Gauging Sentiment of Emerging Technology on Twitter

Business Problem

Gauging sentiment of a market sector, company, or product is very helpful to investment analysis. An invetment firm is analyszing emerging technology and would like a predictive model that can analyze text data to classify the sentiment; poitive or negative. Being able to gauge overall sentiment will help in analysis of the sector and help them strategically place investments in the market.

Data Understanding

The dataset consists of thousands of tweets from the SXSW festival pertaining to Apple and Google products. The tweets are labeled as positive, negative, no opinion, or "I can't tell." We will analyze the data from a binary classification standpoint and only keep the positive and negative classes.

The data is heavily imbalanced with positive tweets outnumbering the negative by a 6:1 ratio.

Methods

Using NLP methods we will pre-process the data to get it ready for modeling.

1. First, we will clean the data by removing stop words, punctuation and other pieces of text that do not add value to the analysis such as numbers, and twitter slang.
2. Then we will tokenize he text with regular expressions
3. Next we will both stem and lemmatize the text separatley so that we can train models on both and see which is better.
4. Finally we will vectorize the text with both TF-IDF and Count vectorization so that we again can see which will provide a better model.
5. We will also look at removing mutually exclusive words from our training set to see if it imporoves our model.

We will split our dataset into training and testing data, and to handle the imbalance we with use SMOTE to provide a balanced training set.

Once the data is ready for modeling we will build a baseline and then train several models with differing parameters, score them with cross validation, and generate predictions from our models to compare with the test set and attain our final results.

In [1]:

```
# Import our dependencies
import pandas as pd
import numpy as np
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.utils import class_weight
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score
from sklearn.manifold import TSNE
from nltk.tokenize import word_tokenize
from nltk.tokenize import RegexpTokenizer
from imblearn.over_sampling import SMOTE
import string
from nltk import FreqDist
from nltk.corpus import stopwords
from nltk.stem import SnowballStemmer
from nltk.stem import WordNetLemmatizer
from sklearn.metrics import classification_report
from sklearn.metrics import plot_confusion_matrix
import matplotlib.pyplot as plt
from sklearn.svm import SVC
from collections import Counter
from imblearn.under_sampling import NearMiss
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_extraction.text import CountVectorizer
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

started 08:23:14 2022-02-21, finished in 1.02s

EDA

In [2]:

```
# Read in our dataset and view the first 5 rows
df = pd.read_csv('data/judge_1377884607_tweet_product_company.csv')
df.head()
```

started 08:23:15 2022-02-21, finished in 29ms

Out[2]:

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

In [3]:

```
# View our columns
df.info()
```

started 08:23:15 2022-02-21, finished in 9ms

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8721 entries, 0 to 8720
Data columns (total 3 columns):
 #   Column                                              Non-Null Count
Dtype
---  ------                                              --------------
-----
 0   tweet_text                                          8720 non-null
object
 1   emotion_in_tweet_is_directed_at                     3169 non-null
object
 2   is_there_an_emotion_directed_at_a_brand_or_product  8721 non-null
object
dtypes: object(3)
memory usage: 204.5+ KB
```

In [4]:
```
# See the various products and companies the tweets are about
df.emotion_in_tweet_is_directed_at.value_counts()
```
started 08:23:15 2022-02-21, finished in 4ms

Out[4]:
```
iPad                               910
Apple                              640
iPad or iPhone App                 451
Google                             412
iPhone                             288
Other Google product or service    282
Android App                         78
Android                             74
Other Apple product or service      34
Name: emotion_in_tweet_is_directed_at, dtype: int64
```

In [5]:
```
# Get a feel for the class labels
df.is_there_an_emotion_directed_at_a_brand_or_product.value_counts()
```
started 08:23:15 2022-02-21, finished in 4ms

Out[5]:
```
No emotion toward brand or product    5156
Positive emotion                      2869
Negative emotion                       545
I can't tell                           151
Name: is_there_an_emotion_directed_at_a_brand_or_product, dtype: int64
```

Data Cleaning

In [6]:
```
# Since we are analyzing sentiment we will drop the labels with no sent
pos_neg = df[df['is_there_an_emotion_directed_at_a_brand_or_product'] !
pos_neg = pos_neg[pos_neg['is_there_an_emotion_directed_at_a_brand_or_p
```
started 08:23:15 2022-02-21, finished in 6ms

> Extremely unbalanced dataset

In [7]:
```
pos_neg.is_there_an_emotion_directed_at_a_brand_or_product.value_counts
```
started 08:23:15 2022-02-21, finished in 6ms

Out[7]:
```
Positive emotion    0.840363
Negative emotion    0.159637
Name: is_there_an_emotion_directed_at_a_brand_or_product, dtype: float64
```

In [8]:

```
# Drop the products/companies column since we will not be using this in
# Change column names to something short and easier to work with
pos_neg = pos_neg.drop('emotion_in_tweet_is_directed_at', axis=1)
pos_neg = pos_neg.rename(columns={'tweet_text':'text', 'is_there_an_emo
pos_neg.head()
```

started 08:23:15 2022-02-21, finished in 7ms

Out[8]:

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

In [9]:

```
# Create a function to remove Twitter lingo like @'s and #'s and map it
def remove_ats_and_hashtags(text):
    entity_prefixes = ['@','#','�']
    for separator in  string.punctuation:
        if separator not in entity_prefixes :
            text = text.replace(separator,' ')
    words = []
    for word in text.split():
        word = word.strip()
        if word:
            if word[0] not in entity_prefixes:
                words.append(word)
    return ' '.join(words)

pos_neg['text'] = pos_neg['text'].map(remove_ats_and_hashtags)
```

started 08:23:15 2022-02-21, finished in 38ms

In [10]:

```
# Encode our classes/targets for modeling
pos_neg.replace({'Negative emotion' : 0, 'Positive emotion' : 1}, inpla
```

started 08:23:15 2022-02-21, finished in 4ms

In [11]:

```
# Tansform our text to all lower case letters
pos_neg['text'] = pos_neg['text'].str.lower()
pos_neg.head()
```

started 08:23:15 2022-02-21, finished in 7ms

Out[11]:

	text	target
0	i have a 3g iphone after 3 hrs tweeting at aus...	0
1	know about awesome ipad iphone app that you ll...	1
2	can not wait for 2 also they should sale them ...	1
3	i hope this year s festival isn t as crashy as...	0
4	great stuff on fri marissa mayer google tim o ...	1

Explore the words

In [12]:

```
# Tokenize our text to split into words
pos_neg['text_tokenized'] = pos_neg['text'].apply(word_tokenize)
```

started 08:23:15 2022-02-21, finished in 334ms

In [13]:

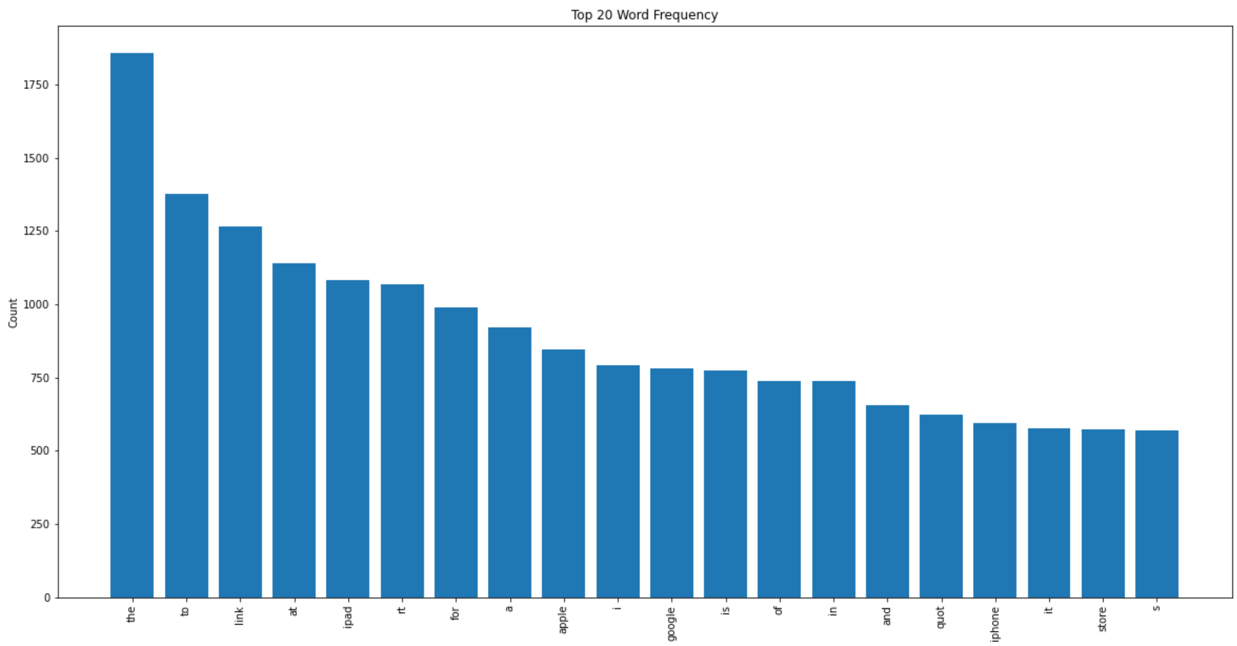
```
# Create a function that will view the 20 most frequently used words
def visualize_top_20(freq_dist, title):

    # Extract data for plotting
    top_20 = list(zip(*freq_dist.most_common(20)))
    tokens = top_20[0]
    counts = top_20[1]

    # Set up plot and plot data
    fig, ax = plt.subplots(figsize=(20,10))
    ax.bar(tokens, counts)

    # Customize plot appearance
    ax.set_title(title)
    ax.set_ylabel("Count")
    ax.tick_params(axis="x", rotation=90)
```

started 08:23:15 2022-02-21, finished in 4ms

In [14]:

```
# create a frequency distribution and view it as a histogram
pos_neg_freq_dist = FreqDist(pos_neg['text_tokenized'].explode())

visualize_top_20(pos_neg_freq_dist, "Top 20 Word Frequency")
```

started 08:23:15 2022-02-21, finished in 220ms



There are a number of stopwords, 1 character and other phrases that won't add value to our model.

Remove stopwords, punctuation and other unwanted phrases

In [15]:

```
# Create a stopwrods list for removal, add punctuation and other phrase
stopwords_list = stopwords.words('english')
stopwords_list += list(string.punctuation)
new_stops = ('quot', 'rt', 'i', 'amp')
stopwords_list += list(new_stops)
```

started 08:23:15 2022-02-21, finished in 4ms

In [16]:

```
# Create a function that will remove the stopwords list from the text a
def remove_stopwords(token_list):
    """
    Given a list of tokens, return a list where the tokens
    that are in stopwords_list have been removed
    """
    stops_rmv_list = [token for token in token_list if token not in sto
    return stops_rmv_list

pos_neg['stopwords_removed'] = pos_neg['text_tokenized'].apply(remove_s
```

started 08:23:15 2022-02-21, finished in 100ms

In [17]:

```
# Remove numbers and single letters and create a text column for modeli
pattern = "([a-z]{4,})"
regex_tokenizer = RegexpTokenizer(pattern)

pos_neg['regex_text'] = [' '.join(text) for text in pos_neg.stopwords_r
pos_neg['regex_text_tokenized'] = [regex_tokenizer.tokenize(text) for t
pos_neg['regex_text'] = [' '.join(text) for text in pos_neg.regex_text_
```

started 08:23:15 2022-02-21, finished in 19ms

In [18]:

```
pos_neg.head()
```

started 08:23:15 2022-02-21, finished in 11ms

Out[18]:

	text	target	text_tokenized	stopwords_removed	regex_text	regex_text_tokenized
0	i have a 3g iphone after 3 hrs tweeting at aus...	0	[i, have, a, 3g, iphone, after, 3, hrs, tweeti...	[3g, iphone, 3, hrs, tweeting, austin, dead, n...	iphone tweeting austin dead need upgrade plugi...	[iphone, tweeting, austin, dead, need, upgrade...
1	know about awesome ipad iphone app that you ll...	1	[know, about, awesome, ipad, iphone, app, that...	[know, awesome, ipad, iphone, app, likely, app...	know awesome ipad iphone likely appreciate des...	[know, awesome, ipad, iphone, likely, apprecia...
2	can not wait for 2 also they should sale them ...	1	[can, not, wait, for, 2, also, they, should, s...	[wait, 2, also, sale]	wait also sale	[wait, also, sale]
3	i hope this year s festival isn t as crashy as...	0	[i, hope, this, year, s, festival, isn, t, as,...	[hope, year, festival, crashy, year, iphone, app]	hope year festival crashy year iphone	[hope, year, festival, crashy, year, iphone]
4	great stuff on fri marissa mayer google tim o ...	1	[great, stuff, on, fri, marissa, mayer, google...	[great, stuff, fri, marissa, mayer, google, ti...	great stuff marissa mayer google reilly tech b...	[great, stuff, marissa, mayer, google, reilly,...

Stem words

In [19]:

```
snow_stemmer = SnowballStemmer(language="english")

pos_neg['stemmed_text'] = [snow_stemmer.stem(text) for text in pos_neg[

pos_neg.head()
```

started 08:23:15 2022-02-21, finished in 70ms

Out[19]:

	text	target	text_tokenized	stopwords_removed	regex_text	regex_text_tokenized
0	i have a 3g iphone after 3 hrs tweeting at aus...	0	[i, have, a, 3g, iphone, after, 3, hrs, tweeti...	[3g, iphone, 3, hrs, tweeting, austin, dead, n...	iphone tweeting austin dead need upgrade plugi...	[iphone, tweeting, austin, dead, need, upgrade...
1	know about awesome ipad iphone app that you ll...	1	[know, about, awesome, ipad, iphone, app, that...	[know, awesome, ipad, iphone, app, likely, app...	know awesome ipad iphone likely appreciate des...	[know, awesome, ipad, iphone, likely, apprecia...
2	can not wait for 2 also they should sale them ...	1	[can, not, wait, for, 2, also, they, should, s...	[wait, 2, also, sale]	wait also sale	[wait, also, sale]
3	i hope this year s festival isn t as crashy as...	0	[i, hope, this, year, s, festival, isn, t, as,...	[hope, year, festival, crashy, year, iphone, app]	hope year festival crashy year iphone	[hope, year, festival, crashy, year, iphone]
4	great stuff on fri marissa mayer google tim o ...	1	[great, stuff, on, fri, marissa, mayer, google...	[great, stuff, fri, marissa, mayer, google, ti...	great stuff marissa mayer google reilly tech b...	[great, stuff, marissa, mayer, google, reilly,...

Lemmatize words

In [20]:

```
lemmer = WordNetLemmatizer()

pos_neg['lemmed_text'] = [lemmer.lemmatize(text) for text in pos_neg['r

pos_neg.head(10)
```

started 08:23:15 2022-02-21, finished in 1.28s

Out[20]:

	text	target	text_tokenized	stopwords_removed	regex_text	regex_text_tokenized
0	i have a 3g iphone after 3 hrs tweeting at aus...	0	[i, have, a, 3g, iphone, after, 3, hrs, tweeti...	[3g, iphone, 3, hrs, tweeting, austin, dead, n...	iphone tweeting austin dead need upgrade plugi...	[iphone, tweeting, austi dead, need, upgrade.
1	know about awesome ipad iphone app that you ll...	1	[know, about, awesome, ipad, iphone, app, that...	[know, awesome, ipad, iphone, app, likely, app...	know awesome ipad iphone likely appreciate des...	[know, awesome, ipa iphone, likely, apprecia.
2	can not wait for 2 also they should sale them ...	1	[can, not, wait, for, 2, also, they, should, s...	[wait, 2, also, sale]	wait also sale	[wait, also, sal
3	i hope this year s festival isn t as crashy as...	0	[i, hope, this, year, s, festival, isn, t, as,...	[hope, year, festival, crashy, year, iphone, app]	hope year festival crashy year iphone	[hope, year, festiva crashy, year, iphon
4	great stuff on fri marissa mayer google tim o ...	1	[great, stuff, on, fri, marissa, mayer, google...	[great, stuff, fri, marissa, mayer, google, ti...	great stuff marissa mayer google reilly tech b...	[great, stuff, mariss mayer, google, reilly,.
7	is just starting is around the corner and is o...	1	[is, just, starting, is, around, the, corner, ...	[starting, around, corner, hop, skip, jump, go...	starting around corner skip jump good time	[starting, around, corne skip, jump, good, t.
8	beautifully smart and simple idea rt wrote abo...	1	[beautifully, smart, and, simple, idea, rt, wr...	[beautifully, smart, simple, idea, wrote, ipad...	beautifully smart simple idea wrote ipad http ...	[beautifully, smar simple, idea, wrot ipad.

	text	target	text_tokenized	stopwords_removed	regex_text	regex_text_tokenized
9	counting down the days to plus strong canadian...	1	[counting, down, the, days, to, plus, strong, ...	[counting, days, plus, strong, canadian, dolla...	counting days plus strong canadian dollar mean...	[counting, days, plu: strong, canadian, dolla.
10	excited to meet the at so i can show them my s...	1	[excited, to, meet, the, at, so, i, can, show,...	[excited, meet, show, sprint, galaxy, still, r...	excited meet show sprint galaxy still running ...	[excited, meet, shov sprint, galaxy, still, r.
11	find amp start impromptu parties at with http ...	1	[find, amp, start, impromptu, parties, at, wit...	[find, start, impromptu, parties, http, bit, l...	find start impromptu parties http gvlrin wait ...	[find, start, impromptu parties, http, gvlrin.

You can see in several of the tweets that stemming removes the 'e' from words like 'sale' and 'iphone' so we will use the lemmatized words for modeling

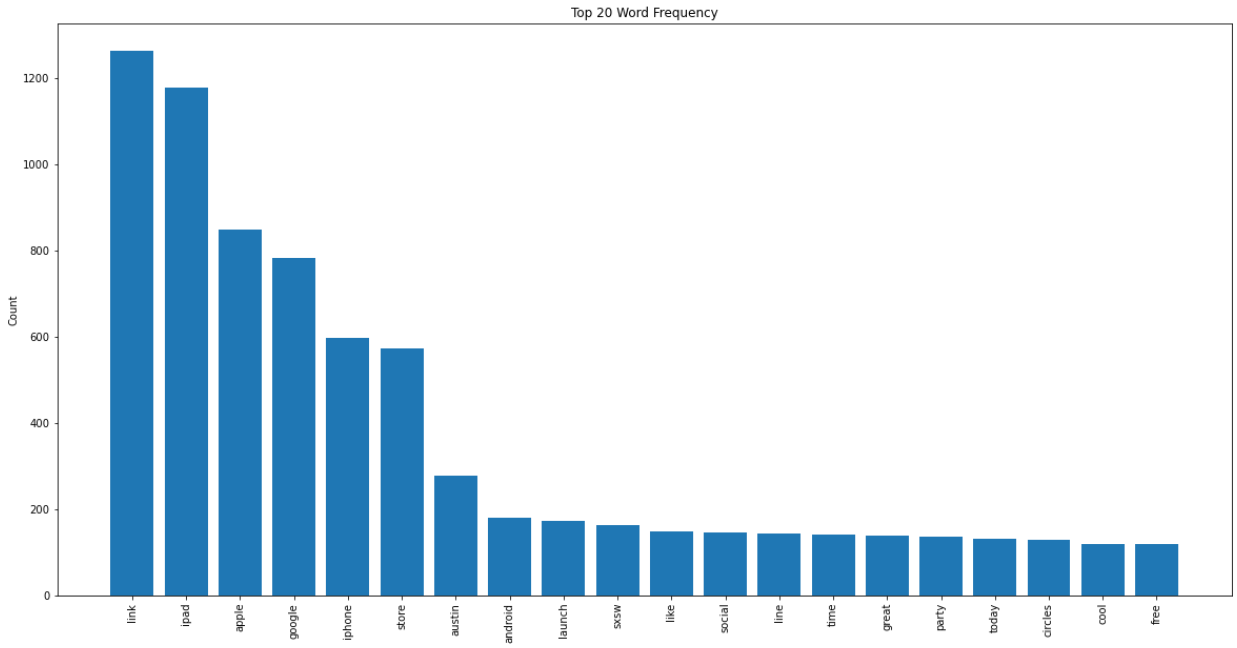
View the new frequency distribution of words after processing

In [21]:

```
pos_neg['lemmed_text_tokenized'] = pos_neg['lemmed_text'].apply(word_to
```

started 08:23:17 2022-02-21, finished in 273ms

In [22]:
```
# create a frequency distribution and view it as a histogram
lemmed_text_freq_dist = FreqDist(pos_neg['lemmed_text_tokenized'].explo

visualize_top_20(lemmed_text_freq_dist, "Top 20 Word Frequency")
```
started 08:23:17 2022-02-21, finished in 190ms



Train Test Split

In [23]:
```
X = pos_neg.drop(['target'], axis=1)
y = pos_neg['target']

X_train , X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=30)
```
started 08:23:17 2022-02-21, finished in 8ms

In [24]:
```
y_train.value_counts(normalize=True)
```
started 08:23:17 2022-02-21, finished in 5ms

Out[24]:
```
1    0.844746
0    0.155254
Name: target, dtype: float64
```

Build and score a baseline model

Using Count Vectorization on lemmatized text

In [25]:
```
# Use count vectorization
count = CountVectorizer()
X_count_vectorized = count.fit_transform(X_train['lemmed_text'])
```
started 08:23:17 2022-02-21, finished in 28ms

In [26]:
```
# With such an imbalanced dataset use SMOTE to balance training data
smote_count = SMOTE(k_neighbors=3)
X_train_resampled, y_train_resampled = smote_count.fit_resample(
    X_count_vectorized, y_train)
```
started 08:23:17 2022-02-21, finished in 14ms

In [27]:
```
# Check that the training set is balanced now
y_train_resampled.value_counts(normalize=True)
```
started 08:23:17 2022-02-21, finished in 5ms

Out[27]:
```
1    0.5
0    0.5
Name: target, dtype: float64
```

In [28]:
```
# Instantiate a MultinomialNB classifier and fi it to training data
baseline_model = MultinomialNB()

baseline_model.fit(X_train_resampled, y_train_resampled)

# Evaluate the model
baseline_cv = cross_val_score(baseline_model, X_train_resampled, y_trai
print("Baseline:", baseline_cv.mean())
```
started 08:23:17 2022-02-21, finished in 19ms

```
Baseline: 0.7986608790067286
```

In [29]:
```
# Use count vectorization with bigrams
count_bigram = CountVectorizer(ngram_range=(1,2))
X_count_vectorized_bigrams = count_bigram.fit_transform(X_train['lemmed
```
started 08:23:17 2022-02-21, finished in 61ms

In [30]:
```
smote_count = SMOTE(k_neighbors=3)
X_train_resampled_bigram, y_train_resampled_bigram = smote_count.fit_re
    X_count_vectorized_bigrams, y_train)
```
started 08:23:17 2022-02-21, finished in 15ms

In [31]:
```
baseline_model_bigram = MultinomialNB()

baseline_model_bigram.fit(X_train_resampled_bigram, y_train_resampled_b

baseline_bigram_cv = cross_val_score(baseline_model_bigram, X_train_res
print("Baseline            :", baseline_cv.mean())
print("Baseline w/ bigrams :", baseline_bigram_cv.mean())
```
started 08:23:17 2022-02-21, finished in 21ms

```
Baseline            : 0.7986608790067286
Baseline w/ bigrams : 0.7373374570802085
```

Score using TF-IDF Vectorization

In [32]:

```
tfidf = TfidfVectorizer(max_features=20)
X_train_vectorized_tfidf = tfidf.fit_transform(X_train['lemmed_text'])
```

started 08:23:17 2022-02-21, finished in 31ms

In [33]:

```
smote_count = SMOTE(k_neighbors=3)
X_train_resampled_tfidf, y_train_resampled_tfidf = smote_count.fit_resa
    X_train_vectorized_tfidf, y_train)
```

started 08:23:17 2022-02-21, finished in 9ms

In [34]:

```
baseline_model_tfidf = MultinomialNB()

baseline_model_tfidf.fit(X_train_resampled_tfidf, y_train_resampled_tfi

baseline_tfidf_cv = cross_val_score(baseline_model_tfidf, X_train_resam
print("Baseline             :", baseline_cv.mean())
print("Baseline w/ bigrams :", baseline_bigram_cv.mean())
print("Baseline TF-IDF     :", baseline_tfidf_cv.mean())
```

started 08:23:17 2022-02-21, finished in 18ms

```
Baseline             : 0.7986608790067286
Baseline w/ bigrams  : 0.7373374570802085
Baseline TF-IDF      : 0.6569201627250572
```

Looks like the regular baseline model scored the best - "Multinomial Naive Bayes"

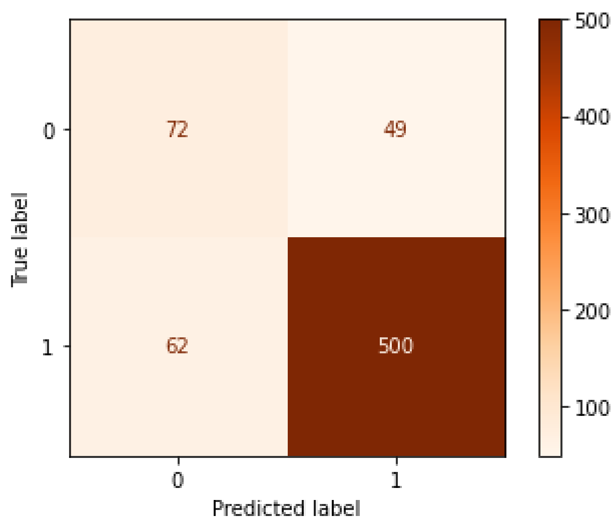
> Lets see how it does on test data

In [35]:

```
X_test_vectorized = count.transform(X_test['lemmed_text'])
baseline_preds = baseline_model.predict(X_test_vectorized)

print(classification_report(y_test, baseline_preds))

plot_confusion_matrix(baseline_model, X_test_vectorized, y_test, cmap=p
plt.grid(False)
plt.show()
```

started 08:23:17 2022-02-21, finished in 130ms

```
              precision    recall  f1-score   support

           0       0.54      0.60      0.56       121
           1       0.91      0.89      0.90       562

    accuracy                           0.84       683
   macro avg       0.72      0.74      0.73       683
weighted avg       0.84      0.84      0.84       683
```



This scores well

Overall Accuracy of 84%

> Predicts positive sentiment with an accuracy of 89%
> Predicts negative sentiment with an accuracy of 61%

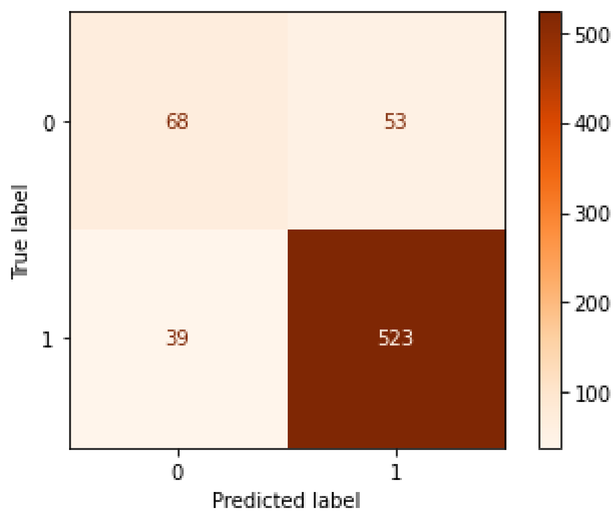
And the bigrams model too

In [36]:

```
X_test_vectorized_bigrams = count_bigram.transform(X_test['lemmed_text'
baseline_preds = baseline_model_bigram.predict(X_test_vectorized_bigram

bigram_preds = baseline_model_bigram.predict(X_test_vectorized_bigrams)

print(classification_report(y_test, bigram_preds))

plot_confusion_matrix(baseline_model_bigram, X_test_vectorized_bigrams,
plt.grid(False)
plt.show()
```

started 08:23:18 2022-02-21, finished in 136ms

```
              precision    recall  f1-score   support

           0       0.64      0.56      0.60       121
           1       0.91      0.93      0.92       562

    accuracy                           0.87       683
   macro avg       0.77      0.75      0.76       683
weighted avg       0.86      0.87      0.86       683
```



Bigrams also score well

Overall Accuracy of 86%

> Predicts positive sentiment with an accuracy of 93%
> Predicts negative sentiment with an accuracy of 55%

Lets run the model on the original text with no processing and see how it does

In [37]:

```
count_og_text = CountVectorizer()
X_count_og_text_vectorized = count_og_text.fit_transform(X_train['text'
```

started 08:23:18 2022-02-21, finished in 40ms

In [38]:

```
smote_og_count = SMOTE(k_neighbors=3)
X_train_resampled_og, y_train_resampled_og = smote_og_count.fit_resampl
    X_count_og_text_vectorized, y_train)
```

started 08:23:18 2022-02-21, finished in 16ms

In [39]:

```
baseline_model_og = MultinomialNB()

baseline_model_og.fit(X_train_resampled_og, y_train_resampled_og)

# Evaluate the model
baseline_og_cv = cross_val_score(baseline_model_og, X_train_resampled_o
print("Baseline              :", baseline_cv.mean())
print("Baseline w/ og text :", baseline_og_cv.mean())
```

started 08:23:18 2022-02-21, finished in 22ms

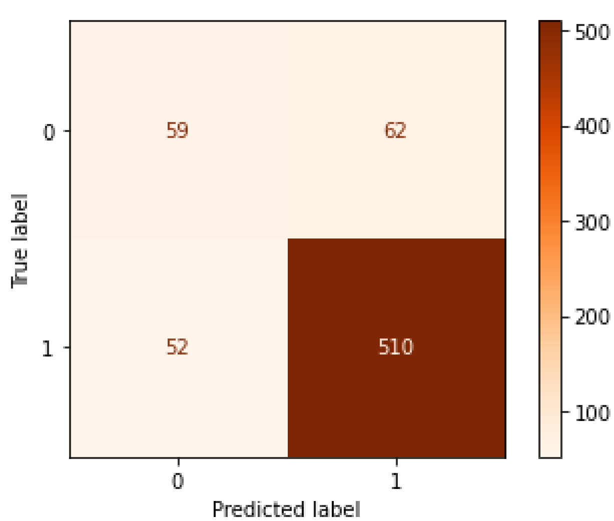
```
Baseline             : 0.7986608790067286
Baseline w/ og text : 0.8129674761400038
```

In [40]:

```
X_test_og_vectorized = count_og_text.transform(X_test['text'])
baseline_og_preds = baseline_model_og.predict(X_test_og_vectorized)

print(classification_report(y_test, baseline_og_preds))

plot_confusion_matrix(baseline_model_og, X_test_og_vectorized, y_test,
plt.grid(False)
plt.show()
```

started 08:23:18 2022-02-21, finished in 115ms

	precision	recall	f1-score	support
0	0.53	0.49	0.51	121
1	0.89	0.91	0.90	562
accuracy			0.83	683
macro avg	0.71	0.70	0.70	683
weighted avg	0.83	0.83	0.83	683



Surprisingly it scores almost as well as the model with lemmatized text

Overall Accuracy of 83%

> Predicts positive sentiment with an accuracy of 91%
> Predicts negative sentiment with an accuracy of 50%

We will stick with the Lemmatized text model

Let's run a few more models to see if we can score better

We will stick with these parameters:

> Lemmatized text
> Count vectorization

In [41]:

```python
# K Nearest Neighbors with n=5
knn_5 = KNeighborsClassifier(n_neighbors=5)
knn_5.fit(X_train_resampled, y_train_resampled)

knn_5_cv = cross_val_score(knn_5, X_train_resampled, y_train_resampled)
print("Baseline :", baseline_cv.mean())
print("KNN_5    :", knn_5_cv.mean())
```

started 08:23:18 2022-02-21, finished in 392ms

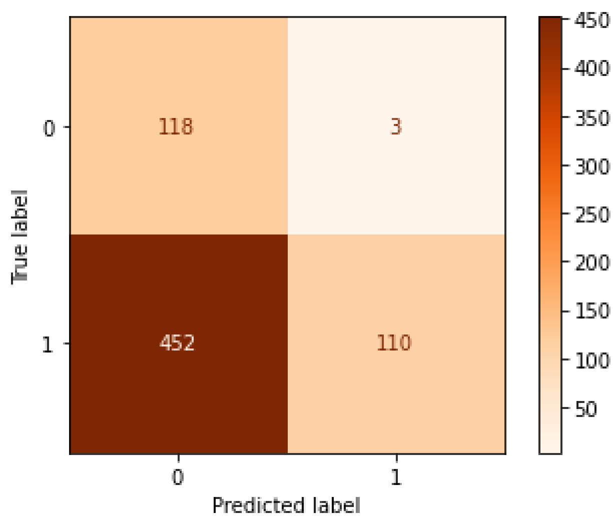
```
Baseline : 0.7986608790067286
KNN_5    : 0.5806259885359211
```

In [42]:

```
knn_5_preds = knn_5.predict(X_test_vectorized)

print(classification_report(y_test, knn_5_preds))

plot_confusion_matrix(knn_5, X_test_vectorized, y_test, cmap=plt.cm.Ora
plt.grid(False)
plt.show()
```

started 08:23:18 2022-02-21, finished in 245ms

```
              precision    recall  f1-score   support

           0       0.21      0.98      0.34       121
           1       0.97      0.20      0.33       562

    accuracy                           0.33       683
   macro avg       0.59      0.59      0.33       683
weighted avg       0.84      0.33      0.33       683
```



In [43]:

```
# K Nearest Neighbors with n=3
knn_3 = KNeighborsClassifier(n_neighbors=3)
knn_3.fit(X_train_resampled, y_train_resampled)

knn_3_cv = cross_val_score(knn_3, X_train_resampled, y_train_resampled)
print("Baseline :", baseline_cv.mean())
print("KNN_5    :", knn_5_cv.mean())
print("KNN_3    :", knn_3_cv.mean())
```

started 08:23:19 2022-02-21, finished in 312ms

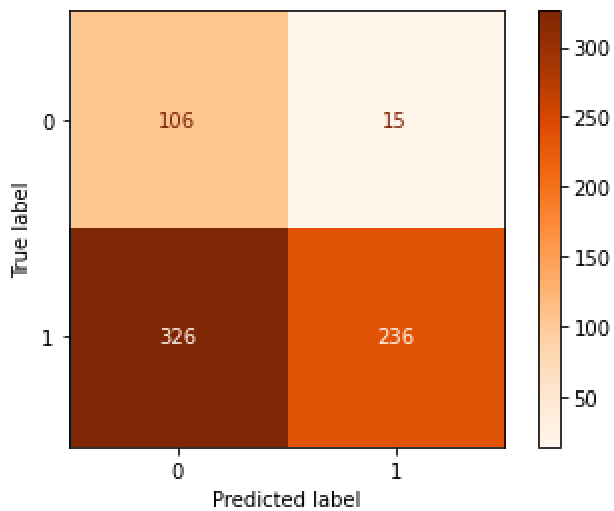
```
Baseline : 0.7986608790067286
KNN_5    : 0.5806259885359211
KNN_3    : 0.6896421411834934
```

In [44]:

```python
knn_3_preds = knn_3.predict(X_test_vectorized)

print(classification_report(y_test, knn_3_preds))

plot_confusion_matrix(knn_3, X_test_vectorized, y_test, cmap=plt.cm.Ora
plt.grid(False)
plt.show()
```

started 08:23:19 2022-02-21, finished in 208ms

```
              precision    recall  f1-score   support

           0       0.25      0.88      0.38       121
           1       0.94      0.42      0.58       562

    accuracy                           0.50       683
   macro avg       0.59      0.65      0.48       683
weighted avg       0.82      0.50      0.55       683
```



In [45]:

```python
# Decision Tree (default)
tree = DecisionTreeClassifier()
tree.fit(X_train_resampled, y_train_resampled)

tree_cv = cross_val_score(tree, X_train_resampled, y_train_resampled)
print("Baseline :", baseline_cv.mean())
print("KNN_5    :", knn_5_cv.mean())
print("KNN_3    :", knn_3_cv.mean())
print("Tree     :", tree_cv.mean())
```

started 08:23:19 2022-02-21, finished in 453ms

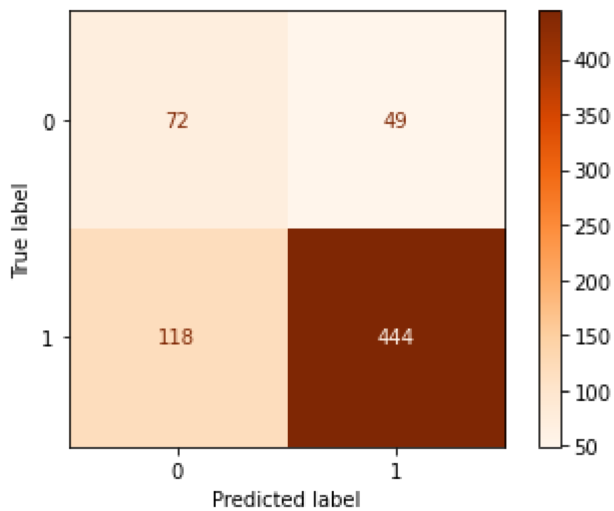
```
Baseline : 0.7986608790067286
KNN_5    : 0.5806259885359211
KNN_3    : 0.6896421411834934
Tree     : 0.8446086161554677
```

In [46]:

```
tree_preds = tree.predict(X_test_vectorized)

print(classification_report(y_test, tree_preds))

plot_confusion_matrix(tree, X_test_vectorized, y_test, cmap=plt.cm.Oran
plt.grid(False)
plt.show()
```

started 08:23:20 2022-02-21, finished in 115ms

```
              precision    recall  f1-score   support

           0       0.38      0.60      0.46       121
           1       0.90      0.79      0.84       562

    accuracy                           0.76       683
   macro avg       0.64      0.69      0.65       683
weighted avg       0.81      0.76      0.77       683
```



In [47]:

```
# Random Forest (default)
forest = RandomForestClassifier()
forest.fit(X_train_resampled, y_train_resampled)

forest_cv = cross_val_score(forest, X_train_resampled, y_train_resample
print("Baseline :", baseline_cv.mean())
print("KNN_5    :", knn_5_cv.mean())
print("KNN_3    :", knn_3_cv.mean())
print("Tree     :", tree_cv.mean())
print("Forest   :", forest_cv.mean())
```

started 08:23:20 2022-02-21, finished in 10.2s

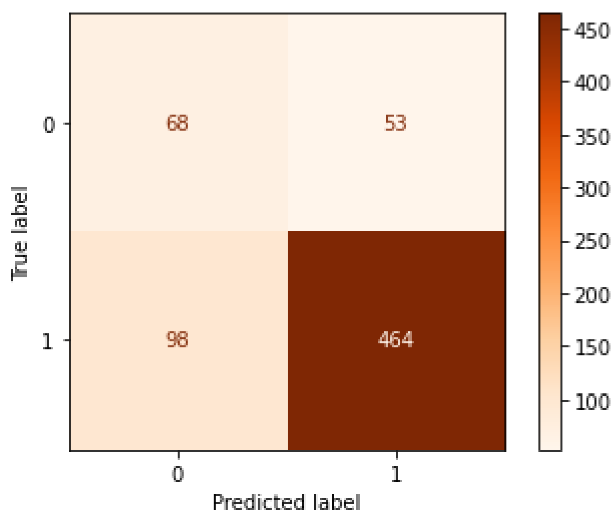
```
Baseline : 0.7986608790067286
KNN_5    : 0.5806259885359211
KNN_3    : 0.6896421411834934
Tree     : 0.8446086161554677
Forest   : 0.8591309579485926
```

In [48]:

```python
forest_preds = forest.predict(X_test_vectorized)

print(classification_report(y_test, forest_preds))

plot_confusion_matrix(forest, X_test_vectorized, y_test, cmap=plt.cm.Or
plt.grid(False)
plt.show()
```

started 08:23:30 2022-02-21, finished in 167ms

```
              precision    recall  f1-score   support

           0       0.41      0.56      0.47       121
           1       0.90      0.83      0.86       562

    accuracy                           0.78       683
   macro avg       0.65      0.69      0.67       683
weighted avg       0.81      0.78      0.79       683
```



In [49]:

```python
# Random Forest w/ bootstrap=False
forest_boot = RandomForestClassifier(bootstrap=False)
forest_boot.fit(X_train_resampled, y_train_resampled)

forest_boot_cv = cross_val_score(forest_boot, X_train_resampled, y_trai
print("Baseline    :", baseline_cv.mean())
print("KNN_5       :", knn_5_cv.mean())
print("KNN_3       :", knn_3_cv.mean())
print("Tree        :", tree_cv.mean())
print("Forest      :", forest_cv.mean())
print("Forest Boot :", forest_boot_cv.mean())
```

started 08:23:30 2022-02-21, finished in 15.8s

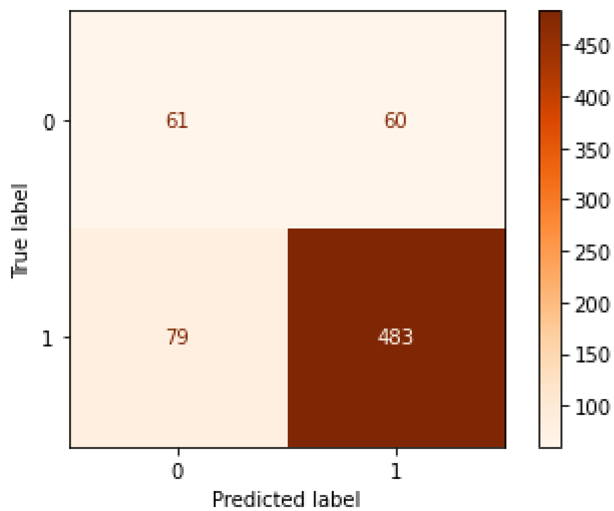
```
Baseline    : 0.7986608790067286
KNN_5       : 0.5806259885359211
KNN_3       : 0.6896421411834934
Tree        : 0.8446086161554677
Forest      : 0.8591309579485926
Forest Boot : 0.8766850057461404
```

In [50]:

```python
forest_boot_preds = forest_boot.predict(X_test_vectorized)

print(classification_report(y_test, forest_boot_preds))

plot_confusion_matrix(forest_boot, X_test_vectorized, y_test, cmap=plt.
plt.grid(False)
plt.show()
```

started 08:23:46 2022-02-21, finished in 174ms

```
              precision    recall  f1-score   support

           0       0.44      0.50      0.47       121
           1       0.89      0.86      0.87       562

    accuracy                           0.80       683
   macro avg       0.66      0.68      0.67       683
weighted avg       0.81      0.80      0.80       683
```



In [51]:

```python
# Support Vector Machine (default)
clf = SVC()
clf.fit(X_train_resampled, y_train_resampled)

clf_cv = cross_val_score(clf, X_train_resampled, y_train_resampled)
print("Baseline    :", baseline_cv.mean())
print("KNN_5       :", knn_5_cv.mean())
print("KNN_3       :", knn_3_cv.mean())
print("Tree        :", tree_cv.mean())
print("Forest      :", forest_cv.mean())
print("Forest Boot :", forest_boot_cv.mean())
print("SVM         :", clf_cv.mean())
```

started 08:23:46 2022-02-21, finished in 3.54s

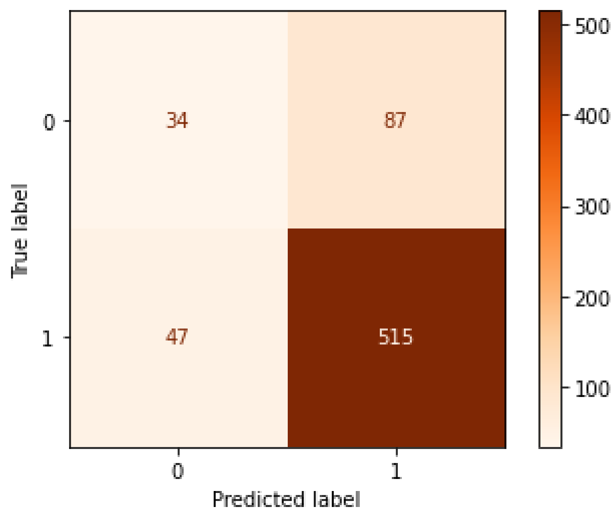
```
Baseline    : 0.7986608790067286
KNN_5       : 0.5806259885359211
KNN_3       : 0.6896421411834934
Tree        : 0.8446086161554677
Forest      : 0.8591309579485926
Forest Boot : 0.8766850057461404
SVM         : 0.9001012918827834
```

In [52]:

```
clf_preds = clf.predict(X_test_vectorized)

print(classification_report(y_test, clf_preds))

plot_confusion_matrix(clf, X_test_vectorized, y_test, cmap=plt.cm.Orang
plt.grid(False)
plt.show()
```

started 08:23:50 2022-02-21, finished in 292ms

```
              precision    recall  f1-score   support

           0       0.42      0.28      0.34       121
           1       0.86      0.92      0.88       562

    accuracy                           0.80       683
   macro avg       0.64      0.60      0.61       683
weighted avg       0.78      0.80      0.79       683
```



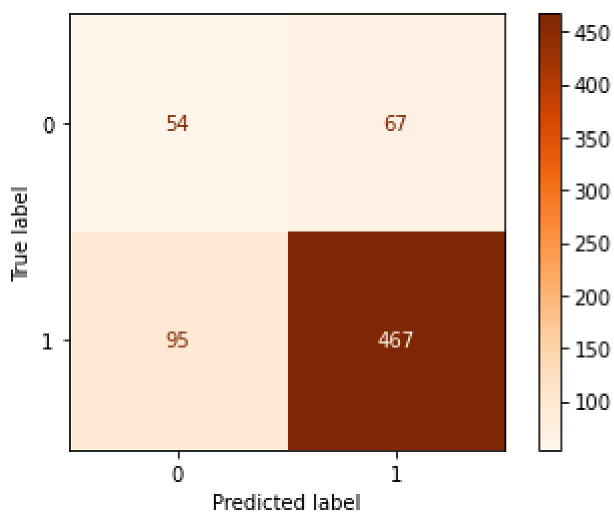
Out of curiousity, let's see how the Decision Tree, The Random Forrests, and the SVM score with the original text

In [53]:

```
tree_og = DecisionTreeClassifier()
tree_og.fit(X_train_resampled_og, y_train_resampled_og)

tree_og_preds = tree_og.predict(X_test_og_vectorized)

print(classification_report(y_test, tree_og_preds))

plot_confusion_matrix(tree_og, X_test_og_vectorized, y_test, cmap=plt.c
plt.grid(False)
plt.show()
```

started 08:23:50 2022-02-21, finished in 220ms

```
              precision    recall  f1-score   support

           0       0.36      0.45      0.40       121
           1       0.87      0.83      0.85       562

    accuracy                           0.76       683
   macro avg       0.62      0.64      0.63       683
weighted avg       0.78      0.76      0.77       683
```

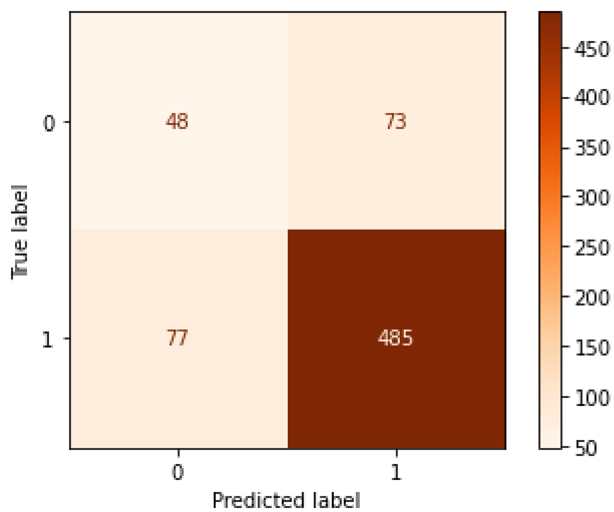


In [54]:

```
forest_og = RandomForestClassifier()
forest_og.fit(X_train_resampled_og, y_train_resampled_og)

forest_og_preds = forest_og.predict(X_test_og_vectorized)

print(classification_report(y_test, forest_og_preds))

plot_confusion_matrix(forest_og, X_test_og_vectorized, y_test, cmap=plt
plt.grid(False)
plt.show()
```

started 08:23:50 2022-02-21, finished in 1.47s

```
              precision    recall  f1-score   support

           0       0.38      0.40      0.39       121
           1       0.87      0.86      0.87       562

    accuracy                           0.78       683
   macro avg       0.63      0.63      0.63       683
weighted avg       0.78      0.78      0.78       683
```

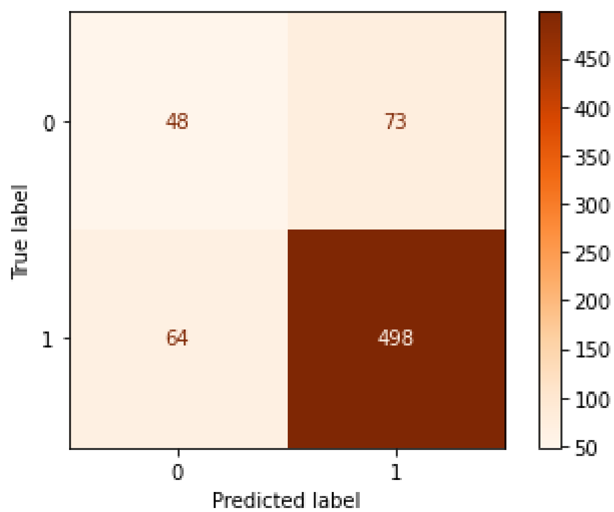


In [55]:

```python
forest_boot_og = RandomForestClassifier(bootstrap=False)
forest_boot_og.fit(X_train_resampled_og, y_train_resampled_og)

forest_boot_og_preds = forest_boot_og.predict(X_test_og_vectorized)

print(classification_report(y_test, forest_boot_og_preds))

plot_confusion_matrix(forest_boot_og, X_test_og_vectorized, y_test, cma
plt.grid(False)
plt.show()
```

started 08:23:52 2022-02-21, finished in 1.82s

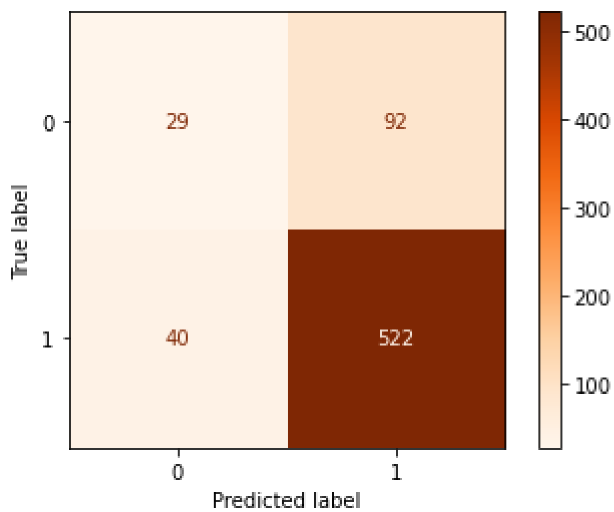
```
              precision    recall  f1-score   support

           0       0.43      0.40      0.41       121
           1       0.87      0.89      0.88       562

    accuracy                           0.80       683
   macro avg       0.65      0.64      0.65       683
weighted avg       0.79      0.80      0.80       683
```



In [56]:
```
clf_og = SVC()
clf_og.fit(X_train_resampled_og, y_train_resampled_og)

clf_og_preds = clf_og.predict(X_test_og_vectorized)

print(classification_report(y_test, clf_og_preds))

plot_confusion_matrix(clf_og, X_test_og_vectorized, y_test, cmap=plt.cm
plt.grid(False)
plt.show()
```

started 08:23:53 2022-02-21, finished in 1.82s

```
              precision    recall  f1-score   support

           0       0.42      0.24      0.31       121
           1       0.85      0.93      0.89       562

    accuracy                           0.81       683
   macro avg       0.64      0.58      0.60       683
weighted avg       0.77      0.81      0.78       683
```



None of these models are as accurate as our Multinomial Naive Bayes models (baseline or bigrams) with lemmatized text

Let's do an experiment with mutually exclusive text

> **We will remove mutually exclusive text from our training data and see how it affects our models.**

Let's do some more EDA and processing for this new data

In [57]:

```
# Rejoin our training data sets
pos_neg_train = X_train.join(y_train)
```

started 08:23:55 2022-02-21, finished in 4ms

In [58]:

```
pos_neg_train.target.value_counts()
```

started 08:23:55 2022-02-21, finished in 6ms

Out[58]:

```
1    2307
0     424
Name: target, dtype: int64
```

In [59]:

```
# Split the data set into positive and negative for analaysis
positive = pos_neg_train.loc[pos_neg['target'] == 1]
negative = pos_neg_train.loc[pos_neg['target'] == 0]
```

started 08:23:55 2022-02-21, finished in 6ms

In [60]:

```
positive.info()
```

started 08:23:55 2022-02-21, finished in 12ms

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2307 entries, 1435 to 4378
Data columns (total 9 columns):
 #   Column                 Non-Null Count  Dtype 
---  ------                 --------------  ----- 
 0   text                   2307 non-null   object
 1   text_tokenized         2307 non-null   object
 2   stopwords_removed      2307 non-null   object
 3   regex_text             2307 non-null   object
 4   regex_text_tokenized   2307 non-null   object
 5   stemmed_text           2307 non-null   object
 6   lemmed_text            2307 non-null   object
 7   lemmed_text_tokenized  2307 non-null   object
 8   target                 2307 non-null   int64 
dtypes: int64(1), object(8)
memory usage: 180.2+ KB
```

In [61]:

```
negative.info()
```

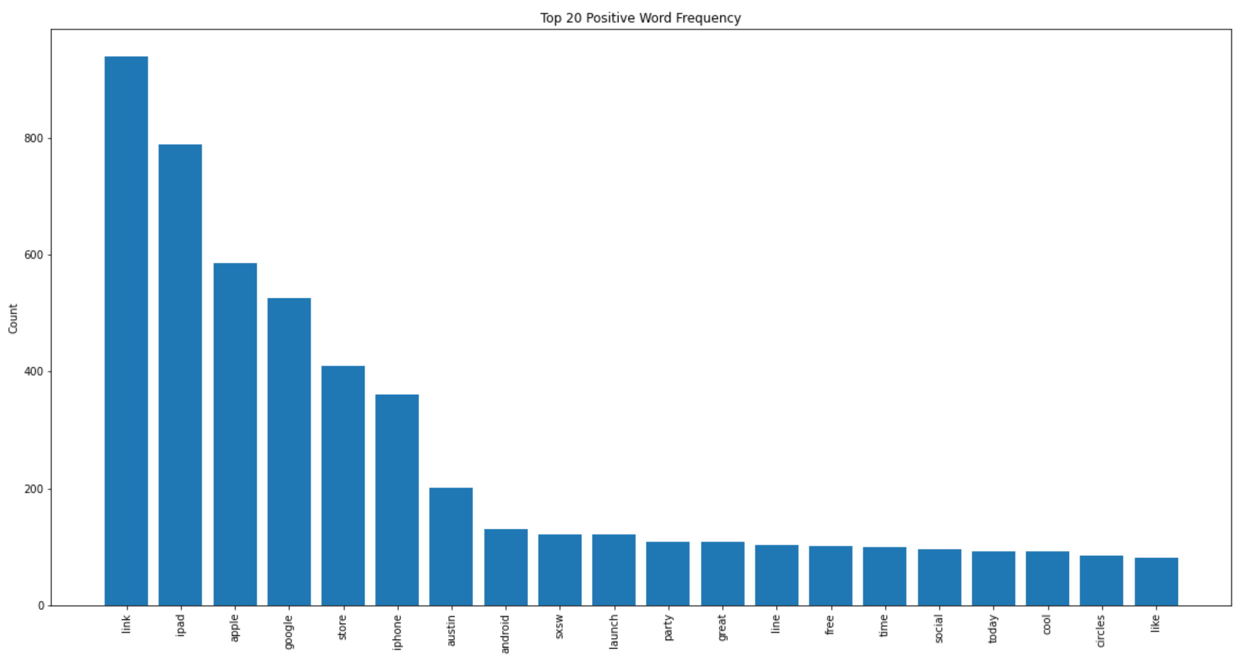
started 08:23:55 2022-02-21, finished in 8ms

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 424 entries, 2997 to 2252
Data columns (total 9 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   text                    424 non-null    object
 1   text_tokenized          424 non-null    object
 2   stopwords_removed       424 non-null    object
 3   regex_text              424 non-null    object
 4   regex_text_tokenized    424 non-null    object
 5   stemmed_text            424 non-null    object
 6   lemmed_text             424 non-null    object
 7   lemmed_text_tokenized   424 non-null    object
 8   target                  424 non-null    int64 
dtypes: int64(1), object(8)
memory usage: 33.1+ KB
```

In [62]:

```
# View the 20 most frequently used words in the positive class
positive_freq_dist = FreqDist(positive['lemmed_text_tokenized'].explode

visualize_top_20(positive_freq_dist, "Top 20 Positive Word Frequency")
```

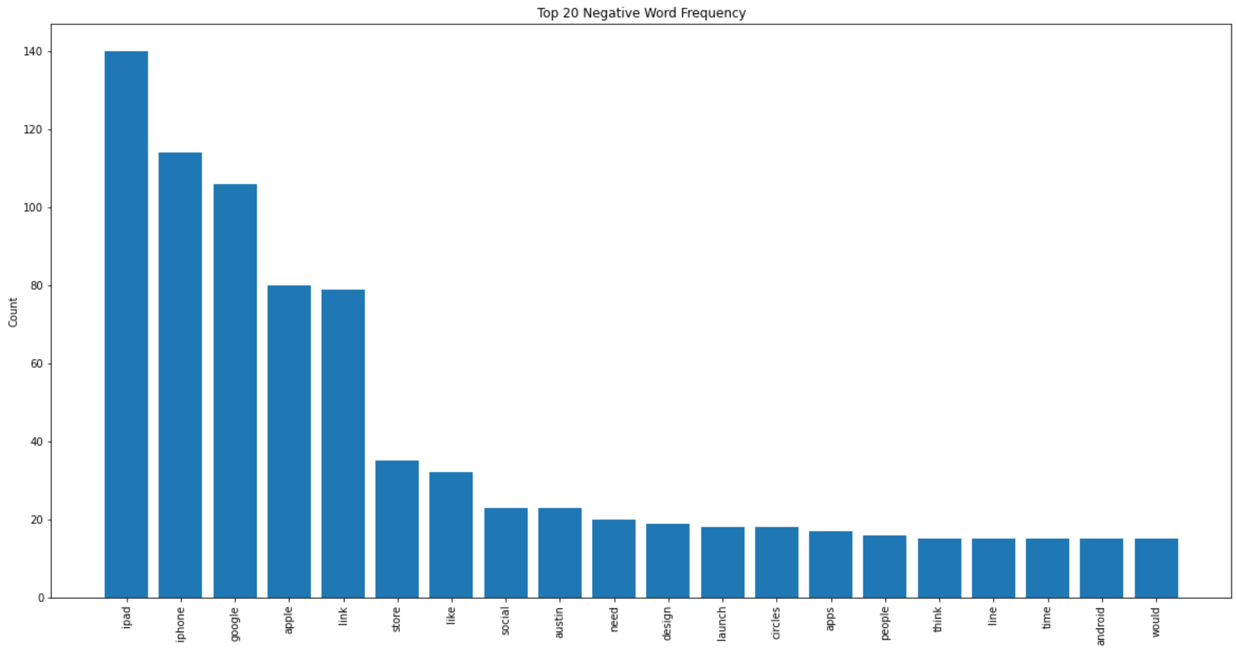
started 08:23:55 2022-02-21, finished in 197ms



In [63]:

```
# View the 20 most frequently used words in the negative class
negative_freq_dist = FreqDist(negative['lemmed_text_tokenized'].explode

visualize_top_20(negative_freq_dist, "Top 20 Negative Word Frequency")
```

started 08:23:55 2022-02-21, finished in 169ms



This is not very telling, and many words are the same, so lets see how removing mutual words affects this

In [64]:

```
# Create a 'Bag of Words' for the positive class
BoW_pos = [word for sentence in positive['lemmed_text_tokenized'] for w
```

started 08:23:56 2022-02-21, finished in 4ms

In [65]:
```
BoW_pos
```
started 08:23:56 2022-02-21, finished in 13ms

Out[65]:
```
['wise',
 'apple',
 'opening',
 'temp',
 'store',
 'austin',
 'link',
 'apparently',
 'tell',
 'bizzy',
 'android',
 'remedied',
 'marissa',
 'mayer',
 'connect',
 'digital',
 'physical',
 'worlds',
 'mobile',
```

In [66]:
```
# Create a 'Bag of Words' for the negative class
BoW_neg = [word for sentence in negative['lemmed_text_tokenized'] for w
```
started 08:23:56 2022-02-21, finished in 3ms

In [67]:
```
BoW_neg
```
started 08:23:56 2022-02-21, finished in 12ms

Out[67]:
```
['turning',
 'twitter',
 'forgotten',
 'reason',
 'google',
 'social',
 'technical',
 'dense',
 'vuelta',
 'para',
 'gran',
 'diferencia',
 'revolution',
 'clumsily',
 'translated',
 'google',
 'seems',
 'like',
 'news',
```

In [68]:
```
# Remove mutual words from the positive BoW
diff_neg = [word for word in BoW_neg if word not in BoW_pos]
```
started 08:23:56 2022-02-21, finished in 239ms

In [69]:

```
# Remove mutual words from the positive BoW
diff_pos = [word for word in BoW_pos if word not in BoW_neg]
```

started 08:23:56 2022-02-21, finished in 346ms

In [70]:

```
# Create a 'Bag of Words' that are mutual (appear in both classes)
sames = [word for word in BoW_pos if word in BoW_neg]
```

started 08:23:56 2022-02-21, finished in 345ms

In [71]:

```
len(sames)
```

started 08:23:57 2022-02-21, finished in 3ms

Out[71]:

```
12434
```

In [72]:

```
# Creat a function that will generate a dictionary of words and their f
def counts (lst, series):
    count_dict = {}
    for word in lst:
        count = 0
        for line in series:
            if word in line:
                count += 1
                count_dict[word] = count
    return count_dict
```

started 08:23:57 2022-02-21, finished in 4ms

In [73]:

```
counts(diff_pos, positive['lemmed_text'])
```

started 08:23:57 2022-02-21, finished in 1.47s

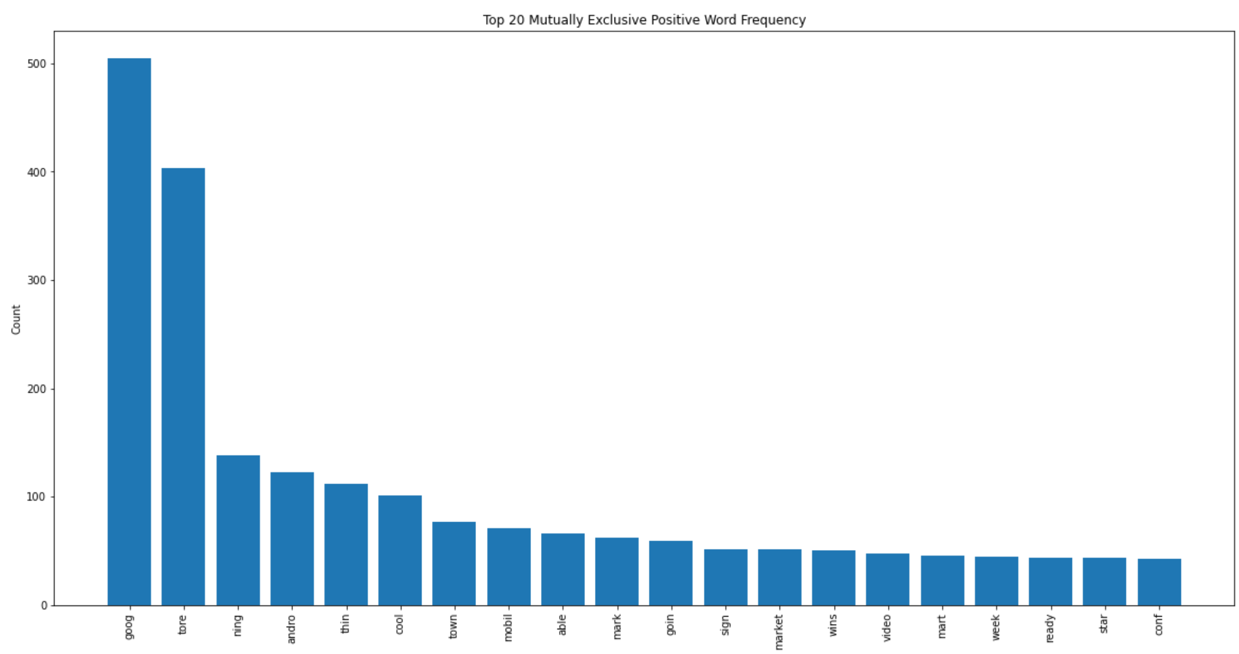
Out[73]:

```
{'wise': 6,
 'bizzy': 4,
 'remedied': 1,
 'physical': 16,
 'worlds': 12,
 'soundtrckr': 1,
 'featured': 8,
 'kick': 9,
 'giving': 23,
 'visit': 7,
 'enter': 28,
 'super': 10,
 'unveiled': 1,
 'notch': 1,
 'hanging': 5,
 'inventory': 4,
 'article': 4,
 'cooler': 4,
 'current': 1,
```

In [74]:
```
counts(diff_neg, negative['lemmed_text'])
```
started 08:23:58 2022-02-21, finished in 52ms

Out[74]:
```
{'forgotten': 1,
 'technical': 3,
 'dense': 2,
 'vuelta': 1,
 'para': 3,
 'gran': 2,
 'diferencia': 1,
 'revolution': 1,
 'clumsily': 1,
 'translated': 1,
 'speaks': 1,
 'watched': 3,
 'staff': 1,
 'facepalmed': 1,
 'bandwidth': 1,
 'tweeted': 1,
 'dawdled': 1,
 'blurs': 1,
 'fades': 7,
```

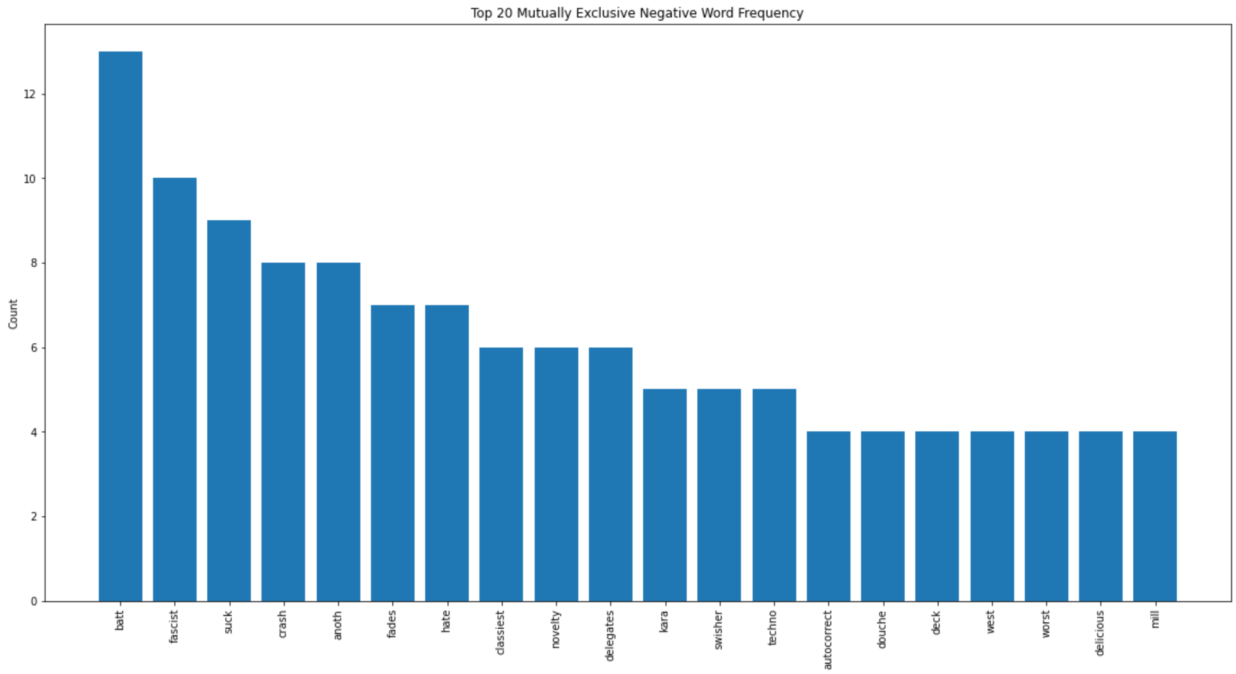
In [75]:
```
# View top 20 mutually exclusive positive words
positives_freq_dist = FreqDist(counts(diff_pos, positive['lemmed_text']

visualize_top_20(positives_freq_dist, "Top 20 Mutually Exclusive Positi
```
started 08:23:58 2022-02-21, finished in 1.59s



In [76]:

```
# # View top 20 mutually exclusive neggative words
negatives_freq_dist = FreqDist(counts(diff_neg, negative['lemmed_text']

visualize_top_20(negatives_freq_dist, "Top 20 Mutually Exclusive Negati
```

started 08:24:00 2022-02-21, finished in 200ms



In [77]:

```
# Create a function to remove the mutual words and apply it to the trai
def remove_samewords(token_list):
    """
    Given a list of tokens, return a list where the tokens
    that are in both pos and neg have been removed
    """
    same_rmv_list = [token for token in token_list if token not in same
    return same_rmv_list

pos_neg_train['sames_removed'] = pos_neg_train['lemmed_text_tokenized']
```

started 08:24:00 2022-02-21, finished in 1.15s

In [78]:

```
pos_neg_train.info()
```

started 08:24:01 2022-02-21, finished in 11ms

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2731 entries, 1435 to 4378
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype 
---  ------                 --------------  ----- 
 0   text                   2731 non-null   object
 1   text_tokenized         2731 non-null   object
 2   stopwords_removed      2731 non-null   object
 3   regex_text             2731 non-null   object
 4   regex_text_tokenized   2731 non-null   object
 5   stemmed_text           2731 non-null   object
 6   lemmed_text            2731 non-null   object
 7   lemmed_text_tokenized  2731 non-null   object
 8   target                 2731 non-null   int64 
 9   sames_removed          2731 non-null   object
dtypes: int64(1), object(9)
memory usage: 299.2+ KB
```

In [79]:

```
# Join the tokenized mutually exclusive word column for modeling
pos_neg_train['sames'] = [' '.join(text) for text in pos_neg_train.same
```

started 08:24:01 2022-02-21, finished in 5ms

In [80]:

```
# Split the dataset back into Training and testing data
# The only thing that should change is the X_train set
X_train_diff = pos_neg_train.drop(['target'], axis=1)
y_train_diff = y_train
X_test_diff = X_test
y_test_diff = y_test
```

started 08:24:01 2022-02-21, finished in 5ms

Create a baseline model for the mutually exclusive data

In [81]:

```
# Vectorize our new training data
count_diff = CountVectorizer()
X_train_diff_vectorized = count_diff.fit_transform(X_train_diff['sames'
```

started 08:24:01 2022-02-21, finished in 18ms

In [82]:

```
# Balance the data
smote_diff = SMOTE(k_neighbors=3)
X_train_diff_resampled, y_train_diff_resampled = smote_diff.fit_resampl
    X_train_diff_vectorized, y_train_diff)
```

started 08:24:01 2022-02-21, finished in 10ms

In [83]:

```
# Build the model
baseline_model_diff = MultinomialNB()

baseline_model_diff.fit(X_train_diff_resampled, y_train_diff_resampled)

# Evaluate the model
baseline_diff_cv = cross_val_score(baseline_model_diff, X_train_diff_re
print("Baseline_diff:", baseline_diff_cv.mean())
```

started 08:24:01 2022-02-21, finished in 19ms

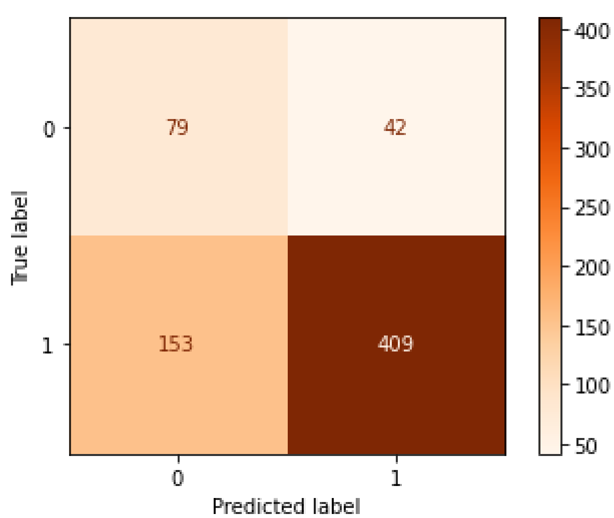
```
Baseline_diff: 0.670819007151536
```

In [84]:

```
# Test the model
X_test_diff_vectorized = count_diff.transform(X_test_diff['lemmed_text'
X_test_diff_preds = baseline_model_diff.predict(X_test_diff_vectorized)

print(classification_report(y_test_diff, X_test_diff_preds))

plot_confusion_matrix(baseline_model_diff, X_test_diff_vectorized, y_te
plt.grid(False)
plt.show()
```

started 08:24:01 2022-02-21, finished in 126ms

```
              precision    recall  f1-score   support

           0       0.34      0.65      0.45       121
           1       0.91      0.73      0.81       562

    accuracy                           0.71       683
   macro avg       0.62      0.69      0.63       683
weighted avg       0.81      0.71      0.74       683
```



And a bigram one too

In [85]:

```
count_diff_bigram = CountVectorizer(ngram_range=(1,2))
X_train_diff_bigram_vectorized = count_diff_bigram.fit_transform(X_trai
```

started 08:24:01 2022-02-21, finished in 169ms

In [86]:

```
smote_diff_bigram = SMOTE(k_neighbors=3)
X_train_diff_resampled_bigram, y_train_diff_resampled_bigram = smote_di
    X_train_diff_bigram_vectorized, y_train_diff)
```

started 08:24:01 2022-02-21, finished in 8ms

In [87]:

```
baseline_model_diff_bigram = MultinomialNB()
baseline_model_diff_bigram.fit(X_train_diff_resampled_bigram, y_train_d

baseline_diff_bigram_cv = cross_val_score(baseline_model_diff_bigram, X
print("Baseline_diff        :", baseline_diff_cv.mean())
print("Baseline_diff_bigram :", baseline_diff_bigram_cv.mean())
```

started 08:24:01 2022-02-21, finished in 18ms

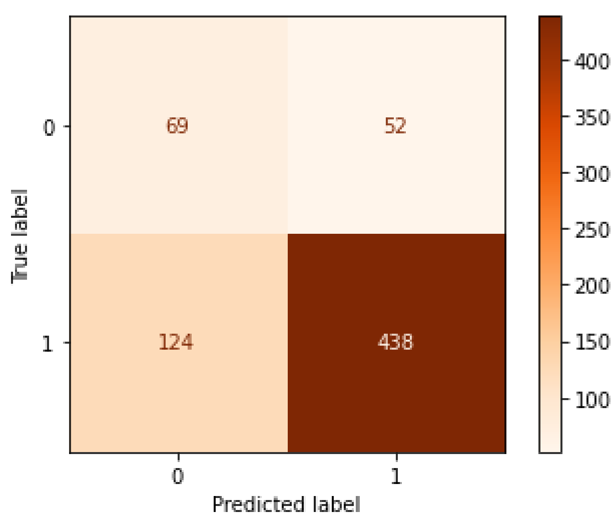
```
Baseline_diff        : 0.670819007151536
Baseline_diff_bigram : 0.6162036460377482
```

In [88]:

```
X_test_diff_bigram_vectorized = count_diff_bigram.transform(X_test_diff
X_test_diff_bigram_preds = baseline_model_diff_bigram.predict(X_test_di

print(classification_report(y_test_diff, X_test_diff_bigram_preds))

plot_confusion_matrix(baseline_model_diff_bigram, X_test_diff_bigram_ve
plt.grid(False)
plt.show()
```

started 08:24:01 2022-02-21, finished in 125ms

```
              precision    recall  f1-score   support

           0       0.36      0.57      0.44       121
           1       0.89      0.78      0.83       562

    accuracy                           0.74       683
   macro avg       0.63      0.67      0.64       683
weighted avg       0.80      0.74      0.76       683
```



Build a few more models with the mutually exclusive data and see how

they score

In [89]:

```python
# Support Vector Machine
clf_diff = SVC()
clf_diff.fit(X_train_diff_resampled, y_train_diff_resampled)
clf_diff_cv = cross_val_score(clf_diff, X_train_diff_resampled, y_train
print("Baseline_diff         :", baseline_diff_cv.mean())
print("Baseline_diff_bigram :", baseline_diff_bigram_cv.mean())
print("SVM_diff              :", clf_diff_cv.mean())
```

started 08:24:02 2022-02-21, finished in 983ms

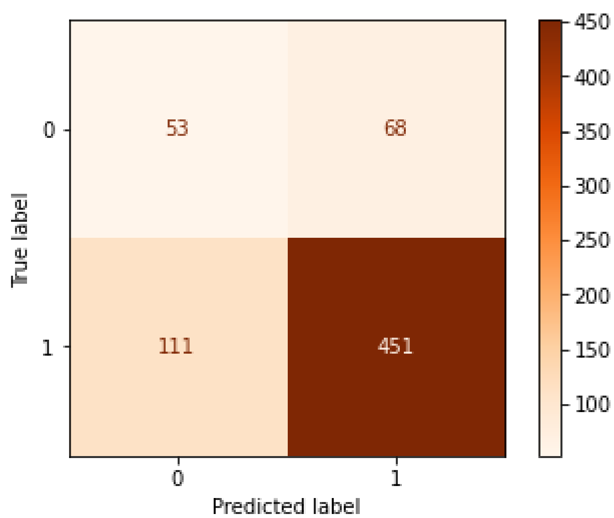
```
Baseline_diff        : 0.670819007151536
Baseline_diff_bigram : 0.6162036460377482
SVM_diff             : 0.8860094993454805
```

In [90]:

```python
X_test_diff_preds_SVM = clf_diff.predict(X_test_diff_vectorized)

print(classification_report(y_test_diff, X_test_diff_preds_SVM))

plot_confusion_matrix(clf_diff, X_test_diff_vectorized, y_test_diff, cm
plt.grid(False)
plt.show()
```

started 08:24:03 2022-02-21, finished in 162ms

```
              precision    recall  f1-score   support

           0       0.32      0.44      0.37       121
           1       0.87      0.80      0.83       562

    accuracy                           0.74       683
   macro avg       0.60      0.62      0.60       683
weighted avg       0.77      0.74      0.75       683
```



In [91]:

```python
# K Nearest Neighbors (n=5)
knn_5_diff = KNeighborsClassifier(n_neighbors=5)
knn_5_diff.fit(X_train_diff_resampled, y_train_diff_resampled)

knn_5_diff_cv = cross_val_score(knn_5_diff, X_train_diff_resampled, y_t
print("Baseline_diff        :", baseline_diff_cv.mean())
print("Baseline_diff_bigram :", baseline_diff_bigram_cv.mean())
print("SVM_diff             :", clf_diff_cv.mean())
print("KNN_5_diff           :", knn_5_diff_cv.mean())
```

started 08:24:03 2022-02-21, finished in 222ms

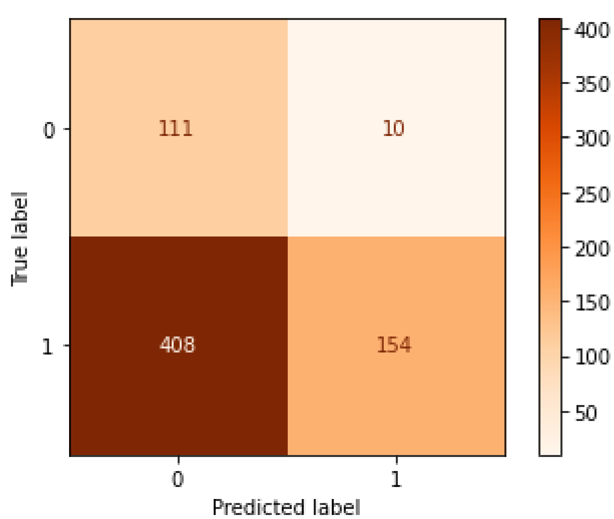
```
Baseline_diff        : 0.670819007151536
Baseline_diff_bigram : 0.6162036460377482
SVM_diff             : 0.8860094993454805
KNN_5_diff           : 0.612049033731842
```

In [92]:

```python
knn_5_diff_preds = knn_5_diff.predict(X_test_diff_vectorized)

print(classification_report(y_test_diff, knn_5_diff_preds))

plot_confusion_matrix(knn_5_diff, X_test_diff_vectorized, y_test_diff,
plt.grid(False)
plt.show()
```

started 08:24:03 2022-02-21, finished in 185ms

```
              precision    recall  f1-score   support

           0       0.21      0.92      0.35       121
           1       0.94      0.27      0.42       562

    accuracy                           0.39       683
   macro avg       0.58      0.60      0.39       683
weighted avg       0.81      0.39      0.41       683
```



In [93]:

```python
# K Nearest Neighbors (n=3)
knn_3_diff = KNeighborsClassifier(n_neighbors=3)
knn_3_diff.fit(X_train_diff_resampled, y_train_diff_resampled)

knn_3_diff_cv = cross_val_score(knn_3_diff, X_train_diff_resampled, y_t
print("Baseline_diff        :", baseline_diff_cv.mean())
print("Baseline_diff_bigram :", baseline_diff_bigram_cv.mean())
print("SVM_diff             :", clf_diff_cv.mean())
print("KNN_5_diff           :", knn_5_diff_cv.mean())
print("KNN_3_diff           :", knn_3_diff_cv.mean())
```

started 08:24:03 2022-02-21, finished in 236ms

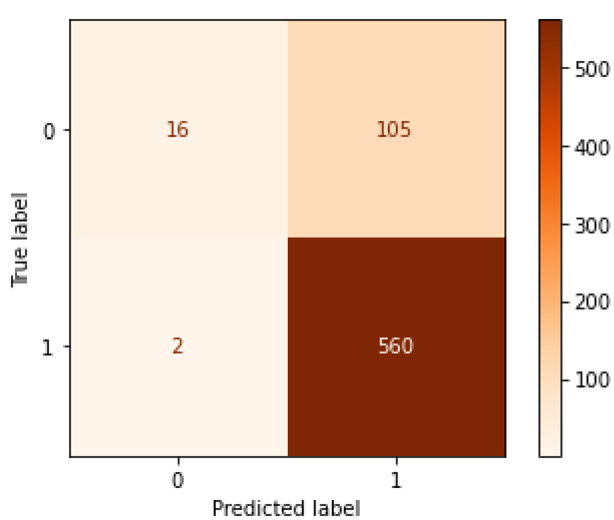
```
Baseline_diff        : 0.670819007151536
Baseline_diff_bigram : 0.6162036460377482
SVM_diff             : 0.8860094993454805
KNN_5_diff           : 0.612049033731842
KNN_3_diff           : 0.5680500490008296
```

In [94]:

```python
knn_3_diff_preds = knn_3_diff.predict(X_test_diff_vectorized)

print(classification_report(y_test_diff, knn_3_diff_preds))

plot_confusion_matrix(knn_3_diff, X_test_diff_vectorized, y_test_diff,
plt.grid(False)
plt.show()
```

started 08:24:03 2022-02-21, finished in 173ms

```
              precision    recall  f1-score   support

           0       0.89      0.13      0.23       121
           1       0.84      1.00      0.91       562

    accuracy                           0.84       683
   macro avg       0.87      0.56      0.57       683
weighted avg       0.85      0.84      0.79       683
```



Very odd, KNN_3 positive accuracy was just about 100%, but only 13% on the negative class.

This is the opposite of what it was doing on the KKN_5 just above it, and on the lemmatized text

> ### Predicted mostly negative

In [95]:

```
tree_diff = DecisionTreeClassifier()

tree_diff.fit(X_train_diff_resampled, y_train_diff_resampled)

tree_diff_cv = cross_val_score(tree_diff, X_train_diff_resampled, y_tra
print("Baseline_diff        :", baseline_diff_cv.mean())
print("Baseline_diff_bigram :", baseline_diff_bigram_cv.mean())
print("SVM_diff             :", clf_diff_cv.mean())
print("KNN_5_diff           :", knn_5_diff_cv.mean())
print("KNN_3_diff           :", knn_3_diff_cv.mean())
print("Tree_diff            :", tree_diff_cv.mean())
```

started 08:24:04 2022-02-21, finished in 648ms

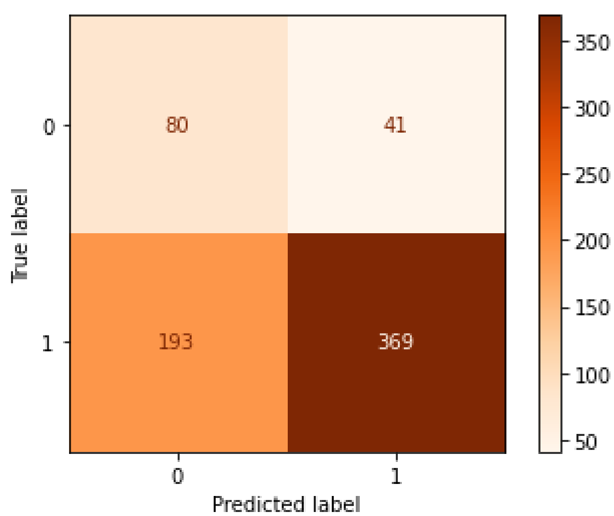
```
Baseline_diff        : 0.670819007151536
Baseline_diff_bigram : 0.6162036460377482
SVM_diff             : 0.8860094993454805
KNN_5_diff           : 0.612049033731842
KNN_3_diff           : 0.5680500490008296
Tree_diff            : 0.819464492612273
```

In [96]:

```
tree_diff_preds = tree_diff.predict(X_test_diff_vectorized)

print(classification_report(y_test_diff, tree_diff_preds))

plot_confusion_matrix(tree_diff, X_test_diff_vectorized, y_test_diff, c
plt.grid(False)
plt.show()
```

started 08:24:04 2022-02-21, finished in 119ms

```
              precision    recall  f1-score   support

           0       0.29      0.66      0.41       121
           1       0.90      0.66      0.76       562

    accuracy                           0.66       683
   macro avg       0.60      0.66      0.58       683
weighted avg       0.79      0.66      0.70       683
```



In [97]:

```
# Random Forest (default)
forest_diff = RandomForestClassifier()

forest_diff.fit(X_train_diff_resampled, y_train_diff_resampled)

forest_diff_cv = cross_val_score(forest_diff, X_train_diff_resampled, y
print("Baseline_diff        :", baseline_diff_cv.mean())
print("Baseline_diff_bigram :", baseline_diff_bigram_cv.mean())
print("SVM_diff             :", clf_diff_cv.mean())
print("KNN_5_diff           :", knn_5_diff_cv.mean())
print("KNN_3_diff           :", knn_3_diff_cv.mean())
print("Tree_diff            :", tree_diff_cv.mean())
print("Forest_diff          :", forest_diff_cv.mean())

```

started 08:24:04 2022-02-21, finished in 11.5s

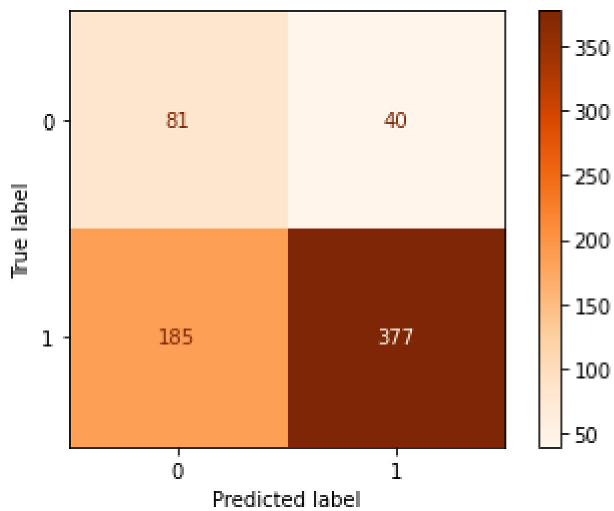
```
Baseline_diff        : 0.670819007151536
Baseline_diff_bigram : 0.6162036460377482
SVM_diff             : 0.8860094993454805
KNN_5_diff           : 0.612049033731842
KNN_3_diff           : 0.5680500490008296
Tree_diff            : 0.819464492612273
Forest_diff          : 0.8166466511399448
```

In [98]:

```
forest_diff_preds = forest_diff.predict(X_test_diff_vectorized)

print(classification_report(y_test_diff, forest_diff_preds))

plot_confusion_matrix(forest_diff, X_test_diff_vectorized, y_test_diff,
plt.grid(False)
plt.show()
```

started 08:24:16 2022-02-21, finished in 289ms

```
              precision    recall  f1-score   support

           0       0.30      0.67      0.42       121
           1       0.90      0.67      0.77       562

    accuracy                           0.67       683
   macro avg       0.60      0.67      0.59       683
weighted avg       0.80      0.67      0.71       683
```



In [99]:

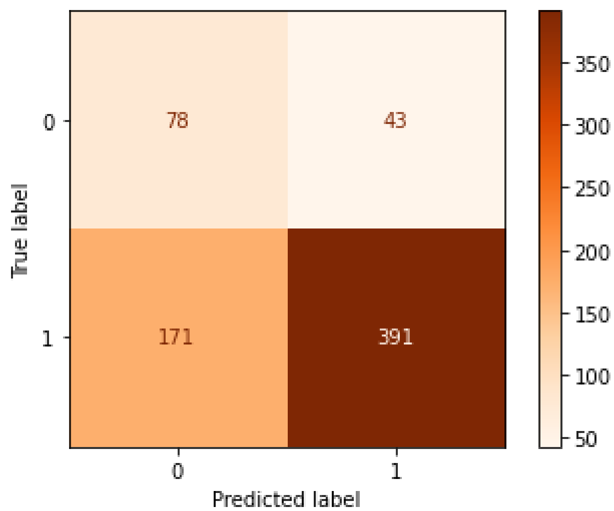
```python
# Random Forest (bootstrap=False)
forest_boot_diff = RandomForestClassifier(bootstrap=False)

forest_boot_diff.fit(X_train_diff_resampled, y_train_diff_resampled)

forest_boot_diff_cv = cross_val_score(forest_boot_diff, X_train_diff_re
print("Baseline_diff        :", baseline_diff_cv.mean())
print("Baseline_diff_bigram :", baseline_diff_bigram_cv.mean())
print("SVM_diff             :", clf_diff_cv.mean())
print("KNN_5_diff           :", knn_5_diff_cv.mean())
print("KNN_3_diff           :", knn_3_diff_cv.mean())
print("Tree_diff            :", tree_diff_cv.mean())
print("Forest_diff          :", forest_diff_cv.mean())
print("Forest_diff_boot     :", forest_boot_diff_cv.mean())

```

started 08:24:16 2022-02-21, finished in 19.6s

```
Baseline_diff        : 0.670819007151536
Baseline_diff_bigram : 0.6162036460377482
SVM_diff             : 0.8860094993454805
KNN_5_diff           : 0.612049033731842
KNN_3_diff           : 0.5680500490008296
Tree_diff            : 0.819464492612273
Forest_diff          : 0.8166466511399448
Forest_diff_boot     : 0.8266160285591406
```

In [100]:
```
forest_boot_diff_preds = forest_boot_diff.predict(X_test_diff_vectorize

print(classification_report(y_test_diff, forest_boot_diff_preds))

plot_confusion_matrix(forest_boot_diff, X_test_diff_vectorized, y_test_
plt.grid(False)
plt.show()
```
started 08:24:36 2022-02-21, finished in 304ms

```
              precision    recall  f1-score   support

           0       0.31      0.64      0.42       121
           1       0.90      0.70      0.79       562

    accuracy                           0.69       683
   macro avg       0.61      0.67      0.60       683
weighted avg       0.80      0.69      0.72       683
```



Let's Check if TF-IDF can do any better ono mutually exclusive words

In [101]:
```
tfidf_diff = TfidfVectorizer(max_features=60)

X_train_diff_tdidf_vectorized = tfidf_diff.fit_transform(X_train_diff['
```
started 08:24:36 2022-02-21, finished in 18ms

In [102]:
```
smote_diff_tdidf = SMOTE(k_neighbors=3)
X_train_diff_resampled_tdidf, y_train_diff_resampled_tdidf = smote_diff
    X_train_diff_tdidf_vectorized, y_train_diff)
```
started 08:24:36 2022-02-21, finished in 10ms

In [103]:

```
baseline_model_diff_tdidf = MultinomialNB()

baseline_model_diff_tdidf.fit(X_train_diff_resampled_tdidf, y_train_dif

# Evaluate the model
baseline_diff_tdidf_cv = cross_val_score(baseline_model_diff_tdidf, X_t
print("Baseline_diff_tdidf:", baseline_diff_tdidf_cv.mean())
```

started 08:24:36 2022-02-21, finished in 20ms

```
Baseline_diff_tdidf: 0.5049990246837273
```

In [104]:

```
X_test_diff_tdidf_vectorized = tfidf_diff.transform(X_test_diff['lemmed
X_test_diff_tdidf_preds = baseline_model_diff_tdidf.predict(X_test_diff

print(classification_report(y_test_diff, X_test_diff_tdidf_preds))
```

started 08:24:36 2022-02-21, finished in 13ms

```
              precision    recall  f1-score   support

           0       0.19      0.91      0.31       121
           1       0.89      0.16      0.27       562

    accuracy                           0.29       683
   macro avg       0.54      0.54      0.29       683
weighted avg       0.77      0.29      0.28       683
```

No, it cannot

Results

While using mutually exclusive words in a Random Forest model showed some accuracy on predictions (negative: 65%, positive: 70%), It was not more accurate than our baseline model using Naive Bayes on the full text with lemmatization. Count Vectorization also prooved to be more accurate than using TF-IDF.

Final Model:

> Multinomial Naive Bayes:
> Lemmatized text with Count Vectorization
>
> > Positive prediction accuracy: 88%
> > Negative prediction accuracy: 64%

Interpretation:

Imbalanced data posed problems when testing the model

- Predicted the true positive class much better than the true negative class leading to a higher false positive rate

Words expressing positive sentiment like "great", and "awesome" appeared in both classes

- Could lead to false negatives
- Did not appear in the mutually exclusive word models

Conclusions

- **Based on a general sense of the dataset the overwhelming sentiment was positive.**
- **This positive sentiment can be used in an overall investment strategy of emerging technologies**
- **This was a small dataset and more data is needed to improve the model**

> - The use of synthetically produced data was used to balance the dataset
> - With more data a downsampling technique could be employed instead

Further Research

> - Gather more data to provide more balance for testing
> - Explore Neural Networking techniques and Word2Vec for modeling
> - Explore techniques for weighting specific words
> - Look at sentiment on an individual product level

In [ ]:

```
 
```