Experiment No. 8	
Develop an NLP application to determine the sentiment expressed in a piece of text, classifying it as positive, negative, or neutral.	
Date of Performance:	
Date of Submission:	

Exp. No.: 8

Title: Develop an NLP application to determine the sentiment expressed in a piece of text, classifying it as positive, negative, or neutral.

Theory:

Sentiment Analysis (also known as opinion mining) is a subfield of Natural Language Processing (NLP) that focuses on determining the emotional tone or sentiment expressed in a piece of text. The primary goal of sentiment analysis is to classify text as expressing a positive, negative, or neutral sentiment. This has significant applications in various domains, including marketing, customer service, social media monitoring, and product reviews**.**

- Sentiment analysis involves analyzing text to identify subjective information and determine the sentiment conveyed by the author.
- It helps in understanding public opinion, brand perception, and customer feedback.

- **Customer Feedback**: Analyzes product reviews to gauge customer satisfaction and areas for improvement.
- **Market Research**: Understands consumer sentiment regarding brands or products to guide marketing strategies.
- **Social Media Monitoring**: Tracks public sentiment on social media platforms regarding events, products, or services.
- **Political Analysis**: Evaluates public sentiment toward political figures, policies, or elections.

3. Sentiment Classification Categories

Sentiment analysis typically involves classifying text into three main categories:

- **Positive Sentiment**: Expresses a favorable opinion or feeling (e.g., "I love this product!").
- **Negative Sentiment**: Indicates an unfavorable opinion or feeling (e.g., "This service is terrible.").

- **Neutral Sentiment**: Reflects a lack of strong emotion or opinion (e.g., "The meeting is scheduled for tomorrow.").

4. Approaches to Sentiment Analysis

1. **Lexicon-Based Approaches**:
   - Utilize predefined dictionaries of words associated with positive or negative sentiments (e.g., "happy," "sad").
   - Sentiment scores are calculated based on the presence of these words in the text.
   - Example tools: AFINN, SentiWordNet, VADER.
2. **Machine Learning Approaches**:
   - Train models on labeled datasets where texts are annotated with sentiment labels.
   - Common algorithms include Naive Bayes, Support Vector Machines (SVM), and Random Forests.
   - Feature extraction techniques such as Bag of Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), and word embeddings (e.g., Word2Vec, GloVe) are often used.
3. **Deep Learning Approaches**:
   - Use neural networks, particularly Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Transformers.
   - These models capture complex patterns in data and dependencies in sentences, leading to improved accuracy in sentiment classification.

Tools and Libraries for Sentiment Analysis

- **NLTK**: Offers basic tools and libraries for sentiment analysis, including VADER for social media sentiment.
- **TextBlob**: Simplified library for processing textual data that provides a straightforward API for sentiment analysis.
- **spaCy**: Can be used with external sentiment analysis models and integrates well with deep learning frameworks.

- **Hugging Face Transformers**: Provides pre-trained models for advanced sentiment analysis tasks using state-of-the-art transformer architectures.

Code|:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import re
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
from bs4 import BeautifulSoup
from sklearn.linear_model import LogisticRegression

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer,CountVectorizer
from sklearn.metrics import precision_recall_curve, confusion_matrix,classification_report
import nltk
from nltk.corpus import stopwords
nltk.download('stopwords')
from joblib import dump, load
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
```

```
nltk_data] Downloading package stopwords to
nltk_data]     /Users/santoshkhatiwada/nltk_data...
nltk_data]   Package stopwords is already up-to-date!
```

In [2]:
```
df = pd.read_csv('../data/three_tweets.csv')
df.head()
```

Out[2]:

	tweet_id	sentiment	author	content
0	1956967341	neutral	xoshayzers	@tiffanylue i know i was listenin to bad habi...
1	1956967666	unpleasant	wannamama	Layin n bed with a headache ughhhh...waitin o...
2	1956967696	unpleasant	coolfunky	Funeral ceremony...gloomy friday...
3	1956967789	pleasant	czareaquino	wants to hang out with friends SOON!
4	1956968416	neutral	xkilljoyx	@dannycastillo We want to trade with someone w...

columns the dataframe.

In [3]:
```
columns = ['content','sentiment']
filteredDf = df[columns]
filteredDf.head()
```

Out[3]:

	content	sentiment
0	@tiffanylue i know i was listenin to bad habi...	neutral
1	Layin n bed with a headache ughhhh...waitin o...	unpleasant
2	Funeral ceremony...gloomy friday...	unpleasant
3	wants to hang out with friends SOON!	pleasant
4	@dannycastillo We want to trade with someone w...	neutral

In [4]:
```
onehotSentiment = pd.get_dummies(filteredDf['sentiment'])
onehotSentiment.head()
```

Out[4]:

	neutral	pleasant	unpleasant
0	1	0	0
1	0	0	1
2	0	0	1
3	0	1	0
4	1	0	0

```
filteredDf= filteredDf.join(onehotSentiment)
filteredDf.head()
```

	content	sentiment	neutral	pleasant	unpleasant
0	@tiffanylue i know i was listenin to bad habi...	neutral	1	0	0
1	Layin n bed with a headache ughhhh...waitin o...	unpleasant	0	0	1
2	Funeral ceremony...gloomy friday...	unpleasant	0	0	1
3	wants to hang out with friends SOON!	pleasant	0	1	0
4	@dannycastillo We want to trade with someone w...	neutral	1	0	0

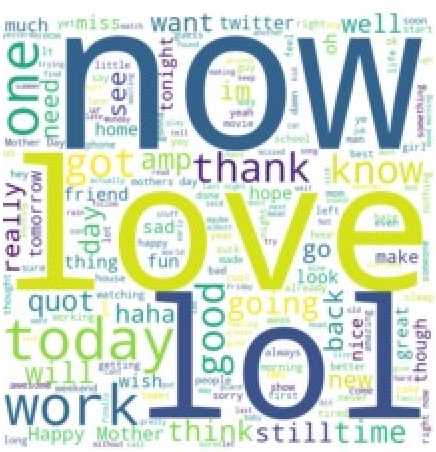
```
#remove url in the content
filteredDf['content'] = filteredDf['content'].replace(r'http\S+', '', regex=True)
#removing the special characters like @, # ,%
removeChar = str.maketrans('', '', '&@#%')
filteredDf['content'] = [s.translate(removeChar) for s in filteredDf['content']]
stpwords = set(STOPWORDS)# removing the stop words.
```

```
def wordCloud(text):
    wordcloud = WordCloud(stopwords=stpwords, background_color="white",width=800,height=800).generate(text)
    return wordcloud
```

```
def plotWordCloud(wordcloud):
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis("off")
    plt.show()
```

```
words = " ".join(line.strip() for line in filteredDf.content)
```

```
wordcloudAllContents = wordCloud(words)
plotWordCloud(wordcloudAllContents)
```




```
stop_words = stopwords.words('english')
countVect = CountVectorizer(binary=False, stop_words=stop_words,
                            token_pattern="[a-zA-Z]{2,}",#only considering words which have 2 alphabets in minimum
                            min_df=5,max_df=0.95)
features = countVect.fit_transform(filteredDf.content)
allFeatures = countVect.get_feature_names()
```

In [12]:
```
X_train1, X_test1, y_train1, y_test1 = train_test_split(features,filteredDf.neutral , test_size=0.1, random_state=6)
X_train2, X_test2, y_train2, y_test2 = train_test_split(features,filteredDf.pleasant , test_size=0.1, random_state=6)
X_train3, X_test3, y_train3, y_test3 = train_test_split(features,filteredDf.unpleasant , test_size=0.1, random_state=6)
```

In [14]:
```
def model(X_train,y_train):
    params = {
        'C':[0.07,0.09,0.1,0.2,0.3,0.5,1]
    }

    logisticModel = LogisticRegression(random_state=6,verbose=0,n_jobs=-1,class_weight='balanced')
    gridSearch = GridSearchCV(logisticModel, params,verbose=3,n_jobs=-1)
    gridSearch.fit(X_train,y_train)

    return(gridSearch.best_estimator_)
```

In [16]:
```
modelNeutral = model(X_train1, y_train1)
print(modelNeutral)
dump(modelNeutral, '../models/neutralClassifier_twitter.joblib')
```

```
/Applications/anaconda3/envs/pytorch/lib/python3.6/site-packages/sklearn/model_selection/_split.py:1978: FutureWarning: T
he default value of cv will change from 3 to 5 in version 0.22. Specify it explicitly to silence this warning.
  warnings.warn(CV_WARNING, FutureWarning)
Fitting 3 folds for each of 7 candidates, totalling 21 fits
```

In [17]:
```
modelPleasant = model(X_train2, y_train2)
print(modelPleasant)
dump(modelPleasant, '../models/pleasantClassifier_twitter.joblib')
```

```
/Applications/anaconda3/envs/pytorch/lib/python3.6/site-packages/sklearn/model_selection/_split.py:1978: FutureWarning: T
he default value of cv will change from 3 to 5 in version 0.22. Specify it explicitly to silence this warning.
  warnings.warn(CV_WARNING, FutureWarning)
Fitting 3 folds for each of 7 candidates, totalling 21 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
LogisticRegression(C=0.07, class_weight='balanced', dual=False,
                   fit_intercept=True, intercept_scaling=1, l1_ratio=None,
                   max_iter=100, multi_class='warn', n_jobs=-1, penalty='l2',
                   random_state=6, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
[Parallel(n_jobs=-1)]: Done  21 out of  21 | elapsed:    6.5s finished
/Applications/anaconda3/envs/pytorch/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:432: FutureWarning: Def
ault solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
/Applications/anaconda3/envs/pytorch/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:1544: UserWarning: 'n_j
obs' > 1 does not have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
```

Out[17]: ['../models/pleasantClassifier_twitter.joblib']

In [18]:
```
modelUnpleasant = model(X_train3, y_train3)
print(modelUnpleasant)
dump(modelUnpleasant, '../models/unpleasantClassifier_twitter.joblib')
```

```
/Applications/anaconda3/envs/pytorch/lib/python3.6/site-packages/sklearn/model_selection/_split.py:1978: FutureWarning: T
he default value of cv will change from 3 to 5 in version 0.22. Specify it explicitly to silence this warning.
  warnings.warn(CV_WARNING, FutureWarning)
Fitting 3 folds for each of 7 candidates, totalling 21 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  21 out of  21 | elapsed:    5.7s finished
/Applications/anaconda3/envs/pytorch/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:432: FutureWarning: Def
ault solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
/Applications/anaconda3/envs/pytorch/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:1544: UserWarning: 'n_j
obs' > 1 does not have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
LogisticRegression(C=0.2, class_weight='balanced', dual=False,
                   fit_intercept=True, intercept_scaling=1, l1_ratio=None,
                   max_iter=100, multi_class='warn', n_jobs=-1, penalty='l2',
                   random_state=6, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
```

Out[18]: ['../models/unpleasantClassifier_twitter.joblib']

In [19]:
```
def wordCloudFromFrequency(dictionary):
    return WordCloud(stopwords=stpwords, background_color="white",width=800,height=800).\
                                             generate_from_frequencies(dictionary)
```

In [20]:
```
loadedModel = load('../models/neutralClassifier_twitter.joblib')
trainPredict1LR = loadedModel.predict(X_train1)
accuracyLR1train = accuracy_score(y_train1, trainPredict1LR)
print("the accuracy of training set is :{}".format(accuracyLR1train))

testPredict1LR = loadedModel.predict(X_test1)
accuracyLR1test = accuracy_score(y_test1, testPredict1LR)
print("the accuracy of testing set is :{}".format(accuracyLR1test))

print(confusion_matrix(y_test1,testPredict1LR))
print(classification_report(y_test1,testPredict1LR))
precision, recall, threshold = precision_recall_curve(y_test1,testPredict1LR)
plt.plot(recall, precision)
plt.xlabel('recall')
plt.ylabel('precision')
plt.title('precsion recall curve for neutral class')
plt.show()
```

```
the accuracy of training set is :0.70075
the accuracy of testing set is :0.61725
[[1600 1082]
 [ 449  869]]
              precision    recall  f1-score   support

           0       0.78      0.60      0.68      2682
           1       0.45      0.66      0.53      1318

    accuracy                           0.62      4000
   macro avg       0.61      0.63      0.60      4000
weighted avg       0.67      0.62      0.63      4000
```

In [21]:
```
modelPleasant = load('../models/pleasantClassifier_twitter.joblib')
trainPredict2LR = modelPleasant.predict(X_train2)
accuracyLR2train = accuracy_score(y_train2, trainPredict2LR)
print("the accuracy of training set is :{}".format(accuracyLR2train))

testPredict2LR = modelPleasant.predict(X_test2)
accuracyLR2test = accuracy_score(y_test2, testPredict2LR)
print("the accuracy of testing set is :{}".format(accuracyLR2test))

print(confusion_matrix(y_test2,testPredict2LR))
print(classification_report(y_test2,testPredict2LR))
precision, recall, threshold = precision_recall_curve(y_test2,testPredict2LR)
plt.plot(recall, precision)
plt.xlabel('recall')
plt.ylabel('precision')
plt.title('precsion recall curve for pleasant class')
plt.show()
```

```
the accuracy of training set is :0.7769722222222222
the accuracy of testing set is :0.7475
[[2264  615]
 [ 395  726]]
              precision    recall  f1-score   support

           0       0.85      0.79      0.82      2879
           1       0.54      0.65      0.59      1121

    accuracy                           0.75      4000
   macro avg       0.70      0.72      0.70      4000
weighted avg       0.76      0.75      0.75      4000
```

recall

In [31]:
```
neutralEg = {}
indicesForNeutralEg = np.argsort(-1*modelNeutral.coef_)[:,0:100][0]
for i in indicesForNeutralEg[0:100]:
    neutralEg[allFeatures[i]] = modelNeutral.coef_[0,i]
```

In [32]:
```
dict(list(neutralEg.items())[0:10])
```

Out[32]:
```
{'professional': 1.3045995019795202,
 'coulda': 1.2612557783101692,
 'spray': 1.197052190820412,
 'ship': 1.1596248108413878,
 'confirmed': 1.1390109387205554,
 'gut': 1.1238480814270304,
 'relief': 1.0737745343135718,
 'madre': 1.0577456850341638,
 'chu': 1.0411500638053592,
 'size': 1.021872404112303}
```

The above list shows 10 top words having high feature importance responsible for classifying neutral sentiments.

In [33]:
```
pleasantEg = {}
indicesForPleasantEg = np.argsort(-1*modelPleasant.coef_)[:,0:100][0]
for i in indicesForPleasantEg[0:100]:
    pleasantEg[allFeatures[i]] = modelPleasant.coef_[0,i]
```

In [34]:
```
dict(list(pleasantEg.items())[0:10])
```

Out[34]:
```
{'love': 1.5400750100011658,
 'awesome': 1.365379174685966,
 'happy': 1.3363442525891633,
 'excited': 1.3250622291828258,
 'amazing': 1.2014371958687065,
 'fun': 1.1922011365902137,
 'great': 1.134455542731601,
 'cute': 1.103021995161011,
 'yay': 1.0866245278579625,
 'loving': 1.0789745691721542}
```

Similarly, the above list shows top 10 words responsible for classifying pleasant sentiments.

In [35]:
```
unpleasantEg = {}
indicesForUnpleasantEg = np.argsort(-1*modelUnpleasant.coef_)[:,0:100][0]
for i in indicesForUnpleasantEg[0:100]:
    unpleasantEg[allFeatures[i]] = modelUnpleasant.coef_[0,i]
```

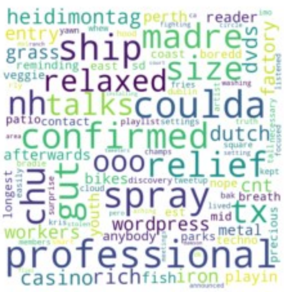
In [36]:
```
dict(list(unpleasantEg.items())[0:10])
```

Out[36]:
```
{'sad': 2.328303505982585,
 'hate': 1.7840246321469797,
 'hurts': 1.6946699456543755,
 'sorry': 1.5747837277880714,
 'poor': 1.5450916031414337,
 'sick': 1.5244596341049574,
 'sucks': 1.490164860024914,
 'hurt': 1.4429825922303625,
 'sadly': 1.4215744858963817,
 'disappointed': 1.3717693185750348}
```

'disappointed': 1.3717693185750348}

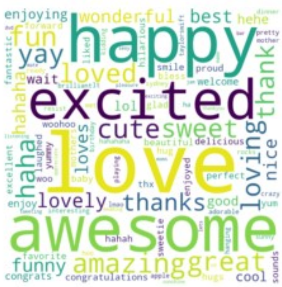
In the same way, the above list shows top 10 words responsible for classifying unpleasant sentiments.

In [37]:
```
wordcloudNeutral = wordCloudFromFrequency(neutralEg)
plotWordCloud(wordcloudNeutral)
```

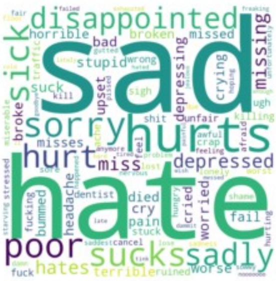


The above wordcloud shows the top 100 words which are used for neutral sentiment description.

In [38]:
```
wordcloudPleasant = wordCloudFromFrequency(pleasantEg)
plotWordCloud(wordcloudPleasant)
```



```
In [39]: wordcloudUnpleasant = wordCloudFromFrequency(unpleasantEg)
         plotWordCloud(wordcloudUnpleasant)
```



Conclusion:

In conclusion, sentiment analysis is a key NLP application that identifies and classifies emotions or opinions expressed in text, categorizing them as positive, negative, or neutral. It has widespread applications in fields like customer feedback analysis, market research, social media monitoring, and political analysis. Sentiment analysis can be approached using lexicon-based methods, machine learning models, or deep learning techniques, with each approach offering varying levels of complexity and accuracy. Tools like NLTK, TextBlob, spaCy, and Hugging Face Transformers provide powerful resources for implementing sentiment analysis in various applications, from simple rule-based systems to advanced neural networks.