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3099704: AI for Digital Health



Pretrained Models & Object Detection

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Outline

- DL & Image classification (recap)
- Pretrained models
- Object detection

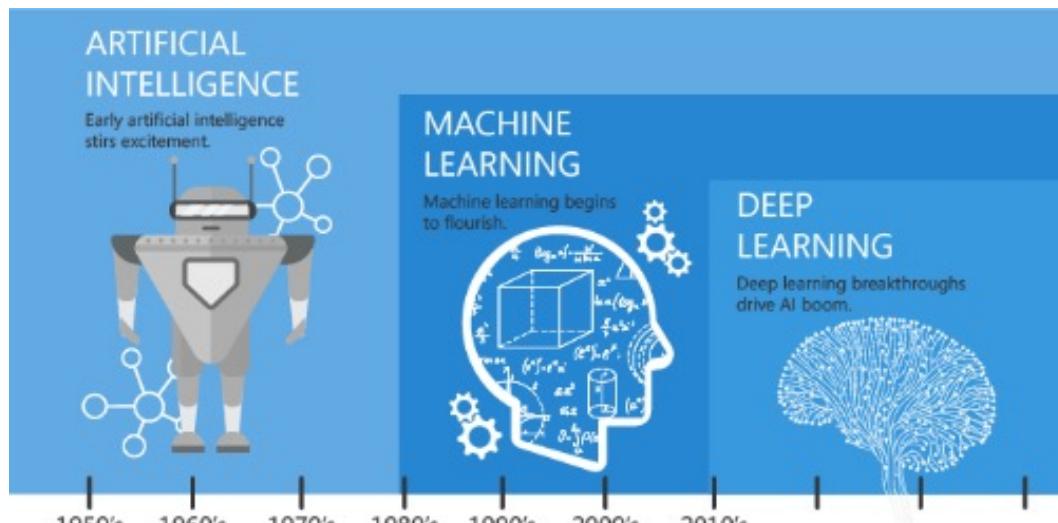
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DL & Image classification (recap)

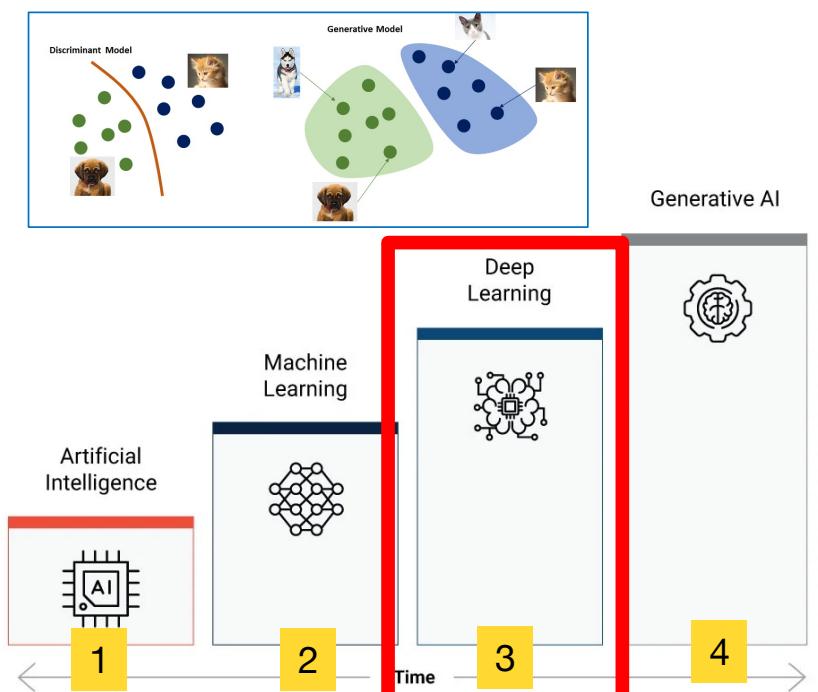
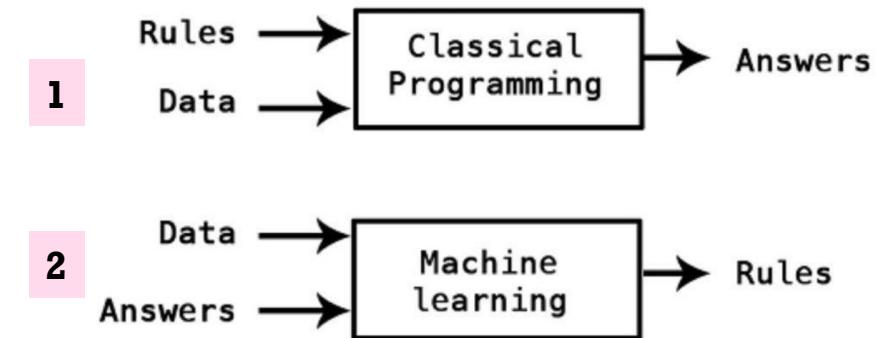


AI = Automation

- 0) Not AI Solution (not automatic)
- 1) Rule-based AI
- 2) Machine Learning (ML)

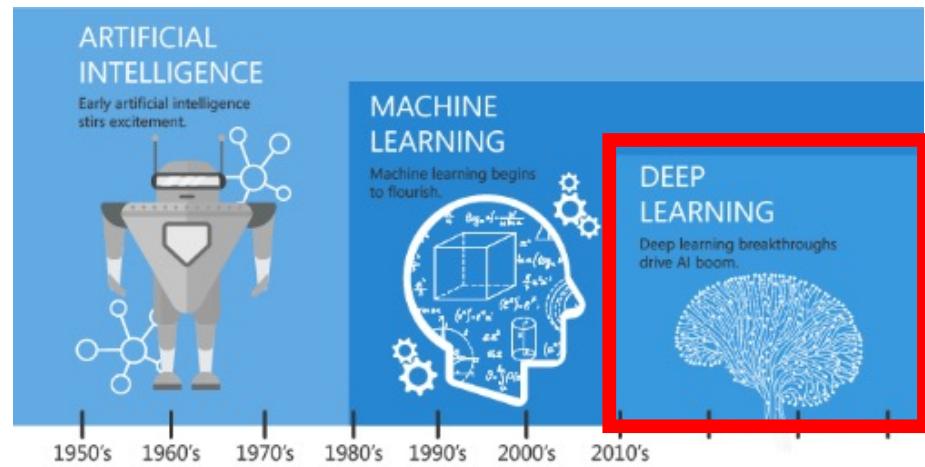


Since an early flush of optimism in the 1950's, smaller subsets of artificial intelligence - first machine learning, then deep learning, a subset of machine learning - have created ever larger disruptions.

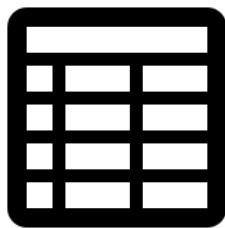


<https://mc.ai/machine-learning-basics-artificial-intelligence-machine-learning-and-deep-learning/>

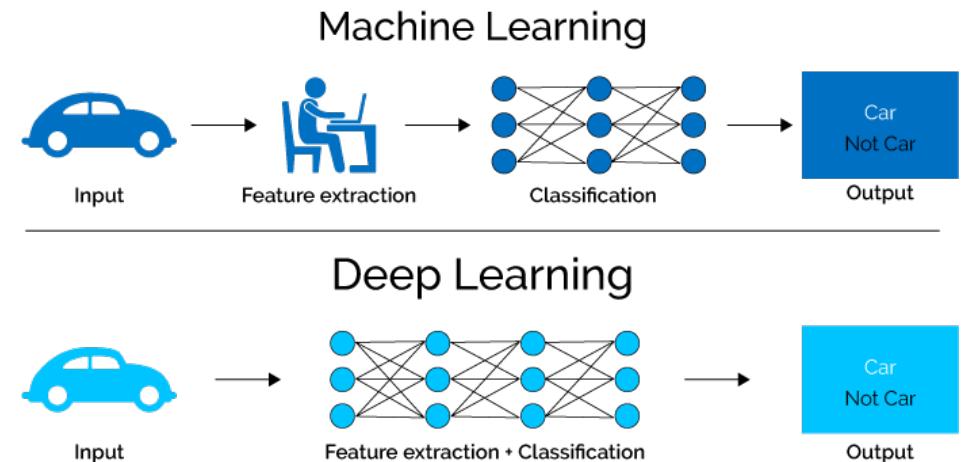
Arise of Deep Learning



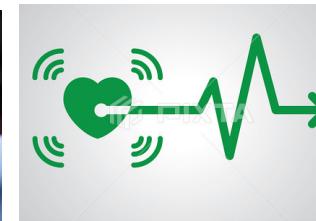
Since an early flush of optimism in the 1950's, smaller subsets of artificial intelligence - first machine learning, then deep learning, a subset of machine learning - have created ever larger disruptions.



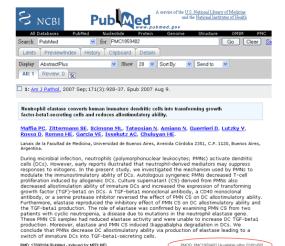
VS



Image, video



signals, voice



NLP



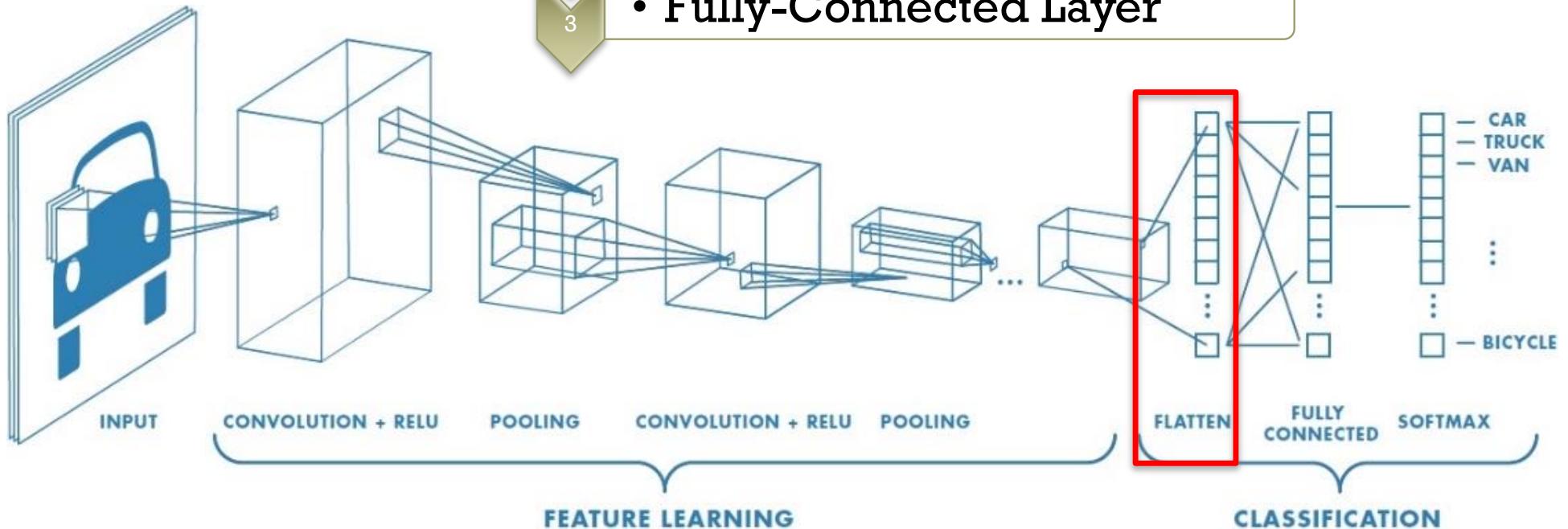
Convolutional Neural Networks

Embedding Vector

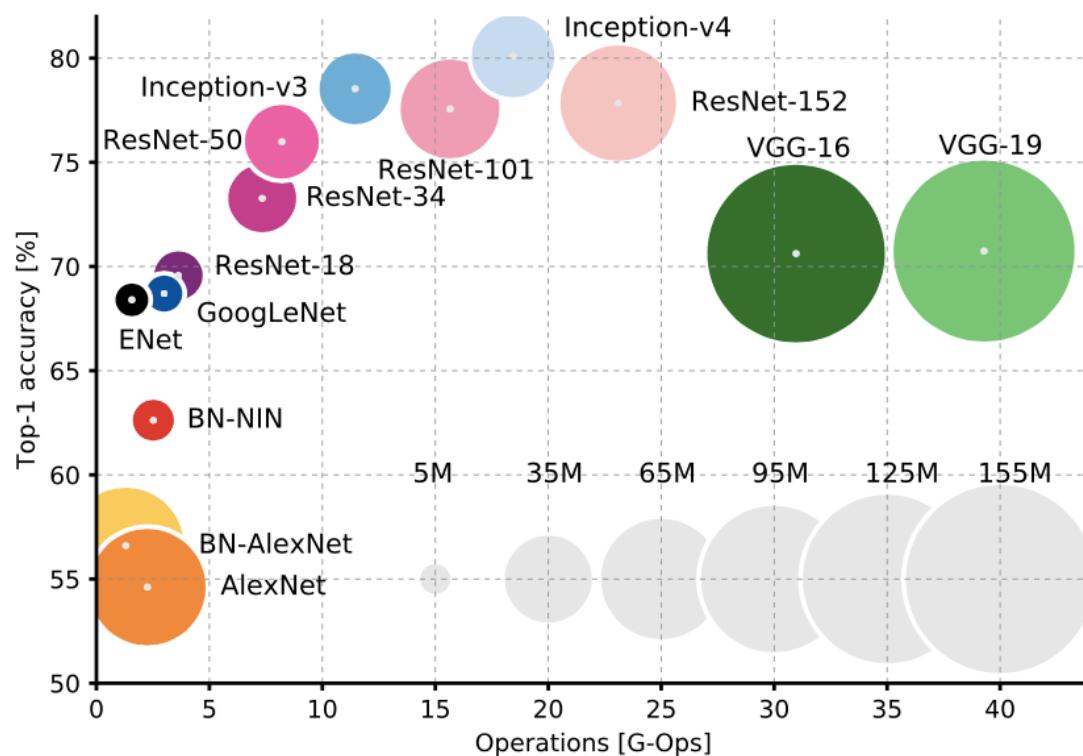
x1	x2	x3	x4	Corona
0.7	0.2	-0.5	-0.1	Yes



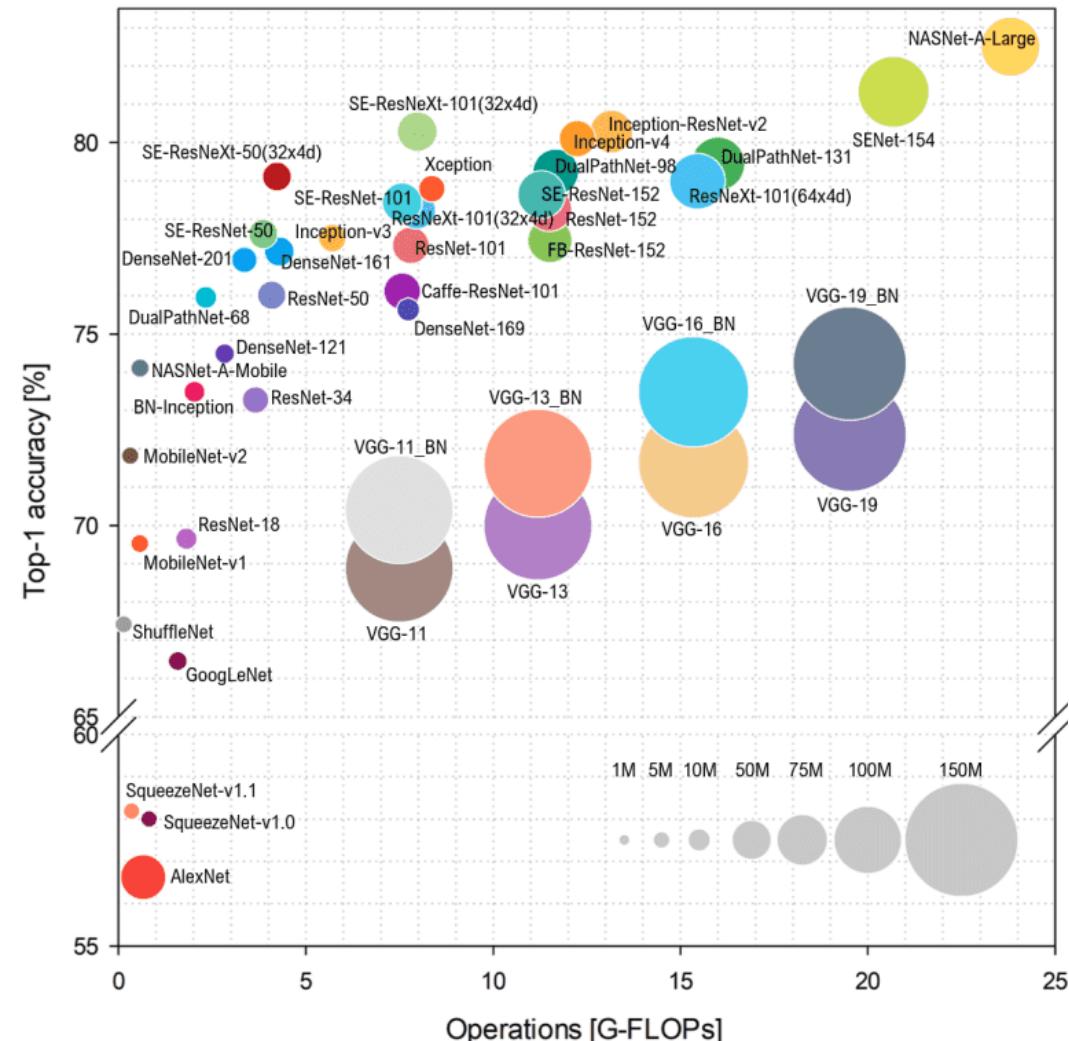
- Convolutional Layer
- Pooling Layer
- Fully-Connected Layer



SOTA of Image Classification Millions of parameters!



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

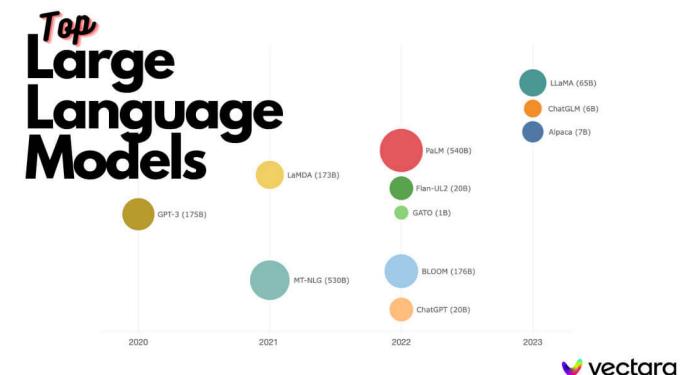
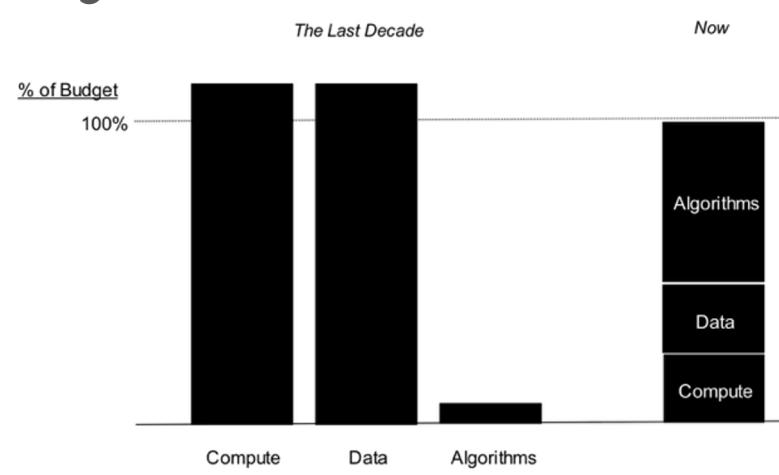


<https://theaisummer.com/cnn-architectures/>



Why now?

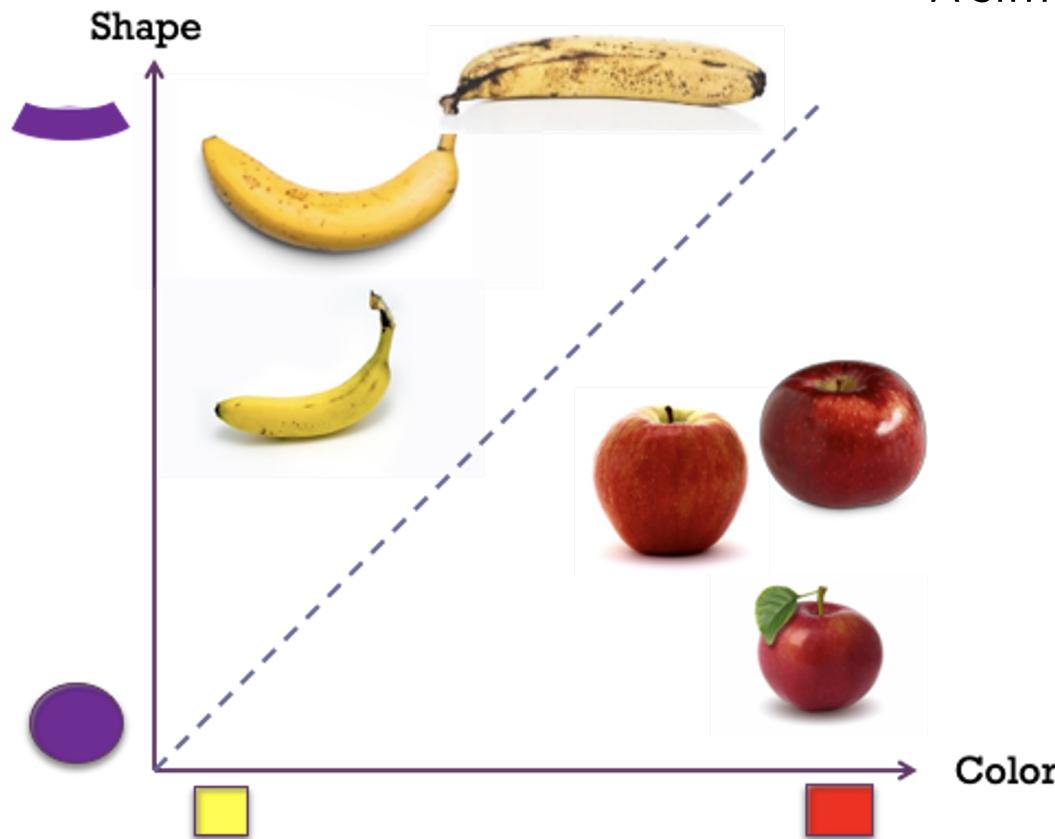
- Neural Networks has been around since 1990s
- 1) Big data – DNN can take advantage of large amounts of data better than other models
- 2) GPU – Enable training bigger models possible
- 3) Deep (pretrained models) – Easier to avoid bad local minima when the model is large



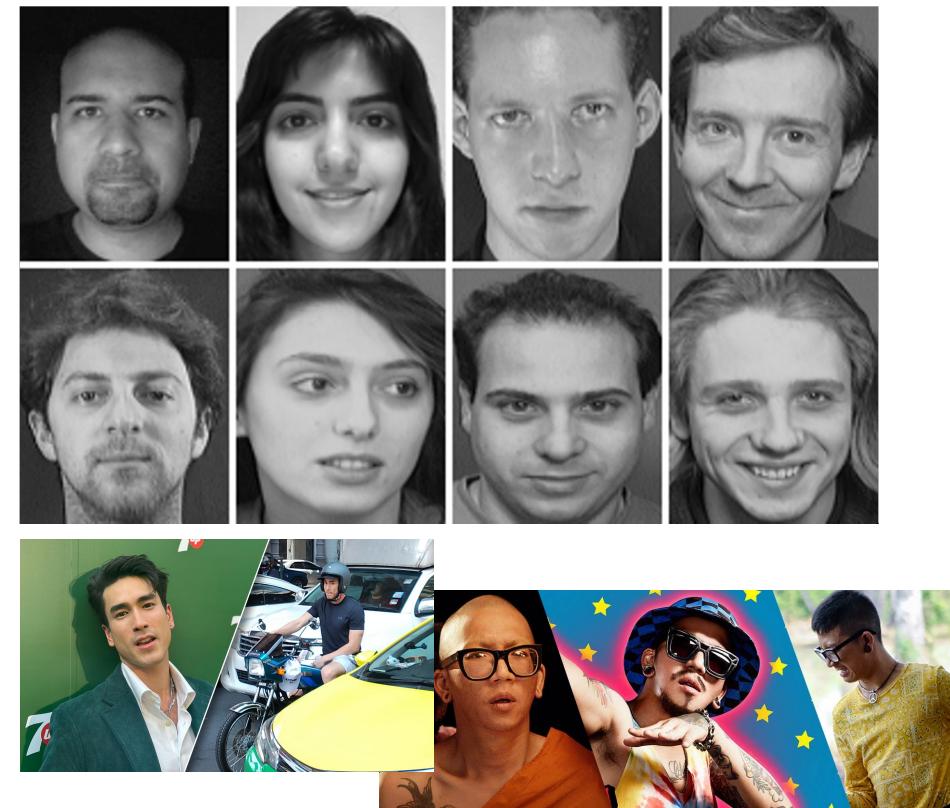
Based on the slide of Aj.Ekapol [/www.kdnuggets.com/2017/06/practical-guide-machine-learning-understand-differentiate-apply.html](http://www.kdnuggets.com/2017/06/practical-guide-machine-learning-understand-differentiate-apply.html)



We need **enough** training data
to infer the data pattern and to create model



A simple problem requires less training data.



+

Pretrained models



**Have you ever seen this creature before?
Can you guess whether it is a land animal or a water animal?**





**Have you ever seen this creature before?
Can you guess whether it is a land animal or a water animal?
You can transfer your knowledge from the past**





Transfer learning

Myth: you **can't do** deep learning unless you have a million labelled examples for your problem.

Reality:

- You can **transfer** learned representations from **a related task**
- You can train on a nearby **surrogate objective** for which it is easy to generate labels



Transfer learning: idea

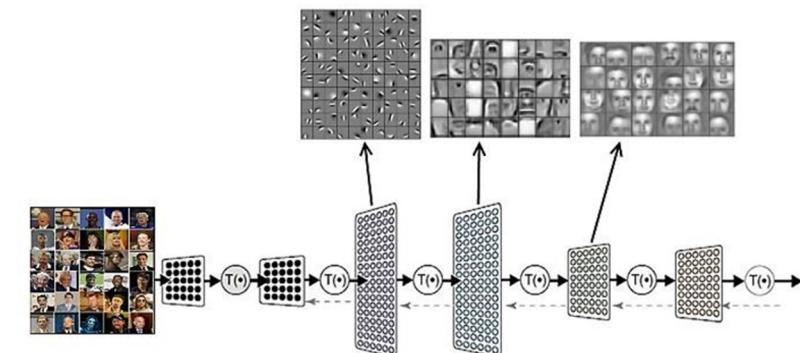
Instead of training a deep network from scratch for your task, you can

- **Take** a network trained on a different domain (data) for a different source task (e.g., LM)
- **Adapt** it for your domain (data) and your target task (e.g., classification)

This lecture will talk about how to do this.

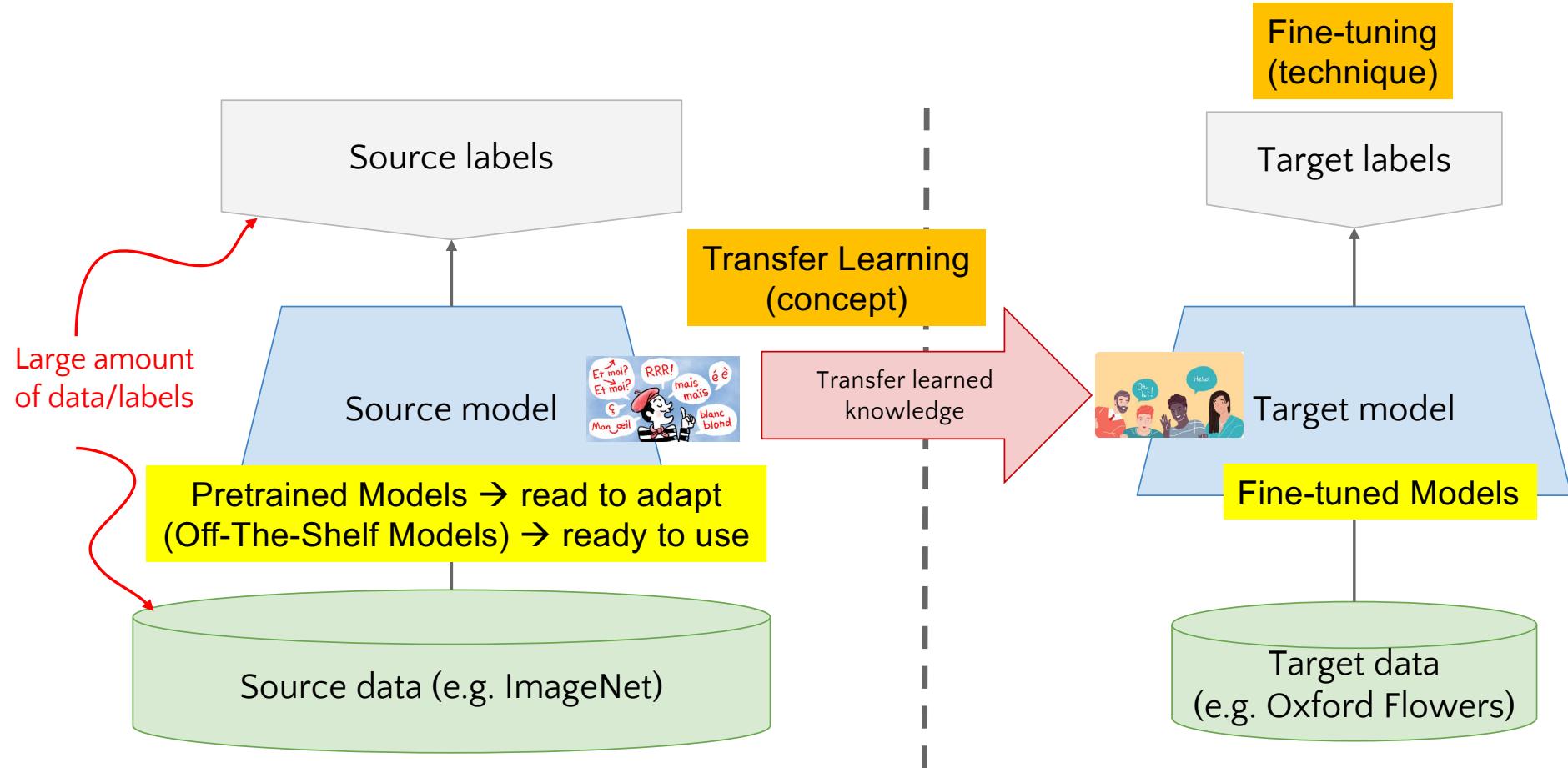
Variations:

- Different domain (data), same task
- Different domain (data), different task





Transfer learning: idea





Object recognition: 14M++ images on 20K++ categories

ImageNet is an image database organized according to the WordNet hierarchy (currently only the nouns), in which each node of the hierarchy is depicted by hundreds and thousands of images. Currently we have an average of over five hundred images per node. We hope ImageNet will become a useful resource for researchers, educators, students and all of you who share our passion for pictures.

[Click here](#) to learn more about ImageNet, [Click here](#) to join the ImageNet mailing list.

ImageNet

From Wikipedia, the free encyclopedia

The **ImageNet** project is a large visual [database](#) designed for use in [visual object recognition software](#) research. More than 14 million^{[1][2]} images have been hand-annotated by the project to indicate what objects are pictured and in at least one million of the images, bounding boxes are also provided.^[3] ImageNet contains more than 20,000 categories^[2] with a typical category, such as "balloon" or "strawberry", consisting of several hundred images.^[4] The database of annotations of third-party



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



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](#)

vgg16

```
torchvision.models.vgg16(*, weights: Optional[VGG16_Weights] = None, progress: bool = True,  
**kwargs: Any) → VGG [SOURCE]
```

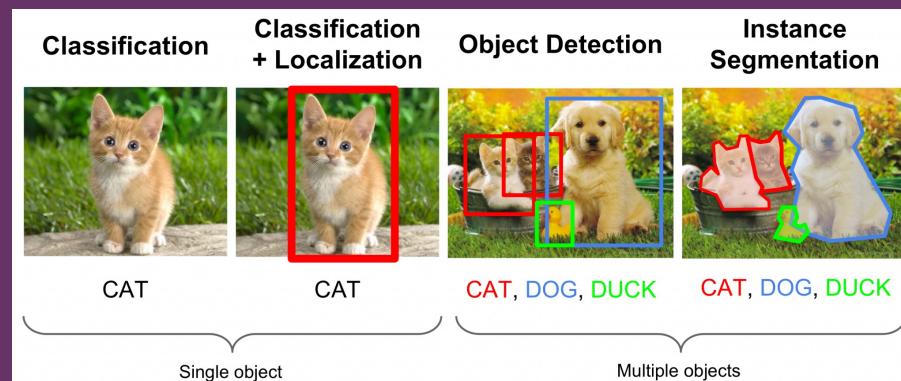
CLASS/vision.models.VGG16_Weights(*value*) [\[SOURCE\]](#)

The model builder above accepts the following values as the `weights` parameter. `VGG16_Weights.DEFAULT` is equivalent to `VGG16_Weights.IMAGENET1K_V1`. You can also use strings, e.g. `weights='DEFAULT'` or `weights='IMAGENET1K_V1'`.

VGG16_Weights.IMAGENET1K_V1:

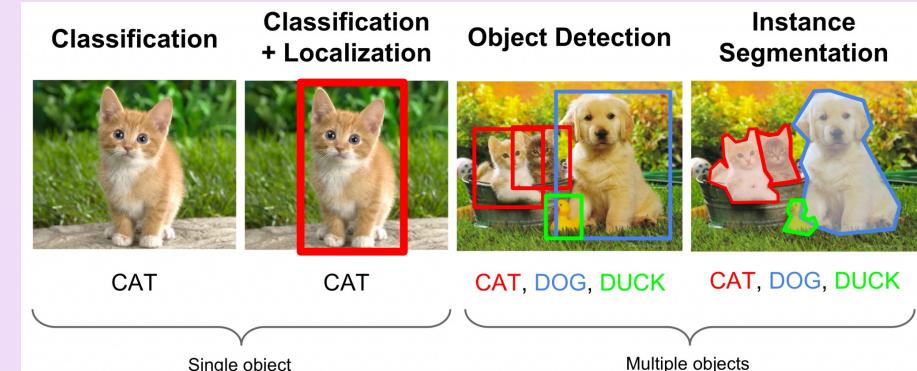
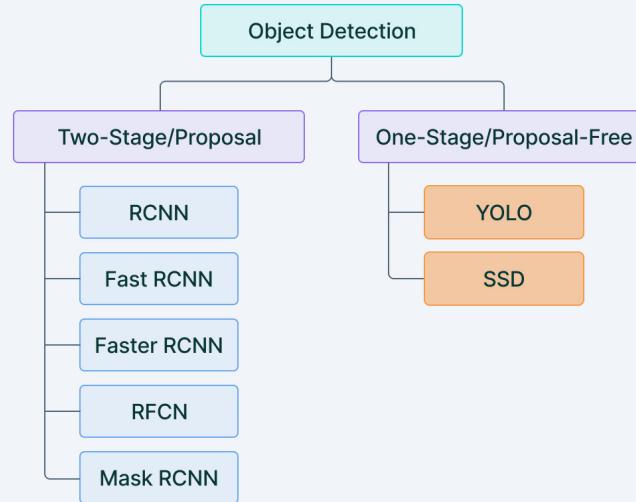
These weights were trained from scratch by using a simplified training recipe. Also available as `VGG16_Weights.DEFAULT`.

Object Detection



SOTA of Object Detection

One and two stage detectors



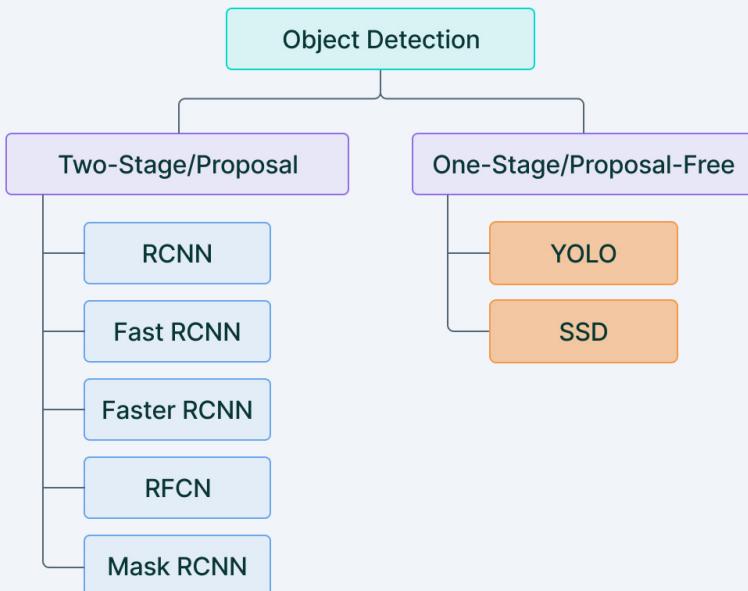
V7 Labs

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

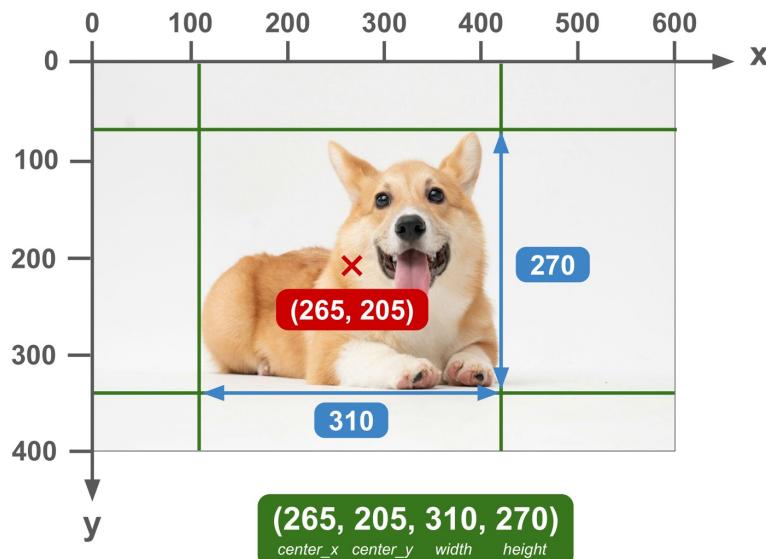


Object Detection

One and two stage detectors



corner coordinate

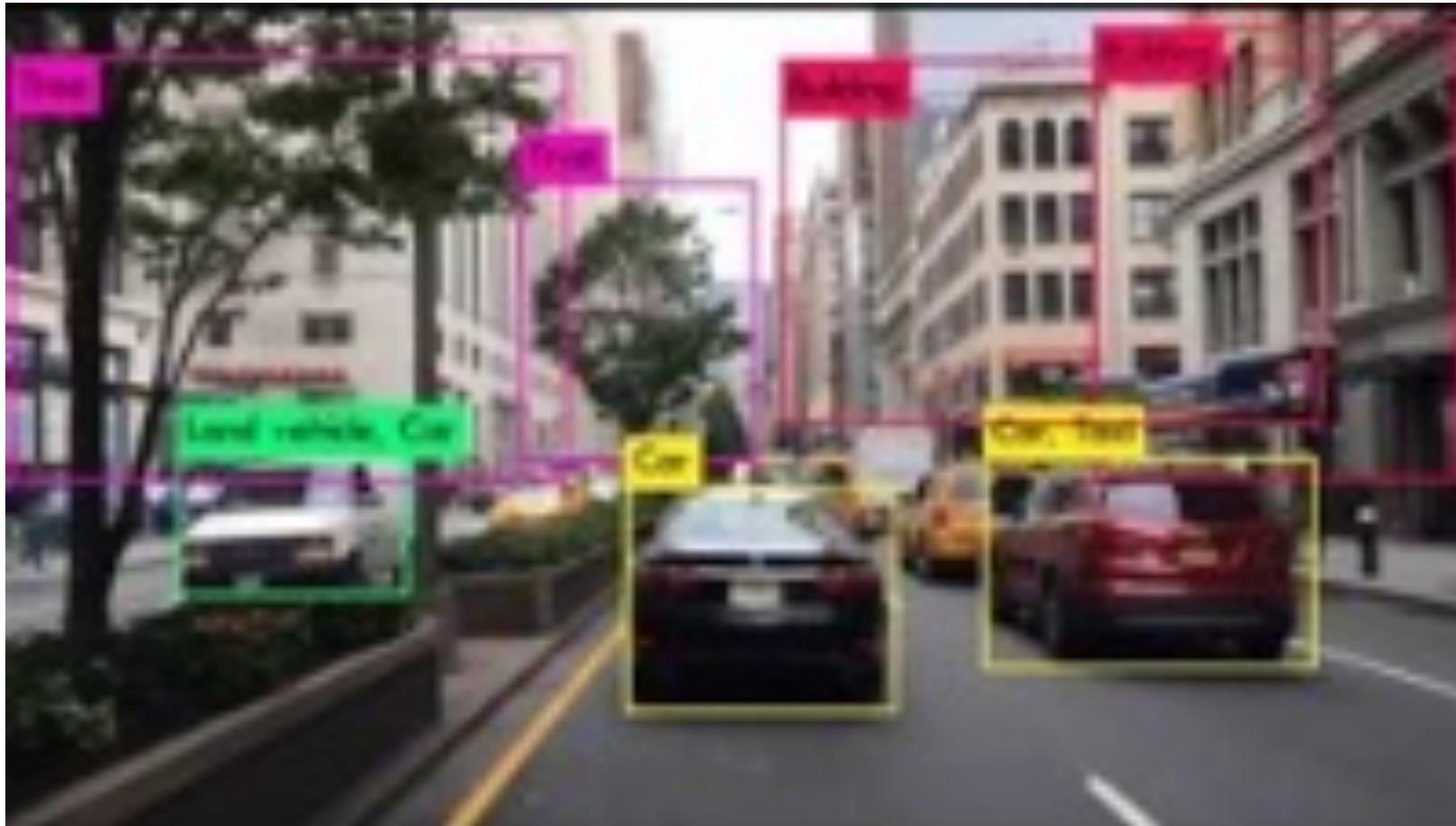


units		
	absolute	normalized
(left, top, right, bottom)		Pascal VOC
(left, top, width, height)		COCO
(center_x, center_y, width, height)		CreateML YOLO

<https://dragoneye.ai/blog/a-guide-to-bounding-box-formats/>



YOLO Open Images in New York



YOLO Open Images in New York



Joseph Redmon
6.95K subscribers

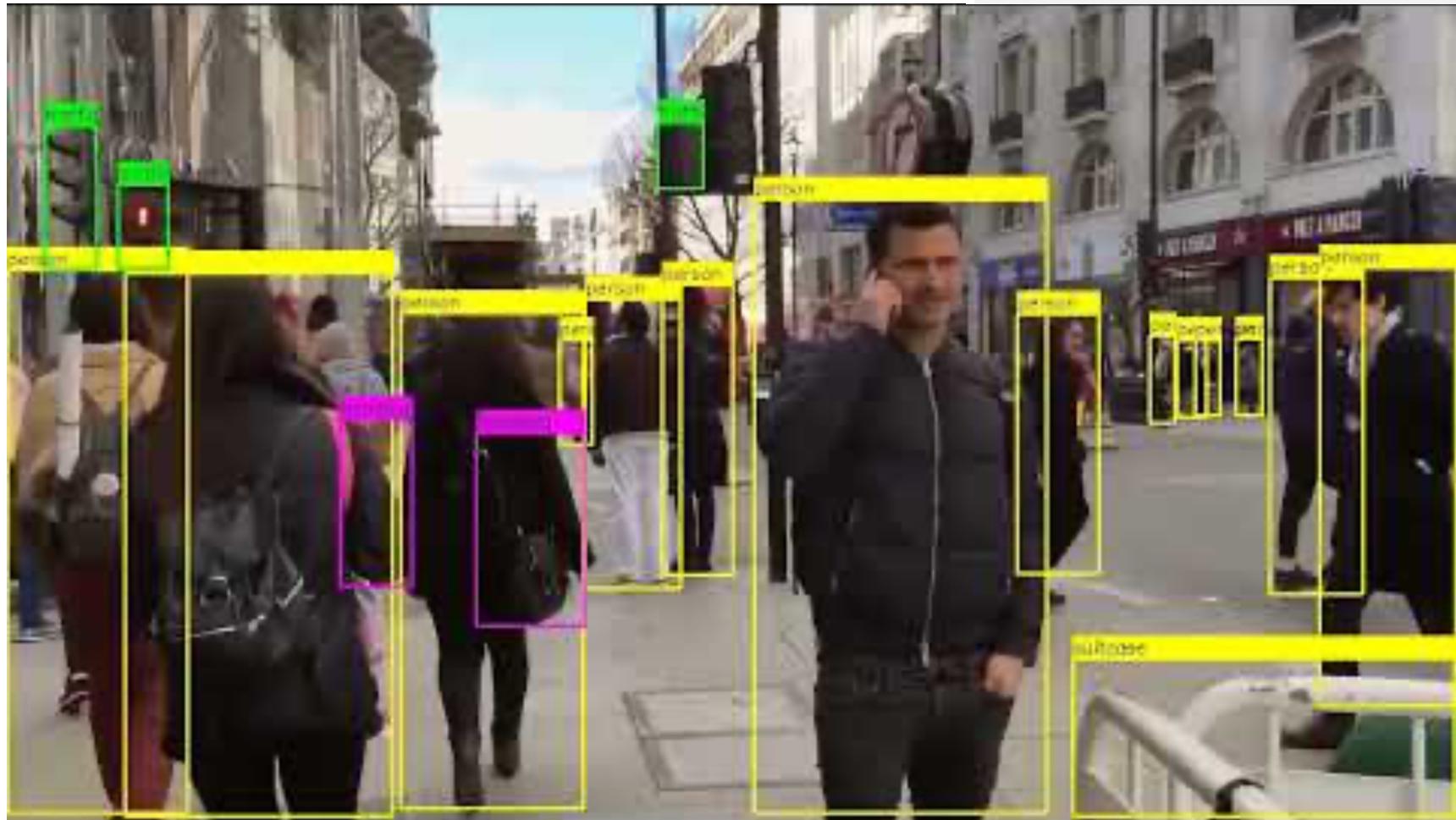
Subscribe

13,911 views Nov 13, 2017

No description has been added to this video.



YOLO v5



Example of YOLO v5 detection on video file

 Luiz doleron
127 subscribers

Subscribe

5,781 views Jan 23, 2022

Video example of YOLOv5 performing object detection.

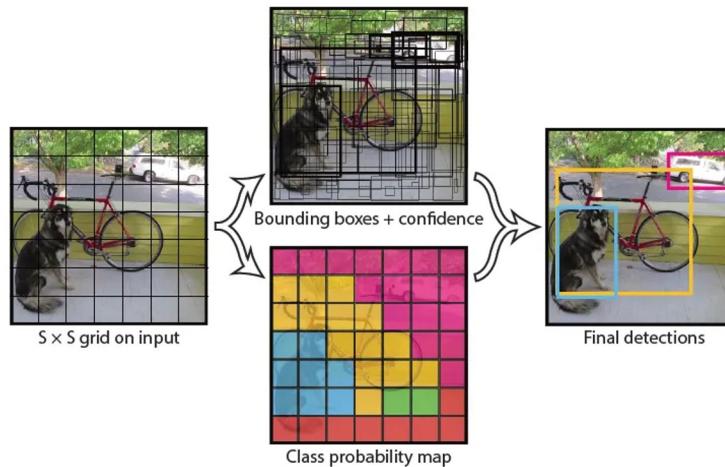
- Check out the explanation at [/ detecting-objects-with-yolov5-opencv-python...](#)
- Github repository is here: <https://github.com/doleron/yolov5-ope...>



What is YOLO?

You Only Look Once (YOLO) is a one-stage, end-to-end object detection framework that predicts bounding boxes and class probabilities in a single forward pass of a neural network.

Unlike earlier object detection approaches that adapted image classifiers into multi-step detection pipelines, YOLO treats object detection as a single regression problem.



<https://medium.com/data-science/yolov1-you-only-look-once-object-detection-e1f3ffec8a89>



Home People Dataset Tasks Evaluate

info@cocodataset.org

News

- We are pleased to announce the [LVIS 2021 Challenge and Workshop](#) to be held at ICCV.
- Please note that there will not be a COCO 2021 Challenge, instead, we encourage people to participate in the LVIS 2021 Challenge.
- We have partnered with the team behind the open-source tool [FiftyOne](#) to make it easier to download, visualize, and evaluate COCO
- [FiftyOne](#) is an open-source tool facilitating visualization and access to COCO data resources and serves as an evaluation tool for model analysis on COCO.

What is COCO?



COCO is a large-scale object detection, segmentation, and captioning dataset. COCO has several features:

- ✓ Object segmentation
- ✓ Recognition in context
- ✓ Superpixel stuff segmentation
- ✓ 330K images (>200K labeled)
- ✓ 1.5 million object instances
- ✓ 80 object categories
- ✓ 91 stuff categories
- ✓ 5 captions per image
- ✓ 250,000 people with keypoints

<https://cocodataset.org/#home>

Collaborators

Tsung-Yi Lin Google Brain
Genevieve Patterson MSR, Trash TV
Matteo R. Ronchi Caltech
Yin Cui Google
Michael Maire TTI-Chicago
Serge Belongie Cornell Tech
Lubomir Bourdev WaveOne, Inc.
Ross Girshick FAIR
James Hays Georgia Tech
Pietro Perona Caltech
Deva Ramanan CMU
Larry Zitnick FAIR
Piotr Dollár FAIR

Sponsors



ultralytics/cfg/datasets/coco8.yaml

Classes
names:

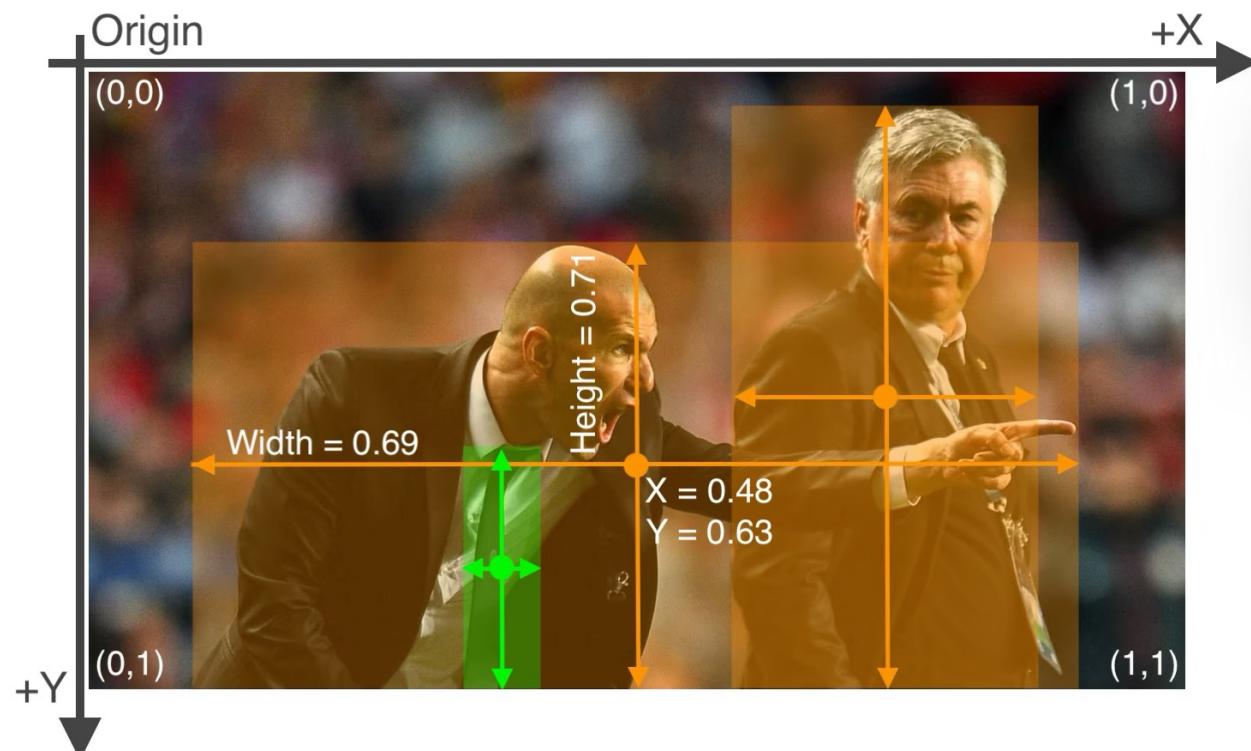
79 classes

```
0: person
1: bicycle
2: car
3: motorcycle
4: airplane
5: bus
6: train
7: truck
8: boat
9: traffic light
10: fire hydrant
11: stop sign
12: parking meter
13: bench
14: bird
15: cat
16: dog
17: horse
18: sheep
19: cow
20: elephant
21: bear
22: zebra
23: giraffe
```

<https://docs.ultralytics.com/datasets/detect/#ultralytics-yolo-format>

YOLO Dataset Format

The label file corresponding to the above image contains 2 persons (class 0) and a tie (class 27):



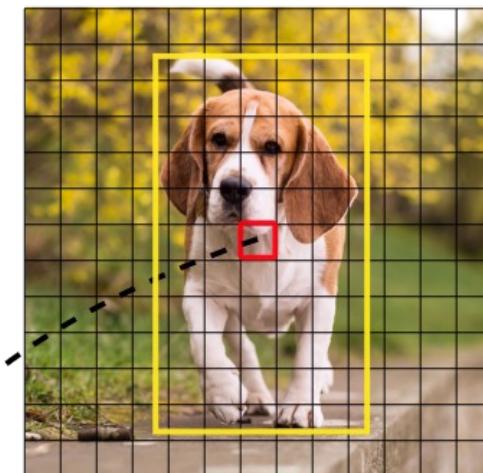
zidane.txt					
0	0.481719	0.634028	0.690625	0.713278	
0	0.741094	0.524306	0.314750	0.933389	
27	0.364844	0.795833	0.078125	0.400000	



YOLO's output



1. Resize image.
2. Run convolutional network.
3. Non-max suppression.



26

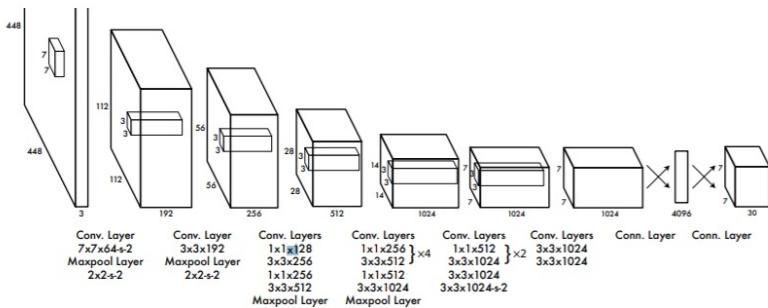
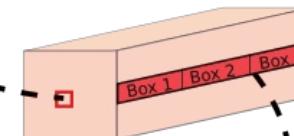
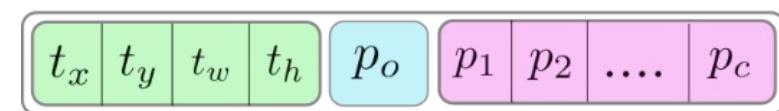


Figure 3: The Architecture. Our detection network has 24 convolutional layers followed by 2 fully connected layers. Alternating 1×1 convolutional layers reduce the features space from preceding layers. We pretrain the convolutional layers on the ImageNet classification task at half the resolution (224×224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

Prediction Feature Map



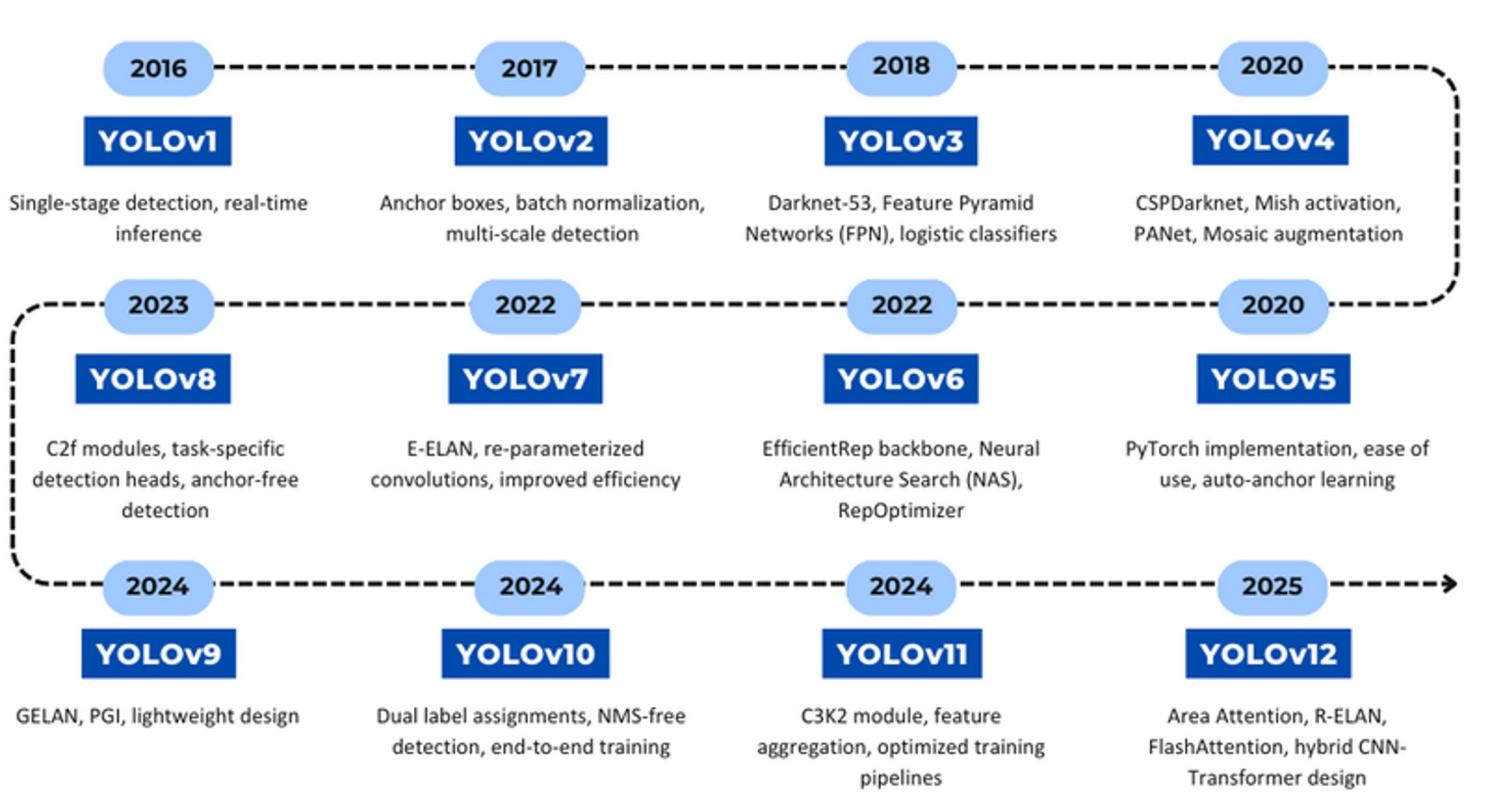
Attributes of a bounding box



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

<https://arxiv.org/abs/2504.11995>

The Evolution of YOLO



Ultralytics YOLO → production-ready, practical framework (YOLOv5 → YOLOv8 → YOLOv11).
Academic YOLO → new research architectures (YOLOv9, v10, v11, v12).

+ Ultralytic's YOLO

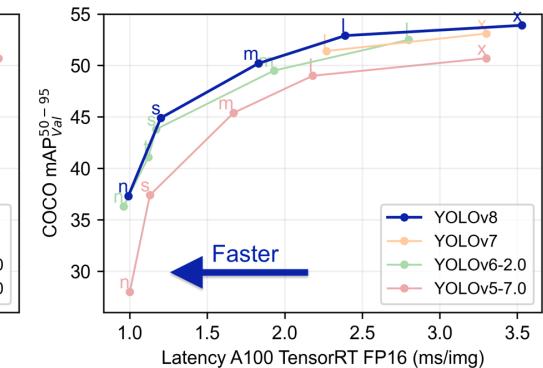
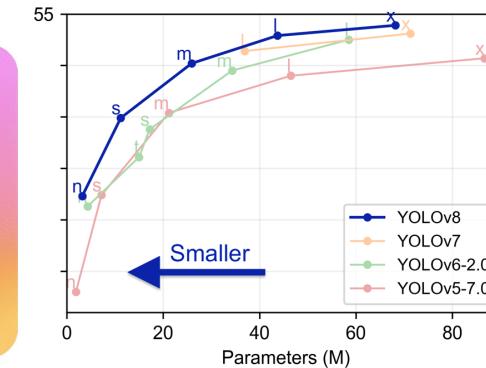
YOLOv5 (2020) → YOLOv8 (2023) → Ultralytics YOLO 11 (2024)



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.

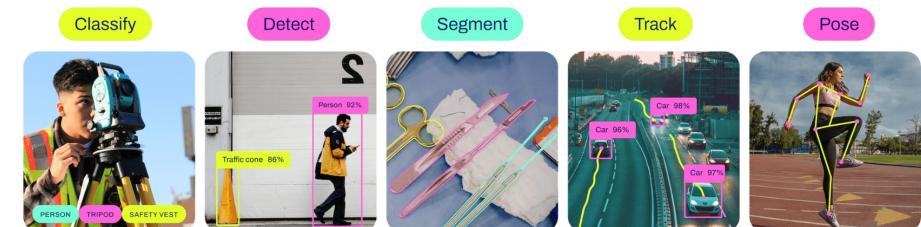
We hope that the resources here will help you get the most out of YOLOv8. Please browse the YOLOv8 [Docs](#) for details, raise an issue on [GitHub](#) for support, and join our [Discord](#) community for questions and discussions!

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.



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



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
YOLOv8 (Ultralytics)	Ultralytics	Up to ~50 AP ₅₀ / ~48.6 AP_{50:95}	Multi-task, production-ready
YOLO11 (Ultralytics)			

Explore Ultralytics YOLOv8

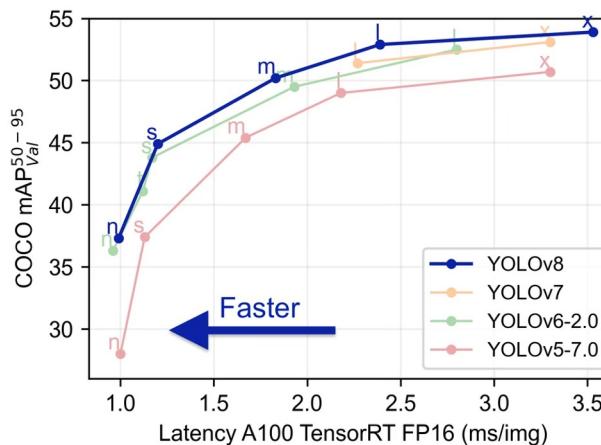
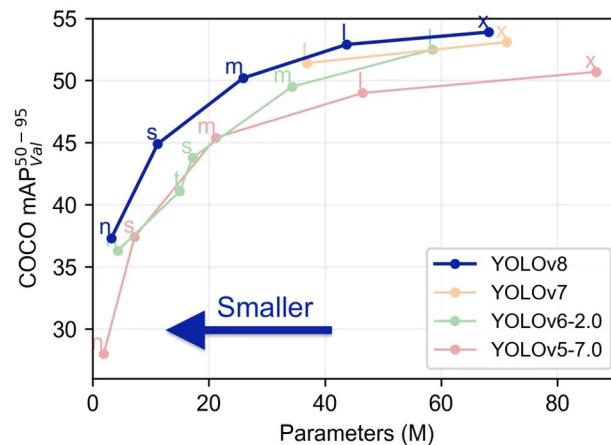
Overview

YOLOv8, launched by Ultralytics on January 10, 2023, enhances accuracy and speed while introducing features that optimize it for various object detection applications.

YOLOv5 (2020) → Anchor-based baseline
YOLOv8 (2023) → Anchor-free & simplified
YOLO11 (2025) → Refined, state-of-the-art

Key Features of YOLOv8

- Advanced Backbone and Neck Architectures
- Anchor-free Split Ultralytics Head
- Optimized Accuracy-Speed Tradeoff
- Variety of Pretrained Models



Parameters (1)

Training

- YOLO training settings rely on hyperparameters that directly influence performance and training speed, making careful tuning essential for optimal results.

Example of training parameters:

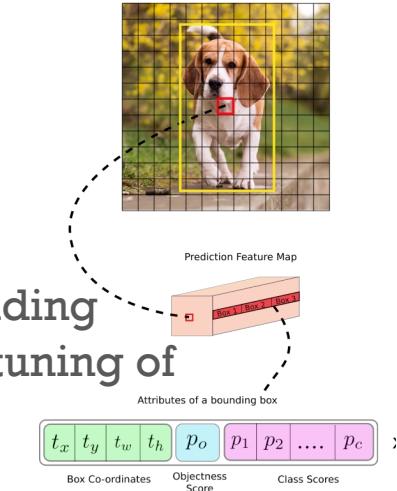
Argument	Type	Default	Description
epochs	int	100	Total number of training epochs (full dataset passes).
batch	int or float	16	Batch size. Supports auto modes (-1 or fraction like 0.7).
imgsz	int	640	Target training image size. Affects accuracy and compute cost.
val	bool	TRUE	Enables validation during training.
patience	int	100	Early stopping patience (epochs without improvement).
seed	int	0	Random seed for reproducibility.

For more details on training parameters: <https://docs.ultralytics.com/usage/cfg/#modes:~:text=Modes%20Guide-,Train%20Settings,-Training%20settings%20for>

Parameters (2)

Prediction

- YOLO prediction settings control inference performance and accuracy, including confidence threshold, NMS threshold, input size, and class handling. Proper tuning of these parameters is essential for optimal results.



Example of prediction parameters:

Parameter	Type	Default	Description
<code>conf</code>	float	0.25	Minimum confidence threshold. Detections below this value are discarded to reduce false positives.
<code>iou</code>	float	0.7	IoU threshold for Non-Maximum Suppression (NMS). Lower values remove more overlapping boxes.
<code>imgsz</code>	int or tuple	640	Inference image size. Can be a single integer (square) or (height, width) tuple.
<code>device</code>	str	None	Compute device selection (e.g., <code>cpu</code> , <code>cuda:0</code> , 0).
<code>max_det</code>	int	300	Maximum number of detections per image to prevent excessive outputs in dense scenes.
<code>agnostic_nms</code>	bool	False	Applies class-agnostic NMS, merging overlapping boxes across different classes.

For more details on training parameters: <https://docs.ultralytics.com/usage/cfg/#train-settings>:~:text=Train%20Guide-,Predict%20Settings,-Prediction%20settings%20for

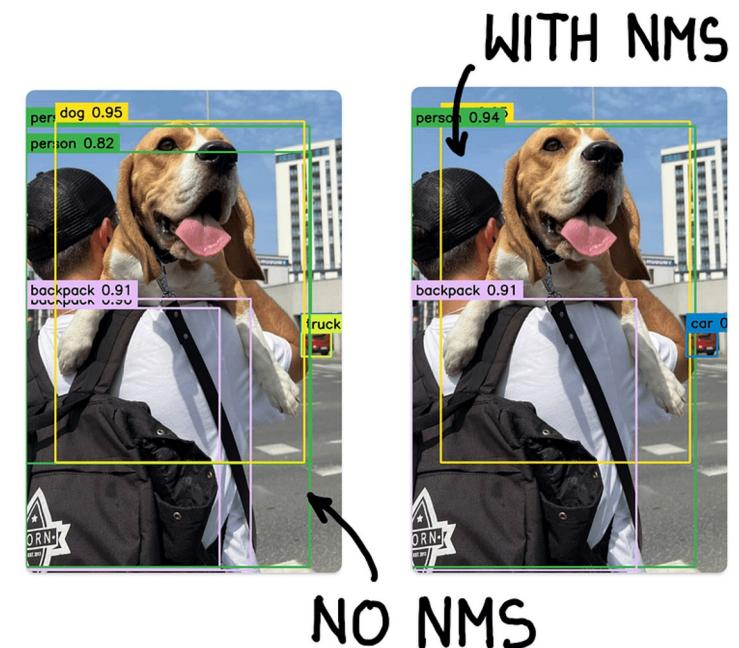
Non-Maximum Suppression (NMS)

What is NMS?

- Removes **duplicate overlapping boxes**
- Keeps the box with the highest confidence
- Controlled mainly by **IoU threshold**

Key Parameter

- Lower IoU → stricter suppression
- Higher IoU → keep more overlapping boxes

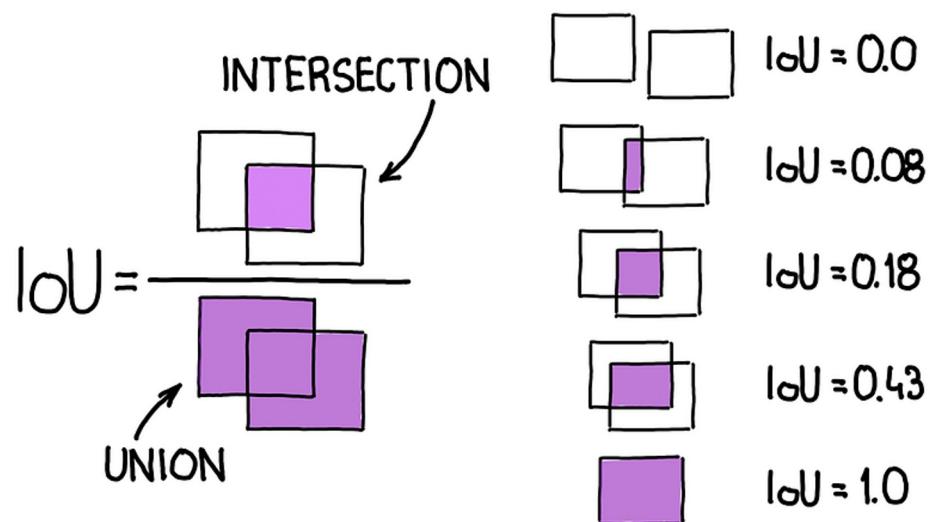


<https://blog.roboflow.com/how-to-code-non-maximum-suppression-nms-in-plain-python/>

IoU Threshold (iou)

Intersection over Union

- Measures how well a predicted bounding box overlaps with a ground-truth bounding box.



<https://blog.roboflow.com/how-to-code-non-maximum-suppression-nms-in-plain-python/>

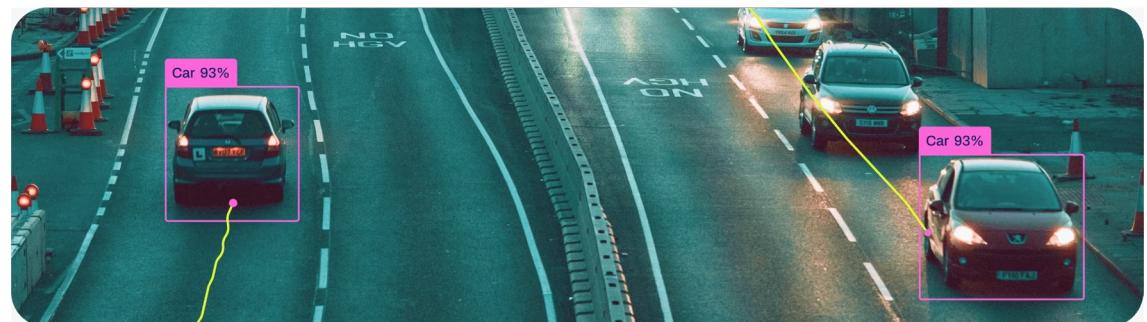
YOLOv8 Tracking

Multi-Object Tracking with Ultralytics YOLO

- Tracks object locations and classes while preserving unique IDs across video frames
- Enables applications such as surveillance, security, and real-time sports analytics

Object Tracking with YOLov8

- Ultralytics YOLO supports the following tracking algorithms:
 - ByteTrack
 - BoT-SORT



<https://docs.ultralytics.com/modes/track/>

YOLOv8 Tracking

Tracker Arguments

- Some tracking behaviors can be fine-tuned by editing the tracking algorithm-specific YAML configuration files.
 - [botsort.yaml](#)
 - [bytetrack.yaml](#)

Example Usage

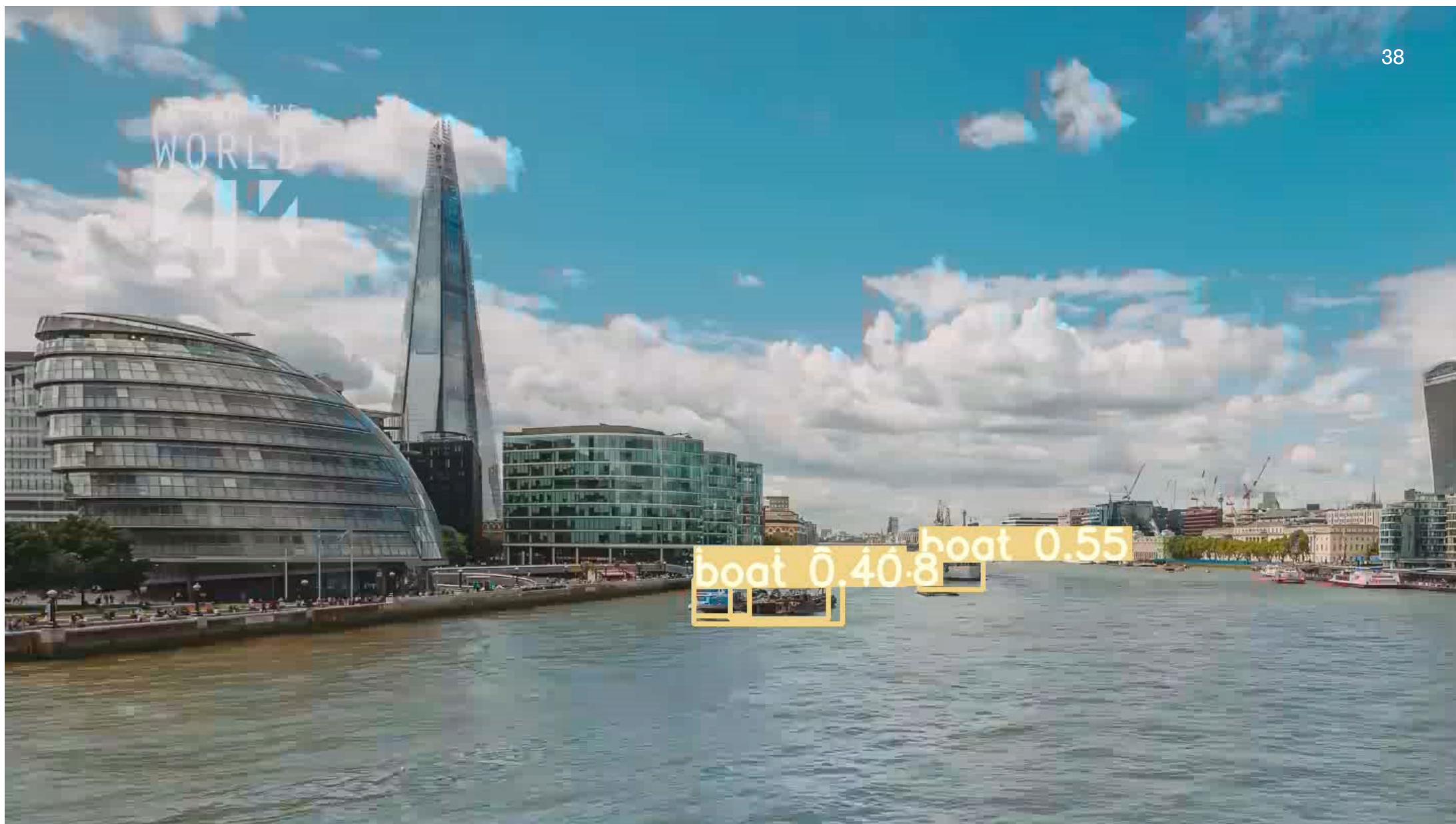
Parameter	Valid Values or Ranges	Description
tracker_type	botsort, bytetrack	Specifies the tracker type. Options are <code>botsort</code> or <code>bytetrack</code> .
track_high_thresh	0.0-1.0	Threshold for the first association during tracking used. Affects how confidently a detection is matched to an existing track.
track_low_thresh	0.0-1.0	Threshold for the second association during tracking. Used when the first association fails, with more lenient criteria.
new_track_thresh	0.0-1.0	Threshold to initialize a new track if the detection does not match any existing tracks. Controls when a new object is considered to appear.
track_buffer	>=0	Buffer used to indicate the number of frames lost tracks should be kept alive before getting removed. Higher value means more tolerance for occlusion.
match_thresh	0.0-1.0	Threshold for matching tracks. Higher values makes the matching more lenient.
fuse_score	True, False	Determines whether to fuse confidence scores with IoU distances before matching. Helps balance spatial and confidence information when associating.
gmc_method	orb, sift, ecc, sparseOptFlow, None	Method used for global motion compensation. Helps account for camera movement to improve tracking.
proximity_thresh	0.0-1.0	Minimum IoU required for a valid match with ReID (Re-identification). Ensures spatial closeness before using appearance cues.
appearance_thresh	0.0-1.0	Minimum appearance similarity required for ReID. Sets how visually similar two detections must be to be linked.
with_reid	True, False	Indicates whether to use ReID. Enables appearance-based matching for better tracking across occlusions. Only supported by BoTSORT.
model	auto, yolov8n.pt	Specifies the model to use. Defaults to <code>auto</code> , which uses native features if the detector is YOLO, otherwise uses <code>yolov8n-cls.pt</code> .

```
from ultralytics import YOLO

# Load an official or custom model
model = YOLO("yolov8n.pt") # Load an official Detect model

# Perform tracking with the model
results = model.track("https://youtu.be/LNwODJXcv4", show=True) # Tracking with default tracker
results = model.track("https://youtu.be/LNwODJXcv4", show=True, tracker="bytetrack.yaml") # with ByteTrack
```

<https://docs.ultralytics.com/modes/track/>



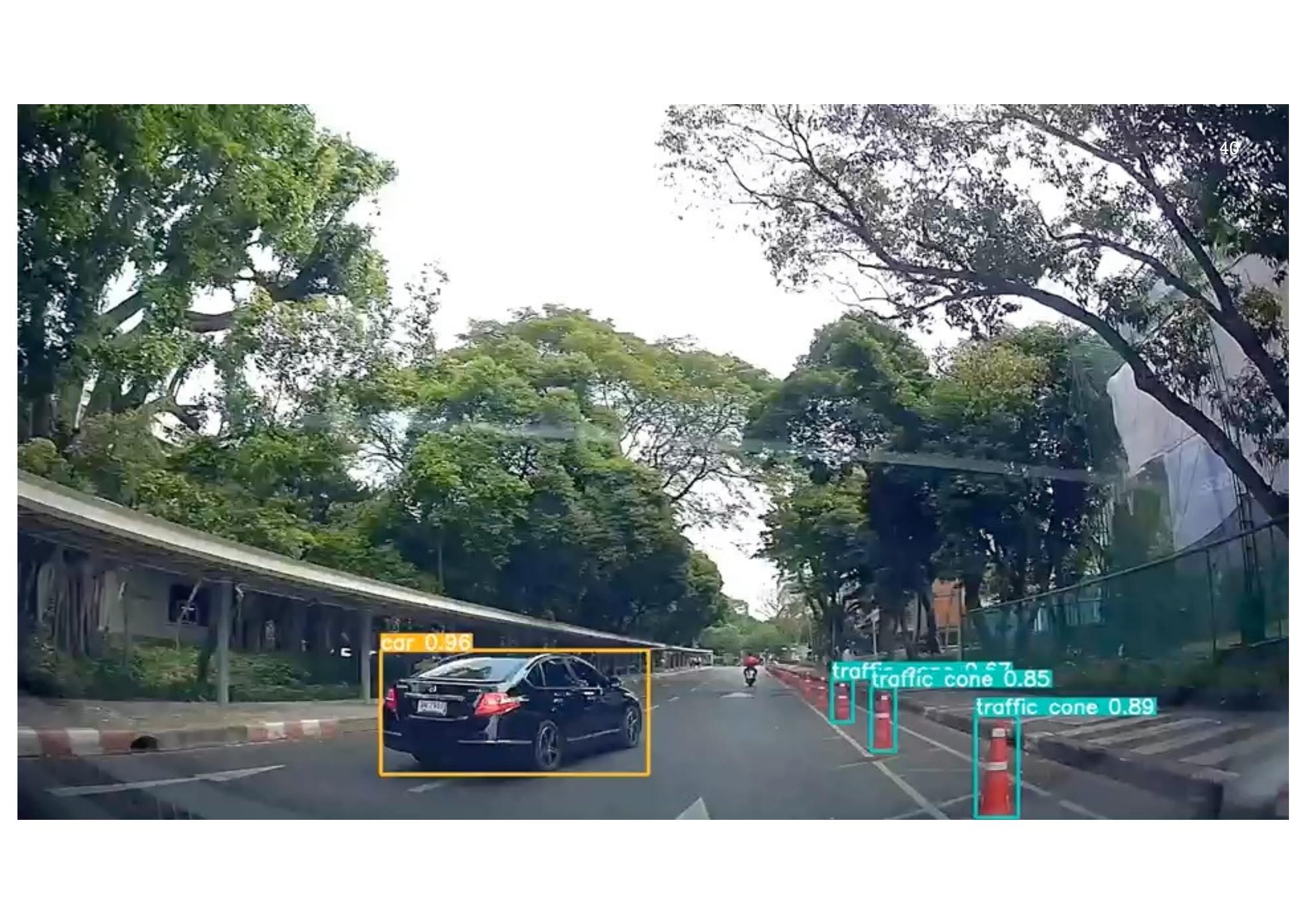
In Frame: 3
Identified: 3



ตัวอย่างความลับกวนปั๊



www.youtube.com/workpointofficial



car 0.96



traffic cone 0.87

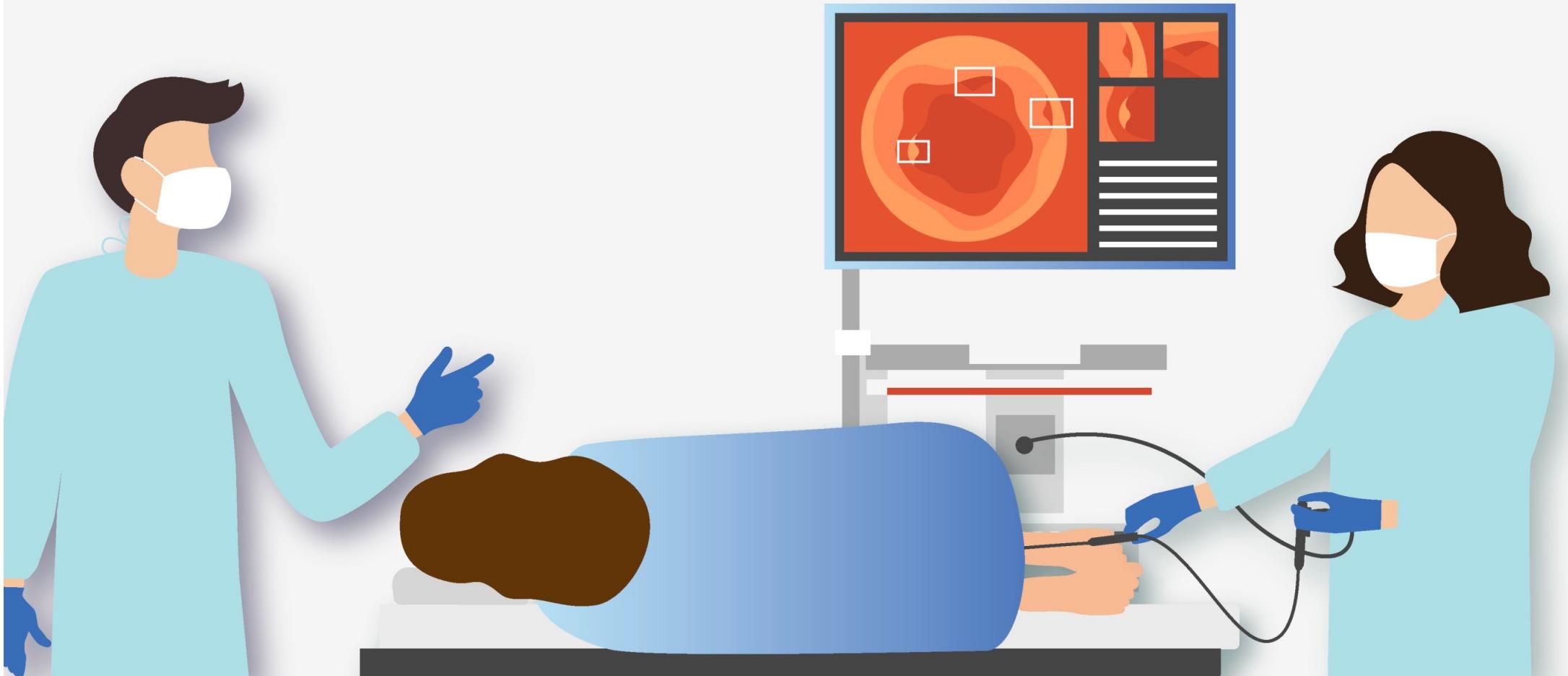
traffic cone 0.85

traffic cone 0.89



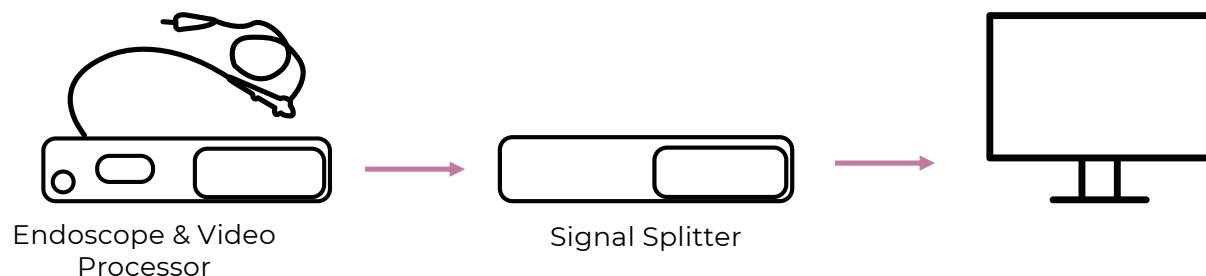
DeepGI: Real-Time Colonic Polyp Detection

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

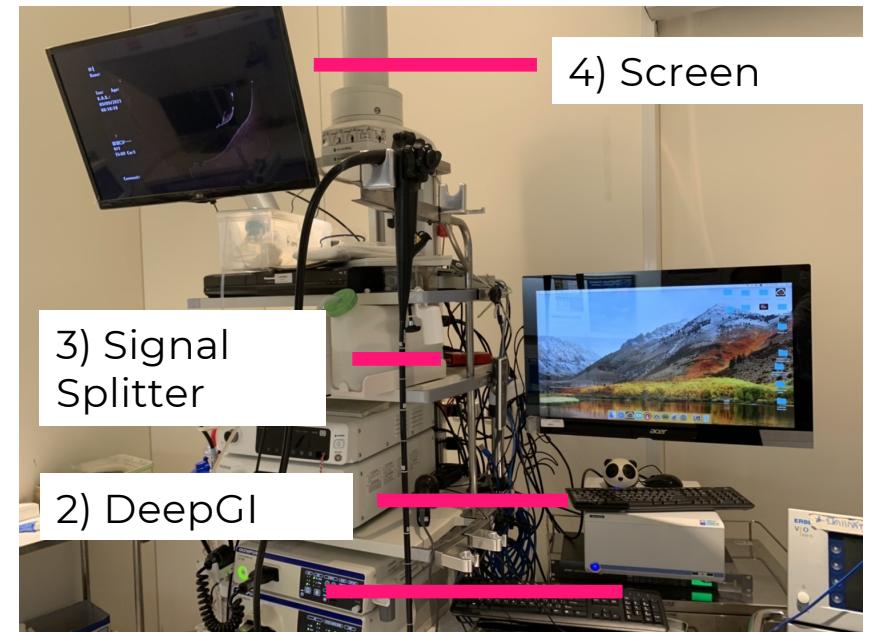
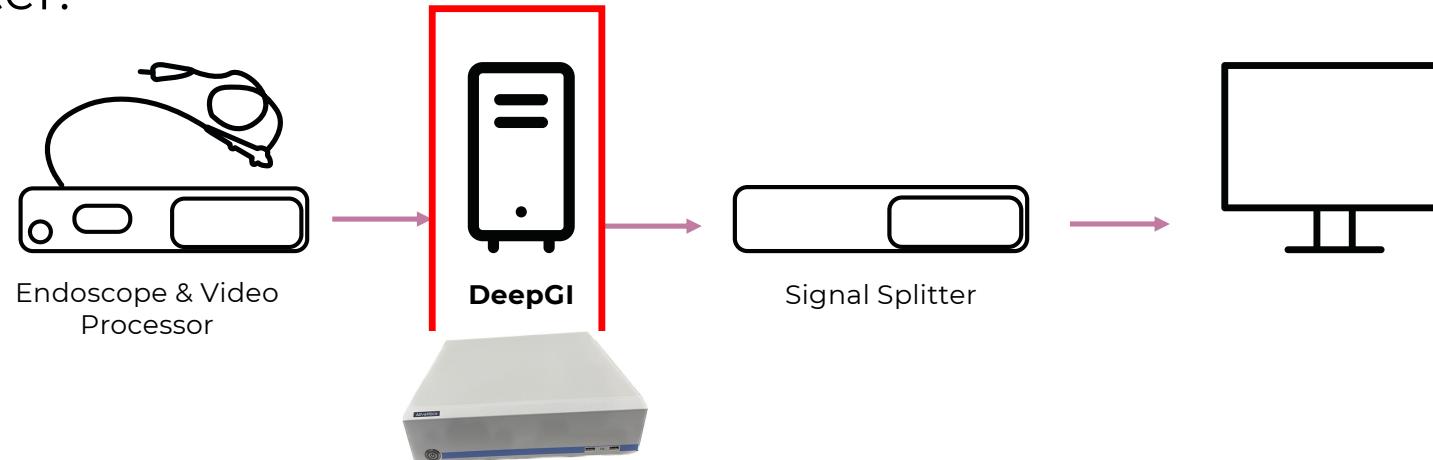


System Architecture

Before:



After:



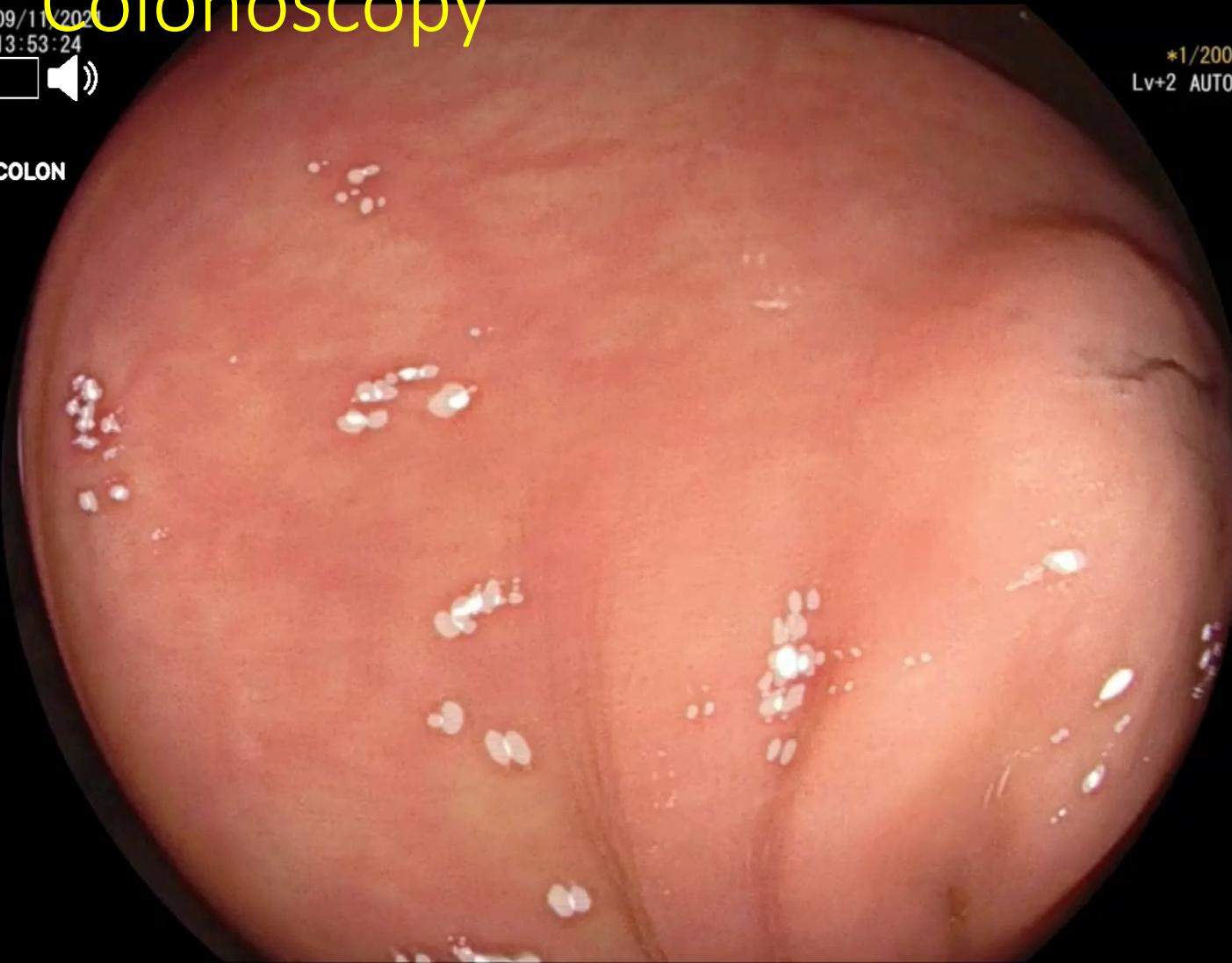
Colonoscopy

09/11/2021

13:53:24



COLON



*1/200
Lv+2 AUTO

43

HT NR

SE

f



*

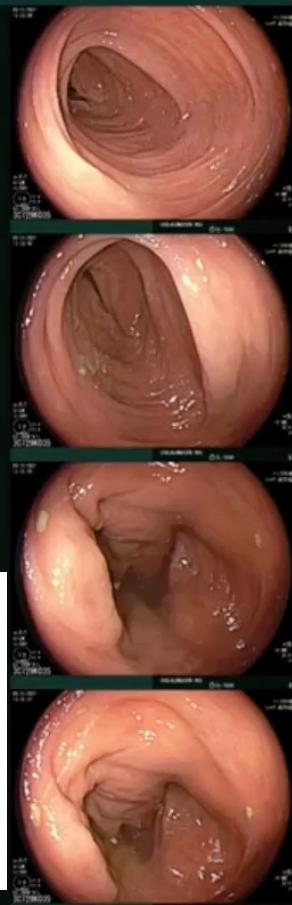
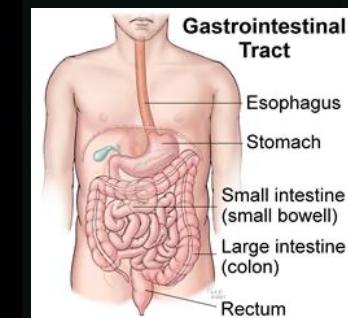
3.8 12.0 S1: F+T
12.0 S2: LM
12.0 S3: CAD
S4:

EC-760R-V/L

3C729K035

BL-7000

CHULALONGKORN HOS



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+ Thank you
& any questions