yuxuanz6_cs544_project

May 9, 2019

1 Enviroment Settings

```
In [8]: from google.colab import drive
        drive.mount('/content/gdrive/')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6

Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/gdrive/
```

```
In [9]: ls
```

```
gdrive/  sample_data/
```

```
In [0]: import os
        os.chdir("/content/gdrive/My Drive/UIUC/2019_spring/CS544--optimizer computer vision/pr
```

```
In [11]: ls # Check if this is your MP4 folder
```

```
 data/                                'yuxuanz6_cs544_project(1).ipynb'
 Drift_Data/                          'yuxuanz6_cs544_project(2).ipynb'
 opt_res_part1/                       'yuxuanz6_cs544_project(3).ipynb'
 opt_res_part2/                       'yuxuanz6_cs544_project(4).ipynb'
 SGD-plot.png                         'yuxuanz6_cs544_project(5-part1).ipynb'
 submission/                          'yuxuanz6_cs544_project(6).ipynb'
'yuxuanz6_cs544_project(0).ipynb'      yuxuanz6_cs544_project.ipynb
```

```
In [0]: !mkdir /data
        !cp data/cifar100.tar.gz /data/
        !tar -xf /data/cifar100.tar.gz -C /data/
        !cp data/test.tar.gz /data
        !tar -xf /data/test.tar.gz -C /data
        !cp data/train.tar.gz /data
        !tar -xf /data/train.tar.gz -C /data/
```

In [13]:
```
ls /data
```

```
cifar100/  cifar100.tar.gz  test/  test.tar.gz  train/  train.tar.gz
```

In [14]:
```
!pip3 install torch torchvision
```

```
Requirement already satisfied: torch in /usr/local/lib/python3.6/dist-packages (1.1.0)
Requirement already satisfied: torchvision in /usr/local/lib/python3.6/dist-packages (0.2.2.po
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from torch) (1
Requirement already satisfied: pillow>=4.1.1 in /usr/local/lib/python3.6/dist-packages (from t
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from torchvision
Requirement already satisfied: olefile in /usr/local/lib/python3.6/dist-packages (from pillow>
```

In [15]:
```
import torch
a = torch.Tensor([1]).cuda()
print(a)
```

```
tensor([1.], device='cuda:0')
```

In [16]:
```
torch.cuda.is_available()
```

Out[16]:
```
True
```

2 Part1 - BaseNet(adapt from vgg net) Optimization

2.1 Part1.0 - Load the CIFAR-100 Data

In [17]:
```
"""Headers"""

from __future__ import print_function
from PIL import Image
import os
import os.path
import numpy as np
import sys
if sys.version_info[0] == 2:
    import cPickle as pickle
else:
    import pickle

import torch.utils.data as data
from torchvision.datasets.utils import download_url, check_integrity

import csv
%matplotlib inline
import matplotlib
```

```python
import matplotlib.pyplot as plt
import numpy as np
import os.path
import sys
import torch
import torch.utils.data
import torchvision
import torchvision.transforms as transforms

from torch.autograd import Variable
import torch.nn as nn
import torch.nn.functional as F

np.random.seed(111)
torch.cuda.manual_seed_all(111)
torch.manual_seed(111)
```

Out[17]: <torch._C.Generator at 0x7f8ef5e71f70>

In [0]:
```python
""""""

class CIFAR10_CS544(data.Dataset):
    """`CIFAR10 <https://www.cs.toronto.edu/~kriz/cifar.html>`_ Dataset.

    Args:
        root (string): Root directory of dataset where directory
            ``cifar-10-batches-py`` exists or will be saved to if download is set to T
        train (bool, optional): If True, creates dataset from training set, otherwise
            creates from test set.
        transform (callable, optional): A function/transform that  takes in an PIL ima
            and returns a transformed version. E.g, ``transforms.RandomCrop``
        target_transform (callable, optional): A function/transform that takes in the
            target and transforms it.
        download (bool, optional): If true, downloads the dataset from the internet an
            puts it in root directory. If dataset is already downloaded, it is not
            downloaded again.

    """
    base_folder = 'cifar100'
    url = "https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz"
    filename = "cifar100.tar.gz"
    tgz_md5 = 'c58f30108f718f92721af3b95e74349a'
    train_list = [
        ['data_batch_1', 'c99cafc152244af753f735de768cd75f'],
        ['data_batch_2', 'd4bba439e000b95fd0a9bffe97cbabec'],
        ['data_batch_3', '54ebc095f3ab1f0389bbae665268c751'],
        ['data_batch_4', '634d18415352ddfa80567beed471001a'],
        ['data_batch_5', '482c414d41f54cd18b22e5b47cb7c3cb'],
```

```
]

test_list = [
    ['test_batch', '40351d587109b95175f43aff81a1287e'],
]

def __init__(self, root, fold="train",
             transform=None, target_transform=None,
             download=False):

    fold = fold.lower()

    self.train = False
    self.test = False
    self.val = False

    if fold == "train":
        self.train = True
    elif fold == "test":
        self.test = True
    elif fold == "val":
        self.val = True
    else:
        raise RuntimeError("Not train-val-test")


    self.root = os.path.expanduser(root)
    self.transform = transform
    self.target_transform = target_transform

    fpath = os.path.join(root, self.filename)
    if not self._check_integrity():
        raise RuntimeError('Dataset not found or corrupted.' +
                           ' Download it and extract the file again.')

    # now load the picked numpy arrays
    if self.train or self.val:
        self.train_data = []
        self.train_labels = []
        for fentry in self.train_list:
            f = fentry[0]
            file = os.path.join(self.root, self.base_folder, f)
            fo = open(file, 'rb')
            if sys.version_info[0] == 2:
                entry = pickle.load(fo)
            else:
                entry = pickle.load(fo, encoding='latin1')
            self.train_data.append(entry['data'])
```

```
                if 'labels' in entry:
                    self.train_labels += entry['labels']
                else:
                    self.train_labels += entry['fine_labels']
                fo.close()

            self.train_data = np.concatenate(self.train_data)
            self.train_data = self.train_data.reshape((50000, 3, 32, 32))
            self.train_data = self.train_data.transpose((0, 2, 3, 1))  # convert to HW

            p = np.arange(0,50000,10)
            mask_train = np.ones((50000,), dtype=bool)
            mask_train[p] = False
            mask_val = np.zeros((50000,), dtype=bool)
            mask_val[p] = True

            copy_all_data = np.array(self.train_data)
            self.val_data = np.array(copy_all_data[mask_val])
            self.train_data = np.array(copy_all_data[mask_train])

            copy_all_labels = np.array(self.train_labels)
            self.val_labels = np.array(copy_all_labels[mask_val])
            self.train_labels = np.array(copy_all_labels[mask_train])

        elif self.test:
            f = self.test_list[0][0]
            file = os.path.join(self.root, self.base_folder, f)
            fo = open(file, 'rb')
            if sys.version_info[0] == 2:
                entry = pickle.load(fo)
            else:
                entry = pickle.load(fo, encoding='latin1')
            self.test_data = entry['data']

            if 'labels' in entry:
                self.test_labels = entry['labels']
            else:
                self.test_labels = entry['fine_labels']
            fo.close()
            self.test_data = self.test_data.reshape((10000, 3, 32, 32))
            self.test_data = self.test_data.transpose((0, 2, 3, 1))  # convert to HWC

    def __getitem__(self, index):
        """
        Args:
            index (int): Index

        Returns:
```

```python
            tuple: (image, target) where target is index of the target class.
        """
        if self.train:
            img, target = self.train_data[index], self.train_labels[index]
        elif self.test:
            img, target = self.test_data[index], self.test_labels[index]
        elif self.val:
            img, target = self.val_data[index], self.val_labels[index]

        # doing this so that it is consistent with all other datasets
        # to return a PIL Image
        img = Image.fromarray(img)

        if self.transform is not None:
            img = self.transform(img)

        if self.target_transform is not None:
            target = self.target_transform(target)

        return img, target

    def __len__(self):
        if self.train:
            return len(self.train_data)
        elif self.test:
            return len(self.test_data)
        elif self.val:
            return len(self.val_data)

    def _check_integrity(self):
        root = self.root
        for fentry in (self.train_list + self.test_list):
            filename, md5 = fentry[0], fentry[1]
            fpath = os.path.join(root, self.base_folder, filename)
            if not check_integrity(fpath, md5):
                return False
        return True

    def __repr__(self):
        fmt_str = 'Dataset ' + self.__class__.__name__ + '\n'
        fmt_str += '    Number of datapoints: {}\n'.format(self.__len__())
        tmp = 'train' if self.train is True else 'test'
        fmt_str += '    Split: {}\n'.format(tmp)
        fmt_str += '    Root Location: {}\n'.format(self.root)
        tmp = '    Transforms (if any): '
        fmt_str += '{0}{1}\n'.format(tmp, self.transform.__repr__().replace('\n', '\n'
        tmp = '    Target Transforms (if any): '
        fmt_str += '{0}{1}'.format(tmp, self.target_transform.__repr__().replace('\n',
```

```
            return fmt_str


    class CIFAR100_CS544(CIFAR10_CS544):
        """`CIFAR100 <https://www.cs.toronto.edu/~kriz/cifar.html>`_ Dataset.

        This is a subclass of the `CIFAR10` Dataset.
        """
        base_folder = 'cifar100'
        filename = "cifar100.tar.gz"
        tgz_md5 = 'e68a4c763591787a0b39fe2209371f32'
        train_list = [
            ['train_cs544', '49eee854445c1e2ebe796cd93c20bb0f'],
        ]

        test_list = [
            ['test_cs544', 'd3fe9f6a9251bd443f428f896d27384f'],
        ]
```

2.2 part1.1 - Define picked optimiers result array

In [0]:
```
optimer_train_loss_over_epochs_opts = []
optimer_val_accuracy_over_epochs_opts = []
optimer_time_cost = []
```

2.3 Part1.2 - Set the Class and Epoches, optimier names

In [0]:
```
# ---------
EPOCHS = 20
# ---------
optimer_name = ['SGD','SGD+momentum0.9','ASGD','Adam','Adadelta_default',
                'Adagrad_default','Adamax_default','RMSprop_default','ASGD_default','R
IS_GPU = True
TEST_BS = 256
TOTAL_CLASSES = 100
TRAIN_BS = 32
PATH_TO_CIFAR100_CS544 = "/data/"
```

In [208]:
```
ls /data/cifar100/
```

```
test_cs544  train_cs544
```

2.4 Part1.3 - Define the val accuracy function

In [0]:
```
def calculate_val_accuracy(valloader, is_gpu):
    """ Util function to calculate val set accuracy,
    both overall and per class accuracy
    Args:
```

```
        valloader (torch.utils.data.DataLoader): val set
        is_gpu (bool): whether to run on GPU
    Returns:
        tuple: (overall accuracy, class level accuracy)
    """
    correct = 0.
    total = 0.
    predictions = []

    class_correct = list(0. for i in range(TOTAL_CLASSES))
    class_total = list(0. for i in range(TOTAL_CLASSES))

    for data in valloader:
        images, labels = data
        if is_gpu:
            images = images.cuda()
            labels = labels.cuda()
        outputs = net(Variable(images))
        _, predicted = torch.max(outputs.data, 1)
        predictions.extend(list(predicted.cpu().numpy()))
        total += labels.size(0)
        correct += (predicted == labels).sum()

        c = (predicted == labels).squeeze()
        for i in range(len(labels)):
            label = labels[i]
            class_correct[label] += c[i]
            class_total[label] += 1

    class_accuracy = 100 * np.divide(class_correct, class_total)
    return 100*correct/total, class_accuracy
```

2.5 Part1.4 - Augument and Normalize input data

In [210]:
```
# The output of torchvision datasets are PILImage images of range [0, 1].
# Using transforms.ToTensor(), transform them to Tensors of normalized range
# [-1, 1].


train_transform = transforms.Compose(
    [
    transforms.RandomCrop(32),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
#     transforms.Normalize([0.505, 0.496, 0.446], [0.259, 0.254, 0.275])
      transforms.Normalize([0.485, 0.456, 0.406],[0.229, 0.224, 0.225])
    ])
test_transform = transforms.Compose(
```

```
        [transforms.ToTensor(),
    #     transforms.Normalize([0.505, 0.496, 0.446], [0.259, 0.254, 0.275])
         transforms.Normalize([0.485, 0.456, 0.406],[0.229, 0.224, 0.225])
        ])

    # ---------------------

    trainset = CIFAR100_CS544(root=PATH_TO_CIFAR100_CS544, fold="train",
                                            download=True, transform=train_transform)
    trainloader = torch.utils.data.DataLoader(trainset, batch_size=TRAIN_BS,
                                              shuffle=True, num_workers=2)
    print("Train set size: "+str(len(trainset)))

    valset = CIFAR100_CS544(root=PATH_TO_CIFAR100_CS544, fold="val",
                                            download=True, transform=test_transform)
    valloader = torch.utils.data.DataLoader(valset, batch_size=TEST_BS,
                                              shuffle=False, num_workers=2)
    print("Val set size: "+str(len(valset)))

    testset = CIFAR100_CS544(root=PATH_TO_CIFAR100_CS544, fold="test",
                                            download=True, transform=test_transform)
    testloader = torch.utils.data.DataLoader(testset, batch_size=TEST_BS,
                                              shuffle=False, num_workers=2)
    print("Test set size: "+str(len(testset)))

    # The 100 classes for CIFAR100
    classes = ['apple', 'aquarium_fish', 'baby', 'bear', 'beaver', 'bed', 'bee', 'beetle
```

```
Train set size: 45000
Val set size: 5000
Test set size: 10000
```

2.6 Part1.5 - Define neural network layers

In [0]:
```
########################################################################
# 2. Define a Convolution Neural Network
# ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^

import torch.nn as nn
import torch.nn.functional as F

def conv2d_norm_relu(in_channel, out_channel, kernel, stride=1, padding=1):
    layer = nn.Sequential(
        nn.Conv2d(in_channel, out_channel, kernel, stride=1, padding=1),
        nn.BatchNorm2d(out_channel),
        nn.ReLU(True)
    )
```

```
    return layer

class BaseNet(nn.Module):
    def __init__(self):
        super(BaseNet, self).__init__()


        self.conv1 = conv2d_norm_relu(3, 64, 3,  padding=1)
        self.conv2 = conv2d_norm_relu(64, 64, 3,  padding=1)
        self.conv3 = conv2d_norm_relu(64, 128, 3,  padding=1)
        self.conv4 = conv2d_norm_relu(128, 128, 3,  padding=1)
        self.conv5 = conv2d_norm_relu(128, 256, 3,  padding=1)
        self.conv6 = conv2d_norm_relu(256, 256, 3,  padding=1)
        self.conv7 = conv2d_norm_relu(256, 512, 3,  padding=1)
        self.conv8 = conv2d_norm_relu(512, 512, 3,  padding=1)
        self.pool = nn.MaxPool2d(2, 2, padding=0)


        class Flatten(torch.nn.Module):
           def forward(self, x):
            return x.view(x.size()[0], -1)

        self.fc_net = nn.Sequential(
            nn.Linear(2048, 1024),
            nn.BatchNorm1d(1024),
            nn.ReLU(inplace=True),
            nn.Linear(1024, 1024),
            nn.BatchNorm1d(1024),
            nn.ReLU(inplace=True),
            nn.Linear(1024, 100)
        )

    def forward(self, x):

        x = self.conv1(x)
        x = self.conv2(x)
        x = self.pool(x) # output: 16 x 16 x 64
        x = self.conv3(x)
        x = self.conv4(x)
        x = self.pool(x) # output: 8 x 8 x 128
        x = self.conv5(x)
        x = self.conv6(x)
        x = self.pool(x)# output: 4 x 4 x 256
        x = self.conv7(x)
        x = self.conv8(x)
        x = self.pool(x)# output: 2 x 2 x 512
        x = x.view(-1, 2048)
#         print('view:',x.shape)
```

```
        x = self.fc_net(x)

        return x

# Create an instance of the nn.module class defined above:
net = BaseNet()

# For training on GPU, we need to transfer net and data onto the GPU
# http://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html#training-on-gpu
if IS_GPU:
    net = net.cuda()
```

2.7 Part1.6 - Define loss function and optimizers

In [0]:
```
########################################################################
# 3. Define a Loss function and optimizer
# ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
# Here we use Cross-Entropy loss and SGD with momentum.
# The CrossEntropyLoss criterion already includes softmax within its
# implementation. That's why we don't use a softmax in our model
# definition.

import torch.optim as optim
criterion = nn.CrossEntropyLoss()

# Tune the learning rate.
# See whether the momentum is useful or not
# optimizer = optim.SGD(net.parameters(),lr=1e-3)
# optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
# optimizer = optim.ASGD(net.parameters(),  lr=1e-3) # remove the alpha
# optimizer = optim.Adam(net.parameters(), lr=1e-3)
# optimizer = optim.Adadelta(net.parameters(), lr=1.0, rho=0.9, eps=1e-06, weight_deca
# optimizer = optim.Adagrad(net.parameters(), lr=0.01, lr_decay=0, weight_decay=0, ini
# optimizer = optim.Adamax(net.parameters(), lr=0.002, betas=(0.9, 0.999), eps=1e-08, 
# optimizer = optim.RMSprop(net.parameters(), lr=0.01, alpha=0.99, eps=1e-08, weight_d
# optimizer = optim.ASGD(net.parameters(), lr=0.01, lambd=0.0001, alpha=0.75, t0=10000
optimizer = optim.Rprop(net.parameters(), lr=0.01, etas=(0.5, 1.2), step_sizes=(1e-06,

timer  = []
train_loss_over_epochs = []
val_accuracy_over_epochs = []
plt.ioff()
fig = plt.figure()
```

2.8 Part1.7- Train, Validation

In [0]:
```
import time
```

```
In [214]: ########################################################################
          # 4. Train the network
          # ^^^^^^^^^^^^^^^^^^^^
          for epoch in range(EPOCHS):  # loop over the dataset multiple times
              start = time.time()
              running_loss = 0.0
              for i, data in enumerate(trainloader, 0):
                  # get the inputs
                  inputs, labels = data

                  if IS_GPU:
                      inputs = inputs.cuda()
                      labels = labels.cuda()

                  # wrap them in Variable
                  inputs, labels = Variable(inputs), Variable(labels)

                  # zero the parameter gradients
                  optimizer.zero_grad()

                  # forward + backward + optimize
                  outputs = net(inputs)
                  loss = criterion(outputs, labels)
                  loss.backward()
                  optimizer.step()

                  # print statistics
                  running_loss += loss.item()

              # Normalizing the loss by the total number of train batches
              running_loss/=len(trainloader)
              print('[%d] loss: %.3f' %
                    (epoch + 1, running_loss))

              # Scale of 0.0 to 100.0
              # Calculate validation set accuracy of the existing model
              val_accuracy, val_classwise_accuracy = \
                  calculate_val_accuracy(valloader, IS_GPU)
              print('Accuracy of the network on the val images: %d %%' % (val_accuracy))

              # # Optionally print classwise accuracies
              # for c_i in range(TOTAL_CLASSES):
              #     print('Accuracy of %5s : %2d %%' % (
              #         classes[c_i], 100 * val_classwise_accuracy[c_i]))
              end = time.time()
              ti = end - start
              timer.append(ti)
              train_loss_over_epochs.append(running_loss)
```

```
        val_accuracy_over_epochs.append(val_accuracy)

    # -----------------------------
```

```
[1] loss: 271.317
Accuracy of the network on the val images: 1 %
[2] loss: 371.431
Accuracy of the network on the val images: 1 %
[3] loss: 353.140
Accuracy of the network on the val images: 1 %
[4] loss: 329.056
Accuracy of the network on the val images: 1 %
[5] loss: 336.361
Accuracy of the network on the val images: 1 %
[6] loss: 330.920
Accuracy of the network on the val images: 1 %
[7] loss: 357.755
Accuracy of the network on the val images: 1 %
[8] loss: 352.342
Accuracy of the network on the val images: 1 %
[9] loss: 327.984
Accuracy of the network on the val images: 1 %
[10] loss: 323.862
Accuracy of the network on the val images: 1 %
[11] loss: 318.324
Accuracy of the network on the val images: 1 %
[12] loss: 349.535
Accuracy of the network on the val images: 1 %
[13] loss: 368.678
Accuracy of the network on the val images: 1 %
[14] loss: 354.838
Accuracy of the network on the val images: 1 %
[15] loss: 352.203
Accuracy of the network on the val images: 1 %
[16] loss: 345.508
Accuracy of the network on the val images: 1 %
[17] loss: 352.870
Accuracy of the network on the val images: 1 %
[18] loss: 413.680
Accuracy of the network on the val images: 1 %
[19] loss: 418.777
Accuracy of the network on the val images: 1 %
[20] loss: 445.755
Accuracy of the network on the val images: 0 %
```

2.9 part1.8 - Visualizing single optimier prediction result

```
In [215]: # Plot train loss over epochs and val set accuracy over epochs
          # Nothing to change here
          # -------------
          plt.subplot(3, 1, 1)
          plt.ylabel('time sec')
          plt.plot(np.arange(EPOCHS), timer, 'g-')
          plt.title(str(optimer_name[9]) + ' train time,loss and val accuracy')
          plt.xticks(np.arange(EPOCHS, dtype=int))
          plt.grid(True)

          plt.subplot(3, 1, 2)
          plt.ylabel('train loss')
          plt.plot(np.arange(EPOCHS), train_loss_over_epochs, 'k-')
          plt.xticks(np.arange(EPOCHS, dtype=int))
          plt.grid(True)

          plt.subplot(3, 1, 3)
          plt.plot(np.arange(EPOCHS), val_accuracy_over_epochs, 'b-')
          plt.ylabel('val accuracy')
          plt.xlabel('Epochs')
          plt.xticks(np.arange(EPOCHS, dtype=int))
          plt.grid(True)
          plt.savefig(str(optimer_name[9])+"_plot.png")
          plt.close(fig)
          print(str(optimer_name[9]) + ' finished training')
          # -------------
```

```
Rprop_default finished training
```

```
In [216]: print("train_loss_over_epochs_opts =  ", train_loss_over_epochs)
          print("val_accuracy_over_epochs_opts = ", val_accuracy_over_epochs)
          print("time_cost = ", timer)
          if(len(train_loss_over_epochs) == 20 and
             len(val_accuracy_over_epochs) == 20 and
             len(timer) == 20):
          #      optimer_train_loss_over_epochs_opts[0] = train_loss_over_epochs
          #      optimer_val_accuracy_over_epochs_opts[0] = val_accuracy_over_epochs
          #      optimer_time_cost[0] = timer
             optimer_train_loss_over_epochs_opts.append(train_loss_over_epochs)
             optimer_val_accuracy_over_epochs_opts.append(val_accuracy_over_epochs)
             optimer_time_cost.append(timer)
             t = np.arange(0, EPOCHS, 1) # equals epoch number
             print(len(train_loss_over_epochs),len(val_accuracy_over_epochs),len(timer),len(t)
             print(len(optimer_train_loss_over_epochs_opts),len(optimer_val_accuracy_over_epoc
```

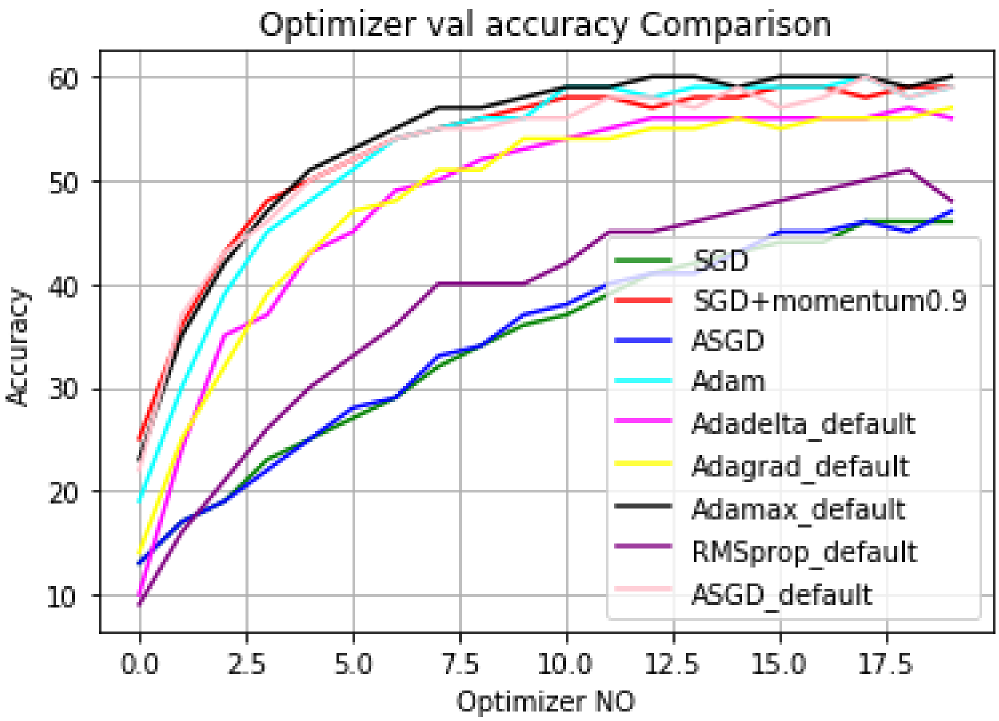
```
train_loss_over_epochs_opts =   [271.31657391909425, 371.43133382926027, 353.1397174162143, 32
val_accuracy_over_epochs_opts =  [tensor(1, device='cuda:0'), tensor(1, device='cuda:0'), tens
```

```
time_cost =  [90.36958765983582, 91.55633068084717, 90.33762764930725, 90.08072853088379, 89.99
20 20 20 20
10 10 10
```

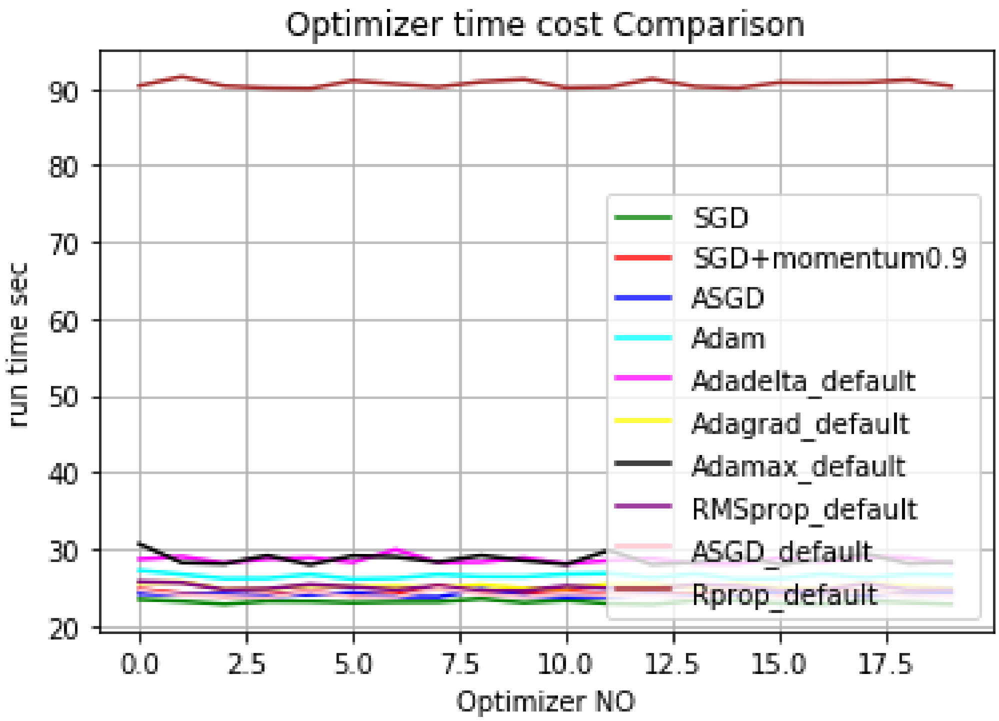
2.10 part1.9 - Visualizing picked optimiers prediction result

```
In [251]: if(len(optimer_train_loss_over_epochs_opts) == 10 and
             len(optimer_val_accuracy_over_epochs_opts) == 10 and
             len(optimer_time_cost) == 10):
             plt.title('Optimizer train loss Comparison')
             plt.ylabel('Loss')
             plt.xlabel('Optimizer NO')
             plt.plot(t,optimer_train_loss_over_epochs_opts[0],label=str(optimer_name[0]),colo
             plt.plot(t,optimer_train_loss_over_epochs_opts[1],label=str(optimer_name[1]),colo
             plt.plot(t,optimer_train_loss_over_epochs_opts[2],label=str(optimer_name[2]),colo
             plt.plot(t,optimer_train_loss_over_epochs_opts[3],label=str(optimer_name[3]),colo
             plt.plot(t,optimer_train_loss_over_epochs_opts[4],label=str(optimer_name[4]),colo
             plt.plot(t,optimer_train_loss_over_epochs_opts[5],label=str(optimer_name[5]),colo
             plt.plot(t,optimer_train_loss_over_epochs_opts[6],label=str(optimer_name[6]),colo
             plt.plot(t,optimer_train_loss_over_epochs_opts[7],label=str(optimer_name[7]),colo
             plt.plot(t,optimer_train_loss_over_epochs_opts[8],label=str(optimer_name[8]),colo
          #    plt.plot(t,optimer_train_loss_over_epochs_opts[9],label=str(optimer_name[9]),co
             plt.grid(True)
             plt.legend([str(optimer_name[0]),str(optimer_name[1]),str(optimer_name[2]),str(op
                         str(optimer_name[4]),str(optimer_name[5]),str(optimer_name[6]),str(opti
                         str(optimer_name[8])], loc='lower right')
             plt.show()
```


```
In [238]: if(len(optimer_train_loss_over_epochs_opts) == 10 and
             len(optimer_val_accuracy_over_epochs_opts) == 10 and
             len(optimer_time_cost) == 10):
             plt.title('Optimizer val accuracy Comparison')
             plt.ylabel('Accuracy')
             plt.xlabel('Optimizer NO')
             plt.plot(t,optimer_val_accuracy_over_epochs_opts[0],label=str(optimer_name[0]),co
             plt.plot(t,optimer_val_accuracy_over_epochs_opts[1],label=str(optimer_name[1]),co
             plt.plot(t,optimer_val_accuracy_over_epochs_opts[2],label=str(optimer_name[2]),co
             plt.plot(t,optimer_val_accuracy_over_epochs_opts[3],label=str(optimer_name[3]),co
             plt.plot(t,optimer_val_accuracy_over_epochs_opts[4],label=str(optimer_name[4]),co
             plt.plot(t,optimer_val_accuracy_over_epochs_opts[5],label=str(optimer_name[5]),co
             plt.plot(t,optimer_val_accuracy_over_epochs_opts[6],label=str(optimer_name[6]),co
             plt.plot(t,optimer_val_accuracy_over_epochs_opts[7],label=str(optimer_name[7]),co
             plt.plot(t,optimer_val_accuracy_over_epochs_opts[8],label=str(optimer_name[8]),co
          #    plt.plot(t,optimer_val_accuracy_over_epochs_opts[9],label=str(optimer_name[9]),
             plt.grid(True)
             plt.legend([str(optimer_name[0]),str(optimer_name[1]),str(optimer_name[2]),str(op
                         str(optimer_name[4]),str(optimer_name[5]),str(optimer_name[6]),str(opt
                         str(optimer_name[8])], loc='lower right')
             plt.show()
```




```
In [250]: if(len(optimer_train_loss_over_epochs_opts) == 10 and
             len(optimer_val_accuracy_over_epochs_opts) == 10 and
             len(optimer_time_cost) == 10):
             plt.title('Optimizer time cost Comparison')
             plt.ylabel('run time sec')
             plt.xlabel('Optimizer NO')
             plt.plot(t,optimer_time_cost[0],label=str(optimer_name[0]),color='green')
             plt.plot(t,optimer_time_cost[1],label=str(optimer_name[1]),color='red')
             plt.plot(t,optimer_time_cost[2],label=str(optimer_name[2]),color='blue')
             plt.plot(t,optimer_time_cost[3],label=str(optimer_name[3]),color='cyan')
             plt.plot(t,optimer_time_cost[4],label=str(optimer_name[4]),color='magenta')
             plt.plot(t,optimer_time_cost[5],label=str(optimer_name[5]),color='yellow')
             plt.plot(t,optimer_time_cost[6],label=str(optimer_name[6]),color='black')
             plt.plot(t,optimer_time_cost[7],label=str(optimer_name[7]),color='purple')
             plt.plot(t,optimer_time_cost[8],label=str(optimer_name[8]),color='pink')
          #    plt.plot(t,optimer_time_cost[9],label=str(optimer_name[9]),color='brown')
             plt.grid(True)
             plt.legend([str(optimer_name[0]),str(optimer_name[1]),str(optimer_name[2]),str(op
                        str(optimer_name[4]),str(optimer_name[5]),str(optimer_name[6]),str(opti
                        str(optimer_name[8])], loc='lower right')
             plt.show()
```



3 Part 2 - ResNet Model Optimization

3.1 part2.0 - Define picked optimiers result array

In [0]:
```
optimer_train_loss_over_epochs_opts2 = []
optimer_train_accuracy_over_epochs_opts2 = []
optimer_time_cost2 = []
optimizer_test_loss = []
optimizer_test_accuracy = []
optimizer_time_cost3  = []
```

In [0]:
```
optimer_name2 = ['SGD','SGD+momentum0.9','ASGD','Adam','Adadelta_default',
                 'Adagrad_default','Adamax_default','RMSprop_default','ASGD_default','Rp
```

3.2 Part 2.1 - Load the pre-trained resnet model

In [0]:
```
"""Headers"""
import os
import os.path as osp
import time

%matplotlib inline
import matplotlib.pyplot as plt
```

```
import torch
import torch.nn as nn
import torchvision.models as models
import torch.optim as optim

from torchvision import datasets
import torchvision.transforms as transforms
```

```
In [0]: class PreTrainedResNet(nn.Module):
          def __init__(self, num_classes, feature_extracting):
            super(PreTrainedResNet, self).__init__()

            self.resnet18 = models.resnet18(pretrained=True)
        #     self.resnet152 = models.resnet152(pretrained=True) # will run out of memory
        #     self.resnet101 = models.resnet101(pretrained=True) # will run out of memory
        #     self.resnet50 = models.resnet50(pretrained=True)
        #     self.inception = models.inception_v3(pretrained=True) # softmax problem
            #Set gradients to false
            if feature_extracting:
              for param in self.resnet18.parameters():
                  param.requires_grad = False

            #Replace last fc layer
            num_feats = self.resnet18.fc.in_features
            self.resnet18.fc = nn.Linear(num_feats, 200)

          def forward(self, x):
            x = self.resnet18(x)
            return x
```

3.3 Part 2.2 - Define train function

```
In [0]: def train(model, optimizer, criterion, epoch, num_epochs):
          model.train()
          epoch_loss = 0.0
          epoch_acc = 0.0

          for batch_idx, (images, labels) in enumerate(dataloaders['train']):
            #zero the parameter gradients
            optimizer.zero_grad()

            #move to GPU
            images, labels = images.cuda(), labels.cuda()

            #forward
            outputs = model.forward(images)
```

```
            loss = criterion(outputs, labels)

            _, preds = torch.max(outputs.data, 1)

            loss.backward()
            optimizer.step()

            epoch_loss += loss.item()
            epoch_acc += torch.sum(preds == labels).item()

        epoch_loss /= dataset_sizes['train']
        epoch_acc /= dataset_sizes['train']

        print('TRAINING Epoch %d/%d Loss %.4f Accuracy %.4f' % (epoch, num_epochs, epoch_loss
        return epoch_loss,epoch_acc
```

3.4 Part 2.3 - Define main function

1. Vary hyperparams
2. Data augmentation

```
In [0]: NUM_EPOCHS = 40
        LEARNING_RATE = 0.01 #
        BATCH_SIZE = 80
        RESNET_LAST_ONLY = False #Fine tunes only the last layer. Set to False to fine tune en

        root_path = '/data/'

        data_transforms = {
            'train': transforms.Compose([
                transforms.Resize(256),
        #       transforms.CenterCrop(224),
                transforms.RandomResizedCrop(224),
                transforms.ToTensor(),
                transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
            ]),
            'test': transforms.Compose([
                transforms.Resize(256),
        #         transforms.CenterCrop(224),
                transforms.RandomResizedCrop(224),
                transforms.ToTensor(),
                transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
            ]),
        }

        # loading datasets with PyTorch ImageFolder
        image_datasets = {x: datasets.ImageFolder(os.path.join(root_path, x),
                                                  data_transforms[x])
```

```
                   for x in ['train', 'test']}

# defining data loaders to load data using image_datasets and transforms, here we also
dataloaders = {x: torch.utils.data.DataLoader(image_datasets[x], batch_size=BATCH_SIZE
                                              shuffle=True, num_workers=4)
              for x in ['train', 'test']}

dataset_sizes = {x: len(image_datasets[x]) for x in ['train', 'test']}
class_names = image_datasets['train'].classes

#Initialize the model
model = PreTrainedResNet(len(class_names), RESNET_LAST_ONLY)
model = model.cuda()
```

3.5 Part 2.4 - Define loss function and optimiers

In [0]:
```
# optimizer = optim.SGD(model.parameters(), lr=LEARNING_RATE, momentum=0.9) -- part 2 
criterion = nn.CrossEntropyLoss()

# optimizer = optim.SGD(model.parameters(),lr=LEARNING_RATE)
# optimizer = optim.SGD(model.parameters(), lr=LEARNING_RATE, momentum=0.9)
# optimizer = optim.ASGD(model.parameters(),  lr=LEARNING_RATE) # remove the alpha
# optimizer = optim.Adam(model.parameters(), lr=LEARNING_RATE)
# optimizer = optim.Adadelta(model.parameters(), lr=1.0, rho=0.9, eps=1e-06, weight_de
# optimizer = optim.Adagrad(model.parameters(), lr=0.01, lr_decay=0, weight_decay=0, i
# optimizer = optim.Adamax(model.parameters(), lr=0.002, betas=(0.9, 0.999), eps=1e-08
# optimizer = optim.RMSprop(model.parameters(), lr=0.01, alpha=0.99, eps=1e-08, weight
# optimizer = optim.ASGD(model.parameters(), lr=0.01, lambd=0.0001, alpha=0.75, t0=100
optimizer = optim.Rprop(model.parameters(), lr=0.01, etas=(0.5, 1.2), step_sizes=(1e-0


timer2  = []
train_loss_over_epochs2 = []
train_accuracy_over_epochs2 = []
plt.ioff()
fig = plt.figure()
```

3.6 Part 2.5 - train the model

In [205]:
```
#Begin Train
for epoch in range(NUM_EPOCHS):
  start = time.time()
  train_epoch_loss,train_epoch_acc = train(model, optimizer, criterion, epoch+1, NUM_
  end = time.time()
  ti = end - start
  timer2.append(ti)
  train_loss_over_epochs2.append(train_epoch_loss)
  train_accuracy_over_epochs2.append(train_epoch_acc)
```

```python
    print("Finished Training")
    print("-"*10)

    optimer_train_loss_over_epochs_opts2.append(train_loss_over_epochs2)
    optimer_train_accuracy_over_epochs_opts2.append(train_accuracy_over_epochs2)
    optimer_time_cost2.append(timer2)
```

```
TRAINING Epoch 1/40 Loss 0.0919 Accuracy 0.0030
TRAINING Epoch 2/40 Loss 0.0784 Accuracy 0.0093
TRAINING Epoch 3/40 Loss 0.1210 Accuracy 0.0090
TRAINING Epoch 4/40 Loss 0.1626 Accuracy 0.0093
TRAINING Epoch 5/40 Loss 0.2677 Accuracy 0.0083
TRAINING Epoch 6/40 Loss 0.2011 Accuracy 0.0090
TRAINING Epoch 7/40 Loss 0.3129 Accuracy 0.0050
TRAINING Epoch 8/40 Loss 0.3288 Accuracy 0.0077
TRAINING Epoch 9/40 Loss 0.3664 Accuracy 0.0073
TRAINING Epoch 10/40 Loss 1.1886 Accuracy 0.0050
TRAINING Epoch 11/40 Loss 1.0636 Accuracy 0.0073
TRAINING Epoch 12/40 Loss 2.1457 Accuracy 0.0083
TRAINING Epoch 13/40 Loss 2.4675 Accuracy 0.0063
TRAINING Epoch 14/40 Loss 4.0406 Accuracy 0.0097
TRAINING Epoch 15/40 Loss 3.7310 Accuracy 0.0090
TRAINING Epoch 16/40 Loss 4.8876 Accuracy 0.0090
TRAINING Epoch 17/40 Loss 4.1615 Accuracy 0.0117
TRAINING Epoch 18/40 Loss 4.8271 Accuracy 0.0100
TRAINING Epoch 19/40 Loss 6.1380 Accuracy 0.0047
TRAINING Epoch 20/40 Loss 5.9884 Accuracy 0.0067
TRAINING Epoch 21/40 Loss 6.4026 Accuracy 0.0103
TRAINING Epoch 22/40 Loss 7.3444 Accuracy 0.0063
TRAINING Epoch 23/40 Loss 5.9234 Accuracy 0.0057
TRAINING Epoch 24/40 Loss 5.0320 Accuracy 0.0083
TRAINING Epoch 25/40 Loss 5.1664 Accuracy 0.0080
TRAINING Epoch 26/40 Loss 7.2598 Accuracy 0.0057
TRAINING Epoch 27/40 Loss 4.2791 Accuracy 0.0100
TRAINING Epoch 28/40 Loss 4.9331 Accuracy 0.0093
TRAINING Epoch 29/40 Loss 4.8941 Accuracy 0.0077
TRAINING Epoch 30/40 Loss 5.9331 Accuracy 0.0093
TRAINING Epoch 31/40 Loss 2.8656 Accuracy 0.0067
TRAINING Epoch 32/40 Loss 4.1043 Accuracy 0.0090
TRAINING Epoch 33/40 Loss 5.0496 Accuracy 0.0057
TRAINING Epoch 34/40 Loss 3.1052 Accuracy 0.0057
TRAINING Epoch 35/40 Loss 5.9857 Accuracy 0.0093
TRAINING Epoch 36/40 Loss 4.8002 Accuracy 0.0083
TRAINING Epoch 37/40 Loss 3.7178 Accuracy 0.0070
TRAINING Epoch 38/40 Loss 4.2180 Accuracy 0.0090
TRAINING Epoch 39/40 Loss 3.5416 Accuracy 0.0063
TRAINING Epoch 40/40 Loss 3.3093 Accuracy 0.0090
Finished Training
```

3.7 Part 2.6 - Visualizing single optimizer train prediction result

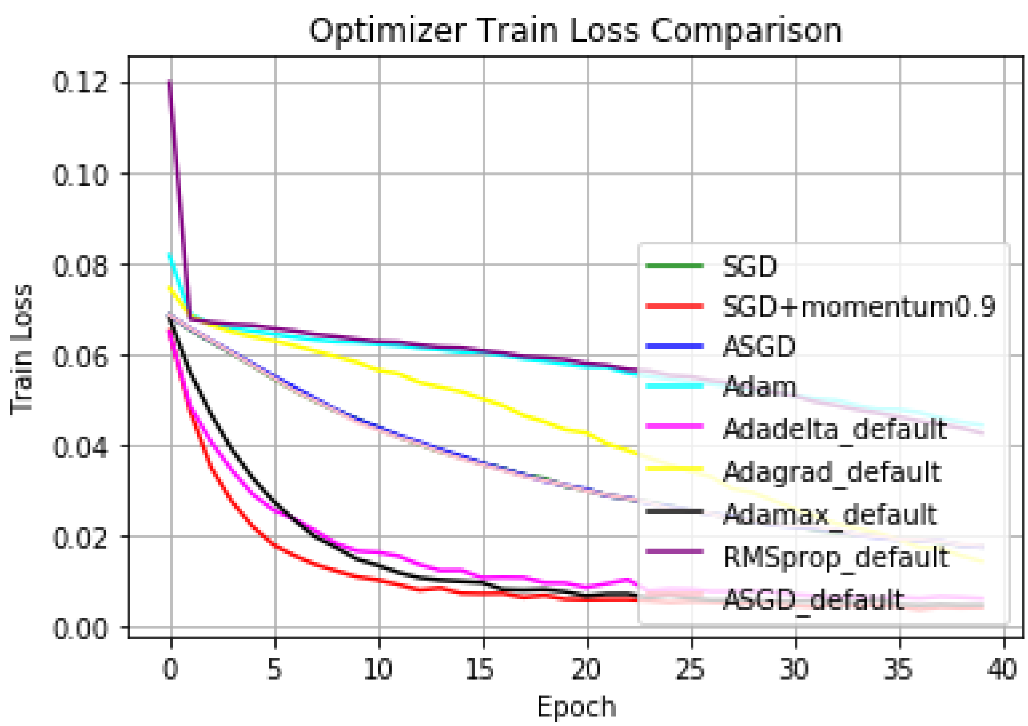
In [206]:
```
# Plot train loss over epochs and val set accuracy over epochs
# Nothing to change here
# --------------
print(NUM_EPOCHS,len(timer2))
plt.subplot(3, 1, 1)
plt.ylabel('time sec')
plt.plot(np.arange(NUM_EPOCHS), timer2, 'g-')
plt.title(str(optimer_name2[9]) + ' train time,loss and accuracy')
plt.xticks(np.arange(NUM_EPOCHS, dtype=int))
plt.grid(True)

plt.subplot(3, 1, 2)
plt.ylabel('train loss')
plt.plot(np.arange(NUM_EPOCHS), train_loss_over_epochs2, 'k-')
plt.xticks(np.arange(NUM_EPOCHS, dtype=int))
plt.grid(True)

plt.subplot(3, 1, 3)
plt.plot(np.arange(NUM_EPOCHS), train_accuracy_over_epochs2, 'b-')
plt.ylabel('train accuracy')
plt.xlabel('Epochs')
plt.xticks(np.arange(NUM_EPOCHS, dtype=int))
plt.grid(True)
plt.savefig('opt_res_part2/' + str(optimer_name2[9])+"-plot.png")
plt.close(fig)
print(str(optimer_name2[9]) + ' finished training')
# --------------
print(len(optimer_train_loss_over_epochs_opts2),len(optimer_train_accuracy_over_epoch
```

```
40 40
Rprop_default finished training
10 10 10
```

3.8 Part 2.7 - Visualizing total optimizers train prediction result

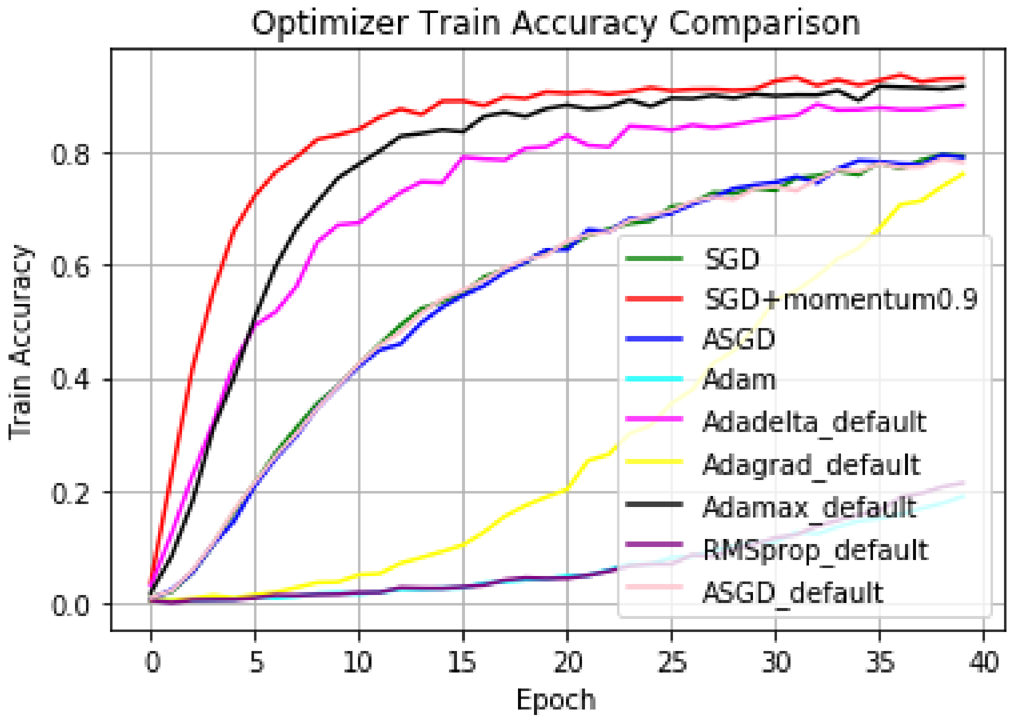
In [218]:
```
if(len(optimer_train_loss_over_epochs_opts2) == 10 and
   len(optimer_train_accuracy_over_epochs_opts2) == 10 and
   len(optimer_time_cost2) == 10):
   t = np.arange(0, NUM_EPOCHS, 1) # equals epoch number
   plt.title('Optimizer Train Loss Comparison')
   plt.ylabel('Train Loss')
   plt.xlabel('Epoch')
```

```
    plt.plot(t,optimer_train_loss_over_epochs_opts2[0],label=str(optimer_name2[0]),co
    plt.plot(t,optimer_train_loss_over_epochs_opts2[1],label=str(optimer_name2[1]),co
    plt.plot(t,optimer_train_loss_over_epochs_opts2[2],label=str(optimer_name2[2]),co
    plt.plot(t,optimer_train_loss_over_epochs_opts2[3],label=str(optimer_name2[3]),co
    plt.plot(t,optimer_train_loss_over_epochs_opts2[4],label=str(optimer_name2[4]),co
    plt.plot(t,optimer_train_loss_over_epochs_opts2[5],label=str(optimer_name2[5]),co
    plt.plot(t,optimer_train_loss_over_epochs_opts2[6],label=str(optimer_name2[6]),co
    plt.plot(t,optimer_train_loss_over_epochs_opts2[7],label=str(optimer_name2[7]),co
    plt.plot(t,optimer_train_loss_over_epochs_opts2[8],label=str(optimer_name2[8]),co
#     plt.plot(t,optimer_train_loss_over_epochs_opts2[9],label=str(optimer_name2[9]),
    plt.grid(True)
    plt.legend([str(optimer_name2[0]),str(optimer_name2[1]),str(optimer_name2[2]),str
                str(optimer_name2[4]),str(optimer_name2[5]),str(optimer_name2[6]),str(
                str(optimer_name2[8])], loc='lower right')
    plt.show()
```



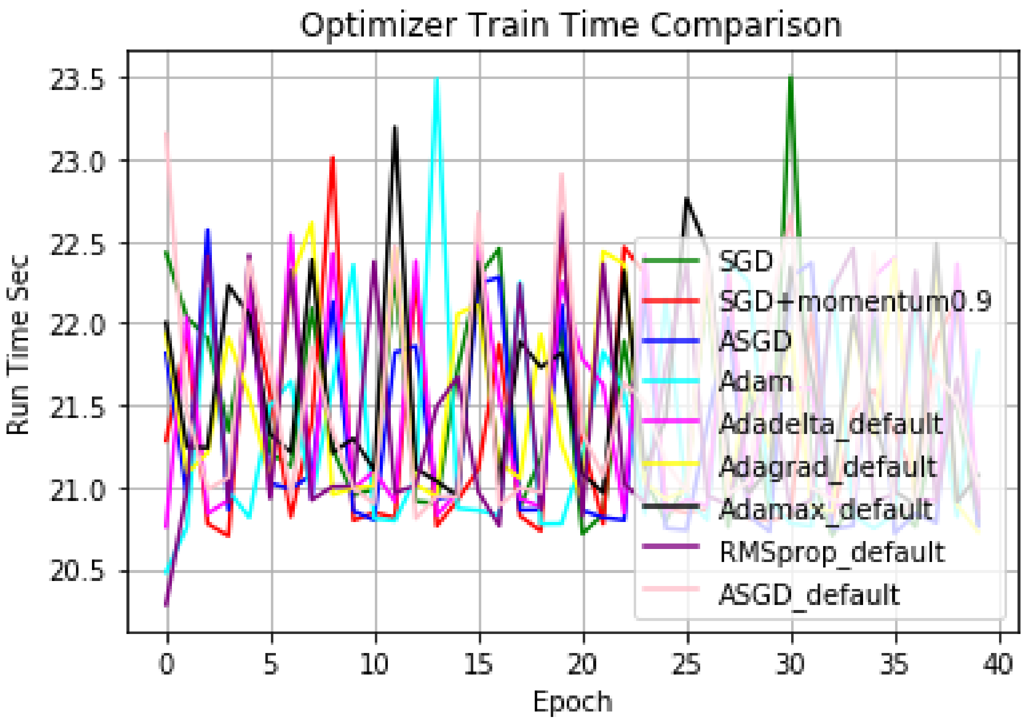

```
In [240]: if(len(optimer_train_loss_over_epochs_opts2) == 10 and
              len(optimer_train_accuracy_over_epochs_opts2) == 10 and
              len(optimer_time_cost2) == 10):
              t = np.arange(0, NUM_EPOCHS, 1) # equals epoch number
              plt.title('Optimizer Train Accuracy Comparison')
              plt.ylabel('Train Accuracy')
              plt.xlabel('Epoch')
              plt.plot(t,optimer_train_accuracy_over_epochs_opts2[0],label=str(optimer_name2[0]
```

```
    plt.plot(t,optimer_train_accuracy_over_epochs_opts2[1],label=str(optimer_name2[1]
    plt.plot(t,optimer_train_accuracy_over_epochs_opts2[2],label=str(optimer_name2[2]
    plt.plot(t,optimer_train_accuracy_over_epochs_opts2[3],label=str(optimer_name2[3]
    plt.plot(t,optimer_train_accuracy_over_epochs_opts2[4],label=str(optimer_name2[4]
    plt.plot(t,optimer_train_accuracy_over_epochs_opts2[5],label=str(optimer_name2[5]
    plt.plot(t,optimer_train_accuracy_over_epochs_opts2[6],label=str(optimer_name2[6]
    plt.plot(t,optimer_train_accuracy_over_epochs_opts2[7],label=str(optimer_name2[7]
    plt.plot(t,optimer_train_accuracy_over_epochs_opts2[8],label=str(optimer_name2[8]
#   plt.plot(t,optimer_train_accuracy_over_epochs_opts2[9],label=str(optimer_name2[9
    plt.grid(True)
    plt.legend([str(optimer_name2[0]),str(optimer_name2[1]),str(optimer_name2[2]),str
                str(optimer_name2[4]),str(optimer_name2[5]),str(optimer_name2[6]),str(
                str(optimer_name2[8])], loc='lower right')
    plt.show()
```




```
In [244]: if(len(optimer_train_loss_over_epochs_opts2) == 10 and
    len(optimer_train_accuracy_over_epochs_opts2) == 10 and
    len(optimer_time_cost2) == 10):
    t = np.arange(0, NUM_EPOCHS, 1) # equals epoch number
    plt.title('Optimizer Train Time Comparison')
    plt.ylabel('Run Time Sec')
    plt.xlabel('Epoch')
    plt.plot(t,optimer_time_cost2[0],label=str(optimer_name2[0]),color='green')
    plt.plot(t,optimer_time_cost2[1],label=str(optimer_name2[1]),color='red')
```

```
    plt.plot(t,optimer_time_cost2[2],label=str(optimer_name2[2]),color='blue')
    plt.plot(t,optimer_time_cost2[3],label=str(optimer_name2[3]),color='cyan')
    plt.plot(t,optimer_time_cost2[4],label=str(optimer_name2[4]),color='magenta')
    plt.plot(t,optimer_time_cost2[5],label=str(optimer_name2[5]),color='yellow')
    plt.plot(t,optimer_time_cost2[6],label=str(optimer_name2[6]),color='black')
    plt.plot(t,optimer_time_cost2[7],label=str(optimer_name2[7]),color='purple')
    plt.plot(t,optimer_time_cost2[8],label=str(optimer_name2[8]),color='pink')
#  plt.plot(t,optimer_time_cost2[9],label=str(optimer_name2[9]),color='brown')
    plt.grid(True)
    plt.legend([str(optimer_name2[0]),str(optimer_name2[1]),str(optimer_name2[2]),str
                str(optimer_name2[4]),str(optimer_name2[5]),str(optimer_name2[6]),str(o
                str(optimer_name2[8])], loc='lower right')
    plt.show()
```




```
In [250]: if(len(optimer_train_loss_over_epochs_opts2) == 10 and
    len(optimer_train_accuracy_over_epochs_opts2) == 10 and
    len(optimer_time_cost2) == 10):
    optimer_total_time_cost2 = []
    for i in range(10):
        total = 0
        for j in range (NUM_EPOCHS):
            print(optimer_time_cost2[i][j])
            total += optimer_time_cost2[i][j]
        optimer_total_time_cost2.append(total)
```

```python
plt.title('Optimizer Train Total Run Time Comparison')
plt.ylabel('Train Loss')
plt.xlabel('Epoch')
plt.scatter(0,optimer_total_time_cost2[0],label=str(optimer_name2[0]),color='green
plt.scatter(1,optimer_total_time_cost2[1],label=str(optimer_name2[1]),color='red')
plt.scatter(2,optimer_total_time_cost2[2],label=str(optimer_name2[2]),color='blue
plt.scatter(3,optimer_total_time_cost2[3],label=str(optimer_name2[3]),color='cyan
plt.scatter(4,optimer_total_time_cost2[4],label=str(optimer_name2[4]),color='mager
plt.scatter(5,optimer_total_time_cost2[5],label=str(optimer_name2[5]),color='yello
plt.scatter(6,optimer_total_time_cost2[6],label=str(optimer_name2[6]),color='black
plt.scatter(7,optimer_total_time_cost2[7],label=str(optimer_name2[7]),color='purpl
plt.scatter(8,optimer_total_time_cost2[8],label=str(optimer_name2[8]),color='pink
plt.scatter(9,optimer_total_time_cost2[9],label=str(optimer_name2[9]),color='brown
plt.grid(True)
plt.legend([str(optimer_name2[0]),str(optimer_name2[1]),str(optimer_name2[2]),str
           str(optimer_name2[4]),str(optimer_name2[5]),str(optimer_name2[6]),str(c
           str(optimer_name2[8]),str(optimer_name2[9])], loc=2)
plt.show()
```

```
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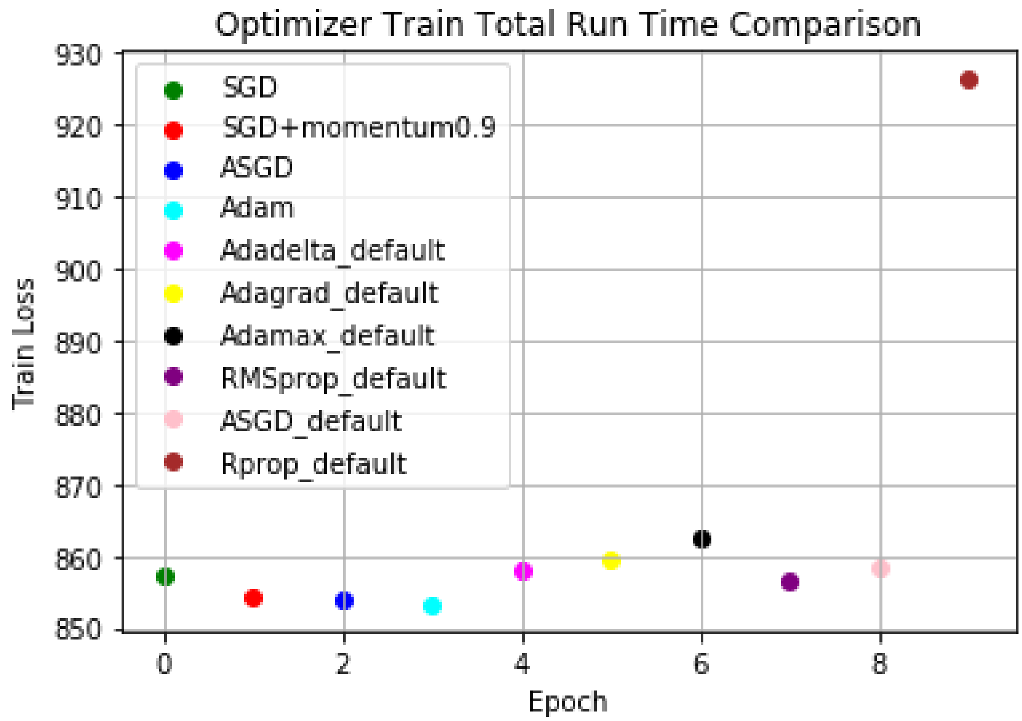


3.9 Part 2.8 - test the model

```
In [0]: def test(model, criterion, repeats=2):

          test_loss = 0.0
          test_acc = 0.0

          start = time
          for itr in range(repeats):
            for batch_idx, (images, labels) in enumerate(dataloaders['train']):
              #move to GPU
              images, labels = images.cuda(), labels.cuda()

              #forward
              outputs = model.forward(images)

              loss = criterion(outputs, labels)

              _, preds = torch.max(outputs.data, 1)

              test_loss += loss.item()
              test_acc += torch.sum(preds == labels).item()
```

```
        test_loss /= (dataset_sizes['test']*repeats)
        test_acc /= (dataset_sizes['test']*repeats)

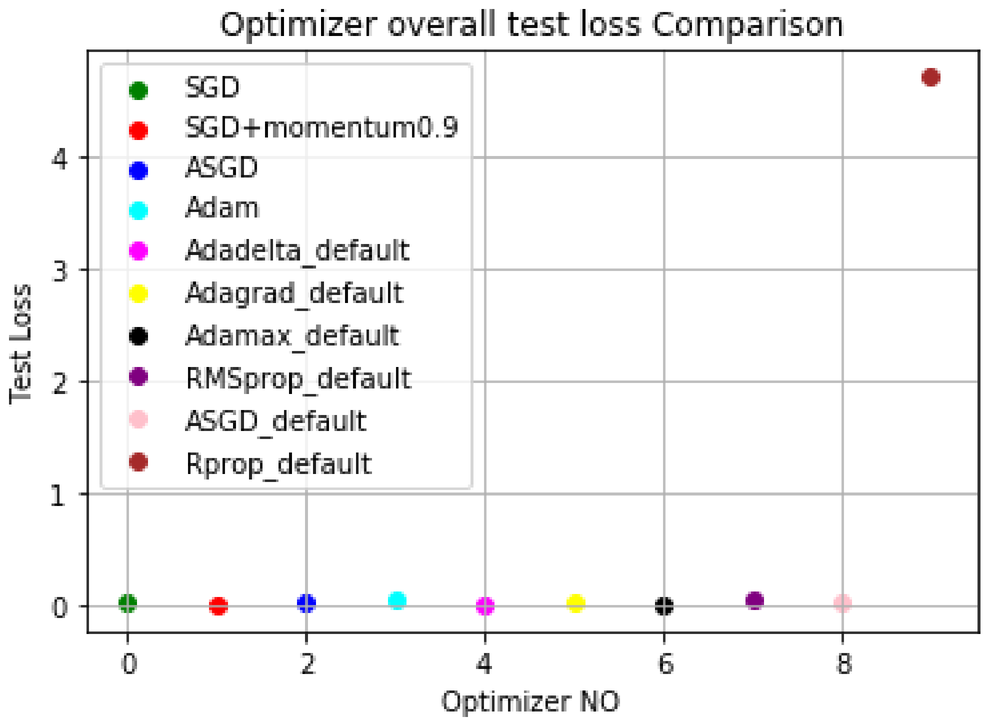
        print('Test Loss: %.4f Test Accuracy %.4f' % (test_loss, test_acc))
        return test_loss, test_acc
```

```
In [212]: start = time.time()
          test_loss, test_acc = test(model, criterion)
          end = time.time()
          test_timer = end - start
          optimizer_test_loss.append(test_loss)
          optimizer_test_accuracy.append(test_acc)
          optimizer_time_cost3.append(test_timer)
          print(len(optimizer_test_loss),len(optimizer_test_accuracy),len(optimizer_time_cost3
```

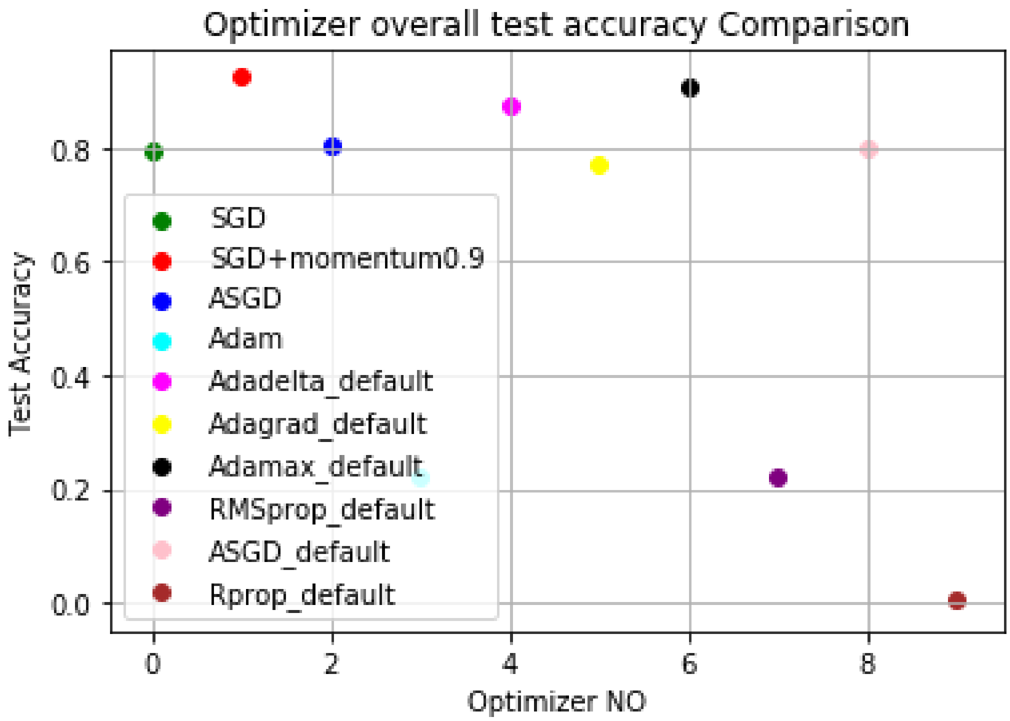
```
Test Loss: 4.7098 Test Accuracy 0.0073
10 10 10
```

3.10 Part 2.9 - Visualizing total optimizers test prediction result

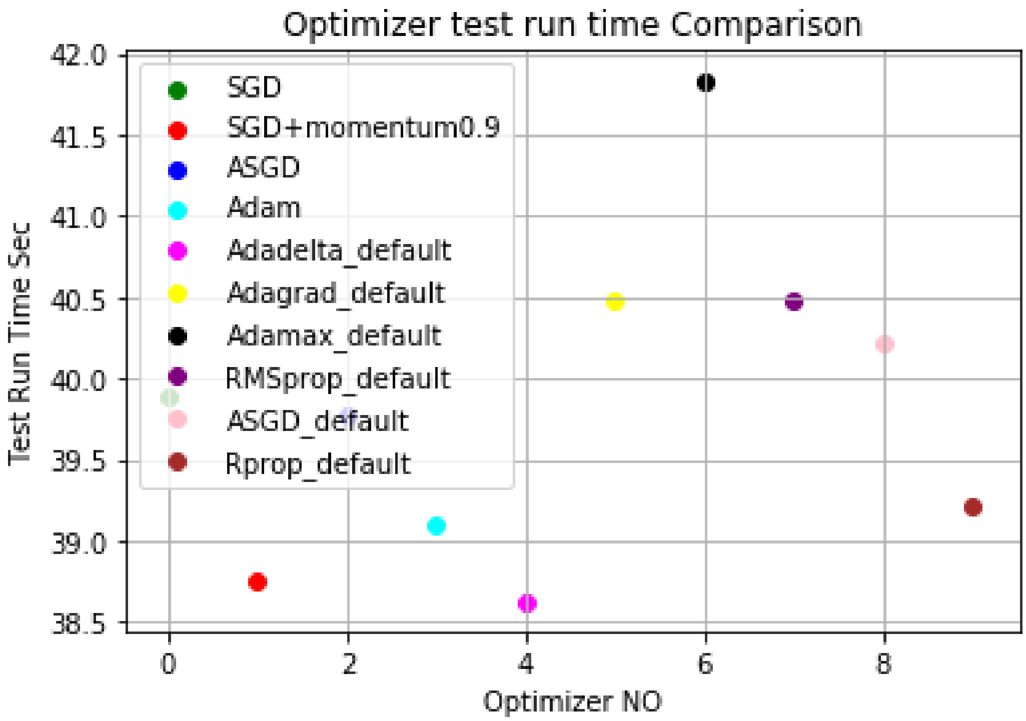
```
In [223]: if(len(optimizer_test_loss) == 10 and
             len(optimizer_test_accuracy) == 10 and
             len(optimizer_time_cost3) == 10):
             plt.title('Optimizer overall test loss Comparison')
             plt.ylabel('Test Loss')
             plt.xlabel('Optimizer NO')
             plt.scatter(0,optimizer_test_loss[0],color='green')
             plt.scatter(1,optimizer_test_loss[1],color='red')
             plt.scatter(2,optimizer_test_loss[2],color='blue')
             plt.scatter(3,optimizer_test_loss[3],color='cyan')
             plt.scatter(4,optimizer_test_loss[4],color='magenta')
             plt.scatter(5,optimizer_test_loss[5],color='yellow')
             plt.scatter(6,optimizer_test_loss[6],color='black')
             plt.scatter(7,optimizer_test_loss[7],color='purple')
             plt.scatter(8,optimizer_test_loss[8],color='pink')
             plt.scatter(9,optimizer_test_loss[9],color='brown')
             plt.grid(True)
             plt.legend([str(optimer_name2[0]),str(optimer_name2[1]),str(optimer_name2[2]),str
                        str(optimer_name2[4]),str(optimer_name2[5]),str(optimer_name2[6]),str(
                        str(optimer_name2[8]),str(optimer_name2[9])], loc=2)
             plt.show()
```




```
In [230]: if(len(optimizer_test_loss) == 10 and
              len(optimizer_test_accuracy) == 10 and
              len(optimizer_time_cost3) == 10):
              plt.title('Optimizer overall test accuracy Comparison')
              plt.ylabel('Test Accuracy')
              plt.xlabel('Optimizer NO')
              plt.scatter(0,optimizer_test_accuracy[0],color='green')
              plt.scatter(1,optimizer_test_accuracy[1],color='red')
              plt.scatter(2,optimizer_test_accuracy[2],color='blue')
              plt.scatter(3,optimizer_test_accuracy[3],color='cyan')
              plt.scatter(4,optimizer_test_accuracy[4],color='magenta')
              plt.scatter(5,optimizer_test_accuracy[5],color='yellow')
              plt.scatter(6,optimizer_test_accuracy[6],color='black')
              plt.scatter(7,optimizer_test_accuracy[7],color='purple')
              plt.scatter(8,optimizer_test_accuracy[8],color='pink')
              plt.scatter(9,optimizer_test_accuracy[9],color='brown')
              plt.grid(True)
              plt.legend([str(optimer_name2[0]),str(optimer_name2[1]),str(optimer_name2[2]),str
                         str(optimer_name2[4]),str(optimer_name2[5]),str(optimer_name2[6]),str(
                         str(optimer_name2[8]),str(optimer_name2[9])], loc=3)
              plt.show()
```




```
In [237]: if(len(optimizer_test_loss) == 10 and
             len(optimizer_test_accuracy) == 10 and
             len(optimizer_time_cost3) == 10):
             plt.title('Optimizer test run time Comparison')
             plt.ylabel('Test Run Time Sec')
             plt.xlabel('Optimizer NO')
             plt.scatter(0,optimizer_time_cost3[0],label= str(optimer_name2[0]),color='green')
             plt.scatter(1,optimizer_time_cost3[1],color='red')
             plt.scatter(2,optimizer_time_cost3[2],color='blue')
             plt.scatter(3,optimizer_time_cost3[3],color='cyan')
             plt.scatter(4,optimizer_time_cost3[4],color='magenta')
             plt.scatter(5,optimizer_time_cost3[5],color='yellow')
             plt.scatter(6,optimizer_time_cost3[6],color='black')
             plt.scatter(7,optimizer_time_cost3[7],color='purple')
             plt.scatter(8,optimizer_time_cost3[8],color='pink')
             plt.scatter(9,optimizer_time_cost3[9],color='brown')
             plt.grid(True)
             plt.legend([str(optimer_name2[0]),str(optimer_name2[1]),str(optimer_name2[2]),str
                         str(optimer_name2[4]),str(optimer_name2[5]),str(optimer_name2[6]),str(
                         str(optimer_name2[8]),str(optimer_name2[9])], loc=0)
             plt.show()
```



3.11 Part 2.10 - Visualizing the model image predictions

```
In [0]: def imshow(inp, title=None):
            """Imshow for Tensor."""
            inp = inp.numpy().transpose((1, 2, 0))
            inp = np.clip(inp, 0, 1)
            plt.imshow(inp)
            if title is not None:
                plt.title(title)
            plt.pause(1)  # pause a bit so that plots are updated

        def visualize_model(model, num_images=8):
            images_so_far = 0
            fig = plt.figure()

            for batch_idx, (images, labels) in enumerate(dataloaders['test']):
                #move to GPU
                images, labels = images.cuda(), labels.cuda()

                outputs = model(images)

                _, preds = torch.max(outputs.data, 1)
```

```
            for j in range(images.size()[0]):
                images_so_far += 1
                ax = plt.subplot(num_images//2, 2, images_so_far)
                ax.axis('off')
                ax.set_title('class: {} predicted: {}'.format(class_names[labels.data[j]],

                imshow(images.cpu().data[j])

                if images_so_far == num_images:
                    return
```

```
In [0]: visualize_model(model)
```