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Project Title: Sentiment analysis for marketing

Problem Definition:

The problem is to perform sentiment analysis on customer feedback to gain insights into competitor products. By understanding customer sentiments, companies can identify strengths and weaknesses in competing products, thereby improving their own offerings. This project requires utilizing various NLP methods to extract valuable insights from customer feedback.

Dataset Link:

https://www.kaggle.com/datasets/crowdflower/twitter-airline-sentiment

```
!pip install nltk scikit-learn pandas matplotlib
```

```
Requirement already satisfied: nltk in /usr/local/lib/python3.10/dist-
packages (3.8.1)
Requirement already satisfied: scikit-learn in
/usr/local/lib/python3.10/dist-packages (1.2.2)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-
packages (1.5.3)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-
packages (3.7.1)
Requirement already satisfied: click in /usr/local/lib/python3.10/dist-
packages (from nltk) (8.1.7)
Requirement already satisfied: joblib in /usr/local/lib/python3.10/dist-
packages (from nltk) (1.3.2)
Requirement already satisfied: regex>=2021.8.3 in
/usr/local/lib/python3.10/dist-packages (from nltk) (2023.6.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-
packages (from nltk) (4.66.1)
Requirement already satisfied: numpy>=1.17.3 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.23.5)
Requirement already satisfied: scipy>=1.3.2 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.11.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.2.0)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/dist-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas) (2023.3.post1)
Requirement already satisfied: contourpy>=1.0.1 in
```

```
/usr/local/lib/python3.10/dist-packages (from matplotlib) (1.1.0)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (4.42.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.5)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (23.1)
Requirement already satisfied: pillow>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (3.1.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
packages (from python-dateutil>=2.8.1->pandas) (1.16.0)
```

```
import nltk
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
from collections import Counter
```

```
# Download NLTK data
nltk.download('stopwords')
nltk.download('punkt')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
```

```
True
```

Data Collection

```
# Load the dataset
data = pd.read_csv('Tweets.csv')
```

```
data.columns
```

```
Index(['tweet_id', 'airline_sentiment', 'airline_sentiment_confidence',
       'negativereason', 'negativereason_confidence', 'airline',
       'airline_sentiment_gold', 'name', 'negativereason_gold',
       'retweet_count', 'text', 'tweet_coord', 'tweet_created',
```

```
       'tweet_location', 'user_timezone', 'cleaned_text'],
      dtype='object')
```

```
data.head()
```

```
             tweet_id airline_sentiment  airline_sentiment_confidence  \
0  570306133677760513           neutral                        1.0000
1  570301130888122368          positive                        0.3486
2  570301083672813571           neutral                        0.6837
3  570301031407624196          negative                        1.0000
4  570300817074462722          negative                        1.0000

  negativereason  negativereason_confidence         airline  \
0            NaN                        NaN  Virgin America
1            NaN                     0.0000  Virgin America
2            NaN                        NaN  Virgin America
3     Bad Flight                     0.7033  Virgin America
4     Can't Tell                     1.0000  Virgin America

  airline_sentiment_gold        name negativereason_gold  retweet_count  \
0                    NaN     cairdin                 NaN              0
1                    NaN    jnardino                 NaN              0
2                    NaN  yvonnalynn                 NaN              0
3                    NaN    jnardino                 NaN              0
4                    NaN    jnardino                 NaN              0

                                                text tweet_coord  \
0                @VirginAmerica What @dhepburn said.         NaN
1  @VirginAmerica plus you've added commercials t...         NaN
2  @VirginAmerica I didn't today... Must mean I n...         NaN
3  @VirginAmerica it's really aggressive to blast...         NaN
4  @VirginAmerica and it's a really big bad thing...         NaN

              tweet_created tweet_location               user_timezone  \
0  2015-02-24 11:35:52 -0800            NaN  Eastern Time (US & Canada)
1  2015-02-24 11:15:59 -0800            NaN  Pacific Time (US & Canada)
2  2015-02-24 11:15:48 -0800      Lets Play  Central Time (US & Canada)
3  2015-02-24 11:15:36 -0800            NaN  Pacific Time (US & Canada)
4  2015-02-24 11:14:45 -0800            NaN  Pacific Time (US & Canada)

                                        cleaned_text
0                        virginamerica dhepburn said
1  virginamerica plus added commercials experienc...
2  virginamerica today must mean need take anothe...
3  virginamerica really aggressive blast obnoxiou...
4                 virginamerica really big bad thing
```

Data Preprocessing

```python
# Data Preprocessing
stop_words = set(stopwords.words('english'))

def preprocess_text(text):
    # Tokenization and removal of stopwords
    words = word_tokenize(text)
    words = [word.lower() for word in words if word.isalnum() and
word.lower() not in stop_words]
    return ' '.join(words)

data['cleaned_text'] = data['text'].apply(preprocess_text)
```

Sentiment Analysis Techniques and Feature Extraction

```python
# Sentiment Analysis using Bag of Words (BoW)
X = data['cleaned_text']
y = data['airline_sentiment']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Vectorize the text using BoW
vectorizer = CountVectorizer()
X_train_bow = vectorizer.fit_transform(X_train)
X_test_bow = vectorizer.transform(X_test)

# Train a Naive Bayes classifier
classifier = MultinomialNB()
classifier.fit(X_train_bow, y_train)
```

```
MultinomialNB()
```

```python
# Predict sentiment on the test set
y_pred = classifier.predict(X_test_bow)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print("Confusion Matrix:")
print(conf_matrix)
print("Classification Report:")
print(classification_rep)
```

```
Accuracy: 0.78
Confusion Matrix:
```

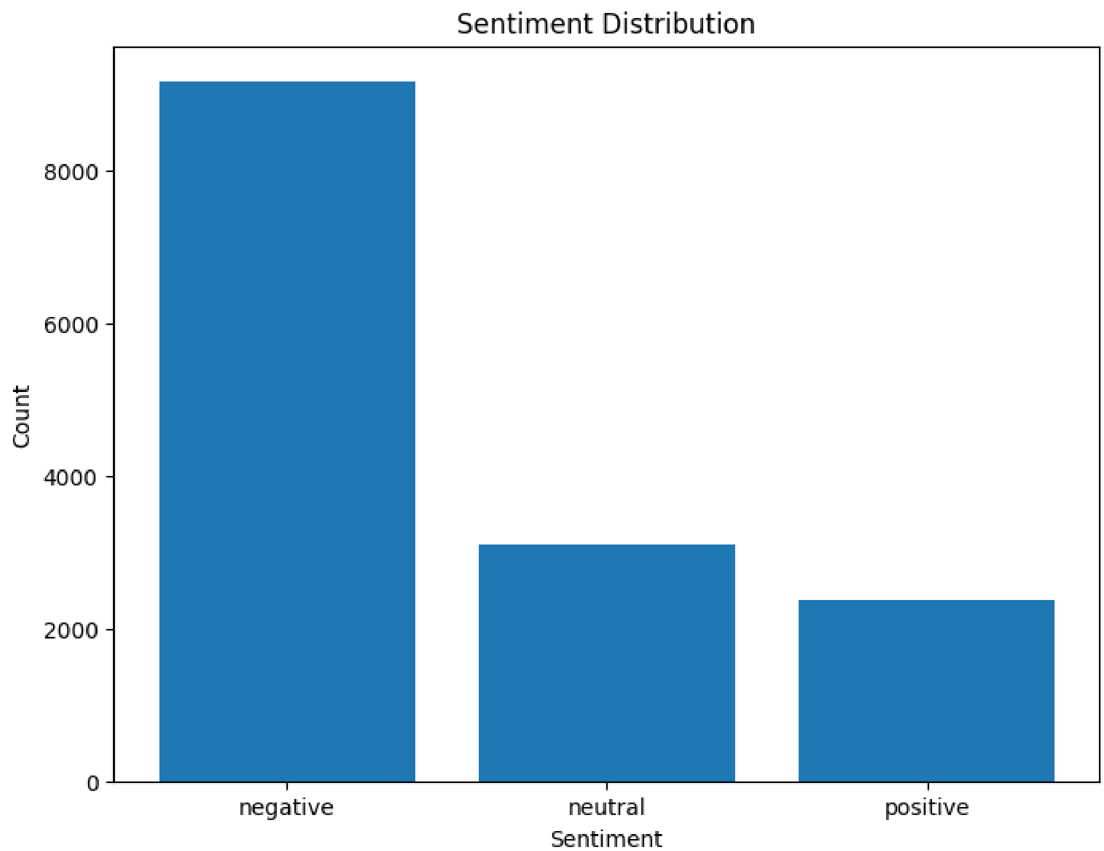
```
[[1796   66   27]
 [ 323  222   35]
 [ 162   42  255]]
Classification Report:
              precision    recall  f1-score   support

    negative       0.79      0.95      0.86      1889
     neutral       0.67      0.38      0.49       580
    positive       0.80      0.56      0.66       459

    accuracy                           0.78      2928
   macro avg       0.75      0.63      0.67      2928
weighted avg       0.77      0.78      0.76      2928
```

Visualization

```
# Visualize sentiment distribution
sentiment_counts = data['airline_sentiment'].value_counts()
plt.figure(figsize=(8, 6))
plt.bar(sentiment_counts.index, sentiment_counts.values)
plt.xlabel('Sentiment')
plt.ylabel('Count')
plt.title('Sentiment Distribution')
plt.show()
```



Insights Generation

```
# Sentiment Distribution
sentiment_counts = data['airline_sentiment'].value_counts()
print("Sentiment Distribution:")
print(sentiment_counts)

# Analyze frequent words or phrases in positive and negative reviews.
positive_reviews = data[data['airline_sentiment'] ==
'positive']['cleaned_text']
negative_reviews = data[data['airline_sentiment'] ==
'negative']['cleaned_text']

# Count the most common words in positive and negative reviews
positive_words = ' '.join(positive_reviews).split()
negative_words = ' '.join(negative_reviews).split()

positive_word_counts = Counter(positive_words)
negative_word_counts = Counter(negative_words)

print("\nTop 10 Words in Positive Reviews:")
print(positive_word_counts.most_common(10))
```

```
print("\nTop 10 Words in Negative Reviews:")
print(negative_word_counts.most_common(10))
```

```
Sentiment Distribution:
negative    9178
neutral     3099
positive    2363
Name: airline_sentiment, dtype: int64

Top 10 Words in Positive Reviews:
[('thanks', 609), ('jetblue', 594), ('southwestair', 576), ('united', 528),
('thank', 452), ('flight', 373), ('americanair', 355), ('usairways', 276),
('great', 236), ('http', 217)]

Top 10 Words in Negative Reviews:
[('flight', 2925), ('united', 2894), ('usairways', 2372), ('americanair',
2108), ('southwestair', 1212), ('jetblue', 1051), ('get', 986), ('cancelled',
920), ('service', 740), ('hours', 646)]
```

Here is simple overview documentation about overall code we used:

Problem Definition *italicized text*

The primary goal of this project is to conduct sentiment analysis on customer feedback to gain valuable insights into competitor products. By analyzing customer sentiments, businesses can identify the strengths and weaknesses of competing products, which can guide them in improving their own offerings. Sentiment analysis is a crucial tool for understanding market dynamics and customer perceptions.

Design Thinking

Data Collection

Data Collection involves the process of obtaining a dataset that contains customer reviews and associated sentiments about competitor products. For this project, we will utilize the Twitter Airlines Sentiment dataset, which is accessible through this link. The dataset includes a collection of tweets expressing sentiment towards various airline companies.

Data Preprocessing

Data Preprocessing is an essential step in preparing the text data for analysis. In this project, we will employ the Natural Language Toolkit (NLTK) library to perform text data cleaning. Specifically, we will remove common stopwords and tokenize the text, which involves breaking it down into individual words or tokens. This preprocessing step enhances the quality of the data and makes it more suitable for natural language processing tasks like sentiment analysis or text classification.

Sentiment Analysis Techniques and Feature Extraction

In this section, we will delve into the techniques used for **Sentiment Analysis**. The primary approach employed is the Bag of Words (BoW) model in combination with a Multinomial Naive Bayes classifier. The BoW approach represents text data as a vector of word frequencies, while the Multinomial Naive Bayes classifier is a popular choice for text classification tasks.

Visualization

Visualization plays a crucial role in understanding and presenting the results of sentiment analysis. To gain insights into the dataset's sentiment distribution, we utilize data visualization libraries such as Matplotlib. Specifically, we create a bar chart that visually represents the frequency of each sentiment label (positive, negative, neutral) in the dataset.

Insights Generation

Insights Generation is the final step of the project, where we extract meaningful information from the sentiment analysis results. We aim to identify the most common words in positive and negative reviews, as well as to understand the overall sentiment distribution. This step is essential for guiding business decisions based on customer feedback.

Word Frequency Visualization

This code snippet provides a detailed explanation of the word frequency visualization section:

The code utilizes libraries such as pandas, matplotlib, WordCloud, and seaborn to create insightful visualizations for word frequency analysis in positive and negative reviews.

1. **Word Clouds**: We generate word clouds for both positive and negative reviews. Word clouds visually represent words where the size of each word corresponds to its frequency. This helps identify the most prominent words in each sentiment category.

2. **Top N Common Words**: We identify and display the top N most common words in each category using bar plots. This approach provides a more detailed understanding of the most frequent terms in positive and negative feedback.

By conducting these analyses, businesses can gain deeper insights into customer sentiments and understand the key themes or words associated with positive and negative feedback.