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Panel-C
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AIES Lab Assignment -6

* Title - Implement a chat bot using techniques of Natural Language Processing.

* Objective - Write a program in C / C++ / Python / Java to create a chat-bot using various Natural Language Processing Libraries.

* Theory -

1) Natural Language Processing
Natural language processing (NLP) refers to the branch of computer science - & more specifically, the branch of artificial intelligence or AI - concerned with giving computers the ability to understand text & spoken words in much the same way human beings can.

2) Various NLP libraries which can be used in Creating Chat-bot

NLTK (Natural Language Tool Kit)

ChatterBot
Genism
Core NLP
spacy
TextBlob
Pattern
PyNLPI

* Input : Python code for chatbot

* Output : A working chat-bot

* Platform : Windows / Linux

* FAQ's

Q1) Explain Natural Language Processing in detail with example.

Ans Natural Language Processing (NLP) is a field of artificial intelligence that focuses on the interaction between computers & humans using natural language. The goal ~~t~~ of NLP is to enable computers to understand, interpret, & generate ~~him~~ human language in a way that is both meaningful & contextually relevant.

Key components in NLP:

1) Tokenization: The process of breaking down

a text into smaller units, usually words or phrases (tokens). For example, the sentence "I love NLP" would be tokenized into three tokens: "I", "Love", "NLP".

2) Part-of-Speech (POS) Tagging: Assigning grammatical parts of speech to each word in a sentence, such as nouns, verbs, adjectives, etc. For instance, in the sentence "She is reading a book", POS tagging would label "She" as a pronoun, "is" is a verb, "reading" as a verb, "a" as an article, & "book" as a noun.

3) Named Entity Recognition (NER): Identifying & classifying entities (such as names of people, organizations, locations, etc) in a text.

4) Sentiment Analysis: Determining the sentiment expressed in a pieces of a text, whether it's positive, negative or neutral.

5) Machine translation: Translating text from one language to another automatically.

6) Text Generation: Creating human-like ~~text~~ text based on a given prompt or context

7) Speech Recognition: Converting spoken language into written text.

Q2) Explain limitations & challenges one face while creating a Chat-bot?

Ans Creating a chatbot comes with several limitations & challenges, including:

1) Understanding Ambiguity: Chatbots may struggle

to understand ambiguous or ~~vg~~ vague queries, leading to inaccurate responses.

2) Lack of Context Understanding : Maintaining context over a conversation is challenging, & chatbots may struggle to understand references to previous messages.

3) Handling Unstructure Data : Processing ~~natural~~ unstructured data, such as informal language or ~~diverse~~ diverse inputs, can be difficult our chatbots.

4) Emotion Recognition : Recognizing & appropriately responding to user emotions expressed through text is a complex task.

5) Integration with Backend systems : Connecting the chatbot to backend systems & databases for retrieving relevant information can be challenging.

6) Security concerns : Ensuring the security of user data & preventing malicious use or exploitation is a significant challenge.

7) Training Data Quality : The quality & representativeness of training data directly impact the chatbot's performance & generalization to diverse user inputs.

8) Ethical Considerations : Addressing ethical concerns, such as bias in language models or unintended consequences of responses, is crucial in chatbot development.

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9) Continuous learning: Keeping the chatbot updated & adaptive to evolving language trends & user behaviours requires ongoing effort

10) User expectation Management: Managing user expectations & providing clear indications when the chatbot may not comprehend or fulfill certain requests is important for user satisfaction.

Q3) Uses of Chat-bot in various domains? (Any 4)

Ans 1) Customer Service : Chatbots assist in handling customer queries, providing information, & offering support 24/7.

2) E-commerce : Chatbots facilitate product recommendations, order tracking, & customer assistance in online shopping

3) Healthcare: Chatbots aid in appointment scheduling, symptoms checking, & providing basic medical information.

4) Finance : Chatbots help with account inquiries, transaction history, & financial advice in banking & finance applications.

11/2/23

```python
import json
import string
import random
import nltk
import numpy as num
from nltk.stem import WordNetLemmatizer
import tensorflow as tensorF
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, Dropout

nltk.download("punkt")
nltk.download("wordnet")
```

```
[nltk_data] Error loading punkt: <urlopen error [Errno 8] nodename nor
[nltk_data]     servname provided, or not known>
[nltk_data] Error loading wordnet: <urlopen error [Errno 8] nodename
[nltk_data]     nor servname provided, or not known>
```

```
False
```

```python
ourData = {"ourIntents": [

             {"tag": "age",
              "patterns": ["how old are you?"],
              "responses": ["Aree Umra me kya rakha hai?"]
             },
              {"tag": "greeting",
              "patterns": [ "Hi", "Hello", "Hey"],
              "responses": ["Hi there", "Hello", "Hi :)"],
             },
              {"tag": "goodbye",
              "patterns": [ "bye", "later"],
              "responses": ["Bye", "take care"]
             },
             {"tag": "name",
              "patterns": ["what's your name?", "who are you?"],
              "responses": ["Aree naam me kya rakha hai?","You can
give me a name, and I will appreciate it"]
             }

]}
```

```python
lm = WordNetLemmatizer() #for getting words
# lists
ourClasses = []
newWords = []
documentX = []
documentY = []
# Each intent is tokenized into words and the patterns and their
associated tags are added to their respective lists.
```

```
for intent in ourData["ourIntents"]:
    for pattern in intent["patterns"]:
        ournewTkns = nltk.word_tokenize(pattern)# tokenize the
patterns
        newWords.extend(ournewTkns)# extends the tokens
        documentX.append(pattern)
        documentY.append(intent["tag"])


    if intent["tag"] not in ourClasses:# add unexisting tags to their
respective classes
        ourClasses.append(intent["tag"])

newWords = [lm.lemmatize(word.lower()) for word in newWords if word
not in string.punctuation] # set words to lowercase if not in
punctuation
newWords = sorted(set(newWords))# sorting words
ourClasses = sorted(set(ourClasses))# sorting classes

trainingData = [] # training list array
outEmpty = [0] * len(ourClasses)
# bow model
for idx, doc in enumerate(documentX):
    bagOfwords = []
    text = lm.lemmatize(doc.lower())
    for word in newWords:
        bagOfwords.append(1) if word in text else bagOfwords.append(0)

    outputRow = list(outEmpty)
    outputRow[ourClasses.index(documentY[idx])] = 1
    trainingData.append([bagOfwords, outputRow])

random.shuffle(trainingData)
trainingData = num.array(trainingData, dtype=object)

x = num.array(list(trainingData[:, 0]))# first trainig phase
y = num.array(list(trainingData[:, 1]))# second training phase

iShape = (len(x[0]),)
oShape = len(y[0])

ourNewModel = Sequential()

# Dense function adds an output layer
ourNewModel.add(Dense(128, input_shape=iShape, activation="relu"))

ourNewModel.add(Dropout(0.5))

ourNewModel.add(Dense(64, activation="relu"))
ourNewModel.add(Dropout(0.3))
ourNewModel.add(Dense(oShape, activation = "softmax"))
```

```python
md = tensorF.keras.optimizers.legacy.Adam(learning_rate=0.01,
decay=1e-6)

ourNewModel.compile(loss='categorical_crossentropy',
              optimizer=md,
              metrics=["accuracy"])
# Output the model in summary
print(ourNewModel.summary())

ourNewModel.fit(x, y, epochs=200, verbose=1)
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 128)               1920

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 64)                8256

 dropout_1 (Dropout)         (None, 64)                0

 dense_2 (Dense)             (None, 4)                 260

=================================================================
Total params: 10436 (40.77 KB)
Trainable params: 10436 (40.77 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
Epoch 1/200
1/1 [==============================] - 0s 139ms/step - loss: 1.3764 -
accuracy: 0.2500
Epoch 2/200
1/1 [==============================] - 0s 2ms/step - loss: 1.3555 -
accuracy: 0.2500
Epoch 3/200
1/1 [==============================] - 0s 2ms/step - loss: 1.2542 -
accuracy: 0.6250
Epoch 4/200
1/1 [==============================] - 0s 2ms/step - loss: 1.0830 -
accuracy: 0.7500
Epoch 5/200
1/1 [==============================] - 0s 2ms/step - loss: 0.9274 -
accuracy: 0.8750
Epoch 6/200
1/1 [==============================] - 0s 1ms/step - loss: 0.9818 -
accuracy: 0.7500
```

```
Epoch 7/200
1/1 [==============================] - 0s 2ms/step - loss: 0.8465 -
accuracy: 0.8750
Epoch 8/200
1/1 [==============================] - 0s 2ms/step - loss: 0.7404 -
accuracy: 1.0000
Epoch 9/200
1/1 [==============================] - 0s 2ms/step - loss: 0.5206 -
accuracy: 1.0000
Epoch 10/200
1/1 [==============================] - 0s 2ms/step - loss: 0.5145 -
accuracy: 1.0000
Epoch 11/200
1/1 [==============================] - 0s 2ms/step - loss: 0.5832 -
accuracy: 0.8750
Epoch 12/200
1/1 [==============================] - 0s 2ms/step - loss: 0.2845 -
accuracy: 1.0000
Epoch 13/200
1/1 [==============================] - 0s 2ms/step - loss: 0.2081 -
accuracy: 1.0000
Epoch 14/200
1/1 [==============================] - 0s 2ms/step - loss: 0.1085 -
accuracy: 1.0000
Epoch 15/200
1/1 [==============================] - 0s 2ms/step - loss: 0.1595 -
accuracy: 1.0000
Epoch 16/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0461 -
accuracy: 1.0000
Epoch 17/200
1/1 [==============================] - 0s 3ms/step - loss: 0.1207 -
accuracy: 1.0000
Epoch 18/200
1/1 [==============================] - 0s 6ms/step - loss: 0.0549 -
accuracy: 1.0000
Epoch 19/200
1/1 [==============================] - 0s 3ms/step - loss: 0.1318 -
accuracy: 0.8750
Epoch 20/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0628 -
accuracy: 1.0000
Epoch 21/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0453 -
accuracy: 1.0000
Epoch 22/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0512 -
accuracy: 1.0000
Epoch 23/200
```

```
1/1 [==============================] - 0s 2ms/step - loss: 0.0140 -
accuracy: 1.0000
Epoch 24/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0203 -
accuracy: 1.0000
Epoch 25/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0162 -
accuracy: 1.0000
Epoch 26/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0024 -
accuracy: 1.0000
Epoch 27/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0823 -
accuracy: 1.0000
Epoch 28/200
1/1 [==============================] - 0s 3ms/step - loss: 0.0019 -
accuracy: 1.0000
Epoch 29/200
1/1 [==============================] - 0s 2ms/step - loss: 4.2206e-04
- accuracy: 1.0000
Epoch 30/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0076 -
accuracy: 1.0000
Epoch 31/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0037 -
accuracy: 1.0000
Epoch 32/200
1/1 [==============================] - 0s 2ms/step - loss: 5.8060e-04
- accuracy: 1.0000
Epoch 33/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0092 -
accuracy: 1.0000
Epoch 34/200
1/1 [==============================] - 0s 3ms/step - loss: 8.1562e-04
- accuracy: 1.0000
Epoch 35/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0118 -
accuracy: 1.0000
Epoch 36/200
1/1 [==============================] - 0s 2ms/step - loss: 5.8493e-04
- accuracy: 1.0000
Epoch 37/200
1/1 [==============================] - 0s 2ms/step - loss: 4.1132e-04
- accuracy: 1.0000
Epoch 38/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0019 -
accuracy: 1.0000
Epoch 39/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0021 -
```

```
accuracy: 1.0000
Epoch 40/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0040 -
accuracy: 1.0000
Epoch 41/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0063 -
accuracy: 1.0000
Epoch 42/200
1/1 [==============================] - 0s 2ms/step - loss: 6.2154e-04
- accuracy: 1.0000
Epoch 43/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0059 -
accuracy: 1.0000
Epoch 44/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0012 -
accuracy: 1.0000
Epoch 45/200
1/1 [==============================] - 0s 2ms/step - loss: 6.9873e-04
- accuracy: 1.0000
Epoch 46/200
1/1 [==============================] - 0s 1ms/step - loss: 0.0013 -
accuracy: 1.0000
Epoch 47/200
1/1 [==============================] - 0s 2ms/step - loss: 9.3499e-04
- accuracy: 1.0000
Epoch 48/200
1/1 [==============================] - 0s 3ms/step - loss: 7.3041e-04
- accuracy: 1.0000
Epoch 49/200
1/1 [==============================] - 0s 2ms/step - loss: 5.5475e-04
- accuracy: 1.0000
Epoch 50/200
1/1 [==============================] - 0s 2ms/step - loss: 7.2829e-04
- accuracy: 1.0000
Epoch 51/200
1/1 [==============================] - 0s 2ms/step - loss: 5.7841e-05
- accuracy: 1.0000
Epoch 52/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0029 -
accuracy: 1.0000
Epoch 53/200
1/1 [==============================] - 0s 2ms/step - loss: 2.5794e-04
- accuracy: 1.0000
Epoch 54/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0020 -
accuracy: 1.0000
Epoch 55/200
1/1 [==============================] - 0s 2ms/step - loss: 2.0051e-04
- accuracy: 1.0000
```

```
Epoch 56/200
1/1 [==============================] - 0s 2ms/step - loss: 1.0307e-04
- accuracy: 1.0000
Epoch 57/200
1/1 [==============================] - 0s 2ms/step - loss: 1.3638e-04
- accuracy: 1.0000
Epoch 58/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0070 -
accuracy: 1.0000
Epoch 59/200
1/1 [==============================] - 0s 1ms/step - loss: 2.0727e-05
- accuracy: 1.0000
Epoch 60/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0015 -
accuracy: 1.0000
Epoch 61/200
1/1 [==============================] - 0s 2ms/step - loss: 1.4651e-04
- accuracy: 1.0000
Epoch 62/200
1/1 [==============================] - 0s 2ms/step - loss: 6.0051e-06
- accuracy: 1.0000
Epoch 63/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0018 -
accuracy: 1.0000
Epoch 64/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0044 -
accuracy: 1.0000
Epoch 65/200
1/1 [==============================] - 0s 1ms/step - loss: 8.4792e-05
- accuracy: 1.0000
Epoch 66/200
1/1 [==============================] - 0s 1ms/step - loss: 1.3962e-05
- accuracy: 1.0000
Epoch 67/200
1/1 [==============================] - 0s 1ms/step - loss: 8.3540e-05
- accuracy: 1.0000
Epoch 68/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0040 -
accuracy: 1.0000
Epoch 69/200
1/1 [==============================] - 0s 2ms/step - loss: 1.7333e-04
- accuracy: 1.0000
Epoch 70/200
1/1 [==============================] - 0s 1ms/step - loss: 0.0030 -
accuracy: 1.0000
Epoch 71/200
1/1 [==============================] - 0s 2ms/step - loss: 1.9460e-05
- accuracy: 1.0000
Epoch 72/200
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```
1/1 [==============================] - 0s 1ms/step - loss: 0.0046 -
accuracy: 1.0000
Epoch 73/200
1/1 [==============================] - 0s 2ms/step - loss: 5.1942e-05
- accuracy: 1.0000
Epoch 74/200
1/1 [==============================] - 0s 2ms/step - loss: 3.2809e-05
- accuracy: 1.0000
Epoch 75/200
1/1 [==============================] - 0s 1ms/step - loss: 2.5646e-04
- accuracy: 1.0000
Epoch 76/200
1/1 [==============================] - 0s 1ms/step - loss: 5.3197e-06
- accuracy: 1.0000
Epoch 77/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0117 -
accuracy: 1.0000
Epoch 78/200
1/1 [==============================] - 0s 2ms/step - loss: 7.1457e-04
- accuracy: 1.0000
Epoch 79/200
1/1 [==============================] - 0s 2ms/step - loss: 1.2579e-04
- accuracy: 1.0000
Epoch 80/200
1/1 [==============================] - 0s 1ms/step - loss: 2.5435e-05
- accuracy: 1.0000
Epoch 81/200
1/1 [==============================] - 0s 1ms/step - loss: 1.2844e-05
- accuracy: 1.0000
Epoch 82/200
1/1 [==============================] - 0s 2ms/step - loss: 3.9495e-04
- accuracy: 1.0000
Epoch 83/200
1/1 [==============================] - 0s 2ms/step - loss: 1.1290e-04
- accuracy: 1.0000
Epoch 84/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0042 -
accuracy: 1.0000
Epoch 85/200
1/1 [==============================] - 0s 2ms/step - loss: 3.8859e-05
- accuracy: 1.0000
Epoch 86/200
1/1 [==============================] - 0s 2ms/step - loss: 9.5217e-06
- accuracy: 1.0000
Epoch 87/200
1/1 [==============================] - 0s 2ms/step - loss: 2.0350e-04
- accuracy: 1.0000
Epoch 88/200
1/1 [==============================] - 0s 2ms/step - loss: 1.8490e-04
- accuracy: 1.0000
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```
Epoch 89/200
1/1 [==============================] - 0s 2ms/step - loss: 6.7775e-04
- accuracy: 1.0000
Epoch 90/200
1/1 [==============================] - 0s 2ms/step - loss: 3.3347e-05
- accuracy: 1.0000
Epoch 91/200
1/1 [==============================] - 0s 2ms/step - loss: 5.7607e-04
- accuracy: 1.0000
Epoch 92/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0011 -
accuracy: 1.0000
Epoch 93/200
1/1 [==============================] - 0s 1ms/step - loss: 5.2193e-05
- accuracy: 1.0000
Epoch 94/200
1/1 [==============================] - 0s 1ms/step - loss: 4.6040e-04
- accuracy: 1.0000
Epoch 95/200
1/1 [==============================] - 0s 1ms/step - loss: 5.3550e-05
- accuracy: 1.0000
Epoch 96/200
1/1 [==============================] - 0s 2ms/step - loss: 9.8535e-05
- accuracy: 1.0000
Epoch 97/200
1/1 [==============================] - 0s 2ms/step - loss: 1.8685e-05
- accuracy: 1.0000
Epoch 98/200
1/1 [==============================] - 0s 2ms/step - loss: 1.0424e-04
- accuracy: 1.0000
Epoch 99/200
1/1 [==============================] - 0s 2ms/step - loss: 2.5782e-04
- accuracy: 1.0000
Epoch 100/200
1/1 [==============================] - 0s 1ms/step - loss: 3.1455e-04
- accuracy: 1.0000
Epoch 101/200
1/1 [==============================] - 0s 1ms/step - loss: 8.3832e-05
- accuracy: 1.0000
Epoch 102/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0055 -
accuracy: 1.0000
Epoch 103/200
1/1 [==============================] - 0s 2ms/step - loss: 3.3539e-04
- accuracy: 1.0000
Epoch 104/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0086 -
accuracy: 1.0000
Epoch 105/200
1/1 [==============================] - 0s 2ms/step - loss: 2.8884e-04
```

```
- accuracy: 1.0000
Epoch 106/200
1/1 [==============================] - 0s 2ms/step - loss: 2.5859e-04
- accuracy: 1.0000
Epoch 107/200
1/1 [==============================] - 0s 2ms/step - loss: 2.5395e-04
- accuracy: 1.0000
Epoch 108/200
1/1 [==============================] - 0s 2ms/step - loss: 2.0713e-06
- accuracy: 1.0000
Epoch 109/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0069 -
accuracy: 1.0000
Epoch 110/200
1/1 [==============================] - 0s 2ms/step - loss: 1.4182e-04
- accuracy: 1.0000
Epoch 111/200
1/1 [==============================] - 0s 2ms/step - loss: 6.0964e-04
- accuracy: 1.0000
Epoch 112/200
1/1 [==============================] - 0s 1ms/step - loss: 3.6505e-05
- accuracy: 1.0000
Epoch 113/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0069 -
accuracy: 1.0000
Epoch 114/200
1/1 [==============================] - 0s 2ms/step - loss: 6.8787e-04
- accuracy: 1.0000
Epoch 115/200
1/1 [==============================] - 0s 2ms/step - loss: 4.4159e-04
- accuracy: 1.0000
Epoch 116/200
1/1 [==============================] - 0s 2ms/step - loss: 1.4741e-04
- accuracy: 1.0000
Epoch 117/200
1/1 [==============================] - 0s 1ms/step - loss: 1.7342e-04
- accuracy: 1.0000
Epoch 118/200
1/1 [==============================] - 0s 2ms/step - loss: 5.4741e-05
- accuracy: 1.0000
Epoch 119/200
1/1 [==============================] - 0s 1ms/step - loss: 8.8618e-04
- accuracy: 1.0000
Epoch 120/200
1/1 [==============================] - 0s 1ms/step - loss: 5.4687e-06
- accuracy: 1.0000
Epoch 121/200
1/1 [==============================] - 0s 2ms/step - loss: 8.0130e-05
- accuracy: 1.0000
Epoch 122/200
```

```
1/1 [==============================] - 0s 2ms/step - loss: 2.1233e-05
- accuracy: 1.0000
Epoch 123/200
1/1 [==============================] - 0s 1ms/step - loss: 0.0012 -
accuracy: 1.0000
Epoch 124/200
1/1 [==============================] - 0s 2ms/step - loss: 9.7897e-06
- accuracy: 1.0000
Epoch 125/200
1/1 [==============================] - 0s 2ms/step - loss: 1.7598e-05
- accuracy: 1.0000
Epoch 126/200
1/1 [==============================] - 0s 2ms/step - loss: 7.0206e-04
- accuracy: 1.0000
Epoch 127/200
1/1 [==============================] - 0s 2ms/step - loss: 1.4367e-04
- accuracy: 1.0000
Epoch 128/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0015 -
accuracy: 1.0000
Epoch 129/200
1/1 [==============================] - 0s 1ms/step - loss: 1.5348e-06
- accuracy: 1.0000
Epoch 130/200
1/1 [==============================] - 0s 2ms/step - loss: 2.1710e-05
- accuracy: 1.0000
Epoch 131/200
1/1 [==============================] - 0s 2ms/step - loss: 1.3604e-05
- accuracy: 1.0000
Epoch 132/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0124 -
accuracy: 1.0000
Epoch 133/200
1/1 [==============================] - 0s 1ms/step - loss: 4.0950e-04
- accuracy: 1.0000
Epoch 134/200
1/1 [==============================] - 0s 2ms/step - loss: 8.3067e-05
- accuracy: 1.0000
Epoch 135/200
1/1 [==============================] - 0s 2ms/step - loss: 5.4309e-05
- accuracy: 1.0000
Epoch 136/200
1/1 [==============================] - 0s 2ms/step - loss: 2.1427e-05
- accuracy: 1.0000
Epoch 137/200
1/1 [==============================] - 0s 3ms/step - loss: 8.1507e-06
- accuracy: 1.0000
Epoch 138/200
1/1 [==============================] - 0s 2ms/step - loss: 1.1459e-05
- accuracy: 1.0000
```

```
Epoch 139/200
1/1 [==============================] - 0s 1ms/step - loss: 1.9515e-04
- accuracy: 1.0000
Epoch 140/200
1/1 [==============================] - 0s 2ms/step - loss: 8.7916e-06
- accuracy: 1.0000
Epoch 141/200
1/1 [==============================] - 0s 1ms/step - loss: 3.5882e-04
- accuracy: 1.0000
Epoch 142/200
1/1 [==============================] - 0s 1ms/step - loss: 7.2364e-05
- accuracy: 1.0000
Epoch 143/200
1/1 [==============================] - 0s 2ms/step - loss: 1.6659e-05
- accuracy: 1.0000
Epoch 144/200
1/1 [==============================] - 0s 2ms/step - loss: 1.9282e-04
- accuracy: 1.0000
Epoch 145/200
1/1 [==============================] - 0s 2ms/step - loss: 0.0021 -
accuracy: 1.0000
Epoch 146/200
1/1 [==============================] - 0s 2ms/step - loss: 4.2617e-06
- accuracy: 1.0000
Epoch 147/200
1/1 [==============================] - 0s 2ms/step - loss: 4.2823e-05
- accuracy: 1.0000
Epoch 148/200
1/1 [==============================] - 0s 2ms/step - loss: 2.5926e-05
- accuracy: 1.0000
Epoch 149/200
1/1 [==============================] - 0s 2ms/step - loss: 1.0854e-04
- accuracy: 1.0000
Epoch 150/200
1/1 [==============================] - 0s 1ms/step - loss: 6.3383e-05
- accuracy: 1.0000
Epoch 151/200
1/1 [==============================] - 0s 2ms/step - loss: 4.5196e-04
- accuracy: 1.0000
Epoch 152/200

1/1 [==============================] - 0s 2ms/step - loss: 1.3411e-06
- accuracy: 1.0000
Epoch 153/200
1/1 [==============================] - 0s 2ms/step - loss: 1.1623e-06
- accuracy: 1.0000
Epoch 154/200
1/1 [==============================] - 0s 1ms/step - loss: 5.0075e-04
- accuracy: 1.0000
Epoch 155/200
```

```
1/1 [==============================] - 0s 2ms/step - loss: 5.5836e-04
- accuracy: 1.0000
Epoch 156/200
1/1 [==============================] - 0s 1ms/step - loss: 1.3440e-05
- accuracy: 1.0000
Epoch 157/200
1/1 [==============================] - 0s 2ms/step - loss: 3.3825e-06
- accuracy: 1.0000
Epoch 158/200
1/1 [==============================] - 0s 2ms/step - loss: 6.3329e-06
- accuracy: 1.0000
Epoch 159/200
1/1 [==============================] - 0s 2ms/step - loss: 4.5622e-05
- accuracy: 1.0000
Epoch 160/200
1/1 [==============================] - 0s 2ms/step - loss: 9.3609e-05
- accuracy: 1.0000
Epoch 161/200
1/1 [==============================] - 0s 2ms/step - loss: 8.6872e-06
- accuracy: 1.0000
Epoch 162/200
1/1 [==============================] - 0s 1ms/step - loss: 2.3817e-04
- accuracy: 1.0000
Epoch 163/200
1/1 [==============================] - 0s 1ms/step - loss: 2.6477e-05
- accuracy: 1.0000
Epoch 164/200
1/1 [==============================] - 0s 1ms/step - loss: 1.0997e-05
- accuracy: 1.0000
Epoch 165/200
1/1 [==============================] - 0s 1ms/step - loss: 0.0045 -
accuracy: 1.0000
Epoch 166/200
1/1 [==============================] - 0s 1ms/step - loss: 2.9057e-06
- accuracy: 1.0000
Epoch 167/200
1/1 [==============================] - 0s 2ms/step - loss: 6.9438e-06
- accuracy: 1.0000
Epoch 168/200
1/1 [==============================] - 0s 2ms/step - loss: 2.2306e-05
- accuracy: 1.0000
Epoch 169/200
1/1 [==============================] - 0s 2ms/step - loss: 2.2712e-04
- accuracy: 1.0000
Epoch 170/200
1/1 [==============================] - 0s 2ms/step - loss: 8.0816e-05
- accuracy: 1.0000
Epoch 171/200
1/1 [==============================] - 0s 2ms/step - loss: 2.1338e-05
```

```
- accuracy: 1.0000
Epoch 172/200
1/1 [==============================] - 0s 1ms/step - loss: 3.9784e-05
- accuracy: 1.0000
Epoch 173/200
1/1 [==============================] - 0s 2ms/step - loss: 6.1095e-07
- accuracy: 1.0000
Epoch 174/200
1/1 [==============================] - 0s 2ms/step - loss: 3.4256e-05
- accuracy: 1.0000
Epoch 175/200
1/1 [==============================] - 0s 2ms/step - loss: 1.8774e-05
- accuracy: 1.0000
Epoch 176/200
1/1 [==============================] - 0s 2ms/step - loss: 3.9739e-05
- accuracy: 1.0000
Epoch 177/200
1/1 [==============================] - 0s 2ms/step - loss: 1.2638e-04
- accuracy: 1.0000
Epoch 178/200
1/1 [==============================] - 0s 1ms/step - loss: 1.6987e-06
- accuracy: 1.0000
Epoch 179/200
1/1 [==============================] - 0s 1ms/step - loss: 2.4720e-05
- accuracy: 1.0000
Epoch 180/200
1/1 [==============================] - 0s 1ms/step - loss: 5.0217e-06
- accuracy: 1.0000
Epoch 181/200
1/1 [==============================] - 0s 1ms/step - loss: 4.8301e-05
- accuracy: 1.0000
Epoch 182/200
1/1 [==============================] - 0s 2ms/step - loss: 2.8312e-07
- accuracy: 1.0000
Epoch 183/200
1/1 [==============================] - 0s 2ms/step - loss: 5.4835e-06
- accuracy: 1.0000
Epoch 184/200
1/1 [==============================] - 0s 2ms/step - loss: 3.3300e-05
- accuracy: 1.0000
Epoch 185/200
1/1 [==============================] - 0s 2ms/step - loss: 2.3603e-05
- accuracy: 1.0000
Epoch 186/200
1/1 [==============================] - 0s 2ms/step - loss: 3.5416e-05
- accuracy: 1.0000
Epoch 187/200
1/1 [==============================] - 0s 1ms/step - loss: 1.1227e-04
- accuracy: 1.0000
```

```
Epoch 188/200
1/1 [==============================] - 0s 1ms/step - loss: 1.4394e-05
- accuracy: 1.0000
Epoch 189/200
1/1 [==============================] - 0s 2ms/step - loss: 3.4441e-04
- accuracy: 1.0000
Epoch 190/200
1/1 [==============================] - 0s 3ms/step - loss: 8.6495e-05
- accuracy: 1.0000
Epoch 191/200
1/1 [==============================] - 0s 2ms/step - loss: 2.2589e-05
- accuracy: 1.0000
Epoch 192/200
1/1 [==============================] - 0s 1ms/step - loss: 9.4919e-06
- accuracy: 1.0000
Epoch 193/200
1/1 [==============================] - 0s 2ms/step - loss: 1.7285e-06
- accuracy: 1.0000
Epoch 194/200
1/1 [==============================] - 0s 1ms/step - loss: 7.0504e-05
- accuracy: 1.0000
Epoch 195/200
1/1 [==============================] - 0s 2ms/step - loss: 1.3902e-05
- accuracy: 1.0000
Epoch 196/200
1/1 [==============================] - 0s 2ms/step - loss: 4.1721e-05
- accuracy: 1.0000
Epoch 197/200
1/1 [==============================] - 0s 3ms/step - loss: 1.4617e-05
- accuracy: 1.0000
Epoch 198/200
1/1 [==============================] - 0s 2ms/step - loss: 3.6806e-06
- accuracy: 1.0000
Epoch 199/200
1/1 [==============================] - 0s 2ms/step - loss: 1.6540e-06
- accuracy: 1.0000
Epoch 200/200
1/1 [==============================] - 0s 1ms/step - loss: 1.9794e-04
- accuracy: 1.0000

<keras.src.callbacks.History at 0x158deb210>
```

```python
def ourText(text):
  newtkns = nltk.word_tokenize(text)
  newtkns = [lm.lemmatize(word) for word in newtkns]
  return newtkns

def wordBag(text, vocab):
  newtkns = ourText(text)
  bagOwords = [0] * len(vocab)
```

```
  for w in newtkns:
    for idx, word in enumerate(vocab):
      if word == w:
        bagOwords[idx] = 1
  return num.array(bagOwords)

def Pclass(text, vocab, labels):
  bagOwords = wordBag(text, vocab)
  ourResult = ourNewModel.predict(num.array([bagOwords]))[0]
  newThresh = 0.2
  yp = [[idx, res] for idx, res in enumerate(ourResult) if res >
newThresh]

  yp.sort(key=lambda x: x[1], reverse=True)
  newList = []
  for r in yp:
    newList.append(labels[r[0]])
  return newList

def getRes(firstlist, fJson):
  tag = firstlist[0]
  listOfIntents = fJson["ourIntents"]
  for i in listOfIntents:
    if i["tag"] == tag:
      ourResult = random.choice(i["responses"])
      break
  return ourResult

while True:
    newMessage = input("Please input your message : ")
    intents = Pclass(newMessage, newWords, ourClasses)
    ourResult = getRes(intents, ourData)
    print(ourResult)

Please input your message : what's your name?
1/1 [==============================] - 0s 16ms/step
You can give me a name, and I will appreciate it
Please input your message : who are you?
1/1 [==============================] - 0s 16ms/step
Aree naam me kya rakha hai?
```