Advanced Deep Learning in Computer Vision

Day 1

Transfer Learning and Object Detection

Materials:
http://bit.ly/ADLCV_Jan21

Warm up!

Step 1: Go to the following url

http://bit.ly/warmup

Step 2: facilitator will walk you through the following questions

10 mins

Introduction of Trainer

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Programme

Day 1	Transfer Learning Activity – Transfer Learning Fine Tuning Object Detection and Localization Activity – Localization using Haar Cascades	More Object Detection and Localization Activity – Using YOLOv3 and SSD Annotation Activity – Annotation Hands-on
Day 2	Image Segmentation Activity – - OpenCV Mask RCNN - Keras Mask RCNN - Training Customized Mask RCNN	Activity: Using Customized Mask RCNN Face Detection and Recognition Activity: - Create Face Database - Face Recognition
Day 3	Advanced Generative Adversarial Network Activity - DCGAN for small color photographs - Conditional GAN	Customised Dataset with Yolo Activity - Thermal Images - Aerial Images

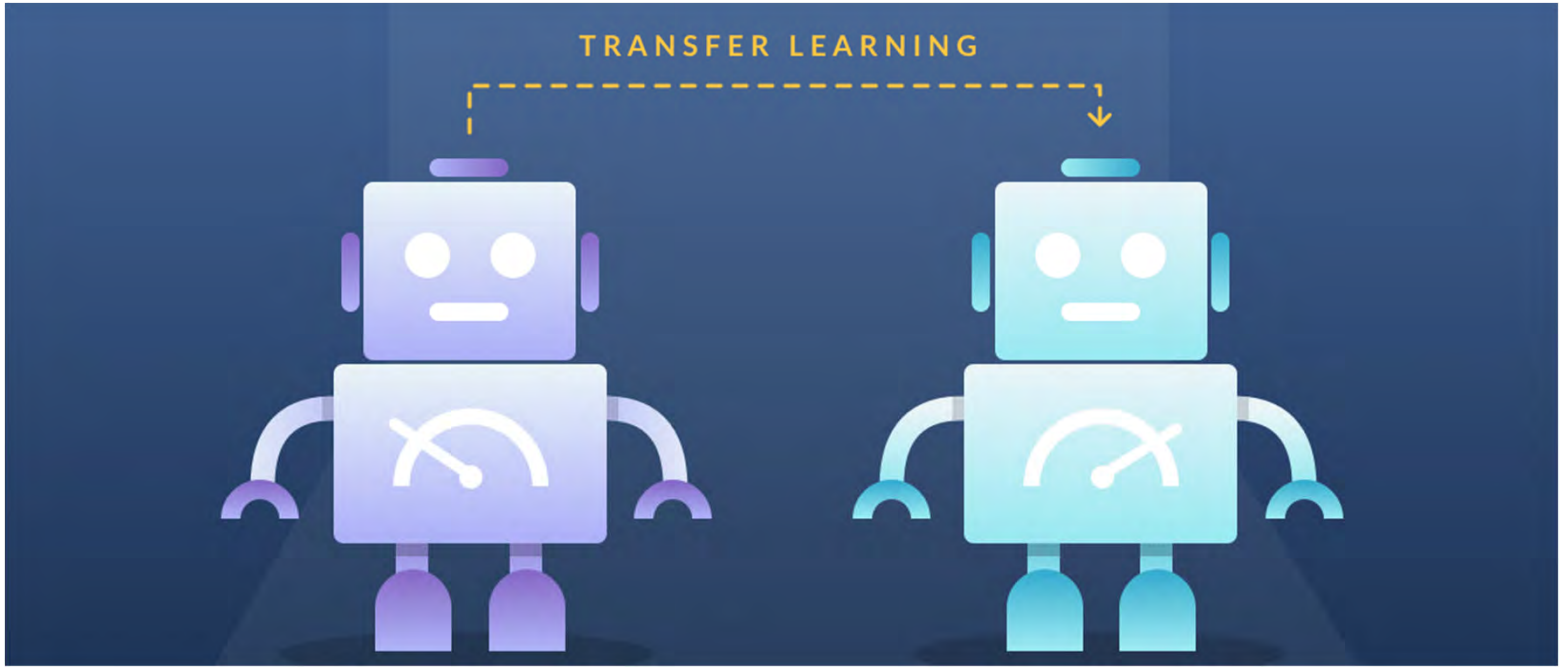


Image credit: Datacamp

Transfer Learning

What is Transfer Learning

- Transfer learning (TL) is a research problem in machine learning (ML) that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem.
  - Wikipedia

- Transfer learning is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned.
  - Chapter 11: Transfer Learning, Handbook of Research on Machine Learning Applications, 2009.

What is Transfer Learning

- **Models are difficult to train from scratch**
  - Huge datasets (like ImageNet)
  - Long number of training iterations
  - Very heavy computing machinery
  - Time experimenting to get hyper-parameters just right

What is Transfer Learning

- **Basic idea**
  - Early layers in a Neural Network are the hardest (i.e. slowest) to train
  - Due to vanishing gradient property
  - But these ”primitive” features should be general across many image classification tasks
  - Later layers in the network are capturing features that are more particular to the specific image classification problem.
  - Later layers are easier (quicker) to train since adjusting their weights has a more immediate impact on the final result.
  - **Idea**: keep the early layers of a pre-trained network, and re-train the later layers for a specific application

Pre-trained CNN models

- **Models for image classification with weights trained on ImageNet:**
  - Xception
  - VGG16
  - VGG19
  - ResNet, ResNetV2
  - InceptionV3
  - InceptionResNetV2
  - MobileNet
  - MobileNetV2
  - DenseNet
  - NASNet

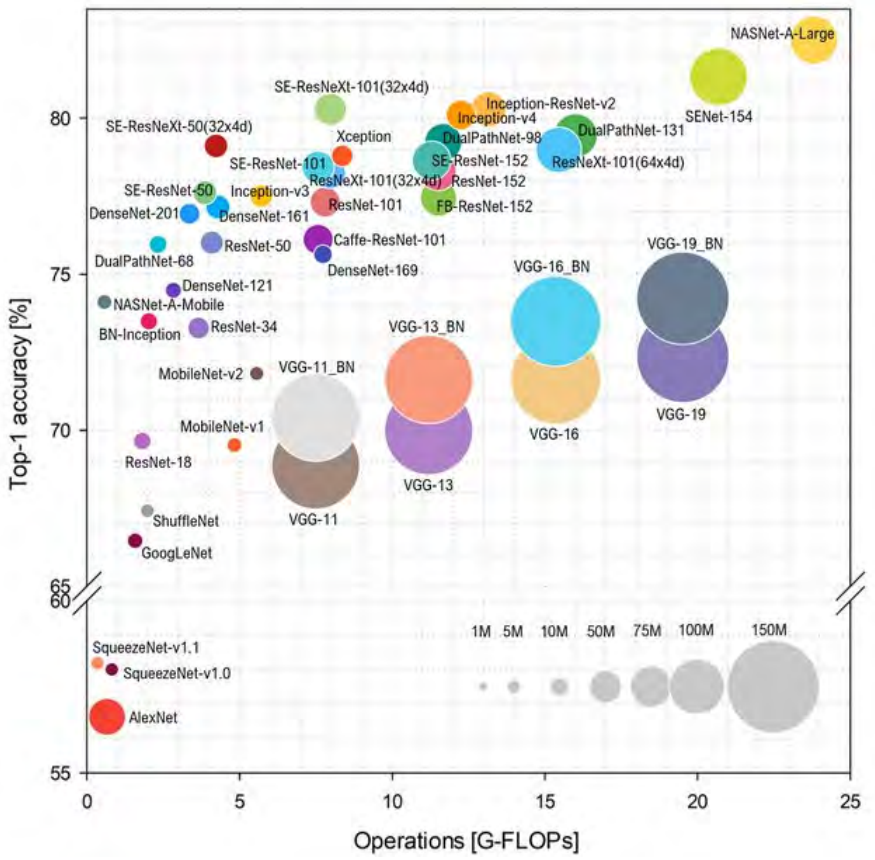


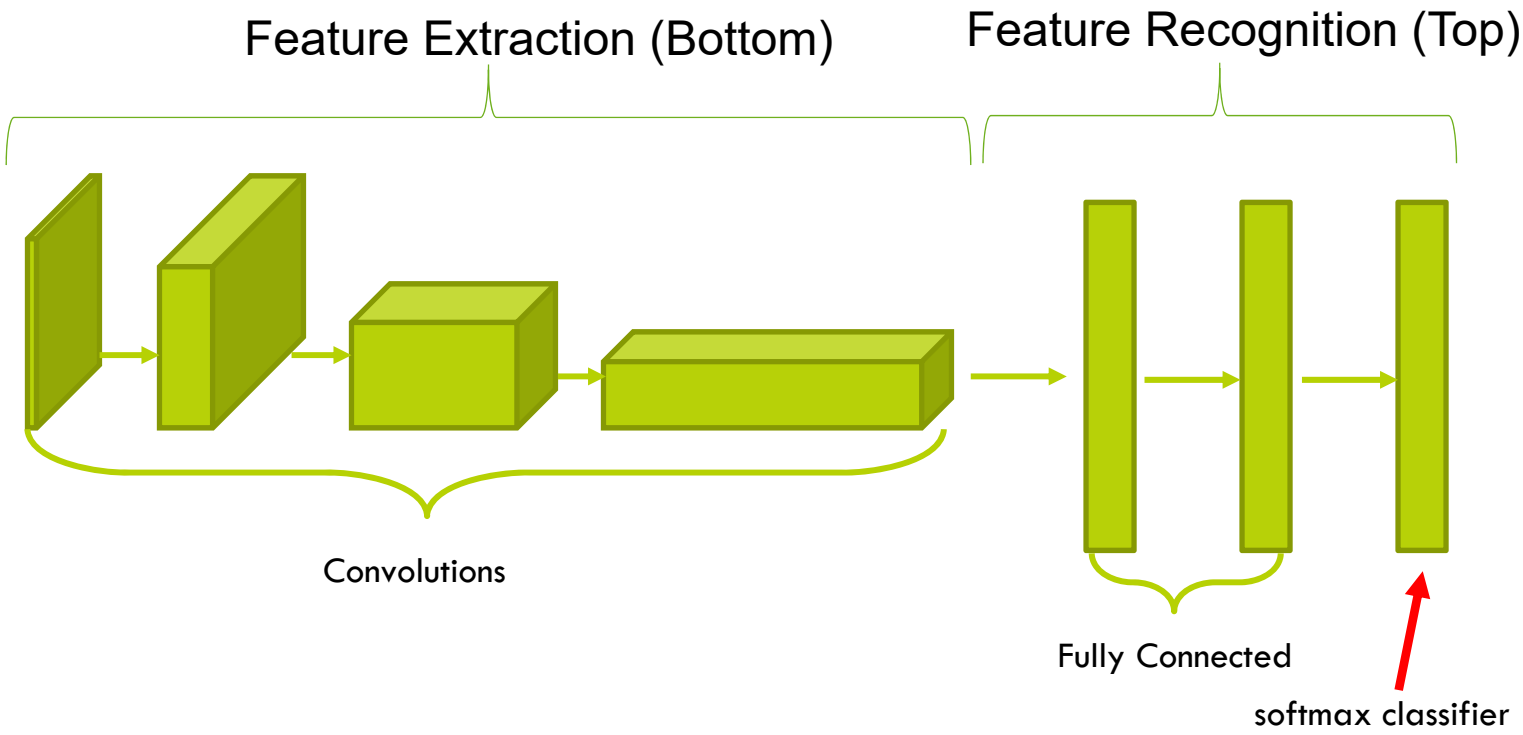
Image: Benchmark Analysis of Representative Deep Neural Network Architectures

Pretrained CNN models

- **ImageNet (http://image-net.org/index)**
  - ImageNet is an image dataset organized according to the WordNet hierarchy. Each meaningful concept in WordNet, possibly described by multiple words or word phrases, is called a "synonym set" or "synset". There are more than 100,000 synsets in WordNet, majority of them are nouns (80,000+). In ImageNet, we aim to provide on average 1000 images to illustrate each synset. Images of each concept are quality-controlled and human-annotated. In its completion, we hope ImageNet will offer tens of millions of cleanly sorted images for most of the concepts in the WordNet hierarchy.

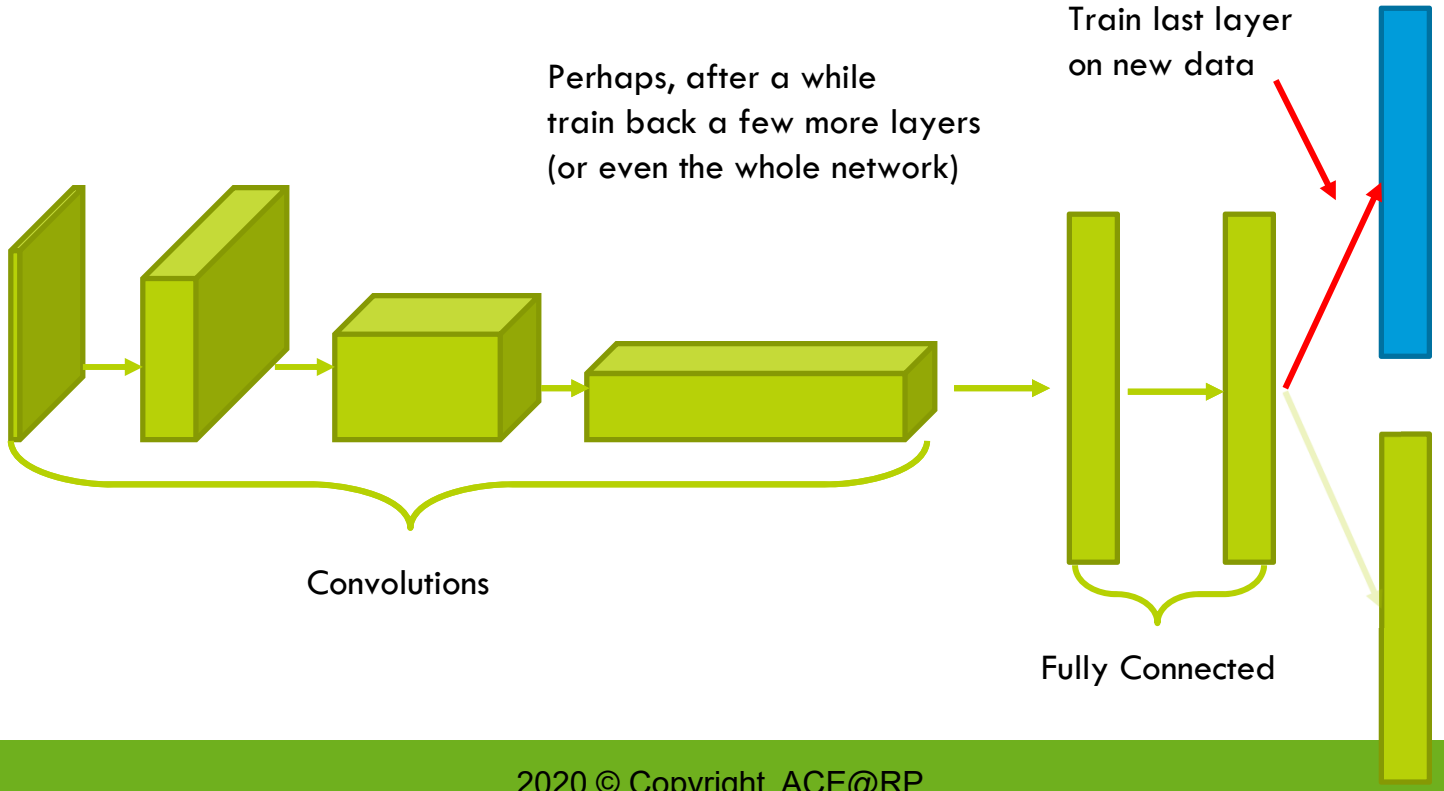
How to do Transfer Learning

- **A typical pre-trained CNN Model**



How to do Transfer Learning

- **Reconstruct Top layer**
  - Change the output layer to suit your needs
    - E.g different number of categories, detect different features
  - Adjust the number of layers and nodes of the hidden layers accordingly



How to do Transfer Learning

- **Fine Tuning**
  - The additional training of a pre-trained network on a specific new dataset is referred to as "***Fine-Tuning***"
  - There are different options on "how much" and "how far back" to fine-tune.
    - Should I train just the very last layer?
    - Go back a few layers?
    - Re-train the entire network (from the starting point of the existing network)?
  - While there are no "hard and fast" rules, there are some guiding principles to keep in mind.

When to use Transfer Learning

- Principle 1:

The more similar your data and problem are to the source data of the pre-trained network, the less fine-tuning is necessary.

- E.g. Using a network trained on ImageNet to distinguish "dogs" from "cats" should need relatively little fine-tuning. It already distinguished different breeds of dogs and cats, so likely has all the features you will need.

When to use Transfer Learning

- Principle 2:

The more data you have about your specific problem, the more the network will benefit from longer and deeper fine-tuning.

- E.g. If you have only 100 dogs and 100 cats in your training data, you probably want to do very little fine-tuning. If you have 10,000 dogs and 10,000 cats you may get more value from longer and deeper fine-tuning.

When to use Transfer Learning

- Principle 3:

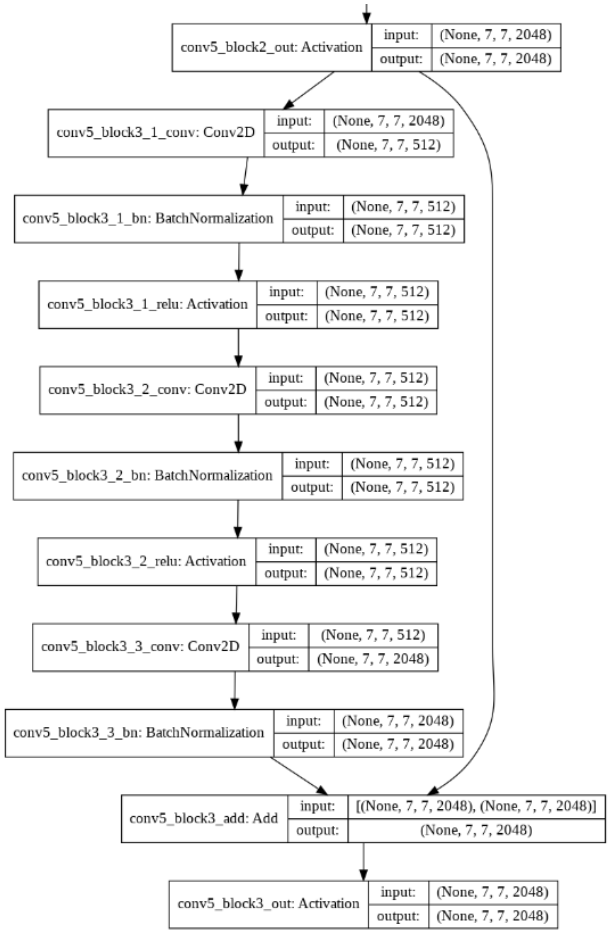
If your data is substantially different in nature than the data the source model was trained on, Transfer Learning may be of little value.

- E.g. A network that was trained on recognizing typed Latin alphabet characters would not be useful in distinguishing cats from dogs. But it likely would be useful as a starting point for recognizing Cyrillic Alphabet characters.

Resnet50

- Total 175 layers

Resnet50_plot.png



The last few layers of Resnet50

Some fine tuning comparison

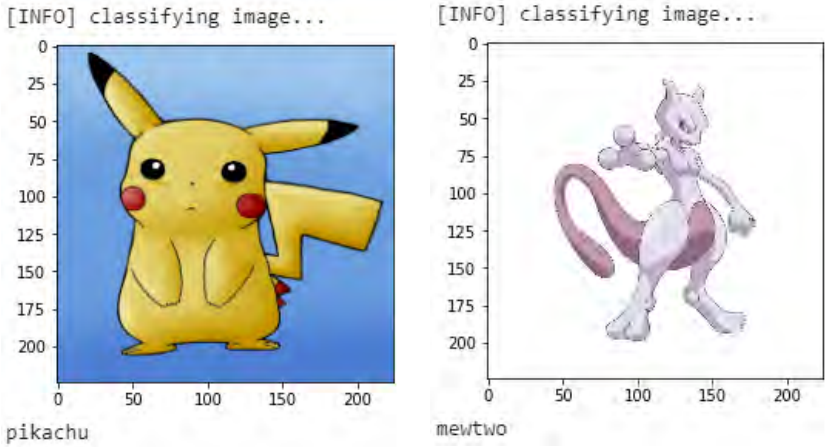
- **Epoch = 200**
- **No fine tuning** test_acc: 0.181818172367859
- **2 dense layer (128,64)** test_acc: 0.18614718317985535
- **Fine tune conv5 block (32 layers)**
  - test_acc: 0.264069259166717 53
  - CPU times: user 4min 52s, sys: 2min, total: 6min 52s
  - Wall time: 13min 45s
- **Fine tune conv5 and conv4 block (94 layers)**
  - test_acc: 0.645021617412567 1
  - CPU times: user 8min 24s, sys: 4min 20s, total: 12min 45s
  - Wall time: 19min 45s
- **Complete training :**
  - test_acc: 0.913419902324676 5
  - CPU times: user 15min 39s, sys: 9min 32s, total: 25min 12s
  - Wall time: 32min 38s

Trainable property

```
10 # Allow fine tuning to go into the convolution layers
11 base_layers_to_train = 5
12 for i in range(0, len(base_layers.layers) - base_layers_to_train):
13     base_layers.layers[i].trainable = False
14 for i in range(len(base_layers.layers) - base_layers_to_train, len(base_layers.layers)):
15     base_layers.layers[i].trainable = True
16     print(base_layers.layers[i].name)
```

Transfer Learning

- **Activity: 1_1_Transfer_Learning**



Exercises:
- Make the Conv5 Block3 block trainable (32)
- Add 2 dense layers with 128 & 64 neuron
- Compare the number of trainable parameters and the final performance

Step 1:
Watch and listen to the instructor's demonstration

10 mins

Step 2:
Work through the activities

Target to finish by 10:30am

30 mins

30 Mins Break

Continue at 11am

Object Detection

What is Object Detection

- Object recognition is a general term to describe a collection of related computer vision tasks that involve identifying objects in digital photographs.

- ***Image classification*** involves predicting the class of one object in an image.
- ***Object localization*** refers to identifying the location of one or more objects in an image and drawing a bounding box around their extent.
- ***Object detection*** combines these two tasks and ***localizes and classifies*** one or more objects in an image.

  - Ref: https://machinelearningmastery.com/object-recognition-with-deep-learning/

What is Object Detection

- Object Detection example:

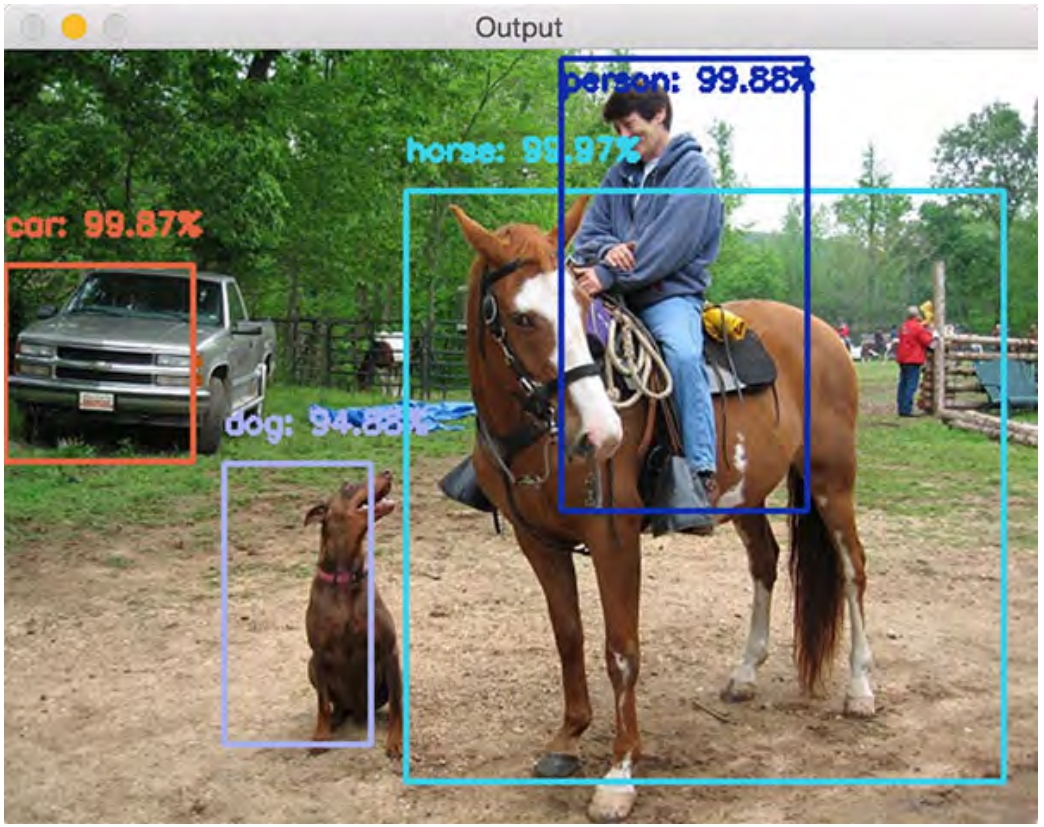


Image from: https://www.pyimagesearch.com/2017/09/11/object-detection-with-deep-learning-and-opencv/

What is Object Detection

- Object Localization example:

Image from:
https://machinelearningmastery.com/object-recognition-with-deep-learning/

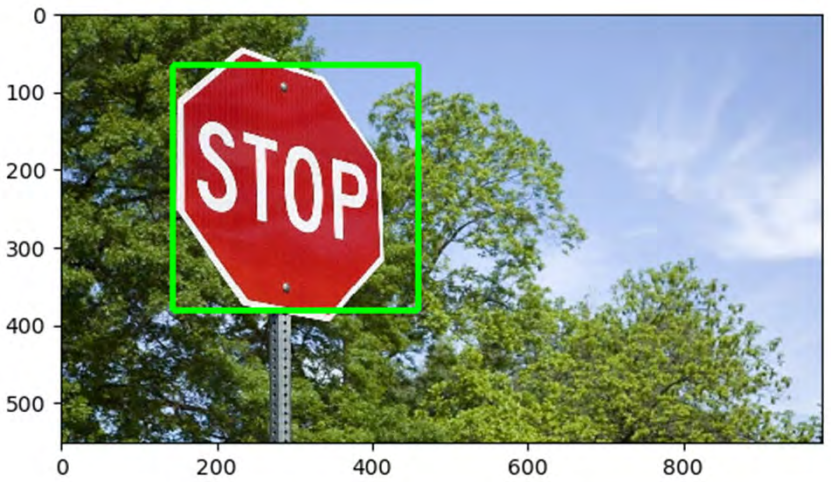


Image from:
https://machinelearningmastery.com/object-recognition-with-deep-learning/

Localization Vs Detection

- Localization
  - Faster
  - Single-object of interest
  - Counting of objects
  - Using more complex recognition algorithm
    - E.g. Face recognition
- Detection
  - Slower
  - Multiple object of interest
  - Understanding the image

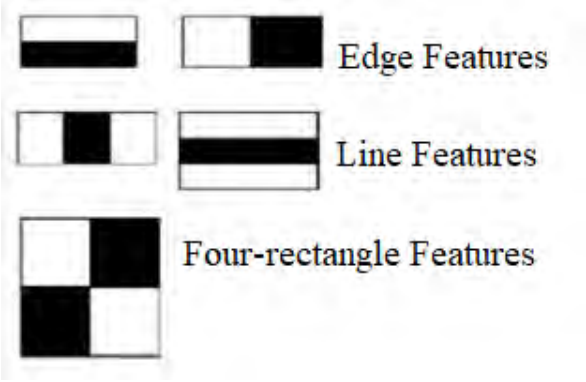
How to do Object Localization

- Haar Cascade classifier is an effective object detection approach which was proposed by *Paul Viola and Michael Jones* in their paper, "**Rapid Object Detection using a Boosted Cascade of Simple Features**" in 2001.
  - Ref: https://towardsdatascience.com/computer-vision-detecting-objects-using-haar-cascade-classifier-4585472829a9

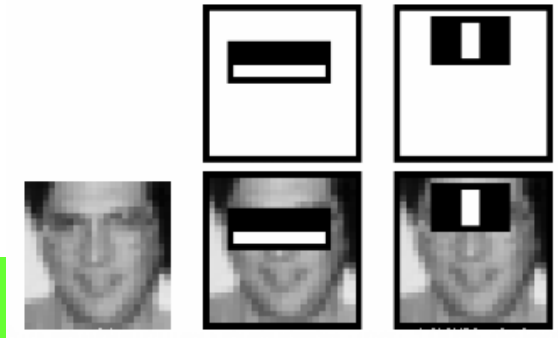
- Viola-Jones Object Detection Framework (Non-Deep Learning)
  - Ref: https://en.wikipedia.org/wiki/Viola%E2%80%93Jones_object_detection_framework

How to do Object Localization

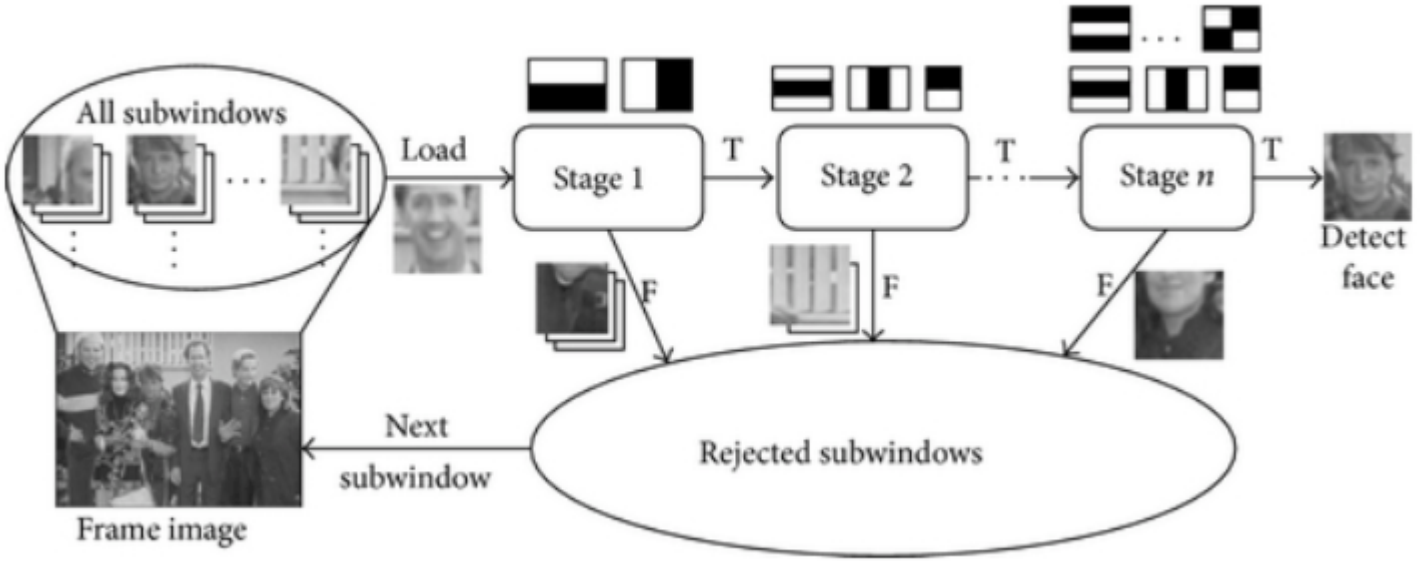
- Viola-Jones Object Detection Framework
  - Haar features
    - *Different sizes* of the Haar features very quickly scan through an image several times.



  - Haar features for Face Detection

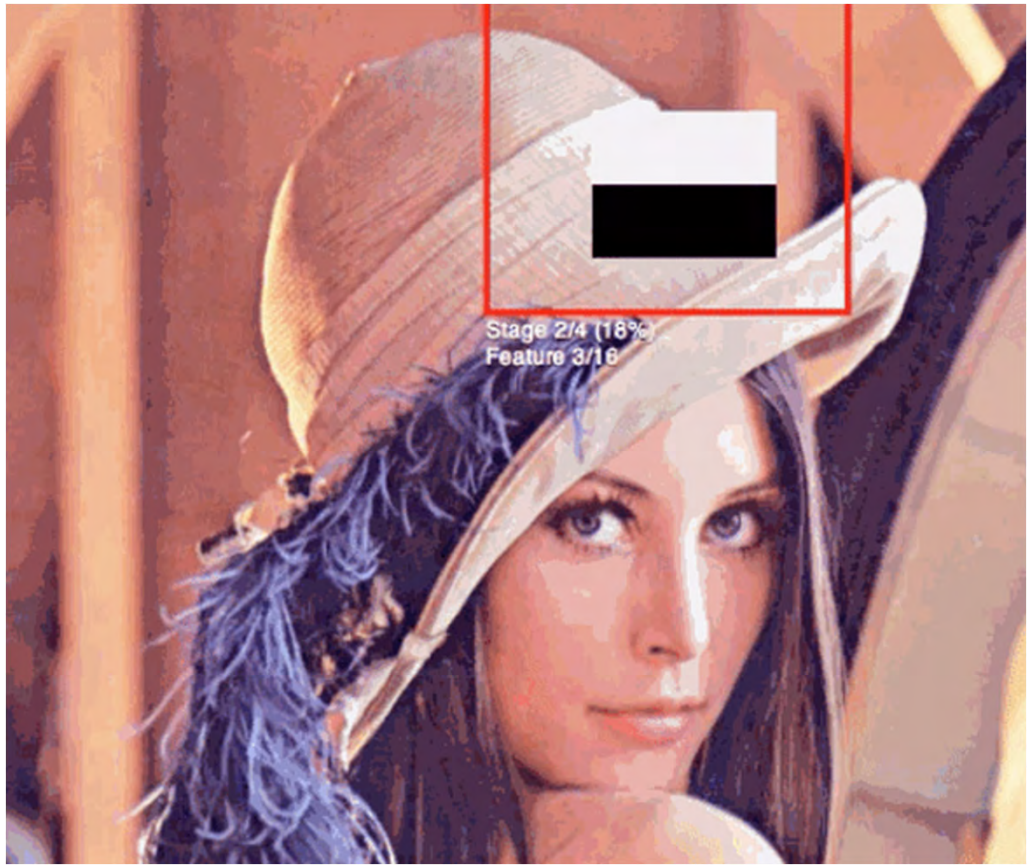


Cascade structure



https://www.researchgate.net/figure/Cascade-structure-for-Haar-classifiers_fig9_277929875

The Paul- Viola visualisation



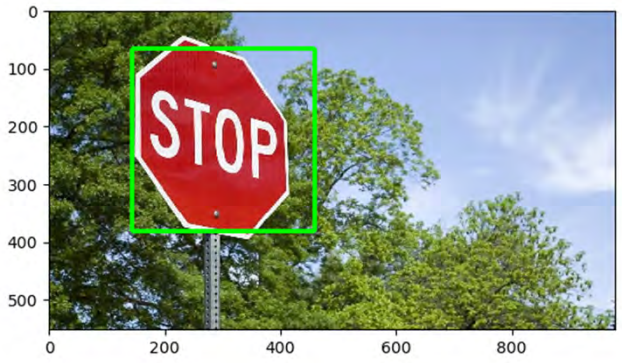
https://vimeo.com/12774628

How to do Object Localization

- Haar Features file (.xml) for different objects
  - Face, eyes, upper body, full body
  - Licence plate, car, clock, signs
  - A lot more….
- Websites to download the Haar Features file
  - https://github.com/opencv/opencv/tree/master/data/haarcascades
  - http://alereimondo.no-ip.org/OpenCV/34/
  - https://github.com/anaustinbeing/haar-cascade-files
- Train your own Haar Features file.
  - https://docs.opencv.org/master/dc/d88/tutorial_traincascade.html
  - https://pythonprogramming.net/haar-cascade-object-detection-python-opencv-tutorial/

Activity – Haar Cascades

- Activity: **2_1_Localization_using_HaarCascades**



Exercises:

- Download the Russian number plate haar cascade xml from https://github.com/anaustinbeing/haar-cascade-files

- Perform a license plate detection on cars.jpg and car2.jpg

Step 1:
Watch and listen to the instructor's demonstration

10 mins

Step 2:
Work through the activities

30 mins

60 mins Lunch Break

Lunch break 12:00 - 13:00

Deep Learning based Object Detection

- **Three primary object detection algorithm using Deep Learning**
  - R-CNN → RCNN, Fast-RCNN, Faster-RCNN
    - Slow
    - Difficult to understand and implement
  - YOLO → YOLO, YOLOv2, YOLOv3, YOLOv4, YOLOv5
    - Fast
    - Ease to customised
    - Works best with natural images
  - SSD
    - Even faster
    - Ease to customised
    - Works best with low resolution or ‘small’ objects

R-CNN

- **R-CNN (Region Proposal – CNN)**
  - **Feature Extractor**
    - To extract features from the image
  - **Region Proposal Network**
    - To both propose and refine region proposals
  - **ROI pooling**
    - To classify region of interest

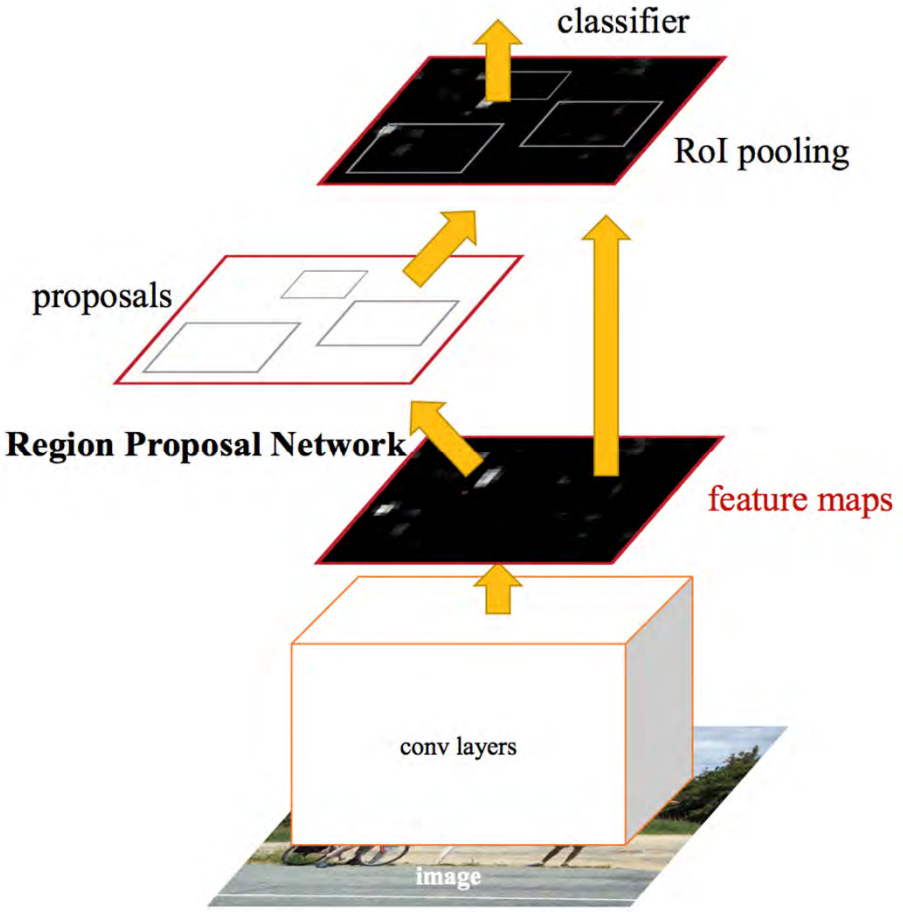
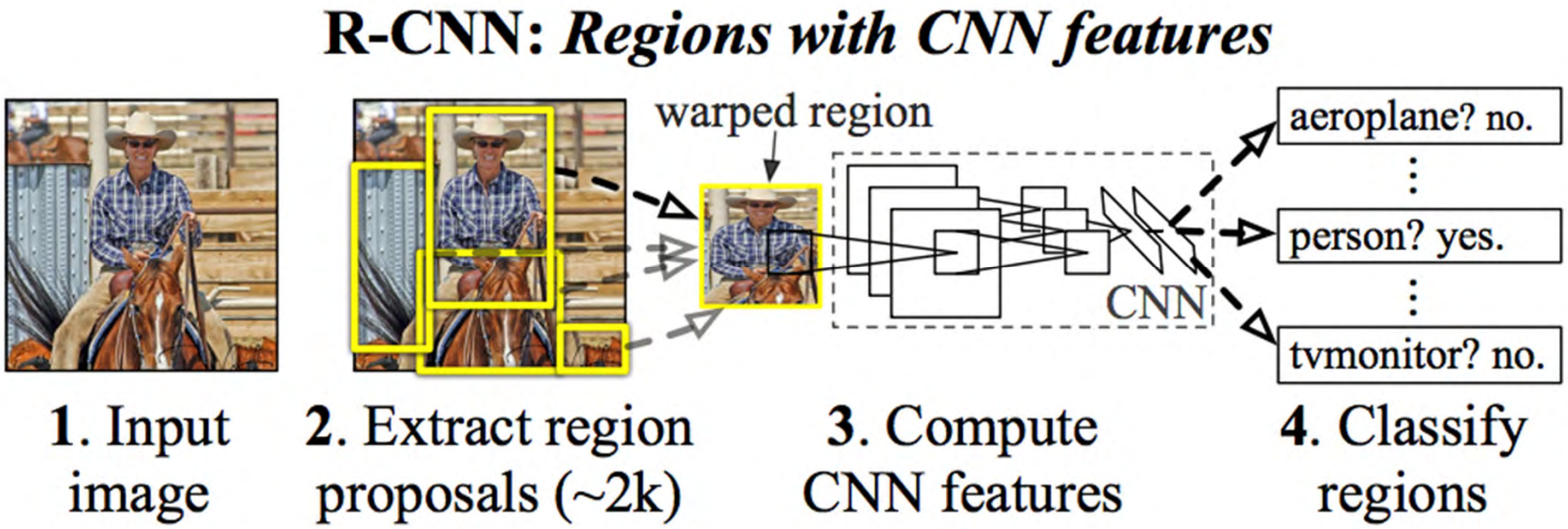


Image from: https://machinelearningmastery.com/object-recognition-with-deep-learning/

R-CNN Model Architecture

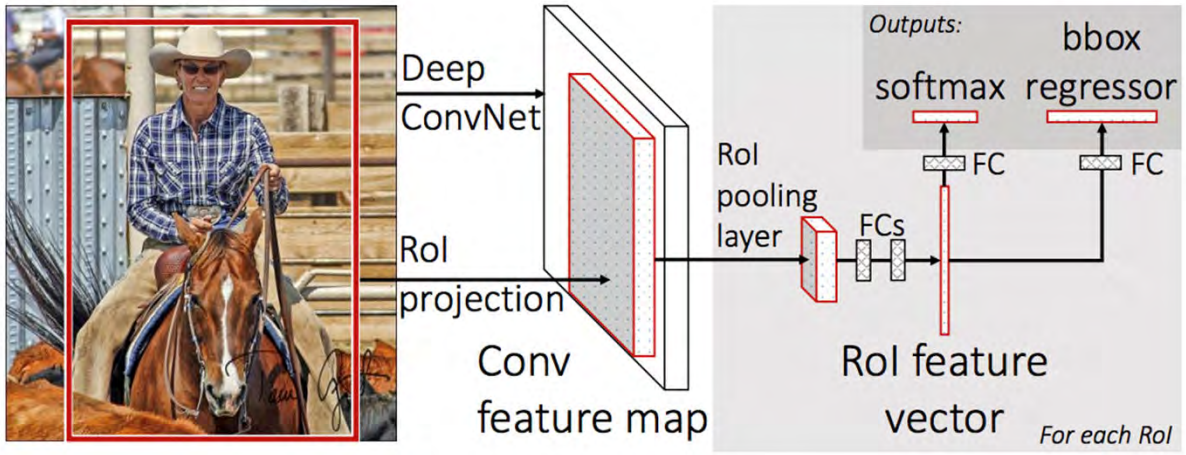


Summary of the R-CNN Model Architecture Taken from Rich feature hierarchies for accurate object detection and semantic segmentation.

Fast R-CNN

- limitations of R-CNN:
  - Training is a multi-stage pipeline. Involves the preparation and operation of three separate models.
  - Training is expensive in space and time. Training a deep CNN on so many region proposals per image is very slow.
  - Object detection is slow. Make predictions using a deep CNN on so many region proposals is very slow.

Fast R-CNN is proposed as a single model instead of a pipeline to learn and output regions and classifications directly.



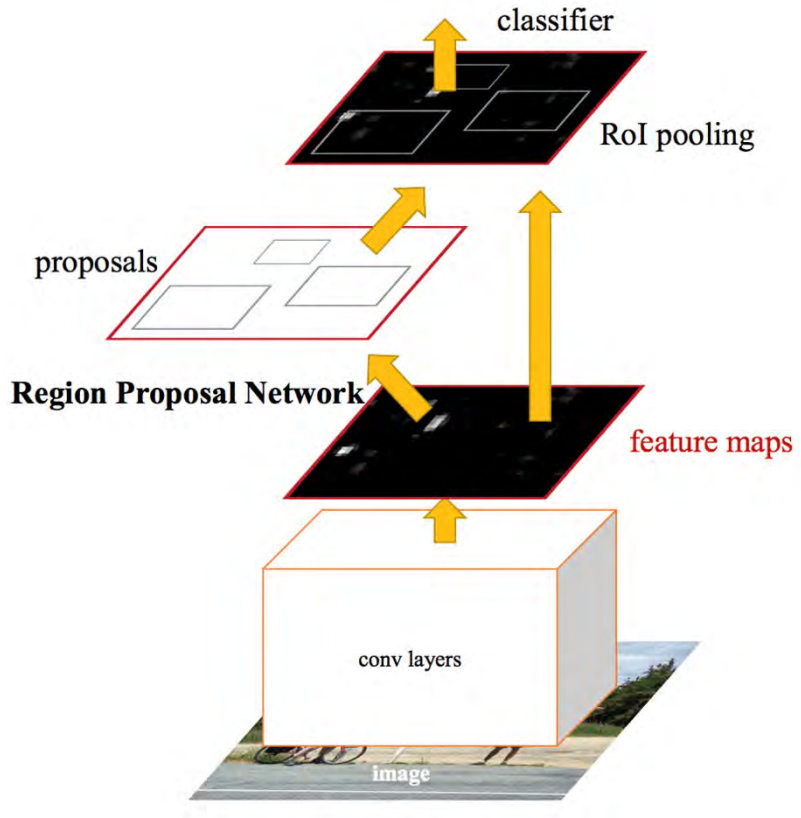
Summary of the Fast R-CNN Model Architecture.
Taken from: Fast R-CNN.

*

Faster R-CNN

The model architecture was further improved for both speed of training and detection by Shaoqing Ren, et al. at Microsoft Research in the 2016 paper titled "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks."

Although it is a single unified model, the architecture is comprised of two modules:
Module 1: Region Proposal Network. Convolutional neural network for proposing regions and the type of object to consider in the region.
Module 2: Fast R-CNN. Convolutional neural network for extracting features from the proposed regions and outputting the bounding box and class labels.



YOLO

- **YOLO (You Only Look Once)**
  - Divide an image into grids
  - Each grid
    - Bounding box prediction
    - Classification
  - Combine results
    - Non-Maximum Suppression (NMS)

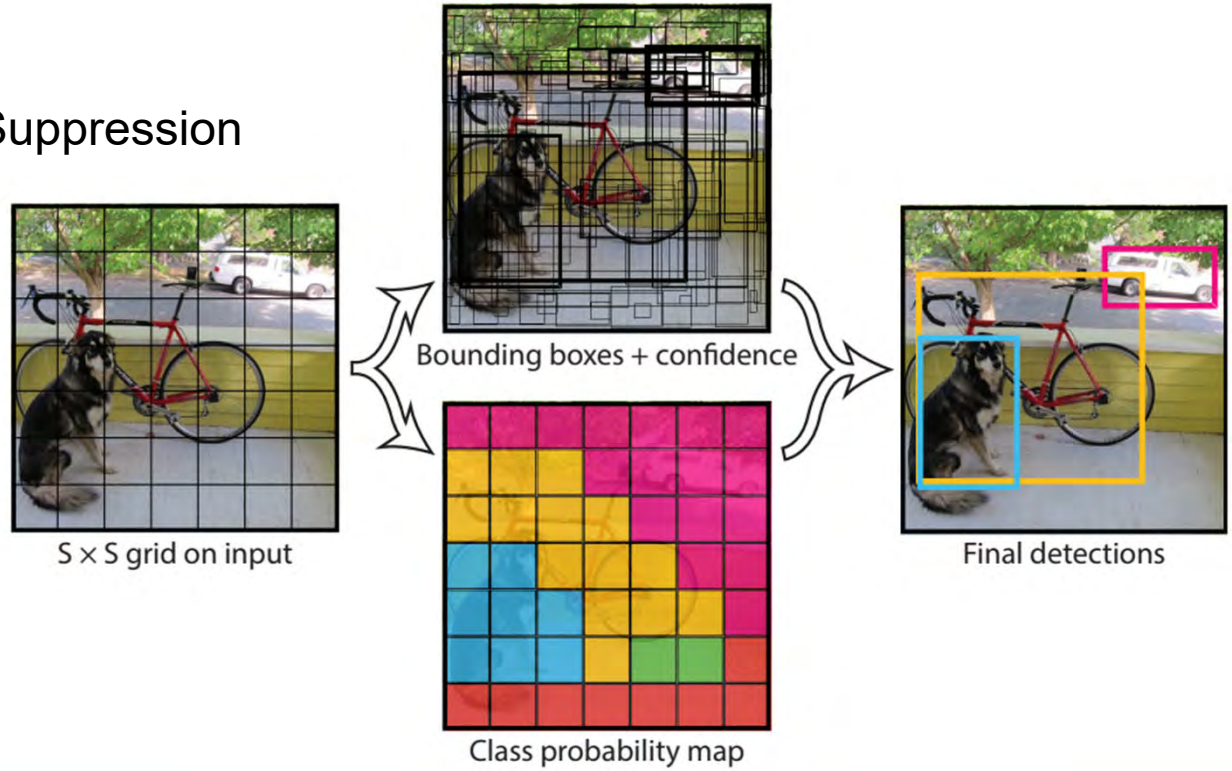


Image from: https://machinelearningmastery.com/object-recognition-with-deep-learning/

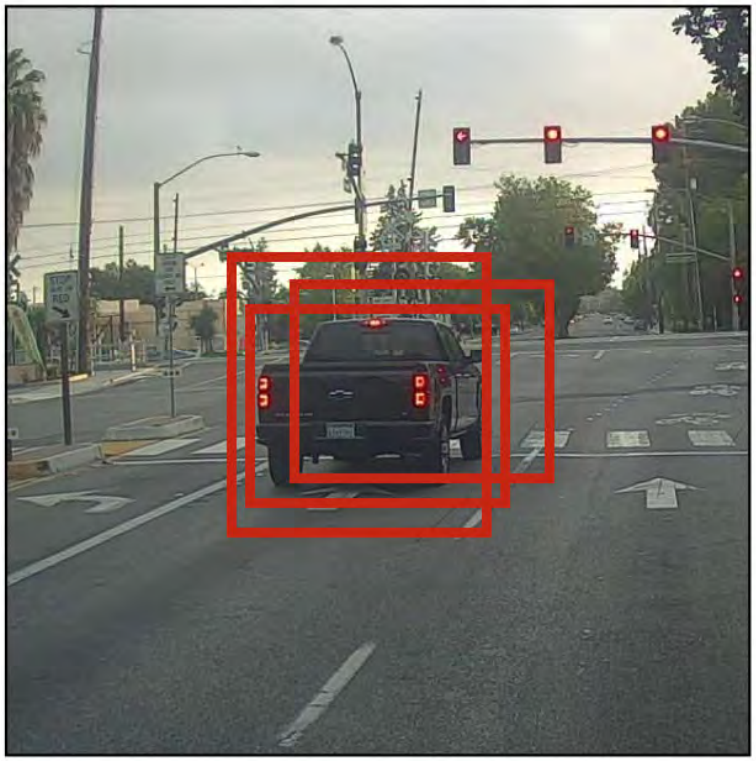
Pre-trained YOLO/SSD Model

- **Using COCO dataset**
  - Common Objects in COntext
  - COCO is a large-scale object detection, segmentation, and captioning dataset.
    - https://cocodataset.org/#home
  - 80 classes, 80,000 training images and 40,000 validation images.

- **Customized training**
  - https://blog.francium.tech/custom-object-training-and-detection-with-yolov3-darknet-and-opencv-41542f2ff44e
  - On Day 3, we will perform customised training on YOLO(V5) and Scaled-YOLO(V4) on satellite and thermal images.

Non Maximal Suppression (NMS)

Before non-max suppression

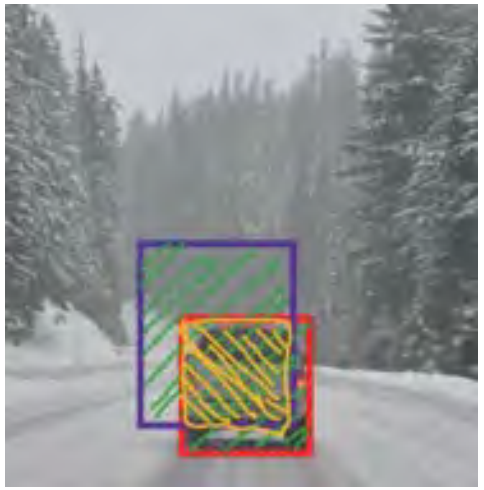


Non-Max Suppression

After non-max suppression

https://towardsdatascience.com/non-maximum-suppression-nms-93ce178e177c

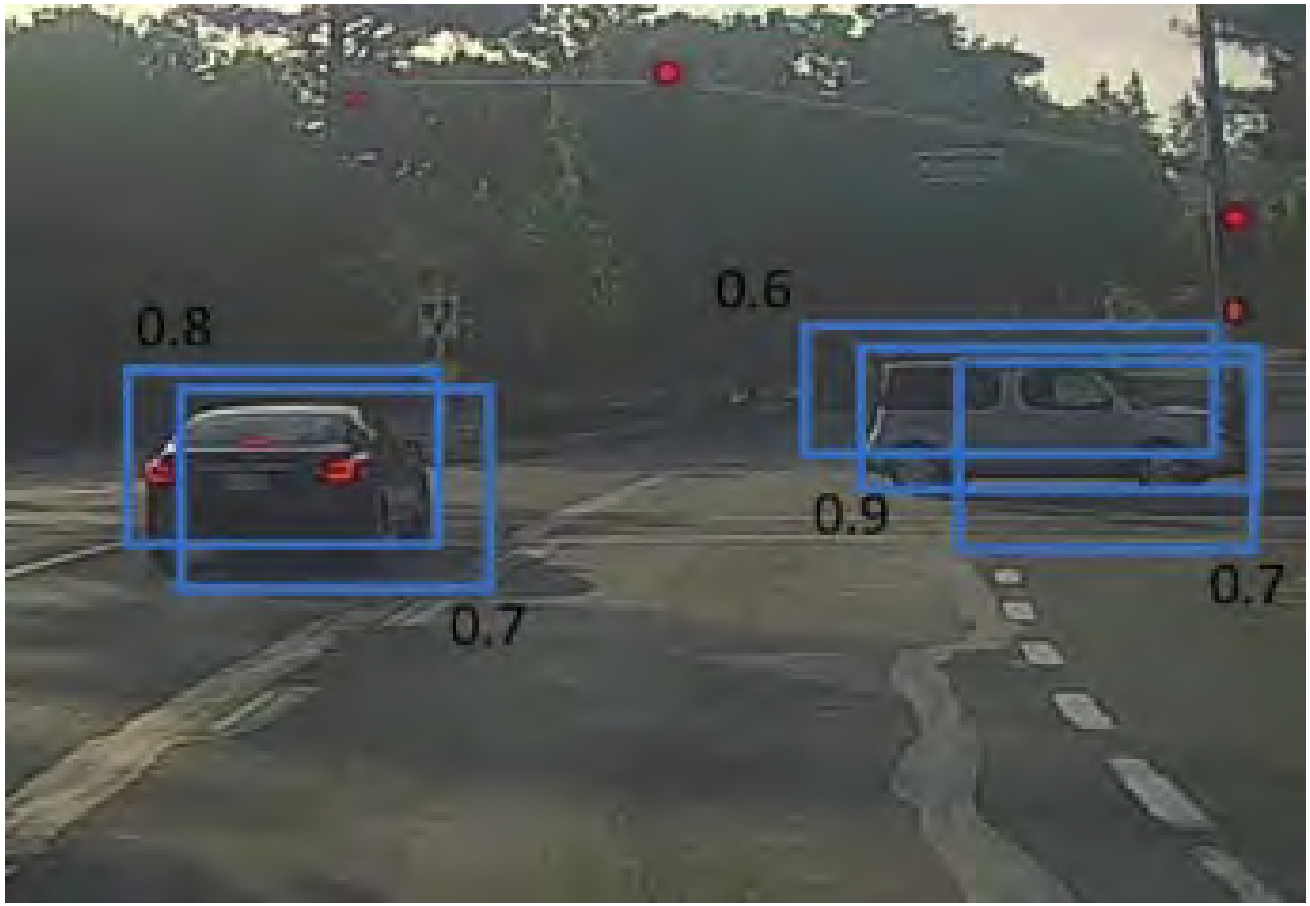
Intersection over Union



IoU = Area of yellow box / Area of green box

If IoU is greater than 0.5, we can say that the prediction is good enough. 0.5 is an arbitrary threshold we have taken here, but it can be changed according to your specific problem. Intuitively, the more you increase the threshold, the better the predictions become.

Non Maximal Suppression (NMS)

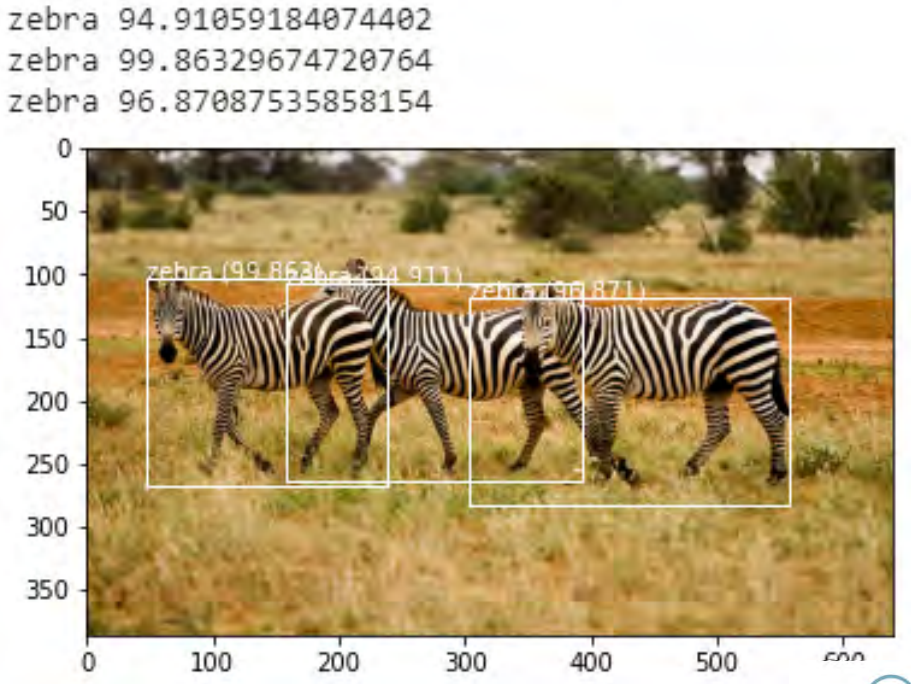


https://www.analyticsvidhya.com/blog/2018/12/practical-guide-object-detection-yolo-framewor-python/

Activity – YOLOv3

- **Activity: 2_2_Object_Detection_using_YOLOv3**

- Load model
- Predict
- Decode the prediction
  - Correct box sizes
  - Perform NMS
  - Filter predicted class
  - Draw boxes



Exercises:
- Modify the code such that only zebras that the model is more than 97% confident are plotted.

Step 1:
Watch and listen to the instructor's demonstration

10 mins

Step 2:
Work through the activities

30 mins

Single Shot MultiBox (SSD)

- **SSD (Single Shot MultiBox Detectors)**
  - Designed for object detection in real-time
  - Speeds up by eliminating the need for region proposal network (Faster R-CNN)
  - Uses multi-scales features and default boxes
  - Match Faster RCNN accuracy using lower resolution images

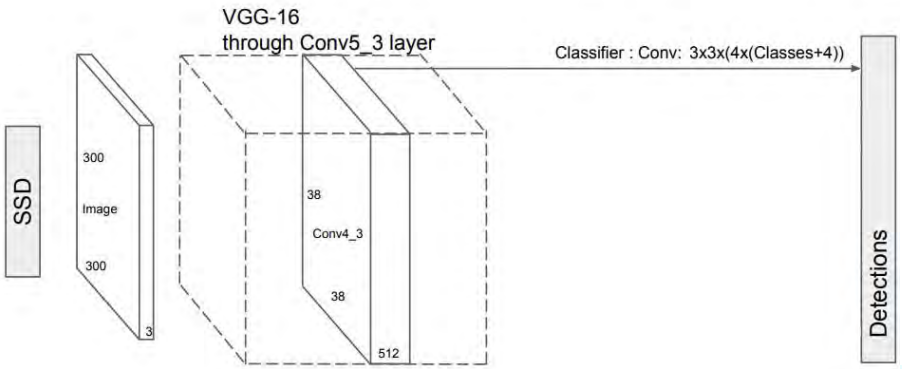
System	VOC2007 test *mAP*	FPS (Titan X)	Number of Boxes	Input resolution
Faster R-CNN (VGG16)	73.2	7	~6000	~1000 x 600
YOLO (customized)	63.4	45	98	448 x 448
SSD300* (VGG16)	77.2	46	8732	300 x 300
SSD512* (VGG16)	**79.8**	19	24564	512 x 512

Source: https://arxiv.org/pdf/1512.02325.pdf

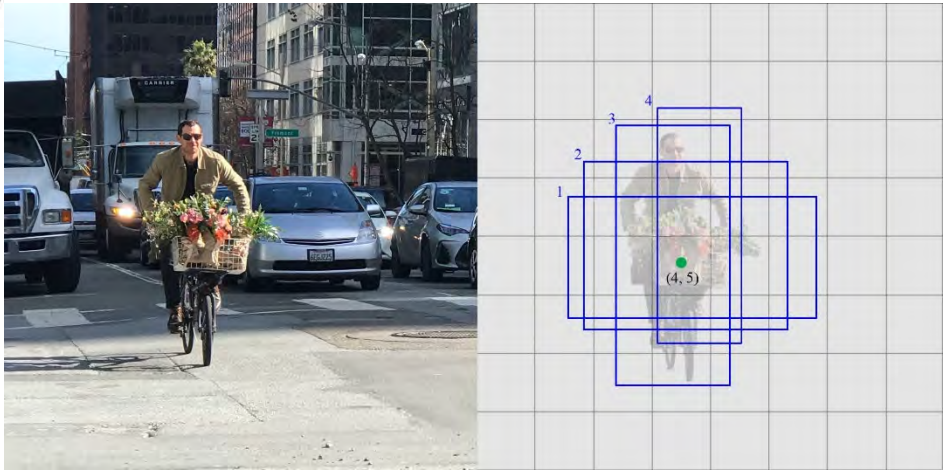
Single Shot MultiBox (SSD)

The SSD object detection composes of 2 parts:

1) **Extract feature maps**



SSD uses **VGG16** to extract feature maps. Then it detects objects using the **Conv4_3** layer. For illustration, we draw the Conv4_3 to be 8 × 8 spatially (it should be 38 × 38). For each cell (also called location), it makes 4 object predictions.



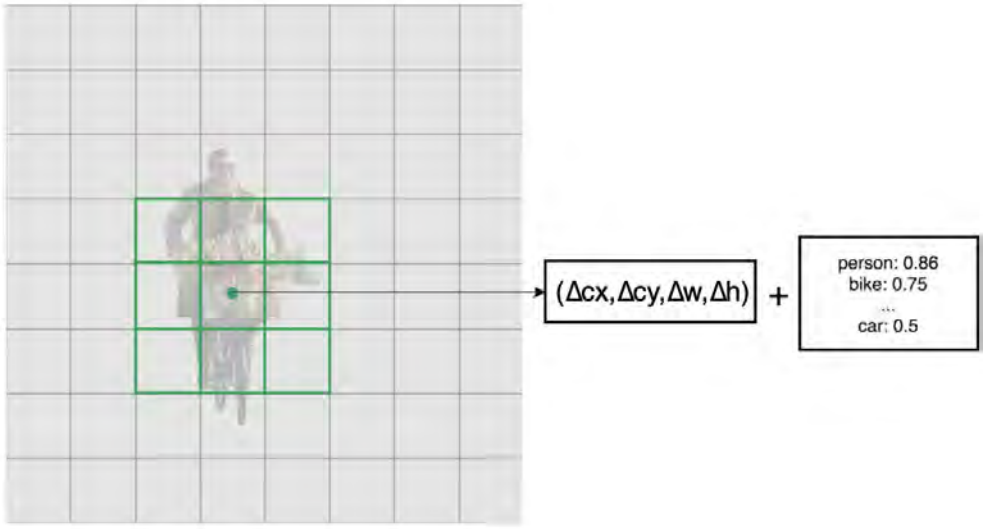
Detailed discussion:
https://medium.com/@jonathan_hui/ssd-object-detection-single-shot-multibox-detector-for-real-time-processing-9bd8deac0e06

Single Shot MultiBox (SSD)

The SSD object detection composes of 2 parts:

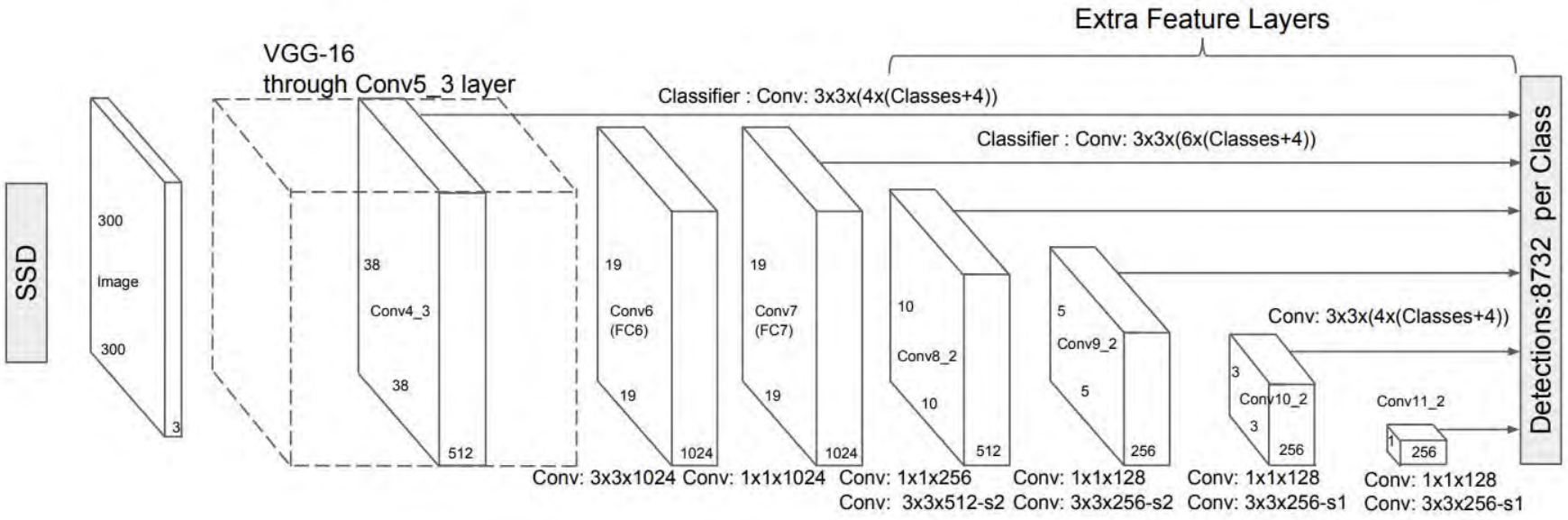
2) **Apply convolution filters to detect objects**.

SSD does not use a delegated region proposal network. Instead, it resolves to a very simple method. It computes both the location and class scores using **small convolution filters**. After extracting the feature maps, SSD applies 3 × 3 convolution filters for each cell to make predictions. (These filters compute the results just like the regular CNN filters.)



Single Shot MultiBox (SSD)

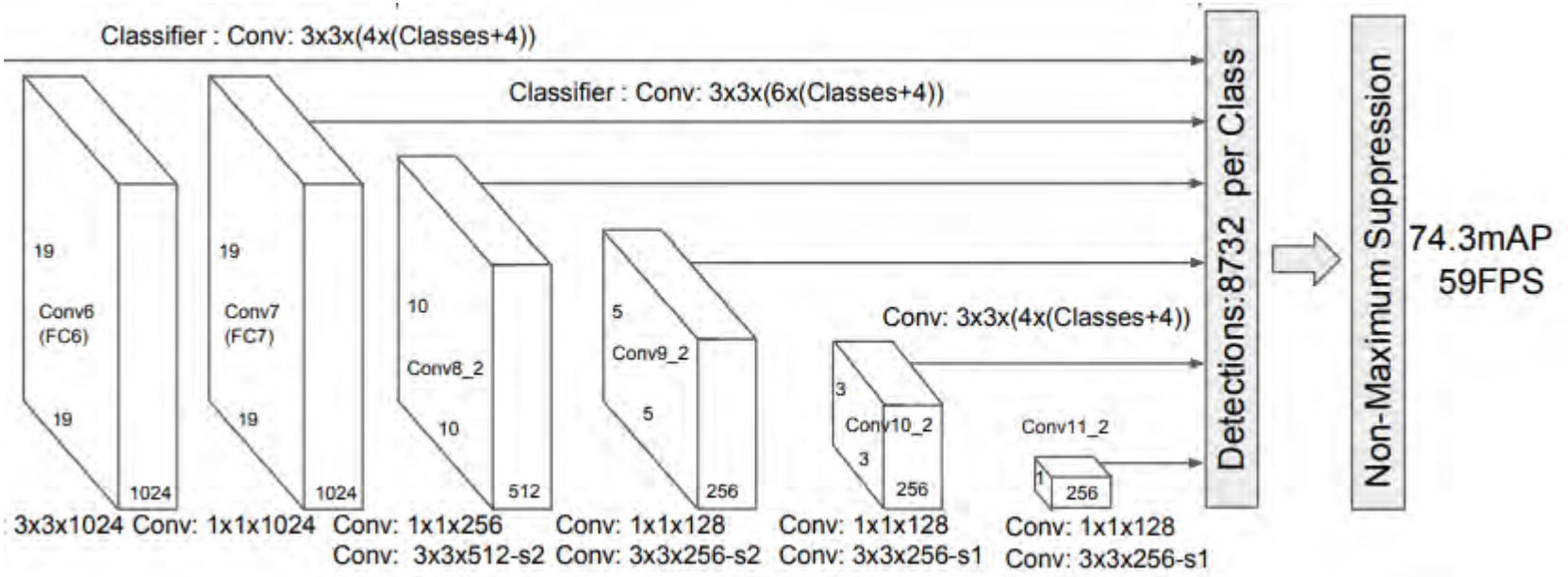
- We describe how SSD detects objects from a single layer. Actually, it uses multiple layers (**multi-scale feature maps)** to detect objects independently.
- SSD adds 6 more auxiliary convolution layers after the VGG16. Five of them will be added for object detection.



Source: [SSD: Single Shot MultiBox Detector]

Single Shot MultiBox (SSD)

- Default boundary boxes are chosen manually for matching.
- SSD uses **non-maximum suppression** to remove duplicate predictions pointing to the same object. SSD sorts the predictions by the confidence scores



Source: [SSD: Single Shot MultiBox Detector]

Some findings

- SSD performs worse than Faster R-CNN for small-scale objects. Accuracy increases with the number of default boundary boxes at the cost of speed.
- Design better default boundary boxes will help accuracy.
- COCO dataset has smaller objects. To improve accuracy, use smaller default boxes (start with a smaller scale at 0.15).
- SSD has lower localization error comparing with R-CNN but more classification error dealing with similar categories. The higher classification errors are likely because we use the same boundary box to make multiple class predictions.

Activity - SSD

- **Activity: 2_3_Object_Detection_using_SSD**

Exercises:
- Use SSD on the zebra image used in activity 2_2.
- Compare the speed and performance of the two models

Step 1:
Watch and listen to the instructor's demonstration

10 mins

Step 2:
Work through the activities

25 mins

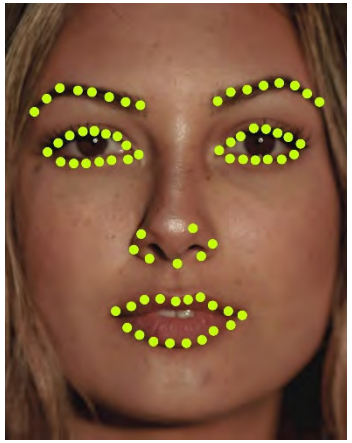
Annotation of Images

- Image annotation is a key technique used to create training data for computer vision.
- Types of Image Annotation

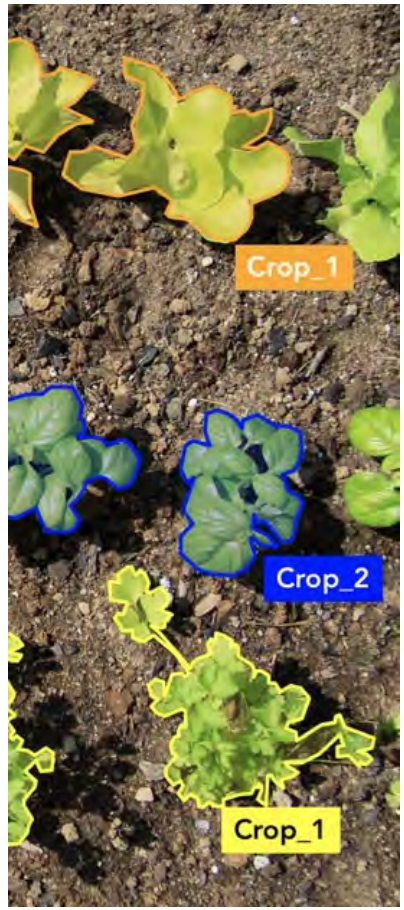
2-D Bounding Box

Segmentation/Mask

Line



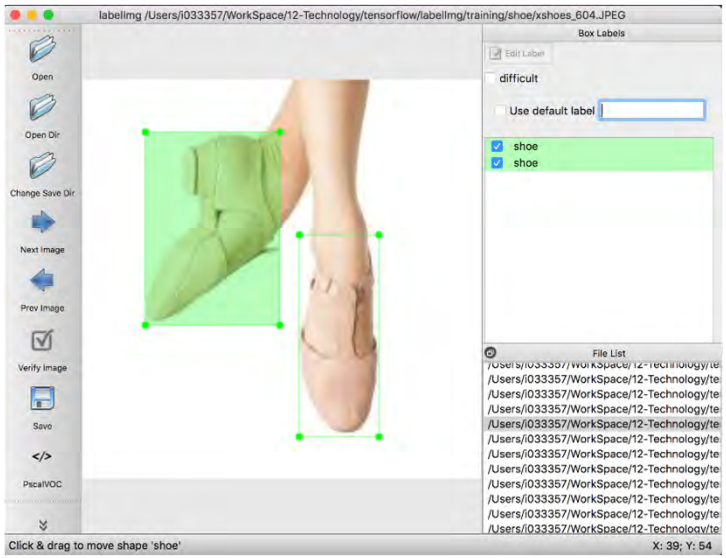
Point



Polygon

ref: https://medium.com/supahands-techblog/what-is-image-annotation-caf4107601b7

Some examples:




```
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    </source>
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        <depth>3</depth>
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            <ymax>238</ymax>
        </bndbox>
    </object>
</annotation>
```

Annotation of Images

- **Activity: 2_4_Annotation_of_images**
- Search on the internet and download 5 images of kick scooters.
- Follow the instructions in "2_4_Annotation_of_images.docx" to perform annotation using www.makesense.ai
- **Ref:** https://towardsdatascience.com/annotate-your-image-using-online-annotation-tool-52d0a742daff

Exercises:
- Create a folder at http://bit.ly/3akfwB9
- Upload your images and annotations to the newly created folder

Step 1:
Watch and listen to the instructor's demonstration

10 mins

Step 2:
Work through the activities

30 mins

Quiz

https://bit.ly/kw_poll

SCAN ME

Thank you