exercise10

November 18, 2022

[1]:
```
# This cell is used for creating a button that hides/unhides code cells to␣
 ↪quickly look only the results.
# Works only with Jupyter Notebooks.

from IPython.display import HTML

HTML('''<script>
code_show=true;
function code_toggle() {
if (code_show){
$('div.input').hide();
} else {
$('div.input').show();
}
code_show = !code_show
}
$( document ).ready(code_toggle);
</script>
<form action="javascript:code_toggle()"><input type="submit" value="Click here␣
 ↪to toggle on/off the raw code."></form>''')
```

[1]:
```
<IPython.core.display.HTML object>
```

[2]:
```
# Description:
#   Exercise10 notebook.
#
# Copyright (C) 2019 Antti Parviainen
# Based on the SSD PyTorch implementation by Max deGroot and Ellis Brown
#
# This software is distributed under the GNU General Public
# Licence (version 2 or later);

import os
import numpy as np
from matplotlib import pyplot as plt
import cv2
```

```
import torch
from torch.autograd import Variable
from ssd import build_ssd
from data import VOCDetection, VOCAnnotationTransform
from data import VOC_CLASSES as labels

import warnings
warnings.filterwarnings("ignore")

# Select data directory
if os.path.isdir('/coursedata'):
    course_data_dir = '/coursedata'
    docker = False
elif os.path.isdir('../../../coursedata'):
    docker = True
    course_data_dir = '../../../coursedata'
else:
    # Specify course_data_dir on your machine
    docker = True
    course_data_dir = '/home/jovyan/work/coursedata/'

print('The data directory is %s' % course_data_dir)
data_dir = os.path.join(course_data_dir, 'exercise-10-data')
print('Data stored in %s' % data_dir)
```

```
The data directory is /coursedata
Data stored in /coursedata/exercise-10-data
```

1 CS-E4850 Computer Vision Exercise Round 10

The problems should be solved before the exercise session and solutions returned via MyCourses. Upload to MyCourses both: this Jupyter Notebook (.ipynb) file containing your solutions and the exported pdf version of this Notebook file. If there are both programming and pen & paper tasks kindly combine the two pdf files (your scanned/LaTeX solutions and the exported Notebook) into a single pdf and submit that with the Notebook (.ipynb) file. Note that you should be sure that everything that you need to implement works with the pictures specified in this exercise round.

Docker users: 1. One file, data file containing the weights, was again above the file size limit imposed by git. I've compressed it to get it under the limit so before you run the code you have to uncompress the file in the folder `coursedata/exercise-10-data/weights`.

1.1 Exercise 1 - Object detection with SSD: Single Shot MultiBox Object Detector, in PyTorch

The goal of this task is to learn the basics of deep learning based object detection with SSD by experimenting with the provided code and by reading the original Single Shot MultiBox Detector publication by Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang, and Alexander C. Berg from 2016.

Read the research paper linked above and experiment with the provided sample code according to the instructions below. Then answer the questions a), b), c) below and return your answers. Note that scientific publications are written for domain experts and some details may be challenging to understand if necessary background information is missing. However, don't worry if you don't understand all details. You should be able to grasp the overall idea and answer the questions even if some details would be difficult to understand.

The code implements the following steps to demonstrate SSD:

1. Build the SSD300 architecture and load pretrained weights on the VOC07 trainval dataset
2. Load 4 random sample images from the VOC07 dataset
3. Preprocess the images to the correct input form and show the preprocessed images
4. Run the sample images through the SSD network, parse the detections and show the results

a) In the beginning of the publication the authors argue about the relevance and novelty of their work. Summarise their main arguments and the evidence they present to support their arguments. Type your answer here:

The authors argue that state-of-the-art approaches before SSD relied on a two-phase approach consisting of a bounding boxes proposal algorithm and a classification step, which even in the best of cases were still too computationally demanding for embedded systems and too slow for real-time applications, even using the best hardware available.
The novelty of SSD comes from the removal of the bounding-box hypothesis phase (which had already been proposed) and a series of optimizations including the employment of a small convolutional filter to predict object categories and bounding-box offset, using diffferent filters for detecting different aspect ratios, and the application of these filters on later stages of the network to be able to detect objects at multiple scales. The summation of these improvements results in a significantly reduced speed for high-accuracy detection and better performance on real-time detection.

b) SSD consists of two networks: a "truncated base network" and a network of added "convolutional feature layers to the end of the truncated base network." What is the purpose of the base network? Which base network do the authors of the SSD publication use, and what dataset was used to train the base network? Type your answer here:

The base network consists of the VGG16 model pre-trained on the ILSVRC CLS-LOC dataset, a model often used for transfer learning image classification as it provides very good performance on very varied sets of images.
As is often done with transfer learning, this base network is used to provide a good general starting point, which is further refined by eliminating the last layers, converting the final ones to convolutional, and fine-tuning the resulting network to the problem at hand.

c) SSD has it's own loss function, defined in chapter 2.2 in the original publication. What are the two attributes this loss function observes? How are these defined (short explanation without any formulas is sufficient) and how do they help the network to minimise the object detection error? Type your answer here:

The loss funcion is a weighted sum of the localization and confidence loss functions: the former is used to correctly determine the width, height, and center offset of the bounding box, whereas the latter is the softmax loss over multiple classes to determine the confidence of the object belonging

to each.
Together, they help the network correctly identifying both the position of the object and its class.

1.1.1 1. Load the SSD architecture and the pretrained weights

[3]:
```
net = build_ssd('test', 300, 21)    # initialize SSD
net.load_weights(data_dir+'/weights/ssd300_mAP_77.43_v2.pth')
```

```
Loading weights into state dict…
Finished!
```

1.1.2 2. Load Sample Images

[7]:
```
images = []
for i in range(4):
    if docker:
        # if local storage use a 300 image subset of the test set
        img_id = np.random.randint(1,high = 300)
        image = cv2.imread(data_dir+'/voc_images/'+f"{img_id:06d}"'.jpg', cv2.
 ↪IMREAD_COLOR)
    else:
        # if JupyterLab use the full test set
        # here we specify year (07 or 12) and dataset ('test', 'val', 'train')
        testset = VOCDetection(data_dir+'/VOCdevkit', [('2007', 'val')], None,␣
 ↪VOCAnnotationTransform())
        img_id = np.random.randint(0,high = len(testset))
        image = testset.pull_image(img_id)

    rgb_image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    images.append(rgb_image)

fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(10,10))
ax = axes.ravel()
ax[0].imshow(images[0])
ax[0].axis('off')
ax[1].imshow(images[1])
ax[1].axis('off')
ax[2].imshow(images[2])
ax[2].axis('off')
ax[3].imshow(images[3])
ax[3].axis('off')
plt.tight_layout()
plt.suptitle("Randomly sampled images from the dataset", fontsize=20)
plt.subplots_adjust(top=0.95)
plt.show()
```

1.1.3 3 Pre-process the input images

Using the torchvision package, we can apply multiple built-in transorms. At test time we resize our image to 300x300, subtract the dataset's mean rgb values, and swap the color channels for input to SSD300.

[8]:
```
def preprocess_inputs(images):
    preprocessed_images = []
    for image in images:
        x = cv2.resize(image, (300, 300)).astype(np.float32)
        x -= (104.0, 117.0, 123.0)
        x = x.astype(np.float32)
        preprocessed_images.append(x)
    return preprocessed_images
```

[9]:
```
preprocessed_images = preprocess_inputs(images)

fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(10,10))
ax = axes.ravel()
ax[0].imshow(preprocessed_images[0])
ax[0].axis('off')
ax[1].imshow(preprocessed_images[1])
ax[1].axis('off')
ax[2].imshow(preprocessed_images[2])
ax[2].axis('off')
ax[3].imshow(preprocessed_images[3])
ax[3].axis('off')
plt.tight_layout()
plt.suptitle("Preprocessed input images", fontsize=20)
plt.subplots_adjust(top=0.95)
plt.show()
```

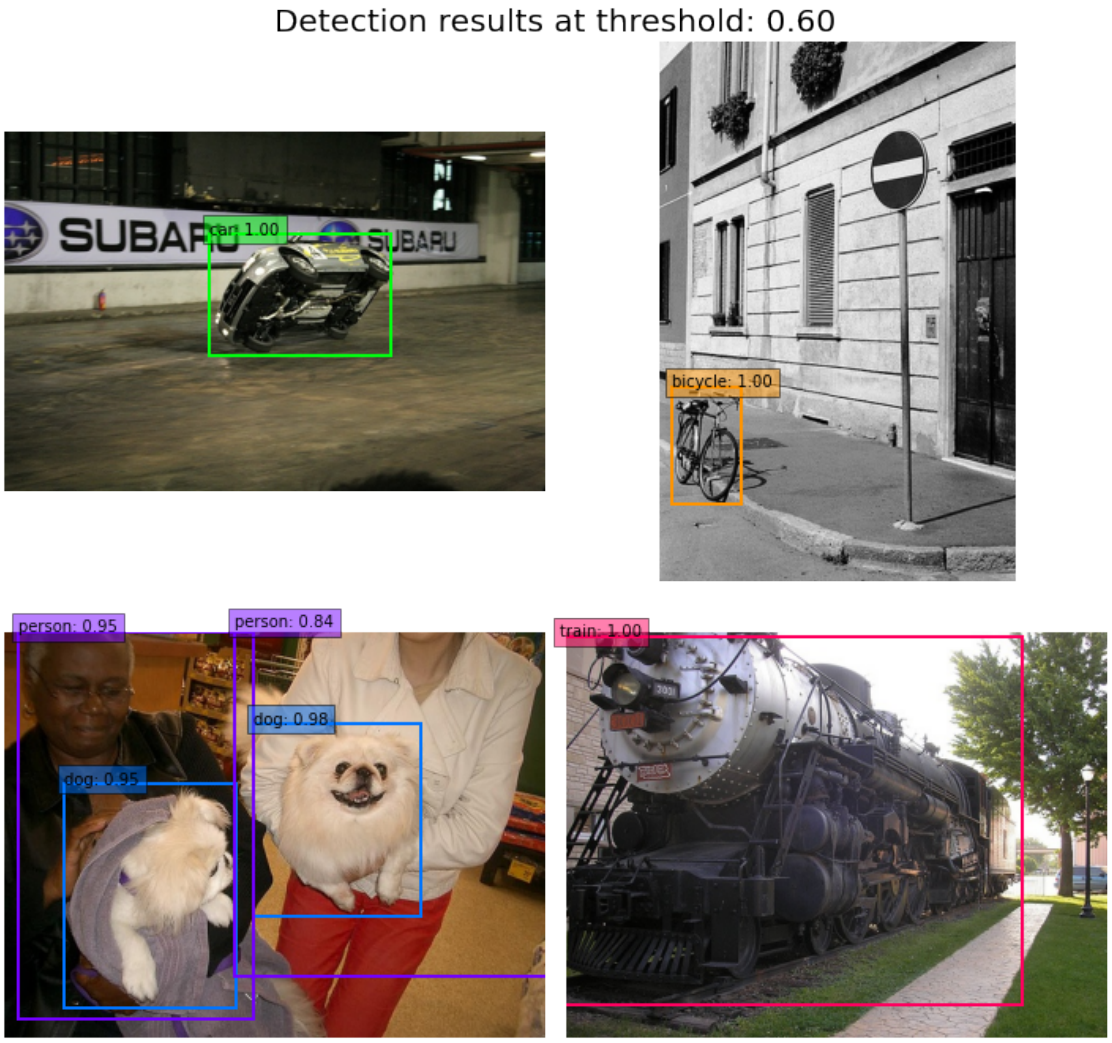
```
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
```

4. Run SSD on the sample images and show the results

[10]:
```
def run_network(images, nrows, ncols, figsize = (10,10), threshold = 0.6,␣
↪title=True):

    if nrows * ncols != len(images):
        print("Subgrid dimensions don't match with the number of images.")
        return

    preprocessed_images = preprocess_inputs(images)
    fig, axes = plt.subplots(nrows=nrows, ncols=ncols, figsize=figsize)
```

```
    if len(images) != 1:
        ax = axes.ravel()
    else:
        ax = [axes]

    for it, input_image in enumerate(images):
        # Process data for the network
        # swap color channels
        x = preprocessed_images[it][:, :, ::-1].copy()
        # change the order
        x = torch.from_numpy(x).permute(2, 0, 1)
        # wrap the image in a Variable so it is recognized by PyTorch autograd
        xx = Variable(x.unsqueeze(0))
        if torch.cuda.is_available():
            xx = xx.cuda()

        # SSD Forward Pass
        y = net(xx)
        detections = y.data

        # colormap for the bounding boxes
        colors = plt.cm.hsv(np.linspace(0, 1, 21)).tolist()

        # scale each detection back up to the image
        scale = torch.Tensor(input_image.shape[1::-1]).repeat(2)
        for i in range(detections.size(1)):
            j = 0
            while detections[0,i,j,0] >= threshold:
                score = detections[0,i,j,0]
                label_name = labels[i-1]
                display_txt = '%s: %.2f'%(label_name, score)
                pt = (detections[0,i,j,1:]*scale).cpu().numpy()
                coords = (pt[0], pt[1]), pt[2]-pt[0]+1, pt[3]-pt[1]+1
                color = colors[i]
                ax[it].add_patch(plt.Rectangle(*coords, fill=False,␣
↪edgecolor=color, linewidth=2))
                ax[it].text(pt[0], pt[1], display_txt, bbox={'facecolor':color,␣
↪'alpha':0.5})
                j+=1
        ax[it].imshow(images[it])
        ax[it].axis('off')
    plt.tight_layout()
    if title:
        plt.suptitle("Detection results at threshold: %1.2f" %threshold,␣
↪fontsize=20)
        plt.subplots_adjust(top=0.95)
    plt.show()
```

[11]:
```
# Filter outputs with confidence scores lower than a threshold. The default␣
↪threshold is 60%.
run_network(images, nrows=2, ncols=2, figsize=(10,10), threshold=0.6)
```



1.2 Exercise 2 - Evaluating the SSD network on some more challenging input images

To better detect challenging inputs the authors have implemented data augmentation described in chapter 2.2 and 3.2 of the publication and in reference 14. Read the chapters in the publication and selectively read the main points of reference 14 and answer the following questions.

1.2.1 2.1

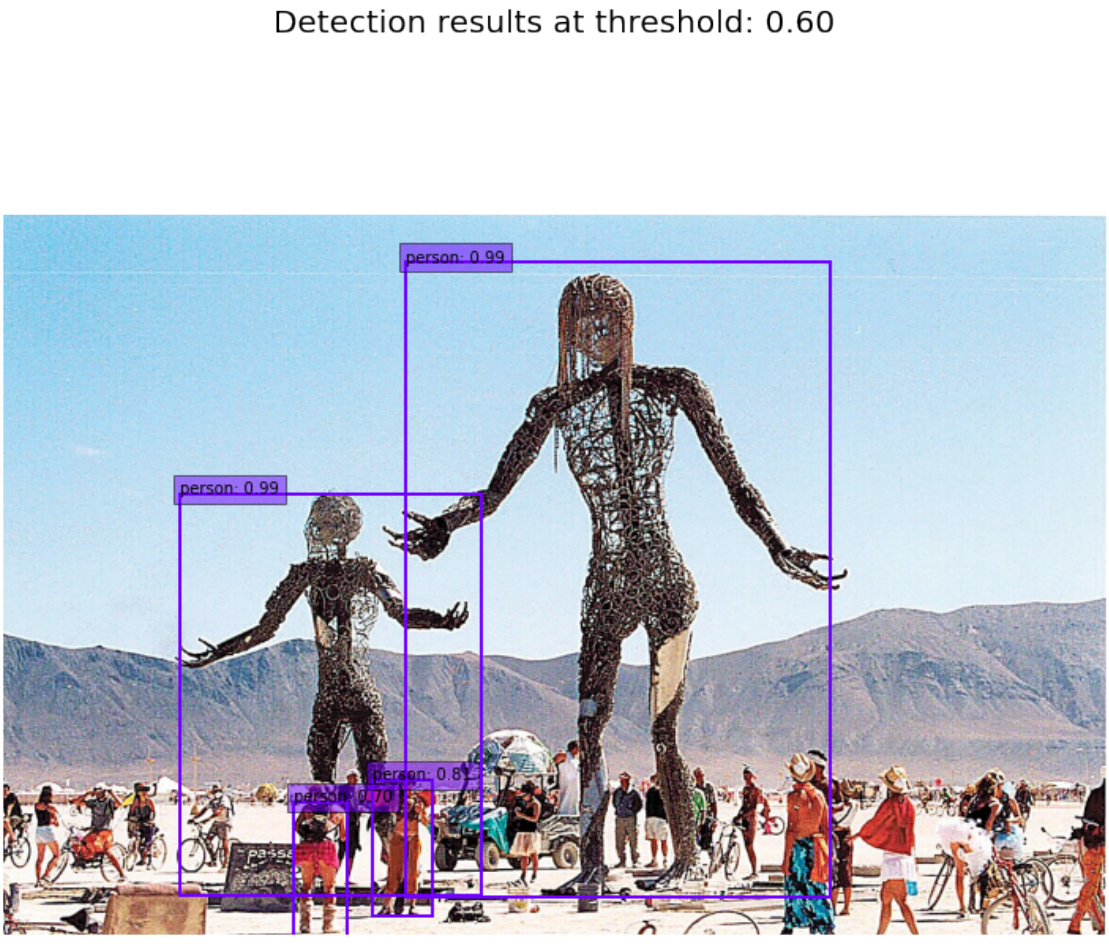
a) Based on the results (test images1) below what kind of objects are easier for the network to detect? Type your answer here:

From the results below, it would appear that the model has an easier time identifying objects framed by a fairly plain background, and that it might struggle when identifying smaller objects of the same class as bigger objects appearing at different sizes in the same image.

b) Would switching from input size 300x300 to 512x512 make the problem better, worse, or have no impact? Elaborate on why or why not. Would designing a object detector that uses HD resolution of 1920x1080, or even higher, images as inputs be a good idea? Elaborate on why or why not. Type your answer here:

Using a greater resolution might improve the identification performance, as the objects might be easier to distinguish from their backgrounds if given a more defined edge. Furthermore, a zoom-in technique appears to net positive effects on the performance. Nevertheless, this would certainly deteriorate the computational power required, and thus slow down predictions.

[12]:
```
# Photo credit: to burningman.org. Used under the fair use principles for␣
↪transformative educational purposes.
image11 = cv2.imread(data_dir+'/test_images/img11.jpg', cv2.IMREAD_COLOR)
images1=[cv2.cvtColor(image11, cv2.COLOR_BGR2RGB)]
run_network(images1, nrows=1, ncols=1, figsize=(10,10), threshold=0.6)
```



1.2.2 2.2

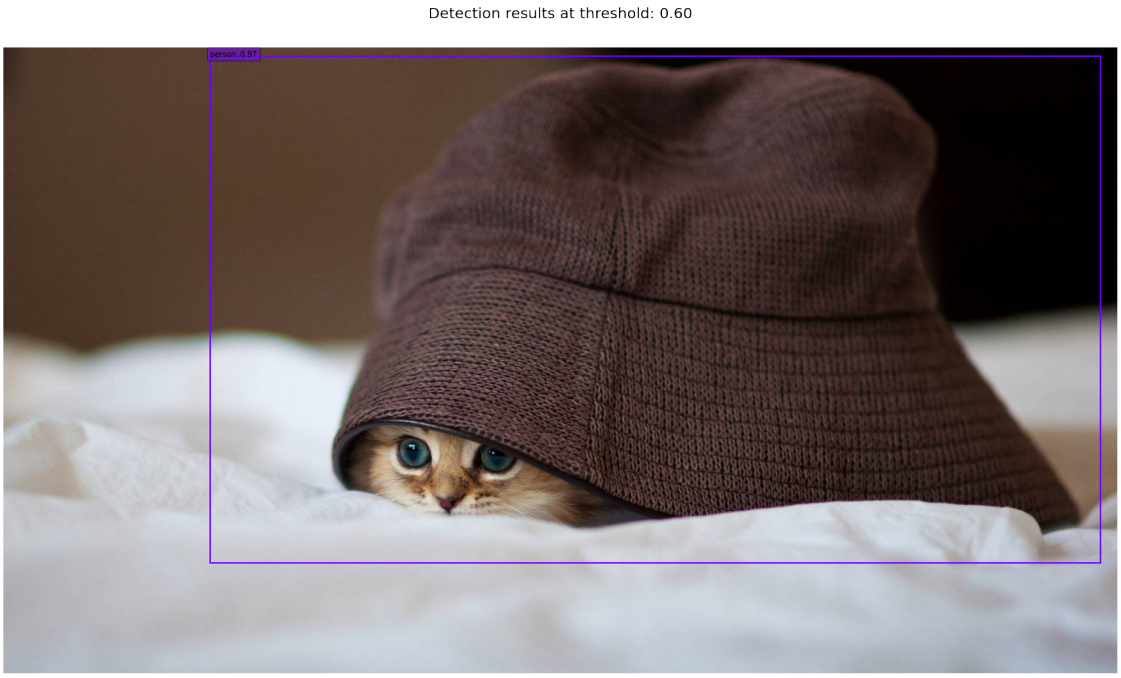
a) Based on the results (test images2) below elaborate why the detector has trouble detecting the objects? Type your answer here:

It appears from the results below that the detector has trouble identifying overlapping objects, as in the first picture it identifies the hat as a part of a human and disregards the cat (perhaps in virtue of the smaller scale of the cat), whereas in the second one only the human and one of the dogs are correctly identified, and they are both suffering from very little occlusion and standing on relatively clear backgrounds compared to the rest of the canines.

b) Have the authors of the SSD publication tried to mitigate this problem? If yes, briefly explain how. Type your answer here:

The authors of the pubblication have suggested the employment of zoom in and zoom out techniques to improve the performance on smaller objects. They have also proposed to better design the tiling of the default boxes to better align and scale them with the receptive field of each position on a feature map.

[13]:
```
# Photo credit: free wallpaper image. Used under the fair use principles for␣
 ↪transformative educational purposes.
image21 = cv2.imread(data_dir+'/test_images/img21.jpg', cv2.IMREAD_COLOR)
# Photo credit: David Dodman, KNOM. Used under the fair use principles for␣
 ↪transformative educational purposes.
image22 = cv2.imread(data_dir+'/test_images/img22.jpg', cv2.IMREAD_COLOR)
images2=[cv2.cvtColor(image21, cv2.COLOR_BGR2RGB),cv2.cvtColor(image22, cv2.
 ↪COLOR_BGR2RGB)]
run_network(images2, nrows=2, ncols=1, figsize=(25,25), threshold=0.6)
```



1.2.3 2.3

a) Based on the results (test images3) below, elaborate why the detector has trouble detecting the objects? Type your answer here:

Once again, the network seems to mostly struggle in recognizing objects that are occluded, on a cluttered background, or not clearly separable from their environment (as is the case for the smaller horse in the second image and some of the individuals in the first image).

The model appears in general to struggle when dealing with smaller objects.

b) Have the authors of the SSD publication tried to mitigate this problem? If yes, briefly explain how. Type your answer here:

The authors, as stated, provide suggestions for improving accuracy on smaller-sized objects, but not when dealing with occluded objects or ones that mix with the background and environment.

[16]:
```
# Photo credit: Duncan Rawlinson - Duncan.co photo from flickr. Creative␣
↪Commons license. https://creativecommons.org/licenses/by-nc/2.0/
image31 = cv2.imread(data_dir+'/test_images/img31.jpg', cv2.IMREAD_COLOR)
# Photo credit: Karri Huhtanen from flickr. Creative Commons license. https://
↪creativecommons.org/licenses/by-nc/2.0/
image32 = cv2.imread(data_dir+'/test_images/img32.jpg', cv2.IMREAD_COLOR)
images3=[cv2.cvtColor(image31, cv2.COLOR_BGR2RGB),cv2.cvtColor(image32, cv2.
↪COLOR_BGR2RGB)]
run_network(images3, nrows=2, ncols=1, figsize=(15,15), threshold=0.6)
```

1.2.4 2.4

a) Based on the results (test images4) below elaborate why the detector has trouble detecting objects in the first/upper image, but is able to detect objects in the second/lower image which contains the left part of the upper image? Note: you can double click the upper image to show it in actual size. Type your answer here:

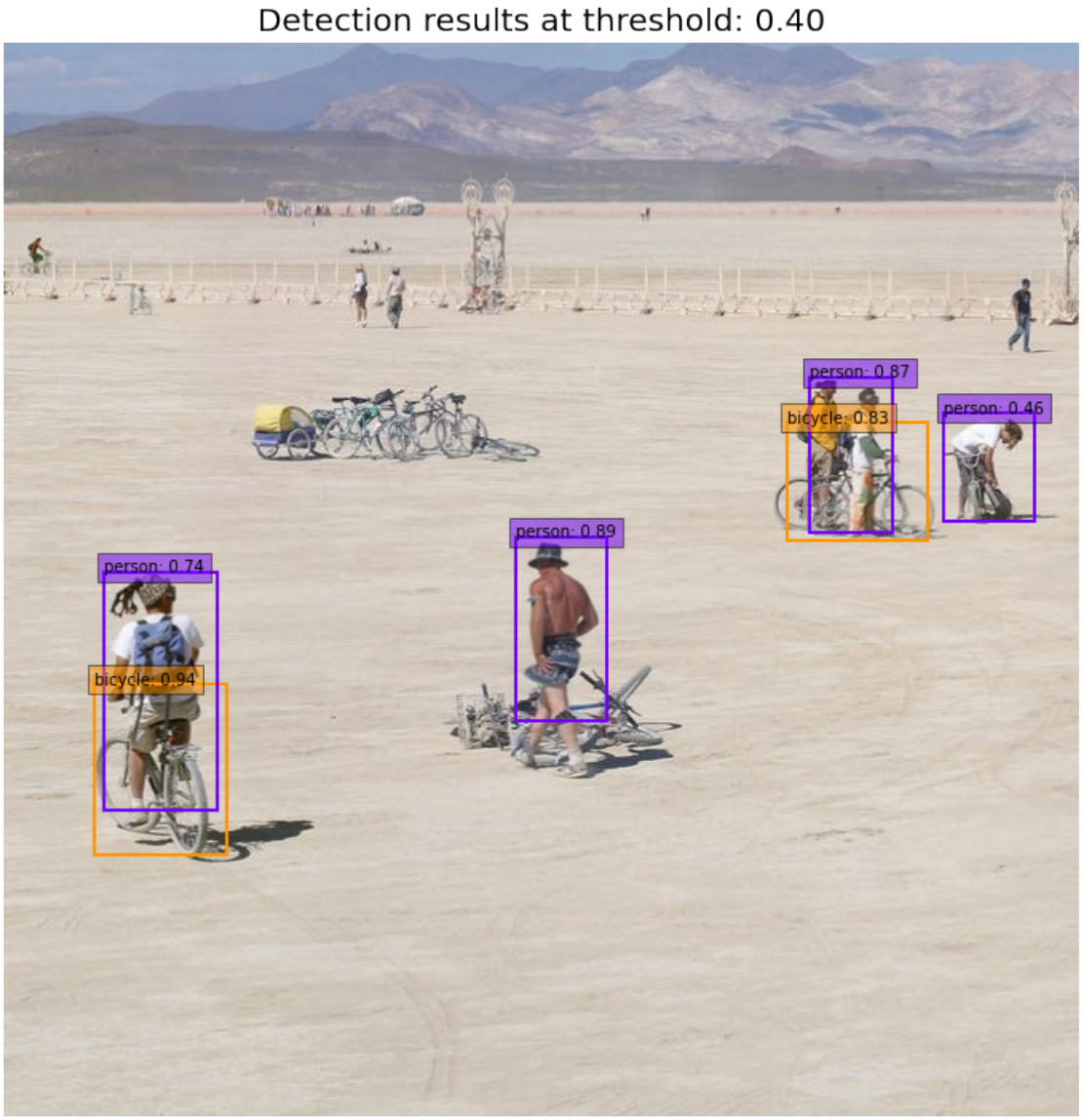
The issue is once again likely tied to the extremely small size of the objects compared to the size of the whole image, as in the second picture, where the individuals in the foreground occupy a significant portion of the image, there appears to be no issue in their identification, while the ones in the background (like those in the first image) are ignored.

b) Have the authors of the SSD publication tried to mitigate this problem? If yes, briefly explain how. Type your answer here:

As explained above, techniques of image augmentation through zooming-in and zooming-out, as well as a better design of bounding boxes, are proposed as solutions to the small object detection problem.

[19]:
```
# Photo credit: Brad Templeton. Used under the fair use principles for␣
 ↪transformative educational purposes.
image41 = cv2.imread(data_dir+'/test_images/img41.jpg', cv2.IMREAD_COLOR)
image42 = cv2.imread(data_dir+'/test_images/img42.jpg', cv2.IMREAD_COLOR)
images4 = [cv2.cvtColor(image41, cv2.COLOR_BGR2RGB), cv2.cvtColor(image42, cv2.
 ↪COLOR_BGR2RGB)]
# run the first image without title information to show it properly
run_network([images4[0]], nrows=1, ncols=1, figsize=(100,100), threshold=0.6,␣
 ↪title=False)
```

[17]:
```
run_network([images4[1]], nrows=1, ncols=1, figsize=(10,10), threshold=0.6)
```



1.2.5 2.5

a) One of the test images in (images5) was perhaps accidentally flipped vertically and as can be seen the detector has trouble detecting objects if there's a significant rotation. Have the authors of the SSD publication tried to mitigate this problem? If yes, briefly explain how. If no, propose a naive method to mitigate it and explain why it usually might not be necessary or a good idea(more harm than good). Type your answer here:

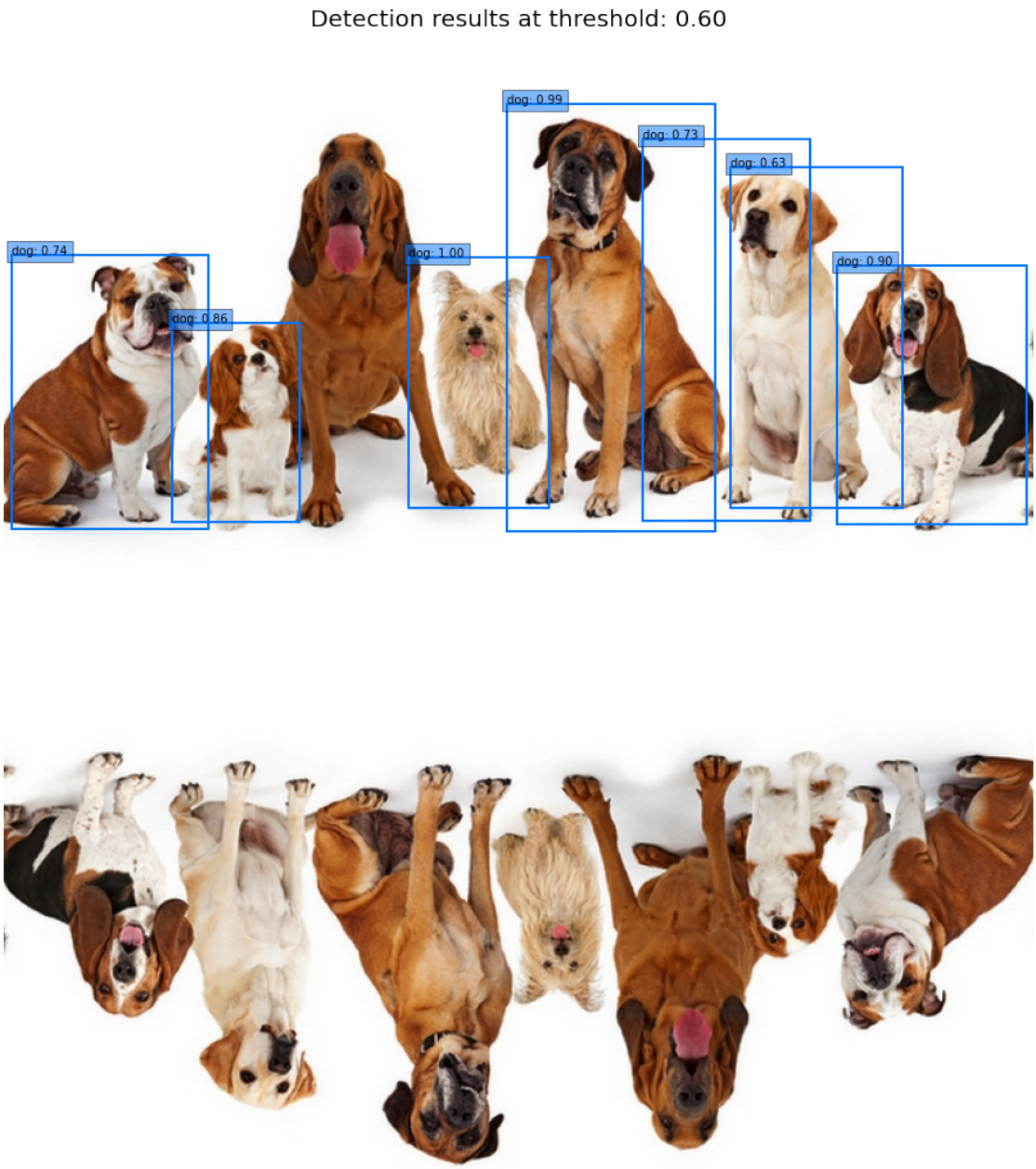
The authors do not provide any specific solutions to vertical flipping, as they consider only horizontal flipping when using image augmentation. A naive method to solve this might be to also augment the dataset with vertically-flipped images, but this might prove undesirable as the need to identify some objects upside down might occur very rarely (dogs do not often appear upside

down in normal situations), while it might be quite hard for the model to identify both versions of the object, as it might appear very different in the two situations (this may result in decreased performance when identifying the "upright" version as well).

b) Is a convolutional network naturally, without specifically adressing the issue, able to detect objects if there are small rotations? If yes, briefly explain which part of the network helps to mitigate the effects of rotation and why. (Hint: what layers are sometimes between two convolutional layers) Type your answer here:

Because of the pooling layers usually placed between convolutional layers to reduce the feature sizes are inherently resistant to small rotations, as they reduce the size of the image and such small changes may go lost in the process.
Furthermore, if the dataset also includes the same objects in various rotated versions, it is likely that the network will learn filters to identify various orientations of the objects.

[20]:
```
# Photo credit: Susan Schmitz / shutterstock. Used under the fair use␣
↪principles for transformative educational purposes.
image51 = cv2.imread(data_dir+'/test_images/img51.jpg', cv2.IMREAD_COLOR)
image52 = cv2.imread(data_dir+'/test_images/img52.jpg', cv2.IMREAD_COLOR)
images5=[cv2.cvtColor(image51, cv2.COLOR_BGR2RGB),cv2.cvtColor(image52, cv2.
↪COLOR_BGR2RGB)]
run_network(images5, nrows=2, ncols=1, figsize=(15,15), threshold=0.6)
```



1.2.6 2.6

a) Incrementally lower the detection confidence threshold, run SSD on the test images and observe the results. What are the upsides and downsides of lowering the confidence threshold? How could you measure the effect of the confidence threshold? Assume you have some object detection task that you want to apply the detector to. What kind of object detection tasks could benefit from a lower confidence threshold and

what kind of tasks need a high confidence threshold? Type your answer here

As the treshold is decreased the number of detections increases: the number of correctly classified objects will likely grow, as even objects for which there was significant uncertainty will be classified as their most likely hypothesis, but this also means that the number of missclassified objects will also grow accordingly.
Measuring the balance between these two numbers could be a useful measure of performance, such as by using mAP (precision or recall on their own are not sufficient measures of performance).
Any application where reducing the number of false positives is imperative with respect to increasing that of true positives is likely a good candidate for increasing the threshold, such as for example for a system that automatically tags individuals in pictures. A system for identifying cancerous cells from medical exams, instead, might want to have a lower threshold, as false positives can always be removed through manual review, but false negatives might have far more disastrous consequences.

b) Watch the following YouTube video of a detector that is similar to SSD called YOLO V2 (You Only Look Once) and use the knowledge from previous tasks to answer the following questions: In what object detection tasks is a state of the art object detector especially useful and able to perform better than a human? In what object detection tasks is a human better than a state of the art object detector? Give examples of both. Type your answer here

It appears that state-of-the-art object detectors are very capable of identifying a high number of objects in a very short time, something that would require slow and methodical counting for a human being, but struggle when it comes to occluded or very small sized objects, and sometimes mislabel objects from one frame to the next in virtue of some change in perspective or background. It is interesting to note that perhaps the advantage of the human mind in some of these situations may come from an understanding of continuity between different frames, as it is obvious to a human being that a tie hanging from an actor's neck will still be there if it was in the previous frame, even though it may now be heavily occluded, and that the bike they are riding will not turn into a bycicle or even a horse between one moment and the next.

[ ]: