Installing Modules

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

```
    Requirement already satisfied: wasabi<1.1.0,>=0.8.1 in /usr/local/lib/pytho
    Requirement already satisfied: typer<0.4.0,>=0.3.0 in /usr/local/lib/python
    Requirement already satisfied: preshed<3.1.0,>=3.0.2 in /usr/local/lib/pytho
    Requirement already satisfied: numpy>=1.15.0 in /usr/local/lib/python3.7/dis
    Requirement already satisfied: smart-open<4.0.0,>=2.2.0 in /usr/local/lib/py
    Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-pa
    Requirement already satisfied: pyparsing>=2.0.2 in /usr/local/lib/python3.7/
    Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /u
    Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.
    Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist
    Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3
    Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.7/
    Requirement already satisfied: click<7.2.0,>=7.1.1 in /usr/local/lib/python
    ✔ Download and installation successful
    You can now load the package via spacy.load('en_core_web_sm')
    Requirement already satisfied: pytorch_lightning in /usr/local/lib/python3.
    Requirement already satisfied: torchmetrics in /usr/local/lib/python3.7/dist
    Requirement already satisfied: tableprint in /usr/local/lib/python3.7/dist-p
    Requirement already satisfied: packaging in /usr/local/lib/python3.7/dist-pa
    Requirement already satisfied: torch>=1.4 in /usr/local/lib/python3.7/dist-p
    Requirement already satisfied: future>=0.17.1 in /usr/local/lib/python3.7/di
    Requirement already satisfied: PyYAML<=5.4.1,>=5.1 in /usr/local/lib/python
    Requirement already satisfied: numpy>=1.17.2 in /usr/local/lib/python3.7/dis
    Requirement already satisfied: pyDeprecate==0.3.0 in /usr/local/lib/python3
    Requirement already satisfied: tqdm>=4.41.0 in /usr/local/lib/python3.7/dist
    Requirement already satisfied: tensorboard!=2.5.0,>=2.2.0 in /usr/local/lib/
    Requirement already satisfied: fsspec[http]!=2021.06.0,>=2021.05.0 in /usr/l
    Requirement already satisfied: wcwidth in /usr/local/lib/python3.7/dist-pack
    Requirement already satisfied: pyparsing>=2.0.2 in /usr/local/lib/python3.7/
    Requirement already satisfied: typing-extensions in /usr/local/lib/python3.
    Requirement already satisfied: six>=1.10.0 in /usr/local/lib/python3.7/dist
    Requirement already satisfied: grpcio>=1.24.3 in /usr/local/lib/python3.7/di
    Requirement already satisfied: setuptools>=41.0.0 in /usr/local/lib/python3
    Requirement already satisfied: werkzeug>=0.11.15 in /usr/local/lib/python3.
    Requirement already satisfied: google-auth<2,>=1.6.3 in /usr/local/lib/pytho
    Requirement already satisfied: absl-py>=0.4 in /usr/local/lib/python3.7/dist
    Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python
    Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in /usr/loca
    Requirement already satisfied: protobuf>=3.6.0 in /usr/local/lib/python3.7/
    Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.7/
    Requirement already satisfied: wheel>=0.26; python_version >= "3" in /usr/l
    Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in /usr/local/
    Requirement already satisfied: aiohttp; extra == "http" in /usr/local/lib/py
    Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/pytho
    Requirement already satisfied: rsa<5,>=3.1.4; python_version >= "3.6" in /u
    Requirement already satisfied: cachetools<5.0,>=2.0.0 in /usr/local/lib/pyt
    Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3
    Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /u
    Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.
    Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist
    Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/py
    Requirement already satisfied: importlib-metadata; python_version < "3.8" in
```

```
Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.7/di
Requirement already satisfied: async-timeout<4.0,>=3.0 in /usr/local/lib/py
Requirement already satisfied: yarl<2.0,>=1.0 in /usr/local/lib/python3.7/d
Requirement already satisfied: multidict<7.0,>=4.5 in /usr/local/lib/python
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /usr/local/lib/pytho
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.7/
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-p
```

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

import collections



# Manual Seed
SEED = 43
torch.manual_seed(SEED)
```

```
<torch._C.Generator at 0x7fd3390bd890>
```

Loading Data

Files have been saved to google drive for faster access!

```
!gdown --id 1HmYahgrwNcZREWtUTr6H11ygJufuFcTc
!gdown --id 14hb3DlvmMeEvWhNYXAZjhE3MFS1T8Nte
!gdown --id 1xwvuoXp35tjE-rV7oAOkq6T42qli344P
```

```
Downloading...
From: https://drive.google.com/uc?id=1HmYahgrwNcZREWtUTr6H11ygJufuFcTc
To: /content/datasetSentences.txt
100% 1.29M/1.29M [00:00<00:00, 83.2MB/s]
Downloading...
From: https://drive.google.com/uc?id=14hb3DlvmMeEvWhNYXAZjhE3MFS1T8Nte
To: /content/sentiment_labels.txt
3.26MB [00:00, 101MB/s]
Downloading...
From: https://drive.google.com/uc?id=1xwvuoXp35tjE-rV7oAOkq6T42qli344P
To: /content/dictionary.txt
12.0MB [00:00, 106MB/s]
```

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

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

```
sentiment_labels["label"] = pd.cut(sentiment_labels.sentiment, [0, 0.2, 0.4, 0.6, 
                                          include_lowest=True,
                                          labels=[0, 1, 2, 3, 4])
sentiment_labels.drop('sentiment', inplace=True, axis=1)
sentiment_labels.head()
```

	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	! '	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_
dataset = pd.merge(sentence_phrase_merge, sentiment_labels, on='id')
dataset.head()
```

	sentence	phrase	id	label
	The gorgeously elaborate continuation	The gorgeously elaborate continuation		

The dataset is cleaned

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

	sentence	phrase	id	label	sentence_cleaned
0	The Rock is destined to be the 21st Century 's...	The Rock is destined to be the 21st Century 's...	226166	3	The Rock is destined to be the 21st Century's ...
1	The gorgeously elaborate continuation of `` Th...	The gorgeously elaborate continuation of `` Th...	226300	4	The gorgeously elaborate continuation of `` Th...
	Effective but too-tepid	Effective but too-tepid			Effective but too-

Only the cleaned sentences and the labels are retained

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

Let's just preview the dataset.

```
dataset.head()
```

```
    label                    sentence
```

```
dataset.shape
```

```
    (11286, 2)
     2     2          Effective but too-tepid biopic
```

```
dataset.label.value_counts()
```

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

Defining Fields

```
from sklearn.model_selection import train_test_split

train_data, test_data = train_test_split(dataset, test_size=0.3)
```

```
print(f'Number of Train Examples: {len(train_data)}')
print(f'Number of Test Examples: {len(test_data)}')
```

```
    Number of Train Examples: 7900
    Number of Test Examples: 3386
```

```
from torchtext.data.utils import get_tokenizer
en_tokenizer = get_tokenizer('spacy', language='en_core_web_sm')
```

```
def build_vocab(df, tokenizer, **vocab_kwarg):

    token_freqs = collections.Counter()

    for index, row  in df.iterrows():
        tokens = tokenizer(row['sentence'])
        token_freqs.update(tokens)

    vocab = torchtext.vocab.Vocab(token_freqs, **vocab_kwarg)

    return vocab
```

```
en_vocab = build_vocab(train_data, en_tokenizer)
```

```
def data_process(df):
    data = []
    for index, row in df.iterrows():
      en_tensor_ = torch.tensor([en_vocab[token] for token in en_tokenizer(row['se
                            dtype=torch.long)
```

```
                                dtype=torch.long)
      label = torch.tensor(row['label'], dtype=torch.long)
      data.append((en_tensor_, label))
    return data

train_dataset = data_process(train_data)
# val_dataset = data_process(val_df)
test_dataset = data_process(test_data)
```

Let's define the collator that will be used to create batches

```
class Collator:
    def __init__(self, pad_idx):

        self.pad_idx = pad_idx

    def collate(self, batch):
        text, labels = zip(*batch)
        labels = torch.LongTensor(labels)
        text = nn.utils.rnn.pad_sequence(text, padding_value=self.pad_idx, batch_f
        return text, labels
```

The collator is intitialized along with the padding token

```
pad_token = '<PAD>'
pad_idx = en_vocab[pad_token]
print(pad_idx)
collator = Collator(pad_idx)
```

```
    0
```

Build the dataset

```
batch_size = 32

train_loader = torch.utils.data.DataLoader(train_dataset,
                                            batch_size,
                                            shuffle = True,
                                            collate_fn = collator.collate
                                          )

test_loader = torch.utils.data.DataLoader(test_dataset,
                                            batch_size,
                                            shuffle = False,
                                            collate_fn = collator.collate
                                          )


device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

Save the vocabulary for later use

```
with open('tokenizer.pkl', 'wb') as tokens:
    pickle.dump(en_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):
        input, target = batch
        output = self(input)
        loss_train = self.loss(output, target).squeeze()
        predictions = torch.argmax(output, dim=1)
        acc_train = self.train_accm(predictions, target)
        return loss_train

    def validation_step(self, batch, batch_idx):
        input, target = batch
        output = self(input)
        loss_valid = self.loss(output, target).squeeze()
        predictions = torch.argmax(output, dim=1)
        acc_valid = self.valid_accm(predictions, target)
        return {"loss": loss_valid, "p": predictions, "y": target}

    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, 'Tr
        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'] for x in outputs]
        yb = [x['y'] for x 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

```
class classifier(TL):
    def __init__(self, vocab_size, embedding_dim, hidden_dim, output_dim, n_layers
        super(classifier, self).__init__()

        self.loss = nn.CrossEntropyLoss()
        self.lr = 1e-3

        # Embedding layer
        self.embedding = nn.Embedding(vocab_size, embedding_dim)

        # LSTM layer
        self.encoder = nn.LSTM(embedding_dim,
                           hidden_dim,
                           num_layers=n_layers,
                           dropout=dropout,
                           batch_first=True)

        # Dense layer
        self.fc = nn.Linear(hidden_dim, output_dim)

    def forward(self, text):

        embedded = self.embedding(text)
        # packed_embedded = nn.utils.rnn.pack_padded_sequence(embedded, text_lengt
        packed_output, (hidden, cell) = self.encoder(embedded)
        dense_outputs = self.fc(hidden)
        return dense_outputs[-1]

    def configure_optimizers(self):
        optim = torch.optim.Adam(self.parameters())
        return optim
        return optim
```

```
len(en_vocab)
```

```
    16378
```

```
# Define hyperparameters
size_of_vocab = len(en_vocab)
embedding_dim = 100
num_hidden_nodes = 20
num_output_nodes = 5
num_layers = 2
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}',
    filename='sst',
    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_loader, val_dataloaders=test_loader)
checkpoint_callback.best_model_path
```

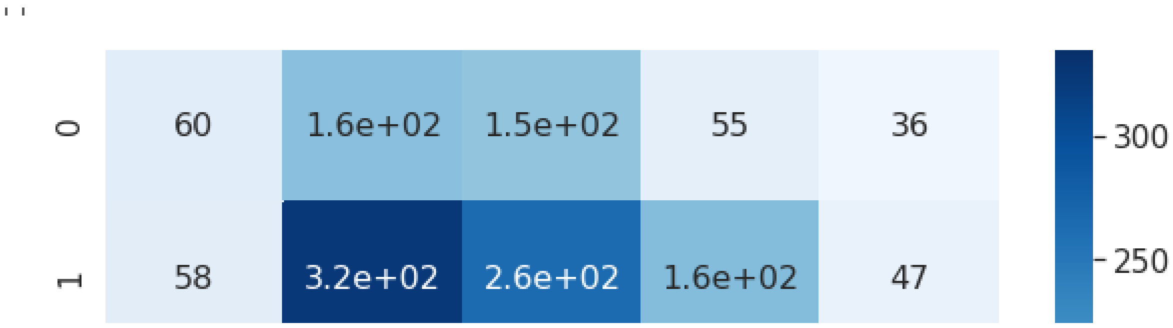
```
GPU available: True, used: True
TPU available: False, using: 0 TPU cores
LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0]

  | Name        | Type             | Params
-------------------------------------------------
0 | train_accm  | Accuracy         | 0
1 | valid_accm  | Accuracy         | 0
2 | loss        | CrossEntropyLoss | 0
3 | embedding   | Embedding        | 1.6 M
4 | encoder     | LSTM             | 13.1 K
5 | fc          | Linear           | 105
-------------------------------------------------
1.7 M     Trainable params
0         Non-trainable params
1.7 M     Total params
6.604     Total estimated model params size (MB)
```

```
Validation sanity check: 0%                                                0/1 [00:00<?, ?it/s]

Epoch 19: 100%                     353/353 [00:02<00:00, 122.73it/s, loss=0.343, v_num=0]
```

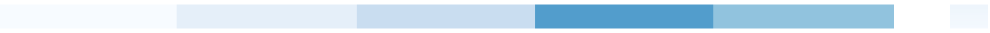
epoch	Train Acc	Train Loss	Valid Acc	Valid Loss
1	26.481	1.5738	25.307	1.5768
2	26.62	1.5705	26.019	1.5752
3	26.57	1.57	27.082	1.5743
4	26.962	1.5692	25.842	1.5763
5	27.215	1.5663	25.694	1.5767
6	27.316	1.5574	26.403	1.5716
7	33.063	1.4942	28.529	1.5997
8	42.949	1.3551	29.829	1.6569
9	52.823	1.1813	30.006	1.7388
10	62.241	1.0161	30.035	1.8491
11	68.633	0.87763	31.276	2.0389
12	74.405	0.75788	30.951	2.0378
13	78.848	0.65064	32.162	2.2488
14	81.962	0.5633	31.719	2.3266
15	85.266	0.4895	31.66	2.5752
16	86.304	0.44724	30.892	2.5232
17	87.722	0.41379	31.512	2.6002
18	88.975	0.37405	31.896	2.6794
19	90.57	0.32838	32.132	2.794
20	91.608	0.29901	31.571	2.7736



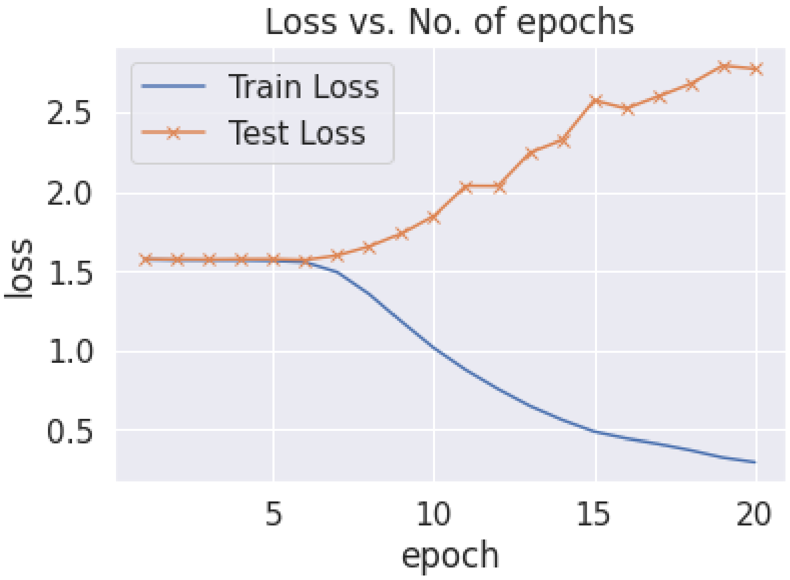
Model Training and Evaluation

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');
```



```
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');
```

Model Testing

```
#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]
    # convert to tensor
    tensor = torch.LongTensor(indexed).to(device)
    # reshape in form of batch, no. of words
    tensor = tensor.unsqueeze(1).T
    # tensor = sentence.unsqueeze(1).T.to(device)
    # Get the model prediction
    with torch.no_grad():
      prediction = model(tensor)

      _, pred = torch.max(prediction, 1)

    # return categories[pred.item()]
    return pred.item()


classify_sentence("This is something you will regret.")
```

```
2
```

```
for i in np.random.randint(0,len(test_data),10):
  sent = test_data.iloc[i,1]
  label = test_data.iloc[i,0]
  pred = classify_sentence(sent)
  print(f'Sentence: {sent[:60]} \t Predicted: {pred} \t Actual: {label}')
```

```
Sentence: The movie is concocted and carried out by folks worthy of sc    Pred
Sentence: Not even Felinni would know what to make of this Italian fre    Pred
Sentence: Some elements of it really blow the big one , but other part    Pred
Sentence: It's that good .       Predicted: 2    Actual: 4
Sentence: Tries to work in the same vein as the brilliance of Animal H    Pred
Sentence: `` Birthday Girl '' is an actor's movie first and foremost .    Pred
Sentence: Thanks largely to Williams , all the interesting development    Pred
Sentence: The off-center humor is a constant , and the ensemble gives     Pred
```

```
Sentence: The boys ' sparring , like the succession of blows dumped on   Pred
Sentence: They should have found Orson Welles ' great-grandson .         Pred
```

✓ 0s completed at 8:14 AM ● ✕