CREATE CHATBOT IN PYTHON

INTRODUCTION:

- In the past few years, chatbots in the Python programming language have become enthusiastically admired in the sectors of technology and business. These intelligent bots are so adept at imitating natural human languages and chatting with humans that companies across different industrial sectors are accepting them.
- From e-commerce industries to healthcare institutions, everyone appears to be leveraging this nifty utility to drive business advantages. In the following tutorial, we will understand the chatbot with the help of the Python programming language and discuss the steps to create a chatbot in Python.
- A Chatbot is an Artificial Intelligence-based software developed to interact with humans in their natural languages.
- These chatbots are generally converse through auditory or textual methods, and they can effortlessly mimic human languages to communicate with human beings in a human-like way. A chatbot is considered one of the best applications of natural languages processing.

Importing libraries

```
#model

import tensorflow as tf

from sklearn.model_selection import train_test_split


#nlp processing

import unicodedata

import re
```

```
import numpy as np
```

```
import warnings
warnings.filterwarnings('ignore')
```

```
/opt/conda/lib/python3.10/site-packages/scipy/__init__.py:146: UserWarning: A NumPy version >=1.16.5 and <1.23.0 is required for this version of SciPy (detected version 1.23.5
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

Data preprocessing

The basic text processing in NLP are:

Sentence Segmentation

Normalization

Tokenization

Segmentation

formatting data to be in a question answer format

```
#reading data
data=open('/kaggle/input/simple-dialogs-for-chatbot/dialogs.txt','r').read()
#paried list of question and corresponding answer
QA_list=[QA.split('\t') for QA in data.split('\n')]
print(QA_list[:5])
```

[['hi, how are you doing?', "i'm fine. how about yourself?"], ["i'm fine. how about yourself?", "i'm pretty good. thanks for asking."], ["i'm pretty good. thanks for asking.", 'no problem. so how have you been?'], ['no problem. so how have you been?', "i've been great. what about you?"], ["i've been great. what about you?", "i've been good. i'm in school right now."]]

questions=[row[0] for row in QA_list]

answers=[row[1] for row in QA_list]

print(questions[0:5])

print(answers[0:5])

['hi, how are you doing?', "i'm fine. how about yourself?", "i'm pretty good. thanks for asking.", 'no problem. so how have you been?', "i've been great. what about you?"]

["i'm fine. how about yourself?", "i'm pretty good. thanks for asking.", 'no problem. so how have you been?', "i've been great. what about you?", "i've been good. i'm in school right now."]

Normalization

To reduce its randomness, bringing it closer to a predefined "standard"

```
def remove_diacritic(text):
    return ''.join(char for char in unicodedata.normalize('NFD',text)
                   if unicodedata.category(char) !='Mn')
def preprocessing(text):

    #Case folding and removing extra whitespaces
    text=remove_diacritic(text.lower().strip())

    #Ensuring punctuation marks to be treated as tokens
```

```
    text=re.sub(r"([?.!,¿])", r" \1 ", text)

    #Removing redundant spaces
    text= re.sub(r'[" "]+', " ", text)

    #Removing non alphabetic characters
    text=re.sub(r"[^a-zA-Z?.!,¿]+", " ", text)

    text=text.strip()

    #Indicating the start and end of each sentence
    text='<start> ' + text + ' <end>'

    return text
preprocessed_questions=[preprocessing(sen) for sen in questions]
preprocessed_answers=[preprocessing(sen) for sen in answers]

print(preprocessed_questions[0])
print(preprocessed_answers[0])
```

```
<start> hi , how are you doing ? <end>
<start> i m fine . how about yourself ? <end>
```

Tokenization

```
def tokenize(lang):
```

```
    lang_tokenizer = tf.keras.preprocessing.text.Tokenizer(
      filters='')

    #build vocabulary on unique words
    lang_tokenizer.fit_on_texts(lang)

    return lang_tokenizer
```

Word Embedding

representing words in form of real-valued vetors

```
def vectorization(lang_tokenizer,lang):

    #word embedding for training the neural network
    tensor = lang_tokenizer.texts_to_sequences(lang)

    tensor = tf.keras.preprocessing.sequence.pad_sequences(tensor,
                                                           padding='post')

    return tensor
```

Creating Dataset

for training and testing the model

```
def load_Dataset(data,size=None):
```

```
    if(size!=None):
        y,X=data[:size]
    else:
        y,X=data

    X_tokenizer=tokenize(X)
    y_tokenizer=tokenize(y)

    X_tensor=vectorization(X_tokenizer,X)
    y_tensor=vectorization(y_tokenizer,y)

    return   X_tensor,X_tokenizer, y_tensor, y_tokenizer
size=30000
data=preprocessed_answers,preprocessed_questions\


X_tensor,X_tokenizer, y_tensor, y_tokenizer=load_Dataset(data,size)
# Calculate max_length of the target tensors
max_length_y, max_length_X = y_tensor.shape[1], X_tensor.shape[1]
```

Splitting Data

Creating training and validation sets using an 80-20 split after the required preprocessing is applied to the whole data

X_train, X_val, y_train, y_val = train_test_split(X_tensor, y_tensor, test_size=0.2)

Show length

print(len(X_train), len(y_train), len(X_val), len(y_val))

2980 2980 745 745

Tensorflow Dataset

BUFFER_SIZE = len(X_train)

BATCH_SIZE = 64

steps_per_epoch = len(X_train)//BATCH_SIZE

embedding_dim = 256

units = 1024

vocab_inp_size = len(X_tokenizer.word_index)+1

vocab_tar_size = len(y_tokenizer.word_index)+1

dataset = tf.data.Dataset.from_tensor_slices((X_train,
y_train)).shuffle(BUFFER_SIZE)

dataset = dataset.batch(BATCH_SIZE, drop_remainder=True)

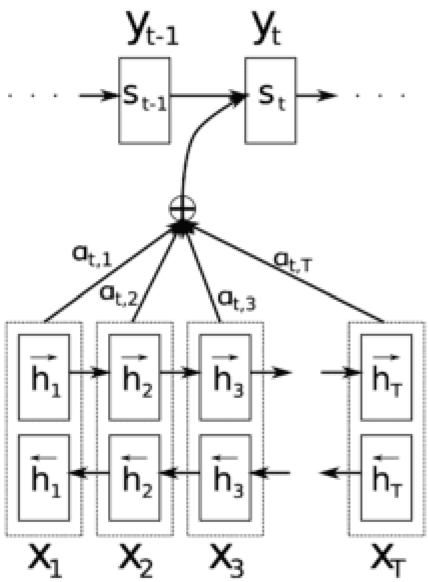
example_input_batch, example_target_batch = next(iter(dataset))

example_input_batch.shape, example_target_batch.shape

(TensorShape([64, 24]), TensorShape([64, 24]))

Model

Bahdanau Attention Mechanism



bahdanau_1-229x300.png

Adding attention mechanism to an Encoder-Decoder Model to make the model focus on specific parts of input sequence by assigning weights to different parts of the input sequence

Buliding Model Architecture

Encoder

```
class Encoder(tf.keras.Model):

    def __init__(self, vocab_size, embedding_dim, enc_units, batch_sz):

        super(Encoder, self).__init__()

        self.batch_sz = batch_sz

        self.enc_units = enc_units
```

```
        self.embedding = tf.keras.layers.Embedding(vocab_size, embedding_dim)
        self.gru = tf.keras.layers.GRU(self.enc_units,
                                       return_sequences=True,
                                       return_state=True,
                                       recurrent_initializer='glorot_uniform')

    def call(self, x, hidden):
        x = self.embedding(x)
        output, state = self.gru(x, initial_state = hidden)
        return output, state

    def initialize_hidden_state(self):
        return tf.zeros((self.batch_sz, self.enc_units))
encoder = Encoder(vocab_inp_size, embedding_dim, units, BATCH_SIZE)


# sample input
sample_hidden = encoder.initialize_hidden_state()
sample_output, sample_hidden = encoder(example_input_batch, sample_hidden)
print ('Encoder output shape: (batch size, sequence length, units)
{}'.format(sample_output.shape))
print ('Encoder Hidden state shape: (batch size, units)
{}'.format(sample_hidden.shape))
Encoder output shape: (batch size, sequence length, units) (64, 24, 1024)
```

Encoder Hidden state shape: (batch size, units) (64, 1024)

Attention Mechanism

```
class BahdanauAttention(tf.keras.layers.Layer):
    def __init__(self, units):
        super(BahdanauAttention, self).__init__()
        self.W1 = tf.keras.layers.Dense(units)
        self.W2 = tf.keras.layers.Dense(units)
        self.V = tf.keras.layers.Dense(1)

    def call(self, query, values):
        # query hidden state shape == (batch_size, hidden size)
        # query_with_time_axis shape == (batch_size, 1, hidden size)
        # values shape == (batch_size, max_len, hidden size)
        # we are doing this to broadcast addition along the time axis to calculate
the score
        query_with_time_axis = tf.expand_dims(query, 1)

        # score shape == (batch_size, max_length, 1)
        # we get 1 at the last axis because we are applying score to self.V
        # the shape of the tensor before applying self.V is (batch_size, max_length,
units)
        score = self.V(tf.nn.tanh(
            self.W1(query_with_time_axis) + self.W2(values)))
```

```
        # attention_weights shape == (batch_size, max_length, 1)
        attention_weights = tf.nn.softmax(score, axis=1)

        # context_vector shape after sum == (batch_size, hidden_size)
        context_vector = attention_weights * values
        context_vector = tf.reduce_sum(context_vector, axis=1)

        return context_vector, attention_weights
attention_layer = BahdanauAttention(10)
attention_result, attention_weights = attention_layer(sample_hidden,
sample_output)

print("Attention result shape: (batch size, units) {}".format(attention_result.shape))
print("Attention weights shape: (batch_size, sequence_length, 1)
{}".format(attention_weights.shape))
```

Attention result shape: (batch size, units) (64, 1024)

Attention weights shape: (batch_size, sequence_length, 1) (64, 24, 1)

Decoder

```
class Decoder(tf.keras.Model):
    def __init__(self, vocab_size, embedding_dim, dec_units, batch_sz):
        super(Decoder, self).__init__()
        self.batch_sz = batch_sz
```

```
        self.dec_units = dec_units
        self.embedding = tf.keras.layers.Embedding(vocab_size, embedding_dim)
        self.gru = tf.keras.layers.GRU(self.dec_units,
                                       return_sequences=True,
                                       return_state=True,
                                       recurrent_initializer='glorot_uniform')
        self.fc = tf.keras.layers.Dense(vocab_size)

        # used for attention
        self.attention = BahdanauAttention(self.dec_units)

    def call(self, x, hidden, enc_output):
        # enc_output shape == (batch_size, max_length, hidden_size)
        context_vector, attention_weights = self.attention(hidden, enc_output)

        # x shape after passing through embedding == (batch_size, 1,
embedding_dim)
        x = self.embedding(x)

        # x shape after concatenation == (batch_size, 1, embedding_dim +
hidden_size)
        x = tf.concat([tf.expand_dims(context_vector, 1), x], axis=-1)
```

```
        # passing the concatenated vector to the GRU
        output, state = self.gru(x)

        # output shape == (batch_size * 1, hidden_size)
        output = tf.reshape(output, (-1, output.shape[2]))

        # output shape == (batch_size, vocab)
        x = self.fc(output)

        return x, state, attention_weights
decoder = Decoder(vocab_tar_size, embedding_dim, units, BATCH_SIZE)

sample_decoder_output, _, _ = decoder(tf.random.uniform((BATCH_SIZE, 1)),
                                      sample_hidden, sample_output)

print ('Decoder output shape: (batch_size, vocab size)
{}'.format(sample_decoder_output.shape))
```

Decoder output shape: (batch_size, vocab size) (64, 2349)

Training Model

Pass the input through the encoder which return encoder output and the encoder hidden state.

The encoder output, encoder hidden state and the decoder input (which is the start token) is passed to the decoder.

The decoder returns the predictions and the decoder hidden state.

The decoder hidden state is then passed back into the model and the predictions are used to calculate the loss.

Use teacher forcing to decide the next input to the decoder.

Teacher forcing is the technique where the target word is passed as the next input to the decoder.

The final step is to calculate the gradients and apply it to the optimizer and backpropagate.

```
optimizer = tf.keras.optimizers.Adam()

loss_object = tf.keras.losses.SparseCategoricalCrossentropy(
    from_logits=True, reduction='none')


def loss_function(real, pred):
    mask = tf.math.logical_not(tf.math.equal(real, 0))
    loss_ = loss_object(real, pred)

    mask = tf.cast(mask, dtype=loss_.dtype)
    loss_ *= mask

    return tf.reduce_mean(loss_)
@tf.function
def train_step(inp, targ, enc_hidden):
    loss = 0

    with tf.GradientTape() as tape:
```

```
        enc_output, enc_hidden = encoder(inp, enc_hidden)

        dec_hidden = enc_hidden

        dec_input = tf.expand_dims([y_tokenizer.word_index['<start>']] *
BATCH_SIZE, 1)

        # Teacher forcing - feeding the target as the next input
        for t in range(1, targ.shape[1]):
            # passing enc_output to the decoder
            predictions, dec_hidden, _ = decoder(dec_input, dec_hidden,
enc_output)

            loss += loss_function(targ[:, t], predictions)

            # using teacher forcing
            dec_input = tf.expand_dims(targ[:, t], 1)

    batch_loss = (loss / int(targ.shape[1]))

    variables = encoder.trainable_variables + decoder.trainable_variables

    gradients = tape.gradient(loss, variables)
```

```
    optimizer.apply_gradients(zip(gradients, variables))

    return batch_loss
EPOCHS = 40

for epoch in range(1, EPOCHS + 1):
    enc_hidden = encoder.initialize_hidden_state()
    total_loss = 0

    for (batch, (inp, targ)) in enumerate(dataset.take(steps_per_epoch)):
        batch_loss = train_step(inp, targ, enc_hidden)
        total_loss += batch_loss

    if(epoch % 4 == 0):
        print('Epoch:{:3d} Loss:{:.4f}'.format(epoch,
                                                  total_loss / steps_per_epoch))
Epoch:   4 Loss:1.5338
Epoch:   8 Loss:1.2803
Epoch: 12 Loss:1.0975
Epoch: 16 Loss:0.9404
Epoch: 20 Loss:0.7773
Epoch: 24 Loss:0.6040
```

Epoch: 28 Loss:0.4042

Epoch: 32 Loss:0.2233

Epoch: 36 Loss:0.0989

Epoch: 40 Loss:0.0470

Model Evaluation

```
def remove_tags(sentence):
    return sentence.split("<start>")[-1].split("<end>")[0]
def evaluate(sentence):
    sentence = preprocessing(sentence)

    inputs = [X_tokenizer.word_index[i] for i in sentence.split(' ')]
    inputs = tf.keras.preprocessing.sequence.pad_sequences([inputs],
                                                           maxlen=max_length_X,
                                                           padding='post')
    inputs = tf.convert_to_tensor(inputs)

    result = ''

    hidden = [tf.zeros((1, units))]
    enc_out, enc_hidden = encoder(inputs, hidden)

    dec_hidden = enc_hidden
    dec_input = tf.expand_dims([y_tokenizer.word_index['<start>']], 0)
```

```
    for t in range(max_length_y):
        predictions, dec_hidden, attention_weights = decoder(dec_input,
                                                             dec_hidden,
                                                             enc_out)

        # storing the attention weights to plot later on
        attention_weights = tf.reshape(attention_weights, (-1, ))

        predicted_id = tf.argmax(predictions[0]).numpy()

        result += y_tokenizer.index_word[predicted_id] + ' '

        if y_tokenizer.index_word[predicted_id] == '<end>':
            return remove_tags(result), remove_tags(sentence)

        # the predicted ID is fed back into the model
        dec_input = tf.expand_dims([predicted_id], 0)

    return remove_tags(result), remove_tags(sentence)
def ask(sentence):
    result, sentence = evaluate(sentence)
```

```
    print('Question: %s' % (sentence))

    print('Predicted answer: {}'.format(result))

ask(questions[1])
```

Question: i m fine . how about yourself ?

Predicted answer: i m pretty good . thanks for asking .

CONCLUSION

- In the Phase 2 conclusion, we will summarize the key findings and insights from the advanced regression techniques. We will reiterate the impact of these techniques on improving the accuracy and robustness of chatbot.
- Future Work: We will discuss potential avenues for future work, such as incorporating additional data sources ,exploring python models for chatbot or expanding the project into a web application with more features and interactivity.

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