Feature Engineering

Feature Engineering is the process of using domain knowledge to select, modify, or create new features from raw data to improve the performance of machine learning models.

Feature Transformation

Feature transformation involves changing the format, values, or distribution of features to make them more suitable for modeling. Two major tasks include:

1. **Encoding Categorical Data**
2. **Scaling Numerical Data**

Types of Data

1. Numerical Data

- Data represented by numbers and can be continuous or discrete.

2. Categorical Data

- Data that consists of categories or labels.
- Further divided into:
  - **Nominal Data**: Categories with no inherent order.
    - Example: `['Red', 'Blue', 'Green']`
  - **Ordinal Data**: Categories with a meaningful order or ranking.
    - Example: `['Poor', 'Average', 'Good']`

Encoding Categorical Data

Ordinal Encoding

- Use **OrdinalEncoder** when dealing with **ordinal data** in **input (X)** features.
- You must specify the order of the categories manually.

In [13]:
```
from sklearn.preprocessing import OrdinalEncoder
import pandas as pd

# Sample data
data = pd.DataFrame({
    'Quality': ['Poor', 'Average', 'Good'],
    'Education': ['School', 'UG', 'PG']
```

```
})

# Define order for each column
encoder = OrdinalEncoder(categories=[
    ['Poor', 'Average', 'Good'],
    ['School', 'UG', 'PG']
])

# Fit and transform
encoded_data = encoder.fit_transform(data)
encoded_df = pd.DataFrame(encoded_data, columns=['Quality', 'Education'])
print(encoded_df)
```

```
   Quality  Education
0      0.0        0.0
1      1.0        1.0
2      2.0        2.0
```

Label Encoding

Label Encoding is used to convert **categorical labels** into **numerical form**, especially for the **target variable (y)**.

When to Use:

- Use **LabelEncoder** when the **target variable (y)** is **categorical**.

What It Does:

- Converts **class labels** (e.g., `'cat'`, `'dog'`, `'mouse'`) into **numeric values** (e.g., `0`, `1`, `2`).
- Helps machine learning models work with categorical outputs.

When Not to Use:

- Do **not** use **Label Encoding** on **input features** (X) if there's **no inherent order** in the categories.
  - Example: Encoding colors (`red`, `blue`, `green`) with `0`, `1`, `2` adds a false sense of order.

Better Alternatives for Input Features:

- Use **One-Hot Encoding** or **Ordinal Encoding** (only if order matters) for input features instead.

In [14]:
```
from sklearn.preprocessing import LabelEncoder

# Sample target data
y = ['Cat', 'Dog', 'Fish', 'Dog']

# Initialize encoder
label_encoder = LabelEncoder()

# Fit and transform
y_encoded = label_encoder.fit_transform(y)
print(y_encoded)
```

```
[0 1 2 1]
```

Summary

Encoder	Use Case	Data Type	Applicable On
OrdinalEncoder	Ordered categories	Ordinal	Input features
LabelEncoder	Categorical target variable	Nominal/Ordinal	Output (target)

- Jab **input features** mein **ordered categorical data** ho to **OrdinalEncoder** lagana hota hai.
- Aur jab **target variable (output y) categorical** ho to **LabelEncoder** use karte hain.

How to Use OrdinalEncoder and LabelEncoder

Step-by-Step: Using `OrdinalEncoder`

To use `OrdinalEncoder`, follow these steps:

1. **Import the Class**
   `from sklearn.preprocessing import OrdinalEncoder`

In [16]:
```
from sklearn.preprocessing import OrdinalEncoder
```

🛠️ Create the Encoder Object

While creating the object, pass a parameter called `categories`, which contains **lists of the category values in order**.

In [17]:
```
encoder = OrdinalEncoder(categories=[
    ['Poor', 'Average', 'Good'],    # Ordered list for "Quality"
    ['School', 'UG', 'PG']          # Ordered list for "Education"
])
```

🔧 Fit and Transform the Training Data

You can now use `fit()` or `fit_transform()` on your training data.

In [18]:
```
import pandas as pd

train = pd.DataFrame({
    'Quality': ['Poor', 'Good', 'Average'],
    'Education': ['PG', 'UG', 'School']
})

encoded_train = encoder.fit_transform(train)
print(pd.DataFrame(encoded_train, columns=['Quality', 'Education']))
```

```
   Quality  Education
0      0.0        2.0
1      2.0        1.0
2      1.0        0.0
```

🧪 Use the Same Encoder to Transform Test Data

Use the same encoder that was fit on the training data to transform the test data.

In [19]:
```
test = pd.DataFrame({
    'Quality': ['Average', 'Good'],
    'Education': ['UG', 'PG']
})

encoded_test = encoder.transform(test)
print(pd.DataFrame(encoded_test, columns=['Quality', 'Education']))
```

```
   Quality  Education
0      1.0        1.0
1      2.0        2.0
```

Important Note on LabelEncoder

- `LabelEncoder` is used **only for target variables (output y)** that are **categorical**.
- It does **not take any parameter**.
- It **automatically assigns** a numerical value to each category,
  but **you can't control the order**.

In [20]:
```
from sklearn.preprocessing import LabelEncoder

y = ['Low', 'High', 'Medium', 'High']

le = LabelEncoder()
y_encoded = le.fit_transform(y)
print(y_encoded)
```

```
[1 0 2 0]
```

LabelEncoder mein aap manually **order define nahi** kar sakte.

Ye **automatic mapping** karta hai — kaun si value ko kaun sa number milega,
wo aap **control nahi kar paate**.

Encoding Nominal Categorical Data Using One Hot Encoder

Example Dataset

Let's assume you have the following nominal categorical data:

Id	Color
1	Red
2	Blue
3	Green
4	Blue

Nominal data means **no natural ordering** among categories — "Red", "Blue", and "Green" are just labels without ranking.

One Hot Encoding (OHE)

One Hot Encoding transforms these values into binary columns — each unique category becomes a separate column:

Id	Color_Blue	Color_Green	Color_Red
1	0	0	1
2	1	0	0
3	0	1	0
4	1	0	0

In [21]:

```
from sklearn.preprocessing import OneHotEncoder
import pandas as pd

# Sample data
df = pd.DataFrame({'Color': ['Red', 'Blue', 'Green', 'Blue']})

# Initialize OHE
encoder = OneHotEncoder(sparse_output=False)  # use sparse_output=False to get a

# Fit and transform
encoded_array = encoder.fit_transform(df[['Color']])

# Convert to DataFrame
encoded_df = pd.DataFrame(encoded_array, columns=encoder.get_feature_names_out([
print(encoded_df)
```

```
   Color_Blue  Color_Green  Color_Red
0         0.0          0.0        1.0
1         1.0          0.0        0.0
2         0.0          1.0        0.0
3         1.0          0.0        0.0
```

Dummy Variable Trap

After **One Hot Encoding**, one column is typically dropped to avoid **multicollinearity**.

If you keep all `n` columns for `n` categories, they will form a **linear dependency**:

$$\text{Color\_Red} + \text{Color\_Blue} + \text{Color\_Green} = 1 \quad \text{(Always)}$$

This violates the **assumption of feature independence** in machine learning.

To avoid this:

- Drop **one dummy variable** column using `drop='first'` in encoders like `OneHotEncoder`.

In [22]:
```
encoder = OneHotEncoder(drop='first', sparse_output=False)
```

High Cardinality Handling (Most Frequent Variables)

When a categorical column has too many unique values, and many of them appear **rarely**:

- It can **increase dimensionality**
- **Slow down processing**
- **Lead to overfitting**

Solution:

Group less frequent categories into `"Others"` and apply **One Hot Encoding** only on frequent ones.

Visual Explanation

Original Categories:

`['India', 'USA', 'UK', 'Germany', 'South Africa', 'Sri Lanka', 'Bhutan']`

After Grouping:

`['India', 'USA', 'UK', 'Others']`

Pandas vs Scikit-learn

Purpose	Tool	Notes
Data Analysis	`pd.get_dummies()`	Fast and easy, but doesn't store mappings
ML Pipeline Training	`sklearn.preprocessing.OneHotEncoder`	Stores fitted mapping, preferred for production

In SHort :

`Pandas get_dummies()` **Baar-baar run karne par same input par alag output mil sakta hai (agar har baar encoder fit karein), isliye ML pipeline mein wahi fitted encoder reuse karo — Scikit-learn ka pipeline is cheez ka dhyan rakhta hai.** chahiye.

Handling High Cardinality in Categorical Data

Problem: High Cardinality

When a categorical feature has **too many unique categories**, it leads to:

- **High dimensionality** after encoding
- **Sparsity** (most values become zeros)
- **Longer training time**
- Potential **overfitting**

Solution: Group Rare Categories into "Others"

Approach:

- Identify categories with **very low frequency**
- Replace them with a single common category like `"Others"`
- Apply One Hot Encoding after this grouping

> **Hinglish Tip:** Jab categories bahut zyada ho jaati hain aur kuchh categories me value bahut kam hoti hai,
> toh un sabko combine karke `"Others"` bana diya jata hai. Isse processing tez ho jaati hai aur dimensionality bhi kam ho jaati hai.

Example

Original Categories:

`['India', 'USA', 'UK', 'Germany', 'South Africa', 'Sri Lanka', 'Bhutan']`

After Grouping:

`['India', 'USA', 'UK', 'Others']`

Pandas `get_dummies()` vs Scikit-learn `OneHotEncoder`

Aspect	Pandas (`get_dummies`)	Scikit-learn (`OneHotEncoder`)
Memory of mappings	No	Yes
Reproducibility on new data	Not guaranteed	Guaranteed
Pipeline Integration	Difficult	Easy (via `ColumnTransformer`)
Use in production	Not preferred	Preferred

> **Why not use `get_dummies()` in ML pipelines?**

- Pandas doesn't **remember** which column was at which index.
- If you run the same code with a slightly different dataset, column order may change — causing **model inconsistency**.

In [24]:
```
# Example using Scikit-learn OHE with handling unknowns
from sklearn.preprocessing import OneHotEncoder

encoder = OneHotEncoder(handle_unknown='ignore', sparse_output=False)
```

Tip: `handle_unknown='ignore'`

`handle_unknown='ignore'` is useful when test data has unseen categories.
It prevents errors by ignoring unknown categories.

Category Grouping Example

Before Grouping → After Grouping
`['A', 'B', 'C', 'D']` → `['A', 'B', 'Others']`

OHE → 4 columns → **OHE** → 3 columns

🚀 Feature Scaling

Feature Scaling

Feature Scaling is a **preprocessing technique** used to **normalize or standardize** the range of independent features (input variables) in your dataset.

Real-world datasets often contain features that vary in **magnitude**, **range**, and **units**. Feature scaling ensures that all features contribute **equally** to the model's learning process.

Why Feature Scaling is Important?

- Algorithms like **KNN**, **K-Means**, **PCA**, and **Gradient Descent-based models** are sensitive to the scale of input data.
- Features with larger scales can **dominate** the learning process.
- Scaling helps:
  - Remove **scale disparities**
  - Improve **convergence speed**
  - Facilitate **fair distance measurements**
  - Handle **gradient descent efficiently**

Types of Feature Scaling

1. Standardization (Z-score Normalization)

- Transforms data to have a **mean = 0** and **standard deviation = 1**
- Formula:

$$\text{Xstandardized}$$

$$X = \frac{X - \mu(X)}{\sigma(X)}$$

Shape of distribution is preserved

Best when data follows a normal distribution

Used In:

- K-Means Clustering
- K-Nearest Neighbors
- Principal Component Analysis (PCA)
- Neural Networks
- Gradient Descent

Advantages:

- Works well when outliers are minimal
- Makes distance-based models fair

2. Normalization (Min-Max Scaling)

Scales values between a fixed range, typically 0 to 1

Formula:

$$X_{\text{scaled}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

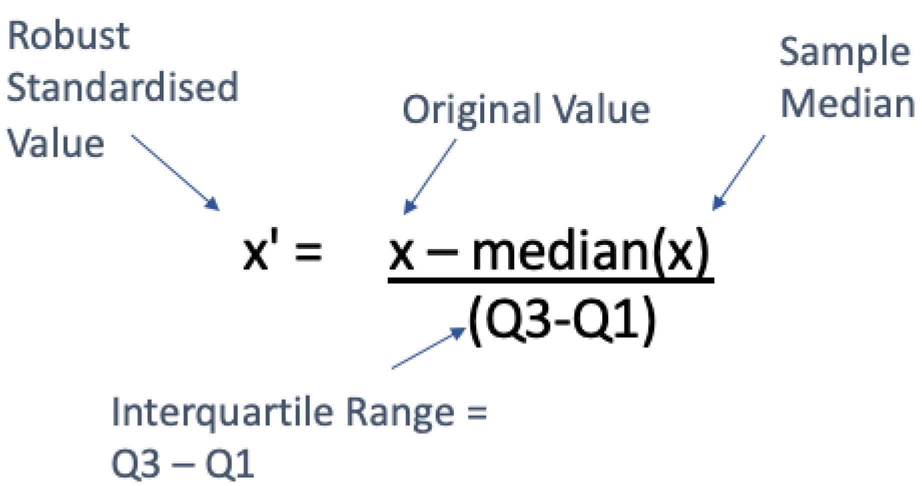
Preserves the shape of distribution but not robust to outliers

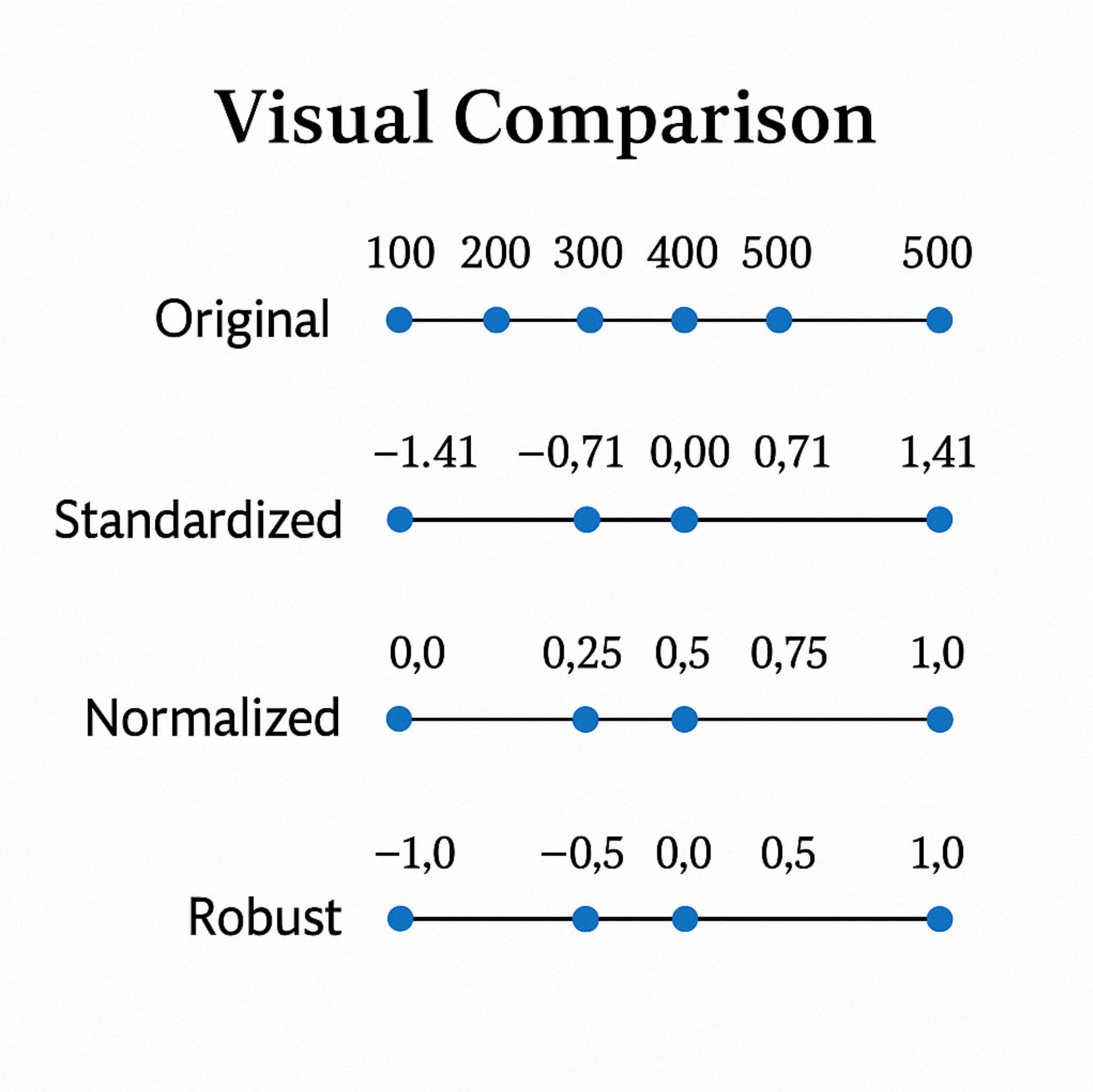
Used In:

- Neural Networks (to speed up convergence)
- Image pixel normalization

3. Robust Scaler

- Uses **median** and **interquartile range (IQR)** instead of mean/std
- Good for datasets with **outliers**





Python Code Examples

In [25]:
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler
import pandas as pd

data = pd.DataFrame({
    'Salary': [30000, 50000, 70000, 90000, 110000]
})

# Standardization
std_scaler = StandardScaler()
data['Standardized'] = std_scaler.fit_transform(data[['Salary']])

# Normalization
minmax_scaler = MinMaxScaler()
data['Normalized'] = minmax_scaler.fit_transform(data[['Salary']])

# Robust Scaling
robust_scaler = RobustScaler()
data['Robust'] = robust_scaler.fit_transform(data[['Salary']])

print(data)
```

```
   Salary  Standardized  Normalized  Robust
0   30000     -1.414214        0.00    -1.0
1   50000     -0.707107        0.25    -0.5
2   70000      0.000000        0.50     0.0
3   90000      0.707107        0.75     0.5
4  110000      1.414214        1.00     1.0
```

Summary Table

Technique	Sensitive to Outliers	Preserves Distribution	Range
Standardization	Yes	Yes	~(-3, +3)
Min-Max Scaling	Yes	Yes	(0, 1)
Robust Scaler	No	No	Varies

🔍 Tip

Jab **features ke units alag-alag** hote hain (kisi ka *salary*, kisi ka *age*),
tab **scale difference model ko confuse** karta hai.

👉 Isliye **sabko ek hi scale par lana** zaroori hota hai using **feature scaling**.

Normalization

Normalization is a technique commonly used during data preprocessing for machine learning tasks. Its primary goal is to **scale numeric columns** to a **common range**, ensuring that features with large values don't dominate those with smaller ones.

Normalization helps in:

- **Preserving relationships** between data values
- **Maintaining the shape** of the distribution
- Avoiding distortion of data variability

Why Normalize?

- Different features may have different units (e.g., age vs. salary)
- Algorithms using **distance metrics** (e.g., KNN, K-means) are sensitive to feature scales
- Normalization ensures **uniform contribution** of features to the model

---

Types of Normalization

1. **Min-Max Scaling**
2. **Mean Normalization**
3. **Max-Absolute Scaling**
4. **Robust Scaling**

1. Min-Max Scaling

Min-Max Scaling transforms features to lie within a **specific range**, usually [0, 1].

Formula:

```
X_scaled = (X - X.min()) / (X.max() - X.min())
```

🔧 Working (Min-Max Scaling)

1. Identify the **minimum** and **maximum** values of the feature
2. Rescale all values to the range **[0, 1]**

In [26]:

```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler

# Sample Data
data = pd.DataFrame({'Age': [15, 30, 45, 60, 75]})

# Apply Min-Max Scaling
scaler = MinMaxScaler()
data['Age_Scaled'] = scaler.fit_transform(data[['Age']])

print(data)
```

```
   Age  Age_Scaled
0   15        0.00
1   30        0.25
2   45        0.50
3   60        0.75
4   75        1.00
```

Hinglish Tip

Jab aapko **saare features ko ek jaisa scale dena** hota hai
bina unke **beech ka relation lose kiye**,
tab **normalization ka use** karte hain — especially **Min-Max Scaling**.

Additional Types of Normalization

2. Mean Normalization

Mean Normalization scales data between **[-1, 1]** by centering it around the mean.

Formula:

```
X_scaled = (X - X.mean()) / (X.max() - X.min())
```

📌 Characteristics (Standardization)

- Centers the data at **0**
- Resulting values lie between **-1 and 1**
- Useful when features have **similar distributions but different means**

✅ Advantages

- Converts data into **mean-centered** format
- Removes **bias due to differing means**
- Improves **model training stability**

3. Max-Absolute Scaling

- **Max-Absolute Scaling** scales the data by dividing each value by the **maximum absolute value** in the feature.
- This ensures all values are in the range **[-1, 1]** (if data contains negatives) or **[0, 1]** (if all values are positive).

$$X_i' = \frac{X_i}{abs(X_{max})}$$

When to Use:

- Especially useful for sparse data (lots of zeros)
- Preserves the sign of the data
- Does not shift/center the data, unlike mean normalization

In [27]:
```
import pandas as pd
from sklearn.preprocessing import MaxAbsScaler

# Sample DataFrame with sparse values
df = pd.DataFrame({'SparseData': [0, -3, 0, 5, 0]})

# Apply MaxAbsScaler
scaler = MaxAbsScaler()
df['Scaled'] = scaler.fit_transform(df[['SparseData']])

print(df)
```

```
   SparseData  Scaled
0           0     0.0
1          -3    -0.6
2           0     0.0
3           5     1.0
4           0     0.0
```

Hinglish Tip:

- Jab data me minimum aur maximum range define ho, use **Min-Max Scaling**.
- Jab aapko mean ke around centered data chahiye, to use **Mean Normalization**.
- Aur jab sparse data ho jisme bahut saare zeros ho, **Max Absolute Scaling** is best.

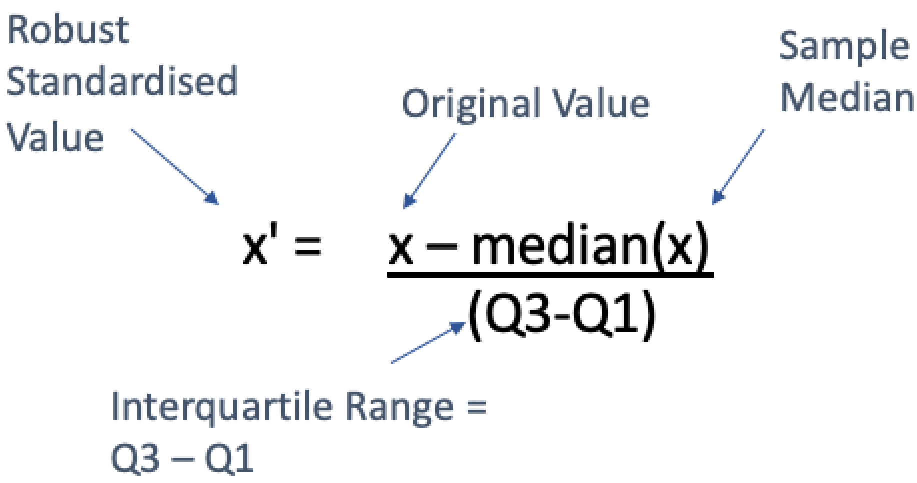
4. Robust Scaling

What is Robust Scaling?

Robust Scaling uses the **median** and **interquartile range (IQR)** for scaling the data, making it highly effective for **datasets with outliers**.

Formula:

```
X_scaled = (X - Median) / IQR
```



Where:

- **Median** = 50th percentile
- **IQR** = 75th percentile − 25th percentile

Characteristics:

- **Robust to Outliers**: Doesn't get influenced by extreme values
- Doesn't assume data is normally distributed
- Scales data around **median** rather than **mean**

In [29]:
```
import pandas as pd
from sklearn.preprocessing import RobustScaler

# Sample DataFrame with outliers
df = pd.DataFrame({'Income': [30000, 35000, 40000, 1000000]})

# Apply RobustScaler
scaler = RobustScaler()
```

```
df['Scaled'] = scaler.fit_transform(df[['Income']])

print(df)
```

```
    Income    Scaled
0    30000 -0.030457
1    35000 -0.010152
2    40000  0.010152
3  1000000  3.908629
```

Comparison: Normalization vs Standardization

Feature	Normalization	Standardization
Goal	Scale to fixed range (e.g. [0,1])	Center to mean 0, std dev 1
Formula	(X − min) / (max − min)	(X − mean) / std
Preserves Outliers	No	No
Sensitive to Outliers	Yes	Yes
Best For	Known range	Unknown distributions

Which Scaling to Use?

Situation	Recommended Scaler
Known Min/Max values	**MinMaxScaler**
Unknown Distribution	**StandardScaler**
Presence of Outliers	**RobustScaler**
Sparse Data (many zeros)	**MaxAbsScaler**

Hinglish Tip:

- Agar aapke dataset me bahut zyada outliers hain, to **RobustScaler** use karna best hota hai kyunki ye median aur IQR ke basis par scale karta hai.
- Jab aapko value ka range pehle se pata ho, to **Min-Max** lagao.
- Aur jab pata hi nahi kya distribution hai, to **StandardScaler** best hai.

In [ ]: