

Intent Classification

NLP Individual Submission

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Group: 1

Intent Classification is mainly used to understand the context of the text words given by the user. In this NLP Individual Submission I have explored some different techniques through which we can classify the intent of the chatbot. This is the 1st Python file (.ipynb) and the second python file contains a initial stage chatbot which works on Intent Classification.

The dataset used in this Python file is a substitution dataset for Intent Classification. In total, I have used 2 datasets to satisfy the conditions using Python NLTK libraries.

The datasets are taken from Kaggle and some of the libraries and specification are referred from GitHub, Kaggle and Python documentation. The links to the dataset are given below.

Dataset Links:

1. Text Commands.csv - [https://github.com/KoushikiDasgupta/Intent-Analysis-for-Offline-Voice-Commanding/blob/main/CNN model/TextCommands.csv](https://github.com/KoushikiDasgupta/Intent-Analysis-for-Offline-Voice-Commanding/blob/main/CNN%20model/TextCommands.csv)

2. Airis Train and Test - <https://www.kaggle.com/datasets/hassanamin/airis-train-test>

Airis Travel Information system

In [1]:

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

Intent Classification using Convolutional Neural Network

In [2]:

```
import pandas as pd
data=pd.read_csv('D:\Burrey\Semester\Semester 2\NLP\TextCommands.csv')
```

In [3]:

```
data.columns=['text', 'label', 'misc']
data.head()
```

Out[3]:

	text	label	misc
0	Undo the last sentence	1	NaN
1	Undo the last word	1	NaN
2	Can you undo the last sentence	1	NaN
3	Please undo the text	1	NaN
4	Undo the selected text	1	NaN

The dataset contains different labels. The total intents labelled are from 1 to 26. The dataset needs to be in a dataframe.

For data preprocessing, we need to go through Tokenizing, Sequence Padding, Tokenization is the collection of unique words from the dataset and are assigned to integer. Padding, on the other hand represents the dataset with zeros.

In [4]:

```
import numpy as np
import tensorflow as tf
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.utils import to_categorical
MAX_SEQUENCE_LENGTH=10
MAX_NUM_WORDS=500
tokenizer=Tokenizer(num_words=MAX_NUM_WORDS)
tokenizer.fit_on_texts(data['text'])
word_index=tokenizer.word_index
seqs=[tokenizer.sequences[seq] for seq in data['text']]
data=pad_sequences(seqs, maxlen=MAX_SEQUENCE_LENGTH)
labels=to_categorical(np.asarray(data['label']))
print('Data tensorflow', data.shape)
print('Labels tensorflow', labels.shape)
```

Data: tensorflow (399, 20)

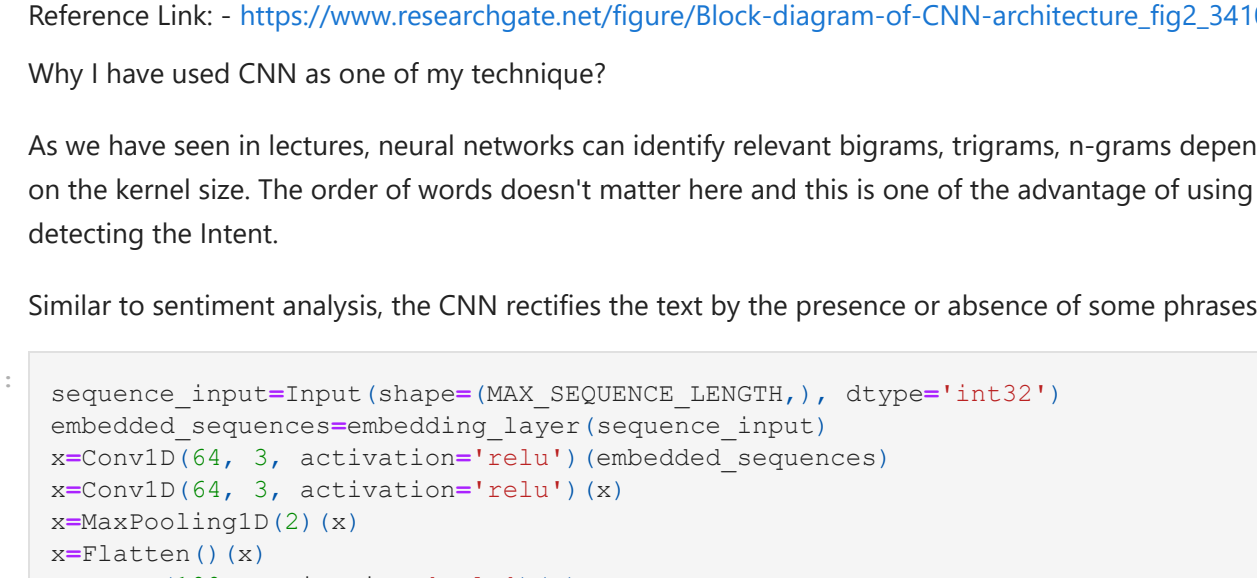
Labels: tensorflow (399, 10)

In [5]:

```
data=np.array(data.shape[0])
np.random.shuffle(indices)
data=data[indices]
labels=labels[indices]
x_train=data[1:-num_validation_samples]
y_train=labels[1:-num_validation_samples]
x_val=data[-num_validation_samples:]
y_val=labels[-num_validation_samples:]
```

In [6]:

```
from keras.layers import Dense, Input, GlobalMaxPooling1D
from keras.layers import Conv1D, MaxPooling1D, Embedding, Flatten
from keras.models import Model
from keras.initializers import Constant
from keras.optimizers import Adam
num_words=max(MAX_NUM_WORDS, len(word_index)+1)
embedding_layer=Embedding(num_words, EMBEDDING_DIM, input_length=MAX_SEQUENCE_LENGTH,
```



Reference link - https://www.researchgate.net/figure/Block-diagram-of-CNN-architecture_fig2_341019121

Why I have used CNN as one of my technique?

As we have seen in lectures, neural networks can identify relevant bigrams, trigrams, n-grams depending on the kernel size. The order of words doesn't matter here and this is one of the advantage of using CNN in detecting the intent.

Similar to sentiment analysis, the CNN rectifies the text by the presence or absence of some phrases.

In [7]:

```
sequence_input=Input(shape=(MAX_SEQUENCE_LENGTH, dtype='int32'))
embedded_sequences=embedding_layer(sequence_input)
x=Conv1D(64, 3, activation='relu')(embedded_sequences)
x=MaxPooling1D(4, 3, activation='relu')(x)
x=Conv1D(128, 2)(x)
x=Flatten()(x)
x=Dense(120, activation='relu')(x)
preds=Dense(27, activation='softmax')(x)
model=Model(sequence_input, preds)
model.compile(loss='categorical_crossentropy', optimizer='rmsprop', metrics=['acc'])
model.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 10, 1)	0
embedding (Embedding)	(None, 10, 60)	8580
conv1d1 (Conv1D)	(None, 8, 64)	11384
conv1d2 (Conv1D)	(None, 6, 64)	12352
max_pooling1d (MaxPooling1D)	(None, 3, 64)	0
flatten (Flatten)	(None, 192)	0
dense (Dense)	(None, 100)	19300
dense1 (Dense)	(None, 27)	2727

Trainable params: 54,543

Non-trainable params: 0

In [8]:

```
for i in range(1, 50):
    score_fit(x_train, y_train, batch_size=50, epochs=30, validation_data=(x_val, y_val))
    model.evaluate(x_val, y_val, verbose=0)
    loss=losses[1][100]
```

Epoch 1/30: loss: 2.5221 - val_loss: 0.2821

Epoch 2/30: loss: 2.4629 - val_loss: 0.3333

Epoch 3/30: loss: 2.4212 - val_loss: 0.4359

Epoch 4/30: loss: 2.3716 - val_loss: 0.5897

Epoch 5/30: loss: 2.3176 - val_loss: 0.7179

Epoch 6/30: loss: 2.2637 - val_loss: 0.8487

Epoch 7/30: loss: 2.2037 - val_loss: 0.9541

Epoch 8/30: loss: 2.1536 - val_loss: 1.0487

Epoch 9/30: loss: 2.1037 - val_loss: 1.1324

Epoch 10/30: loss: 2.0537 - val_loss: 1.2054

Epoch 11/30: loss: 2.0037 - val_loss: 1.2681

Epoch 12/30: loss: 1.9537 - val_loss: 1.3204

Epoch 13/30: loss: 1.9037 - val_loss: 1.3722

Epoch 14/30: loss: 1.8537 - val_loss: 1.4239

Epoch 15/30: loss: 1.8037 - val_loss: 1.4756

Epoch 16/30: loss: 1.7537 - val_loss: 1.5273

Epoch 17/30: loss: 1.7037 - val_loss: 1.5790

Epoch 18/30: loss: 1.6537 - val_loss: 1.6307

Epoch 19/30: loss: 1.6037 - val_loss: 1.6824

Epoch 20/30: loss: 1.5537 - val_loss: 1.7341

Epoch 21/30: loss: 1.5037 - val_loss: 1.7858

Epoch 22/30: loss: 1.4537 - val_loss: 1.8375

Epoch 23/30: loss: 1.4037 - val_loss: 1.8892

Epoch 24/30: loss: 1.3537 - val_loss: 1.9409

Epoch 25/30: loss: 1.3037 - val_loss: 1.9926

Epoch 26/30: loss: 1.2537 - val_loss: 2.0443

Epoch 27/30: loss: 1.2037 - val_loss: 2.0960

Epoch 28/30: loss: 1.1537 - val_loss: 2.1477

Epoch 29/30: loss: 1.1037 - val_loss: 2.1994

Epoch 30/30: loss: 1.0537 - val_loss: 2.2511

Epoch 31/30: loss: 1.0037 - val_loss: 2.3028

Epoch 32/30: loss: 0.9537 - val_loss: 2.3545

Epoch 33/30: loss: 0.9037 - val_loss: 2.4062

Epoch 34/30: loss: 0.8537 - val_loss: 2.4579

Epoch 35/30: loss: 0.8037 - val_loss: 2.5096

Epoch 36/30: loss: 0.7537 - val_loss: 2.5613

Epoch 37/30: loss: 0.7037 - val_loss: 2.6130

Epoch 38/30: loss: 0.6537 - val_loss: 2.6647

Epoch 39/30: loss: 0.6037 - val_loss: 2.7164

Epoch 40/30: loss: 0.5537 - val_loss: 2.7681

Epoch 41/30: loss: 0.5037 - val_loss: 2.8198

Epoch 42/30: loss: 0.4537 - val_loss: 2.8715

Epoch 43/30: loss: 0.4037 - val_loss: 2.9232

Epoch 44/30: loss: 0.3537 - val_loss: 2.9749

Epoch 45/30: loss: 0.3037 - val_loss: 3.0266

Epoch 46/30: loss: 0.2537 - val_loss: 3.0783

Epoch 47/30: loss: 0.2037 - val_loss: 3.1300

Epoch 48/30: loss: 0.1537 - val_loss: 3.1817

Epoch 49/30: loss: 0.1037 - val_loss: 3.2334

Epoch 50/30: loss: 0.0537 - val_loss: 3.2851

Epoch 51/30: loss: 0.0037 - val_loss: 3.3368

Epoch 52/30: loss: 0.0037 - val_loss: 3.3885

Epoch 53/30: loss: 0.0037 - val_loss: 3.4402

Epoch 54/30: loss: 0.0037 - val_loss: 3.4919

Epoch 55/30: loss: 0.0037 - val_loss: 3.5436

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Epoch 60/30: loss: 0.0037 - val_loss: 3.8021

Epoch 61/30: loss: 0.0037 - val_loss: 3.8538

Epoch 62/30: loss: 0.0037 - val_loss: 3.9055

Epoch 63/30: loss: 0.0037 - val_loss: 3.9572

Epoch 64/30: loss: 0.0037 - val_loss: 4.0089

Epoch 65/30: loss: 0.0037 - val_loss: 4.0606

Epoch 66/30: loss: 0.0037 - val_loss: 4.1123

Epoch 67/30: loss: 0.0037 - val_loss: 4.1640

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Epoch 71/30: loss: 0.0037 - val_loss: 4.3708

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Epoch 73/30: loss: 0.0037 - val_loss: 4.4742

Epoch 74/30: loss: 0.0037 - val_loss: 4.5259

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Epoch 200/30: loss: 0.0037 - val_loss: 11.0400

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Epoch 246/30: loss: 0.0037 - val_loss: 13.4182

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Epoch 249/30: loss: 0.0037 - val_loss: 13.5733

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Epoch 252/30: loss: 0.0037 - val_loss: 13.7284

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Epoch 254/30: loss: 0.0037 - val_loss: 13.8318

Epoch 255/30: loss: 0.0037 - val_loss: 13.8835

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Epoch 259/30: loss: 0.0037 - val_loss: 14.0903

Epoch 260/30: loss: 0.0037 - val_loss: 14.1420

Epoch 261/30: loss: 0.0037 - val_loss: 14.1937

Epoch 262/30: loss: 0.0037 - val_loss: 14.2454

Epoch 263/30: loss: 0.0037 - val_loss: 14.2971

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Epoch 265/30: loss: 0.0037 - val_loss: 14.4005

Epoch 266/30: loss: 0.0037 - val_loss: 14.4522

Epoch 267/30: loss: 0.0037 - val_loss: 14.5039

Epoch 268/30: loss: 0.0037 - val_loss: 14.5556

Epoch 269/30: loss: 0.0037 - val_loss: 14.6073

Epoch 270/30: loss: 0.0037 - val_loss: 14.6590</

val_loss: 0.4840 - val_acc: 0.9487			
val_loss: 0.5531 - val_acc: 0.9487	- 0s 7ms/step	loss: 6.6227e-09	acc: 1.0000
Epoch 1/30			
val_loss: 0.5532 - val_acc: 0.9487	- 0s 6ms/step	loss: 6.2916e-09	acc: 1.0000
Epoch 4/30			
val_loss: 0.4664 - val_acc: 0.9231	- 0s 7ms/step	loss: 5.6293e-09	acc: 1.0000
Epoch 5/30			
val_loss: 0.5324 - val_acc: 0.9487	- 0s 8ms/step	loss: 4.9671e-09	acc: 1.0000
Epoch 6/30			
val_loss: 0.5387 - val_acc: 0.9487	- 0s 8ms/step	loss: 4.9671e-09	acc: 1.0000
Epoch 7/30			
val_loss: 0.5330 - val_acc: 0.9487	- 0s 7ms/step	loss: 4.3048e-09	acc: 1.0000
Epoch 8/30			
val_loss: 0.5316 - val_acc: 0.9487	- 0s 8ms/step	loss: 2.9802e-09	acc: 1.0000
Epoch 9/30			
val_loss: 0.5296 - val_acc: 0.9487	- 0s 8ms/step	loss: 2.3180e-09	acc: 1.0000
Epoch 10/30			
val_loss: 0.5335 - val_acc: 0.9487	- 0s 8ms/step	loss: 2.3180e-09	acc: 1.0000
Epoch 11/30			
val_loss: 0.5399 - val_acc: 0.9487	- 0s 7ms/step	loss: 1.9868e-09	acc: 1.0000
Epoch 12/30			
val_loss: 0.5549 - val_acc: 0.9487	- 0s 7ms/step	loss: 3.6425e-09	acc: 1.0000
Epoch 13/30			
val_loss: 0.5474 - val_acc: 0.9487	- 0s 7ms/step	loss: 3.6425e-09	acc: 1.0000
Epoch 14/30			
val_loss: 0.5550 - val_acc: 0.9487	- 0s 8ms/step	loss: 1.0265e-08	acc: 1.0000
Epoch 15/30			
val_loss: 0.5920 - val_acc: 0.9487	- 0s 7ms/step	loss: 3.3114e-09	acc: 1.0000
Epoch 16/30			
val_loss: 0.7078 - val_acc: 0.9487	- 0s 8ms/step	loss: 1.9868e-09	acc: 1.0000
Epoch 17/30			
val_loss: 0.892 - val_acc: 0.9487	- 0s 8ms/step	loss: 3.3114e-09	acc: 1.0000
Epoch 18/30			
val_loss: 0.831 - val_acc: 0.9487	- 0s 7ms/step	loss: 4.6359e-09	acc: 1.0000
Epoch 19/30			
val_loss: 0.919 - val_acc: 0.9487	- 0s 7ms/step	loss: 5.9605e-09	acc: 1.0000
Epoch 20/30			
val_loss: 0.9284 - val_acc: 0.9487	- 0s 8ms/step	loss: 1.0596e-08	acc: 1.0000
Epoch 21/30			
val_loss: 0.9842 - val_acc: 0.9487	- 0s 9ms/step	loss: 1.5895e-08	acc: 1.0000
Epoch 22/30			
val_loss: 0.891 - val_acc: 0.8974	- 0s 7ms/step	loss: 0.2082 - acc: 0.9639 - val_loss: 0.8891	acc: 0.8974
Epoch 23/30			
val_loss: 0.9094 - val_acc: 0.8974	- 0s 6ms/step	loss: 1.3318e-05	acc: 1.0000
Epoch 24/30			
val_loss: 0.9359 - val_acc: 0.8974	- 0s 7ms/step	loss: 9.8869e-06	acc: 1.0000
Epoch 25/30			
val_loss: 0.9603 - val_acc: 0.8974	- 0s 7ms/step	loss: 8.2637e-06	acc: 1.0000
Epoch 26/30			
val_loss: 0.9764 - val_acc: 0.8974	- 0s 8ms/step	loss: 7.0497e-06	acc: 1.0000
Epoch 27/30			
val_loss: 0.8902 - val_acc: 0.8974	- 0s 8ms/step	loss: 5.9179e-06	acc: 1.0000
Epoch 28/30			
val_loss: 0.9815 - val_acc: 0.8974	- 0s 7ms/step	loss: 5.0863e-06	acc: 1.0000
Epoch 29/30			
val_loss: 0.9837 - val_acc: 0.8974	- 0s 7ms/step	loss: 4.1822e-06	acc: 1.0000
Epoch 30/30			
val_loss: 1.023 - val_acc: 0.8974	- 0s 6ms/step	loss: 3.4790e-06	acc: 1.0000
Epoch 1/30			
val_loss: 1.0227 - val_acc: 0.8974	- 0s 13ms/step	loss: 2.3781e-06	acc: 1.0000
Epoch 2/30			
val_loss: 1.0095 - val_acc: 0.8974	- 0s 8ms/step	loss: 1.6189e-06	acc: 1.0000
Epoch 3/30			
val_loss: 0.9975 - val_acc: 0.8974	- 0s 8ms/step	loss: 1.3308e-06	acc: 1.0000
Epoch 4/30			
val_loss: 0.9716 - val_acc: 0.8974	- 0s 8ms/step	loss: 1.0341e-06	acc: 1.0000
Epoch 5/30			
val_loss: 0.9901 - val_acc: 0.8974	- 0s 6ms/step	loss: 7.9041e-07	acc: 1.0000
Epoch 6/30			
val_loss: 0.9811 - val_acc: 0.8974	- 0s 8ms/step	loss: 5.7187e-07	acc: 1.0000
Epoch 7/30			
val_loss: 0.9626 - val_acc: 0.8974	- 0s 6ms/step	loss: 4.0266e-07	acc: 1.0000
Epoch 8/30			
val_loss: 0.9496 - val_acc: 0.8974	- 0s 7ms/step	loss: 2.8809e-07	acc: 1.0000
Epoch 9/30			
val_loss: 0.9416 - val_acc: 0.9231	- 0s 6ms/step	loss: 2.0564e-07	acc: 1.0000
Epoch 10/30			
val_loss: 0.9236 - val_acc: 0.9231	- 0s 6ms/step	loss: 1.4626e-07	acc: 1.0000
Epoch 11/30			
val_loss: 0.9050 - val_acc: 0.9231	- 0s 8ms/step	loss: 1.0928e-07	acc: 1.0000
Epoch 12/30			
val_loss: 0.8895 - val_acc: 0.9231	- 0s 6ms/step	loss: 7.5168e-08	acc: 1.0000
Epoch 13/30			
val_loss: 0.8749 - val_acc: 0.9231	- 0s 6ms/step	loss: 5.5300e-08	acc: 1.0000
Epoch 14/30			
val_loss: 0.8682 - val_acc: 0.9231	- 0s 8ms/step	loss: 3.9405e-08	acc: 1.0000
Epoch 15/30			
val_loss: 0.8412 - val_acc: 0.9231	- 0s 8ms/step	loss: 2.5829e-08	acc: 1.0000
Epoch 16/30			
val_loss: 0.8322 - val_acc: 0.9231	- 0s 8ms/step	loss: 1.8875e-08	acc: 1.0000
Epoch 17/30			
val_loss: 0.8346 - val_acc: 0.9231	- 0s 8ms/step	loss: 1.2914e-08	acc: 1.0000
Epoch 18/30			
val_loss: 0.8231 - val_acc: 0.9487	- 0s 8ms/step	loss: 8.6096e-09	acc: 1.0000
Epoch 19/30			
val_loss: 0.8154 - val_acc: 0.9487	- 0s 8ms/step	loss: 6.9539e-09	acc: 1.0000
Epoch 20/30			
val_loss: 0.8042 - val_acc: 0.9487	- 0s 7ms/step	loss: 5.6293e-09	acc: 1.0000
Epoch 21/30			
val_loss: 0.8257 - val_acc: 0.9231	- 0s 9ms/step	loss: 4.3048e-09	acc: 1.0000
Epoch 22/30			
val_loss: 0.8048 - val_acc: 0.9487	- 0s 8ms/step	loss: 2.3180e-09	acc: 1.0000
Epoch 23/30			
val_loss: 0.8244 - val_acc: 0.9487	- 0s 7ms/step	loss: 1.9868e-09	acc: 1.0000
Epoch 24/30			
val_loss: 0.8216 - val_acc: 0.9487	- 0s 8ms/step	loss: 9.9341e-10	acc: 1.0000
Epoch 25/30			
val_loss: 0.7987 - val_acc: 0.9487	- 0s 7ms/step	loss: 1.9868e-09	acc: 1.0000
Epoch 26/30			
val_loss: 0.7899 - val_acc: 0.9487	- 0s 7ms/step	loss: 1.3245e-09	acc: 1.0000
Epoch 27/30			
val_loss: 0.8088 - val_acc: 0.9487	- 0s 7ms/step	loss: 2.8809e-07	acc: 1.0000
Epoch 28/30			
val_loss: 0.7585 - val_acc: 0.9487	- 0s 9ms/step	loss: 1.9868e-09	acc: 1.0000
Epoch 29/30			
val_loss: 0.7910 - val_acc: 0.9487	- 0s 8ms/step	loss: 4.9671e-09	acc: 1.0000
Epoch 30/30			
val_loss: 0.7888 - val_acc: 0.9487	- 0s 9ms/step	loss: 1.5232e-08	acc: 1.0000
Epoch 1/30			
val_loss: 0.7895 - val_acc: 0.6410	- 0s 10ms/step	loss: 3.3114e-09	acc: 1.0000
Epoch 2/30			
val_loss: 0.9203 - val_acc: 0.8974	- 0s 7ms/step	loss: 1.8328e-06	acc: 1.0000
Epoch 3/30			
val_loss: 0.9156 - val_acc: 0.8974	- 0s 8ms/step	loss: 0.1863 - acc: 0.9528 - val_loss: 0.9203	acc: 0.8974
Epoch 4/30			
val_loss: 0.9139 - val_acc: 0.8974	- 0s 8ms/step	loss: 3.4914e-05	acc: 1.0000
Epoch 5/30			
val_loss: 0.9146 - val_acc: 0.8974	- 0s 9ms/step	loss: 1.2553e-05	acc: 1.0000
Epoch 6/30			
val_loss: 0.9164 - val_acc: 0.8974	- 0s 9ms/step	loss: 1.4393e-05	acc: 1.0000
Epoch 7/30			
val_loss: 0.9129 - val_acc: 0.8974	- 0s 8ms/step	loss: 9.9578e-06	acc: 1.0000
Epoch 8/30			
val_loss: 0.9200 - val_acc: 0.8974	- 0s 8ms/step	loss: 7.2387e-06	acc: 1.0000
Epoch 9/30			
val_loss: 0.9246 - val_acc: 0.8974	- 0s 8ms/step	loss: 5.1276e-06	acc: 1.0000
Epoch 10/30			
val_loss: 0.9246 - val_acc: 0.8974	- 0s 6ms/step	loss: 3.8806e-06	acc: 1.0000
Epoch 11/30			
val_loss: 0.9291 - val_acc: 0.8974	- 0s 9ms/step	loss: 2.6999e-06	acc: 1.0000
Epoch 12/30			
val_loss: 0.9291 - val_acc: 0.8974	- 0s 10ms/step	loss: 2.0927e-06	acc: 1.0000
Epoch 13/30			
val_loss: 0.8809 - val_acc: 0.8974	- 0s 9ms/step	loss: 1.6123e-06	acc: 1.0000
Epoch 14/30			
val_loss: 0.9245 - val_acc: 0.8974	- 0s 9ms/step	loss: 1.3090e-06	acc: 1.0000
Epoch 15/30			
val_loss: 0.9003 - val_acc: 0.8974	- 0s 8ms/step	loss: 9.5730e-07	acc: 1.0000
Epoch 16/30			
val_loss: 0.8858 - val_acc: 0.8974	- 0s 10ms/step	loss: 1.9730e-07	acc: 1.0000
Epoch 17/30			
val_loss: 0.9143 - val_acc: 0.8974	- 0s 9ms/step	loss: 7.3710e-07	acc: 1.0000
Epoch 18/30			
val_loss: 0.8624 - val_acc: 0.9231	- 0s 8ms/step	loss: 6.8909e-07	acc: 1.0000
Epoch 19/30			
val_loss: 0.8936 - val_acc: 0.8974	- 0s 7ms/step	loss: 4.1723e-07	acc: 1.0000
Epoch 20/30			
val_loss: 0.9072 - val_acc: 0.8974	- 0s 9ms/step	loss: 3.3114e-07	acc: 1.0000
Epoch 21/30			
val_loss: 0.9102 - val_acc: 0.8974	- 0s 10ms/step	loss: 2.2319e-07	acc: 1.0000
Epoch 22/30			
val_loss: 0.9102 - val_acc: 0.8974	- 0s 9ms/step	loss: 1.7318e-07	acc: 1.0000
Epoch 23/30			
val_loss: 0.8775 - val_acc: 0.9231	- 0s 9ms/step	loss: 1.7252e-07	acc: 1.0000
Epoch 24/30			
val_loss: 0.8823 - val_acc: 0.8974	- 0s 9ms/step	loss: 7.6824e-08	acc: 1.0000
Epoch 25/30			
val_loss: 0.8856 - val_acc: 0.8974	- 0s 9ms/step	loss: 6.8824e-08	acc: 1.0000
Epoch 26/30			
val_loss: 0.8773 - val_acc: 0.9231	- 0s 13ms/step	loss: 5.8611e-08	acc: 1.0000
Epoch 27/30			
val_loss: 0.8799 - val_acc: 0.9231	- 0s 7ms/step	loss: 4.2717e-08	acc: 1.0000
Epoch 28/30			
val_loss: 0.8799 - val_acc: 0.9231	- 0s 8ms/step	loss: 3.1127e-08	acc: 1.0000
Epoch 29/30			
val_loss: 0.9099 - val_acc: 0.9231	- 0s 11ms/step	loss: 2.9848e-08	acc: 1.0000
Epoch 30/30			
val_loss: 0.8886 - val_acc: 0.9231	- 0s 10ms/step	loss: 1.6557e-08	acc: 1.0000
Epoch 1/30			
val_loss: 0.8866 - val_acc: 0.9231	- 0s 7ms/step	loss: 1.0928e-08	acc: 1.0000
Epoch 2/30			
val_loss: 0.8767 - val_acc: 0.9487	- 0s 7ms/step	loss: 8.9407e-09	acc: 1.0000
Epoch 3/30			
val_loss: 0.8421 - val_acc: 0.9487	- 0s 8ms/step	loss: 4.6359e-09	acc: 1.0000
Epoch 4/30			
val_loss: 0.8471 - val_acc: 0.9487	- 0s 8ms/step	loss: 3.9736e-09	acc: 1.0000
Epoch 5/30			
val_loss: 0.8659 - val_acc: 0.9487	- 0s 8ms/step	loss: 2.9802e-09	acc: 1.0000
Epoch 6/30			
val_loss: 0.8836 - val_acc: 0.9487	- 0s 8ms/step	loss: 2.9802e-09	acc: 1.0000
Epoch 7/30			
val_loss: 0.9284 - val_acc: 0.9231	- 0s 8ms/step	loss: 2.6491e-09	acc: 1.0000
Epoch 8/30			
val_loss: 0.8698 - val_acc: 0.9487	- 0s 6ms/step	loss: 3.3114e-09	acc: 1.0000
Epoch 9/30			
val_loss: 0.8772 - val_acc: 0.9487	- 0s 7ms/step	loss: 2.3180e-09	acc: 1.0000
Epoch 10/30			
val_loss: 0.8844 - val_acc: 0.9487	- 0s 7ms/step	loss: 1.9868e-09	acc: 1.0000
Epoch 11/30			
val_loss: 0.8988 - val_acc: 0.9231	- 0s 7ms/step	loss: 3.6425e-09	acc: 1.0000
Epoch 12/30			
val_loss: 0.9694 - val_acc: 0.9231	- 0s 7ms/step	loss: 6.2916e-09	acc: 1.0000
Epoch 13/30			
val_loss: 0.8642 - val_acc: 0.9487	- 0s 10ms/step	loss: 6.2916e-09	acc: 1.0000
Epoch 14/30			
val_loss: 0.8642 - val_acc: 0.9487	- 0s 6ms/step	loss: 2.2848e-08	acc: 1.0000
Epoch 15/30			
val_loss: 0.7892 - val_acc: 0.8205	- 0s 7ms/step	loss: 0.0714 - acc: 0.9861 - val_loss: 1.7892	acc: 0.8205
Epoch 16/30			
val_loss: 1.1501 - val_acc: 0.8974	- 0s 7ms/step	loss: 0.0136 - acc: 0.9944 - val_loss: 1.1501	acc: 0.8974
Epoch 17/30			
val_loss: 1.125 - val_acc: 0.8974	- 0s 5ms/step	loss: 1.3105e-05	acc: 1.0000
Epoch 18/30			
val_loss: 1.099 - val_acc: 0.8974	- 0s 7ms/step	loss: 7.9804e-06	acc: 1.0000
Epoch 19/30			
val_loss: 1.0942 - val_acc: 0.9231	- 0s 5ms/step	loss: 6.2294e-06	acc: 1.0000
Epoch 20/30			
val_loss: 1.0960 - val_acc: 0.8974	- 0s 7ms/step	loss: 4.7728e-06	acc: 1.0000
Epoch 21/30			
val_loss: 1.1181 - val_acc: 0.8974	- 0s 9ms/step	loss: 3.4842e-06	acc: 1.0000
Epoch 22/30			
val_loss: 1.0932 - val_acc: 0.8974	- 0s 10ms/step	loss: 2.5655e-06	acc: 1.0000
Epoch 23/30			
val_loss: 1.0886 - val_acc: 0.8974	- 0s 7ms/step	loss: 1.9056e-06	acc: 1.0000
Epoch 24/30			
val_loss: 1.0962 - val_acc: 0.8974	- 0s 6ms/step	loss: 1.3834e-06	acc: 1.0000
Epoch 25/30			
val_loss: 1.0773 - val_acc: 0.9231	- 0s 8ms/step	loss: 9.3445e-07	acc: 1.0000
Epoch 26/30			
val_loss: 1.0807 - val_acc: 0.8974	- 0s 7ms/step	loss: 4.9438e-07	acc: 1.0000
Epoch 27/30			
val_loss: 1.0696 - val_acc: 0.9231	- 0s 13ms/step	loss: 3.8806e-07	acc: 1.0000
Epoch 28/30			
val_loss: 1.0645 - val_acc: 0.9231	- 0s 8ms/step	loss: 2.8080e-07	acc: 1.0000
Epoch 29/30			
val_loss: 1.0610 - val_acc: 0.9231	- 0s 8ms/step	loss: 2.0497e-07	acc: 1.0000
Epoch 30/30			
val_loss: 1.0751 - val_acc: 0.9231	- 0s 10ms/step	loss: 1.4769e-07	acc: 1.0000
Epoch 1/30			
val_loss: 1.0401 - val_acc: 0			

[illegible]

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8/8 [=====] - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7455 - val_acc: 0.9487
Epoch 24/30
8/8 [=====] - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7482 - val_acc: 0.9487
Epoch 25/30
8/8 [=====] - loss: 3.3114e-10 - acc: 1.0000 -
    val_loss: 0.7595 - val_acc: 0.9487
Epoch 26/30

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8/8 [=====] - 5s 5ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7627 - val_acc: 0.9231
Epoch 27/30
8/8 [=====] - 5s 7ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7660 - val_acc: 0.9231
Epoch 28/30
8/8 [=====] - 5s 9ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7702 - val_acc: 0.9231
Epoch 29/30
8/8 [=====] - 5s 10ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7749 - val_acc: 0.9231
Epoch 30/30
8/8 [=====] - 5s 7ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7783 - val_acc: 0.9231
Epoch 1/30
8/8 [=====] - 5s 13ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7810 - val_acc: 0.9231
Epoch 2/30
8/8 [=====] - 5s 8ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7820 - val_acc: 0.9487
Epoch 3/30
8/8 [=====] - 5s 9ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7803 - val_acc: 0.9487
Epoch 4/30
8/8 [=====] - 5s 11ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.8025 - val_acc: 0.9231
Epoch 5/30
8/8 [=====] - 5s 8ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7717 - val_acc: 0.9487
Epoch 6/30
8/8 [=====] - 5s 8ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7757 - val_acc: 0.9487
Epoch 7/30
8/8 [=====] - 5s 7ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7774 - val_acc: 0.9487
Epoch 8/30
8/8 [=====] - 5s 8ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7903 - val_acc: 0.9487
Epoch 9/30

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8/8 [=====] - 0s 7ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7967 - val_acc: 0.9487
Epoch 10/30
8/8 [=====] - 0s 7ms/step - loss: 3.3114e-10 - acc: 1.0000 -
    val_loss: 0.7774 - val_acc: 0.9487
Epoch 11/30
8/8 [=====] - 0s 7ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.8133 - val_acc: 0.9231
Epoch 12/30
8/8 [=====] - 0s 9ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.8087 - val_acc: 0.9231
Epoch 13/30
8/8 [=====] - 0s 10ms/step - loss: 3.3114e-10 - acc: 1.0000 -
    val_loss: 0.7283 - val_acc: 0.9231
Epoch 14/30
8/8 [=====] - 0s 9ms/step - loss: 3.3114e-09 - acc: 1.0000 -
    val_loss: 0.6569 - val_acc: 0.9487
Epoch 15/30
8/8 [=====] - 0s 10ms/step - loss: 3.3114e-10 - acc: 1.0000 -

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    val_loss: 0.6959 - val_acc: 0.9231
Epoch 16/30
8/8 [=====] - 0s 10ms/step - loss: 0.0000e+00 - acc: 1.0000 -
    val_loss: 0.7090 - val_acc: 0.9231
Epoch 17/30
8/8 [=====] - 0s 11ms/step - loss: 0.6555 - acc: 0.9472 - val_
    _loss: 11.8923 - val_acc: 0.5128
Epoch 18/30
8/8 [=====] - 0s 9ms/step - loss: 0.5378 - acc: 0.9528 - val_
    _loss: 1.6039 - val_acc: 0.8718
Epoch 19/30
8/8 [=====] - 0s 9ms/step - loss: 8.5589e-04 - acc: 1.0000 -
    val_loss: 1.4108 - val_acc: 0.8974
Epoch 20/30
8/8 [=====] - 0s 10ms/step - loss: 7.0532e-05 - acc: 1.0000 -
    val_loss: 1.3945 - val_acc: 0.8974
Epoch 21/30
8/8 [=====] - 0s 7ms/step - loss: 3.3655e-05 - acc: 1.0000 -
    val_loss: 1.3795 - val_acc: 0.8974

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Epoch 22/30
8/8 [=====] - loss: 2.0275e-05 - acc: 1.0000 -
    val_loss: 1.3704 - val_acc: 0.8974
Epoch 23/30
8/8 [=====] - loss: 1.5002e-05 - acc: 1.0000 -
    val_loss: 1.3622 - val_acc: 0.8974
Epoch 24/30
8/8 [=====] - loss: 1.1450e-05 - acc: 1.0000 -
    val_loss: 1.3513 - val_acc: 0.8974
Epoch 25/30
8/8 [=====] - loss: 8.2859e-06 - acc: 1.0000 -
    val_loss: 1.3409 - val_acc: 0.9231
Epoch 26/30
8/8 [=====] - loss: 6.1476e-06 - acc: 1.0000 -
    val_loss: 1.3305 - val_acc: 0.9231
Epoch 27/30
8/8 [=====] - loss: 4.5904e-06 - acc: 1.0000 -
    val_loss: 1.3209 - val_acc: 0.9231
Epoch 28/30
8/8 [=====] - loss: 3.3320e-06 - acc: 1.0000 -
    val_loss: 1.3105 - val_acc: 0.9231
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8/8 |=====| - Os 5ms/step - loss: 5.3579e-06 - acc: 1.0000 -
val_loss: 1.3109 - val_acc: 0.9231
Epoch 29/30
8/8 |=====| - Os 9ms/step - loss: 2.4463e-06 - acc: 1.0000 -
val_loss: 1.3007 - val_acc: 0.9231
Epoch 30/30
8/8 |=====| - Os 6ms/step - loss: 1.7212e-06 - acc: 1.0000 -
val_loss: 1.2914 - val_acc: 0.9231
Epoch 1/30
8/8 |=====| - Os 11ms/step - loss: 1.2603e-06 - acc: 1.0000 -
val_loss: 1.2796 - val_acc: 0.9231
Epoch 2/30
8/8 |=====| - Os 7ms/step - loss: 8.7187e-07 - acc: 1.0000 -
val_loss: 1.2702 - val_acc: 0.9231
Epoch 3/30
8/8 |=====| - Os 6ms/step - loss: 5.7683e-07 - acc: 1.0000 -
val_loss: 1.2610 - val_acc: 0.9231
Epoch 4/30
8/8 |=====| - Os 8ms/step - loss: 4.0167e-07 - acc: 1.0000 -

```

```
Epoch 5/30
8/8 [=====] - 0s 9ms/step - loss: 2.5266e-07 - acc: 1.0000 -
    val_loss: 1.2467 - val_acc: 0.9231
Epoch 6/30
8/8 [=====] - 0s 10ms/step - loss: 1.7815e-07 - acc: 1.0000 -
    val_loss: 1.2376 - val_acc: 0.9231
Epoch 7/30
8/8 [=====] - 0s 8ms/step - loss: 1.2418e-07 - acc: 1.0000 -
    val_loss: 1.2292 - val_acc: 0.9231
Epoch 8/30
8/8 [=====] - 0s 8ms/step - loss: 8.5433e-08 - acc: 1.0000 -
    val_loss: 1.2227 - val_acc: 0.8974
Epoch 9/30
8/8 [=====] - 0s 9ms/step - loss: 5.7287e-08 - acc: 1.0000 -
    val_loss: 1.2219 - val_acc: 0.8974
Epoch 10/30
8/8 [=====] - 0s 9ms/step - loss: 3.7418e-08 - acc: 1.0000 -
    val_loss: 1.2149 - val_acc: 0.8974
Epoch 11/30
```

```

8/8 [=====] - 0s 7ms/step - loss: 2.7815e-08 - acc: 1.0000 -
val_loss: 1.2068 - val_acc: 0.8974
Epoch 12/30
8/8 [=====] - 0s 8ms/step - loss: 1.9537e-08 - acc: 1.0000 -
val_loss: 1.2354 - val_acc: 0.8974
Epoch 13/30
8/8 [=====] - 0s 9ms/step - loss: 1.5895e-08 - acc: 1.0000 -
val_loss: 1.2051 - val_acc: 0.8974
Epoch 14/30
8/8 [=====] - 0s 9ms/step - loss: 1.0596e-08 - acc: 1.0000 -
val_loss: 1.1785 - val_acc: 0.8974
Epoch 15/30
8/8 [=====] - 0s 9ms/step - loss: 7.2850e-09 - acc: 1.0000 -
val_loss: 1.1718 - val_acc: 0.8974
Epoch 16/30
8/8 [=====] - 0s 7ms/step - loss: 4.9671e-09 - acc: 1.0000 -
val_loss: 1.1618 - val_acc: 0.8974
Epoch 17/30
8/8 [=====] - 0s 7ms/step - loss: 3.3114e-09 - acc: 1.0000 -

```

```

val_loss: 1.1426 - val_acc: 0.8974
Epoch 18/30
8/8 [=====] - 0s 6ms/step - loss: 1.6557e-09 - acc: 1.0000 -
val_loss: 1.1986 - val_acc: 0.8718
Epoch 19/30
8/8 [=====] - 0s 5ms/step - loss: 9.6030e-09 - acc: 1.0000 -
val_loss: 1.0155 - val_acc: 0.9231
Epoch 20/30
8/8 [=====] - 0s 5ms/step - loss: 6.9539e-09 - acc: 1.0000 -
val_loss: 1.2027 - val_acc: 0.8718
Epoch 21/30
8/8 [=====] - 0s 7ms/step - loss: 4.9671e-09 - acc: 1.0000 -
val_loss: 1.0348 - val_acc: 0.9231
Epoch 22/30
8/8 [=====] - 0s 8ms/step - loss: 0.0000e+00 - acc: 1.0000 -
val_loss: 1.0403 - val_acc: 0.9231
Epoch 23/30
8/8 [=====] - 0s 7ms/step - loss: 0.0000e+00 - acc: 1.0000 -
val_loss: 1.0331 - val_acc: 0.9231

```

```
Epoch 24/30 [=====] - loss: 0.0000e+00 - acc: 1.0000 -
8/8 [=====] - loss: 1.0366 - val_acc: 0.9231
Epoch 25/30 [=====] - loss: 0.0000e+00 - acc: 1.0000 -
8/8 [=====] - loss: 1.0396 - val_acc: 0.9231
Epoch 26/30 [=====] - loss: 0.0000e+00 - acc: 1.0000 -
8/8 [=====] - loss: 1.0434 - val_acc: 0.9231
Epoch 27/30 [=====] - loss: 0.0000e+00 - acc: 1.0000 -
8/8 [=====] - loss: 0.8ms/step - loss: 0.0000e+00 - acc: 1.0000 -
val_loss: 1.0509 - val_acc: 0.9231
Epoch 28/30 [=====] - loss: 0.0000e+00 - acc: 1.0000 -
8/8 [=====] - loss: 0.8ms/step - loss: 0.0000e+00 - acc: 1.0000 -
val_loss: 1.0519 - val_acc: 0.9231
Epoch 29/30 [=====] - loss: 0.0000e+00 - acc: 1.0000 -
8/8 [=====] - loss: 0.5ms/step - loss: 0.0000e+00 - acc: 1.0000 -
val_loss: 1.0534 - val_acc: 0.9231
Epoch 30/30 [=====] - loss: 0.0000e+00 - acc: 1.0000 -
8/8 [=====] - loss: 0.6ms/step - loss: 0.0000e+00 - acc: 1.0000 -
val_loss: 1.0534 - val_acc: 0.9231
```

```
8      - val_loss: 1.0568 - val_acc: 0.9231      - us: ems/step - loss: 0.0000e+00 - acc: 1.0000e+00
```

```
In [9]: scores=model.evaluate(x_val, y_val, verbose=0)
print(model.metrics_names[1], scores[1]*100)

('acc', 92.30769276618958)
```

The accuracy of the model varies from 85% - 95%. We can improve the accuracy by fluctuating the hyperparameters.

```
In [10]: Xnew=["kindly undo the texts","Can you please undo the last paragraph","Make bold ti
sequence=tokenizer.texts_to_sequences(Xnew)
data=pad_sequences(sequences_new, maxlen=MAX_SEQUENCE_LENGTH)
yprob=model.predict(data)
yclassess=yprob.argmax(axis=1)
```

```
print('X%s, Predicted=%s \nX%s, \nPredicted=%s \nX%s, \nPredicted=%s' % (X[0], Predicted=1, X[1], Predicted=1, X[2], Predicted=2))
```

X<kindly undo the changes, Predicted=1
X=Can you please undo the last paragraph,
Predicted=1
X=Make bold this,
Predicted=2
X=Would you be kind enough to bold the last word?, Predicted=2
X=Please remove bold from the last paragraph, Predicted=3
X<kindly unbold the selected text, Predicted=3
X<Kindly insert comment here, Predicted=3
X=Can you please put a comment here, Predicted=15
X=Can you please centre align this text, Predicted=14
X=Can you please position this text in the middle, Predicted=14

CNN worked well when passed through the dataset.

```
In [ ]:
```

```
[11]: import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report
from tqdm.auto import tqdm
tqdm.pandas()

import tensorflow as tf
import tensorflow_hub as hub
from tensorflow.keras.optimizers import Adam, SGD
from tensorflow.keras.layers import Dense, Input, Flatten, BatchNormalization, Dropout
from tensorflow.keras.models import Model, Sequential
```

```
from tensorflow.keras.callbacks import ModelCheckpoint
```

ATIS is a most common dataset used for intent classification. The dataset contains large number of messages and their intents.

```
In [12]: train=pd.read_csv(r'D:\Surrey\Semester\Semester 2\NLP\atis_intents_train.csv')
train.columns=['intent', 'snippet']
```

```
In [13]: train.head()
```

```
Out [13]:
```

	intent	snippet
0	atis_flight	what flights are available from pittsburgh to...
1	atis_flight,time	what is the arrival time in san francisco for...

```

3      atis_airfare      cheapest airfare from tacoma to orlando
4      atis_airfare      round trip fares from pittsburgh to philadelp...
5      atis_flight       i need a flight tomorrow from columbus to min...

```

In [14]:

```

train.intent.value_counts(), train.intent.value_counts(normalize=True)

```

Out[14]:

atis_flight	3665
atis_airfare	423
atis_ground_service	255
atis_airline	157
atis_abbreviation	147
atis_aircraft	81
atis_flight_time	54
atis_quantity	51

```
Name: intent, dtype: int64,
  atis_flight      0.758328
  atis_airfare     0.087523
  atis_ground_service 0.052762
  atis_airline     0.032465
  atis_abbreviation 0.030416
  atis_aircraft    0.016760
  atis_flight_time 0.011173
  atis_quantity    0.010552
Name: intent, dtype: float64)
```

```
In [15]: train.intent.value_counts(), train.intent.value_counts(normalize=True)
```

```
Out[15]: (atis_flight      3665
  atis_airfare      423
  atis_ground_service 255
  atis_airline       157
  atis_abbreviation  147
```

```

      atis_aircraft      81
      atis_flight_time  84
      atis_quantity     51
      Name: intent, dtype: int64,
      atis_intent        0.758328
      atis_airfare       0.087523
      atis_ground_service 0.052762
      atis_airline       0.032485
      atis_abbreviation  0.030416
      atis_aircraft      0.016760
      atis_flight_time   0.011173
      atis_quantity      0.010552
      Name: intent, dtype: float64)

```

In [16]:

```

test=pd.read_csv(r'D:\Survey\Semester 2\NLP\atis_intents_test.csv')
test.columns=['intent', 'snippet']
test.head()

```

```
Out[16]:
```

	intent	snippet
0	atis_airfare	on april first i need a ticket from tacoma to...
1	atis_flight	on april first i need a flight going from pho...
2	atis_flight	i would like a flight traveling one way from ...
3	atis_flight	i would like a flight from orlando to salt la...
4	atis_flight	i need a flight from toronto to newark one wa...

```
In [17]:
```

```
test.intent.value_counts(), test.intent.value_counts(normalize=True)
```

```
Out[17]:
```

atis_flight	631
atis_airfare	48
atis_airline	38


```
Epoch 4/60
124/124 [=====] - 2s 16ms/step - loss: 1.5406 - auc: 0.9877 - val_loss: 2.0554 - val_auc: 0.8637
Epoch 5/60
124/124 [=====] - 2s 16ms/step - loss: 1.1348 - auc: 0.9905 - val_loss: 1.6535 - val_auc: 0.8905
Epoch 6/60
124/124 [=====] - 2s 16ms/step - loss: 0.9098 - auc: 0.9941 - val_loss: 0.9878 - val_auc: 0.9782
Epoch 7/60
124/124 [=====] - 2s 16ms/step - loss: 0.7803 - auc: 0.9951 - val_loss: 0.9267 - val_auc: 0.9777
Epoch 8/60
124/124 [=====] - 2s 14ms/step - loss: 0.6922 - auc: 0.9957 - val_loss: 0.7734 - val_auc: 0.9866
Epoch 9/60
124/124 [=====] - 2s 17ms/step - loss: 0.6229 - auc: 0.9973 - val_loss: 0.7804 - val_auc: 0.9864
Epoch 10/60
124/124 [=====] - 2s 17ms/step - loss: 0.5670 - auc: 0.9985 - val_loss: 0.7645 - val_auc: 0.9868
Epoch 11/60
124/124 [=====] - 2s 16ms/step - loss: 0.5054 - auc: 0.9985 - val_loss: 0.6055 - val_auc: 0.9908
Epoch 12/60
124/124 [=====] - 2s 14ms/step - loss: 0.4663 - auc: 0.9988 - val_loss: 0.6738 - val_auc: 0.9888
Epoch 13/60
124/124 [=====] - 2s 17ms/step - loss: 0.4369 - auc: 0.9988 - val_loss: 0.5955 - val_auc: 0.9915
Epoch 14/60
124/124 [=====] - 2s 16ms/step - loss: 0.4059 - auc: 0.9989 - val_loss: 0.5972 - val_auc: 0.9907
Epoch 15/60
124/124 [=====] - 2s 15ms/step - loss: 0.3760 - auc: 0.9990 - val_loss: 0.5297 - val_auc: 0.9917
Epoch 16/60
124/124 [=====] - 2s 15ms/step - loss: 0.3577 - auc: 0.9993 - val_loss: 0.5295 - val_auc: 0.9916
Epoch 17/60
124/124 [=====] - 2s 14ms/step - loss: 0.3374 - auc: 0.9994 - val_loss: 0.4395 - val_auc: 0.9935
Epoch 18/60
124/124 [=====] - 2s 15ms/step - loss: 0.3129 - auc: 0.9993 - val_loss: 0.4077 - val_auc: 0.9926
Epoch 19/60
124/124 [=====] - 2s 15ms/step - loss: 0.2943 - auc: 0.9994 - val_loss: 0.4566 - val_auc: 0.9931
Epoch 20/60
124/124 [=====] - 2s 14ms/step - loss: 0.2869 - auc: 0.9996 - val_loss: 0.4159 - val_auc: 0.9935
Epoch 21/60
124/124 [=====] - 2s 15ms/step - loss: 0.2775 - auc: 0.9994 - val_loss: 0.4507 - val_auc: 0.9930
Epoch 22/60
124/124 [=====] - 2s 15ms/step - loss: 0.2630 - auc: 0.9996 - val_loss: 0.3984 - val_auc: 0.9939
Epoch 23/60
124/124 [=====] - 2s 15ms/step - loss: 0.2505 - auc: 0.9996 - val_loss: 0.3542 - val_auc: 0.9956
Epoch 24/60
124/124 [=====] - 2s 16ms/step - loss: 0.2403 - auc: 0.9997 - val_loss: 0.3584 - val_auc: 0.9955
Epoch 25/60
124/124 [=====] - 2s 13ms/step - loss: 0.2276 - auc: 0.9998 - val_loss: 0.3255 - val_auc: 0.9957
Epoch 26/60
124/124 [=====] - 2s 16ms/step - loss: 0.2221 - auc: 0.9997 - val_loss: 0.3321 - val_auc: 0.9960
Epoch 27/60
124/124 [=====] - 2s 16ms/step - loss: 0.2143 - auc: 0.9996 - val_loss: 0.3215 - val_auc: 0.9962
Epoch 28/60
124/124 [=====] - 2s 16ms/step - loss: 0.2060 - auc: 0.9996 - val_loss: 0.3129 - val_auc: 0.9955
Epoch 29/60
124/124 [=====] - 2s 16ms/step - loss: 0.1958 - auc: 0.9998 - val_loss: 0.2804 - val_auc: 0.9967
Epoch 30/60
124/124 [=====] - 2s 17ms/step - loss: 0.1934 - auc: 0.9998 - val_loss: 0.3018 - val_auc: 0.9966
Epoch 31/60
124/124 [=====] - 2s 16ms/step - loss: 0.1858 - auc: 0.9998 - val_loss: 0.2747 - val_auc: 0.9964
Epoch 32/60
124/124 [=====] - 2s 17ms/step - loss: 0.1731 - auc: 0.9998 - val_loss: 0.2766 - val_auc: 0.9960
Epoch 33/60
124/124 [=====] - 2s 13ms/step - loss: 0.1707 - auc: 0.9999 - val_loss: 0.2584 - val_auc: 0.9968
Epoch 34/60
124/124 [=====] - 2s 15ms/step - loss: 0.1665 - auc: 0.9998 - val_loss: 0.2821 - val_auc: 0.9961
Epoch 35/60
124/124 [=====] - 2s 16ms/step - loss: 0.1661 - auc: 0.9999 - val_loss: 0.2456 - val_auc: 0.9971
Epoch 36/60
124/124 [=====] - 2s 16ms/step - loss: 0.1601 - auc: 0.9997 - val_loss: 0.2297 - val_auc: 0.9972
Epoch 37/60
124/124 [=====] - 2s 16ms/step - loss: 0.1506 - auc: 0.9999 - val_loss: 0.2281 - val_auc: 0.9970
Epoch 38/60
124/124 [=====] - 2s 15ms/step - loss: 0.1484 - auc: 0.9999 - val_loss: 0.2207 - val_auc: 0.9967
Epoch 39/60
124/124 [=====] - 2s 16ms/step - loss: 0.1439 - auc: 0.9999 - val_loss: 0.2252 - val_auc: 0.9974
Epoch 40/60
124/124 [=====] - 2s 17ms/step - loss: 0.1408 - auc: 0.9999 - val_loss: 0.2152 - val_auc: 0.9971
Epoch 41/60
124/124 [=====] - 2s 15ms/step - loss: 0.1363 - auc: 0.9999 - val_loss: 0.2267 - val_auc: 0.9966
Epoch 42/60
124/124 [=====] - 1s 10ms/step - loss: 0.1339 - auc: 0.9999 - val_loss: 0.2173 - val_auc: 0.9969
Epoch 43/60
124/124 [=====] - 1s 11ms/step - loss: 0.1293 - auc: 0.9999 - val_loss: 0.2101 - val_auc: 0.9966
Epoch 44/60
124/124 [=====] - 1s 10ms/step - loss: 0.1279 - auc: 0.9998 - val_loss: 0.2118 - val_auc: 0.9968
Epoch 45/60
124/124 [=====] - 2s 13ms/step - loss: 0.1241 - auc: 0.9999 - val_loss: 0.1939 - val_auc: 0.9971
Epoch 46/60
124/124 [=====] - 2s 16ms/step - loss: 0.1204 - auc: 0.9999 - val_loss: 0.2020 - val_auc: 0.9965
Epoch 47/60
124/124 [=====] - 2s 15ms/step - loss: 0.1187 - auc: 1.0000 - val_loss: 0.2005 - val_auc: 0.9971
Epoch 48/60
124/124 [=====] - 2s 15ms/step - loss: 0.1170 - auc: 0.9999 - val_loss: 0.1922 - val_auc: 0.9972
Epoch 49/60
124/124 [=====] - 2s 16ms/step - loss: 0.1144 - auc: 1.0000 - val_loss: 0.2036 - val_auc: 0.9968
Epoch 50/60
124/124 [=====] - 2s 16ms/step - loss: 0.1128 - auc: 1.0000 - val_loss: 0.1870 - val_auc: 0.9968
Epoch 51/60
124/124 [=====] - 1s 12ms/step - loss: 0.1097 - auc: 1.0000 - val_loss: 0.1807 - val_auc: 0.9960
Epoch 52/60
124/124 [=====] - 2s 15ms/step - loss: 0.1061 - auc: 1.0000 - val_loss: 0.2123 - val_auc: 0.9945
Epoch 53/60
124/124 [=====] - 2s 15ms/step - loss: 0.1091 - auc: 0.9999 - val_loss: 0.1809 - val_auc: 0.9963
Epoch 54/60
124/124 [=====] - 2s 14ms/step - loss: 0.1023 - auc: 1.0000 - val_loss: 0.1824 - val_auc: 0.9967
Epoch 55/60
124/124 [=====] - 2s 14ms/step - loss: 0.0982 - auc: 1.0000 - val_loss: 0.1762 - val_auc: 0.9954
Epoch 56/60
124/124 [=====] - 2s 14ms/step - loss: 0.0968 - auc: 1.0000 - val_loss: 0.1694 - val_auc: 0.9966
Epoch 57/60
124/124 [=====] - 2s 18ms/step - loss: 0.0939 - auc: 1.0000 - val_loss: 0.1773 - val_auc: 0.9959
Epoch 58/60
124/124 [=====] - 2s 17ms/step - loss: 0.0925 - auc: 1.0000 - val_loss: 0.1690 - val_auc: 0.9965
Epoch 59/60
124/124 [=====] - 2s 17ms/step - loss: 0.0924 - auc: 0.9998 - val_loss: 0.1652 - val_auc: 0.9970
Epoch 60/60
124/124 [=====] - 2s 14ms/step - loss: 0.0897 - auc: 1.0000 - val_loss: 0.1868 - val_auc: 0.9958
```

```
In [53]: from sklearn.metrics import classification_report
prediction=y_encoder.inverse_transform(model.predict(xtr_transformed))
print(classification_report(train_data.target, prediction))
```

	precision	recall	f1-score	support
atis_abbreviation	0.85	1.00	0.92	147
atis_aircraft	0.97	0.94	0.96	81
atis_airfare	1.00	0.99	0.99	423
atis_airline	0.99	0.87	0.93	157
atis_flight	1.00	1.00	1.00	3666
atis_flight_time	0.96	0.96	0.96	108
atis_ground_service	0.97	1.00	0.99	255
atis_quantity	1.00	1.00	1.00	102
accuracy			0.99	4939
macro avg	0.97	0.97	0.97	4939
weighted avg	0.99	0.99	0.99	4939

By programming through LSTM algorithm we can see the training data accuracy is 98%. So the training is recognized well by the library. The next step is whether this can be same in test data or not.

```
In [52]: from sklearn.metrics import classification_report

prediction_test=y_encoder.inverse_transform(model.predict(xts_transformed))
print(classification_report(test_data.target, prediction_test))
```

	precision	recall	f1-score	support
atis_abbreviation	0.60	1.00	0.75	33
atis_aircraft	0.83	0.56	0.67	9
atis_airfare	1.00	0.92	0.96	48
atis_airline	1.00	0.42	0.59	38
atis_flight	0.99	0.99	0.99	632
atis_flight_time	1.00	1.00	1.00	7
atis_ground_service	0.97	0.97	0.97	36
atis_quantity	0.38	1.00	0.55	3
accuracy			0.95	800
macro avg	0.85	0.86	0.81	800
weighted avg	0.97	0.95	0.95	800

LSTM test data accuracy is same as train data, which is 98%. This executors on an average this model will give 98% accurate data.

```
In [ ]:
```

Intent Classification using Spacy

```
In [53]: import numpy as np
import pandas as pd
import os
import spacy
import csv
```

The library Spacy is also one of the most used library for intent classifiers. The following experiment is a failed experiment because I need "en_vectors_web_lg" and this doesn't supports in the latest version of Spacy.

```
In [54]: python -m spacy download en_vectors_web_lg
python -m spacy link en_vectors_web_lg en_vectors_web_lg
```

[x] No compatible package found for 'en_vectors_web_lg' (spacy v3.2.4)

```
2022-04-28 14:50:48.321987: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'cudart64_110.dll'; dlerror: cudart64_110.dll not found
2022-04-28 14:50:48.322023: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignored cuda runtime error if you do not have a GPU set up on your machine.
(11) As of spacy v3.0, model symlinks are not supported anymore. You can load the pipeline packages using their full names or from a directory path.
2022-04-28 14:50:57.250268: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'cudart64_110.dll'; dlerror: cudart64_110.dll not found
2022-04-28 14:50:57.250295: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignored cuda runtime error if you do not have a GPU set up on your machine.
DeprecationWarning: The command link is deprecated.
```

```
In [55]: path=r'D:\Surrey\Semester\Semester 2\NLP\atis_intent'
```

```
In [56]: def read_data(path):
        with open(path, 'r') as csvfile:
            readCSV=csv.reader(csvfile, delimiter=',')
            labels=[]
            sentences=[]
            for row in readCSV:
                label=row[0]
                sentence=row[1]
                labels.append(label)
                sentences.append(sentence)
            return sentences, labels
```

```
In [57]: sentences_test, labels_test=read_data(r'D:\Surrey\Semester\Semester 2\NLP\atis_intent')
print(sentences_test[:3], '\n')
print(labels_test[:3])
```

```
['i would like to find a flight from charlotte to las vegas that makes a stop in st. louis', ' on april first i need a ticket from tacoma to san jose departing before 7 a m', ' on april first i need a flight going from phoenix to san diego']
['atis_flight', 'atis_airfare', 'atis_flight']
```

```
In [58]: sentences_train, labels_train = read_data(r'D:\Surrey\Semester\Semester 2\NLP\atis_intent')
```

```
In [59]: df1=pd.read_csv(r'D:\Surrey\Semester\Semester 2\NLP\atis_intents_train.csv', delimiter=',', data_frame_name='atis_intents_train.csv')
nRow, nCol=df1.shape
print('r'(nRow) rows & (nCol) columns')
```

4933 rows & 2 columns

```
In [60]: df1.sample(10)
```

	atis_flight	i want to fly from boston at 838 am and arrive in denver at 1110 in the morning
795	atis_flight	flights from clevaland to kansas city on monday
4022	atis_ground_service	what ground transportation is available at th...
393	atis_abbreviation	what is mco
2865	atis_flight	show me the flights from baltimore to oakland
274	atis_flight	i need a flight this saturday from miami to las...
280	atis_flight	show me the flights from baltimore to oakland
4826	atis_flight	please list all flights from san francisco to...
3460	atis_flight	i want to go from boston to oakland
3333	atis_aifare	what's the lowest round trip fare from dallas...
4054	atis_flight	show me the flights from atlanta to boston

```
In [61]: df1.describe()
```

	atis_flight	i want to fly from boston at 838 am and arrive in denver at 1110 in the morning
count	4833	4833
unique	8	4498
top	atis_flight	what is fare code h
freq	3665	8

```
In [62]: def label_encoding(labels):
        # Calculate the length of labels
        n_labels = len(labels)
        print('Number of labels :-'+n_labels)
        from sklearn.preprocessing import LabelEncoder
        # instantiate LabelEncoder object
        le = LabelEncoder()
        y = le.fit_transform(labels)
        print('y:(100)')
        print('Length of y :- ',y.shape)
        return y
train_y = label_encoding(labels_train)
test_y = label_encoding(labels_test)
```

Number of labels :- 4834
4 4 5 2 2 4 1 4 4 6 4 4 4 4 2 6 4 4 4 4 4 1 2 4 3 4 6 4 2 4 4 4 4 2 4 4
4 4 4 3 3 4 3 0 0 4 4 5 4 4 4 0 4 4 4 4 4 4 4 3 4 4 4 0 4 4 4 1 2 4
4 4 4 4 4 4 3 4 4 4 4 4 4 4 4 2 4 6 7 4 4 4 4 4 4 4
Length of y :- (4834,)
Number of labels :- 800
124/124 [=====] - 4s 4
4
4 2 3 5]
Length of y :- (800,)

```
In [63]: import matplotlib.pyplot as plt
import seaborn as sns

plt.hist(train_y)
plt.title('Intent Labels')
plt.xlabel('Types')
plt.ylabel('Frequency')
#df1['atis_flight'].hist()
```

```
Out[63]: Text(0, 0.5, 'Frequency')
```



The above visualisation shows the number of intent present in the dataset. As the program needs some specific library to go forward. This experiment is halted in between.

References

Links :-

- <https://blog.vsoftconsulting.com/blog/intent-classification-and-its-significance-in-chatbot-develop>
- <https://paperswithcode.com/task/intent-classification>
- <https://dasha.ai/en-us/blog/intent-classification>
- <https://www.helpshift.com/glossary/intent-classification/>
- <https://monkeylearn.com/blog/intent-classification/#:-text=intent classification is the automated, Unsubscribe, and Demo Request.>

This is first python file in which I have tried various experiments using Python NLTK libraries. The second Python file is demonstration of Intent based chatbot, the file will be executed through different inbuilt python file. The intention chatbot will be given at the start of the program.

The folder named as, 'Intent Classification' consists of 4 different python files which are related to each other. There is a separate 'ReadMe.txt' file on how to execute that folder.