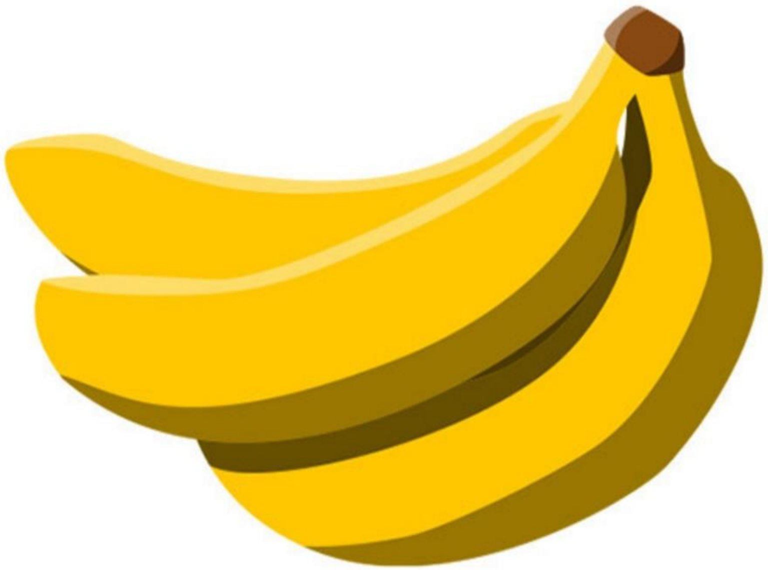
All about Feature Transformation

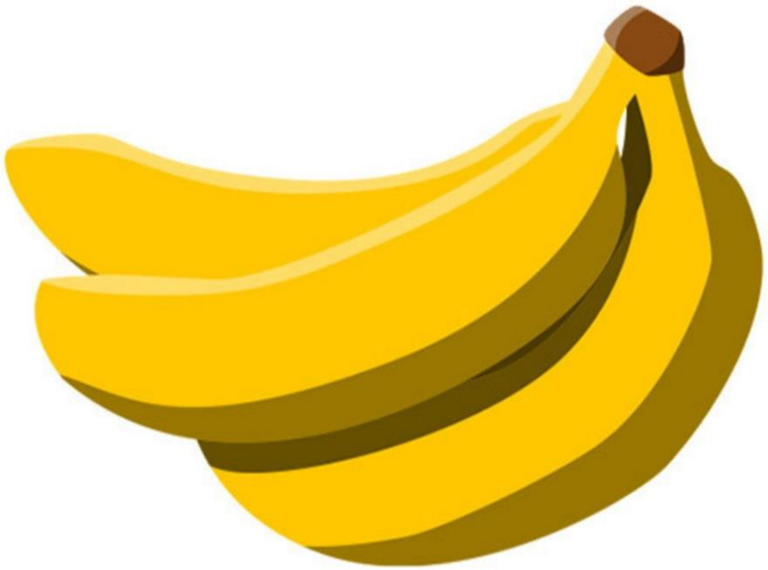
Feature transformation in machine learning refers to the process of modifying or converting input features in a dataset to improve the performance of a machine learning model. It involves applying mathematical or statistical operations to the features in order to make them more suitable for the learning algorithm.

Feature transformation techniques can include scaling, normalization, binarization, polynomial expansion, logarithmic transformation, and more. These transformations can help address issues such as different scales or distributions of features, nonlinearity, and outliers, which can affect the performance of the model. By transforming features, the goal is to create a new set of features that better capture the underlying patterns and relationships in the data, ultimately enhancing the model's ability to make accurate predictions or classifications.

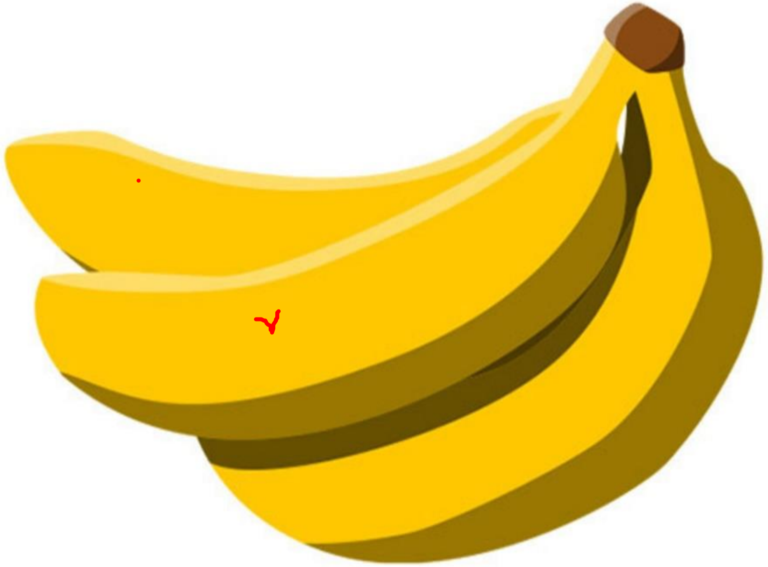
All about Feature Transformation

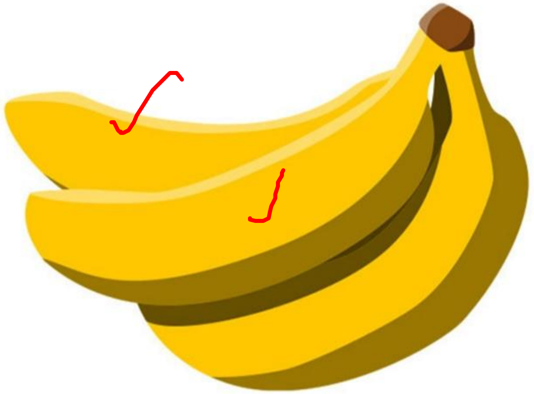


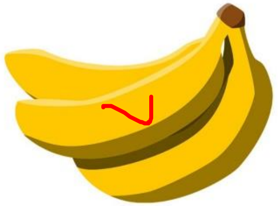
All about Feature Transformation



All about Feature Transformation







All about Feature Transformation

Features: Length = 100m

- Magnitude (100)
- Units (m)

All about Feature Transformation

AI Quest

Before

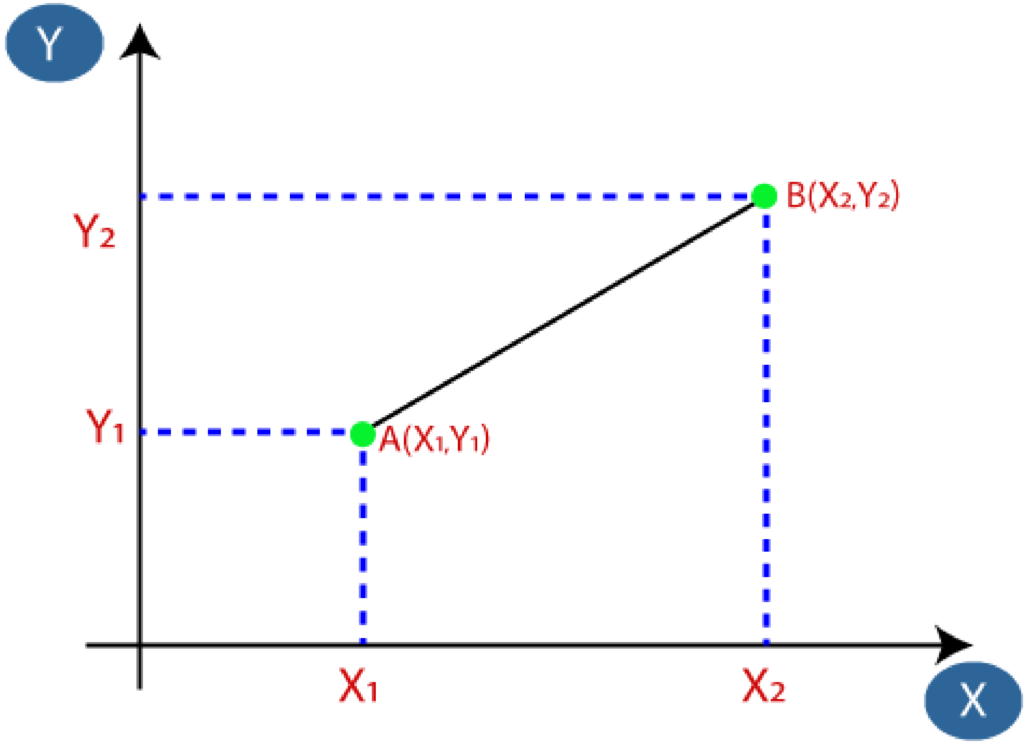
	Marketing Spend	Administration	Transport
8	120542.52	148718.95	311613.29
3	144372.41	118671.85	383199.62
6	134615.46	147198.87	127716.82
41	27892.92	84710.77	164470.71
46	1315.46	115816.21	297114.46
47	0.00	135426.92	0.00
15	165349.20	122616.84	261776.23
9	123334.88	108679.17	304981.62
16	78013.11	121597.55	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 ,
```

Calculating Distance for ML Algorithm

The Euclidean Distance between two points is calculated using a simple formula.



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

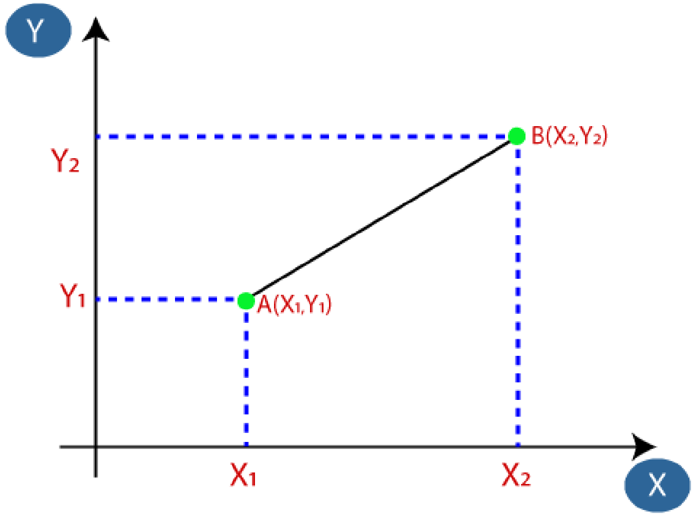
Calculating Distance for ML Algorithm

The Manhattan Distance between two points is calculated using a simple formula.

Manhattan Distance = $|x_1 - x_2| + |y_1 - y_2|$

Manhattan Distance = $d(x, y) = \sum_{i=1}^{n} |x_i - y_i|$

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

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

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 Tree based algorithms and probability based algo. 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, Decision Tree, Random Forest & All tree-based models are not affected by feature scaling.

Feature Transformation

Techniques to perform Feature Transformation:

- Normalization
- Standardization
- Log Transformation
- Robust Scaler
- Max Absolute Scaler

Min Max Scaler

	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

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

Python Implementation:

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

Standard Scaler

	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

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

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

σ = population standard deviation

N = the size of the population

x_i = each value from the population

μ = the population mean

Python Implementation:

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

Log Transformation

The log transform can be applied as follows:

1. Check if the feature has any zero or negative values. If so, consider using a modified version of the log transform (e.g., adding a constant value or using the logarithm of the absolute values).

2. Add a small constant value (e.g., 5) to the feature before applying the logarithm. This is done to avoid taking the logarithm of zero or close-to-zero values, which would result in undefined or infinite values.

3. Apply the natural logarithm function (base e) to each value of the feature.

https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.FunctionTransformer.html

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: $$xscaled = \frac{x}{max(x)}$$

Python Implementation:

```
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= (Xi – X.Median)/IQR

Python Implementation:

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

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

Let’s do it with PYTHON