

▼ Assignment 6 : Pretrain and Transfer Learning (20 pts)

▼ Before working on the assignment please read papers as following

- SUPERVISED CONTRASTIVE LEARNING FOR PRE-TRAINED LANGUAGE MODEL FINE-TUNING
 - link: <https://openreview.net/pdf?id=cu7IUiO>
- Few-Shot Intent Detection via Contrastive Pre-Training and Fine-Tuning
 - link: <https://arxiv.org/abs/2109.06349>

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

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

```
path = '/content/drive/MyDrive/NLU Assignments/A6/'
os.chdir(path)
```

```
!pip install transformers
```

```
Requirement already satisfied: transformers in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: huggingface-hub<1.0,>=0.1.0 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: importlib-metadata in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: tokenizers!=0.11.3,>=0.11.1 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: sacremoses in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: filelock in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: urllib3!=1.25.0,!1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: joblib in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: click in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages
```

▼ Question 1: Why do we need transfer learning ? (1.5pts)

#answer1

Answer1:

We need transfer learning because it can make removing the need for a large set of labelled training data for every new model, improving the efficiency of machine learning development and deployment for multiple models. Moreover, a more generalised approach to machine problem solving, leveraging different algorithms to solve new challenges and models can be trained within simulations instead of real-world environments.

Ref <https://www.seldon.io/transfer-learning>

▼ Question 2: When transfer learning makes sense ? (1.5pts)

#answer2

Answer2:

Transfer learning makes sense when the training of a system to solve a new task would take a huge amount of resources. The process takes relevant parts of an existing machine learning model and applies it to solve a new but similar problem.

Ref : <https://www.seldon.io/transfer-learning>

```
import os
import numpy as np
import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader
from transformers import RobertaConfig, RobertaModel, RobertaTokenizer, RobertaForSeq2Seq
from transformers import AdamW
import random
from IPython.display import clear_output
from utils import create_supervised_pair, supervised_contrastive_loss, Similarity

# #comment this if you are not using puffer
# os.environ['http_proxy'] = 'http://192.41.170.23:3128'
# os.environ['https_proxy'] = 'http://192.41.170.23:3128'
```

▼ To download data from file directory both text samples and labels

```
def load_examples(file_path, do_lower_case=True):
    examples = []
```

```

with open('{} /seq.in'.format(file_path), 'r', encoding="utf-8") as f_text, open(
    for text, label in zip(f_text, f_label):

    e = Inputexample(text.strip(), label=label.strip())
    examples.append(e)

return examples

```

▼ Each sample has a sentence and label format

```

class Inputexample(object):
    def __init__(self, text_a, label = None):
        self.text = text_a
        self.label = label

```

Question3 : Write the code to be able to control batching data process for the

▼ sake of fine-tuning models with combining cross entropy and supervised contrastive loss in question 5, and only cross entropy in question 4. (7pts)

- assume : we have batch size = 4 but we have 64 classes, so sometime batching process will random sample in a batch, and then it has no any samples come from the same classes like below
 - samples_sentence = ['a','b','c','d'] : assume that one alphabet represent one sentence or one sample
 - labels = [0,1,2,3] ; Therefore, if a batch has unique classes equal to batch size, this batch will be skipped due to equation " $1y_i=y_j$ " of supervised contrastive loss (equation in question 5) that's reason why we need to force like below buttlet.
 - you can see at least one pair that come from the same class.

Therefore, we want dataloader to output like below

- samples_sentence = ['a','b','c','f']
- labels = [0,1,2,0] ; this batch will pass condition as " $1y_i=y_j$ " because the label of $y[0] = 0, y[3] = 0$ in list of labels.

```

## create custom dataset class
## === = Hint = ===
## can train on two condition
## 1.) training training with supervise contrastive loss and cross entropy loss us:
##     when self.repeated_label == True:
## 2.) train only cross entropy loss use in question 4.)
##     when self.repeated_label == False:

```

```

class CustomTextDataset(Dataset):

```

```

def __init__(self, labels, text, batch_size, repeated_label: bool=False):
    self.labels = labels
    self.text = text
    self.batch_size = batch_size
    self.count = 0
    self.repeated_label = repeated_label

    if self.repeated_label == True:
        self.exist_classes = []
        self.ids_ = []
        self.data_length = len(self.labels)
        self.left_batch = False
        self.label_ = None
        self.num_batch = 0

        self.max_count = self.data_length // self.batch_size
        if self.data_length % self.batch_size != 0:
            self.max_count += 1

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

def __getitem__(self, idx):

    if self.repeated_label == True:
        self.count += 1
        self.exist_classes.append(self.labels[idx])
        self.ids_.append(idx)
        if self.num_batch == self.max_count - 1:
            self.num_batch = +1
            self.num_batch = 0
            if self.data_length % self.batch_size != 0:
                self.batch_size = self.data_length % self.batch_size
                self.left_batch = True

        if self.count == self.batch_size:
            unique_labels_keys = list(set(self.exist_classes))
            table = [0] * len(unique_labels_keys)
            unique_labels = dict(zip(unique_labels_keys, table))
            if self.left_batch == True:
                self.left_batch = False
                self.batch_size = 4
            else:
                self.num_batch += 1
            for class_key in self.exist_classes:
                unique_labels[class_key] = +1
            for index, key in enumerate(unique_labels):
                if unique_labels[key] > 1:
                    print("v>1 :", unique_labels[key])
                    break
            if index == len(unique_labels.keys()) - 1:
                while True:
                    pos_idx = random.randint(0, self.data_length-1)

```

```

        if self.labels[pos_idx] in unique_labels.keys():
            if self.labels[pos_idx] == self.labels[idx]:
                pass
            else:
                idx = pos_idx
                unique_labels[self.labels[idx]] += 1
                self.exist_classes[-1] = self.labels[idx]
                if len(set(self.exist_classes)) == len(self.exist_classes):
                    print(unique_labels)
                self.count = 0
                self.exist_classes = []
                self.ids_ = []
                break

    label = self.labels[idx]
    data = self.text[idx]
    sample = {"Class": label, "Text": data}
    return sample

```

What is Few-shot Learning ?

- few-shot learning is the process of train model on small amount of data in each class to guide model on specific tasks, opposed to standard fine-tuning method which requires a large amount of training data for the pretrained model to adapt to the desired task with accuracy.

source : <https://huggingface.co/blog/few-shot-learning-gpt-neo-and-inference-api>

▼ Define Parameters

```

N = 5
data = []
labels = []
train_samples = []
train_labels = []
embed_dim = 768
batch_size = 4
lr= 1e-5 # you can adjust
temp = 0.3 # you can adjust
lamda = 0.01 # you can adjust
skip_time = 0 # the number of time that yi not equal to yj in supervised contrastive loss
device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')

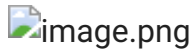
```

▼ The Aim of these training is to fine tuning on few shot setting on text classification task

Path example of train, validation and test

```
path_5shot = f'./HWU64/train_5/'
path_test = f'./HWU64/test/'
path_valid = f'./HWU64/valid/'
```

▼ Dataset Structure



```
#!/unzip HWU64.zip
```

```
Archive: HWU64.zip
replace HWU64/valid/label? [y]es, [n]o, [A]ll, [N]one, [r]ename: n
replace HWU64/valid/seq.in? [y]es, [n]o, [A]ll, [N]one, [r]ename: n
replace HWU64/train_5/label? [y]es, [n]o, [A]ll, [N]one, [r]ename: n
replace HWU64/train_5/seq.in? [y]es, [n]o, [A]ll, [N]one, [r]ename: n
replace HWU64/train_10/label? [y]es, [n]o, [A]ll, [N]one, [r]ename: n
replace HWU64/train_10/seq.in? [y]es, [n]o, [A]ll, [N]one, [r]ename: n
replace HWU64/train/seq.in? [y]es, [n]o, [A]ll, [N]one, [r]ename: n
replace HWU64/train/label? [y]es, [n]o, [A]ll, [N]one, [r]ename: n
replace HWU64/test/label? [y]es, [n]o, [A]ll, [N]one, [r]ename: n
replace HWU64/test/seq.in? [y]es, [n]o, [A]ll, [N]one, [r]ename: n
```

```
# https://downgit.github.io/#/home?url=https:%2F%2Fgithub.com%2Fjianguoz%2FFew-Shot
```

```
# downloading training samples
train_samples = load_examples(path_5shot)
```

```
# write code here : for downloading validation samples
val_samples = load_examples(path_valid)
```

```
#write code here : for downloading test samples
test_samples = load_examples(path_test)
```

```
data_val = []
labels_val = []
data_test = []
labels_test = []
```

```
# preprocess for training
for i in range(len(train_samples)):
    data.append(train_samples[i].text)
    labels.append(train_samples[i].label)
```

```
# write code here :preprocess validation samples
for i in range(len(val_samples)):
    data_val.append(val_samples[i].text)
    labels_val.append(val_samples[i].label)
```

```

# write code here : preprocess test samples
for i in range(len(test_samples)):
    data_test.append(test_samples[i].text)
    labels_test.append(test_samples[i].label)

# dataloader for training
train_data = CustomTextDataset(labels,data,batch_size=batch_size,repeated_label=True)
train_loader = DataLoader(train_data,batch_size=batch_size,shuffle=True)

# write code here : dataloader for validation
val_data = CustomTextDataset(labels_val,data_val,batch_size=batch_size,repeated_label=True)
val_loader = DataLoader(val_data,batch_size=batch_size,shuffle=True)

# write code here : dataloader for test
test_data = CustomTextDataset(labels_test,data_test,batch_size=batch_size,repeated_label=True)
test_loader = DataLoader(test_data,batch_size=batch_size,shuffle=True)

# got the number of unique classes from dataset
num_class = len(np.unique(np.array(labels)))

# get text label of unigue classes
unique_label = np.unique(np.array(labels))

# map text label to index classes
label_maps = {unique_label[i]: i for i in range(len(unique_label))}

# Download tokenizer that use to tokenize sentence into words by using Pretrain from Pytorch
tokenizer = RobertaTokenizer.from_pretrained('roberta-base')

```

▼ Download Pretrain Model

```

# download config of Roberta config
config = RobertaConfig.from_pretrained("roberta-base",output_hidden_states=True)

#chnage modifying the number of classes
config.num_labels = num_class
# Download pretrain models weight
model = RobertaForSequenceClassification.from_pretrained('roberta-base')
# change from binary classification to muli-classification and loss automatically change
model.num_labels = config.num_labels
# change the output of last layer to num_class that we want to predict
model.classifier.out_proj = nn.Linear(in_features=embed_dim,out_features=num_class)
# move to model to device that we set
model = model.to(device)

```

Some weights of the model checkpoint at roberta-base were not used when initializing the model.

```
optimizer = optim.Adam(model.parameters())
```

```
/usr/local/lib/python3.7/dist-packages/transformers/optimization.py:309: FutureWarning,
FutureWarning,
```

```
def freeze_layers(model, freeze_layers_count: int):

    """
    model : model object that we create
    freeze_layers_count : the number of layers to freeze
    """

    # write the code here
    # freeze_layers_count = sum(p.numel() for p in model.parameters() if p.requires_grad)
    for params in model.roberta.embeddings.parameters():
        params.requires_grad = False
    # print("Embeddings: ", params.requires_grad)
    for i, layer in enumerate(model.roberta.encoder.layer):
        if i < freeze_layers_count:
            for params in layer.parameters():
                params.requires_grad = False


    # return freeze_layers_count
    return model
```

```
model= freeze_layers(model, 10)
```

[illegible]



- Using API of hugging face of RobertaForSequenceClassification
 - source :
https://huggingface.co/transformers/v3.0.2/model_doc/roberta.html#robertaforsequenceclassification
- report performance of models (test acc) with different experiment of unfreezing of bottom layers and compare the result of each

- 4.1. freeze weight from pretrain model all layer except classifier
-  image.png

- 4.2. freeze all from top embeddings to encoder layers (9)
 - embeddings
 - ![image.png](attachment:2a69ebel-6893-45ca-b7ea-38f9715b8c9a.png)
 - layer 9
 - ![image.png](attachment:ef8674dc-7743-40d4-bde4-21a3819e62fb.png)
- 4.3 add code to collect loss and accuracy of training history of (4.1 and 4.2)
- 4.4 add the code in below in training loop collect validation loss and accuracy history

- hint: for this training on Cross entropy loss no need to control the outcome of class in each batch using code below to train model base on how many layers that you freeze
 - to see whole architecture look like you can use mode.eval()

this code training models on Cross entropy loss

```

train_losses = []
#valid_losses = []
best_train_loss = float('inf')
total_acc_train = []
acc_train = 0.0
n_correct = 0.0
n_wrong = 0.0

for epoch in range(30): # loop over the dataset multiple times
#for epoch in range(2): # loop over the dataset multiple times

    running_loss = 0.0

    for (idx, batch) in enumerate(train_loader):
        sentence = batch["Text"]
        inputs = tokenizer(sentence,padding=True,truncation=True,return_tensors="pt")

        # move parameter to device
        inputs = {k:v.to(device) for k,v in inputs.items()}

        # map string labels to class index
        labels = [label_maps[stringtoId] for stringtoId in (batch['Class'])]

        #print("show out: ",np.unique(labels, return_counts=True))
        # convert list to tensor
        labels = torch.tensor(labels).unsqueeze(0)
        labels = labels.to(device)

        #(batch_size, seq_len)
        #print(inputs["input_ids"].shape)

        # zero the parameter gradients

```

```
optimizer.zero_grad()

outputs = model(**inputs, labels=labels)
# you can check
loss, logits = outputs[:2]

loss.backward()
optimizer.step()

train_losses.append(loss.item())
#acc = (outputs.argmax(dim=1) == labels).sum().item()
#acc = (np.argmax(logits) == labels).sum().detach().cpu().numpy())

pred_class = torch.argmax(logits)
if pred_class in labels:
    n_correct += 1
else:
    n_wrong += 1

acc_train = (n_correct * 1.0) / (n_correct + n_wrong)
total_acc_train.append(acc_train)
#print(total_acc_train)

# write code here
# to save model eg. model.pth look at pytorch document how to save model

if loss.item() < best_train_loss:
    best_train_loss = loss.item()
    torch.save(model.state_dict(), 'best_model.pt')

print(f'[{epoch + 1}, {idx}] loss: {loss.item()}')
print(running_loss)
clear_output(wait=True)

[30, 79] loss: 0.15687458217144012
0.0

#next(iter(train_loader))

# this code training models on Cross entropy loss

valid_losses = []
#valid_losses = []
best_valid_loss = float('inf')

total_acc_valid = []
acc_valid = 0.0
n_correct = 0.0
n_wrong = 0.0

model.eval()
```

```

for epoch in range(30): # loop over the dataset multiple times
#for epoch in range(2):# loop over the dataset multiple times

    running_loss = 0.0
    with torch.no_grad():
        for (idx, batch) in enumerate(val_loader):
            sentence = batch["Text"]
            inputs = tokenizer(sentence,padding=True,truncation=True,return_tensors='pt')

            # move parameter to device
            inputs = {k:v.to(device) for k,v in inputs.items()}

            # map string labels to class index
            labels = [label_maps[stringtoId] for stringtoId in (batch['Class'])]

            #print("show out: ",np.unique(labels, return_counts=True))
            # convert list to tensor
            labels = torch.tensor(labels).unsqueeze(0)
            labels = labels.to(device)

            # (batch_size, seq_len)
            #print(inputs["input_ids"].shape)

            # zero the parameter gradients
            # optimizer.zero_grad()

            outputs = model(**inputs,labels=labels)
            # you can check
            loss, logits = outputs[:2]

            # loss.backward()
            # optimizer.step()

            valid_losses.append(loss.item())

            pred_class = torch.argmax(logits)
            if pred_class in labels:
                n_correct += 1
            else:
                n_wrong += 1
            acc_valid = (n_correct * 1.0) / (n_correct + n_wrong)
            total_acc_valid.append(acc_valid)

            # write code here
            # to save model eg. model.pth look at pytorch document how to save model

            if loss.item() < best_valid_loss:
                best_valid_loss = loss.item()
                torch.save(model.state_dict(), 'best_model_valid.pt')

```

```
print(f'[{epoch + 1}, {idx}] loss: {loss.item()}')  
print(running_loss)  
clear_output(wait=True)
```

```
[30, 268] loss: 1.429790735244751  
0.0
```

- 4.5 write code to plot both loss and accuracy for training and validation repectively.
- 4.6 write test function to get test accuracy for (4.1,4.2)

```
# write code here for 4.5  
import matplotlib.pyplot as plt  
fig = plt.figure(figsize=(15, 10))  
ax1 = fig.add_subplot(2, 1, 1)  
ax2 = fig.add_subplot(2, 1, 2)  
ax1.plot(train_losses, label = 'train loss')  
ax1.plot(valid_losses, label = 'valid loss')  
ax2.plot(total_acc_train, label = 'train acc')  
ax2.plot(total_acc_valid, label = 'valid acc')  
plt.legend()  
ax1.set_xlabel('epoches')  
ax1.set_ylabel('Losses')  
ax2.set_xlabel('epoches')  
ax2.set_ylabel('Accuracy')
```

Question 5: Training on text classification task on combine two losses Cross Entropy and Supervised Contrastive. (3.5 pts)

- Cross Entropy loss

$$\mathcal{L}_{CE} = -\frac{1}{m} \sum_{i=1}^m y_i \cdot \log(\hat{y}_i)$$

- Supervised Contrastive learning loss

$$\mathcal{L}_{S_{cl}} = -\frac{1}{T} \sum_{i=1}^N \sum_{j=1}^N \mathbf{1}_{y_i=y_j} \log \frac{e^{\text{sim}(h_i, h_j)/\tau}}{\sum_{n=1}^N e^{\text{sim}(h_i, h_n)/\tau}}$$

- detail

- $u_i \sim$ sentence i
- $h_i \sim \text{BERT}(u_i)$ in our case using Roberta as a encoder
- h_i : (batch_size, sequence_len, embed_size)
- h_i is the output of model which is last hidden layers before classifier head in the model architecture
- $\mathbf{1}_{y_i=y_j} \sim$ we select only the sample that come from the same class to compute in each i and j
- $T \sim$ the number of pairs that come from the same classes
- $\tau \sim$ temperature parameter
- $\text{Sim}(x_1, x_2)$: cosine similarity $[-1, 1]$
- λ' is just weighted of cross entropy loss
- Sim function is the cosine similarity
- $N \sim$ the number of samples in a batch

$$\text{sim}(A, B) = \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$

- Loss total

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{S_{cl}} + \lambda' \mathcal{L}_{CE}$$

- you can get cross entropy loss like below

- `outputs = model(input_ids, labels=labels)`
- `loss, logits = outputs[:2]`



```
for epoch in range(30): # loop over the dataset multiple times

    running_loss = 0.0
```

<https://colab.research.google.com/drive/1V30gXTkwCJWfOuQ1-gMxgDjZ7-gakfcR#scrollTo=Ka-LDiXDSyFt&printMode=true>


```

# map string labels to class index
labels = [label_maps[stringtoId] for stringtoId in (batch['Class'])]

# convert list to tensor
labels = torch.tensor(labels).unsqueeze(0)
labels = labels.to(device)

#(batch_size, seq_len)
#print(inputs["input_ids"].shape)

# zero the parameter gradients
optimizer.zero_grad()

outputs = model(**inputs, labels=labels, output_hidden_states=True)

hidden_states = outputs.hidden_states

last_hidden_states = hidden_states[12]

# https://stackoverflow.com/questions/63040954/how-to-extract-and-use-bert-
# (batch_size, seq_len, embed_dim)
h = last_hidden_states[:, 0, :]

# create pair samples
T, h_i, h_j, idx_yij = create_supervised_pair(h, batch['Class'], debug=False)

if h_i is None:
    print("skip this batch")
    skip_time += 1
    continue

# supervised contrastive loss
loss_s_cl = supervised_contrastive_loss(h_i, h_j, h, T, temp=temp, idx_yij=idx_yij)

# cross entropy loss
loss_classify, logits = outputs[:, 2]

# loss total
loss = loss_s_cl + (lamda * loss_classify)

loss.backward()
optimizer.step()

train_losses_.append(loss.item())
#acc = (outputs.argmax(dim=1) == labels).sum().item()
#acc = (np.argmax(logits) == labels).sum().detach().cpu().numpy()

pred_class_ = torch.argmax(logits)
if pred_class_ in labels:
    n_correct_ += 1
else:

```

```

    n_wrong_ += 1

    acc_train_ = (n_correct_ * 1.0) / (n_correct_ + n_wrong_)
    total_acc_train_.append(acc_train_)

    if loss.item() < best_train_loss_:
        best_train_loss_ = loss.item()
        torch.save(model.state_dict(), 'best_model_combine.pt')

    print(f'[{epoch + 1}, {idx}] loss_total: {loss.item()}, loss_s_cl:{loss_s_c

    clear_output(wait=True)

```

```

val_losses_ = []
best_val_loss_ = float('inf')
total_acc_val_ = []
acc_val_ = 0.0
n_correct_ = 0.0
n_wrong_ = 0.0

```

```

model.eval()

```

```

for epoch in range(30): # loop over the dataset multiple times

```

```

    running_loss = 0.0
    with torch.no_grad():

```

```

        for (idx, batch) in enumerate(val_loader):
            sentence = batch["Text"]
            inputs = tokenizer(sentence, padding=True, truncation=True, return_tensors='
            inputs = {k:v.to(device) for k,v in inputs.items()}

```

```

# map string labels to class index
labels = [label_maps[stringtoId] for stringtoId in (batch['Class'])]

# convert list to tensor
labels = torch.tensor(labels).unsqueeze(0)
labels = labels.to(device)

#(batch_size, seq_len)
#print(inputs["input_ids"].shape)

# zero the parameter gradients
#optimizer.zero_grad()

outputs = model(**inputs, labels=labels, output_hidden_states=True)

hidden_states = outputs.hidden_states

last_hidden_states = hidden_states[12]

# https://stackoverflow.com/questions/63040954/how-to-extract-and-use-bei
# (batch_size, seq_len, embed_dim)
h = last_hidden_states[:, 0, :]

# create pair samples
T, h_i, h_j, idx_yij = create_supervised_pair(h, batch['Class'], debug=False)

if h_i is None:
    print("skip this batch")
    skip_time += 1
    continue

# supervised contrastive loss
loss_s_cl = supervised_contrastive_loss(h_i, h_j, h, T, temp=temp, idx_yij=idx_yij)

# cross entropy loss
loss_classify, logits = outputs[:2]

# loss total
loss = loss_s_cl + (lamda * loss_classify)

# loss.backward()
# optimizer.step()

val_losses_.append(loss.item())
#acc = (outputs.argmax(dim=1) == labels).sum().item()
#acc = (np.argmax(logits) == labels).sum().detach().cpu().numpy()

pred_class_ = torch.argmax(logits)
if pred_class_ in labels:
    n_correct_ += 1

```

```

else:
    n_wrong_ += 1

acc_val_ = (n_correct_ * 1.0) / (n_correct_ + n_wrong_)
total_acc_val_.append(acc_val_)

if loss.item() < best_val_loss_:
    best_val_loss_ = loss.item()
    torch.save(model.state_dict(), 'best_model_combine_valid.pt')

print(f'[{epoch + 1}, {idx}] loss_total: {loss.item()}, loss_s_cl:{loss_s_cl}')

clear_output(wait=True)

```

```

# write code here for 4.5
import matplotlib.pyplot as plt
fig = plt.figure(figsize=(15, 10))
ax1 = fig.add_subplot(2, 1, 1)
ax2 = fig.add_subplot(2, 1, 2)
ax1.plot(train_losses_, label = 'train loss')
ax1.plot(valid_losses_, label = 'valid loss')
ax2.plot(total_acc_train_, label = 'train acc')
ax2.plot(total_acc_valid_, label = 'valid acc')
plt.legend()
ax1.set_xlabel('epoches')
ax1.set_ylabel('Losses')
ax2.set_xlabel('epoches')
ax2.set_ylabel('Accuracy')

```

I got CUDA error. I also tried on puffer with various cuda but it still get that error. Moreover, eventhough i tried on colab with GPU and CUDA, it still get CUDA error.

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