Assignment-11: Apply Truncated SVD On Amazon Fine Food Reviews DataSet

Introduction

(i).A random forest consists of multiple random decision trees. Two types of randomnesses are built into the trees. First, each tree is built on a random sample from the original data. Second, at each tree node, a subset of features are randomly selected to generate the best split.

Objective

To Predict the Polarity of Amazon Fine Food Review Using Random Forest Algorithm.

Importing All Required Library

In [1]:
```
%matplotlib inline
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
import math


from sklearn.metrics.pairwise import cosine_similarity
from sklearn.decomposition import TruncatedSVD
from sklearn.cluster import KMeans

from sklearn.metrics import classification_report
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import TimeSeriesSplit

from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from sklearn import preprocessing
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score

from gensim.models import Word2Vec
from gensim.models import KeyedVectors


import pickle


from tqdm import tqdm
import os
import warnings
warnings.filterwarnings("ignore")
```

```
C:\Users\User\Anaconda3\lib\site-packages\gensim\utils.py:1197: UserWarning: detected Windows; aliasing chunkize to c
hunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

Importing Amazon Fine Food Review Dataset

In [2]:
```
if os.path.isfile("final.sqlite"):
    conn=sqlite3.connect("final.sqlite")
    Data=pd.read_sql_query("select * from Reviews where Score!=3",conn)
    conn.close()
else :
    print("Error Importing the file")
```

In [3]:
```
# Printing some data of DataFrame

Data['Score'].value_counts()
```

Out[3]:
```
1    307061
0     57110
Name: Score, dtype: int64
```

In [4]:
```
Data.columns
```

Out[4]:
```
Index(['index', 'Id', 'ProductId', 'UserId', 'ProfileName',
       'HelpfulnessNumerator', 'HelpfulnessDenominator', 'Score', 'Time',
       'Summary', 'Text', 'CleanedText'],
      dtype='object')
```

Information About DataSet

In [5]:
```
print("\nNumber of Reviews: ",Data["Text"].count())
print("\nNumber of Users: ",len(Data["UserId"].unique())) # Unique returns 1-D array of unique values of DataFrame.
print("\nNumber of Products: ",len(Data["ProductId"].unique()))
print("\nShape of Data: ", Data.shape)
print("\nColumn Name of DataSet : ",Data.columns)
print("\n\nNumber of Attributes/Columns in data: 12")
print("\nNumber of Positive Reviews : ", Data['Score'].value_counts()[1])
print("\nNumber of Negative Reviews : ", Data['Score'].value_counts()[0])
```

```
Number of Reviews:  364171

Number of Users:  243414

Number of Products:  65442

Shape of Data:  (364171, 12)

Column Name of DataSet :  Index(['index', 'Id', 'ProductId', 'UserId', 'ProfileName',
       'HelpfulnessNumerator', 'HelpfulnessDenominator', 'Score', 'Time',
       'Summary', 'Text', 'CleanedText'],
      dtype='object')


Number of Attributes/Columns in data: 12

Number of Positive Reviews :  307061

Number of Negative Reviews :  57110
```

In [6]:
```
print("\nNumber of Reviews: ",Data["Text"].count())
```

```
Number of Reviews:  364171
```

Attribute Information About DataSet

1.Id - A unique value starts from 1

2.ProductId - A unique identifier for the product

3.UserId - A unqiue identifier for the user

4.ProfileName - Name of user profile

5.HelpfulnessNumerator - Number of users who found the review helpful

6.HelpfulnessDenominator - Number of users who indicated whether they found the review helpful or not

7.Score - Rating 0 or 1

8.Time - Timestamp for the review

9.Summary - Brief summary of the review

10.Text - Text of the review

11.Cleaned Text - Text that only alphabets

In [7]:
```
# Sorting on the basis of Time Parameter
Data.sort_values('Time',inplace=True)
```

In [8]:
```
Data=Data.head(100000)
```

In [9]:
```
Y = Data['Score']
X = Data['CleanedText']
```

Defining Some Function

Co-Variance Matrix

In [10]:
```python
# Evaluate the Co-occurence matrix with context window '5'
def get_co_occur_matrix(data, vocab, context_window=5):
    a = pd.DataFrame(np.zeros((len(vocab), len(vocab))), index=vocab, columns=vocab)
    for review in data:
        words = review.split()
        for idx in range(len(words)):
            if a.get(words[idx]) is None:
                continue
            for i in range(1, context_window+1):
                if idx-i >= 0:
                    if a.get(words[idx-i]) is not None:
                        a[words[idx-i]].loc[words[idx]] = a.get(words[idx-i]).loc[words[idx]] + 1
                        a[words[idx]].loc[words[idx-i]] = a.get(words[idx]).loc[words[idx-i]] + 1
                if idx+i < len(words):
                    if a.get(words[idx+i]) is not None:
                        a[words[idx+i]].loc[words[idx]] = a.get(words[idx+i]).loc[words[idx]] + 1
                        a[words[idx]].loc[words[idx+i]] = a.get(words[idx]).loc[words[idx+i]] + 1
    np.fill_diagonal(a.values, 0)
    return a
```

Word Cloud

In [11]:
```python
def Word_Cloud(df):
    from wordcloud import WordCloud, STOPWORDS

    cloud = " ".join(word for word in df)
    stopwords = set(STOPWORDS)
    wordcloud = WordCloud(width = 1000, height = 600, background_color ='white', stopwords = stopwords).generate(cloud
)

    # plot the WordCloud image
    plt.figure(figsize = (10, 8))
    plt.imshow(wordcloud, interpolation = 'bilinear')
    plt.axis("off")
    #plt.title("Top 100 most important features\n")
    plt.tight_layout(pad = 0)

    plt.show()
```

TF-IDF Vectorizer

In [12]:
```
vectorizer_tfidf=TfidfVectorizer(max_features=15000,min_df=5)
vectors=vectorizer_tfidf.fit_transform(X)
vectors=preprocessing.normalize(vectors)
```

In [13]:
```
%%time
# Evaluate and store the top 3000 TFIDF Vectors and their corresponding words idf_ gives the weight
indices = np.argsort(vectorizer_tfidf.idf_)[::-1]
features = vectorizer_tfidf.get_feature_names()
top_n = 3000
top_feats = [features[i] for i in indices[:top_n]]
top_idf = [vectorizer_tfidf.idf_[i] for i in indices[:top_n]]
```

```
Wall time: 1.36 s
```

In [14]:
```
co_matrix = get_co_occur_matrix(X,top_feats)
```

In [15]:
```
counter = 0
for i in co_matrix.index:
    if counter == 20:
        break
    for j in co_matrix.index:
        if co_matrix.loc[j][i] != 0:
            print (i,j,"===>", co_matrix.loc[j][i])
            counter += 1
```

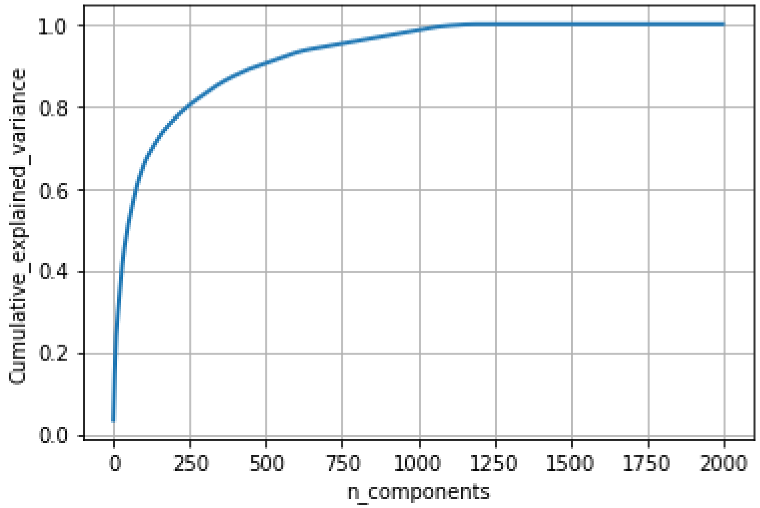
```
niederegg swede ===> 4.0
niederegg wwii ===> 4.0
nile percentil ===> 2.0
traditionalist staunch ===> 2.0
eliya nuwara ===> 10.0
eliya dimbula ===> 10.0
elmer fudd ===> 8.0
elmer coyot ===> 4.0
hornet wasp ===> 10.0
travesti putti ===> 2.0
salin sealer ===> 2.0
salin dna ===> 2.0
sandra dissatisfact ===> 2.0
nicu preemi ===> 2.0
hypocrit espous ===> 2.0
hypocrit bald ===> 2.0
crayon tar ===> 2.0
hyderabadi hyderabad ===> 4.0
hyderabad hyderabadi ===> 4.0
sarcast giver ===> 2.0
```

Dim-reduction using Truncated SVD and get the Top Singular Values explaining the most variance

In [16]:
```
svd = TruncatedSVD(n_components=1999, random_state=42)
svd_matrix = svd.fit_transform(co_matrix)
cum_var_explained = np.cumsum(svd.explained_variance_ratio_)

# Plot the Truncated SVD spectrum
plt.figure(1, figsize=(6, 4))

plt.clf()
plt.plot(cum_var_explained, linewidth=2)
plt.axis('tight')
plt.grid()
plt.xlabel('n_components')
plt.ylabel('Cumulative_explained_variance')
plt.show()
```



Minimum Components using max explained variance

In [17]:

```
for i in range(len(cum_var_explained)):
    if cum_var_explained[i] >= 1.0:
        print(i)
        break
```

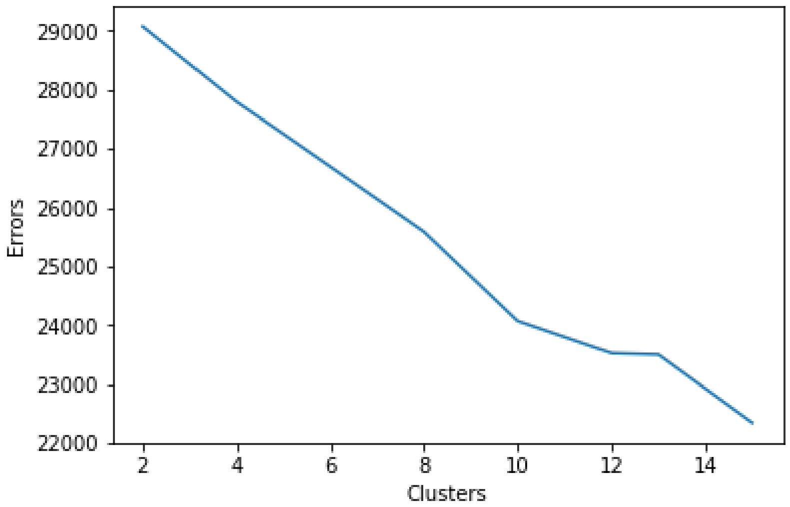
```
1202
```

Finding the best valve number of cluster

In [18]:
```
errors = []; clusters = [2, 4, 5, 7, 8, 10,12,13,15];
for i in clusters:
    print(f'Starting Cluster #{i}')
    model = KMeans(n_clusters=i, random_state=42, verbose=0)
    model.fit(svd_matrix)
    errors.append(model.inertia_)

plt.plot(clusters, errors)
plt.xlabel('Clusters')
plt.ylabel('Errors')
plt.show()
```

```
Starting Cluster #2
Starting Cluster #4
Starting Cluster #5
Starting Cluster #7
Starting Cluster #8
Starting Cluster #10
Starting Cluster #12
Starting Cluster #13
Starting Cluster #15
```



In [19]:
```
model = KMeans(n_clusters=12, random_state=42, verbose=0)
model.fit(svd_matrix)
```

Out[19]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=12, n_init=10, n_jobs=None, precompute_distances='auto',
    random_state=42, tol=0.0001, verbose=0)
```

In [20]:
```
df=pd.DataFrame(svd_matrix)
df['Cluster_labels']=model.labels_
df['Words']= top_feats
```

In [21]:
```
for i in range(model.n_clusters):
    l=list()

    # Group at each label
    label = df.groupby(["Cluster_labels"]).groups[i]

    for j in range(len(label)):
        l.append(df.loc[label[j]]["Words"])
    print("Total no of Words in cluster {} is {}".format(i,len(label)))
    Word_Cloud(l)
```

Total no of Words in cluster 0 is 2984

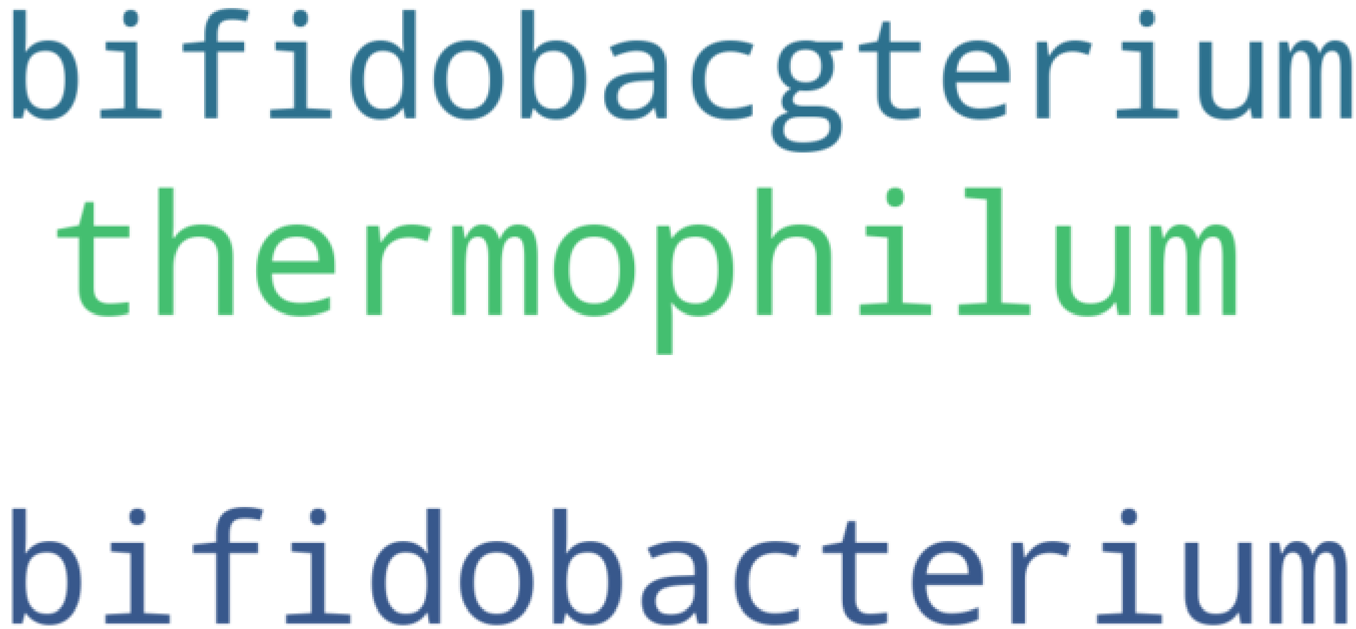
Total no of Words in cluster 1 is 1


```
Total no of Words in cluster 2 is 3
```


```
Total no of Words in cluster 3 is 1
```


```
Total no of Words in cluster 4 is 1
```


```
Total no of Words in cluster 5 is 3
```




```
Total no of Words in cluster 6 is 1
```


```
Total no of Words in cluster 7 is 1
```


```
Total no of Words in cluster 8 is 1
```


```
Total no of Words in cluster 9 is 1
```


```
Total no of Words in cluster 10 is 1
```


```
Total no of Words in cluster 11 is 2
```

Create the Cosine Similarity matrix

In [22]:
```
SVD_DF = pd.DataFrame(svd_matrix, index=co_matrix.index)
SVD_DF.head()
```

Out[22]:

	0	1	2	3	4	5	6	7	8	9	...	
circulatori	-4.845491e-15	7.234432e-16	3.979309e-15	1.828163e-17	2.631942e-17	3.720469e-16	1.615732e-16	-4.928113e-18	-2.561086e-16	8.581383e-18	...	-1.4276
niederegg	-4.505993e-15	-6.901532e-15	6.954971e-15	2.966494e-16	4.757325e-16	-1.141843e-14	1.021558e-01	-1.526909e-15	-5.551801e-16	-5.383455e-16	...	1.4727
nile	3.490555e-16	-4.148997e-16	1.280014e-15	-5.162675e-16	4.143736e-16	1.566999e-16	-8.560301e-17	-2.051829e-19	-2.166478e-16	5.314556e-16	...	-1.2063
calabria	2.789408e-16	4.419285e-17	-7.267655e-17	-1.408123e-15	3.798918e-15	9.311061e-16	-3.132747e-15	-5.286803e-15	-6.254263e-15	-4.601201e-16	...	7.1912
aril	3.581611e-16	1.951675e-16	-7.362645e-16	-2.283839e-15	-1.121689e-15	9.421691e-15	1.722078e-15	6.082137e-15	-1.300207e-14	-3.818235e-16	...	1.2106

5 rows × 1999 columns

In [23]:
```
sim_matrix = pd.DataFrame(cosine_similarity(SVD_DF), index=co_matrix.index, columns=co_matrix.index)
vocab = list(sim_matrix.index)
sim_matrix.head()
```

Out[23]:

	circulatori	niederegg	nile	calabria	aril	traditionalist	nina	nishiki	eliya	elkhound	...	pare	gravi
circulatori	1.000000	-1.099998e-01	5.028762e-03	-0.041672	0.011708	5.078156e-02	-0.022380	0.019616	-4.818881e-03	-0.052871	...	0.0	0.(
niederegg	-0.110000	1.000000e+00	-1.663682e-16	-0.001813	0.003989	-4.797430e-17	-0.004167	0.089602	-1.335866e-16	0.033297	...	0.0	0.(
nile	0.005029	-1.663682e-16	1.000000e+00	-0.028114	0.009866	9.714451e-17	0.034043	-0.026125	1.571691e-16	0.025244	...	0.0	0.(
calabria	-0.041672	-1.813339e-03	-2.811423e-02	1.000000	0.253732	3.880262e-02	-0.030994	-0.086661	-1.777869e-02	-0.039692	...	0.0	0.(
aril	0.011708	3.988930e-03	9.865688e-03	0.253732	1.000000	5.176707e-03	-0.031837	0.452409	-1.120639e-03	-0.631176	...	0.0	0.(

5 rows × 3000 columns

In [26]:
```
def print_similar_words(query):
    print(f'Top 10 similar words to "{query}" :-\n')
    top_idx = np.argsort(sim_matrix[query].values)[1:11]
    [print(vocab[i], sim_matrix[query].iloc[i]) for i in top_idx]

print_similar_words('nile')
```

```
Top 10 similar words to "nile" :-

wakeup -0.1323320825023048
christ -0.12979734014406835
gloopi -0.1290928342170854
suchard -0.12170926397399902
havarti -0.10870374554948284
flashlight -0.10429083574919273
inka -0.1042587798423363
cocao -0.10379368858523001
mailman -0.1008051347065944
personn -0.0977733960311233
```

Conclusion

1. I have used 100 K Data Points.
2. Calculated co-variance matrix and applied TruncatedSvd for dimension reduction .
3. I applied Kmeans clustering algorithm on data obtained after performing TruncatedSvd.