Sentiment Analysis for Marketing: Loading and Preprocessing the dataset (Part 1)

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<u>Introduction</u>: Sentiment Analysis using Machine Learning

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 as done in previous phase. This can help the models to better understand the context of customer reviews and social media posts, and to produce more accurate sentiment predictions.

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	airline_sentiment...	negativereason	negativereason_c...	airline
567588279b 570310600b	negative 63% neutral 21% Other (2363) 16%	0.34 1	[null] 37% Customer Service ... 20% Other (6268) 43%	0 1	United US Airwa Other (7
570306133677760513	neutral	1.0			Virgin
570301130888122368	positive	0.3486		0.0	Virgin
570301083672813571	neutral	0.6837			Virgin
570301031407624196	negative	1.0	Bad Flight	0.7033	Virgin
570300817074462722	negative	1.0	Can't Tell	1.0	Virgin
570300767074181121	negative	1.0	Can't Tell	0.6842	Virgin
570300616901320704	positive	0.6745		0.0	Virgin
570300248553349120	neutral	0.634			Virgin
570299953286942721	positive	0.6559			Virgin
570295459631263746	positive	1.0			Virgin
570294189143031808	neutral	0.6769		0.0	Virgin
570289724453216256	positive	1.0			Virgin
570289584061480960	positive	1.0			Virgin
570287408438120448	positive	0.6451			Virgin

In this Phase, to begin building our project on sentiment analysis for marketing using AI, we need to load and preprocess the dataset.

Loading the Dataset

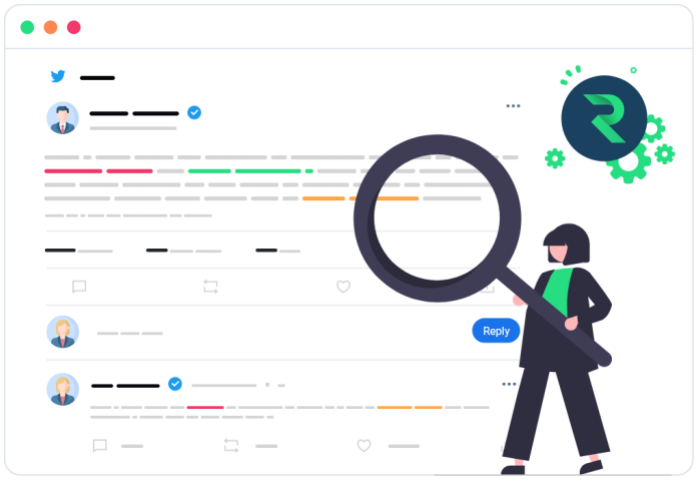
The dataset that we will use is the Twitter Airline Sentiment dataset from Kaggle. This dataset contains over 14,000 tweets that have been labeled with the sentiment (positive, negative, or neutral).

To load the dataset, we can use the following Python code:

```
import pandas as pd

# Load the dataset from the CSV file
df = pd.read_csv('airline_sentiment.csv')

# Print the first few rows of the dataset

print(df.head())
```

This will print the first few rows of the dataset to the console. You can then use this data to train your sentiment analysis model.

Preprocessing the Dataset



Data preprocessing is a predominant step in machine learning to yield highly accurate and insightful results. Greater the quality of data, greater is the reliance on the produced results. **Incomplete, noisy, and inconsistent data** are the properties of large real-world datasets. Data preprocessing helps in increasing the quality of data by filling in missing incomplete data, smoothing noise and resolving inconsistencies.

- **Incomplete data** can occur for a number of reasons. Attributes of interest may not always be available, such as customer information for sales transaction data. Relevant data may not be recorded due to a misunderstanding, or because of equipment malfunctions.
- There are many possible reasons for **noisy data** (having incorrect attribute values). The data collection instruments used may be faulty. There may have been human or computer errors occurring at data entry. Errors in data

transmission can also occur. Incorrect data may also result from inconsistencies in naming conventions or data codes used, or inconsistent formats for input fields, such as date.

There are a number of data preprocessing techniques available such as:

1. **Data cleaning** can be applied to filling in missing values, remove noise, resolving inconsistencies, identifying and removing outliers in the data.
2. **Data integration** merges data from multiple sources into a coherent data store, such as a data warehouse.
3. **Data transformations**, such as normalization, may be applied. For example, normalization may improve the accuracy and efficiency of mining algorithms involving distance measurements.
4. **Data reduction** can reduce the data size by eliminating redundant features, or clustering, for instance.

Let us import them now as well as a few other libraries we will be using.

```
import nltk
from nltk.corpus import twitter_samples
import matplotlib.pyplot as plt
import random
```

Now let's download the dataset.

```
import kaggle

# Download the dataset
kaggle.datasets.download('crowdflower/twitter-airline-sentiment')

# Extract the dataset from the ZIP file
with zipfile.ZipFile('twitter-airline-sentiment.zip', 'r') as zip_ref:
    zip_ref.extractall()
```

Now let us load the positive and negative examples separately and then we will have a detalied look at them.

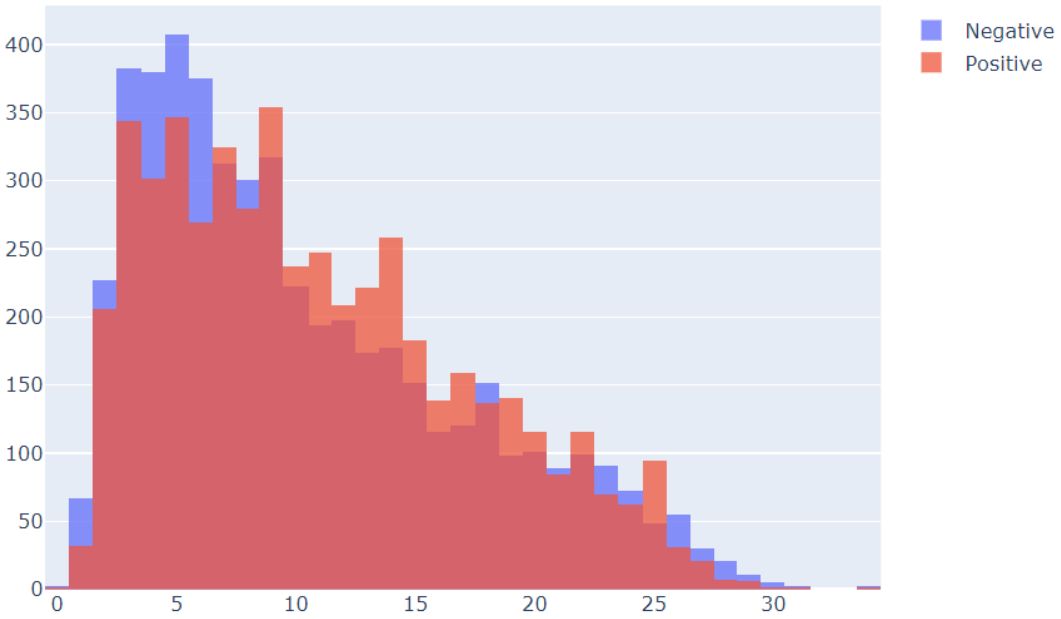
```
all_positive_tweets = twitter_samples.strings('positive_tweets.json')
all_negative_tweets = twitter_samples.strings('negative_tweets.json')

print('Number of positive tweets: ', len(all_positive_tweets))
print('Number of negative tweets: ', len(all_negative_tweets))
```

```
print('\nThe type of all_positive_tweets is: ', type(all_positive_tweets))
print('The type of a tweet entry is: ', type(all_negative_tweets[0]))
```

```
Number of positive tweets:  5000
Number of negative tweets:  5000

The type of all_positive_tweets is:  <class 'list'>
The type of a tweet entry is:  <class 'str'>
```

We observe that the tweet dataset are two list of strings. The individual s trings contains tweeter handles, punctuations, emoticons, urls etc. We need to do some good preprocessing to work with them. Just before that, let's check their comparative lengths.

```
total_positive_words = []
for sentence in all_positive_tweets:
    total_positive_words.append(sentence.count(' '))

total_negative_words = []
for sentence in all_negative_tweets:
    total_negative_words.append(sentence.count(' '))

import plotly.graph_objects as go
import numpy as np

x0 = np.array(total_positive_words)
x1 = np.array(total_negative_words)

fig = go.Figure()
fig.add_trace(go.Histogram(x=x1, name = 'Negative'))
fig.add_trace(go.Histogram(x=x0, name = 'Positive'))

# Overlay both histograms
fig.update_layout(barmode='overlay')
# Reduce opacity to see both histograms
fig.update_traces(opacity=0.75)
fig.show()
```



Data preprocessing is one of the critical steps in any machine learning project. It includes cleaning and formatting the data before feeding into a machine learning algorithm. For NLP, the preprocessing steps are comprised of the following tasks:

- Tokenizing the string
- Lowercasing
- Removing stop words and punctuation
- Stemming

Let us select any sample from the data given and we will successively work our way up to the higher level of processing and download the stopwords for the NLTK library.

```
tweet = all_positive_tweets[1455]
print(tweet)

nltk.download('stopwords')

import re
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.tokenize import TweetTokenizer
```

Remove hyperlinks, Twitter marks and styles

Since we have a Twitter dataset, we'd like to remove some substrings commonly used on the platform like the hashtag, retweet marks, and hyperlinks. We'll use the re library to perform regular expression operations on our tweet. We'll define our search pattern and use the `sub()` method to remove matches by substituting with an empty character (i.e. `''`)

```
print('Original Tweet: ')
print(tweet)

# it will remove the old style retweet text "RT"
tweet2 = re.sub(r'^RT[\s]+', '', tweet)

# it will remove hyperlinks
tweet2 = re.sub(r'https?:\/\/.*[\r\n]*', '', tweet2)

# it will remove hashtags. We have to be careful here not to remove
# the whole hashtag because text of hashtags contains huge information.
# only removing the hash # sign from the word
tweet2 = re.sub(r'#', '', tweet2)

# it will remove single numeric terms in the tweet.
tweet2 = re.sub(r'[0-9]', '', tweet2)
print('\nAfter removing old style tweet, hyperlinks and # sign')
print(tweet2)
```

```
Original Tweet:
Stats for the day have arrived. 1 new follower and NO unfollowers :) via h
ttp://t.co/0s8GQYOeus.

After removing old style tweet, hyperlinks and # sign
Stats for the day have arrived.  new follower and NO unfollowers :) via
```

Tokenize the string

To tokenize means to split the strings into individual words without blanks or tabs. In this same step, we will also convert each word in the string to lower case. The tokenize module from NLTK allows us to do these easily:

```
print('Before Tokenizing: ')
print(tweet2)

# instantiate the tokenizer class
tokenizer = TweetTokenizer(preserve_case=False,
                           strip_handles=True,
                           reduce_len=True)

# tokenize the tweets
tweet_tokens = tokenizer.tokenize(tweet2)
```

```
print('\nTokenized string:')
print(tweet_tokens)
```

```
Before Tokenizing:
Stats for the day have arrived.  new follower and NO unfollowers :) via

Tokenized string:
['stats', 'for', 'the', 'day', 'have', 'arrived', '.', 'new', 'follower',
'and', 'no', 'unfollowers', ':)', 'via']
```

Remove stop words and punctuations

The next step is to remove stop words and punctuation. Stop words are words that don't add significant meaning to the text. You'll see the list provided by NLTK when you run the cells below.

```
#Import the english stop words list from NLTK
stopwords_english = stopwords.words('english')

print('Stop words\n')
print(stopwords_english)

print('\nPunctuation\n')
print(string.punctuation)
```

```
Stop words

['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you'
re", "you've", "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves
', 'he', 'him', 'his', 'himself', 'she', "she's", 'her', 'hers', 'herself'
, 'it', "it's", 'its', 'itself', 'they', 'them', 'their', 'theirs', 'thems
elves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll", 'these'
, 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have'
, 'has', 'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the',
'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'of', 'at', '
by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'dur
ing', 'before', 'after', 'above', 'below', 'to', 'from', 'up', 'down', 'in
', 'out', 'on', 'off', 'over', 'under', 'again', 'further', 'then', 'once'
, 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'e
ach', 'few', 'more', 'most', 'other', 'some', 'such', 'no', 'nor', 'not',
'only', 'own', 'same', 'so', 'than', 'too', 'very', 's', 't', 'can', 'will
', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll', 'm', '
o', 're', 've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn'
, "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "hasn't", 'haven
', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn', "mustn'
t", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn',
"wasn't", 'weren', "weren't", 'won', "won't", 'wouldn', "wouldn't"]

Punctuation
```

```
!"#$%&'()*+,-./:;<=>?@[\]^_`{|}~
```

Observation regarding Stop words and Punctuations

- We can see that the stop words list above contains some words that could be important in some contexts. These could be words like *i, not, between, because, won, against*. You might need to customize the stop words list for some applications. For our exercise, we will use the entire list.
- For the punctuation, we saw earlier that certain groupings like ':)' and '...' should be retained when dealing with tweets because they are used to express emotions. In other contexts, like medical analysis, these should also be removed.

```
print('Before tokenization')
print(tweet_tokens)


tweets_clean = []

for word in tweet_tokens: # Go through every word in your tokens list
    if (word not in stopwords_english and  # remove stopwords
        word not in string.punctuation):  # remove punctuation
        tweets_clean.append(word)

print('\n\nAfter removing stop words and punctuation:')
print(tweets_clean)
```

```
Before tokenization
['stats', 'for', 'the', 'day', 'have', 'arrived', '.', 'new', 'follower',
'and', 'no', 'unfollowers', ':)', 'via']


After removing stop words and punctuation:
['stats', 'day', 'arrived', 'new', 'follower', 'unfollowers', ':)', 'via']
```

Stemming

Stemming is the process of converting a word to its most general form, or stem. This helps in reducing the size of our vocabulary.

NLTK has different modules for stemming and we will be using the PorterStemmer module which uses the Porter Stemming Algorithm. Let's see how we can use it in the cell below.

```
# Instantiate stemming class
stemmer = PorterStemmer()

# Create an empty list to store the stems
tweets_stem = []
```

```
for word in tweets_clean:
    stem_word = stemmer.stem(word)  # stemming word
    tweets_stem.append(stem_word)  # append to the list

print('Words after stemming: ')
print(tweets_stem)
```

```
Words after stemming:
['stat', 'day', 'arriv', 'new', 'follow', 'unfollow', ':)', 'via']
```

Conclusion

To conclude, in this phase of our project on sentiment analysis for marketing using AI, we have loaded and preprocessed the Twitter Airline Sentiment dataset. We have loaded the dataset using the Python Pandas library and preprocessed it by removing stop words, stemming the words, and converting the text data to a numerical representation using word embedding.

In the next phase, we will split the preprocessed data into training and test sets. We will then use the training set to train our sentiment analysis model and the test set to evaluate the model's performance.