```
!pip3 install torch torchvision torchaudio pandas pyYAML tqdm seaborn opencv-pythor
Requirement already satisfied: torch in c:\users\jmess\appdata\local\programs\pyth
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Requirement already satisfied: urllib3<1.27,>=1.21.1 in c:\users\jmess\appdata\loc
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Requirement already satisfied: certifi>=2017.4.17 in c:\users\jmess\appdata\local
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5)
Requirement already satisfied: idna<4,>=2.5 in c:\users\jmess\appdata\local\progra
ms\python\python39\lib\site-packages (from requests->torchvision) (3.3)
```

In [ ]: %matplotlib inline

In [ ]: import torch

```
import cv2
        from matplotlib import pyplot as plt
In [ ]: model = torch.hub.load('ultralytics/yolov5', 'yolov5s')
        Using cache found in C:\Users\jmess/.cache\torch\hub\ultralytics_yolov5_master
        YOLOv5 2022-7-18 Python-3.9.13 torch-1.12.0+cpu CPU
        Fusing layers...
        YOLOv5s summary: 213 layers, 7225885 parameters, 0 gradients
        Adding AutoShape...
In [ ]: def load_image(path):
            return cv2.imread(path)[:, :, ::-1]
In [ ]: def process_image(img):
            result = model([img], size=640)
            print(result.pandas().xyxy[0])
            return result
In [ ]: IMGS_PATH = ['imgs/all.png', 'imgs/bus.png', 'imgs/people.png']
In [ ]: IMGS = []
        for i in IMGS_PATH:
            IMGS.append(load_image(i))
        a)
In [ ]: def getRGBfromI(RGBint):
            blue = RGBint & 255
            green = (RGBint >> 8) & 255
            red = (RGBint >> 16) & 255
            return red, green, blue
In [ ]: def draw_result(frame, results):
            frame = frame.copy()
            for box in results.xyxy[0]:
                    xB = int(box[2])
                    xA = int(box[0])
                    yB = int(box[3])
                    yA = int(box[1])
                    cv2.rectangle(frame, (xA, yA), (xB, yB), getRGBfromI(int(box[5]) * 1000
            return frame
In [ ]: def process(img):
            plt.imshow(img)
            plt.show()
            result = process_image(img)
            print(result)
```

```
plt.imshow(draw_result(img, result))
plt.show()
```

## In [ ]: process(IMGS[0])



```
ymax
                                                        confidence class
           xmin
                       ymin
                                     xmax
0
     726.216492
                 870.891785
                               967.580078
                                           1088.871460
                                                          0.846512
                                                                         2
                                                                         2
1
    1104.301514
                 841.032959
                             1196.471558
                                            923,366333
                                                           0.829974
2
                                                                         2
     393.870117
                 922.003052
                               694.894958
                                           1192.261230
                                                           0.800172
3
       1.707250
                 910.309021
                               84.191330
                                           1184.690308
                                                           0.776526
                                                                         0
4
                                                                         2
     636.185120
                 826.378418
                              760.100464
                                            929.397766
                                                          0.770256
5
                804.348999
                             1140.609253
                                                                         2
    1045.868408
                                            883.489014
                                                          0.762862
6
    1600.351807
                 493.414764
                             1672.191406
                                            587.836914
                                                           0.680482
                                                                         9
7
     256.838928
                 852.810669
                              328.951660 1052.742432
                                                           0.631074
                                                                         0
8
                                                                         5
     447.830383
                 725.431458
                               625.831116
                                            910.149231
                                                           0.628749
9
    1189.572998
                 697.095337
                             1907.240234
                                           1186.575684
                                                           0.597191
                                                                         7
10
                 593.303833
                                                                         9
   1206.703735
                             1252.806030
                                            651.825256
                                                          0.585567
                                                                         0
     878.548706
                 793.447327
                                            870.598999
11
                              911.642090
                                                          0.522277
12
     971.822571
                 797.682190
                             1003.063477
                                            869.149353
                                                          0.472607
                                                                         0
13
     718.716797
                 753.658752
                               812.098267
                                            850.487915
                                                          0.451698
                                                                         2
14
     396.205566
                 838.769409
                               441.134613
                                            986.398010
                                                          0.450832
                                                                         0
15
     507.221191
                 523.475037
                                            602.472778
                                                          0.437403
                                                                         9
                               573.016846
16
   1020.958191
                                            708.367859
                                                                         9
                 670.210266
                             1041.742432
                                                          0.422663
                                                                         7
17
     392.386963
                 924.273560
                              691.774841 1186.112305
                                                          0.386347
18
   1196.590454
                 700.699097
                             1843.417358
                                           1188.745605
                                                           0.296920
                                                                         5
19
                                                                         0
     964.837463
                 767.659180
                             1010.002258
                                            861.787720
                                                           0.285839
```

name 0 car 1 car 2 car 3 person 4 car 5 car 6 traffic light 7 person 8 bus 9 truck 10 traffic light 11 person 12 person 13 car 14 person 15 traffic light 16 traffic light 17 truck 18 bus 19 person

image 1/1: 1235x1920 6 persons, 6 cars, 2 buss, 2 trucks, 4 traffic lights
Speed: 13.0ms pre-process, 106.7ms inference, 2.0ms NMS per image at shape (1, 3, 416, 640)



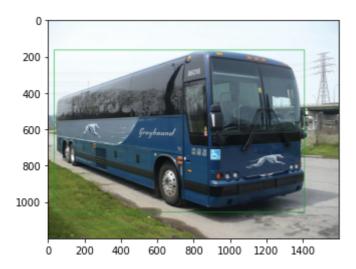
Como podemos ver, já que existem varios elementos na foto boa parte deles foi encontrado pelo modelo. Mas dá para ver que quanto mais profundo na foto o elemento está menor a confiança na classificação temos. Provavelmente devido menor informação de pixels para representá-lo dentro da foto.

## In [ ]: process(IMGS[1])



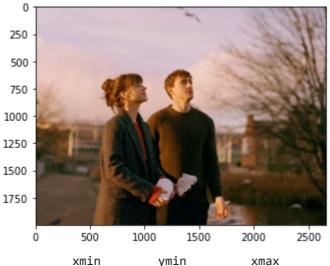
xmin ymin xmax ymax confidence class name 0 35.439453 164.285309 1411.653564 1055.357544 0.862536 5 bus image 1/1: 1200x1600 1 bus

Speed: 13.0ms pre-process, 131.3ms inference, 2.0ms NMS per image at shape (1, 3, 480, 640)



O unico elementos da foto propositalmente é um onibus e podemos ver que o modelo o identifica, com um nivel consideravel de confiança.

In [ ]: process(IMGS[2])



```
    xmin
    ymin
    xmax
    ymax
    confidence
    class

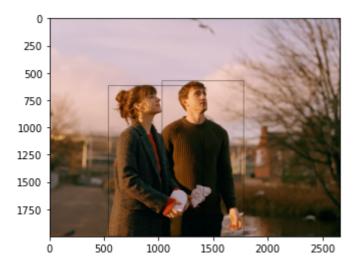
    0
    1028.121338
    574.823120
    1774.388672
    1998.000000
    0.915181
    0

    1
    537.640442
    618.084961
    1406.829224
    1992.961426
    0.865246
    0
```

name 0 person 1 person

image 1/1: 1998x2664 2 persons

Speed: 24.9ms pre-process, 116.6ms inference, 1.0ms NMS per image at shape (1, 3, 480, 640)



Os dois unico elementos da foto propositalmente são duas pessoas e podemos ver que o modelo o identifica, com um nivel consideravel de confiança as duas pessoas.

## b)

```
In []: # Transforma o video em imagens para ser usado no modelo

def get_frames(path):
    vidcap = cv2.VideoCapture(path)
    vidcap.set(cv2.CAP_PROP_FRAME_WIDTH, 1280)
    vidcap.set(cv2.CAP_PROP_FRAME_HEIGHT, 720)
    lista_results = []

    success,image = vidcap.read()
    while success:
        image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
        lista_results.append(image)
```

```
success,image = vidcap.read()
            return lista_results
In [ ]: # Pega todos os frames
        results = get_frames('videos/cross.mp4')
In [ ]: # Executa os frames no modelo
        t = model(results)
        pd = t.pandas().xyxy
In [ ]: # Verifica e calcula os centros dos quadrados demarcadores
        def get_path(pd):
            path = []
            for j in pd:
                i = j[j['class'] == 0]
                if len(i) > 0:
                     i = i.iloc[0]
                     x = (i['xmax'] + i['xmin']) // 2
                    y = (i['ymax'] + i['ymin']) // 2
                    path.append((int(x), int(y)))
            return path
In [ ]: # Pinta aréa a partir dos centros dos quadrados demarcadores calculado
        def print_area(img, point, w):
            for i in range(point[0] - w, point[0] + w):
                for j in range(point[1] - w, point[1] + w):
                     try:
                         img[j][i] = (255, 0, 0)
                     except IndexError:
                        pass
In [ ]: # Angraria os centros
        a = get_path(pd)
In [ ]: # Pinta o caminho na imagem
        img = results[0].copy()
        for i in a:
            print_area(img, i, 30)
In [ ]: # Exibe a imagem
        plt.imshow(img)
        plt.show()
```

