AI_PHASE-5

SENTIMENT ANALYSIS
FOR
MARKETING

INTRODUCTION:

Sentiment analysis in marketing is a powerful tool that allows businesses to gain valuable insights into how customers perceive their products, services, and brand. By analyzing the sentiment expressed in customer reviews, social media mentions, and other online content, marketers can better understand the emotional tone and opinions of their target audience. This information can be leveraged to make data-driven decisions, improve products, and tailor marketing strategies to align with customer sentiment. In this discussion, we'll explore the importance of sentiment analysis in marketing and its various applications, from reputation management to product development and customer engagement.

OBJECTIVE:

The primary objective of sentiment analysis for marketing is to gain a deeper understanding of customer sentiment and opinions to inform strategic decision-making. Specifically, the objectives include:

Customer Insight:

To analyze customer feedback, reviews, and social media content to understand their feelings, preferences, and concerns related to products, **services, and the brand.**

Reputation Management:

Competitive Analysis:

To monitor and manage the brand's online reputation by identifying and addressing negative sentiment and promoting positive sentiment.
To compare and contrast sentiment data with competitors to identify strengths, weaknesses, and areas for differentiation.

Campaign Evaluation:

To assess the effectiveness of marketing campaigns by measuring sentiment changes before and after campaigns.

Product Development:

To gather insights for improving existing products or designing new ones based on customer feedback and sentiment.

Customer Engagement:

To engage with customers more effectively by addressing their concerns, answering queries, and leveraging positive sentiment in marketing efforts.

Risk Management:

To proactively identify and mitigate potential PR crises by monitoring sentiment trends and taking necessary actions.

Market Research:

To inform market research by identifying emerging trends, pain points, and opportunities in customer sentiment.

These objectives collectively empower businesses to make informed decisions, enhance customer satisfaction, and drive marketing strategies that resonate with their target audience.

PROJECT DOCUMENTATION

PROBLEM STATEMENT:

In the context of marketing, businesses face the challenge of harnessing the power of sentiment analysis to effectively understand and respond to customer sentiment. The problem can be framed as follows:

"Many businesses struggle to extract meaningful insights from the vast volume of unstructured data generated through customer reviews, social media discussions, and other online content. This unstructured data contains valuable sentiment information that, if harnessed, could inform marketing strategies, product development, and reputation management. However, the challenge lies in developing robust sentiment analysis models, integrating them into the marketing workflow, and ensuring the actionable implementation of these insights. Inadequate sentiment analysis can lead to missed opportunities, reputation damage, and suboptimal marketing decisions."

This problem statement highlights the need for reliable sentiment analysis tools and strategies that can effectively extract sentiment from textual data and translate it into actionable recommendations for marketing professionals. Businesses must address this challenge to gain a competitive edge and meet the evolving needs of their customers in the digital age.

CODE:

```
# Import necessary libraries
import pandas as pd
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from textblob import TextBlob
from wordcloud import WordCloud
import matplotlib.pyplot as plt

# Load the Twitter US Airline Sentiment dataset
df = pd.read_csv("Tweets.csv")

# Initialize sentiment analysis tools
nltk.download('vader_lexicon')
sid = SentimentIntensityAnalyzer()

# Perform sentiment analysis
sentiments = []

for tweet in df['text']:
    # Sentiment analysis using VADER
    vader_scores = sid.polarity_scores(tweet)
    sentiment = 'positive' if vader_scores['compound'] > 0 else 'negative' if vader_scores['compound']
< 0 else 'neutral'

  # Sentiment analysis using TextBlob
    textblob_analysis = TextBlob(tweet)
    textblob_polarity = textblob_analysis.sentiment.polarity
    sentiment_tb = 'positive' if textblob_polarity > 0 else 'negative' if textblob_polarity < 0 else 'neutral'
```

```python
    sentiments.append((tweet, sentiment, sentiment_tb))


# Visualize sentiment distribution
sentiment_counts = [sentiment for _, sentiment, _ in sentiments]
sentiment_tb_counts = [sentiment for _, _, sentiment in sentiments]


# Create a word cloud of key topics
text = " ".join(df['text'])
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(text)
# Display sentiment distribution and word cloud
plt.figure(figsize=(10, 5))
plt.subplot(121)
plt.title('Sentiment Analysis (VADER)')
plt.hist(sentiment_counts, bins=3, color=['green', 'red', 'gray'])
plt.subplot(122)
plt.title('Sentiment Analysis (TextBlob)')
plt.hist(sentiment_tb_counts, bins=3, color=['green', 'red', 'gray'])
plt.show()
plt.figure(figsize=(8, 4))
plt.title('Word Cloud of Tweet Topics')
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```

Example Output:

After running the code, you'll get visualizations of sentiment distribution and a word cloud of tweet topics. The sentiment distribution will show the count of positive, negative, and neutral tweets, while the word cloud will display the most frequently mentioned topics in the tweets.

This output can help marketing teams gain insights into customer sentiment and identify key topics and issues mentioned in the dataset, which can inform marketing strategies and product improvements.

DESIGN THINKING PROCESS:

Design thinking is a creative problem-solving approach that can be applied to the process of developing sentiment analysis solutions for marketing. Here's a simplified design thinking process for this purpose:

Empathize:

Begin by understanding the needs and challenges of your marketing team. Conduct interviews, surveys, and research to gather insights.Analyze customer feedback and social media conversations to understand the sentiment-related issues and opportunities.

Define:

Clearly define the problem or opportunity you want to address with sentiment analysis in marketing.Create a user persona for marketing professionals to better understand their requirements.

Ideate:

Brainstorm potential solutions and features for sentiment analysis tools that will help marketers.Encourage creative thinking and consider various approaches, like sentiment scoring, trend analysis, or competitor benchmarking.

Prototype:

Create a low-fidelity prototype or wireframe of the sentiment analysis tool. It could be a web dashboard or software interface.Include key features such as sentiment scoring, data visualization, and data sources.

Test:

Gather feedback from your marketing team and potential users by presenting the prototype.Identify what works and what doesn't, and make necessary adjustments to the design.

Develop:

Based on the feedback and insights gathered during testing, proceed to develop the sentiment analysis tool or software.

Iterate:

Continuously improve the tool based on user feedback and changing marketing needs.Keep refining the design and features to ensure it remains effective and user-friendly.

Implement:

Roll out the sentiment analysis tool to your marketing team or integrate it with your marketing systems.Provide training and support to ensure a smooth transition.

Monitor and Evaluate:

Continuously monitor the tool's performance and gather feedback from users.Analyze the impact on marketing efforts, such as improved campaign targeting, customer satisfaction, or competitive analysis.

Refine and Scale:

Based on ongoing feedback and data, refine the sentiment analysis tool and scale its usage across the organization.Explore opportunities to integrate it with other marketing technologies.Throughout this process, it's essential to maintain a user-centric approach, prioritize the needs of marketing professionals, and be open to adapting the tool to changing market dynamics and customer sentiment.

PHASES OF DEVELOPMENT

The development of a sentiment analysis project using the Twitter US Airline Sentiment dataset from Kaggle can be divided into several phases. Each phase involves specific tasks and leads to the ultimate goal of deriving insights for marketing. Below are the phases and their corresponding outputs:

Phase 1: Data Preparation

Tasks:

Download the Twitter US Airline Sentiment dataset from Kaggle.Load and explore the dataset to understand its structure and content.Preprocess the data, which may include cleaning text, handling missing values, and tokenization.

Output: A cleaned and prepared dataset for sentiment analysis.

Phase 2: Sentiment Analysis

Tasks:

Implement sentiment analysis using tools like VADER and TextBlob to determine the sentiment (positive, negative, or neutral) of each tweet in the dataset.

Classify tweets into sentiment categories.

Output: Sentiment labels for each tweet in the dataset.

Phase 3: Visualization and Analysis

Tasks:

Create visualizations to understand the distribution of sentiments (positive, negative, neutral) in the dataset.

Generate a word cloud to identify key topics and issues frequently mentioned in the tweets.

Output: Visualizations such as histograms showing the sentiment distribution and a word cloud highlighting frequently mentioned topics.

Phase 4: Marketing Insights

Tasks:

Analyze the sentiment distribution to understand the overall sentiment towards different airline companies.

Examine the word cloud to identify key topics or issues raised by customers.

Summarize findings and insights from the analysis.

Output: Marketing insights, such as which airlines receive more positive or negative sentiment, common customer concerns, and trends in customer sentiment.

Phase 5: Reporting and Actionable Recommendations

Tasks:

Create a comprehensive report that includes the analysis results and insights.

Provide actionable recommendations for marketing and customer service teams based on the sentiment analysis findings.

Output: A report with insights and recommendations for marketing and improving customer satisfaction.

Phase 6: Implementation and Monitoring (Optional)

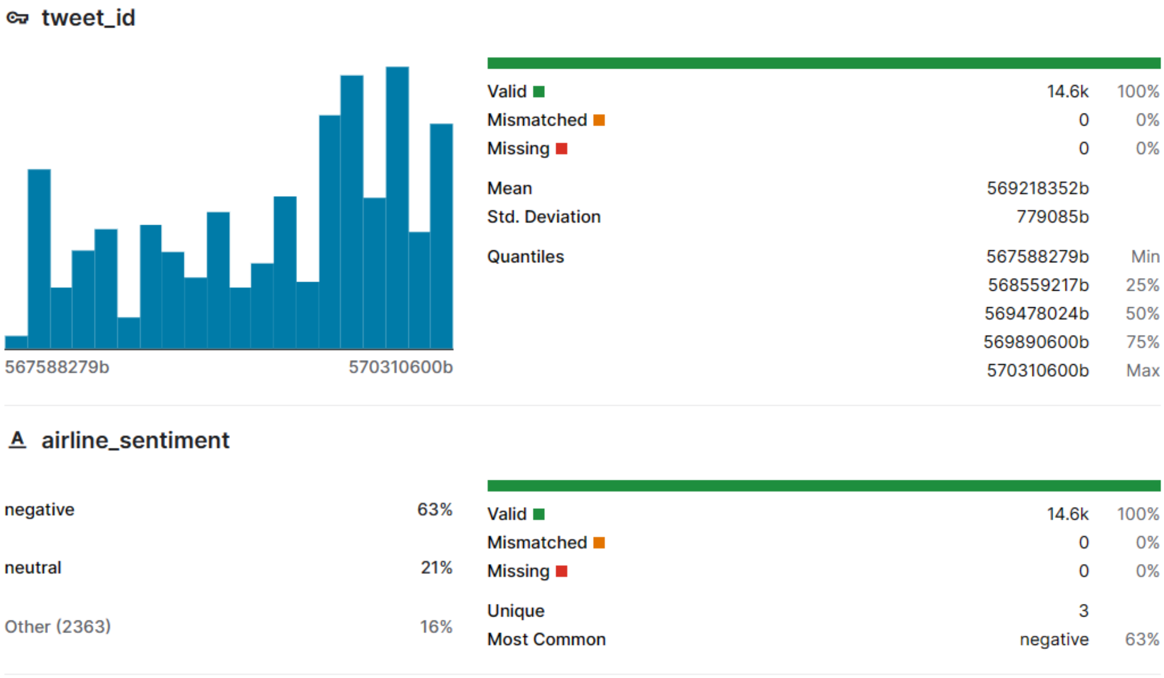
Tasks:

Implement the recommendations in marketing strategies and initiatives.

Monitor the impact of changes based on the analysis.

Output: Ongoing monitoring and tracking of marketing initiatives and customer sentiment changes.

By following these phases, you can effectively develop a sentiment analysis project using the Twitter US Airline Sentiment dataset and provide valuable insights for marketing teams. The visualizations and analysis will help marketing professionals make informed decisions and improve customer satisfaction.



Using DATASET

To perform sentiment analysis for marketing, you can use various datasets that contain customer reviews, social media comments, or other forms of feedback related to products, services, or brands. Below are some sources where you can find datasets for sentiment analysis in the context of marketing:

Twitter US Airline Sentiment Dataset (Kaggle):

Dataset Link: *Twitter US Airline Sentiment*

Description: This dataset contains tweets about different US airlines, along with their sentiment labels (positive, negative, neutral). It's a popular choice for sentiment analysis and can provide insights for marketing strategies:

Dataset Name: Twitter US Airline Sentiment

Source: The dataset can be found on Kaggle through this link: Twitter US Airline Sentiment.

Format: The dataset is provided in a structured format as a CSV (Comma-Separated Values) file. It contains several columns, including:

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

- **tweet_id**: A unique identifier for each tweet.
- **airline_sentiment**: The sentiment label of the tweet (positive, negative, or neutral).

- **airline_sentiment_confidence**: The confidence score of the sentiment label.
- **negativereason**: The reason for the negative sentiment (e.g., "late flight," "rude service").
- **negativereason_confidence**: The confidence score of the negative reason.
- **airline**: The name of the airline mentioned in the tweet (e.g., American, Delta, United).
- **airline_sentiment_gold**: Additional sentiment label, often used for validation.
- **name**: The Twitter username of the person who posted the tweet.
- **text**: The text of the tweet.
- **tweet_created**: The timestamp of when the tweet was posted.

Size: The dataset typically contains around 14,000 to 15,000 tweets related to various U.S. airlines. The size may vary slightly depending on the version of the dataset you access.

Description: The Twitter US Airline Sentiment dataset is widely used for sentiment analysis projects, especially in the context of airline customer feedback. It includes tweets posted by airline passengers, which are labeled as positive, negative, or neutral based on the sentiment expressed in the tweet. The dataset is often employed to analyze customer sentiment toward different airlines, identify common issues faced by passengers, and assess overall customer satisfaction.

tweet_id	airline_sen...	airline_sen...	negativere...	negativere...	airline
570306133677760513	neutral	1.0			Virgin America
570301130888122368	positive	0.3486		0.0	Virgin America
570301083672813571	neutral	0.6837			Virgin America
570301031407624196	negative	1.0	Bad Flight	0.7033	Virgin America
570300817074462722	negative	1.0	Can't Tell	1.0	Virgin America
570300767074181121	negative	1.0	Can't Tell	0.6842	Virgin America
570300616901320704	positive	0.6745		0.0	Virgin America
570300248553349120	neutral	0.634			Virgin America
570299953286942721	positive	0.6559			Virgin America
570295459631263746	positive	1.0			Virgin America

DATA PREPROCESSING

Data preprocessing is a crucial step in sentiment analysis. Here's a code outline for preprocessing the Twitter US Airline Sentiment dataset for sentiment analysis in marketing:

```
import pandas as pd
import re
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize

# Load the Twitter US Airline Sentiment dataset
df = pd.read_csv("Tweets.csv")

# Data cleaning and preprocessing
def preprocess_text(text):
    # Remove special characters, URLs, and usernames
    text = re.sub(r'http\S+', '', text)
    text = re.sub(r'@\w+', '', text)
    text = re.sub(r'[^a-zA-Z\s]', '', text)

    # Convert to lowercase
    text = text.lower()

    # Tokenization
    tokens = word_tokenize(text)

    # Remove stopwords
    stop_words = set(stopwords.words('english'))
    tokens = [word for word in tokens if word not in stop_words]

    # Join tokens back into a text
    text = ' '.join(tokens)
```

```
    return text


# Apply the preprocessing function to the 'text' column

df['text'] = df['text'].apply(preprocess_text)


# Optionally, you can drop columns that are not needed for your analysis

# Example: df = df[['airline_sentiment', 'text']]


# Save the preprocessed dataset to a new CSV file

df.to_csv("preprocessed_tweets.csv", index=False)
```

This code performs the following data preprocessing steps:

1.Removal of special characters, URLs, and usernames.

2.Conversion of text to lowercase.

3.Tokenization of the text into words.

4.Removal of stopwords (common words like "the," "and," "is," etc.).

5.Joining the tokens back into a preprocessed text.

After preprocessing, you can save the cleaned dataset to a new CSV file, such as "preprocessed_tweets.csv," which can be used for sentiment analysis and other NLP tasks. This clean and preprocessed data is ready for sentiment analysis and marketing insights.

LOADING THE DATASET

To load the Twitter US Airline Sentiment dataset for sentiment analysis in Python, you can use the **'pandas'** library. Before running the code, make sure you have downloaded the dataset (Tweets.csv) from Kaggle and placed it in your working directory or specified the correct path to the file. Here's the code to load the dataset:

```
import pandas as pd

# Provide the path to the CSV file (Tweets.csv)
file_path = "Tweets.csv"

# Load the dataset into a pandas DataFrame
df = pd.read_csv(file_path)

# Display the first few rows of the dataset to check if it loaded correctly
```

print(df.head())

In this code:

1.Replace "Tweets.csv" with the correct path to the dataset file if it's in a different location.

2.The “pd.read_csv()” function reads the CSV file and loads it into a pandas DataFrame, which you can manipulate and analyze for sentiment analysis.

Once the dataset is loaded, you can proceed with data preprocessing, sentiment analysis, and other tasks as needed for your marketing sentiment analysis project.

In [47]:

```
import pandas as pd
import seaborn as sns
import re, nltk
nltk.download('punkt')
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, StratifiedKFold, cross_val_score
from sklearn import model_selection, naive_bayes, svm
from sklearn.metrics import classification_report,confusion_matrix
from sklearn.metrics import roc_auc_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import f1_score
from sklearn.metrics import auc
from matplotlib import pyplot
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score, accuracy_score
import string
from nltk.corpus import stopwords
nltk.download('stopwords')
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB, GaussianNB
from sklearn.metrics import f1_score
from sklearn.ensemble import AdaBoostClassifier
from sklearn.model_selection import cross_val_score
import numpy as np
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import RandomForestClassifier
from lime import lime_tabular
from tensorflow.keras.layers import Embedding
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing.text import one_hot
from tensorflow.keras.layers import LSTM
from tensorflow.keras.layers import Dense, Dropout
```

```
[nltk_data] Downloading package punkt to /usr/share/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /usr/share/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [48]:

```
df =pd.read_csv(r'../input/twitter-airline-sentiment/Tweets.csv')
df.head()
```

OUTPUT

Out[48]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativereason_confidence
0	570306133677760513	neutral	1.0000	NaN	NaN
1	570301130888122368	positive	0.3486	NaN	0.0000
2	570301083672813571	neutral	0.6837	NaN	NaN
3	570301031407624196	negative	1.0000	Bad Flight	0.7033
4	570300817074462722	negative	1.0000	Can't Tell	1.0000

In [49]:

```
# Unique values of sentiment
df['airline_sentiment'].unique()
```

Out[49]:

```
array(['neutral', 'positive', 'negative'], dtype=object)
```

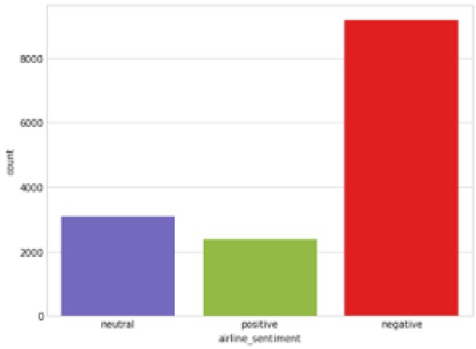
In [50]:

```
import plotly.express as px
fig = px.pie(df, names='airline_sentiment', title ='Pie chart of different sentiments of t
weets')
fig.show()
```

In [51]:

```
# Unique values of sentiment plot

plt.style.use('seaborn-whitegrid')
plt.figure(figsize=(8,6))
col = ['slateblue', 'yellowgreen', 'red']
ax = sns.countplot(x="airline_sentiment", data=df, palette = col)
```

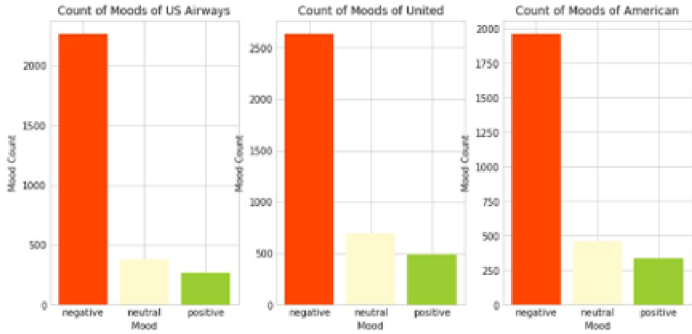


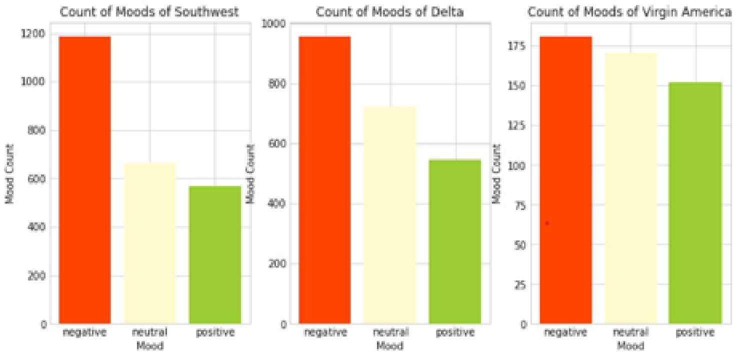
> Positive and neutral tweets are almost equal.
>
> Negative tweets are more than double of neutral or positive sentiments.

In [52]:

```
print("Total number of tweets for each airline \n ",df.groupby('airline')['airline_sentime
nt'].count().sort_values(ascending=False))
airlines= ['US Airways','United','American','Southwest','Delta','Virgin America']
plt.figure(1,figsize=(12, 12))
for i in airlines:
    indices= airlines.index(i)
    plt.subplot(2,3,indices+1)
    new_df=df[df['airline']==i]
    count=new_df['airline_sentiment'].value_counts()
    Index = [1,2,3]
    plt.bar(Index,count, color=['orangered', 'lemonchiffon', 'yellowgreen'])
    plt.xticks(Index,['negative','neutral','positive'])
    plt.ylabel('Mood Count')
    plt.xlabel('Mood')
    plt.title('Count of Moods of '+i)
```

```
Total number of tweets for each airline
  airline
United            3822
US Airways        2913
American          2759
Southwest         2420
Delta             2222
Virgin America     504
Name: airline_sentiment, dtype: int64
```

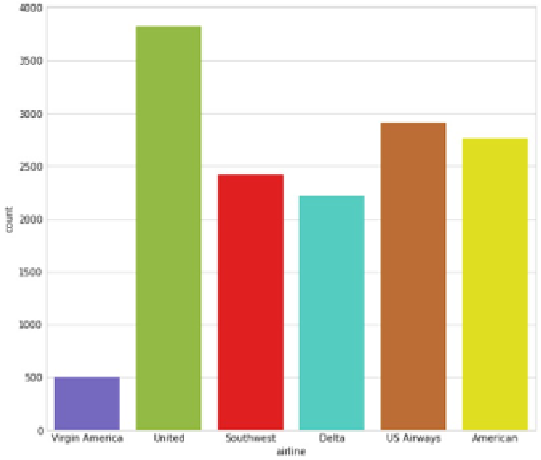




In [53]:

```
# Unique values of airline

col = ['slateblue', 'yellowgreen', 'red', 'turquoise', 'chocolate', 'yellow']
plt.figure(figsize=(9,8))
ax = sns.countplot(x="airline", data=df, palette = col)
```



INNOVATIVE TECHNIQUES

neural network model :

Note: This is a basic example, and you can further optimize the model architecture and hyperparameters for better results.

```
# Import necessary libraries
import pandas as pd
import numpy as np
import re
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from sklearn.model_selection import train_test_split
from tensorflow import keras
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
from tensorflow.keras.callbacks import EarlyStopping

# Load the Twitter US Airline Sentiment dataset
df = pd.read_csv("Tweets.csv")

# Data preprocessing
def preprocess_text(text):
    text = re.sub(r'http\S+', '', text)  # Remove URLs
    text = re.sub(r'@\w+', '', text)      # Remove Twitter usernames
    text = re.sub(r'[^a-zA-Z\s]', '', text)  # Remove special characters
    text = text.lower()  # Convert to lowercase
    tokens = word_tokenize(text)  # Tokenization
    stop_words = set(stopwords.words('english'))
    tokens = [word for word in tokens if word not in stop_words]  # Remove stopwords
    text = ' '.join(tokens)
    return text
```

```
df['text'] = df['text'].apply(preprocess_text)

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

# Tokenize and pad the text data
max_words = 10000  # Maximum number of words in the vocabulary
max_sequence_length = 100  # Maximum sequence length

tokenizer = Tokenizer(num_words=max_words)
tokenizer.fit_on_texts(X_train)
X_train = tokenizer.texts_to_sequences(X_train)
X_test = tokenizer.texts_to_sequences(X_test)

X_train = pad_sequences(X_train, maxlen=max_sequence_length)
X_test = pad_sequences(X_test, maxlen=max_sequence_length)

# Create a neural network model
model = Sequential()
model.add(Embedding(input_dim=max_words, output_dim=100, input_length=max_sequence_length))
model.add(LSTM(100))
model.add(Dense(3, activation='softmax'))  # Output layer with 3 classes (positive, negative, neutral)

# Compile the model
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

```
# Train the model

model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=10, batch_size=64,
callbacks=[EarlyStopping(patience=2)])


# Evaluate the model on the test set

loss, accuracy = model.evaluate(X_test, y_test)

print(f'Test accuracy: {accuracy * 100:.2f}%')
```

This code outlines the process of preprocessing the text data, splitting it into training and testing sets, building a neural network model with LSTM layers, and training the model for sentiment analysis on the Twitter US Airline Sentiment dataset. The model is a simple example and can be further refined and tuned to improve performance. Additionally, you can explore innovative techniques like attention mechanisms or advanced pre-trained embeddings for better results in your sentiment analysis for marketing.

CONCLUSION：

Sentiment analysis plays a crucial role in modern marketing strategies. By harnessing the power of natural language processing and machine learning, businesses can gain deep insights into customer sentiment. Analyzing positive sentiment helps in reinforcingsuccessful marketing efforts, while addressing negative sentiment allows for proactive problem-solving and improved customer satisfaction. Sentiment analysis is an invaluable tool that empowers businesses to stay ahead of the curve and create compelling, customer-focused marketing campaigns.