

Customer Spending Score Prediction

```
In [1]: import pandas as pd
import numpy as np
```

```
In [2]: df=pd.read_csv(r'C:\Users\USER\Downloads\Mall_Customers.csv')
```

```
In [3]: df.head()
```

```
Out[3]:
```

	CustomerID	Genre	Age	Annual Income (k\$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

```
In [4]: df.tail(3)
```

```
Out[4]:
```

	CustomerID	Genre	Age	Annual Income (k\$)	Spending Score (1-100)
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

```
In [5]: df.sample(4)
```

```
Out[5]:
```

	CustomerID	Genre	Age	Annual Income (k\$)	Spending Score (1-100)
127	128	Male	40	71	95
189	190	Female	36	103	85
47	48	Female	27	40	47
139	140	Female	35	74	72

NEED TO RENAME SOME COLUMN NAME

```
In [6]: df.rename(columns={'CustomerID':'ID'},inplace=True)
```

```
In [7]: df.head()
```

```
Out[7]:
```

	ID	Genre	Age	Annual Income (k\$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

```
In [8]: df.rename(columns={"Annual Income (k$)": 'Annual Income'},
inplace=True)
df.rename(columns = {'Spending Score (1-100)': 'Spending_Score'},
inplace=True)
```

```
In [9]: df.head()
```

```
Out[9]:
```

	ID	Genre	Age	Annual Income	Spending_Score
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

LETS CHECK DATA

```
In [10]: df.info()
```

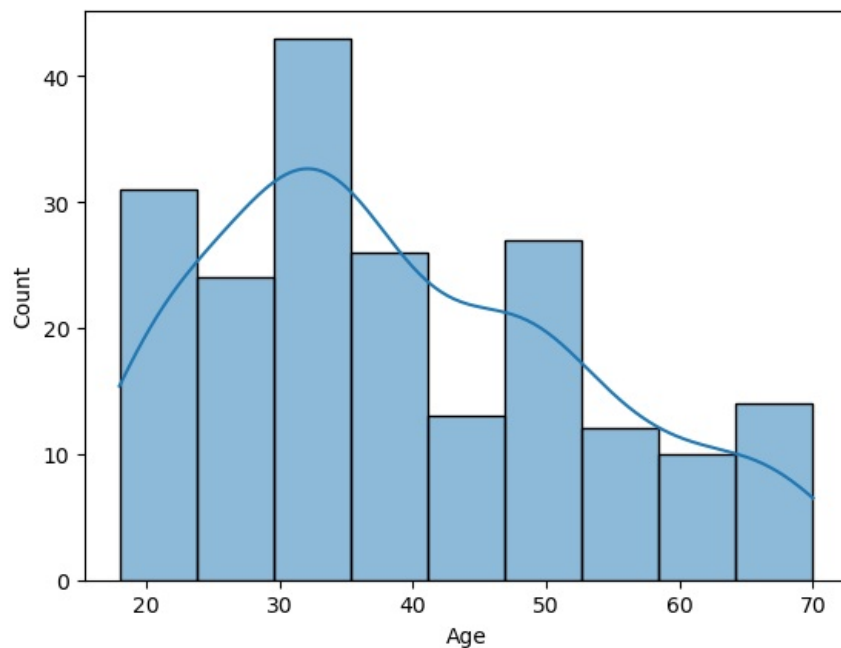
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
#   Column          Non-Null Count  Dtype
---  -
0   ID              200 non-null   int64
1   Genre           200 non-null   object
2   Age             200 non-null   int64
3   Annual Income   200 non-null   int64
4   Spending_Score  200 non-null   int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

GLANCE OF DATA AND ITS RELATION USING BASIC VISUALIZATION

```
In [11]: import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

```
In [12]: sns.histplot(df,x="Age",kde=True)
```

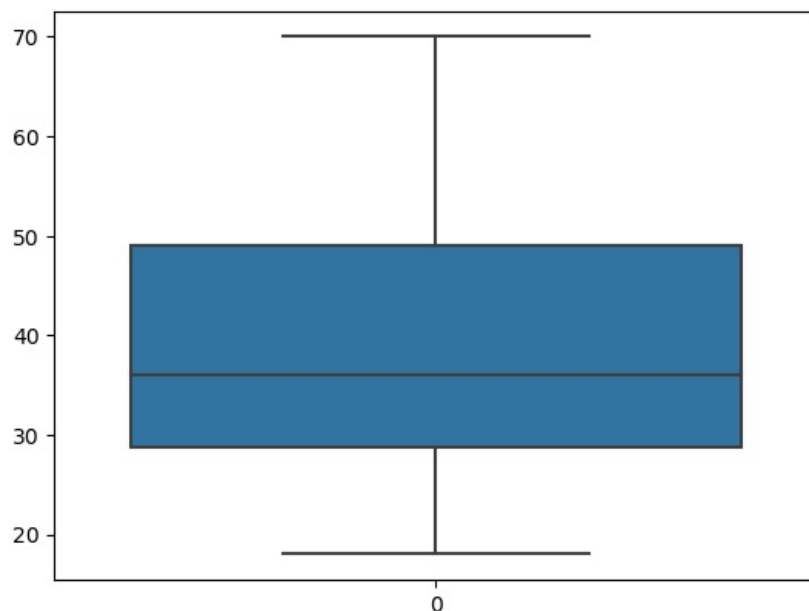
```
Out[12]: <Axes: xlabel='Age', ylabel='Count'>
```



From above Graph, we can say that age group data is rightly sekewed means there may be some outlier, it can be more easily seen via box-plot.

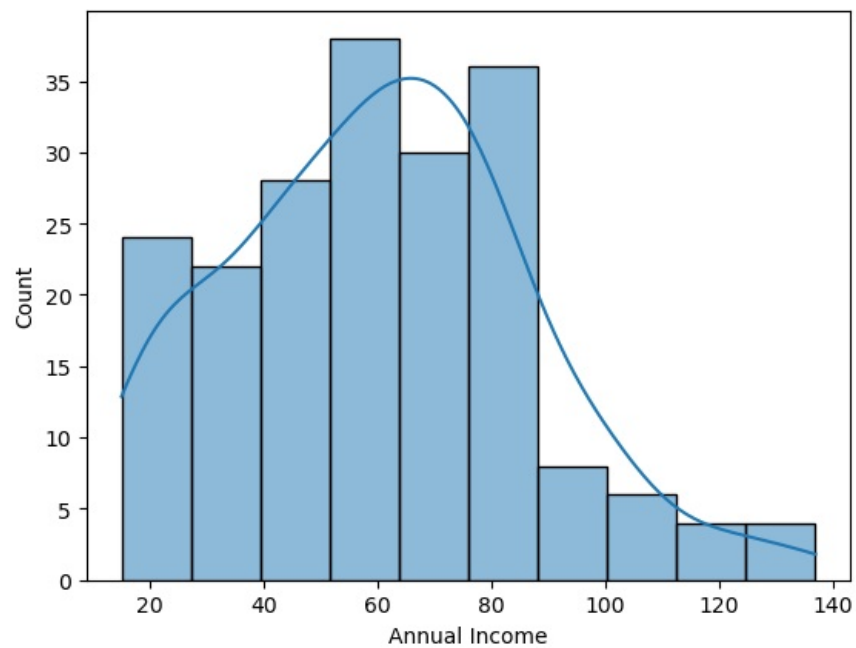
```
In [13]: sns.boxplot(df["Age"])
```

```
Out[13]: <Axes: >
```



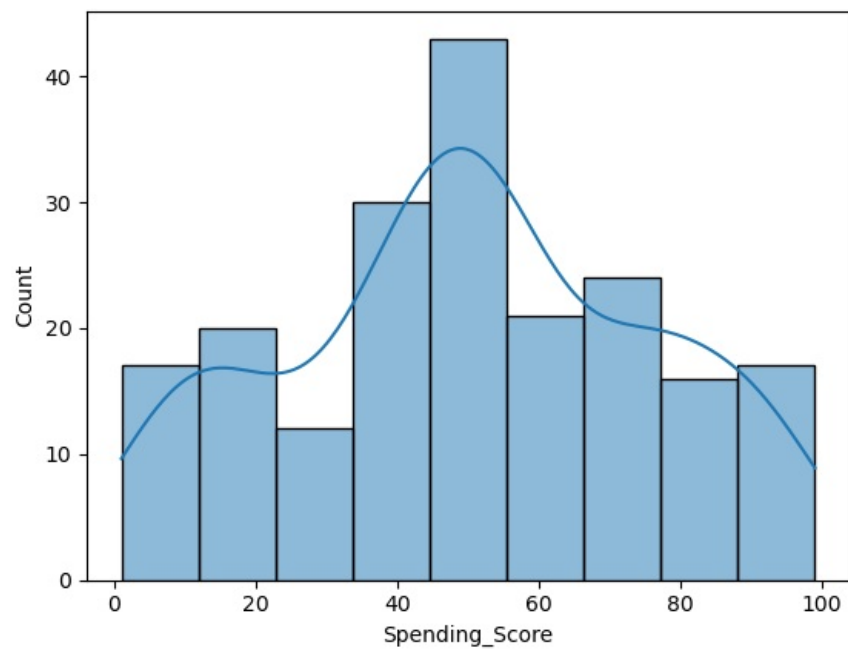
```
In [14]: sns.histplot(df,x="Annual Income",kde=True)
```

Out[14]: <Axes: xlabel='Annual Income', ylabel='Count'>



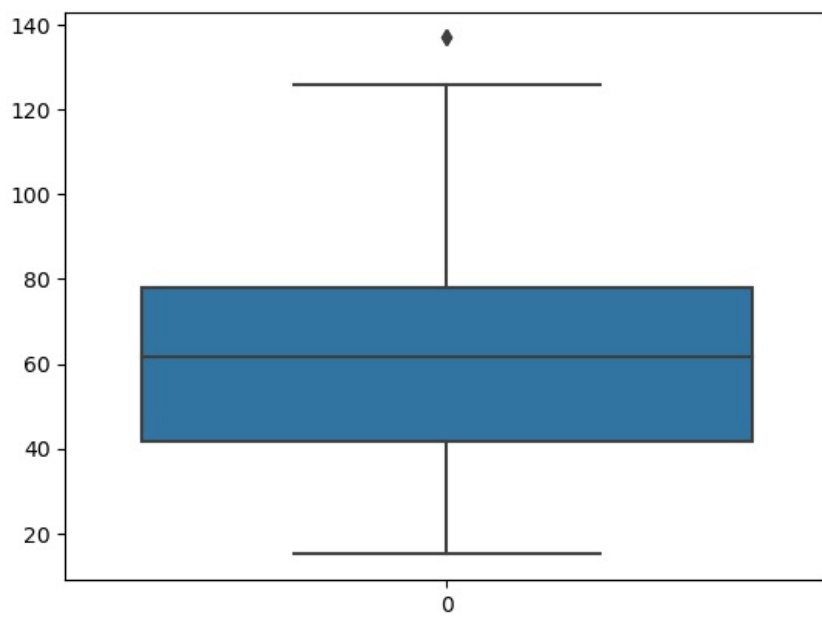
In [15]: sns.histplot(df,x="Spending_Score",kde=True)

Out[15]: <Axes: xlabel='Spending_Score', ylabel='Count'>



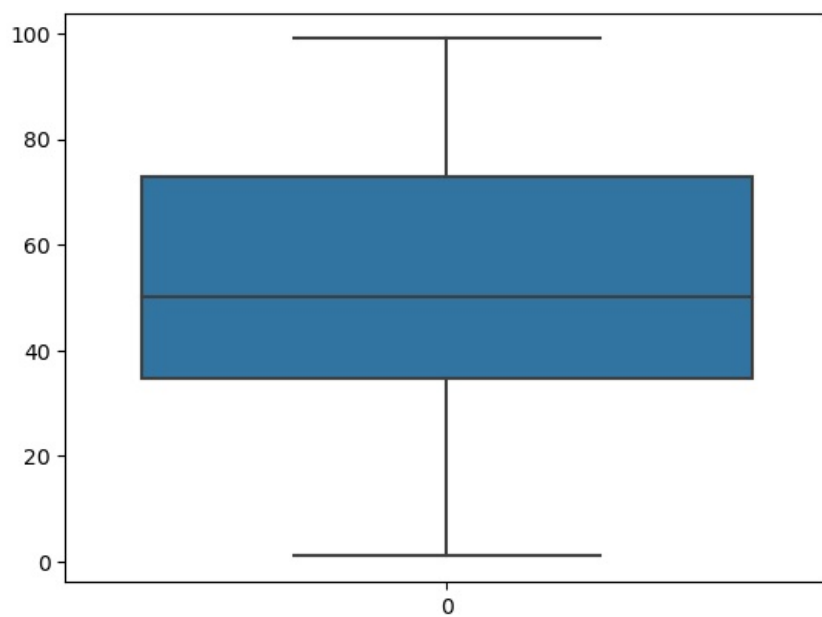
In [16]: sns.boxplot(df["Annual Income"])

Out[16]: <Axes: >



```
In [17]: sns.boxplot(df["Spending_Score"])
```

```
Out[17]: <Axes: >
```

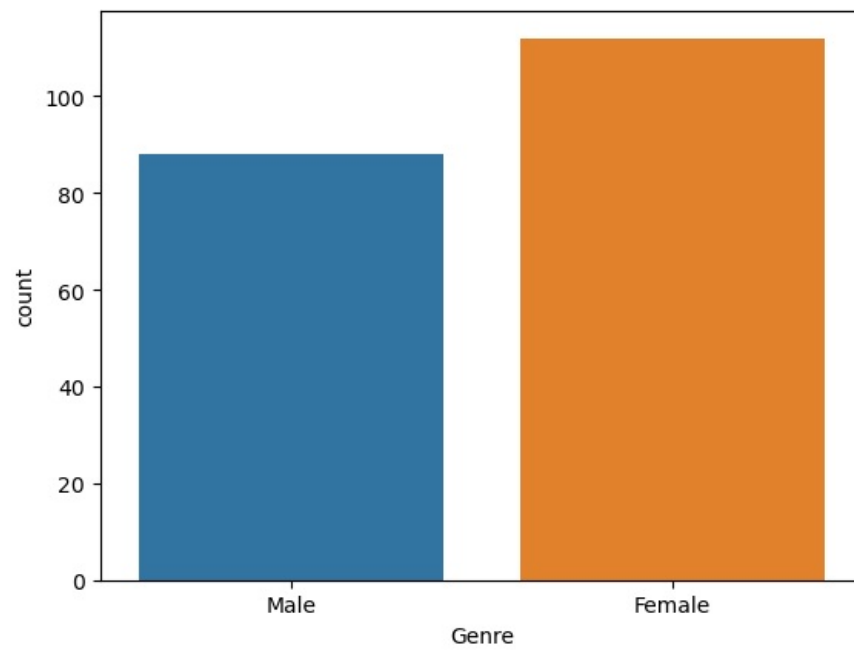


From above graphs, we only find outlier in Annual Income.

Similarly, for objective data, we can just look for countplot for now

```
In [18]: sns.countplot(data=df, x="Genre")
```

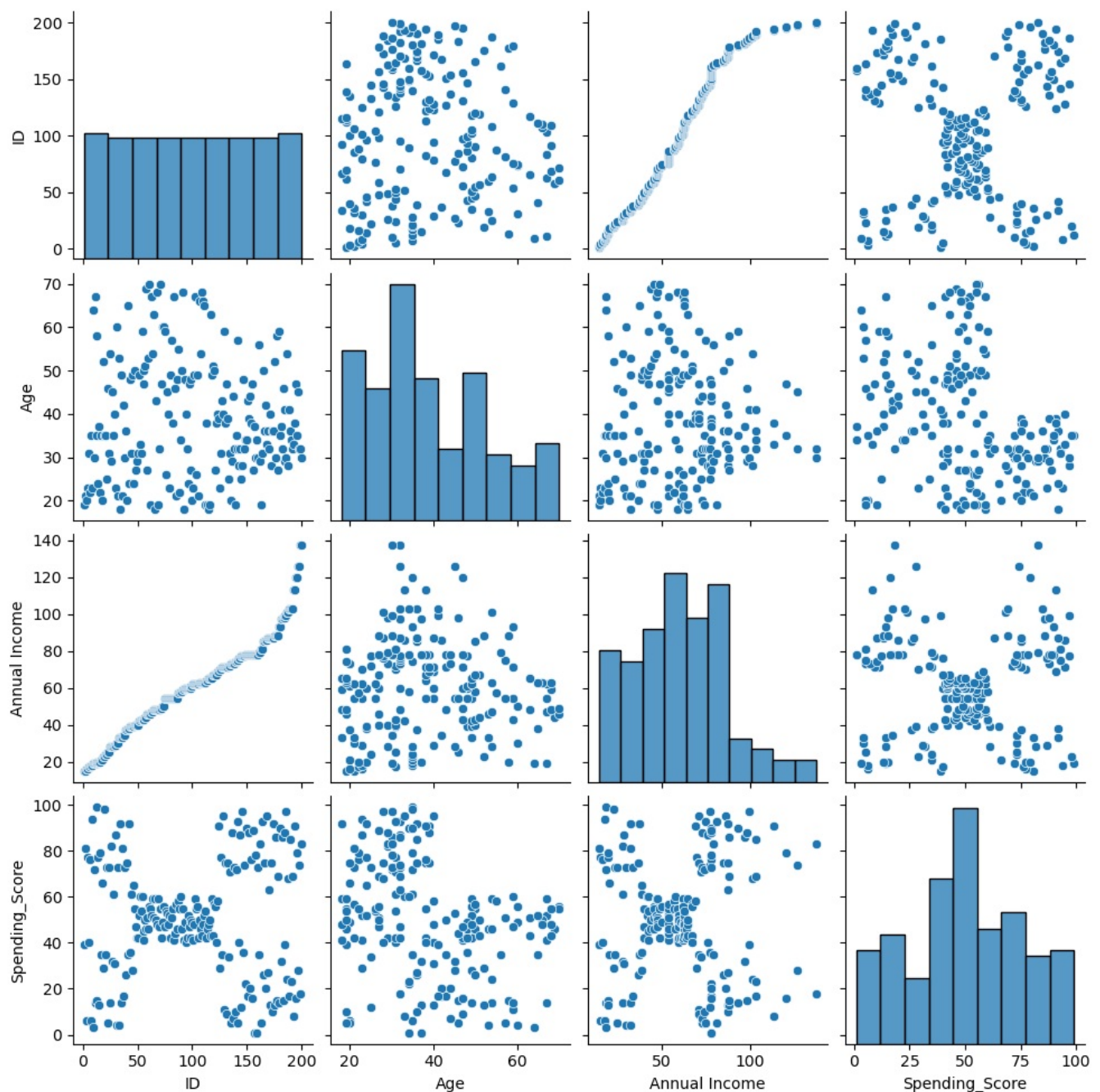
Out[18]: <Axes: xlabel='Genre', ylabel='count'>



AT A GLANCE, WE CAN SEE RELATION BETWEEN ALL COLUMNS AT A ONCE

In [19]: `sns.pairplot(df)`

Out[19]: <seaborn.axisgrid.PairGrid at 0x1e550c71a10>



We see few visualization, now lets see our data once and lets drop S.N

```
In [20]: df.head()
```

```
Out[20]:
```

	ID	Genre	Age	Annual Income	Spending_Score
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

Checking for Null values before separating it in features(X) and labels(y)

```
In [21]: df.isnull().sum()
```

```
Out[21]:
```

ID	0
Genre	0
Age	0
Annual Income	0
Spending_Score	0
dtype:	int64

```
In [22]: y = df['Spending_Score']
X = df.drop(columns='Spending_Score')
```

```
In [23]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
```

```
random_state=45)
```

Lets check shape whether it got splited or not

```
In [24]: X_train.shape, y_train.shape
```

```
Out[24]: ((160, 4), (160,))
```

```
In [25]: X_test.shape, y_test.shape
```

```
Out[25]: ((40, 4), (40,))
```

Before feeding our data to a machine-learning model we need to convert the categorical column to a numerical column, and we need to do column transfer too so,

```
In [30]: from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
```

```
In [31]: # Define the numerical and categorical columns
numerical_cols = ['Age', 'Annual Income']
categorical_cols = ['Genre']
```

```
In [32]: # Define the preprocessing steps
numeric_transformer = StandardScaler()
categorical_transformer = OneHotEncoder(handle_unknown='ignore')
```

```
In [33]: # Create the ColumnTransformer
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numerical_cols),
        ('cat', categorical_transformer, categorical_cols)
    ])
```

```
In [34]: # Fit and transform the training data
X_train_transformed = preprocessor.fit_transform(X_train)

# Transform the test data (using the same transformations as training data)
X_test_transformed = preprocessor.transform(X_test)
```

Lets see now how data looks like

```
In [35]: X_train_transformed
```

```
Out[35]: array([[ -8.62675496e-01,  -3.84078599e-02,  1.00000000e+00,
  0.00000000e+00],
 [  9.60199298e-01,  1.04377587e+00,  1.00000000e+00,
  0.00000000e+00],
 [-1.44599543e+00,  5.02684003e-01,  0.00000000e+00,
  1.00000000e+00],
 [  2.12683917e+00, -5.02200885e-01,  1.00000000e+00,
  0.00000000e+00],
 [-6.43930521e-01,  1.04377587e+00,  1.00000000e+00,
  0.00000000e+00],
 [  1.76226421e+00,  1.54839234e-01,  1.00000000e+00,
  0.00000000e+00],
 [-7.16845513e-01,  4.64034584e-01,  1.00000000e+00,
  0.00000000e+00],
 [-1.15433546e+00, -1.23653984e+00,  1.00000000e+00,
  0.00000000e+00],
 [-1.44599543e+00, -5.79499723e-01,  0.00000000e+00,
  1.00000000e+00],
 [  5.22709347e-01, -2.70304372e-01,  1.00000000e+00,
  0.00000000e+00],
 [-7.16845513e-01,  1.43027005e+00,  1.00000000e+00,
  0.00000000e+00],
 [  1.58134388e-01,  1.46891947e+00,  1.00000000e+00,
  0.00000000e+00],
 [  1.39768925e+00,  1.04377587e+00,  0.00000000e+00,
  1.00000000e+00],
 [-4.25185546e-01,  9.66477028e-01,  1.00000000e+00,
  0.00000000e+00],
 [-2.06440570e-01, -9.27344491e-01,  1.00000000e+00,
  0.00000000e+00],
 [  7.41454323e-01, -2.70304372e-01,  1.00000000e+00,
  0.00000000e+00],
 [  1.10602928e+00,  1.54621831e+00,  1.00000000e+00,
  0.00000000e+00],
 [  1.58134388e-01,  1.62351715e+00,  1.00000000e+00,
  0.00000000e+00],
 [-1.30016545e+00, -2.70304372e-01,  1.00000000e+00,
  0.00000000e+00],
 [-2.06440570e-01,  1.00512645e+00,  1.00000000e+00,
  0.00000000e+00],
 [  1.47060424e+00, -2.70304372e-01,  0.00000000e+00,
```

1.00000000e+00],
[-1.44599543e+00, 1.16189815e-01, 0.00000000e+00,
1.00000000e+00],
[4.49794355e-01, -2.70304372e-01, 1.00000000e+00,
0.00000000e+00],
[-1.44599543e+00, 1.54839234e-01, 1.00000000e+00,
0.00000000e+00],
[2.12683917e+00, -7.70572786e-02, 1.00000000e+00,
0.00000000e+00],
[-2.79355562e-01, 5.02684003e-01, 1.00000000e+00,
0.00000000e+00],
[-7.16845513e-01, 6.95931097e-01, 1.00000000e+00,
0.00000000e+00],
[7.41454323e-01, -1.08194217e+00, 1.00000000e+00,
0.00000000e+00],
[-1.51891042e+00, 1.54839234e-01, 1.00000000e+00,
0.00000000e+00],
[-4.98100538e-01, -3.84078599e-02, 1.00000000e+00,
0.00000000e+00],
[-6.43930521e-01, 6.57281678e-01, 1.00000000e+00,
0.00000000e+00],
[3.03964372e-01, -5.02200885e-01, 1.00000000e+00,
0.00000000e+00],
[8.14369314e-01, -1.15706697e-01, 1.00000000e+00,
0.00000000e+00],
[-2.79355562e-01, -1.54573519e+00, 1.00000000e+00,
0.00000000e+00],
[-1.15433546e+00, 3.88909776e-02, 1.00000000e+00,
0.00000000e+00],
[-1.51891042e+00, -7.70572786e-02, 0.00000000e+00,
1.00000000e+00],
[1.47060424e+00, 3.86735746e-01, 0.00000000e+00,
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[-5.71015529e-01, -8.50045654e-01, 1.00000000e+00,
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1.00000000e+00],
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1.00000000e+00],
[5.95624339e-01, -3.84078599e-02, 1.00000000e+00,
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[-1.30016545e+00, -1.77763170e+00, 0.00000000e+00,
1.00000000e+00],
[3.03964372e-01, 6.57281678e-01, 0.00000000e+00,
1.00000000e+00],
[-1.37308044e+00, 2.41558867e-04, 0.00000000e+00,
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[6.68539331e-01, -2.70304372e-01, 0.00000000e+00,
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1.00000000e+00],
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0.00000000e+00],
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1.00000000e+00],
[-5.71015529e-01, -8.11396235e-01, 1.00000000e+00,
0.00000000e+00],
[3.76879364e-01, 4.64034584e-01, 1.00000000e+00,
0.00000000e+00],
[-2.79355562e-01, -1.62303403e+00, 1.00000000e+00,
0.00000000e+00],
[6.68539331e-01, -8.50045654e-01, 0.00000000e+00,
1.00000000e+00],
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1.00000000e+00],
[-2.79355562e-01, -1.66168345e+00, 1.00000000e+00,
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[-7.89760505e-01, 6.18632259e-01, 0.00000000e+00,
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[8.14369314e-01, 9.27827609e-01, 0.00000000e+00,
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[1.17894427e+00, -1.54356116e-01, 1.00000000e+00,
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0.00000000e+00],
[2.31049380e-01, -1.04329275e+00, 1.00000000e+00,
0.00000000e+00],
[-1.33525579e-01, -1.58438461e+00, 0.00000000e+00,
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1.00000000e+00],
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1.00000000e+00],
[1.39768925e+00, -1.58438461e+00, 1.00000000e+00,
0.00000000e+00],
[1.10602928e+00, -1.27518926e+00, 1.00000000e+00,
0.00000000e+00],
[-4.98100538e-01, 2.51245378e+00, 0.00000000e+00,
1.00000000e+00],
[-1.44599543e+00, 7.73229934e-01, 0.00000000e+00,
1.00000000e+00],
[1.32477426e+00, 5.41333421e-01, 1.00000000e+00,
0.00000000e+00],
[-4.98100538e-01, 1.39162063e+00, 1.00000000e+00,
0.00000000e+00],
[1.83517920e+00, -1.62303403e+00, 0.00000000e+00,
1.00000000e+00],
[8.14369314e-01, -8.11396235e-01, 1.00000000e+00,
0.00000000e+00],
[8.87284306e-01, 2.32138071e-01, 1.00000000e+00,
0.00000000e+00],
[2.19975416e+00, -6.56798560e-01, 0.00000000e+00,
1.00000000e+00],
[1.47060424e+00, -6.95447979e-01, 0.00000000e+00,
1.00000000e+00],
[-7.89760505e-01, 5.79982840e-01, 1.00000000e+00,
0.00000000e+00],
[-1.51891042e+00, -5.02200885e-01, 0.00000000e+00,
1.00000000e+00],
[-1.22725046e+00, -1.58438461e+00, 0.00000000e+00,
1.00000000e+00],
[-8.62675496e-01, 2.32138071e-01, 0.00000000e+00,
1.00000000e+00],
[-6.06105869e-02, 2.32138071e-01, 1.00000000e+00,
0.00000000e+00],
[-1.44599543e+00, -5.02200885e-01, 0.00000000e+00,
1.00000000e+00],
[-5.71015529e-01, 7.73229934e-01, 1.00000000e+00,
0.00000000e+00],

```
[ -2.06440570e-01, 1.62351715e+00, 1.00000000e+00,
 0.00000000e+00],
[ -1.08142047e+00, -3.84078599e-02, 0.00000000e+00,
 1.00000000e+00],
[ 1.03311429e+00, -1.08194217e+00, 0.00000000e+00,
 1.00000000e+00],
[ -1.15433546e+00, 3.48086328e-01, 1.00000000e+00,
 0.00000000e+00],
[ 1.23044049e-02, 3.86735746e-01, 0.00000000e+00,
 1.00000000e+00],
[ -3.52270554e-01, 6.57281678e-01, 0.00000000e+00,
 1.00000000e+00]])
```

Lets create model

Linear Regression

```
In [37]: from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

```
In [38]: model1=LinearRegression()
```

```
In [40]: model1.fit(X_train_transformed, y_train)
y_pred = model1.predict(X_test_transformed)
mse = mean_squared_error(y_test, y_pred)
rmse = mean_squared_error(y_test, y_pred, squared=False)
r2 = r2_score(y_test, y_pred)
```

```
In [41]: print(mse)
print(rmse)
print(r2)

555.6660712716779
23.572570315340624
0.07214919444219348
```

Decision Tree Regression

```
In [43]: from sklearn.tree import DecisionTreeRegressor
model2=DecisionTreeRegressor(random_state=42)
```

```
In [44]: model2.fit(X_train_transformed, y_train)
y_pred = model2.predict(X_test_transformed)
mse = mean_squared_error(y_test, y_pred)
rmse = mean_squared_error(y_test, y_pred, squared=False)
r2 = r2_score(y_test, y_pred)
```

```
In [45]: print(mse)
print(rmse)
print(r2)

922.05
30.36527622136838
-0.5396384258384741
```

Random Forest Regressor

```
In [46]: from sklearn.ensemble import RandomForestRegressor
model3=RandomForestRegressor(random_state=42)
```

```
In [47]: model3.fit(X_train_transformed, y_train)
y_pred = model3.predict(X_test_transformed)
mse = mean_squared_error(y_test, y_pred)
rmse = mean_squared_error(y_test, y_pred, squared=False)
r2 = r2_score(y_test, y_pred)
```

```
In [48]: print(mse)
print(rmse)
print(r2)

489.0080875
22.11352725143594
0.1834546477297514
```

From here we can judge that Linear regression model looks good among other 2 model with highest rmse and lowest r2.