

ECE 60146 HW5 Report

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1 Images From My Own Dataset



Figure 1: Three images from the class of bus



Figure 2: Three images from the class of cat



Figure 3: Three images from the class of pizza

2 Implementation of The Skipblock and Deep Network

```
# The Resnet block with skip connection
class ResnetBlock(nn.Module):

    def __init__(self, in_ch, out_ch):
        super(ResnetBlock, self).__init__()

        self.conv = nn.Conv2d(in_ch, out_ch, kernel_size=3, stride=1, padding=1)
        self.bn = nn.BatchNorm2d(out_ch)

    def forward(self, x):
        identity = x

        out = F.relu(self.bn(self.conv(x)))
        out = self.bn(self.conv(out))
        out += identity #skip connection
        out = F.relu(out)

        return out
```

Figure 4: My implementation of the ResBlock

```
class HW5Net(nn.Module):

    def __init__(self, input_nc, ngf=8, n_blocks=4):
        super(HW5Net, self).__init__()

        # The first conv layer
        model = [nn.ReflectionPad2d(3),
                 nn.Conv2d(input_nc, ngf, kernel_size=7, padding=0),
                 nn.BatchNorm2d(ngf),
                 nn.ReLU(True)]

        # Add downsampling layers
        n_downsampling = 5
        for i in range(n_downsampling):
            mult = 2**i
            model += [nn.Conv2d(ngf*mult, ngf*mult*2, kernel_size=3, stride=2, padding=1),
                      nn.BatchNorm2d(ngf*mult*2),
                      nn.ReLU(True)]

        # My own ResNet blocks
        mult = 2**n_downsampling
        for i in range(n_blocks):
            model += [ResnetBlock(ngf*mult, ngf*mult)]
        self.model = nn.Sequential(*model)

        wh = int(256/mult)
        # The classification head
        class_head = [nn.Flatten(),
                      nn.Linear(ngf*mult*wh*wh, 1024),
                      nn.ReLU(True),
                      nn.Linear(1024, 512),
                      nn.ReLU(True),
                      nn.Linear(512, 3)]
        self.class_head = nn.Sequential(*class_head)

        # The bounding box regression head
        bbox_head = [nn.Flatten(),
                     nn.Linear(ngf*mult*wh*wh, 1024),
                     nn.ReLU(True),
                     nn.Linear(1024, 512),
                     nn.ReLU(True),
                     nn.Linear(512, 4)]
        self.bbox_head = nn.Sequential(*bbox_head)
```

Figure 5: My implementation of the deep network

```
In [27]: 1 num_layers = len(list(net.parameters()))
          2 print(num_layers)

52
```

Figure 6: Number of layers in the network

The deep network of my implementation has 52 layers.

3 Implementation of The Skipblock and Deep Network

```
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```

Figure 7: My implementation of the ResBlock

```

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        self.model = nn.Sequential(*model)

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        class_head = [nn.Flatten(),
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                     nn.ReLU(True),
                     nn.Linear(512, 4)]
        self.bbox_head = nn.Sequential(*bbox_head)

```

Figure 8: My implementation of the deep network

```

In [27]: 1 num_layers = len(list(net.parameters()))
          2 print(num_layers)

```

52

Figure 9: Number of layers in the network

4 Evaluation of The Network

4.1 Network Trained with MSE Loss

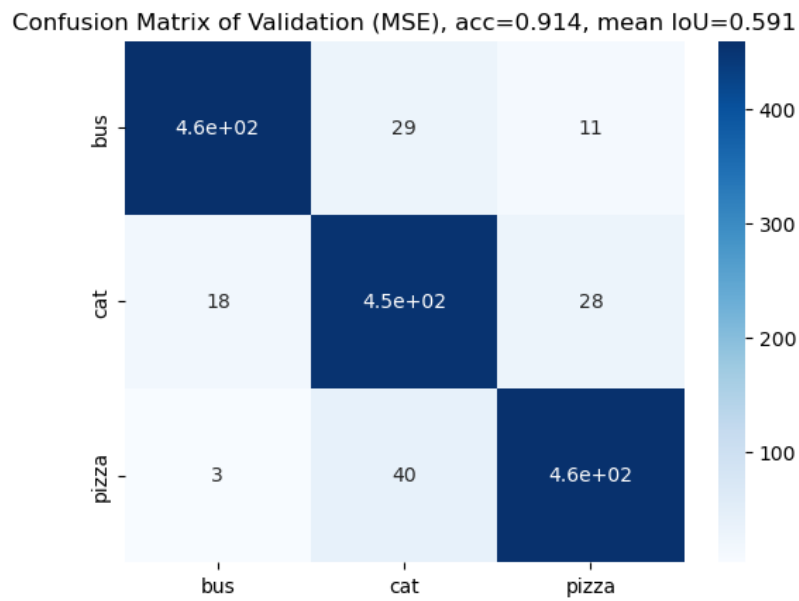


Figure 10: Confusion matrix of the network (MSE)

The network trained with MSE loss has the accuracy of 0.914 and the mean IoU of 0.591.

4.2 Network Trained with CIoU Loss

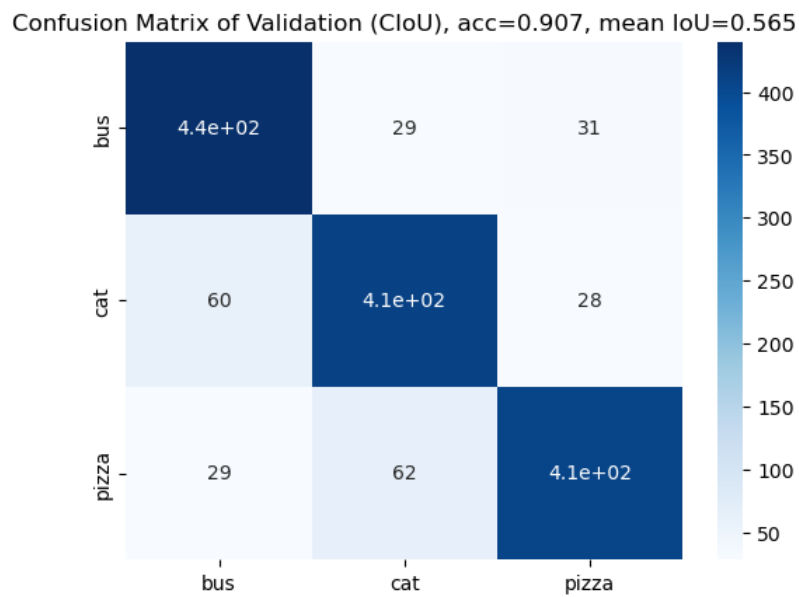


Figure 11: Confusion matrix of the network (CIoU)

The network trained with CIoU loss has the accuracy of 0.907 and the mean IoU of 0.565.

5 Visualization of the validation result



Figure 12: Visualization of the result on the class of bus



Figure 13: Visualization of the result on the class of cat

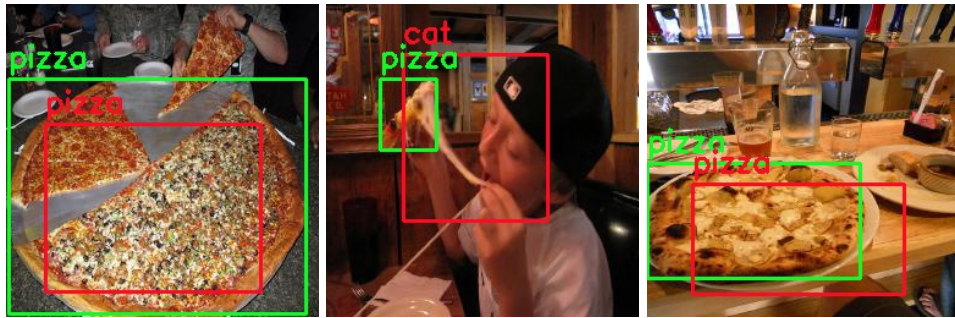


Figure 14: Visualization of the result on the class of pizza

6 Discussion

The performance of the use of MSE loss and CIoU loss are similar. The network can reach the test accuracy around 0.9 and the mean IoU loss around 0.5-0.6. Further works might include improvement on the network architecture.

7 Source code

```
# ECE60146 HW5
# Zhengxin Jiang
# jiang839

import numpy as np
import os
import matplotlib.pyplot as plt
from PIL import Image
from pycocotools.coco import COCO
import seaborn as sn
import random
import json

import torch
import torch.nn as nn
import torch.nn.functional as F
import torchvision
import torchvision.transforms as tvt
from torch.utils.data import DataLoader

import cv2

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print(device)

# Function for preparing the training data
def prepData(rawDataDir, hwDataDir):

    coco = COCO('{}/annotations/instances_train2014.json'.format(rawDataDir))

    bbox_list_train = []
    bbox_list_val = []

    catIds = coco.getCatIds(catNms=['bus', 'cat', 'pizza'])

    for catCount, catId in enumerate(catIds):

        ImgIds = coco.getImgIds(catIds=catId)
        random.shuffle(ImgIds)

        imgCount = 0
        for imgId in ImgIds:

            coco_img = coco.loadImgs(imgId)[0]
            imgName = coco_img['file_name']
            img = Image.open(rawDataDir+'/'+imgName)

            annId = coco.getAnnIds(imgIds=coco_img['id'], catIds=catId, iscrowd=None)
            ann = coco.loadAnns(annId)[0]
```

```

if ann['area'] < 4000:
    continue

bbox = ann['bbox']

resize_ratio = (256/img.size[0], 256/img.size[1])
bbox_resized = np.zeros(4)
bbox_resized[0] = bbox[0]*resize_ratio[0]
bbox_resized[2] = bbox[2]*resize_ratio[0]
bbox_resized[1] = bbox[1]*resize_ratio[1]
bbox_resized[3] = bbox[3]*resize_ratio[1]
bbox_resized[2:] += bbox_resized[:2] # change the format to [x1, y1, x2, y2]
bbox_resized[2:] -= 1e-3
bbox_resized[:2] += 1e-3 # let bbox reside in (0,1)

if img.mode != "RGB":
    img = img.convert(mode="RGB")
img = img.resize((256, 256), Image.BOX)

# Save training and validation images
if imgCount<1400:

    imgNewName = str(catCount*1400+imgCount) + '.jpg'
    fp = open('{} /train/{}'.format(hwDataDir, imgNewName), 'w')
    img.save(fp)
    bbox_list_train.append(bbox_resized)

elif imgCount<1900:

    imgNewName = str(catCount*500+imgCount-1400) + '.jpg'
    fp = open('{} /val/{}'.format(hwDataDir, imgNewName), 'w')
    img.save(fp)
    bbox_list_val.append(bbox_resized)

else:
    break

imgCount += 1

np.save('{} /train/bbox'.format(hwDataDir), bbox_list_train)
np.save('{} /val/bbox'.format(hwDataDir), bbox_list_val)

return

```

The Dataset class for hw4

```
class hwDataset(torch.utils.data.Dataset):
```

```

    def __init__(self, root, tasktype):
        super().__init__()

```



```

    if tasktype == 'training':
        self.root = os.path.join(root, 'train').replace("\\", "/")
        self.bbox = np.load(os.path.join(self.root, 'bbox.npy').replace("\\", "/"))
        self.classlen = 1400

    if tasktype == 'validation':
        self.root = os.path.join(root, 'val').replace("\\", "/")
        self.bbox = np.load(os.path.join(self.root, 'bbox.npy').replace("\\", "/"))
        self.classlen = 500

def __len__(self):
    return self.classlen * 3

def __getitem__(self, index):
    name = str(index) + '.jpg'

    img = Image.open(os.path.join(self.root, name).replace("\\", "/"))

    tr = tvn.Compose([
        tvn.ToTensor(),
        tvn.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])

    img_tensor = tr(img)

    label = index // self.classlen

    bbox_tensor = torch.tensor(self.bbox[index]/256)

    return img_tensor, bbox_tensor.float(), label

# The Resnet block with skip connection
class ResnetBlock(nn.Module):

    def __init__(self, in_ch, out_ch):
        super(ResnetBlock, self).__init__()

        self.conv = nn.Conv2d(in_ch, out_ch, kernel_size=3, stride=1, padding=1)
        self.bn = nn.BatchNorm2d(out_ch)

    def forward(self, x):
        identity = x

        out = F.relu(self.bn(self.conv(x)))
        out = self.bn(self.conv(out))
        out += identity #skip connection
        out = F.relu(out)

    return out

```

```

class HW5Net(nn.Module):

    def __init__(self, input_nc, ngf=8, n_blocks=4):
        super(HW5Net, self).__init__()

        # The first conv layer
        model = [nn.ReflectionPad2d(3),
                  nn.Conv2d(input_nc, ngf, kernel_size=7, padding=0),
                  nn.BatchNorm2d(ngf),
                  nn.ReLU(True)]

        # Add downsampling layers
        n_downsampling = 5
        for i in range(n_downsampling):
            mult = 2**i
            model += [nn.Conv2d(ngf*mult, ngf*mult*2, kernel_size=3, stride=2, padding=1),
                      nn.BatchNorm2d(ngf*mult*2),
                      nn.ReLU(True)]

        # My own ResNet blocks
        mult = 2**n_downsampling
        for i in range(n_blocks):
            model += [ResnetBlock(ngf*mult, ngf*mult)]
        self.model = nn.Sequential(*model)

        wh = int(256/mult)
        # The classification head
        class_head = [nn.Flatten(),
                      nn.Linear(ngf*mult*wh*wh, 1024),
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        self.class_head = nn.Sequential(*class_head)

        # The bounding box regression head
        bbox_head = [nn.Flatten(),
                     nn.Linear(ngf*mult*wh*wh, 1024),
                     nn.ReLU(True),
                     nn.Linear(1024, 512),
                     nn.ReLU(True),
                     nn.Linear(512, 4)]
        self.bbox_head = nn.Sequential(*bbox_head)

    def forward(self, x):
        ft = self.model(x)
        cls = self.class_head(ft)
        bbox = self.bbox_head(ft)

        return cls, bbox

def drawBBox(imgnum, label, predicted_label, gt, predict):

```

```

gt = gt*256
predict = predict*256

class_name = ['bus', 'cat', 'pizza']

img = cv2.imread('D:/coco/hw5/val/{}.jpg'.format(imgnum))
img = cv2.rectangle(img, (int(gt[0]), int(gt[1])), (int(gt[2]), int(gt[3])), (36,
    255, 12), 2)
img = cv2.rectangle(img, (int(predict[0]), int(predict[1])), (int(predict[2]), int(
    predict[3])), (36, 12, 255), 2)

img = cv2.putText(img, class_name[label], (int(gt[0]), int(gt[1]-10)), cv2.
    FONT_HERSHEY_SIMPLEX, 0.8, (36, 255, 12), 2)
img = cv2.putText(img, class_name[predicted_label], (int(predict[0]), int(predict
    [1]-10)), cv2.FONT_HERSHEY_SIMPLEX, 0.8, (36, 12, 255), 2)

cv2.imwrite('{} .jpg'.format(imgnum), img)

return img

##### Main #####
rawDataDir = 'D:/coco/train2014'
hwDataDir = 'D:/coco/hw5'

prepData(rawDataDir, hwDataDir)

root = 'D:/coco/hw5'

traindataset = hwDataset(root, 'training')
train_data_loader = DataLoader(traindataset, batch_size=4, num_workers=0, shuffle=True)

#### Training ####

net = HW5Net(3)
net = net.to(device)

criterion1 = torch.nn.CrossEntropyLoss()
criterion2 = torch.nn.MSELoss()
# optimizer = torch.optim.SGD(net.parameters(), lr=1e-4, momentum=0.9)
optimizer = torch.optim.Adam(net.parameters(), lr=1e-4, betas=(0.9, 0.99))

for epoch in range(50):
    running_loss_labeling = 0.0
    running_loss_regression = 0.0

    for i, data in enumerate(train_data_loader):
        inputs, bbox_gt, labels = data

        inputs = inputs.to(device)
        bbox_gt = bbox_gt.to(device)
        labels = labels.to(device)

```

```

optimizer.zero_grad()
outputs = net(inputs)

loss_labeling = criterion1(outputs[0], labels)
loss_labeling.backward(retain_graph=True)
# loss_regression = criterion2(outputs[1], bbox_gt)
loss_regression = torchvision.ops.complete_box_iou_loss(bbox_gt, outputs[1],
    reduction='mean')
loss_regression.backward()
optimizer.step()

running_loss_labeling += loss_labeling.item()
running_loss_regression += loss_regression.item()

if (i+1) % 100 == 0:
    print("[epoch: %d, batch: %5d] loss_label: %.4f" % (epoch + 1, i + 1,
        running_loss_labeling / 100))
    running_loss_labeling = 0.0
    print("[epoch: %d, batch: %5d] loss_reg: %.4f" % (epoch + 1, i + 1,
        running_loss_regression / 100))
    running_loss_regression = 0.0

torch.save(net.state_dict(), 'mse.pth')

net = HW5Net(3)
net = net.to(device)
# load trained parameters
net.load_state_dict(torch.load('mse.pth', map_location=torch.device(device)))

valdataset = hwDataset(root, 'validation')
val_data_loader = DataLoader(valdataset, batch_size=5, num_workers=0, shuffle=False)

# Validation
cm = torch.zeros(3,3)
true_count = 0
total_iouloss = 0

# no grad for inference
with torch.no_grad():
    for i, data in enumerate(val_data_loader):

        inputs, bbox_gt, labels = data
        inputs = inputs.to(device)
        labels = labels.to(device)
        bbox_gt = bbox_gt.to(device)
        outputs = net(inputs)

        # The predicted labels
        max_vals, predicted_labels = torch.max(outputs[0], 1)
        predicted_bbox = outputs[1]

        total_iouloss += torchvision.ops.complete_box_iou_loss(bbox_gt, predicted_bbox,
            reduction='sum')

```

```

for j in range(len(labels)):
    cm[labels[j]][predicted_labels[j]] += 1
    if labels[j] == predicted_labels[j]:
        true_count += 1

# save bbox for visualization
if i == 0:
    for j in range(3):
        img = drawBBox(j, labels[j], predicted_labels[j], bbox_gt[j],
            predicted_bbox[j])

if i == 100:
    for j in range(3):
        img = drawBBox(i*5+j, labels[j], predicted_labels[j], bbox_gt[j],
            predicted_bbox[j])

if i == 200:
    for j in range(3):
        img = drawBBox(i*5+j, labels[j], predicted_labels[j], bbox_gt[j],
            predicted_bbox[j])

mean_iouloss = total_iouloss/1500
acc = true_count/1500
print(acc)
print(mean_iouloss)

plt.figure()
plt.title("Confusion_Matrix_of_Validation_(MSE),_acc=%.3f,_mean_IoU=%.3f" % (acc,
    mean_iouloss))
sn.heatmap(cm, annot=True, cmap="Blues",xticklabels=['bus','cat','pizza'], yticklabels=['
    bus','cat','pizza'])

```