Problem Statement

- This data set is a Beer data-set for your Data Science case-study round. You are expected to build a Machine Learning model which predicts the overall rating of the beer. ("review/overall" column in "train.csv" is your dependent variable.)

Machine Learning Problem Formulation:

- Formulating this prediction problem as a regression problem.

Metric Used :

- Root Mean Square Error(RMSE) : https://scikit-learn.org/stable/modules/generated/sklearn.metrics.mean_squared_error.html
- R^2 or Coefficient of Determination : https://scikit-learn.org/stable/modules/generated/sklearn.metrics.r2_score.html

Data and Datatypes:

- index int64
- beer/ABV float64
- beer/beerId int64
- beer/brewerId int64
- beer/name object
- beer/style object
- review/appearance float64
- review/aroma float64
- review/overall float64
- review/palate float64
- review/taste float64
- review/text object
- review/timeStruct object
- review/timeUnix int64
- user/ageInSeconds float64
- user/birthdayRaw object
- user/birthdayUnix float64
- user/gender object
- user/profileName object

Approach:

1. Data Acquisition
2. Data Loading
3. Exploratory Data Analysis and Handling nulls
4. Data Preprocessing
5. Data Vectorisation
6. Modelling
7. Conclusion

Let's Begin !!

In [2]:

```
cd drive/My\ Drive/Algoscale
```

```
/content/drive/My Drive/Algoscale
```

Load Libraries

In [378]:

```
import nltk
```

```
nltk.download('stopwords')

import pandas as pd
import seaborn as sns
import numpy as np
import xgboost as xgb
from tqdm import tqdm
from sklearn.svm import SVC
from keras.models import Sequential
from keras.layers.recurrent import LSTM, GRU
from keras.layers.core import Dense, Activation, Dropout
from keras.layers.embeddings import Embedding
from keras.layers.normalization import BatchNormalization
from keras.utils import np_utils
from sklearn import preprocessing, decomposition, model_selection, metrics, pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.decomposition import TruncatedSVD
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from keras.layers import GlobalMaxPooling1D, Conv1D, MaxPooling1D, Flatten, Bidirectional, SpatialD
ropout1D
from keras.preprocessing import sequence, text
from keras.callbacks import EarlyStopping
from nltk import word_tokenize
from nltk.corpus import stopwords
stop_words = stopwords.words('english')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Load Dataset

In [379]:

```
train = pd.read_csv('train.csv')
```

Exploratory Data Analysis

In [380]:

```
train.head()
```

Out[380]:

	index	beer/ABV	beer/beerId	beer/brewerId	beer/name	beer/style	review/appearance	review/aroma	review/overall	review/palate
0	40163	5.0	46634	14338	Chiostro	Herbed / Spiced Beer	4.0	4.0	4.0	4.0
1	8135	11.0	3003	395	Bearded Pat's Barleywine	American Barleywine	4.0	3.5	3.5	3.5
2	10529	4.7	961	365	Naughty Nellie's Ale	American Pale Ale (APA)	3.5	4.0	3.5	3.5
3	44610	4.4	429	1	Pilsner Urquell	Czech Pilsener	3.0	3.0	2.5	3.0
4	37062	4.4	4904	1417	Black Sheep Ale (Special)	English Pale Ale	4.0	3.0	3.0	3.5

In [381]:

```
train.shape
```

Out[381]:

```
(37500, 19)
```

In [382]:

```
train.columns
```

Out[382]:

```
Index(['index', 'beer/ABV', 'beer/beerId', 'beer/brewerId', 'beer/name',
       'beer/style', 'review/appearance', 'review/aroma', 'review/overall',
       'review/palate', 'review/taste', 'review/text', 'review/timeStruct',
       'review/timeUnix', 'user/ageInSeconds', 'user/birthdayRaw',
       'user/birthdayUnix', 'user/gender', 'user/profileName'],
      dtype='object')
```

In [383]:

```
features = train[['index', 'beer/ABV', 'beer/beerId', 'beer/brewerId', 'beer/name',
       'beer/style', 'review/appearance', 'review/aroma', 'review/overall',
       'review/palate', 'review/taste', 'review/text', 'review/timeStruct',
       'review/timeUnix', 'user/ageInSeconds', 'user/birthdayRaw',
       'user/birthdayUnix', 'user/gender', 'user/profileName']]
```

In [384]:

```
label = train[['review/overall']]
```

In [385]:

```
features.shape
```

Out[385]:

```
(37500, 19)
```

In [386]:

```
label.shape
```

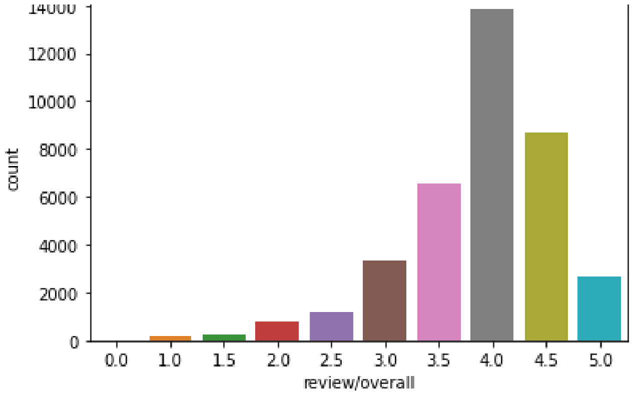
Out[386]:

```
(37500, 1)
```

In [387]:

```
#Imbalanced Data
ax = sns.countplot(x=label['review/overall'], data=label)
print(label['review/overall'].value_counts())
```

```
4.0    13868
4.5     8666
3.5     6551
3.0     3319
5.0     2671
2.5     1193
2.0      807
1.5      248
1.0      176
0.0        1
Name: review/overall, dtype: int64
```



- Imbalanced Dataset
- Maximum rating : 4
- Minimum rating : 0

In [388]:

```
features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 37500 entries, 0 to 37499
Data columns (total 19 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   index               37500 non-null  int64  
 1   beer/ABV            37500 non-null  float64
 2   beer/beerId         37500 non-null  int64  
 3   beer/brewerId       37500 non-null  int64  
 4   beer/name           37500 non-null  object 
 5   beer/style          37500 non-null  object 
 6   review/appearance   37500 non-null  float64
 7   review/aroma        37500 non-null  float64
 8   review/overall      37500 non-null  float64
 9   review/palate       37500 non-null  float64
 10  review/taste        37500 non-null  float64
 11  review/text         37490 non-null  object 
 12  review/timeStruct   37500 non-null  object 
 13  review/timeUnix     37500 non-null  int64  
 14  user/ageInSeconds   7856 non-null   float64
 15  user/birthdayRaw    7856 non-null   object 
 16  user/birthdayUnix   7856 non-null   float64
 17  user/gender         15314 non-null  object 
 18  user/profileName    37495 non-null  object 
dtypes: float64(8), int64(4), object(7)
memory usage: 5.4+ MB
```

Columns having null values :

- review/text
- user/ageInSeconds,
- user/birthdayRaw,
- user/birthdayUnix,
- user/gender,
- user/profileName

In [389]:

```
features.isnull().sum()
```

Out[389]:

```
index                        0
beer/ABV                     0
beer/beerId                  0
beer/brewerId                0
```

```
beer/name              0
beer/style             0
review/appearance      0
review/aroma           0
review/overall         0
review/palate          0
review/taste           0
review/text           10
review/timeStruct      0
review/timeUnix        0
user/ageInSeconds  29644
user/birthdayRaw   29644
user/birthdayUnix  29644
user/gender        22186
user/profileName       5
dtype: int64
```

Handling nulls

In [390]:

```
from datetime import timezone
# Imputing with mean values of birthdays in unix timestamp
features['user/birthdayRaw'] = pd.to_datetime(features['user/birthdayRaw'],errors='coerce')
df = features[features['user/birthdayRaw'].notnull()]

birthDays = []
for i in df['user/birthdayRaw']:
  birthDays.append(time.mktime(i.timetuple()))

def Average(lst):
    return sum(lst) / len(lst)
mean =  Average(birthDays)
```

In [391]:

```
# Replace empty/null values with median since i am taking age groups to be near  and robust from o
utliers
features['user/ageInSeconds'].fillna(features['user/ageInSeconds'].median(), inplace=True)
features['user/birthdayRaw'].fillna(mean, inplace=True)
features['user/birthdayUnix'].fillna(features['user/birthdayUnix'].median(), inplace=True)
features['user/gender'].fillna('missing', inplace=True)
```

In [392]:

```
features = features.dropna()
```

In [393]:

```
features.isnull().sum()
```

Out[393]:

```
index                0
beer/ABV             0
beer/beerId          0
beer/brewerId        0
beer/name            0
beer/style           0
review/appearance    0
review/aroma         0
review/overall       0
review/palate        0
review/taste         0
review/text          0
review/timeStruct    0
review/timeUnix      0
user/ageInSeconds    0
user/birthdayRaw     0
user/birthdayUnix    0
user/gender          0
user/profileName     0
```

```
user/profileName      0
dtype: int64
```

In [394]:

```
features.head()
```

Out[394]:

	index	beer/ABV	beer/beerId	beer/brewerId	beer/name	beer/style	review/appearance	review/aroma	review/overall	review/palate
0	40163	5.0	46634	14338	Chiostro	Herbed / Spiced Beer	4.0	4.0	4.0	4.0
1	8135	11.0	3003	395	Bearded Pat's Barleywine	American Barleywine	4.0	3.5	3.5	3.5
2	10529	4.7	961	365	Naughty Nellie's Ale	American Pale Ale (APA)	3.5	4.0	3.5	3.5
3	44610	4.4	429	1	Pilsner Urquell	Czech Pilsener	3.0	3.0	2.5	3.0
4	37062	4.4	4904	1417	Black Sheep Ale (Special)	English Pale Ale	4.0	3.0	3.0	3.5

In [395]:

```
features=features.reset_index()
```

Data Preprocessing:

Q) How can you use "beer/name", "beer/style" and "review/text" as features to predict the overall rating of the beer ?

In [396]:

```
### Dataset Preprocessing
from nltk.stem.porter import PorterStemmer
import re
ps = PorterStemmer()

def preprocessor(dataset,col):
  corpus = []
  for i in range(0, len(dataset)):
      review = re.sub('[^a-zA-Z]', ' ', dataset[col][i])
      review = review.lower()
      review = review.split()
      review = [ps.stem(word) for word in review if not word in stopwords.words('english')]
      review = ' '.join(review)
      corpus.append(review)
  return corpus
```

In [397]:

```
beerNames = preprocessor(features,'beer/name') ## Preprocessing Beer Names
features['clean_beerNames'] = beerNames
features.drop('beer/name',axis=1,inplace=True)
```

In [398]:

```
beerTypes = preprocessor(features,'beer/style') ## Preprocessing Beer types
features['clean_beerTypes'] = beerTypes
features.drop('beer/style',axis=1,inplace=True)
```

```
features.drop('beer/style',axis=1,inplace=True)
```

In [399]:

```
#View the top types of beer in our dataset whose frequency is greater than 500

beernames = features['clean_beerNames'].value_counts()
print('Number of beer names are : {0}'.format(len(beernames)))
print(beernames[beernames > 500])
```

```
Number of beer names are : 1671
founder breakfast stout                1882
founder kb kentucki breakfast stout    1438
founder centenni ipa                   1063
founder red rye pa                     1051
founder dirti bastard                   983
pilsner urquel                          948
founder doubl troubl                    857
founder imperi stout                    805
founder devil dancer                    799
founder backwood bastard                778
founder porter                          675
founder nemesi                          670
aecht schlenkerla rauchbier rzen        665
b r crusher oatmeal imperi stout        635
founder curmudgeon old ale              574
stoudt doubl ipa india pale ale         538
Name: clean_beerNames, dtype: int64
```

In [400]:

```
beerNameList = []
for i in range(16):
  beerNameList.append(beernames.index[i])
print(beerNameList)
```

```
['founder breakfast stout', 'founder kb kentucki breakfast stout', 'founder centenni ipa', 'founde
r red rye pa', 'founder dirti bastard', 'pilsner urquel', 'founder doubl troubl', 'founder imperi
stout', 'founder devil dancer', 'founder backwood bastard', 'founder porter', 'founder nemesi', 'a
echt schlenkerla rauchbier rzen', 'b r crusher oatmeal imperi stout', 'founder curmudgeon old ale'
, 'stoudt doubl ipa india pale ale']
```

In [401]:

```
beertype = features['clean_beerTypes'].value_counts()
print('Number of beer types are : {0}'.format(len(beertype)))
print(beertype[beertype > 500])
```

```
Number of beer types are : 95
american doubl imperi stout        4490
american ipa                       3048
american doubl imperi ipa          2871
scotch ale wee heavi               2133
russian imperi stout               2030
american pale ale apa              1711
american porter                    1687
rauchbier                          1462
rye beer                           1355
czech pilsen                       1130
fruit veget beer                   1021
english pale ale                    971
old ale                             783
doppelbock                          669
american barleywin                  634
euro pale lager                     522
extra special strong bitter esb     505
Name: clean_beerTypes, dtype: int64
```

In [402]:

```
beerTypeList = []
for i in range(17):
```

```python
for i in range(17):
  beerTypeList.append(beertype.index[i])
print(beerTypeList)
```

```
['american doubl imperi stout', 'american ipa', 'american doubl imperi ipa', 'scotch ale wee
heavi', 'russian imperi stout', 'american pale ale apa', 'american porter', 'rauchbier', 'rye beer
', 'czech pilsen', 'fruit veget beer', 'english pale ale', 'old ale', 'doppelbock', 'american barl
eywin', 'euro pale lager', 'extra special strong bitter esb']
```

In [403]:

```python
#Recode the beer names keeping only top beer names (all others at NA)
from pandas.api.types import CategoricalDtype
features.clean_beerNames= features.clean_beerNames.astype(CategoricalDtype(categories=beerNameList
))
```

In [404]:

```python
#Recode the beer types keeping only top beer types (all others at NA)
features.clean_beerTypes= features.clean_beerTypes.astype(CategoricalDtype(categories=beerTypeList
))
```

In [405]:

```python
features.info() ## Introduced NA into clean_beerNames and clean_beerTypes
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 37485 entries, 0 to 37484
Data columns (total 20 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   level_0             37485 non-null  int64
 1   index               37485 non-null  int64
 2   beer/ABV            37485 non-null  float64
 3   beer/beerId         37485 non-null  int64
 4   beer/brewerId       37485 non-null  int64
 5   review/appearance   37485 non-null  float64
 6   review/aroma        37485 non-null  float64
 7   review/overall      37485 non-null  float64
 8   review/palate       37485 non-null  float64
 9   review/taste        37485 non-null  float64
 10  review/text         37485 non-null  object
 11  review/timeStruct   37485 non-null  object
 12  review/timeUnix     37485 non-null  int64
 13  user/ageInSeconds   37485 non-null  float64
 14  user/birthdayRaw    37485 non-null  object
 15  user/birthdayUnix   37485 non-null  float64
 16  user/gender         37485 non-null  object
 17  user/profileName    37485 non-null  object
 18  clean_beerNames     14361 non-null  category
 19  clean_beerTypes     27022 non-null  category
dtypes: category(2), float64(8), int64(5), object(5)
memory usage: 5.2+ MB
```

In [322]:

```python
beertext = preprocessor(features,'review/text') ## Preprocessing Beer text
features['clean_beerText'] = beertext
features.drop('review/text',axis=1,inplace=True)
```

In [406]:

```python
features.isnull().sum()
```

Out[406]:

```
level_0                  0
index                    0
beer/ABV                 0
beer/beerId              0
beer/brewerId            0
```

```
review/appearance        0
review/aroma             0
review/overall           0
review/palate            0
review/taste             0
review/text              0
review/timeStruct        0
review/timeUnix          0
user/ageInSeconds        0
user/birthdayRaw         0
user/birthdayUnix        0
user/gender              0
user/profileName         0
clean_beerNames      23124
clean_beerTypes      10463
dtype: int64
```

In [408]:

```
features['beer/beerId'].value_counts()
```

Out[408]:

```
11757    1882
19960    1438
5441     1063
16074    1051
7463      983
         ... 
63735       1
26853       1
42273       1
41116       1
67406       1
Name: beer/beerId, Length: 1731, dtype: int64
```

In [409]:

```
beerId = features['beer/beerId'].value_counts()
print('Number of beer ids are : {0}'.format(len(beerId)))
print(beerId[beerId > 500])
```

```
Number of beer ids are : 1731
11757    1882
19960    1438
5441     1063
16074    1051
7463      983
429       946
34146     857
21822     805
17538     799
35036     778
7348      675
727       665
33644     635
24905     574
20470     538
Name: beer/beerId, dtype: int64
```

In [410]:

```
beerIdList = []
for i in range(15):
  beerIdList.append(beerId.index[i])
print(beerIdList)
```

```
[11757, 19960, 5441, 16074, 7463, 429, 34146, 21822, 17538, 35036, 7348, 727, 33644, 24905, 20470]
```

In [411]:

```
#Recode the beer names keeping only top beer names (all others at NA)
from pandas.api.types import CategoricalDtype
features['beer/beerId']= features['beer/beerId'].astype(CategoricalDtype(categories=beerIdList))
```

In [412]:

```
features['beer/brewerId'].value_counts()
```

Out[412]:

```
1199     14968
394       2936
14879     2349
263       1809
3268      1277
         ...
27133        1
15607        1
3207         1
3408         1
17783        1
Name: beer/brewerId, Length: 212, dtype: int64
```

In [413]:

```
brewerId = features['beer/brewerId'].value_counts()
print('Number of brewer ids are : {0}'.format(len(brewerId)))
print(brewerId[brewerId > 500])
```

```
Number of brewer ids are : 212
1199     14968
394       2936
14879     2349
263       1809
3268      1277
395       1225
365       1069
1         1016
1417       908
14         834
568        785
1075       666
1315       601
Name: beer/brewerId, dtype: int64
```

In [414]:

```
brewerIdList = []
for i in range(15):
  brewerIdList.append(brewerId.index[i])
print(brewerIdList)
```

```
[1199, 394, 14879, 263, 3268, 395, 365, 1, 1417, 14, 568, 1075, 1315, 9020, 60]
```

In [415]:

```
#Recode the beer names keeping only top beer names (all others at NA)
from pandas.api.types import CategoricalDtype
features['beer/brewerId']= features['beer/brewerId'].astype(CategoricalDtype(categories=brewerIdLis
t))
```

In [416]:

```
features.columns
```

Out[416]:

```
Index(['level_0', 'index', 'beer/ABV', 'beer/beerId', 'beer/brewerId',
       'review/appearance', 'review/aroma', 'review/overall', 'review/palate',
       'review/taste', 'review/text', 'review/timeStruct', 'review/timeUnix',
       'user/ageInSeconds', 'user/birthdayRaw', 'user/birthdayUnix',
```

```
        'user/ageInSeconds', 'user/birthdayRaw', 'user/birthdayUnix',
        'user/gender', 'user/profileName', 'clean_beerNames',
        'clean_beerTypes'],
      dtype='object')
```

In [417]:

```
features.drop(['level_0', 'index','review/timeStruct','user/profileName','user/birthdayRaw'],axis=
1,inplace=True)
```

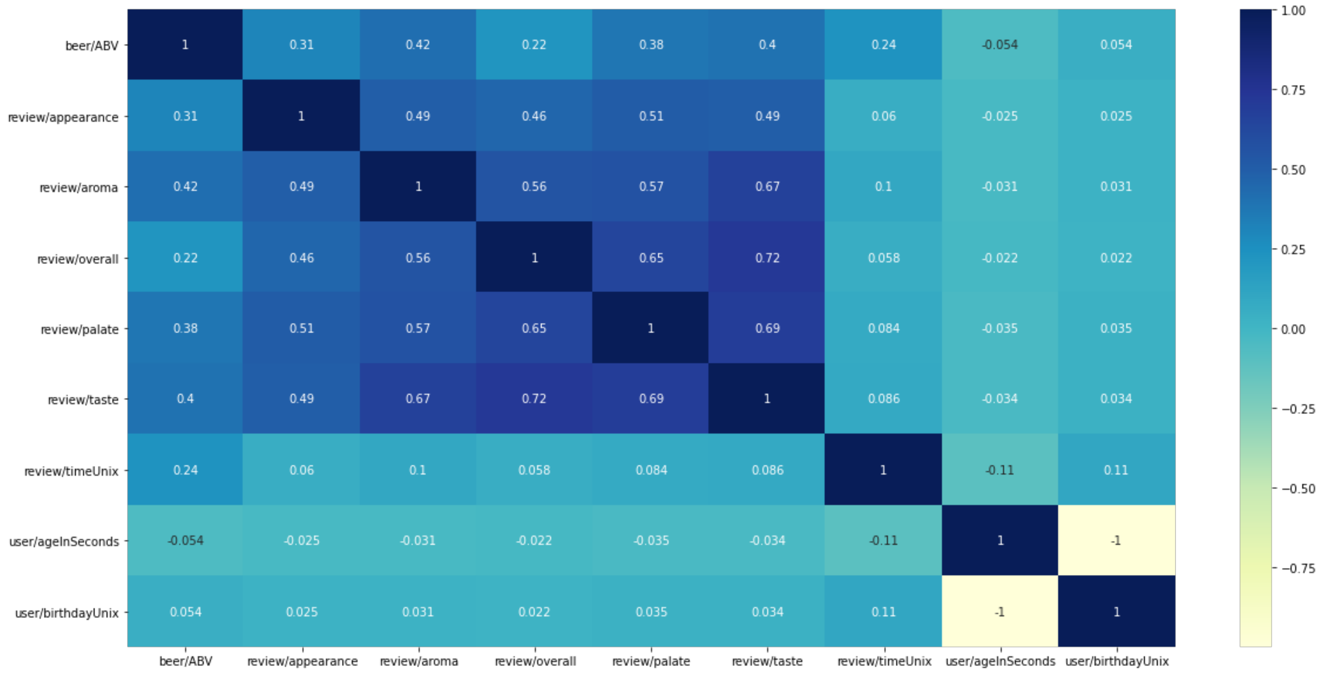
Checking Correlations

In [418]:

```
f, ax = plt.subplots(figsize=(20, 10))
sns.heatmap(features.corr(method='spearman'), annot=True, cmap="YlGnBu")
```

Out[418]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f39290b0be0>
```



In [419]:

```
features['beer/brewerId'] = features['beer/brewerId'].cat.add_categories('0')
features['beer/brewerId'].fillna('0', inplace=True)
```

In [420]:

```
features['beer/beerId'] = features['beer/beerId'].cat.add_categories('0')
features['beer/beerId'].fillna('0', inplace=True)
```

In [421]:

```
features = features.sample(frac=1).reset_index(drop=True)
```

In [422]:

```
features
```

Out[422]:

	beer/ABV	beer/beerId	beer/brewerId	review/appearance	review/aroma	review/overall	review/palate	review/taste	review/text

	beer/ABV	beer/beerId	beer/brewerId	review/appearance	review/aroma	review/overall	review/palate	review/taste	review/text
0	5.20	0	263	3.5	4.0	3.5	3.5	4.0	Pours a slightly hazy, brownish-orange with a ...
1	3.80	0	0	3.5	3.5	4.0	4.0	4.0	Had a bottle purchased from my Local Netto sto...
2	10.50	21822	1199	5.0	5.0	4.5	5.0	5.0	acquired through trade with rysberg01 (good tr...
3	8.30	11757	1199	5.0	4.0	4.5	4.5	4.5	Kudos to Derek for getting this gem on draft i...
4	8.30	11757	1199	4.5	4.0	4.0	2.5	4.0	Bottle tasted side by side with KBS.\t\tPours ...
...	...	...	...	...	...	...	...	...	...
37480	5.79	0	395	4.5	4.5	4.5	4.0	4.0	I really enjoyed BBC's Dark Star Porter so I'm...
37481	10.50	21822	1199	4.5	4.0	5.0	4.5	4.5	A- Pours very dark brown and settles pitch bla...
37482	9.00	0	394	4.5	4.5	5.0	3.5	4.5	750ml bottle from hopdog via trade. Thanks for...
37483	10.00	20470	394	4.0	3.0	4.0	4.0	4.5	Pouring into a snifter from a room temperature...
37484	7.00	0	394	4.5	3.0	4.0	3.5	4.0	A_pours a slightly dark golden hue with a crea...

37485 rows × 15 columns

In [375]:

```
# features['review/overall'] = train['review/overall']
```

Train-Test Split(70:30)

In [428]:

```
#spit data into train and test
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(features, features['review/overall'], test_size
=0.3, random_state=64)
```

In [429]:

```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[429]:

```
((26239, 15), (11246, 15), (26239,), (11246,))
```

In [362]:

```
# features.drop(['product_category_2'],axis=1,inplace=True)
```

Vectorise Numerical Features

In [430]:

```
from sklearn.preprocessing import StandardScaler
import warnings
warnings.filterwarnings("ignore")

def numerical_vectorizations(m,o):

    scalars = StandardScaler()
    scalars.fit(m.values.reshape(-1,1))
    print(f"Mean : {scalars.mean_[0]}, Standard deviation : {np.sqrt(scalars.var_[0])}")

    standardized_train = scalars.transform(m.values.reshape(-1, 1))
    standardized_test = scalars.transform(o.values.reshape(-1, 1))
    return standardized_train,standardized_test
```

In [439]:

```
X_train.head(5)
```

Out[439]:

	beer/ABV	beer/beerId	beer/brewerId	review/appearance	review/aroma	review/overall	review/palate	review/taste	review/text	r
7109	6.1	0	1075	4.5	3.0	3.5	3.5	3.0	I dont believe that I tasted the freshest can,...	
35069	6.5	0	1199	3.0	4.0	3.0	3.0	4.5	a- pours into my Ommegang glass a yellow/ almo...	
19313	11.2	19960	1199	4.0	4.5	4.5	5.0	4.5	Serving glass: Poured from bottle into Snifter...	
26489	5.6	0	9020	4.0	3.0	4.0	4.0	4.0	A: Very dark brown, almost black in color. Nic...	
17543	5.0	0	394	4.0	3.5	4.0	3.5	3.5	A 12 ounce bottle poured into a standard shake...	

In [433]:

```
std_train_1 ,std_test_1 = numerical_vectorizations(X_train['beer/ABV'],X_test['beer/ABV'])
print("After Column Standardisation: ")
print(std_train_1.shape, y_train.shape)
print(std_test_1.shape)
```

```
Mean : 7.406236899272076, Standard deviation : 2.319127447613784
After Column Standardisation:
(26239, 1) (26239,)
(11246, 1)
```

In [443]:

```
X_train['beer/beerId']= pd.to_numeric(X_train['beer/beerId'], errors='coerce')
```

```
X_test['beer/beerId']= pd.to_numeric(X_test['beer/beerId'], errors='coerce')

std_train_2 ,std_test_2 = numerical_vectorizations(X_train['beer/beerId'],X_test['beer/beerId'])
print("After Column Standardisation: ")
print(std_train_2.shape, y_train.shape)
print(std_test_2.shape)
```

```
Mean : 5943.76675940394, Standard deviation : 10100.361946145329
After Column Standardisation:
(26239, 1) (26239,)
(11246, 1)
```

In [445]:

```
X_train['beer/brewerId']= pd.to_numeric(X_train['beer/brewerId'], errors='coerce')
X_test['beer/brewerId']= pd.to_numeric(X_test['beer/brewerId'], errors='coerce')

std_train_3 ,std_test_3 = numerical_vectorizations(X_train['beer/brewerId'],X_test['beer/brewerId'
])
print("After Column Standardisation: ")
print(std_train_3.shape, y_train.shape)
print(std_test_3.shape)
```

```
Mean : 1797.1352947901978, Standard deviation : 3589.554166655147
After Column Standardisation:
(26239, 1) (26239,)
(11246, 1)
```

In [446]:

```
X_train['review/appearance']= pd.to_numeric(X_train['review/appearance'], errors='coerce')
X_test['review/appearance']= pd.to_numeric(X_test['review/appearance'], errors='coerce')

std_train_4 ,std_test_4 =
numerical_vectorizations(X_train['review/appearance'],X_test['review/appearance'])
print("After Column Standardisation: ")
print(std_train_4.shape, y_train.shape)
print(std_test_4.shape)
```

```
Mean : 3.900605968215252, Standard deviation : 0.5862084923908392
After Column Standardisation:
(26239, 1) (26239,)
(11246, 1)
```

In [447]:

```
X_train['review/aroma']= pd.to_numeric(X_train['review/aroma'], errors='coerce')
X_test['review/aroma']= pd.to_numeric(X_test['review/aroma'], errors='coerce')

std_train_5 ,std_test_5 = numerical_vectorizations(X_train['review/aroma'],X_test['review/aroma'])
print("After Column Standardisation: ")
print(std_train_5.shape, y_train.shape)
print(std_test_5.shape)
```

```
Mean : 3.8724227295247533, Standard deviation : 0.6758052389772954
After Column Standardisation:
(26239, 1) (26239,)
(11246, 1)
```

In [448]:

```
X_train['review/palate']= pd.to_numeric(X_train['review/palate'], errors='coerce')
X_test['review/palate']= pd.to_numeric(X_test['review/palate'], errors='coerce')

std_train_6 ,std_test_6 = numerical_vectorizations(X_train['review/palate'],X_test['review/palate'
])
print("After Column Standardisation: ")
print(std_train_6.shape, y_train.shape)
print(std_test_6.shape)
```

```
Mean : 3.854624795152254, Standard deviation : 0.6642882434802061
After Column Standardisation:
(26239, 1) (26239,)
(11246, 1)
```

In [449]:

```
X_train['review/taste']= pd.to_numeric(X_train['review/taste'], errors='coerce')
X_test['review/taste']= pd.to_numeric(X_test['review/taste'], errors='coerce')

std_train_7 ,std_test_7 = numerical_vectorizations(X_train['review/taste'],X_test['review/taste'])
print("After Column Standardisation: ")
print(std_train_7.shape, y_train.shape)
print(std_test_7.shape)
```

```
Mean : 3.9232440260680668, Standard deviation : 0.7122330678961271
After Column Standardisation:
(26239, 1) (26239,)
(11246, 1)
```

In [450]:

```
X_train['review/timeUnix']= pd.to_numeric(X_train['review/timeUnix'], errors='coerce')
X_test['review/timeUnix']= pd.to_numeric(X_test['review/timeUnix'], errors='coerce')

std_train_8 ,std_test_8 =
numerical_vectorizations(X_train['review/timeUnix'],X_test['review/timeUnix'])
print("After Column Standardisation: ")
print(std_train_8.shape, y_train.shape)
print(std_test_8.shape)
```

```
Mean : 1232749622.1694806, Standard deviation : 71678951.5104187
After Column Standardisation:
(26239, 1) (26239,)
(11246, 1)
```

In [452]:

```
X_train['user/ageInSeconds']= pd.to_numeric(X_train['user/ageInSeconds'], errors='coerce')
X_test['user/ageInSeconds']= pd.to_numeric(X_test['user/ageInSeconds'], errors='coerce')

std_train_9 ,std_test_9 =
numerical_vectorizations(X_train['user/ageInSeconds'],X_test['user/ageInSeconds'])
print("After Column Standardisation: ")
print(std_train_9.shape, y_train.shape)
print(std_test_9.shape)
```

```
Mean : 1115745687.1463852, Standard deviation : 153821653.59656808
After Column Standardisation:
(26239, 1) (26239,)
(11246, 1)
```

In [453]:

```
X_train['user/birthdayUnix']= pd.to_numeric(X_train['user/birthdayUnix'], errors='coerce')
X_test['user/birthdayUnix']= pd.to_numeric(X_test['user/birthdayUnix'], errors='coerce')

std_train_10 ,std_test_10 =
numerical_vectorizations(X_train['user/birthdayUnix'],X_test['user/birthdayUnix'])
print("After Column Standardisation: ")
print(std_train_10.shape, y_train.shape)
print(std_test_10.shape)
```

```
Mean : 302589759.8841419, Standard deviation : 153821653.59224394
After Column Standardisation:
(26239, 1) (26239,)
(11246, 1)
```

In [468]:

In [468]:

```
features.head(5)
```

Out[468]:

	beer/ABV	beer/beerId	beer/brewerId	review/appearance	review/aroma	review/overall	review/palate	review/taste	review/text	revi
0	5.2	0	263	3.5	4.0	3.5	3.5	4.0	Pours a slightly hazy, brownish-orange with a ...	
1	3.8	0	0	3.5	3.5	4.0	4.0	4.0	Had a bottle purchased from my Local Netto sto...	
2	10.5	21822	1199	5.0	5.0	4.5	5.0	5.0	acquired through trade with rysberg01 (good tr...	
3	8.3	11757	1199	5.0	4.0	4.5	4.5	4.5	Kudos to Derek for getting this gem on draft i...	
4	8.3	11757	1199	4.5	4.0	4.0	2.5	4.0	Bottle tasted side by side with KBS.\t\tPours ...	

Vectorise Categorical Features

In [458]:

```
from collections import Counter

def categorical_vectorization(m,o):


    my_counter = Counter()
    for word in m.values:
        my_counter.update(str(word).split())
    category_dict = dict(my_counter)
    sorted_dict = dict(sorted(category_dict.items(), key=lambda kv: kv[1]))

    ## we use count vectorizer to convert the values into one hot encoded features
    vectorizer = CountVectorizer(vocabulary=list(sorted_dict.keys()), lowercase=False, binary=True)
    vectorizer.fit(m.values)
    print(vectorizer.get_feature_names())

    one_hot_train = vectorizer.transform(m.values)
    one_hot_test = vectorizer.transform(o.values)
    return one_hot_train, one_hot_test
```

In [459]:

```
std_train_11 ,std_test_11 = categorical_vectorization(X_train['user/gender'],X_test['user/gender']
)
print("After Column Standardisation: ")
print(std_train_11.shape, y_train.shape)
print(std_test_11.shape)
```

```
['Female', 'Male', 'missing']
After Column Standardisation:
(26239, 3) (26239,)
(11246, 3)
```

In [465]:

```
X_train['clean_beerNames'] = X_train['clean_beerNames'].cat.add_categories('missing')
X_test['clean_beerNames'] = X_test['clean_beerNames'].cat.add_categories('missing')

X_train['clean_beerNames'].fillna('missing', inplace=True)
X_test['clean_beerNames'].fillna('missing', inplace=True)

X_train['clean_beerTypes'] = X_train['clean_beerTypes'].cat.add_categories('missing')
X_test['clean_beerTypes'] = X_test['clean_beerTypes'].cat.add_categories('missing')

X_train['clean_beerTypes'].fillna('missing', inplace=True)
X_test['clean_beerTypes'].fillna('missing', inplace=True)
```

In [471]:

```
preprocessed_beerNames_tr = []
for i in X_train['clean_beerNames']:
  preprocessed_beerNames_tr.append(i.replace(' ','_'))

preprocessed_beerNames_te = []
for i in X_test['clean_beerNames']:
  preprocessed_beerNames_te.append(i.replace(' ','_'))
```

In [473]:

```
preprocessed_beerTypes_tr = []
for i in X_train['clean_beerTypes']:
  preprocessed_beerTypes_tr.append(i.replace(' ','_'))

preprocessed_beerTypes_te = []
for i in X_test['clean_beerTypes']:
  preprocessed_beerTypes_te.append(i.replace(' ','_'))
```

In [474]:

```
X_train['clean_beerNames_processed'] = preprocessed_beerNames_tr
X_train.drop('clean_beerNames',axis=1,inplace=True)

X_test['clean_beerNames_processed'] = preprocessed_beerNames_te
X_test.drop('clean_beerNames',axis=1,inplace=True)

X_train['clean_beerTypes_processed'] = preprocessed_beerTypes_tr
X_train.drop('clean_beerTypes',axis=1,inplace=True)

X_test['clean_beerTypes_processed'] = preprocessed_beerTypes_te
X_test.drop('clean_beerTypes',axis=1,inplace=True)
```

In [476]:

```
std_train_12 ,std_test_12 = categorical_vectorization(X_train['clean_beerNames_processed'],X_test[
'clean_beerNames_processed'])
print("After Column Standardisation: ")
print(std_train_12.shape, y_train.shape)
print(std_test_12.shape)
```

```
['stoudt_doubl_ipa_india_pale_ale', 'founder_curmudgeon_old_ale',
'b_r_crusher_oatmeal_imperi_stout', 'founder_nemesi', 'aecht_schlenkerla_rauchbier_rzen',
'founder_porter', 'founder_backwood_bastard', 'founder_devil_dancer', 'founder_imperi_stout',
'founder_doubl_troubl', 'pilsner_urquel', 'founder_dirti_bastard', 'founder_centenni_ipa',
'founder_red_rye_pa', 'founder_kb_kentucki_breakfast_stout', 'founder_breakfast_stout', 'missing']
After Column Standardisation:
(26239, 17) (26239,)
(11246, 17)
```

In [477]:

```
std_train_13 ,std_test_13 = categorical_vectorization(X_train['clean_beerTypes_processed'],X_test[
'clean_beerTypes_processed'])
print("After Column Standardisation: ")
print(std_train_13.shape, y_train.shape)
print(std_test_13.shape)
```

```
['extra_special_strong_bitter_esb', 'euro_pale_lager', 'american_barleywin', 'doppelbock',
'old_ale', 'english_pale_ale', 'fruit_veget_beer', 'czech_pilsen', 'rye_beer', 'rauchbier',
'american_porter', 'american_pale_ale_apa', 'russian_imperi_stout', 'scotch_ale_wee_heavi',
'american_doubl_imperi_ipa', 'american_ipa', 'american_doubl_imperi_stout', 'missing']
After Column Standardisation:
(26239, 18) (26239,)
(11246, 18)
```

Vectorise Text Features

In [481]:

```
tfv = TfidfVectorizer(min_df=3,  max_features=5000,
            strip_accents='unicode', analyzer='word',token_pattern=r'\w{1,}',
            ngram_range=(1, 3), use_idf=1,smooth_idf=1,sublinear_tf=1,
            stop_words = 'english')

# Fitting TF-IDF to both training and test sets (semi-supervised learning)
tfv.fit(list(X_train['review/text']) + list(X_test['review/text']))
std_train_14 =  tfv.transform(X_train['review/text'])
std_test_14 = tfv.transform(X_test['review/text'])
```

In [483]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack

X_tr = hstack((std_train_1,std_train_2,std_train_3,std_train_4,std_train_5,std_train_6,std_train_7,
std_train_8,std_train_9,std_train_10,std_train_11,std_train_12,std_train_13,std_train_14)).tocsr()
X_te =
hstack((std_test_1,std_test_2,std_test_3,std_test_4,std_test_5,std_test_6,std_test_7,std_test_8,st
d_test_9,std_test_10,std_test_11,std_test_12,std_test_13,std_test_14)).tocsr()
```

In [494]:

```
print("Final Data matrix")
print(X_tr.shape, y_train.shape)
print(X_te.shape,y_test.shape)
```

```
Final Data matrix
(26239, 5048) (26239,)
(11246, 5048) (11246,)
```

In [509]:

```
y_train_enc=np.array(list(y_train))
y_test_enc=np.array(list(y_test))
```

MODEL 1 : RandomForest Regressor

In [500]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV



# initialize Our first RandomForestRegressor model...
regr2 = RandomForestRegressor(max_features='sqrt')

# declare parameters for hyperparameter tuning
parameters = {'n_estimators':[100,300,500,700],'max_depth':[1,3,5]}

# Perform cross validation
clf = GridSearchCV(regr2,
                    param_grid = parameters,
                    scoring="neg_mean_squared_error",
                    cv = 5,
```

```
                    n_jobs = -1,
                    verbose = 1)
result = clf.fit(X_tr, y_train_enc)

# Summarize results
print("Best: %f using %s" % (result.best_score_, result.best_params_))
means = result.cv_results_['mean_test_score']
stds = result.cv_results_['std_test_score']
params = result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f 1(%f) with: %r" % (mean, stdev, param))
```

```
Fitting 5 folds for each of 12 candidates, totalling 60 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed:  1.7min
[Parallel(n_jobs=-1)]: Done  60 out of  60 | elapsed:  2.9min finished
```

```
Best: -0.374505 using {'max_depth': 5, 'n_estimators': 100}
-0.454021 1(0.010649) with: {'max_depth': 1, 'n_estimators': 100}
-0.459571 1(0.011199) with: {'max_depth': 1, 'n_estimators': 300}
-0.457620 1(0.010934) with: {'max_depth': 1, 'n_estimators': 500}
-0.457919 1(0.011349) with: {'max_depth': 1, 'n_estimators': 700}
-0.416678 1(0.013544) with: {'max_depth': 3, 'n_estimators': 100}
-0.414791 1(0.010798) with: {'max_depth': 3, 'n_estimators': 300}
-0.414401 1(0.008702) with: {'max_depth': 3, 'n_estimators': 500}
-0.412911 1(0.008955) with: {'max_depth': 3, 'n_estimators': 700}
-0.374505 1(0.019761) with: {'max_depth': 5, 'n_estimators': 100}
-0.380577 1(0.013408) with: {'max_depth': 5, 'n_estimators': 300}
-0.380776 1(0.012326) with: {'max_depth': 5, 'n_estimators': 500}
-0.379835 1(0.012900) with: {'max_depth': 5, 'n_estimators': 700}
```

In [502]:

```
rfr = RandomForestRegressor(max_depth=5,n_estimators=100)
rfr.fit(X_tr, y_train_enc)
```

Out[502]:

```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=5, 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=100, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

In [514]:

```
from sklearn.externals import joblib
# Save the model as a pickle in a file
joblib.dump(rfr, 'rfr.pkl')
```

Out[514]:

```
['rfr.pkl']
```

In [584]:

```
from sklearn.metrics import mean_squared_error
from math import sqrt

predict_train = rfr.predict(X_tr)
predict_target = rfr.predict(X_te)


rms = sqrt(mean_squared_error(y_test_enc, predict_target))
print(rms)
```

```
0.4038541839384915
```

In [585]:

```
from sklearn.metrics import r2_score

coefficient_of_dermination = r2_score(y_test_enc, predict_target)

print(coefficient_of_dermination)
```

```
0.6761037707275874
```

MODEL 2 : XGBoost Regressor

In [513]:

```
import xgboost as xgb

# initialize Our first XGBoost model...
regr = xgb.XGBRegressor(silent=False, random_state=15)
#regr = MultiOutputRegressor(regr1)

# declare parameters for hyperparameter tuning
parameters = {'learning_rate':[0.01,0.1],'n_estimators':[200,300,500],'max_depth':[1,2,3]}

# Perform cross validation
clf = GridSearchCV(regr,
                    param_grid = parameters,
                    scoring="neg_mean_squared_error",
                    cv=2,
                    n_jobs = -1,
                    verbose = 1)
result = clf.fit(X_tr, y_train_enc)

# Summarize results
print("Best: %f using %s" % (result.best_score_, result.best_params_))
means = result.cv_results_['mean_test_score']
stds = result.cv_results_['std_test_score']
params = result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f 1(%f) with: %r" % (mean, stdev, param))
```

```
Fitting 2 folds for each of 18 candidates, totalling 36 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  36 out of  36 | elapsed: 15.5min finished
```

```
[14:03:21] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated i
n favor of reg:squarederror.
Best: -0.151329 using {'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 300}
-0.430181 1(0.004293) with: {'learning_rate': 0.01, 'max_depth': 1, 'n_estimators': 200}
-0.225236 1(0.001070) with: {'learning_rate': 0.01, 'max_depth': 1, 'n_estimators': 300}
-0.178862 1(0.000172) with: {'learning_rate': 0.01, 'max_depth': 1, 'n_estimators': 500}
-0.391738 1(0.005370) with: {'learning_rate': 0.01, 'max_depth': 2, 'n_estimators': 200}
-0.200125 1(0.002185) with: {'learning_rate': 0.01, 'max_depth': 2, 'n_estimators': 300}
-0.163583 1(0.000525) with: {'learning_rate': 0.01, 'max_depth': 2, 'n_estimators': 500}
-0.382820 1(0.005374) with: {'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 200}
-0.191962 1(0.002092) with: {'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 300}
-0.157296 1(0.000189) with: {'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 500}
-0.158629 1(0.000190) with: {'learning_rate': 0.1, 'max_depth': 1, 'n_estimators': 200}
-0.156491 1(0.000178) with: {'learning_rate': 0.1, 'max_depth': 1, 'n_estimators': 300}
-0.155045 1(0.000182) with: {'learning_rate': 0.1, 'max_depth': 1, 'n_estimators': 500}
-0.153168 1(0.000642) with: {'learning_rate': 0.1, 'max_depth': 2, 'n_estimators': 200}
-0.152583 1(0.000671) with: {'learning_rate': 0.1, 'max_depth': 2, 'n_estimators': 300}
-0.152508 1(0.000494) with: {'learning_rate': 0.1, 'max_depth': 2, 'n_estimators': 500}
-0.151579 1(0.000055) with: {'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 200}
-0.151329 1(0.000320) with: {'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 300}
-0.151749 1(0.000193) with: {'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 500}
```

In [516]:

```
xgb1 = xgb.XGBRegressor(learning_rate= 0.1, max_depth= 3, n_estimators= 300)
xgb1.fit(X_tr, y_train_enc)
```

```
[14:05:46] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated i
n favor of reg:squarederror.
```

Out[516]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=300,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

In [518]:

```
from sklearn.externals import joblib
# Save the model as a pickle in a file
joblib.dump(xgb1, 'xgb.pkl')
```

Out[518]:

```
['xgb.pkl']
```

In [586]:

```
from sklearn.metrics import mean_squared_error
from math import sqrt

predict_train = xgb1.predict(X_tr)
predict_target = xgb1.predict(X_te)


rms = sqrt(mean_squared_error(y_test_enc, predict_target))
print(rms)
```

```
0.37872831629803483
```

In [587]:

```
from sklearn.metrics import r2_score

coefficient_of_dermination = r2_score(y_test_enc, predict_target)

print(coefficient_of_dermination)
```

```
0.7151525911018723
```

In [520]:

```
result = pd.DataFrame()
result['y_test'] = y_test
result['y_predicted'] = predict_target
```

In [524]:

```
result[10:15]
```

Out[524]:

	y_test	y_predicted
30632	4.0	3.857816
17353	3.5	3.662436
31272	3.5	3.929962

	y_test	y_predicted
28899	4.5	4.122451
12446	4.0	4.211697

MODEL 3 : Linear Regression

In [532]:

```
from sklearn import linear_model
from sklearn import ensemble

alpha = [10 ** x for x in range(-6, 3)]

# initialize Our first XGBoost model...
regr = linear_model.LinearRegression()

# declare parameters for hyperparameter tuning
parameters = {'fit_intercept':[True,False], 'normalize':[True,False], 'copy_X':[True, False]}

# Perform cross validation
clf = GridSearchCV(regr,
                    param_grid = parameters,
                    scoring="neg_mean_squared_error",
                    cv=2,
                    n_jobs = -1,
                    verbose = 1)
result = clf.fit(X_tr, y_train_enc)

# Summarize results
print("Best: %f using %s" % (result.best_score_, result.best_params_))
means = result.cv_results_['mean_test_score']
stds = result.cv_results_['std_test_score']
params = result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Fitting 2 folds for each of 8 candidates, totalling 16 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  16 out of  16 | elapsed:  2.8min finished
```

```
Best: -0.241081 using {'copy_X': True, 'fit_intercept': True, 'normalize': False}
-0.241083 (0.004304) with: {'copy_X': True, 'fit_intercept': True, 'normalize': True}
-0.241081 (0.004302) with: {'copy_X': True, 'fit_intercept': True, 'normalize': False}
-0.241081 (0.004301) with: {'copy_X': True, 'fit_intercept': False, 'normalize': True}
-0.241081 (0.004301) with: {'copy_X': True, 'fit_intercept': False, 'normalize': False}
-0.241083 (0.004304) with: {'copy_X': False, 'fit_intercept': True, 'normalize': True}
-0.241081 (0.004302) with: {'copy_X': False, 'fit_intercept': True, 'normalize': False}
-0.241081 (0.004301) with: {'copy_X': False, 'fit_intercept': False, 'normalize': True}
-0.241081 (0.004301) with: {'copy_X': False, 'fit_intercept': False, 'normalize': False}
```

In [533]:

```
lr = linear_model.LinearRegression(copy_X= True, fit_intercept= True, normalize=False)
lr.fit(X_tr, y_train_enc)
```

Out[533]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [588]:

```
from sklearn.metrics import mean_squared_error
from math import sqrt

predict_train = lr.predict(X_tr)
predict_target = lr.predict(X_te)


rms = sqrt(mean_squared_error(y_test_enc, predict_target))
print(rms)
```

```
print(rms)
```

```
0.4193538332053493
```

In [589]:

```
from sklearn.metrics import r2_score

coefficient_of_dermination = r2_score(y_test_enc, predict_target)

print(coefficient_of_dermination)
```

```
0.6507648460116796
```

MODEL 4: Deep Learning Models (MLP)

In [535]:

```
import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasRegressor
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from keras.callbacks import ModelCheckpoint
```

In [592]:

```
from keras.initializers import he_normal
from keras.layers.normalization import BatchNormalization

#Inıtialising the ANN
model = Sequential()
#Adding the input layer and first hidden layer
model.add(Dense(units =150, kernel_initializer=he_normal(seed=None), activation= 'tanh',
                input_dim=X_tr.shape[1]))



#Add the first hidden layer
model.add(Dense(units =100, kernel_initializer=he_normal(seed=None), activation= 'tanh'))
model.add(Dropout(0.2))

#Add the second hidden layer
model.add(Dense(units =80, kernel_initializer=he_normal(seed=None), activation= 'tanh'))
model.add(BatchNormalization())
model.add(Dropout(0.2))

#Add the third hidden layer
model.add(Dense(units =50, kernel_initializer=he_normal(seed=None), activation= 'tanh'))


#Add the fourth hidden layer
model.add(Dense(units =30, kernel_initializer=he_normal(seed=None), activation= 'relu'))
model.add(BatchNormalization())

#Add the fifth hidden layer
model.add(Dense(units =10, kernel_initializer=he_normal(seed=None), activation= 'relu'))
model.add(BatchNormalization())

#The output layer
model.add(Dense(units =1, kernel_initializer=he_normal(seed=None), activation= 'elu'))

print(model.summary())
```

```
Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
```

```
dense_32 (Dense)             (None, 150)               757350
_________________________________________________________________
dense_33 (Dense)             (None, 100)               15100
_________________________________________________________________
dropout_11 (Dropout)         (None, 100)               0
_________________________________________________________________
dense_34 (Dense)             (None, 80)                8080
_________________________________________________________________
batch_normalization_7 (Batch (None, 80)                320
_________________________________________________________________
dropout_12 (Dropout)         (None, 80)                0
_________________________________________________________________
dense_35 (Dense)             (None, 50)                4050
_________________________________________________________________
dense_36 (Dense)             (None, 30)                1530
_________________________________________________________________
batch_normalization_8 (Batch (None, 30)                120
_________________________________________________________________
dense_37 (Dense)             (None, 10)                310
_________________________________________________________________
batch_normalization_9 (Batch (None, 10)                40
_________________________________________________________________
dense_38 (Dense)             (None, 1)                 11
=================================================================
Total params: 786,911
Trainable params: 786,671
Non-trainable params: 240
_________________________________________________________________
None
```

In [593]:

```
#Compiling the ANN
#opt = keras.optimizers.Adam(lr=0.0015, beta_1=0.9, beta_2=0.999, epsilon=None, decay=0.0, amsgrad
=False)
model.compile(optimizer='adam', loss='mean_squared_logarithmic_error', metrics=['mse'])
#Fitting the ANN to the training set
model_filepath = 'ann2.h5'
checkpoint = ModelCheckpoint(model_filepath, monitor = 'val_loss', verbose=1, save_best_only = True
, mode='min' )
history=model.fit(X_tr,y_train_enc, validation_data=(X_te, y_test_enc), batch_size=32, nb_epoch=50,
callbacks=[checkpoint])
model.load_weights(model_filepath)
```

```
Train on 26239 samples, validate on 11246 samples
Epoch 1/50
26239/26239 [==============================] - 11s 434us/step - loss: 0.3873 - mse: 4.0829 - val_l
oss: 0.0296 - val_mse: 0.4580

Epoch 00001: val_loss improved from inf to 0.02957, saving model to ann2.h5
Epoch 2/50
26239/26239 [==============================] - 11s 411us/step - loss: 0.0184 - mse: 0.3447 - val_l
oss: 0.0134 - val_mse: 0.2362

Epoch 00002: val_loss improved from 0.02957 to 0.01342, saving model to ann2.h5
Epoch 3/50
26239/26239 [==============================] - 11s 424us/step - loss: 0.0139 - mse: 0.2654 - val_l
oss: 0.0120 - val_mse: 0.2185

Epoch 00003: val_loss improved from 0.01342 to 0.01195, saving model to ann2.h5
Epoch 4/50
26239/26239 [==============================] - 11s 420us/step - loss: 0.0123 - mse: 0.2354 - val_l
oss: 0.0092 - val_mse: 0.1798

Epoch 00004: val_loss improved from 0.01195 to 0.00923, saving model to ann2.h5
Epoch 5/50
26239/26239 [==============================] - 11s 413us/step - loss: 0.0111 - mse: 0.2158 - val_l
oss: 0.0087 - val_mse: 0.1705

Epoch 00005: val_loss improved from 0.00923 to 0.00873, saving model to ann2.h5
Epoch 6/50
26239/26239 [==============================] - 11s 412us/step - loss: 0.0104 - mse: 0.2035 - val_l
oss: 0.0085 - val_mse: 0.1689

Epoch 00006: val_loss improved from 0.00873 to 0.00851, saving model to ann2.h5
```

```
Epoch 7/50
26239/26239 [==============================] - 11s 413us/step - loss: 0.0098 - mse: 0.1930 - val_l
oss: 0.0081 - val_mse: 0.1614

Epoch 00007: val_loss improved from 0.00851 to 0.00810, saving model to ann2.h5
Epoch 8/50
26239/26239 [==============================] - 11s 412us/step - loss: 0.0095 - mse: 0.1878 - val_l
oss: 0.0084 - val_mse: 0.1648

Epoch 00008: val_loss did not improve from 0.00810
Epoch 9/50
26239/26239 [==============================] - 11s 413us/step - loss: 0.0089 - mse: 0.1766 - val_l
oss: 0.0084 - val_mse: 0.1651

Epoch 00009: val_loss did not improve from 0.00810
Epoch 10/50
26239/26239 [==============================] - 11s 410us/step - loss: 0.0085 - mse: 0.1681 - val_l
oss: 0.0083 - val_mse: 0.1613

Epoch 00010: val_loss did not improve from 0.00810
Epoch 11/50
26239/26239 [==============================] - 11s 411us/step - loss: 0.0080 - mse: 0.1605 - val_l
oss: 0.0086 - val_mse: 0.1656

Epoch 00011: val_loss did not improve from 0.00810
Epoch 12/50
26239/26239 [==============================] - 11s 412us/step - loss: 0.0076 - mse: 0.1554 - val_l
oss: 0.0089 - val_mse: 0.1687

Epoch 00012: val_loss did not improve from 0.00810
Epoch 13/50
26239/26239 [==============================] - 11s 408us/step - loss: 0.0074 - mse: 0.1517 - val_l
oss: 0.0084 - val_mse: 0.1624

Epoch 00013: val_loss did not improve from 0.00810
Epoch 14/50
26239/26239 [==============================] - 11s 409us/step - loss: 0.0072 - mse: 0.1486 - val_l
oss: 0.0091 - val_mse: 0.1713

Epoch 00014: val_loss did not improve from 0.00810
Epoch 15/50
26239/26239 [==============================] - 11s 412us/step - loss: 0.0068 - mse: 0.1422 - val_l
oss: 0.0086 - val_mse: 0.1665

Epoch 00015: val_loss did not improve from 0.00810
Epoch 16/50
26239/26239 [==============================] - 11s 410us/step - loss: 0.0067 - mse: 0.1377 - val_l
oss: 0.0090 - val_mse: 0.1740

Epoch 00016: val_loss did not improve from 0.00810
Epoch 17/50
26239/26239 [==============================] - 11s 411us/step - loss: 0.0063 - mse: 0.1326 - val_l
oss: 0.0090 - val_mse: 0.1701

Epoch 00017: val_loss did not improve from 0.00810
Epoch 18/50
26239/26239 [==============================] - 11s 415us/step - loss: 0.0060 - mse: 0.1280 - val_l
oss: 0.0087 - val_mse: 0.1709

Epoch 00018: val_loss did not improve from 0.00810
Epoch 19/50
26239/26239 [==============================] - 11s 408us/step - loss: 0.0056 - mse: 0.1212 - val_l
oss: 0.0091 - val_mse: 0.1765

Epoch 00019: val_loss did not improve from 0.00810
Epoch 20/50
26239/26239 [==============================] - 11s 413us/step - loss: 0.0055 - mse: 0.1180 - val_l
oss: 0.0092 - val_mse: 0.1738

Epoch 00020: val_loss did not improve from 0.00810
Epoch 21/50
26239/26239 [==============================] - 11s 415us/step - loss: 0.0052 - mse: 0.1131 - val_l
oss: 0.0091 - val_mse: 0.1767

Epoch 00021: val_loss did not improve from 0.00810
Epoch 22/50
26239/26239 [==============================] - 11s 409us/step - loss: 0.0049 - mse: 0.1083 - val_l
```

```
oss: 0.0099 - val_mse: 0.1927

Epoch 00022: val_loss did not improve from 0.00810
Epoch 23/50
26239/26239 [==============================] - 11s 413us/step - loss: 0.0048 - mse: 0.1049 - val_l
oss: 0.0096 - val_mse: 0.1870

Epoch 00023: val_loss did not improve from 0.00810
Epoch 24/50
26239/26239 [==============================] - 11s 412us/step - loss: 0.0046 - mse: 0.1020 - val_l
oss: 0.0099 - val_mse: 0.1886

Epoch 00024: val_loss did not improve from 0.00810
Epoch 25/50
26239/26239 [==============================] - 11s 412us/step - loss: 0.0043 - mse: 0.0962 - val_l
oss: 0.0098 - val_mse: 0.1898

Epoch 00025: val_loss did not improve from 0.00810
Epoch 26/50
26239/26239 [==============================] - 11s 416us/step - loss: 0.0043 - mse: 0.0960 - val_l
oss: 0.0098 - val_mse: 0.1916

Epoch 00026: val_loss did not improve from 0.00810
Epoch 27/50
26239/26239 [==============================] - 11s 413us/step - loss: 0.0040 - mse: 0.0893 - val_l
oss: 0.0098 - val_mse: 0.1901

Epoch 00027: val_loss did not improve from 0.00810
Epoch 28/50
26239/26239 [==============================] - 11s 411us/step - loss: 0.0039 - mse: 0.0877 - val_l
oss: 0.0101 - val_mse: 0.1967

Epoch 00028: val_loss did not improve from 0.00810
Epoch 29/50
26239/26239 [==============================] - 11s 409us/step - loss: 0.0038 - mse: 0.0856 - val_l
oss: 0.0102 - val_mse: 0.1981

Epoch 00029: val_loss did not improve from 0.00810
Epoch 30/50
26239/26239 [==============================] - 11s 411us/step - loss: 0.0039 - mse: 0.0879 - val_l
oss: 0.0101 - val_mse: 0.1962

Epoch 00030: val_loss did not improve from 0.00810
Epoch 31/50
26239/26239 [==============================] - 11s 410us/step - loss: 0.0035 - mse: 0.0788 - val_l
oss: 0.0105 - val_mse: 0.2045

Epoch 00031: val_loss did not improve from 0.00810
Epoch 32/50
26239/26239 [==============================] - 11s 433us/step - loss: 0.0034 - mse: 0.0779 - val_l
oss: 0.0102 - val_mse: 0.1993

Epoch 00032: val_loss did not improve from 0.00810
Epoch 33/50
26239/26239 [==============================] - 11s 410us/step - loss: 0.0034 - mse: 0.0767 - val_l
oss: 0.0104 - val_mse: 0.2036

Epoch 00033: val_loss did not improve from 0.00810
Epoch 34/50
26239/26239 [==============================] - 11s 410us/step - loss: 0.0033 - mse: 0.0756 - val_l
oss: 0.0104 - val_mse: 0.2058

Epoch 00034: val_loss did not improve from 0.00810
Epoch 35/50
26239/26239 [==============================] - 11s 413us/step - loss: 0.0030 - mse: 0.0699 - val_l
oss: 0.0105 - val_mse: 0.2063

Epoch 00035: val_loss did not improve from 0.00810
Epoch 36/50
26239/26239 [==============================] - 11s 411us/step - loss: 0.0030 - mse: 0.0687 - val_l
oss: 0.0101 - val_mse: 0.1972

Epoch 00036: val_loss did not improve from 0.00810
Epoch 37/50
26239/26239 [==============================] - 11s 412us/step - loss: 0.0029 - mse: 0.0664 - val_l
oss: 0.0107 - val_mse: 0.2076
```

```
Epoch 00037: val_loss did not improve from 0.00810
Epoch 38/50
26239/26239 [==============================] - 11s 412us/step - loss: 0.0028 - mse: 0.0660 - val_l
oss: 0.0107 - val_mse: 0.2100

Epoch 00038: val_loss did not improve from 0.00810
Epoch 39/50
26239/26239 [==============================] - 11s 410us/step - loss: 0.0027 - mse: 0.0637 - val_l
oss: 0.0110 - val_mse: 0.2166

Epoch 00039: val_loss did not improve from 0.00810
Epoch 40/50
26239/26239 [==============================] - 11s 413us/step - loss: 0.0027 - mse: 0.0634 - val_l
oss: 0.0106 - val_mse: 0.2086

Epoch 00040: val_loss did not improve from 0.00810
Epoch 41/50
26239/26239 [==============================] - 11s 412us/step - loss: 0.0026 - mse: 0.0606 - val_l
oss: 0.0107 - val_mse: 0.2117

Epoch 00041: val_loss did not improve from 0.00810
Epoch 42/50
26239/26239 [==============================] - 11s 412us/step - loss: 0.0025 - mse: 0.0594 - val_l
oss: 0.0105 - val_mse: 0.2069

Epoch 00042: val_loss did not improve from 0.00810
Epoch 43/50
26239/26239 [==============================] - 11s 412us/step - loss: 0.0025 - mse: 0.0572 - val_l
oss: 0.0111 - val_mse: 0.2198

Epoch 00043: val_loss did not improve from 0.00810
Epoch 44/50
26239/26239 [==============================] - 11s 412us/step - loss: 0.0023 - mse: 0.0550 - val_l
oss: 0.0105 - val_mse: 0.2078

Epoch 00044: val_loss did not improve from 0.00810
Epoch 45/50
26239/26239 [==============================] - 11s 410us/step - loss: 0.0023 - mse: 0.0538 - val_l
oss: 0.0108 - val_mse: 0.2142

Epoch 00045: val_loss did not improve from 0.00810
Epoch 46/50
26239/26239 [==============================] - 11s 413us/step - loss: 0.0022 - mse: 0.0520 - val_l
oss: 0.0106 - val_mse: 0.2102

Epoch 00046: val_loss did not improve from 0.00810
Epoch 47/50
26239/26239 [==============================] - 11s 410us/step - loss: 0.0023 - mse: 0.0529 - val_l
oss: 0.0107 - val_mse: 0.2133

Epoch 00047: val_loss did not improve from 0.00810
Epoch 48/50
26239/26239 [==============================] - 11s 411us/step - loss: 0.0022 - mse: 0.0513 - val_l
oss: 0.0111 - val_mse: 0.2209

Epoch 00048: val_loss did not improve from 0.00810
Epoch 49/50
26239/26239 [==============================] - 11s 412us/step - loss: 0.0021 - mse: 0.0491 - val_l
oss: 0.0111 - val_mse: 0.2233

Epoch 00049: val_loss did not improve from 0.00810
Epoch 50/50
26239/26239 [==============================] - 11s 410us/step - loss: 0.0021 - mse: 0.0505 - val_l
oss: 0.0109 - val_mse: 0.2171

Epoch 00050: val_loss did not improve from 0.00810
```

In [594]:

```
y_pred = model.predict(X_te)
```

In [597]:

```
from sklearn.metrics import mean_squared_error
from math import sqrt
```

```python
predict_target = model.predict(X_te)

rms = sqrt(mean_squared_error(y_test_enc, y_pred))
print(rms)
```

In [597]:

```python
from sklearn.metrics import r2_score

coefficient_of_dermination = r2_score(y_test_enc, y_pred)

print(coefficient_of_dermination)
```

```
0.6795726965998063
```

Pretty Table

In [599]:

```python
# Please compare all your models using Prettytable library
# http://zetcode.com/python/prettytable/

from prettytable import PrettyTable

#If you get a ModuleNotFoundError error , install prettytable using: pip3 install prettytable

x = PrettyTable()
x.field_names = ["Model Used", "RMSE","R^2 (Coefficient of Determination)"]

x.add_row(["Random Forest Regressor",  0.4038, 0.6761])
x.add_row(["XGBoost Regressor",  0.3787, 0.7151])
x.add_row(["Linear Regression",  0.4193,0.6507])
x.add_row(["MLP(Deep Learning",  0.3975,0.6795])

print(x)
```

```
+-------------------------+--------+------------------------------------+
|        Model Used       |  RMSE  | R^2 (Coefficient of Determination) |
+-------------------------+--------+------------------------------------+
| Random Forest Regressor | 0.4038 |               0.6761               |
|    XGBoost Regressor    | 0.3787 |               0.7151               |
|    Linear Regression    | 0.4193 |               0.6507               |
|    MLP(Deep Learning    | 0.3975 |               0.6795               |
+-------------------------+--------+------------------------------------+
```

Conclusion :

- XGBoost has performed best.
- I have taken only the top frequent values for few features to decrease the categories , so that procesing is fast. If we would work with the entire categories then may be the result would have changed for good.

In [ ]:

In [ ]: