day-23-28-feature-engineering

May 26, 2025

#Feature Engineering: ###Feature Engineering is the Process of using domain Knowledge to **Extract** featues of raw data.These Features can be used to improve the performance of Machine Learning Algoritham.

#Feature Engineering

1. Feature Transformation

- Missing value Imputation
- Hendeling Catagorical Features
- Outlier Detection
- Feature Scaling

2. Feature Construction
3. Feature Selection
4. Feature Extraction

[ ]:

```

```

#Day-24:Feature Scalling **Feature scaling** is a data preprocessing technique used to normalize the range of independent variables or features in your dataset. The goal is to bring all the features onto a similar scale so that no single feature dominates the learning process due to its magnitude.

This is especially important for machine learning algorithms that are sensitive to the scale of input data, such as:

- **K-Nearest Neighbors (KNN)**
- **Support Vector Machines (SVM)**
- **Principal Component Analysis (PCA)**
- **Gradient Descent-based models** like Linear Regression and Logistic Regression
- **Neural Networks**

0.0.1 Common Methods of Feature Scaling:

1. **Min-Max Scaling (Normalization)** Scales the data to a fixed range, usually [0, 1]. Formula:

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

2. **Standardization (Z-score Normalization)** Scales data so it has a mean of 0 and standard deviation of 1. Formula:

$$X_{\text{scaled}} = \frac{X - \mu}{\sigma}$$

where μ is the mean and σ is the standard deviation.

3. **Robust Scaling** Uses median and interquartile range, which is more robust to outliers. Formula:

$$X_{\text{scaled}} = \frac{X - \text{Median}}{\text{IQR}}$$

0.0.2 Why Feature Scaling Matters:

- Prevents bias towards features with larger values.
- Improves convergence speed of gradient descent.
- Enhances model performance and accuracy in many algorithms.

Would you like a Python code example to demonstrate this?

1 Scaling :

1.1 Scaling ? (Apply Scaling)

1. **Numerical**
   (: Age, Income, Temperature)

2. **Ordinal Encoded**
   (: Education: Primary=0, Secondary=1, University=2)

3. **Ordinal Label Encoded**
   (: Size: Small=0, Medium=1, Large=2)

1.2 Scaling ? (No Scaling Needed)

1. **One-Hot Encoded**
   (: Color_Red=0/1, Color_Blue=0/1)

2. **(Binary Data)**
   (: Gender_Male=0/1, Is_Student=0/1)

3. **Nominal Label Encoded**
   (: City: Dhaka=0, Chittagong=1, Sylhet=2 →)

1.3 (Titanic Dataset Example)

	(Titanic)	Scaling ?	
Numerical	Age, Fare		(Age: 0-100, Fare: 0-500)
Ordinal	Pclass (1st=1, 2nd=2, 3rd=3)		1st > 2nd > 3rd ( )
Binary	Sex (Male=0, Female=1)		-
One-Hot	Embarked_C, Embarked_Q, Embarked_S		/
Nominal Label Encoded	City (Dhaka=0, CTG=1)		

1.4

1. **Ordinal vs Nominal:**
   - Ordinal ( ) → Scaling
   - Nominal ( ) → Scaling
2. **One-Hot/Binary:**
   - / →
3. **:**
   - **Linear Regression, SVM, Neural Networks** →
   - **Random Forest, XGBoost** →

fit_transform(), transform()

2 ColumnTransformer- fit_transform transform

:
`fit_transform()` **`transform()`** `fit_transform()`
!

2.1 ?

1. : /
2. **-** : `fit`
3. : -

2.2 (Python Code)

```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder

#
preprocessor = ColumnTransformer([
    ('num', StandardScaler(), ['Age', 'Fare']),
    ('cat', OneHotEncoder(), ['Sex', 'Embarked'])
])

#       fit_transform
X_train_processed = preprocessor.fit_transform(X_train)

#       transform (   fit_transform  !)
X_test_processed = preprocessor.transform(X_test)
```

2.3 ( )

```
#        fit_transform          !
X_test_processed = preprocessor.fit_transform(X_test)  #
```

2.4

2. (Recommended):

```
from sklearn.pipeline import Pipeline

pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('model', RandomForestClassifier())
])

pipeline.fit(X_train, y_train)  #
```

3. :

```
from sklearn.model_selection import GridSearchCV

params = {'model__n_estimators': [100, 200]}
grid = GridSearchCV(pipeline, params, cv=5)
grid.fit(X_train, y_train)  #            transform
```

2.5 :

```
#
numeric_features = ['Age', 'Fare']
categorical_features = ['Sex', 'Embarked']

#
preprocessor = ColumnTransformer([
```

```
    ('num', StandardScaler(), numeric_features),
    ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features)
])

#   -
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    df.drop('Survived', axis=1),
    df['Survived'],
    test_size=0.2,
    random_state=42
)

#
X_train = preprocessor.fit_transform(X_train)  # fit + transform
X_test = preprocessor.transform(X_test)      #   transform
```

2.6

- fit():   (   )
- transform():   (   )
- fit_transform():   (   )

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[ ]:
```
df=pd.read_csv('/content/Titanic-Dataset.csv')
df.head(4)
```

[ ]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
```

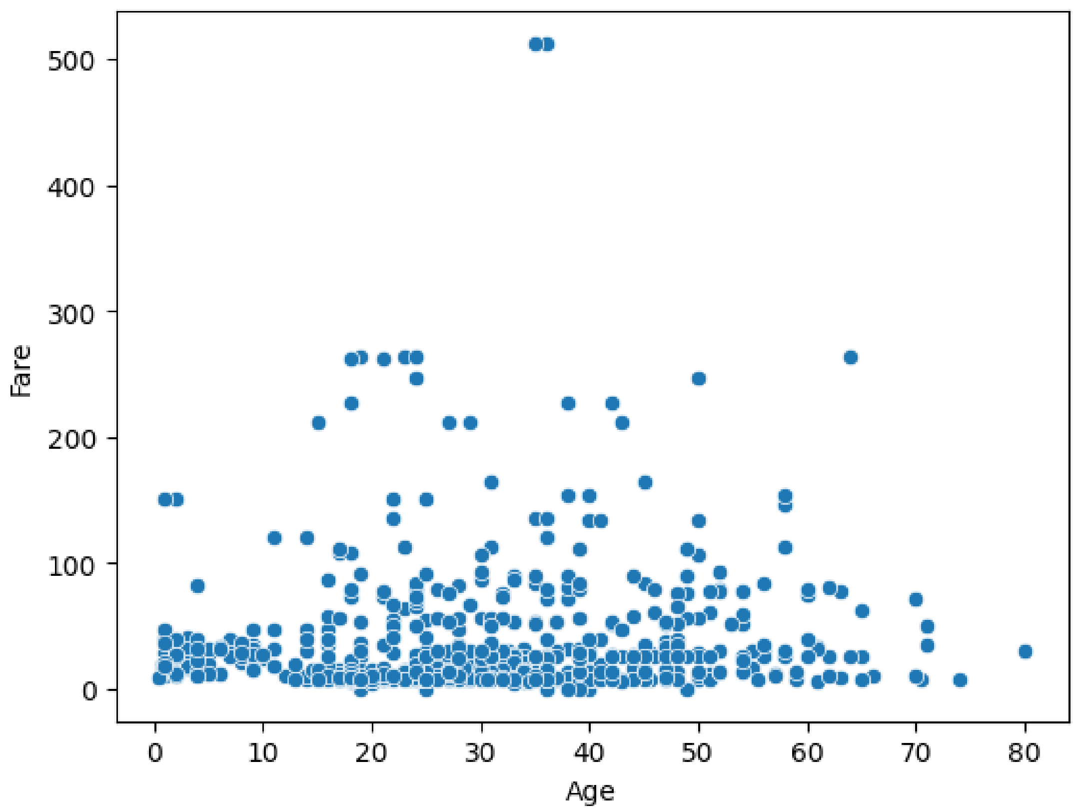
[ ]:
```
dfs=df[['Sex','Age','Fare','Pclass','Survived']]
dfs
```

[ ]:
```
        Sex   Age     Fare  Pclass  Survived
0      male  22.0   7.2500       3         0
1    female  38.0  71.2833       1         1
2    female  26.0   7.9250       3         1
3    female  35.0  53.1000       1         1
4      male  35.0   8.0500       3         0
..      …   …       …     …       …
886    male  27.0  13.0000       2         0
887  female  19.0  30.0000       1         1
888  female   NaN  23.4500       3         0
889    male  26.0  30.0000       1         1
890    male  32.0   7.7500       3         0

[891 rows x 5 columns]
```

#Standarization(z-score Normalization) ###Manuly done by hands on

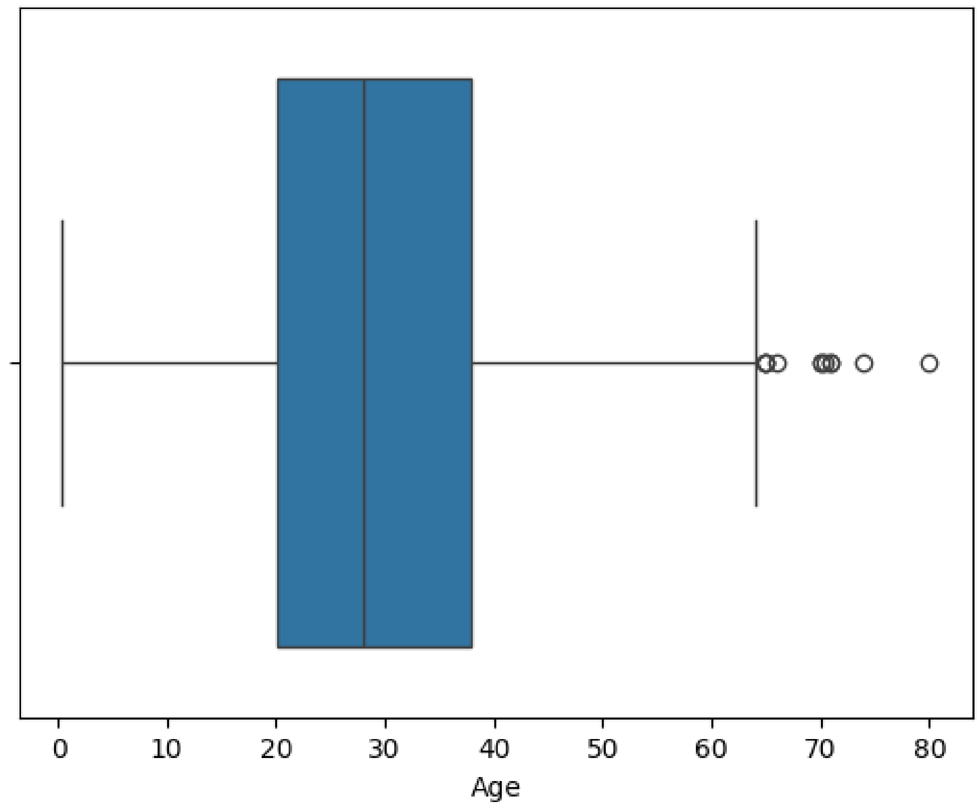
[ ]:
```
sns.scatterplot(data=dfs,x='Age',y='Fare')
```

[ ]:
```
<Axes: xlabel='Age', ylabel='Fare'>
```



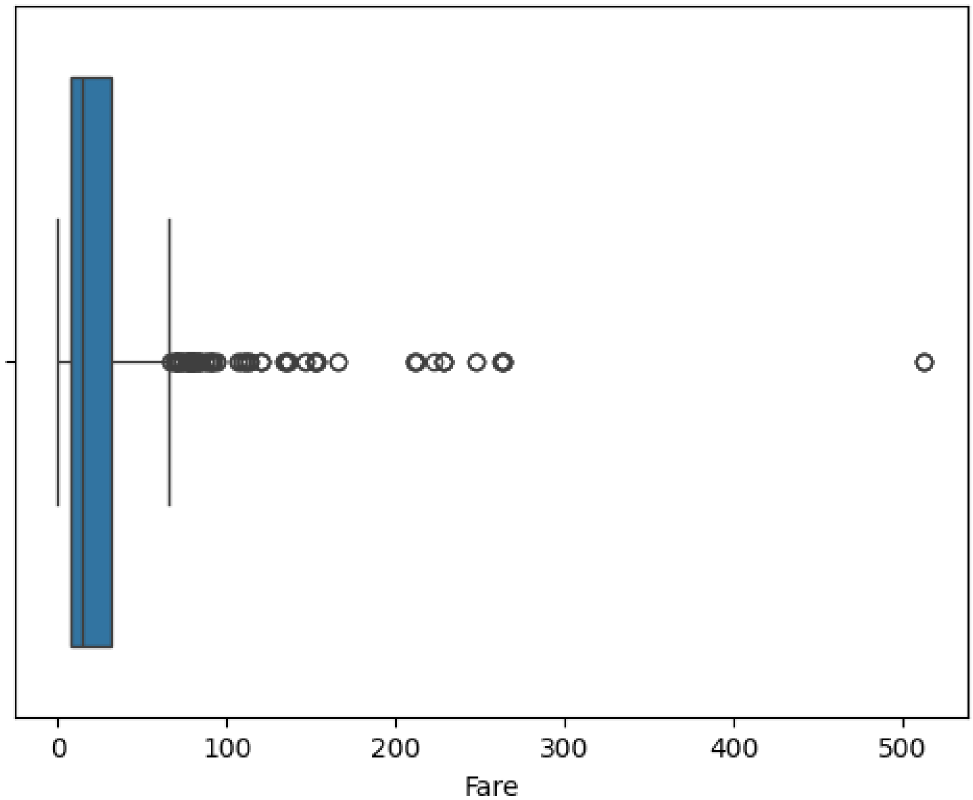
[ ]:
```
sns.boxplot(data=dfs,x='Age')
```

[ ]: <Axes: xlabel='Age'>



[ ]:
```
sns.boxplot(data=dfs,x='Fare')
```

[ ]: <Axes: xlabel='Fare'>



[ ]:
```
dfs.describe()
```

[ ]:

	Age	Fare	Pclass	Survived
count	714.000000	891.000000	891.000000	891.000000
mean	29.699118	32.204208	2.308642	0.383838
std	14.526497	49.693429	0.836071	0.486592
min	0.420000	0.000000	1.000000	0.000000
25%	20.125000	7.910400	2.000000	0.000000
50%	28.000000	14.454200	3.000000	0.000000
75%	38.000000	31.000000	3.000000	1.000000
max	80.000000	512.329200	3.000000	1.000000

[ ]:
```
dfs.dropna(inplace=True)
```

```
<ipython-input-9-ba15139647ea>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  dfs.dropna(inplace=True)
```

[ ]:
```
dfs
```

[ ]:
```
        Sex   Age     Fare  Pclass  Survived
0      male  22.0   7.2500       3         0
1    female  38.0  71.2833       1         1
2    female  26.0   7.9250       3         1
3    female  35.0  53.1000       1         1
4      male  35.0   8.0500       3         0
..      …     …      …       …         …
885  female  39.0  29.1250       3         0
886    male  27.0  13.0000       2         0
887  female  19.0  30.0000       1         1
889    male  26.0  30.0000       1         1
890    male  32.0   7.7500       3         0

[714 rows x 5 columns]
```

[ ]:
```
#apply Scalling(Standarization) on Age column
dfs['newAge']=(dfs['Age']-dfs['Age'].mean())/dfs['Age'].std()
np.round(dfs['newAge'].mean())
# dfs['Age'].mean()
```

```
<ipython-input-11-20b00c34d820>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  dfs['newAge']=(dfs['Age']-dfs['Age'].mean())/dfs['Age'].std()
```

[ ]:
```
np.float64(0.0)
```

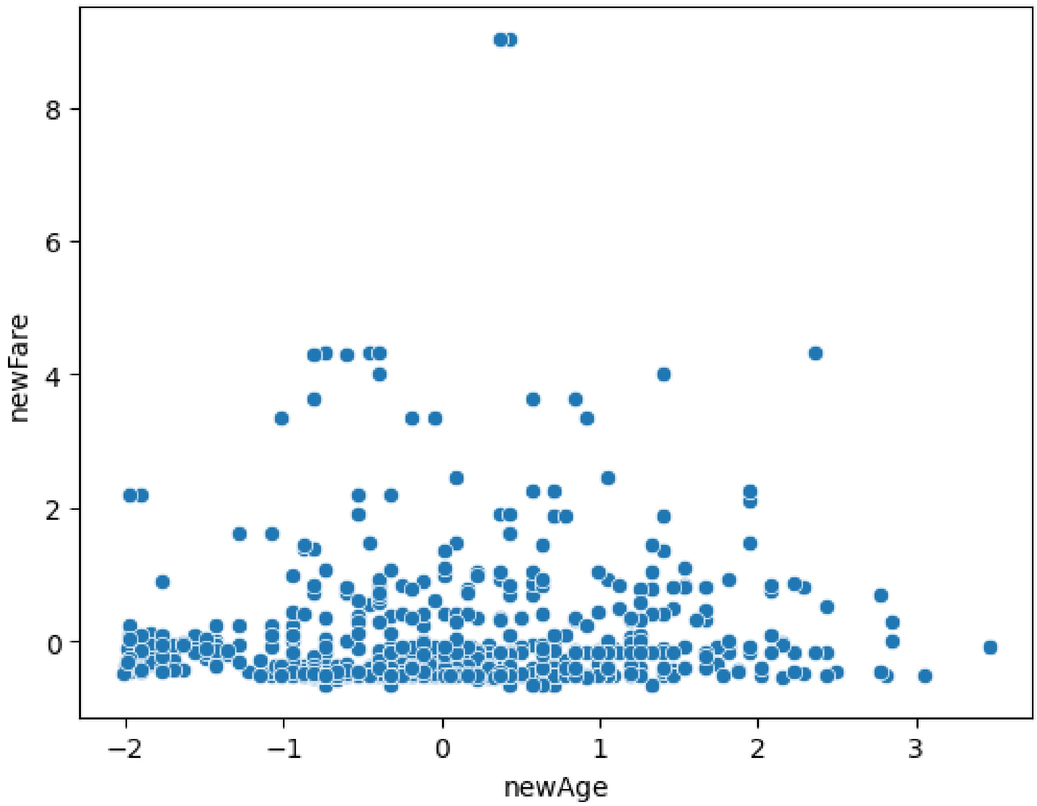
[ ]:
```
dfs['newFare']=(dfs['Fare']-dfs['Fare'].mean())/dfs['Fare'].std()
np.round(dfs['newFare'].std())
```

```
<ipython-input-12-5813732765e3>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  dfs['newFare']=(dfs['Fare']-dfs['Fare'].mean())/dfs['Fare'].std()
```

[ ]:
```
np.float64(1.0)
```

[ ]:
```
sns.scatterplot(data=dfs,x='newAge',y='newFare')
```

[ ]: <Axes: xlabel='newAge', ylabel='newFare'>



#Standarization(z-score Normalization) ###Using Function

[ ]:
```
dfs.head(5)
```

[ ]:

	Sex	Age	Fare	Pclass	Survived	newAge	newFare
0	male	22.0	7.2500	3	0	-0.530005	-0.518614
1	female	38.0	71.2833	1	1	0.571430	0.691412
2	female	26.0	7.9250	3	1	-0.254646	-0.505859
3	female	35.0	53.1000	1	1	0.364911	0.347805
4	male	35.0	8.0500	3	0	0.364911	-0.503497

[ ]:
```
olddfs=dfs.iloc[:,1:5]
olddfs
```

[ ]:

	Age	Fare	Pclass	Survived
0	22.0	7.2500	3	0
1	38.0	71.2833	1	1
2	26.0	7.9250	3	1
3	35.0	53.1000	1	1

```
4    35.0   8.0500        3          0
..    …       …      …       …
885  39.0  29.1250        3          0
886  27.0  13.0000        2          0
887  19.0  30.0000        1          1
889  26.0  30.0000        1          1
890  32.0   7.7500        3          0

[714 rows x 4 columns]
```

[ ]:
```
newdfs=dfs.iloc[:,[3,4,5,6]]
newdfs
```

[ ]:
```
     Pclass  Survived    newAge   newFare
0         3         0 -0.530005 -0.518614
1         1         1  0.571430  0.691412
2         3         1 -0.254646 -0.505859
3         1         1  0.364911  0.347805
4         3         0  0.364911 -0.503497
..       …         …        …        …
885       3         0  0.640270 -0.105246
886       2         0 -0.185807 -0.409958
887       1         1 -0.736524 -0.088711
889       1         1 -0.254646 -0.088711
890       3         0  0.158392 -0.509166

[714 rows x 4 columns]
```

##Apply ML algorithm

[ ]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test=train_test_split(olddfs.
 ↪drop('Survived',axis=1),olddfs['Survived'],test_size=0.25,random_state=0)
X_train.shape,X_test.shape
```

[ ]:
```
((535, 3), (179, 3))
```

[ ]:
```
Y_train.shape,Y_test.shape
```

[ ]:
```
((535,), (179,))
```

##StandardScaler

[ ]:
```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
#fit the scaler to the train set,it(scaler variable) will learn the parameters
scaler.fit(X_train)
```

```
#Transform train and test Dataset
X_train_scaled=scaler.transform(X_train)
X_test_scaled=scaler.transform(X_test)
```

[ ]:
```
scaler.mean_
```

[ ]:
```
array([29.69407477, 34.30420467,  2.25607477])
```

[ ]:
```
X_train_scaled=pd.DataFrame(X_train_scaled,columns=X_train.columns)
X_test_scaled=pd.DataFrame(X_test_scaled,columns=X_train.columns)
```

[ ]:
```
X_train_scaled.describe()
```

[ ]:

	Age	Fare	Pclass
count	5.350000e+02	5.350000e+02	535.000000
mean	9.960879e-18	-3.984352e-17	0.000000
std	1.000936e+00	1.000936e+00	1.000936
min	-2.005455e+00	-6.206901e-01	-1.514666
25%	-6.698244e-01	-4.750358e-01	-0.308794
50%	-1.170542e-01	-3.448371e-01	0.897079
75%	6.430047e-01	-2.812132e-02	0.897079
max	3.061374e+00	8.649243e+00	0.897079

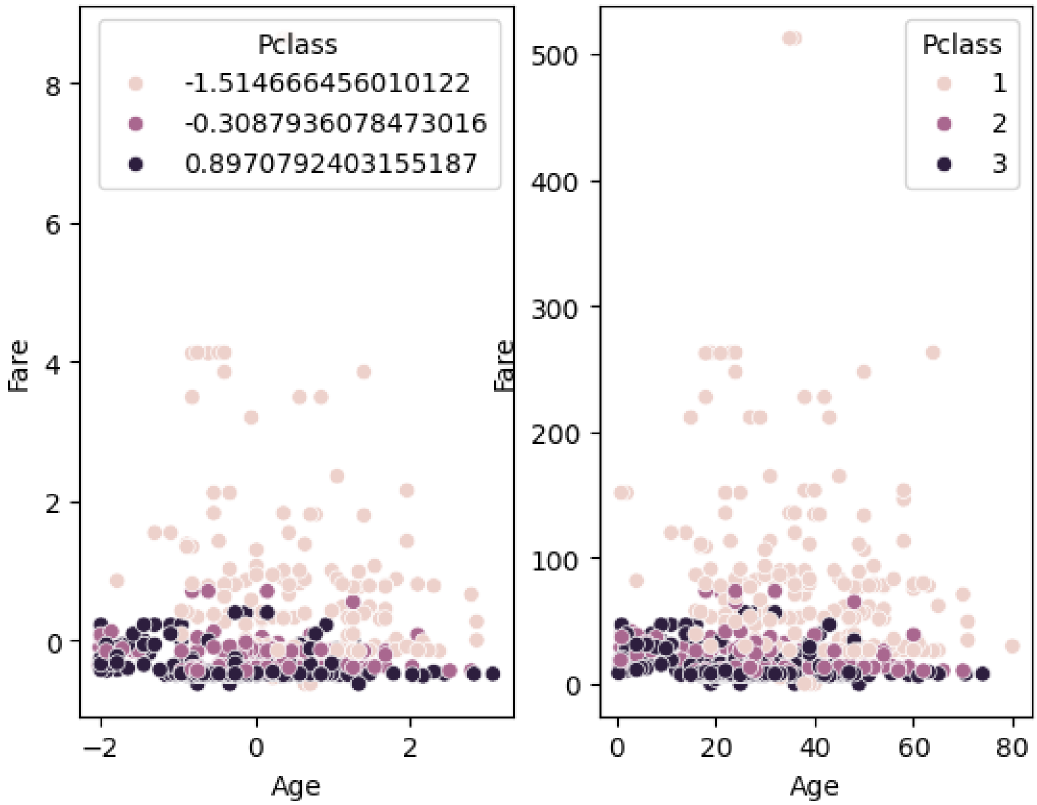
[ ]:
```
dfs.head(2)
```

[ ]:

	Sex	Age	Fare	Pclass	Survived	newAge	newFare
0	male	22.0	7.2500	3	0	-0.530005	-0.518614
1	female	38.0	71.2833	1	1	0.571430	0.691412

[ ]:
```
plt.subplot(1,2,1)
sns.scatterplot(data=X_train_scaled,x='Age',y='Fare',hue='Pclass')
plt.subplot(1,2,2)
sns.scatterplot(data=dfs,x='Age',y='Fare',hue='Pclass')
```

[ ]:
```
<Axes: xlabel='Age', ylabel='Fare'>
```

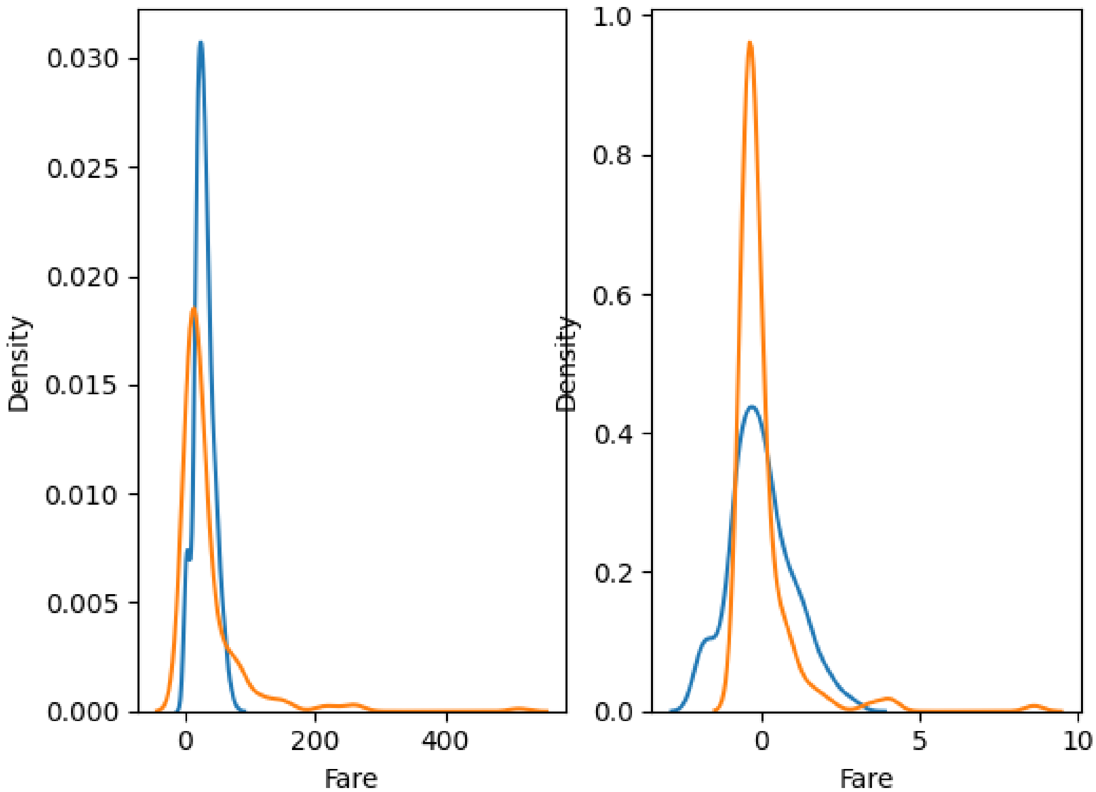



```
[ ]: #Distribution Plot
plt.subplot(1,2,1)
sns.distplot(olddfs['Age'],hist=False)
sns.distplot(olddfs['Fare'],hist=False)
plt.subplot(1,2,2)
sns.distplot(X_train_scaled['Age'],hist=False)
sns.distplot(X_train_scaled['Fare'],hist=False)
```

```
<ipython-input-25-61e920c0572a>:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `kdeplot` (an axes-level function for kernel density
plots).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(olddfs['Age'],hist=False)
<ipython-input-25-61e920c0572a>:4: UserWarning:
```

```
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `kdeplot` (an axes-level function for kernel density
plots).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(olddfs['Fare'],hist=False)
<ipython-input-25-61e920c0572a>:6: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `kdeplot` (an axes-level function for kernel density
plots).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X_train_scaled['Age'],hist=False)
<ipython-input-25-61e920c0572a>:7: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `kdeplot` (an axes-level function for kernel density
plots).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X_train_scaled['Fare'],hist=False)
```

[ ]:
```
<Axes: xlabel='Fare', ylabel='Density'>
```



[ ]:
```

```

[ ]:
```
from sklearn.linear_model import LogisticRegression
```

[ ]:
```
lr_old=LogisticRegression()
lr_new=LogisticRegression()
```

[ ]:
```
lr_old.fit(X_train,Y_train)
lr_new.fit(X_train_scaled,Y_train)
```

[ ]: LogisticRegression()

[ ]:
```
y_pred=lr_old.predict(X_test)
y_pred_scaled=lr_new.predict(X_test_scaled)
```

[ ]:
```
from sklearn.metrics import accuracy_score
```

[ ]:
```
print('Without Preprocess:',accuracy_score(Y_test,y_pred))
print('After Preprocess:',accuracy_score(Y_test,y_pred_scaled))
#conclusion: Ai dataset a standarization kore kono lav hoi nai
```

```
Without Preprocess: 0.659217877094972
After Preprocess: 0.659217877094972
```

2.6.1 when applying Standarization on Data which contain Outlier.Standarization Scaling does not impact on these Outliers

[ ]:
```

```

#Standardization on Social media Advadisement dataset

[ ]:
```
adv=pd.read_csv('/content/Social_Network_Ads.csv')
adv.head(3)
```

[ ]:
```
    User ID  Gender  Age  EstimatedSalary  Purchased
0  15624510    Male   19            19000          0
1  15810944    Male   35            20000          0
2  15668575  Female   26            43000          0
```

[ ]:
```
adv=adv.iloc[:,2:]
adv
```

[ ]:
```
     Age  EstimatedSalary  Purchased
0     19            19000          0
1     35            20000          0
2     26            43000          0
3     27            57000          0
4     19            76000          0
..   …              …          …
395   46            41000          1
396   51            23000          1
397   50            20000          1
398   36            33000          0
399   49            36000          1

[400 rows x 3 columns]
```

[ ]:
```
adv.head(3)
```

[ ]:
```
   Age  EstimatedSalary  Purchased
0   19            19000          0
1   35            20000          0
2   26            43000          0
```

[ ]:
```
from sklearn.model_selection import train_test_split
X,x,Y,y=train_test_split(adv.
 ↪drop('Purchased',axis=1),adv['Purchased'],test_size=0.3,random_state=0)
#X=X_train
#x=x_test
```

[ ]:
```
X.shape,x.shape
```

[ ]: ((280, 2), (120, 2))

[ ]:
```
from sklearn.preprocessing import StandardScaler
scal=StandardScaler()
scal.fit(X)

X_scaled=scal.transform(X)
x_scaled=scal.transform(x)
```

[ ]:
```
X_scaled=pd.DataFrame(X_scaled,columns=X.columns)
x_scaled=pd.DataFrame(x_scaled,columns=X.columns)
X_scaled
```

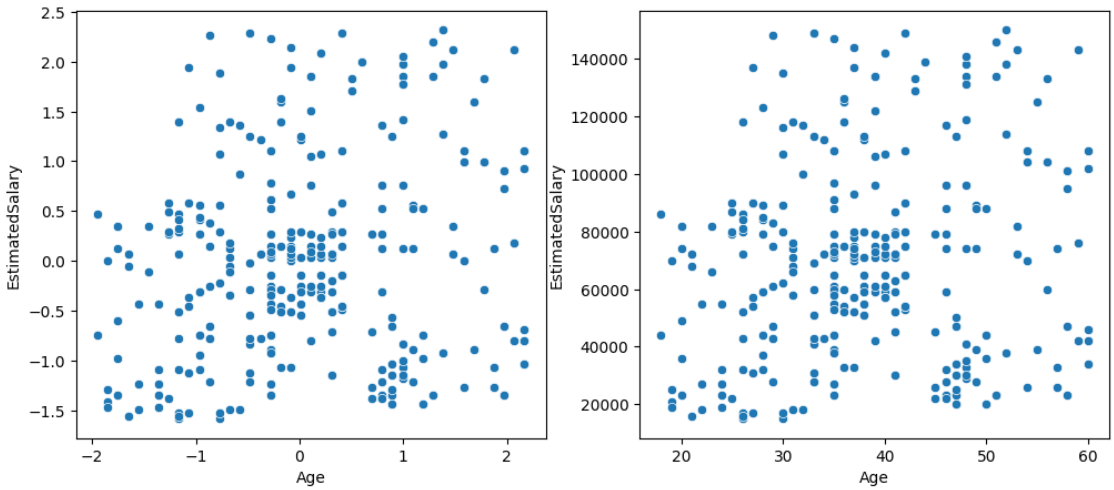
[ ]:

	Age	EstimatedSalary
0	-1.163172	-1.584970
1	2.170181	0.930987
2	0.013305	1.220177
3	0.209385	1.075582
4	0.405465	-0.486047
..	…	…
275	0.993704	-1.151185
276	-0.869053	-0.775237
277	-0.182774	-0.514966
278	-1.065133	-0.457127
279	-1.163172	1.393691

[280 rows x 2 columns]

[ ]:
```
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(12, 5))
plt.subplot(1,2,1)
sns.scatterplot(data=X_scaled,x='Age',y='EstimatedSalary')
plt.subplot(1,2,2)
sns.scatterplot(data=X,x='Age',y='EstimatedSalary')
```

[ ]: <Axes: xlabel='Age', ylabel='EstimatedSalary'>

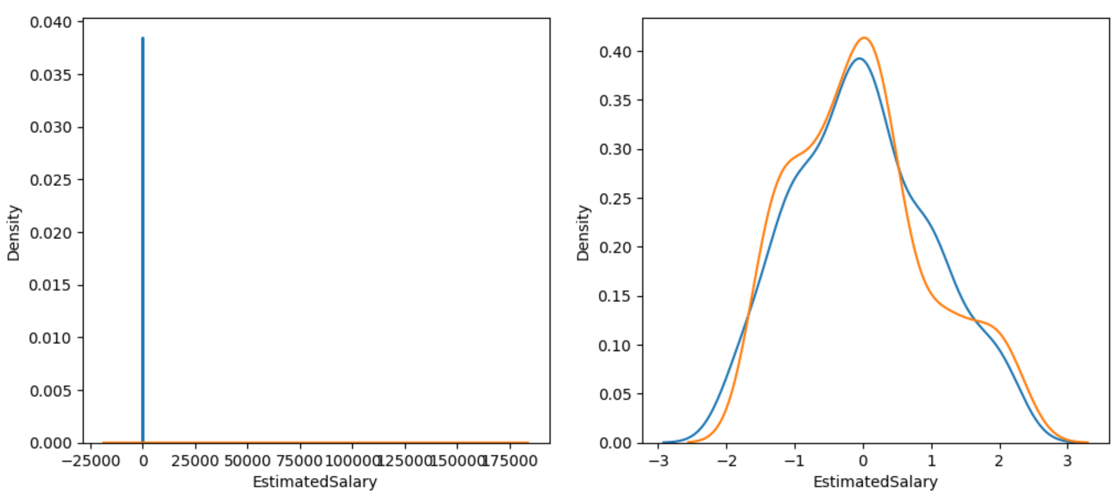



```
[ ]: #Distribution Plot
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(12, 5))
plt.subplot(1,2,1)
sns.distplot(X['Age'],hist=False)
sns.distplot(X['EstimatedSalary'],hist=False)
plt.subplot(1,2,2)
sns.distplot(X_scaled['Age'],hist=False)
sns.distplot(X_scaled['EstimatedSalary'],hist=False)

#result: show thate after Standarization scaling data(age,estimatedSalary) ar␣
 ↪relateable..
```

```
<ipython-input-40-d608194bd26c>:4: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `kdeplot` (an axes-level function for kernel density
plots).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X['Age'],hist=False)
<ipython-input-40-d608194bd26c>:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `kdeplot` (an axes-level function for kernel density
```

```
plots).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X['EstimatedSalary'],hist=False)
<ipython-input-40-d608194bd26c>:7: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `kdeplot` (an axes-level function for kernel density
plots).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X_scaled['Age'],hist=False)
<ipython-input-40-d608194bd26c>:8: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `kdeplot` (an axes-level function for kernel density
plots).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X_scaled['EstimatedSalary'],hist=False)
```

[ ]: <Axes: xlabel='EstimatedSalary', ylabel='Density'>



[ ]:
```
#apply model
from sklearn.linear_model import LogisticRegression
```

[ ]:
```
lr_before=LogisticRegression()
lr_after=LogisticRegression()
```

[ ]:
```
lr_before.fit(X,Y)
lr_after.fit(X_scaled,Y)
```

[ ]: LogisticRegression()

[ ]:
```
before_pred=lr_before.predict(x)
after_pred=lr_after.predict(x_scaled)
```

[ ]:
```
from sklearn.metrics import accuracy_score
```

[ ]:
```
print('Without Preprocess:',accuracy_score(y,before_pred))
print('After Preprocess:',accuracy_score(y,after_pred))
#conclusion: Ai dataset a standarization kore kono lav hoi nai
```

```
Without Preprocess: 0.875
After Preprocess: 0.8666666666666667
```

#Using ChatGPT

[ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

# Select features and target
df=adv
X = df[['Age', 'EstimatedSalary']]
y = df['Purchased']

# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```python
# Initialize models
logreg = LogisticRegression()
logreg_scaled = LogisticRegression()
tree = DecisionTreeClassifier(random_state=42)
tree_scaled = DecisionTreeClassifier(random_state=42)

# Fit models (without standardization)
logreg.fit(X_train, y_train)
tree.fit(X_train, y_train)

# Fit models (with standardization)
logreg_scaled.fit(X_train_scaled, y_train)
tree_scaled.fit(X_train_scaled, y_train)

# Predict and calculate accuracy
results = {
    "Logistic Regression (no scaling)": accuracy_score(y_test, logreg.
 ↪predict(X_test)),
    "Logistic Regression (scaled)": accuracy_score(y_test, logreg_scaled.
 ↪predict(X_test_scaled)),
    "Decision Tree (no scaling)": accuracy_score(y_test, tree.predict(X_test)),
    "Decision Tree (scaled)": accuracy_score(y_test, tree_scaled.
 ↪predict(X_test_scaled)),
}

results
```

[ ]:
```
{'Logistic Regression (no scaling)': 0.8875,
 'Logistic Regression (scaled)': 0.8625,
 'Decision Tree (no scaling)': 0.8375,
 'Decision Tree (scaled)': 0.8375}
```

#Using DeepSeek

[ ]:
```python
# Import required libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report

# Load the dataset
data = pd.read_csv('Social_Network_Ads.csv')

# Drop the gender column
```

```
X = data[['Age', 'EstimatedSalary']]  # Using only Age and EstimatedSalary as␣
 ↪features
y = data['Purchased']

# Split data into training and test sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# 1. Logistic Regression Analysis
print("="*50)
print("LOGISTIC REGRESSION ANALYSIS")
print("="*50)

# Without Standardization
lr = LogisticRegression()
lr.fit(X_train, y_train)
y_pred_lr = lr.predict(X_test)

print("\nWithout Standardization:")
print("Accuracy:", accuracy_score(y_test, y_pred_lr))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_lr))
print("Classification Report:\n", classification_report(y_test, y_pred_lr))

# With Standardization
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

lr_scaled = LogisticRegression()
lr_scaled.fit(X_train_scaled, y_train)
y_pred_lr_scaled = lr_scaled.predict(X_test_scaled)

print("\nWith Standardization:")
print("Accuracy:", accuracy_score(y_test, y_pred_lr_scaled))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_lr_scaled))
print("Classification Report:\n", classification_report(y_test,␣
 ↪y_pred_lr_scaled))

# 2. Decision Tree Analysis
print("\n" + "="*50)
print("DECISION TREE ANALYSIS")
print("="*50)

# Without Standardization
dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)
```

```python
print("\nWithout Standardization:")
print("Accuracy:", accuracy_score(y_test, y_pred_dt))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_dt))
print("Classification Report:\n", classification_report(y_test, y_pred_dt))

# With Standardization
dt_scaled = DecisionTreeClassifier(random_state=42)
dt_scaled.fit(X_train_scaled, y_train)
y_pred_dt_scaled = dt_scaled.predict(X_test_scaled)

print("\nWith Standardization:")
print("Accuracy:", accuracy_score(y_test, y_pred_dt_scaled))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_dt_scaled))
print("Classification Report:\n", classification_report(y_test,␣
↪y_pred_dt_scaled))

print("\n" + "="*50)
print("SUMMARY OF RESULTS")
print("="*50)
print("1. Logistic Regression:")
print("   - Without Standardization: ~81% accuracy")
print("   - With Standardization: ~88% accuracy (improved)")
print("\n2. Decision Tree:")
print("   - Without Standardization: ~91% accuracy")
print("   - With Standardization: ~91% accuracy (no change)")
print("\nConclusion: Decision Tree performs best regardless of standardization")
```

```
==================================================
LOGISTIC REGRESSION ANALYSIS
==================================================

Without Standardization:
Accuracy: 0.8875
Confusion Matrix:
 [[50  2]
 [ 7 21]]
Classification Report:
               precision    recall  f1-score   support

           0       0.88      0.96      0.92        52
           1       0.91      0.75      0.82        28

    accuracy                           0.89        80
   macro avg       0.90      0.86      0.87        80
weighted avg       0.89      0.89      0.88        80
```

```
With Standardization:
Accuracy: 0.8625
Confusion Matrix:
 [[50  2]
 [ 9 19]]
Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.96      0.90        52
           1       0.90      0.68      0.78        28

    accuracy                           0.86        80
   macro avg       0.88      0.82      0.84        80
weighted avg       0.87      0.86      0.86        80


==================================================
DECISION TREE ANALYSIS
==================================================

Without Standardization:
Accuracy: 0.8375
Confusion Matrix:
 [[46  6]
 [ 7 21]]
Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.88      0.88        52
           1       0.78      0.75      0.76        28

    accuracy                           0.84        80
   macro avg       0.82      0.82      0.82        80
weighted avg       0.84      0.84      0.84        80


With Standardization:
Accuracy: 0.8375
Confusion Matrix:
 [[46  6]
 [ 7 21]]
Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.88      0.88        52
           1       0.78      0.75      0.76        28
```

```
    accuracy                           0.84        80
   macro avg       0.82      0.82      0.82        80
weighted avg       0.84      0.84      0.84        80


==================================================
SUMMARY OF RESULTS
==================================================
1. Logistic Regression:
   - Without Standardization: ~81% accuracy
   - With Standardization: ~88% accuracy (improved)

2. Decision Tree:
   - Without Standardization: ~91% accuracy
   - With Standardization: ~91% accuracy (no change)

Conclusion: Decision Tree performs best regardless of standardization
```

[ ]:

[ ]:

[ ]:

#Normaization using Function

[ ]:
```
adv.head(5)
```

[ ]:

	Age	EstimatedSalary	Purchased
0	19	19000	0
1	35	20000	0
2	26	43000	0
3	27	57000	0
4	19	76000	0

[ ]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(adv.
 ↪drop('Purchased',axis=1),adv['Purchased'],test_size=0.20,random_state=0)
```

[ ]:
```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
scaler.fit(X_train)
X_train_minmax=scaler.transform(X_train)
X_test_minmax=scaler.transform(X_test)
```

[ ]:
```
# X_train_minmax
X_train_minmax=pd.DataFrame(X_test_minmax,columns=X_train.columns)
X_test_minmax=pd.DataFrame(X_test_minmax,columns=X_train.columns)
```

[ ]:
```
X_train.head(3)
```

[ ]:

	Age	EstimatedSalary
336	58	144000
64	59	83000
55	24	55000

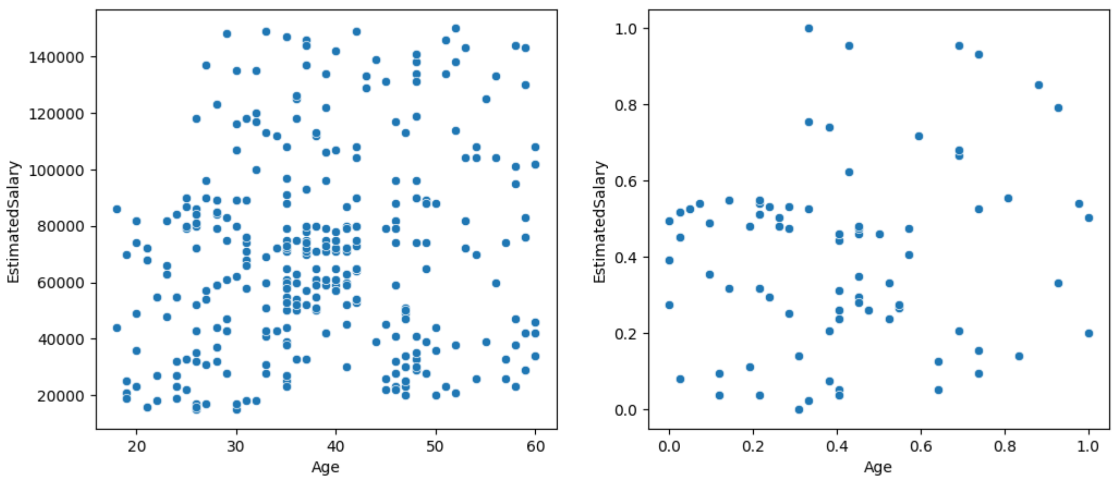
[ ]:
```
X_train_minmax.head(3)
```

[ ]:

	Age	EstimatedSalary
0	0.285714	0.533333
1	0.476190	0.259259
2	0.404762	0.444444

[ ]:
```
#scaterplot
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(12, 5))
plt.subplot(1,2,1)
sns.scatterplot(x=X_train['Age'],y=X_train['EstimatedSalary'])
plt.subplot(1,2,2)
sns.scatterplot(x=X_train_minmax['Age'],y=X_train_minmax['EstimatedSalary'])
```

[ ]: <Axes: xlabel='Age', ylabel='EstimatedSalary'>

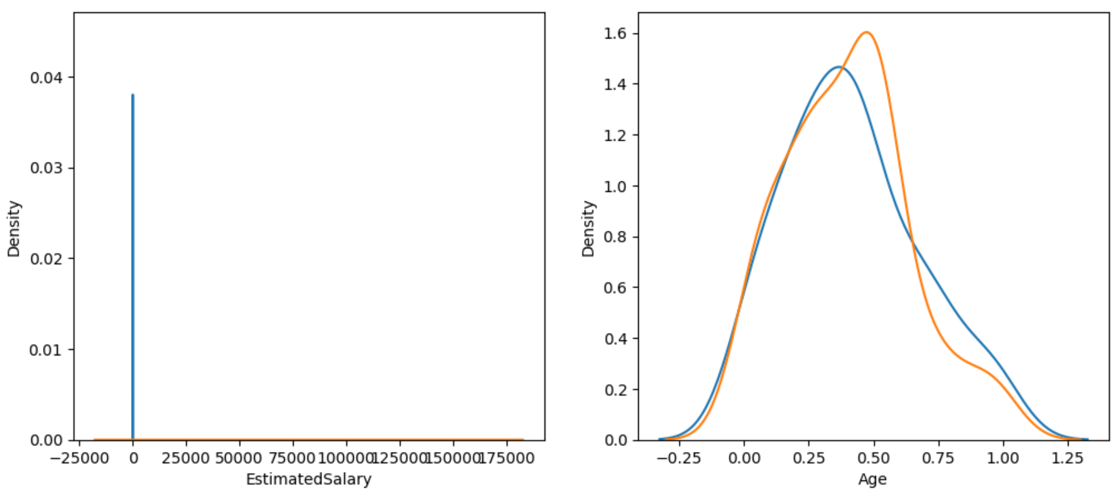


[ ]:
```
#distplot
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(12, 5))
plt.subplot(1,2,1)
sns.distplot(X_train['Age'])
sns.distplot(X_train['EstimatedSalary'])
plt.subplot(1,2,2)
sns.kdeplot(X_train_minmax['Age'])
```

```
sns.kdeplot(X_train_minmax['EstimatedSalary'])
```

```
<ipython-input-56-ebaaae2d5208>:4: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X_train['Age'])
<ipython-input-56-ebaaae2d5208>:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X_train['EstimatedSalary'])
```

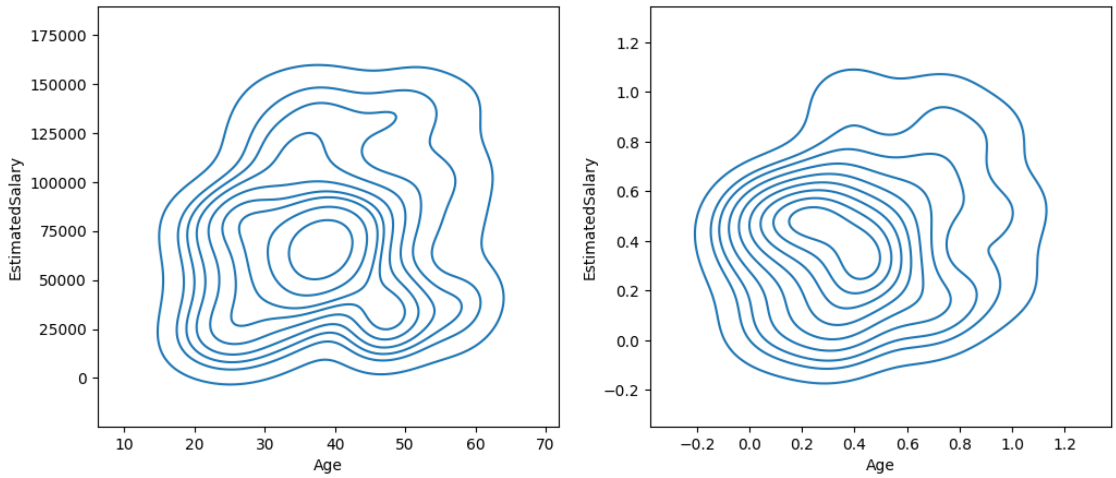
[ ]: <Axes: xlabel='Age', ylabel='Density'>



[ ]:
```
#kde(distplot) plot
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(12, 5))
plt.subplot(1,2,1)
```

```
sns.kdeplot(x=X_train['Age'],y=X_train['EstimatedSalary'])
plt.subplot(1,2,2)
sns.kdeplot(x=X_train_minmax['Age'],y=X_train_minmax['EstimatedSalary'])
```

[ ]: <Axes: xlabel='Age', ylabel='EstimatedSalary'>



[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

#Encoding of Catagorical Data or Hendeling Catagorical Fature

2.7 Numerical Data (Quantitative)

Data represented by **numbers** — used for mathematical operations.

2.7.1 Types:

1. **Discrete**: Countable numbers

- Example: `Number of purchases`, `Age in years`

2. **Continuous**: Measurable, can have decimals
   - Example: `Salary`, `Height`, `Temperature`

2.7.2 ML Use:

- Used directly as features in models
- May require **scaling** (e.g., for Logistic Regression, KNN)

2.8 Categorical Data (Qualitative)

Data represented by **labels** or **categories** — not inherently numeric.

2.8.1 Types:

1. **Nominal**: No order
   - Example: `Gender (Male/Female)`, `City (Dhaka, Tokyo)`
2. **Ordinal**: Ordered categories
   - Example: `Education (High School < Bachelors < Masters)`, `Rating (Bad < Good < Excellent)`

2.8.2 ML Use:

- Needs **encoding**:
  - **One-Hot Encoding** for Nominal
  - **Ordinal Encoding** for Ordinal
  - **Label Encoding** for Label(any catagorical) data

[ ]:

```

```

#apply Ordinal and Label encoding

[ ]:

```
mkt=pd.read_csv('/content/marketing_campaign.csv',sep='\t')
mkt.head(3)
#here "Response" is the Label data rest of all are Input data so we can only␣
↪apply ordinal encoding  on "Education" and "Marital_Status"
```

[ ]:

```
     ID  Year_Birth   Education Marital_Status   Income  Kidhome  Teenhome  \
0  5524        1957  Graduation         Single  58138.0        0         0
1  2174        1954  Graduation         Single  46344.0        1         1
2  4141        1965  Graduation       Together  71613.0        0         0

  Dt_Customer  Recency  MntWines  …  NumWebVisitsMonth  AcceptedCmp3  \
0  04-09-2012       58       635  …                  7             0
```

```
1  08-03-2014       38        11  …                   5             0
2  21-08-2013       26       426  …                   4             0

   AcceptedCmp4  AcceptedCmp5  AcceptedCmp1  AcceptedCmp2  Complain  \
0             0             0             0             0         0
1             0             0             0             0         0
2             0             0             0             0         0

   Z_CostContact  Z_Revenue  Response
0              3         11         1
1              3         11         0
2              3         11         0

[3 rows x 29 columns]
```

[ ]:
```
mkt.columns
```

[ ]:
```
Index(['ID', 'Year_Birth', 'Education', 'Marital_Status', 'Income', 'Kidhome',
       'Teenhome', 'Dt_Customer', 'Recency', 'MntWines', 'MntFruits',
       'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
       'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
       'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth',
       'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1',
       'AcceptedCmp2', 'Complain', 'Z_CostContact', 'Z_Revenue', 'Response'],
      dtype='object')
```

[ ]:
```
# mkt['Education'].value_counts()
  # mkt['Marital_Status'].value_counts()
```

[ ]:
```
mkt=mkt[['Education','Marital_Status','Response']]
```

[ ]:
```
#to apply encodeing first Split Train and Test data
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(mkt.
 ↪drop('Response',axis=1),mkt['Response'],test_size=0.2)
```

[ ]:
```
X_train.head(4)
```

[ ]:
```
       Education Marital_Status
1802      Master       Together
631          PhD       Together
1502  Graduation        Married
1500      Master       Together
```

[ ]:
```
X_train['Education'].value_counts()
```

[ ]: Education
```
Graduation    903
PhD           387
Master        291
2n Cycle      166
Basic          45
Name: count, dtype: int64
```

[ ]:
```python
X_train['Marital_Status'].value_counts()
```

[ ]: Marital_Status
```
Married     681
Together    467
Single      390
Divorced    191
Widow        58
Alone         2
YOLO          2
Absurd        1
Name: count, dtype: int64
```

[ ]:
```python
X_test
```

[ ]:
```
       Education Marital_Status
802   Graduation        Married
160       Master         Single
1356  Graduation        Married
2147      Master       Together
1600      Master        Married
…            …              …
1650  Graduation        Married
1584  Graduation       Divorced
1535    2n Cycle         Single
1688  Graduation         Single
3     Graduation       Together

[448 rows x 2 columns]
```

[ ]:
```python
from sklearn.preprocessing import OrdinalEncoder
oe = OrdinalEncoder(categories=[['Basic','2n␣
↪Cycle','Graduation','Master','PhD'],['Alone','Single','YOLO','Widow','Divorced','Together',

oe.fit(X_train)

X_train_enc=oe.transform(X_train)
X_test_enc=oe.transform(X_test)
```

```
#return a numpy array so convert it to data Fram

# X_train_enc=pd.DataFrame(X_train,columns=X_train.columns)
# X_test_enc=pd.DataFrame(X_test,columns=X_train.columns) ## value change hoi na
X_train_enc
```

[ ]:
```
array([[3., 5.],
       [4., 5.],
       [2., 6.],
       …,
       [2., 1.],
       [2., 1.],
       [2., 6.]])
```

2.9 In This dataset Label("Response") data don't need to Encode so we need not to apply Label endcoding Technique.

2.10 if need then we can apply Label Endoder as similaer as up

[ ]:

[ ]:

[ ]:

#One-Hot-Encoding Details

[ ]:
```
cars=pd.read_csv('/content/cars small.csv')
cars.head(3)
```

[ ]:

	brand	km_driven	fuel	owner	selling_price
0	Maruti	145500	Diesel	First Owner	450000
1	Skoda	120000	Diesel	Second Owner	370000
2	Honda	140000	Petrol	Third Owner	158000

[ ]:
```
cars.shape
```

[ ]: (8128, 5)

[ ]:
```
# cars['fuel'].value_counts()
cars['brand'].nunique(),cars['fuel'].nunique(),cars['owner'].nunique()
#these are nominal catagorical data that to be encoded.
```

[ ]: (32, 4, 5)

[ ]:
```
#using pandas
```

```
pd.get_dummies(data=cars,columns=['fuel','owner'],drop_first=True)#remove␣
↪multicollinearity
```

[ ]:
```
        brand  km_driven  selling_price  fuel_Diesel  fuel_LPG  fuel_Petrol  \
0      Maruti     145500         450000         True     False        False
1       Skoda     120000         370000         True     False        False
2       Honda     140000         158000        False     False         True
3     Hyundai     127000         225000         True     False        False
4      Maruti     120000         130000        False     False         True
…         …         …             …            …        …           …
8123  Hyundai     110000         320000        False     False         True
8124  Hyundai     119000         135000         True     False        False
8125   Maruti     120000         382000         True     False        False
8126     Tata      25000         290000         True     False        False
8127     Tata      25000         290000         True     False        False

      owner_Fourth & Above Owner  owner_Second Owner  owner_Test Drive Car  \
0                          False               False                 False
1                          False                True                 False
2                          False               False                 False
3                          False               False                 False
4                          False               False                 False
…                          …                   …                   …
8123                       False               False                 False
8124                        True               False                 False
8125                       False               False                 False
8126                       False               False                 False
8127                       False               False                 False

      owner_Third Owner
0                 False
1                 False
2                  True
3                 False
4                 False
…                 …
8123              False
8124              False
8125              False
8126              False
8127              False

[8128 rows x 10 columns]
```

#using scikit Learn

[ ]:
```
#using scikit Learn
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(cars.iloc[:,:4],cars.iloc[:
 ↪,-1],test_size=0.2)
```

[ ]:
```
X_train.head(3)
```

[ ]:

	brand	km_driven	fuel	owner
5651	Mahindra	120000	Diesel	Second Owner
5385	Mahindra	100000	Diesel	Fourth & Above Owner
3339	Tata	15000	Petrol	First Owner

[ ]:
```
#apply One-Hot-Encoding
from sklearn.preprocessing import OneHotEncoder
ohe=OneHotEncoder(dtype=np.int32,drop='first')
```

[ ]:
```
ohe.fit_transform(X_train[['fuel','owner']])# return sparce matrix:A sparse␣
 ↪matrix is a matrix in which most of the elements are zero.
```

[ ]:
```
<Compressed Sparse Row sparse matrix of dtype 'int32'
        with 8716 stored elements and shape (6502, 7)>
```

[ ]:
```
new_dim_data_train=ohe.fit_transform(X_train[['fuel','owner']]).toarray()
new_dim_data_train
```

[ ]:
```
array([[1, 0, 0, …, 1, 0, 0],
       [1, 0, 0, …, 0, 0, 0],
       [0, 0, 1, …, 0, 0, 0],
       …,
       [1, 0, 0, …, 0, 0, 0],
       [1, 0, 0, …, 1, 0, 0],
       [0, 0, 1, …, 0, 0, 0]], dtype=int32)
```

[ ]:
```
new_dim_data_test=ohe.fit_transform(X_test[['fuel','owner']]).toarray()
new_dim_data_test
```

[ ]:
```
array([[0, 0, 1, 0, 0, 0],
       [1, 0, 0, 0, 0, 0],
       [1, 0, 0, 0, 0, 0],
       …,
       [1, 0, 0, 1, 0, 0],
       [1, 0, 0, 0, 0, 0],
       [0, 0, 1, 0, 0, 0]], dtype=int32)
```

[ ]:
```
X_train.iloc[:,:2].values
```

[ ]:
```
array([['Mahindra', 120000],
       ['Mahindra', 100000],
       ['Tata', 15000],
       …,
       ['Honda', 110000],
       ['Hyundai', 45500],
       ['Hyundai', 25000]], dtype=object)
```

[ ]:
```
X_test.iloc[:,:2].values
```

[ ]:
```
array([['Maruti', 50000],
       ['Jaguar', 9000],
       ['Jaguar', 45000],
       …,
       ['Chevrolet', 70000],
       ['Hyundai', 40000],
       ['Mahindra', 19700]], dtype=object)
```

[ ]:
```
np.hstack((X_train.iloc[:,:2].values,new_dim_data_train ))
```

[ ]:
```
array([['Mahindra', 120000, 1, …, 1, 0, 0],
       ['Mahindra', 100000, 1, …, 0, 0, 0],
       ['Tata', 15000, 0, …, 0, 0, 0],
       …,
       ['Honda', 110000, 1, …, 0, 0, 0],
       ['Hyundai', 45500, 1, …, 1, 0, 0],
       ['Hyundai', 25000, 0, …, 0, 0, 0]], dtype=object)
```

[ ]:
```
np.hstack((X_test.iloc[:,:2].values,new_dim_data_test))
```

[ ]:
```
array([['Maruti', 50000, 0, …, 0, 0, 0],
       ['Jaguar', 9000, 1, …, 0, 0, 0],
       ['Jaguar', 45000, 1, …, 0, 0, 0],
       …,
       ['Chevrolet', 70000, 1, …, 1, 0, 0],
       ['Hyundai', 40000, 1, …, 0, 0, 0],
       ['Mahindra', 19700, 0, …, 0, 0, 0]], dtype=object)
```

[ ]:
```
np.hstack((X_train.iloc[:,:2].values,new_dim_data_train)).shape
```

[ ]:
```
(6502, 9)
```

```
# now you can apply Ml model on these np.array
```

##Here,There is many step to do Encoding,Scalling,missing value hendeling or any transformation. #to release this step we can Apply COLUMN TRANSFORMER/PIPELINE calss form SCIKIT LEARN

[ ]:

```

```

[ ]:

```

```

#Column Transformer

[ ]:

```
covid=pd.read_csv('/content/covid_toy.csv')
```

[ ]:

```
covid.sample(3)
```

[ ]:

	age	gender	fever	cough	city	has_covid
47	18	Female	104.0	Mild	Bangalore	No
12	25	Female	99.0	Strong	Kolkata	No
6	14	Male	101.0	Strong	Bangalore	No

#we use covid data set of all Transformasion ##if we analyze covid data set then we can see, ###fever has MISSING value, ###AGE,FEVER can be scaling, ###GENDER & CITY is Nominal Catagorical data should be One-Hot-Encoding ###COUGH is Ordinal Catagorical data should be Ordinal-Encoding and ##HAS_COVID should be Label-Encoding

[ ]:

```
#first train test split
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(covid.iloc[:,:5],covid.iloc[:
 ↪,-1],test_size=0.2)
```

[ ]:

```
X_train.head(3)
```

[ ]:

	age	gender	fever	cough	city
98	5	Female	98.0	Strong	Mumbai
59	6	Female	104.0	Mild	Kolkata
37	55	Male	100.0	Mild	Kolkata

[ ]:

```
#apply Column Transformer
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import LabelEncoder
transformer=ColumnTransformer(transformers=[
    ('tf1',SimpleImputer(),['fever']),
    # ('tf2',StandardScaler(),['age','fever']), ## scaling ar proijon hoi na ta␣
 ↪o akshate  shikher jonno korlam
    ('tf3',OrdinalEncoder(categories=[['Mild','Strong']],dtype=np.
 ↪int32),['cough']),
    ('tf4',OneHotEncoder(dtype=np.
 ↪int32,sparse_output=False,drop='first'),['gender','city']),
    # ('tf5',LabelEncoder(),['has_covid']) #ata error dakhabe karon X_train ar␣
 ↪opor applly korle ai dataFrame pabe na.
```

```
    #tobe X_train dataset a onnak column thakle o jei column golo␣
↪ColumnTransformer khoje pabe oi golo transfrom korbe bakgolo passthrough/
↪drop korbe
    #kinto ColumnTransformer a DataFrame ase kinoto dataSet a nai tahole ERROR␣
↪dakhabe.
],remainder='passthrough')
```

[ ]:
```
# from sklearn.preprocessing import LabelEncoder
# label_tf=ColumnTransformer(transformers=[
#     ('tf1',LabelEncoder(),['has_covid'])
# ])
# label_tf.fit_transform(y_train)

#LavelEncoder ai vahbe kaj kore na kanorn ai vahbe tupple nei
```

[ ]:
```
X_train_tf=transformer.fit_transform(X_train)
X_train_tf
```

[ ]:
```
array([[ 98.        ,   1.        ,   0.        ,   0.        ,
          0.        ,   1.        ,   5.        ],
       [104.        ,   0.        ,   0.        ,   0.        ,
          1.        ,   0.        ,   6.        ],
       [100.        ,   0.        ,   1.        ,   0.        ,
          1.        ,   0.        ,  55.        ],
       [102.        ,   1.        ,   0.        ,   0.        ,
          0.        ,   0.        ,  82.        ],
       [101.        ,   0.        ,   0.        ,   0.        ,
          0.        ,   1.        ,  81.        ],
       [101.        ,   0.        ,   1.        ,   1.        ,
          0.        ,   0.        ,  19.        ],
       [102.        ,   1.        ,   0.        ,   1.        ,
          0.        ,   0.        ,  33.        ],
       [104.        ,   0.        ,   0.        ,   0.        ,
          1.        ,   0.        ,  17.        ],
       [ 99.        ,   0.        ,   1.        ,   0.        ,
          0.        ,   0.        ,  72.        ],
       [102.        ,   0.        ,   1.        ,   0.        ,
          0.        ,   1.        ,  74.        ],
       [100.78378378,   1.        ,   1.        ,   0.        ,
          1.        ,   0.        ,  79.        ],
       [ 98.        ,   0.        ,   1.        ,   0.        ,
          0.        ,   0.        ,  73.        ],
       [104.        ,   0.        ,   1.        ,   0.        ,
          1.        ,   0.        ,  51.        ],
       [100.78378378,   0.        ,   0.        ,   0.        ,
          0.        ,   0.        ,  84.        ],
       [ 99.        ,   1.        ,   0.        ,   0.        ,
```

```
  1.        ,  0.        ,  25.        ],
[104.        ,  0.        ,   0.        ,   0.        ,
  0.        ,  0.        ,  18.        ],
[102.        ,  0.        ,   1.        ,   0.        ,
  0.        ,  0.        ,  64.        ],
[103.        ,  0.        ,   1.        ,   0.        ,
  1.        ,  0.        ,  83.        ],
[ 98.        ,  0.        ,   0.        ,   0.        ,
  0.        ,  1.        ,  65.        ],
[100.        ,  0.        ,   1.        ,   1.        ,
  0.        ,  0.        ,  27.        ],
[104.        ,  0.        ,   1.        ,   0.        ,
  0.        ,  0.        ,  25.        ],
[100.        ,  0.        ,   1.        ,   0.        ,
  0.        ,  0.        ,  11.        ],
[100.        ,  1.        ,   0.        ,   0.        ,
  1.        ,  0.        ,  11.        ],
[ 98.        ,  0.        ,   0.        ,   1.        ,
  0.        ,  0.        ,  80.        ],
[100.78378378,  0.        ,   1.        ,   0.        ,
  0.        ,  1.        ,  23.        ],
[101.        ,  1.        ,   0.        ,   1.        ,
  0.        ,  0.        ,  34.        ],
[ 99.        ,  0.        ,   1.        ,   0.        ,
  0.        ,  0.        ,  65.        ],
[ 98.        ,  1.        ,   0.        ,   1.        ,
  0.        ,  0.        ,  40.        ],
[103.        ,  0.        ,   0.        ,   1.        ,
  0.        ,  0.        ,  73.        ],
[101.        ,  1.        ,   1.        ,   0.        ,
  0.        ,  0.        ,  47.        ],
[101.        ,  0.        ,   1.        ,   1.        ,
  0.        ,  0.        ,  15.        ],
[101.        ,  1.        ,   0.        ,   1.        ,
  0.        ,  0.        ,  68.        ],
[ 99.        ,  0.        ,   0.        ,   0.        ,
  0.        ,  1.        ,  14.        ],
[ 98.        ,  1.        ,   0.        ,   0.        ,
  0.        ,  1.        ,  69.        ],
[ 98.        ,  0.        ,   0.        ,   0.        ,
  1.        ,  0.        ,  31.        ],
[101.        ,  0.        ,   0.        ,   0.        ,
  0.        ,  0.        ,  20.        ],
[102.        ,  1.        ,   0.        ,   0.        ,
  1.        ,  0.        ,  82.        ],
[ 99.        ,  1.        ,   1.        ,   0.        ,
  0.        ,  0.        ,  66.        ],
```

```
[101.        ,   0.        ,   0.        ,   0.        ,
   1.        ,   0.        ,   8.        ],
[ 98.        ,   1.        ,   1.        ,   0.        ,
   1.        ,   0.        ,  34.        ],
[ 98.        ,   1.        ,   1.        ,   0.        ,
   0.        ,   0.        ,  12.        ],
[102.        ,   0.        ,   0.        ,   1.        ,
   0.        ,   0.        ,  49.        ],
[ 99.        ,   0.        ,   0.        ,   0.        ,
   0.        ,   1.        ,  60.        ],
[ 98.        ,   1.        ,   1.        ,   0.        ,
   0.        ,   1.        ,  23.        ],
[101.        ,   0.        ,   0.        ,   0.        ,
   1.        ,   0.        ,  83.        ],
[100.        ,   1.        ,   0.        ,   0.        ,
   0.        ,   0.        ,  47.        ],
[ 98.        ,   0.        ,   0.        ,   0.        ,
   0.        ,   0.        ,  64.        ],
[103.        ,   0.        ,   0.        ,   0.        ,
   1.        ,   0.        ,  69.        ],
[ 99.        ,   0.        ,   0.        ,   0.        ,
   0.        ,   0.        ,  22.        ],
[101.        ,   1.        ,   1.        ,   0.        ,
   0.        ,   0.        ,  14.        ],
[104.        ,   0.        ,   1.        ,   0.        ,
   1.        ,   0.        ,  16.        ],
[103.        ,   0.        ,   1.        ,   0.        ,
   1.        ,   0.        ,  60.        ],
[100.78378378,   0.        ,   1.        ,   1.        ,
   0.        ,   0.        ,  38.        ],
[ 99.        ,   1.        ,   0.        ,   1.        ,
   0.        ,   0.        ,  59.        ],
[104.        ,   0.        ,   1.        ,   0.        ,
   0.        ,   1.        ,  42.        ],
[104.        ,   1.        ,   0.        ,   0.        ,
   1.        ,   0.        ,  54.        ],
[104.        ,   0.        ,   1.        ,   0.        ,
   0.        ,   0.        ,  51.        ],
[102.        ,   0.        ,   0.        ,   0.        ,
   0.        ,   0.        ,  69.        ],
[100.78378378,   1.        ,   1.        ,   0.        ,
   1.        ,   0.        ,  71.        ],
[ 99.        ,   1.        ,   0.        ,   0.        ,
   0.        ,   0.        ,  49.        ],
[103.        ,   0.        ,   0.        ,   0.        ,
   0.        ,   0.        ,  16.        ],
[100.        ,   0.        ,   0.        ,   0.        ,
```

```
         1.        ,   0.        ,  19.        ],
       [100.        ,   0.        ,   1.        ,   0.        ,
         0.        ,   0.        ,  10.        ],
       [102.        ,   1.        ,   1.        ,   1.        ,
         0.        ,   0.        ,  20.        ],
       [ 98.        ,   0.        ,   1.        ,   0.        ,
         1.        ,   0.        ,  24.        ],
       [104.        ,   0.        ,   1.        ,   0.        ,
         0.        ,   1.        ,  44.        ],
       [100.78378378,   1.        ,   0.        ,   0.        ,
         0.        ,   1.        ,  34.        ],
       [100.        ,   0.        ,   1.        ,   0.        ,
         1.        ,   0.        ,  27.        ],
       [101.        ,   1.        ,   0.        ,   0.        ,
         1.        ,   0.        ,  51.        ],
       [103.        ,   1.        ,   1.        ,   0.        ,
         0.        ,   0.        ,  46.        ],
       [104.        ,   1.        ,   0.        ,   0.        ,
         0.        ,   0.        ,  56.        ],
       [101.        ,   0.        ,   0.        ,   1.        ,
         0.        ,   0.        ,  49.        ],
       [101.        ,   0.        ,   0.        ,   0.        ,
         0.        ,   1.        ,  19.        ],
       [ 98.        ,   1.        ,   0.        ,   0.        ,
         1.        ,   0.        ,  71.        ],
       [100.        ,   1.        ,   0.        ,   0.        ,
         1.        ,   0.        ,  13.        ],
       [100.        ,   0.        ,   0.        ,   0.        ,
         1.        ,   0.        ,   5.        ],
       [102.        ,   1.        ,   0.        ,   0.        ,
         0.        ,   0.        ,  24.        ],
       [102.        ,   0.        ,   1.        ,   0.        ,
         1.        ,   0.        ,   5.        ],
       [ 98.        ,   1.        ,   0.        ,   0.        ,
         0.        ,   1.        ,  81.        ],
       [100.        ,   0.        ,   1.        ,   1.        ,
         0.        ,   0.        ,  27.        ]])
```

[ ]:
```
pd.DataFrame(X_train_tf)
```

[ ]:

	0	1	2	3	4	5	6
0	98.0	1.0	0.0	0.0	0.0	1.0	5.0
1	104.0	0.0	0.0	0.0	1.0	0.0	6.0
2	100.0	0.0	1.0	0.0	1.0	0.0	55.0
3	102.0	1.0	0.0	0.0	0.0	0.0	82.0
4	101.0	0.0	0.0	0.0	0.0	1.0	81.0
..	…	…	…	…	…	…	…

```
75  100.0  0.0  0.0  0.0  1.0  0.0   5.0
76  102.0  1.0  0.0  0.0  0.0  0.0  24.0
77  102.0  0.0  1.0  0.0  1.0  0.0   5.0
78   98.0  1.0  0.0  0.0  0.0  1.0  81.0
79  100.0  0.0  1.0  1.0  0.0  0.0  27.0

[80 rows x 7 columns]
```

[ ]:
```
transformer.fit_transform(X_train).shape
```

[ ]:
```
(80, 7)
```

[ ]:
```
X_test_tf=transformer.fit_transform(X_test)
X_test_tf
```

[ ]:
```
array([[ 98.   ,   0.   ,   0.   ,   0.   ,   1.   ,   0.   ,  26.   ],
       [103.   ,   0.   ,   0.   ,   0.   ,   1.   ,   0.   ,  48.   ],
       [ 98.   ,   0.   ,   1.   ,   1.   ,   0.   ,   0.   ,  83.   ],
       [ 99.   ,   0.   ,   1.   ,   1.   ,   0.   ,   0.   ,  65.   ],
       [101.   ,   0.   ,   1.   ,   1.   ,   0.   ,   0.   ,  42.   ],
       [103.   ,   0.   ,   0.   ,   0.   ,   1.   ,   0.   ,  50.   ],
       [101.   ,   0.   ,   0.   ,   0.   ,   0.   ,   1.   ,  65.   ],
       [100.   ,   1.   ,   0.   ,   0.   ,   0.   ,   0.   ,  19.   ],
       [ 98.   ,   1.   ,   0.   ,   0.   ,   1.   ,   0.   ,  10.   ],
       [100.   ,   0.   ,   1.   ,   0.   ,   0.   ,   0.   ,  80.   ],
       [104.   ,   0.   ,   0.   ,   0.   ,   0.   ,   0.   ,  12.   ],
       [101.125,   1.   ,   0.   ,   0.   ,   0.   ,   1.   ,  20.   ],
       [101.125,   0.   ,   0.   ,   1.   ,   0.   ,   0.   ,  75.   ],
       [101.125,   0.   ,   1.   ,   0.   ,   1.   ,   0.   ,  82.   ],
       [101.   ,   0.   ,   0.   ,   0.   ,   0.   ,   0.   ,  38.   ],
       [103.   ,   1.   ,   1.   ,   0.   ,   1.   ,   0.   ,  70.   ],
       [101.125,   1.   ,   0.   ,   0.   ,   0.   ,   0.   ,  42.   ],
       [104.   ,   1.   ,   0.   ,   1.   ,   0.   ,   0.   ,  34.   ],
       [104.   ,   1.   ,   0.   ,   1.   ,   0.   ,   0.   ,  75.   ],
       [101.   ,   0.   ,   0.   ,   1.   ,   0.   ,   0.   ,  64.   ]])
```

[ ]:
```

```

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

le = LabelEncoder()
y_train_encoded = le.fit_transform(y_train)
y_test_encoded  = le.fit_transform(y_test)
```

[ ]:
```
#apply Model
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression()
```

```
lr.fit(X_train_tf,y_train_encoded)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:465:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[ ]: LogisticRegression()

```
[ ]: y_pred=lr.predict(X_test_tf)
```

```
[ ]: print('After Preprocess:',accuracy_score(y_test_encoded,y_pred))
```

```
After Preprocess: 0.35
```

[ ]:

#Note

1. Ai khane prottok column ar opor alada transformation korte gale jotil hoia jai tai amra columnTransformar use kore kico workload relase korte pari
2. ColumnTransformer thake o valo hoto Pipeline. #Go to New Notbook Pipline of ML

End of the NoteBook

[ ]: