DISCUSSION ON KURTOSIS:

According to some research Kurtosis is the ‘peakedness’ of the distribution or we can say the measure of tailness of the distribution. We can say this as the historic definition.

The standard measure of a distribution's kurtosis, originating with Karl Pearson, is a scaled version of the fourth moment of the distribution. This number is related to the tails of the distribution, not its peak.

$$\frac{1}{n}\Sigma\frac{(x-\mu)^4}{\sigma^4}$$

Here into the equation the complete game is around the variance and the standard deviations. Kurtosis gets change across the tail. Though the peakeness of the distribution does not matter.

Now fundamentally we can see the relation between the value Kurtosis is along the above equation, where we are dealing with variance and standard deviation. If the observation value increase tremendously then according to the formula we observe a giant change into the Kurtosis.

$$\frac{1}{n}\left(\frac{\sum(x-\mu)^4}{\left(\sum(x-\mu)^2/_{n^2}\right)}\right)$$

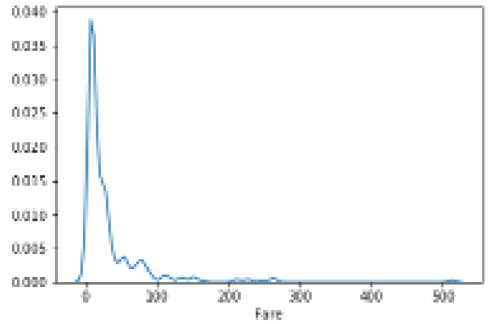
Here into the explicit formula we can observe the complete scenario, how the outlier is affecting the kurtosis values. We see here the change in variance after just squaring, spreads the data. According to the definition, we assume that the higher peak gives the higher Kurtosis value, but calculation shows a different scenario, may be opposite of this. Just because the term $\sum(x-\mu)^4$ is increased enormously, this was not purposely; this was actually the existence of outlier.

Hence we are yearning to say our statement that the **Kurtosis is nothing but the measure of the thickness of the tail of the distribution**.

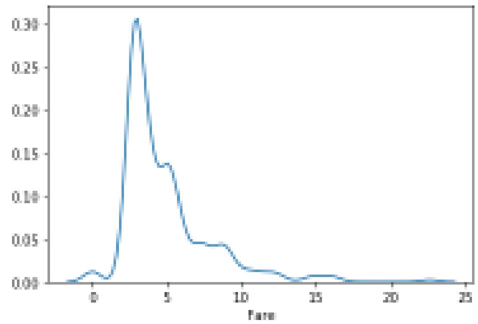
Let’s observe the different Kurtosis values with respect to the variance along the same data:

```
a = data.Fare.dropna()
b = np.sqrt(a) ; c = np.sqrt(b)
```

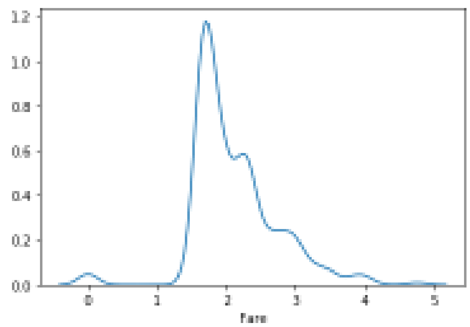
```
sns.distplot(a, hist=False)
plt.show()
```




```
sns.distplot(b, hist=False)
plt.show()
```




```
sns.distplot(c, hist=False)
plt.show()
```




```
a.kurt() , b.kurt(), c.kurt()
```

```
(33.39814088089868, 6.282211915236795, 2.8876280985790888)
```

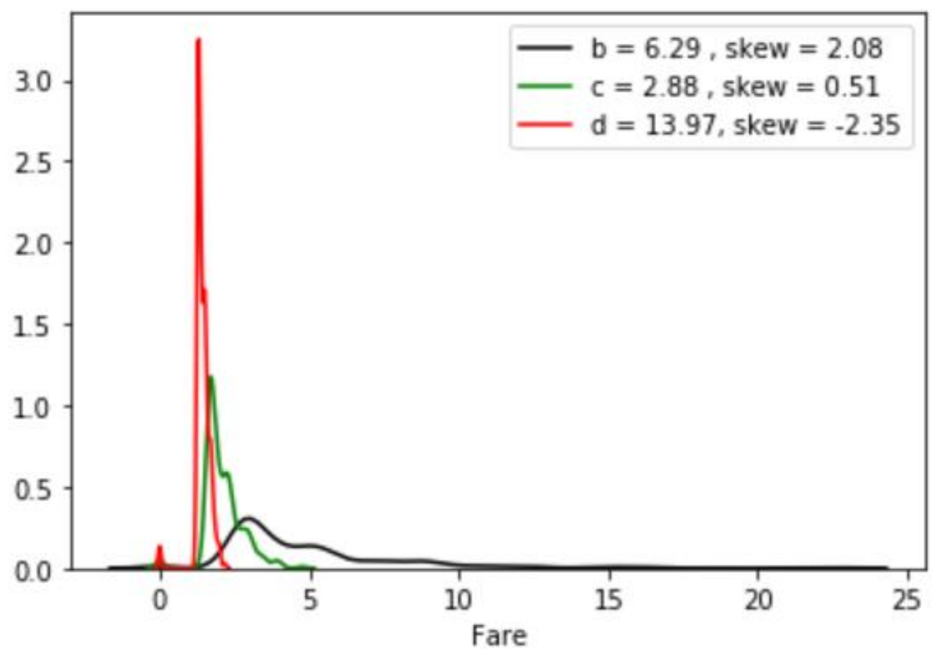
Here all the graphs of **Fare** from Titanic dataset; we can observe how the Kurtosis value decrease as we decrease the **slope** of the graph.

Along with the graphs, we are observing that the graph has a tilted slope has less Kurtosis value. This means the graph which has titled has less spread, in other words, we say, minimum variance gives the Kurtosis values minimum values as well. **As the graph gets normal, the Kurtosis value decreases and if the peak gets heavier, Kurtosis values increases.**

```
a.skew() , b.skew() , c.skew()
(4.787316519674893, 2.08500441820235, 0.519678888206381)
```

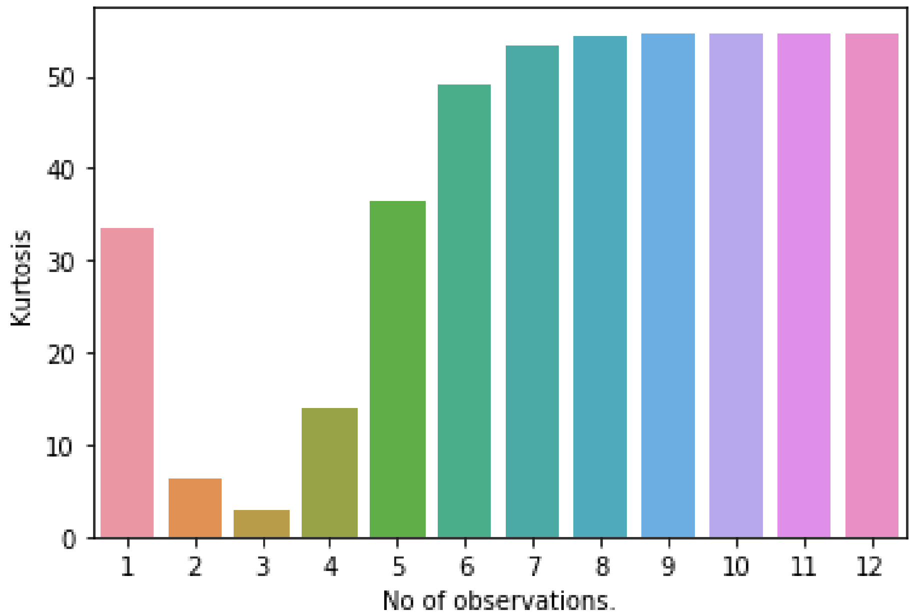
Even we can make the relation of Kurtosis and Skewness of the distribution. As Kurtosis goes down that gives the signal which gives the information of normality of the graph.

Take a look on the simultaneous graph of the kurtosis along skewness:

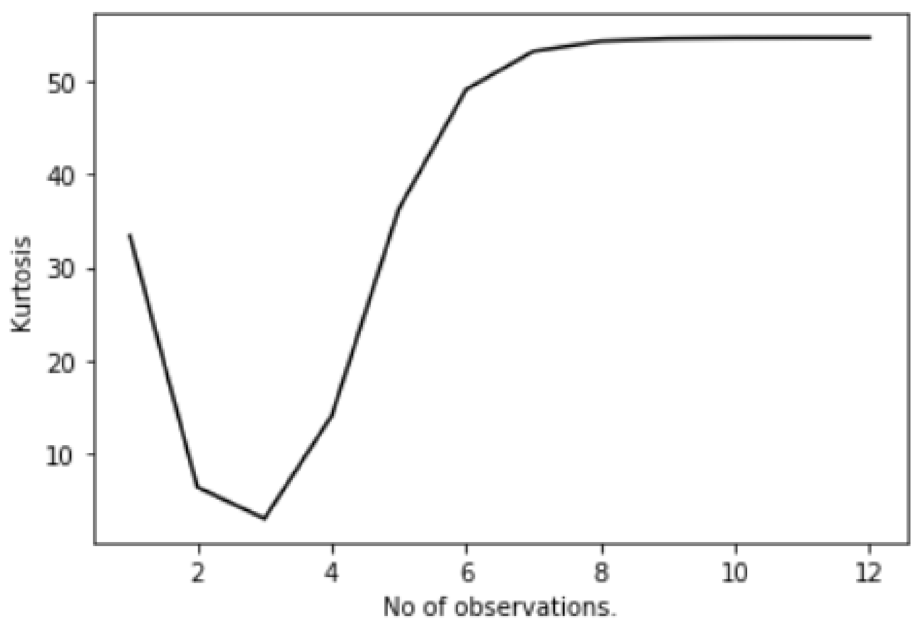


Now we see the difference in Skewness and Kurtosis values, such that, as soon the Skewness goes left,, Kurtosis values again goes on decreasing. Where the graph is normal, Kurtosis seems to be low, again after the graph changes its face, it again shows the same scenario of spreading the data.

What if we change our axis consecutively?



We can see, as the graph going towards left, Kurtosis values goes on increasing, after the while again it retains towards decreasing, but little more.



Hence we concluded that, Kurtosis value is dependent upon the weight on tail and variance of the data, as well as the slope of the graph edge.

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