PA Assignment 2

March 4, 2024

1 BDA STUDY REPLICATION

ASSIGNMENT 2 by DONATO SCARANO

In this assignment, I am replicating the study conducted by Muller at al 16: https://canvas.ltu.se/courses/21054/files/3591424?wrap=1 to predict the helpfulness of online customer reviews.

I am using as in the study the reviews for the video games category.

1.1 RESEARCH QUESTION

What we want to address is the question of 'What makes a helpful online review?' (Mudambi & Schuff, 2010). We are building a predictive model for review helpfulnews that can be valuable in many practical and theoretical contexts from proper sorting to filtering to understanding how to write effective reviews and discovering hidden relationships between features.

1.2 DATA COLLECTION

We pre-process and transform the data to restrict our focus on valuable information and remove duplicates and reduce our dataset.

[6]:
```
#import libraries

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import gzip
import json

#import json review data
reviews_data = []
with gzip.open('reviews_Video_Games.json.gz', 'rt', encoding='utf-8') as file:
    for line in file:
        review = json.loads(line)
        reviews_data.append(review)

#count the number of reviews in the file
num_reviews = len(reviews_data)
print('Number of Reviews:',num_reviews)
```

```
reviews_data[:5]
```

```
Number of Reviews: 1324753
```

[6]:

```
[{'reviewerID': 'AB9S9279OZ3QO',
  'asin': '0078764343',
  'reviewerName': 'Alan',
  'helpful': [1, 1],
  'reviewText': "I haven't gotten around to playing the campaign but the
multiplayer is solid and pretty fun. Includes Zero Dark Thirty pack, an Online
Pass, and the all powerful Battlefield 4 Beta access.",
  'overall': 5.0,
  'summary': 'Good game and Beta access!!',
  'unixReviewTime': 1373155200,
  'reviewTime': '07 7, 2013'},
 {'reviewerID': 'A24SSUT5CSW8BH',
  'asin': '0078764343',
  'reviewerName': 'Kindle Customer',
  'helpful': [0, 0],
  'reviewText': 'I want to start off by saying I have never played the Call of
Duty games. This is only the second first person shooter game that I have own. I
think it is a lot of fun. Has good graphics and nice story line. It does take
some skill to get through the levels. I think all players can enjoy this game.
There are three levels to choose from based on your skill level. If your looking
for first person shooter game that has current military type play than this is a
good buy.',
  'overall': 5.0,
  'summary': 'Love the game',
  'unixReviewTime': 1377302400,
  'reviewTime': '08 24, 2013'},
 {'reviewerID': 'AK3V0HEBJMQ7J',
  'asin': '0078764343',
  'reviewerName': 'Miss Kris "Krissy"',
  'helpful': [0, 0],
  'reviewText': 'this will be my second medal of honor I love how the
incorporate real life military stories in the game great',
  'overall': 4.0,
  'summary': 'MOH nice',
  'unixReviewTime': 1372896000,
  'reviewTime': '07 4, 2013'},
 {'reviewerID': 'A10BECPH7W8HM7',
  'asin': '043933702X',
  'reviewerName': 'GMC "Old Time Modeler"',
  'helpful': [0, 0],
  'reviewText': 'great game when it first came out, and still a great game',
  'overall': 5.0,
```

```
  'summary': 'Five Stars',
  'unixReviewTime': 1404950400,
  'reviewTime': '07 10, 2014'},
 {'reviewerID': 'A2PRV9OULX1TWP',
  'asin': '043933702X',
  'reviewerName': 'grimi',
  'helpful': [0, 0],
  'reviewText': 'this is the first need for speed I bought years and years ago.
I lost it so I bought this for a trip down memory lane.  Pretty tame by todays
games.  It brought back memories of fun times.',
  'overall': 5.0,
  'summary': 'memory lane',
  'unixReviewTime': 1386115200,
  'reviewTime': '12 4, 2013'}]
```

[8]:
```python
# Create a DataFrame from the list of dictionaries
df = pd.DataFrame(reviews_data)

# Check for duplicate reviews based on a subset of columns
duplicate_reviews = df[df.duplicated(subset=['reviewerID', 'reviewText'])]

# Count the number of unique reviews
num_unique_reviews = df.drop_duplicates(subset=['reviewerID', 'reviewText']).
 ↪shape[0]

num_unique_reviews
```

[8]: 1324753

[10]:
```python
# Display the DataFrame
display(df.head())
```

```
       reviewerID        asin            reviewerName helpful  \
0   AB9S9279OZ3QO  0078764343                    Alan  [1, 1]
1  A24SSUT5CSW8BH  0078764343         Kindle Customer  [0, 0]
2   AK3V0HEBJMQ7J  0078764343      Miss Kris "Krissy"  [0, 0]
3  A10BECPH7W8HM7  043933702X  GMC "Old Time Modeler"  [0, 0]
4  A2PRV9OULX1TWP  043933702X                   grimi  [0, 0]

                                          reviewText  overall  \
0  I haven't gotten around to playing the campaig…      5.0
1  I want to start off by saying I have never pla…      5.0
2  this will be my second medal of honor I love h…      4.0
3  great game when it first came out, and still a…      5.0
4  this is the first need for speed I bought year…      5.0

                    summary  unixReviewTime   reviewTime
0  Good game and Beta access!!      1373155200   07 7, 2013
```

```
1                Love the game      1377302400  08 24, 2013
2                     MOH nice      1372896000   07 4, 2013
3                   Five Stars      1404950400  07 10, 2014
4                  memory lane      1386115200   12 4, 2013
```

[12]:
```python
review_counts = df['asin'].value_counts().reset_index()
review_counts.columns = ['Game ID', 'Review Count']
display(review_counts)
```

```
          Game ID  Review Count
0      B00DJFIMW6         16221
1      B00BGA9WK2          7561
2      B00FAX6XQC          5713
3      B009KS4XRO          5489
4      B002VBWIP6          5190
…             …            …
50205  B005CT3MZO             1
50206  B005CTCT76             1
50207  B005CTXMH2             1
50208  B005CU87LW             1
50209  B00LIWF1GW             1

[50210 rows x 2 columns]
```

[14]:
```python
display("Average Rating", df['overall'].mean())  # Average rating
```

```
'Average Rating'

3.9787537752320623
```

[16]:
```python
#overview of helpfulness rating

# Count the frequency of each helpfulness ratio value
helpfulness_counts = df['helpful'].value_counts().reset_index()
helpfulness_counts.columns = ['Helpfulness Ratio', 'Frequency']
display(helpfulness_counts)
```

```
     Helpfulness Ratio  Frequency
0               [0, 0]     626596
1               [1, 1]     121624
2               [0, 1]      83396
3               [1, 2]      48551
4               [2, 2]      43158
…                  …          …
7934        [781, 823]          1
7935         [97, 141]          1
7936        [280, 361]          1
7937        [117, 143]          1
7938         [24, 113]          1
```

[7939 rows x 2 columns]

Over half of the reviews do not have any helpfulness rating (neither positive nor negative) We are going to exclude reviews with less than two helpfulness ratings to increase the reliability of the analysis

[19]:
```
# Filter out reviews with less than two helpfulness ratings

def filter_helpful(row):
    return row[0] >= 2 and row[1] >= 2

# Apply the function to the 'helpful' column
df2 = df[df['helpful'].apply(filter_helpful)]

# Display the filtered DataFrame
display(df2)
```

```
            reviewerID        asin              reviewerName   helpful  \
9        A182S3ANC0W7DL  0439342260                     James    [2, 2]
12        APDCEJMFD02YT  0439394422  L. Murray "common sense"    [2, 3]
13        AFJ7A9CSEPZNY  043940133X                  B. Vega  [22, 24]
15       A2H3TQWU51W1WE  043940133X                ethans mom    [3, 3]
16       A3K010N20DLHBR  043940133X         Golden Gopher Mom    [8, 8]
…                   …           …                       …       …
1324722  A3RK6IJ1BLFJKX  B00L3KU0S8                   Pete p.    [2, 2]
1324723   AGV7DRPGUQRRJ  B00L3KU0S8                  Wayne B.    [3, 3]
1324724  A3LEQ0LIXQU7KS  B00L45HS50                 nuttytoad    [2, 2]
1324741  A2FDUH8LZBYS7G  B00LBAM588                      Sary    [2, 2]
1324742  A1K7X23UDT0R7V  B00LBAM588           Winston D. Jen    [7, 7]

                                                  reviewText  overall  \
9        I am an Ice Cream Truck Vendor (I lease out 20…      4.0
12       Such fast shipping, games is such great condit…      5.0
13       My son hates math!  But, he loves Star Wars an…      4.0
15       My son who hates doing math loves to play this…      5.0
16       My seven year old has had a lot of fun with th…      5.0
…                                                   …        …
1324722                              It's good dust cover      5.0
1324723  Let me say that i bought covers in the past an…      5.0
1324724  I really liked this game.  The graphics were e…      4.0
1324741                                       badass game      5.0
1324742  I was fortunate enough to purchase and enjoy t…      5.0

                                                 summary  unixReviewTime  \
9                        Teach Business to Kids & Adults      1355875200
12                                       AMAZING COMPANY      1285545600
13                 Math fun for the mathmatically challenged      1168300800
15                Great math game for your little Star Wars fan      1299456000
```

```
16                                              Great game!      1258329600
…                                                         …               …
1324722                                          Five Stars      1405382400
1324723                                     Awesome cover!!      1404864000
1324724                                         Great game!      1404518400
1324741  this is my first time playing this game, amazi…      1404691200
1324742                        Outstrips all other DWG Games!      1404086400

          reviewTime
9        12 19, 2012
12       09 27, 2010
13        01 9, 2007
15        03 7, 2011
16       11 16, 2009
…                ...
1324722  07 15, 2014
1324723   07 9, 2014
1324724   07 5, 2014
1324741   07 7, 2014
1324742  06 30, 2014

[348994 rows x 9 columns]
```

[87]:

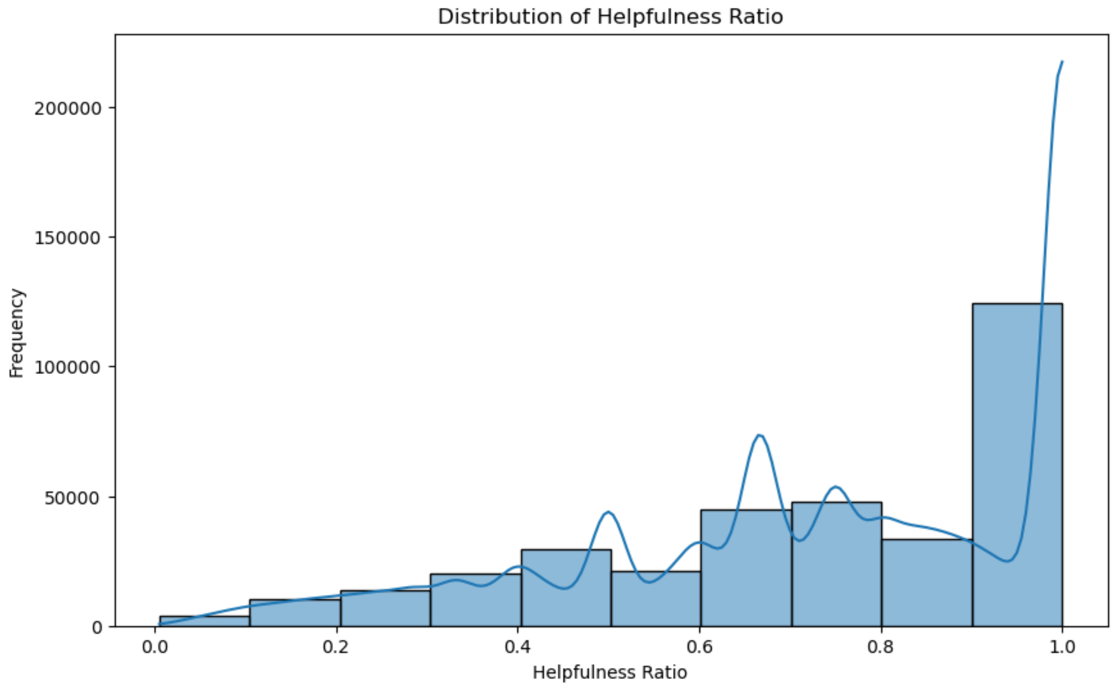
```python
# Define a function to calculate the helpfulness ratio
def calculate_helpfulness(row):
    helpful_votes, total_votes = row['helpful']
    if total_votes > 0:
        return helpful_votes / total_votes
    else:
        return 0

# Create a copy of the DataFrame
df2 = df2.copy()

# Now you can safely perform the assignment without warnings
df2.loc[:,'Helpfulness_ratio'] = df2.apply(calculate_helpfulness, axis=1)

# Display the DataFrame
display(df2.head())
```

```
       reviewerID        asin              reviewerName   helpful  \
9   A182S3ANCOW7DL  0439342260                     James    [2, 2]
12   APDCEJMFDO2YT  0439394422  L. Murray "common sense"    [2, 3]
13   AFJ7A9CSEPZNY  043940133X                  B. Vega  [22, 24]
15  A2H3TQWU51W1WE  043940133X                ethans mom    [3, 3]
16  A3KO1ON2ODLHBR  043940133X         Golden Gopher Mom    [8, 8]

                                          reviewText  overall  \
```

```
9   I am an Ice Cream Truck Vendor (I lease out 20…      4.0
12  Such fast shipping, games is such great condit…      5.0
13  My son hates math!  But, he loves Star Wars an…      4.0
15  My son who hates doing math loves to play this…      5.0
16  My seven year old has had a lot of fun with th…      5.0

                                          summary  unixReviewTime  \
9                  Teach Business to Kids & Adults      1355875200
12                                 AMAZING COMPANY      1285545600
13      Math fun for the mathmatically challenged      1168300800
15  Great math game for your little Star Wars fan      1299456000
16                                     Great game!      1258329600

     reviewTime  Helpfulness_ratio Helpfulness_dichotomized  \
9   12 19, 2012           1.000000                  helpful
12  09 27, 2010           0.666667                  helpful
13   01 9, 2007           0.916667                  helpful
15   03 7, 2011           1.000000                  helpful
16  11 16, 2009           1.000000                  helpful

                                     processed_text  \
9   [ice, cream, truck, vendor, lease, 20+, trucks…
12  [fast, shipping, games, great, condition, even…
13  [son, hates, math, loves, star, wars, jabba, m…
15  [son, hates, math, loves, play, game, like, fa…
16  [seven, year, old, lot, fun, game, learning, m…

                                       topic_vector
9   [(1, 0.17666943), (3, 0.34843966), (4, 0.42206…
12                 [(0, 0.4769955), (1, 0.5013463)]
13  [(1, 0.4695875), (3, 0.28728595), (5, 0.127228…
15  [(1, 0.34097922), (3, 0.16749965), (4, 0.19994…
16  [(0, 0.15206017), (1, 0.68123645), (4, 0.13124…
```

[31]:

```
# Plot the distribution of the 'Helpfulness_ratio'
plt.figure(figsize=(10, 6))
sns.histplot(df2['Helpfulness_ratio'], bins=10, kde=True)
plt.title('Distribution of Helpfulness Ratio')
plt.xlabel('Helpfulness Ratio')
plt.ylabel('Frequency')
plt.show()
```



In order to avoid statistical concerns arising from the extreme distribution of values, we dichotomised the review helpfulness variable (i.e., reviews with a helpfulness ratio of > 0.5 were recoded as helpful, and reviews 0.5 as not helpful).

[36]:
```python
# Define a function to dichotomize the helpfulness ratio
def dichotomize_helpfulness(df2):
    if df2['Helpfulness_ratio'] > 0.5:
        return 'helpful'
    else:
        return 'not helpful'

# Apply the function to each review
df2['Helpfulness_dichotomized'] = df2.apply(dichotomize_helpfulness, axis=1)

# Display the DataFrame
display(df2)
```

```
             reviewerID        asin              reviewerName   helpful  \
9        A182S3ANC0W7DL  0439342260                     James    [2, 2]
12        APDCEJMFD02YT  0439394422  L. Murray "common sense"    [2, 3]
13        AFJ7A9CSEPZNY  043940133X                  B. Vega  [22, 24]
15       A2H3TQWU51W1WE  043940133X                ethans mom    [3, 3]
16       A3K010N20DLHBR  043940133X         Golden Gopher Mom    [8, 8]
…                     …           …                         …         …
1324722  A3RK6IJ1BLFJKX  B00L3KU0S8                   Pete p.    [2, 2]
1324723   AGV7DRPGUQRRJ  B00L3KU0S8                  Wayne B.    [3, 3]
```

```
1324724  A3LEQOLIXQU7KS  B00L45HS50              nuttytoad    [2, 2]
1324741  A2FDUH8LZBYS7G  B00LBAM588                   Sary    [2, 2]
1324742  A1K7X23UDTOR7V  B00LBAM588         Winston D. Jen    [7, 7]

                                                reviewText  overall  \
9        I am an Ice Cream Truck Vendor (I lease out 20…      4.0
12       Such fast shipping, games is such great condit…      5.0
13       My son hates math!  But, he loves Star Wars an…      4.0
15       My son who hates doing math loves to play this…      5.0
16       My seven year old has had a lot of fun with th…      5.0
…                                                      …      …
1324722                               It's good dust cover      5.0
1324723  Let me say that i bought covers in the past an…      5.0
1324724  I really liked this game.  The graphics were e…      4.0
1324741                                        badass game      5.0
1324742  I was fortunate enough to purchase and enjoy t…      5.0

                                                   summary  unixReviewTime  \
9                             Teach Business to Kids & Adults      1355875200
12                                         AMAZING COMPANY      1285545600
13                  Math fun for the mathmatically challenged      1168300800
15              Great math game for your little Star Wars fan      1299456000
16                                             Great game!      1258329600
…                                                        …               …
1324722                                         Five Stars      1405382400
1324723                                    Awesome cover!!      1404864000
1324724                                        Great game!      1404518400
1324741  this is my first time playing this game, amazi…      1404691200
1324742                      Outstrips all other DWG Games!      1404086400

          reviewTime  Helpfulness_ratio Helpfulness_dichotomized
9        12 19, 2012           1.000000                  helpful
12       09 27, 2010           0.666667                  helpful
13        01 9, 2007           0.916667                  helpful
15        03 7, 2011           1.000000                  helpful
16       11 16, 2009           1.000000                  helpful
…                  …                  …                      …
1324722  07 15, 2014           1.000000                  helpful
1324723   07 9, 2014           1.000000                  helpful
1324724   07 5, 2014           1.000000                  helpful
1324741   07 7, 2014           1.000000                  helpful
1324742  06 30, 2014           1.000000                  helpful

[348994 rows x 11 columns]
```

1.3 DATA ANALYSIS

Early researches focused mostly on the overall rating or the star rating although recently many studies have started to analyze the text of the reviews(e.g.,Mudambi & Schuff, 2010;Cao et al, 2011; Ghose & Ipeirotis, 2011; Pan & Zhang, 2011; Korfiatisa et al, 2012). To capture the review content and its impact on the helpfulness of the review we use probabilistic topic modelling using LDA (Latent Dirichlet Allocation) algorithm.

Probabilistic topic models are unsupervised algorithms that annotate the documents with topic labels.

The foundational idea is the distributional hypothesis of statistical semantics; words that occur togheter in similar contexts tend to have similar meanings (Turney & Pantel, 2010).

[40]:
```
import nltk
from gensim import corpora, models
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
import string
nltk.download('stopwords')
nltk.download('punkt')

# Preprocess the text
stop_words = set(stopwords.words('english'))
df2['processed_text'] = df2['reviewText'].apply(lambda x: [word for word in␣
↪word_tokenize(x.lower()) if word not in stop_words and word not in string.
↪punctuation])

# Create a dictionary representation of the documents
dictionary = corpora.Dictionary(df2['processed_text'])

# Convert the collection of texts to a bag of words
corpus = [dictionary.doc2bow(text) for text in df2['processed_text']]

# Train the LDA model and reduce the num_topics to 10 from 100 in the study to␣
↪avoid issues with computing resources as my machine is not powerful enough␣
↪and tend to crash
lda_model = models.LdaModel(corpus, num_topics=10, id2word=dictionary,␣
↪passes=10)

# Annotate each review with a vector of topic probabilities
df2['topic_vector'] = df2['processed_text'].apply(lambda x: lda_model.
↪get_document_topics(dictionary.doc2bow(x)))
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\donsc\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\donsc\AppData\Roaming\nltk_data…
```

```
[nltk_data]   Package punkt is already up-to-date!
```

[360]:
```python
# Display the DataFrame
display(df2['topic_vector'].head())
```

```
0    [(1, 0.17666943), (3, 0.34843966), (4, 0.42206…
1                       [(0, 0.4769955), (1, 0.5013463)]
2    [(1, 0.4695875), (3, 0.28728595), (5, 0.127228…
3    [(1, 0.34097922), (3, 0.16749965), (4, 0.19994…
4    [(0, 0.15206017), (1, 0.68123645), (4, 0.13124…
Name: topic_vector, dtype: object
```

[378]:
```python
import pandas as pd

# Create a new DataFrame to store the separated values
separated_df = pd.DataFrame(df2['topic_vector'].tolist())

# Remove the first pair values (1, 0, 5, etc.) and keep only the second values
separated_df = separated_df.apply(lambda row: row.apply(lambda x: x[1] if x is␣
↪not None else None))

# Add a column to store the length of each list
separated_df['length'] = separated_df.apply(lambda row: len(row), axis=1)

# Rename the columns to match the desired format
separated_df.columns = [str(i) for i in range(len(separated_df.columns))]

# Remove NaN values by replacing them with an empty string
separated_df = separated_df.fillna('0')

print(separated_df)
```

```
               0         1         2         3         4         5         6  \
0       0.176669   0.34844  0.422061  0.041456         0         0         0
1       0.476995  0.501346         0         0         0         0         0
2       0.469588  0.287286  0.127228  0.090886         0         0         0
3       0.340979    0.1675  0.199947  0.266546         0         0         0
4       0.152060  0.681236  0.131242         0         0         0         0
…            …         …         …         …         …         …
348989  0.819929   0.02001  0.020004  0.020008  0.020005  0.020011  0.020005
348990  0.710530  0.227915         0         0         0         0         0
348991  0.245390  0.710145         0         0         0         0         0
348992  0.033347  0.033365  0.033347   0.03335  0.033354  0.033355  0.033347
348993  0.038489  0.073482  0.121959   0.46353  0.068847  0.229033         0

               7         8         9  10
0              0         0         0  10
1              0         0         0  10
2              0         0         0  10
```

```
3               0         0         0  10
4               0         0         0  10
…               …         …         …  ..
348989   0.020016  0.020008  0.020004  10
348990          0         0         0  10
348991          0         0         0  10
348992   0.033347  0.699843  0.033347  10
348993          0         0         0  10

[348994 rows x 11 columns]
```

To train the predictive model we use random forests.

Random forests is an ensemble supervised-learning technique that is able to process high-dimensional data sets and is robust against data anomalies.

A random forest model is constructed by generating a multitude of decision trees based on bootstrapped sub-samples such that only a random sample of the available variables at each split of the tree is considered a potential split candidate (Breiman, 2001a).

We use the implementation provided by the scikit-learn Python package and set the number of trees to 128.

[433]:
```python
import sklearn
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_squared_error

from sklearn.inspection import plot_partial_dependence
from sklearn.inspection import partial_dependence
from mpl_toolkits.mplot3d import Axes3D


df2.loc[df2['Helpfulness_ratio'] > 0.5, 'Helpfulness_ratio'] = 1
df2.loc[df2['Helpfulness_ratio'] <= 0.5, 'Helpfulness_ratio'] = 0


X = pd.concat([df2['overall'],df2['unixReviewTime'],separated_df],axis=1)


# Extract the input features (X) and the target variable (y)

y = df2['Helpfulness_ratio'].apply(lambda x: 1 if x > 0.5 else 0)

# Split the data into training and testing sets
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Create and fit the RandomForestRegressor
forest = RandomForestClassifier(n_estimators=128, n_jobs=8, random_state=42)
forest = forest.fit(X_train, y_train)

# Make predictions and evaluate the model
y_pred = forest.predict(X_test)

#RF Model Accuracy
print("Forest Score:", forest.score(X_test,y_test))
```

```
Forest Score: 0.7731915930027651
```

Reciever Operating Characteristic (ROC) Curve show the predictive performance of our classification on the holdout test set (20% of the overall dataset).

It plots the true positive rate against the false positive rate.

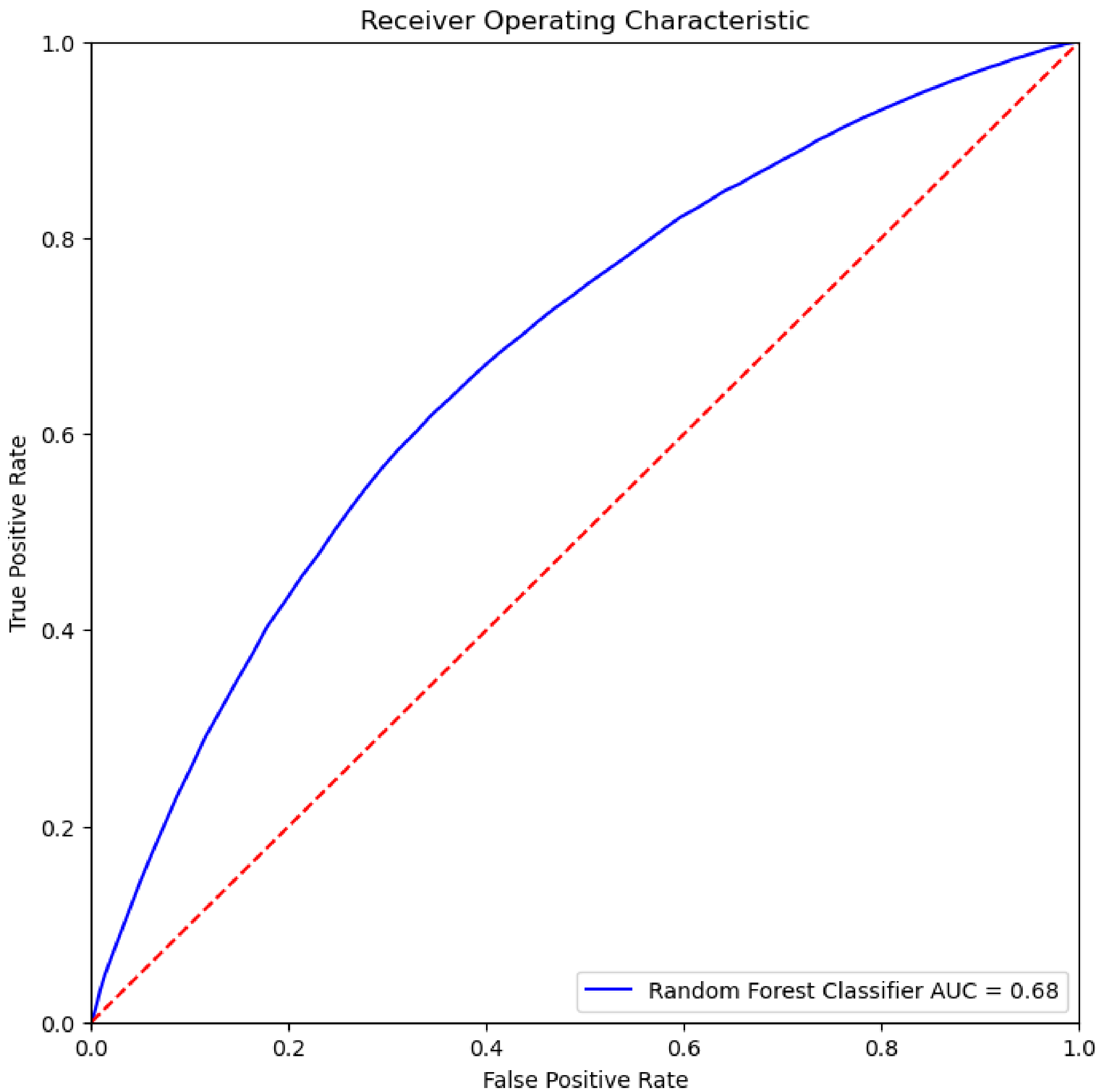
The are under the ROC Curve amounts to 0.644460256983775 which means that the model has an accuracy of 64% in distinguishing between a randomly drawn helpful review and a non-helpful one.

[436]:
```
import numpy as np
from sklearn.metrics import roc_curve, auc

# RF model ROC AUC
preds = forest.predict(X_test)
probs = forest.predict_proba(X_test)

prob_1 = np.ndarray(len(probs))
count = 0
for i in probs:
    prob_1[count] = i[1]
    count = count + 1

fpr, tpr, thresholds = metrics.roc_curve(y_test, prob_1, pos_label=1)
roc_auc = metrics.auc(fpr, tpr)
print("ROC AUC: ", roc_auc)
```

```
ROC AUC:  0.6816272869001151
```

[438]:
```
# plot ROC curve
plt.figure(figsize=(8, 8))
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label='Random Forest Classifier AUC = %0.2f'% roc_auc)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([0.0,1.0])
```

```
plt.ylim([0.0,1.0])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.savefig('fig1.pdf', dpi=600)
plt.show()
```



The only way to interpret a random forest model are the variable importance measures.

We ehow the most influential variables for predicting the helpfulness of a review.

The most important variables are ranked below.

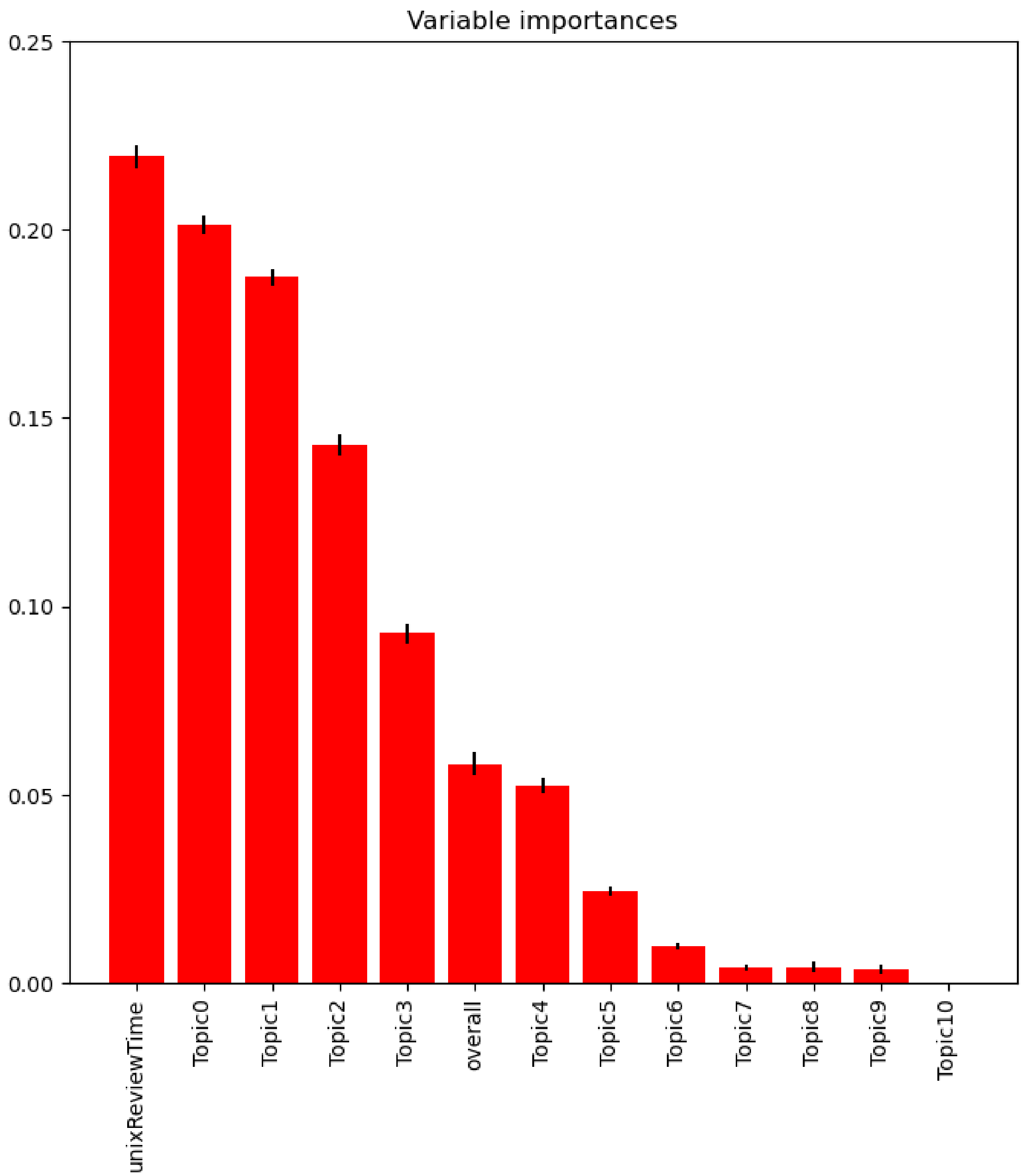
[441]:
```
# extract feature importances
importances = forest.feature_importances_
```

```
indices = np.argsort(importances)[::-1]
std = np.std([tree.feature_importances_ for tree in forest.estimators_],axis=0)

print ("Feature ranking:")
for f in range(len(indices)):
    print ("%d. Feature %d (%s): %f" % (f + 1, indices[f], list(X.columns.
 ↪values)[indices[f]], importances[indices[f]]))
```

```
Feature ranking:
1. Feature 1 (unixReviewTime): 0.219470
2. Feature 2 (0): 0.201327
3. Feature 3 (1): 0.187303
4. Feature 4 (2): 0.142838
5. Feature 5 (3): 0.092845
6. Feature 0 (overall): 0.058151
7. Feature 6 (4): 0.052152
8. Feature 7 (5): 0.024311
9. Feature 8 (6): 0.009646
10. Feature 9 (7): 0.004126
11. Feature 11 (9): 0.004082
12. Feature 10 (8): 0.003748
13. Feature 12 (10): 0.000000
```

[449]:

```
# Plot the feature importances of the forest
labels = ['unixReviewTime','Topic0',␣
 ↪'Topic1','Topic2','Topic3','overall','Topic4','Topic5','Topic6','Topic7','Topic8','Topic9',
plt.figure(figsize=(8, 8))
plt.title("Variable importances")
plt.bar(range(len(labels)), importances[indices][0:len(labels)], color="r",␣
 ↪yerr=std[indices][0:len(labels)], align="center")
plt.xlim((-1,len(labels)))
plt.xticks(range(len(labels)), labels, rotation=90)
plt.ylim((0,0.25))
plt.savefig('fig2.pdf', dpi=600)
plt.show()
```



We have to empirically triangulated the LDA results, that is, the pertopic word distributions and the per-document topic distributions. In a first step, we employed a word intrusion task to measure the semantic coherence of topics. Since topics are represented by words that co-occur with high probability, the idea behind the word intrusion task is to insert a randomly chosen word (intruder) into a set of words representative of a topic and ask human judges to identify the intruder. For each topic, we generated five randomly ordered sets of six words: the five most probable words for the given topic plus one randomly chosen word with low probability for the respective topic.

[452]:
```python
import random

# Function to generate word sets for word intrusion task
def generate_word_sets(lda_model, num_sets=5, num_words=5):
    word_sets = []
    num_topics = lda_model.num_topics

    for topic_id in range(num_topics):
        top_words = [word for word, _ in lda_model.show_topic(topic_id,␣
 ↪topn=num_words)]
        for _ in range(num_sets):
            intruder = random.choice(list(lda_model.id2word.values()))  #␣
 ↪Choose a random word as intruder
            while intruder in top_words:  # Ensure intruder is not in the top␣
 ↪words
                intruder = random.choice(lda_model.id2word.values())
            word_set = top_words + [intruder]
            random.shuffle(word_set)  # Randomly order the word set
            word_sets.append(word_set)

    return word_sets

# Generate word sets for the word intrusion task
word_sets = generate_word_sets(lda_model, num_sets=5, num_words=5)

# Display the generated word sets
for i, word_set in enumerate(word_sets):
    print(f"Word Set {i+1}: {word_set}")
```

```
Word Set 1: ["'ask", 'one', 'xbox', "n't", "'s", 'ps4']
Word Set 2: ['one', "n't", 'xbox', 'ps4', "'s", 'moombas']
Word Set 3: ["n't", 'xbox', 'right.c', 'ps4', 'one', "'s"]
Word Set 4: ['xbox', "'s", 'one', 'capacity.graphically', 'ps4', "n't"]
Word Set 5: ['one', "'s", 'xbox', "n't", 'immuersion', 'ps4']
Word Set 6: ['game', "n't", 'play', 'get', 'like', 'valgas.my']
Word Set 7: ['turd.but', 'game', "n't", 'play', 'get', 'like']
Word Set 8: ['get', 'game', 'play', 'like', "n't", 'stealth.']
Word Set 9: ['came.so', 'get', 'play', "n't", 'like', 'game']
Word Set 10: ['keuth', 'like', 'play', 'get', 'game', "n't"]
Word Set 11: ['34', 'pokemon', 'unit.now', '8220', '8221', 'simcity']
Word Set 12: ['8220', 'pokemon', '34', '8221', 'ventrillo.needs', 'simcity']
Word Set 13: ['34', 'simcity', 'bobbled', '8220', 'pokemon', '8221']
Word Set 14: ['8221', 'pokemon', 'simcity', 'however.before', '34', '8220']
Word Set 15: ['8220', '8221', 'simcity', '34', 'pokemon', 'orange.please']
Word Set 16: ['cars', 'mode', 'like', 'disney.com', 'game', "'s"]
Word Set 17: ['cars', 'like', 'game', 'headcams', "'s", 'mode']
Word Set 18: ['game', "'s", 'mode', 'cars', 'update.in', 'like']
```

```
Word Set 19: ['like', 'mode', "'s", 'alivei', 'game', 'cars']
Word Set 20: ["'s", 'mode', 'like', 'cheerleader-routines', 'cars', 'game']
Word Set 21: ["n't", '--', 'play', 'weapons+detailed', 'game', '``']
Word Set 22: ['--', 'only-multiplayer', "n't", 'play', '``', 'game']
Word Set 23: ['game', 'purchase.simply', 'play', '``', '--', "n't"]
Word Set 24: ['drawback.recommended', "n't", '``', 'play', '--', 'game']
Word Set 25: ['--', '``', 'paced.you', 'game', 'play', "n't"]
Word Set 26: ["'s", 'game', "n't", '``', 'games', 'forwardy']
Word Set 27: ["'s", 'far.fans', '``', 'game', "n't", 'games']
Word Set 28: ["'s", 'games', '``', 'game', "n't", 'hacking/database']
Word Set 29: ["'s", 'speculated', 'game', "n't", '``', 'games']
Word Set 30: ["n't", 'game', 'games', '``', "'s", 'dumb-heads']
Word Set 31: ['mario', 'itdoes', 'wii', 'u', 'nintendo', 'games']
Word Set 32: ['u', 'mario', 'wii', 'nintendo', 'fun.contra', 'games']
Word Set 33: ['wii', 'u', 'mario', 'touch.really', 'nintendo', 'games']
Word Set 34: ['nintendo', 'mario', 'games', 'box-', 'u', 'wii']
Word Set 35: ['wii', 'mario', 'nintendo', 'enourmes', 'games', 'u']
Word Set 36: ['much.enemys', 'multiplayer', 'cod', 'battlefield', 'campaign',
'headset']
Word Set 37: ['simluations', 'campaign', 'cod', 'multiplayer', 'battlefield',
'headset']
Word Set 38: ['multiplayer', 'headset', 'shot.thank', 'cod', 'campaign',
'battlefield']
Word Set 39: ['-rolls', 'battlefield', 'campaign', 'headset', 'cod',
'multiplayer']
Word Set 40: ['battlefield', 'campaign', 'multiplayer', 'headset',
'marine/alien', 'cod']
Word Set 41: ["'s", 'like', 'cord-nest', 'get', "n't", 'game']
Word Set 42: ['game', "n't", "'s", 'like', 'playeranyway', 'get']
Word Set 43: ["'s", 'get', 'like', 'game', 'booma', "n't"]
Word Set 44: ['response.buyer', "n't", 'game', 'get', "'s", 'like']
Word Set 45: ['get', 'game', 'like', "n't", "'s", 'screen.beware']
Word Set 46: ['62', 'tales', 'card', 'cards', 'memory', 'premote']
Word Set 47: ['hughely', '62', 'tales', 'cards', 'memory', 'card']
Word Set 48: ['card', '62', 'tales', 'memory', 'biessman', 'cards']
Word Set 49: ['grab-itas', 'card', 'tales', 'memory', 'cards', '62']
Word Set 50: ['cards', 'memory', '62', 'tales', 'card', "'upgraded"]
```

We will present these sets to three independent human coders via the crowdsourcing platform Amazon Mechanical Turk and prompt them to identify the intruder.

In a second step, we conduct a best topic task to validate the topic assignments for each review. (The task is a variation of the topic intrusion task developed by Chang et al (2009). Instead of identifying an intruder among a set of highly probable topics, we chose to identify the best match of a topic.

[461]:
```python
import random
```

```
# Function to generate topic sets for the best topic task
def generate_topic_sets(lda_model, df, num_sets=5):
    topic_sets = []
    num_topics = lda_model.num_topics

    for index, row in df.iterrows():
        review_topics = lda_model.get_document_topics(dictionary.
 ↪doc2bow(row['processed_text']))
        top_topics = sorted(review_topics, key=lambda x: x[1], reverse=True)[:
 ↪num_sets]
        topic_set = [topic for topic, _ in top_topics]  # Extract topics␣
 ↪without indexing
        random.shuffle(topic_set)  # Randomly order the topic set
        topic_sets.append(topic_set)

    return topic_sets

# Generate topic sets for the best topic task
topic_sets = generate_topic_sets(lda_model, df2, num_sets=5)


# Display a summary of the generated topic sets limiting the output to avoid␣
 ↪Jupyter Notebook IOPub data issues.
# Display a summary of the generated topic sets for the first 5 reviews
for i in range(5):
    print(f"Topic Set for Review {i+1}: {topic_sets[i][:5]} ... (truncated)")
```

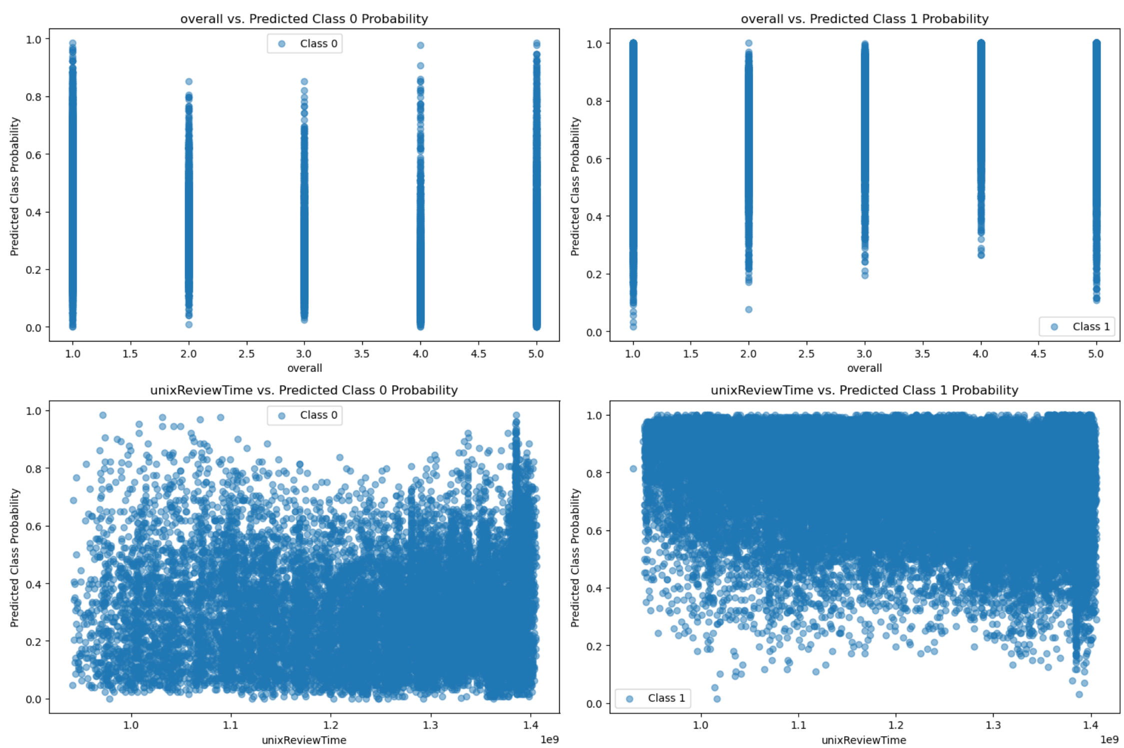
```
Topic Set for Review 1: [4, 1, 5, 3] … (truncated)
Topic Set for Review 2: [0, 1] … (truncated)
Topic Set for Review 3: [3, 8, 1, 5] … (truncated)
Topic Set for Review 4: [1, 3, 4, 5] … (truncated)
Topic Set for Review 5: [1, 4, 0] … (truncated)
```

1.4 RESULT INTERPRETATION

Interpreting the results of a black-box algorithm like random forests can be challenging. One way to shed more light on a random forest model is to plot the values of a selected independent variable against the class probabilities predicted by the model (i.e., predictions of the dependent variable) (Friedman et al, 2013).

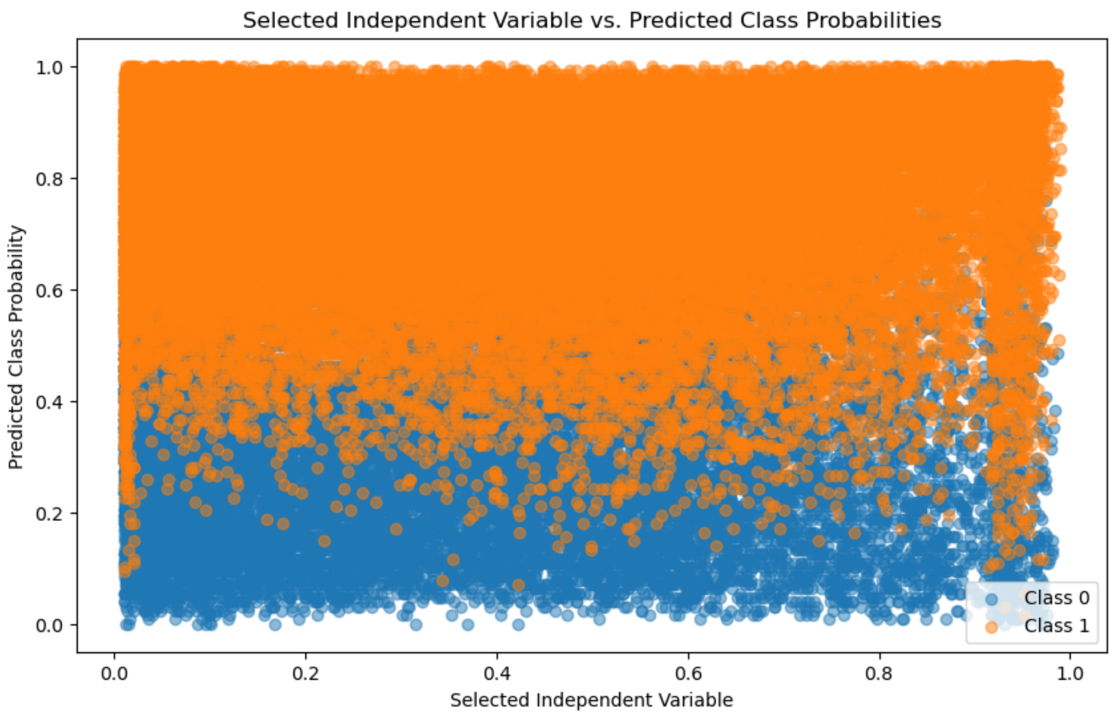
[495]:
```
# Make predictions on the testing set
y_pred_prob = forest.predict_proba(X_test)

# Select the independent variables for plotting
selected_variables = ['overall','unixReviewTime']

# Create a multi-dimensional scatter plot for each pair of selected independent␣
 ↪variables and class probabilities
```

```
fig, axes = plt.subplots(nrows=len(selected_variables), ncols=len(forest.
 ↪classes_), figsize=(15, 10))

for i, variable in enumerate(selected_variables):
    for j, class_index in enumerate(forest.classes_):
        axes[i, j].scatter(X_test[variable][y_test == class_index],␣
 ↪y_pred_prob[y_test == class_index, j], label=f'Class {class_index}', alpha=0.
 ↪5)
        axes[i, j].set_xlabel(variable)
        axes[i, j].set_ylabel('Predicted Class Probability')
        axes[i, j].set_title(f'{variable} vs. Predicted Class {class_index}␣
 ↪Probability')
        axes[i, j].legend()

plt.tight_layout()
plt.show()
```



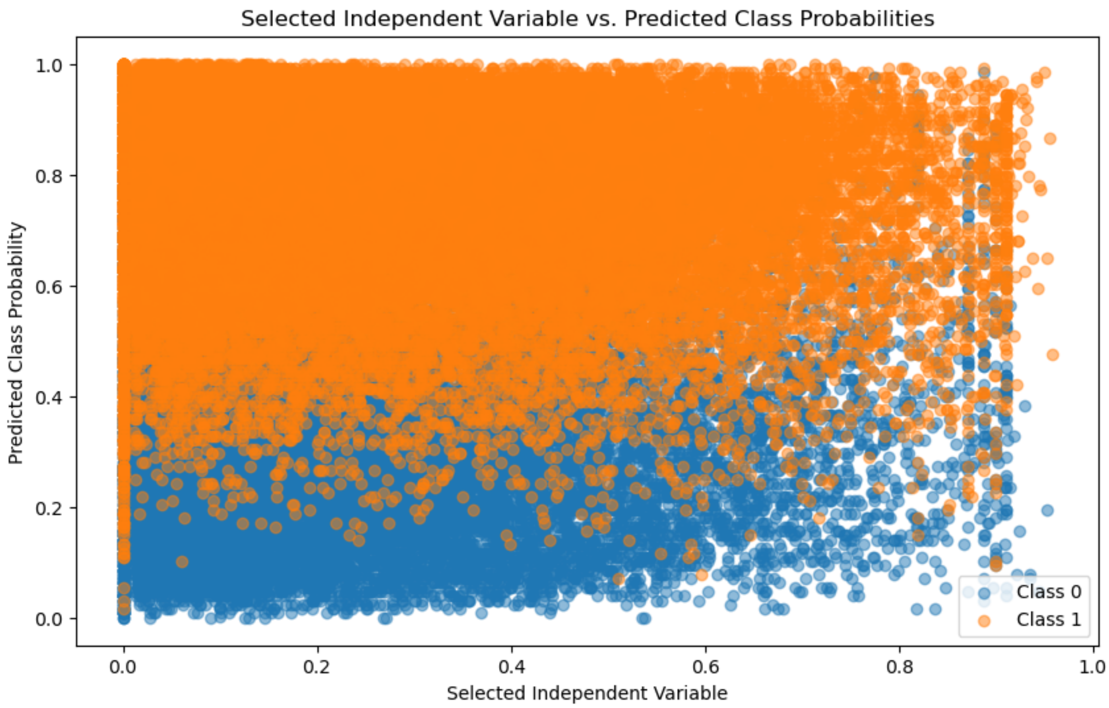
[473]:
```
# Make predictions on the testing set
y_pred_prob = forest.predict_proba(X_test)

# Select the independent variable for plotting (e.g., review rating)
selected_variable = X_test[['0']]
```

```
# Plot the selected independent variable against the class probabilities
plt.figure(figsize=(10, 6))
for class_index in range(len(forest.classes_)):
    plt.scatter(selected_variable[y_test == class_index], y_pred_prob[y_test ==␣
↪class_index, class_index], label=f'Class {class_index}', alpha=0.5)

plt.xlabel('Selected Independent Variable')
plt.ylabel('Predicted Class Probability')
plt.title('Selected Independent Variable vs. Predicted Class Probabilities')
plt.legend()
plt.show()
```



[483]:
```
# Make predictions on the testing set
y_pred_prob = forest.predict_proba(X_test)

# Select the independent variable for plotting (e.g., review rating)
selected_variable = X_test[['1']]

# Plot the selected independent variable against the class probabilities
plt.figure(figsize=(10, 6))
for class_index in range(len(forest.classes_)):
    plt.scatter(selected_variable[y_test == class_index], y_pred_prob[y_test ==␣
↪class_index, class_index], label=f'Class {class_index}', alpha=0.5)
```

```
plt.xlabel('Selected Independent Variable')
plt.ylabel('Predicted Class Probability')
plt.title('Selected Independent Variable vs. Predicted Class Probabilities')
plt.legend()
plt.show()
```



We analyze selected variables and find out whether a variable has a positive or negative influence on the probability of belonging to a certain class (i.e. helpful or hunhelpful).

Final step of the result interpretation is then to compare and contrast the discoveries with theory and literature.

1.5 SUMMARY AND COMPARISON

The studies both the original and the replication have highlighted the potential of Machine learning and NLP to discover patterns and relationships and use human verification to interpret those results in a human context.

Visualizations helped to discover those trends and highlight patterns that would be difficoult to understand by mere number analysis.

Big data analytics have the potential to provide a new and innovative approach to using large datasets to increase scientific knowledge and the comprehension of our world and its patterns.

From my study and the source original work I have had the chance to understand better the process to adopt and the relative weights assigned to each phase.

Initial objectives (asking the questions you want to answer) and exploring the way of achieving I found out it is extremely important in the first phase even before data collection. The initial questions and its framing have guided the rest of the process.

Understanding and preparing the data is also vital to set the ground for analysis.

I have followed the original research phases and its guidelines and even if computing resources did not allow me to reach the same depth of analysis the results are quite similar and showing the value of the guidelines for IS researchers in applying BDA.

These are an excellent starting point for further iterative testing and researching.

1.6 REFLECTION

1) 3 THINGS I HAVE LEARNED

1) Human feedback to detect the intruder in Amazon Mechanical Turk, I used Mechanical Turk for other purpouses and I was intrigued by the possibility to bring in the human equation in the study and enrich the research with those contributions.

2) The empirical triangulation of the LDA results using a word intrusion task to measure the semantic coherence of topics by inserting a random word into a set of words.

3) The shift of focus from a star rating system in the early researches to a text analysis approach in the reviews (e.g.,Mudambi & Schuff, 2010;Cao et al, 2011; Ghose & Ipeirotis, 2011; Pan & Zhang, 2011; Korfiatisa et al, 2012).

2) 2 QUESTIONS STILL OPEN

1) We are facing an explosion of data and it is still open the question if and how difficult will be for BDA to keep the pace and overcome the difficulties to measure and theorize.

2) Will guidelines remain applicable to future researches and how we will have to adapt and modify them if necessary.

3) 1 THING I HAVE ENJOYED

The challenge to overcome the roadblocks that I have faced due to my computer limited computing capabilities. More than that also the way to find a solution to problems I had never faced and that I did not know hoow to address but after a deep research was able to understand and overcome.