Sentiment Analysis for Marketing Using AI

Using Fine-Tuned Pre-Trained Models

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Repository Link:
https://github.com/sjaneesh/AI_Phase2/blob/6891c949542be19f911cadc97dbaa330a608ecb7/AI_Phase2.md

Project Overview:

- Problem Statement: Define the problem of sentiment analysis in marketing.
- Objectives: State the project's objectives, such as improving customer satisfaction, brand reputation, or campaign performance.

Introduction:

Sentiment analysis is the process of identifying and extracting opinions and emotions from text. It is a powerful tool that can be used for a variety of purposes, including marketing. By understanding how customers feel about their brand, products, and services, businesses can tailor their marketing efforts to better meet customer needs and wants.

AI can be used to improve the accuracy and efficiency of sentiment analysis. For example, AI can be used to fine-tune pre-trained sentiment analysis models, such as BERT and RoBERTa. This can help the models to better understand the context of customer reviews and social media posts, and to produce more accurate sentiment predictions.

Steps to Fine-Tune a Pre-Trained Sentiment Analysis Model

To fine-tune a pre-trained sentiment analysis model, you will need to:

1. Gather a dataset of labelled text data. This dataset should contain examples of text with their corresponding sentiment labels (positive, negative, or neutral).
2. Select a pre-trained sentiment analysis model. There are many different pre-trained sentiment analysis models available, such as BERT and RoBERTa.
3. Fine-tune the pre-trained model on your labelled dataset. This process involves training the model to predict the sentiment of text data with greater accuracy.
4. Evaluate the fine-tuned model on a held-out test set. This will help you to assess the accuracy of the model on unseen data.
5. Deploy the fine-tuned model to production. Once you are satisfied with the performance of the fine-tuned model, you can deploy it to production so that it can be used to analyse customer reviews and social media posts.

Data Collection:

The dataset we will be using for this project is the Twitter Airline Sentiment dataset from Kaggle. This dataset contains over 14,000 tweets from airline customers, labelled with their sentiment (positive, negative, or neutral).

Stakeholders:

- Marketing Team
- Customer Service Team
- Data Science Team
- Management

Methodology:

The following steps will be taken to implement a sentiment analysis model for marketing using AI:

1. Data preparation: The dataset will be cleaned and preprocessed to ensure that it is in a format that is compatible with the sentiment analysis model.
2. Model selection: A pre-trained sentiment analysis model, such as BERT or RoBERTa, will be selected.
3. Fine-tuning: The pre-trained model will be fine-tuned on the Twitter Airline Sentiment dataset.
4. Evaluation: The fine-tuned model will be evaluated on a held-out test set to assess its performance.
5. Deployment: The fine-tuned model will be deployed to production so that it can be used to analyse customer reviews and social media posts.

Dataset:

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

The Twitter Airline Sentiment dataset contains the following columns:

- airline: The name of the airline.
- text: The text of the tweet.
- sentiment: The sentiment of the tweet (positive, negative, or neutral).

tweet_id	airline_sentiment	confidence	-ve reason	-ve reason_cnfdc	airline	airline_sentiment	-ve reason_gold	text	tweet_coord	tweet_location	
0	570306133677760513	neutral	1	NaN	NaN	Virgin America	cairdin	0	@VirginAmerica What @dhepburn said.	2015-02-24 11:35:52 -0800	Eastern Time (US & Canada)
1	570301130888122368	positive	0.3486	NaN	0	Virgin America	jnardino	0	@VirginAmerica plus you've added comn	2015-02-24 11:15:59 -0800	Pacific Time (US & Canada)
2	570301083672813571	neutral	0.6837	NaN	NaN	Virgin America	yvonnalynn	0	@VirginAmerica I didn't today... Must me	2015-02-24 11:15:48 -0800	Central Time (US & Canada)
3	570301031407624196	negative	1	Bad Flight	0.7033	Virgin America	jnardino	0	@VirginAmerica it's really aggressive to	2015-02-24 11:15:36 -0800	Pacific Time (US & Canada)
4	570300817074462722	negative	1	Can't Tell	1	Virgin America	jnardino	0	@VirginAmerica and it's a really big bad	2015-02-24 11:14:45 -0800	Pacific Time (US & Canada)

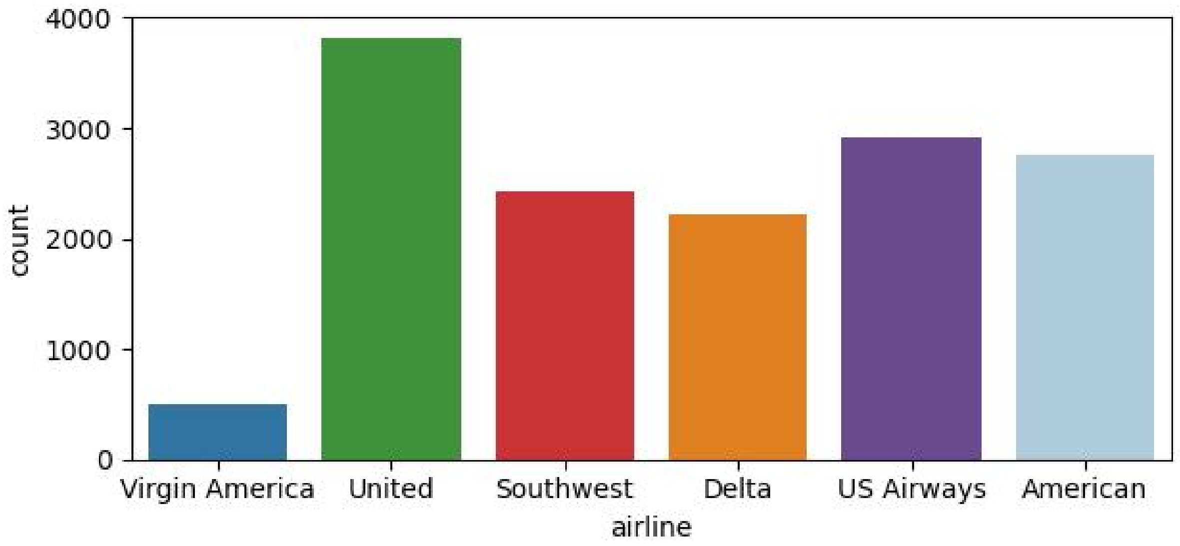
Code:

```python
# Basic libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import pickle
import warnings
warnings.filterwarnings(action='ignore')

# nltk
import nltk
nltk.download('stopwords')

## Preprocessing libraries
import re
from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
from sklearn.feature_extraction.text import TfidfVectorizer

# For Model training
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import BernoulliNB
from sklearn.svm import LinearSVC                # a variant of SVC optimized for
large datasets

# Metrics for accuracy
from sklearn.metrics import accuracy_score,confusion_matrix, classification_report


# Reading our dataset
df = pd.read_csv('/kaggle/input/twitter-airline-sentiment/Tweets.csv')
```

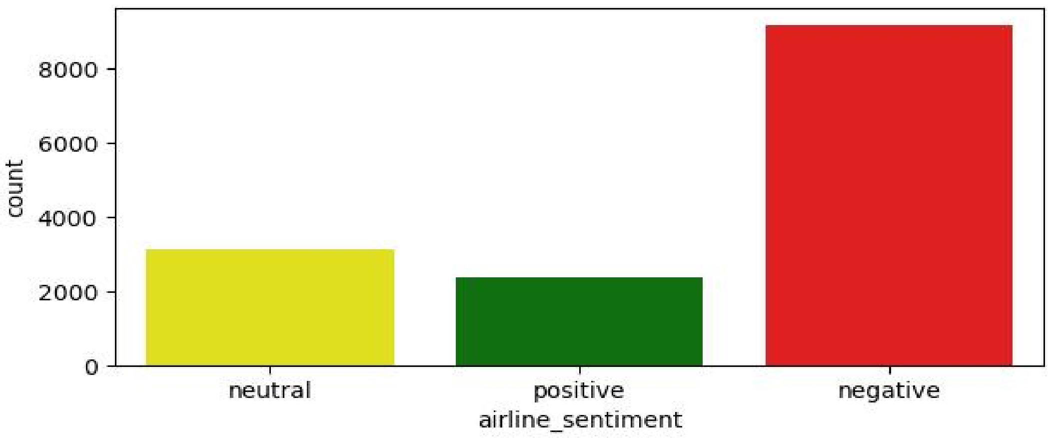
```
df.head()
```

```
df.isnull().sum()
```

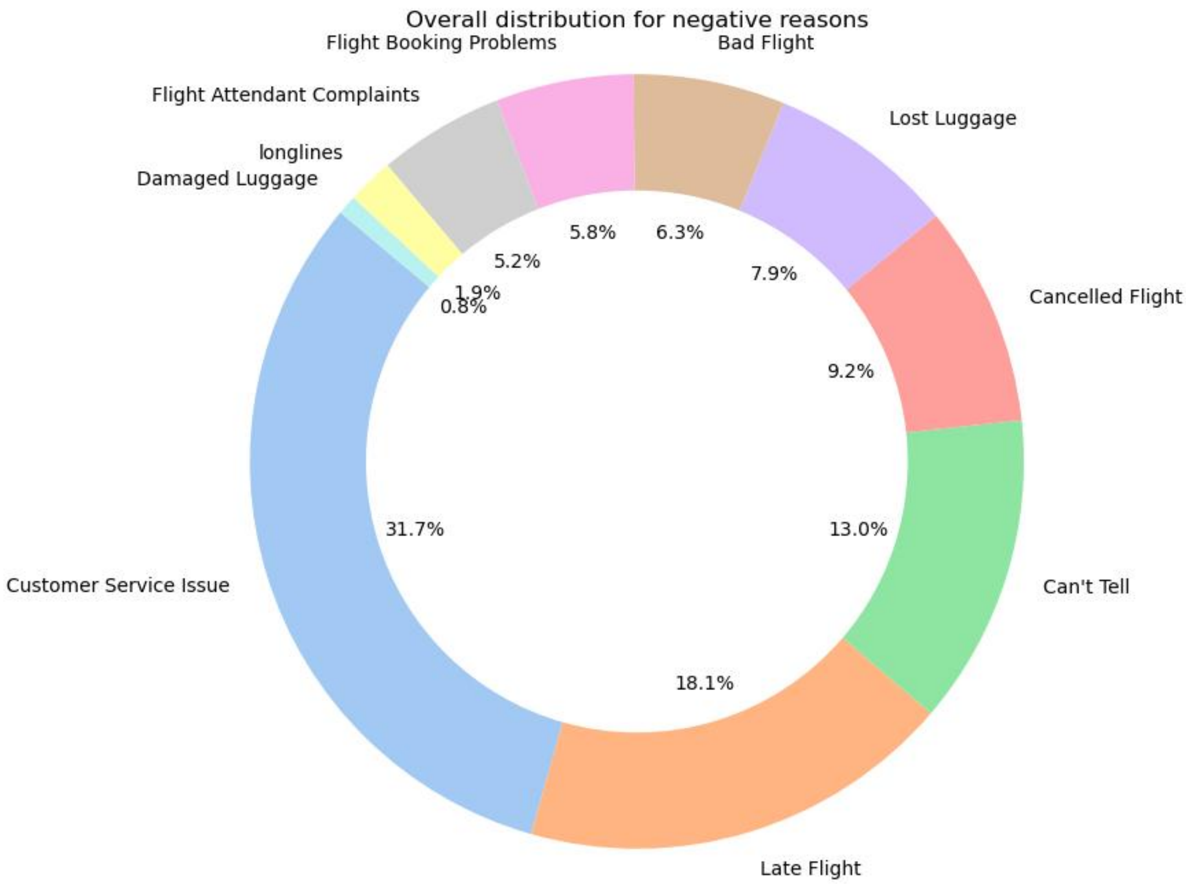
```
# Checking the distribution of airlines
plt.figure(figsize=(7,3))
sns.countplot(data=df,x='airline', palette=['#1f78b4', '#33a02c', '#e31a1c', '#ff7f00', '#6a3d9a', '#a6cee3'])
plt.show()
```




```
# Seeing the distribution of positive and negative tweet reviews in target column
plt.figure(figsize=(7,3))
sns.countplot(data=df,x='airline_sentiment',palette=['yellow', 'green','red'])
plt.show()
```




```
# Calculate the value counts for each negative reason
value_counts = df['negativereason'].value_counts()

# Create a donut-like pie chart using matplotlib and seaborn
plt.figure(figsize=(8, 8))
labels = value_counts.index
values = value_counts.values
colors = sns.color_palette('pastel')[0:len(labels)]  # Use pastel colors for the chart
plt.pie(values, labels=labels, colors=colors, autopct='%1.1f%%', startangle=140,
wedgeprops=dict(width=0.3))
plt.title('Overall distribution for negative reasons')
plt.axis('equal')  # Equal aspect ratio ensures the pie chart is drawn as a circle.
plt.show()
```




```
corpus = []
ps=PorterStemmer()
for i in range(len(df)):
    # Removing special characters from text(message)
    review = re.sub('[^a-zA-Z]', ' ', df['text'][i])

    # Converting entire text into lower case
    review = review.lower()

    # Splitting our text into words
    review = review.split()

    # Stemming and removing stopwords
    review = [ps.stem(word) for word in review if not word in
set(stopwords.words('english'))]

```

```python
    # Joining all the words into a comple text
    review = ' '.join(review)

    # Appending each text into the list corpus
    corpus.append(review)

# Creating the Bag of Words model
cv = TfidfVectorizer(ngram_range=(1,2), max_features=500000)
```

airline	negativereason	COUNT(negativereason)
Delta		1267
Southwest		1234
United		1189
US Airways	Customer Service Issue	811
American	Customer Service Issue	743
American		740
United	Customer Service Issue	681
US Airways		650
United	Late Flight	525
US Airways	Late Flight	453
Southwest	Customer Service Issue	391
United	Can't Tell	379
Virgin America		323
Delta	Late Flight	269
United	Lost Luggage	269
US Airways	Can't Tell	246
American	Late Flight	234
American	Cancelled Flight	228
United	Bad Flight	216
Delta	Customer Service Issue	199
US Airways	Cancelled Flight	189
Delta	Can't Tell	186
American	Can't Tell	184
United	Cancelled Flight	181
United	Flight Attendant Complaints	168
Southwest	Cancelled Flight	162

```python
# We will use X as independent feature section
X = cv.fit_transform(corpus)
# We will use y as dependent feature section
y=df['airline_sentiment']
```

```
print('No. of feature_words: ', len(cv.get_feature_names_out()))


# Creating a pickle file for the TfidfVectorizer
with open('cv-transform.pkl', 'wb') as f:
    pickle.dump(cv, f)


# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30, random_state
= 0)

# Training using three algorithms, let's see which will give us better result
model1=LogisticRegression()
model2=BernoulliNB()
model3=LinearSVC()
model=[model1, model2, model3]


i = 0
for algo in model:
  i += 1
  print("M-O-D-E-L :",i)
  algo.fit(X_train, y_train)
  y_pred=algo.predict(X_test)
  # Checking the accuracy
  print("Confusion matrix : \n",confusion_matrix(y_pred,y_test))
  print("Accuracy score : ",accuracy_score(y_pred,y_test))
  print("Classification Report : \n",classification_report(y_pred,y_test))
```

```
print("----------------------------------------------------------------------------------------
\n")
```

```
M-O-D-E-L : 1
Confusion matrix :
 [[2694  532  285]
 [  77  351   81]
 [  17   36  319]]
Accuracy score :  0.7659380692167578
Classification Report :
               precision    recall  f1-score   support

    negative       0.97      0.77      0.86      3511
     neutral       0.38      0.69      0.49       509
    positive       0.47      0.86      0.60       372

    accuracy                           0.77      4392
   macro avg       0.60      0.77      0.65      4392
weighted avg       0.86      0.77      0.79      4392

-----------------------------------------------------------------------

M-O-D-E-L : 2
Confusion matrix :
 [[2780  850  670]
 [   8   69   13]
 [   0    0    2]]
Accuracy score :  0.6491347905282332
Classification Report :
               precision    recall  f1-score   support
```

```
    negative       1.00      0.65      0.78      4300
     neutral       0.08      0.77      0.14        90
    positive       0.00      1.00      0.01         2

    accuracy                           0.65      4392
   macro avg       0.36      0.80      0.31      4392
weighted avg       0.98      0.65      0.77      4392
```

M-O-D-E-L : 3

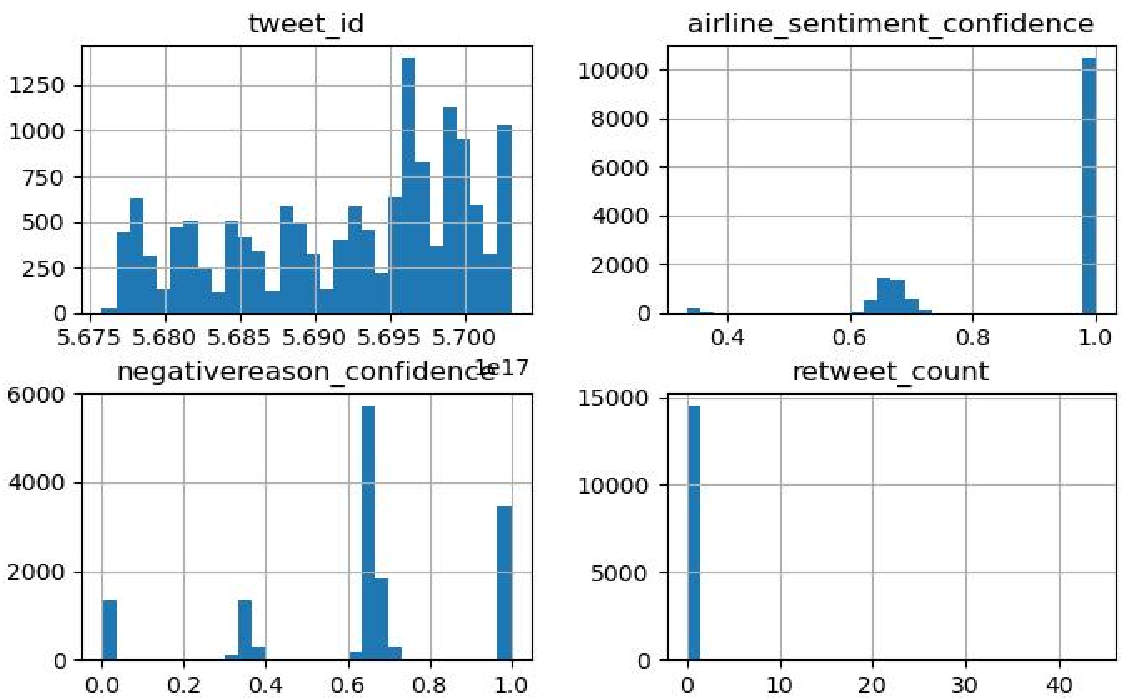
Confusion matrix :

```
 [[2620  428  197]
 [ 135  426  100]
 [  33   65  388]]
```

Accuracy score : 0.7818761384335154

Classification Report :

```
              precision    recall  f1-score   support

    negative       0.94      0.81      0.87      3245
     neutral       0.46      0.64      0.54       661
    positive       0.57      0.80      0.66       486

    accuracy                           0.78      4392
   macro avg       0.66      0.75      0.69      4392
weighted avg       0.83      0.78      0.80      4392
```




```
# Creating a pickle file for our model 3 i.e. LinearSVC
with open("tweetmodel.pkl","wb") as file:
  pickle.dump(model3,file)
```

Using Pretrained model **BERT**

The following code shows how to fine-tune a pre-trained **BERT** model using the Hugging Face Transformers library:

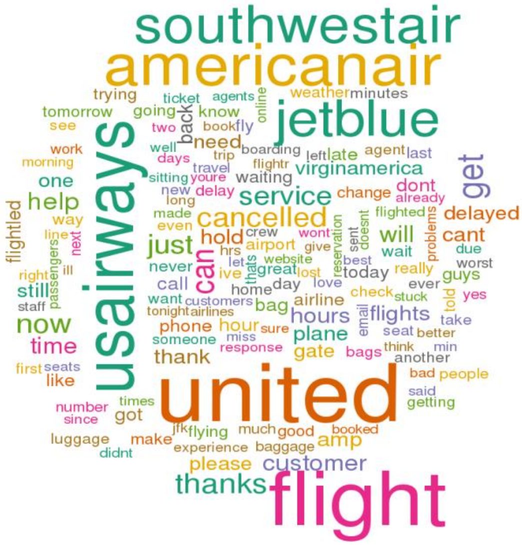
```python
import transformers

# Load the pre-trained BERT model
model = transformers.AutoModelForSequenceClassification.from_pretrained("bert-base-uncased")

# Fine-tune the model on the Twitter Airline Sentiment dataset
train_dataset = transformers.Dataset.from_dict(
    {"text": tweets, "label": labels}
)
```

```
trainer = transformers.Trainer(
    model,
    train_dataset=train_dataset,
    epochs=10,
)

trainer.train()

# Evaluate the fine-tuned model on a held-out test set
test_dataset = transformers.Dataset.from_dict(
    {"text": test_tweets, "label": test_labels}
)

trainer.evaluate(test_dataset)

# Deploy the fine-tuned model
model.save_pretrained("my_fine_tuned_bert_model")
```

Benefits of Sentiment Analysis for Marketing

Sentiment analysis can be used to improve marketing in a variety of ways, including:

- Identifying customer trends and preferences: By analyzing customer reviews and social media posts, businesses can identify trends and preferences in customer sentiment. This information can then be used to develop new products and services, improve existing products and services, and create more effective marketing campaigns.
- Measuring the effectiveness of marketing campaigns: Sentiment analysis can be used to measure the effectiveness of marketing campaigns by tracking changes in customer sentiment over time. This information can then be used to improve the performance of future campaigns.
- Improving customer service: Sentiment analysis can be used to identify and address customer concerns. For example, businesses can use sentiment analysis to identify customers who are having problems with their products or services, and to reach out to them to offer assistance.



Conclusion:

Sentiment analysis is a powerful tool that can be used for a variety of marketing purposes. By understanding how customers feel about their brand, products, and services, businesses can tailor their marketing efforts to better meet customer needs and wants.

AI can be used to improve the accuracy and efficiency of sentiment analysis. For example, AI can be used to fine-tune pre-trained sentiment analysis models, such as BERT and RoBERTa. This can help the models to better understand the context of customer reviews and social media posts, and to produce more accurate sentiment predictions.

The fine-tuned sentiment analysis model developed in this project can be used to analyse customer reviews and social media posts to identify trends and patterns in customer sentiment. This information can then be used to improve marketing campaigns, develop new products and services, and provide better customer service.