YOLO object detection using Keras

Original Source: https://www.kaggle.com/code/mirzamujtaba/yolo-object-detection-using-keras/notebook

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Step 1: Download the necessary data

Data for Yolo v3 kernel: https://www.kaggle.com/datasets/aruchomu/data-for-yolo-v3-kernel

```
import struct
import numpy as np
from numpy import expand_dims
from keras.layers import Conv2D
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 keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array
from matplotlib import pyplot
from matplotlib.patches import Rectangle
```

Step 2: Create an isntance of YOLOv3 model

```
In [2]:
                                 #This function is used to create convolutional layers
                                                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 \ leading \ prefer \ leading \ prefer \ leading \ prefer \ 
                                                                               strides=conv['stride'],
                                                                                                                           padding='valid' if conv['stride'] > 1 else 'same', # peculiar padding as darknet prefe
                                                                                                                           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
```

```
In [3]: ▶ #This function define the Keras model for YOLOv3
          def make yolov3 model():
              input_image = Input(shape=(None, None, 3))
              # Layer 0 => 4
              {'filter': 64, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True,
              # Laver 5 \Rightarrow 8
              # Layer 9 => 11
              x = _conv_block(x, [{'filter': 64, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_id
                                {'filter': 128, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_id
              # Layer 12 => 15
              x = _conv_block(x, [{'filter': 256, 'kernel': 3, 'stride': 2, 'bnorm': True, 'leaky': True, 'layer_id
                               {'filter': 128, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_id {'filter': 256, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_id
              # Laver 16 => 36
              for i in range(7):
                 skip 36 = x
              # Laver 37 => 40
              {'filter': 512, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_id
              # Layer 41 => 61
              for i in range(7):
                 skip_61 = x
              # Layer 62 => 65
              # Layer 66 => 74
              for i in range(3):
                 x = _conv_block(x, [{'filter': 512, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'lay
                                   {'filter': 1024, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'lay
              # Laver 75 => 79
              x = _conv_block(x, [{'filter': 512, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_i
                               {'filter': 1024, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_i
{'filter': 512, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_i
{'filter': 1024, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_i
{'filter': 512, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_i
              # Layer 80 => 82
              # Layer 83 => 86
              x = _conv_block(x, [{'filter': 256, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_id
              x = UpSampling2D(2)(x)
              x = concatenate([x, skip_61])
              # Laver 87 => 91
              {'filter': 256, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_id
                                {'filter': 512, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_id
{'filter': 256, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, 'layer_id
              # Layer 92 => 94
              # Layer 95 => 98
                                                                                                'layer_
              x = conv block(x, [{'filter': 128, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True,
              x = UpSampling2D(2)(x)
              x = concatenate([x, skip_36])
              # Layer 99 => 106
              'leaky': True,
                                                                                          'leaky': True,
                                      {'filter': 128, 'kernel': 1, 'stride': 1, 'bnorm': True, {'filter': 256, 'kernel': 3, 'stride': 1, 'bnorm': True,
                                                                                         'leaky': True,
                                                                                         'leaky': True,
                                      {'filter': 128, 'kernel': 1, 'stride': 1, 'bnorm': True, 'leaky': True, {'filter': 256, 'kernel': 3, 'stride': 1, 'bnorm': True, 'leaky': True, {'filter': 255, 'kernel': 1, 'stride': 1, 'bnorm': False, 'leaky': False,
              model = Model(input_image, [yolo_82, yolo_94, yolo_106])
              return model
          4
```

```
In [4]: ▶ #This class reads and weights from file and rather manually
            #decoding the weights from yolo weights file than we can use it.
            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:</pre>
                            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]
                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
                                      = self.read_bytes(size) # variance
                                 weights = norm_layer.set_weights([gamma, beta, mean, var])
                             if len(conv_layer.get_weights()) > 1:
                                       = 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])
                                 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))
                def reset(self):
                     self.offset = 0
```

Step 3: Define the Bound Boxes Operations

If we use the above model and try to make predictions, we'll get an encoded output which is encoded candidate bounding boxes from different grid sizes, and the boxes are defined the context of anchor boxes, carefully chosen based on an analysis of the size of objects in the MSCOCO dataset. The function decode_netout() is defined 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. 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.

```
In [5]: ▶ 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
            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]
                 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</pre>
                         # 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
```

```
In [6]: ▶ #The correct_yolo_boxes() function to perform the 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.
             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
                      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
```

```
In [8]: № # get_boxes() function takes the list of boxes, known labels, and our classification threshold as argumen
            # returns parallel lists of boxes, labels, and scores
            # 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(filename, v_boxes, v_labels, v_scores):
                pyplot.figure(figsize=(20,10))
                # Load the image
                data = pyplot.imread(filename)
                # plot the image
                pyplot.imshow(data)
                # 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='blue',lw=3)
                    # 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(x1-20, y1-20, label, color='red',fontsize=16)
                # show the plot
                pyplot.show()
```

Step 4: Create Load Image Function

```
In [9]:
        ▶ # Load and prepare an image
            def load_image_pixels(filename, shape):
                # Load the image to get its shape
                image = load_img(filename)
                width, height = image.size
                # load the image with the required size
                image = load_img(filename, target_size=shape)
                # 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
```

Step 5: Create Model and Load Weights

Now let us use all the above defined functions to detect objects in an image. First we define a model and load weights in it. Then we start loading the picture and preprocessing it.

```
In [16]: ▶ # set the model weights into the model
             weight reader.load weights(model)
             loading weights of convolution #0
             loading weights of convolution #1
             loading weights of convolution #2
             loading weights of convolution #3
             no convolution #4
             loading weights of convolution #5
             loading weights of convolution #6
             loading weights of convolution #7
             no convolution #8
             loading weights of convolution #9
             loading weights of convolution #10
             no convolution #11
             loading weights of convolution #12
             loading weights of convolution #13
             loading weights of convolution #14
             no convolution #15
             loading weights of convolution #16
             loading weights of convolution #17
             no convolution #18
```

Step 6: Use YOLO to Detect Objects in New Images

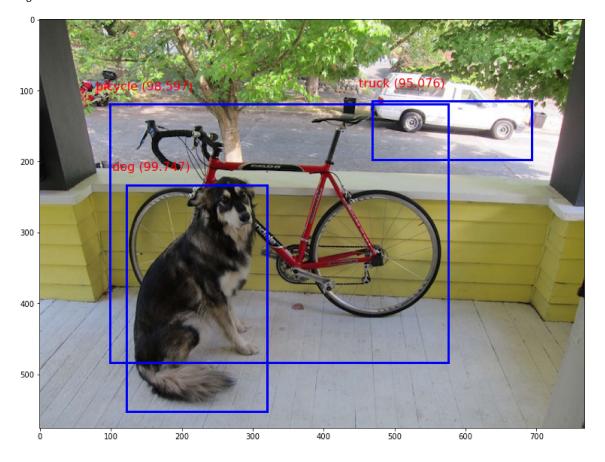
```
In [20]: # define the labels
labels = []
with open("data-for-yolo-v3-kernel/coco.names", "r") as f:
    labels = [line.strip() for line in f.readlines()]

# 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 = 0.7
```

```
In [21]: ▶ # define the expected input shape for the model
             input_w, input_h = 416, 416
             # define our new photo
             photo_filename = 'data-for-yolo-v3-kernel/dog.jpg'
             # Load and prepare image
             image, image_w, image_h = load_image_pixels(photo_filename, (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])
             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, 0.4)
             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(photo_filename, v_boxes, v_labels, v_scores)
```

[(1, 13, 13, 255), (1, 26, 26, 255), (1, 52, 52, 255)] truck 95.0762391090393 bicycle 98.59656095504761 dog 99.74659085273743



```
In [22]:  

# define our new photo
             photo filename = 'data-for-yolo-v3-kernel/office.jpg'
             # Load and prepare image
             image, image_w, image_h = load_image_pixels(photo_filename, (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])
             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, 0.4)
             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(photo_filename, v_boxes, v_labels, v_scores)
```

```
[(1, 13, 13, 255), (1, 26, 26, 255), (1, 52, 52, 255)]
person 97.65632748603821
tvmonitor 92.88041591644287
person 84.24031138420105
person 99.7834324836731
person 97.21069931983948
chair 74.42909479141235
chair 84.44295525550842
chair 99.31058883666992
```

