# object-detection-yolo

April 2, 2020

# Object detection and classification with YOLOv2

Project created during the Deep Learning Specialization course on www.coursera.org

```
[1]: import warnings
     warnings.filterwarnings(action='ignore')
     import os
     import matplotlib.pyplot as plt
     from matplotlib.pyplot import imshow
     import numpy as np
     import imageio
     import tensorflow as tf
     from PIL import Image, ImageDraw, ImageFont
     from keras import backend as K
     import colorsys
     import random
     from io import BytesIO
     from keras.models import load_model
     %matplotlib inline
     Using TensorFlow backend.
```

### Input image preprocessing

```
[2]: # Preprocess input images to match model input size

def preprocess_image(img_path, model_image_size):

image = Image.open(img_path)

# Retrieve image shape (necessary to scale predicted bounding boxes later on)
image_shape = image.size[::-1]

# Resize image to correspond to model image size with BICUBIC interpolation

mode (cubic spline interpolation)

resized_image = image.resize(model_image_size, Image.BICUBIC)
```

```
# Convert image to a numpy array
        image_data = np.array(resized_image, dtype='float32')
        # Normalize image
        image_data /= 255.
        # Add batch dimension
        image_data = np.expand_dims(image_data, 0)
        # Display the image
        plt.show()
        return image, image_data, image_shape
    Defining anchor boxes
[3]: # Load anchor boxes dimensions (predefined)
     def read_anchors(anchors_path):
         with open(anchors_path) as f:
             anchors = f.readline()
             anchors = [float(x) for x in anchors.split(',')]
             anchors = np.array(anchors).reshape(-1, 2)
         return anchors
[4]: anchors = read_anchors('./yad2k/model_data/yolo_anchors.txt')
     anchors
 [4]: array([[0.57273, 0.677385],
             [1.87446 , 2.06253 ],
             [3.33843 , 5.47434 ],
             [7.88282 , 3.52778 ],
             [9.77052 , 9.16828 ]])
      Defining labels
  [5]: # Load labels from COCO dataset
       def read_classes(classes_path):
           with open(classes_path) as f:
               class_names = f.readlines()
           class_names = [c.strip() for c in class_names]
           return class_names
```

```
[6]: class_names = read_classes('./yad2k/model_data/coco_classes.txt')
     class_names[:10]
[6]: ['person',
       'bicycle',
       'car',
       'motorbike',
       'aeroplane',
       'bus',
       'train',
       'truck',
       'boat',
       'traffic light']
 [7]: # Generate colors to represent classes on the image (for drawing bounding boxes)
      def generate_colors(class_names):
          hsv_tuples = [(x / len(class_names), 1., 1.) for x in_{\sqcup}
        →range(len(class_names))]
          colors = list(map(lambda x: colorsys.hsv_to_rgb(*x), hsv_tuples))
          colors = list(map(lambda x: (int(x[0] * 255), int(x[1] * 255), int(x[2] *
       \rightarrow255)), colors))
          # Fixed seed for consistent colors across runs
          random.seed(10101)
          # Shuffle colors to decorrelate adjacent classes
          random.shuffle(colors)
          # Reset seed to default
          random.seed(None)
          return colors
      Loading pretrained YOLOv2
  [8]: sess = K.get_session()
  [9]: # Load pre-trained model from the official YOLO site, according to instructions
         \rightarrow in this repo:
        # https://github.com/allanzelener/YAD2K
        model = load_model('./yad2k/model_data/yolo.h5')
        WARNING:tensorflow:From /usr/local/lib/python3.6/site-
        packages/keras/backend/tensorflow_backend.py:4070: The name tf.nn.max_pool is
        deprecated. Please use tf.nn.max_pool2d instead.
```

WARNING:tensorflow:From /Users/alicjamazur/Desktop/dl/keras/utils\_yolo/yad2k/yad 2k/models/keras\_yolo.py:32: The name tf.space\_to\_depth is deprecated. Please use tf.compat.v1.space\_to\_depth instead.

## [10]: # Show model summary

model.summary()

Model: "model\_1"

Model: "model_1"						
Layer (type)			e 		Param #	Connected to
input_1 (InputLayer)	(None,	608,	608,	3)	0	
conv2d_1 (Conv2D)					864	_
batch_normalization_1 (BatchNor						
leaky_re_lu_1 (LeakyReLU) batch_normalization_1[0][0]	(None,	608,	608,	32)	0	
max_pooling2d_1 (MaxPooling2D) leaky_re_lu_1[0][0]	(None,	304,	304,	32)	0	
conv2d_2 (Conv2D) max_pooling2d_1[0][0]	(None,					
batch_normalization_2 (BatchNor						
leaky_re_lu_2 (LeakyReLU) batch_normalization_2[0][0]	(None,	304,	304,	64)	0	
	(None,	152,			0	
conv2d_3 (Conv2D)	(None,	152,				

max_pooling2d_2[0][0]		
	(None, 152, 152, 128 512 conv2d_3[	
leaky_re_lu_3 (LeakyReLU) batch_normalization_3[0][0]	(None, 152, 152, 128 0	
conv2d_4 (Conv2D) leaky_re_lu_3[0][0]	(None, 152, 152, 64) 8192	
batch_normalization_4 (BatchNor	(None, 152, 152, 64) 256 conv2d_4[	[0] [0]
leaky_re_lu_4 (LeakyReLU) batch_normalization_4[0][0]	(None, 152, 152, 64) 0	
conv2d_5 (Conv2D) leaky_re_lu_4[0][0]	(None, 152, 152, 128 73728	
	(None, 152, 152, 128 512 conv2d_5	
leaky_re_lu_5 (LeakyReLU) batch_normalization_5[0][0]	(None, 152, 152, 128 0	
max_pooling2d_3 (MaxPooling2D) leaky_re_lu_5[0][0]	(None, 76, 76, 128) 0	
	(None, 76, 76, 256) 294912	
batch_normalization_6 (BatchNor	(None, 76, 76, 256) 1024 conv2d_6[	[0]
leaky_re_lu_6 (LeakyReLU) batch_normalization_6[0][0]	(None, 76, 76, 256) 0	
conv2d_7 (Conv2D)	(None, 76, 76, 128) 32768	

leaky_re_lu_6[0][0]						
batch_normalization_7 (BatchNor					512	
leaky_re_lu_7 (LeakyReLU) batch_normalization_7[0][0]	(None,	76,				
conv2d_8 (Conv2D) leaky_re_lu_7[0][0]			76,	256)	294912	
batch_normalization_8 (BatchNor		76,	76,	256)	1024	conv2d_8[0][0]
leaky_re_lu_8 (LeakyReLU) batch_normalization_8[0][0]	(None,	76,	76,	256)	0	
max_pooling2d_4 (MaxPooling2D) leaky_re_lu_8[0][0]	(None,	38,	38,	256)	0	
conv2d_9 (Conv2D) max_pooling2d_4[0][0]	(None,					
batch_normalization_9 (BatchNor						
leaky_re_lu_9 (LeakyReLU) batch_normalization_9[0][0]	(None,	38,	38,		0	
conv2d_10 (Conv2D) leaky_re_lu_9[0][0]				256)	131072	
batch_normalization_10 (BatchNo	(None,	38,	38,	256)	1024	conv2d_10[0][0]
leaky_re_lu_10 (LeakyReLU) batch_normalization_10[0][0]	(None,	38,	38,	256)	0	
conv2d_11 (Conv2D)	(None,					

leaky_re_lu_10[0][0]						
batch_normalization_11 (BatchNo						
leaky_re_lu_11 (LeakyReLU) batch_normalization_11[0][0]						
conv2d_12 (Conv2D) leaky_re_lu_11[0][0]					131072	
batch_normalization_12 (BatchNo						
	(None,	38,	38,	256)	0	
conv2d_13 (Conv2D) leaky_re_lu_12[0][0]	(None,	38,	38,	512)	1179648	
batch_normalization_13 (BatchNo	(None,	38,	38,	512)	2048	conv2d_13[0][0]
leaky_re_lu_13 (LeakyReLU) batch_normalization_13[0][0]						
 max_pooling2d_5 (MaxPooling2D) leaky_re_lu_13[0][0]						
 conv2d_14 (Conv2D) max_pooling2d_5[0][0]	(None,	19,	19,	1024)	4718592	
batch_normalization_14 (BatchNo	(None,	19,	19,	1024)	4096	conv2d_14[0][0]
leaky_re_lu_14 (LeakyReLU) batch_normalization_14[0][0]	(None,	19,	19,	1024)	0	
conv2d_15 (Conv2D)					524288	<b>-</b>

leaky_re_lu_14[0][0]						
batch_normalization_15 (BatchNo						
leaky_re_lu_15 (LeakyReLU) batch_normalization_15[0][0]	(None,	19,	19,	512)	0	
conv2d_16 (Conv2D) leaky_re_lu_15[0][0]	(None,	19,	19,	1024)	4718592	
batch_normalization_16 (BatchNo						
leaky_re_lu_16 (LeakyReLU) batch_normalization_16[0][0]	(None,	19,	19,	1024)	0	
conv2d_17 (Conv2D) leaky_re_lu_16[0][0]					524288	
batch_normalization_17 (BatchNo						
leaky_re_lu_17 (LeakyReLU) batch_normalization_17[0][0]						
conv2d_18 (Conv2D) leaky_re_lu_17[0][0]					4718592	
batch_normalization_18 (BatchNo	(None,	19,	19,	1024)	4096	conv2d_18[0][0]
leaky_re_lu_18 (LeakyReLU) batch_normalization_18[0][0]	(None,	19,	19,	1024)	0	
conv2d_19 (Conv2D) leaky_re_lu_18[0][0]	(None,	19,	19,	1024)	9437184	
batch_normalization_19 (BatchNo						conv2d_19[0][0]

conv2d_21 (Conv2D) leaky_re_lu_13[0][0]	(None,	-			32768	
leaky_re_lu_19 (LeakyReLU) batch_normalization_19[0][0]	(None,					
batch_normalization_21 (BatchNo	-	-	-			
conv2d_20 (Conv2D) leaky_re_lu_19[0][0]	(None,	19,	19,	1024)	9437184	
leaky_re_lu_21 (LeakyReLU) batch_normalization_21[0][0]	(None,	38,	38,	64)	0	
batch_normalization_20 (BatchNo	(None,	19,	19,	1024)	4096	conv2d_20[0][0]
space_to_depth_x2 (Lambda) leaky_re_lu_21[0][0]	(None,	19,	19,	256)	0	
leaky_re_lu_20 (LeakyReLU) batch_normalization_20[0][0]	(None,	19,	19,	1024)	0	
concatenate_1 (Concatenate) space_to_depth_x2[0][0] leaky_re_lu_20[0][0]	(None,					
conv2d_22 (Conv2D) concatenate_1[0][0]	(None,	19,	19,	1024)	11796480	
batch_normalization_22 (BatchNo						
leaky_re_lu_22 (LeakyReLU) batch_normalization_22[0][0]	(None,					

#### Feature extraction and conversion to bounding box params

```
[11]: # Retrieve features from the final layer of the model
      features = model.output
[12]: # Convert model features to bounding box parameters
      def features_to_boxes(features, anchors, num_classes):
          num_anchors = len(anchors)
           # Reshape to batch, height, width, num_anchors, box_params
          anchors_tensor = K.reshape(K.variable(anchors), [1, 1, 1, num_anchors, 2])
           # Dynamic implementation of conv dims for fully convolutional model
          conv_dims = K.shape(features)[1:3] # assuming channels last
           # In YOLO the height index is the inner most iteration
          conv_height_index = K.arange(0, stop=conv_dims[0])
          conv_width_index = K.arange(0, stop=conv_dims[1])
          conv_height_index = K.tile(conv_height_index, [conv_dims[1]])
          conv_width_index = K.tile(
              K.expand_dims(conv_width_index, 0), [conv_dims[0], 1])
          conv_width_index = K.flatten(K.transpose(conv_width_index))
          conv_index = K.transpose(K.stack([conv_height_index, conv_width_index]))
          conv_index = K.reshape(conv_index, [1, conv_dims[0], conv_dims[1], 1, 2])
          conv_index = K.cast(conv_index, K.dtype(features))
          features = K.reshape(
              features, [-1, conv_dims[0], conv_dims[1], num_anchors, num_classes + 5])
          conv_dims = K.cast(K.reshape(conv_dims, [1, 1, 1, 1, 2]), K.dtype(features))
          box_xy = K.sigmoid(features[..., :2])
          box_wh = K.exp(features[..., 2:4])
          box_confidence = K.sigmoid(features[..., 4:5])
          box_class_probs = K.softmax(features[..., 5:])
```

```
# Adjust preditions to each spatial grid point and anchor size.
         # Note: YOLO iterates over height index before width index.
         box_xy = (box_xy + conv_index) / conv_dims
         box_wh = box_wh * anchors_tensor / conv_dims
         return box_xy, box_wh, box_confidence, box_class_probs
[13]: yolo_outputs = features_to_boxes(features, anchors, len(class_names))
      Evaluation of detected objects
      Selection of most probable bounding boxes
[14]: # Evaluate detected objects
      def yolo_evaluate(yolo_outputs, image_shape=(720., 1280.), max_output_size=10,_u
        →score_threshold=.6, iou_threshold=.5):
           # Unpack bounding box params
          xy, wh, confidence, class_probs = yolo_outputs
           # Convert boxes information from (middle-point-coordinates, width-height) to \Box
        →corners coordinates
          boxes = boxes_to_corners(xy, wh)
           # Step 1: eliminate boxes with low probabilities - filter boxes with scoresu
        → lower than the threshold
           scores, boxes, classes = filter_boxes(confidence, boxes, class_probs,_
        ⇒score_threshold)
           # Step 2: eliminate boxes with non-max scores and high overlap - filter
        →boxes with IoU lower than the threshold
          scores, boxes, classes = non_max_suppression(scores, boxes, classes, ⊔
        →max_output_size, iou_threshold)
           # Scale boxes to match input image size
          boxes = scale_boxes(boxes, image_shape)
          return scores, boxes, classes
 [15]: # Helper function: convert boxes to corners
       def boxes_to_corners(box_xy, box_wh):
           box_mins = box_xy - (box_wh / 2.)
```

 $box_maxes = box_xy + (box_wh / 2.)$ 

```
return K.concatenate([
              box_mins[..., 1:2], \# y_min
              box_mins[..., 0:1], \# x_min
              box_maxes[..., 1:2], \# y_max
              box_maxes[..., 0:1]]) # x_max
[16]: # Helper function: eliminate boxes data with low predicted probability
      def filter_boxes(confidence, boxes, class_probs, threshold = 0.6):
           # Compute the score for each box (object probability multiplied by class_{f \sqcup}
       \rightarrow probability)
          scores = confidence * class_probs
          # Find class with maximum score for each box and respective score
          classes_with_max_score = K.argmax(scores, axis=-1)
          max_scores = K.max(scores, axis=-1)
          # Define a mask (binary filter) to discard boxes with score lower than the
       \rightarrowset threshold
          mask = (max_scores >= threshold)
          # Apply the mask to discard boxes data with the score lower than the set \Box
       \rightarrow threshold
          scores = tf.boolean_mask(max_scores, mask)
          boxes = tf.boolean_mask(boxes, mask)
          classes = tf.boolean_mask(classes_with_max_score, mask)
          return scores, boxes, classes
[17]: '''
       Calculate intersection over union ratio. This function is not used in this \sqcup
        \hookrightarrow implementation.
       Here just as an exercise.
       111
       def iou(box1, box2):
           # Unpack vertices information
           (x1_1, y1_1, x2_1, y2_1) = box1
           (x1_2, y1_2, x2_2, y2_2) = box2
           # Find area of intersection
           width = min(x2_1, x2_2) - max(x1_1, x1_2)
           height = min(y2_1, y2_2) - max(y1_1, y1_2)
           intersection = max(width, 0) * max(height, 0)
```

```
# Find union area
         area_1 = (x2_1 - x1_1) * (y2_1 - y1_1)
         area_2 = (x2_2 - x1_2) * (y2_2 - y1_2)
         union = area_1 + area_2 - intersection
         # Compute IoU
         iou = intersection / union
         return iou
[18]: # Helper function: perform non-max suppression to make sure algorithm detects
       → objects only once
      def non_max_suppression(scores, boxes, classes, max_output_size = 10,__
       →iou_threshold = 0.5):
          # Initialize max_output_size variable (we need it later to perform tf.image.
       \rightarrownon_max_suppression)
          max_output_size_tensor = K.variable(max_output_size, dtype='int32')
          K.get_session().run(tf.variables_initializer([max_output_size_tensor]))
          # Return indices from the boxes data to keep: eliminate non-max scores with _{f L}
       →a significant overlap with the max score
          remaining_indices = tf.image.non_max_suppression(boxes, scores,
       →max_output_size_tensor, iou_threshold=0.5)
          # Get rid of bounding box data with non-max scores and significant overlap_{\sqcup}
       \rightarrow with max score
          scores = K.gather(scores, remaining_indices)
          boxes = K.gather(boxes, remaining_indices)
          classes = K.gather(classes, remaining_indices)
          return scores, boxes, classes
[19]: # Helper function: Scale predicted boxes to make them drawble on the image,
        → (normalize boxes by image dimensions)
       def scale_boxes(boxes, image_shape):
           # Retrieve image dimensions
           height = image_shape[0]
           width = image_shape[1]
           # Stack and reshape image dimensions to correspond to boxes coordinates ...
        \hookrightarrow (b_x, b_y, b_h, b_w)
```

```
image_dims = K.stack([height, width, height, width])
image_dims = K.reshape(image_dims, [1, 4])
image_dims = K.cast(image_dims, 'float32')
# Normalize boxes by image dimensions
boxes = boxes * image_dims
return boxes
```

#### **Testing**

```
[20]: # Make predictions and draw predicted bounding boxes on the input image
      def predict(sess, img_path):
          # Preprocess input images to match model input size
          image, image_data, image_shape = preprocess_image(img_path, model_image_size_
       \Rightarrow= (608, 608))
          # Optimize: perform forward propagation
          out_scores, out_boxes, out_classes = sess.run(yolo_evaluate(yolo_outputs,_
       →image_shape), feed_dict={model.input: image_data,
                                                                                       ш
                               K.learning_phase(): 0})
          # Draw bounding boxes on the input image
          draw_boxes(image, out_scores, out_boxes, out_classes, class_names)
          # Save edited image
          path, filename = os.path.split(img_path)
          image.save(os.path.join('./out', filename), quality=90)
          # Display the image
          output_image = imageio.imread(os.path.join('out/', filename))
          imshow(output_image)
          return out_scores, out_boxes, out_classes
[21]: # Helper function: draw selected bounding boxes on the image
      def draw_boxes(image, out_scores, out_boxes, out_classes, class_names):
           # Generate colors for drawing predicted bounding boxes
           colors = generate_colors(class_names)
           # Load a font - workaround for ImageFont.truetype OSError
           file = open("./font/FiraMono-Medium.otf", "rb")
           bytes_font = BytesIO(file.read())
```

```
font = ImageFont.truetype(bytes_font, size=np.floor(3e-2 * image.size[1] + 0.

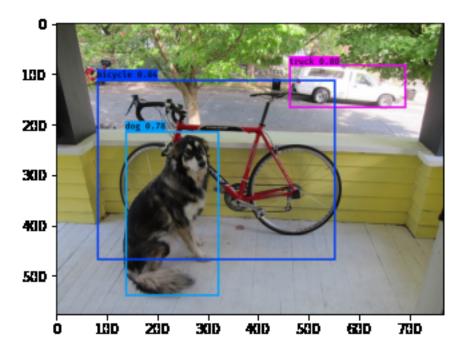
→5).astype('int32'))
  file.close()
  # Set bounding box line thickness
  thickness = (image.size[0] + image.size[1]) // 300
  for i, c in reversed(list(enumerate(out_classes))):
       # Retrieve box parameters
      predicted_class = class_names[c]
      box = out_boxes[i]
      score = out_scores[i]
       # Create output label
      label = '{} {:.2f}'.format(predicted_class, score)
       # Draw the bounding box on the image
      draw = ImageDraw.Draw(image)
      label_size = draw.textsize(label, font)
       # Retrieve box coordinates
      top, left, bottom, right = box
       # Limit bounding box coordinates to the image dimensions
      top = max(0, np.floor(top + 0.5).astype('int32'))
      left = max(0, np.floor(left + 0.5).astype('int32'))
      bottom = min(image.size[1], np.floor(bottom + 0.5).astype('int32'))
      right = min(image.size[0], np.floor(right + 0.5).astype('int32'))
       # Set origin for the label text
      if top - label_size[1] >= 0:
          text_origin = np.array([left, top - label_size[1]])
      else:
          text_origin = np.array([left, top + 1])
       # My kingdom for a good redistributable image drawing library.
      for i in range(thickness):
          draw.rectangle([left + i, top + i, right - i, bottom - i],__
→outline=colors[c])
      draw.rectangle([tuple(text_origin), tuple(text_origin + label_size)],__
→fill=colors[c])
      draw.text(text_origin, label, fill=(0, 0, 0), font=font)
      del draw
```

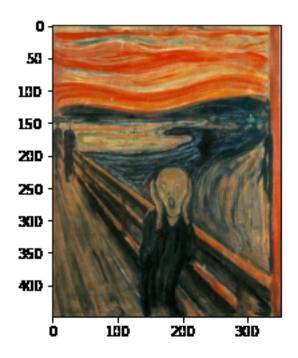
WARNING:tensorflow:From /usr/local/lib/python3.6/site-packages/tensorflow/python/ops/array\_ops.py:1354:

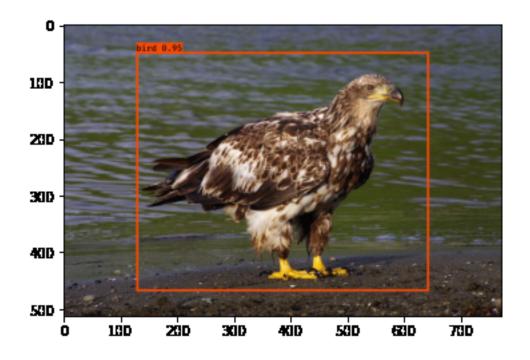
add\_dispatch\_support.<locals>.wrapper (from tensorflow.python.ops.array\_ops) is deprecated and will be removed in a future version.

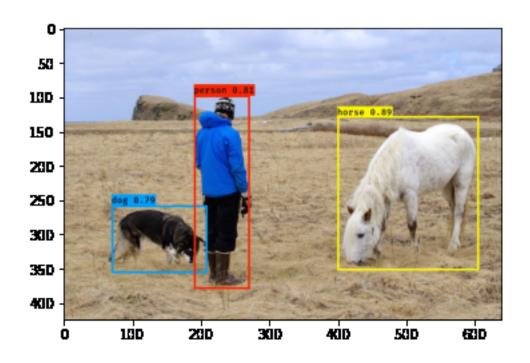
Instructions for updating:

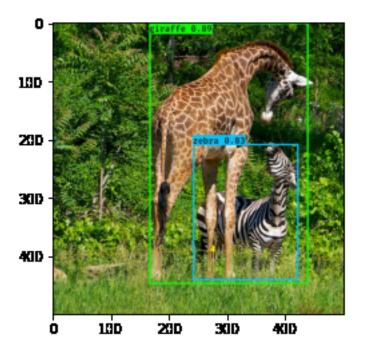
Use tf.where in 2.0, which has the same broadcast rule as np.where

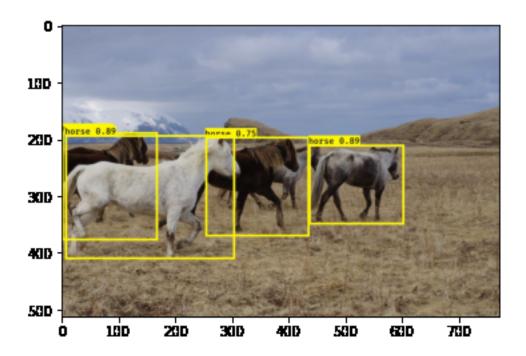


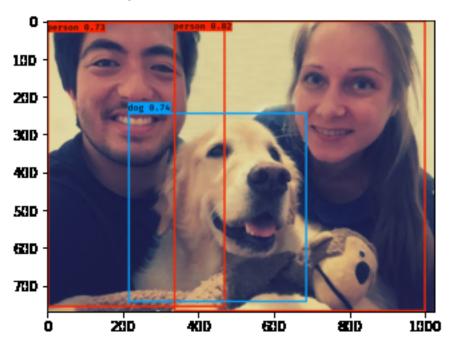


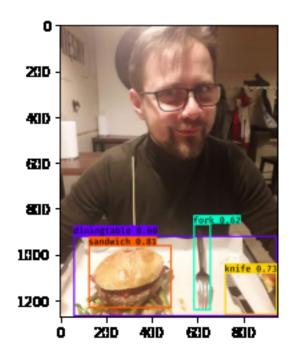


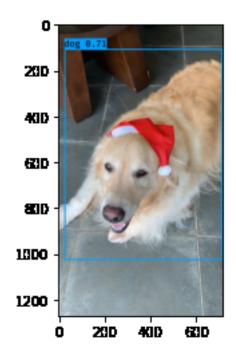


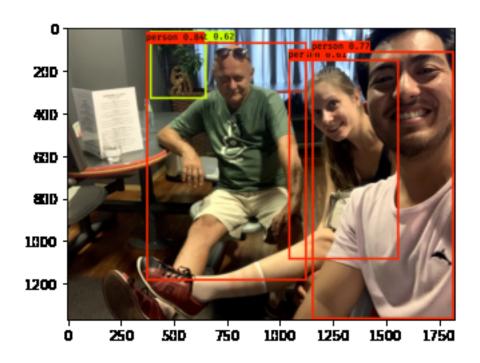












[]: