ICP-10 Neural Networks & Deep Learning

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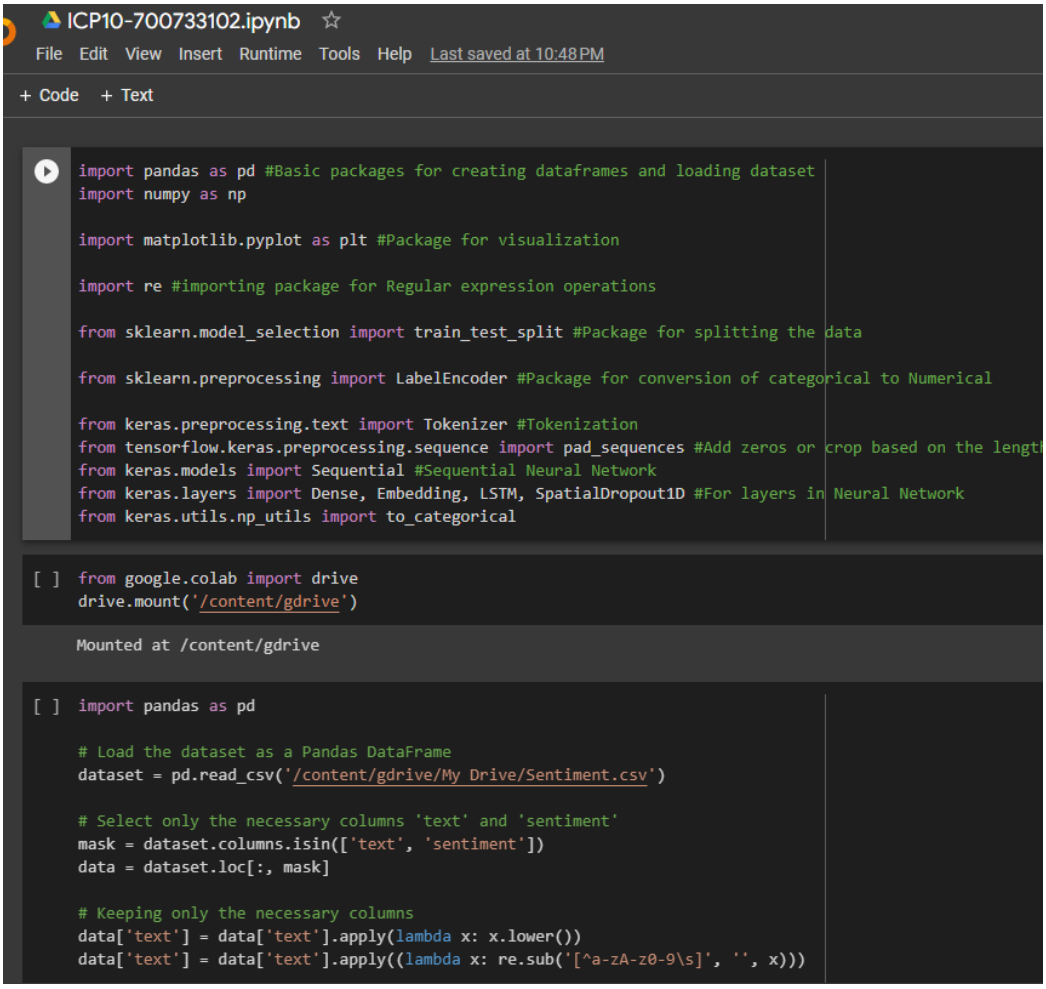
GitHub link: https://github.com/niryarjessy22/ICP-10-Assign.git

Video link: https://drive.google.com/file/d/1oR-Sgi3iPp06XIQlLgm8AIqpUxOMsXA9/view?usp=share_link

In class programming: 1. Save the model and use the saved model to predict on new text data (ex, “A lot of good things are happening. We are respected again throughout the world, and that's a great thing. @realDonaldTrump”)

2. Apply GridSearchCV on the source code provided in the class



ICP10-700733102.ipynb

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```
import pandas as pd #Basic packages for creating dataframes and loading dataset
import numpy as np

import matplotlib.pyplot as plt #Package for visualization

import re #importing package for Regular expression operations

from sklearn.model_selection import train_test_split #Package for splitting the data

from sklearn.preprocessing import LabelEncoder #Package for conversion of categorical to Numerical

from keras.preprocessing.text import Tokenizer #Tokenization
from tensorflow.keras.preprocessing.sequence import pad_sequences #Add zeros or crop based on the length
from keras.models import Sequential #Sequential Neural Network
from keras.layers import Dense, Embedding, LSTM, SpatialDropout1D #For layers in Neural Network
from keras.utils.np_utils import to_categorical
```

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

```
Mounted at /content/gdrive
```

```
[ ] import pandas as pd

    # Load the dataset as a Pandas DataFrame
    dataset = pd.read_csv('/content/gdrive/My Drive/Sentiment.csv')

    # Select only the necessary columns 'text' and 'sentiment'
    mask = dataset.columns.isin(['text', 'sentiment'])
    data = dataset.loc[:, mask]

    # Keeping only the necessary columns
    data['text'] = data['text'].apply(lambda x: x.lower())
    data['text'] = data['text'].apply((lambda x: re.sub('[^a-zA-z0-9\s]', '', x)))
```

Use Case Description:

1. Sentiment Analysis on the Twitter dataset

```
[ ]  for idx, row in data.iterrows():
         row[0] = row[0].replace('rt', ' ') #Removing Retweets
         max_fatures = 2000
     tokenizer = Tokenizer(num_words=max_fatures, split=' ') #Maximum words is 2000 to tokenize sentence
     tokenizer.fit_on_texts(data['text'].values)
     X = tokenizer.texts_to_sequences(data['text'].values) #taking values to feature matrix
     X = pad_sequences(X) #Padding the feature matrix

     embed_dim = 128 #Dimension of the Embedded layer
     lstm_out = 196 #Long short-term memory (LSTM) layer neurons
     def createmodel():
         model = Sequential() #Sequential Neural Network
         model.add(Embedding(max_fatures, embed_dim,input_length = X.shape[1])) #input dimension 2000 Neurons, output dimension 128 Neurons
         model.add(LSTM(lstm_out, dropout=0.2, recurrent_dropout=0.2)) #Drop out 20%, 196 output Neurons, recurrent dropout 20%
         model.add(Dense(3,activation='softmax')) #3 output neurons[positive, Neutral, Negative], softmax as activation
         model.compile(loss = 'categorical_crossentropy', optimizer='adam',metrics = ['accuracy']) #Compiling the model
         return model
     # print(model.summary())
     labelencoder = LabelEncoder() #Applying label Encoding on the label matrix
     integer_encoded = labelencoder.fit_transform(data['sentiment']) #fitting the model
     y = to_categorical(integer_encoded)
     X_train, X_test, Y_train, Y_test = train_test_split(X,y, test_size = 0.33, random_state = 42) #67% training data, 33% test data split
     batch_size = 32 #Batch size 32
     model = createmodel() #Function call to Sequential Neural Network
     model.fit(X_train, Y_train, epochs = 1, batch_size=batch_size, verbose = 2) #verbose the higher, the more messages
     score,acc = model.evaluate(X_test,Y_test,verbose=2,batch_size=batch_size) #evaluating the model
     print(score)
     print(acc)
```

```
291/291 - 42s - loss: 0.8306 - accuracy: 0.6441 - 42s/epoch - 144ms/step
144/144 - 3s - loss: 0.7514 - accuracy: 0.6791 - 3s/epoch - 22ms/step
0.7513718008995056
0.6791175007820129
```

```
[ ]  print(model.metrics_names) #metrics of the model
```

```
['loss', 'accuracy']
```

```
#1. Save the model and use the saved model to predict on new text data.
```

```
model.save('sentimentAnalysis.h5') #Saving the model
```

```
from keras.models import load_model #Importing the package for importing the saved model
model= load_model('sentimentAnalysis.h5') #loading the saved model
```

```
print(integer_encoded)
print(data['sentiment'])
```

```
[1 2 1 ... 2 0 2]
0         Neutral
1        Positive
2         Neutral
3        Positive
4        Positive
           ...
13866    Negative
13867    Positive
13868    Positive
13869    Negative
13870    Positive
Name: sentiment, Length: 13871, dtype: object
```

```
# Predicting on the text data
sentence = ['A lot of good things are happening. We are respected again throughout the world, and that is a great thing.@realDonaldTrump']
sentence = tokenizer.texts_to_sequences(sentence) # Tokenizing the sentence
sentence = pad_sequences(sentence, maxlen=28, dtype='int32', value=0) # Padding the sentence
sentiment_probs = model.predict(sentence, batch_size=1, verbose=2)[0] # Predicting the sentence text
sentiment = np.argmax(sentiment_probs)

print(sentiment_probs)
if sentiment == 0:
    print("Neutral")
elif sentiment < 0:
    print("Negative")
elif sentiment > 0:
    print("Positive")
```

Programming elements:

1. Basics of LSTM

2. Types of RNN

3. Use case: Sentiment Analysis on the Twitter data set

```
elif sentiment > 0:
    print("Positive")
else:
    print("Cannot be determined")
```

```
1/1 - 0s - 270ms/epoch - 270ms/step
[0.72844136 0.10584743 0.16571125]
Neutral
```

```
#2. Apply GridSearchCV on the source code provided in the class
```

```
from keras.wrappers.scikit_learn import KerasClassifier #importing Keras classifier
from sklearn.model_selection import GridSearchCV #importing Grid search CV

model = KerasClassifier(build_fn=createmodel,verbose=2) #initiating model to test performance by applying multiple hyper parameters
batch_size= [10, 20, 40] #hyper parameter batch_size
epochs = [1, 2] #hyper parameter no. of epochs
param_grid= {'batch_size':batch_size, 'epochs':epochs} #creating dictionary for batch size, no. of epochs
grid  = GridSearchCV(estimator=model, param_grid=param_grid) #Applying dictionary with hyper parameters
grid_result= grid.fit(X_train,Y_train) #Fitting the model
# summarize results
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_)) #best score, best hyper parameters
```

```
186/186 - 2s - loss: 0.7761 - accuracy: 0.6686 - 2s/epoch - 13ms/step
744/744 - 84s - loss: 0.8271 - accuracy: 0.6425 - 84s/epoch - 113ms/step
186/186 - 2s - loss: 0.7908 - accuracy: 0.6738 - 2s/epoch - 12ms/step
744/744 - 84s - loss: 0.8205 - accuracy: 0.6451 - 84s/epoch - 113ms/step
186/186 - 2s - loss: 0.7877 - accuracy: 0.6615 - 2s/epoch - 12ms/step
Epoch 1/2
744/744 - 88s - loss: 0.8231 - accuracy: 0.6426 - 88s/epoch - 119ms/step
Epoch 2/2
744/744 - 83s - loss: 0.6856 - accuracy: 0.7103 - 83s/epoch - 112ms/step
186/186 - 2s - loss: 0.7281 - accuracy: 0.6859 - 2s/epoch - 13ms/step
Epoch 1/2
744/744 - 85s - loss: 0.8195 - accuracy: 0.6469 - 85s/epoch - 114ms/step
Epoch 2/2
744/744 - 82s - loss: 0.6761 - accuracy: 0.7093 - 82s/epoch - 110ms/step
186/186 - 2s - loss: 0.7433 - accuracy: 0.6772 - 2s/epoch - 12ms/step
```

```
47/47 - 1s - loss: 0.7577 - accuracy: 0.6787 - 1s/epoch - 24ms/step
186/186 - 33s - loss: 0.8412 - accuracy: 0.6383 - 33s/epoch - 179ms/step
47/47 - 1s - loss: 0.7749 - accuracy: 0.6642 - 1s/epoch - 26ms/step
Epoch 1/2
186/186 - 31s - loss: 0.8417 - accuracy: 0.6414 - 31s/epoch - 167ms/step
Epoch 2/2
186/186 - 30s - loss: 0.6924 - accuracy: 0.7037 - 30s/epoch - 161ms/step
47/47 - 1s - loss: 0.7302 - accuracy: 0.6832 - 1s/epoch - 28ms/step
Epoch 1/2
186/186 - 31s - loss: 0.8377 - accuracy: 0.6377 - 31s/epoch - 166ms/step
Epoch 2/2
186/186 - 27s - loss: 0.6905 - accuracy: 0.7086 - 27s/epoch - 148ms/step
47/47 - 2s - loss: 0.7384 - accuracy: 0.6826 - 2s/epoch - 41ms/step
Epoch 1/2
186/186 - 31s - loss: 0.8403 - accuracy: 0.6391 - 31s/epoch - 168ms/step
Epoch 2/2
186/186 - 29s - loss: 0.6859 - accuracy: 0.7066 - 29s/epoch - 153ms/step
47/47 - 2s - loss: 0.7515 - accuracy: 0.6724 - 2s/epoch - 42ms/step
Epoch 1/2
186/186 - 31s - loss: 0.8492 - accuracy: 0.6293 - 31s/epoch - 164ms/step
Epoch 2/2
186/186 - 28s - loss: 0.6843 - accuracy: 0.7050 - 28s/epoch - 150ms/step
47/47 - 2s - loss: 0.7519 - accuracy: 0.6787 - 2s/epoch - 41ms/step
Epoch 1/2
186/186 - 30s - loss: 0.8361 - accuracy: 0.6401 - 30s/epoch - 160ms/step
Epoch 2/2
186/186 - 27s - loss: 0.6828 - accuracy: 0.7119 - 27s/epoch - 148ms/step
47/47 - 3s - loss: 0.7860 - accuracy: 0.6625 - 3s/epoch - 58ms/step
Epoch 1/2
233/233 - 40s - loss: 0.8312 - accuracy: 0.6396 - 40s/epoch - 170ms/step
Epoch 2/2
233/233 - 37s - loss: 0.6839 - accuracy: 0.7096 - 37s/epoch - 158ms/step
Best: 0.675884 using {'batch_size': 40, 'epochs': 2}
```