# DS PRACTICAL 4

## 4. Handling Outliers In A Dataset

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## 4.1 Outliers Percentile

```
import pandas as pd
```

```
df = pd.read_csv("heights.csv")
df.head()
```

| | name | height |
|---|---|---|
| **0** | mohan | 5.9 |
| **1** | maria | 5.2 |
| **2** | sakib | 5.1 |
| **3** | tao | 5.5 |
| **4** | virat | 4.9 |

---

## Detect outliers using percentile

```
max_thresold = df['height'].quantile(0.95)
max_thresold
```

```
np.float64(9.689999999999998)
```

```
df[df['height']>max_thresold]
```

| | name | height |
|---|---|---|
| **9** | imran | 14.5 |

```
min_thresold = df['height'].quantile(0.05)
min_thresold
```

```
np.float64(3.6050000000000004)
```

```
df[df['height']<min_thresold]
```

| | name | height |
|---|---|---|
| **12** | yoseph | 1.2 |

---

## Remove outliers

```
df[(df['height']<max_thresold) & (df['height']>min_thresold)]
```

| | name | height |
|---|---|---|
| **0** | mohan | 5.9 |
| **1** | maria | 5.2 |
| **2** | sakib | 5.1 |
| **3** | tao | 5.5 |
| **4** | virat | 4.9 |
| **5** | khusbu | 5.4 |
| **6** | dmitry | 6.2 |
| **7** | selena | 6.5 |
| **8** | john | 7.1 |
| **10** | jose | 6.1 |
| **11** | deepika | 5.6 |
| **13** | binod | 5.5 |

## Banglore Property Prices Dataset

```
df = pd.read_csv("bhp.csv")
df.head()
```

| | location | size | total_sqft | bath | price | bhk | price_per_sqft |
|---|---|---|---|---|---|---|---|
| **0** | Electronic City Phase II | 2 BHK | 1056.0 | 2.0 | 39.07 | 2 | 3699 |
| **1** | Chikka Tirupathi | 4 Bedroom | 2600.0 | 5.0 | 120.00 | 4 | 4615 |
| **2** | Uttarahalli | 3 BHK | 1440.0 | 2.0 | 62.00 | 3 | 4305 |
| **3** | Lingadheeranahalli | 3 BHK | 1521.0 | 3.0 | 95.00 | 3 | 6245 |
| **4** | Kothanur | 2 BHK | 1200.0 | 2.0 | 51.00 | 2 | 4250 |

```
df.shape
```

```
(13200, 7)
```

```
df.describe()
```

| | total_sqft | bath | price | bhk | price_per_sqft |
|---|---|---|---|---|---|
| **count** | 13200.000000 | 13200.000000 | 13200.000000 | 13200.000000 | 1.320000e+04 |
| **mean** | 1555.302783 | 2.691136 | 112.276178 | 2.800833 | 7.920337e+03 |
| **std** | 1237.323445 | 1.338915 | 149.175995 | 1.292843 | 1.067272e+05 |
| **min** | 1.000000 | 1.000000 | 8.000000 | 1.000000 | 2.670000e+02 |
| **25%** | 1100.000000 | 2.000000 | 50.000000 | 2.000000 | 4.267000e+03 |
| **50%** | 1275.000000 | 2.000000 | 71.850000 | 3.000000 | 5.438000e+03 |
| **75%** | 1672.000000 | 3.000000 | 120.000000 | 3.000000 | 7.317000e+03 |
| **max** | 52272.000000 | 40.000000 | 3600.000000 | 43.000000 | 1.200000e+07 |

## Samples that are above 99.90% percentile and below 1% percentile rank

```
min_thresold, max_thresold = df.price_per_sqft.quantile([0.001, 0.999])
min_thresold, max_thresold
```

```
(1366.184, 50959.36200000098)
```

```
df[df.price_per_sqft < min_thresold]
```

| | location | size | total_sqft | bath | price | bhk | price_per_sqft |
|---|---|---|---|---|---|---|---|
| **665** | Yelahanka | 3 BHK | 35000.0 | 3.0 | 130.0 | 3 | 371 |
| **798** | other | 4 Bedroom | 10961.0 | 4.0 | 80.0 | 4 | 729 |
| **1867** | other | 3 Bedroom | 52272.0 | 2.0 | 140.0 | 3 | 267 |
| **2392** | other | 4 Bedroom | 2000.0 | 3.0 | 25.0 | 4 | 1250 |
| **3934** | other | 1 BHK | 1500.0 | 1.0 | 19.5 | 1 | 1300 |
| **5343** | other | 9 BHK | 42000.0 | 8.0 | 175.0 | 9 | 416 |
| **5417** | Ulsoor | 4 BHK | 36000.0 | 4.0 | 450.0 | 4 | 1250 |
| **5597** | JP Nagar | 2 BHK | 1100.0 | 1.0 | 15.0 | 2 | 1363 |
| **7166** | Yelahanka | 1 Bedroom | 26136.0 | 1.0 | 150.0 | 1 | 573 |
| **7862** | JP Nagar | 3 BHK | 20000.0 | 3.0 | 175.0 | 3 | 875 |
| **8300** | Kengeri | 1 BHK | 1200.0 | 1.0 | 14.0 | 1 | 1166 |
| **9144** | other | 4 Bedroom | 10961.0 | 4.0 | 80.0 | 4 | 729 |
| **11635** | Begur | 3 BHK | 2400.0 | 3.0 | 12.0 | 3 | 500 |
| **12355** | other | 4 BHK | 16335.0 | 4.0 | 149.0 | 4 | 912 |

```
df[df.price_per_sqft > max_thresold]
```

| | location | size | total_sqft | bath | price | bhk | price_per_sqft |
|---|---|---|---|---|---|---|---|
| **345** | other | 3 Bedroom | 11.0 | 3.0 | 74.0 | 3 | 672727 |
| **1005** | other | 1 BHK | 15.0 | 1.0 | 30.0 | 1 | 200000 |
| **1106** | other | 5 Bedroom | 24.0 | 2.0 | 150.0 | 5 | 625000 |
| **4044** | Sarjapur Road | 4 Bedroom | 1.0 | 4.0 | 120.0 | 4 | 12000000 |
| **4924** | other | 7 BHK | 5.0 | 7.0 | 115.0 | 7 | 2300000 |
| **5911** | Mysore Road | 1 Bedroom | 45.0 | 1.0 | 23.0 | 1 | 51111 |
| **6356** | Bommenahalli | 4 Bedroom | 2940.0 | 3.0 | 2250.0 | 4 | 76530 |
| **7012** | other | 1 BHK | 650.0 | 1.0 | 500.0 | 1 | 76923 |
| **7575** | other | 1 BHK | 425.0 | 1.0 | 750.0 | 1 | 176470 |
| **7799** | other | 4 BHK | 2000.0 | 3.0 | 1063.0 | 4 | 53150 |
| **8307** | Bannerghatta Road | 5 BHK | 2500.0 | 4.0 | 1400.0 | 5 | 56000 |
| **9436** | Indira Nagar | 4 Bedroom | 2400.0 | 5.0 | 1250.0 | 4 | 52083 |
| **11447** | Whitefield | 4 Bedroom | 60.0 | 4.0 | 218.0 | 4 | 363333 |
| **12328** | other | 4 Bedroom | 4350.0 | 8.0 | 2600.0 | 4 | 59770 |

---

## Remove Outliers

```
df2 = df[(df.price_per_sqft<max_thresold) & (df.price_per_sqft>min_thresold)]
df2.shape
```

```
(13172, 7)
```

```
df2.describe()
```

| | total_sqft | bath | price | bhk | price_per_sqft |
|---|---|---|---|---|---|
| **count** | 13172.000000 | 13172.000000 | 13172.000000 | 13172.000000 | 13172.000000 |
| **mean** | 1537.861049 | 2.690100 | 111.591865 | 2.799651 | 6663.653735 |
| **std** | 967.123711 | 1.337026 | 145.372047 | 1.291130 | 4141.020700 |
| **min** | 250.000000 | 1.000000 | 8.000000 | 1.000000 | 1379.000000 |
| **25%** | 1100.000000 | 2.000000 | 50.000000 | 2.000000 | 4271.000000 |
| **50%** | 1274.500000 | 2.000000 | 71.550000 | 3.000000 | 5438.000000 |
| **75%** | 1670.000000 | 3.000000 | 120.000000 | 3.000000 | 7311.000000 |
| **max** | 30400.000000 | 40.000000 | 3600.000000 | 43.000000 | 50349.000000 |

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# Exercise

Q) Use air bnb new york city data set and remove outliers using percentile based on price per night for a given apartment/home. You can use suitable upper and lower limits on percentile based on your intuition. Your goal is to come up with new pandas dataframe that doesn't have the outliers present in it.

```
import pandas as pd
```

```
df = pd.read_csv("AB_NYC_2019.csv")
df.head()
```

| | id | name | host_id | host_name | neighbourhood_group | neighbourhood | lat |
|---|---|---|---|---|---|---|---|
| **0** | 2539 | Clean & quiet apt home by the park | 2787 | John | Brooklyn | Kensington | 40 |
| **1** | 2595 | Skylit Midtown Castle | 2845 | Jennifer | Manhattan | Midtown | 40 |
| **2** | 3647 | THE VILLAGE OF HARLEM....NEW YORK ! | 4632 | Elisabeth | Manhattan | Harlem | 40 |
| **3** | 3831 | Cozy Entire Floor of Brownstone | 4869 | LisaRoxanne | Brooklyn | Clinton Hill | 40 |
| **4** | 5022 | Entire Apt: Spacious Studio/Loft by central park | 7192 | Laura | Manhattan | East Harlem | 40 |

```
df.price.describe()
```

```
count    48895.000000
mean       152.720687
std        240.154170
min          0.000000
25%         69.000000
50%        106.000000
75%        175.000000
max      10000.000000
Name: price, dtype: float64
```

```
min_thresold, max_thresold = df.price.quantile([0.01,0.999])
min_thresold, max_thresold
```

```
(30.0, 3000.0)
```

```
df[df.price<min_thresold]
```

| | id | name | host_id | host_name | neighbourhood_group | neighbourhoo |
|---|---|---|---|---|---|---|
| **957** | 375249 | Enjoy Staten Island Hospitality | 1887999 | Rimma & Jim | Staten Island | Granitevil |
| **2675** | 1428154 | Central, Peaceful Semi-Private Room | 5912572 | Tangier | Brooklyn | Flatbus |
| **2860** | 1620248 | Large furnished 2 bedrooms- - 30 days Minimum | 2196224 | Sally | Manhattan | East Villag |
| **3020** | 1767037 | Small Cozy Room Wifi & AC near JFK | 9284163 | Antonio | Queens | Woodhave |
| **3918** | 2431607 | Bright, Airy Room Share for 2 | 4973668 | Gloria | Brooklyn | Bedfor Stuyvesa |
| **...** | ... | ... | ... | ... | ... | |
| **48486** | 36280646 | Cable and wfi, L/G included. | 272872092 | Chris | Queens | Forest Hi |
| **48647** | 36354776 | Cozy bedroom in diverse neighborhood near JFK | 273393150 | Liza | Queens | Richmond H |
| **48832** | 36450814 | FLATBUSH HANG OUT AND GO | 267223765 | Jarmel | Brooklyn | Flatbus |
| **48867** | 36473044 | The place you were dreaming for. (only for guys) | 261338177 | Diana | Brooklyn | Gravesen |
| **48868** | 36473253 | Heaven for you(only for guy) | 261338177 | Diana | Brooklyn | Gravesen |

404 rows × 16 columns

```
df2 = df[(df.price>min_thresold)&(df.price<max_thresold)]
df2.shape
```

```
(48183, 16)
```

```
df2.sample(5)
```

| | id | name | host_id | host_name | neighbourhood_group | neighbourh |
|---|---|---|---|---|---|---|
| **24530** | 19729892 | One room in a beautiful two bedroom appartment | 4452444 | Jūrate | Brooklyn | Williamsb |
| **17785** | 13952384 | Large Upper East Side Alcove Studio | 14945903 | Nicole | Manhattan | Upper E S |
| **37027** | 29439494 | VERREZZANO HOUSE | 221760432 | Daniel | Staten Island | Conc |
| **24132** | 19439956 | LUXURY APARTMENT 5 MIN TO LGA 20 TO JFK | 136300414 | Gonzalo | Queens | East Elmh |
| **1128** | 478832 | Gorgeous 2 bdrm in Carroll Gardens | 2371814 | Jennifer | Brooklyn | Carroll Gard |

```
df2.price.describe()
```

```
count    48183.000000
mean       148.772036
std        153.594795
min         31.000000
25%         70.000000
50%        110.000000
75%        179.000000
max       2999.000000
Name: price, dtype: float64
```

---

## 4.2 Outlier detection and removal using z-score and standard deviation in python pandas

```
pip install matplotlib
```

```
Requirement already satisfied: matplotlib in c:\users\harsh\appdata\local\programs\py
Requirement already satisfied: contourpy>=1.0.1 in c:\users\harsh\appdata\local\progr
Requirement already satisfied: cycler>=0.10 in c:\users\harsh\appdata\local\programs\
Requirement already satisfied: fonttools>=4.22.0 in c:\users\harsh\appdata\local\prog
Requirement already satisfied: kiwisolver>=1.3.1 in c:\users\harsh\appdata\local\prog
Requirement already satisfied: numpy>=1.23 in c:\users\harsh\appdata\local\programs\p
Requirement already satisfied: packaging>=20.0 in c:\users\harsh\appdata\local\progra
```

```
Requirement already satisfied: pillow>=8 in c:\users\harsh\appdata\local\programs\pyt
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\harsh\appdata\local\progr
Requirement already satisfied: python-dateutil>=2.7 in c:\users\harsh\appdata\local\p
Requirement already satisfied: six>=1.5 in c:\users\harsh\appdata\local\programs\pyth
Note: you may need to restart the kernel to use updated packages.
```

```
import pandas as pd
import matplotlib
from matplotlib import pyplot as plt
%matplotlib inline
matplotlib.rcParams['figure.figsize'] = (10,6)
```

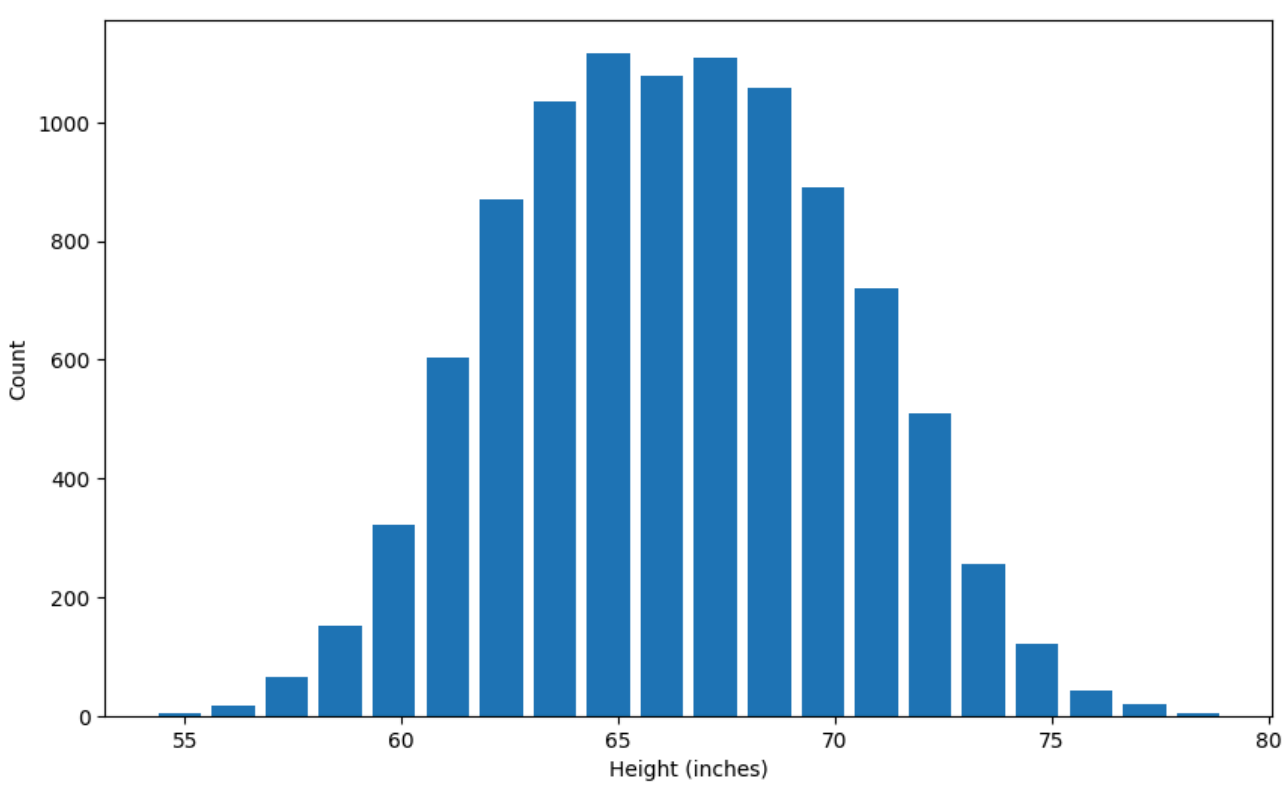
We are going to use heights dataset from kaggle.com. Dataset has heights and weights both but I have removed weights to make it simple

https://www.kaggle.com/mustafaali96/weight-height

```
df = pd.read_csv("heights (2).csv")
df.sample(5)
```

| | gender | height |
|---|---|---|
| **2002** | Male | 70.214947 |
| **4472** | Male | 70.949770 |
| **9292** | Female | 62.234939 |
| **2666** | Male | 71.154717 |
| **615** | Male | 70.413869 |

```
plt.hist(df.height, bins=20, rwidth=0.8)
plt.xlabel('Height (inches)')
plt.ylabel('Count')
plt.show()
```




---

## Plot bell curve along with histogram for our dataset

```
pip install scipy
```

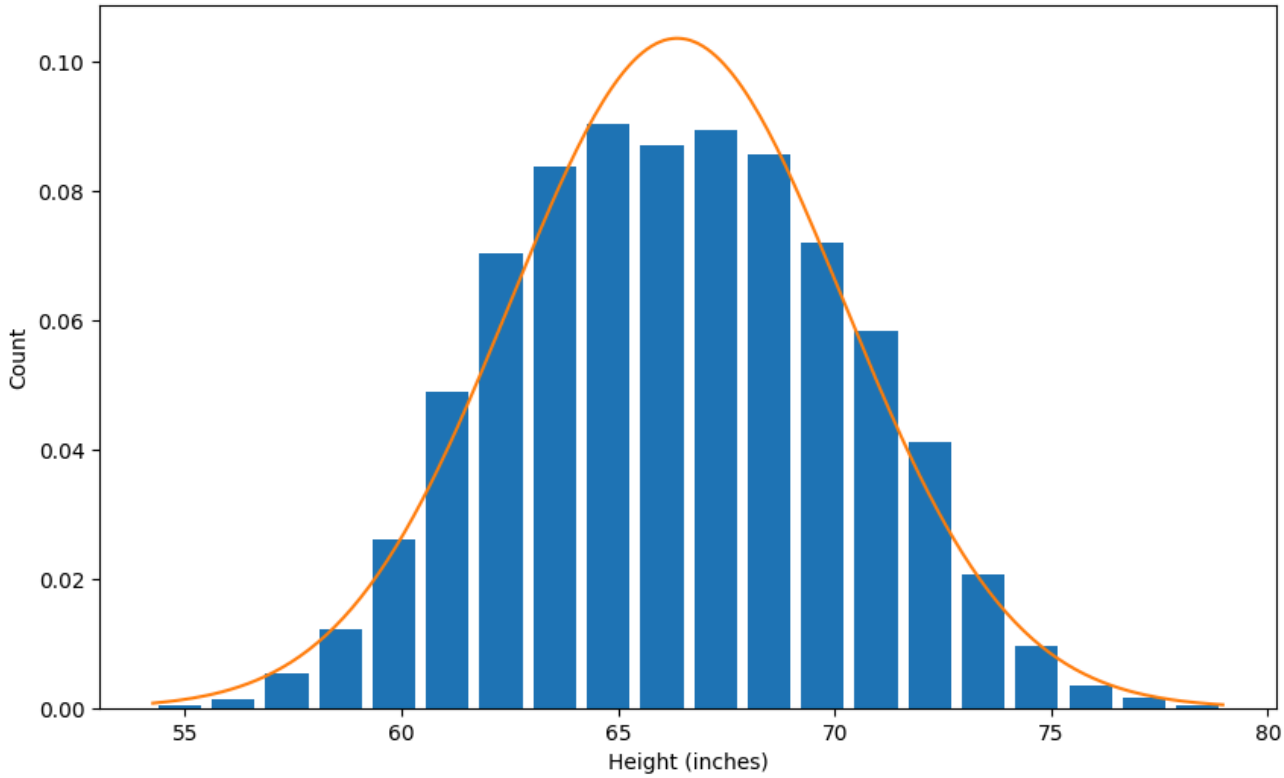
```
Requirement already satisfied: scipy in c:\users\harsh\appdata\local\programs\python\
Requirement already satisfied: numpy<2.3,>=1.23.5 in c:\users\harsh\appdata\local\prc
Note: you may need to restart the kernel to use updated packages.
```

```
from scipy.stats import norm
import numpy as np
df = pd.read_csv("heights (2).csv")

plt.hist(df.height, bins=20, rwidth=0.8, density=True)
plt.xlabel('Height (inches)')
plt.ylabel('Count')

rng = np.arange(df.height.min(), df.height.max(), 0.1)
plt.plot(rng, norm.pdf(rng,df.height.mean(),df.height.std()))
```

```
[<matplotlib.lines.Line2D at 0x1ae4288acf0>]
```




```
df.height.mean()
```

```
np.float64(66.367559754866)
```

```
df.height.std()
```

```
np.float64(3.847528120795573)
```

Here the mean is 66.37 and standard deviation is 3.84.

---

## (1) Outlier detection and removal using 3 standard deviation

One of the ways we can remove outliers is remove any data points that are beyond 3 standard deviation from mean. Which means we can come up with following upper and lower bounds

```
upper_limit = df.height.mean() + 3*df.height.std()
upper_limit
```

```
np.float64(77.91014411725271)
```

```
lower_limit = df.height.mean() -3*df.height.std()
lower_limit
```

```
np.float64(54.824975392479274)
```

```
df[(df.height>upper_limit) | (df.height<lower_limit)]
```

| | gender | height |
|---|---|---|
| **994** | Male | 78.095867 |
| **1317** | Male | 78.462053 |
| **2014** | Male | 78.998742 |
| **3285** | Male | 78.528210 |
| **3757** | Male | 78.621374 |
| **6624** | Female | 54.616858 |
| **9285** | Female | 54.263133 |

Above the heights on higher end is 78 inch which is around 6 ft 6 inch. Now that is quite unusual height. There are people who have this height but it is very uncommon and it is ok if you remove those data points. Similarly on lower end it is 54 inch which is around 4 ft 6 inch. While this is also a legitimate height you don't find many people having this height so it is safe to consider both of these cases as outliers

## Now remove these outliers and generate new dataframe

```
df_no_outlier_std_dev = df[(df.height<upper_limit) & (df.height>lower_limit)]
df_no_outlier_std_dev.head()
```

| | gender | height |
|---|---|---|
| **0** | Male | 73.847017 |
| **1** | Male | 68.781904 |
| **2** | Male | 74.110105 |
| **3** | Male | 71.730978 |
| **4** | Male | 69.881796 |

```
df_no_outlier_std_dev.shape
```

```
(9993, 2)
```

```
df.shape
```

```
(10000, 2)
```

Above shows original dataframe data 10000 data points. Out of that we removed 7 outliers (i.e. 10000-9993)

---

## (2) Outlier detection and removal using Z Score

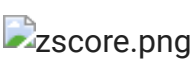
Z score is a way to achieve same thing that we did above in part (1)

Z score indicates how many standard deviation away a data point is.

For example in our case mean is 66.37 and standard deviation is 3.84.

If a value of a data point is 77.91 then Z score for that is 3 because it is 3 standard deviation away (77.91 = 66.37 + 3 * 3.84)

## Calculate the Z Score



```
df['zscore'] = ( df.height - df.height.mean() ) / df.height.std()
df.head(5)
```

| | gender | height | zscore |
|---|---|---|---|
| **0** | Male | 73.847017 | 1.943964 |
| **1** | Male | 68.781904 | 0.627505 |
| **2** | Male | 74.110105 | 2.012343 |
| **3** | Male | 71.730978 | 1.393991 |
| **4** | Male | 69.881796 | 0.913375 |

Above for first record with height 73.84, z score is 1.94. This means 73.84 is 1.94 standard deviation away from mean

```
(73.84-66.37)/3.84
```

```
1.9453124999999998
```

Get data points that has z score higher than 3 or lower than -3. Another way of saying same thing is get data points that are more than 3 standard deviation away

```
df[df['zscore']>3]
```

| | gender | height | zscore |
|---|---|---|---|
| **994** | Male | 78.095867 | 3.048271 |
| **1317** | Male | 78.462053 | 3.143445 |
| **2014** | Male | 78.998742 | 3.282934 |
| **3285** | Male | 78.528210 | 3.160640 |
| **3757** | Male | 78.621374 | 3.184854 |

```
df[df['zscore']<-3]
```

| | gender | height | zscore |
|---|---|---|---|
| **6624** | Female | 54.616858 | -3.054091 |
| **9285** | Female | 54.263133 | -3.146027 |

# Here is the list of all outliers

```
df[(df.zscore<-3) | (df.zscore>3)]
```

| | gender | height | zscore |
|---|---|---|---|
| **994** | Male | 78.095867 | 3.048271 |
| **1317** | Male | 78.462053 | 3.143445 |
| **2014** | Male | 78.998742 | 3.282934 |
| **3285** | Male | 78.528210 | 3.160640 |
| **3757** | Male | 78.621374 | 3.184854 |
| **6624** | Female | 54.616858 | -3.054091 |
| **9285** | Female | 54.263133 | -3.146027 |

---

## Remove the outliers and produce new dataframe

```
df_no_outliers = df[(df.zscore>-3) & (df.zscore<3)]
df_no_outliers.head()
```

| | gender | height | zscore |
|---|---|---|---|
| **0** | Male | 73.847017 | 1.943964 |
| **1** | Male | 68.781904 | 0.627505 |
| **2** | Male | 74.110105 | 2.012343 |
| **3** | Male | 71.730978 | 1.393991 |
| **4** | Male | 69.881796 | 0.913375 |

```
df_no_outliers.shape
```

```
(9993, 3)
```

```
df.shape
```

```
(10000, 3)
```

---

# Exercise

## Q) You are given bhp.csv which contains property prices in the city of banglore, India. You need to examine price_per_sqft column and do following,

(1) Remove outliers using percentile technique first. Use [0.001, 0.999] for lower and upper bound percentiles

(2) After removing outliers in step 1, you get a new dataframe.

(3) On step(2) dataframe, use 4 standard deviation to remove outliers

(4) Plot histogram for new dataframe that is generated after step (3). Also plot bell curve on same histogram

(5) On step(2) dataframe, use zscore of 4 to remove outliers. This is quite similar to step (3) and you will get exact same result

```
import pandas as pd

import matplotlib
from matplotlib import pyplot as plt
%matplotlib inline
matplotlib.rcParams['figure.figsize'] = (12,8)
```

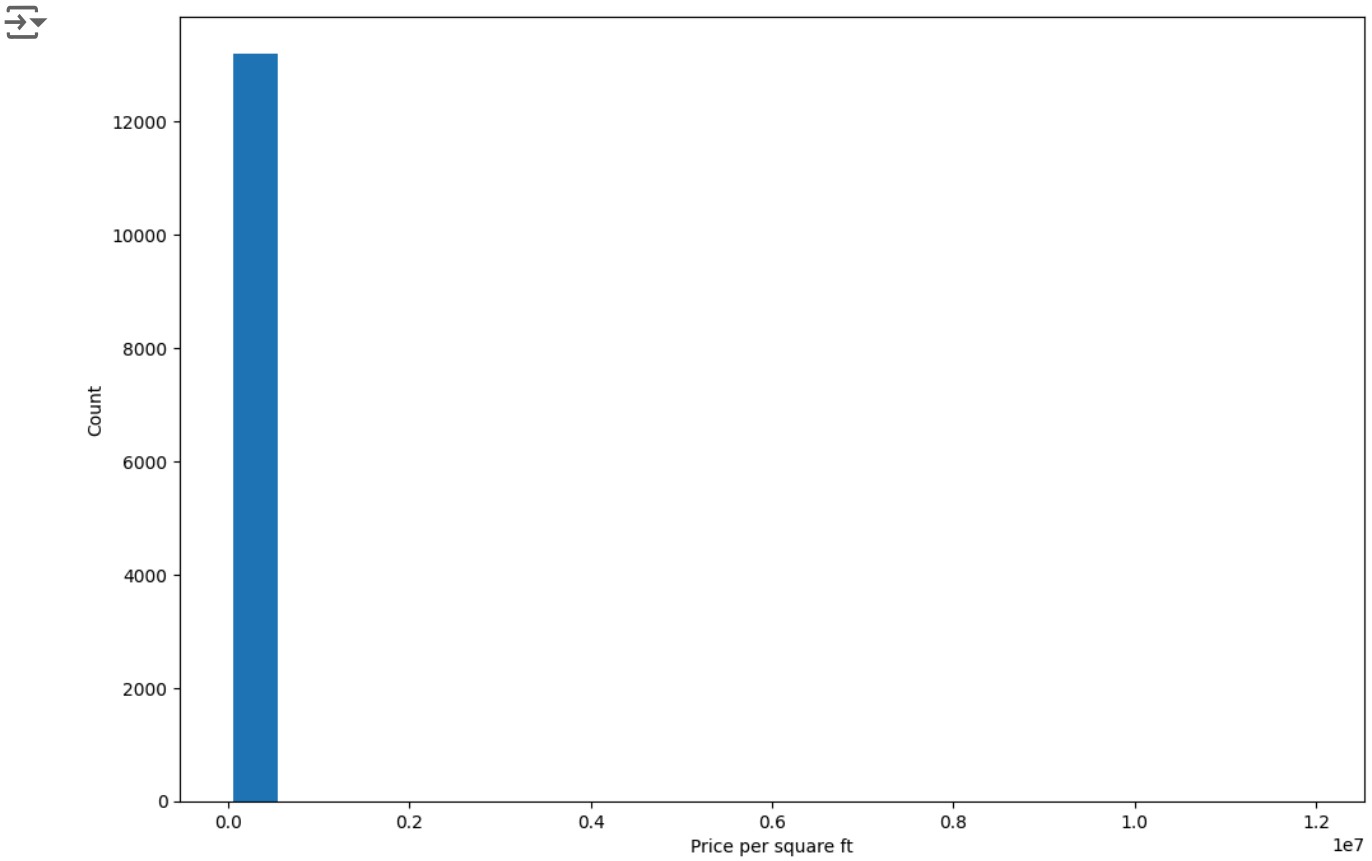
```
df = pd.read_csv("bhp.csv")
df.head()
```

| | location | size | total_sqft | bath | price | bhk | price_per_sqft |
|---|---|---|---|---|---|---|---|
| **0** | Electronic City Phase II | 2 BHK | 1056.0 | 2.0 | 39.07 | 2 | 3699 |
| **1** | Chikka Tirupathi | 4 Bedroom | 2600.0 | 5.0 | 120.00 | 4 | 4615 |
| **2** | Uttarahalli | 3 BHK | 1440.0 | 2.0 | 62.00 | 3 | 4305 |
| **3** | Lingadheeranahalli | 3 BHK | 1521.0 | 3.0 | 95.00 | 3 | 6245 |
| **4** | Kothanur | 2 BHK | 1200.0 | 2.0 | 51.00 | 2 | 4250 |

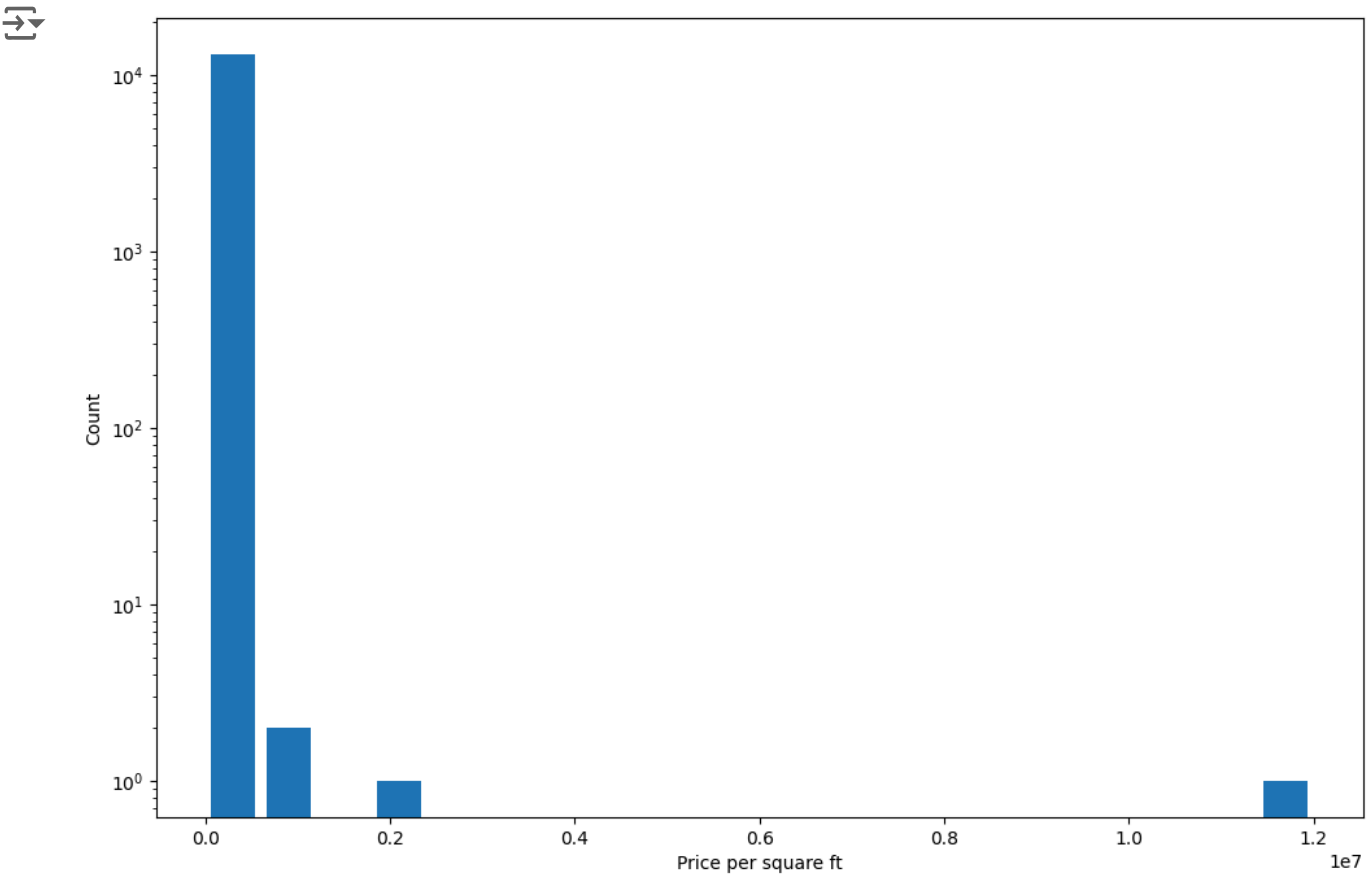
```
df.price_per_sqft.describe()
```

```
count    1.320000e+04
mean     7.920337e+03
std      1.067272e+05
min      2.670000e+02
25%      4.267000e+03
50%      5.438000e+03
75%      7.317000e+03
max      1.200000e+07
Name: price_per_sqft, dtype: float64
```

```
plt.hist(df.price_per_sqft, bins=20, rwidth=0.8)
plt.xlabel('Price per square ft')
plt.ylabel('Count')
plt.show()
```




```
plt.hist(df.price_per_sqft, bins=20, rwidth=0.8)
plt.xlabel('Price per square ft')
plt.ylabel('Count')
plt.yscale('log')
plt.show()
```




---

## (1) Treat outliers using percentile first

```
lower_limit, upper_limit = df.price_per_sqft.quantile([0.001, 0.999])
lower_limit, upper_limit
```

```
(1366.184, 50959.36200000098)
```

```
outliers = df[(df.price_per_sqft>upper_limit) | (df.price_per_sqft<lower_limit)]
outliers.sample(10)
```

| | location | size | total_sqft | bath | price | bhk | price_per_sqft |
|---|---|---|---|---|---|---|---|
| **2392** | other | 4 Bedroom | 2000.0 | 3.0 | 25.0 | 4 | 1250 |
| **12328** | other | 4 Bedroom | 4350.0 | 8.0 | 2600.0 | 4 | 59770 |
| **9144** | other | 4 Bedroom | 10961.0 | 4.0 | 80.0 | 4 | 729 |
| **11635** | Begur | 3 BHK | 2400.0 | 3.0 | 12.0 | 3 | 500 |
| **12355** | other | 4 BHK | 16335.0 | 4.0 | 149.0 | 4 | 912 |
| **7166** | Yelahanka | 1 Bedroom | 26136.0 | 1.0 | 150.0 | 1 | 573 |
| **7862** | JP Nagar | 3 BHK | 20000.0 | 3.0 | 175.0 | 3 | 875 |
| **7012** | other | 1 BHK | 650.0 | 1.0 | 500.0 | 1 | 76923 |
| **1867** | other | 3 Bedroom | 52272.0 | 2.0 | 140.0 | 3 | 267 |
| **7799** | other | 4 BHK | 2000.0 | 3.0 | 1063.0 | 4 | 53150 |

```
df2 = df[(df.price_per_sqft<upper_limit) & (df.price_per_sqft>lower_limit)]
df2.shape
```

```
(13172, 7)
```

```
df.shape
```

```
(13200, 7)
```

```
df.shape[0] - df2.shape[0]
```

```
28
```

We removed total 28 outliers

---

## (2) Now remove outliers using 4 standard deviation

```
max_limit = df2.price_per_sqft.mean() + 4*df2.price_per_sqft.std()
min_limit = df2.price_per_sqft.mean() - 4*df2.price_per_sqft.std()
max_limit, min_limit
```

```
(np.float64(23227.73653589432), np.float64(-9900.429065502582))
```

```
df2[(df2.price_per_sqft>max_limit) | (df2.price_per_sqft<min_limit)].sample(10)
```

| | location | size | total_sqft | bath | price | bhk | price_per_sqft |
|---|---|---|---|---|---|---|---|
| **12900** | HAL 2nd Stage | 5 Bedroom | 2040.0 | 4.0 | 500.0 | 5 | 24509 |
| **10000** | other | 6 Bedroom | 1200.0 | 5.0 | 280.0 | 6 | 23333 |
| **45** | HSR Layout | 8 Bedroom | 600.0 | 9.0 | 200.0 | 8 | 33333 |
| **3500** | Kundalahalli | 1 BHK | 2400.0 | 1.0 | 650.0 | 1 | 27083 |
| **3675** | Kasturi Nagar | 5 Bedroom | 1650.0 | 5.0 | 450.0 | 5 | 27272 |
| **1281** | Chamrajpet | 9 Bedroom | 4050.0 | 7.0 | 1200.0 | 9 | 29629 |
| **9873** | other | 3 Bedroom | 2400.0 | 6.0 | 775.0 | 3 | 32291 |
| **8157** | other | 4 BHK | 2230.0 | 4.0 | 792.0 | 4 | 35515 |
| **12393** | Electronic City Phase II | 1 BHK | 1200.0 | 1.0 | 295.0 | 1 | 24583 |
| **10536** | other | 4 Bedroom | 2400.0 | 4.0 | 595.0 | 4 | 24791 |

```
df3 = df2[(df2.price_per_sqft>min_limit) & (df2.price_per_sqft<max_limit)]
df3.shape
```

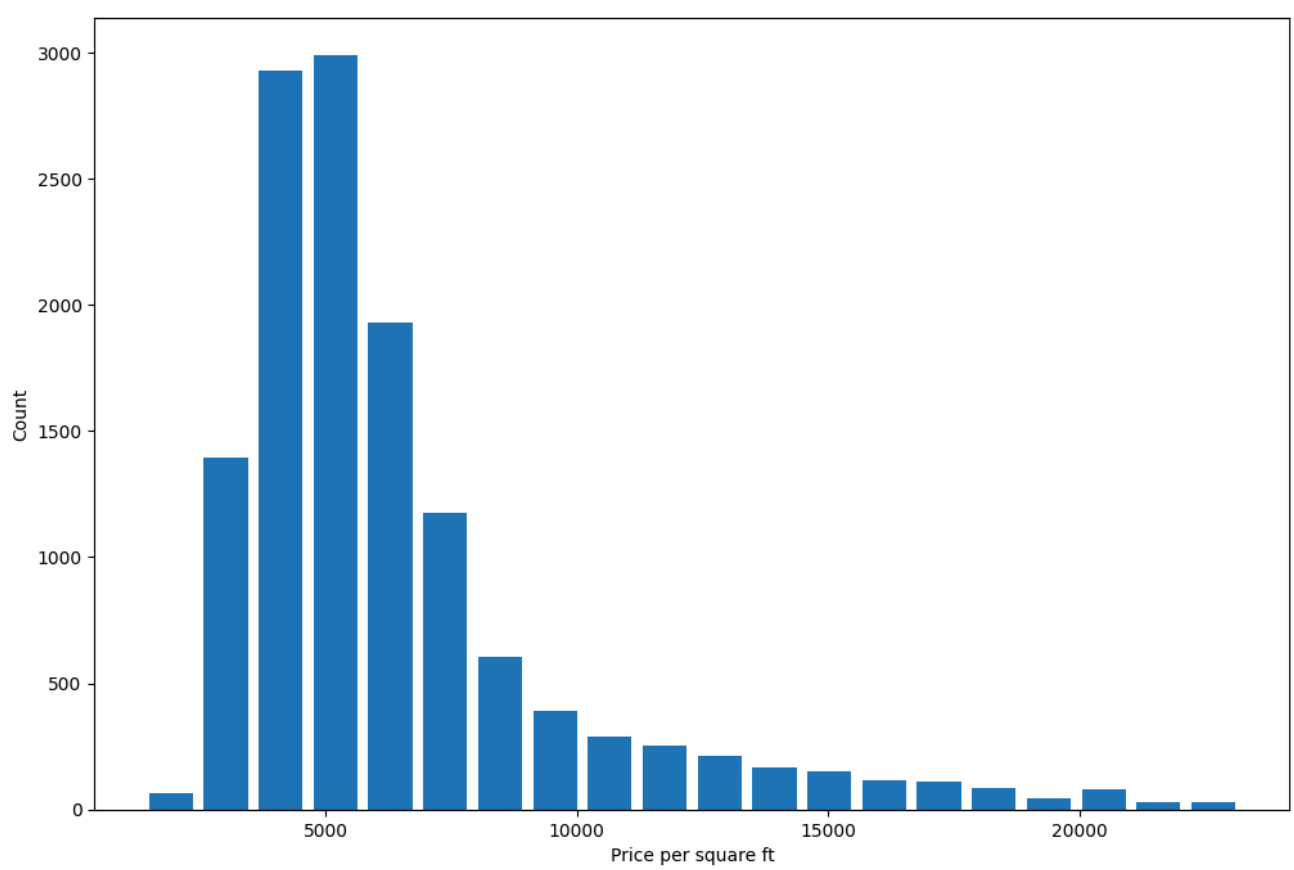
```
(13047, 7)
```

```
df2.shape[0]-df3.shape[0]
```

```
125
```

In this step we removed total 125 outliers

```
plt.hist(df3.price_per_sqft, bins=20, rwidth=0.8)
plt.xlabel('Price per square ft')
plt.ylabel('Count')
plt.show()
```

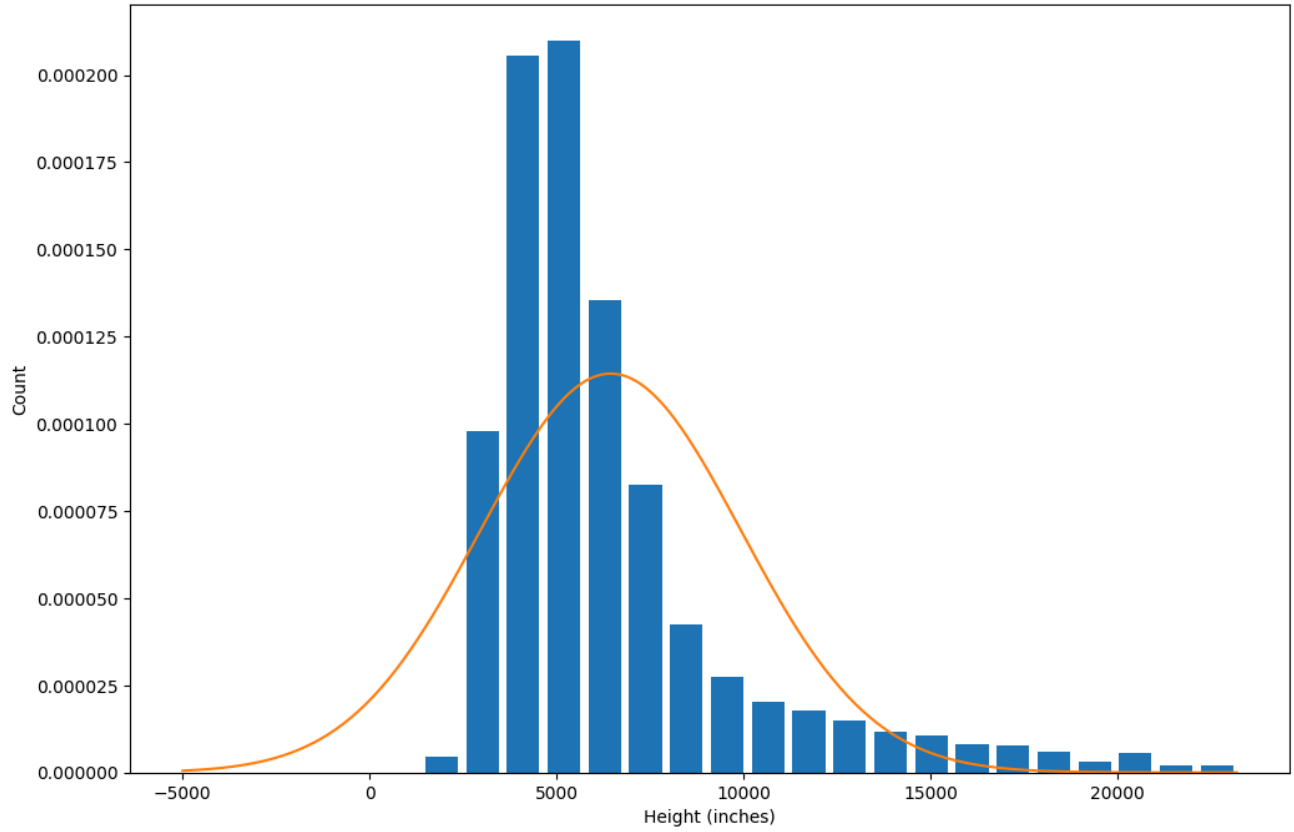



```
from scipy.stats import norm
import numpy as np

plt.hist(df3.price_per_sqft, bins=20, rwidth=0.8, density=True)
plt.xlabel('Height (inches)')
plt.ylabel('Count')

rng = np.arange(-5000, df3.price_per_sqft.max(), 100)
plt.plot(rng, norm.pdf(rng,df3.price_per_sqft.mean(),df3.price_per_sqft.std()))
```

```
[<matplotlib.lines.Line2D at 0x1ae443cda60>]
```




## ----------

## (3) Now remove outliers using z score. Use z score of 4 as your thresold

```
df2['zscore'] = (df2.price_per_sqft-df2.price_per_sqft.mean())/df2.price_per_sqft.std()
df2.sample(10)
```

```
C:\Users\harsh\AppData\Local\Temp\ipykernel_18888\722868599.py:1: SettingWithCopyWarn
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
  df2['zscore'] = (df2.price_per_sqft-df2.price_per_sqft.mean())/df2.price_per_sqft.s
```

| | location | size | total_sqft | bath | price | bhk | price_per_sqft | zscore |
|---|---|---|---|---|---|---|---|---|
| **11060** | Talaghattapura | 2 BHK | 1062.0 | 2.0 | 42.48 | 2 | 4000 | -0.643236 |
| **5011** | Marathahalli | 3 BHK | 1730.0 | 3.0 | 110.00 | 3 | 6358 | -0.073811 |
| **4963** | NRI Layout | 2 BHK | 1060.0 | 2.0 | 35.00 | 2 | 3301 | -0.812035 |
| **5024** | BTM 2nd Stage | 2 BHK | 1280.0 | 2.0 | 80.00 | 2 | 6250 | -0.099892 |
| **3987** | Gottigere | 3 BHK | 1304.0 | 3.0 | 80.00 | 3 | 6134 | -0.127904 |
| **12990** | Whitefield | 3 BHK | 1404.0 | 2.0 | 59.00 | 3 | 4202 | -0.594456 |
| **6955** | Vijayanagar | 3 BHK | 2047.0 | 3.0 | 136.00 | 3 | 6643 | -0.004988 |
| **4672** | 7th Phase JP Nagar | 2 BHK | 1130.0 | 2.0 | 73.00 | 2 | 6460 | -0.049180 |

5

```
outliers_z = df2[(df2.zscore < -4) | (df2.zscore>4)]
outliers_z.shape
```

```
(125, 8)
```

```
outliers_z.sample(5)
```

| | location | size | total_sqft | bath | price | bhk | price_per_sqft | zscore |
|---|---|---|---|---|---|---|---|---|
| **3401** | Indira Nagar | 6 Bedroom | 2480.0 | 4.0 | 750.0 | 6 | 30241 | 5.693607 |
| **3816** | Domlur | 6 BHK | 2400.0 | 4.0 | 600.0 | 6 | 25000 | 4.427977 |
| **6597** | other | 2 BHK | 1030.0 | 2.0 | 300.0 | 2 | 29126 | 5.424350 |
| **3340** | other | 19 BHK | 2000.0 | 16.0 | 490.0 | 19 | 24500 | 4.307234 |
| **7262** | other | 4 Bedroom | 1200.0 | 5.0 | 325.0 | 4 | 27083 | 4.930994 |

```
df4 = df2[(df2.zscore>-4)&(df2.zscore<4)]
df4.shape
```

```
(13047, 8)
```

```
df2.shape[0] - df4.shape[0]
```

```
125
```

In this step also we removed 125 outliers. The result would be exactly same as 4 standard deviation

---

## 4.3 Outlier Detection and Removal Using IQR

```
import pandas as pd
df = pd.read_csv("heights (3).csv")
df
```

| | name | height |
|---|---|---|
| **0** | mohan | 1.2 |
| **1** | maria | 2.3 |
| **2** | sakib | 4.9 |
| **3** | tao | 5.1 |
| **4** | virat | 5.2 |
| **5** | khusbu | 5.4 |
| **6** | dmitry | 5.5 |
| **7** | selena | 5.5 |
| **8** | john | 5.6 |
| **9** | imran | 5.6 |
| **10** | jose | 5.8 |
| **11** | deepika | 5.9 |
| **12** | yoseph | 6.0 |
| **13** | binod | 6.1 |
| **14** | gulshan | 6.2 |
| **15** | johnson | 6.5 |
| **16** | donald | 7.1 |
| **17** | aamir | 14.5 |
| **18** | ken | 23.2 |
| **19** | Liu | 40.2 |

```
df.describe()
```

| | height |
|---|---|
| **count** | 20.000000 |
| **mean** | 8.390000 |
| **std** | 8.782812 |
| **min** | 1.200000 |
| **25%** | 5.350000 |
| **50%** | 5.700000 |
| **75%** | 6.275000 |
| **max** | 40.200000 |

## # Detect outliers using IQR

```
Q1 = df.height.quantile(0.25)
Q3 = df.height.quantile(0.75)
Q1, Q3
```

```
(np.float64(5.3500000000000005), np.float64(6.275))
```

```
IQR = Q3 - Q1
IQR
```

```
np.float64(0.9249999999999998)
```

```
lower_limit = Q1 - 1.5*IQR
upper_limit = Q3 + 1.5*IQR
lower_limit, upper_limit
```

```
(np.float64(3.962500000000001), np.float64(7.6625))
```

## # Here are the outliers

```
df[(df.height<lower_limit)|(df.height>upper_limit)]
```

| | name | height |
|---|---|---|
| **0** | mohan | 1.2 |
| **1** | maria | 2.3 |
| **17** | aamir | 14.5 |
| **18** | ken | 23.2 |
| **19** | Liu | 40.2 |

---

## Remove outliers

```
df_no_outlier = df[(df.height>lower_limit)&(df.height<upper_limit)]
df_no_outlier
```

| | name | height |
|---|---|---|
| **2** | sakib | 4.9 |
| **3** | tao | 5.1 |
| **4** | virat | 5.2 |
| **5** | khusbu | 5.4 |
| **6** | dmitry | 5.5 |
| **7** | selena | 5.5 |
| **8** | john | 5.6 |
| **9** | imran | 5.6 |
| **10** | jose | 5.8 |
| **11** | deepika | 5.9 |
| **12** | yoseph | 6.0 |
| **13** | binod | 6.1 |
| **14** | gulshan | 6.2 |
| **15** | johnson | 6.5 |
| **16** | donald | 7.1 |

---

# Exercise

You are given height_weight.csv file which contains heights and weights of 1000 people. Dataset is taken from here, https://www.kaggle.com/mustafaali96/weight-height

You need to do this,

(1) Load this csv in pandas dataframe and first plot histograms for height and weight parameters

(2) Using IQR detect weight outliers and print them

(3) Using IQR, detect height outliers and print them

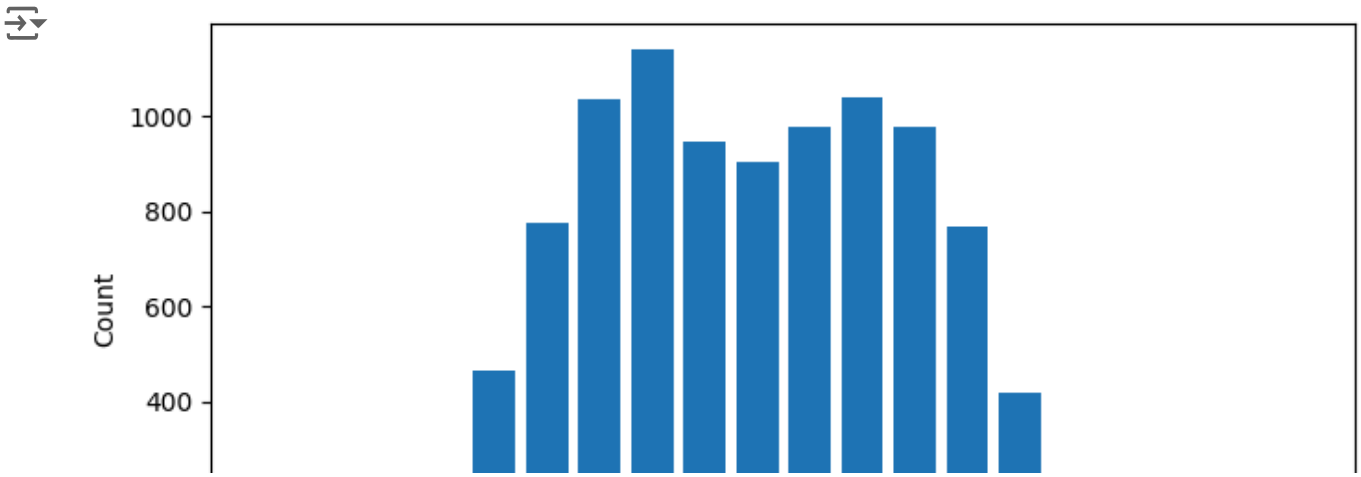
```
import pandas as pd
import matplotlib
from matplotlib import pyplot as plt
%matplotlib inline
matplotlib.rcParams['figure.figsize'] = (8,4)
```

```
df = pd.read_csv("height_weight.csv")
df.head(5)
```

| | gender | height | weight |
|---|---|---|---|
| **0** | Male | 73.847017 | 241.893563 |
| **1** | Male | 68.781904 | 162.310473 |
| **2** | Male | 74.110105 | 212.740856 |
| **3** | Male | 71.730978 | 220.042470 |
| **4** | Male | 69.881796 | 206.349801 |

# # Histgram for weights

```
plt.hist(df.weight, bins=20, rwidth=0.8)
plt.xlabel('Weight')
plt.ylabel('Count')
plt.show()
```




## # Histgram for heights


```
plt.hist(df.height, bins=20, rwidth=0.8)
plt.xlabel('Height')
plt.ylabel('Count')
plt.show()
```