Part 2 Model Creation and Prediction

DSC 483 Capstone Mini Project

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In [2]:
```
# mount Google Drive to import data
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [3]:
```
import numpy as np
import pandas as pd
import time
import datetime

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

# Load the regular expression library
import re
# Import the wordcloud library
from wordcloud import WordCloud

import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```
# %%time
# amazon = pd.read_csv("/content/drive/MyDrive/Mini Project/amazon_revie
ws.csv")
# submission = pd.read_csv("/content/drive/MyDrive/Mini Project/sampleSu
bmission.csv")
```

```
CPU times: user 23.6 ms, sys: 6.02 ms, total: 29.6 ms
Wall time: 475 ms
```

In [21]:
```
# Import After processed data to save time
%%time
amazon = pd.read_parquet("/content/drive/MyDrive/Mini Project/amazon_rev
iews4.parquet.gzip")
submission = pd.read_csv("/content/drive/MyDrive/Mini Project/sampleSubm
ission.csv")
```

```
CPU times: user 12 s, sys: 7.76 s, total: 19.8 s
Wall time: 7.84 s
```

2.1 non-Text part feature engineering

- Convert delta time to datetime and parse Day, Month, Week, Year
- Calculate varaibles' length and help ratio
- Missing value imputation
- Count userID for review times

In [ ]:
```
# Convert delta time to datetime and parse Day, Month, Week, Year
startdate = datetime.datetime.strptime('1970-01-01 00:00:00', '%Y-%m-%d
 %H:%M:%S')
amazon['Time'] = amazon['Time'].apply(lambda x: (startdate + datetime.ti
medelta(seconds = x)))
amazon["Day"] = amazon["Time"].dt.day
amazon["Weekday"] = amazon["Time"].dt.weekday
amazon["Month"] = amazon["Time"].dt.month
amazon["Year"] = amazon["Time"].dt.year
```

In [ ]:
```
# Calculate varaibles' length and help ratio
amazon['Title_len'] = amazon['ProfileName'].str.len()
amazon['Summary_len'] = amazon['Summary'].str.len()
amazon['Helpful_ratio'] = amazon['HelpfulnessNumerator'] / amazon['Helpf
ulnessDenominator']
amazon['Review_len'] = amazon['Text'].str.len()
```

In [ ]:
```
# Check missing values
amazon.isnull().sum()
```

Out[ ]:
```
Id                         0
ProductId                  0
UserId                     0
ProfileName               16
HelpfulnessNumerator       0
HelpfulnessDenominator     0
Score                      0
Time                       0
Summary                   27
Text                       0
Title_len                  0
Summary_len                0
Helpful_ratio              0
Review_len                 0
UserId_count               0
ProductId_count            0
Day                        0
Weekday                    0
Month                      0
Year                       0
dtype: int64
```

In [ ]:
```
# Missing value imputation
amazon['Helpful_ratio'].loc[amazon['Helpful_ratio'].isnull()] = -1
amazon['Summary_len'].loc[amazon['Summary_len'].isnull()] = 0
amazon['Title_len'].loc[amazon['Title_len'].isnull()] = 0
```

In [ ]:
```
# Count userID for review times
amazon['UserId_count'] = amazon['UserId'].map(amazon['UserId'].value_cou
nts(dropna=False))
amazon['ProductId_count'] = amazon['ProductId'].map(amazon['ProductId'].
value_counts(dropna=False))
```

In [34]:
```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
amazon['UserId'] = le.fit_transform(amazon['UserId'])
amazon['ProductId'] = le.fit_transform(amazon['ProductId'])
```

2.2 Clean Text data (Summary + Text = Review)

In [ ]:

```
from nltk.stem import WordNetLemmatizer
import nltk
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import re
import nltk
import string
from nltk.corpus import stopwords
from nltk.corpus import wordnet
nltk.download('wordnet')
nltk.download("stopwords")
stop_words = stopwords.words('english')
nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')
nltk.download("stopwords")

lemmatizer = WordNetLemmatizer()

##Tags the words in the tweets
def nltk_tag_to_wordnet_tag(nltk_tag):
    if nltk_tag.startswith('J'):
        return(wordnet.ADJ)
    elif nltk_tag.startswith('V'):
        return(wordnet.VERB)
    elif nltk_tag.startswith('N'):
        return(wordnet.NOUN)
    elif nltk_tag.startswith('R'):
        return(wordnet.ADV)
    else:
        return(None)

##Lemmatizes the words in tweets and returns the cleaned and lemmatized
 tweet
def lemmatize_tweet(tweet):
    #tokenize the tweet and find the POS tag for each token
    tweet = tweet_cleaner(tweet) #tweet_cleaner() will be the function y
ou will write
    nltk_tagged = nltk.pos_tag(nltk.word_tokenize(tweet))
    #tuple of (token, wordnet_tag)
    wordnet_tagged = map(lambda x: (x[0], nltk_tag_to_wordnet_tag(x[1
])), nltk_tagged)
    lemmatized_tweet = []
    for word, tag in wordnet_tagged:
        if tag is None:
            #if there is no available tag, append the token as is
            lemmatized_tweet.append(word)
        else:
            #else use the tag to lemmatize the token
            lemmatized_tweet.append(lemmatizer.lemmatize(word, tag))
    return(" ".join(lemmatized_tweet))


def tweet_cleaner(x):
  # lower case
  x = x.lower()
```

```
  # remove stop words
  x = ' '.join([word for word in x.split(' ') if word not in stop_words
])
  # remove emoji
  x = x.encode(encoding="ascii", errors="ignore").decode()
  # remove hashtags
  x = re.sub("#\S+", " ", x)
  # remove mentions
  x = re.sub("@\S+", " ", x)
  # remove URL/links
  x = re.sub("https*\S+", " ", x)
  #remove punctuation
  x = re.sub('[%s]' % re.escape(string.punctuation), ' ', x)
  # remove overspaces
  x = re.sub('\s{2,}', " ", x)
  # remove ticks
  x = re.sub("\'\w+", '', x)
  # remove words shorter than 3
  x = re.sub(r'\b\w{1,2}\b', '', x)
  # decontracred phrase


  return x
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Unzipping corpora/wordnet.zip.
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data...
[nltk_data]   Unzipping taggers/averaged_perceptron_tagger.zip.
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [ ]:

```
# compute clean data for text
amazon['Text_clean'] = amazon.Text.apply(lemmatize_tweet)
```

In [ ]:

```
# compute clean data for summary
amazon['Summary_clean'] = amazon.Summary.astype(str).apply(lemmatize_twe
et)
```

In [ ]:

```
# combine Summary + Text as Review_clean for text mining
amazon['Review_clean']= amazon['Summary_clean'] + ' '+ amazon['Text_clea
n']
```

2.3 Text Sentiment polarity analysis

In [ ]:

```
# add sentiment anaylsis columns
import nltk
nltk.download('vader_lexicon')
from nltk.sentiment.vader import SentimentIntensityAnalyzer

sid = SentimentIntensityAnalyzer()
amazon["sentiments"] = amazon["Review_clean"].apply(lambda x: sid.polari
ty_scores(x))
amazon = pd.concat([amazon.drop(['sentiments'], axis=1), amazon['sentime
nts'].apply(pd.Series)], axis=1)
```

Check the correlation between Variables. The new created polarity variables are correlated with prediction target (Score)

In [ ]:

```
amazon.select_dtypes('number').columns
```

Out[ ]:

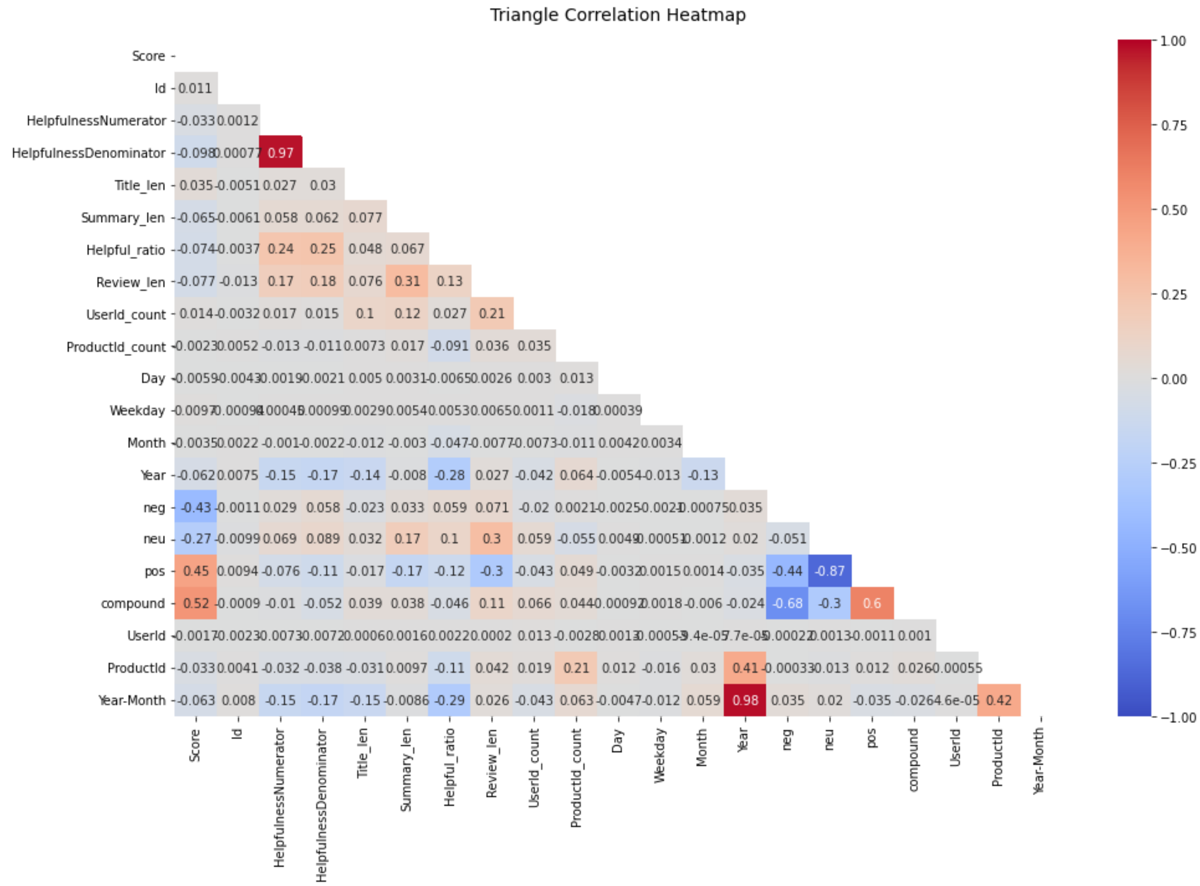
```
Index(['Id', 'HelpfulnessNumerator', 'HelpfulnessDenominator', 'Score',
       'Title_len', 'Summary_len', 'Helpful_ratio', 'Review_len',
       'UserId_count', 'ProductId_count', 'Day', 'Weekday', 'Month', 'Y
ear',
       'neg', 'neu', 'pos', 'compound'],
      dtype='object')
```

In [36]:

```
corr_list = ['Score','Id', 'HelpfulnessNumerator', 'HelpfulnessDenominat
or',
       'Title_len', 'Summary_len', 'Helpful_ratio', 'Review_len',
       'UserId_count', 'ProductId_count', 'Day', 'Weekday', 'Month', 'Ye
ar',
       'neg', 'neu', 'pos', 'compound', 'UserId', 'ProductId', 'Year-Mon
th']
```

In [37]:

```python
# Create Correlation heatmap
plt.figure(figsize=(16, 10))
mask = np.triu(np.ones_like(amazon[corr_list].corr(), dtype=np.bool))
heatmap = sns.heatmap(amazon[corr_list].corr(), mask=mask, vmin=-1, vmax
=1, annot=True, cmap="coolwarm")
heatmap.set_title('Triangle Correlation Heatmap', fontdict={'fontsize':1
4}, pad=16);
```



2.4 Convert text to vector by Dec2Vec

In [ ]:

```python
# create doc2vec vector columns
from gensim.test.utils import common_texts
from gensim.models.doc2vec import Doc2Vec, TaggedDocument

documents = [TaggedDocument(doc, [i]) for i, doc in enumerate(amazon["Re
view_clean"].apply(lambda x: x.split(" ")))]

# train a Doc2Vec model with our text data
model = Doc2Vec(documents, vector_size=50, window=2, min_count=1, worker
s=4) # choose vector size = 50

# transform each document into a vector data
doc2vec_df = amazon["Review_clean"].apply(lambda x: model.infer_vector(x
.split(" "))).apply(pd.Series)
doc2vec_df.columns = ["doc2vec_vector_" + str(x) for x in doc2vec_df.col
umns]
amazon = pd.concat([amazon, doc2vec_df], axis=1)
```

In [ ]:
```
amazon.columns
```

Out[ ]:
```
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerato
r',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text',
       ...
       'doc2vec_vector_90', 'doc2vec_vector_91', 'doc2vec_vector_92',
       'doc2vec_vector_93', 'doc2vec_vector_94', 'doc2vec_vector_95',
       'doc2vec_vector_96', 'doc2vec_vector_97', 'doc2vec_vector_98',
       'doc2vec_vector_99'],
      dtype='object', length=127)
```

In [62]:
```
amazon.columns
```

Out[62]:
```
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerato
r',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text',
       ...
       'word_two', 'word_use', 'word_want', 'word_water', 'word_way',
       'word_well', 'word_without', 'word_work', 'word_would', 'word_ye
ar'],
      dtype='object', length=247)
```

2.5 Convert Text to TF-IDFS vector

In [ ]:
```
# add tf-idfs columns
from sklearn.feature_extraction.text import TfidfVectorizer
tfidf = TfidfVectorizer(max_df=0.50, min_df=0.05, ngram_range=(1,2))
tfidf_result = tfidf.fit_transform(amazon['Review_clean']).toarray()
tfidf_df = pd.DataFrame(tfidf_result, columns = tfidf.get_feature_names
())
tfidf_df.columns = ["word_" + str(x) for x in tfidf_df.columns]
tfidf_df.index = amazon.index
amazon = pd.concat([amazon, tfidf_df], axis=1)
```

In [ ]:
```
amazon.columns
```

Out[ ]:
```
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerato
r',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text',
       ...
       'word_two', 'word_use', 'word_want', 'word_water', 'word_way',
       'word_well', 'word_without', 'word_work', 'word_would', 'word_ye
ar'],
      dtype='object', length=247)
```

2.6 Prediction Model selection

In [38]:
```python
# Create feature list for prediction, numerical feature only
feature_list = amazon.select_dtypes('number').columns.tolist()
feature_list.remove('Score')

len(feature_list)
```

Out[38]:
```
240
```

In [39]:
```python
# split train and test data accordingly
train = amazon.loc[amazon['Id'].isin(submission['Id'])==False]
test = amazon.loc[amazon['Id'].isin(submission['Id'])]
```

In [40]:
```python
# Initial models performance
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split, KFold
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn import metrics
from sklearn.model_selection import ShuffleSplit

lr = LinearRegression()
rdg = Ridge()
las = Lasso()


def model_score(X, y):
  Classifiers = ['Linear regression','Ridge regression','Lasso regressio
n']
  scores = []
  models = [lr, rdg, las]

  cv_split = ShuffleSplit(n_splits = 10, test_size = .3, train_size = .6
, random_state = 0 )

  for model in models:
    score = cross_val_score(model, X, y, scoring="neg_root_mean_squared_
error", cv=cv_split).mean()
    scores.append(score)

  results = pd.DataFrame(scores, index=Classifiers, columns=["Score"]).s
ort_values(by = 'Score', ascending = False)

  print(results)

model_score(train[feature_list], train['Score'])
```

```
                      Score
Ridge regression  -0.938207
Linear regression -0.938222
Lasso regression  -1.304367
```

It looks that Linear regression and Ridge regression got the better RMSE result

In [ ]:
```
# from sklearn.pipeline import Pipeline
# from sklearn.model_selection import train_test_split, GridSearchCV
# from sklearn.preprocessing import StandardScaler
# X_train, X_test, y_train, y_test = train_test_split(train[feature_lis
t], train['Score'], test_size=0.33, random_state=42)
# pipeline = Pipeline([
#                        ('scaler',StandardScaler()),
#                        ('model',Lasso())
# ])
# search = GridSearchCV(pipeline,
#                        {'model__alpha':np.arange(0.1,10,0.1)},
#                        cv = 5, scoring="neg_mean_squared_error",verbose
=3
#                        )
# search.fit(X_train,y_train)
```

In [66]:
```
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LinearRegression
from sklearn import metrics

X = train[feature_list]
y = train['Score']


lr = LinearRegression()
scores = -cross_val_score(lr, X, y, cv=5, scoring='neg_root_mean_squared
_error').mean()
scores
```

Out[66]: 0.9397581885235446

2.7 Feature reduction (RFE)

In [48]:
```
from sklearn.feature_selection import RFE
# final model
n_features_optimal = len(feature_list)

X = train[feature_list]
y = train['Score']

lm = LinearRegression()
lm.fit(X, y)

rfe = RFE(lm, n_features_to_select=n_features_optimal)
rfe = rfe.fit(X, y)

# predict prices of X_test
y_pred = lm.predict(test[feature_list])
mse = metrics.mean_squared_error(test['Score'], y_pred)
mse
```

Out[48]: 0.8944641021229289

In [57]:
```
len(feature_list)
```
Out[57]:
```
240
```

In [52]:
```
X.columns[rfe.support_]
```
Out[52]:
```
Index(['Id', 'ProductId', 'UserId', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Title_len', 'Summary_len', 'Helpful_r
atio',
       'Review_len', 'UserId_count',
       ...
       'word_use', 'word_want', 'word_water', 'word_way', 'word_well',
       'word_without', 'word_work', 'word_would', 'word_year', 'Year-Mo
nth'],
      dtype='object', length=240)
```

In [ ]:
```
feature_select = pd.DataFrame()
feature_select["Features"] = X.columns
feature_select['Select'] =  rfe.support_
feature_select
```
Out[ ]:

	Features	Select
0	Id	True
1	HelpfulnessNumerator	True
2	HelpfulnessDenominator	True
3	Title_len	True
4	Summary_len	True
...	...	...
232	word_well	True
233	word_without	True
234	word_work	True
235	word_would	True
236	word_year	True

237 rows × 2 columns

2.8 Final RMSE & Confusion Matrix for test data set

RMSE for test data set

In [233]:
```
# round the decimal and conver value < 0 to rate 1
test['Predicted'] = y_pred
test['Predicted'].loc[test['Predicted'] < 1] = 1
test['Predicted'].loc[test['Predicted'] > 4] = 5
test['Predicted'] = test['Predicted'].round().astype(int)
sub = test[['Id', 'Predicted']]
sub['Predicted'] = test['Predicted']

from math import floor, ceil
metrics.mean_squared_error(test['Score'], sub['Predicted'])
```

Out[233]: 0.91641

Confusion Matrix for test data set

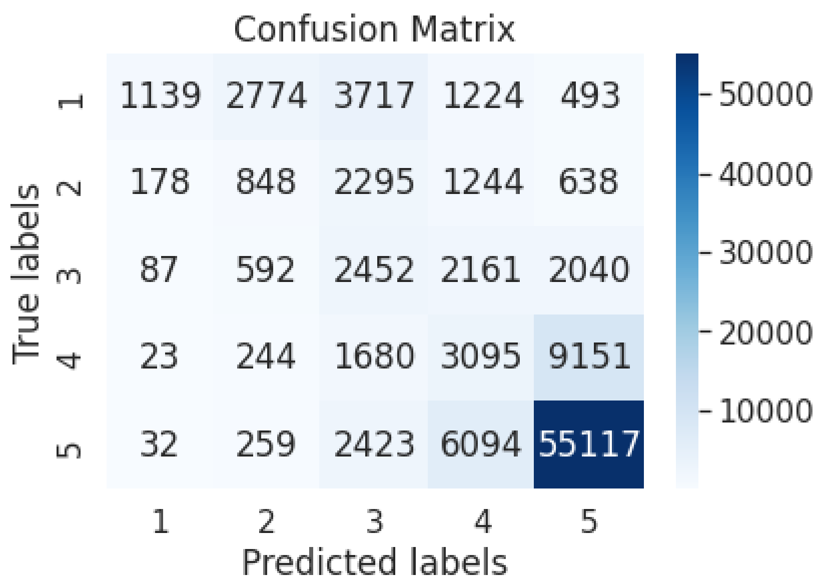
In [234]:
```
from sklearn.metrics import plot_confusion_matrix, confusion_matrix
cm_df = pd.DataFrame(confusion_matrix(test['Score'], sub['Predicted']))
cm_df
```

Out[234]:

	0	1	2	3	4
0	1139	2774	3717	1224	493
1	178	848	2295	1244	638
2	87	592	2452	2161	2040
3	23	244	1680	3095	9151
4	32	259	2423	6094	55117

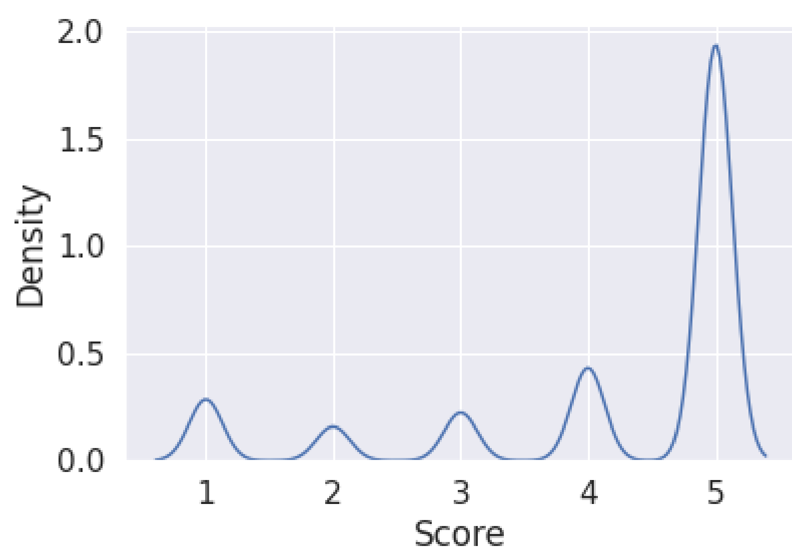
In [235]:
```
ax= plt.subplot()
sns.heatmap(cm_df, annot=True, fmt='g', ax=ax, cmap="Blues");  #annot=True to annotate cells, ftm='g' to disable scientific notation

# labels, title and ticks
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
ax.set_title('Confusion Matrix');
ax.xaxis.set_ticklabels(['1', '2', '3', '4', '5']); ax.yaxis.set_ticklabels(['1', '2', '3', '4', '5']);
```

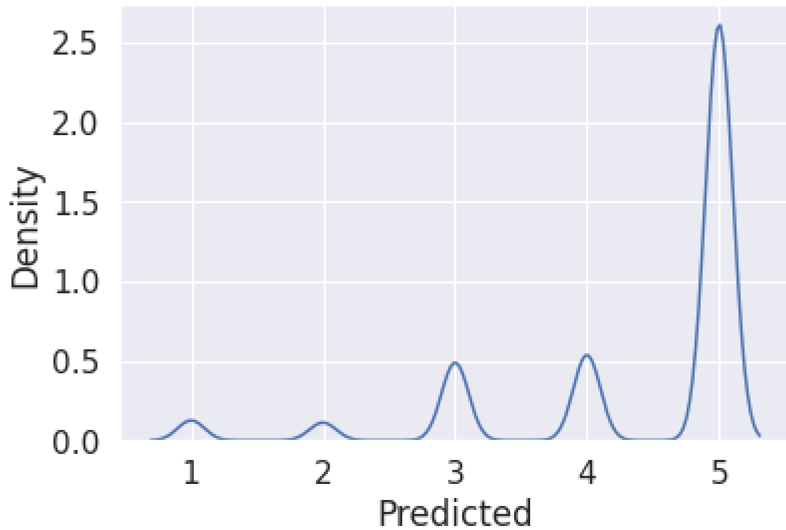


In [231]:
```
sns.kdeplot(test['Score'])
```

Out[231]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5e000ad910>



In [232]:
```
sns.kdeplot(test['Predicted'])
```
Out[232]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5dfff51790>



In [170]:
```
sub.head(3)
```
Out[170]:

	Id	Predicted
8	9	5
9	10	5
15	16	4

In [169]:
```
sub.to_csv('sub.csv', index=False)
!cp sub.csv "/content/drive/MyDrive/Mini Project/"
```

In [56]:
```
amazon.to_parquet('amazon_reviews5.parquet.gzip', compression="gzip")
!cp amazon_reviews5.parquet.gzip "/content/drive/MyDrive/Mini Project/"
```