ICP – 10

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GitHub Link: https://github.com/SurajGamini18/Neural-Networks-Deep-Learning-Assignments
Video Link: https://drive.google.com/file/d/1Pg1O73kh2dk15DqurVja6tciqTnvbQe8/view?usp=share_link

Q1:
Code:

```
from tensorflow.keras.utils import to_categorical
import re

from sklearn.preprocessing import LabelEncoder

data = pd.read_csv('/content/Sentiment (3).csv')
# Keeping only the neccessary columns
data = data[['text','sentiment']]

data['text'] = data['text'].apply(lambda x: x.lower())
data['text'] = data['text'].apply((lambda x: re.sub('[^a-zA-z0-9\s]', '', x)))

for idx, row in data.iterrows():
    row[0] = row[0].replace('rt', ' ')

max_fatures = 2000
tokenizer = Tokenizer(num_words=max_fatures, split=' ')
tokenizer.fit_on_texts(data['text'].values)
X = tokenizer.texts_to_sequences(data['text'].values)

X = pad_sequences(X)

embed_dim = 128
lstm_out = 196
def createmodel():
    model = Sequential()
    model.add(Embedding(max_fatures, embed_dim,input_length = X.shape[1]))
    model.add(LSTM(lstm_out, dropout=0.2, recurrent_dropout=0.2))
    model.add(Dense(3,activation='softmax'))
    model.compile(loss = 'categorical_crossentropy', optimizer='adam',metrics = ['accuracy'])
    return model
# print(model.summary())

labelencoder = LabelEncoder()
integer_encoded = labelencoder.fit_transform(data['sentiment'])
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)

batch_size = 32
model = createmodel()
model.fit(X_train, Y_train, epochs = 1, batch_size=batch_size, verbose = 2)
score,acc = model.evaluate(X_test,Y_test,verbose=2,batch_size=batch_size)
print(score)
print(acc)
print(model.metrics_names)
```

```
291/291 - 48s - loss: 0.8208 - accuracy: 0.6428 - 48s/epoch - 166ms/step
144/144 - 4s - loss: 0.7668 - accuracy: 0.6614 - 4s/epoch - 31ms/step
0.7668231725692749
0.6614242196083069
['loss', 'accuracy']
```

```
[4] model.save("sentiment_model.h5")
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 file via `model.save()`. This file format is considered l
  saving_api.save_model(
```

```
import tweepy
from keras.models import load_model
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
import re

# Load the saved model
model = load_model("/content/sentiment_model.h5")

# Define a function for preprocessing text
def preprocess_text(text):
    text = text.lower()
    text = re.sub('[^a-zA-z0-9\s]', '', text)
    return text

# Example new text data
new_text = "A lot of good things are happening. We are respected again throughout the world, and that's a great thing. @realDonaldTrump"

# Preprocess the new text data
new_text = preprocess_text(new_text)

# Tokenize and pad the new text data
max_fatures = 2000
tokenizer = Tokenizer(num_words=max_fatures, split=' ')
tokenizer.fit_on_texts([new_text])
X_new = tokenizer.texts_to_sequences([new_text])
X_new = pad_sequences(X_new, maxlen=model.input_shape[1])

# Make predictions
predictions = model.predict(X_new)

# Determine the sentiment based on the prediction
sentiments = ['Negative', 'Neutral', 'Positive']
predicted_sentiment = sentiments[predictions.argmax()]

# Print the result
print("Predicted Sentiment: " + predicted_sentiment)
```

```
1/1 [==============================] - 0s 296ms/step
Predicted Sentiment: Negative
```

Explanation:

1.Import Libraries:It starts by importing necessary libraries. `tweepy` is used for accessing the Twitter API, `keras` is used for building and loading the neural network model, and `re` for regular expression operations.

2.Load Pre-trained Model:The pre-trained sentiment analysis model is loaded from a saved file (`sentiment_model.h5`). This model is assumed to be trained to classify text into sentiments.

3.Preprocess Text:The `preprocess_text` function is defined to clean the input text by converting it to lowercase and removing non-alphanumeric characters. This ensures the model receives the text in the format it expects.

4.Example Text:A sample tweet is provided as `new_text`. This text is then preprocessed to remove unwanted characters and format it properly.

5.Tokenize and Pad the Text: The text is tokenized using Keras' `Tokenizer`, which converts the text into a sequence of integers where each integer represents a specific word in a dictionary. The sequence is then padded to ensure it has a fixed length, matching the model's input requirements.

6.Make Predictions:The preprocessed and formatted text is fed into the model to predict its sentiment. The model outputs a probability distribution across the possible sentiment classes (Negative, Neutral, Positive).

7.Determine Sentiment: The sentiment with the highest probability is selected as the predicted sentiment for the input text.

Output:

```
1/1 [==============================] - 0s 296ms/step
Predicted Sentiment: Negative
```

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

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Q2:
Code:

```python
from scikeras.wrappers import KerasClassifier
```

```python
import pandas as pd
import re
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Embedding, LSTM, SpatialDropout1D
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import LabelEncoder
from scikeras.wrappers import KerasClassifier

# Assuming the data loading and preprocessing steps are the same

max_features = 2000
tokenizer = Tokenizer(num_words=max_features, split=' ')
# Assuming tokenizer fitting and text preprocessing is done here

def createmodel(optimizer='adam'):
    model = Sequential()
    model.add(Embedding(max_features, embed_dim, input_length=X.shape[1]))
    model.add(SpatialDropout1D(0.2))
    model.add(LSTM(lstm_out, dropout=0.2, recurrent_dropout=0.2))
    model.add(Dense(3, activation='softmax'))
    model.compile(loss='categorical_crossentropy', optimizer=optimizer, metrics=['accuracy'])
    return model

# Define the KerasClassifier with the build_fn as our model creation function
model = KerasClassifier(model=createmodel, verbose=2)

# Define hyperparameters to tune
param_grid = {
    'batch_size': [32, 64],
    'epochs': [1, 2],
    'optimizer': ['adam', 'rmsprop']
}

# Initialize GridSearchCV
grid = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=1, cv=3)
# Fit GridSearchCV
grid_result = grid.fit(X_train, Y_train)

# Summarize results
```

Explanation:

1.Library Imports: It starts by importing necessary libraries. `pandas` for data manipulation, `re` for regular expressions, `tensorflow.keras` for building and training the neural network model, `sklearn.model_selection` for splitting the dataset and conducting grid search, and `scikeras.wrappers` to wrap Keras models for use with scikit-learn.

2. Model Building Function:The `createmodel` function defines the architecture of the neural network using Keras' Sequential API. It includes an Embedding layer for text input, a SpatialDropout1D layer to reduce overfitting, an LSTM layer for learning from the sequence data, and a Dense output layer with a softmax activation function for classification. The optimizer for compiling the model can be adjusted, making the model flexible for hyperparameter tuning.

3. KerasClassifier Wrapper: A `KerasClassifier` wrapper is used to make the Keras model compatible with scikit-learn's grid search functionality. This allows the use of scikit-learn's `GridSearchCV` for hyperparameter tuning.

4. Hyperparameter Tuning:A parameter grid is defined with different values for batch size, number of epochs, and optimizer type. `GridSearchCV` is then used to exhaustively search through the parameter grid for the best model configuration based on cross-validation performance. It evaluates model performance for each combination of parameters across a specified number of folds of the training data.

5. Model Training and Selection: `grid.fit(X_train, Y_train)` trains the model using the training data across all combinations of parameters specified in `param_grid`, using cross-validation. After fitting, it identifies the combination of parameters that resulted in the best model performance.

6. Results Summary: Finally, the best performance score and the hyperparameters that led to this best score are printed. This provides insights into which settings worked best for the given text classification task.

Output:

```
97/97 - 30s - loss: 0.8955 - accuracy: 0.6165 - 30s/epoch - 307ms/step
49/49 - 2s - 2s/epoch - 51ms/step
97/97 - 29s - loss: 0.8696 - accuracy: 0.6263 - 29s/epoch - 298ms/step
49/49 - 2s - 2s/epoch - 50ms/step
97/97 - 29s - loss: 0.8740 - accuracy: 0.6218 - 29s/epoch - 304ms/step
49/49 - 3s - 3s/epoch - 65ms/step
97/97 - 28s - loss: 0.8783 - accuracy: 0.6241 - 28s/epoch - 289ms/step
49/49 - 3s - 3s/epoch - 67ms/step
Epoch 1/2
97/97 - 29s - loss: 0.8779 - accuracy: 0.6242 - 29s/epoch - 302ms/step
Epoch 2/2
97/97 - 25s - loss: 0.7220 - accuracy: 0.6949 - 25s/epoch - 259ms/step
49/49 - 3s - 3s/epoch - 68ms/step
Epoch 1/2
97/97 - 29s - loss: 0.8862 - accuracy: 0.6176 - 29s/epoch - 303ms/step
Epoch 2/2
97/97 - 25s - loss: 0.7242 - accuracy: 0.6894 - 25s/epoch - 254ms/step
49/49 - 2s - 2s/epoch - 50ms/step
Epoch 1/2
97/97 - 28s - loss: 0.8839 - accuracy: 0.6164 - 28s/epoch - 287ms/step
Epoch 2/2
97/97 - 25s - loss: 0.7149 - accuracy: 0.6877 - 25s/epoch - 255ms/step
49/49 - 3s - 3s/epoch - 52ms/step
Epoch 1/2
97/97 - 30s - loss: 0.8833 - accuracy: 0.6216 - 30s/epoch - 309ms/step
Epoch 2/2
97/97 - 26s - loss: 0.7304 - accuracy: 0.6931 - 26s/epoch - 272ms/step
49/49 - 4s - 4s/epoch - 83ms/step
Epoch 1/2
97/97 - 39s - loss: 0.8786 - accuracy: 0.6179 - 39s/epoch - 398ms/step
Epoch 2/2
97/97 - 27s - loss: 0.7233 - accuracy: 0.6889 - 27s/epoch - 278ms/step
49/49 - 4s - 4s/epoch - 83ms/step
Epoch 1/2
97/97 - 33s - loss: 0.8707 - accuracy: 0.6198 - 33s/epoch - 336ms/step
Epoch 2/2
97/97 - 30s - loss: 0.7207 - accuracy: 0.6833 - 30s/epoch - 308ms/step
49/49 - 3s - 3s/epoch - 52ms/step
Epoch 1/2
291/291 - 49s - loss: 0.8301 - accuracy: 0.6416 - 49s/epoch - 170ms/step
Epoch 2/2
291/291 - 46s - loss: 0.6884 - accuracy: 0.7066 - 46s/epoch - 158ms/step
Best: 0.672548 using {'batch_size': 32, 'epochs': 2, 'optimizer': 'adam'}
```