CNN Applied to EEG Data to classify subject 1 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])
```

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

```
#filter data for subject 1 only

train_val_subject1_idx =  []
for i, n in enumerate(person_train_valid):
  if n==0:
    train_val_subject1_idx.append(i)
X_train_val_subject1 = X_train_valid[train_val_subject1_idx]
y_train_val_subject1 = y_train_valid[train_val_subject1_idx]
print(len(y_train_val_subject1))
test_subject1_index = []
for i, n in enumerate(person_test):
  if n==0:
    test_subject1_index.append(i)
print(test_subject1_index)
X_test_subject1 = X_test[test_subject1_index]
y_test_subject1 = y_test[test_subject1_index]
print(len(y_test_subject1))
```

```
237
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23,
50
```

```
# copy numpy data to tensor

X_train_valid_tensor = torch.from_numpy(X_train_valid).float().to(device)
X_train_valid_s1_tensor = torch.from_numpy(X_train_val_subject1).float().to(device)
y_train_valid_tensor = torch.from_numpy(y_train_valid).float().long().to(device) # do not for
y_train_valid_s1_tensor = torch.from_numpy(y_train_val_subject1).float().long().to(device)
X_test_tensor = torch.from_numpy(X_test_subject1).float().to(device)
```

```
y_test_tensor = torch.from_numpy(y_test_subject1).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])


print ('Training/Valid data shape: {}'.format(X_train_valid.shape))
print ('Training/Valid for s1 data shape: {}'.format(X_train_val_subject1.shape))
print ('Test data shape: {}'.format(X_test_subject1.shape))
print ('Training/Valid target shape: {}'.format(y_train_valid.shape))
print ('Training/Valid for s1 target shape: {}'.format(y_train_val_subject1.shape))
print ('Test target shape: {}'.format(y_test_subject1.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)
Training/Valid for s1 data shape: (237, 22, 1000)
Test data shape: (50, 22, 1000)
Training/Valid target shape: (2115,)
Training/Valid for s1 target shape: (237,)
Test target shape: (50,)
```

```
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)
init_s1_dataset = TensorDataset(X_train_valid_s1_tensor,y_train_valid_s1_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)]
print(lengths)
subset_train, subset_val = random_split(init_dataset, lengths)
lengths_s1 = [int(len(init_s1_dataset)*0.8), 237-int(len(init_s1_dataset)*0.8)]
print(lengths_s1)
subset_train_s1,subset_val_s1 = random_split(init_s1_dataset,lengths_s1)
train_data = EEGDataset(
```

```
    subset_train, transform=None)


val_data = EEGDataset(
    subset_val, transform=None)

train_data_s1 = EEGDataset(subset_train_s1,transform=None)
val_data_s1 = EEGDataset(subset_val_s1,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),
    'train_s1': torch.utils.data.DataLoader(train_data_s1, batch_size=32, shuffle=True, num_w
    'val_s1': torch.utils.data.DataLoader(val_data_s1, batch_size=32, shuffle=True, num_worke
    'test':torch.utils.data.DataLoader(test_data, batch_size=64, shuffle=False, num_workers=6
}
```

```
[1692, 423]
[189, 48]
```

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)
```

```
        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
```

```
## train a model to classify subject1 with data from all subjects
def train_model_with_alldata(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
```

```
# 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:
  #   # 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


# train a model to classify subject 1 data with only subject 1 data

def train_model_with_s1data(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_s1', 'val_s1']:
        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_s1':
          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]:
          #print(inputs.size())
          #print(labels.size())
          inputs = inputs.to(device)
          labels = labels.to(device)
```

```
            batch_idx += 1

            optimizer.zero_grad()

            with torch.set_grad_enabled(phase == 'train_s1'):
            #    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
              #print(outputs.size())




              loss = loss_fn(outputs, labels)
              # backward + optimize only if in training phase
              if phase == 'train_s1':
                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:
          #   # 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_s1':
              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)
```

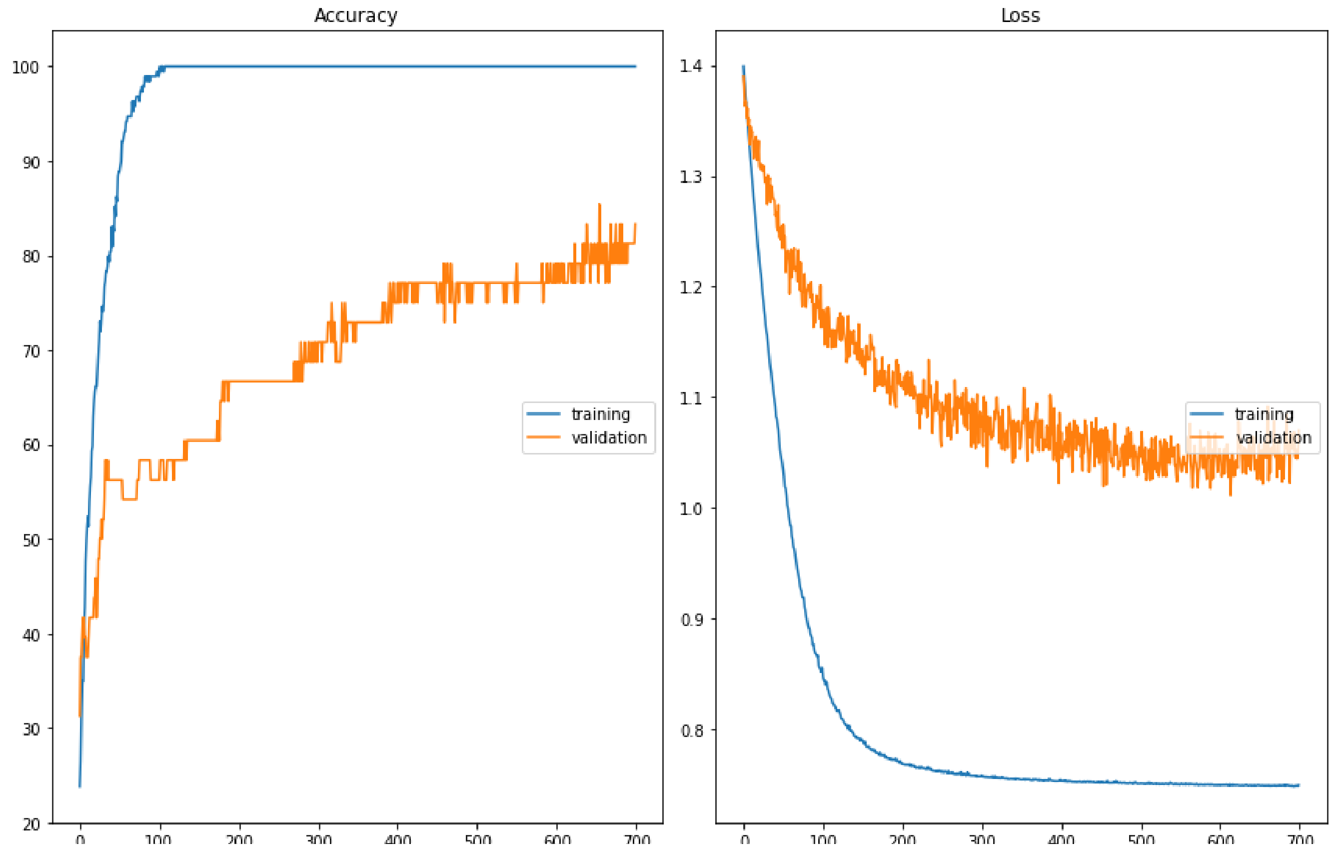
```
    model.eval()
    test_loss, correct = 0, 0
    with torch.no_grad():
        for X, y in dataloader:
            X, y = X.to(device), y.to(device)
            pred = model(X)
            test_loss += loss_fn(pred, y).item()
            correct += (pred.argmax(1) == y).type(torch.float).sum().item()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

Train the Model with only subject 1 data and then classify subject 1 data

```
# 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_with_s1data(model, optimizer, num_epochs=700)
test(model)
```



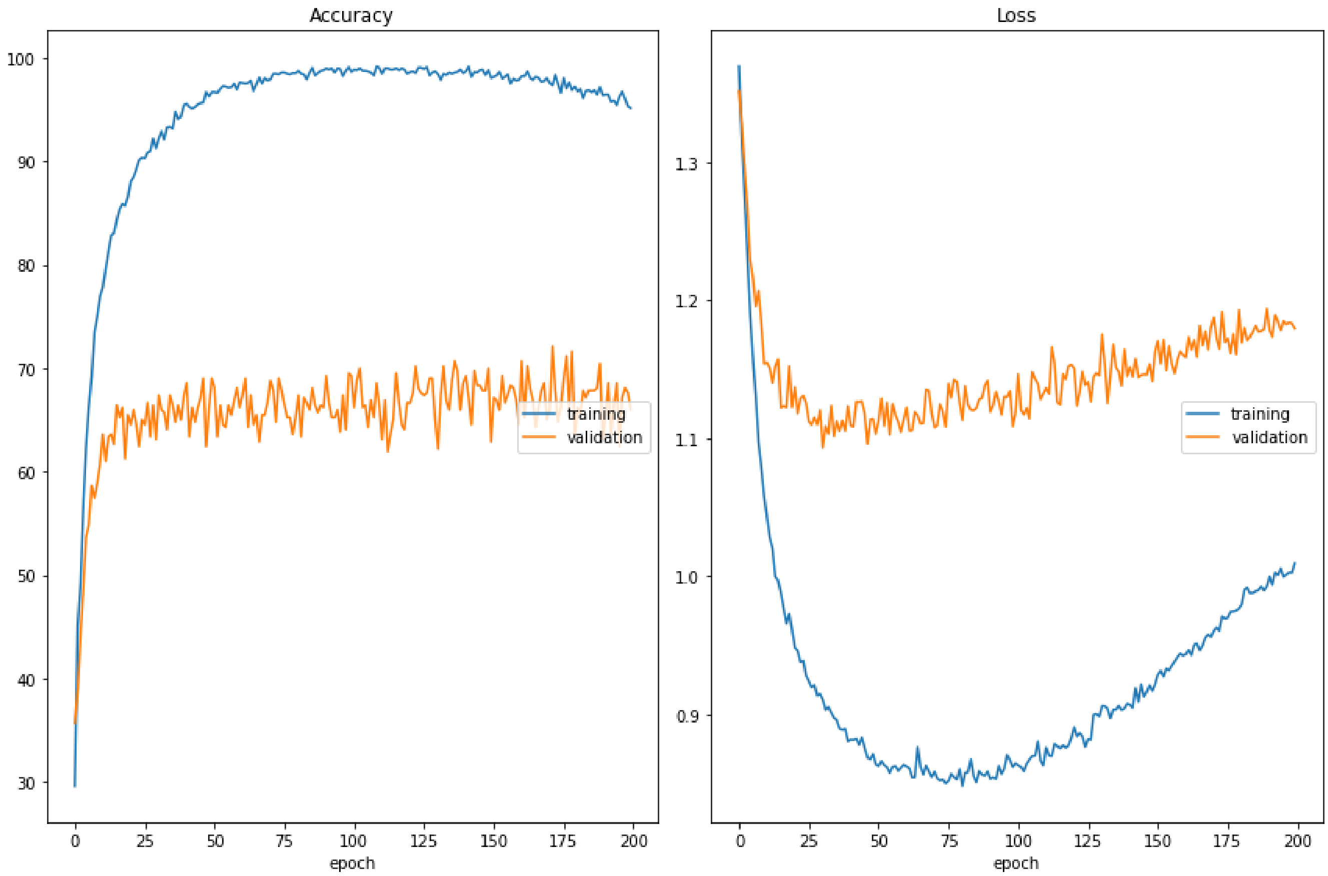
Train the model with all data and then then classify subject 1 data

```
validation (min: 31.250, max: 85.417, cur: 83.333)
```

```
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 = 1e-4, weight_decay=weight_decay)
```

```
model parameters amount 46204
```

```
model=train_model_with_alldata(model, optimizer, num_epochs=200)
test(model)
```




```
Accuracy
	training           	 (min:   29.610, max:   99.173, cur:   95.154)
	validation         	 (min:   35.697, max:   72.104, cur:   65.957)
Loss
	training           	 (min:    0.848, max:    1.369, cur:    1.009)
	validation         	 (min:    1.093, max:    1.351, cur:    1.179)
Test Error: 
 Accuracy: 78.0%, Avg loss: 0.023357
```