DSE 220 Final: Random Forest Regressor Model for Amazon Review Helpfulness

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Code

This section will display the code for our predictive Random Forest Regressor Model for Amazon Review Helpfulness.

In [ ]:
```
import xgboost as xgb
import random
from random import randint
from sklearn.model_selection import cross_val_predict, TimeSeriesSplit
from sklearn.model_selection import RandomizedSearchCV
import time
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import GridSearchCV
from keras.models import Sequential
import tensorflow as tf
from tensorflow.python.keras.models import Sequential
from tensorflow.python.keras.layers import Dense
```

In [391]:
```
from __future__ import print_function
import matplotlib.pyplot as plt
import numpy as np
import os
import sys
from six.moves import cPickle as pickle
import pandas as pd
import gzip
import seaborn as sns
import string
from time import time
import nltk
from nltk.corpus import stopwords
#stops = set(stopwords.words("english"))
```

In [392]:
```
# Import the classifier
from sklearn.neighbors import KNeighborsClassifier
from matplotlib.colors import ListedColormap          # Visualization
import numpy as np                                    # Numerical opera
import matplotlib.pyplot as plt                       # Plotting
```

```
from sklearn.model_selection import train_test_split # Data splitting
import pandas as pd
from sklearn import datasets
from sklearn.metrics import accuracy_score
from sklearn import preprocessing
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier
from scipy import interp
import itertools
from sklearn.metrics import confusion_matrix
from sklearn.naive_bayes import GaussianNB, MultinomialNB
from sklearn import metrics
from sklearn.mixture import GaussianMixture
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn import datasets, decomposition, feature_extraction
from sklearn.datasets import fetch_20newsgroups
from nltk.corpus import stopwords
import nltk
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.svm import SVC
from sklearn.feature_selection import SelectKBest, chi2
from nltk.corpus import brown
import collections
import operator
import math
from sklearn.decomposition import TruncatedSVD
from sklearn.random_projection import sparse_random_matrix
from mpl_toolkits.mplot3d import Axes3D
from sklearn.cluster import KMeans
from sklearn import datasets
from sklearn.metrics.pairwise import cosine_similarity as cs
from sklearn.neighbors import NearestNeighbors
from sklearn.decomposition import PCA
from nltk.cluster import KMeansClusterer, euclidean_distance, cosine_d
from sklearn.preprocessing import StandardScaler
import xgboost as xgb
import random
from random import randint
from sklearn.model_selection import cross_val_predict, TimeSeriesSplit
from sklearn.model_selection import RandomizedSearchCV
import time
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import GridSearchCV
from keras.models import Sequential
import tensorflow as tf
from tensorflow.python.keras.models import Sequential
```

```
from tensorflow.python.keras.layers import Dense
```

In [393]:
```
import gzip
from collections import defaultdict
```

Helpfulness baseline

Compute the global average helpfulness rate, and the average helpfulness rate for each user

In [394]:
```
def readGz(f):
  for l in gzip.open(f):
    yield eval(l)

allHelpful = []
userHelpful = defaultdict(list)

for l in readGz("train.json.gz"):
  user,item = l['reviewerID'],l['itemID']
  allHelpful.append(l['helpful'])
  userHelpful[user].append(l['helpful'])

averageRate = sum([x['nHelpful'] for x in allHelpful]) * 1.0 / sum([x
userRate = {}
for u in userHelpful:
  totalU = sum([x['outOf'] for x in userHelpful[u]])
  if totalU > 0:
    userRate[u] = sum([x['nHelpful'] for x in userHelpful[u]]) * 1.0 /
  else:
    userRate[u] = averageRate

predictions = open("predictions_Helpful.txt", 'w')
for l in open("pairs_Helpful.txt"):
  if l.startswith("userID"):
    #header
    predictions.write(l)
    continue
  u,i,outOf = l.strip().split('-')
  outOf = int(outOf)
  if u in userRate:
    predictions.write(u + '-' + i + '-' + str(outOf) + ',' + str(outOf
  else:
    predictions.write(u + '-' + i + '-' + str(outOf) + ',' + str(outOf

predictions.close()
```

In [395]:
```
averageRate
```

Out[395]:
```
0.8519720886532813
```

In [396]:
```
userHelpful
```

Out[396]:
```
defaultdict(list,
            {'U745881038': [{'outOf': 0, 'nHelpful': 0},
              {'outOf': 0, 'nHelpful': 0},
              {'outOf': 0, 'nHelpful': 0},
              {'outOf': 2, 'nHelpful': 2}],
             'U023577405': [{'outOf': 0, 'nHelpful': 0},
              {'outOf': 6, 'nHelpful': 6},
              {'outOf': 1, 'nHelpful': 1},
              {'outOf': 1, 'nHelpful': 1},
              {'outOf': 0, 'nHelpful': 0},
              {'outOf': 0, 'nHelpful': 0}],
             'U441384838': [{'outOf': 2, 'nHelpful': 2},
              {'outOf': 0, 'nHelpful': 0},
              {'outOf': 5, 'nHelpful': 3},
              {'outOf': 0, 'nHelpful': 0},
              {'outOf': 5, 'nHelpful': 5}],
             'U654041297': [{'outOf': 0, 'nHelpful': 0},
              {'outOf': 0, 'nHelpful': 0},
              {'outOf': 0, 'nHelpful': 0},
```

For reading the files in a pandas Dataframe.

In [397]:
```
import pandas as pd
from collections import defaultdict

def readGz(f):
    for l in gzip.open(f):
        yield eval(l)

def parse(path):
    g = gzip.open(path, 'rb')
    for l in g:
        yield eval(l)

def getDF(path):
    i = 0
    df = {}
    for d in parse(path):
        df[i] = d
        i += 1
    return pd.DataFrame.from_dict(df, orient='index')

df = getDF('train.json.gz')
test_df = getDF('test_Helpful.json.gz')
```

In [398]:
```
df.head(5)
```

Out[398]:

	categoryID	categories	itemID	reviewerID	rating	reviewText	reviewHash	reviewTim
0	0	[[Clothing, Shoes & Jewelry, Women], [Clothing...	I655355328	U745881038	3.0	These are cute, but they are a little small. ...	R115160670	05 20, 20
1	0	[[Clothing, Shoes & Jewelry, Women, Clothing, ...	I241092314	U023577405	4.0	I love the look of this bra, it is what I want...	R800651687	02 7, 20
2	0	[[Clothing, Shoes & Jewelry, Wedding Party Gif...	I408260822	U441384838	3.0	it's better on a man's hand.I didn't find it v...	R345042616	05 13, 20
3	0	[[Clothing, Shoes & Jewelry, Women, Clothing, ...	I770448753	U654041297	4.0	Comfortable and easy to wear for a day of shop...	R875466866	05 25, 20
4	0	[[Clothing, Shoes & Jewelry, Women, Plus-Size,...	I919238161	U096604734	5.0	I'm quite small and the XS fits me like a regu...	R317526520	07 30, 20

In [399]:
```
df.shape
```

Out[399]: (200000, 12)

In [400]:
```
test_df.head()
```

Out[400]:

	categoryID	categories	itemID	reviewerID	rating	reviewText	reviewHash	reviewTir
0	0	[[Sports & Outdoors, Other Sports, Dance, Clot...	I520932398	U816789534	3.0	I ordered according to the size chart but it's...	R157684793	07 15, 20
1	0	[[Sports & Outdoors, Clothing, Women, Hoodies]...	I969532331	U987148846	4.0	Super thin but really cute and not cheap-looki...	R732719858	07 17, 20
2	0	[[Clothing, Shoes & Jewelry, Women, Accessorie...	I149943341	U628436634	5.0	It was a present for my sis, and she loves Fle...	R352659313	12 8, 20
3	0	[[Clothing, Shoes & Jewelry, Women, Accessorie...	I909025835	U924107228	5.0	I love this thing! I guess they don't make th...	R277416618	11 22, 20
4	0	[[Clothing, Shoes & Jewelry, Women, Clothing, ...	I228439768	U060135484	4.0	I liked it and I wear it...it's a little bit s...	R645892076	04 1, 20

In [401]:
```
test_df.shape
```

Out[401]: (14000, 12)

In [402]:
```
#This function will get the first review time for each item
def first_review_time(data_df):
    time_dict = {}
    for i in range(len(data_df)):
        pid = data_df['itemID'][i]
        #print (pid)
        time_i = data_df['reviewTime'][i]
        if pid in time_dict:
            if time_i < time_dict[pid]:
                time_dict[pid] = time_i
        else:
            time_dict[pid] = time_i
    data_df['firstReviewTime'] = data_df['itemID'].map(time_dict).valu
    return data_df
# convert reviewTime to datatime data type
df['reviewTime'] = pd.to_datetime(df['reviewTime'])
df = first_review_time(df)
df['review_first_dif'] = (df['reviewTime'] - df['firstReviewTime']).as
test_df['reviewTime'] = pd.to_datetime(test_df['reviewTime'])
test_df = first_review_time(test_df)
test_df['review_first_dif'] = (test_df['reviewTime'] - test_df['firstR
```

In [403]:
```
#This will tell us the rating score deviation from mean
def deviation_mean(data_df):
    rating_mean_dict = data_df['rating'].groupby(data_df['itemID']).me
    data_df['rating_mean'] = data_df['itemID'].map(rating_mean_dict).v
    data_df['rating_mean_dev'] = data_df['rating'] - data_df['rating_m
    return data_df['rating_mean_dev']
df['rating_mean_dev'] = deviation_mean(df)
test_df['rating_mean_dev'] = deviation_mean(test_df)
```

In [404]:
```
#This will get the number of words of each review text
df['reviewWords'] = df['reviewText'].apply(lambda x: len(x.split()))
test_df['reviewWords'] = test_df['reviewText'].apply(lambda x: len(x.s
```

In [405]:
```
#This will tell us the number of words of each review summary
df['summaryWords'] = df['summary'].apply(lambda x: len(x.split()))
test_df['summaryWords'] = test_df['summary'].apply(lambda x: len(x.spl
#df.head(5)
```

In [406]:
```
#This will tell us the ratio of summary words to review text words
df['ratiosuWord'] = df['summaryWords'] / df['reviewWords']
test_df['ratiosuWord'] = test_df['summaryWords'] / test_df['reviewWorc
```

In [407]:
```
#This will tell us the number of sentences of each review text
def count_sentence(data_df, text):
    pun_sen = ['.', '!', '?']
    text_col = data_df[text]
    sentence_counts = []
    for i in text_col:
        sentence_count = []
        for j in pun_sen:
            count_a = i.count(j)
            sentence_count.append(count_a)
        sentence_counts.append(sum(sentence_count))
    data_df['reviewSentences'] = sentence_counts
    return data_df['reviewSentences']
df['reviewSentences'] = count_sentence(df, 'reviewText')
test_df['reviewSentences'] = count_sentence(test_df, 'reviewText')
```

In [408]:
```
#This will extract number of sentences of each summary text
df['summarySentences'] = count_sentence(df, 'summary')
test_df['summarySentences'] = count_sentence(test_df, 'summary')
#summarySentences = []
#for i in df['summary']:
#    j = i.count('.')
#    summarySentences.append(j)
#df['summarysentences'] = summarySentences
#df.head()
```

In [409]:
```
#This will tell us the number of characters of each review text
punctuation = ['!','"','#','$','%','&',"'",'(',')','*','+',',','-','.'
def count_characters(data_df):
    reviewcharacters = []
    text_col = data_df['reviewText']
    for i in text_col:
        a = dict(collections.Counter(i))
        b = {k:v for k, v in a.items() if k not in punctuation}
        c = sum(list(b.values()))
        reviewcharacters.append(c)
    data_df['reviewChars'] = reviewcharacters
    return data_df['reviewChars']
df['reviewChars'] = count_characters(df)
test_df['reviewChars'] = count_characters(test_df)
#df.head(5)
```

In [410]:
```
#punctuation = ['!','"','#','$','%','&',"'",'(',')','*','+',',','-','.
#lowercase_words = [x.lower() for x in brown.words()]
#punctuation_stopwords = punctuation + stopwords.words('english')
#filtered_words = [x for x in lowercase_words if x not in punctuation_
#final_filtered_words = list(filter(lambda x: x.isalpha() and len(x) >
```

In [411]:
```
#This will tell us the readability of each review (ARI as index to mea
def readability(data_df):
    wordperSen = []
    charperWord = []
    reviewRead = []
    len_df = len(data_df)
    a = list(data_df['reviewWords'])
    b = list(data_df['reviewSentences'])
    c = list(data_df['reviewChars'])
    for i in range(len_df):
        if b[i] == 0:
            wordperSen.append(0)
        else:
            j = a[i] / b[i]
            wordperSen.append(j)
        if a[i] == 0:
            charperWord.append(0)
        else:
            l = c[i] / a[i]
            charperWord.append(l)
        ari = 4.71 * charperWord[i] + 0.5 * wordperSen[i] - 21.43
        reviewRead.append(ari)
    data_df['reviewRead'] = reviewRead
    return data_df['reviewRead']
df['reviewRead'] = readability(df)
test_df['reviewRead'] = readability(df)
```

In [412]:
```
#This will tell us the number of punctuations of each review text
def numpunct(data_df):
    reviewPuncts = []
    for i in data_df['reviewText']:
        a = dict(collections.Counter(i))
        b = {k:v for k,v in a.items() if k in punctuation}
        c = sum(list(b.values()))
        reviewPuncts.append(c)
    data_df['reviewPuncts'] = reviewPuncts
    return data_df['reviewPuncts']
df['reviewPuncts'] = numpunct(df)
test_df['reviewPuncts'] = numpunct(test_df)
```

In [413]:
```
#This will tell us the ratio of punctuations with characters
def ratio_puncts_chars(data_df):
    return data_df['reviewPuncts'] / data_df['reviewChars']
df['ratiopunChar'] = ratio_puncts_chars(df)
test_df['ratiopunChar'] = ratio_puncts_chars(test_df)
```

In [414]:
```
#This will tell us the number of capital words of each review text
def numcapwords(data_df):
    reviewCwords = []
    for i in data_df['reviewText']:
        a = i.split()
        b = [word for word in a if word.isupper()]
        c = len(b)
        reviewCwords.append(c)
    data_df['reviewCwords'] = reviewCwords
    return data_df['reviewCwords']
df['reviewCwords'] = numcapwords(df)
test_df['reviewCwords'] = numcapwords(test_df)
```

In [415]:
```
#This will tell us the number of capital words of each summary
def numcapwords(data_df):
    reviewCwords = []
    for i in data_df['summary']:
        a = i.split()
        b = [word for word in a if word.isupper()]
        c = len(b)
        reviewCwords.append(c)
    data_df['summaryCwords'] = reviewCwords
    return data_df['summaryCwords']
df['summaryCwords'] = numcapwords(df)
test_df['summaryCwords'] = numcapwords(test_df)
```

In [416]:
```
import re
#This will tell us the number of exclimation and question marks of eac
def numexclquest(data_df):
    suexcqueMarks = []
    for i in data_df['reviewText']:
        a = re.findall(r'[!?]', i)
        suexcqueMarks.append(len(a))
    data_df['numexclquest'] = suexcqueMarks
    return data_df['numexclquest']
df['numexclquest'] = numexclquest(df)
test_df['numexclquest'] = numexclquest(test_df)
```

In [417]:
```
#This will tell us the number of exclimation and question marks of eac
def numexclquest(data_df):
    suexcqueMarks = []
    for i in data_df['summary']:
        a = re.findall(r'[!?]', i)
        suexcqueMarks.append(len(a))
    data_df['sunumexclquest'] = suexcqueMarks
    return data_df['sunumexclquest']
df['sunumexclquest'] = numexclquest(df)
test_df['sunumexclquest'] = numexclquest(test_df)
```

In [418]:
```
#This will tell us the number of reviews of each product (measure the
def numreviewPro(data_df):
    itemid_dict = data_df.groupby('itemID')['itemID'].count().to_dict(
    data_df['numreviewPro'] = data_df['itemID'].map(itemid_dict).value
    return data_df['numreviewPro']
df['numreviewPro'] = numreviewPro(df)
test_df['numreviewPro'] = numreviewPro(test_df)
```

In [419]:
```
#This will tell us the number of reviews of each reviewers (measure re
def numreviewPro(data_df):
    itemid_dict = data_df.groupby('reviewerID')['reviewerID'].count().
    data_df['numreviews'] = data_df['reviewerID'].map(itemid_dict).val
    return data_df['numreviews']
df['numreviews'] = numreviewPro(df)
test_df['numreviews'] = numreviewPro(test_df)
```

In [420]:
```
from textblob import TextBlob
import textstat
```

In [421]:
```
#This will tell us the ratio of reviewText words to review text words
df['ratiosCWords'] = df['reviewCwords'] / df['reviewWords']
test_df['ratiosCWords'] = test_df['reviewCwords'] / test_df['reviewWor
```

In [422]:
```
#This will tell us the positivity of each of the reviewtext and the su
df['summarypolarity'] = df['summary'].iloc[:].apply(lambda x: TextBlob
df['summarysubjectivity'] = df['summary'].iloc[:].apply(lambda x: Text
df['reviewTextpolarity'] = df['reviewText'].iloc[:].apply(lambda x: Te
df['reviewTextsubjectivity'] = df['reviewText'].iloc[:].apply(lambda x

test_df['summarypolarity'] = test_df['summary'].iloc[:].apply(lambda x
test_df['summarysubjectivity'] = test_df['summary'].iloc[:].apply(lamb
test_df['reviewTextpolarity'] = test_df['reviewText'].iloc[:].apply(la
test_df['reviewTextsubjectivity'] = test_df['reviewText'].iloc[:].appl
```

In [423]:
```
#This python package to calculate statistics from text to determine re
#complexity and grade level of a particular corpus.
df['reviewText_flesch_reading_ease'] = df['reviewText'].apply(lambda x
df['reviewText_smog_index'] = df['reviewText'].apply(lambda x: teststa
df['reviewText_coleman_liau_index'] = df['reviewText'].apply(lambda x:
df['reviewText_automated_readability_index'] = df['reviewText'].apply(
df['reviewText_dale_chall_readability_score'] = df['reviewText'].apply
df['reviewText_difficult_word'] = df['reviewText'].apply(lambda x: tex
df['reviewText_linsear_write_formula'] = df['reviewText'].apply(lambda
df['reviewText_gunning_fog'] = df['reviewText'].apply(lambda x: textst
df['reviewText_text_standard'] = df['reviewText'].apply(lambda x: text

test_df['reviewText_flesch_reading_ease'] = test_df['reviewText'].appl
test_df['reviewText_smog_index'] = test_df['reviewText'].apply(lambda
test_df['reviewText_coleman_liau_index'] = test_df['reviewText'].apply
test_df['reviewText_automated_readability_index'] = test_df['reviewTex
test_df['reviewText_dale_chall_readability_score'] = test_df['reviewTe
test_df['reviewText_difficult_word'] = test_df['reviewText'].apply(lam
test_df['reviewText_linsear_write_formula'] = test_df['reviewText'].ap
test_df['reviewText_gunning_fog'] = test_df['reviewText'].apply(lambda
test_df['reviewText_text_standard'] = test_df['reviewText'].apply(lamb

df['summary_flesch_reading_ease'] = df['summary'].apply(lambda x: text
df['summary_smog_index'] = df['summary'].apply(lambda x: textstat.smog
df['summary_coleman_liau_index'] = df['summary'].apply(lambda x: texts
df['summary_automated_readability_index'] = df['summary'].apply(lambda
df['summary_dale_chall_readability_score'] = df['summary'].apply(lambd
df['summary_difficult_word'] = df['summary'].apply(lambda x: textstat.
df['summary_linsear_write_formula'] = df['summary'].apply(lambda x: te
df['summary_gunning_fog'] = df['summary'].apply(lambda x: textstat.gun
df['summary_text_standard'] = df['summary'].apply(lambda x: textstat.t

test_df['summary_flesch_reading_ease'] = test_df['summary'].apply(lamb
test_df['summary_smog_index'] = test_df['summary'].apply(lambda x: tex
test_df['summary_coleman_liau_index'] = test_df['summary'].apply(lambd
test_df['summary_automated_readability_index'] = test_df['summary'].ap
test_df['summary_dale_chall_readability_score'] = test_df['summary'].a
test_df['summary_difficult_word'] = test_df['summary'].apply(lambda x:
test_df['summary_linsear_write_formula'] = test_df['summary'].apply(la
test_df['summary_gunning_fog'] = test_df['summary'].apply(lambda x: te
test_df['summary_text_standard'] = test_df['summary'].apply(lambda x:
```

In [569]:
```
#This python package to calculate statistics from text to determine re
#complexity and grade level of a particular corpus.
df['reviewText_flesch_kincaid_grade'] = df['reviewText'].apply(lambda 
test_df['reviewText_flesch_kincaid_grade'] = test_df['reviewText'].app


df['summary_flesch_kincaid_grade'] = df['summary'].apply(lambda x: tex
test_df['summary_flesch_kincaid_grade'] = test_df['summary'].apply(lam
```

In [576]:
```
#This python package to calculate statistics from text to determine re
#complexity and grade level of a particular corpus.
df['reviewText_text_standardcat']=df['reviewText_text_standard'].astyp
test_df['reviewText_text_standardcat']=test_df['reviewText_text_standa

df['summary_text_standardcat']=df['summary_text_standard'].astype('cat
test_df['summary_text_standardcat']=test_df['summary_text_standard'].a
```

In [424]:
```
#This will tell us the ratio of the average number of the overall rati
#This will tell us the ratio of the average rating number per item in 
df_reviewerIDavg = df.groupby(['reviewerID']).mean()['rating'].reset_i
df_reviewerIDavg.columns = ['reviewerID','reviewerratingavg']

test_df_reviewerIDavg = test_df.groupby(['reviewerID']).mean()['rating
test_df_reviewerIDavg.columns = ['reviewerID','reviewerratingavg']

df_itemIDavg = df.groupby(['itemID']).mean()['rating'].reset_index()
df_itemIDavg.columns = ['itemID','itemratingavg']

test_df_itemIDavg = test_df.groupby(['itemID']).mean()['rating'].reset
test_df_itemIDavg.columns = ['itemID','itemratingavg']

df = df.merge(df_reviewerIDavg,how='left',left_on='reviewerID',right_o
df = df.merge(df_itemIDavg,how='left',left_on='itemID',right_on='itemI

test_df = test_df.merge(df_reviewerIDavg,how='left',left_on='reviewerI
test_df = test_df.merge(df_itemIDavg,how='left',left_on='itemID',right
```

In [425]:
```
#This will tell us the ratio of each rating divided by the average rat
#This will tell us the ratio for each item of each rating divided by t
df['reviewerratingratio'] = df['rating']/df['reviewerratingavg']
df['itemratingratio'] = df['rating']/df['itemratingavg']

test_df['reviewerratingratio'] = test_df['rating']/test_df['reviewerra
test_df['itemratingratio'] = test_df['rating']/test_df['itemratingavg'
```

In [426]:
```
#This tells us a ratio for each summary text of the number of words
#in the summary text divided by the number of words of the summary wor
df['suratioCwords'] = df['summaryCwords']/df['summaryWords']
test_df['suratioCwords'] = test_df['summaryCwords']/test_df['summaryWo
```

In [427]:
```
#Breaking up helpful column into two features
df['helpful_numerator'] = df['helpful'].apply(lambda x: x['nHelpful'])

df['helpful_denominator'] = df['helpful'].apply(lambda x: x['outOf'])
test_df['helpful_denominator'] = test_df['helpful'].apply(lambda x: x[

df['helpratio'] = df['helpful_numerator'] / df['helpful_denominator']
df['helpratio'] = df['helpratio'].fillna(0)
```

In [555]:
```
#We also fill all prices with NaNs by filling them with the mean of th
df['price'] = df['price'].fillna(np.mean(df['price']))
test_df['price'] = test_df['price'].fillna(np.mean(test_df['price']))
```

In [464]:
```
#df0=df[df['helpratio']>0]
```

In [465]:
```
#df1=df[df['helpratio']>0]
```

In [ ]:
```
#df = df.replace([np.inf, -np.inf], np.nan).fillna(0)
```

In [572]:
```
#This will tell us the number of punctuations of each review text
def numpunct_summary(data_df):
    reviewPuncts = []
    for i in data_df['summary']:
        a = dict(collections.Counter(i))
        b = {k:v for k,v in a.items() if k in punctuation}
        c = sum(list(b.values()))
        reviewPuncts.append(c)
    data_df['summaryPuncts'] = reviewPuncts
    return data_df['summaryPuncts']
df['summaryPuncts'] = numpunct_summary(df)
test_df['summaryPuncts'] = numpunct_summary(test_df)
```

In [573]:
```
#This will tell us the ratio of punctuations with characters in our su
def ratio_puncts_chars_summary(data_df):
    return data_df['summaryPuncts'] / data_df['summaryChars']
df['summaryratiopunChar'] = ratio_puncts_chars_summary(df)
test_df['summaryratiopunChar'] = ratio_puncts_chars_summary(test_df)
```

In [564]:
```
#This will tell us the number of characters of each summary
punctuation = ['!','"','#','$','%','&',"'",'(',')','*','+',',','-','.'
def count_characters_summary(data_df):
    reviewcharacters = []
    text_col = data_df['summary']
    for i in text_col:
        a = dict(collections.Counter(i))
        b = {k:v for k, v in a.items() if k not in punctuation}
        c = sum(list(b.values()))
        reviewcharacters.append(c)
    data_df['summaryChars'] = reviewcharacters
    return data_df['summaryChars']
df['summaryChars'] = count_characters_summary(df)
test_df['summaryChars'] = count_characters_summary(test_df)
```

In [558]:
```
#This is telling us the averageword count by the reviewer
reviewwordavgdf = pd.DataFrame(df.groupby(['reviewerID'])['reviewWords
reviewwordavgdf.columns = ['reviewerID','rwavgwords']
df = df.merge(reviewwordavgdf,how='left',left_on='reviewerID',right_or

reviewwordavgtestdf = pd.DataFrame(test_df.groupby(['reviewerID'])['re
reviewwordavgtestdf.columns = ['reviewerID','rwavgwords']
test_df = test_df.merge(reviewwordavgtestdf,how='left',left_on='reviev
```

In [559]:
```
#This is telling us the ratio of the word length of the review text
#This is telling us the mean of the review text by the reviewer
#This is telling us the ratio of the summary word length
df['review_word_length_ratio']  = df['reviewWords'] / np.mean(df['revi
df['review_word_mean_by_reviewer'] = df['reviewWords'] / df['rwavgword
df['summary_word_length_ratio'] = df['summaryWords'] /  np.mean(df['su
test_df['review_word_length_ratio']  =test_df['reviewWords'] / np.mear
test_df['review_word_mean_by_reviewer'] = test_df['reviewWords'] / tes
test_df['summary_word_length_ratio'] = test_df['summaryWords'] /  np.m
```

In [561]:
```
#This is telling us the deviation of the rating from its mean, along v
ratingmean = df['rating'].groupby(df['itemID']).transform('mean')
ratDevmean = df['rating'] - ratingmean
df['ratDevmean'] = ratDevmean
df['ratDevmean_abs'] = df['ratDevmean'].abs()
```

In [562]:
```
#This is telling us the deviation of the rating from its mean, along v
ratingmean = test_df['rating'].groupby(test_df['itemID']).transform('n
ratDevmean = test_df['rating'] - ratingmean
test_df['ratDevmean'] = ratDevmean
test_df['ratDevmean_abs'] = test_df['ratDevmean'].abs()
```

In [768]:
```
df1 = df[['rating',
```

```
 'price',
 'helpful_denominator',
 'unixReviewTime',
 'review_first_dif',
 'ratDevmean',
'reviewRead',
'ratiosCWords',
'reviewerratingavg',
'itemratingavg',
'itemratingratio',
'summarypolarity',
'summarysubjectivity',
'reviewerratingratio',
'reviewWords',
'summaryWords',
'ratiosuWord',
'reviewSentences',
'summarySentences',
'reviewChars',
'summaryChars',
'reviewText_flesch_reading_ease',
'reviewText_smog_index',
'reviewText_flesch_kincaid_grade',
'reviewText_coleman_liau_index',
'reviewText_automated_readability_index',
'reviewText_dale_chall_readability_score',
'reviewText_difficult_word',
'reviewText_linsear_write_formula',
'reviewText_text_standardcat',
'reviewText_gunning_fog',
'reviewPuncts',
'summaryPuncts',
'ratiopunChar',
'suratioCwords',
'summaryratiopunChar',
'reviewCwords',
'summaryCwords',
'numexclquest',
'sunumexclquest',
'numreviewPro',
'numreviews',
'reviewTextpolarity',
'reviewTextsubjectivity',
'rwavgwords',
'review_word_length_ratio',
'review_word_mean_by_reviewer',
'summary_word_length_ratio',
'summary_automated_readability_index',
'summary_flesch_reading_ease',
'summary_smog_index',
'summary_coleman_liau_index',
```

```
           'summary_coleman_liau_index',
           'summary_dale_chall_readability_score',
           'summary_difficult_word',
           'summary_linsear_write_formula',
           'summary_flesch_kincaid_grade']]
```

In [769]:
```
df1.columns.to_series()[np.isinf(df1).any()]
```

Out[769]:
```
ratiosuWord                           ratiosuWord
summaryratiopunChar    summaryratiopunChar
dtype: object
```

In [770]:
```
nan_values = df1.isna()
nan_columns = nan_values.any()

columns_with_nan = df1.columns[nan_columns].tolist()
print(columns_with_nan)
```

```
['ratiosCWords', 'ratiopunChar']
```

In [771]:
```
#df1 = df[['rating',
#           'price',
#           'unixReviewTime',
#           'helpful_denominator',
#           #'reviewWords',
#           #'summaryWords',
#           #'summaryCwords',
#           #'ratiosuWord',
#           #'reviewSentences',
#           #'summarySentences',
#           'reviewChars',
#           'reviewRead',
#           #'reviewPuncts',
#           'ratiopunChar',
#           #'reviewCwords',
#           'ratiosCWords',
#           #'suratioCwords',
#           #'numexclquest',
#           #'sunumexclquest',
#           'numreviewPro',
#           'numreviews',
#           'reviewerratingavg',
#           'itemratingavg',
#           'reviewerratingratio',
#           'itemratingratio',
#           #'summarypolarity',
#           #'summarysubjectivity',
#           'reviewTextpolarity',
#           'reviewTextsubjectivity',
#           'reviewText_flesch_reading_ease',
#           #'reviewText_smog_index',
#           'reviewText_coleman_liau_index',
#           #'reviewText_automated_readability_index',
#           'reviewText_dale_chall_readability_score',
#           #'reviewText_difficult_word',
#           'reviewText_linsear_write_formula',
#           #'reviewText_gunning_fog',
#           #'reviewText_text_standard',
#           #'summary_flesch_reading_ease',
#           #'summary_smog_index',
#           #'summary_coleman_liau_index',
#           'summary_automated_readability_index',
#           #'summary_dale_chall_readability_score',
#           #'summary_difficult_word',
#           #'summary_linsear_write_formula',
#           #'summary_gunning_fog',
#           #'summary_text_standard',
#          ]]
```

In [772]:
```
df1 = df1.replace([np.inf, -np.inf], np.nan).fillna(0)
```

In [773]:
```
nan_values = df1.isna()
nan_columns = nan_values.any()

columns_with_nan = df1.columns[nan_columns].tolist()
print(columns_with_nan)
```

```
[]
```

In [774]:
```
test_df1 = test_df[['rating',
           'price',
           'helpful_denominator',
           'unixReviewTime',
           'review_first_dif',
           'ratDevmean',
          'reviewRead',
          'ratiosCWords',
          'reviewerratingavg',
          'itemratingavg',
          'itemratingratio',
          'summarypolarity',
          'summarysubjectivity',
          'reviewerratingratio',
          'reviewWords',
          'summaryWords',
          'ratiosuWord',
          'reviewSentences',
          'summarySentences',
          'reviewChars',
          'summaryChars',
          'reviewText_flesch_reading_ease',
          'reviewText_smog_index',
          'reviewText_flesch_kincaid_grade',
          'reviewText_coleman_liau_index',
          'reviewText_automated_readability_index',
          'reviewText_dale_chall_readability_score',
          'reviewText_difficult_word',
          'reviewText_linsear_write_formula',
          'reviewText_text_standardcat',
          'reviewText_gunning_fog',
          'reviewPuncts',
          'summaryPuncts',
          'ratiopunChar',
          'suratioCwords',
          'summaryratiopunChar',
          'reviewCwords',
          'summaryCwords',
          'numexclquest',
```

```
          'sunumexclquest',
          'numreviewPro',
          'numreviews',
          'reviewTextpolarity',
          'reviewTextsubjectivity',
          'rwavgwords',
          'review_word_length_ratio',
          'review_word_mean_by_reviewer',
          'summary_word_length_ratio',
          'summary_automated_readability_index',
          'summary_flesch_reading_ease',
          'summary_smog_index',
          'summary_coleman_liau_index',
          'summary_dale_chall_readability_score',
          'summary_difficult_word',
          'summary_linsear_write_formula',
          'summary_flesch_kincaid_grade']]
```

In [775]:

```
#test_df1['reviewerratingratio'] = test_df1['reviewerratingratio'].rep
#test_df1['reviewerratingavg'] = test_df1['reviewerratingavg'].replace
```

In [776]:

```
nan_values = test_df1.isna()
nan_columns = nan_values.any()

columns_with_nan = test_df1.columns[nan_columns].tolist()
print(columns_with_nan)
```

```
['reviewerratingavg', 'reviewerratingratio']
```

In [777]:

```
test_df1 = test_df1.replace([np.inf, -np.inf], np.nan).fillna(0)
```

In [778]:

```
from sklearn.model_selection import train_test_split
from sklearn import datasets
from sklearn.ensemble import RandomForestRegressor
from sklearn.feature_selection import SelectFromModel
```

In [779]:

```
X = df1
y = df[['helpratio','helpful_numerator','helpful_denominator']]
```

In [780]:
```
X_0 = X[X['helpful_denominator']>1]
X_0 = X[X['helpful_denominator']<=200]

y_0 = y[y['helpful_denominator']>1]
y_0 = y[y['helpful_denominator']<=200]

X_train0, X_val0, y_train0, y_val0 = train_test_split(X_0,y_0, test_s

y_trainadj0 = y_train0['helpratio']
clf0 = RandomForestRegressor(bootstrap=True,
                             criterion='mse',
                             max_depth=None,
                             max_features='auto',
                             max_leaf_nodes=None,
                             #max_samples=None,
                             min_impurity_decrease=0.0,
                             min_impurity_split=None,
                             min_samples_leaf=1,
                             min_samples_split=2,
                             min_weight_fraction_leaf=0.0,
                             n_estimators=88,
                             n_jobs=None,
                             oob_score=False,random_state=42,
                             verbose=0,
                             warm_start=False)

clf0.fit(X_train0, y_trainadj0)
y_val_pred0 = clf0.predict(X_val0)
mean_absolute_error(y_val0['helpful_numerator'],np.round((X_val0['help
```

Out[780]: 0.16970045506826023

In [781]:
```
X_train_valid0 = X_0
y_train_valid0 = y_0['helpratio']
clf0.fit(X_train_valid0,y_train_valid0)
y_val_pred0 = clf0.predict(X_val0)
mean_absolute_error(y_val0['helpful_numerator'],np.round((X_val0['help
```

Out[781]: 0.026679001850277754

In [782]:
```
X_train_valid0 = X
y_train_valid0 = y['helpratio']
clf0.fit(X_train_valid0,y_train_valid0)
y_val_pred0 = clf0.predict(X_val0)
mean_absolute_error(y_val0['helpful_numerator'],np.round((X_val0['help
```

Out[782]: 0.027554133119967995

In [788]:
```
X50 = X[X['helpful_denominator']>1]
X50 = X[X['helpful_denominator']<=50]

y50 = y[y['helpful_denominator']>1]
y50 = y[y['helpful_denominator']<=50]

X_train50, X_val50, y_train50, y_val50 = train_test_split(X50,y50, tes

y_trainadj50 = y_train50['helpratio']
clf50 = RandomForestRegressor(bootstrap=True,
                              criterion='mse',
                              max_depth=None,
                              max_features='auto',
                              max_leaf_nodes=None,
                              #max_samples=None,
                              min_impurity_decrease=0.0,
                              min_impurity_split=None,
                              min_samples_leaf=1,
                              min_samples_split=2,
                              min_weight_fraction_leaf=0.0,
                              n_estimators=88,
                              n_jobs=None,
                              oob_score=False,random_state=42,
                              verbose=0,
                              warm_start=False)

clf50.fit(X_train50, y_trainadj50)
y_val_pred50 = clf50.predict(X_val50)
mean_absolute_error(y_val50['helpful_numerator'],np.round((X_val50['he
```

Out[788]: 0.1638153445382361

In [789]:
```
X_train_valid50 = X50
y_train_valid50 = y50['helpratio']
clf50.fit(X_train_valid50,y_train_valid50)
y_val_pred50 = clf50.predict(X_val50)
mean_absolute_error(y_val50['helpful_numerator'],np.round((X_val50['he
```

Out[789]: 0.023319890789770308

In [790]:
```
X_train_valid50 = X
y_train_valid50 = y['helpratio']
clf50.fit(X_train_valid50,y_train_valid50)
y_val_pred50 = clf50.predict(X_val50)
mean_absolute_error(y_val50['helpful_numerator'],np.round((X_val50['he
```

Out[790]: 0.023420083661047517

In [786]:
```
X100 = X[X['helpful_denominator']>50]
X100 = X[X['helpful_denominator']<=100]

y100 = y[y['helpful_denominator']>50]
y100 = y[y['helpful_denominator']<=100]

X_train100, X_val100, y_train100, y_val100 = train_test_split(X100,y10

y_trainadj100 = y_train100['helpratio']
clf100 = RandomForestRegressor(bootstrap=True,
                              criterion='mse',
                              max_depth=None,
                              max_features='auto',
                              max_leaf_nodes=None,
                              #max_samples=None,
                              min_impurity_decrease=0.0,
                              min_impurity_split=None,
                              min_samples_leaf=1,
                              min_samples_split=2,
                              min_weight_fraction_leaf=0.0,
                              n_estimators=88,
                              n_jobs=None,
                              oob_score=False,random_state=42,
                              verbose=0,
                              warm_start=False)

clf100.fit(X_train100, y_trainadj100)
y_val_pred100 = clf100.predict(X_val100)
mean_absolute_error(y_val100['helpful_numerator'],np.round((X_val100['
```

Out[786]: 0.1697848924462231

In [787]:
```
X_train_valid100 = X100
y_train_valid100 = y100['helpratio']
clf100.fit(X_train_valid100,y_train_valid100)
y_val_pred100 = clf100.predict(X_val100)
mean_absolute_error(y_val100['helpful_numerator'],np.round((X_val100['
```

Out[787]: 0.025512756378189096

In [695]:
```
X_train_valid100 = X
y_train_valid100 = y['helpratio']
clf100.fit(X_train_valid100,y_train_valid100)
y_val_pred100 = clf100.predict(X_val100)
mean_absolute_error(y_val100['helpful_numerator'],np.round((X_val100['
```

Out[695]: 0.026613306653326663

In [487]:
```
sel = SelectFromModel(RandomForestRegressor(bootstrap=True,
                           criterion='mse',
                           max_depth=None,
                           max_features='auto',
                           max_leaf_nodes=None,
                           #max_samples=None,
                           min_impurity_decrease=0.0,
                           min_impurity_split=None,
                           min_samples_leaf=1,
                           min_samples_split=2,
                           min_weight_fraction_leaf=0.0,
                           n_estimators=87,
                           n_jobs=None,
                           oob_score=False,random_state=42,
                           verbose=0,
                           warm_start=False))
sel.fit(X_trainadj, y_trainadj)
sel.get_support()
selected_feat= X_train.columns[(sel.get_support())]
len(selected_feat)
print(selected_feat)
#pd.series(sel.estimator_,feature_importances_,.ravel()).hist()
```

```
Index(['unixReviewTime', 'helpful_denominator', 'ratiosuWord', 'revie
wChars',
       'reviewRead', 'ratiopunChar', 'ratiosCWords', 'numreviewPro',
       'reviewerratingavg', 'itemratingavg', 'reviewerratingratio',
       'itemratingratio', 'reviewTextpolarity', 'reviewTextsubjectivi
ty',
       'reviewText_flesch_reading_ease', 'reviewText_coleman_liau_ind
ex',
       'reviewText_dale_chall_readability_score',
       'reviewText_linsear_write_formula', 'summary_coleman_liau_inde
x',
       'summary_automated_readability_index'],
      dtype='object')
```

In [791]:
```
y_test_pred0 = clf0.predict(test_df1)
y_test_pred50 = clf50.predict(test_df1)
y_test_pred100 = clf100.predict(test_df1)

test_df['votingprob0'] = y_test_pred0
test_df['votingprob50'] = y_test_pred50
test_df['votingprob100'] = y_test_pred100
```

In [792]:
```
counter_test = 0
prediction_values = []
for i in test_df['helpful_denominator']:
    if i == 0:
```

```
            prediction_values.append(0)
    elif i == 1:
        if test_df.loc[counter_test,['rating']].item() >=3:
            prediction_values.append(1)
        else:
            prediction_values.append(0)
    elif i == 2:
        if test_df.loc[counter_test,['rating']].item() >=3:
            prediction_values.append(2)
        else:
            prediction_values.append(int(round(i*test_df.loc[counter_t
#    elif test_df.loc[counter_test,['rating']].item() ==5:
#        prediction_values.append(i)
#    elif test_df.loc[counter_test,['rating']].item() ==4:
#        prediction_values.append(i)
    #elif test_df.loc[counter_test,['rating']].item() ==1:
    #    if probas3[counter_test][1] < .5:
    #        prediction_values.append(0)
    #    else:
    #        prediction_values.append(int(round(i*probas3[counter_test
    #elif probas3[counter_test][1] <= .5:
    #    prediction_values.append(int(round(i*probas3[counter_test][0]
    #elif probas3[counter_test][1] <=.65:
        #print(probas3[counter_test][1])
    #    prediction_values.append(int(round(i*probas3[counter_test][1]
    #elif test_df.loc[counter_test,['helpful_denominator']].item() >=
    #    prediction_values.append(int(round(i*test_df.loc[counter_test
    elif test_df.loc[counter_test,['helpful_denominator']].item() > 10
        prediction_values.append(int(round(i*test_df.loc[counter_test,
    elif 100 >= test_df.loc[counter_test,['helpful_denominator']].item
        prediction_values.append(int(round(i*test_df.loc[counter_test,
    #elif 100 > test_df.loc[counter_test,['helpful_denominator']].item
    #    prediction_values.append(int(round(i*test_df.loc[counter_test
    #elif 50 > test_df.loc[counter_test,['helpful_denominator']].item(
    #    prediction_values.append(int(round(i*test_df.loc[counter_test
    else:
        prediction_values.append(int(round(i*test_df.loc[counter_test,
    counter_test += 1
prediction_values
```

```
/Users/felipegomez/anaconda3/lib/python3.7/site-packages/ipykernel_la
uncher.py:12: FutureWarning: `item` has been deprecated and will be r
emoved in a future version
  if sys.path[0] == '':
/Users/felipegomez/anaconda3/lib/python3.7/site-packages/ipykernel_la
uncher.py:7: FutureWarning: `item` has been deprecated and will be re
moved in a future version
  import sys
/Users/felipegomez/anaconda3/lib/python3.7/site-packages/ipykernel_la
uncher.py:32: FutureWarning: `item` has been deprecated and will be r
emoved in a future version
```

```
emoved in a future version
/Users/felipegomez/anaconda3/lib/python3.7/site-packages/ipykernel_la
uncher.py:34: FutureWarning: `item` has been deprecated and will be r
emoved in a future version
```

Out[792]:

```
[2,
 0,
 1,
 1,
 0,
```

In [793]:

```
len(prediction_values)
```

Out[793]:

```
14000
```

In [794]:

```
test_df.drop(columns=['predictions'])
```

Out[794]:

	categoryID	categories	itemID	reviewerID	rating	reviewText	reviewHash	revie
0	0	[[Sports & Outdoors, Other Sports, Dance, Clot...	I520932398	U816789534	3.0	I ordered according to the size chart but it's...	R157684793	201
1	0	[[Sports & Outdoors, Clothing, Women, Hoodies]...	I969532331	U987148846	4.0	Super thin but really cute and not cheap-looki...	R732719858	201
2	0	[[Clothing, Shoes & Jewelry, Women, Accessorie...	I149943341	U628436634	5.0	It was a present for my sis, and she loves Fle...	R352659313	201
3	0	[[Clothing, Shoes & Jewelry, Women, Accessorie...	I909025835	U924107228	5.0	I love this thing! I guess they don't make th...	R277416618	201
4	0	[[Clothing, Shoes & Jewelry, Women, Clothing, ...	I228439768	U060135484	4.0	I liked it and I wear it...it's a little bit s...	R645892076	201
...	...	...	...	...	...	...	...	
13995	1	[[Clothing, Shoes & Jewelry, Men, Clothing, Un...	I406509423	U574353061	5.0	Finding quality T-shirts that have a nice weig...	R049154817	201

13996	1	[[Clothing, Shoes & Jewelry, Jewelry: Internat...	I218952654	U171188645	5.0	If you're looking for a simple, no-frills watc...	R151835792	201(
13997	0	[[Clothing, Shoes & Jewelry, Shoes & Accessori...	I688499627	U531823347	5.0	What a steal, these croc shoes look like 500.0...	R365412489	201:
13998	4	[[Clothing, Shoes & Jewelry, Baby, Baby Girls,...	I989375414	U210776132	5.0	Perfect for a summer baby. I would not recomme...	R398291129	201‹
13999	0	[[Clothing, Shoes & Jewelry, Women], [Clothing...	I185673007	U012801435	5.0	These leggings fit great and look awesome! The...	R905355699	201:

14000 rows × 80 columns

In [795]:
```
test_df['predictions'] = prediction_values
```

In [796]:
```
counter = 0
predictions = open("predictions_Helpful_testdfRFR8.txt", 'w')
for l in open("pairs_Helpful.txt"):
  if l.startswith("userID"):
    #header
    predictions.write(l)
    continue
  u,i,outOf = l.strip().split('-')
  outOf = int(outOf)
  #for pred in b:
  predictions.write(u + '-' + i + '-' + str(outOf) + ',' + str(test_d
  counter +=1
  #else:
  #  predictions.write(u + '-' + i + '-' + str(outOf) + ',' + str(out(
predictions.close()
```

Final Report: Random Forest Regressor Model

In this project we develop predictive models for amazon reviews that will automatically predict the helpfulness of specific reviews to customers for items sold on Amazon. The objective of this project is to practice and learn how to adopt machine-learning algorithms to develop predictive models that automatically predict the helpfulness of specific reviews to customers. In this project as we focus soley on Amazon reviews, we must understand the relationship between Amazon, the customer and the reveiws for products left by customers.

The practicality of this project is illustrated in many e-commercial companies and companies that rely on the reviews of customers for products sold by their business in order to provide accurate details and information for each product. With each review, an evaluation of a product provides description for how useful an item will be for a company to sell online. All e-commercial businesses allow its users to write their opinions about products as voting either helpful or not helpful. All of these opinions are valuable and important for any potential buyers. Since e-commercial companies have the ability to sell online and therefore have competitive advantage over local businesses, these comapnies must rely on reliable reviews in order to inform and compete against other e-commerical and local businesses. Online customers must also rely on other information to help them make their purchase decisions. Thus, the importance of developing online communication channels between e-commerce businesses and customers as well as a form of communication between the customers becomes critically important for online buying.

In order to begin doing analysis of the Amazon product reviews, we must understand the information that is given to us to be able to apply models that will predict the helpfulness for each review. We use the code below to first read and open the two sets of data into dataframes. We have a train and test dataset, where we will use the training data to train a model to predict the usefulness of a review and with this model, we will predict the usefuless of the reviews in our test dataset.

In [ ]:
```
import pandas as pd
from collections import defaultdict

def readGz(f):
    for l in gzip.open(f):
        yield eval(l)

def parse(path):
    g = gzip.open(path, 'rb')
    for l in g:
        yield eval(l)

def getDF(path):
    i = 0
    df = {}
    for d in parse(path):
        df[i] = d
        i += 1
    return pd.DataFrame.from_dict(df, orient='index')

df = getDF('train.json.gz')
test_df = getDF('test_Helpful.json.gz')
```

Our datasets are composed of the following features:

categoryID: The ID of the category of products we will be focusing on.

categories: The description of the categories that the products are in.

itemID: The ID of the product, i.e. the product identification.

reviewerID: The ID of the reviewer, i.e. the reviewer identification.

rating: The score and rate of the product which ranges between 1 and 5.

reviewText: The review information and content that is provided by a user.

reviewHash: The review Hash of the review left by a customer.

reviewTime: The time posted for the review left by a customer.

summary: The summary is a short description and title about the review content that has been provided.

unixReviewTime: This is the unix time of review post.

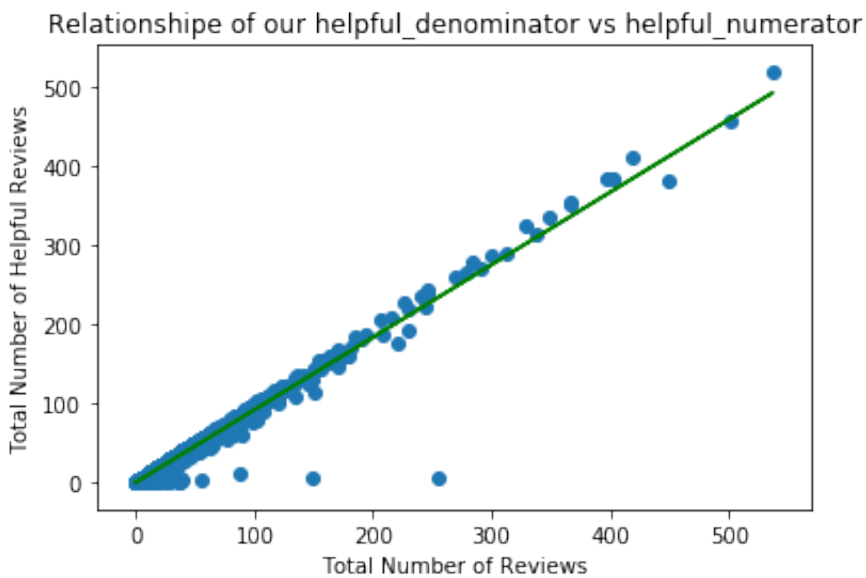
helpful: For the training set, we have how many reviews ended up becoming useful e.j. 4 out of 5. The test set will only have the "out of" number since we are predicting how many of those "out of" reveiws were helpful.

price: The price of a product.

Since we have as our main objective the task to predict the number of helpful reviews for the test data sets, we find that to receive a better accuracy on our prediction, we must predict on the ratio of the number of helpful reviews out of the total number of reviews. The reason behind this is that predicting the true number of helpful votes is many times more difficult than just predicting the ratio. By predicting the ratio, we can then easily get our number of useful votes by multiplying our ratio with the total number of reviews given for a product. We also focus only on products that have total number of reviews greater than 1 (so we filter out those with less than 2 reviews. We do this in order to not have our data skewed since if we have 0 voters, then we receive a ratio of 0% and if we have 1 review, we will receive either be 100% or 0%. We also fill all prices with NaNs by filling them with the mean of the prices.

Below is a graph where we can see and try to distinguish the ratio and relationship between the number our number of reviews vs the total number of helpful reviews.

In [554]:
```
#relationship between total votes and helpful votes
import matplotlib.pyplot as plt
import numpy as np
x_graph1 = df['helpful_denominator']
y_graph1 = df['helpful_numerator']
fig, ax = plt.subplots()
fit = np.polyfit(x_graph1,y_graph1,deg=1)
ax.plot(x_graph1, fit[0] * x_graph1 + fit[1], color = 'green')
ax.scatter(x_graph1,y_graph1)
ax.set_title('Relationshipe of our helpful_denominator vs helpful_nume
ax.set_xlabel("Total Number of Reviews")
ax.set_ylabel("Total Number of Helpful Reviews")
plt.show()
```



We can see a linear relationship between the number of helpful_denominators and helpful_numerators. We lso notice htat the majority of the points lie between 0-200 total number of reviews with the highest density being between 0 and 100. In this project, we focus on using the Random Forest Regressor Model to predict on the number of helpful numerators for each review in our test dataframe.

Our first approach to developing our Random Forest Regressor predictive model is to first develop and engineer features that we can use to train our model. Below is a list of the features we develop and include in our model and a brief description of the purpose for each feature.

'review_first_dif', This function will get the first review time for each item

'rating_mean_dev', This will tell us the rating score deviation from mean 'reviewWords', This will get the number of words of each review text

'summaryWords', This will tell us the mumber of words of each review summary

'ratiosuWord', This will tell us the ratio of summary words to review text words

'reviewSentences', This will tell us the number of sentences of each review text

'summarySentences', This will extract number of sentences of each summary text

'reviewChars', This will tell us the number of characters of each review text

''summaryChars', This will tell us the number of characters of each summary

'reviewRead', This will tell us the readability of each review (ARI as index to measure)

'reviewPuncts', This will tell us the number of punctuations of each review text

'ratiopunChar', This will tell us the ratio of punctuations with characters

'reviewCwords', This will tell us the number of capital words of each review text

'summaryCwords', This will tell us the number of capital words of each summary

'numexclquest', This will tell us the number of exclimation and question marks of each review text

'sunumexclquest', This will tell us the number of exclimation and question marks of each summary text

'numreviewPro', This will tell us the number of reviews of each product (measure the popularity of each product)

'numreviews', This will tell us the number of reviews of each reviewers (measure reviewer’s experience)

'ratiosCWords', This will tell us the ratio of reviewText words to review text words

These features will tell us about the sentiment for the reviewtext and the summary for each review: 'summarypolarity','summarysubjectivity','reviewTextpolarity', 'reviewTextsubjectivity'.

These features will tell us information on the reviewtext and summary by calculating statistics from text to determine readability, complexity and grade level of a particular corpus: 'reviewTextpolarity', 'reviewTextsubjectivity', 'reviewText_flesch_reading_ease', 'reviewText_smog_index', 'reviewText_coleman_liau_index', 'reviewText_automated_readability_index', 'reviewText_dale_chall_readability_score', 'reviewText_difficult_word', 'reviewText_linsear_write_formula', 'reviewText_gunning_fog', 'reviewText_text_standard', 'summary_flesch_reading_ease', 'summary_smog_index', 'summary_coleman_liau_index', 'summary_automated_readability_index', 'summary_dale_chall_readability_score', 'summary_difficult_word', 'summary_linsear_write_formula', 'summary_gunning_fog', 'summary_text_standard','reviewText_flesch_kincaid_grade','summary_flesch_kincaid_grade', 'summary_text_standartcat'.

'reviewerratingavg', This will tell us the ratio of the average number of the overall ratings.

'itemratingavg', This will tell us the ratio of the average rating number per item in our data set.

'reviewerratingratio', This will tell us the ratio of each rating divided by the average rating overall.

'itemratingratio', This will tell us the ratio for each item of each rating divided bby the average item rating.

'suratioCwords', This tells us a ratio for each summary text of the number of words in the summary text divided by the number of words of the summary words.

'helpful_numerator' (only for our training set), This will tell us the number of helpful reviews for each review.

'helpful_denominator', This will tell us the overall number of reviews.

'helpratio' (only for our training set), This is the ratio of the number of our helpful reviews divided by the overall number of reviews.

'rwavgwords', This is telling us the averageword count by the reviewer

'review_word_length_ratio', This is telling us the ratio of the word length of the review text.

'review_word_mean_by_reviewer', This is telling us the mean of the review text by the reviewer

'summary_word_length_ratio', This is telling us the ratio of the summary word length

'ratDevmean', This is telling us the deviation of the rating from its mean, along with the absolute deviation

'ratDevmean_abs', This is telling us the deviation of the rating from its mean, along with the absolute deviation

We take a look at some of our top features that we include in our final Random Forest Regressor model:

'rating', 'price', 'helpful_denominator', 'unixReviewTime', 'review_first_dif', 'ratDevmean', 'reviewRead',
'ratiosCWords', 'reviewerratingavg', 'itemratingavg',
'itemratingratio', 'summarypolarity', 'summarysubjectivity', 'reviewerratingratio',
'reviewWords', 'summaryWords', 'ratiosuWord', 'reviewSentences', 'summarySentences',
'reviewChars', 'summaryChars', 'reviewText_flesch_reading_ease', 'reviewText_smog_index',
'reviewText_flesch_kincaid_grade', 'reviewText_coleman_liau_index',
'reviewText_automated_readability_index', 'reviewText_dale_chall_readability_score',
'reviewText_difficult_word', 'reviewText_linsear_write_formula',
'reviewText_text_standardcat', 'reviewText_gunning_fog', 'reviewPuncts', 'summaryPuncts',
'ratiopunChar', 'suratioCwords', 'summaryratiopunChar', 'reviewCwords',
'summaryCwords', 'numexclquest', 'sunumexclquest', 'numreviewPro', 'numreviews',
'reviewTextpolarity', 'reviewTextsubjectivity', 'rwavgwords', 'review_word_length_ratio',
'review_word_mean_by_reviewer', 'summary_word_length_ratio',
'summary_automated_readability_index', 'summary_flesch_reading_ease',
'summary_smog_index', 'summary_coleman_liau_index',
'summary_dale_chall_readability_score', 'summary_difficult_word',
'summary_linsear_write_formula', 'summary_flesch_kincaid_grade'

These features will be filtered on both our train and test dataframes. We then select our model: "Random Forest Regressor" as our method of predicting our ratio to use to get our predicted number of helpful votes.

Before testing our model we have to replace all NaNs, -inf and inf from out train and test dataframes by applying replace([np.inf, -np.inf], np.nan).fillna(0). This is part of the data cleansing process, since our random forest regressor model would error out on NaNs and inf. values.

We set our X and y dataframe for which we will use our train_test_split function will be:

X = df1

y = df[['helpratio','helpful_numerator','helpful_denominator']]

Before we apply our train_test_split function, we split our X and y dataframes into 3 seperate groups. We distinguish the rows that have total number of reviews between 2 and 50, 50 and 100 and one

Here we want to illustrate the correlations between each feature to see which features are high correlated with other features.

In [667]:
```
X.corr()
```

Out[667]:

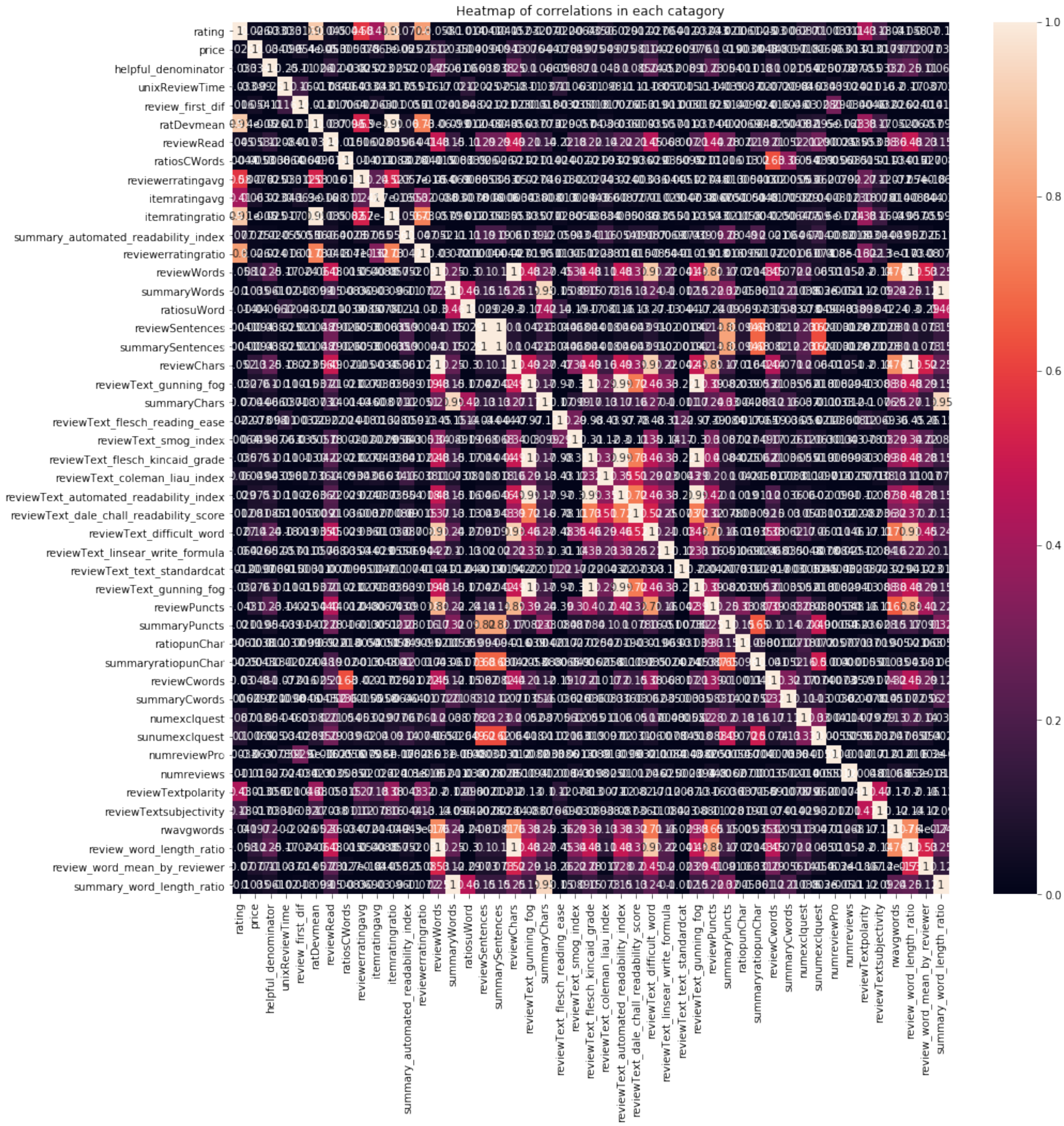
	rating	price	helpful_denominator	unixReviewTi
rating	1.000000	0.025807	-0.032558	-0.032
price	0.025807	1.000000	0.033624	-0.099
helpful_denominator	-0.032558	0.033624	1.000000	-0.250
unixReviewTime	-0.032988	-0.099423	-0.250942	1.000
review_first_dif	0.015930	0.054453	-0.109646	0.163
ratDevmean	0.913310	-0.000054	-0.025581	-0.017
reviewRead	0.045302	0.052526	0.124233	-0.084
ratiosCWords	0.004354	-0.005296	-0.003780	0.006
reviewerratingavg	0.577399	0.007787	-0.024720	-0.032
itemratingavg	0.407266	0.063488	-0.022577	-0.042
itemratingratio	0.905441	-0.000051	-0.024726	-0.016
summary_automated_readability_index	0.077051	0.024600	0.020160	-0.055
reviewerratingratio	0.802533	0.025858	-0.024098	-0.015
reviewWords	-0.058035	0.124098	0.249519	-0.170
summaryWords	-0.102549	0.034867	0.060557	-0.020
ratiosuWord	-0.014193	-0.040413	-0.066322	0.118
reviewSentences	0.004129	0.009354	0.037974	-0.025
summarySentences	0.004129	0.009354	0.037974	-0.025

reviewChars	-0.052321	0.127330	0.252435	-0.175
reviewText_gunning_fog	-0.032193	0.076190	0.099801	-0.108
summaryChars	-0.070225	0.044330	0.066183	-0.037
reviewText_flesch_reading_ease	0.021579	-0.078111	-0.098367	0.111
reviewText_smog_index	-0.006429	0.049057	0.086591	-0.062
reviewText_flesch_kincaid_grade	-0.034609	0.075422	0.100618	-0.109
reviewText_coleman_liau_index	0.060090	0.048925	0.043281	-0.098
reviewText_automated_readability_index	-0.029455	0.075279	0.101837	-0.111
reviewText_dale_chall_readability_score	0.011940	0.080632	0.085331	-0.109
reviewText_difficult_word	-0.027486	0.141870	0.242014	-0.181
reviewText_linsear_write_formula	-0.064462	0.026496	0.051899	-0.056
reviewText_text_standardcat	0.011584	-0.009672	-0.008898	0.001
reviewText_gunning_fog	-0.032193	0.076190	0.099801	-0.108
reviewPuncts	-0.043229	0.103054	0.231345	-0.142
summaryPuncts	-0.020625	0.019397	0.053825	-0.038
ratiopunChar	0.006122	-0.003778	0.011250	0.003
summaryratiopunChar	0.002490	-0.004252	0.017782	-0.019
reviewCwords	-0.030189	0.047508	0.102341	-0.071
summaryCwords	-0.006248	0.009654	0.021425	-0.009
numexclquest	0.086529	0.017520	0.054257	-0.046
sunumexclquest	0.102837	0.006852	0.025191	-0.033
numreviewPro	0.003291	-0.063240	-0.007828	0.039

numreviews	0.011284	-0.012925	0.027390	-0.023
reviewTextpolarity	0.425880	-0.012579	-0.055445	0.020
reviewTextsubjectivity	0.182651	-0.017228	-0.033040	0.016
rwavgwords	-0.041354	0.097409	0.203996	-0.195
review_word_length_ratio	-0.058035	0.124098	0.249519	-0.170
review_word_mean_by_reviewer	-0.070188	0.076785	0.107365	-0.037
summary_word_length_ratio	-0.102549	0.034867	0.060557	-0.020

47 rows × 47 columns

In [668]:
```
correlations = X.corr()
plt.figure(figsize = (15,15))
plt.title("Heatmap of correlations in each catagory")
_ = sns.heatmap(correlations, vmin=0, vmax=1, annot=True)
```



We notice that there are some features that have high correlations with other features (those with brighter colors). The correlations heat map can also tell us which features will add of more importance to our model.

The code below is an excerpt of our training model that uses Random Forest Regressor on all the rows of our training set where we have total number of reviews greater than 0. This is the format we use to train our model and to predict on our validation set. We use train_test_split for this grouping with test_size = .2. We call this test group our validation group. After we fit our model, we retrain our model with the entire group which includes the train and validation group in order to have a better model for our test predictions. We decide to use a random forest regerssor as our model with 88 number of estimators because, a random forest is a meta estimator that fits a number of classifying decision trees on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. A Random Forest is an ensemble technique capable of performing both regression and classification tasks with the use of multiple decision trees and a technique called Bootstrap Aggregation, commonly known as bagging, where bagging, in the Random Forest method, involves training each decision tree on a different data sample where sampling is done with replacement. The basic idea behind this is to combine multiple decision trees in determining the final output rather than relying on individual decision trees. It operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. A random forest is a meta-estimator (i.e. it combines the result of multiple predictions) which aggregates many decision trees, with some helpful modifications: The number of features that can be split on at each node is limited to some percentage of the total (which is known as the hyperparameter). This ensures that the ensemble model does not rely too heavily on any individual feature, and makes fair use of all potentially predictive features. Each tree draws a random sample from the original data set when generating its splits, adding a further element of randomness that prevents overfitting.

This is the beginning of the code for this group of our Random Forest Regressor Modeling.

X_0 = X[X['helpful_denominator']>1]

y_0 = y[y['helpful_denominator']>1]

X_train0, X_val0, y_train0, y_val0 = train_test_split(X_0,y_0, test_size=0.2, random_state=42)

y_trainadj0 = y_train0['helpratio'] clf0 = RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None, max_features='auto', max_leaf_nodes=None,

```
                                    #max_samples=None,
                                    min_impurity_decrease=0.0,
                                    min_impurity_split=None,
                                    min_samples_leaf=1,
                                    min_samples_split=2,
                                    min_weight_fraction_leaf=0.0,
                                    n_estimators=88,
                                    n_jobs=None,
                                    oob_score=False,random_state=42,
                                    verbose=0,
                                    warm_start=False)
```

clf0.fit(X_train0, y_trainadj0) y_val_pred0 = clf0.predict(X_val0) mean_absolute_error(y_val0['helpful_numerator'],np.round((X_val0['helpful_denominator']*y_va

X_train_valid0 = X_0 y_train_valid0 = y_0['helpratio'] clf0.fit(X_train_valid0,y_train_valid0) y_val_pred0 = clf0.predict(X_val0) mean_absolute_error(y_val0['helpful_numerator'],np.round((X_val0['helpful_denominator']*y_va

Optional: This set of code can look at our current final list of features and tell you which features would be considered the most important for our model.

sel = SelectFromModel(RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None, max_features='auto', max_leaf_nodes=None,

```
                                    #max_samples=None,
                                    min_impurity_decrease=0.0,
                                    min_impurity_split=None,
                                    min_samples_leaf=1,
                                    min_samples_split=2,
                                    min_weight_fraction_leaf=0.0,
                                    n_estimators=87,
                                    n_jobs=None,
                                    oob_score=False,random_state=42,
                                    verbose=0,
                                    warm_start=False))
```

sel.fit(X_trainadj, y_trainadj) sel.get_support() selected_feat= X_train.columns[(sel.get_support())] len(selected_feat) print(selected_feat)

In my approach, I try to obtain the lowest Mean Absolute Error (MAE) for all of the 3 groups against the validation sets. Mean Absolute Error of your model refers to the mean of the absolute values of each prediction error on all instances of the test data-set. Prediction error is the difference between the actual value and the predicted value for that instance. This was of course done by adding and removing features when hypertuning. I would get around .16-.17 in my MAEs against the validation sets.

Once we train and retrain our models for each grouping, we get our final probabilities for each prediction from each group and we append these probabilities to our final test dataframe.

y_test_pred0 = clf0.predict(test_df1)

y_test_pred50 = clf50.predict(test_df1)

y_test_pred100 = clf100.predict(test_df1)

#y_test_pred200 = clf200.predict(test_df1)

test_df['votingprob0'] = y_test_pred0

test_df['votingprob50'] = y_test_pred50

test_df['votingprob100'] = y_test_pred100

Once this step is completed, it becomes time to get our final prediction for the number of helpful reviews. This for loop looks at each row, and based on the number of the helpful denominator reviews, it will predict the final number by multiplying that helpful denominator times the probability we get from the specific group it lies in. So if the row has 45 number of reviews, we search in our 'votingprob50' column for the probability and multiply that probability by 45 to get our final number of helpful reviews.

"counter_test = 0

prediction_values = []

for i in test_df['helpful_denominator']:

```
if i == 0:

    prediction_values.append(0)

elif i == 1:

    if test_df.loc[counter_test,['rating']].item() >=3:
```

```
            prediction_values.append(1)

        else:

            prediction_values.append(0)

    elif i == 2:

        if test_df.loc[counter_test,['rating']].item() >=3:

            prediction_values.append(2)

        else:

            prediction_values.append(int(round(i*test_df.loc[count
    er_test,'votingprob50'],0)))

    elif test_df.loc[counter_test,['helpful_denominator']].item()
    > 100:

        prediction_values.append(int(round(i*test_df.loc[counter_t
    est,'votingprob0'],0)))

    elif 100 >= test_df.loc[counter_test,['helpful_denominator']].
    item() > 50:

        prediction_values.append(int(round(i*test_df.loc[counter_t
    est,'votingprob100'],0)))

    else:

        prediction_values.append(int(round(i*test_df.loc[counter_t
    est,'votingprob50'],0)))

    counter_test += 1
```

prediction_values"

Once this code is finished running, we double check to make sure we have 14000 values in our column and then we append these final values to our test dataframe.

Once this has been completed, we then run our last set of code to create a text file with our final predictions and finish the job!

"counter = 0 predictions = open("predictions_Helpful_testdf.txt", 'w') for l in open("pairs_Helpful.txt"): if l.startswith("userID"):

```
#header
predictions.write(l)
continue
```

u,i,outOf = l.strip().split('-') outOf = int(outOf)

#for pred in b: predictions.write(u + '-' + i + '-' + str(outOf) + ',' + str(test_df.loc[counter,'predictions']) + '\n') counter +=1

#else:

#predictions.write(u + '-' + i + '-' + str(outOf) + ',' + str(outOf*averageRate) + '\n') predictions.close()"

We then submit this file to Kaggle and upload!

In [ ]: