Task-2 : Next Word Prediction (Advance Level Task)

Using Tensorflow and keras library train a RNN, to predict the next word.

Dataset used link :
https://drive.google.com/file/d/1GeUzNVqiixXHnTl8oNiQ2W3CynX_lsu2/view

A look into dataset

```
#importing libraries
import numpy as np
np.random.seed(42)
import tensorflow as tf
tf.random.set_seed(42)
from tensorflow import keras
from tensorflow.keras.models import Sequential, load_model
from tensorflow.keras.layers import Dense, Activation
from tensorflow.keras.layers import LSTM, Dropout
from tensorflow.keras.layers import TimeDistributed
from tensorflow.keras.layers import Dense, Activation, Dropout, RepeatVector
from tensorflow.keras.optimizers import  RMSprop
import matplotlib.pyplot as plt
import pickle
import heapq
```

```
path = '/content/1661-0.txt'
text = open(path,encoding = "utf8").read().lower()
print('corpus length:', len(text))
```

```
    corpus length: 581888
```

splitting dataset into words without some special characters

```
from nltk.tokenize import RegexpTokenizer
#A ``RegexpTokenizer`` splits a string into substrings using a regular expression.
#For example, the following tokenizer forms tokens out of alphabetic sequences,
#money expressions, and any other non-whitespace sequences
#To separate a sentence into words without puctuation, we use RegexpTokenizer(r'\w+') as c
tokenizer = RegexpTokenizer(r'\w+')
words = tokenizer.tokenize(text)
words
```

```
      'that',
      'you',
      'intended',
      'to',
      'go',
      'into',
      'harness',
      'then',
      'how',
      'do',
      'you',
      'know',
      'i',
      'see',
      'it',
      'i',
      'deduce',
      'it',
      'how',
      'do',
      'i',
      'know',
      'that',
      'you',
      'have',
      'been',
      'getting',
      'yourself',
      'very',
      'wet',
      'lately',
      'and',
      'that',
      'you',
      'have',
      'a',
      'most',
      'clumsy',
      'and',
      'careless',
      'servant',
      'girl',
      'my',
      'dear',
      'holmes',
      'said',
      'i',
      'this',
      'is'
```

```
 'is',
 'too',
 'much',
 'you',
 'would',
 'certainly',
 'have',
 'been',
 'burned',
 'had',
```

Preprocessing Data

```
ca = sorted(list(set(text)))
char_indices = dict((c, i) for i, c in enumerate(ca))
i_char = dict((i, c) for i, c in enumerate(ca))

print(f'unique chars: {len(ca)}')
```

```
unique chars: 73
```

```
#chunk 40 characters with 3 sequences
seq_len = 40
step = 3
sentences = []
next_chars = []
for i in range(0, len(text) - seq_len, step):
    sentences.append(text[i: i + seq_len ])
    next_chars.append(text[i + seq_len])
print(f'num training examples: {len(sentences)}')
```

```
num training examples: 193950
```

Storing Features and their labels accordingly

```
# generating our features and labels
#one hot encoding
X = np.zeros((len(sentences), seq_len, len(ca)), dtype=bool)
y = np.zeros((len(sentences), len(ca)), dtype=bool)
for i, sentence in enumerate(sentences):
    for t, char in enumerate(sentence):
        X[i, t, char_indices[char]] = 1
    y[i, char_indices[next_chars[i]]] = 1

sentences[124]
next_chars[100]
```

```
'e'
```

```
#enocoded data
```

```
print(X[0][0])
```

```
[False False False False False False False False False False False False
 False False False False False False False False False False False False
 False False False False False False False False False False False False
 False False False False False False False False False False False False
 False False False False False False False False False False False False
 False False False False False False False False False False False False
  True]
```

```
#one hot encoded data
y[0]
```

```
array([False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False,  True, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False])
```

```
X.shape
```

```
(193950, 40, 73)
```

```
y.shape
```

```
(193950, 73)
```

Using LSTM (long short term memory) very powerful RNN for building the model

```
# Creating the model
model = Sequential()
model.add(LSTM(128, input_shape=(seq_len, len(ca))))
model.add(Dense(len(ca)))
model.add(Activation('softmax'))
```

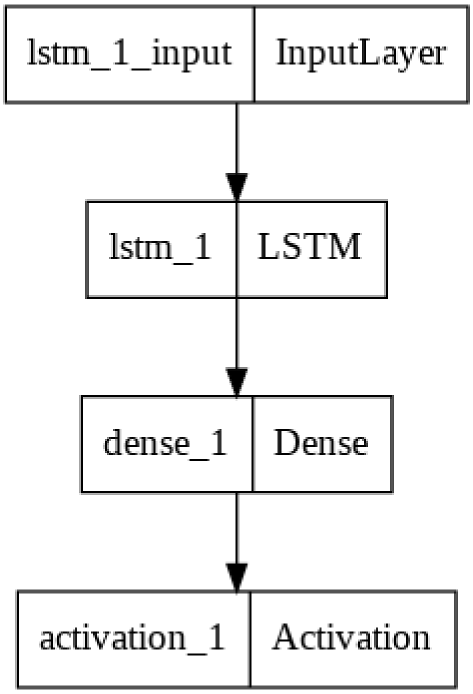
```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_1 (LSTM)               (None, 128)               103424

 dense_1 (Dense)             (None, 73)                9417

 activation_1 (Activation)   (None, 73)                0
```

```
=================================================================
Total params: 112,841
Trainable params: 112,841
Non-trainable params: 0
_________________________________________________________________
```

Visualisation of the model built

```
from tensorflow import keras
from keras.utils.vis_utils import plot_model
keras.utils.plot_model(model, to_file='model.png', show_layer_names=True)
```



Training the model

```
# Training our model
optimizer = RMSprop(learning_rate=0.01)
model.compile(loss='categorical_crossentropy', optimizer=optimizer, metrics=['accuracy'])
history = model.fit(X, y,
                    validation_split=0.01,
                    batch_size=128,
                    epochs=4,
                    shuffle=True).history
```

```
Epoch 1/4
1501/1501 [==============================] - 203s 134ms/step - loss: 1.4399 - accura
Epoch 2/4
1501/1501 [==============================] - 201s 134ms/step - loss: 1.4123 - accura
Epoch 3/4
1501/1501 [==============================] - 190s 126ms/step - loss: 1.3948 - accura
```

```
Epoch 4/4
1501/1501 [==============================] - 185s 123ms/step - loss: 1.3797 - accura
```

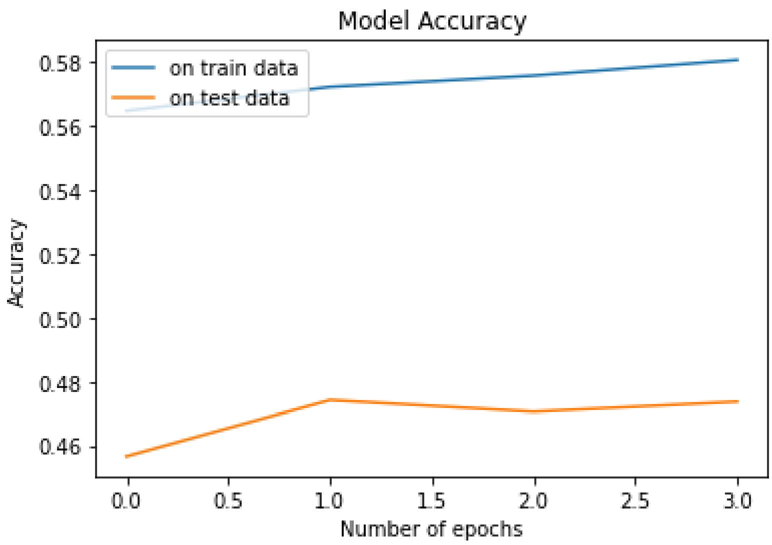
Save and load the model

```
model.save('next_word_model.h5')
pickle.dump(history, open("history.p", "wb"))
model = load_model('next_word_model.h5')
history = pickle.load(open("history.p", "rb"))
```

Visualising Loss and Accuracy of the model

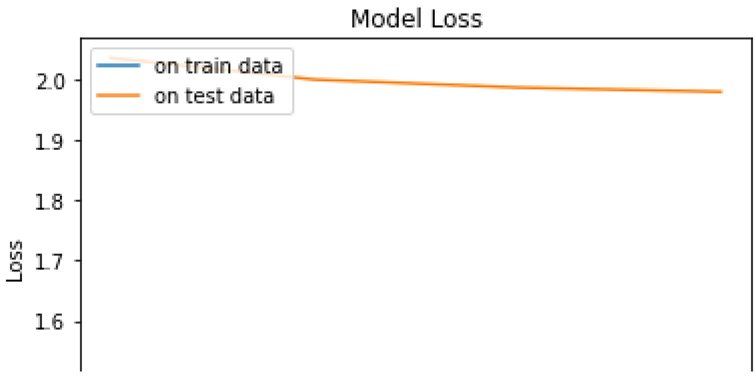
```
plt.plot(history['accuracy'])
plt.plot(history['val_accuracy'])
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Number of epochs')
plt.legend(['on train data', 'on test data'], loc='upper left')
```

```
<matplotlib.legend.Legend at 0x7f823083d400>
```




```
plt.plot(history['loss'])
plt.plot(history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Number of epochs')
plt.legend(['on train data', 'on test data'], loc='upper left')
```

```
<matplotlib.legend.Legend at 0x7f8232290f40>
```



Predicting Next Word

```
def prepare_input(text):
    x = np.zeros((1, seq_len, len(ca)))
    for t, char in enumerate(text):
        x[0, t, char_indices[char]] = 1.

    return x

prepare_input("This is an example of input of our model".lower())
```

```
array([[[0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.],
        ...,
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.]]])
```

```
#functions to get next probable characters
def sample(preds, top_n=3):
    preds = np.asarray(preds).astype('float64')
    preds = np.log(preds)
    exp_preds = np.exp(preds)
    preds = exp_preds / np.sum(exp_preds)

    return heapq.nlargest(top_n, range(len(preds)), preds.take)


def predict_completion(text):
    original_text = text
    generated = text
    completion = ''
    while True:
        x = prepare_input(text)
        preds = model.predict(x, verbose=0)[0]
        next_index = sample(preds, top_n=1)[0]
        next_char = i_char[next_index]
        text = text[1:] + next_char
        completion += next_char
```

```
        if len(original_text + completion) + 2 > len(original_text) and next_char == ' ':
            return completion

def predict_completions(text, n=3):
    x = prepare_input(text)
    preds = model.predict(x, verbose=0)[0]
    next_indices = sample(preds, n)
    return [i_char[idx] + predict_completion(text[1:] + i_char[idx]) for idx in next_indic


quotes = [
    "Predicting the future isn’t magic, it’s artificial intelligence",
    "The potential benefits of artificial intelligence are huge, so are the dangers",
    "Humans should be worried about the threat posed by artificial intelligence.",
    "Machine learning and deep learning will create a new set of hot jobs in the next 5 ye
    "Data is the new science. Big Data holds the answers"

]


for q in quotes:
    seq = q[:40].lower()
    print(seq)
    print(predict_completions(seq, 5))
    print()
```

```
predicting the future isn’t magic, it’s
['a ', 'the ', 'nothing ', 'more ', 'so ']

the potential benefits of artificial int
['erest ', 'o ', 'rust ', 'aining ', 'ious ']

humans should be worried about the threa
['thing ', 'rs ', 'd ', 'm ', 'king ']

machine learning and deep learning will
['be ', 'for ', 'soon ', 'have ', 'a ']

data is the new science. big data holds
['the ', 'and ', 'in ', 'of ', 'he ']
```

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