# Deep learning - computer vision

Object Detection: SSD

### Learning Objectives



At the end of this module, you will understand:



Working of SSD

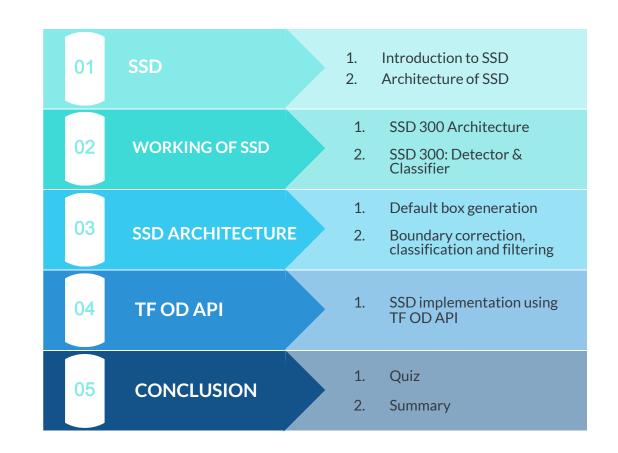


**Architecture of SSD** 



Implementation of SSD using tensorflow object detection API

### Agenda



SSD
Introduction to SSD
Architecture of SSD



#### SSD

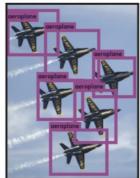
Single Shot MultiBox Detector

Single Shot Multibox Detector is a method for detecting objects in images using a single deep neural network.









## Object Detection Approach





FPS: 0.5 mAP: 70

#### Faster R-CNN

FPS: 7 mAP: 73.2

#### YOLO

FPS: 45 mAP: 63.4

#### SSD

FPS: 58 mAP: 72.1

#### R-CNN

FPS: mAP: 58.5

#### DPM

FPS: 0.5 mAP: 34.3



Time

Nov 2013 Apr 2015 June 2015

Dec 2015

Results on PASCAL VOC 2007 sample dataset

### Ssd - single shot multibox detector

- SSD was released on November 2016.
- It reached new records in terms of performance and over 74% mAP (mean Average Precision) at 59 fr as PascalVOC and COCO.



### Why ssd?

- SSD are designed for object detection in real-time.
- SSD speeds up the process by eliminating the need of the region proposal network.
- To recover the drop in accuracy, SSD applies a few improvements including multi-scale features and default boxes.

#### Architecture of ssd

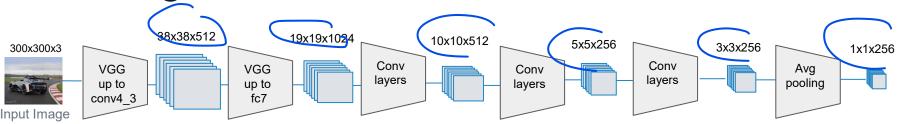
- Single Shot: Tasks of object localization and classification are done in a single forward pass of the network
- MultiBox: name of a technique for bounding box regression
- Detector: The network is an object detector that also classifies those detected objects

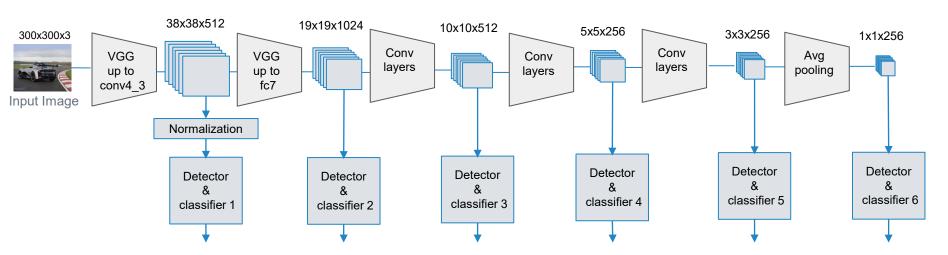
# 02 WORKING OF SSD

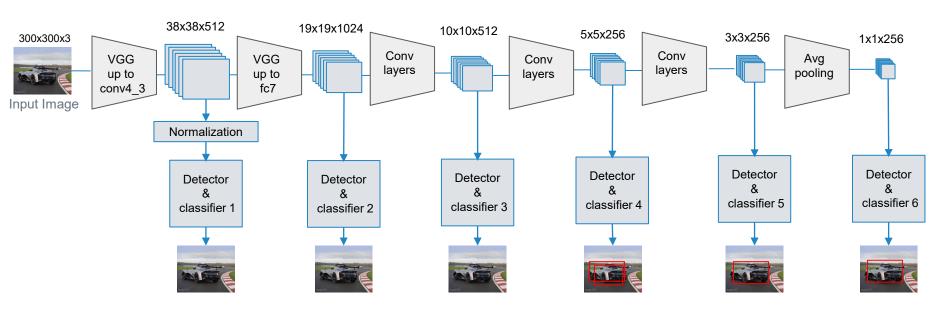
- SSD 300 Architecture
- SSD 300: Detector & Classifier

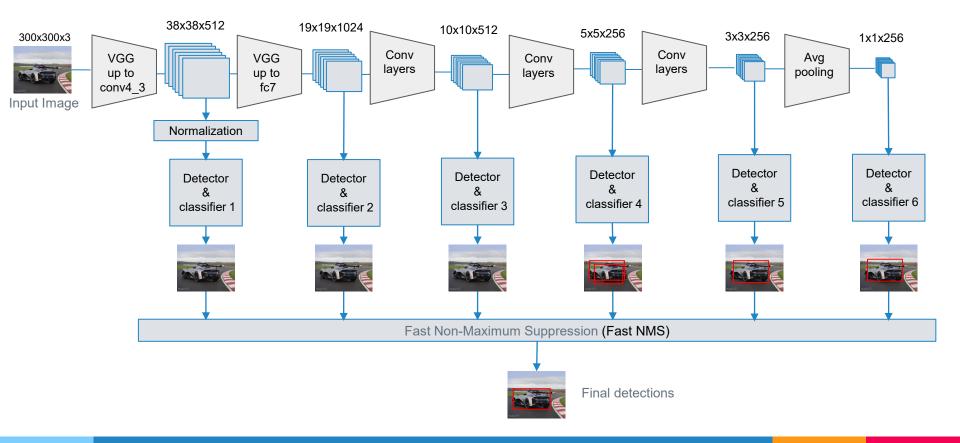


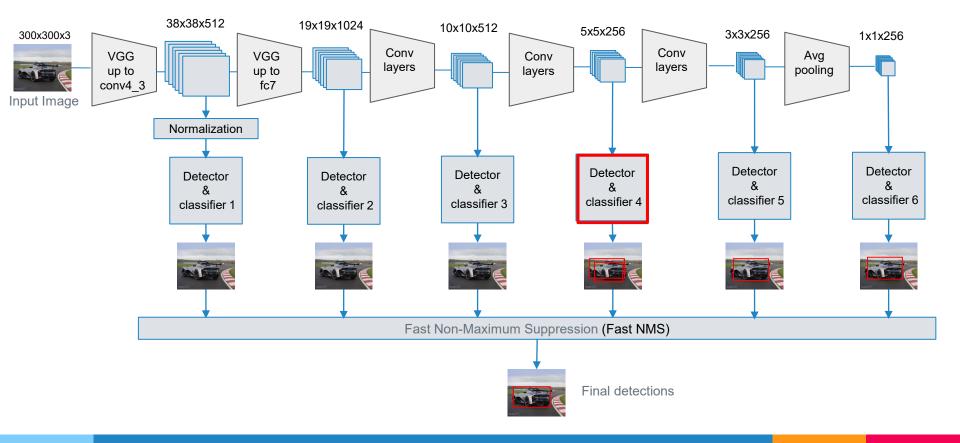












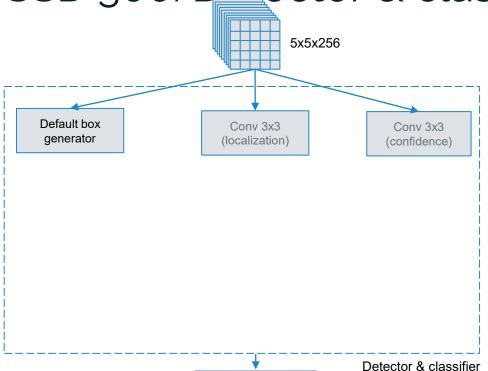
5x5x256

#### Considering the following parameters:

- Size of original image (300 x 300)
- Dimension of feature maps (5 x 5 x 256)
- #default boxes = 3

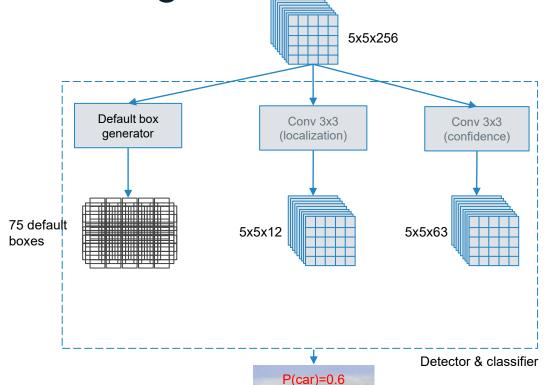
Detector & classifier



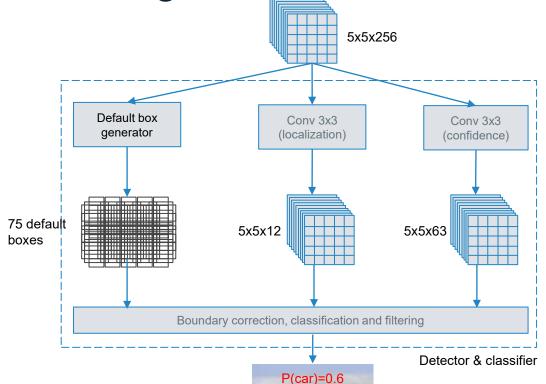


- Size of original image (300 x 300)
- Dimension of feature maps (5 x 5 x 256)
- #default boxes = 3

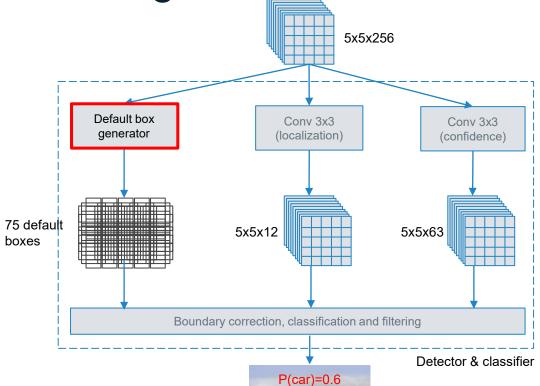




- Size of original image (300 x 300)
- Dimension of feature maps (5 x 5 x 256)
- #default boxes = 3



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- Dimension of feature maps (5 x 5 x 256)
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- Size of original image (300 x 300)
- Dimension of feature maps (5 x 5 x 256)
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# 03 SSD ARCHITECTURE

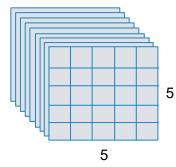
- Default box generation
- Boundary correction, classification and filtering



300



Input Image



300

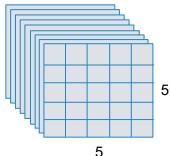
300



Input Image

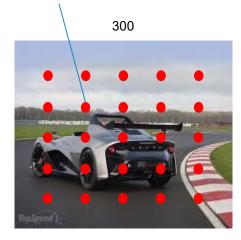
#### Considering following parameters:

- Size of original image (300 x 300)
- Spatial dimension of Feature maps (5 x 5)
- #default boxes = 3, (one point in feature map leads to 3 rectangles)
- min\_size=168
- aspect\_ratio=2



300

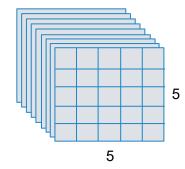
Centers of generated default boxes (xc, yc)



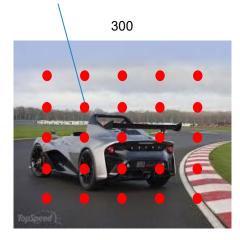
300

Input Image

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- Spatial dimension of Feature maps (5 x 5)
- #default boxes = 3, (one point in feature map leads to 3 rectangles)
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Centers of generated default boxes (xc, yc)

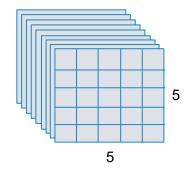


300

Input Image

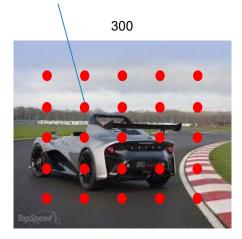
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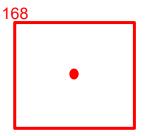
- xc, centre of the rectangle on x
- yc centre of the rectangle on y
- w width of the rectangle
- h − height of the rectangle

Centers of generated default boxes (xc, yc)



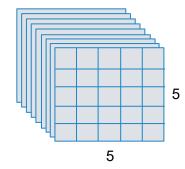
300

Input Image



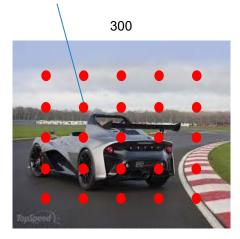
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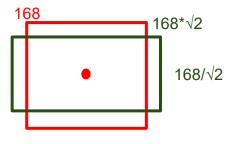
- xc, centre of the rectangle on x
- yc centre of the rectangle on y
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Centers of generated default boxes (xc, yc)



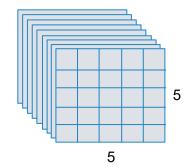
300

Input Image



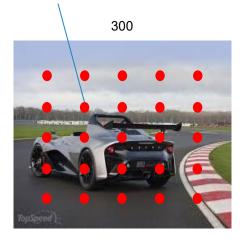
#### Considering following parameters:

- Size of original image (300 x 300)
- Spatial dimension of Feature maps (5 x 5)
- #default boxes = 3, (one point in feature map leads to 3 rectangles)
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- aspect\_ratio=2



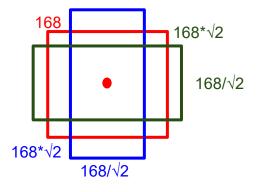
- xc, centre of the rectangle on x
- yc centre of the rectangle on y
- w width of the rectangle
- h − height of the rectangle

Centers of generated default boxes (xc, yc)



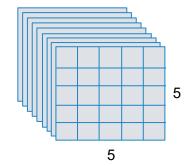
300

Input Image



#### Considering following parameters:

- Size of original image (300 x 300)
- Spatial dimension of Feature maps (5 x 5)
- #default boxes = 3, (one point in feature map leads to 3 rectangles)
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- aspect\_ratio=2



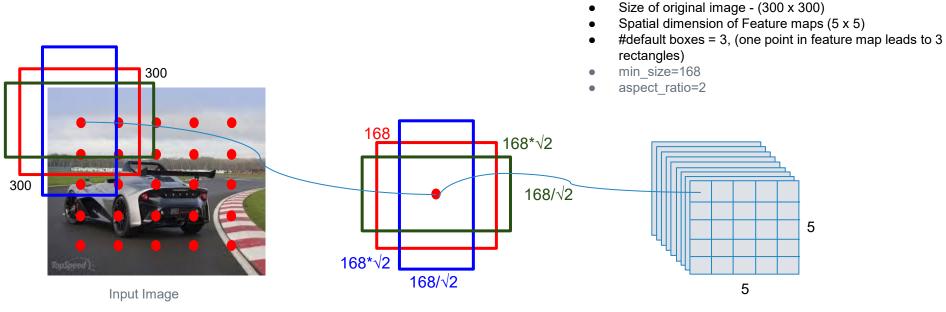
- xc, centre of the rectangle on x
- yc centre of the rectangle on y
- w width of the rectangle
- h − height of the rectangle

Centers of generated default boxes (xc, yc) rectangles) 300 min size=168 aspect ratio=2 168 168\*√2 300 168/√2 5 168\*√2 168/√2 5 Input Image

#### Considering following parameters:

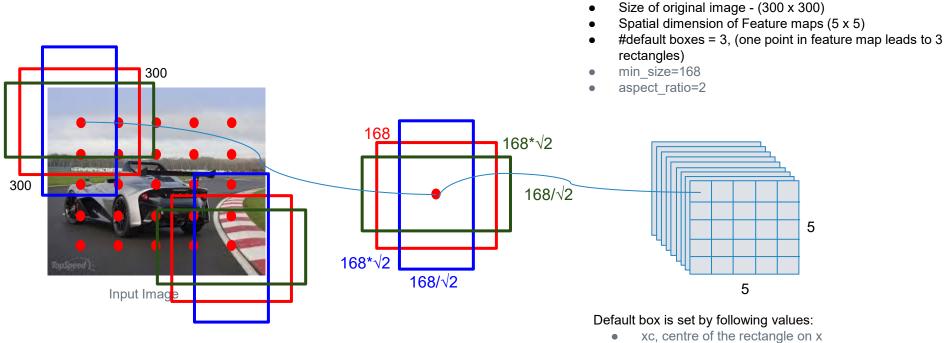
- Size of original image (300 x 300)
- Spatial dimension of Feature maps (5 x 5)
- #default boxes = 3, (one point in feature map leads to 3

- xc, centre of the rectangle on x
- yc centre of the rectangle on y
- w width of the rectangle
- h height of the rectangle



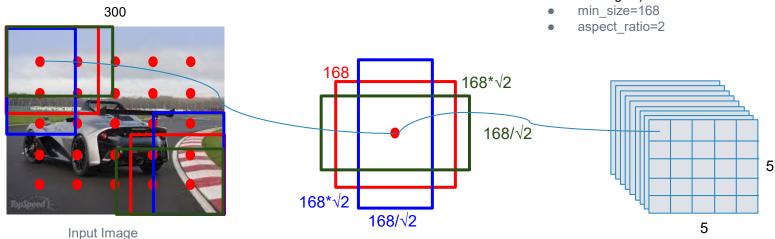
#### Default box is set by following values:

- xc, centre of the rectangle on x
- yc centre of the rectangle on y
- w width of the rectangle
- h height of the rectangle



Considering following parameters:

yc - centre of the rectangle on y w - width of the rectangle h - height of the rectangle



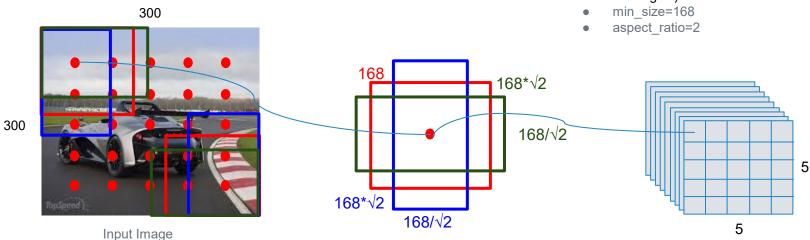
#### Considering following parameters:

- Size of original image (300 x 300)
- Spatial dimension of Feature maps (5 x 5)
- #default boxes = 3, (one point in feature map leads to 3 rectangles)

#### Default box is set by following values:

- xc, centre of the rectangle on x
- yc centre of the rectangle on y
- w width of the rectangle
  - h height of the rectangle

300



#### Considering following parameters:

- Size of original image (300 x 300)
- Spatial dimension of Feature maps (5 x 5)
- #default boxes = 3, (one point in feature map leads to 3 rectangles)

#### Default box is set by following values:

- xc, centre of the rectangle on x
- yc centre of the rectangle on y
- w width of the rectangle
- h height of the rectangle

A total of 5\*5\*3=75 rectangles will be generated

Architecture of SSD 300: Detector & 5x5x256

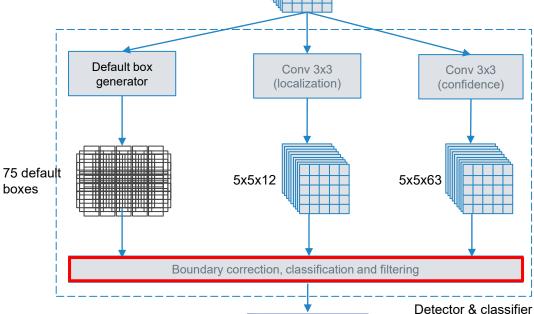
classifier Default box Conv 3x3 Conv 3x3 generator (localization) (confidence) 75 default 5x5x12 5x5x63 Boundary correction, classification and filtering Detector & classifier

P(car)=0.6

boxes

- Size of original image (300 x 300)
- Dimension of feature maps (5 x 5 x 256)
- #default boxes = 3

Architecture of SSD 300: Detector & classifier 5x5x256



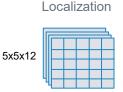
P(car)=0.6

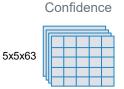
boxes

- Size of original image (300 x 300)
- Dimension of feature maps (5 x 5 x 256)
- #default boxes = 3

Default boxes

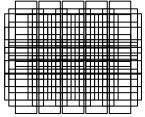
Only 5 \* 5 \* 3 = 75 rectangles



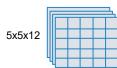


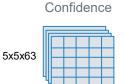
Localization

Default boxes



Only 5 \* 5 \* 3 = 75 rectangles

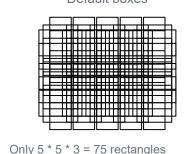


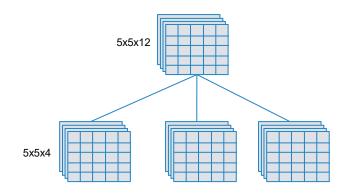


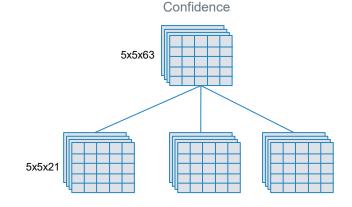


Input Image (300 x 300)

Localization



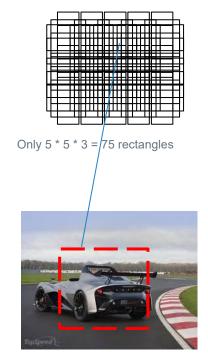


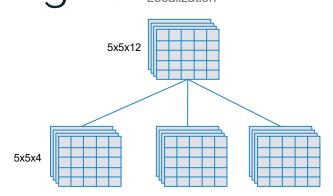


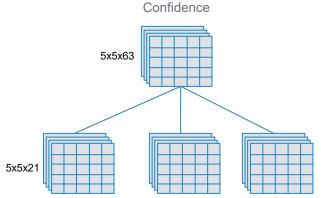


Input Image (300 x 300)

Boundary correction, classification and filtering (1) Localization

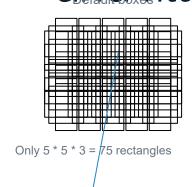


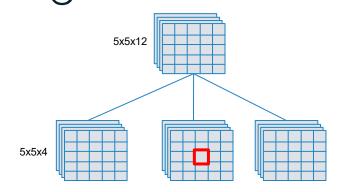


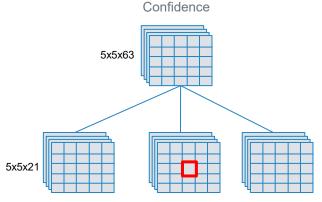


Input Image (300 x 300)

# Boundary correction, classification and filtering (1) Localization



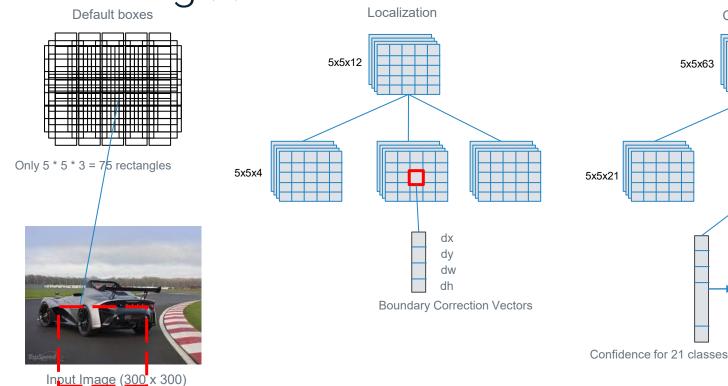






Input Image (300 x 300)

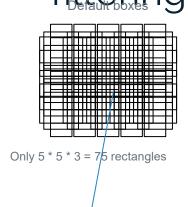
Confidence



Boundary correction, classification and filtering (1)

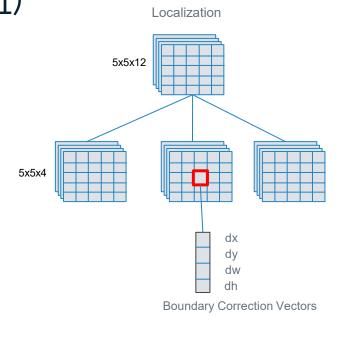
Localization

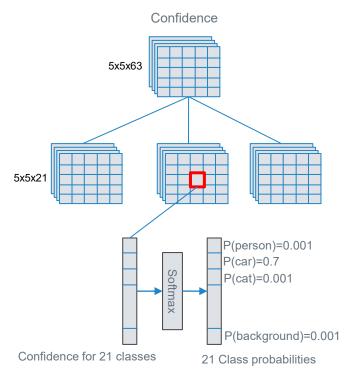
Conf

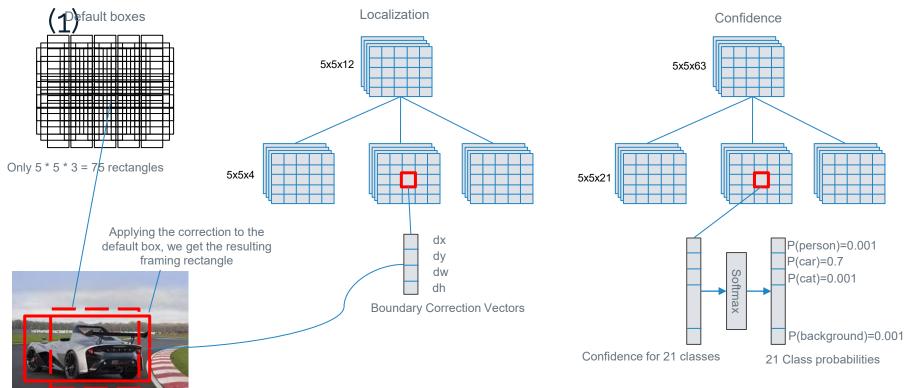




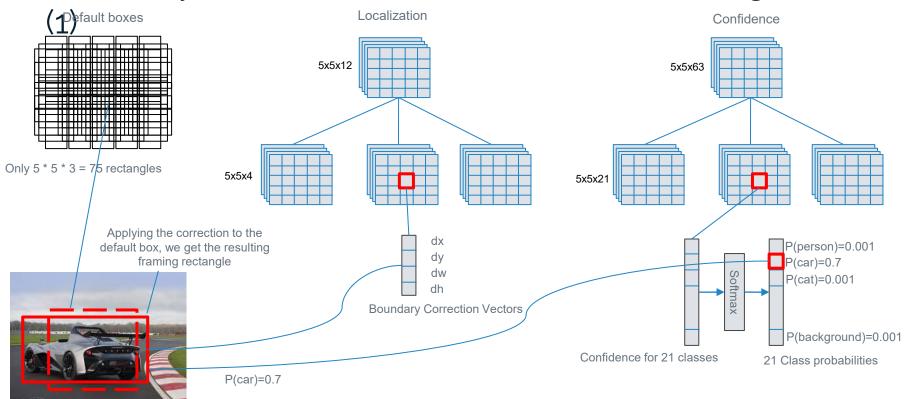
Input Image (300 x 300)



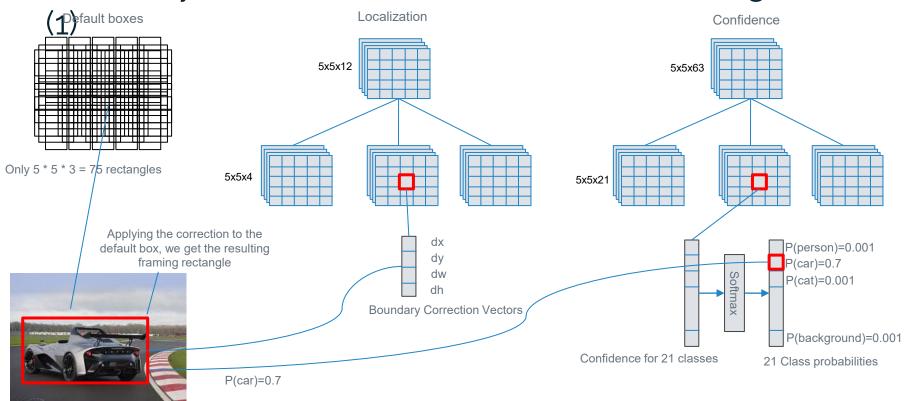




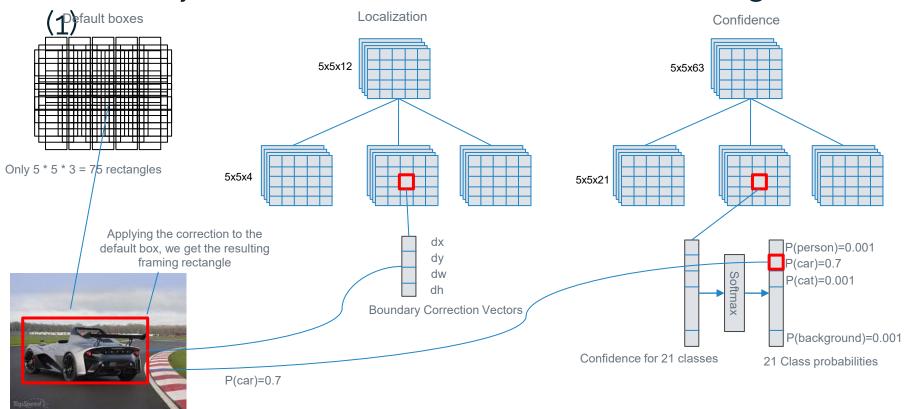
Input Image (300 x 300)



Input Image (300 x 300)

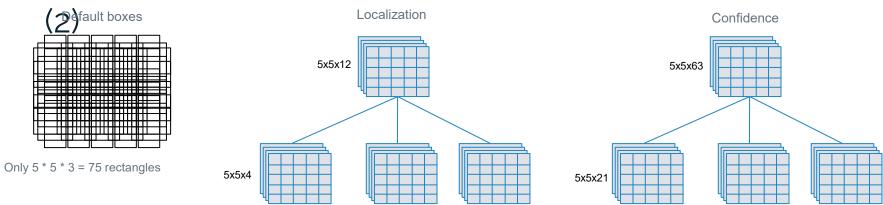


Input Image (300 x 300)



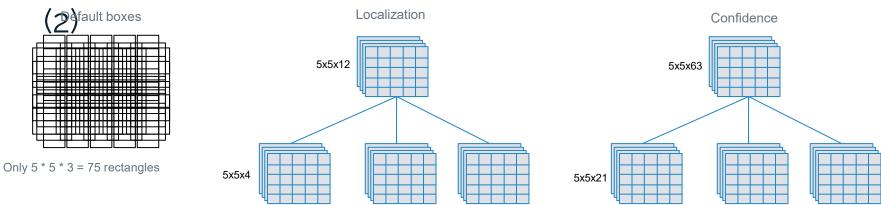
Input Image (300 x 300)

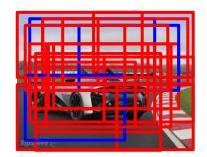
Result: 75 class-specific detections



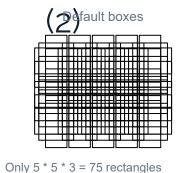


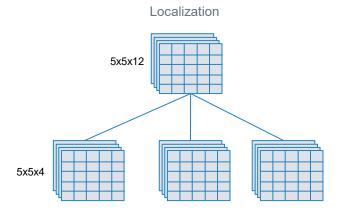
75 detectable objects

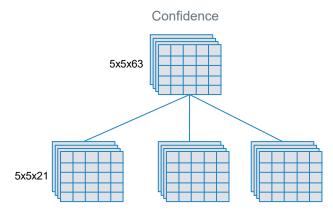


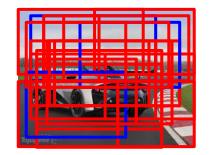


75 detectable objects





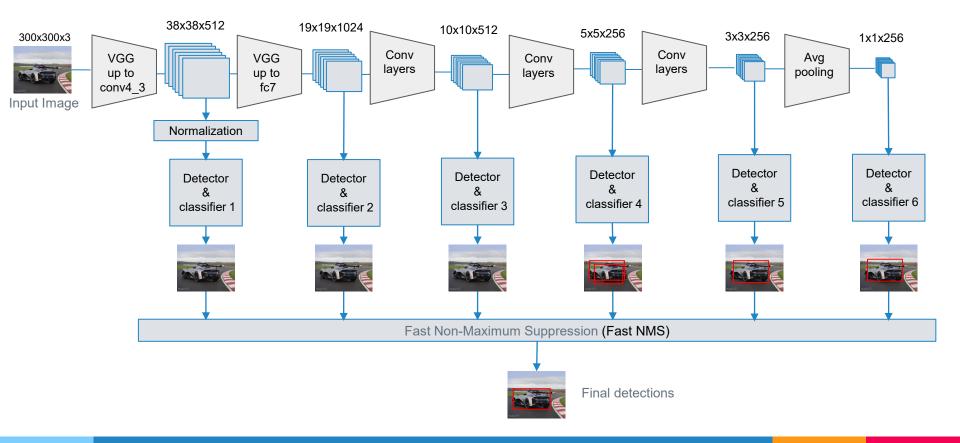


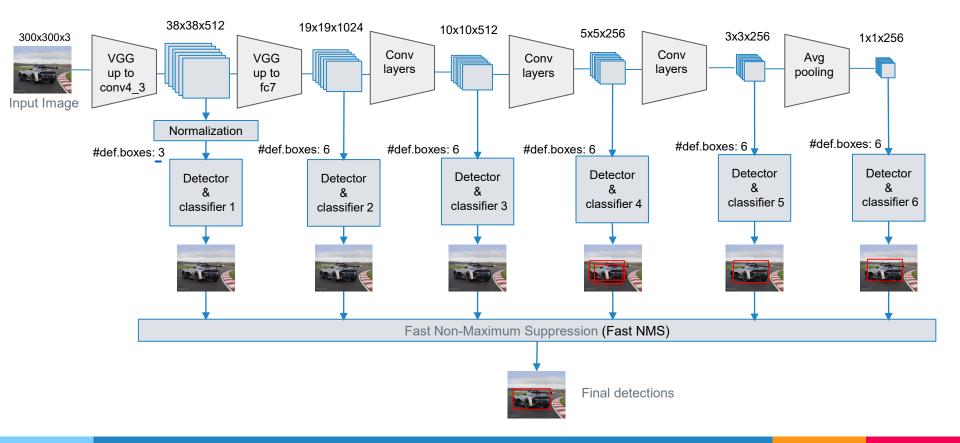


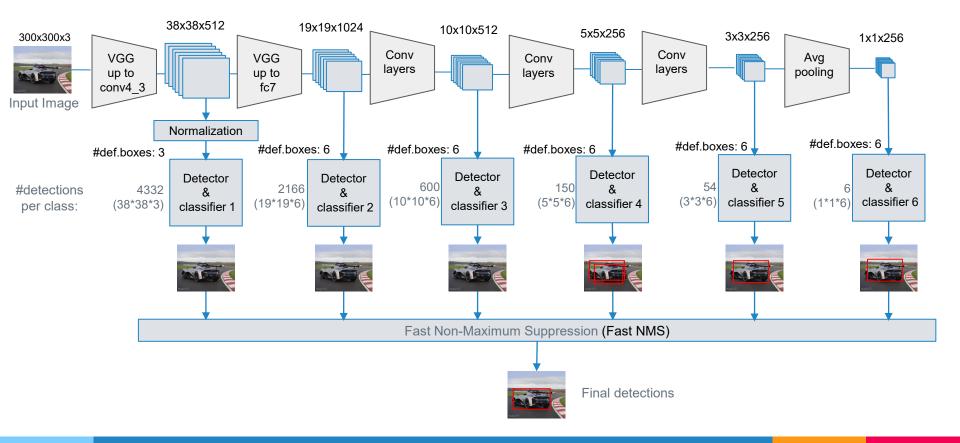
75 detectable objects

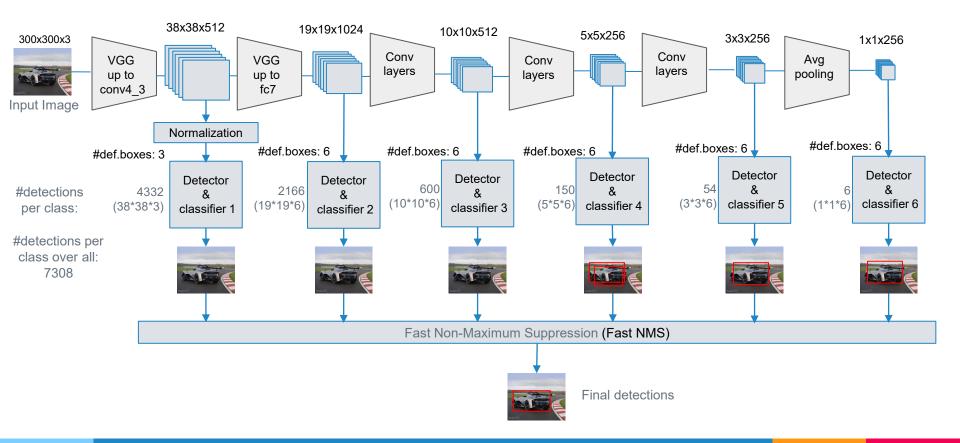
Confidence filtering





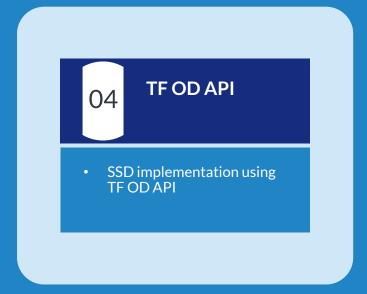




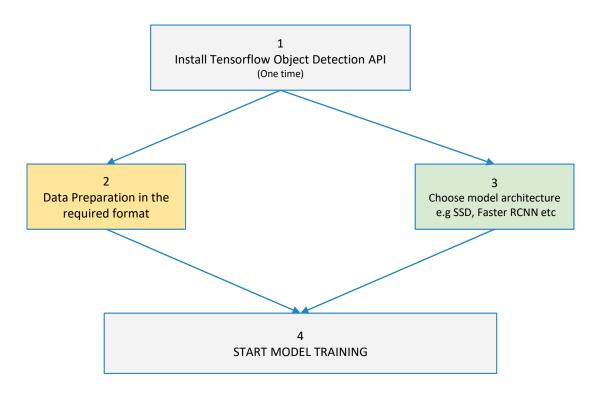


# **Key Points**

- SSD architecture allows real-time detection of objects
- Performance close to Faster R-CNN
- o Detection takes place at different scales, which allows you to localize objects of different sizes
- A large number of default boxes are used, covering the input image at different scales.
- At the Inference stage, the SSD 300 architecture detects 7308 objects, most of which are subsequently
   filtered





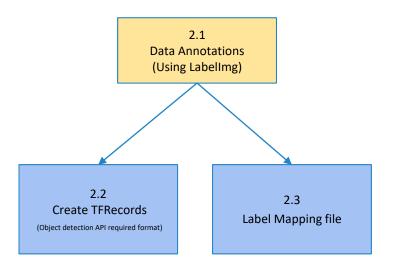


#### Installation Documentation

https://github.com/tensorflow/models/blob/master/research/object\_detection/g3doc/installation.md

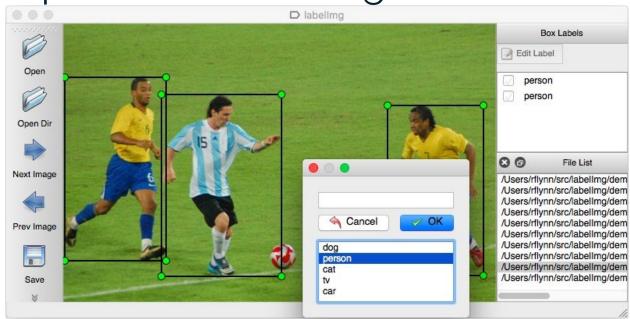
#### 1. Installing TensorFlow Object Detection API

One time (on Google Colab every time)



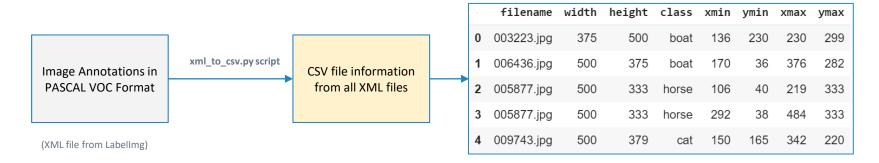
### 2. Data Preparation

Involves 3 key steps



2.1 Data Annotations

Use Labelimg tool (<a href="https://github.com/tzutalin/labelimg">https://github.com/tzutalin/labelimg</a>) for data annotation. It will create an XML file for each image. This will act as input to Object Detection API.

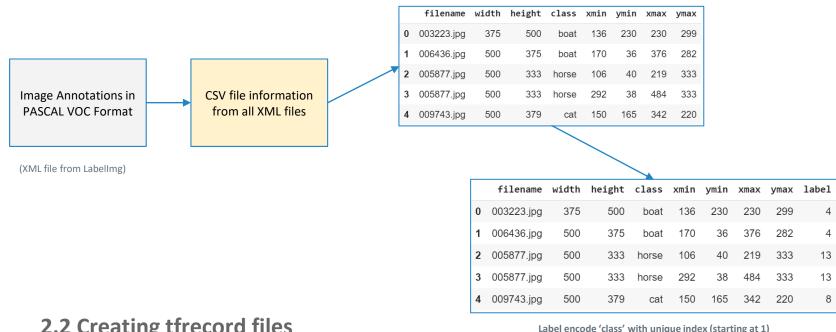


#### Key observations about CSV file:

- 1. It has 7 columns.
- 2. It will have one record for each object
- 3. An image can have multiple records in csv file if it has multiple objects

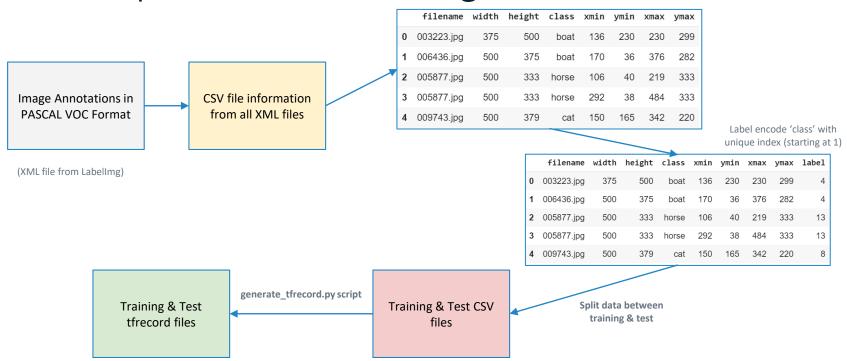
#### 2.2 Creating tfrecord files

Multi-step process but steps are repeatable for every dataset



2.2 Creating tfrecord files

Multi-step process but steps are repeatable for every dataset



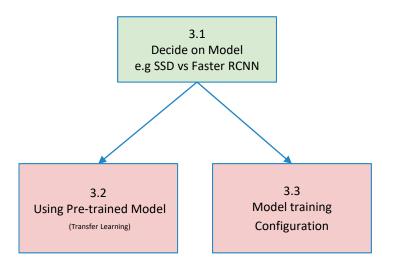
#### 2.2 Creating tfrecord files

Multi-step process but steps are repeatable for every dataset

```
id: 1
 name: 'aeroplane'
item {
 id: 2
 name: 'bicycle'
item {
 id: 3
 name: 'bird'
item {
 id: 4
 name: 'boat'
item {
 id: 5
 name: 'bottle'
item {
  id: 6
  name: 'bus'
```

#### 2.3 Creating Label Mapping file

Single file with 'item' dict with unique class 'id' and 'name'. The 'id' should start from '1'. Make sure class name has quotes around it.



#### 3. Choose Model Architecture

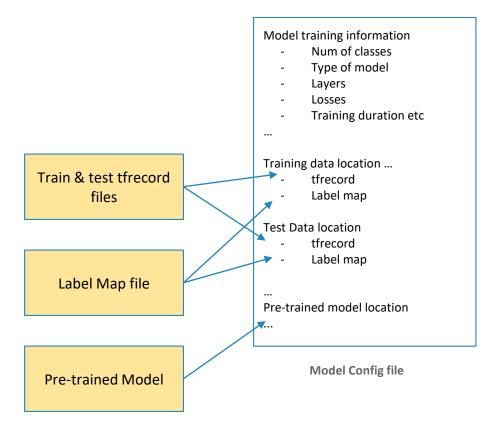
API supports both Faster RCNN and SSD

# TensorFlow Object Detection API provides several pre-trained models for us to start training

https://github.com/tensorflow/models/blob/master/research/object\_detection/g3doc/detection\_model\_zoo.md

3.2 Transfer Learning: Pre-trained Model

**Model Training** 



# 3.3 Model Training Configuration

What does Model config file contains?

TensorFlow Object Detection API
provides model training configuration files which can be fine tuned for
our model training

https://github.com/tensorflow/models/tree/master/research/object\_detection/samples/configs

3.3 Model Training Configuration

**Model Training** 

- 1. Change num\_classes parameter to number of classes in your dataset (e.g. 20 classes in pascal voc dataset)
- 2. For 'train\_input\_reader' change 'input\_path' to filepath of train.record file.
- 3. For 'train\_input\_reader' change 'label\_map\_path' to filepath of pascal\_voc.pbtxt file.
- 4. Repeat above two steps for 'eval\_input\_reader'.
- 5. Change **fine\_tune\_checkpoint** to filepath where pre-trained model.ckpt file is available e.g ssd\_mobilenet\_v1\_coco\_2018\_01\_28/model.ckpt
- 6. Change 'batch size' accordingly to available memory.
- 7. Change 'num\_steps' to indicate how long the training will done e.g. 200000. Removing this parameter means that you can train indefinitely.

#### 3.3 Model Training Configuration

Key things to change in Sample file

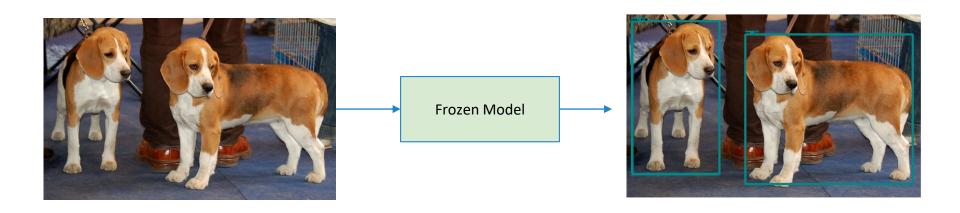
SSD implementation using TF OD API Num of classes Type of model Start training using train script in Layers **Object Detection API** Losses Training duration etc Training data location ... Train & test tfrecord tfrecord Label map files Saved model at Test Data location tfrecord iteration x Label map Label Map file Pre-trained model location Training script will automatically **7...** save model every few hundred iterations. We can always restart training from the last saved **Model Config file** model. Pre-trained Model

#### 4. Model Training



#### 5. Freezing Trained Model

Remove nodes which are not used during prediction e.g Loss, Gradient Descent etc



#### 6. Model Prediction

Object Detection API makes a notebook available for model prediction which can be used with any model trained with TensorFlow object detection APIc

#### SSD implementation using TF OD API 2.1 Data Annotations 2.2 CSV File **Model Training E2E** Using TensorFlow Object Detection API 2.3 Tfrecord files 2.4 Label Mapping file (Train & Test) 3.2 Download Pre-3.1 Choose Model trained Model 3.3 Model Architecture (Transfer Learning) **Configuration File** 5. Frozen Model (Ready for Prediction) 1. Install TensorFlow 4. Model Training using Object Detection API training script Saved Models

# CONCLUSION 1. Quiz 2. Summary



# Quiz

#### Question

Adding more default/anchor boxes in SSD can result in which of the following things?

- A. improve accuracy
- B. Decrease accuracy
- C. Increase the speed
- D. All of above

# Quiz

#### Question

Adding more default/anchor boxes in SSD can result in which of the following things?

- A. improve accuracy
- B. Decrease accuracy
- C. Increase the speed
- D. All of above

Answer - A

# Summary

#### In a nutshell you will understand

- Concept of SSD- single shot multibox detector
- Concept of object detection approach
- SSD 300 architecture
- Working of SSD which includes default boxes generation and boundary correction, classification and filtering (1)

# Thank You

Happy Learning!

