

# All about Feature Transformation



# All about Feature Transformation Techniques

Before

	Marketing Spend	Administration	Transport
8	120542.52	148718.95	311613.29
3	144372.41	118671.85	383199.62
6	134615.46	147198.87	127716.82
41	27892.92	84710.77	164470.71
46	1315.46	115816.21	297114.46
47	0.00	135426.92	0.00
15	165349.20	122616.84	261776.23
9	123334.88	108679.17	304981.62
16	78013.11	121597.55	264346.06
24	77044.01	99281.34	140574.81
34	46426.07	157693.92	210797.67
31	61136.38	152701.92	88218.23
0	114523.61	136897.80	471784.10

After

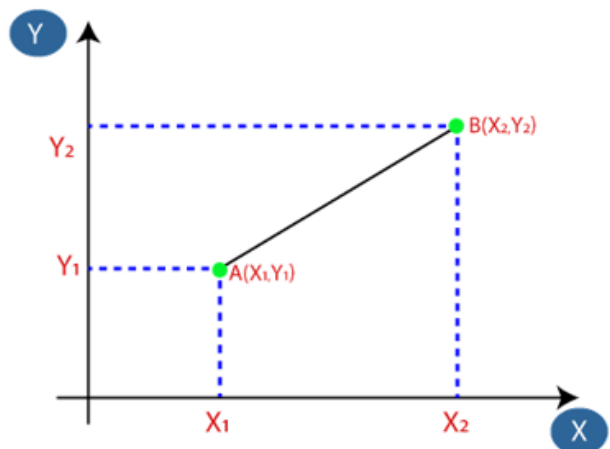
```
[ 0.51045637, 0.65435014, 0.39465254,
[ 0.7717808 , -0.07058751, 0.85129231,
[ 0.66478369, 0.61767561, -0.77839882,
[-0.50556192, -0.88995663, -0.54395059,
[-0.79701687, -0.13948471, 0.30216642,
[-0.81144253, 0.33365719, -1.59308759,
[ 1.00181744, 0.02459211, 0.0767485 ,
[ 0.54107808, -0.311678 , 0.35234999,
[ 0.04406841, 0. , 0.09314111,
[ 0.03344102, -0.53841672, -0.69637939,
[-0.30232284, 0.87088664, -0.24843702,
[-0.14100596, 0.7504461 , -1.03035512,
[ 0.44445152, 0.36914469, 1.41636104,
[-0.56823598, 0.80121401, -1.41234414,
[-0.02069287, 0.15120209, 0.65982542,
[-0.20288224, -0.44731064, -0.22396041,
[ 0.63475197, -0.52554826, 0.72155723,
[-0.09199671, 0.75841129, -0.90966598,
[ 0.29255093, -0.71914339, 0. ,
[-0.49710869, 0.1316995 , -0.3101261 ,
[ 0.97164381, 0.71849438, 1.23848267,
[ 0.04819566, 0.77629811, 0.3188971 .
```

# All about Feature Transformation Techniques

Features: Length = 100m

- Magnitude (100)
- Units (m)

## Calculating Distance for ML Algorithm



Euclidean Distance between  $A_1$  and  $B_2 = \sqrt{(X_2 - X_1)^2 + (Y_2 - Y_1)^2}$

	Student	CGPA	Salary '000
0	1	3.0	60
1	2	3.0	40
2	3	4.0	40
3	4	4.5	50
4	5	4.2	52

- Distance AB before scaling  $\Rightarrow \sqrt{(40 - 60)^2 + (3 - 3)^2} = 20$
- Distance BC before scaling  $\Rightarrow \sqrt{(40 - 40)^2 + (4 - 3)^2} = 1$

## Calculating Distance for ML Algorithm

	Student	CGPA	Salary '000
0	1	-1.184341	1.520013
1	2	-1.184341	-1.100699
2	3	0.416120	-1.100699
3	4	1.216350	0.209657
4	5	0.736212	0.471728

- Distance AB after scaling  $\Rightarrow \sqrt{(1.1 + 1.5)^2 + (1.18 - 1.18)^2} = 2.6$
- Distance BC after scaling  $\Rightarrow \sqrt{(1.1 - 1.1)^2 + (0.41 + 1.18)^2} = 1.59$

# All about Feature Transformation Techniques

Few advantages of feature scaling the data are as follows:

1. It makes your training faster.
2. It prevents you from getting stuck in local optima.
3. It gives you a better error surface shape.

However, there are few algorithms such as Logistic Regression and Decision Trees that are not affected by scaling of input data.

# All about Feature Transformation Techniques

Examples of Algorithms where Feature Scaling matters:

1. **K-Means** uses the Euclidean distance measure here feature scaling matters.
2. **K-Nearest - Neighbours** also require feature scaling.
3. **Principal Component Analysis (PCA)**: Tries to get the feature with maximum variance, here too feature scaling is required.
4. **Gradient Descent**: Calculation speed increase as Theta calculation becomes faster after feature scaling.

**Note:** Naive Bayes, Tree-Based models are not affected by feature scaling.

# Feature Transformation

Techniques to perform Feature Transformation:

- Normalization
- Standardization
- Robust Scaler
- Max Absolute Scaler



# Feature Transformation

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3	4	4.5	50
4	5	4.2	52

**Normalization:** 
$$X_{\text{new}} = \frac{X_i - \min(X)}{\max(x) - \min(X)}$$

```
from sklearn.preprocessing import MinMaxScaler  
scaler = MinMaxScaler()
```

# Feature Transformation

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Standardization:  $X_{\text{new}} = \frac{X_i - X_{\text{mean}}}{\text{Standard Deviation}}$

Standard Deviation:  $\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{N}}$

```
from sklearn.preprocessing import StandardScaler  
scaler = StandardScaler()
```

$\sigma$  = population standard deviation

$N$  = the size of the population

$x_i$  = each value from the population

$\mu$  = the population mean

# Feature Transformation

In simplest terms, the **Max Absolute Scaler** takes the absolute **maximum** value of each column and **divides** each value in the column by the maximum value.

Formula:

$$x_{scaled} = \frac{x}{\max(x)}$$

Python:

```
from sklearn.preprocessing import MaxAbsScaler  
scaler = MaxAbsScaler()
```

# Feature Transformation

**Robust Scaler** are robust to outliers. It is used to scale the feature to median and quantiles. Scaling using median and quantiles consists of subtracting the median to all the observations, and then dividing by the interquartile difference. The interquartile difference is the difference between the 75th and 25th quantile:

Formula:

$$X_{\text{scale}} = \frac{x_i - x_{\text{med}}}{x_{75} - x_{25}}$$

- IQR = 75th quantile - 25th quantile
- RobustScaler =  $(X_i - X.\text{Median}) / \text{IQR}$

Python:

```
from sklearn.preprocessing import RobustScaler  
RoSc=RobustScaler()
```

Video: <https://youtu.be/U9N-ELpCpc8>

Let's do it with PYTHON