Ways to deal with outliers

In [1]:

```
#Importing the dataset
import pandas as p
import numpy as n
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_boston
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
boston=load_boston() #it is stored as dictionary
df= p.DataFrame(boston['data'],columns=boston['feature_names']) #converting dictionary to
```

In [3]:

```
df.head()
```

Out[3]:

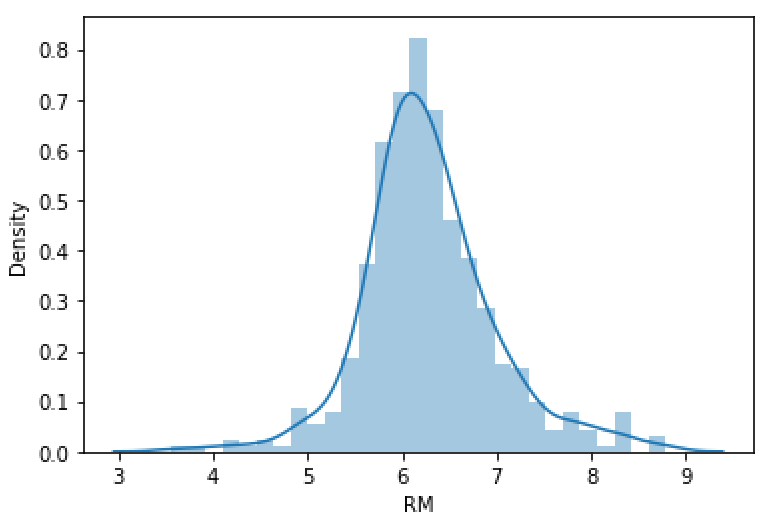
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

In [77]:

```
sns.distplot(df['RM'])
```

Out[77]:

```
<AxesSubplot:xlabel='RM', ylabel='Density'>
```

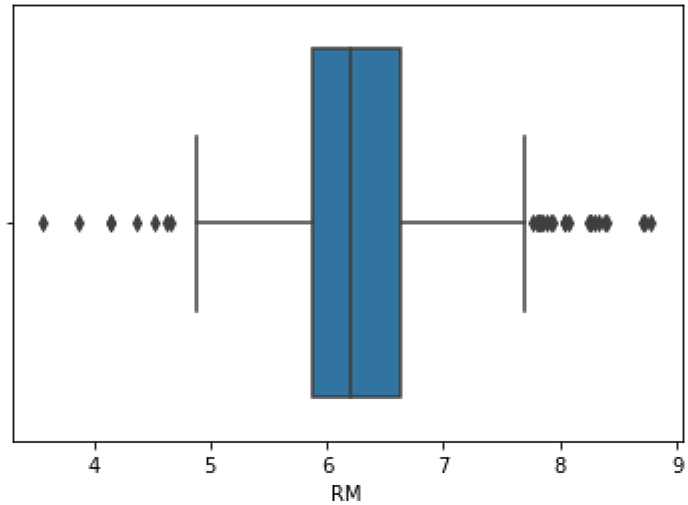


In [70]:

```
#As we can see outliers
sns.boxplot(df['RM'])
```

Out[70]:

```
<AxesSubplot:xlabel='RM'>
```



Trimming outliers from the dataset

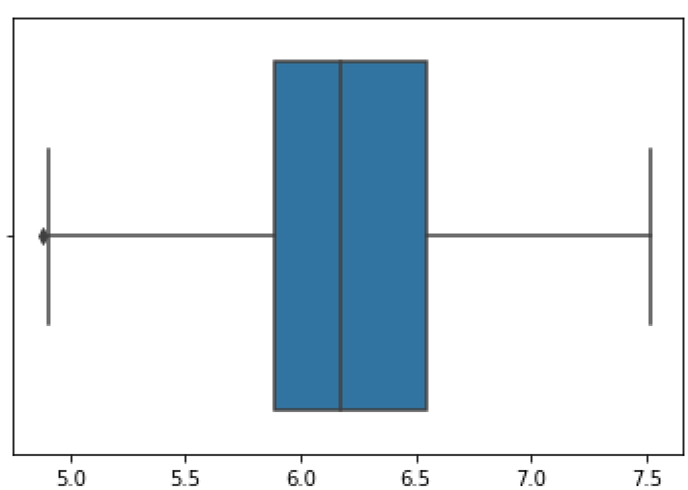
In [49]:
```
def outliers(data):
    IQR=data.quantile(0.75)-data.quantile(0.25)
    lr=data.quantile(0.25)-(1.5*IQR) #lower range
    hr=data.quantile(0.70)+(1.5*IQR) #higher range
    return data.loc[~(n.where(data<lr,True,n.where(data>hr,True,False)))] #Without outlie
```

In [50]:
```
outliers(df['RM']) #as we csn there is no outliers
```

Out[50]:
```
0      6.575
1      6.421
2      7.185
3      6.998
4      7.147
       ...
501    6.593
502    6.120
503    6.976
504    6.794
505    6.030
Name: RM, Length: 472, dtype: float64
```

In [51]:
```
sns.boxplot(outliers(df['RM']))
```

Out[51]: <AxesSubplot:xlabel='RM'>



In [97]:
```
#We can find outlier with using mean and standard deviation in case of IQR
def outliers(data,k):
    lr=data.mean()-(data.std()*k) #where n is number
    hr=data.mean()+(data.std()*k)
    return data.loc[~(n.where(data<lr,True,n.where(data>hr,True,False)))] #Without outlie
```

In [99]:
```
outliers(df['RM'],1.5)
```

Out[99]:
```
0      6.575
1      6.421
2      7.185
3      6.998
4      7.147
       ...
501    6.593
502    6.120
503    6.976
504    6.794
505    6.030
Name: RM, Length: 449, dtype: float64
```

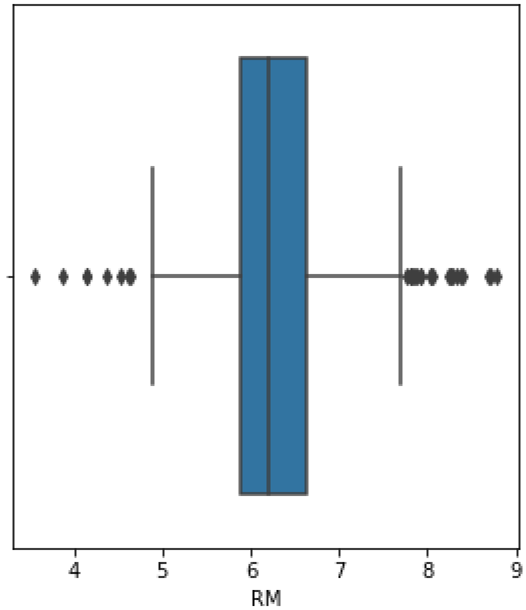
Performing winsorization

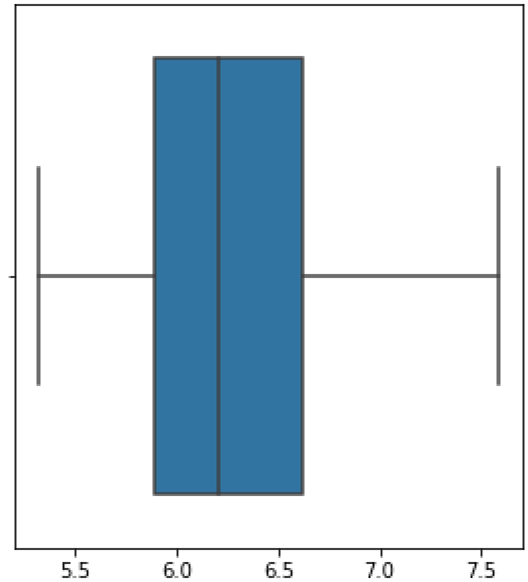
Winsorizing is different from trimming because the extreme values are not removed, but are instead replaced by other values. Data greater then qurantile 90 percent is replace by value at 90 qurantile similarly less then qurantile 5 percent is replace by value at 5 qurantile

In [105…
```
def fn(data,lw,h):
    lr=data.quantile(lw)
    hr=data.quantile(h)
    return n.where(data<lr,lr,n.where(data>hr,hr,data))
```

In [104…
```
plt.figure(figsize=(10,5))
plt.subplot(1,2,1)
sns.boxplot(df['RM'])
plt.subplot(1,2,2)
sns.boxplot(fn(df['RM'],0.05,0.95))
```

Out[104…
```
<AxesSubplot:>
```





Capping the variable at arbitrary maximum and minimum values

Similarly to winsorization, we can replace the extreme values by values closer to other values in the variable, by determining the maximum and minimum boundaries with the mean plus or minus the standard deviation, or the inter-quartile range proximity rule.

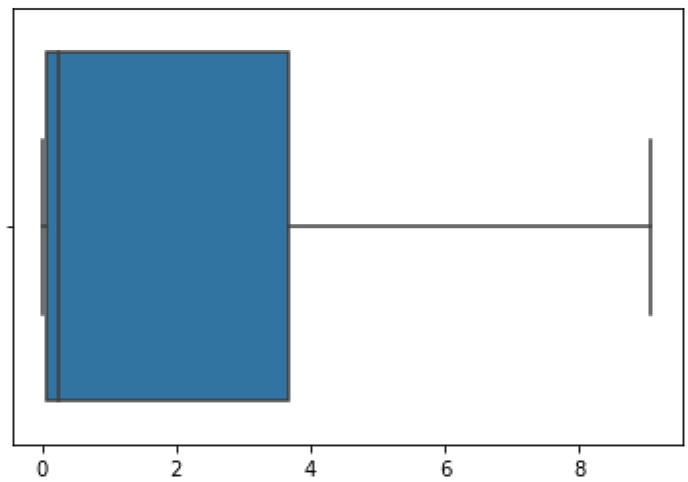
In [21]:

```
def outliers(data):
    IQR=data.quantile(0.75)-data.quantile(0.25)
    lr=data.quantile(0.25)-(1.5*IQR) #lower range
    hr=data.quantile(0.75)+(1.5*IQR) #higher range
    return n.where(data<lr,lr,n.where(data>hr,hr,data))
def outliers_mean(data,k):
    lr=data.mean()-(data.std()*k) #where k is number
    hr=data.mean()+(data.std()*k)
    return n.where(data<lr,lr,n.where(data>hr,hr,data))
```

In [26]:

```
sns.boxplot(outliers(df['CRIM']))
```

Out[26]: <AxesSubplot:>



In [24]:

```
sns.boxplot(df['CRIM'])
```

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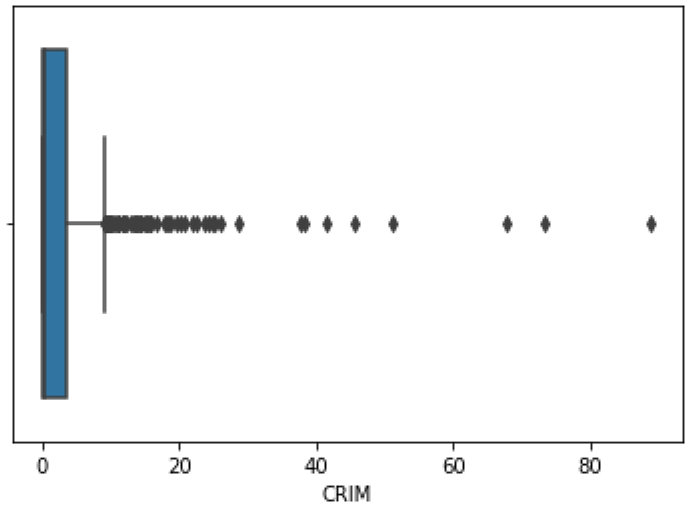
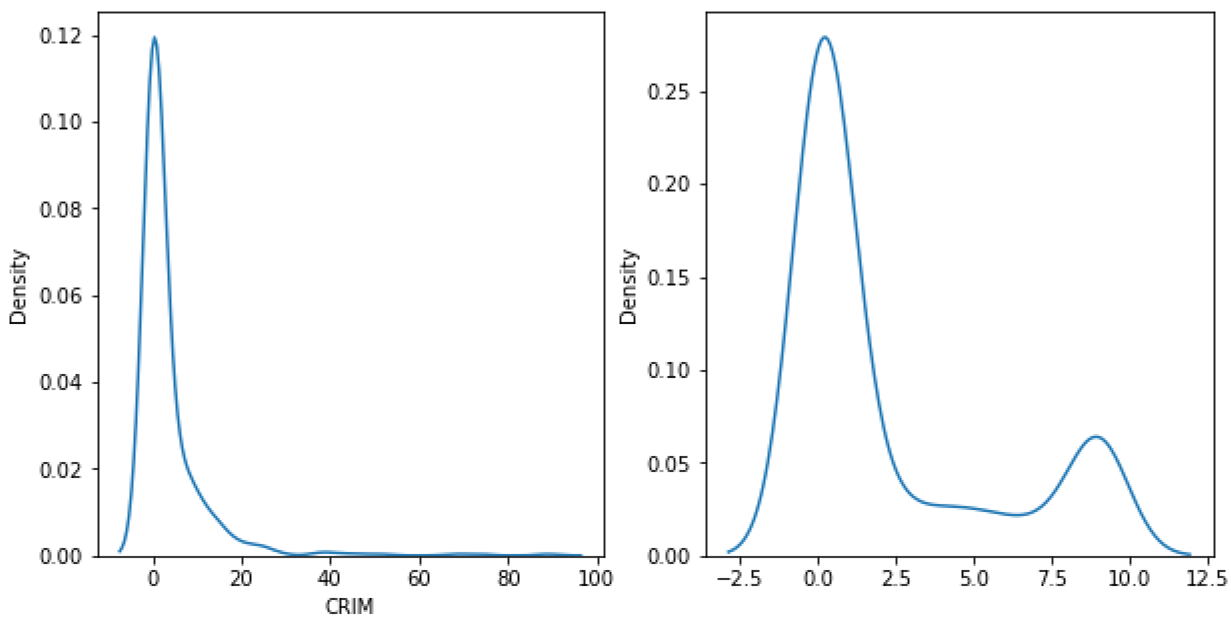
Out[24]: <AxesSubplot:xlabel='CRIM'>



In [42]:
```
plt.figure(figsize=(10,5))
plt.subplot(1,2,1)
sns.kdeplot(df['CRIM'])
plt.subplot(1,2,2)
sns.kdeplot(outliers(df['CRIM']))
```

Out[42]: <AxesSubplot:ylabel='Density'>



here is one problem in this and winsorization when we have outliers in one tail so it will create the bump that is shown in this graph .

Performing zero-coding – capping the variable at zero

Zero-coding is a variant of bottom-coding and refers to the process of capping, usually the lower value of the variable, at zero. It is commonly used for variables that cannot take negative values, such as age or income.

In [43]:
```
#creating a dummy dataset
n.random.seed(29)
x=n.random.randn(200)
y=n.random.randn(200)*2
z=n.random.randn(200)*6+5
```

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```
:z})
```

In [45]:
```python
df.head()
```

Out[45]:

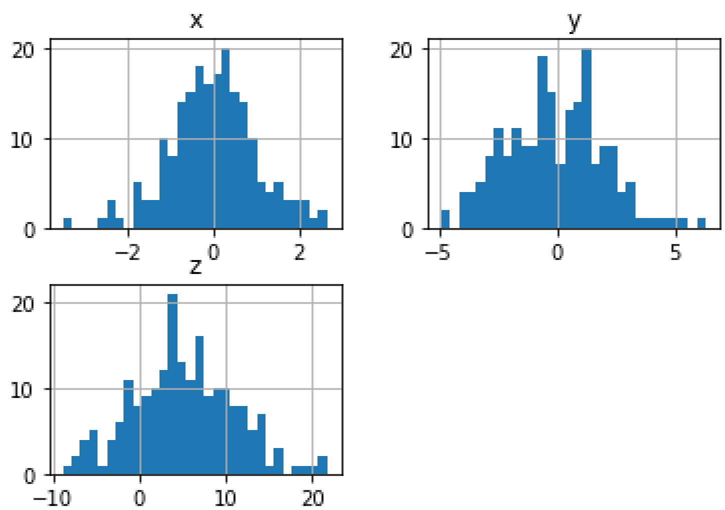
	x	y	z
0	-0.417482	2.903260	4.634786
1	0.706032	0.930279	10.236479
2	1.915985	0.688840	11.964026
3	-2.141755	-0.511348	13.884419
4	0.719057	-1.611499	18.030882

In [51]:
```python
df.min() #minmum values are negative
```

Out[51]:
```
x   -3.505401
y   -4.901451
z   -8.863583
dtype: float64
```

In [55]:
```python
plt.figure(figsize=(15,5))
df.hist(bins= 30)
```

Out[55]:
```
array([[<AxesSubplot:title={'center':'x'}>,
        <AxesSubplot:title={'center':'y'}>],
       [<AxesSubplot:title={'center':'z'}>, <AxesSubplot:>]], dtype=object)
<Figure size 1080x360 with 0 Axes>
```



In [56]:
```python
#AS we can see the negtive values
```

In [59]:
```python
#Replacing the negative values with zeros
df['x'].loc[df['x']<0]=0
df['y'].loc[df['y']<0]=0
df['z'].loc[df['z']<0]=0
```

In [60]:
```python
plt.figure(figsize=(15,5))
df.hist(bins= 30)
```

Out[60]:
```
array([[<AxesSubplot:title={'center':'x'}>,
        <AxesSubplot:title={'center':'y'}>],
                                    ter':'z'}>, <AxesSubplot:>]], dtype=object)
```

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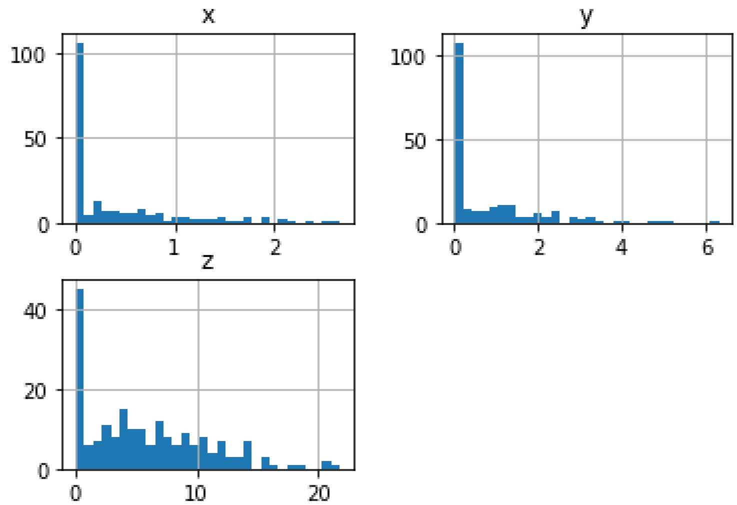
<Figure size 1080x360 with 0 Axes>



In [61]:
```
#now we can see increase in the nuber of zero values present
```

In [ ]: