car object detection with YOLO algorithm on drown video with Opencv.

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Object detection is a task in computer vision that involves identifying the presence, location, and type of one or more objects in a given photograph or a video.

It is a challenging problem that involves building upon methods for object recognition, object localization, and object classification.
In recent years, deep learning techniques are achieving state-of-the-art results for object detection, such as on standard benchmark datasets and in computer vision competitions. Notable is the “You Only Look Once,” or YOLO, family of Convolutional Neural Networks that achieve near state-of-the-art results with a single end-to-end model that can perform object detection in real-time.

The official DarkNet GitHub repository contains the source code for the YOLO versions mentioned in the papers, written in C. The repository provides a step-by-step tutorial on how to use the code for object detection.

The first step is to download the pre-trained model weights.These were trained using the DarkNet code base on the MSCOCO dataset. Download the model weights and place them into your current working directory with the filename “*yolov3.weights*.” It is a large file and may take a moment to download depending on the speed of your internet connection.Next, we need to define a Keras model that has the right number and type of layers to match the downloaded model weights.The “yolo3_one_file_to_detect_them_all.py” script provides the *make_yolov3_model()* function to create the model for us, and the helper function *_conv_block()* that is used to create blocks of layers. These two functions can be copied directly from the script.To use the *WeightReader*, it is instantiated with the path to our weights file (e.g. ‘*yolov3.weights*‘). This will parse the file and load the model weights into memory in a format that we can set into our Keras model.We can then call the *load_weights()* function of the *WeightReader* instance, passing in our defined Keras model to set the weights into the layers.That’s it; we now have a YOLOv3 model for use.We can save this model to a Keras compatible .h5 model file ready for later use.

We can tie all of this together; the complete code example including functions copied directly from the "*yolo3_one_file_to_detect_them_all.py*" script.

```
import struct

import cv2
import numpy as np
from keras.layers import Conv2D
from keras.layers import Input
from keras.layers import BatchNormalization
from keras.layers import LeakyReLU
from keras.layers import ZeroPadding2D
from keras.layers import UpSampling2D
from keras.layers.merge import add, concatenate
from keras.models import Model
from numpy import expand_dims
from keras.models import load_model
from keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array
from numpy import expand_dims
from keras.models import load_model
from matplotlib import pyplot
from matplotlib.patches import Rectangle
```

```
def _conv_block(inp, convs, skip=True):
    x = inp
    count = 0
    for conv in convs:
        if count == (len(convs) - 2) and skip:
            skip_connection = x
        count += 1
        if conv['stride'] > 1: x = ZeroPadding2D(((1, 0), (1, 0)))(x)  # peculiar padding as darknet prefer left and top
        x = Conv2D(conv['filter'],
                   conv['kernel'],
                   strides=conv['stride'],
                   padding='valid' if conv['stride'] > 1 else 'same',  # peculiar padding as darknet prefer left and top
                   name='conv_' + str(conv['layer_idx']),
                   use_bias=False if conv['bnorm'] else True)(x)
        if conv['bnorm']: x = BatchNormalization(epsilon=0.001, name='bnorm_' + str(conv['layer_idx']))(x)
        if conv['leaky']: x = LeakyReLU(alpha=0.1, name='leaky_' + str(conv['layer_idx']))(x)
    return add([skip_connection, x]) if skip else x
```

```python
def make_yolov3_model():
    input_image = Input(shape=(None, None, 3))
    # Layer  0 => 4
    x = _conv_block(input_image,
                    [{'filter': 32, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 0},
                     {'filter': 64, 'kernel': 3, 'stride': 2, 'bnorm': True, 'leaky': True, 'layer_idx': 1},
                     {'filter': 32, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 2},
                     {'filter': 64, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 3}])
    # Layer  5 => 8
    x = _conv_block(x, [{'filter': 128, 'kernel': 3, 'stride': 2, 'bnorm': True, 'leaky': True, 'layer_idx': 5},
                        {'filter': 64, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 6},
                        {'filter': 128, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 7}])
    # Layer  9 => 11
    x = _conv_block(x, [{'filter': 64, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 9},
                        {'filter': 128, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 10}])
    # Layer 12 => 15
    x = _conv_block(x, [{'filter': 256, 'kernel': 3, 'stride': 2, 'bnorm': True, 'leaky': True, 'layer_idx': 12},
                        {'filter': 128, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 13},
                        {'filter': 256, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 14}])
    # Layer 16 => 36
    for i in range(7):
        x = _conv_block(x, [
            {'filter': 128, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 16 + i * 3},
            {'filter': 256, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 17 + i * 3}])
    skip_36 = x
    # Layer 37 => 40
    x = _conv_block(x, [{'filter': 512, 'kernel': 3, 'stride': 2, 'bnorm': True, 'leaky': True, 'layer_idx': 37},
                        {'filter': 256, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 38},
                        {'filter': 512, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 39}])
    # Layer 41 => 61
    for i in range(7):
        x = _conv_block(x, [
            {'filter': 256, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 41 + i * 3},
            {'filter': 512, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 42 + i * 3}])
    skip_61 = x
    # Layer 62 => 65
    x = _conv_block(x, [{'filter': 1024, 'kernel': 3, 'stride': 2, 'bnorm': True, 'leaky': True, 'layer_idx': 62},
                        {'filter': 512, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 63},
                        {'filter': 1024, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 64}])
    # Layer 66 => 74
    for i in range(3):
        x = _conv_block(x, [
            {'filter': 512, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 66 + i * 3},
            {'filter': 1024, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 67 + i * 3}])
    # Layer 75 => 79
    x = _conv_block(x, [{'filter': 512, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 75},
                        {'filter': 1024, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 76},
                        {'filter': 512, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 77},
                        {'filter': 1024, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 78},
                        {'filter': 512, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 79}],
                    skip=False)
    # Layer 80 => 82
    yolo_82 = _conv_block(x, [{'filter': 1024, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 80},
                              {'filter': 255, 'kernel': 1, 'stride': 1, 'bnorm': False, 'leaky': False,
                               'layer_idx': 81}], skip=False)
```

```python
    # Layer 83 => 86
    x = _conv_block(x, [{'filter': 256, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 84}],
                    skip=False)
    x = UpSampling2D(2)(x)
    x = concatenate([x, skip_61])
    # Layer 87 => 91
    x = _conv_block(x, [{'filter': 256, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 87},
                        {'filter': 512, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 88},
                        {'filter': 256, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 89},
                        {'filter': 512, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 90},
                        {'filter': 256, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 91}],
                    skip=False)
    # Layer 92 => 94
    yolo_94 = _conv_block(x, [{'filter': 512, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 92},
                              {'filter': 255, 'kernel': 1, 'stride': 1, 'bnorm': False, 'leaky': False,
                               'layer_idx': 93}], skip=False)
    # Layer 95 => 98
    x = _conv_block(x, [{'filter': 128, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 96}],
                    skip=False)
    x = UpSampling2D(2)(x)
    x = concatenate([x, skip_36])
    # Layer 99 => 106
    yolo_106 = _conv_block(x, [{'filter': 128, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_idx': 99},
                               {'filter': 256, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True,
                                'layer_idx': 100},
                               {'filter': 128, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True,
                                'layer_idx': 101},
                               {'filter': 256, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True,
                                'layer_idx': 102},
                               {'filter': 128, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True,
                                'layer_idx': 103},
                               {'filter': 256, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True,
                                'layer_idx': 104},
                               {'filter': 255, 'kernel': 1, 'stride': 1, 'bnorm': False, 'leaky': False,
                                'layer_idx': 105}], skip=False)
    model = Model(input_image, [yolo_82, yolo_94, yolo_106])
    return model
```

```python
class WeightReader:
    def __init__(self, weight_file):
        with open(weight_file, 'rb') as w_f:
            major, = struct.unpack('i', w_f.read(4))
            minor, = struct.unpack('i', w_f.read(4))
            revision, = struct.unpack('i', w_f.read(4))
            if (major * 10 + minor) >= 2 and major < 1000 and minor < 1000:
                w_f.read(8)
            else:
                w_f.read(4)
            transpose = (major > 1000) or (minor > 1000)
            binary = w_f.read()
        self.offset = 0
        self.all_weights = np.frombuffer(binary, dtype='float32')

    def read_bytes(self, size):
        self.offset = self.offset + size
        return self.all_weights[self.offset - size:self.offset]
```

```python
    def load_weights(self, model):
        for i in range(106):
            try:
                conv_layer = model.get_layer('conv_' + str(i))
                print("loading weights of convolution #" + str(i))
                if i not in [81, 93, 105]:
                    norm_layer = model.get_layer('bnorm_' + str(i))
                    size = np.prod(norm_layer.get_weights()[0].shape)
                    beta = self.read_bytes(size)  # bias
                    gamma = self.read_bytes(size)  # scale
                    mean = self.read_bytes(size)  # mean
                    var = self.read_bytes(size)  # variance
                    weights = norm_layer.set_weights([gamma, beta, mean, var])
                if len(conv_layer.get_weights()) > 1:
                    bias = self.read_bytes(np.prod(conv_layer.get_weights()[1].shape))
                    kernel = self.read_bytes(np.prod(conv_layer.get_weights()[0].shape))
                    kernel = kernel.reshape(list(reversed(conv_layer.get_weights()[0].shape)))
                    kernel = kernel.transpose([2, 3, 1, 0])
                    conv_layer.set_weights([kernel, bias])
                else:
                    kernel = self.read_bytes(np.prod(conv_layer.get_weights()[0].shape))
                    kernel = kernel.reshape(list(reversed(conv_layer.get_weights()[0].shape)))
                    kernel = kernel.transpose([2, 3, 1, 0])
                    conv_layer.set_weights([kernel])
            except ValueError:
                print("no convolution #" + str(i))
```

The first step is to load the Keras model. This might be the slowest part of making a prediction.

```python
# load yolov3 model
model = load_model('model.h5')
# define the expected input shape for the model
input_w, input_h = 416, 416
# define our new photo
#photo_filename = 'video.mp4'
```

Next we will use opencv library to load the video and working with that.
We can tie all of this together into a convenience function named *load_image_pixels()* that takes the filename and target size and returns the scaled pixel data ready to provide as input to the Keras model, as well as the original width and height of the video.We can now feed the photo into the Keras model and make a prediction.

```python
# load and prepare an image
def load_image_pixels(image, shape):
    # load the image to get its shape
    #image = load_img(filename)
    #print("HIIIIIIIIIIIIIIIIIIIIIII ::::: ", image.size) ##1280X720X3=2764800

    #width, height, _ = image.size
    width, height = 1280, 720

    # load the image with the required size
    image = cv2.resize(image, shape)
    #print("HIIIIIIIIIIIIIIIIIIIIIII222222222222 ::::: ", image.size)

    # convert to numpy array
    image = img_to_array(image)
    # scale pixel values to [0, 1]
    image = image.astype('float32')
    image /= 255.0
    # add a dimension so that we have one sample
    image = expand_dims(image, 0)
    return image, width, height
```

```python
cap = cv2.VideoCapture("video.mp4")

while (cap.isOpened()):
    ret, image = cap.read()
    if not ret:
        break

    count += 1
    if count % 25 != 0:
        continue

    # load and prepare image
    image, image_w, image_h = load_image_pixels(image, (input_w, input_h))

    # make prediction
    yhat = model.predict(image)
    # summarize the shape of the list of arrays
    print([a.shape for a in yhat])
```

The script provided by experiencor provides a function called *decode_netout()* that will take each one of the NumPy arrays, one at a time, and decode the candidate bounding boxes and class predictions. Further, any bounding boxes that don't confidently describe an object (e.g. all class probabilities are below a threshold) are ignored. We will use a probability of 60% or 0.6. The function returns a list of *BoundBox* instances that define the corners of each bounding box in the context of the input image shape and class probabilities.Next, the bounding boxes can be stretched back into the shape of the original image. This is helpful as it means that later we can plot the original image and draw the bounding boxes, hopefully detecting real objects.

The experiencor script provides the *correct_yolo_boxes()* function to perform this translation of bounding box coordinates, taking the list of bounding boxes, the original shape of our loaded photograph, and the shape of the input to the network as arguments. The coordinates of the bounding boxes are updated directly.The model has predicted a lot of candidate bounding boxes, and most of the boxes will be referring to the same objects. The list of bounding boxes can be filtered and those boxes that overlap and refer to the same object can be merged. We can define the amount of overlap as a configuration parameter, in this case,

50% or 0.5. This filtering of bounding box regions is generally referred to as non-maximal suppression and is a required post-processing step.

The experiencor script provides this via the *do_nms()* function that takes the list of bounding boxes and a threshold parameter. Rather than purging the overlapping boxes, their predicted probability for their overlapping class is cleared. This allows the boxes to remain and be used if they also detect another object type.This will leave us with the same number of boxes, but only very few of interest. We can retrieve just those boxes that strongly predict the presence of an object: that is are more than 60% confident. This can be achieved by enumerating over all boxes and checking the class prediction values. We can then look up the corresponding class label for the box and add it to the list. Each box must be considered for each class label, just in case the same box strongly predicts more than one object.We can develop a *get_boxes()* function that does this and takes the list of boxes, known labels, and our classification threshold as arguments and returns parallel lists of boxes, labels, and scores.We also need a list of strings containing the class labels known to the model in the correct order used during training, specifically those class labels from the MSCOCO dataset. Thankfully, this is provided in the experiencor script.w that we have those few boxes of strongly predicted objects, we can summarize them.We can also draw a string with the class label and confidence.The *draw_boxes()* function below implements this, taking the filename of the original photograph and the parallel lists of bounding boxes, labels and scores, and creates a plot showing all detected objects.we can then call this function to plot our final result.We now have all of the elements required to make a prediction using the YOLOv3 model, interpret the results, and plot them for review.The full code listing, including the original and modified functions taken from the experience script, are listed below for completeness.

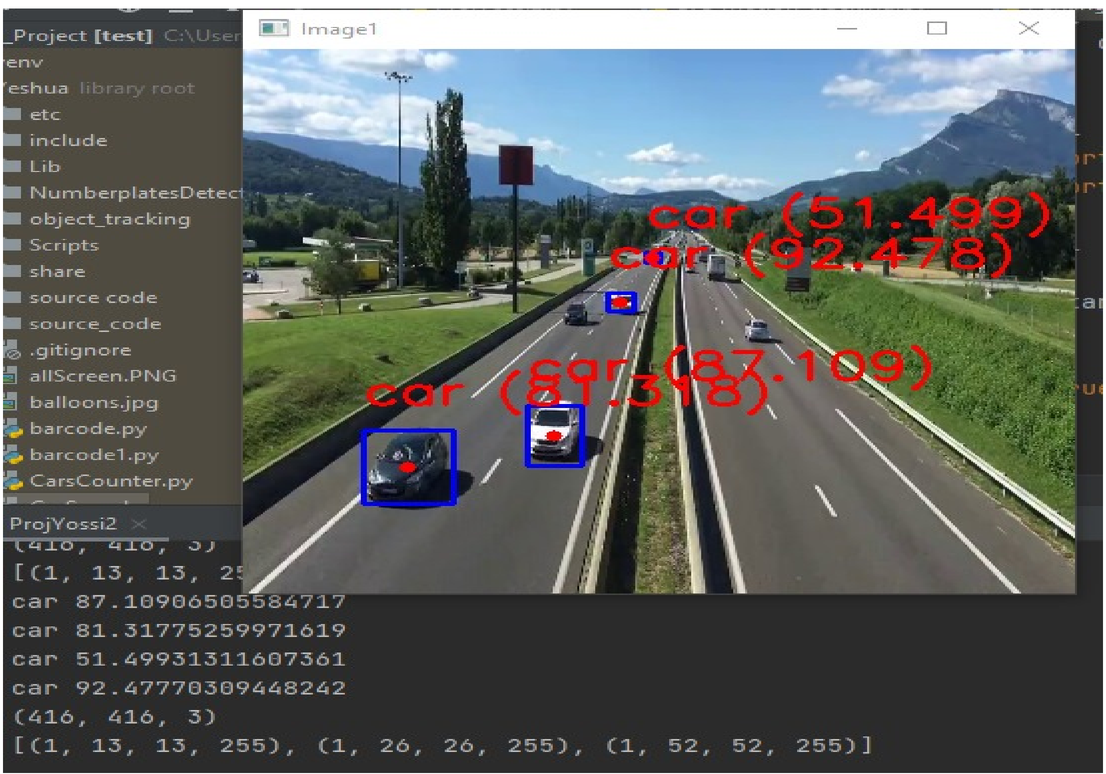
```python
def _sigmoid(x):
    return 1. / (1. + np.exp(-x))

def decode_netout(netout, anchors, obj_thresh, net_h, net_w):
    grid_h, grid_w = netout.shape[:2]
    nb_box = 3
    netout = netout.reshape((grid_h, grid_w, nb_box, -1))
    nb_class = netout.shape[-1] - 5
    boxes = []
    netout[..., :2] = _sigmoid(netout[..., :2])
    netout[..., 4:] = _sigmoid(netout[..., 4:])
    netout[..., 5:] = netout[..., 4][..., np.newaxis] * netout[..., 5:]
    netout[..., 5:] *= netout[..., 5:] > obj_thresh

    for i in range(grid_h * grid_w):
        row = i / grid_w
        col = i % grid_w
        for b in range(nb_box):
            # 4th element is objectness score
            objectness = netout[int(row)][int(col)][b][4]
            if (objectness.all() <= obj_thresh): continue
            # first 4 elements are x, y, w, and h
            x, y, w, h = netout[int(row)][int(col)][b][:4]
            x = (col + x) / grid_w  # center position, unit: image width
            y = (row + y) / grid_h  # center position, unit: image height
            w = anchors[2 * b + 0] * np.exp(w) / net_w  # unit: image width
            h = anchors[2 * b + 1] * np.exp(h) / net_h  # unit: image height
            # last elements are class probabilities
            classes = netout[int(row)][col][b][5:]
            box = BoundBox(x - w / 2, y - h / 2, x + w / 2, y + h / 2, objectness, classes)
            boxes.append(box)
    return boxes


def correct_yolo_boxes(boxes, image_h, image_w, net_h, net_w):
    new_w, new_h = net_w, net_h
    for i in range(len(boxes)):
        x_offset, x_scale = (net_w - new_w) / 2. / net_w, float(new_w) / net_w
        y_offset, y_scale = (net_h - new_h) / 2. / net_h, float(new_h) / net_h
        boxes[i].xmin = int((boxes[i].xmin - x_offset) / x_scale * image_w)
        boxes[i].xmax = int((boxes[i].xmax - x_offset) / x_scale * image_w)
        boxes[i].ymin = int((boxes[i].ymin - y_offset) / y_scale * image_h)
        boxes[i].ymax = int((boxes[i].ymax - y_offset) / y_scale * image_h)


def _interval_overlap(interval_a, interval_b):
    x1, x2 = interval_a
    x3, x4 = interval_b
    if x3 < x1:
        if x4 < x1:
            return 0
        else:
            return min(x2, x4) - x1
    else:
        if x2 < x3:
            return 0
        else:
            return min(x2, x4) - x3




def bbox_iou(box1, box2):
    intersect_w = _interval_overlap([box1.xmin, box1.xmax], [box2.xmin, box2.xmax])
    intersect_h = _interval_overlap([box1.ymin, box1.ymax], [box2.ymin, box2.ymax])
    intersect = intersect_w * intersect_h
    w1, h1 = box1.xmax - box1.xmin, box1.ymax - box1.ymin
    w2, h2 = box2.xmax - box2.xmin, box2.ymax - box2.ymin
    union = w1 * h1 + w2 * h2 - intersect
    return float(intersect) / union


def do_nms(boxes, nms_thresh):
    if len(boxes) > 0:
        nb_class = len(boxes[0].classes)
    else:
        return
    for c in range(nb_class):
        sorted_indices = np.argsort([-box.classes[c] for box in boxes])
        for i in range(len(sorted_indices)):
            index_i = sorted_indices[i]
            if boxes[index_i].classes[c] == 0: continue
            for j in range(i + 1, len(sorted_indices)):
                index_j = sorted_indices[j]
                if bbox_iou(boxes[index_i], boxes[index_j]) >= nms_thresh:
                    boxes[index_j].classes[c] = 0
```

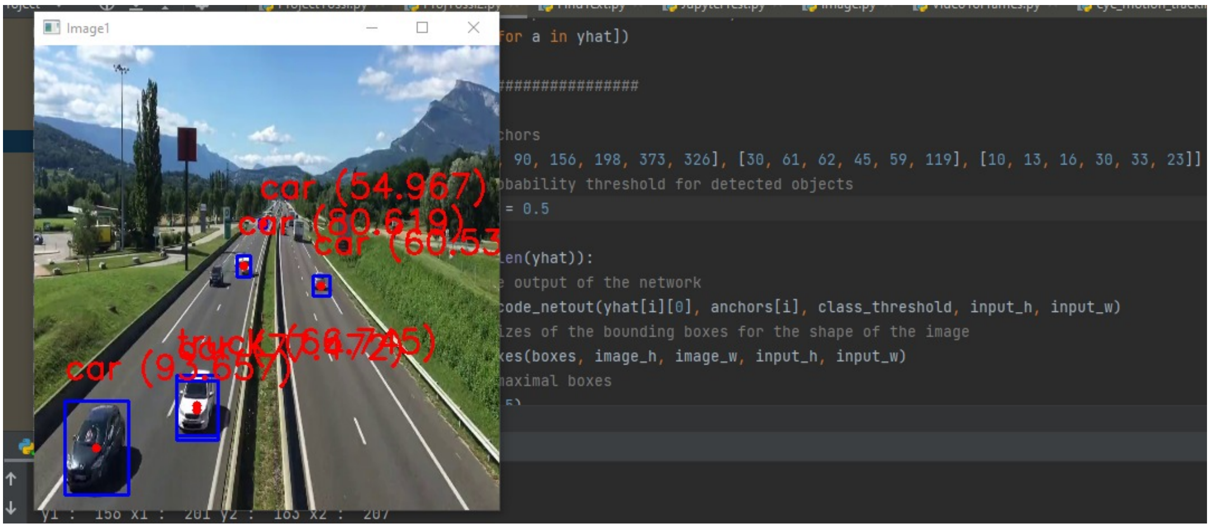
```python
# get all of the results above a threshold
def get_boxes(boxes, labels, thresh):
    v_boxes, v_labels, v_scores = list(), list(), list()
    # enumerate all boxes
    for box in boxes:
        # enumerate all possible labels
        for i in range(len(labels)):
            # check if the threshold for this label is high enough
            if box.classes[i] > thresh:
                v_boxes.append(box)
                v_labels.append(labels[i])
                v_scores.append(box.classes[i] * 100)
            # don't break, many labels may trigger for one box
    return v_boxes, v_labels, v_scores


# draw all results
def draw_boxes(image, v_boxes, v_labels, v_scores):

    #data = pyplot.imread(filename)
    # plot the image
    image.shape=image.shape[1:]
    pyplot.imshow(image)
    # get the context for drawing boxes
    ax = pyplot.gca()
    # plot each box
    for i in range(len(v_boxes)):
        box = v_boxes[i]
        # get coordinates
        y1, x1, y2, x2 = box.ymin, box.xmin, box.ymax, box.xmax
        # calculate width and height of the box
        width, height = x2 - x1, y2 - y1
        # create the shape
        rect = Rectangle((x1, y1), width, height, fill=False, color='red')
        # draw the box
        ax.add_patch(rect)
        # draw text and score in top left corner
        label = "%s (%.3f)" % (v_labels[i], v_scores[i])
        pyplot.text(x1, y1, label, color='blue')
    # show the plot
    pyplot.show()
```

```python
class BoundBox:
    def __init__(self, xmin, ymin, xmax, ymax, objness=None, classes=None):
        self.xmin = xmin
        self.ymin = ymin
        self.xmax = xmax
        self.ymax = ymax
        self.objness = objness
        self.classes = classes
        self.label = -1
        self.score = -1

    def get_label(self):
        if self.label == -1:
            self.label = np.argmax(self.classes)

        return self.label

    def get_score(self):
        if self.score == -1:
            self.score = self.classes[self.get_label()]

        return self.score

count=0
################################

# define the model
model = make_yolov3_model()
# load the model weights
weight_reader = WeightReader('yolov3.weights')
# set the model weights into the model
weight_reader.load_weights(model)
# save the model to file
model.save('model.h5')
```

```python
cap = cv2.VideoCapture("video.mp4")

while (cap.isOpened()):
    ret, image = cap.read()
    if not ret:
        break

    count += 1
    if count % 25 != 0:
        continue


    # Load and prepare image
    image, image_w, image_h = load_image_pixels(image, (input_w, input_h))


    # make prediction
    yhat = model.predict(image)
    # summarize the shape of the list of arrays
    print([a.shape for a in yhat])

    ################################

    # define the anchors
    anchors = [[116, 90, 156, 198, 373, 326], [30, 61, 62, 45, 59, 119], [10, 13, 16, 30, 33, 23]]
    # define the probability threshold for detected objects
    class_threshold = 0.6
    boxes = list()
    for i in range(len(yhat)):
        # decode the output of the network
        boxes += decode_netout(yhat[i][0], anchors[i], class_threshold, input_h, input_w)
    # correct the sizes of the bounding boxes for the shape of the image
    correct_yolo_boxes(boxes, image_h, image_w, input_h, input_w)
    # suppress non-maximal boxes
    do_nms(boxes, 0.5)
    # define the labels
    labels = ["person", "bicycle", "car", "motorbike", "aeroplane", "bus", "train", "truck",
              "boat", "traffic light", "fire hydrant", "stop sign", "parking meter", "bench",
              "bird", "cat", "dog", "horse", "sheep", "cow", "elephant", "bear", "zebra", "giraffe",
              "backpack", "umbrella", "handbag", "tie", "suitcase", "frisbee", "skis", "snowboard",
              "sports ball", "kite", "baseball bat", "baseball glove", "skateboard", "surfboard",
              "tennis racket", "bottle", "wine glass", "cup", "fork", "knife", "spoon", "bowl", "banana",
              "apple", "sandwich", "orange", "broccoli", "carrot", "hot dog", "pizza", "donut", "cake",
              "chair", "sofa", "pottedplant", "bed", "diningtable", "toilet", "tvmonitor", "laptop", "mouse",
              "remote", "keyboard", "cell phone", "microwave", "oven", "toaster", "sink", "refrigerator",
              "book", "clock", "vase", "scissors", "teddy bear", "hair drier", "toothbrush"]
    # get the details of the detected objects
    v_boxes, v_labels, v_scores = get_boxes(boxes, labels, class_threshold)
    # summarize what we found
    for i in range(len(v_boxes)):
        print(v_labels[i], v_scores[i])
    # draw what we found
    draw_boxes(image, v_boxes, v_labels, v_scores)

#cap.release()
#cv2.destroyAllWindows()
```

the results:





reference:https://machinelearningmastery.com/how-to-perform-object-detection-with-yolov3-in-keras/