MP3_P2

April 3, 2023

[1]:
```
import os
import random

import cv2
import numpy as np

import torch
from torch.utils.data import DataLoader
from torchvision import models

from src.resnet_yolo import resnet50
from yolo_loss import YoloLoss
from src.dataset import VocDetectorDataset
from src.eval_voc import evaluate
from src.predict import predict_image
from src.config import VOC_CLASSES, COLORS
from kaggle_submission import output_submission_csv

import matplotlib.pyplot as plt
import collections

%matplotlib inline
%load_ext autoreload
%autoreload 2
```

[ ]:
```
#!pip install opencv-python
```

0.1 Initialization

[2]:
```
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
```

[3]:
```
print(device)
```

```
cuda:0
```

[4]:
```
# YOLO network hyperparameters
B = 2  # number of bounding box predictions per cell
```

```
S = 14  # width/height of network output grid (larger than 7x7 from paper since␣
↪we use a different network)
```

To implement Yolo we will rely on a pretrained classifier as the backbone for our detection network. PyTorch offers a variety of models which are pretrained on ImageNet in the `torchvision.models` package. In particular, we will use the ResNet50 architecture as a base for our detector. This is different from the base architecture in the Yolo paper and also results in a different output grid size (14x14 instead of 7x7).

Models are typically pretrained on ImageNet since the dataset is very large (> 1 million images) and widely used. The pretrained model provides a very useful weight initialization for our detector, so that the network is able to learn quickly and effectively.

[5]:
```
load_network_path = 'checkpoints/best_detector.pth'
pretrained = True

# use to load a previously trained network
if load_network_path is not None:
    print('Loading saved network from {}'.format(load_network_path))
    net = resnet50().to(device)
    net.load_state_dict(torch.load(load_network_path))
else:
    print('Load pre-trained model')
    net = resnet50(pretrained=pretrained).to(device)
```

```
Loading saved network from checkpoints/best_detector.pth
```

[10]:
```
learning_rate = 0.001
num_epochs = 50
batch_size = 24

# Yolo loss component coefficients (as given in Yolo v1 paper)
lambda_coord = 5
lambda_noobj = 0.5
```

0.2 Reading Pascal Data

Since Pascal is a small dataset (5000 in train+val) we have combined the train and val splits to train our detector. This is not typically a good practice, but we will make an exception in this case to be able to get reasonable detection results with a comparatively small object detection dataset.

The train dataset loader also using a variety of data augmentation techniques including random shift, scaling, crop, and flips. Data augmentation is slightly more complicated for detection datasets since the bounding box annotations must be kept consistent throughout the transformations.

Since the output of the detector network we train is an SxSx(B*5+C), we use an encoder to convert the original bounding box coordinates into relative grid bounding box coordinates corresponding to the expected output. We also use a decoder which allows us to convert the opposite direction into image coordinate bounding boxes.

[11]:
```
file_root_train = 'data/VOCdevkit_2007/VOC2007/JPEGImages/'
annotation_file_train = 'data/voc2007.txt'

train_dataset =␣
 ↪VocDetectorDataset(root_img_dir=file_root_train,dataset_file=annotation_file_train,train=Tr
 ↪S=S)
train_loader =␣
 ↪DataLoader(train_dataset,batch_size=batch_size,shuffle=True,num_workers=2)
print('Loaded %d train images' % len(train_dataset))
```

```
Initializing dataset
Loaded 5011 train images
```

[12]:
```
file_root_test = 'data/VOCdevkit_2007/VOC2007test/JPEGImages/'
annotation_file_test = 'data/voc2007test.txt'

test_dataset =␣
 ↪VocDetectorDataset(root_img_dir=file_root_test,dataset_file=annotation_file_test,train=Fals
 ↪S=S)
test_loader =␣
 ↪DataLoader(test_dataset,batch_size=batch_size,shuffle=False,num_workers=2)
print('Loaded %d test images' % len(test_dataset))
```

```
Initializing dataset
Loaded 4950 test images
```

[ ]:
```
#!sh download_data.sh
```

[13]:
```
data = train_dataset[0]
```

0.3 Set up training tools

[14]:
```
criterion = YoloLoss(S, B, lambda_coord, lambda_noobj)
optimizer = torch.optim.SGD(net.parameters(), lr=learning_rate, momentum=0.9,␣
 ↪weight_decay=5e-4)
```

0.4 Train detector

[15]:
```
best_test_loss = np.inf
learning_rate = 1e-3
for epoch in range(num_epochs):
    net.train()

    # Update learning rate late in training
    if epoch == 30 or epoch == 40:
        learning_rate /= 10.0
```

```python
    for param_group in optimizer.param_groups:
        param_group['lr'] = learning_rate

    print('\n\nStarting epoch %d / %d' % (epoch + 1, num_epochs))
    print('Learning Rate for this epoch: {}'.format(learning_rate))

    total_loss = collections.defaultdict(int)

    for i, data in enumerate(train_loader):
        data = (item.to(device) for item in data)
        images, target_boxes, target_cls, has_object_map = data
        pred = net(images)
        loss_dict = criterion(pred, target_boxes, target_cls, has_object_map)
        for key in loss_dict:
            total_loss[key] += loss_dict[key].item()

        optimizer.zero_grad()
        loss_dict['total_loss'].backward()
        optimizer.step()

        if (i+1) % 50 == 0:
            outstring = 'Epoch [%d/%d], Iter [%d/%d], Loss: ' % ((epoch+1, num_epochs, i+1, len(train_loader)))
            outstring += ', '.join( "%s=%.3f" % (key[:-5], val / (i+1)) for key, val in total_loss.items() )
            print(outstring)

    # evaluate the network on the test data
    if (epoch + 1) % 5 == 0:
        test_aps = evaluate(net, test_dataset_file=annotation_file_test, img_root=file_root_test)
        print(epoch, test_aps)
    with torch.no_grad():
        test_loss = 0.0
        net.eval()
        for i, data in enumerate(test_loader):
            data = (item.to(device) for item in data)
            images, target_boxes, target_cls, has_object_map = data

            pred = net(images)
            loss_dict = criterion(pred, target_boxes, target_cls, has_object_map)
            test_loss += loss_dict['total_loss'].item()
        test_loss /= len(test_loader)

    if best_test_loss > test_loss:
```

```
        best_test_loss = test_loss
        print('Updating best test loss: %.5f' % best_test_loss)
        torch.save(net.state_dict(),'checkpoints/best_detector.pth')

    if (epoch+1) in [5, 10, 20, 30, 40]:
        torch.save(net.state_dict(),'checkpoints/detector_epoch_%d.pth' %␣
↪(epoch+1))

    torch.save(net.state_dict(),'checkpoints/detector.pth')
```

```
Starting epoch 1 / 50
Learning Rate for this epoch: 0.001
Epoch [1/50], Iter [50/209], Loss: total=5.105, reg=48.588,
containing_obj=17.907, no_obj=4.983, cls=51.039
Epoch [1/50], Iter [100/209], Loss: total=5.072, reg=49.503,
containing_obj=18.342, no_obj=4.664, cls=49.214
Epoch [1/50], Iter [150/209], Loss: total=4.994, reg=48.776,
containing_obj=18.496, no_obj=4.397, cls=48.186
Epoch [1/50], Iter [200/209], Loss: total=4.911, reg=48.040,
containing_obj=18.681, no_obj=4.171, cls=46.983
Updating best test loss: 4.61536


Starting epoch 2 / 50
Learning Rate for this epoch: 0.001
Epoch [2/50], Iter [50/209], Loss: total=4.442, reg=45.734,
containing_obj=19.313, no_obj=3.173, cls=38.388
Epoch [2/50], Iter [100/209], Loss: total=4.415, reg=45.592,
containing_obj=19.651, no_obj=3.066, cls=37.642
Epoch [2/50], Iter [150/209], Loss: total=4.346, reg=45.189,
containing_obj=19.818, no_obj=2.977, cls=36.319
Epoch [2/50], Iter [200/209], Loss: total=4.294, reg=44.770,
containing_obj=19.855, no_obj=2.902, cls=35.520
Updating best test loss: 4.20480


Starting epoch 3 / 50
Learning Rate for this epoch: 0.001
Epoch [3/50], Iter [50/209], Loss: total=4.007, reg=42.232,
containing_obj=20.305, no_obj=2.576, cls=31.059
Epoch [3/50], Iter [100/209], Loss: total=3.977, reg=42.407,
containing_obj=20.252, no_obj=2.547, cls=30.237
Epoch [3/50], Iter [150/209], Loss: total=3.950, reg=42.391,
containing_obj=20.333, no_obj=2.531, cls=29.555
```

```
Epoch [3/50], Iter [200/209], Loss: total=3.940, reg=42.554,
containing_obj=20.311, no_obj=2.526, cls=29.181
Updating best test loss: 3.96465


Starting epoch 4 / 50
Learning Rate for this epoch: 0.001
Epoch [4/50], Iter [50/209], Loss: total=3.704, reg=41.183,
containing_obj=20.191, no_obj=2.563, cls=24.960
Epoch [4/50], Iter [100/209], Loss: total=3.718, reg=41.508,
containing_obj=20.023, no_obj=2.582, cls=25.111
Epoch [4/50], Iter [150/209], Loss: total=3.698, reg=41.425,
containing_obj=19.963, no_obj=2.620, cls=24.740
Epoch [4/50], Iter [200/209], Loss: total=3.713, reg=41.703,
containing_obj=19.961, no_obj=2.651, cls=24.786
Updating best test loss: 3.69330


Starting epoch 5 / 50
Learning Rate for this epoch: 0.001
Epoch [5/50], Iter [50/209], Loss: total=3.519, reg=40.478,
containing_obj=19.963, no_obj=2.796, cls=21.219
Epoch [5/50], Iter [100/209], Loss: total=3.509, reg=39.783,
containing_obj=19.961, no_obj=2.789, cls=21.674
Epoch [5/50], Iter [150/209], Loss: total=3.502, reg=39.873,
containing_obj=19.744, no_obj=2.847, cls=21.586
Epoch [5/50], Iter [200/209], Loss: total=3.498, reg=39.979,
containing_obj=19.747, no_obj=2.868, cls=21.368
---Evaluate model on test samples---
```

100%|
| 4950/4950 [02:06<00:00, 39.06it/s]

```
---class aeroplane ap 0.17161408094659775---
---class bicycle ap 0.12407119539845314---
---class bird ap 0.12509523509711784---
---class boat ap 0.03435442495945951---
---class bottle ap 0.022105720785812268---
---class bus ap 0.02880921895006402---
---class car ap 0.2944033183821323---
---class cat ap 0.2733435763080989---
---class chair ap 0.06894892670918898---
---class cow ap 0.02544586560980003---
---class diningtable ap 0.0--- (no predictions for this class)
---class dog ap 0.024158074621938162---
---class horse ap 0.056447351037125115---
---class motorbike ap 0.06598290598290599---
---class person ap 0.21043284115664698---
---class pottedplant ap 0.01762218045112782---
```

```
---class sheep ap 0.128162425226115---
---class sofa ap 0.022058823529411766---
---class train ap 0.02718676122931442---
---class tvmonitor ap 0.25263426427212976---
---map 0.09864385953267199---
4 [0.17161408094659775, 0.12407119539845314, 0.12509523509711784,
0.03435442495945951, 0.022105720785812268, 0.02880921895006402,
0.2944033183821323, 0.2733435763080989, 0.06894892670918898,
0.02544586560980003, 0.0, 0.024158074621938162, 0.056447351037125115,
0.06598290598290599, 0.21043284115664698, 0.01762218045112782,
0.128162425226115, 0.022058823529411766, 0.02718676122931442,
0.25263426427212976]
Updating best test loss: 3.57612


Starting epoch 6 / 50
Learning Rate for this epoch: 0.001
Epoch [6/50], Iter [50/209], Loss: total=3.417, reg=40.652,
containing_obj=19.863, no_obj=2.992, cls=18.513
Epoch [6/50], Iter [100/209], Loss: total=3.371, reg=39.568,
containing_obj=19.635, no_obj=2.975, cls=18.730
Epoch [6/50], Iter [150/209], Loss: total=3.349, reg=39.116,
containing_obj=19.627, no_obj=2.975, cls=18.665
Epoch [6/50], Iter [200/209], Loss: total=3.338, reg=39.033,
containing_obj=19.469, no_obj=2.986, cls=18.635
Updating best test loss: 3.45863


Starting epoch 7 / 50
Learning Rate for this epoch: 0.001
Epoch [7/50], Iter [50/209], Loss: total=3.135, reg=37.005,
containing_obj=18.716, no_obj=3.044, cls=16.478
Epoch [7/50], Iter [100/209], Loss: total=3.164, reg=37.122,
containing_obj=19.219, no_obj=3.063, cls=16.540
Epoch [7/50], Iter [150/209], Loss: total=3.179, reg=37.327,
containing_obj=19.234, no_obj=3.051, cls=16.688
Epoch [7/50], Iter [200/209], Loss: total=3.202, reg=37.674,
containing_obj=19.326, no_obj=3.047, cls=16.799
Updating best test loss: 3.35230


Starting epoch 8 / 50
Learning Rate for this epoch: 0.001
Epoch [8/50], Iter [50/209], Loss: total=2.980, reg=34.806,
containing_obj=18.782, no_obj=3.168, cls=14.767
Epoch [8/50], Iter [100/209], Loss: total=3.062, reg=36.180,
containing_obj=19.122, no_obj=3.139, cls=15.043
Epoch [8/50], Iter [150/209], Loss: total=3.042, reg=35.912,
```

```
containing_obj=18.968, no_obj=3.169, cls=14.967
Epoch [8/50], Iter [200/209], Loss: total=3.047, reg=36.022,
containing_obj=18.874, no_obj=3.159, cls=15.073
Updating best test loss: 3.29986


Starting epoch 9 / 50
Learning Rate for this epoch: 0.001
Epoch [9/50], Iter [50/209], Loss: total=3.029, reg=36.266,
containing_obj=19.209, no_obj=3.259, cls=13.966
Epoch [9/50], Iter [100/209], Loss: total=2.975, reg=35.572,
containing_obj=18.915, no_obj=3.327, cls=13.586
Epoch [9/50], Iter [150/209], Loss: total=2.952, reg=35.149,
containing_obj=18.731, no_obj=3.314, cls=13.658
Epoch [9/50], Iter [200/209], Loss: total=2.959, reg=35.229,
containing_obj=18.948, no_obj=3.293, cls=13.545
Updating best test loss: 3.20154


Starting epoch 10 / 50
Learning Rate for this epoch: 0.001
Epoch [10/50], Iter [50/209], Loss: total=2.930, reg=35.337,
containing_obj=19.019, no_obj=3.360, cls=12.594
Epoch [10/50], Iter [100/209], Loss: total=2.901, reg=34.839,
containing_obj=18.630, no_obj=3.446, cls=12.706
Epoch [10/50], Iter [150/209], Loss: total=2.883, reg=34.423,
containing_obj=18.504, no_obj=3.486, cls=12.779
Epoch [10/50], Iter [200/209], Loss: total=2.866, reg=34.201,
containing_obj=18.486, no_obj=3.487, cls=12.619
---Evaluate model on test samples---
```

```
100%|
 | 4950/4950 [02:16<00:00, 36.28it/s]
```

```
---class aeroplane ap 0.32759125212979573---
---class bicycle ap 0.2806299021772848---
---class bird ap 0.24621451942621908---
---class boat ap 0.13699185600372224---
---class bottle ap 0.07022158907754457---
---class bus ap 0.3138167077967387---
---class car ap 0.47780032497471103---
---class cat ap 0.4405938485684612---
---class chair ap 0.16775552496483914---
---class cow ap 0.23351364344935527---
---class diningtable ap 0.10728885320096357---
---class dog ap 0.3911063680415837---
---class horse ap 0.48397160269570394---
---class motorbike ap 0.27429137660884956---
---class person ap 0.30876007249015247---
```

```
---class pottedplant ap 0.05856926544982607---
---class sheep ap 0.3782851615033031---
---class sofa ap 0.16976982126716098---
---class train ap 0.3759915357708211---
---class tvmonitor ap 0.36201211142801215---
---map 0.28025876685125245---
9 [0.32759125212979573, 0.2806299021772848, 0.24621451942621908,
0.13699185600372224, 0.07022158907754457, 0.3138167077967387,
0.47780032497471103, 0.4405938485684612, 0.16775552496483914,
0.23351364344935527, 0.10728885320096357, 0.3911063680415837,
0.48397160269570394, 0.27429137660884956, 0.30876007249015247,
0.05856926544982607, 0.3782851615033031, 0.16976982126716098,
0.3759915357708211, 0.36201211142801215]
Updating best test loss: 3.15408


Starting epoch 11 / 50
Learning Rate for this epoch: 0.001
Epoch [11/50], Iter [50/209], Loss: total=2.831, reg=33.824,
containing_obj=18.707, no_obj=3.735, cls=11.668
Epoch [11/50], Iter [100/209], Loss: total=2.778, reg=33.494,
containing_obj=17.770, no_obj=3.770, cls=11.642
Epoch [11/50], Iter [150/209], Loss: total=2.800, reg=33.665,
containing_obj=17.982, no_obj=3.760, cls=11.799
Epoch [11/50], Iter [200/209], Loss: total=2.803, reg=33.791,
containing_obj=17.949, no_obj=3.768, cls=11.774
Updating best test loss: 3.12403


Starting epoch 12 / 50
Learning Rate for this epoch: 0.001
Epoch [12/50], Iter [50/209], Loss: total=2.824, reg=34.198,
containing_obj=18.121, no_obj=3.948, cls=11.510
Epoch [12/50], Iter [100/209], Loss: total=2.742, reg=33.280,
containing_obj=17.700, no_obj=3.900, cls=10.936
Epoch [12/50], Iter [150/209], Loss: total=2.733, reg=33.099,
containing_obj=17.706, no_obj=3.877, cls=10.908
Epoch [12/50], Iter [200/209], Loss: total=2.726, reg=33.096,
containing_obj=17.649, no_obj=3.902, cls=10.782
Updating best test loss: 3.05727


Starting epoch 13 / 50
Learning Rate for this epoch: 0.001
Epoch [13/50], Iter [50/209], Loss: total=2.630, reg=31.986,
containing_obj=17.309, no_obj=4.026, cls=9.791
Epoch [13/50], Iter [100/209], Loss: total=2.673, reg=32.380,
containing_obj=17.617, no_obj=4.005, cls=10.161
```

```
Epoch [13/50], Iter [150/209], Loss: total=2.657, reg=32.008,
containing_obj=17.549, no_obj=3.965, cls=10.235
Epoch [13/50], Iter [200/209], Loss: total=2.636, reg=31.566,
containing_obj=17.535, no_obj=3.998, cls=10.164


Starting epoch 14 / 50
Learning Rate for this epoch: 0.001
Epoch [14/50], Iter [50/209], Loss: total=2.559, reg=30.224,
containing_obj=17.272, no_obj=4.174, cls=9.743
Epoch [14/50], Iter [100/209], Loss: total=2.610, reg=31.321,
containing_obj=17.475, no_obj=4.092, cls=9.755
Epoch [14/50], Iter [150/209], Loss: total=2.584, reg=31.053,
containing_obj=17.290, no_obj=4.100, cls=9.581
Epoch [14/50], Iter [200/209], Loss: total=2.610, reg=31.348,
containing_obj=17.362, no_obj=4.117, cls=9.818
Updating best test loss: 3.04060


Starting epoch 15 / 50
Learning Rate for this epoch: 0.001
Epoch [15/50], Iter [50/209], Loss: total=2.569, reg=31.172,
containing_obj=17.182, no_obj=4.181, cls=9.131
Epoch [15/50], Iter [100/209], Loss: total=2.550, reg=30.841,
containing_obj=17.009, no_obj=4.206, cls=9.138
Epoch [15/50], Iter [150/209], Loss: total=2.555, reg=30.985,
containing_obj=17.064, no_obj=4.191, cls=9.084
Epoch [15/50], Iter [200/209], Loss: total=2.547, reg=30.710,
containing_obj=17.039, no_obj=4.253, cls=9.123
---Evaluate model on test samples---

100%|
 | 4950/4950 [02:11<00:00, 37.61it/s]

---class aeroplane ap 0.45760976198934705---
---class bicycle ap 0.483975939867958---
---class bird ap 0.3909963843033205---
---class boat ap 0.2065613736401713---
---class bottle ap 0.14027800044297506---
---class bus ap 0.4421503108864963---
---class car ap 0.5443822123183203---
---class cat ap 0.6100382413355905---
---class chair ap 0.2600885162904431---
---class cow ap 0.3190303776133878---
---class diningtable ap 0.18883260247107206---
---class dog ap 0.5318155908690119---
---class horse ap 0.5734505727517876---
---class motorbike ap 0.4378733061225123---
---class person ap 0.4039076974993444---
```

```
---class pottedplant ap 0.1230559714345031---
---class sheep ap 0.36970504012094274---
---class sofa ap 0.3736092488888728---
---class train ap 0.4805555359481768---
---class tvmonitor ap 0.39534086979619854---
---map 0.3866628777295216---
14 [0.45760976198934705, 0.483975939867958, 0.3909963843033205,
0.2065613736401713, 0.14027800044297506, 0.4421503108864963, 0.5443822123183203,
0.6100382413355905, 0.2600885162904431, 0.3190303776133878, 0.18883260247107206,
0.5318155908690119, 0.5734505727517876, 0.4378733061225123, 0.4039076974993444,
0.1230559714345031, 0.36970504012094274, 0.3736092488888728, 0.4805555359481768,
0.39534086979619854]
Updating best test loss: 2.97255


Starting epoch 16 / 50
Learning Rate for this epoch: 0.001
Epoch [16/50], Iter [50/209], Loss: total=2.445, reg=29.536,
containing_obj=16.319, no_obj=4.309, cls=8.527
Epoch [16/50], Iter [100/209], Loss: total=2.525, reg=30.525,
containing_obj=16.878, no_obj=4.240, cls=8.963
Epoch [16/50], Iter [150/209], Loss: total=2.528, reg=30.626,
containing_obj=16.776, no_obj=4.267, cls=9.008
Epoch [16/50], Iter [200/209], Loss: total=2.513, reg=30.295,
containing_obj=16.816, no_obj=4.287, cls=8.908


Starting epoch 17 / 50
Learning Rate for this epoch: 0.001
Epoch [17/50], Iter [50/209], Loss: total=2.465, reg=29.383,
containing_obj=17.205, no_obj=4.182, cls=8.392
Epoch [17/50], Iter [100/209], Loss: total=2.421, reg=28.715,
containing_obj=16.601, no_obj=4.342, cls=8.437
Epoch [17/50], Iter [150/209], Loss: total=2.455, reg=29.451,
containing_obj=16.808, no_obj=4.320, cls=8.343
Epoch [17/50], Iter [200/209], Loss: total=2.443, reg=29.395,
containing_obj=16.500, no_obj=4.350, cls=8.384


Starting epoch 18 / 50
Learning Rate for this epoch: 0.001
Epoch [18/50], Iter [50/209], Loss: total=2.525, reg=30.017,
containing_obj=17.533, no_obj=4.273, cls=8.765
Epoch [18/50], Iter [100/209], Loss: total=2.467, reg=29.315,
containing_obj=16.981, no_obj=4.460, cls=8.445
Epoch [18/50], Iter [150/209], Loss: total=2.418, reg=28.568,
containing_obj=16.751, no_obj=4.463, cls=8.241
Epoch [18/50], Iter [200/209], Loss: total=2.401, reg=28.548,
```

```
containing_obj=16.624, no_obj=4.396, cls=8.066
Updating best test loss: 2.89940


Starting epoch 19 / 50
Learning Rate for this epoch: 0.001
Epoch [19/50], Iter [50/209], Loss: total=2.383, reg=28.328,
containing_obj=16.354, no_obj=4.348, cls=8.159
Epoch [19/50], Iter [100/209], Loss: total=2.318, reg=27.666,
containing_obj=16.016, no_obj=4.473, cls=7.480
Epoch [19/50], Iter [150/209], Loss: total=2.318, reg=27.612,
containing_obj=16.229, no_obj=4.418, cls=7.374
Epoch [19/50], Iter [200/209], Loss: total=2.346, reg=27.981,
containing_obj=16.423, no_obj=4.434, cls=7.464


Starting epoch 20 / 50
Learning Rate for this epoch: 0.001
Epoch [20/50], Iter [50/209], Loss: total=2.344, reg=27.857,
containing_obj=16.465, no_obj=4.591, cls=7.333
Epoch [20/50], Iter [100/209], Loss: total=2.322, reg=27.639,
containing_obj=16.138, no_obj=4.563, cls=7.385
Epoch [20/50], Iter [150/209], Loss: total=2.302, reg=27.474,
containing_obj=15.978, no_obj=4.525, cls=7.278
Epoch [20/50], Iter [200/209], Loss: total=2.312, reg=27.542,
containing_obj=16.099, no_obj=4.488, cls=7.356
---Evaluate model on test samples---

100%|
 | 4950/4950 [02:09<00:00, 38.37it/s]

---class aeroplane ap 0.4580853917059431---
---class bicycle ap 0.5137566530463874---
---class bird ap 0.40684898748325127---
---class boat ap 0.19001753072379723---
---class bottle ap 0.13638244719115208---
---class bus ap 0.5585260946192399---
---class car ap 0.5781000258876633---
---class cat ap 0.6210478984024825---
---class chair ap 0.23057758812250395---
---class cow ap 0.42142932216252593---
---class diningtable ap 0.2769178707474026---
---class dog ap 0.5636917042302402---
---class horse ap 0.6097232977789369---
---class motorbike ap 0.41536568303208676---
---class person ap 0.44598011678419486---
---class pottedplant ap 0.13901001953079187---
---class sheep ap 0.39698731257114983---
---class sofa ap 0.4474361883914806---
```

```
---class train ap 0.5510717806646239---
---class tvmonitor ap 0.46832822615833064---
---map 0.4214642069617092---
19 [0.4580853917059431, 0.5137566530463874, 0.40684898748325127,
0.19001753072379723, 0.13638244719115208, 0.5585260946192399,
0.5781000258876633, 0.6210478984024825, 0.23057758812250395,
0.42142932216252593, 0.2769178707474026, 0.5636917042302402, 0.6097232977789369,
0.41536568303208676, 0.44598011678419486, 0.13901001953079187,
0.39698731257114983, 0.4474361883914806, 0.5510717806646239,
0.46832822615833064]


Starting epoch 21 / 50
Learning Rate for this epoch: 0.001
Epoch [21/50], Iter [50/209], Loss: total=2.246, reg=26.680,
containing_obj=15.845, no_obj=4.556, cls=6.831
Epoch [21/50], Iter [100/209], Loss: total=2.251, reg=26.689,
containing_obj=15.764, no_obj=4.500, cls=7.060
Epoch [21/50], Iter [150/209], Loss: total=2.235, reg=26.503,
containing_obj=15.723, no_obj=4.439, cls=6.968
Epoch [21/50], Iter [200/209], Loss: total=2.263, reg=26.991,
containing_obj=15.914, no_obj=4.456, cls=6.960
Updating best test loss: 2.85074


Starting epoch 22 / 50
Learning Rate for this epoch: 0.001
Epoch [22/50], Iter [50/209], Loss: total=2.210, reg=25.705,
containing_obj=15.677, no_obj=4.721, cls=6.936
Epoch [22/50], Iter [100/209], Loss: total=2.241, reg=26.188,
containing_obj=15.898, no_obj=4.608, cls=7.091
Epoch [22/50], Iter [150/209], Loss: total=2.237, reg=26.223,
containing_obj=15.788, no_obj=4.647, cls=7.020
Epoch [22/50], Iter [200/209], Loss: total=2.229, reg=26.355,
containing_obj=15.748, no_obj=4.616, cls=6.784
Updating best test loss: 2.83620


Starting epoch 23 / 50
Learning Rate for this epoch: 0.001
Epoch [23/50], Iter [50/209], Loss: total=2.167, reg=25.478,
containing_obj=15.590, no_obj=4.501, cls=6.449
Epoch [23/50], Iter [100/209], Loss: total=2.142, reg=25.058,
containing_obj=15.164, no_obj=4.652, cls=6.543
Epoch [23/50], Iter [150/209], Loss: total=2.196, reg=25.980,
containing_obj=15.480, no_obj=4.682, cls=6.563
Epoch [23/50], Iter [200/209], Loss: total=2.205, reg=26.143,
containing_obj=15.504, no_obj=4.676, cls=6.586
```

```
Updating best test loss: 2.79819


Starting epoch 24 / 50
Learning Rate for this epoch: 0.001
Epoch [24/50], Iter [50/209], Loss: total=2.202, reg=26.410,
containing_obj=15.717, no_obj=4.632, cls=6.090
Epoch [24/50], Iter [100/209], Loss: total=2.116, reg=25.037,
containing_obj=15.137, no_obj=4.587, cls=6.012
Epoch [24/50], Iter [150/209], Loss: total=2.173, reg=25.760,
containing_obj=15.512, no_obj=4.597, cls=6.275
Epoch [24/50], Iter [200/209], Loss: total=2.168, reg=25.632,
containing_obj=15.536, no_obj=4.612, cls=6.247


Starting epoch 25 / 50
Learning Rate for this epoch: 0.001
Epoch [25/50], Iter [50/209], Loss: total=2.143, reg=25.409,
containing_obj=15.564, no_obj=4.692, cls=5.761
Epoch [25/50], Iter [100/209], Loss: total=2.185, reg=25.996,
containing_obj=15.628, no_obj=4.640, cls=6.185
Epoch [25/50], Iter [150/209], Loss: total=2.128, reg=25.227,
containing_obj=15.190, no_obj=4.682, cls=5.973
Epoch [25/50], Iter [200/209], Loss: total=2.131, reg=25.103,
containing_obj=15.178, no_obj=4.647, cls=6.219
---Evaluate model on test samples---
```

100%|
 | 4950/4950 [02:20<00:00, 35.33it/s]

```
---class aeroplane ap 0.45510018025967164---
---class bicycle ap 0.5846697139557637---
---class bird ap 0.38218254677423863---
---class boat ap 0.21184449611113207---
---class bottle ap 0.15503145008282587---
---class bus ap 0.577843809461452---
---class car ap 0.6440837504025503---
---class cat ap 0.6242860539447227---
---class chair ap 0.29104001081275166---
---class cow ap 0.43222827078027104---
---class diningtable ap 0.2314115586669184---
---class dog ap 0.5630229402431015---
---class horse ap 0.6298300706096287---
---class motorbike ap 0.5409960409042666---
---class person ap 0.47873133600612494---
---class pottedplant ap 0.09288633771099122---
---class sheep ap 0.3622713980124518---
---class sofa ap 0.48002371312579883---
---class train ap 0.6470192992540734---
```

```
---class tvmonitor ap 0.456772805866415---
---map 0.4420637891492575---
24 [0.45510018025967164, 0.5846697139557637, 0.38218254677423863,
0.21184449611113207, 0.15503145008282587, 0.577843809461452, 0.6440837504025503,
0.6242860539447227, 0.29104001081275166, 0.43222827078027104,
0.2314115586669184, 0.5630229402431015, 0.6298300706096287, 0.5409960409042666,
0.47873133600612494, 0.09288633771099122, 0.3622713980124518,
0.48002371312579883, 0.6470192992540734, 0.456772805866415]


Starting epoch 26 / 50
Learning Rate for this epoch: 0.001
Epoch [26/50], Iter [50/209], Loss: total=2.103, reg=24.355,
containing_obj=15.516, no_obj=4.663, cls=5.941
Epoch [26/50], Iter [100/209], Loss: total=2.113, reg=24.604,
containing_obj=15.396, no_obj=4.778, cls=5.938
Epoch [26/50], Iter [150/209], Loss: total=2.106, reg=24.608,
containing_obj=15.441, no_obj=4.726, cls=5.780
Epoch [26/50], Iter [200/209], Loss: total=2.106, reg=24.606,
containing_obj=15.462, no_obj=4.749, cls=5.729
Updating best test loss: 2.79690


Starting epoch 27 / 50
Learning Rate for this epoch: 0.001
Epoch [27/50], Iter [50/209], Loss: total=2.105, reg=24.837,
containing_obj=14.947, no_obj=4.905, cls=5.824
Epoch [27/50], Iter [100/209], Loss: total=2.080, reg=24.454,
containing_obj=15.105, no_obj=4.746, cls=5.604
Epoch [27/50], Iter [150/209], Loss: total=2.098, reg=24.623,
containing_obj=15.288, no_obj=4.757, cls=5.680
Epoch [27/50], Iter [200/209], Loss: total=2.087, reg=24.547,
containing_obj=15.109, no_obj=4.739, cls=5.698


Starting epoch 28 / 50
Learning Rate for this epoch: 0.001
Epoch [28/50], Iter [50/209], Loss: total=2.025, reg=23.715,
containing_obj=14.605, no_obj=4.794, cls=5.493
Epoch [28/50], Iter [100/209], Loss: total=2.035, reg=24.003,
containing_obj=14.749, no_obj=4.752, cls=5.328
Epoch [28/50], Iter [150/209], Loss: total=2.055, reg=24.281,
containing_obj=14.806, no_obj=4.738, cls=5.488
Epoch [28/50], Iter [200/209], Loss: total=2.055, reg=24.266,
containing_obj=14.851, no_obj=4.746, cls=5.458


Starting epoch 29 / 50
```

```
Learning Rate for this epoch: 0.001
Epoch [29/50], Iter [50/209], Loss: total=1.928, reg=22.624,
containing_obj=14.062, no_obj=4.616, cls=4.962
Epoch [29/50], Iter [100/209], Loss: total=2.005, reg=23.581,
containing_obj=14.683, no_obj=4.614, cls=5.244
Epoch [29/50], Iter [150/209], Loss: total=2.040, reg=23.997,
containing_obj=14.854, no_obj=4.678, cls=5.430
Epoch [29/50], Iter [200/209], Loss: total=2.032, reg=23.911,
containing_obj=14.777, no_obj=4.747, cls=5.337
Updating best test loss: 2.76463


Starting epoch 30 / 50
Learning Rate for this epoch: 0.001
Epoch [30/50], Iter [50/209], Loss: total=2.068, reg=24.125,
containing_obj=15.540, no_obj=4.830, cls=5.132
Epoch [30/50], Iter [100/209], Loss: total=2.026, reg=23.525,
containing_obj=15.219, no_obj=4.729, cls=5.142
Epoch [30/50], Iter [150/209], Loss: total=2.004, reg=23.333,
containing_obj=14.846, no_obj=4.743, cls=5.164
Epoch [30/50], Iter [200/209], Loss: total=1.995, reg=23.170,
containing_obj=14.762, no_obj=4.704, cls=5.235
---Evaluate model on test samples---

100%|
 | 4950/4950 [02:17<00:00, 35.92it/s]

---class aeroplane ap 0.4115328180936668---
---class bicycle ap 0.5637730765213327---
---class bird ap 0.44284741967336805---
---class boat ap 0.2525873230816146---
---class bottle ap 0.17490276978211083---
---class bus ap 0.6263552283480822---
---class car ap 0.6143877957083295---
---class cat ap 0.6321776559192652---
---class chair ap 0.303396889853553---
---class cow ap 0.441115191184278---
---class diningtable ap 0.3310075915106198---
---class dog ap 0.5441947975445298---
---class horse ap 0.6452467850052113---
---class motorbike ap 0.5450542458998258---
---class person ap 0.5084211623349233---
---class pottedplant ap 0.166398368993029---
---class sheep ap 0.4256020615360726---
---class sofa ap 0.45191950028193906---
---class train ap 0.6112519665205188---
---class tvmonitor ap 0.45523816741516565---
---map 0.45737054076037176---
29 [0.4115328180936668, 0.5637730765213327, 0.44284741967336805,
```

```
0.2525873230816146, 0.17490276978211083, 0.6263552283480822, 0.6143877957083295,
0.6321776559192652, 0.303396889853553, 0.441115191184278, 0.3310075915106198,
0.5441947975445298, 0.6452467850052113, 0.5450542458998258, 0.5084211623349233,
0.166398368993029, 0.4256020615360726, 0.45191950028193906, 0.6112519665205188,
0.45523816741516565]


Starting epoch 31 / 50
Learning Rate for this epoch: 0.0001
Epoch [31/50], Iter [50/209], Loss: total=1.970, reg=22.787,
containing_obj=14.786, no_obj=4.598, cls=5.116
Epoch [31/50], Iter [100/209], Loss: total=1.947, reg=22.280,
containing_obj=14.925, no_obj=4.539, cls=4.973
Epoch [31/50], Iter [150/209], Loss: total=1.911, reg=22.026,
containing_obj=14.480, no_obj=4.622, cls=4.728
Epoch [31/50], Iter [200/209], Loss: total=1.905, reg=21.902,
containing_obj=14.505, no_obj=4.615, cls=4.688
Updating best test loss: 2.73661


Starting epoch 32 / 50
Learning Rate for this epoch: 0.0001
Epoch [32/50], Iter [50/209], Loss: total=1.946, reg=22.625,
containing_obj=14.850, no_obj=4.641, cls=4.591
Epoch [32/50], Iter [100/209], Loss: total=1.902, reg=22.125,
containing_obj=14.278, no_obj=4.755, cls=4.491
Epoch [32/50], Iter [150/209], Loss: total=1.881, reg=21.850,
containing_obj=14.099, no_obj=4.782, cls=4.403
Epoch [32/50], Iter [200/209], Loss: total=1.870, reg=21.534,
containing_obj=14.164, no_obj=4.791, cls=4.404
Updating best test loss: 2.71220


Starting epoch 33 / 50
Learning Rate for this epoch: 0.0001
Epoch [33/50], Iter [50/209], Loss: total=1.874, reg=21.718,
containing_obj=13.874, no_obj=4.709, cls=4.667
Epoch [33/50], Iter [100/209], Loss: total=1.863, reg=21.470,
containing_obj=14.019, no_obj=4.700, cls=4.527
Epoch [33/50], Iter [150/209], Loss: total=1.845, reg=21.184,
containing_obj=14.057, no_obj=4.745, cls=4.294
Epoch [33/50], Iter [200/209], Loss: total=1.841, reg=21.173,
containing_obj=13.983, no_obj=4.765, cls=4.250
Updating best test loss: 2.69821


Starting epoch 34 / 50
Learning Rate for this epoch: 0.0001
```

```
Epoch [34/50], Iter [50/209], Loss: total=1.816, reg=20.667,
containing_obj=14.198, no_obj=4.778, cls=3.941
Epoch [34/50], Iter [100/209], Loss: total=1.795, reg=20.292,
containing_obj=14.048, no_obj=4.823, cls=3.913
Epoch [34/50], Iter [150/209], Loss: total=1.815, reg=20.484,
containing_obj=14.270, no_obj=4.847, cls=3.970
Epoch [34/50], Iter [200/209], Loss: total=1.799, reg=20.455,
containing_obj=13.887, no_obj=4.858, cls=3.973


Starting epoch 35 / 50
Learning Rate for this epoch: 0.0001
Epoch [35/50], Iter [50/209], Loss: total=1.845, reg=22.004,
containing_obj=13.826, no_obj=4.841, cls=3.599
Epoch [35/50], Iter [100/209], Loss: total=1.825, reg=21.481,
containing_obj=13.751, no_obj=4.801, cls=3.768
Epoch [35/50], Iter [150/209], Loss: total=1.835, reg=21.415,
containing_obj=13.780, no_obj=4.841, cls=3.996
Epoch [35/50], Iter [200/209], Loss: total=1.826, reg=21.175,
containing_obj=13.773, no_obj=4.891, cls=3.979
---Evaluate model on test samples---
```

```
100%|
 | 4950/4950 [02:13<00:00, 36.97it/s]
```

```
---class aeroplane ap 0.5015841828619411---
---class bicycle ap 0.5737645009502131---
---class bird ap 0.4415587018017179---
---class boat ap 0.2657245059389986---
---class bottle ap 0.20585613029694622---
---class bus ap 0.6074486178360536---
---class car ap 0.6671725977016119---
---class cat ap 0.6889047894184854---
---class chair ap 0.29716188657577514---
---class cow ap 0.47647227446061174---
---class diningtable ap 0.29130837187201464---
---class dog ap 0.6184621372595114---
---class horse ap 0.6924931836275818---
---class motorbike ap 0.5706526806347401---
---class person ap 0.5274832119788899---
---class pottedplant ap 0.1865703405441458---
---class sheep ap 0.4505184922055523---
---class sofa ap 0.482668307755021---
---class train ap 0.6573379631525498---
---class tvmonitor ap 0.4812228131797921---
---map 0.4842182845026077---
34 [0.5015841828619411, 0.5737645009502131, 0.4415587018017179,
0.2657245059389986, 0.20585613029694622, 0.6074486178360536, 0.6671725977016119,
0.6889047894184854, 0.29716188657577514, 0.47647227446061174,
```

```
0.29130837187201464, 0.6184621372595114, 0.6924931836275818, 0.5706526806347401,
0.5274832119788899, 0.1865703405441458, 0.4505184922055523, 0.482668307755021,
0.6573379631525498, 0.4812228131797921]


Starting epoch 36 / 50
Learning Rate for this epoch: 0.0001
Epoch [36/50], Iter [50/209], Loss: total=1.816, reg=21.054,
containing_obj=13.920, no_obj=4.849, cls=3.761
Epoch [36/50], Iter [100/209], Loss: total=1.799, reg=20.268,
containing_obj=14.032, no_obj=4.926, cls=3.954
Epoch [36/50], Iter [150/209], Loss: total=1.796, reg=20.362,
containing_obj=13.990, no_obj=4.867, cls=3.873
Epoch [36/50], Iter [200/209], Loss: total=1.787, reg=20.413,
containing_obj=13.790, no_obj=4.875, cls=3.819


Starting epoch 37 / 50
Learning Rate for this epoch: 0.0001
Epoch [37/50], Iter [50/209], Loss: total=1.729, reg=19.856,
containing_obj=12.871, no_obj=4.973, cls=3.806
Epoch [37/50], Iter [100/209], Loss: total=1.741, reg=19.667,
containing_obj=13.336, no_obj=4.853, cls=3.927
Epoch [37/50], Iter [150/209], Loss: total=1.801, reg=20.529,
containing_obj=13.719, no_obj=4.837, cls=4.132
Epoch [37/50], Iter [200/209], Loss: total=1.810, reg=20.840,
containing_obj=13.715, no_obj=4.815, cls=4.075


Starting epoch 38 / 50
Learning Rate for this epoch: 0.0001
Epoch [38/50], Iter [50/209], Loss: total=1.820, reg=21.041,
containing_obj=13.914, no_obj=4.922, cls=3.801
Epoch [38/50], Iter [100/209], Loss: total=1.806, reg=20.750,
containing_obj=13.856, no_obj=4.828, cls=3.909
Epoch [38/50], Iter [150/209], Loss: total=1.776, reg=20.386,
containing_obj=13.757, no_obj=4.803, cls=3.682
Epoch [38/50], Iter [200/209], Loss: total=1.791, reg=20.669,
containing_obj=13.765, no_obj=4.806, cls=3.747


Starting epoch 39 / 50
Learning Rate for this epoch: 0.0001
Epoch [39/50], Iter [50/209], Loss: total=1.826, reg=21.058,
containing_obj=13.726, no_obj=4.898, cls=4.136
Epoch [39/50], Iter [100/209], Loss: total=1.817, reg=20.857,
containing_obj=14.047, no_obj=4.851, cls=3.843
Epoch [39/50], Iter [150/209], Loss: total=1.790, reg=20.449,
```

```
containing_obj=13.839, no_obj=4.862, cls=3.804
Epoch [39/50], Iter [200/209], Loss: total=1.782, reg=20.367,
containing_obj=13.691, no_obj=4.856, cls=3.850
Updating best test loss: 2.69353


Starting epoch 40 / 50
Learning Rate for this epoch: 0.0001
Epoch [40/50], Iter [50/209], Loss: total=1.804, reg=20.610,
containing_obj=13.922, no_obj=4.838, cls=3.930
Epoch [40/50], Iter [100/209], Loss: total=1.782, reg=20.428,
containing_obj=13.761, no_obj=4.841, cls=3.738
Epoch [40/50], Iter [150/209], Loss: total=1.763, reg=20.167,
containing_obj=13.521, no_obj=4.907, cls=3.714
Epoch [40/50], Iter [200/209], Loss: total=1.767, reg=20.246,
containing_obj=13.544, no_obj=4.929, cls=3.687
---Evaluate model on test samples---

100%|
 | 4950/4950 [02:07<00:00, 38.75it/s]

---class aeroplane ap 0.5471852377030704---
---class bicycle ap 0.599880677438095---
---class bird ap 0.44006415978243024---
---class boat ap 0.2879810203603893---
---class bottle ap 0.1993108871277625---
---class bus ap 0.6079927205703958---
---class car ap 0.6742644566294846---
---class cat ap 0.7103924163413364---
---class chair ap 0.2928207489572525---
---class cow ap 0.4841433220484835---
---class diningtable ap 0.35502103352448594---
---class dog ap 0.630113264958524---
---class horse ap 0.6776080391034103---
---class motorbike ap 0.5968619274463705---
---class person ap 0.5331282853094794---
---class pottedplant ap 0.176486826695477---
---class sheep ap 0.4553342929706228---
---class sofa ap 0.48457882706917166---
---class train ap 0.6778597169235471---
---class tvmonitor ap 0.48879488823939055---
---map 0.49599113745995893---
39 [0.5471852377030704, 0.599880677438095, 0.44006415978243024,
0.2879810203603893, 0.1993108871277625, 0.6079927205703958, 0.6742644566294846,
0.7103924163413364, 0.2928207489572525, 0.4841433220484835, 0.35502103352448594,
0.630113264958524, 0.6776080391034103, 0.5968619274463705, 0.5331282853094794,
0.176486826695477, 0.4553342929706228, 0.48457882706917166, 0.6778597169235471,
0.48879488823939055]
```

```
Starting epoch 41 / 50
Learning Rate for this epoch: 1e-05
Epoch [41/50], Iter [50/209], Loss: total=1.782, reg=20.412,
containing_obj=13.515, no_obj=5.079, cls=3.774
Epoch [41/50], Iter [100/209], Loss: total=1.797, reg=20.606,
containing_obj=13.872, no_obj=4.968, cls=3.673
Epoch [41/50], Iter [150/209], Loss: total=1.780, reg=20.385,
containing_obj=13.642, no_obj=4.968, cls=3.729
Epoch [41/50], Iter [200/209], Loss: total=1.753, reg=19.937,
containing_obj=13.480, no_obj=4.979, cls=3.665


Starting epoch 42 / 50
Learning Rate for this epoch: 1e-05
Epoch [42/50], Iter [50/209], Loss: total=1.753, reg=19.605,
containing_obj=13.457, no_obj=4.979, cls=4.026
Epoch [42/50], Iter [100/209], Loss: total=1.758, reg=19.781,
containing_obj=13.507, no_obj=4.930, cls=3.983
Epoch [42/50], Iter [150/209], Loss: total=1.759, reg=19.921,
containing_obj=13.594, no_obj=4.916, cls=3.788
Epoch [42/50], Iter [200/209], Loss: total=1.754, reg=19.887,
containing_obj=13.581, no_obj=4.898, cls=3.735


Starting epoch 43 / 50
Learning Rate for this epoch: 1e-05
Epoch [43/50], Iter [50/209], Loss: total=1.791, reg=20.130,
containing_obj=14.103, no_obj=4.782, cls=3.974
Epoch [43/50], Iter [100/209], Loss: total=1.775, reg=20.036,
containing_obj=13.865, no_obj=4.826, cls=3.880
Epoch [43/50], Iter [150/209], Loss: total=1.757, reg=20.038,
containing_obj=13.608, no_obj=4.842, cls=3.687
Epoch [43/50], Iter [200/209], Loss: total=1.749, reg=19.954,
containing_obj=13.481, no_obj=4.867, cls=3.664


Starting epoch 44 / 50
Learning Rate for this epoch: 1e-05
Epoch [44/50], Iter [50/209], Loss: total=1.726, reg=19.772,
containing_obj=12.937, no_obj=4.987, cls=3.739
Epoch [44/50], Iter [100/209], Loss: total=1.740, reg=19.944,
containing_obj=13.065, no_obj=4.970, cls=3.769
Epoch [44/50], Iter [150/209], Loss: total=1.759, reg=20.151,
containing_obj=13.348, no_obj=4.914, cls=3.794
Epoch [44/50], Iter [200/209], Loss: total=1.755, reg=20.163,
containing_obj=13.356, no_obj=4.921, cls=3.688
```

```
Starting epoch 45 / 50
Learning Rate for this epoch: 1e-05
Epoch [45/50], Iter [50/209], Loss: total=1.742, reg=20.028,
containing_obj=13.298, no_obj=4.793, cls=3.695
Epoch [45/50], Iter [100/209], Loss: total=1.727, reg=19.826,
containing_obj=13.154, no_obj=4.867, cls=3.597
Epoch [45/50], Iter [150/209], Loss: total=1.760, reg=20.268,
containing_obj=13.423, no_obj=4.839, cls=3.711
Epoch [45/50], Iter [200/209], Loss: total=1.752, reg=20.054,
containing_obj=13.402, no_obj=4.864, cls=3.731
---Evaluate model on test samples---

100%|
 | 4950/4950 [02:06<00:00, 38.98it/s]

---class aeroplane ap 0.5230456491690038---
---class bicycle ap 0.6017178189255944---
---class bird ap 0.461376535155851---
---class boat ap 0.27407296969560446---
---class bottle ap 0.20438050065782964---
---class bus ap 0.6156374613125809---
---class car ap 0.6719657440438076---
---class cat ap 0.7026668826881459---
---class chair ap 0.3103430988456956---
---class cow ap 0.4856754308039742---
---class diningtable ap 0.35032276127213585---
---class dog ap 0.6224744623066669---
---class horse ap 0.6775241432203234---
---class motorbike ap 0.5902145320416573---
---class person ap 0.5322799397388385---
---class pottedplant ap 0.1717838443088106---
---class sheep ap 0.452098954508532---
---class sofa ap 0.48323955383364725---
---class train ap 0.6811050116266878---
---class tvmonitor ap 0.4943698211724163---
---map 0.4953147557663901---
44 [0.5230456491690038, 0.6017178189255944, 0.461376535155851,
0.27407296969560446, 0.20438050065782964, 0.6156374613125809,
0.6719657440438076, 0.7026668826881459, 0.3103430988456956, 0.4856754308039742,
0.35032276127213585, 0.6224744623066669, 0.6775241432203234, 0.5902145320416573,
0.5322799397388385, 0.1717838443088106, 0.452098954508532, 0.48323955383364725,
0.6811050116266878, 0.4943698211724163]


Starting epoch 46 / 50
Learning Rate for this epoch: 1e-05
Epoch [46/50], Iter [50/209], Loss: total=1.725, reg=19.746,
containing_obj=12.893, no_obj=5.110, cls=3.649
```

```
Epoch [46/50], Iter [100/209], Loss: total=1.758, reg=20.241,
containing_obj=13.188, no_obj=5.006, cls=3.752
Epoch [46/50], Iter [150/209], Loss: total=1.759, reg=20.340,
containing_obj=13.320, no_obj=4.966, cls=3.592
Epoch [46/50], Iter [200/209], Loss: total=1.761, reg=20.367,
containing_obj=13.261, no_obj=4.954, cls=3.676


Starting epoch 47 / 50
Learning Rate for this epoch: 1e-05
Epoch [47/50], Iter [50/209], Loss: total=1.705, reg=19.236,
containing_obj=12.992, no_obj=4.838, cls=3.844
Epoch [47/50], Iter [100/209], Loss: total=1.746, reg=19.768,
containing_obj=13.502, no_obj=4.884, cls=3.753
Epoch [47/50], Iter [150/209], Loss: total=1.750, reg=19.999,
containing_obj=13.505, no_obj=4.823, cls=3.675
Epoch [47/50], Iter [200/209], Loss: total=1.753, reg=20.083,
containing_obj=13.461, no_obj=4.878, cls=3.658


Starting epoch 48 / 50
Learning Rate for this epoch: 1e-05
Epoch [48/50], Iter [50/209], Loss: total=1.702, reg=19.046,
containing_obj=12.787, no_obj=5.031, cls=3.993
Epoch [48/50], Iter [100/209], Loss: total=1.726, reg=19.612,
containing_obj=13.078, no_obj=4.956, cls=3.773
Epoch [48/50], Iter [150/209], Loss: total=1.732, reg=19.594,
containing_obj=13.322, no_obj=4.931, cls=3.722
Epoch [48/50], Iter [200/209], Loss: total=1.753, reg=19.988,
containing_obj=13.472, no_obj=4.884, cls=3.716


Starting epoch 49 / 50
Learning Rate for this epoch: 1e-05
Epoch [49/50], Iter [50/209], Loss: total=1.769, reg=20.327,
containing_obj=13.754, no_obj=4.863, cls=3.520
Epoch [49/50], Iter [100/209], Loss: total=1.752, reg=20.046,
containing_obj=13.459, no_obj=5.014, cls=3.523
Epoch [49/50], Iter [150/209], Loss: total=1.752, reg=20.032,
containing_obj=13.457, no_obj=4.976, cls=3.571
Epoch [49/50], Iter [200/209], Loss: total=1.751, reg=20.131,
containing_obj=13.494, no_obj=4.868, cls=3.532
Updating best test loss: 2.69256


Starting epoch 50 / 50
Learning Rate for this epoch: 1e-05
Epoch [50/50], Iter [50/209], Loss: total=1.769, reg=20.975,
```

```
containing_obj=13.127, no_obj=4.931, cls=3.414
Epoch [50/50], Iter [100/209], Loss: total=1.761, reg=20.258,
containing_obj=13.391, no_obj=4.894, cls=3.712
Epoch [50/50], Iter [150/209], Loss: total=1.762, reg=20.194,
containing_obj=13.506, no_obj=4.914, cls=3.670
Epoch [50/50], Iter [200/209], Loss: total=1.754, reg=20.172,
containing_obj=13.325, no_obj=4.925, cls=3.667
---Evaluate model on test samples---

100%|
 | 4950/4950 [02:07<00:00, 38.92it/s]

---class aeroplane ap 0.5152544744284651---
---class bicycle ap 0.5920777658191306---
---class bird ap 0.45535406184016874---
---class boat ap 0.27986742452993696---
---class bottle ap 0.20548321104585845---
---class bus ap 0.6117309020759428---
---class car ap 0.6718466477606162---
---class cat ap 0.7060565989229535---
---class chair ap 0.2980292398784073---
---class cow ap 0.48919652335636443---
---class diningtable ap 0.3528964567761616---
---class dog ap 0.6319911024488902---
---class horse ap 0.6741013742724802---
---class motorbike ap 0.5930620028875222---
---class person ap 0.5321600338111911---
---class pottedplant ap 0.17018685546734325---
---class sheep ap 0.4597273489878889---
---class sofa ap 0.48982974968452814---
---class train ap 0.6701924283859848---
---class tvmonitor ap 0.5064760178649267---
---map 0.495276011012238---
49 [0.5152544744284651, 0.5920777658191306, 0.45535406184016874,
0.27986742452993696, 0.20548321104585845, 0.6117309020759428,
0.6718466477606162, 0.7060565989229535, 0.2980292398784073, 0.48919652335636443,
0.3528964567761616, 0.6319911024488902, 0.6741013742724802, 0.5930620028875222,
0.5321600338111911, 0.17018685546734325, 0.4597273489878889,
0.48982974968452814, 0.6701924283859848, 0.5064760178649267]
```

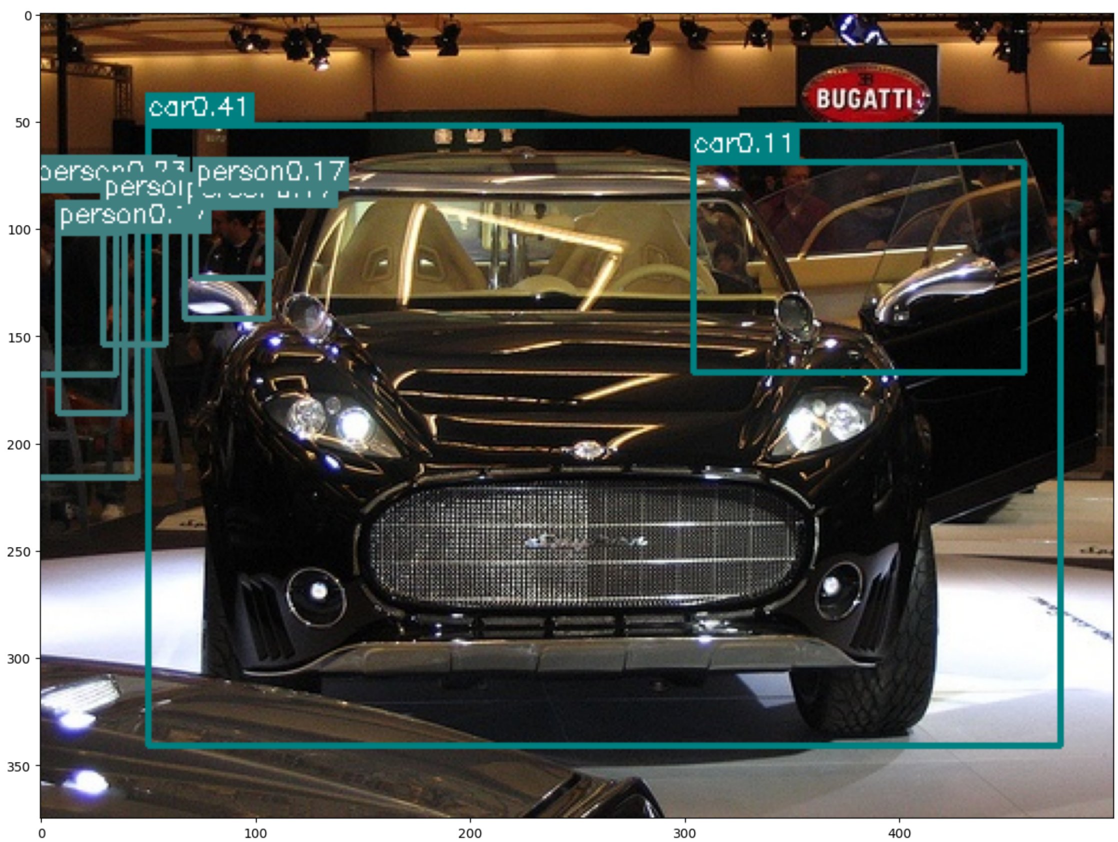
1 View example predictions

[16]:
```
net.eval()

# select random image from test set
image_name = random.choice(test_dataset.fnames)
image = cv2.imread(os.path.join(file_root_test, image_name))
image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
```

```
print('predicting...')
result = predict_image(net, image_name, root_img_directory=file_root_test)
for left_up, right_bottom, class_name, _, prob in result:
    color = COLORS[VOC_CLASSES.index(class_name)]
    cv2.rectangle(image, left_up, right_bottom, color, 2)
    label = class_name + str(round(prob, 2))
    text_size, baseline = cv2.getTextSize(label, cv2.FONT_HERSHEY_SIMPLEX, 0.4,␣
↪1)
    p1 = (left_up[0], left_up[1] - text_size[1])
    cv2.rectangle(image, (p1[0] - 2 // 2, p1[1] - 2 - baseline), (p1[0] +␣
↪text_size[0], p1[1] + text_size[1]),
                  color, -1)
    cv2.putText(image, label, (p1[0], p1[1] + baseline), cv2.
↪FONT_HERSHEY_SIMPLEX, 0.4, (255, 255, 255), 1, 8)

plt.figure(figsize = (15,15))
plt.imshow(image)
```

predicting…

[16]: <matplotlib.image.AxesImage at 0x7fc1eb483bd0>



1.1 Evaluate on Test

To evaluate detection results we use mAP (mean of average precision over each class)

[17]:
```
test_aps = evaluate(net, test_dataset_file=annotation_file_test,␣
↪img_root=file_root_test)
```

```
---Evaluate model on test samples---

100%|
 | 4950/4950 [02:05<00:00, 39.42it/s]

---class aeroplane ap 0.5152544744284651---
---class bicycle ap 0.5920777658191306---
---class bird ap 0.45535406184016874---
---class boat ap 0.27986742452993696---
---class bottle ap 0.20548321104585845---
---class bus ap 0.6117309020759428---
---class car ap 0.6718466477606162---
---class cat ap 0.7060565989229535---
---class chair ap 0.2980292398784073---
---class cow ap 0.48919652335636443---
---class diningtable ap 0.3528964567761616---
---class dog ap 0.6319911024488902---
---class horse ap 0.6741013742724802---
---class motorbike ap 0.5930620028875222---
---class person ap 0.5321600338111911---
---class pottedplant ap 0.17018685546734325---
---class sheep ap 0.4597273489878889---
---class sofa ap 0.48982974968452814---
---class train ap 0.6701924283859848---
---class tvmonitor ap 0.5064760178649267---
---map 0.495276011012238---
```

1.1.1 Cell added to get intermediate mAP values for students

[18]:
```
network_paths = ['detector_epoch_%d.pth' % epoch for epoch in [5, 10, 20, 30,␣
↪40]]+['detector.pth']
for load_network_path in network_paths:
    print('Loading saved network from {}'.format(load_network_path))
    net_loaded =  resnet50().to(device)
    net_loaded.load_state_dict(torch.load(load_network_path))
    evaluate(net_loaded, test_dataset_file=annotation_file_test)
```

```
Loading saved network from detector_epoch_5.pth
```

```
---------------------------------------------------------------------------
FileNotFoundError                         Traceback (most recent call last)
/var/tmp/ipykernel_27360/2271641507.py in <module>
      3     print('Loading saved network from {}'.format(load_network_path))
      4     net_loaded =  resnet50().to(device)
----> 5     net_loaded.load_state_dict(torch.load(load_network_path))
      6     evaluate(net_loaded, test_dataset_file=annotation_file_test)

/opt/conda/lib/python3.7/site-packages/torch/serialization.py in load(f,␣
↪map_location, pickle_module, weights_only, **pickle_load_args)
    769         pickle_load_args['encoding'] = 'utf-8'
    770
--> 771     with _open_file_like(f, 'rb') as opened_file:
    772         if _is_zipfile(opened_file):
    773             # The zipfile reader is going to advance the current file␣
↪position.

/opt/conda/lib/python3.7/site-packages/torch/serialization.py in␣
↪_open_file_like(name_or_buffer, mode)
    268 def _open_file_like(name_or_buffer, mode):
    269     if _is_path(name_or_buffer):
--> 270         return _open_file(name_or_buffer, mode)
    271     else:
    272         if 'w' in mode:

/opt/conda/lib/python3.7/site-packages/torch/serialization.py in __init__(self,␣
↪name, mode)
    249 class _open_file(_opener):
    250     def __init__(self, name, mode):
--> 251         super(_open_file, self).__init__(open(name, mode))
    252
    253     def __exit__(self, *args):

FileNotFoundError: [Errno 2] No such file or directory: 'detector_epoch_5.pth'
```

[19]:
```
output_submission_csv('my_new_solution.csv', test_aps)
```