CNN Applied to EEG Data

Preparation and Loading Data

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
%pwd
```

```
'/content'
```

```
% cd 'drive/My Drive/ECE C147'
% cd 'project'
% ls
```

```
/content/drive/My Drive/ECE C147
/content/drive/My Drive/ECE C147/project
EEG_loading.ipynb  person_train_valid.npy  X_train_valid.npy  y_train_valid.npy
person_test.npy    X_test.npy              y_test.npy
```

```
def count_parameters(model):
  """Function for count model's parameters"""
  return sum(p.numel() for p in model.parameters() if p.requires_grad)
```

```
import numpy as np
import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader, TensorDataset, random_split
from torchvision import transforms, utils
import time

# specific package for visualization
!pip install livelossplot --quiet
from livelossplot import PlotLosses

# get the device type of machine
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
# device = 'cpu'
print(device)
```

```
cuda
```

```
X_test = np.load("X_test.npy")
y_test = np.load("y_test.npy")
person_train_valid = np.load("person_train_valid.npy")
X_train_valid = np.load("X_train_valid.npy")
y_train_valid = np.load("y_train_valid.npy")
person_test = np.load("person_test.npy")

# adjust labels
y_train_valid -= 769
y_test -= 769


print('y_train_valid', y_train_valid[:10])

# copy numpy data to tensor
X_train_valid_tensor = torch.from_numpy(X_train_valid).float().to(device)
y_train_valid_tensor = torch.from_numpy(y_train_valid).float().long().to(device) # do not for
X_test_tensor = torch.from_numpy(X_test).float().to(device)
y_test_tensor = torch.from_numpy(y_test).float().long().to(device)


# # convert int labels to one hot labels
# y_train_valid_tensor = nn.functional.one_hot(y_train_valid_tensor)
# print('y_train_valid_onehot', y_train_valid_tensor[:10])
```

```
y_train_valid [2 3 0 0 0 0 2 1 3 3]
```

```
print ('Training/Valid data shape: {}'.format(X_train_valid.shape))
print ('Test data shape: {}'.format(X_test.shape))
print ('Training/Valid target shape: {}'.format(y_train_valid.shape))
print ('Test target shape: {}'.format(y_test.shape))
print ('Person train/valid shape: {}'.format(person_train_valid.shape))
print ('Person test shape: {}'.format(person_test.shape))
```

```
Training/Valid data shape: (2115, 22, 1000)
Test data shape: (443, 22, 1000)
Training/Valid target shape: (2115,)
Test target shape: (443,)
Person train/valid shape: (2115, 1)
Person test shape: (443, 1)
```

```
class EEGDataset(Dataset):
    """EEG dataset."""
    def __init__(self, subset, transform=None):
        self.subset = subset
        self.transform = transform

    def __getitem__(self, index):
        x, y = self.subset[index]
```

```
        if self.transform:
          pass
            # x = self.transform(x)
            # y = self.transform(y)
        return x, y

    def __len__(self):
        return len(self.subset)

init_dataset = TensorDataset(X_train_valid_tensor, y_train_valid_tensor)
test_dataset = TensorDataset(X_test_tensor,y_test_tensor)
# split train and val
lengths = [int(len(init_dataset)*0.8), int(len(init_dataset)*0.2)]
subset_train, subset_val = random_split(init_dataset, lengths)

train_data = EEGDataset(
    subset_train, transform=None)

val_data = EEGDataset(
    subset_val, transform=None)

test_data=EEGDataset(test_dataset,transform=None)

dataloaders = {
    'train': torch.utils.data.DataLoader(train_data, batch_size=32, shuffle=True, num_workers
    'val': torch.utils.data.DataLoader(val_data, batch_size=32, shuffle=True, num_workers=0),
    'test':torch.utils.data.DataLoader(test_data, batch_size=64, shuffle=False, num_workers=0
}
```

Model

```
class ShallowConv(nn.Module):

    # Defining the building blocks of shallow conv net

    def __init__(self, in_channels, num_conv_filters, num_samples_frame, num_eeg_channels,cla

        # Defining as a subclass
        super(ShallowConv, self).__init__()

        self.num_samples_frame = num_samples_frame
        self.num_conv_filters = num_conv_filters
        self.num_eeg_channels = num_eeg_channels

        # Define the convolution layer, https://pytorch.org/docs/stable/generated/torch.nn.Co
        self.conv1 = nn.Conv2d(in_channels, self.num_conv_filters, (1, 25), stride=1)
        self.conv_output_width =  int(self.num_samples_frame - (25-1) - 1 + 1)

        # Define the 2d batchnorm layer
```

```
        self.bnorm2d = nn.BatchNorm2d(self.num_conv_filters)

        # Define the 1d batchnorm layer
        self.bnorm1d = nn.BatchNorm1d(self.num_conv_filters)


        # Define the fc layer, https://pytorch.org/docs/stable/generated/torch.nn.Linear.html
        self.fc1 = nn.Linear(self.num_eeg_channels*self.num_conv_filters, self.num_conv_filte

        # Define the elu activation
        self.elu = nn.ELU(0.2)

        # Define the avg pooling layer
        self.avgpool = nn.AvgPool1d(75, stride=15)

        self.num_features_linear = int(np.floor(((self.conv_output_width - 75)/15)+1))



        # Define the fc layer for generating the scores for classes
        self.fc2 = nn.Linear(self.num_features_linear*self.num_conv_filters, classes)

        # Define the softmax layer for converting the class scores to probabilities
        self.softmax = nn.Softmax(dim=1)

    # Defining the connections of shallow conv net

    def forward(self, x):

        # Reshaping the input for 2-D convolution (B,22,num_samples_frame) -> (B,1,22,num_sam

        x = x.view(-1, 1, 22, self.num_samples_frame)

        # Performing the 2-D convolution (B,1,22,300) -> (B,40,22,x_shape_4dim)

        x = self.conv1(x)
        x_shape_4dim = x.shape[3]

        # ELU activation

        x = self.elu(x)

        # 2d Batch normalization

        x = self.bnorm2d(x)


        # Reshaping the input to dense layer (B,40,22,x_shape_4dim) -> (B,x_shape_4dim,880)

        x = x.permute(0,3,1,2) # (B,40,22,x_shape_4dim) -> (B,x_shape_4dim,40,22)
        x = x.view(-1,x_shape_4dim,880)
```

```
        # Passing through the dense layer (B,x_shape_4dim,880) -> (B,x_shape_4dim,40)

        x = self.fc1(x)

        # ELU activation

        x = self.elu(x)

        # Square activation

        x = torch.square(x)

        # Reshaping the input for average pooling layer (B,x_shape_4dim,40) -> (B,40,x_shape_

        x = x.permute(0,2,1)

        # Passing through the average pooling layer (B,40,x_shape_4dim) -> (B,40,x_pool_3dim)

        x = self.avgpool(x)
        x_pool_3dim = x.shape[2]

        # Log activation

        x = torch.log(x)

        # 1D Batch normalization

        x = self.bnorm1d(x)
        #print(x.shape)

        # Reshaping the input to dense layer (B,40,x_pool_3dim) -> (B,40*x_pool_3dim)

        x = x.reshape(-1, 40*x_pool_3dim)

        # Passing through the dense layer (B,40*x_pool_3dim) -> (B,classes)

        x = self.fc2(x)

        # Passing through the softmax layer

        x = self.softmax(x)

        return x
```

```
def train_model(model, optimizer, num_epochs):
    # for each epoch...
    liveloss = PlotLosses()
```

```
for epoch in range(num_epochs):
  print('Epoch {}/{}'.format(epoch, num_epochs - 1))
  print('-' * 10)
  logs = {}

  # let every epoch go through one training cycle and one validation cycle
  # TRAINING AND THEN VALIDATION LOOP...
  for phase in ['train', 'val']:
    train_loss = 0
    correct = 0
    total = 0
    batch_idx = 0

    start_time = time.time()
    # first loop is training, second loop through is validation
    # this conditional section picks out either a train mode or validation mode
    # depending on where we are in the overall training process
    # SELECT PROPER MODE- train or val
    if phase == 'train':
      for param_group in optimizer.param_groups:
        print("LR", param_group['lr']) # print out the learning rate
      model.train()  # Set model to training mode
    else:
      model.eval()   # Set model to evaluate mode

    for inputs, labels in dataloaders[phase]:
      inputs = inputs.to(device)
      labels = labels.to(device)
      batch_idx += 1

      optimizer.zero_grad()

      with torch.set_grad_enabled(phase == 'train'):
      #    the above line says to disable gradient tracking for validation
      #    which makes sense since the model is in evluation mode and we
      #    don't want to track gradients for validation)
        outputs = model(inputs)
        # compute loss where the loss function will be defined later

        loss = loss_fn(outputs, labels)
        # backward + optimize only if in training phase
        if phase == 'train':
          loss.backward()
          optimizer.step()
        train_loss += loss
        _, predicted = outputs.max(1)

        total += labels.size(0)
        correct += predicted.eq(labels).sum().item()

    # if phase == 'train':
    #   if epoch%5 == 0:
```

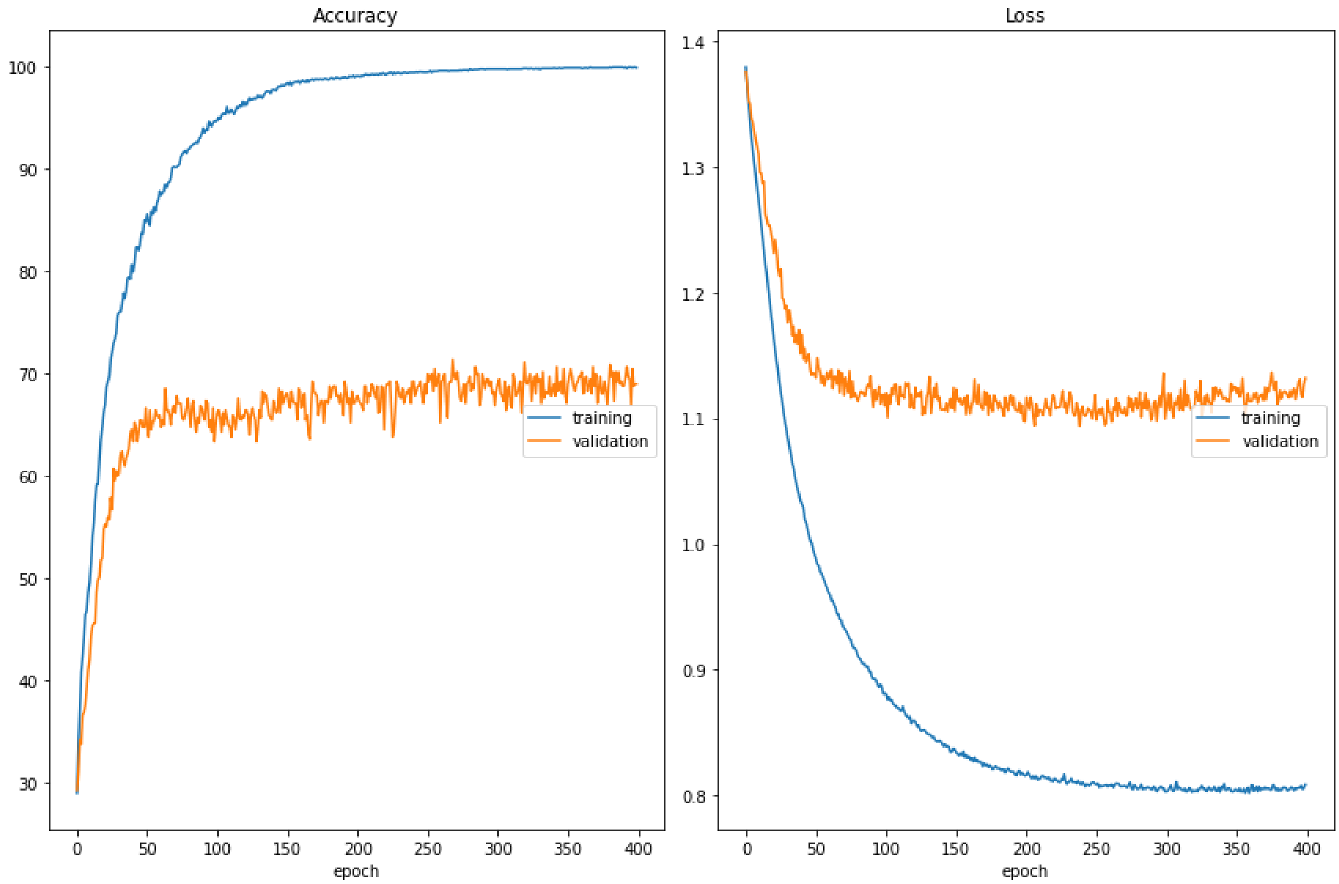
```
        #   if  epoch%5 == 0:
        #   # prints for training and then validation (since the network will be in either tr
        #     print(" Training Epoch %d, Total loss %0.6f, iteration time %0.6f" % (epoch, tr

        # if phase == 'val' and epoch%5 == 0:
        #   print(" Validation Epoch %d, Total loss %0.6f, iteration time %0.6f" % (epoch, tr


        prefix = ''
        if phase == 'val':
            prefix = 'val_'

        logs[prefix + 'loss'] = train_loss.item()/(batch_idx)
        logs[prefix + 'acc'] = correct/total*100.

      liveloss.update(logs)
      liveloss.send()

    # end of single epoch iteration... repeat of n epochs
    return model


def test(model):
    dataloader = dataloaders['test']
    size = len(dataloader.dataset)
    model.eval()
    test_loss, correct = 0, 0
    with torch.no_grad():
        for X, y in dataloader:
            X, y = X.to(device), y.to(device)
            pred = model(X)
            test_loss += loss_fn(pred, y).item()
            correct += (pred.argmax(1) == y).type(torch.float).sum().item()
    test_loss /= size
    correct /= size
    print(f"Test Error: \n Accuracy: {(100*correct):>0.1f}%, Avg loss: {test_loss:>8f} \n")
```

Train the Model

```
# define the hyperparamters
weight_decay = 0.15  # weight decay to alleviate overfiting

model = ShallowConv(in_channels=1, num_conv_filters=40,num_samples_frame=1000,num_eeg_channel

count = count_parameters(model)
print ('model parameters amount {}'.format(count))

loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr = 2e-5, weight_decay=weight_decay)
```

```
model parameters amount 46204
```

```
model=train_model(model, optimizer, num_epochs=400)
test(model)
```




```
Accuracy
        training                 (min:   29.019, max:  100.000, cur:   99.941)
        validation               (min:   29.314, max:   71.395, cur:   69.031)
Loss
        training                 (min:    0.802, max:    1.379, cur:    0.809)
        validation               (min:    1.094, max:    1.375, cur:    1.132)
Test Error: 
 Accuracy: 65.5%, Avg loss: 0.018062
```