sentiment-analy

June 28, 2024

[]: import pandas as pd

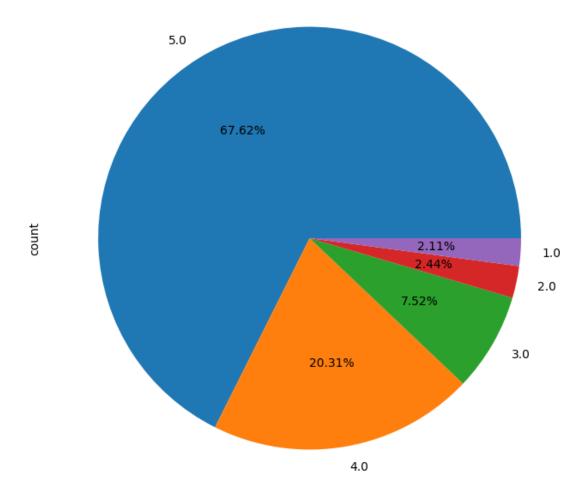
```
import numpy as np
     import matplotlib.pyplot as plt
[]: import string
     import re
     import nltk
     import nltk.corpus
     nltk.download("punkt")
     nltk.download("stopwords")
     nltk.download("wordnet")
     from nltk.stem import WordNetLemmatizer
    [nltk_data] Downloading package punkt to /root/nltk_data...
                  Unzipping tokenizers/punkt.zip.
    [nltk data]
    [nltk data] Downloading package stopwords to /root/nltk data...
    [nltk_data] Unzipping corpora/stopwords.zip.
    [nltk_data] Downloading package wordnet to /root/nltk_data...
[]: # Text Polarity
     from textblob import TextBlob
     # Text Vectorizer
     from sklearn.feature_extraction.text import CountVectorizer
     # Word Cloud
     from wordcloud import WordCloud
[]: # Label Encoding
     from sklearn.preprocessing import LabelEncoder
     # TF-IDF Vectorizer
     from sklearn.feature_extraction.text import TfidfVectorizer
     # Resampling
     from imblearn.over_sampling import SMOTE
     from collections import Counter
```

```
# Splitting Dataset
     from sklearn.model_selection import train_test_split
[]: # Model Building
     from sklearn.svm import SVC
     from sklearn.tree import DecisionTreeClassifier
     from sklearn.linear_model import LogisticRegression
     from sklearn.ensemble import RandomForestClassifier
     from sklearn.naive_bayes import BernoulliNB
     from sklearn.neighbors import KNeighborsClassifier
     from sklearn.model_selection import cross_val_score
     # Hyperparameter Tuning
     from sklearn.model_selection import GridSearchCV
     # Model Metrics
     from sklearn.metrics import confusion_matrix, accuracy_score,_
      →classification_report
[]: from google.colab import drive
     drive.mount('/content/drive')
    Drive already mounted at /content/drive; to attempt to forcibly remount, call
    drive.mount("/content/drive", force_remount=True).
[]: dataset = pd.read_csv("/content/drive/MyDrive/Senti/Instruments_Reviews.csv")
[]: dataset.shape
[]: (10261, 9)
[]: dataset.isnull().sum()
[]: reviewerID
                        0
     asin
                        0
    reviewerName
                       27
    helpful
                        0
                        7
    reviewText
    overall
     summary
    unixReviewTime
     reviewTime
    dtype: int64
[]: dataset.reviewText.fillna(value = "", inplace = True)
```

```
[]: dataset["reviews"] = dataset["reviewText"] + " " + dataset["summary"]
     dataset.drop(columns = ["reviewText", "summary"], axis = 1, inplace = True)
[]: dataset.describe(include = "all")
[]:
                 reviewerID
                                              reviewerName helpful
                                                                           overall
                                    asin
     count
                      10261
                                   10261
                                                     10234
                                                              10261
                                                                     10261.000000
     unique
                       1429
                                     900
                                                      1397
                                                                269
                                                                               NaN
             ADHOO8UVJOT10
                             B003VWJ2K8
                                           Amazon Customer
                                                             [0, 0]
                                                                               NaN
     top
     freq
                         42
                                     163
                                                         66
                                                               6796
                                                                               NaN
                                                       NaN
                                                                          4.488744
     mean
                        NaN
                                     NaN
                                                                NaN
     std
                        NaN
                                     NaN
                                                       NaN
                                                                NaN
                                                                          0.894642
     min
                        NaN
                                     NaN
                                                       NaN
                                                                NaN
                                                                          1.000000
     25%
                        NaN
                                     NaN
                                                       NaN
                                                                NaN
                                                                          4.000000
     50%
                        NaN
                                     NaN
                                                       NaN
                                                                NaN
                                                                          5.000000
     75%
                                     NaN
                                                       NaN
                                                                NaN
                                                                          5.000000
                        NaN
                                                       NaN
                        NaN
                                     NaN
                                                                NaN
                                                                          5.000000
     max
                                reviewTime
             unixReviewTime
                1.026100e+04
                                     10261
     count
     unique
                         NaN
                                      1570
                               01 22, 2013
     top
                         NaN
     freq
                         NaN
                                        40
     mean
                1.360606e+09
                                       NaN
     std
                3.779735e+07
                                       NaN
     min
                1.095466e+09
                                       NaN
     25%
                1.343434e+09
                                       NaN
     50%
                1.368490e+09
                                       NaN
     75%
                1.388966e+09
                                       NaN
                1.405987e+09
     max
                                       NaN
                                                           reviews
                                                             10261
     count
     unique
                                                             10261
             Not much to write about here, but it does exac...
     top
     freq
                                                                 1
     mean
                                                               NaN
                                                               NaN
     std
     min
                                                               NaN
     25%
                                                               NaN
     50%
                                                               NaN
     75%
                                                               NaN
     max
                                                               NaN
[]: dataset.overall.value_counts().plot(kind = "pie", legend = False, autopct = "%1.
      \rightarrow 2f\%", fontsize = 10, figsize=(8,8))
     plt.title("Percentages of Ratings Given from The Customers", loc = "center")
```

```
plt.show()
```

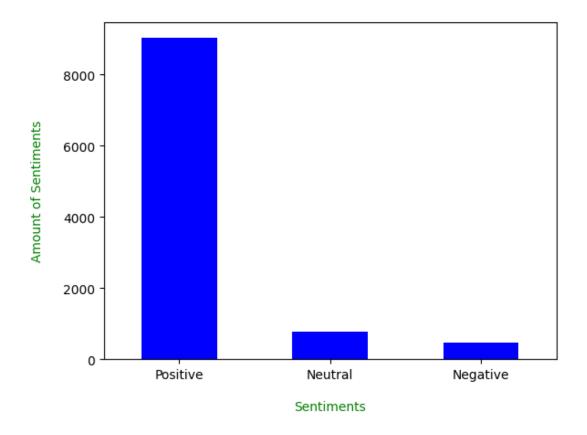
Percentages of Ratings Given from The Customers



```
[]: def Labelling(Rows):
    if(Rows["overall"] > 3.0):
        Label = "Positive"
    elif(Rows["overall"] < 3.0):
        Label = "Negative"
    else:
        Label = "Neutral"
    return Label</pre>
```

```
[]: dataset["sentiment"] = dataset.apply(Labelling, axis = 1)
```

Amount of Each Sentiments Based On Rating Given



```
[]: def Text_Cleaning(Text):
    # Lowercase the texts
    Text = Text.lower()

# Cleaning punctuations in the text
    punc = str.maketrans(string.punctuation, ' '*len(string.punctuation))
    Text = Text.translate(punc)

# Removing numbers in the text
    Text = re.sub(r'\d+', '', Text)
```

```
# Remove possible links
      Text = re.sub('https?://\S+|www\.\S+', '', Text)
       # Deleting newlines
      Text = re.sub('\n', '', Text)
       return Text
[]: # Stopwords
    Stopwords = set(nltk.corpus.stopwords.words("english")) - set(["not"])
    def Text_Processing(Text):
      Processed_Text = list()
      Lemmatizer = WordNetLemmatizer()
       # Tokens of Words
      Tokens = nltk.word_tokenize(Text)
       # Removing Stopwords and Lemmatizing Words
       # To reduce noises in our dataset, also to keep it simple and still
       # powerful, we will only omit the word `not` from the list of stopwords
      for word in Tokens:
        if word not in Stopwords:
          Processed_Text.append(Lemmatizer.lemmatize(word))
      return(" ".join(Processed_Text))
[]: dataset["reviews"] = dataset["reviews"].apply(lambda Text: Text_Cleaning(Text))
    dataset["reviews"] = dataset["reviews"].apply(lambda Text:__
      →Text Processing(Text))
[]: dataset.head(n = 10)
[]:
           reviewerID
                             asin \
    0 A2IBPI20UZIROU 1384719342
    1 A14VAT5EAX3D9S 1384719342
    2 A195EZSQDW3E21 1384719342
    3 A2C00NNG1ZQQG2 1384719342
       A94QU4C90B1AX 1384719342
    5 A2A039TZMZHH9Y B00004Y2UT
    6 A1UPZM995ZAH90 B00004Y2UT
       AJNFQI3YR6XJ5 B00004Y2UT
    8 A3M1PLEYNDEY08 B00004Y2UT
    9 AMNTZU1YQN1TH B00004Y2UT
```

```
reviewerName
                                                              helpful
                                                                        overall \
                                                              [0, 0]
                                                                          5.0
        cassandra tu "Yeah, well, that's just like, u...
     1
                                                              [13, 14]
                                                                            5.0
     2
                                                                            5.0
                            Rick Bennette "Rick Bennette"
                                                                [1, 1]
     3
                                 RustyBill "Sunday Rocker"
                                                                [0, 0]
                                                                            5.0
     4
                                             SEAN MASLANKA
                                                                [0, 0]
                                                                            5.0
                                       Bill Lewey "blewey"
     5
                                                                [0, 0]
                                                                            5.0
     6
                                                      Brian
                                                                [0, 0]
                                                                            5.0
     7
                                         Fender Guy "Rick"
                                                                [0, 0]
                                                                            3.0
     8
                                           G. Thomas "Tom"
                                                                [0, 0]
                                                                            5.0
     9
                                               Kurt Robair
                                                                [0, 0]
                                                                            5.0
        unixReviewTime
                          reviewTime \
                         02 28, 2014
     0
            1393545600
                         03 16, 2013
     1
            1363392000
     2
                         08 28, 2013
            1377648000
     3
                         02 14, 2014
            1392336000
     4
                         02 21, 2014
            1392940800
     5
            1356048000
                         12 21, 2012
                         01 19, 2014
     6
            1390089600
     7
                         11 16, 2012
            1353024000
     8
            1215302400
                          07 6, 2008
     9
            1389139200
                          01 8, 2014
                                                     reviews sentiment
        not much write exactly supposed filter pop sou... Positive
        product exactly quite affordable not realized ... Positive
        primary job device block breath would otherwis...
                                                            Positive
     3
        nice windscreen protects mxl mic prevents pop ...
                                                            Positive
       pop filter great look performs like studio fil...
                                                            Positive
        good bought another one love heavy cord gold c...
                                                            Positive
       used monster cable year good reason lifetime w...
                                                            Positive
        use cable run output pedal chain input fender ...
                                                             Neutral
        perfect epiphone sheraton ii monster cable wel...
                                                            Positive
        monster make best cable lifetime warranty does...
                                                            Positive
[]: dataset.describe(include = "all")
[]:
                 reviewerID
                                    asin
                                             reviewerName helpful
                                                                          overall
     count
                      10261
                                   10261
                                                     10234
                                                             10261
                                                                     10261.000000
                       1429
                                     900
                                                      1397
                                                               269
     unique
                                                                               NaN
             ADHOO8UVJOT10
     top
                             B003VWJ2K8
                                          Amazon Customer
                                                             [0, 0]
                                                                              NaN
                         42
                                     163
                                                        66
                                                               6796
                                                                              NaN
     freq
     mean
                        NaN
                                     NaN
                                                       NaN
                                                               NaN
                                                                         4.488744
                                     NaN
                                                       NaN
     std
                        NaN
                                                               NaN
                                                                         0.894642
                                     NaN
                                                       NaN
     min
                        NaN
                                                               NaN
                                                                         1.000000
     25%
                                     NaN
                                                       NaN
                                                               NaN
                                                                         4.000000
                        NaN
```

```
50%
                                                                       5.000000
                    NaN
                                 NaN
                                                    NaN
                                                             NaN
75%
                                 {\tt NaN}
                                                    NaN
                                                             NaN
                                                                       5.000000
                    NaN
max
                    NaN
                                 NaN
                                                    NaN
                                                             NaN
                                                                       5.000000
         unixReviewTime
                            reviewTime
                                                         reviews sentiment
           1.026100e+04
                                 10261
                                                           10261
                                                                      10261
count
unique
                     NaN
                                  1570
                                                           10254
                                                                           3
                           01 22, 2013
                                         good string five star
top
                     NaN
                                                                   Positive
                                     40
                                                                       9022
                     NaN
freq
mean
           1.360606e+09
                                   NaN
                                                             NaN
                                                                        NaN
std
           3.779735e+07
                                   NaN
                                                             NaN
                                                                        NaN
min
           1.095466e+09
                                    NaN
                                                             NaN
                                                                        NaN
25%
           1.343434e+09
                                   NaN
                                                             NaN
                                                                        NaN
50%
           1.368490e+09
                                   NaN
                                                             NaN
                                                                        NaN
75%
           1.388966e+09
                                    NaN
                                                             NaN
                                                                        NaN
           1.405987e+09
max
                                    NaN
                                                             NaN
                                                                        NaN
```

```
[]: dataset["polarity"] = dataset["reviews"].map(lambda Text: TextBlob(Text).

sentiment.polarity)
```

```
[]: dataset["polarity"].plot(kind = "hist", bins = 40, edgecolor = "blue", | clinewidth = 1, color = "orange", figsize = (10,5))

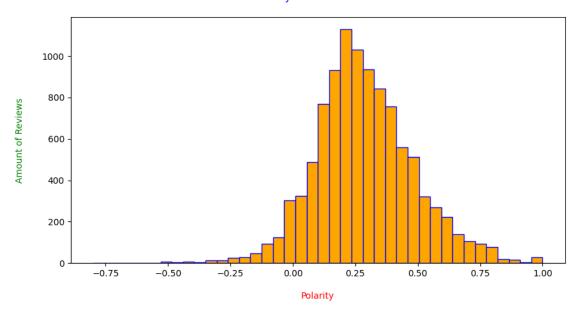
plt.title("Polarity Score in Reviews", color = "blue", pad = 20)

plt.xlabel("Polarity", labelpad = 15, color = "red")

plt.ylabel("Amount of Reviews", labelpad = 20, color = "green")

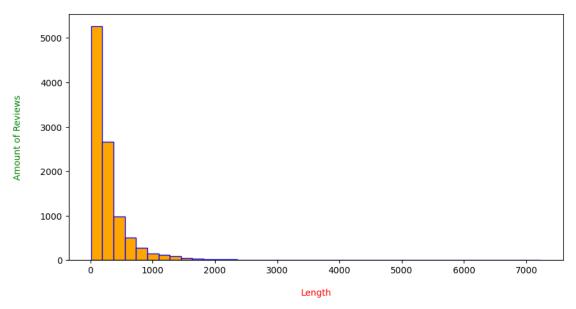
plt.show()
```

Polarity Score in Reviews



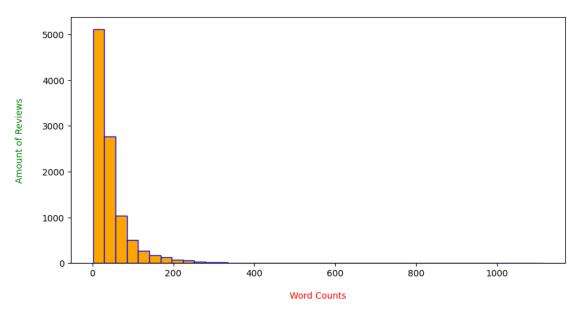
```
[]: dataset["length"] = dataset["reviews"].astype(str).apply(len)
```

Length of Reviews



```
[]: dataset["word_counts"] = dataset["reviews"].apply(lambda x: len(str(x).split()))
```

Word Counts in Reviews



```
[]: def Gram_Analysis(Corpus, Gram, N):
       # Vectorizer
       Vectorizer = CountVectorizer(stop_words = Stopwords, ngram_range=(Gram,Gram))
       # N-Grams Matrix
      ngrams = Vectorizer.fit_transform(Corpus)
       # N-Grams Frequency
       Count = ngrams.sum(axis=0)
       # List of Words
       words = [(word, Count[0, idx]) for word, idx in Vectorizer.vocabulary_.
      →items()]
       # Sort Descending With Key = Count
       words = sorted(words, key = lambda x:x[1], reverse = True)
       return words[:N]
[]: # Use dropna() so the base DataFrame is not affected
     Positive = dataset[dataset["sentiment"] == "Positive"].dropna()
     Neutral = dataset[dataset["sentiment"] == "Neutral"].dropna()
     Negative = dataset[dataset["sentiment"] == "Negative"].dropna()
```

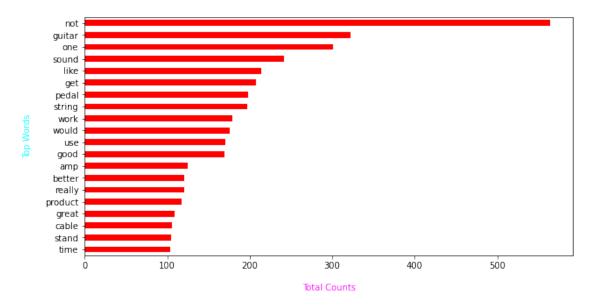
words = Gram_Analysis(Negative["reviews"], 1, 20)

[]: # Finding Unigram

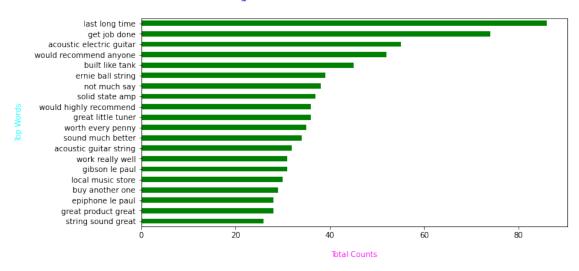
```
Unigram = pd.DataFrame(words, columns = ["Words", "Counts"])

# Visualization
Unigram.groupby("Words").sum()["Counts"].sort_values().plot(kind = "barh", usecolor = "red", figsize = (10, 5))
plt.title("Unigram of Reviews with Negative Sentiments", loc = "center", usefontsize = 15, color = "blue", pad = 25)
plt.xlabel("Total Counts", color = "magenta", fontsize = 10, labelpad = 15)
plt.xticks(rotation = 0)
plt.ylabel("Top Words", color = "cyan", fontsize = 10, labelpad = 15)
plt.show()
```

Unigram of Reviews with Negative Sentiments



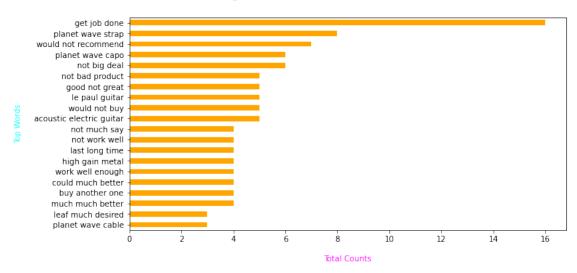
Trigram of Reviews with Positive Sentiments

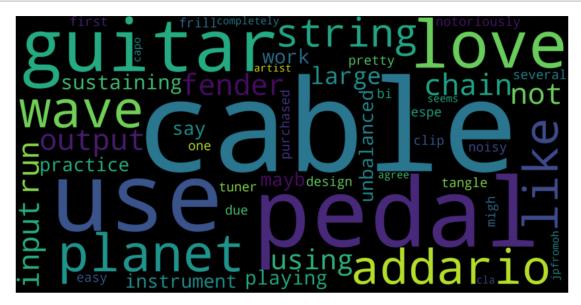


```
[]: # Finding Trigram
words = Gram_Analysis(Neutral["reviews"], 3, 20)
Trigram = pd.DataFrame(words, columns = ["Words", "Counts"])

# Visualization
Trigram.groupby("Words").sum()["Counts"].sort_values().plot(kind = "barh", using color = "orange", figsize = (10, 5))
plt.title("Trigram of Reviews with Neutral Sentiments", loc = "center", using contsize = 15, color = "blue", pad = 25)
plt.xlabel("Total Counts", color = "magenta", fontsize = 10, labelpad = 15)
plt.xticks(rotation = 0)
plt.ylabel("Top Words", color = "cyan", fontsize = 10, labelpad = 15)
plt.show()
```

Trigram of Reviews with Neutral Sentiments





Word Cloud of Reviews with Negative Sentiments

```
[]: Columns = ["reviewerID", "asin", "reviewerName", "helpful", "unixReviewTime",
     dataset.drop(columns = Columns, axis = 1, inplace = True)
[]: dataset.head()
[]:
                                               reviews sentiment
    O not much write exactly supposed filter pop sou... Positive
    1 product exactly quite affordable not realized ... Positive
    2 primary job device block breath would otherwis... Positive
    3 nice windscreen protects mxl mic prevents pop ... Positive
    4 pop filter great look performs like studio fil... Positive
[]: Encoder = LabelEncoder()
    dataset["sentiment"] = Encoder.fit_transform(dataset["sentiment"])
[]: dataset["sentiment"].value counts()
[]: 2
         9022
          772
          467
    Name: sentiment, dtype: int64
[]: # Defining our vectorizer with total words of 5000 and with bigram model
    TF_IDF = TfidfVectorizer(max_features = 5000, ngram_range = (2, 2))
    # Fitting and transforming our reviews into a matrix of weighed words
    # This will be our independent features
    X = TF_IDF.fit_transform(dataset["reviews"])
    # Check our matrix shape
    X.shape
[]: (10261, 5000)
[]: # Declaring our target variable
    y = dataset["sentiment"]
[]: Counter(y)
[]: Counter({0: 467, 1: 772, 2: 9022})
[]: Balancer = SMOTE(random_state = 42)
    X_final, y_final = Balancer.fit_resample(X, y)
    /usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
```

FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated

```
warnings.warn(msg, category=FutureWarning)
[]: Counter(y final)
[]: Counter({0: 9022, 1: 9022, 2: 9022})
[]: X_train, X_test, y_train, y_test = train_test_split(X_final, y_final, test_size_
     \Rightarrow= 0.25, random_state = 42)
[ ]: DTree = DecisionTreeClassifier()
    LogReg = LogisticRegression()
    SVC = SVC()
    RForest = RandomForestClassifier()
    Bayes = BernoulliNB()
    KNN = KNeighborsClassifier()
    Models = [DTree, LogReg, SVC, RForest, Bayes, KNN]
    Models_Dict = {0: "Decision Tree", 1: "Logistic Regression", 2: "SVC", 3:11
     →"Random Forest", 4: "Naive Bayes", 5: "K-Neighbors"}
    for i, model in enumerate(Models):
      print("{} Test Accuracy: {}".format(Models_Dict[i], cross_val_score(model, X,_
      Decision Tree Test Accuracy: 0.8197050968869757
    Logistic Regression Test Accuracy: 0.8818828283518491
    SVC Test Accuracy: 0.8805184008381876
    Random Forest Test Accuracy: 0.8770101983293189
    Naive Bayes Test Accuracy: 0.8091794454219505
    K-Neighbors Test Accuracy: 0.8474810714983934
    Hyperparameter Tuning
[]: accuracy_score(y_test, Prediction)
[]: 0.9521205851928476
[]: ConfusionMatrix = confusion_matrix(y_test, Prediction)
[ ]:  # Plotting Function for Confusion Matrix
    def plot_cm(cm, classes, title, normalized = False, cmap = plt.cm.Blues):
      plt.imshow(cm, interpolation = "nearest", cmap = cmap)
      plt.title(title, pad = 20)
      plt.colorbar()
      tick marks = np.arange(len(classes))
      plt.xticks(tick_marks, classes)
```

in version 0.22 and will be removed in version 0.24.

```
plt.yticks(tick_marks, classes)

if normalized:
    cm = cm.astype('float') / cm.sum(axis = 1)[: np.newaxis]
    print("Normalized Confusion Matrix")

else:
    print("Unnormalized Confusion Matrix")

threshold = cm.max() / 2
for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
        plt.text(j, i, cm[i, j], horizontalalignment = "center", color = "white"
        if cm[i, j] > threshold else "black")

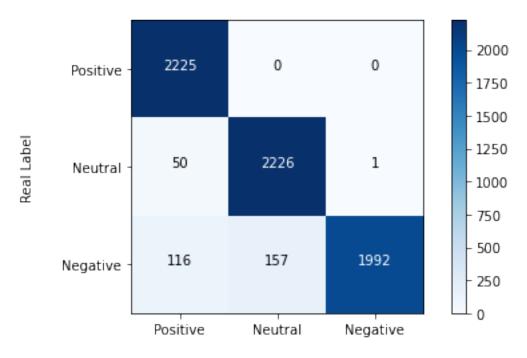
plt.tight_layout()
plt.xlabel("Predicted Label", labelpad = 20)
plt.ylabel("Real Label", labelpad = 20)
```

```
[]: plot_cm(ConfusionMatrix, classes = ["Positive", "Neutral", "Negative"], title =

□ "Confusion Matrix of Sentiment Analysis")
```

Unnormalized Confusion Matrix

Confusion Matrix of Sentiment Analysis



Predicted Label

[]: print(classification_report(y_test, Prediction))

support	f1-score	recall	precision	
2225	0.96	1.00	0.93	0
2277	0.96	0.98	0.93	1
2265	0.94	0.88	1.00	2
6767	0.95			accuracy
6767	0.95	0.95	0.95	macro avg
6767	0.95	0.95	0.95	weighted avg