# Feature Engineering > Feature Transformation

## Outliers Handling

### z-score (For normally or sort of normally distributed data)

#### Importing Dependencies

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
```

#### Loading Data

In [2]:
```
#load dataset
df1=pd.read_csv('placement.csv')
#read first 5 rows
df1.head()
```

Out[2]:

| | cgpa | placement_exam_marks | placed |
|---|---|---|---|
| **0** | 7.19 | 26.0 | 1 |
| **1** | 7.46 | 38.0 | 1 |
| **2** | 7.54 | 40.0 | 1 |
| **3** | 6.42 | 8.0 | 1 |
| **4** | 7.23 | 17.0 | 0 |

In [3]:
```
#shape
df1.shape
```

Out[3]:
```
(1000, 3)
```

In [4]:
```
#basic information(data-type, missing values)
df1.info()
#no missing values
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 3 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   cgpa                  1000 non-null   float64
 1   placement_exam_marks  1000 non-null   float64
 2   placed                1000 non-null   int64  
dtypes: float64(2), int64(1)
memory usage: 23.6 KB
```

In [5]:
```
#duplicated values
df1.duplicated().sum()
#for now we are just keeping duplicates
```

Out[5]:
```
19
```

In [6]:
```
#statistical analysis
df1.describe().T
#observation-->looks like 'cgpa' is sort of normally distributed
```

```
#observation-->'placement_exam_marks' are right skewed and have outliers
```

Out[6]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **cgpa** | 1000.0 | 6.96124 | 0.615898 | 4.89 | 6.55 | 6.96 | 7.37 | 9.12 |
| **placement_exam_marks** | 1000.0 | 32.22500 | 19.130822 | 0.00 | 17.00 | 28.00 | 44.00 | 100.00 |
| **placed** | 1000.0 | 0.48900 | 0.500129 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |

In [7]:

```
#correaltion between features
df1.corr()
#observation-->placement has positive correlation with cgpa, and negative correlation with placement_exam_marks
```

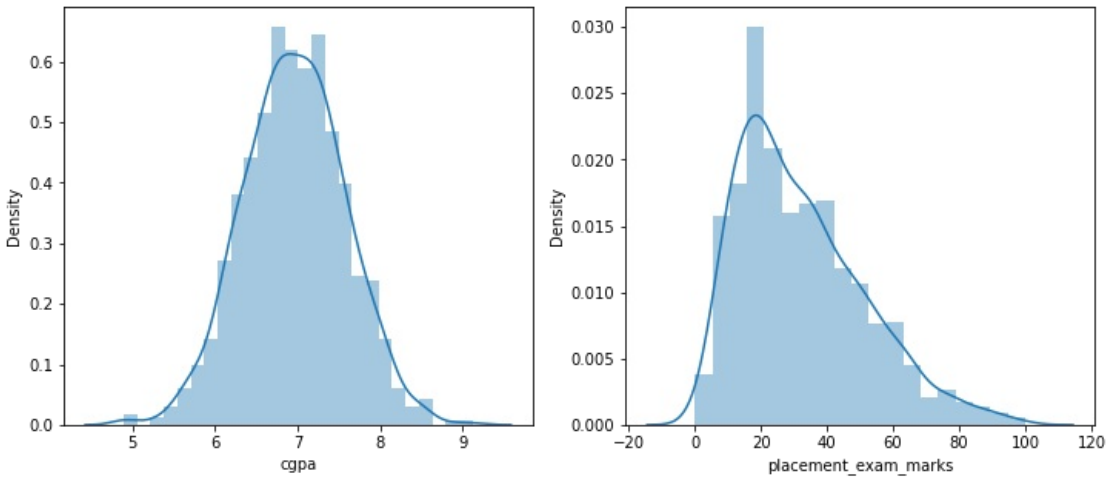
Out[7]:

| | cgpa | placement_exam_marks | placed |
|---|---|---|---|
| **cgpa** | 1.000000 | -0.027371 | 0.027212 |
| **placement_exam_marks** | -0.027371 | 1.000000 | -0.025530 |
| **placed** | 0.027212 | -0.025530 | 1.000000 |

## Graphical Analysis

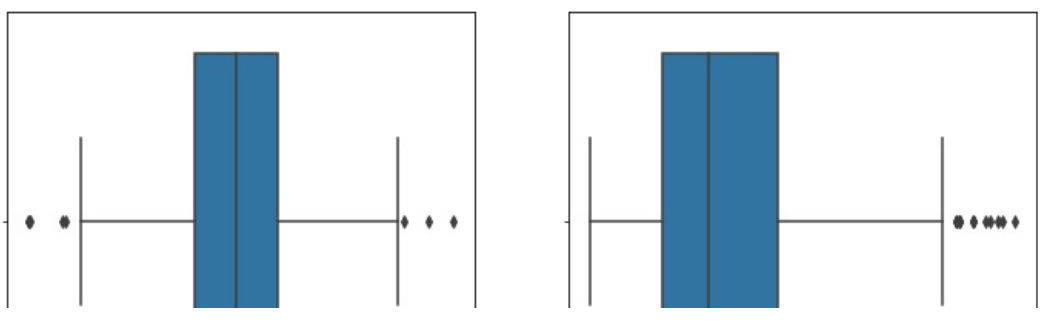
In [8]:

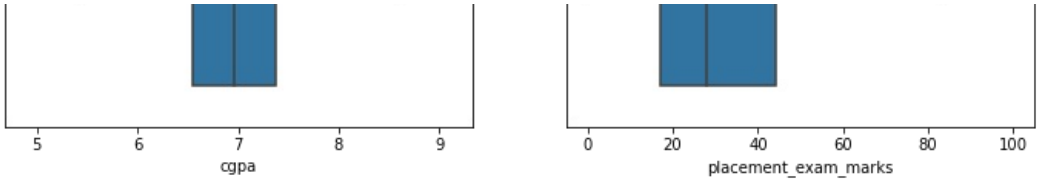
```
#distplot of 'cgpa' and 'placement_exam_marks'
plt.figure(figsize=(12,5))

plt.subplot(1,2,1)
sns.distplot(df1['cgpa'])
plt.subplot(1,2,2)
sns.distplot(df1['placement_exam_marks'])
plt.show()
#observation-->'cgpa' is sort of normally distributed
#observation-->'placement_exam_marks' is right skewed and has right outliers
```




In [9]:

```
#boxplot of 'cgpa' and 'placement_exam_marks'
plt.figure(figsize=(12,5))

plt.subplot(1,2,1)
sns.boxplot(df1['cgpa'])
plt.subplot(1,2,2)
sns.boxplot(df1['placement_exam_marks'])
plt.show()
#observation-->'cgpa' is sort of normally distributed
#observation-->'placement_exam_marks' is right skewed and has right outliers
```






**so here we will focus on 'cgpa' being sort of normally distributed data**

In [10]:
```
print(df1['cgpa'].skew())
#observation-->'cgpa' is very little negatively skewed(approx 1.5%)
print(df1['placement_exam_marks'].skew())
#observation-->'placement_exam_marks' is highly postively skewed(approx 84%)
```

```
-0.014529938929314918
0.8356419499466834
```

## z-score (for normal or sort of normally distributed data)

In [11]:
```
#'cgpa' data description
df1['cgpa'].describe()
```

Out[11]:
```
count    1000.000000
mean        6.961240
std         0.615898
min         4.890000
25%         6.550000
50%         6.960000
75%         7.370000
max         9.120000
Name: cgpa, dtype: float64
```

In [12]:
```
#mean, std, min, max
mean_=df1['cgpa'].mean()
std_=df1['cgpa'].std()
min_=df1['cgpa'].min()
max_=df1['cgpa'].max()
print(f'mean={mean_}, std={std_}, min={min_}, max={max_}')
```

```
mean=6.96124000000001, std=0.6158978751323894, min=4.89, max=9.12
```

In [13]:
```
print('lower limit', mean_-3*std_)
print('upper limit', mean_+3*std_)
```

```
lower limit 5.113546374602842
upper limit 8.808933625397177
```

In [14]:
```
#'cgpa'(normally distributed)-->(mean-3*std.dev., mean+3*std.dev.)-->z-score=3
df1[(df1['cgpa']<(mean_-3*std_)) | (df1['cgpa']>(mean_+3*std_))]
#observation-->filter data having outliers(5-rows)
```

Out[14]:

| | cgpa | placement_exam_marks | placed |
|---|---|---|---|
| **485** | 4.92 | 44.0 | 1 |
| **995** | 8.87 | 44.0 | 1 |
| **996** | 9.12 | 65.0 | 1 |
| **997** | 4.89 | 34.0 | 0 |
| **999** | 4.90 | 10.0 | 1 |

## Trimming (remove outliers)

Trimming using lower and upper fence [mean-3*std, mean+3*std]

In [15]:
```
#Trimming using lower and  upper fence [mean-3*std, mean+3*std]
df2=df1.drop(df1[(df1['cgpa']<(mean_-3*std_)) | (df1['cgpa']>(mean_+3*std_))].index)
df2
#observation-->995=(1000-5)
```

Out[15]:

| | cgpa | placement_exam_marks | placed |
|---|---|---|---|
| **0** | 7.19 | 26.0 | 1 |
| **1** | 7.46 | 38.0 | 1 |
| **2** | 7.54 | 40.0 | 1 |
| **3** | 6.42 | 8.0 | 1 |
| **4** | 7.23 | 17.0 | 0 |
| **...** | ... | ... | ... |
| **991** | 7.04 | 57.0 | 0 |
| **992** | 6.26 | 12.0 | 0 |
| **993** | 6.73 | 21.0 | 1 |
| **994** | 6.48 | 63.0 | 0 |
| **998** | 8.62 | 46.0 | 1 |

995 rows × 3 columns

Trimming using z-score= (x-mean)/std

In [16]:
```
#Trimming using z-score=(x-mean)/std
df1['cgpa_z_score']=(df1['cgpa']-df1['cgpa'].mean())/df1['cgpa'].std()
```

In [17]:
```
#first 5 rows of new df1
df1.head()
```

Out[17]:

| | cgpa | placement_exam_marks | placed | cgpa_z_score |
|---|---|---|---|---|
| **0** | 7.19 | 26.0 | 1 | 0.371425 |
| **1** | 7.46 | 38.0 | 1 | 0.809810 |
| **2** | 7.54 | 40.0 | 1 | 0.939701 |
| **3** | 6.42 | 8.0 | 1 | -0.878782 |
| **4** | 7.23 | 17.0 | 0 | 0.436371 |

In [18]:
```
#z-score range(-3, +3)
df1[(df1.cgpa_z_score<-3) | (df1.cgpa_z_score>3)]
#filterd data haviing outliers(5-rows)
```

Out[18]:

| | cgpa | placement_exam_marks | placed | cgpa_z_score |
|---|---|---|---|---|
| **485** | 4.92 | 44.0 | 1 | -3.314251 |
| **995** | 8.87 | 44.0 | 1 | 3.099150 |
| **996** | 9.12 | 65.0 | 1 | 3.505062 |
| **997** | 4.89 | 34.0 | 0 | -3.362960 |
| **999** | 4.90 | 10.0 | 1 | -3.346724 |

In [19]:
```
#Trimming using lower and  upper fence [mean-3*std, mean+3*std]
df2=df1.drop(df1[(df1.cgpa_z_score<-3) | (df1.cgpa_z_score>3)].index)
df2
#observation-->995=(1000-5)rows
```

Out[19]:

| | cgpa | placement_exam_marks | placed | cgpa_z_score |
|---|---|---|---|---|
| **0** | 7.19 | 26.0 | 1 | 0.371425 |
| **1** | 7.46 | 38.0 | 1 | 0.809810 |
| **2** | 7.54 | 40.0 | 1 | 0.939701 |
| **3** | 6.42 | 8.0 | 1 | -0.878782 |

| | | | | |
|---|---|---|---|---|
| **4** | 7.23 | 17.0 | 0 | 0.436371 |
| **...** | ... | ... | ... | ... |
| **991** | 7.04 | 57.0 | 0 | 0.127878 |
| **992** | 6.26 | 12.0 | 0 | -1.138565 |
| **993** | 6.73 | 21.0 | 1 | -0.375452 |
| **994** | 6.48 | 63.0 | 0 | -0.781363 |
| **998** | 8.62 | 46.0 | 1 | 2.693239 |

995 rows × 4 columns

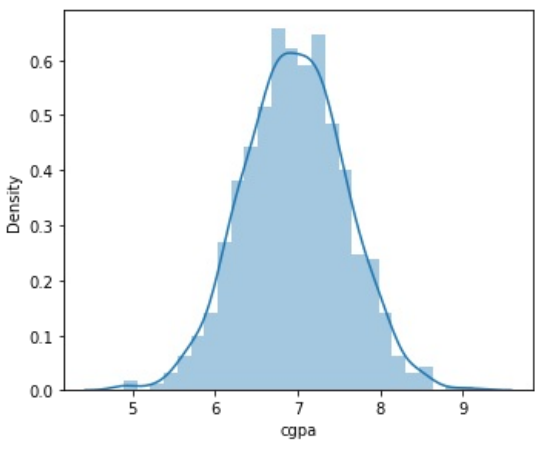
In [20]:
```
#before trimming description of 'cgpa'
df1['cgpa'].describe()
```

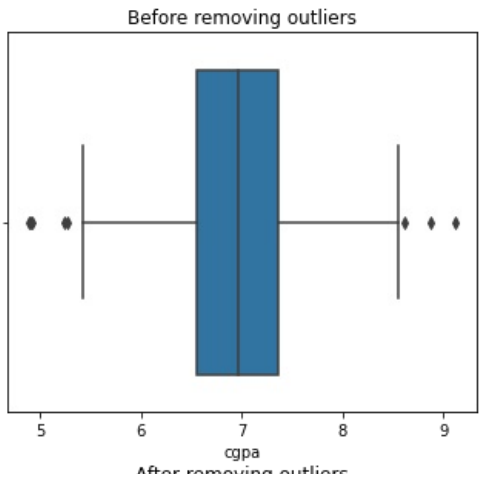
Out[20]:
```
count    1000.000000
mean        6.961240
std         0.615898
min         4.890000
25%         6.550000
50%         6.960000
75%         7.370000
max         9.120000
Name: cgpa, dtype: float64
```

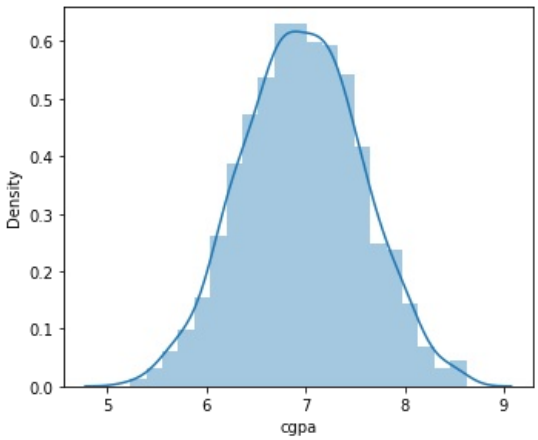
In [21]:
```
#after trimming description of 'cgpa'
df2['cgpa'].describe()
```

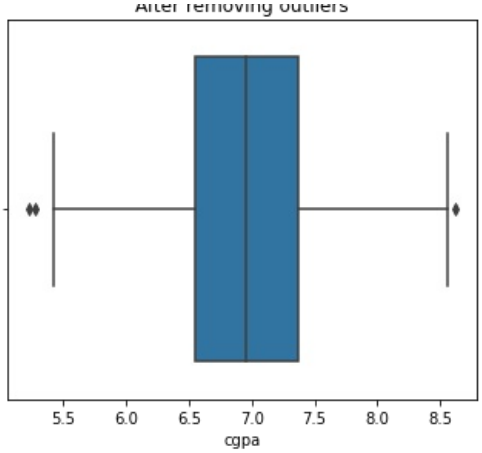
Out[21]:
```
count    995.000000
mean       6.963357
std        0.600082
min        5.230000
25%        6.550000
50%        6.960000
75%        7.365000
max        8.620000
Name: cgpa, dtype: float64
```

In [22]:
```
#distplot and boxplot of 'cgpa' before and after triming outliers
plt.figure(figsize=(12,10))

plt.subplot(2,2,1)
sns.distplot(df1['cgpa'])
plt.subplot(2,2,2)
sns.boxplot(df1['cgpa'])
plt.title("Before removing outliers", loc='center')

plt.subplot(2,2,3)
sns.distplot(df2['cgpa'])
plt.subplot(2,2,4)
sns.boxplot(df2['cgpa'])
plt.title("After removing outliers", loc='center')

plt.show()
#observation-->'cgpa' some outliers removed
```






Capping (set lower and upper bound values to outliers)

In [23]:
```
#Capping
lower_limit=df1['cgpa'].mean()-3*df1['cgpa'].std()
upper_limit=df1['cgpa'].mean()+3*df1['cgpa'].std()
print(lower_limit, upper_limit)
```

```
5.113546374602842 8.808933625397177
```

In [24]:
```
#setting lower and upper limit values on outliers using np.where
df1['cgpa_new']=np.where(df1['cgpa']>upper_limit,upper_limit, np.where(df1['cgpa']<lower_limit, lower_limit, df1[
#into array
```

In [25]:
```
#'cgpa' and 'cgpa_new' data description
df1.describe()
```

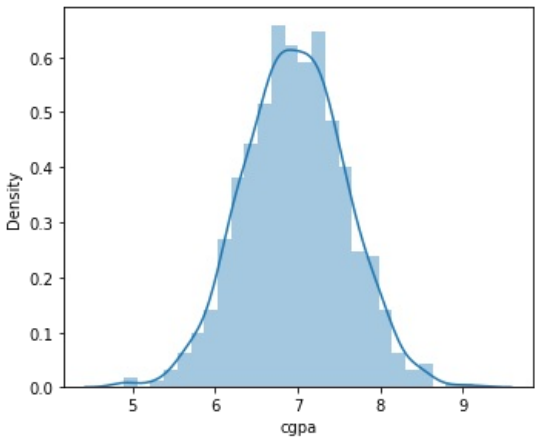
Out[25]:

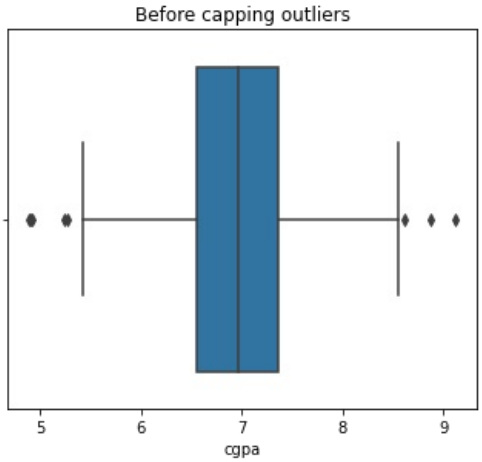
| | cgpa | placement_exam_marks | placed | cgpa_z_score | cgpa_new |
|---|---|---|---|---|---|
| **count** | 1000.000000 | 1000.000000 | 1000.000000 | 1.000000e+03 | 1000.000000 |
| **mean** | 6.961240 | 32.225000 | 0.489000 | -1.600275e-14 | 6.961499 |
| **std** | 0.615898 | 19.130822 | 0.500129 | 1.000000e+00 | 0.612688 |
| **min** | 4.890000 | 0.000000 | 0.000000 | -3.362960e+00 | 5.113546 |
| **25%** | 6.550000 | 17.000000 | 0.000000 | -6.677081e-01 | 6.550000 |
| **50%** | 6.960000 | 28.000000 | 0.000000 | -2.013321e-03 | 6.960000 |
| **75%** | 7.370000 | 44.000000 | 1.000000 | 6.636815e-01 | 7.370000 |
| **max** | 9.120000 | 100.000000 | 1.000000 | 3.505062e+00 | 8.808934 |

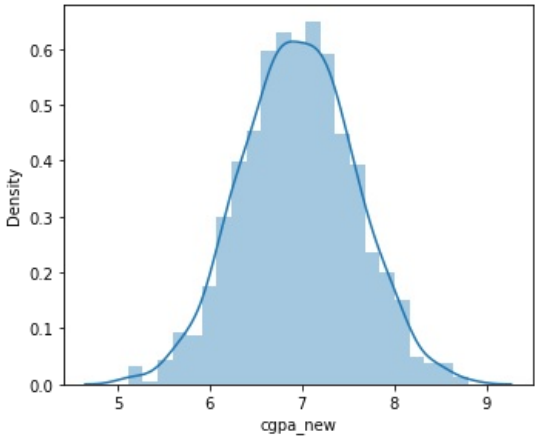
In [26]:
```
#shape(no rows are removd here, instead outliers are set to new values)
df1.shape
```

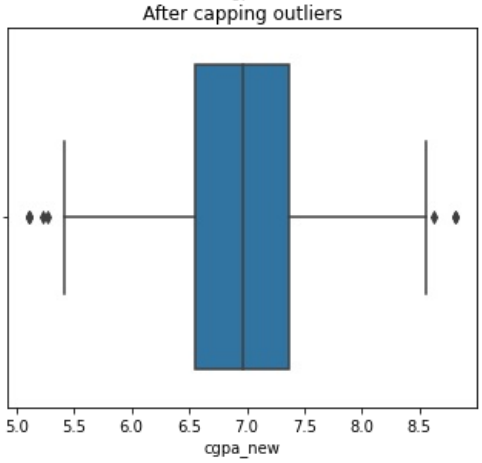
Out[26]: (1000, 5)

In [27]:
```
#distplot and boxplot of 'cgpa' before and after capping outliers
plt.figure(figsize=(12,10))

plt.subplot(2,2,1)
sns.distplot(df1['cgpa'])
plt.subplot(2,2,2)
sns.boxplot(df1['cgpa'])
plt.title("Before capping outliers", loc='center')

plt.subplot(2,2,3)
sns.distplot(df1['cgpa_new'])
plt.subplot(2,2,4)
sns.boxplot(df1['cgpa_new'])
plt.title("After capping outliers", loc='center')

plt.show()
#observation-->'cgpa' some outliers removed
```

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