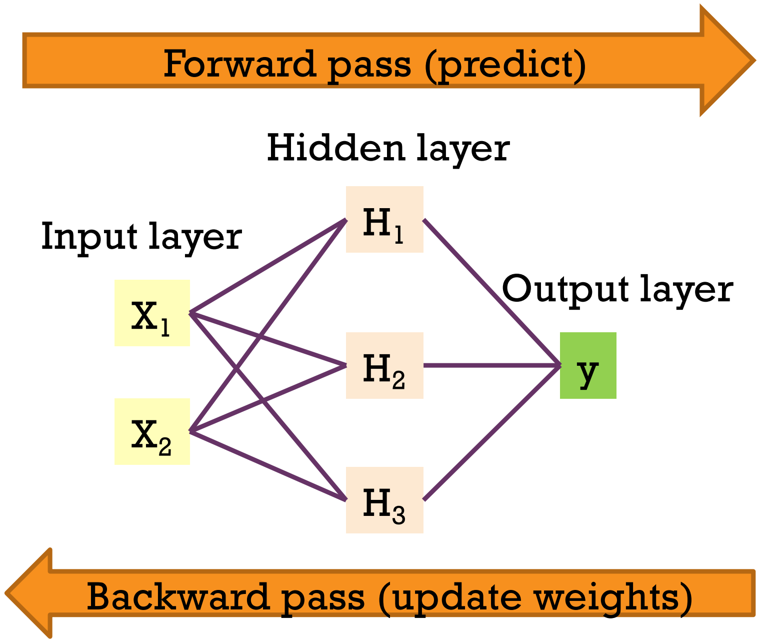


Stop when?
- Converge (no change in loss)
- Max epochs

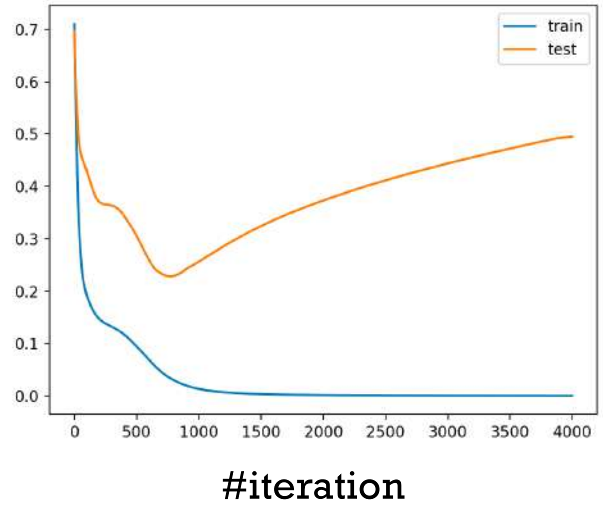
Important Params:
- #hidden units, #hidden layers
- Learning rate, Momentum, decay
- Seed number, etc.

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



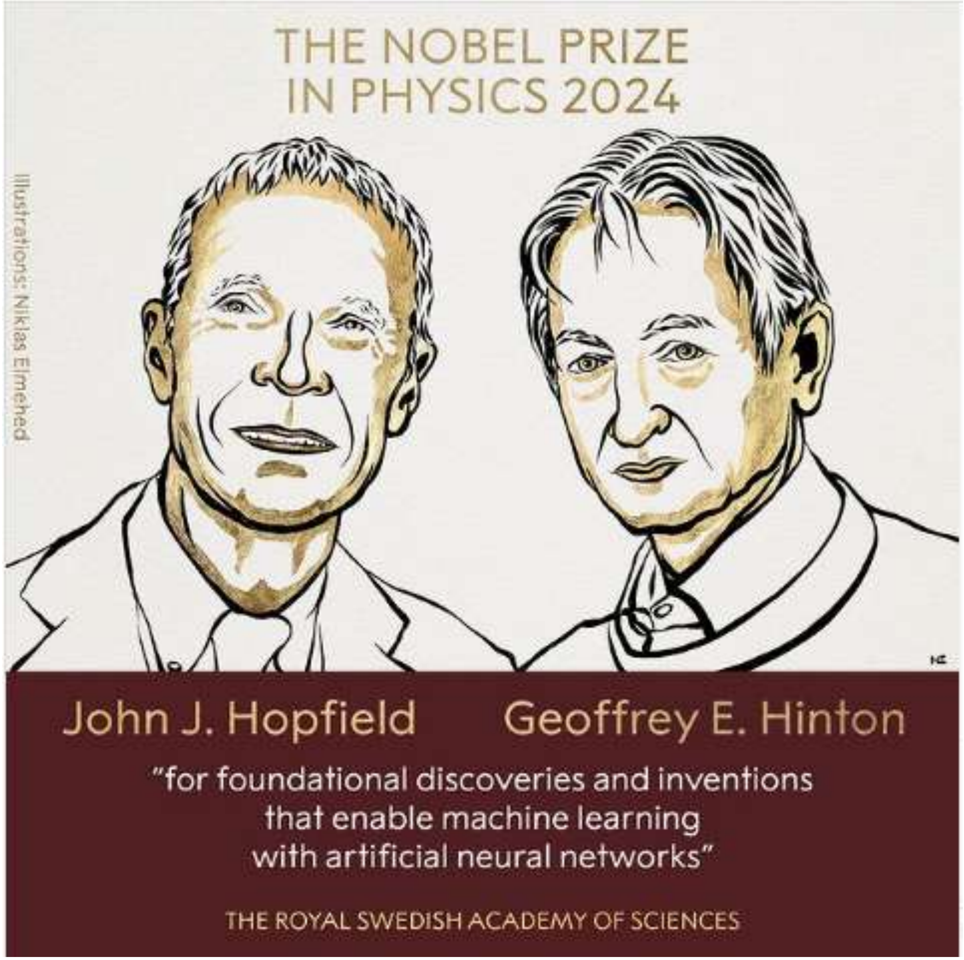
$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \hat{w}_0 + \hat{w}_1 H_1 + \hat{w}_2 H_2 + \hat{w}_3 H_3$$

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

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

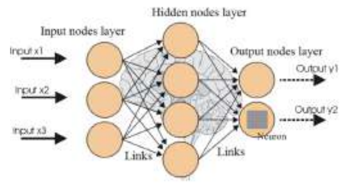
$$H_3 = \tanh(\hat{w}_{30} + \hat{w}_{31} x_1 + \hat{w}_{32} x_2)$$

Nobel Prize to Backpropagation’s Inventors



8 October 2024

The Royal Swedish Academy of Sciences has decided to award the Nobel Prize in Physics 2024 to



John J. Hopfield
Princeton University, NJ, USA

Geoffrey E. Hinton
University of Toronto, Canada

“for foundational discoveries and inventions that enable machine learning with artificial neural networks”

They trained artificial neural networks using physics

John Hopfield invented a network that uses a method for saving and recreating patterns. We can imagine the nodes as pixels. The *Hopfield network* utilises physics that describes a material’s characteristics due to its atomic spin – a property that makes each atom a tiny magnet.

Geoffrey Hinton used the Hopfield network as the foundation for a new network that uses a different method: the *Boltzmann machine*. This can learn to recognise characteristic elements in a given type of data.

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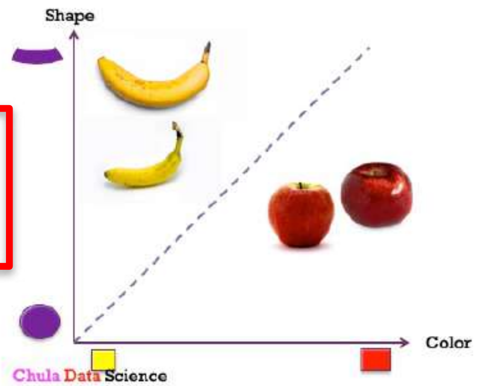
Handcrafted features

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

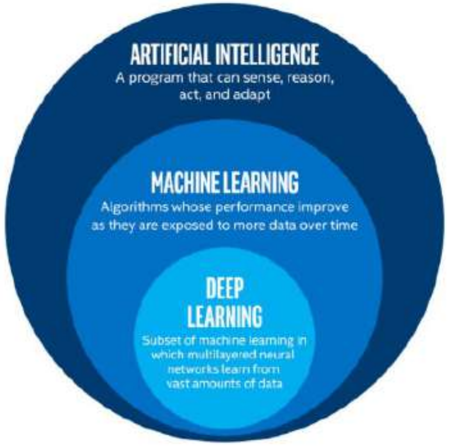


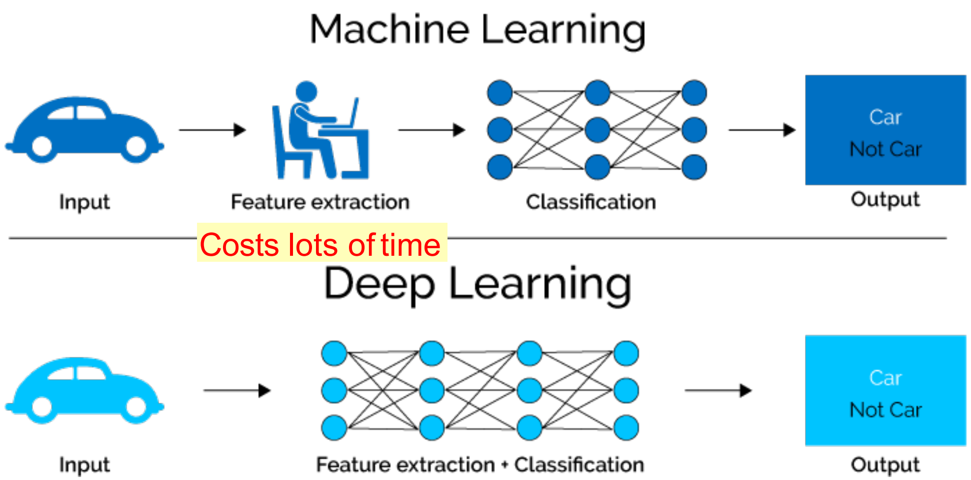
Can we still tell the features (columns)?

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.



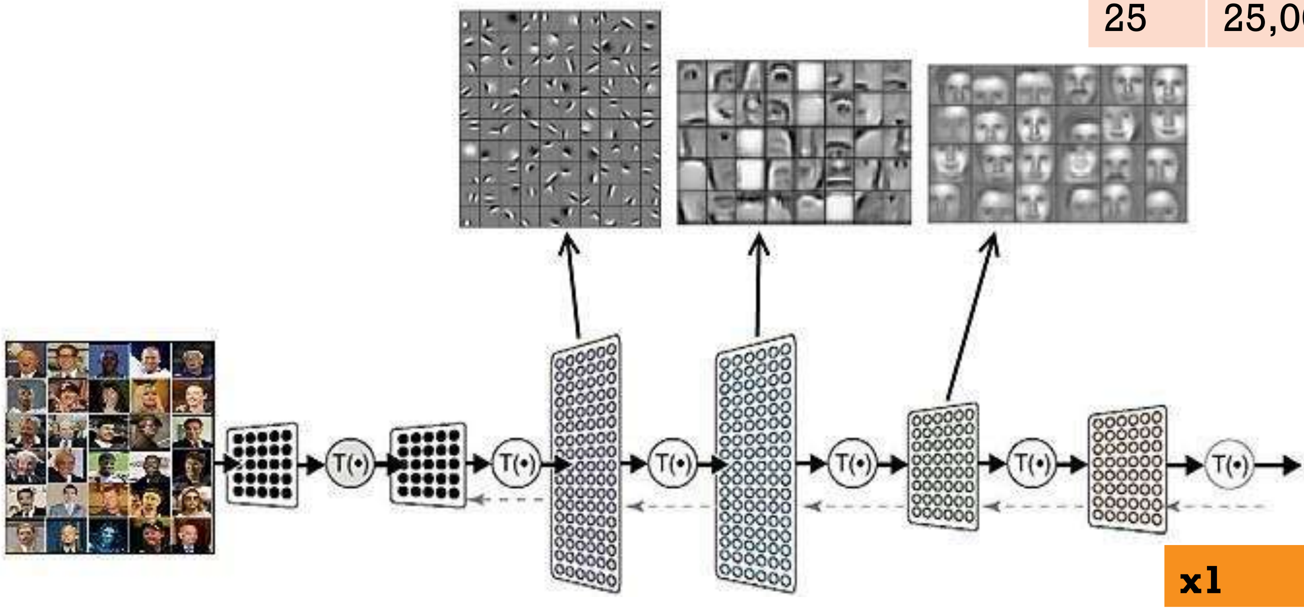


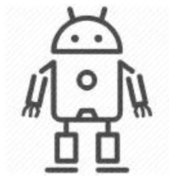
Deep Learning – Basics (cont.)

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

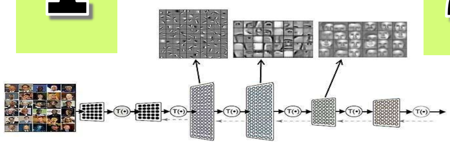
Deep Learning Application

Speech Recognition

Computer Vision

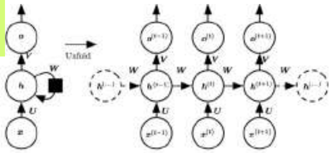
Natural Language Processing

1



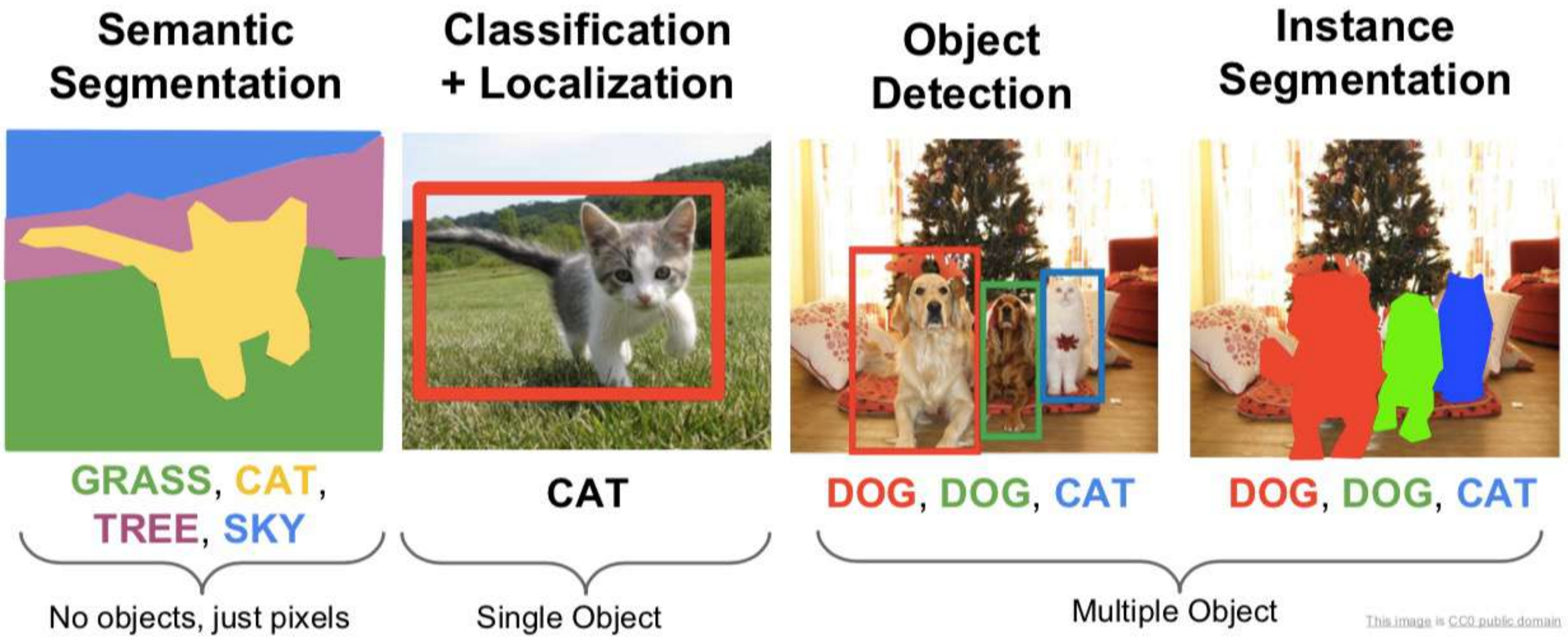
CNN

2



RNN

Type of image tasks



Face Recognition

Smart Medical Diagnosis

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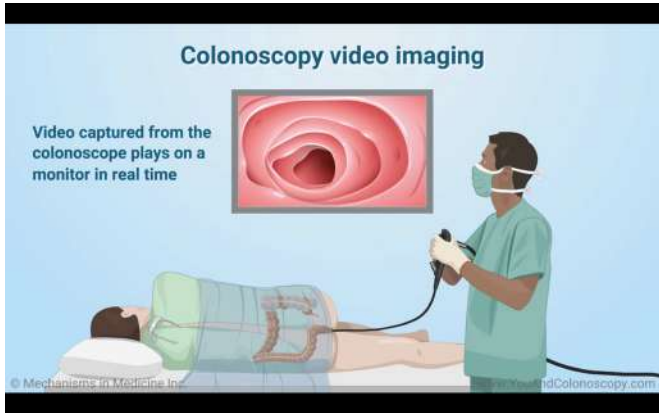
King Chulalongkorn Memorial Hospital
The Thai Red Cross Society



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Convolutional Neural Networks (CNN)

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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:

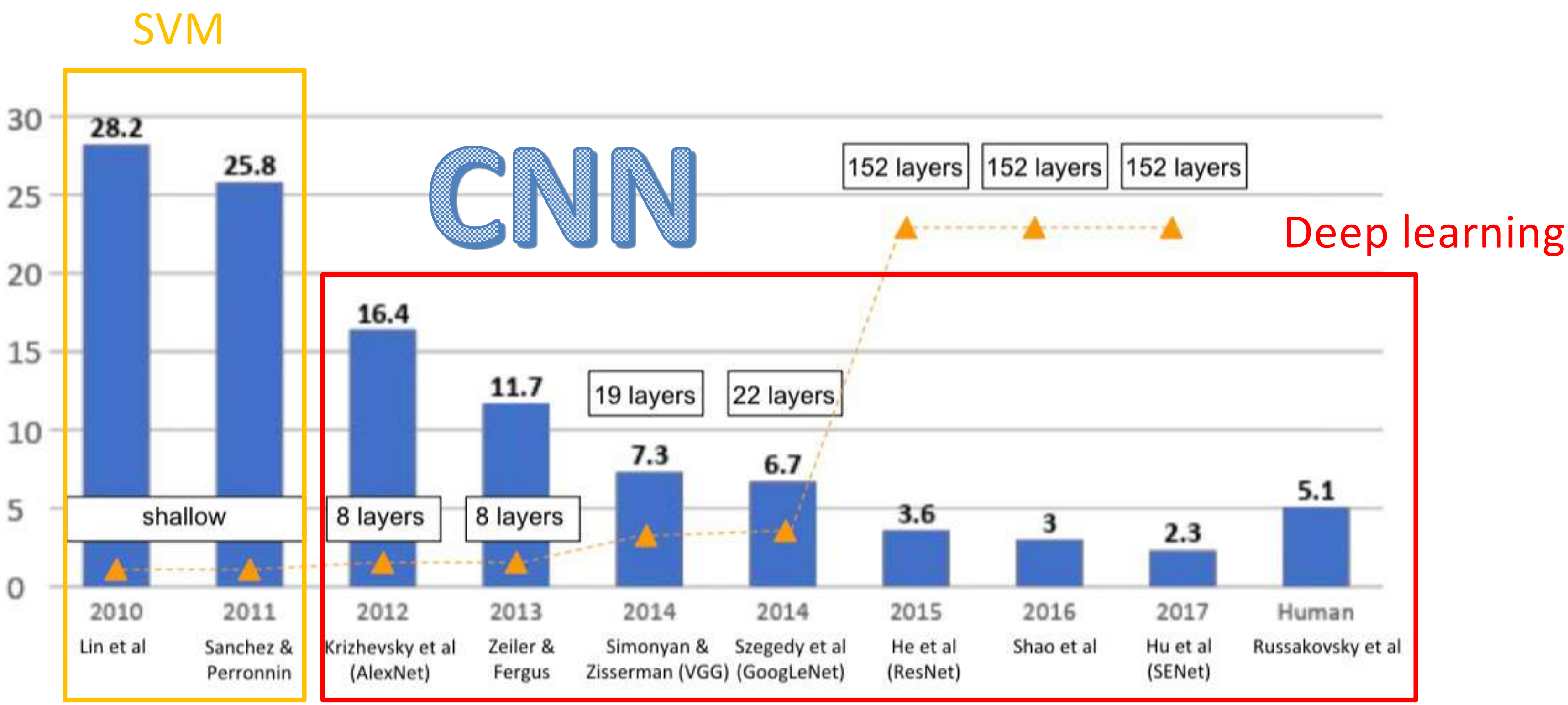
1,000 object classes

1,431,167 images

ImageNet 2017 is the last challenge.

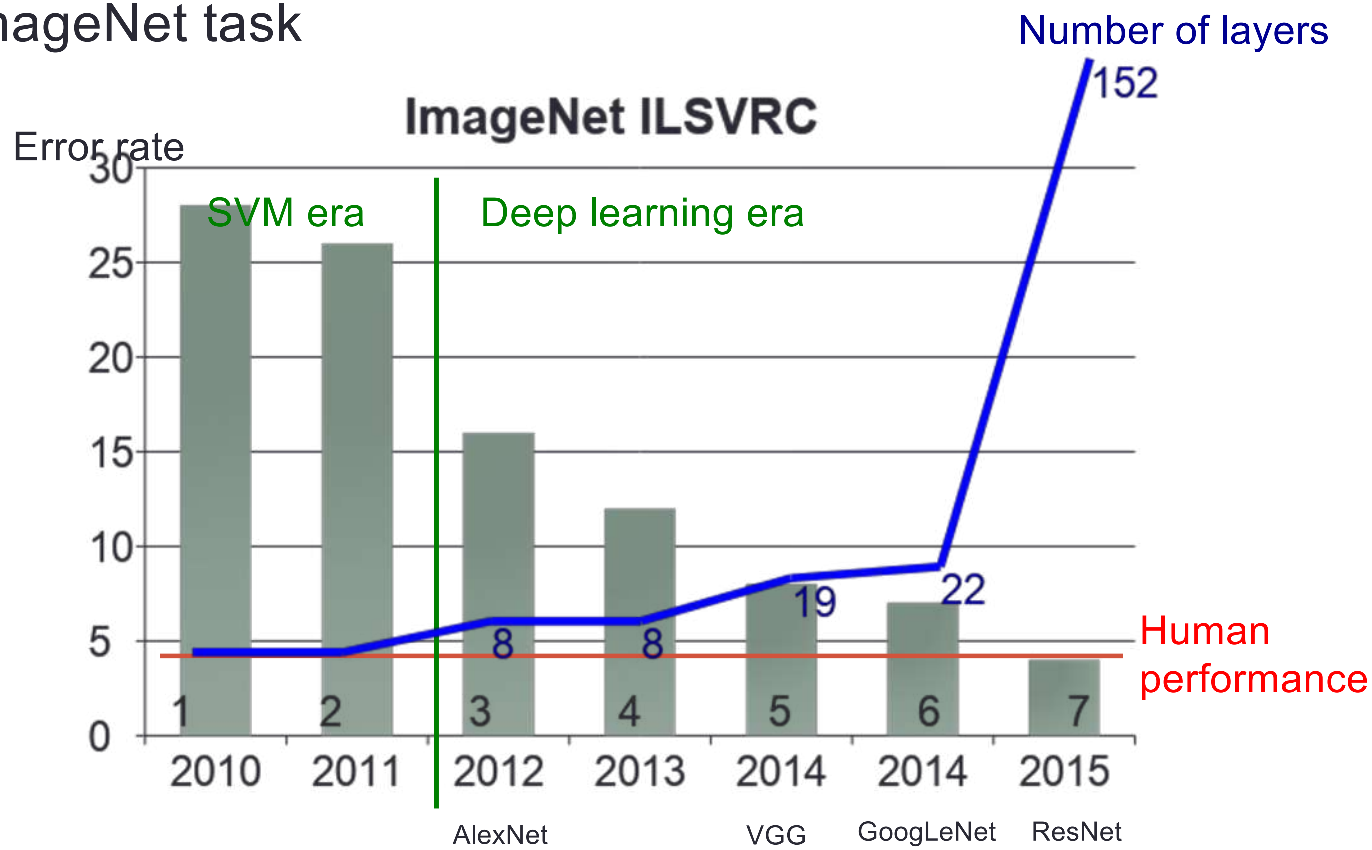
22

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



Wider and deeper networks (Beyond Human)

- ImageNet task

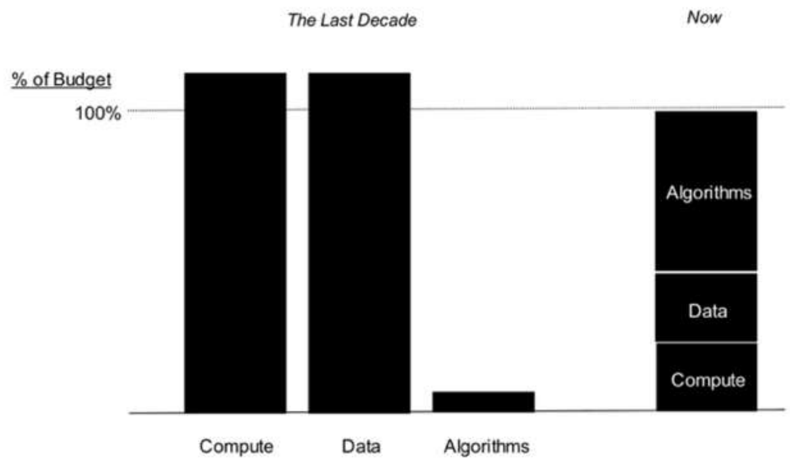


Based on the slide of Aj.Ekapol

-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/

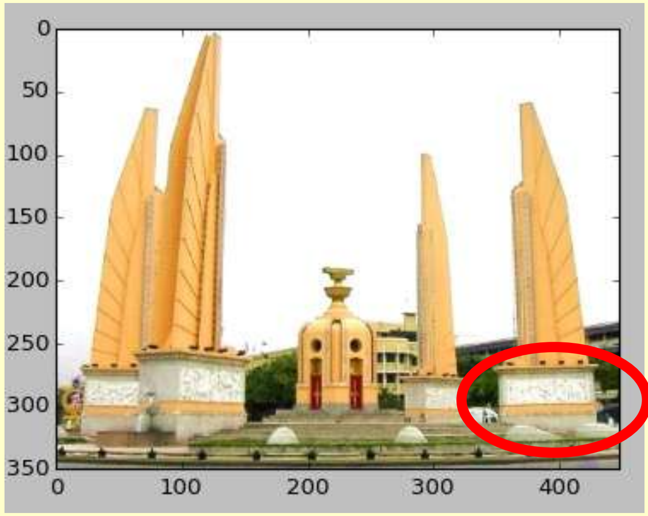
```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

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

plt.show()
```

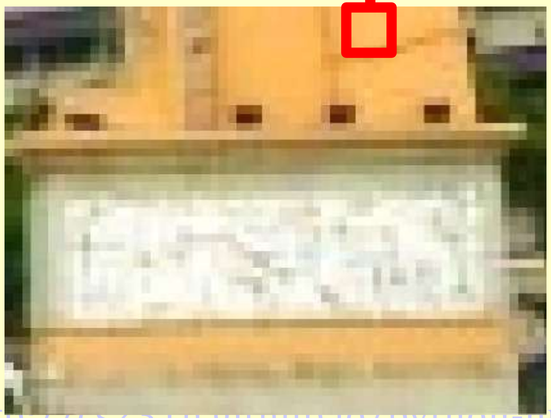
เพื่อความง่ายโปรแกรมที่จะเขียน จากนี้ไปใช้กับแฟ้ม png เท่านั้น

image เป็นอาเรย์ที่แต่ละช่อง มีค่า 0 ถึง 1 แทนความเข้มของสี

1 pixel = 1 จุดสี มี 3 สีย่อย

0.98762	0.72549	0.35294

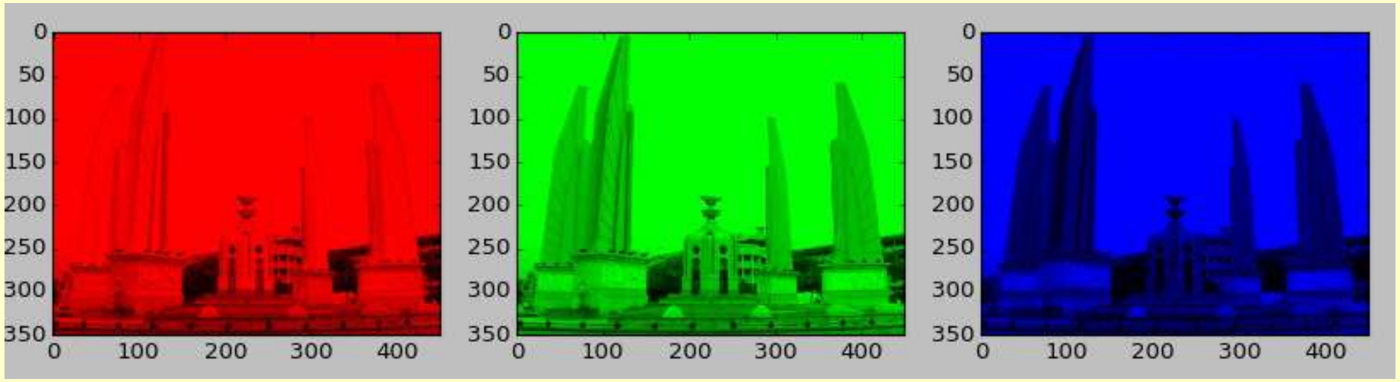




http://cs231n.github.io/python-numpy-tutorial/#numpy

It is an array of R,G,B (3 channels)

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



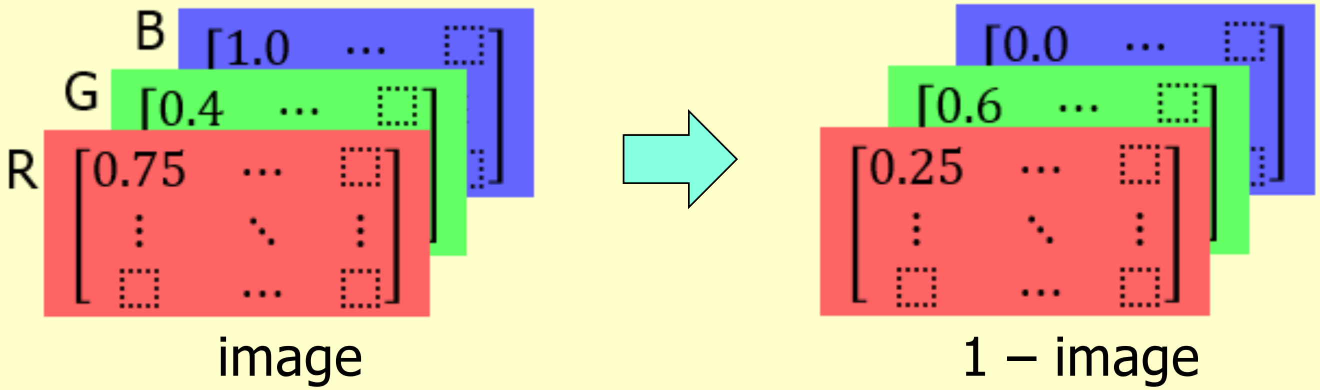
Red
image[:,:,0]

Green
image[:,:,1]

Blue
image[:,:,2]

Basic Image Processing

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

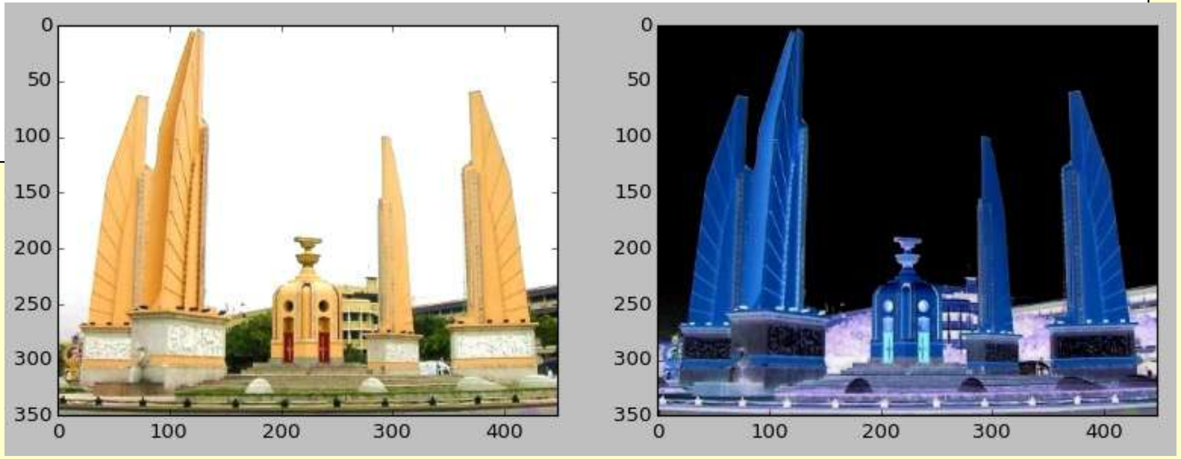


How's it changed?

Basic Image Processing (1): Negative Image

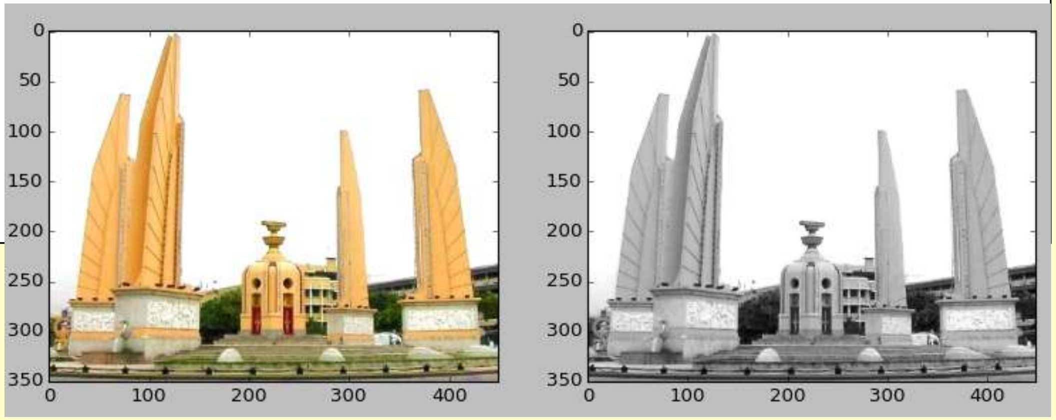
```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

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 = Invert Tone
(White → Black, Yellow → Blue, ...)
broadcast & element-wise subtract

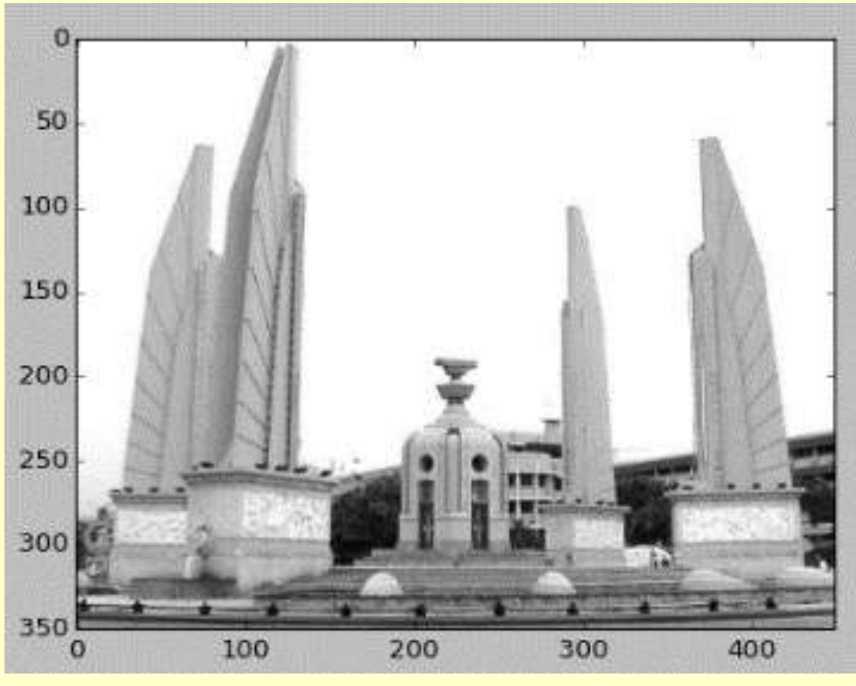


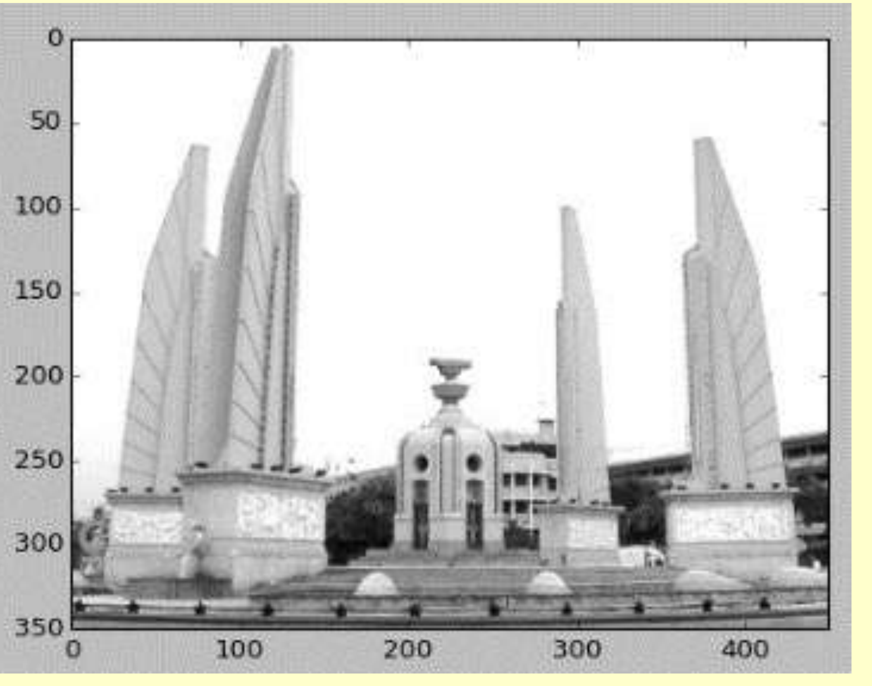
Basic Image Processing (2): Grayscale Image

```
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()
```

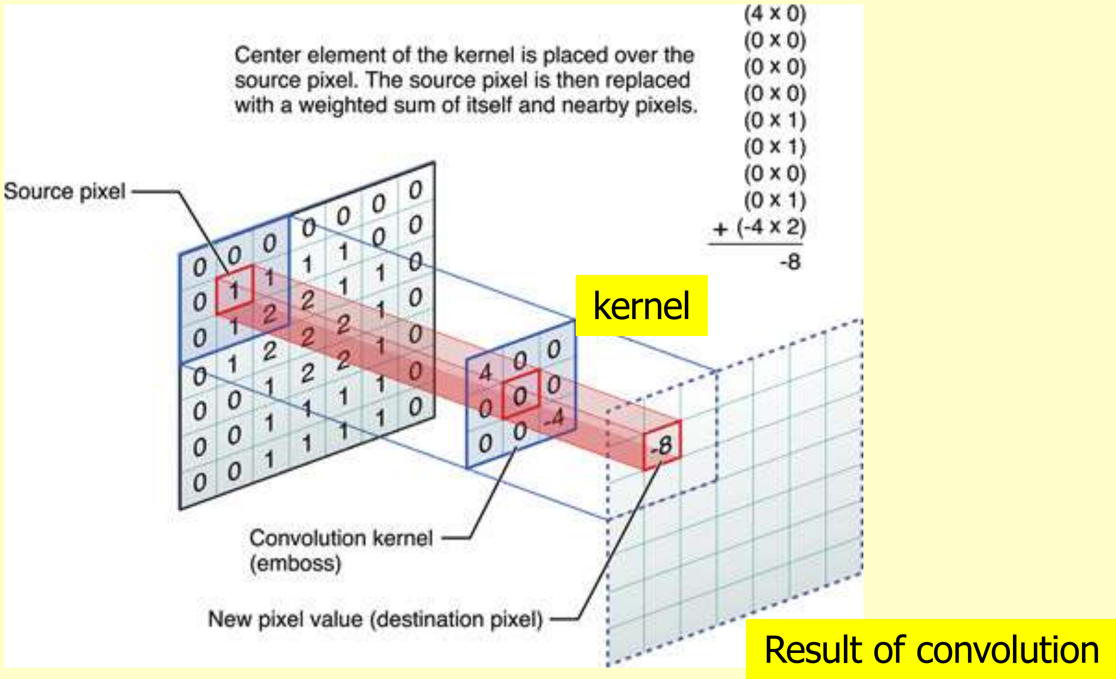


Another Grayscale Image: 0.299*R + 0.587*G + 0.114*B



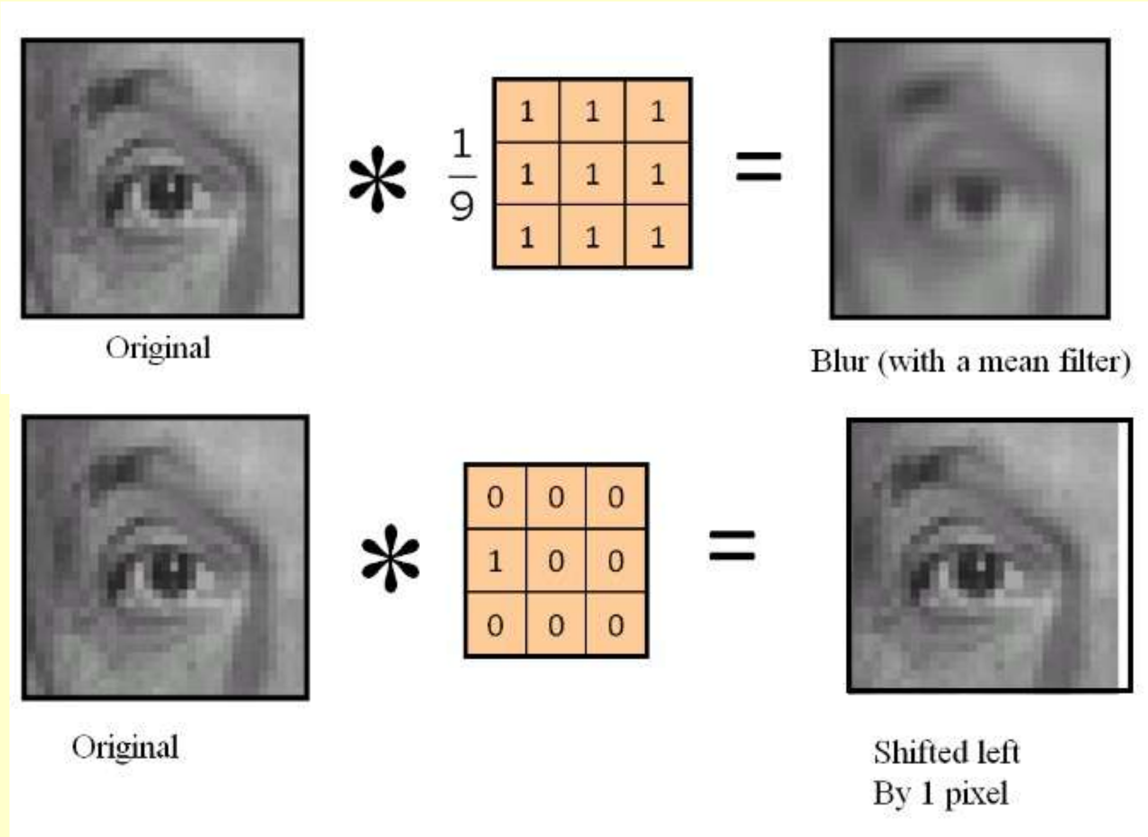


Convolution



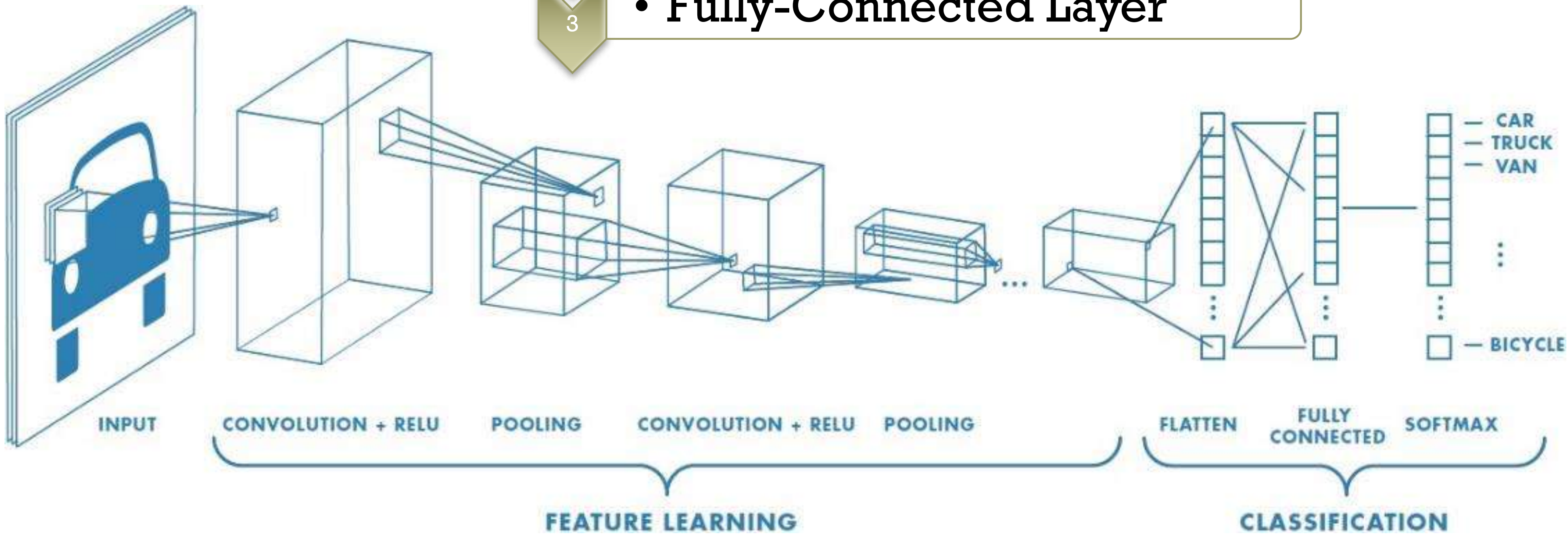
Changing the kernel (filter) results in different image processing outcomes

Image Convolution

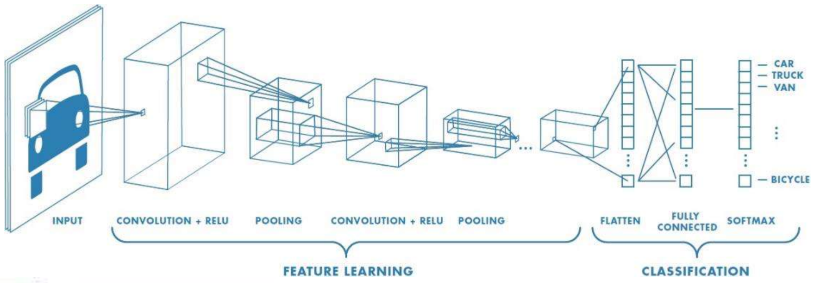


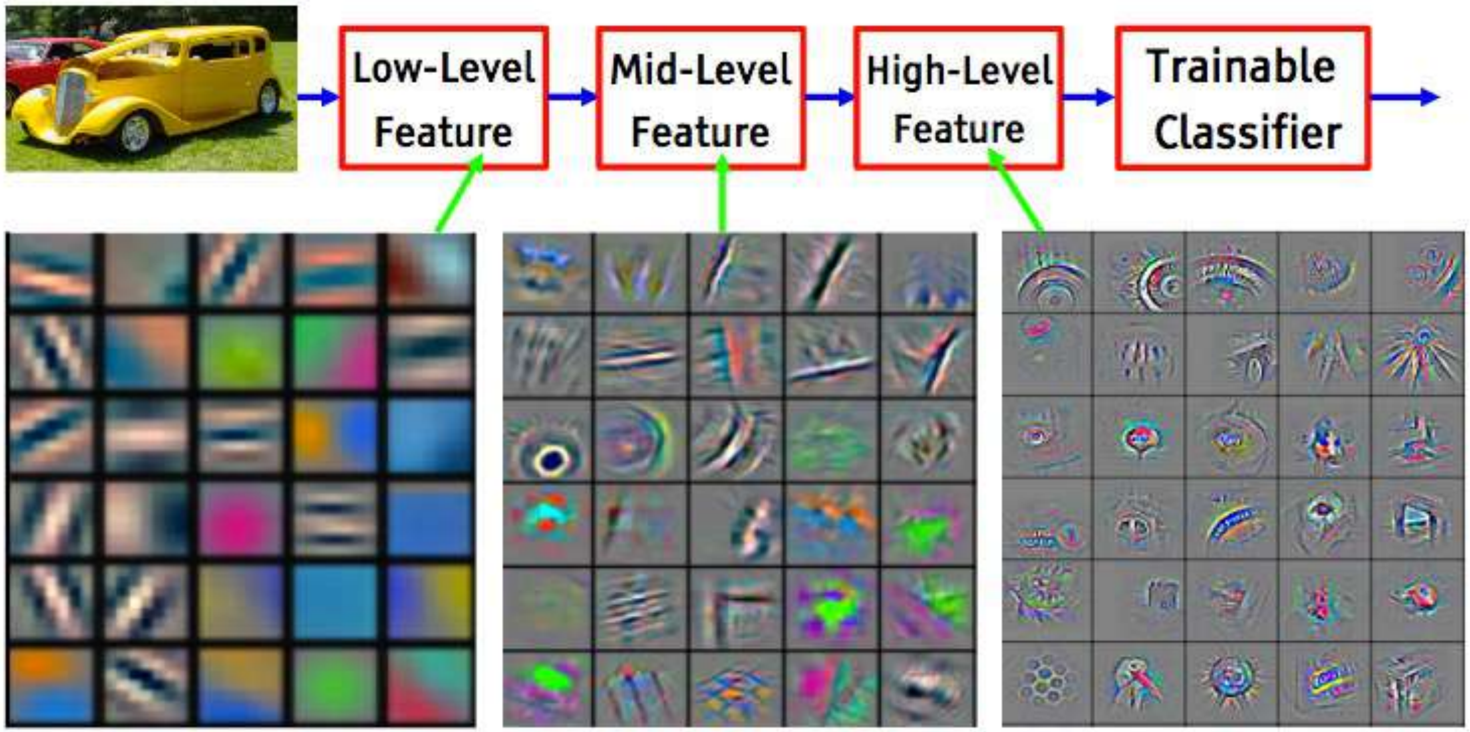
Convolutional Neural Networks (CNN)

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



CNN (cont.)

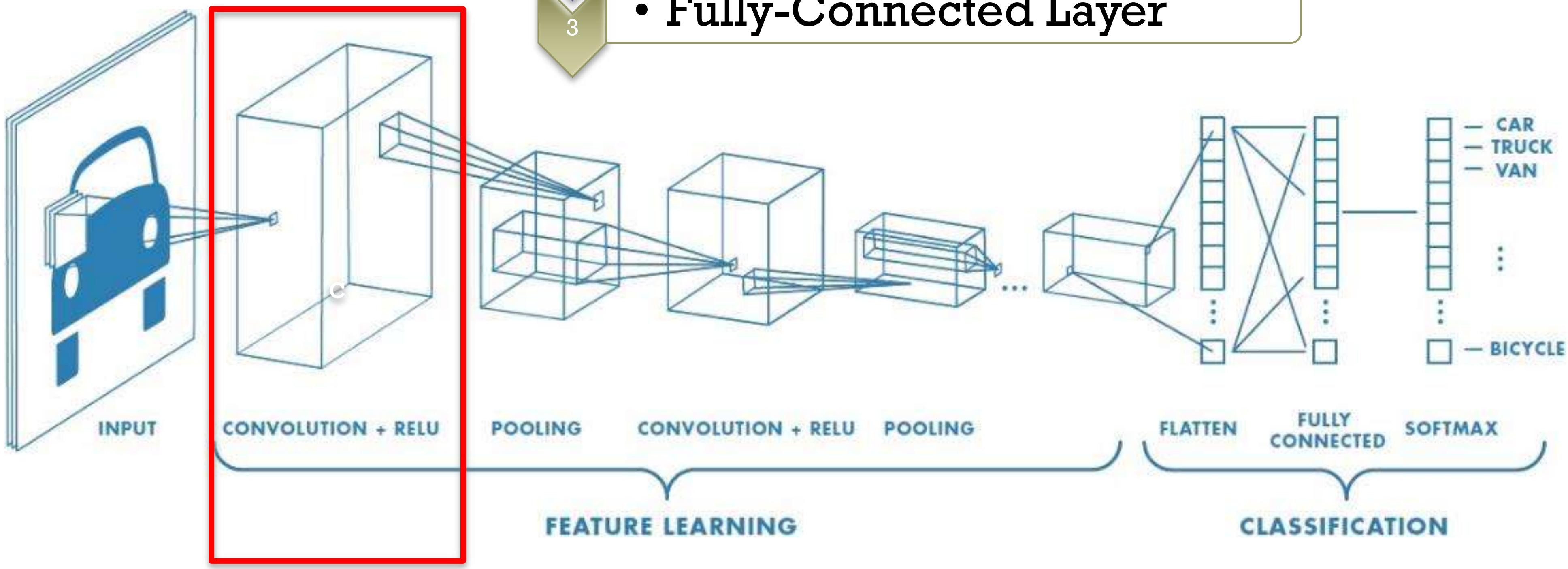

INPUT
CONVOLUTION + RELU
POOLING
CONVOLUTION + RELU
POOLING
FLATTEN
FULLY CONNECTED
SOFTMAX
CAR
TRUCK
VAN
BICYCLE
FEATURE LEARNING
CLASSIFICATION


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



Layer1: Convolutional Layer

(3*3 filter)

1	0	1
0	1	0
1	0	1

- **Convolutional Layer**
- Pooling Layer
- Fully-Connected Layer

1 ×1	1 ×0	1 ×1	0	0
0 ×0	1 ×1	1 ×0	1	0
0 ×1	0 ×0	1 ×1	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved Feature

Input Volume (+pad 1) (7x7x3)

x[:,:,0]

0	0	0	0	0	0	0
0	1	0	2	2	2	0
0	0	0	0	0	0	0
0	2	0	2	2	2	0
0	1	0	0	0	0	0
0	1	0	0	2	1	0
0	0	0	0	0	0	0

x[:,:,1]

0	0	0	0	0	0	0
0	1	0	1	0	1	0
0	0	0	0	0	1	0
0	0	0	2	0	0	0
0	2	0	0	0	0	0
0	0	0	1	0	0	0
0	0	0	0	0	0	0

x[:,:,2]

0	0	0	0	0	0	0
0	0	2	2	0	0	0
0	0	0	0	0	1	0
0	1	1	2	0	2	0
0	2	0	0	0	0	0
0	0	1	1	0	1	0
0	0	0	0	0	0	0

Filter W0 (3x3x3)

w0[:,:,0]

1	0	0
−1	0	0
0	−1	1

w0[:,:,1]

−1	−1	0
−1	−1	1
1	0	0

w0[:,:,2]

1	1	0
0	−1	1
1	1	1

Bias b0 (1x1x1)

b0[:,:,0]

1

Filter W1 (3x3x3)

w1[:,:,0]

1	−1	0
−1	0	0
0	1	−1

w1[:,:,1]

0	1	−1
0	0	0
0	1	1

w1[:,:,2]

0	−1	0
1	1	−1
−1	0	1

Bias b1 (1x1x1)

b1[:,:,0]

0

Output Volume (3x3x2)

o[:,:,0]

2	−2	−1
2	−3	−3
2	−1	−2

o[:,:,1]

−2	4	−1
3	3	0
−2	2	−1

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

CNNs: 1) Convolutional Layer

Feature Extraction

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

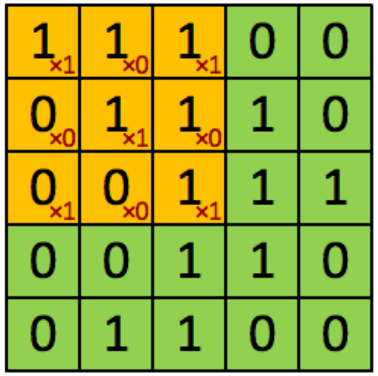
Summary: **4 parameters** for convolutional layer
- (1) Filter size, (2) #Filters, (3) Stride, (4) Padding

Output size = (N + 2*P – F) / S + 1

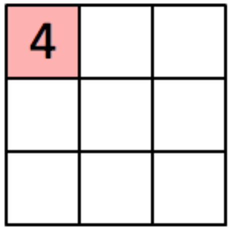
$$w^T x + b$$

(3*3 filter)

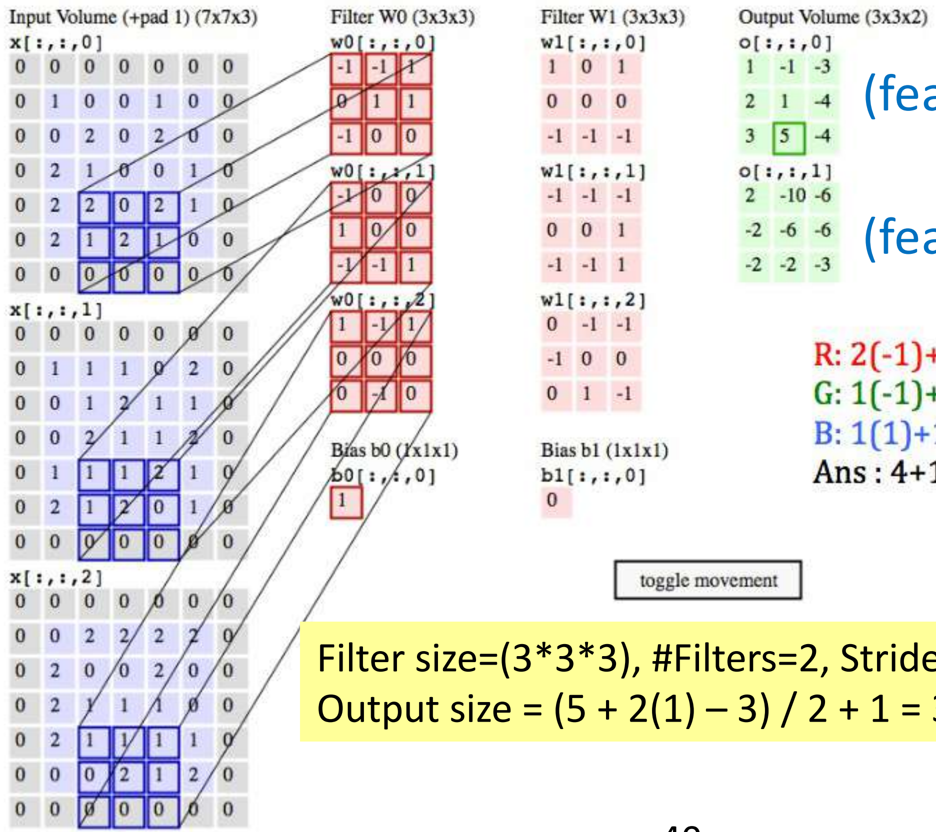
1	0	1
0	1	0
1	0	1



Image



Convolved Feature (feature map)



(feature map1)

(feature map2)

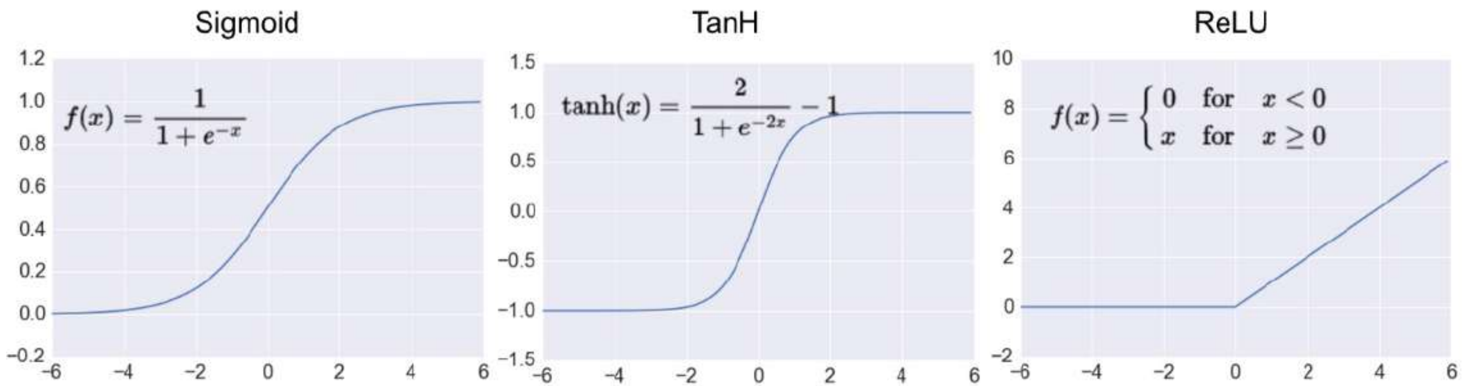
R: 2(-1)+2(1)+2(1)+1(1) = 3
G: 1(-1)+1(1) = 0
B: 1(1)+1(-1)+1(1)= 1
Ans : 4+1 = 5

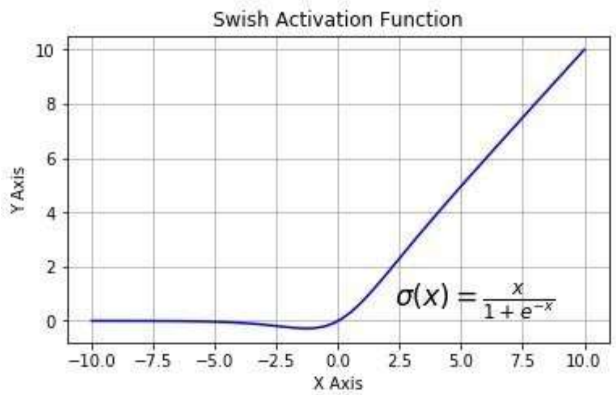
Filter size=(3*3), #Filters=1, Stride=1, Padding=0
Output size = (5 +2(0) – 3) / 1 + 1 = 3

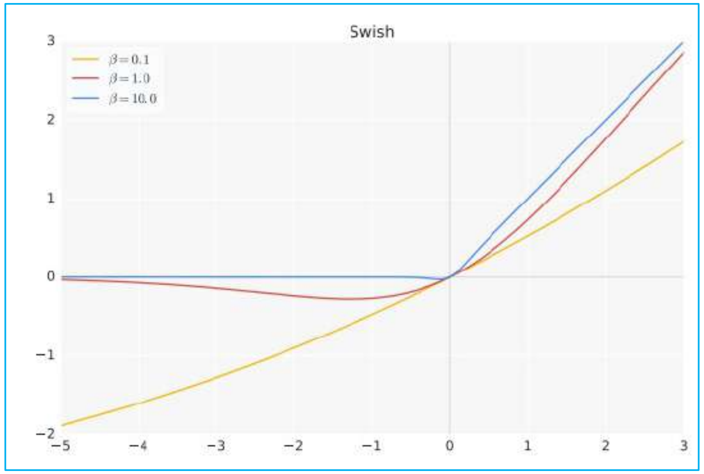
Filter size=(3*3*3), #Filters=2, Stride=2, Padding=1
Output size = (5 + 2(1) – 3) / 2 + 1 = 3

CNNs: 1) Convolutional Layer (cont.)

Non-Linear Activation Function



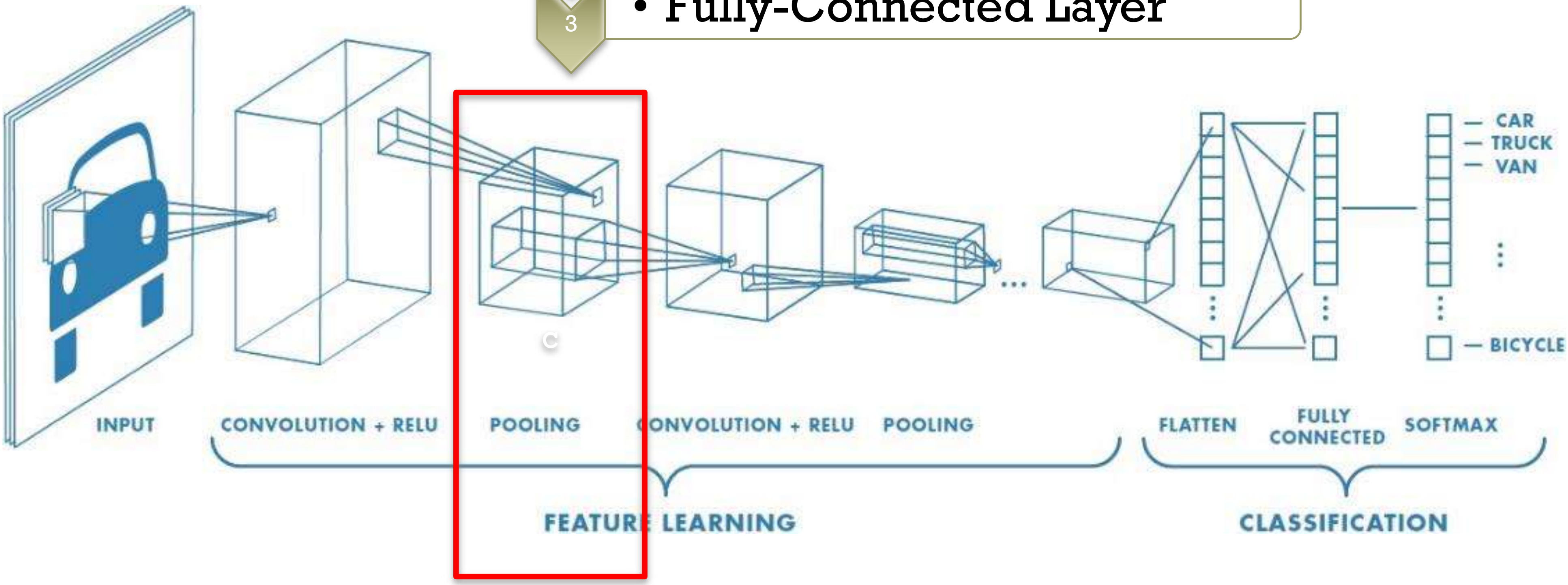




Convolutional Neural Networks (CNN)

2) Pooling Layer

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



CNNs: 2) Pooling Layer

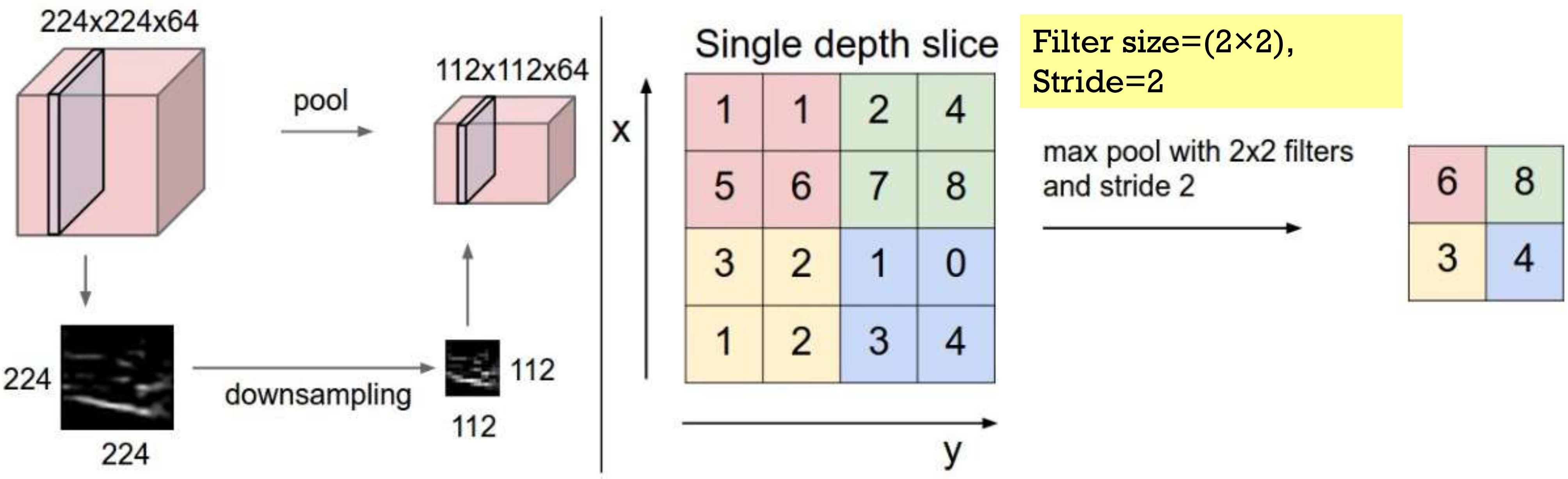
http://cs231n.github.io/convolutional-networks/

Summary: **2 parameters** for pooling layer

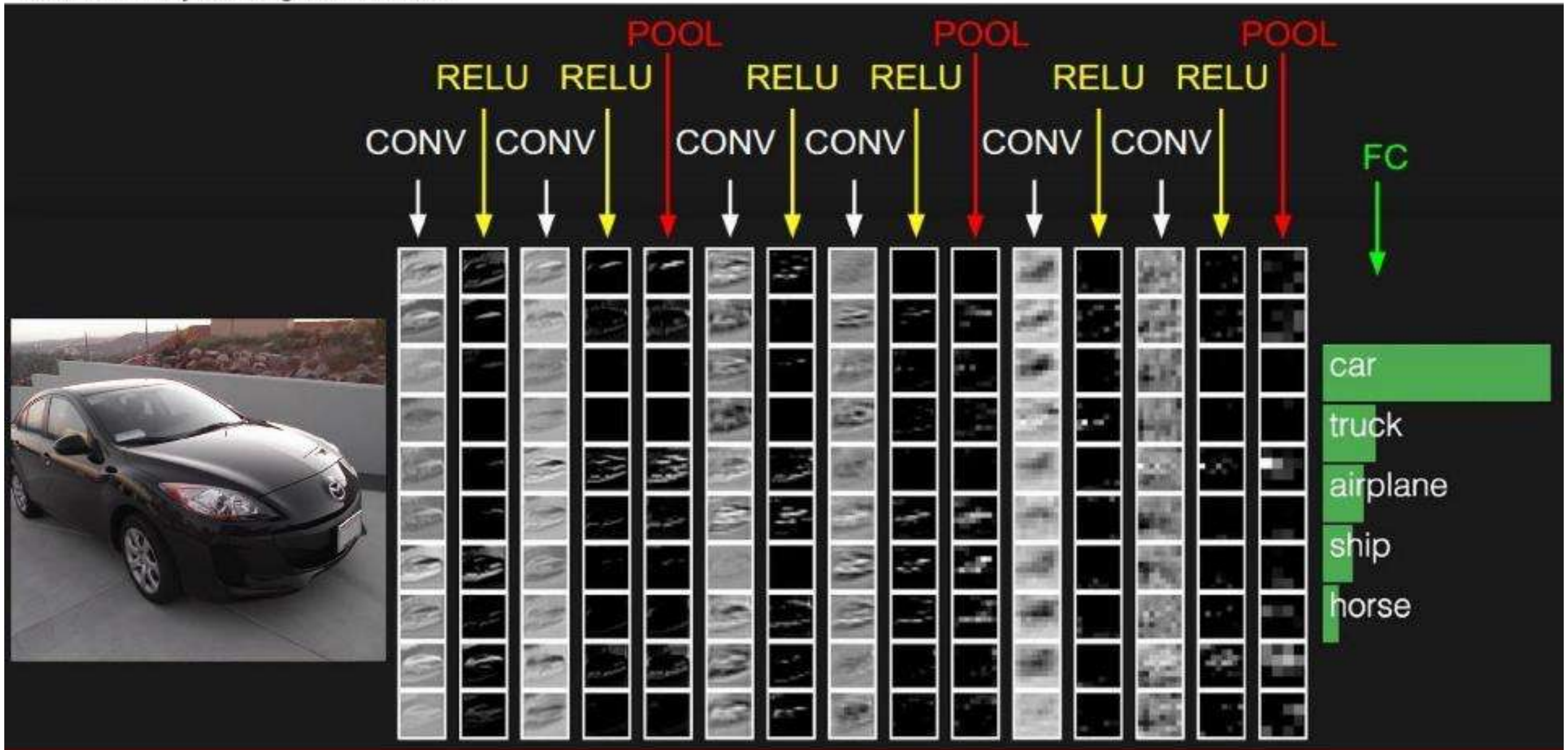
- Filter size, Stride

- Feature selection (reduction); downsampling

Filter size=(2×2), Stride=2



two more layers to go: POOL/FC

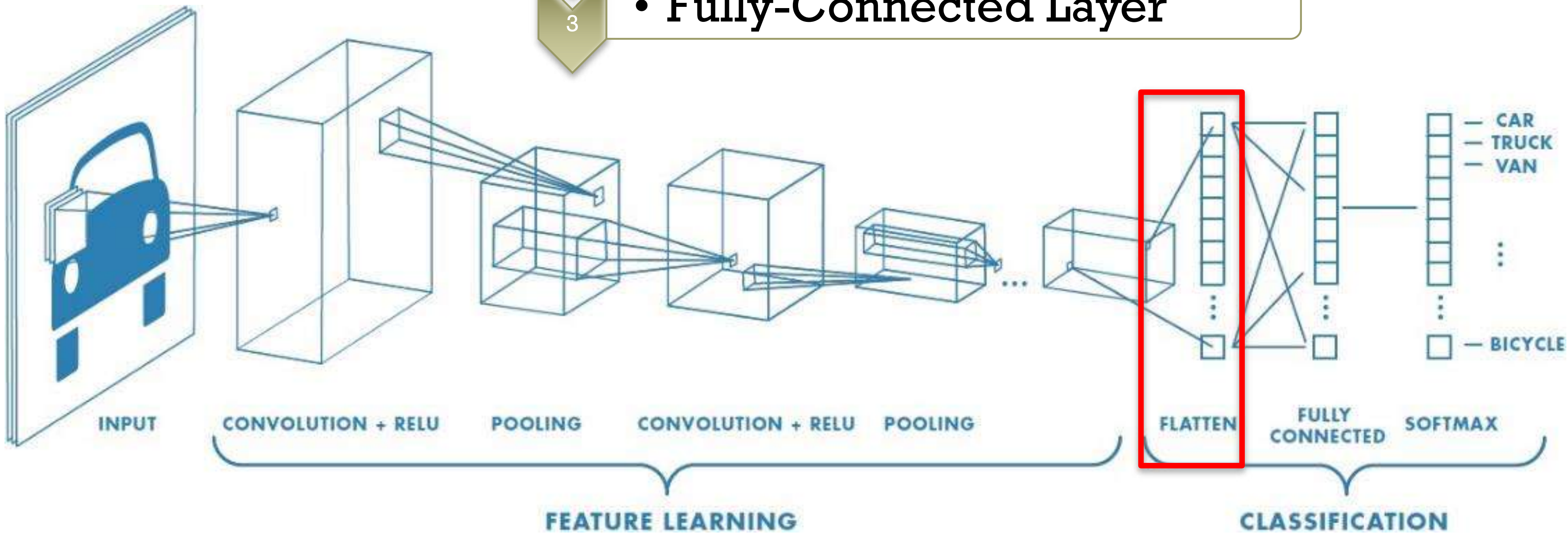


Convolutional Neural Networks

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



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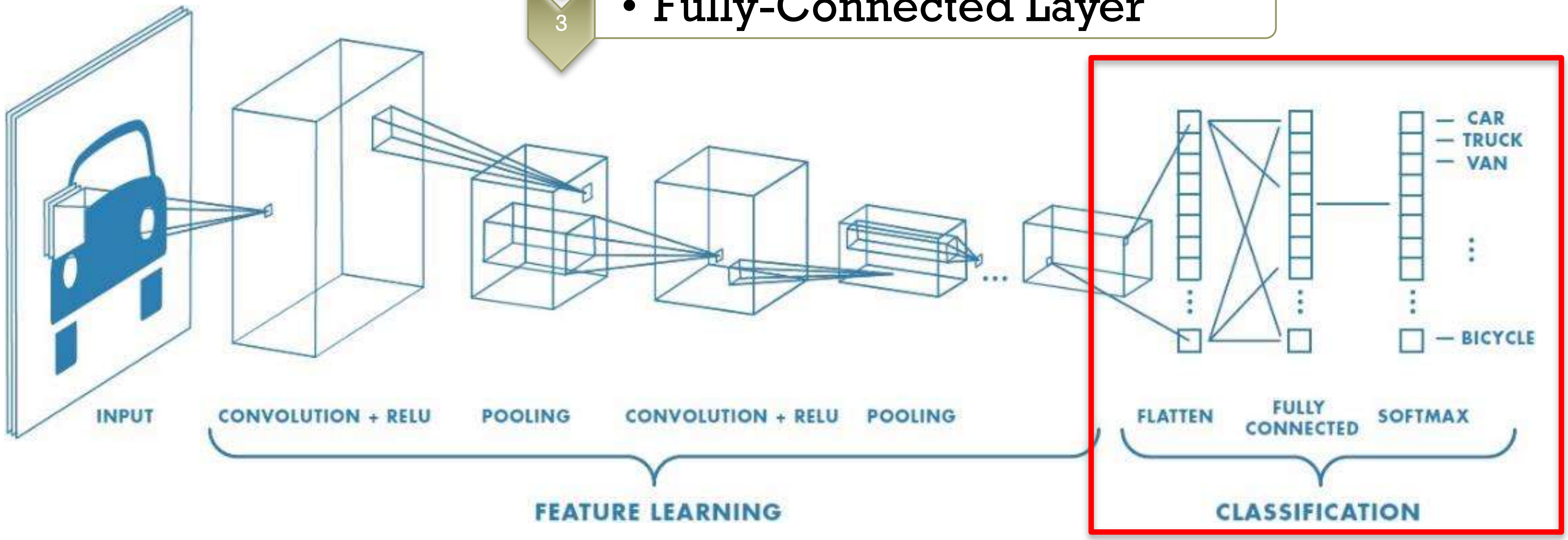
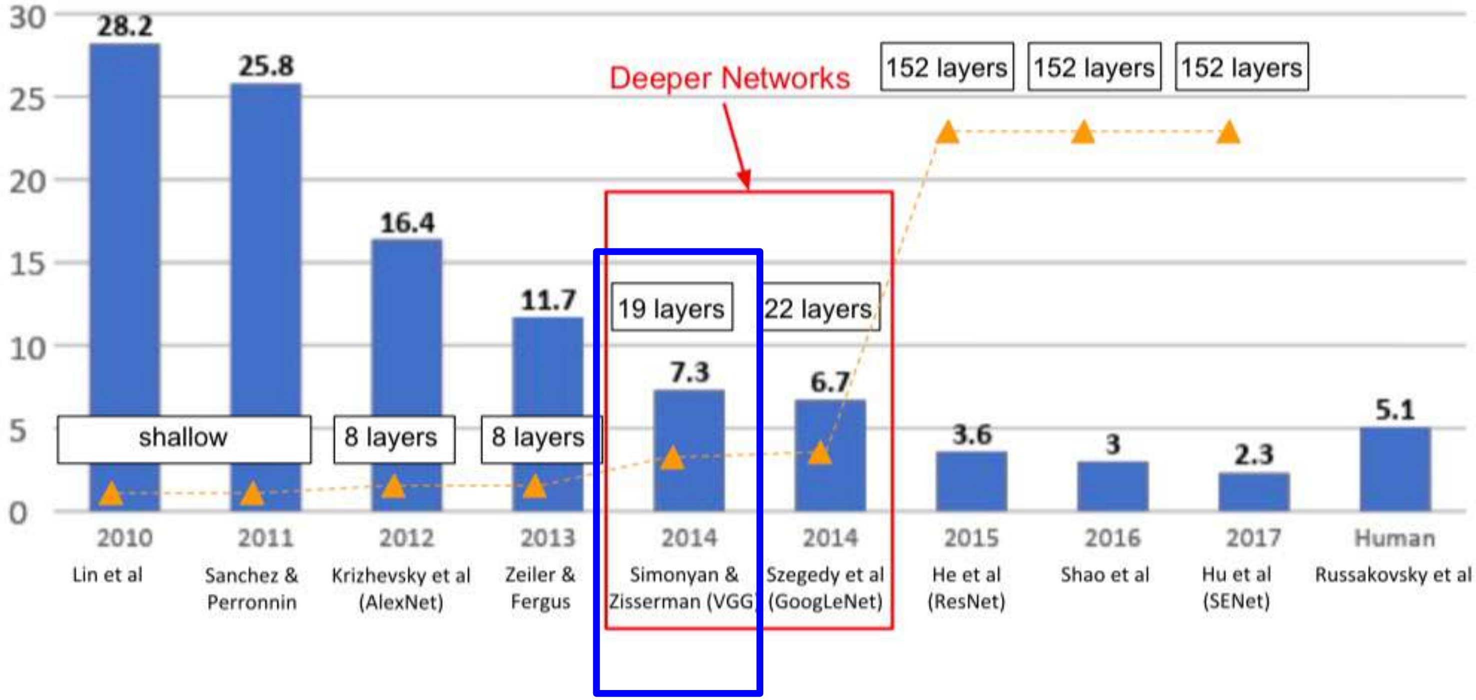
Convolutional Neural Networks (CNN)

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



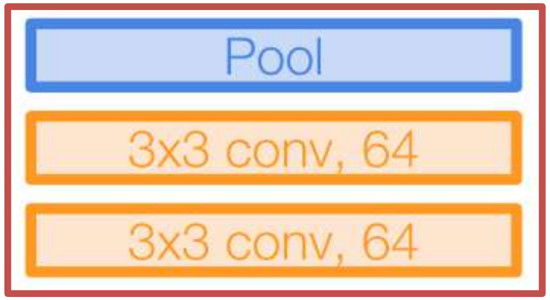
Case Study: VGGNet (2014)

[Simonyan and Zisserman, 2014]

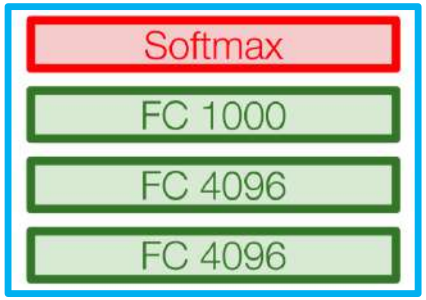
Small filters, Deeper networks

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

Case Study: VGGNet (2014)

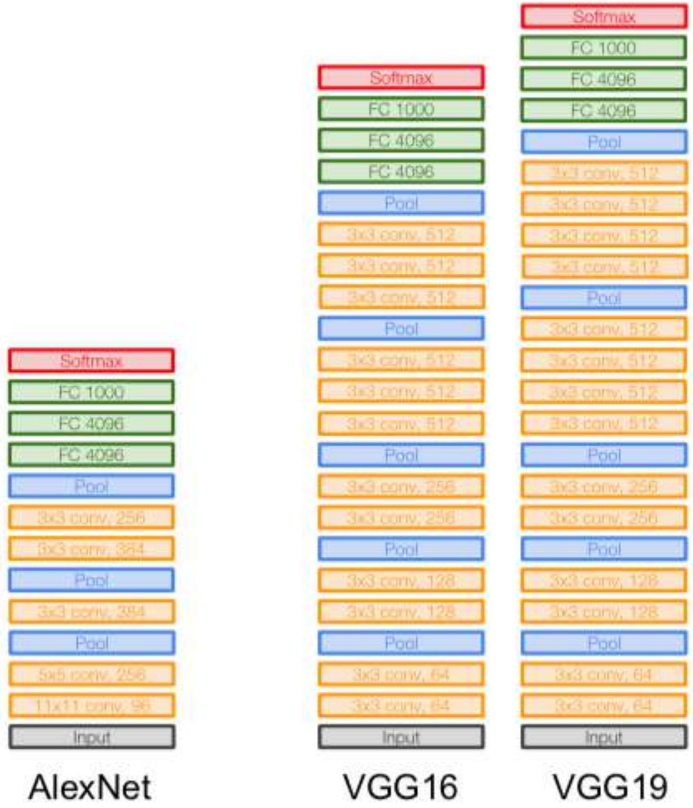
[Simonyan and Zisserman, 2014]

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
```

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				VGG16	VGG19
FC-4096					
FC-4096					
FC-1000					
soft-max					

50

11/04/2018 | DEEP LEARNING, IMAGE PROCESSING, MATHEMATICS, POST, TECHNOLOGY

Calculate the number of parameters on VGG Net

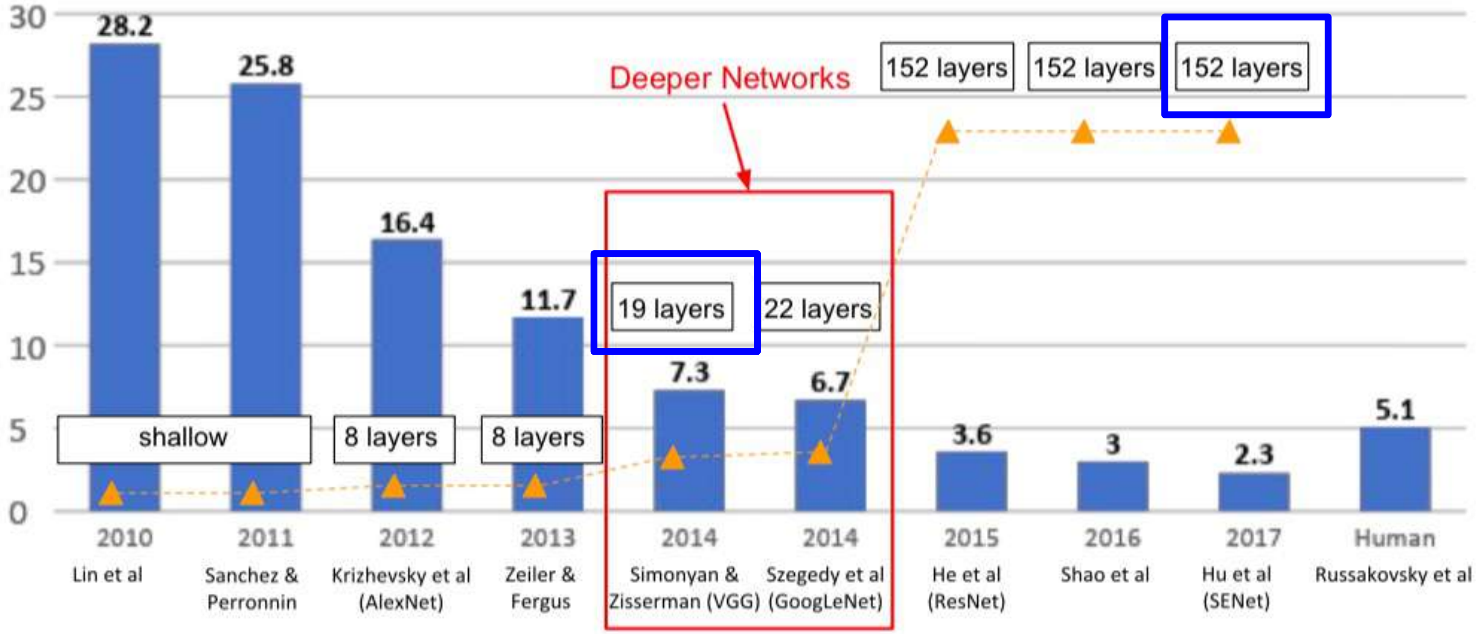
ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128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

Network	A	B	C	D	E
Number of parameters $\boxed{\text{(Millions)}}$	133	133	134	138	144

maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

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

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



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)

```

TensorFlow   Install   Learn   API   Resources   Community   Why TensorFlow

- Overview
- Input
- Model
- Sequential
- activations
- applications
  - Overview
  - DenseNet121
  - DenseNet169
  - DenseNet201
  - EfficientNetB0
  - EfficientNetB1
  - EfficientNetB2
  - EfficientNetB3
  - EfficientNetB4
  - EfficientNetB5
  - EfficientNetB6
  - EfficientNetB7
  - InceptionResNetV2
  - InceptionV3
  - MobileNet
  - MobileNetV2
  - MobileNetV3Large
  - MobileNetV3Small
  - NASNetLarge
  - NASNetMobile

Modules

`densenet` module: DenseNet models for Keras.

`efficientnet` module: EfficientNet models for Keras.

`imagenet_utils` module: Utilities for ImageNet data preprocessing & prediction decoding.

`inception_resnet_v2` module: Inception-ResNet V2 model for Keras.

`inception_v3` module: Inception V3 model for Keras.

`mobilenet` module: MobileNet v1 models for Keras.

`mobilenet_v2` module: MobileNet v2 models for Keras.

`nasnet` module: NASNet-A models for Keras.

`resnet` module: ResNet models for Keras.

`resnet50` module: Public API for tf.keras.applications.resnet50 namespace.

`resnet_v2` module: ResNet v2 models for Keras.

`vgg16` module: VGG16 model for Keras.

`vgg19` module: VGG19 model for Keras.

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

0.9.0 ▼

Search Docs

Package Reference

torchvision.datasets
torchvision.io
torchvision.models
torchvision.ops
torchvision.transforms
torchvision.utils

PyTorch Libraries

PyTorch
torchaudio
torchtext
torchvision
TorchElastic
TorchServe
PyTorch on XLA Devices

Docs > torchvision.models

PyTorch

TORCHVISION.MODELS

The models subpackage contains definitions of models for addressing different tasks, including: image classification, pixelwise semantic segmentation, object detection, instance segmentation, person keypoint detection and video classification.

Classification

The models subpackage contains definitions for the following model architectures for image classification:

- AlexNet
- VGG
- ResNet
- SqueezeNet
- DenseNet
- Inception v3
- GoogLeNet
- ShuffleNet v2
- MobileNetV2
- MobileNetV3
- ResNeXt
- Wide ResNet
- MNASNet

We provide pre-trained models, using the PyTorch `torch.utils.model_zoo`. These can be constructed by passing `pretrained=True`:

```
import torchvision.models as models
resnet18 = models.resnet18(pretrained=True)
alexnet = models.alexnet(pretrained=True)
squeezenet = models.squeezenet1_0(pretrained=True)
vgg16 = models.vgg16(pretrained=True)
densenet = models.densenet161(pretrained=True)
inception = models.inception_v3(pretrained=True)
googlenet = models.googlenet(pretrained=True)
shufflenet = models.shufflenet_v2_x1_0(pretrained=True)
mobilenet_v2 = models.mobilenet_v2(pretrained=True)
mobilenet_v3_large = models.mobilenet_v3_large(pretrained=True)
mobilenet_v3_small = models.mobilenet_v3_small(pretrained=True)
resnext50_32x4d = models.resnext50_32x4d(pretrained=True)
wide_resnet50_2 = models.wide_resnet50_2(pretrained=True)
mnasnet = models.mnasnet1_0(pretrained=True)
```

https://pytorch.org/vision/0.9/models.html v1.1.0 ▼

pytorch-transformers

Star 131,473

Search docs

NOTES

- Installation
- Quickstart
- Pretrained models
- Examples
- Notebooks
- Loading Google AI or OpenAI pre-trained weights or PyTorch dump
- Serialization best-practices
- Converting Tensorflow Checkpoints
- Migrating from pytorch-pretrained-bert
- BERTology

ⓘ You are viewing legacy docs. Go to latest documentation instead.

Docs » Pytorch-Transformers

Pytorch-Transformers

PyTorch-Transformers is a library of state-of-the-art pre-trained models for Natural Language Processing (NLP).

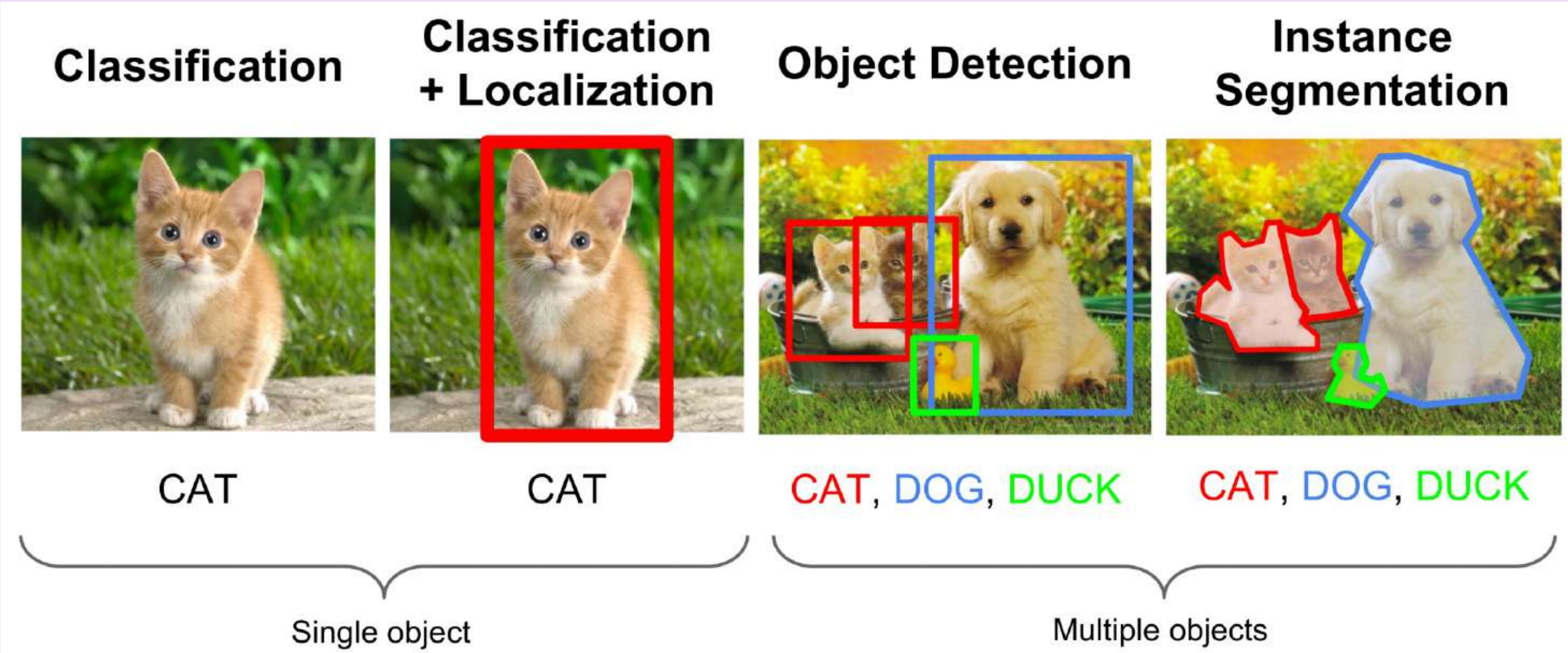
The library currently contains PyTorch implementations, pre-trained model weights, usage scripts and conversion utilities for the following models:

1. BERT (from Google) released with the paper BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding by Jacob Devlin, Ming-Wei Lee and Kristina Toutanova.
2. GPT (from OpenAI) released with the paper Improving Language Understanding by Generative Pre-Training by Alec Radford, Karthik Narasimhan, Tim Salim Sutskever.
3. GPT-2 (from OpenAI) released with the paper Language Models are Unsupervised Multitask Learners by Alec Radford*, Jeffrey Wu*, Rewon Child, David Lua and Ilya Sutskever**.
4. Transformer-XL (from Google/CMU) released with the paper Transformer-XL: Attentive Language Models Beyond a Fixed-Length Context by Zihang Dai*, Z Yang, Jaime Carbonell, Quoc V. Le, Ruslan Salakhutdinov.
5. XLNet (from Google/CMU) released with the paper XLNet: Generalized Autoregressive Pretraining for Language Understanding by Zhilin Yang*, Zihang Dai Jaime Carbonell, Ruslan Salakhutdinov, Quoc V. Le.
6. XLM (from Facebook) released together with the paper Cross-lingual Language Model Pretraining by Guillaume Lample and Alexis Conneau.

Notes

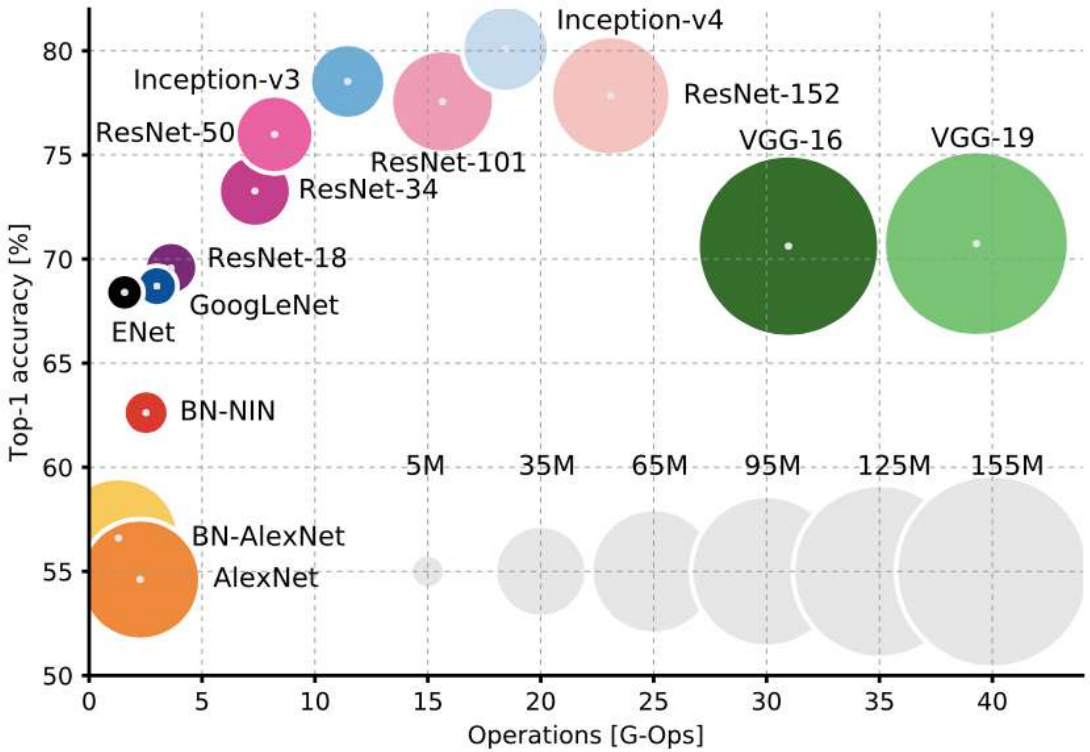
- Installation

Image Classification Tasks

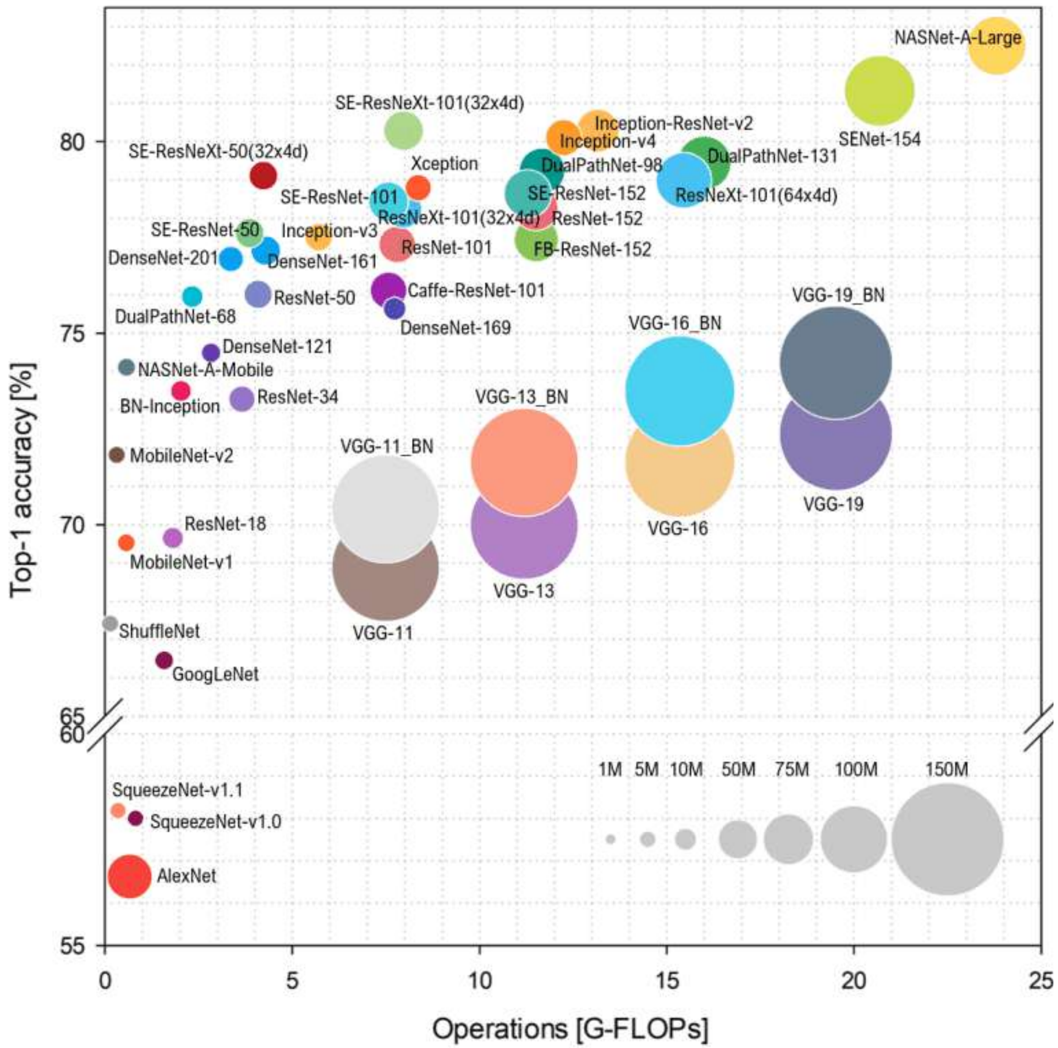


https://analyticsindiamag.com/top-5-image-classification-research-papers-every-data-scientist-should-know/

SOTA of Image Classification

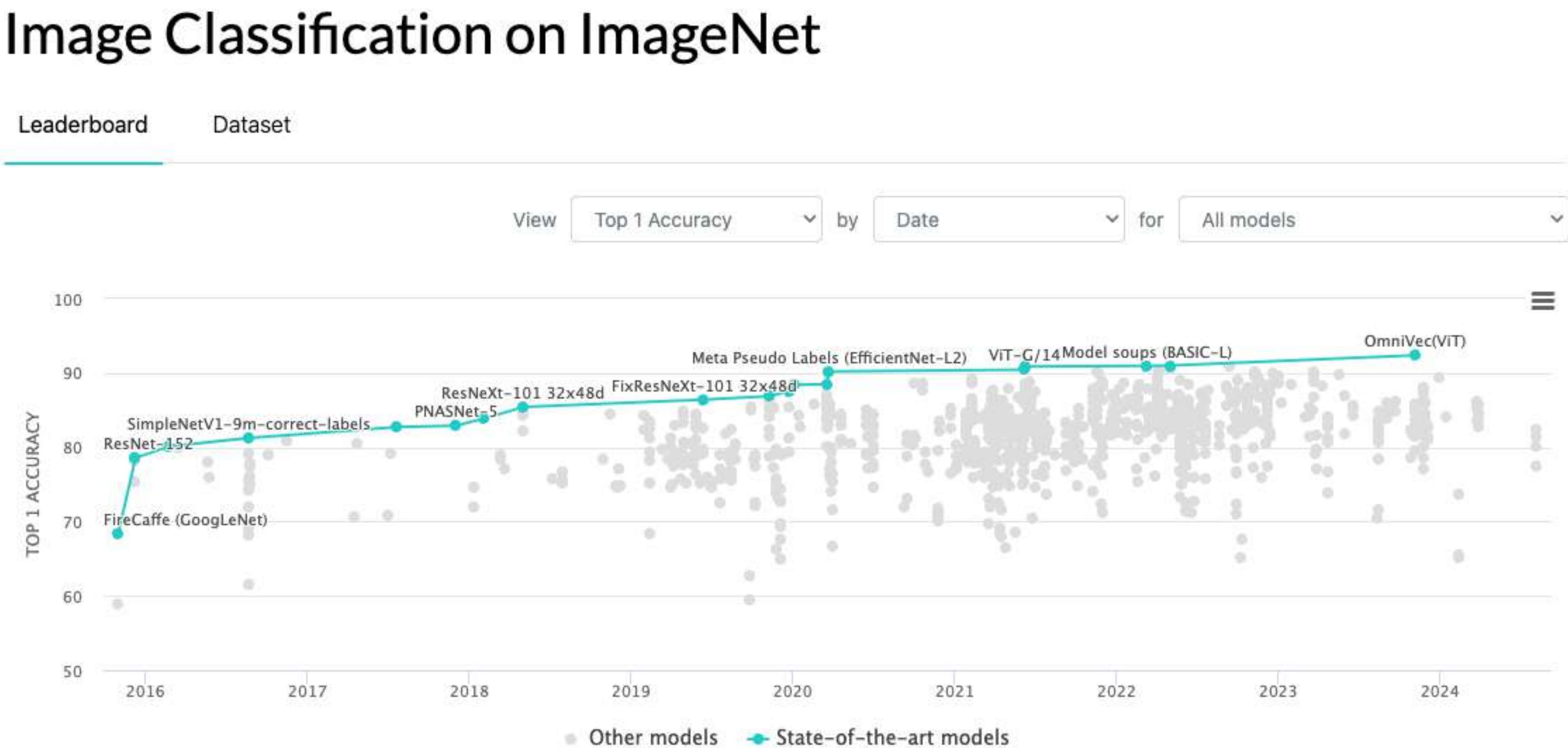


https://blog.csdn.net/qq_34216467/article/details/83061692



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

Image classfication dashboard (2024)



https://paperswithcode.com/sota/image-classification-on-imagenet

Image classfication dashboard (2025)

- CNN, Transformer (ViT, VLM)
  - 2021–2022 → CNNs (EfficientNetV2) were strong, but Transformers started dominating.
  - 2022–2023 → Vision–Language models (VLM) like CoCa + giant ViTs (EVA, Model Soups) pushed past 90%.
  - 2024 → Specialized ViT variants (DaViT, Florence-CoSwin) consolidated.
  - 2025 → Large-scale foundation models (DINOv3) + fine-tuned CoCa remain at the frontier.
- Note:
  - CoCa / CLIP → Vision–Language, trained with image–text pairs, suitable for cross-modal tasks such as captioning and retrieval
  - DINOv3 → Vision-only, self-supervised ViT, backbone for computer vision

https://paperswithcode.com/sota/image-classification-on-imagenet

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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

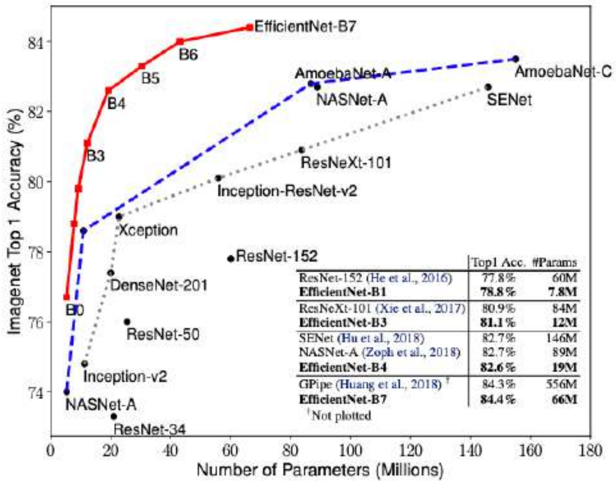
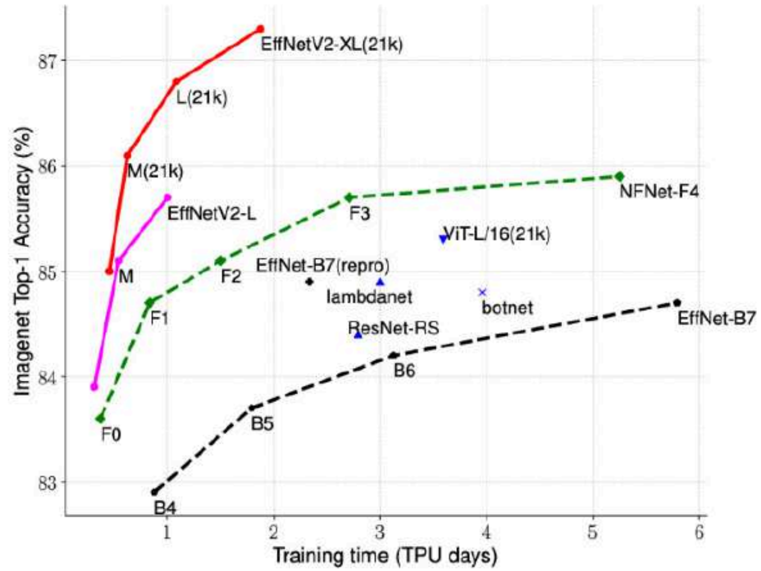


Figure 1. **Model Size vs. ImageNet Accuracy.** All numbers are



(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

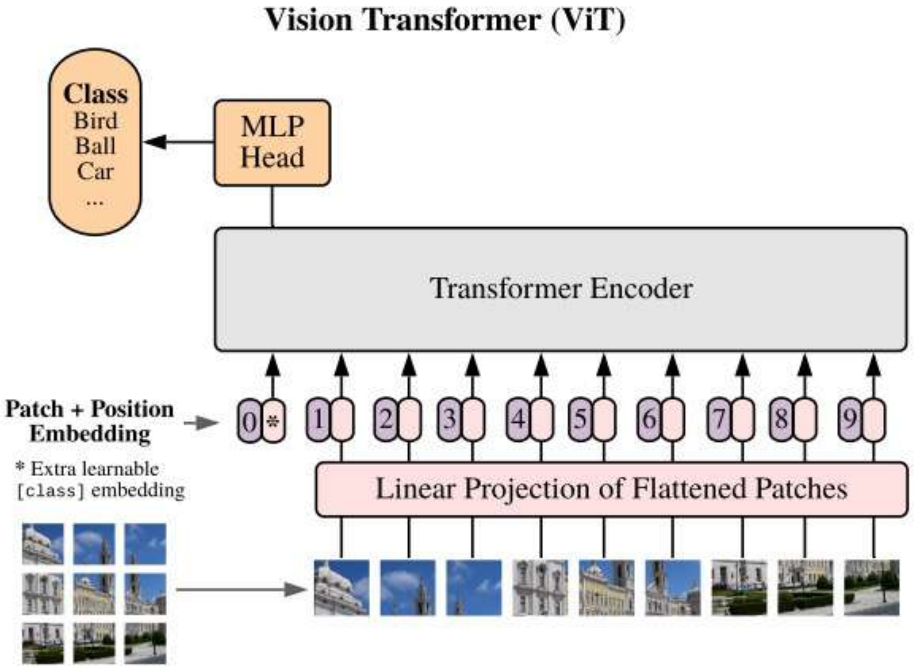
(b) Parameter efficiency.

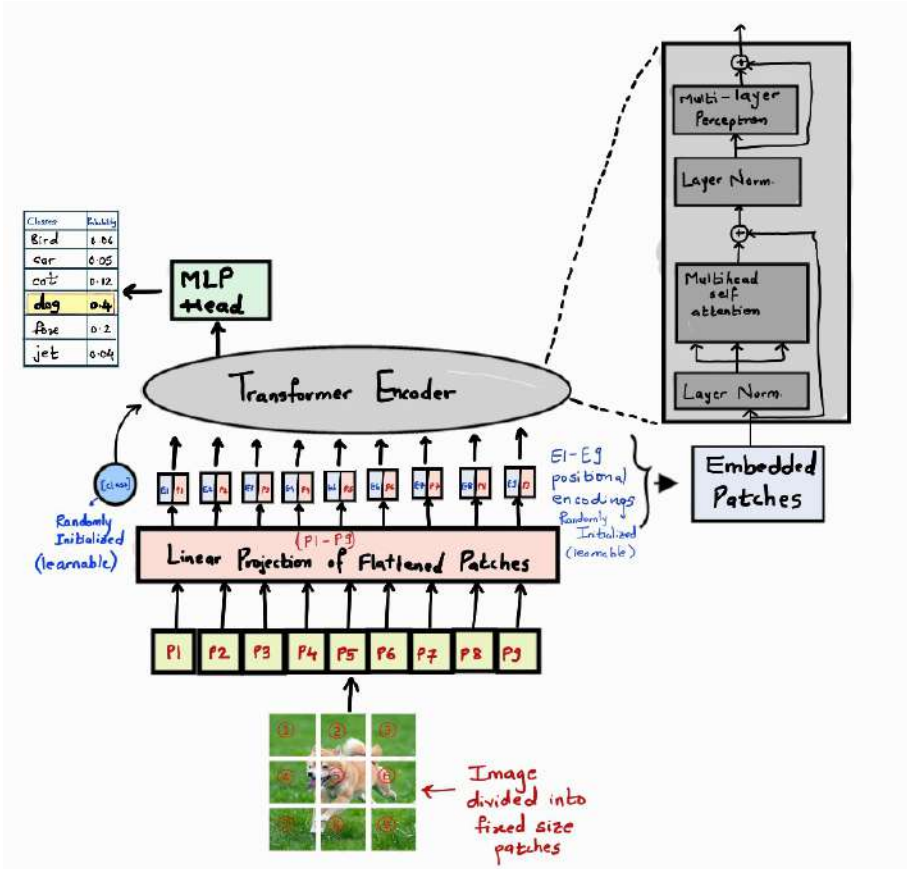
http://proceedings.mlr.press/v97/tan19a/tan19a.pdf

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

Vision Transformer (ViT) (ICLR2021)

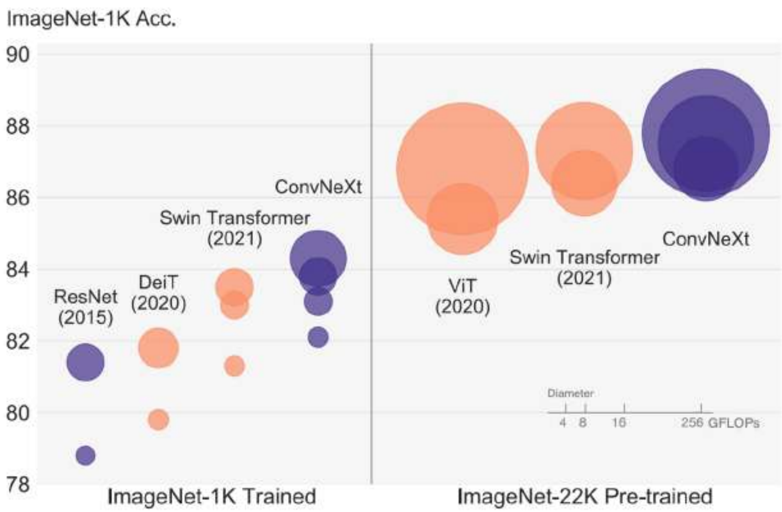
Hugging Face

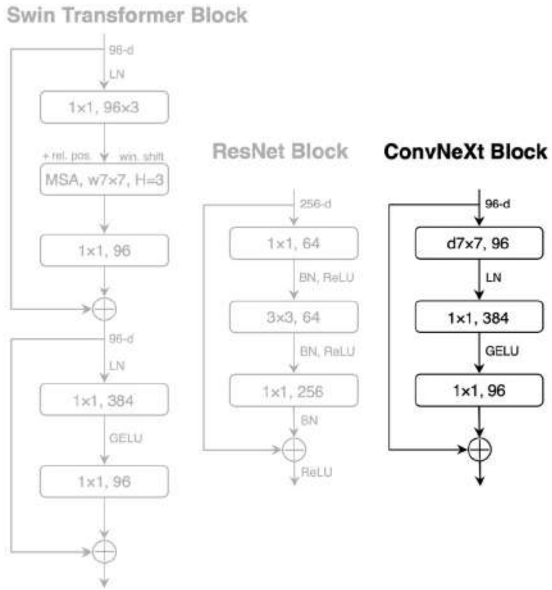


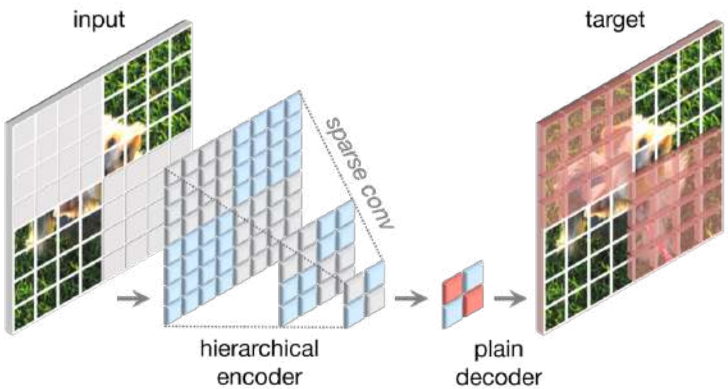


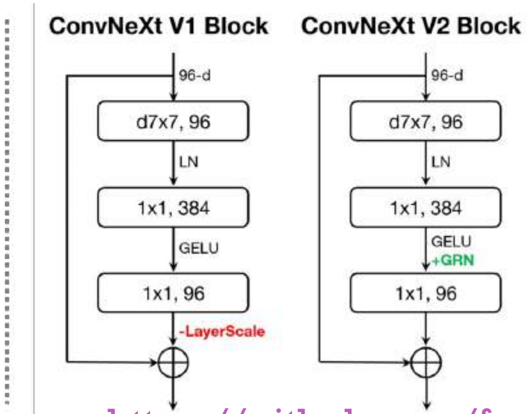
https://medium.com/machine-intelligence-and-deep-learning-lab/vit-vision-transformer-cc56c8071a20

+ ConvNeXt (CVPR2022) → ConvNeXt V2 (2023)









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

https://github.com/facebookresearch/ConvNeXt

Open Source

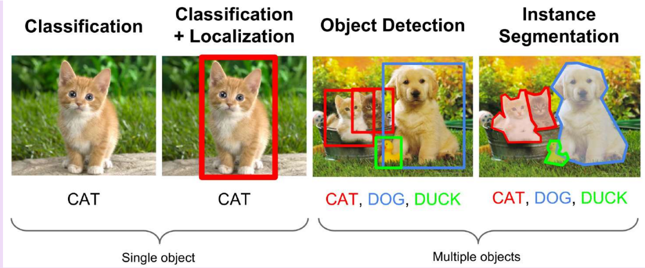
DINOv3: Self-supervised learning for vision at unprecedented scale

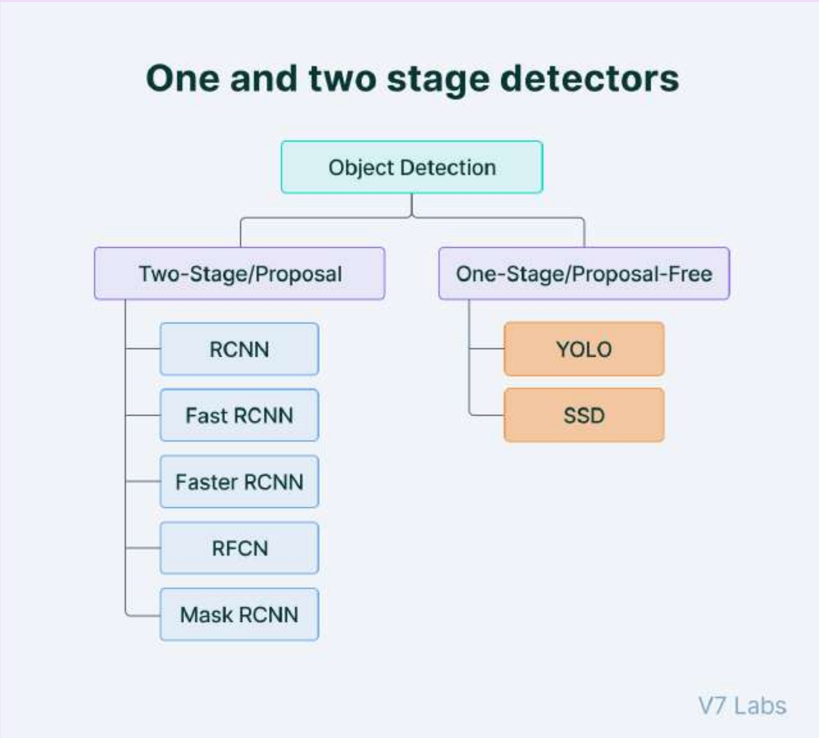
August 14, 2025 · 11 minute read

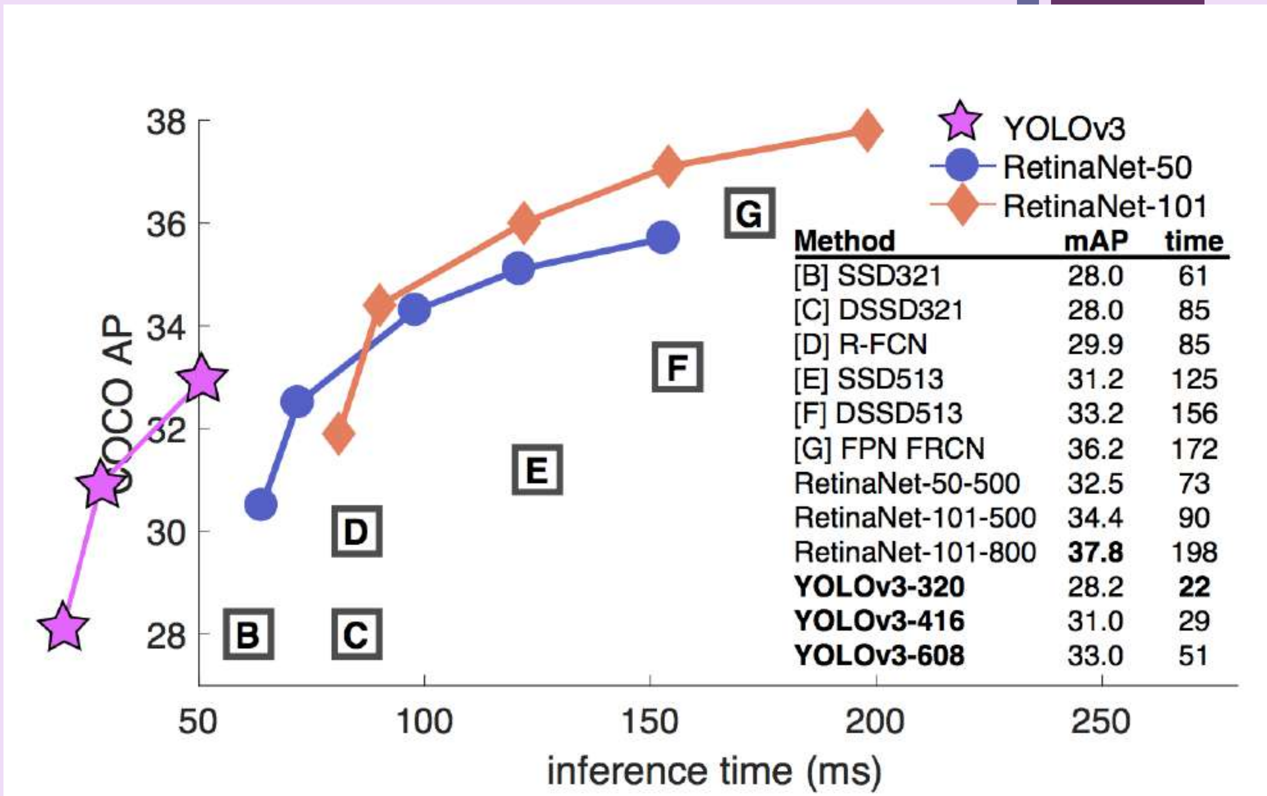
- DINOv3: Self-Supervised Vision Transformer (Meta AI, 2025)
- Vision-only (encoder-only) backbone (not multimodal, unlike CLIP/CoCa).
- Self-supervised learning → no human labels needed.
- Massive scale: up to 7B parameters, trained on 1.7B images.
- Key innovations:
  - Gram Anchoring → stabilizes feature learning.
  - Axial RoPE → improved positional encoding.
  - Resolution robustness → better handling of varied image sizes.
- Strengths:
  - Provides general-purpose visual representations.
  - Excels in downstream tasks (classification, detection, segmentation).
  - Foundation model role for vision, similar to LLMs in NLP.

Link

SOTA of Object Detection







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

YOLO Open Images in New York

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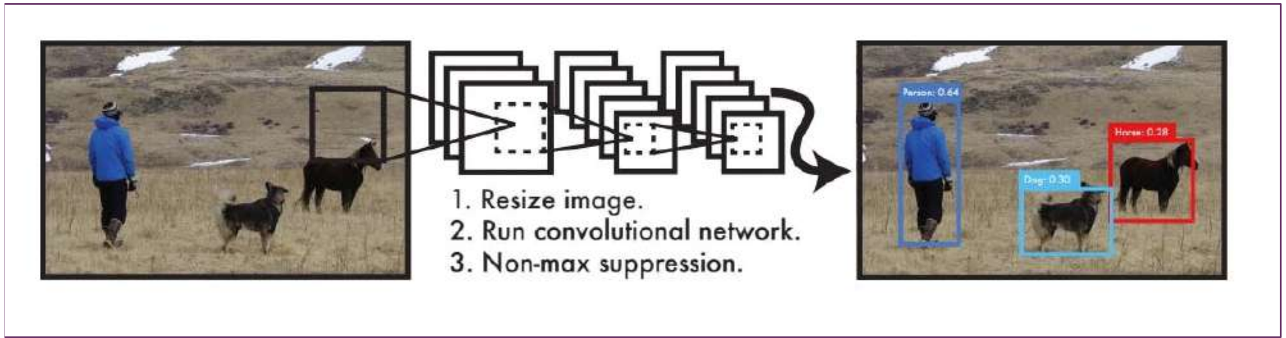
+ YOLO's output



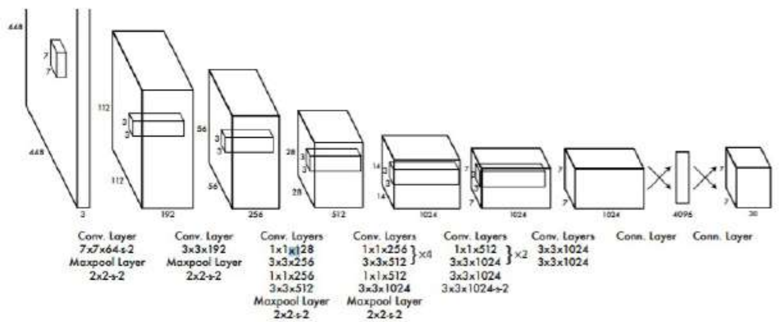
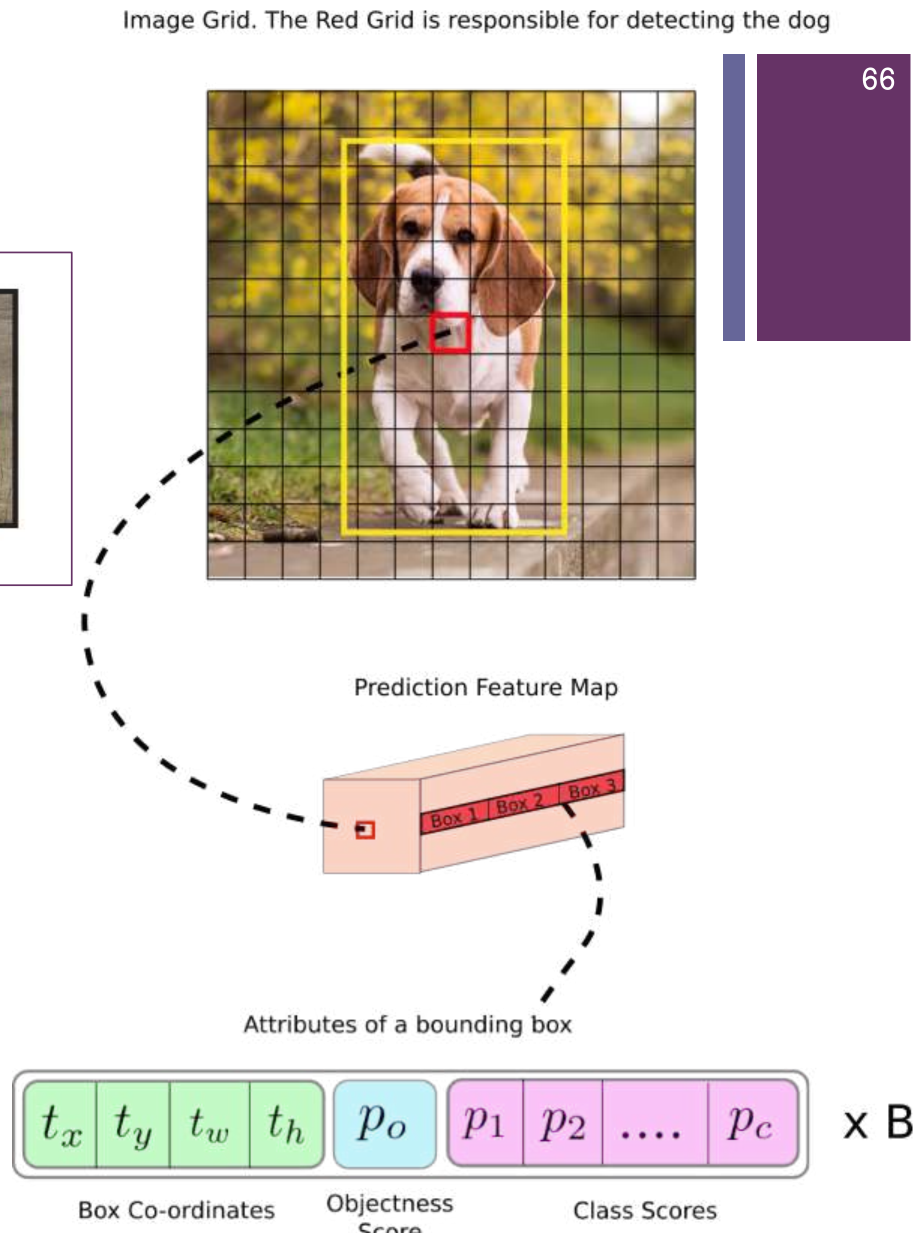
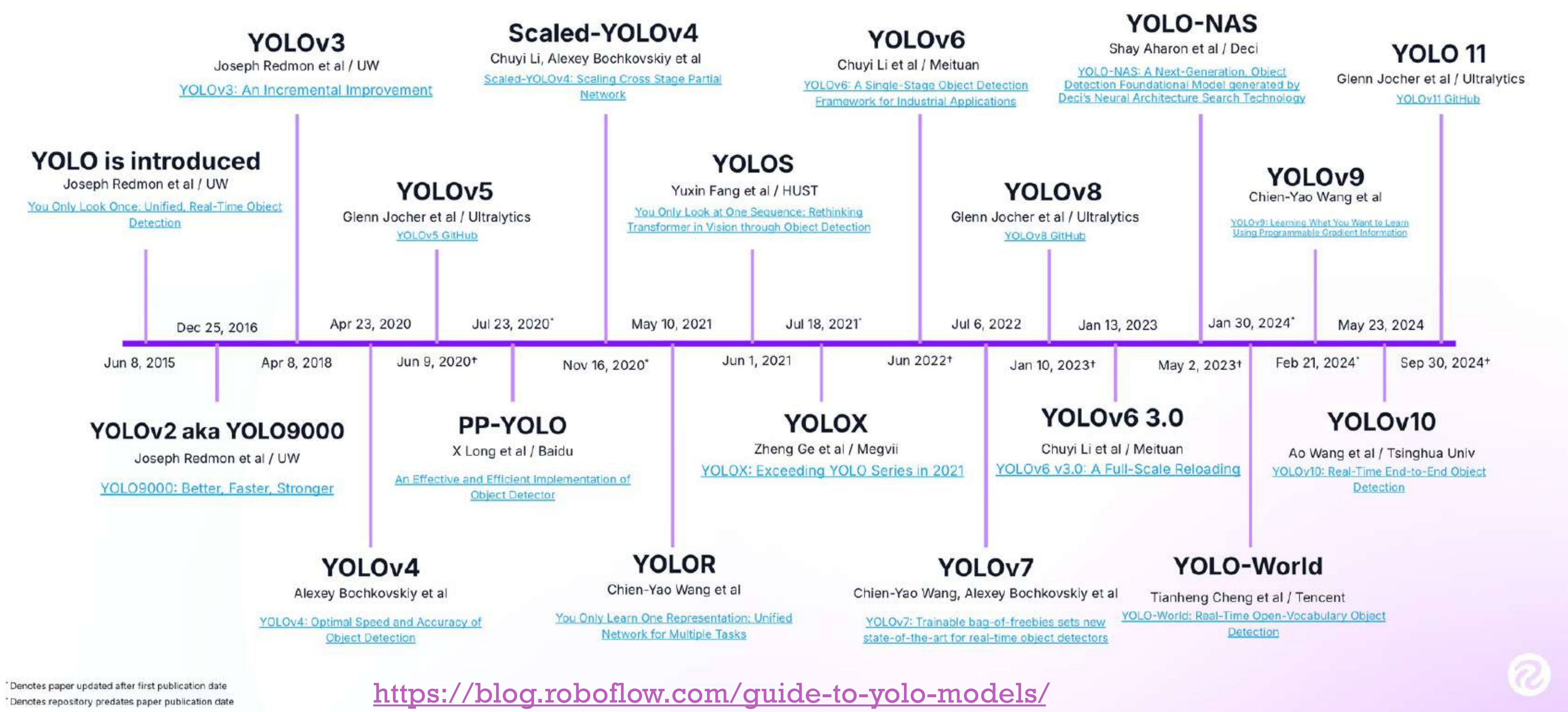


Figure 3: The Architecture. Our detection network has 24 convolutional layers followed by 2 fully connected layers. Alternating 1 × 1 convolutional layers reduce the features space from preceding layers. We pretrain the convolutional layers on the ImageNet classification task at half the resolution (224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



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

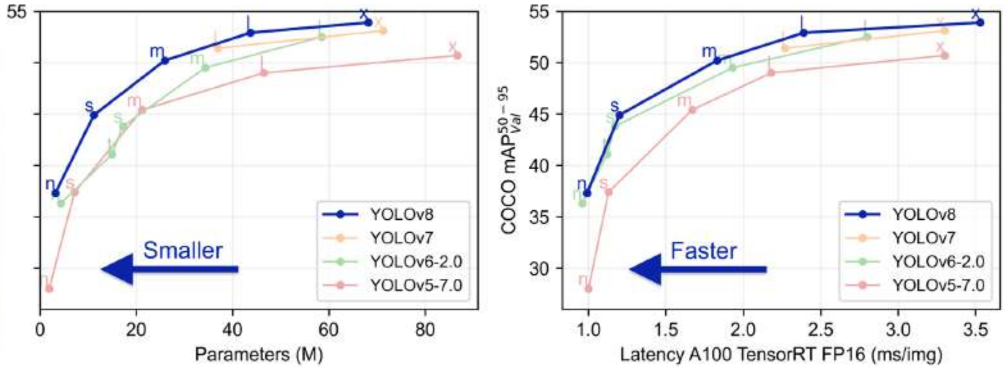
Ultralytics YOLO → production-ready, practical framework (YOLOv5 → YOLOv8 → YOLO11).
Academic YOLO → new research architectures (YOLOv9, v10, v11, v12).



https://blog.roboflow.com/guide-to-yolo-models/

Ultralytic's YOLO

YOLOv5 (2020) → YOLOv8 (2023) → Ultralytics YOLO 11 (2024)



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.

Classify | Detect | Segment | Track | Pose

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

YOLO Models (v9 – v12) Timeline

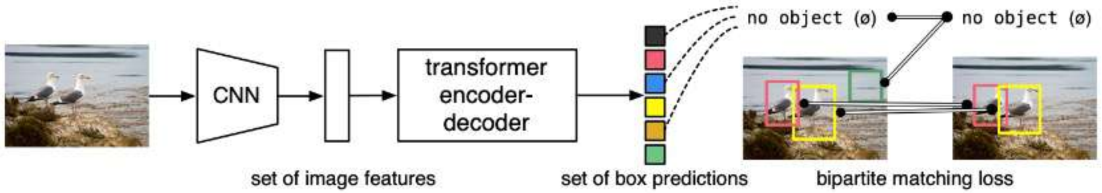
Model	Release Timeframe	Team / Organization	Key Highlight
YOLOv12	Feb 2025	**Google Research + Tsinghua University** (collaboration)	Attention-centric architecture with high accuracy and real-time speed
YOLOv11	Late 2024	**Tencent Youtu Lab**	Enhanced architecture (C3k2, SPPF, C2PSA), versatile across detection, segmentation, pose
YOLOv10	Mid 2024	**Tsinghua University + Huawei Noah's Ark Lab**	End-to-end design without NMS, major speed and efficiency gains
YOLOv9	Early 2024	**Wong Kin Yiu (original YOLO contributor) + Community researchers**	PGI and GELAN for better gradients and efficiency
Ultralytics YOLO11	2024–2025	**Ultralytics**	Practical SOTA release, supports detection, segmentation, pose, classification, track

+ DETR (Detection Transformer) [Meta, 2020]

DE:TR: End-to-End Object Detection with Transformers

Support Ukraine

PyTorch training code and pretrained models for **DETR** (**DE**tection **TR**ansformer). We replace the full complex hand-crafted object detection pipeline with a Transformer, and match Faster R-CNN with a ResNet-50, obtaining **42 AP** on COCO using half the computation power (FLOPs) and the same number of parameters. Inference in 50 lines of PyTorch.



- 1. Deformable DETR (2020)
- Team: Microsoft Research Asia

- 2. Conditional DETR (2021)
- Team: Chinese Academy of Sciences

- 3. Anchor DETR (2021)
- Team: SenseTime and Shanghai Jiao Tong University

- 4. Efficient DETR (2021)
- Team: UC Berkeley and Google Research

- 5. DINO (DETR with Improved Non-Autoregressive Decoding) (2022)
- Team: Meta AI (formerly Facebook AI Research)

- 6. RT-DETR (Real-Time DETR) (2024)
- Team: Alibaba DAMO Academy

Top Object Detection Models (2025)

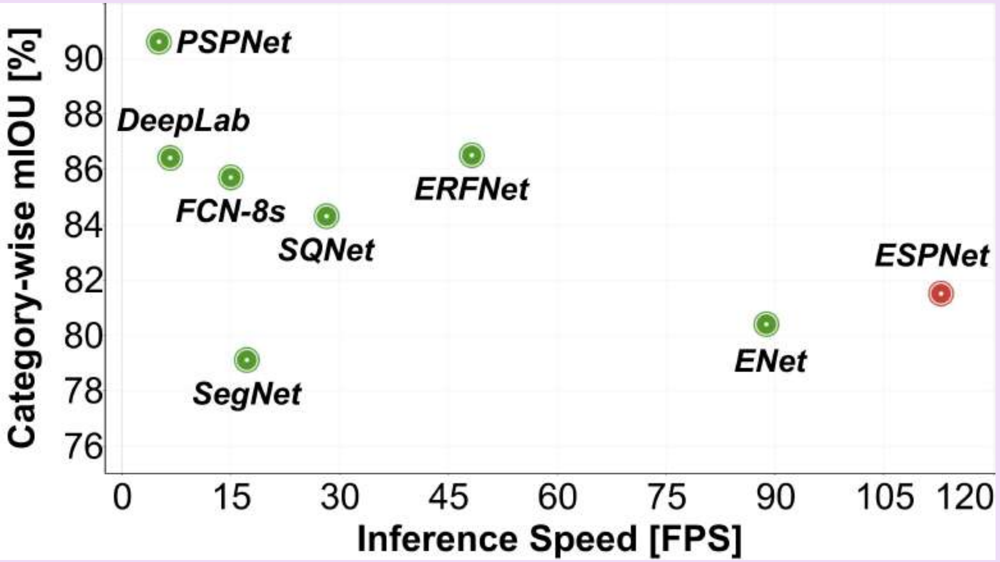
Model	**Team / Source**	**Notable Metric (COCO)**	**Strengths**
RF-DETR	Roboflow	73.6 AP_{50} / 54.7 AP_{50:95} (Medium)	Real-time DETR; best mAP at low latency
YOLOv12	YOLO authors (YOLO Series)	—	Latest YOLO, attention-enhanced
YOLO11 (Ultralytics)	Ultralytics	Up to ~50 AP_{50} / ~48.6 AP_{50:95}	Multi-task, production-ready

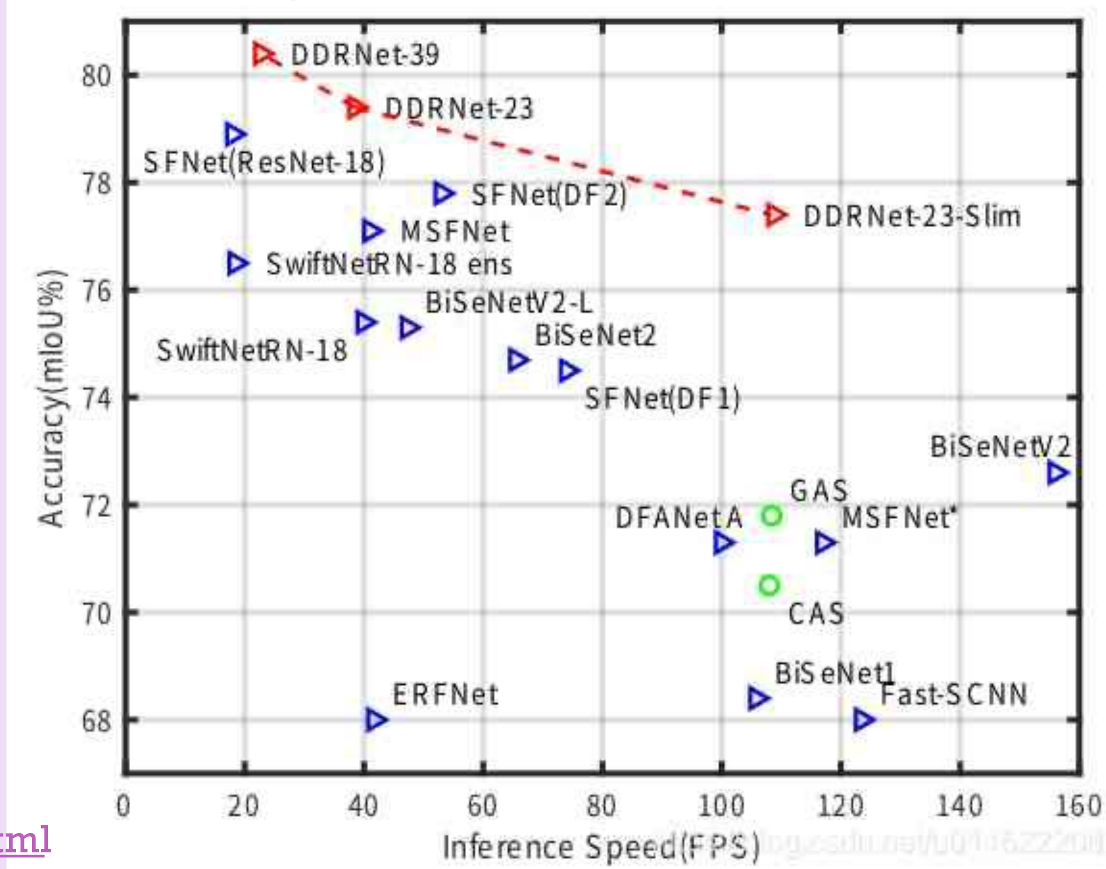
SOTA of Semantic Segmentation

当前位置： 网站首页>[Pers

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

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



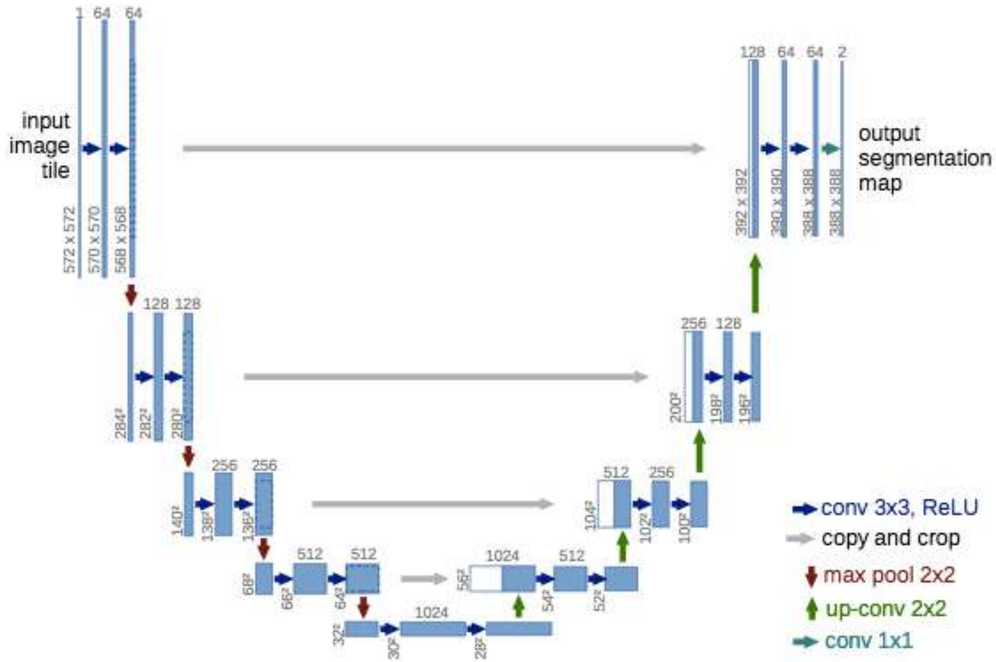


- **Real-time semantic segmentation**
- BiSeNet V1,V2
- DDRNet

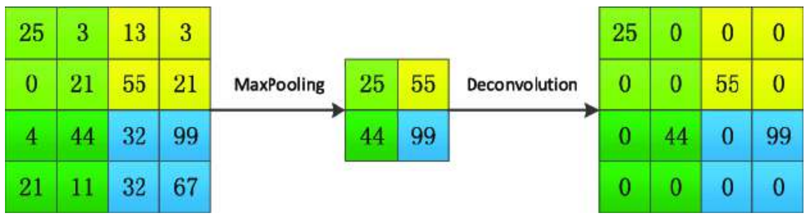
https://chowdera.com/2021/11/20211109042359120o.html

UNet: Encoder-Decoder Network

- **U-Net**



Deconvolutional layer



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)]

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Recent interesting segmentation networks

- 1. ContextFormer (2025)
- Team: Abid, Mehta, Wu, Dharejo, Timofte
- Architecture: Hybrid CNN + Vision Transformer
- Strengths: Combines high accuracy with real-time efficiency
- Applications: Urban scene understanding, robotics, autonomous driving

- 2. Segment Anything Model (SAM) [Meta, 2023] → SAM V2 [Meta, 2024]
- Explanation: SAM is a highly versatile model designed to segment any object within an image with minimal user input. It uses a prompt-based approach, where the user provides a prompt (e.g., a point or bounding box), and the model generates a mask for the object. SAM is particularly noted for its generalizability across different segmentation tasks.

- 3. Mask2Former [Meta, 2022]
- Explanation: Mask2Former is a unified model for instance, semantic, and panoptic segmentation tasks. It improves upon the original MaskFormer by incorporating transformers into the architecture, enabling it to handle different segmentation tasks within a single framework efficiently.

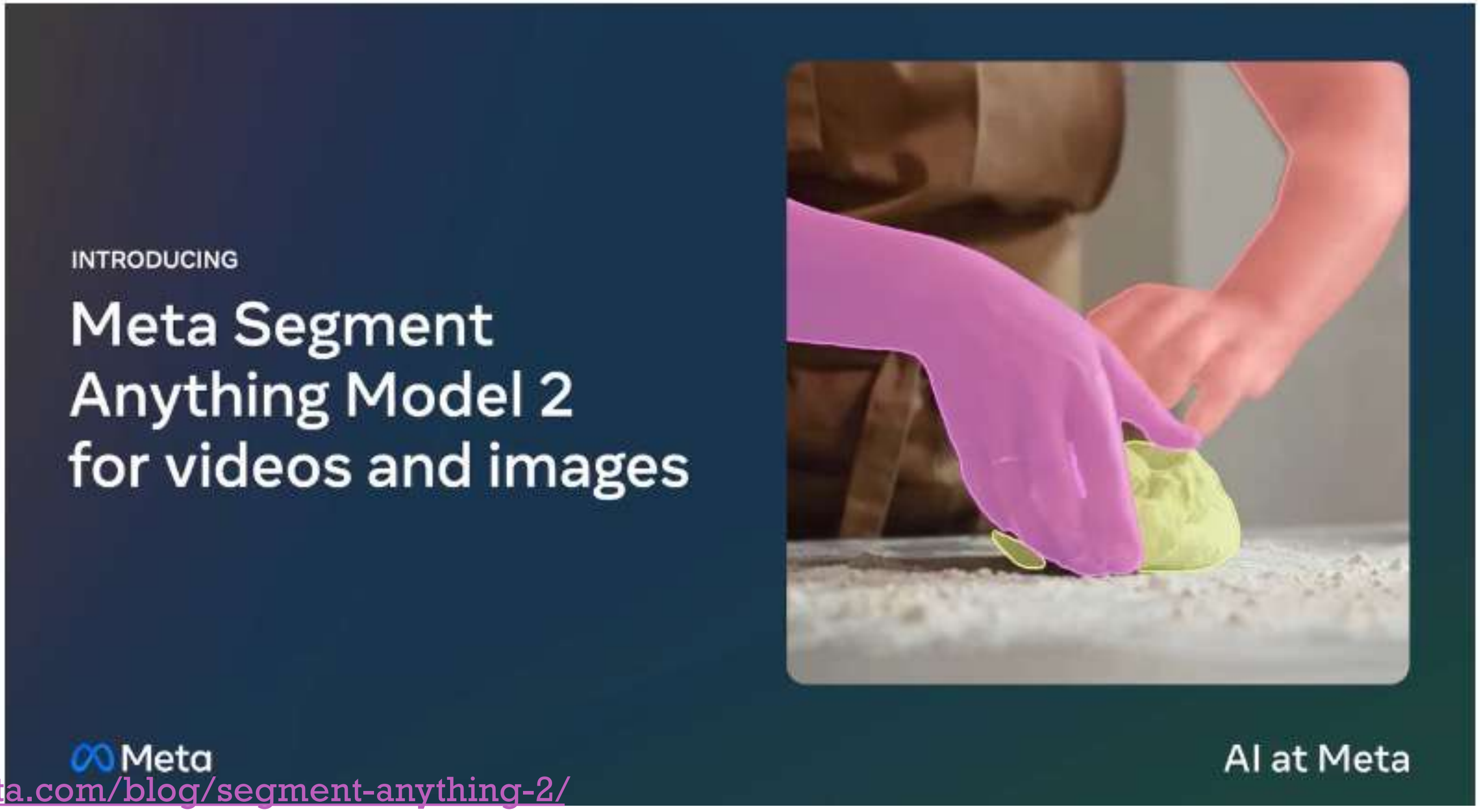
- 4. Swin Transformer V2 [Microsoft, 2022]
- Explanation: Swin Transformer V2 builds on the hierarchical vision transformer design introduced in the original Swin Transformer. It enhances performance in both segmentation and classification tasks and has achieved SOTA results on benchmarks such as COCO and ADE20K.

- 5. SegFormer [NVIDIA, 2021]
- Explanation: SegFormer is a transformer-based model that is designed to be both efficient and accurate for semantic segmentation tasks. It integrates transformers with lightweight MLP decoders, enabling high performance while maintaining computational efficiency.

- 6. DeepLabV3+ [Google, 2018]
- Explanation: DeepLabV3+ is an extension of the DeepLab series, which combines spatial pyramid pooling and atrous convolutions. The "+" version introduces a decoder module to improve object boundary delineation, making it a strong performer in semantic segmentation.

Introducing SAM 2: The next generation of Meta Segment Anything Model for videos and images

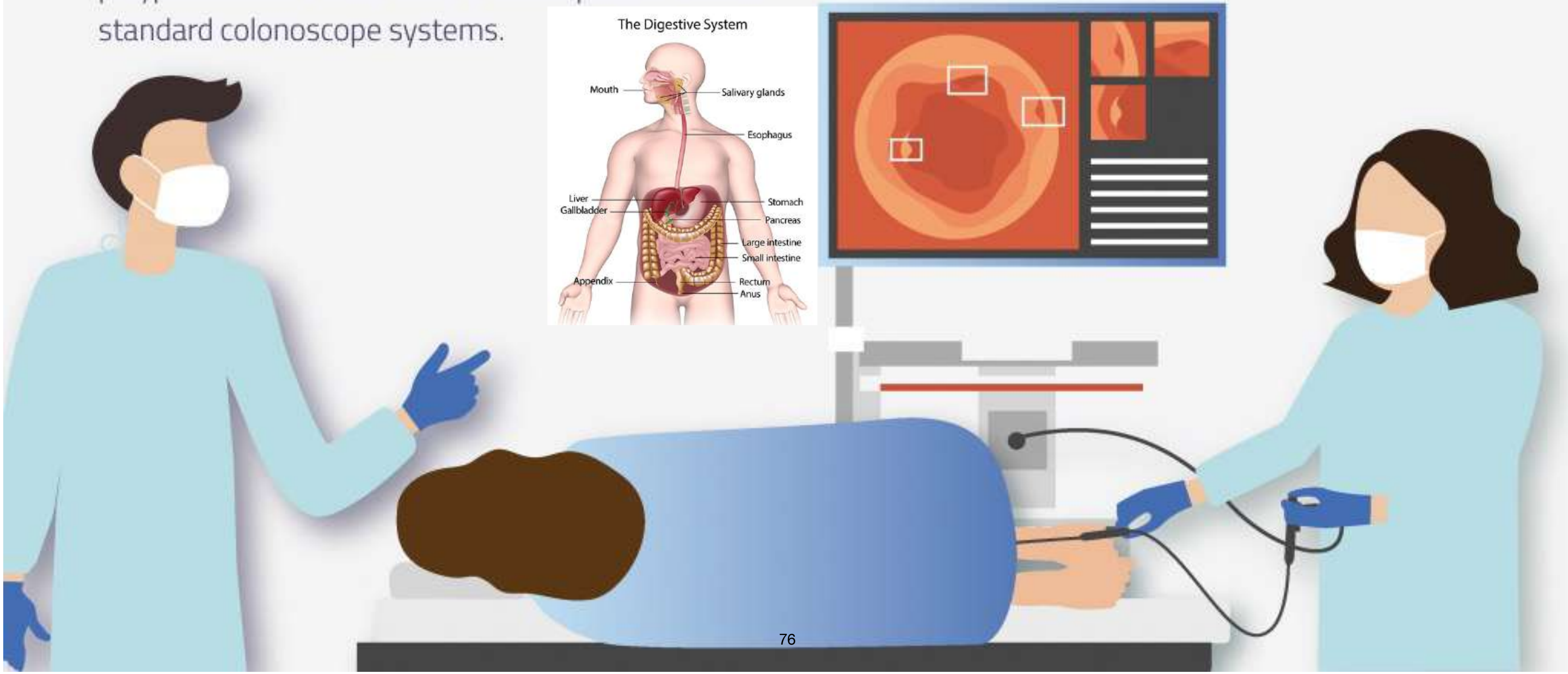
July 29, 2024 • 15 minute read



https://ai.meta.com/blog/segment-anything-2/

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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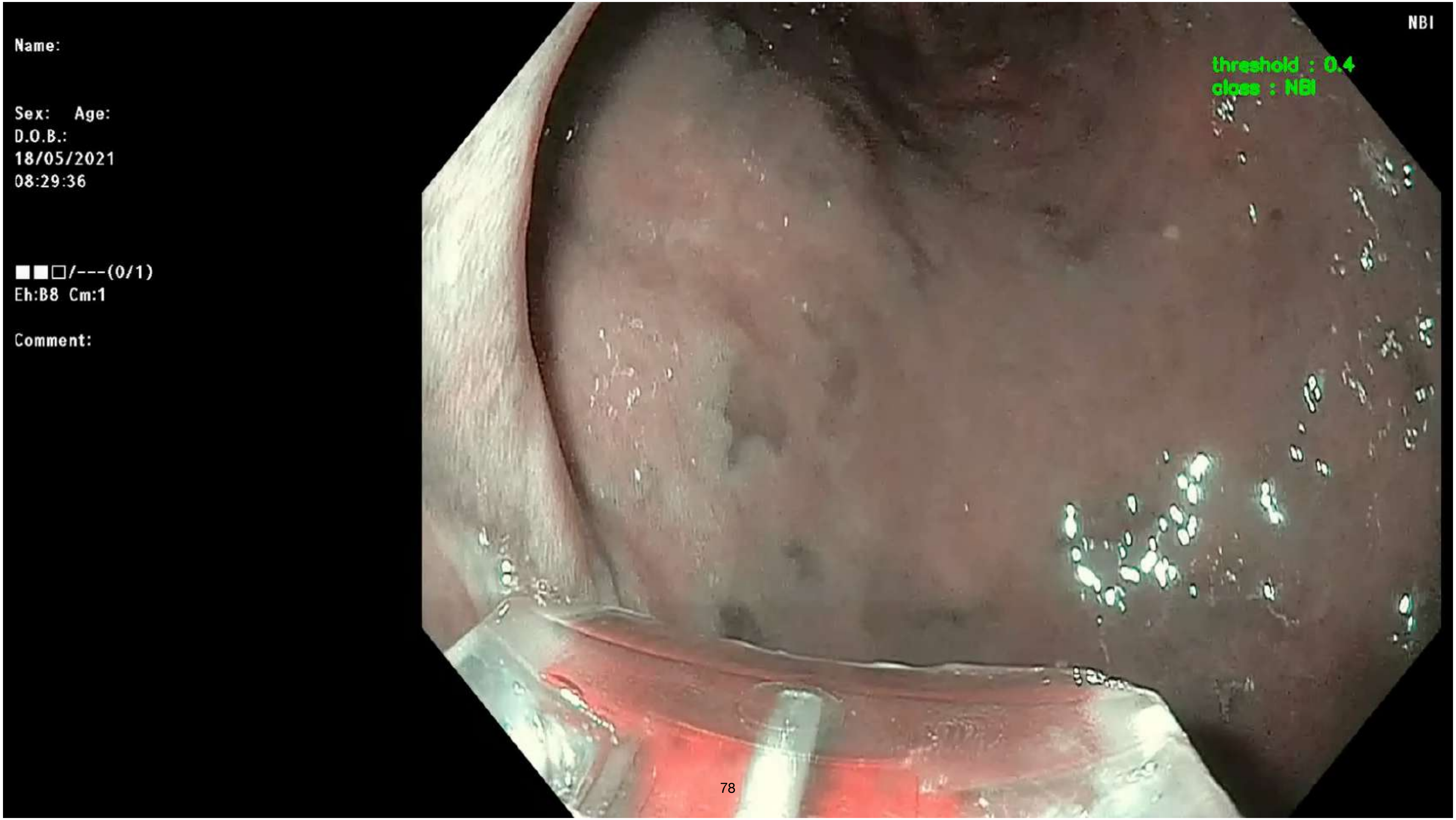
COLON
*1/200
Lv+2 AUTO
HT NR
SE
3. 8
12. 0
12. 0
S1: F+T
S2: LM
S3: CAD
S4:
EC-760R-V/L
3C729K035
BL-7000
CHULALONGKORN HOS
6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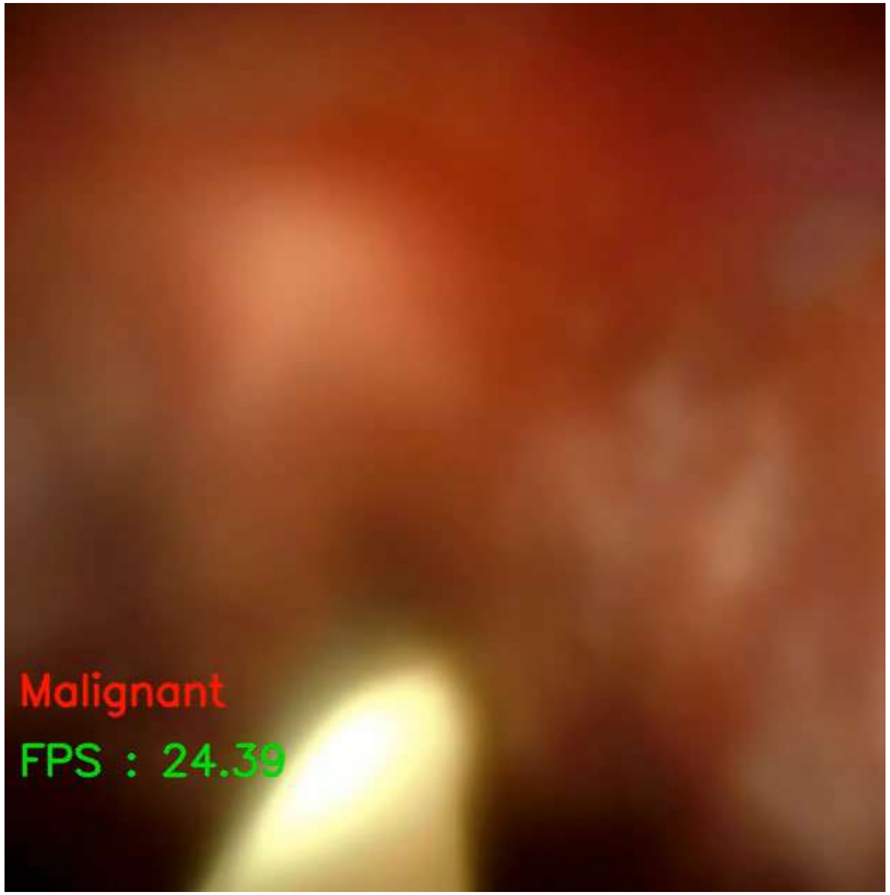
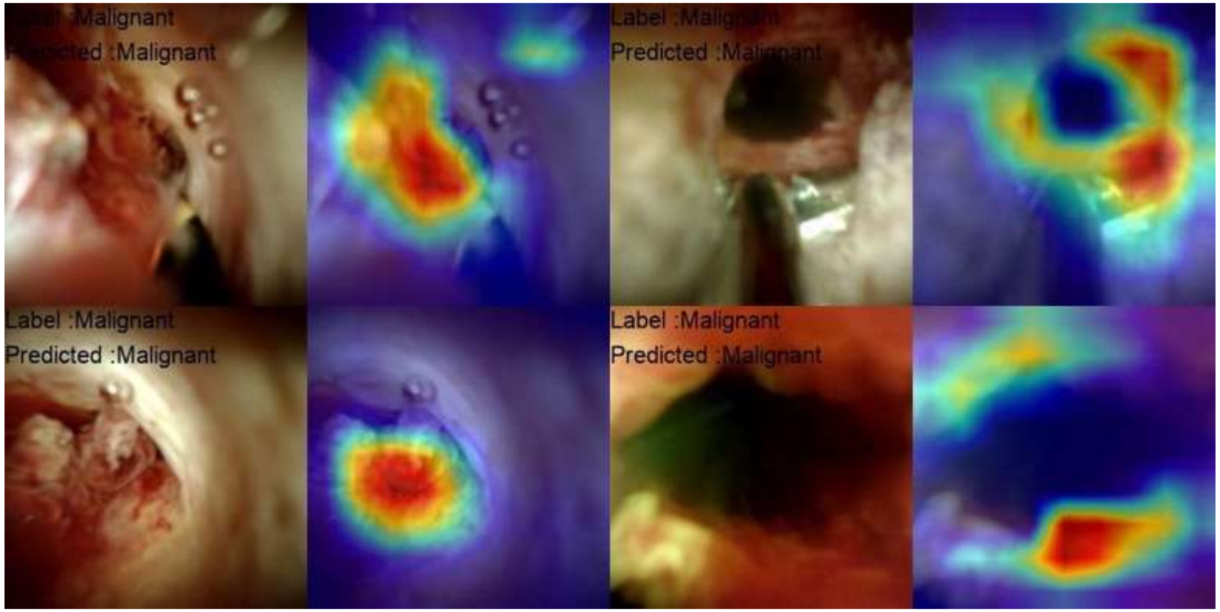
Eh:B8 Cm:1
Comment:
NBI
threshold : 0.4
class : NBI

Cholangioscopy





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+

RNN

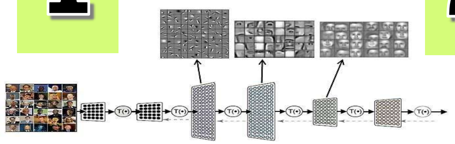
+ Deep Learning Application

Speech Recognition

Computer Vision

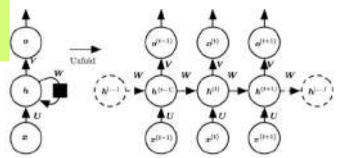
Natural Language Processing

1



CNN

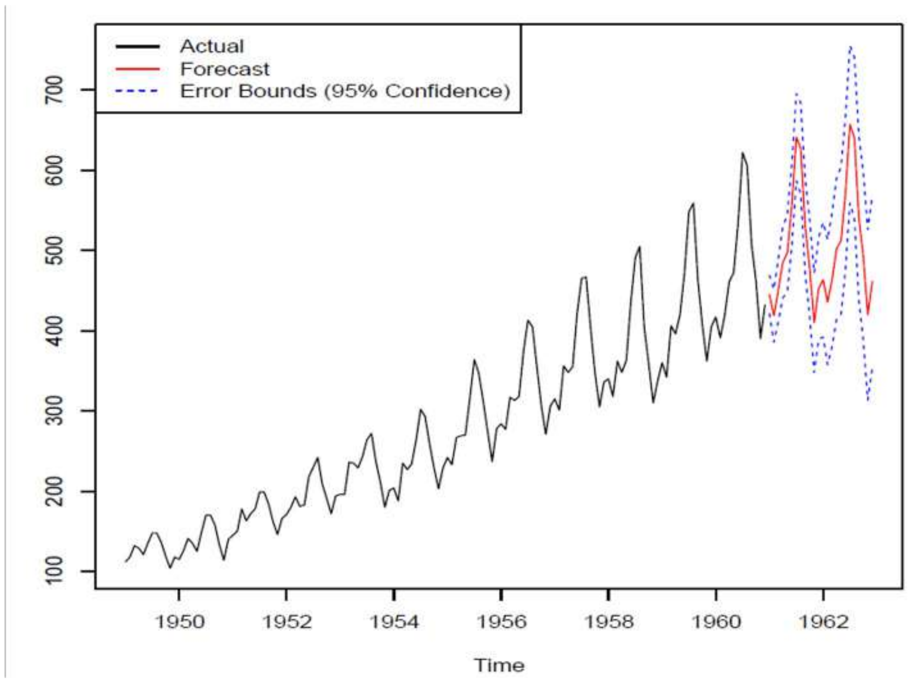
2



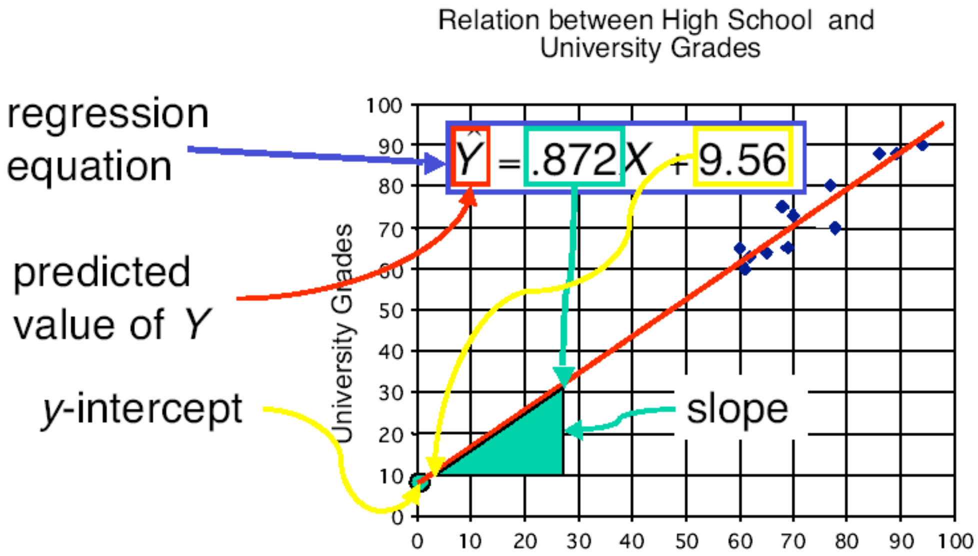
RNN (LSTM)


Top 10 Strategic Technology Trends for 2020
People-centric
Smart spaces
Hyperautomation
Empowered Edge
Multiexperience
Distributed Cloud
Democratization
Autonomous Things
Human Augmentation
Practical Blockchain
Transparency and Traceability
AI Security
gartner.com/SmarterWithGartner
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
Gartner


Actual
Forecast
Error Bounds (95% Confidence)
100
200
300
400
500
600
700
1950
1952
1954
1956
1958
1960
1962
Time

Regression – Linear Relationship



weight, coefficient

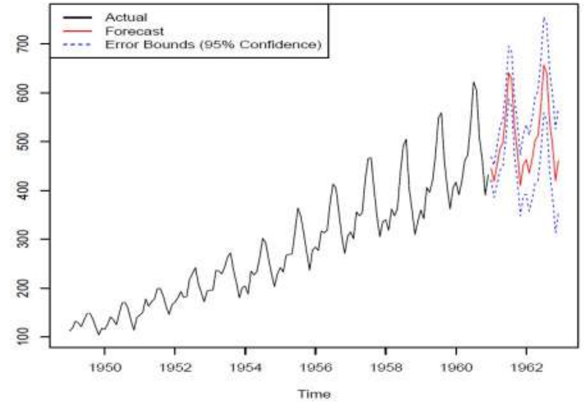
$$\hat{y} = \widehat{w}_0 + \widehat{w}_1 x_1 + \widehat{w}_2 x_2$$

target intercept input

- The least square method aims to minimize the following term

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

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

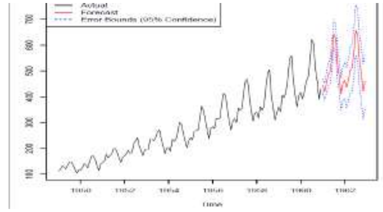
$$X_t = c + \varphi_1 X_{t-1} + \varphi_2 X_{t-2}$$

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

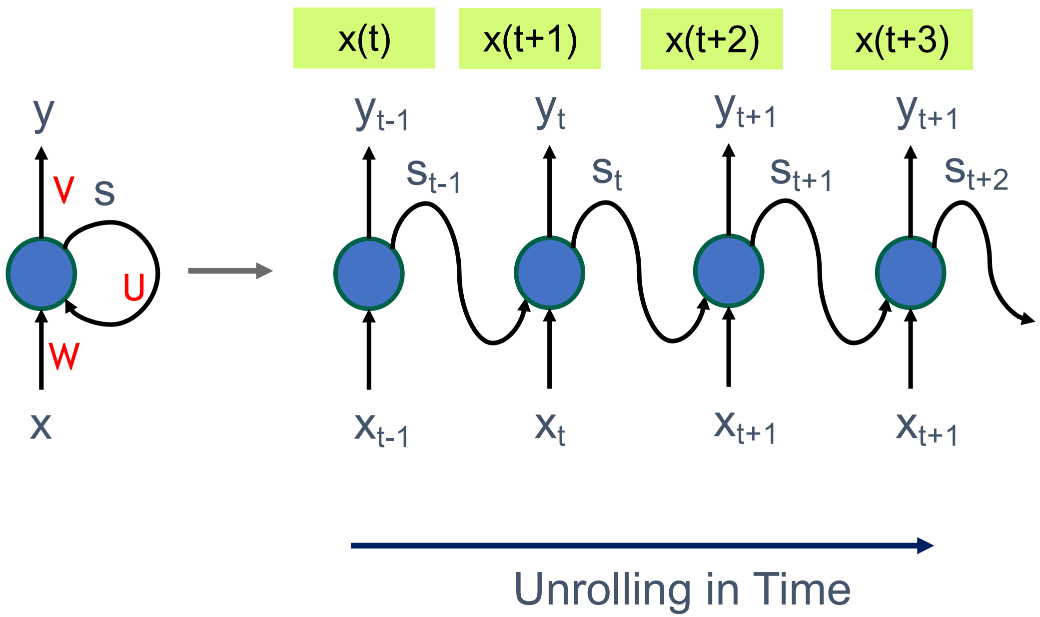
$$x(t+1) = \hat{w}_0 + \hat{w}_1 x(t) + \hat{w}_2 x(t-1)$$

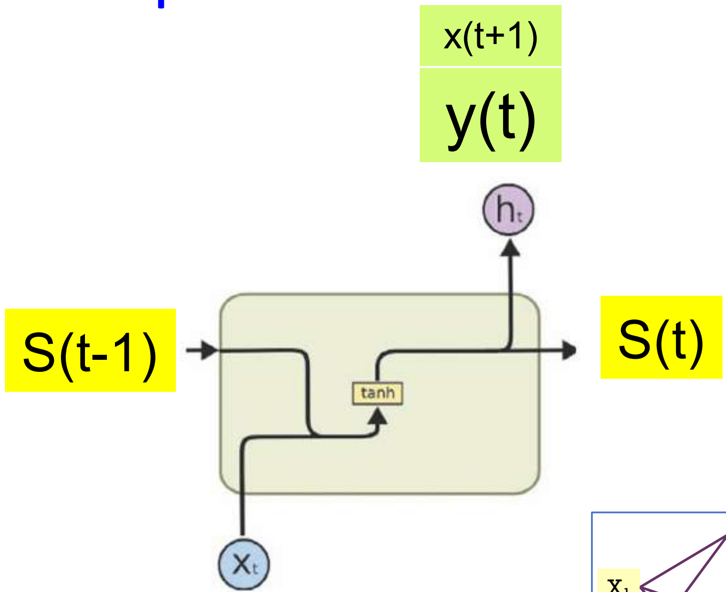
RECURRENT NEURONS (RNN)

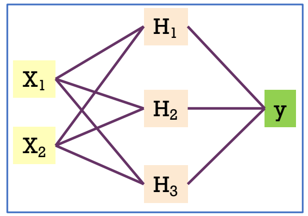
Non-Linear Relationship

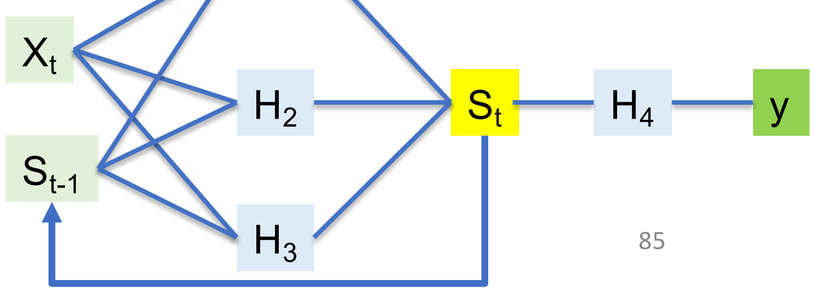


Forward Pass









$$s_t = \tanh\left(\boxed{U}x_t + \boxed{W}s_{t-1}\right)$$

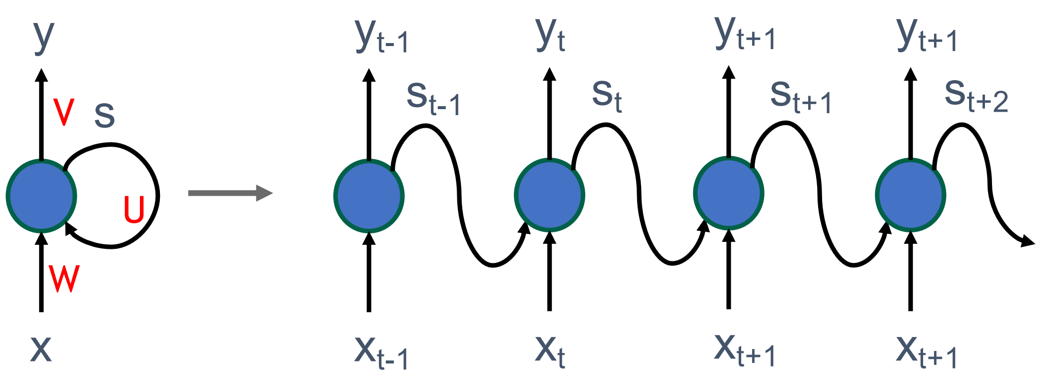
x(t+1) $\hat{y}_t = softmax\left(\boxed{V}s_t\right)$

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

RECURRENT NEURONS (RNN)

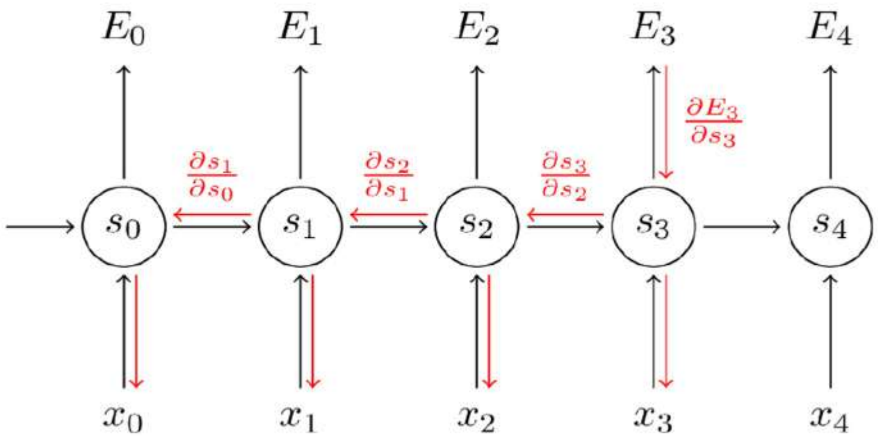
Ggradient vanishing
= multiplication

Forward Pass



Unrolling in Time

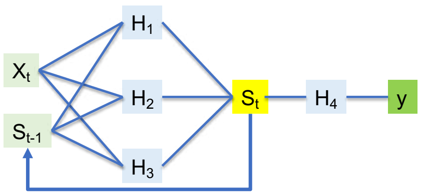
Backward Pass



Backpropagation-Through-Time (BPTT)

$$s_t = \tanh(\boxed{U}x_t + \boxed{W}s_{t-1})$$

$$\hat{y}_t = softmax(\boxed{V}s_t)$$

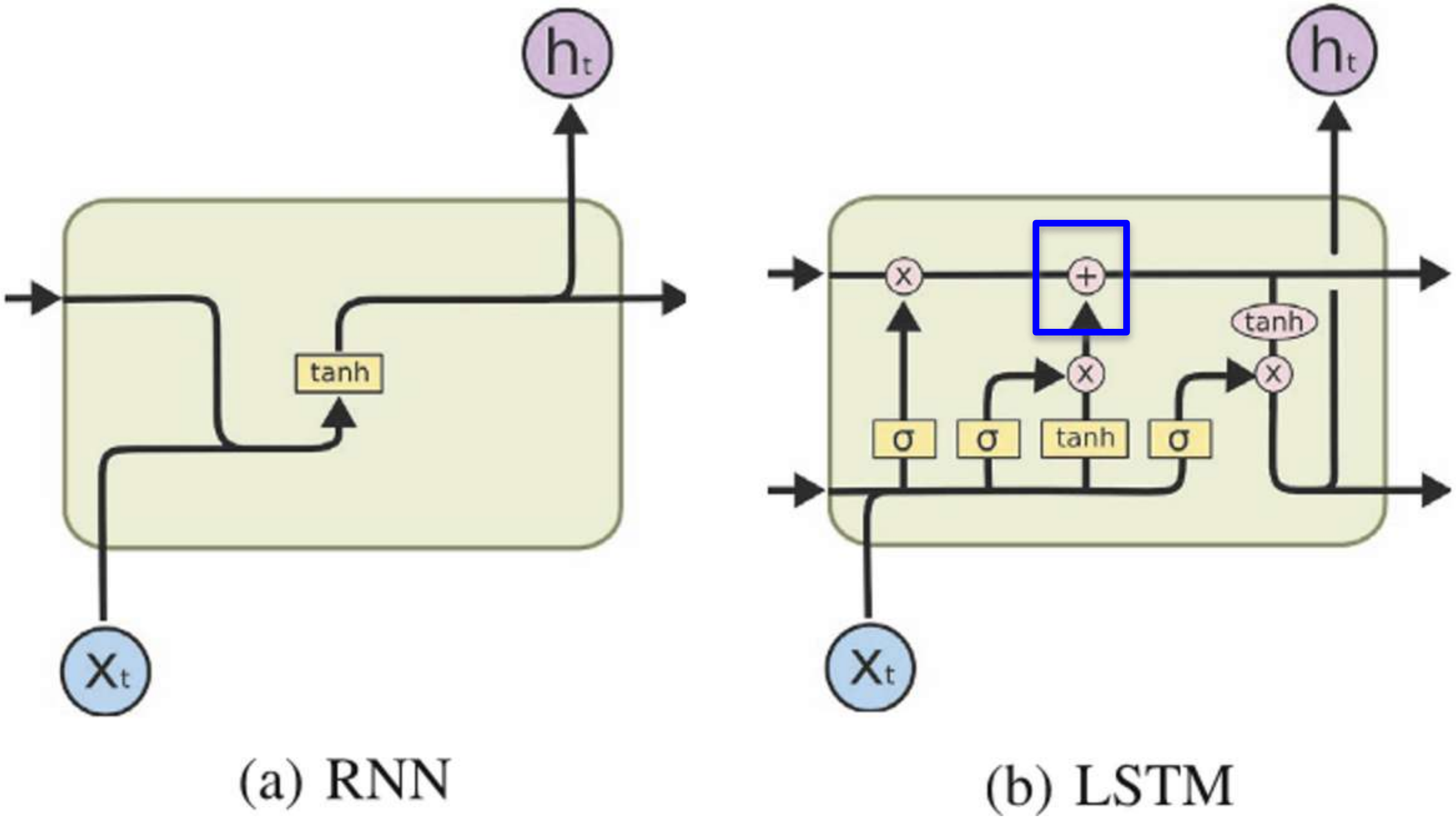


$$\frac{\partial E}{\partial W} = \sum_t \frac{\partial E_t}{\partial W}$$

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

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

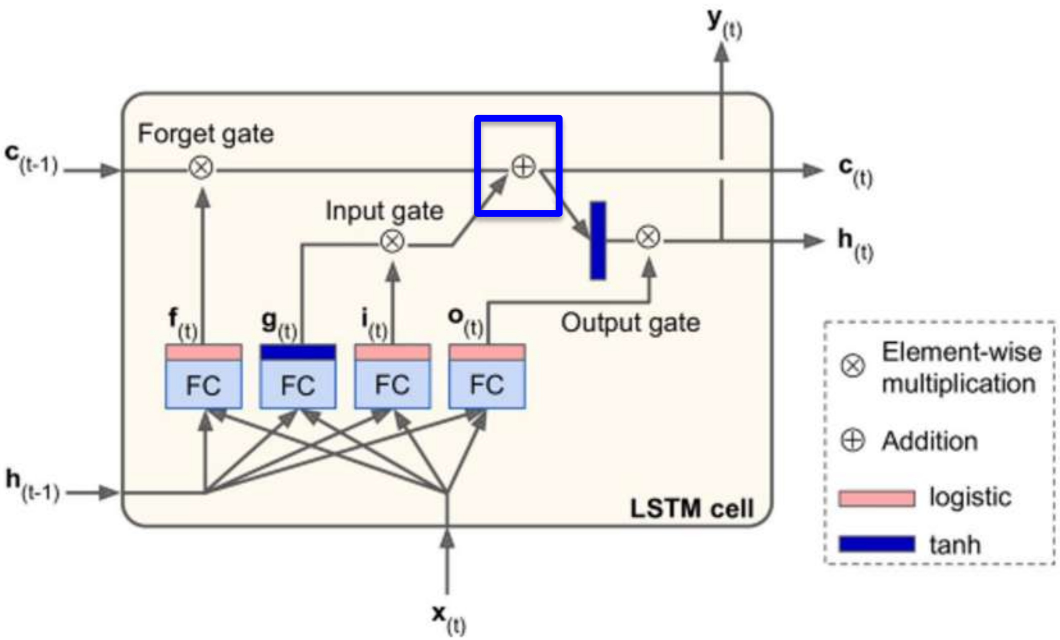
RNN VS LSTM



(a) RNN (b) LSTM

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

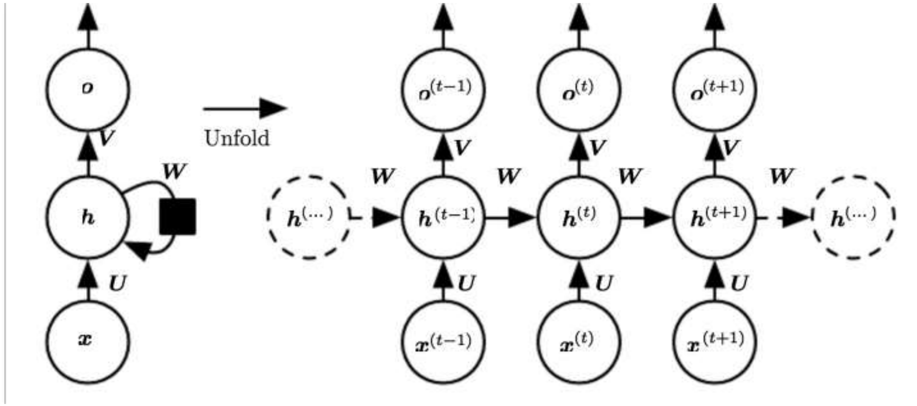
LONG SHORT TERM (LSTM) CELL

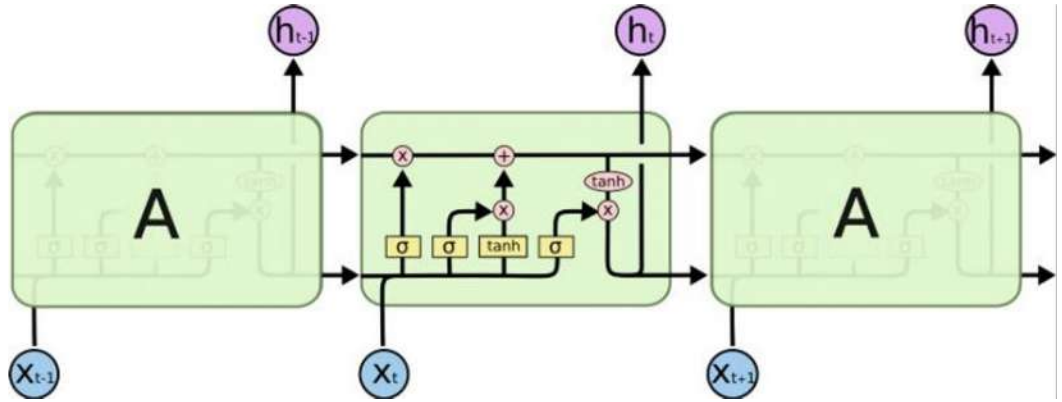


There are 3 gates with 2 outputs.

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

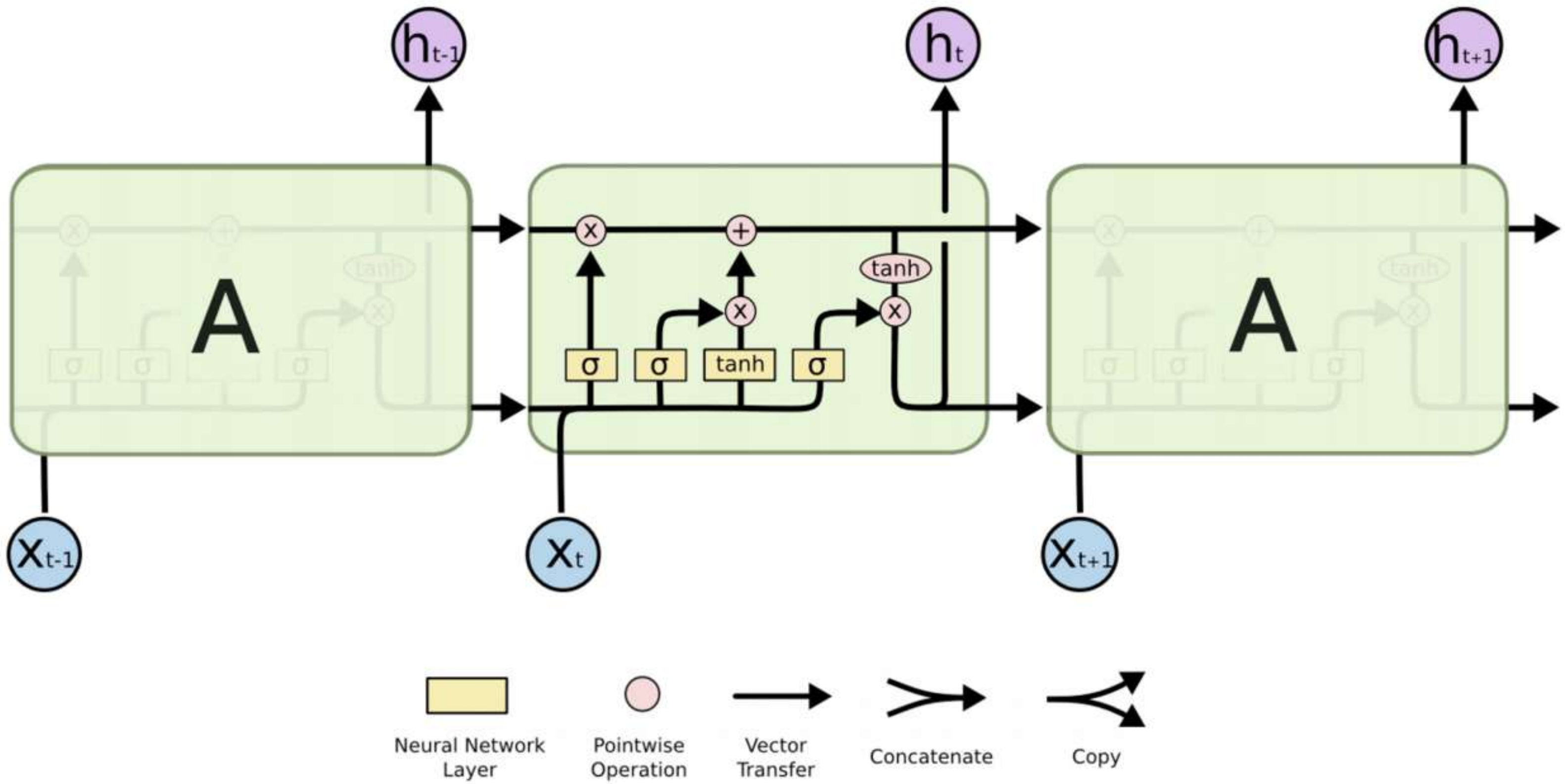
Deep Learning Approach: LSTM





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

Inside LSTM



A
A
tanh
σ
σ
tanh
σ
Neural Network Layer
Pointwise Operation
Vector Transfer
Concatenate
Copy

Inside LSTM

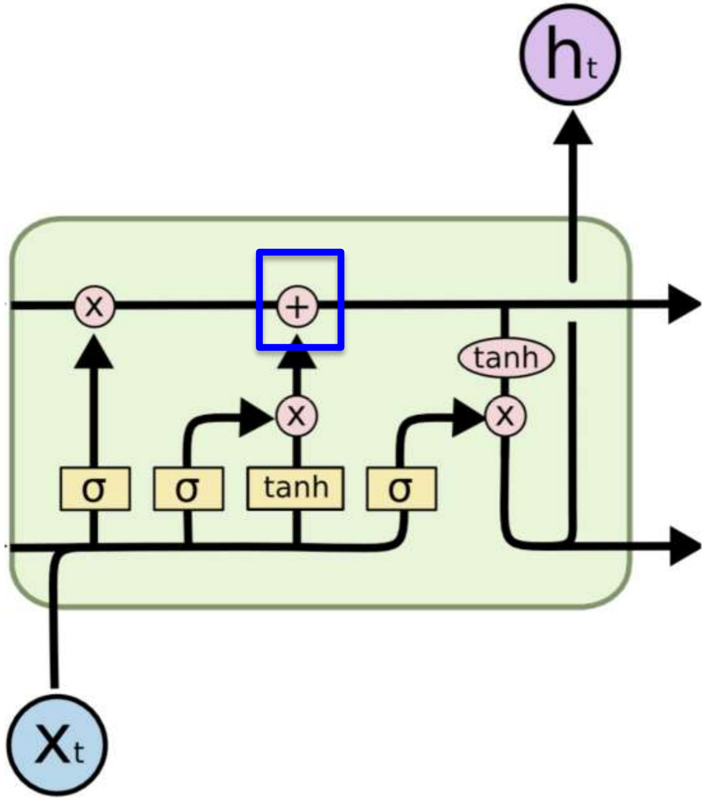
This block's output

Last block's Memory cell

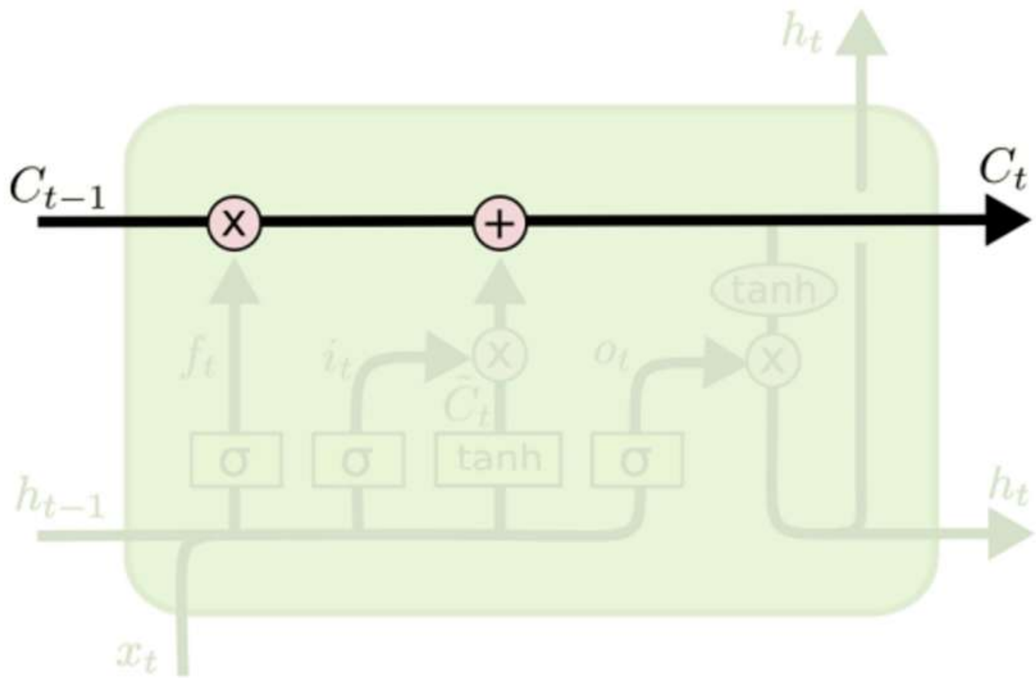
This block's Memory cell

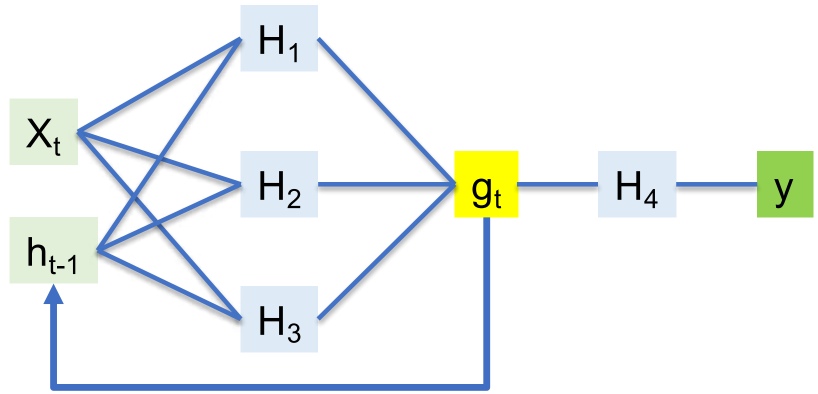
Last block's output

This block's output



Inside LSTM: (1) Cell Memory





There are 3 gates with 2 outputs.

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

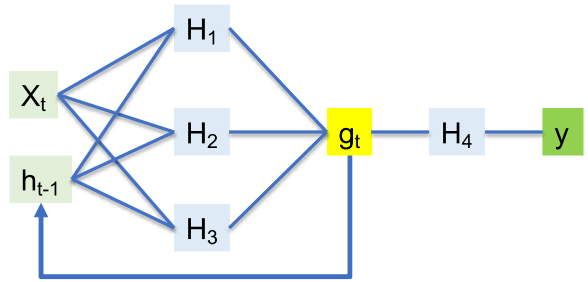
$$\mathbf{f}_{(t)} = \sigma(\mathbf{W}_{xf}{}^T \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hf}{}^T \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_f)$$

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

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

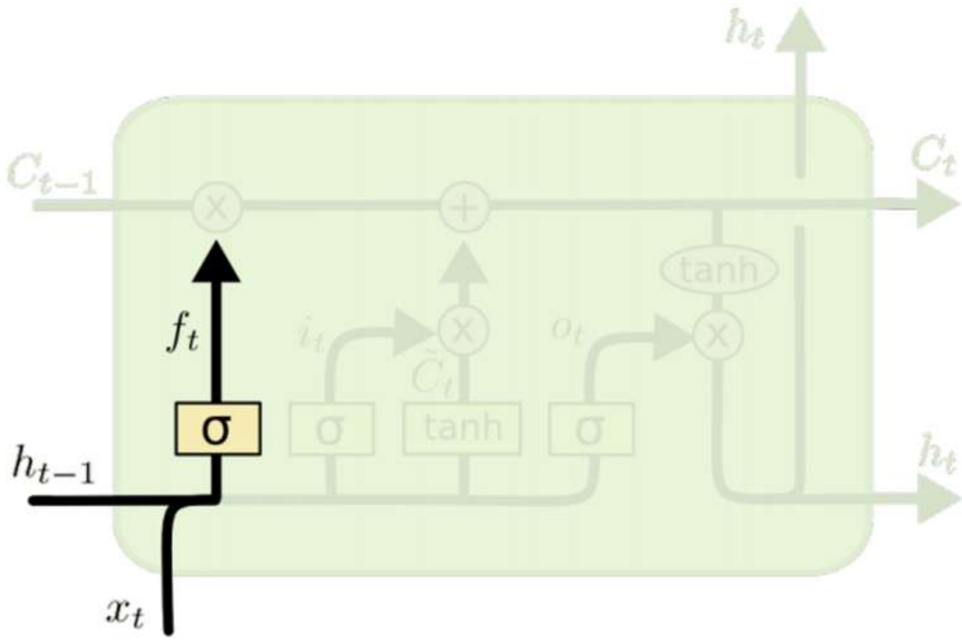
$$\boxed{\mathbf{c}_{(t)} = \mathbf{f}_{(t)} \otimes \mathbf{c}_{(t-1)} + \mathbf{i}_{(t)} \otimes \mathbf{g}_{(t)}}$$

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



Inside LSTM: (2) Forget Gate

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

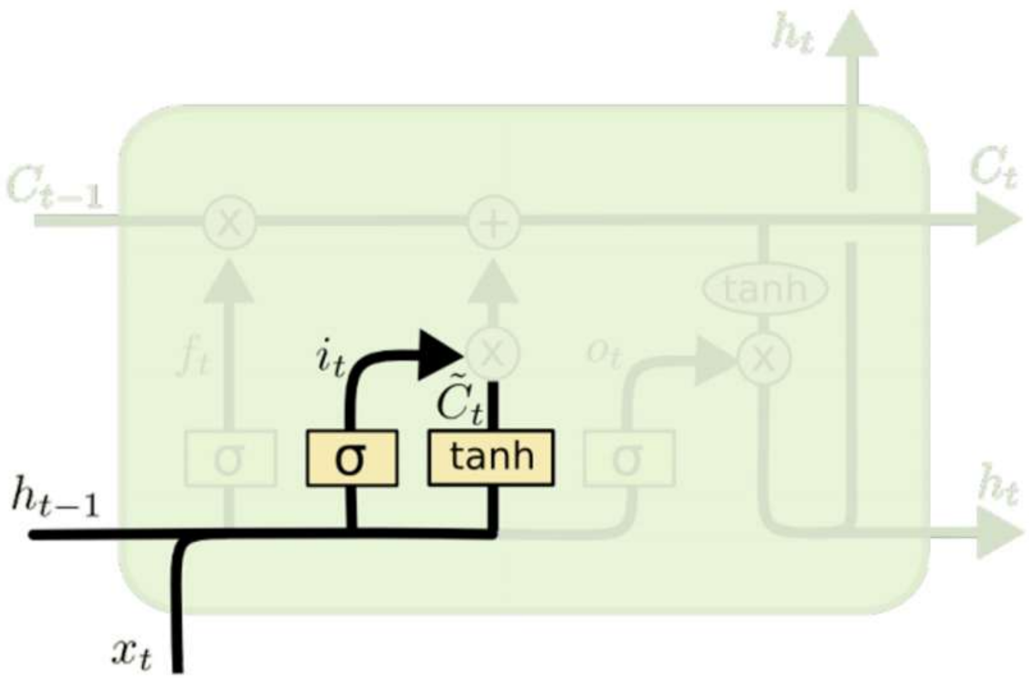


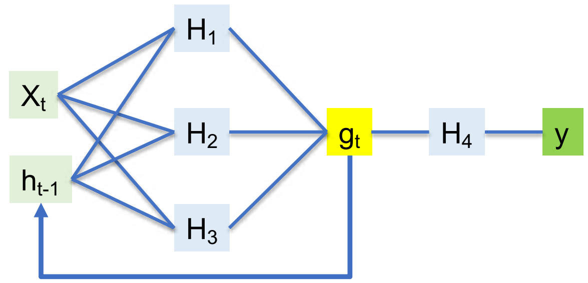
There are 3 gates with 2 outputs.

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

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.

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

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

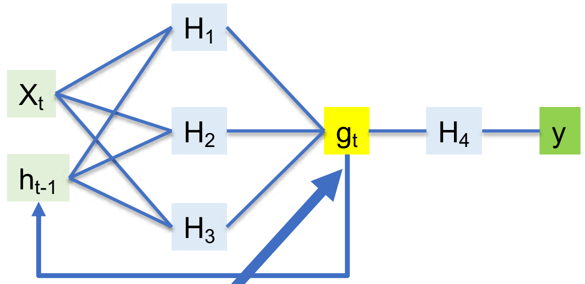
$$\mathbf{o}_{(t)} = \sigma(\mathbf{W}_{xo}{}^T \cdot \mathbf{x}_{(t)} + \mathbf{W}_{ho}{}^T \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_o)$$

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

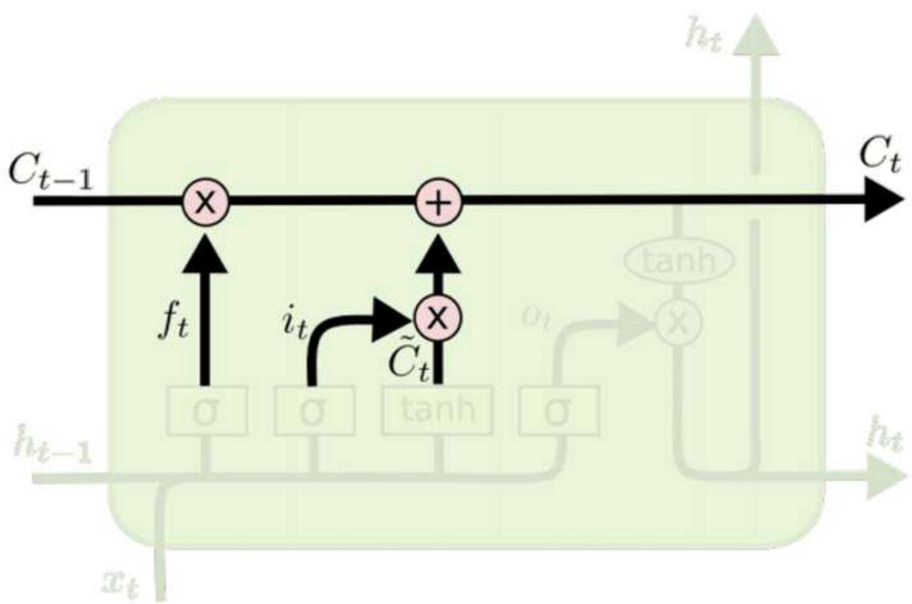
$$\mathbf{c}_{(t)} = \mathbf{f}_{(t)} \otimes \mathbf{c}_{(t-1)} + \mathbf{i}_{(t)} \otimes \mathbf{g}_{(t)}$$

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

Inside LSTM: (4) Memory Update



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



There are 3 gates with 2 outputs.

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

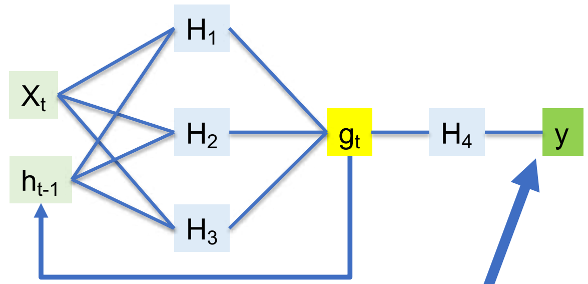
$$\mathbf{f}_{(t)} = \sigma(\mathbf{W}_{xf}{}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hf}{}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_{f})$$

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

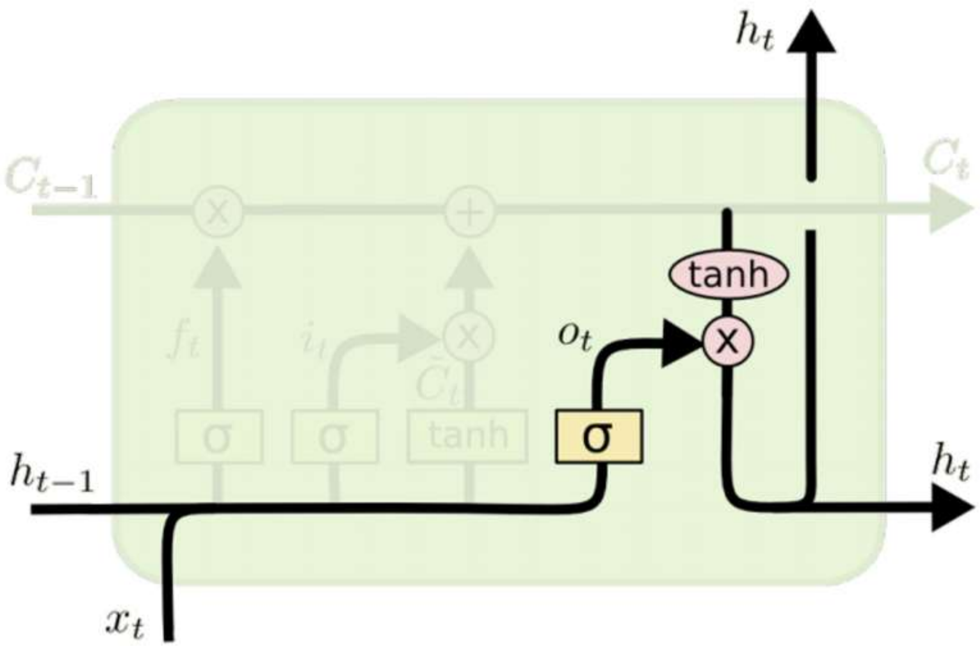
$$\boxed{\begin{aligned} \mathbf{g}_{(t)} &= \tanh\left(\mathbf{W}_{xg}{}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hg}{}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_{g}\right) \\ \mathbf{c}_{(t)} &= \mathbf{f}_{(t)} \otimes \mathbf{c}_{(t-1)} + \mathbf{i}_{(t)} \otimes \mathbf{g}_{(t)} \end{aligned}}$$

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

Inside LSTM: Output Gate



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



There are 3 gates with 2 outputs.

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

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

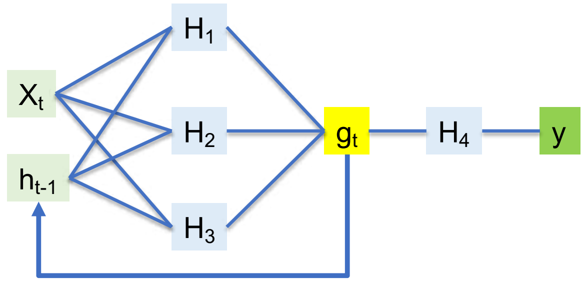
$$\mathbf{o}_{(t)} = \sigma(\mathbf{W}_{xo}{}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{ho}{}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_o)$$

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

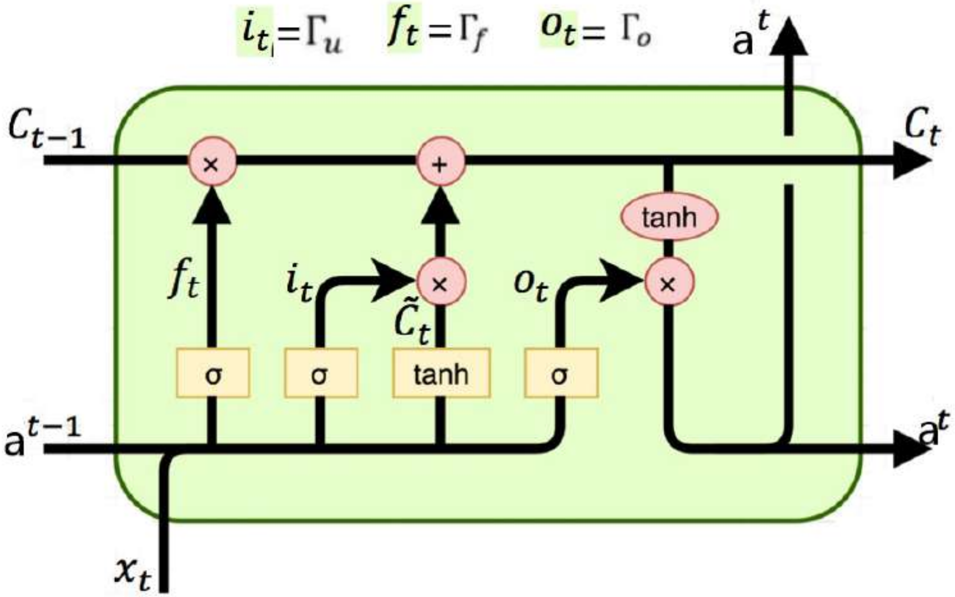
$$\mathbf{c}_{(t)} = \mathbf{f}_{(t)} \otimes \mathbf{c}_{(t-1)} + \mathbf{i}_{(t)} \otimes \mathbf{g}_{(t)}$$

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

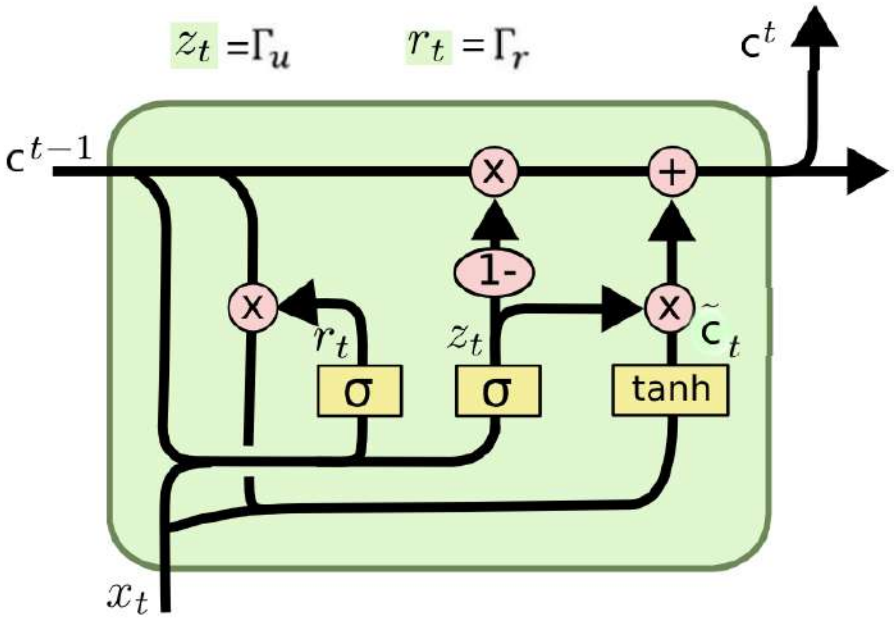
LSTM vs. Gated Recurrent Units (GRU)



There are 3 gates (i_t, f_t, o_t)
2 outputs (C(t), a(t)),
3 inputs (x(t), C(t-1), a(t-1))



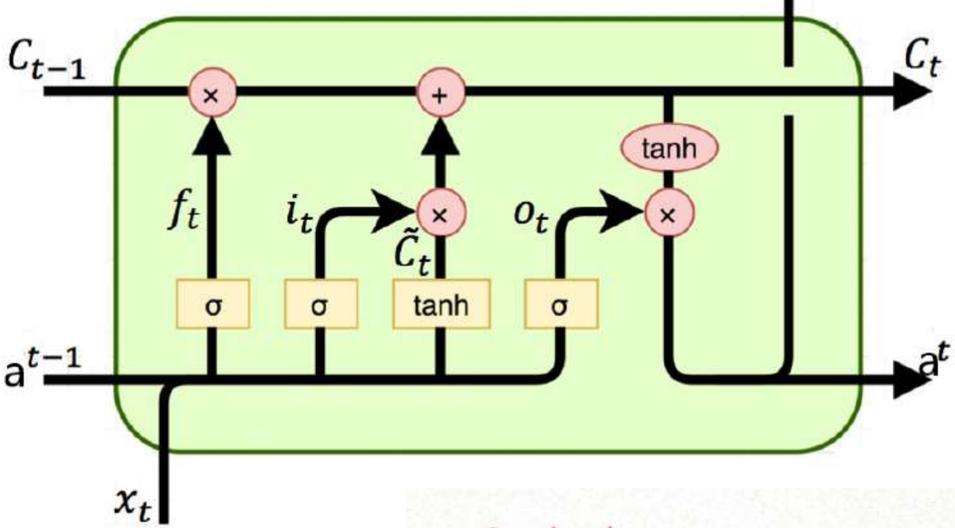
- There are 2 gates (update & reset gates)
- 1 output
- 2 inputs (x(t), C(t-1), ~~a(t-1)~~)



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

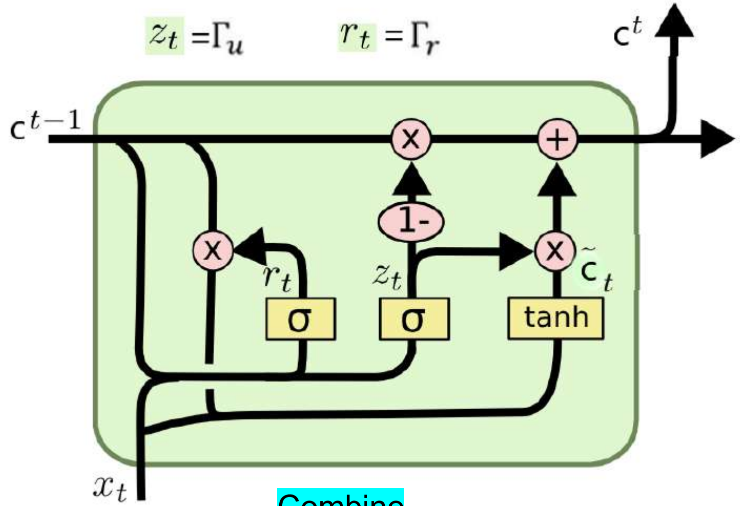
There are 3 gates with 2 outputs.

$i_t = \Gamma_u$ $f_t = \Gamma_f$ $o_t = \Gamma_o$



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

$z_t = \Gamma_u$ $r_t = \Gamma_r$



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

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

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

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

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

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

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

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

reset previous memory

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

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

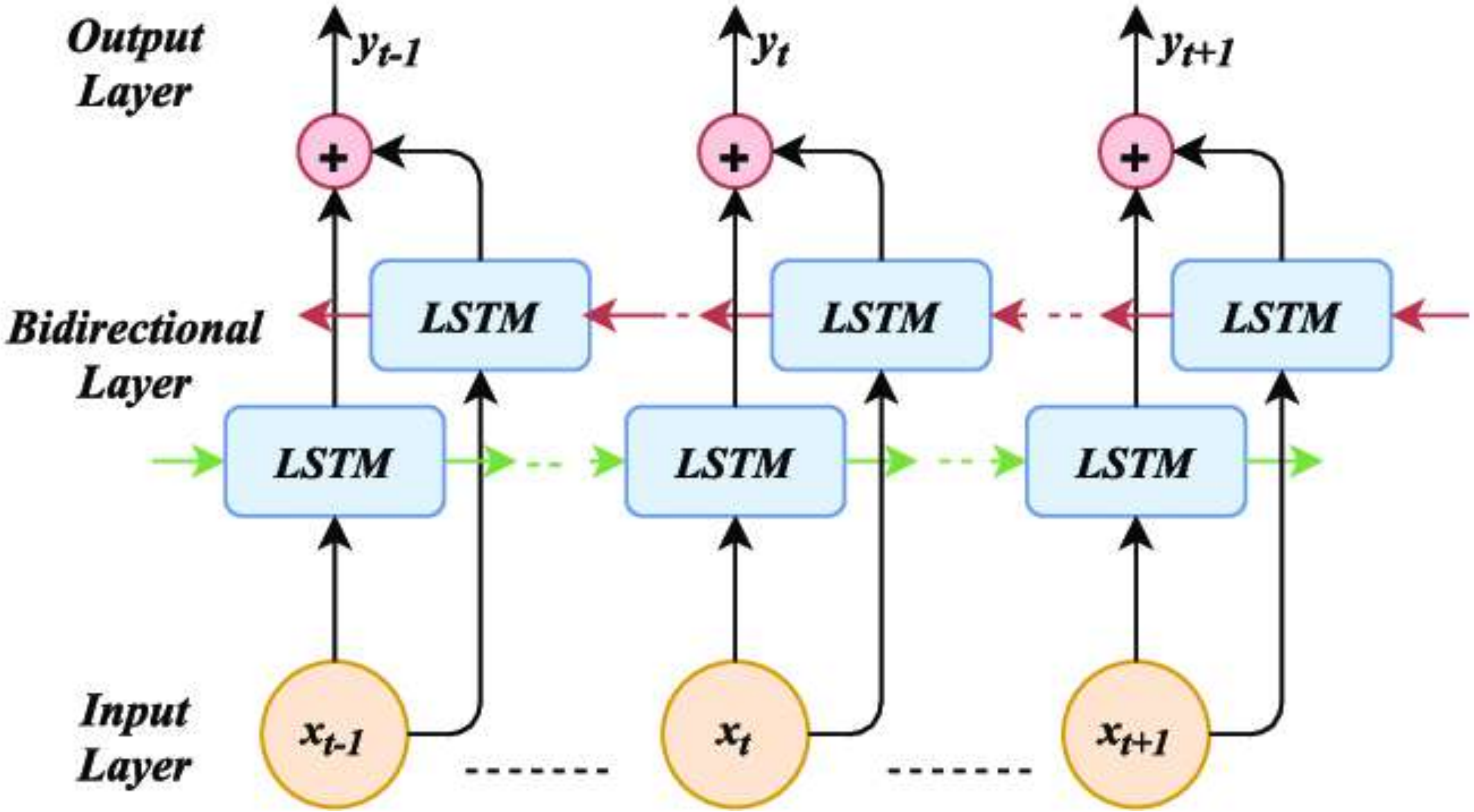
f(t) Reset gate $\rightarrow \Gamma_r = \sigma(W_r[c^{\langle t-1\rangle}, x^{\langle t\rangle}] + b_r)$

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

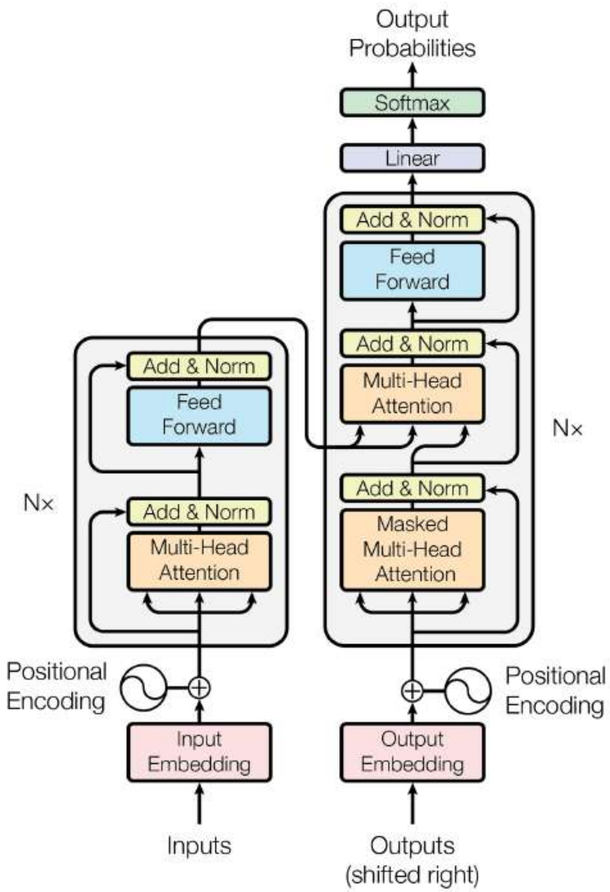
Update current memory

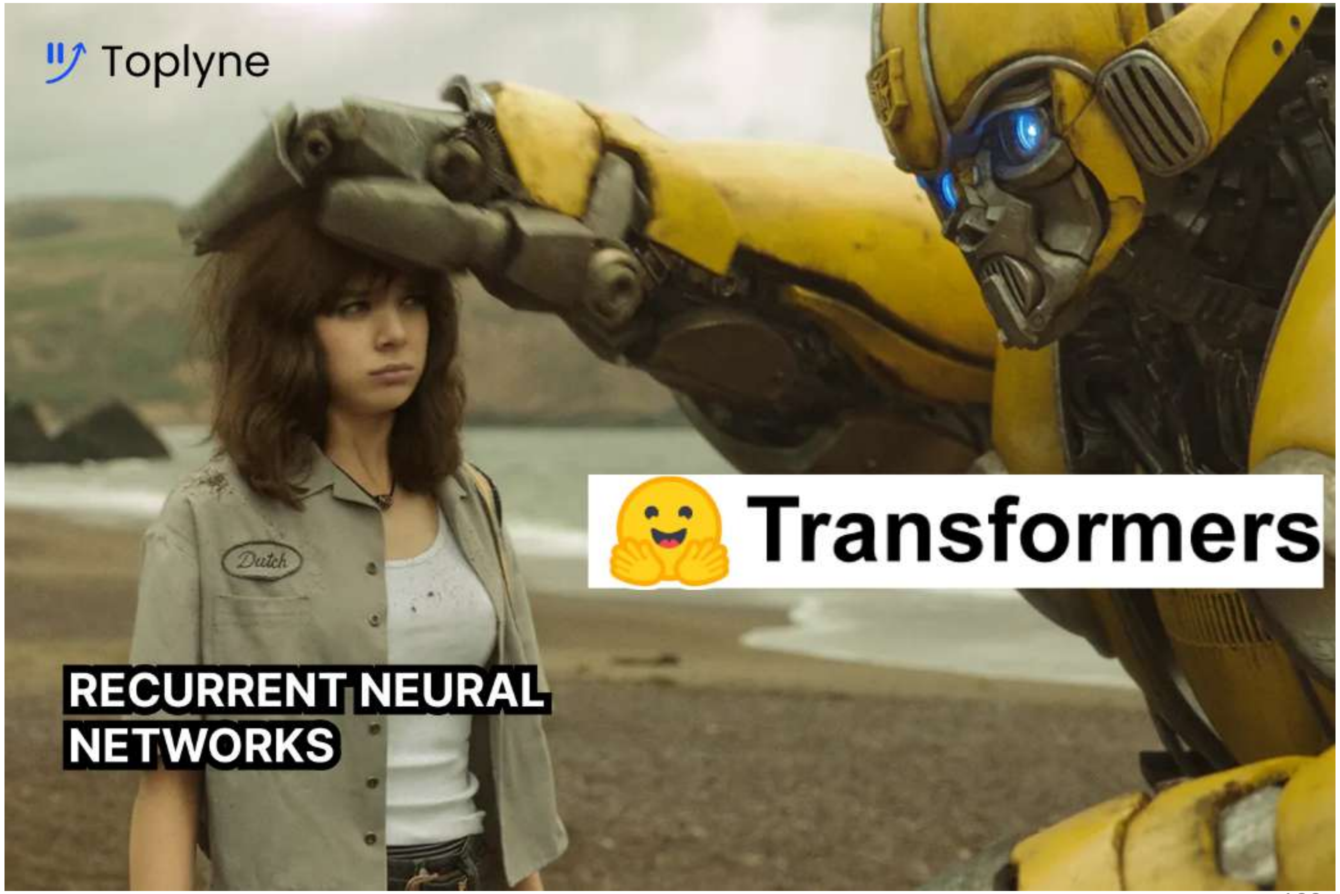
y(t) Activation / Output $\rightarrow a^{\langle t\rangle} = c^{\langle t\rangle}$

Bidirectional LSTM



Rise of Transformer (2017)





Appendix