Spam Message Classification using Deep Learning

Natural language processing (NLP) for classifying SMS-messages as spam or not spam, based on the SMS contents.

Install the Required Libraries

In [1]:
```
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

First, warnings are filtered to avoid cluttering of the notebook and %matplotlib inline style set

In [2]:
```
!pip install scikit-learn
!pip install torchtext==0.10.0
```

```
Looking in indexes: https://pypi.org/simple, (https://pypi.org/simple,) https://us-python.pkg.dev
/colab-wheels/public/simple/ (https://us-python.pkg.dev/colab-wheels/public/simple/)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/dist-packages (1.0.2)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from sciki
t-learn) (1.2.0)
Requirement already satisfied: numpy>=1.14.6 in /usr/local/lib/python3.7/dist-packages (from scik
it-learn) (1.21.6)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-packages (fr
om scikit-learn) (3.1.0)
Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.7/dist-packages (from sciki
t-learn) (1.7.3)
Looking in indexes: https://pypi.org/simple, (https://pypi.org/simple,) https://us-python.pkg.dev
/colab-wheels/public/simple/ (https://us-python.pkg.dev/colab-wheels/public/simple/)
Collecting torchtext==0.10.0
  Downloading torchtext-0.10.0-cp37-cp37m-manylinux1_x86_64.whl (7.6 MB)
     |████████████████████████████████| 7.6 MB 6.8 MB/s
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from torchtext==
0.10.0) (1.21.6)
Collecting torch==1.9.0
  Downloading torch-1.9.0-cp37-cp37m-manylinux1_x86_64.whl (831.4 MB)
     |████████████████████████████████| 831.4 MB 2.8 kB/s
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/dist-packages (from torchtext==0.
10.0) (4.64.1)
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-packages (from torchtext
==0.10.0) (2.23.0)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-packages (from
torch==1.9.0->torchtext==0.10.0) (4.1.1)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-packages (from reque
sts->torchtext==0.10.0) (2.10)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.
7/dist-packages (from requests->torchtext==0.10.0) (1.24.3)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/dist-packages (from
requests->torchtext==0.10.0) (2022.9.24)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dist-packages (from
requests->torchtext==0.10.0) (3.0.4)
Installing collected packages: torch, torchtext
  Attempting uninstall: torch
    Found existing installation: torch 1.12.1+cu113
```

```
    Uninstalling torch-1.12.1+cu113:
      Successfully uninstalled torch-1.12.1+cu113
  Attempting uninstall: torchtext
    Found existing installation: torchtext 0.13.1
    Uninstalling torchtext-0.13.1:
      Successfully uninstalled torchtext-0.13.1
ERROR: pip's dependency resolver does not currently take into account all the packages that are i
nstalled. This behaviour is the source of the following dependency conflicts.
torchvision 0.13.1+cu113 requires torch==1.12.1, but you have torch 1.9.0 which is incompatible.
torchaudio 0.12.1+cu113 requires torch==1.12.1, but you have torch 1.9.0 which is incompatible.
Successfully installed torch-1.9.0 torchtext-0.10.0
```

Other required libraries not available in Google Colab are then installed

Import Libraries

In [3]:

```python
import time
import spacy
import numpy as np
import pandas as pd
import random
import matplotlib.pyplot as plt
import tensorflow as tf
import torch
import torch.optim as optim
import torch.nn as nn
from torchtext.legacy import data
from torchtext.legacy import datasets
from keras.preprocessing.text import Tokenizer
from keras_preprocessing.sequence import pad_sequences
from keras.layers import Embedding, LSTM, Dropout, Dense
from keras.models import Sequential
from keras.utils import to_categorical, plot_model
from sklearn.model_selection import train_test_split
from collections import Counter
```

All the required libraries for the project are then imported

In [4]:
```
torch.cuda.is_available()
```

Out[4]:
```
True
```

A check is to made to ensure cuda is available as the project works best on a GPU

Load the Dataset

In [5]:
```
from google.colab import files
uploaded = files.upload()
```

Browse... No files selected.

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving hamspam.csv to hamspam.csv
```

Using the above code, the required datasets can be uploaded, in this case being the *spam.csv* dataset to be used in the Spam filtering part of the project.

In [6]:
```
sms_messages = pd.read_csv('hamspam.csv', encoding='latin1')
sms_messages = sms_messages.iloc[:, [0, 1]]
sms_messages.columns = ["label", "message"]
sms_messages.head()
```

Out[6]:

	label	message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

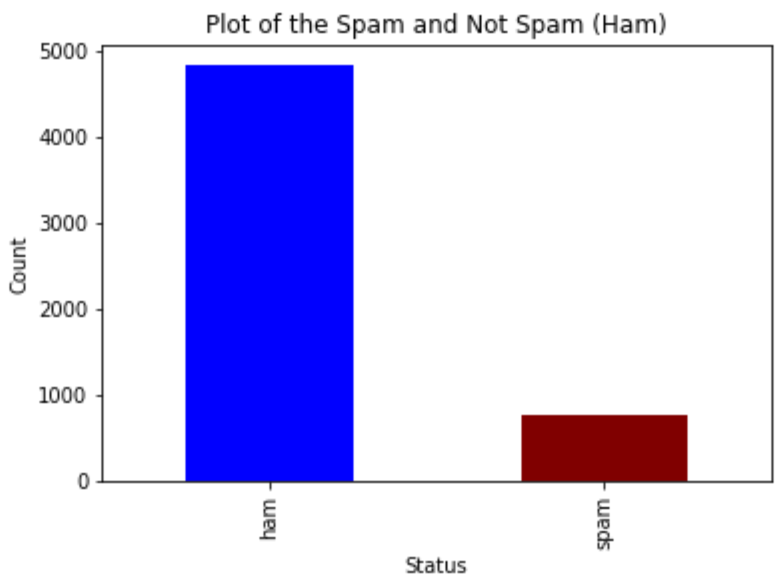
The above code reads the uploded dataset and prints the first five rows of the dataset.

In [7]:
```
# print the shape of the loaded dataset
sms_messages.shape
```

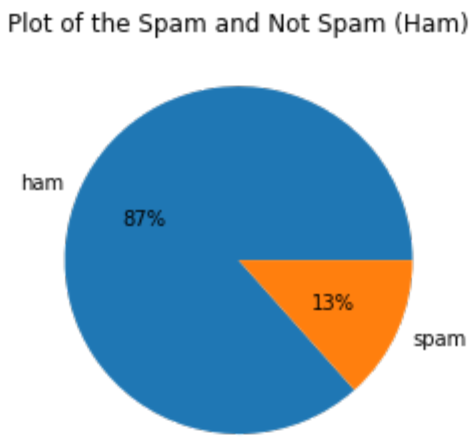
Out[7]: (5572, 2)

Exploratory Data Analysis

In [8]:
```
label_count = pd.value_counts(sms_messages["label"], sort=True)
label_count.plot(kind = "bar", color = ["blue", "maroon"])
plt.title("Plot of the Spam and Not Spam (Ham)")
plt.ylabel("Count")
plt.xlabel("Status")
plt.show()
```



In [9]:
```
label_count = pd.value_counts(sms_messages["label"], sort=True)
label_count.plot(kind = "pie", autopct='%.0f%%')
plt.title("Plot of the Spam and Not Spam (Ham)")
plt.ylabel("")
plt.xlabel("")
plt.show()
```



The above plot is a visualization of the spam and ham in the dataset.

In [10]:
```
sms_messages.groupby("label").describe()
```

Out[10]:

	message			
	count	unique	top	freq
label				
ham	4825	4516	Sorry, I'll call later	30
spam	747	653	Please call our customer service representativ...	4

After grouping the dataset by the labels (Spam and Ham), the above code shows the dataset description showing the count of each label.

In [11]:
```
sms_messages["length"] = sms_messages["message"].apply(len)
sms_messages.head()
```

Out[11]:

	label	message	length
0	ham	Go until jurong point, crazy.. Available only ...	111
1	ham	Ok lar... Joking wif u oni...	29
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	155
3	ham	U dun say so early hor... U c already then say...	49
4	ham	Nah I don't think he goes to usf, he lives aro...	61

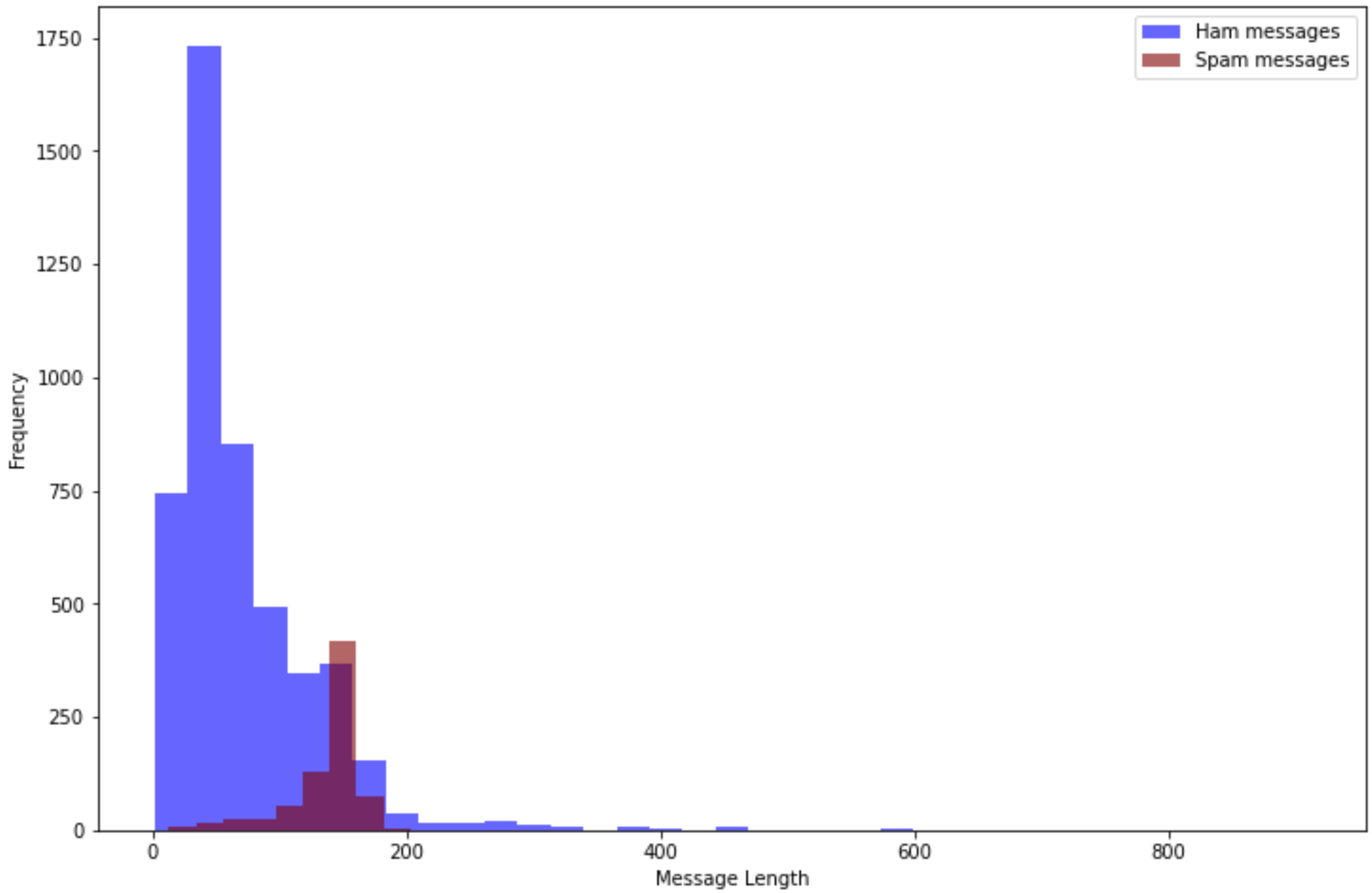
This cell implements feature engineering in message length. The message length is then compared against the identified labels as can be seen in the following code block and plot.

In [12]:
```
plt.figure(figsize=(12, 8))

sms_messages[sms_messages.label=="ham"].length.plot(
    bins=35, kind="hist", color="blue", label="Ham messages", alpha=0.6)
sms_messages[sms_messages.label=="spam"].length.plot(
    kind="hist", color="maroon", label="Spam messages", alpha=0.6)

plt.legend()
plt.xlabel("Message Length")
```

Out[12]:
```
Text(0.5, 0, 'Message Length')
```



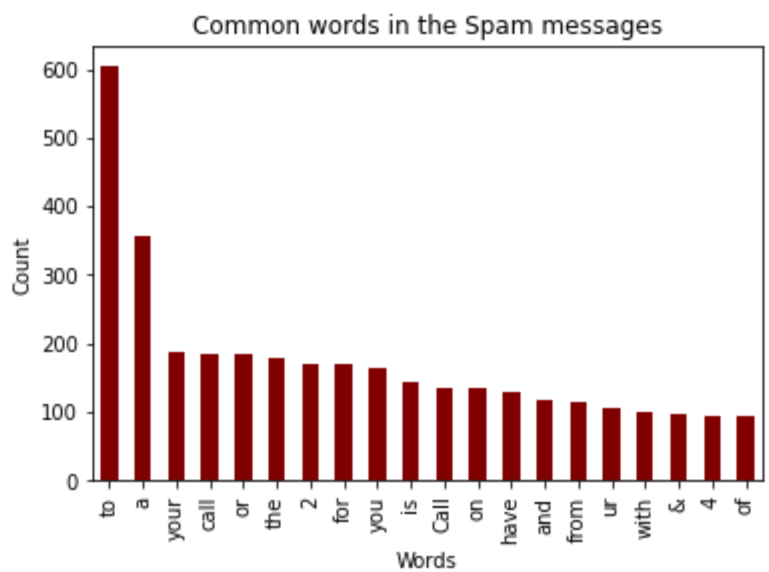
In [13]:
```
common_ham = Counter(" ".join(sms_messages[sms_messages["label"] == "ham"]["message"]).split()).mos
df_common_ham = pd.DataFrame.from_dict(common_ham)
df_common_ham = df_common_ham.rename(columns={0: "Word", 1: "Count"})

df_common_ham.plot.bar(legend = False, color = "blue")
y_pos = np.arange(len(df_common_ham["Word"]))
plt.xticks(y_pos, df_common_ham["Word"])
plt.title("Common words in the Non-spam messages")
plt.xlabel("Words")
plt.ylabel("Count")
plt.show()
```

A list of common words is then derived. The above plot shows a list of common words for the Non-spam dataset and their respective count.

In [14]:
```
common_spam = Counter(" ".join(sms_messages[sms_messages["label"] == "spam"]["message"]).split()).m
df_common_spam = pd.DataFrame.from_dict(common_spam)
df_common_spam = df_common_spam.rename(columns={0: "Word", 1: "Count"})

df_common_spam.plot.bar(legend = False, color = "maroon")
y_pos = np.arange(len(df_common_spam["Word"]))
plt.xticks(y_pos, df_common_spam["Word"])
plt.title("Common words in the Spam messages")
plt.xlabel("Words")
plt.ylabel("Count")
plt.show()
```



The bar plot above is a visualization for the most common words in the spam messages

Build the Model

Preprocessing

In [15]:
```
vocabular_size = 400
oov_token = "<OOV>"
max_length = 250
embedding_dimension = 16
number_of_epochs = 50

column_encoding = ({"ham": 0, "spam": 1})
sms_messages = sms_messages.replace(column_encoding)
sms_messages.head()
```

Out[15]:

	label	message	length
0	0	Go until jurong point, crazy.. Available only ...	111
1	0	Ok lar... Joking wif u oni...	29
2	1	Free entry in 2 a wkly comp to win FA Cup fina...	155
3	0	U dun say so early hor... U c already then say...	49
4	0	Nah I don't think he goes to usf, he lives aro...	61

In [16]:
```
X = sms_messages["message"]
Y = sms_messages["label"]

tokenizer = Tokenizer(num_words = vocabular_size, oov_token = oov_token)
tokenizer.fit_on_texts(X)
X = tokenizer.texts_to_sequences(X)

X = np.array(X)
y = np.array(Y)
```

In [17]:
```
X = pad_sequences(X, maxlen = max_length)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 7)
```

Design the Model Architecture

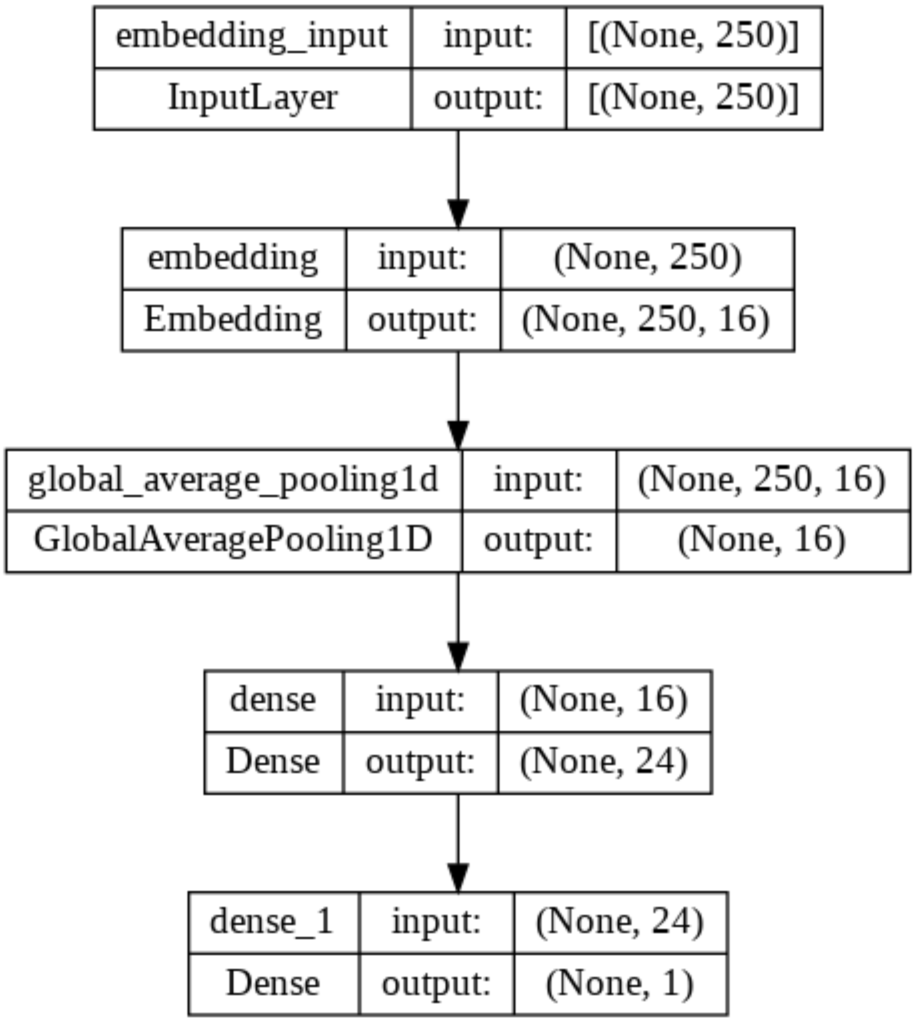
In [18]:
```
model = tf.keras.Sequential([
    tf.keras.layers.Embedding(vocabular_size, embedding_dimension, input_length = max_length),
    tf.keras.layers.GlobalAveragePooling1D(),
    tf.keras.layers.Dense(24, activation = "relu"),
    tf.keras.layers.Dense(1, activation = "sigmoid")
])

model.compile(loss = "binary_crossentropy", optimizer = "adam", metrics = ["accuracy"])
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding (Embedding)       (None, 250, 16)           6400      
                                                                 
 global_average_pooling1d (G  (None, 16)               0         
 lobalAveragePooling1D)                                          
                                                                 
 dense (Dense)               (None, 24)                408       
                                                                 
 dense_1 (Dense)             (None, 1)                 25        
                                                                 
=================================================================
Total params: 6,833
Trainable params: 6,833
Non-trainable params: 0
_________________________________________________________________
```

In [19]:
```
# Requires graphviz installed to work
plot_model(model, to_file='model_plot.png', show_shapes=True, show_layer_names=True)
```

Out[19]:



In [20]:
```
history = model.fit(X_train, y_train, epochs = number_of_epochs, validation_data = (X_test, y_test
```

```
Epoch 1/50
131/131 - 3s - loss: 0.5457 - accuracy: 0.8423 - val_loss: 0.3931 - val_accuracy: 0.8693 - 3s/epo
ch - 26ms/step
Epoch 2/50
131/131 - 1s - loss: 0.3841 - accuracy: 0.8648 - val_loss: 0.3694 - val_accuracy: 0.8693 - 585ms/
epoch - 4ms/step
Epoch 3/50
131/131 - 1s - loss: 0.3728 - accuracy: 0.8648 - val_loss: 0.3586 - val_accuracy: 0.8693 - 507ms/
epoch - 4ms/step
Epoch 4/50
131/131 - 1s - loss: 0.3602 - accuracy: 0.8648 - val_loss: 0.3436 - val_accuracy: 0.8693 - 578ms/
epoch - 4ms/step
Epoch 5/50
131/131 - 1s - loss: 0.3406 - accuracy: 0.8648 - val_loss: 0.3219 - val_accuracy: 0.8693 - 512ms/
epoch - 4ms/step
Epoch 6/50
131/131 - 1s - loss: 0.3042 - accuracy: 0.8646 - val_loss: 0.2685 - val_accuracy: 0.8693 - 544ms/
epoch - 4ms/step
Epoch 7/50
131/131 - 1s - loss: 0.2401 - accuracy: 0.8775 - val_loss: 0.1982 - val_accuracy: 0.9167 - 575ms/
epoch - 4ms/step
Epoch 8/50
131/131 - 1s - loss: 0.1792 - accuracy: 0.9375 - val_loss: 0.1502 - val_accuracy: 0.9490 - 584ms/
epoch - 4ms/step
Epoch 9/50
131/131 - 1s - loss: 0.1440 - accuracy: 0.9550 - val_loss: 0.1267 - val_accuracy: 0.9555 - 539ms/
epoch - 4ms/step
Epoch 10/50
131/131 - 1s - loss: 0.1242 - accuracy: 0.9612 - val_loss: 0.1088 - val_accuracy: 0.9627 - 521ms/
epoch - 4ms/step
Epoch 11/50
131/131 - 1s - loss: 0.1097 - accuracy: 0.9655 - val_loss: 0.0979 - val_accuracy: 0.9655 - 594ms/
epoch - 5ms/step
Epoch 12/50
131/131 - 1s - loss: 0.1002 - accuracy: 0.9675 - val_loss: 0.0890 - val_accuracy: 0.9684 - 509ms/
epoch - 4ms/step
Epoch 13/50
131/131 - 1s - loss: 0.0925 - accuracy: 0.9708 - val_loss: 0.0813 - val_accuracy: 0.9691 - 598ms/
epoch - 5ms/step
```

```
Epoch 14/50
131/131 - 1s - loss: 0.0858 - accuracy: 0.9732 - val_loss: 0.0779 - val_accuracy: 0.9691 - 520ms/
epoch - 4ms/step
Epoch 15/50
131/131 - 1s - loss: 0.0809 - accuracy: 0.9725 - val_loss: 0.0718 - val_accuracy: 0.9749 - 527ms/
epoch - 4ms/step
Epoch 16/50
131/131 - 1s - loss: 0.0750 - accuracy: 0.9749 - val_loss: 0.0679 - val_accuracy: 0.9756 - 586ms/
epoch - 4ms/step
Epoch 17/50
131/131 - 1s - loss: 0.0701 - accuracy: 0.9761 - val_loss: 0.0650 - val_accuracy: 0.9770 - 608ms/
epoch - 5ms/step
Epoch 18/50
131/131 - 1s - loss: 0.0673 - accuracy: 0.9768 - val_loss: 0.0627 - val_accuracy: 0.9785 - 532ms/
epoch - 4ms/step
Epoch 19/50
131/131 - 1s - loss: 0.0636 - accuracy: 0.9789 - val_loss: 0.0606 - val_accuracy: 0.9792 - 533ms/
epoch - 4ms/step
Epoch 20/50
131/131 - 1s - loss: 0.0611 - accuracy: 0.9789 - val_loss: 0.0616 - val_accuracy: 0.9792 - 590ms/
epoch - 5ms/step
Epoch 21/50
131/131 - 1s - loss: 0.0593 - accuracy: 0.9801 - val_loss: 0.0584 - val_accuracy: 0.9806 - 509ms/
epoch - 4ms/step
Epoch 22/50
131/131 - 1s - loss: 0.0571 - accuracy: 0.9799 - val_loss: 0.0571 - val_accuracy: 0.9813 - 549ms/
epoch - 4ms/step
Epoch 23/50
131/131 - 1s - loss: 0.0552 - accuracy: 0.9825 - val_loss: 0.0572 - val_accuracy: 0.9813 - 586ms/
epoch - 4ms/step
Epoch 24/50
131/131 - 1s - loss: 0.0535 - accuracy: 0.9828 - val_loss: 0.0550 - val_accuracy: 0.9821 - 568ms/
epoch - 4ms/step
Epoch 25/50
131/131 - 1s - loss: 0.0519 - accuracy: 0.9835 - val_loss: 0.0541 - val_accuracy: 0.9835 - 523ms/
epoch - 4ms/step
Epoch 26/50
131/131 - 1s - loss: 0.0500 - accuracy: 0.9830 - val_loss: 0.0568 - val_accuracy: 0.9821 - 535ms/
epoch - 4ms/step
Epoch 27/50
131/131 - 1s - loss: 0.0496 - accuracy: 0.9840 - val_loss: 0.0535 - val_accuracy: 0.9856 - 574ms/
epoch - 4ms/step
```

```
Epoch 28/50
131/131 - 1s - loss: 0.0473 - accuracy: 0.9840 - val_loss: 0.0524 - val_accuracy: 0.9842 - 506ms/
epoch - 4ms/step
Epoch 29/50
131/131 - 1s - loss: 0.0467 - accuracy: 0.9844 - val_loss: 0.0525 - val_accuracy: 0.9856 - 519ms/
epoch - 4ms/step
Epoch 30/50
131/131 - 1s - loss: 0.0449 - accuracy: 0.9849 - val_loss: 0.0565 - val_accuracy: 0.9828 - 570ms/
epoch - 4ms/step
Epoch 31/50
131/131 - 1s - loss: 0.0449 - accuracy: 0.9854 - val_loss: 0.0515 - val_accuracy: 0.9849 - 580ms/
epoch - 4ms/step
Epoch 32/50
131/131 - 1s - loss: 0.0438 - accuracy: 0.9861 - val_loss: 0.0520 - val_accuracy: 0.9864 - 506ms/
epoch - 4ms/step
Epoch 33/50
131/131 - 1s - loss: 0.0422 - accuracy: 0.9859 - val_loss: 0.0512 - val_accuracy: 0.9864 - 599ms/
epoch - 5ms/step
Epoch 34/50
131/131 - 1s - loss: 0.0415 - accuracy: 0.9871 - val_loss: 0.0529 - val_accuracy: 0.9856 - 507ms/
epoch - 4ms/step
Epoch 35/50
131/131 - 1s - loss: 0.0413 - accuracy: 0.9880 - val_loss: 0.0509 - val_accuracy: 0.9842 - 527ms/
epoch - 4ms/step
Epoch 36/50
131/131 - 1s - loss: 0.0404 - accuracy: 0.9883 - val_loss: 0.0510 - val_accuracy: 0.9856 - 529ms/
epoch - 4ms/step
Epoch 37/50
131/131 - 1s - loss: 0.0395 - accuracy: 0.9871 - val_loss: 0.0552 - val_accuracy: 0.9849 - 592ms/
epoch - 5ms/step
Epoch 38/50
131/131 - 1s - loss: 0.0380 - accuracy: 0.9873 - val_loss: 0.0508 - val_accuracy: 0.9849 - 521ms/
epoch - 4ms/step
Epoch 39/50
131/131 - 1s - loss: 0.0375 - accuracy: 0.9880 - val_loss: 0.0517 - val_accuracy: 0.9856 - 669ms/
epoch - 5ms/step
Epoch 40/50
131/131 - 1s - loss: 0.0362 - accuracy: 0.9885 - val_loss: 0.0512 - val_accuracy: 0.9835 - 762ms/
epoch - 6ms/step
Epoch 41/50
131/131 - 1s - loss: 0.0373 - accuracy: 0.9868 - val_loss: 0.0524 - val_accuracy: 0.9821 - 748ms/
epoch - 6ms/step
```

```
Epoch 42/50
131/131 - 1s - loss: 0.0349 - accuracy: 0.9895 - val_loss: 0.0522 - val_accuracy: 0.9856 - 807ms/
epoch - 6ms/step
Epoch 43/50
131/131 - 1s - loss: 0.0354 - accuracy: 0.9888 - val_loss: 0.0554 - val_accuracy: 0.9849 - 636ms/
epoch - 5ms/step
Epoch 44/50
131/131 - 1s - loss: 0.0338 - accuracy: 0.9895 - val_loss: 0.0515 - val_accuracy: 0.9835 - 577ms/
epoch - 4ms/step
Epoch 45/50
131/131 - 1s - loss: 0.0331 - accuracy: 0.9895 - val_loss: 0.0547 - val_accuracy: 0.9864 - 572ms/
epoch - 4ms/step
Epoch 46/50
131/131 - 1s - loss: 0.0333 - accuracy: 0.9897 - val_loss: 0.0519 - val_accuracy: 0.9849 - 515ms/
epoch - 4ms/step
Epoch 47/50
131/131 - 1s - loss: 0.0324 - accuracy: 0.9899 - val_loss: 0.0534 - val_accuracy: 0.9835 - 508ms/
epoch - 4ms/step
Epoch 48/50
131/131 - 1s - loss: 0.0328 - accuracy: 0.9890 - val_loss: 0.0523 - val_accuracy: 0.9842 - 516ms/
epoch - 4ms/step
Epoch 49/50
131/131 - 1s - loss: 0.0310 - accuracy: 0.9907 - val_loss: 0.0528 - val_accuracy: 0.9849 - 525ms/
epoch - 4ms/step
Epoch 50/50
131/131 - 1s - loss: 0.0312 - accuracy: 0.9904 - val_loss: 0.0556 - val_accuracy: 0.9864 - 515ms/
```

In [21]:

```
result = model.evaluate(X_test, y_test)
loss = result[0]
accuracy = result[1]

print(f">> Accuracy: {accuracy * 100:.2f}%")
```

```
44/44 [==============================] - 0s 2ms/step - loss: 0.0556 - accuracy: 0.9864
>> Accuracy: 98.64%
```

Save the Model

In [22]:
```
tf.keras.models.save_model(
    model,
    "model",
)
```

Test Prediction

In [23]:
```
loaded_model = tf.keras.models.load_model(
    "model",
    custom_objects = None,
    compile = True,
)

sms_messages = pd.read_csv('hamspam.csv', encoding='latin1')
sms_messages = sms_messages.iloc[:, [1]]
sms_messages.columns = ["message"]
X = sms_messages["message"]
```

In [24]:
```
def get_predictions(txts):
    tokenizer = Tokenizer(num_words = 400, oov_token = "<OOV>")
    tokenizer.fit_on_texts(X)

    txts = tokenizer.texts_to_sequences(txts)
    txts = pad_sequences(txts, maxlen=250)
    preds = loaded_model.predict(txts)
    print(preds)

    if(preds[0] > 0.5):
        print("SPAM")
    else:
        print("NOT SPAM")
```

In [25]:
```
# Spam message
txts = ["Win a free iPhone worth $2,000 by 1st April 2023"]
get_predictions(txts)
```

```
1/1 [==============================] - 0s 69ms/step
[[0.5051657]]
SPAM
```

In [26]:
```
# Not Spam
txts = ["We shall be having our class tomorrow at noon."]
get_predictions(txts)
```

```
1/1 [==============================] - 0s 15ms/step
[[0.00057115]]
NOT SPAM
```

In [27]:
```
# Spam
txts = ["Our records show you overpaid for (a product or service). Kindly supply your bank routing
get_predictions(txts)
```

```
1/1 [==============================] - 0s 15ms/step
[[0.99072474]]
SPAM
```

In [28]:
```
# Spam
txts = ["Hello. I hope your night was great."]
get_predictions(txts)
```

```
1/1 [==============================] - 0s 16ms/step
[[0.00013712]]
NOT SPAM
```

Sentiment analysis

Preparation of data

In [29]:
```
seed = 50

torch.manual_seed(seed)
torch.backends.cudnn.deterministic = True
device = torch.device('cuda')

txt = data.Field(tokenize = 'spacy',
                  tokenizer_language = 'en_core_web_sm',
                  include_lengths = True)

labels = data.LabelField(dtype = torch.float)
```

In [30]:
```
train_data, test_data = datasets.IMDB.splits(txt, labels)
```

```
downloading aclImdb_v1.tar.gz

aclImdb_v1.tar.gz: 100%|██████████| 84.1M/84.1M [00:01<00:00, 67.3MB/s]
```

In [31]:
```
train_data, valid_data = train_data.split(random_state = random.seed(seed))
```

In [32]:
```
num_words = 50_000

txt.build_vocab(train_data,
                 max_size = num_words,
                 vectors = "glove.6B.100d",
                 unk_init = torch.Tensor.normal_)

labels.build_vocab(train_data)
```

```
.vector_cache/glove.6B.zip: 862MB [02:39, 5.41MB/s]
100%|██████████| 399999/400000 [00:12<00:00, 30925.69it/s]
```

In [33]:
```
btch_size = 128

train_itr, valid_itr, test_itr = data.BucketIterator.splits(
    (train_data, valid_data, test_data),
    batch_size = btch_size,
    sort_within_batch = True,
    device = device)
```

Defining python sentiment analysis model

In [34]:
```
class RNN(nn.Module):
    def __init__(self, word_limit, dimension_embedding, dimension_hidden, dimension_output, num_la
                 bidirectional, dropout, pad_idx):

        super().__init__()

        self.embedding = nn.Embedding(word_limit, dimension_embedding, padding_idx = pad_idx)

        self.rnn = nn.LSTM(dimension_embedding,
                           dimension_hidden,
                           num_layers=num_layers,
                           bidirectional=bidirectional,
                           dropout=dropout)

        self.fc = nn.Linear(dimension_hidden * 2, dimension_output)

        self.dropout = nn.Dropout(dropout)

    def forward(self, text, len_txt):


        embedded = self.dropout(self.embedding(text))


        packed_embedded = nn.utils.rnn.pack_padded_sequence(embedded, len_txt.to('cpu'))

        packed_output, (hidden, cell) = self.rnn(packed_embedded)

        output, output_lengths = nn.utils.rnn.pad_packed_sequence(packed_output)


        hidden = self.dropout(torch.cat((hidden[-2,:,:], hidden[-1,:,:]), dim = 1))

        return self.fc(hidden)
```

In [35]:
```
dimension_input = len(txt.vocab)
dimension_embedding = 100
dimension_hddn = 256
dimension_out = 1
layers = 2
bidirectional = True
droupout = 0.5
idx_pad = txt.vocab.stoi[txt.pad_token]

model = RNN(dimension_input,
            dimension_embedding,
            dimension_hddn,
            dimension_out,
            layers,
            bidirectional,
            droupout,
            idx_pad)
```

In [36]:
```
def count_parameters(model):
    return sum(p.numel() for p in model.parameters() if p.requires_grad)

print(f'The model has {count_parameters(model):,} trainable parameters')
```

```
The model has 7,310,857 trainable parameters
```

In [37]:
```
pretrained_embeddings = txt.vocab.vectors

print(pretrained_embeddings.shape)
```

```
torch.Size([50002, 100])
```

In [38]:
```
model.embedding.weight.data.copy_(pretrained_embeddings)
```

Out[38]:
```
tensor([[-1.1588,  0.3673,  0.7110,  ..., -0.7083, -0.4158, -0.1077],
        [-0.5612,  1.1481, -0.7240,  ..., -0.0684, -0.1460, -1.1966],
        [-0.0382, -0.2449,  0.7281,  ..., -0.1459,  0.8278,  0.2706],
        ...,
        [ 1.7765, -0.0532,  0.1279,  ..., -0.9538, -2.4998, -0.3557],
        [ 0.0564,  0.6554, -0.7455,  ..., -0.7413, -0.2614,  0.4580],
        [-0.0776,  0.1700,  0.3863,  ...,  0.1003, -0.2844,  0.4265]])
```

In [39]:
```
unique_id = txt.vocab.stoi[txt.unk_token]

model.embedding.weight.data[unique_id] = torch.zeros(dimension_embedding)
model.embedding.weight.data[idx_pad] = torch.zeros(dimension_embedding)

print(model.embedding.weight.data)
```

```
tensor([[ 0.0000,  0.0000,  0.0000,  ...,  0.0000,  0.0000,  0.0000],
        [ 0.0000,  0.0000,  0.0000,  ...,  0.0000,  0.0000,  0.0000],
        [-0.0382, -0.2449,  0.7281,  ..., -0.1459,  0.8278,  0.2706],
        ...,
        [ 1.7765, -0.0532,  0.1279,  ..., -0.9538, -2.4998, -0.3557],
        [ 0.0564,  0.6554, -0.7455,  ..., -0.7413, -0.2614,  0.4580],
        [-0.0776,  0.1700,  0.3863,  ...,  0.1003, -0.2844,  0.4265]])
```

In [40]:
```
optimizer = optim.Adam(model.parameters())
```

In [41]:
```
criterion = nn.BCEWithLogitsLoss()

model = model.to(device)
criterion = criterion.to(device)
```

Training of the model

In [42]:
```
def bin_acc(preds, y):

    predictions = torch.round(torch.sigmoid(preds))
    correct = (predictions == y).float()
    acc = correct.sum() / len(correct)
    return acc
```

In [43]:
```
def train(model, itr, optimizer, criterion):

    epoch_loss = 0
    epoch_acc = 0

    model.train()

    for i in itr:

        optimizer.zero_grad()

        text, len_txt = i.text

        predictions = model(text, len_txt).squeeze(1)

        loss = criterion(predictions, i.label)

        acc = bin_acc(predictions, i.label)

        loss.backward()

        optimizer.step()

        epoch_loss += loss.item()
        epoch_acc += acc.item()

    return epoch_loss / len(itr), epoch_acc / len(itr)
```

In [44]:
```
def evaluate(model, itr, criterion):

    epoch_loss = 0
    epoch_acc = 0

    model.eval()

    with torch.no_grad():

        for i in itr:

            text, len_txt = i.text

            predictions = model(text, len_txt).squeeze(1)

            loss = criterion(predictions, i.label)

            acc = bin_acc(predictions, i.label)

            epoch_loss += loss.item()
            epoch_acc += acc.item()

    return epoch_loss / len(itr), epoch_acc / len(itr)
```

In [45]:
```
def epoch_time(start_time, end_time):
    used_time = end_time - start_time
    used_mins = int(used_time / 60)
    used_secs = int(used_time - (used_mins * 60))
    return used_mins, used_secs
```

In [46]:
```
num_epochs = 10

best_valid_loss = float('inf')

for epoch in range(num_epochs):
    print(f"Starting epoch {epoch+1:02} of {num_epochs}...", end="")
    start_time = time.time()

    train_loss, train_acc = train(model, train_itr, optimizer, criterion)
    valid_loss, valid_acc = evaluate(model, valid_itr, criterion)

    end_time = time.time()

    epoch_mins, epoch_secs = epoch_time(start_time, end_time)

    if valid_loss < best_valid_loss:
        best_valid_loss = valid_loss
        torch.save(model.state_dict(), 'tut2-model.pt')

    print(f'Took: {epoch_mins}m {epoch_secs}s')
    print(f'  Train Loss: {train_loss:.3f} | Train Acc: {train_acc*100:.2f}%')
    print(f'   Val. Loss: {valid_loss:.3f} |  Val. Acc: {valid_acc*100:.2f}%')
```

```
Starting epoch 01 of 10...Took: 0m 30s
  Train Loss: 0.678 | Train Acc: 56.91%
   Val. Loss: 0.636 |  Val. Acc: 65.78%
Starting epoch 02 of 10...Took: 0m 30s
  Train Loss: 0.587 | Train Acc: 69.17%
   Val. Loss: 0.577 |  Val. Acc: 72.05%
Starting epoch 03 of 10...Took: 0m 31s
  Train Loss: 0.503 | Train Acc: 76.50%
   Val. Loss: 0.486 |  Val. Acc: 76.67%
Starting epoch 04 of 10...Took: 0m 31s
  Train Loss: 0.425 | Train Acc: 81.31%
   Val. Loss: 0.346 |  Val. Acc: 85.58%
Starting epoch 05 of 10...Took: 0m 31s
  Train Loss: 0.375 | Train Acc: 84.04%
   Val. Loss: 0.540 |  Val. Acc: 68.68%
Starting epoch 06 of 10...Took: 0m 31s
  Train Loss: 0.518 | Train Acc: 75.51%
   Val. Loss: 0.410 |  Val. Acc: 82.90%
```

```
Starting epoch 07 of 10...Took: 0m 31s
  Train Loss: 0.372 | Train Acc: 84.33%
   Val. Loss: 0.334 |  Val. Acc: 86.76%
Starting epoch 08 of 10...Took: 0m 31s
  Train Loss: 0.282 | Train Acc: 88.71%
   Val. Loss: 0.283 |  Val. Acc: 88.56%
Starting epoch 09 of 10...Took: 0m 31s
  Train Loss: 0.240 | Train Acc: 90.63%
   Val. Loss: 0.278 |  Val. Acc: 88.78%
Starting epoch 10 of 10...Took: 0m 31s
  Train Loss: 0.225 | Train Acc: 91.41%
   Val. Loss: 1.069 |  Val. Acc: 69.73%
```

Testing sentiment analysis model

In [ ]:

```
model.load_state_dict(torch.load('tut2-model.pt'))

test_loss, test_acc = evaluate(model, test_itr, criterion)

print(f'Test Loss: {test_loss:.3f} | Test Acc: {test_acc*100:.2f}%')
```

```
Test Loss: 0.343 | Test Acc: 85.79%
```

In [ ]:

```
nlp = spacy.load('en_core_web_sm')

def pred(model, sentence):
    model.eval()
    tokenized = [tok.text for tok in nlp.tokenizer(sentence)]
    indexed = [txt.vocab.stoi[t] for t in tokenized]
    length = [len(indexed)]
    tensor = torch.LongTensor(indexed).to(device)
    tensor = tensor.unsqueeze(1)
    length_tensor = torch.LongTensor(length)
    prediction = torch.sigmoid(model(tensor, length_tensor))
    return prediction.item()
```

In [ ]:
```
def formatted_sentiment(sentiment_value):
    if (sentiment_value < 0.2):
        sentiment_status = "Very Positive"
    elif (sentiment_value >= 0.2 and sentiment_value < 0.4):
        sentiment_status = "Positive"
    elif (sentiment_value >= 0.4 and sentiment_value < 0.6):
        sentiment_status = "Neutral"
    elif (sentiment_value >= 0.6 and sentiment_value < 0.8):
        sentiment_status = "Negative"
    else:
        sentiment_status = "Very Negative"
    return sentiment_status
```

In [ ]:
```
sentiment = formatted_sentiment(pred(model, "My friends are the best in the whole world"))
print(sentiment)
```

```
Very Positive
```

In [ ]:
```
sentiment = formatted_sentiment(pred(model, "She was 10 year old last year"))
print(sentiment)
```

```
Positive
```

In [ ]:
```
sentiment = formatted_sentiment(pred(model, "I like watching the movie with my girlfriend all the
print(sentiment)
```

```
Negative
```

In [ ]:
```
sentiment = formatted_sentiment(pred(model, "I hate horror movies"))
print(sentiment)
```

```
Very Positive
```

In [ ]:
```
sentiment = formatted_sentiment(pred(model, "Most people hate bad vibes"))
print(sentiment)
```

```
Negative
```

Blending spam filtering and sentiment analysis

In [ ]:

```
def get_analysis(model, sentence):
    sentiment_value = pred(model, sentence)
    sentiment_percentage = round(sentiment_value * 100, 2)

    if (sentiment_value < 0.2):
        sentiment_status = "Very Positive"
    elif (sentiment_value >= 0.2 and sentiment_value < 0.4):
        sentiment_status = "Positive"
    elif (sentiment_value >= 0.4 and sentiment_value < 0.6):
        sentiment_status = "Neutral"
    elif (sentiment_value >= 0.6 and sentiment_value < 0.8):
        sentiment_status = "Negative"
    else:
        sentiment_status = "Very Negative"

    tokenizer = Tokenizer(num_words = 400, oov_token = "<OOV>")
    tokenizer.fit_on_texts(X)

    txts = [sentence]
    txts = tokenizer.texts_to_sequences(txts)
    txts = pad_sequences(txts, maxlen=250)
    preds = loaded_model.predict(txts)

    if(preds[0] > 0.5):
        spam_status = "SPAM"
    else:
        spam_status = "NOT SPAM"

    print(f"-> Spam Status: {spam_status}")
    print(f"-> Sentiment Status: {sentiment_status} @ {round(sentiment_value, 2)}")
```

In [ ]:

```
txts = "Our records show you overpaid for (a product or service). Kindly supply your bank routing a
get_analysis(model, txts)
```

```
1/1 [==============================] - 0s 16ms/step
-> Spam Status: SPAM
-> Sentiment Status: Very Negative @ 0.98
```

In [ ]:
```
txts = "Free entry in 2 a weekly competition to win FA Cup final tkts 21st May 2005"
get_analysis(model, txts)
```

```
1/1 [==============================] - 0s 16ms/step
-> Spam Status: SPAM
-> Sentiment Status: Very Positive @ 0.04
```

In [ ]:
```
sms_messages = pd.read_csv('hamspam.csv', encoding='latin1')
sms_messages = sms_messages.iloc[:, [0, 1]]
sms_messages.columns = ["label", "message"]
sms_messages.head()
```

Out[58]:

	label	message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

In [ ]:
```
def sentiment_text(txt):
    sent = pred(model, txt)
    return formatted_sentiment(sent).lower()
```

In [ ]:
```
sentiment_column = []
for i, message in enumerate(sms_messages['message'], 1):
    sentiment_column.append(formatted_sentiment(pred(model, message)).lower())

print(sentiment_column[:5])
```

```
['very positive', 'negative', 'very positive', 'negative', 'negative']
```

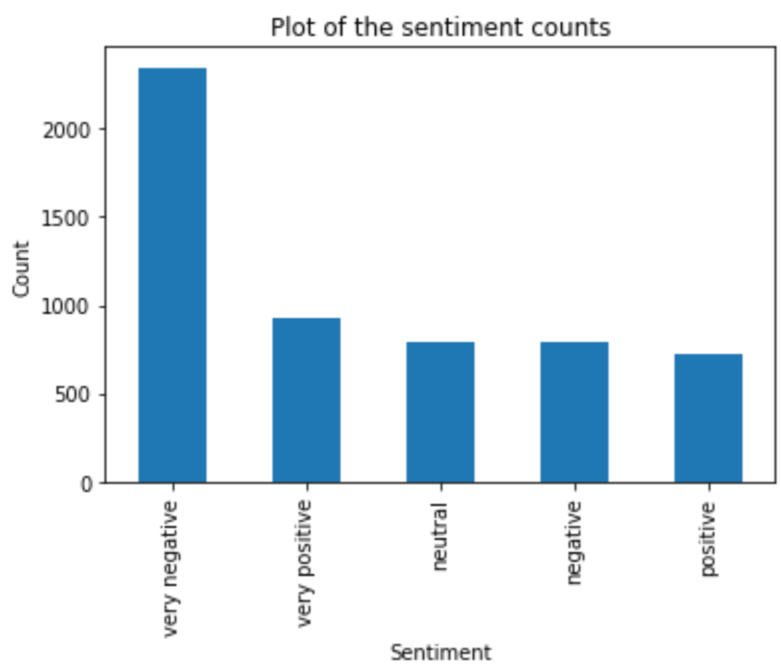
In [ ]:
```
sms_messages["sentiment"] = sentiment_column
```

In [ ]:
```
sms_messages.head()
```

Out[62]:

	label	message	sentiment
0	ham	Go until jurong point, crazy.. Available only ...	very positive
1	ham	Ok lar... Joking wif u oni...	negative
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	very positive
3	ham	U dun say so early hor... U c already then say...	negative
4	ham	Nah I don't think he goes to usf, he lives aro...	negative

In [ ]:
```
label_count = pd.value_counts(sms_messages["sentiment"], sort=True)
label_count.plot(kind = "bar")
plt.title("Plot of the sentiment counts")
plt.xlabel("Sentiment")
plt.ylabel("Count")
plt.show()
```



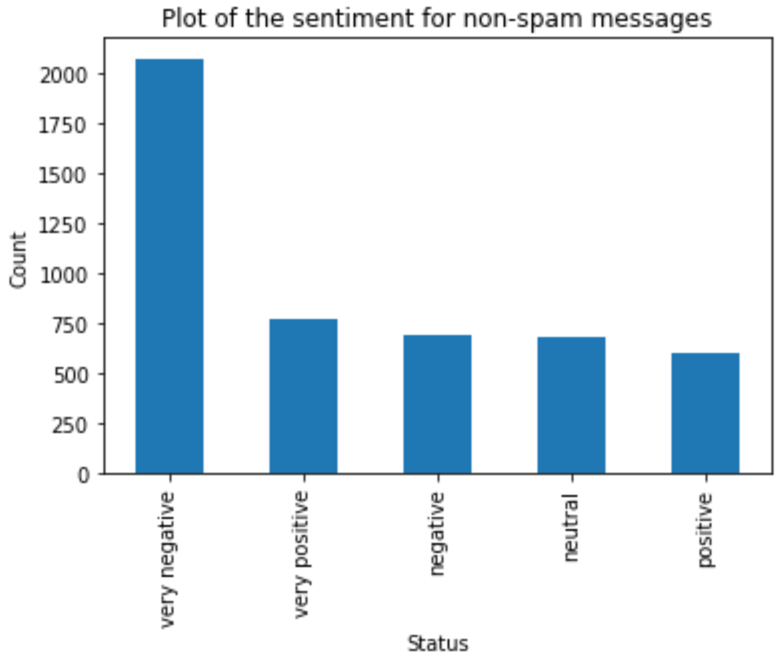
In [ ]:
```
sms_messages = pd.read_csv('hamspam.csv', encoding='latin1')
sms_messages = sms_messages.iloc[:, [0, 1]]
sms_messages.columns = ["label", "message"]
sms_messages["sentiment"] = sentiment_column

ham_messages = sms_messages[sms_messages["label"] == "ham"]
ham_messages.head()
```

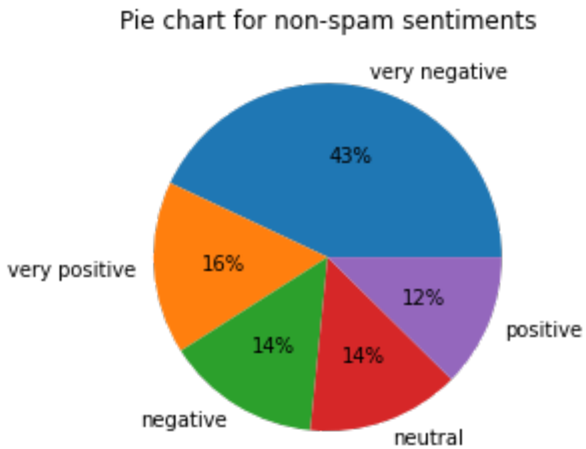
Out[75]:

	label	message	sentiment
0	ham	Go until jurong point, crazy.. Available only ...	very positive
1	ham	Ok lar... Joking wif u oni...	negative
3	ham	U dun say so early hor... U c already then say...	negative
4	ham	Nah I don't think he goes to usf, he lives aro...	negative
6	ham	Even my brother is not like to speak with me. ...	neutral

In [ ]:
```
label_count = pd.value_counts(ham_messages["sentiment"], sort=True)
label_count.plot(kind = "bar")
plt.title("Plot of the sentiment for non-spam messages")
plt.ylabel("Count")
plt.xlabel("Status")
plt.show()
```



In [ ]:
```
label_count = pd.value_counts(ham_messages["sentiment"], sort=True)
label_count.plot(kind = "pie", autopct='%.0f%%')
plt.title("Pie chart for non-spam sentiments")
plt.ylabel("")
plt.xlabel("")
plt.show()
```

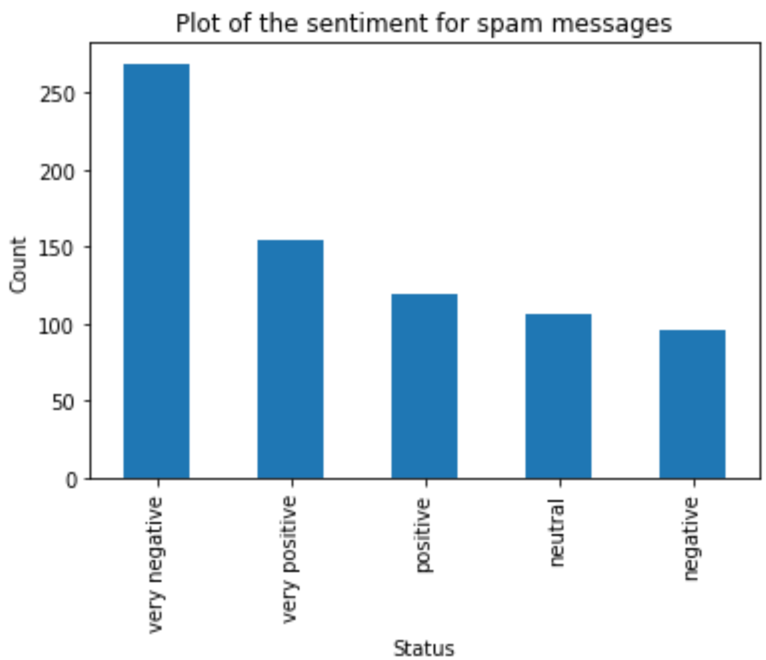


In [ ]:
```
spam_messages = sms_messages[sms_messages["label"] == "spam"]
spam_messages.head()
```

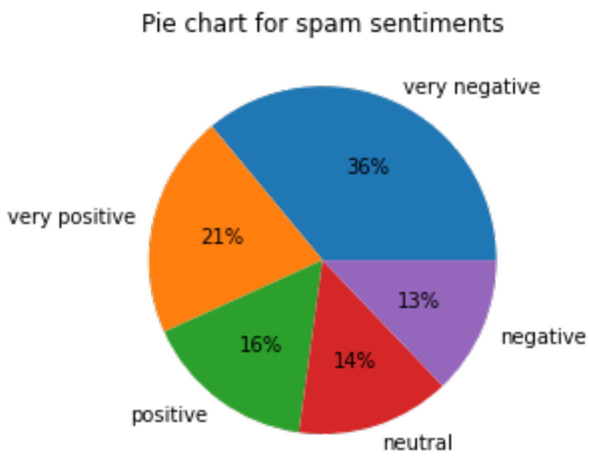
Out[76]:

	label	message	sentiment
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	very positive
5	spam	FreeMsg Hey there darling it's been 3 week's n...	neutral
8	spam	WINNER!! As a valued network customer you have...	very positive
9	spam	Had your mobile 11 months or more? U R entitle...	very positive
11	spam	SIX chances to win CASH! From 100 to 20,000 po...	negative

In [ ]:
```
label_count = pd.value_counts(spam_messages["sentiment"], sort=True)
label_count.plot(kind = "bar")
plt.title("Plot of the sentiment for spam messages")
plt.ylabel("Count")
plt.xlabel("Status")
plt.show()
```



In [ ]:
```
label_count = pd.value_counts(spam_messages["sentiment"], sort=True)
label_count.plot(kind = "pie", autopct='%.0f%%')
plt.title("Pie chart for spam sentiments")
plt.ylabel("")
plt.xlabel("")
plt.show()
```



In [ ]:
```
# plot of sentiment in ham messages
# plot of sentiment in spam messages
```