Object Detection and Localization with Deep Networks

Lecture Notes on Deep Learning

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Preamble

Object detection in images is a more difficult problem than the problem of image classification.

Object detection is made challenging by the fact that a good solution to this problem must also do a good job of localizing the object. And when an image contains multiple objects of interest, an object detector must identify them and localize them individually.

In this lecture, we will assume that an image has only one object in it. The job of the CNN is to recognize the category of the object **and** to estimate the coordinates of the smallest bounding-box rectangle that contains the object.

Estimating the bounding-box rectangle is referred to as regression.

So our goal is to design a convolutional network that can make two inferences simultaneously, one for classification and the other for regression.

Preamble (contd.)

It follows that our convolutional network must use two loss functions, one for classification and the other for regression.

Backpropagating two losses through a network raises interesting issues related to the programming involved and also whether the gradients of the two losses with respect to the learnable parameters that are in common between the two inference paths can somehow "interfere" with one another.

Regarding the programming issue raised by using two loss functions, as you know, ordinarily when one calls `backwards()` on a loss, that causes the computational graph constructed during the forward propagation to be dismantled. But we obviously cannot allow for that to happen when using two loss functions.

The goal of this lecture is to present a convolutional network that carries out both the classification and the regression simultaneously.

Preamble (contd.)

Obviously, training such networks requires image data that must include bounding-box annotations in addition to the object labels.

This lecture will also introduces you to a new dataset, PurdueShapes5, of 32x32 images that I have created for experimenting with object detection and localization problems. Associated with each image is the label of the object in the image and also the coordinates of the bounding box rectangle for the object.

As you would expect, any new dataset for training a CNN calls for a custom dataloader. A dataloader for the PurdueShapes5 dataset is included in Version 1.0.7 of the DLStudio module.

Outline

Outline

A Dual-Inferencing CNN

- Obviously, what we need to implement is a dual-inferencing CNN that has two different outputs for the same input image: one for classification and the other for regression.
- The classification output must map the input image to its category label, and the regression output must map the same input to the coordinates of the bounding box rectangle.

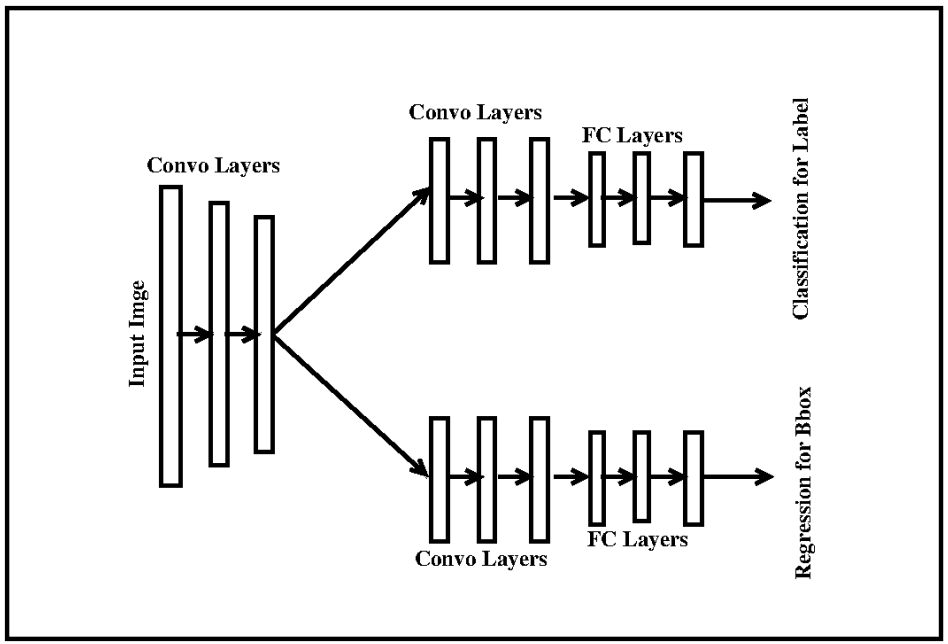


Figure: A dual-inferencing CNN

Now We Need Two Different Loss Functions

- For all of the classification work we have done so far, we have used for the loss the cross-entropy measure through the PyTorch class `torch.nn.CrossEntropyLoss`.
- In what follows, I'll argue that whereas the cross-entropy is great as a measure of the misclassification error, it doesn't have the right properties for what is needed for the regression error.
- Consider the classification of the CIFAR-10 images. The output layer for a CNN for this dataset will have 10 nodes, one for each of the 10 classes.
- Let the vector $\mathbf{x}$ represent the output for a given input image whose category label is `c`, which is an integer between 0 and 9. The cross-entropy loss for this output would be given by

$$cross\_entropy(\mathbf{x}, c) \quad = \quad -\log \frac{e^{\mathbf{x}[c]}}{\sum_{j=0}^{9} e^{\mathbf{x}[j]}}$$

Appropriateness of Cross-Entropy Loss for Measuring Classification Error

- To see why the formula shown on the previous slide makes total sense, first focus on the fact that, if the inferencing was perfect, only the output element $\mathbf{x}[c]$ would light up and all the other elements in the vector $\mathbf{x}$ would be 0. So the error in the label prediction for the input image under consideration is proportional to the extent $\mathbf{x}$ satisfies this property.
- The question now is: **What's the best way to measure the above mentioned property for the output vector?**
- To answer the question, **let's switch to a probabilistic interpretation of the output.**
- The 10 output values given by the ratio $\frac{e^{\mathbf{x}[c]}}{\sum_{j=0}^{9} e^{\mathbf{x}[j]}}$ can be interpreted as the probabilities because the numerator is guaranteed to be positive regardless of the sign of the value $\mathbf{x}[c]$ and because these 10 numbers are guaranteed to add up to 1.0.

Cross-Entropy Loss for Measuring the Classification Error

- The probabilistic interpretation of the output allows for it to be characterized by **cross-entropy** vis-a-vis the input.
- In general, if $p([j])$ is a probabilistic characterization of the class label for the input image and $q(\mathbf{x}[j])$ a probabilistic characterization of output as explained above, the cross-entropy between the two probability distributions would be given by

$$H(p,q) \quad = \quad -\sum_{j} p([j]) \cdot \log_2 q(\mathbf{x}[j])$$

- Now consider the case when we are sure that the class label for the input image is c, meaning that $p[j] = 1$ *for* $j = c$ *and* 0 *otherwise*, the above formula becomes

$$H(p,q) \quad = \quad -\log_2 q(\mathbf{x}[c])$$

Cross-Entropy Loss for Measuring the Classification Error (contd.)

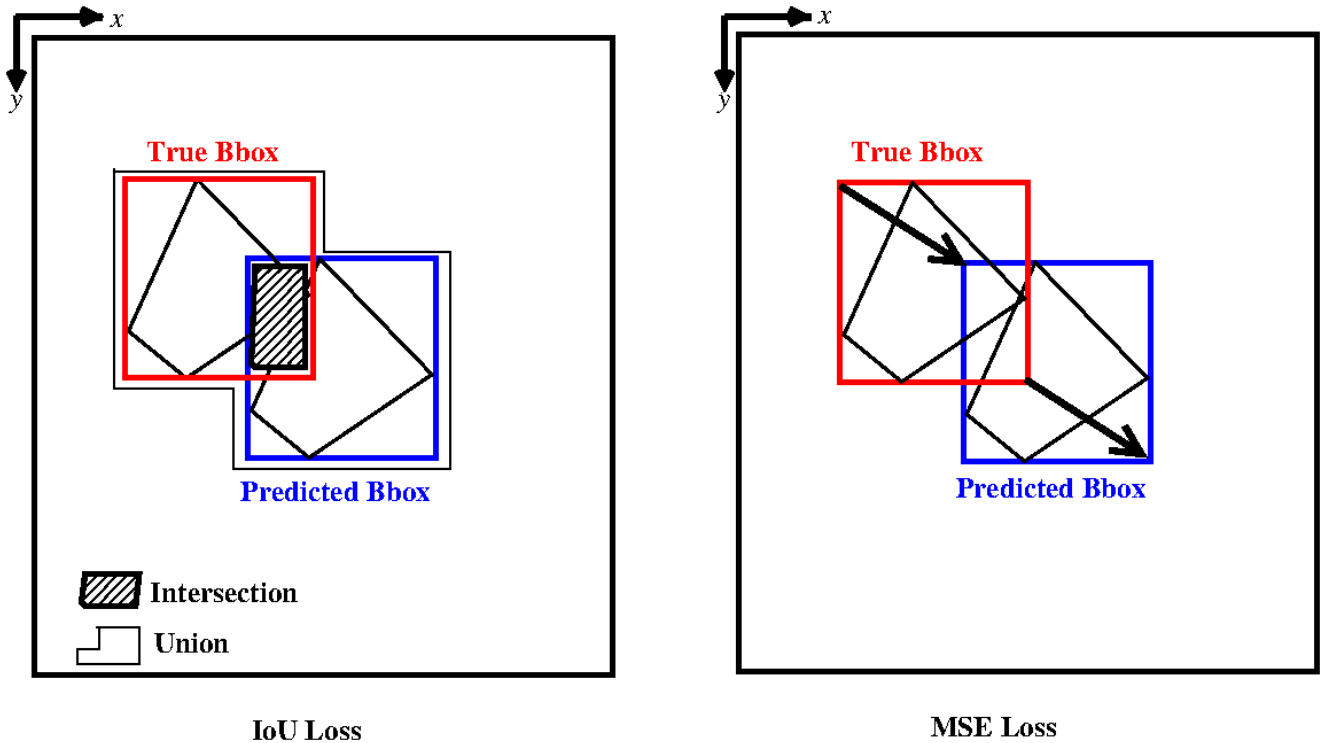
- To gain an even deeper understanding of the power of the cross-entropy criterion for measuring the classification error, it's best to work out a few examples of $q(\mathbf{x}[c])$ by hand.
- Let's start by choosing a value for c — let's say $c = 4$.
- Now assign different values to the 10 elements of $q(\mathbf{x}[j])$ and see what you get for the cross-entropy loss. For example, you could choose $q = (0.1, 0.2, 0.1, 0.3, 0.2, 0.2, 0.0, 0.0, 0.0)$. Keep in mind that the quantity $x \cdot \log x \rightarrow 0$ as $x \rightarrow 0$. Additionally, $\log x \rightarrow -\infty$ as $x \rightarrow 0$.
- You will notice that should the CNN produce a value of 0 for $\mathbf{x}[4]$, the loss as calculated by cross-entropy would be very large indeed (theoretically approaching ∞), which would then propagate backwards through the network as the weights undergo significant changes in response to such a large loss. Typically, if the cross-entropy loss exceeds 2.0, the predicted labels are mostly noise.

But What About the Regression Loss?

- While the cross-entropy loss takes care of the classification error, it's not appropriate as a measure of the bounding-box regression error.
- Bounding-box regression is about the numerics of where exactly the object is in an image and requires a measure that is more geometrical in nature.
- **Bounding-box regression loss is best measured by the two loss functions illustrated on the next slide.**
- The acronym "IoU" stands for "Intersection over Union". In problems that require measuring the similarity between two sets, this loss is more commonly known as the "Jaccard Distance".
- The acronym "MSE" stands for the "Mean-Squared Error".

IoU and MSE Losses Illustrated

- You can use the `torch.nn.MSELoss` class for measuring the MSE loss.
- However, you have to program up the IoU loss yourself.



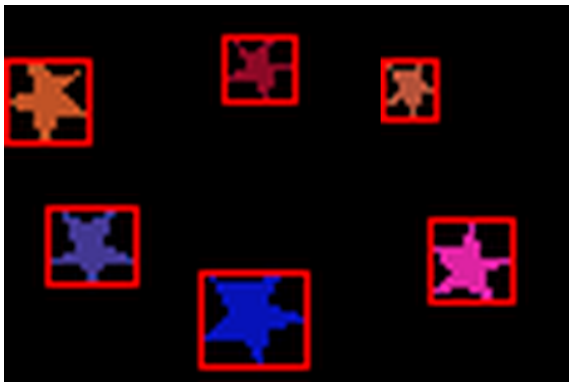
Outline

The PurdueShapes5 Dataset with Bbox Annotations

- Before I demonstrate how to write code for implementing in PyTorch the network architecture shown in Slide 7, let me first talk about a dataset I have created for CNN training that involves both the class labels and the bounding box annotations.
- I have been impressed with how useful the CIFAR-10 dataset has become for demonstrating in a classroom setting several of the core notions related to image classification with deep networks.
- I felt that there was a need for a similar dataset based on small images (just 32×32) (or, perhaps, 64×64 in the future) for demonstrating concepts related to object detection and localization.
- **So I have created the `PurdueShapes5` dataset to fill this void.**
- The program that generates the dataset **also generates the bounding-box (bbox) annotations for the objects.**

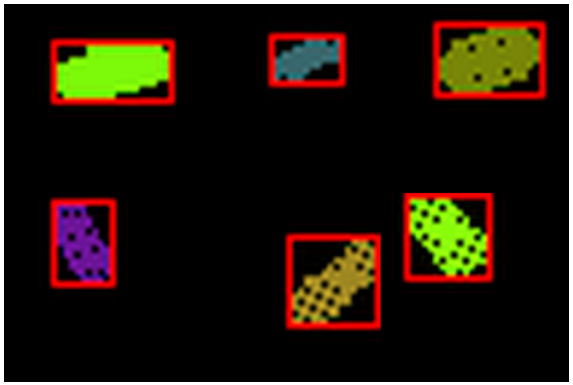
Some Example Images from the PurdueShapes5 Dataset

(a) random stars



(b) with bbox annotations

(a) noisy ovals

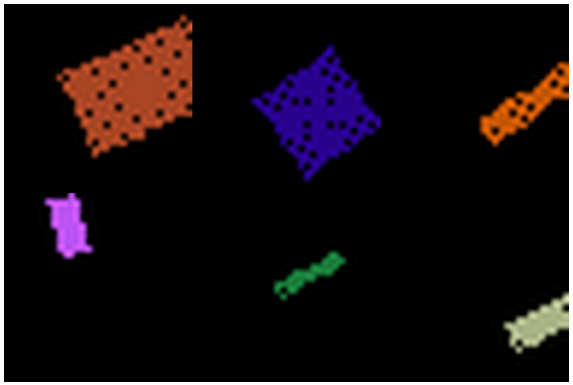


(b) with bbox annotations

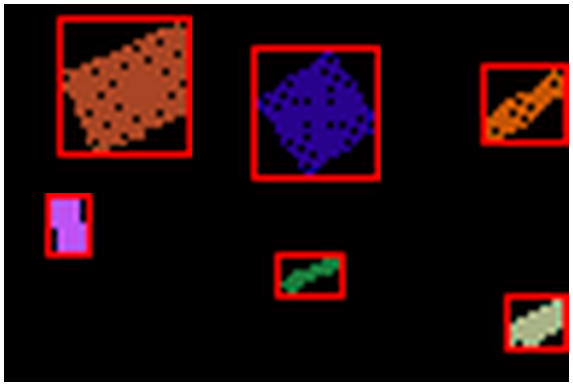
Some Example Images from the PurdueShapes5 Dataset (contd.)

(a) random triangles

(b) with bbox annotations



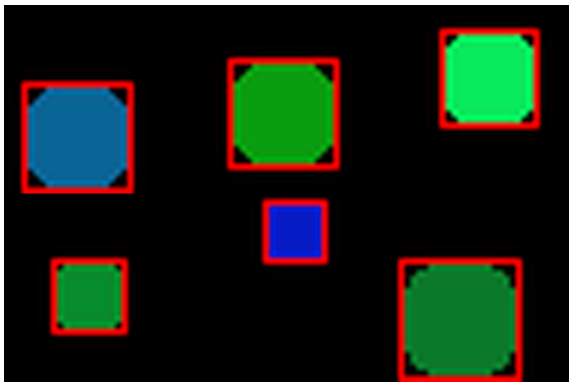
(a) noisy rectangles



(b) with bbox annotations

Some Example Images from the PurdueShapes5 Dataset (contd.)

(a) random disks



(b) with bbox annotations

- This dataset is available in the following files in the "data' subdirectory of the "Examples" directory of the DLStudio distribution (version 1.0.7). You will see the following archive files there:
  - PurdueShapes5-10000-train.gz
  - PurdueShapes5-1000-test.gz
  - PurdueShapes5-20-train.gz
  - PurdueShapes5-20-test.gz

Data Format Used for the PurdueShapes5 Dataset

- Each 32×32 image in the dataset is stored using the following format: vspace0.1in

```
Image stored as the list:
                              [R, G, B, Bbox, Label]
where

R      :   is a 1024 element list of int values for the red component
           of the color at all the pixels
B      :   the same as above but for the blue component of the color
G      :   the same as above but for the green component of the color
Bbox   :   a list like [x1,y1,x2,y2] that defines the bounding box for
           the object in the image
Label  :   the shape category of the object
```

- Each shape generated for the dataset is subject to randomization with respect to its size, its orientation, and its exact location in the image frame. Since the orientation randomization is carried out with a very simple non-interpolating transform, just the act of random rotations can introduce boundary and even interior noise in the patterns.
- **I serialize the dataset with Python's `pickle` module and then compress it with Python's `gzip` module.**

Extracting the Pixels and the Bbox from the Images

- The PIL's `Image` class has a convenient function `getdata()` that returns in a single call all the pixels in an image as a list of 3-element tuples:

```
data = list(im.getdata())                    ## 'im' is an object of type Image
R = [pixel[0] for pixel in data]             ## data for the input channels
G = [pixel[1] for pixel in data]
B = [pixel[2] for pixel in data]

## Find bounding rectangle
non_zero_pixels = []
for k,pixel in enumerate(data):
    x = k % 32
    y = k // 32
    if any( pixel[p] is not 0 for p in range(3) ):
        non_zero_pixels.append((x,y))
min_x = min( [pixel[0] for pixel in non_zero_pixels] )
max_x = max( [pixel[0] for pixel in non_zero_pixels] )
min_y = min( [pixel[1] for pixel in non_zero_pixels] )
max_y = max( [pixel[1] for pixel in non_zero_pixels] )
```

- Subsequently, you can call on Python's `pickle` to serialize the data for its persistent storage:

```
dataset,label_map = gen_dataset(how_many_images)
serialized = pickle.dumps([dataset, label_map])
f = gzip.open(dataset_name, 'wb')
f.write(serialized)
```

Outline

Custom Dataloaders and PyTorch

- Creating a custom dataloader for a DL framework is not as simple as what you did for your second homework. All you had to there was to extend the `torchvision.datasets.CIFAR10` class and tell it that you only wanted to download data for the two images classes, cat and dog.
- The new inner class `CustomDataLoading` of the `DLStudio` module presents a custom dataloader for the `PurdueShapes5` dataset. This dataloader understands the data format presented on Slide 19.
- The next slide presents the implementation of the dataloader. Note that in the last two statements on the next slide, the arguments `dataserver_train` and `dataserver_test` are both instances of the class `PurdueShapes5Dataset`. One of these points to where the training data is and the other that points to where the test data is.

A Custom Dataloader for PurdueShapes5

- You must extend the class `torch.utils.data.Dataset` and provide your own implementations for the methods `__len__()` and `__getitem__()`:

```
class PurdueShapes5Dataset(torch.utils.data.Dataset):
    def __init__(self, dl_studio, dataset_file, transform=None):
        super(DLStudio.CustomDataLoading.PurdueShapes5Dataset, self).__init__()
        root_dir = dl_studio.dataroot
        f = gzip.open(root_dir + dataset_file, 'rb')
        dataset = f.read()
        self.dataset, self.label_map = pickle.loads(dataset)
        # reverse the key-value pairs in the label dictionary:
        self.class_labels = dict(map(reversed, self.label_map.items()))
        self.transform = transform

    def __len__(self):                              ## must return the size of the dataset
        return len(self.dataset)

    def __getitem__(self, idx):                     ## extracts each image from dataset
        r = np.array( self.dataset[idx][0] )
        g = np.array( self.dataset[idx][1] )
        b = np.array( self.dataset[idx][2] )
        R,G,B = r.reshape(32,32), g.reshape(32,32), b.reshape(32,32)
        im_tensor = torch.zeros(3,32,32, dtype=torch.float)
        im_tensor[0,:,:] = torch.from_numpy(R)
        im_tensor[1,:,:] = torch.from_numpy(G)
        im_tensor[2,:,:] = torch.from_numpy(B)
        sample = {'image' : im_tensor,
                  'bbox' : self.dataset[idx][3],
                  'label' : self.dataset[idx][4] }
        return sample

def load_PurdueShapes5_dataset(self, dataset_server_train, dataset_server_test ):
    transform = tvt.Compose([tvt.ToTensor(),
                         tvt.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
    self.train_data_loader = torch.utils.data.DataLoader(dataserver_train,
                         batch_size=self.dl_studio.batch_size,shuffle=True, num_workers=4)
    self.test_data_loader = torch.utils.data.DataLoader(dataserver_test,
                         batch_size=self.dl_studio.batch_size,shuffle=False, num_workers=4)
```

Outline

The LOADnet (LOcalizing And Detecting Network) Classes in DLStudio

- The inner class DetectAndLocalize contains a couple of different versions of the LOADnet network for experimenting with different topologies for predicting both the object class and its bounding box.
- One can argue whether one needs as much convolutional depth in the bbox regression part of a network as in the labeling part. The labeling part needs convolutional depth because you do not know in advance at what level of data abstraction the objects in the image would be best detectable.
- **For the regression part, if you want to predict the exact locations of the corners, perhaps being at the same abstraction as for the labeling part is not even desirable.**
- **The next two slides present the LOADnet2 network that I have worked with the most for developing Version 1.0.7 of DLStudio.**

The LOADnet2 Network

```
class LOADnet2(nn.Module):
    """
    The acronym 'LOAD' stands for 'LOcalization And Detection'.
    LOADnet2 uses both convo and linear layers for regression
    """
    def __init__(self, skip_connections=True, depth=8):
        super(DLStudio.DetectAndLocalize.LOADnet2, self).__init__()
        if depth not in [8,10,12,14,16]:
            sys.exit("LOADnet2 has only been tested for 'depth' values 8, 10, 12, 14, and 16")
        self.depth = depth // 2
        self.conv = nn.Conv2d(3, 64, 3, padding=1)
        self.pool = nn.MaxPool2d(2, 2)
        self.bn1  = nn.BatchNorm2d(64)
        self.bn2  = nn.BatchNorm2d(128)
        self.skip64_arr = nn.ModuleList()
        for i in range(self.depth):
            self.skip64_arr.append(DLStudio.DetectAndLocalize.SkipBlock(64, 64, skip_connections=skip_connections))
        self.skip64ds = DLStudio.DetectAndLocalize.SkipBlock(64, 64, downsample=True, skip_connections=skip_connections)
        self.skip64to128 = DLStudio.DetectAndLocalize.SkipBlock(64, 128, skip_connections=skip_connections )
        self.skip128_arr = nn.ModuleList()
        for i in range(self.depth):
            self.skip128_arr.append(DLStudio.DetectAndLocalize.SkipBlock(128, 128, skip_connections=skip_connections))
        self.skip128ds = DLStudio.DetectAndLocalize.SkipBlock(128,128, downsample=True, skip_connections=skip_connections)
        self.fc1 =  nn.Linear(2048, 1000)
        self.fc2 =  nn.Linear(1000, 10)

        ##  for regression
        self.conv_seqn = nn.Sequential(
            nn.Conv2d(in_channels=64, out_channels=64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.Conv2d(in_channels=64, out_channels=64, kernel_size=3, padding=1),
            nn.ReLU(inplace=True)
        )
```

(Continued on the next slide .....)

The LOADnet2 Network (contd.)

(..... continued from the previous slide)

```
        self.fc_seqn = nn.Sequential(
            nn.Linear(16384, 1024),
            nn.ReLU(inplace=True),
            nn.Linear(1024, 512),
            nn.ReLU(inplace=True),
            nn.Linear(512, 4)
        )


    def forward(self, x):
        x = self.pool(torch.nn.functional.relu(self.conv(x)))

        ## THE LABELING SECTION:

        x1 = x.clone()
        for i,skip64 in enumerate(self.skip64_arr[:self.depth//4]):
            x1 = skip64(x1)
        x1 = self.skip64ds(x1)
        for i,skip64 in enumerate(self.skip64_arr[self.depth//4:]):
            x1 = skip64(x1)
        x1 = self.bn1(x1)
        x1 = self.skip64to128(x1)
        for i,skip128 in enumerate(self.skip128_arr[:self.depth//4]):
            x1 = skip128(x1)
        x1 = self.bn2(x1)
        x1 = self.skip128ds(x1)
        for i,skip128 in enumerate(self.skip128_arr[self.depth//4:]):
            x1 = skip128(x1)
        x1 = x1.view(-1, 2048 )
        x1 = torch.nn.functional.relu(self.fc1(x1))
        x1 = self.fc2(x1)

        ## THE REGRESSION SECTION:

        x2 = self.conv_seqn(x)
        x2 = self.conv_seqn(x2)
        # flatten
        x2 = x2.view(x.size(0), -1)
        x2 = self.fc_seqn(x2)
        return x1,x2
```

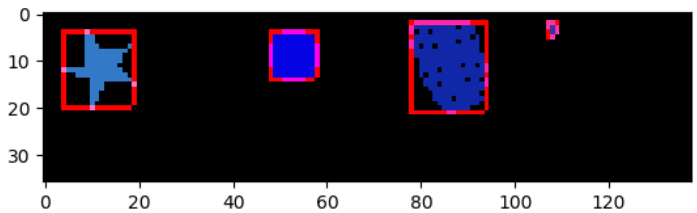
Outline

Training the LOADnet2 Network

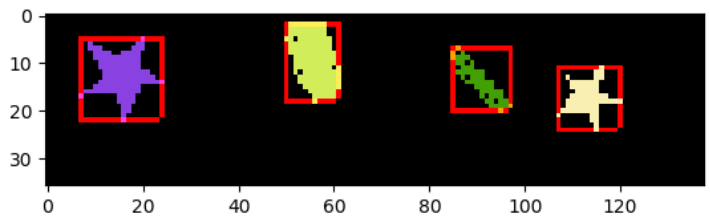
```
def run_code_for_training_with_CrossEntropy_and_MSE_Losses(self, net):
    ...
    net = net.to(self.dl_studio.device)
    criterion1 = nn.CrossEntropyLoss()
    criterion2 = nn.MSELoss()
    optimizer = optim.SGD(net.parameters(), lr=self.dl_studio.learning_rate, momentum=self.dl_studio.momentum)
    for epoch in range(self.dl_studio.epochs):
        running_loss_labeling = 0.0
        running_loss_regression = 0.0
        for i, data in enumerate(self.train_dataloader):
            inputs, bbox_gt, labels = data['image'], data['bbox'], data['label']
            if self.dl_studio.debug_train and i % 500 == 499:
                print("\n\n[epoch=%d iter=%d:] Ground Truth:     " % (epoch+1, i+1) +
                ' '.join('%10s' % self.dataserver_train.class_labels[labels[j].item()] for j in range(self.dl_studio.batch_size)))
            inputs = inputs.to(self.dl_studio.device)
            labels = labels.to(self.dl_studio.device)
            bbox_gt = bbox_gt.to(self.dl_studio.device)
            optimizer.zero_grad()

            outputs = net(inputs)

            outputs_label = outputs[0]              ##   prediction from the classification side

            bbox_pred = outputs[1]                  ##   prediction from the regression side

            ## code for displaying intermediate results

            loss_labeling = criterion1(outputs_label, labels)
            loss_labeling.backward(retain_graph=True)
            loss_regression = criterion2(bbox_pred, bbox_gt)
            loss_regression.backward()
            optimizer.step()
            running_loss_labeling += loss_labeling.item()
            running_loss_regression += loss_regression.item()

            ## code for displaying intermediate results
```

The Two Losses vs. the Iterations During Training

```
[epoch=1 iter=1:] Ground Truth:           star       disk       oval  rectangle
[epoch=1 iter=1:] Predicted Labels:       oval       disk       disk       disk
                    gt_bb:  [2,2,17,18]
                  pred_bb:  [0,0,0,0]
                    gt_bb:  [12,2,22,12]
                  pred_bb:  [0,0,0,0]
                    gt_bb:  [8,0,24,19]
                  pred_bb:  [0,0,0,0]
                    gt_bb:  [3,0,5,3]
                  pred_bb:  [0,0,0,0]
```

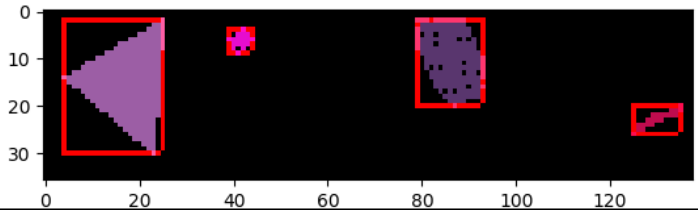


```
[epoch=1 iter=10:] Ground Truth:           star       oval       oval       star
[epoch=1 iter=10:] Predicted Labels:  rectangle  rectangle  rectangle  rectangle
                     gt_bb:  [5,3,22,20]
                   pred_bb:  [0,0,0,0]
                     gt_bb:  [14,0,25,16]
                   pred_bb:  [0,0,0,0]
                     gt_bb:  [15,5,27,18]
                   pred_bb:  [0,0,0,0]
                     gt_bb:  [3,9,16,22]
                   pred_bb:  [0,0,0,0]
```

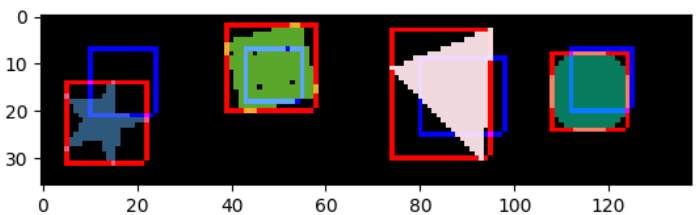


The Two Losses vs. the Iterations During Training (contd.)

```
[epoch=1 iter=100:] Ground Truth:       triangle  rectangle       oval       oval
[epoch=1 iter=100:] Predicted Labels:   triangle       star       star       disk
                      gt_bb:  [2,0,23,28]
                    pred_bb:  [0,0,0,0]
                      gt_bb:  [3,2,8,7]
                    pred_bb:  [0,0,0,0]
                      gt_bb:  [9,0,23,18]
                    pred_bb:  [0,0,0,0]
                      gt_bb:  [21,18,31,2
                    pred_bb:  [0,0,0,0]
```

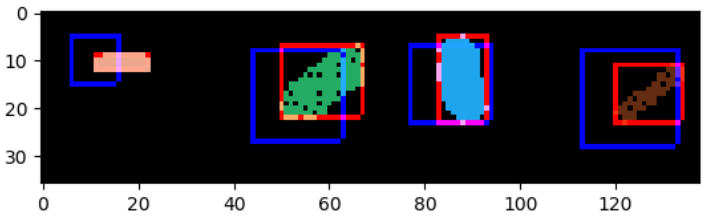



```
[epoch=1 iter=500:] Ground Truth:           star  rectangle   triangle       disk
[epoch=1 iter=500:] Predicted Labels:   triangle  rectangle   triangle       disk
                      gt_bb:  [3,12,20,29]
                    pred_bb:  [8,5,22,19]
                      gt_bb:  [3,0,22,18]
                    pred_bb:  [7,5,19,16]
                      gt_bb:  [4,1,25,28]
                    pred_bb:  [10,7,28,23]
                      gt_bb:  [4,6,20,22]
                    pred_bb:  [8,5,21,18]
[epoch:1, iteration:  500]  loss_labeling: 1.209  loss_regression: 166.813
```

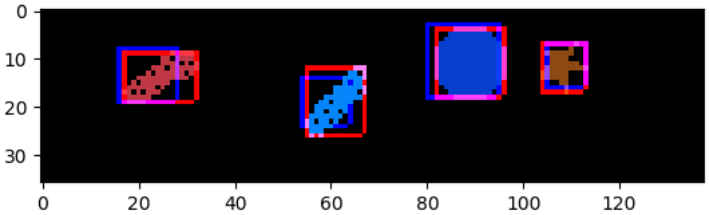


The Two Losses vs. the Iterations During Training (contd.)

```
[epoch=1 iter=1000:] Ground Truth:           oval       oval       oval  rectangle
[epoch=1 iter=1000:] Predicted Labels:       oval       oval       oval       oval
                     gt_bb:  [9,7,20,10]
                   pred_bb:  [4,3,14,13]
                     gt_bb:  [14,5,31,20]
                   pred_bb:  [8,6,27,25]
                     gt_bb:  [13,3,23,21]
                   pred_bb:  [7,5,24,21]
                     gt_bb:  [16,9,30,21]
                   pred_bb:  [9,6,29,26]
[epoch:1, iteration: 1000]  loss_labeling: 0.636  loss_regression: 20.696
```

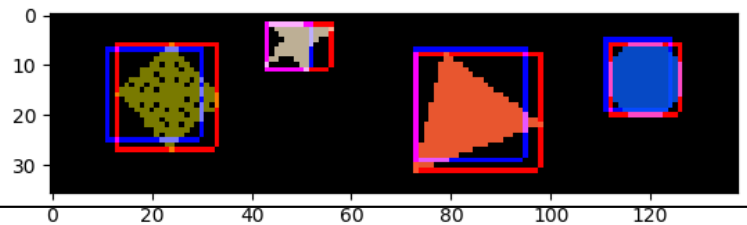



```
[epoch=1 iter=1500:] Ground Truth:           oval       oval       disk       star
[epoch=1 iter=1500:] Predicted Labels:       oval       oval       disk       star
                     gt_bb:  [15,7,30,17]
                   pred_bb:  [14,6,26,17]
                     gt_bb:  [19,10,31,24]
                   pred_bb:  [18,12,28,22]
                     gt_bb:  [12,2,26,16]
                   pred_bb:  [10,1,25,16]
                     gt_bb:  [0,5,9,15]
                   pred_bb:  [1,5,9,14]
[epoch:1, iteration: 1500]  loss_labeling: 0.434  loss_regression: 8.058
```

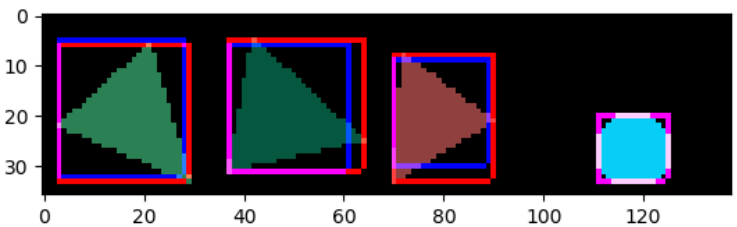


The Two Losses vs. the Iterations During Training (contd.)

```
[epoch=1 iter=2000:] Ground Truth:      rectangle       star   triangle       disk
[epoch=1 iter=2000:] Predicted Labels:       oval       star   triangle       disk
                     gt_bb:  [11,4,31,25]
                   pred_bb:  [9,5,28,23]
                     gt_bb:  [7,0,20,9]
                   pred_bb:  [7,0,16,9]
                     gt_bb:  [3,6,28,29]
                   pred_bb:  [3,5,25,27]
                     gt_bb:  [8,4,22,18]
                   pred_bb:  [7,3,20,17]
[epoch:1, iteration: 2000]  loss_labeling: 0.345  loss_regression: 2.526
```

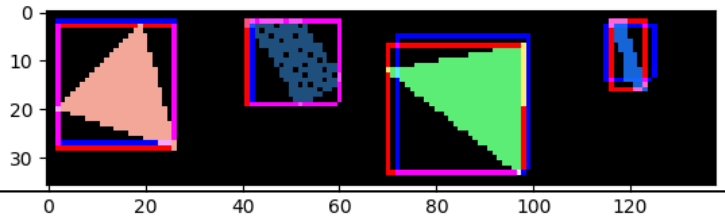



```
[epoch=1 iter=2500:] Ground Truth:      triangle   triangle   triangle       disk
[epoch=1 iter=2500:] Predicted Labels:  triangle   triangle   triangle       disk
                     gt_bb:  [1,4,27,31]
                   pred_bb:  [1,3,26,30]
                     gt_bb:  [1,3,28,29]
                   pred_bb:  [1,4,25,29]
                     gt_bb:  [0,6,20,31]
                   pred_bb:  [0,7,19,28]
                     gt_bb:  [7,18,21,31]
                   pred_bb:  [7,18,21,31]
[epoch:1, iteration: 2500]  loss_labeling: 0.324  loss_regression: 2.210
```

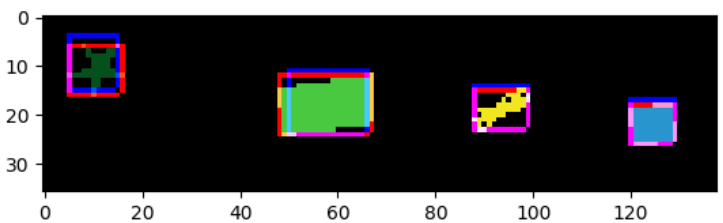


The Two Losses vs. the Iterations During Training (contd.)

```
[epoch=2 iter=500:] Ground Truth:       triangle  rectangle   triangle       oval
[epoch=2 iter=500:] Predicted Labels:   triangle  rectangle   triangle       oval
                      gt_bb:  [0,1,24,26]
                    pred_bb:  [0,0,24,25]
                      gt_bb:  [5,0,24,17]
                    pred_bb:  [6,0,24,17]
                      gt_bb:  [0,5,28,31]
                    pred_bb:  [2,3,29,31]
                      gt_bb:  [12,0,19,14]
                    pred_bb:  [11,1,21,12]

[epoch:2, iteration:  500]  loss_labeling: 0.242  loss_regression: 1.722
```

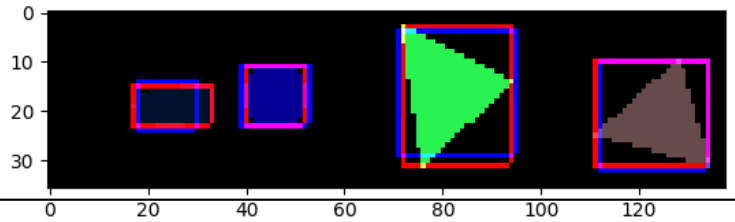



```
[epoch=2 iter=1000:] Ground Truth:          star  rectangle       oval  rectangle
[epoch=2 iter=1000:] Predicted Labels:      star  rectangle       oval  rectangle
                       gt_bb:  [3,4,14,14]
                     pred_bb:  [3,2,13,13]
                       gt_bb:  [12,10,31,22]
                     pred_bb:  [14,9,30,22]
                       gt_bb:  [18,13,29,21]
                     pred_bb:  [18,12,29,21]
                       gt_bb:  [16,16,25,24]
                     pred_bb:  [16,15,25,24]

[epoch:2, iteration: 1000]  loss_labeling: 0.231  loss_regression: 1.437
```

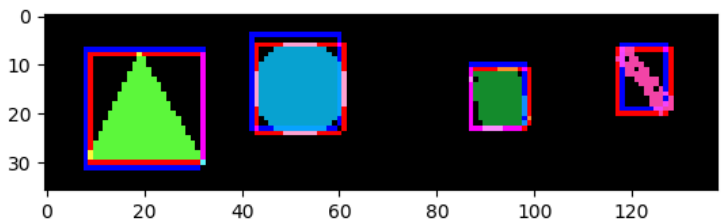


The Two Losses vs. the Iterations During Training (contd.)

```
[epoch=2 iter=1500:] Ground Truth:           oval       disk   triangle   triangle
[epoch=2 iter=1500:] Predicted Labels:       disk       disk   triangle   triangle
                     gt_bb:  [15,13,31,21]
                   pred_bb:  [16,12,28,22]
                     gt_bb:  [4,9,16,21]
                   pred_bb:  [3,9,17,21]
                     gt_bb:  [2,1,24,29]
                   pred_bb:  [1,2,25,27]
                     gt_bb:  [7,8,30,29]
                   pred_bb:  [8,8,30,30]

[epoch:2, iteration: 1500]  loss_labeling: 0.217  loss_regression: 1.172
```

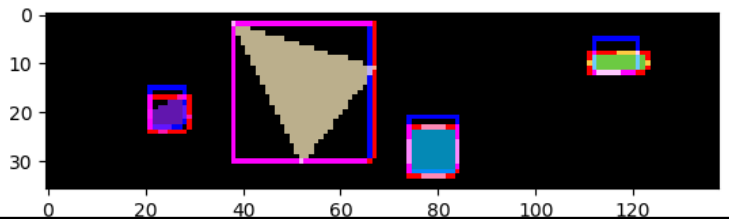



```
[epoch=2 iter=2500:] Ground Truth:       triangle       disk  rectangle  rectangle
[epoch=2 iter=2500:] Predicted Labels:   triangle       disk  rectangle       oval
                     gt_bb:  [7,6,30,28]
                   pred_bb:  [6,5,30,29]
                     gt_bb:  [7,4,25,22]
                   pred_bb:  [6,2,24,21]
                     gt_bb:  [17,9,29,21]
                   pred_bb:  [17,8,28,21]
                     gt_bb:  [13,5,24,18]
                   pred_bb:  [14,4,23,17]

[epoch:2, iteration: 2500]  loss_labeling: 0.198  loss_regression: 0.682
```

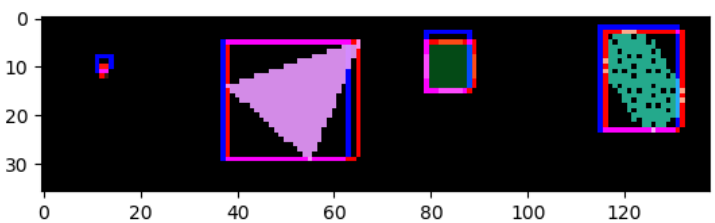


Results on Unseen Test Data

```
[i=0:] Ground Truth:      rectangle   triangle       disk       oval
[i=0:] Predicted Labels:  rectangle   triangle       disk       oval
                  gt_bb:  [19,15,27,22]
                pred_bb:  [19,13,26,21]
                  gt_bb:  [2,0,31,28]
                pred_bb:  [2,0,30,28]
                  gt_bb:  [4,21,14,31]
                pred_bb:  [4,19,14,30]
                  gt_bb:  [7,6,19,10]
                pred_bb:  [8,3,17,10]
```




```
[i=50:] Ground Truth:      rectangle   triangle       disk       oval
[i=50:] Predicted Labels:  rectangle   triangle       disk  rectangle
                  gt_bb:  [10,8,11,10]
                pred_bb:  [9,6,12,9]
                  gt_bb:  [2,3,29,27]
                pred_bb:  [1,3,27,27]
                  gt_bb:  [9,3,19,13]
                pred_bb:  [9,1,18,13]
                  gt_bb:  [12,1,28,21]
                pred_bb:  [11,0,27,21]
```



Classification Accuracy on the Unseen Test Data (After 2 Epochs of Training)

```
Prediction accuracy for rectangle : 80 %
Prediction accuracy for triangle :  99 %
Prediction accuracy for  disk :     100 %
Prediction accuracy for  oval :     77 %
Prediction accuracy for  star :     99 %

Overall accuracy of the network on the 1000 test images: 91 %


Displaying the confusion matrix:

                  rectangle       triangle           disk           oval           star

   rectangle:         80.00           0.00           0.00          20.00           0.00
    triangle:          0.00          99.50           0.00           0.00           0.50
        disk:          0.00           0.00         100.00           0.00           0.00
        oval:         22.00           0.00           0.50          77.50           0.00
        star:          0.00           0.50           0.00           0.00          99.50
```