Phase-4_Project

November 20, 2022

1 Text Sentiment

Phase 4 Project This project was a collaboration between * Benito Ywani * Patrick Arnold * Ahmad Samiee

1.1 Project Overview

In this project we measured text content sentiment in Twitter for two technology firms. Using natural langguage processing (NLP) methods, we generated models to make predictiions for ternary (negative, neutral and positive) classification output.

1.2 Technical Summary

Our best model for Twitter sentiment prediction was Support Vector Classification which gave an overal accuracy of about 67%. The model under-predicted for all three classifications relative to actual for both firms. It missed predicting correctly negative sentiment the most followed by positive and then neutral. This may be because the dataset contained the fewest negative sentiment tweets. There were a moderate number of positive tweets and the most were neutral tweets. However, our model was able to correctly predict the overall trend for classification ratios where tweets with neutral sentiment had the highest ratio followed by positive and then negative. In addition, our model was able to correctly predict which of the two firms had a higher positive sentiment.

1.3 Business Problem

Our stakeholder an equity investment firm is considering to purchase equity in a technology compnay and they have narrowed down their selection between two compnaies. As an additional analysis tool they like to take a look at (potential customer) sentiment toward these two final selections. Therefore, they want a machine learning model that can predict sentiment in social media paltform like Twitter and also want to know how acurrately it can predict sentiment.

1.4 Master Dataset

The data comes from CrowdFlower via data.world which are tweets from Twitter collected during 2011 at South by Southwest Conference. It consists of about 9000 tweets and the tweet sentiments are labelled as negative, neutral or positive.

1.5 EDA and Feature Engineering

Created a column to identify whether the tweet was about Apple, Google or neither. Duplicated tweets, tweets for which there is no sentiment label and tweets that were neither about Apple or

Google were dropped. Created another column to convert text sentiment into a numerical where 0 is for negative, 1 for neutral and 2 for positive sentiment. The cleaned data was then split into apple and google dataframes. These were then split into train (60% of data) and test (40%) dataframes where the three classification ratios for sentiment were split proportionally. The trained datasets for apple and google were combined into a single dataframe to be used for model training. The tweet text was then processed for natural language processing(NLP) as described in nlp_doc_preparer function.

[2]:
```
# Load all the libraries

import pandas as pd
import numpy as np
import string
import re
import time

import matplotlib.pyplot as plt
import seaborn as sns

import nltk
from nltk.tokenize import RegexpTokenizer
from nltk.corpus import stopwords, wordnet
from nltk import pos_tag
from nltk.stem import WordNetLemmatizer
from nltk.probability import FreqDist
from nltk.tokenize import word_tokenize

from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, recall_score,precision_score,␣
↪confusion_matrix
from sklearn.metrics import make_scorer
from sklearn.metrics import plot_confusion_matrix
from sklearn.dummy import DummyClassifier
from imblearn.over_sampling import SMOTE
from imblearn.over_sampling import RandomOverSampler

%matplotlib inline
```

[3]:
```python
# Read file
filename = 'data/judge-1377884607_tweet_product_company.csv'

sentiments_df = pd.read_csv(filename, encoding= 'unicode_escape')
```

[4]:
```python
# Data overview

sentiments_df.head()
```

[4]:
```
                                          tweet_text  \
0  .@wesley83 I have a 3G iPhone. After 3 hrs twe…
1  @jessedee Know about @fludapp ? Awesome iPad/i…
2  @swonderlin Can not wait for #iPad 2 also. The…
3  @sxsw I hope this year's festival isn't as cra…
4  @sxtxstate great stuff on Fri #SXSW: Marissa M…

  emotion_in_tweet_is_directed_at  \
0                          iPhone
1              iPad or iPhone App
2                            iPad
3              iPad or iPhone App
4                          Google

  is_there_an_emotion_directed_at_a_brand_or_product
0                                   Negative emotion
1                                   Positive emotion
2                                   Positive emotion
3                                   Negative emotion
4                                   Positive emotion
```

[5]:
```python
# Randomly check tweet text for a couple of rows

pd.set_option('display.max_colwidth', None)
indexes = np.random.randint(0,len(sentiments_df),6)
sentiments_df['tweet_text'].loc[indexes]
```

[5]:
```
2897     Sweet siren call of #gsdm #google party starting downstairs, but I am
wrapping #sxsw work at desk. Help me, Obi-Wan, you're my only hope!
1296                                                              My ipad 2 vs
Android panel starts at 330 at Radisson. Bloody Mary starts now! #SXSW
134                                                     #Samsung, #Sony follow
#Apple, #HP lead @mention {link} #Austin #atx #SXSW /via @mention ^rg
1443                                  Good News! Austin Eats: BBQ for iPhone is now
available - {link} #iTunes #Austin #BBQ #SXSW #SXSWi /via @mention
5105                                   RT @mention @mention @mention will have some
apple v android things going on tomorrow during the @mention #SXSW
1950    @mention also check out @mention for #Android &amp; web. Has group chat,
```

```
whiteboarding, location &amp; image sharing, and more. #app #SXSW
Name: tweet_text, dtype: object
```

[6]:
```python
# Check number of records, data types and which columns have nan

sentiments_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9093 entries, 0 to 9092
Data columns (total 3 columns):
 #   Column                                              Non-Null Count  Dtype
---  ------                                              --------------  -----
 0   tweet_text                                          9092 non-null   object
 1   emotion_in_tweet_is_directed_at                     3291 non-null   object
 2   is_there_an_emotion_directed_at_a_brand_or_product  9093 non-null   object
dtypes: object(3)
memory usage: 213.2+ KB
```

[7]:
```python
# Check values for column 'emotion_in_tweet_is_directed_at'

sentiments_df['emotion_in_tweet_is_directed_at'].value_counts()
```

[7]:
```
iPad                               946
Apple                              661
iPad or iPhone App                 470
Google                             430
iPhone                             297
Other Google product or service    293
Android App                         81
Android                             78
Other Apple product or service      35
Name: emotion_in_tweet_is_directed_at, dtype: int64
```

[8]:
```python
# Confirm number of NaN in column 'emotion_in_tweet_is_directed_at'

sentiments_df['emotion_in_tweet_is_directed_at'].isna().sum()
```

[8]:
```
5802
```

[9]:
```python
# Check values for column 'is_there_an_emotion_directed_at_a_brand_or_product'

sentiments_df['is_there_an_emotion_directed_at_a_brand_or_product'].
 ↪value_counts()
```

[9]:
```
No emotion toward brand or product    5389
Positive emotion                      2978
Negative emotion                       570
```

```
I can't tell                                    156
Name: is_there_an_emotion_directed_at_a_brand_or_product, dtype: int64
```

[10]:
```
def find_company_name(text,emotion_at):

    '''
    Go through text ('tweet_text' column) and determine whether it is about␣
↪apple or google and
    return either 'apple' or 'google' according to search.
    If cannot tell company id from text, check emotion_at␣
↪('emotion_in_tweet_is_directed_at'
    column) for comapy id. If cannot find company id return 'cannot tell'.
    '''

    revised_emotion_at = str(emotion_at).lower()


    revised_text = str(text).lower()

    apple = ['apple','iphone','ipad']
    google = ['google','android']

    apple_count = 0
    google_count = 0

    for a in apple:
        apple_count += sum(1 for _ in re.finditer(r'\b%s\b' % re.escape(a),␣
↪revised_text))

    for g in google:
        google_count += sum(1 for _ in re.finditer(r'\b%s\b' % re.escape(g),␣
↪revised_text))


    if apple_count > google_count:
        return 'apple'
    elif google_count > apple_count:
        return 'google'
    elif revised_emotion_at != 'nan' and revised_emotion_at != 'default':
        for idx, item in enumerate(revised_emotion_at.split()):
            if item in apple:
                return 'apple'
            elif item in google:
                return 'google'
            else:
                if idx == len(revised_emotion_at.split()):
                    return 'cannot tell'
```

```
    else:
        return 'cannot tell'
```

[11]:
```
# Create a new column called 'company_name' and find whether the tweet is about␣
↪apple,
# google or cannot tell using function find_company_name

sentiments_df['company_name'] = sentiments_df.apply(
    lambda s:␣
↪find_company_name(s['tweet_text'],s['emotion_in_tweet_is_directed_at']),axis=1)

sentiments_df['company_name'].value_counts()
```

[11]:
```
apple          5331
google         2814
cannot tell     948
Name: company_name, dtype: int64
```

[12]:
```
# Tweets for which cannot tell whether comment directed to apple or google the
# sentiment is mostly neutral (over 95%)

cannot_tell = sentiments_df[sentiments_df['company_name'] == 'cannot tell']
cannot_tell['is_there_an_emotion_directed_at_a_brand_or_product'].value_counts()
```

[12]:
```
No emotion toward brand or product    911
Positive emotion                       23
I can't tell                           10
Negative emotion                        4
Name: is_there_an_emotion_directed_at_a_brand_or_product, dtype: int64
```

[13]:
```
# Drop any row where 'tweet_text' is nan
sentiments_df.drop(sentiments_df[sentiments_df['tweet_text'].isna()].
↪index,inplace=True)

# Drop any row where 'is_there_an_emotion_directed_at_a_brand_or_product' says␣
↪'I can't tell'
column_name = 'is_there_an_emotion_directed_at_a_brand_or_product'
match = 'I can\'t tell'
sentiments_df.drop(sentiments_df[sentiments_df[column_name] == match].index,␣
↪inplace=True)


# Drop any rows where column 'company_name' says 'cannot tell'
sentiments_df.drop(sentiments_df[sentiments_df['company_name'] == 'cannot␣
↪tell'].index,
                   inplace=True)
```

```
# Drop any duplicated rows
sentiments_df.drop(sentiments_df[sentiments_df.duplicated()].index,inplace=True)

sentiments_df['company_name'].value_counts()
```

[13]:
```
apple     5231
google    2748
Name: company_name, dtype: int64
```

[14]:
```
def convert_emotion_tonumber(emotion):
    '''
    Return 0 for negative sentiment, 1 for neutral sentiment and 2 for positive␣
 ↪sentiment.
    '''

    if emotion == 'Negative emotion':
        return 0
    elif emotion == 'Positive emotion':
        return 2
    else:
        return 1  # for neutral emotion
```

[15]:
```
# Create a column called 'sentiment' and pass value from
# 'is_there_an_emotion_directed_at_a_brand_or_product' to function␣
 ↪convert_emotion_tonumber.

sentiments_df['sentiment'] = sentiments_df[
    'is_there_an_emotion_directed_at_a_brand_or_product'].map(
    lambda s: convert_emotion_tonumber(s))

sentiments_df['sentiment'].value_counts(normalize=True)
```

[15]:
```
1    0.559845
2    0.369345
0    0.070811
Name: sentiment, dtype: float64
```

[16]:
```
sentiments_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7979 entries, 0 to 9092
Data columns (total 5 columns):
 #   Column                                              Non-Null Count  Dtype
---  ------                                              --------------  -----
 0   tweet_text                                          7979 non-null   object
 1   emotion_in_tweet_is_directed_at                     3273 non-null   object
```

```
 2   is_there_an_emotion_directed_at_a_brand_or_product  7979 non-null   object
 3   company_name                                        7979 non-null   object
 4   sentiment                                           7979 non-null   int64
dtypes: int64(1), object(4)
memory usage: 374.0+ KB
```

[17]:
```
# Create an intermediate dataframe that only contains columns␣
↪'tweet_text','company_name'
# sentiment

sentiments2_df = sentiments_df[['tweet_text','company_name','sentiment']].copy()
```

[18]:
```
sentiments2_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7979 entries, 0 to 9092
Data columns (total 3 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   tweet_text    7979 non-null   object
 1   company_name  7979 non-null   object
 2   sentiment     7979 non-null   int64
dtypes: int64(1), object(2)
memory usage: 249.3+ KB
```

[18]:
```
# Determine approximate total number of unique words in sentiments['tweet_text']

tweet_words = sentiments_df['tweet_text'].map(word_tokenize).values
total_vocabulary = set(word for tweet in tweet_words for word in tweet)
print (f'Total number of unique words in tweet_words: {len(total_vocabulary)}')
```

```
Total number of unique words in tweet_words: 12131
```

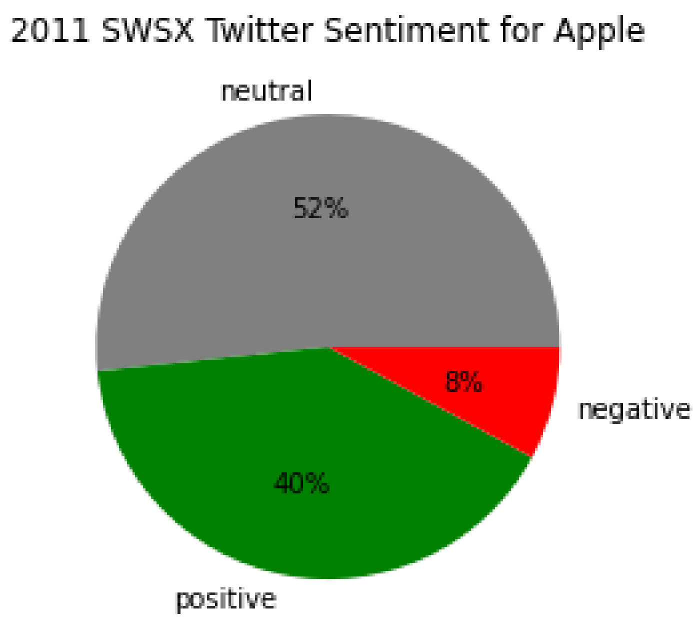
[19]:
```
# Split sentiments2_df into two data frames where apple_df contains all tweets␣
↪about apple
# google_df contains all tweets about google

apple_df = sentiments2_df[sentiments2_df['company_name'] == 'apple'].copy()
google_df = sentiments2_df[sentiments2_df['company_name'] == 'google'].copy()
```

[37]:
```
google_df['sentiment'].value_counts(normalize=True)
```

[37]:
```
1    0.642285
2    0.302402
0    0.055313
Name: sentiment, dtype: float64
```

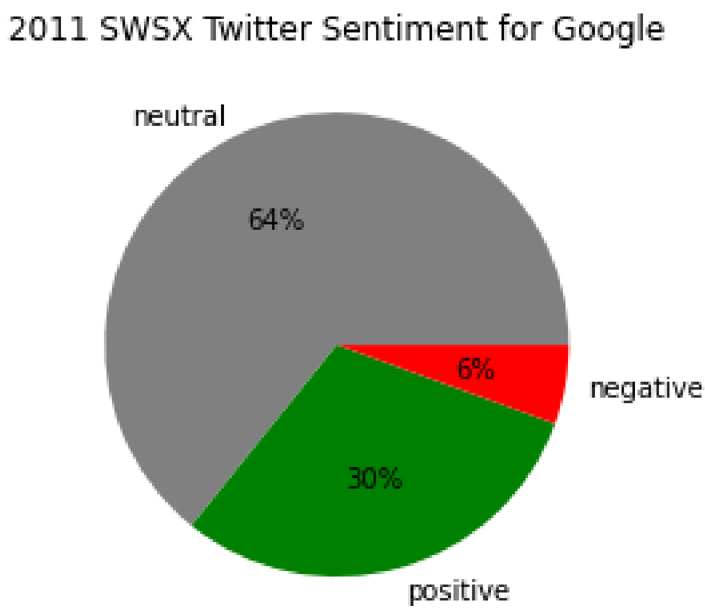
[34]:

```
def func(pct):
    '''
    Convert float to string, round to whole number and place percent(%) after␣
 ↪the number.
    '''

    return '{:.0f}%'.format(pct)

a_size = list(apple_df['sentiment'].value_counts())
a_labels = ['neutral','positive','negative']
fig,axs = plt.subplots()
axs.pie(a_size,labels=a_labels,autopct=lambda pct: func(pct),
        colors=['grey','green','red']);
axs.set_title('2011 SWSX Twitter Sentiment for Apple');
#fig.savefig('apple_sentiment')
```



[36]:

```
g_size = list(google_df['sentiment'].value_counts())
g_labels = ['neutral','positive','negative']
fig,axs = plt.subplots()
axs.pie(g_size,labels=g_labels,autopct=lambda pct: func(pct),
        colors=['grey','green','red']);
axs.set_title('2011 SWSX Twitter Sentiment for Google');
#fig.savefig('google_sentiment');
```

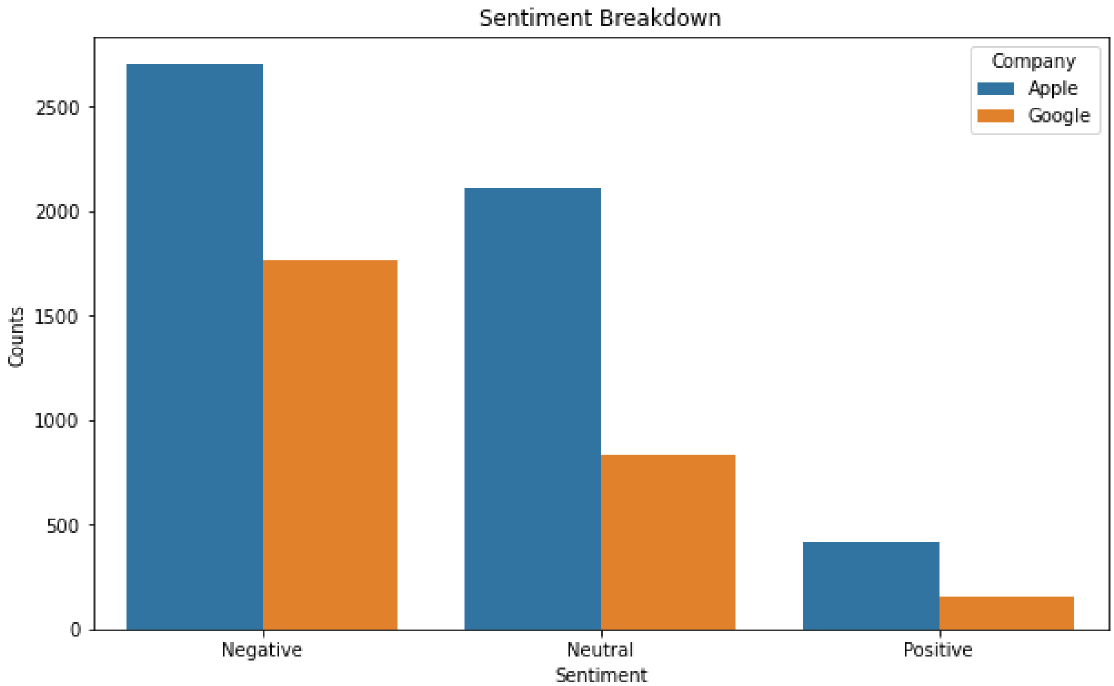


[38]:
```
def get_wordnet_pos(tag):
    '''
    Translate nltk POS to wordnet tags
    '''

    if tag.startswith('J'):
        return wordnet.ADJ
    elif tag.startswith('V'):
        return wordnet.VERB
    elif tag.startswith('N'):
        return wordnet.NOUN
    elif tag.startswith('R'):
        return wordnet.ADV
    else:
        return wordnet.NOUN
```

[39]:
```
def nlp_doc_preparer(doc,array='no'):
    '''
     - Customize nltk stop_words to include all punction marks, numbers and␣
 ↪acronym 'sxsw'
     - Split text into words containing letters
     - Make all letters lower case
     - Use pos_tag to mark up the words for a particular part of a speech
     - Use get_wordnet_pos to convert pos_tag to wordnet_pos
     - Convert word to root word with WordNetLemmatizer
```

```
     - Return processed document as a string of words
    '''

    custom_sw = stopwords.words('english')
    punctuation = [c for c in list(string.punctuation)]
    numbers = [n for n in range(0,10)]
    custom_sw.extend(punctuation+numbers)
    custom_sw.extend(['sxsw','SXSW','Sxsw'])


    regex_token = RegexpTokenizer(r"([a-zA-Z]+(?:’[a-z]+)?)")
    doc = regex_token.tokenize(doc)

    doc = [word.lower() for word in doc]
    doc = [word for word in doc if word not in custom_sw]

    doc = pos_tag(doc)
    doc = [(word[0], get_wordnet_pos(word[1])) for word in doc]

    lemmatizer = WordNetLemmatizer()
    doc = [lemmatizer.lemmatize(word[0], word[1]) for word in doc]

    if array == 'no':
        return ' '.join(doc)
    else:
        return doc
```

[40]:
```
# Show sentiment breakdown for Apple and Google

apple_sentiment = apple_df['sentiment'].value_counts()
google_sentiment = google_df['sentiment'].value_counts()

sentiments = pd.DataFrame({'Sentiment': ['Negative','Neutral','Positive',
                                         'Negative','Neutral','Positive'],
                   'Counts': (list(apple_sentiment) + list(google_sentiment)),
                   'Company': (['Apple']*3 + ['Google']*3)})

fig,ax = plt.subplots(figsize=(10,6))
sentiment_plot = sns.barplot(x='Sentiment', y='Counts', hue='Company',␣
 ↪data=sentiments);
sentiment_plot.set_title('Sentiment Breakdown');
```

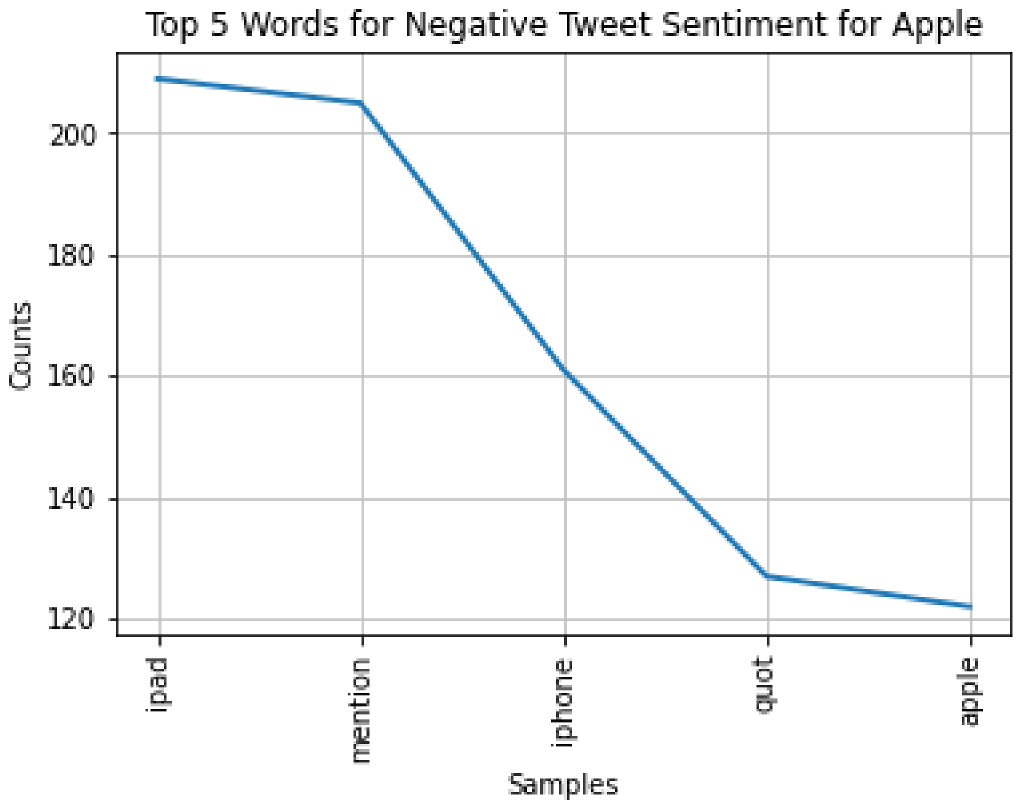


[41]:

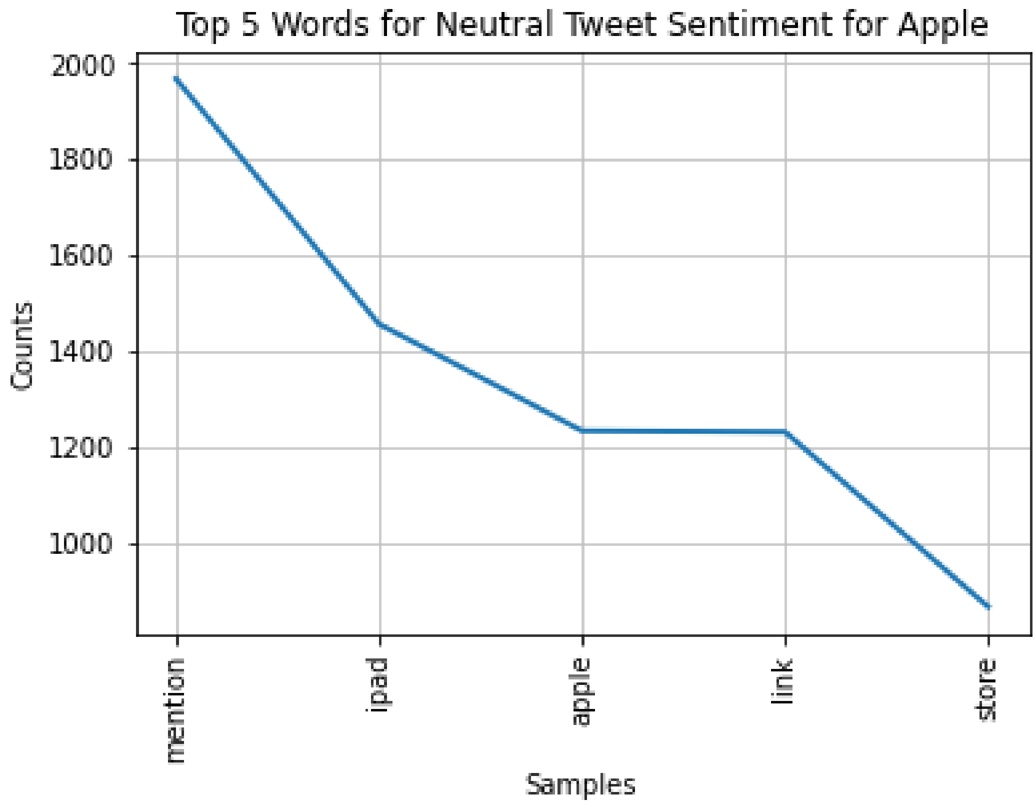
```
# Create data frames for each of the three sentiments for each company

apple_neg_tw = apple_df[apple_df['sentiment'] == 0]
apple_neu_tw = apple_df[apple_df['sentiment'] == 1]
apple_pos_tw = apple_df[apple_df['sentiment'] == 2]

google_neg_tw = google_df[google_df['sentiment'] == 0]
google_neu_tw = google_df[google_df['sentiment'] == 1]
google_pos_tw = google_df[google_df['sentiment'] == 2]

app_neg_tw = [nlp_doc_preparer(tweet,'yes') for tweet in␣
 ↪apple_neg_tw['tweet_text']]
app_neu_tw = [nlp_doc_preparer(tweet,'yes') for tweet in␣
 ↪apple_neu_tw['tweet_text']]
app_pos_tw = [nlp_doc_preparer(tweet,'yes') for tweet in␣
 ↪apple_pos_tw['tweet_text']]

goo_neg_tw = [nlp_doc_preparer(tweet,'yes') for tweet in␣
 ↪google_neg_tw['tweet_text']]
goo_neu_tw = [nlp_doc_preparer(tweet,'yes') for tweet in␣
 ↪google_neu_tw['tweet_text']]
goo_pos_tw = [nlp_doc_preparer(tweet,'yes') for tweet in␣
 ↪google_pos_tw['tweet_text']]
```

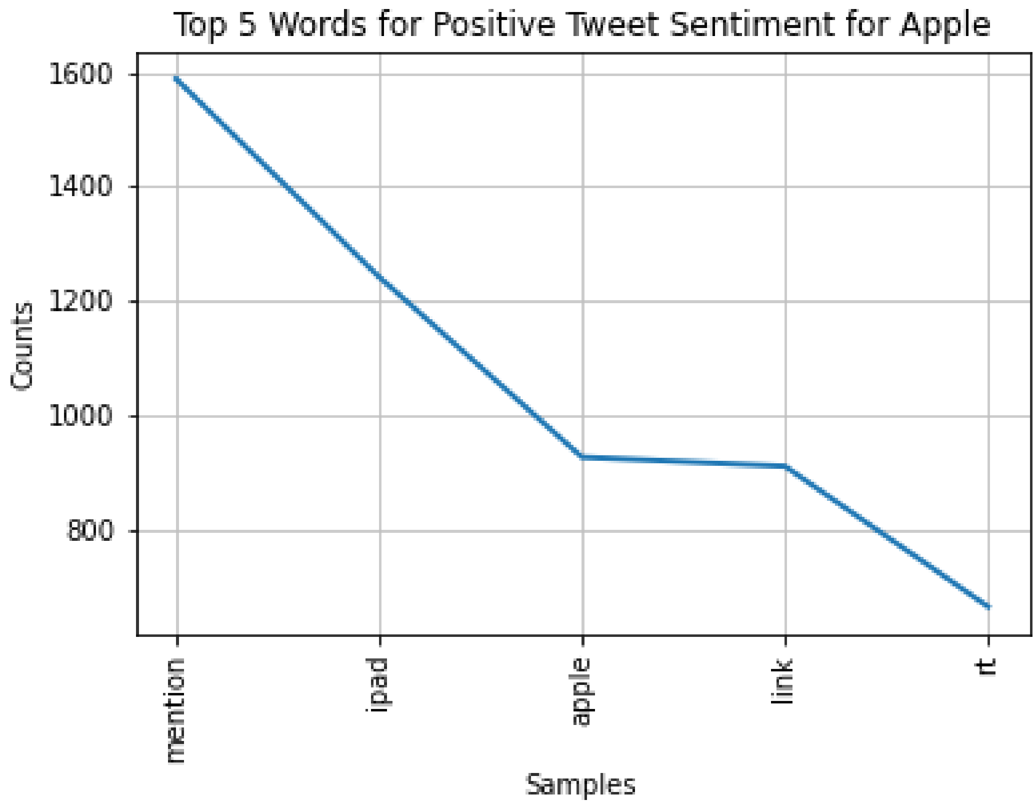
[44]:
```
def flatten_list(list_of_lists):
    '''
    Flatten array of arrays and return the flattened array
    '''
    return [word for line in list_of_lists for word in line]
```

[45]:
```
# Show top 5 frequenly occuring words for Apple for each sentiment

app_neg_tw_f = flatten_list(app_neg_tw)
app_neu_tw_f = flatten_list(app_neu_tw)
app_pos_tw_f = flatten_list(app_pos_tw)

apple_tweets = [['Top 5 Words for Negative Tweet Sentiment for␣
 ↪Apple',app_neg_tw_f],
                ['Top 5 Words for Neutral Tweet Sentiment for␣
 ↪Apple',app_neu_tw_f],
                ['Top 5 Words for Positive Tweet Sentiment for␣
 ↪Apple',app_pos_tw_f]]

fig, axs = plt.subplots()
for i in range(3):
    t = FreqDist(apple_tweets[i][1])
    t.plot(5,title=apple_tweets[i][0]);
```



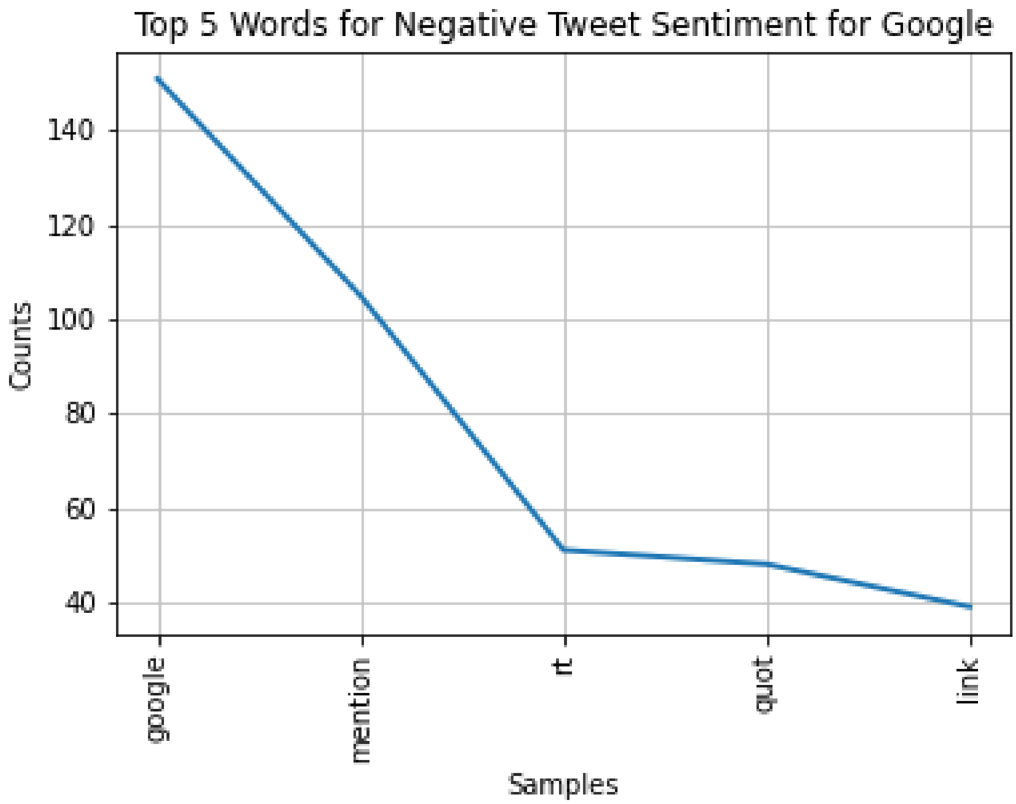
Top 5 Words for Negative Tweet Sentiment for Apple
Counts
200
180
160
140
120
ipad
mention
iphone
quot
apple
Samples

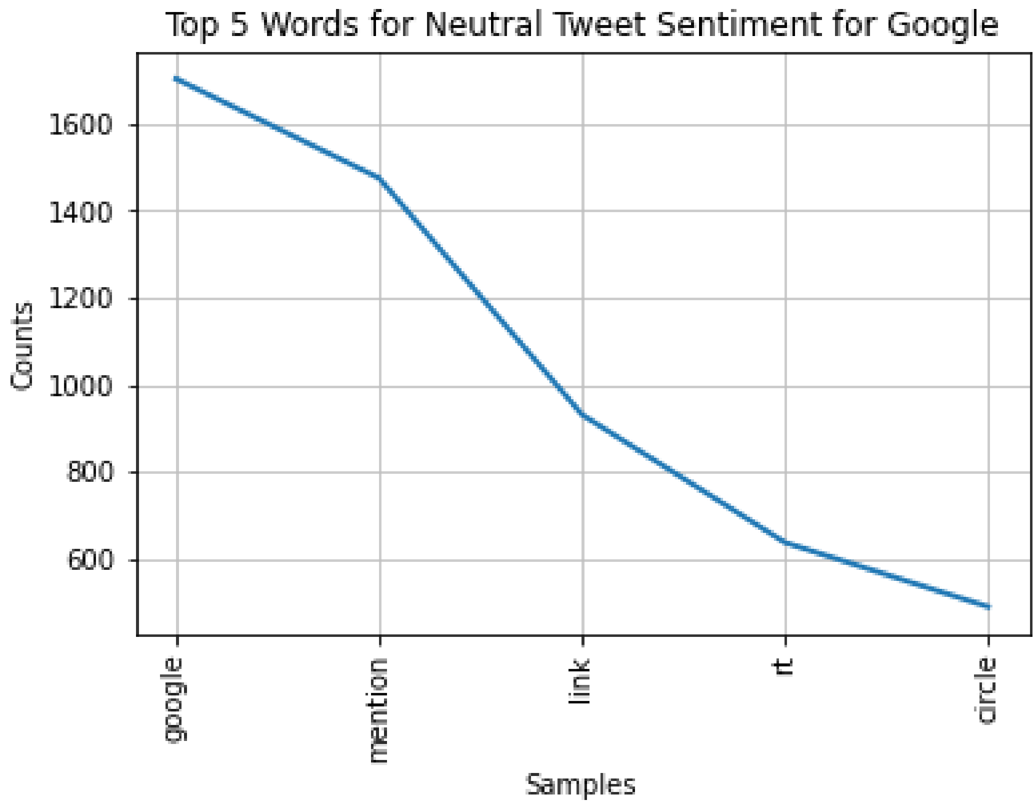

Top 5 Words for Neutral Tweet Sentiment for Apple
2000
1800
1600
1400
1200
1000
Counts
mention
ipad
apple
link
store
Samples

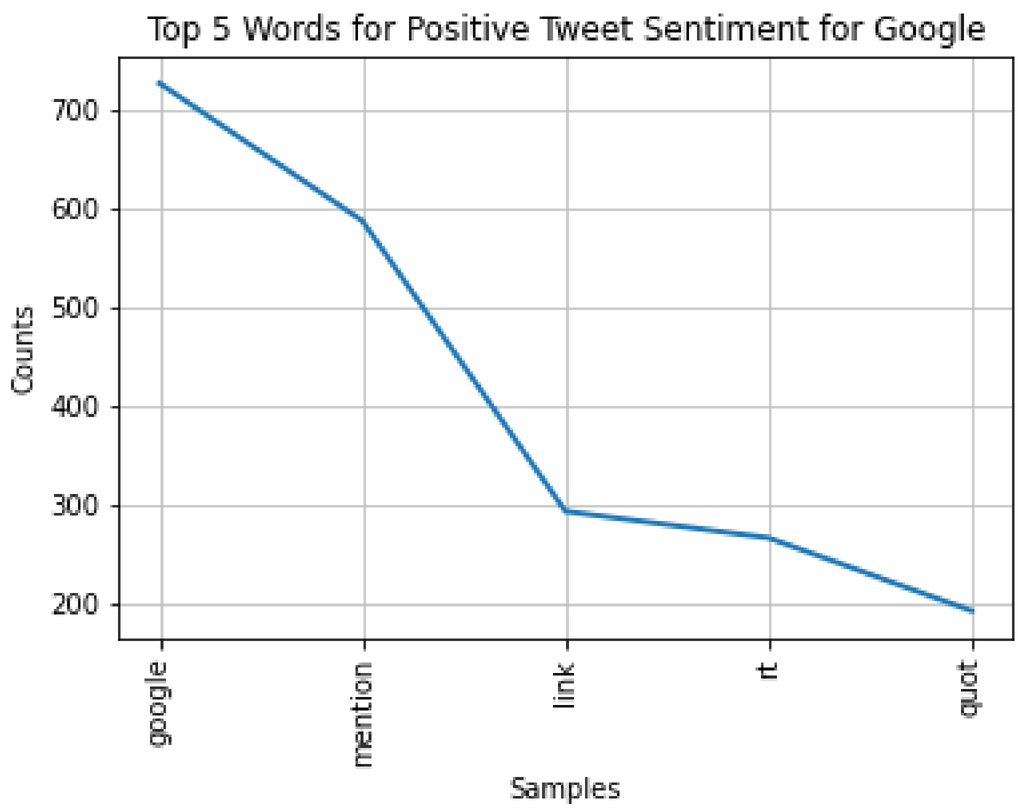


[46]:

```
# Show top 5 frequenly occuring words for Google for each sentiment

goo_neg_tw_f = flatten_list(goo_neg_tw)
goo_neu_tw_f = flatten_list(goo_neu_tw)
goo_pos_tw_f = flatten_list(goo_pos_tw)

apple_tweets = [['Top 5 Words for Negative Tweet Sentiment for␣
↪Google',goo_neg_tw_f],
                ['Top 5 Words for Neutral Tweet Sentiment for␣
↪Google',goo_neu_tw_f],
                ['Top 5 Words for Positive Tweet Sentiment for␣
↪Google',goo_pos_tw_f]]

fig, axs = plt.subplots()
for i in range(3):
    t = FreqDist(apple_tweets[i][1])
    t.plot(5,title=apple_tweets[i][0]);
```


Top 5 Words for Negative Tweet Sentiment for Google
Counts
140
120
100
80
60
40
google
mention
rt
quot
link
Samples


Top 5 Words for Neutral Tweet Sentiment for Google
Counts
1600
1400
1200
1000
800
600
google
mention
link
rt
circle
Samples



[ ]:

[47]:
```
# Split apple_df and google_df into train and test samples using␣
↪train_test_split

X_train_app, X_test_app, y_train_app, y_test_app =␣
↪train_test_split(apple_df['tweet_text'],
                                                    apple_df['sentiment'],test_size␣
↪= 0.4,
                                                    stratify =␣
↪apple_df['sentiment'],
                                                    random_state = 6781)

X_train_goo, X_test_goo, y_train_goo, y_test_goo =␣
↪train_test_split(google_df['tweet_text'],
                                                   ␣
↪google_df['sentiment'],test_size = 0.4,
                                                    stratify =␣
↪google_df['sentiment'],
                                                    random_state = 6782)
```

[48]:
```python
a = len(X_train_app)
g = len(X_train_goo)
a+g
```

[48]: 4786

[ ]:
```python

```

[49]:
```python
# Combined X_train_app and X_train_goo into single series
# and y_train_app and y_train_goo

X_train_combined = pd.concat([X_train_app,X_train_goo])
y_train_combined = pd.concat([y_train_app,y_train_goo])
```

[50]:
```python
len(X_train_combined) == len(y_train_combined)
```

[50]: True

[51]:
```python
sum(X_train_combined.index == y_train_combined.index)
```

[51]: 4786

[52]:
```python
# Process X_train_combined, X_test_app, X_test_goo with nlp_doc_preparer␣
↪function

X_train_combined_processed = [nlp_doc_preparer(tweet) for tweet in␣
↪X_train_combined]

X_test_app_processed = [nlp_doc_preparer(tweet) for tweet in X_test_app]
X_test_goo_processed = [nlp_doc_preparer(tweet) for tweet in X_test_goo]
```

[53]:
```python
def display_cross_validation_results(cross_val,model_name):
    '''
    Incoporate cross validation results into a pandas dataframe and display␣
↪validation scores
    '''

    cross_val_results = pd.DataFrame(cross_val)

    accuracy = cross_val_results['mean_test_accuracy'][0]
    recall = cross_val_results['mean_test_recall'][0]
    precision = cross_val_results['mean_test_precision'][0]

    print('Validation','='*60)
    print(f'Validation results for {model_name}:')
    print(f'Accuracy: {accuracy}')
    print(f'Recall: {recall}')
```

```
    print(f'Precision: {precision}\n')
```

[54]:
```
def display_prediction_results(prediction, actuall, company_name, model_name):
    '''
    Get predictions for X_test samples and display scores
    '''

    accuracy = accuracy_score(actuall,prediction)
    recall = recall_score(actuall, prediction, average = 'micro')
    precision = precision_score(actuall, prediction, average = 'micro')

    print('='*60)
    print(f'Predictions for {company_name}: {model_name}')
    print(f'Accuracy: {accuracy}')
    print(f'Recall: {recall}')
    print(f'Precision: {precision}\n')
```

[58]:
```
def display_confusion_matrix_v2(actuall_y,predicted_y,company_name):
    '''
    Compute confusion matrix and plot matrix. This is version 2.
    '''

    conf_matrix = confusion_matrix(y_true=actuall_y, y_pred=predicted_y)

    fig, ax = plt.subplots(figsize=(6, 6))
    ax.matshow(conf_matrix, cmap=plt.cm.Blues, alpha=0.3)

    for i in range(conf_matrix.shape[0]):
        for j in range(conf_matrix.shape[1]):
            ax.text(x=j, y=i,s=conf_matrix[i, j], va='center', ha='center',␣
 ↪size='xx-large')

    plt.xlabel('Predictions', fontsize=14)
    plt.ylabel('Actuals', fontsize=14)
    plt.title(f'{company_name}', fontsize=18);
    #save_image_as = company_name
    #fig.savefig(save_image_as)
```

[59]:
```
def display_confusion_matrix(model, X, y,company_name, model_name):
    '''
    Plot confusion matrix. This is version 1.
    '''

    print(f'Confusion matrix for: {company_name}')
    print(f'Model: {model_name}')
```

```
    plot_confusion_matrix(model,X,y)
    print('='*80)
```

1.6 Model Training and Model Prediction

Used CountVectorizer (and to lesser extent TfidfVectorizer) to convert text tweet into matrix of tokens. The models were trained and validated with the combined train dataframe from apple and google tweets. Used pipes to minimize redundant code an gridsearchcv for model tuning and validation. Model predictions were made with apple and google test dataframes.

[60]:
```
# DummyClassifier
# Use pipes to countVectorize X_train_combined_processed and then train␣
 ↪DummyClassifier

start = time.time()

cv_dm_pipe = Pipeline([('countvect',CountVectorizer()),
                 ('dm',DummyClassifier())])

grid_accuracy = make_scorer(accuracy_score)
grid_recall_micro = make_scorer(recall_score, average = 'micro')
grid_precision_micro = make_scorer(precision_score, average = 'micro')

cv_dm_params = {'countvect__input' : ['content'],
                'dm__random_state' : [1234],
                'dm__strategy' : ['prior']}

cv_dm_model_grid = GridSearchCV(estimator = cv_dm_pipe, param_grid =␣
 ↪cv_dm_params,
                                scoring = {'accuracy' : grid_accuracy,
                                           'recall' : grid_recall_micro,
                                          'precision' : grid_precision_micro},
                                refit = 'accuracy')

cv_dm_model_grid.fit(X_train_combined_processed,y_train_combined)
end = time.time()
print(f'Training time: {end-start}')
cv_dm_model_grid.best_params_
```

```
Training time: 0.4720919132232666
```

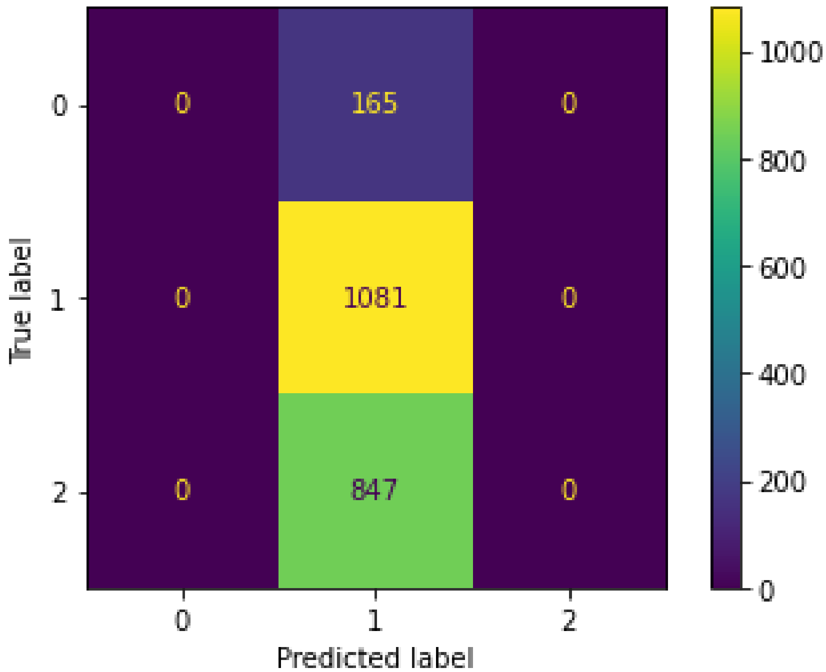
[60]:
```
{'countvect__input': 'content',
 'dm__random_state': 1234,
 'dm__strategy': 'prior'}
```

[61]:
```python
# Display cross validation results, make prediction for X_test_app and␣
 ↪X_test_goo
# diplay results.  Use respective functions.

model_name = 'DummyClassifier with Count Vectorize'

display_cross_validation_results(cv_dm_model_grid.cv_results_,model_name)

y_test_app_hat = cv_dm_model_grid.predict(X_test_app_processed)
y_test_goo_hat = cv_dm_model_grid.predict(X_test_goo_processed)

display_prediction_results(y_test_app_hat, y_test_app,'Apple',model_name)

display_prediction_results(y_test_goo_hat, y_test_goo, 'Google',model_name)
```

```
Validation ============================================================
Validation results for DummyClassifier with Count Vectorize:
Accuracy: 0.5599666668848153
Recall: 0.5599666668848153
Precision: 0.5599666668848153

============================================================
Predictions for Apple: DummyClassifier with Count Vectorize
Accuracy: 0.5164835164835165
Recall: 0.5164835164835165
Precision: 0.5164835164835165

============================================================
Predictions for Google: DummyClassifier with Count Vectorize
Accuracy: 0.6418181818181818
Recall: 0.6418181818181818
Precision: 0.6418181818181818
```

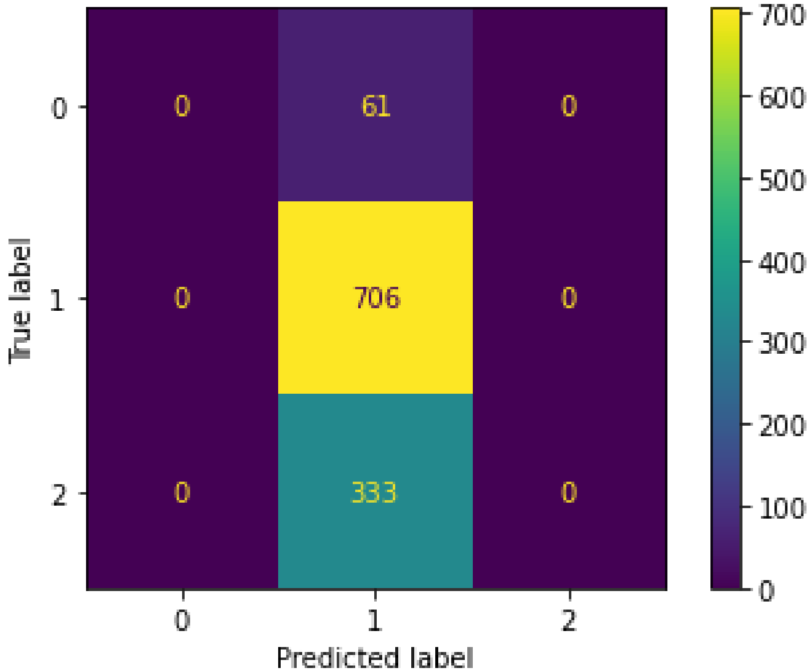
[62]:
```python
# Diplay confusion matrix for X_test_app

#display_confusion_matrix_v2(y_test_app,y_test_app_hat,'Apple')
display_confusion_matrix(cv_dm_model_grid, X_test_app_processed,
                         y_test_app, 'Apple',model_name)
```

```
Confusion matrix for: Apple
Model: DummyClassifier with Count Vectorize
================================================================================
```



[63]:
```
# Diplay confusion matrix for X_test_goo
#display_confusion_matrix_v2(y_test_goo,y_test_goo_hat,'Google')
display_confusion_matrix(cv_dm_model_grid,X_test_goo_processed,
                         y_test_goo, 'Google',model_name)
```

```
Confusion matrix for: Google
Model: DummyClassifier with Count Vectorize
================================================================================
```



[64]:

```
# MultinomialNB
# Use pipes to countVectorize X_train_combined_processed and then train␣
↪MultinomialNB

start = time.time()

cv_mnb_pipe = Pipeline([('countvect',CountVectorizer()),
                 ('mnb', MultinomialNB())])

cv_mnb_params = {'countvect__input' : ['content'],'mnb__alpha' : [1.0]}

cv_mnb_model_grid = GridSearchCV(estimator = cv_mnb_pipe, param_grid =␣
↪cv_mnb_params,
                                scoring = {'accuracy' : grid_accuracy,
                                           'recall' : grid_recall_micro,
                                          'precision' : grid_precision_micro},
                                refit = 'accuracy')

cv_mnb_model_grid.fit(X_train_combined_processed,y_train_combined)
end = time.time()
print(f'Training time: {end-start}')
```

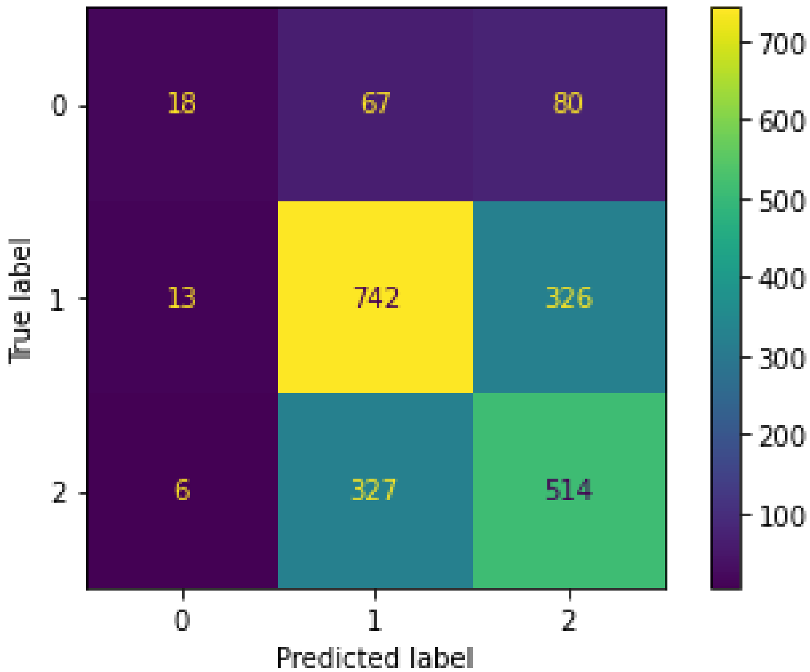
```
Training time: 0.47927284240722656
```

[65]:
```
# Display cross validation results, make prediction for X_test_app and␣
↪X_test_goo
# diplay results.  Use respective functions.

model_name = 'MultinomialNB with Count Vectorize'

display_cross_validation_results(cv_mnb_model_grid.cv_results_,model_name)

y_test_app_hat2 = cv_mnb_model_grid.predict(X_test_app_processed)
y_test_goo_hat2 = cv_mnb_model_grid.predict(X_test_goo_processed)

display_prediction_results(y_test_app_hat2, y_test_app,'Apple',model_name)

display_prediction_results(y_test_goo_hat2, y_test_goo, 'Google',model_name)
```

```
Validation ============================================================
Validation results for MultinomialNB with Count Vectorize:
Accuracy: 0.6276688852385346
Recall: 0.6276688852385346
Precision: 0.6276688852385346

============================================================
Predictions for Apple: MultinomialNB with Count Vectorize
Accuracy: 0.6086956521739131
Recall: 0.6086956521739131
Precision: 0.6086956521739131

============================================================
Predictions for Google: MultinomialNB with Count Vectorize
Accuracy: 0.6854545454545454
Recall: 0.6854545454545454
Precision: 0.6854545454545454
```

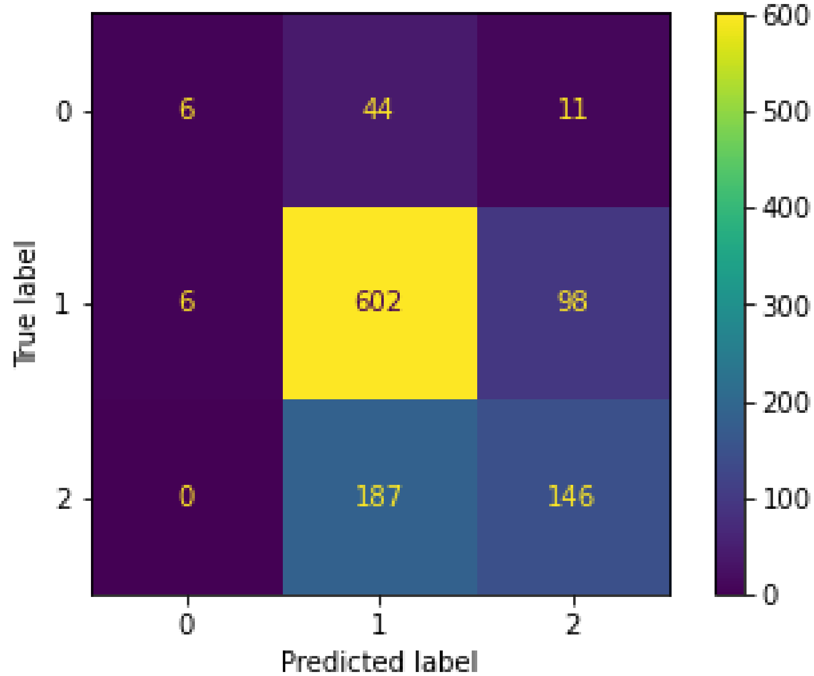
[66]:
```
# Diplay confusion matrix for X_test_app

display_confusion_matrix(cv_mnb_model_grid, X_test_app_processed,
                         y_test_app, 'Apple',model_name)
```

```
Confusion matrix for: Apple
Model: MultinomialNB with Count Vectorize
================================================================================
```



[67]:
```
# Diplay confusion matrix for X_test_goo

display_confusion_matrix(cv_mnb_model_grid,X_test_goo_processed,
                        y_test_goo, 'Google',model_name)
```

```
Confusion matrix for: Google
Model: MultinomialNB with Count Vectorize
================================================================================
```



[68]:

```
# Use pipes to TfidfVectorize X_train_combined_processed and then train␣
↪MultinomialNB()

start = time.time()

tf_mnb_pipe = Pipeline([('tfvect',TfidfVectorizer()),
                  ('mnb', MultinomialNB())])

tf_mnb_params = {'tfvect__input' : ['content'],'mnb__alpha' : [1.0]}

tf_mnb_model_grid = GridSearchCV(estimator = tf_mnb_pipe, param_grid =␣
↪tf_mnb_params,
                                scoring = {'accuracy' : grid_accuracy,
                                           'recall' : grid_recall_micro,
                                          'precision' : grid_precision_micro},
                                refit = 'accuracy')


tf_mnb_model_grid.fit(X_train_combined_processed,y_train_combined)
end = time.time()
print(f'Training time: {end-start}')
```

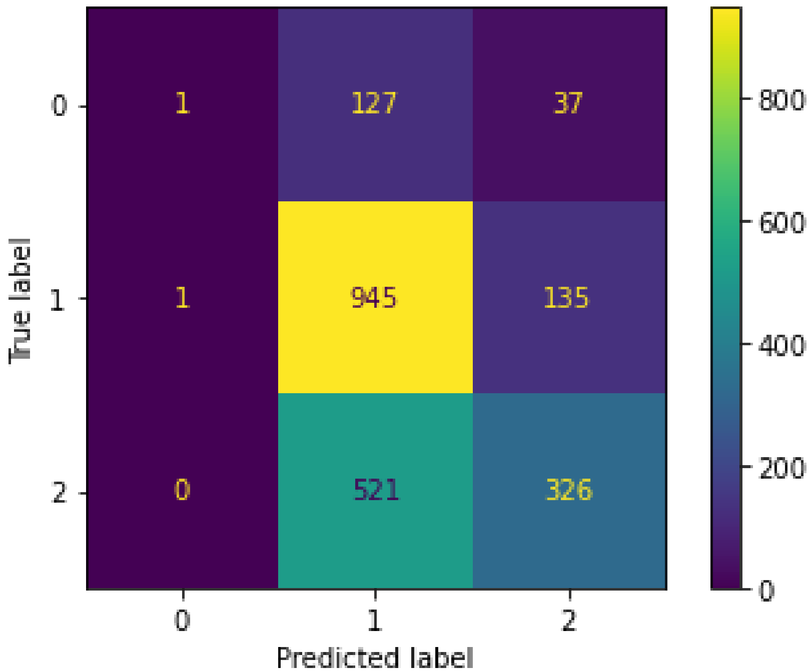
```
Training time: 0.48676490783691406
```

[69]:
```
# Display cross validation results, make prediction for X_test_app and␣
↪X_test_goo
# diplay results.  Use respective functions.

model_name = 'MultinomialNB with TF-IDF Vectorize'

display_cross_validation_results(tf_mnb_model_grid.cv_results_,model_name)

y_test_app_hat3 = tf_mnb_model_grid.predict(X_test_app_processed)
y_test_goo_hat3 = tf_mnb_model_grid.predict(X_test_goo_processed)

display_prediction_results(y_test_app_hat3, y_test_app,'Apple',model_name)

display_prediction_results(y_test_goo_hat3, y_test_goo, 'Google',model_name)
```

```
Validation ============================================================
Validation results for MultinomialNB with TF-IDF Vectorize:
Accuracy: 0.6305925135743002
Recall: 0.6305925135743002
Precision: 0.6305925135743002

============================================================
Predictions for Apple: MultinomialNB with TF-IDF Vectorize
Accuracy: 0.6077400860009555
Recall: 0.6077400860009555
Precision: 0.6077400860009555

============================================================
Predictions for Google: MultinomialNB with TF-IDF Vectorize
Accuracy: 0.6863636363636364
Recall: 0.6863636363636364
Precision: 0.6863636363636364
```

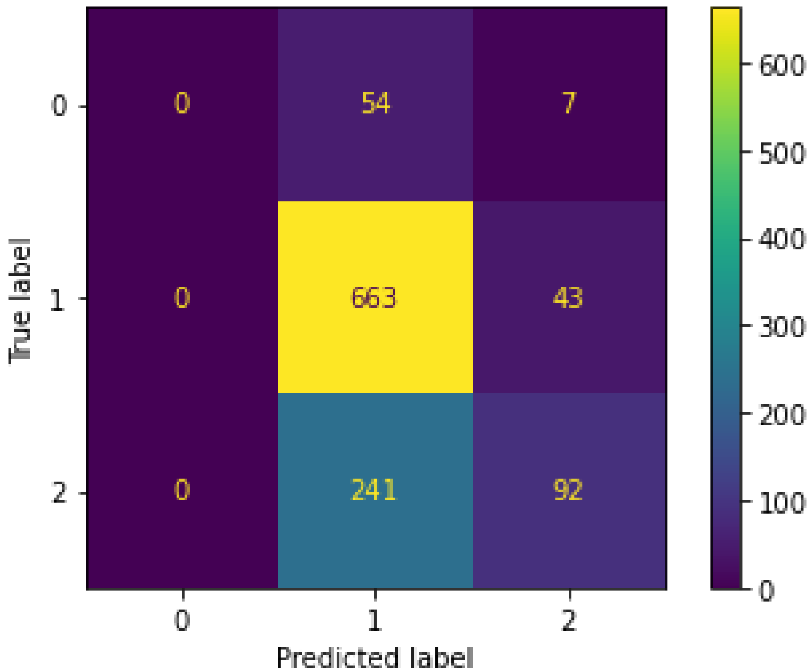
[70]:
```
# Diplay confusion matrix for X_test_app

display_confusion_matrix(tf_mnb_model_grid, X_test_app_processed,
                         y_test_app, 'Apple',model_name)
```

```
Confusion matrix for: Apple
Model: MultinomialNB with TF-IDF Vectorize
================================================================================
```



[71]:
```
# Diplay confusion matrix for X_test_goo

display_confusion_matrix(tf_mnb_model_grid,X_test_goo_processed,
                         y_test_goo, 'Google',model_name)
```

```
Confusion matrix for: Google
Model: MultinomialNB with TF-IDF Vectorize
================================================================================
```



[72]:

```
# KNeighborsClassifier
# Use pipes to CountVectorize X_train_combined_processed and then train␣
↪KNeighborsClassifier

start = time.time()

cv_knn_pipe = Pipeline([('countvect',CountVectorizer()),
                 ('knn', KNeighborsClassifier())])

cv_knn_params = {'countvect__input' : ['content'],
                 'knn__n_neighbors' : [7],  # tried 3,7,21
                'knn__weights' : ['distance'], # tried 'uniform
                'knn__leaf_size' : [7]}  #tried 3,15,30,45

cv_knn_model_grid = GridSearchCV(estimator = cv_knn_pipe, param_grid =␣
↪cv_knn_params,
                                scoring = {'accuracy' : grid_accuracy,
                                           'recall' : grid_recall_micro,
                                          'precision' : grid_precision_micro},
                                refit = 'accuracy')


cv_knn_model_grid.fit(X_train_combined_processed,y_train_combined)
end = time.time()
```

```
print(f'Training time: {end-start}')
cv_knn_model_grid.best_params_
```

```
Training time: 1.1171519756317139
```

[72]:
```
{'countvect__input': 'content',
 'knn__leaf_size': 7,
 'knn__n_neighbors': 7,
 'knn__weights': 'distance'}
```

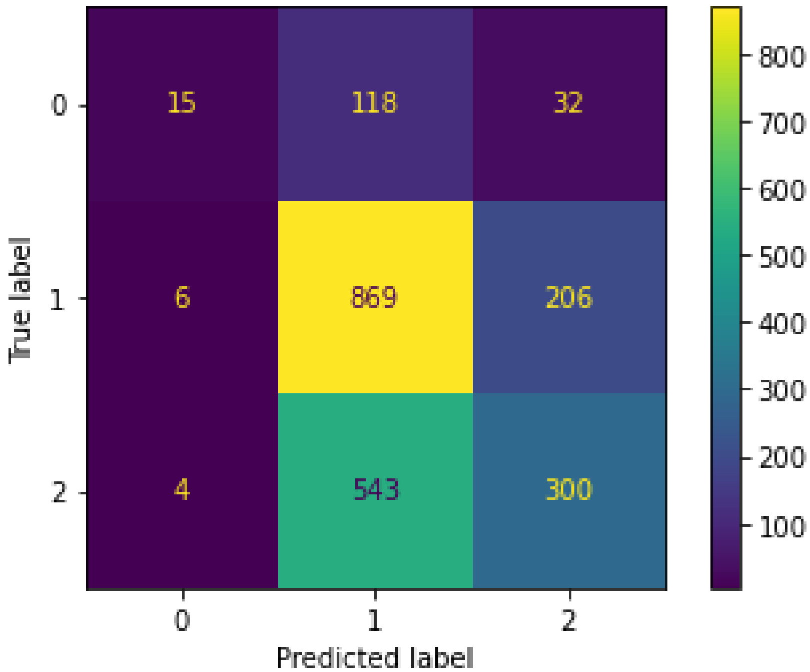
[73]:
```
# Display cross validation results, make prediction for X_test_app and␣
↪X_test_goo
# diplay results.  Use respective functions.

model_name = 'KNeighborsClassifier with Count Vectorize'

display_cross_validation_results(cv_knn_model_grid.cv_results_,model_name)

y_test_app_hat4 = cv_knn_model_grid.predict(X_test_app_processed)
y_test_goo_hat4 = cv_knn_model_grid.predict(X_test_goo_processed)

display_prediction_results(y_test_app_hat4, y_test_app,'Apple',model_name)

display_prediction_results(y_test_goo_hat4, y_test_goo, 'Google',model_name)
```

```
Validation ============================================================
Validation results for KNeighborsClassifier with Count Vectorize:
Accuracy: 0.5927709897186537
Recall: 0.5927709897186537
Precision: 0.5927709897186537

============================================================
Predictions for Apple: KNeighborsClassifier with Count Vectorize
Accuracy: 0.5656951743908266
Recall: 0.5656951743908266
Precision: 0.5656951743908266

============================================================
Predictions for Google: KNeighborsClassifier with Count Vectorize
Accuracy: 0.6563636363636364
Recall: 0.6563636363636364
Precision: 0.6563636363636364
```

[74]:
```
# Diplay confusion matrix for X_test_app

display_confusion_matrix(cv_knn_model_grid, X_test_app_processed,
```

```
                          y_test_app, 'Apple',model_name)
```

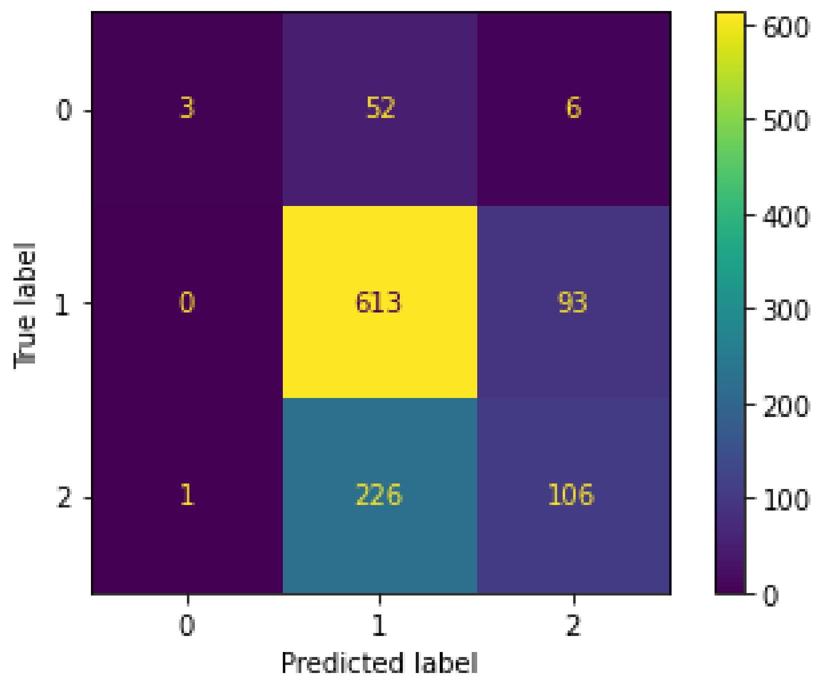
```
Confusion matrix for: Apple
Model: KNeighborsClassifier with Count Vectorize
================================================================================
```



[75]:

```
# Diplay confusion matrix for X_test_goo

display_confusion_matrix(cv_knn_model_grid, X_test_goo_processed,
                          y_test_goo, 'Google',model_name)
```

```
Confusion matrix for: Google
Model: KNeighborsClassifier with Count Vectorize
================================================================================
```



[76]:
```
# Use pipes to TfidfVectorize X_train_combined_processed and then train␣
↪KNeighborsClassifier

start = time.time()

tf_knn_pipe = Pipeline([('tfvect',TfidfVectorizer()),
                 ('knn', KNeighborsClassifier())])

tf_knn_params = {'tfvect__input' : ['content'],
                 'knn__n_neighbors' : [7],  # tried 3,7,21
                'knn__weights' : ['distance'], # tried 'uniform
                'knn__leaf_size' : [3]}  #tried 30,45

tf_knn_model_grid = GridSearchCV(estimator = cv_knn_pipe, param_grid =␣
↪cv_knn_params,
                                scoring = {'accuracy' : grid_accuracy,
                                           'recall' : grid_recall_micro,
                                          'precision' : grid_precision_micro},
                                refit = 'accuracy')


tf_knn_model_grid.fit(X_train_combined_processed,y_train_combined)
end = time.time()
print(f'Training time: {end-start}')
```

```
tf_knn_model_grid.best_params_
```

```
Training time: 1.011580228805542
```

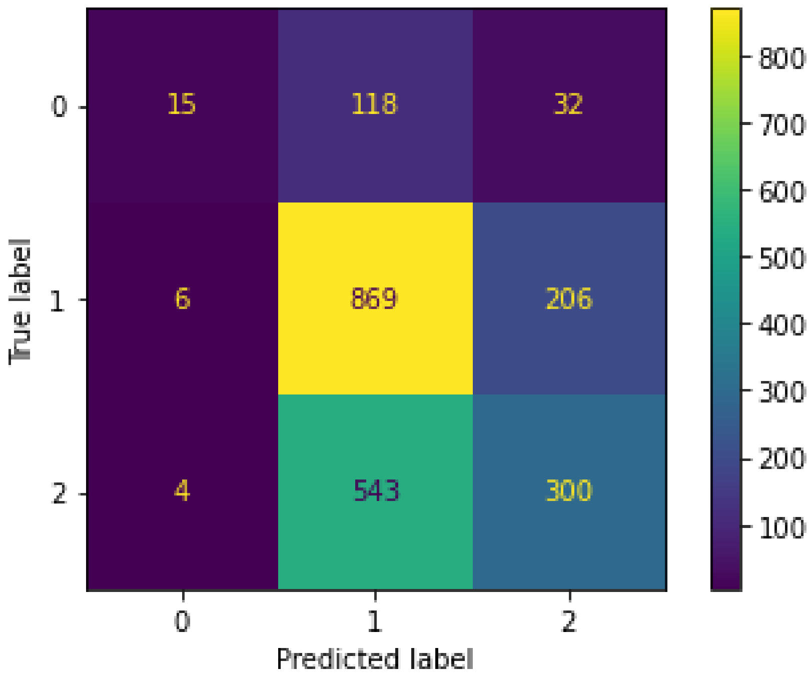
[76]:
```
{'countvect__input': 'content',
 'knn__leaf_size': 7,
 'knn__n_neighbors': 7,
 'knn__weights': 'distance'}
```

[77]:
```
# Display cross validation results, make prediction for X_test_app and␣
 ↪X_test_goo
# diplay results.  Use respective functions.

model_name = 'KNeighborsClassifier with TF-IDF Vectorize'

display_cross_validation_results(tf_knn_model_grid.cv_results_,model_name)

y_test_app_hat5 = tf_knn_model_grid.predict(X_test_app)
y_test_goo_hat5 = tf_knn_model_grid.predict(X_test_goo)

display_prediction_results(y_test_app_hat5, y_test_app,'Apple',model_name)

display_prediction_results(y_test_goo_hat5, y_test_goo, 'Google',model_name)
```

```
Validation ============================================================
Validation results for KNeighborsClassifier with TF-IDF Vectorize:
Accuracy: 0.5927709897186537
Recall: 0.5927709897186537
Precision: 0.5927709897186537

============================================================
Predictions for Apple: KNeighborsClassifier with TF-IDF Vectorize
Accuracy: 0.5642618251313903
Recall: 0.5642618251313903
Precision: 0.5642618251313903

============================================================
Predictions for Google: KNeighborsClassifier with TF-IDF Vectorize
Accuracy: 0.6327272727272727
Recall: 0.6327272727272727
Precision: 0.6327272727272727
```

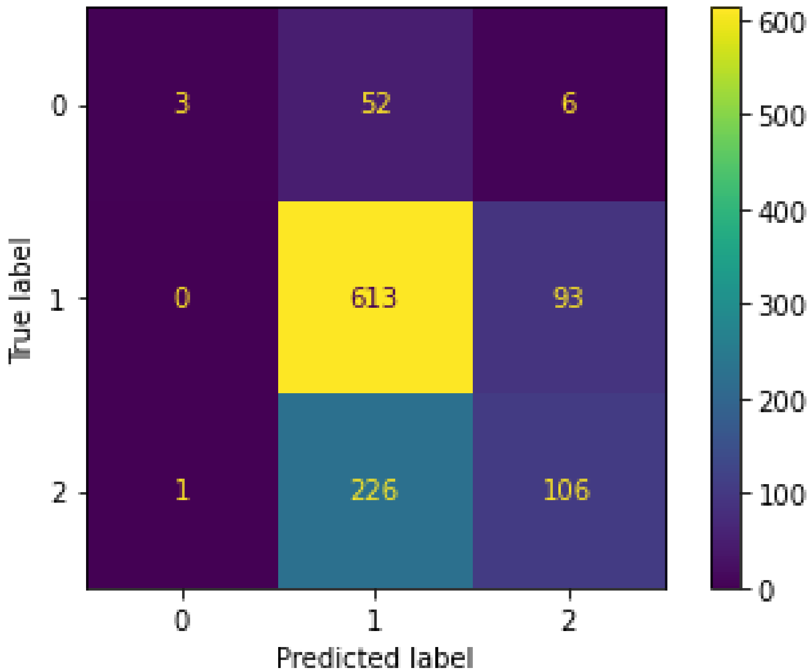
[78]:
```
# Diplay confusion matrix for X_test_app

display_confusion_matrix(tf_knn_model_grid, X_test_app_processed,
                         y_test_app, 'Apple',model_name)
```

```
Confusion matrix for: Apple
Model: KNeighborsClassifier with TF-IDF Vectorize
================================================================================
```



[79]:
```
# Diplay confusion matrix for X_test_app

display_confusion_matrix(tf_knn_model_grid, X_test_goo_processed,
                         y_test_goo, 'Google',model_name)
```

```
Confusion matrix for: Google
Model: KNeighborsClassifier with TF-IDF Vectorize
================================================================================
```




```
[ ]:
```

```
[80]: # RandomForestClassifier
# Use pipes to CountVectorize X_train_combined_processed and then train␣
↪RandomForestClassifier

start = time.time()

cv_rf_pipe = Pipeline([('countvect',CountVectorizer()),
                       ('rf', RandomForestClassifier())])

cv_rf_params = {'countvect__input' : ['content'],
                'rf__random_state' : [42],
                'rf__max_depth' : [87],  # tried 3,11,57,121
                'rf__criterion' : ['gini'],  #log_loss gives warning
                'rf__max_features' : [None]} # tried 'sqrt' and 'log2'

cv_rf_model_grid = GridSearchCV(estimator = cv_rf_pipe, param_grid =␣
↪cv_rf_params,
                                scoring = {'accuracy' : grid_accuracy,
                                           'recall' : grid_recall_micro,
                                         'precision' : grid_precision_micro},
                                refit = 'accuracy')
```

```
cv_rf_model_grid.fit(X_train_combined_processed,y_train_combined)
end = time.time()
print(f'Training time: {end-start}')
cv_rf_model_grid.best_params_
```

```
Training time: 124.89110398292542
```

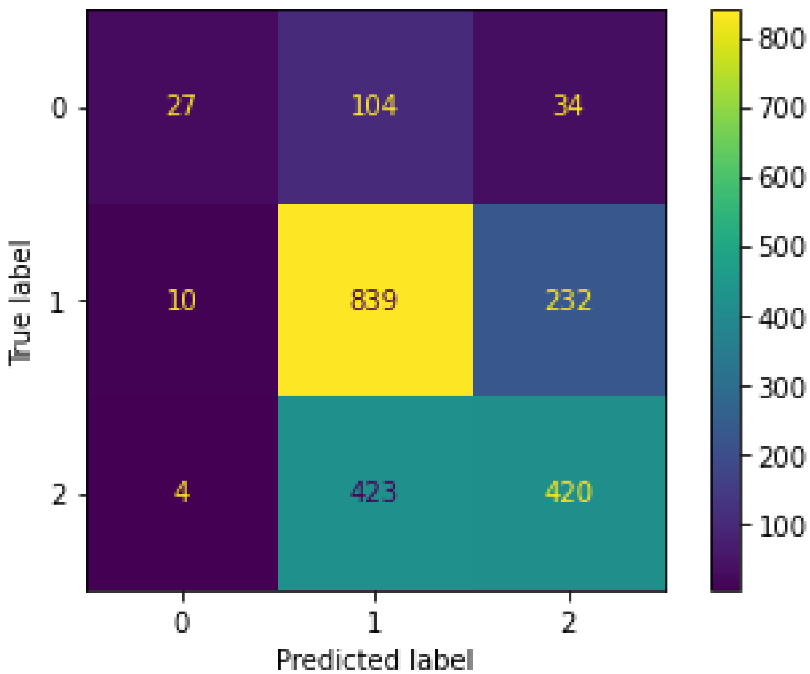
[80]:
```
{'countvect__input': 'content',
 'rf__criterion': 'gini',
 'rf__max_depth': 87,
 'rf__max_features': None,
 'rf__random_state': 42}
```

[81]:
```
# Display cross validation results, make prediction for X_test_app and␣
 ↪X_test_goo
# diplay results.  Use respective functions.

model_name = 'RandomForestClassifier with Count Vectorize'

display_cross_validation_results(cv_rf_model_grid.cv_results_,model_name)

y_test_app_hat6 = cv_rf_model_grid.predict(X_test_app_processed)
y_test_goo_hat6 = cv_rf_model_grid.predict(X_test_goo_processed)

display_prediction_results(y_test_app_hat6, y_test_app,'Apple',model_name)

display_prediction_results(y_test_goo_hat6, y_test_goo, 'Google',model_name)
```

```
Validation ============================================================
Validation results for RandomForestClassifier with Count Vectorize:
Accuracy: 0.6385335610805339
Recall: 0.6385335610805339
Precision: 0.6385335610805339

============================================================
Predictions for Apple: RandomForestClassifier with Count Vectorize
Accuracy: 0.6144290492116579
Recall: 0.6144290492116579
Precision: 0.6144290492116579

============================================================
Predictions for Google: RandomForestClassifier with Count Vectorize
Accuracy: 0.7054545454545454
Recall: 0.7054545454545454
Precision: 0.7054545454545454
```

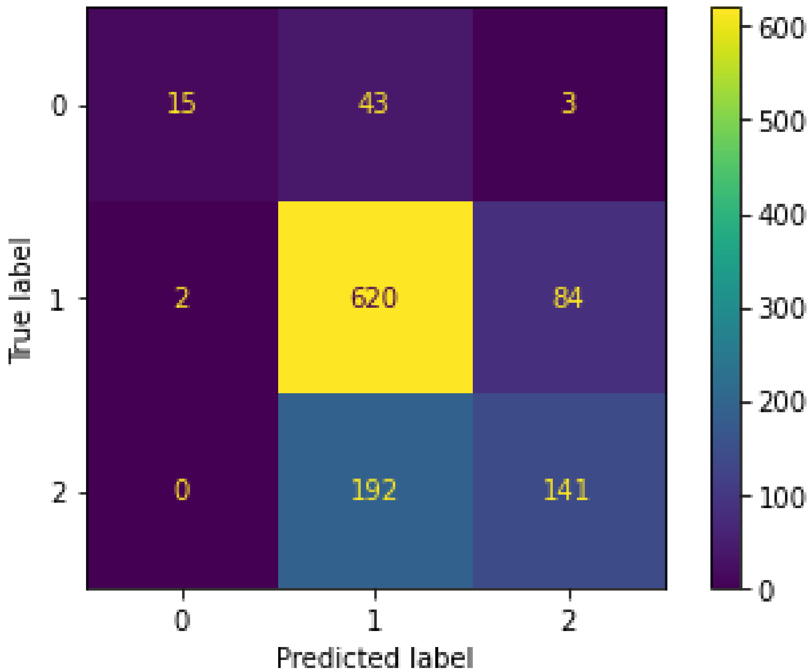
[82]:
```python
# Diplay confusion matrix for X_test_app

display_confusion_matrix(cv_rf_model_grid, X_test_app_processed,
                         y_test_app, 'Apple',model_name)
```

```
Confusion matrix for: Apple
Model: RandomForestClassifier with Count Vectorize
================================================================================
```



[83]:
```python
# Diplay confusion matrix for X_test_app

display_confusion_matrix(cv_rf_model_grid, X_test_goo_processed,
                         y_test_goo, 'Google',model_name)
```

```
Confusion matrix for: Google
Model: RandomForestClassifier with Count Vectorize
================================================================================
```



[ ]:

[84]:
```
# LogisticRegression
# Use pipes to CountVectorize X_train_combined_processed and then train␣
↪LogisticRegression

start = time.time()

cv_lr_pipe = Pipeline([('countvect',CountVectorizer()),
                 ('lr', LogisticRegression())])

cv_lr_params = {'countvect__input' : ['content'],
                'lr__random_state' : [321],
                'lr__penalty' : ['l2'],
                'lr__C' : [1.0],  # tried 1 and 1000
                'lr__class_weight' : [None],  # tried None and 'balanced'
                'lr__solver' : ['liblinear'], # tried 'newton-cg', 'lbfgs',␣
↪'liblinear', 'sag', 'saga'
                'lr__max_iter' : [1000]} # treid 100,1000 and 10000

cv_lr_model_grid = GridSearchCV(estimator = cv_lr_pipe, param_grid =␣
↪cv_lr_params,
                                scoring = {'accuracy' : grid_accuracy,
                                           'recall' : grid_recall_micro,
```

```
                                            'precision' : grid_precision_micro},
                                refit = 'accuracy')


cv_lr_model_grid.fit(X_train_combined_processed,y_train_combined)
end = time.time()
print(f'Training time: {end-start}')
cv_lr_model_grid.best_params_
```

```
Training time: 0.8133320808410645
```

[84]:
```
{'countvect__input': 'content',
 'lr__C': 1.0,
 'lr__class_weight': None,
 'lr__max_iter': 1000,
 'lr__penalty': 'l2',
 'lr__random_state': 321,
 'lr__solver': 'liblinear'}
```

[85]:
```
# Display cross validation results, make prediction for X_test_app and␣
 ↪X_test_goo
# diplay results.  Use respective functions.

model_name = 'LogisticRegression with Count Vectorize'

display_cross_validation_results(cv_lr_model_grid.cv_results_,model_name)

y_test_app_hat7 = cv_lr_model_grid.predict(X_test_app_processed)
y_test_goo_hat7 = cv_lr_model_grid.predict(X_test_goo_processed)

display_prediction_results(y_test_app_hat7, y_test_app,'Apple',model_name)

display_prediction_results(y_test_goo_hat7, y_test_goo, 'Google',model_name)
```

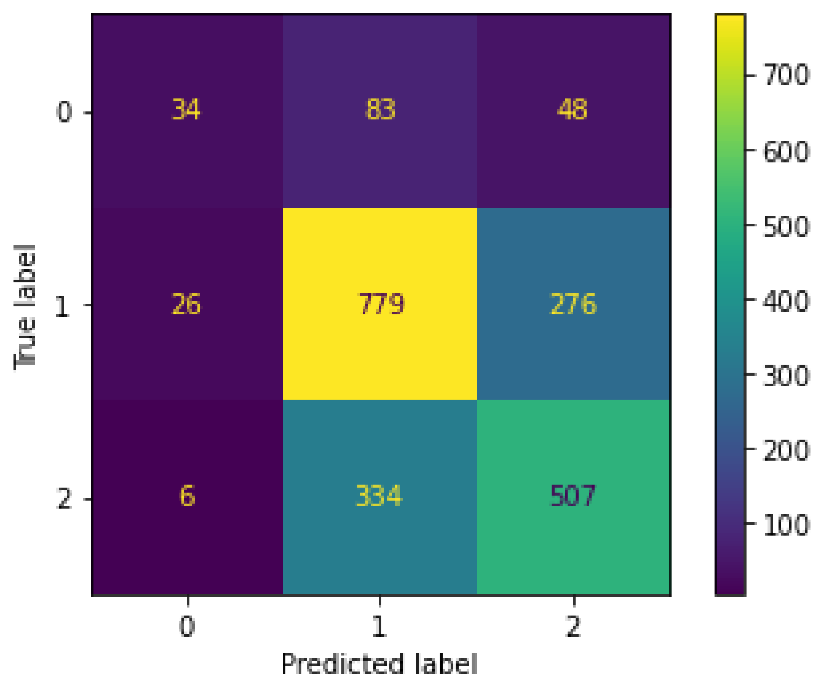
```
Validation ============================================================
Validation results for LogisticRegression with Count Vectorize:
Accuracy: 0.6519049831698309
Recall: 0.6519049831698309
Precision: 0.6519049831698309

============================================================
Predictions for Apple: LogisticRegression with Count Vectorize
Accuracy: 0.630673674151935
Recall: 0.630673674151935
Precision: 0.630673674151935

============================================================
```

```
Predictions for Google: LogisticRegression with Count Vectorize
Accuracy: 0.7027272727272728
Recall: 0.7027272727272728
Precision: 0.7027272727272728
```

[86]:

```
# Diplay confusion matrix for X_test_app

display_confusion_matrix(cv_lr_model_grid, X_test_app_processed,
                         y_test_app, 'Apple',model_name)
```

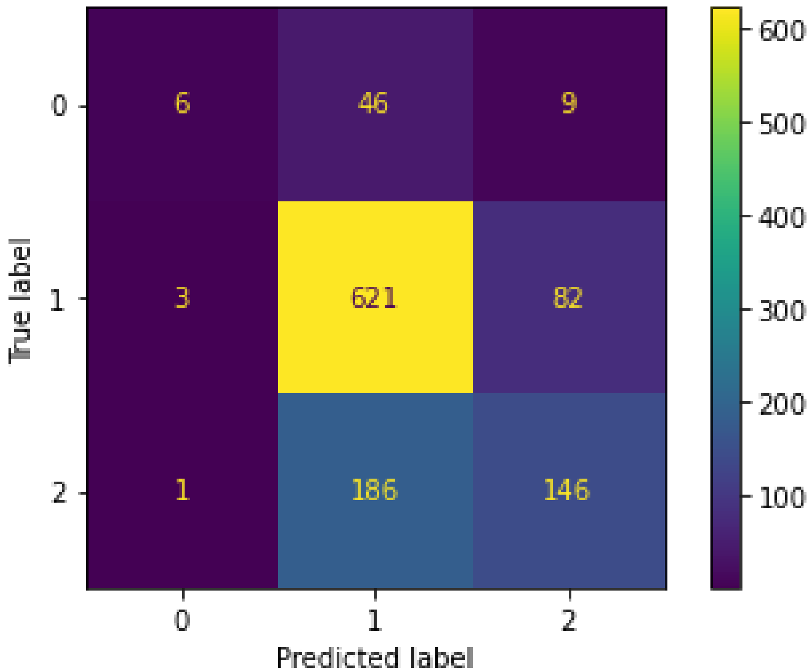
```
Confusion matrix for: Apple
Model: LogisticRegression with Count Vectorize
================================================================================
```



[87]:

```
# Diplay confusion matrix for X_test_app

display_confusion_matrix(cv_lr_model_grid, X_test_goo_processed,
                         y_test_goo, 'Google',model_name)
```

```
Confusion matrix for: Google
Model: LogisticRegression with Count Vectorize
================================================================================
```



[ ]:

[88]:
```
# SVC
# Use pipes to CountVectorize X_train_combined_processed and then train SVC

start = time.time()

cv_svc_pipe = Pipeline([('countvect',CountVectorizer()),
                        ('svc', SVC())])

cv_svc_params = {'countvect__input' : ['content'],
                 'svc__random_state': [234],
                 'svc__kernel' : ['rbf'], # tried 'poly','rbf', 'sigmoid'
                 'svc__degree' : [3], # tried 3,4,5
                 'svc__C' : [1.0],   # tried 1 and 1000
                 'svc__class_weight' : [None]} # tried None and 'balanced

cv_svc_model_grid = GridSearchCV(estimator = cv_svc_pipe, param_grid =␣
 ↪cv_svc_params,
                                 scoring = {'accuracy' : grid_accuracy,
                                            'recall' : grid_recall_micro,
                                           'precision' : grid_precision_micro},
                                 refit = 'accuracy')
```

```
cv_svc_model_grid.fit(X_train_combined_processed,y_train_combined)
end = time.time()
print(f'Training time: {end-start}')
cv_svc_model_grid.best_params_
```

```
Training time: 14.72945785522461
```

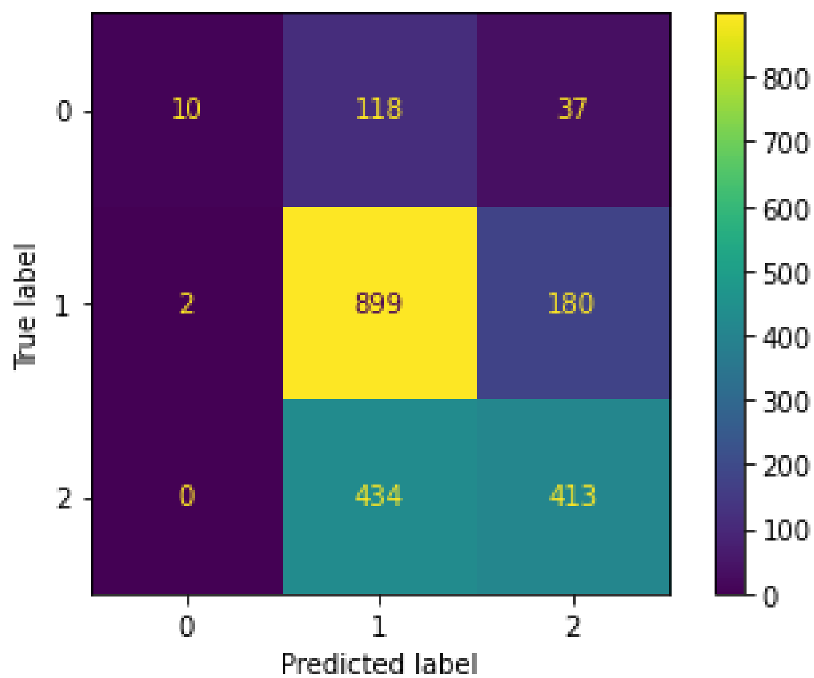
[88]:
```
{'countvect__input': 'content',
 'svc__C': 1.0,
 'svc__class_weight': None,
 'svc__degree': 3,
 'svc__kernel': 'rbf',
 'svc__random_state': 234}
```

[89]:
```
# Display cross validation results, make prediction for X_test_app and␣
 ↪X_test_goo
# diplay results.  Use respective functions.

model_name = 'SVC with Count Vectorize'

display_cross_validation_results(cv_svc_model_grid.cv_results_,model_name)

y_test_app_hat8 = cv_svc_model_grid.predict(X_test_app_processed)
y_test_goo_hat8 = cv_svc_model_grid.predict(X_test_goo_processed)

display_prediction_results(y_test_app_hat8, y_test_app,'Apple',model_name)

display_prediction_results(y_test_goo_hat8, y_test_goo, 'Google',model_name)
```

```
Validation ============================================================
Validation results for SVC with Count Vectorize:
Accuracy: 0.6487671328503521
Recall: 0.6487671328503521
Precision: 0.6487671328503521

============================================================
Predictions for Apple: SVC with Count Vectorize
Accuracy: 0.6316292403248925
Recall: 0.6316292403248925
Precision: 0.6316292403248925

============================================================
Predictions for Google: SVC with Count Vectorize
Accuracy: 0.7127272727272728
Recall: 0.7127272727272728
Precision: 0.7127272727272728
```

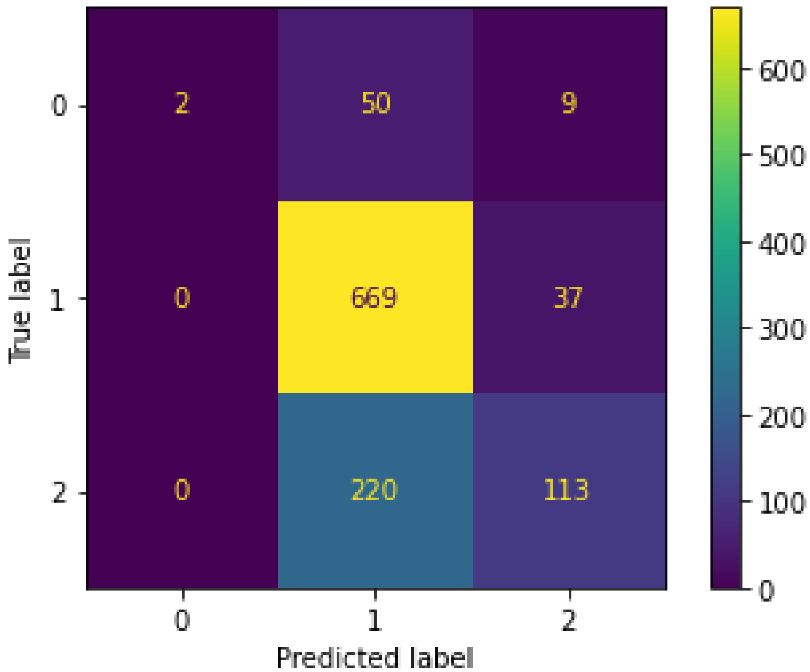
[90]:
```
# Diplay confusion matrix for X_test_app
#display_confusion_matrix_v2(y_test_app,y_test_app_hat8,'Apple')
display_confusion_matrix(cv_svc_model_grid, X_test_app_processed,
                         y_test_app, 'Apple',model_name)
```

```
Confusion matrix for: Apple
Model: SVC with Count Vectorize
================================================================================
```



[91]:
```
# Diplay confusion matrix for X_test_app

#display_confusion_matrix_v2(y_test_goo,y_test_goo_hat8,'Google')
display_confusion_matrix(cv_svc_model_grid, X_test_goo_processed,
                         y_test_goo, 'Google',model_name)
```

```
Confusion matrix for: Google
Model: SVC with Count Vectorize
================================================================================
```



[ ]:

```

```

[92]:

```
# Balance classification ratio with ROS for X_train_combined_processed

cvect = CountVectorizer()
X_train_combined_vected = cvect.fit_transform(X_train_combined_processed)

ros = RandomOverSampler(random_state=3211)
X_train_combined_vec_ros, y_train_combined_ros = ros.fit_resample(
    X_train_combined_vected,y_train_combined)
```

[93]:

```
# Classification ratio without SMOTE

y_train_combined.value_counts()
```

[93]:

```
1    2680
2    1767
0     339
Name: sentiment, dtype: int64
```

[94]:

```
# Classification ratio with SMOTE

y_train_combined_ros.value_counts()
```

[94]:
```
2    2680
1    2680
0    2680
Name: sentiment, dtype: int64
```

[95]:
```
# Train SVC model with SMOTED data

start = time.time()

ros_svc = SVC()

ros_svc_params = {'random_state' : [234],'kernel' : ['rbf'],'degree' : [3],'C' :
 ↪ [1.0],'class_weight' : [None]}

ros_svc_model_grid = GridSearchCV(estimator = ros_svc, param_grid =␣
 ↪ros_svc_params,
                                scoring = {'accuracy' : grid_accuracy,
                                           'recall' : grid_recall_micro,
                                          'precision' : grid_precision_micro},
                                refit = 'accuracy')


ros_svc_model_grid.fit(X_train_combined_vec_ros,y_train_combined_ros)
end = time.time()
print(f'Training time: {end-start}')
ros_svc_model_grid.best_params_
```

```
Training time: 28.633917331695557
```

[95]:
```
{'C': 1.0,
 'class_weight': None,
 'degree': 3,
 'kernel': 'rbf',
 'random_state': 234}
```

[96]:
```
# Display cross validation results, make prediction for X_test_app and␣
 ↪X_test_goo
# diplay results.  Use respective functions.

model_name = 'SVC with CountVectorizer and RandomOverSampler'

X_test_app_vec = cvect.transform(X_test_app_processed)
X_test_goo_vec = cvect.transform(X_test_goo_processed)

display_cross_validation_results(ros_svc_model_grid.cv_results_,model_name)

y_test_app_hat9 = ros_svc_model_grid.predict(X_test_app_vec)
```

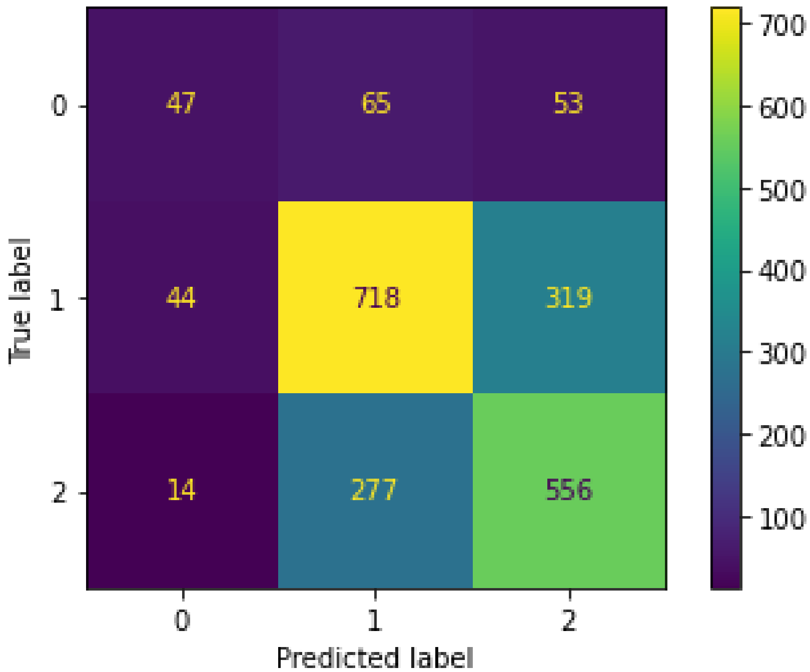
```python
y_test_goo_hat9 = ros_svc_model_grid.predict(X_test_goo_vec)

display_prediction_results(y_test_app_hat9, y_test_app,'Apple',model_name)

display_prediction_results(y_test_goo_hat9, y_test_goo, 'Google',model_name)
```

```
Validation ============================================================
Validation results for SVC with CountVectorizer and RandomOverSampler:
Accuracy: 0.7888059701492537
Recall: 0.7888059701492537
Precision: 0.7888059701492537

============================================================
Predictions for Apple: SVC with CountVectorizer and RandomOverSampler
Accuracy: 0.6311514572384138
Recall: 0.6311514572384138
Precision: 0.6311514572384138

============================================================
Predictions for Google: SVC with CountVectorizer and RandomOverSampler
Accuracy: 0.7218181818181818
Recall: 0.7218181818181818
Precision: 0.7218181818181818
```

[97]:

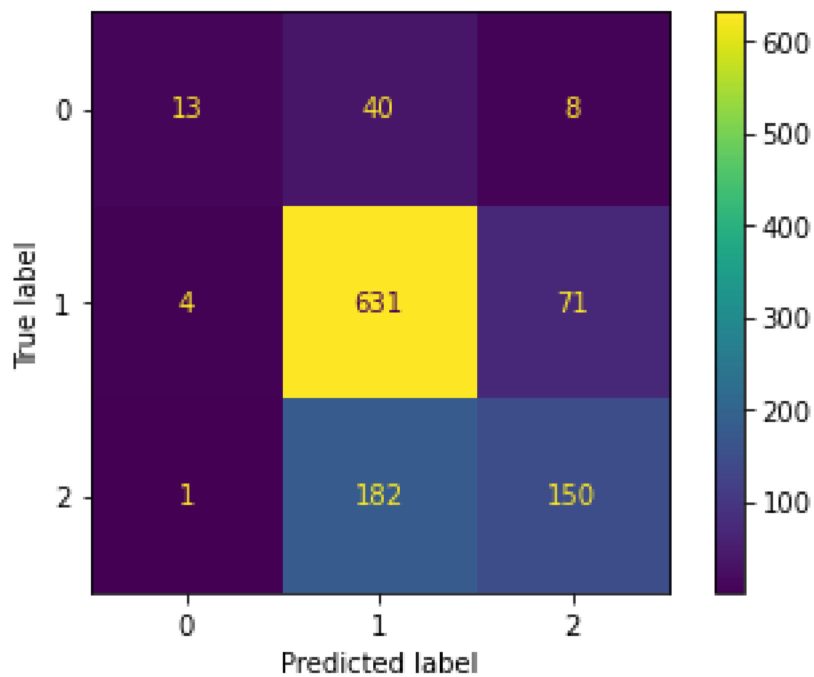
```python
# Diplay confusion matrix for X_test_app

display_confusion_matrix(ros_svc_model_grid, X_test_app_vec,
                         y_test_app, 'Apple',model_name)
```

```
Confusion matrix for: Apple
Model: SVC with CountVectorizer and RandomOverSampler
================================================================================
```



[98]:
```
# Diplay confusion matrix for X_test_app

display_confusion_matrix(ros_svc_model_grid, X_test_goo_vec,
                         y_test_goo, 'Google',model_name)
```

```
Confusion matrix for: Google
Model: SVC with CountVectorizer and RandomOverSampler
================================================================================
```




```
[ ]:
```

1.7 Conclusion

The base model, DummyClassifier, had a validation accuracy of about 56% on the combined apple and google tweet dataframe (train dataframe). Predictions for apple and google tweet test samples were performed separately to be able to compare the two between one another for sentiment. The base model gave a prediction of 52% accuracy for apple and 64% for google with an overal average accuracy of 58%. Five additioanl models (Multinomial NB, KNeighbor, Random Forest, Logistic Regression and SupportVectorClassifier(SVC))were then evaluated for their prediction performance and they all gave similar accuracy within 5% of each other. SVC model was selected as our best model as it gave overall better performance relative to the other four. Validation accuracy for SVC model was about 65%. For test samples, accuracy for apple was about 63% and for google 71% with an overall accuracy of 67% for our best model. Utilized gridsearchcv to adjust hyper-paramters(tunning) for these models. Following NLP processing the tweet text was converted into matrix of tokens using mostly CountVectorizer for TfidfVectorizer diminished model performance a little bit. To correct for data classification imbalance (7% negative, 56% neutral and 37% positive sentiment) the combined trained data was synthetically balanced using RandomOverSampler. However, this did not improve model performance.

Our best model for Twitter sentiment prediction was therefore SVC which gave an overal accuracy of about 67%. The model under-predicted for all three classifications relative to actual for both firms. Also, it missed predicting correctly negative sentiment the most followed by positive and then neutral. This may be because the dataset contained the fewest mumber of negative sentiment tweets. The dataset has a moderate number of positive tweets and the most for neutral tweets.

However, our model was able to correctly predict the overall trend for classification ratios where tweets with neutral sentiment had the highest ratio followed by positive and then negative. In addition, our model was able to correctly predict which of the two firms had a higher positive sentiment.

1.8 Next Steps:

To potentially improve models performance * Take a closer look at tweets that had negative sentiment. Our best model missed these more than positive and neutral sentiments * Setup a model based on scoring words or phrases for negative, neutral or positive sentiment * Consider data from other social media platforms like review sites for products and services

```
[ ]:
```