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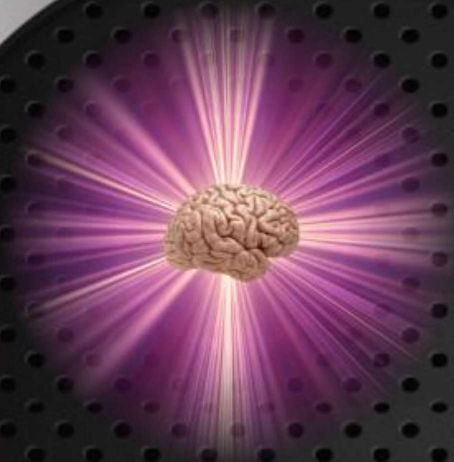
Faculty of Electrical Engineering, Automatics, Computer Science and Biomedical Engineering
Department of Biocybernetics and Biomedical Engineering



Computational Intelligence

Object and Key Points Detection, Localization, Classification, and Segmentation

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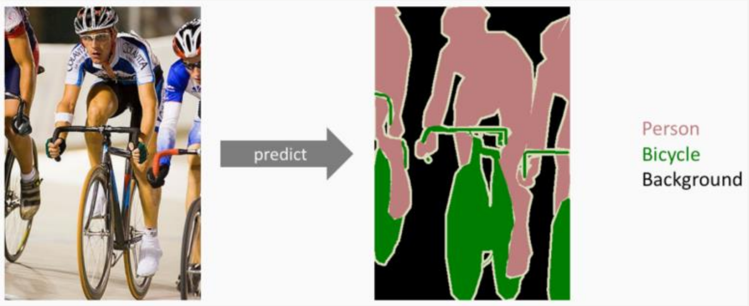
Object and Key Point Detection and Classification and Semantic and Instance Segmentation

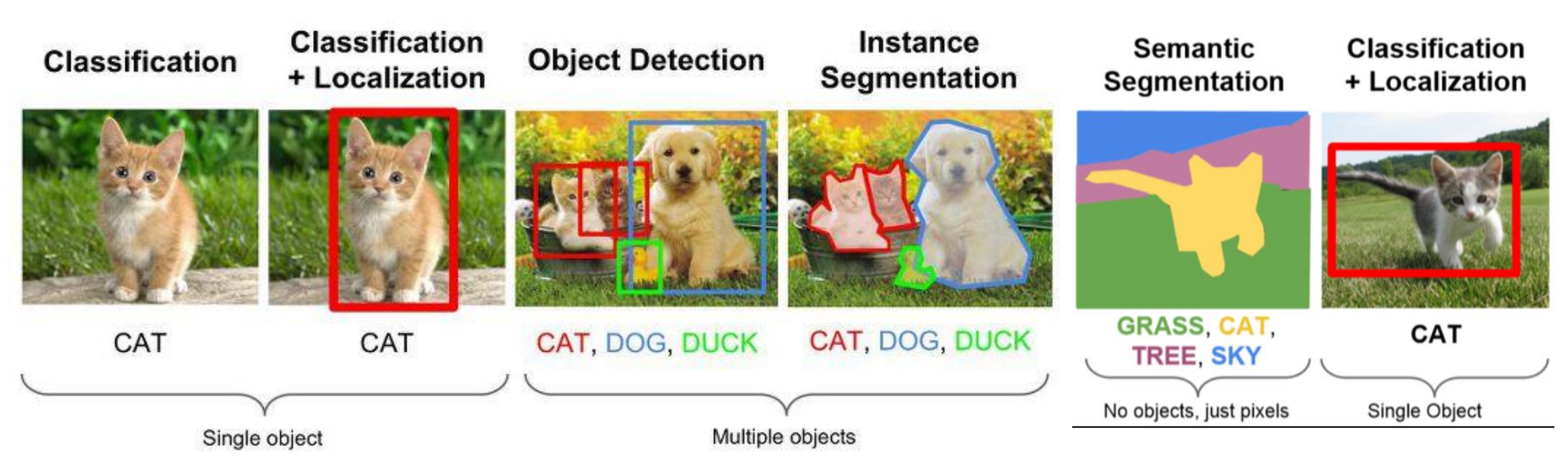
What can we detect or segment in images?

Classify, Detect, Localize, and Segment

Ordinary and popular tasks performed on images:

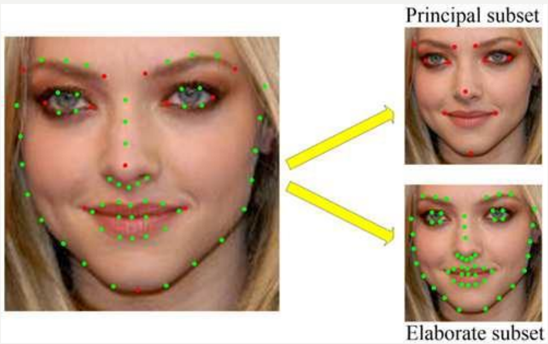
- Object Classification
- Object Classification with Localization (using bounding boxes)
- Object Detection
- Object Key Point (Landmark) Detection
- Object Instance Segmentation
- Object Semantic Segmentation
- Scene parsing and understanding

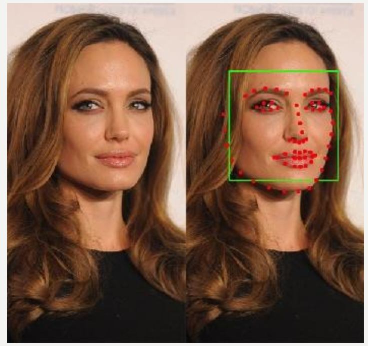


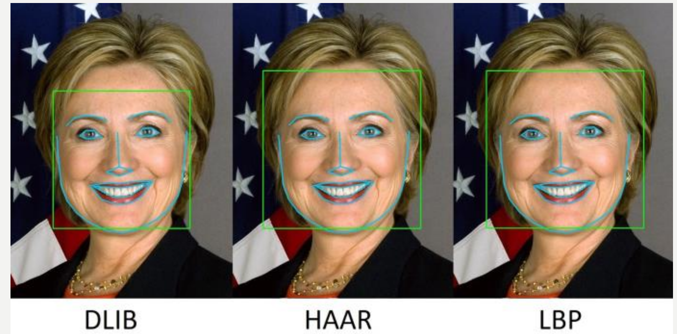


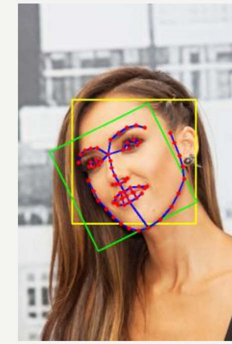
Landmark (Key Points) Detection

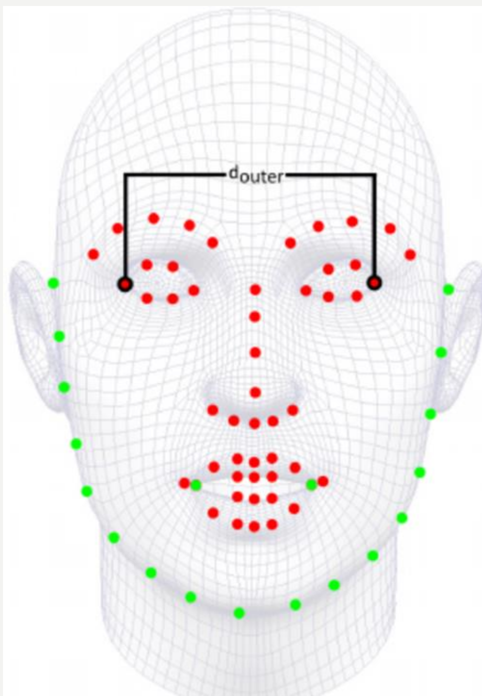
We can detect various landmarks (key points) in images and use them to model and recognize facial gesture, emotion expressions, body poses etc.:

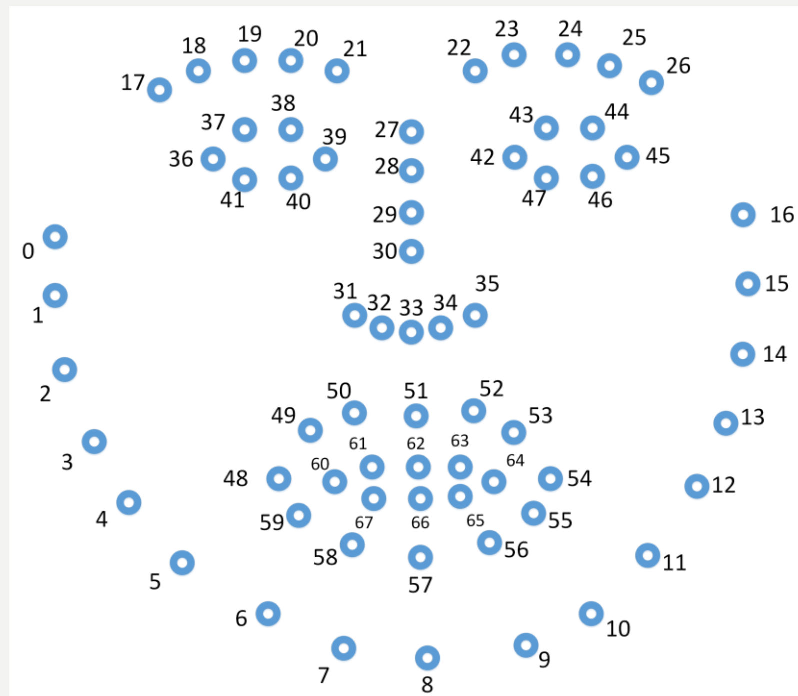












Landmark (Key-Points) Detection

Key point detection is crucial from the semantic point of view to interpret the states and actions that are visible in the images or movies:

Keypoints annotations along with visualized edges between keypoints. Images are from the COCO dataset.

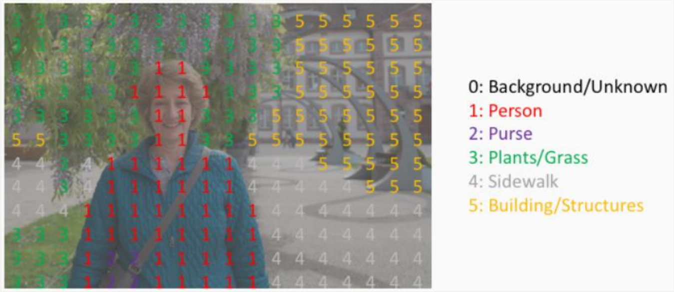
Definitions

Classification is to determine to which class belongs the main object (or sometimes all objects) in the image.

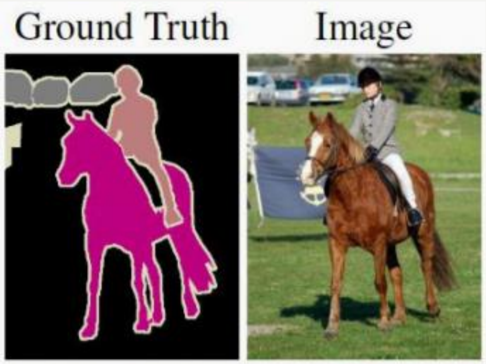
Classification with localization not only classifies the main object in the image but also localizes it in the image determining its bounding box (position and size or localization anchors).

Detection is to find all object of the previously trained (known) classes in the image and localize them (detect their position and size).

Semantic Segmentation is to label specific regions of an image according in the pixel level to understand relationships between objects or recognize important objects in the context (location) of the other objects or their states, actions, and dependencies.



Instance Segmentation is the process of dividing an image into parts known as areas that are homogeneous with respect to certain selected properties, where these areas are collections of pixels. We do not only label these areas with class labels but separate individual instances of the same class. Properties that are often selected as criteria for the uniformity of areas are: gray level, color, texture.



Object and Key Point Detection Localization, and Classification

How to detect, localize, and classify objects?

Classification with Localization

Classification using DL is to determine the class of the main object (that is usually in the centre of the image):

- **The number of classes is usually limited, and the rest is classified as background or nothing:**

- **When localizing the object the output of the network contains extra outputs for a defining bounding box (b_x, b_y, b_h, b_w) of the object:**
- **b_x – x-axis coordinate of the center of the object**
- **b_y – y-axis coordinate of the center of the object**
- **b_h – the height of the bounding box of the object**
- **b_w – the width of the bounding box of the object**

Defining Target Labels for Training

Example 1: If there is an object of class c_2:

$$\boldsymbol{y} = \begin{bmatrix} \mathbf{1} \\ \boldsymbol{b_x} \\ \boldsymbol{b_y} \\ \boldsymbol{b_h} \\ \boldsymbol{b_w} \\ \mathbf{0} \\ \mathbf{1} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix}$$

Example 2: If there is no object of any of the defined classes:

$$\boldsymbol{y} = \begin{bmatrix} \mathbf{0} \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \end{bmatrix}$$

$$\boldsymbol{y} = \begin{bmatrix} \boldsymbol{p_c} \\ \boldsymbol{b_x} \\ \boldsymbol{b_y} \\ \boldsymbol{b_h} \\ \boldsymbol{b_w} \\ \boldsymbol{c_1} \\ \boldsymbol{c_2} \\ \vdots \\ \boldsymbol{c_K} \end{bmatrix}$$

where

p_c – probability of the detection of an object of the specified class in the image, which is equal to 1 when the object is present and 0 otherwise during the training

b_x – x-coordinate of the bounding box of the object

b_y – y-coordinate of the bounding box of the object

b_h – the height of the bounding box of the object

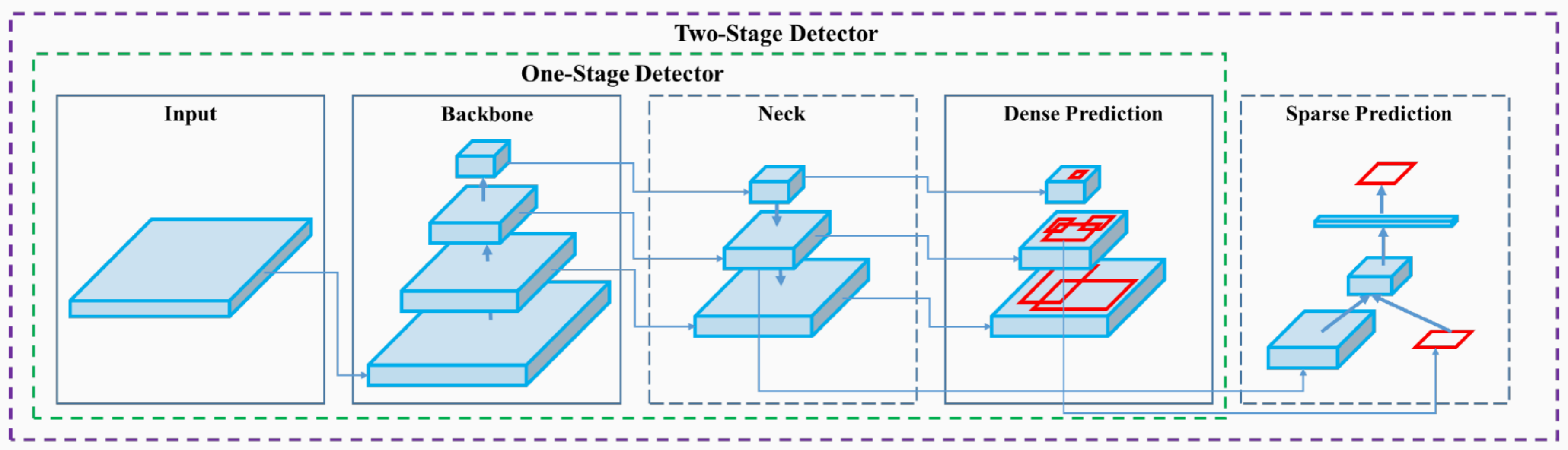
b_w – the width of the bounding box of the object

$c_1, c_2, \dots, c_K$ – the possible trained classes of the input image, where only one c_k is equal to 1 and the others are equal to 0

? – are not taken into account in the loss function because we do not care these values while no object is detected

How Do Detectors Work?

Ordinary object detectors are typically composed of several parts:



Input: Image, Patches, Image Pyramid

Backbone: VGG16, ResNet-50, SpineNet, EfficientNet-B0/B7, CSPResNeXt50, CSPDarknet53

Neck: **Additional blocks:** SPP, ASPP, RFB, SAM

Path-aggregation blocks: FPN, PAN, NAS-FPN, Fully-connected FPN, BiFPN, ASFF, SFAM

Heads: **Dense Prediction (one-stage):**

- **Anchor-based:** RPN, SSD, YOLO, RetinaNet
- **Anchor-free:** CornerNet, CenterNet, MatrixNet, FCOS

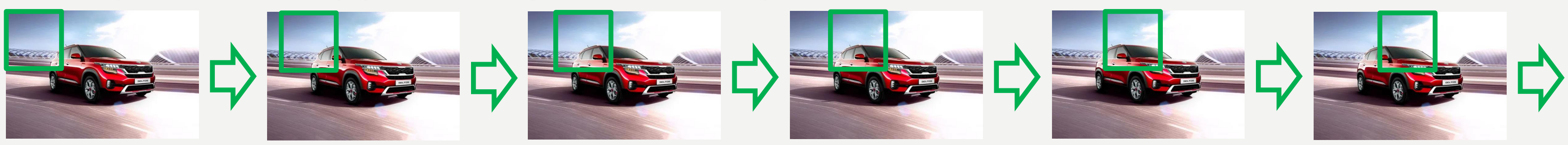
Sparse Prediction (two-stage):

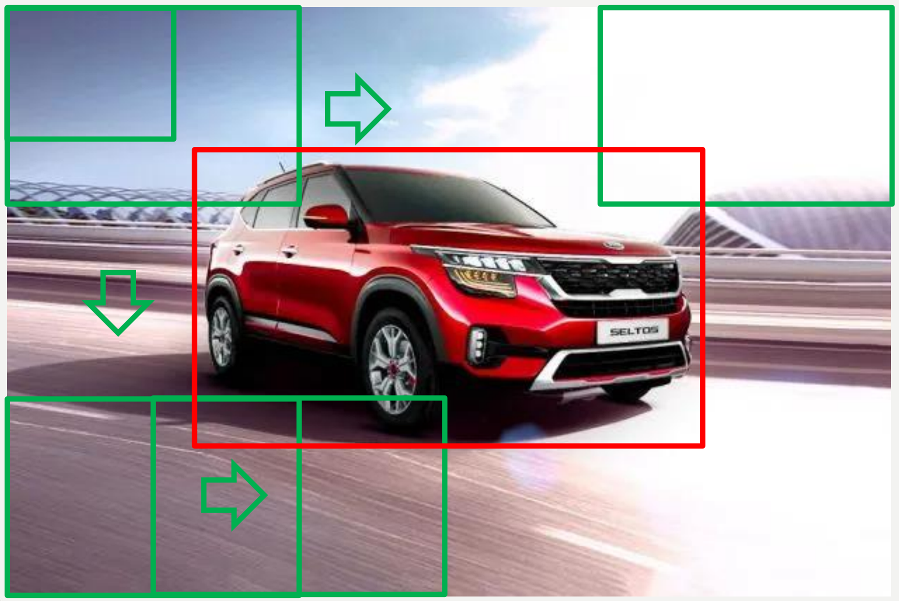
- **Anchor-based:** Faster R-CNN, R-FCN, Mask RCNN
- **Anchor-free:** RepPoints

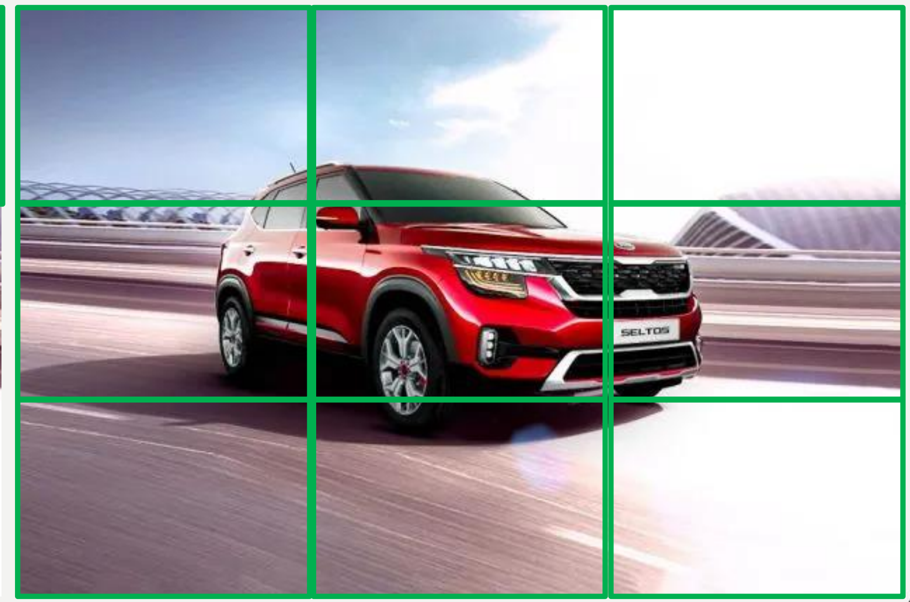
Object Detection and Cropping Out

Object detection can be made in a few ways:

- using sliding window of the same size or various sizes with different strides (high computational cost because of many strides) – sliding window detection
- using a grid (mesh) of fixed windows (e.g. YOLO – you only look once)
- and put the cropped image on the input of the ConvNet:

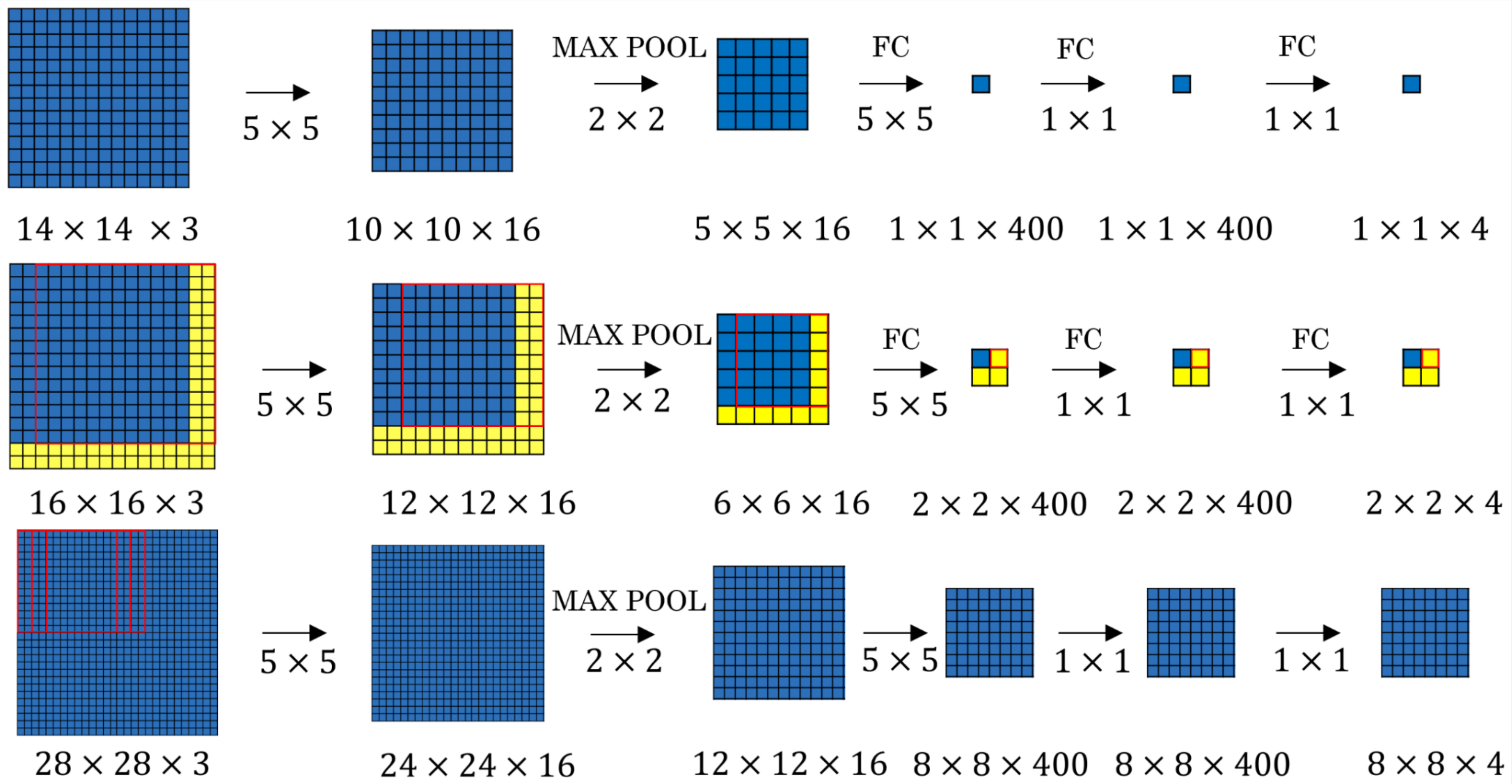






Convolutional Implementation of Sliding Windows

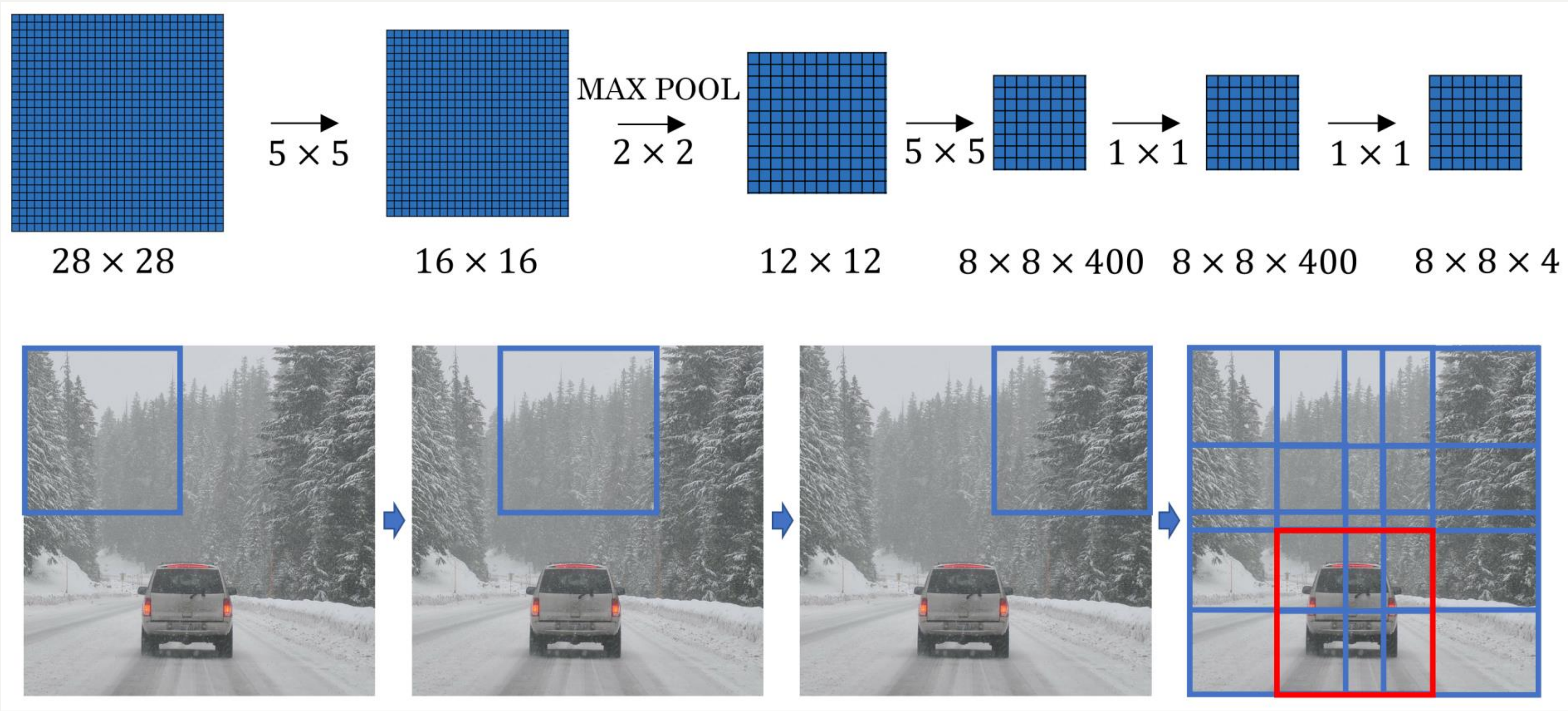
Many computations for sliding windows repeat as presented by the blue sliding window and the red one (the shared area) after the two-pixel stride.



Therefore, we implement sliding windows parallelly and share these computations that are the same for different sliding windows to proceed computations faster.

Convolutional Implementation of Sliding Windows

How the convolutional implementation of the sliding window works on the image?



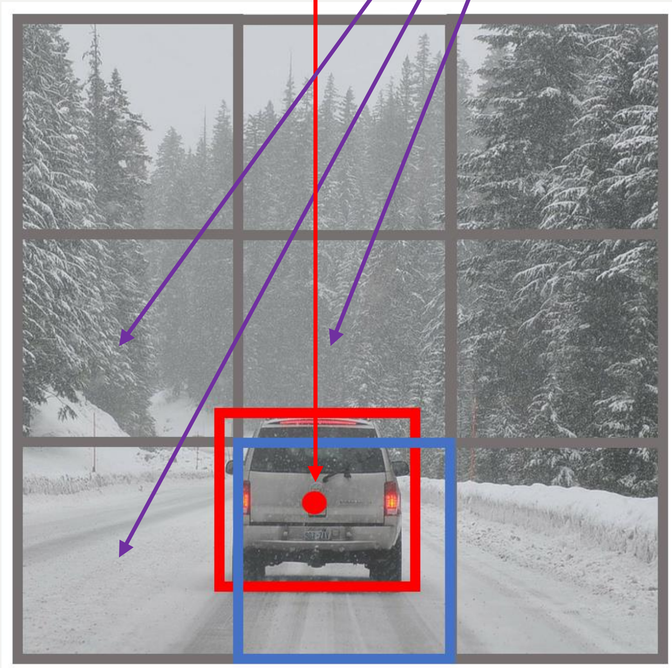
The drawback is the position of the bounding box designated by the sliding window that might not be very accurate. Moreover, if we want to fit each object better, we have to use many such parallel convolutional networks for various sizes of sliding windows. Even though we cannot use appropriately adjusted sizes of such windows and achieve poor bounding boxes for the classified objects.

YOLO – You Only Look Once

In YOLO, we put the grid of the fixed sizes on the image:

- **Each object is classified only in a single grid cell where is the midpoint of this object taking into account the ground-truth frame of it defined in the training dataset:**
- **In all other cells, this object is not represented even if they contain fragments of this object or its bounding box (frame).**
- **For each of the grid cell, we create an (K+5)-dimensional vector storing bounding box and class parameters:**
- **The target (trained) output is a 3D matrix of S x S x (K+5) dimensions, where S is the number of grid cells in each row and column.**
- **This approach works as long as there is only one object in each grid cell. In practice, the grid is usually bigger than in this example, e.g. 19x19, so there is a less chance to have more than one middle point of the object inside each grid cell.**

$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ \vdots \\ c_K \end{bmatrix}$$



YOLO's bounding boxes

The YOLO's bounding boxes are computed using the following formulas:

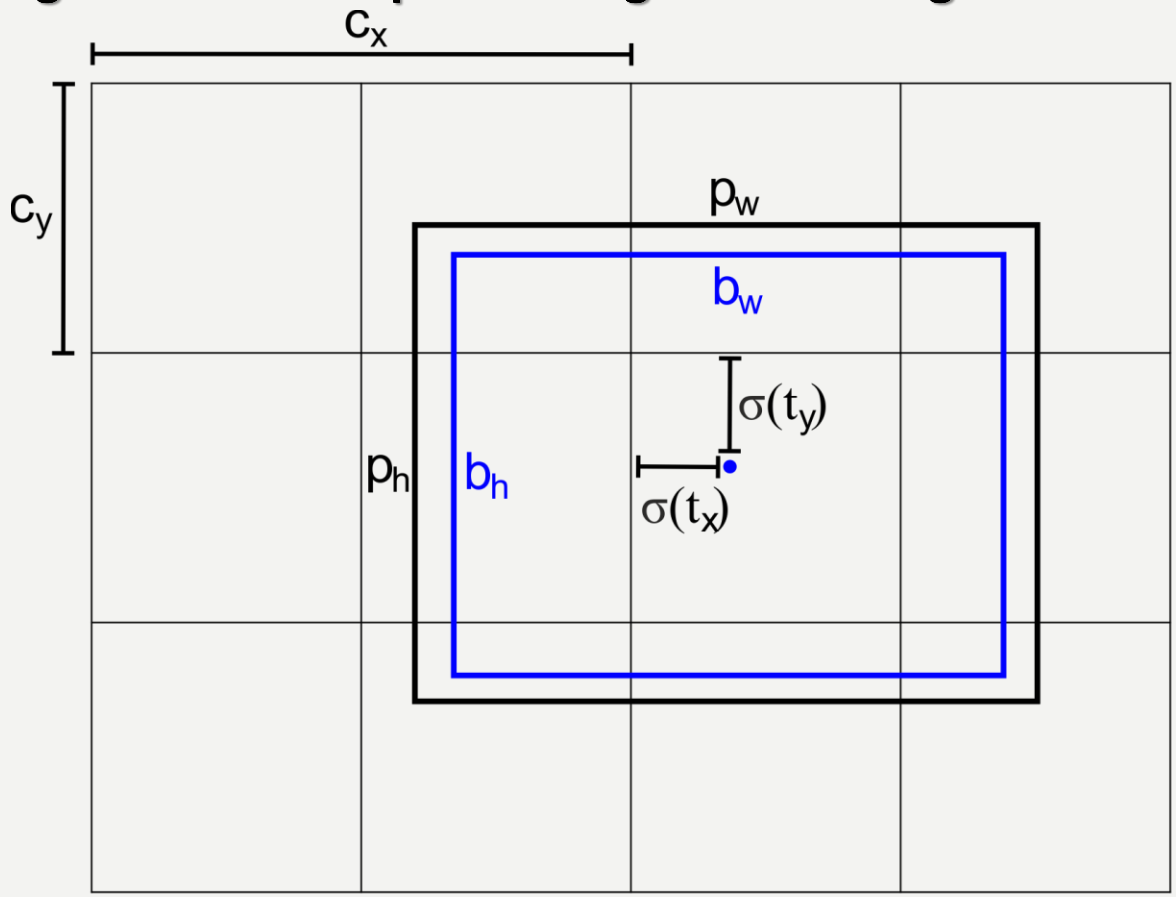
$$(b_x, b_y, b_w, b_h)$$

$$b_x = \sigma(t_x) + c_x$$

$$b_y = \sigma(t_y) + c_y$$

$$b_w = p_w \cdot e^{t_w}$$

$$b_h = p_h \cdot e^{t_h}$$



where

t_x, t_y, t_w, t_h is what the YOLO network outputs,

c_x and c_y are the top-left coordinates of the grid cell, and

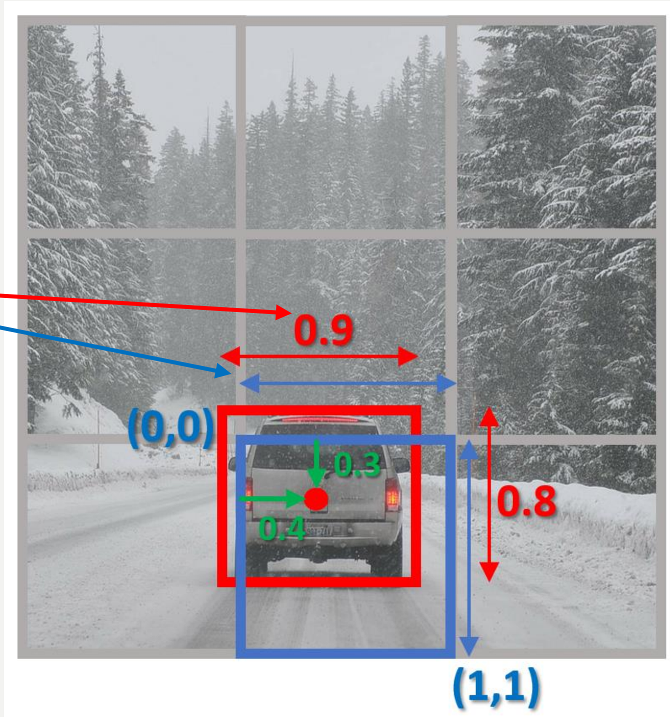
p_w and p_h are the anchors dimensions for the grid cell (box).

Specifying the Bounding Boxes in YOLO

We specify the bounding boxes in YOLO in such a way:

- **Each upper-left corner of each grid cell has (0,0) coordinates.**
- **Each bottom-right corner of each grid cell has (1,1) coordinates.**
- **We measure the midpoint of the object in these coordinates, here (0.4,0.3).**
- **The width (height) of the object is measured as the fraction of the overall width (height) of this grid cell box (frame).**

$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ \vdots \\ c_K \end{bmatrix} = \begin{bmatrix} 1 \\ 0.4 \\ 0.3 \\ 0.9 \\ 0.8 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

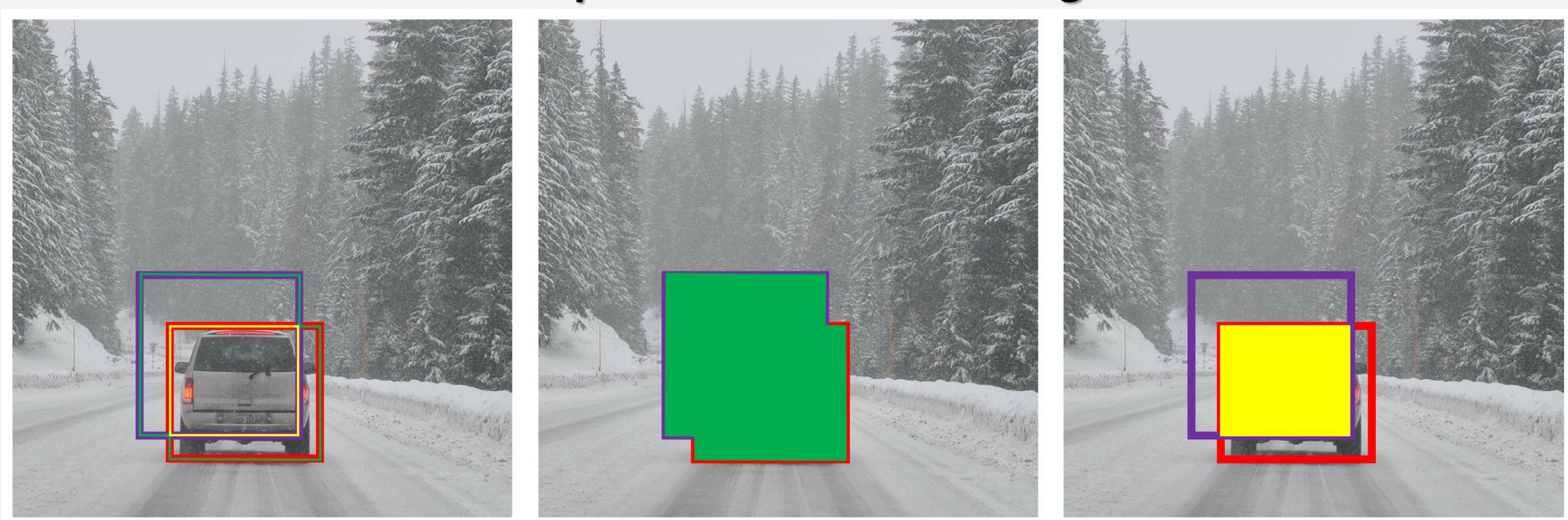


- **The midpoints are always between 0 and 1, while widths and heights could be greater than 1.**
- **If we want to use a sigmoid function (not ReLU) in an output layer and we need to have all widths and heights between 0 and 1, we can divide widths by the number of grid cells in a row (b_w/S), and divide heights by the number of grid cells in a column (b_h/S).**

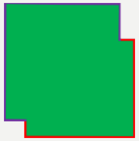
Intersection Over Union

Intersection Over Union (IOU):

- Is used to measure the quality of the estimated bounding box to the ground-truth bounding box defined in the training dataset.
- Is treated as correct if IOU ≥ 0.5 or more dependently on the application.
- Is a measure of the overlap between two bounding boxes.



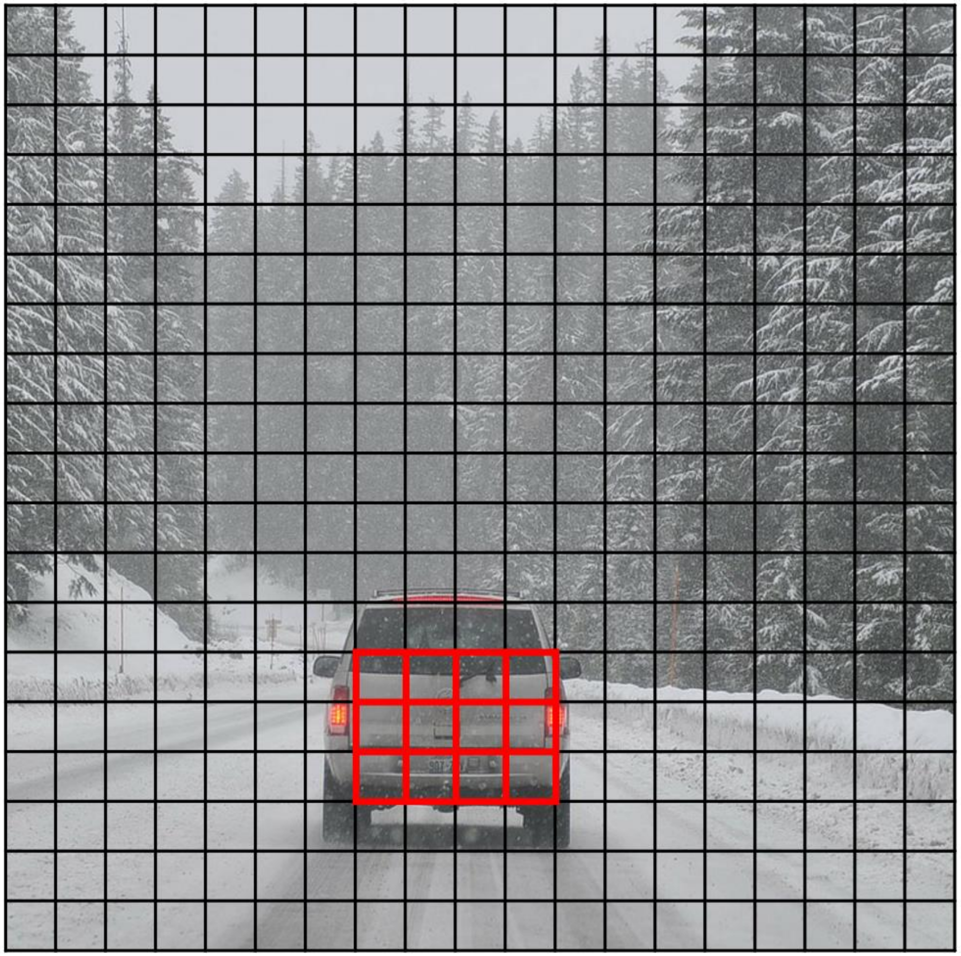
- Is computed as the ratio of the size of the intersection between two bounding boxes and the union of these bounding boxes:

IOU = size of  / size of 

Non-Max Suppression of YOLO

Non-max suppression avoids multiple bounding boxes for the detected objects leaving only one with the highest IOU.

- **When using bigger grids, many grid cells might think that they represent the midpoint of the detected object.**
- **In result, every such cell will produce a bounding box, so we get multiple bounding boxes for the same object, but they will be reduced using Non-Max Suppression.**
- **YOLO chooses the one with the highest probability p_c computed for each grid cell.**



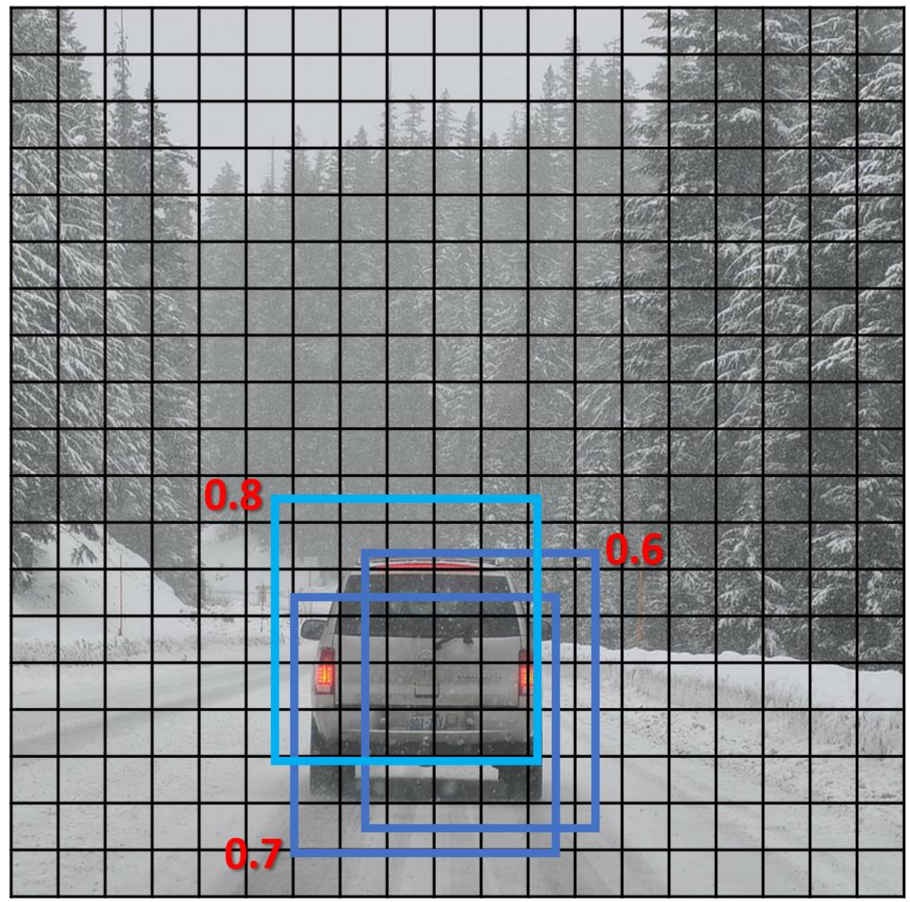
Grid 19x19

Non-Max Suppression of YOLO

Non-Max Suppression works as follows:

1. **Discard all bounding boxes estimated by the convolutional network which probability is $p_c \leq 0.6$.**
2. **While there are any remaining bounding boxes:**
   1. **Pick this one with the largest p_c, and output that as a prediction of the detected object. (selection step)**
   2. **Discard any remaining bounding box with IOU ≥ 0.5 with the box output in the previous step. (pruning/suppression step)**

For multiple object detection of the different classes, we perform the non-max suppression for each of these classes independently.



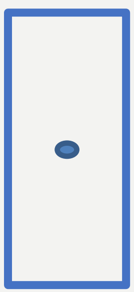
Grid 19x19

Anchor Boxes for Multiple Object Detection

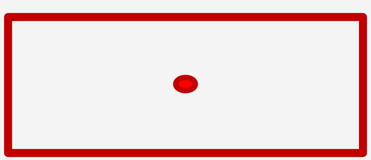
When two or more objects are in almost the same place in the image and their midpoints of their ground-truth bounding boxes fall into the same grid cell, we cannot use the previous algorithm but define a few anchor boxes with the predefined shapes associated with different classes of objects that can occur in the same grid cell:

Example:

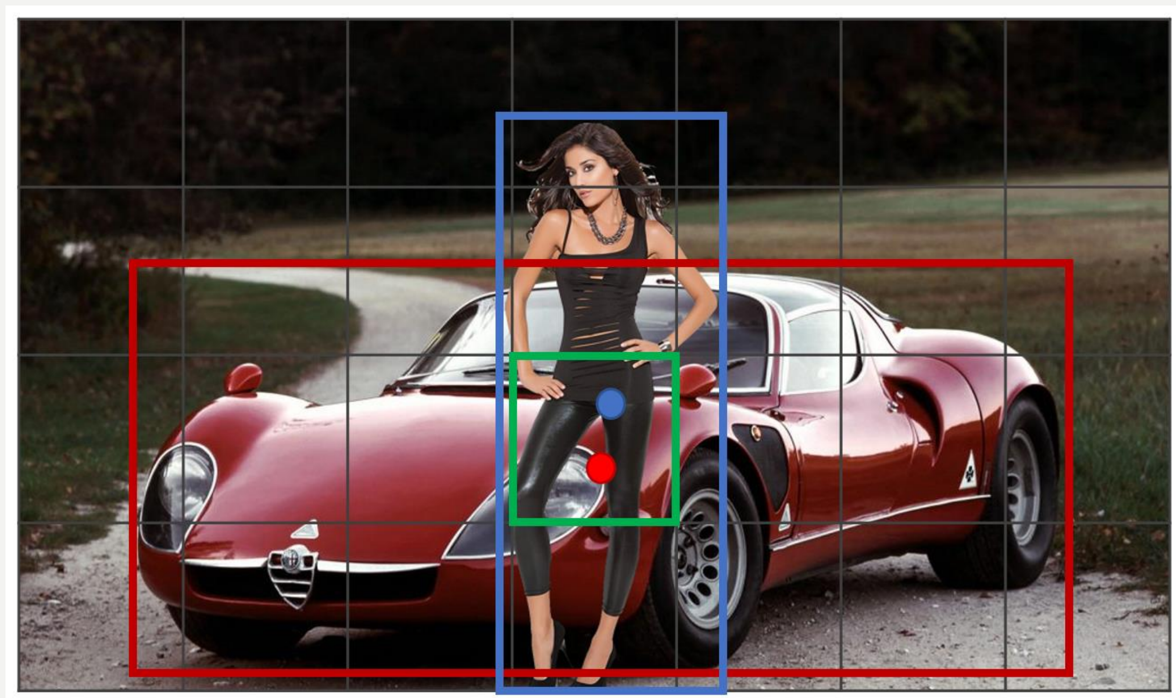
Anchor box 1 (A1):



Anchor box 2 (A2):



$$y = \begin{bmatrix} p_c^{A1} \\ b_x^{A1} \\ b_y^{A1} \\ b_h^{A1} \\ b_w^{A1} \\ c_1^{A1} \\ c_2^{A1} \\ \vdots \\ c_K^{A1} \\ p_c^{A2} \\ b_x^{A2} \\ b_y^{A2} \\ b_h^{A2} \\ b_w^{A2} \\ c_1^{A2} \\ c_2^{A2} \\ \vdots \\ c_K^{A2} \end{bmatrix}$$



The YOLO algorithm with anchor boxes assigns each object in training image to the grid cell that contains the object's midpoint and the appropriate anchor box for the grid cell with the highest IOU.

Anchor Boxes and Target Setup

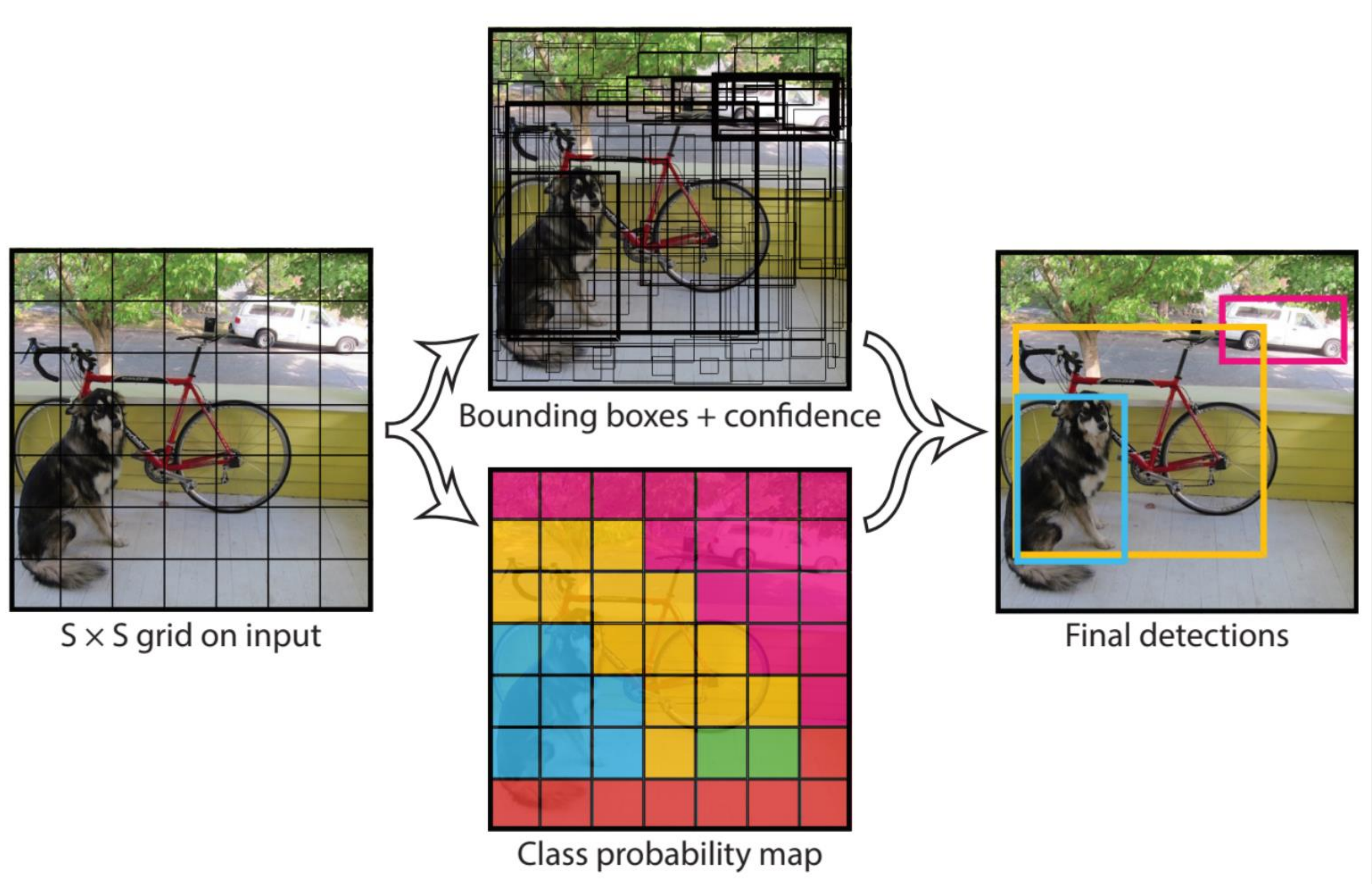
For two anchor boxes in the grid cell, we consider four cases:

1. **There are no midpoints of objects in the cell.**
2. **There is one midpoint of the object of the anchor 1 and class c_1 in the cell.**
3. **There is one midpoint of the object of the anchor 2 and class c_2 in the cell.**
4. **There is two midpoints of two object of the anchor 1 and the anchor 2 and both classes c_1 and c_2 in the cell.**

$$y = \begin{bmatrix} p_c^{A1} \\ b_x^{A1} \\ b_y^{A1} \\ b_h^{A1} \\ b_w^{A1} \\ c_1^{A1} \\ c_2^{A1} \\ \vdots \\ c_K^{A1} \\ p_c^{A2} \\ b_x^{A2} \\ b_y^{A2} \\ b_h^{A2} \\ b_w^{A2} \\ c_1^{A2} \\ c_2^{A2} \\ \vdots \\ c_K^{A2} \end{bmatrix} \qquad (1) \quad y = \begin{bmatrix} 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ \vdots \\ ? \\ 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ \vdots \\ ? \end{bmatrix} \qquad (2) \quad y = \begin{bmatrix} 1 \\ b_x^{A1} \\ b_y^{A1} \\ b_h^{A1} \\ b_w^{A1} \\ 1 \\ 0 \\ \vdots \\ 0 \\ 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ \vdots \\ ? \end{bmatrix} \qquad (3) \quad y = \begin{bmatrix} 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ \vdots \\ ? \\ 1 \\ b_x^{A2} \\ b_y^{A2} \\ b_h^{A2} \\ b_w^{A2} \\ 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix} \qquad (4) \quad y = \begin{bmatrix} 1 \\ b_x^{A1} \\ b_y^{A1} \\ b_h^{A1} \\ b_w^{A1} \\ 1 \\ 0 \\ \vdots \\ 0 \\ 1 \\ b_x^{A2} \\ b_y^{A2} \\ b_h^{A2} \\ b_w^{A2} \\ 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}$$

YOLO Detection Model

How does it work?

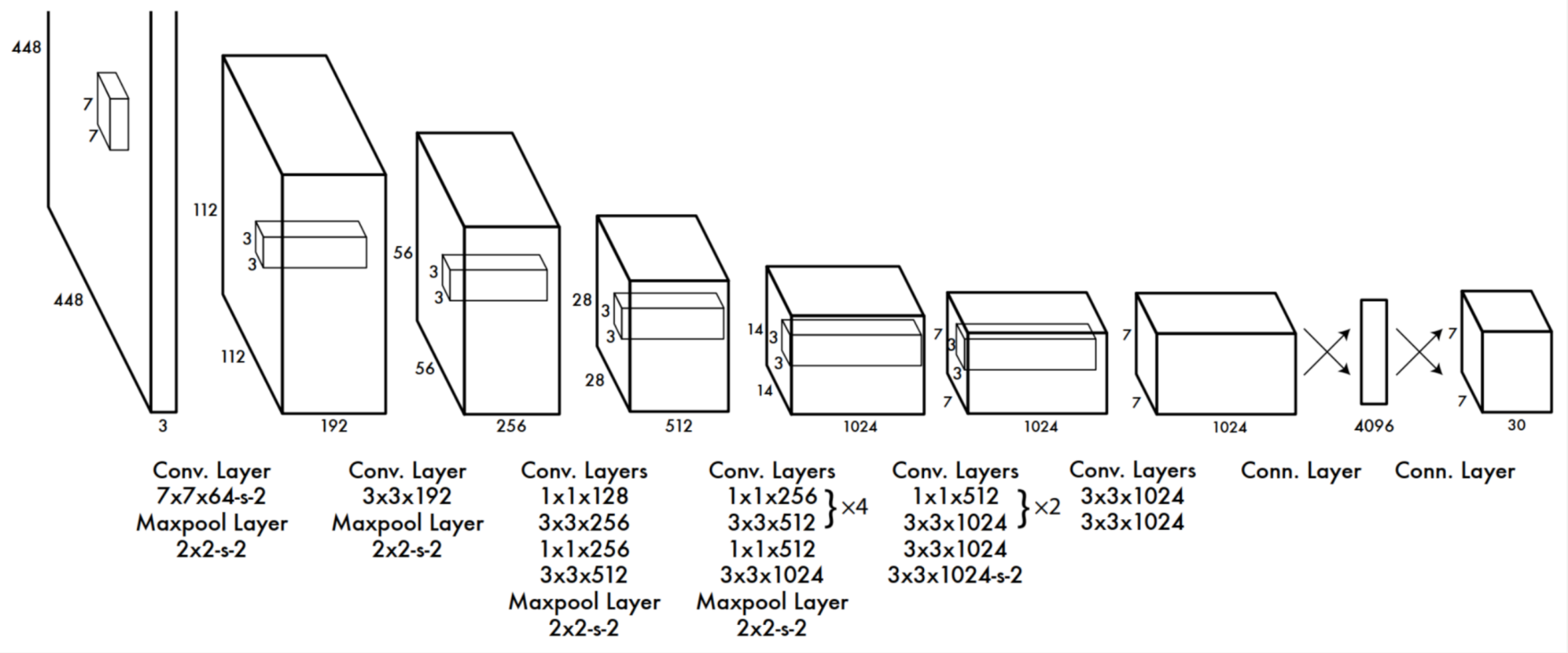


Classic YOLO Network Architecture

YOLO network architecture is convolutional with the output defined as a 3D matrix of the S x S x (A x 8) sizes:

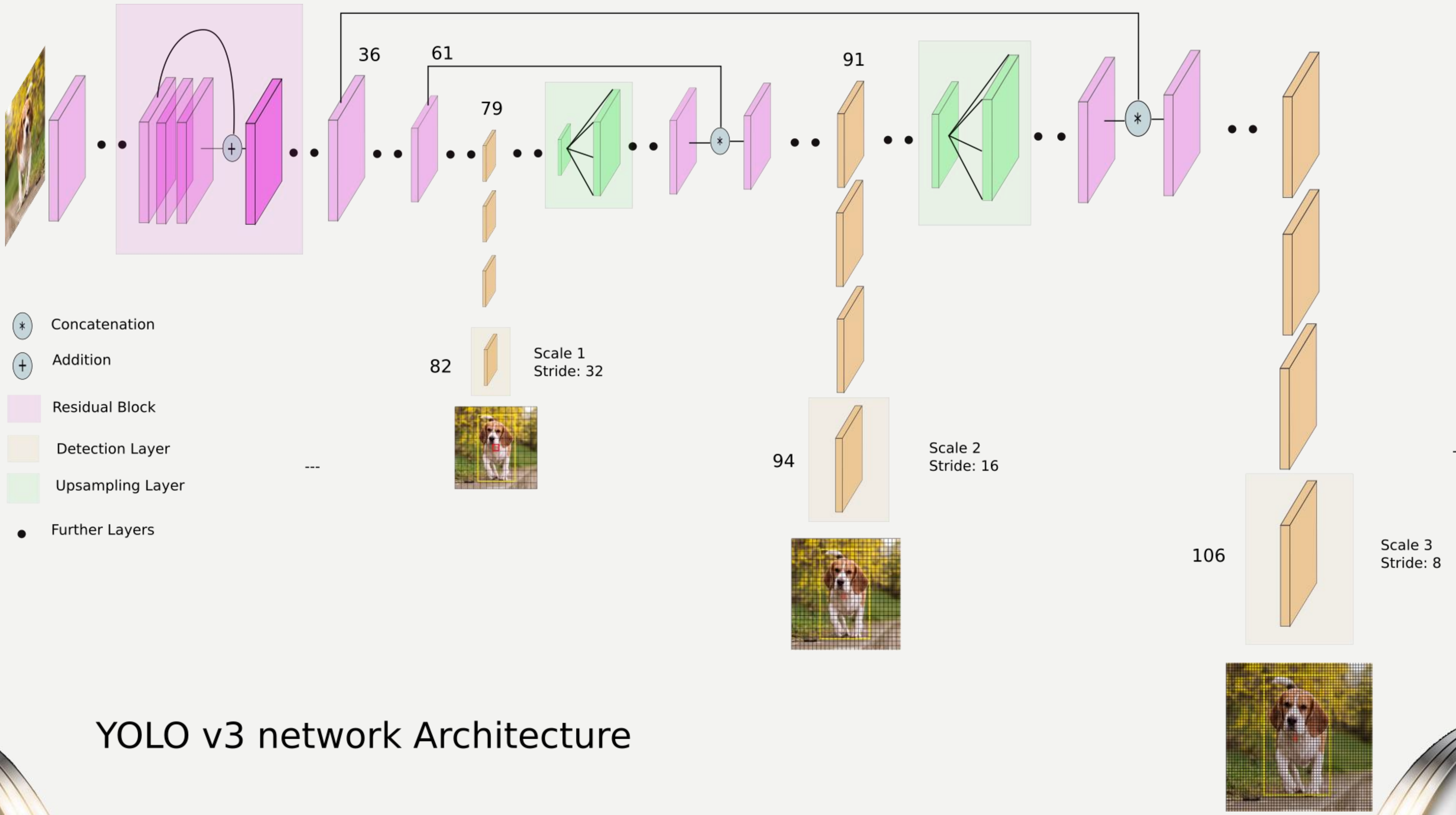
- **S – is the number or cells in each row and column**
- **A – is the number of anchors**

However, we can modify the original YOLO model in such a way that the numbers of cells in rows and columns differ.



YOLO v3 Network Architecture

It detects better different size objects:



YOLO v3 network Architecture

Bag of Freebies and Bag of Specials

Usually, a conventional object detector is trained offline. Therefore, researchers always like to take this advantage and develop better training methods which can make the object detector receive better accuracy without increasing the inference cost.

We call these methods that only change the training strategy or only increase the training cost as "bag of freebies."

What is often adopted by object detection methods and meets the definition of bag of freebies is data augmentation, which purpose is to increase the variability of the input images, so that the designed object detection model has higher robustness to the images obtained from different environments.

These modules and post-processing methods that only increase the inference cost by a small amount but can significantly improve the accuracy of object detection,

are call "bag of specials". Generally speaking, these plugin modules are for enhancing certain attributes in a model, such as enlarging receptive field, introducing attention mechanism, or strengthening feature integration capability, etc., and post-processing is a method for screening model prediction results.

Common modules that can be used to enhance receptive field are SPP, ASPP, and RFB.

https://arxiv.org/pdf/2004.10934.pdf

Improving Object Detection Training

For improving the object detection training, a CNN usually uses the following:

- **Activations:** ReLU, leaky-ReLU, parametric-ReLU, ReLU6, SELU, Swish, or Mish
- **Bounding box regression loss:** MSE, IoU, GIoU, CIoU, DIoU
- **Data augmentation:** CutOut, MixUp, CutMix
- **Regularization method:** DropOut, DropPath, Spatial DropOut, or DropBlock
- **Normalization of the network activations by their mean and variance:** Batch Normalization (BN), Cross-GPU Batch Normalization (CGBN or SyncBN), Filter Response Normalization (FRN), or Cross-Iteration Batch Normalization (CBN)
- **Skip-connections:** Residual Connections, Weighted Residual Connections, Multi-input Weighted Residual Connections, or Cross Stage Partial Connections (CSP)

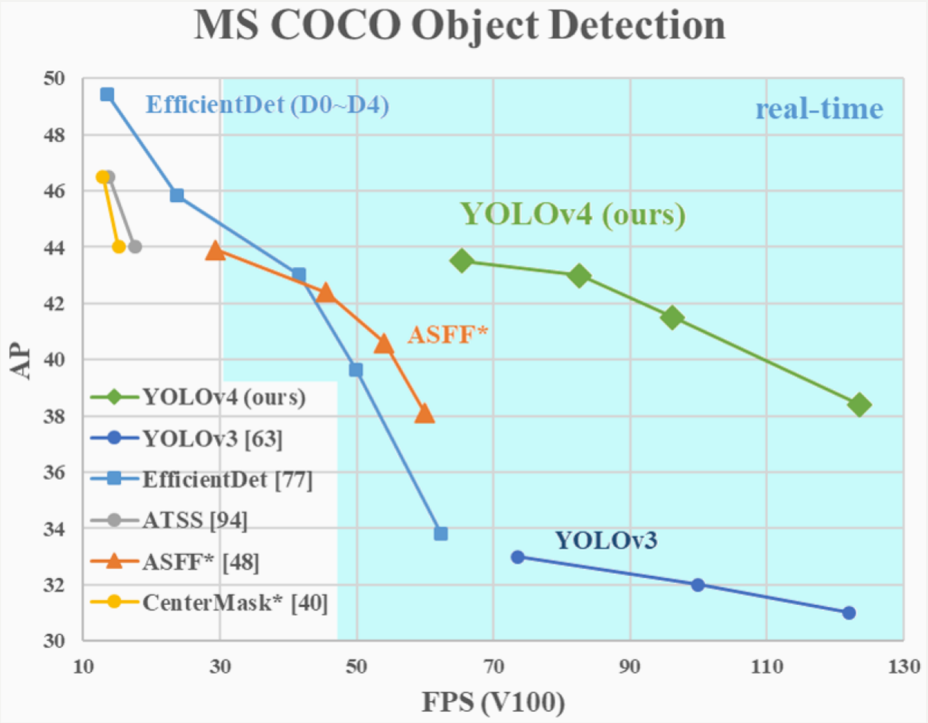
https://arxiv.org/pdf/2004.10934.pdf

YOLO v4 Network Architecture

YOLO v4 takes the influence of state of the art bag of freebies (BoF) and several bag of specials (BoS):

- The BoF improves the accuracy of the detector, without increasing the inference time, only increasing the training cost.
- The BoS increases the inference cost by a small amount; however, significantly improving the accuracy of object detection.

YOLO v4 also based on the Darknet and has obtained an AP value of 43.5 percent on the COCO dataset along with a real-time speed of 65 FPS on the Tesla V100, beating the fastest and most accurate detectors in terms of both speed and accuracy.



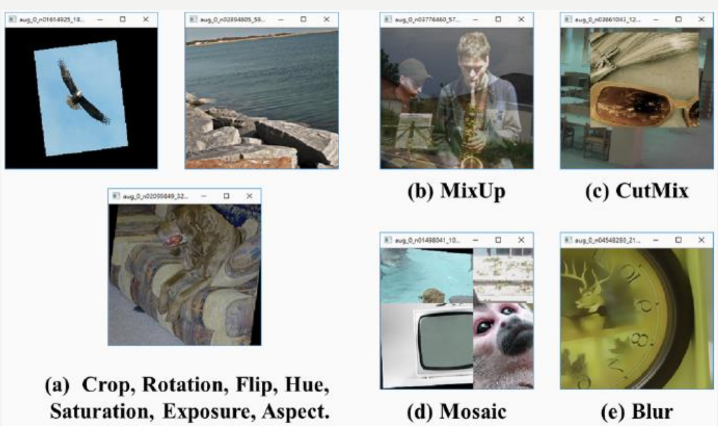
YOLO v4 Network Architecture

YOLOv4 consists of:

- **Backbone**: CSPDarknet53 [81]
- **Neck**: SPP [25], PAN [49]
- **Head**: YOLOv3 [63]

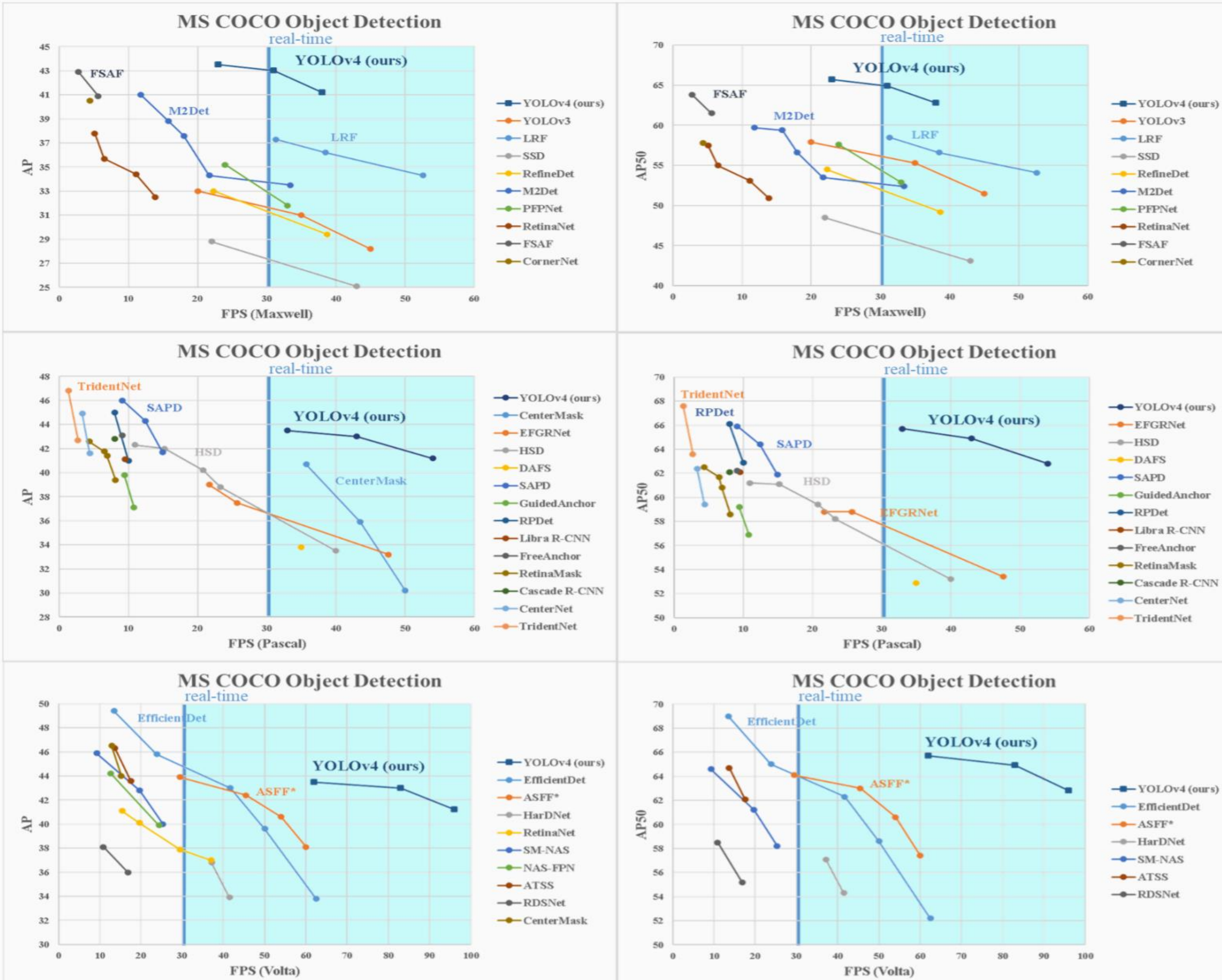
YOLO v4 uses:

- Bag of Freebies (BoF) for backbone:
  - CutMix and Mosaic data augmentation,
  - DropBlock regularization,
  - Class label smoothing
- Bag of Specials (BoS) for backbone:
  - Mish activation,
  - Cross-stage partial connections (CSP),
  - Multiinput weighted residual connections (MiWRC)



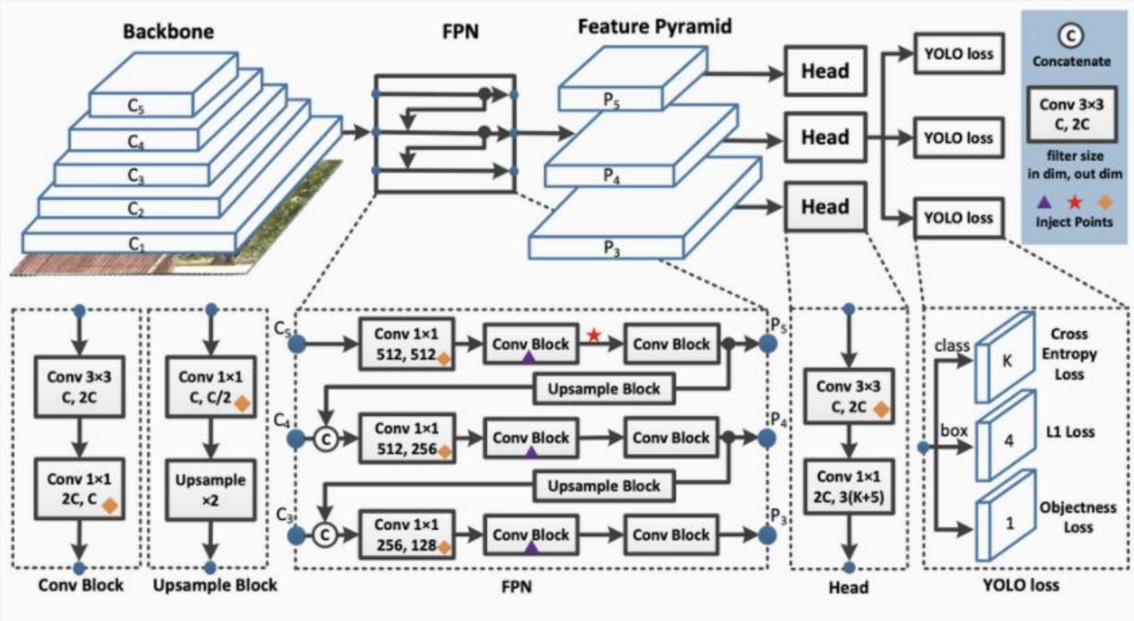
- Bag of Freebies (BoF) for detector:
  - CIoU-loss,
  - CmBN,
  - DropBlock regularization,
  - Mosaic data augmentation,
  - Self-Adversarial Training,
  - Eliminate grid sensitivity,
  - Using multiple anchors for a single ground truth,
  - Cosine annealing scheduler,
  - Optimal hyperparameters,
  - Random training shapes
- Bag of Specials (BoS) for detector:
  - Mish activation,
  - SPP-block,
  - SAM-block,
  - PAN path-aggregation block,
  - DIoU-NMS

Comparisons of YOLO v4 on the Different GPU Cards: Maxwell, Pascal and Volta

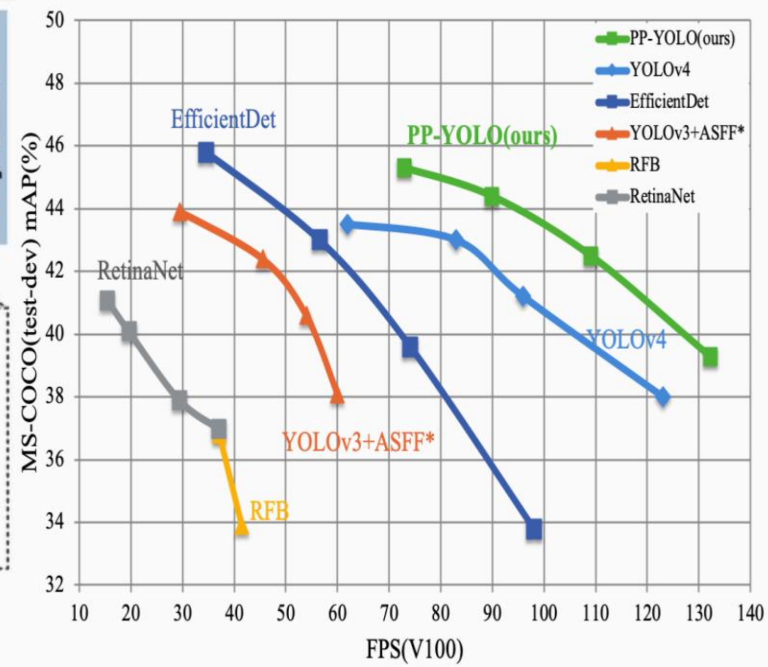


PP-YOLO

PP-YOLO has been introduced in July 2020. It is based on PaddlePaddle and on YOLO v3. This object detector with relatively balanced effectiveness and efficiency that can be directly applied in actual application scenarios. The notable changes include the replacement of Darknet53 backbone of YOLO v3 with a ResNet backbone and increase of training batch size from 64 to 192 (as mini-batch size of 24 on 8 GPUs):



The modeling process in PP-YOLO



https://arxiv.org/abs/2007.12099 (Original paper: PP-YOLO: An Effective and Efficient Implementation of Object Detector, by Xiang Long et al)

https://towardsdatascience.com/yolo-v4-or-yolo-v5-or-pp-yolo-dad8e40f7109

YOLO v5

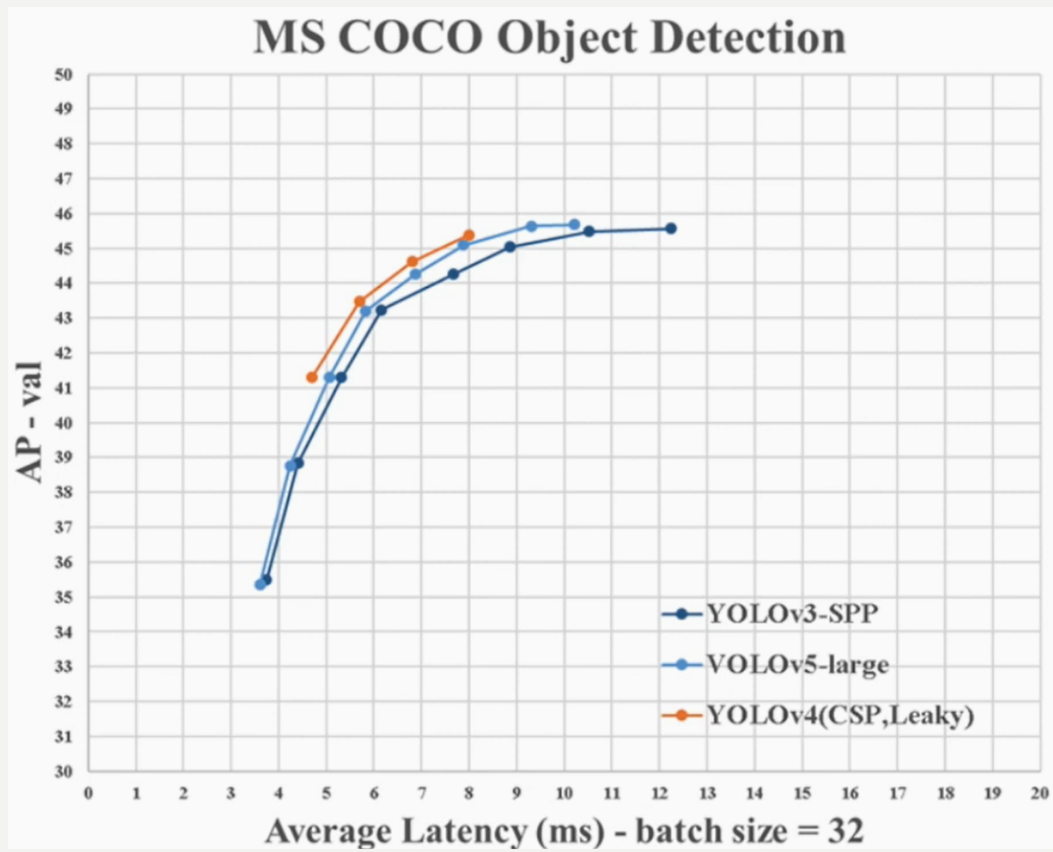
YOLO v5 is different from all other prior releases (developed by Roboflow team), as this is a PyTorch implementation rather than a fork from original Darknet.

Same as YOLO v4, the YOLO v5 has a CSP backbone and PA-NET neck.

The major improvements includes mosaic data augmentation and auto learning bounding box anchors.

YOLO v5 is not to achieve the best mAP, but instead:

- easy of use
- exportability
- low memory requirements
- high speed
- high mAP
- market size (small)
- new PyTorch framework



Let's Play with Object Detection and Segmentation Algorithms in Roboflow:

There is a nice application with build-in modules, datasets and models:

1. http://app.roboflow.ai
2. http://public.roboflow.ai
3. http://models.roboflow.ai

Create Project

Extract `chessSampleData.zip` and have a look at its contents. It has 12 `jpg` images of chess boards and 11 `xml` files labeling the pieces in voc format.

In this tutorial, we will prepare this dataset for training by

- Uploading the images
- Annotating an unlabeled image
- Splitting the dataset into `train`, `valid` and `test` sets
- Downsizing and grayscaling the images
- Generating additional training examples
- Converting the annotation format
- And creating a hosted link to use in our training script

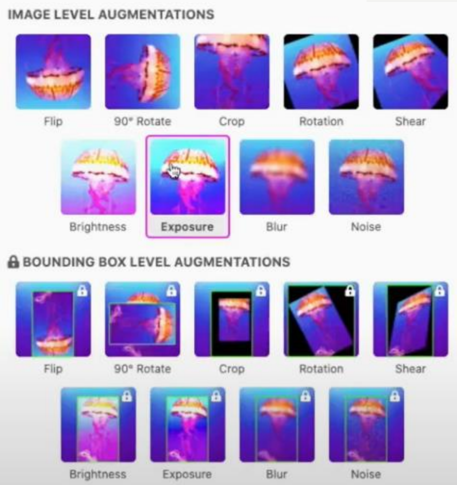
⏱ This guided tutorial will take about 5 minutes.

Roboflow Train

Roboflow Train is our new one-click model training service that enables you to train your model without writing any code.

Once training is complete, you'll get the results along with a hosted API endpoint you can use for making predictions in your project.

- ✔ **Model Evaluation Metrics**
- ✔ **Hosted API Endpoint for Inference**
- ✔ **Use with Model Assisted Labeling** PRO
- ✔ **On-Device Inference** PRO



Use video tutorials of creating and training YOLO v5 models:

https://www.youtube.com/watch?v=MdF6x6ZmLAY

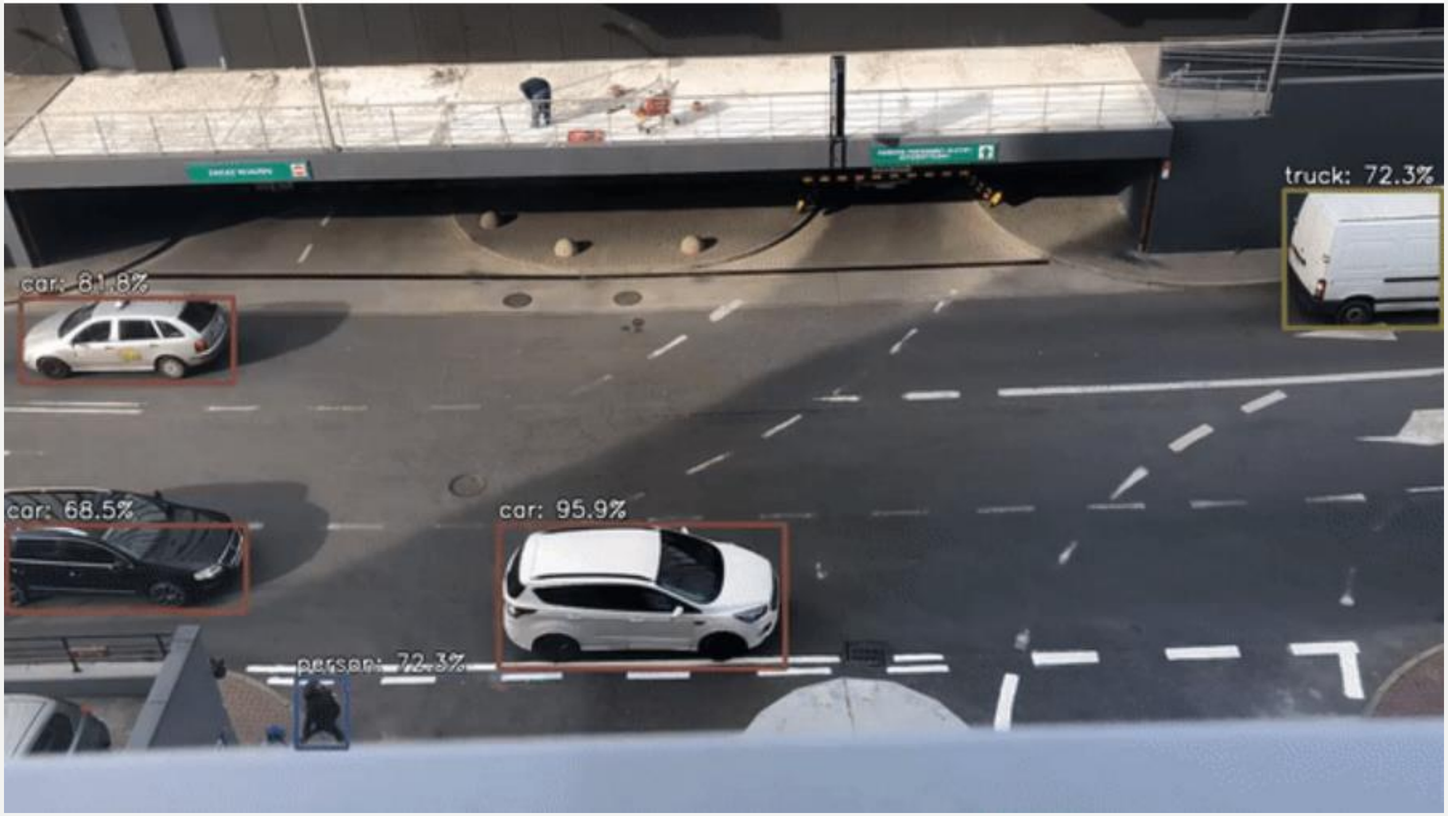
https://www.youtube.com/watch?v=R1Bf067Z5uM

Watch the video and construct your model as an optional assignment if you like?

RetinaNet

RetinaNet:

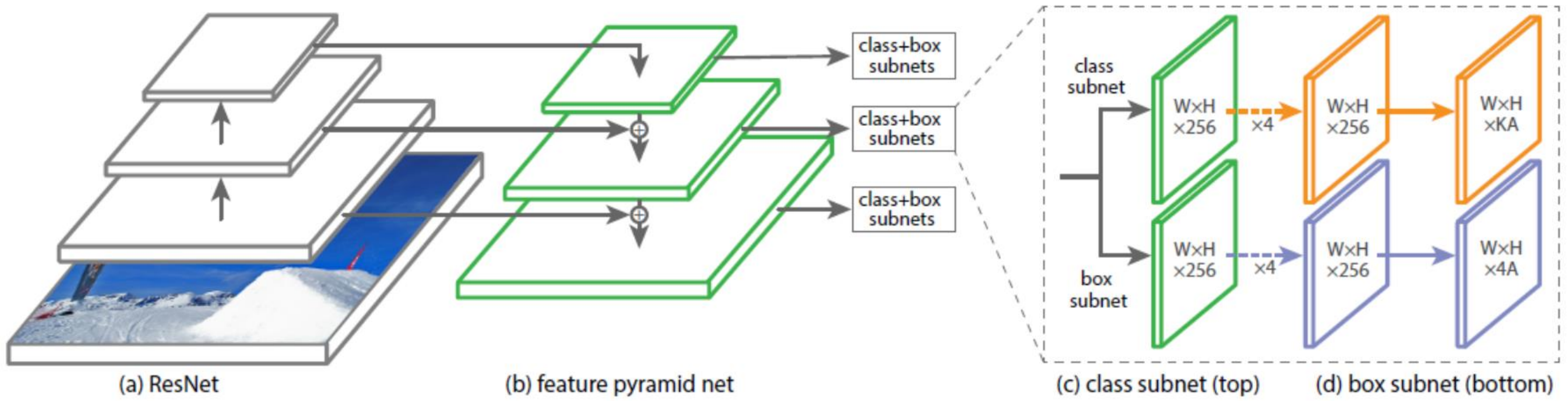
- **can have ~100k boxes with the resolve of class imbalance problem using focal loss.**
- **Many one-stage detectors do not achieve good enough performance, so there are build new two-stage detectors.**



RetinaNet

RetinaNet:

- In RetinaNet, a one-stage detector, by using focal loss, lower loss is contributed by “easy” negative samples so that the loss is focusing on “hard” samples, which improves the prediction accuracy. With ResNet+FPN as backbone for feature extraction, plus two task-specific subnetworks for classification and bounding box regression, forming the RetinaNet, which achieves state-of-the-art performance, outperforms Faster R-CNN, the well-known two-stage detectors. It is a 2017 ICCV Best Student Paper Award paper with more than 500 citations. (The first author, Tsung-Yi Lin, has become Research Scientist at Google Brain when he was presenting RetinaNet in 2017 ICCV.) (Sik-Ho Tsang @ Medium).
- https://www.youtube.com/watch?v=44tlnmmt3h0



RetinaNet Detector Architecture

Precision and Recall

To define Mean Average Measure (mAP), we will use the following:

Confusion Matrix

- Specifies how many examples were correctly classified as positive (TP), negative (TN) and how many were misclassified as positive (FP) or negative (FN).

		Actual Value (as confirmed by experiment)	
		positives	negatives
Predicted Value (predicted by the test)	positives	**TP** True Positive	**FP** False Positive
	negatives	**FN** False Negative	**TN** True Negative

Precision

- measures how accurate is your predictions, i.e., the percentage of your predictions are correct.

$$Precision = \frac{TP}{TP+FP}$$

Recall

- measures how good you find all the positives. For example, we can find 80% of the possible positive cases in our top K predictions.

$$Recall = \frac{TP}{TP+FN}$$

Mean Average Precision

Average Precision (AP):

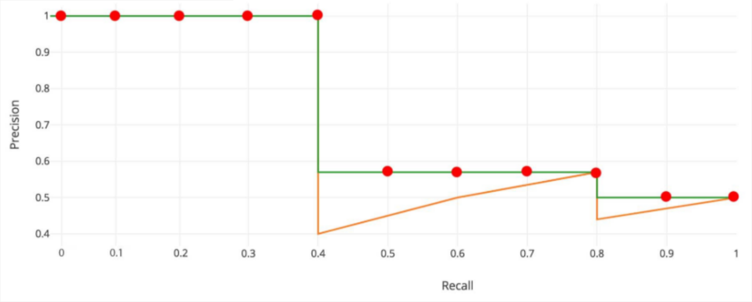
- is a popular metric in measuring the accuracy of object detectors like Faster R-CNN, SSD, YOLO, etc. Average precision computes the average precision value for recall value over 0 to 1:

$$AP = \int_0^1 p(r)\, dr$$

$$\mathrm{AP} = \sum \left(r_{n+1} - r_n \right) p_{interp}(r_{n+1})$$

$$p_{interp}(r_{n+1}) = \max_{\tilde{r} \geq r_{n+1}} p(\tilde{r})$$

- where $p(r)$ is a precision-recall curve.



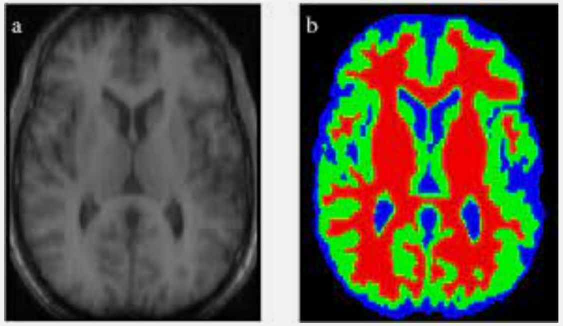
Mean Average Precision (mAP):

- is a mean average precision computes the average precision value for recall value over 0 to 1.

Semantic Segmentation and Instance Segmentation

How can we segment objects in images?

Semantic Segmentation

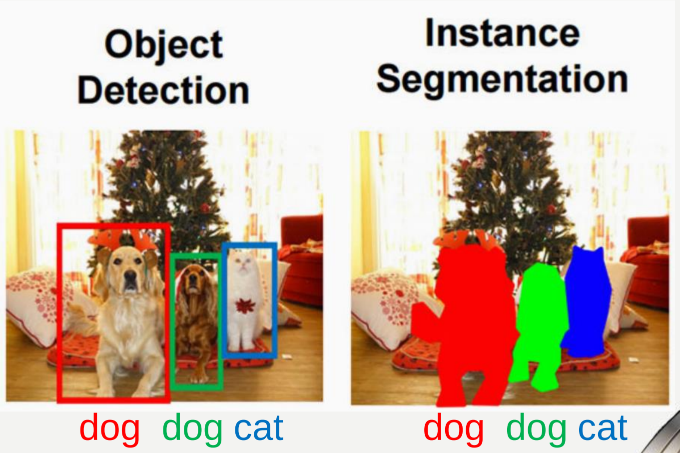


Semantic segmentation is one of the key problems in the field of computer vision. It paves the way towards complete scene understanding. An increasing number of applications nourish from inferring knowledge from imagery. Some of those applications include self-driving vehicles, human-computer interaction, virtual reality etc.

With the popularity of deep learning in recent years, many semantic segmentation problems are being tackled using deep architectures, like CNN, which surpass other approaches in terms of accuracy and efficiency.

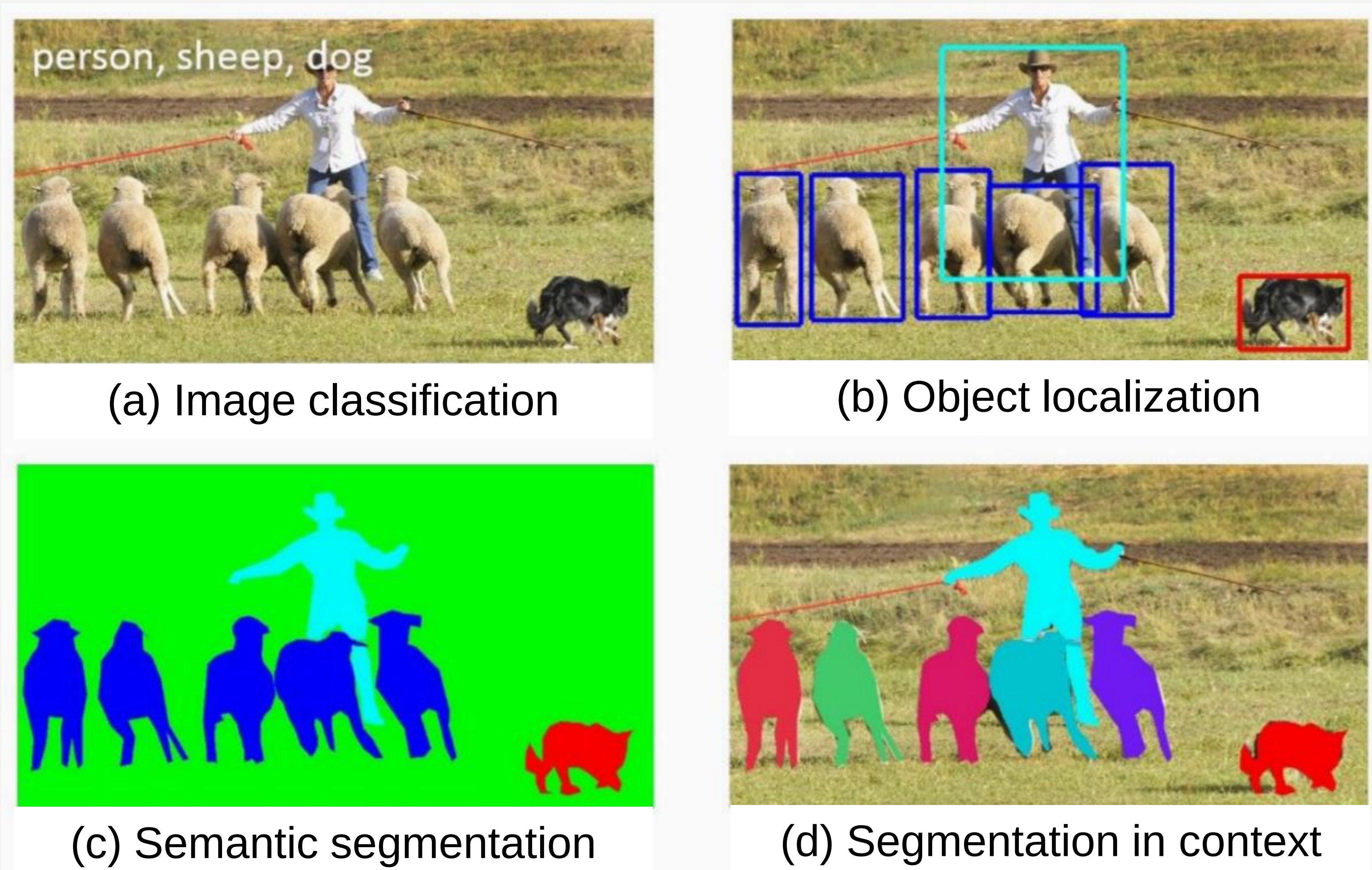
Semantic segmentation is a natural step in the progression from coarse to fine inference:

1. The origin could be located at classification of objects, which consists of making a prediction for a whole input.
2. The next step is localization / detection of objects, which provides not only the classes but also additional information regarding the spatial location of those classes.
3. Finally, semantic segmentation of objects achieves fine-grained inference by making dense predictions inferring labels for every pixel so that each pixel is labeled with the class of its enclosing object or region.



Segmentation and Localization

We can localize, segment and describe objects:



(a) Image classification

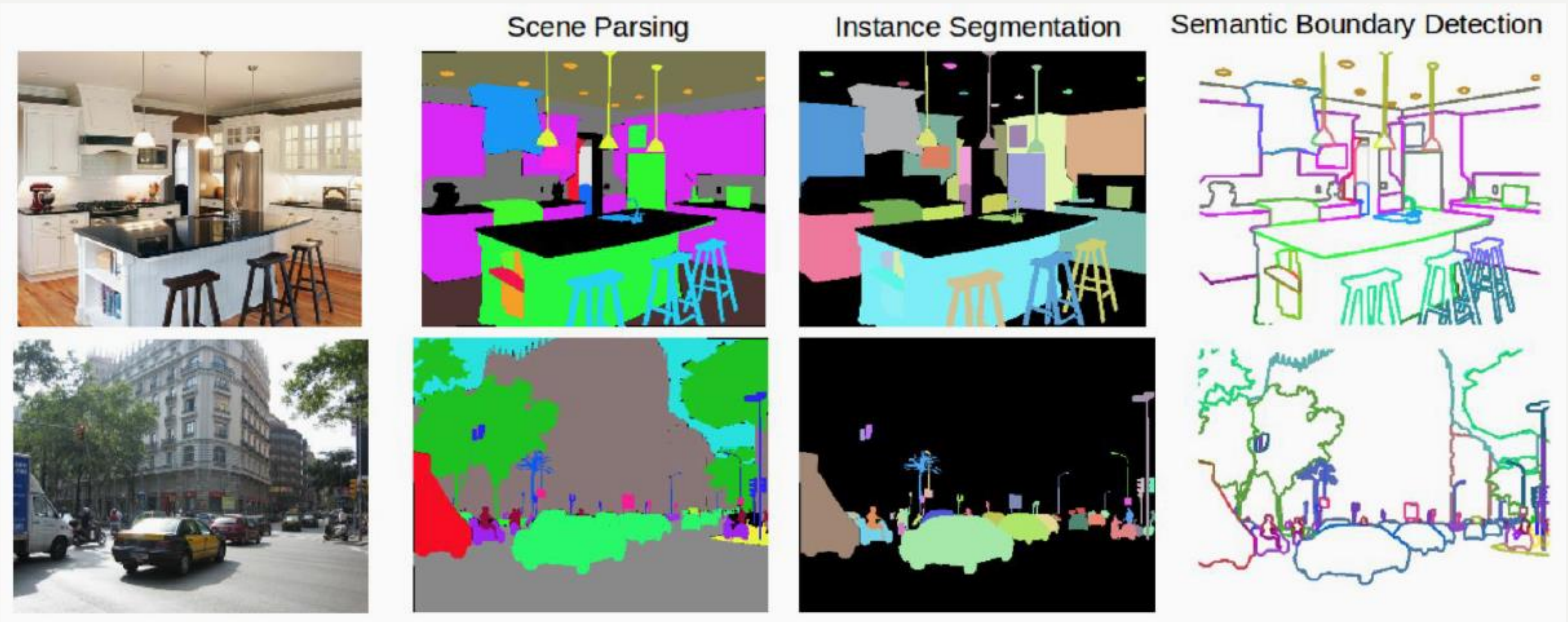
(b) Object localization

(c) Semantic segmentation

(d) Segmentation in context

Scene Parsing, Segmentation and Boundary Detection

To understand the scene, we must detect objects, their boundaries, key points, segment them, mask, and process in context.



Kaiming He, Georgia Gkioxari, Piotr Dollar, and Ross Girshick. "Mask R-CNN." ICCV, 2017

R-CNN, Fast R-CNN, and Faster R-CNN

R-CNN stands for Regions with ConvNet detection:

- Is a two-step segmentation algorithm.
- The algorithm is run on a big number of blocks to classify them
- R-CNN proposes regions at a time.
- We get an output label + bounding box

Fast R-CNN:

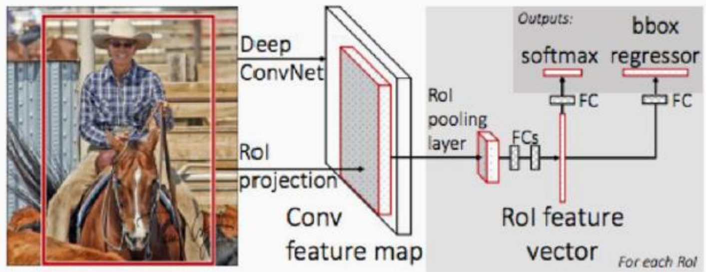
- A convolutional implementation of sliding windows to classify all the proposed regions.

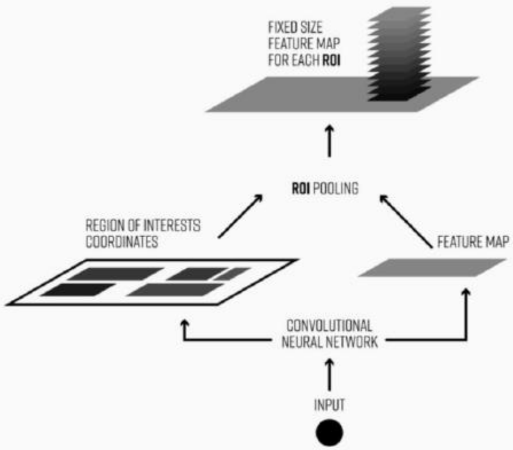
Faster R-CNN:

- Uses a convolutional network to propose regions.

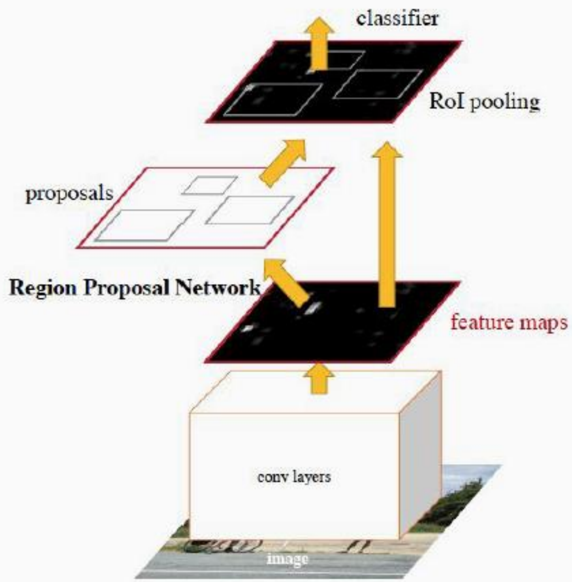
Fast R-CNN and Faster R-CNN

Fast R-CNN

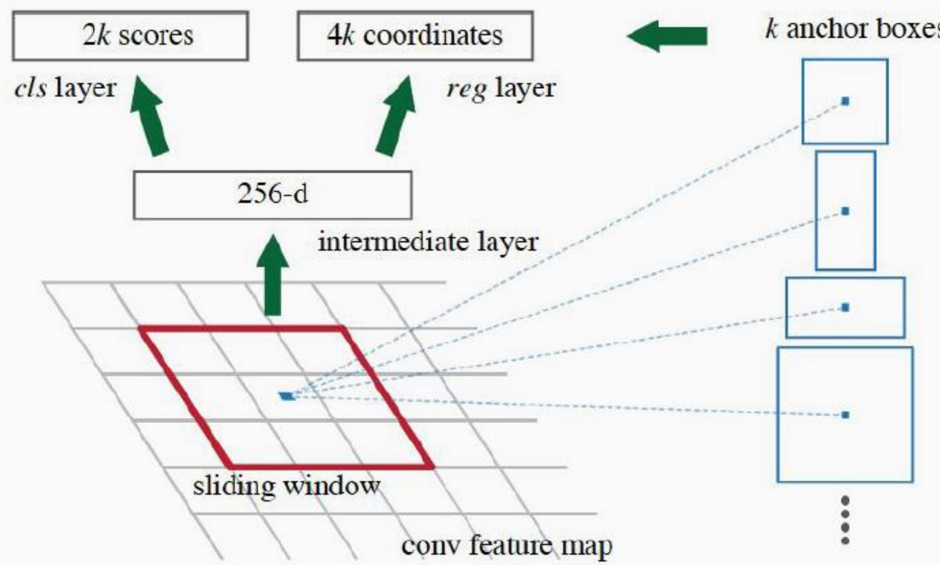




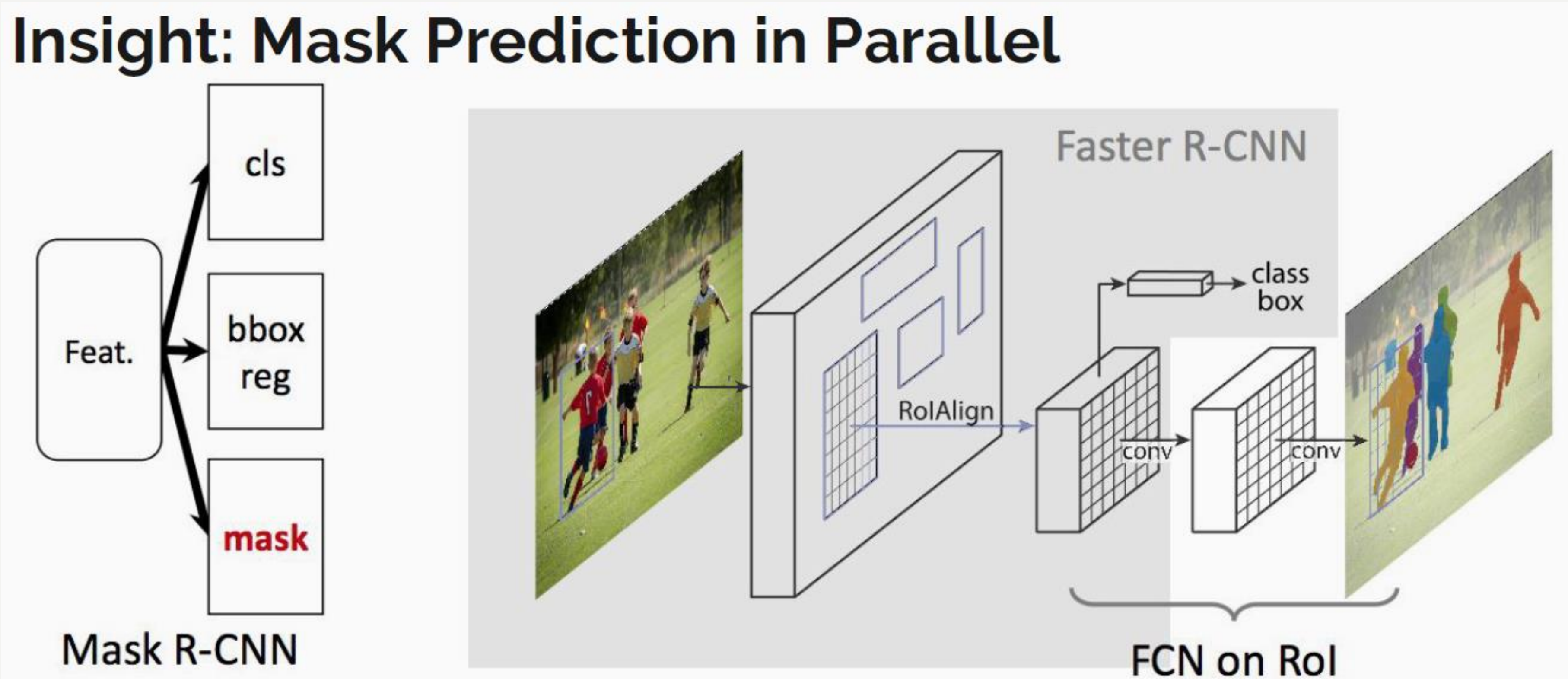
Faster R-CNN = RPN + Fast R-CNN



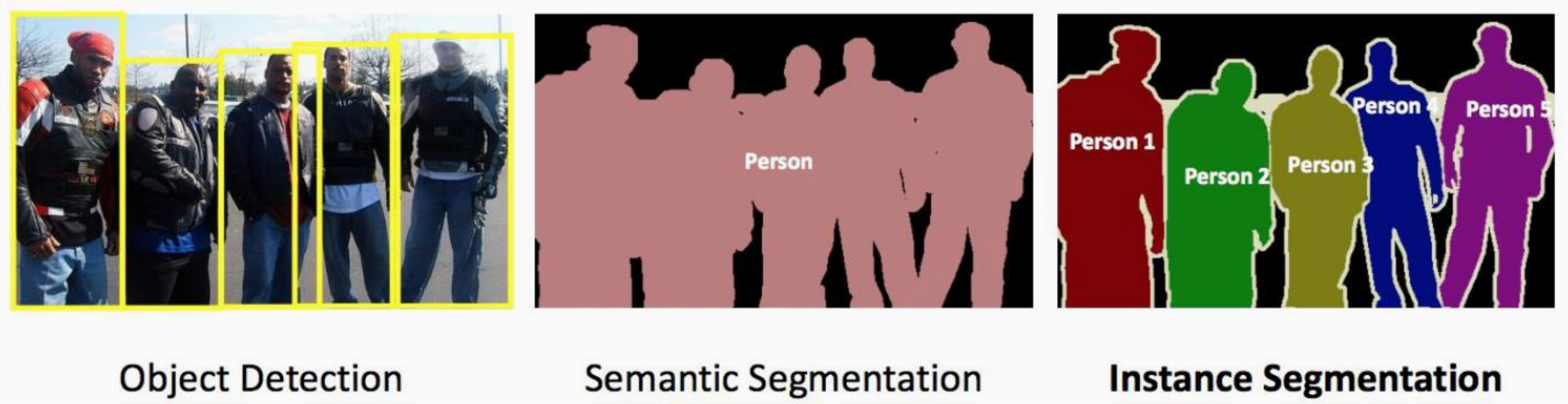
RPN = Fully Convolutional Network



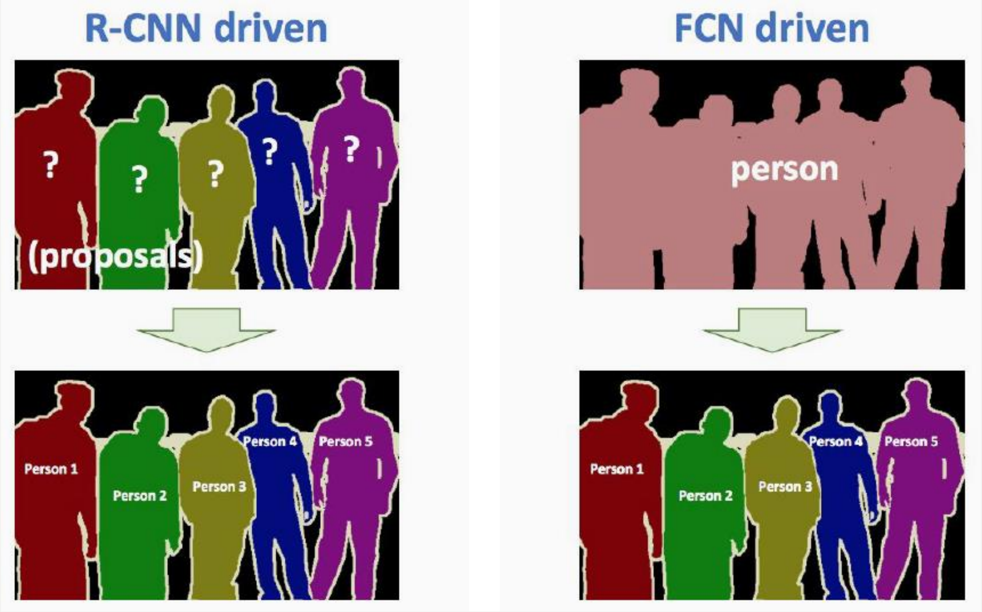
Mask Prediction using Faster R-CNN



Semantic and Instance Segmenation



Instance Segmentation Methods can be divided into:



Examples of Masks

Figure 5. More results of **Mask R-CNN** on COCO test images, using ResNet-101-FPN and running at 5 fps, with 35.7 mask AP (Table 1).

Human Pose Estimations

Human Pose Estimations are used to detect and track actions performed by people to control the mor to react to what they do.

They may be used for movement improvements in sport, to detect undesirable behaviors or gathering training data for robots:

Figure 7. Keypoint detection results on COCO `test` using Mask R-CNN (ResNet-50-FPN), with person segmentation masks predicted from the same model. This model has a keypoint AP of 63.1 and runs at 5 fps.

Sample Implementation of Detection Model

Let's use Roboflow to implement detection!

Implementation of Detection Models

You can find many implemented frameworks for object detections, localization, detection and segmentation online (on the github) and utilize them for free.

You can also use applications like Roboflow:

1. http://app.roboflow.ai
2. http://public.roboflow.ai
3. http://models.roboflow.ai

Use video tutorials of creating and training YOLO v5 models:
https://www.youtube.com/watch?v=MdF6x6ZmLAY
https://www.youtube.com/watch?v=R1Bf067Z5uM

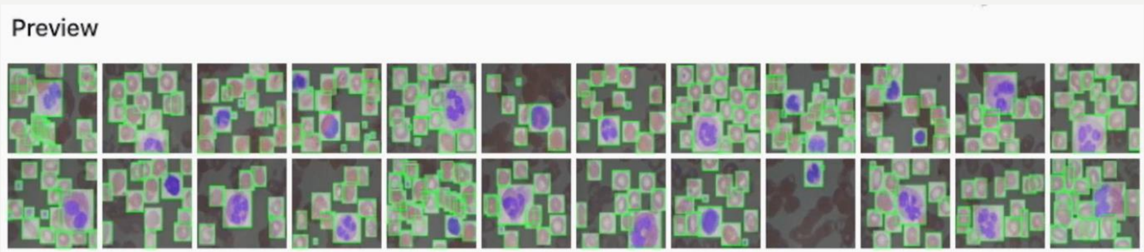
```
%%writetemplate /content/yolov5/models/custom_yolov5s.yaml

# parameters
nc: {num_classes}  # number of classes
depth_multiple: 0.33  # model depth multiple
width_multiple: 0.50  # layer channel multiple

# anchors
anchors:
  - [10,13, 16,30, 33,23]  # P3/8
  - [30,61, 62,45, 59,119]  # P4/16
  - [116,90, 156,198, 373,326]  # P5/32

# YOLOv5 backbone
backbone:
  # [from, number, module, args]
  [[-1, 1, Focus, [64, 3]],  # 0-P1/2
   [-1, 1, Conv, [128, 3, 2]],  # 1-P2/4
   [-1, 3, BottleneckCSP, [128]],
   [-1, 1, Conv, [256, 3, 2]],  # 3-P3/8
   [-1, 9, BottleneckCSP, [256]],
   [-1, 1, Conv, [512, 3, 2]],  # 5-P4/16
   [-1, 9, BottleneckCSP, [512]],
   [-1, 1, Conv, [1024, 3, 2]],  # 7-P5/32
   [-1, 1, SPP, [1024, [5, 9, 13]]],
   [-1, 3, BottleneckCSP, [1024, False]],  # 9
  ]

# YOLOv5 head
head:
  [[-1, 1, Conv, [512, 1, 1]],
   [-1, 1, nn.Upsample, [None, 2, 'nearest']],
   [[-1, 6], 1, Concat, [1]],  # cat backbone P4
   [-1, 3, BottleneckCSP, [512, False]],  # 13

   [-1, 1, Conv, [256, 1, 1]],
   [-1, 1, nn.Upsample, [None, 2, 'nearest']],
   [[-1, 4], 1, Concat, [1]],  # cat backbone P3
   [-1, 3, BottleneckCSP, [256, False]],  # 17 (P3/8-small)

   [-1, 1, Conv, [256, 3, 2]],
   [[-1, 14], 1, Concat, [1]],  # cat head P4
   [-1, 3, BottleneckCSP, [512, False]],  # 20 (P4/16-medium)

   [-1, 1, Conv, [512, 3, 2]],
   [[-1, 10], 1, Concat, [1]],  # cat head P5
   [-1, 3, BottleneckCSP, [1024, False]],  # 23 (P5/32-large)

   [[17, 20, 23], 1, Detect, [nc, anchors]],  # Detect(P3, P4, P5)
  ]
```

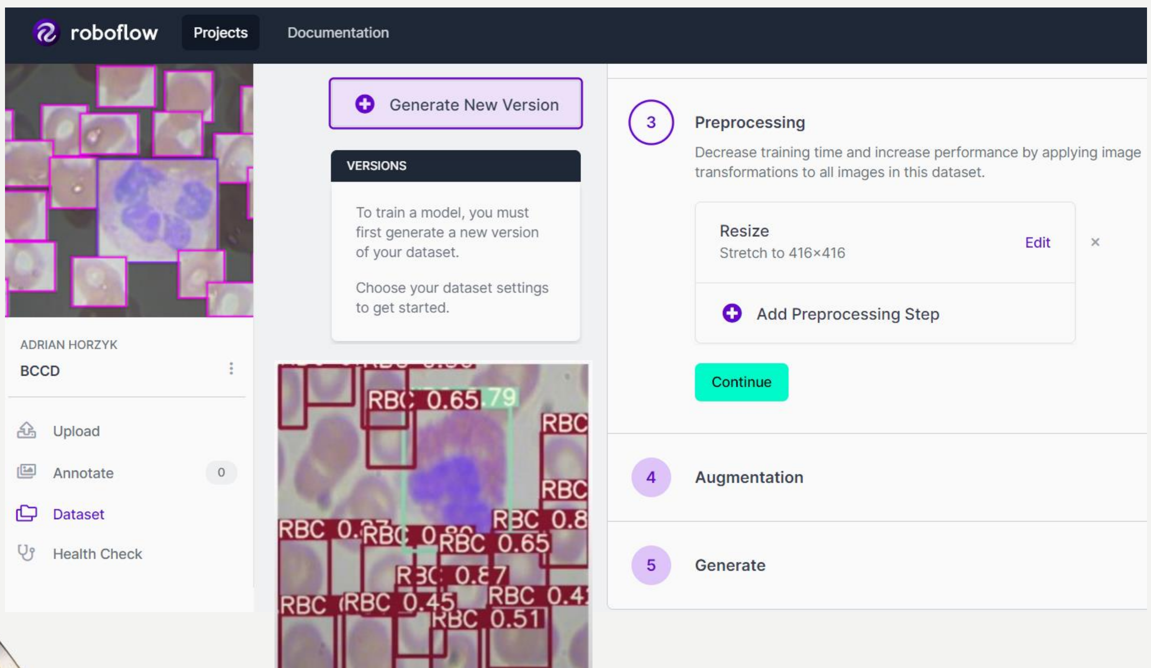
```
                 from  n    params  module                                  arguments
  0                -1  1      3520  models.common.Focus                     [3, 32, 3]
  1                -1  1     18560  models.common.Conv                      [32, 64, 3, 2]
  2                -1  1     19904  models.common.BottleneckCSP             [64, 64, 1]
  3                -1  1     73984  models.common.Conv                      [64, 128, 3, 2]
  4                -1  1    161152  models.common.BottleneckCSP             [128, 128, 3]
  5                -1  1    295424  models.common.Conv                      [128, 256, 3, 2]
  6                -1  1    641792  models.common.BottleneckCSP             [256, 256, 3]
  7                -1  1   1180672  models.common.Conv                      [256, 512, 3, 2]
  8                -1  1    656896  models.common.SPP                       [512, 512, [5, 9, 13]]
  9                -1  1   1248768  models.common.BottleneckCSP             [512, 512, 1, False]
 10                -1  1    131584  models.common.Conv                      [512, 256, 1, 1]
 11                -1  1         0  torch.nn.modules.upsampling.Upsample    [None, 2, 'nearest']
 12           [-1, 6]  1         0  models.common.Concat                    [1]
 13                -1  1    378624  models.common.BottleneckCSP             [512, 256, 1, False]
 14                -1  1     33024  models.common.Conv                      [256, 128, 1, 1]
 15                -1  1         0  torch.nn.modules.upsampling.Upsample    [None, 2, 'nearest']
 16           [-1, 4]  1         0  models.common.Concat                    [1]
 17                -1  1     95104  models.common.BottleneckCSP             [256, 128, 1, False]
 18                -1  1    147712  models.common.Conv                      [128, 128, 3, 2]
 19          [-1, 14]  1         0  models.common.Concat                    [1]
 20                -1  1    313088  models.common.BottleneckCSP             [256, 256, 1, False]
 21                -1  1    590336  models.common.Conv                      [256, 256, 3, 2]
 22          [-1, 10]  1         0  models.common.Concat                    [1]
 23                -1  1   1248768  models.common.BottleneckCSP             [512, 512, 1, False]
 24      [17, 20, 23]  1     21576  models.yolo.Detect                      [3, [[10, 13, 16, 30, 33, 23], [30, 61, 62, 45, 59, 119], [116, 90, 156, 198, 373, 326]], [128, 256, 512]]
Model Summary: 283 layers, 7260488 parameters, 7260488 gradients, 16.8 GFLOPS
```

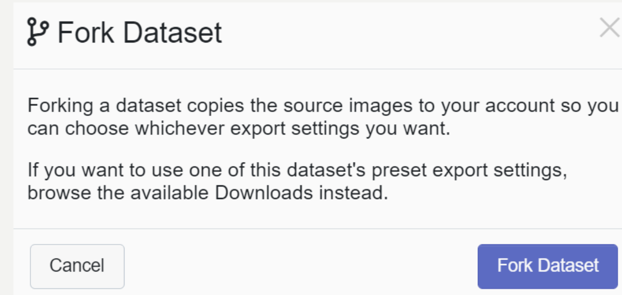
Roboflow Detection Implementation

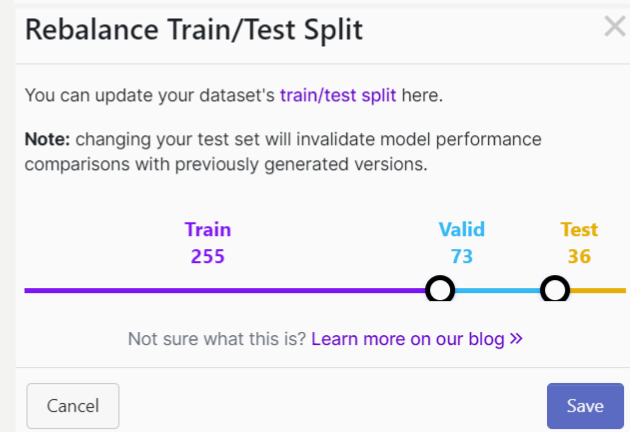
https://www.youtube.com/watch?v=MdF6x6ZmLAY

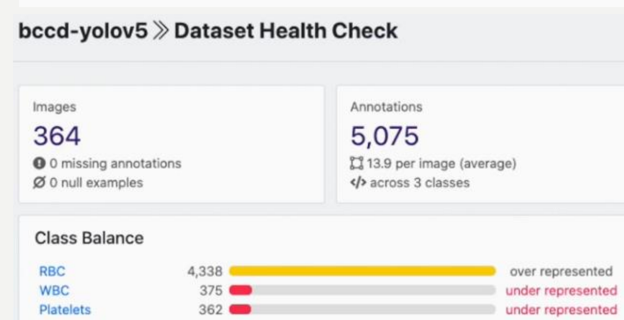
1. Create a free account: https://app.roboflow.com/
2. Fork sample dataset, e.g. BCCD, and use it.







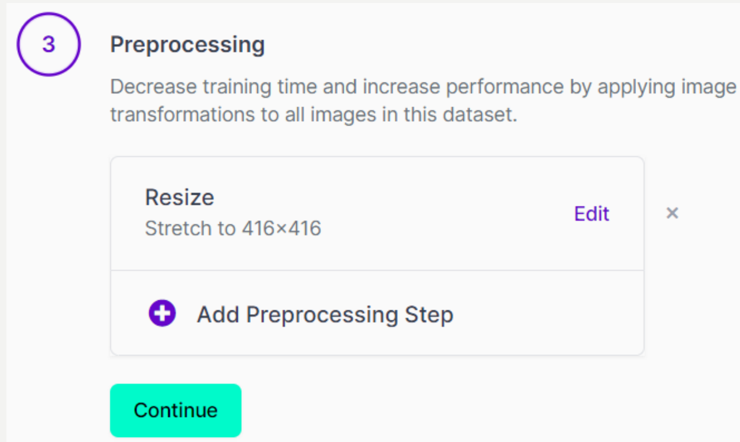


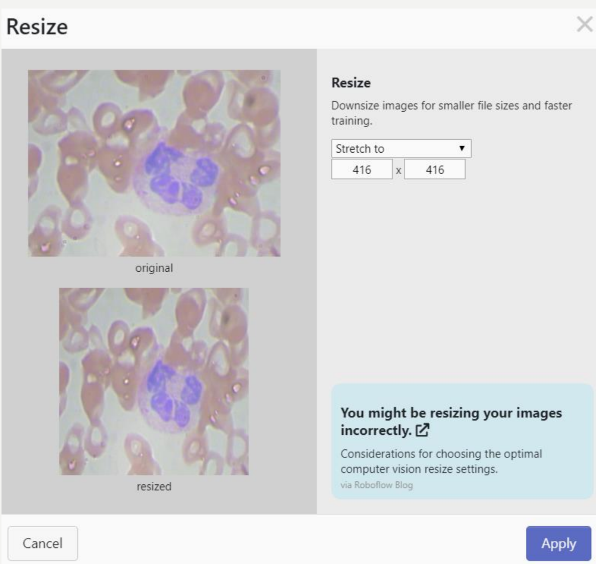


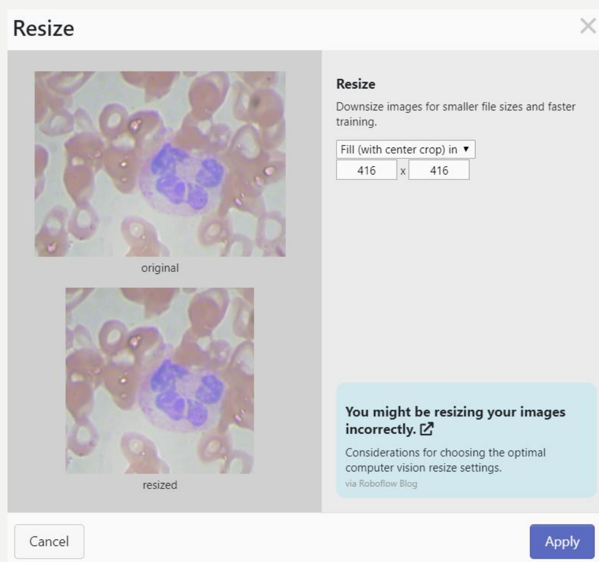
Roboflow Detection Implementation

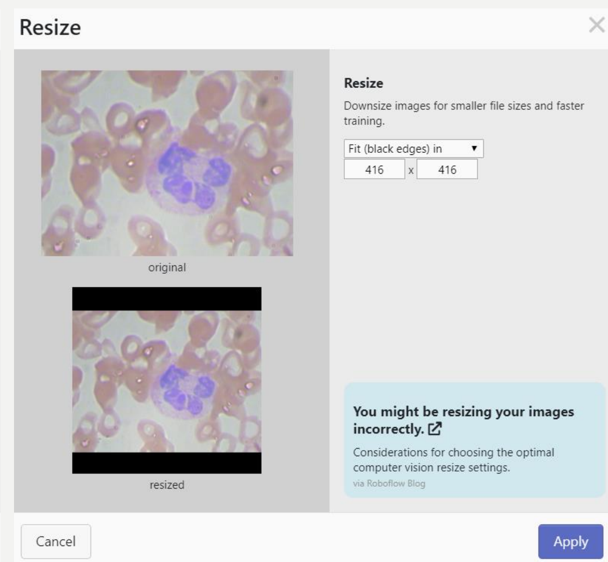
https://www.youtube.com/watch?v=MdF6x6ZmLAY

3. **Preprocessing of the training data:**
   - Stretching
   - Filling
   - Fitting
   - etc.









Roboflow Detection Implementation

https://www.youtube.com/watch?v=MdF6x6ZmLAY

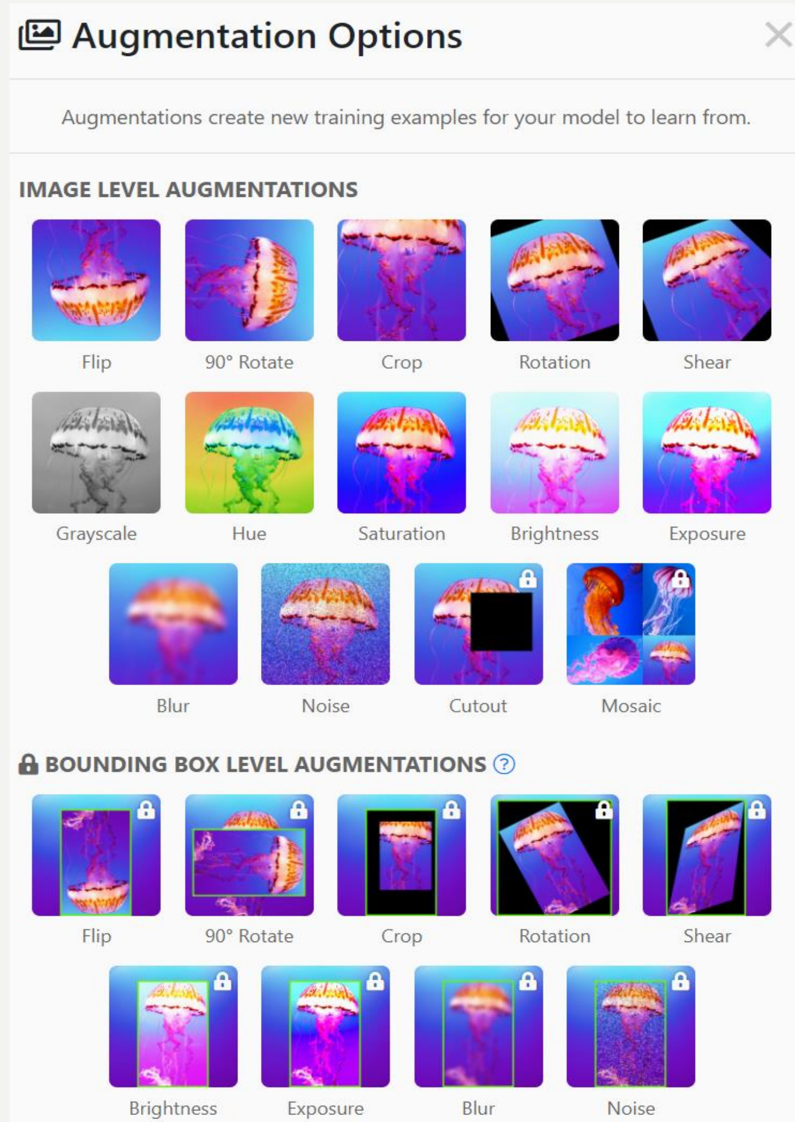
4. Augmentation for the enrichment of training data to achieve better performance

4 Augmentation

Create new training examples for your model to learn from by generating augmented versions of each image in your training set.

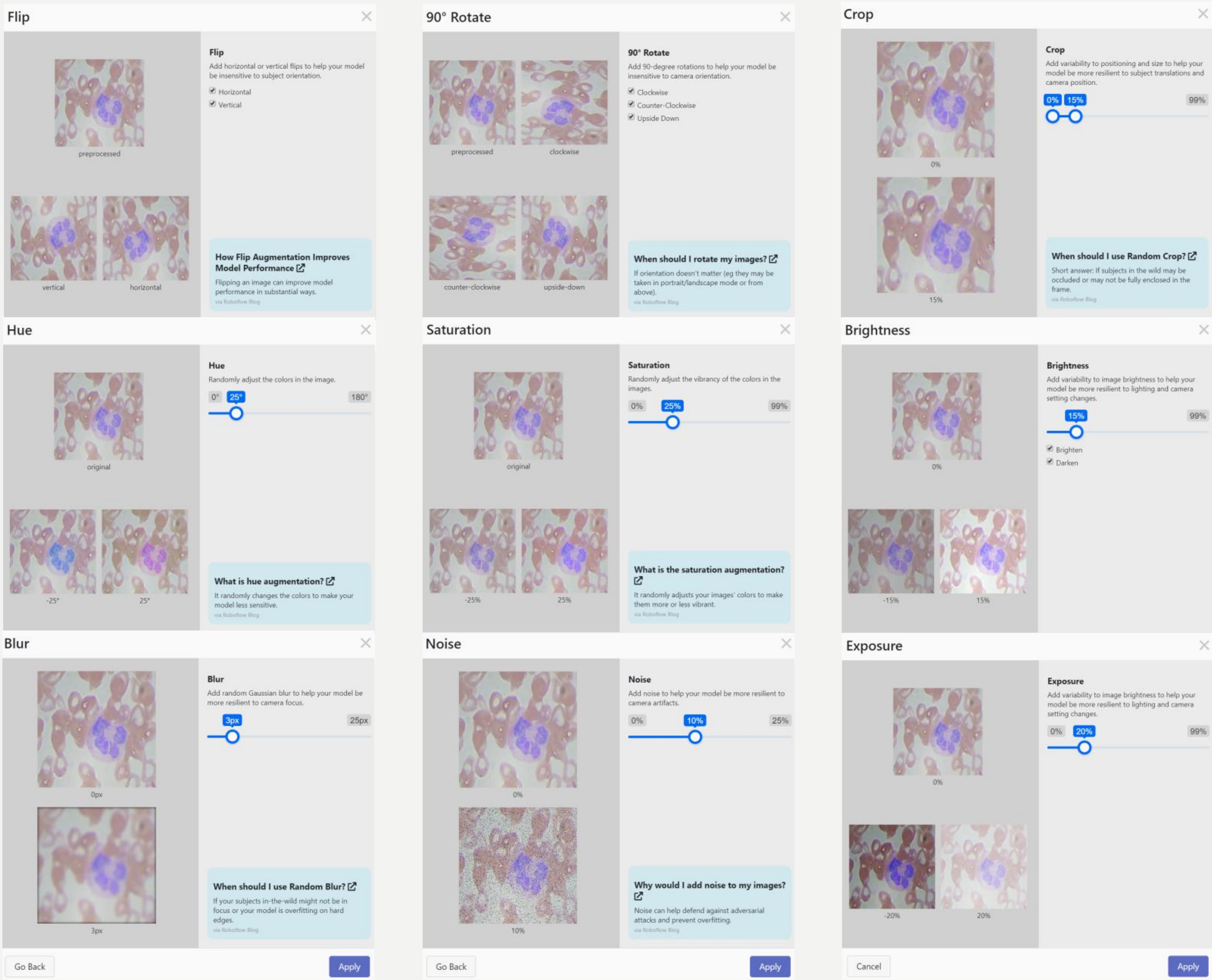
Flip Horizontal, Vertical	Edit	×
90° Rotate Clockwise, Counter-Clockwise, Upside Down	Edit	×
Crop 0% Minimum Zoom, 15% Maximum Zoom	Edit	×
Hue Between -25° and +25°	Edit	×
Saturation Between -25% and +25%	Edit	×
Brightness Between -15% and +15%	Edit	×
Exposure Between -20% and +20%	Edit	×
Blur Up to 3px	Edit	×
Noise Up to 10% of pixels	Edit	×

⊕ Add Augmentation Step



Roboflow Detection Implementation

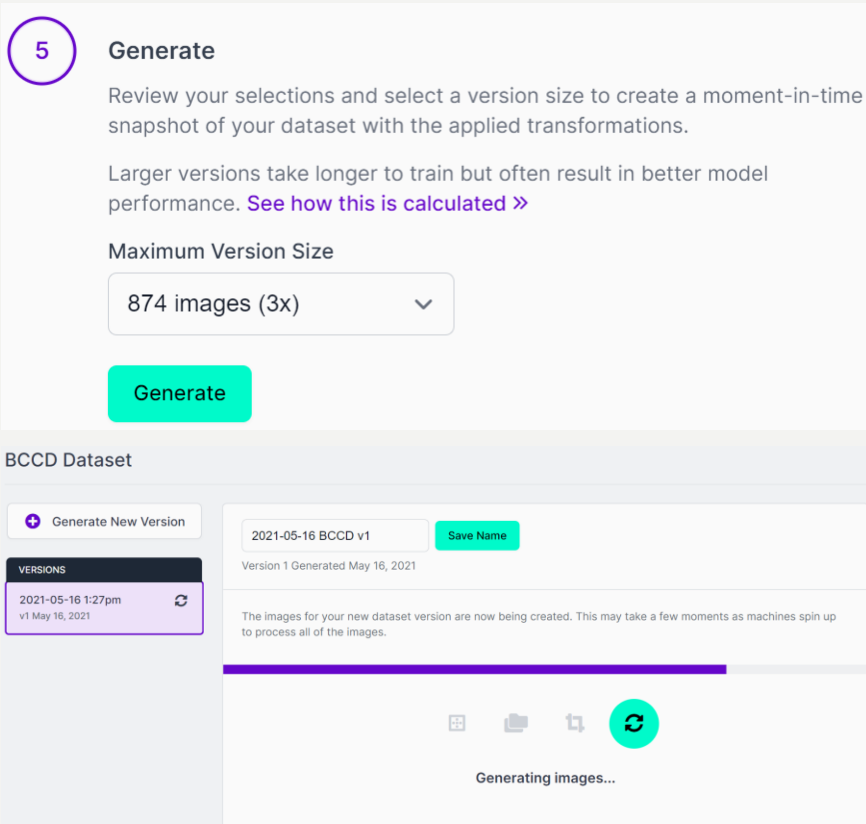
https://www.youtube.com/watch?v=MdF6x6ZmLAY

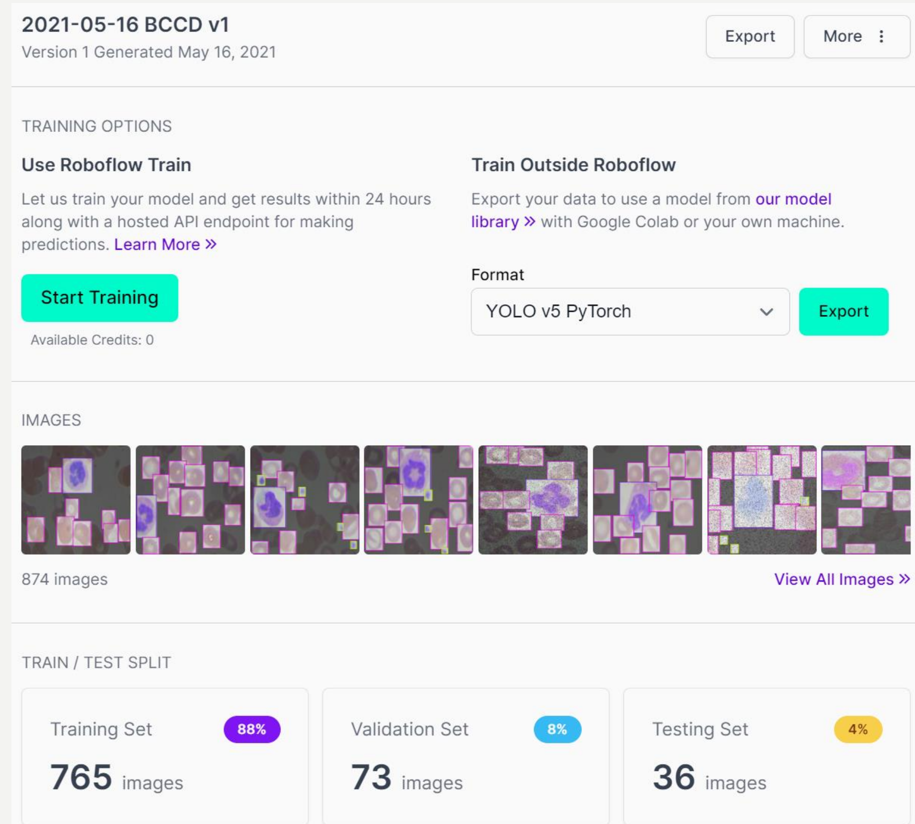


Roboflow Detection Implementation

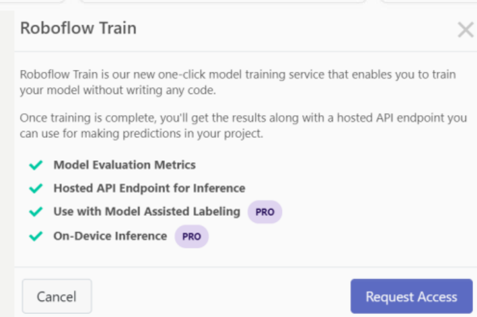
https://www.youtube.com/watch?v=MdF6x6ZmLAY

5. **Generation step creates a ready-to-use training data set using the data augmentation:**





6. **After these five steps, we are ready to Start Training:**



Roboflow Detection Implementation

https://www.youtube.com/watch?v=MdF6x6ZmLAY

7. Export the data to use the created model with Google Colab or your own machine:

8. Open YOLOv5 Colab Notebook

PyTorch Object Detection :: YOLOv5 TXT

YOLOv5

A very fast and easy to use PyTorch model that achieves state of the art (or near state of the art) results. Read More...

YOLOv5 Tutorial | YOLOv5 Video | YOLOv5 Repo | YOLOv5 Colab Notebook

Your Download Code

Jupyter | Terminal | Raw URL

Paste this snippet into a notebook from our model library to download and unzip your dataset:

Warning: Do not share this link beyond your team, it contains a private key that is tied to your Roboflow account. Acceptable use policy applies.

Done

9. Use your secret code with your dataset:

```
# Export code snippet and paste here
%cd /content
!curl -L "https://app.roboflow.com/ds/REPLACE-THIS-LINK" > roboflow.zip; unzip roboflow.zip; rm roboflow.zip
```

10. And start training:

```
# train yolov5s on custom data for 100 epochs
# time its performance
%%time
%cd /content/yolov5/
!python train.py --img 416 --batch 16 --epochs 100 --data '../data.yaml' --cfg ./models/custom_yolov5s.yaml --weights '' --name yolov5s_results  --cache
```

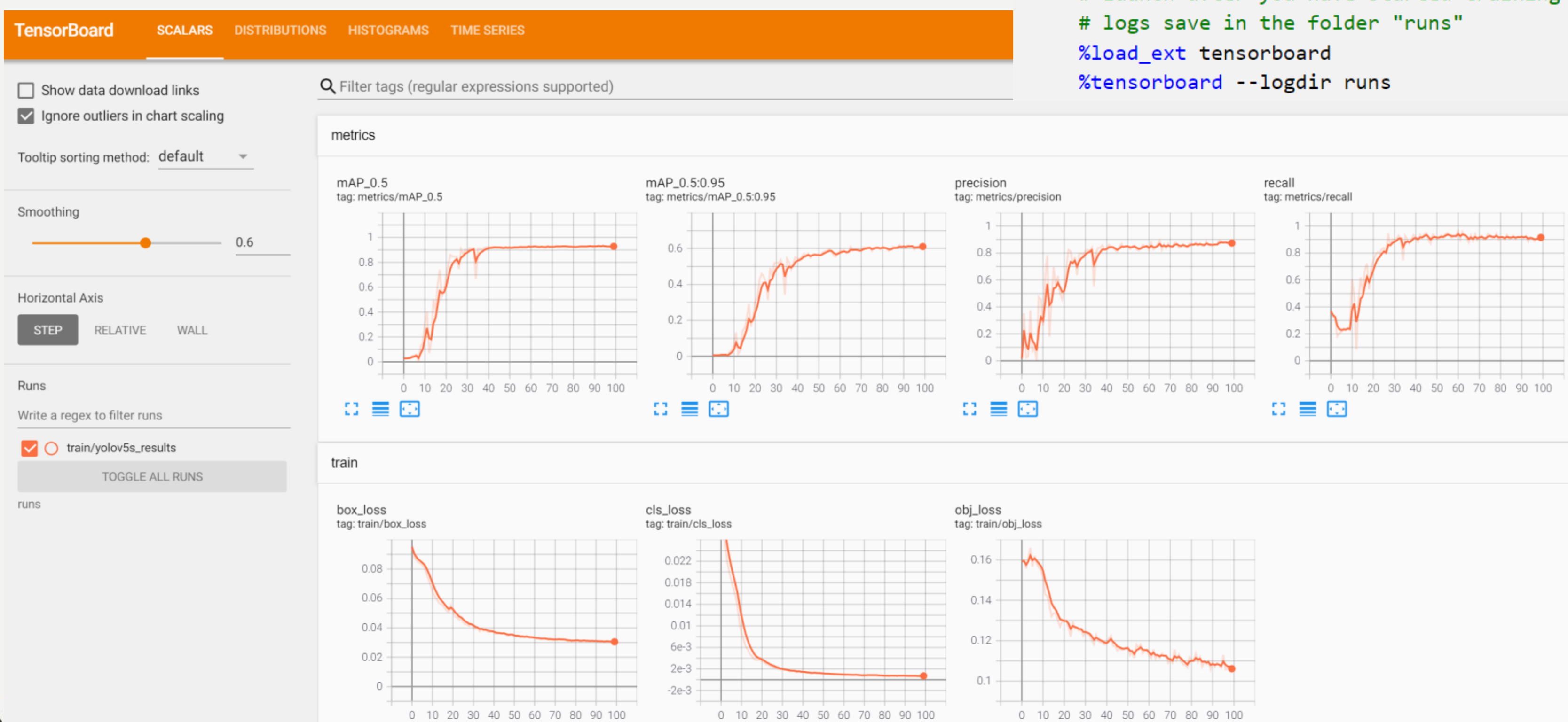
Roboflow Detection Implementation

https://www.youtube.com/watch?v=MdF6x6ZmLAY

11. When training is finished, we can see the result using the tensorboard:

```
     Epoch   gpu_mem       box       obj       cls     total   targets  img_size
     99/99     1.39G   0.03056    0.1046 0.0007596    0.1359       396       416: 100% 45/45 [00:05<00:00,  7.52it/s]
               Class    Images   Targets         P         R    mAP@.5  mAP@.5:.95: 100% 3/3 [00:01<00:00,  1.89it/s]
                 all        73       967     0.874     0.926     0.931     0.617
           Platelets        73        76     0.845     0.934     0.912     0.476
                 RBC        73       819      0.81     0.844     0.901      0.62
                 WBC        73        72     0.967         1     0.978     0.753
Optimizer stripped from runs/train/yolov5s_results/weights/last.pt, 14.8MB
Optimizer stripped from runs/train/yolov5s_results/weights/best.pt, 14.8MB
100 epochs completed in 0.202 hours.

CPU times: user 8.39 s, sys: 1.01 s, total: 9.4 s
Wall time: 12min 29s
```

```
[10] # Start tensorboard
     # Launch after you have started training
     # logs save in the folder "runs"
     %load_ext tensorboard
     %tensorboard --logdir runs
```

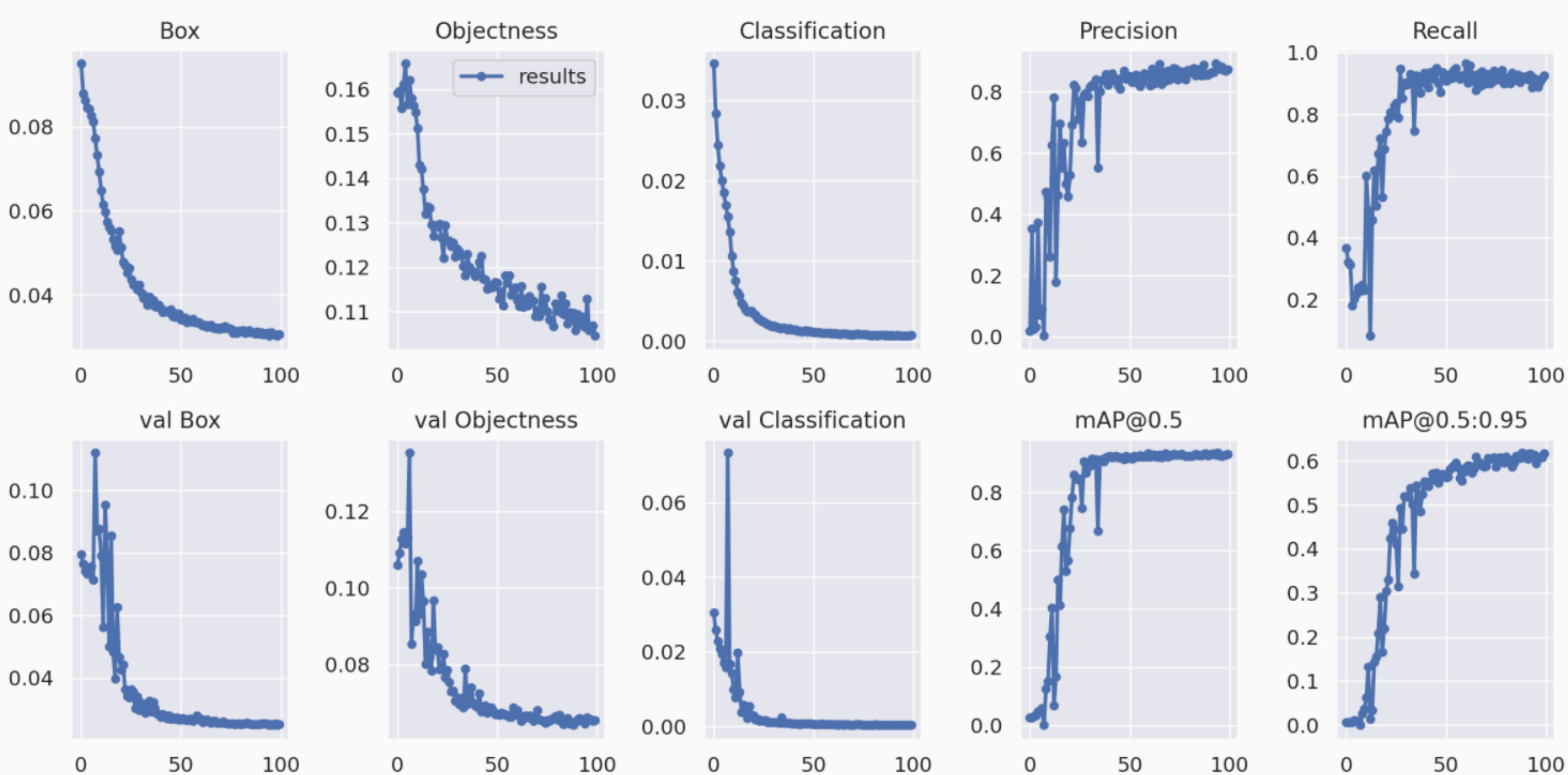


Roboflow Detection Implementation

https://www.youtube.com/watch?v=MdF6x6ZmLAY

12. The view of the training metrices and the model correctness:

```
[11] # we can also output some older school graphs if the tensor board isn't working for whatever reason...
     from utils.plots import plot_results  # plot results.txt as results.png
     Image(filename='/content/yolov5/runs/train/yolov5s_results/results.png', width=1000)  # view results.png
```

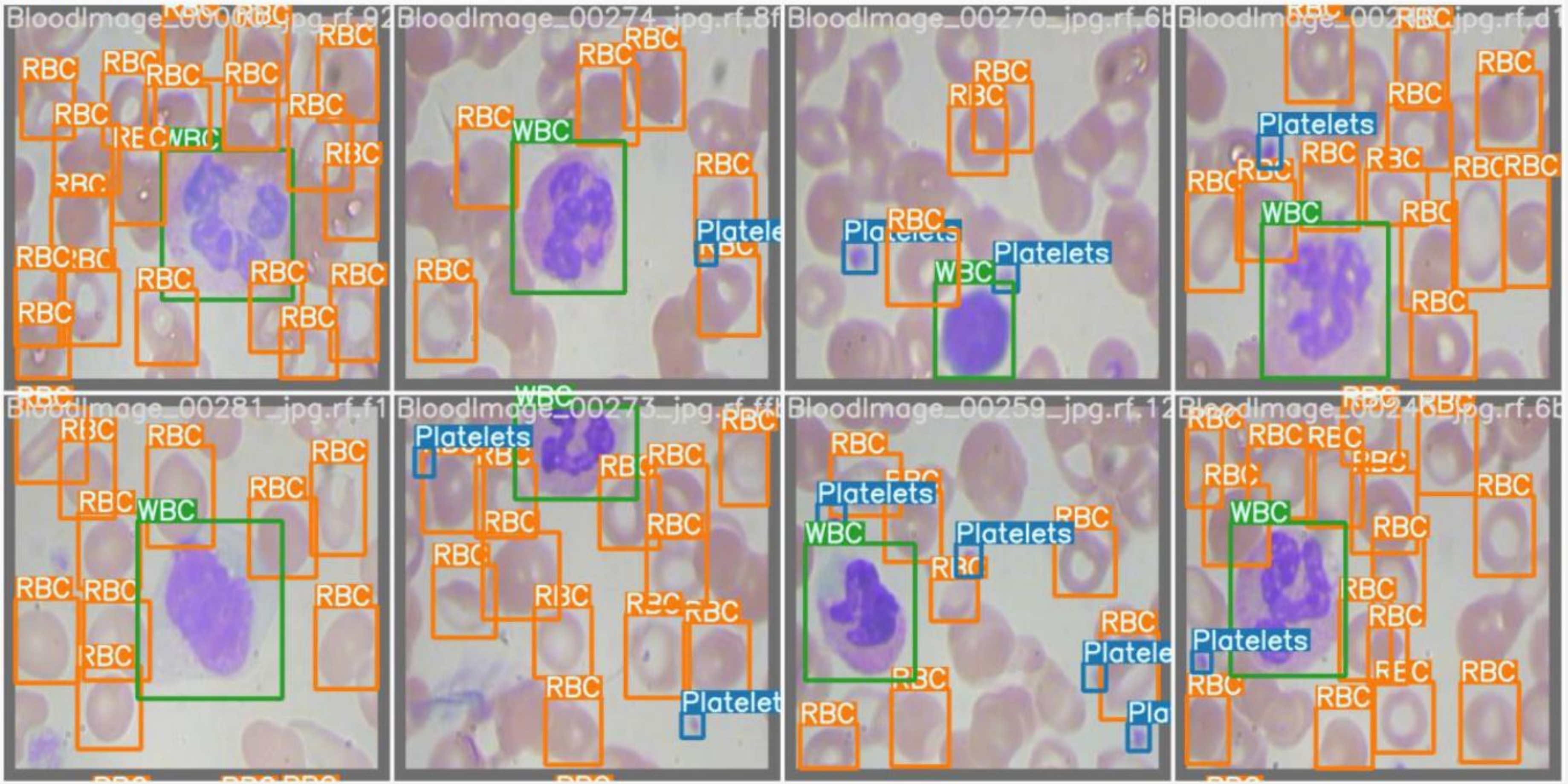


Roboflow Detection Implementation

https://www.youtube.com/watch?v=MdF6x6ZmLAY

13. Look at the ground truth BCCD training data:

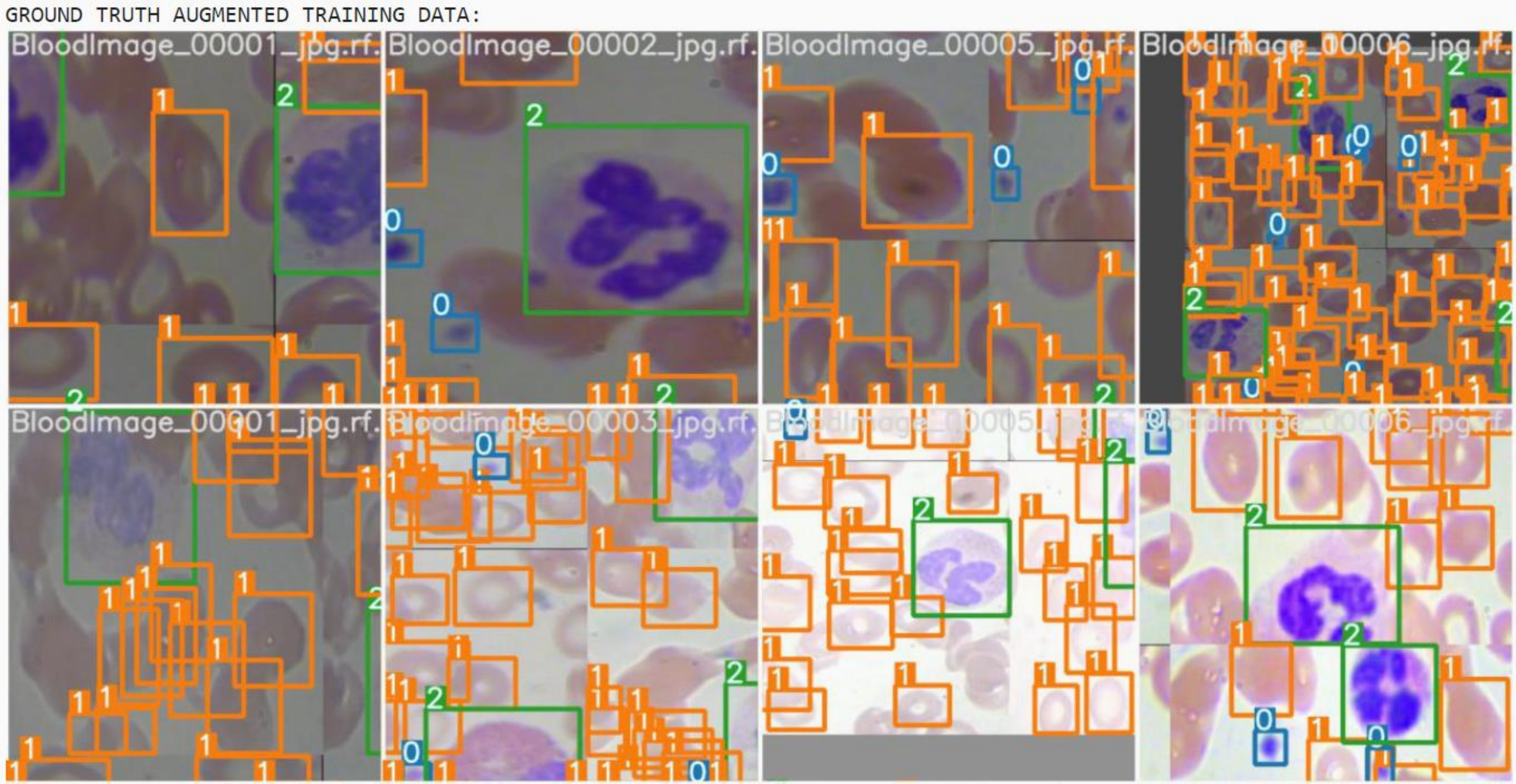
GROUND TRUTH TRAINING DATA:



Roboflow Detection Implementation

https://www.youtube.com/watch?v=MdF6x6ZmLAY

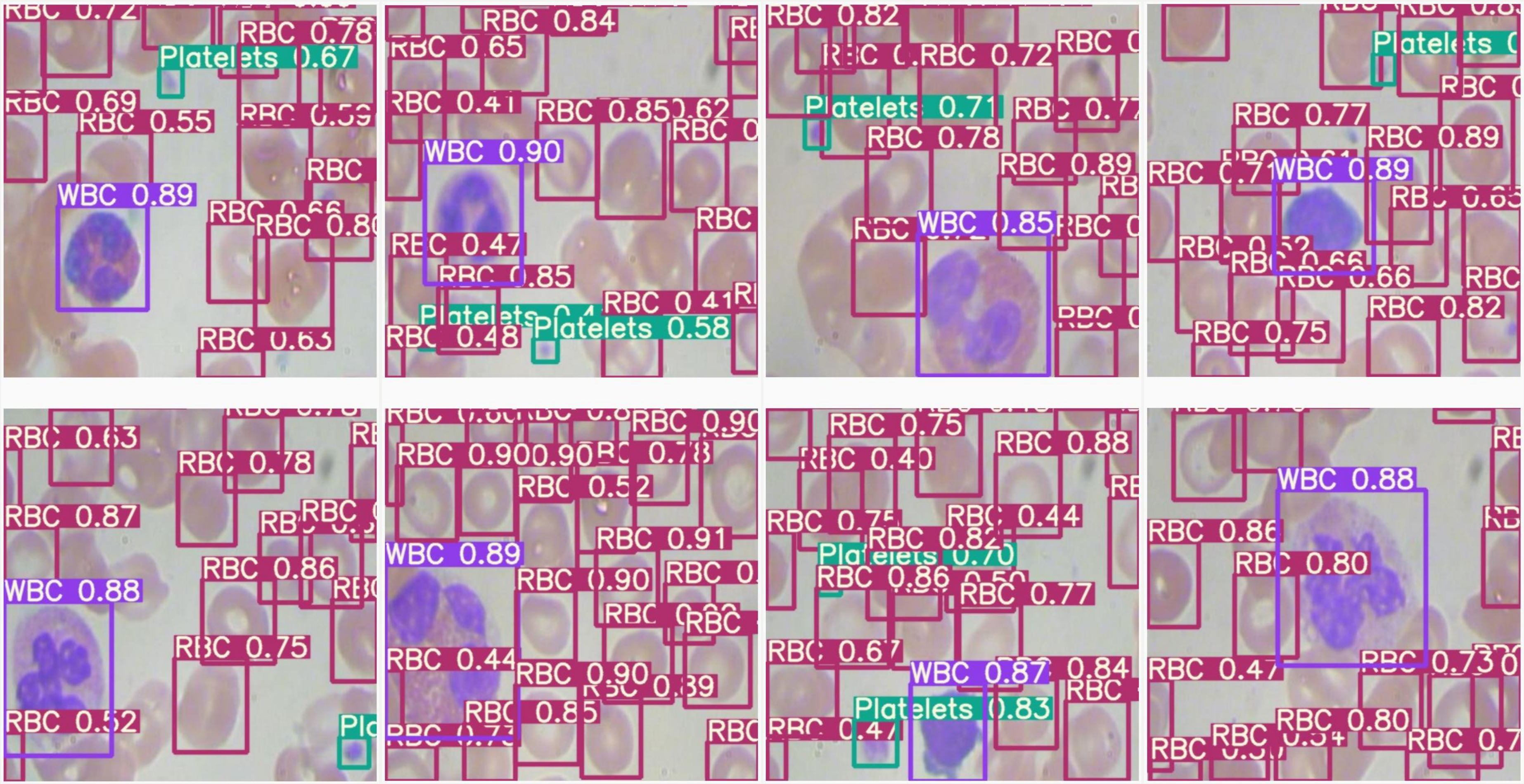
14. Look at the augmented ground truth BCCD training data:



Roboflow Detection Implementation

https://www.youtube.com/watch?v=MdF6x6ZmLAY

15. Finally, we can run inference and look at BCCD test images with detected objects:



Many cells were detected and classified correctly, but some of them are missing!

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http://home.agh.edu.pl/~horzyk/lectures/ahdydci.php

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COURSE CERTIFICATE

07/02/2019

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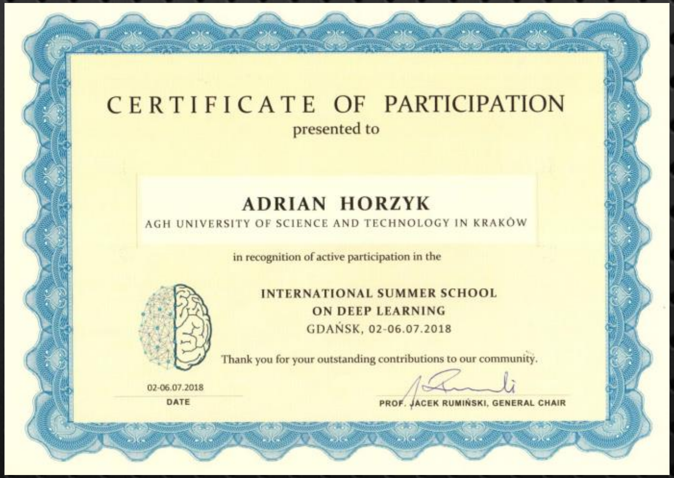

CERTIFICATE OF PARTICIPATION
presented to

ADRIAN HORZYK
AGH UNIVERSITY OF SCIENCE AND TECHNOLOGY IN KRAKÓW

in recognition of active participation in the

INTERNATIONAL SUMMER SCHOOL
ON DEEP LEARNING
GDAŃSK, 02-06.07.2018

Thank you for your outstanding contributions to our community.

02-06.07.2018
DATE

PROF. JACEK RUMIŃSKI, GENERAL CHAIR