

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 introduce 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 the DLStudio module.

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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.

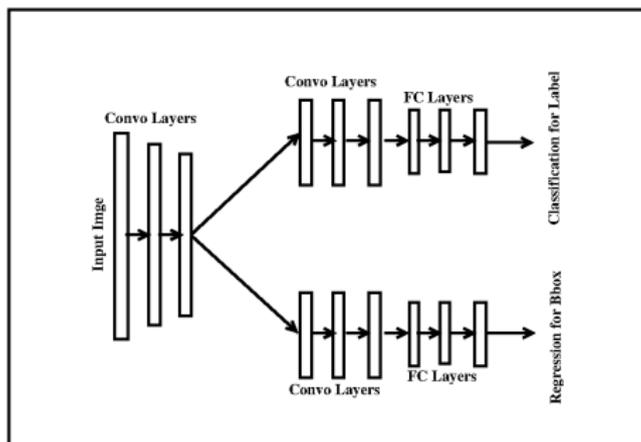


Figure: A dual-inferencing CNN

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 x represent the input image and let the vector y represent the values at the 10 output nodes. We assume that the **true** class label for the input x is c , **which is an integer between 0 and 9**. The cross-entropy loss for this output would be given by

$$\text{cross_entropy}(x, c) = -\log \frac{e^{y[c]}}{\sum_{j=0}^9 e^{y[j]}} \quad (1)$$

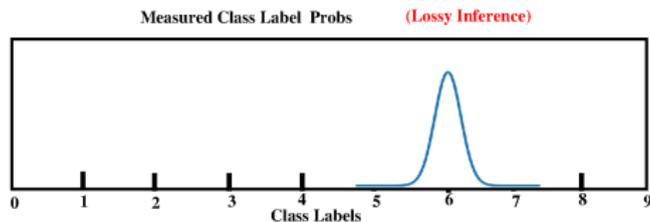
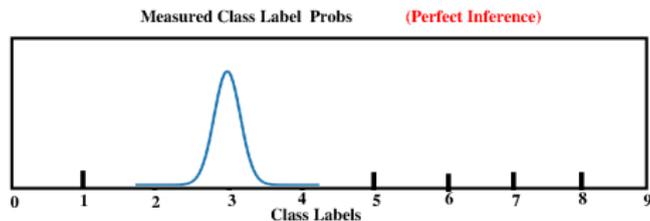
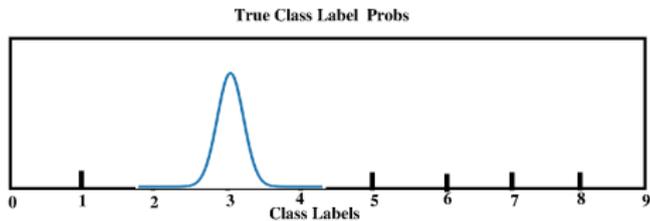
Appropriateness of Cross-Entropy Loss for Measuring Classification Error

- To see why the formula shown on the previous slide makes total sense for measuring the quality of the predicted label for a given input, first focus on the fact that, **if the inferencing were to be perfect**, the output element $y[c]$ would light up strongly in relation to all the other elements in the vector y .
- Assuming $c = 3$, perfect inference is illustrated by the middle plot on Slide 11. **The top plot in the slide shows the probabilities associated with the different possible class labels for the input image.**
- For perfect inference, both the numerator and the denominator in the formula on the previous slide would be roughly equal to 1. And since the log of 1 is zero, the loss in this case would be zero.
- The bottom plot on Slide 11 shows an example of lossy inference. Now the output node that lights up the strongest does not correspond to the true class label of the input image.

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

- Continuing with the lossy inference case mentioned at the bottom of the previous slide, since the true class label $c = 3$, the numerator in the formula shown on Slide 8 would evaluate to a very small value corresponding the value depicted at $c = 3$ in the bottom plot on the next slide.
- Therefore, for lossy inference, the ratio in the formula on Slide 8 would be a small fractional number whose logarithm would be a large negative number. The formula would therefore return a large positive number for loss.
- Note that, for at least the example illustrated on the next slide, for both the perfect inference and the lossy inference, the denominator in the formula on Slide 8 would add up to more-or-less the same value. However, the numerator would change significantly from error-free inference to lossy inference.

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



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

- As it turns out, the loss function shown at the bottom of Slide 8 has deep roots in information sciences — roots that are based on a probabilistic interpretation of that formula.
- The 10 output values given by the ratios $\frac{e^{y[i]}}{\sum_{j=0}^9 e^{y[j]}}$ for the 10 different value of the index i can be interpreted as probabilities because the numerator is guaranteed to be positive regardless of the sign of the values $y[i]$ and because these 10 numbers add up to 1.0.
- The probabilistic interpretation of the ratios $\frac{e^{y[i]}}{\sum_{j=0}^9 e^{y[j]}}$ for $i = 0, \dots, 9$ allows for them to be characterized by **cross-entropy** vis-a-vis the input, as explained in the next section.

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Understanding Entropy

- Ideally, the starting point for understanding the notion of cross-entropy is the idea of entropy itself: **Entropy is a measure of uncertainty** and its value for a discrete random variable X that can take N different values is given by one of the most famous formulas in information sciences: $H(X) = -\sum_{i=1}^N p(x_i) \log_2 p(x_i)$ where $p(X_i)$ is the probability mass associated with the value x_i of X .
- Using the formula shown above, convince yourself of the following:
(1) When the random variable X takes 8 ($= 2^3$) different values, each with a probability of $1/8$, the entropy $H(X) = 3$ bits; **(2)** When X takes 256 ($= 2^8$) different values, each with a probability of $1/256$, we have $H(X) = 8$ bits; and **(3)** If only one specific value is observed for X , $H(X) = 0$. **In general, the wider the distribution of the values for a random variable and also when it is more uniform, the greater the entropy. A non-uniform distribution has a lower entropy compared to the uniform case for the same width of the distribution.**

Understanding Cross Entropy

- Cross entropy is a measure of the uncertainty that remains in the *predicted or estimated* probability distribution for a given random variable vis-a-vis its *true* probability distribution.
- In general, when we use a neural network for image classification, we assume that the classification label for the input image is known precisely. But, just for the sake of presenting a general formula for cross-entropy, let's assume that we are somewhat uncertain about the true identity of the input image and this uncertainty is described by the probability distribution $p_i, i = 0, \dots, 9$, assuming we are still dealing with the 10-class example mentioned in the previous section.
- At the same time, let $q_i, i = 0, \dots, 9$ represent the probabilities estimated at the 10 output nodes of the neural network through the ratios shown earlier: $q_i = \frac{e^{y[i]}}{\sum_{j=0}^9 e^{y[j]}}$, $i = 0, \dots, 9$

Revisiting the Cross-Entropy Loss

- In general, if p_i is the probability that the input image belongs to class i and that q_j is the probability associated with the output value at the j^{th} output node **through a probabilistic characterization of the output as explained previously**, the cross-entropy between the two probability distributions would be given by

$$H_{\text{cross}}(p, q) = - \sum_{i=0}^{C-1} p_i \cdot \log_2 q_i \quad (2)$$

where I have assumed that we have C classes in our training data.

- The summation shown on the right in the definition shown above takes its smallest value when the estimated probabilities q_i 's are identical to the true probabilities p_i 's, **in which case the right hand side shown above yields the entropy for the random variable in question.**

Revisiting the Cross-Entropy Loss (contd.)

- Any departure in the estimated q_i values vis-a-vis the true p_i can only increase the value of the cross-entropy as given by Eq.(2).
- For an easy-to-visualize example of the cross-entropy becoming larger than its least possible value mentioned at the bottom of the previous slide, first note that the q_i 's must always all add up to 1 since they are after all probabilities.
- Now consider the case with one of the q_i goes to zero (while the value some other q_j acquires the mass that was previously in q_i). Since $\log x \rightarrow -\infty$ as $x \rightarrow 0$, the value of the cross-entropy will become infinity.

Revisiting the Cross-Entropy Loss (contd.)

- Getting back to how the cross-entropy loss is actually used in a network, **we always assume that the class label for the input image is known with certainty**. If the integer c is the class label for a given image, we assume that $p_j = 1$ for $j = c$ and 0 otherwise. For such cases, the cross-entropy formula of Eq. (2) becomes:

$$H_{cross}(p, q) = -\log_2 q_c \quad (3)$$

- Recall that if $y[i]$ is the value at the i^{th} node of the output layer of a neural network meant for classification, $q_c = \frac{e^{y[c]}}{\sum_{j=0}^9 e^{y[j]}}$ for the case when we have 10 classes in our data.

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PyTorch's `torch.nn.CrossEntropyLoss` Class

- The cross-entropy value shown in Eq. (??) on the previous slide is what is measured as the cross entropy loss by a callable instance of the PyTorch class `torch.nn.CrossEntropyLoss` that you can access through the link:

<https://pytorch.org/docs/stable/generated/torch.nn.CrossEntropyLoss.html>

- As the documentation page says, the `torch.nn.CrossEntropyLoss` function expects to see at output of the final layer of your neural network an **unnormalized scores for each class**. What that translates into is that in your own code you do not have to worry about translating the output in the final layer of your neural network into numbers that look like probability masses; **the `torch.nn.CrossEntropyLoss` class will take care of that for you.**
- **IMPORTANT:** `torch.nn.CrossEntropyLoss` expects that if C is the total number of classes in your training data, your class labels are integers between 0 and $C - 1$.

PyTorch's `torch.nn.CrossEntropyLoss` Class (contd.)

- Given the values $y[i], i = 0, \dots, C - 1$, at the nodes of the output layer, for each image x in the input batch, `CrossEntropyLoss` calculates

$$\text{Loss}(x, c) = -\log\left(\frac{e^{y[c]}}{\sum_{j=0}^{C-1} e^{y[j]}}\right) = -y[c] + \log\left(\sum_{j=0}^{C-1} e^{y[j]}\right) \quad (4)$$

where y is the tensor that represents the values in the output layer of the neural network and c is the index value of the true class for the input image x .

- `torch.nn.CrossEntropyLoss` returns the average of the loss values for all the images in a batch and that's what is backproped when you call `.backward()` on it.
- A nice thing about the `torch.nn.CrossEntropyLoss` is that it lets you weight the loss calculations to deal with what is referred to as the class imbalance problem in your training data.

PyTorch's `torch.nn.CrossEntropyLoss` Class (contd.)

- One more thing about `torch.nn.CrossEntropyLoss`: This criterion combines the `torch.nn.LogSoftmax` activation function and the `torch.nn.NLLoss` loss function in one single class. The `LogSoftmax` activation function calculates the log-ratio $\log\left(\frac{e^{y[i]}}{\sum_{j=0}^{C-1} e^{y[j]}}\right)$ for every node index i in the output layer of the neural network. Subsequently, the `NLLoss` loss function returns the negative of one of these values that corresponds to the true label of the input image. The name `NLLoss` stands for “Negative Log Likelihood Loss”.
- Most neural networks for image classification consist of convolutional layers followed by a small number of fully connected (FC) layers. The number of nodes in the last FC layer equals the number of image classes in your training data. The comment made above implies that when you use the `torch.nn.CrossEntropyLoss` loss criterion, you do **NOT** need an activation function for the final layer since the `LogSoftmax` activation is built into the loss calculation.

Training vs. Testing “Asymmetry” in Assessing the Output of a Classifier

- As mentioned earlier, a typical CNN for classification consists of several convolutional layers followed by a one or more fully-connected (`torch.nn.Linear`) layers. For example, shown below are the uppermost layers of DLStudio’s neural-network class `Net2` for a CIFAR-10 based demo of image classification:

```
class Net2(nn.Module):
    def __init__(self):
        super(DLStudio.ExperimentsWithCIFAR.Net2, self).__init__()
        // several convolutional layers go here
        self.conv3 = nn.Conv2d(in_ch, out_ch, ker_size, padding=1)
        self.pool3 = nn.MaxPool2d(patch_size, pool_stride)
        // what follows are the fully connected layers:
        in_size_for_fc = out_ch * (32 // np.prod(strides)) ** 2
        self.fc1 = nn.Linear(in_size_for_fc, 150)
        self.fc2 = nn.Linear(150, 100)
        self.fc3 = nn.Linear(100, 10)

    def forward(self, x):
        // the rest of what goes into forward
        // ...
        x = self.pool2(x)
        x = self.pool3(self.relu(self.conv3(x)))
        x = x.view(-1, self.in_size_for_fc)
        x = self.relu(self.fc1( x ))
        x = self.relu(self.fc2( x ))
        x = self.fc3(x)
        return x
```

Training vs. Testing “Asymmetry” ... (contd.)

- As shown on the previous slide, the final layer of this network consists of 10 nodes for the 10 classes in the CIFAR-10 dataset.
- In the training loop shown below, we get those 10 output values for each image in the batch in the call to the network in line (B). With the loss criterion set to `CrossEntropyLoss` in line (A), **what's interesting is that at training time we never have to identify explicitly the node that has the predicted label for the input image.** That's because the awareness of that node and what to do with it is internal to `CrossEntropyLoss` called in line (C):

```
def run_code_for_training(self, net, display_images=False):
    // ...
    criterion = nn.CrossEntropyLoss()                                ## (A)
    for epoch in range(self.epochs):
        for i, data in enumerate(self.train_data_loader):
            inputs, labels = data
            inputs = inputs.to(self.device)
            labels = labels.to(self.device)
            optimizer.zero_grad()
            outputs = net(inputs)                                    # 'outputs' is a tensor of 10 elements ## (B)
            loss = criterion(outputs, labels)                       # All 10 values go into the criterion ## (C)
            running_loss += loss.item()
```

Training vs. Testing “Asymmetry” ... (contd.)

- However, at test time, we have no choice but to identify the output node that corresponds to the predicted label. At test time, we feed the input batch into the network in line (D), and the output is – as was the case in the training loop – a tensor with 10 elements.

```
def run_code_for_testing(self, net, display_images=False):
    net.load_state_dict(torch.load(self.path_saved_model))
    net = net.eval()
    net = net.to(self.device)
    // ...
    // ...
    with torch.no_grad():
        for i,data in enumerate(self.test_data_loader):
            images, labels = data
            images = images.to(self.device)
            labels = labels.to(self.device)
            outputs = net(images)                # 'outputs' is a tensor of 10 elements    ## (D)
            _, predicted = torch.max(outputs.data, 1)    ## (E)
            // ...
            // ...
```

- The call to `max()` shown in line (E) returns two things: the max value and its index in the 10 element output vector. We are only interested in the index – since that is the predicted class label.

Binary Cross Entropy Loss – Theory

- While I am on the topic of using cross-entropies for measuring the label prediction loss, let's also consider the special case when our classification involves only two classes. In this case, the cross-entropy formula shown in Eq.(??) can be expressed as

$$\begin{aligned}
 H_{cross}(p, q) &= - \left[p_0 \cdot \log_2 q(y[0]) + p_1 \cdot \log_2 q(y[1]) \right] \\
 &= - \left[p \cdot \log_2 q + (1 - p) \cdot \log_2(1 - q) \right] \quad (5)
 \end{aligned}$$

- In the first equation shown above, p_0 and p_1 are the probabilities associated with the input image that it either belongs to class '0' or to class '1' and q_0 and q_1 the two output probabilities for the same input image. Note that $y[0]$ and $y[1]$ denote the values at the two output nodes. The quantities $q(y[0])$ $q(y[1])$ denote the probabilistic interpretations of the values at the nodes.

Binary Cross Entropy Loss (contd.)

- The second equation shown on the previous slide simplifies the notation by taking advantage of the fact that $p_0 + p_1 = 1$ and $q_0 + q_1 = 1$. So if we represent p_0 by just p , we have $p_1 = 1 - p$. Similarly, if we represent q_0 by q , we have $q_1 = 1 - q$.
- As with the earlier multi-class formula, if you are certain that the input pattern belongs to class 0, the loss function shown above reduces to just $-\log_2 q$. On the other hand, if the input image definitely belongs to class 1, the loss becomes $-\log_2(1 - q)$.

Binary Cross Entropy Loss – In Practice

- In practice, Binary Cross-Entropy Loss (BCELoss) is used for solving the one-verses-the-rest classification or detection problems. Let's say we are scraping the web and our goal is to collect just the face images. In this case, you would want to incorporate a good face detector in the web scraping algorithm.
- A neural network for such a detector is likely to have a single output node in the final layer. The value at this node would be construed as the value of q in Eq. (5). The value at the other node implied by a literal interpretation of Eq. (5) can be treated implicitly because of the normalization constraint.
- The value you find at the solitary output node in such a network is the output produced by the `nn.Sigmoid()` activation function. That guarantees that the final output value will be between 0 and 1.0 — a necessary condition on a numeric value if it is to be interpreted as a probability. Ordinarily, the numeric values in a neural network range between -1.0 and 1.0.

Binary Cross Entropy Loss – In Practice (contd.)

- PyTorch provides the class `nn.BCELoss` “Binary Cross Entropy Loss” for the sort of applications mentioned on the previous slide. Here is the documentation page for this loss function:

<https://pytorch.org/docs/stable/nn.html#bceloss>

- When using `nn.BCELoss` class as a loss criterion, for the target we typically use 1.0 since the goal is to maximize the probability of correct detection of the object of interest. That is, when the input image is of the desired class, we want it to be detected with a probability that is as close as possible to 1.0.
- An example of such a network that produces a single-node output is shown on Slide 70 of the Week 11 slides. Using 1.0 as the target for the loss criterion is shown on Slide 74 (of the same slide deck) in the (A) section of the code.

Binary Cross Entropy Loss – In Practice (contd.)

- While you are likely to use the target of 1.0 in most cases, PyTorch allows you to use any value for the target. As you will see later in this class in Week 11, I'll present an example that requires us to use 0 as the target. That is, instead of maximizing the probability of detection of a category of objects, we would want to minimize it. [Yes, it does sound weird that anyone would want to do that. You'll just have to wait until the Week 11 lecture to see why that would be a desirable thing to do in some cases.]
- The value you supply for the criterion target is the value for p in the formula shown in Eq. (5) on Slide 26. When the target is $p = 1$, the loss is equal to $-\log_2 q$. On the other hand, if the criterion target is $p = 0$ the loss becomes $-\log_2(1 - q)$. Recall, q is the value at the output of the `nn.Sigmoid` activation at the output node.

Outline

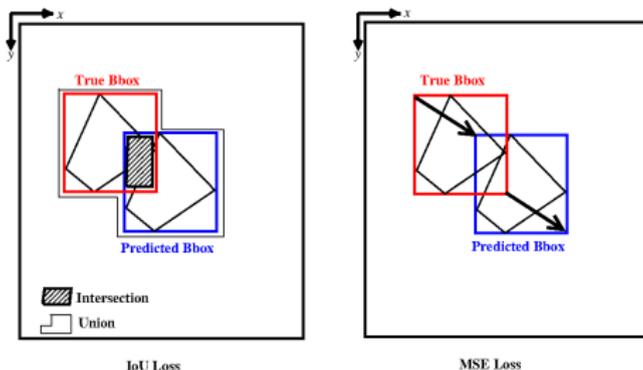
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Measuring the Regression Loss

- 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”. For a specific value for IoU, the loss would be given by $1 - IoU$.
- 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. Since IoU loss is not very useful if there is no overlap between the ground-truth bounding box and the predicted bounding-box (you'll get a zero value for IoU regardless of how far apart they are), IoU loss is best used in conjunction with the `MSELoss`.



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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.**

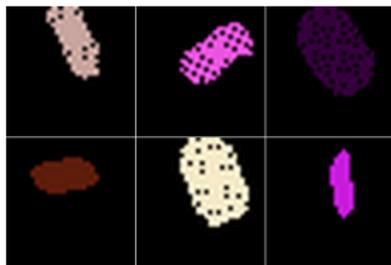
Some Example Images from the PurdueShapes5 Dataset



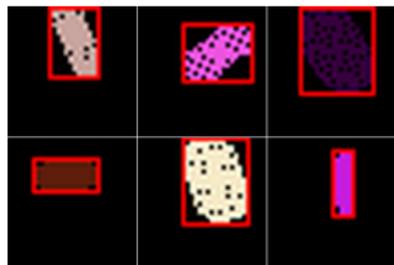
(a) random stars



(b) with bbox annotations



(a) noisy ovals



(b) with bbox annotations

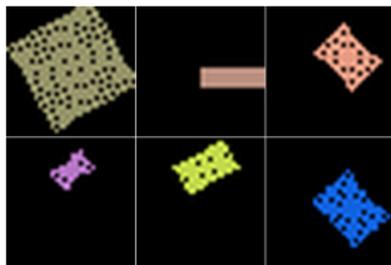
Some Example Images from the PurdueShapes5 Dataset (contd.)



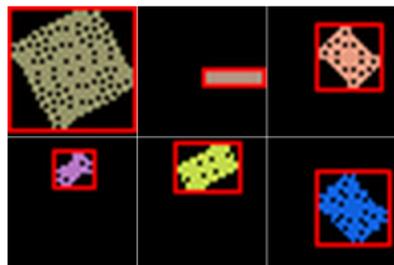
(a) random triangles



(b) with bbox annotations

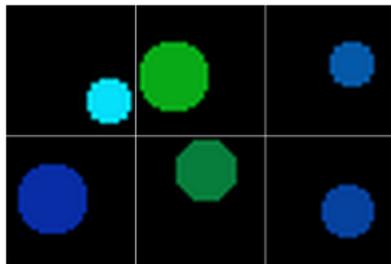


(a) noisy rectangles

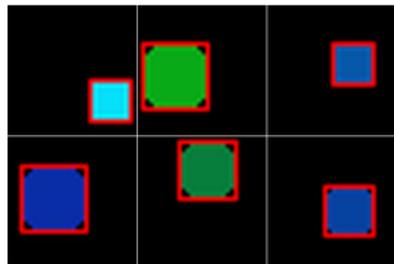


(b) with bbox annotations

Some Example Images from the PurdueShapes5 Dataset (contd.)



(a) random disks



(b) with bbox annotations

- This dataset is available through the archive `datasets_for_DLStudio.tar.gz` at the link “Download the image datasets for the main DLStudio Class” at the top of the main documentation page for DLStudio. If you install the dataset as recommended, you will see the following data archive files in the “data” subdirectory of the “Examples” directory of the DLStudio distribution:
 - `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:

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)

```

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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 21.
- 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):
        Return len(self.dataset)                ## must return the size of the 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 = tvf.Compose([tvf.ToTensor(),
                             tvf.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)
```

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The LOADnet (L^Ocalizing And Detecting Network) Classes in DLStudio

- The inner class `DetectAndLocalize` contains a couple of different versions of the `LOADnet` network for experimenting with the predictions of both the object class label and the 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 object detection and localization with**

The LOADnet2 Network

```

class LOADnet2(nn.Module):
    """
    '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, 5)                ## for the 5 output classes

        ## 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)
        )
        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)                ## output for the 4 coords (x_min,y_min,x_max,y_max) of BBox
        )

```

The LOADnet2 Network (contd.)

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

```
def forward(self, x):
    x = nn.MaxPool2d(2,2)(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 Bounding Box regression:
    x2 = self.conv_seqn(x)
    # flatten
    x2 = x2.view(x.size(0), -1)
    x2 = self.fc_seqn(x2)
    return x1,x2
```

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Training the LOADnet2 Network

```

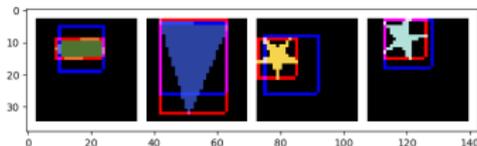
def run_code_for_training_with_CrossEntropy_and_MSE_Losses(self, net):
    ...
    net = net.to(self.dl_studio.device)
    criterion1 = nn.CrossEntropyLoss()
    criterion2 = nn.MSELoss()
    optimizer = optim.SGD(net.parameters(), lr=self.dl_studio.learning_rate, momentum=self.dl_studio.momentum)
    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

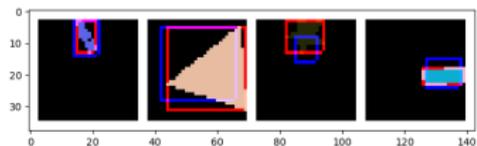
```
[epoch:1/2 iter= 500 elapsed_time= 17 secs]   Ground Truth:   oval   triangle   star   star
[epoch:1/2 iter= 500 elapsed_time= 17 secs]   Predicted Labels:  oval   triangle   star   star
gt_bb: [6,6,21,12]
pred_bb: [7,2,21,16]
gt_bb: [4,0,25,29]
pred_bb: [4,1,25,23]
gt_bb: [0,6,12,18]
pred_bb: [2,5,19,23]
gt_bb: [5,0,18,12]
pred_bb: [5,0,20,15]

[epoch:1/2 iter= 500 elapsed_time= 17 secs]   loss_labelling 1.007   loss_regression: 29.076
```



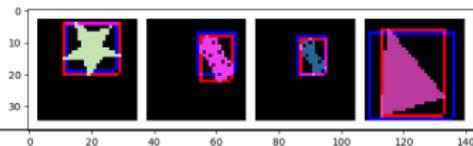
```
[epoch:1/2 iter=1000 elapsed_time= 95 secs]   Ground Truth:   rectangle  triangle   star  rectangle
[epoch:1/2 iter=1000 elapsed_time= 95 secs]   Predicted Labels:  oval   triangle   star   disk
gt_bb: [12,0,18,10]
pred_bb: [11,0,19,11]
gt_bb: [6,2,31,28]
pred_bb: [4,2,28,25]
gt_bb: [9,0,21,10]
pred_bb: [12,5,19,13]
gt_bb: [18,15,31,20]
pred_bb: [19,12,30,21]

[epoch:1/2 iter=1000 elapsed_time= 95 secs]   loss_labelling 0.676   loss_regression: 9.106
```

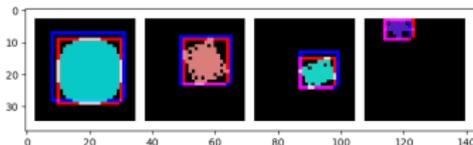


The Two Losses vs. the Iterations During Training (contd.)

```
epoch:1/2 iter=1500 elapsed_time= 156 secs]      Ground Truth:      star      oval rectangle triangle
[epoch:1/2 iter=1500 elapsed_time= 156 secs] Predicted Labels:      star      oval rectangle triangle
      gt_bb: [8,1,26,17]
      pred_bb: [9,1,25,16]
      gt_bb: [17,5,27,19]
      pred_bb: [16,4,28,17]
      gt_bb: [14,6,22,17]
      pred_bb: [13,5,22,17]
      gt_bb: [5,3,25,30]
      pred_bb: [1,4,28,31]
[epoch:1/2 iter=1500 elapsed_time= 156 secs]      loss_labelling 0.602      loss_regression: 5.423
```



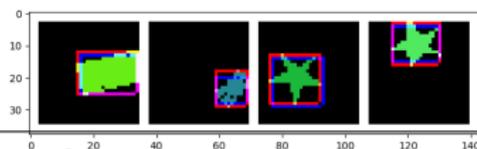
```
[epoch:1/2 iter=2000 elapsed_time= 263 secs]      Ground Truth:      disk rectangle rectangle star
[epoch:1/2 iter=2000 elapsed_time= 263 secs] Predicted Labels:      disk rectangle oval star
      gt_bb: [7,6,27,26]
      pred_bb: [5,4,28,25]
      gt_bb: [12,6,26,20]
      pred_bb: [11,5,27,20]
      gt_bb: [14,12,25,21]
      pred_bb: [14,10,26,21]
      gt_bb: [6,0,15,6]
      pred_bb: [6,0,14,6]
[epoch:1/2 iter=2000 elapsed_time= 263 secs]      loss_labelling 0.470      loss_regression: 3.161
```



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

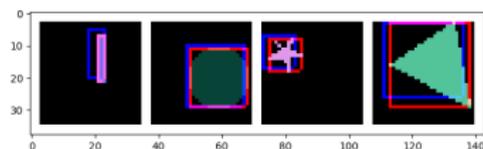
```
[epoch:1/2 iter=2500 elapsed_time= 330 secs] Ground Truth:   rectangle rectangle   star   star
[epoch:1/2 iter=2500 elapsed_time= 330 secs] Predicted Labels:  oval   oval   star   star
gt_bb: [12,9,31,22]
pred_bb: [13,10,31,22]
gt_bb: [21,15,31,26]
pred_bb: [21,17,31,25]
gt_bb: [3,10,19,25]
pred_bb: [4,11,20,26]
gt_bb: [7,0,22,13]
pred_bb: [7,1,22,12]
```

```
[epoch:1/2 iter=2500 elapsed_time= 330 secs] loss_labelling 0.448 loss_regression: 2.864
```



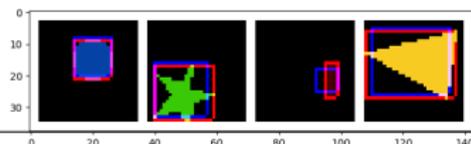
```
[epoch:2/2 iter= 500 elapsed_time= 409 secs] Ground Truth:   oval   disk   star   triangle
[epoch:2/2 iter= 500 elapsed_time= 409 secs] Predicted Labels:  oval   disk   star   triangle
gt_bb: [18,4,20,18]
pred_bb: [15,2,20,17]
gt_bb: [12,8,30,26]
pred_bb: [11,7,29,26]
gt_bb: [2,5,12,15]
pred_bb: [0,4,10,14]
gt_bb: [5,0,30,26]
pred_bb: [3,0,28,23]
```

```
[epoch:2/2 iter= 500 elapsed_time= 409 secs] loss_labelling 0.336 loss_regression: 2.196
```

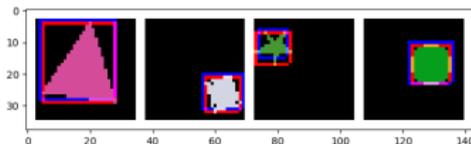


The Two Losses vs. the Iterations During Training (contd.)

```
[epoch:2/2 iter=1000 elapsed_time= 479 secs]   Ground Truth:      disk      star      oval      triangle
[epoch:2/2 iter=1000 elapsed_time= 479 secs]   Predicted Labels:  disk      star      oval      triangle
      gt_bb: [11,6,23,18]
      pred_bb: [11,5,23,17]
      gt_bb: [2,14,21,31]
      pred_bb: [2,13,19,30]
      gt_bb: [22,13,26,24]
      pred_bb: [19,15,26,22]
      gt_bb: [0,3,29,24]
      pred_bb: [2,2,27,23]
[epoch:2/2 iter=1000 elapsed_time= 479 secs]   loss_labelling 0.300      loss_regression: 2.318
```



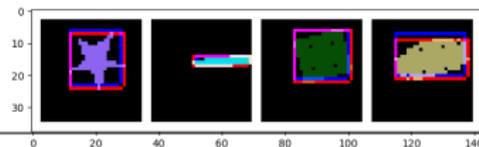
```
[epoch:2/2 iter=1500 elapsed_time= 599 secs]   Ground Truth:      triangle  rectangle  star      disk
[epoch:2/2 iter=1500 elapsed_time= 599 secs]   Predicted Labels:  triangle  rectangle  star      disk
      gt_bb: [2,1,25,26]
      pred_bb: [1,0,25,25]
      gt_bb: [19,18,30,29]
      pred_bb: [18,17,31,28]
      gt_bb: [0,4,11,14]
      pred_bb: [1,3,10,12]
      gt_bb: [15,8,27,20]
      pred_bb: [14,7,28,20]
[epoch:2/2 iter=1500 elapsed_time= 599 secs]   loss_labelling 0.299      loss_regression: 1.433
```



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

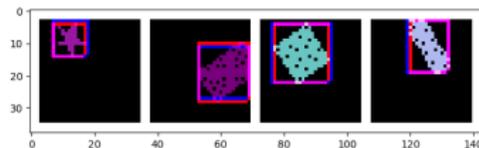
```
[epoch:2/2 iter=2000 elapsed_time= 657 secs] Ground Truth:      star   oval  rectangle   oval
[epoch:2/2 iter=2000 elapsed_time= 657 secs] Predicted Labels:  star   oval   disk       oval
      gt_bb: [9,4,26,21]
      pred_bb: [9,3,25,20]
      gt_bb: [13,11,31,14]
      pred_bb: [14,11,29,13]
      gt_bb: [10,3,28,19]
      pred_bb: [10,3,27,18]
      gt_bb: [7,6,30,18]
      pred_bb: [7,4,29,17]
```

```
[epoch:2/2 iter=2000 elapsed_time= 657 secs]      loss_labelling 0.297      loss_regression: 1.266
```

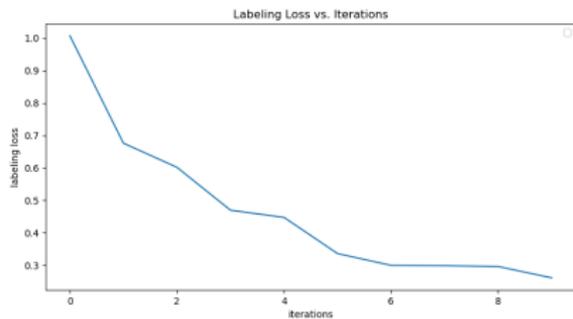


```
[epoch:2/2 iter=2500 elapsed_time= 754 secs] Ground Truth:      star  rectangle  rectangle   oval
[epoch:2/2 iter=2500 elapsed_time= 754 secs] Predicted Labels:  star   oval  rectangle   oval
      gt_bb: [4,1,14,11]
      pred_bb: [4,0,15,11]
      gt_bb: [15,7,31,25]
      pred_bb: [15,8,31,24]
      gt_bb: [4,1,21,19]
      pred_bb: [3,1,22,19]
      gt_bb: [12,0,24,16]
      pred_bb: [11,0,24,16]
```

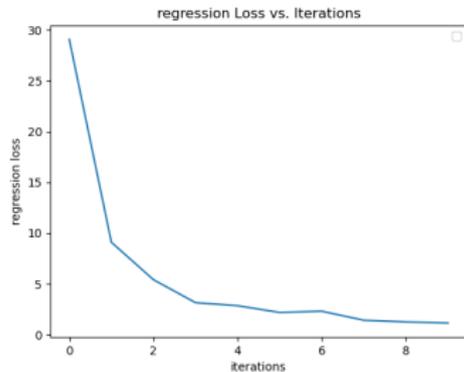
```
[epoch:2/2 iter=2500 elapsed_time= 754 secs]      loss_labelling 0.262      loss_regression: 1.158
```



Training and Regression Losses versus Iterations



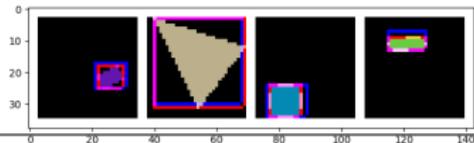
(a) labeling loss vs. iterations



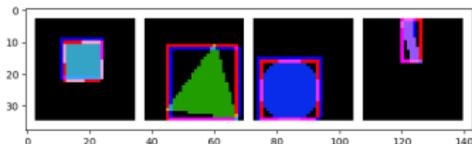
(b) regression loss vs. iterations

Results on Unseen Test Data

```
[i=0:] Ground Truth:   rectangle  triangle  disk  oval
[i=0:] Predicted Labels: rectangle  triangle  disk  rectangle
                        gt_bb: [19,15,27,22]
                        pred_bb: [18,14,28,22]
                        gt_bb: [2,0,31,28]
                        pred_bb: [2,0,30,27]
                        gt_bb: [4,21,14,31]
                        pred_bb: [3,21,16,31]
                        gt_bb: [7,6,19,10]
                        pred_bb: [7,4,19,10]
```



```
[i=100:] Ground Truth:  rectangle  triangle  disk  oval
[i=100:] Predicted Labels: rectangle  disk  disk  oval
                        gt_bb: [9,7,21,19]
                        pred_bb: [8,6,21,18]
                        gt_bb: [7,8,29,31]
                        pred_bb: [8,9,30,31]
                        gt_bb: [2,13,20,31]
                        pred_bb: [1,12,21,31]
                        gt_bb: [12,0,18,13]
                        pred_bb: [12,0,16,13]
```



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

Prediction accuracy for rectangle : 64 %
Prediction accuracy for triangle : 97 %
Prediction accuracy for disk : 99 %
Prediction accuracy for oval : 81 %
Prediction accuracy for star : 99 %

Overall accuracy of the network on the 1000 test images: 88 %

Displaying the confusion matrix:

	rectangle	triangle	disk	oval	star
rectangle:	64.00	0.50	1.00	31.50	3.00
triangle:	1.50	97.50	1.00	0.00	0.00
disk:	1.00	0.00	99.00	0.00	0.00
oval:	18.50	0.00	0.50	81.00	0.00
star:	0.00	0.50	0.00	0.00	99.50