Dataset:

```
https://data.world/crowdflower/sentiment-analysis-in-text
```

In [ ]:

```
import pandas as pd
# Reading the csv dataset into a pandas dataframe
df = pd.read_csv('E:/Internships/TCS-iON/Code/MyCode/Tweets/text_emotion.csv', encoding = '
# Adding a column representing 1 for positive and 0 for negative sentiments
df['senti'] = df.apply(lambda x: 1 if (x['sentiment'] == 'enthusiasm' or x['sentiment'] ==
# Deleting unnecessary columns
df = df.drop(['tweet_id', 'sentiment', 'author'], axis = 1)
# Converting the data type to string
df['content'] = df["content"].astype("str")
# Converting all text to lowercase for use
df['content'] = df['content'].str.lower()
df.head()
```

review	senti
@tiffanylue i know i was listenin to bad habi...	0
layin n bed with a headache ughhhh...waitin o...	0
funeral ceremony...gloomy friday...	0
wants to hang out with friends soon!	1
@dannycastillo we want to trade with someone w...	0

i am going to start reading the harry potter series again because that is one awesome story.

In [ ]:

```
import re
import string
from nltk import WordNetLemmatizer
from nltk.stem.snowball import SnowballStemmer
from nltk.corpus import stopwords
# Initialising the nltk stop_words, stemmer and lemmatizer functions
stop_words = set(stopwords.words("english"))
lemmatizer = WordNetLemmatizer()
stemmer = SnowballStemmer("english")
# Creating a function for text cleaning
def textCleanser(myText):
    # Converting each tweet to string
    myText = str(myText)
    # Removing the name titles and the period symbols after it
    myText = re.sub(r'[mdsr]r(s)?\.', '', myText)
    # Removing the '@username' mentions
    myText = re.sub(r'@\w+\s', '', myText)
    myText = re.sub(r'@\w+', '', myText)
    # Removing hashtags
    myText = re.sub(r'#', '', myText)
    # Removing punctuation
    myPunct = string.punctuation
    punctToSpace = str.maketrans(myPunct, len(myPunct)*' ')
    myText = myText.translate(punctToSpace)
    # Removing urls
    myText = re.sub(r'((http(s?)?):/?/?)(www\.?).+\.com', '', myText)
    myText = re.sub(r'http(s?)', '', myText)
    # Removing numbers
    myText = re.sub(r'\d+', '', myText)
    # Removing stopwords
    myText = [word for word in myText.split(' ') if not word in stop_words]
    myText = [word for word in myText if word != '']
    # Lemmatizing the text
    myText = [lemmatizer.lemmatize(token) for token in myText]
    # Stemming the text
    # myText = [stemmer.stem(token) for token in myText]
    return myText
for i in range(len(df['content'])):
    df['content'][i] = textCleanser(df['content'][i])
df.head()
```

review	senti
[know, listenin, bad, habit, earlier, started,...	0
[layin, n, bed, headache, ughhhh, waitin, call]	0
[funeral, ceremony, gloomy, friday]	0
[want, hang, friend, soon]	1
[want, trade, someone, houston, ticket, one]	0

['going', 'start', 'reading', 'harry', 'potter', 'series', 'one', 'awesome', 'story']

In [ ]:

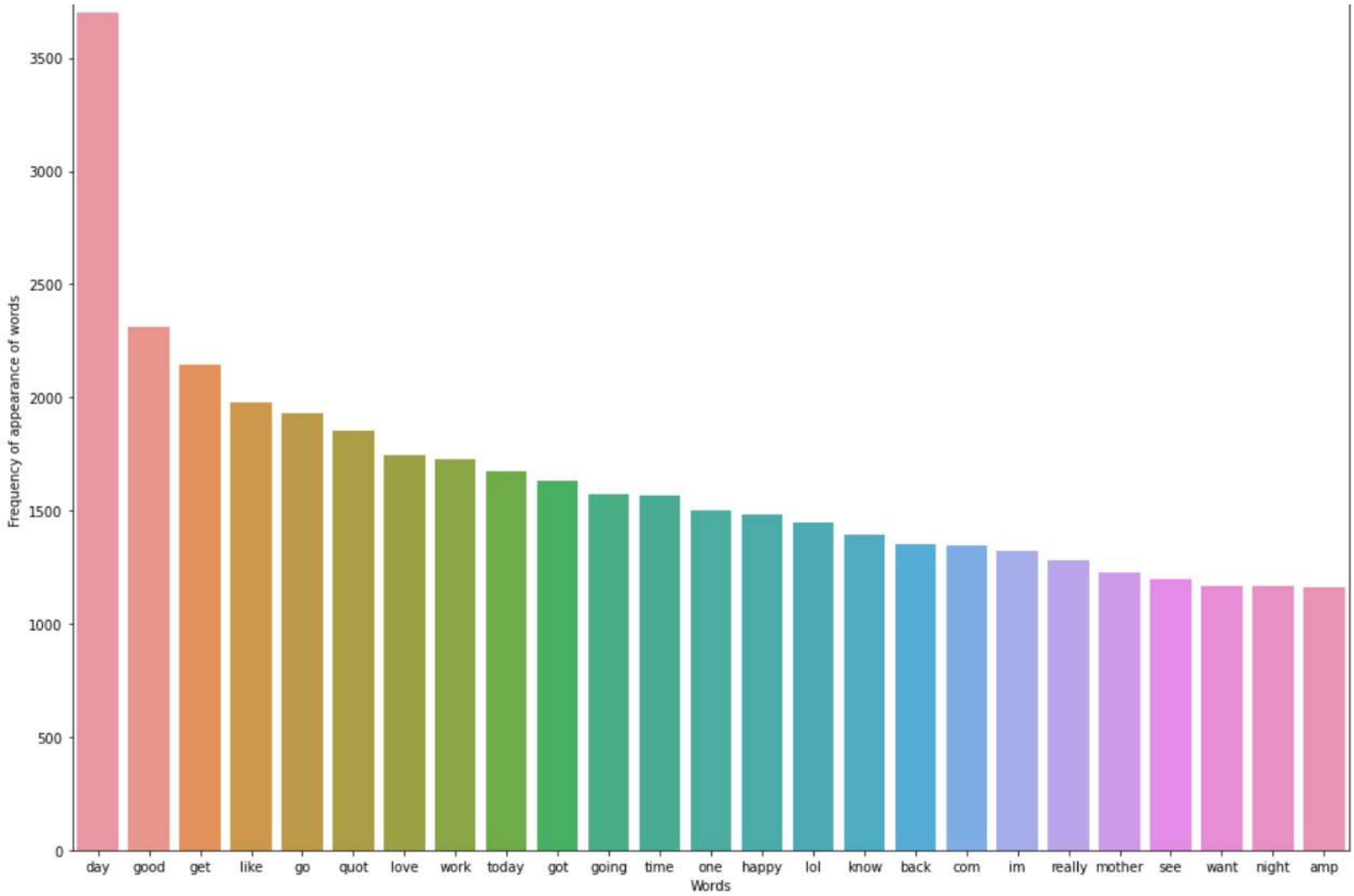
```
myReviews = []
for i in range(len(df['content'])):
    for j in df['content'][i]:
        if j != 'br' and j != 'http':
            myReviews.append(j)
```

In [ ]:

```
from collections import Counter
import collections
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.pipeline import Pipeline, FeatureUnion
from sklearn.metrics import classification_report
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
import numpy as np
np.random.seed(1234)
# Initialising the Count Vectorizer
cv = CountVectorizer()
myBow = cv.fit_transform(myReviews)
wordFrequency = dict(zip(cv.get_feature_names(), np.asarray(myBow.sum(axis = 0)).ravel()))
wordCounter = collections.Counter(wordFrequency)
# Storing the frequency of appearance of words
dfWordCounter = pd.DataFrame(wordCounter.most_common(25), columns = ['word', 'frequency'])
```

In [ ]:

```
# Plotting the top 25 most frequently occuring words
plt.close('all')
fig, ax = plt.subplots(figsize = (17, 12))
sns.barplot(x = 'word', y = 'frequency', data = dfWordCounter, ax = ax)
sns.set_palette('pastel')
plt.xlabel('Words')
plt.ylabel('Frequency of appearance of words')
plt.show()
```


Frequency of appearance of words
0
500
1000
1500
2000
2500
3000
3500
day
good
get
like
go
quot
love
work
today
got
going
time
one
happy
lol
know
back
com
im
really
mother
see
want
night
amp
Words

In [ ]:

```
from sklearn.model_selection import train_test_split
import random
import torch
import torchtext
from torchtext import data
import spacy
import en_core_web_sm
import torch.nn as nn
import torch.nn.functional as fn
SEED = 1234
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.backends.cudnn.deterministic = True
# Creating Field objects and setting batch_first to true so that we can input the batches t
TEXT = data.Field(tokenize = 'spacy', batch_first = True)
LABEL = data.LabelField(dtype = torch.float)
# Creating training and testing datasets
training, testing = train_test_split(df, test_size=0.2, random_state=42)
training, validating = train_test_split(training, test_size=0.2, random_state=42)
training.to_csv('training.csv')
validating.to_csv('validating.csv')
testing.to_csv('testing.csv')
fields = [(None, None), ('c', TEXT), ('s', LABEL)]
train_data, valid_data, test_data = data.TabularDataset.splits(
    path = 'E:/Internships/TCS-iON/Code/MyCode/Tweets/',
    train = 'training.csv',
    validation = 'validating.csv',
    test = 'testing.csv',
    format = 'csv',
    fields = fields,
    skip_header = True
)
MAX_VOCAB_SIZE = 50000
# Building the vocabularies
TEXT.build_vocab(
    train_data,
    max_size = MAX_VOCAB_SIZE,
    # Using the glove.6B.100d vector
    vectors = "glove.6B.100d",
    unk_init = torch.Tensor.normal_)
LABEL.build_vocab(train_data)
BATCH_SIZE = 64
device = torch.device('cpu')
# Creating vocabulary iterators
train_iterator, valid_iterator, test_iterator = data.BucketIterator.splits(
    (train_data, valid_data, test_data),
    sort = False,
    batch_size = BATCH_SIZE,
    device = device)
# Building the training model
class myModel(nn.Module):
    def __init__(self, vocab_size, embedding_dim, n_filters, filter_sizes, output_dim,
                 dropout, pad_idx):
        super().__init__()
        self.embedding = nn.Embedding(vocab_size, embedding_dim, padding_idx = pad_idx)
        self.convs = nn.ModuleList([
                                    nn.Conv2d(in_channels = 1,
                                              out_channels = n_filters,
```

```
                                    kernel_size = (fs, embedding_dim))
                          for fs in filter_sizes
                          ])
        self.fc = nn.Linear(len(filter_sizes) * n_filters, output_dim)
        self.dropout = nn.Dropout(dropout)
    def forward(self, text):
        embedded = self.embedding(text)
        embedded = embedded.unsqueeze(1)
        conved = [fn.relu(conv(embedded)).squeeze(3) for conv in self.convs]
        pooled = [fn.max_pool1d(conv, conv.shape[2]).squeeze(2) for conv in conved]
        cat = self.dropout(torch.cat(pooled, dim = 1))
        return self.fc(cat)
inputDimension = len(TEXT.vocab)
embeddingDimension = 100
outputDimension = 1
padding = TEXT.vocab.stoi[TEXT.pad_token]
filterCount = 100
filterSize = [3,4,5]
dropout = 0.5
model = myModel(inputDimension, embeddingDimension, filterCount, filterSize, outputDimensio
```

In [ ]:

```
# Copying the pre-trained vectors to the embedding layer
pretrained_embeddings = TEXT.vocab.vectors
model.embedding.weight.data.copy_(pretrained_embeddings)
# Setting the unknown and padding elements to zero since they are of no use
unknown = TEXT.vocab.stoi[TEXT.unk_token]
model.embedding.weight.data[unknown] = torch.zeros(embeddingDimension)
model.embedding.weight.data[padding] = torch.zeros(embeddingDimension)
# Counting the number of trainable parameters
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 2,282,101 trainable parameters
```

In [ ]:

```
import time
import torch.optim as optim
optimizer = optim.Adam(model.parameters())
criterion = nn.BCEWithLogitsLoss()
# Defining function to calculate accuracy
def binary_accuracy(preds, y):
    rounded_preds = torch.round(torch.sigmoid(preds))
    correct = (rounded_preds == y).float()
    acc = correct.sum() / len(correct)
    return acc
# Defining function for training
def train(model, iterator, optimizer, criterion):
    epoch_loss = 0
    epoch_acc = 0
    model.train()
    for batch in iterator:
        optimizer.zero_grad()
        predictions = model(batch.c).squeeze(1)
        loss = criterion(predictions, batch.s)
        acc = binary_accuracy(predictions, batch.s)
        loss.backward()
        optimizer.step()
        epoch_loss += loss.item()
        epoch_acc += acc.item()
    return epoch_loss / len(iterator), epoch_acc / len(iterator)
# Defining function for testing
def evaluate(model, iterator, criterion):
    epoch_loss = 0
    epoch_acc = 0
    model.eval()
    with torch.no_grad():
        for batch in iterator:
            predictions = model(batch.c).squeeze(1)
            loss = criterion(predictions, batch.s)
            acc = binary_accuracy(predictions, batch.s)
            epoch_loss += loss.item()
            epoch_acc += acc.item()
    return epoch_loss / len(iterator), epoch_acc / len(iterator)
# Defining function to calculate time
def epoch_time(start_time, end_time):
    elapsed_time = end_time - start_time
    elapsed_mins = int(elapsed_time / 60)
    elapsed_secs = int(elapsed_time - (elapsed_mins * 60))
    return elapsed_mins, elapsed_secs
```

In [ ]:

```
# Training the model
N_EPOCHS = 5
best_valid_loss = float('inf')
for epoch in range(N_EPOCHS):
    start_time = time.time()
    train_loss, train_acc = train(model, train_iterator, optimizer, criterion)
    valid_loss, valid_acc = evaluate(model, valid_iterator, 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(), 'myModelCNN.pt')
    print(f'Epoch: {epoch+1:02}')
    print(f'\tEpoch Time: {epoch_mins}m {epoch_secs}s')
    print(f'\tTrain Loss: {train_loss:.3f} | Train Acc: {train_acc*100:.2f}%')
    print(f'\t Val. Loss: {valid_loss:.3f} |  Val. Acc: {valid_acc*100:.2f}%')
```

Epoch: 01

```
    Epoch Time: 3m 27s
    Train Loss: 0.601 | Train Acc: 68.18%
     Val. Loss: 0.573 |  Val. Acc: 71.77%
```

Epoch: 02

```
    Epoch Time: 1m 21s
    Train Loss: 0.543 | Train Acc: 73.35%
     Val. Loss: 0.552 |  Val. Acc: 73.00%
```

Epoch: 03

```
    Epoch Time: 1m 24s
    Train Loss: 0.498 | Train Acc: 76.39%
     Val. Loss: 0.583 |  Val. Acc: 72.14%
```

Epoch: 04

```
    Epoch Time: 1m 16s
    Train Loss: 0.450 | Train Acc: 79.11%
     Val. Loss: 0.601 |  Val. Acc: 71.67%
```

Epoch: 05

```
    Epoch Time: 1m 16s
    Train Loss: 0.398 | Train Acc: 82.38%
     Val. Loss: 0.627 |  Val. Acc: 71.48%
```

In [ ]:

```
# Testing the model
model.load_state_dict(torch.load('myModelCNN.pt'))
test_loss, test_acc = evaluate(model, test_iterator, criterion)
# Calculating test accuracy
print(f'Test Loss: {test_loss:.3f} | Test Acc: {test_acc*100:.2f}%')
```

```
Test Loss: 0.541
Test Acc: 73.52%
```

In [ ]:

```

```