ResNet18

April 16, 2019

0.1 Loading Files from drive

The command below is to load files from drive

```
In [0]: from google.colab import drive
        drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/co
```

0.2 Importing Libraries

Numpy, Pandas, Torch, PIL, Torchvision, matplotlib and os libraries are imported

```
In [0]: import numpy as np
        import pandas as pd
        import os
        import torch
        import torchvision
        from PIL import Image
        import matplotlib.pyplot as plt
        from torch.utils.data import Dataset
        from torchvision import datasets, transforms
```

0.3 Dataset loading

The dataset class is inherited and customized as per the dataset given. RandomResizedCrop, RandomHorizontalFlip are used as data augmentation techniques. The dataset is also normalized to obtain better results.

```
In [0]: class DataSet(Dataset):
            def __init__(self, root_dir, total_no, csv_file, transform=None):
                self.root_dir = root_dir
                self.transform = transform
                self.total_no = total_no
                self.csv_file = np.array(pd.read_csv(csv_file, header=None))[0]

            def __len__(self):
                return self.total_no
```

```
    def __getitem__(self, image_no):
        img_name = os.path.join(self.root_dir, str(image_no+1)+".jpg")
        image = Image.open(img_name)
        sample = {'image': image, 'category': self.csv_file[image_no]-1}
        if self.transform:
            sample['image'] = self.transform(sample['image'])
        return sample

trainDataset = DataSet('/content/drive/My Drive/HW3_data/train/',
                       1888,
                       '/content/drive/My Drive/HW3_data/train_labels.csv',
                       transforms.Compose([
        transforms.RandomResizedCrop(224),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]))
testDataset = DataSet('/content/drive/My Drive/HW3_data/test/', 800, '/content/drive/My
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]))
```

0.4 Dataloaders for loading the datasets defined

Train and test dataloaders are defined with batch size 4, number of workers 4 and shuffling while loading data has been enabled.

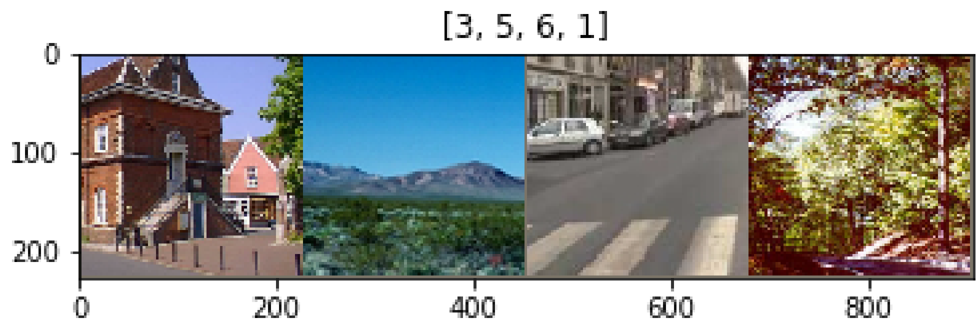
```
In [0]: trainDataloader = torch.utils.data.DataLoader(trainDataset, batch_size=4, shuffle=True
        testDataloader = torch.utils.data.DataLoader(testDataset, batch_size=4, shuffle=True, n
        device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
```

0.5 Displaying the images

The images are displayed along with their classes after loading data

```
In [0]: def imshow(inp, title=None):
            inp = inp.numpy().transpose((1, 2, 0))
            mean = np.array([0.485, 0.456, 0.406])
            std = np.array([0.229, 0.224, 0.225])
            inp = std * inp + mean
            inp = np.clip(inp, 0, 1)
            plt.imshow(inp)
            if title is not None:
                plt.title(title)
        inputs = next(iter(trainDataloader))
```

```
out = torchvision.utils.make_grid(inputs['image'])
imshow(out, title=[int(x) for x in inputs['category']])
```



0.6 Defining the ResNet18 model

The 18 layers for ResNet has been built as follows consisting of 4 blocks each consisting of 2 similar blocks each having 2 convolution layers. The input image is immediately passed into a convolution layer followed by these 4 blocks and then finally into a fully connected layer leading to 18 layers.

```
In [0]: class BasicBlock(torch.nn.Module):
          def __init__(self, in_filters, out_filters, stride=1, downsample=None):
            super(BasicBlock, self).__init__()

            self.conv1 = torch.nn.Conv2d(in_filters, out_filters, 3, stride, 1, bias = False)
            self.bn1 = torch.nn.BatchNorm2d(out_filters)
            self.relu = torch.nn.ReLU(inplace = True)

            self.conv2 = torch.nn.Conv2d(out_filters, out_filters, 3, 1, 1, bias = False)
            self.bn2 = torch.nn.BatchNorm2d(out_filters)

            self.downsample = downsample
            self.stride = stride
          def forward(self, inp):
            previous_inp = inp
            output = self.conv1(inp)
            output = self.bn1(output)
            output = self.relu(output)
            output = self.conv2(output)
            output = self.bn2(output)
            if(self.downsample is not None):
              previous_inp = self.downsample(inp)
            output += previous_inp
            output = self.relu(output)
            return output
```

```python
class ResNet18(torch.nn.Module):
  def __init__(self, num_classes=8):
    super(ResNet18, self).__init__()
    self.inplanes = 64
    self.conv1 = torch.nn.Conv2d(3, self.inplanes, 7, 2, 3, bias = False)
    self.bn1 = torch.nn.BatchNorm2d(self.inplanes)
    self.relu = torch.nn.ReLU(inplace = True)
    self.maxpool = torch.nn.MaxPool2d(3, 2, 1)

    self.layer1 = self._make_layer(64, 2)
    self.layer2 = self._make_layer(128, 2, stride = 2)
    self.layer3 = self._make_layer(256, 2, stride = 2)
    self.layer4 = self._make_layer(512, 2, stride = 2)

    self.avgpool = torch.nn.AdaptiveAvgPool2d((1, 1))
    self.fc = torch.nn.Linear(512, num_classes)

    for module in self.modules():
      if isinstance(module, torch.nn.Conv2d):
        torch.nn.init.kaiming_normal_(module.weight, mode='fan_out',
                                      nonlinearity='relu')
      elif isinstance(module, torch.nn.BatchNorm2d):
        torch.nn.init.constant_(module.weight, 1)
        torch.nn.init.constant_(module.bias, 0)

  def _make_layer(self, out_planes, blocks, stride = 1):
    downsample = None
    if(stride != 1 or out_planes != self.inplanes):
      downsample = torch.nn.Sequential(
          torch.nn.Conv2d(self.inplanes, out_planes, kernel_size=1,
                          stride=stride, bias = False),
          torch.nn.BatchNorm2d(out_planes)
      )
    layers = []
    layers.append(BasicBlock(self.inplanes, out_planes, stride, downsample))
    self.inplanes = out_planes
    for _ in range(1, blocks):
      layers.append(BasicBlock(self.inplanes, out_planes))
    return torch.nn.Sequential(*layers)

  def forward(self, inp):
    inp = self.conv1(inp)
    inp = self.bn1(inp)
    inp = self.relu(inp)
    inp = self.maxpool(inp)
```

```
        inp = self.layer1(inp)
        inp = self.layer2(inp)
        inp = self.layer3(inp)
        inp = self.layer4(inp)

        inp = self.avgpool(inp)
        inp = inp.view(inp.size(0), -1)
        inp = self.fc(inp)

        return inp
```

0.7 Printing the ResNet model

The ResNet architecture is shifted to CUDA(GPU) and is printed in the following lines.

```
In [0]: myResnet = ResNet18().to(device)
        print(myResnet)
```

```
ResNet18(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
```

```
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer3): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer4): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
```

```
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Linear(in_features=512, out_features=8, bias=True)
)
```

0.8 Defining Optimizer, Loss functions and Learning rate scheduler

The optimizer function, loss function and the learning rate scheduler are defined in the following segment of code.

```
In [0]: Loss = torch.nn.CrossEntropyLoss()
        Optimizer = torch.optim.Adam(myResnet.parameters(), lr=0.01)
        exp_lr_scheduler = torch.optim.lr_scheduler.StepLR(Optimizer, step_size=2, gamma=0.9)
```

0.9 Function for running the defined model

The function is defined for loading the data for each epoch, outputing the output for the batch and performing backpropagation using the defined optimizer.

```
In [0]: def run_model(model, epochs, loss, optimizer, trainDataloader, testDataloader):
          model.to(device)
          for epoch in range(epochs):
            current_loss = 0.0
            exp_lr_scheduler.step()
            for i, data in enumerate(trainDataloader, 0):
              images, labels = data['image'], data['category']
              images, labels = images.to(device), labels.to(device)
              optimizer.zero_grad()
              obtained_outputs = model(images)
              obtained_loss = loss(obtained_outputs, labels)
              obtained_loss.backward()
              optimizer.step()
              current_loss += obtained_loss.item()
              if(i%100 == 99):
                print("EPOCH:", epoch+1)
                print("BATCH:", i+1)
                print("LOSS:", current_loss/100)
                print("-----------------------------")
                current_loss = 0.0
          print("Training Done!!!")
          correct = 0
          total = 0
          with torch.no_grad():
            for data in testDataloader:
```

```
            images, labels = data['image'], data['category']
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            predicted_output = torch.argmax(outputs, 1)
            correct += (predicted_output == labels).sum().item()
            total += labels.size(0)
        print("Accuracy:", correct*100/total, "%")
```

0.10 Running the model

Resnet model is run for 200 epochs with the defined Cross Entropy Loss and Adam Optimizer.

```
In [0]: run_model(myResnet, 200, Loss, Optimizer, trainDataloader, testDataloader)
```

0.11 Training Accuracy

The trained model is run on the train dataset. Accuracy of 88.88% is obtained.

```
In [0]: correct = 0
        total = 0
        with torch.no_grad():
          for data in trainDataloader:
            images, labels = data['image'], data['category']
            images, labels = images.to(device), labels.to(device)
            outputs = myResnet(images)
            predicted_output = torch.argmax(outputs, 1)
            correct += (predicted_output == labels).sum().item()
            total += labels.size(0)
        print("Training Accuracy:", correct*100/total, "%")
```

```
Training Accuracy: 88.87711864406779 %
```

0.12 Testing Accuracy

The trained model is run on the test dataset. Accuracy of 90.375% is obtained.

```
In [0]: correct = 0
        total = 0
        with torch.no_grad():
          for data in testDataloader:
            images, labels = data['image'], data['category']
            images, labels = images.to(device), labels.to(device)
            outputs = myResnet(images)
            predicted_output = torch.argmax(outputs, 1)
            correct += (predicted_output == labels).sum().item()
            total += labels.size(0)
        print("Test Accuracy:", correct*100/total, "%")
```

```
Test Accuracy: 90.375 %
```

0.13 Loading the CIFAR10 dataset

The train dataset and test dataset are loaded and appropriate transformations are applied. The dataloaders are also loaded with batch size 256 and number of workers=2

```
In [0]: cifarTrainSet = torchvision.datasets.CIFAR10(root='./data', train=True,
                                                     download = True,
                                                     transform = transforms.Compose([
                                                          transforms.RandomHorizontalFlip(),
                                                          transforms.ToTensor(),
                                                          transforms.Normalize((0.5, 0.5, 0.5)
                                                                               (0.5, 0.5, 0.5)
        cifarTestSet = torchvision.datasets.CIFAR10(root='./data', train=False,
                                                   download = True,
                                                   transform = transforms.Compose([
                                                       transforms.RandomHorizontalFlip(),
                                                       transforms.ToTensor(),
                                                       transforms.Normalize((0.5, 0.5, 0.5),
                                                                            (0.5, 0.5, 0.5))
                                                   ]))
        cifarTrainLoader = torch.utils.data.DataLoader(cifarTrainSet, batch_size=256,
                                                      shuffle=True, num_workers=2)
        cifarTestLoader = torch.utils.data.DataLoader(cifarTestSet, batch_size=256,
                                                      shuffle=False, num_workers=2)
        classes = ('plane', 'car', 'bird', 'cat',
                   'deer', 'dog', 'frog', 'horse', 'ship', 'truck')
```

```
Files already downloaded and verified
Files already downloaded and verified
```

0.14 Configuring Resnet18

The Resnet18 is configured as per CIFAR10 dataset with 10 nodes in the final layer, representing probabilities for each output.

```
In [0]: cifarResnet = ResNet18(num_classes=10).to(device)
        print(cifarResnet)
```

```
ResNet18(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
```

```
    (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (1): BasicBlock(
    (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
    (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
)
(layer2): Sequential(
  (0): BasicBlock(
    (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (downsample): Sequential(
      (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (1): BasicBlock(
    (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
)
(layer3): Sequential(
  (0): BasicBlock(
    (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
    (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (downsample): Sequential(
      (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (1): BasicBlock(
    (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
    (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
```

```
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer4): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Linear(in_features=512, out_features=10, bias=True)
)
```

0.15 Loss function and optimizer

The loss function and optimizer are defined for the new model of Resnet as follows:

```
In [0]: Loss = torch.nn.CrossEntropyLoss()
        Optimizer = torch.optim.Adam(cifarResnet.parameters(), lr=0.01)
```

0.16 Function for running the new model

The function is defined for loading CIFAR10 data for each epoch, outputing the output for the batch and performing backpropagation using the defined optimizer.

```
In [0]: def run_model(model, epochs, loss, optimizer, trainDataloader, testDataloader):
          model.to(device)
          for epoch in range(epochs):
            current_loss = 0.0
            for i, data in enumerate(trainDataloader, 0):
              images, labels = data
              images, labels = images.to(device), labels.to(device)
              optimizer.zero_grad()
```

```
            obtained_outputs = model(images)
            obtained_loss = loss(obtained_outputs, labels)
            obtained_loss.backward()
            optimizer.step()
            current_loss += obtained_loss.item()
            if(i%100 == 99):
              print("EPOCH:", epoch+1)
              print("BATCH:", i+1)
              print("LOSS:", current_loss/100)
              print("----------------------------")
              current_loss = 0.0
        print("Training Done!!!")
        correct = 0
        total = 0
        with torch.no_grad():
          for data in testDataloader:
            images, labels = data
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            predicted_output = torch.argmax(outputs, 1)
            correct += (predicted_output == labels).sum().item()
            total += labels.size(0)
        print("Accuracy:", correct*100/total, "%")
```

0.17 Running the model

Resnet model is run for 20 epochs with the defined Cross Entropy Loss and Adam Optimizer.

```
In [0]: run_model(cifarResnet, 20, Loss, Optimizer, cifarTrainLoader, cifarTestLoader)
```

0.18 Training Accuracy

The trained model is run on the train dataset. Accuracy of 94.736% is obtained.

```
In [0]: correct = 0
        total = 0
        with torch.no_grad():
            for data in cifarTrainLoader:
              images, labels = data
              images, labels = images.to(device), labels.to(device)
              outputs = cifarResnet(images)
              predicted_output = torch.argmax(outputs, 1)
              correct += (predicted_output == labels).sum().item()
              total += labels.size(0)
        print("Training Accuracy:", correct*100/total, "%")
```

```
Training Accuracy: 94.736 %
```

0.19 Testing Accuracy

The trained model is run on the test dataset. Accuracy of 78.51% is obtained.

```
In [0]: correct = 0
        total = 0
        with torch.no_grad():
            for data in cifarTestLoader:
              images, labels = data
              images, labels = images.to(device), labels.to(device)
              outputs = cifarResnet(images)
              predicted_output = torch.argmax(outputs, 1)
              correct += (predicted_output == labels).sum().item()
              total += labels.size(0)
        print("Testing Accuracy:", correct*100/total, "%")
```

```
Testing Accuracy: 78.51 %
```

0.20 Comparision among KNN, Alexnet, Resnet18

0.20.1 KNN : 55.5% accuracy.

0.20.2 Alexnet pretrained model : 93.25% accuracy

0.20.3 Resnet18 : 90.375% accuracy.

```
In [0]:
```