Get started Open in app

Follow 580K Followers

This is your **last** free member-only story this month. Sign up for Medium and get an extra one

DEEP LEARNING | NATURAL LANGUAGE PROCESSING

Generative chatbots using the seq2seq model!

A chatbot that generates a response instead of selecting from existing ones!

Dhruvil Shah May 20, 2020 · 11 min read ★

> *A chatbot is a software that provides a real conversational experience to the user. There are closed domain chatbots and open domain (generative) chatbots. Closed domain chatbot is a chatbot that responses with predefined texts. A generative chatbot generates a response as the name implies.*

dont want

Photo by NeONBRAND on Unsplash

The below article shows how to create closed domain chatbots with the help of Machine learning classifier.

A Naive Bayes approach towards creating closed domain Chatbots!

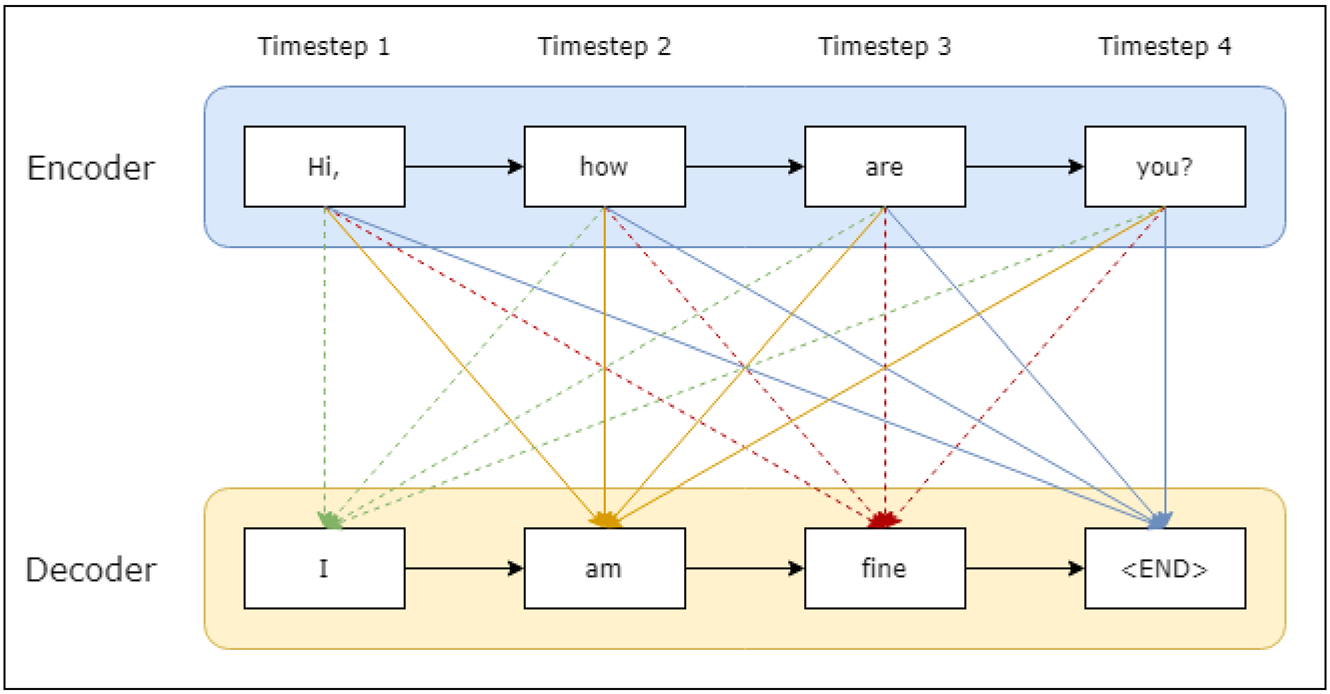
There is an easy and efficient approach for creating a closed domain chatbot that uses the Naive Bayes classifier.

towardsdatascience.com

In the above article, the responses were fixed and the machine learning helped to select the correct response given in the user's question. But here, we are not going to select from pre-defined responses but instead, we will generate a response based on the training corpus. We are going to use the encoder-decoder (seq2seq) model for this approach.

Introduction to seq2seq approach for creating generative chatbots

The seq2seq model also called the encoder-decoder model uses Long Short Term Memory- LSTM for text generation from the training corpus. The seq2seq model is also useful in machine translation applications. What does the seq2seq or encoder-decoder model do in simple words? It predicts a word given in the user input and then each of the next words is predicted using the probability of likelihood of that word to occur. In building our Generative chatbot we will use this approach for *text generation* given in the user input.



Encoder-decoder model

The encoder outputs a final state vector (memory) which becomes the initial state for the decoder. We use a method called *teacher forcing* to train the decoder which enables it to predict the following words in a target sequence given in the previous words. As shown above, states are passed through the encoder to each layer of the decoder. 'Hi,', 'how', 'are', and 'you' are called input tokens while 'I', 'am', and 'fine' are called target tokens. The likelihood of token 'am' depends on the previous words and the encoder states. We are adding '<END>' token to let our decoder know when to stop. You can learn more about the seq2seq model here.

Let's start building our generative chatbot from scratch! The first task we will have to do is preprocess our dataset.

Preprocessing the dataset

The dataset we are going to use is collected from Kaggle. You can find it below. It contains human responses and bot responses. There are 2363 entries for each.

'rDany' Chat

157 chats & 6300+ messages with a (fake) virtual companion

www.kaggle.com

First, we will have to clean our corpus with the help of Regular Expressions. Then, we will need to make pairs like human response-bot response so that we can train our seq2seq model. We will do these tasks as shown below.

```
import re
import random
data_path = "human_text.txt"
data_path2 = "robot_text.txt"
# Defining lines as a list of each line
with open(data_path, 'r', encoding='utf-8') as f:
  lines = f.read().split('\n')

with open(data_path2, 'r', encoding='utf-8') as f:
  lines2 = f.read().split('\n')

lines = [re.sub(r"\[\w+\]",'hi',line) for line in lines]
lines = [" ".join(re.findall(r"\w+",line)) for line in lines]
lines2 = [re.sub(r"\[\w+\]",'',line) for line in lines2]
lines2 = [" ".join(re.findall(r"\w+",line)) for line in lines2]
# grouping lines by response pair
pairs = list(zip(lines,lines2))
#random.shuffle(pairs)
```

After creating pairs we can also shuffle those before training. Our pairs will look like this now:

```
[('hi', 'hi there how are you'), ('oh thanks i m fine this is an
evening in my timezone', 'here is afternoon'),...]
```

Here, 'hi' is input sequence, and 'hi there how are you' is a target sequence. We will have to create separate lists for input sequences and target sequences and we will also need to create lists for unique tokens (input tokens and target tokens) in our dataset. For target sequences, we will add '<START>' at the beginning of the sequence and '<END>' at the end of the sequence so that our model knows where to start and end *text generation*. We will do this as shown below.

```
import numpy as np

input_docs = []
target_docs = []
input_tokens = set()
target_tokens = set()

for line in pairs[:400]:
  input_doc, target_doc = line[0], line[1]
  # Appending each input sentence to input_docs
  input_docs.append(input_doc)
  # Splitting words from punctuation
  target_doc = " ".join(re.findall(r"[\w']+|[^\s\w]", target_doc))
  # Redefine target_doc below and append it to target_docs
  target_doc = '<START> ' + target_doc + ' <END>'
  target_docs.append(target_doc)

  # Now we split up each sentence into words and add each unique word
to our vocabulary set
  for token in re.findall(r"[\w']+|[^\s\w]", input_doc):
    if token not in input_tokens:
      input_tokens.add(token)
  for token in target_doc.split():
    if token not in target_tokens:
      target_tokens.add(token)

input_tokens = sorted(list(input_tokens))
target_tokens = sorted(list(target_tokens))
num_encoder_tokens = len(input_tokens)
num_decoder_tokens = len(target_tokens)
```

Note: We are only taking the first 400 pairs to keep things simple but as a result, we will get very low accuracy.

We have unique input tokens and target tokens for our dataset. Now we will create an input features dictionary that will store our input tokens as key-value pairs, the word being the key and value is the index. Similarly, for target tokens, we will create a target features dictionary. Features dictionary will help us encode our sentences into one-hot vectors. After all, computers only understand the numbers. To decode the sentences we will need to create the reverse features dictionary that stores index as a key and word as a value.

```
input_features_dict = dict(
    [(token, i) for i, token in enumerate(input_tokens)])
target_features_dict = dict(
    [(token, i) for i, token in enumerate(target_tokens)])

reverse_input_features_dict = dict(
    (i, token) for token, i in input_features_dict.items())
reverse_target_features_dict = dict(
    (i, token) for token, i in target_features_dict.items())
```

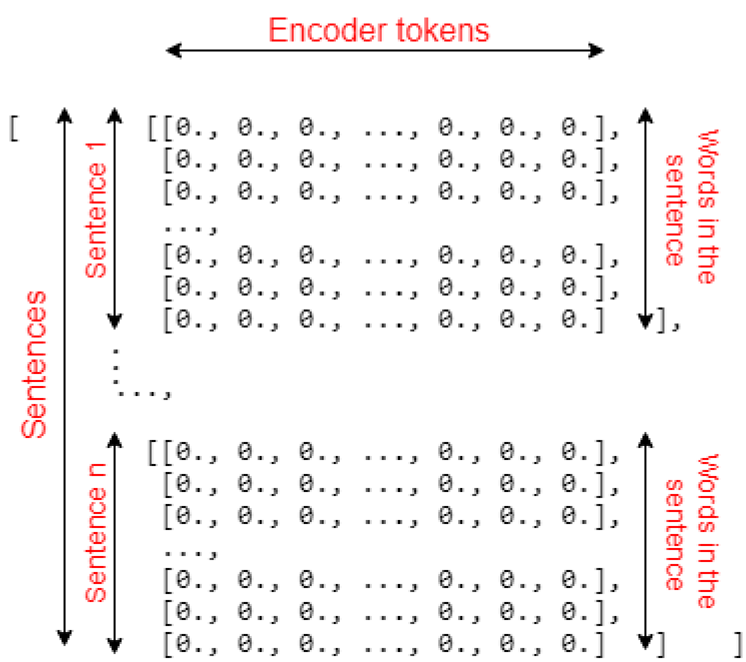
Training setup

To train our seq2seq model we will use three matrices of one-hot vectors, Encoder input data, Decoder input data, and Decoder output data. The reason we are using two matrices for the Decoder is a method called *teacher forcing* which is used by the seq2seq model while training. What is the idea behind this? We have an input token from the previous timestep to help the model train for the current target token. Let's create these matrices.

```
#Maximum length of sentences in input and target documents
max_encoder_seq_length = max([len(re.findall(r"[\w']+|[^\s\w]",
input_doc)) for input_doc in input_docs])
max_decoder_seq_length = max([len(re.findall(r"[\w']+|[^\s\w]",
target_doc)) for target_doc in target_docs])

encoder_input_data = np.zeros(
    (len(input_docs), max_encoder_seq_length, num_encoder_tokens),
    dtype='float32')
decoder_input_data = np.zeros(
    (len(input_docs), max_decoder_seq_length, num_decoder_tokens),
    dtype='float32')
decoder_target_data = np.zeros(
    (len(input_docs), max_decoder_seq_length, num_decoder_tokens),
    dtype='float32')

for line, (input_doc, target_doc) in enumerate(zip(input_docs,
target_docs)):
    for timestep, token in enumerate(re.findall(r"[\w']+|[^\s\w]",
```

```
input_doc)):
        #Assign 1. for the current line, timestep, & word in
encoder_input_data
        encoder_input_data[line, timestep,
input_features_dict[token]] = 1.

    for timestep, token in enumerate(target_doc.split()):
        decoder_input_data[line, timestep,
target_features_dict[token]] = 1.
        if timestep > 0:
            decoder_target_data[line, timestep - 1,
target_features_dict[token]] = 1.
```

To get a clear understanding of how the dimensions of *encoder_input_data* works see the below figure. The *decoder_input_data* and *decoder_target_data* similarly have the dimensions.



Encoder-decoder training setup

Our encoder model requires an input layer which defines a matrix for holding the one-hot vectors and an LSTM layer with some number of hidden states. Decoder model structure is almost the same as encoder's but here we pass in the state data along with the decoder inputs.

```
from tensorflow import keras
from keras.layers import Input, LSTM, Dense
from keras.models import Model

#Dimensionality
dimensionality = 256

#The batch size and number of epochs
batch_size = 10
epochs = 600

#Encoder
encoder_inputs = Input(shape=(None, num_encoder_tokens))
encoder_lstm = LSTM(dimensionality, return_state=True)
encoder_outputs, state_hidden, state_cell =
encoder_lstm(encoder_inputs)
encoder_states = [state_hidden, state_cell]

#Decoder
decoder_inputs = Input(shape=(None, num_decoder_tokens))
decoder_lstm = LSTM(dimensionality, return_sequences=True,
return_state=True)
decoder_outputs, decoder_state_hidden, decoder_state_cell =
decoder_lstm(decoder_inputs, initial_state=encoder_states)
decoder_dense = Dense(num_decoder_tokens, activation='softmax')
decoder_outputs = decoder_dense(decoder_outputs)
```

You can learn more about how to code the encoder-decoder model here as a full explanation of it is out of scope for this article.

Building and training seq2seq model

Now we will create our seq2seq model and train it with encoder and decoder data as shown below.

```
#Model
training_model = Model([encoder_inputs, decoder_inputs],
decoder_outputs)

#Compiling
training_model.compile(optimizer='rmsprop',
loss='categorical_crossentropy', metrics=['accuracy'],
sample_weight_mode='temporal')

#Training
training_model.fit([encoder_input_data, decoder_input_data],
```

```
decoder_target_data, batch_size = batch_size, epochs = epochs,
validation_split = 0.2)
training_model.save('training_model.h5')
```

Here, we are using *rmsprop* as an optimizer and *categorical_crossentropy* as our loss function. We call the *.fit()* method by giving the encoder and decoder input data (X/input) and decoder target data (Y/label). After training finishes, we get training accuracy of around 20%. The reason for this lower accuracy is that we used only 400 pairs of the dataset. If trained on a larger dataset, greater accuracy can be achieved.

Testing setup

Now, to handle an input that the model has not seen we will need a model that decodes step-by-step instead of using *teacher forcing* because the model we created only works when the target sequence is known. In the Generative chatbot application, we will not know what the generated response will be for input the user passes in. For doing this, we will have to build a seq2seq model in individual pieces. Let's first build an encoder model with encoder inputs and encoder output states. We will do this with the help of the previously trained model.

```
from keras.models import load_model
training_model = load_model('training_model.h5')

encoder_inputs = training_model.input[0]
encoder_outputs, state_h_enc, state_c_enc =
training_model.layers[2].output
encoder_states = [state_h_enc, state_c_enc]
encoder_model = Model(encoder_inputs, encoder_states)
```

Next, we will need to create placeholders for decoder input states as we do not know what we need to decode or what hidden state we will get.

```
latent_dim = 256
decoder_state_input_hidden = Input(shape=(latent_dim,))
decoder_state_input_cell = Input(shape=(latent_dim,))
decoder_states_inputs = [decoder_state_input_hidden,
decoder_state_input_cell]
```

Now we will create new decoder states and outputs with the help of decoder LSTM and Dense layer that we trained earlier.

```
decoder_outputs, state_hidden, state_cell =
decoder_lstm(decoder_inputs, initial_state=decoder_states_inputs)
decoder_states = [state_hidden, state_cell]
decoder_outputs = decoder_dense(decoder_outputs)
```

Finally, we have the decoder input layer, the final states from the encoder, the decoder outputs from the Dense layer of the decoder, and decoder output states which is the memory during the network from one word to the next. We can bring this all together now and set up the decoder model as shown below.

```
decoder_model = Model([decoder_inputs] + decoder_states_inputs,
[decoder_outputs] + decoder_states)
```

Testing our model

At last, we will create a function that accepts our text inputs and generates a response using encoder and decoder that we created. In the function below, we pass in the NumPy matrix that represents our text sentence and we get the generated response back from it. I have added comments for almost every line of code for you to understand it quickly. What happens in the below function is this: 1.) We retrieve output states from the encoder 2.) We pass in the output states to the decoder (which is our initial hidden state of the decoder) to decode the sentence word by word 3.) Update the hidden state of decoder after decoding each word so that we can use previously decoded words to help decode new ones

We will stop once we encounter ‘<END>’ token that we added to target sequences in our preprocessing task or we hit the maximum length of the sequence.

```
def decode_response(test_input):
    #Getting the output states to pass into the decoder
    states_value = encoder_model.predict(test_input)
    #Generating empty target sequence of length 1
    target_seq = np.zeros((1, 1, num_decoder_tokens))
```

```
    #Setting the first token of target sequence with the start token
    target_seq[0, 0, target_features_dict['<START>']] = 1.

    #A variable to store our response word by word
    decoded_sentence = ''

    stop_condition = False

while not stop_condition:
      #Predicting output tokens with probabilities and states
      output_tokens, hidden_state, cell_state =
decoder_model.predict([target_seq] + states_value)

#Choosing the one with highest probability
      sampled_token_index = np.argmax(output_tokens[0, -1, :])
      sampled_token =
reverse_target_features_dict[sampled_token_index]
      decoded_sentence += " " + sampled_token

#Stop if hit max length or found the stop token
      if (sampled_token == '<END>' or len(decoded_sentence) >
max_decoder_seq_length):
        stop_condition = True

#Update the target sequence
      target_seq = np.zeros((1, 1, num_decoder_tokens))
      target_seq[0, 0, sampled_token_index] = 1.
      #Update states
      states_value = [hidden_state, cell_state]

return decoded_sentence
```

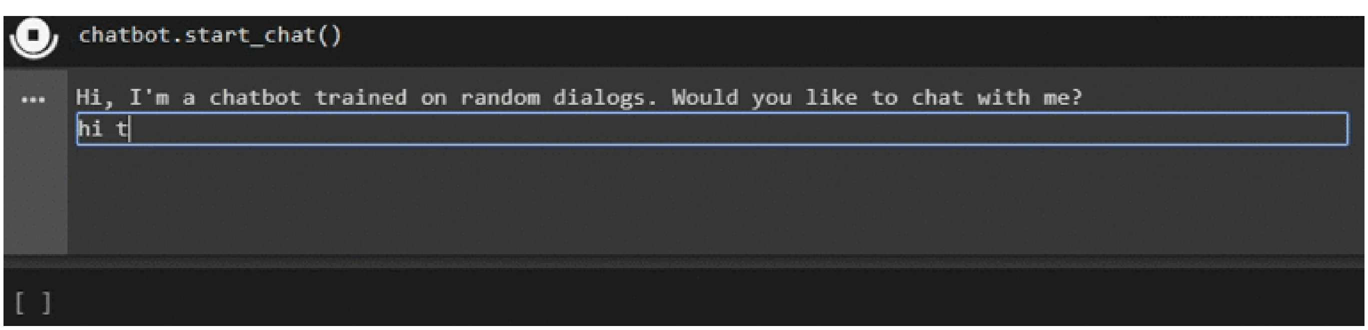
Putting it all together — Generative Chatbot

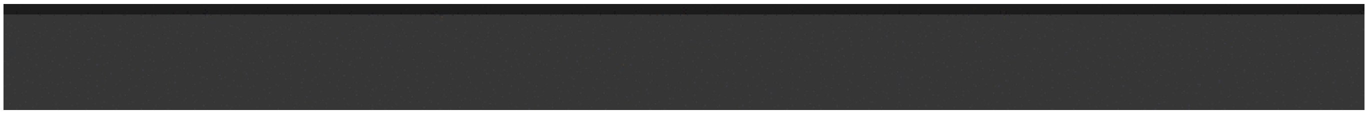
Let’s create a class that contains methods required for running a chatbot.

```
class ChatBot:
  negative_responses = ("no", "nope", "nah", "naw", "not a chance",
"sorry")
  exit_commands = ("quit", "pause", "exit", "goodbye", "bye",
"later", "stop")

#Method to start the conversation
  def start_chat(self):
    user_response = input("Hi, I'm a chatbot trained on random
dialogs. Would you like to chat with me?\n")

    if user_response in self.negative_responses:
      print("Ok, have a great day!")
```

```
      return
    self.chat(user_response)

#Method to handle the conversation
  def chat(self, reply):
    while not self.make_exit(reply):
      reply = input(self.generate_response(reply)+"\n")

  #Method to convert user input into a matrix
  def string_to_matrix(self, user_input):
    tokens = re.findall(r"[\w']+|[^\s\w]", user_input)
    user_input_matrix = np.zeros(
      (1, max_encoder_seq_length, num_encoder_tokens),
      dtype='float32')
    for timestep, token in enumerate(tokens):
      if token in input_features_dict:
        user_input_matrix[0, timestep, input_features_dict[token]] =
1.
    return user_input_matrix

  #Method that will create a response using seq2seq model we built
  def generate_response(self, user_input):
    input_matrix = self.string_to_matrix(user_input)
    chatbot_response = decode_response(input_matrix)
    #Remove <START> and <END> tokens from chatbot_response
    chatbot_response = chatbot_response.replace("<START>",'')
    chatbot_response = chatbot_response.replace("<END>",'')
    return chatbot_response

#Method to check for exit commands
  def make_exit(self, reply):
    for exit_command in self.exit_commands:
      if exit_command in reply:
        print("Ok, have a great day!")
        return True
    return False

chatbot = ChatBot()
```

All methods are self-explanatory in the above code. Below is the final output for our Generative chatbot!





Conversation with the chatbot!

You can find all of the code above here on GitHub and find me here on LinkedIn.

Future scope vs limitation

Here we used a very small dataset and got an accuracy of around 20%. In the future for a larger dataset, the model might give better accuracy. The limitation of using this approach for creating chatbots is that we need a very large dataset to give the best responses to the user as we can see in the above output that chatbot does not give the right responses in some cases because of a smaller dataset.

A similar task we can do with the above-shown approach is Machine Translation. The below article shows how we can use the seq2seq model to perform Machine Translation.

Machine translation with the seq2seq model: Different approaches

Discussing the two different approaches for machine translation using the seq2seq model.

towardsdatascience.com

Conclusion

Closed domain architecture focuses on response selection from a set of predefined responses when the open domain architecture enables us to perform boundless *text generation*. Closed domain systems use intent classification, entity identification, and response selection. But for an open domain chatbot, intent classification is harder and an immense number of intents are likely. Rather than selecting full responses, the open domain or generative model generates the response word by word, allowing for new combinations of language.

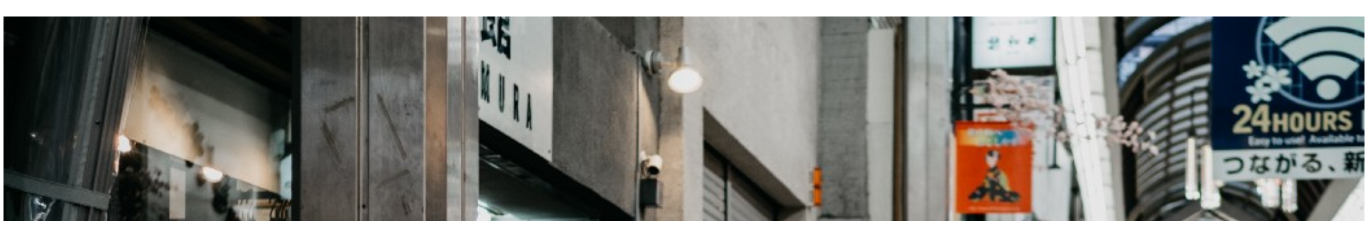


Photo by Lukas on Unsplash

In industries, some companies use the closed domain chatbots to ensure that the user always receives the right response from the predefined ones. The Natural Language Processing- NLP domain is developing and training neural networks for approximating the approach the human brain takes towards language processing. This deep learning strategy allows computers to handle human language much more efficiently.

Sign up for The Variable

By Towards Data Science

Every Thursday, the Variable delivers the very best of Towards Data Science: from hands-on tutorials and cutting-edge research to original features you don't want to miss. Take a look.

Get this newsletter

Deep Learning Data Science Chatbots Python NLP

About Write Help Legal

Get the Medium app

Download on the App Store

GET IT ON Google Play