```
In [1]: |
        # import libraries and magics
         import numpy as np
         import matplotlib.pyplot as plt
         import pandas as pd
         from PIL import Image
         import cv2
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import MinMaxScaler
         from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
         import tensorflow as tf
         from tensorflow import keras
In [2]:
        # Define function for evaluating performance
         def Evaluate_performance(model, Name, X_test, t_test, history=None, display=True):
             y test = np. argmax (model. predict (X test), axis=1)
             # Accuracy
             test_acc = accuracy_score(y_test, t_test)
             # Print performance
             print('Performance of {}:\n'. format(Name))
             print('In test set: ')
             print(classification_report(t_test, y_test))
             print('Accuracy: {}'. format(test acc))
             print('Confusion Matrix')
             print(confusion_matrix(t_test, y_test))
             # Display learning curve
             if display == True:
                 key_names = list(history. history. keys())
                 colors = ['-r', '-b', '-og', '-.k']
                 plt. figure (figsize= (8, 5))
                 for i in [0,2]:
                     plt. plot(history. history[key_names[i]], colors[i], label=key_names[i])
                 plt. legend (fontsize=15, ncol=2)
                 plt. title ('Learning Curves with loss', size=15);
                 plt. figure (figsize= (8, 5))
                 for i in [1, 3]:
                     plt.plot(history.history[key names[i]], colors[i], label=key names[i])
                 plt. legend (fontsize=15, ncol=2)
                 plt. title ('Learning Curves with accuracy', size=15);
```

Problem 1

```
Out[3]: ((415, 270000), (415,))
In [5]: X_{\text{test\_rs}} = \text{tf. constant}(X_{\text{test\_scaled. reshape}}((X_{\text{test\_scaled. shape}}[0], 300, 300, 3)),
                                 dtype=tf. float16)
        model = keras. models. load model('Model/model problem1 three. h5')
In [6]:
        Evaluate_performance(model=model, Name='Transfer learning model', X_test=X_test_rs,
        Performance of Transfer learning model:
        In test set:
                       precision
                                   recall f1-score
                                                       support
                 0.0
                           0.80
                                                0.82
                                      0.83
                                                            48
                 1.0
                           0.95
                                      0.91
                                                0.93
                                                            44
                 2.0
                           0.80
                                     0.76
                                                0.78
                                                            46
                 3.0
                           1.00
                                     0.92
                                                0.96
                                                            36
                 4.0
                           0.88
                                     0.80
                                                0.84
                                                            45
                 5.0
                           0.88
                                     0.95
                                                0.92
                                                            40
                 6.0
                           0.87
                                     0.91
                                                0.89
                                                            43
                 7.0
                                                0.88
                           0.85
                                     0.92
                                                            37
                 8.0
                           0.91
                                     0.91
                                                0.91
                                                            32
                           0.76
                 9.0
                                     0.77
                                                0.76
                                                            44
                                                0.86
            accuracy
                                                           415
                           0.87
                                      0.87
                                                0.87
                                                           415
           macro avg
                           0.86
                                      0.86
                                                0.86
                                                           415
        weighted avg
        Accuracy: 0.8626506024096385
        Confusion Matrix
         [[40 0 1 0 0
                          2
                                2
                                   0
                                       2]
                            1
         [ 0 40 1 0 1 0 0 2 0 0 ]
         Γ 1
              1 35
                    0 3 0 1
                                1
                                   0 4]
          [ 0
              0 0 33 0
                          1
                             0
                                0 1 1]
              0
                 5
                   0 36 0
                             0
                                 0
                                    0
                                       2]
           ()
              ()
                 0
                    0 0 38 0
                                ()
                                   1 1]
           3 0 0 0 0 1 39 0 0 0]
         [ 0 \ 1 \ 0 \ 0 \ 0 \ 0 ]
                            1 34 1
                                       0]
         [3 \ 0 \ 2 \ 0 \ 1 \ 1 \ 3 \ 0 \ 0 \ 34]]
```

Problem 2 & 3

```
In [3]: # Load ten of the test data
bbox = pd. read_csv('test_bounding_boxes.csv')

N = len(bbox)

# Create a numpy array with all images
for i in range(N):
    filename='car_detection_dataset/testing_images/'+bbox['image_name'][i]
    image = np. array(Image.open(filename))
    image_col = image.ravel()[:,np. newaxis]

if i==0:
    X_test = image_col
    else:
        X_test = np. hstack((X_test, image_col))

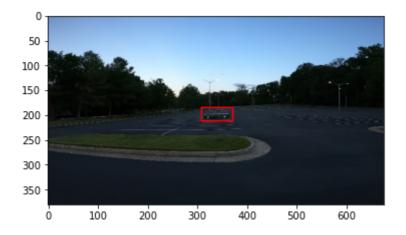
# Test feature matrices
X_test = X_test. T
```

```
# Test labels
t_test = bbox[['bbox_x', 'bbox_y', 'bbox_width', 'bbox_height']].round().to_numpy().a
t_test[:,2] = t_test[:,0] + t_test[:,2]
t_test[:,3] = t_test[:,1] + t_test[:,3]
(Nx, Ny, Nz) = image. shape
X_test. shape, t_test. shape
((10, 770640), (10, 4))
```

Out[3]:

```
In [4]:
         # Example of object visualization using opency rectangle function
         idx=9
         x = image
         cv2. rectangle(x, (t_test[idx, 0], t_test[idx, 1]),
                        (t_{test}[idx, 2], t_{test}[idx, 3]),
                        (255, 0, 0), 2);
         plt. imshow(image)
```

<matplotlib.image.AxesImage at 0x2b050c843460> Out[4]:



```
In [6]: X_test_scaled = X_test / 255.0
                                                                                                                                   t_{t_s} = \frac{1}{N} \cdot \frac{1}
                                                                                                                                   X_test_rs = tf. constant(X_test_scaled.reshape((X_test_scaled.shape[0], Nx, Ny, 3)),
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        dtype=tf. float16)
                                                                                                                                   X_{\text{test\_rs.}} shape, t_{\text{test\_scaled.}} shape
```

(TensorShape([10, 380, 676, 3]), (10, 4)) Out[6]:

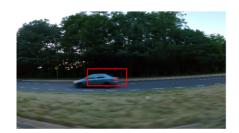
```
In [7]:
         # Load the model
         model = keras. models. load model('Model/model problem2. h5')
```

```
y_test_scaled = model.predict(X_test_rs)
In [9]:
        y_test = np. vstack((y_test_scaled[:,0]*Ny, y_test_scaled[:,1]*Nx, y_test_scaled[:,2]
        y_test = np. array(y_test, dtype='int')
        y_test
```

```
Out[9]: array([[229, 186, 355, 241], [514, 181, 611, 205], [70, 188, 182, 237], [352, 188, 501, 234], [530, 174, 625, 205], [125, 186, 250, 248], [56, 190, 184, 241], [195, 185, 292, 232], [461, 183, 583, 224], [430, 184, 545, 228]])
```

Discuss how you would validate performance in the test set given that no target labels are provided:

Firstly, I use the MakeSenseAI creating my own test labels. Then use ROI to validate performance.



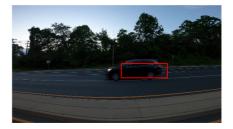


















The validation metric I use is overlapping Region of Interest.It calculates the overlapping region between test bounding box and predict bounding box divided by area of test bounding box. The accuracy score is between 0 and 1, and when the accuracy score is 1.0, it represents an exact match. In practice, an accuracy score below 0.5 is probably an incorrect match.

```
In [13]:
         # Define intersection over union function to validate the performance of the test da
          def Region_of_Interest(box_a, box_b):
              # Assign value for each coordinate in two boxes
              a_xmin = box_a[0]
             a_{ymin} = box_a[1]
              a \times max = box a[2]
              a_ymax = box_a[3]
              b_xmin = box_b[0]
              b_{ymin} = box_b[1]
              b_{xmax} = box_b[2]
              b_{ymax} = box_b[3]
              # Determine the coordinates of each of the two boxes
              xA = max(a_xmin, b_xmin)
              yA = max(a_ymin, b_ymin)
              xB = min(a_xmax, b_xmax)
              yB = min(a_ymax, b_ymax)
              # Calculate the area of the intersection area
              area_of_intersection = (xB - xA + 1) * (yB - yA + 1)
              # Calculate the area of both rectangles
              box a area = (a_xmax - a_xmin + 1) * (a_ymax - a_ymin + 1)
              box_b_area = (b_xmax - b_xmin + 1) * (b_xmax - b_xmin + 1)
              # Calculate the area of intersection divided by the area of union
              # Area of union = sum both areas less the area of intersection
              roi = area_of_intersection / float(box_a_area)
              if roi <= 0:
                 roi = 0
              return roi
```

```
In [14]: # Define a empty list to restore the accuracy score of each image
    acc_score = []

for i in range(t_test. shape[0]):
    box_a = t_test[i,:]
    box_b = y_test[i,:]
    score = Region_of_Interest(box_a, box_b)
    acc_score. append(score)

acc_score
```

Discuss also how you would address the case where no car is present in the image:

Consider the case where no car is present in the images. I have two approaches to achieve it. First approach is to train two CNN models. One model does the image classification task to determine whether there is a car in the image, and if the determination is positive, then the other model will do the car detection work. The second approach is to train the images all together and set a certain bounding boxed' coordinates to the image without cars, for instance, set the label [0, 0, 0, 0] for all images without a car.

In []: