Let's understand Analysis of Variance(ANOVA)

The objective for creating this notebook is to build understanding of ANOVA by working on some real examples;

- Post-Hoc tests
- Normality tests
- Hommogenity tests

Notebook Contents

Notes_CheatSheet

In [1]:
```
from IPython.core.display import Image
```

In [2]:
```
Image(filename="Handwritten_Notes/Stats_Revision-1.png",width=1800,height=1800)
```

Out[2]:

In [3]:
```
Image(filename="Handwritten_Notes/Stats_Revision-2.png",width=1800,height=1800)
```

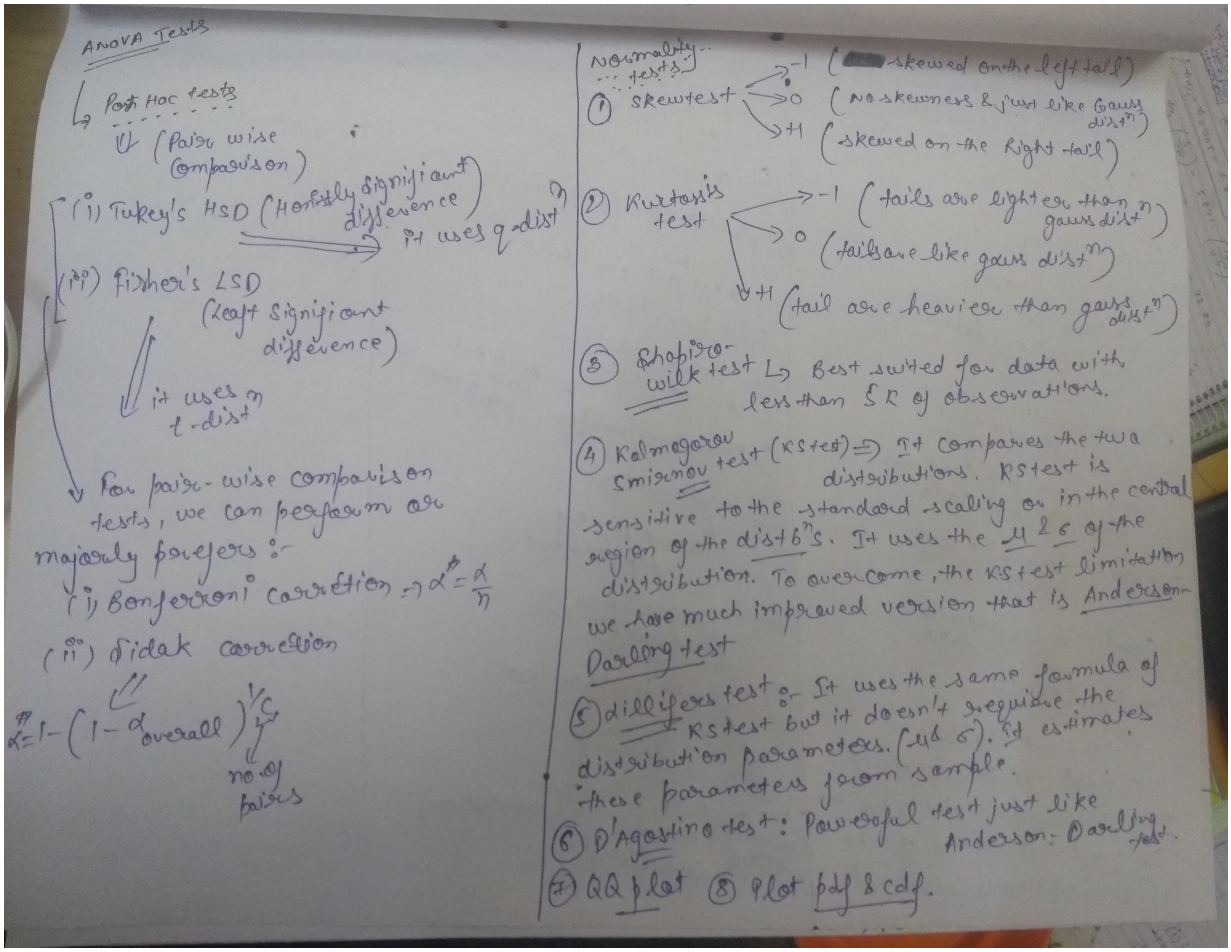
Out[3]:

In [4]:
```
Image(filename="Handwritten_Notes/Stats_Revision-3.png",width=1800,height=1800)
```

Out[4]:

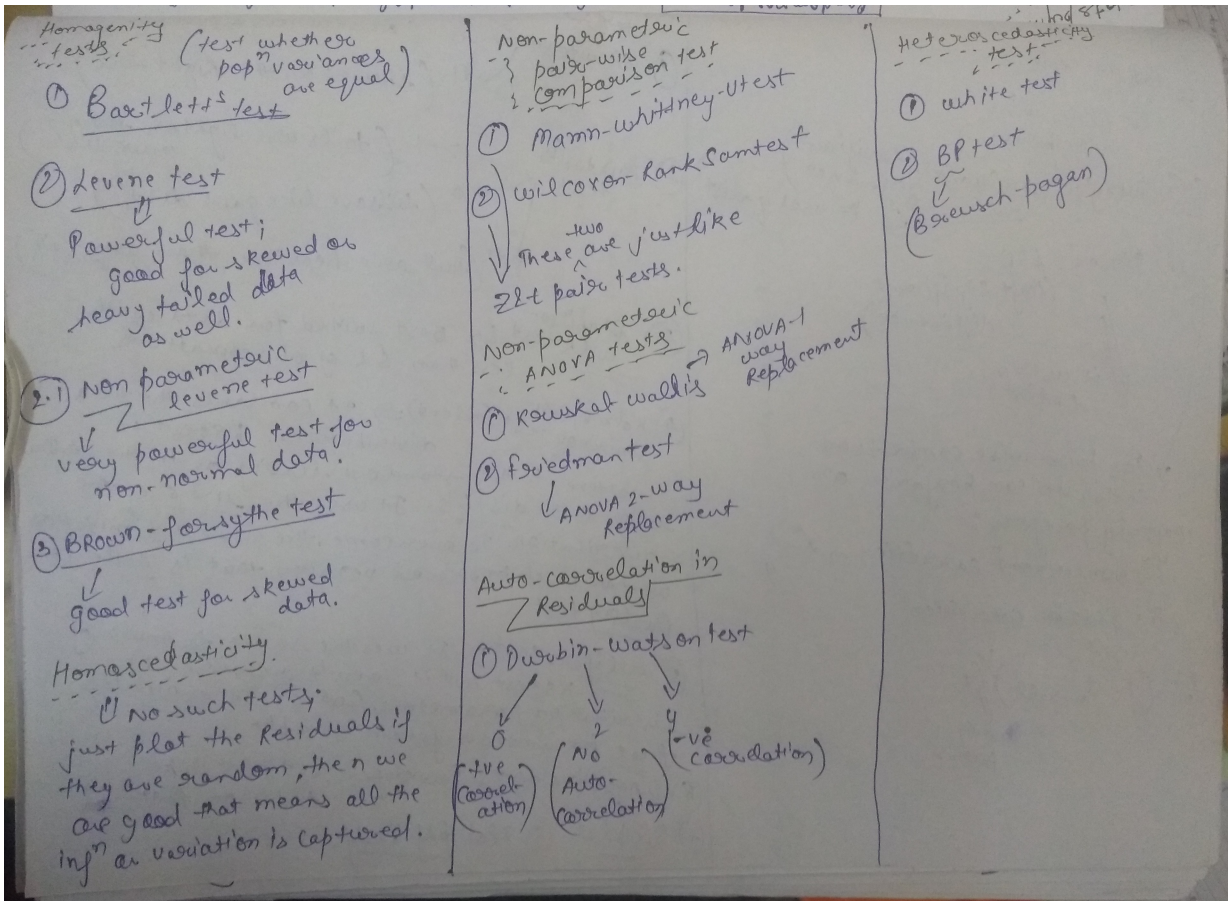
In [245…
```
Image(filename="Handwritten_Notes/Stats_Tests_Cheatsheet1.jpg",width=1800,height=180
```

Out[245…



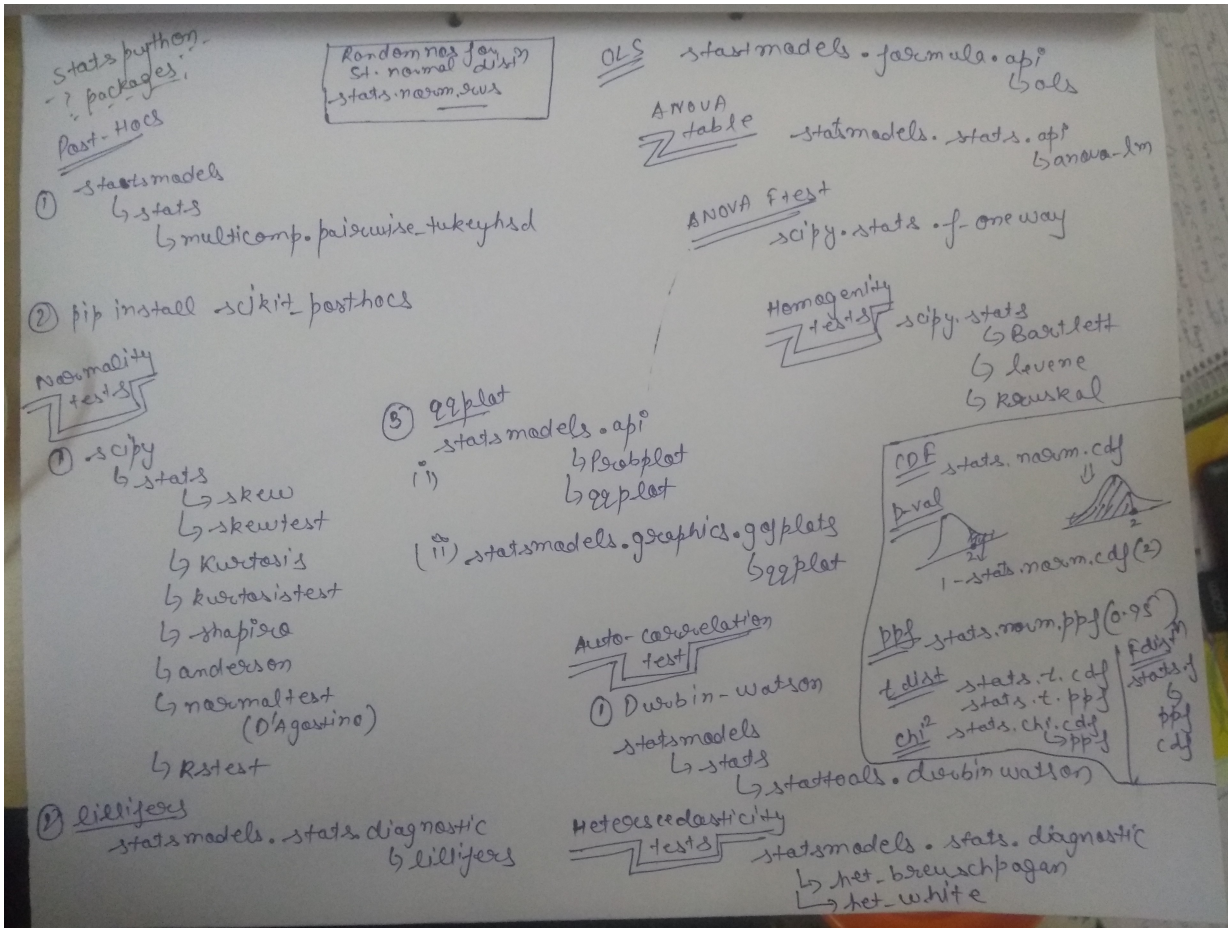
In [246…
```
Image(filename="Handwritten_Notes/Stats_Tests_Cheatsheet2.jpg",width=1800,height=180
```

Out[246…



In [247…
```
Image(filename="Handwritten_Notes/Stats_Tests_Python_Pkgs_Cheatsheet.jpg",width=1800
```

Out[247…



Importing_Libraries

In [5]:
```
## Data-preprocessing and visualization libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

## Colored print statements on the console
from termcolor import colored

## Feature scalers and transformers
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler, PowerT

## Scientific python and statistical packages
import scipy
import statsmodels as stm

## QQ plot
from statsmodels.api import ProbPlot, qqplot
from statsmodels.graphics.gofplots import qqplot
## Lillifers
from statsmodels.stats.diagnostic import lilliefors
## Ordinary Least Squares
from statsmodels.formula.api import ols
## ANOVA Table
from statsmodels.stats.api import anova_lm
## POST-Hoc Tests
from statsmodels.stats.multicomp import pairwise_tukeyhsd as tukeyhsd
import scikit_posthocs as post_hocs
## HETEROSCADASTICITY Tests
from statsmodels.stats.diagnostic import het_breuschpagan
from statsmodels.stats.diagnostic import het_white

%matplotlib inline
```

In [6]:
```
pd.set_option('display.max_rows',50)
```

CASE_STUDY:1

Working with India's Population & COVID-19 datasets

In [7]:
```
state_dly_cases = pd.read_csv("Datasets/covid_19_india.csv")
```

In [8]:
```
state_dly_cases.tail()
```

Out[8]:

	Sno	Date	Time	State/UnionTerritory	ConfirmedIndianNational	ConfirmedForeignNation
8481	8482	16/11/20	8:00 AM	Telengana	-	
8482	8483	16/11/20	8:00 AM	Tripura	-	
8483	8484	16/11/20	8:00 AM	Uttarakhand	-	
8484	8485	16/11/20	8:00 AM	Uttar Pradesh	-	
8485	8486	16/11/20	8:00 AM	West Bengal	-	

In [9]:
```
state_ws_test = pd.read_csv("Datasets/StatewiseTestingDetails.csv")
```

In [10]:
```
state_ws_test.tail()
```

Out[10]:

	Date	State	TotalSamples	Negative	Positive
7307	2020-11-11	West Bengal	5047335.0	NaN	NaN
7308	2020-11-12	West Bengal	5091700.0	NaN	NaN
7309	2020-11-13	West Bengal	5136012.0	NaN	NaN
7310	2020-11-14	West Bengal	5180139.0	NaN	NaN
7311	2020-11-15	West Bengal	5218797.0	NaN	NaN

In [11]:
```
state_ws_test.shape
```

Out[11]:
```
(7312, 5)
```

In [12]:
```
india_pop = pd.read_csv("Datasets/population_india_census2011.csv.txt")
```

In [13]:
```
india_pop.head()
```

Out[13]:

	Sno	State / Union Territory	Population	Rural population	Urban population	Area	Density	Gender Ratio
0	1	Uttar Pradesh	199812341	155317278	44495063	240,928 km2 (93,023 sq mi)	828/km2 (2,140/sq mi)	912

	Sno	State / Union Territory	Population	Rural population	Urban population	Area	Density	Gender Ratio
1	2	Maharashtra	112374333	61556074	50818259	307,713 km2 (118,809 sq mi)	365/km2 (950/sq mi)	929
2	3	Bihar	104099452	92341436	11758016	94,163 km2 (36,357 sq mi)	1,102/km2 (2,850/sq mi)	918
3	4	West Bengal	91276115	62183113	29093002	88,752 km2 (34,267 sq mi)	1,029/km2 (2,670/sq mi)	953
4	5	Madhya Pradesh	72626809	52557404	20069405	308,245 km2 (119,014 sq mi)	236/km2 (610/sq mi)	931

In [14]:
```
india_pop.shape
```

Out[14]:
```
(36, 8)
```

Merging the State Population and State wise testing dataframes

In [15]:
```
np.count_nonzero(state_ws_test['State'].unique())
```

Out[15]:
```
35
```

In [16]:
```
np.count_nonzero(india_pop['State / Union Territory'].unique())
```

Out[16]:
```
36
```

In [17]:
```
set(india_pop['State / Union Territory'].unique()) - set(state_ws_test['State'].uniq
```

Out[17]:
```
{'Lakshadweep', 'Telengana'}
```

In [18]:
```
np.sort(india_pop['State / Union Territory'].unique())
```

Out[18]:
```
array(['Andaman and Nicobar Islands', 'Andhra Pradesh',
       'Arunachal Pradesh', 'Assam', 'Bihar', 'Chandigarh',
       'Chhattisgarh', 'Dadra and Nagar Haveli and Daman and Diu',
       'Delhi', 'Goa', 'Gujarat', 'Haryana', 'Himachal Pradesh',
       'Jammu and Kashmir', 'Jharkhand', 'Karnataka', 'Kerala', 'Ladakh',
       'Lakshadweep', 'Madhya Pradesh', 'Maharashtra', 'Manipur',
       'Meghalaya', 'Mizoram', 'Nagaland', 'Odisha', 'Puducherry',
       'Punjab', 'Rajasthan', 'Sikkim', 'Tamil Nadu', 'Telengana',
       'Tripura', 'Uttar Pradesh', 'Uttarakhand', 'West Bengal'],
      dtype=object)
```

In [19]:
```
np.sort(state_ws_test['State'].unique())
```

Out[19]:
```
array(['Andaman and Nicobar Islands', 'Andhra Pradesh',
       'Arunachal Pradesh', 'Assam', 'Bihar', 'Chandigarh',
       'Chhattisgarh', 'Dadra and Nagar Haveli and Daman and Diu',
       'Delhi', 'Goa', 'Gujarat', 'Haryana', 'Himachal Pradesh',
       'Jammu and Kashmir', 'Jharkhand', 'Karnataka', 'Kerala', 'Ladakh',
       'Madhya Pradesh', 'Maharashtra', 'Manipur', 'Meghalaya', 'Mizoram',
       'Nagaland', 'Odisha', 'Puducherry', 'Punjab', 'Rajasthan',
       'Sikkim', 'Tamil Nadu', 'Telangana', 'Tripura', 'Uttar Pradesh',
       'Uttarakhand', 'West Bengal'], dtype=object)
```

Here, I found out that `State wise COVID testing dataset` has no information about

testing carried out in `Lakshadweep`. And, `Telangana` spelling is incorrect in `Indian Pop dataset`.

In [20]:
```
india_pop['State / Union Territory'] = india_pop['State / Union Territory'].\
apply(lambda state: 'Telangana' if state == 'Telengana' else state)
```

In [21]:
```
set(india_pop['State / Union Territory'].unique()) - set(state_ws_test['State'].uniq
```

Out[21]:
```
{'Lakshadweep'}
```

In [22]:
```
pop_test_df = pd.merge(left=state_ws_test.copy(deep=True),right=india_pop.copy(deep=
                       left_on='State',right_on='State / Union Territory',how='outer
```

In [23]:
```
pop_test_df.shape
```

Out[23]:
```
(7313, 13)
```

In [24]:
```
pop_test_df.tail()
```

Out[24]:

	Date	State	TotalSamples	Negative	Positive	Sno	State / Union Territory	Population	Rural population
7308	2020-11-12	West Bengal	5091700.0	NaN	NaN	4	West Bengal	91276115	62183113
7309	2020-11-13	West Bengal	5136012.0	NaN	NaN	4	West Bengal	91276115	62183113
7310	2020-11-14	West Bengal	5180139.0	NaN	NaN	4	West Bengal	91276115	62183113
7311	2020-11-15	West Bengal	5218797.0	NaN	NaN	4	West Bengal	91276115	62183113
7312	NaN	NaN	NaN	NaN	NaN	36	Lakshadweep	64473	14141

Getting rid of few features :: `Sno` as it is a dummy running sequence number and `State` as we already have `State / Union Territory` providing the same information.

In [25]:
```
pop_test_df.drop(labels=['Sno','State'],axis=1,inplace=True)
```

Renaming `State / Union Territory` as `State`.

In [26]:
```
pop_test_df.rename(columns={'State / Union Territory':'State'},inplace=True)
```

In [27]:
```
pd.concat([pop_test_df.head(3),pop_test_df.tail(3)],axis=0)
```

Out[27]:

	Date	TotalSamples	Negative	Positive	State	Population	Rural population	Urban population

	Date	TotalSamples	Negative	Positive	State	Population	Rural population	Urban population	
0	2020-04-17	1403.0	1210	12.0	Andaman and Nicobar Islands	380581	237093	143488	
1	2020-04-24	2679.0	NaN	27.0	Andaman and Nicobar Islands	380581	237093	143488	
2	2020-04-27	2848.0	NaN	33.0	Andaman and Nicobar Islands	380581	237093	143488	
7310	2020-11-14	5180139.0	NaN	NaN	West Bengal	91276115	62183113	29093002	8 (3
7311	2020-11-15	5218797.0	NaN	NaN	West Bengal	91276115	62183113	29093002	8 (3
7312	NaN	NaN	NaN	NaN	Lakshadweep	64473	14141	50332	3

Generating the "Density in km2" Feature from Density variable

In [28]:
```
pop_test_df['Density in km2'] = pop_test_df['Density'].apply(lambda row : np.float(r
```

In [29]:
```
## Printing some of the top &  bottom records
pd.concat([pop_test_df.head(3),pop_test_df.tail(3)],axis=0)
```

Out[29]:

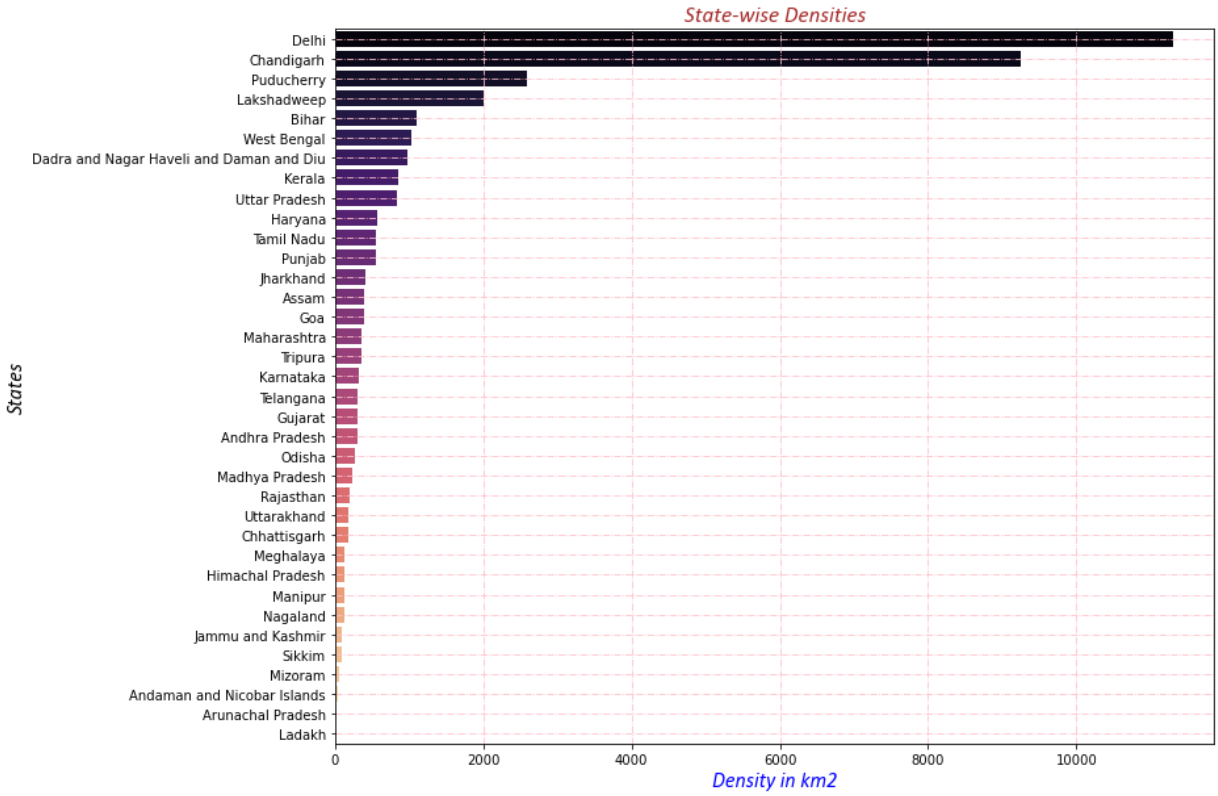
	Date	TotalSamples	Negative	Positive	State	Population	Rural population	Urban population	
0	2020-04-17	1403.0	1210	12.0	Andaman and Nicobar Islands	380581	237093	143488	
1	2020-04-24	2679.0	NaN	27.0	Andaman and Nicobar Islands	380581	237093	143488	
2	2020-04-27	2848.0	NaN	33.0	Andaman and Nicobar Islands	380581	237093	143488	
7310	2020-11-14	5180139.0	NaN	NaN	West Bengal	91276115	62183113	29093002	8 (3

	Date	TotalSamples	Negative	Positive	State	Population	Rural population	Urban population	
7311	2020-11-15	5218797.0	NaN	NaN	West Bengal	91276115	62183113	29093002	8 (3
7312	NaN	NaN	NaN	NaN	Lakshadweep	64473	14141	50332	3

In [30]:
```
def font_dicts(kind=['xlabel','ylabel','title']):
    """
    Description: This function is created for defining the font dictionaries of labe

    Input parameters: It accepts only one below agrument:
            1. kind : Can take one of values --> ['xlabel','ylabel','title']

    Retuns: fdict with values of 'size', 'family' and 'color'
    """
    try:
        if kind == 'xlabel':
            fdict = {'size':16,'family':'calibri','style':'oblique','color':'blue'}
        elif kind == 'ylabel':
            fdict = {'size':16,'family':'calibri','style':'oblique','color':'k'}
        elif kind == 'title':
            fdict = {'size':17,'family':'calibri','style':'oblique','color':'brown'}
        else:
            fdict = {'size':16,'family':'calibri','style':'oblique','color':'k'}
    except ValueError as err:
        pass
    return fdict
```

In [31]:
```
## Generating States Density dataframe
state_density_df = pop_test_df.groupby(['State'])[['Density in km2']].max().reset_in
```

In [32]:
```
with plt.style.context('seaborn-bright'):
    plt.figure(figsize=(12,10))
    sns.barplot(data=state_density_df.sort_values(by='Density in km2',ascending=Fals
                orient='h',palette='magma')
    plt.grid(which='major',linestyle='-.',color='pink')
    plt.title('State-wise Densities',fontdict=font_dicts(kind='title'))
    plt.ylabel('States',fontdict=font_dicts(kind='ylabel'))
    plt.xlabel('Density in km2',fontdict=font_dicts(kind='xlabel'))
    plt.show()
```



`'Delhi'` and `'Chandigarh'` totally stands out in this plot with the highest densities values.

In [33]:
```
def dense_groups(density=0):
    """
    Description: This function defines the density group based on the state's densit
    Input: It accepts only one parameter -- density (by default its 0)
    Return: Returns the density group name.
    """
    try:
        if 0<density<=300:
            grp_name = 'Dense1'
        elif 300<density<=600:
            grp_name = 'Dense2'
        elif 600<density<=900:
            grp_name = 'Dense3'
        elif 900<density<=1200:
            grp_name = 'Dense4'
        else:
            grp_name = 'Dense5'
    except ValueError as err:
        pass
    return grp_name
```

In [34]:
```
## Generating Density Group Feature
pop_test_df['Dense_grp'] = list(map(dense_groups,pop_test_df['Density in km2']))
```

In [35]:
```
pop_test_df.head()
```

Out[35]:

	Date	TotalSamples	Negative	Positive	State	Population	Rural population	Urban population	Area	D
0	2020-04-17	1403.0	1210	12.0	Andaman and Nicobar Islands	380581	237093	143488	8,249 km2 (3,185 sq mi)	

	Date	TotalSamples	Negative	Positive	State	Population	Rural population	Urban population	Area	D
1	2020-04-24	2679.0	NaN	27.0	Andaman and Nicobar Islands	380581	237093	143488	8,249 km2 (3,185 sq mi)	4 (
2	2020-04-27	2848.0	NaN	33.0	Andaman and Nicobar Islands	380581	237093	143488	8,249 km2 (3,185 sq mi)	4 (
3	2020-05-01	3754.0	NaN	33.0	Andaman and Nicobar Islands	380581	237093	143488	8,249 km2 (3,185 sq mi)	4 (
4	2020-05-16	6677.0	NaN	33.0	Andaman and Nicobar Islands	380581	237093	143488	8,249 km2 (3,185 sq mi)	4 (

In [36]:
```
state_ws_nulls_in_pos = pop_test_df[pop_test_df['Positive'].isna()].groupby(['State'
rename(columns={'State':'Nulls_in_pos'}).reset_index()
```

In [37]:
```
state_ws_nulls_in_pos
```

Out[37]:

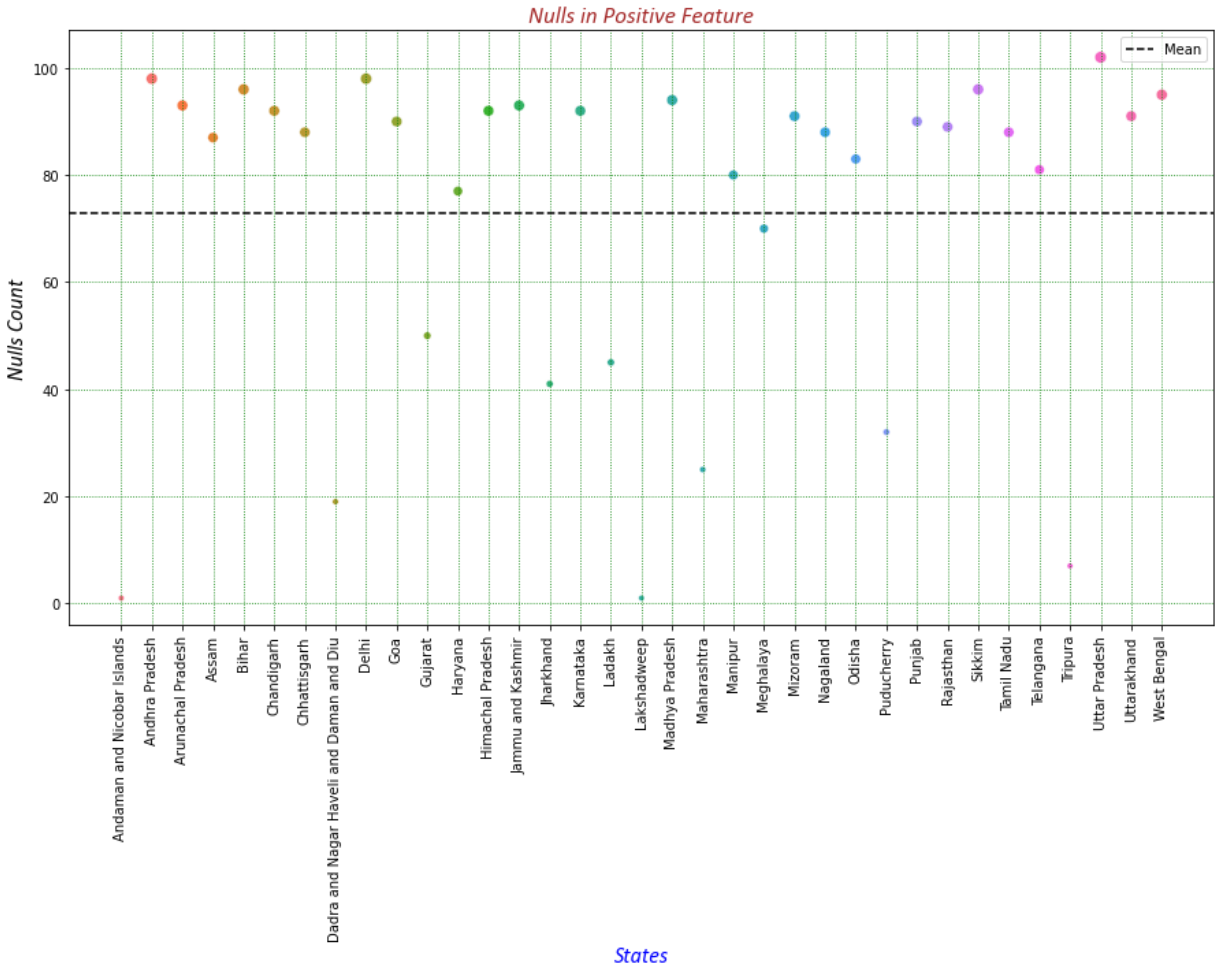
	State	Nulls_in_pos
0	Andaman and Nicobar Islands	1
1	Andhra Pradesh	98
2	Arunachal Pradesh	93
3	Assam	87
4	Bihar	96
5	Chandigarh	92
6	Chhattisgarh	88
7	Dadra and Nagar Haveli and Daman and Diu	19
8	Delhi	98
9	Goa	90
10	Gujarat	50
11	Haryana	77
12	Himachal Pradesh	92
13	Jammu and Kashmir	93
14	Jharkhand	41
15	Karnataka	92
16	Ladakh	45
17	Lakshadweep	1
18	Madhya Pradesh	94

	State	Nulls_in_pos
19	Maharashtra	25
20	Manipur	80
21	Meghalaya	70
22	Mizoram	91
23	Nagaland	88
24	Odisha	83
25	Puducherry	32
26	Punjab	90
27	Rajasthan	89
28	Sikkim	96
29	Tamil Nadu	88
30	Telangana	81
31	Tripura	7
32	Uttar Pradesh	102
33	Uttarakhand	91
34	West Bengal	95

In [38]:
```
state_ws_nulls_in_pos['Nulls_in_pos'].mean()
```

Out[38]: 73.0

In [39]:
```
with plt.style.context('seaborn-bright'):
    plt.figure(figsize=(15,8))
    sns.scatterplot(data=state_ws_nulls_in_pos,x='State',y='Nulls_in_pos',size=((sta
    plt.axhline(y=state_ws_nulls_in_pos['Nulls_in_pos'].mean(),linestyle='--',color=
    plt.xticks(rotation=90)
    plt.ylabel("Nulls in Positive", fontdict={'size':19,'family':'calibri','style':'
    plt.grid(which='major',linestyle=':',color='g')
    plt.title('Nulls in Positive Feature',fontdict=font_dicts(kind='title'))
    plt.xlabel('States',fontdict=font_dicts(kind='xlabel'))
    plt.ylabel('Nulls Count',fontdict=font_dicts(kind='ylabel'))
    plt.legend()
```



Here, although we have some states where Nulls in the positive are less than the entire mean but overall we can say that majority of the states have same number of NULLS in the positive cases.

In [40]:
```
pop_test_df.head()
```

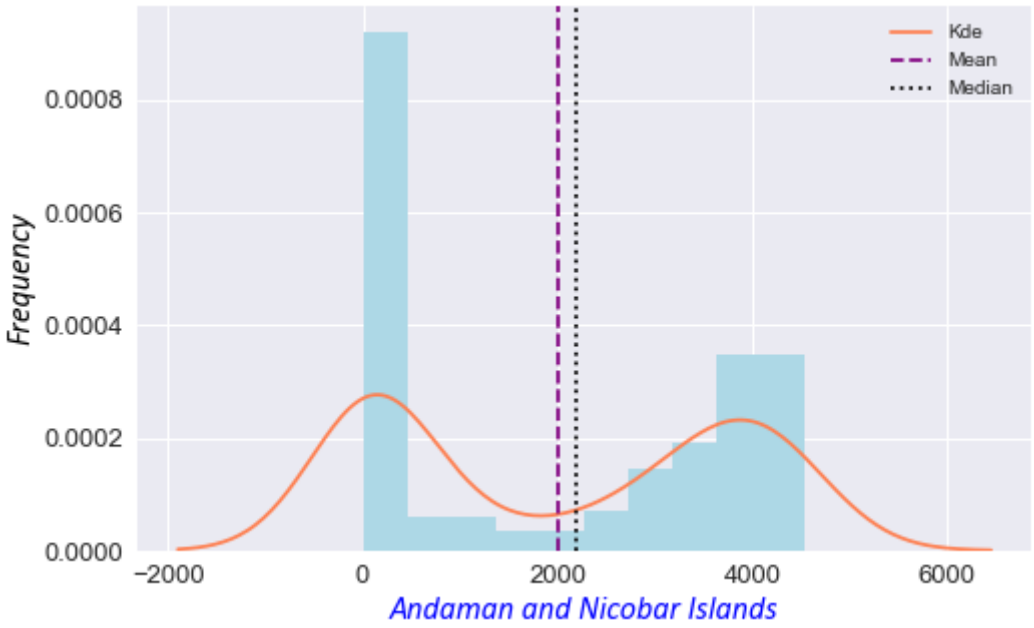
Out[40]:

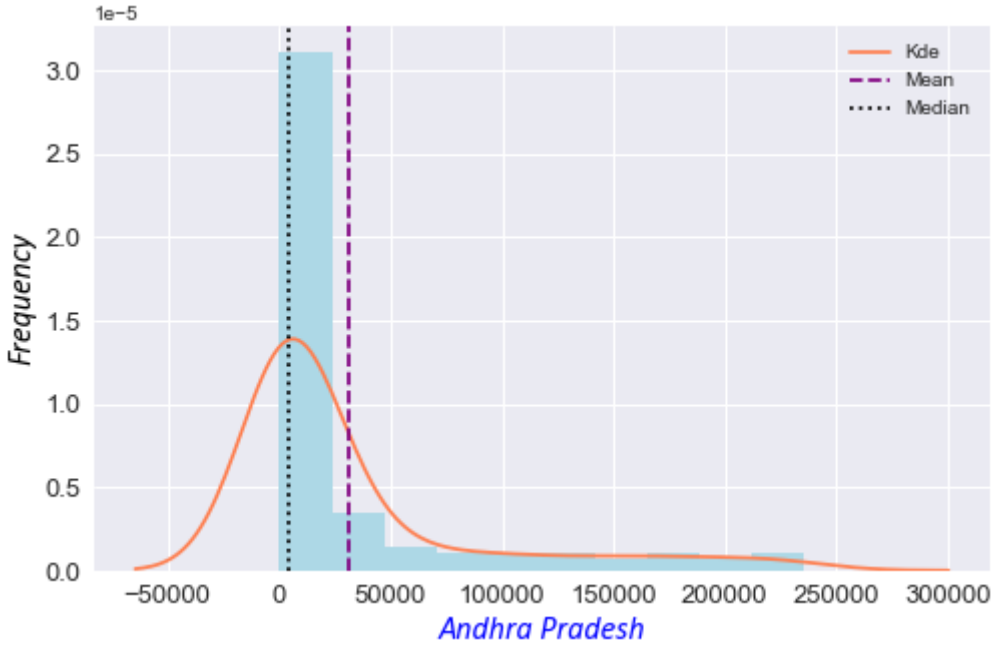
	Date	TotalSamples	Negative	Positive	State	Population	Rural population	Urban population	Area	D
0	2020-04-17	1403.0	1210	12.0	Andaman and Nicobar Islands	380581	237093	143488	8,249 km2 (3,185 sq mi)	4 (
1	2020-04-24	2679.0	NaN	27.0	Andaman and Nicobar Islands	380581	237093	143488	8,249 km2 (3,185 sq mi)	4 (
2	2020-04-27	2848.0	NaN	33.0	Andaman and Nicobar Islands	380581	237093	143488	8,249 km2 (3,185 sq mi)	4 (
3	2020-05-01	3754.0	NaN	33.0	Andaman and Nicobar Islands	380581	237093	143488	8,249 km2 (3,185 sq mi)	4 (
4	2020-05-16	6677.0	NaN	33.0	Andaman and Nicobar Islands	380581	237093	143488	8,249 km2 (3,185 sq mi)	4 (

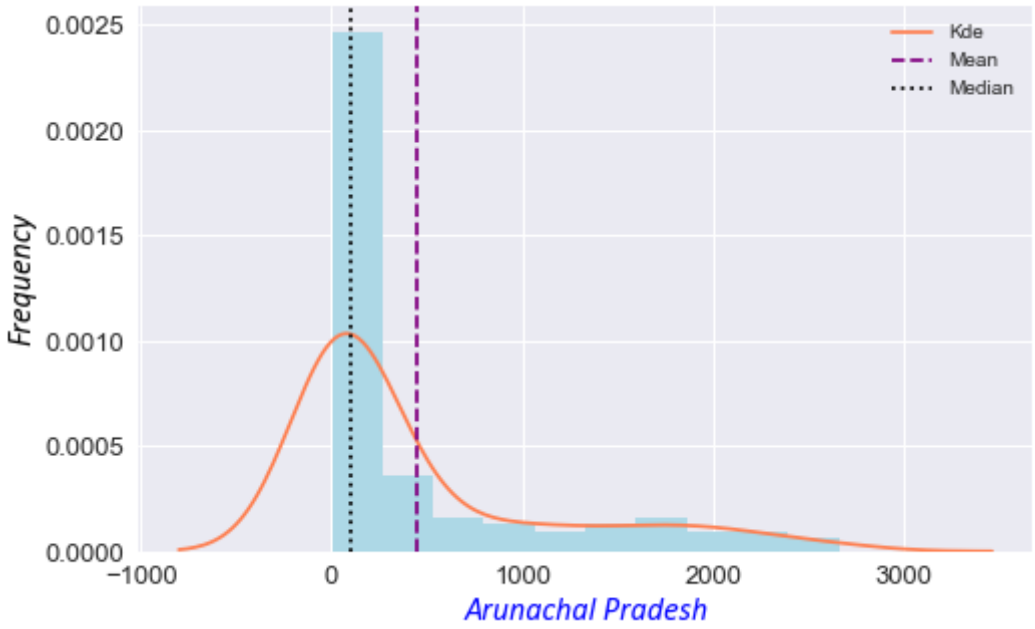
In [41]:
```
def plot_hist_kde(d_frame,grp_by_col,dist_col,title=None):
    """
    Description: This function plot the distribution of data

    Input Parameters: It accepts below arguments:
            1. d_frame : Dataset of type pandas dataframe
            2. grp_by_col : Column for grouping the data of several states
            3. dist_col : Column whose data distribution to be visualized
            4. title : Title of the plot

    Return: None
    """
    all_states = d_frame[grp_by_col].unique()
    with plt.style.context('seaborn'):
        for state in all_states:
            plt.figure(figsize=(8,5))
            d_frame[d_frame[grp_by_col] == state][dist_col].plot(kind='hist',density
            sns.kdeplot(data=d_frame[d_frame[grp_by_col] == state][dist_col],color='
            plt.axvline(d_frame[d_frame[grp_by_col] == state][dist_col].mean(),lines
            plt.axvline(d_frame[d_frame[grp_by_col] == state][dist_col].median(),lin
            plt.title(title,fontdict=font_dicts(kind='title'))
            plt.xlabel(state,fontdict=font_dicts(kind='xlabel'))
            plt.ylabel('Frequency',fontdict=font_dicts(kind='ylabel'))
            plt.xticks(size=13)
            plt.yticks(size=13)
            plt.legend(("Kde","Mean","Median"))
            plt.show()
```

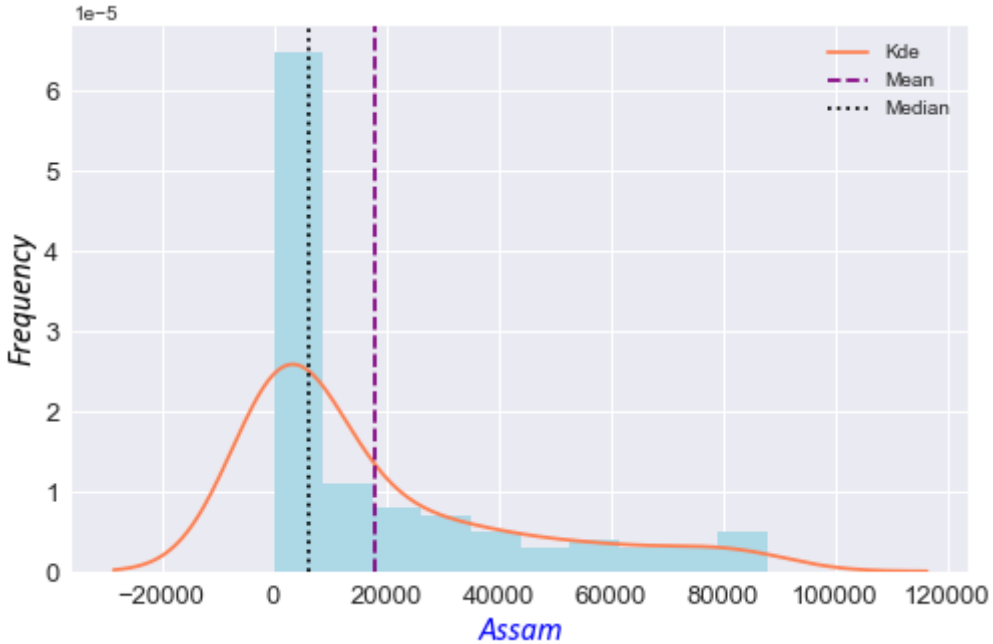
In [42]:
```
## Plotting the State-wise distributions of Positives before performing the simple i
print(colored("Positive cases distribution:",'red'),colored("Before filling NA's",'g
plot_hist_kde(pop_test_df,grp_by_col='State',dist_col='Positive')
```

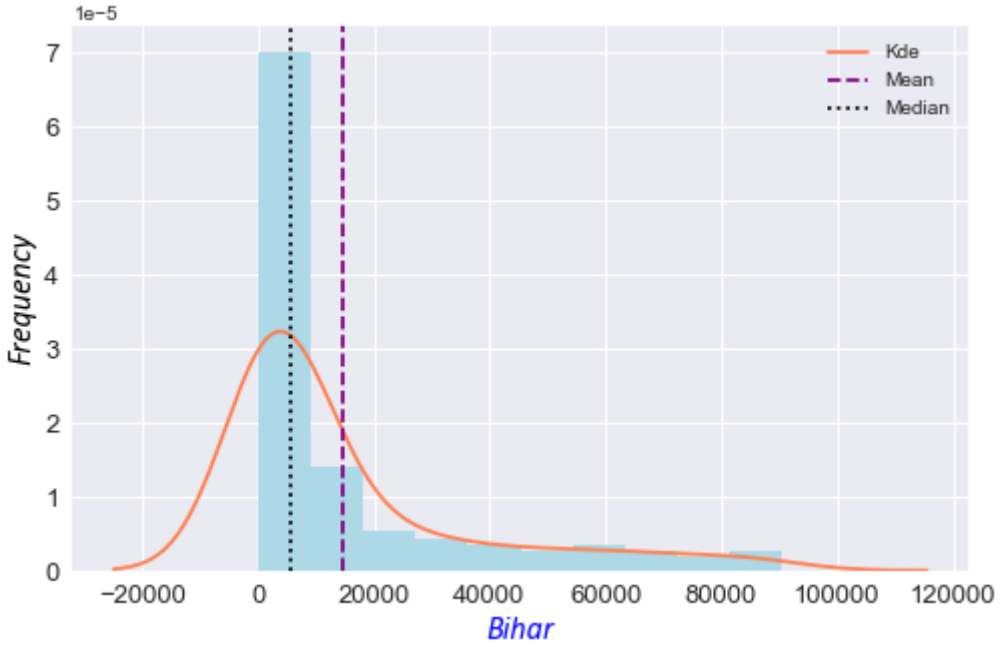
```
Positive cases distribution: Before filling NA's
```

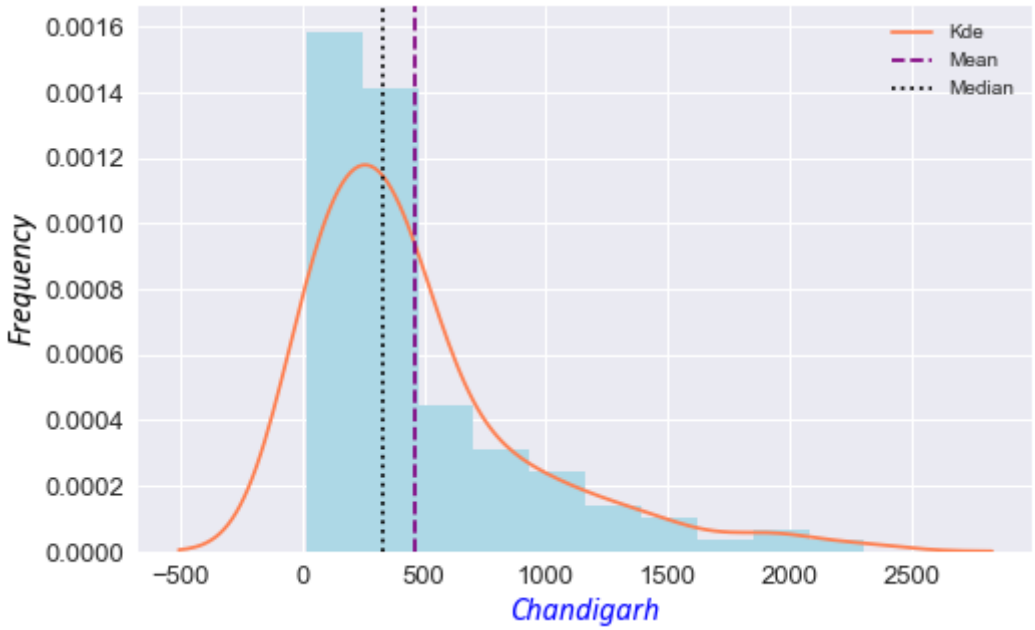


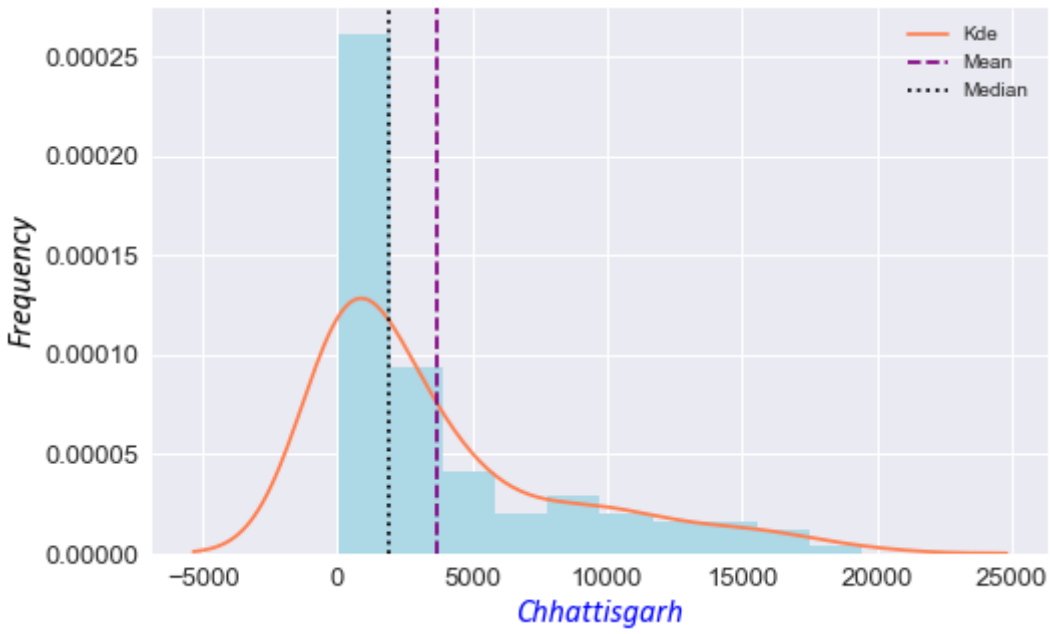

1e−5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Frequency
Kde
Mean
Median
−50000
0
50000
100000
150000
200000
250000
300000
Andhra Pradesh

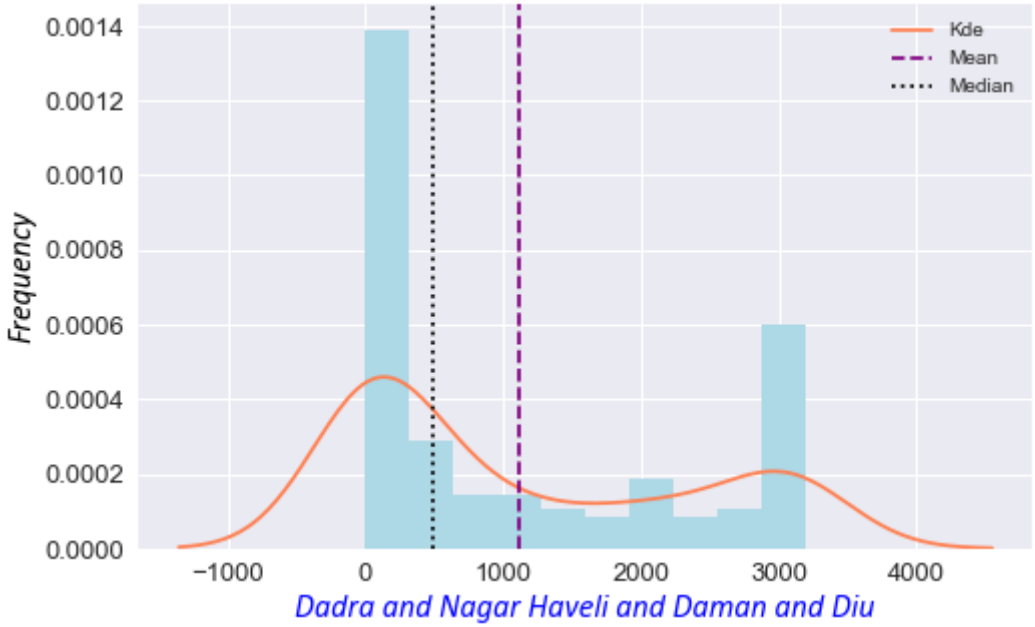

0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
Frequency
Kde
Mean
Median
−1000
0
1000
2000
3000
Arunachal Pradesh

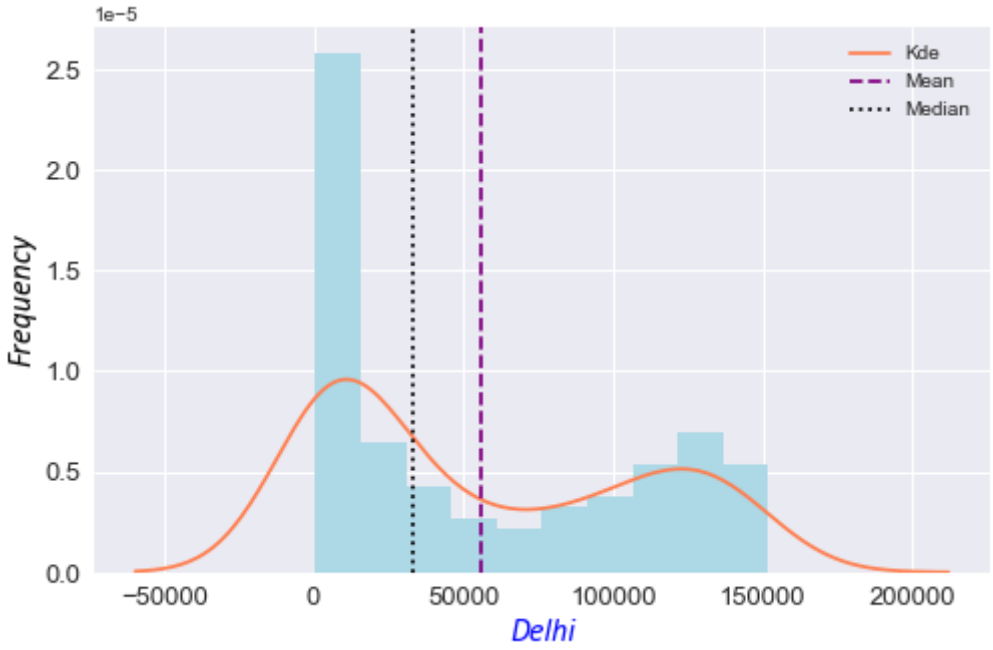

1e−5
6
5
4
3
2
1
0
Frequency
Kde
Mean
Median
−20000
0
20000
40000
60000
80000
100000
120000
Assam

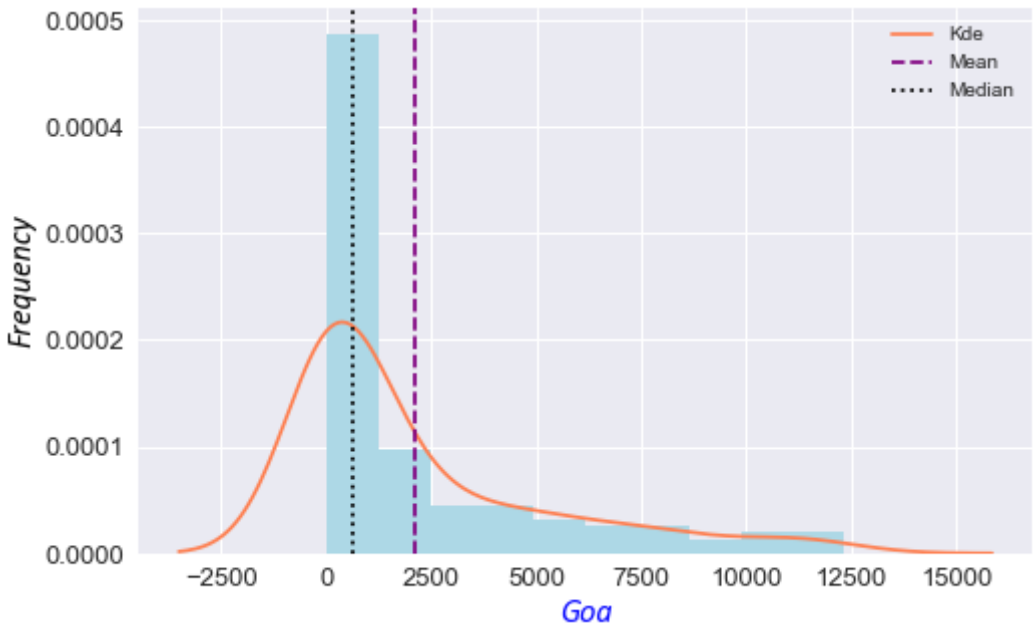

1e−5
Kde
Mean
Median
Frequency
Bihar

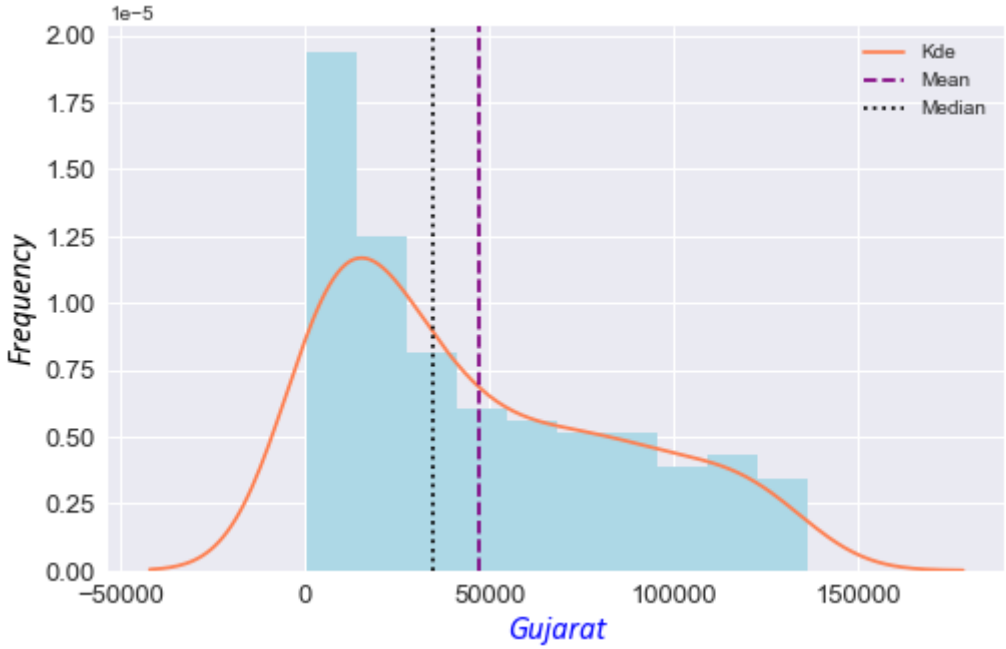

Kde
Mean
Median
Frequency
Chandigarh

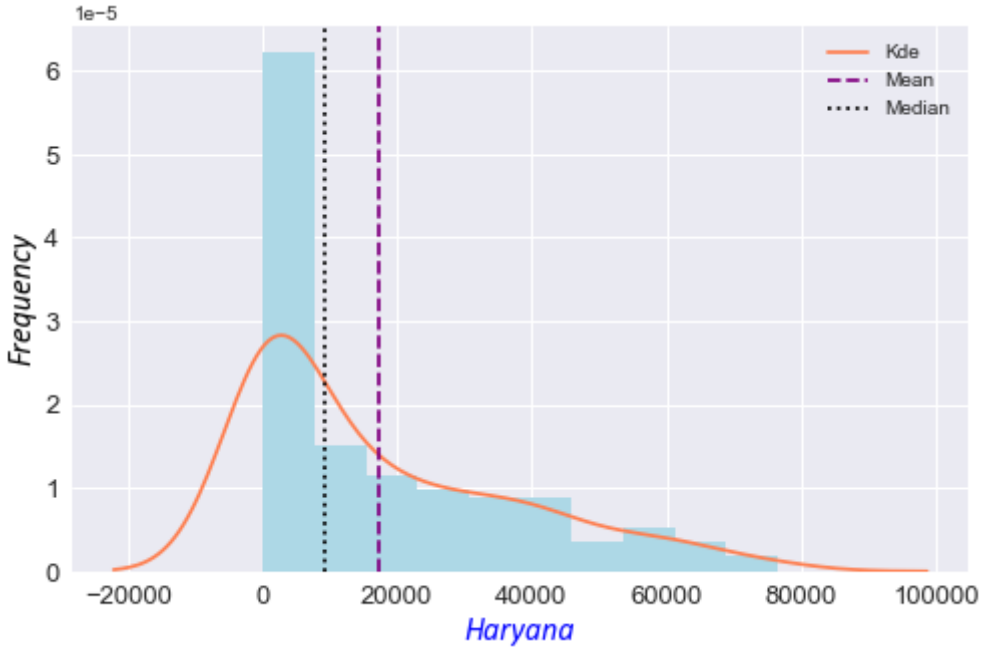

Kde
Mean
Median
Frequency
Chhattisgarh

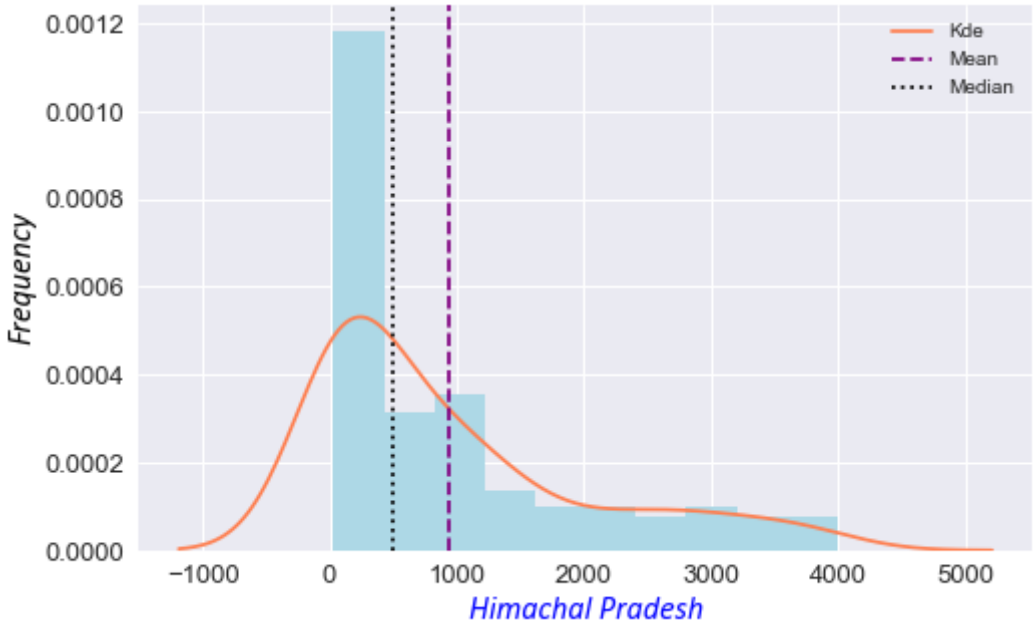

Kde
Mean
Median
Frequency
0.0014
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
−1000
0
1000
2000
3000
4000
Dadra and Nagar Haveli and Daman and Diu

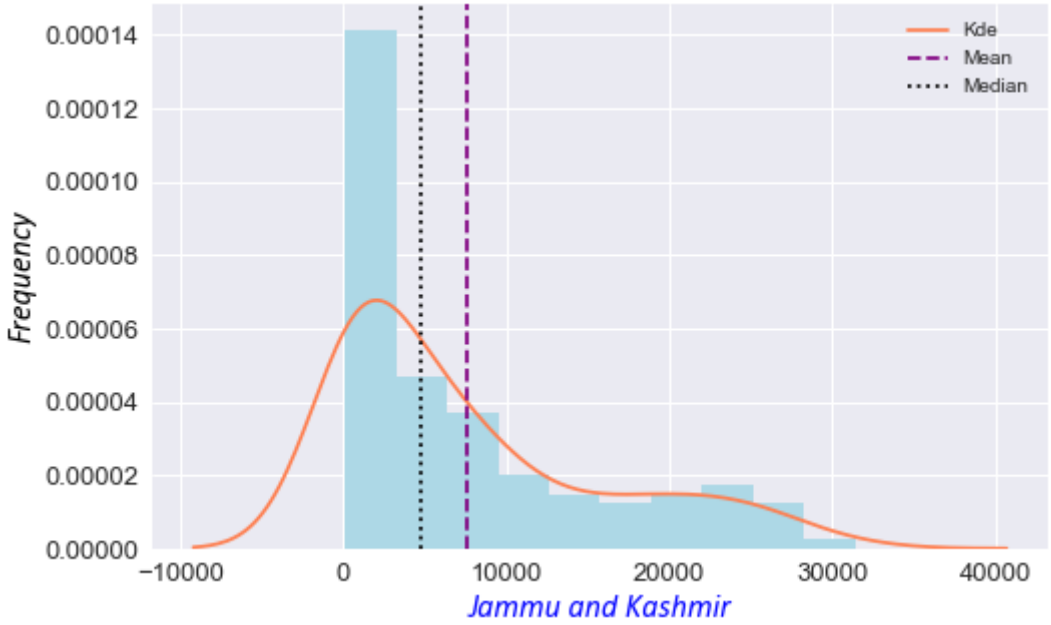

1e−5
Kde
Mean
Median
Frequency
2.5
2.0
1.5
1.0
0.5
0.0
−50000
0
50000
100000
150000
200000
Delhi

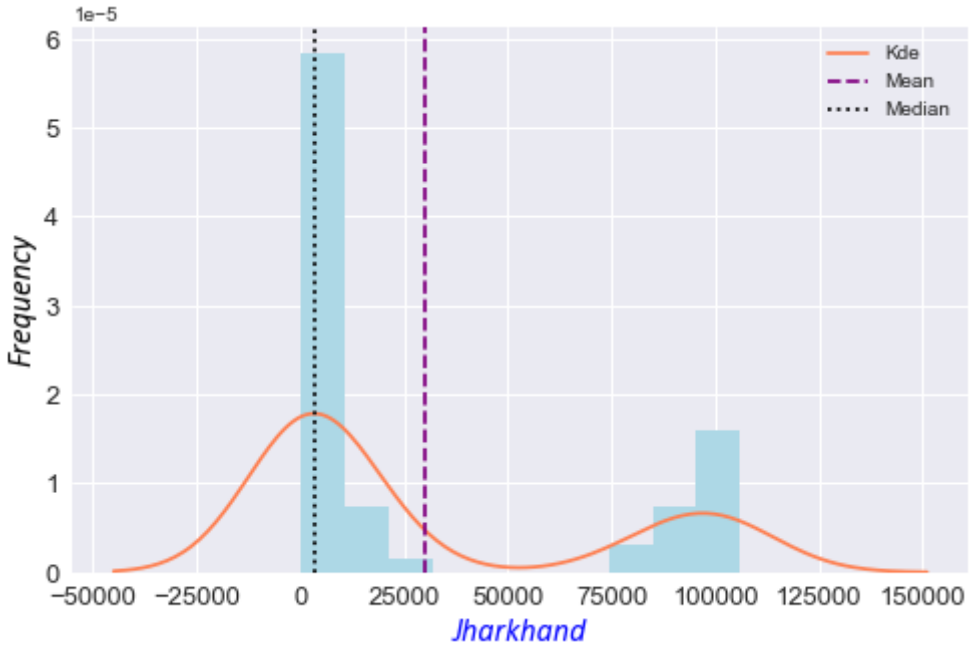

Kde
Mean
Median
Frequency
0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
−2500
0
2500
5000
7500
10000
12500
15000
Goa

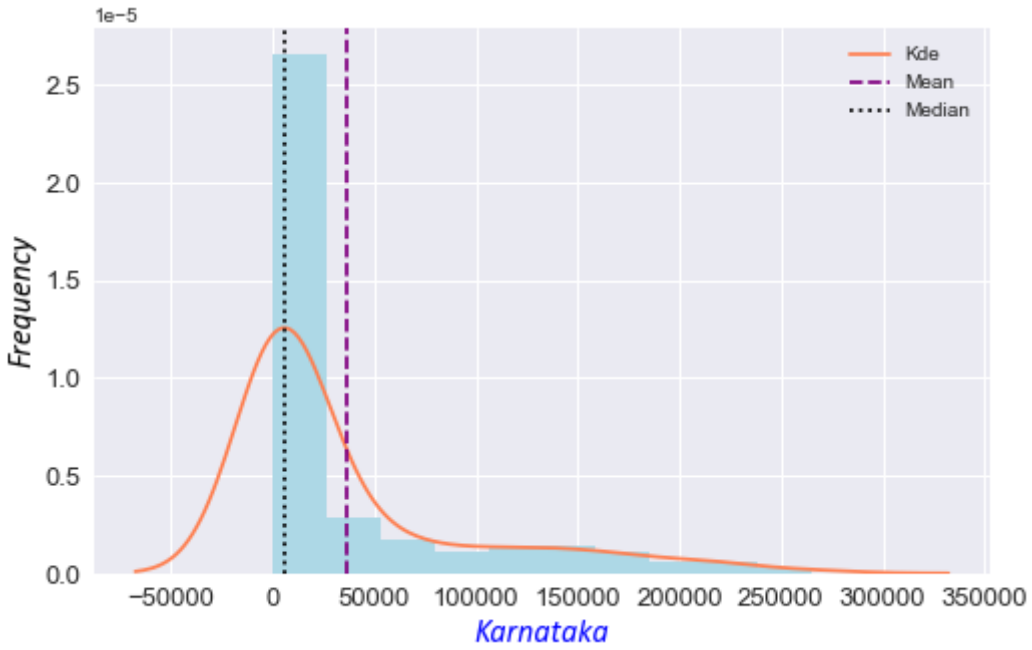

1e−5
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Frequency
Kde
Mean
Median
−50000
0
50000
100000
150000
Gujarat

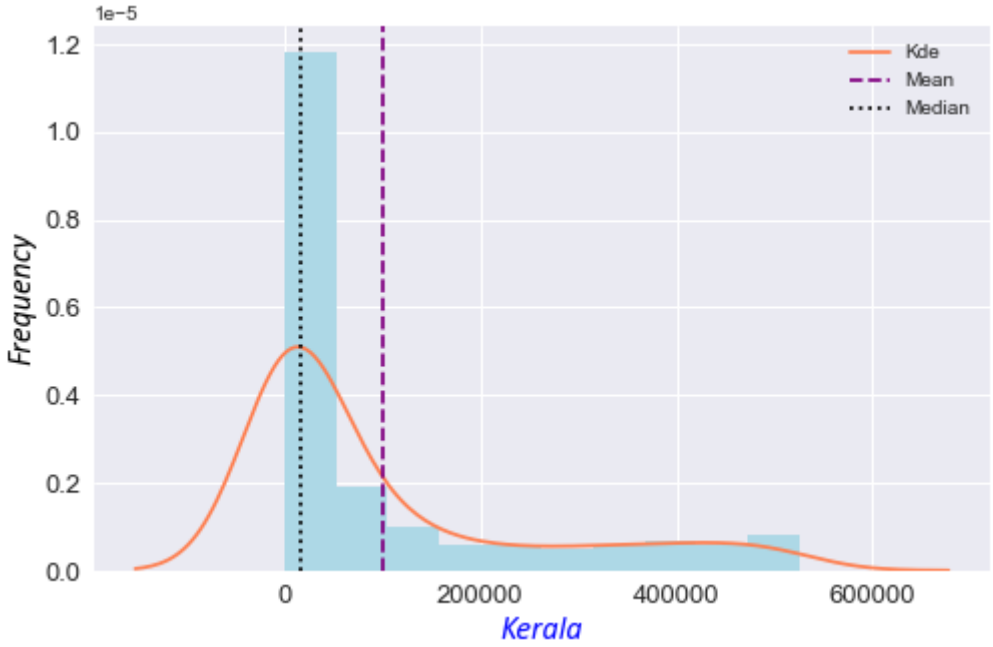

1e−5
6
5
4
3
2
1
0
Frequency
Kde
Mean
Median
−20000
0
20000
40000
60000
80000
100000
Haryana

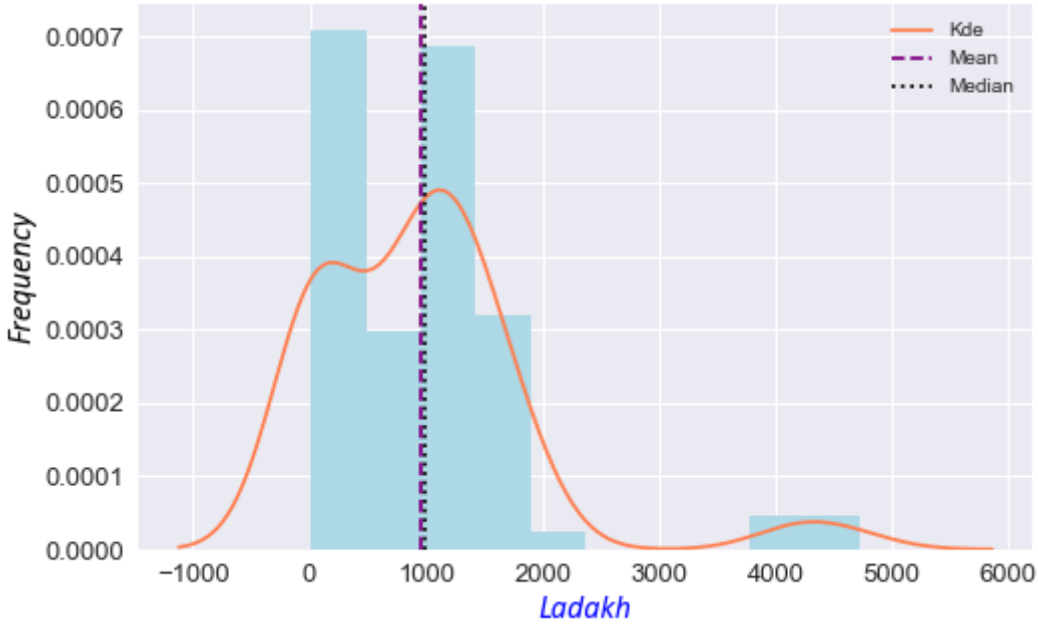

0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
Frequency
Kde
Mean
Median
−1000
0
1000
2000
3000
4000
5000
Himachal Pradesh

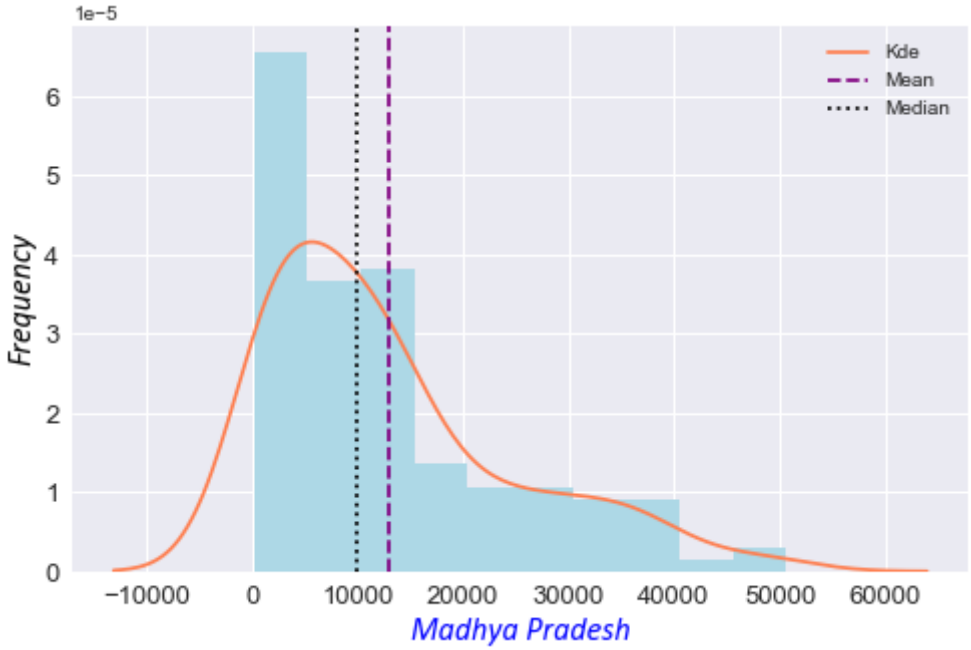

Kde
Mean
Median
Frequency
0.00014
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
−10000
0
10000
20000
30000
40000
Jammu and Kashmir

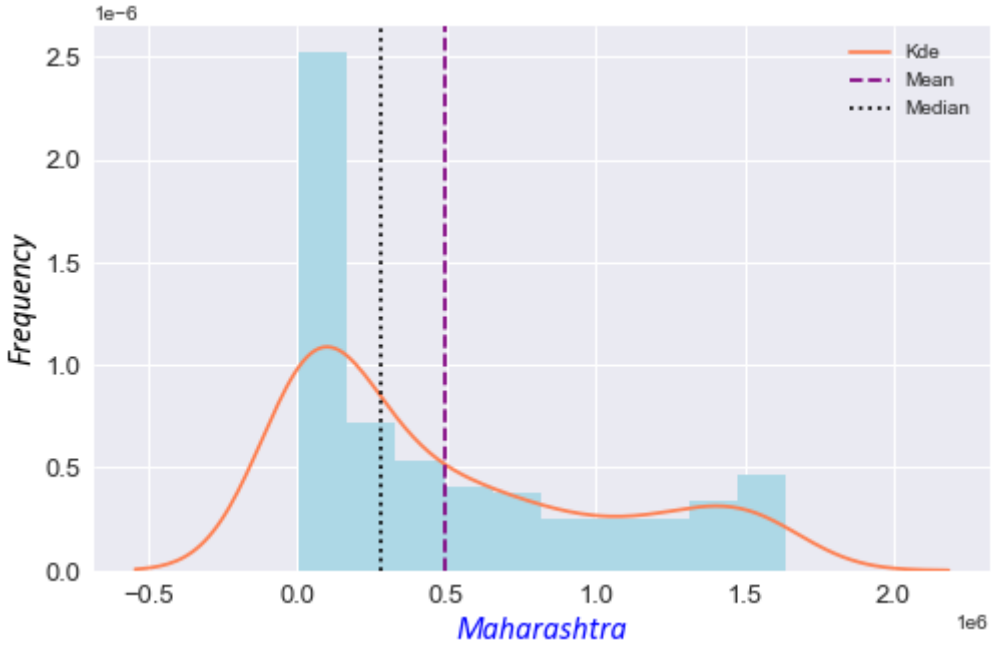

1e−5
Kde
Mean
Median
Frequency
6
5
4
3
2
1
0
−50000
−25000
0
25000
50000
75000
100000
125000
150000
Jharkhand

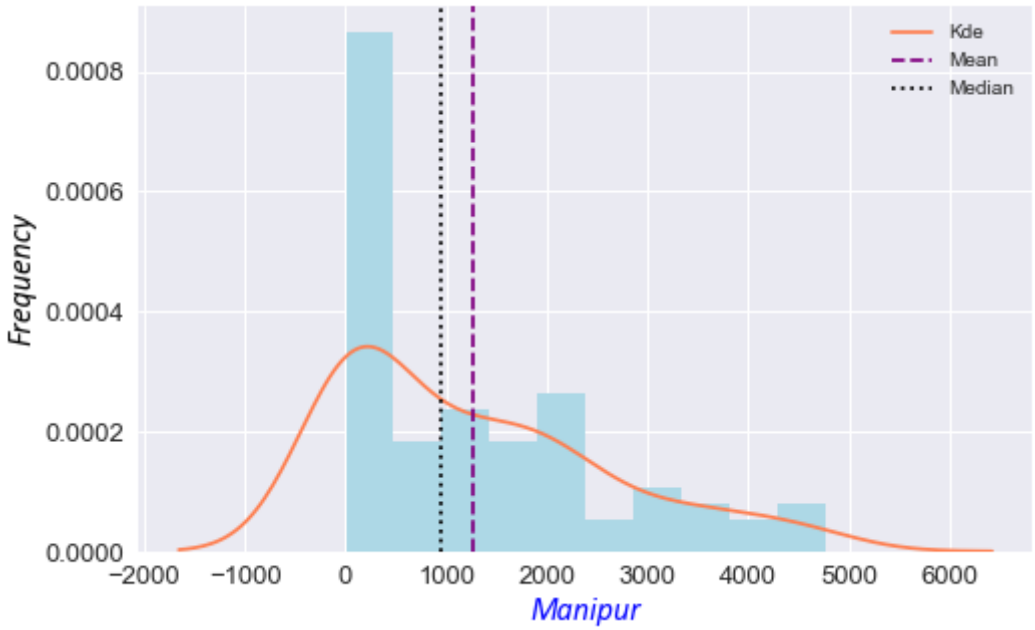

1e−5
Kde
Mean
Median
Frequency
2.5
2.0
1.5
1.0
0.5
0.0
−50000
0
50000
100000
150000
200000
250000
300000
350000
Karnataka

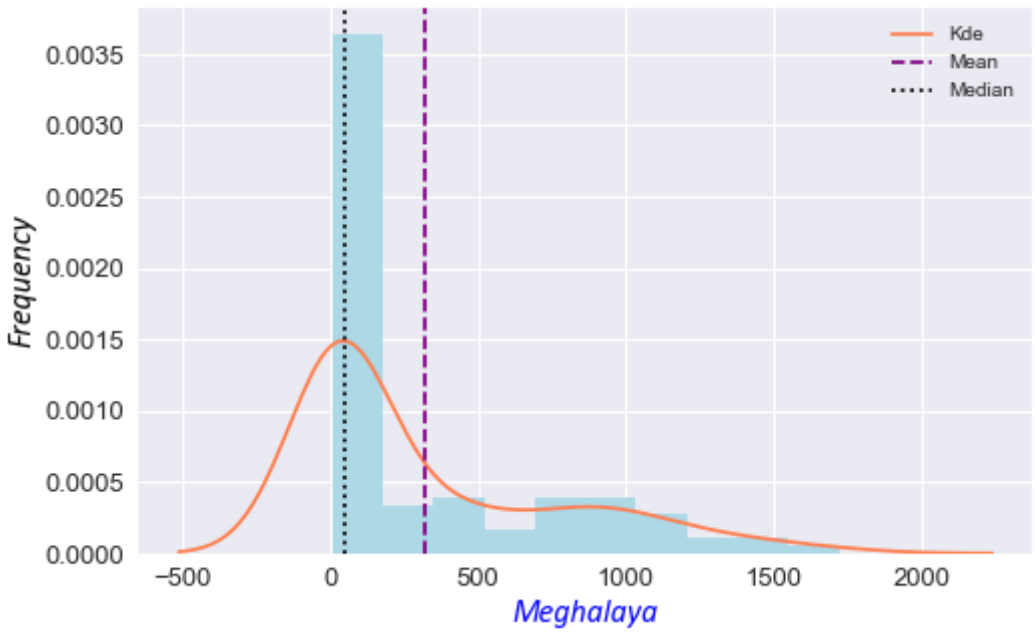

1e−5
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Frequency
Kde
Mean
Median
0
200000
400000
600000
Kerala

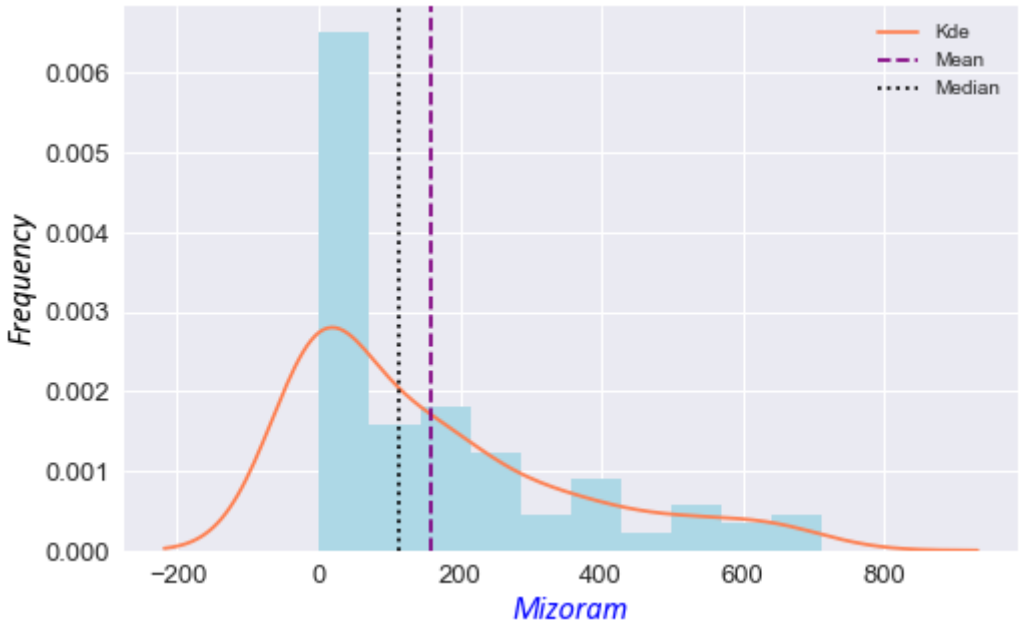

0.0007
0.0006
0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
Frequency
Kde
Mean
Median
−1000
0
1000
2000
3000
4000
5000
6000
Ladakh

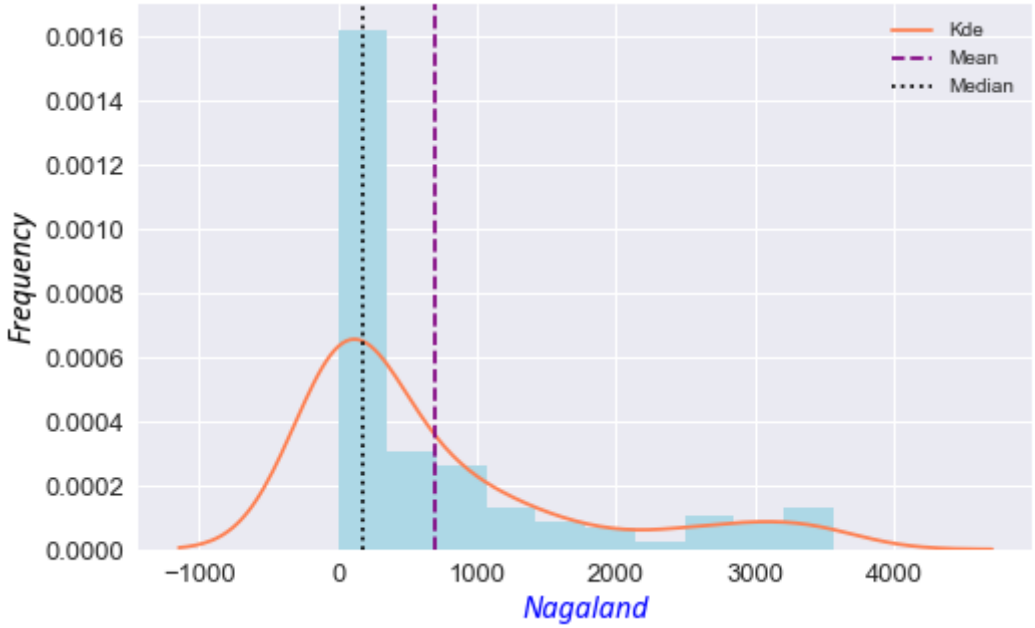

1e−5
6
5
4
3
2
1
0
Frequency
Kde
Mean
Median
−10000
0
10000
20000
30000
40000
50000
60000
Madhya Pradesh

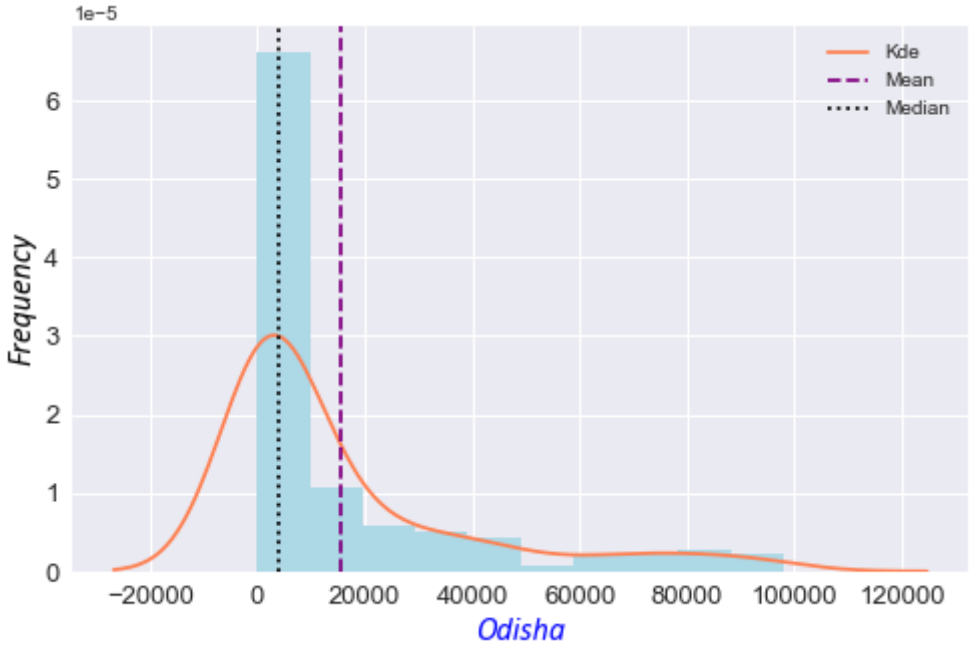

1e−6
2.5
2.0
1.5
1.0
0.5
0.0
Frequency
Kde
Mean
Median
−0.5
0.0
0.5
1.0
1.5
2.0
1e6
Maharashtra

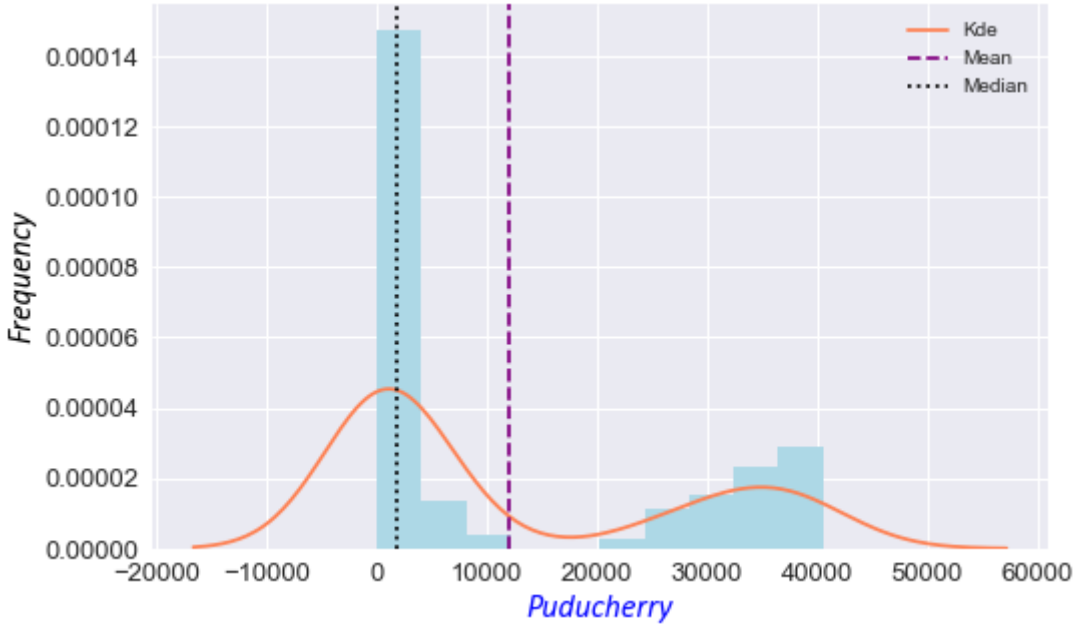

0.0008
0.0006
0.0004
0.0002
0.0000
Frequency
Kde
Mean
Median
−2000
−1000
0
1000
2000
3000
4000
5000
6000
Manipur

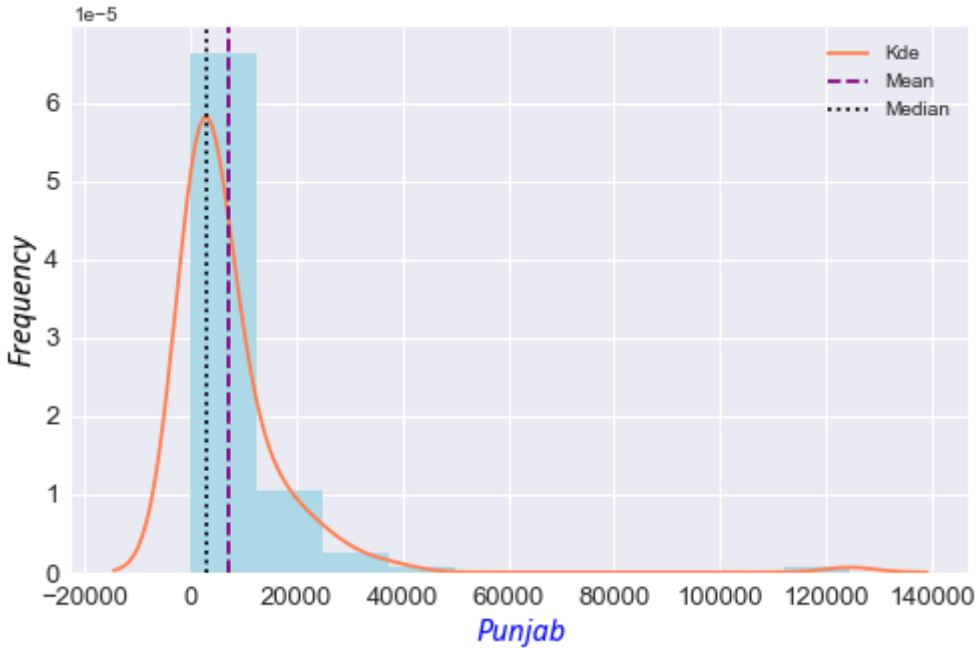

0.0035
0.0030
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
Frequency
Kde
Mean
Median
−500
0
500
1000
1500
2000
Meghalaya

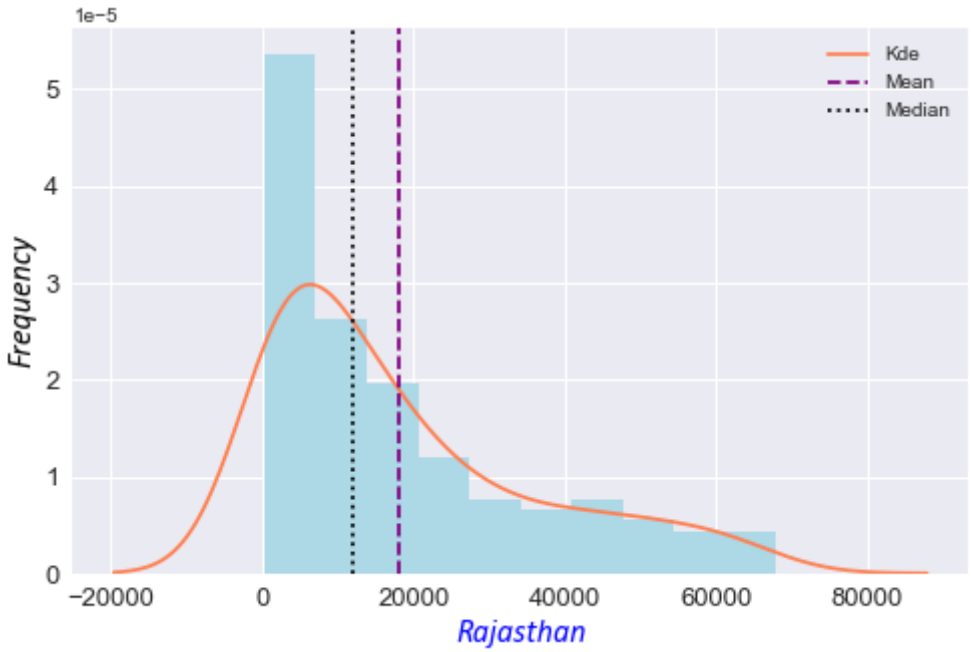

Kde
Mean
Median
Frequency
0.006
0.005
0.004
0.003
0.002
0.001
0.000
−200
0
200
400
600
800
Mizoram

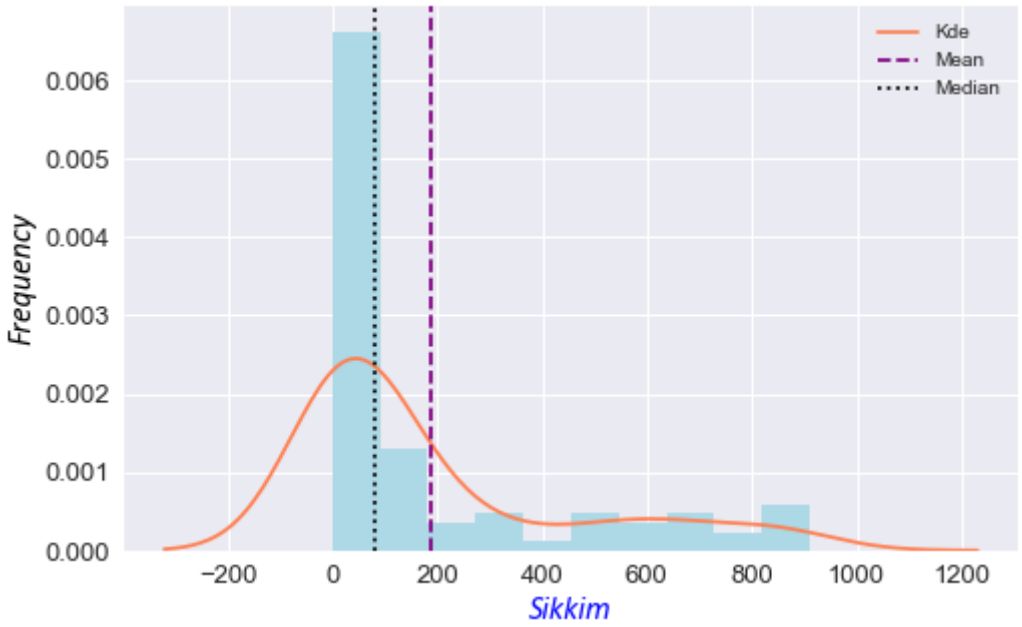

Kde
Mean
Median
Frequency
0.0016
0.0014
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
−1000
0
1000
2000
3000
4000
Nagaland

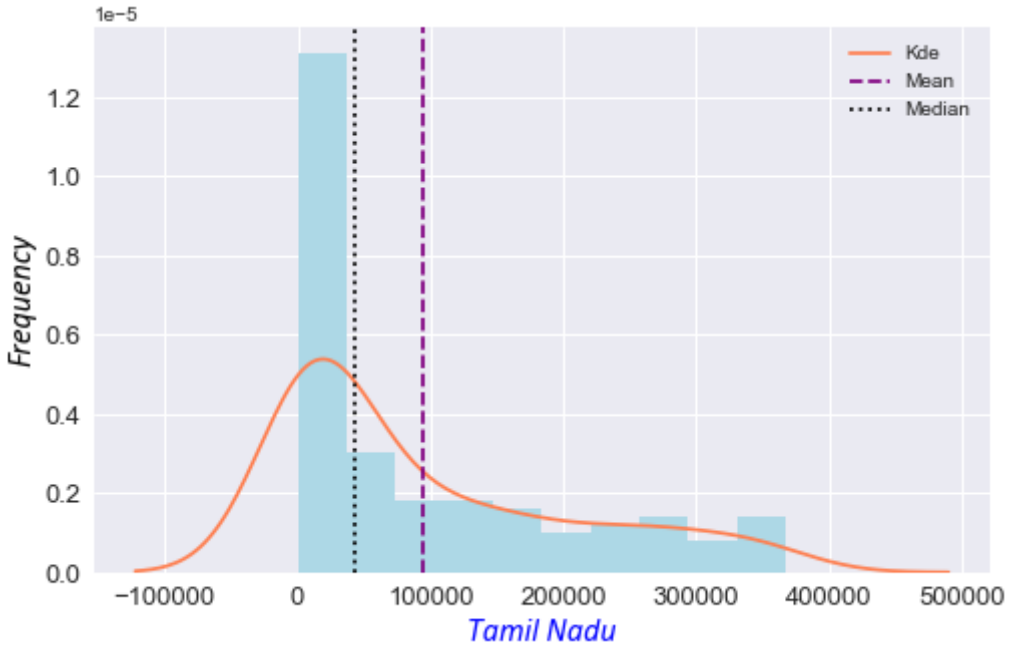

1e−5
Kde
Mean
Median
Frequency
6
5
4
3
2
1
0
−20000
0
20000
40000
60000
80000
100000
120000
Odisha

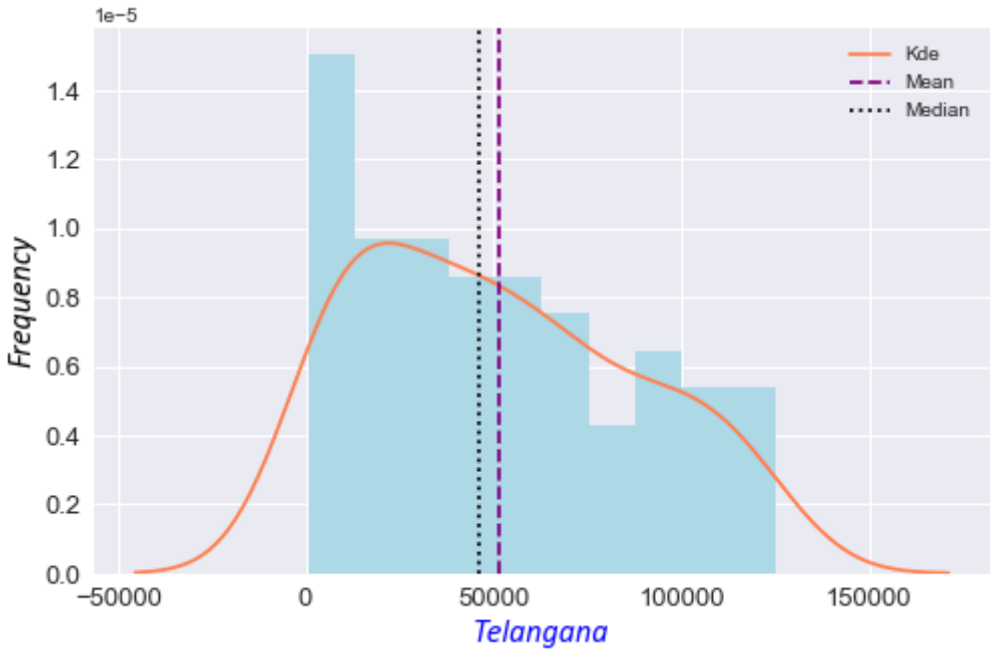

Kde
Mean
Median
0.00014
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
Frequency
−20000
−10000
0
10000
20000
30000
40000
50000
60000
Puducherry

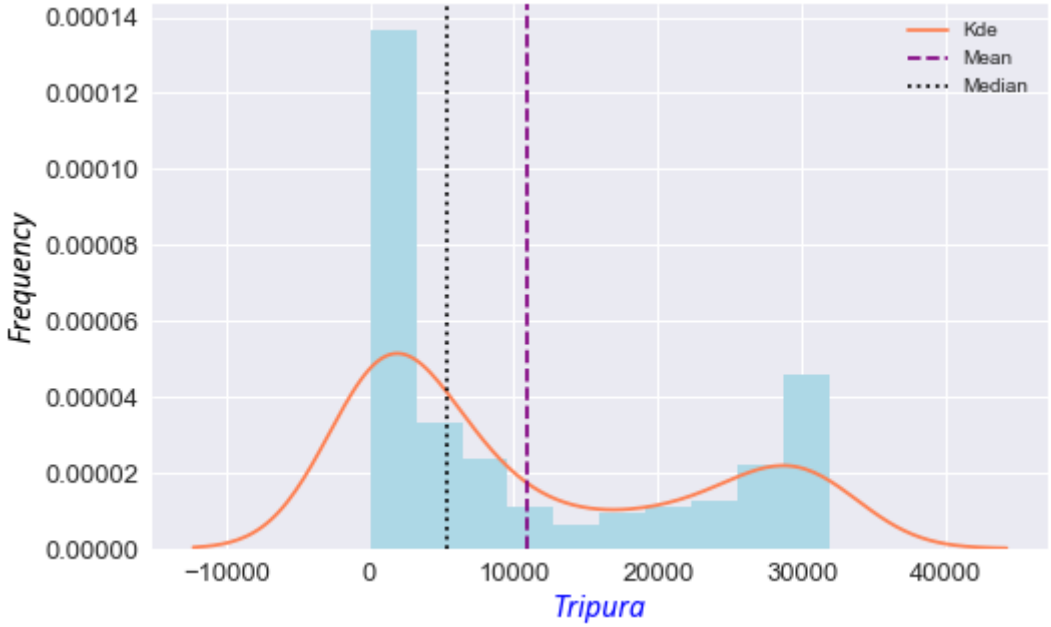

1e−5
Kde
Mean
Median
6
5
4
3
2
1
0
Frequency
−20000
0
20000
40000
60000
80000
100000
120000
140000
Punjab

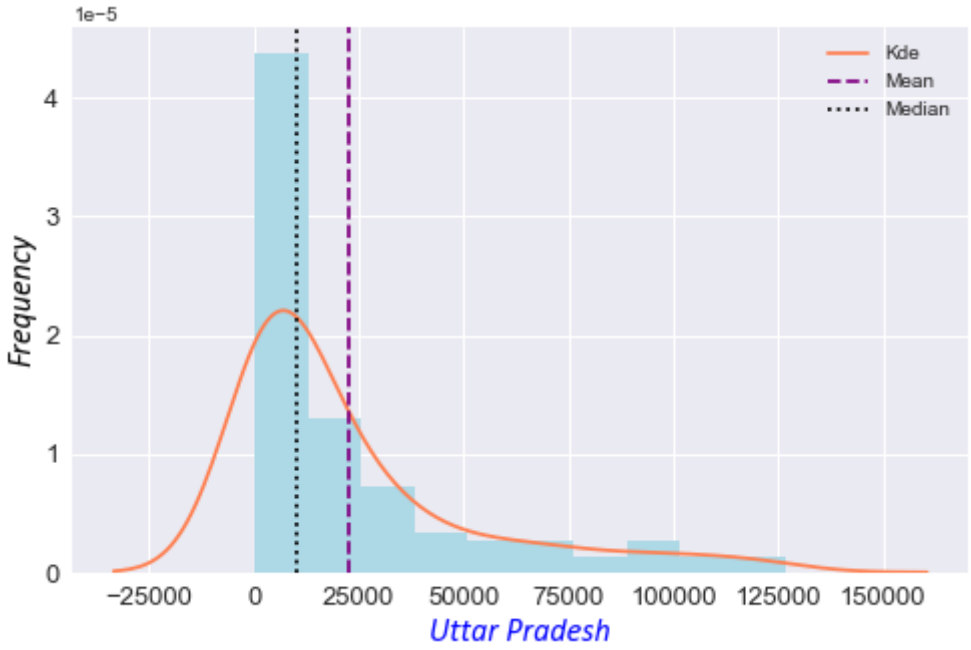

1e−5
Kde
Mean
Median
5
4
3
2
1
0
Frequency
−20000
0
20000
40000
60000
80000
Rajasthan

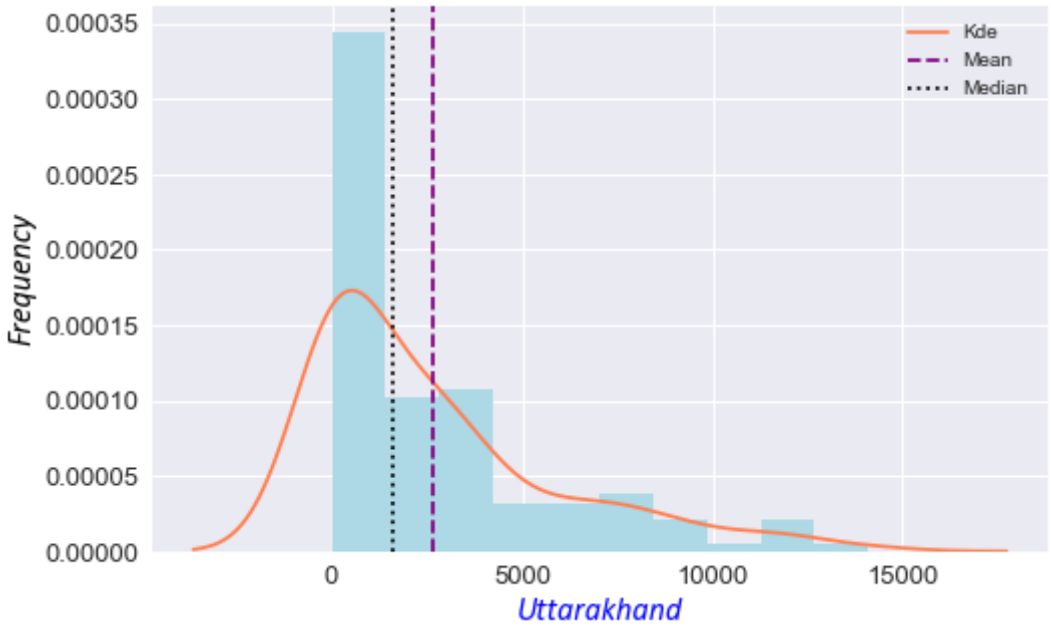

Kde
Mean
Median
Frequency
0.006
0.005
0.004
0.003
0.002
0.001
0.000
−200
0
200
400
600
800
1000
1200
Sikkim

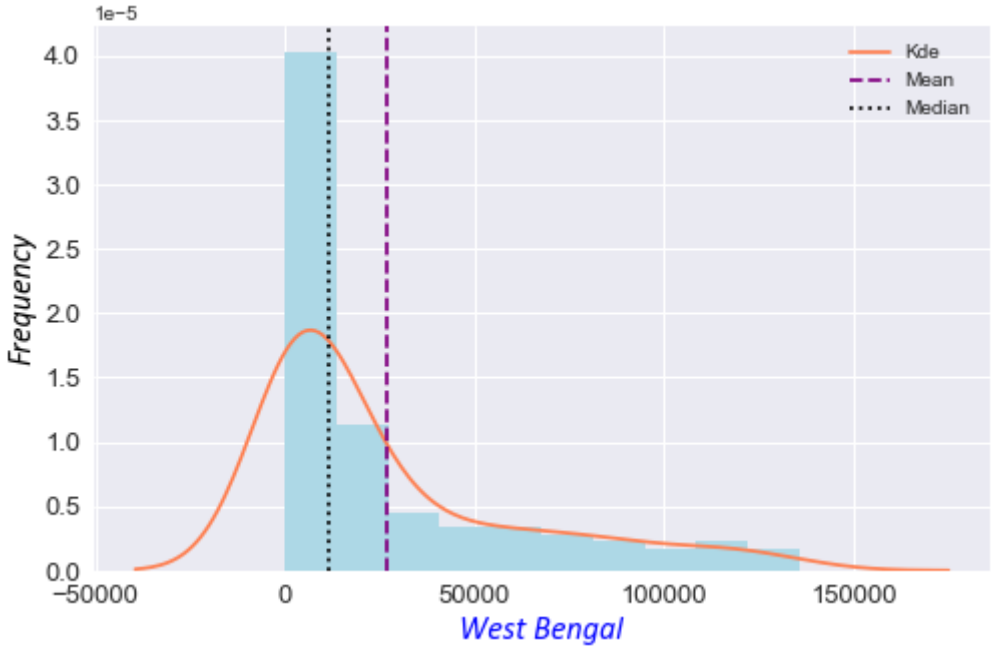

1e−5
Kde
Mean
Median
Frequency
1.2
1.0
0.8
0.6
0.4
0.2
0.0
−100000
0
100000
200000
300000
400000
500000
Tamil Nadu


1e−5
Kde
Mean
Median
Frequency
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
−50000
0
50000
100000
150000
Telangana

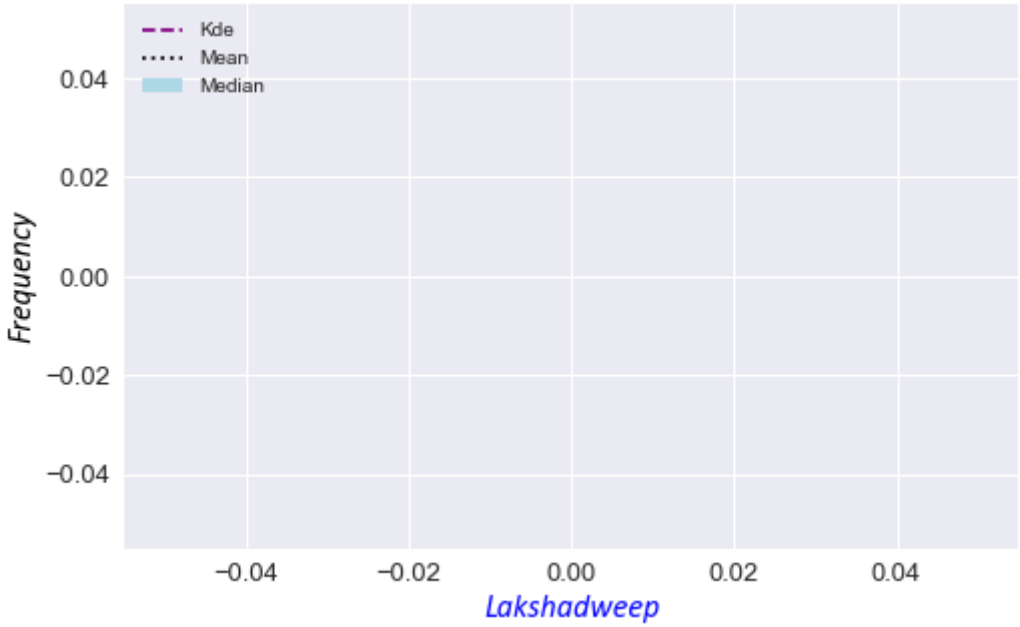

Kde
Mean
Median
Frequency
0.00014
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
−10000
0
10000
20000
30000
40000
Tripura


1e−5
Kde
Mean
Median
Frequency
4
3
2
1
0
−25000
0
25000
50000
75000
100000
125000
150000
Uttar Pradesh


Kde
Mean
Median
Frequency
0.00035
0.00030
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
0
5000
10000
15000
Uttarakhand




```
c:\users\rajsh\appdata\local\programs\python\python36\lib\site-packages\numpy\lib\hi
stograms.py:905: RuntimeWarning: invalid value encountered in true_divide
  return n/db/n.sum(), bin_edges
c:\users\rajsh\appdata\local\programs\python\python36\lib\site-packages\seaborn\dist
ributions.py:306: UserWarning: Dataset has 0 variance; skipping density estimate.
  warnings.warn(msg, UserWarning)
```



By seeing the above plots we are going ahead with Simple Imputation using Median.

Imputing NULL values in 'Positive' statewise

In [43]:
```
## Calculating median of every state
states_pop_median = pop_test_df.groupby(['State'])[['Positive']].median().reset_inde
```

In [44]:
```
states_pop_median
```

Out[44]:

	State	Pos_Median
0	Andaman and Nicobar Islands	2186.0
1	Andhra Pradesh	4126.0
2	Arunachal Pradesh	101.0

	State	Pos_Median
3	Assam	6067.5
4	Bihar	5695.0
5	Chandigarh	334.0
6	Chhattisgarh	1905.0
7	Dadra and Nagar Haveli and Daman and Diu	495.0
8	Delhi	32810.0
9	Goa	629.0
10	Gujarat	34686.0
11	Haryana	9218.0
12	Himachal Pradesh	489.5
13	Jammu and Kashmir	4730.0
14	Jharkhand	3393.0
15	Karnataka	6041.0
16	Kerala	16996.0
17	Ladakh	990.0
18	Lakshadweep	NaN
19	Madhya Pradesh	9949.0
20	Maharashtra	276571.5
21	Manipur	945.5
22	Meghalaya	48.0
23	Mizoram	112.0
24	Nagaland	178.0
25	Odisha	4109.0
26	Puducherry	1832.0
27	Punjab	2936.5
28	Rajasthan	12068.0
29	Sikkim	79.0
30	Tamil Nadu	42687.0
31	Telangana	46274.0
32	Tripura	5389.0
33	Uttar Pradesh	10103.0
34	Uttarakhand	1598.5
35	West Bengal	11290.5

Filling the missing value fpr `Lakshadweep`

In [45]:
```
states_pop_median['Pos_Median'].fillna(value=states_pop_median['Pos_Median'].median(
states_pop_median
```

Out[45]:

	State	Pos_Median
0	Andaman and Nicobar Islands	2186.0
1	Andhra Pradesh	4126.0
2	Arunachal Pradesh	101.0
3	Assam	6067.5
4	Bihar	5695.0
5	Chandigarh	334.0
6	Chhattisgarh	1905.0
7	Dadra and Nagar Haveli and Daman and Diu	495.0
8	Delhi	32810.0
9	Goa	629.0
10	Gujarat	34686.0
11	Haryana	9218.0
12	Himachal Pradesh	489.5
13	Jammu and Kashmir	4730.0
14	Jharkhand	3393.0
15	Karnataka	6041.0
16	Kerala	16996.0
17	Ladakh	990.0
18	Lakshadweep	4109.0
19	Madhya Pradesh	9949.0
20	Maharashtra	276571.5
21	Manipur	945.5
22	Meghalaya	48.0
23	Mizoram	112.0
24	Nagaland	178.0
25	Odisha	4109.0
26	Puducherry	1832.0
27	Punjab	2936.5
28	Rajasthan	12068.0
29	Sikkim	79.0
30	Tamil Nadu	42687.0
31	Telangana	46274.0
32	Tripura	5389.0
33	Uttar Pradesh	10103.0
34	Uttarakhand	1598.5

	State	Pos_Median
35	West Bengal	11290.5

In [46]:
```
## Imputing Median for every state
pop_test_df['Positive'] = pop_test_df[['State','Positive']].\
apply(lambda row: np.float(states_pop_median[states_pop_median['State'] == row['Stat
      if str(row['Positive']).lower() == str('NaN').lower() else row['Positive'],axi
```

In [47]:
```
pop_test_df
```

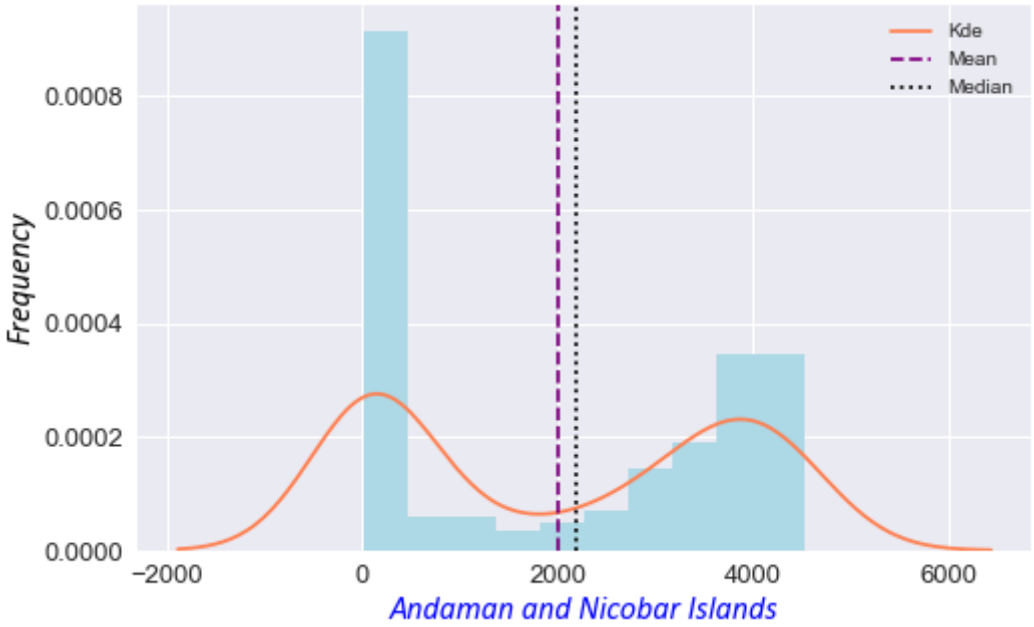
Out[47]:

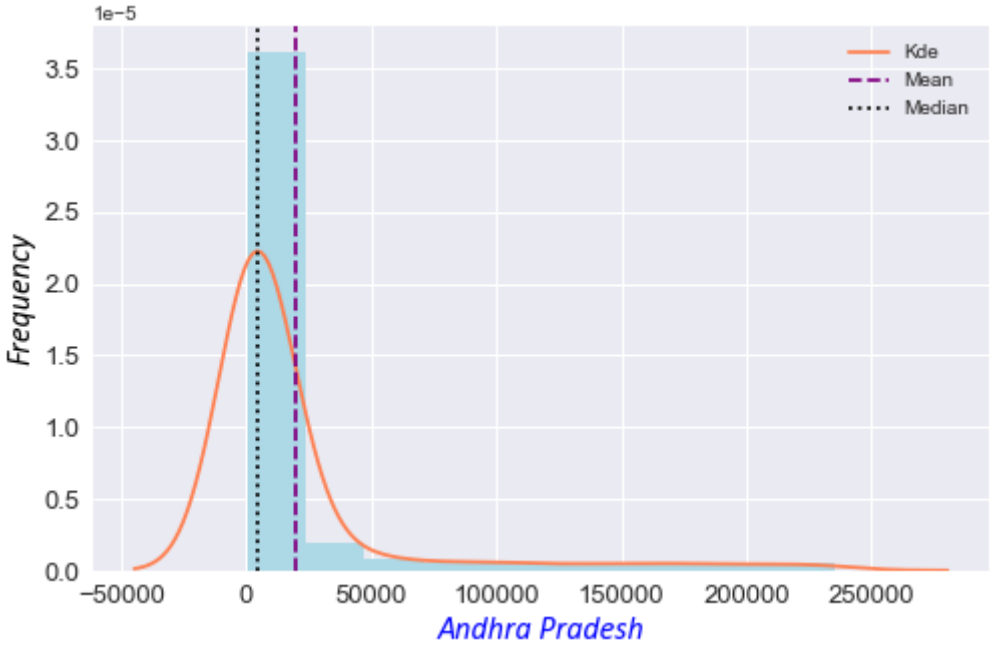
	Date	TotalSamples	Negative	Positive	State	Population	Rural population	Urban population	
0	2020-04-17	1403.0	1210	12.0	Andaman and Nicobar Islands	380581	237093	143488	
1	2020-04-24	2679.0	NaN	27.0	Andaman and Nicobar Islands	380581	237093	143488	
2	2020-04-27	2848.0	NaN	33.0	Andaman and Nicobar Islands	380581	237093	143488	
3	2020-05-01	3754.0	NaN	33.0	Andaman and Nicobar Islands	380581	237093	143488	
4	2020-05-16	6677.0	NaN	33.0	Andaman and Nicobar Islands	380581	237093	143488	
...	...	...	...	...	...	...	...	...	
7308	2020-11-12	5091700.0	NaN	11290.5	West Bengal	91276115	62183113	29093002	
7309	2020-11-13	5136012.0	NaN	11290.5	West Bengal	91276115	62183113	29093002	
7310	2020-11-14	5180139.0	NaN	11290.5	West Bengal	91276115	62183113	29093002	
7311	2020-11-15	5218797.0	NaN	11290.5	West Bengal	91276115	62183113	29093002	
7312	NaN	NaN	NaN	4109.0	Lakshadweep	64473	14141	50332	

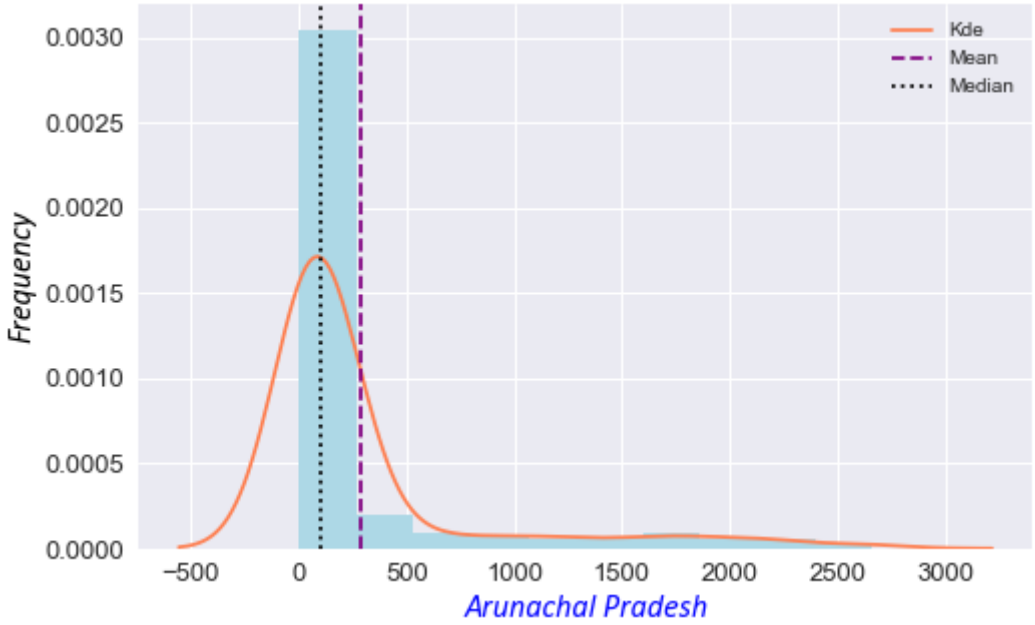
7313 rows × 13 columns

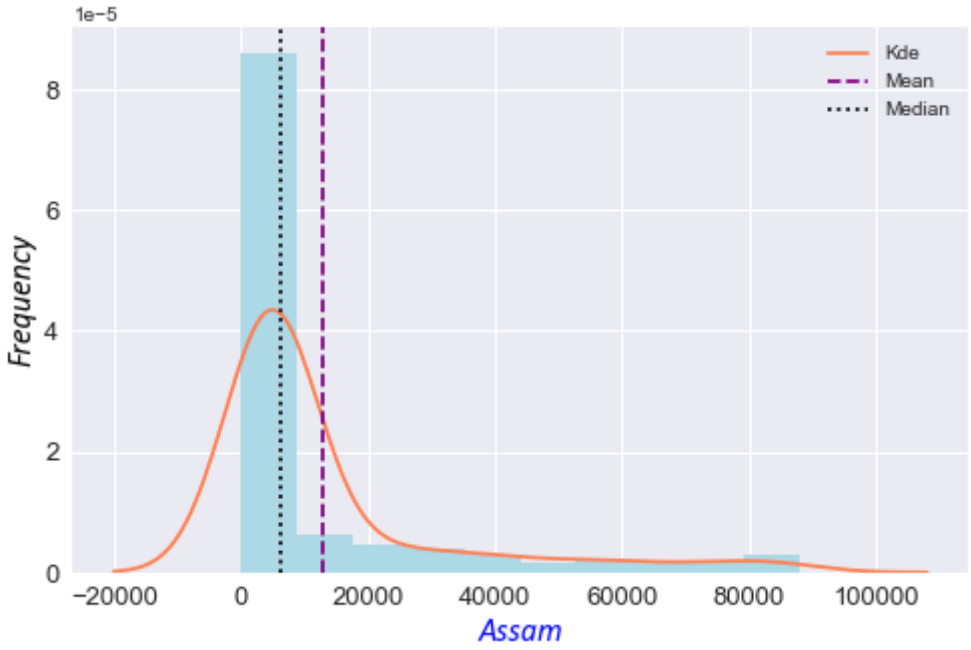
In [48]:
```
## Plotting the State-wise distributions of Positives after median imputation
print(colored("Positive cases distribution:",'red'),colored("After Median Imputation
plot_hist_kde(pop_test_df,grp_by_col='State',dist_col='Positive')
```

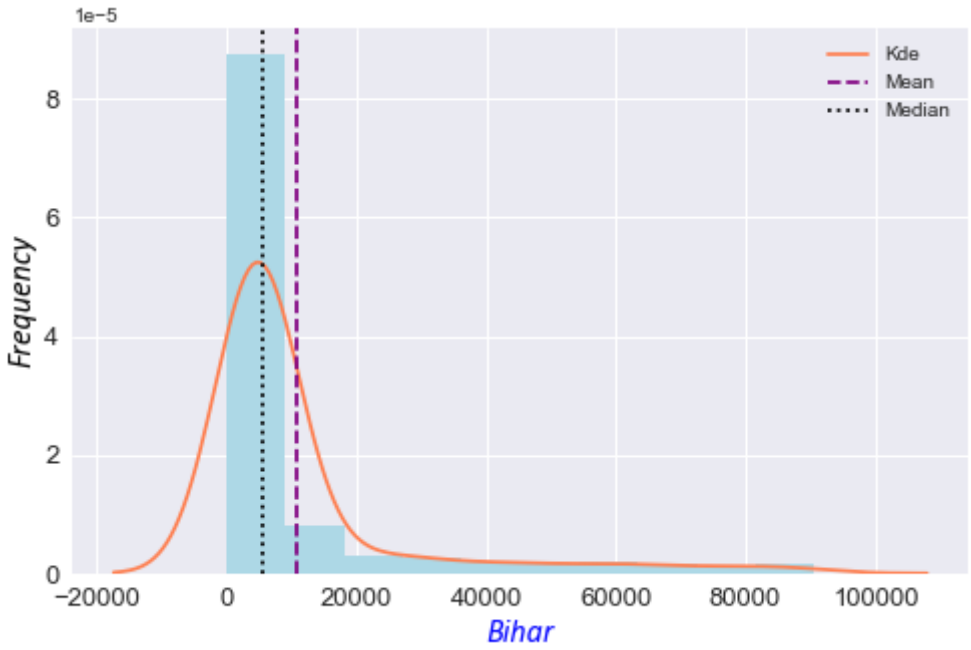
```
Positive cases distribution: After Median Imputation
```

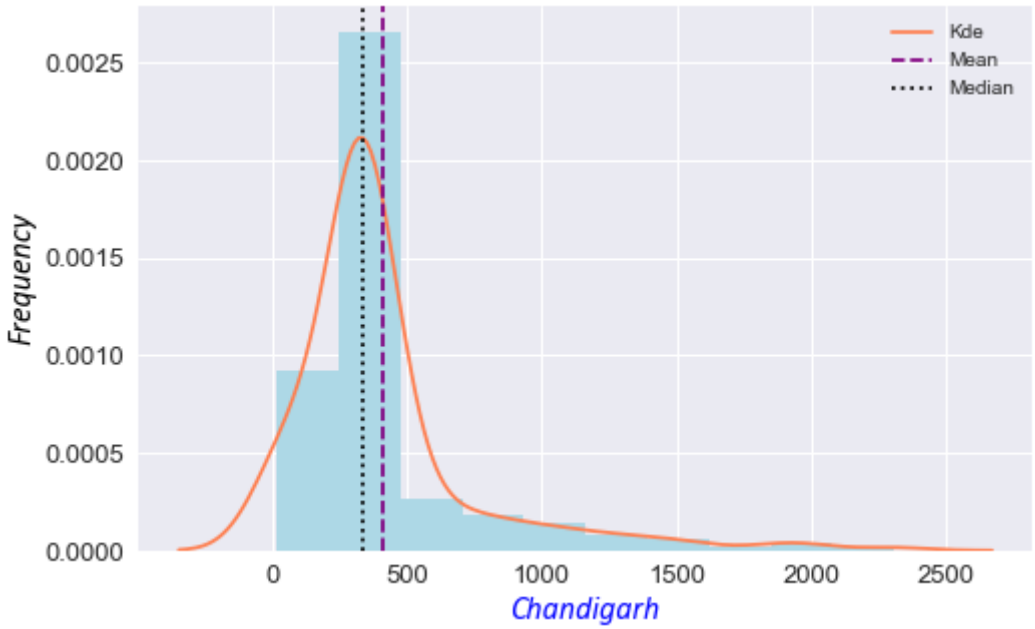


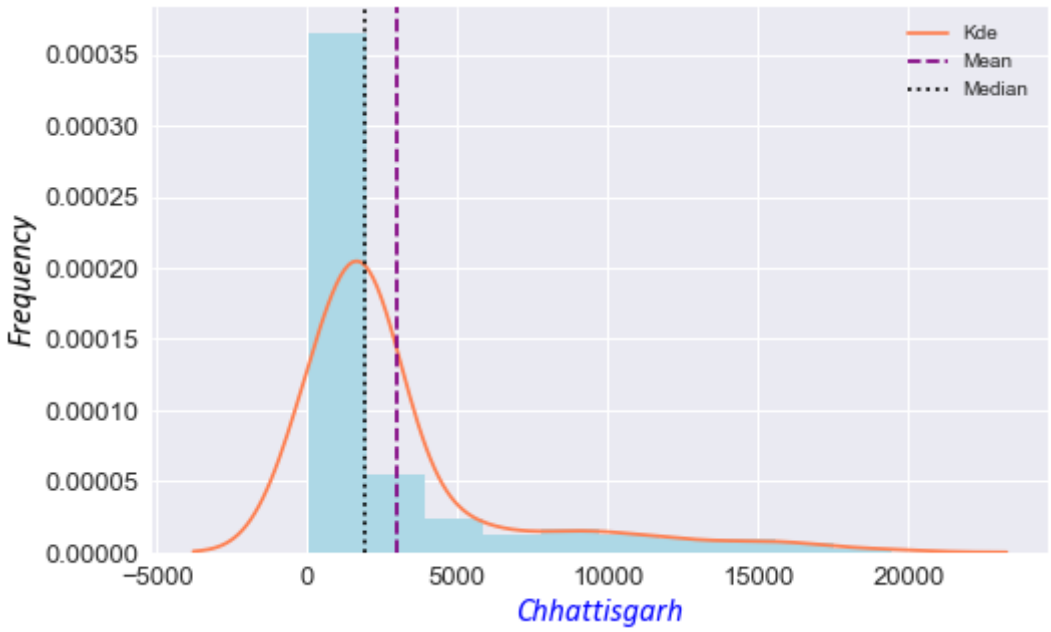


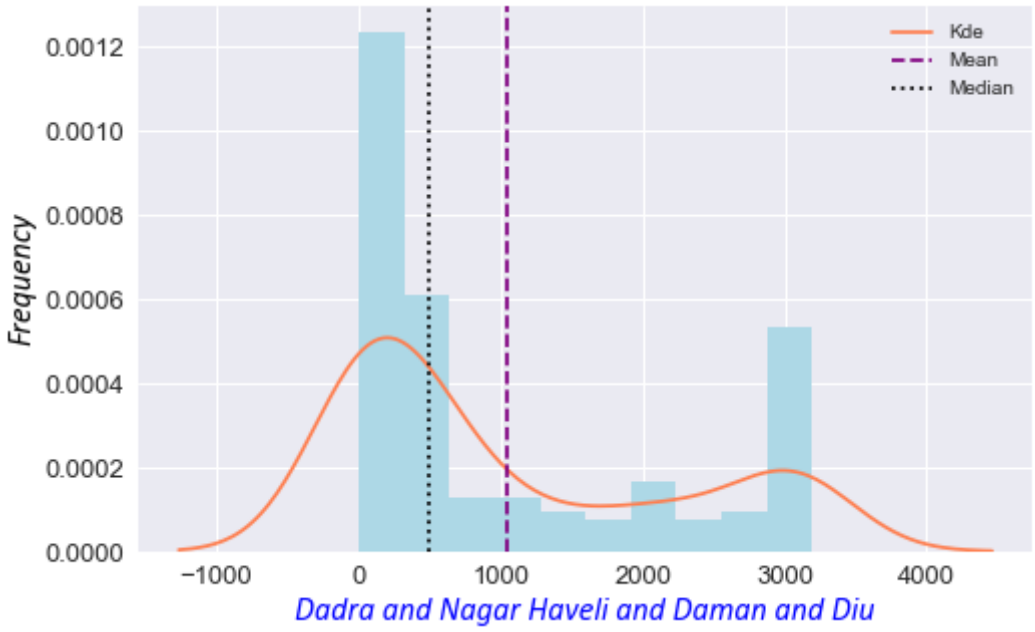

Kde
Mean
Median
Frequency
0.0030
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
−500
0
500
1000
1500
2000
2500
3000
Arunachal Pradesh


1e−5
Kde
Mean
Median
Frequency
8
6
4
2
0
−20000
0
20000
40000
60000
80000
100000
Assam


1e−5
Kde
Mean
Median
Frequency
8
6
4
2
0
−20000
0
20000
40000
60000
80000
100000
Bihar


Kde
Mean
Median
Frequency
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
0
500
1000
1500
2000
2500
Chandigarh


Kde
Mean
Median
Frequency
0.00035
0.00030
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
−5000
0
5000
10000
15000
20000
Chhattisgarh


Kde
Mean
Median
Frequency
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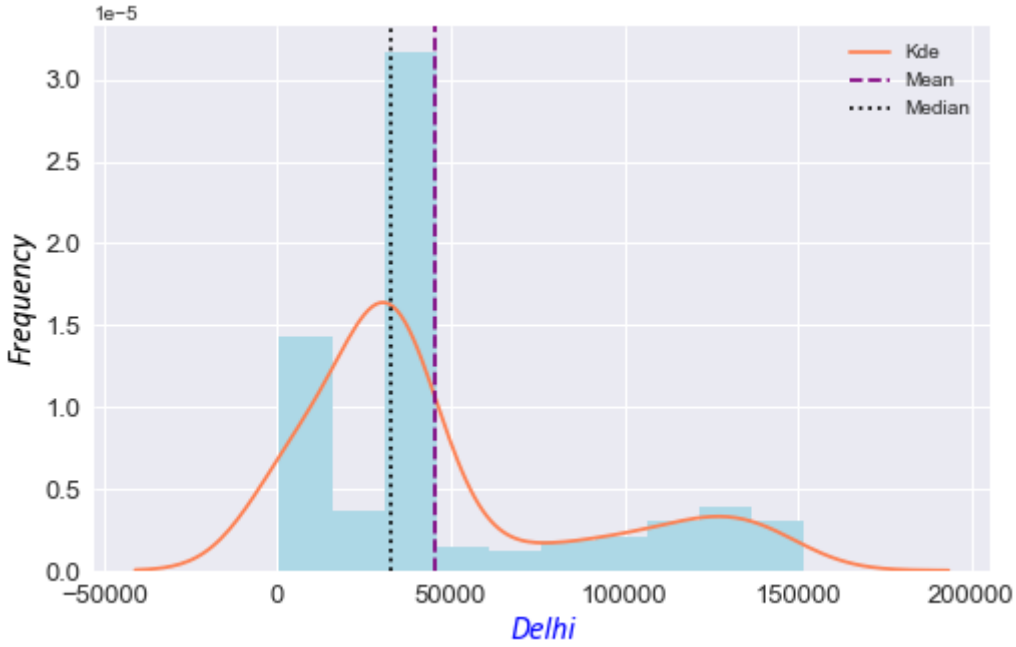
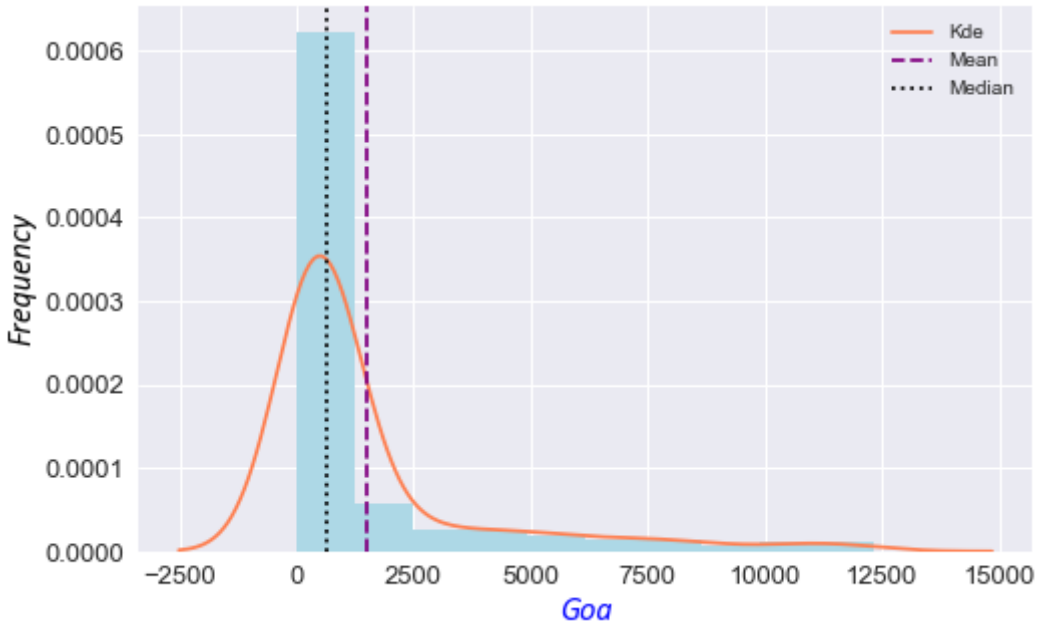
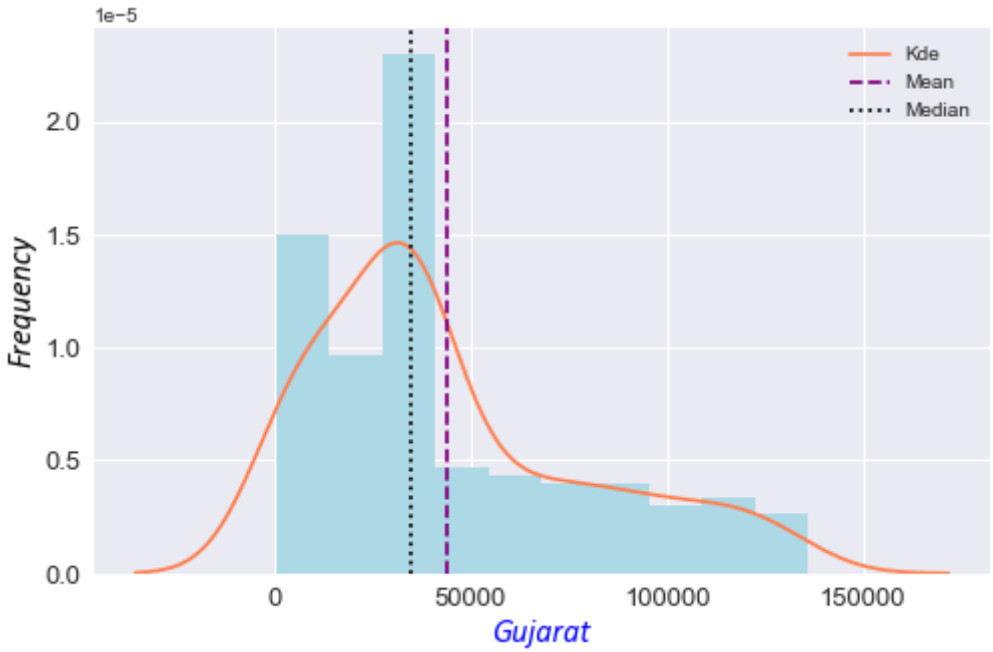
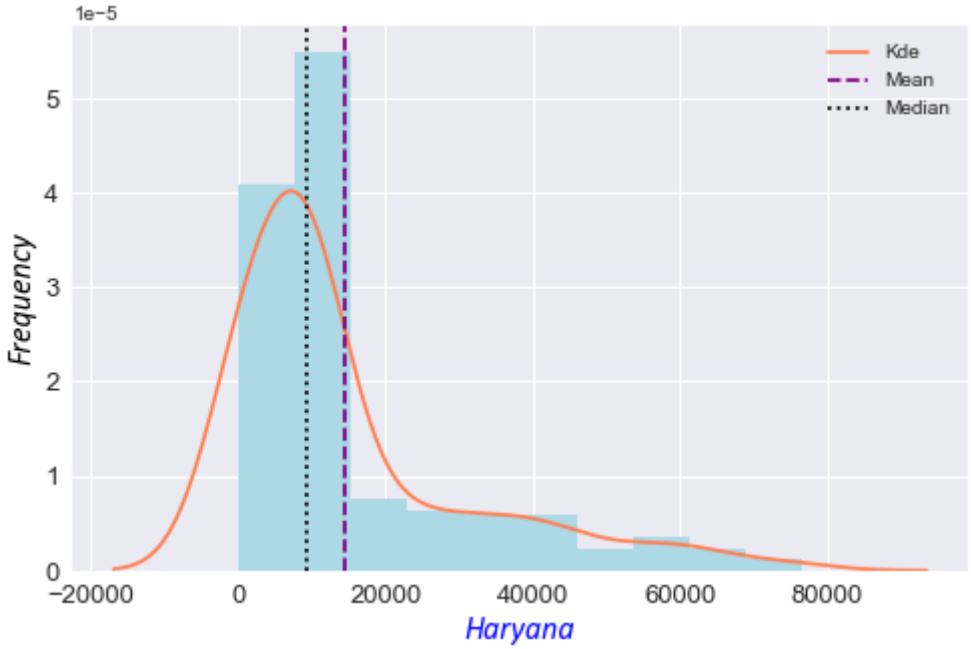
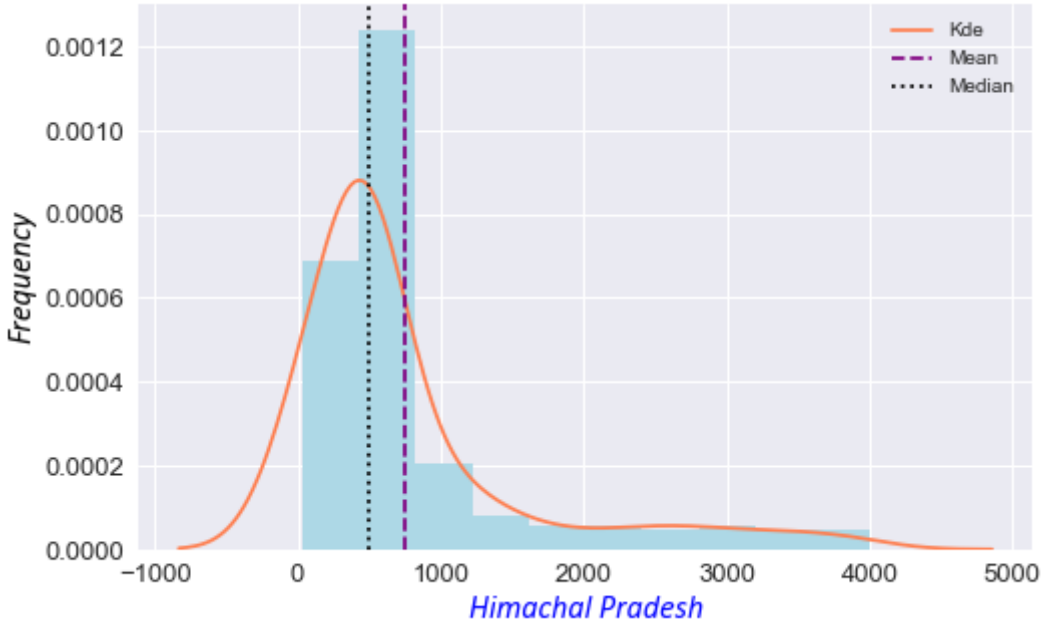
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
−1000
0
1000
2000
3000
4000
Dadra and Nagar Haveli and Daman and Diu


1e−5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Frequency
Kde
Mean
Median
−50000
0
50000
100000
150000
200000
Delhi


0.0006
0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
Frequency
Kde
Mean
Median
−2500
0
2500
5000
7500
10000
12500
15000
Goa


1e−5
2.0
1.5
1.0
0.5
0.0
Frequency
Kde
Mean
Median
0
50000
100000
150000
Gujarat


1e−5
Kde
Mean
Median
Frequency
0
1
2
3
4
5
−20000
0
20000
40000
60000
80000
Haryana


Kde
Mean
Median
Frequency
0.0000
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0.0008
0.0010
0.0012
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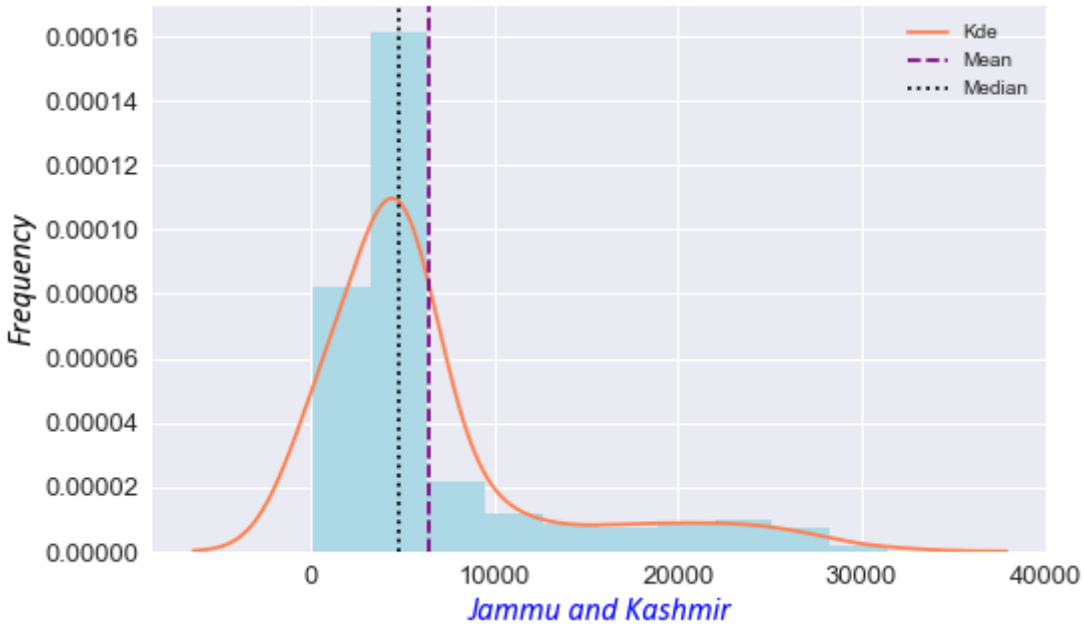
0
1000
2000
3000
4000
5000
Himachal Pradesh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Median
Frequency
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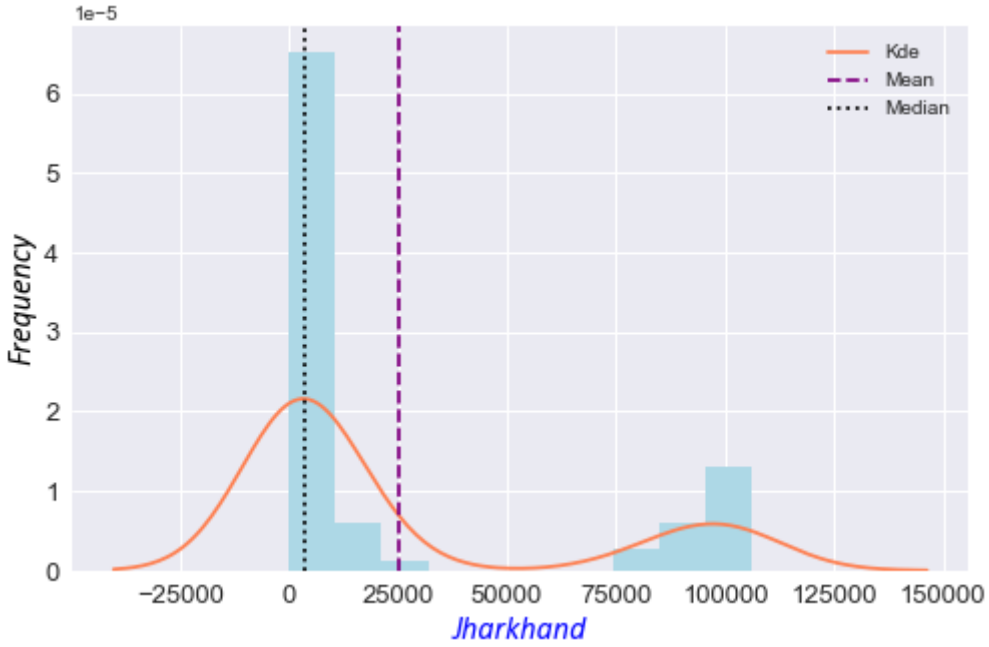
0.00014
0.00016
0
10000
20000
30000
40000
Jammu and Kashmir


1e−5
Kde
Mean
Median
Frequency
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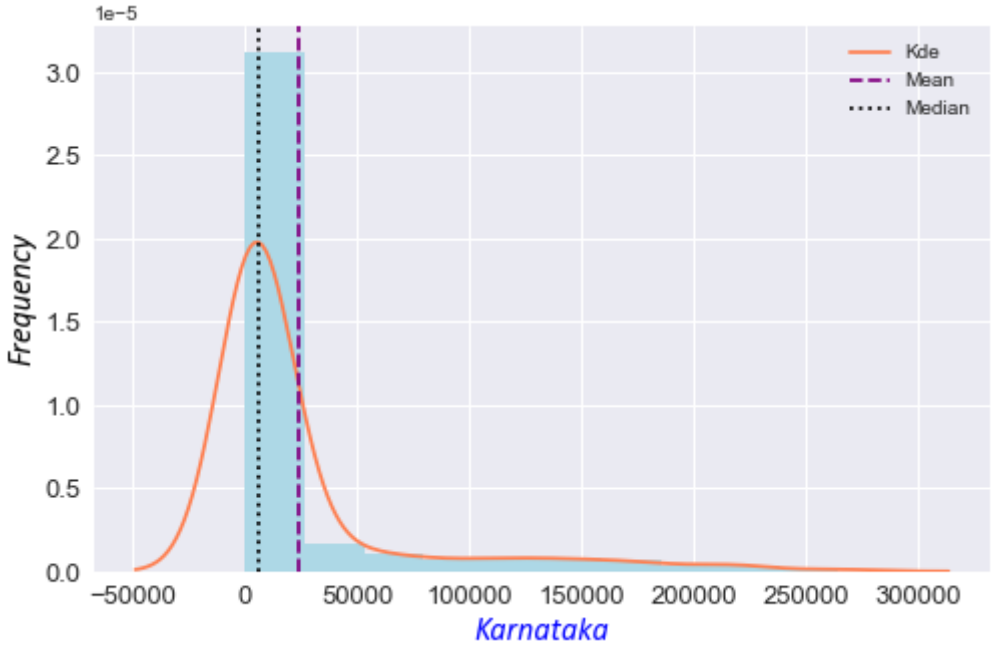
2
3
4
5
6
−25000
0
25000
50000
75000
100000
125000
150000
Jharkhand


1e−5
Kde
Mean
Median
Frequency
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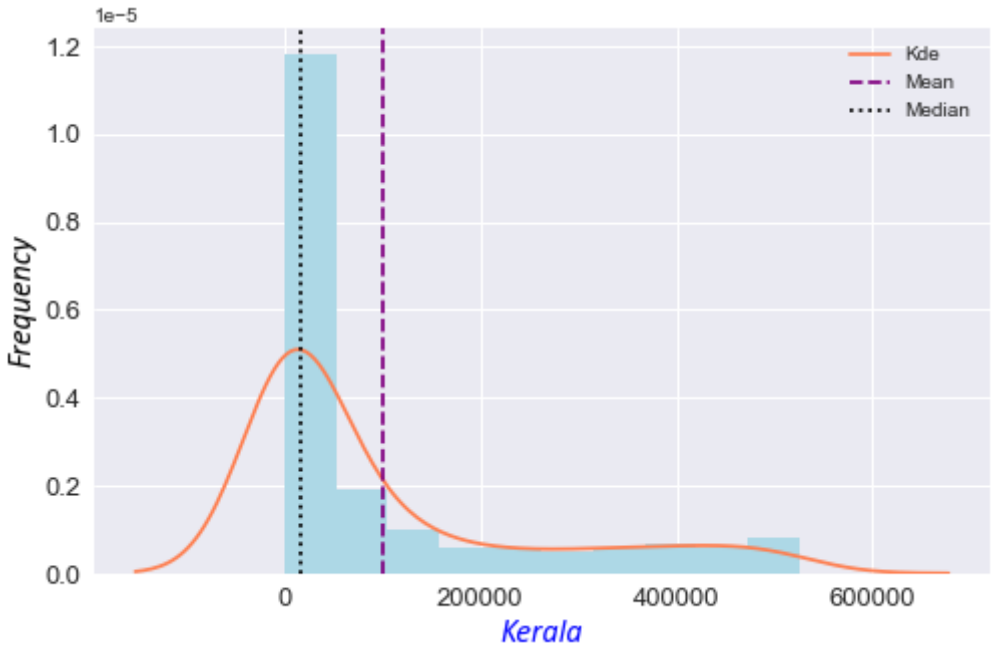
0.5
1.0
1.5
2.0
2.5
3.0
−50000
0
50000
100000
150000
200000
250000
300000
Karnataka


1e−5
Kde
Mean
Median
Frequency
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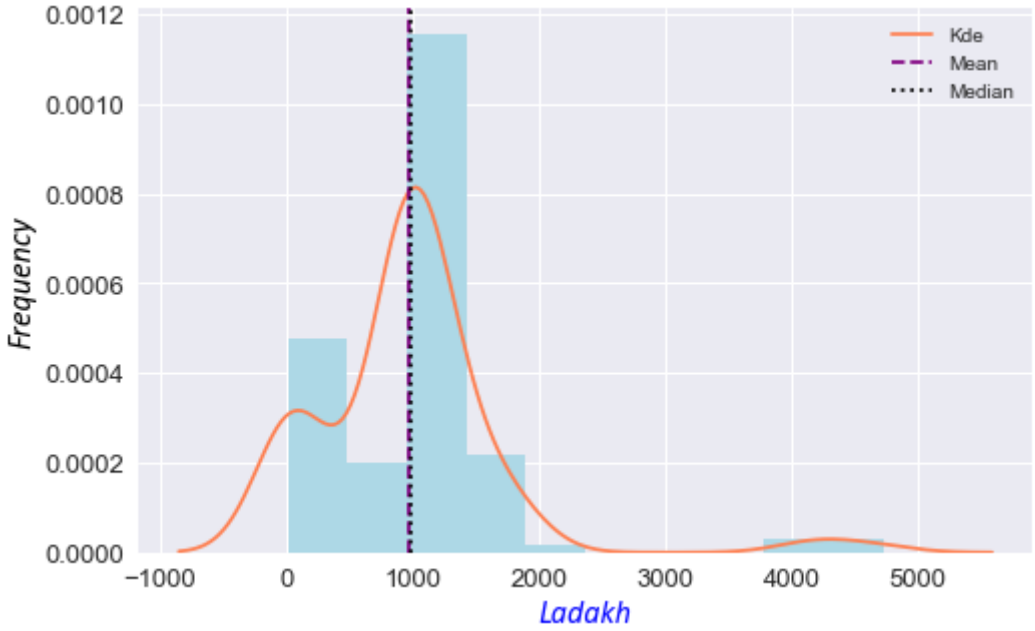
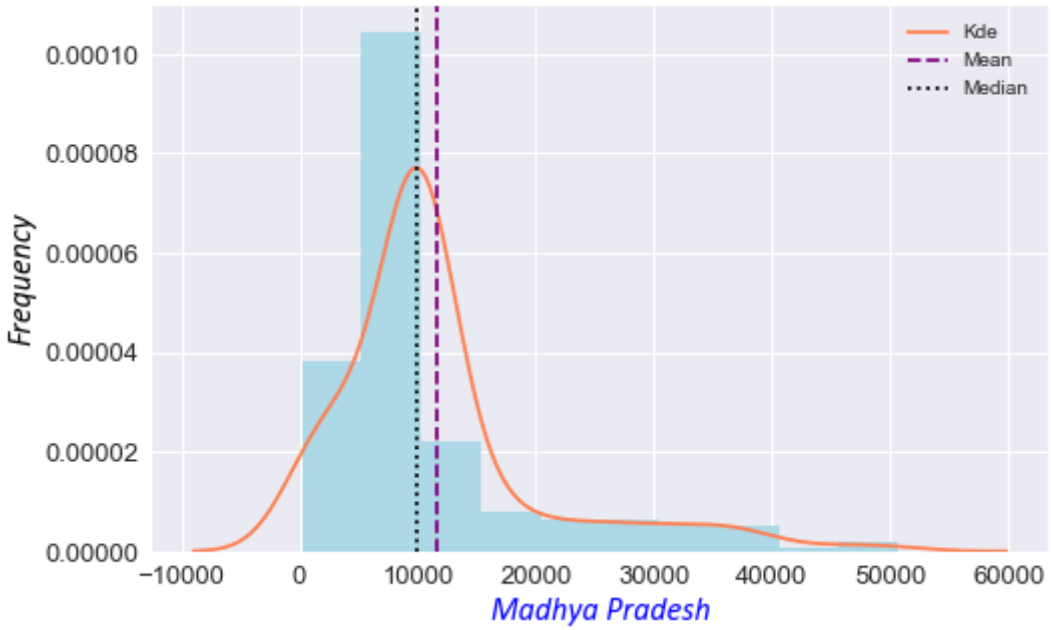
0.2
0.4
0.6
0.8
1.0
1.2
0
200000
400000
600000
Kerala


Kde
Mean
Median
Frequency
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
−1000
0
1000
2000
3000
4000
5000
Ladakh


Kde
Mean
Median
Frequency
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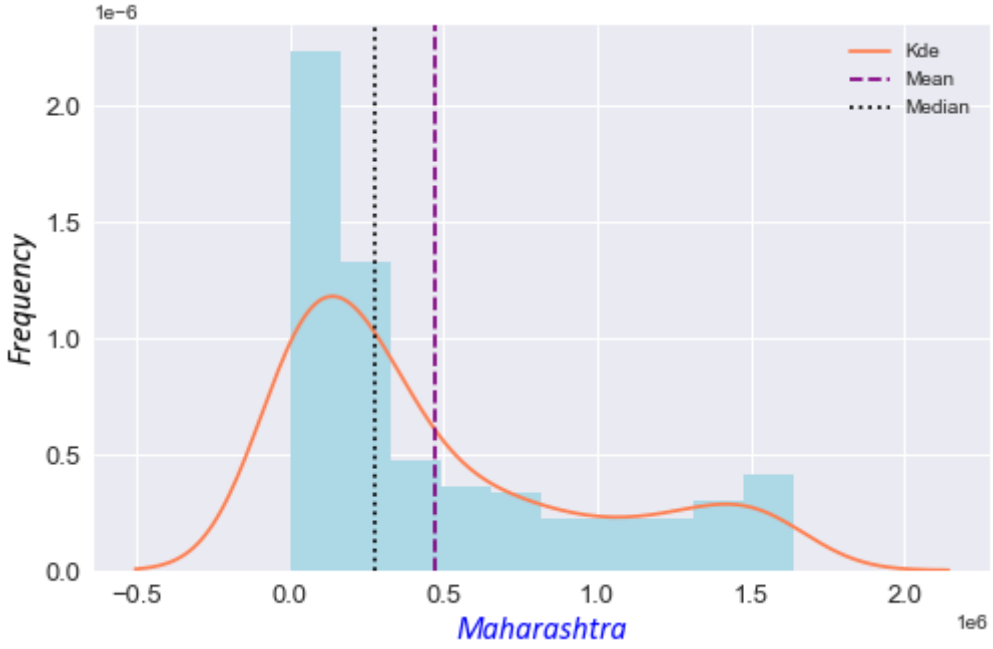
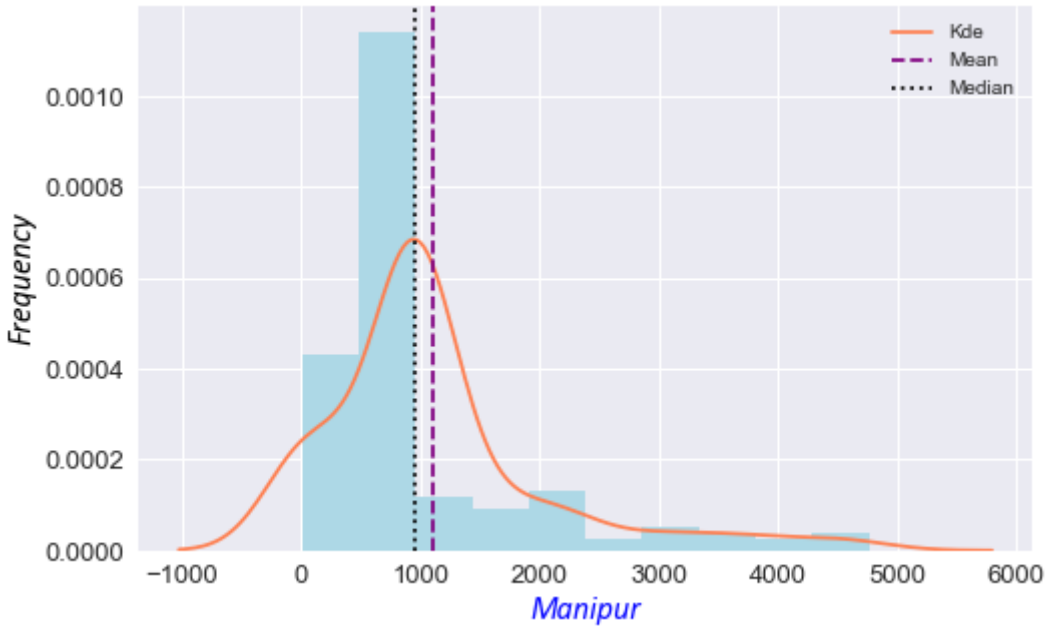
0.00008
0.00006
0.00004
0.00002
0.00000
−10000
0
10000
20000
30000
40000
50000
60000
Madhya Pradesh


1e−6
Kde
Mean
Median
Frequency
2.0
1.5
1.0
0.5
0.0
−0.5
0.0
0.5
1.0
1.5
2.0
1e6
Maharashtra


Kde
Mean
Median
Frequency
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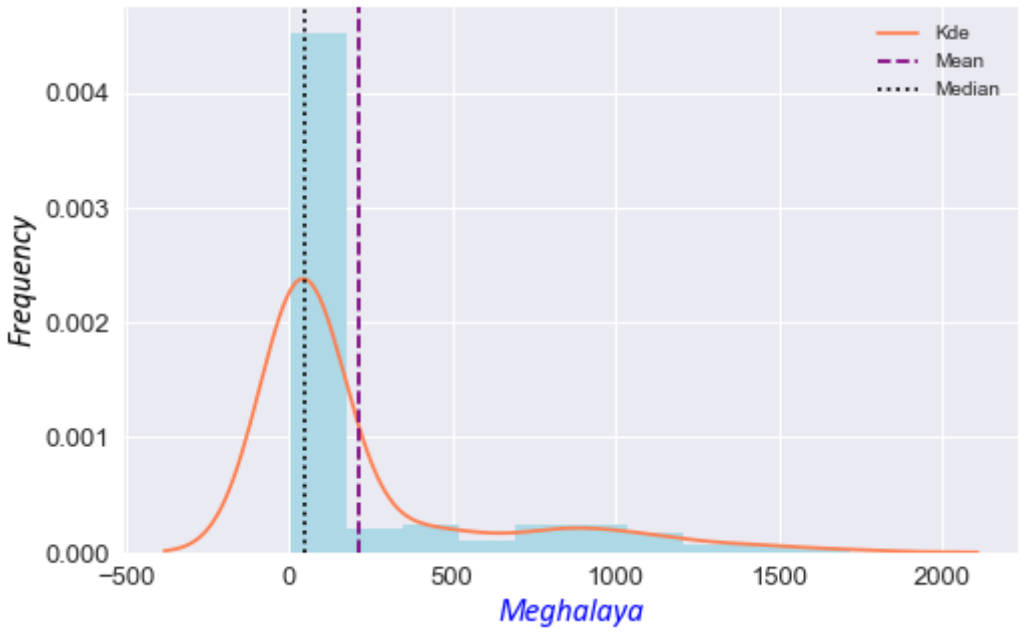
0.0008
0.0006
0.0004
0.0002
0.0000
−1000
0
1000
2000
3000
4000
5000
6000
Manipur


Kde
Mean
Median
Frequency
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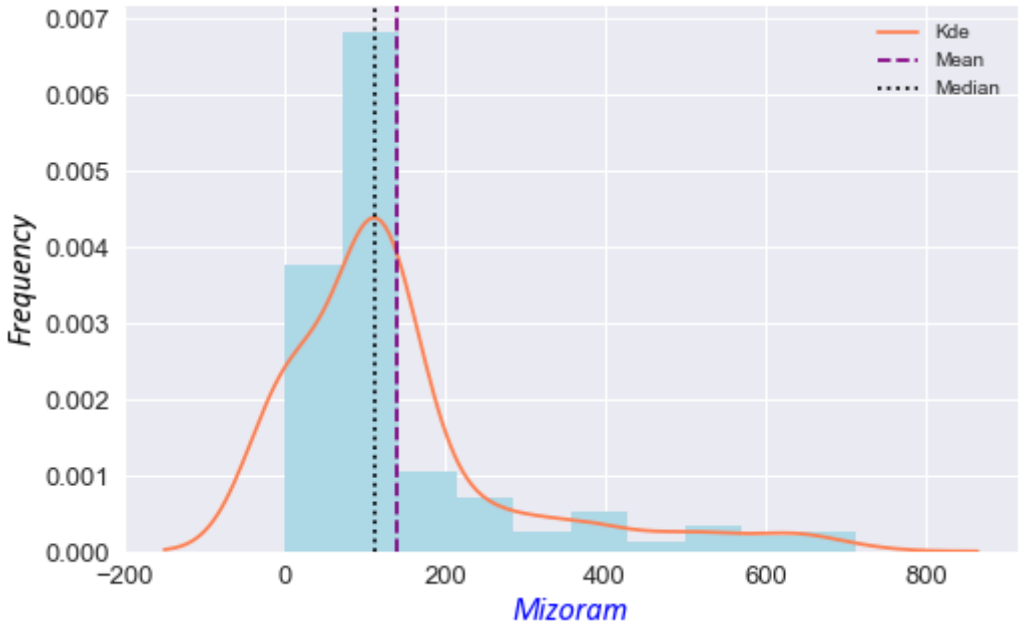
0.003
0.002
0.001
0.000
−500
0
500
1000
1500
2000
Meghalaya


Kde
Mean
Median
Frequency
0.007
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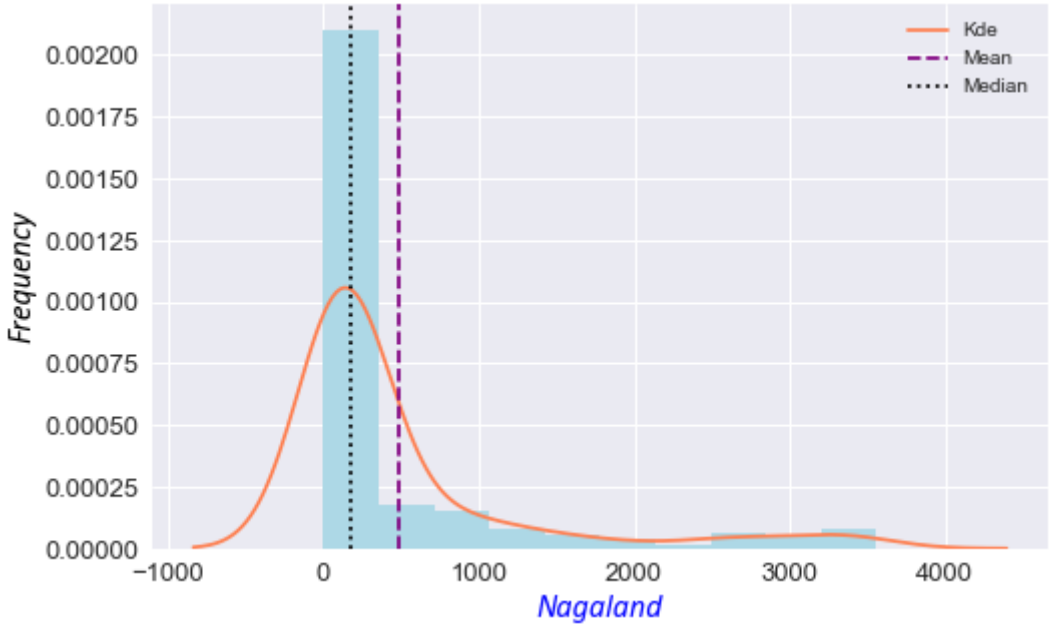
0.004
0.003
0.002
0.001
0.000
−200
0
200
400
600
800
Mizoram


Kde
Mean
Median
Frequency
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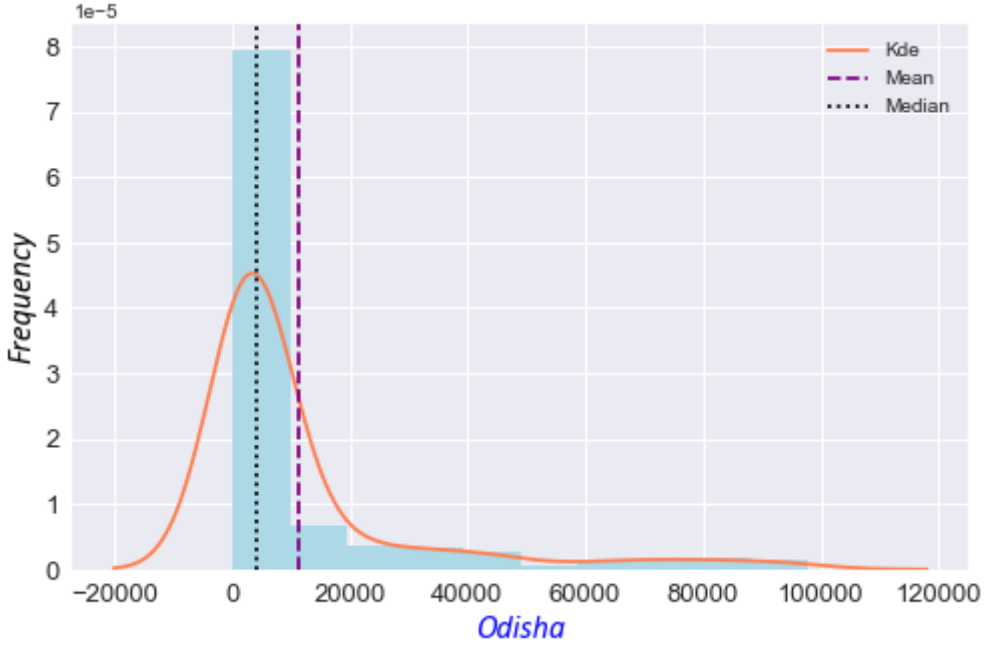
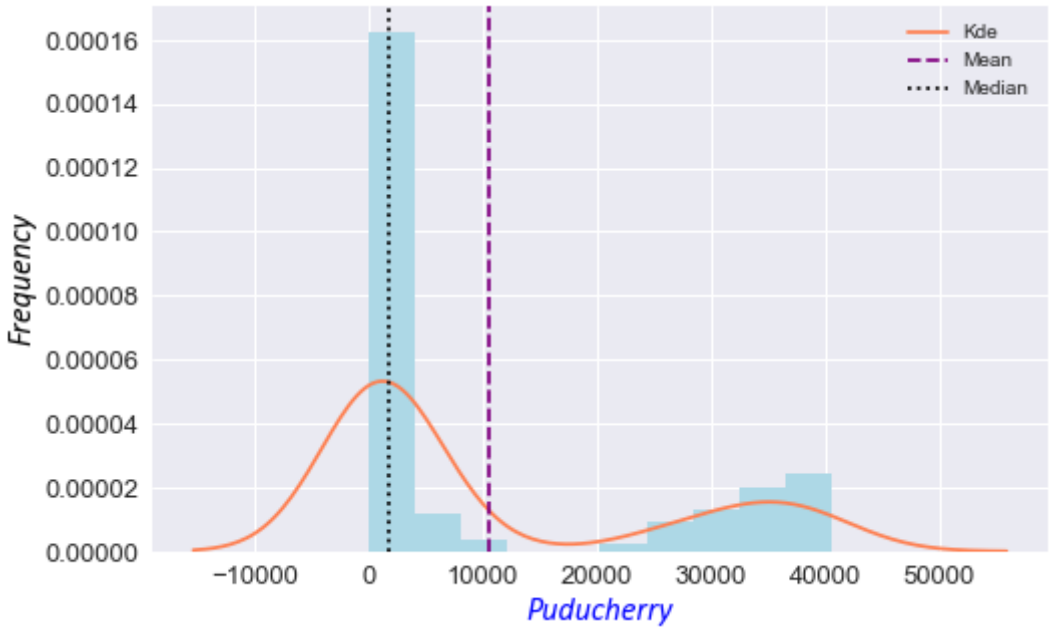
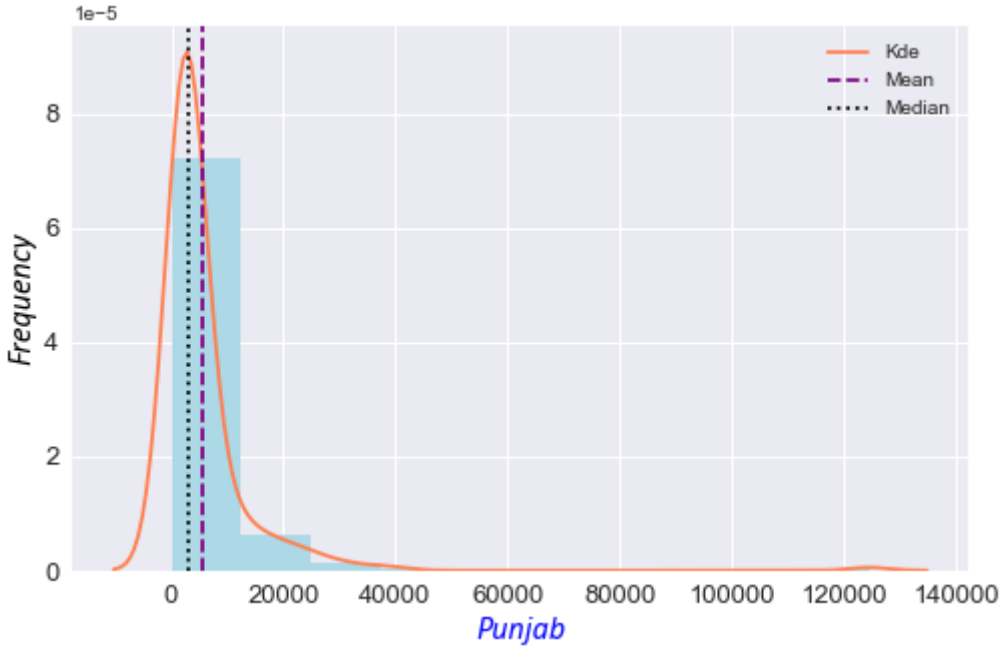
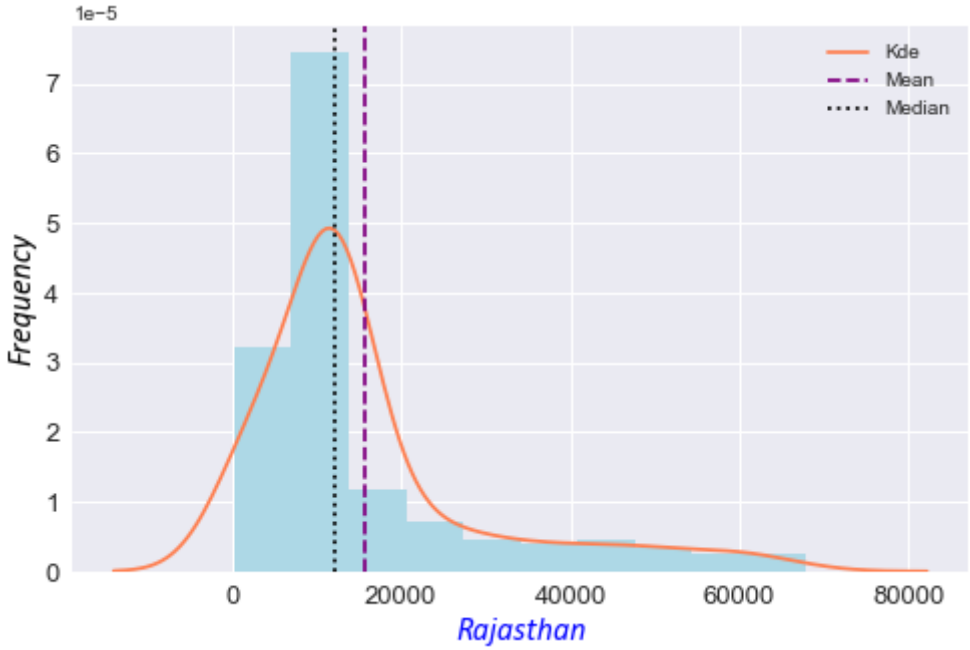
0.00175
0.00150
0.00125
0.00100
0.00075
0.00050
0.00025
0.00000
−1000
0
1000
2000
3000
4000
Nagaland


1e−5
Kde
Mean
Median
Frequency
8
7
6
5
4
3
2
1
0
−20000
0
20000
40000
60000
80000
100000
120000
Odisha


Kde
Mean
Median
Frequency
0.00016
0.00014
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
−10000
0
10000
20000
30000
40000
50000
Puducherry


1e−5
Kde
Mean
Median
Frequency
0
2
4
6
8
0
20000
40000
60000
80000
100000
120000
140000
Punjab


1e−5
Kde
Mean
Median
Frequency
0
1
2
3
4
5
6
7
0
20000
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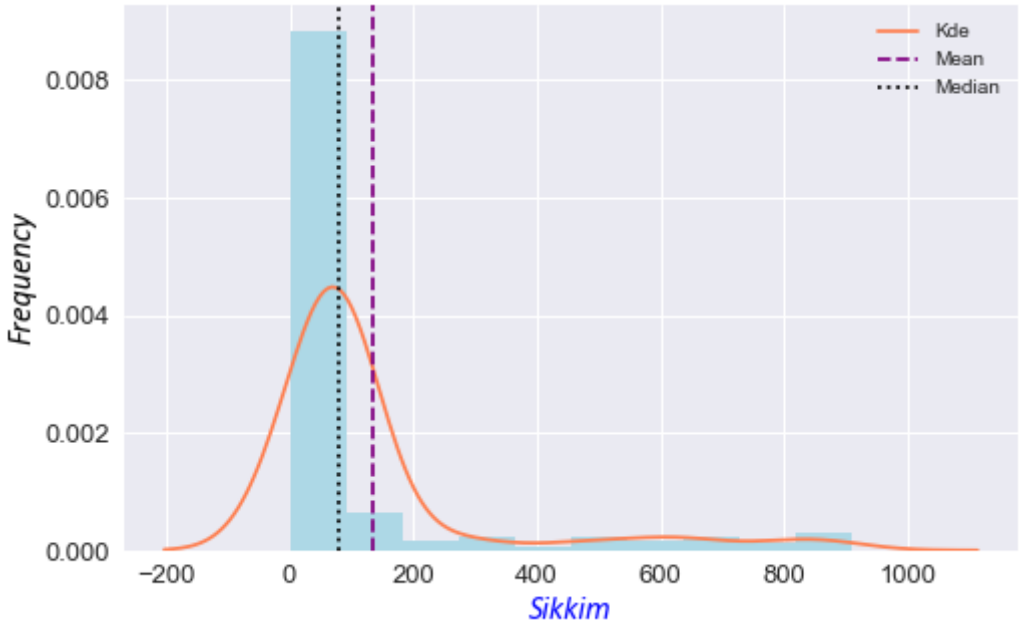
60000
80000
Rajasthan


Kde
Mean
Median
Frequency
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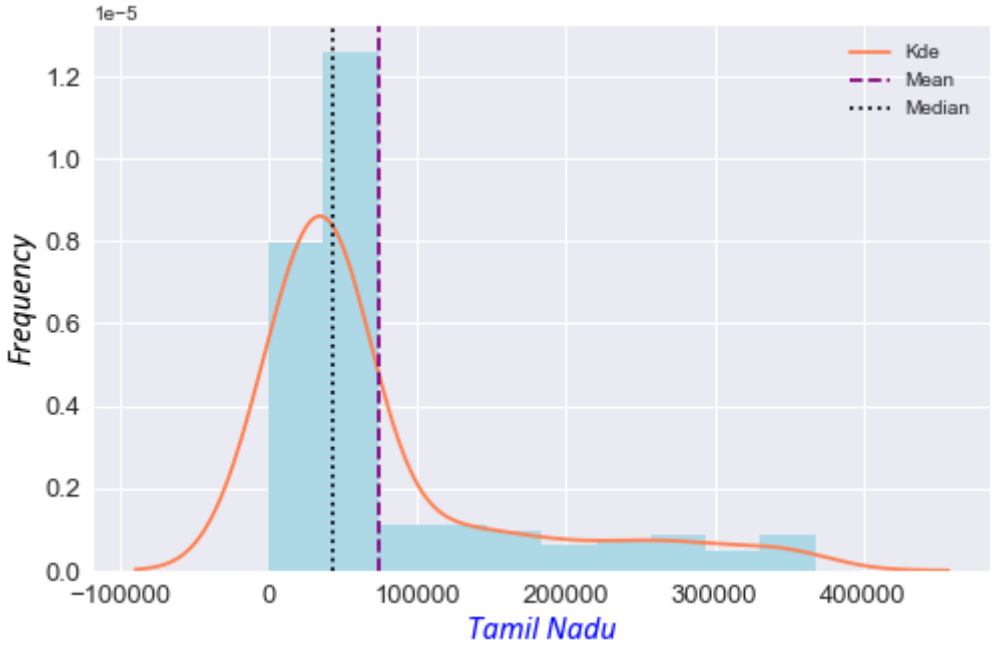
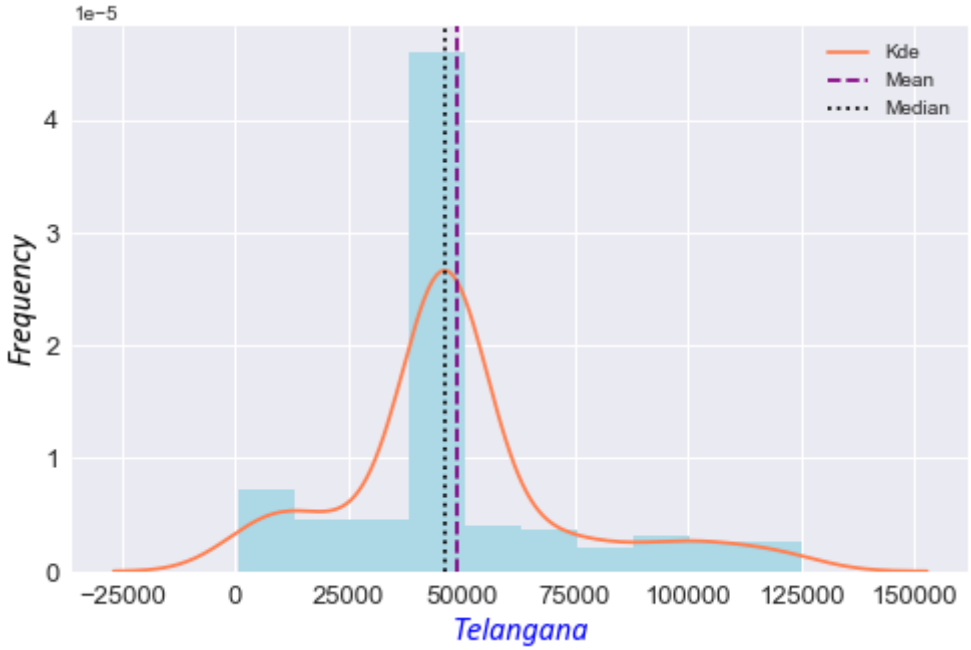
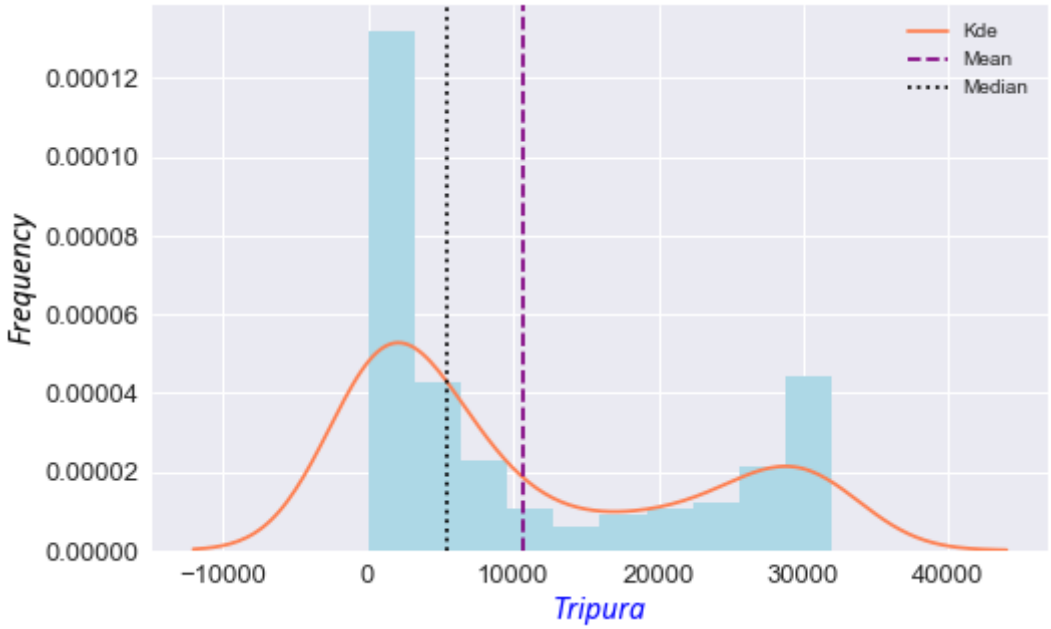
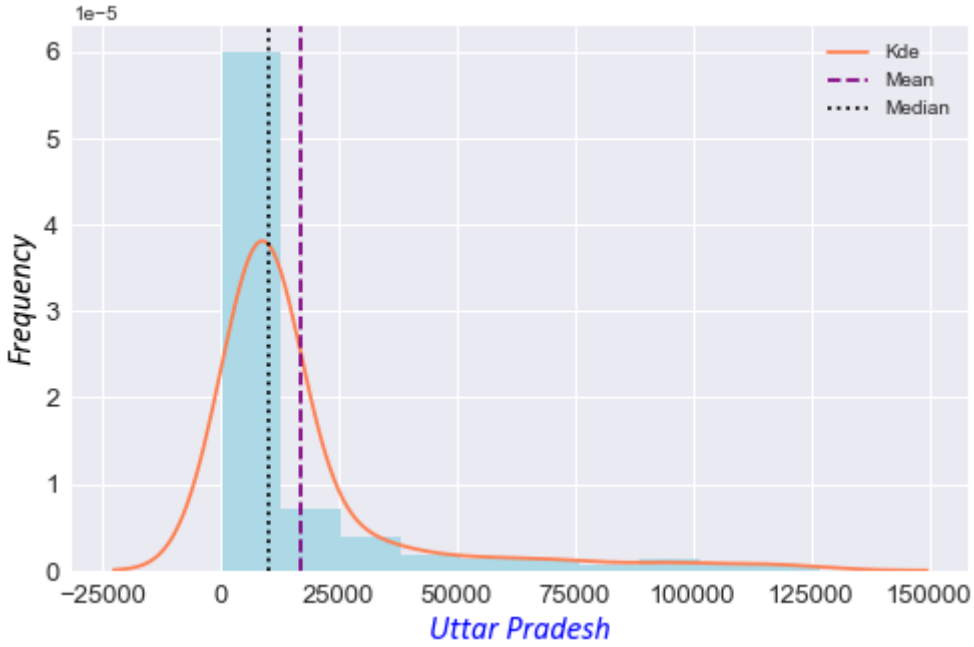
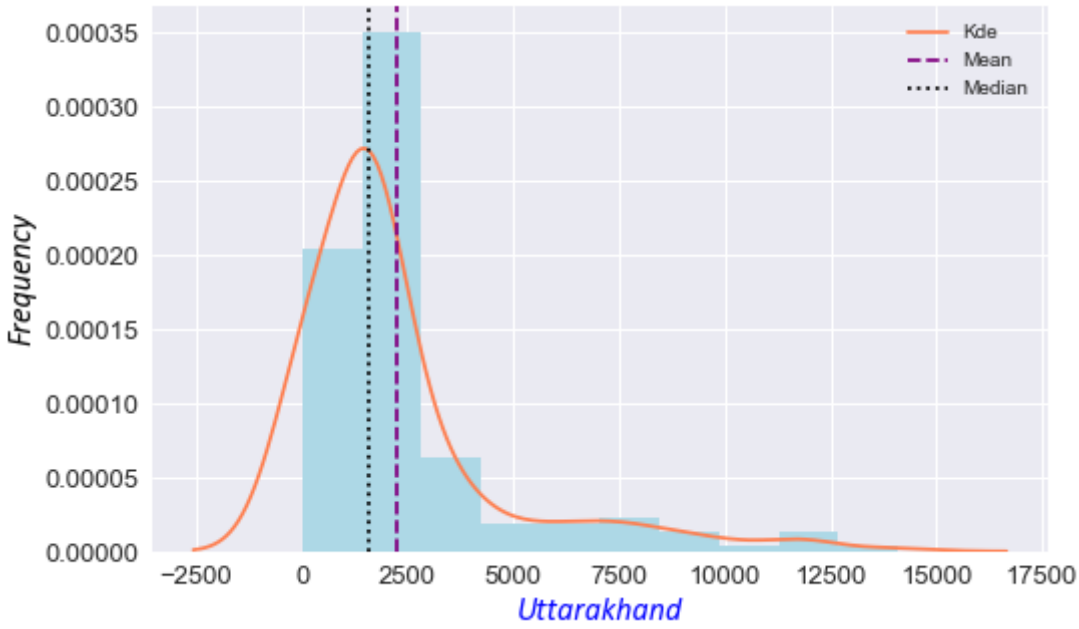
0.002
0.004
0.006
0.008
−200
0
200
400
600
800
1000
Sikkim

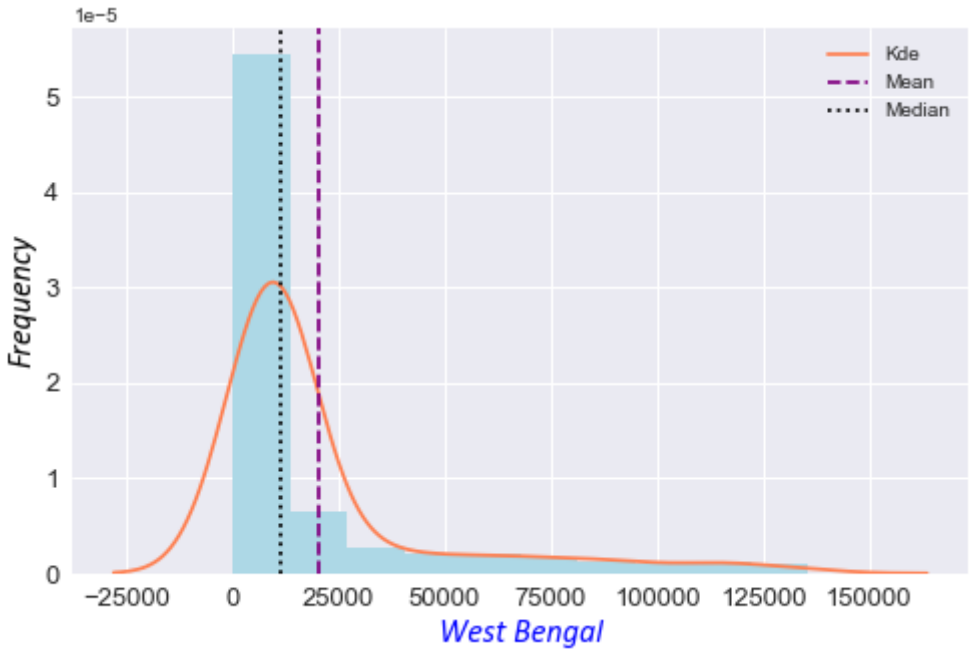

1e−5
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Frequency
Kde
Mean
Median
−100000
0
100000
200000
300000
400000
Tamil Nadu


1e−5
4
3
2
1
0
Frequency
Kde
Mean
Median
−25000
0
25000
50000
75000
100000
125000
150000
Telangana


0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
Frequency
Kde
Mean
Median
−10000
0
10000
20000
30000
40000
Tripura

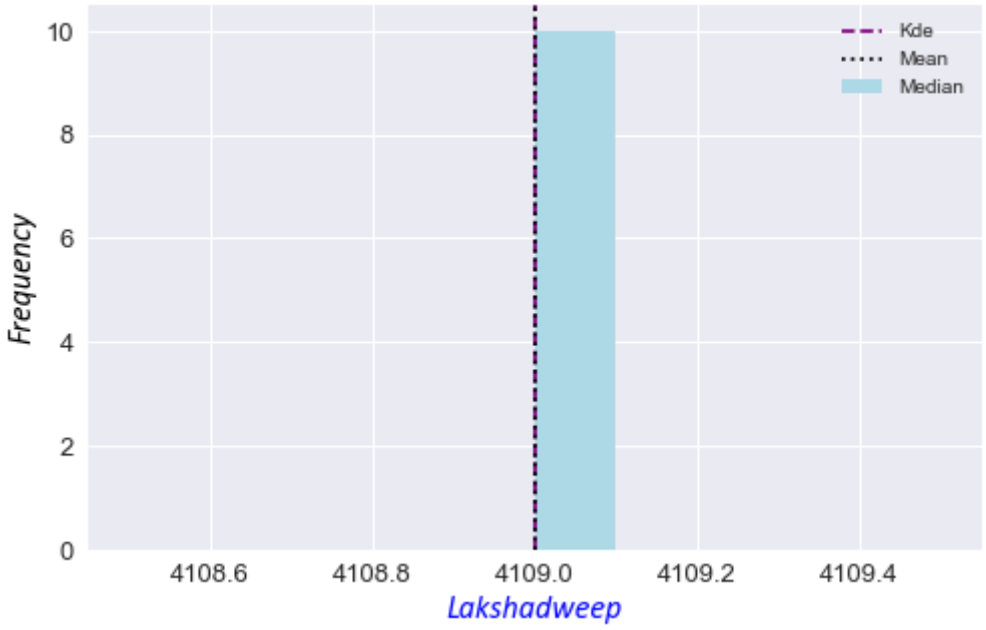






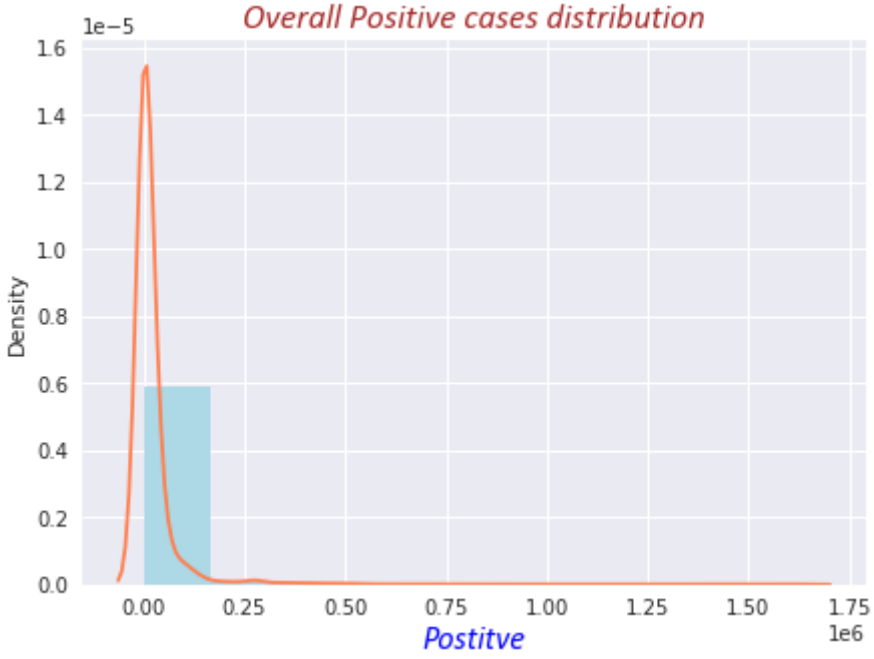

```
c:\users\rajsh\appdata\local\programs\python\python36\lib\site-packages\seaborn\dist
ributions.py:306: UserWarning: Dataset has 0 variance; skipping density estimate.
```

```
warnings.warn(msg, UserWarning)
```



Overall Distribution of `Positive` cases

In [49]:
```
with plt.style.context('seaborn'):
    plt.figure(figsize=(7,5))
    plt.hist(pop_test_df['Positive'],density=True,color='lightblue')
    sns.kdeplot(data=pop_test_df['Positive'],color='coral')
    plt.xlabel("Postitve",fontdict=font_dicts(kind='xlabel'))
    plt.title("Overall Positive cases distribution",fontdict=font_dicts(kind="title"
```



By seeing the above distribution, the first impression looks like 'Positive' follows the Power-Rule thus apply the PowerTransformer.

Here, in the power transformer I have selected the method as `'yeo-johnson'` because `'box-cox'` strictly deals with positive values and it looks for the minimum value in the array should be grater than 0. However, in the `'Positive'` array the minimum value is 0, therefore going ahead with `'yeo-johnson'`.

Checking the sign of values (-1 for negative, 1 for positive and 0 for 0)

In [50]:
```
check_pos_signs = pd.DataFrame(np.sign(pop_test_df['Positive']))
```

In [51]:
```
check_pos_signs[check_pos_signs.Positive==0].shape
```

Out[51]: (77, 1)

In [52]:
```
check_pos_signs[check_pos_signs.Positive==1].shape
```

Out[52]: (7236, 1)

In [53]:
```
pop_test_df['Positive'].shape
```

Out[53]: (7313,)

In [54]:
```
check_pos_signs[check_pos_signs.Positive==0].shape[0]+check_pos_signs[check_pos_sign
```

Out[54]: 7313

The above results tells us that there are no negative values.

In [55]:
```
## Return minimum of an array or minimum along an axis, ignoring any NaNs.
np.nanmin(pop_test_df['Positive'])
```

Out[55]: 0.0

In [56]:
```
## Creating Dataset for 1-Factor ANOVA
annv1_dense_grp = pop_test_df[['Positive','Dense_grp']].iloc[0:-1,:].drop_duplicates
annv1_dense_grp.shape
```

Out[56]: (3976, 2)

In [57]:
```
## Density groups wise number of positives
annv1_dense_grp
```

Out[57]:

	Positive	Dense_grp
0	12.0	Dense1
1	27.0	Dense1
2	33.0	Dense1
3	35.0	Dense1
4	38.0	Dense1
...	...	...
3971	116498.0	Dense4
3972	119578.0	Dense4
3973	122753.0	Dense4
3974	132364.0	Dense4
3975	135596.0	Dense4

3976 rows × 2 columns

In [58]:
```
## Checking NULLS in the 1-Factor ANOVA dataset
annv1_dense_grp['Positive'].isna().sum()
```

Out[58]: 0

In [59]:
```
ss=StandardScaler()
```

Difference between sklearn and scipy power transformation

In [60]:
```
## Sklearn Power Transformer using method 'yeo-johnson' with default settings (stand
pt = PowerTransformer(method='yeo-johnson',standardize=True)
```

In [61]:
```
print(colored("Mean","green","on_yellow"),'::',np.round(np.mean(pt.fit_transform(ann
print(colored("Std-dev","green","on_yellow"),'::',np.round(np.var(pt.fit_transform(a
```

```
Mean :: -0.0
Std-dev :: 1.0
```

This tells us that by default sklearn power transformer standardize the dataset with 0 centric mean and unit variance.

In [62]:
```
print(colored("Mean","green","on_yellow"),'::',np.round(np.mean(scipy.stats.yeojohns
print(colored("Mean","green","on_yellow"),'::',np.round(np.var(scipy.stats.yeojohnso
```

```
Mean :: 9.2005
Mean :: 7.3033
```

In [63]:
```
## Sklearn Power Transformer using method 'yeo-johnson' with changed settings (stand
pt1 = PowerTransformer(method='yeo-johnson',standardize=False)
print(colored("Mean","green","on_yellow"),'::',np.round(np.mean(pt1.fit_transform(an
print(colored("Std-dev","green","on_yellow"),'::',np.round(np.var(pt1.fit_transform(
```

```
Mean :: 9.2005
Std-dev :: 7.3033
```

Thus the sklearn power transformer standardize the dataset with 0 centric mean and unit variance by default and scipy returns the results with no standardization.

In [64]:
```
## Applying power transformed with standardization
annv1_dense_grp = pd.concat([annv1_dense_grp,pd.DataFrame(pt.fit_transform(annv1_den
```

In [65]:
```
annv1_dense_grp
```

Out[65]:

	Positive	Dense_grp	positive_pt
0	12.0	Dense1	-2.434070
1	27.0	Dense1	-2.135350
2	33.0	Dense1	-2.059129
3	35.0	Dense1	-2.036642
4	38.0	Dense1	-2.005114
...	...	...	...
3971	116498.0	Dense4	1.376988
3972	119578.0	Dense4	1.388798
3973	122753.0	Dense4	1.400664
3974	132364.0	Dense4	1.434825
3975	135596.0	Dense4	1.445767

3976 rows × 3 columns

In [66]:
```
## Creating 4 different dataframes of the density groups
pt_dense_grp1 = pd.DataFrame(annv1_dense_grp[annv1_dense_grp['Dense_grp']=='Dense1']
```

```
pt_dense_grp2 = pd.DataFrame(annv1_dense_grp[annv1_dense_grp['Dense_grp']=='Dense2']
pt_dense_grp3 = pd.DataFrame(annv1_dense_grp[annv1_dense_grp['Dense_grp']=='Dense3']
pt_dense_grp4 = pd.DataFrame(annv1_dense_grp[annv1_dense_grp['Dense_grp']=='Dense4']
pt_dense_grp5 = pd.DataFrame(annv1_dense_grp[annv1_dense_grp['Dense_grp']=='Dense5']
```

Check if any NAN's exist post Power Transformation

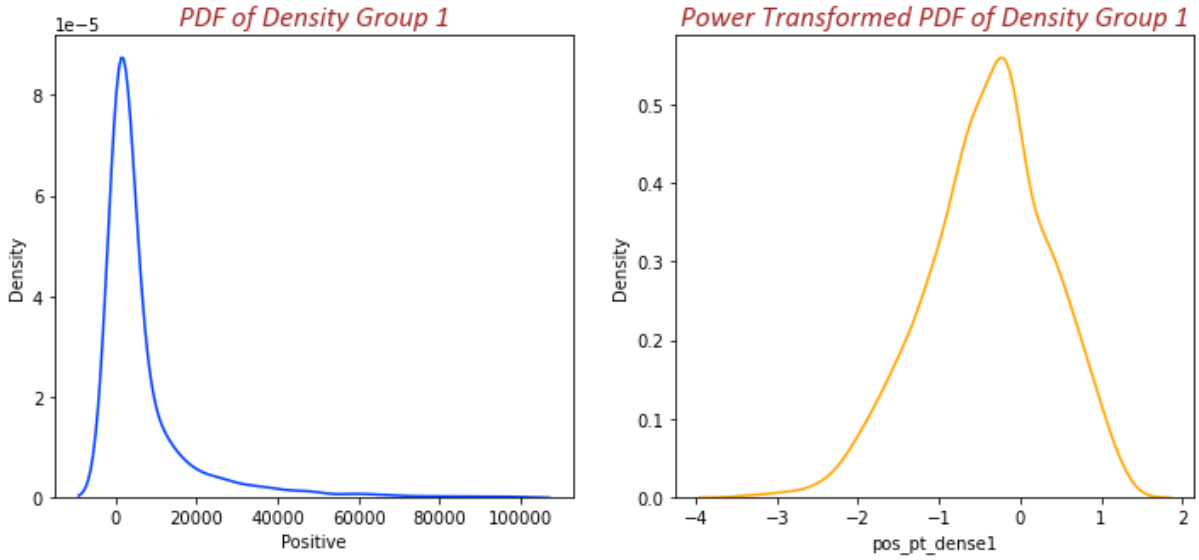
In [67]:
```
pd.DataFrame({'Grp1':[pt_dense_grp1['pos_pt_dense1'].isna().sum()],
              'Grp2':[pt_dense_grp2['pos_pt_dense2'].isna().sum()],
              'Grp3':[pt_dense_grp3['pos_pt_dense3'].isna().sum()],
              'Grp4':[pt_dense_grp4['pos_pt_dense4'].isna().sum()],
              'Grp5':[pt_dense_grp5['pos_pt_dense5'].isna().sum()]})
```

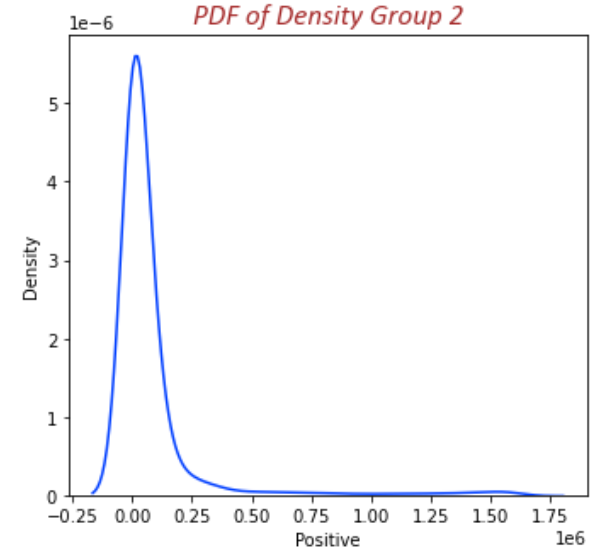
Out[67]:

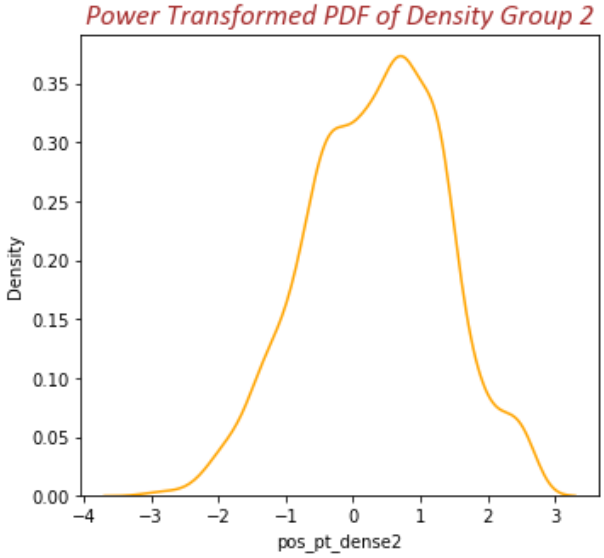
	Grp1	Grp2	Grp3	Grp4	Grp5
0	0	0	0	0	0

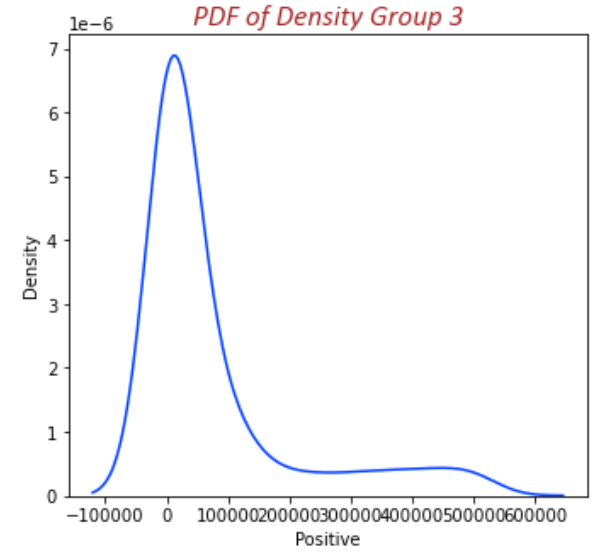
In [68]:
```
## Plotting pre and post power-transformed groups distributions
print(colored("Plotting Pre and Post Transformed distributions of groups","green","o
with plt.style.context('seaborn-bright'):
    fig , ax = plt.subplots(nrows=5,ncols=2,figsize=(12,29))
    sns.kdeplot(annv1_dense_grp[annv1_dense_grp['Dense_grp']=='Dense1']['Positive'],
    sns.kdeplot(pt_dense_grp1['pos_pt_dense1'],ax=ax[0,1],label='Power Trans Grp-1',
    ax[0,0].set_title('PDF of Density Group 1',fontdict=font_dicts(kind='title'))
    ax[0,1].set_title('Power Transformed PDF of Density Group 1',fontdict=font_dicts

    sns.kdeplot(annv1_dense_grp[annv1_dense_grp['Dense_grp']=='Dense2']['Positive'],
    sns.kdeplot(pt_dense_grp2['pos_pt_dense2'],ax=ax[1,1],label='Power Trans Grp-2',
    ax[1,0].set_title('PDF of Density Group 2',fontdict=font_dicts(kind='title'))
    ax[1,1].set_title('Power Transformed PDF of Density Group 2',fontdict=font_dicts

    sns.kdeplot(annv1_dense_grp[annv1_dense_grp['Dense_grp']=='Dense3']['Positive'],
    sns.kdeplot(pt_dense_grp3['pos_pt_dense3'],ax=ax[2,1],label='Power Trans Grp-3',
    ax[2,0].set_title('PDF of Density Group 3',fontdict=font_dicts(kind='title'))
    ax[2,1].set_title('Power Transformed PDF of Density Group 3',fontdict=font_dicts

    sns.kdeplot(annv1_dense_grp[annv1_dense_grp['Dense_grp']=='Dense4']['Positive'],
    sns.kdeplot(pt_dense_grp4['pos_pt_dense4'],ax=ax[3,1],label='Power Trans Grp-4',
    ax[3,0].set_title('PDF of Density Group 4',fontdict=font_dicts(kind='title'))
    ax[3,1].set_title('Power Transformed PDF of Density Group 4',fontdict=font_dicts

    sns.kdeplot(annv1_dense_grp[annv1_dense_grp['Dense_grp']=='Dense5']['Positive'],
    sns.kdeplot(pt_dense_grp5['pos_pt_dense5'],ax=ax[4,1],label='Power Trans Grp-5',
    ax[4,0].set_title('PDF of Density Group 5',fontdict=font_dicts(kind='title'))
    ax[4,1].set_title('Power Transformed PDF of Density Group 5',fontdict=font_dicts
```

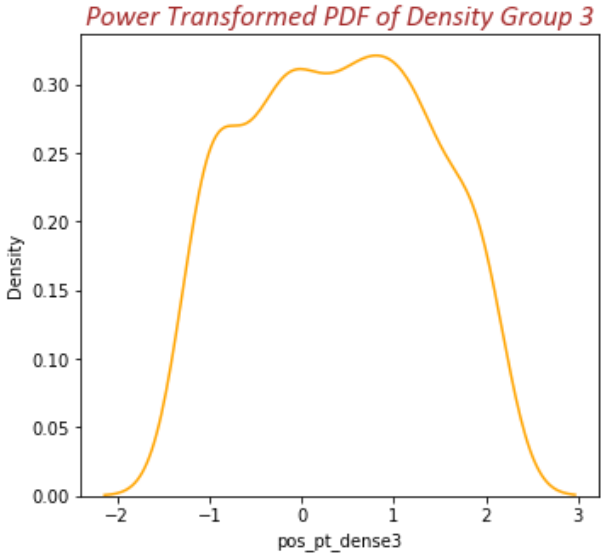
```
Plotting Pre and Post Transformed distributions of groups
```

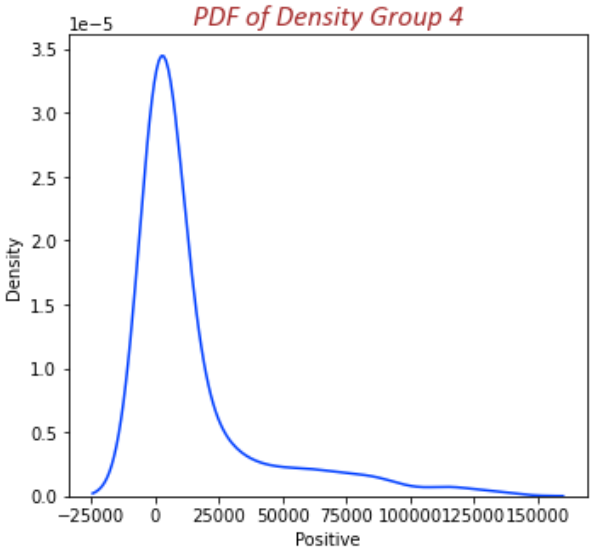


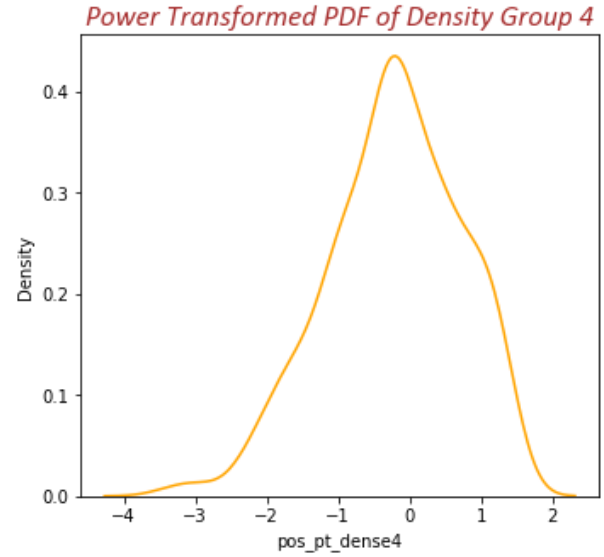

PDF of Density Group 2
1e−6
Density
Positive
1e6

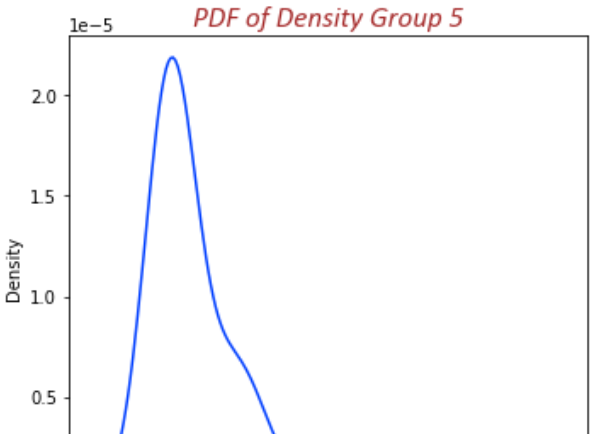

Power Transformed PDF of Density Group 2
Density
pos_pt_dense2

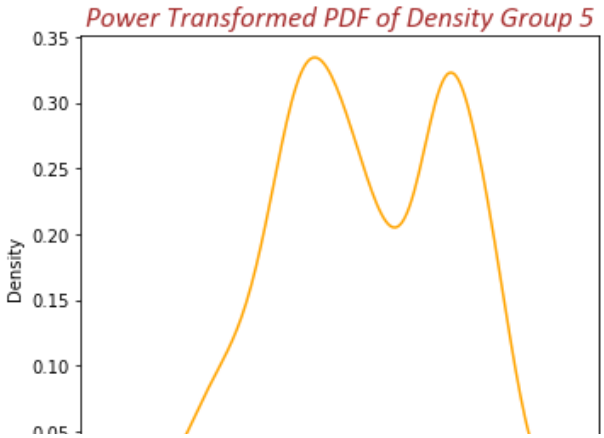

PDF of Density Group 3
1e−6
Density
Positive


Power Transformed PDF of Density Group 3
Density
pos_pt_dense3


PDF of Density Group 4
1e−5
Density
Positive


Power Transformed PDF of Density Group 4
Density
pos_pt_dense4


PDF of Density Group 5
1e−5
Density


Power Transformed PDF of Density Group 5
Density

- **`Group3` and `Group5` are clearly the non-normals even after applying the power transformation.**
- **However, power transformed `Group1` and `Group4` are the closest enough to be put in the bucket of normal distributions.**
- **And, `Group2` has some deviations but can be fit into the normal distribution.**

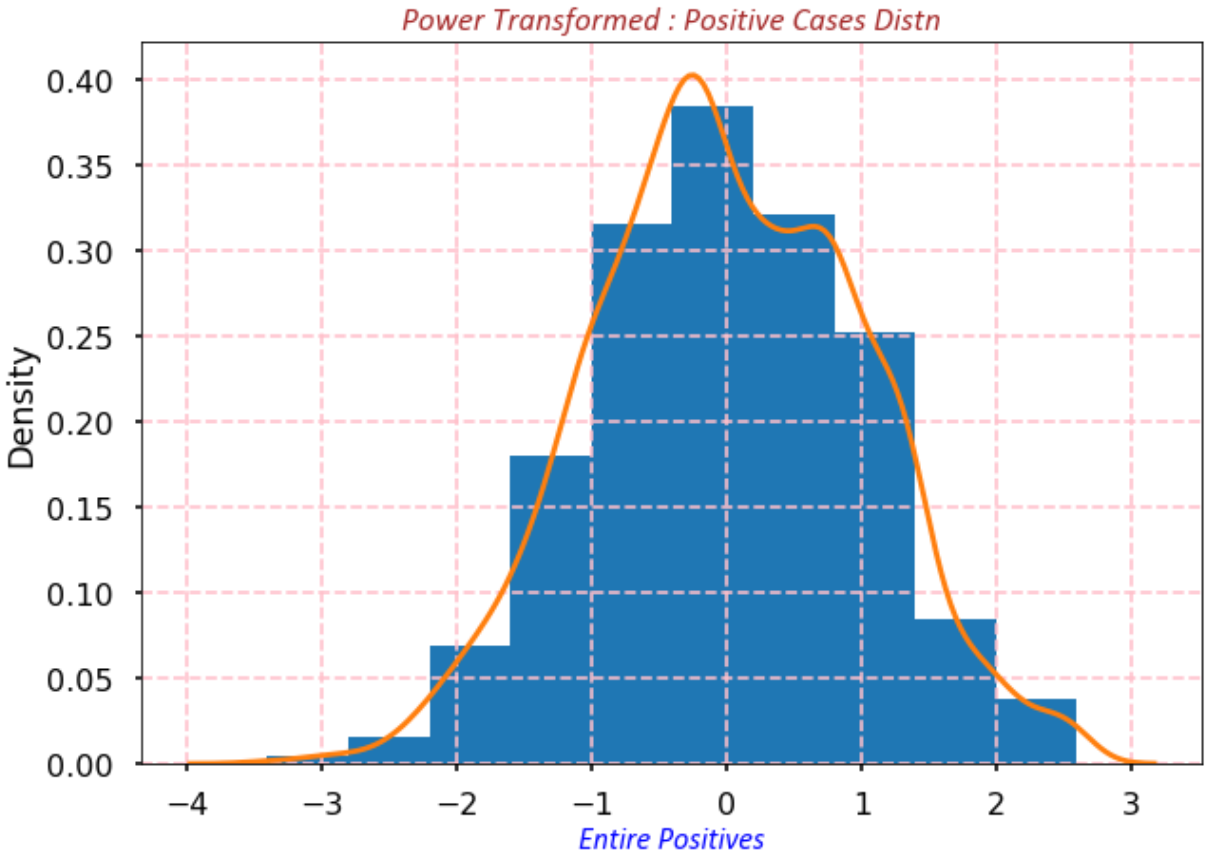
In [69]:
```
all_states_pt_pos = pd.DataFrame(pd.concat([pt_dense_grp1['pos_pt_dense1'],
                                pt_dense_grp2['pos_pt_dense2'],
                                pt_dense_grp3['pos_pt_dense3'],
                                pt_dense_grp4['pos_pt_dense4'],
                                pt_dense_grp5['pos_pt_dense5']],axis=0),columns=['pos

all_states_pt_pos['positive_pt']
```

Out[69]:
```
0      -2.434070
1      -2.135350
2      -2.059129
3      -2.036642
4      -2.005114
          ...
2997    0.901550
2998    0.902276
2999    0.903100
3000    0.903626
3001    0.903900
Name: positive_pt, Length: 3976, dtype: float64
```

In [70]:
```
all_states_pt_pos['positive_pt'].isna().sum()
```

Out[70]:
```
0
```

In [71]:
```
with plt.style.context('seaborn-poster'):
    plt.figure(figsize=(10,7))
    plt.hist(all_states_pt_pos['positive_pt'] ,density=True)
    sns.kdeplot(data=all_states_pt_pos['positive_pt'],bw_method='scott',bw_adjust=1)
    ## `bw_method` should be 'scott', 'silverman', a scalar or a callable
    ## increasing `bw_adjust` will make the curve smoother
    plt.title("Power Transformed : Positive Cases Distn",fontdict=font_dicts(kind='t
    plt.grid(which='major',linestyle='--',color='pink')
    plt.xlabel("Entire Positives",fontdict=font_dicts(kind='xlabel'))
```



Here, it is not a perfect Gaussian or Normal Bell Curve and despite having some deviations on both the tails, overall we can say that it is a normal distribution.

In [72]:
```
scipy.stats.skew(all_states_pt_pos['positive_pt'],bias=False)
```

Out[72]:
```
-0.003036158234518849
```

In [73]:
```
scipy.stats.skewtest(all_states_pt_pos['positive_pt'])
```

Out[73]:
```
SkewtestResult(statistic=-0.07827477685213896, pvalue=0.9376094810463458)
```

No such skewness in the power transformed 'Positive'

In [74]:
```
scipy.stats.kurtosis(all_states_pt_pos['positive_pt'],bias=False)
```

Out[74]:
```
-0.23000557248373132
```

In [75]:
```
scipy.stats.kurtosistest(all_states_pt_pos['positive_pt'])
```

Out[75]:
```
KurtosistestResult(statistic=-3.3224770370815593, pvalue=0.0008922201469807335)
```

We have negative kurtosis that means the tails are lighter than the normal distribution. But, the degree of lightness is not super high as kurtosis is -0.23.

Let's Run some `Normality Tests` on the entire Power Transformed 'Positive' feature

Shapiro-Wilk Test

In [76]:
```
all_states_pt_pos['positive_pt'].shape
```

Out[76]:
```
(3976,)
```

In [77]:
```
scipy.stats.shapiro(all_states_pt_pos['positive_pt'])
```

Out[77]:
```
ShapiroResult(statistic=0.9976674318313599, pvalue=9.815064004214946e-06)
```

The number of records are 4000 therefore, we can run Shapiro-Wilk test because it works pretty well with the record size less than 5K. And, the p-value is highly significant that suggests that it doesn't follow the normal distribution.

Anderson-Darling Test

In [78]:
```
scipy.stats.anderson(all_states_pt_pos['positive_pt'])
```

Out[78]:
```
AndersonResult(statistic=2.652252075263732, critical_values=array([0.575, 0.655, 0.7
86, 0.917, 1.091]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
```

Anderson-Darling test is the much improved version of KS test and it eliminates the major limitation of sensitivity near the center of the distribution than at the tails. Here, we are 99% confident that it doesn't belongs to a normal distribution.

D-Agostino Test

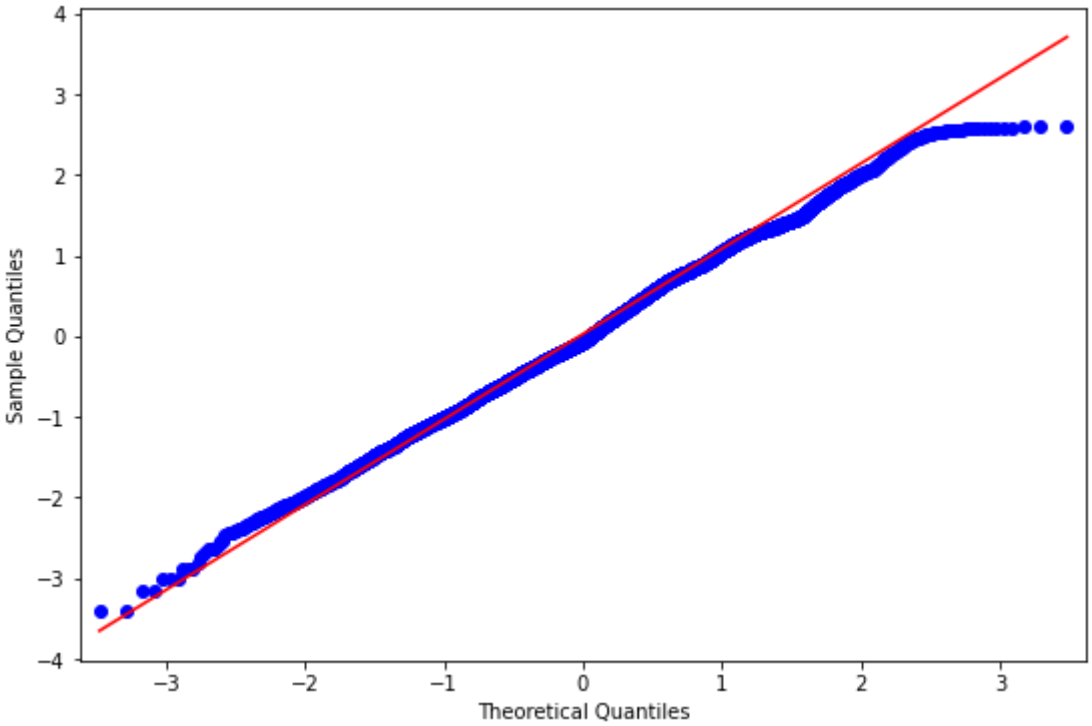
In [79]:
```
scipy.stats.normaltest(all_states_pt_pos['positive_pt'])
```

Out[79]:
```
NormaltestResult(statistic=11.04498060262551, pvalue=0.003995884584731554)
```

Anderson-Darling and Agostino both are powerful normality tests and gives us the highly significant results.

QQ Plot

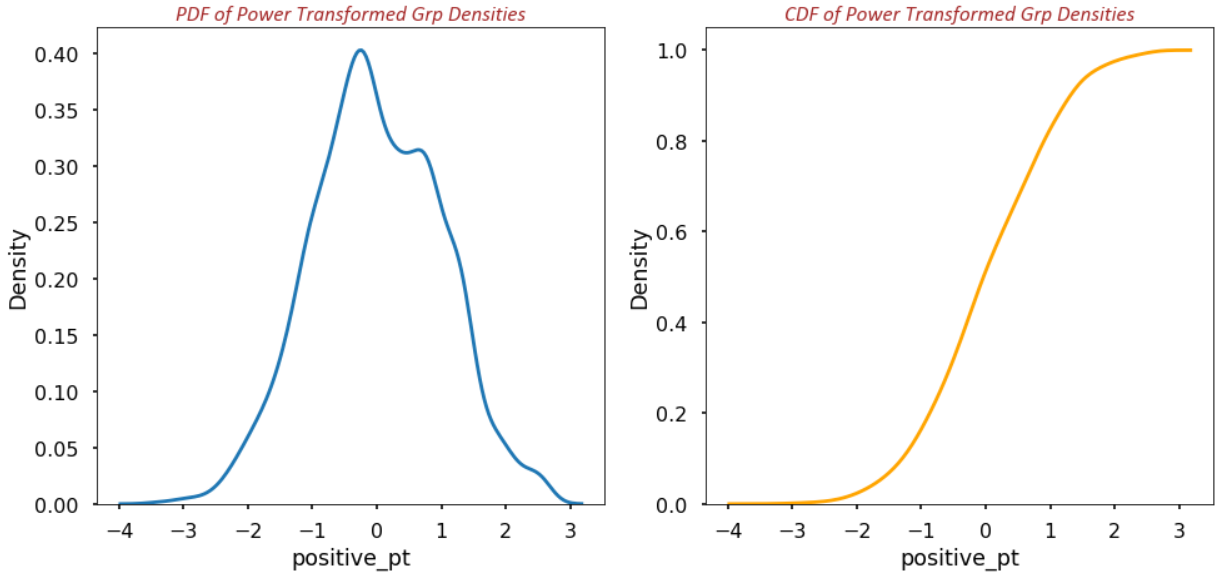
In [80]:
```
with plt.style.context('seaborn-bright'):
    fig, ax = plt.subplots(nrows=1,ncols=1,figsize=(9,6))
    stm.graphics.gofplots.qqplot(all_states_pt_pos['positive_pt'],ax=ax,line='q')
```



Majority of the points are following the straight line with some deviations at the ends. Ideally, all the points should fall on this straight line. Therefore, we can say that it doesn't belong to a normal distribution.

In [81]:
```
with plt.style.context('seaborn-poster'):
    fig, ax = plt.subplots(nrows=1,ncols=2,figsize=(16,7))
    sns.kdeplot(all_states_pt_pos['positive_pt'],label='Kde',ax=ax[0],bw_method='sco
    ax[0].set_title('PDF of Power Transformed Grp Densities',fontdict=font_dicts(kin
    sns.kdeplot(all_states_pt_pos['positive_pt'],cumulative=True,bw_method='scott',b
```

```
    ax[1].set_title('CDF of Power Transformed Grp Densities',fontdict=font_dicts(kin
    plt.show()
```



Although Normality tests have given us highly statistically significant results but graphically(QQ, KDE and CDF plots) speaking it is not be a perfect gaussian like distribution but a slight non-normal data can be put in the bucket of normal distributions.

- **Because nothing can be completely normal and when the data or observations increases normaliity tests gives everything as significant means non-normal.**
- **Majority of the time Scientists also consider slightly non-normal data as normal.**
- **we can move away from Normality assumption either using Resampling/bootstrapping or non-parametric tests.**

Reference Links

https://stats.stackexchange.com/questions/284033/qq-plot-looks-normal-but-shapiro-wilk-test-says-otherwise

https://stats.stackexchange.com/questions/2492/is-normality-testing-essentially-useless

https://stats.stackexchange.com/questions/99621/should-the-shapiro-wilk-test-and-qq-plot-always-be-combined/99622#99622

Lillifers Test

In [82]:
```
np.round(np.mean(all_states_pt_pos['positive_pt']),3), np.round(np.std(all_states_pt
```

Out[82]: (-0.0, 1.0)

In [83]:
```
## It is a Kolmogorov-Smirnov Test with estimated parameters
## That means we can use this test even when we don't know the mean and stddev of th
## It will estimate the parameters from the sample
## Both lillifers and KS Test performs the test statistics calculation using the sam
## the test statistics of both the tests as it is same
lilliefors(all_states_pt_pos['positive_pt'],dist='norm',pvalmethod='table')
```

Out[83]: (0.025661731372888796, 0.0009999999999998899)

Kolmogorov Smirnov Test

In [84]:
```
np.round(np.mean(all_states_pt_pos['positive_pt']),3), np.round(np.std(all_states_pt
```

Out[84]: (-0.0, 1.0)

In [85]:
```
scipy.stats.kstest(all_states_pt_pos['positive_pt'],cdf='norm',mode='auto')
```

Out[85]: KstestResult(statistic=0.025663976892299267, pvalue=0.010441759115162142)

Both Lillifers and KS tests have suggested that distribution is not like a gaussian distribution.

Majority of the tests have suggested that it's not following a normal distribution.

Will also conduct tests related to ANOVA assumptions, model residuals, homogenity(equal variances among the groups).

Let's first perform the ANOVA test for verifying the difference in means then perform the Non-parametric Kruskal-Wallis test.

`Running One-Way ANOVA`

$$\begin{align} H_{0} : \mu_{1} = \mu_{2} = \mu_{3} = \mu_{4} = \mu_{5} \\ H_{A} : \mu_{1} != \mu_{2} != \mu_{3} != \mu_{4} != \mu_{5} \end{align}$$

In [86]:
```
scipy.stats.f_oneway(pt_dense_grp1['pos_pt_dense1'],
                     pt_dense_grp2['pos_pt_dense2'],
                     pt_dense_grp3['pos_pt_dense3'],
                     pt_dense_grp4['pos_pt_dense4'],
                     pt_dense_grp5['pos_pt_dense5'])
```

Out[86]: F_onewayResult(statistic=137.43244292966435, pvalue=3.834952237442604e-110)

As, we know that ANOVA performs F-test under the hood thus by just performing the F test 1-Way we can compute the test statistic and p-value.

- **Here, p-value is highly significant which means groups have different means.**

In [87]:
```
grp_pos_cases = pd.DataFrame({'Dense1':pt_dense_grp1['pos_pt_dense1'],
                              'Dense2':pt_dense_grp2['pos_pt_dense2'],
                              'Dense3':pt_dense_grp3['pos_pt_dense3'],
                              'Dense4':pt_dense_grp4['pos_pt_dense4'],
                              'Dense5':pt_dense_grp5['pos_pt_dense5']})
```

In [88]:
```
grp_pos_cases
```

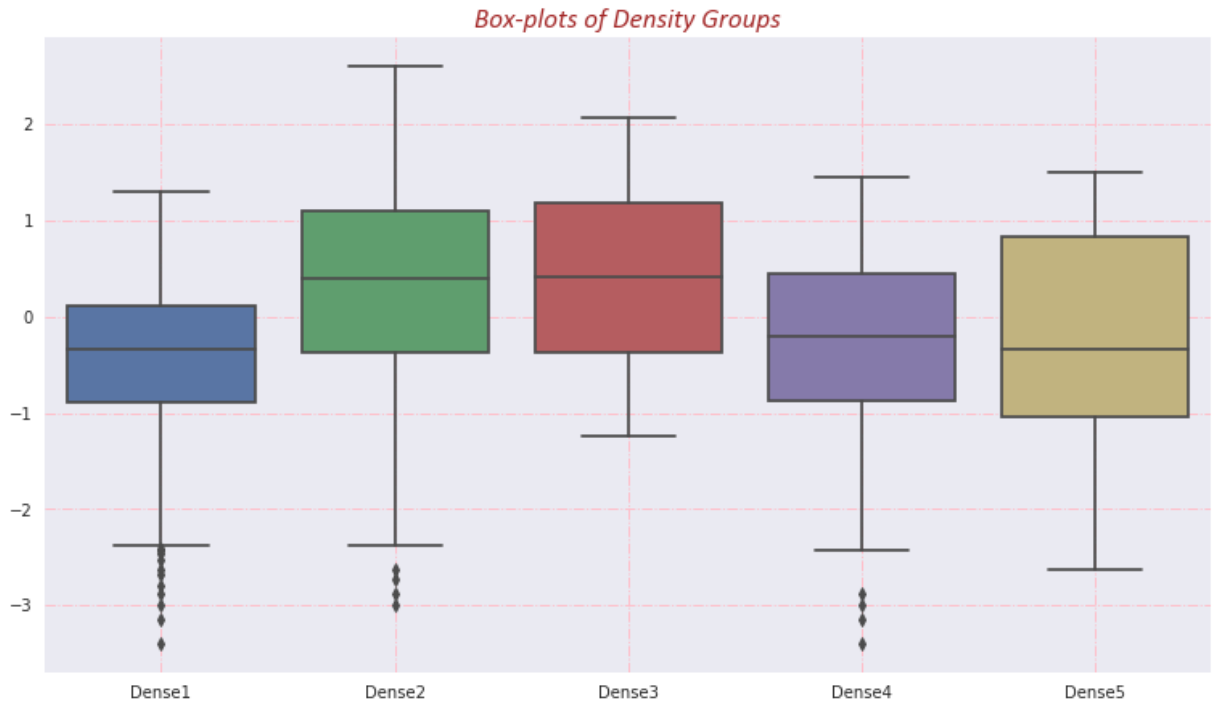
Out[88]:

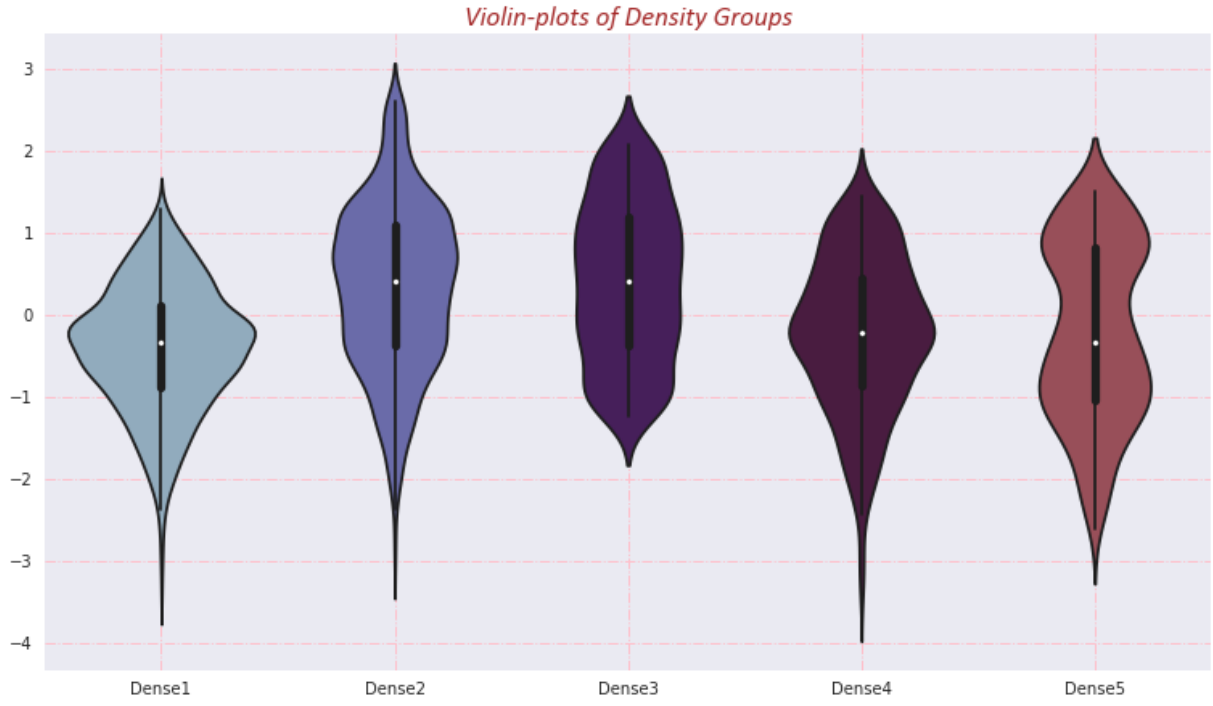
	Dense1	Dense2	Dense3	Dense4	Dense5
0	-2.434070	NaN	NaN	NaN	NaN
1	-2.135350	NaN	NaN	NaN	NaN
2	-2.059129	NaN	NaN	NaN	NaN
3	-2.036642	NaN	NaN	NaN	NaN
4	-2.005114	NaN	NaN	NaN	NaN
...	...	...	...	...	...
3971	NaN	NaN	NaN	1.376988	NaN
3972	NaN	NaN	NaN	1.388798	NaN

	Dense1	Dense2	Dense3	Dense4	Dense5
3973	NaN	NaN	NaN	1.400664	NaN
3974	NaN	NaN	NaN	1.434825	NaN
3975	NaN	NaN	NaN	1.445767	NaN

3976 rows × 5 columns

In [89]:
```
with plt.style.context('seaborn'):
    fig, ax = plt.subplots(nrows=2,ncols=1,figsize=(13,16))
    sns.boxplot(data=grp_pos_cases,ax=ax[0])
    ax[0].set_title("Box-plots of Density Groups",fontdict=font_dicts(kind='title'))
    ax[0].grid(which='major',color='pink',linestyle='-.')
    sns.violinplot(data=grp_pos_cases,ax=ax[1],palette=sns.color_palette('twilight')
    ax[1].set_title("Violin-plots of Density Groups",fontdict=font_dicts(kind='title
    ax[1].grid(which='major',color='pink',linestyle='-.')
```





Group2 and Group3 are closer to each other. And, Group1 , Group4 and Group5 are closer to each other.

In [90]:
```
# Prepared the data in the format such that Model can be built
grp_pos_cases_melt = pd.melt(frame=grp_pos_cases.reset_index(),id_vars='index',
                             value_vars=grp_pos_cases.columns,var_name='Dense_Grps',
.dropna().reset_index(drop=True).drop(columns=['index'],axis=1).reset_index()

grp_pos_cases_melt.head(10)
```

Out[90]:

	index	Dense_Grps	Positive
0	0	Dense1	-2.434070
1	1	Dense1	-2.135350
2	2	Dense1	-2.059129

	index	Dense_Grps	Positive
3	3	Dense1	-2.036642
4	4	Dense1	-2.005114
5	5	Dense1	-1.975884
6	6	Dense1	-1.948639
7	7	Dense1	-1.939953
8	8	Dense1	-1.923123
9	9	Dense1	-1.914965

In [91]:
```
# Create the Ordinary Least Squares model
dense_grp_model = ols('Positive ~ C(Dense_Grps)',data=grp_pos_cases_melt).fit()
```

In [92]:
```
# Generating ANOVA table
dense_grp_model_anova_table = anova_lm(dense_grp_model,robust='hc3',typ='I')
dense_grp_model_anova_table
```

Out[92]:

	df	sum_sq	mean_sq	F	PR(>F)
C(Dense_Grps)	4.0	483.489543	120.872386	137.432443	3.834952e-110
Residual	3971.0	3492.510457	0.879504	NaN	NaN

In [93]:
```
dense_grps_f = scipy.stats.f(dense_grp_model_anova_table['df'][0],dense_grp_model_an
dense_grp_model_anova_table['alpha'] = [0.05,None]
dense_grp_model_anova_table['F_crit'] = [dense_grps_f.ppf(0.95),None]
dense_grp_model_anova_table
```

Out[93]:

	df	sum_sq	mean_sq	F	PR(>F)	alpha	F_crit
C(Dense_Grps)	4.0	483.489543	120.872386	137.432443	3.834952e-110	0.05	2.37417
Residual	3971.0	3492.510457	0.879504	NaN	NaN	NaN	NaN

So, here it becomes quite evident that Null Hypothesis has been rejected by a great margin as there is a huge difference in the Critical value and Test Statistic. And, p-value is highly significant, thus, we can say that means of the groups varying alot.

In [94]:
```
dense_grp_model.summary()
```

Out[94]:

OLS Regression Results

Dep. Variable:	Positive	**R-squared:**	0.122
Model:	OLS	**Adj. R-squared:**	0.121
Method:	Least Squares	**F-statistic:**	137.4
Date:	Mon, 26 Apr 2021	**Prob (F-statistic):**	3.83e-110
Time:	16:38:19	**Log-Likelihood:**	-5383.9
No. Observations:	3976	**AIC:**	1.078e+04
Df Residuals:	3971	**BIC:**	1.081e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-0.4036	0.026	-15.373	0.000	-0.455	-0.352
C(Dense_Grps)[T.Dense2]	0.7416	0.035	21.096	0.000	0.673	0.811
C(Dense_Grps)[T.Dense3]	0.8035	0.057	14.088	0.000	0.692	0.915
C(Dense_Grps)[T.Dense4]	0.1729	0.056	3.103	0.002	0.064	0.282
C(Dense_Grps)[T.Dense5]	0.1897	0.055	3.476	0.001	0.083	0.297

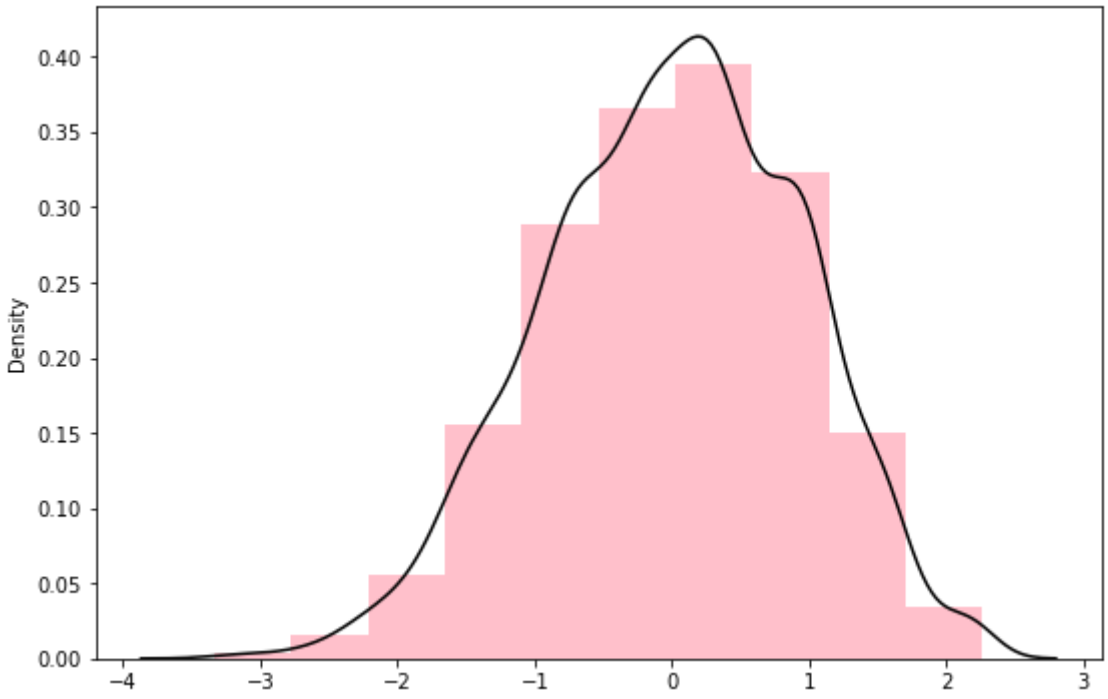
Omnibus:	40.304	**Durbin-Watson:**	0.094
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	37.461
Skew:	-0.199	**Prob(JB):**	7.34e-09
Kurtosis:	2.741	**Cond. No.**	5.40

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

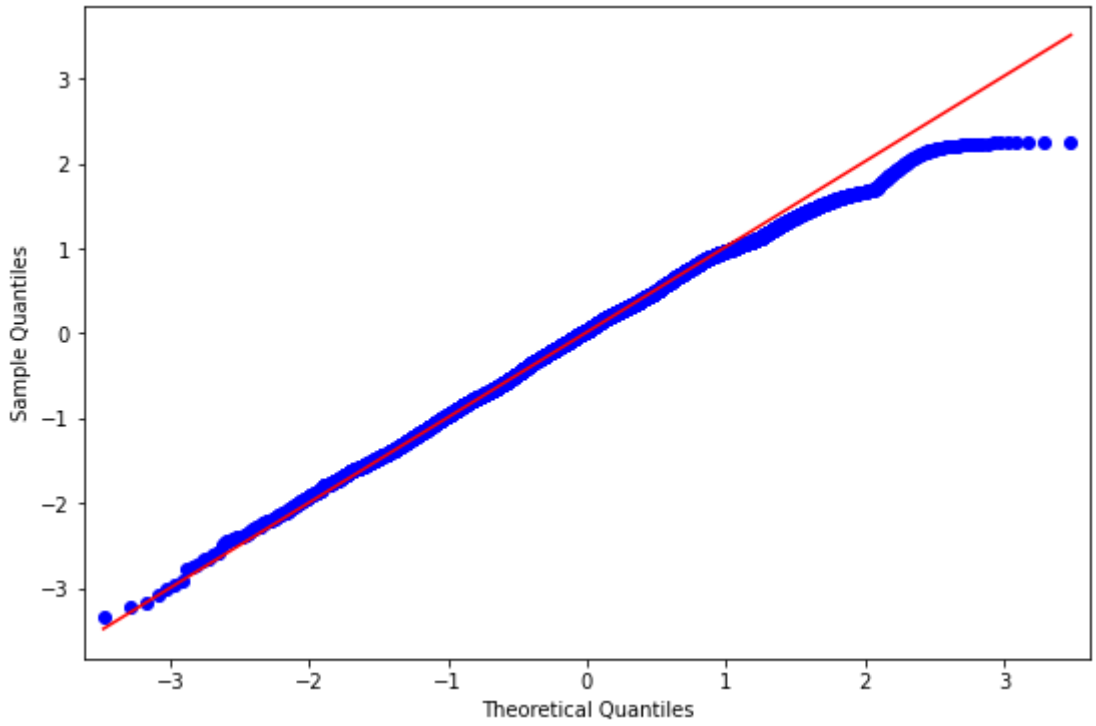
In [95]:
```
dense_grp_resid = dense_grp_model.resid
```

In [96]:
```
with plt.style.context('seaborn-bright'):
    fig, ax = plt.subplots(nrows=1,ncols=1,figsize=(9,6))
    plt.hist(dense_grp_resid,density=True,color='pink')
    sns.kdeplot(dense_grp_resid,ax=ax,color='black')
```



The first gave me a feeling of normal like distribution which has a non-smooth curve with some skewness on the left tail.

In [97]:
```
with plt.style.context('seaborn-bright'):
    fig, ax = plt.subplots(nrows=1,ncols=1,figsize=(9,6))
    stm.graphics.gofplots.qqplot(dense_grp_resid,ax=ax,line='q')
```



Deviations are quite evident at the upper end of the curve. So, we cannot say that the residuals are normal.

Post-Hoc Tukey's HSD Test

In [98]:
```
# It performs the pair wise comparison and uses q-distribution
post_hoc_results = tukeyhsd(grp_pos_cases_melt['Positive'],groups=grp_pos_cases_melt
```

In [99]:
```
post_hoc_results.summary()
```

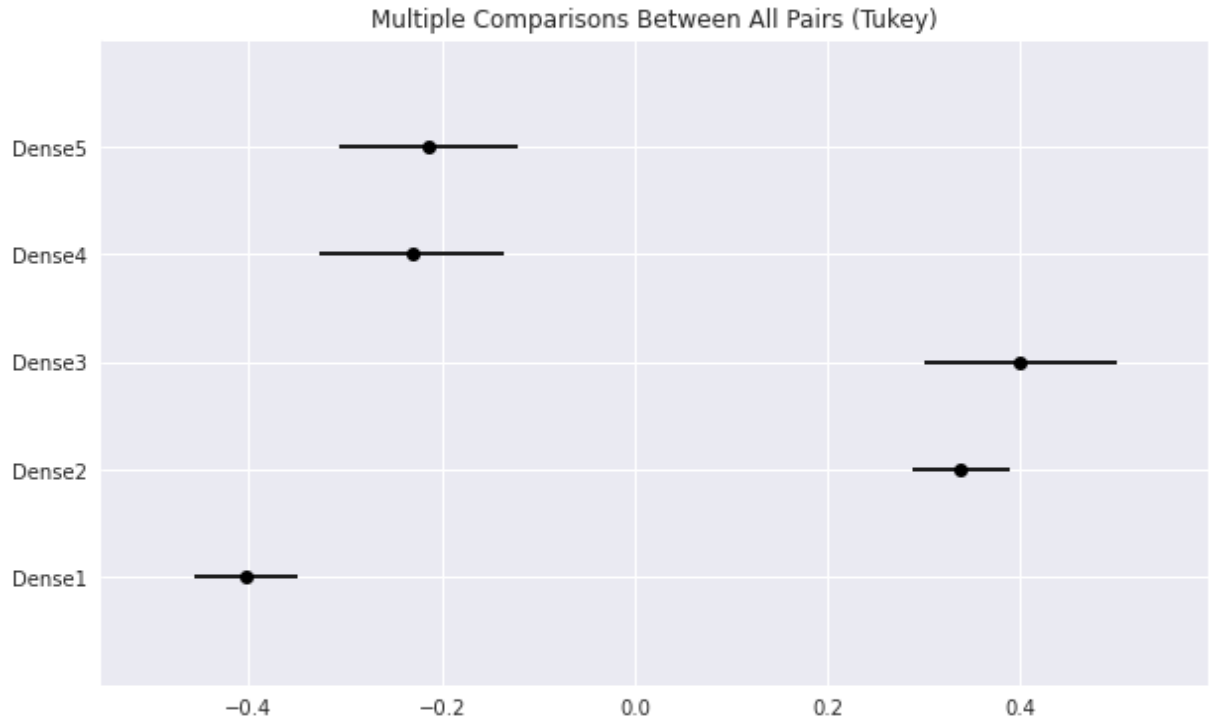
Out[99]:

Multiple Comparison of Means - Tukey HSD, FWER=0.05

group1	group2	meandiff	p-adj	lower	upper	reject
Dense1	Dense2	0.7416	0.001	0.6457	0.8376	True
Dense1	Dense3	0.8035	0.001	0.6479	0.9592	True
Dense1	Dense4	0.1729	0.0165	0.0208	0.325	True
Dense1	Dense5	0.1897	0.0047	0.0408	0.3387	True
Dense2	Dense3	0.0619	0.7752	-0.0903	0.2141	False
Dense2	Dense4	-0.5687	0.001	-0.7172	-0.4202	True
Dense2	Dense5	-0.5519	0.001	-0.6972	-0.4065	True
Dense3	Dense4	-0.6306	0.001	-0.8232	-0.438	True
Dense3	Dense5	-0.6138	0.001	-0.8039	-0.4237	True
Dense4	Dense5	0.0168	0.9	-0.1704	0.204	False

In [100…
```
with plt.style.context('seaborn'):
    post_hoc_results.plot_simultaneous()
```

```
c:\users\rajsh\appdata\local\programs\python\python36\lib\site-packages\statsmodels
\sandbox\stats\multicomp.py:775: UserWarning: FixedFormatter should only be used tog
ether with FixedLocator
  ax1.set_yticklabels(np.insert(self.groupsunique.astype(str), 0, ''))
```



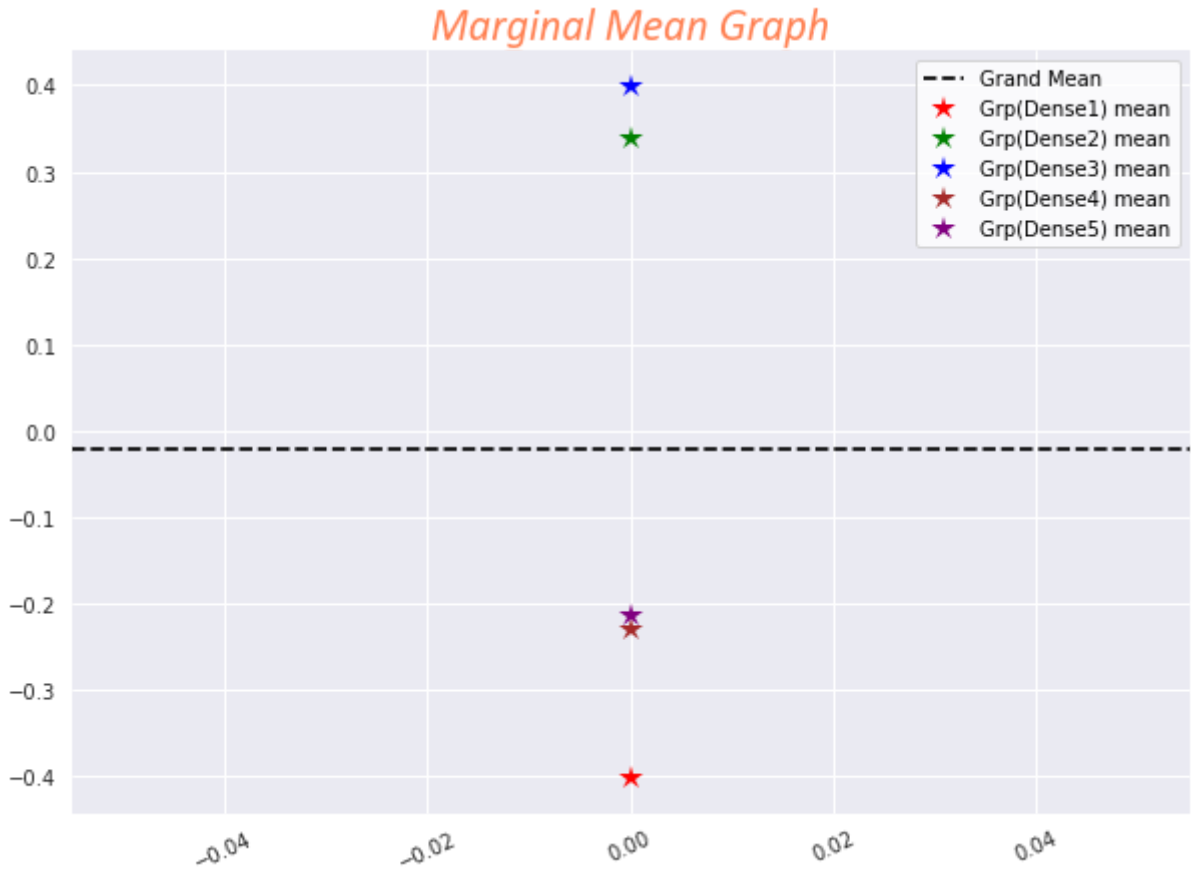
In [101…
```
dense_grps_grand_mean = np.mean(grp_pos_cases.describe().loc['mean'])
```

In [102…
```
def marginal_row_mean_plot(df,grand_mean,row1=False,row2=False,row3=False,row4=False
    """
    Description: This function is created for plotting the marginal mean graph of a

    Input parameter:
        1. df : DataFrame having treatment or group data
        2. grand_mean : Overall mean of groups or str
        3. row1 : Row or Block 1 or str
        4. row2 : Row or Block 2 or str
        5. row3 : Row or Block 3 or str
        6. row4 : Row or Block 4 or str
        7. row5 : Row or Block 5 or str
        8. row6 : Row or Block 6 or str

    Output: Generate the Marginal Mean Graph

    Work-in-progress :: These two marginal mean plot functions to be combined in one
    """
    plt.figure(figsize=(10,7))
    with plt.style.context("seaborn"):
        plt.axhline(grand_mean,linestyle='--',color='black',label='Grand Mean')
        if row1 != False:
            plt.plot(df[row1][0],marker='>',ls='',ms=12,color='pink',label='Row/Bloc
        if row2 != False:
            plt.plot(df[row2][1],marker='>',ls='',ms=12,color='gray',label='Row/Bloc
        if row3 != False:
            plt.plot(df[row3][2],marker='>',ls='',ms=12,color='yellow',label='Row/Bl
        if row4 != False:
            plt.plot(df[row4][3],marker='>',ls='',ms=12,color='skyblue',label='Row/B
        if row5 != False:
            plt.plot(df[row5][4],marker='>',ls='',ms=12,color='lightgray',label='Row
        if row6 != False:
            plt.plot(df[row6][5],marker='>',ls='',ms=12,color='orange',label='Row/Bl
        plt.xticks(rotation=25)
        plt.title('Marginal Mean Graph of Blocks or Rows',fontdict={'size':20, 'fami
    plt.legend()
    return None
```

```
def marginal_mean_plot(df,grand_mean,grp1,grp2,grp3=False,grp4=False,grp5=False,grp6
                       row_graph_flg=False,row1=False,row2=False,row3=False,row4=Fal
    """
    Description: This function is created for plotting the marginal mean graph of a

    Input parameter:
        1. df : DataFrame having treatment or group data
        2. grand_mean : Overall mean of groups or str
        3. grp1 : Column or Treatment 1 or str
        4. grp2 : Column or Treatment 2 or str
        5. grp3 : Column or Treatment 3 or str
        6. grp4 : Column or Treatment 4 or str
        7. grp5 : Column or Treatment 5 or str
        8. grp6 : Column or Treatment 6 or str

    Output: Generate the Marginal Mean Graphs
    """
    plt.figure(figsize=(10,7))
    with plt.style.context("seaborn"):
        plt.axhline(grand_mean,linestyle='--',color='black',label='Grand Mean')
        plt.plot(np.mean(df[~df[grp1].isna()][grp1]),marker='*',ls='',ms=12,color='r
        plt.plot(np.mean(df[~df[grp2].isna()][grp2]),marker='*',ls='',ms=12,color='g
        if grp3 != False:
            plt.plot(np.mean(df[~df[grp3].isna()][grp3]),marker='*',ls='',ms=12,colo
        if grp4 != False:
            plt.plot(np.mean(df[~df[grp4].isna()][grp4]),marker='*',ls='',ms=12,colo
        if grp5 != False:
            plt.plot(np.mean(df[~df[grp5].isna()][grp5]),marker='*',ls='',ms=12,colo
        if grp6 != False:
            plt.plot(np.mean(df[~df[grp6].isna()][grp6]),marker='*',ls='',ms=12,colo
        plt.xticks(rotation=25)
        plt.title('Marginal Mean Graph',fontdict={'size':22, 'family':'calibri', 'co
    plt.legend()

    if row_graph_flg!=False:
        marginal_row_mean_plot(df=df,grand_mean=grand_mean,row1=row1,row2=row2,row3=
    return None
```

In [103…

```
marginal_mean_plot(grp_pos_cases,dense_grps_grand_mean,
                   grp1='Dense1',
                   grp2='Dense2',
                   grp3='Dense3',
                   grp4='Dense4',
                   grp5='Dense5')
```



Here, its also been proved that Grp4 and Grp5 have closer means.

Normlity Tests on Model Residuals

In [104...
```
scipy.stats.anderson(dense_grp_resid)
```

Out[104...
```
AndersonResult(statistic=3.9950042327282063, critical_values=array([0.575, 0.655, 0.
786, 0.917, 1.091]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
```

In [105...
```
scipy.stats.normaltest(dense_grp_resid)
```

Out[105...
```
NormaltestResult(statistic=40.30410635651301, pvalue=1.7704126565201233e-09)
```

In [106...
```
lilliefors(dense_grp_resid)
```

Out[106...
```
(0.02237560488258883, 0.0009999999999998899)
```

In [107...
```
scipy.stats.kstest(dense_grp_resid,cdf='norm')
```

Out[107...
```
KstestResult(statistic=0.025651036031644425, pvalue=0.01049714753962541)
```

So, clearly the residuals are non-normal.

Homogenity Tests

In [108...
```
scipy.stats.bartlett(grp_pos_cases[~grp_pos_cases['Dense1'].isna()]['Dense1'],
                     grp_pos_cases[~grp_pos_cases['Dense2'].isna()]['Dense2'],
                     grp_pos_cases[~grp_pos_cases['Dense3'].isna()]['Dense3'],
                     grp_pos_cases[~grp_pos_cases['Dense4'].isna()]['Dense4'],
                     grp_pos_cases[~grp_pos_cases['Dense5'].isna()]['Dense5'])
```

Out[108...
```
BartlettResult(statistic=130.2137139048428, pvalue=3.505078917545573e-27)
```

Parametric Levene Test

In [109…
```
scipy.stats.levene(grp_pos_cases[~grp_pos_cases['Dense1'].isna()]['Dense1'],
                   grp_pos_cases[~grp_pos_cases['Dense2'].isna()]['Dense2'],
                   grp_pos_cases[~grp_pos_cases['Dense3'].isna()]['Dense3'],
                   grp_pos_cases[~grp_pos_cases['Dense4'].isna()]['Dense4'],
                   grp_pos_cases[~grp_pos_cases['Dense5'].isna()]['Dense5'],center
```

Out[109…
```
LeveneResult(statistic=43.88995730432964, pvalue=4.2273834535615835e-36)
```

All the above tests concludes that Density Groups have a significant role in the variantion of number of cases reported in the states.

Now, there is one important point that in the earlier plotting we found that our data doesn't belongs to a normal distribution which is one of the ANOVA assumptions. And, the variances of data are also not equal across the groups. Therefore, we will conduct the Non-parametric tests.

Non-parametric replacement of ANOVA is `Kruskal-Wallis` Test

In [110…
```
scipy.stats.kruskal(pt_dense_grp1['pos_pt_dense1'],
                    pt_dense_grp2['pos_pt_dense2'],
                    pt_dense_grp3['pos_pt_dense3'],
                    pt_dense_grp4['pos_pt_dense4'],
                    pt_dense_grp5['pos_pt_dense5'])
```

Out[110…
```
KruskalResult(statistic=465.62372045417294, pvalue=1.819534601931187e-99)
```

Post-Hoc -- MannWhitney Test with no correction of alpha

In [111…
```
pd.DataFrame(post_hocs.posthoc_mannwhitney(grp_pos_cases_melt[['Dense_Grps','Positiv
                                                               val_col='Positive',
                                                               group_col='Dense_Grps')).applymap(l
```

Out[111…

	Dense1	Dense2	Dense3	Dense4	Dense5
Dense1	1.00000	0.00000	0.00000	0.00027	0.00360
Dense2	0.00000	1.00000	0.43591	0.00000	0.00000
Dense3	0.00000	0.43591	1.00000	0.00000	0.00000
Dense4	0.00027	0.00000	0.00000	1.00000	0.99716
Dense5	0.00360	0.00000	0.00000	0.99716	1.00000

Quite similar results here too, Grp4 and Grp5 tends to have some similarities. But, `Group2` and `Group3` are not so similar as per the MannWhitney Test.

- **Now, to get more precise results I would use `Sidak` correction for alpha as it is a very powerful concept and personally like this concept. ##### NOTE: We can also use Bonferroni Correction but it might be not so accurate some times.**

Post-Hoc -- MannWhitney Test with Sidak correction of alpha

In [112…
```
pd.DataFrame(post_hocs.posthoc_mannwhitney(grp_pos_cases_melt[['Dense_Grps','Positiv
                                                               val_col='Positive',
                                                               group_col='Dense_Grps',
                                                               p_adjust='sidak')).applymap(lambda
```

Out[112…

	Dense1	Dense2	Dense3	Dense4	Dense5
Dense1	1.00000	0.00000	0.00000	0.00274	0.03543
Dense2	0.00000	1.00000	0.99674	0.00000	0.00000

	Dense1	Dense2	Dense3	Dense4	Dense5
Dense3	0.00000	0.99674	1.00000	0.00000	0.00000
Dense4	0.00274	0.00000	0.00000	1.00000	1.00000
Dense5	0.03543	0.00000	0.00000	1.00000	1.00000

`Group4` and `Group5` tends to have some similarities. And, `Group2` and `Group3` are also marked as similar as per the MannWhitney Test with Sidak Correction.

Post-Hoc -- MannWhitney Test with Bonferroni correction of alpha

In [113…
```
pd.DataFrame(post_hocs.posthoc_mannwhitney(grp_pos_cases_melt[['Dense_Grps','Positiv
                                                               val_col='Positive',
                                                               group_col='Dense_Grps',
                                                               p_adjust='bonferroni')).applymap(la
```

Out[113…

	Dense1	Dense2	Dense3	Dense4	Dense5
Dense1	1.00000	0.0	0.0	0.00274	0.036
Dense2	0.00000	1.0	1.0	0.00000	0.000
Dense3	0.00000	1.0	1.0	0.00000	0.000
Dense4	0.00274	0.0	0.0	1.00000	1.000
Dense5	0.03600	0.0	0.0	1.00000	1.000

Results are similar to Sidak Correction.

Non-Parametric Levene Test

In [114…
```
# Levene test is performed for checking the equality of variances. And, a replacemen
scipy.stats.levene(grp_pos_cases[~grp_pos_cases['Dense1'].isna()]['Dense1'],
                   grp_pos_cases[~grp_pos_cases['Dense2'].isna()]['Dense2'],
                   grp_pos_cases[~grp_pos_cases['Dense3'].isna()]['Dense3'],
                   grp_pos_cases[~grp_pos_cases['Dense4'].isna()]['Dense4'],
                   grp_pos_cases[~grp_pos_cases['Dense5'].isna()]['Dense5'],center
```

Out[114…
```
LeveneResult(statistic=42.883650220306166, pvalue=2.844472046993574e-35)
```

Two Factor ANOVA

CASE_STUDY:2

Case study prepared by: Emily Zitek

Overview

- People have different ways of improving their mood when angry. We have all seen people punch a wall when mad, and indeed, previous research has indicated that some people aggress to improve their mood (Bushman, Baumeister & Phillips, 2001). What do the top athletes do when angry? Striegel (1994) found that anger often hurts an athlete's performance and that capability to control anger is what makes good athletes even better. This study adds to the past research and examines the difference in ways to improve an angry mood by gender and sports participation.

- The participants were 78 Rice University undergraduates, ages 17 to 23. Of these 78 participants, 48 were females and 30 were males and 25 were athletes and 53 were non-athletes. People who did not play a varsity or club sport were considered non-athletes. The 13 contact sport athletes played soccer, football, rugby, or basketball, and the 12 non-contact sport athletes participated in Ultimate Frisbee, baseball, tennis, swimming, volleyball, crew, or dance.
- The participants were asked to respond to a questionnaire that asked about what they do to improve their mood when angry or furious. Then they filled out a demographics questionnaire.

- Note: This study used the most recent version of the State-Trait Anger Expression Inventory (STAXI-2) (Spielberger, Sydeman, Owen & Marsh, 1999) which was modified to create an Angry Mood Improvement Inventory similar to that created by Bushman et al. (2001).

Questions to Answer

- Do athletes and non-athletes deal with anger in the same way? Are there any gender differences? Specifically, are men more likely to believe that aggressive behavior can improve an angry mood?

Descriptions of Variables

In [115…
```
anger_mood = pd.read_excel('Datasets/angry_moods.xls')
```

In [116…
```
anger_mood.head()
```

Out[116…

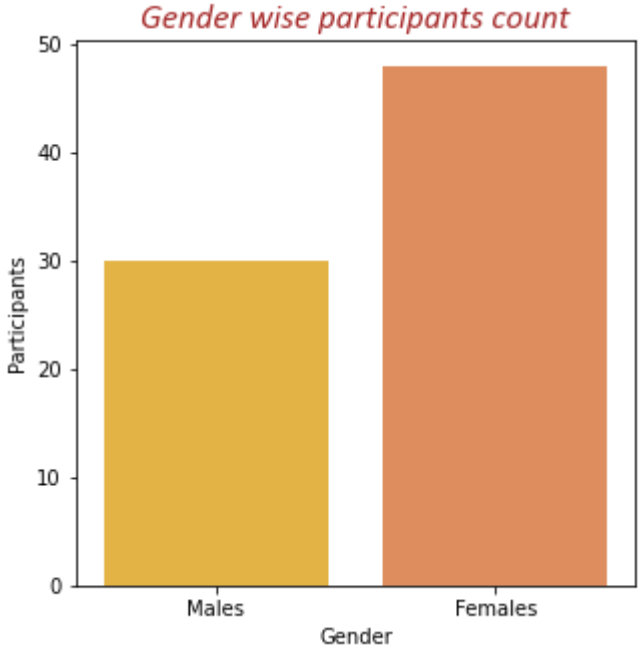
	Gender	Sports	Anger-Out	Anger-In	Control-Out	Control-In	Anger_Expression
0	2	1	18	13	23	20	36
1	2	1	14	17	25	24	30
2	2	1	13	14	28	28	19
3	2	1	17	24	23	23	43
4	1	1	16	17	26	28	27

In [117…
```
anger_mood.describe()
```

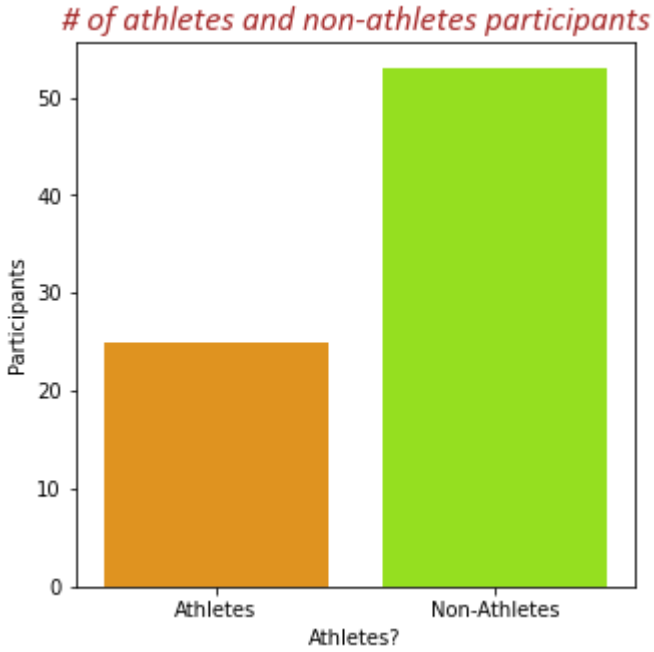
Out[117…

	Gender	Sports	Anger-Out	Anger-In	Control-Out	Control-In	Anger_Expression
count	78.000000	78.000000	78.000000	78.000000	78.000000	78.000000	78.000000
mean	1.615385	1.679487	16.076923	18.576923	23.692308	21.961538	37.000000
std	0.489653	0.469694	4.217370	4.697386	4.688498	4.945002	12.941426
min	1.000000	1.000000	9.000000	10.000000	14.000000	11.000000	7.000000
25%	1.000000	1.000000	13.000000	15.000000	21.000000	18.250000	27.000000
50%	2.000000	2.000000	16.000000	18.500000	24.000000	22.000000	36.000000
75%	2.000000	2.000000	18.000000	22.000000	27.000000	24.750000	44.750000
max	2.000000	2.000000	27.000000	31.000000	32.000000	32.000000	68.000000

In [118…
```
with plt.style.context('seaborn-bright'):
    plt.figure(figsize=(5,5))
    sns.barplot(data=anger_mood['Gender'].value_counts().reset_index().rename(column
                x='Gender',y='Participants',palette=sns.color_palette('plasma_r'))
    plt.xticks([0,1],['Males','Females'])
    plt.title('Gender wise participants count',fontdict=font_dicts(kind='title'))
```



In [119…
```
with plt.style.context('seaborn-bright'):
    plt.figure(figsize=(5,5))
    sns.barplot(data=anger_mood['Sports'].value_counts().reset_index().rename(column
                x='Athletes?',y='Participants',palette=sns.color_palette('gist_rainb
    plt.xticks([0,1],['Athletes','Non-Athletes'])
    plt.title('# of athletes and non-athletes participants',fontdict=font_dicts(kind
```



In [120…
```
def feat_pt_ss(frame,col):
    """
    Description: This function is created for performing the Power Transformation an

    Input: It accepts below input parameters:
        1. frame: pandas DataFrame
```

```
                Dataset containing features
            2. col: str
                Features which you want to transform

        Return: None
            It creates the transformed features in the dataset.
        """
        col_pt_name = str(col)+'_pt'
        col_pt_ss_name = str(col)+'_pt_ss'
        frame[col_pt_name] = scipy.stats.boxcox(frame[col])[0]
        frame[col_pt_ss_name] = ss.fit_transform(frame[[col_pt_name]])
```

In [121…
```
df_cols = ['Anger-Out','Anger-In','Control-Out','Control-In','Anger_Expression']
for feat in df_cols:
    feat_pt_ss(anger_mood,feat)
```

In [122…
```
anger_mood.head()
```

Out[122…

	Gender	Sports	Anger-Out	Anger-In	Control-Out	Control-In	Anger_Expression	Anger-Out_pt	Anger-Out_pt_ss	An I
0	2	1	18	13	23	20	36	2.938922	0.564209	4.51
1	2	1	14	17	25	24	30	2.679492	-0.406073	5.31
2	2	1	13	14	28	28	19	2.603134	-0.691656	4.72
3	2	1	17	24	23	23	43	2.879852	0.343284	6.48
4	1	1	16	17	26	28	27	2.817242	0.109120	5.31

Visualizing the features distribution post transformation and scaling

In [123…
```
## Here, I'm plotting all the 3 versions of the distributions
# Raw/original data, Power-transformed data and Power-transformed + Scaled data
# Although, SS doesn't really impact the distribution of the data

with plt.style.context('seaborn-bright'):
    fig , ax = plt.subplots(nrows=4,ncols=3,figsize=(18,20))
    sns.distplot(anger_mood['Anger-Out'],ax=ax[0,0],color='coral')
    sns.kdeplot(anger_mood['Anger-Out'],ax=ax[0,0],label='Anger-Out',color='purple')
    sns.kdeplot(anger_mood['Anger-Out_pt'],ax=ax[0,1],label='PT Anger-Out',color='or
    sns.kdeplot(anger_mood['Anger-Out_pt_ss'],ax=ax[0,2],label='SS PT Anger-Out',col
    ax[0,0].set_title('Raw Data KDE',fontdict=font_dicts(kind='title'))
    ax[0,1].set_title('Power Transformed',fontdict=font_dicts(kind='title'))
    ax[0,2].set_title('Standard Scaled Power Transformed',fontdict=font_dicts(kind='

    sns.distplot(anger_mood['Anger-In'],ax=ax[1,0],color='coral')
    sns.kdeplot(anger_mood['Anger-In'],ax=ax[1,0],label='Anger-In',color='purple')
    sns.kdeplot(anger_mood['Anger-In_pt'],ax=ax[1,1],label='PT Anger-In',color='oran
    sns.kdeplot(anger_mood['Anger-In_pt_ss'],ax=ax[1,2],label='SS PT Anger-In',color
    ax[1,0].set_title('Raw Data KDE',fontdict=font_dicts(kind='title'))
    ax[1,1].set_title('Power Transformed',fontdict=font_dicts(kind='title'))
    ax[2,2].set_title('Standard Scaled Power Transformed',fontdict=font_dicts(kind='

    sns.distplot(anger_mood['Control-Out'],ax=ax[2,0],color='coral')
    sns.kdeplot(anger_mood['Control-Out'],ax=ax[2,0],label='Control-Out',color='purp
    sns.kdeplot(anger_mood['Control-Out_pt'],ax=ax[2,1],label='PT Control-Out',color
    sns.kdeplot(anger_mood['Control-Out_pt_ss'],ax=ax[2,2],label='SS PT Control-Out'
    ax[2,0].set_title('Raw Data KDE',fontdict=font_dicts(kind='title'))
    ax[2,1].set_title('Power Transformed',fontdict=font_dicts(kind='title'))
    ax[2,2].set_title('Standard Scaled Power Transformed',fontdict=font_dicts(kind='
```

```
    sns.distplot(anger_mood['Control-In'],ax=ax[3,0],color='coral')
    sns.kdeplot(anger_mood['Control-In'],ax=ax[3,0],label='Control-In',color='purple
    sns.kdeplot(anger_mood['Control-In_pt'],ax=ax[3,1],label='PT Control-In',color='
    sns.kdeplot(anger_mood['Control-In_pt_ss'],ax=ax[3,2],label='SS PT Control-In',c
    ax[3,0].set_title('Raw Data KDE',fontdict=font_dicts(kind='title'))
    ax[3,1].set_title('Power Transformed',fontdict=font_dicts(kind='title'))
    ax[3,2].set_title('Standard Scaled Power Transformed',fontdict=font_dicts(kind='
```

```
c:\users\rajsh\appdata\local\programs\python\python36\lib\site-packages\seaborn\dist
ributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be re
moved in a future version. Please adapt your code to use either `displot` (a figure-
level function with similar flexibility) or `histplot` (an axes-level function for h
istograms).
  warnings.warn(msg, FutureWarning)
c:\users\rajsh\appdata\local\programs\python\python36\lib\site-packages\seaborn\dist
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moved in a future version. Please adapt your code to use either `displot` (a figure-
level function with similar flexibility) or `histplot` (an axes-level function for h
istograms).
  warnings.warn(msg, FutureWarning)
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moved in a future version. Please adapt your code to use either `displot` (a figure-
level function with similar flexibility) or `histplot` (an axes-level function for h
istograms).
  warnings.warn(msg, FutureWarning)
c:\users\rajsh\appdata\local\programs\python\python36\lib\site-packages\seaborn\dist
ributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be re
moved in a future version. Please adapt your code to use either `displot` (a figure-
level function with similar flexibility) or `histplot` (an axes-level function for h
istograms).
  warnings.warn(msg, FutureWarning)
```
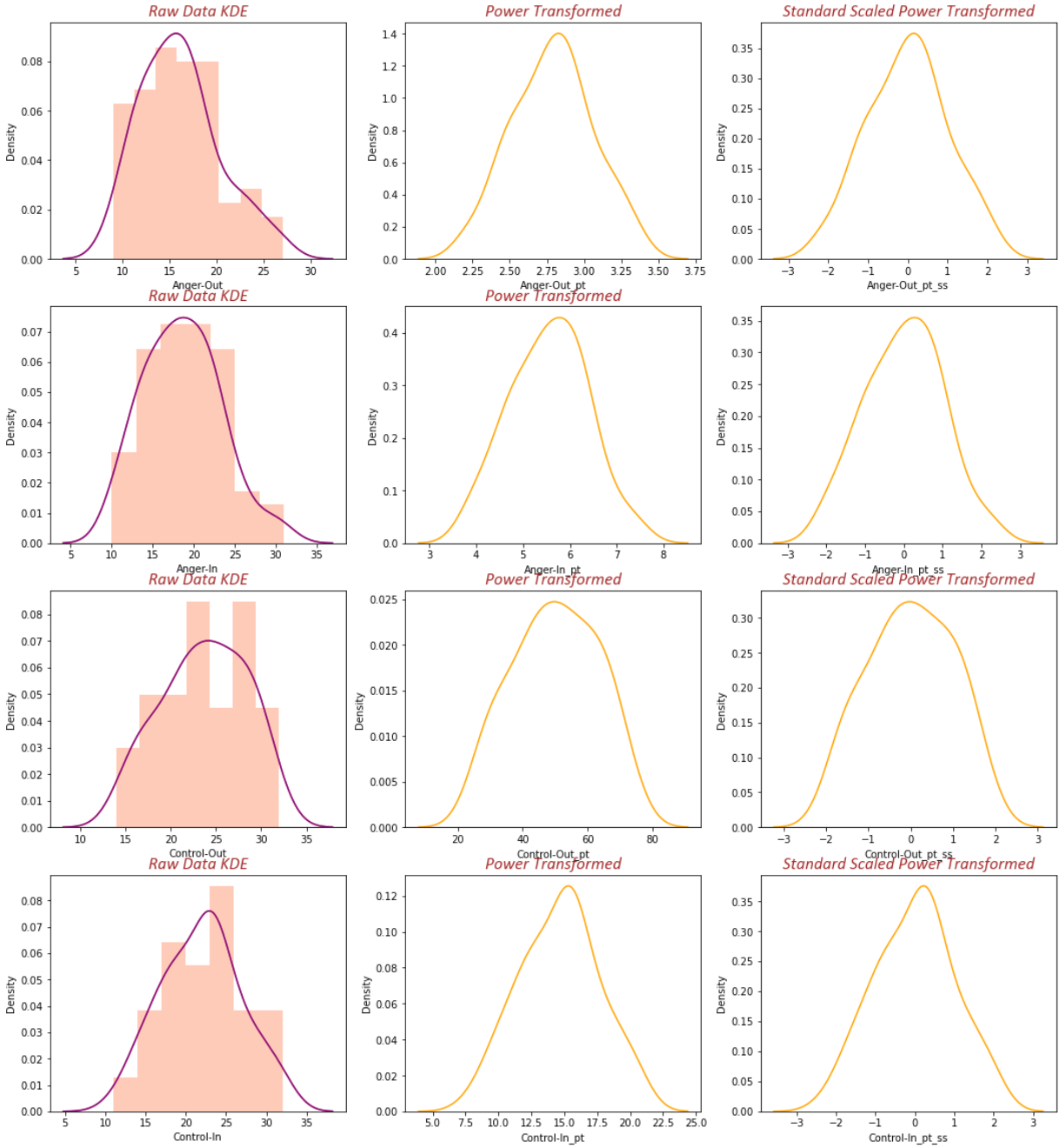



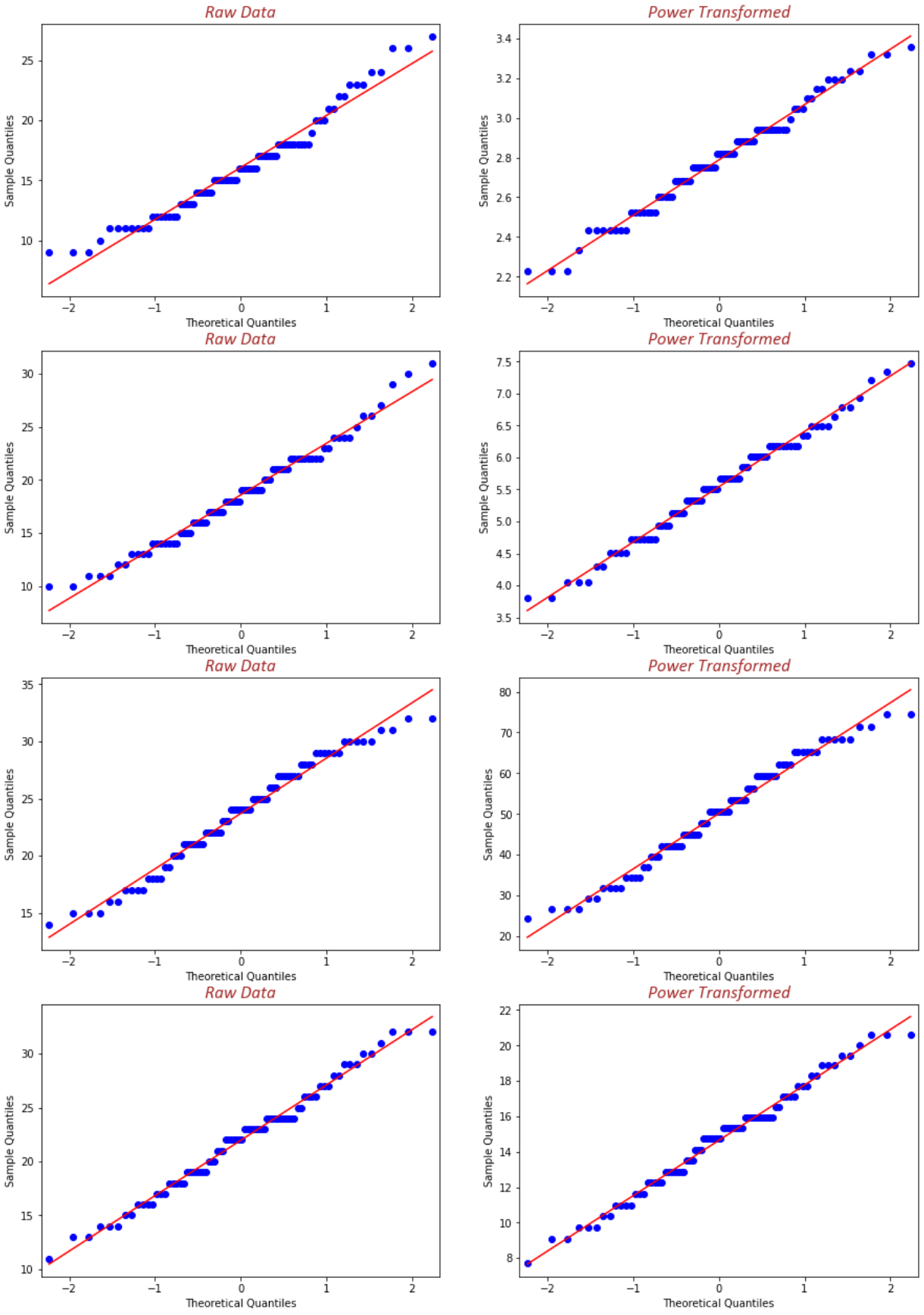
- **Well, none of the original groups have clear pareto or non-normal distributions, I'm just giving a try here with power-transformation.**
- **The original data also looks like fairly normally distributed.**
- **After seeing the above KDE, its been evident that Power Transformation has introduced very slight variation in the distribution towards normality, however, the raw data distribution of features pretty much looks gaussian-like.**

Visualizing QQ plots

In [124…

```
with plt.style.context('seaborn-bright'):
    fig , ax = plt.subplots(nrows=4,ncols=2,figsize=(15,22))
    stm.graphics.gofplots.qqplot(anger_mood['Anger-Out'],ax=ax[0,0],line='r',label='
    stm.graphics.gofplots.qqplot(anger_mood['Anger-Out_pt'],ax=ax[0,1],line='r')
    ax[0,0].set_title('Raw Data',fontdict=font_dicts(kind='title'))
    ax[0,1].set_title('Power Transformed',fontdict=font_dicts(kind='title'))

    stm.graphics.gofplots.qqplot(anger_mood['Anger-In'],ax=ax[1,0],line='r')
    stm.graphics.gofplots.qqplot(anger_mood['Anger-In_pt'],ax=ax[1,1],line='r')
    ax[1,0].set_title('Raw Data',fontdict=font_dicts(kind='title'))
    ax[1,1].set_title('Power Transformed',fontdict=font_dicts(kind='title'))
```

```
stm.graphics.gofplots.qqplot(anger_mood['Control-Out'],ax=ax[2,0],line='r')
stm.graphics.gofplots.qqplot(anger_mood['Control-Out_pt'],ax=ax[2,1],line='r')
ax[2,0].set_title('Raw Data',fontdict=font_dicts(kind='title'))
ax[2,1].set_title('Power Transformed',fontdict=font_dicts(kind='title'))

stm.graphics.gofplots.qqplot(anger_mood['Control-In'],ax=ax[3,0],line='r')
stm.graphics.gofplots.qqplot(anger_mood['Control-In_pt'],ax=ax[3,1],line='r')
ax[3,0].set_title('Raw Data',fontdict=font_dicts(kind='title'))
ax[3,1].set_title('Power Transformed',fontdict=font_dicts(kind='title'))
```



QQ plots are also telling us the same story, power transformed does minimizes some amount of deviations and raw data can fit in the bucket of gaussian-like.

Now, lets run some normality tests because we have very small dataset then these tests can help us in identifying some insights.

Normality Tests

Anger-Out

In [125…
```
print(np.round(scipy.stats.shapiro(anger_mood['Anger-Out']),4),
      np.round(scipy.stats.normaltest(anger_mood['Anger-Out']),4),
      scipy.stats.anderson(anger_mood['Anger-Out']),
      scipy.stats.kstest(pd.DataFrame(ss.fit_transform(anger_mood[['Anger-Out']]))[0
```

```
[0.9597 0.0147]
[4.4764 0.1067]
AndersonResult(statistic=0.8866161999077633, critical_values=array([0.55 , 0.626, 0.
752, 0.877, 1.043]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
KstestResult(statistic=0.11801006873469855, pvalue=0.21016099597115612)
```

- **Other than Shapiro-wilk test all are saying raw data is normal.**

In [126…
```
print(np.round(scipy.stats.shapiro(anger_mood['Anger-Out_pt']),4),
      np.round(scipy.stats.normaltest(anger_mood['Anger-Out_pt']),4),
      scipy.stats.anderson(anger_mood['Anger-Out_pt']),
      scipy.stats.kstest(anger_mood['Anger-Out_pt_ss'],cdf='norm'),sep='\n')
```

```
[0.9813 0.3063]
[0.7455 0.6888]
AndersonResult(statistic=0.42091177774017297, critical_values=array([0.55 , 0.626,
0.752, 0.877, 1.043]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
KstestResult(statistic=0.08117785751780704, pvalue=0.6527048356296961)
```

- **All tests are saying that power-transformed data is normal.**

Anger-In

In [127…
```
print(np.round(scipy.stats.shapiro(anger_mood['Anger-In']),4),
      np.round(scipy.stats.normaltest(anger_mood['Anger-In']),4),
      scipy.stats.anderson(anger_mood['Anger-In']),
      scipy.stats.kstest(pd.DataFrame(ss.fit_transform(anger_mood[['Anger-In']]))[0]
```

```
[0.9793 0.2346]
[1.6838 0.4309]
AndersonResult(statistic=0.38757509282743285, critical_values=array([0.55 , 0.626,
0.752, 0.877, 1.043]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
KstestResult(statistic=0.06738948552710411, pvalue=0.8469621917851082)
```

- **All tests are saying that raw data is normal.**

In [128…
```
print(np.round(scipy.stats.shapiro(anger_mood['Anger-In_pt']),4),
      np.round(scipy.stats.normaltest(anger_mood['Anger-In_pt']),4),
      scipy.stats.anderson(anger_mood['Anger-In_pt']),
      scipy.stats.kstest(anger_mood['Anger-In_pt_ss'],cdf='norm'),sep='\n')
```

```
[0.9861 0.5571]
[0.5535 0.7583]
```

```
AndersonResult(statistic=0.3421858878821098, critical_values=array([0.55 , 0.626, 0.
752, 0.877, 1.043]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
KstestResult(statistic=0.07561264312054072, pvalue=0.7350991362050974)
```

- **All tests are saying that power-transformed data is normal.**

Control-Out

In [129…
```
print(np.round(scipy.stats.shapiro(anger_mood['Control-Out']),4),
      np.round(scipy.stats.normaltest(anger_mood['Control-Out']),4),
      scipy.stats.anderson(anger_mood['Control-Out']),
      scipy.stats.kstest(pd.DataFrame(ss.fit_transform(anger_mood[['Control-Out']])))
```

```
[0.969  0.0544]
[6.9335 0.0312]
AndersonResult(statistic=0.6212161705866492, critical_values=array([0.55 , 0.626, 0.
752, 0.877, 1.043]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
KstestResult(statistic=0.0944989633727723, pvalue=0.46106545331192683)
```

- **All tests other than D'Agostino are saying that raw data is normal.**

In [130…
```
print(np.round(scipy.stats.shapiro(anger_mood['Control-Out_pt']),4),
      np.round(scipy.stats.normaltest(anger_mood['Control-Out_pt']),4),
      scipy.stats.anderson(anger_mood['Control-Out_pt']),
      scipy.stats.kstest(anger_mood['Control-Out_pt_ss'],cdf='norm'),sep='\n')
```

```
[0.9708 0.07  ]
[7.8824 0.0194]
AndersonResult(statistic=0.5741237073639383, critical_values=array([0.55 , 0.626, 0.
752, 0.877, 1.043]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
KstestResult(statistic=0.09114203775949703, pvalue=0.507088307466719)
```

- **All tests other than D'Agostino are saying that power-transformed data is normal.**

Control-In

In [131…
```
print(np.round(scipy.stats.shapiro(anger_mood['Control-In']),4),
      np.round(scipy.stats.normaltest(anger_mood['Control-In']),4),
      scipy.stats.anderson(anger_mood['Control-In']),
      scipy.stats.kstest(pd.DataFrame(ss.fit_transform(anger_mood[['Control-In']])))[
```

```
[0.9831 0.3885]
[1.1044 0.5757]
AndersonResult(statistic=0.37670142865145806, critical_values=array([0.55 , 0.626,
0.752, 0.877, 1.043]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
KstestResult(statistic=0.08269920968992817, pvalue=0.6299932997185698)
```

- **All tests are saying that raw data is normal.**

In [132…
```
print(np.round(scipy.stats.shapiro(anger_mood['Control-In_pt']),4),
      np.round(scipy.stats.normaltest(anger_mood['Control-In_pt']),4),
      scipy.stats.anderson(anger_mood['Control-In_pt']),
      scipy.stats.kstest(anger_mood['Control-In_pt_ss'],cdf='norm'),sep='\n')
```

```
[0.9836 0.4157]
[1.0368 0.5955]
AndersonResult(statistic=0.37677245211017407, critical_values=array([0.55 , 0.626,
0.752, 0.877, 1.043]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
KstestResult(statistic=0.08740098100613486, pvalue=0.5605715367622379)
```

- **All tests are saying that power-transformed data is normal.**

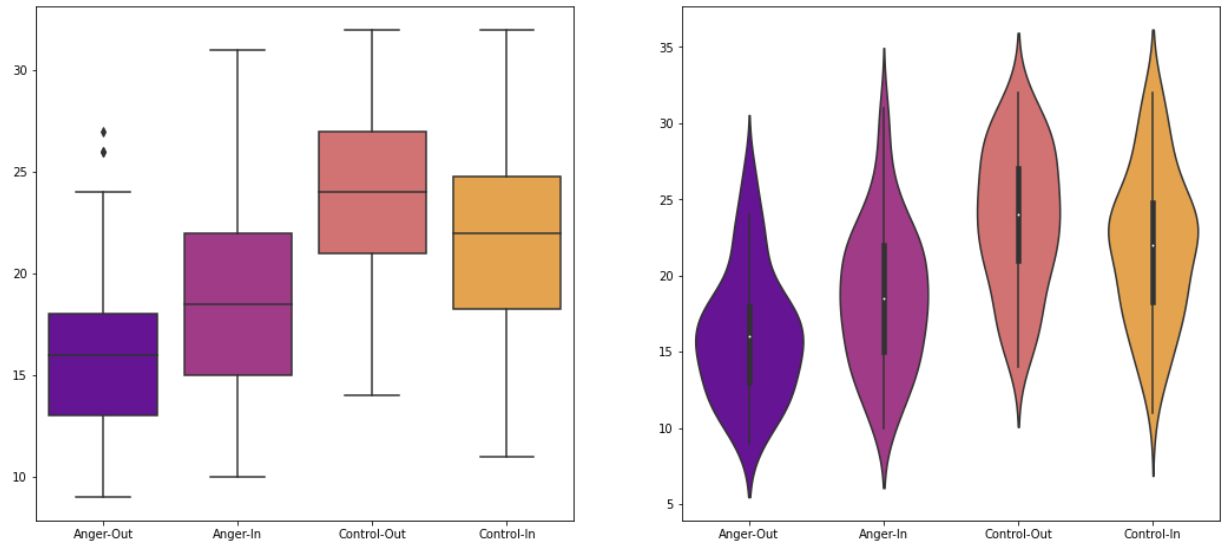
Quite similar results here generated by various normality tests. So, will be using Raw Data for further 2-Way ANOVA.

In [133...
```
anger_mood.head()
```

Out[133...

	Gender	Sports	Anger-Out	Anger-In	Control-Out	Control-In	Anger_Expression	Anger-Out_pt	Anger-Out_pt_ss	An I
0	2	1	18	13	23	20	36	2.938922	0.564209	4.51
1	2	1	14	17	25	24	30	2.679492	-0.406073	5.31
2	2	1	13	14	28	28	19	2.603134	-0.691656	4.72
3	2	1	17	24	23	23	43	2.879852	0.343284	6.48
4	1	1	16	17	26	28	27	2.817242	0.109120	5.31

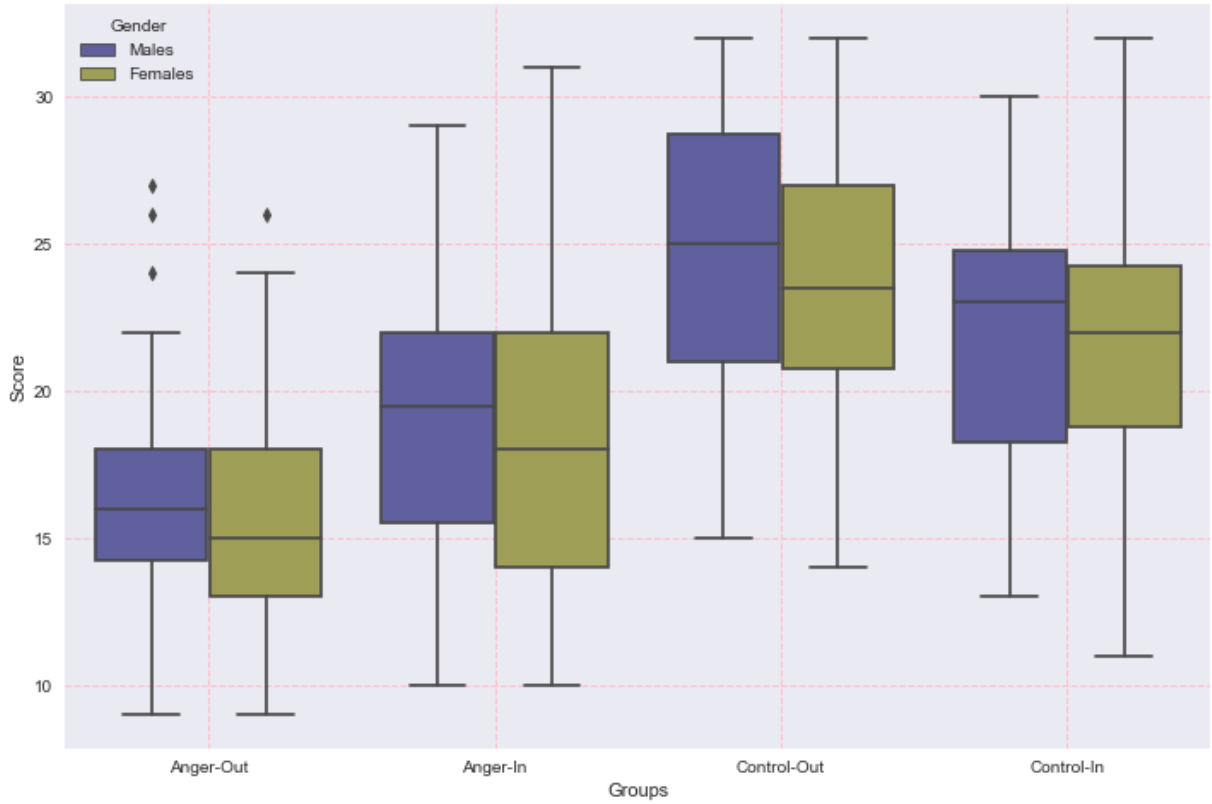
In [134...
```
with plt.style.context('seaborn-bright'):
    fig,ax = plt.subplots(nrows=1,ncols=2,figsize=(18,8))
    sns.boxplot(data=anger_mood[['Anger-Out','Anger-In','Control-Out','Control-In']]
    sns.violinplot(data=anger_mood[['Anger-Out','Anger-In','Control-Out','Control-In
```



Here, it is quite clear that means are not equal across the groups. And, more number of people are able to control their anger.

In [135...
```
anger_mood_melt = pd.melt(frame=anger_mood,
                          id_vars=['Gender','Sports'],
                          value_vars=['Anger-Out','Anger-In','Control-Out','Control-
                          var_name='Groups',
                          value_name='Score')
```

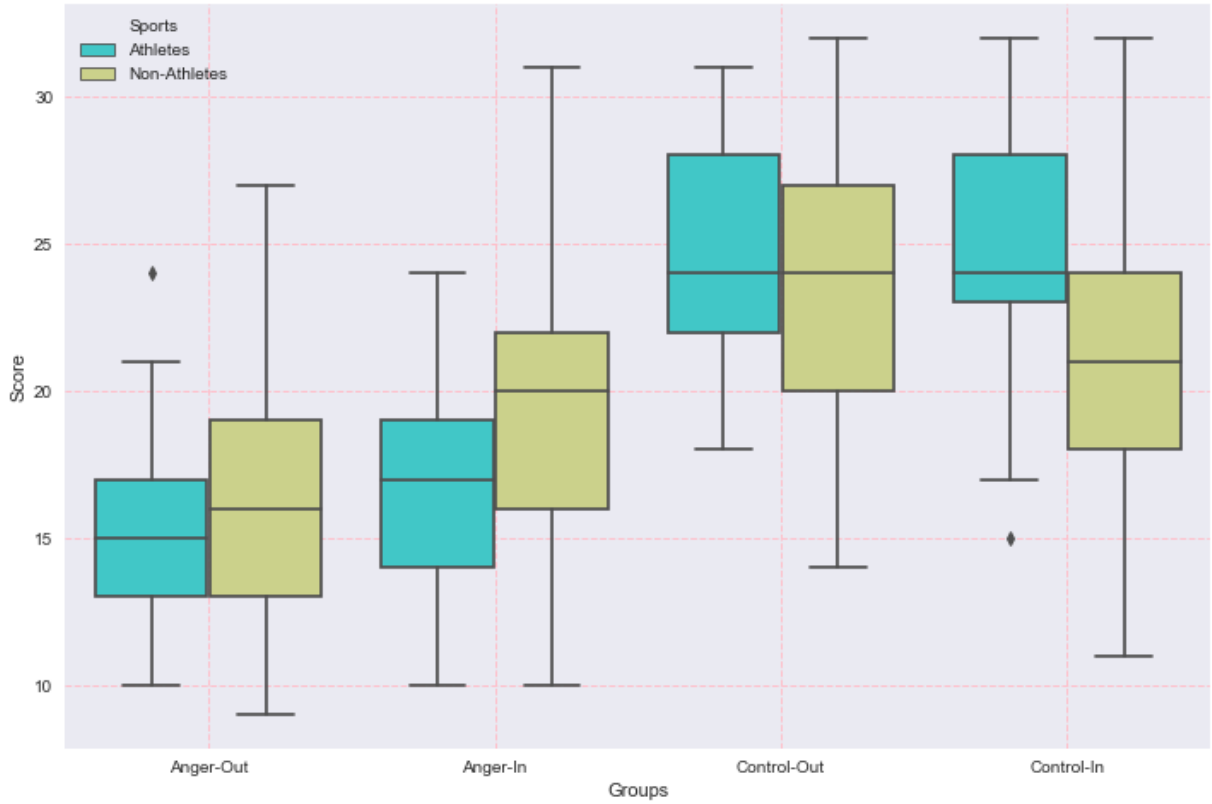
In [136...
```
with plt.style.context('seaborn'):
    plt.figure(figsize=(12,8))
    g = sns.boxplot(data=anger_mood_melt,x='Groups',y='Score',hue='Gender',palette='
    plt.grid(which='major',linestyle='--',color='pink')
    leg = g.axes.get_legend()
    new_title = 'Gender'
    leg.set_title(new_title)
    new_labels = ['Males', 'Females']
    for t, l in zip(leg.texts, new_labels): t.set_text(l)
    plt.show()
```



Here, on an average we can say that Males believe in expressing anger verbally or physically, however, this is also true for some females as well. The difference in both the genders is quite small when it comes to applying cooling or calming off techniques, but, womens can be very slightly better in it.

In [137…

```
with plt.style.context('seaborn'):
    plt.figure(figsize=(12,8))
    g = sns.boxplot(data=anger_mood_melt,x='Groups',y='Score',hue='Sports',palette='
    plt.grid(which='major',linestyle='--',color='pink')
    leg = g.axes.get_legend()
    new_title = 'Sports'
    leg.set_title(new_title)
    new_labels = ['Athletes', 'Non-Athletes']
    for t, l in zip(leg.texts, new_labels): t.set_text(l)
    plt.show()
```



One thing pretty clear here that athletes are good with calming or cooling off techniques. And, same group also believe less in expressing anger verbally or physically aggressive. There is one more thing that athletes tend to experience less number of anger issues. However, few non-athletes are good in controlling the outward expression of angry feelings better than athletes.

In [138…
```
## Dataset for ANOVA
anger_mood_melt.head()
```

Out[138…

	Gender	Sports	Groups	Score
0	2	1	Anger-Out	18
1	2	1	Anger-Out	14
2	2	1	Anger-Out	13
3	2	1	Anger-Out	17
4	1	1	Anger-Out	16

In [139…
```
anger_mood_model = ols('Score ~ C(Groups)+C(Gender)+C(Sports)',data=anger_mood_melt)
```

In [140…
```
anger_mood_model_annova_table = anova_lm(anger_mood_model)
anger_mood_fdist_grps = scipy.stats.f(3,306)
anger_mood_fdist_gender = scipy.stats.f(1,306)
anger_mood_fdist_sports = scipy.stats.f(1,306)
anger_mood_model_annova_table['F_Crit'] = [anger_mood_fdist_grps.ppf(0.95),
                                           anger_mood_fdist_gender.ppf(0.95),
                                           anger_mood_fdist_sports.ppf(0.95),
                                           None]

anger_mood_model_annova_table['Alpha'] = [0.05,0.05,0.05,None]
```

```
anger_mood_model_annova_table = anger_mood_model_annova_table.applymap(lambda val: n
anger_mood_model_annova_table
```

Out[140…

	df	sum_sq	mean_sq	F	PR(>F)	F_Crit	Alpha
C(Groups)	3.0	2720.0769	906.6923	42.0026	0.0000	2.6341	0.05
C(Gender)	1.0	36.2924	36.2924	1.6812	0.1957	3.8720	0.05
C(Sports)	1.0	2.2860	2.2860	0.1059	0.7451	3.8720	0.05
Residual	306.0	6605.4985	21.5866	NaN	NaN	NaN	NaN

In [141…

```
anger_mood_model.summary()
```

Out[141…

OLS Regression Results

Dep. Variable:	Score	**R-squared:**	0.295
Model:	OLS	**Adj. R-squared:**	0.283
Method:	Least Squares	**F-statistic:**	25.56
Date:	Mon, 26 Apr 2021	**Prob (F-statistic):**	1.53e-21
Time:	16:38:40	**Log-Likelihood:**	-918.92
No. Observations:	312	**AIC:**	1850.
Df Residuals:	306	**BIC:**	1872.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	19.1249	0.718	26.633	0.000	17.712	20.538
C(Groups)[T.Anger-Out]	-2.5000	0.744	-3.360	0.001	-3.964	-1.036
C(Groups)[T.Control-In]	3.3846	0.744	4.549	0.000	1.921	4.849
C(Groups)[T.Control-Out]	5.1154	0.744	6.876	0.000	3.651	6.579
C(Gender)[T.2]	-0.6872	0.542	-1.267	0.206	-1.754	0.380
C(Sports)[T.2]	-0.1840	0.565	-0.325	0.745	-1.296	0.929

Omnibus:	4.840	**Durbin-Watson:**	1.998
Prob(Omnibus):	0.089	**Jarque-Bera (JB):**	3.998
Skew:	0.182	**Prob(JB):**	0.135
Kurtosis:	2.581	**Cond. No.**	6.56

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Post-Hoc Test

In [142…

```
import scikit_posthocs as post_hocs
from statsmodels.stats.multicomp import pairwise_tukeyhsd as tukeyhsd
```

In [143...
```
post_hoc_tukey = tukeyhsd(endog=anger_mood_melt['Score'],groups=anger_mood_melt['Gro
```

In [144...
```
post_hoc_tukey.summary()
```

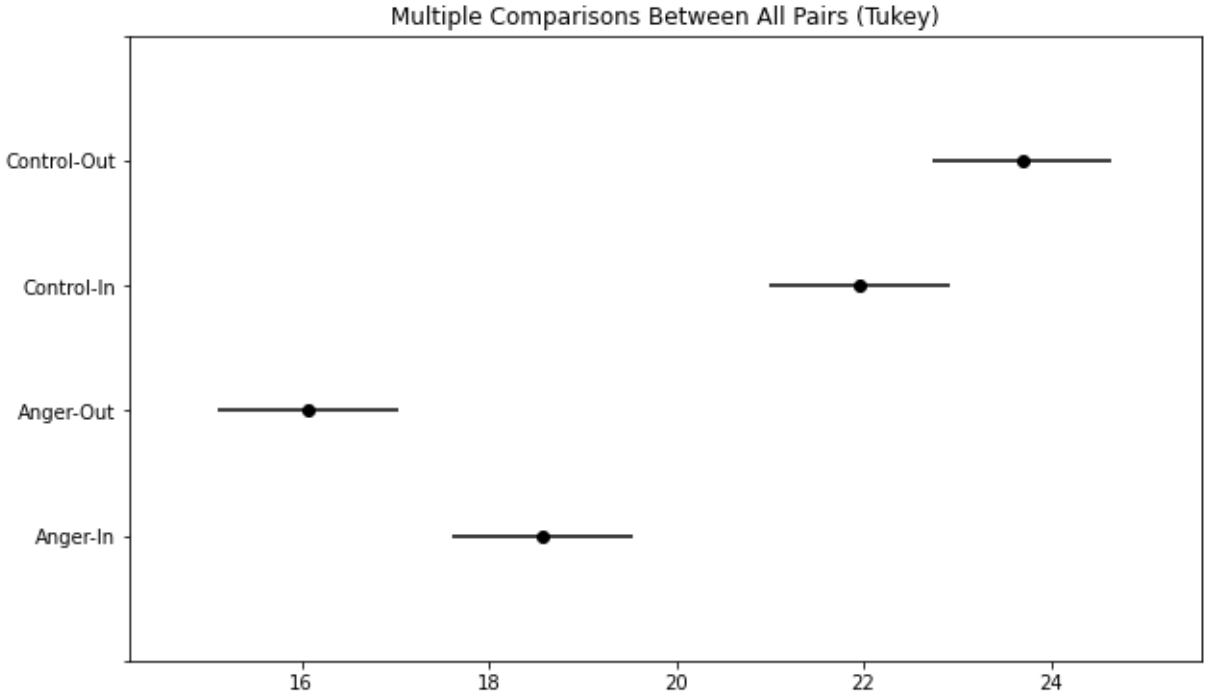
Out[144...

Multiple Comparison of Means - Tukey HSD, FWER=0.05

group1	group2	meandiff	p-adj	lower	upper	reject
Anger-In	Anger-Out	-2.5	0.0048	-4.4212	-0.5788	True
Anger-In	Control-In	3.3846	0.001	1.4634	5.3058	True
Anger-In	Control-Out	5.1154	0.001	3.1942	7.0366	True
Anger-Out	Control-In	5.8846	0.001	3.9634	7.8058	True
Anger-Out	Control-Out	7.6154	0.001	5.6942	9.5366	True
Control-In	Control-Out	1.7308	0.0941	-0.1904	3.652	False

In [145...
```
post_hoc_tukey.plot_simultaneous();
```

```
c:\users\rajsh\appdata\local\programs\python\python36\lib\site-packages\statsmodels
\sandbox\stats\multicomp.py:775: UserWarning: FixedFormatter should only be used tog
ether with FixedLocator
  ax1.set_yticklabels(np.insert(self.groupsunique.astype(str), 0, ''))
```



Interaction Among variables

In [146...
```
anger_mood_model_intr_grp_gender = ols('Score ~ C(Groups)*C(Gender)',data=anger_mood
```

In [147...
```
anova_lm(anger_mood_model_intr_grp_gender).applymap(lambda val : np.round(val,4))
```

Out[147...

	df	sum_sq	mean_sq	F	PR(>F)
C(Groups)	3.0	2720.0769	906.6923	41.8072	0.0000
C(Gender)	1.0	36.2924	36.2924	1.6734	0.1968
C(Groups):C(Gender)	3.0	14.7887	4.9296	0.2273	0.8774
Residual	304.0	6592.9958	21.6875	NaN	NaN

In [148...
```
anger_mood_melt.groupby(['Gender'])['Score'].mean()
```

Out[148...
```
Gender
1    20.508333
2    19.807292
Name: Score, dtype: float64
```

In [149...
```
anger_mood_melt.groupby(['Gender','Groups'])[['Score']].mean().T
```

Out[149...

Gender	1				2			
Groups	**Anger-In**	**Anger-Out**	**Control-In**	**Control-Out**	**Anger-In**	**Anger-Out**	**Control-In**	**Control-Out**
Score	19.033333	16.566667	21.966667	24.466667	18.291667	15.770833	21.958333	23.208333

The test shows no significant interaction between Groups and Gender. Also, the means across groups is very close for both the genders. Thus, we can say that there are no gener differences.

In [150...
```
anger_mood_model_intr_grp_sports = ols('Score ~ C(Groups)*C(Sports)',data=anger_mood
```

In [151...
```
anova_lm(anger_mood_model_intr_grp_sports).applymap(lambda val : np.round(val,4))
```

Out[151...

	df	sum_sq	mean_sq	F	PR(>F)
C(Groups)	3.0	2720.0769	906.6923	44.1172	0.0000
C(Sports)	1.0	3.9138	3.9138	0.1904	0.6629
C(Groups):C(Sports)	3.0	392.3880	130.7960	6.3642	0.0003
Residual	304.0	6247.7751	20.5519	NaN	NaN

In [152...
```
anger_mood_melt.groupby(['Sports'])['Score'].mean()
```

Out[152...
```
Sports
1    20.24
2    20.00
Name: Score, dtype: float64
```

In [153...
```
anger_mood_melt.groupby(['Sports','Groups'])[['Score']].mean().T
```

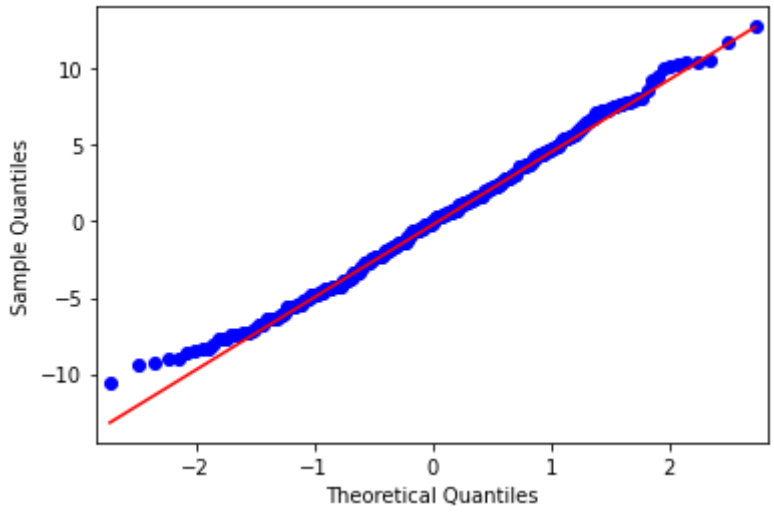
Out[153...

Sports	1				2			
Groups	**Anger-In**	**Anger-Out**	**Control-In**	**Control-Out**	**Anger-In**	**Anger-Out**	**Control-In**	**Control-Out**
Score	16.68	15.28	24.32	24.68	19.471698	16.45283	20.849057	23.226415

The test shows significant interaction between Groups and Athletes status. And, it clearly shows that athletes are better in cooling off techniques and they deal with anger very much differently as compare to others.

Normality Tests

In [154...
```
stm.graphics.gofplots.qqplot(anger_mood_model.resid,line='q');
```



In [155…
```
scipy.stats.anderson(anger_mood_model.resid)
```

Out[155…
```
AndersonResult(statistic=0.43044544886271296, critical_values=array([0.569, 0.648,
0.777, 0.907, 1.078]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
```

In [156…
```
scipy.stats.normaltest(anger_mood_model.resid)
```

Out[156…
```
NormaltestResult(statistic=4.839692299736987, pvalue=0.08893529911436146)
```

Pretty good here. Now, as normlaity tests have been passed therefore we will perform parametric homogenity tests.

Bartlett test

In [157…
```
scipy.stats.bartlett(anger_mood['Anger-Out'],anger_mood['Anger-In'],anger_mood['Cont
```

Out[157…
```
BartlettResult(statistic=1.9996104310731075, pvalue=0.5724875648993066)
```

Levene test

In [158…
```
scipy.stats.levene(anger_mood['Anger-Out'],anger_mood['Anger-In'],anger_mood['Contro
```

Out[158…
```
LeveneResult(statistic=0.9134212779534832, pvalue=0.43472151627992617)
```

Pretty good here as well that means the variances in the groups are also equal.

White test

In [159…
```
anger_mood_model.model.exog_names
```

Out[159…
```
['Intercept',
 'C(Groups)[T.Anger-Out]',
 'C(Groups)[T.Control-In]',
 'C(Groups)[T.Control-Out]',
 'C(Gender)[T.2]',
 'C(Sports)[T.2]']
```

In [160…
```
white_test = het_white(anger_mood_model.resid,anger_mood_model.model.exog)
```

In [161…
```
labels = ['LM Statistic', 'LM-Test p-value', 'F-Statistic', 'F-Test p-value']
```

In [162…
```
dict(zip(labels, white_test))
```

Out[162…
```
{'LM Statistic': 12.351023449755298,
 'LM-Test p-value': 0.4179161019156023,
 'F-Statistic': 1.0270228112664146,
 'F-Test p-value': 0.4236543113708347}
```

Breusch-Pagan test

In [163…
```
bp_test = het_breuschpagan(anger_mood_model.resid,exog_het=anger_mood_model.model.ex
```

In [164…
```
dict(zip(labels, bp_test))
```

Out[164…
```
{'LM Statistic': 6.958054139855664,
 'LM-Test p-value': 0.22377861456398046,
 'F-Statistic': 1.3959815007028675,
 'F-Test p-value': 0.22550477343744865}
```

This model is not heteroskedastic.

Self_Question:1

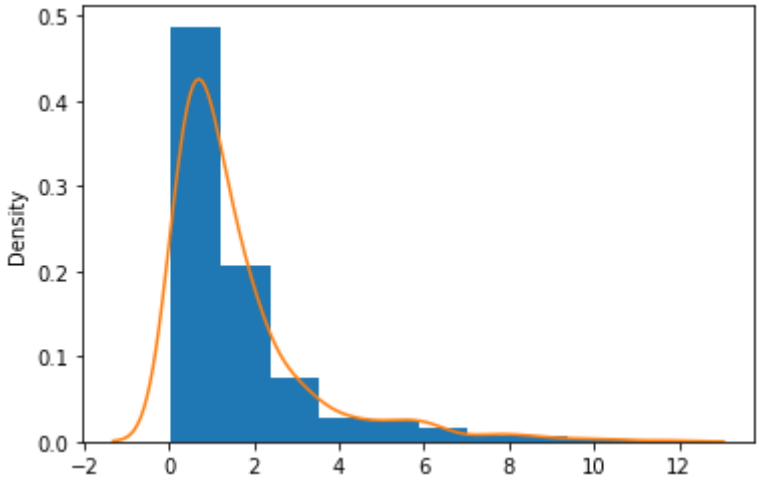
Does Normality Tests are sensitive to data normalization?

Exp-A1

Random Data

In [165…
```
rand_data = np.random.lognormal(size=800)
#rand_data = np.random.randint(low=1000,high=4000,size=900)
```

In [166…
```
plt.hist(rand_data,density=True)
sns.kdeplot(rand_data);
```



Perfect example of Power-Law distribution

In [167…
```
from sklearn.preprocessing import MinMaxScaler, RobustScaler
```

In [168…
```
mm=MinMaxScaler()
rb=RobustScaler()
```

In [169…
```
rand_data_pt = pd.DataFrame(scipy.stats.boxcox(rand_data,lmbda=None)[0])[0]
rand_data_pt
```

Out[169…
```
0     -0.064057
1     -0.308311
2      0.095681
3     -0.944226
4      0.644085
         ...
795    0.100683
796   -1.202231
797    0.787827
798    0.048707
799   -1.242496
Name: 0, Length: 800, dtype: float64
```

In [170…
```
rand_data_pt_ss = pd.DataFrame(ss.fit_transform(pd.DataFrame(rand_data_pt)))[0]
rand_data_pt_ss
```

Out[170…
```
0     -0.102799
1     -0.344150
2      0.055042
3     -0.972510
4      0.596930
         ...
795    0.059985
796   -1.227450
797    0.738964
798    0.008626
799   -1.267236
Name: 0, Length: 800, dtype: float64
```

Mean and Std dev of raw data

In [171…
```
np.mean(rand_data), np.std(rand_data)
```

Out[171…
```
(1.6144739825888297, 1.7293429288474458)
```

Mean and Std dev of power-transformed data

In [172…
```
np.mean(rand_data_pt), np.std(rand_data_pt)
```

Out[172…
```
(0.0399775470373607, 1.012024345278867)
```

Mean and Std dev of standard-scaled power-transformed data

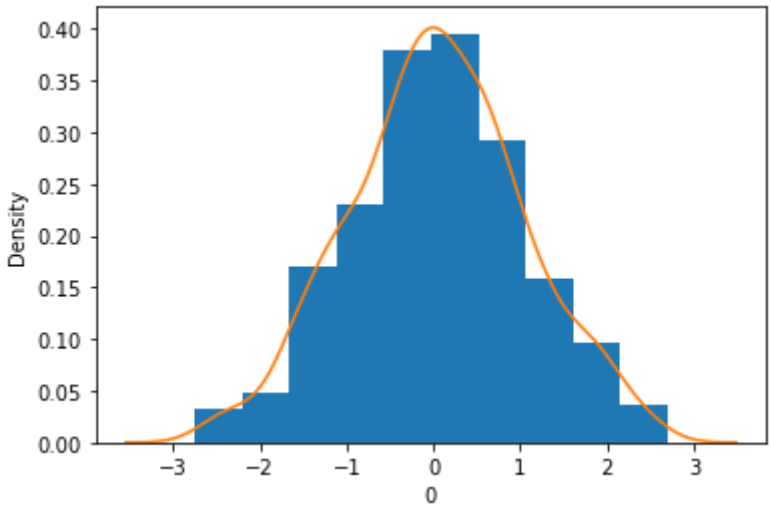
In [173…
```
np.round(np.mean(rand_data_pt_ss),4), np.std(rand_data_pt_ss)
```

Out[173…
```
(0.0, 1.0000000000000002)
```

Distribution of power transformed data

In [174…
```
plt.hist(rand_data_pt,density=True)
sns.kdeplot(data=rand_data_pt)
```

Out[174…
```
<AxesSubplot:xlabel='0', ylabel='Density'>
```

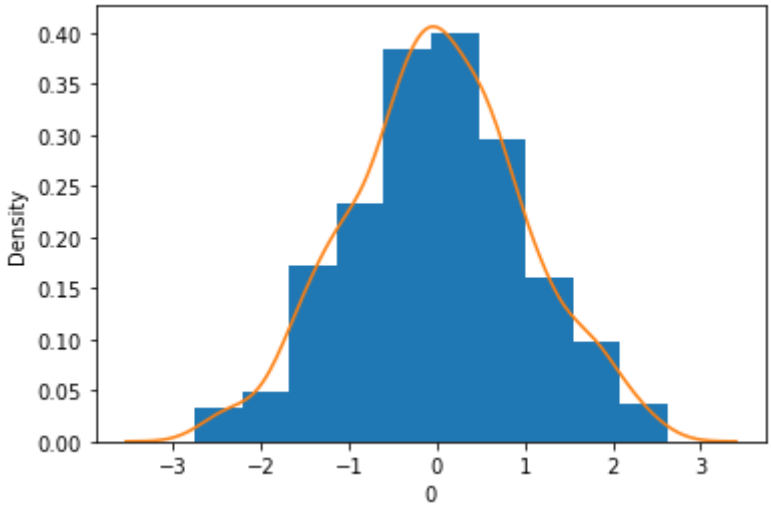


A potential candidate to be named as Normal Distribution.

Distribution of standard scaled power transformed data

In [175…
```
plt.hist(rand_data_pt_ss,density=True)
sns.kdeplot(data=rand_data_pt_ss)
```

Out[175… <AxesSubplot:xlabel='0', ylabel='Density'>



As expected no difference in the distribution plot as compared to power-transformed data distribution.

Skew Test

In [176…
```
scipy.stats.skew(rand_data), scipy.stats.skewtest(rand_data)
```

Out[176…
```
(2.3459241054022066,
 SkewtestResult(statistic=17.022979690349768, pvalue=5.547432176906116e-65))
```

In [177…
```
scipy.stats.skew(rand_data_pt), scipy.stats.skewtest(rand_data_pt)
```

Out[177…
```
(-0.004866398297557393,
 SkewtestResult(statistic=-0.056707320257866733, pvalue=0.9547783426788923))
```

In [178…
```
scipy.stats.skew(rand_data_pt_ss), scipy.stats.skewtest(rand_data_pt_ss)
```

Out[178…
```
(-0.004866398297557444,
 SkewtestResult(statistic=-0.056707320257866733, pvalue=0.9547783426788923))
```

Kurtosis Test

In [179…
```
scipy.stats.kurtosis(rand_data), scipy.stats.kurtosistest(rand_data)
```

Out[179…
```
(6.508709297907771,
 KurtosistestResult(statistic=10.763290570317, pvalue=5.1304825269906875e-27))
```

In [180…
```
scipy.stats.kurtosis(rand_data_pt), scipy.stats.kurtosistest(rand_data_pt)
```

Out[180…
```
(-0.20162655491151105,
 KurtosistestResult(statistic=-1.1820040844875324, pvalue=0.23720408018679096))
```

In [181…
```
scipy.stats.kurtosis(rand_data_pt_ss), scipy.stats.kurtosistest(rand_data_pt_ss)
```

Out[181…
```
(-0.20162655491151193,
 KurtosistestResult(statistic=-1.1820040844875377, pvalue=0.23720408018678896))
```

Shapiro-Wilk Test

In [182…
```
scipy.stats.shapiro(rand_data)
```

Out[182…
```
ShapiroResult(statistic=0.7420974373817444, pvalue=1.895059993366704e-33)
```

In [183…
```
scipy.stats.shapiro(rand_data_pt)
```

Out[183…
```
ShapiroResult(statistic=0.9968069195747375, pvalue=0.11134199053049088)
```

In [184…
```
scipy.stats.shapiro(rand_data_pt_ss)
```

Out[184…
```
ShapiroResult(statistic=0.9968070983886719, pvalue=0.11136817932128906)
```

Anderson-Darling Test

In [185…
```
scipy.stats.anderson(rand_data)
```

Out[185…
```
AndersonResult(statistic=60.137937312830786, critical_values=array([0.573, 0.653, 0.
783, 0.913, 1.087]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
```

In [186…
```
scipy.stats.anderson(rand_data_pt)
```

Out[186…
```
AndersonResult(statistic=0.3970273865584204, critical_values=array([0.573, 0.653, 0.
783, 0.913, 1.087]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
```

In [187…
```
scipy.stats.anderson(rand_data_pt_ss)
```

Out[187…
```
AndersonResult(statistic=0.3970273865584204, critical_values=array([0.573, 0.653, 0.
783, 0.913, 1.087]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]))
```

D-Agastino Test

In [188…
```
scipy.stats.normaltest(rand_data)
```

Out[188…
```
NormaltestResult(statistic=405.63026143913555, pvalue=8.289109600310493e-89)
```

In [189…
```
scipy.stats.normaltest(rand_data_pt)
```

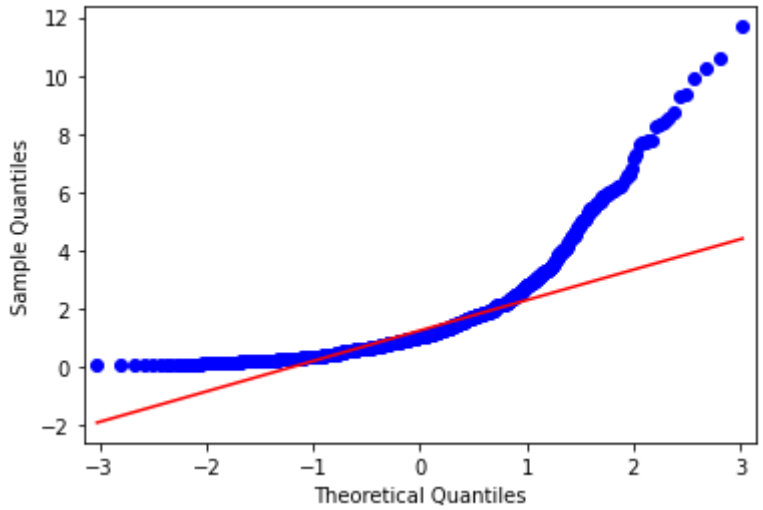
Out[189…
```
NormaltestResult(statistic=1.4003493759160377, pvalue=0.49649856389513625)
```

In [190…
```
scipy.stats.normaltest(rand_data_pt_ss)
```

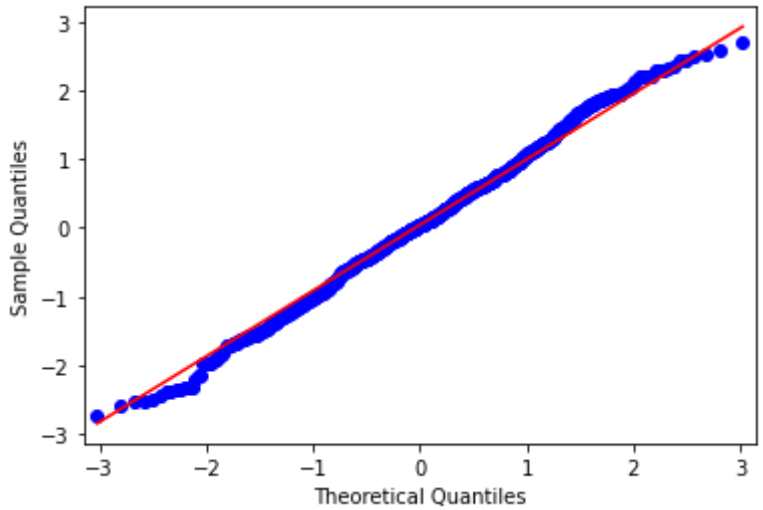
Out[190…
```
NormaltestResult(statistic=1.4003493759160504, pvalue=0.49649856389513314)
```

QQ Plot

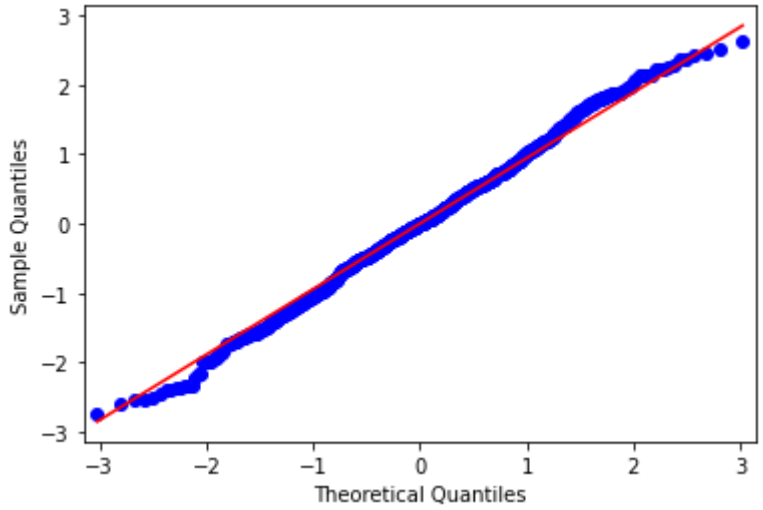
In [191…
```
ProbPlot(rand_data).qqplot(line='q');
```



In [192…
```
ProbPlot(rand_data_pt).qqplot(line='q');
```



In [193…
```
ProbPlot(rand_data_pt_ss).qqplot(line='q');
```



KS Test

In [194…
```
np.round(np.mean(rand_data),4), np.round(np.std(rand_data),4)
```

Out[194…
```
(1.6145, 1.7293)
```

In [195…
```
scipy.stats.kstest(rand_data,cdf='norm')   ## Raw sample data was used
```

Out[195…
```
KstestResult(statistic=0.5295834492124549, pvalue=7.748859122469261e-210)
```

In [196…
```
np.round(np.mean(rand_data_pt),4), np.round(np.std(rand_data_pt),4)
```

Out[196…
```
(0.04, 1.012)
```

In [197…
```
scipy.stats.kstest(rand_data_pt,cdf='norm') ## Power Transformed Sample Data was use
```

Out[197…
```
KstestResult(statistic=0.031698846525372915, pvalue=0.38939706016353903)
```

In [198…
```
np.round(np.mean(rand_data_pt_ss),4), np.round(np.std(rand_data_pt_ss),4)
```

Out[198…
```
(0.0, 1.0)
```

In [199…
```
scipy.stats.kstest(rand_data_pt_ss,cdf='norm') ## Standard Scaled Power-Transformed
```

Out[199…
```
KstestResult(statistic=0.020000683643091155, pvalue=0.8996731149584402)
```

In this experiment it is quite evident that KS test is very sensitive to the data normalization and even the slightest variation in the mean and std dev can affect the result by a great margin.

In my analysis, I found that KS test focuses more on the sensitivity in the central region of the data with less focus on the tails. This limitation is removed in much improved versions of tests like Anderson-Darling & D'Agastino for large datasets and Shapiro-Wilk for smaller dataset.

Exp-A2

Anger Mood Improvement Dataset

In [200…
```
anger_mood = pd.read_excel('Datasets/angry_moods.xls')
```

In [201…
```
anger_mood.head()
```

Out[201…

	Gender	Sports	Anger-Out	Anger-In	Control-Out	Control-In	Anger_Expression
0	2	1	18	13	23	20	36
1	2	1	14	17	25	24	30
2	2	1	13	14	28	28	19
3	2	1	17	24	23	23	43
4	1	1	16	17	26	28	27

In [202…
```
anger_out_pt = pd.DataFrame(scipy.stats.boxcox(anger_mood['Anger-Out'])[0])[0]
```

In [203…
```
anger_out_pt
```

Out[203…
```
0    2.938922
1    2.679492
2    2.603134
```

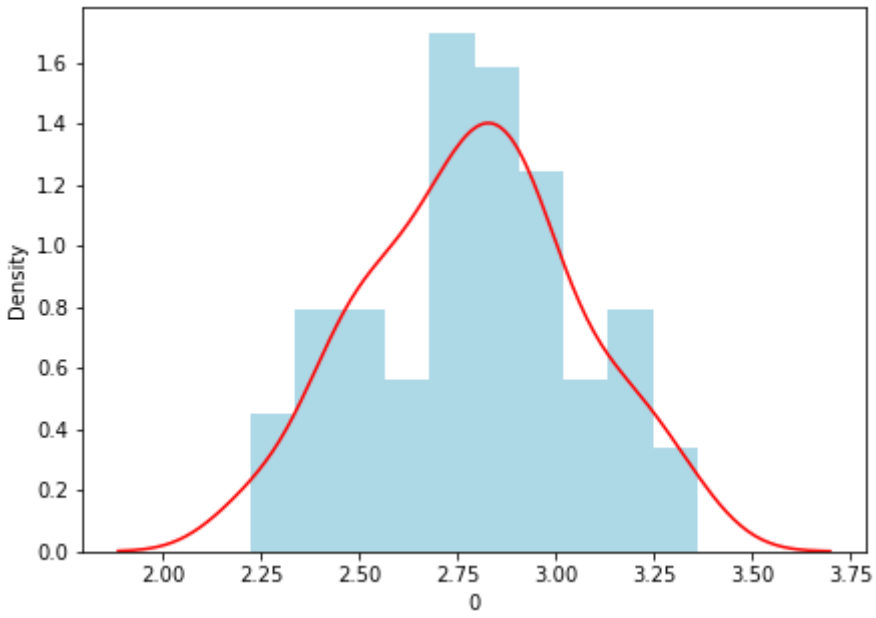
```
3     2.879852
4     2.817242
        ...
73    2.679492
74    2.333327
75    2.431247
76    2.750638
77    2.750638
Name: 0, Length: 78, dtype: float64
```

In [204…
```
anger_out_pt_ss = pd.DataFrame(ss.fit_transform(pd.DataFrame(scipy.stats.boxcox(ange
```

In [205…
```
anger_out_pt_ss
```

Out[205…
```
0     0.564209
1    -0.406073
2    -0.691656
3     0.343284
4     0.109120
        ...
73   -0.406073
74   -1.700753
75   -1.334526
76   -0.139982
77   -0.139982
Name: 0, Length: 78, dtype: float64
```

In [206…
```
with plt.style.context('seaborn-bright'):
    plt.figure(figsize=(7,5))
    plt.hist(anger_out_pt,density=True,color='lightblue')
    sns.kdeplot(anger_out_pt,color='red')
```



Skew Test

In [207…
```
scipy.stats.skew(anger_mood['Anger-Out'],bias=False)
```

Out[207…
```
0.5856542652644214
```

In [208…
```
scipy.stats.skew(anger_out_pt,bias=False)
```

Out[208…
```
-0.0004965443387343199
```

In [209…
```
scipy.stats.skew(anger_out_pt_ss,bias=False)
```

Out[209… -0.0004965443387389054

In [210…
```
scipy.stats.skewtest(anger_mood['Anger-Out'])
```

Out[210… SkewtestResult(statistic=2.114149991165024, pvalue=0.03450245856975766)

In [211…
```
scipy.stats.skewtest(anger_out_pt)
```

Out[211… SkewtestResult(statistic=-0.0018956488195151877, pvalue=0.998487491980067)

In [212…
```
scipy.stats.skewtest(anger_out_pt_ss)
```

Out[212… SkewtestResult(statistic=-0.0018956488195325171, pvalue=0.9984874919800533)

Kurtosis Test

In [213…
```
scipy.stats.kurtosis(anger_mood['Anger-Out'],bias=False)
```

Out[213… -0.0579720414522944

In [214…
```
scipy.stats.kurtosis(anger_out_pt,bias=False)
```

Out[214… -0.4424467016261513

In [215…
```
scipy.stats.kurtosis(anger_out_pt_ss,bias=False)
```

Out[215… -0.4424467016261526

In [216…
```
scipy.stats.kurtosistest(anger_mood['Anger-Out'])
```

Out[216… KurtosistestResult(statistic=0.08226222673612164, pvalue=0.9344381912761975)

In [217…
```
scipy.stats.kurtosistest(anger_out_pt)
```

Out[217… KurtosistestResult(statistic=-0.8634396349496412, pvalue=0.38789579550255027)

In [218…
```
scipy.stats.kurtosistest(anger_out_pt_ss)
```

Out[218… KurtosistestResult(statistic=-0.8634396349496458, pvalue=0.3878957955025477)

Anderson-Darling Test

In [219…
```
scipy.stats.anderson(anger_mood['Anger-Out'])
```

Out[219… AndersonResult(statistic=0.8866161999077633, critical_values=array([0.55 , 0.626, 0.752, 0.877, 1.043]), significance_level=array([15. , 10. , 5. , 2.5, 1.]))

In [220…
```
scipy.stats.anderson(anger_out_pt)
```

Out[220… AndersonResult(statistic=0.42091177774017297, critical_values=array([0.55 , 0.626, 0.752, 0.877, 1.043]), significance_level=array([15. , 10. , 5. , 2.5, 1.]))

In [221…
```
scipy.stats.anderson(anger_out_pt_ss)
```

Out[221… AndersonResult(statistic=0.42091177774017297, critical_values=array([0.55 , 0.626, 0.752, 0.877, 1.043]), significance_level=array([15. , 10. , 5. , 2.5, 1.]))

D'Agastino Test

In [222…
```
scipy.stats.normaltest(anger_mood['Anger-Out'])
```

Out[222…
```
NormaltestResult(statistic=4.476397259090656, pvalue=0.10665044841294197)
```

In [223…
```
scipy.stats.normaltest(anger_out_pt)
```

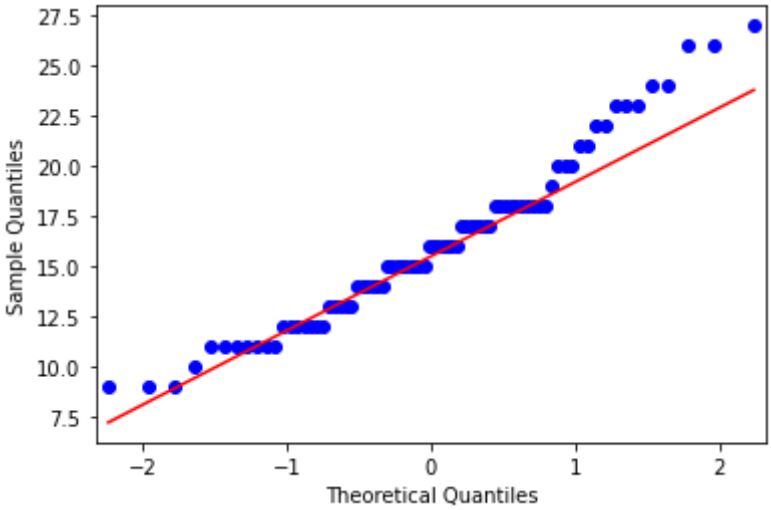
Out[223…
```
NormaltestResult(statistic=0.7455315966864164, pvalue=0.6888265382707246)
```

In [224…
```
scipy.stats.normaltest(anger_out_pt_ss)
```

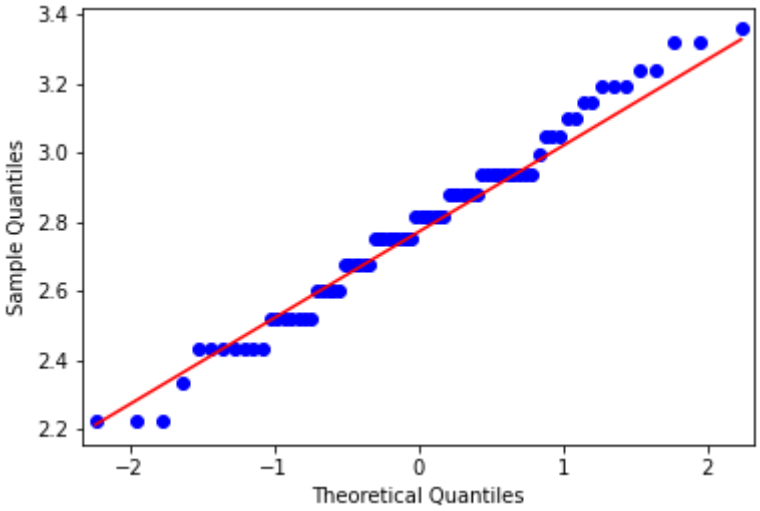
Out[224…
```
NormaltestResult(statistic=0.7455315966864247, pvalue=0.6888265382707217)
```

QQ Plot

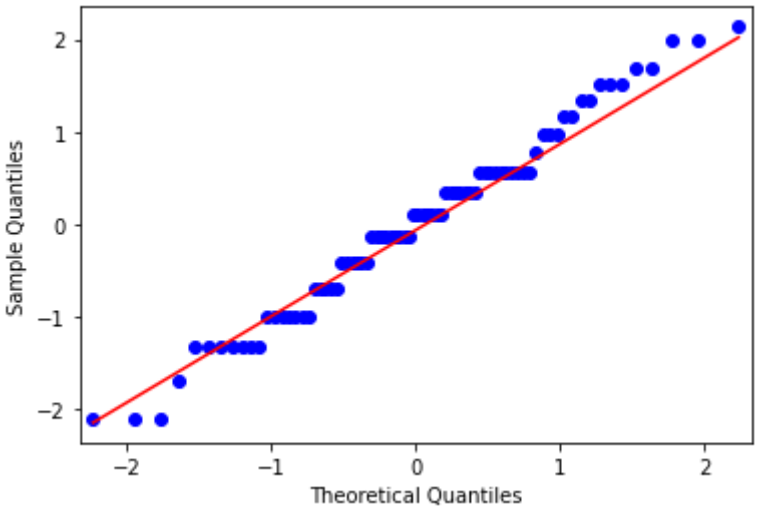
In [225…
```
stm.graphics.gofplots.qqplot(data=anger_mood['Anger-Out'],line='q');
```



In [226…
```
stm.graphics.gofplots.qqplot(data=anger_out_pt,line='q');
```



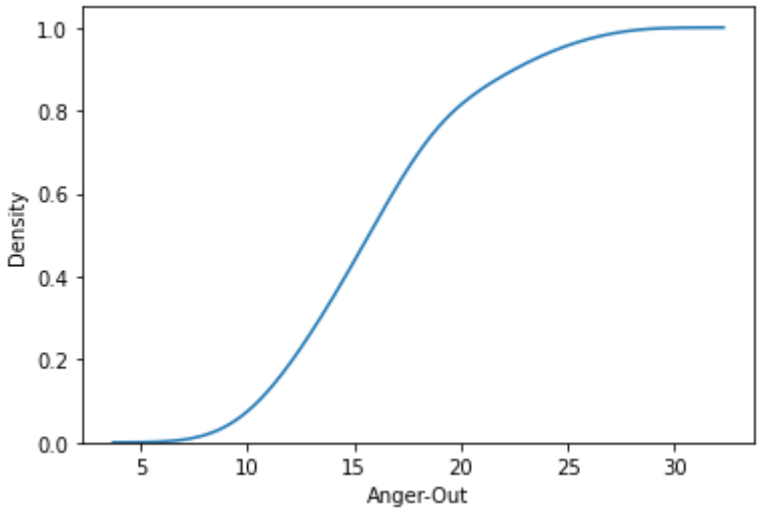
In [227…
```
stm.graphics.gofplots.qqplot(data=anger_out_pt_ss,line='q');
```



CDF Plot

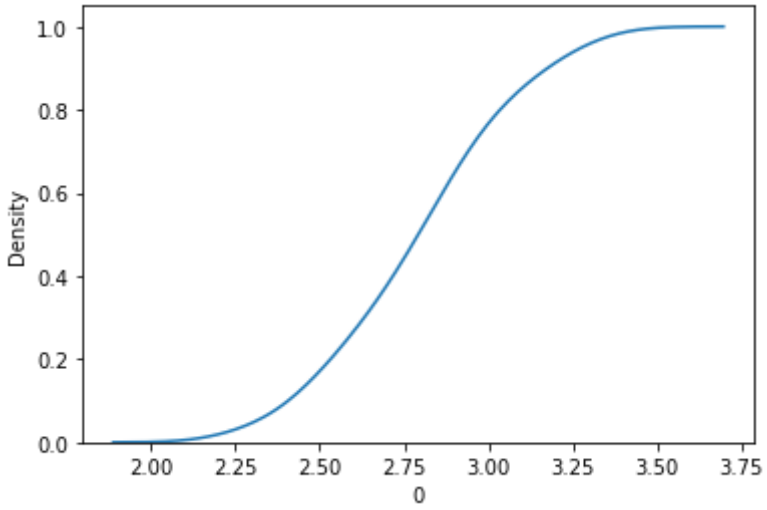
In [228…
```
sns.kdeplot(anger_mood['Anger-Out'],cumulative=True)
```

Out[228…
```
<AxesSubplot:xlabel='Anger-Out', ylabel='Density'>
```



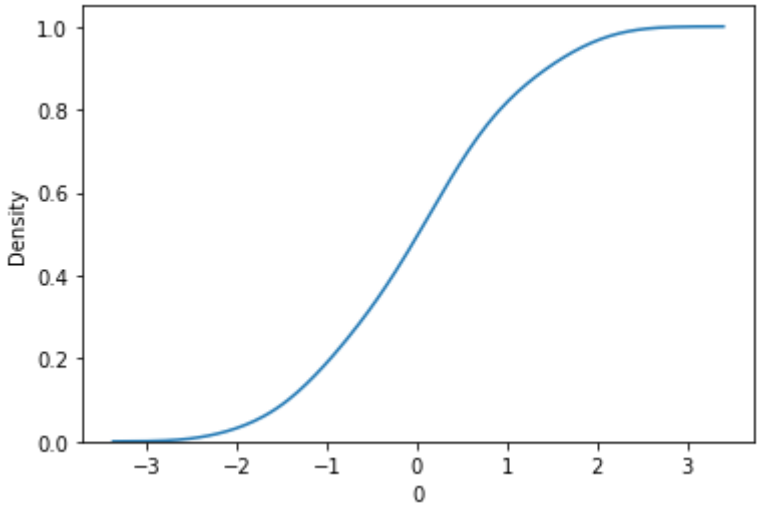
In [229…
```
sns.kdeplot(anger_out_pt,cumulative=True)
```

Out[229…
```
<AxesSubplot:xlabel='0', ylabel='Density'>
```



In [230…
```
sns.kdeplot(anger_out_pt_ss,cumulative=True)
```

Out[230…
```
<AxesSubplot:xlabel='0', ylabel='Density'>
```



KS Test

In [231...
```
np.round(np.mean(anger_mood['Anger-Out']),3), np.round(np.std(anger_mood['Anger-Out'
```

Out[231...
```
(16.077, 4.19)
```

In [232...
```
scipy.stats.kstest(anger_mood['Anger-Out'],'norm')
```

Out[232...
```
KstestResult(statistic=1.0, pvalue=0.0)
```

In [233...
```
np.round(np.mean(anger_out_pt),3), np.round(np.std(anger_out_pt),3)
```

Out[233...
```
(2.788, 0.267)
```

In [234...
```
scipy.stats.kstest(anger_out_pt,'norm')
```

Out[234...
```
KstestResult(statistic=0.9869662951831715, pvalue=1.889403494844932e-147)
```

In [235...
```
anger_out_pt_ss = pd.DataFrame(ss.fit_transform(pd.DataFrame(anger_out_pt)))[0]
```

In [236...
```
np.round(np.mean(anger_out_pt_ss),3), np.round(np.std(anger_out_pt_ss),3)
```

Out[236...
```
(0.0, 1.0)
```

In [237...
```
scipy.stats.kstest(anger_out_pt_ss,'norm')
```

Out[237...
```
KstestResult(statistic=0.08117785751780704, pvalue=0.6527048356296961)
```

In this experiment as well, it is quite evident that KS test is very sensitive to the data normalization and even the slightest variation in the mean and std dev can affect the result by a great margin.

In my analysis, I found that KS test focuses more on the sensitivity in the central region of the data with less focus on the tails. This limitation is removed in much improved versions of tests like Anderson-Darling & D'Agastino for large datasets and Shapiro-Wilk for smaller dataset.

Some calculations

In [238…
```
scipy.stats.norm.ppf(0.975)
```
Out[238…
```
1.959963984540054
```

In [239…
```
scipy.stats.norm.ppf(0.95)
```
Out[239…
```
1.6448536269514722
```

In [240…
```
scipy.stats.norm.ppf(0.05)
```
Out[240…
```
-1.6448536269514729
```

In [241…
```
scipy.stats.norm.ppf(0.025)
```
Out[241…
```
-1.9599639845400545
```

In [242…
```
scipy.stats.t.ppf(0.95,df=19)
```
Out[242…
```
1.729132811521367
```

In [243…
```
scipy.stats.t.ppf(0.975,df=19)
```
Out[243…
```
2.093024054408263
```

In [244…
```
scipy.stats.norm.cdf(1.9599)
```
Out[244…
```
0.9749962601845973
```