Sentiment Analysis Model Script

In [12]:
```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings("ignore")
from numpy import mean
from numpy import std
import matplotlib.pyplot as plt
import seaborn as sns
import nltk
import re
from textblob import TextBlob
from nltk.corpus import stopwords
from sklearn.feature_extraction import text
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score, recall_score
from sklearn.metrics import f1_score
from sklearn.model_selection import KFold
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
```

Functions

Functions related to Machine Learning

In [13]:
```
# Function to perform K-fold Cross Validation.
def perform_cv(df: pd.DataFrame, target: pd.DataFrame, models):

    results = []
    mean_fpr = np.linspace(0, 1, 100)
    models_predictions = {}

    for model_alias in models:

        print("Model: {}\n".format(model_alias))
        tprs = []
        aucs = []
        thresholds = []
        y_preds = []
        y_preds_prob = []
        y_tests = []
        model = models[model_alias]

        i = 0
        kf = KFold(n_splits=n_folds, random_state=100)
        model_predicted = []
        model_gt = []

        for index in kf.split(df):
```

```
            print("Fold[{}]\n".format(i+1))


            X_train, X_test, y_train, y_test = df.iloc[index[0]], df.iloc[index[1]],
            model_fit, y_pred, y_pred_proba = evaluate_model(model, X_train, X_test,

            print( y_pred_proba)
            print("")
            y_pred = y_pred_proba[:,1] > thresh
            y_pred = y_pred.astype(int)
            model_predicted = np.concatenate((np.array(model_predicted),y_pred))
            model_gt = np.concatenate((np.array(model_gt),y_test))

            generate_performance_stats(y_test, y_pred)

            # Compute ROC curve and area the curve
            fpr, tpr, threshold = roc_curve(y_test, y_pred_proba[:,1])
            prec, rec, tre = precision_recall_curve(y_test, y_pred_proba[:,1])

            tprs.append(interp(mean_fpr, fpr, tpr))
            tprs[-1][0] = 0.0
            roc_auc = auc(fpr, tpr)
            aucs.append(roc_auc)
            thresholds.append(threshold)

            y_preds = np.append(y_preds, y_pred)
            y_preds_prob = np.append(y_preds_prob, y_pred_proba[:,1])
            y_tests = np.append(y_tests, y_test)

            i = i + 1

        generate_performance_stats(model_gt, model_predicted)

        result = RESULT(model_alias, tprs, aucs, thresholds, y_preds, y_preds_prob,
        results.append(result)
        models_predictions[model_alias] = (model_predicted,model_gt)
        print("############################################################\n")

    return results, models_predictions
```

In [14]:

```
def sentiment_predict(alg,x_train,y_train,x_cv,y_cv,cols,name):

    alg.fit(x_train,y_train)
    predictions = alg.predict(x_cv)
    prob = alg.predict_proba(x_cv)

    print(alg)
    print("\nClassification report :\n", classification_report(y_cv,predictions))


    conf_matrix = confusion_matrix(y_cv,predictions)

    acc = accuracy_score(y_cv, predictions)
    prec = precision_score(y_cv, predictions)
    recall = recall_score(y_cv, predictions)

    print("Accuracy score:", acc)
    print("Precision score:", prec)
    print("Recall score:", recall)
    print("Unique predictions:",np.unique( predictions ) )

    conf_mat = confusion_matrix(y_true=y_cv, y_pred=predictions)
```

```
    print('Confusion matrix:\n', conf_mat)
    labels = ['Class 0', 'Class 1']
    fig = plt.figure()
    ax = fig.add_subplot(111)
    cax = ax.matshow(conf_mat, cmap=plt.cm.Blues)
    fig.colorbar(cax)
    ax.set_xticklabels([''] + labels)
    ax.set_yticklabels([''] + labels)
    plt.xlabel('Expected')
    plt.ylabel('Predicted')
    plt.show()
```

Functions related to Text Preprocessing - NLP

In [15]:
```
# Importing SKLearn's list of stopwords
stop_list = text.ENGLISH_STOP_WORDS

# Text cleaning function
def remove_noise_text(text_input):

    # Remove extra whitespaces
    # The apply() function allows to pass a function and apply it on every single va
    text_input = text_input.apply(lambda x: " ".join(x.strip() for x in x.split()))

    # Remove punctuation such as .,;,""
    text_input = text_input.str.replace('[^\w\s]', '')

    # Remove numbers
    text_input = text_input.str.replace('\d+', '')

    # Remove Stopwords imported from Sklearn
    text_input = text_input.apply(lambda x: ' '.join([word for word in x.split() if

    # Remove special characters
    # The ord() function returns the number representing the unicode of a specified
    text_input = text_input.apply(lambda x: "".join([" " if ord(i) < 32 or ord(i) >

    # Convert to string type
    text_input = text_input.astype(str)

    return text_input
```

In [16]:
```
def sentiment_analyser(text_input):
    return text_input.apply(lambda Text: pd.Series(TextBlob(Text).sentiment.polarity
```

1. File Collection

In [17]:
```
df = pd.read_csv(r"C:\Users\alinu\Womens Clothing E-Commerce Reviews\Womens Clothing
```

2. Data Understanding phase

2.1. Data Description stage

In [18]:
```
del df["Unnamed: 0"]
```

In [19]:
```
df.head(5)
```

Out[19]:

Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name

	Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name	I
0	767	33	NaN	Absolutely wonderful - silky and sexy and comf...	4	1	0	Initmates	Intimate	
1	1080	34	NaN	Love this dress! it's sooo pretty. i happene...	5	1	4	General	Dresses	
2	1077	60	Some major design flaws	I had such high hopes for this dress and reall...	3	0	0	General	Dresses	
3	1049	50	My favorite buy!	I love, love, love this jumpsuit. it's fun, fl...	5	1	0	General Petite	Bottoms	
4	847	47	Flattering shirt	This shirt is very flattering to all due to th...	5	1	6	General	Tops	

In [20]:
```
df.dtypes
```

Out[20]:
```
Clothing ID                int64
Age                        int64
Title                     object
Review Text               object
Rating                     int64
Recommended IND            int64
Positive Feedback Count    int64
Division Name             object
Department Name           object
Class Name                object
dtype: object
```

In [21]:
```
df.shape
```

Out[21]:
```
(23486, 10)
```

In [22]:
```
df_null=df.isnull()
df_null.sum()
```

Out[22]:
```
Clothing ID                0
Age                        0
Title                   3810
Review Text              845
Rating                     0
Recommended IND            0
Positive Feedback Count    0
Division Name             14
Department Name           14
```

```
Class Name                  14
dtype: int64
```

In [23]:
```
(df.isnull().sum() / len(df))*100
```

Out[23]:
```
Clothing ID                 0.000000
Age                         0.000000
Title                      16.222430
Review Text                 3.597888
Rating                      0.000000
Recommended IND             0.000000
Positive Feedback Count     0.000000
Division Name               0.059610
Department Name             0.059610
Class Name                  0.059610
dtype: float64
```

• Perform volumetric analysis on the Review dataset to understand its nature (variable identification, identification of data types)

Variable Name	Variable Type
Clothing ID	Categorical (Nominal)
Age	Numerical (Discrete)
Title	Categorical (Nominal)
Review Text	Categorical (Nominal)
Rating	Numerical (Discrete)
Recommend IND	Categorical (Nominal)
Positive Feedback C.	Numerical (Continuous)
Division Name	Categorical (Nominal)
Department Name	Categorical (Nominal)
Class Name	Categorical (Nominal)

Variable Name	Data Type
Clothing ID	int64
Age	int64
Title	object
Review Text	object
Rating	int64
Recommend IND	int64
Positive Feedback C.	int64
Division Name	object
Department Name	object
Class Name	object

2.2. Data Exploration stage

• Handle Missing Values (1)

In [24]:
```
df.dropna(subset=['Title'], how='all', inplace=True)
```

In [25]:
```
df.dropna(subset=['Division Name'], how='all', inplace=True)
```

In [26]:
```
df.dropna(subset=['Department Name'], how='all', inplace=True)
```

In [27]:
```
df.dropna(subset=['Class Name'], how='all', inplace=True)
```

In [29]:
```
df.dropna(subset=['Review Text'], how='all', inplace=True)
```

In [30]:
```
df_null=df.isnull()
df_null.sum()
```

Out[30]:
```
Clothing ID                 0
Age                         0
Title                       0
Review Text                 0
Rating                      0
Recommended IND             0
Positive Feedback Count     0
Division Name               0
Department Name             0
```

```
Class Name                0
dtype: int64
```

• Perform Univariate Analysis in order to understand variables one by one in more detail

A. Categorical data

Clothing ID

In [31]:
```
df["Clothing ID"].value_counts()
counts = df["Clothing ID"].value_counts()
percent = df["Clothing ID"].value_counts(normalize=True)
percent100 = df["Clothing ID"].value_counts(normalize=True).mul(100).round(1).astype
pd.DataFrame({'Frequency': counts, 'Percentage': percent100})
```

Out[31]:

	Frequency	Percentage
1078	871	4.4%
862	658	3.3%
1094	651	3.3%
1081	487	2.5%
829	452	2.3%
...	...	...
776	1	0.0%
744	1	0.0%
728	1	0.0%
712	1	0.0%
16	1	0.0%

1095 rows × 2 columns

Clothing ID is not unique, indicating that there are multiple reviews for a product

Title

In [32]:
```
df["Title"].value_counts()
counts = df["Title"].value_counts()
percent = df["Title"].value_counts(normalize=True)
percent100 = df["Title"].value_counts(normalize=True).mul(100).round(1).astype(str)
pd.DataFrame({'Frequency': counts, 'Percentage': percent100})
```

Out[32]:

	Frequency	Percentage
Love it!	136	0.7%
Beautiful	95	0.5%
Love	88	0.4%
Love!	83	0.4%
Beautiful!	72	0.4%
...	...	...
Perfect every day neutral	1	0.0%
So beautiful! gorgeous orange color!	1	0.0%

	Frequency	Percentage
Comfortable but not flattering	1	0.0%
Body con	1	0.0%
Fabric not comfortable	1	0.0%

13983 rows × 2 columns

Title is not distinct, suggesting that some reviews have identic titles

Review Text

Review Text represents the essential feature for building the classifier as it contains the text that needs to be pre-processed and converted so that the algorithms understand it.

This variable cannot be analyzed as the written review needs to first be converted to text features – a task which will be performed in the "Data Preparation" phase

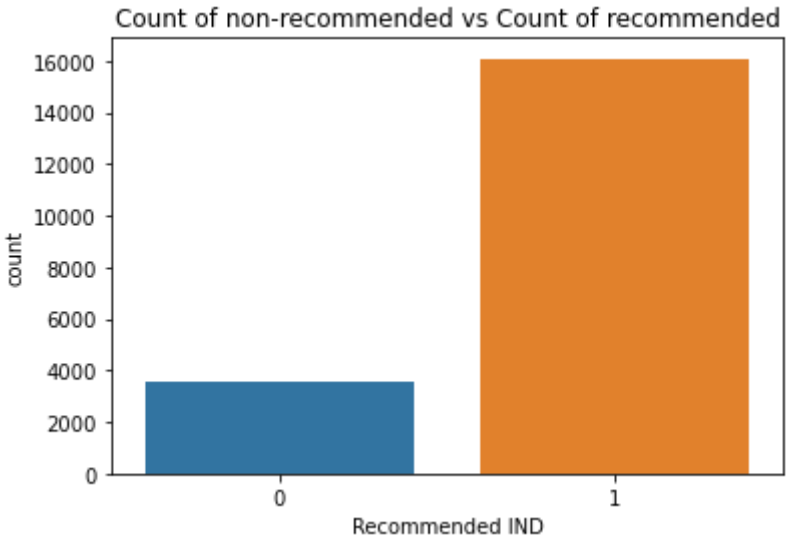
Recommended IND

In [33]:
```
df["Recommended IND"].value_counts()
counts = df["Recommended IND"].value_counts()
percent = df["Recommended IND"].value_counts(normalize=True)
percent100 = df["Recommended IND"].value_counts(normalize=True).mul(100).round(1).as
pd.DataFrame({'Frequency': counts, 'Percentage': percent100})
```

Out[33]:

	Frequency	Percentage
1	16087	81.8%
0	3575	18.2%

In [34]:
```
sns.countplot(df['Recommended IND'])
plt.title("Count of non-recommended vs Count of recommended")
plt.show()
```



We can state that this dataset is highly imbalanced as the classes are not represented equally

Division Name

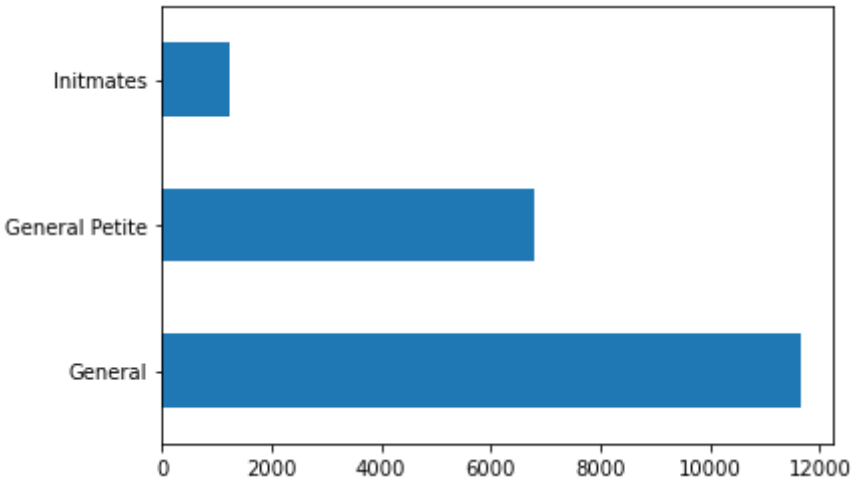
In [35]:
```
df["Division Name"].value_counts()
counts = df["Division Name"].value_counts()
percent = df["Division Name"].value_counts(normalize=True)
```

```
percent100 = df["Division Name"].value_counts(normalize=True).mul(100).round(1).asty
pd.DataFrame({'Frequency': counts, 'Percentage': percent100})
```

Out[35]:

	Frequency	Percentage
General	11664	59.3%
General Petite	6778	34.5%
Initmates	1220	6.2%

In [36]:
```
df['Division Name'].value_counts().plot(kind='barh');
```



Regarding Division Name, the General one has the highest number of reviews, followed by General Petite and Initmates

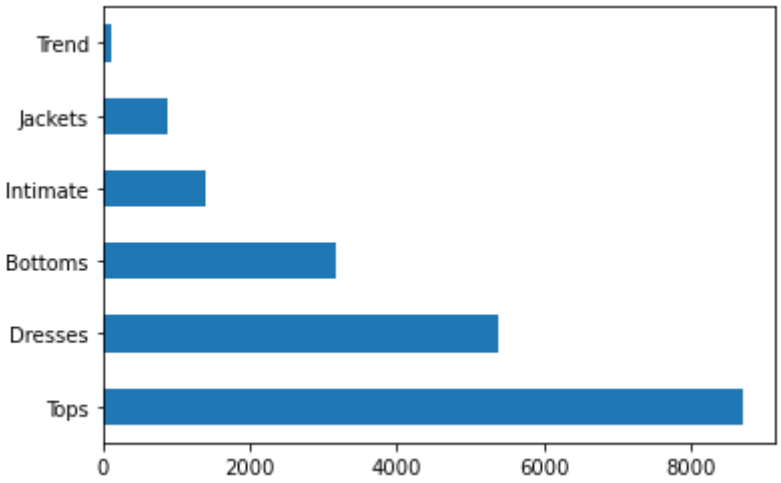
Department Name

In [37]:
```
df["Department Name"].value_counts()
counts = df["Department Name"].value_counts()
percent = df["Department Name"].value_counts(normalize=True)
percent100 = df["Department Name"].value_counts(normalize=True).mul(100).round(1).as
pd.DataFrame({'Frequency': counts, 'Percentage': percent100})
```

Out[37]:

	Frequency	Percentage
Tops	8713	44.3%
Dresses	5371	27.3%
Bottoms	3184	16.2%
Intimate	1408	7.2%
Jackets	879	4.5%
Trend	107	0.5%

In [38]:
```
df['Department Name'].value_counts().plot(kind='barh');
```



Concerning Department Name, Tops presents the most reviews whereas Trend has the lowest number of observations

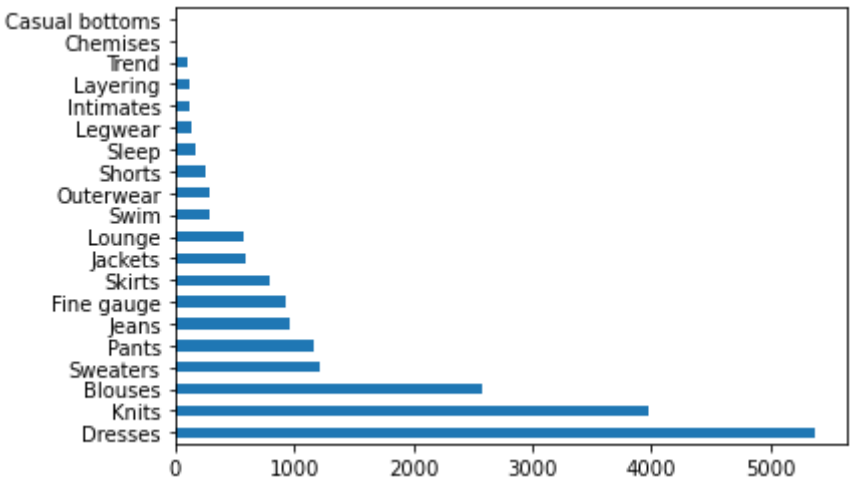
Class Name

In [39]:
```
df["Class Name"].value_counts()
counts = df["Class Name"].value_counts()
percent = df["Class Name"].value_counts(normalize=True)
percent100 = df["Class Name"].value_counts(normalize=True).mul(100).round(1).astype(
pd.DataFrame({'Frequency': counts, 'Percentage': percent100})
```

Out[39]:

	Frequency	Percentage
Dresses	5371	27.3%
Knits	3981	20.2%
Blouses	2587	13.2%
Sweaters	1218	6.2%
Pants	1157	5.9%
Jeans	970	4.9%
Fine gauge	927	4.7%
Skirts	796	4.0%
Jackets	598	3.0%
Lounge	574	2.9%
Swim	293	1.5%
Outerwear	281	1.4%
Shorts	260	1.3%
Sleep	174	0.9%
Legwear	131	0.7%
Intimates	120	0.6%
Layering	115	0.6%
Trend	107	0.5%
Chemises	1	0.0%
Casual bottoms	1	0.0%

In [40]:
```
df['Class Name'].value_counts().plot(kind='barh');
```



When it comes to Class Name, the Dresses have the highest frequency

Polarity Score - Creation

A new feature was created named Polarity_Score

In [42]:
```
# Applying function to reviews
df['Polarity_Score'] = sentiment_analyser(df['Review Text'])
df.head(10)
```

Out[42]:

	Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name
2	1077	60	Some major design flaws	I had such high hopes for this dress and reall...	3	0	0	General	Dresses
3	1049	50	My favorite buy!	I love, love, love this jumpsuit. it's fun, fl...	5	1	0	General Petite	Bottoms
4	847	47	Flattering shirt	This shirt is very flattering to all due to th...	5	1	6	General	Tops
5	1080	49	Not for the very petite	I love tracy reese dresses, but this one is no...	2	0	4	General	Dresses

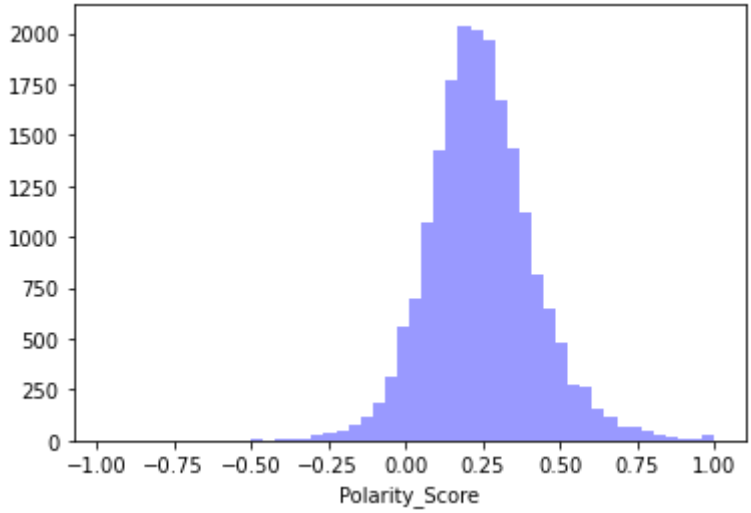
	Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name
6	858	39	Cagrcoal shimmer fun	I aded this in my basket at hte last mintue to...	5	1	1	General Petite	Tops
7	858	39	Shimmer, surprisingly goes with lots	I ordered this in carbon for store pick up, an...	4	1	4	General Petite	Tops
8	1077	24	Flattering	I love this dress. i usually get an xs but it ...	5	1	0	General	Dresses
9	1077	34	Such a fun dress!	I'm 5"5' and 125 lbs. i ordered the s petite t...	5	1	0	General	Dresses
10	1077	53	Dress looks like it's made of cheap material	Dress runs small esp where the zipper area run...	3	0	14	General	Dresses
12	1095	53	Perfect!!!	More and more i find myself reliant on the rev...	5	1	2	General Petite	Dresses

B. Numerical data

Polarity Score

In [43]:
```
sns.distplot(df['Polarity_Score'], kde=False, color='blue', bins=50)
```

Out[43]:
```
<AxesSubplot:xlabel='Polarity_Score'>
```

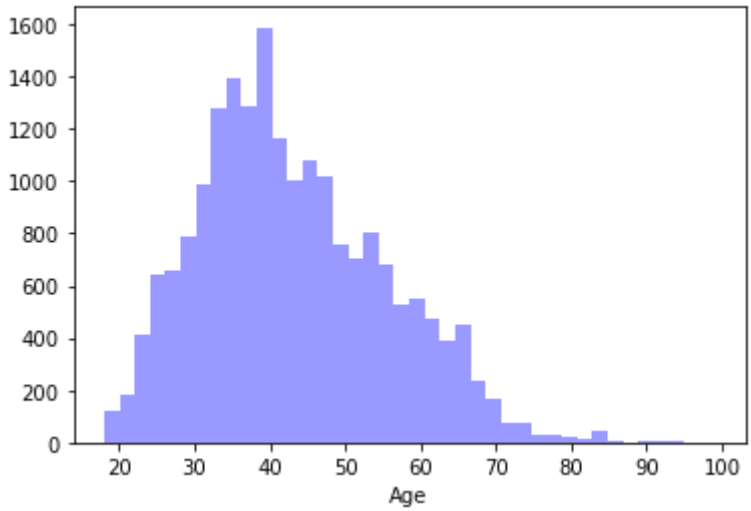


By analyzing the distribution, we can state that the polarity score has an approximate range between 0.18 and 0.26, indicating that most of the customers did indeed express a positive sentiment towards their past purchase.

Age

In [44]:
```
sns.distplot(df['Age'], kde=False, color='blue', bins=40)
```

Out[44]:
```
<AxesSubplot:xlabel='Age'>
```

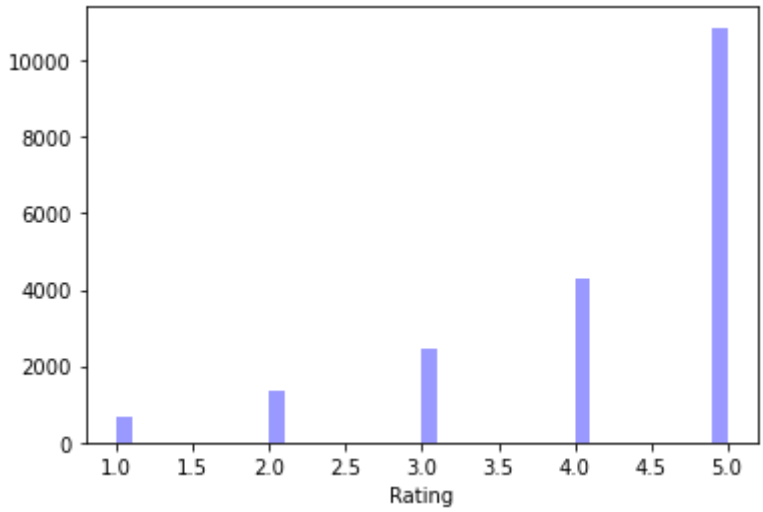


By analyzing the Age feature, it came to my attention that most customers who provide reviews for products are in their 30s or 40s

Rating

In [45]:
```
sns.distplot(df['Rating'], kde=False, color='blue', bins=40)
```

Out[45]:
```
<AxesSubplot:xlabel='Rating'>
```

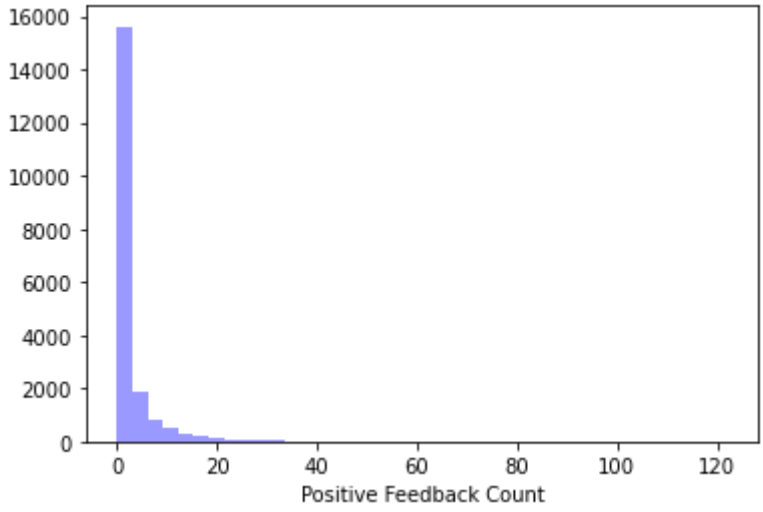


Most clients gave high rates of 4 and 5 to their past clothes purchases, confirming that a high number of customers is content with the shop's products

Positive_Feedback_Count

In [46]:
```
sns.distplot(df['Positive Feedback Count'], kde=False, color='blue', bins=40)
```

Out[46]:
```
<AxesSubplot:xlabel='Positive Feedback Count'>
```



Concerning the Positive_Feedback_Count, most clients had a positive feedback count between 0 and 4

• Perform Bi-variate Analysis in order to explore the relation of multiple variables

Age_Range Creation

In [47]:
```
df['AGE_RANGE']=pd.cut(x=df['Age'],bins
=[18,30,40,50,60,70,80,90,100])
```

In [48]:
```
df.head(5)
```

Out[48]:

Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name	N

	Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name	N
2	1077	60	Some major design flaws	I had such high hopes for this dress and reall...	3	0	0	General	Dresses	Dr
3	1049	50	My favorite buy!	I love, love, love this jumpsuit. it's fun, fl...	5	1	0	General Petite	Bottoms	I
4	847	47	Flattering shirt	This shirt is very flattering to all due to th...	5	1	6	General	Tops	Blc
5	1080	49	Not for the very petite	I love tracy reese dresses, but this one is no...	2	0	4	General	Dresses	Dr
6	858	39	Cagrcoal shimmer fun	I aded this in my basket at hte last mintue to...	5	1	1	General Petite	Tops	

In [49]:
```
df['AGE_RANGE'].value_counts()
```

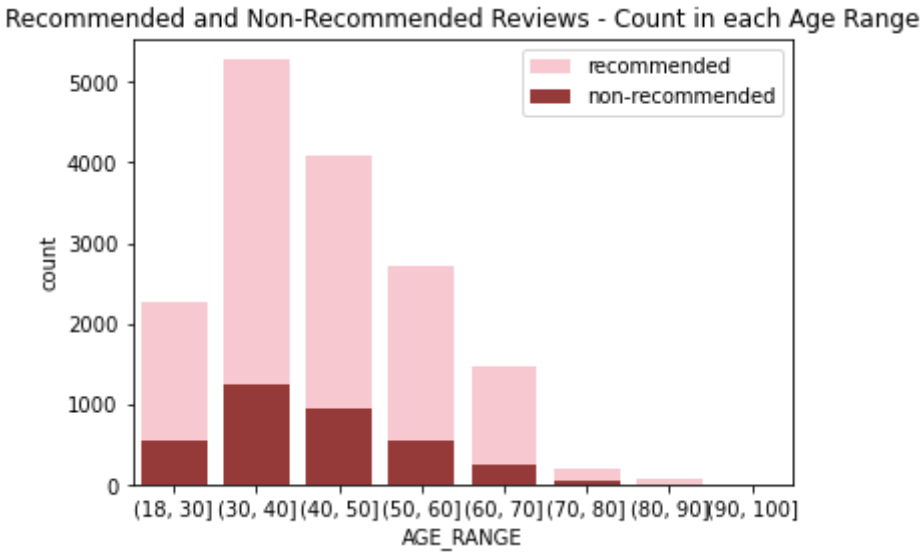
Out[49]:
```
(30, 40]     6526
(40, 50]     5018
(50, 60]     3270
(18, 30]     2802
(60, 70]     1722
(70, 80]      238
(80, 90]       74
(90, 100]       8
Name: AGE_RANGE, dtype: int64
```

In [50]:
```
clients_recommended = df[df['Recommended IND']==1]
clients_not_recommended = df[df['Recommended IND']==0]
```

In [51]:
```
fig = plt.figure(figsize=(13, 9))


plt.subplot2grid((2, 2), (0, 1))
sns.countplot(clients_recommended['AGE_RANGE'],color='pink',alpha=1,label="recommend
```

```
sns.countplot(clients_not_recommended['AGE_RANGE'],color='brown',alpha=1,label="non-
plt.title("Recommended and Non-Recommended Reviews - Count in each Age Range")
plt.legend(loc='best')
```

Out[51]: <matplotlib.legend.Legend at 0x1438fb51cd0>



By looking at the above figure, we can state that customers in their 30s left the highest number of reviews, followed by customers in their 40s and 50s

In [52]:
```
recommended_age = clients_recommended[clients_recommended['Age']> 29 ]
not_recommended_age =clients_not_recommended[clients_not_recommended['Age']> 29 ]
```

In [53]:
```
recommended_age = clients_recommended[clients_recommended['Age']< 41 ]
not_recommended_age = clients_not_recommended[clients_not_recommended['Age']< 41 ]
```

In [54]:
```
recommended_age ['AGE_RANGE']=pd.cut(x=df['Age'],bins
=[30,40])
not_recommended_age ['AGE_RANGE']=pd.cut(x=df['Age'],bins
=[30,40])
```

In [55]:
```
not_recommended_age['AGE_RANGE'].value_counts()
```

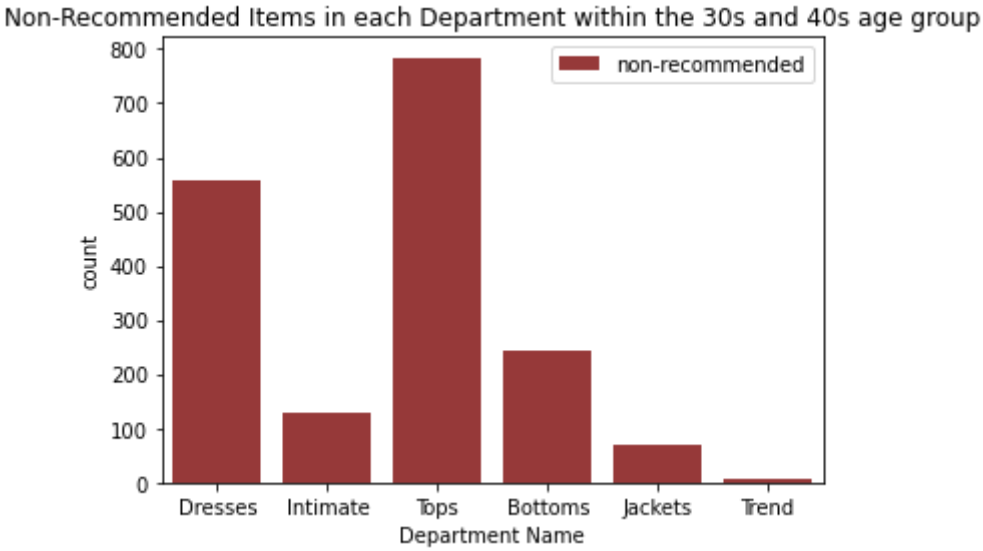
Out[55]:
```
(30, 40]    1248
Name: AGE_RANGE, dtype: int64
```

In [56]:
```
recommended_age['AGE_RANGE'].value_counts()
```

Out[56]:
```
(30, 40]    5278
Name: AGE_RANGE, dtype: int64
```

In [57]:
```
fig = plt.figure(figsize=(13, 9))


plt.subplot2grid((2, 2), (0, 1))

sns.countplot(not_recommended_age['Department Name'],color='brown',alpha=1,label="no
plt.title("Non-Recommended Items in each Department within the 30s and 40s age group
plt.legend(loc='best')
```

Out[57]: <matplotlib.legend.Legend at 0x1438f764a30>



In [58]:
```
not_recommended_age['Department Name'].value_counts()
counts = not_recommended_age['Department Name'].value_counts()
percent = not_recommended_age['Department Name'].value_counts(normalize=True)
percent100 = not_recommended_age['Department Name'].value_counts(normalize=True).mul
pd.DataFrame({'Frequency': counts, 'Percentage': percent100})
```

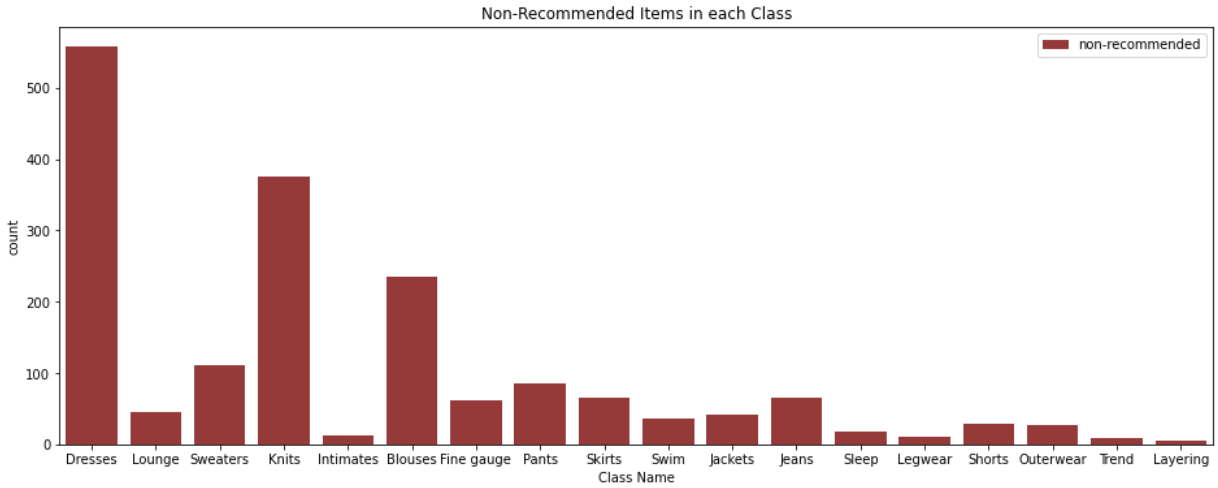
Out[58]:

	Frequency	Percentage
Tops	783	43.7%
Dresses	558	31.2%
Bottoms	244	13.6%
Intimate	129	7.2%
Jackets	69	3.9%
Trend	8	0.4%

We can clearly observe that the Tops (43.7%) and Dresses (31.2%) departments have the highest number of non-recommendations within the (30,40] age group. Items in the Jackets and Trend departments received the fewest negative reviews.

In [59]:
```
fig = plt.figure(figsize=(35, 13))


plt.subplot2grid((2, 2), (0, 1))

sns.countplot(not_recommended_age['Class Name'],color='brown',alpha=1,label="non-rec
plt.title("Non-Recommended Items in each Class")
plt.legend(loc='best')
```

Out[59]:
```
<matplotlib.legend.Legend at 0x1438f834970>
```



3. Data Preparation phase

In [60]:
```
df = pd.read_csv(r"C:\Users\alinu\Womens Clothing E-Commerce Reviews\Womens Clothing
```

In [61]:
```
del df["Unnamed: 0"]
```

In [62]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23486 entries, 0 to 23485
Data columns (total 10 columns):
 #   Column                   Non-Null Count  Dtype 
---  ------                   --------------  ----- 
 0   Clothing ID              23486 non-null  int64 
 1   Age                      23486 non-null  int64 
 2   Title                    19676 non-null  object
 3   Review Text              22641 non-null  object
 4   Rating                   23486 non-null  int64 
 5   Recommended IND          23486 non-null  int64 
 6   Positive Feedback Count  23486 non-null  int64 
 7   Division Name            23472 non-null  object
 8   Department Name          23472 non-null  object
 9   Class Name               23472 non-null  object
dtypes: int64(5), object(5)
memory usage: 1.8+ MB
```

In [63]:
```
df['Review Text'].fillna('unknown', inplace=True)
```

In [64]:
```
df_null=df.isnull()
df_null.sum()
```

Out[64]:
```
Clothing ID                  0
Age                          0
Title                     3810
Review Text                  0
Rating                       0
Recommended IND              0
Positive Feedback Count      0
Division Name               14
Department Name             14
Class Name                  14
dtype: int64
```

In [65]:
```
# Importing the list of stopwords
stop_list = text.ENGLISH_STOP_WORDS

# Text cleaning function
def remove_noise(text_input):
```

```
    # Make lowercase
    text_input = text_input.apply(lambda x: " ".join(x.lower() for x in x.split()))

    # Remove extra whitespaces
    text_input = text_input.apply(lambda x: " ".join(x.strip() for x in x.split()))

    # Remove special characters
    text_input = text_input.apply(lambda x: "".join([" " if ord(i) < 32 or ord(i) >

    # Remove punctuation
    text_input = text_input.str.replace('[^\w\s]', '')

    # Remove numbers
    text_input = text_input.str.replace('\d+', '')

    # Remove Stopwords
    text_input = text_input.apply(lambda x: ' '.join([word for word in x.split() if

    # Convert to string
    text_input = text_input.astype(str)

    return text_input
```

In [66]:
```
# Applying noise removal function to data
df['Cleaned Review Text'] = remove_noise(df['Review Text'])
df.head()
```

Out[66]:

	Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name	
0	767	33	NaN	Absolutely wonderful - silky and sexy and comf...	4	1	0	Initmates	Intimate	I
1	1080	34	NaN	Love this dress! it's sooo pretty. i happene...	5	1	4	General	Dresses	
2	1077	60	Some major design flaws	I had such high hopes for this dress and reall...	3	0	0	General	Dresses	
3	1049	50	My favorite buy!	I love, love, love this jumpsuit. it's fun, fl...	5	1	0	General Petite	Bottoms	
4	847	47	Flattering shirt	This shirt is very flattering to all due to th...	5	1	6	General	Tops	

In [67]:
```
# Instantiate the Word tokenizer & Word lemmatizer
```

```
w_tokenizer = nltk.tokenize.WhitespaceTokenizer()
lemmatizer = nltk.stem.WordNetLemmatizer()

# Define the word lemmatizer function
def lemmatize_text(text):
    return [lemmatizer.lemmatize(w) for w in w_tokenizer.tokenize(text)]

# Apply the word lemmatizer function to data
df['Cleaned Review Text'] = df['Cleaned Review Text'].apply(lemmatize_text)
df.head()
```

Out[67]:

	Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name	
0	767	33	NaN	Absolutely wonderful - silky and sexy and comf...	4	1	0	Initmates	Intimate	In
1	1080	34	NaN	Love this dress! it's sooo pretty. i happene...	5	1	4	General	Dresses	
2	1077	60	Some major design flaws	I had such high hopes for this dress and reall...	3	0	0	General	Dresses	
3	1049	50	My favorite buy!	I love, love, love this jumpsuit. it's fun, fl...	5	1	0	General Petite	Bottoms	
4	847	47	Flattering shirt	This shirt is very flattering to all due to th...	5	1	6	General	Tops	

In [68]:
```
# Getting a count of words from the documents - Bag of Words
cvec = CountVectorizer(min_df=.005, max_df=.9, ngram_range=(1,2), tokenizer=lambda d
cvec.fit(df['Cleaned Review Text'])
```

Out[68]:
```
CountVectorizer(lowercase=False, max_df=0.9, min_df=0.005, ngram_range=(1, 2),
                tokenizer=<function <lambda> at 0x000001438F778670>)
```

In [69]:
```
len(cvec.vocabulary_)
```

Out[69]:
```
886
```

In [70]:
```
print(sorted(cvec.vocabulary_))
```

```
['able', 'absolutely', 'absolutely love', 'actually', 'add', 'added', 'addition', 'a
dorable', 'adore', 'ago', 'agree', 'agree reviewer', 'airy', 'aline', 'amazing', 'an
kle', 'appears', 'appropriate', 'area', 'arent', 'arm', 'arm hole', 'armhole', 'arri
ved', 'athletic', 'available', 'away', 'awesome', 'awkward', 'b', 'baby', 'bad', 'ba
g', 'baggy', 'band', 'barely', 'based', 'based review', 'basic', 'bc', 'beach', 'bea
utiful', 'beautiful color', 'beautiful dress', 'beautifully', 'believe', 'belly', 'b
```

```
elt', 'best', 'better', 'better person', 'big', 'bigger', 'bit', 'bit large', 'blac
k', 'blazer', 'blouse', 'blue', 'blue color', 'bodice', 'body', 'body type', 'boot',
'booty', 'bottom', 'bought', 'bought dress', 'bought size', 'boxy', 'bra', 'brand',
'bright', 'broad', 'broad shoulder', 'brown', 'build', 'bulky', 'bust', 'busty', 'bu
tt', 'button', 'buy', 'buying', 'c', 'came', 'cami', 'cami underneath', 'camisole',
'cardigan', 'care', 'case', 'casual', 'caught', 'chance', 'cheap', 'chest', 'cheste
d', 'chic', 'classic', 'classy', 'clean', 'clingy', 'close', 'closet', 'clothes', 'c
lothing', 'coat', 'cold', 'collar', 'color', 'color beautiful', 'color great', 'colo
r nice', 'color vibrant', 'colored', 'come', 'comfort', 'comfortable', 'comfortable
flattering', 'comfy', 'complaint', 'completely', 'compliment', 'considering', 'coo
l', 'cooler', 'cotton', 'couple', 'cover', 'coverage', 'cozy', 'cream', 'cropped',
'cuff', 'cup', 'curve', 'curvy', 'cut', 'cute', 'd', 'dark', 'darker', 'daughter',
'day', 'dd', 'deal', 'decided', 'deep', 'definitely', 'definitely recommend', 'delic
ate', 'denim', 'depending', 'description', 'design', 'despite', 'detail', 'detailin
g', 'did', 'didnt', 'didnt work', 'different', 'difficult', 'dinner', 'disappointe
d', 'disappointing', 'doe', 'doe run', 'doesnt', 'doesnt look', 'dont', 'dont like',
'dont think', 'dot', 'drape', 'dress', 'dress beautiful', 'dress comfortable', 'dres
s fit', 'dress flattering', 'dress great', 'dress just', 'dress look', 'dress perfec
t', 'dress run', 'dress wear', 'dressed', 'dressy', 'dry', 'easily', 'easy', 'easy w
ear', 'edge', 'elastic', 'elegant', 'embroidery', 'end', 'ended', 'especially', 'eve
ning', 'event', 'exactly', 'excellent', 'exchange', 'excited', 'expect', 'expected',
'expecting', 'expensive', 'extra', 'extra small', 'extremely', 'eye', 'fabric', 'fab
ric nice', 'fabric soft', 'fabulous', 'fact', 'fairly', 'fall', 'fan', 'fantastic',
'far', 'favorite', 'feel', 'feel like', 'feeling', 'fell', 'fell love', 'felt', 'fel
t like', 'feminine', 'figure', 'finally', 'finding', 'fine', 'fit', 'fit better', 'f
it fine', 'fit flattering', 'fit great', 'fit just', 'fit like', 'fit little', 'fit
nicely', 'fit perfect', 'fit perfectly', 'fit true', 'fit tt', 'fitted', 'fitting',
'flare', 'flat', 'flattering', 'flattering fit', 'flaw', 'floral', 'flow', 'flower',
'flowy', 'foot', 'forgiving', 'form', 'form fitting', 'forward', 'frame', 'friend',
'frumpy', 'fun', 'gave', 'generally', 'getting', 'girl', 'give', 'given', 'glad', 'g
lad did', 'glove', 'go', 'going', 'gold', 'gone', 'good', 'good quality', 'gorgeou
s', 'got', 'got compliment', 'got size', 'gotten', 'gray', 'great', 'great color',
'great dress', 'great fit', 'great jean', 'great quality', 'green', 'green color',
'grey', 'guess', 'half', 'hand', 'hang', 'hanging', 'happy', 'happy purchase', 'har
d', 'havent', 'having', 'heavier', 'heavy', 'heel', 'height', 'help', 'hem', 'hide',
'high', 'high quality', 'higher', 'highly', 'highly recommend', 'hip', 'hit', 'hit j
ust', 'hit right', 'hold', 'hole', 'holiday', 'home', 'hope', 'hoping', 'hot', 'hou
r', 'hourglass', 'house', 'hug', 'huge', 'hung', 'husband', 'id', 'idea', 'ill', 'i
m', 'im glad', 'im going', 'im happy', 'im lb', 'im normally', 'im sure', 'im usuall
y', 'imagine', 'immediately', 'inch', 'incredibly', 'inside', 'instead', 'interestin
g', 'isnt', 'issue', 'itchy', 'item', 'ive', 'ive worn', 'ivory', 'jacket', 'jean',
'jumpsuit', 'just', 'just didnt', 'just knee', 'just like', 'just right', 'justice',
'keeper', 'keeping', 'kept', 'kind', 'knee', 'knew', 'knit', 'know', 'l', 'lace', 'l
ady', 'large', 'large fit', 'larger', 'larger size', 'lay', 'layer', 'layering', 'l
b', 'lb ordered', 'leather', 'left', 'leg', 'legging', 'length', 'length perfect',
'let', 'life', 'light', 'light weight', 'lighter', 'lightweight', 'like', 'like dres
s', 'like glove', 'like model', 'like picture', 'like reviewer', 'like wearing', 'li
ked', 'line', 'lined', 'linen', 'lining', 'little', 'little big', 'little bit', 'lit
tle large', 'live', 'local', 'local retailer', 'local store', 'long', 'long sleeve',
'long torso', 'longer', 'look', 'look better', 'look cute', 'look good', 'look grea
t', 'look like', 'looked', 'looked like', 'looking', 'loose', 'looser', 'lot', 'lot
compliment', 'love', 'love color', 'love design', 'love dress', 'love fit', 'love lo
ok', 'love love', 'love pant', 'love shirt', 'love sweater', 'loved', 'lovely', 'lo
w', 'lower', 'm', 'maeve', 'mail', 'make', 'make feel', 'make look', 'making', 'matc
h', 'material', 'material soft', 'maternity', 'maxi', 'maybe', 'mean', 'meant', 'med
ium', 'medium fit', 'mentioned', 'mid', 'middle', 'mind', 'model', 'money', 'month',
'motif', 'narrow', 'natural', 'navy', 'neck', 'necklace', 'neckline', 'need', 'neede
d', 'neutral', 'new', 'nice', 'nicely', 'night', 'normal', 'normal size', 'normall
y', 'normally wear', 'note', 'noticed', 'nude', 'occasion', 'odd', 'office', 'ok',
'old', 'online', 'open', 'opinion', 'option', 'orange', 'order', 'order size', 'orde
red', 'ordered medium', 'ordered online', 'ordered petite', 'ordered size', 'ordered
small', 'ordered usual', 'ordered x', 'ordering', 'originally', 'outfit', 'overall',
'oversized', 'p', 'pair', 'paired', 'pant', 'party', 'past', 'pattern', 'people', 'p
eplum', 'perfect', 'perfect fit', 'perfect length', 'perfect summer', 'perfectly',
'person', 'petite', 'petite fit', 'petite size', 'photo', 'pic', 'picture', 'picture
d', 'piece', 'pilcro', 'pink', 'place', 'plan', 'pleased', 'pleat', 'plenty', 'plu
s', 'pocket', 'point', 'pop', 'portion', 'pound', 'prefer', 'pregnant', 'prettier',
'pretty', 'previous', 'previous reviewer', 'price', 'print', 'probably', 'problem',
'product', 'pull', 'pulled', 'purchase', 'purchased', 'purchasing', 'purple', 'quali
```

```
ty', 'quality fabric', 'quite', 'ran', 'read', 'read review', 'reading', 'real', 're
ally', 'really cute', 'really like', 'really love', 'really nice', 'really pretty',
'really wanted', 'reason', 'received', 'received compliment', 'recently', 'recommen
d', 'red', 'reference', 'reference im', 'regular', 'regular size', 'relaxed', 'res
t', 'retailer', 'retailer top', 'return', 'returned', 'returning', 'review', 'review
er', 'reviewer said', 'rich', 'right', 'rise', 'romper', 'room', 'roomy', 'ruffle',
'run', 'run big', 'run bit', 'run large', 'run little', 'run small', 'run true', 'ru
nning', 's', 'sad', 'sadly', 'said', 'sale', 'sale price', 'sandal', 'saw', 'saw onl
ine', 'saw store', 'say', 'scratchy', 'seam', 'season', 'second', 'seen', 'seethroug
h', 'send', 'sewn', 'sexy', 'shade', 'shape', 'sheer', 'shirt', 'short', 'shorter',
'shoulder', 'show', 'showing', 'shown', 'shrink', 'side', 'silhouette', 'silk', 'sil
ky', 'similar', 'simple', 'simply', 'size', 'size fit', 'size im', 'size large', 'si
ze medium', 'size ordered', 'size s', 'size size', 'size small', 'size smaller', 'si
ze x', 'sized', 'sizing', 'skin', 'skinny', 'skinny jean', 'skirt', 'sleeve', 'slend
er', 'slight', 'slightly', 'slim', 'slimming', 'slip', 'slit', 'small', 'small fit',
'small medium', 'smaller', 'smaller size', 'snag', 'snug', 'soft', 'soft comfortabl
e', 'sold', 'solid', 'somewhat', 'soon', 'sort', 'special', 'spot', 'spring', 'stan
d', 'staple', 'star', 'stay', 'stiff', 'stitching', 'stock', 'stomach', 'store', 'st
raight', 'strange', 'strap', 'stretch', 'stretchy', 'stripe', 'structured', 'stunnin
g', 'style', 'styling', 'stylish', 'substantial', 'subtle', 'suit', 'summer', 'supe
r', 'super comfortable', 'super comfy', 'super cute', 'super flattering', 'super sof
t', 'sure', 'surprise', 'surprised', 'sweater', 'sweatshirt', 'swing', 'swingy',
't', 'tad', 'tag', 'tailored', 'tall', 'taller', 'tank', 'tee', 'tell', 'tent', 'tex
ture', 'th', 'thats', 'there', 'theyre', 'thicker', 'thigh', 'thing', 'think', 'thin
king', 'thought', 'thread', 'throw', 'tie', 'tight', 'tights', 'time', 'tiny', 'toda
y', 'ton', 'took', 'top', 'torso', 'totally', 'touch', 'transition', 'tried', 'tried
store', 'true', 'true size', 'truly', 'try', 'trying', 'tshirt', 'tt', 'tucked', 'tu
mmy', 'tunic', 'type', 'typical', 'typically', 'typically wear', 'uncomfortable', 'u
nderneath', 'unflattering', 'unfortunately', 'unique', 'unknown', 'unless', 'upper',
'use', 'used', 'usual', 'usual size', 'usually', 'usually size', 'usually wear',
'v', 'versatile', 'version', 'vest', 'vibrant', 'w', 'waist', 'waistband', 'waiste
d', 'wait', 'wait wear', 'want', 'want wear', 'wanted', 'wanted love', 'wardrobe',
'warm', 'wash', 'washed', 'washing', 'wasnt', 'wasnt sure', 'way', 'wear', 'wear cam
i', 'wear dress', 'wear medium', 'wear size', 'wear small', 'wear work', 'wear x',
'wearing', 'weather', 'wedding', 'wedge', 'week', 'weekend', 'weight', 'weird', 'wen
t', 'white', 'wide', 'wider', 'winter', 'wish', 'woman', 'wonderful', 'wont', 'woo
l', 'wore', 'work', 'worked', 'worn', 'worried', 'worth', 'worth price', 'wouldnt',
'wrinkle', 'wrong', 'x', 'x fit', 'x petite', 'x s', 'xl', 'xx', 'year', 'yellow',
'yes', 'yesterday', 'youre', 'zip', 'zipper']
```

In [71]:
```
# Creating the bag-of-words representation
cvec_counts = cvec.transform(df['Cleaned Review Text'])
```

In [72]:
```
print(cvec_counts.shape)
print(cvec_counts.toarray())
```

```
(23486, 886)
[[0 1 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 1 1]
 ...
 [1 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```

In [73]:
```
# Instantiating the TfidfTransformer
transformer = TfidfTransformer()

# Transforming
transformed_weights = transformer.fit_transform(cvec_counts)
transformed_weights
```

Out[73]:
```
<23486x886 sparse matrix of type '<class 'numpy.float64'>'
        with 473238 stored elements in Compressed Sparse Row format>
```

In [74]:
```
# Getting a list of all weights
transformed_weights = transformed_weights.toarray()
vocab = cvec.get_feature_names()
```

```
# Putting weights into a DataFrame called model
model = pd.DataFrame(transformed_weights, columns=vocab)

model.head(10)
```

Out[74]:

	able	absolutely	absolutely love	actually	add	added	addition	adorable	adore	ago	...	x s	xl
0	0.0	0.384864	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
1	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
2	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
3	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
4	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
5	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
6	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
7	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
8	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
9	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0

10 rows × 886 columns

In [75]:
```
# Merging td-idf weight model with original df dataFrame
model = pd.merge(df, model, left_index=True, right_index=True)
```

In [77]:
```
model.head()
```

Out[77]:

	Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name	
0	767	33	NaN	Absolutely wonderful - silky and sexy and comf...	4	1	0	Initmates	Intimate	Ir
1	1080	34	NaN	Love this dress! it's sooo pretty. i happene...	5	1	4	General	Dresses	
2	1077	60	Some major design flaws	I had such high hopes for this dress and reall...	3	0	0	General	Dresses	
3	1049	50	My favorite buy!	I love, love, love this jumpsuit. it's fun, fl...	5	1	0	General Petite	Bottoms	

	Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name
4	847	47	Flattering shirt	This shirt is very flattering to all due to th...	5	1	6	General	Tops

5 rows × 897 columns

In [79]:
```
# Drop all columns not part of the text matrix
ml_model = model.drop(['Review Text', 'Cleaned Review Text','Clothing ID','Age','Tit

# Create X & y variables

y = ml_model['Recommended IND']

X = ml_model.drop('Recommended IND', axis=1)

# split the data into test and train by maintaining same distribution of output vara
X_train, X_test, y_train, y_test = train_test_split(X,y, stratify=y,test_size=0.15,r

# split the train data into train and cross validation by maintaining same distribut
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, stratify=y_train,
```

In [80]:
```
X
```

Out[80]:

	able	absolutely	absolutely love	actually	add	added	addition	adorable	adore	ago	...
0	0.000000	0.384864	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
2	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
3	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
4	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
...	...	...	...	...	...	...	...	...	...	...	...
23481	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
23482	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
23483	0.334141	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
23484	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
23485	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...

23486 rows × 886 columns

In [81]:
```
y
```

Out[81]:
```
0        1
1        1
2        0
3        1
```

```
4        1
        ..
23481    1
23482    1
23483    0
23484    1
23485    1
Name: Recommended IND, Length: 23486, dtype: int64
```

4. Modelling phase

A. Random forest

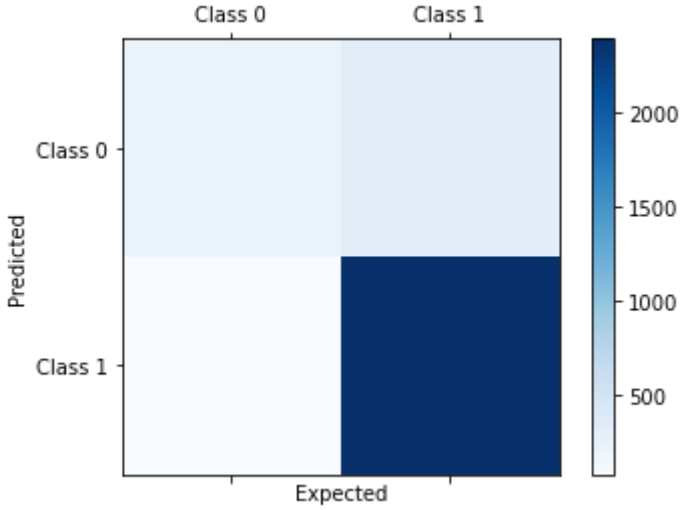
In [82]:
```
rf= RandomForestClassifier(n_estimators=200, class_weight='balanced').fit(X_train, y
```

In [83]:
```
from sklearn.metrics import roc_curve

# predict probabilities
pred_prob2d = rf.predict_proba(X_cv)

#roc for model
fpr2d, tpr2d, thresh2d = roc_curve(y_cv,pred_prob2d[:,1], pos_label=1)

#roc curve for tpr=fpr
random_probs = [0 for i in range(len(y_cv))]
p_fpr, p_tpr, _ = roc_curve(y_cv, random_probs, pos_label=1)

auc_score2d = roc_auc_score(y_cv, pred_prob2d[:,1])

print(auc_score2d)
```

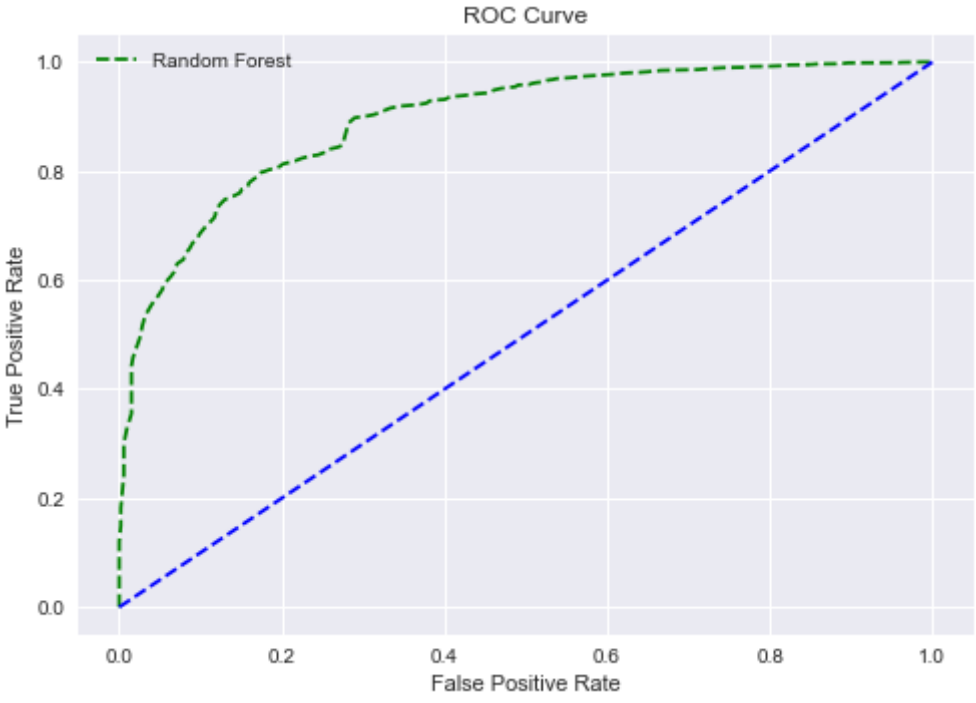
```
0.8945380350999301
```

In [84]:
```
sentiment_predict(rf,X_train,y_train,X_cv,y_cv,y,"RF")
```

```
RandomForestClassifier(class_weight='balanced', n_estimators=200)

Classification report :
              precision    recall  f1-score   support

           0       0.75      0.41      0.53       532
           1       0.88      0.97      0.93      2463

    accuracy                           0.87      2995
   macro avg       0.82      0.69      0.73      2995
weighted avg       0.86      0.87      0.85      2995

Accuracy score: 0.8707846410684474
Precision score: 0.8835920177383592
Recall score: 0.9707673568818515
Unique predictions: [0 1]
Confusion matrix:
 [[ 217  315]
 [  72 2391]]
```



In [85]:
```
import matplotlib.pyplot as plt
plt.style.use ('seaborn')

#plot rox curves

plt.plot(fpr2d, tpr2d, linestyle='--', color='green', label='Random Forest' )

plt.plot(p_fpr, p_tpr, linestyle='--', color='blue' )

#title
plt.title('ROC Curve')

# X label
plt.xlabel('False Positive Rate')

# Y label
plt.ylabel('True Positive Rate')

plt.legend(loc='best')
plt.savefig('ROC',dpi=300)
plt.show()
```



Cross Validation KFold Random Forest

In [86]:
```
# prepare the cross-validation procedure
cv = KFold(n_splits=10, random_state=None)
```

In [87]:
```
scores2 = cross_val_score(rf, X_train, y_train, scoring='roc_auc', cv=cv, n_jobs=-1)
scores2
```

Out[87]:
```
array([0.89499811, 0.900434  , 0.88047498, 0.9065182 , 0.90253516,
       0.87854598, 0.8833874 , 0.88499139, 0.90435293, 0.88930537])
```

In [88]:
```
# report performance
print('AUC Performance: %.3f (%.3f)' % (mean(scores2), std(scores2)))
```

```
AUC Performance: 0.893 (0.010)
```

B. Naive Bayes

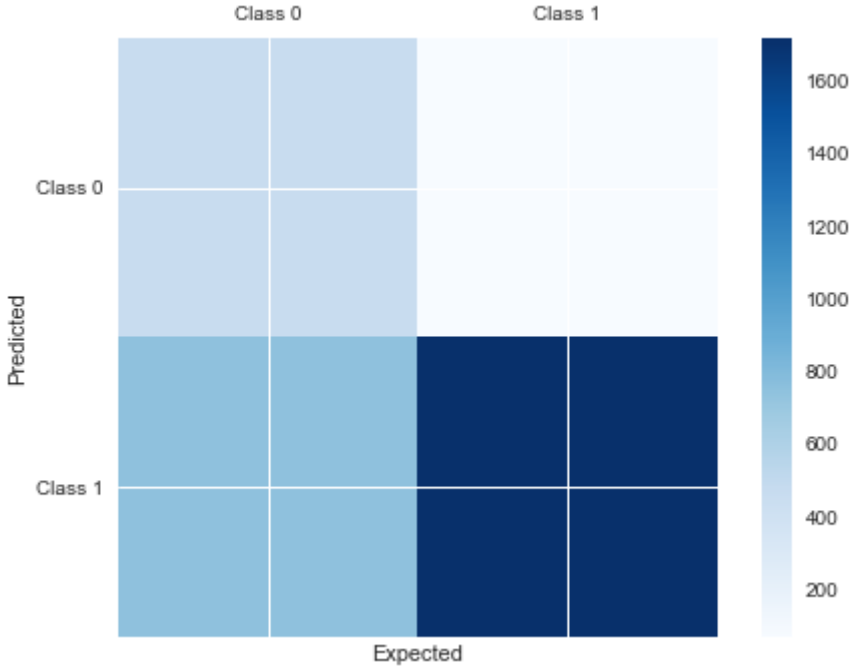
In [89]:
```
gnb = GaussianNB().fit(X_train, y_train)
```

In [90]:
```
from sklearn.metrics import roc_curve

# predict probabilities
pred_prob2e = gnb.predict_proba(X_cv)

#roc for model
fpr2e, tpr2e, thresh2e = roc_curve(y_cv,pred_prob2e[:,1], pos_label=1)

#roc curve for tpr=fpr
random_probs = [0 for i in range(len(y_cv))]
p_fpr, p_tpr, _ = roc_curve(y_cv, random_probs, pos_label=1)

auc_score2e = roc_auc_score(y_cv, pred_prob2e[:,1])

print(auc_score2e)
```

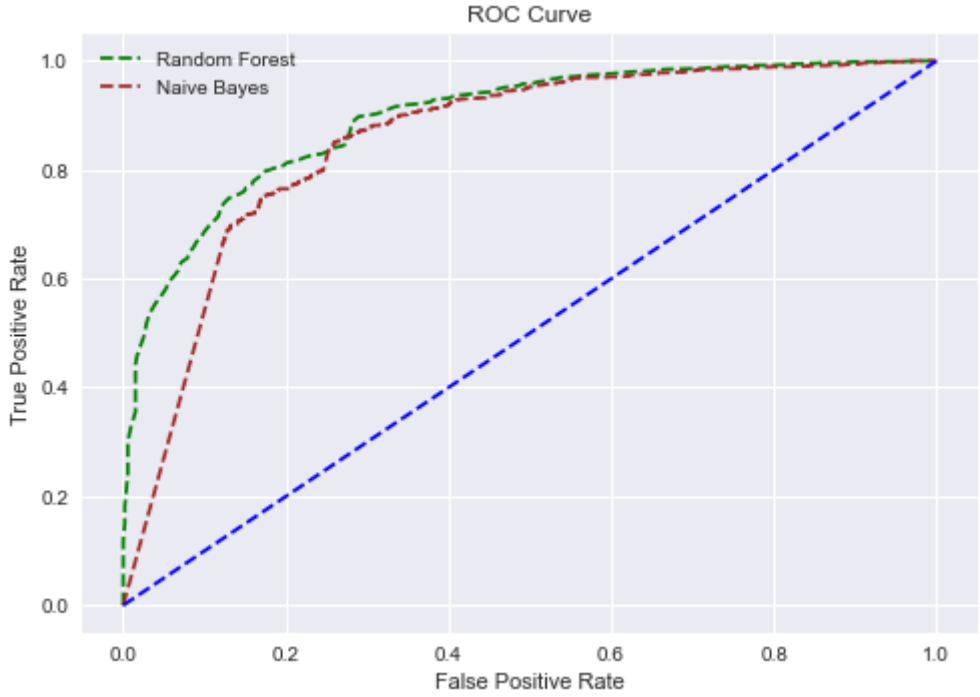
```
0.8542069241312783
```

In [91]:
```
sentiment_predict(gnb,X_train,y_train,X_cv,y_cv,y,"GNB")
```

```
GaussianNB()

Classification report :
              precision    recall  f1-score   support

           0       0.38      0.87      0.53       532
           1       0.96      0.70      0.81      2463

    accuracy                           0.73      2995
   macro avg       0.67      0.78      0.67      2995
weighted avg       0.86      0.73      0.76      2995

Accuracy score: 0.7275459098497495
Precision score: 0.9608282036933408
Recall score: 0.6971173365814048
Unique predictions: [0 1]
Confusion matrix:
 [[ 462   70]
 [ 746 1717]]
```



In [92]:
```
import matplotlib.pyplot as plt
plt.style.use ('seaborn')

#plot rox curves

plt.plot(fpr2d, tpr2d, linestyle='--', color='green', label='Random Forest' )

plt.plot(fpr2e, tpr2e, linestyle='--', color='brown', label='Naive Bayes' )

plt.plot(p_fpr, p_tpr, linestyle='--', color='blue' )

#title
plt.title('ROC Curve')

# X label
plt.xlabel('False Positive Rate')

# Y label
plt.ylabel('True Positive Rate')

plt.legend(loc='best')
plt.savefig('ROC',dpi=300)
plt.show()
```



Cross Validation KFold Naive Bayes

In [93]:
```
# prepare the cross-validation procedure
cv = KFold(n_splits=10, random_state=None)
```

In [94]:
```
scores2 = cross_val_score(gnb, X_train, y_train, scoring='roc_auc', cv=cv, n_jobs=-1
scores2
```

Out[94]:
```
array([0.85088468, 0.84933345, 0.84236856, 0.8473518 , 0.85141578,
       0.83672898, 0.84082704, 0.83529252, 0.84644801, 0.84631891])
```

In [95]:
```
# report performance
print('AUC Performance: %.3f (%.3f)' % (mean(scores2), std(scores2)))
```

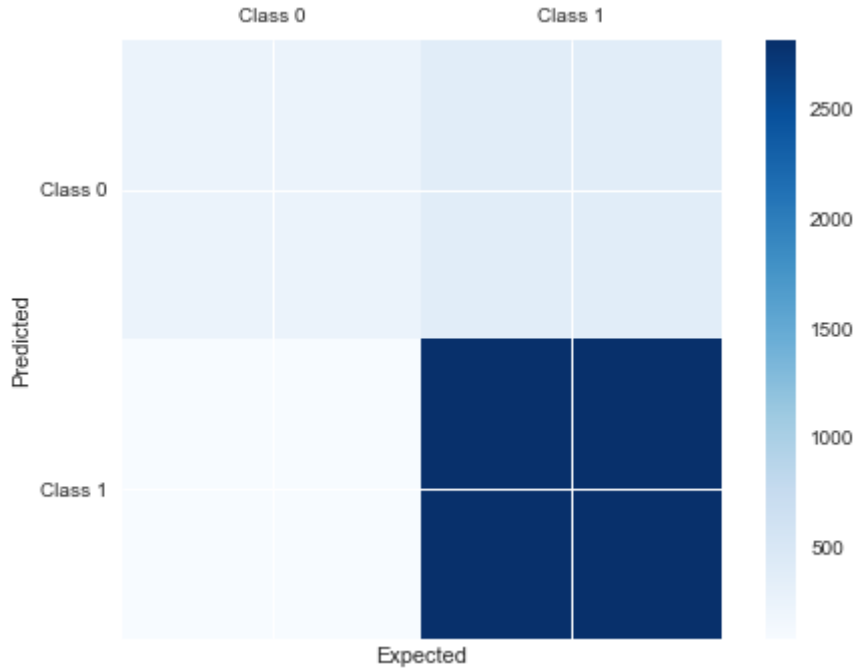
```
AUC Performance: 0.845 (0.005)
```

5. Evaluation phase

1. Random Forest Evaluation

In [96]:
```
sentiment_predict(rf,X_train,y_train,X_test,y_test,y,"RF")
```

```
RandomForestClassifier(class_weight='balanced', n_estimators=200)

Classification report :
              precision    recall  f1-score   support

           0       0.75      0.40      0.53       626
           1       0.88      0.97      0.93      2897

    accuracy                           0.87      3523
   macro avg       0.82      0.69      0.73      3523
weighted avg       0.86      0.87      0.85      3523

Accuracy score: 0.8705648594947488
Precision score: 0.8829620332601192
Recall score: 0.9713496720745599
Unique predictions: [0 1]
Confusion matrix:
 [[ 253  373]
 [  83 2814]]
```



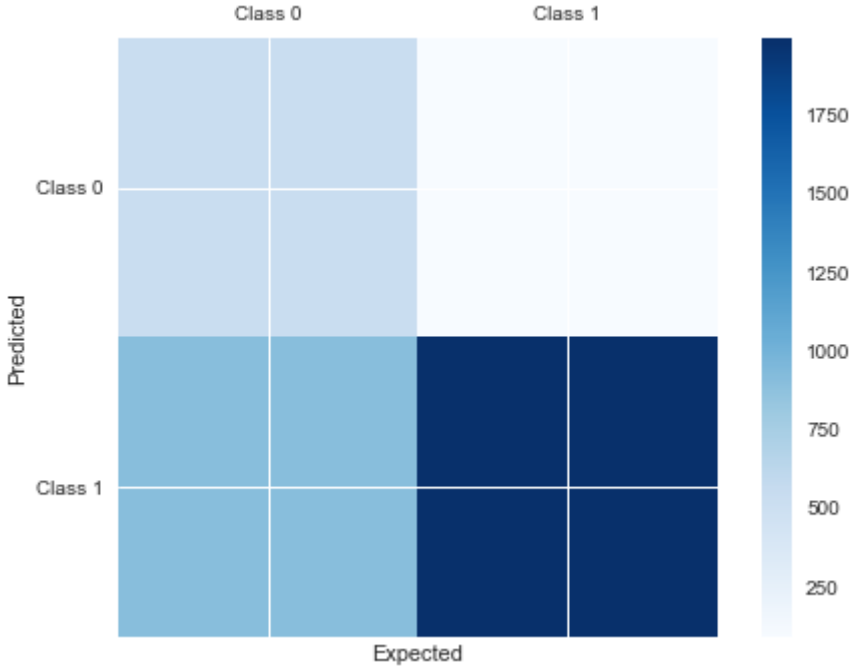
In [97]:
```
from sklearn.metrics import roc_curve

# predict probabilities
pred_prob2d_test = rf.predict_proba(X_test)

#roc for model
fpr2d_test, tpr2d_test, thresh2d_test = roc_curve(y_test,pred_prob2d_test[:,1], pos_

#roc curve for tpr=fpr
random_probs = [0 for i in range(len(y_test))]
p_fpr, p_tpr, _ = roc_curve(y_test, random_probs, pos_label=1)

auc_score2d_test = roc_auc_score(y_test, pred_prob2d_test[:,1])

print(auc_score2d_test)
```

```
0.9029843586126884
```

2. Naive Bayes Evaluation

In [98]:
```
sentiment_predict(gnb,X_train,y_train,X_test,y_test,y,"GNB")
```

```
GaussianNB()

Classification report :
              precision    recall  f1-score   support

           0       0.37      0.86      0.52       626
           1       0.96      0.69      0.80      2897

    accuracy                           0.72      3523
   macro avg       0.66      0.77      0.66      3523
weighted avg       0.85      0.72      0.75      3523

Accuracy score: 0.7184217996026114
Precision score: 0.9568345323741008
Recall score: 0.6886434242319641
Unique predictions: [0 1]
Confusion matrix:
 [[ 536   90]
 [ 902 1995]]
```



In [99]:
```
from sklearn.metrics import roc_curve

# predict probabilities
pred_prob2e_test = gnb.predict_proba(X_test)

#roc for model
fpr2e_test, tpr2e_test, thresh2e_test = roc_curve(y_test,pred_prob2e_test[:,1], pos_

#roc curve for tpr=fpr
random_probs = [0 for i in range(len(y_test))]
p_fpr, p_tpr, _ = roc_curve(y_test, random_probs, pos_label=1)

auc_score2e_test = roc_auc_score(y_test, pred_prob2e_test[:,1])

print(auc_score2e_test)
```

```
0.8463966800513034
```