Take Home Assignment:

Beer Data Science Project

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1: Basic Preprocessing & Data Cleaning

In [1]:

```
import warnings
warnings.filterwarnings("ignore")
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import seaborn as sns
```

1.1: Data Reading using Pandas DataFrame

In [2]:

```
data=pd.read_csv('BeerDataScienceProject.csv',encoding='latin-1')
```

In [3]:

```
data.head(2)
```

Out[3]:

	beer_ABV	beer_beerId	beer_brewerId	beer_name	beer_style	review_appearance	review_p
0	5.0	47986	10325	Sausa Weizen	Hefeweizen	2.5	
1	6.2	48213	10325	Red Moon	English Strong Ale	3.0	

1.2: Number Datapoints & Columns in the Dataset

In [4]:

```
print("="*50)
print("Number of rows or Datapoints in the Datasets:",data.shape[0])
print("-"*50)
print("number of clumns in the datasets: ", data.shape[1])
print("="*50)
```

```
==================================================
Number of rows or Datapoints in the Datasets: 528870
--------------------------------------------------
number of clumns in the datasets:  13
==================================================
```

1.3: Colmuns Names & Datatype of Columns

In [5]:

```
data.columns
```

Out[5]:

```
Index(['beer_ABV', 'beer_beerId', 'beer_brewerId', 'beer_name', 'beer_styl
e',
       'review_appearance', 'review_palette', 'review_overall', 'review_tast
e',
       'review_profileName', 'review_aroma', 'review_text', 'review_time'],
      dtype='object')
```

In [6]:

```
data.dtypes
```

Out[6]:

```
beer_ABV              float64
beer_beerId             int64
beer_brewerId           int64
beer_name              object
beer_style             object
review_appearance     float64
review_palette        float64
review_overall        float64
review_taste          float64
review_profileName     object
review_aroma          float64
review_text            object
review_time             int64
dtype: object
```

1.4: Null Value Check & Missing Value Imputation

In [7]:

```
print("="*50)
print("Null values in the Dataset(Percentage):")
print("-"*50)
print(data.isnull().sum()/len(data)*100)
print("="*50)
```

```
==================================================
Null values in the Dataset(Percentage):
--------------------------------------------------
beer_ABV              3.834591
beer_beerId           0.000000
beer_brewerId         0.000000
beer_name             0.000000
beer_style            0.000000
review_appearance     0.000000
review_palette        0.000000
review_overall        0.000000
review_taste          0.000000
review_profileName    0.021744
review_aroma          0.000000
review_text           0.022501
review_time           0.000000
dtype: float64
==================================================
```

In [8]:

```
print("="*80)
print("Mean Value of Feature beer_ABV(Alcohol by Volume):",data['beer_ABV'].mean())
print("-"*80)
print("Mean Value of Feature beer_ABV(Alcohol by Volume):",data['beer_ABV'].median())
print("="*80)
```

```
============================================================================
====
Mean Value of Feature beer_ABV(Alcohol by Volume): 7.017441593423365
----------------------------------------------------------------------------
----
Mean Value of Feature beer_ABV(Alcohol by Volume): 6.5
============================================================================
====
```

In [9]:

```
#Mean Value Impute the Beer_ABV Feature
beer_ABV_mean=data['beer_ABV'].mean()

data['beer_ABV'].fillna(value=beer_ABV_mean,inplace=True)
```

In [10]:

```
data.dropna(inplace=True)
```

In [11]:

```
print("="*50)
print("Null values in the Dataset(Percentage):")
print("-"*50)
print(data.isnull().sum()/len(data)*100)
print("="*50)
```

```
==================================================
Null values in the Dataset(Percentage):
--------------------------------------------------
beer_ABV              0.0
beer_beerId           0.0
beer_brewerId         0.0
beer_name             0.0
beer_style            0.0
review_appearance     0.0
review_palette        0.0
review_overall        0.0
review_taste          0.0
review_profileName    0.0
review_aroma          0.0
review_text           0.0
review_time           0.0
dtype: float64
==================================================
```

OBSERVATION:

From Above Analysis,

1. As There are 3.83% Values Missing in the Beer_ABV Column that are replaced by the mean of colmun
2. Features like 'review_profileName' & "review_text" Very low Percentage missing values so dropped (row droppped)

2: Exploratary Data Analysis & Data Visualization

2.1: Basic Statistics of all the Features

In [12]:

```
data.describe().T
```

Out[12]:

	count	mean	std	min	25%	
beer_ABV	528636.0	7.017402e+00	2.161832e+00	1.000000e-02	5.300000e+00	6.50000
beer_beerId	528636.0	2.210187e+04	2.215998e+04	3.000000e+00	1.745000e+03	1.43780
beer_brewerId	528636.0	2.598903e+03	5.282495e+03	1.000000e+00	1.320000e+02	3.94000
review_appearance	528636.0	3.864509e+00	6.039861e-01	0.000000e+00	3.500000e+00	4.00000
review_palette	528636.0	3.758944e+00	6.852722e-01	1.000000e+00	3.500000e+00	4.00000
review_overall	528636.0	3.833179e+00	7.099392e-01	0.000000e+00	3.500000e+00	4.00000
review_taste	528636.0	3.765985e+00	6.689742e-01	1.000000e+00	3.500000e+00	4.00000
review_aroma	528636.0	3.817346e+00	7.188361e-01	1.000000e+00	3.500000e+00	4.00000
review_time	528636.0	1.224890e+09	7.605932e+07	8.843904e+08	1.174617e+09	1.24037

In [13]:

```
data.columns
```

Out[13]:

```
Index(['beer_ABV', 'beer_beerId', 'beer_brewerId', 'beer_name', 'beer_styl
e',
       'review_appearance', 'review_palette', 'review_overall', 'review_tast
e',
       'review_profileName', 'review_aroma', 'review_text', 'review_time'],
      dtype='object')
```

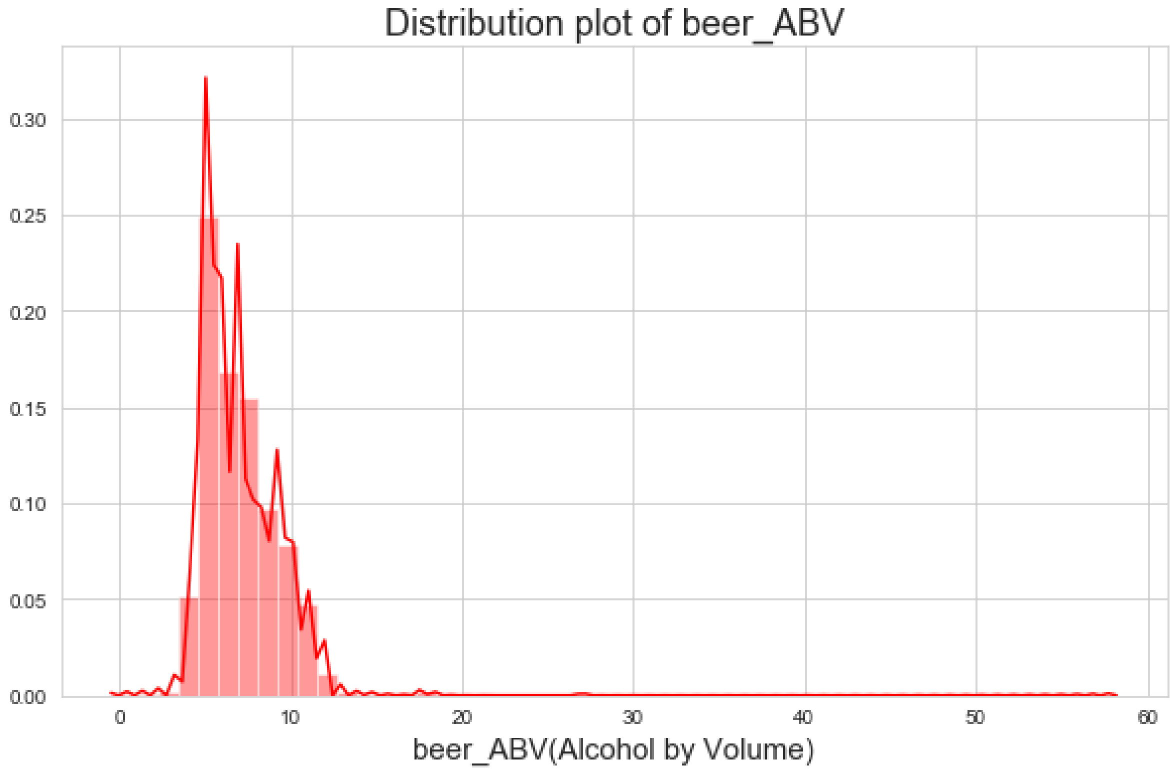
2.2: Distribution of the Features & Its Visualizaiton

In [14]:

```
plt.figure(figsize=(10,6))
sns.set_style("whitegrid")
sns.distplot(a=data['beer_ABV'],color="r")
plt.title("Distribution plot of beer_ABV",fontsize=18)
plt.xlabel(f"beer_ABV(Alcohol by Volume)",fontsize='15')
```

Out[14]:

```
Text(0.5, 0, 'beer_ABV(Alcohol by Volume)')
```



OBSERVATION:

From Above Distribution Plot Analysis,

1. BeerABV: Disribution is right Skewed so we can say there are outlier towards the extreme positive values

In [15]:

```
reviews_all_f=['review_appearance','review_palette',
          'review_overall','review_taste',
          'review_aroma']
for i in reviews_all_f:
    print("="*50)
    print(f"Value counts(%) for the feature {i}:")
    print("-"*50)
    print(data[i].value_counts(normalize=True)*100)
    print("="*50)
```

```
==================================================
Value counts(%) for the feature review_appearance:
--------------------------------------------------
4.0    42.750777
3.5    19.615577
4.5    19.008732
3.0    10.054934
5.0     4.367277
2.5     2.318230
2.0     1.420448
1.5     0.305692
1.0     0.157765
0.0     0.000567
Name: review_appearance, dtype: float64
==================================================
==================================================
Value counts(%) for the feature review_palette:
--------------------------------------------------
4.0    35.640214
3.5    22.710523
4.5    17.756831
3.0    12.217859
5.0     4.219160
2.5     3.957354
2.0     2.461618
1.5     0.677025
1.0     0.359416
Name: review_palette, dtype: float64
==================================================
==================================================
Value counts(%) for the feature review_overall:
--------------------------------------------------
4.0    37.165649
4.5    20.974357
3.5    18.702472
3.0    10.153868
5.0     5.864338
2.5     3.503923
2.0     2.256373
1.5     0.755529
1.0     0.622924
0.0     0.000567
Name: review_overall, dtype: float64
==================================================
==================================================
Value counts(%) for the feature review_taste:
--------------------------------------------------
4.0    38.944945
```

```
3.5    20.991382
4.5    16.433425
3.0    12.656913
5.0     4.091095
2.5     3.713708
2.0     2.218540
1.5     0.601926
1.0     0.348066
Name: review_taste, dtype: float64
==================================================
==================================================
Value counts(%) for the feature review_aroma:
--------------------------------------------------
4.0    34.475707
4.5    22.018175
3.5    20.087546
3.0    10.113954
5.0     5.486384
2.5     3.981000
2.0     2.459727
1.5     0.840654
1.0     0.536853
Name: review_aroma, dtype: float64
==================================================
```

OBSERVATION:

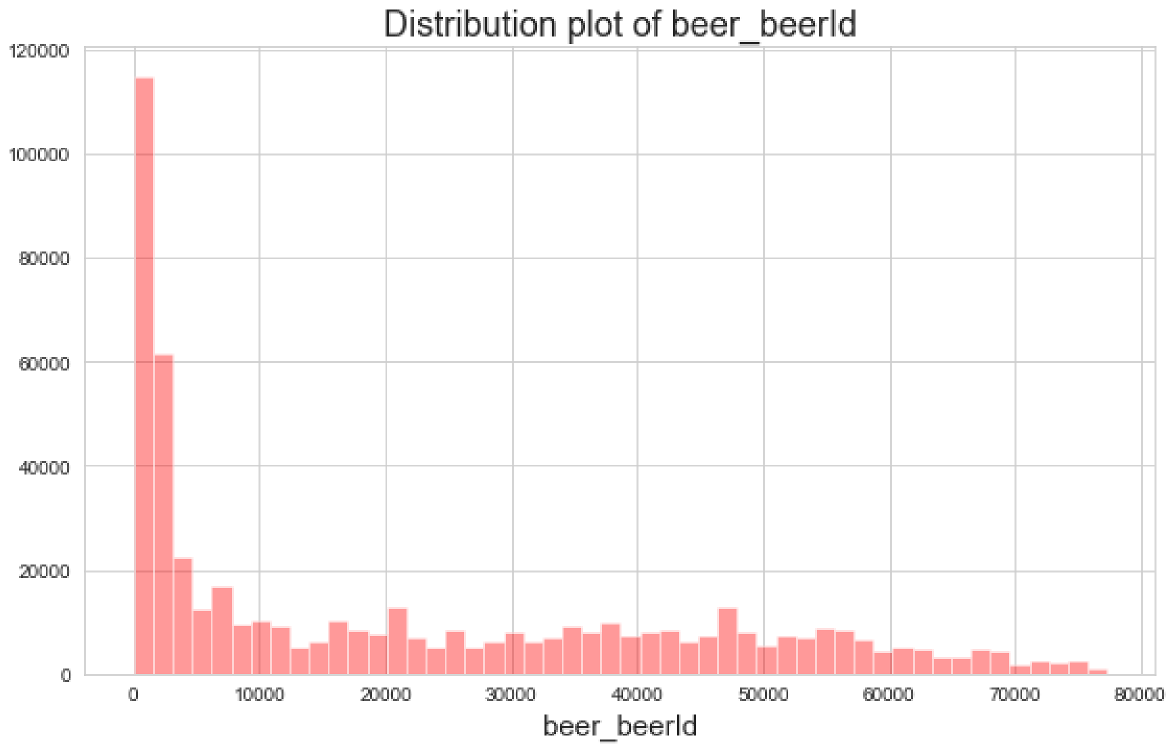
From Above Analysis,

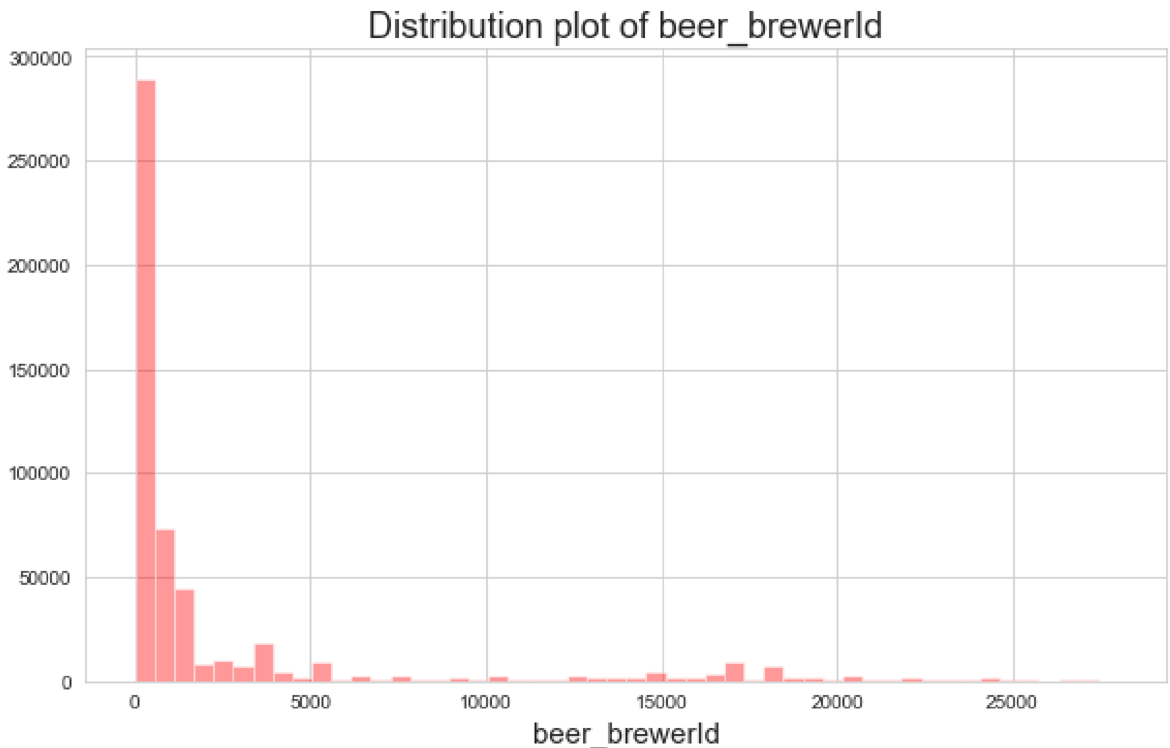
1. All Reviews: Review number 4 is got the most % share in all reviews

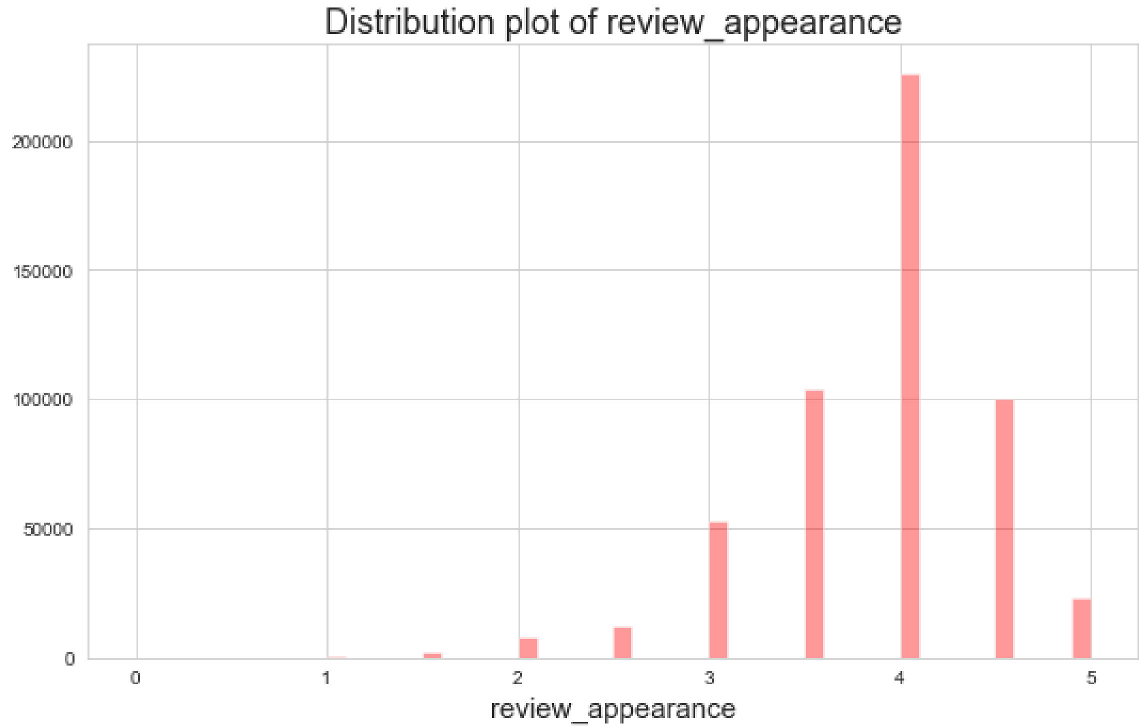
In [16]:

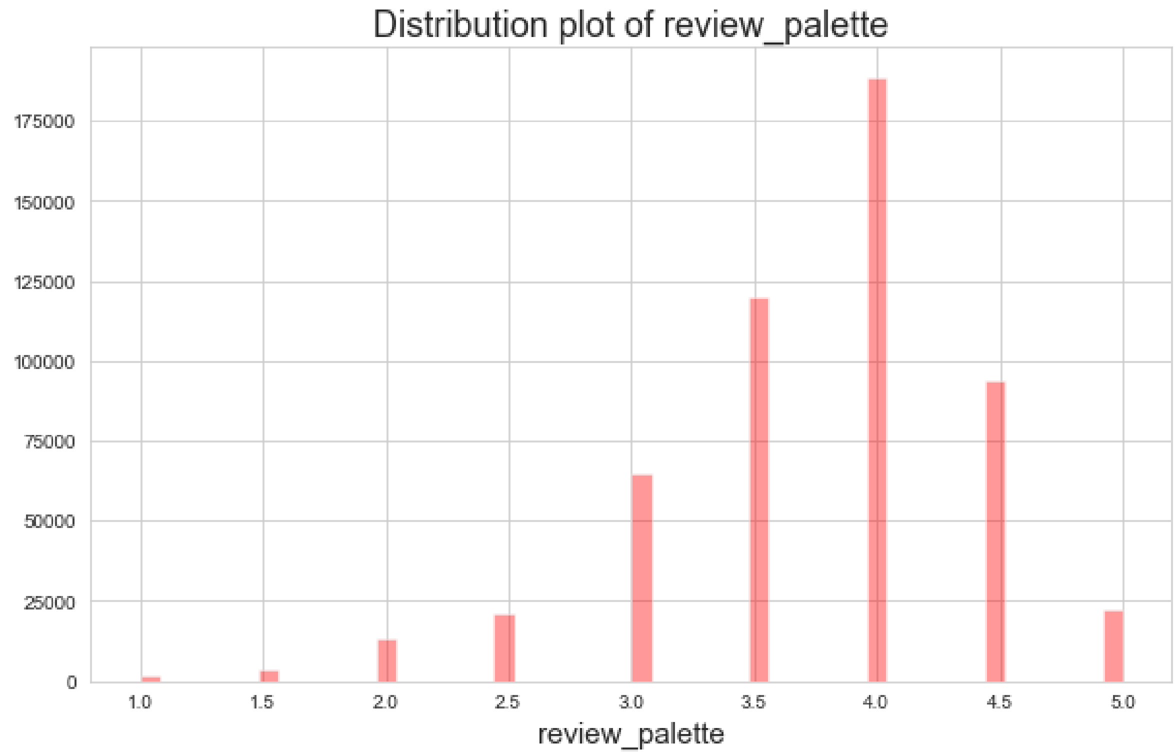
```
col_list=['beer_beerId','beer_brewerId',
          'review_appearance','review_palette',
          'review_overall','review_taste',
          'review_aroma']

for i in col_list:
    plt.figure(figsize=(10,6))
    sns.set_style("whitegrid")
    sns.distplot(a=data[i],color="r",kde=False)
    plt.title("Distribution plot of {}".format(i),fontsize=18)
    plt.xlabel(f"{i}",fontsize='15')
```

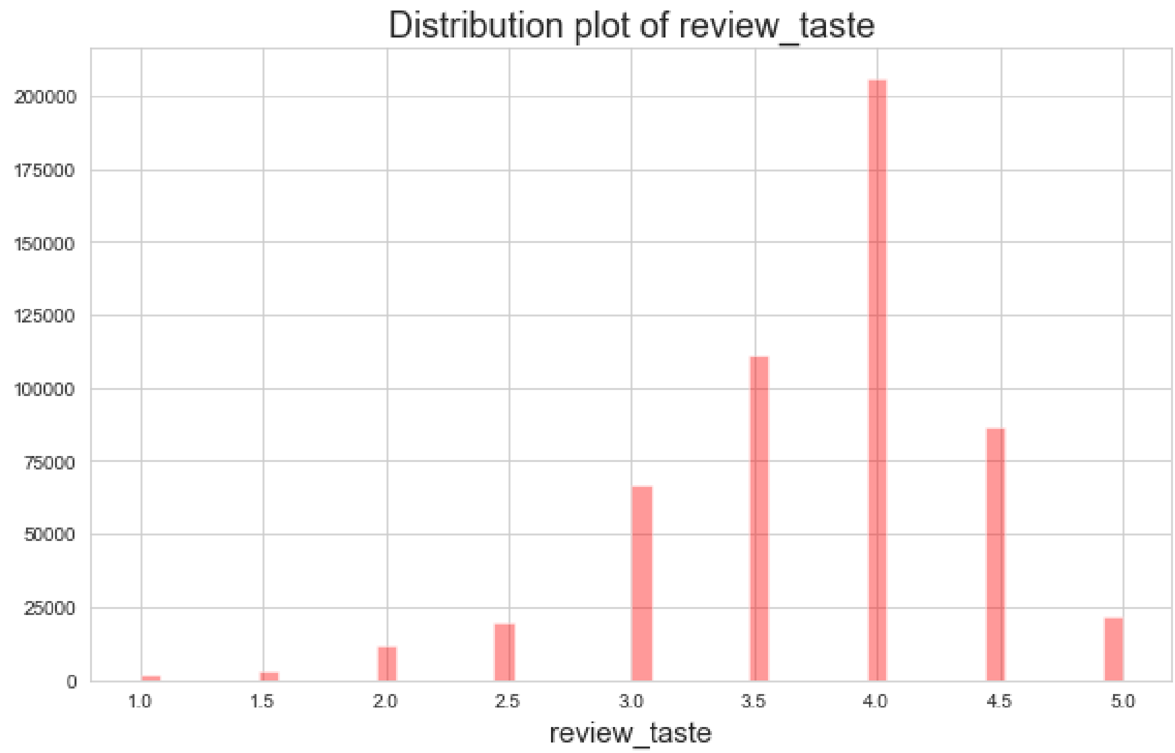


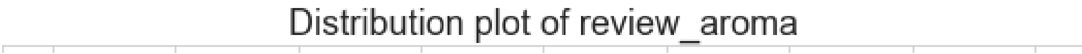



Distribution plot of review_appearance
200000
150000
100000
50000
0
0
1
2
3
4
5
review_appearance


Distribution plot of review_palette
175000
150000
125000
100000
75000
50000
25000
0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
review_palette


Distribution plot of review_overall
200000
175000
150000
125000
100000
75000
50000


Distribution plot of review_taste
200000
175000
150000
125000
100000
75000
50000
25000
0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
review_taste



OBSERVATION:

From Above Distribution Plot Analysis,

1. For beer_beerId & beer_brewerId : From Distribution plot is concentrcetaed for very few IDs & very few occurences are for IDs on right right skewed nature
2. All Reviews: From Distrubtion plot we can observe Review number 4 is occuring most time

2.3: Boxplot of Feature BeerABV

In [17]:

```
data.columns
```

Out[17]:

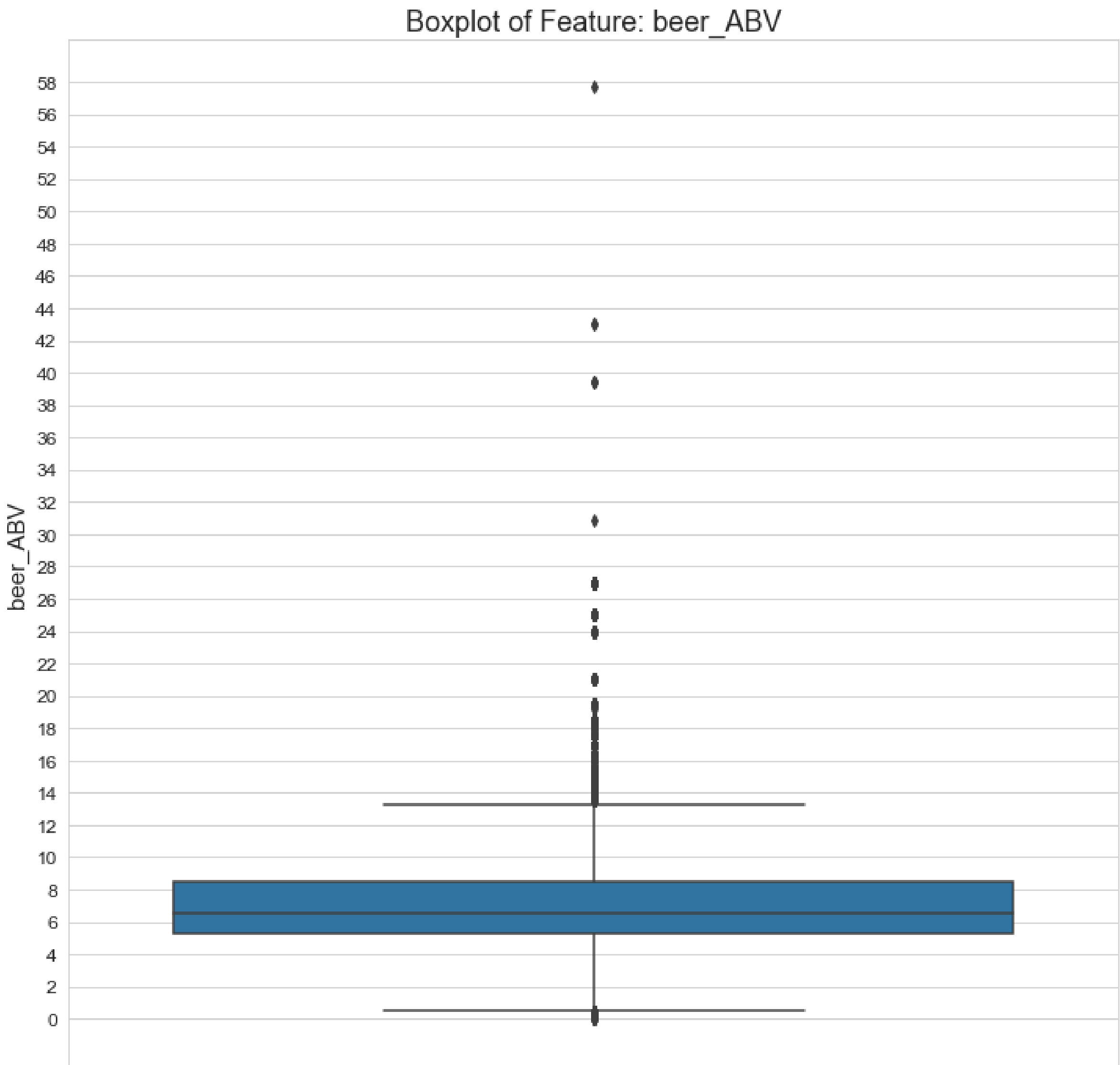
```
Index(['beer_ABV', 'beer_beerId', 'beer_brewerId', 'beer_name', 'beer_styl
e',
       'review_appearance', 'review_palette', 'review_overall', 'review_tast
e',
       'review_profileName', 'review_aroma', 'review_text', 'review_time'],
      dtype='object')
```

In [18]:

```
plt.figure(figsize=(12,12))
sns.set_style("whitegrid")
sns.boxplot(y=data['beer_ABV'],data=data)
plt.yticks(np.arange(0,60,2),fontsize=12)
plt.title("Boxplot of Feature: beer_ABV",fontsize=18)
plt.ylabel("beer_ABV",fontsize=15)
```

Out[18]:

```
Text(0, 0.5, 'beer_ABV')
```



OBSERVATION:

From Above Box Plot Analysis,

1. Outlier exists in the positive side of the plot & it goes upto 60% ABV
2. From graph we can observe Interquantile range for Beer_ABV is appr. 5% to 8.5% (Q3-Q1)(same conclusion can be drawn from the pandas.df.describe() functionality)

2.4: Total Number of Different beerIDs & Its Counts

In [19]:

```
print("="*60)
print("Total Number of Different beerIDs:",data['beer_beerId'].nunique())
print("="*60)
```

```
============================================================
Total Number of Different beerIDs: 20200
============================================================
```

In [20]:

```
print("="*60)
print("Total Number of Counts for each beer_beerId (top 10)")
print("-"*60)
print(data['beer_beerId'].value_counts().head(10))
print("="*60)
print("Percentage for each beer_beerId (top 10)")
print("-"*60)
print(data['beer_beerId'].value_counts(normalize=True).head(10)*100)
print("="*60)
```

```
============================================================
Total Number of Counts for each beer_beerId (top 10)
------------------------------------------------------------
1904     2998
276      2586
11757    2501
2671     2491
34       2480
104      2416
355      2229
645      2170
30420    2028
571      2024
Name: beer_beerId, dtype: int64
============================================================
Percentage for each beer_beerId (top 10)
------------------------------------------------------------
1904     0.567120
276      0.489183
11757    0.473104
2671     0.471213
34       0.469132
104      0.457025
355      0.421651
645      0.410490
30420    0.383629
571      0.382872
Name: beer_beerId, dtype: float64
============================================================
```

In [21]:

```
df_beer_beerId=pd.DataFrame(data['beer_beerId'].value_counts())
len(df_beer_beerId[(df_beer_beerId["beer_beerId"]<10)])/len(df_beer_beerId)*100
```

Out[21]:

```
78.76732673267327
```

OBSERVATION:

From Above Analysis,

1. Total Number of Different beerIDs: 20200
2. beerIDs:1904 contributes 2998 values with % of 0.567120%
3. beer_beerIds 78.76% having less than 10 counts

2.5: Total Number of Different brewerIds & Its Counts

In [22]:

```
print("="*60)
print("Total Number of different brewerID:",data['beer_brewerId'].nunique())
print("="*60)
```

```
============================================================
Total Number of different brewerID: 1803
============================================================
```

In [23]:

```
print("="*60)
print("Total Number of Counts for each brewerID (top 10)")
print("-"*60)
print(data['beer_brewerId'].value_counts().head(10))
print("="*60)
print("Percentage for each brewerID (top 10)")
print("-"*60)
print(data['beer_brewerId'].value_counts(normalize=True).head(10)*100)
print("="*60)
```

```
============================================================
Total Number of Counts for each brewerID (top 10)
------------------------------------------------------------
35      39431
140     28741
132     24070
1199    19990
3818    15863
158     14928
22      13906
192     13405
392     12241
694     11838
Name: beer_brewerId, dtype: int64
============================================================
Percentage for each brewerID (top 10)
------------------------------------------------------------
35      7.459008
140     5.436822
132     4.553228
1199    3.781430
3818    3.000742
158     2.823871
22      2.630544
192     2.535771
392     2.315582
694     2.239348
Name: beer_brewerId, dtype: float64
============================================================
```

In [24]:

```
df_beer_brewerId=pd.DataFrame(data['beer_brewerId'].value_counts())
len(df_beer_brewerId[(df_beer_brewerId["beer_brewerId"]<10)])/len(df_beer_brewerId)*100
```

Out[24]:

```
44.42595673876872
```

OBSERVATION:

From Above Analysis,

1. Total Number of Different beer_brewerId: 1803
2. beer_brewerId:35 contributes 2998 values with % of 7.45%
3. beer_brewerId 44.42% having less than 10 counts

2.6: Total Number of Different Beer_Name & Its Counts

In [25]:

```
print("="*60)
print("Total Number of different beer_name:",data['beer_name'].nunique())
print("="*60)
```

```
============================================================
Total Number of different beer_name: 18339
============================================================
```

In [26]:

```
print("="*60)
print("Total Number of Counts for each beer_name (top 10)")
print("-"*60)
print(data['beer_name'].value_counts().head(10))
print("="*60)
print("Percentage for each beer_name (top 10)")
print("-"*60)
print(data['beer_name'].value_counts(normalize=True).head(10)*100)
print("="*60)
```

```
============================================================
Total Number of Counts for each beer_name (top 10)
------------------------------------------------------------
Sierra Nevada Celebration Ale                2998
Sierra Nevada Pale Ale                       2586
Founders Breakfast Stout                     2501
Sierra Nevada Bigfoot Barleywine Style Ale   2491
La Fin Du Monde                              2480
Samuel Adams Boston Lager                    2416
Chocolate Stout                              2253
Dead Guy Ale                                 2229
Trappistes Rochefort 10                      2170
Sierra Nevada Torpedo Extra IPA              2028
Name: beer_name, dtype: int64
============================================================
Percentage for each beer_name (top 10)
------------------------------------------------------------
Sierra Nevada Celebration Ale                0.567120
Sierra Nevada Pale Ale                       0.489183
Founders Breakfast Stout                     0.473104
Sierra Nevada Bigfoot Barleywine Style Ale   0.471213
La Fin Du Monde                              0.469132
Samuel Adams Boston Lager                    0.457025
Chocolate Stout                              0.426191
Dead Guy Ale                                 0.421651
Trappistes Rochefort 10                      0.410490
Sierra Nevada Torpedo Extra IPA              0.383629
Name: beer_name, dtype: float64
============================================================
```

In [27]:

```
df_beer_name=pd.DataFrame(data['beer_name'].value_counts())
len(df_beer_name[(df_beer_name["beer_name"]<10)])/len(df_beer_name)*100
```

Out[27]:

```
76.79262773324609
```

OBSERVATION:

From Above Analysis,

1. Total Number of Different beer_name: 18339
2. beer_name:'Sierra Nevada Celebration Ale' contributes 2998 values with % of 0.56%
3. beer_name: 76.79% having less than 10 counts

2.7: Total Number of Different beer_style & Its Counts

In [28]:

```
print("="*60)
print("Total Number of different beer_style:",data['beer_style'].nunique())
print("="*60)
```

```
============================================================
Total Number of different beer_style: 104
============================================================
```

In [29]:

```
print("="*60)
print("Total Number of Counts for each beer_style (top 10)")
print("-"*60)
print(data['beer_style'].value_counts().head(10))
print("="*60)
print("Percentage for each beer_style (top 10)")
print("-"*60)
print(data['beer_style'].value_counts(normalize=True).head(10)*100)
print("="*60)
```

```
============================================================
Total Number of Counts for each beer_style (top 10)
------------------------------------------------------------
American IPA                        43358
American Double / Imperial IPA      26092
American Double / Imperial Stout    23346
American Pale Ale (APA)             20511
American Amber / Red Ale            18725
Russian Imperial Stout              17181
American Porter                     16597
Belgian Strong Dark Ale             15398
Fruit / Vegetable Beer              15144
Witbier                             13528
Name: beer_style, dtype: int64
============================================================
Percentage for each beer_style (top 10)
------------------------------------------------------------
American IPA                        8.201863
American Double / Imperial IPA      4.935721
American Double / Imperial Stout    4.416271
American Pale Ale (APA)             3.879985
American Amber / Red Ale            3.542135
Russian Imperial Stout              3.250062
American Porter                     3.139589
Belgian Strong Dark Ale             2.912779
Fruit / Vegetable Beer              2.864731
Witbier                             2.559039
Name: beer_style, dtype: float64
============================================================
```

OBSERVATION:

From Above Analysis,

1. Total Number of different beer_style: 104
2. beer_style.:'American IPA' contributes 2998 values with % of 8.2%

2.8: Total Number of Different review_profileName & Its Counts

In [30]:

```
print("="*60)
print("Total Number of different review_profileName:",data['review_profileName'].nunique())
print("="*60)
```

```
============================================================
Total Number of different review_profileName: 22789
============================================================
```

In [31]:

```
print("="*60)
print("Total Number of Counts for each review_profileName (top 10)")
print("-"*60)
print(data['review_profileName'].value_counts().head(10))
print("="*60)
print("Percentage for each review_profileName (top 10)")
print("-"*60)
print(data['review_profileName'].value_counts(normalize=True).head(10)*100)
print("="*60)
```

```
============================================================
Total Number of Counts for each review_profileName (top 10)
------------------------------------------------------------
northyorksammy    1858
mikesgroove       1403
BuckeyeNation     1298
womencantsail     1238
Phyl21ca          1164
ChainGangGuy      1155
Thorpe429         1042
brentk56          1026
NeroFiddled       1012
feloniousmonk     1008
Name: review_profileName, dtype: int64
============================================================
Percentage for each review_profileName (top 10)
------------------------------------------------------------
northyorksammy    0.351471
mikesgroove       0.265400
BuckeyeNation     0.245538
womencantsail     0.234188
Phyl21ca          0.220189
ChainGangGuy      0.218487
Thorpe429         0.197111
brentk56          0.194084
NeroFiddled       0.191436
feloniousmonk     0.190679
Name: review_profileName, dtype: float64
============================================================
```

In [32]:

```
df_review_profileName=pd.DataFrame(data['review_profileName'].value_counts())
len(df_review_profileName[(df_review_profileName["review_profileName"]<10)])/len(df_review_
```

Out[32]:

```
71.57839308438282
```

OBSERVATION:
From Above Analysis,

1. Total Number of different review_profileName: 22800
2. review_profileName:'northyorksammy' contributes 1858 values with % of 0.0.35%
3. review_profileName: 71.57% having less than 10 counts

2.9: Numerical, Categorical & Text Feature Check

In [33]:

```
data.select_dtypes(include=['object']).columns.tolist()
```

Out[33]:

```
['beer_name', 'beer_style', 'review_profileName', 'review_text']
```

In [34]:

```
print(data.select_dtypes(exclude=['object']).columns.tolist())
```

```
['beer_ABV', 'beer_beerId', 'beer_brewerId', 'review_appearance', 'review_pa
lette', 'review_overall', 'review_taste', 'review_aroma', 'review_time']
```

OBSERVATION:
From Above Analysis,

1. Numerical Features:'beer_ABV'
2. Categorical Feature(numbers from 0 to 5):'review_appearance', 'review_palette', 'review_overall', 'review_taste', 'review_aroma'
3. Categorical Feature: 'beer_beerId', 'beer_brewerId','Beer_Name','beer_style', 'review_profileName'
4. Time Feature :'review_time'
5. Text Feature :'review_text'

3: Assessment Questions

3.1: Q1- Rank Top 3 Breweries which produce the strongest beers?

3.1.1: Q1- Approach 1

In [35]:

```
df_strongest_beer=data.groupby("beer_brewerId")["beer_ABV"].max()
```

In [36]:

```
df_strongest_beer_final=pd.DataFrame(df_strongest_beer).sort_values(by=['beer_ABV'],ascendi
```

In [37]:

```
df_strongest_beer_final
```

Out[37]:

	beer_brewerId	beer_ABV
0	6513	57.7
1	35	27.0
2	2958	19.5

In [38]:

```
df_strongest_beer_final.index=df_strongest_beer_final['beer_brewerId']
```

In [39]:

```
df_strongest_beer_final.columns
```

Out[39]:

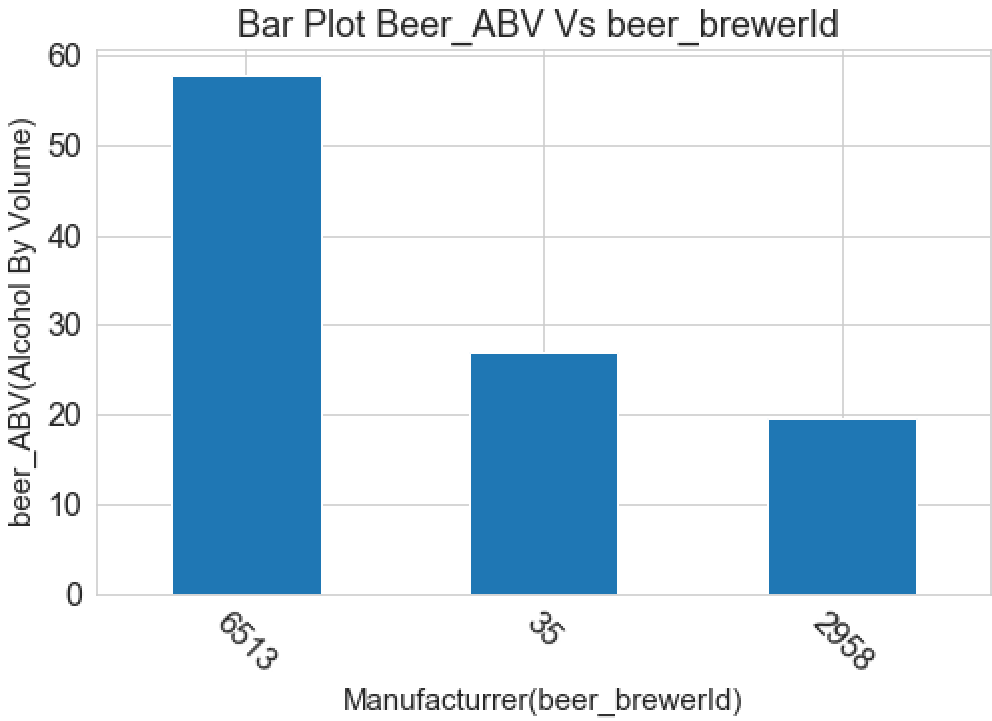
```
Index(['beer_brewerId', 'beer_ABV'], dtype='object')
```

In [40]:

```
df_strongest_beer_final['beer_ABV'].plot(kind='bar',
                                          x=df_strongest_beer_final['beer_brewerId'],
                                          figsize=(8,5))
plt.title('Bar Plot Beer_ABV Vs beer_brewerId ',fontsize=18)
plt.xlabel("Manufacturrer(beer_brewerId)",fontsize=15)
plt.ylabel("beer_ABV(Alcohol By Volume)",fontsize=15)
plt.xticks(fontsize=16,rotation=-45)
plt.yticks(fontsize=16)
```

Out[40]:

```
(array([ 0., 10., 20., 30., 40., 50., 60., 70.]),
 <a list of 8 Text yticklabel objects>)
```



Observation/Conclusion

Top 3 Breweries which produce the strongest beers

a. beer_brewerId:6513 & beer_ABV(Alcohol_by_Volume):57.7%

b. beer_brewerId:35 & beer_ABV(Alcohol_by_Volume):27%

c. beer_brewerId:2958 & beer_ABV(Alcohol_by_Volume):19.5%

3.1.2: Q1- Approach 2

In [41]:

```
brewer_id_list=data.groupby("beer_ABV").first().tail(50)["beer_brewerId"].tolist()[::-1]
unique_brewer_id=[]
for i in brewer_id_list:
    if i in unique_brewer_id:
        pass
    else:
        unique_brewer_id.append(i)

unique_brewer_id[0:3]
```

Out[41]:

```
[6513, 35, 16866]
```

Observation/Conclusion

Top 3 Breweries which produce the strongest beers Approach 2
a. beer_brewerId:6513
b. beer_brewerId:35
c. beer_brewerId:2958
Note:By Approach 2 we getting only BrewerIDs

3.2: Q2-Which year did beers enjoy the highest ratings?

3.2.1: Q2-Approach 1

In [42]:

```
data.columns
```

Out[42]:

```
Index(['beer_ABV', 'beer_beerId', 'beer_brewerId', 'beer_name', 'beer_styl
e',
       'review_appearance', 'review_palette', 'review_overall', 'review_tast
e',
       'review_profileName', 'review_aroma', 'review_text', 'review_time'],
      dtype='object')
```

In [43]:

```
data["review_time"]
```

Out[43]:

```
0         1234817823
1         1235915097
2         1235916604
3         1234725145
4         1293735206
             ...
528865    1205212721
528866    1203490783
528867    1201320897
528868    1201215290
528869    1200336367
Name: review_time, Length: 528636, dtype: int64
```

In [44]:

```
pd.to_datetime(data['review_time'], unit='s')
```

Out[44]:

```
0        2009-02-16 20:57:03
1        2009-03-01 13:44:57
2        2009-03-01 14:10:04
3        2009-02-15 19:12:25
4        2010-12-30 18:53:26
                 ...
528865   2008-03-11 05:18:41
528866   2008-02-20 06:59:43
528867   2008-01-26 04:14:57
528868   2008-01-24 22:54:50
528869   2008-01-14 18:46:07
Name: review_time, Length: 528636, dtype: datetime64[ns]
```

In [45]:

```
data["date"]=pd.to_datetime(data['review_time'], unit='s')
```

In [46]:

```
pd.DatetimeIndex(data['date']).year
```

Out[46]:

```
Int64Index([2009, 2009, 2009, 2009, 2010, 2012, 2011, 2011, 2010, 2010,
            ...
            2008, 2008, 2008, 2008, 2008, 2008, 2008, 2008, 2008, 2008],
           dtype='int64', name='date', length=528636)
```

In [47]:

```
data['year']=pd.DatetimeIndex(data['date']).year
```

In [48]:

```
data.columns
```

Out[48]:

```
Index(['beer_ABV', 'beer_beerId', 'beer_brewerId', 'beer_name', 'beer_styl
e',
       'review_appearance', 'review_palette', 'review_overall', 'review_tast
e',
       'review_profileName', 'review_aroma', 'review_text', 'review_time',
       'date', 'year'],
      dtype='object')
```

In [49]:

```
df_year_review=pd.DataFrame(data.groupby('year')['review_overall'].mean())
```

In [50]:

```
df_year_review.columns
```

Out[50]:

```
Index(['review_overall'], dtype='object')
```

In [51]:

```
df_year_review.sort_values(by='review_overall',ascending=False).index[0]
```

Out[51]:

```
2000
```

3.2.2: Q2-Approach 2

In [52]:

```
#df_year_review['year'] = df_year_review.index
```

In [53]:

```
df_year_review.head(2)
```

Out[53]:

	review_overall
year	
1998	3.891304
1999	4.000000

In [54]:

```
df_year_review['review_overall']==df_year_review['review_overall'].max()
```

Out[54]:

```
year
1998    False
1999    False
2000     True
2001    False
2002    False
2003    False
2004    False
2005    False
2006    False
2007    False
2008    False
2009    False
2010    False
2011    False
2012    False
Name: review_overall, dtype: bool
```

In [55]:

```
df_year_review_final=df_year_review[df_year_review['review_overall']==df_year_review['revie
```

In [56]:

```
df_year_review_final.head()
```

Out[56]:

	review_overall
year	
1998	3.891304
1999	4.000000
2000	4.181818
2001	3.927741
2002	3.798905

In [57]:

```
df_year_review_final.head().index
```

Out[57]:

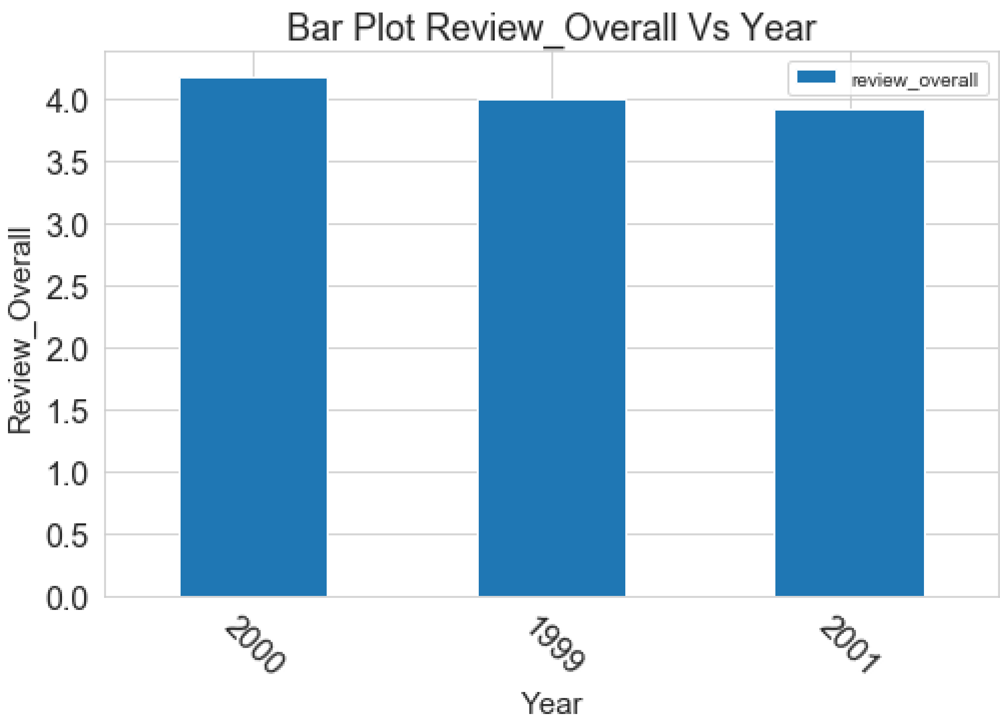
```
Int64Index([1998, 1999, 2000, 2001, 2002], dtype='int64', name='year')
```

In [58]:

```
df_year_review_final.sort_values("review_overall",
                                 ascending=False).head(3).plot(kind='bar',
                                                               figsize=(8,5))
plt.title('Bar Plot Review_Overall Vs Year',fontsize=18)
plt.xlabel("Year",fontsize=15)
plt.ylabel("Review_Overall",fontsize=15)
plt.xticks(fontsize=16,rotation=-45)
plt.yticks(fontsize=16)
```

Out[58]:

```
(array([0. , 0.5, 1. , 1.5, 2. , 2.5, 3. , 3.5, 4. , 4.5]),
 <a list of 10 Text yticklabel objects>)
```



Observation/Conclusion

From Above Bar Plot we clearly obeseve

1. Year **2000** enjoy the highest overall ratings with mean of 4.18 ratings.

In [59]:

```
df_year_review_final=df_year_review[df_year_review['review_overall']==df_year_review['revie
```

In [60]:

```
df_year_review_final
```

Out[60]:

	review_overall
year	
2000	4.181818

Observation/Conclusion

1. Year **2000** enjoy the highest overall ratings with mean of 4.18 ratings.

3.3: Q3- Based on the user's ratings which factors are important among taste, aroma, appearance, and palette?

3.3.1: Q3 Approach 1 Correlation

In [61]:

```
data.columns
```

Out[61]:

```
Index(['beer_ABV', 'beer_beerId', 'beer_brewerId', 'beer_name', 'beer_styl
e',
       'review_appearance', 'review_palette', 'review_overall', 'review_tast
e',
       'review_profileName', 'review_aroma', 'review_text', 'review_time',
       'date', 'year'],
      dtype='object')
```

In [62]:

```
df_reviews_all=data[['review_appearance', 'review_palette', 'review_overall', 'review_taste
```

In [63]:

```
df_reviews_all.head(2)
```

Out[63]:

	review_appearance	review_palette	review_overall	review_taste	review_aroma
0	2.5	2.0	1.5	1.5	1.5
1	3.0	2.5	3.0	3.0	3.0

In [64]:

```
df_reviews_all.columns
```

Out[64]:

```
Index(['review_appearance', 'review_palette', 'review_overall', 'review_tast
e',
       'review_aroma'],
      dtype='object')
```

In [65]:

```
review_list_col=['review_appearance', 'review_palette', 'review_taste','review_aroma']
print("="*80)
for i in review_list_col:
    print("-"*80)
    print(f"Correlaion of review_overall with {i} is :",
          df_reviews_all['review_overall'].corr(df_reviews_all[i]))
    print("-"*80)
print("="*80)
```

```
============================================================================
====
----------------------------------------------------------------------------
----
Correlaion of review_overall with review_appearance is : 0.4866815095411411
----------------------------------------------------------------------------
----
----------------------------------------------------------------------------
----
Correlaion of review_overall with review_palette is : 0.6019481902309212
----------------------------------------------------------------------------
----
----------------------------------------------------------------------------
----
Correlaion of review_overall with review_taste is : 0.6924322218759309
----------------------------------------------------------------------------
----
----------------------------------------------------------------------------
----
Correlaion of review_overall with review_aroma is : 0.7829946894831371
----------------------------------------------------------------------------
----
============================================================================
====
```

In [66]:

```
df_reviews_all.columns
```

Out[66]:

```
Index(['review_appearance', 'review_palette', 'review_overall', 'review_tast
e',
       'review_aroma'],
      dtype='object')
```

Observation/Conclusion

1. Correlaion of **review_overall** with **review_aroma** is : 0.78

3.3.2: Q3 Approach 2-Correlation & Heatmap

In [67]:

```
df_reviews_all.head(2)
```

Out[67]:

	review_appearance	review_palette	review_overall	review_taste	review_aroma
0	2.5	2.0	1.5	1.5	1.5
1	3.0	2.5	3.0	3.0	3.0

In [68]:

```
df_reviews_all.corr()
```

Out[68]:

	review_appearance	review_palette	review_overall	review_taste	review_aron
review_appearance	1.000000	0.547641	0.486682	0.554804	0.53425
review_palette	0.547641	1.000000	0.601948	0.604250	0.70613
review_overall	0.486682	0.601948	1.000000	0.692432	0.78299
review_taste	0.554804	0.604250	0.692432	1.000000	0.72525
review_aroma	0.534257	0.706134	0.782995	0.725251	1.00000

In [69]:

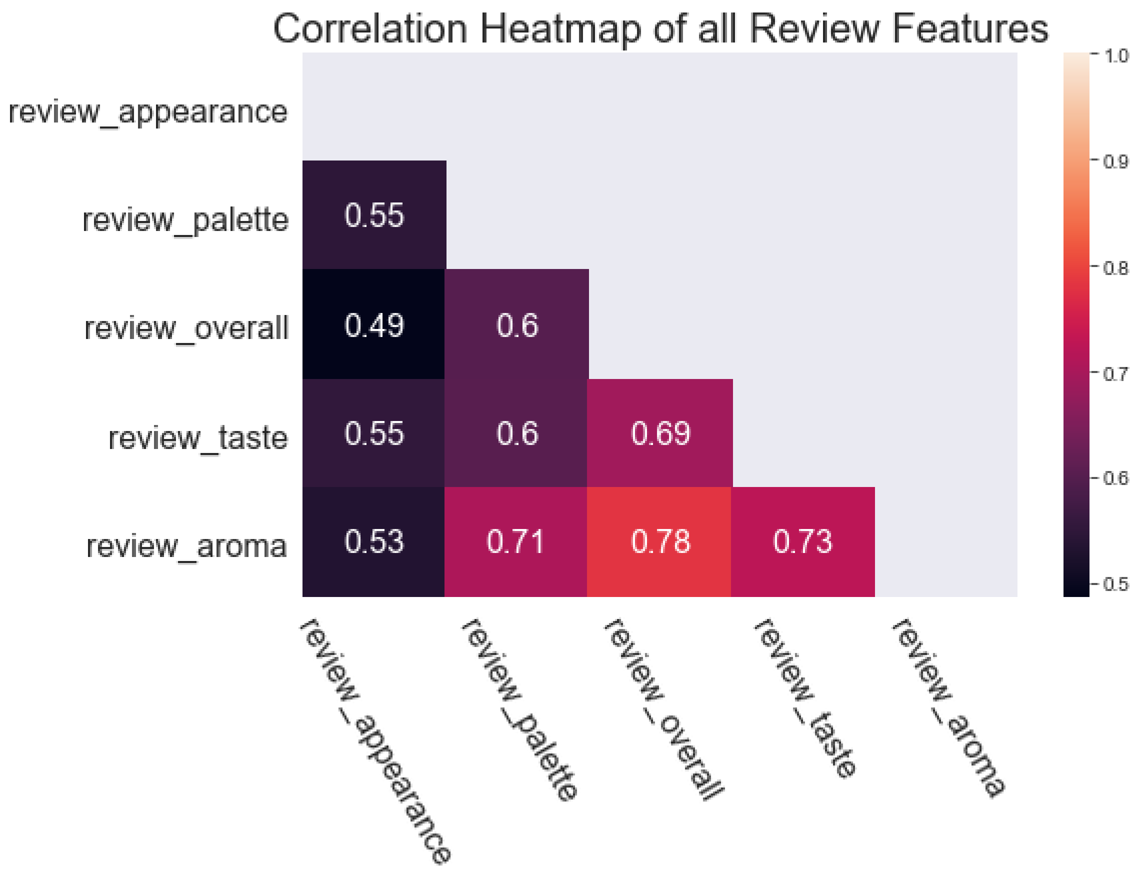
```
corr_mask = np.triu(np.ones_like(df_reviews_all.corr(), dtype=bool))
```

In [70]:

```
corr_mask = np.triu(np.ones_like(df_reviews_all.corr(), dtype=bool))
sns.set_style("darkgrid")
plt.figure(figsize=(8,5))
plt.title("Correlation Heatmap of all Review Features",fontsize=20)
sns.heatmap(df_reviews_all.corr(),mask=corr_mask,annot=True,annot_kws={"size": 16})
plt.xticks(fontsize=16,rotation=-60)
plt.yticks(fontsize=16)
```

Out[70]:

```
(array([0.5, 1.5, 2.5, 3.5, 4.5]), <a list of 5 Text yticklabel objects>)
```



Observation/Conclusion

1. From Above Correlation Plot bar Plot we can say that,
   Review_overall & **Review_Aroma** are most correlated features with correlation of 0.78

3.3.3: Q3 Approach 3-VIF: Variation Inflation Factor

In [71]:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [72]:

```
vif_data = pd.DataFrame()
vif_data["feature"] = df_reviews_all.columns
```

In [73]:

```
vif_data["VIF"]=[variance_inflation_factor(df_reviews_all.values, i) for i in range((df_rev
```

In [74]:

```
vif_data.sort_values("VIF",ascending=False,inplace=True)
```

In [75]:

```
vif_data
```

Out[75]:

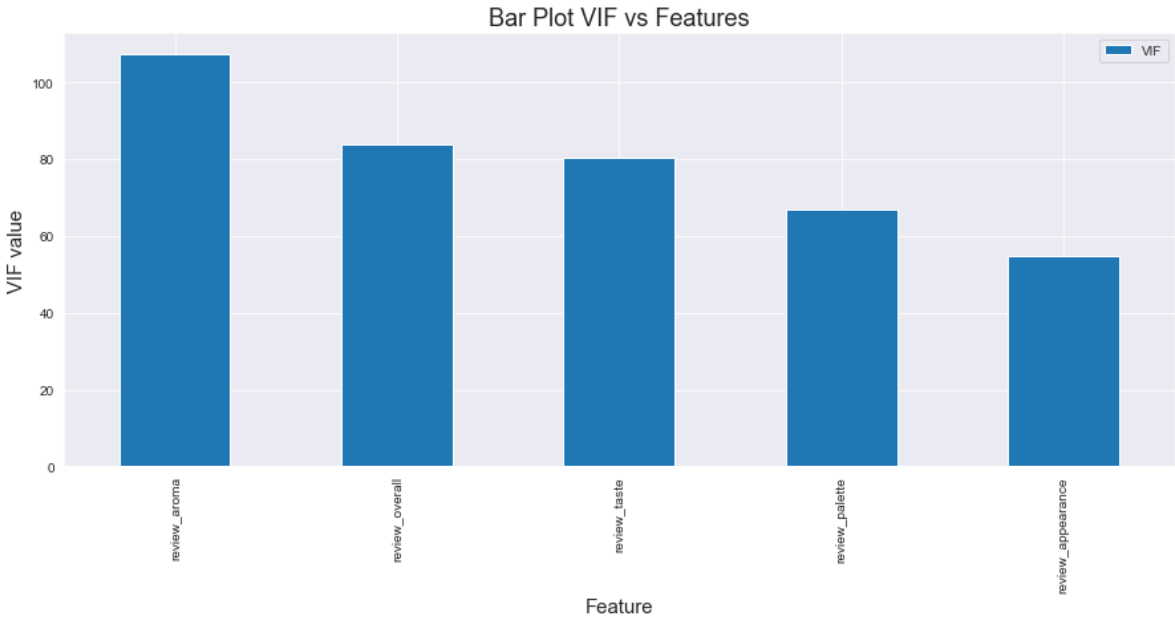
	feature	VIF
4	review_aroma	107.384740
2	review_overall	83.676943
3	review_taste	80.276929
1	review_palette	66.980315
0	review_appearance	54.669849

In [76]:

```
vif_data.plot(kind='bar',
              x="feature",
              figsize=(15,6))
plt.title("Bar Plot VIF vs Features",fontsize=18)
plt.xlabel("Feature",fontsize=15)
plt.ylabel("VIF value",fontsize=15)
```

Out[76]:

```
Text(0, 0.5, 'VIF value')
```



Observation/Conclusion

1. From Above VIF bar Plot we can say that **Review_overall** & **Review_Aroma** are most correlated features

3.4: Q4- If you were to recommend 3 beers to your friends based on this data which ones will you recommend?

3.4.1 Q4- Approach 1

In [77]:

```
data.columns
```

Out[77]:

```
Index(['beer_ABV', 'beer_beerId', 'beer_brewerId', 'beer_name', 'beer_styl
e',
       'review_appearance', 'review_palette', 'review_overall', 'review_tast
e',
       'review_profileName', 'review_aroma', 'review_text', 'review_time',
       'date', 'year'],
      dtype='object')
```

In [78]:

```
df_beer_name_ol_review=data[['beer_name','review_overall']]
```

In [79]:

```
df_beer_name_ol_review.groupby('beer_name')["review_overall"].mean()
```

Out[79]:

```
beer_name
"100" Pale Ale                            4.000000
"33" Export                               3.000000
"76" Anniversary Ale                      4.000000
"76" Anniversary Ale With English Hops    4.000000
"Fade To Black" Porter                    4.000000
                                            ...
Über Pils                                 4.057018
ÜberFest Pilsner                          4.000000
ÜberSun (Imperial Summer Wheat Beer)      4.060086
à L'Agave Et Au Citron Vert               2.500000
überPils                                  3.857143
Name: review_overall, Length: 18339, dtype: float64
```

In [80]:

```
df_beer_name_ol_review.groupby('beer_name')["review_overall"].mean().sort_values(ascending=
```

Out[80]:

```
beer_name
Fat Bottom Ale                                                  5.0
Schwindel Alt                                                   5.0
Quaker Oatmeal Stout                                            5.0
Kösslarn Hefeweisse                                             5.0
Celtic Red                                                      5.0
Yarmouth Town Brown                                             5.0
Cellar Door With Pineapple And Dry-hopped With Citra And Perle    5.0
Becken Beer Dunkel Bock                                         5.0
Boiler Room Golden Ale                                          5.0
Spicy Plum Sour Ale                                             5.0
Willamette Pale Ale                                             5.0
Sierra Nevada Oaked Imperial Porter                             5.0
HopCat Raging Centaur                                           5.0
Cauldron Brew                                                   5.0
Czechmate Ale                                                   5.0
Frostbite Ice                                                   5.0
Mother Pucker                                                   5.0
Fritzkrieg Hop IPA                                              5.0
Replic Ale (2010)                                               5.0
Guava Grove - Wild                                              5.0
Skull And Bones Foxy                                            5.0
McBane's Strawberry Wit                                         5.0
Høst Bryg Kirsebær                                              5.0
Wexford Wheat                                                   5.0
Ramstein Project Z                                              5.0
Hopback Amber (Simcoe Dry Hopped)                               5.0
Cask-conditioned Oatmeal Stout                                  5.0
Mango Double Simcoe                                             5.0
Wet Hop Citra Ale                                               5.0
Lemon Light                                                     5.0
Bubba Imperial Pilsner                                          5.0
Grand Cru 2004                                                  5.0
Fuggit Stout                                                    5.0
Roth Weissbier Premium                                          5.0
Graf Arco Arcolator                                             5.0
Golding Bitter                                                  5.0
Spring Forward Fall Bock                                        5.0
Dunkel Keller                                                   5.0
Banana Wheat                                                    5.0
Goodes Highland Scotch Ale                                      5.0
Snowplow                                                        5.0
Belgian Siberian Night Imperial Stout Aged On Cherries          5.0
Galaxy Golden Ale                                               5.0
MELVIN India Pale Ale                                           5.0
Triplexxx                                                       5.0
Tado Helles                                                     5.0
Triple OOO                                                      5.0
Jai Alai IPA - Strawberry-Kiwi                                  5.0
Tado Dunkel                                                     5.0
Ramstein India Pale Ale                                         5.0
Name: review_overall, dtype: float64
```

Observation/Conclusion

1. Based on the Overall Review we cannot come to conclusion because all top beers is having Review_overall rating 5.

3.4.2 Q4- Approach 2 with Beer_ABV & review_overall Feature

In [81]:

```
df_ABV_beer_name_ol_review=data[["beer_ABV",'beer_name','review_overall']]
```

In [82]:

```
df_ABV_beer_name_ol_review.head(2)
```

Out[82]:

	beer_ABV	beer_name	review_overall
0	5.0	Sausa Weizen	1.5
1	6.2	Red Moon	3.0

In [83]:

```
df_best_beers=df_ABV_beer_name_ol_review \
              .groupby(('beer_name'))['review_overall',
                                      'beer_ABV'] \
                                      .mean() \
                                      .reset_index() \
                                      .sort_values(by=['review_overall',
                                                       'beer_ABV'],ascending=False)
```

In [84]:

```
df_best_beers.head(3)
```

Out[84]:

	beer_name	review_overall	beer_ABV
582	AleSmith Speedway Stout - Oak Aged	5.0	12.0
12616	Pilot Series Imperial Sweet Stout - Palm Ridge...	5.0	12.0
1764	Bees Knees Barleywine	5.0	11.2

Observation/Conclusion

1. Based on the Reviews Overall Review & Alcohol by Volume(Beer_ABV) will recommmend the beer to friends as follows
   a. AleSmith Speedway Stout - Oak Aged
   b. Pilot Series Imperial Sweet Stout - Palm Ridge
   c. Bees Knees Barleywine

3.4.3 Q4- Approach 3 with all reviews & beer_ABV Features

In [85]:

```
data.columns
```

Out[85]:

```
Index(['beer_ABV', 'beer_beerId', 'beer_brewerId', 'beer_name', 'beer_styl
e',
       'review_appearance', 'review_palette', 'review_overall', 'review_tast
e',
       'review_profileName', 'review_aroma', 'review_text', 'review_time',
       'date', 'year'],
      dtype='object')
```

In [86]:

```
'review_appearance', 'review_palette', 'review_taste','review_aroma'
```

Out[86]:

```
('review_appearance', 'review_palette', 'review_taste', 'review_aroma')
```

In [87]:

```
df_ABV_beer_name_ol_review_1=data[['beer_name',
                                   'review_overall',
                                   'review_aroma',
                                   'review_taste',
                                   "review_appearance",
                                   "beer_ABV"]]
```

In [88]:

```
df_ABV_beer_name_ol_review_1.head(2)
```

Out[88]:

	beer_name	review_overall	review_aroma	review_taste	review_appearance	beer_ABV
0	Sausa Weizen	1.5	1.5	1.5	2.5	5.0
1	Red Moon	3.0	3.0	3.0	3.0	6.2

In [89]:

```
df_best_beers_all=df_ABV_beer_name_ol_review_1 \
                  .groupby(('beer_name'))['review_overall',
                                          'review_aroma',
                                          'review_taste',
                                          "review_appearance",
                                          "beer_ABV"] \
                                                       .mean() \
                                                       .reset_index() \
                                                       .sort_values(by=['review_overall',
                                                                        'review_aroma',
                                                                        'review_taste',
                                                                        "review_appearance",
                                                                        "beer_ABV"],
                                                                   ascending=False)
```

In [90]:

```
df_best_beers_all.head(3)
```

Out[90]:

	beer_name	review_overall	review_aroma	review_taste	review_appearance	beer_ABV
5394	Edsten Triple-Wit	5.0	5.0	5.0	5.0	10.0
11912	Old Gander Barley Wine	5.0	5.0	5.0	5.0	9.5
13725	Rogue Black Brutal	5.0	5.0	5.0	5.0	9.0

Observation/Conclusion

1. Based on the all Reviews & Alcohol by Volume(Beer_ABV) will recommmend the beer to friends as follows
   a. Edsten Triple-Wit
   b. Old Gander Barley Wine
   c. Rogue Black Brutal

3.5: Q5- Which Beer style seems to be the favorite based on reviews written by users?

3.5.1 Decontration Function

In [91]:

```
#https://stackoverflow.com/questions/19790188/expanding-english-language-contractions-in-py
import re

def decontracted(phrase):
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    phrase = re.sub('[^A-Za-z0-9]+', ' ', phrase)
    phrase = phrase.replace('\\r', ' ')
    phrase = phrase.replace('\\"', ' ')
    phrase = phrase.replace('\\n', ' ')
    return phrase
```

In [92]:

```
data.columns
```

Out[92]:

```
Index(['beer_ABV', 'beer_beerId', 'beer_brewerId', 'beer_name', 'beer_styl
e',
       'review_appearance', 'review_palette', 'review_overall', 'review_tast
e',
       'review_profileName', 'review_aroma', 'review_text', 'review_time',
       'date', 'year'],
      dtype='object')
```

In [93]:

```
data['review_text'].isna().sum()
```

Out[93]:

```
0
```

In [94]:

```
%%time
data['cleaned_text']=data['review_text'].apply(decontracted)
```

```
Wall time: 1min 19s
```

In [95]:

```
data['cleaned_text'].head()
```

Out[95]:

```
0    A lot of foam But a lot In the smell some bana...
1    Dark red color light beige foam average In the...
2    Almost totally black Beige foam quite compact ...
3    Golden yellow color White compact foam quite c...
4    According to the website the style for the Cal...
Name: cleaned_text, dtype: object
```

In [96]:

```
data['cleaned_text']=data['cleaned_text'].apply(lambda text: text.lower())
```

In [97]:

```
data['cleaned_text'].head()
```

Out[97]:

```
0    a lot of foam but a lot in the smell some bana...
1    dark red color light beige foam average in the...
2    almost totally black beige foam quite compact ...
3    golden yellow color white compact foam quite c...
4    according to the website the style for the cal...
Name: cleaned_text, dtype: object
```

3.5.2 Stop Word Removal

In [98]:

```
stopwords= ['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they'
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'l
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had',
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'u
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'd
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over',
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', '
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too', 'v
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now',
```

In [99]:

```
data['cleaned_text']=data['cleaned_text'].apply(lambda text: " ".join([word for word in tex
```

In [100]:

```
data['cleaned_text'].head()
```

Out[100]:

```
0    lot foam lot smell banana lactic tart not good...
1    dark red color light beige foam average smell ...
2    almost totally black beige foam quite compact ...
3    golden yellow color white compact foam quite c...
4    according website style caldera cauldron chang...
Name: cleaned_text, dtype: object
```

3.5.3 Vader Sentiment Analyzer

In [101]:

```
#topic:Vader_Sentiment vs TextBlob: https://pub.towardsai.net/textblob-vs-vader-for-sentime
```

In [102]:

```
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer
nltk.download('vader_lexicon')
```

```
[nltk_data] Downloading package vader_lexicon to C:\Users\DR SNEHAL
[nltk_data]     BANKAR\AppData\Roaming\nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

Out[102]:

```
True
```

In [103]:

```
data['text_sentiment_score'] = 0.0
```

In [104]:

```
sentiment_analyzer = SentimentIntensityAnalyzer()
```

In [105]:

```
data['cleaned_text'][0]
```

Out[105]:

```
'lot foam lot smell banana lactic tart not good start quite dark orange colo
r lively carbonation visible foam tending lactic sourness taste yeast banan
a'
```

In [106]:

```
sentiment_analyzer.polarity_scores(data['cleaned_text'][0])['compound']
```

Out[106]:

```
0.1265
```

In [107]:

```
def vader_sentiment_ana(text):
    return sentiment_analyzer.polarity_scores(text)['compound']
```

In [108]:

```
%%time
data['text_sentiment_score']=data['cleaned_text'].apply(vader_sentiment_ana)
```

```
Wall time: 18min 31s
```

In [109]:

```
data.tail(2)
```

Out[109]:

	beer_ABV	beer_beerId	beer_brewerId	beer_name	beer_style	review_appearance	revi
528868	7.017442	4032	3340	Dinkel Acker Dark	Munich Dunkel Lager	4.0	
528869	7.017442	4032	3340	Dinkel Acker Dark	Munich Dunkel Lager	4.0	

In [110]:

```
#data.to_csv("Cleaned_Beer_Dataset.csv")
```

In [111]:

```
pd.DataFrame(data.groupby('beer_style')['text_sentiment_score'].mean().sort_values(ascendin
```

Out[111]:

	text_sentiment_score
beer_style	
Braggot	0.863941
Quadrupel (Quad)	0.863022

Observation/Conclusion

1. Review Text Sentiment is calculated using Vader Sentiment Analyzer
2. For the ***Braggot*** beer_style, the average senitiment score is max i.e. 0.863941

3.6: Q6- How does written review compare to overall review score for the beer styles?

In [112]:

```
data.head(2)
```

Out[112]:

	beer_ABV	beer_beerId	beer_brewerId	beer_name	beer_style	review_appearance	review_p
0	5.0	47986	10325	Sausa Weizen	Hefeweizen	2.5	
1	6.2	48213	10325	Red Moon	English Strong Ale	3.0	

In [113]:

```
print("="*100)
print("Overall Correlation of Review Overall between Review_Text(Sentiment_Score)")
print("-"*100)
print(data['review_overall'].corr(data['text_sentiment_score']))
print("="*100)
```

```
============================================================================
========================
Overall Correlation of Review Overall between Review_Text(Sentiment_Score)
----------------------------------------------------------------------------
------------------------
0.35463849509851525
============================================================================
========================
```

In [114]:

```
df_sentiment_review_style=data.groupby('beer_style')['text_sentiment_score',
                                                     'review_overall'].mean(). \
                                                      sort_values(['text_sentiment_score',
                                                                   'review_overall'],ascend
```

In [115]:

```
df_sentiment_review_style.head(2)
```

Out[115]:

	beer_style	text_sentiment_score	review_overall
0	Braggot	0.863941	3.645729
1	Quadrupel (Quad)	0.863022	4.049371

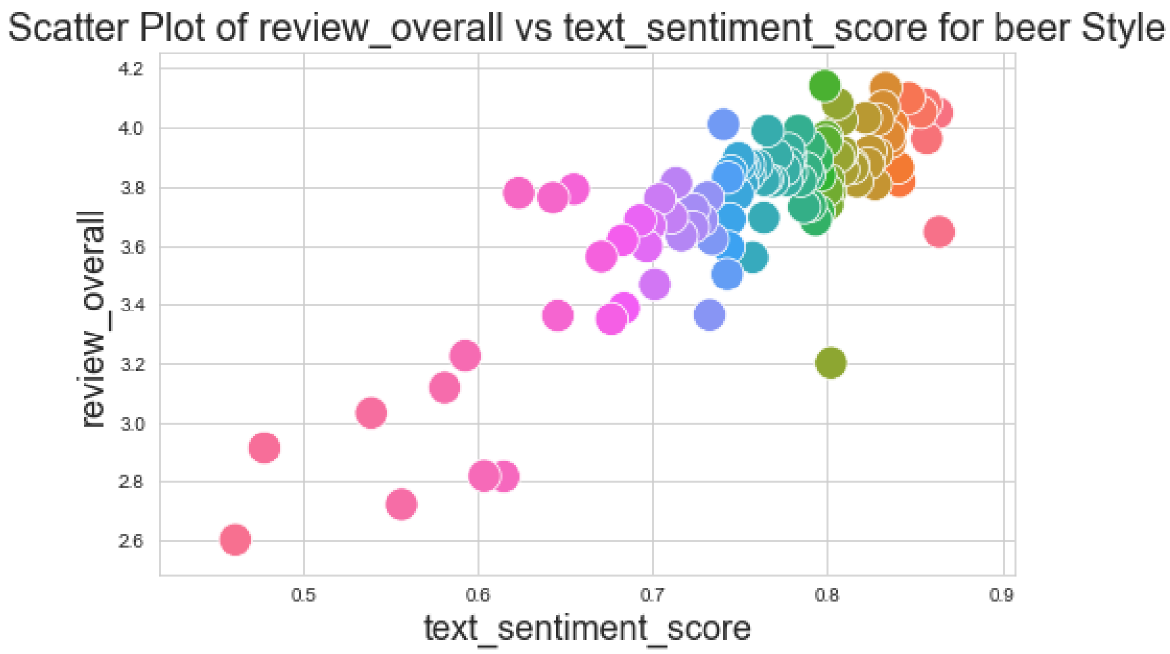
In [116]:

```
print("="*100)
print("Correlation of Review Overall between Review_Text(Sentiment_Score) based on the Beer
print("-"*100)
print(df_sentiment_review_style['review_overall'].corr(df_sentiment_review_style['text_sent
print("="*100)
```

```
============================================================================
========================
Correlation of Review Overall between Review_Text(Sentiment_Score) based on
the Beer_Style:
----------------------------------------------------------------------------
------------------------
0.826573074280782
============================================================================
========================
```

In [117]:

```
plt.figure(figsize=(8,5))
sns.set_style("whitegrid")
sns.scatterplot(x=df_sentiment_review_style['text_sentiment_score'],
                y=df_sentiment_review_style['review_overall'],
                hue=df_sentiment_review_style['beer_style'],
                s=300)
plt.xlabel("text_sentiment_score",fontsize=18)
plt.ylabel("review_overall",fontsize=18)
plt.legend("",frameon=False)
plt.title("Scatter Plot of review_overall vs text_sentiment_score for beer Style",fontsize=
plt.show()
```



Observation/Conclusion

1. Correlation of Review Overall between Review_Text(Sentiment_Score) based on the Beer_Style:0.82657
2. From Above Scatter Plot of review_overall vs text_sentiment_score for beer Style we can say that there is significat linear relation between the text review & review overall

3.7: Q7- How do find similar beer drinkers by using written reviews only?

In [118]:

```
data=pd.read_csv('Cleaned_Beer_Dataset.csv',encoding='latin-1')
```

In [119]:

```
data.columns
```

Out[119]:

```
Index(['Unnamed: 0', 'beer_ABV', 'beer_beerId', 'beer_brewerId', 'beer_nam
e',
       'beer_style', 'review_appearance', 'review_palette', 'review_overal
l',
       'review_taste', 'review_profileName', 'review_aroma', 'review_text',
       'review_time', 'cleaned_text', 'text_sentiment_score'],
      dtype='object')
```

In [120]:

```
%%time
from sklearn.feature_extraction.text import CountVectorizer
count_vectorizer = CountVectorizer()
count_vectorizer.fit(data['cleaned_text'].values)
review_text_features=count_vectorizer.transform(data['cleaned_text'].values)
review_text_features.get_shape() # get number of rows and columns in feature matrix.
```

```
Wall time: 2min 29s
```

Out[120]:

```
(528636, 150420)
```

In [121]:

```
data.columns
```

Out[121]:

```
Index(['Unnamed: 0', 'beer_ABV', 'beer_beerId', 'beer_brewerId', 'beer_nam
e',
       'beer_style', 'review_appearance', 'review_palette', 'review_overal
l',
       'review_taste', 'review_profileName', 'review_aroma', 'review_text',
       'review_time', 'cleaned_text', 'text_sentiment_score'],
      dtype='object')
```

In [122]:

```
from sklearn.metrics.pairwise import cosine_similarity
```

In [123]:

```
def bag_of_words_model(doc_id, num_results):
    """
    doc_id: Index of query datapoint
    num_results: Number of Datapoints similar to the Query datapoint
    """
    #the metric we used here is cosine, the coside distance is mesured as K(X, Y) = <X, Y>
    # http://scikit-learn.org/stable/modules/metrics.html#cosine-similarity
    print('='*120)
    print("beer_beerId of Query Datapoint :",data.iloc[doc_id]['beer_beerId'])
    print('-'*120)
    print("beer_name of Query Datapoint:",data.iloc[doc_id]['beer_name'])
    print('-'*120)
    print("Review Text of Query Datapoint :",data.iloc[doc_id]['cleaned_text'])
    print('='*120)
    pairwise_dist = cosine_similarity(review_text_features,review_text_features[doc_id])

    # np.argsort will return indices of the smallest distances
    indices = np.argsort(pairwise_dist.flatten())[::-1][0:num_results]
    #pdists will store the smallest distances
    pdists  = np.sort(pairwise_dist.flatten())[::-1][0:num_results]
    df_indices = list(data.index[indices])

    for i in range(0,len(indices)):
        print('beer_beerId of Similar Datapoint:',data['beer_beerId'].loc[df_indices[i]])
        print('-'*120)
        print ('beer_nameof Similar Datapoint:', data['beer_name'].loc[df_indices[i]])
        print('-'*120)
        print ('review_text of Similar Datapoint:', data['cleaned_text'].loc[df_indices[i]]
        print('-'*120)
        print ('Cosine similarity with the query point',pdists[i])
        print('='*120)
```

In [124]:

```
%%time
bag_of_words_model(4000, 5)
```

```
============================================================================
============================================
beer_beerId of Query Datapoint : 33624
----------------------------------------------------------------------------
--------------------------------------------
beer_name of Query Datapoint: Hoppin' To Heaven IPA
----------------------------------------------------------------------------
--------------------------------------------
Review Text of Query Datapoint : got de bierkoning amsterdam bomber snifter
appearance pours bit 3 finger thick tight white head great retention perfect
ly clear higher active levels carbonation burnt orange color head slowly fad
es thick foam cap stays leaves lots nice lacing glass looks great way smell
decent strength nose pale toasted malts citrus grapefruit hints lemon floral
notes taste interesting spin one hops esters seem come front bitter grapefru
it citrus lemon sweet malt shows middle caramel mostly pale toasted malts bi
scuit well good dose bitter floral hops finishes beginning middle seem backw
ards aftertaste bitter sweet lots pine grapefruit notes pretty good palate m
edium body medium carbonation creamy smooth palate goes smooth finishes rath
er sticky mouth coating not bad overall balanced ipa good amount malt sweetn
ess balance nice hop profile glad found one fuller palate would help get one
hump accentuate taste profile better non less good beer
============================================================================
============================================
beer_beerId of Similar Datapoint: 33624
----------------------------------------------------------------------------
--------------------------------------------
beer_nameof Similar Datapoint: Hoppin' To Heaven IPA
----------------------------------------------------------------------------
--------------------------------------------
review_text of Similar Datapoint: got de bierkoning amsterdam bomber snifter
appearance pours bit 3 finger thick tight white head great retention perfect
ly clear higher active levels carbonation burnt orange color head slowly fad
es thick foam cap stays leaves lots nice lacing glass looks great way smell
decent strength nose pale toasted malts citrus grapefruit hints lemon floral
notes taste interesting spin one hops esters seem come front bitter grapefru
it citrus lemon sweet malt shows middle caramel mostly pale toasted malts bi
scuit well good dose bitter floral hops finishes beginning middle seem backw
ards aftertaste bitter sweet lots pine grapefruit notes pretty good palate m
edium body medium carbonation creamy smooth palate goes smooth finishes rath
er sticky mouth coating not bad overall balanced ipa good amount malt sweetn
ess balance nice hop profile glad found one fuller palate would help get one
hump accentuate taste profile better non less good beer
----------------------------------------------------------------------------
--------------------------------------------
Cosine similarity with the query point 1.0
============================================================================
============================================
beer_beerId of Similar Datapoint: 47647
----------------------------------------------------------------------------
--------------------------------------------
beer_nameof Similar Datapoint: YuleSmith (Winter)
----------------------------------------------------------------------------
--------------------------------------------
review_text of Similar Datapoint: got de bierkoning amsterdam bomber snifter
appearance thick looking one finger white head good retention color deep bur
nt umber brown little carbonation evident head slowly fades decent film thic
```

```
k ring splotchy film remains end leaves good lacing sides nice color well sm
ell decent strength nose pale toasted malt biscuit hints caramel toffee note
s good hop presence hints grapefruit pine sweet citrus fruits well nice tast
e taste follows nose nicely pale toasted malt caramel toffee notes hop profi
le grapefruit pine flavors really nice spiciness end clove coriander tyme pe
rhaps well spicy alcohol finish bitter ending story leading long bold aftert
aste bitter spicy hops sweet malty biscuit finish fantastic palate medium bo
dy medium carbonation creamy smooth palate goes smooth finishes touch drynes
s palate no bite end abv not noticeable good overall outstanding beer couple
alesmith impressive say least like bottle says really deliciously malty hopp
y drinkable enjoyable balanced brew one better beers ever recommended
----------------------------------------------------------------------------
--------------------------------------------
Cosine similarity with the query point 0.6245021436316043
============================================================================
============================================
beer_beerId of Similar Datapoint: 5441
----------------------------------------------------------------------------
--------------------------------------------
beer_nameof Similar Datapoint: Founders Centennial IPA
----------------------------------------------------------------------------
--------------------------------------------
review_text of Similar Datapoint: got de bierkoning amsterdam bottle snifter
appearance pours two finger medium thick looking white head great retention
mahogany tawny orange color clear medium carbonation evident head slowly fad
es good film cap bubbly frothy ring splotchy wisp remains end leaves lacing
sides smell pale toasted malt good dose citrus grapefruit hops notes lemon f
aint touches pine well decent strength well taste pale toasted malt mild gra
pefruit piney hops though middle not bold nose suggested moves bitter piney
hop aftertaste quite bold long lasting not much malt sweetness one really af
tertaste definitely bolder impressive initial taste palate medium body cream
y smooth palate goes smooth no bite finishes slightly dry palate nice feel o
verall good ipa sure quite drinkable well unfortunately initial taste lacked
somewhat not get malt backbone reviewers allude one like milder version doub
le trouble ask not necessary good beer not one worth writing home
----------------------------------------------------------------------------
--------------------------------------------
Cosine similarity with the query point 0.6210590034081188
============================================================================
============================================
beer_beerId of Similar Datapoint: 22505
----------------------------------------------------------------------------
--------------------------------------------
beer_nameof Similar Datapoint: Green Flash West Coast I.P.A.
----------------------------------------------------------------------------
--------------------------------------------
review_text of Similar Datapoint: got de cracked kettle amsterdam bottle sni
fter appearance pours big three finger thicker perfectly white head great re
tention tawny burnt orange color medium levels carbonation evident head slow
ly recedes thick healthy foam cap good film stays end leaves lots nice lacin
g glass looks really good smell pine floral notes hints citrus pale malts no
ticeable little muted liking fine not bold enough taste flavors definitely b
older pale malts lots hops everywhere pine floral notes citrus light grapefr
uit flavors finishes lots bitterness well bold lingering aftertaste plenty b
itter pine citrus notes hoppy bitter much impressive nose palate medium ligh
t body medium carbonation creamy smooth palate goes smooth finishes nicely m
outh coating overall another good offering green flash nose gave worries wou
ld not quite deliver punch flavors definitely came end good looking beer lot
s flavor recommended
----------------------------------------------------------------------------
--------------------------------------------
```

```
Cosine similarity with the query point 0.6168577597152108
============================================================================
============================================
beer_beerId of Similar Datapoint: 33243
----------------------------------------------------------------------------
--------------------------------------------
beer_nameof Similar Datapoint: Wipeout I.P.A.
----------------------------------------------------------------------------
--------------------------------------------
review_text of Similar Datapoint: found de bierkoning amsterdam bomber snift
er appearance pours two finger thicker looking white head great retention co
lor persian reddish brown gamboge held light clear no visible carbonation he
ad slowly fades good film leaves immediate lacing wisp remains notil end lea
ves great lacing glass good looking head beautiful lacing though color not a
bsolute favorite smell bold smell already toasted pale malt grapefruit pine
citrus notes background nice floral notes well hoppy grapefruit flowers bold
nice exploded glass taste pale toasted malt beginning lots hoppy grapefruit
pine notes well flowery hops middle end touch spiciness alcohol delayed mild
good bitter hop punch end rides strong long lasting aftertaste good not quit
e bold nose strange finish little disappearing act aftertaste shows vengeanc
e palate medium body medium carbonation semi creamy palate goes pretty smoot
h no bite finishes somewhat mouth coating palate could little creamier prett
y fine whole overall good ipa bigger nose taste profile lot others style dri
nkable brew thoroughly enjoyed recommended
----------------------------------------------------------------------------
--------------------------------------------
Cosine similarity with the query point 0.6086053178377864
============================================================================
============================================
Wall time: 2.01 s
```

Observation/Conclusion

1. For review text Similarity, Text is converted into BOW representation.
2. Then cosine Similarity is calculated between the Query point & other Datapoint.
3. For beerId of Query Datapoint : 33624 most similar datapoint is
   beer_beerId : 47647 & beer_name: YuleSmith (Winter)

__Note:__
(Approach 2):We can use Semantic Based Text Vectorizer for text Featurization like *__W2V__* ,
__Sentence_Transformers__ & to reduce the time Complexity we can use *__FAISS__* similarity search