

# Autonomous driving - Car detection

Welcome to your week 3 programming assignment. You will learn about object detection using the very powerful YOLO model. Many of the ideas in this notebook are described in the two YOLO papers: Redmon et al., 2016 (<https://arxiv.org/abs/1506.02640>) and Redmon and Farhadi, 2016 (<https://arxiv.org/abs/1612.08242>).

## You will learn to:

- Use object detection on a car detection dataset
- Deal with bounding boxes

Run the following cell to load the packages and dependencies that are going to be useful for your journey!

In [1]:

```
import argparse
import os
import matplotlib.pyplot as plt
from matplotlib import imshow
import scipy.io
import scipy.misc
import numpy as np
import pandas as pd
import PIL
import tensorflow as tf
from keras import backend as K
from keras.layers import Input, Lambda, Conv2D
from keras.models import load_model, Model
from yolo_utils import read_classes, read_anchors, generate_colors, preprocess_image, draw_boxes, scale_boxes
from yad2k.models.keras_yolo import yolo_head, yolo_boxes_to_corners, preprocess_true_boxes, yolo_loss
%matplotlib inline
```

**Important Note:** As you can see, we import Keras's backend as K. This means that to use a Keras function in this notebook, you will need to write: K.function(...).

## 1 - Problem Statement

You are working on a self-driving car. As a critical component of this project, you'd like to first build a car detection system. To collect data, you've mounted a camera to the hood (meaning the front) of the car, which takes pictures of the road ahead every few seconds while you drive around.



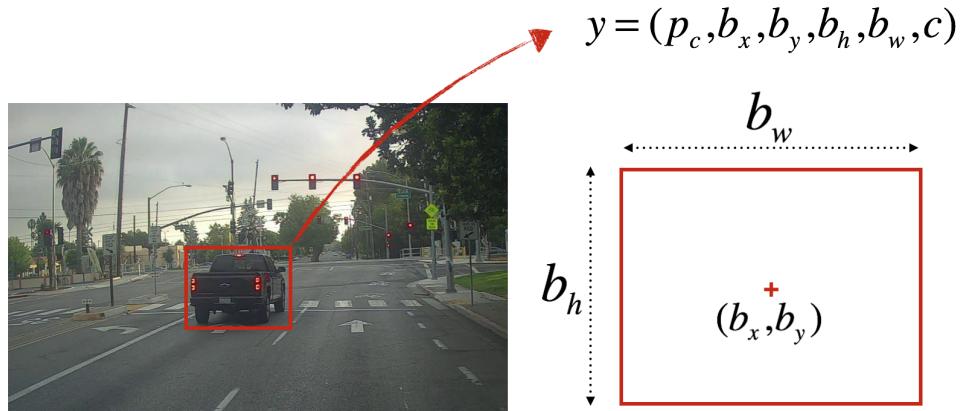
▶ 0:00 / 0:20

Pictures taken from a car-mounted camera while driving around Silicon Valley.

We would like to especially thank [drive.ai \(https://www.drive.ai/\)](https://www.drive.ai/) for providing this dataset! Drive.ai is a company building the brains of self-driving vehicles.



You've gathered all these images into a folder and have labelled them by drawing bounding boxes around every car you found. Here's an example of what your bounding boxes look like.



$p_c = 1$  : confidence of an object being present in the bounding box  
 $c = 3$  : class of the object being detected (here 3 for "car")

**Figure 1 : Definition of a box**

If you have 80 classes that you want YOLO to recognize, you can represent the class label  $c$  either as an integer from 1 to 80, or as an 80-dimensional vector (with 80 numbers) one component of which is 1 and the rest of which are 0. The video lectures had used the latter representation; in this notebook, we will use both representations, depending on which is more convenient for a particular step.

In this exercise, you will learn how YOLO works, then apply it to car detection. Because the YOLO model is very computationally expensive to train, we will load pre-trained weights for you to use.

## 2 - YOLO

YOLO ("you only look once") is a popular algorithm because it achieves high accuracy while also being able to run in real-time. This algorithm "only looks once" at the image in the sense that it requires only one forward propagation pass through the network to make predictions. After non-max suppression, it then outputs recognized objects together with the bounding boxes.

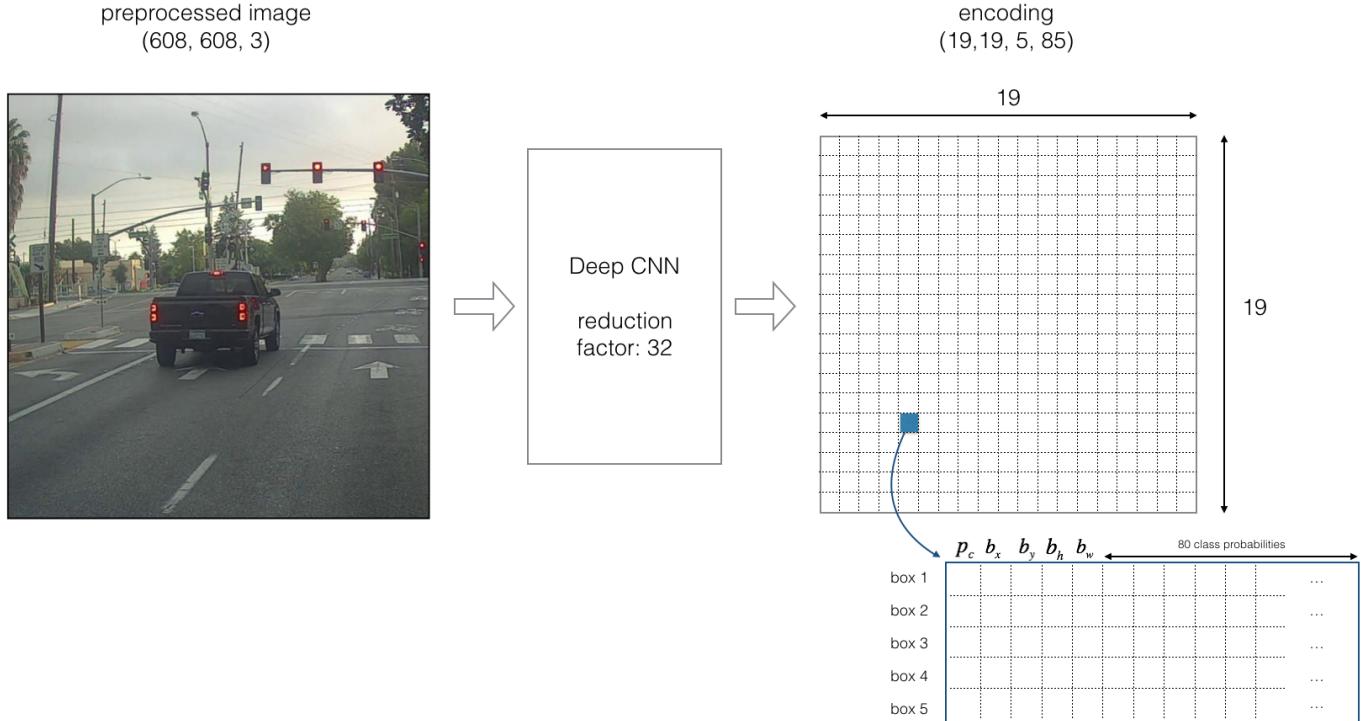
### 2.1 - Model details

First things to know:

- The **input** is a batch of images of shape  $(m, 608, 608, 3)$
- The **output** is a list of bounding boxes along with the recognized classes. Each bounding box is represented by 6 numbers  $(p_c, b_x, b_y, b_h, b_w, c)$  as explained above. If you expand  $c$  into an 80-dimensional vector, each bounding box is then represented by 85 numbers.

We will use 5 anchor boxes. So you can think of the YOLO architecture as the following: IMAGE  $(m, 608, 608, 3)$  -> DEEP CNN -> ENCODING  $(m, 19, 19, 5, 85)$ .

Lets look in greater detail at what this encoding represents.

**Figure 2 : Encoding architecture for YOLO**

If the center/midpoint of an object falls into a grid cell, that grid cell is responsible for detecting that object.

Since we are using 5 anchor boxes, each of the 19 x19 cells thus encodes information about 5 boxes. Anchor boxes are defined only by their width and height.

For simplicity, we will flatten the last two last dimensions of the shape (19, 19, 5, 85) encoding. So the output of the Deep CNN is (19, 19, 425).

**Figure 3 : Flattening the last two last dimensions**

Now, for each box (of each cell) we will compute the following elementwise product and extract a probability that the box contains a certain class.

$$\begin{aligned}
 & \text{box 1} \quad \begin{matrix} p_c & b_x & b_y & b_h & b_w & c_1 & c_2 & c_3 & c_4 & c_5 & \dots & c_{76} & c_{77} & c_{78} & c_{79} & c_{80} \end{matrix} \quad \text{80 class probabilities} \\
 & \text{scores} = p_c * \begin{pmatrix} c_1 \\ c_2 \\ c_3 \\ \vdots \\ c_{78} \\ c_{79} \\ c_{80} \end{pmatrix} = \begin{pmatrix} p_c c_1 \\ p_c c_2 \\ p_c c_3 \\ \vdots \\ p_c c_{78} \\ p_c c_{79} \\ p_c c_{80} \end{pmatrix} = \begin{pmatrix} 0.12 \\ 0.13 \\ 0.44 \\ \vdots \\ 0.07 \\ 0.01 \\ 0.09 \end{pmatrix} \quad \text{find the max} \rightarrow \\
 & \text{score: } 0.44 \\
 & \text{box: } (b_x, b_y, b_h, b_w) \\
 & \text{class: } c = 3 (\text{"car"})
 \end{aligned}$$

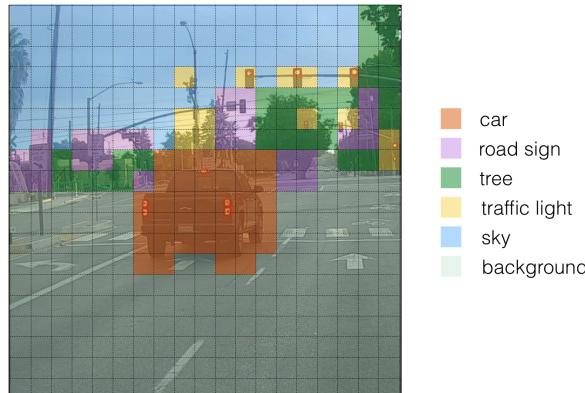
the box  $(b_x, b_y, b_h, b_w)$  has detected  $c = 3$  ("car") with probability score: 0.44

**Figure 4 : Find the class detected by each box**

Here's one way to visualize what YOLO is predicting on an image:

- For each of the  $19 \times 19$  grid cells, find the maximum of the probability scores (taking a max across both the 5 anchor boxes and across different classes).
- Color that grid cell according to what object that grid cell considers the most likely.

Doing this results in this picture:



**Figure 5** : Each of the  $19 \times 19$  grid cells colored according to which class has the largest predicted probability in that cell.

Note that this visualization isn't a core part of the YOLO algorithm itself for making predictions; it's just a nice way of visualizing an intermediate result of the algorithm.

Another way to visualize YOLO's output is to plot the bounding boxes that it outputs. Doing that results in a visualization like this:



**Figure 6** : Each cell gives you 5 boxes. In total, the model predicts:  $19 \times 19 \times 5 = 1805$  boxes just by looking once at the image (one forward pass through the network)! Different colors denote different classes.

In the figure above, we plotted only boxes that the model had assigned a high probability to, but this is still too many boxes. You'd like to filter the algorithm's output down to a much smaller number of detected objects. To do so, you'll use non-max suppression. Specifically, you'll carry out these steps:

- Get rid of boxes with a low score (meaning, the box is not very confident about detecting a class)
- Select only one box when several boxes overlap with each other and detect the same object.

## 2.2 - Filtering with a threshold on class scores

You are going to apply a first filter by thresholding. You would like to get rid of any box for which the class "score" is less than a chosen threshold.

The model gives you a total of  $19 \times 19 \times 5 \times 85$  numbers, with each box described by 85 numbers. It'll be convenient to rearrange the  $(19, 19, 5, 85)$  (or  $(19, 19, 425)$ ) dimensional tensor into the following variables:

- `box_confidence`: tensor of shape  $(19 \times 19, 5, 1)$  containing  $p_c$  (confidence probability that there's some object) for each of the 5 boxes predicted in each of the  $19 \times 19$  cells.
- `boxes`: tensor of shape  $(19 \times 19, 5, 4)$  containing  $(b_x, b_y, b_h, b_w)$  for each of the 5 boxes per cell.
- `box_class_probs`: tensor of shape  $(19 \times 19, 5, 80)$  containing the detection probabilities  $(c_1, c_2, \dots, c_{80})$  for each of the 80 classes for each of the 5 boxes per cell.

**Exercise:** Implement `yolo_filter_boxes()`.

1. Compute box scores by doing the elementwise product as described in Figure 4. The following code may help you choose the right operator:

```
a = np.random.randn(19*19, 5, 1)
b = np.random.randn(19*19, 5, 80)
c = a * b # shape of c will be (19*19, 5, 80)
```

2. For each box, find:

- the index of the class with the maximum box score ([Hint \(<https://keras.io/backend/#argmax>\)](https://keras.io/backend/#argmax)) (Be careful with what axis you choose; consider using `axis=-1`)
- the corresponding box score ([Hint \(<https://keras.io/backend/#max>\)](https://keras.io/backend/#max)) (Be careful with what axis you choose; consider using `axis=-1`)

3. Create a mask by using a threshold. As a reminder:  $([0.9, 0.3, 0.4, 0.5, 0.1] < 0.4)$  returns: [False, True, False, False, True]. The mask should be True for the boxes you want to keep.
4. Use TensorFlow to apply the mask to `box_class_scores`, `boxes` and `box_classes` to filter out the boxes we don't want. You should be left with just the subset of boxes you want to keep. ([Hint \(\[https://www.tensorflow.org/api\\\_docs/python/tf/boolean\\\_mask\]\(https://www.tensorflow.org/api\_docs/python/tf/boolean\_mask\)\)](https://www.tensorflow.org/api_docs/python/tf/boolean_mask))

Reminder: to call a Keras function, you should use `K.function(...)`.

In [ ]:

```
# GRADED FUNCTION: yolo_filter_boxes
```

```
def yolo_filter_boxes(box_confidence, boxes, box_class_probs, threshold = .6):
    """Filters YOLO boxes by thresholding on object and class confidence.
```

Arguments:

box\_confidence -- tensor of shape (19, 19, 5, 1)

boxes -- tensor of shape (19, 19, 5, 4)

box\_class\_probs -- tensor of shape (19, 19, 5, 80)

threshold -- real value, if [ highest class probability score < threshold], then get rid of the

Returns:

scores -- tensor of shape (None, ), containing the class probability score for selected boxes

boxes -- tensor of shape (None, 4), containing (b\_x, b\_y, b\_h, b\_w) coordinates of selected boxes

classes -- tensor of shape (None, ), containing the index of the class detected by the selected boxes

Note: "None" is here because you don't know the exact number of selected boxes, as it depends on the threshold.

For example, the actual output size of scores would be (10,) if there are 10 boxes.

"""

*# Step 1: Compute box scores*

### START CODE HERE ### (≈ 1 line)

box\_scores = None

### END CODE HERE ###

*# Step 2: Find the box\_classes thanks to the max box\_scores, keep track of the corresponding scores*

### START CODE HERE ### (≈ 2 lines)

box\_classes = None

box\_class\_scores = None

### END CODE HERE ###

*# Step 3: Create a filtering mask based on "box\_class\_scores" by using "threshold". The mask should be the same dimension as box\_class\_scores, and be True for the boxes you want to keep (with probability above the threshold). You can use `box_class_scores > threshold`.*

### START CODE HERE ### (≈ 1 line)

filtering\_mask = None

### END CODE HERE ###

*# Step 4: Apply the mask to scores, boxes and classes*

### START CODE HERE ### (≈ 3 lines)

scores = None

boxes = None

classes = None

### END CODE HERE ###

return scores, boxes, classes

In [ ]:

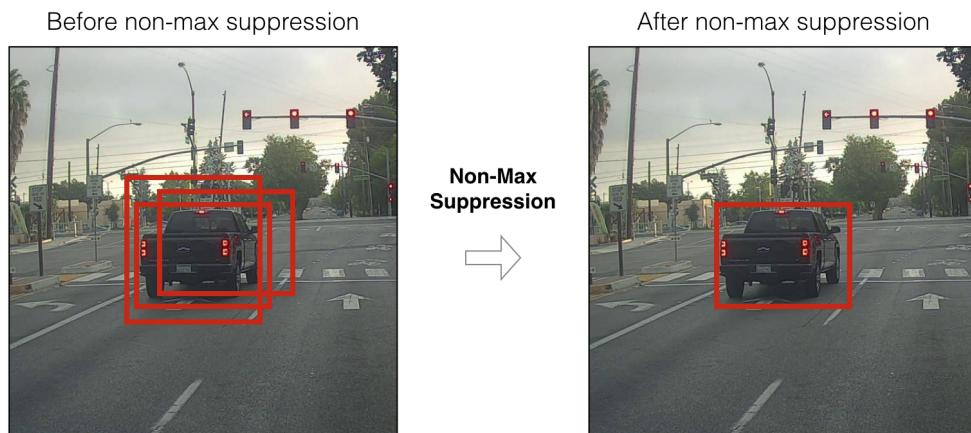
```
with tf.Session() as test_a:
    box_confidence = tf.random_normal([19, 19, 5, 1], mean=1, stddev=4, seed = 1)
    boxes = tf.random_normal([19, 19, 5, 4], mean=1, stddev=4, seed = 1)
    box_class_probs = tf.random_normal([19, 19, 5, 80], mean=1, stddev=4, seed = 1)
    scores, boxes, classes = yolo_filter_boxes(box_confidence, boxes, box_class_probs, threshold = 0.5)
    print("scores[2] = " + str(scores[2].eval()))
    print("boxes[2] = " + str(boxes[2].eval()))
    print("classes[2] = " + str(classes[2].eval()))
    print("scores.shape = " + str(scores.shape))
    print("boxes.shape = " + str(boxes.shape))
    print("classes.shape = " + str(classes.shape))
```

**Expected Output:**

<b>scores[2]</b>	10.7506
<b>boxes[2]</b>	[ 8.42653275 3.27136683 -0.5313437 -4.94137383]
<b>classes[2]</b>	7
<b>scores.shape</b>	(?,)
<b>boxes.shape</b>	(?, 4)
<b>classes.shape</b>	(?,)

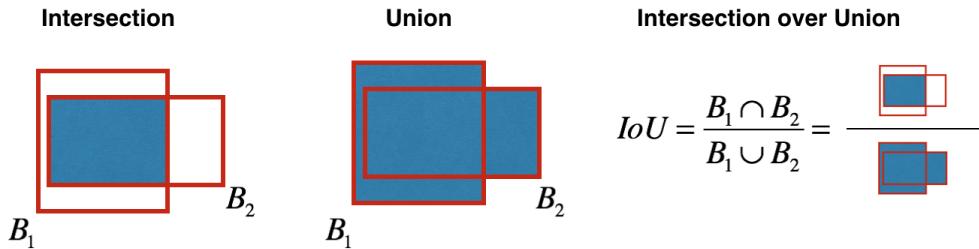
**2.3 - Non-max suppression**

Even after filtering by thresholding over the classes scores, you still end up a lot of overlapping boxes. A second filter for selecting the right boxes is called non-maximum suppression (NMS).



**Figure 7**: In this example, the model has predicted 3 cars, but it's actually 3 predictions of the same car. Running non-max suppression (NMS) will select only the most accurate (highest probability) one of the 3 boxes.

Non-max suppression uses the very important function called "**Intersection over Union**", or IoU.

**Figure 8**: Definition of "Intersection over Union".

**Exercise:** Implement `iou()`. Some hints:

- In this exercise only, we define a box using its two corners (upper left and lower right):  $(x_1, y_1, x_2, y_2)$  rather than the midpoint and height/width.
- To calculate the area of a rectangle you need to multiply its height ( $y_2 - y_1$ ) by its width ( $x_2 - x_1$ )
- You'll also need to find the coordinates ( $x_{i1}, y_{i1}, x_{i2}, y_{i2}$ ) of the intersection of two boxes. Remember that:
  - $x_{i1}$  = maximum of the  $x_1$  coordinates of the two boxes
  - $y_{i1}$  = maximum of the  $y_1$  coordinates of the two boxes
  - $x_{i2}$  = minimum of the  $x_2$  coordinates of the two boxes
  - $y_{i2}$  = minimum of the  $y_2$  coordinates of the two boxes

In this code, we use the convention that  $(0,0)$  is the top-left corner of an image,  $(1,0)$  is the upper-right corner, and  $(1,1)$  the lower-right corner.

In [ ]:

```
# GRADED FUNCTION: iou

def iou(box1, box2):
    """Implement the intersection over union (IoU) between box1 and box2

    Arguments:
    box1 -- first box, list object with coordinates (x1, y1, x2, y2)
    box2 -- second box, list object with coordinates (x1, y1, x2, y2)
    """

    # Calculate the (y1, x1, y2, x2) coordinates of the intersection of box1 and box2. Calculate its
    # area. Use None as argument if no intersection exists (e.g. if they are disjoint)
    #### START CODE HERE #### (≈ 5 lines)
    x1l = None
    y1l = None
    x1r = None
    y1r = None
    inter_area = None
    #### END CODE HERE ####

    # Calculate the Union area by using Formula: Union(A,B) = A + B - Inter(A,B)
    # Calculate the Union area by using Formula: Union(A,B) = A + B - Inter(A,B)
    #### START CODE HERE #### (≈ 3 lines)
    box1_area = None
    box2_area = None
    union_area = None
    #### END CODE HERE ####

    # compute the IoU
    #### START CODE HERE #### (≈ 1 line)
    iou = None
    #### END CODE HERE ####

    return iou
```

In [ ]:

```
box1 = (2, 1, 4, 3)
box2 = (1, 2, 3, 4)
print("iou = " + str(iou(box1, box2)))
```

### Expected Output:

iou = 0.14285714285714285

You are now ready to implement non-max suppression. The key steps are:

1. Select the box that has the highest score.
2. Compute its overlap with all other boxes, and remove boxes that overlap it more than `iou_threshold`.
3. Go back to step 1 and iterate until there's no more boxes with a lower score than the current selected box.

This will remove all boxes that have a large overlap with the selected boxes. Only the "best" boxes remain.

**Exercise:** Implement `yolo_non_max_suppression()` using TensorFlow. TensorFlow has two built-in functions that are used to implement non-max suppression (so you don't actually need to use your `iou()` implementation):

- [tf.image.non\\_max\\_suppression\(\)](#)  
([https://www.tensorflow.org/api\\_docs/python/tf/image/non\\_max\\_suppression](https://www.tensorflow.org/api_docs/python/tf/image/non_max_suppression))
- [K.gather\(\)](#) ([https://www.tensorflow.org/api\\_docs/python/tf/gather](https://www.tensorflow.org/api_docs/python/tf/gather))

In [ ]:

```
# GRADED FUNCTION: yolo_non_max_suppression

def yolo_non_max_suppression(scores, boxes, classes, max_boxes = 10, iou_threshold = 0.5):
    """
    Applies Non-max suppression (NMS) to set of boxes

    Arguments:
    scores -- tensor of shape (None, ), output of yolo_filter_boxes()
    boxes -- tensor of shape (None, 4), output of yolo_filter_boxes() that have been scaled to the image
    classes -- tensor of shape (None, ), output of yolo_filter_boxes()
    max_boxes -- integer, maximum number of predicted boxes you'd like
    iou_threshold -- real value, "intersection over union" threshold used for NMS filtering

    Returns:
    scores -- tensor of shape (, None), predicted score for each box
    boxes -- tensor of shape (4, None), predicted box coordinates
    classes -- tensor of shape (, None), predicted class for each box

    Note: The "None" dimension of the output tensors has obviously to be less than max_boxes. Note also that
    function will transpose the shapes of scores, boxes, classes. This is made for convenience.
    """

    max_boxes_tensor = K.variable(max_boxes, dtype='int32')      # tensor to be used in tf.image.non_max_suppression()
    K.get_session().run(tf.variables_initializer([max_boxes_tensor])) # initialize variable max_boxes

    # Use tf.image.non_max_suppression() to get the list of indices corresponding to boxes you keep
    ### START CODE HERE ### (≈ 1 line)
    nms_indices = None
    ### END CODE HERE ###

    # Use K.gather() to select only nms_indices from scores, boxes and classes
    ### START CODE HERE ### (≈ 3 lines)
    scores = None
    boxes = None
    classes = None
    ### END CODE HERE ###

    return scores, boxes, classes
```

In [ ]:

```
with tf.Session() as test_b:
    scores = tf.random_normal([54, ], mean=1, stddev=4, seed = 1)
    boxes = tf.random_normal([54, 4], mean=1, stddev=4, seed = 1)
    classes = tf.random_normal([54, ], mean=1, stddev=4, seed = 1)
    scores, boxes, classes = yolo_non_max_suppression(scores, boxes, classes)
    print("scores[2] = " + str(scores[2].eval()))
    print("boxes[2] = " + str(boxes[2].eval()))
    print("classes[2] = " + str(classes[2].eval()))
    print("scores.shape = " + str(scores.eval().shape))
    print("boxes.shape = " + str(boxes.eval().shape))
    print("classes.shape = " + str(classes.eval().shape))
```

**Expected Output:**

scores[2]

6.9384

```

boxes[2] [-5.299932 3.13798141 4.45036697 0.95942086]
classes[2] -2.24527
scores.shape (10,)
boxes.shape (10, 4)
classes.shape (10,)

```

## 2.4 Wrapping up the filtering

It's time to implement a function taking the output of the deep CNN (the 19x19x5x85 dimensional encoding) and filtering through all the boxes using the functions you've just implemented.

**Exercise:** Implement `yolo_eval()` which takes the output of the YOLO encoding and filters the boxes using score threshold and NMS. There's just one last implementational detail you have to know. There're a few ways of representing boxes, such as via their corners or via their midpoint and height/width. YOLO converts between a few such formats at different times, using the following functions (which we have provided):

```
boxes = yolo_boxes_to_corners(box_xy, box_wh)
```

which converts the yolo box coordinates (x,y,w,h) to box corners' coordinates (x1, y1, x2, y2) to fit the input of `yolo_filter_boxes`

```
boxes = scale_boxes(boxes, image_shape)
```

YOLO's network was trained to run on 608x608 images. If you are testing this data on a different size image--for example, the car detection dataset had 720x1280 images--this step rescales the boxes so that they can be plotted on top of the original 720x1280 image.

Don't worry about these two functions; we'll show you where they need to be called.

In [ ]:

```
# GRADED FUNCTION: yolo_eval
```

```
def yolo_eval(yolo_outputs, image_shape = (720., 1280.), max_boxes=10, score_threshold=.6, iou_threshold=.5):
    """
    Converts the output of YOLO encoding (a lot of boxes) to your predicted boxes along with their scores and classes.

    Arguments:
    yolo_outputs -- output of the encoding model (for image_shape of (608, 608, 3)), contains 4 tensors:
        box_confidence: tensor of shape (None, 19, 19, 5, 1)
        box_xy: tensor of shape (None, 19, 19, 5, 2)
        box_wh: tensor of shape (None, 19, 19, 5, 2)
        box_class_probs: tensor of shape (None, 19, 19, 5, 80)
    image_shape -- tensor of shape (2,) containing the input shape, in this notebook we use (608., 608.)
    max_boxes -- integer, maximum number of predicted boxes you'd like
    score_threshold -- real value, if [ highest class probability score < threshold], then get rid of the box
    iou_threshold -- real value, "intersection over union" threshold used for NMS filtering
    """

    Returns:
    scores -- tensor of shape (None, ), predicted score for each box
    boxes -- tensor of shape (None, 4), predicted box coordinates
    classes -- tensor of shape (None, ), predicted class for each box
    """
    """
```

```
### START CODE HERE ###
```

```
# Retrieve outputs of the YOLO model (≈1 line)
box_confidence, box_xy, box_wh, box_class_probs = None

# Convert boxes to be ready for filtering functions
boxes = yolo_boxes_to_corners(box_xy, box_wh)

# Use one of the functions you've implemented to perform Score-filtering with a threshold of score_threshold
scores, boxes, classes = None

# Scale boxes back to original image shape.
boxes = scale_boxes(boxes, image_shape)

# Use one of the functions you've implemented to perform Non-max suppression with a threshold of iou_threshold
scores, boxes, classes = None

### END CODE HERE ###
```

```
return scores, boxes, classes
```

In [ ]:

```
with tf.Session() as test_b:
    yolo_outputs = (tf.random_normal([19, 19, 5, 1], mean=1, stddev=4, seed = 1),
                    tf.random_normal([19, 19, 5, 2], mean=1, stddev=4, seed = 1),
                    tf.random_normal([19, 19, 5, 2], mean=1, stddev=4, seed = 1),
                    tf.random_normal([19, 19, 5, 80], mean=1, stddev=4, seed = 1))
    scores, boxes, classes = yolo_eval(yolo_outputs)
    print("scores[2] = " + str(scores[2].eval()))
    print("boxes[2] = " + str(boxes[2].eval()))
    print("classes[2] = " + str(classes[2].eval()))
    print("scores.shape = " + str(scores.eval().shape))
    print("boxes.shape = " + str(boxes.eval().shape))
    print("classes.shape = " + str(classes.eval().shape))
```

**Expected Output:**

<b>scores[2]</b>	138.791
<b>boxes[2]</b>	[ 1292.32971191 -278.52166748 3876.98925781 -835.56494141]
<b>classes[2]</b>	54
<b>scores.shape</b>	(10,)
<b>boxes.shape</b>	(10, 4)
<b>classes.shape</b>	(10,)

**Summary for YOLO:**

- Input image (608, 608, 3)
- The input image goes through a CNN, resulting in a (19,19,5,85) dimensional output.
- After flattening the last two dimensions, the output is a volume of shape (19, 19, 425):
  - Each cell in a 19x19 grid over the input image gives 425 numbers.
  - 425 = 5 x 85 because each cell contains predictions for 5 boxes, corresponding to 5 anchor boxes, as seen in lecture.
  - 85 = 5 + 80 where 5 is because  $(p_c, b_x, b_y, b_h, b_w)$  has 5 numbers, and 80 is the number of classes we'd like to detect
- You then select only few boxes based on:
  - Score-thresholding: throw away boxes that have detected a class with a score less than the threshold
  - Non-max suppression: Compute the Intersection over Union and avoid selecting overlapping boxes
- This gives you YOLO's final output.

### 3 - Test YOLO pretrained model on images

In this part, you are going to use a pretrained model and test it on the car detection dataset. As usual, you start by **creating a session to start your graph**. Run the following cell.

In [ ]:

```
sess = K.get_session()
```

#### 3.1 - Defining classes, anchors and image shape.

Recall that we are trying to detect 80 classes, and are using 5 anchor boxes. We have gathered the information about the 80 classes and 5 boxes in two files "coco\_classes.txt" and "yolo\_anchors.txt". Let's load these quantities into the model by running the next cell.

The car detection dataset has 720x1280 images, which we've pre-processed into 608x608 images.

In [ ]:

```
class_names = read_classes("model_data/coco_classes.txt")
anchors = read_anchors("model_data/yolo_anchors.txt")
image_shape = (720., 1280.)
```

## 3.2 - Loading a pretrained model

Training a YOLO model takes a very long time and requires a fairly large dataset of labelled bounding boxes for a large range of target classes. You are going to load an existing pretrained Keras YOLO model stored in "yolo.h5". (These weights come from the official YOLO website, and were converted using a function written by Allan Zelener. References are at the end of this notebook. Technically, these are the parameters from the "YOLOv2" model, but we will more simply refer to it as "YOLO" in this notebook.) Run the cell below to load the model from this file.

In [ ]:

```
yolo_model = load_model("model_data/yolo.h5")
```

This loads the weights of a trained YOLO model. Here's a summary of the layers your model contains.

In [ ]:

```
yolo_model.summary()
```

**Note:** On some computers, you may see a warning message from Keras. Don't worry about it if you do--it is fine.

**Reminder:** this model converts a preprocessed batch of input images (shape: (m, 608, 608, 3)) into a tensor of shape (m, 19, 19, 5, 85) as explained in Figure (2).

## 3.3 - Convert output of the model to usable bounding box tensors

The output of `yolo_model` is a (m, 19, 19, 5, 85) tensor that needs to pass through non-trivial processing and conversion. The following cell does that for you.

In [ ]:

```
yolo_outputs = yolo_head(yolo_model.output, anchors, len(class_names))
```

You added `yolo_outputs` to your graph. This set of 4 tensors is ready to be used as input by your `yolo_eval` function.

## 3.4 - Filtering boxes

yolo\_outputs gave you all the predicted boxes of yolo\_model in the correct format. You're now ready to perform filtering and select only the best boxes. Lets now call yolo\_eval, which you had previously implemented, to do this.

In [ ]:

```
scores, boxes, classes = yolo_eval(yolo_outputs, image_shape)
```

### 3.5 - Run the graph on an image

Let the fun begin. You have created a (sess) graph that can be summarized as follows:

1. yolo\_model.input is given to yolo\_model. The model is used to compute the output yolo\_model.output
2. yolo\_model.output is processed by yolo\_head. It gives you yolo\_outputs
3. yolo\_outputs goes through a filtering function, yolo\_eval. It outputs your predictions: scores, boxes, classes

**Exercise:** Implement predict() which runs the graph to test YOLO on an image. You will need to run a TensorFlow session, to have it compute scores, boxes, classes.

The code below also uses the following function:

```
image, image_data = preprocess_image("images/" + image_file, model_image_size = (608, 608))
```

which outputs:

- image: a python (PIL) representation of your image used for drawing boxes. You won't need to use it.
- image\_data: a numpy-array representing the image. This will be the input to the CNN.

**Important note:** when a model uses BatchNorm (as is the case in YOLO), you will need to pass an additional placeholder in the feed\_dict {K.learning\_phase(): 0}.

In [ ]:

```
def predict(sess, image_file):
    """
```

Runs the graph stored in "sess" to predict boxes for "image\_file". Prints and plots the predictions.

Arguments:

sess -- your tensorflow/Keras session containing the YOLO graph  
 image\_file -- name of an image stored in the "images" folder.

Returns:

out\_scores -- tensor of shape (None, ), scores of the predicted boxes  
 out\_boxes -- tensor of shape (None, 4), coordinates of the predicted boxes  
 out\_classes -- tensor of shape (None, ), class index of the predicted boxes

Note: "None" actually represents the number of predicted boxes, it varies between 0 and max\_boxes.

```
# Preprocess your image
image, image_data = preprocess_image("images/" + image_file, model_image_size = (608, 608))

# Run the session with the correct tensors and choose the correct placeholders in the feed_dict.
# You'll need to use feed_dict={yolo_model.input: ... , K.learning_phase(): 0})
### START CODE HERE ### (≈ 1 line)
out_scores, out_boxes, out_classes = None
### END CODE HERE ###

# Print predictions info
print('Found {} boxes for {}'.format(len(out_boxes), image_file))
# Generate colors for drawing bounding boxes.
colors = generate_colors(class_names)
# Draw bounding boxes on the image file
draw_boxes(image, out_scores, out_boxes, out_classes, class_names, colors)
# Save the predicted bounding box on the image
image.save(os.path.join("out", image_file), quality=90)
# Display the results in the notebook
output_image = scipy.misc.imread(os.path.join("out", image_file))
imshow(output_image)

return out_scores, out_boxes, out_classes
```

Run the following cell on the "test.jpg" image to verify that your function is correct.

In [ ]:

```
out_scores, out_boxes, out_classes = predict(sess, "test.jpg")
```

### Expected Output:

**Found 7 boxes for test.jpg**

<b>car</b>	0.60 (925, 285) (1045, 374)
<b>car</b>	0.66 (706, 279) (786, 350)
<b>bus</b>	0.67 (5, 266) (220, 407)
<b>car</b>	0.70 (947, 324) (1280, 705)
<b>car</b>	0.74 (159, 303) (346, 440)