Object Detection using RCNN

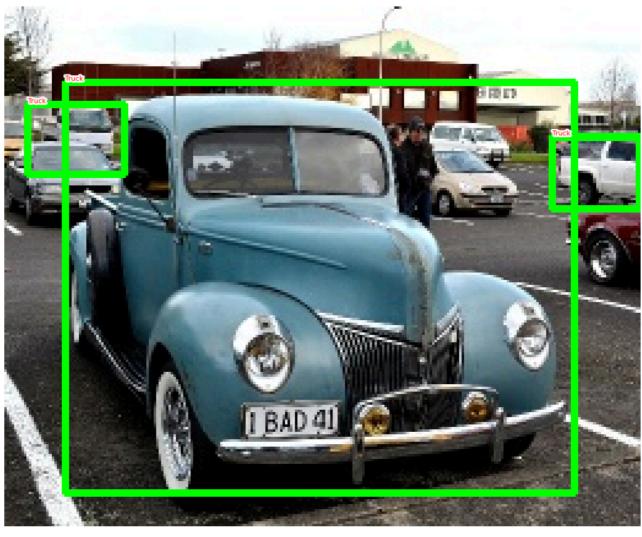
!pip install -q --upgrade selectivesearch torch_snippets

```
Preparing metadata (setup.py) ... done
                                              - 79.8/79.8 kB 2.7 MB/s eta 0:00:00
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                                    — 3.4/3.4 MB 82.9 MB/s eta 0:00:00
                                              — 468.9/468.9 kB 43.8 MB/s eta 0:00:00
      Building wheel for selectivesearch (setup.py) ... done
      Building wheel for typing (setup.py) ... done
from torch_snippets import *
import selectivesearch
from torchvision import transforms, models, datasets
from torch_snippets import Report
from torchvision.ops import nms
device = 'cuda' if torch.cuda.is_available() else 'cpu'
import numpy as np
IMAGE_ROOT = '../input/open-images-bus-trucks/images/images'
DF_RAW = pd.read_csv('../input/open-images-bus-trucks/df.csv')
print(DF RAW.head())
```

```
ImageID Source LabelName Confidence
                                                       XMin XMax \
    0 0000599864fd15b3 xclick Bus 1 0.343750 0.908750
    1 00006bdb1eb5cd74 xclick
                                 Truck
                                               1 0.276667 0.697500
    2 00006bdb1eb5cd74 xclick Truck
3 00010hf498h64hah xclick Puc
                                                1 0.702500 0.999167
                                  Bus
    3 00010bf498b64bab xclick
                                               1 0.156250 0.371250
    4 00013f14dd4e168f xclick
                                  Bus
                                                1 0.287500 0.999375
                  YMax IsOccluded IsTruncated ... IsDepiction IsInside \
           YMin
    0 0.156162 0.650047 1 0 ...
                                                              a
                                                                        a
                                              0 ...
    1 0.141604 0.437343
                                                              0
                                                                        0
                              1
    2 0.204261 0.409774
                                             1 ...
                                                             0
                                                                        0
    3 0.269188 0.705228
                                 0
                                              0 ...
                                                               0
                                                                        0
    4 0.194184 0.999062
                                              1 ...
       XClick1X XClick2X XClick3X XClick4X XClick1Y XClick2Y XClick3Y \
    0 0.421875 0.343750 0.795000 0.908750 0.156162 0.512700 0.650047
    1 0.299167 0.276667 0.697500 0.659167 0.141604 0.241855 0.352130
    2 0.849167 0.702500 0.906667 0.999167 0.204261 0.398496 0.409774
    3 0.274375 0.371250 0.311875 0.156250 0.269188 0.493882 0.705228
    4 0.920000 0.999375 0.648750 0.287500 0.194184 0.303940 0.999062
       XClick4Y
    0 0.457197
    1 0.437343
    2 0.295739
    3 0.521691
    4 0.523452
    [5 rows x 21 columns]
class OpenImages(Dataset):
   def __init__(self, df, image_folder=IMAGE_ROOT):
       self.root = image_folder
       self.df = df
       self.unique images = df['ImageID'].unique()
   def __len__(self): return len(self.unique_images)
   def __getitem__(self, ix):
       image id = self.unique images[ix]
       image_path = f'{self.root}/{image_id}.jpg'
       image = cv2.imread(image_path, 1)[...,::-1] # convert BGR to RGB
       # Basically x[...], it is similar to cv2.imread(image_path, 1)[:, :, ::-1], but t
       h, w, _ = image.shape
       df = self.df.copy()
       df = df[df['ImageID'] == image id]
       boxes = df['XMin,YMin,XMax,YMax'.split(',')].values
       boxes = (boxes * np.array([w,h,w,h])).astype(np.uint16).tolist() #boxes in accord
       classes = df['LabelName'].values.tolist()
       return image, boxes, classes, image path
ds = OpenImages(df=DF RAW)
```

For some images, there are multiple bounding boxes that may/may not belong to the same class. Below is an example:

im, bbs, clss, $_ = ds[6]$ show(im, bbs=bbs, texts=clss, sz=10) print(bbs)



[[9, 39, 48, 67], [24, 30, 229, 195], [220, 52, 255, 81]]

im, bbs, clss, $_ = ds[15]$ show(im, bbs=bbs, texts=clss, sz=10) print(bbs)



[[77, 90, 104, 118]]

The dimensions of the bounding box of the bus object is best understood in the following way - 2193EA1-F670-417C-B5CD-37714DDBD836_1_201_a.jpeg

SelectiveSearch to generate region proposals

SelectiveSearch is a region proposal algorithm used for object localization where it generates proposals of regions that are likely to be grouped together based on their pixel intensities. SelectiveSearch groups pixels based on the hierarchical grouping of similar pixels, which, in turn, leverages the color, texture, size, and shape compatibility of content within an image.

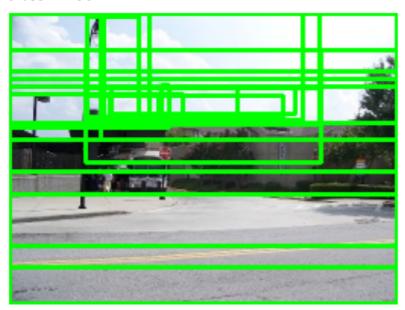
```
def extract_candidates(img):
   img_lbl, regions = selectivesearch.selective_search(img, scale=200, min_size=100)
   img_area = np.prod(img.shape[:2])
   candidates = []
   for r in regions:
        if r['rect'] in candidates: continue
        if r['size'] < (0.05*img_area): continue</pre>
        if r['size'] > (1*img_area): continue
       x, y, w, h = r['rect']
        candidates.append(list(r['rect']))
   return candidates
#how iou works
def extract_iou(boxA, boxB, epsilon=1e-5):
   x1 = max(boxA[0], boxB[0])
   y1 = max(boxA[1], boxB[1])
   x2 = min(boxA[2], boxB[2])
   y2 = min(boxA[3], boxB[3])
   width = (x2 - x1) #change in x-direction
   height = (y2 - y1) #change in y-direction
   if (width<0) or (height <0):
        return 0.0
   area_overlap = width * height # this was calculated by x1, y1, x2, y2
   area_a = (boxA[2] - boxA[0]) * (boxA[3] - boxA[1])
   area_b = (boxB[2] - boxB[0]) * (boxB[3] - boxB[1])
   area_combined = area_a + area_b - area_overlap
   iou = area_overlap / (area_combined+epsilon)
   return iou
```

Selectivesearch module

The selectivesearch creates multiple candidate bounding boxes randomly, to be passed along with the input image. The IoU (Intersection over Union) is the loss metric here, hence, the bounding box with the highest IoU to the original bounding box target will be accepted.

```
# Example of df[15]
candidates = extract candidates(im)
print(np.shape(candidates))
print(type(candidates))
show(im, bbs = candidates)
```

(38, 4)<class 'list'>



help(show)

Help on function show in module torch_snippets.loader:

show(img=None, ax=None, title=None, sz=None, bbs=None, confs=None, texts=None, bb_col show an image

np.shape(ds[15])

```
(im, bbs, labels, fpath) = ds[15]
H, W, _{-} = im.shape
candidates = extract_candidates(im)
candidates = np.array([(x,y,x+w,y+h) for x,y,w,h in candidates]) # candidates extracted
ious, rois, clss, deltas, best_ious = [], [], [], [], []
temp_best_bbs = []
ious = np.array([[extract_iou(candidate, _bb_) for candidate in candidates] for _bb_ in b
for jx, candidate in enumerate(candidates):
    cx,cy,cX,cY = candidate
   candidate_ious = ious[jx] #ious for that candidate
   best_iou_at = np.argmax(candidate_ious) #best candidate iou is taken (index) ~ alway
   best_iou = candidate_ious[best_iou_at] #gets the best score here
   best_ious.append(best_iou)
   best_bb = x, y, X, Y = bbs[best_iou_at] # gets the target label bounding box where t
   temp_best_bbs.append(best_bb)
    if best_iou > 0.3: clss.append(labels[best_iou_at]) # if iou is more than 0.3 it is n
   else : clss.append('background')
   delta = np.array([_x-cx, _y-cy, _X-cX, _Y-cY]) / np.array([W,H,W,H]) #normalizing th
   deltas.append(delta)
    rois.append(candidate / np.array([W,H,W,H]))
best_ious_at = np.argmax(best_ious)
print("Best IoU:", best_ious[best_ious_at])
best_candidate = candidates[best_ious_at]
best_bbs = temp_best_bbs[best_ious_at]
# Example of df[15]
candidates = extract candidates(im)
show(im, bbs = [best_bbs, best_candidate], confs= [0,0.5], texts = ['Bbox', 'Best candida
```

Best IoU: 0.14555256036666817



```
FPATHS, GTBBS, CLSS, DELTAS, ROIS, IOUS = [], [], [], [], []
N = 500
for ix, (im, bbs, labels, fpath) in enumerate(ds):
    if(ix==N):
        break
   H, W, _ = im.shape
    candidates = extract_candidates(im)
    candidates = np.array([(x,y,x+w,y+h) for x,y,w,h in candidates])
   ious, rois, clss, deltas = [], [], [], []
    ious = np.array([[extract_iou(candidate, _bb_) for candidate in candidates] for _bb_
    for jx, candidate in enumerate(candidates):
        cx,cy,cX,cY = candidate
        candidate_ious = ious[jx]
        best_iou_at = np.argmax(candidate_ious)
        best_iou = candidate_ious[best_iou_at]
        best_bb = _x,_y,_X,_Y = bbs[best_iou_at]
        # if iou is more than 0.3 it is not the background
        if best_iou > 0.3: clss.append(labels[best_iou_at])
        else : clss.append('background')
        delta = np.array([_x-cx, _y-cy, _X-cX, _Y-cY]) / np.array([W,H,W,H])
        deltas.append(delta)
        rois.append(candidate / np.array([W,H,W,H]))
   FPATHS.append(fpath)
   IOUS.append(ious)
   ROIS.append(rois)
   CLSS.append(clss)
   DELTAS.append(deltas)
   GTBBS.append(bbs)
FPATHS = [f'{IMAGE_ROOT}/{stem(f)}.jpg' for f in FPATHS]
FPATHS, GTBBS, CLSS, DELTAS, ROIS = [item for item in [FPATHS, GTBBS, CLSS, DELTAS, ROIS]
targets = pd.DataFrame(flatten(CLSS), columns=['label'])
label2target = {1:t for t,1 in enumerate(targets['label'].unique())}
target2label = {t:l for l,t in label2target.items()}
background_class = label2target['background']
print("The label to target values dictionary formed is:" ,label2target)
     The label to target values dictionary formed is:
     {'Bus': 0, 'background': 1, 'Truck': 2}
```

```
# normalizing with the mean, std used while training the model
normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225])
def preprocess_image(img):
    img = torch.tensor(img).permute(2,0,1)
   img = normalize(img)
   return img.to(device).float()
def decode(_y):
   _, preds = _y.max(-1)
   return preds
class RCNNDataset(Dataset):
   def __init__(self, fpaths, rois, labels, deltas, gtbbs):
        self.fpaths = fpaths
        self.gtbbs = gtbbs
        self.rois = rois
        self.labels = labels
        self.deltas = deltas
   def __len__(self): return len(self.fpaths)
   def __getitem__(self, ix):
        fpath = str(self.fpaths[ix])
        image = cv2.imread(fpath, 1)[...,::-1]
        H, W, _ = image.shape
        sh = np.array([W,H,W,H])
        gtbbs = self.gtbbs[ix]
        rois = self.rois[ix]
        bbs = (np.array(rois)*sh).astype(np.uint16)
        labels = self.labels[ix]
        deltas = self.deltas[ix]
        crops = [image[y:Y,x:X] for (x,y,X,Y) in bbs] # bounding box image crops
        return image, crops, bbs, labels, deltas, gtbbs, fpath
   def collate fn(self, batch):
        '''Performing actions on a batch of images'''
        input, rois, rixs, labels, deltas = [], [], [], []
        for ix in range(len(batch)):
            image, crops, image bbs, image labels, image deltas, image gt bbs, image fpat
            crops = [cv2.resize(crop, (224,224)) for crop in crops]
            crops = [preprocess image(crop/255.)[None] for crop in crops]
            input.extend(crops)
            labels.extend([label2target[c] for c in image_labels])
            deltas.extend(image deltas)
        input = torch.cat(input).to(device)
        labels = torch.Tensor(labels).long().to(device)
        deltas = torch.Tensor(deltas).float().to(device)
        return input, labels, deltas
```

```
n_train = 9*len(FPATHS)//10 # 0.9 is the train size
train_ds = RCNNDataset(FPATHS[:n_train], ROIS[:n_train], CLSS[:n_train], DELTAS[:n_train]
test_ds = RCNNDataset(FPATHS[n_train:], ROIS[n_train:], CLSS[n_train:], DELTAS[n_train:],
from torch.utils.data import TensorDataset, DataLoader
train loader = DataLoader(train ds, batch size=2, collate fn=train ds.collate fn, drop la
test loader = DataLoader(test ds, batch size=2, collate fn=test ds.collate fn, drop last=
vgg_backbone = models.vgg16(pretrained=True)
vgg backbone.classifier = nn.Sequential()
for param in vgg_backbone.parameters():
    param.requires_grad = False #not to do a re-train
vgg backbone.eval().to(device)
     /usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: UserWarning
       warnings.warn(
     /usr/local/lib/python3.10/dist-packages/torchvision/models/ utils.py:223: UserWarning
       warnings.warn(msg)
     Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.cache
              528M/528M [00:07<00:00, 69.6MB/s]
     100%||
    VGG(
       (features): Sequential(
         (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (1): ReLU(inplace=True)
         (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (3): ReLU(inplace=True)
         (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
         (5): Conv2d(64, 128, kernel size=(3, 3), stride=(1, 1), padding=(1, 1))
         (6): ReLU(inplace=True)
         (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (8): ReLU(inplace=True)
         (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
         (10): Conv2d(128, 256, kernel size=(3, 3), stride=(1, 1), padding=(1, 1))
         (11): ReLU(inplace=True)
         (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (13): ReLU(inplace=True)
         (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (15): ReLU(inplace=True)
         (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
         (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (18): ReLU(inplace=True)
         (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (20): ReLU(inplace=True)
         (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (22): ReLU(inplace=True)
         (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
         (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (25): ReLU(inplace=True)
         (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (27): ReLU(inplace=True)
         (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (29): ReLU(inplace=True)
         (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
       (avgpool): AdaptiveAvgPool2d(output size=(7, 7))
       (classifier): Sequential()
     )
```

```
class RCNN(nn.Module):
   def __init__(self):
        super().__init__()
        feature_dim = 25088
        self.backbone = vgg backbone
        self.cls_score = nn.Linear(feature_dim, len(label2target))
        self.bbox = nn.Sequential(
              nn.Linear(feature dim, 512),
              nn.ReLU(),
              nn.Linear(512, 4),
              nn.Tanh(),
            )
        self.cel = nn.CrossEntropyLoss() # loss for classification
        self.sl1 = nn.L1Loss() # loss for regression
   def forward(self, input):
        feat = self.backbone(input) # both classification and regression takes 'feat' as
        cls_score = self.cls_score(feat)
        bbox = self.bbox(feat)
        return cls score, bbox
   def calc_loss(self, probs, _deltas, labels, deltas):
        # probs is basically the predicted class
        detection_loss = self.cel(probs, labels)
        ixs, = torch.where(labels != 1) #removing the label 1, which is background
        _deltas = _deltas[ixs]
       deltas = deltas[ixs]
        self.lmb = 10.0
        if len(ixs) > 0:
            regression_loss = self.sl1(_deltas, deltas)
            return detection_loss + self.lmb * regression_loss, detection_loss.detach(),
        else:
            # every ix is detected as background
            regression loss = 0
            return detection_loss + self.lmb * regression_loss, detection_loss.detach(),
def train batch(inputs, model, optimizer, criterion):
    input, clss, deltas = inputs
   model.train()
   optimizer.zero grad()
   _clss, _deltas = model(input) # as model outputs we will be getting classes and delt
   loss, loc_loss, regr_loss = criterion(_clss, _deltas, clss, deltas)
   accs = clss == decode(_clss)
   loss.backward()
   optimizer.step()
    return loss.detach(), loc_loss, regr_loss, accs.cpu().numpy()
```

```
@torch.no_grad()
def validate_batch(inputs, model, criterion):
    input, clss, deltas = inputs
   with torch.no_grad():
        model.eval()
rcnn = RCNN().to(device)
criterion = rcnn.calc_loss
optimizer = optim.SGD(rcnn.parameters(), lr=1e-3)
n_{epochs} = 5
log = Report(n_epochs) #records the metrics as report, can be used to plot later
# loc_loss: loss on classification
# regr_loss: loss on regression
for epoch in range(n_epochs):
   _n = len(train_loader)
   for ix, inputs in enumerate(train_loader):
        loss, loc_loss, regr_loss, accs = train_batch(inputs, rcnn,
                                                       optimizer, criterion)
        pos = (epoch + (ix+1)/_n)
        log.record(pos, trn_loss=loss.item(), trn_loc_loss=loc_loss,
                   trn_regr_loss=regr_loss,
                   trn_acc=accs.mean(), end='\r')
   _n = len(test_loader)
   for ix,inputs in enumerate(test_loader):
        _clss, _deltas, loss, \
```

