Introduction

This project was done as our fifth semster mini project under the mentorship of Prof. Mahendra Patil. In this project , we learned about various advance machine learning concepts like text classification,sentiment analysis,information retrieval,text summarization,next word prediction,languge translation and detection,etc.

Based on these concepts and using data given [here (http://jmcauley.ucsd.edu/data/amazon/)](http://jmcauley.ucsd.edu/data/amazon/), we have created a project.

I would like to thank [Prof. Mahendra Patil (https://www.linkedin.com/in/mahendra-patil-66b725129/)](https://www.linkedin.com/in/mahendra-patil-66b725129/) and my partners [Nachiketa Patil (https://www.linkedin.com/in/nachiketa-p-552525110/)](https://www.linkedin.com/in/nachiketa-p-552525110/) and Sayyam Jain for helping me with this project.

Based on data we thought of two problem statements:

> Problem Statement 1: Prediction of Helpfulness from given data.

> Problem Statement 2: Classification of genuine and fake/sarcastic reviews.

Data Preparation

Before we start with the problem statements, we have to do a little data preparation.

First, let's import all required files.

In [1]:

```
# Importing the required files.
from __future__ import print_function
import matplotlib.pyplot as plt
import numpy as np
import os
import sys
import pandas as pd
import string
from time import time
import nltk
from nltk.corpus import stopwords
stops = set(stopwords.words("english"))
import re
from IPython.display import display # Allows the use of display() for DataFrames
import warnings
warnings.filterwarnings('ignore')

%matplotlib inline
RAN_STATE = 42 # Setting the random state
```

We will now read the data.

The dataset is a JSON file so we are using the read_json() function of Pandas. We have used *lines=True* to read the file as a JSON object per line, else it will give an error.

For more information,see [here (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.read_json.html)](https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.read_json.html)

Content of dataset -

- 5-core dataset of product reviews from Amazon Electronics category from May 1996 - July 2014.
- Contains total of 1689188 entries.
- Each reviewer has at least 5 reviews and each product has at least 5 reviews in this dataset.

Columns are:

- asin - ID of the product, like B000FA64PK
- helpful - helpfulness rating of the review - example: 2/3.
- overall - rating of the product.
- reviewText - text of the review (heading).
- reviewTime - time of the review (raw).
- reviewerID - ID of the reviewer, like A3SPTOKDG7WBLN
- reviewerName - name of the reviewer.
- summary - summary of the review (description).
- unixReviewTime - unix timestamp.

In [2]:

```
# Read json data
data=pd.read_json('Electronics_5.json',lines=True,orient='columns')
data
```

Out[2]:

	reviewerID	asin	reviewerName	helpful	reviewText	overall	su
0	AO94DHGC771SJ	0528881469	amazdnu	[0, 0]	We got this GPS for my husband who is an (OTR)...	5	Got
1	AMO214LNFCEI4	0528881469	Amazon Customer	[12, 15]	I'm a professional OTR truck driver, and I bou...	1	Disap
2	A3N7T0DY83Y4IG	0528881469	C. A. Freeman	[43, 45]	Well, what can I say. I've had this unit in m...	3	imp
3	A1H8PY3QHMQQA0	0528881469	Dave M. Shaw "mack dave"	[9, 10]	Not going to write a long review, even thought...	2	Great POC
4	A24EV6RXELQZ63	0528881469	Wayne Smith	[0, 0]	I've had mine for a year and here's what we go...	1	Major only e for
...	...	...	...	...	...	...	
1689183	A34BZM6S9L7QI4	B00LGQ6HL8	Candy Cane "Is it just me?"	[1, 1]	Burned these in before listening to them for a...	5	Boom - Pow
1689184	A1G650TTTHEAL5	B00LGQ6HL8	Charles Spanky "Zumina Reviews"	[0, 0]	Some people like DJ style headphones or earbud...	5	T light, compr on s
1689185	A25C2M3QF9G7OQ	B00LGQ6HL8	Comdet	[0, 0]	I’m a big fan of the Brainwavz S1 (actua...	5	Sar fac dura the S
1689186	A1E1LEVQ9VQNK	B00LGQ6HL8	J. Chambers	[0, 0]	I've used theBrainwavz S1 In Ear Headphones, a...	5	Super qua com
1689187	A2NYK9KWFMJV4Y	B00LGQ6HL8	Mike Tarrani "Jazz Drummer"	[0, 0]	Normally when I receive a review sample I can ...	5	Exce

1689188 rows × 9 columns

Since our reviews may also contain duplicates, we are using the drop_duplicate() function to remove duplicates. For more info,see [here (https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.drop_duplicates.html)](https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.drop_duplicates.html).

In [3]:

```
# Remove duplicate reviews(if any)
print("The shape of the data set before removing duplicate reviews : {}".format(data.shape))
data=data.drop_duplicates(subset=["reviewText"], keep='first', inplace=False)
print("The shape of the data set after removing duplicate reviews : {}".format(data.shape))
```

```
The shape of the data set before removing duplicate reviews : (1689188, 9)
The shape of the data set after removing duplicate reviews : (1687169, 9)
```

As we can see, our data did have duplicate reviews. Now let's go-to text preprocessing.

Text Preprocessing

Since we are having two problem statements, both of which require the same kind of preprocessing, we are going to preprocess before starting with the problem statements.

Preprocessing before going to problem statements will save a lot of time since just to preprocess once, I required about an hour.

In [4]:

```
def preprocess(x):
    x = x.replace(",000,000", " m").replace(",000", " k").replace("′", "'").replace("’", "'")\
                        .replace("won't", " will not").replace("cannot", " can not").replace("can't", " can not")\
                        .replace("n't", " not").replace("what's", " what is").replace("it's", " it is")\
                        .replace("'ve", " have").replace("'m", " am").replace("'re", " are")\
                        .replace("he's", " he is").replace("she's", " she is").replace("'s", " own")\
                        .replace("%", " percent ").replace("₹", " rupee ").replace("$", " dollar ")\
                        .replace("€", " euro ").replace("'ll", " will").replace("how's"," how has").replace("y'all"," you all")\
                        .replace("o'clock"," of the clock").replace("ne'er"," never").replace("let's"," let us")\
                        .replace("finna"," fixing to").replace("gonna"," going to").replace("gimme"," give me").replace("got
                        .replace("daresn't"," dare not").replace("dasn't"," dare not").replace("e'er"," ever").replace("everyo
                        .replace("'cause'"," because").replace("i'm"," i am")

    x = re.sub(r"([0-9]+)000000", r"\1m", x)
    x = re.sub(r"([0-9]+)000", r"\1k", x)
    x=re.sub(r'((www\.[^\s]+)|(https?://[^\s]+))',' ',x)
    x=re.sub(r"\\s*\\b(?=\\w*(\\w)\\1{2,})\\w*\\b",' ',x)
    x=re.sub(r'<.*?>',' ',x)
    x=re.sub('[^a-zA-Z]',' ',x)
    x=''.join([i for i in x if not i.isdigit()])
    return x
```

Here we are going to first convert reviews to lowercase. Then we are going to do preprocessing. And finally, go to lemmatization.

Here we could also use stemming but I am going to use lemmatization.

> **Stemming:** Stemming is a process of extracting a root word. For example, “fish,” “fishes,” and “fishing” are stemmed into fish.
>
> **Lemmatization:** Lemmatization is a process of extracting a root word by considering the vocabulary. For example, “good,” “better,” or “best” is lemmatized into good. The part of speech of a word is determined in lemmatization. It will return the dictionary form of a word, which must be valid while stemming just extracts the root word.

Lemmatization handles matching “car” to “cars” along with matching “car” to “automobile.”

Stemming handles matching “car” to “cars.”

For more info see [here (https://nlp.stanford.edu/IR-book/html/htmledition/stemming-and-lemmatization-1.html)](https://nlp.stanford.edu/IR-book/html/htmledition/stemming-and-lemmatization-1.html).

In [5]:

```
# Import libraries
from nltk.corpus import stopwords
from textblob import TextBlob
from textblob import Word

# Lower casing and removing punctuations
data['reviewText'] = data['reviewText'].apply(lambda x: " ".join(x.lower() for x in x.split()))
data['reviewText'] = data['reviewText'].str.replace('[^\w\s]','')

# Removing stopwords
#stop = stopwords.words('english')
#data['reviewText'] = data['reviewText'].apply(lambda x: " ".join(x for x in x.split() if x not in stop))
data['reviewText'] = data['reviewText'].apply(lambda x: preprocess(x))
# Lemmatization

data['reviewText'] = data['reviewText'].apply(lambda x: " ".join([Word(word).lemmatize() for word in x.split()]))
data.reviewText.head(5)
```

Out[5]:

```
0    we got this gps for my husband who is an otr o...
1    im a professional otr truck driver and i bough...
2    well what can i say ive had this unit in my tr...
3    not going to write a long review even thought ...
4    ive had mine for a year and here what we got i...
Name: reviewText, dtype: object
```

Now, let's start with problem statements.

Problem Statement 1

A Rough Overview

Marketing is an essential part of the business. Digital marketing was already in hype for the past few years, but due to this pandemic, it has increased exponentially. Since a customer cannot physically check the product, he/she has to depend on reviews of the given product.

Amazon has a helpfulness rating system, that allows users to see top-rated reviews which can help a customer to make an informed decision.

But even if this helps, poor-quality reviews can still come on top of forums.

Having poor quality reviews displayed in forums hurts Amazon’s business since the major reason as stated above is that people are willing to buy consumer goods online without seeing the items themselves because they have access to other people's opinions of the item.

Problem Statement

The problem addressed here is Amazon Reviews of poor quality that are there, at the top of forums despite the helpfulness rating system of Amazon. This problem mainly arises due to the new reviews are directly placed on top of the forum which would give the community a chance to rate them.

The solution to this problem is to create a model using machine learning techniques that would pre-rate the helpfulness of a given customer review before they are posted on the top of the forum. This way poor quality reviews would not be shown on top of forums.

The model will be trained on Amazon Reviews for Electronic Category to predict if a given review is helpful or not helpful.

Let's see the given data.

In [6]:

```
data.head()
```

Out[6]:

	reviewerID	asin	reviewerName	helpful	reviewText	overall	summary	ui
0	AO94DHGC771SJ	0528881469	amazdnu	[0, 0]	we got this gps for my husband who is an otr o...	5	Gotta have GPS!	
1	AMO214LNFCEI4	0528881469	Amazon Customer	[12, 15]	im a professional otr truck driver and i bough...	1	Very Disappointed	
2	A3N7T0DY83Y4IG	0528881469	C. A. Freeman	[43, 45]	well what can i say ive had this unit in my tr...	3	1st impression	
3	A1H8PY3QHMQQA0	0528881469	Dave M. Shaw "mack dave"	[9, 10]	not going to write a long review even thought ...	2	Great grafics, POOR GPS	
4	A24EV6RXELQZ63	0528881469	Wayne Smith	[0, 0]	ive had mine for a year and here what we got i...	1	Major issues, only excuses for support	

Based on the above data we can say:

> Input Features : reviewText,overall

> Output labels: helpfulness

Reason for selecting input features: When we give any review, along with text(reviewText) of the review we also give a rating in stars(overall).

A brief explanation about the helpful column: helpful column given above is a list containing two values---no of helpful ratings and the total no of ratings--- separated by a comma.

We are dividing the helpful column into two parts i.e.

> helpful_numerator => contains no. of helpful rating.

> helpful_denominator => contains total no. of ratings.

and then we are deleting the helpful column.

In [7]:

```
#select the columns
df = data.iloc[:, [5,4,3]]

#split numerator and denominator
df['helpful_numerator'] = df['helpful'].apply(lambda x: x[0])
df['helpful_denominator'] = df['helpful'].apply(lambda x: x[1])

# delete un-needed helpful column
del df['helpful']

#Check if we have any null values
print (df.isnull().sum())
```

```
overall              0
reviewText           0
helpful_numerator    0
helpful_denominator  0
dtype: int64
```

Let's see some stats.

In [8]:

```
df.describe()
```

Out[8]:

	overall	helpful_numerator	helpful_denominator
count	1.687169e+06	1.687169e+06	1.687169e+06
mean	4.222604e+00	3.129790e+00	3.747861e+00
std	1.185743e+00	3.865623e+01	4.035785e+01
min	1.000000e+00	0.000000e+00	0.000000e+00
25%	4.000000e+00	0.000000e+00	0.000000e+00
50%	5.000000e+00	0.000000e+00	0.000000e+00
75%	5.000000e+00	1.000000e+00	2.000000e+00
max	5.000000e+00	3.073500e+04	3.145300e+04

Here, since our dataset is huge(about 1687169 records), we are taking only those records that have at least 20 ratings in total.

In [9]:

```
# include reviews that have more than 20 helpfulness data point only
df1 = df[(df.helpful_denominator > 20)].copy()
df1.shape
```

Out[9]:

(50185, 4)

Here to get our output label **helpfulness**, we have to take the ratio of helpful_numerator to helpful_denominator. The result is compared with a threshold value(*we are taking threshold as 50%, but we can change it as per our requirement*).

- If result > threshold ==> helpful = 1
- if result < treshold ==> not helpful = 0

In [10]:

```
# transform Helpfulness into a binary variable with 0.5 ratio
threshold = 0.5
df1.loc[:, 'Helpful'] = np.where(df1.loc[:, 'helpful_numerator'] \
                        / df1.loc[:, 'helpful_denominator'] > threshold, 1, 0)
df1.head(3)
```

Out[10]:

	overall	reviewText	helpful_numerator	helpful_denominator	Helpful
2	3	well what can i say ive had this unit in my tr...	43	45	1
211	3	i purchased this mount for my inch lcd tv inst...	70	92	1
221	5	do not listen to other reviewer screw that thi...	18	23	1

Now let's do the count of data to get an idea about the distribution of helpfulness.

In [11]:

```
#Check the balance
print ('Count:')
display(df1.groupby('Helpful').count())
```

Count:

	overall	reviewText	helpful_numerator	helpful_denominator
Helpful				
0	4896	4896	4896	4896
1	45289	45289	45289	45289

Now let's see the whole data since we are going to creating our model.

In [12]:

```
df1
```

Out[12]:

	overall	reviewText	helpful_numerator	helpful_denominator	Helpful
2	3	well what can i say ive had this unit in my tr...	43	45	1
211	3	i purchased this mount for my inch lcd tv inst...	70	92	1
221	5	do not listen to other reviewer screw that thi...	18	23	1
263	5	the nook tablet is a solid hybrid tabletebook ...	33	39	1
273	1	update sep put on cm android last week ive got...	52	57	1
...	...	...	...	...	...
1689042	5	to put it in perspective for people who say it...	20	21	1
1689045	3	suck that id have to buy a whole new motherboa...	5	63	0
1689071	5	yes usd seems to be a very big amount for rout...	11	21	1
1689082	5	wow after year of fighting weak wifi really ye...	28	32	1
1689180	5	my short reviewif you have the money to spend ...	18	23	1

50185 rows × 5 columns

Since we have already prepared the data above. We are now directly applying TF-IDF Vectorizer to generate more features. TF-IDF is an acronym of Term Frequency Inverse Document Frequency. It is a statistical measure used to find how important a word is to document in a collection or corpus. It is generally used in text mining and information retrieval.

> TF: Term Frequency, which measures how frequently a term occurs in a document. Since every document is different in length, it may possible that a term would appear much more times in long documents than shorter ones. Thus, the term frequency is often divided by the document length (aka. the total number of terms in the document) as a way of normalization:
>
> TF(t) = (Number of times term t appears in a document) / (Total number of terms in the document).
>
> IDF: Inverse Document Frequency, which measures how important a term is. While computing TF, all terms are considered equally important. However, it is known that certain terms, such as "is", "of", and "that", may appear a lot of times but have little importance. Thus we need to weigh down the frequent terms while scaling up the rare ones, by computing the following:
>
> IDF(t) = log_e(Total number of documents / Number of documents with term t in it).

To get more information about TF-IDF see [here (http://www.tfidf.com/)](http://www.tfidf.com/).

In [13]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
# define the vectorizer
vectorizer = TfidfVectorizer(min_df = 0.01)
# fit the vectorizers to the data.
features = vectorizer.fit_transform(df1['reviewText'])
features
```

Out[13]:

```
<50185x2232 sparse matrix of type '<class 'numpy.float64'>'
	with 7272025 stored elements in Compressed Sparse Row format>
```

Since we don't have a separate dataset for testing we are splitting data as 80% for training and 20% for testing.

In [14]:

```
# split and shuffle data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(features,df1['Helpful'], test_size=0.2, random_state=RAN_STATE
```

Since our problem is of binary classification(helpful or not helpful), we are using roc_auc_score to evaluate our model.

The roc_auc_score computes the area under the receiver operating characteristic (ROC) curve which is also denoted by AUC or AUROC. By computing the area under the roc curve, the curve information is summarized in one number.

This curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR). The area under the curve is used to give a score to the model.

> If AUC = 0.5 => TPR = FPR, and the model is doing just random computations.
>
> If AUC= 1.0 => TPR = 100%,and it is an ideal model.

- True Positive: the truth is positive, and the test predicts a positive. e.g. The person is sick, and the test accurately reports this.
- False Positive: the truth is negative, but the test predicts a positive. e.g. The person is not sick, but the test inaccurately reports that they are. It is also called a Type I error in statistics.

For more information about roc_auc_score,see [here (https://scikit-learn.org/stable/modules/model_evaluation.html#roc-metrics)](https://scikit-learn.org/stable/modules/model_evaluation.html#roc-metrics).

In [15]:

```
from sklearn.metrics import roc_auc_score, roc_curve

def train_classifier(clf, X_train, y_train):
    ''' Fits a classifier to the training data. '''

    # Start the clock, train the classifier, then stop the clock
    start = time()
    clf.fit(X_train, y_train)
    end = time()

    # Print the results
    print ("Trained model in {:.4f} seconds".format(end - start))


def predict_labels(clf, features, target):
    ''' Makes predictions using a fit classifier based on roc_auc score. '''

    # Start the clock, make predictions, then stop the clock
    start = time()
    probas = clf.predict_proba(features)
    end = time()

    # Print and return results
    print ("Made predictions in {:.4f} seconds.".format(end - start))
    return roc_auc_score(target.values, probas[:,1].T)


def train_predict(clf, X_train, y_train, X_test, y_test):
    ''' Train and predict using a classifer based on roc_auc score. '''

    # Indicate the classifier and the training set size
    print ("Training a {} using a training set size of {}. . .".format(clf.__class__.__name__, X_train.shape[0]))

    # Train the classifier
    train_classifier(clf, X_train, y_train)

    # Print the results of prediction for both training and testing
    print ("ROC_AUC score for training set: {:.4f}.".format(predict_labels(clf, X_train, y_train)))
    print ("ROC_AUC score for test set: {:.4f}.\n".format(predict_labels(clf, X_test, y_test)))

def clf_test_roc_score(clf, X_train, y_train, X_test, y_test):
    clf.fit(X_train, y_train)
    probas = probas =clf.predict_proba(X_test)
    return roc_auc_score(y_test, probas[:,1].T)
```

To make a baseline model for our project we are going to use the following algorithms :

- **GaussianNB**: GaussianNB implements the Gaussian Naive Bayes algorithm for classification. In Gaussian Naive Bayes, continuous values associated with each feature are assumed to be distributed according to a Gaussian distribution. A Gaussian distribution is also called Normal distribution. When plotted, it gives a bell-shaped curve that is symmetric about the mean of the feature values.

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} exp\left(-\frac{(x_i-\mu_y)^2}{2\sigma_y^2}\right)$$

- **Logistic Regression**: Logistic regression, despite its name, is a linear model for classification rather than regression. Logistic regression is also known in the literature as logit regression, maximum-entropy classification (MaxEnt), or the log-linear classifier
- **Decision tree**: DecisionTreeClassifier is a classifier capable of performing both binary and multi-class classification on a dataset. A Decision tree is a flowchart-like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (terminal node) holds a class label.

All the algorithms used here are popular algorithms for classification. However, since we are doing binary classification, I think *Logistic Regression* would give better results than *Decision tree* or *Gaussian Naive Bayes*.

For more information, see [here (https://scikit-learn.org/stable/supervised_learning.html)](https://scikit-learn.org/stable/supervised_learning.html).

In [16]:

```
# Import the supervised learning models from sklearn
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier


# Initialize the models using a random state were applicable.
clf_list = [GaussianNB(),
            LogisticRegression(random_state = RAN_STATE),
            DecisionTreeClassifier(random_state = RAN_STATE)]
x_tr = X_train.toarray()
x_te = X_test.toarray()


# Set up the training set sizes for 10000, 20000 and 40000 respectively.
train_feature_list = [x_tr[0:10000],x_tr[0:20000],x_tr]
train_target_list = [y_train[0:10000], y_train[0:20000], y_train]


# Execute the 'train_predict' function for each of the classifiers and each training set size
for clf in clf_list:
    for a, b in zip(train_feature_list, train_target_list):
        train_predict(clf, a, b, x_te, y_test)
```

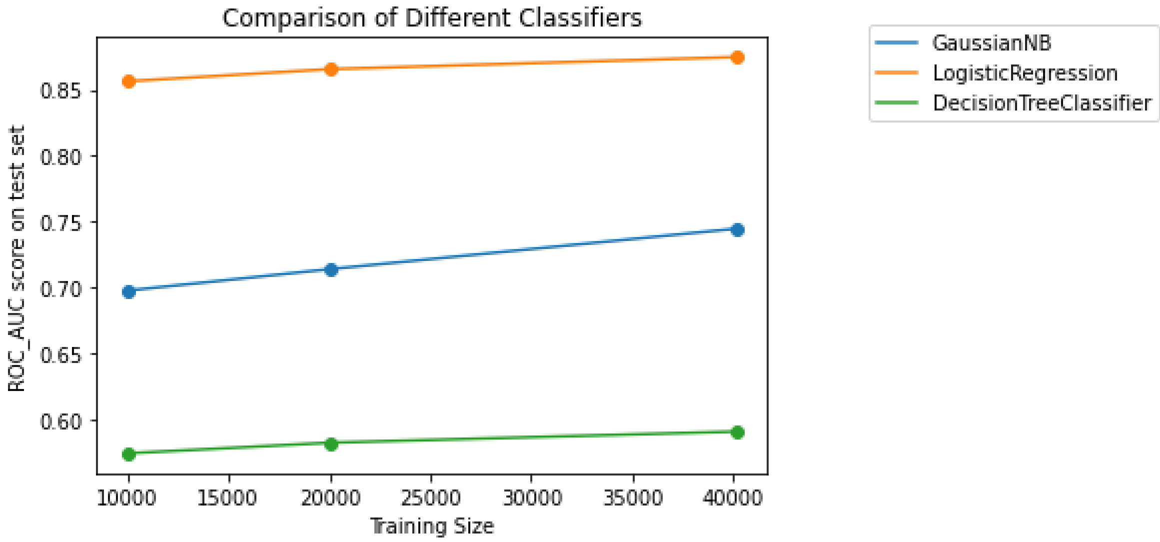
```
Training a GaussianNB using a training set size of 10000. . .
Trained model in 1.8382 seconds
Made predictions in 2.8137 seconds.
ROC_AUC score for training set: 0.8883.
Made predictions in 1.1662 seconds.
ROC_AUC score for test set: 0.6976.

Training a GaussianNB using a training set size of 20000. . .
Trained model in 1.3963 seconds
Made predictions in 2.5011 seconds.
ROC_AUC score for training set: 0.8468.
Made predictions in 0.9581 seconds.
ROC_AUC score for test set: 0.7139.

Training a GaussianNB using a training set size of 40148. . .
Trained model in 2.2633 seconds
Made predictions in 3.2108 seconds.
ROC_AUC score for training set: 0.8198.
Made predictions in 0.7775 seconds.
ROC_AUC score for test set: 0.7447.

Training a LogisticRegression using a training set size of 10000. . .
Trained model in 1.6040 seconds
Made predictions in 0.0625 seconds.
ROC_AUC score for training set: 0.9187.
Made predictions in 0.0469 seconds.
ROC_AUC score for test set: 0.8564.

Training a LogisticRegression using a training set size of 20000. . .
Trained model in 3.4460 seconds
Made predictions in 0.1093 seconds.
ROC_AUC score for training set: 0.9139.
Made predictions in 0.0469 seconds.
ROC_AUC score for test set: 0.8657.
```

```
Training a LogisticRegression using a training set size of 40148. . .
Trained model in 8.8501 seconds
Made predictions in 0.1599 seconds.
ROC_AUC score for training set: 0.9088.
Made predictions in 0.0551 seconds.
ROC_AUC score for test set: 0.8749.

Training a DecisionTreeClassifier using a training set size of 10000. . .
Trained model in 29.0487 seconds
Made predictions in 0.0626 seconds.
ROC_AUC score for training set: 1.0000.
Made predictions in 0.0624 seconds.
ROC_AUC score for test set: 0.5742.

Training a DecisionTreeClassifier using a training set size of 20000. . .
Trained model in 109.6313 seconds
Made predictions in 0.1406 seconds.
ROC_AUC score for training set: 1.0000.
Made predictions in 0.0848 seconds.
ROC_AUC score for test set: 0.5823.

Training a DecisionTreeClassifier using a training set size of 40148. . .
Trained model in 192.0529 seconds
Made predictions in 0.3111 seconds.
ROC_AUC score for training set: 1.0000.
Made predictions in 0.0625 seconds.
ROC_AUC score for test set: 0.5908.
```

It's a hassle to find each value. So let's just visualize the outputs for all models.

In [17]:

```
FIG_SIZE = (14,8)
# Visualize all of the classifiers
for clf in clf_list:
    x_graph = []
    y_graph = []
    for a, b in zip(train_feature_list, train_target_list):
        y_graph.append(clf_test_roc_score(clf, a, b, x_te, y_test))
        x_graph.append(len(a))
    plt.scatter(x_graph,y_graph)
    plt.plot(x_graph,y_graph, label = clf.__class__.__name__)

plt.title('Comparison of Different Classifiers')
plt.xlabel('Training Size')
plt.ylabel('ROC_AUC score on test set')
plt.legend(bbox_to_anchor=(1.6, 1.05))
plt.figure(figsize=FIG_SIZE)
plt.show()
```



<Figure size 1008x576 with 0 Axes>

Just as we thought Logistic Regression gives us the best accuracy. Its final score for the area under the ROC curve was 0.8704 and a sample size of ~40,000. Besides, it is the fastest. The training speed and prediction speed were 19.993s and 0.955s for a sample size of 40,000. Since our model has to consider the accuracy and speed, the Logistic Regression algorithm represents the ideal model for us.

Now, let's add values of scores to the review text and see if we can increase the accuracy of our model.

In [18]:

```
#add Score column to features
import scipy as scipy

overall = np.array(list(df1.overall))
overall = overall.reshape(features.shape[0], 1)

features = scipy.sparse.hstack((features,scipy.sparse.csr_matrix(overall)))

features = scipy.sparse.csr_matrix(features)
features
```

Out[18]:

```
<50185x2233 sparse matrix of type '<class 'numpy.float64'>'
	with 7322210 stored elements in Compressed Sparse Row format>
```

We can now split the dataset and try to optimize our initial model.

In [19]:

```
X_train2, X_test2, y_train, y_test = train_test_split(features, df1['Helpful'], test_size=0.2, random_state=RAN_STA
```

Hyper-parameters are parameters that are not directly learned within estimators. In scikit-learn, they are passed as arguments to the constructor of the estimator classes. Hyperparameter tuning helps us in optimizing our model. For more information see here (https://scikit-learn.org/stable/modules/grid_search.html#grid-search).

We will now be applying Gridsearch and Cross-Validation techniques to optimize and hypertune our model.

- **GridSearch:** Exhaustive search over specified parameter values for an estimator.
- **Cross-Validation:** In the train-test split, we use only 20% for testing. The performance metric we get on that 20% test data may not be accurate. So Cross-Validation allows you to consume 100% of the data for training and testing both.

For more information see here (https://scikit-learn.org/stable/modules/classes.html#module-sklearn.model_selection)

In [20]:

```
from sklearn.model_selection import GridSearchCV,cross_validate,StratifiedKFold
#make the grid search object
gs2 = GridSearchCV(
    estimator=LogisticRegression(),
    param_grid={'C': [10**i for i in range(-5,5)], 'class_weight': [None, 'balanced']},
    cv=StratifiedKFold(n_splits=5),
    scoring='roc_auc'
)

#fit the grid search object to our new dataset
print ('Fitting grid search...')
gs2.fit(X_train2, y_train)
print ("Grid search fitted.")
```

```
Fitting grid search...
Grid search fitted.
```

Let's the best estimator for our model.

In [21]:

```
#print the grid search scores.
gs2.best_params_
```

Out[21]:

```
{'C': 1, 'class_weight': None}
```

We can see our optimized classifier is a LogisticRession with a 'C' parameter of 1 and a 'class_weight' = 'None'. This is the same as default, meaning our optimization step did not change the parameters of our model. Let's now find our ROC_AUC Score.

In [22]:

```
clf2 = gs2.best_estimator_
probas =clf2.predict_proba(X_test2)


# ROC/AUC score
print ('ROC_AUC Score:',roc_auc_score(y_test, probas[:,1].T))
```

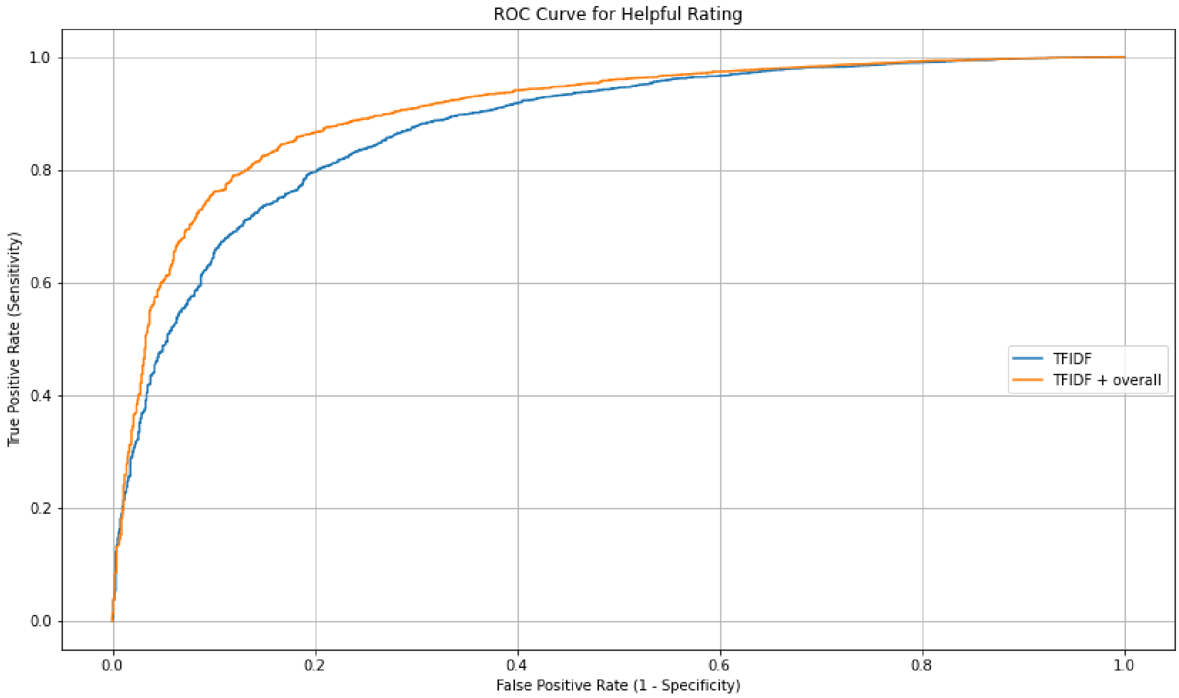
```
ROC_AUC Score: 0.904495237567837
```

Wow! 90 % ROC_AUC Score. That means our model has been trained well.

Let's now plot the graph to find the ROC Curve for Helpful Rating of both TFIDF and TFIDF along with the overall score.

In [23]:

```
clf = LogisticRegression()
clf.fit(X_train,y_train)
probas = clf.predict_proba(X_test)
clf2 = gs2.best_estimator_
probas2 =clf2.predict_proba(X_test2)
plt.figure(figsize = FIG_SIZE)

# plot graph to show roc_auc_score.
plt.plot(roc_curve(y_test, probas[:,1])[0], roc_curve(y_test, probas[:,1])[1], label = 'TFIDF')
plt.plot(roc_curve(y_test, probas2[:,1])[0], roc_curve(y_test, probas2[:,1])[1], label = 'TFIDF + overall')
plt.title('ROC Curve for Helpful Rating')
plt.grid()
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')

plt.legend(bbox_to_anchor=(1.0, .5))
plt.figure(figsize=FIG_SIZE)
plt.show()
```



<Figure size 1008x576 with 0 Axes>

As we can see in the above ROC Curve, adding an overall score to TFIDF vectors would give us a higher Area Under Curve(AUC).

Conclusion:

The important quality of this problem statement is the effect of introducing a new key feature to our model. Here, we mainly looked at the TFIDF features generated from Amazon's Electronic Reviews text and added the 'overall_rating' (star rating) that was given to the product by the reviewer. We used these features to predict how 'helpful' other users would find the review.

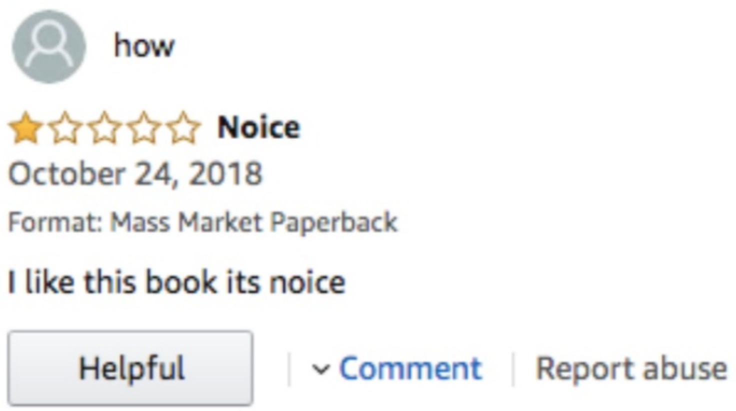
Problem Statement 2

A Rough Overview

Marketing is an essential part of the business. Digital marketing was already in hype for the past few years but due to this pandemic, it has increased exponentially. Since a customer cannot physically check the product, he/she has to depend on reviews of the given product.

Despite this there are some people who do not give genuine review or give a sarcastic review.

Here are some examples:



Having such reviews displayed in forums hurts Amazon’s business since the major reason as stated above is that people are willing to buy consumer goods online without seeing the items themselves because they have access to other people's opinions of the item.

Problem Statement

The problem that is being addressed here is if Amazon Review is fake or not genuine. Sometimes some people give fake reviews on forums. This could harm the sale of the product if such a review came on top.

By fake review I mean which is given a 5-star rating but in review text, the person gives a negative review and since it is rated 5 stars, so chances are that review would come on top of the forum.

The possibility exists that such reviews be given by competitors to harm the sale of the product.

The solution to this problem is to create a model using machine learning techniques that would classify given customer reviews based on sentiment analysis before they are posted on the top of the forum. This way fake reviews would not be shown on top of forums.

The model will be trained on Amazon Reviews for Electronic Category to classify if a given review is genuine or not.

Let's see the given data.

In [24]:

```
data.head()
```

Out[24]:

	reviewerID	asin	reviewerName	helpful	reviewText	overall	summary	u
0	AO94DHGC771SJ	0528881469	amazdnu	[0, 0]	we got this gps for my husband who is an otr o...	5	Gotta have GPS!	
1	AMO214LNFCEI4	0528881469	Amazon Customer	[12, 15]	im a professional otr truck driver and i bough...	1	Very Disappointed	
2	A3N7T0DY83Y4IG	0528881469	C. A. Freeman	[43, 45]	well what can i say ive had this unit in my tr...	3	1st impression	
3	A1H8PY3QHMQQA0	0528881469	Dave M. Shaw "mack dave"	[9, 10]	not going to write a long review even thought ...	2	Great grafics, POOR GPS	
4	A24EV6RXELQZ63	0528881469	Wayne Smith	[0, 0]	ive had mine for a year and here what we got i...	1	Major issues, only excuses for support	

Here, we are going to select **reviewText** and **overall** score rating since we going to classify reviews based on these two features.

In [25]:

```
#select the columns
df2 = data.iloc[:, [5,4]]
df2.head(10)
```

Out[25]:

	overall	reviewText
0	5	we got this gps for my husband who is an otr o...
1	1	im a professional otr truck driver and i bough...
2	3	well what can i say ive had this unit in my tr...
3	2	not going to write a long review even thought ...
4	1	ive had mine for a year and here what we got i...
5	5	i am using this with a nook hd it work a descr...
6	2	the cable is very wobbly and sometimes disconn...
7	5	this adaptor is real easy to setup and use rig...
8	4	this adapter easily connects my nook hd to my ...
9	5	this product really work great but i found the...

Now let's first classify score ratings as Positive, Negative, and Neutral.

> - If the **score rating => 4 or 5**,we are taking it as **Positive**.
> - If the **score rating => 3**,we are taking it as **Neutral**.
> - And if the **score rating => 1 or 2**,we are taking it as **Negative**.

Then we are saving the result in a column named **Overall_Sentiment**. This would tell us the sentiment of the review based on the star rating.

In [26]:

```
def score_classify(x):
    if x>3:
        return 'Positive'
    elif x<3:
        return 'Negative'
    else:
        return 'Neutral'
df2['Overall_Sentiment']=df2.apply(lambda x: score_classify(x['overall']),axis=1)
df2
```

Out[26]:

	overall	reviewText	Overall_Sentiment
0	5	we got this gps for my husband who is an otr o...	Positive
1	1	im a professional otr truck driver and i bough...	Negative
2	3	well what can i say ive had this unit in my tr...	Neutral
3	2	not going to write a long review even thought ...	Negative
4	1	ive had mine for a year and here what we got i...	Negative
...	...	...	...
1689183	5	burned these in before listening to them for a...	Positive
1689184	5	some people like dj style headphone or earbud ...	Positive
1689185	5	i m a big fan of the brainwavz s actually all ...	Positive
1689186	5	ive used thebrainwavz s in ear headphone and t...	Positive
1689187	5	normally when i receive a review sample i can ...	Positive

1687169 rows × 3 columns

Now, let's find out how the number of Positive, Negative, and Neutral reviews.

In [27]:

```
df2.Overall_Sentiment.value_counts()
```

Out[27]:

```
Positive    1354351
Negative     190693
Neutral      142125
Name: Overall_Sentiment, dtype: int64
```

Here we can see that 1354351 reviews are Positive,190693 are Negative while 142125 are Neutral.

But it may also be possible that some data may be missing or null.

So let's drop null values if there are any. Then recheck the number of reviews.

In [28]:

```
df2.dropna(
    axis=0,
    how='any',
    thresh=None,
    subset=None,
    inplace=True
)
df2.Overall_Sentiment.value_counts()
```

Out[28]:

```
Positive    1354351
Negative     190693
Neutral      142125
Name: Overall_Sentiment, dtype: int64
```

So we can see that there are no missing or null values.

Let's now go for sentiment analysis of review text.

Sentiment analysis is a process in which we computationally analyze and identify opinions and judgments of a customer from a piece of text. You can understand if a piece of text is positive, negative, or neutral, based on their sentiment analysis.

There are various types of sentiment analysis, but we are using aspect-based sentiment analysis here.

Aspect-based sentiment analysis is generally for one or more aspects of a service or product.

For example, if a company that sells mobile phones uses this type of sentiment analysis, it could be for one aspect of mobile phones – like battery life, processor, USF storage, etc.

So they can understand how customers feel about specific attributes of the product.

For more information, see [here (https://www.upgrad.com/blog/types-of-sentiment-analysis/)](https://www.upgrad.com/blog/types-of-sentiment-analysis/).

We can implement aspect-based sentiment analysis in different ways.

The most famous is Sentiment Intensity Analyzer(commonly known as SIA) from vaderSentiment.

But I found that sentiment from Textblob gives better results than SIA here. So we have used the sentiment from Textblob.

For more information see [here (https://textblob.readthedocs.io/en/dev/quickstart.html#sentiment-analysis)](https://textblob.readthedocs.io/en/dev/quickstart.html#sentiment-analysis).

In [29]:

```
from textblob import TextBlob

sentiment_score_list = []
sentiment_label_list = []

for i in df2['reviewText'].values.tolist():
    sentiment_text=TextBlob(i)
    sentiment_score = sentiment_text.sentiment.polarity
    #print(sentiment_score)

    if sentiment_score > 0:
        sentiment_score_list.append(sentiment_score)
        sentiment_label_list.append('Positive')
    elif sentiment_score < 0:
        sentiment_score_list.append(sentiment_score)
        sentiment_label_list.append('Negative')
    else:
        sentiment_score_list.append(sentiment_score)
        sentiment_label_list.append('Neutral')

df2['Review_Sentiment'] = sentiment_label_list
df2['sentiment score'] = sentiment_score_list

display(df2.head(10))
```

	overall	reviewText	Overall_Sentiment	Review_Sentiment	sentiment score
0	5	we got this gps for my husband who is an otr o...	Positive	Positive	0.250000
1	1	im a professional otr truck driver and i bough...	Negative	Positive	0.062441
2	3	well what can i say ive had this unit in my tr...	Neutral	Positive	0.086977
3	2	not going to write a long review even thought ...	Negative	Positive	0.047284
4	1	ive had mine for a year and here what we got i...	Negative	Positive	0.002778
5	5	i am using this with a nook hd it work a descr...	Positive	Positive	1.000000
6	2	the cable is very wobbly and sometimes disconn...	Negative	Negative	-0.100000
7	5	this adaptor is real easy to setup and use rig...	Positive	Positive	0.274439
8	4	this adapter easily connects my nook hd to my ...	Positive	Positive	0.297718
9	5	this product really work great but i found the...	Positive	Positive	0.212487

We can see that some reviews are of Neutral, sentiment based on star rating bit are Positive, based on the sentiment of review text.

Such reviews may be harmful to our model as they could be classified wrongly.

So we are removing all Neutral reviews.

In [30]:

```
before=df2.shape[0]
df2 = df2[df2.Overall_Sentiment != 'Neutral']
df2 = df2[df2.Review_Sentiment != 'Neutral']
df2.head(10)
after=df2.shape[0]
#EDA for finding how many neutral labels have been removed
```

Now let's find out how many Neutral reviews we have removed.

In [31]:

```
print("The number of neutral labels have been removed : {}".format(before-after))
```

The number of neutral labels have been removed : 176941

Wow! That is a lot of reviews.

Now, let's classify reviews as true or false.

The true review would one in which the sentiment of star rating matches the sentiment of review text.

If it does not match, then we could say that review is false.

In [32]:

```
comparison_column = np.where(df2["Overall_Sentiment"] == df2["Review_Sentiment"], True, False)
df2["result"] = comparison_column
df2.head()
```

Out[32]:

	overall	reviewText	Overall_Sentiment	Review_Sentiment	sentiment score	result
0	5	we got this gps for my husband who is an otr o...	Positive	Positive	0.250000	True
1	1	im a professional otr truck driver and i bough...	Negative	Positive	0.062441	False
3	2	not going to write a long review even thought ...	Negative	Positive	0.047284	False
4	1	ive had mine for a year and here what we got i...	Negative	Positive	0.002778	False
5	5	i am using this with a nook hd it work a descr...	Positive	Positive	1.000000	True

Now, let's find the total number of all the fake reviews.

And also see some as an example.

In [33]:

```
df2 = df2[df2.result != True]
print(df2.shape)
df2.head()
```

(202988, 6)

Out[33]:

	overall	reviewText	Overall_Sentiment	Review_Sentiment	sentiment score	result
1	1	im a professional otr truck driver and i bough...	Negative	Positive	0.062441	False
3	2	not going to write a long review even thought ...	Negative	Positive	0.047284	False
4	1	ive had mine for a year and here what we got i...	Negative	Positive	0.002778	False
22	4	this wall mount doe everything it supposed to ...	Positive	Negative	-0.092143	False
36	5	didnt think it would work a well a it hasbecau...	Positive	Negative	-0.063889	False

Finally, we found all the reviews that are not genuine and that is a lot of reviews.

Conclusion:

The importance of this problem statement is that we can easily find out if the given review is genuine or not. Here, we used review text and star rating from Amazon's Electronic Reviews that was given to the product by the reviewer. We used these features to classify if the given review is truly genuine or not.

Conclusion of Project

In this project, we first predicted the helpfulness of review. In the second part, we found out about the genuinity of reviews.

I would like to thank [Prof Mahendra Patil (https://www.linkedin.com/in/mahendra-patil-66b725129/)](https://www.linkedin.com/in/mahendra-patil-66b725129/) for guiding us in this project.

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