#### Information about data:

- ->We have the amazon reviews dataset from kaggle
- ->Reviews are given for the product
- ->The features of the data were:

Ιd

ProductId- unique identifier for the product

UserId- unqiue identifier for the user

ProfileName

 $\label{eq:helpfullnessNumerator-number of users who foliand the review helpful} HelpfullnessNumerator- number of users who foliated the second seco$ 

 ${\tt HelpfulnessDenominator-\ number\ of\ users\ who\ ir}$  dicated whether they found the review

helpful or not

Score-rating between 1 and 5

Time-timestamp for the review

Summary- brief summary of the review

Text- text of the review

 $\,$  -> Based on the score of the review we review we classify them into positive and negative

Number of reviews: 568,454

4

objective:

-> Cleaning the dataset by classifying them into positive and negati ve reviews based on the

rating provided and removing the duplicates

- -> Converting the text data to vectors by using word2vec, Average wor d2vec

- $\rightarrow$  Here we can use both random based splitting of data or time based splitting of data
- -> The accurancy which we obtained by random based splitting may change for the future data
- -> We can assure about the accurancy obtained in time base splitting for unseen future data also.
- ->Random based splitting is possible for every dataset, but for time based splitting there should time attribute

# Importing the required libraries

## In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as mp
import seaborn as s
import sqlite3
import nltk
import string
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
```

- ->loading the data and information about the data
- -> Shape of the data
- -> Dimensionality of the data
- -> Attributes if the data

#### In [2]:

#### Removing the Duplicates from the data

```
TII [3]:
```

```
####function to categorise rating into positive and negatives
def change(n):
    if n>3:
        return 'positive'
    return 'negative'

rating = data['Score']
####take the ratings
rating = rating.map(change)
#####apply function change on ratings column
data['Score'] = rating
####updating the column with positive and negatives
data.head(6)
##### head with first 6 elements in data
```

## Out[3]:

	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	Helpfulness
C	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0
						,

	5	ld	ProductId	Userid	ProfileName	HelpfulnessNumerator	Helpfulness			
			BOOOKEZZIK	7.5 1 001 (11110010	- Wodporniy annig	0				
L										

# **Data Cleaning:Removing Duplicates**

# In [4]:

```
user = pd.read sql query("""SELECT * FROM Reviews WHERE UserId= "AR5J8UI46C")
URR" ORDER BY ProductId """, con)
print(user)
       Ιd
            ProductId
                              UserId
                                          ProfileName HelpfulnessNumerator
   78445 B000HDL1RQ AR5J8UI46CURR Geetha Krishnan
                                                                          2
  138317 B000HDOPYC AR5J8UI46CURR Geetha Krishnan
                                                                          2
  138277 B000HDOPYM AR5J8UI46CURR Geetha Krishnan
                                                                          2
3
   73791 B000HDOPZG AR5J8UI46CURR Geetha Krishnan
                                                                          2
   155049 B000PAQ75C AR5J8UI46CURR Geetha Krishnan
                                                                          2
   HelpfulnessDenominator
                           Score
                                        Time
0
                        2
                               5 1199577600
1
                        2
                                 1199577600
                        2
2
                               5
                                 1199577600
3
                        2
                               5
                                 1199577600
4
                        2
                               5
                                 1199577600
                             Summary
  LOACKER QUADRATINI VANILLA WAFERS
  LOACKER QUADRATINI VANILLA WAFERS
1
2
  LOACKER QUADRATINI VANILLA WAFERS
  LOACKER QUADRATINI VANILLA WAFERS
  LOACKER QUADRATINI VANILLA WAFERS
                                                Text
  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
0
1
  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
```

## Observation:

- -> Here we can see that for the same time span we got five reviews, practically which is not possible
- ->This happened because when the user given review for a product it is applied to all the flavors of the product

```
In [5]:
```

```
sorteddata = data.sort_values('ProductId',axis=0,ascending=True,inplace=Fal
se,kind='quicksort',na_position='last')
finaldata = sorteddata.drop_duplicates(subset={"UserId","ProfileName","Time
","Text"},keep='first',inplace=False)
```

#### Information about the modified data:

- -> Shape of the data
- -> Dimensionality of the data
- -> Attributes if the data
- -> Sample of modified data

```
In [6]:
print(finaldata.shape)
print(finaldata.ndim)
print(finaldata.columns)
print(finaldata.head(5))
(364173, 10)
2
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text'],
      dtype='object')
                                                           ProfileName \
           Id
               ProductId
                                   UserId
138706 150524 0006641040 ACITT7DI6IDDL
                                                       shari zychinski
138688 150506 0006641040 A2IW4PEEKO2ROU
                                                                 Tracy
138689 150507 0006641040 A1S4A3IQ2MU7V4
                                                sally sue "sally sue"
138690 150508 0006641040
                              AZGXZ2UUK6X Catherine Hallberg "(Kate)"
138691 150509 0006641040 A3CMRKGE0P909G
                                                                Teresa
       HelpfulnessNumerator HelpfulnessDenominator
                                                                     Time
                                                        Score
138706
                          0
                                                  0 positive 939340800
                                                  1 positive 1194739200
138688
                          1
138689
                          1
                                                  1 positive 1191456000
138690
                          1
                                                  1 positive 1076025600
                          3
138691
                                                  4 positive 1018396800
                                          Summary \
138706
                        EVERY book is educational
138688 Love the book, miss the hard cover version
                    chicken soup with rice months
138689
           a good swingy rhythm for reading aloud
138690
138691
                  A great way to learn the months
                                                    Text
138706 this witty little book makes my son laugh at l...
138688 I grew up reading these Sendak books, and watc...
138689 This is a fun way for children to learn their ...
138690 This is a great little book to read aloud- it ...
138691 This is a book of poetry about the months of t...
4
```

#### CONSTRUCTING VECTOR REPRESENTATION OF EACH IN THE DATA BY USING WORD2VEC

```
In [7]:
```

```
import gensim
from gensim.models import word2vec
```

- -> Importing the required libraries
- -> Functions to clean the sentences
- -> Constructing the word2vec from the sample subset data

#### In [8]:

```
import re
def cleanhtml(sentence):
    clean = re.compile("<.*?>")
    cleantext = re.sub(clean," ",sentence)
    return cleantext
def cleanpunct(sentence):
    cleanr = re.sub(r"[?|!|\|'|#|.|,|)|(|/]",r' ',sentence)
    return cleanr
```

#### In [9]:

```
sorted_w2vec = finaldata.sort_values("Time",axis=0,ascending=True,kind='qui
cksort',na_position='last',inplace=False)
```

# Information about the sorted data:

- -> Shape of the data
- -> Dimensionality of the data
- -> Attributes if the data
- -> Sample of modified data

#### In [10]:

```
print(sorted w2vec.shape)
print(sorted w2vec.ndim)
print(sorted w2vec.columns)
print(sorted w2vec.head(5))
(364173, 10)
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
      'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text'],
     dtype='object')
           Id ProductId
                                  UserId
                                                       ProfileName
138706 150524 0006641040 ACITT7DI6IDDL
                                                  shari zychinski
138683 150501 0006641040 AJ46FKXOVC7NR
                                               Nicholas A Mesiano
417839 451856 B00004CXX9
                          AIUWLEQ1ADEG5
                                                  Elizabeth Medina
      271250
               D000040+04
                                                   TTI TO DO DO
```

```
346U55 3/4359 BUUUU4C184 A344SM1A5JECGM
                                                      Vincent P. Koss
417838 451855 B00004CXX9 AJH6LUC1UT1ON The Phantom of the Opera
        HelpfulnessNumerator HelpfulnessDenominator
                                                          Score
                                                                      Time
138706
                                                    0 positive 939340800
                           2
                                                    2 positive 940809600
138683
                           0
417839
                                                    0 positive 944092800
346055
                           1
                                                    2 positive 944438400
417838
                           0
                                                       positive 946857600
                                                   Summary
138706
                                EVERY book is educational
138683 This whole series is great way to spend time w...
417839
                                     Entertainingl Funny!
346055
                                  A modern day fairy tale
417838
                                                FANTASTIC!
                                                      Text
138706 this witty little book makes my son laugh at l...
138683 I can remember seeing the show when it aired o...
417839 Beetlejuice is a well written movie ..... ever...
346055 A twist of rumplestiskin captured on film, sta...
417838 Beetlejuice is an excellent and funny movie. K...
In [11]:
i=0
sentences list=[]
for sent in sorted w2vec['Text'].values:
    filtered sentences = []
    sent = cleanhtml(sent)
    for w in sent.split():
        for cleanedwords in cleanpunct(w).split():
            if (cleanedwords.isalpha()):
                filtered_sentences.append(cleanedwords.lower())
    sentences list.append(filtered sentences)
In [12]:
print(len(sentences list))
print(type(sentences list))
364173
<class 'list'>
In [13]:
w2vmodel =
gensim.models.Word2Vec(sentences list,min count=4,size=200,workers=4)
-> Most similar word
-> Similarity between the words
```

-> Dimensionality representation of a word

```
In [14]:
```

```
print(w2vmodel.most_similar("where"))
```

```
print(w2vmodel.wv['what'])
[('wherever', 0.4594731330871582), ('what', 0.45790600776672363), ('when',
0.4426317811012268), ('atlanta', 0.417472779750824), ('everywhere', 0.40873
72124195099), ('somewhere', 0.4012754559516907), ('why',
0.39789170026779175), ('miami', 0.39658424258232117), ('nyc',
0.3958161771297455), ('florida', 0.39461496472358704)]
0.44263175693579765
[ \ 1.6331531 \ \ -0.79845667 \ \ -0.45216376 \ \ \ 0.42539343 \ \ -0.33658674 \ \ \ 0.59380037
-0.5263159 0.5842386 1.466138 -0.3119752 -0.21973877 0.8555864
-3.6795366 0.8617518 3.0770397 -0.11212743 -0.72588176 2.4425774
-1.5533571 -0.59036565 1.7174312 -0.77355695 1.3786777 0.6814901
 0.6741636 0.8354629 -1.707923
                                  1.3012035 0.9157588 3.9978266
           0.1697004 -2.1428678 -1.0298405 0.60593456 1.6675051
-0.631389
 1.2019076 1.3818147 1.8297708 0.06275181 -0.2328718 0.8112764
 -4.7815714 2.254828 -1.2480936 -0.20308697 -1.0630426 0.92793036
 1.8030949 -1.7717417 -1.681844
                                  0.18603978 0.7955026 0.89024246
 1.9989334 0.9757756 1.3316698 4.8155875 -1.3277873 3.258908
 1.1285194 - 0.2615028 1.6847275 0.1742869 1.8900928 - 0.19013865
 2.279615
           -2.3754504 -0.38275328 -1.6026828 -2.2104282 -2.6147068
-1.3613904 -0.75397664 -1.3671336 -2.3176205 1.3250021 -0.8424476
 -2.2235625 1.9410805 -2.5142384 -1.0206442 0.41692322 0.11198874
 0.03515576 \quad 1.5786471 \quad 0.19432983 \quad -2.0514994 \quad -1.4727927 \quad 0.40654066
 0.88286346 -2.428184
                       1.0518938 -1.2216723 -1.0388702 -0.623032
-0.41029868 -1.2505282 0.70760673 1.0133395 -0.3811332 -1.3858659
-0.36918342 \ -2.7233331 \qquad 0.9510346 \ -0.35236558 \quad 0.97679293 \quad 0.7148403
-0.78331006 - 0.61408746 - 0.3376292 - 0.27254063 0.555511 - 1.062949
 1.2672429 -0.8551705 0.07587209 -2.0158272 -0.322324
                                                         0.6007844
            1.457027
                       2.5418932 2.4028869
                                               1.0896951 -0.24308997
 -0.9152724
-2.1541197 -1.385261
                       1.7806646 -1.4152241 1.0486333 -1.5356334
 -1.763022
            1.7497728 1.2591652 1.1417272 -1.5481972 -2.2717617
 1.3790187 -1.8005618 -0.06050143 -2.5310838 -1.4711559
                                                         2.5667489
 1.0004866 - 1.3947448 - 1.7634138 - 0.58484435 0.7129905 2.835419
 0.45729092 0.4322272 0.30003986 -2.8693535 1.5222995 -0.45841023
                      1.583578 -1.9039611 -2.0539722 0.796204
 -1.6101103 -1.1513519
                                   0.59110135 -1.1242639 1.0625143
 0.5662639 -3.0849988 1.1563088
 1.8337064 0.07630508 -0.00891196 -0.1754792 -0.7249214 2.6913538
 -3.177442 -0.28687838 -3.4646447 -0.68664604 -2.9991336 -1.0978917
 1.0261513 -1.767935
                       -1.0438273 0.12836058 -0.5314205 -1.8073746
            1.3502879 -2.0460868 -1.7149078 -3.5365427 0.15722775
 -1.30182
 0.12164022 -3.0982144 ]
/Users/vthumati/anaconda3/lib/python3.6/site-
packages/ipykernel launcher.py:1: DeprecationWarning: Call to deprecated `m
ost similar` (Method will be removed in 4.0.0, use self.wv.most similar() i
nstead).
  """Entry point for launching an IPython kernel.
/Users/vthumati/anaconda3/lib/python3.6/site-
```

print(w2vmodel.similarity("where", 'when'))

# Observation:

ad).

- -> We have constructed the vector representation of each word
- -> Using this model to construct vector representation of each sente

packages/ipykernel\_launcher.py:2: DeprecationWarning: Call to deprecated `s imilarity` (Method will be removed in 4.0.0, use self.wv.similarity() inste

#### **AVERAGE WORD2VEC**

-> Here i am using the word2vec model to construct vector representation of each sentence

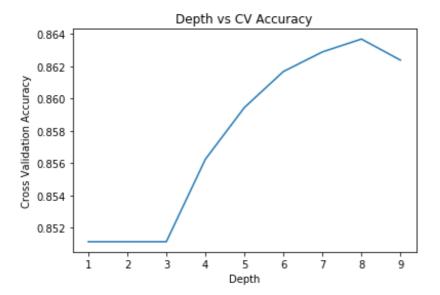
```
In [15]:
```

```
sent vectors = []
for sent in sentences_list:
    sent vec = np.zeros(200)
    cnt=0
    for word in sent:
        try:
            vec = w2vmodel.wv[word]
            sent vec += vec
            cnt += 1
        except:
            pass
    sent_vec /= cnt
    sent vectors.append(sent vec)
print(len(sent vectors))
print(len(sent_vectors[364000]))
/Users/vthumati/anaconda3/lib/python3.6/site-
packages/ipykernel launcher.py:13: RuntimeWarning: invalid value
encountered in true divide
 del sys.path[0]
364173
200
In [16]:
np.isnan(sent_vectors).any()
Out[16]:
True
In [17]:
sent_vectors = np.nan_to_num(sent_vectors)
In [18]:
np.isnan(sent vectors).any()
Out[18]:
False
In [19]:
sent vectors.shape
Out[19]:
(364173, 200)
```

```
In [20]:
xtrain = sent vectors[0:250000]
xtest = sent vectors[250000:]
ytrain = sorted w2vec['Score'][0:250000]
ytest = sorted w2vec['Score'][250000:]
In [21]:
print(xtrain.shape)
print(xtest.shape)
print(ytrain.shape)
print(ytest.shape)
(250000, 200)
(114173, 200)
(250000,)
(114173,)
In [43]:
1 = np.arange(1, 10, 1)
Out[43]:
array([1, 2, 3, 4, 5, 6, 7, 8, 9])
In [25]:
from sklearn.cross validation import cross val score
In [28]:
cross validation scores = []
for d in 1:
    model = DecisionTreeClassifier(criterion='gini', max depth=d,
min samples split=10)
    score = cross val score(model,xtrain,ytrain,cv=3,scoring='accuracy')
    cross validation scores.append(score.mean())
In [30]:
error = [1 - x for x in cross_validation_scores]
print(error)
print(cross validation scores)
[0.14885599995505316, 0.14885599995505316, 0.14885599995505316,
0.14375999109033, 0.14055999768197314, 0.13833199467366386,
0.13711999659352403, 0.13632399374539939, 0.13762799550558047]
[0.8511440000449468, 0.8511440000449468, 0.8511440000449468,
0.85624000890967, 0.8594400023180269, 0.8616680053263361,
0.862880003406476, 0.8636760062546006, 0.8623720044944195]
In [31]:
mp.plot(l,cross_validation_scores)
mp.xlabel('Depth')
mp.ylabel('Cross Validation Accuracy')
mp.title("Depth vs CV Accuracy")
```

#### Out[31]:

Text(0.5,1,'Depth vs CV Accuracy')

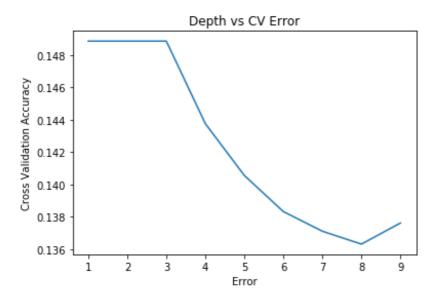


#### In [33]:

```
mp.plot(l,error)
mp.xlabel('Error')
mp.ylabel('Cross Validation Accuracy')
mp.title("Depth vs CV Error")
```

# Out[33]:

Text(0.5,1,'Depth vs CV Error')



# In [35]:

```
best_d = l[error.index(min(error))]
print("the best value of d is {}".format(best_d))
```

the best value of d is 8

# In [36]:

```
model = DecisionTreeClassifier(criterion='gini',max_depth=best_d, min_sampl
es_split=10)
model.fit(xtrain,ytrain)
pred = model.predict(xtest)
```

```
score = accuracy_score(ytest,pred)
print(score)
0.8490185945889133
Observation:
    \rightarrow The optimal depth of the decision tree is 8
    -> The accuracy with depth of 8 is 84.90
TFIDF WORD2VEC:
    -> Here i am using the word2vec model to construct vector
    representation of each sentence
In [22]:
data = finaldata.sort values("Time",axis=0,ascending=True,kind='quicksort',
na position='last',inplace=False)
In [23]:
data.shape
Out [23]:
(364173, 10)
In [24]:
from sklearn.feature_extraction.text import TfidfVectorizer
In [25]:
tfid = TfidfVectorizer(ngram range=(1,2))
In [26]:
tfid vect = tfid.fit transform(data['Text'].values)
In [27]:
tfid vect.shape
Out[27]:
(364173, 2910206)
In [28]:
tfidf feat = tfid.get feature names()
print(len(tfidf feat))
2910206
In [30]:
FC; 1C C--F FC; 1 --F C--F --- //
```

```
triar reat = tria.get reature names()
tfidf sent vectors = [];
row=0;
for sent in sentences list:
    sent vec = np.zeros(200)
    sum = 0;
    for word in sent:
        try:
            vec = w2v model.wv[word]
            tfidf = tfid_vect[row, tfidf_feat.index(word)]
            sent vec += (vec * tf idf)
            sum += tf idf
        except:
            pass
    sent vec /= sum
    tfidf sent vectors.append(sent vec)
/Users/vthumati/anaconda3/lib/python3.6/site-
packages/ipykernel launcher.py:15: RuntimeWarning: invalid value
encountered in true divide
  from ipykernel import kernelapp as app
In [31]:
print(len(tfidf sent vectors))
print(len(tfidf_sent_vectors[300000]))
364173
200
In [32]:
type (tfidf sent vectors)
Out[32]:
list
In [35]:
tfidf_sent_vectors = np.nan_to_num(tfidf sent vectors)
In [37]:
np.isnan(tfidf sent vectors).any()
Out[371:
False
In [39]:
xtrain = tfidf sent vectors[0:250000]
xtest = tfidf sent vectors[250000:]
ytrain = data['Score'][0:250000]
ytest = data['Score'][250000:]
In [40]:
print(xtrain.shape)
print(xtest.shape)
print (vtrain shape)
```

```
PITIL (YCIATII.DIIAPC)
print(ytest.shape)
(250000, 200)
(114173, 200)
(250000,)
(114173,)
In [41]:
from sklearn.cross validation import cross val score
/Users/vthumati/anaconda3/lib/python3.6/site-
packages/sklearn/cross validation.py:41: DeprecationWarning: This module wa
s deprecated in version 0.18 in favor of the model selection module into wh
ich all the refactored classes and functions are moved. Also note that the
interface of the new CV iterators are different from that of this module. T
his module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
In [45]:
cross validation scores = []
for d in 1:
    model = DecisionTreeClassifier(criterion='gini', max depth=d,
min samples split=10)
    score = cross val score(model,xtrain,ytrain,cv=3,scoring='accuracy')
    cross validation scores.append(score.mean())
In [46]:
error = [1 - x for x in cross validation scores]
print(error)
print(cross validation scores)
[0.14885599995505316, 0.14885599995505316, 0.14885599995505316,
0.14885599995505316, 0.14885599995505316, 0.14885599995505316,
0.14885599995505316, 0.14885599995505316, 0.14885599995505316]
[0.8511440000449468, 0.8511440000449468, 0.8511440000449468,
0.8511440000449468, 0.8511440000449468, 0.8511440000449468,
0.8511440000449468, 0.8511440000449468, 0.8511440000449468]
In [47]:
mp.plot(l,cross validation scores)
mp.xlabel('Depth')
mp.ylabel('Cross Validation Accuracy')
mp.title("Depth vs CV Accuracy")
Out [47]:
Text(0.5,1,'Depth vs CV Accuracy')
                  Depth vs CV Accuracy
  0.88
/alidation Accuracy
  0.86
```

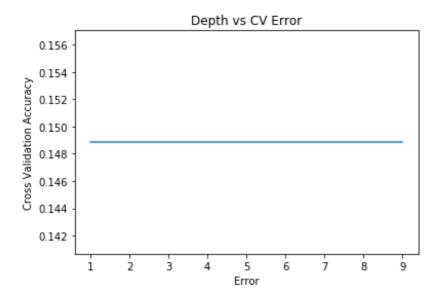
```
0.82 -
1 2 3 4 5 6 7 8 9
Depth
```

# In [48]:

```
mp.plot(l,error)
mp.xlabel('Error')
mp.ylabel('Cross Validation Accuracy')
mp.title("Depth vs CV Error")
```

#### Out[48]:

Text(0.5,1,'Depth vs CV Error')



#### In [49]:

```
best_d = l[error.index(min(error))]
print("the best value of d is {}".format(best_d))
```

the best value of d is 1

# In [51]:

```
model = DecisionTreeClassifier(criterion='gini',max_depth=best_d, min_sampl
es_split=10)
model.fit(xtrain,ytrain)
pred = model.predict(xtest)
score = accuracy_score(ytest,pred)
print(score)
```

0.8257381342348892

# Observation:

- -> The optimal depth of the decision tree is 1
- -> The accuracy with depth of 1 is 82.57

# **CONCLUSION:**

 $\rightarrow$  Determined the optimal depth with the help of cross validation

# AVERAGE WORD2VEC:

- $\rightarrow$  The optimal depth of the decision tree is 8
- -> The accuracy with depth of 8 is 84.90

# TFIDF WORD2VEC:

- $\ensuremath{\mathord{ ext{--}}}$  The optimal depth of the decision tree is 1
- -> The accuracy with depth of 1 is 82.57