Installing Modules

```
!pip install spacy==3
!python -m spacy download en_core_web_sm
!pip install pytorch_lightning torchmetrics tableprint
```

```
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✓ Download and installation successful
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```

Imports

```
# Import Library
import random
import torch, torchtext
from torchtext.legacy import data
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import pandas as pd
import sys, os, pickle
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import spacy
nlp = spacy.load('en core web sm')
import pytorch lightning as pl
import torchmetrics
from pytorch lightning.loggers import CSVLogger
from pytorch_lightning.callbacks import ModelCheckpoint
from sklearn.metrics import confusion matrix
import tableprint as tp
# Manual Seed
SEED = 43
torch.manual_seed(SEED)
    <torch. C.Generator at 0x7f377210c890>
```

Loading Data

Files have been saved to google drive for faster access!

```
!gdown --id 1HmYahgrwNcZREWtUTr6H11ygJufuFcTc
!gdown --id 14hb3DlvmMeEvWhNYXAZjhE3MFS1T8Nte
```

```
!gdown --id 1xwvuoXp35tjE-rV7oA0kq6T42qli344P
```

```
Downloading...
From: <a href="https://drive.google.com/uc?id=1HmYahgrwNcZREWtUTr6H11ygJufuFcTc">https://drive.google.com/uc?id=1HmYahgrwNcZREWtUTr6H11ygJufuFcTc</a>
To: /content/datasetSentences.txt
100% 1.29M/1.29M [00:00<00:00, 4.88MB/s]
Downloading...
From: <a href="https://drive.google.com/uc?id=14hb3DlvmMeEvWhNYXAZjhE3MFS1T8Nte">https://drive.google.com/uc?id=14hb3DlvmMeEvWhNYXAZjhE3MFS1T8Nte</a>
To: /content/sentiment_labels.txt
3.26MB [00:00, 12.4MB/s]
Downloading...
From: <a href="https://drive.google.com/uc?id=1xwvuoXp35tjE-rV7oA0kq6T42qli344P">https://drive.google.com/uc?id=1xwvuoXp35tjE-rV7oA0kq6T42qli344P</a>
To: /content/dictionary.txt
```

The sentiments are read for the phrases (with their ids as the mapping index)

```
sentiment_labels = pd.read_csv("sentiment_labels.txt", sep="|", header=0)
sentiment_labels.columns = ["id", "sentiment"]
sentiment labels.head()
```

	id	sentiment
0	0	0.50000
1	1	0.50000
2	2	0.44444
3	3	0.50000
4	4	0.42708

12.0MB [00:00, 33.0MB/s]

The sentiments are mapped onto a discrete set of 5-values (and will be referred to as the label)

	id	label
0	0	2
1	1	2
2	2	2
3	3	2
4	4	2

The sentences are read here!

sentences = pd.read_csv("datasetSentences.txt", index_col="sentence_index",sep="\t
sentences.head()

sentence

sentence_index	
1	The Rock is destined to be the 21st Century 's
2	The gorgeously elaborate continuation of `` Th
3	Effective but too-tepid biopic
4	If you sometimes like to go to the movies to h
5	Emerges as something rare , an issue movie tha

The dictionary.txt file maps the phrases to the ids

```
dictionary = pd.read_csv("dictionary.txt", sep="|", header=0)
dictionary.columns = ["phrase", "id"]
dictionary.head()
```

	phrase	id
0	i,	22935
1	! "	18235
2	! Alas	179257
3	! Brilliant	22936
4	! Brilliant !	40532

Here, the mapping is done from phrase ids to phrases themselves, followed by mapping of sentences to the labels.

sentence_phrase_merge = pd.merge(sentences, dictionary, left_on='sentence', right_odataset = pd.merge(sentence_phrase_merge, sentiment_labels, on='id')
dataset.head()

	sentence	phrase	id	label
0	The Rock is destined to be the 21st Century 's	The Rock is destined to be the 21st Century 's	226166	3
1	The gorgeously elaborate continuation of `` Th	The gorgeously elaborate continuation of `` Th	226300	4
2	Effective but too-tepid biopic	Effective but too-tepid biopic	13995	2
3	If you sometimes like to go to the movies to h	If you sometimes like to go to the movies to h	14123	3

The dataset is cleaned

dataset['sentence_cleaned'] = dataset['sentence'].str.replace(r"\s('s|'d|'re|'ll|')
dataset.head()

d	sentence_cleane	label	id	phrase	sentence	
st	The Rock is destine to be the 21 Century's	3	226166	The Rock is destined to be the 21st Century 's	The Rock is destined to be the 21st Century 's	0
e	The gorgeous elabora continuation of Th	4	226300	The gorgeously elaborate continuation of `` Th	The gorgeously elaborate continuation of `` Th	1
۱–	Effective but to			Effective hut too-tenid	Effective but too-tenid	

Only the cleaned sentences and the labels are retained

```
dataset.drop(['phrase', 'id', 'sentence'], inplace=True,axis=1)
dataset.columns = ["label", "sentence"]
dataset.head()
```

sentence	label	
The Rock is destined to be the 21st Century's	3	0
The gorgeously elaborate continuation of `` Th	4	1
Effective but too-tepid biopic	2	2
If you sometimes like to go to the movies to h	3	3
Emerges as something rare, an issue movie tha	4	4

▼ Dataset Preview

Let's just preview the dataset.

dataset.head()

label		sentence
0	3	The Rock is destined to be the 21st Century's
1	4	The gorgeously elaborate continuation of `` Th
2	2	Effective but too-tepid biopic
3	3	If you sometimes like to go to the movies to h
4	4	Emerges as something rare, an issue movie tha

```
dataset.shape
     (11286, 2)

dataset.label.value_counts()

1      2971
      3      2966
      2      2144
      4      1773
      0      1432
      Name: label, dtype: int64
```

Defining Fields

Now we shall be defining Label as a LabelField, which is a subclass of Field that sets sequen tial to False (as it's our numerical category class). Sentence is a standard Field object, where we have decided to use the spaCy tokenizer and convert all the text to lower- case.

```
Sentence = data.Field(sequential = True, tokenize = 'spacy', batch_first =True, included = data.LabelField(tokenize = 'spacy', is_target=True, batch_first =True, sequential = data.LabelField(tokenize = 'spacy', is_target=True, batch_first =True, sequential = data.LabelField(tokenize = 'spacy', is_target=True, batch_first =True, included = data.LabelField(tokenize = 'spacy', batch_first =True, included = data.LabelField(tokenize = 'spacy', is_target=True, batch_first =True, included = data.LabelField(tokenize = 'spacy', is_target=True, batch_first =True, sequential = data.LabelField(tokenize = 'spacy', is_target=True, batch_first = data
```

Having defined those fields, we now need to produce a list that maps them onto the list of rows that are in the CSV:

```
fields = [('sentence', Sentence),('label',Label)]
```

Armed with our declared fields, lets convert from pandas to list to torchtext. We could also use TabularDataset to apply that definition to the CSV directly but showing an alternative approach too.

```
example = [data.Example.fromlist([dataset.sentence[i],dataset.label[i]], fields) for stanfordDataset = data.Dataset(example, fields)
```

Finally, we can split into training, testing, and validation sets by using the split() method:

```
(train, test) = stanfordDataset.split(split_ratio=[0.70, 0.30], random_state=randor
```

```
Double-click (or enter) to edit
(len(train), len(test))
     (7900, 3386)
An example from the dataset:
vars(train.examples[10])
     {'label': 1,
       sentence': ['Disney',
       'again',
       'ransacks',
       'its',
        'archives',
       'for',
       'a',
       'quick',
       '-',
       'buck',
       'sequel',
        '.']}
" ".join((vars(train.examples[10]))['sentence'])
```

Building Vocabulary

We will build vocabulary only using the train dataset and not the test dataset

'Disney again ransacks its archives for a quick - buck sequel .'

```
Sentence.build_vocab(train)
Label.build vocab(train)
```

By default, torchtext will add two more special tokens, for unknown words and, a padding token that will be used to pad all our text to roughly the same size to help with efficient batching on the GPU.

```
print('Size of input vocab : ', len(Sentence.vocab))
print('Size of label vocab : ', len(Label.vocab))
print('Top 10 words appreared repeatedly :', list(Sentence.vocab.freqs.most_common
print('Labels : ', Label.vocab.stoi)

Size of input vocab : 16378
Size of label vocab : 5
Top 10 words appreared repeatedly : [('.', 7452), (',', 6567), ('the', 5603),
Labels : defaultdict(None, {1: 0, 3: 1, 2: 2, 4: 3, 0: 4})
```

Initializing GPU as the device

Save the vocabulary for later use

```
with open('tokenizer.pkl', 'wb') as tokens:
    pickle.dump(Sentence.vocab.stoi, tokens)
```

Defining Our Model

▼ Boilerplate code for PyTorchLightning

```
class TL(pl.LightningModule):
   def init (self):
        super(TL, self).__init__()
        self.train accm = torchmetrics.Accuracy()
        self.valid accm = torchmetrics.Accuracy()
        self.train_acc = torch.tensor(0.)
        self.avg_train_loss = torch.tensor(0.)
        self.table_context = None
   def training_step(self, batch, batch_idx):
        sent, sent_lengths = batch.sentence
        output = self(sent, sent lengths)
        loss_train = self.loss(output, batch.label).squeeze()
        predictions = torch.argmax(output, dim=1)
        acc_train = self.train_accm(predictions, batch.label)
        return loss train
   def validation_step(self, batch, batch_idx):
        sent, sent_lengths = batch.sentence
        output = self(sent, sent_lengths)
        loss_valid = self.loss(output, batch.label).squeeze()
        predictions = torch.argmax(output, dim=1)
        acc valid = self.valid accm(predictions, batch.label)
        return {"loss": loss_valid, "p": predictions, "y": batch.label}
```

```
def training_epoch_end(self, outputs):
          self.train acc = self.train_accm.compute() * 100
          self.avg train loss = torch.stack([x['loss'] for x in outputs]).mean()
          self.train accm.reset()
def validation epoch end(self, outputs):
          if trainer.running sanity check:
                    return
          valid acc = self.valid accm.compute() * 100
          avg valid loss = torch.stack([x['loss'] for x in outputs]).mean()
          metrics = {'epoch': self.current epoch+1, 'Train Acc': self.train acc, 'Train Acc': self.train acc': s
          if self.table context is None:
                    self.table context = tp.TableContext(headers=['epoch', 'Train Acc', 'T
                    self.table_context.__enter__()
          self.table context([self.current epoch+1, self.train acc.item(), self.avg -
          self.logger.log metrics(metrics)
          self.valid accm.reset()
          if self.current epoch == self.trainer.max epochs - 1:
                    self.validation end(outputs)
def validation end(self, outputs):
          pb = [x['p'] \text{ for } x \text{ in outputs}]
          yb = [x['y'] \text{ for } x \text{ in outputs}]
          p = torch.cat(pb, 0).view(-1).cpu()
          y = torch.cat(yb, 0).view(-1).cpu()
          self.table context. exit ()
          # confusion matrix here!
          cm = confusion matrix(y.tolist(), p.tolist())
          df cm = pd.DataFrame(cm, columns=np.unique(y), index = np.unique(y))
          df cm.index.name = 'Actual'
          df cm.columns.name = 'Predicted'
          plt.figure(figsize = (10,7))
          sns.set(font scale=1.4)#for label size
          fig = sns.heatmap(df cm, annot=True, cmap="Blues",annot kws={"size": 16})
```

The Actual Model

```
# Dense layer
        self.fc = nn.Linear(hidden_dim, output_dim)
    def forward(self, text, text lengths):
        embedded = self.embedding(text)
        packed_embedded = nn.utils.rnn.pack_padded_sequence(embedded, text_lengths
        packed_output, (hidden, cell) = self.encoder(packed embedded)
        dense outputs = self.fc(hidden)
        return dense outputs[-1]
    def configure optimizers(self):
        optim = torch.optim.Adam(self.parameters())
        return optim
# Define hyperparameters
size of vocab = len(Sentence.vocab)
embedding dim = 100
num hidden nodes = 20
num \ output \ nodes = 5
num layers = 4
dropout = 0.4
# Instantiate the model
model = classifier(size of vocab, embedding dim, num hidden nodes, num output node:
```

▼ Model Checkpoint

This saves the best model (best => model with lowest val loss)

```
checkpoint_callback = ModelCheckpoint(
    monitor='val_loss',
    dirpath='/content',
    filename='sst-{epoch:02d}-{val_loss:.2f}',
    mode='min'
)

!rm -rf csv_logs
csvlogger = CSVLogger('csv_logs', name='END2 Assign 7_1_TL', version=0)
trainer = pl.Trainer(max_epochs=20, num_sanity_val_steps=1, logger=csvlogger, gpus:trainer.fit(model, train_dataloader=train_iterator, val_dataloaders=test_iterator)
checkpoint_callback.best_model_path
```

С→

GPU available: True, used: True

TPU available: False, using: 0 TPU cores LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0]

Name	Type	Params		
0 train_accm 1 valid_accm 2 loss 3 embedding 4 encoder 5 fc		0 0 0 1.6 M 19.8 K 105		
1.7 M Trainable params 0 Non-trainable params 1.7 M Total params 6.631 Total estimated model params size (MB)				

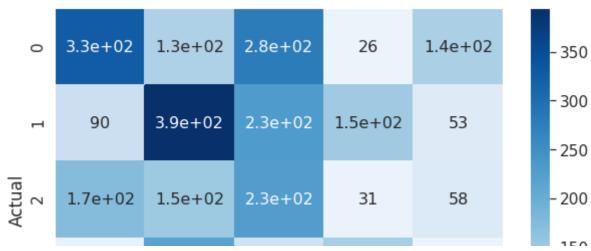
Validation sanity check: 0%

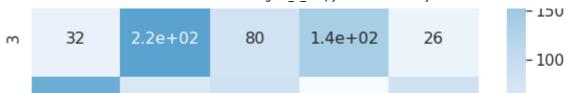
0/1 [00:00<?, ?it/s]

Epoch 19: 100%

353/353 [00:03<00:00, 102.39it/s, loss=0.203, v_num=0]

epoch	Train Acc	Train Loss	Valid Acc	Valid Loss
1	26.38	1.5746	30.018	1.5603
2	30.886	1.5308	32.487	1.51
3	37.709	1.4197	34.879	1.4888
4	44.81	1.2915	36.799	1.4885
5	50.962	1.1527	34.82	1.562
6	57.532	1.0284	36.031	1.6687
7	63.532	0.90568	35.204	1.85
8	68.924	0.80161	35.145	1.9615
9	73.595	0.70365	34.495	2.1086
10	77.354	0.62018	35.263	2.1964
11	80.241	0.55864	34.79	2.3029
12	83.038	0.49319	34.672	2.4138
13	85.848	0.43099	35.351	2.5511
14	86.911	0.38719	33.579	2.6121
15	88.481	0.35891	34.997	2.7361
16	89.418	0.32695	34.406	2.8067
17	91.025	0.29164	34.702	2.8948
18	91.797	0.26694	34.377	2.9899
19	92.253	0.25037	34.584	3.0636
20	92.962	0.22841	34.584	3.0698





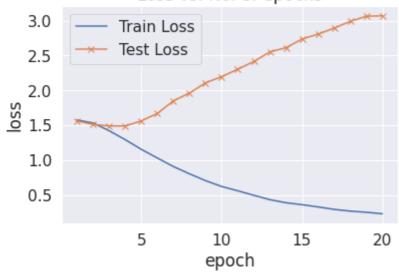
▼ Model Training and Evaluation

First define the optimizer and loss functions

```
root='./csv_logs/' + 'END2 Assign 7_1_TL' + '/'
dirlist = [ item for item in os.listdir(root) if os.path.isdir(os.path.join(root, :
metricfile = root + dirlist[-1:][0] + '/metrics.csv'
metrics = pd.read_csv(metricfile)

plt.plot(metrics['epoch'], metrics['Train Loss'], label="Train Loss")
plt.plot(metrics['epoch'], metrics['Valid Loss'], '-x', label="Test Loss")
plt.xlabel('epoch')
plt.ylabel('loss')
plt.legend()
plt.title('Loss vs. No. of epochs');
```

Loss vs. No. of epochs



```
plt.plot(metrics['epoch'], metrics['Train Acc'], label="Train Acc")
plt.plot(metrics['epoch'], metrics['Valid Acc'], '-x', label="Test Acc")
plt.xlabel('epoch')
plt.ylabel('accuracy')
plt.legend()
plt.title('Accuracy vs. No. of epochs');
```

Accuracy vs. No. of epochs



Model Testing

```
Э
                              ΤU
                                        TD
                                                 ZU
#load weights and tokenizer
model = model.to(device)
model.eval()
tokenizer file = open('./tokenizer.pkl', 'rb')
tokenizer = pickle.load(tokenizer file)
#inference
def classify sentence(sentence):
    categories = {0: "Worst", 1:"Negative", 2:"Neutral", 3:"Positive", 4:"Great"}
    # tokenize the sentence
    tokenized = [tok.text for tok in nlp.tokenizer(sentence)]
    # convert to integer sequence using predefined tokenizer dictionary
    indexed = [tokenizer[t] for t in tokenized]
    # compute no. of words
    length = [len(indexed)]
    # convert to tensor
    tensor = torch.LongTensor(indexed).to(device)
    # reshape in form of batch, no. of words
    tensor = tensor.unsqueeze(1).T
    # convert to tensor
    length tensor = torch.LongTensor(length).to(device)
    # Get the model prediction
    with torch.no grad():
      prediction = model(tensor, length tensor)
      _, pred = torch.max(prediction, 1)
    # return categories[pred.item()]
    return pred.item()
classify_sentence("This is something you will regret.")
    1
for i in np.random.randint(0,len(test),10):
```

sent = " ".ioin((vars(test.examples[i]))['sentence'])

```
pred = classify_sentence(sent)
label = (vars(test.examples[i]))['label']
print(f'Sentence: {sent[:60]} \t Predicted: {pred} \t Actual: {label}')
```

```
Sentence: Terrific casting and solid execution give all three stories
                                                                         Pred
Sentence: If it seems like a minor miracle that its septuagenarian sta
                                                                         Pred
Sentence: Like its script , which nurses plot holes gaping enough to p
                                                                         Pred
Sentence: Murder by Numbers ' is n't a great movie , but it 's a perfe
                                                                         Pred
Sentence: The weird thing about The Santa Clause 2 , purportedly a chi
                                                                         Pred
Sentence: Allen shows he can outgag any of those young whippersnappers
                                                                         Pred
Sentence: I 've had more interesting -- and , dare I say , thematicall
                                                                         Pred
Sentence: Miller has crafted an intriguing story of maternal instincts
                                                                         Pred
Sentence: that it 'll probably be the best and most mature comedy of t
                                                                         Pred
Sentence: A bittersweet contemporary comedy about benevolent deception
                                                                         Pred
```

✓ 0s completed at 9:34 AM