CREATE A CHATBOT IN PYTHON

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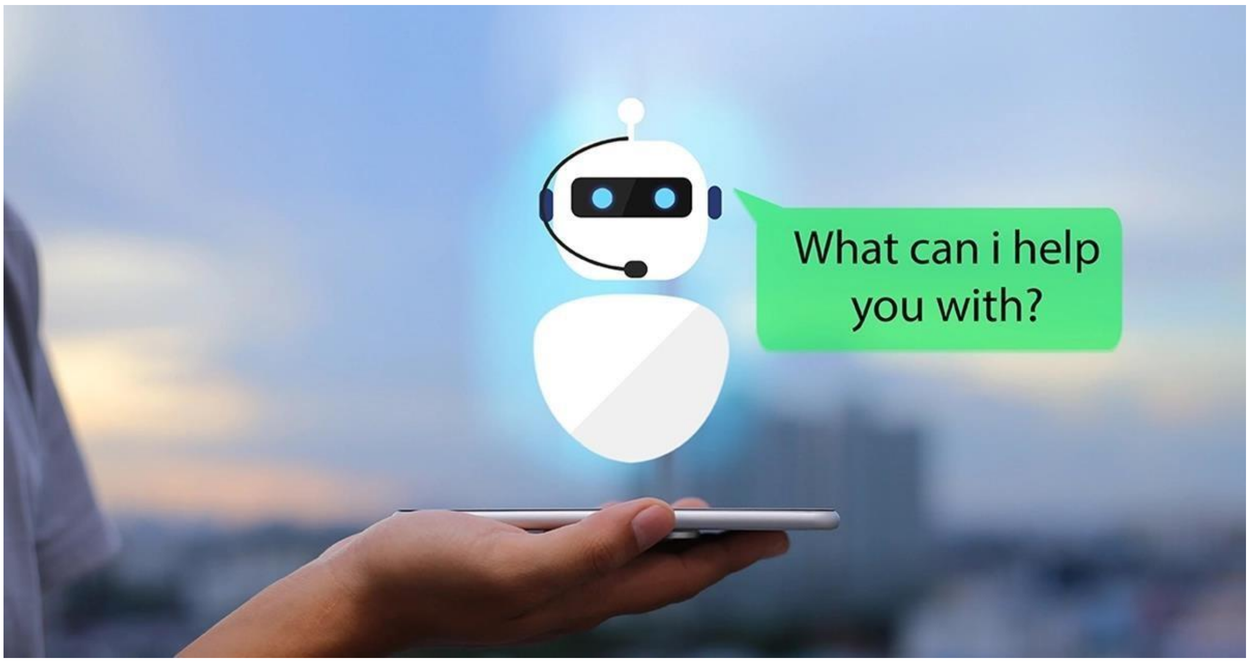
Domain Name: Artificial Intelligence

Phase-3 Document Submission

Project: To create a Chatbot in Python that provides exceptional answering user queries (diabetes) on a website.



Introduction:

- Deep Learning and Natural Language Processing (NLP) are two exciting and rapidly advancing fields within artificial intelligence (AI) and machine learning.
- They are at the forefront of creating intelligent systems that can understand, process, and generate human language, paving the way for applications like chatbots, language translation, sentiment analysis, and more.
- In the context of chatbots, RNNs can be used to create intelligent conversational agents capable of understanding and generating human-like responses in a dynamic and context-aware manner.
- Deep Learning and NLP are driving innovations in various industries, including healthcare, customer service, finance, and entertainment.
- These technologies are enabling chatbot to communicate with humans more naturally and understand the nuances of human language.

- As the fields continue to evolve, they hold the potential to revolutionize the way we interact with computers and the digital world.

This kernel covers the main concepts behind Attention techniques used in recurrent neural network.

- Part I: focusing on the attention understanding
- Part II: Applying attention mechanism in building chatbot seq2seq step by step

PART I: ATTENTION UNDERSTANDING

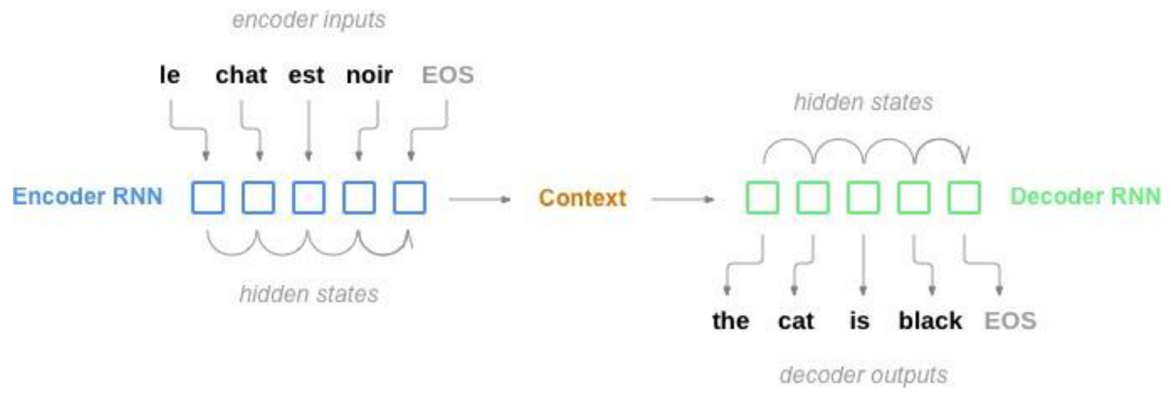
Just like in “Attention” meaning, in real life when we looking at a picture or hearing the song, we usally focus more on some parts and pay less attention in the rest. The Attention mechanism in Deep Learning is also the same flow, paying greater attention to certain parts when processing the data

Attention is one component of a network’s architecture.

Follow the specific tasks, the encoder & decoder will be different. In machine translation, the encoder often set to LSTM/GRU/Bi_RNN, in image captioning, the encoder often set to CNN.

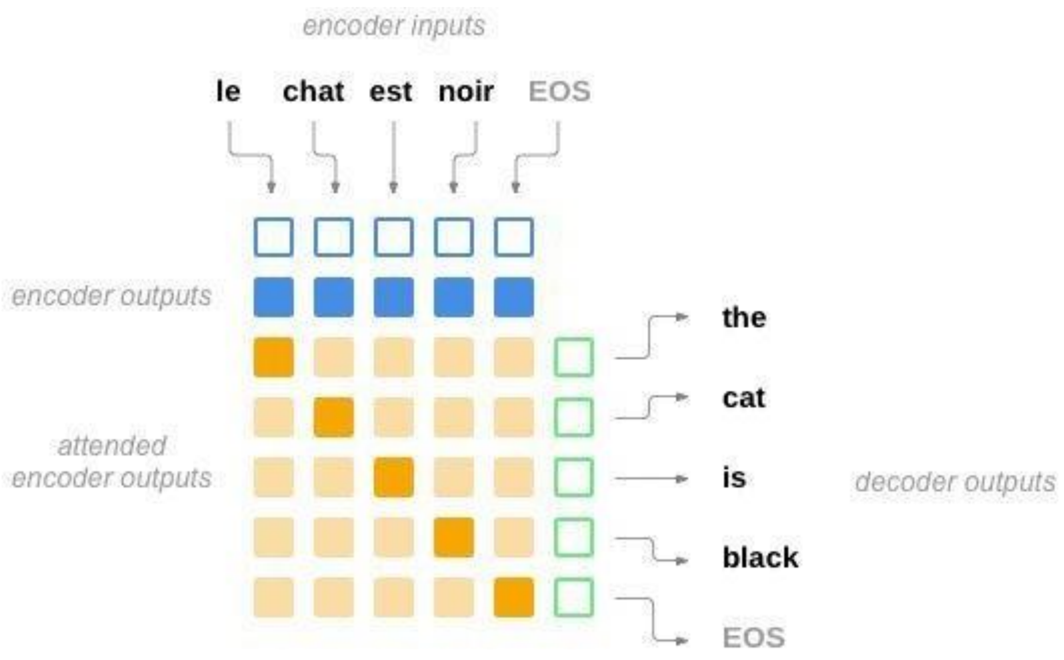
Such as for the task: **Translating the sentence: 'le chat est noir' to English sentence (the cat is black)**

The input has 4 words, plus EOS token at the end (stop word) corresponding 5 time steps in translating to English. Each time step, Attention is applied by assigning weights to input words, the more important words, the bigger weights will be assigned (Done by backprob gradient process). So There are 5 differrent times weights assigned (coresponding to 5 time steps) The general architecture in seq2seq as follow:



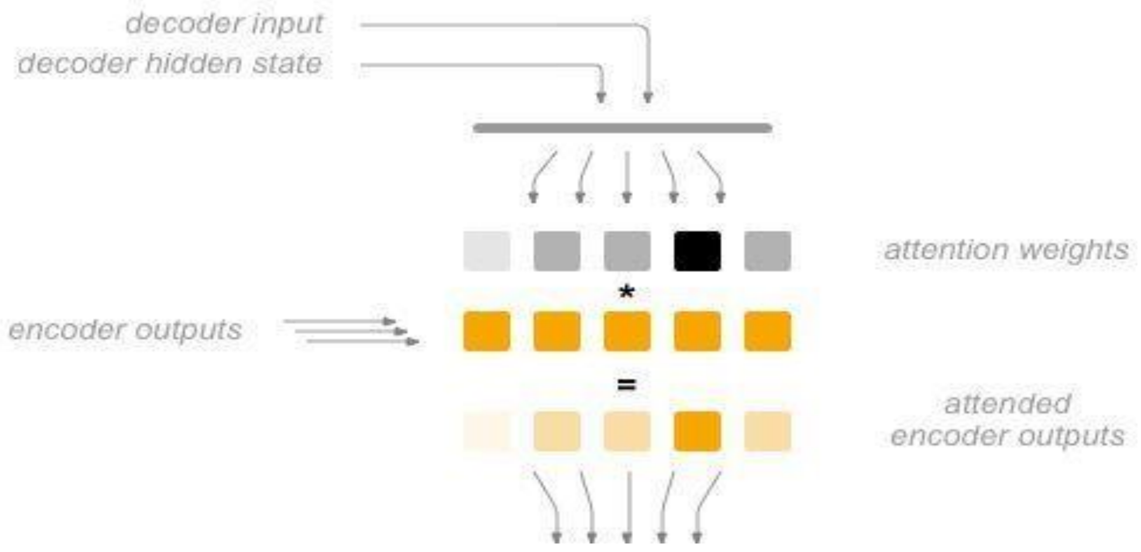
- Without attention, The input in **decoder** based on 2 component: the initial decoder input (often we set it to EOS token first (start word)) and the last hidden encoder.

- This way has the drawback in case some informations of very first encoder cell would be loss during the process. To handle this problem, the attention weight is added to all encoder outputs.



- As we can see, through each decoder output word, the attention weights colors of encoder input is changed differently along itself importance

- You may ask how can we appropriately set the weight to encoder outputs. The answer is: we just randomly set the weights, and the backpropagation gradient process will take care about it during the training. What we have to do is correctly build the forward computational graph.



Example:

```
import torch
import torch.nn as nn
```

STEP 1: CACULATING ENCODER HIDDEN STATE

```
class Encoder_LSTM(nn.Module):
    def__init_(self, input_size, hidden_size, n_layers=1, drop_prob=0):
        super(EncoderLSTM, self)._init_()
        self.hidden_size = hidden_size
        self.n_layers = n_layers
        self.embedding = nn.Embedding(input_size, hidden_size)
        self.lstm = nn.LSTM(hidden_size, hidden_size, n_layers, dropout=drop_prob, batch_first=True)

    def forward(self, inputs, hidden):
        # Embed input words
        embedded = self.embedding(inputs)
        # Pass the embedded word vectors into LSTM and return all outputs
        output, hidden = self.lstm(embedded, hidden)
        return output, hidden
```

Step 2--->6

```
class Luong_Decoder(nn.Module):
    def__init_(self, hidden_size, output_size, attention, n_layers=1, drop_prob=0.1):
        super(LuongDecoder, self)._init_()
        self.hidden_size = hidden_size
        self.output_size = output_size
        self.n_layers = n_layers
        self.drop_prob = drop_prob
    # The Attention layer is defined in a separate class
        self.attention = attention
        self.embedding = nn.Embedding(self.output_size, self.hidden_size)
        self.dropout = nn.Dropout(self.drop_prob)
        self.lstm = nn.LSTM(self.hidden_size, self.hidden_size)
        self.classifier = nn.Linear(self.hidden_size*2, self.output_size)
    def forward(self, inputs, hidden, encoder_outputs):
        # Embed input words
        embedded = self.embedding(inputs).view(1,1,-1)
        embedded = self.dropout(embedded)
```

STEP 2: GENERATE NEW HIDDEN STATE FOR DECODER

```
        lstm_out, hidden = self.lstm(embedded, hidden)
```

STEP 3: CALCULATING ALIGNMENT SCORES

```
        alignment_scores = self.attention(lstm_out,encoder_outputs)
```

STEP 4: SOFTMAXING ALIGNMENT SCORES TO OBTAIN ATTENTION WEIGHTS

```
        attn_weights = F.softmax(alignment_scores.view(1,-1), dim=1)
```

STEP 5: CACULATING CONTEXT VECTOR by Multiplying Attention weights with encoder outputs

```
        context_vector = torch.bmm(attn_weights.unsqueeze(0),encoder_outputs)
```

STEP 6: CACULATING THE FINAL DECODER OUTPUT by Concatenating output from LSTM with context vector

```
        output = torch.cat((lstm_out, context_vector),-1)
        # Pass concatenated vector through Linear layer acting as a Classifier
        output = F.log_softmax(self.classifier(output[0]), dim=1)
        return output, hidden, attn_weights
```

Exploring the attention class in STEP 3: Caculating alignment score
In Luong Attention, there are 3 different ways (dot, general, concat) to caculate the alignment scores.

1. Dot function

This is the simplest of the functions: alignment score calculated by multiplying the hidden encoder and the hidden decoder.
SCORE = H(encoder) * H(decoder)

2. General function

similar to the dot function, except that a weight matrix is added into the equation
SCORE = W(H(encoder) * H(decoder))

3. Concat function

Concating encoder and decoder first, the feed to nn.Linear and activation it, finally we add W2 to get final Score
SCORE = W2 * tanh(W1(H(encoder) + H(decoder)))

Implementing attention class:

```
class Luong_attention_layer(nn.Module):
    def___init_(self, method, hidden_size):
        super(Luong_attention_layer, self)._init_()
        self.method = method
        self.hidden_size = hidden_size
        if self.method not in ['dot', 'general', 'concat']:
            raise ValueError(self.method, 'is not appropriate attention method')
        if self.method == 'general':
            self.attn = torch.nn.Linear(self.hidden_size, hidden_size)
        elif self.method == 'concat':
            self.attn = torch.nn.Linear(self.hidden_size * 2, hidden_size)
            self.weight = nn.Parameter(torch.FloatTensor(hidden_size))
    def get_dot_score(self, hidden, encoder_outputs):
        return torch.sum(hidden*encoder_outputs, dim=2)
    def get_general_score(self, hidden, encoder_outputs):
        energy = self.attn(encoder_outputs)
        return torch.sum(hidden * energy, dim=2)
    def get_concat_score(self, hidden, encoder_outputs):
        concat = torch.cat((hidden.expand(encoder_outputs.size(0),-1,-1), encoder_outputs), dim=2)
        energy = torch.tanh(self.attn(concat))
        return torch.sum(self.weight * energy, dim=2)
    def forward(self, hidden, encoder_outputs):
        if self.method == 'dot':
            attn_energy = self.get_dot_score(hidden, encoder_outputs)
        elif self.method == 'general':
            attn_energy = self.get_general_score(hidden, encoder_outputs)
        elif self.method == 'concat':
            attn_energy = self.get_concat_score(hidden, encoder_outputs)
        ## Transpose  attn_energy
        attn_energy = attn_energy.t()
        # Softmanx the attn_energy to return the weight corresponding to each encoder output
        return F.softmax(attn_energy, dim=1).unsqueeze(1)
```

Part II: Building chatbot seq2seq with Luong attention mechanism

The step by step for building chatbot with attention as follow:Capture%204.JPG

After running this kernel. you can play with chatbot and have some fun with him like this:)) :Capture6.JPG

The code is based on : https://pytorch.org/tutorials/beginner/chatbot_tutorial.html. I have modified this toturial on something because the Author used some pytorch features that currently depressed. Through this kernel, I added explaination on my own understanding step by step so you might find it friendly to understand all the concepts.

Step 1: Preparing data

```
from__future__import absolute_import
from__future__import division
from__future__import print_function
from__future__import unicode_literals
import numpy as np
import os
import torch
from torch.jit import script, trace
import torch.nn as nn
from torch import optim
import torch.nn.functional as F
import csv
import random
import re
import os
import unicodedata
import codecs
from io import open
import itertools
import math

%matplotlib inline
use_cuda = torch.cuda.is_available()
device = torch.device('cuda' if use_cuda else 'cpu')
device
corpus_name = 'cornell-moviedialog-corpus'
corpus = os.path.join('/kaggle/input', corpus_name)
def printLines(filename, n=10):
    with open(filename, 'rb') as f:
        lines = f.readlines()
    for line in lines[:n]:
        print(line)

printLines(os.path.join(corpus,'movie_lines.txt'))

column_names = ["lineID","characterID","movieID","character","text"]
def LoadLines(file, column_names):
    lines = {}
    with open(file, 'r', encoding='iso-8859-1') as f:
        for line in f:
            dict = {}
            list_field = line.split(' +++$+++ ')
            for i, field in enumerate(list_field):
                dict[column_names[i]] = field
            lines[dict['lineID']] = dict
    return lines
lines = LoadLines(os.path.join(corpus, 'movie_lines.txt'), column_names)
# as we can see, after split the "utteranceIDs" is a string : " ['L2460', 'L2461', 'L2462']\n", what we want is
retrieve the list inside the string,
# to do this we use eva function that do the expression inside the input
# In the 'movie_conversations.txt', the columns are: ["character1ID", "character2ID", "movieID",
"utteranceIDs"]

def Loadconversation(file, lines, column_names):
    conversation = []
    with open(file, 'r', encoding='iso-8859-1') as f:
        for line in f:
            dict_column = {}
            list_column = line.split(' +++$+++ ')
            for i, col in enumerate(list_column):
                dict_column[column_names[i]] = col
            line_id_list = eval(dict_column['utteranceIDs'])
            dict_column['lines'] = []
            for line in line_id_list:
                dict_column['lines'].append(lines[line])
            conversation.append(dict_column)
    return conversation
conversations = Loadconversation(os.path.join(corpus, 'movie_conversations.txt'),lines,["character1ID",
"character2ID", "movieID", "utteranceIDs"])
def get_pair_conversation(conversations):
    """
    return list of pair conversation  [[input1, response1], [input2, response2], ...]
    """
    pair = []
    for conversation in conversations:
        num_sentence = len(conversation['lines'])
        for i in range(num_sentence-1):
            input = conversation['lines'][i]['text'].strip()
            response = conversation['lines'][i+1]['text'].strip()
            if input and response:
                pair.append([input, response])
    return pair
# create new file to overwrite into it
os.chdir('/kaggle/')
os.getcwd()
if not os.path.exists('data_save'):
    os.makedirs('data_save')
os.chdir('data_save')

path_save = '/kaggle/data_save'
datafile = os.path.join(path_save, "formatted_movie_lines.txt")

delimiter = '\t'
# Unescape the delimiter
delimiter = str(codecs.decode(delimiter, "unicode_escape"))

print("\nWriting newly formatted file.  ")
with open(datafile, 'w', encoding='utf-8') as outputfile:
    writer = csv.writer(outputfile, delimiter=delimiter, lineterminator='\n')
    for pair in get_pair_conversation(conversations):
        writer.writerow(pair)
```

For this we define a Voc class, which keeps a mapping from words to indexes, a reverse mapping of indexes to words, a count of each word and a total word count. The class provides methods for adding a word to the vocabulary (addWord), adding all words in a sentence (addSentence) and trimming infrequently seen words (trim). More on trimming later.

```
pad_token = 0
sos_token = 1
eos_token = 2

class Voc:
    def__init_(self, name):
        self.name = name
        self.trimmed = False
        self.word2index = {}
        self.word2count = {}
        self.index2word = {pad_token:'PAD', sos_token:'SOS', eos_token : 'EOS'}
        self.numword = 3

    def add_sentence(self, sentence):
        for word in sentence.split(' '):
            self.addword(word)

    def addword(self, word):
        if word not in self.word2index:
            self.word2index[word] = self.numword
```

```
   self.word2count[word] = 1
            self.index2word[self.numword] = word
            self.numword += 1
        else:
            self.word2count[word] += 1
    def trim(self, min_count):
        """
        based on the wordcount dictionary, Filter of the word frequency at least more than min_count
        """
        if self.trimmed:
            return
        self.trimmed = True

        keep_word = []
        for word, num_frequency in self.word2count.items():
            if num_frequency >= min_count:
                keep_word.append(word)

        # reinitialize dictionaries
        self.word2index = {}
        self.word2count = {}
        self.index2word = {pad_token:'PAD', sos_token:'SOS', eos_token : 'EOS'}
        self.numword = 3
        for word in keep_word:
            self.addword(word)
# Convert (or remove accents) sentence to non_accents sentence
def unicodeToAscii(s):
    return ''.join(
        c for c in unicodedata.normalize('NFD', s)
        if unicodedata.category(c) != 'Mn'
    )

# Lowercase, trim, and remove non-letter characters
def normalizeString(s):
    s = unicodeToAscii(s.lower().strip())
    s = re.sub(r"([.!?])", r" \1", s)
    s = re.sub(r"[^a-zA-Z.!?]+", r" ", s)
    s = re.sub(r"\s+", r" ", s).strip()
    return s
lines = open(datafile, encoding='utf-8').\
        read().strip().split('\n')
lines[0] ## Each string in lines list is a pair (input, response)
def readVocs(datafile, corpus_name):
    lines = open(datafile, 'r', encoding='utf-8').\
            read().strip().split('\n')
    pairs = [[normalizeString(s) for s in l.split('\t')] for l in lines]
    voc = Voc(corpus_name)
    return voc, pairs

## we ensure every sentences must have the length smaller than max_length
## max_length value is based on our choice, the greater value, the more data training we have and also
the more parameter the model have to train on
def filterpair(pairs, max_length):
    """
    Input: pair with format: [input, response] such as:  ['how are you', 'I am ok']
    we check the length of both input, response to identify where or not they smaller than max_length
    return pair with length < max_length
    """
    valid_pair = []
    for pair in pairs:
        input_words, response_words = pair[0].split(' '), pair[1].split(' ')
        if len(input_words) < max_length and len(response_words) < max_length:
            valid_pair.append(pair)
    return valid_pair
```

```
def loadPrepareData(datafile, corpus_name, max_length):
    voc, pairs = readVocs(datafile, corpus_name)
    valid_pair = filterpair(pairs, max_length)
    print(f'load total {len(pairs)} pairs')
    print(f'load total {len(valid_pair)} pairs with length <= max_length (10)')
    for pair in valid_pair:
        voc.add_sentence(pair[0])
        voc.add_sentence(pair[1])
    print(f'total word in vocabulary is : {voc.numword}')
    return voc, valid_pair

voc, valid_pair = loadPrepareData(datafile, corpus_name, max_length = 10)
print('examples of 10 first pairs')
for pair in valid_pair[:3]:
    print(pair)
```

In the vocabulary pairs, it's include some rare words and this make model difficult to convergance because it try hard to approximate in output predict and real output when one of them they include rare word. make the rest hard to approximate ==> take out these word from pairs

```
def trim_rareword(voc, pairs, min_count):
    voc.trim(min_count) ## trim the voc class with min_count word so that every word in voc.word2index
will satisfied the min_count frequency requirement
    trimmed_pair = []
    for pair in pairs:
        input_sentence = pair[0]
        response_sentence = pair[1]
        keep_input = True
        keep_response = True
        ## Loop over every word in both input and response sentence
        # Loop over input sentence
        for word in input_sentence.split(' '):
            if word not in voc.word2index: # condition
                keep_input = False
                break ## it will end the process right away as long as meet condition, the rest loop process will
not run anymore
         # Loop over output sentence
        for word in response_sentence.split(' '):
            if word not in voc.word2index: # condition
                keep_input = False
                break

        if keep_input and keep_response:
            trimmed_pair.append(pair)
    print(f'the trimming process make the total {len(pairs)} ==> {len(trimmed_pair)} trimmed pair)')
    return voc,trimmed_pair
voc, trimmed_pair =  trim_rareword(voc, valid_pair, min_count=3)
```

Transform data to tensor

```
def index_from_sentence(voc, sentence):
    """
    Input: a single sentence
    output: return index respectively matching with words in sentence based on voc.word2index
    """
    return [voc.word2index[word] for word in sentence.split(' ')] + [eos_token] ## to indicate that the
sentence is ended here
# def indexesFromSentence(voc, sentence):
#     return [voc.word2index[word] for word in sentence.split(' ')] + [eos_token]
index_from_sentence(voc, trimmed_pair[5][0])
# Python’s Itertool is a module that provides various functions that work on iterators (list, tuple, string,...)
def zeroPadding(l,fillvalue=pad_token):
    return list(itertools.zip_longest(*l, fillvalue = fillvalue))
```

```
def binaryMatrix(l, value=pad_token):
    m = []
    for i, seq in enumerate(l):
        m.append([])
        for token in seq:
            if token == pad_token:
                m[i].append(0)
            else:
                m[i].append(1)
    return m

def input_to_torch(l, voc):
    """
    Purpos: convert to torch.tensor , (Returns padded input sequence tensor and lengths)
    """
    indexes_batch = [index_from_sentence(voc, sentence) for sentence in l]
    padded_list_index = zeroPadding(indexes_batch)
    padded_tensor_index = torch.LongTensor(padded_list_index)
    lengths = torch.tensor([len(indexes) for indexes in indexes_batch])
    return padded_tensor_index, lengths
def output_to_torch(l, voc):
    """
    Purpos: convert to torch.tensor , (Returns padded output sequence tensor, mask tensor, max_lengths)
    """
    indexes_batch = [index_from_sentence(voc, sentence) for sentence in l]
    padded_list_index = zeroPadding(indexes_batch)
    padded_tensor_index = torch.LongTensor(padded_list_index)
    max_output_length = max([len(indexes) for indexes in indexes_batch])
    mask = binaryMatrix(padded_list_index)
    mask = torch.ByteTensor(mask)
    return padded_tensor_index, mask, max_output_length
## Combine all and return all items needed given a batch of pairs
def get_batch_pair(voc, batch_pair):
    """
    sort the len of input sentence in desc
    return all input and output items
    """
    # sort len(input sentence) in batch_pair with decreasing order
    batch_pair.sort(key = lambda x: len(x[0].split(" ")), reverse = True )
    # devide the batch pair to batch_input and batch_response
    input_batch, response_batch = [], []
    for pair in batch_pair:
        input_batch.append(pair[0])
        response_batch.append(pair[1])

    input_tensor, length_input = input_to_torch(input_batch, voc)
    output_tensor, mask, max_length = output_to_torch(response_batch, voc)
    return input_tensor, length_input, output_tensor, mask, max_length
```

Step 2: Define model

```
# Things to remember : output_size : (seq_len, batch, num_directions * hidden_size), num_directions = 1
if unidirectional and 2 if bidirectional

class EncoderRNN(nn.Module):
    def__init_(self, embedding, hidden_size, num_layers = 1,dropout = 0):
        super(EncoderRNN, self)._init_()
        self.num_layers = num_layers
        self.embedding = embedding
        self.hidden_size = hidden_size
        # Define GRU layers, this GRU cell return 2 things: Output and hidden_state cell
        self.gru = nn.GRU(  input_size = hidden_size  ## in input_size, number of features = hidden_size
                          , hidden_size = hidden_size
```

```
                    , num_layers = num_layers
                    , dropout = (0 if num_layers == 1 else dropout)
                    , bidirectional = True)
    def forward(self, input_seq, input_length, hidden = None):
        ## Convert input seq to embedding format
        embedding = self.embedding(input_seq)
        packed_input = torch.nn.utils.rnn.pack_padded_sequence(embedding, input_length)
        ## forward to gru cell
        output, hidden_cell = self.gru(packed_input, hidden)
        output, _ = torch.nn.utils.rnn.pad_packed_sequence(output)
        ## Sum bidirectional GRU output
        output = output[:,:,:self.hidden_size] + output[:,:,self.hidden_size:]
        return output, hidden_cell

class Luong_attention_layer(nn.Module):
    def___init_(self, method, hidden_size):
        super(Luong_attention_layer, self)._init_()
        self.method = method
        self.hidden_size = hidden_size

        if self.method not in ['dot', 'general', 'concat']:
            raise ValueError(self.method, 'is not appropriate attention method')
        if self.method == 'general':
            self.attn = torch.nn.Linear(self.hidden_size, hidden_size)
        elif self.method == 'concat':
            self.attn = torch.nn.Linear(self.hidden_size * 2, hidden_size)
            self.weight = nn.Parameter(torch.FloatTensor(hidden_size))

    def get_dot_score(self, hidden, encoder_outputs):
        return torch.sum(hidden*encoder_outputs, dim=2)

    def get_general_score(self, hidden, encoder_outputs):
        energy = self.attn(encoder_outputs)
        return torch.sum(hidden * energy, dim=2)

    def get_concat_score(self, hidden, encoder_outputs):
        concat = torch.cat((hidden.expand(encoder_outputs.size(0),-1,-1), encoder_outputs), dim=2)
        energy = torch.tanh(self.attn(concat))
        return torch.sum(self.weight * energy, dim=2)

    def forward(self, hidden, encoder_outputs):
        if self.method == 'dot':
            attn_energy = self.get_dot_score(hidden, encoder_outputs)
        elif self.method == 'general':
            attn_energy = self.get_general_score(hidden, encoder_outputs)
        elif self.method == 'concat':
            attn_energy = self.get_concat_score(hidden, encoder_outputs)

        ## Transpose attn_energy
        attn_energy = attn_energy.t()

        # Softmanx the attn_energy to return the weight corresponding to each encoder output
        return F.softmax(attn_energy, dim=1).unsqueeze(1)
class Luong_attention_decoder(nn.Module):
    def___init_(self, embedding, attn_model, hidden_size, output_size, n_layers=1, dropout = 0.1):
        super(Luong_attention_decoder, self)._init_()
        ## Define properties for self
        self.hidden_size = hidden_size
        self.output_size = output_size
        self.n_layers = n_layers
        self.dropout = dropout
        self.attn_model = attn_model
        ## Define layers
        self.embedding = embedding
        self.embedding_dropout = nn.Dropout(dropout)
        self.gru = nn.GRU(hidden_size, hidden_size, n_layers, dropout=(0 if n_layers == 1 else dropout))
        ## self.concat for transform the concat tensor size [hidden,encoder_output] with size =
(hidden_size*2) ==> (hidden_size)
        self.concat = nn.Linear(hidden_size*2, hidden_size)
        ## self.out for Dense the gru_ouput to return predict value
        self.out = nn.Linear(hidden_size, output_size)
        self.attention = Luong_attention_layer(attn_model, hidden_size)

    def forward(self, input_step, last_hidden, encoder_outputs):
        ## One step one word through batch
        embedded = self.embedding(input_step)
        embedded = self.embedding_dropout(embedded)
        # forward through unidirrectional GRU
        rnn_output, hidden = self.gru(embedded, last_hidden)
        # Feed output and encoder_outputs to attention layer
        attention_weights = self.attention(rnn_output, encoder_outputs)
        # caculate context vector
        context = attention_weights.bmm(encoder_outputs.transpose(0,1))
        # concat context vector with output
        rnn_output = rnn_output.squeeze(0)
        context = context.squeeze(1)
        concat_input = torch.cat((rnn_output, context), 1)
        concat_output = torch.tanh(self.concat(concat_input))
        # return output predict
        output = self.out(concat_output)
        output = F.softmax(output, dim=1)
        return output, hidden
```

Understand torch.gather
https://stackoverflow.com/questions/50999977/what-does-the-gather-function-do-in-pytorch-in-layman-terms in torch.gather(input, dim = (0 or 1 or 2), index)

if dim = 0, we go through rows, from top to bottom,
if dim = 1, we go through columns, left to right

```
def maskNLLLoss(input, target, mask):
    nTotal = mask.sum()
    crossEntropy = -torch.log(torch.gather(input, 1, target.view(-1, 1)).squeeze(1))
    loss = crossEntropy.masked_select(mask).mean()
    loss = loss.to(device)
    return loss, nTotal.item()
```

Step 3: Creating training function

```
np.random.seed(42)
max_length = 10
def train(input_variable, lengths, target_variable, embedding, encoder, decoder, encoder_optimizer,
decoder_optimizer, max_target_lens
          , batch_size, clip, mask,max_length = max_length):
    """
    this train function is responsible for one iteration
    """
    ## Zeros gradients
    encoder_optimizer.zero_grad()
    decoder_optimizer.zero_grad()
    ## Set device
    input_variable = input_variable.to(device)
    target_variable = target_variable.to(device)
    lengths = lengths.to(device)
    mask = mask.bool()
    mask = mask.to(device)
```

```
## Initialize variable
    loss = 0
    print_loss = []
    n_totals = 0
    ## Pass input through encoder
    output_encoders, hidden_encoders = encoder(input_variable, lengths)
    ## Create initial hidden input
    input_decoders = torch.LongTensor([[sos_token for _ in range(batch_size)]])
    input_decoders = input_decoders.to(device)
    ## Set initial decoder hidden
    hidden_decoders = hidden_encoders[:decoder.n_layers]
    ## Determine to use teacher forcing or not
    teacher_forcing = True if random.random() < teacher_forcing_rate else False


    if teacher_forcing:
        for t in range(max_target_lens):
            output_decoders, hidden_decoders = decoder(input_decoders, hidden_decoders,
output_encoders)
            # in case teacher forcing, current target is set to next decoder input
            input_decoders = target_variable[t].view(1, -1)
            # Caculate loss
            mask_loss, nTotal = maskNLLLoss(output_decoders, target_variable[t], mask[t])
            loss+=mask_loss  # the most important is loss function, this is place where all gradients will be
calculated
            print_loss.append(mask_loss.item() * nTotal)
            n_totals += nTotal
    else:
        for t in range(max_target_lens):
            output_decoders, hidden_encoders = decoder(input_decoders, hidden_decoders,
output_encoders)
            # in case None teacher forcing, current output decoder is set to next decoder input
            # torch.topk(i) return (value,index of that value) of "i" highest values of tensor, in this case,we
want return the only
            # (__, index) with highest probability value, so we set i ==> 1
            _, topi = output_decoders.topk(1) ## output_decoder is tensor softmax: ex: [0.3,0.6,01], topk(1)
meaning return one highest value
            input_decoders = torch.LongTensor([[topi[i][0] for i in range(batch_size)]])
            input_decoders = input_decoders.to(device) ## because decoder_input in this case is newly
created and have to switch to device
            # Caculate loss
            mask_loss, nTotal = maskNLLLoss(output_decoders, target_variable[t], mask[t])
            loss += mask_loss
            print_loss.append(mask_loss.item() * nTotal)
            n_totals += nTotal
    # Backprob gradient in loss function
    loss.backward()
    # Clip the gradients in both encoder, decoder
    _ = torch.nn.utils.clip_grad_norm_(encoder.parameters(), clip)
    _ = torch.nn.utils.clip_grad_norm_(decoder.parameters(), clip)
    # Calling the step function on an Optimizer makes an update to its parameters
    encoder_optimizer.step()
    decoder_optimizer.step()
    # return average loss
    return sum(print_loss) / n_totals

def trainIters(model_name, voc, trimmed_pair, encoder, decoder, encoder_optimizer, decoder_optimizer,
embedding, encoder_n_layers,
               decoder_n_layers, save_dir, n_iteration, batch_size, print_every, save_every, clip,
corpus_name, loadFilename):
    # Load batch for each iteration
    training_batches = [get_batch_pair(voc, [random.choice(trimmed_pair) for _ in range(batch_size)]) for
_ in range(n_iteration)]
```

```
    # Initialization
    print('initializing...')
    start_iteration = 1
    print_loss = 0
    if loadFilename:
        start_iteration = checkpoint['iteration'] + 1

    # Training loop
    print('tranining')
    for iteration in range(start_iteration, n_iteration +1):
        training_batch = training_batches[iteration-1]
        # Extract fields from batch
        input_variable, lengths, target_variable, mask, max_target_lens = training_batch
        # training on batch
        loss = train(input_variable, lengths, target_variable, embedding, encoder, decoder,
encoder_optimizer, decoder_optimizer, max_target_lens
            , batch_size, clip, mask)
        print_loss += loss
        # Print loss after "print_every step"
        if (iteration % print_every) == 0:
            print_loss_avg = print_loss / print_every
            print(f'loss_avg at {iteration} is: {print_loss_avg}, in {100 * iteration / n_iteration } % progress
complete')
            print_loss = 0
        # Save checkpoint
        if (iteration % save_every) == 0:
           directory = os.path.join(path_save, model_name, corpus_name, f'{encoder_n_layers}-
{decoder_n_layers}_{hidden_size}')
           if not os.path.exists(directory):
               os.makedirs(directory)
           torch.save({
               'iteration': iteration,
               'encoder' : encoder.state_dict(),
               'decoder' : decoder.state_dict(),
               'encoder_optimizer': encoder_optimizer.state_dict(),
               'decoder_optimizer': decoder_optimizer.state_dict(),
               'loss' : loss,
               'voc_dict'    :    voc.______dict______,
               'embedding': embedding.state_dict()
            }, os.path.join(directory, '{}_{}.tar'.format(iteration, 'checkpoint')))
```

To facilite the greedy decoding operation, we define a GreedySearchDecoder class. When run, an object of this class takes an input sequence (input_seq) of shape (input_seq length, 1), a scalar input length (input_length) tensor, and a max_length to bound the response sentence length. The input sentence is evaluated using the following computational graph:

Computation Graph:

Forward input through encoder model.
Prepare encoder's final hidden layer to be first hidden input to the decoder.
Initialize decoder's first input as SOS_token.
Initialize tensors to append decoded words to.
Iteratively decode one word token at a time:
Forward pass through decoder.
Obtain most likely word token and its softmax score.
Record token and score.
Prepare current token to be next decoder input.
Return collections of word tokens and scores.

Step 4: Create function to interact with chatbot

```
class Greedysearch_decoder(nn.Module):
    def__init_(self, encoder, decoder):
```

```
super(Greedysearch_decoder, self)._init_()
        self.encoder = encoder
        self.decoder = decoder


def forward(self, input_seq, input_length, max_length):
        output_encoder, hidden_encoder = self.encoder(input_seq, input_length)
        # Set the final hidden encoder to be initial hidden decoder
        hidden_decoder = hidden_encoder[:decoder.n_layers]
        # Initialize decoder input with sos_token
        input_decoder = torch.ones(1,1,device = device, dtype = torch.long) * sos_token
        # Create tensors to contain output word
        all_tokens = torch.zeros([0], device=device, dtype = torch.long)
        all_score = torch.zeros([0], device=device)
        # Loop over decoder - one word per time step
        for _ in range(max_length):
            output_decoder, hidden_decoder = self.decoder(input_decoder, hidden_decoder,
output_encoder)
            # Feed output_decoder to torch.max() to return (max_value, index) ( softmax)
            max_score, output_index = torch.max(output_decoder, dim = 1)
            # Append to all_tokens and all_scores
            all_tokens = torch.cat((all_tokens, output_index), dim = 0)
            all_score = torch.cat((all_score, max_score), dim = 0)
            # Set current output_index to the next input decoder
            input_decoder = torch.unsqueeze(output_index, 0)
        # Return collections of words token and score
        return all_tokens, all_score
```

Evaluate our own sentence:

```
def evaluate(encoder, decoder, searcher, voc, sentence, max_length = max_length):
    # transform word to index
    index_sentence_list = [index_from_sentence(voc, sentence)]
    input_lengths = torch.tensor([len(index) for index in index_sentence_list])
    # transform index list to tensor
    index_sentence = torch.LongTensor(index_sentence_list)
    # Now index_sentence is [[idx1, idx2,...]], what we want is       [[idx1], as we defince our sentence
shape before ( here batchsize = 1)
                                                                      # [idx2],
                                                                      # [...]]
    # Transform index_sentence to shape (n_words, 1) to act as input
    input_batch = index_sentence.transpose(0,1)
    # Feed to device
    input_batch = input_batch.to(device)
    input_lengths = input_lengths.to(device)
    # Now we pass index_sentence, lengths through encoder to return output, hidden encoder
    output_tokens, output_scores = searcher(input_batch, input_lengths, max_length)
    words_decoder = [voc.index2word[index.item()] for index in output_tokens]
    return words_decoder

def Loop_evaluate(encoder, decoder, search, voc):
    """
    This function take input sentence from your keyboard,
    loop through evaluate function above util it reach 'q' or 'quit' input, the process will end here
    """
    input_sentence = ''
    while True:
        try:
            input_sentence = input('Me: ')
            if input_sentence in ['q','quit']: break
            # normalize string
            input_sentence = normalizeString(input_sentence)
            # feed to evaluate to return words
            words_decoder = evaluate(encoder, decoder, search, voc, input_sentence)
            words_decoder[:] = [word for word in words_decoder if word not in ['PAD','EOS']]
            print('Bot: ', ' '.join(words_decoder))
        except KeyError:



            print('Unknown word in memory, please try another word')
```

Run our model

```
# Configure models
model_name = 'cb_model'
attn_model = 'concat'
#attn_model = 'general'
#attn_model = 'concat'
hidden_size = 500
encoder_n_layers = 3
decoder_n_layers = 3
dropout = 0.1
batch_size = 64

# Set checkpoint to load from; set to None if starting from scratch
loadFilename = None
checkpoint_iter = 10000
#loadFilename = os.path.join(save_dir, model_name, corpus_name,
#                            '{}-{}_{}'.format(encoder_n_layers, decoder_n_layers, hidden_size),
#                            '{}_checkpoint.tar'.format(checkpoint_iter))
# Load model if a loadFilename is provided
if loadFilename:
    # If loading on same machine the model was trained on
    checkpoint = torch.load(loadFilename)
    # If loading a model trained on GPU to CPU
    #checkpoint = torch.load(loadFilename, map_location=torch.device('cpu'))
    encoder_sd = checkpoint['encoder']
    decoder_sd = checkpoint['decoder']
    encoder_optimizer_sd = checkpoint['encoder_optimizer']
    decoder_optimizer_sd = checkpoint['decoder_optimizer']
    embedding_sd = checkpoint['embedding']
    voc.__dict__= checkpoint['voc_dict']


print('Building encoder and decoder ...')
# Initialize word embeddings
embedding = nn.Embedding(voc.numword, hidden_size)
if loadFilename:
    embedding.load_state_dict(embedding_sd)
# Initialize encoder & decoder models
encoder = EncoderRNN(embedding, hidden_size, encoder_n_layers, dropout)
decoder = Luong_attention_decoder(embedding, attn_model, hidden_size, voc.numword,
decoder_n_layers, dropout)
if loadFilename:
    encoder.load_state_dict(encoder_sd)
    decoder.load_state_dict(decoder_sd)
# Use appropriate device
encoder = encoder.to(device)
decoder = decoder.to(device)
print('Models built and ready to go!')
clip = 50.0
teacher_forcing_rate = 1.0
learning_rate = 3e-4
decoder_learning_rate = 5.0
n_iteration = 10000
print_every = 1000
save_every = 500
```

```
# Ensure dropout layers are in train mode
encoder.train()
decoder.train()




# Initialize optimizers
print('Building optimizers ...')
encoder_optimizer = optim.Adam(encoder.parameters(), lr=learning_rate)
decoder_optimizer = optim.Adam(decoder.parameters(), lr=learning_rate * decoder_learning_rate)
if loadFilename:
    encoder_optimizer.load_state_dict(encoder_optimizer_sd)
    decoder_optimizer.load_state_dict(decoder_optimizer_sd)

# Run training iterations
print("Starting Training!")
trainIters(model_name, voc, trimmed_pair, encoder, decoder, encoder_optimizer, decoder_optimizer,
           embedding, encoder_n_layers, decoder_n_layers, path_save, n_iteration, batch_size,
           print_every, save_every, clip, corpus_name, loadFilename)
```

Play with chatbot:

```
# Set dropout layers to eval mode
encoder.eval()
decoder.eval()

# Initialize search module
searcher = Greedysearch_decoder(encoder, decoder)

# Begin chatting, we type some sentence and play with chatbot
Loop_evaluate(encoder, decoder, searcher, voc)
```

Conclusion:

In an age where healthcare information and support are critical, the Diabetes Chatbot stands as a valuable companion on your journey towards understanding, managing, and living well with diabetes. This intelligent conversational agent has been designed to offer information, answer questions, and provide guidance to individuals seeking clarity on diabetes-related matters.

Throughout your interaction with our chatbot, you've had the opportunity to explore essential aspects of diabetes, from the basics of the condition to strategies for effective management. You've received insights into nutrition, exercise, medication, and the prevention of complications. The chatbot has served as a 24/7 resource, ready to address your inquiries and concerns.

The Diabetes Chatbot remains committed to being a trustworthy resource that complements your healthcare journey. It aims to empower you with knowledge and encourage healthier choices while fostering a sense of community and support. Our chatbot is available to assist you whenever you need guidance or simply wish to learn more about diabetes.