Final Report

March 12, 2021

1 MGTA415 Group Project

1.1 Reviews Analysis And Recommendation System For E-commerce Retails

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import re
import os
import time

from unidecode import unidecode
import contractions
import itertools
from collections import Counter

from nltk import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
import nltk
from gensim.models import word2vec
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
from sklearn.feature_extraction.text import (
    CountVectorizer,
    TfidfTransformer,
    TfidfVectorizer,
)
from sklearn import metrics
from sklearn.metrics import f1_score
import xgboost
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC
from keras.utils.np_utils import to_categorical
from keras.callbacks import EarlyStopping
from keras.layers import Dense
from keras.models import Sequential
from sklearn.preprocessing import LabelEncoder
```

```python
from math import sqrt
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from math import sqrt
import warnings
from wordcloud import WordCloud
warnings.filterwarnings("ignore")
```

1.2 Load data

[2]:
```python
reviews=pd.read_csv("data/Womens Clothing E-Commerce Reviews.csv")
reviews["Rating"]=reviews["Rating"].astype("category")
reviews=reviews[reviews['Review Text'].notnull()]
reviews.head(2)
```

[2]:
```
   Unnamed: 0  Clothing ID  Age Title  \
0           0          767   33   NaN
1           1         1080   34   NaN

                                         Review Text Rating  Recommended IND  \
0  Absolutely wonderful - silky and sexy and comf…      4                1
1  Love this dress!  it's sooo pretty.  i happene…      5                1

   Positive Feedback Count Division Name Department Name Class Name
0                        0     Initmates        Intimate  Intimates
1                        4       General         Dresses    Dresses
```

[3]:
```python
reviews.Rating.value_counts()
```

[3]:
```
5    12540
4     4908
3     2823
2     1549
1      821
Name: Rating, dtype: int64
```

1.3 Data preprocessing

1.3.1 2.1 inital method

[4]:
```python
def text_clean(df,colname):

    nltk.download('stopwords')
    stop_words = stopwords.words('english')
#     stop_words.extend(add_stop_words)
    stop_words = set(stop_words)
```

```
    ps = PorterStemmer()

    preprocessed_t_sentences = []

    for i, row in df.iterrows():
        # Expand contractions
        sent= contractions.fix(str(row[colname]))
        # Remove HTML tags
        sent=re.sub("(<.*?>)","",sent)
        # Remove numbers and puncs
        sent=re.sub("(\r\n)"," ",sent)
        sent=re.sub("[^a-zA-Z\s]"," ",sent.lower())
        sent=re.sub("\s+"," ",sent)
        sent=re.sub(r'([\w])\1\1+', r'\1', sent)
#         sent_t=re.sub("(\\W|\\d)"," ",sent_t)
        words_list = sent.strip().split()
        #lowercasing, standardized english, remove stop words
        filtered_words = [ps.stem(unidecode(word)) for word in words_list if␣
↪word not in stop_words and len(word) != 1 and ps.stem(word) not in␣
↪stop_words]
#         preprocessed_t_sentences.append(" ".join(filtered_t_words))
#         preprocessed_t_sentences.append(filtered_t_words)
        preprocessed_t_sentences.append(" ".join(filtered_words))
    df[colname+"_processed"]=preprocessed_t_sentences
    return df
```

[5]:
```
df=text_clean(reviews,"Review Text")
df.head()
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     D:\WispZ\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[5]:
```
   Unnamed: 0  Clothing ID  Age                    Title  \
0           0          767   33                      NaN
1           1         1080   34                      NaN
2           2         1077   60  Some major design flaws
3           3         1049   50         My favorite buy!
4           4          847   47         Flattering shirt

                                         Review Text Rating  Recommended IND  \
0  Absolutely wonderful - silky and sexy and comf…      4                1
1  Love this dress!  it's sooo pretty.  i happene…      5                1
2  I had such high hopes for this dress and reall…      3                0
3  I love, love, love this jumpsuit. it's fun, fl…      5                1
4  This shirt is very flattering to all due to th…      5                1
```

```
   Positive Feedback Count   Division Name Department Name Class Name  \
0                        0       Initmates        Intimate  Intimates
1                        4         General         Dresses    Dresses
2                        0         General         Dresses    Dresses
3                        0  General Petite         Bottoms      Pants
4                        6         General            Tops    Blouses

                            Review Text_processed
0                  absolut wonder silki sexi comfort
1  love dress pretti happen find store glad bc ne…
2  high hope dress realli want work initi order p…
3  love love love jumpsuit fun flirti fabul everi…
4  shirt flatter due adjust front tie perfect len…
```

1.3.2 2.2 filter low frequency words

[6]:
```
tagged_data=[d for d in df["Review Text_processed"].apply(lambda x:x.split("␣
↪"))]
word_counts=Counter(itertools.chain(*tagged_data))
freq_dict={pair[0]:pair[1] for pair in word_counts.most_common()}
df_freq=pd.DataFrame(freq_dict.items()).rename(columns={0:"word",1:"freq"})
low_frequent_words=df_freq[df_freq.freq<5].word.tolist()
len(low_frequent_words)
```

[6]: 5768

[7]:
```
def text_clean_freq(df,colname,low_freq_list):

    nltk.download('stopwords')
    stop_words = stopwords.words('english')
    stop_words.extend(low_freq_list)
    stop_words = set(stop_words)
    ps = PorterStemmer()

    preprocessed_t_sentences = []

    for i, row in df.iterrows():
        # Expand contractions
        sent= contractions.fix(str(row[colname]))
        # Remove HTML tags
        sent=re.sub("(<.*?>)","",sent)
        # Remove numbers and puncs
        sent=re.sub("(\r\n)"," ",sent)
        sent=re.sub("[^a-zA-Z\s]"," ",sent.lower())
        sent=re.sub("\s+"," ",sent)
        sent=re.sub(r'([\w])\1\1+', r'\1', sent)
#         sent_t=re.sub("(\\W|\\d)"," ",sent_t)
```

```
        words_list = sent.strip().split()
        #lowercasing, standardized english, remove stop words
        filtered_words = [ps.stem(unidecode(word)) for word in words_list if␣
 ↪word not in stop_words and len(word) != 1 and ps.stem(word) not in␣
 ↪stop_words]
#         preprocessed_t_sentences.append(" ".join(filtered_t_words))
#         preprocessed_t_sentences.append(filtered_t_words)
        preprocessed_t_sentences.append(" ".join(filtered_words))
    df[colname+"_processed"]=preprocessed_t_sentences
    return df
```

[8]:
```
df_lf=text_clean_freq(reviews,"Review Text",low_frequent_words)
df_lf.head()
```

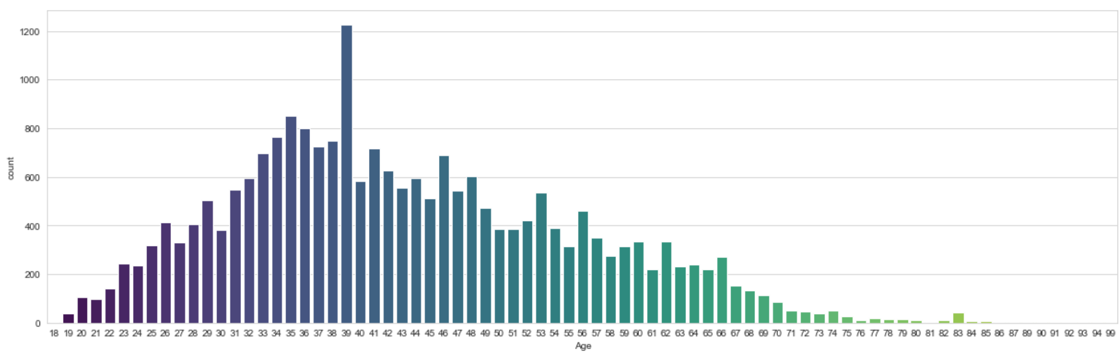
```
[nltk_data] Downloading package stopwords to
[nltk_data]     D:\WispZ\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[8]:
```
   Unnamed: 0  Clothing ID  Age                    Title  \
0           0          767   33                      NaN
1           1         1080   34                      NaN
2           2         1077   60  Some major design flaws
3           3         1049   50         My favorite buy!
4           4          847   47         Flattering shirt

                                         Review Text  Rating  Recommended IND  \
0  Absolutely wonderful - silky and sexy and comf…       4                1
1  Love this dress!  it's sooo pretty.  i happene…       5                1
2  I had such high hopes for this dress and reall…       3                0
3  I love, love, love this jumpsuit. it's fun, fl…       5                1
4  This shirt is very flattering to all due to th…       5                1

   Positive Feedback Count   Division Name Department Name Class Name  \
0                        0       Initmates        Intimate  Intimates
1                        4         General         Dresses    Dresses
2                        0         General         Dresses    Dresses
3                        0  General Petite         Bottoms      Pants
4                        6         General            Tops    Blouses

                              Review Text_processed
0                        absolut wonder silki comfort
1  love dress pretti happen find store glad bc ne…
2  high hope dress realli want work initi order p…
3  love love love jumpsuit fun flirti fabul everi…
4  shirt flatter due adjust front tie perfect len…
```

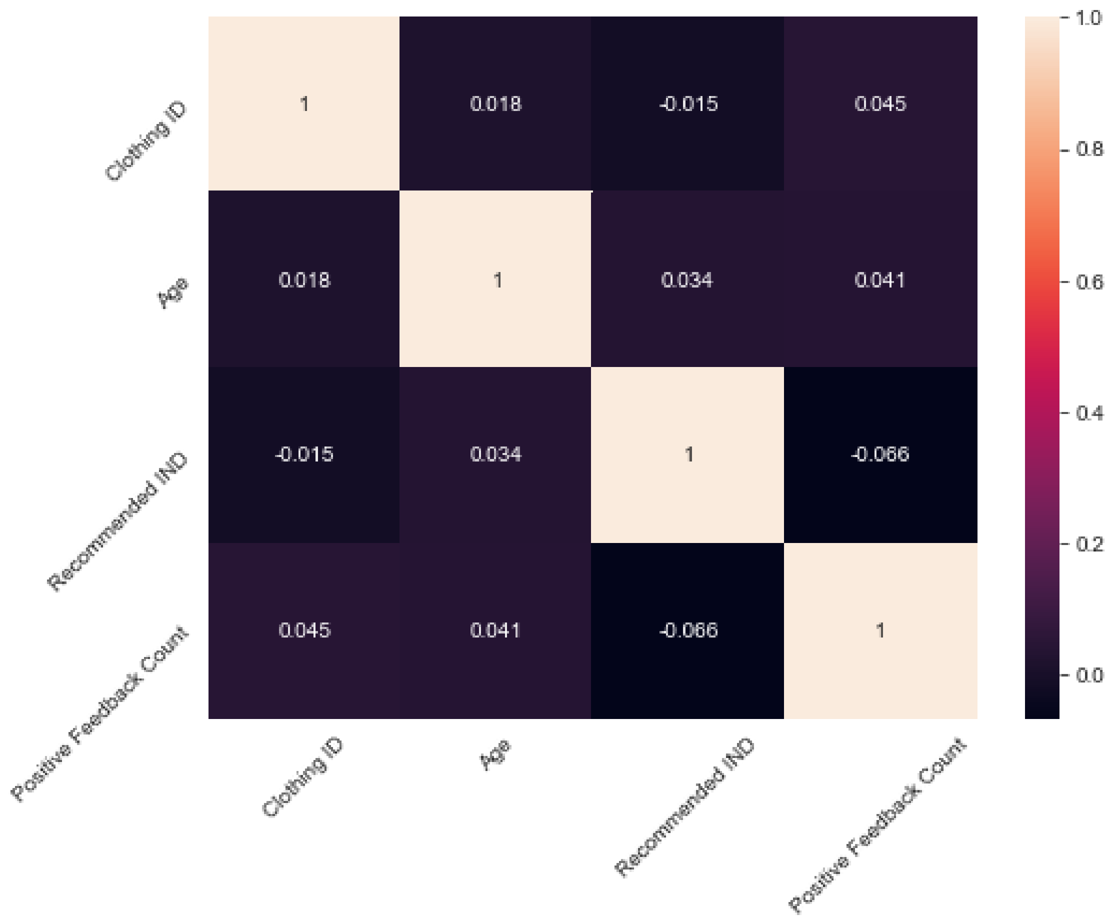
1.4 Exploratory Data Analysis

[9]:
```
sns.set_style("whitegrid")
test = df_lf
test = test[~test['Review Text'].isnull()]
```

[10]:
```
plt.figure(figsize = (20,6))
ax = sns.countplot(x = 'Age', data = reviews,palette = 'viridis')

plt.show()
figure = ax.get_figure()
figure.savefig('age.png', dpi=500)
```



[11]:
```
plt.figure(figsize = (8,6))
y = test['Review Text_processed']
X = test.drop(columns = 'Review Text_processed')
X = X.drop(columns ='Unnamed: 0')
sns.heatmap(X.corr(), annot = True )
plt.xticks(rotation = 45)
plt.yticks(rotation = 45)
plt.savefig('heatmap.png', dpi=500)
```



1.4.1 WordCloud

[13]:
```
nltk.download('brown')
```

```
[nltk_data] Downloading package brown to /home/jovyan/nltk_data…
[nltk_data]   Package brown is already up-to-date!
```

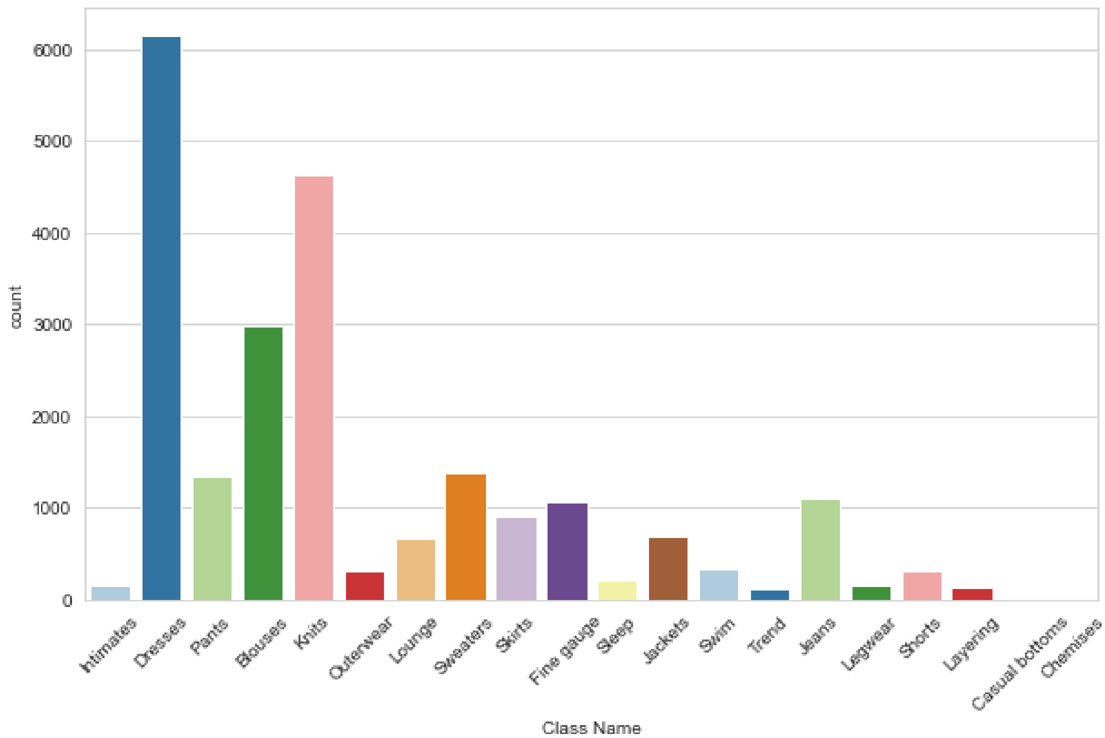
[13]: True

[22]:
```
from textblob import *
nltk.download('averaged_perceptron_tagger')
comment_words = ''
stop_words = set(stopwords.words("english"))
for val in reviews['Review Text']:
    # typecaste each val to string
    val = str(val)

    # split the value
```

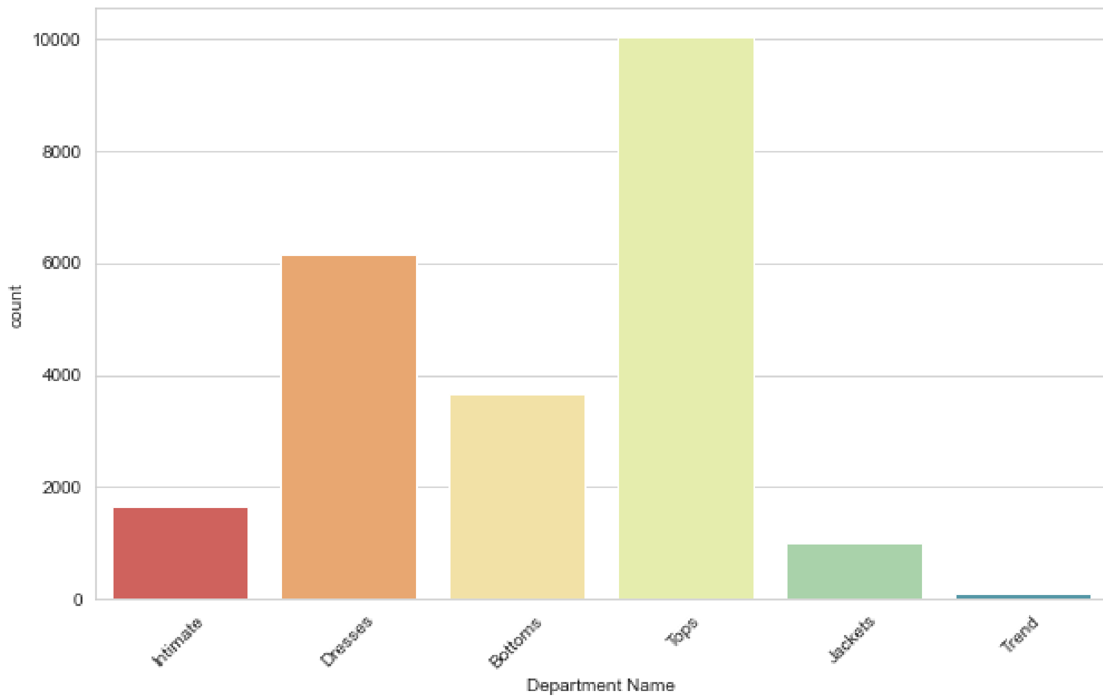
```
    tokens = val.split()

    # Converts each token into lowercase
    for i in range(len(tokens)):
        tokens[i] = tokens[i].lower()

    comment_words += " ".join(tokens)+" "


def extract_NN(sent):
    grammar = r"""
    NBAR:
        # Nouns and Adjectives, terminated with Nouns
        {<NN.*>*<NN.*>}

    NP:
        {<NBAR>}
        # Above, connected with in/of/etc...
        {<NBAR><IN><NBAR>}
    """
    chunker = nltk.RegexpParser(grammar)
    ne = ''
    chunk = chunker.parse(nltk.pos_tag(nltk.word_tokenize(sent)))
    for tree in chunk.subtrees(filter=lambda t: t.label() == 'NP'):
        ne += ' '.join([child[0] for child in tree.leaves()]) + " "
    return ne

words = extract_NN(comment_words)
wordcloud = WordCloud(width = 800, height = 800,
                background_color ='white',
                stopwords = stop_words,
                min_font_size = 16).generate(words)

# plot the WordCloud image
plt.figure(figsize = (8, 8), facecolor = None)
ax = plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 0)

plt.show()
figure = ax.get_figure()
figure.savefig('wordcloud.png', dpi=500)
```

```
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /home/jovyan/nltk_data…
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
```


```
[12]: plt.figure(figsize = (10,6))
      ax = sns.countplot(x = 'Class Name', data = test,palette = 'Paired')
      plt.xticks(rotation = 45)
      plt.show()
      figure = ax.get_figure()
      figure.savefig('category.png', dpi=500)
```

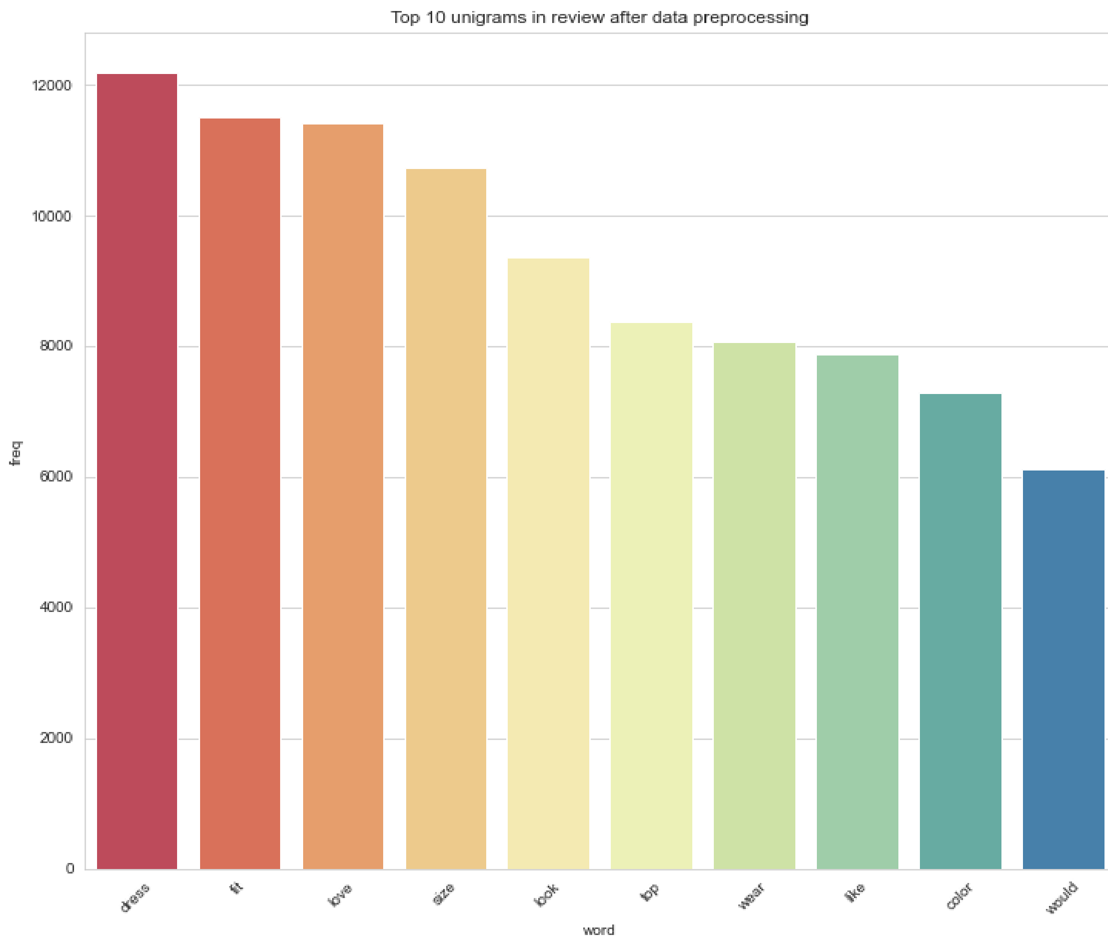


[13]:
```
plt.figure(figsize = (10,6))
ax = sns.countplot(x = 'Department Name', data = test,palette = 'Spectral')
plt.xticks(rotation = 45)
plt.show()
figure = ax.get_figure()
figure.savefig('Department.png', dpi=500)
```



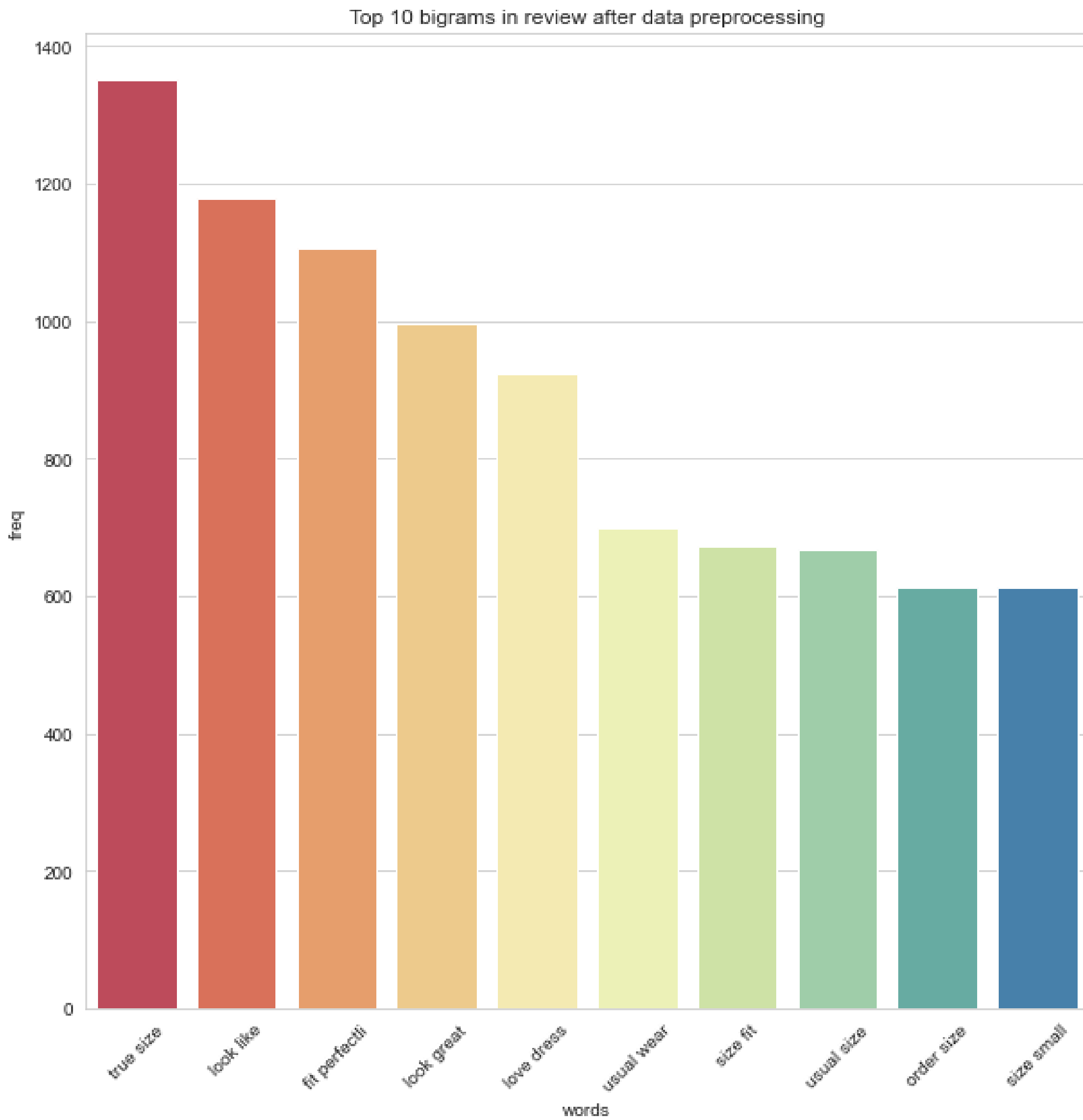
1.4.2 Unigram and Bigram

[14]:
```
plt.figure(figsize = (12,10))
sns.barplot(data = df_freq[:10],y = 'freq',x = 'word',palette = 'Spectral').
 ↪set_title('Top 10 unigrams in review after data preprocessing')
plt.xticks(rotation = 45)
plt.savefig('Frequent Words.png', dpi=400)
```



[15]:
```
from sklearn.feature_extraction.text import CountVectorizer
def top_n_ngram(corpus,n = None,ngram = 1):
    vec = CountVectorizer(stop_words = 'english',ngram_range=(ngram,ngram)).
 ↪fit(corpus)
    bag_of_words = vec.transform(corpus) #Have the count of  all the words for␣
 ↪each review
    sum_words = bag_of_words.sum(axis =0) #Calculates the count of all the word␣
 ↪in the whole review
    words_freq = [(word,sum_words[0,idx]) for word,idx in vec.vocabulary_.
 ↪items()]
    words_freq = sorted(words_freq,key = lambda x:x[1],reverse = True)
    return words_freq[:n]

common_words = top_n_ngram(y, 10,2)
data = pd.DataFrame(common_words, columns = ['ReviewText' , 'count'])
plt.figure(figsize =(10,10))
bigram = data.groupby('ReviewText').sum()['count'].sort_values(ascending=False)
```

```
t = pd.DataFrame(data = {'words':bigram.index,'freq':bigram[:]})
sns.barplot(data = t,x ='words',y = 'freq',palette = 'Spectral').set_title('Top␣
↪10 bigrams in review after data preprocessing')
plt.xticks(rotation = 45)
plt.savefig('Frequent Words bigram.jpg', dpi=400)
```



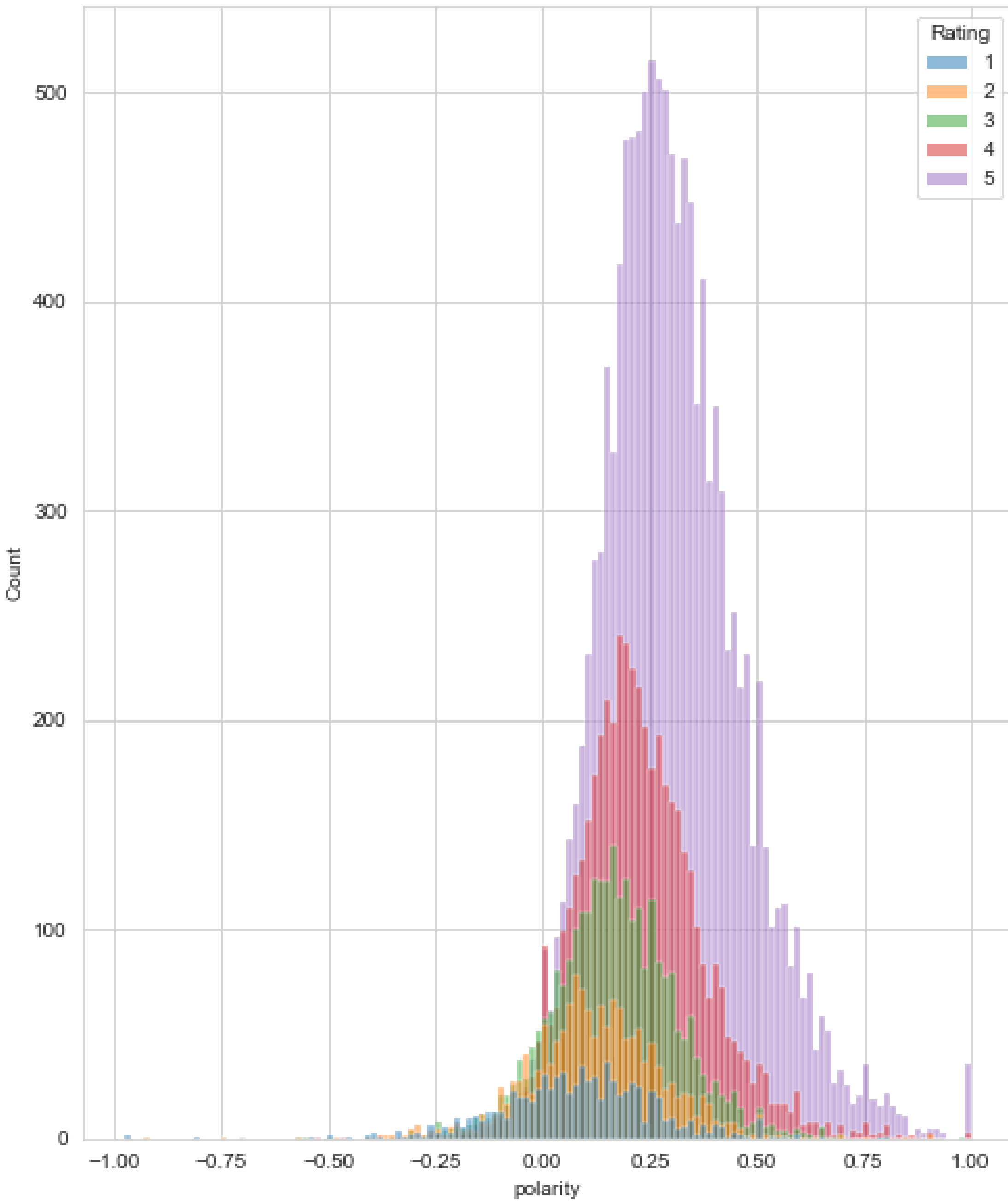
1.4.3 Polarity plot

[18]:
```
from textblob import *
test['polarity'] = test['Review Text'].map(lambda text: TextBlob(text).
↪sentiment.polarity)
```

```python
test['polarity']
```

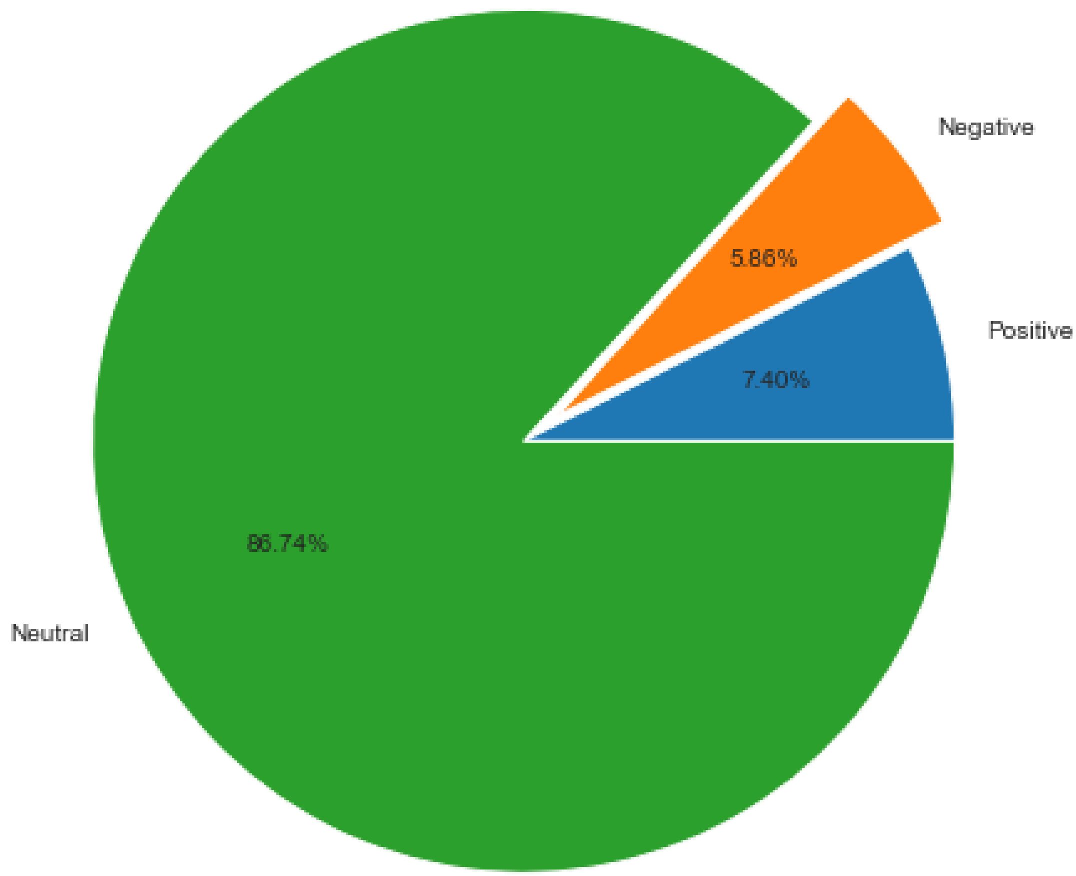
[18]:
```
0        0.633333
1        0.339583
2        0.073675
3        0.550000
4        0.512891
           …
23481    0.552667
23482    0.091667
23483    0.414286
23484    0.322222
23485    0.413889
Name: polarity, Length: 22641, dtype: float64
```

[19]:
```python
plt.figure(figsize = (8,10))
ax = sns.histplot(test, x = 'polarity',hue="Rating")
figure = ax.get_figure()
figure.savefig('polarity.png', dpi=500)
```



[20]:
```
df = test
negative = (len(df.loc[df.polarity < 0, ['Review Text']].values)/len(df))*100
positive = (len(df.loc[df.polarity > 0.5, ['Review Text']].values)/len(df))*100
neutral = len(df.loc[df.polarity >0 ,['Review Text']].values) - len(df.loc[df.
↪polarity >0.5 ,['Review Text']].values)
neutral = neutral/len(df)*100
plt.figure(figsize =(8, 8))
```

```
plt.pie([positive,negative,neutral], labels =
    ['Positive','Negative','Neutral'],shadow = False, autopct='%2.2f%%',explode
    = (0, 0.1, 0))
plt.savefig('Percentage.jpg', dpi=500)
```



1.5 Text representation

1.5.1 3.1 One-hot encoding

[21]:
```
# train_vec=np.concatenate([np.array(train_vec),df_train["Recommended IND"].
    to_numpy().reshape(len(train_vec),1)],axis=1)
def one_hot_encoding(df):
```

```
    X_train,X_test,y_train,y_test=train_test_split(df[["Review␣
↪Text_processed"]],df["Rating"],test_size=0.2,random_state=123)
    cv = CountVectorizer(binary=True,min_df=1,max_df=17448)
    cv.fit(X_train["Review Text_processed"])
    X_train_encoding=cv.transform(X_train["Review Text_processed"])
    X_train_encoding=pd.DataFrame(X_train_encoding.A, columns=cv.
↪get_feature_names(),index=X_train.index)
    X_test_encoding=cv.transform(X_test["Review Text_processed"])
    X_test_encoding=pd.DataFrame(X_test_encoding.A, columns=cv.
↪get_feature_names(),index=X_test.index)

    return X_train_encoding,X_test_encoding,y_train,y_test
```

[22]:
```
X_train_oh,X_test_oh,y_train_oh,y_test_oh=one_hot_encoding(df_lf)
X_train_oh.head()
```

[22]:
```
       aa  ab  abdomen  abil  abl  absolut  abstract  abt  abund  ac  …  \
10365   0   0        0     0    0        0         0    0      0   0  …
2579    0   0        0     0    0        0         0    0      0   0  …
17002   0   0        0     0    0        0         0    0      0   0  …
4121    0   0        0     0    0        0         0    0      0   0  …
5440    0   0        0     0    0        0         0    0      0   0  …

       yoke  young  younger  yr  yummi  zero  zip  zipper  zone  zoom
10365     0      0        0   0      0     0    0       0     0     0
2579      0      0        0   0      0     0    0       0     0     0
17002     0      0        0   0      0     0    0       0     0     0
4121      0      0        0   0      0     0    0       0     0     0
5440      0      0        0   0      0     0    0       0     0     0

[5 rows x 3360 columns]
```

1.5.2 3.2 TF-IDF

[23]:
```
def tf_vectorization(df):
    X_train,X_test,y_train,y_test=train_test_split(df[["Review␣
↪Text_processed"]],df["Rating"],test_size=0.2,random_state=123)
    tfidf = TfidfVectorizer(
        strip_accents=None,
        lowercase=True,
        preprocessor=None,  # applied preprocessor in Data Cleaning
        tokenizer=None,
        use_idf=True,
        norm="l2",
        smooth_idf=True,
        min_df=2,
    ).fit(X_train["Review Text_processed"])
```

```
    X_train_encoding=tfidf.transform(X_train["Review Text_processed"])
    X_train_encoding=pd.DataFrame(X_train_encoding.A, columns=tfidf.
 ↪get_feature_names(),index=X_train.index)
    X_test_encoding=tfidf.transform(X_test["Review Text_processed"])
    X_test_encoding=pd.DataFrame(X_test_encoding.A, columns=tfidf.
 ↪get_feature_names(),index=X_test.index)

    return X_train_encoding,X_test_encoding,y_train,y_test
```

[24]:
```
X_train_tf,X_test_tf,y_train_tf,y_test_tf=tf_vectorization(df_lf)
X_test_tf.shape
```

[24]: (4529, 3355)

1.5.3 3.3 Word embedding

[25]:
```
def word2vec_prep(tagged_data):
#     tagged_data=[word_tokenize(_d) for i, _d in␣
 ↪enumerate(df_train["Text_processed"])]
    word_counts=Counter(itertools.chain(*tagged_data)) #dict
#     vocabulary_inv=[x[0] for x in word_counts.most_common()]
#     vocabulary = {x: i for i, x in enumerate(vocabulary_inv)}
    return word_counts

def embedding_weights(vocabulary_inv,inp_data):
    model_name = "embedding"
    model_name = os.path.join(model_name)
    num_workers = 8  # Number of threads to run in parallel
    downsampling = 1e-3  # Downsample setting for frequent words
    sentences = [[vocabulary_inv[w] for w in s] for s in inp_data]
    size_features=200
    min_word_count=2
    context=5
    downsampling = 1e-3
    embedding_model = word2vec.Word2Vec(sentences, workers=num_workers,
                                        sg=0,
                                        size=size_features,
                                        min_count=min_word_count,
                                        window=context,
                                        sample=downsampling)
    embedding_model.init_sims(replace=True) #clean from RAM
    embedding_weights = np.zeros((len(vocabulary_inv), size_features))
    for i in range(len(vocabulary_inv)):
        word = vocabulary_inv[i]
        if word in embedding_model:
            embedding_weights[i] = embedding_model[word]
```

```
        else:
            embedding_weights[i] = np.random.uniform(-0.1, 0.1,size_features)

    return embedding_weights

def train_test_word2vec(tagged_train_data,tagged_test_data,weights,vocabulary):
    train_vec = []
    for doc in tagged_train_data:
        vec = 0
        for w in doc:
            vec += weights[vocabulary[w]]
        vec = vec / len(doc)
        train_vec.append(vec)

    test_vec = []
    for doc in tagged_test_data:
        vec = 0
        length = 0
        for w in doc:
            try:
                vec += weights[vocabulary[w]]
                length += 1
            except:
                continue
        vec = vec / length
        test_vec.append(vec)

    return np.array(train_vec), np.array(test_vec)


def word_embedding(df):

    df_train,df_test=train_test_split(df,test_size=0.2,shuffle=True)
    tagged_data=[word_tokenize(_d) for i, _d in enumerate(df_train["Review␣
 ↪Text_processed"])]
    word_counts=Counter(itertools.chain(*tagged_data))
    vocabulary_inv=[x[0] for x in word_counts.most_common()]
    vocabulary = {x: i for i, x in enumerate(vocabulary_inv)}
    inp_data = [[vocabulary[word] for word in text] for text in tagged_data]

    print("------generating weights------")
    weights=embedding_weights(vocabulary_inv,inp_data)

    tagged_train_data = [word_tokenize(_d) for i, _d in␣
 ↪enumerate(df_train["Review Text_processed"])]
    tagged_test_data = [word_tokenize(_d) for i, _d in␣
 ↪enumerate(df_test["Review Text_processed"])]
```

```
    print("------generating train/test dataset------")
    ␣
↪train_vec,test_vec=train_test_word2vec(tagged_train_data,tagged_test_data,weights,vocabular
#     train_vec=np.concatenate([train_vec,df_train["Recommended IND"].
↪to_numpy().reshape(len(train_vec),1)],axis=1)
#     test_vec=np.concatenate([test_vec,df_test["Recommended IND"].to_numpy().
↪reshape(len(test_vec),1)],axis=1)

    return train_vec,test_vec,df_train.Rating,df_test.Rating
```

[26]:
```
X_train_we,X_test_we,y_train_we,y_test_we=word_embedding(df_lf)
```

```
------generating weights------
------generating train/test dataset------
```

1.6 Sentiment Analysis Model

1.6.1 BernoulliNB with Bag of words

[27]:
```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import train_test_split
count = CountVectorizer()
X_count = count.fit_transform(reviews["Review Text_processed"]).toarray()
y=reviews['Recommended IND']
```

[28]:
```
X_train, X_test, y_train, y_test = train_test_split(X_count, y, test_size = 0.
↪20, random_state = 0)
```

[29]:
```
from sklearn.naive_bayes import BernoulliNB
classifier = BernoulliNB()
classifier.fit(X_train, y_train)
```

[29]:
```
BernoulliNB(alpha=1.0, binarize=0.0, class_prior=None, fit_prior=True)
```

[30]:
```
y_pred = classifier.predict(X_test)
y_train_pred = classifier.predict(X_train)
from sklearn.metrics import accuracy_score
from sklearn import metrics
acc1 = accuracy_score(y_test, y_pred)
score = accuracy_score(y_train,y_train_pred)
score
print("Accuracy of the classifier using Bag of words: ",acc1)
print("Confusion matrix is :\n",metrics.confusion_matrix(y_test,y_pred))
print("Classification report: \n" ,metrics.classification_report(y_test,y_pred))
```

```
Accuracy of the classifier using Bag of words:  0.8743652020313535
Confusion matrix is :
```

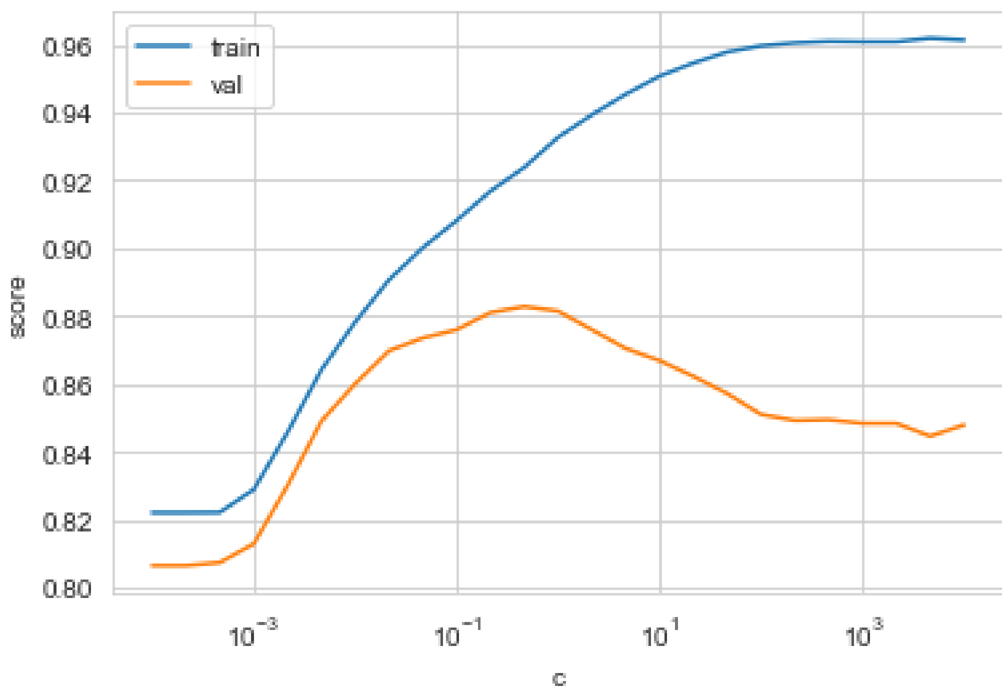
```
[[ 625  252]
 [ 317 3335]]
Classification report:
              precision    recall  f1-score   support

          0       0.66      0.71      0.69       877
          1       0.93      0.91      0.92      3652

avg / total       0.88      0.87      0.88      4529
```

[31]:
```
score
```

[31]: 0.8894655477031802

1.6.2 Logistic Regression with Bag of Words

[32]:
```
res_train = []
res_test = []
c_range = np.logspace(-4,4,25)
import matplotlib.pyplot as plt
import numpy as np
from sklearn.linear_model import LogisticRegression
for cc in c_range:
    clf = LogisticRegression(random_state = 42, C=cc,␣
 ↪penalty='l2',solver='liblinear').fit(X_train, y_train)
    res_train.append(clf.score(X_train,y_train))
    res_test.append(clf.score(X_test,y_test))


plt.semilogx(c_range,res_train,label='train')
plt.semilogx(c_range,res_test,label='val')
plt.xlabel('c')
plt.ylabel('score')
plt.legend()
plt.show()
print(f'Best of c for the model is about ',[x for _,x in␣
 ↪sorted(zip(res_test,c_range))][-1])
```




```
Best of c for the model is about  0.46415888336127775
```

[33]:
```
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression(random_state = 42, C=0.46,␣
 ↪penalty='l2',solver='liblinear').fit(X_train, y_train)
print(clf.score(X_train,y_train))
print(clf.score(X_test,y_test))
y_pred = clf.predict(X_test)
acc2 = accuracy_score(y_test, y_pred)
```

```
0.9237522084805654
0.8827555751821594
```

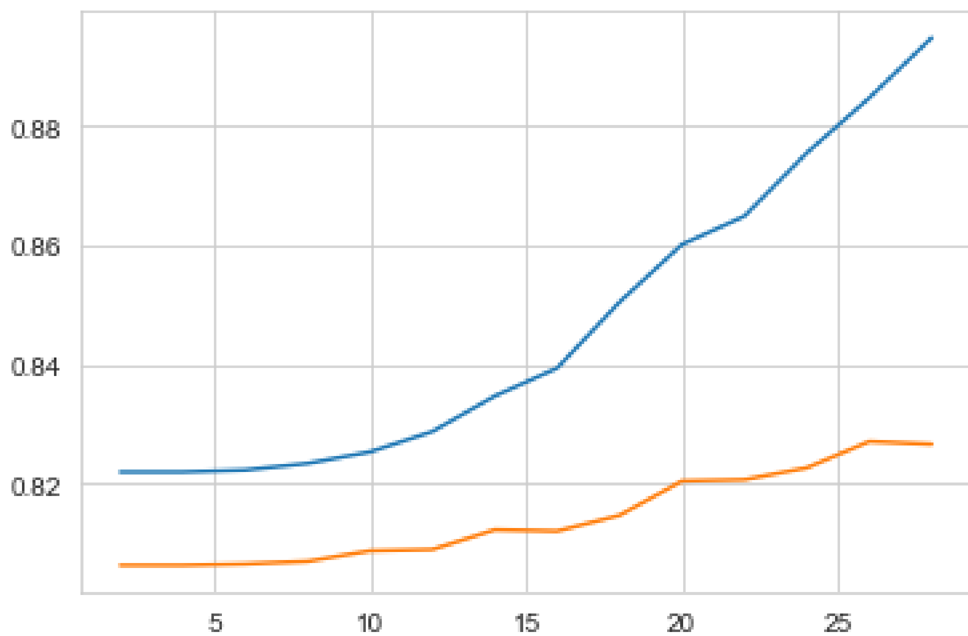
[34]:
```
print("Accuracy of the LogisticRegression using Bag of words: ",acc2)
print("Confusion matrix is :\n",metrics.confusion_matrix(y_test,y_pred))
print("Classification report: \n" ,metrics.classification_report(y_test,y_pred))
```

```
Accuracy of the LogisticRegression using Bag of words:  0.8827555751821594
Confusion matrix is :
 [[ 502  375]
 [ 156 3496]]
Classification report:
               precision    recall  f1-score   support

           0       0.76      0.57      0.65       877
```

```
           1       0.90      0.96      0.93      3652

avg / total       0.88      0.88      0.88      4529
```

1.6.3 Random Forest with Bag of Words

[35]:
```
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
depth_list = np.arange(2,30,2)
acc_train, acc_test = [], []
for dp in depth_list:

    clf = RandomForestClassifier(max_depth=dp,random_state=0).
 ↪fit(X_train,y_train)
    acc_train.append(np.sum(clf.predict(X_train)==y_train)/len(X_train))
    acc_test.append(np.sum(clf.predict(X_test)==y_test)/len(X_test))

plt.plot(depth_list,acc_train)
plt.plot(depth_list,acc_test)
plt.show()
```



[36]:
```
from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier(max_depth=26,random_state=0).fit(X_train,y_train)
print(np.sum(clf.predict(X_train)==y_train)/len(X_train))
print(np.sum(clf.predict(X_test)==y_test)/len(X_test))
```

```
y_pred = clf.predict(X_test)
acc3 = accuracy_score(y_test, y_pred)
```

```
0.8847725265017667
0.8271141532347096
```

[37]:
```
print("Accuracy of the Random Forest using Bag of words: ",acc3)
print("Confusion matrix is :\n",metrics.confusion_matrix(y_test,y_pred))
print("Classification report: \n" ,metrics.classification_report(y_test,y_pred))
```

```
Accuracy of the Random Forest using Bag of words:  0.8271141532347096
Confusion matrix is :
 [[ 115  762]
 [  21 3631]]
Classification report:
              precision    recall  f1-score   support

          0       0.85      0.13      0.23       877
          1       0.83      0.99      0.90      3652

avg / total       0.83      0.83      0.77      4529
```

1.6.4 Linear SVC with Bag of Words

[38]:
```
## Final method
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVC, SVC
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split
clf = make_pipeline(StandardScaler(),LinearSVC(random_state=0, tol=1e-4,C=0.
 ↪0001)).fit(X_train,y_train)

#clf = LogisticRegression(max_iter=100000000).fit(train_cat_vec,␣
 ↪df_train["label"])

print(np.sum(clf.predict(X_train)==y_train)/len(X_train))
print(np.sum(clf.predict(X_test)==y_test)/len(X_test))
```

```
0.9260159010600707
0.870611614042835
```

[39]:
```
clf = make_pipeline(StandardScaler(),LinearSVC(random_state=0, tol=1e-4,C=0.
 ↪00001)).fit(X_train,y_train)
```

```
#clf = LogisticRegression(max_iter=100000000).fit(train_cat_vec,␣
 ↪df_train["label"])

print(np.sum(clf.predict(X_train)==y_train)/len(X_train))
print(np.sum(clf.predict(X_test)==y_test)/len(X_test))
```

```
0.9022195229681979
0.8703908147493928
```

[40]:
```
y_pred = clf.predict(X_test)
acc4 = accuracy_score(y_test, y_pred)
print("Accuracy of the LinearSVC using Bag of words: ",acc4)
print("Confusion matrix is :\n",metrics.confusion_matrix(y_test,y_pred))
print("Classification report: \n" ,metrics.classification_report(y_test,y_pred))
```

```
Accuracy of the LinearSVC using Bag of words:  0.8703908147493928
Confusion matrix is :
 [[ 635  242]
 [ 345 3307]]
Classification report:
              precision    recall  f1-score   support

          0       0.65      0.72      0.68       877
          1       0.93      0.91      0.92      3652

avg / total       0.88      0.87      0.87      4529
```

1.6.5 Multinomial NB with TF-IDF

[41]:
```
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
tfidf = TfidfVectorizer(max_features = 5000,ngram_range=(1, 2))
X_tfidf = tfidf.fit_transform(reviews["Review Text_processed"]).toarray()
```

[42]:
```
from sklearn import feature_selection

y=reviews['Recommended IND']
X_names = tfidf.get_feature_names()
p_value_limit = 0.997 # 3 sigma cutoff
df_features = pd.DataFrame()

for cat in np.unique(y):
    chi2, p = feature_selection.chi2(X_tfidf, y==cat)
    df_features = df_features.append(pd.DataFrame(
                    {"feature":X_names, "score":1-p, "label":cat}))
    df_features = df_features.sort_values(["label","score"],
                     ascending=[True,False])
```

```
    df_features = df_features[df_features["score"]>p_value_limit]

X_names = df_features["feature"].unique().tolist()
print(len(X_names))
```

```
238
```

[43]:
```
X_train, X_test, y_train, y_test = train_test_split(X_tfidf, y, test_size = 0.
↪20, random_state = 0)
```

[44]:
```
X_train
```

[44]:
```
array([[0., 0., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 0.],
       …,
       [0., 0., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 0.]])
```

[45]:
```
classifier = MultinomialNB()
classifier.fit(X_train, y_train)
```

[45]:
```
MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)
```

[46]:
```
y_pred = classifier.predict(X_test)
y_train_pred = classifier.predict(X_train)
acc5 = accuracy_score(y_test, y_pred)
score = accuracy_score(y_train,y_train_pred)
```

[47]:
```
score
```

[47]:
```
0.8849381625441696
```

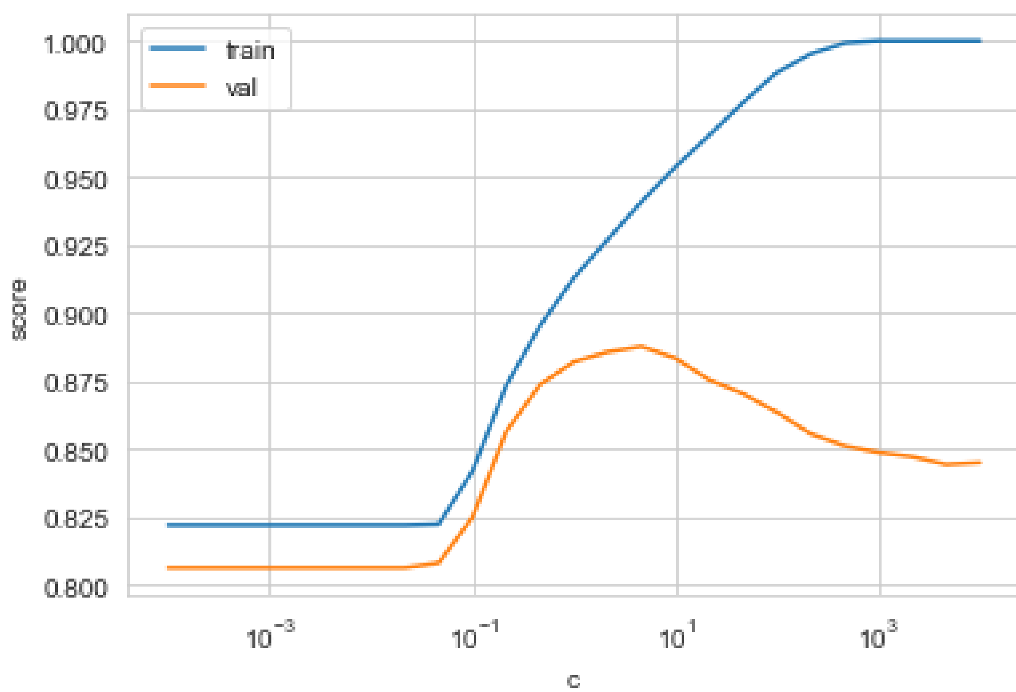
[48]:
```
print("Accuracy of the classifier using TF-IDF: ",acc5)
print("Confusion matrix is :\n",metrics.confusion_matrix(y_test,y_pred))
print("Classification report: \n" ,metrics.classification_report(y_test,y_pred))
```

```
Accuracy of the classifier using TF-IDF:  0.8593508500772797
Confusion matrix is :
 [[ 289  588]
 [  49 3603]]
Classification report:
               precision    recall  f1-score   support

           0       0.86      0.33      0.48       877
           1       0.86      0.99      0.92      3652
```

```
avg / total       0.86      0.86      0.83      4529
```

1.6.6 Logistic Regression with TF-IDF

[49]:
```
res_train = []
res_test = []
c_range = np.logspace(-4,4,25)
import matplotlib.pyplot as plt
import numpy as np

for cc in c_range:
    clf = LogisticRegression(random_state = 42, C=cc,␣
 ↪penalty='l2',solver='liblinear').fit(X_train, y_train)
    res_train.append(clf.score(X_train,y_train))
    res_test.append(clf.score(X_test,y_test))


plt.semilogx(c_range,res_train,label='train')
plt.semilogx(c_range,res_test,label='val')
plt.xlabel('c')
plt.ylabel('score')
plt.legend()
plt.show()
print(f'Best of c for the model is about ',[x for _,x in␣
 ↪sorted(zip(res_test,c_range))][-1])
```



```
Best of c for the model is about  4.641588833612772
```

[52]:
```
clf = LogisticRegression(random_state = 42, C=4.64,␣
↪penalty='l2',solver='liblinear').fit(X_train, y_train)
print(clf.score(X_train,y_train))
print(clf.score(X_test,y_test))
y_pred = clf.predict(X_test)
acc6 = accuracy_score(y_test, y_pred)
```

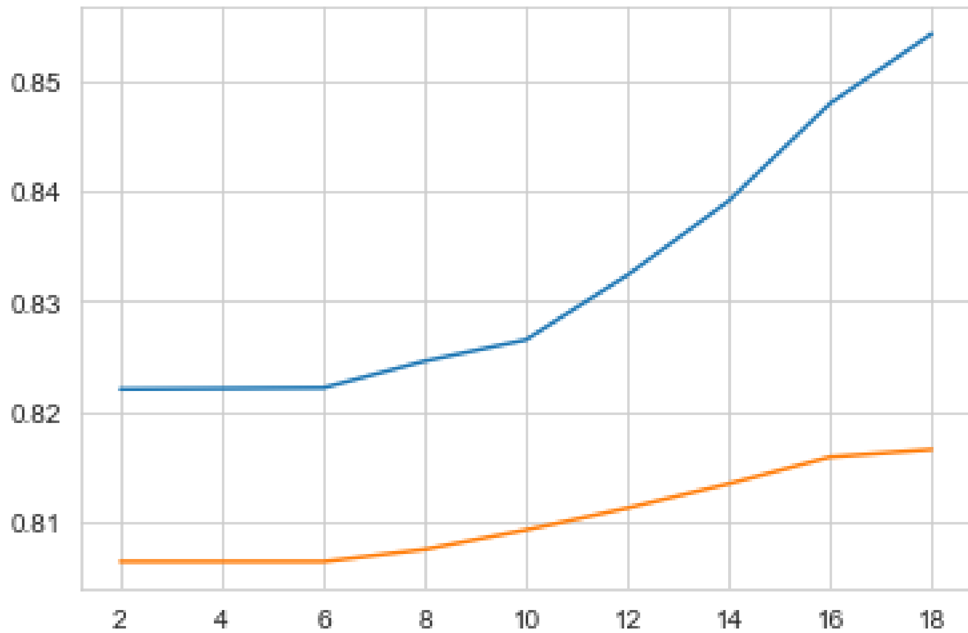
```
0.9408679328621908
0.8876131596378891
```

[53]:
```
print("Accuracy of the LogisticRegression using TF-IDF: ",acc6)
print("Confusion matrix is :\n",metrics.confusion_matrix(y_test,y_pred))
print("Classification report: \n" ,metrics.classification_report(y_test,y_pred))
```

```
Accuracy of the LogisticRegression using TF-IDF:  0.8876131596378891
Confusion matrix is :
 [[ 515  362]
 [ 147 3505]]
Classification report:
              precision    recall  f1-score   support

          0       0.78      0.59      0.67       877
          1       0.91      0.96      0.93      3652

avg / total       0.88      0.89      0.88      4529
```

1.6.7 Random Forest with TF-IDF

[54]:
```
import matplotlib.pyplot as plt
depth_list = np.arange(2,20,2)
acc_train, acc_test = [], []
for dp in depth_list:

    clf = RandomForestClassifier(max_depth=dp,random_state=0).
↪fit(X_train,y_train)
    acc_train.append(np.sum(clf.predict(X_train)==y_train)/len(X_train))
    acc_test.append(np.sum(clf.predict(X_test)==y_test)/len(X_test))

plt.plot(depth_list,acc_train)
plt.plot(depth_list,acc_test)
plt.show()
```



[55]:
```
clf = RandomForestClassifier(max_depth=20,random_state=0).fit(X_train,y_train)
print(clf.score(X_train,y_train))
print(clf.score(X_test,y_test))
y_pred = clf.predict(X_test)
acc7 = accuracy_score(y_test, y_pred)
print("Accuracy of the Random Forest using TF-IDF: ",acc7)
print("Confusion matrix is :\n",metrics.confusion_matrix(y_test,y_pred))
print("Classification report: \n" ,metrics.classification_report(y_test,y_pred))
```

```
0.8646201413427562
0.8222565687789799
Accuracy of the Random Forest using TF-IDF:  0.8222565687789799
Confusion matrix is :
 [[  94  783]
 [  22 3630]]
Classification report:
              precision    recall  f1-score   support

          0       0.81      0.11      0.19       877
          1       0.82      0.99      0.90      3652

avg / total       0.82      0.82      0.76      4529
```

1.6.8 Linear SVC with TF-IDF

[56]:
```
## Final method
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVC, SVC
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split
clf = make_pipeline(StandardScaler(),LinearSVC(random_state=0, tol=1e-4,C=0.
↪0001)).fit(X_train,y_train)

#clf = LogisticRegression(max_iter=100000000).fit(train_cat_vec,␣
↪df_train["label"])

print(np.sum(clf.predict(X_train)==y_train)/len(X_train))
print(np.sum(clf.predict(X_test)==y_test)/len(X_test))
```

```
0.9479902826855123
0.8827555751821594
```

[57]:
```
y_pred = clf.predict(X_test)
acc8 = accuracy_score(y_test, y_pred)
print("Accuracy of the LinearSVC using TF-IDF: ",acc8)
print("Confusion matrix is :\n",metrics.confusion_matrix(y_test,y_pred))
print("Classification report: \n" ,metrics.classification_report(y_test,y_pred))
```

```
Accuracy of the LinearSVC using TF-IDF:  0.8827555751821594
Confusion matrix is :
 [[ 580  297]
 [ 234 3418]]
Classification report:
              precision    recall  f1-score   support

          0       0.71      0.66      0.69       877
          1       0.92      0.94      0.93      3652

avg / total       0.88      0.88      0.88      4529
```

1.6.9 word2vec

[58]:
```
import multiprocessing

from gensim.models import Word2Vec

w2v_model = Word2Vec()
w2v_model.build_vocab(reviews["Review Text_processed"], progress_per=10000)
```

```
w2v_model.train(reviews["Review Text_processed"], total_examples=w2v_model.
↪corpus_count, epochs=30, report_delay=1)

w2v_model.init_sims(replace=True)
```

[59]:
```
import numpy as np
from numpy import dot
from numpy.linalg import norm
def document_vector_w2v(doc):
    """Create document vectors by averaging word vectors. Remove␣
↪out-of-vocabulary words."""
    doc = [word for word in doc if word in w2v_model.wv.vocab]
    return np.mean(w2v_model[doc], axis=0)
```

[60]:
```
X_w2v=reviews["Review Text_processed"].apply(lambda x: ' '.join(x)).
↪apply(document_vector_w2v)
y_w2v = reviews['Recommended IND']
```

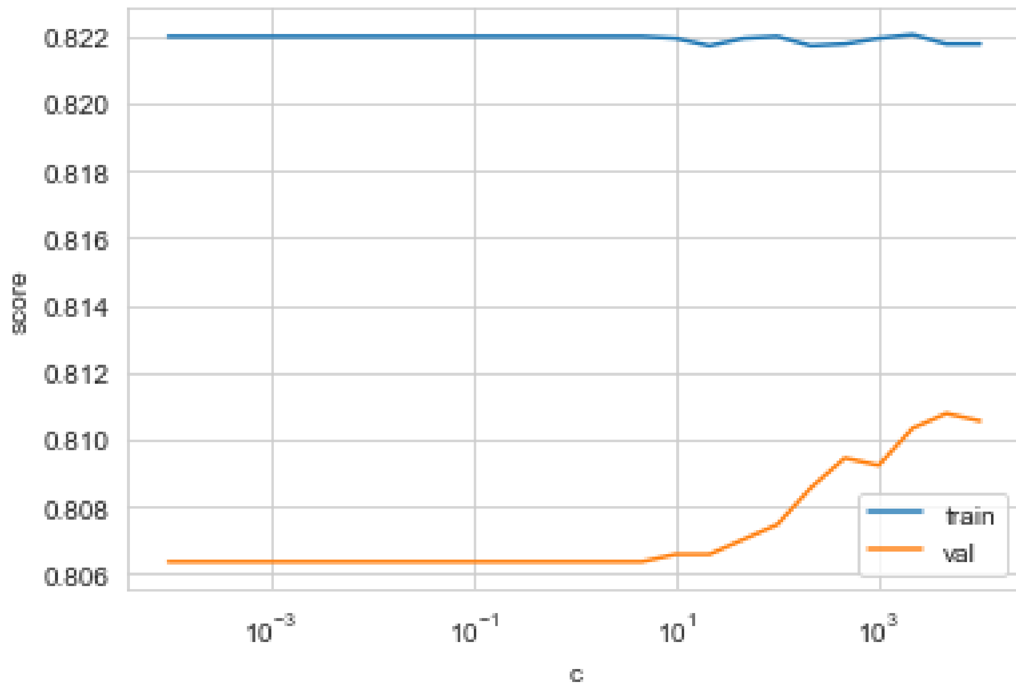
[61]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_w2v, y_w2v, test_size = 0.
↪20, random_state = 0)
```

[62]:
```
X_train, X_test, y_train, y_test = list(X_train), list(X_test), list(y_train),␣
↪list(y_test)
```

1.6.10 Logistic Regression with word2vec

[63]:
```
res_train = []
res_test = []
c_range = np.logspace(-4,4,25)
import matplotlib.pyplot as plt
import numpy as np
from sklearn.linear_model import LogisticRegression
for cc in c_range:
    clf = LogisticRegression(random_state = 42, C=cc,␣
↪penalty='l2',solver='liblinear').fit(X_train, y_train)
    res_train.append(clf.score(X_train,y_train))
    res_test.append(clf.score(X_test,y_test))


plt.semilogx(c_range,res_train,label='train')
plt.semilogx(c_range,res_test,label='val')
plt.xlabel('c')
plt.ylabel('score')
plt.legend()
plt.show()
```

```python
print(f'Best of c for the model is about ',[x for _,x in␣
↪sorted(zip(res_test,c_range))][-1])
```




```
Best of c for the model is about  4641.588833612773
```

[66]:
```python
from sklearn.metrics import accuracy_score
from sklearn import metrics
clf = LogisticRegression(random_state = 42, C=1000,␣
↪penalty='l2',solver='liblinear').fit(X_train, y_train)
print(clf.score(X_train,y_train))
print(clf.score(X_test,y_test))
y_pred = clf.predict(X_test)
acc9 = accuracy_score(y_test, y_pred)
```

```
0.8219412544169611
0.8092294104658865
```

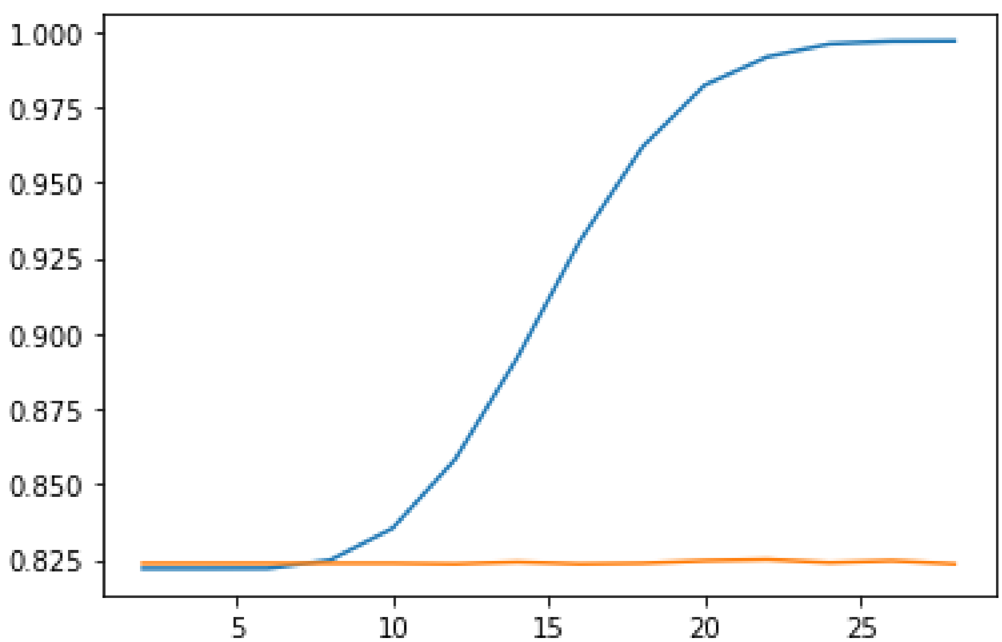
[67]:
```python
print("Accuracy of the LogisticRegression using word2vec: ",acc9)
print("Confusion matrix is :\n",metrics.confusion_matrix(y_test,y_pred))
print("Classification report: \n" ,metrics.classification_report(y_test,y_pred))
```

```
Accuracy of the LogisticRegression using word2vec:  0.8092294104658865
Confusion matrix is :
 [[  29  848]
 [  16 3636]]
```

```
Classification report:
              precision    recall  f1-score   support

          0       0.64      0.03      0.06       877
          1       0.81      1.00      0.89      3652

avg / total       0.78      0.81      0.73      4529
```

1.6.11 Random Forest with word2vec

[21]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVC, SVC
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder
import matplotlib.pyplot as plt
depth_list = np.arange(2,30,2)
acc_train, acc_test = [], []
for dp in depth_list:

    clf = RandomForestClassifier(max_depth=dp,random_state=0).
 ↪fit(X_train,y_train)
    acc_train.append(np.sum(clf.predict(X_train)==y_train)/len(X_train))
    acc_test.append(np.sum(clf.predict(X_test)==y_test)/len(X_test))

plt.plot(depth_list,acc_train)
plt.plot(depth_list,acc_test)
plt.show()
```



[68]:
```
clf = RandomForestClassifier(max_depth=20,random_state=0).fit(X_train,y_train)
print(clf.score(X_train,y_train))
print(clf.score(X_test,y_test))
y_pred = clf.predict(X_test)
acc10 = accuracy_score(y_test, y_pred)
print("Accuracy of the Random Forest using word2vec: ",acc10)
print("Confusion matrix is :\n",metrics.confusion_matrix(y_test,y_pred))
print("Classification report: \n" ,metrics.classification_report(y_test,y_pred))
```

```
0.969357332155477
0.7895782733495252
Accuracy of the Random Forest using word2vec:  0.7895782733495252
Confusion matrix is :
 [[  68  809]
 [ 144 3508]]
Classification report:
              precision    recall  f1-score   support

          0       0.32      0.08      0.12       877
          1       0.81      0.96      0.88      3652

avg / total       0.72      0.79      0.73      4529
```

1.6.12 Linear SVC with word2vec

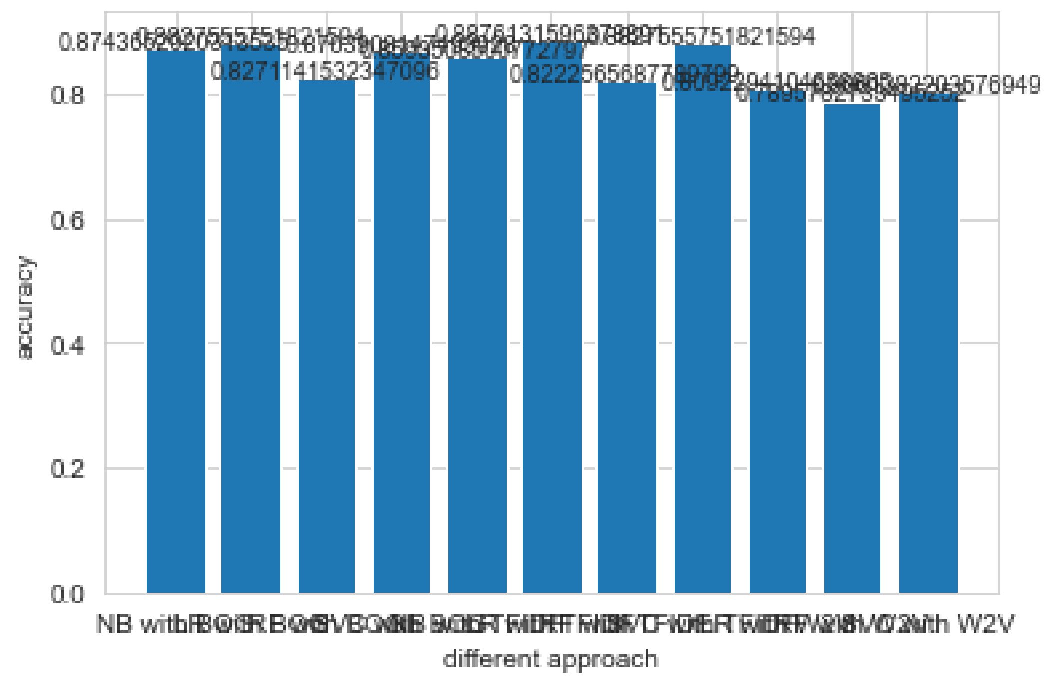
[69]:
```
## Final method
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVC, SVC
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split
clf = make_pipeline(StandardScaler(),LinearSVC(random_state=0, tol=1e-4,C=0.
 ↪00001)).fit(X_train,y_train)

#clf = LogisticRegression(max_iter=100000000).fit(train_cat_vec,␣
 ↪df_train["label"])

print(np.sum(clf.predict(X_train)==y_train)/len(X_train))
print(np.sum(clf.predict(X_test)==y_test)/len(X_test))
```

```
0.8197327738515902
0.8061382203576949
```

[70]:
```
y_pred = clf.predict(X_test)
acc11 = accuracy_score(y_test, y_pred)
print("Accuracy of the LinearSVC using word2vec: ",acc11)
print("Confusion matrix is :\n",metrics.confusion_matrix(y_test,y_pred))
print("Classification report: \n" ,metrics.classification_report(y_test,y_pred))
```

```
Accuracy of the LinearSVC using word2vec:  0.8061382203576949
Confusion matrix is :
 [[  47  830]
 [  48 3604]]
Classification report:
              precision    recall  f1-score   support

          0       0.49      0.05      0.10       877
          1       0.81      0.99      0.89      3652

avg / total       0.75      0.81      0.74      4529
```

[71]:
```
import matplotlib.pyplot as plt
index=['NB with BOG','LR with BOG','RF with BOG','SVC with BOG','NB with␣
 ↪TFIDF','LR with TFIDF','RF with TFIDF','SVC with TFIDF','LR with W2V','RF␣
 ↪with W2V','SVC with W2V']
acc = [acc1,acc2,acc3,acc4,acc5,acc6,acc7,acc8,acc9,acc10,acc11]
plt.bar(index,acc)
for index,value in enumerate(acc):
    plt.text(index,value, str(value),fontsize=9,horizontalalignment='center')
plt.ylabel('accuracy')
plt.xlabel('different approach')
plt.show()
```



[72]:
```
index=['NB with BOG','LR with BOG','RF with BOG','SVC with BOG','NB with␣
↪TFIDF','LR with TFIDF','RF with TFIDF','SVC with TFIDF','LR with W2V','RF␣
↪with W2V','SVC with W2V']
acc = [acc1,acc2,acc3,acc4,acc5,acc6,acc7,acc8,acc9,acc10,acc11]
d = {'approach':index,'accuracy':acc}
df=pd.DataFrame(data=d)
df
```

[72]:

	approach	accuracy
0	NB with BOG	0.874365
1	LR with BOG	0.882756
2	RF with BOG	0.827114
3	SVC with BOG	0.870391
4	NB with TFIDF	0.859351
5	LR with TFIDF	0.887613
6	RF with TFIDF	0.822257
7	SVC with TFIDF	0.882756
8	LR with W2V	0.809229
9	RF with W2V	0.789578
10	SVC with W2V	0.806138

1.6.13 Deep Learning

[73]:
```
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

[74]:
```
tokenizer = Tokenizer(num_words = 3000)
tokenizer.fit_on_texts(reviews["Review Text_processed"])
```

[75]:
```
sequences = tokenizer.texts_to_sequences(reviews["Review Text_processed"])
padded = pad_sequences(sequences, padding='post')
```

[76]:
```
word_index = tokenizer.word_index
count = 0
for i,j in word_index.items():
    if count == 11:
        break
    print(i,j)
    count = count+1
```

```
dress 1
fit 2
love 3
size 4
look 5
top 6
wear 7
like 8
color 9
would 10
great 11
```

[77]:
```
embedding_dim = 64
model = tf.keras.Sequential([
    tf.keras.layers.Embedding(3000, embedding_dim),
    tf.keras.layers.GlobalAveragePooling1D(),
    tf.keras.layers.Dense(6, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
])

model.summary()
```

```
Model: "sequential"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, None, 64)          192000
_________________________________________________________________
```

```
global_average_pooling1d (Gl (None, 64)               0
_________________________________________________________________
dense (Dense)                (None, 6)                390
_________________________________________________________________
dense_1 (Dense)              (None, 1)                7
=================================================================
Total params: 192,397
Trainable params: 192,397
Non-trainable params: 0
_________________________________________________________________
```

[78]:
```
num_epochs = 10

model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
```

[79]:
```
model.fit(padded,y,epochs= num_epochs)
```

```
Epoch 1/10
708/708 [==============================] - 3s 4ms/step - loss: 0.4099 -
accuracy: 0.8247
Epoch 2/10
708/708 [==============================] - 3s 4ms/step - loss: 0.2554 -
accuracy: 0.8906
Epoch 3/10
708/708 [==============================] - 3s 4ms/step - loss: 0.2294 -
accuracy: 0.9037
Epoch 4/10
708/708 [==============================] - 3s 4ms/step - loss: 0.2166 -
accuracy: 0.9103
Epoch 5/10
708/708 [==============================] - 3s 4ms/step - loss: 0.2079 -
accuracy: 0.9146
Epoch 6/10
708/708 [==============================] - 3s 4ms/step - loss: 0.2000 -
accuracy: 0.9189
Epoch 7/10
708/708 [==============================] - 3s 4ms/step - loss: 0.1934 -
accuracy: 0.9216
Epoch 8/10
708/708 [==============================] - 3s 4ms/step - loss: 0.1875 -
accuracy: 0.9231
Epoch 9/10
708/708 [==============================] - 3s 4ms/step - loss: 0.1810 -
accuracy: 0.9262
Epoch 10/10
708/708 [==============================] - 3s 4ms/step - loss: 0.1754 -
accuracy: 0.9275
```

```
[79]: <tensorflow.python.keras.callbacks.History at 0x266528c67b8>
```

```
[80]: sample_string = "I Will tell my friends for sure"
      sample = tokenizer.texts_to_sequences(sample_string)
      padded_sample = pad_sequences(sample, padding='post')
```

```
[81]: padded_sample.T
```

```
[81]: array([], shape=(0, 31), dtype=int32)
```

1.7 Rating Prediction Model

1.7.1 Neural Network (Keras)

```
[15]: def NN_fit(X_train,y_train):
          model=Sequential()
          n_cols=X_train.shape[1]
          model.add(Dense(11,activation='relu',input_shape=(n_cols,)))
          model.add(Dense(11,activation='relu'))
      #     model.add(Dense(20,activation='relu'))
      #     model.add(Dense(20,activation='relu'))

          model.add(Dense(5,activation='softmax'))
          model.
       ↪compile(optimizer='adam',loss='categorical_crossentropy',metrics=["accuracy"])
          early_stopping_monitor=EarlyStopping(patience=3)
          model.fit(X_train,pd.get_dummies(y_train).to_numpy(),validation_split=0.
       ↪2,epochs=100,callbacks=[early_stopping_monitor])

          return model
```

```
[59]: model_test=NN_fit(X_train_we,y_train_we)
```

```
Epoch 1/100
453/453 [==============================] - 1s 1ms/step - loss: 1.3091 -
accuracy: 0.5473 - val_loss: 1.0176 - val_accuracy: 0.5904
Epoch 2/100
453/453 [==============================] - 0s 870us/step - loss: 1.0120 -
accuracy: 0.5975 - val_loss: 0.9920 - val_accuracy: 0.5945
Epoch 3/100
453/453 [==============================] - 0s 944us/step - loss: 1.0046 -
accuracy: 0.5898 - val_loss: 0.9819 - val_accuracy: 0.6050
Epoch 4/100
453/453 [==============================] - 0s 915us/step - loss: 0.9809 -
accuracy: 0.5974 - val_loss: 0.9740 - val_accuracy: 0.6064
Epoch 5/100
453/453 [==============================] - 0s 923us/step - loss: 0.9772 -
```

```
accuracy: 0.6048 - val_loss: 0.9687 - val_accuracy: 0.6072
Epoch 6/100
453/453 [==============================] - 0s 934us/step - loss: 0.9741 -
accuracy: 0.6042 - val_loss: 0.9667 - val_accuracy: 0.6089
Epoch 7/100
453/453 [==============================] - 0s 883us/step - loss: 0.9861 -
accuracy: 0.6005 - val_loss: 0.9609 - val_accuracy: 0.6122
Epoch 8/100
453/453 [==============================] - 0s 903us/step - loss: 0.9791 -
accuracy: 0.5987 - val_loss: 0.9574 - val_accuracy: 0.6130
Epoch 9/100
453/453 [==============================] - 0s 887us/step - loss: 0.9759 -
accuracy: 0.6022 - val_loss: 0.9549 - val_accuracy: 0.6147
Epoch 10/100
453/453 [==============================] - 0s 956us/step - loss: 0.9605 -
accuracy: 0.6056 - val_loss: 0.9525 - val_accuracy: 0.6125
Epoch 11/100
453/453 [==============================] - 0s 933us/step - loss: 0.9662 -
accuracy: 0.6000 - val_loss: 0.9530 - val_accuracy: 0.6133
Epoch 12/100
453/453 [==============================] - 0s 850us/step - loss: 0.9697 -
accuracy: 0.6053 - val_loss: 0.9485 - val_accuracy: 0.6144
Epoch 13/100
453/453 [==============================] - 0s 885us/step - loss: 0.9723 -
accuracy: 0.5970 - val_loss: 0.9493 - val_accuracy: 0.6128
Epoch 14/100
453/453 [==============================] - 0s 909us/step - loss: 0.9527 -
accuracy: 0.6079 - val_loss: 0.9453 - val_accuracy: 0.6169
Epoch 15/100
453/453 [==============================] - 0s 923us/step - loss: 0.9569 -
accuracy: 0.6054 - val_loss: 0.9429 - val_accuracy: 0.6163
Epoch 16/100
453/453 [==============================] - 0s 887us/step - loss: 0.9580 -
accuracy: 0.6056 - val_loss: 0.9433 - val_accuracy: 0.6163
Epoch 17/100
453/453 [==============================] - 0s 915us/step - loss: 0.9529 -
accuracy: 0.6040 - val_loss: 0.9458 - val_accuracy: 0.6180
Epoch 18/100
453/453 [==============================] - 0s 921us/step - loss: 0.9653 -
accuracy: 0.6051 - val_loss: 0.9418 - val_accuracy: 0.6199
Epoch 19/100
453/453 [==============================] - 0s 967us/step - loss: 0.9476 -
accuracy: 0.6142 - val_loss: 0.9428 - val_accuracy: 0.6166
Epoch 20/100
453/453 [==============================] - 0s 938us/step - loss: 0.9496 -
accuracy: 0.6104 - val_loss: 0.9414 - val_accuracy: 0.6221
Epoch 21/100
453/453 [==============================] - 0s 986us/step - loss: 0.9403 -
```

```
accuracy: 0.6102 - val_loss: 0.9446 - val_accuracy: 0.6191
Epoch 22/100
453/453 [==============================] - 0s 909us/step - loss: 0.9401 -
accuracy: 0.6124 - val_loss: 0.9392 - val_accuracy: 0.6197
Epoch 23/100
453/453 [==============================] - 0s 959us/step - loss: 0.9544 -
accuracy: 0.6073 - val_loss: 0.9423 - val_accuracy: 0.6172
Epoch 24/100
453/453 [==============================] - 0s 942us/step - loss: 0.9445 -
accuracy: 0.6115 - val_loss: 0.9380 - val_accuracy: 0.6213
Epoch 25/100
453/453 [==============================] - 0s 964us/step - loss: 0.9454 -
accuracy: 0.6114 - val_loss: 0.9362 - val_accuracy: 0.6208
Epoch 26/100
453/453 [==============================] - 0s 995us/step - loss: 0.9402 -
accuracy: 0.6148 - val_loss: 0.9390 - val_accuracy: 0.6188
Epoch 27/100
453/453 [==============================] - 0s 931us/step - loss: 0.9390 -
accuracy: 0.6112 - val_loss: 0.9394 - val_accuracy: 0.6219
Epoch 28/100
453/453 [==============================] - 0s 964us/step - loss: 0.9461 -
accuracy: 0.6182 - val_loss: 0.9363 - val_accuracy: 0.6230
```

[63]:
```
np.unique(model_test.predict_classes(X_train_we))
```

[63]:
```
array([0, 1, 2, 3, 4])
```

[77]:
```
encoding_name=["One-hot+NN","TF-IDF+NN","Word_embedding+NN"]
data_pool=[[X_train_oh.to_numpy(),X_test_oh.to_numpy(),y_train_oh,y_test_oh],
           [X_train_tf.to_numpy(),X_test_tf.to_numpy(),y_train_tf,y_test_tf],
          [X_train_we,X_test_we,y_train_we,y_test_we]]

score_list=[]

for data in data_pool:
    clf=NN_fit(data[0],data[2])
    y_train_pred_nn=clf.predict_classes(data[0])+1
    y_test_pred_nn=clf.predict_classes(data[1])+1
#     train_score=clf.predict(data[0],pd.get_dummies(data[2]))[1]
#     test_score=clf.predict(data[1],pd.get_dummies(data[3]))[1]
    score_list.append([metrics.accuracy_score(data[2], y_train_pred_nn),
                      metrics.accuracy_score(data[3], y_test_pred_nn),
                     f1_score(data[2], y_train_pred_nn, average="macro"),
                       f1_score(data[3], y_test_pred_nn, average="macro")])

result_nn=pd.
 ↪DataFrame(score_list,columns=["Train_acc","Test_acc","Train_f1","Test_f1"],index=encoding_n
```

```
result_nn
```

```
Epoch 1/100
453/453 [==============================] - 1s 2ms/step - loss: 1.1646 -
accuracy: 0.5546 - val_loss: 0.9048 - val_accuracy: 0.6335
Epoch 2/100
453/453 [==============================] - 1s 1ms/step - loss: 0.8308 -
accuracy: 0.6567 - val_loss: 0.8895 - val_accuracy: 0.6332
Epoch 3/100
453/453 [==============================] - 1s 1ms/step - loss: 0.7435 -
accuracy: 0.6954 - val_loss: 0.9008 - val_accuracy: 0.6296
Epoch 4/100
453/453 [==============================] - 1s 1ms/step - loss: 0.6621 -
accuracy: 0.7345 - val_loss: 0.9335 - val_accuracy: 0.6174
Epoch 5/100
453/453 [==============================] - 1s 1ms/step - loss: 0.6154 -
accuracy: 0.7598 - val_loss: 0.9643 - val_accuracy: 0.6119
```

```
/Users/yinuochen/opt/anaconda3/lib/python3.8/site-
packages/tensorflow/python/keras/engine/sequential.py:450: UserWarning:
`model.predict_classes()` is deprecated and will be removed after 2021-01-01.
Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model
does multi-class classification   (e.g. if it uses a `softmax` last-layer
activation).* `(model.predict(x) > 0.5).astype("int32")`,   if your model does
binary classification   (e.g. if it uses a `sigmoid` last-layer activation).
  warnings.warn('`model.predict_classes()` is deprecated and '
```

```
Epoch 1/100
453/453 [==============================] - 1s 1ms/step - loss: 1.3463 -
accuracy: 0.5313 - val_loss: 0.9450 - val_accuracy: 0.6114
Epoch 2/100
453/453 [==============================] - 1s 1ms/step - loss: 0.8831 -
accuracy: 0.6314 - val_loss: 0.8740 - val_accuracy: 0.6351
Epoch 3/100
453/453 [==============================] - 1s 1ms/step - loss: 0.7815 -
accuracy: 0.6789 - val_loss: 0.8686 - val_accuracy: 0.6390
Epoch 4/100
453/453 [==============================] - 1s 1ms/step - loss: 0.7146 -
accuracy: 0.7092 - val_loss: 0.8846 - val_accuracy: 0.6329
Epoch 5/100
453/453 [==============================] - 1s 1ms/step - loss: 0.6659 -
accuracy: 0.7306 - val_loss: 0.9045 - val_accuracy: 0.6323
Epoch 6/100
453/453 [==============================] - 1s 1ms/step - loss: 0.6409 -
accuracy: 0.7419 - val_loss: 0.9310 - val_accuracy: 0.6147
Epoch 1/100
453/453 [==============================] - 1s 1ms/step - loss: 1.3001 -
accuracy: 0.5276 - val_loss: 1.0313 - val_accuracy: 0.5702
```

```
Epoch 2/100
453/453 [==============================] - 0s 864us/step - loss: 1.0341 -
accuracy: 0.5833 - val_loss: 1.0002 - val_accuracy: 0.6001
Epoch 3/100
453/453 [==============================] - 0s 925us/step - loss: 0.9960 -
accuracy: 0.6013 - val_loss: 0.9832 - val_accuracy: 0.6034
Epoch 4/100
453/453 [==============================] - 0s 901us/step - loss: 0.9918 -
accuracy: 0.5989 - val_loss: 0.9755 - val_accuracy: 0.6070
Epoch 5/100
453/453 [==============================] - 0s 883us/step - loss: 0.9829 -
accuracy: 0.5938 - val_loss: 0.9703 - val_accuracy: 0.6083
Epoch 6/100
453/453 [==============================] - 0s 916us/step - loss: 0.9925 -
accuracy: 0.5973 - val_loss: 0.9704 - val_accuracy: 0.6025
Epoch 7/100
453/453 [==============================] - 0s 963us/step - loss: 0.9932 -
accuracy: 0.5900 - val_loss: 0.9641 - val_accuracy: 0.6072
Epoch 8/100
453/453 [==============================] - 0s 913us/step - loss: 0.9603 -
accuracy: 0.6080 - val_loss: 0.9616 - val_accuracy: 0.6072
Epoch 9/100
453/453 [==============================] - 0s 884us/step - loss: 0.9677 -
accuracy: 0.6052 - val_loss: 0.9584 - val_accuracy: 0.6094
Epoch 10/100
453/453 [==============================] - 0s 939us/step - loss: 0.9618 -
accuracy: 0.6096 - val_loss: 0.9569 - val_accuracy: 0.6097
Epoch 11/100
453/453 [==============================] - 0s 966us/step - loss: 0.9631 -
accuracy: 0.6071 - val_loss: 0.9546 - val_accuracy: 0.6116
Epoch 12/100
453/453 [==============================] - 0s 865us/step - loss: 0.9653 -
accuracy: 0.6026 - val_loss: 0.9531 - val_accuracy: 0.6128
Epoch 13/100
453/453 [==============================] - 0s 921us/step - loss: 0.9698 -
accuracy: 0.6040 - val_loss: 0.9666 - val_accuracy: 0.6036
Epoch 14/100
453/453 [==============================] - 0s 862us/step - loss: 0.9641 -
accuracy: 0.6030 - val_loss: 0.9518 - val_accuracy: 0.6128
Epoch 15/100
453/453 [==============================] - 0s 947us/step - loss: 0.9581 -
accuracy: 0.6082 - val_loss: 0.9494 - val_accuracy: 0.6083
Epoch 16/100
453/453 [==============================] - 0s 874us/step - loss: 0.9553 -
accuracy: 0.6048 - val_loss: 0.9514 - val_accuracy: 0.6144
Epoch 17/100
453/453 [==============================] - 0s 943us/step - loss: 0.9553 -
accuracy: 0.6063 - val_loss: 0.9472 - val_accuracy: 0.6119
```

```
Epoch 18/100
453/453 [==============================] - 0s 870us/step - loss: 0.9586 -
accuracy: 0.6084 - val_loss: 0.9459 - val_accuracy: 0.6163
Epoch 19/100
453/453 [==============================] - 0s 875us/step - loss: 0.9546 -
accuracy: 0.6057 - val_loss: 0.9585 - val_accuracy: 0.6047
Epoch 20/100
453/453 [==============================] - 0s 922us/step - loss: 0.9587 -
accuracy: 0.6069 - val_loss: 0.9447 - val_accuracy: 0.6125
Epoch 21/100
453/453 [==============================] - 0s 985us/step - loss: 0.9448 -
accuracy: 0.6120 - val_loss: 0.9430 - val_accuracy: 0.6183
Epoch 22/100
453/453 [==============================] - 0s 886us/step - loss: 0.9625 -
accuracy: 0.6104 - val_loss: 0.9439 - val_accuracy: 0.6161
Epoch 23/100
453/453 [==============================] - 0s 895us/step - loss: 0.9440 -
accuracy: 0.6140 - val_loss: 0.9435 - val_accuracy: 0.6180
Epoch 24/100
453/453 [==============================] - 0s 869us/step - loss: 0.9398 -
accuracy: 0.6147 - val_loss: 0.9412 - val_accuracy: 0.6174
Epoch 25/100
453/453 [==============================] - 0s 931us/step - loss: 0.9396 -
accuracy: 0.6132 - val_loss: 0.9422 - val_accuracy: 0.6128
Epoch 26/100
453/453 [==============================] - 0s 944us/step - loss: 0.9450 -
accuracy: 0.6061 - val_loss: 0.9404 - val_accuracy: 0.6205
Epoch 27/100
453/453 [==============================] - 0s 912us/step - loss: 0.9483 -
accuracy: 0.6074 - val_loss: 0.9448 - val_accuracy: 0.6161
Epoch 28/100
453/453 [==============================] - 0s 964us/step - loss: 0.9261 -
accuracy: 0.6167 - val_loss: 0.9389 - val_accuracy: 0.6177
Epoch 29/100
453/453 [==============================] - 0s 869us/step - loss: 0.9386 -
accuracy: 0.6158 - val_loss: 0.9407 - val_accuracy: 0.6177
Epoch 30/100
453/453 [==============================] - 0s 966us/step - loss: 0.9529 -
accuracy: 0.5990 - val_loss: 0.9439 - val_accuracy: 0.6243
Epoch 31/100
453/453 [==============================] - 0s 924us/step - loss: 0.9330 -
accuracy: 0.6116 - val_loss: 0.9387 - val_accuracy: 0.6199
Epoch 32/100
453/453 [==============================] - 0s 968us/step - loss: 0.9368 -
accuracy: 0.6113 - val_loss: 0.9370 - val_accuracy: 0.6232
Epoch 33/100
453/453 [==============================] - 0s 871us/step - loss: 0.9373 -
accuracy: 0.6120 - val_loss: 0.9358 - val_accuracy: 0.6210
```

```
Epoch 34/100
453/453 [==============================] - 0s 909us/step - loss: 0.9310 -
accuracy: 0.6158 - val_loss: 0.9379 - val_accuracy: 0.6241
Epoch 35/100
453/453 [==============================] - 0s 939us/step - loss: 0.9329 -
accuracy: 0.6132 - val_loss: 0.9354 - val_accuracy: 0.6252
Epoch 36/100
453/453 [==============================] - 0s 878us/step - loss: 0.9441 -
accuracy: 0.6079 - val_loss: 0.9361 - val_accuracy: 0.6232
Epoch 37/100
453/453 [==============================] - 0s 875us/step - loss: 0.9368 -
accuracy: 0.6151 - val_loss: 0.9429 - val_accuracy: 0.6133
Epoch 38/100
453/453 [==============================] - 0s 976us/step - loss: 0.9395 -
accuracy: 0.6095 - val_loss: 0.9362 - val_accuracy: 0.6172
```

[77]:

	Train_acc	Test_acc	Train_f1	Test_f1
One-hot+NN	0.755411	0.618238	0.636620	0.443728
TF-IDF+NN	0.741884	0.612497	0.621029	0.421230
Word_embedding+NN	0.613626	0.608302	0.356031	0.346883

1.7.2 LinearSVC

[88]:
```
# from sklearn import svm
# from sklearn import metrics

# clf = svm.SVC(kernel='linear')
# clf.fit(X_train_oh,y_train_oh)
# y_pred = clf.predict(X_test_oh)
# print("Accuracy:",metrics.accuracy_score(y_test_oh, y_pred))
```

[50]:
```
start_time = time.time()
# print(start_time)
clf = OneVsRestClassifier(SVC(kernel='linear', probability=False), n_jobs=-1)
clf.fit(X_train_oh,y_train_oh)
y_train_pred_oh = clf.predict(X_train_oh)
y_test_pred_oh = clf.predict(X_test_oh)
end_time = time.time()
print("Completed")
print(round((end_time-start_time)/60,2))
```

```
Completed
100.05
```

[22]:
```
score_list_svc=[]
```

[ ]:
```
# score_list_svc=[]
score_list.append([metrics.accuracy_score(y_train_oh, y_train_pred_oh),
                   metrics.accuracy_score(y_test_oh, y_test_pred_oh),
                   f1_score(y_train_oh, y_train_pred_oh, average="macro"),
                   f1_score(y_test_oh, y_test_pred_oh, average="macro"))
```

[52]:
```
start_time = time.time()
clf = OneVsRestClassifier(SVC(kernel='linear', probability=False), n_jobs=-1)
clf.fit(X_train_tf,y_train_tf)
y_train_pred_tf = clf.predict(X_train_tf)
y_test_pred_tf = clf.predict(X_test_tf)
end_time = time.time()
print("Completed")
print(round((end_time-start_time)/60,2))
```

```
Completed
58.17
```

[17]:
```
start_time = time.time()
clf = OneVsRestClassifier(SVC(kernel='linear', probability=False), n_jobs=-1)
clf.fit(X_train_we,y_train_we)
y_train_pred_we = clf.predict(X_train_we)
y_test_pred_we = clf.predict(X_test_we)
end_time = time.time()
print("Completed")
print(round(end_time-start_time,2))
```

```
Completed
194.55
```

[57]:
```
score_list_svc=[]
score_list_svc=[[metrics.accuracy_score(y_train_oh, y_train_pred_oh),
                   metrics.accuracy_score(y_test_oh, y_test_pred_oh),
                   f1_score(y_train_oh, y_train_pred_oh, average="macro"),
                   f1_score(y_test_oh, y_test_pred_oh, average="macro")],
                [metrics.accuracy_score(y_train_tf, y_train_pred_tf),
                   metrics.accuracy_score(y_test_tf, y_test_pred_tf),
                   f1_score(y_train_tf, y_train_pred_tf, average="macro"),
                   f1_score(y_test_tf, y_test_pred_tf, average="macro")],
                [metrics.accuracy_score(y_train_we, y_train_pred_we),
                   metrics.accuracy_score(y_test_we, y_test_pred_we),
                   f1_score(y_train_we, y_train_pred_we, average="macro"),
                   f1_score(y_test_we, y_test_pred_we, average="macro")]
               ]
result_svc=pd.
 ↪DataFrame(score_list_svc,columns=["Train_acc","Test_acc","Train_f1","Test_f1"],index=encodi
result_svc
```

[57]:
```
                     Train_acc  Test_acc  Train_f1   Test_f1
One-hot+SVC           0.794335  0.612056  0.745194  0.403464
TF-IDF+SVC            0.733271  0.627512  0.647086  0.383204
Word_embedding+SVC    0.598222  0.592184  0.317670  0.300082
```

1.8 Feature selection

[26]:
```
from sklearn import feature_selection
X_names=X_train_tf.columns
p_value_limit = 0.997
df_features = pd.DataFrame()

for cat in np.unique(y_train_tf):
    chi2, p = feature_selection.chi2(X_train_tf, y_train_tf==cat)
    df_features = df_features.append(pd.DataFrame(
                   {"feature":X_names, "score":1-p, "label":cat}))
    df_features = df_features.sort_values(["label","score"],
                    ascending=[True,False])
    df_features = df_features[df_features["score"]>p_value_limit]
```

[27]:
```
X_train_tf_fs=X_train_tf.loc[:,df_features.feature.unique()]
X_test_tf_fs=X_test_tf.loc[:,df_features.feature.unique()]
```

[28]:
```
X_train_tf_fs.shape
```

[28]:
```
(18112, 206)
```

[29]:
```
X_names=X_train_oh.columns
p_value_limit = 0.997
df_features = pd.DataFrame()

for cat in np.unique(y_train_oh):
    chi2, p = feature_selection.chi2(X_train_oh, y_train_oh==cat)
    df_features = df_features.append(pd.DataFrame(
                   {"feature":X_names, "score":1-p, "label":cat}))
    df_features = df_features.sort_values(["label","score"],
                    ascending=[True,False])
    df_features = df_features[df_features["score"]>p_value_limit]

for cat in np.unique(y_train_oh):
   print("# {}:".format(cat))
   print("  . selected features:",len(df_features[df_features["label"]==cat]))
   print("  . top features:", ",".
 ↪join(df_features[df_features["label"]==cat]["feature"].values[:10]))
   print(" ")
```

```
# 1:
```

```
  . selected features: 285
  . top features:
aw,cheap,disappoint,disintegr,excit,hideou,horribl,huge,mess,money

# 2:
  . selected features: 281
  . top features:
back,bad,cheap,comfort,disappoint,great,huge,model,perfect,return

# 3:
  . selected features: 315
  . top features:
back,bad,comfort,compliment,disappoint,excit,great,howev,jean,much

# 4:
  . selected features: 137
  . top features: bit,complaint,keep,littl,run,star,perfect,though,overal,nice

# 5:
  . selected features: 577
  . top features: absolut,amaz,area,arm,awkward,back,bad,beauti,big,boot
```

[31]:
```
X_train_oh_fs=X_train_oh.loc[:,df_features.feature.unique()]
X_test_oh_fs=X_test_oh.loc[:,df_features.feature.unique()]
```

[32]:
```
X_train_oh_fs.shape
```

[32]:
```
(18112, 836)
```

1.8.1 Retain on Neural Network (Keras)

[72]:
```
encoding_name=["One-hot+NN+FS","TF-IDF+NN+FS"]
data_pool=[[X_train_oh_fs.to_numpy(),X_test_oh_fs.
 ↪to_numpy(),y_train_oh,y_test_oh],
           [X_train_tf_fs.to_numpy(),X_test_tf_fs.
 ↪to_numpy(),y_train_tf,y_test_tf]]

score_list=[]

for data in data_pool:
    clf=NN_fit(data[0],data[2])
#     train_score=clf.evaluate(data[0],pd.get_dummies(data[2]))[1]
#     test_score=clf.evaluate(data[1],pd.get_dummies(data[3]))[1]
#     score_list.append([train_score,test_score])
    y_train_pred_nn=clf.predict_classes(data[0])+1
    y_test_pred_nn=clf.predict_classes(data[1])+1
```

```python
    score_list.append([metrics.accuracy_score(data[2], y_train_pred_nn),
                      metrics.accuracy_score(data[3], y_test_pred_nn),
                     f1_score(data[2], y_train_pred_nn, average="macro"),
                       f1_score(data[3], y_test_pred_nn, average="macro")])

result_nn_fs=pd.
 ↪DataFrame(score_list,columns=["Train_acc","Test_acc","Train_f1","Test_f1"],index=encoding_n
result_nn_fs
```

```
Epoch 1/100
453/453 [==============================] - 1s 1ms/step - loss: 1.2319 -
accuracy: 0.5268 - val_loss: 0.9058 - val_accuracy: 0.6243
Epoch 2/100
453/453 [==============================] - 0s 1ms/step - loss: 0.8731 -
accuracy: 0.6374 - val_loss: 0.8751 - val_accuracy: 0.6392
Epoch 3/100
453/453 [==============================] - 0s 1ms/step - loss: 0.8075 -
accuracy: 0.6687 - val_loss: 0.8736 - val_accuracy: 0.6420
Epoch 4/100
453/453 [==============================] - 0s 987us/step - loss: 0.8011 -
accuracy: 0.6699 - val_loss: 0.8764 - val_accuracy: 0.6404
Epoch 5/100
453/453 [==============================] - 0s 978us/step - loss: 0.7722 -
accuracy: 0.6856 - val_loss: 0.8771 - val_accuracy: 0.6420
Epoch 6/100
453/453 [==============================] - 0s 980us/step - loss: 0.7500 -
accuracy: 0.7001 - val_loss: 0.8857 - val_accuracy: 0.6409
Epoch 1/100
453/453 [==============================] - 1s 1ms/step - loss: 1.4440 -
accuracy: 0.5028 - val_loss: 1.0281 - val_accuracy: 0.5702
Epoch 2/100
453/453 [==============================] - 0s 851us/step - loss: 0.9845 -
accuracy: 0.5946 - val_loss: 0.9300 - val_accuracy: 0.6133
Epoch 3/100
453/453 [==============================] - 0s 857us/step - loss: 0.9307 -
accuracy: 0.6151 - val_loss: 0.9074 - val_accuracy: 0.6241
Epoch 4/100
453/453 [==============================] - 0s 857us/step - loss: 0.8950 -
accuracy: 0.6323 - val_loss: 0.9004 - val_accuracy: 0.6252
Epoch 5/100
453/453 [==============================] - 0s 859us/step - loss: 0.8842 -
accuracy: 0.6345 - val_loss: 0.8962 - val_accuracy: 0.6257
Epoch 6/100
453/453 [==============================] - 0s 858us/step - loss: 0.8756 -
accuracy: 0.6385 - val_loss: 0.8949 - val_accuracy: 0.6279
Epoch 7/100
453/453 [==============================] - 0s 861us/step - loss: 0.8599 -
```

```
accuracy: 0.6427 - val_loss: 0.8937 - val_accuracy: 0.6288
Epoch 8/100
453/453 [==============================] - 0s 968us/step - loss: 0.8763 -
accuracy: 0.6335 - val_loss: 0.8946 - val_accuracy: 0.6288
Epoch 9/100
453/453 [==============================] - 0s 935us/step - loss: 0.8649 -
accuracy: 0.6421 - val_loss: 0.8913 - val_accuracy: 0.6293
Epoch 10/100
453/453 [==============================] - 0s 936us/step - loss: 0.8547 -
accuracy: 0.6508 - val_loss: 0.8951 - val_accuracy: 0.6271
Epoch 11/100
453/453 [==============================] - 0s 910us/step - loss: 0.8691 -
accuracy: 0.6394 - val_loss: 0.8933 - val_accuracy: 0.6268
Epoch 12/100
453/453 [==============================] - 0s 992us/step - loss: 0.8557 -
accuracy: 0.6531 - val_loss: 0.8968 - val_accuracy: 0.6227
```

[72]:

	Train_acc	Test_acc	Train_f1	Test_f1
One-hot+NN+FS	0.698929	0.631486	0.545134	0.417691
TF-IDF+NN+FS	0.643883	0.619121	0.458443	0.402997

1.8.2 Retrain on linear SVC

[41]:
```
score_list_svc_fs=[]
```

[42]:
```
start_time = time.time()
clf = OneVsRestClassifier(SVC(kernel='linear', probability=False), n_jobs=-1)
clf.fit(X_train_oh_fs,y_train_oh)
y_train_pred_oh_fs = clf.predict(X_train_oh_fs)
y_test_pred_oh_fs = clf.predict(X_test_oh_fs)
end_time = time.time()
print("Completed")
print(round(end_time-start_time,2))
```

```
Completed
1753.59
```

[43]:
```
score_list_svc_fs.append([metrics.accuracy_score(y_train_oh,␣
 ↪y_train_pred_oh_fs),
                   metrics.accuracy_score(y_test_oh, y_test_pred_oh_fs),
                   f1_score(y_train_oh, y_train_pred_oh_fs, average="macro"),
                   f1_score(y_test_oh, y_test_pred_oh_fs, average="macro")])
```

[44]:
```
clf = OneVsRestClassifier(SVC(kernel='linear', probability=False), n_jobs=-1)
clf.fit(X_train_tf_fs,y_train_tf)
y_train_pred_tf_fs = clf.predict(X_train_tf_fs)
y_test_pred_tf_fs = clf.predict(X_test_tf_fs)
```

[45]:
```
# score_list_svc=[]
score_list_svc_fs.append([metrics.accuracy_score(y_train_tf,␣
↪y_train_pred_tf_fs),
                   metrics.accuracy_score(y_test_tf, y_test_pred_tf_fs),
                   f1_score(y_train_tf, y_train_pred_tf_fs, average="macro"),
                   f1_score(y_test_tf, y_test_pred_tf_fs, average="macro")])
```

[75]:
```
result_svc_fs=pd.
↪DataFrame(score_list_svc_fs,columns=["Train_acc","Test_acc","Train_f1","Test_f1"],index=["O
result_svc_fs
```

[75]:

	Train_acc	Test_acc	Train_f1	Test_f1
One-hot+SVC+FS	0.676734	0.609848	0.533671	0.366183
TF-IDF+SVC+FS	0.615007	0.603444	0.380943	0.321392

[81]:
```
result_nn.append(result_svc).round(4)
```

[81]:

	Train_acc	Test_acc	Train_f1	Test_f1
One-hot+NN	0.7554	0.6182	0.6366	0.4437
TF-IDF+NN	0.7419	0.6125	0.6210	0.4212
Word_embedding+NN	0.6136	0.6083	0.3560	0.3469
One-hot+SVC	0.7943	0.6121	0.7452	0.4035
TF-IDF+SVC	0.7333	0.6275	0.6471	0.3832
Word_embedding+SVC	0.5982	0.5922	0.3177	0.3001

[84]:
```
result_nn_fs.append(result_svc_fs).round(4)
```

[84]:

	Train_acc	Test_acc	Train_f1	Test_f1
One-hot+NN+FS	0.6989	0.6315	0.5451	0.4177
TF-IDF+NN+FS	0.6439	0.6191	0.4584	0.4030
One-hot+SVC+FS	0.6767	0.6098	0.5337	0.3662
TF-IDF+SVC+FS	0.6150	0.6034	0.3809	0.3214

[83]:
```
result_nn.append(result_svc).append(result_svc_fs).append(result_nn_fs).round(4)
```

[83]:

	Train_acc	Test_acc	Train_f1	Test_f1
One-hot+NN	0.7554	0.6182	0.6366	0.4437
TF-IDF+NN	0.7419	0.6125	0.6210	0.4212
Word_embedding+NN	0.6136	0.6083	0.3560	0.3469
One-hot+SVC	0.7943	0.6121	0.7452	0.4035
TF-IDF+SVC	0.7333	0.6275	0.6471	0.3832
Word_embedding+SVC	0.5982	0.5922	0.3177	0.3001
One-hot+SVC+FS	0.6767	0.6098	0.5337	0.3662
TF-IDF+SVC+FS	0.6150	0.6034	0.3809	0.3214
One-hot+NN+FS	0.6989	0.6315	0.5451	0.4177
TF-IDF+NN+FS	0.6439	0.6191	0.4584	0.4030

1.9 Recommender System

[82]:
```python
reviews=pd.read_csv("data/Womens Clothing E-Commerce Reviews.csv")
df = reviews
```

[83]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23486 entries, 0 to 23485
Data columns (total 11 columns):
Unnamed: 0                 23486 non-null int64
Clothing ID                23486 non-null int64
Age                        23486 non-null int64
Title                      19676 non-null object
Review Text                22641 non-null object
Rating                     23486 non-null int64
Recommended IND            23486 non-null int64
Positive Feedback Count    23486 non-null int64
Division Name              23472 non-null object
Department Name            23472 non-null object
Class Name                 23472 non-null object
dtypes: int64(6), object(5)
memory usage: 2.0+ MB
```

[84]:
```python
df[df['Division Name'].isnull()]
```

[84]:
```
       Unnamed: 0  Clothing ID  Age                                 Title  \
9444         9444           72   25                 My favorite socks!!!
13767       13767          492   23                             So soft!
13768       13768          492   49                      Wardrobe staple
13787       13787          492   48                                  NaN
16216       16216          152   36                       Warm and cozy
16221       16221          152   37                                Love!
16223       16223          152   39                     "long and warm"
18626       18626          184   34                 Nubby footless tights
18671       18671          184   54                      New workhorse
20088       20088          772   50                  Comfy sweatshirt!
21532       21532          665   43                         So worth it!
22997       22997          136   47  Charcoal, pale gray, a bit of silver!
23006       23006          136   33                     Cute itsy socks
23011       23011          136   36                          Super socks

                                             Review Text  Rating  \
9444   I never write reviews, but these socks are so …       5
13767  I just love this hoodie! it is so soft and com…       5
13768  Love this hoodie. so soft and goes with everyt…       5
13787                                                NaN       5
```

```
16216  Just what i was looking for. soft, cozy and warm.       5
16221  I am loving these. they are quite long but are…       5
16223  These leg warmers are perfect for me. they are…       5
18626  These are amazing quality. i agree, size up to…       5
18671  These tights are amazing! if i care for them w…       5
20088  This sweatshirt is really nice!  it's oversize…       5
21532  Got these on sale…absolutely love eberjey! f…       5
22997  These socks are soft and comfortable, and they…       5
23006  Love polkadots, love sparkle. these little soc…       5
23011  I love these little socks ? and the dots spark…       5

       Recommended IND  Positive Feedback Count Division Name Department Name  \
9444                 1                        0           NaN             NaN
13767                1                        1           NaN             NaN
13768                1                        0           NaN             NaN
13787                1                        0           NaN             NaN
16216                1                        0           NaN             NaN
16221                1                        0           NaN             NaN
16223                1                        0           NaN             NaN
18626                1                        5           NaN             NaN
18671                1                        0           NaN             NaN
20088                1                        0           NaN             NaN
21532                1                        0           NaN             NaN
22997                1                        1           NaN             NaN
23006                1                        0           NaN             NaN
23011                1                        0           NaN             NaN

      Class Name
9444         NaN
13767        NaN
13768        NaN
13787        NaN
16216        NaN
16221        NaN
16223        NaN
18626        NaN
18671        NaN
20088        NaN
21532        NaN
22997        NaN
23006        NaN
23011        NaN
```

[85]:
```
df_filter = df.dropna(subset = ['Division Name','Department Name', 'Class␣
↪Name'])
```

[86]:
```
df_filter.head()
```

[86]:
```
   Unnamed: 0  Clothing ID  Age                    Title  \
0           0          767   33                      NaN
1           1         1080   34                      NaN
2           2         1077   60  Some major design flaws
3           3         1049   50         My favorite buy!
4           4          847   47         Flattering shirt

                                         Review Text  Rating  Recommended IND  \
0  Absolutely wonderful - silky and sexy and comf…       4                1
1  Love this dress!  it's sooo pretty.  i happene…       5                1
2  I had such high hopes for this dress and reall…       3                0
3  I love, love, love this jumpsuit. it's fun, fl…       5                1
4  This shirt is very flattering to all due to th…       5                1

   Positive Feedback Count   Division Name Department Name Class Name
0                        0       Initmates        Intimate  Intimates
1                        4         General         Dresses    Dresses
2                        0         General         Dresses    Dresses
3                        0  General Petite         Bottoms      Pants
4                        6         General            Tops    Blouses
```

[87]:
```python
bins = [18, 30, 40, 50, 60, 70, 120]
labels = ['18-29', '30-39', '40-49', '50-59', '60-69', '70+']
df_filter['Age_group'] = pd.cut(df_filter.Age, bins, labels=labels,␣
↪include_lowest = True, right = False)
```

[88]:
```python
df_filter['Group_rating'] = df_filter.groupby(['Clothing␣
↪ID','Age_group'])[['Rating']].transform('mean')
```

[89]:
```python
df_filter['Group_recommend_prop'] = df_filter.groupby(['Clothing␣
↪ID','Age_group'])[['Recommended IND']].transform('mean')
```

[90]:
```python
Age_groups = pd.get_dummies(df_filter.Age_group)
Age_groups[:10]
```

[90]:

Age_group	18-29	30-39	40-49	50-59	60-69	70+
0	0	1	0	0	0	0
1	0	1	0	0	0	0
2	0	0	0	0	1	0
3	0	0	0	1	0	0
4	0	0	1	0	0	0
5	0	0	1	0	0	0
6	0	1	0	0	0	0
7	0	1	0	0	0	0
8	1	0	0	0	0	0
9	0	1	0	0	0	0

[91]:
```
df_filter = pd.concat([df_filter, Age_groups], axis = 1)
```

[92]:
```
df_filter['Rating(18-29)'] = df_filter['Rating'] * df_filter['18-29']
df_filter['Rating(30-39)'] = df_filter['Rating'] * df_filter['30-39']
df_filter['Rating(40-49)'] = df_filter['Rating'] * df_filter['40-49']
df_filter['Rating(50-59)'] = df_filter['Rating'] * df_filter['50-59']
df_filter['Rating(60-69)'] = df_filter['Rating'] * df_filter['60-69']
df_filter['Rating(70+)'] = df_filter['Rating'] * df_filter['70+']
df_filter['Recommend_prop(18-29)'] = df_filter['Recommended IND'] *␣
 ↪df_filter['18-29']
df_filter['Recommend_prop(30-39)'] = df_filter['Recommended IND'] *␣
 ↪df_filter['30-39']
df_filter['Recommend_prop(40-49)'] = df_filter['Recommended IND'] *␣
 ↪df_filter['40-49']
df_filter['Recommend_prop(50-59)'] = df_filter['Recommended IND'] *␣
 ↪df_filter['50-59']
df_filter['Recommend_prop(60-69)'] = df_filter['Recommended IND'] *␣
 ↪df_filter['60-69']
df_filter['Recommend_prop(70+)'] = df_filter['Recommended IND'] *␣
 ↪df_filter['70+']
```

[93]:
```
product_vec = df_filter.groupby('Clothing ID')[['18-29', '30-39', '40-49',
       '50-59', '60-69', '70+', 'Rating(18-29)', 'Rating(30-39)',
       'Rating(40-49)', 'Rating(50-59)', 'Rating(60-69)', 'Rating(70+)',
       'Recommend_prop(18-29)', 'Recommend_prop(30-39)',
       'Recommend_prop(40-49)', 'Recommend_prop(50-59)',
       'Recommend_prop(60-69)', 'Recommend_prop(70+)']].agg('sum').reset_index()
```

[94]:
```
for i in ['18-29','30-39', '40-49','50-59', '60-69', '70+']:
    col_rating = 'Rating('+i+')'
    col_recom = 'Recommend_prop('+i+')'
    product_vec[col_rating] = round(product_vec[col_rating] / product_vec[i],3)
    product_vec[col_recom] = round(product_vec[col_recom] / product_vec[i],3)
```

[95]:
```
product_vec = product_vec.fillna(0)
```

[96]:
```
division = pd.pivot_table(df_filter[["Clothing ID","Division␣
 ↪Name"]],index="Clothing ID",columns="Division Name",values="Clothing␣
 ↪ID",aggfunc=lambda x:1 if len(x)>0 else 0).fillna(0).reset_index()
```

[97]:
```
division.index=product_vec.index
```

[98]:
```
product_vec = product_vec.merge(division, on='Clothing ID', how='left')
```

[99]:
```
# scale the number of each age group
```

```python
product_vec['total'] =␣
↪product_vec['18-29']+product_vec['30-39']+product_vec['40-49']+product_vec['50-59']+product_
product_vec['18-29'] = round(product_vec['18-29']/product_vec['total'],3)
product_vec['30-39'] = round(product_vec['30-39']/product_vec['total'],3)
product_vec['40-49'] = round(product_vec['40-49']/product_vec['total'],3)
product_vec['50-59'] = round(product_vec['50-59']/product_vec['total'],3)
product_vec['60-69'] = round(product_vec['60-69']/product_vec['total'],3)
product_vec['70+'] = round(product_vec['70+']/product_vec['total'],3)
del product_vec['total']
product_vec
```

[99]:

```
      Clothing ID  18-29  30-39  40-49  50-59  60-69  70+  Rating(18-29)  \
0               0  1.000  0.000  0.000  0.000  0.000  0.0            5.0
1               1  0.333  0.333  0.000  0.333  0.000  0.0            2.0
2               2  1.000  0.000  0.000  0.000  0.000  0.0            4.0
3               3  0.000  1.000  0.000  0.000  0.000  0.0            0.0
4               4  1.000  0.000  0.000  0.000  0.000  0.0            5.0
…               …      …      …      …      …      …    …              …
1194         1201  0.000  1.000  0.000  0.000  0.000  0.0            0.0
1195         1202  0.111  0.333  0.333  0.111  0.111  0.0            4.0
1196         1203  0.182  0.455  0.182  0.182  0.000  0.0            4.0
1197         1204  0.000  1.000  0.000  0.000  0.000  0.0            0.0
1198         1205  0.000  0.500  0.000  0.000  0.500  0.0            0.0

      Rating(30-39)  Rating(40-49)  …  Rating(70+)  Recommend_prop(18-29)  \
0               0.0          0.000  …          0.0                    1.0
1               5.0          0.000  …          0.0                    0.0
2               0.0          0.000  …          0.0                    1.0
3               5.0          0.000  …          0.0                    0.0
4               0.0          0.000  …          0.0                    1.0
…                 …              …  …            …                      …
1194            4.0          0.000  …          0.0                    0.0
1195            5.0          3.333  …          0.0                    1.0
1196            4.8          5.000  …          0.0                    0.5
1197            4.5          0.000  …          0.0                    0.0
1198            5.0          0.000  …          0.0                    0.0

      Recommend_prop(30-39)  Recommend_prop(40-49)  Recommend_prop(50-59)  \
0                       0.0                    0.0                    0.0
1                       1.0                    0.0                    1.0
2                       0.0                    0.0                    0.0
3                       1.0                    0.0                    0.0
4                       0.0                    0.0                    0.0
…                         …                      …                      …
1194                    1.0                    0.0                    0.0
1195                    1.0                    1.0                    1.0
1196                    1.0                    1.0                    0.5
```

```
1197                   1.0                  0.0                  0.0
1198                   1.0                  0.0                  0.0

      Recommend_prop(60-69)  Recommend_prop(70+)  General  General Petite  \
0                       0.0                  0.0      1.0             0.0
1                       0.0                  0.0      0.0             0.0
2                       0.0                  0.0      1.0             0.0
3                       0.0                  0.0      1.0             0.0
4                       0.0                  0.0      1.0             0.0
…                     …                   …      …             …
1194                    0.0                  0.0      1.0             0.0
1195                    1.0                  0.0      0.0             1.0
1196                    0.0                  0.0      0.0             0.0
1197                    0.0                  0.0      0.0             1.0
1198                    1.0                  0.0      1.0             0.0

      Initmates
0           0.0
1           1.0
2           0.0
3           0.0
4           0.0
…         …
1194        0.0
1195        0.0
1196        1.0
1197        0.0
1198        0.0

[1199 rows x 22 columns]
```

Calculate similarity

[100]:
```python
product_vec = product_vec.set_index('Clothing ID')
```

[101]:
```python
general_prod = product_vec.loc[product_vec.General == 1, "18-29":
↪"Recommend_prop(70+)"]
```

[102]:
```python
general_petite_prod = product_vec.loc[product_vec['General Petite'] == 1,␣
↪"18-29":"Recommend_prop(70+)"]
```

[103]:
```python
initmates_prod = product_vec.loc[product_vec.Initmates == 1, "18-29":
↪"Recommend_prop(70+)"]
```

[104]:
```python
from sklearn.neighbors import NearestNeighbors
neigh = NearestNeighbors(metric='cosine', algorithm='brute', n_neighbors=6)
```

[105]:
```python
neigh.fit(general_prod)
neighbors_general = neigh.kneighbors(general_prod, return_distance = False)
```

[106]:
```python
# fit models for general product
neigh.fit(general_prod)
neighbors_general = neigh.kneighbors(general_prod, return_distance = False)
neighbors_general = pd.DataFrame(neighbors_general,index = general_prod.index)
neighbors_general.columns = ['Top1','Top2','Top3','Top4','Top5','Top6']
neighbors_general['Top1'] = neighbors_general.index[neighbors_general.Top1]
neighbors_general['Top2'] = neighbors_general.index[neighbors_general.Top2]
neighbors_general['Top3'] = neighbors_general.index[neighbors_general.Top3]
neighbors_general['Top4'] = neighbors_general.index[neighbors_general.Top4]
neighbors_general['Top5'] = neighbors_general.index[neighbors_general.Top5]
neighbors_general['Top6'] = neighbors_general.index[neighbors_general.Top6]
neighbors_general
```

[106]:

Clothing ID	Top1	Top2	Top3	Top4	Top5	Top6
0	54	958	36	12	75	575
2	19	989	633	45	526	2
3	541	485	25	548	1043	299
4	54	958	36	12	75	575
5	541	485	25	548	1043	299
…	…	…	…	…	…	…
1197	1197	551	177	882	1118	1137
1198	1198	550	588	1039	1113	925
1200	438	429	1200	53	1127	982
1201	20	587	9	1186	26	13
1205	1205	543	979	1120	1145	542

[454 rows x 6 columns]

[107]:
```python
# fit models for general petite product
neigh.fit(general_petite_prod)
neighbors_petite = neigh.kneighbors(general_petite_prod, return_distance =␣
↪False)
neighbors_petite = pd.DataFrame(neighbors_petite,index = general_petite_prod.
↪index)
neighbors_petite.columns = ['Top1','Top2','Top3','Top4','Top5','Top6']
neighbors_petite['Top1'] = neighbors_petite.index[neighbors_petite.Top1]
neighbors_petite['Top2'] = neighbors_petite.index[neighbors_petite.Top2]
neighbors_petite['Top3'] = neighbors_petite.index[neighbors_petite.Top3]
neighbors_petite['Top4'] = neighbors_petite.index[neighbors_petite.Top4]
neighbors_petite['Top5'] = neighbors_petite.index[neighbors_petite.Top5]
neighbors_petite['Top6'] = neighbors_petite.index[neighbors_petite.Top6]
neighbors_petite
```

[107]:

```
              Top1  Top2  Top3  Top4  Top5  Top6
Clothing ID
18              18   421  1179   615   703    23
21             340  1014  1124    21   756  1007
23             639    23   703   957   615  1179
29              29  1196   356   849   561  1140
30              30  1199   771   473  1204  1149
…             …    …     …    …    …    …
1190          1190  1067   490   649   959  1184
1196            29  1196   356   849   561  1140
1199            30  1199   771   473  1204  1149
1202          1202  1042  1131   876  1051   839
1204           473  1204  1149   589  1029  1182

[308 rows x 6 columns]
```

[108]:

```
# fit models for initmates product
neigh.fit(initmates_prod)
neighbors_initmates = neigh.kneighbors(initmates_prod, return_distance = False)
neighbors_initmates = pd.DataFrame(neighbors_initmates,index = initmates_prod.
 ↪index)
neighbors_initmates.columns = ['Top1','Top2','Top3','Top4','Top5','Top6']
neighbors_initmates['Top1'] = neighbors_initmates.index[neighbors_initmates.
 ↪Top1]
neighbors_initmates['Top2'] = neighbors_initmates.index[neighbors_initmates.
 ↪Top2]
neighbors_initmates['Top3'] = neighbors_initmates.index[neighbors_initmates.
 ↪Top3]
neighbors_initmates['Top4'] = neighbors_initmates.index[neighbors_initmates.
 ↪Top4]
neighbors_initmates['Top5'] = neighbors_initmates.index[neighbors_initmates.
 ↪Top5]
neighbors_initmates['Top6'] = neighbors_initmates.index[neighbors_initmates.
 ↪Top6]
neighbors_initmates
```

[108]:

```
              Top1  Top2  Top3  Top4  Top5  Top6
Clothing ID
1                1   684   441   163   268   231
8                8   225   360   242   107   442
10             140   126   637   655   149   544
14              98   707   519   729   517   716
15              15   625   706  1167   741   259
…             …    …     …    …    …    …
1175           114    87   218   410   207   434
1176           219   432  1176   305    96   210
1177           140   126   637   655   149   544
```

```
1178          140   126   637   655   149   544
1203         1203   504   260   378   300   715

[633 rows x 6 columns]
```

[109]:
```python
product_vec_all = product_vec
neigh.fit(product_vec_all)
neighbors = neigh.kneighbors(product_vec_all, return_distance=False)
```

[110]:
```python
neighbors = pd.DataFrame(neighbors)
neighbors.columns = ['Top1','Top2','Top3','Top4','Top5','Top6']
neighbors
```

[110]:
```
      Top1  Top2  Top3  Top4  Top5  Top6
0       54     0   570   444    12   951
1        1   264   227   160   437   678
2      628    45   982   541     2    19
3       16   600   561   592  1033    17
4       54     0   570   444    12   951
…     …    …    …    …    …    …
1194    13    26  1129  1179   405     9
1195  1195  1035   869  1044  1124   832
1196  1196   499   256   374   296   709
1197   469  1197   756   560  1022   715
1198   538  1198   972  1113   804   358

[1199 rows x 6 columns]
```

[111]:
```python
recommendation = pd.DataFrame({'Clothing ID': division['Clothing ID']})
recommendation = pd.concat([recommendation, neighbors], axis = 1)
recommendation[recommendation['Clothing ID'] == 767]
```

[111]:
```
     Clothing ID  Top1  Top2  Top3  Top4  Top5  Top6
761          767   279   619   318   761   235    40
```

[112]:
```python
product_vec[product_vec.index.isin([18,421,1179,615,703,23])]
```

[112]:
```
             18-29  30-39  40-49  50-59  60-69  70+  Rating(18-29)  \
Clothing ID
18             0.0    0.0    1.0    0.0    0.0  0.0            0.0
23             0.0    0.0    1.0    0.0    0.0  0.0            0.0
421            0.0    0.0    1.0    0.0    0.0  0.0            0.0
615            0.0    0.0    1.0    0.0    0.0  0.0            0.0
703            0.0    0.0    1.0    0.0    0.0  0.0            0.0
1179           0.0    0.0    1.0    0.0    0.0  0.0            0.0

             Rating(30-39)  Rating(40-49)  Rating(50-59)  …  Rating(70+)  \
```

```
Clothing ID                                                   …
18                     0.0            1.0            0.0  …            0.0
23                     0.0            5.0            0.0  …            0.0
421                    0.0            1.0            0.0  …            0.0
615                    0.0            4.0            0.0  …            0.0
703                    0.0            5.0            0.0  …            0.0
1179                   0.0            4.0            0.0  …            0.0

             Recommend_prop(18-29)  Recommend_prop(30-39)  \
Clothing ID
18                             0.0                    0.0
23                             0.0                    0.0
421                            0.0                    0.0
615                            0.0                    0.0
703                            0.0                    0.0
1179                           0.0                    0.0

             Recommend_prop(40-49)  Recommend_prop(50-59)  \
Clothing ID
18                             0.0                    0.0
23                             1.0                    0.0
421                            0.0                    0.0
615                            1.0                    0.0
703                            1.0                    0.0
1179                           1.0                    0.0

             Recommend_prop(60-69)  Recommend_prop(70+)  General  \
Clothing ID
18                             0.0                  0.0      0.0
23                             0.0                  0.0      0.0
421                            0.0                  0.0      0.0
615                            0.0                  0.0      0.0
703                            0.0                  0.0      0.0
1179                           0.0                  0.0      0.0

             General Petite  Initmates
Clothing ID
18                      1.0        0.0
23                      1.0        0.0
421                     1.0        0.0
615                     1.0        0.0
703                     1.0        0.0
1179                    1.0        0.0

[6 rows x 21 columns]
```

1.10 Testing Recommendation System on Another Dataset

[113]:
```
df_book = pd.read_csv("data/Books.csv")
df_rating = pd.read_csv("data/Ratings.csv")
df_user = pd.read_csv("data/Users.csv")
```

[114]:
```
df_book = df_book.iloc[:100000,:]
df_rating = df_rating.iloc[:100000,:]
df_user = df_user.iloc[:100000,:]
df_user = df_user.drop(['Location'],axis = 1)
df_rating = df_rating.iloc[:, 0:3]
df_user
```

[114]:
```
       User-ID   Age
0            1   NaN
1            2  18.0
2            3   NaN
3            4  17.0
4            5   NaN
…          …    …
99995    99996  43.0
99996    99997  33.0
99997    99998  22.0
99998    99999  46.0
99999   100000  43.0

[100000 rows x 2 columns]
```

[115]:
```
df_book_rating = pd.merge(df_book, df_rating, on="ISBN")
df_all = pd.merge(df_book_rating, df_user, on="User-ID")
```

[116]:
```
df_all = df_all.dropna(subset = ['Age'])
df_all = df_all.drop(['Image-URL-S','Image-URL-M','Image-URL-L'],axis = 1)
df_all.rename(columns = {'Book-Rating':'Rating'}, inplace = True)
df_all['Year-Of-Publication'] = df_all['Year-Of-Publication'].astype('category')
#i = df_all[((df_all['Year-Of-Publication'] == 0) | (␣
↪df_all['Year-Of-Publication'] == 2030))].index
#df_all = df_all.drop(i,axis = 0)
df_all
```

[116]:
```
             ISBN                                       Book-Title  \
0      0195153448                              Classical Mythology
18     0002005018                                     Clara Callan
19     0786868716              The Five People You Meet in Heaven
20     0151008116                                      Life of Pi
21     0671021001          She's Come Undone (Oprah's Book Club)
…           …                                                …
```

```
74543  0140327592                                          Matilda
74545  1400049520  Slander : Liberal Lies About the American Right
74546  8440655193                   Avicena, O La Ruta de Isfahan
74547  0886771404                                The Shapechangers
74548  0312422288                            Sellevision: A Novel

                Book-Author Year-Of-Publication                Publisher  \
0         Mark P. O. Morford                2002  Oxford University Press
18      Richard Bruce Wright                2001    HarperFlamingo Canada
19                Mitch Albom                2003                 Hyperion
20               Yann Martel                2002                 Harcourt
21                 Wally Lamb                1998                   Pocket
…                        …                   …                       …
74543             Roald Dahl                1990       Viking Penguin Inc
74545            ANN COULTER                2003       Three Rivers Press
74546         Gilbert Sinove                1997             Ediciones B
74547      Jennifer Roberson                1992                Daw Books
74548      Augusten Burroughs                2003              Picador USA

       User-ID  Rating   Age
0            2       0  18.0
18       11400       0  49.0
19       11400       9  49.0
20       11400       6  49.0
21       11400       0  49.0
…          …      …    …
74543    16923       6  16.0
74545     4806       9  29.0
74546     9131       0  37.0
74547     5775       6  34.0
74548    10594       4  57.0

[49156 rows x 8 columns]
```

[117]:
```python
bins = [1920,1930, 1940, 1950, 1960, 1970, 1980,1990,2000,2010,2020]
labels = ['1920-1930','1930-1940', '1940-1950', '1950-1960','1960-1970',␣
↪'1970-1980', '1980-1990', '1990-2000','2000-2010','2010-2020']
df_all['Year_group'] = pd.cut(df_all['Year-Of-Publication'], bins,␣
↪labels=labels, include_lowest = True, right = False)
df_all = df_all.dropna(subset = ['Year_group'])

bins = [1,18, 30, 40, 50, 60, 70, 120]
labels = ['1-17','18-29', '30-39', '40-49', '50-59', '60-69', '70+']
df_all['Age_group'] = pd.cut(df_all.Age, bins, labels=labels, include_lowest =␣
↪True, right = False)
```

```
df_all['Group_rating'] = df_all.groupby(['ISBN','Age_group'])[['Rating']].
 ↪transform('mean')
df_all['Group_Year_rating'] = df_all.groupby(['Year_group'])[['Rating']].
 ↪transform('mean')
df_all
```

```
[117]:          ISBN                                        Book-Title  \
0      0195153448                               Classical Mythology
18     0002005018                                      Clara Callan
19     0786868716              The Five People You Meet in Heaven
20     0151008116                                       Life of Pi
21     0671021001            She's Come Undone (Oprah's Book Club)
…          …                                                     …
74543  0140327592                                           Matilda
74545  1400049520  Slander : Liberal Lies About the American Right
74546  8440655193                       Avicena, O La Ruta de Isfahan
74547  0886771404                              The Shapechangers
74548  0312422288                             Sellevision: A Novel

                Book-Author Year-Of-Publication             Publisher  \
0        Mark P. O. Morford                2002  Oxford University Press
18     Richard Bruce Wright                2001    HarperFlamingo Canada
19              Mitch Albom                2003                Hyperion
20              Yann Martel                2002                Harcourt
21               Wally Lamb                1998                  Pocket
…                     …                     …                     …
74543            Roald Dahl                1990       Viking Penguin Inc
74545           ANN COULTER                2003       Three Rivers Press
74546        Gilbert Sinove                1997            Ediciones B
74547     Jennifer Roberson                1992               Daw Books
74548    Augusten Burroughs                2003             Picador USA

       User-ID  Rating   Age Year_group Age_group  Group_rating  \
0            2       0  18.0  2000-2010     18-29           NaN
18       11400       0  49.0  2000-2010     40-49           NaN
19       11400       9  49.0  2000-2010     40-49           NaN
20       11400       6  49.0  2000-2010     40-49           NaN
21       11400       0  49.0  1990-2000     40-49           0.0
…          …      …    …         …         …
74543    16923       6  16.0  1990-2000      1-17           NaN
74545     4806       9  29.0  2000-2010     18-29           NaN
74546     9131       0  37.0  1990-2000     30-39           NaN
74547     5775       6  34.0  1990-2000     30-39           NaN
74548    10594       4  57.0  2000-2010     50-59          10.0

       Group_Year_rating
0               3.222195
```

```
18          3.222195
19          3.222195
20          3.222195
21          3.015357
…              …
74543       3.015357
74545       3.222195
74546       3.015357
74547       3.015357
74548       3.222195

[48459 rows x 12 columns]
```

[118]:
```
Age_groups = pd.get_dummies(df_all.Age_group)
Year_groups = pd.get_dummies(df_all['Year_group'])
```

[119]:
```
df_all = pd.concat([df_all, Age_groups,Year_groups], axis = 1)
```

[120]:
```
df_all['Rating(1-17)'] = df_all['Rating'] * df_all['1-17']
df_all['Rating(18-29)'] = df_all['Rating'] * df_all['18-29']
df_all['Rating(30-39)'] = df_all['Rating'] * df_all['30-39']
df_all['Rating(40-49)'] = df_all['Rating'] * df_all['40-49']
df_all['Rating(50-59)'] = df_all['Rating'] * df_all['50-59']
df_all['Rating(60-69)'] = df_all['Rating'] * df_all['60-69']
df_all['Rating(70+)'] = df_all['Rating'] * df_all['70+']

df_all['Rating(1920-1930)'] = df_all['Rating'] * df_all['1920-1930']
df_all['Rating(1930-1940)'] = df_all['Rating'] * df_all['1930-1940']
df_all['Rating(1940-1950)'] = df_all['Rating'] * df_all['1940-1950']
df_all['Rating(1950-1960)'] = df_all['Rating'] * df_all['1950-1960']
df_all['Rating(1960-1970)'] = df_all['Rating'] * df_all['1960-1970']
df_all['Rating(1970-1980)'] = df_all['Rating'] * df_all['1970-1980']
df_all['Rating(1980-1990)'] = df_all['Rating'] * df_all['1980-1990']
df_all['Rating(1990-2000)'] = df_all['Rating'] * df_all['1990-2000']
df_all['Rating(2000-2010)'] = df_all['Rating'] * df_all['2000-2010']
df_all['Rating(2010-2020)'] = df_all['Rating'] * df_all['2010-2020']
```

[121]:
```
product_vec = df_all.groupby('ISBN')[['1-17','18-29', '30-39', '40-49',
       '50-59', '60-69', '70+', 'Rating(1-17)','Rating(18-29)', 'Rating(30-39)',
       'Rating(40-49)', 'Rating(50-59)', 'Rating(60-69)', 'Rating(70+)',␣
 ↪'1920-1930',
        '1930-1940', '1940-1950', '1950-1960','1960-1970', '1970-1980',
        '1980-1990', '1990-2000','2000-2010','2010-2020',␣
 ↪'Rating(1920-1930)','Rating(1930-1940)',
       ␣
 ↪'Rating(1940-1950)','Rating(1950-1960)','Rating(1960-1970)','Rating(1970-1980)','Rating(198
        'Rating(1990-2000)', 'Rating(2000-2010)', 'Rating(2010-2020)'
```

```
    ]].agg('sum').reset_index()
```

[122]:
```
for i in ['1-17','18-29','30-39', '40-49','50-59', '60-69', '70+']:
    col_rating = 'Rating('+i+')'
    product_vec[col_rating] = round(product_vec[col_rating] / product_vec[i],3)

for i in ['1920-1930','1930-1940', '1940-1950', '1950-1960','1960-1970',␣
↪'1970-1980',
          '1980-1990', '1990-2000','2000-2010','2010-2020']:
    col_rating = 'Rating('+i+')'
    product_vec[col_rating] = round(product_vec[col_rating] / product_vec[i],3)
```

[123]:
```
product_vec = product_vec.fillna(0)
product_vec
```

[123]:
```
             ISBN  1-17  18-29  30-39  40-49  50-59  60-69  70+  Rating(1-17)  \
0      0001047973     0      1      0      0      0      0    0           0.0
1      0001360469     0      0      0      0      0      1    0           0.0
2      0001372564     0      0      0      1      0      0    0           0.0
3      0001374869     0      0      0      0      0      1    0           0.0
4      0001939203     0      0      1      0      0      0    0           0.0
…             …   …     …     …      …      …   …  …               …
32450  9997405307     0      1      0      0      0      0    0           0.0
32451  9997522052     0      0      1      0      0      0    0           0.0
32452  9999364497     0      0      1      0      0      0    0           0.0
32453  B00007MF56     0      1      0      0      0      0    0           0.0
32454  B0000DAPP1     0      0      1      0      0      0    0           0.0

       Rating(18-29)  …  Rating(1920-1930)  Rating(1930-1940)  \
0                9.0  …                0.0                0.0
1                0.0  …                0.0                0.0
2                0.0  …                0.0                0.0
3                0.0  …                0.0                0.0
4                0.0  …                0.0                0.0
…                … …                  …                  …
32450            0.0  …                0.0                0.0
32451            0.0  …                0.0                0.0
32452            0.0  …                0.0                0.0
32453            9.0  …                0.0                0.0
32454            0.0  …                0.0                0.0

       Rating(1940-1950)  Rating(1950-1960)  Rating(1960-1970)  \
0                    0.0                0.0                0.0
1                    0.0                0.0                0.0
2                    0.0                0.0                0.0
3                    0.0                0.0                0.0
4                    0.0                0.0                0.0
```

```
...                   ...               ...               ...
32450                 0.0               0.0               0.0
32451                 0.0               0.0               0.0
32452                 0.0               0.0               0.0
32453                 0.0               0.0               0.0
32454                 0.0               0.0               0.0

       Rating(1970-1980)  Rating(1980-1990)  Rating(1990-2000)  \
0                    0.0                0.0                9.0
1                    0.0                0.0               10.0
2                    0.0                0.0                0.0
3                    0.0                0.0               10.0
4                    0.0                0.0                8.0
...                  ...                ...                ...
32450                0.0                0.0                0.0
32451                0.0                0.0                0.0
32452                0.0                0.0                0.0
32453                0.0                0.0                0.0
32454                0.0                0.0                0.0

       Rating(2000-2010)  Rating(2010-2020)
0                    0.0                0.0
1                    0.0                0.0
2                    0.0                0.0
3                    0.0                0.0
4                    0.0                0.0
...                  ...                ...
32450                0.0                0.0
32451                0.0                0.0
32452                0.0                0.0
32453                9.0                0.0
32454                5.0                0.0

[32455 rows x 35 columns]
```

[124]:

```
product_vec['total_age'] = product_vec['1-17'] +␣
 ↪product_vec['18-29']+product_vec['30-39']+product_vec['40-49']+product_vec['50-59']+product
product_vec['1-17'] = round(product_vec['1-17']/product_vec['total_age'],3)
product_vec['18-29'] = round(product_vec['18-29']/product_vec['total_age'],3)
product_vec['30-39'] = round(product_vec['30-39']/product_vec['total_age'],3)
product_vec['40-49'] = round(product_vec['40-49']/product_vec['total_age'],3)
product_vec['50-59'] = round(product_vec['50-59']/product_vec['total_age'],3)
product_vec['60-69'] = round(product_vec['60-69']/product_vec['total_age'],3)
product_vec['70+'] = round(product_vec['70+']/product_vec['total_age'],3)
del product_vec['total_age']
```

```
product_vec['total_year'] = product_vec['1920-1930'] +␣
↪product_vec['1930-1940']+product_vec['1940-1950']+product_vec['1950-1960']+product_vec['196
↪+  product_vec['1990-2000'] + product_vec['2000-2010'] +␣
↪product_vec['2010-2020']

product_vec['1920-1930'] = round(product_vec['1920-1930']/
↪product_vec['total_year'],3)
product_vec['1930-1940'] = round(product_vec['1930-1940']/
↪product_vec['total_year'],3)
product_vec['1940-1950'] = round(product_vec['1940-1950']/
↪product_vec['total_year'],3)
product_vec['1950-1960'] = round(product_vec['1950-1960']/
↪product_vec['total_year'],3)
product_vec['1960-1970'] = round(product_vec['1960-1970']/
↪product_vec['total_year'],3)
product_vec['1970-1980'] = round(product_vec['1970-1980']/
↪product_vec['total_year'],3)
product_vec['1980-1990'] = round(product_vec['1980-1990']/
↪product_vec['total_year'],3)
product_vec['1990-2000'] = round(product_vec['1990-2000']/
↪product_vec['total_year'],3)
product_vec['2000-2010'] = round(product_vec['2000-2010']/
↪product_vec['total_year'],3)
product_vec['2010-2020'] = round(product_vec['2010-2020']/
↪product_vec['total_year'],3)
del product_vec['total_year']
product_vec
```

[124]:

```
             ISBN  1-17  18-29  30-39  40-49  50-59  60-69  70+  Rating(1-17)  \
0      0001047973   0.0    1.0    0.0    0.0    0.0    0.0  0.0           0.0
1      0001360469   0.0    0.0    0.0    0.0    0.0    1.0  0.0           0.0
2      0001372564   0.0    0.0    0.0    1.0    0.0    0.0  0.0           0.0
3      0001374869   0.0    0.0    0.0    0.0    0.0    1.0  0.0           0.0
4      0001939203   0.0    0.0    1.0    0.0    0.0    0.0  0.0           0.0
…             …  …    …     …     …     …     …  …           …
32450  9997405307   0.0    1.0    0.0    0.0    0.0    0.0  0.0           0.0
32451  9997522052   0.0    0.0    1.0    0.0    0.0    0.0  0.0           0.0
32452  9999364497   0.0    0.0    1.0    0.0    0.0    0.0  0.0           0.0
32453  B00007MF56   0.0    1.0    0.0    0.0    0.0    0.0  0.0           0.0
32454  B0000DAPP1   0.0    0.0    1.0    0.0    0.0    0.0  0.0           0.0

       Rating(18-29)  …  Rating(1920-1930)  Rating(1930-1940)  \
0                9.0  …                0.0                0.0
1                0.0  …                0.0                0.0
2                0.0  …                0.0                0.0
3                0.0  …                0.0                0.0
```

```
4                0.0  …                0.0                0.0
…                  …  …                  …                  …
32450            0.0  …                0.0                0.0
32451            0.0  …                0.0                0.0
32452            0.0  …                0.0                0.0
32453            9.0  …                0.0                0.0
32454            0.0  …                0.0                0.0

       Rating(1940-1950)  Rating(1950-1960)  Rating(1960-1970)  \
0                    0.0                0.0                0.0
1                    0.0                0.0                0.0
2                    0.0                0.0                0.0
3                    0.0                0.0                0.0
4                    0.0                0.0                0.0
…                      …                  …                  …
32450                0.0                0.0                0.0
32451                0.0                0.0                0.0
32452                0.0                0.0                0.0
32453                0.0                0.0                0.0
32454                0.0                0.0                0.0

       Rating(1970-1980)  Rating(1980-1990)  Rating(1990-2000)  \
0                    0.0                0.0                9.0
1                    0.0                0.0               10.0
2                    0.0                0.0                0.0
3                    0.0                0.0               10.0
4                    0.0                0.0                8.0
…                      …                  …                  …
32450                0.0                0.0                0.0
32451                0.0                0.0                0.0
32452                0.0                0.0                0.0
32453                0.0                0.0                0.0
32454                0.0                0.0                0.0

       Rating(2000-2010)  Rating(2010-2020)
0                    0.0                0.0
1                    0.0                0.0
2                    0.0                0.0
3                    0.0                0.0
4                    0.0                0.0
…                      …                  …
32450                0.0                0.0
32451                0.0                0.0
32452                0.0                0.0
32453                9.0                0.0
32454                5.0                0.0
```

```
[32455 rows x 35 columns]
```

Calculate similarity

[125]:
```python
product_vec = product_vec.set_index('ISBN')

product_vec = product_vec.dropna(subset = ['1-17'])
```

This is our automatic function to recommend product

[126]:
```python
def recommend_decade(year_range,ISBN,use_all_year = False):
    neigh = NearestNeighbors(metric='cosine', algorithm='brute', n_neighbors=6)
    book = []
    if use_all_year == False:
        vec = product_vec.loc[product_vec[year_range]== 1,'1-17':
 ↪'Rating(2010-2020)']
        if vec.shape[0] <6:
            print('No enough Books to Recommend!')
        else:
            neigh.fit(vec)
            book = neigh.kneighbors(vec, return_distance = False)
            book = pd.DataFrame(book,index = vec.index)
            book.columns = ['Top1','Top2','Top3','Top4','Top5','Top6']
            book['Top1'] = book.index[book.Top1]
            book['Top2'] = book.index[book.Top2]
            book['Top3'] = book.index[book.Top3]
            book['Top4'] = book.index[book.Top4]
            book['Top5'] = book.index[book.Top5]
            book['Top6'] = book.index[book.Top6]
            result = book[book.index== ISBN]
    if use_all_year == True:
        vec = product_vec
        neigh.fit(vec)
        book = neigh.kneighbors(vec, return_distance = False)
        book = pd.DataFrame(book,index = vec.index)
        book.columns = ['Top1','Top2','Top3','Top4','Top5','Top6']
        book['Top1'] = book.index[book.Top1]
        book['Top2'] = book.index[book.Top2]
        book['Top3'] = book.index[book.Top3]
        book['Top4'] = book.index[book.Top4]
        book['Top5'] = book.index[book.Top5]
        book['Top6'] = book.index[book.Top6]
        result = book[book.index== ISBN]
    return result
```

Recommend books within a specific decade

[127]:
```python
recommend_decade('2000-2010','0002005018',use_all_year = False)
```

[127]:

```
                 Top1        Top2        Top3        Top4        Top5  \
ISBN
0002005018  207042314X  0374253536  2070423530  0671027573  0826452310

                 Top6
ISBN
0002005018  047121888X
```

Recommend books using all data

[128]:

```python
recommend_decade('2000-2010','0002005018',use_all_year = True)
```

[128]:

```
                 Top1        Top2        Top3        Top4        Top5  \
ISBN
0002005018  0875969313  157765692X  0786014652  0786014512  0786014881

                 Top6
ISBN
0002005018  0786015233
```

[ ]: