

Amazon_Fine_Food_Reviews_Analysis_Truncated_SVD

July 25, 2019

1 Amazon Fine Food Reviews Analysis

Data Source: <https://www.kaggle.com/snap/amazon-fine-food-reviews>

EDA: <https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/>

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454 Number of users: 256,059 Number of products: 74,258 Timespan: Oct 1999 - Oct 2012 Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unique identifier for the user
4. ProfileName
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 between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective: Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative? [Ans] We could use Score/Rating. A rating of 4 or 5 can be considered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered neutral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

2 [1]. Reading Data

2.1 [1.1] Loading the data

The dataset is available in two forms 1. .csv file 2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score is above 3, then the recommendation will be set to "positive". Otherwise, it will be set to "negative".

```
In [0]: %matplotlib inline
import warnings
warnings.filterwarnings("ignore")

import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

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

from tqdm import tqdm
import os

# importing Cross validation libs
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn import model_selection

from matplotlib import pyplot
import seaborn as sns

import numpy as np
```

```

from sklearn.cluster import KMeans
from wordcloud import WordCloud
from sklearn.decomposition import TruncatedSVD
from sklearn.metrics.pairwise import cosine_similarity
import pickle

```

In [53]: *# Code to read csv file into colab:*

```

!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials

```

1. Authenticate and create the PyDrive client.

```

auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)

```

load SQLite

```

id = '1VDFn9tpw00ecnr5DiC7TQwg-GVoPJUEK'

```

```

downloaded = drive.CreateFile({'id':id})
downloaded.GetContentFile('database.sqlite')

```

```

# df2 = pd.read_csv(io.BytesIO(uploaded['Filename.csv']))

```

using the SQLite Table to read data.

```

con = sqlite3.connect('database.sqlite')

```

```

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 100000 """)

```

Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative rating

```

def partition(x):
    if x < 3:
        return 0
    return 1

```

#changing reviews with score less than 3 to be positive and vice-versa

```

actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)

```

Number of data points in our data (100000, 10)

```
Out [53]:
```

	Id	...	Text
0	1	...	I have bought several of the Vitality canned d...
1	2	...	Product arrived labeled as Jumbo Salted Peanut...
2	3	...	This is a confection that has been around a fe...

[3 rows x 10 columns]

```
In [0]: display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

```
In [4]: print(display.shape)
display.head()
```

(80668, 7)

```
Out [4]:
```

	UserId	...	COUNT(*)
0	#oc-R115TNMSPFT9I7	...	2
1	#oc-R11D9D7SHXIJB9	...	3
2	#oc-R11DNU2NBKQ23Z	...	2
3	#oc-R1105J5ZVQE25C	...	3
4	#oc-R12KPBODL2B5ZD	...	2

[5 rows x 7 columns]

```
In [5]: display[display['UserId']=='AZY10LLTJ71NX']
```

```
Out [5]:
```

	UserId	...	COUNT(*)
80638	AZY10LLTJ71NX	...	5

[1 rows x 7 columns]

```
In [6]: display['COUNT(*)'].sum()
```

```
Out [6]: 393063
```

3 [2] Exploratory Data Analysis

3.1 [2.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

```
In [7]: display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

```
Out[7]:
```

	Id	...	Text
0	78445	...	DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
1	138317	...	DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
2	138277	...	DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
3	73791	...	DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
4	155049	...	DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...

[5 rows x 10 columns]

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8) ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delete the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

```
In [0]: #Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False)
```

```
In [9]: #Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first')
final.shape
```

```
Out[9]: (87775, 10)
```

```
In [10]: #Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

```
Out[10]: 87.775
```

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calculations

```

In [11]: display= pd.read_sql_query("""
        SELECT *
        FROM Reviews
        WHERE Score != 3 AND Id=44737 OR Id=64422
        ORDER BY ProductID
        """, con)

        display.head()

Out[11]:
      Id  ...                               Text
0  64422  ...  My son loves spaghetti so I didn't hesitate or...
1  44737  ...  It was almost a 'love at first bite' - the per...

[2 rows x 10 columns]

In [0]: final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]

In [13]: #Before starting the next phase of preprocessing lets see the number of entries left
        print(final.shape)

        #How many positive and negative reviews are present in our dataset?
        final['Score'].value_counts()

(87773, 10)

Out[13]:
1    73592
0    14181
Name: Score, dtype: int64

```

4 [3] Preprocessing

4.1 [3.1]. Preprocessing Review Text

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was observed to be better than Porter Stemming)

After which we collect the words used to describe positive and negative reviews

```
In [14]: # printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)

sent_1000 = final['Text'].values[1000]
print(sent_1000)
print("="*50)

sent_1500 = final['Text'].values[1500]
print(sent_1500)
print("="*50)

sent_4900 = final['Text'].values[4900]
print(sent_4900)
print("="*50)
```

My dogs loves this chicken but its a product from China, so we wont be buying it anymore. Its
=====

The Candy Blocks were a nice visual for the Lego Birthday party but the candy has little taste
=====

was way to hot for my blood, took a bite and did a jig lol
=====

My dog LOVES these treats. They tend to have a very strong fish oil smell. So if you are afraid
=====

```
In [15]: # remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_1500 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

My dogs loves this chicken but its a product from China, so we wont be buying it anymore. Its

```
In [16]: # https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all
from bs4 import BeautifulSoup

soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
```

```

print("="*50)

soup = BeautifulSoup(sent_1500, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_4900, 'lxml')
text = soup.get_text()
print(text)

```

My dogs loves this chicken but its a product from China, so we wont be buying it anymore. Its
=====

The Candy Blocks were a nice visual for the Lego Birthday party but the candy has little taste
=====

was way to hot for my blood, took a bite and did a jig lol
=====

My dog LOVES these treats. They tend to have a very strong fish oil smell. So if you are afraid

```

In [0]: # https://stackoverflow.com/a/47091490/4084039
import re

```

```

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can't", "can not", phrase)

    # general
    phrase = re.sub(r"n't", " not", phrase)
    phrase = re.sub(r"\ 're", " are", phrase)
    phrase = re.sub(r"\ 's", " is", phrase)
    phrase = re.sub(r"\ 'd", " would", phrase)
    phrase = re.sub(r"\ 'll", " will", phrase)
    phrase = re.sub(r"\ 't", " not", phrase)
    phrase = re.sub(r"\ 've", " have", phrase)
    phrase = re.sub(r"\ 'm", " am", phrase)
    return phrase

```

```

In [18]: sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)

```

was way to hot for my blood, took a bite and did a jig lol
=====

```

In [19]: #remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)

```


My dogs loves this chicken but its a product from China, so we wont be buying it anymore. Its

```
In [20]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

was way to hot for my blood took a bite and did a jig lol

```
In [0]: # https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have reumoved in the 1st step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves',
'you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him',
'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 't
'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "th
'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'ha
'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as
'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through
'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'ov
'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any
'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too
's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'n
've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't"
'hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'migh
'mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'v
'won', "won't", 'wouldn', "wouldn't"])
```

```
In [0]: #filtered out whole reviews
```

```
from bs4 import BeautifulSoup
# Combining all the above stundents
from tqdm import tqdm
# tqdm is for printing the status bar
word_counter = []
def filterised_text(text):
    preprocessed_text = []
    for sentence in tqdm(text):
        sentence = re.sub(r"http\S+", "", sentence)
        sentence = BeautifulSoup(sentence, 'lxml').get_text()
        sentence = decontracted(sentence)
        sentence = re.sub("\S*\d\S*", "", sentence).strip()
        sentence = re.sub('[^A-Za-z]+', ' ', sentence)
        # https://gist.github.com/sebleier/554280
        sentence = ' '.join(e.lower() for e in sentence.split() if e.lower() not in stop
```

```

        count = len(sentance.split())
        word_counter.append(count)
        preprocessed_text.append(sentance.strip())
    return preprocessed_text

```

```

In [23]: preprocessed_reviews = filterised_text(final['Text'].values)
        final['preprocessed_reviews'] = preprocessed_reviews
        preprocessed_reviews[18]

```

100%|| 87773/87773 [00:39<00:00, 2224.95it/s]

Out[23]: 'could rate fly trap lower one star would think flies come miles away come laugh thing

4.2 [3.2] Preprocessing Review Summary

```

In [24]: preprocessed_summary = filterised_text(final['Summary'].values)
        final['preprocessed_summary'] = preprocessed_summary
        preprocessed_summary[18]

```

100%|| 87773/87773 [00:28<00:00, 3124.85it/s]

Out[24]: 'day zero flies'

5 [4] Featurization

5.1 [4.3] TF-IDF

```

In [27]: tf_idf_vect = TfidfVectorizer(ngram_range=(1,1), min_df=10, use_idf=True)
        tf_idf_vect.fit(preprocessed_reviews)
        print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_names())
        print('='*50)

```

```

        final_tf_idf = tf_idf_vect.transform(preprocessed_reviews)
        print("the type of count vectorizer ",type(final_tf_idf))
        print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape())
        print("the number of unique words including both unigrams and bigrams ", final_tf_idf

```

some sample features(unique words in the corpus) ['aa', 'aafco', 'aback', 'abandon', 'abandoned',
=====

```

the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer (87773, 11524)
the number of unique words including both unigrams and bigrams 11524

```

6 [5] Assignment 11: Truncated SVD

```
In [0]: K = list(range(2, 13, 2))
```

```
def finding_best_k(X_tr):  
  
    train_ = []  
  
    for i in K:  
        tr_kmeans = KMeans(n_clusters=i, verbose=1)  
        tr_kmeans.fit(X_tr)  
  
        train_inertia = tr_kmeans.inertia_  
  
        train_.append(train_inertia)  
    return train_
```

```
def plotErrorplot(train_):  
    plt.plot(K, train_, label='Train AUC')  
    plt.legend()  
    plt.xlabel("K: hyperparameter")  
    plt.ylabel("Inertia")  
    plt.grid()  
    plt.title("ERROR PLOTS")  
    plt.show()
```

fetch result from dataframe, where matchlabel== expected label, finally convert to s

```
def returnWordCloudString(df, matchlabel):  
    return df['Features'][df.label == matchlabel].to_string()
```

```
def plotWordCloud(text):
```

<https://www.geeksforgeeks.org/generating-word-cloud-python/>

```
wordcloud = WordCloud(width = 800, height = 800,  
                        background_color = 'black',  
                        min_font_size = 10).generate(text)
```

plot the WordCloud image

```
plt.figure(figsize = (10, 10), facecolor = None)  
plt.imshow(wordcloud)  
plt.axis("off")  
plt.tight_layout(pad = 0)
```

```
plt.show()
```

6.1 Truncated-SVD

6.1.1 [5.1] Taking top features from TFIDF

```
In [29]: top_words_freq = tf_idf_vect.idf_
         print(top_words_freq.shape)

         top_word_count = 2000

         features = tf_idf_vect.get_feature_names()

         top_df = pd.DataFrame({'Features' : features, 'Idf_score' : top_words_freq})
         top_df = top_df.sort_values("Idf_score", ascending = True)[:top_word_count]
         print("shape of selected features :", top_df.shape)

         top2000 = top_df['Features'][:2000]

(11524,)
shape of selected features : (2000, 2)
```

6.1.2 [5.2] Calculation of Co-occurrence matrix

```
In [35]: # https://stackoverflow.com/questions/41661801/python-calculate-the-co-occurrence-matrix
         # https://github.com/premvardhan/Amazon-fine-food-review-analysis/blob/master/Truncated-SVD.ipynb
         # https://medium.com/data-science-group-iitr/word-embedding-2d05d270b285
         # https://www.analyticsvidhya.com/blog/2017/06/word-embeddings-count-word2vec/

         co_occurrence_matrix = np.zeros((len(top_df), len(top_df)))
         preprocess_review_df = pd.DataFrame(co_occurrence_matrix, index = top_df["Features"], columns = top_df["Features"])

         window_size = 6
         for sent in tqdm(final["preprocessed_reviews"]):
             word = sent.split(" ")
             for i, d in enumerate(word):
                 for j in range(max(i - window_size, 0), min(i + window_size, len(word))):
                     if (word[i] != word[j]):
                         try:
                             preprocess_review_df.loc[word[i], word[j]] += 1
                         except:
                             pass

100%|| 87773/87773 [2:48:11<00:00, 8.70it/s]

In [0]: import pickle
         output = open('trunctSVD.pkl', 'wb')
         pickle.dump(preprocess_review_df, output)
```

```

from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials

# 1. Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
folder_id = '1WSEkuSi3HSyJ_4v0UH_JdyTZRQmeqHdj'
# get the folder id where you want to save your file
file = drive.CreateFile({'parents': [{u'id': folder_id}]})
file.SetContentFile('trunctSVD.pkl')
file.Upload()

```

```
In [38]: preprocess_review_df.head()
```

```

Out[38]: Features      not      like      good      great      ...      email      allowed      kiwi      eaters
Features
not                0.0  15880.0  9529.0  5361.0  ...    72.0        83.0  94.0    79.0
like             15934.0      0.0  3532.0  2112.0  ...     7.0        14.0  54.0    29.0
good             9549.0   3525.0    0.0  1932.0  ...    11.0        10.0  26.0    16.0
great            5386.0   2109.0  1914.0    0.0  ...     5.0        11.0  11.0    13.0
one              7012.0   2904.0  2134.0  1380.0  ...     9.0        18.0  16.0    18.0

```

```
[5 rows x 2000 columns]
```

```
In [0]: top2000 = []
```

```

for col in preprocess_review_df.columns:
    top2000.append(col)

```

6.1.3 [5.3] Finding optimal value for number of components (n) to be retained.

```
In [40]: # TruncatedSVD
```

```

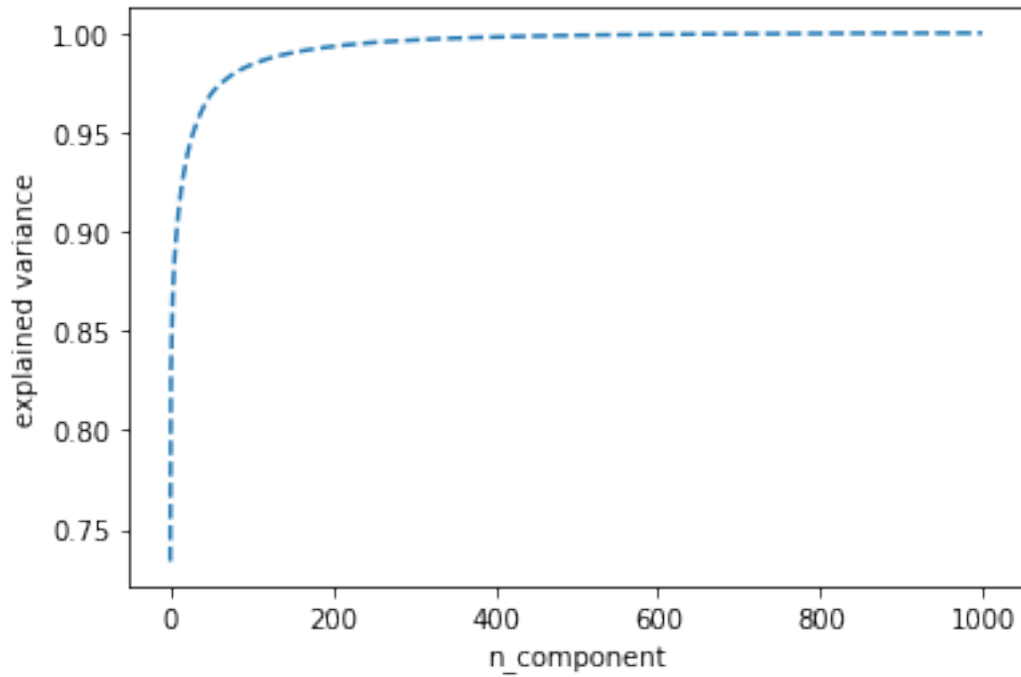
tsvd = TruncatedSVD(n_components = 1000)
ts_data = tsvd.fit_transform(preprocess_review_df)

var_explained = tsvd.explained_variance_ / np.sum(tsvd.explained_variance_)

cum_var_explained = np.cumsum(var_explained)

plt.plot(cum_var_explained, "--")
plt.xlabel('n_component')
plt.ylabel('explained variance')
plt.show()

```



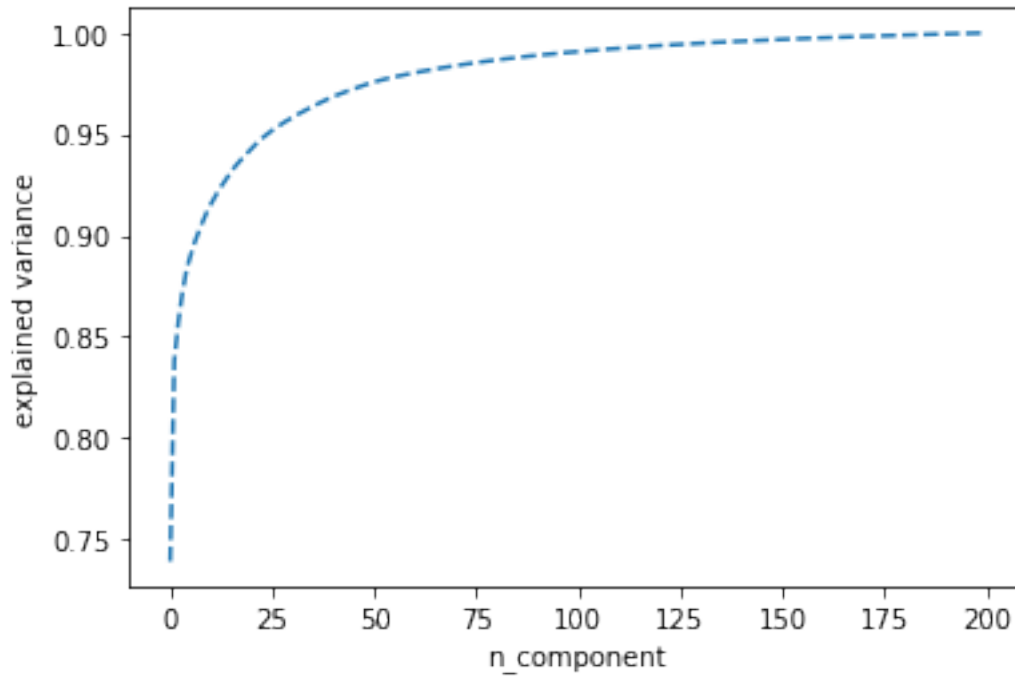
```
In [41]: # TruncatedSVD
```

```
tsvd = TruncatedSVD(n_components = 200)
ts_data = tsvd.fit_transform(preprocess_review_df)

var_explained = tsvd.explained_variance_ / np.sum(tsvd.explained_variance_)

cum_var_explained = np.cumsum(var_explained)

plt.plot(cum_var_explained, "--")
plt.xlabel('n_component')
plt.ylabel('explained variance')
plt.show()
```



From above graph, it can observe that only 90 components can explain almost 99% of variance.

```
In [0]: # TruncatedSVD
```

```
tsvd = TruncatedSVD(n_components = 90)
ts_data = tsvd.fit_transform(preprocess_review_df)

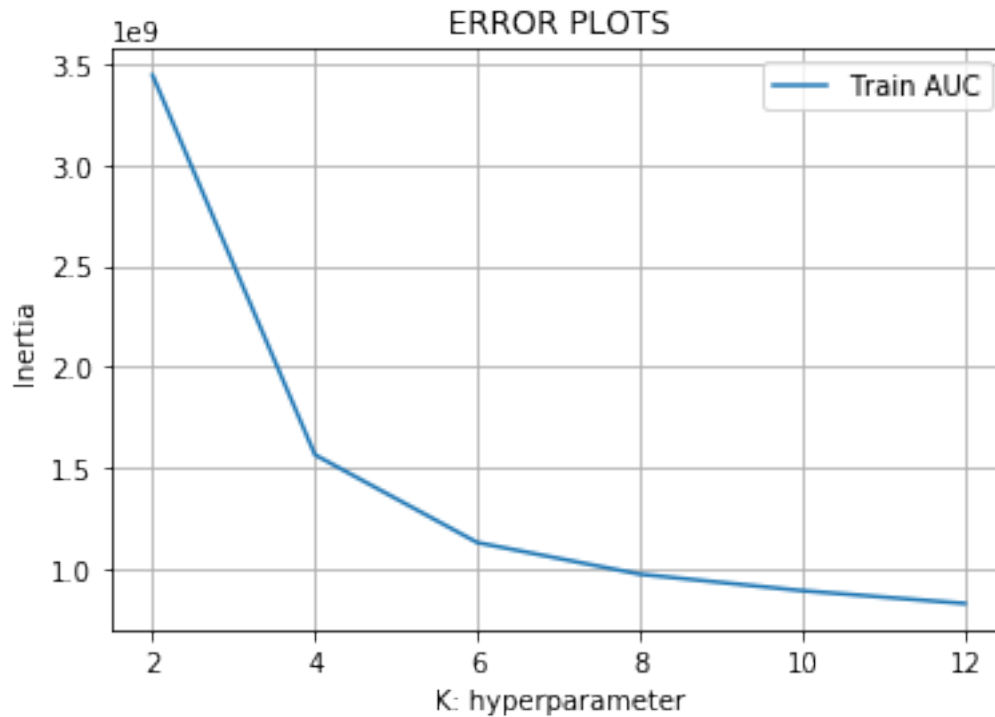
var_explained = tsvd.explained_variance_ / np.sum(tsvd.explained_variance_)

cum_var_explained = np.cumsum(var_explained)
```

6.1.4 [5.4] Applying k-means clustering

```
In [0]: bow_train = finding_best_k(ts_data)
```

```
In [44]: plotErrorplot(bow_train)
```



```
In [45]: kmeans = KMeans(n_clusters=6, n_jobs=-1).fit(ts_data)
labels = kmeans.labels_
```

```
no_of_clusters = set(labels.flatten())
no_of_clusters
```

```
Out[45]: {0, 1, 2, 3, 4, 5}
```

```
In [0]: # create duplicate copy of original dataframe as final2
preprocess_review_df2 = preprocess_review_df.copy()
```

```
# adding this labels result to duplicate copy dataframe
preprocess_review_df2['label'] = labels
```

```
preprocess_review_df2['Features'] = top_df['Features']
```

```
# remove nan
```

```
preprocess_review_df2 = preprocess_review_df2.replace(np.nan, '', regex=True)
```

```
# fetch reviews, those label==0, also convert to string
cluster_0 = returnWordCloudString(preprocess_review_df2,0)
```

```
# fetch reviews, those label==1, also convert to string
```



```

cluster_1 = returnWordCloudString(preprocess_review_df2,1)

# fetch reviews, those label==2, also convert to string
cluster_2 = returnWordCloudString(preprocess_review_df2,2)

# fetch reviews, those label==3, also convert to string
cluster_3 = returnWordCloudString(preprocess_review_df2,3)

# fetch reviews, those label==4, also convert to string
cluster_4 = returnWordCloudString(preprocess_review_df2,4)

# fetch reviews, those label==5, also convert to string
cluster_5 = returnWordCloudString(preprocess_review_df2,5)

cluster_list = [cluster_0,cluster_1,cluster_2,cluster_3,cluster_4,cluster_5]

```

6.1.5 [5.5] Wordclouds of clusters obtained in the above section

```

In [47]: for i in cluster_list:
          plotWordCloud(i)

```


A word cloud on a black background. The words are arranged in a roughly rectangular shape. The words and their approximate colors and sizes are: 'great' (blue, large), 'tea' (purple, medium), 'coffee' (green, medium), 'one' (teal, large), 'flavor' (teal, medium), 'product' (yellow-green, medium), 'Features' (teal, large), 'good' (purple, medium), 'really' (teal, medium), and 'taste' (teal, large).

great tea
coffee one
flavor product
Features
good
really taste

Features

Features

6.1.6 [5.6] Function that returns most similar words for a given word.

```
In [0]: # https://stackoverflow.com/questions/18424228/cosine-similarity-between-2-number-list.  
        # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.pairwise.cosine\_similarity.html  
  
def findSimilaryWords(word):  
  
    # find the index of word  
    ind = top2000.index(word)  
  
    # cosine similarity  
    cos_similarity = cosine_similarity(ts_data)  
    sim_vect_ = cos_similarity[ind]  
    index = sim_vect_.argsort()[::-1][1:10]
```

```
for j in range(len(index)):
    print((j+1),top2000[index[j]] , "===",word,"\n")
```

```
In [49]: findSimilaryWords('calories')
```

```
1 fiber === calories
2 low === calories
3 sodium === calories
4 content === calories
5 protein === calories
6 carbs === calories
7 iron === calories
8 total === calories
9 reduced === calories
```

```
In [50]: findSimilaryWords('cheaper')
```

```
1 prices === cheaper
2 target === cheaper
3 walmart === cheaper
4 bulk === cheaper
5 sale === cheaper
6 costs === cheaper
7 selling === cheaper
8 sells === cheaper
9 cost === cheaper
```

```
In [51]: findSimilaryWords('good')
```



```
1 amazing === good
2 fine === good
3 however === good
4 awesome === good
5 course === good
6 ok === good
7 type === good
8 appreciate === good
9 totally === good
```

7 [6] Conclusions

7.0.1 Procedure

- We have consider '100k' datapoints for this experiement.
- Firstly took TFIDF weighted vector and find "top 2000" feature using idf_ (**The inverse document frequency vector**)
- Then build Co-Occurance matrix, which have 2000*2000 dimension.
- Then find optimal n_component value using 'elbow' method. we found **n_component = 90**
- Applied this Top feature to KMean algorithm and build cluster. While applying Kmean, firstly hyperparam tune and find number of cluster require again using 'elbow' method, we found **no_clusters = 6**
- plot word cloud on basis of clusters build by Kmean algorithm
- Using Cosine Similarity create function which will return most similar word from given corpus