SENTIMENT ANALYSIS FOR MARKETING

PHASE 5

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INTODUCTION:

In today's dynamic marketing landscape, understanding and leveraging the power of customer sentiment is paramount. With the explosion of digital data, the art of making data-driven marketing decisions has become a game-changer. As explores the evolving realms of marketing, we embrace the fusion of Artificial Intelligence (AI) and Machine Learning (ML) techniques to decipher the hidden gems within customer feedback. Welcome to the realm of Sentiment Analysis for Marketing – where AI and ML unlock invaluable insights that revolutionize marketing strategies.

Overview of the process:

Sentiment analysis in marketing is a process that involves the use of natural language processing (NLP) techniques to assess and understand the sentiment or emotions expressed in customer feedback, comments, reviews, and other textual data. Here's an overview of the sentiment analysis process for marketing.

IMPORT LIBRARIES :

import pandas as pd

import numpy as np

import torch

```
import tokenize
import seaborn as sns
import matplotlib.pyplot as plt
import nltk
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
from transformers import BertTokenizer,
BertForSequenceClassification, Trainer, TrainingArguments
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LogisticRegression
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import re
import nltk
nltk.download('stopwords')
nltk.download('wordnet')
import tensorflow as tf
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
```

```
from tensorflow.keras.preprocessing.sequence import pad_sequences
import torch
from transformers import TFBertForSequenceClassification,BertTokenizer,AdamW,get_linear_schedule_with_warmup,AutoModel,AutoTokenizer,BertModel

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

# Display the first 5 rows of the dataframe
data.head()
```

OUT:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativereason_confidence	airline
0	5.703060e+17	neutral	1.0000	NaN	NaN	Virgin America
1	5.703010e+17	positive	0.3486	NaN	0.0000	Virgin America
2	5.703010e+17	neutral	0.6837	NaN	NaN	Virgin America
3	5.703010e+17	negative	1.0000	Bad Flight	0.7033	Virgin America
4	5.703010e+17	negative	1.0000	Can't Tell	1.0000	Virgin America

airline_sentiment_gold	name	negativereason_gold	retweet_count	text	tweet_coord	tweet_created	tweet_location	user_timezone
NaN	cairdin	NaN	0	@VirginAmerica What @dhepburn said.	NaN	24-02-2015 11:35	NaN	Eastern Time (US & Canada)
NaN	jnardino	NaN	0	@VirginAmerica plus you've added commercials t...	NaN	24-02-2015 11:15	NaN	Pacific Time (US & Canada)
NaN	yvonnalynn	NaN	0	@VirginAmerica I didn't today... Must mean I n...	NaN	24-02-2015 11:15	Lets Play	Central Time (US & Canada)
NaN	jnardino	NaN	0	@VirginAmerica it's really aggressive to blast...	NaN	24-02-2015 11:15	NaN	Pacific Time (US & Canada)
NaN	jnardino	NaN	0	@VirginAmerica and it's a really big bad thing...	NaN	24-02-2015 11:14	NaN	Pacific Time (US & Canada)

```
#load the dataset
data.columns
data.info()
print(data.shape)
print(data['airline_sentiment'].value_counts())
```

OUT:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14640 entries, 0 to 14639
Data columns (total 15 columns):
```

```
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   tweet_id                      14640 non-null  float64
 1   airline_sentiment             14640 non-null  object 
 2   airline_sentiment_confidence  14640 non-null  float64
 3   negativereason                9178 non-null   object 
 4   negativereason_confidence     10522 non-null  float64
 5   airline                       14640 non-null  object 
 6   airline_sentiment_gold        40 non-null     object 
 7   name                          14640 non-null  object 
 8   negativereason_gold           32 non-null     object 
 9   retweet_count                 14640 non-null  int64  
 10  text                          14640 non-null  object 
 11  tweet_coord                   1019 non-null   object 
 12  tweet_created                 14640 non-null  object 
 13  tweet_location                9907 non-null   object 
 14  user_timezone                 9820 non-null   object 
dtypes: float64(3), int64(1), object(11)
memory usage: 1.7+ MB
(14640, 15)
negative    9178
neutral     3099
positive    2363
Name: airline_sentiment, dtype: int64
```

data.head()

df = data[['airline_sentiment','text']]

df

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

...	...	...
14635	positive	@AmericanAir thank you we got on a different f...
14636	negative	@AmericanAir leaving over 20 minutes Late Flig...
14637	neutral	@AmericanAir Please bring American Airlines to...
14638	negative	@AmericanAir you have my money, you change my ...
14639	neutral	@AmericanAir we have 8 ppl so we need 2 know h...

14640 rows × 2 columns

```
#preprocess the data
def no_emo(text):
    emoji_pattern = re.compile("[" u"\U0001F600-\U0001F64F"
# emoticons
                                u"\U0001F300-\U0001F5FF"
# symbols & pictographs
                                u"\U0001F680-\U0001F6FF"
# transport & map symbols
                                u"\U0001F1E0-\U0001F1FF"
 # flags (iOS)
                                "]+", flags=re.UNICODE)
    return (emoji_pattern.sub(r'', text))
def preprocess_text(df):
```

```
    df['text'] =df['text'].apply(lambda x : x.lower().strip())
    #case norm
    df['text'] =df['text'].apply(lambda x: re.sub("\S*@\S*\s?", '', x))
    #email remove
    df['text'] =df['text'].apply(lambda x: re.sub(r'http\S+', '', x))
    # http remove
    df['text'].apply(no_emo)
    # remove emojis
    df['text'] =df['text'].apply(lambda x: re.sub('[^a-zA-Z\n\.]', ' ', x))
    #Remove special characters, non-text characters
    df['text'] =df['text'].apply(lambda x:re.sub(r'([^\w\s]|_)+', ' ', x))
    #Remove repeated punctuations
    df['text'] =df['text'].apply(lambda x:re.sub(r'\s+', ' ',x))
    #Remove white spaces
    df['text'] = df['text'].apply(lambda x: re.sub(r'\bamp\b', '', x))
    df['text'] =df['text'].apply(lambda x:x.strip())
    return df
data['labels'] = data["airline_sentiment"].apply(lambda x: 0 if x ==
"negative" else 1 if x == "neutral" else 2)
data = preprocess_text(data)


def convert_to_numeric(text):
  tokenizer = tf.keras.preprocessing.text.Tokenizer()
  tokenizer.fit_on_texts(data['text'])
```

```
  word_index = tokenizer.word_index
  sequences = tokenizer.texts_to_sequences(data['text'])
  padded_sequences = pad_sequences(sequences, maxlen=100)
  return padded_sequences

nltk.download('punkt')
nltk.download('stopwords')
```

OUT:

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
True
```

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

OUT:

```
<ipython-input-17-919540b8885e>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['text'] = df['text'].apply(preprocess_text)
```

	airline_sentiment	**text**
0	neutral	virginamericadhepburnsaid
1	positive	virginamericaplusaddedcommercialsexperiencetacky

	airline_sentiment	text
2	neutral	virginamericatodaymustmeanneedtakeanothertrip
3	negative	virginamericareallyaggressiveblastobnoxiousent...
4	negative	virginamericareallybigbadthing
...	...	...
14635	positive	americanairthankgotdifferentflightchicago
14636	negative	americanairleaving20minuteslateflightwarningsc...
14637	neutral	americanairpleasebringamericanairlinesblackber...
14638	negative	americanairmoneychangeflightanswerphonessugges...
14639	neutral	americanair8pplneed2knowmanyseatsnextflightplz...

14640 rows × 2 columns

```
#Tokenization & Vectorization
import torch
from transformers import TFBertForSequenceClassification,BertTokenizer,AdamW,get_linear_schedule_with_warmup,AutoModel,AutoTokenizer,BertModel


from sklearn.feature_extraction.text import TfidfVectorizer
# Create TF-IDF vectorizer
tfidf_vectorizer = TfidfVectorizer(max_features=5000)


# Fit and transform your cleaned text data into numerical features
X = tfidf_vectorizer.fit_transform(df['text'])
print(X)
#splitting the data
```

X_train, X_test, y_train, y_test = train_test_split(X, df['airline_sentiment'], test_size=0.2, random_state=42)

Create and train a Logistic Regression model

model = LogisticRegression()

model.fit(X_train, y_train)

Make predictions

y_pred = model.predict(X_test)

Evaluate the model

accuracy = accuracy_score(y_test, y_pred)

print(f"Accuracy: {accuracy}")

OUT:

```
(0, 4600)   1.0
  (1, 4831) 1.0
  (2, 4925) 1.0
  (3, 4847) 1.0
  (4, 4848) 1.0
  (5, 4867) 1.0
  (6, 4981) 1.0
  (7, 4851) 1.0
  (8, 4968) 1.0
  (10, 4728)     1.0
  (11, 4769)     1.0
  (12, 4676)     1.0
  (13, 4954)     1.0
  (14, 4903)     1.0
  (16, 4616)     1.0
  (17, 4625)     1.0
  (19, 4729)     1.0
  (20, 4622)     1.0
  (21, 4759)     1.0
  (22, 4762)     1.0
```

```
  (23, 4775)      1.0
  (24, 4688)      1.0
  (25, 4889)      1.0
  (26, 4692)      1.0
  (27, 4788)      1.0
  :   :
  (13151, 133)    1.0
  (13169, 4999)   1.0
  (13210, 131)    1.0
  (13213, 38)     1.0
  (13278, 36)     1.0
  (13322, 23)     1.0
  (13339, 131)    1.0
  (13346, 1)      1.0
  (13442, 131)    1.0
  (13522, 54)     1.0
  (13552, 131)    1.0
  (13565, 23)     1.0
  (13680, 4984)   1.0
  (13766, 133)    1.0
  (13864, 122)    1.0
  (13884, 60)     1.0
  (13995, 5)      1.0
  (14020, 36)     1.0
  (14386, 148)    1.0
  (14392, 111)    1.0
  (14512, 92)     1.0
  (14543, 109)    1.0
  (14544, 92)     1.0
  (14556, 131)    1.0
  (14630, 133)    1.0
Accuracy: 0.655396174863388
```

```
#Evaluate the model on the test set
accuracy = model.score(test_vec, test_labels)
print(f'Test accuracy: {accuracy:.4f}')
```

OUT:

```
Test accuracy: 0.6554
```

```
train_data, val_data = train_test_split(df, test_size=0.2,
random_state=42)
```

```
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')


train_encoding=tokenizer(list(train_data['text']),truncation=True,padding
=True)

valid_encoding=tokenizer(list(val_data['text']),truncation=True,padding
=True)


sentiment_dict = {'positive': 0, 'negative': 1, 'neutral': 2}

train_labels =
train_data['airline_sentiment'].map(sentiment_dict).values.astype('int64')

valid_labels =
val_data['airline_sentiment'].map(sentiment_dict).values.astype('int64')

print(len(train_labels))

print(len(valid_labels))

print(len(train_encoding))

print(len(valid_encoding))
```

OUT:

```
11712

2928
3
3
```

```
# Calculate the distribution of sentiment

sentiment_distribution = data['airline_sentiment'].value_counts()


# Most common reasons for negative sentiments
```

common_negative_reasons = data[data['airline_sentiment'] == 'negative']['negativereason'].value_counts()

Analyze the impact of airline sentiment confidence

data['airline_sentiment_confidence'].groupby(data['airline_sentiment']).mean()

Explore the relationship between sentiment and airline

sentiment_by_airline = data.groupby(['airline', 'airline_sentiment']).size().unstack()

sentiment_by_airline

OUT:

airline_sentiment	negative	neutral	positive
airline			
American	1960	463	336
Delta	955	723	544
Southwest	1186	664	570
US Airways	2263	381	269
United	2633	697	492
Virgin America	181	171	152

#Count plotting

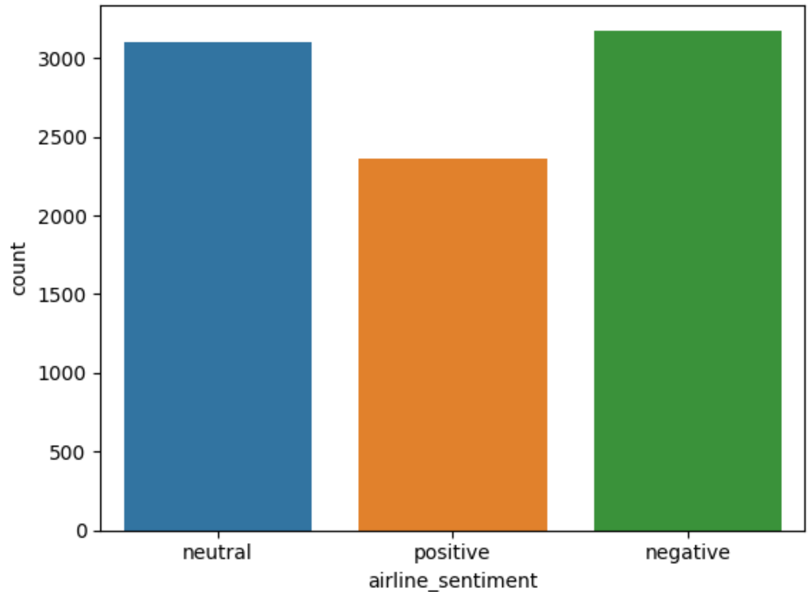
import seaborn as sns

df_new=data.drop(data[data.airline_sentiment =='negative'].iloc[:6000].index)

sns.countplot(data=df_new, x='airline_sentiment')

OUT:

`<Axes: xlabel='airline_sentiment', ylabel='count'>`



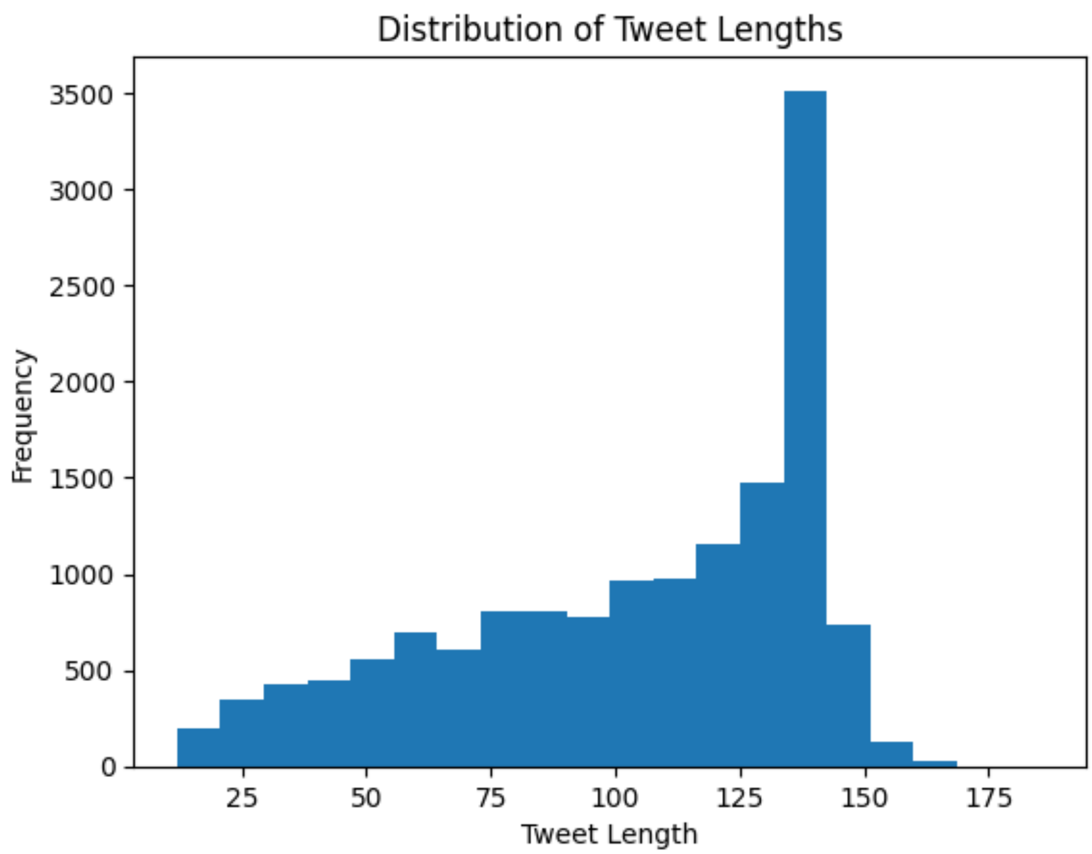

```
from wordcloud import WordCloud


text = " ".join(tweet for tweet in data['text'])
wordcloud = WordCloud(width=800, height=400,
background_color='white').generate(text)


plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.title("Word Cloud for Tweets")
plt.show()
```

OUT:

Word Cloud for Tweets


```
data['tweet_length'] = data['text'].apply(len)
plt.hist(data['tweet_length'], bins=20)
plt.title("Distribution of Tweet Lengths")
plt.xlabel("Tweet Length")
plt.ylabel("Frequency")
plt.show()
```

OUT:



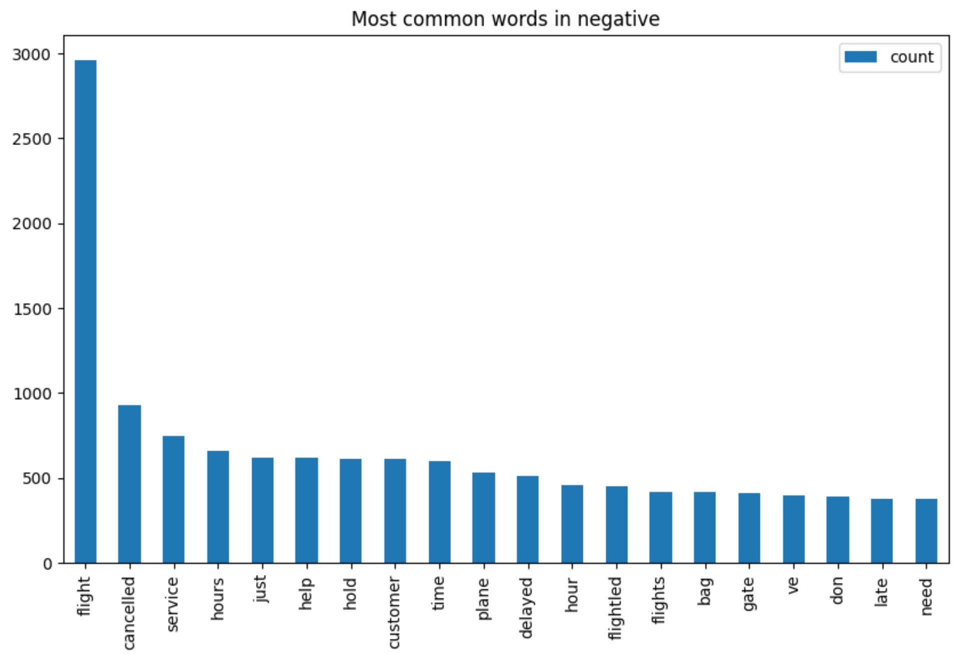
from sklearn.feature_extraction.text import CountVectorizer # top 20 most common words function

```
def common_words(rev):
  texts = data[data['airline_sentiment'] == rev]['text'].values
  vec = CountVectorizer(stop_words='english').fit(texts)
  bag_of_words = vec.transform(texts)
  sum_words = bag_of_words.sum(axis=0)
  words_freq = [(word, sum_words[0, idx])  for word, idx in 
vec.vocabulary_.items()]
  return sorted(words_freq, key = lambda x: x[1], reverse=True)[:20]
```

top_neg = dict(common_words('negative'))

pd.DataFrame.from_dict(top_neg, orient='index', columns=['count']).plot(kind='bar', figsize=(10, 6),title = 'Most common words in negative');

OUT:

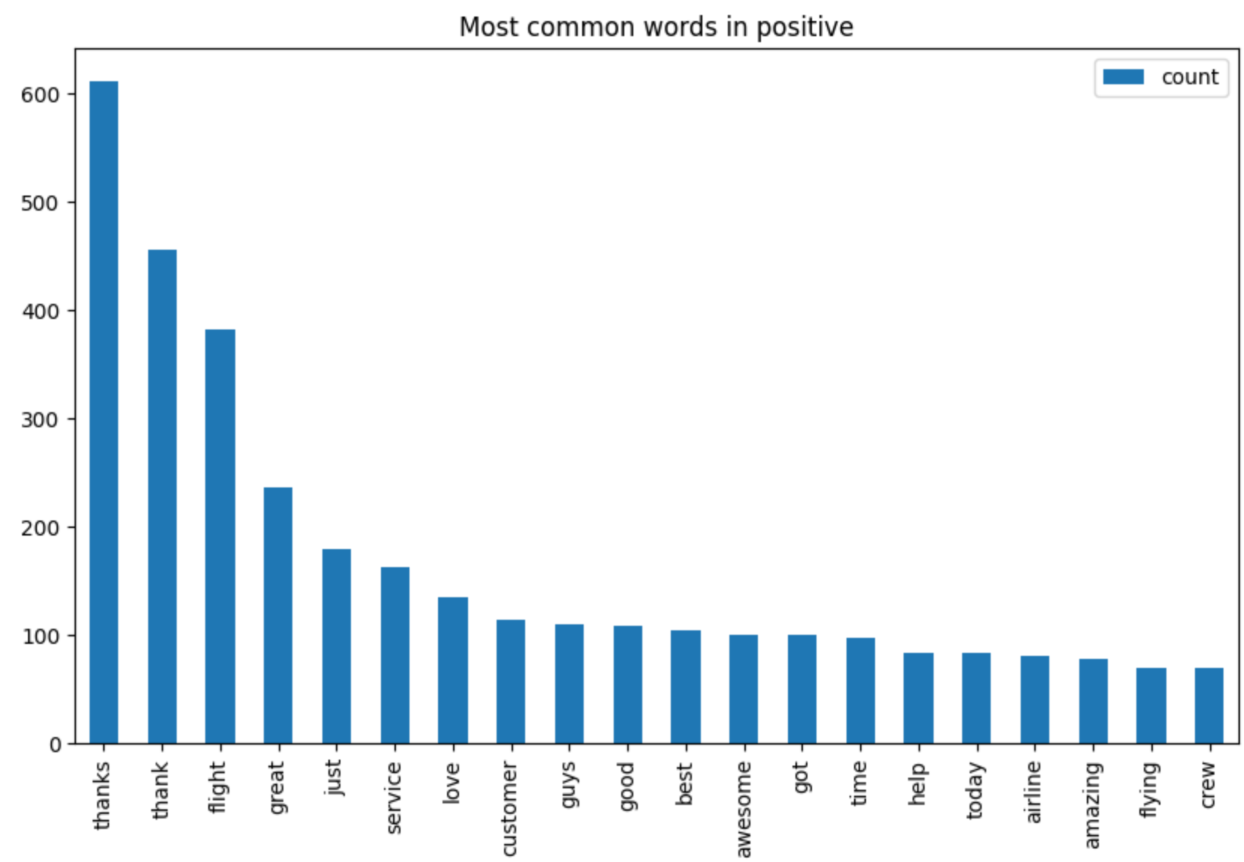


#positive words

top_neg = dict(common_words('positive'))

pd.DataFrame.from_dict(top_neg, orient='index', columns=['count']).plot(kind='bar', figsize=(10, 6),title = 'Most common words in positive');

OUT:



!pip install datasets

x = data['text']

y = data['labels']

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=101)

from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer

tfv = TfidfVectorizer(min_df=3, max_features=None, strip_accents='unicode', analyzer='word',token_pattern=r'\w{1,}', ngram_range=(1, 2), use_idf=1,smooth_idf=1,sublinear_tf=1, stop_words = 'english')

```
tfv.fit(X_train)

TfidfVectorizer(min_df=3, ngram_range=(1, 2), smooth_idf=1,
stop_words='english', strip_accents='unicode', sublinear_tf=1,
token_pattern='\\w{1,}', use_idf=1)

X_train_tfv = tfv.transform(X_train)

X_test_tfv = tfv.transform(X_test)

X_train_tfv


from sklearn.svm import LinearSVC

svc = LinearSVC()

svc.fit(X_train_tfv,y_train)

LinearSVC()

from sklearn.pipeline import Pipeline

pipe = Pipeline([('tfidf',TfidfVectorizer()), ('svc',LinearSVC())])

pipe.fit(data['text'],data['labels'])

Pipeline(steps=[('tfidf', TfidfVectorizer()), ('svc', LinearSVC())])

new_positive_tweet = ['good flight']

pipe.predict(new_positive_tweet)


new_negative_tweet = ['bad flight']

pipe.predict(new_negative_tweet)


new_neutral_tweet = ['ok flight']

pipe.predict(new_neutral_tweet)
```

```
##pandasDF --> Hugging Face dataset

from datasets import Dataset

dataset = {"text": data["text"].tolist(), "labels":data["labels"].tolist()}

dataset = Dataset.from_dict(dataset)

dataset = dataset.train_test_split(train_size=0.8, seed=101)

dataset
```

OUT:

```
DatasetDict({
    train: Dataset({
        features: ['text', 'labels'],
        num_rows: 11712
    })
    test: Dataset({
        features: ['text', 'labels'],
        num_rows: 2928
    })
})
```

```
import tensorflow as tf

from transformers import TFAutoModelForSequenceClassification,
AutoTokenizer, AutoConfig,DataCollatorWithPadding

from scipy.special import softmax

checkpoint = 'cardiffnlp/twitter-roberta-base-sentiment-latest'

batch_size = 16

num_epochs = 5

config = AutoConfig.from_pretrained(checkpoint)

tokenizer = AutoTokenizer.from_pretrained(checkpoint)

model =
TFAutoModelForSequenceClassification.from_pretrained(checkpoint,
num_labels=3)
```

```
def tokenize_function(example):
    return tokenizer(example['text'], truncation=True, max_length = 35)
tokenized_datasets = dataset.map(tokenize_function, batched=True,)
data_collator = DataCollatorWithPadding(tokenizer=tokenizer,
return_tensors="tf")


from transformers import pipeline
classifier = pipeline("sentiment-
analysis",tokenizer=tokenizer,model=model)
predicted_labels = []
for text in X_test:
    result = classifier(text)
    predicted_label = result[0]['label']
    predicted_labels.append(predicted_label)
df = pd.DataFrame(X_test)
df['predictions'] = predicted_labels
df['labels'] = df["predictions"].apply(lambda x: 0 if x == "negative" else
1
                                 if x == "neutral" else 2)
df.head()
```

OUT:

	text	predictions	Labels
4814	thanks very excited to see it d	positive	2

150	does that mean you don t have a policy for des...	neutral	1
5322	any official word whether flight from bwi to m...	neutral	1
4885	i miss mine terribly a for my th anniversary w...	neutral	1
7504	at what time all these passengers were sitting...	neutral	1

from sklearn.metrics import confusion_matrix

import seaborn as sns

print(classification_report(y_test,df['labels']))

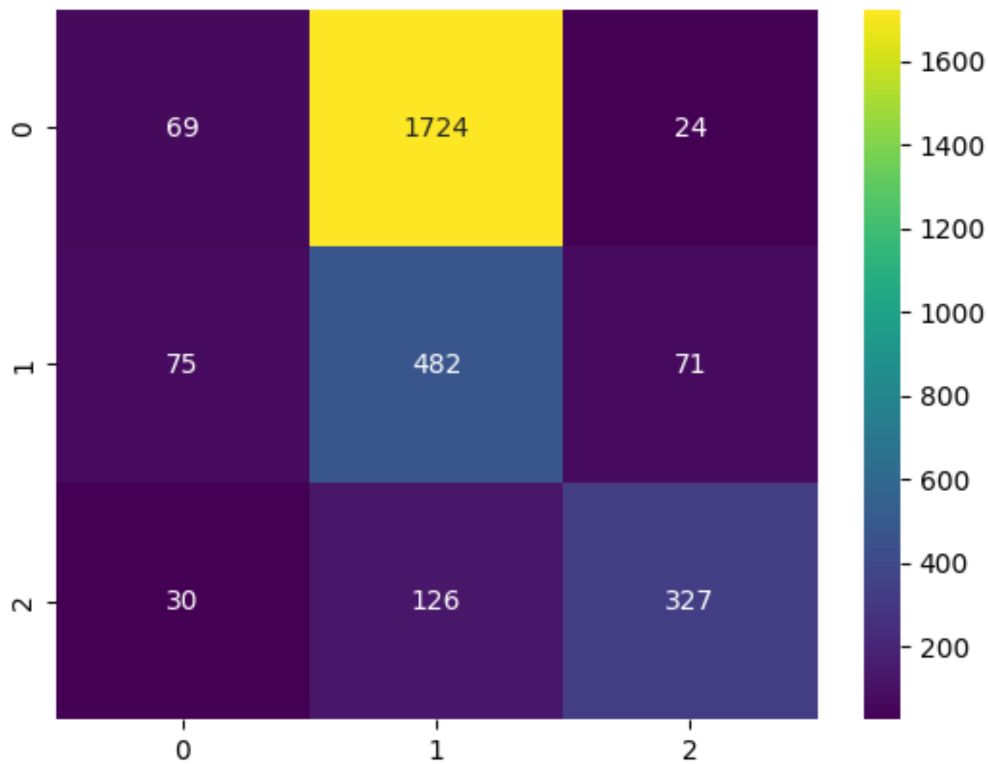
OUT:

```
              precision    recall  f1-score   support


           0       0.40      0.04      0.07      1817
           1       0.21      0.77      0.33       628
           2       0.77      0.68      0.72       483
```

sns.heatmap(confusion_matrix(y_test,df['labels']),cmap='viridis',annot=True,fmt='d')

OUT:

```
<Axes: >
```



new_tweet = ['amazing product ']

classifier(new_positive_tweet)

OUT:

```
[{'label': 'positive', 'score': 0.402895987033844}]
```

new_tweet = ['worst experience in flight']

classifier(new_negative_tweet)

OUT:

```
[{'label': 'negative', 'score': 0.3756020665168762}]
```

new_tweet = ['ok flight']

classifier(new_neutral_tweet)

OUT:

```
[{'label': 'negative', 'score': 0.3681403398513794}]
```

CONCLUSION:

Sentiment analysis of Twitter US airline data using the BERT model is a powerful and effective tool for understanding customer opinions and emotions in the airline industry. This approach allows airlines to gain valuable insights into passenger sentiment, which can be pivotal for various aspects of their operations and customer service:

1**. Improved Customer Service**: By monitoring sentiment, airlines can proactively address customer concerns and issues, leading to better customer experiences.

2. **Crisis Management**: Sentiment analysis using BERT can help airlines identify and respond to potential PR crises quickly.

3**. Marketing and Campaigns**: Airlines can fine-tune their marketing strategies based on the sentiments expressed by customers on social media, enabling more targeted and resonant campaigns.

4. **Product and Service Enhancement**: Understanding customer sentiment provides valuable feedback for improving in-flight services, amenities, and operational aspects.

5. **Real-time Feedback Loop**: The use of BERT in sentiment

analysis ensures that airlines have access to real-time feedback, enabling them to adapt swiftly to customer preferences and concerns.

In essence, sentiment analysis using BERT is a vital tool for airlines to gauge and react to customer sentiment, thereby enhancing customer satisfaction, refining marketing strategies, and ultimately improving their overall services. It demonstrates the power of NLP and machine learning in gaining insights from vast social media data.

Sentiment analysis for marketing is a valuable tool for understanding customer perceptions of competitor products. By following the outlined design thinking process, we can gather, preprocess, analyze, and visualize customer feedback data to derive meaningful insights that drive informed business decisions and marketing strategies.