Sprint 9

Tasca M9 T01

In [1]:
```
import pandas as pd
import numpy as np
import nltk
import matplotlib.pyplot as plt
import seaborn as sns

from nltk.corpus import stopwords

from nltk.tokenize import sent_tokenize, word_tokenize, WordPunctTokenizer, regexp_tok

from nltk.probability import FreqDist

from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from nltk.sentiment.vader import SentimentIntensityAnalyzer

import warnings
#warnings.filterwarnings(action='once')
warnings.filterwarnings('ignore')

#nltk.download('all')
```

Example amazon reviews

In [2]:
```
df = pd.read_csv('https://raw.githubusercontent.com/pycaret/pycaret/master/datasets/am

df
```

Out[2]:

	reviewText	Positive
0	This is a one of the best apps acording to a b...	1
1	This is a pretty good version of the game for ...	1
2	this is a really cool game. there are a bunch ...	1
3	This is a silly game and can be frustrating, b...	1
4	This is a terrific game on any pad. Hrs of fun...	1
...	...	...
19995	this app is fricken stupid.it froze on the kin...	0
19996	Please add me!!!!! I need neighbors! Ginger101...	1
19997	love it! this game. is awesome. wish it had m...	1
19998	I love love love this app on the side of fashio...	1
19999	This game is a rip off. Here is a list of thin...	0

20000 rows × 2 columns

In [3]:
```
# create preprocess_text function
def preprocess_text(text):

    # Tokenize the text

    tokens = word_tokenize(text.lower())

    # Remove stop words

    filtered_tokens = [token for token in tokens if token not in stopwords.words('eng

    # Lemmatize the tokens

    lemmatizer = WordNetLemmatizer()

    lemmatized_tokens = [lemmatizer.lemmatize(token) for token in filtered_tokens]

    # Join the tokens back into a string

    processed_text = ' '.join(lemmatized_tokens)

    return processed_text

# apply the function df

df['reviewText'] = df['reviewText'].apply(preprocess_text)

df
```

Out[3]:

	reviewText	Positive
0	one best apps acording people agree bomb...	1
1	pretty good version game free . lot different ...	1
2	really cool game . bunch level find golden egg...	1
3	silly game frustrating , lot fun definitely re...	1
4	terrific game pad . hr fun . grandkids love ...	1
...	...	...
19995	app fricken stupid.it froze kindle wont allow ...	0
19996	please add ! ! ! ! ! need neighbor ! ginger101...	1
19997	love ! game . awesome . wish free stuff house ...	1
19998	love love app side fashion story fight wo...	1
19999	game rip . list thing make better & bull ; fir...	0

20000 rows × 2 columns

In [4]:
```
# initialize NLTK sentiment analyzer

analyzer = SentimentIntensityAnalyzer()

# create get_sentiment function

def get_sentiment(text):

    scores = analyzer.polarity_scores(text)

    sentiment = 1 if scores['pos'] > 0 else 0

    return sentiment

# apply get_sentiment function

df['sentiment'] = df['reviewText'].apply(get_sentiment)

df
```

Out[4]:

	reviewText	Positive	sentiment
0	one best apps acording people agree bomb...	1	1
1	pretty good version game free . lot different ...	1	1
2	really cool game . bunch level find golden egg...	1	1
3	silly game frustrating , lot fun definitely re...	1	1
4	terrific game pad . hr fun . grandkids love ...	1	1
...	...	...	...
19995	app fricken stupid.it froze kindle wont allow ...	0	0
19996	please add ! ! ! ! ! need neighbor ! ginger101...	1	1
19997	love ! game . awesome . wish free stuff house ...	1	1
19998	love love app side fashion story fight wo...	1	1
19999	game rip . list thing make better & bull ; fir...	0	1

20000 rows × 3 columns

In [5]:
```
from sklearn.metrics import confusion_matrix

print(confusion_matrix(df['Positive'], df['sentiment']))
```

```
[[ 1131  3636]
 [  576 14657]]
```

In [6]:
```
from sklearn.metrics import classification_report

print(classification_report(df['Positive'], df['sentiment']))
```

```
              precision    recall  f1-score   support

           0       0.66      0.24      0.35      4767
           1       0.80      0.96      0.87     15233

    accuracy                           0.79     20000
   macro avg       0.73      0.60      0.61     20000
weighted avg       0.77      0.79      0.75     20000
```

Exercici 1

Agafa un text en anglès que vulguis, i calcula'n la freqüència de les paraules.

- He decidit agafar un text sobre els beneficis de la IA, generat per ChatGPT-3 i també unes reviews positives i negatives de Twitter per a un anàlisis posterior.

In [7]:
```
text_IA= """ Artificial intelligence (AI) has the potential to revolutionize the way w

Firstly, AI has the potential to improve efficiency and productivity in numerous indu

Secondly, AI has the potential to create new industries and job opportunities. As AI t

Thirdly, AI has the potential to improve safety and security in various contexts. For

Finally, AI has the potential to help solve some of the world's most pressing challen

In conclusion, AI has enormous potential to improve our lives in numerous ways. While

print(text_IA)
```

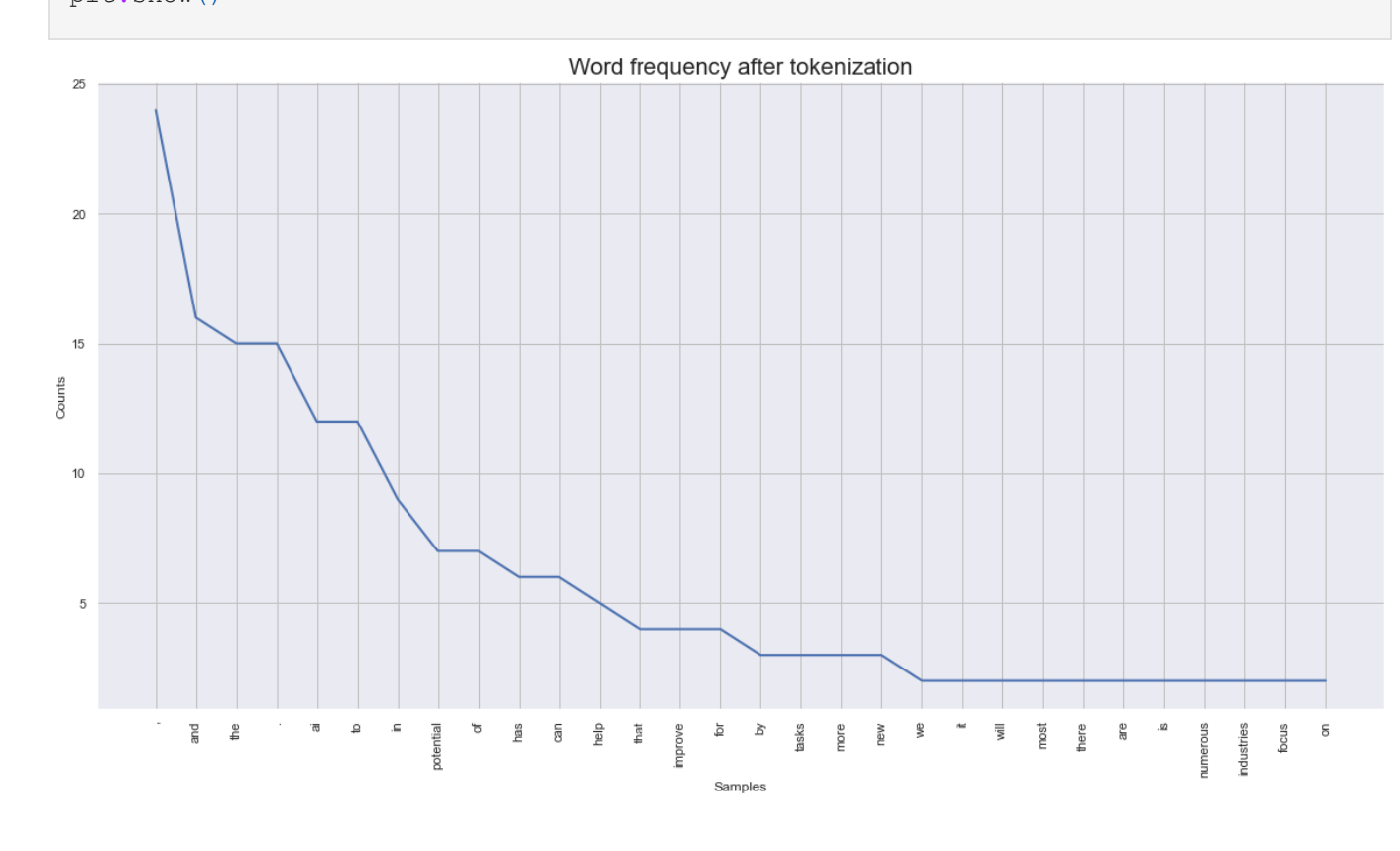
```
 Artificial intelligence (AI) has the potential to revolutionize the way we live and w
ork, and many experts believe that it will be one of the most significant technologica
l advancements of the 21st century. There are several reasons why AI is viewed in a po
sitive light.

Firstly, AI has the potential to improve efficiency and productivity in numerous indus
tries. By automating tasks that were previously done manually, businesses can save tim
e and resources, allowing them to focus on more important tasks. For example, in the h
ealthcare industry, AI-powered systems can help doctors and nurses make more accurate
diagnoses, leading to better patient outcomes.

Secondly, AI has the potential to create new industries and job opportunities. As AI t
echnology continues to advance, new products and services will emerge, creating jobs f
or developers, engineers, and other professionals. In addition, the use of AI can free
up workers to focus on more creative and higher-level tasks that require human skills
and judgment.

Thirdly, AI has the potential to improve safety and security in various contexts. For
instance, self-driving cars equipped with AI can help prevent accidents caused by huma
n error. AI-powered security systems can also help detect and prevent crime in public
places, making cities safer for residents.

Finally, AI has the potential to help solve some of the world's most pressing challeng
es, such as climate change and disease outbreaks. By analyzing vast amounts of data an
d identifying patterns, AI can help researchers develop new treatments, predict the sp
read of diseases, and improve environmental sustainability.

In conclusion, AI has enormous potential to improve our lives in numerous ways. While
there are certainly challenges associated with the use of AI, the benefits outweigh th
e risks, and it is important that we continue to invest in this technology to unlock i
ts full potential.
```

In [8]:
```
tokens = nltk.word_tokenize(text_IA.lower())
print('\033[1m','Tokens:','\033[0m',tokens[:10])

tagged = nltk.pos_tag(tokens)
print('\033[1m','\nTagged tokens:','\033[0m',tagged[:10])

fdist = FreqDist(tokens)
print('\033[1m','\nParaules més comuns al text:')
fdist.most_common(15)
```

```
 Tokens:  ['artificial', 'intelligence', '(', 'ai', ')', 'has', 'the', 'potential', 't
o', 'revolutionize']

 Tagged tokens:  [('artificial', 'JJ'), ('intelligence', 'NN'), ('(', '('), ('ai', 'N
N'), (')', ')'), ('has', 'VBZ'), ('the', 'DT'), ('potential', 'JJ'), ('to', 'TO'), ('r
evolutionize', 'VB')]

 Paraules més comuns al text:
```

Out[8]:
```
[(',', 24),
 ('and', 16),
 ('the', 15),
 ('.', 15),
 ('ai', 12),
 ('to', 12),
 ('in', 9),
 ('potential', 7),
 ('of', 7),
 ('has', 6),
 ('can', 6),
 ('help', 5),
 ('that', 4),
 ('improve', 4),
 ('for', 4)]
```

In [9]:
```
# Frequency words Distribution Plot
sns.set_theme(style='darkgrid', palette='deep')

plt.subplots(figsize=(20,10))
plt.title('Word frequency after tokenization',fontsize=20)
fdist.plot(30,cumulative=False)
plt.show()
```



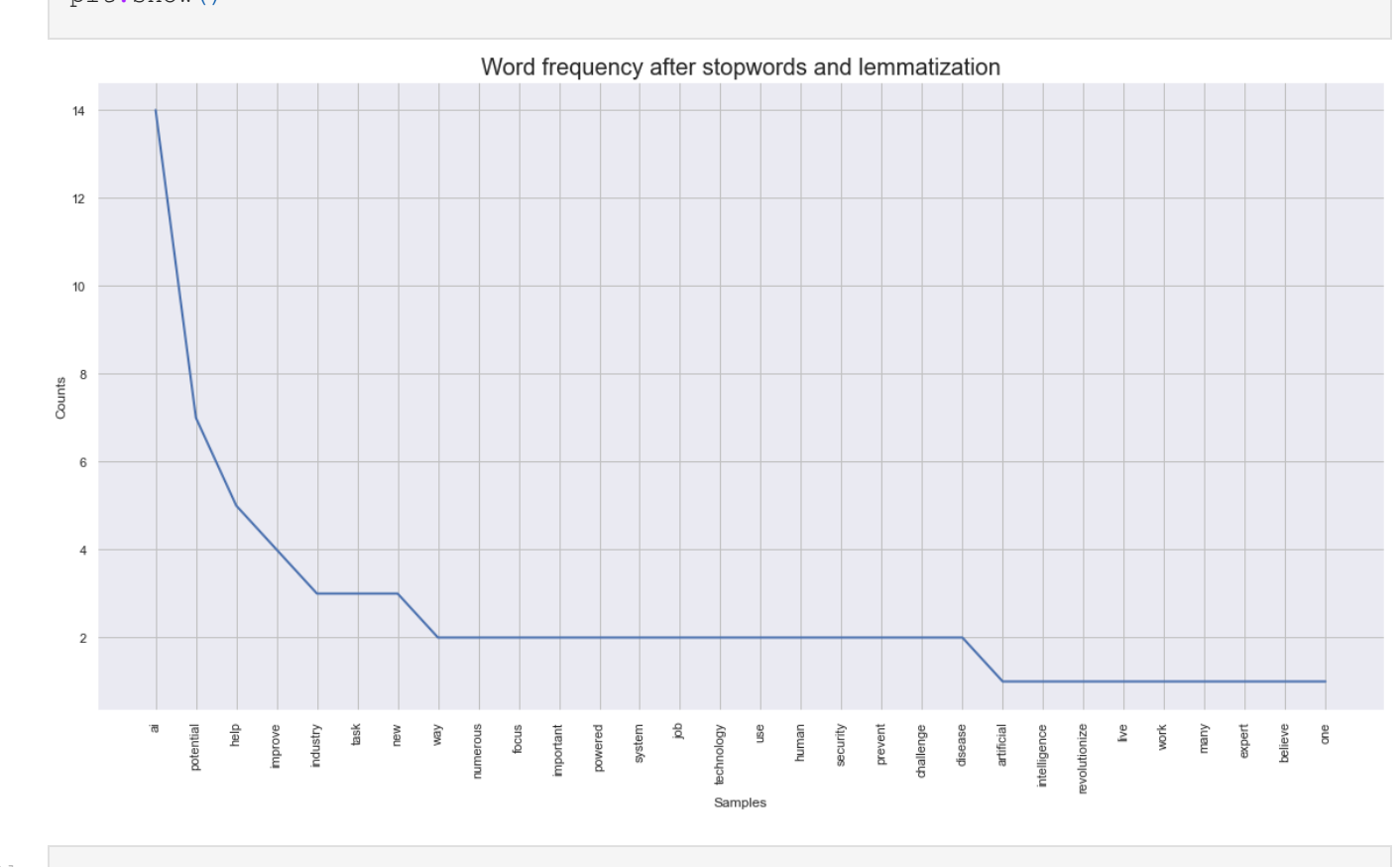
Exercici 2

Treu les stopwords i realitza stemming al teu conjunt de dades.

In [10]:
```
# Regex Tokens
stokr = regexp_tokenize(text_IA.lower(), "[\w']+")
print('\033[1m','Regexp Tokenized:')
display(stokr[:15])

filtered_tokens = [token for token in stokr if token not in stopwords.words('english')]
print('\033[1m','Without Stopwords:')
display(filtered_tokens[:15])

lemmatizer = WordNetLemmatizer()
lemmatized_tokens = [lemmatizer.lemmatize(token) for token in filtered_tokens]
print('\033[1m','Lemmatized:')
display(lemmatized_tokens[:15])
```

```
 Regexp Tokenized:
['artificial',
 'intelligence',
 'ai',
 'has',
 'the',
 'potential',
 'to',
 'revolutionize',
 'the',
 'way',
 'we',
 'live',
 'and',
 'work',
 'and']
 Without Stopwords:
['artificial',
 'intelligence',
 'ai',
 'potential',
 'revolutionize',
 'way',
 'live',
 'work',
 'many',
 'experts',
 'believe',
 'one',
 'significant',
 'technological',
 'advancements']
 Lemmatized:
['artificial',
 'intelligence',
 'ai',
 'potential',
 'revolutionize',
 'way',
 'live',
 'work',
 'many',
 'expert',
 'believe',
 'one',
 'significant',
 'technological',
 'advancement']
```

In [11]:
```
fdist1 = FreqDist(lemmatized_tokens)

plt.subplots(figsize=(20,10))
plt.title('Word frequency after stopwords and lemmatization',fontsize=20)
fdist1.plot(30,cumulative=False)
plt.show()
```



In [12]:
```
ps = PorterStemmer()

stemmed_words=[]

for w in filtered_tokens:
    stemmed_words.append(ps.stem(w))

print('\033[1m',"Stemmed Text:",'\033[0m', stemmed_words)
```

```
 Stemmed Text:  ['artifici', 'intellig', 'ai', 'potenti', 'revolut', 'way', 'live',
'work', 'mani', 'expert', 'believ', 'one', 'signific', 'technolog', 'advanc', '21st',
'centuri', 'sever', 'reason', 'ai', 'view', 'posit', 'light', 'firstli', 'ai', 'poten
ti', 'improv', 'effici', 'product', 'numer', 'industri', 'autom', 'task', 'previous',
'done', 'manual', 'busi', 'save', 'time', 'resourc', 'allow', 'focu', 'import', 'tas
k', 'exampl', 'healthcar', 'industri', 'ai', 'power', 'system', 'help', 'doctor', 'nur
s', 'make', 'accur', 'diagnos', 'lead', 'better', 'patient', 'outcom', 'secondli', 'a
i', 'potenti', 'creat', 'new', 'industri', 'job', 'opportun', 'ai', 'technolog', 'cont
inu', 'advanc', 'new', 'product', 'servic', 'emerg', 'creat', 'job', 'develop', 'engi
n', 'profession', 'addit', 'use', 'ai', 'free', 'worker', 'focu', 'creativ', 'higher',
'level', 'task', 'requir', 'human', 'skill', 'judgment', 'thirdli', 'ai', 'potenti',
'improv', 'safeti', 'secur', 'variou', 'context', 'instanc', 'self', 'drive', 'car',
'equip', 'ai', 'help', 'prevent', 'accid', 'caus', 'human', 'error', 'ai', 'power',
'secur', 'system', 'also', 'help', 'detect', 'prevent', 'crime', 'public', 'place',
'make', 'citi', 'safer', 'resid', 'final', 'ai', 'potenti', 'help', 'solv', 'world'",
'press', 'challeng', 'climat', 'chang', 'diseas', 'outbreak', 'analyz', 'vast', 'amou
nt', 'data', 'identifi', 'pattern', 'ai', 'help', 'research', 'develop', 'new', 'treat
ment', 'predict', 'spread', 'diseas', 'improv', 'environment', 'sustain', 'conclus',
'ai', 'enorm', 'potenti', 'improv', 'live', 'numer', 'way', 'certainli', 'challeng',
'associ', 'use', 'ai', 'benefit', 'outweigh', 'risk', 'import', 'continu', 'invest',
'technolog', 'unlock', 'full', 'potenti']
```

Exercici 3

Realitza sentiment analysis al teu conjunt de dades.

In [13]:
```
# create preprocess_text function
def preprocess_text(text):

    # Tokenize the text

    tokens = word_tokenize(text.lower())
    #tokens = regexp_tokenize(text.lower(),"[\w']+")

    # Remove stop words

    filtered_tokens = [token for token in tokens if token not in stopwords.words('engl

    # Lemmatize the tokens

    lemmatizer = WordNetLemmatizer()

    lemmatized_tokens = [lemmatizer.lemmatize(token) for token in filtered_tokens]

    # Join the tokens back into a string

    processed_text = ' '.join(lemmatized_tokens)

    return processed_text

# create get_sentiment function

def get_sentiment(text):

    scores = analyzer.polarity_scores(text)

    if scores['pos'] > scores['neg']:
        sentiment = 1
    else:
        sentiment = -1
    return sentiment
```

In [14]:
```
# initialize NLTK sentiment analyzer

analyzer = SentimentIntensityAnalyzer()

pt = ' '.join(lemmatized_tokens)
scores = analyzer.polarity_scores(pt)
print('\33[1m','Polarity scores:','\33[0m',scores)
```

```
 Polarity scores:  {'neg': 0.048, 'neu': 0.611, 'pos': 0.341, 'compound': 0.9956}
```

In [15]:
```
# initialize NLTK sentiment analyzer

analyzer = SentimentIntensityAnalyzer()

pt=preprocess_text(text_IA)
print(pt)

scores = analyzer.polarity_scores(pt)
s=get_sentiment(pt)
if s==1:
    print('\n\33[1m','Positive text sentiment: 1','\n\33[0m')
else:
    print('\n\33[1m','Negative text sentiment: -1','\n\33[0m')
print('\n\33[1m','Polarity scores:','\33[0m',scores)
```

```
artificial intelligence ( ai ) potential revolutionize way live work , many expert bel
ieve one significant technological advancement 21st century . several reason ai viewed
positive light . firstly , ai potential improve efficiency productivity numerous indus
try . automating task previously done manually , business save time resource , allowin
g focus important task . example , healthcare industry , ai-powered system help doctor
nurse make accurate diagnosis , leading better patient outcome . secondly , ai potenti
al create new industry job opportunity . ai technology continues advance , new product
service emerge , creating job developer , engineer , professional . addition , use ai
free worker focus creative higher-level task require human skill judgment . thirdly ,
ai potential improve safety security various context . instance , self-driving car equ
ipped ai help prevent accident caused human error . ai-powered security system also he
lp detect prevent crime public place , making city safer resident . finally , ai poten
tial help solve world 's pressing challenge , climate change disease outbreak . analyz
ing vast amount data identifying pattern , ai help researcher develop new treatment ,
predict spread disease , improve environmental sustainability . conclusion , ai enormo
us potential improve life numerous way . certainly challenge associated use ai , benef
it outweigh risk , important continue invest technology unlock full potential .

 Positive text sentiment: 1


 Polarity scores:  {'neg': 0.048, 'neu': 0.606, 'pos': 0.345, 'compound': 0.9956}
```

- Veiem que entre fer el word_tokenize o el regexp_tokenize no hi ha una diferència massa significativa en aquest cas.

Reviews extretes de: https://www.kaggle.com/datasets/cosmos98/twitter-and-reddit-sentimental-analysis-dataset?resource=download&select=Twitter_Data.csv

Content: These tweets and Comments Were Made on Narendra Modi and Other Leaders as well as Peoples Opinion Towards the Next Prime Minister of The Nation (In Context with General Elections Held In India - 2019).

In [16]:
```
dfrr=pd.read_csv('Twitter_Data.csv', delimiter=',')
dfrr=dfrr.dropna()
dfrr
```

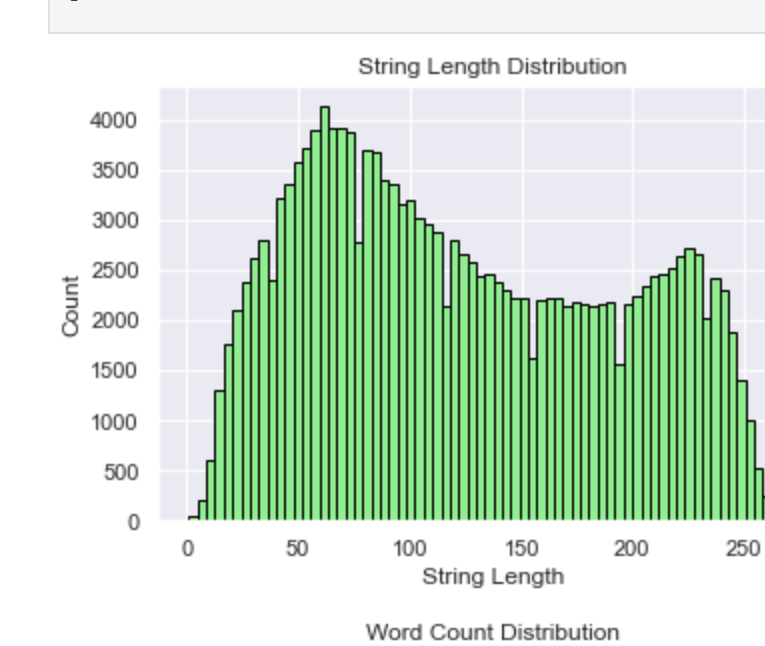
Out[16]:

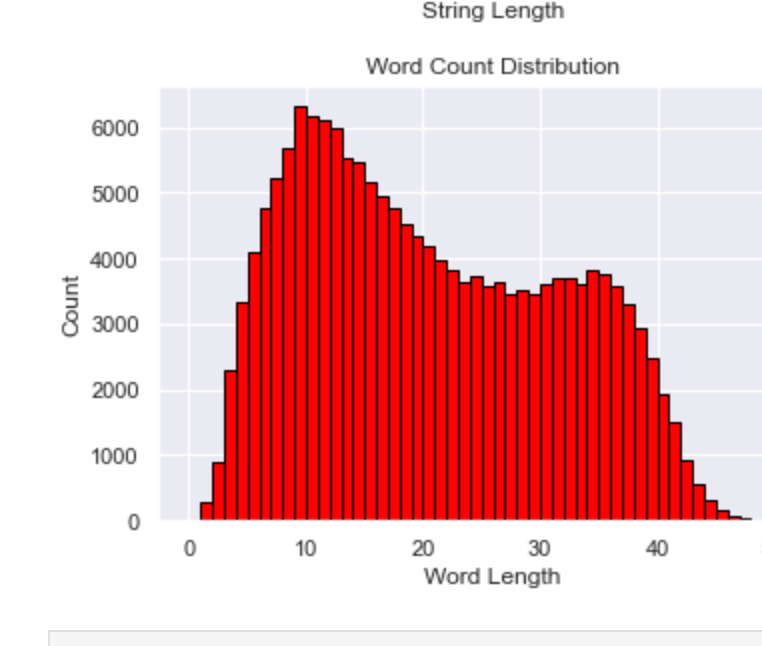
	clean_text	category
0	when modi promised "minimum government maximum...	-1.0
1	talk all the nonsense and continue all the dra...	0.0
2	what did just say vote for modi welcome bjp t...	1.0
3	asking his supporters prefix chowkidar their n...	1.0
4	answer who among these the most powerful world...	1.0
...	...	...
162975	why these 456 crores paid neerav modi not reco...	-1.0
162976	dear rss terrorist payal gawar what about modi...	-1.0
162977	did you cover her interaction forum where she ...	0.0
162978	there big project came into india modi dream p...	0.0
162979	have you ever listen about like gurukul where ...	1.0

162969 rows × 2 columns

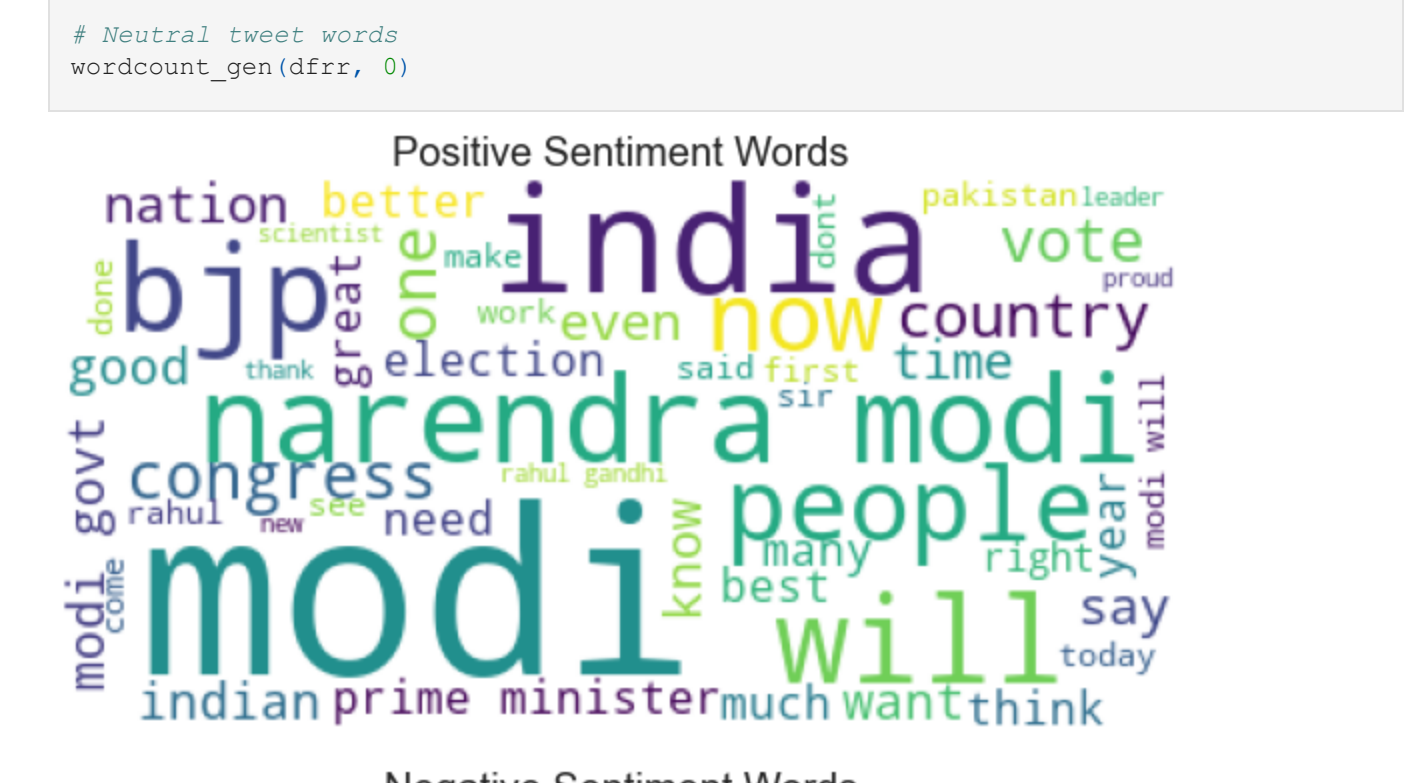
In [17]:
```
plt.hist(dfrr['category'], color='lightblue', edgecolor='black',bins=3)
plt.xlabel('Categories')
plt.ylabel('Count')
plt.title('Category Distribution')
plt.show()
```

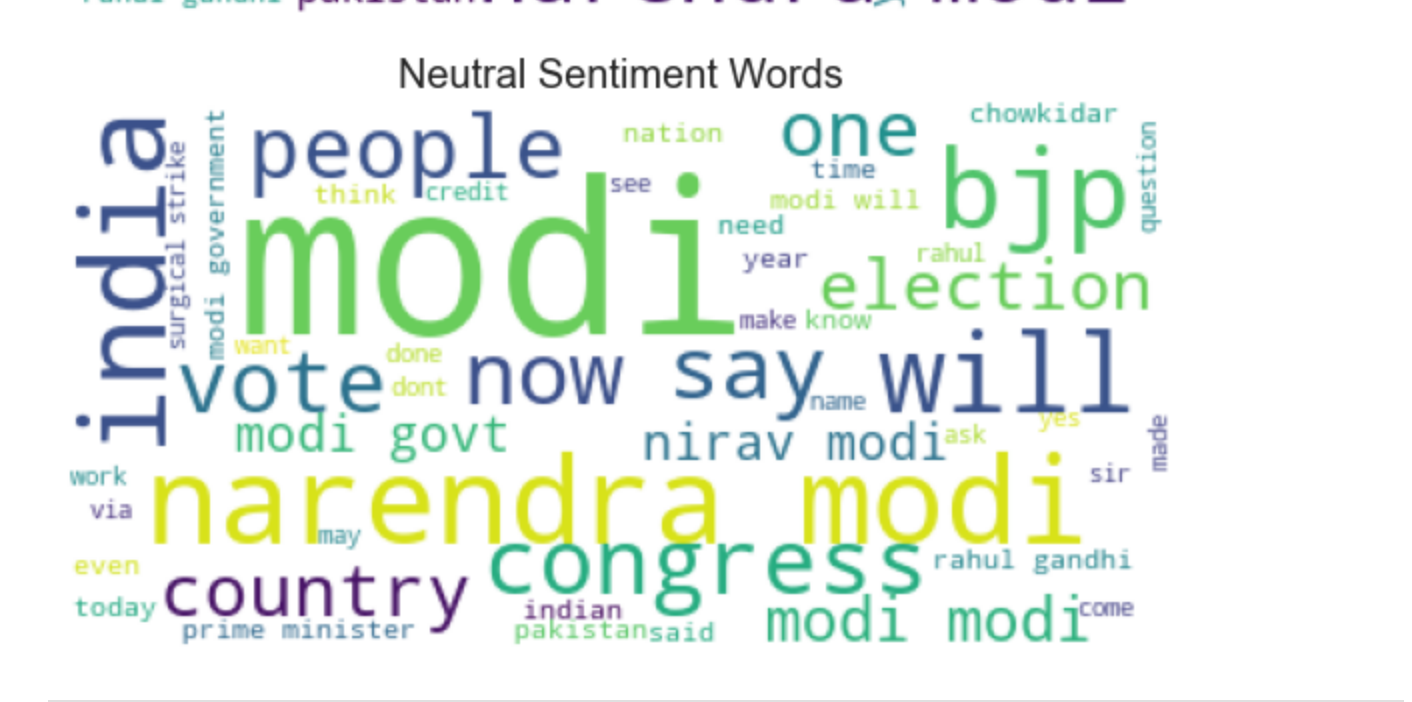
In [18]:
```
plt.hist(dfrr['clean_text'].str.len(), color='lightgreen', edgecolor='black', bins=70)
plt.xlabel('String Length')
plt.ylabel('Count')
plt.title('String Length Distribution')
plt.show()

plt.hist(dfrr['clean_text'].str.split().str.len(), color='red', edgecolor='black', bi
plt.xlabel('Word Length')
plt.ylabel('Count')
plt.title('Word Count Distribution')
plt.show()
```





In [19]:
```
from wordcloud import WordCloud, STOPWORDS

def wordcount_gen(df, category):

    # Combine all tweets
    combined_tweets = " ".join([tweet for tweet in df[df.category==category]['clean_te

    # Initialize wordcloud object
    wc = WordCloud(background_color='white',
                   max_words=50,
                   stopwords = STOPWORDS)

    # Generate and plot wordcloud
    plt.figure(figsize=(10,10))
    plt.imshow(wc.generate(combined_tweets))
    if category==-1:
        plt.title('Negative Sentiment Words', fontsize=20)
    elif category==0:
        plt.title('Neutral Sentiment Words', fontsize=20)
    else:
        plt.title('Positive Sentiment Words', fontsize=20)
    plt.axis("off")
    plt.show()

# Positive tweet words
wordcount_gen(dfrr, 1)

# Negative tweet words
wordcount_gen(dfrr, -1)

# Neutral tweet words
wordcount_gen(dfrr, 0)
```





In [20]:
```
# apply the function df
dfr = dfrr.sample(n=8000,random_state=77)
dfr.info()
dfr=dfr.dropna()
dfr=dfr.loc[(dfr['category'] != 0)]
dfr['clean_text'] = dfr['clean_text'].apply(preprocess_text)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8000 entries, 108132 to 122247
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   clean_text  8000 non-null   object
 1   category    8000 non-null   float64
dtypes: float64(1), object(1)
memory usage: 187.5+ KB
```

In [21]:
```
dfr.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5282 entries, 108132 to 104385
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   clean_text  5282 non-null   object
 1   category    5282 non-null   float64
dtypes: float64(1), object(1)
memory usage: 123.8+ KB
```

In [22]:
```
dfr.head()
```

Out[22]:

	clean_text	category
108132	holy saint speaking modi pot calling kettle black	-1.0
18298	elect biggest world seen dance finger tip rahu...	1.0
24629	guilty shrinking economy undermined notebandi ...	-1.0
124412	interestingly englishspeaking polished bhakts ...	1.0
154709	basically sir appreciate hard work try everyth...	1.0

In [23]:
```
# create get_sentimentT function

def get_sentimentT(text):

    scores = analyzer.polarity_scores(text)

    if scores['pos'] > scores['neg']-0.05:
        sentiment = 1
    else:
        sentiment = -1
    return sentiment
```

In [24]:
```
def scoresP(text):

    scores = analyzer.polarity_scores(text)
    P=scores['pos']
    return P

def scoresN(text):

    scores = analyzer.polarity_scores(text)
    N=scores['neg']
    return N

def scoresM(text):

    scores = analyzer.polarity_scores(text)
    M=scores['neu']
    return M


dfr['pos_coeff'] = dfr['clean_text'].apply(scoresP)
dfr['neg_coeff'] = dfr['clean_text'].apply(scoresN)
dfr['neu_coeff'] = dfr['clean_text'].apply(scoresM)

dfcl=dfr.drop('clean_text',axis=1)
```

In [25]:
```
# initialize NLTK sentiment analyzer

analyzer = SentimentIntensityAnalyzer()

# apply get_sentiment function

dfr['sentiment'] = dfr['clean_text'].apply(get_sentimentT)

dfr
```

Out[25]:

	clean_text	category	pos_coeff	neg_coeff	neu_coeff	sentiment
108132	holy saint speaking modi pot calling kettle black	-1.0	0.000	0.000	1.000	1
18298	elect biggest world seen dance finger tip rahu...	1.0	0.000	0.263	0.737	-1
24629	guilty shrinking economy undermined notebandi ...	-1.0	0.000	0.363	0.637	-1
124412	interestingly englishspeaking polished bhakts ...	1.0	0.297	0.067	0.636	1
154709	basically sir appreciate hard work try everyth...	1.0	0.183	0.336	0.482	-1
...	...	...	...	...	...	...
143059	country billion population diverse state cant ...	1.0	0.063	0.397	0.539	-1
160790	rang badalna aap kaam siddu bjpthen changed co...	1.0	0.154	0.132	0.714	1
94799	guy anti modi name youth aawaz congress awaaz	1.0	0.000	0.247	0.753	-1
85845	poor guy keep searching google wikipedia googl...	-1.0	0.000	0.552	0.448	-1
104385	modi first entry kashmir pulwama attack via	1.0	0.000	0.341	0.659	-1

5282 rows × 6 columns

In [26]:
```
print(confusion_matrix(dfr['category'], dfr['sentiment']))
```

```
[[ 922  792]
 [ 597 2971]]
```

In [27]:
```
print(classification_report(dfr['category'], dfr['sentiment']))
```

```
              precision    recall  f1-score   support

        -1.0       0.61      0.54      0.57      1714
         1.0       0.79      0.83      0.81      3568

    accuracy                           0.74      5282
   macro avg       0.70      0.69      0.69      5282
weighted avg       0.73      0.74      0.73      5282
```

- Podem veure que amb obtenim una *Accuracy* del 74% pels nostres textos de Twitter usant que si s'obté un *positive score* més gran que el *negative* amb una petita correcció sigui considerat un text positiu. Caldria fer un anàlisi i preprocessament de les dades més exhastiu i focalitzat pel cas dels nostres Tweets per tal de millorar l'accuracy però depenent de l'ús que necessitem un 74% pot ser suficient si volem un anàlisis més qualitatiu.

A continuació veurem com a extra si tenint en compte el *neutral score* amb un algoritme de classificació ML podem obtenir millores significatives en la classificació de textos.

In [28]:
```
import math
import seaborn as sns
from sklearn.model_selection import train_test_split
import lazypredict
from lazypredict.Supervised import LazyClassifier
```

```python
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
```

In [29]:

```python
data = dfcl
X = data.iloc[:,1:]
y= data['category']
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=.2,random_state =12

# Normalize the features
scaler = StandardScaler()
X_trainS = scaler.fit_transform(X_train)
X_testS = scaler.transform(X_test)

clf = LazyClassifier(verbose=0,ignore_warnings=True, custom_metric=None)
models,predictions = clf.fit(X_train, X_test, y_train, y_test)
models
```

```
100%|██████████| 29/29 [00:05<00:00,  5.42it/s]
```

Out[29]:

Model	Accuracy	Balanced Accuracy	ROC AUC	F1 Score	Time Taken
NearestCentroid	0.70	0.71	0.71	0.71	0.02
BernoulliNB	0.75	0.69	0.69	0.74	0.02
GaussianNB	0.75	0.67	0.67	0.73	0.02
XGBClassifier	0.74	0.66	0.66	0.73	0.13
LogisticRegression	0.75	0.66	0.66	0.73	0.03
CalibratedClassifierCV	0.75	0.66	0.66	0.73	0.32
LinearDiscriminantAnalysis	0.75	0.66	0.66	0.73	0.02
SVC	0.75	0.66	0.66	0.73	0.88
LinearSVC	0.75	0.65	0.65	0.73	0.10
RidgeClassifier	0.75	0.65	0.65	0.73	0.02
RidgeClassifierCV	0.75	0.65	0.65	0.73	0.02
LGBMClassifier	0.74	0.65	0.65	0.72	0.10
AdaBoostClassifier	0.74	0.65	0.65	0.72	0.20
SGDClassifier	0.75	0.65	0.65	0.72	0.02
RandomForestClassifier	0.72	0.65	0.65	0.71	0.52
BaggingClassifier	0.72	0.65	0.65	0.71	0.11
QuadraticDiscriminantAnalysis	0.73	0.64	0.64	0.71	0.02
KNeighborsClassifier	0.72	0.64	0.64	0.71	0.05
ExtraTreesClassifier	0.70	0.63	0.63	0.69	0.37
DecisionTreeClassifier	0.69	0.62	0.62	0.68	0.03
ExtraTreeClassifier	0.68	0.62	0.62	0.68	0.02
PassiveAggressiveClassifier	0.73	0.60	0.60	0.69	0.02
NuSVC	0.62	0.56	0.56	0.62	1.11
LabelSpreading	0.68	0.50	0.50	0.56	0.68
LabelPropagation	0.68	0.50	0.50	0.56	0.47
DummyClassifier	0.68	0.50	0.50	0.56	0.01
Perceptron	0.58	0.46	0.46	0.55	0.02

In [30]:

```python
# Train the logistic regression model
lr2 = LogisticRegression()
lr2.fit(X_trainS, y_train)
lr_pred2 = lr2.predict(X_testS)
lr_acc2 = accuracy_score(y_test, lr_pred2)
print("Logistic regression accuracy:", lr_acc2)
```

```
Logistic regression accuracy: 0.7549668874172185
```

- Amb el model Logistic no sembla que poguem trobar un mètode de classificació significativament més precís a partir dels coefficients que obtenim del *Polarity score*.

In [ ]: