

# Data Treatment

## Part 2

# Data Sorting

## ➤ *Meaning:*

### ➤ *Change the order of the data values in a data-frame as*

- Sorting values in one column
  - `df.sort_values(by, axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')`
- Sorting values in multiple column
  - `df.sort_values(['Column 1', 'Column 2'], ascending = False)`
- Documentation: [pandas.DataFrame.sort values](#)
  - **axis:** determines sorting along the row/column
  - **ascending:**
    - **True:** by default, and sort the list in ascending order
    - **False:** sort list in descending order
    - **[True, False]:** this list can be based on the column/row preference ascending/descending

### ➤ *For example*

```
data.sort_values(['Month'], inplace = True)
data.head()
```

# Your Turn!

- Try to sort the column “number\_of\_reviews” in descending order
- Which Airbnb has less price and top number of reviews?

# Data Subsetting

## ➤ *Meaning:*

- *To view specific group of data*
- *To filter your data*

- Subsetting value in one column
  - `df.column_1.unique()`
- Sorting values in multiple column
  - `df[['Column 1', 'Column 2'], ascending = False]`
- *For example:*

```
subset_2 = data[['neighbourhood', 'latitude', 'longitude', 'price']]
```

# Data Filtering

## ➤ *Meaning:*

- Filter a group of the data which we would look at for analysis

## ○ Methods

### 1. .loc method:

- *Access a group of rows and columns by label(s) or a boolean array*
- Documentation: [pandas.DataFrame.loc](#)

### 2. .iloc method (i – integer)

- Purely integer-location based indexing for selection by position
- Documentation: [pandas.DataFrame.iloc](#)

### 3. groupby method:

- Documentation: [pandas.DataFrame.groupby](#)
- **DataFrame.groupby(*by=None, axis=0, level=None, as\_index=True, sort=True, dropna=True*)**

# Your turn!

- Which host(host name) of which neighborhood had the last\_review?
- Based on the above how to see the reviews\_per\_month for them.

# Your turn!

- List all the Airbnb's name ,hostname, availability\_365 and year
- List the hostname and year when the availability\_365 was zero



# Data Melting & Reshaping

## ➤ Meaning:

- Transferring data from a wide format to a long format
- It is useful when we have a data frame where we want to create one of the columns as identifier and another column contains the measure
- Documentation: [pandas.DataFrame.melt](#)
- `pd.melt(dataFrame, id_vars = ['Col1', 'Col2'], var_name='Date', value_name='GDPperCapGrowth%')`
  - *id\_vars: Column which you would like to keep*
  - *var\_name: Column which you create*
  - *Value\_name: values*

For Example:

| Country Name         | Country Code | 1990-12-31<br>00:00:00 | 2000-12-31<br>00:00:00 | 2011-12-31<br>00:00:00 | 2012-12-31<br>00:00:00 | 2013-12-31<br>00:00:00 | 2014-12-31<br>00:00:00 | 2015-12-31<br>00:00:00 | 2016-12-31<br>00:00:00 | 2017-12-31<br>00:00:00 | 2018-12-31<br>00:00:00 |
|----------------------|--------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| Australia            | AUS          | 3.107811e+11           | 4.152226e+11           | 1.386650e+12           | 1.546153e+12           | 1.576184e+12           | 1.467484e+12           | 1.351694e+12           | 1.208847e+12           | 1.329188e+12           | 1.432911e+12           |
| Brazil               | BRA          | 4.818518e+11           | 6.584206e+11           | 2.616201e+12           | 2.485189e+12           | 2.472807e+12           | 2.435984e+12           | 1.802214e+12           | 1.785700e+12           | 2.082831e+12           | 1.685111e+12           |
| Hong Kong SAR, China | HKG          | 7.692829e+10           | 1.716682e+11           | 2.485136e+11           | 2.626294e+11           | 2.756696e+11           | 2.814584e+11           | 3.003036e+11           | 3.298376e+11           | 3.412443e+11           | 3.616111e+11           |
| Japan                | JPN          | 1.132618e+12           | 4.867520e+12           | 6.157450e+12           | 6.283213e+12           | 5.155717e+12           | 4.858414e+12           | 4.388476e+12           | 4.925236e+12           | 4.688864e+12           | 4.958111e+12           |
| Singapore            | SGP          | 3.814434e+10           | 9.807446e+10           | 2.783612e+11           | 2.860872e+11           | 3.075764e+11           | 3.148512e+11           | 3.060041e+11           | 3.166522e+11           | 3.418853e+11           | 3.732111e+11           |



|     | Country Name         | Country Code | Date       | GDPperCapGrowth% |
|-----|----------------------|--------------|------------|------------------|
| 0   | Australia            | AUS          | 1990-12-31 | 3.107811e+11     |
| 1   | Brazil               | BRA          | 1990-12-31 | 4.619518e+11     |
| 2   | Hong Kong SAR, China | HKG          | 1990-12-31 | 7.692829e+10     |
| 3   | Japan                | JPN          | 1990-12-31 | 3.132818e+12     |
| 4   | Singapore            | SGP          | 1990-12-31 | 3.614434e+10     |
| ... | ...                  | ...          | ...        | ...              |
| 61  | Brazil               | BRA          | 2019-12-31 | 1.839758e+12     |
| 62  | Hong Kong SAR, China | HKG          | 2019-12-31 | 3.657115e+11     |
| 63  | Japan                | JPN          | 2019-12-31 | 5.081770e+12     |
| 64  | Singapore            | SGP          | 2019-12-31 | 3.720625e+11     |



# Data Pivoting

## ➤ Meaning:

- Let you return the reshaped data back to wide format
- Let you insert the index to the data. The index can be your column

## ➤ Two Ways:

1. `df.pivot(index="lev1", columns=["lev2", "lev3"], values="values")`

```
>>> df
  lev1 lev2 lev3 lev4 values
0    1    1    1    1     0
1    1    1    2    2     1
2    1    2    1    3     2
3    2    1    2    4     3
4    2    1    1    5     4
5    2    2    2    6     5
```

```
      lev3    1    2
lev1 lev2
  1    1  0.0  1.0
     2  2.0  NaN
  2    1  4.0  3.0
     2  NaN  5.0
```

*Disadvantage: It does not recognize the duplicated values*

**Value Error: Index contains duplicate entries, cannot reshape**

# Data Pivoting

2)

`pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'], agg=np.sum)`

```
>>> df
   A  B    C  D  E
0  foo one small 1  2
1  foo one large 2  4
2  foo one large 2  5
3  foo two small 3  5
4  foo two small 3  6
5  bar one large 4  6
6  bar one small 5  8
7  bar two small 6  9
8  bar two large 7  9
```



|     |     | C     |       |
|-----|-----|-------|-------|
|     |     | large | small |
| A   | B   |       |       |
| bar | one | 4.0   | 5.0   |
|     | two | 7.0   | 6.0   |
| foo | one | 4.0   | 1.0   |
|     | two | NaN   | 6.0   |

# Your Turn!

|   | id      | year | month | element | d1  | d2   | d3   | d4  | d5   | d6  | d7  | d8  |
|---|---------|------|-------|---------|-----|------|------|-----|------|-----|-----|-----|
| 2 | MX17004 | 2010 | 2     | tmax    | NaN | 27.3 | 24.1 | NaN | NaN  | NaN | NaN | NaN |
| 3 | MX17004 | 2010 | 2     | tmin    | NaN | 14.4 | 14.4 | NaN | NaN  | NaN | NaN | NaN |
| 0 | MX17004 | 2010 | 1     | tmax    | NaN | NaN  | NaN  | NaN | NaN  | NaN | NaN | NaN |
| 7 | MX17004 | 2010 | 4     | tmin    | NaN | NaN  | NaN  | NaN | NaN  | NaN | NaN | NaN |
| 5 | MX17004 | 2010 | 3     | tmin    | NaN | NaN  | NaN  | NaN | 14.2 | NaN | NaN | NaN |
| 6 | MX17004 | 2010 | 4     | tmax    | NaN | NaN  | NaN  | NaN | NaN  | NaN | NaN | NaN |
| 4 | MX17004 | 2010 | 3     | tmax    | NaN | NaN  | NaN  | NaN | 32.1 | NaN | NaN | NaN |
| 8 | MX17004 | 2010 | 5     | tmax    | NaN | NaN  | NaN  | NaN | NaN  | NaN | NaN | NaN |
| 9 | MX17004 | 2010 | 5     | tmin    | NaN | NaN  | NaN  | NaN | NaN  | NaN | NaN | NaN |
| 1 | MX17004 | 2010 | 1     | tmin    | NaN | NaN  | NaN  | NaN | NaN  | NaN | NaN | NaN |

- Why should we be applying melt(reshape data) function here?
- How can you apply the melt function on this?

# Data Merging

## ➤ *Meaning:*

*Joining two data series and data frames*

- *Where to use: Two data files to extract specific query answer*
  1. Concatenate Data Frames along row and column.
  2. Merge Data Frames on specific keys by different join logics like left-join, inner-join, etc.

# Data Concatenate

- Documentation: [pandas.concat](https://pandas.pydata.org/pandas-docs/stable/10min/concat.html)

`pd.concat(objs, axis=0, join='outer', ignore_index=False, keys=None, levels=None, names=None, verify_integrity=False, sort=False, copy=True`

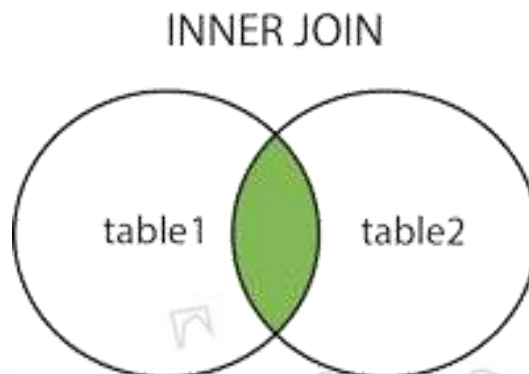
- *objs: a sequence or mapping of Series or DataFrame objects*
- *axis: 0/index/row, 1/columns*

# Data Merging

Documentation: [pandas.DataFrame.merge](#)

```
pd.merge(right, how='inner', on=None, left_on=None, right_on=None, left_index=False, right_index=False, sort=False,
         suffixes=('_x', '_y'), copy=True, indicator=False, validate=None)
```

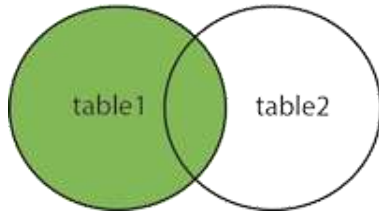
- How :{'left', 'right', 'outer', 'inner', 'cross'}



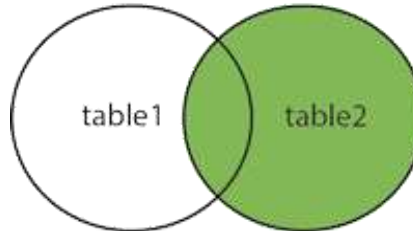


# Different Types of SQL JOINS

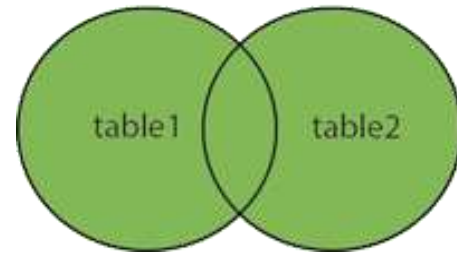
LEFT JOIN



RIGHT JOIN



FULL OUTER JOIN



- **(INNER) JOIN:** Returns records that have matching values in both tables
- **LEFT (OUTER) JOIN:** Returns all records from the left table, and the matched records from the right table
- **RIGHT (OUTER) JOIN:** Returns all records from the right table, and the matched records from the left table
- **FULL (OUTER) JOIN:** Returns all records when there is a match in either left or right table



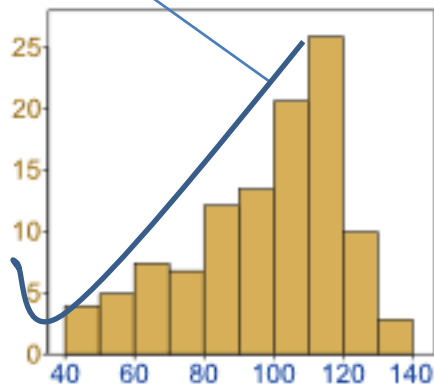
# Fundamental Statistics

# Skewness

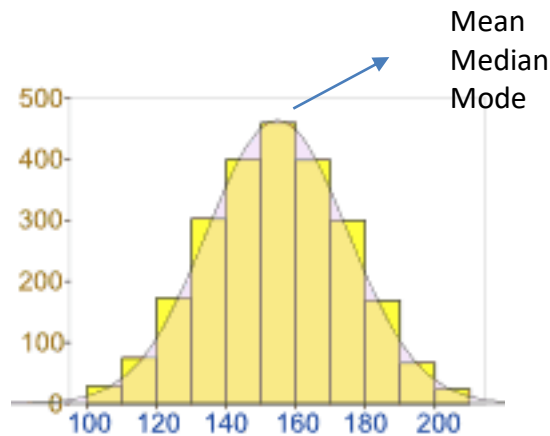
## ➤ *Meaning:*

Data tends to have a **long tail** on one side or the other

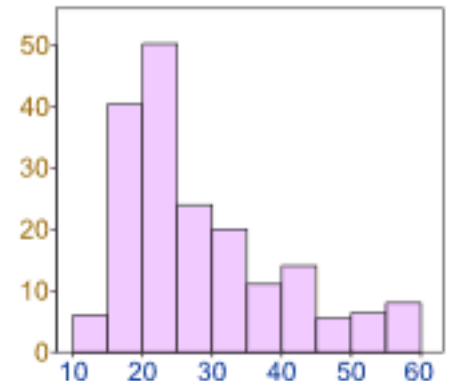
Mean



Negative skew



Normal distribution  
has no skew



Positive skew

# How to detect the skewness?

## ➤ Method 1: Using `.skew()` function

- Documentation: [pandas.DataFrame.skew](#)
- `DataFrame.skew(axis=None, skipna=None, level=None, numeric_only=None)`

- **axis:** `{index (0), columns (1)}`; Axis for the function to be applied on

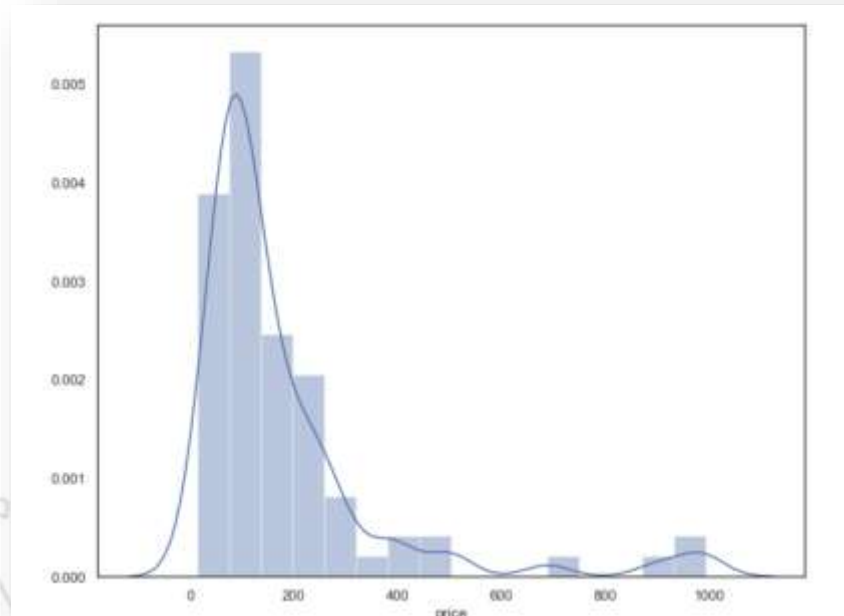
```
DataFrame:
   0  1  2  3  4  5  6
0  10 20 30 40 50 60 70
1  10 10 40 40 50 60 70
2  10 20 30 50 50 60 80
Skew:
0  0.000000
1 -0.340998
2  0.121467
dtype: float64
```

Which  
skewness?

# How to detect the skewness?

- *Method 2: Using the distplot()*
  - Documentation : [seaborn.distplot\(\)](#)
  - Comes under Seaborn library

Flexibly plot a univariate distribution of observations



Right skewed

```
sns.distplot(data2.price.head(80))
```

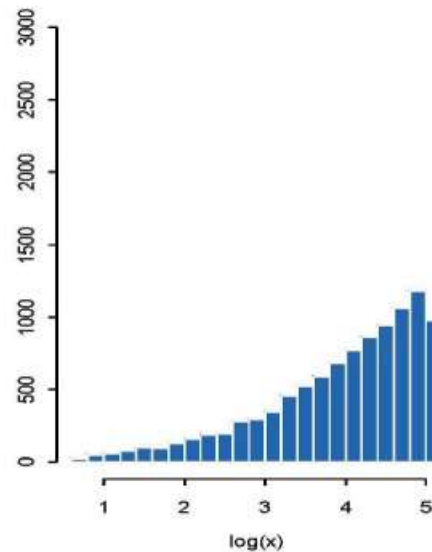
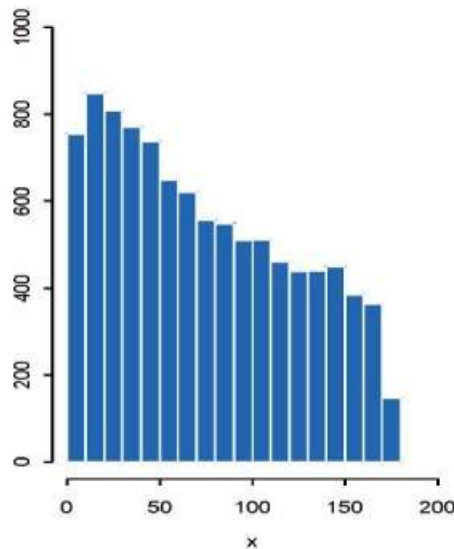
# How to remove the skewness?

## ➤ Method 1: Using Log transform

- Documentation : [numpy.log](https://numpy.org/doc/stable/reference/generated/numpy.log.html)
- Comes under NumPy library
- `np.log(x: input array)`

By default:

Log base to e



- `np.log2()`
- `np.log10()`

Histograms of original data (left plot) and log-transformed data (right plot) from a simulation study that examines the effect of log-transformation on reducing skewness.



# How to remove the skewness?

When numbers are too large, one can try fractional exponents as a means of transformation

- *Method 2: Using square root or cube root transform*
  - Documentation: [numpy.sqrt\(\)](#)
  - `np.sqrt(array)`
    - Return the non-negative square-root of an array, element-wise
- `df.col_name**(1/2)`

# Normalization

## ➤ *Meaning:*

- *Rescaling the values in the range of  $[0,1]$*

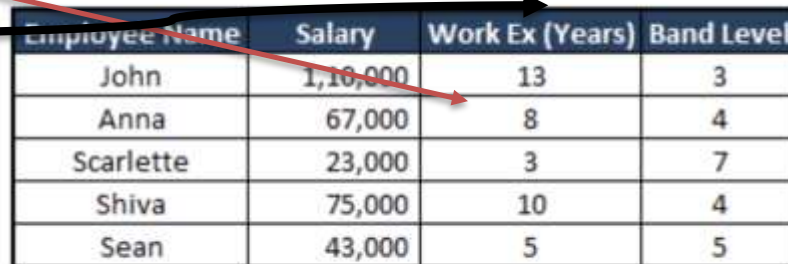
## ➤ *Why:*

- *When your data-set has multiple features(or column) with different measurement scale*

## ➤ *Keep in mind:*

- *Magnitude*
- *Units*

*For example:*



| Employee Name | Salary   | Work Ex (Years) | Band Level |
|---------------|----------|-----------------|------------|
| John          | 1,10,000 | 13              | 3          |
| Anna          | 67,000   | 8               | 4          |
| Scarlette     | 23,000   | 3               | 7          |
| Shiva         | 75,000   | 10              | 4          |
| Sean          | 43,000   | 5               | 5          |

Notice

- Salary
- Work EX

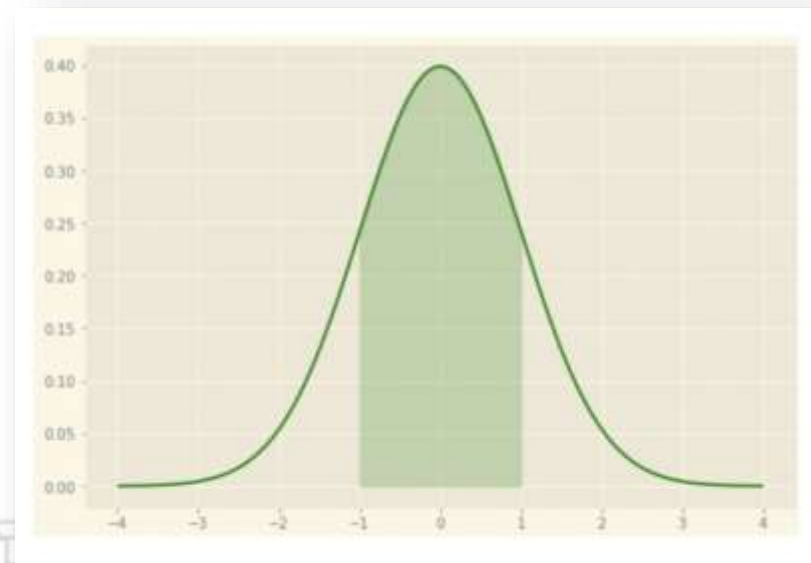
*“Not every and not always feature/columns in your dataset requires normalization”*

# Note: Check if your data Normally/Gaussian distributed

What is Normal distribution/Gaussian distribution?

It is symmetric about the mean -> data around the mean is more frequent

- Mean is "Zero"
- Standard deviation is "One"
- Normal distributions are **symmetrical**,  
but not all symmetrical distributions are **normal**



Bell Shaped curve

Source: [www.investopedia.com](http://www.investopedia.com)

# How to perform Normalization?

- Simple Feature Scaling
- Min-Max Feature Scaling
- Z-Score/ **Standard scores**

**\*\*Considering the data does not follow Gaussian distribution**

# Simple Feature Scaling

```
DataFrame.loc[:, 'columns/feature']  
/  
DataFrame.loc[:, 'columns/feature'].max()
```

# Min-Max Feature Scaling

$$X' = (X - X_{\min}) / (X_{\max} - X_{\min})$$

Feature scaling is used to bring all values into the range [0,1]. This is also called unity-based normalization. This can be generalized to restrict the range of values in the dataset between any arbitrary points  $a$  and  $b$ , using for example  $X' = a + \frac{(X - X_{\min})(b - a)}{X_{\max} - X_{\min}}$ .

Source: [Normalization \(statistics\)](#)

```
(DataFrame.loc[:, 'Feature/column'] -  
DataFrame.loc[:, 'Feature/column'].min())  
/  
(DataFrame.loc[:, 'Feature/column'].max() -  
DataFrame.loc[:, 'Feature/column'].min())
```

Example:  
calculated\_host\_listings\_count

|      |          |
|------|----------|
| 1728 | 0.000000 |
| 4840 | 0.008065 |
| 2561 | 0.000000 |
| 8258 | 0.000000 |
| 3799 | 0.016129 |
|      | ...      |
| 4369 | 0.209677 |
| 1606 | 0.016129 |
| 4020 | 0.008065 |
| 3107 | 0.016129 |
| 5413 | 0.008065 |



# Z- Score/ Standard Scores

**\*\*Your data follows Normal distribution**

$$\text{Z-score} = \frac{X - \mu}{\sigma}$$

Where:  $\mu \rightarrow$  mean

$\sigma \rightarrow$  standard deviation(SD)

Z-Score tells how many standard deviations away from the mean is your score

For example:

- if your Z-score is 1.2  $\rightarrow$  1.2 SD above the mean
- if your Z-score is -0.6  $\rightarrow$  0.6 SD below the mean

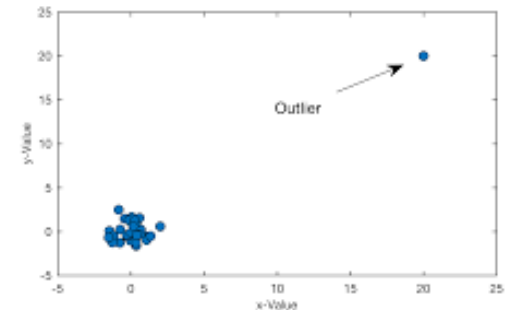
# Outlier

A z-score of **zero** tells us the value is **exactly the mean/ average** while a score of +6 tells you that the value is **much higher than average** (probably **an outlier**)

➤ *Meaning: These are the points which are way to far from the regular pattern*

Outliers are two types:

- Univariate
- Multi-variate



# Univariate Outlier

Univariate: These outliers are the points consists of an **extreme value** on **one** variable

How to detect these kind of outliers?

- **IQR and Box-and-Whisker's plot**

# INTER-QUARTILE RANGE(IQR)

IQR – THIRD QUARTILE – FIRST QUARTILE

75<sup>TH</sup> PERCENTILE – 25<sup>TH</sup> PERCENTILE

LOWER BOUND = FIRST QUARTILE – 1.5times(IQR)

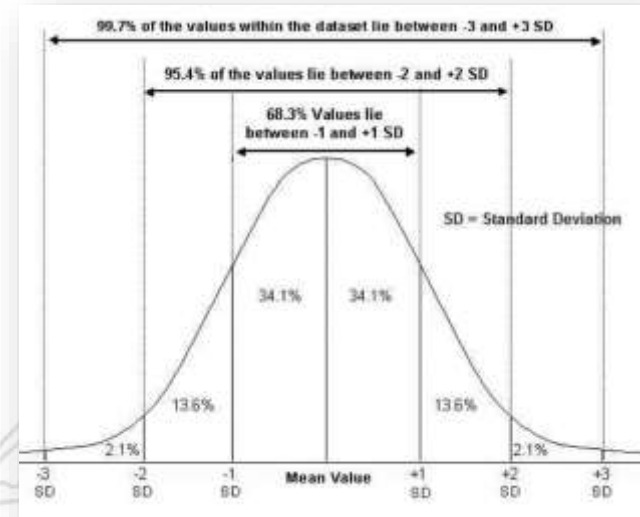
UPPER BOUND = THIRD QUARTILE +1.5times(IQR)

Any values outside these values ranges:

- below lower bound
- above upper bound



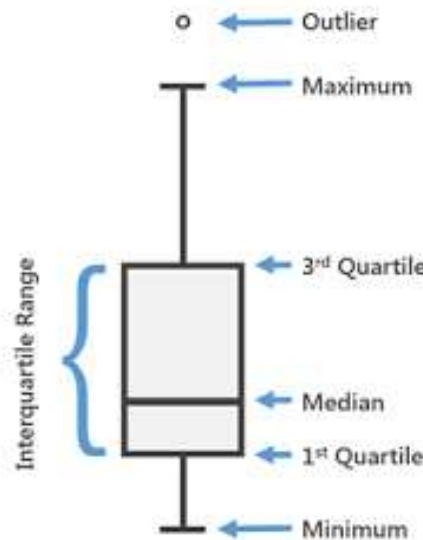
OUTLIERS



# Box-and-Whisker plot

A robust method for detecting outliers is the

- IQR (Inter Quartile Range) method
- It was developed by **John Tukey**, pioneer of exploratory data analysis
- Box-and-Whisker's plot uses quartiles to plot the shape of a variable



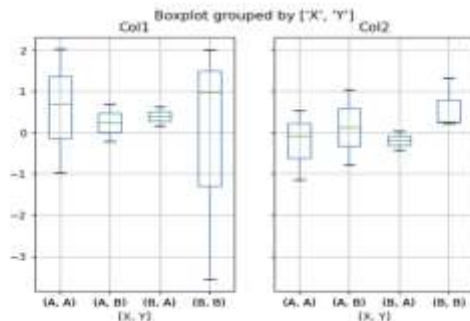
[Image Source](#)

# How to create the boxplot?

## 1. Using Pandas library

- Documentation: [pandas.DataFrame.boxplot](#)

```
>>> df = pd.DataFrame(np.random.randn(10, 3),
...                   columns=['Col1', 'Col2', 'Col3'])
... df['X'] = pd.Series(['A', 'A', 'A', 'A', 'A',
...                     'B', 'B', 'B', 'B', 'B'])
... df['Y'] = pd.Series(['A', 'B', 'A', 'B', 'A',
...                     'B', 'A', 'B', 'A', 'B'])
... boxplot = df.boxplot(column=['Col1', 'Col2'], by=['X', 'Y'])
```



by: str or array-like, optional Column in the DataFrame to [pandas.DataFrame.groupby\(\)](#)

- ax = sns.boxplot(x=tips["total\_bill"])

## 2. Using Seaborn library

- import **seaborn** as **sns**
- Documentation: [seaborn.boxplot](#)

- sns.boxplot(x='room\_type', y='price', data=data2)

