Insurance Premium Charge Prediction using Multiple Linear Regression

In [1]:
```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```python
data= pd.read_csv('insurance.csv')
```

In [3]:
```python
data.head()
```

Out[3]:

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

In [4]:
```python
data.shape
```

Out[4]:
```
(1338, 7)
```

Data cleaning

1. Check datatype of each column

In [5]:
```python
data.dtypes
```

Out[5]:
```
age           int64
sex          object
bmi         float64
children      int64
smoker       object
region       object
charges     float64
dtype: object
```

2. Check for duplicates

In [6]:
```python
data.duplicated()
```

Out[6]:
```
0       False
1       False
2       False
3       False
4       False
        ...  
1333    False
1334    False
1335    False
1336    False
1337    False
Length: 1338, dtype: bool
```

In [7]:
```python
data.duplicated().sum()
# there occurs one duplicate row
```

Out[7]:
```
1
```

In [8]:
```python
data.drop_duplicates(inplace = True)
```

In [9]:
```python
data.duplicated().sum()
# One duplicate row removed
```

Out[9]:
```
0
```

3. Check for null values

In [10]:
```python
data.isnull()
```

Out[10]:

	age	sex	bmi	children	smoker	region	charges
0	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...
1333	False	False	False	False	False	False	False
1334	False	False	False	False	False	False	False
1335	False	False	False	False	False	False	False
1336	False	False	False	False	False	False	False
1337	False	False	False	False	False	False	False

1337 rows × 7 columns

In [11]:
```python
data.isnull().sum()
# there is no null value
```

Out[11]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

4.Check for missing values

In [12]:
```python
data.isna().sum()
# no missing values found
```

Out[12]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

5. Check for Outliers

In [13]:
```python
data.describe()
```

Out[13]:

	age	bmi	children	charges
count	1337.000000	1337.000000	1337.000000	1337.000000
mean	39.222139	30.663452	1.095737	13279.121487
std	14.044333	6.100468	1.205571	12110.359656
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.290000	0.000000	4746.344000
50%	39.000000	30.400000	1.000000	9386.161300
75%	51.000000	34.700000	2.000000	16657.717450
max	64.000000	53.130000	5.000000	63770.428010

Data Preprocessing

6. Encode categorical variables

In [14]:
```python
label_encoder= LabelEncoder()
data['sex']= label_encoder.fit_transform(data['sex'])
data['smoker']= label_encoder.fit_transform(data['smoker'])
data['region']= label_encoder.fit_transform(data['region'])
```

7. Define the dependent and independent variables

In [15]:
```python
X= data[['age', 'sex', 'bmi', 'children', 'smoker', 'region']]
X
```

Out[15]:

	age	sex	bmi	children	smoker	region
0	19	0	27.900	0	1	3
1	18	1	33.770	1	0	2
2	28	1	33.000	3	0	2
3	33	1	22.705	0	0	1
4	32	1	28.880	0	0	1
...	...	...	...	...	...	...
1333	50	1	30.970	3	0	1
1334	18	0	31.920	0	0	0
1335	18	0	36.850	0	0	2
1336	21	0	25.800	0	0	3
1337	61	0	29.070	0	1	1

1337 rows × 6 columns

In [16]:
```python
X.to_csv('insu.csv')
```

In [17]:
```python
y= data['charges']
```

In [18]:
```python
y.to_csv('outpu.csv')
```

8. Split the data into training and testing sets

In [19]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size= 0.2, random_state= 42)
```

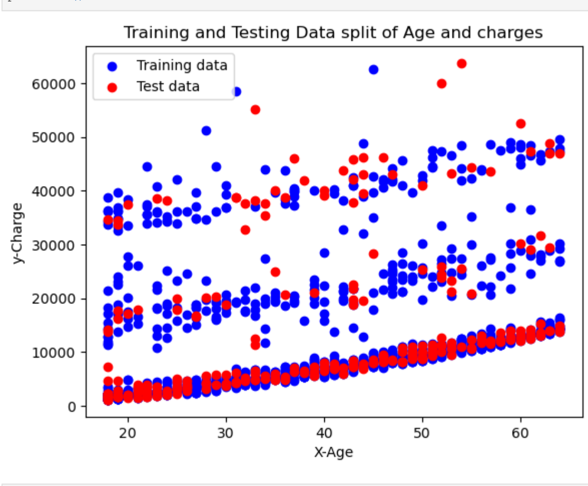
In [20]:
```python
X_train.shape # 2D array
```

Out[20]:
```
(1069, 6)
```

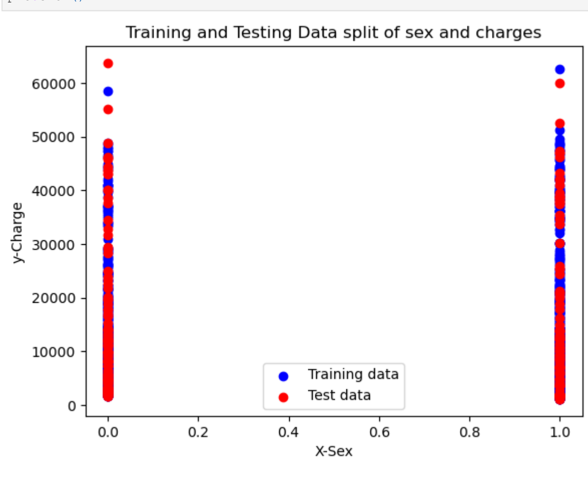
In [21]:
```python
y_train.shape # 1D array
```

Out[21]:
```
(1069,)
```

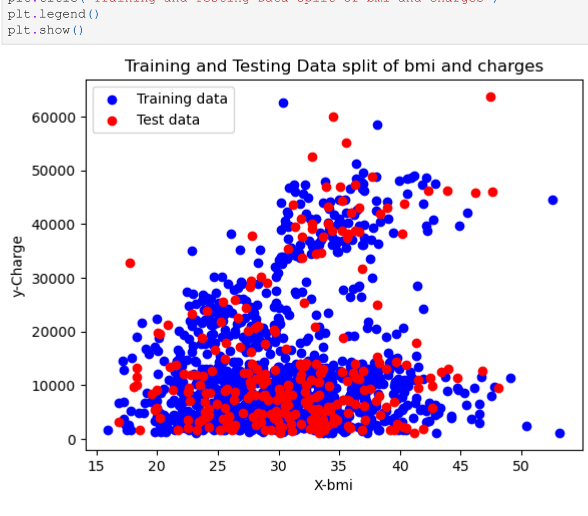
In [22]:
```python
plt.scatter(X_train['age'], y_train, color='blue', label ='Training data')
plt.scatter(X_test['age'], y_test, color = 'red', label ='Test data')
plt.xlabel('X-Age')
plt.ylabel('y-Charge')
plt.title('Training and Testing Data split of Age and charges')
plt.legend()
plt.show()
```



In [23]:
```python
plt.scatter(X_train['sex'], y_train, color='blue', label ='Training data')
plt.scatter(X_test['sex'], y_test, color = 'red', label ='Test data')
plt.xlabel('X-Sex')
plt.ylabel('y-Charge')
plt.title('Training and Testing Data split of sex and charges')
plt.legend()
plt.show()
```

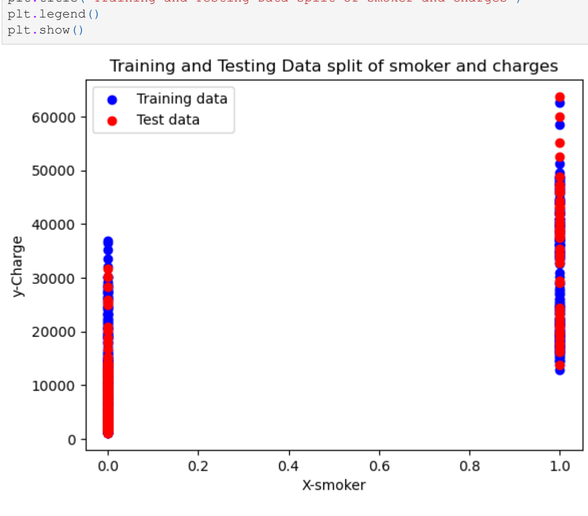


In [24]:
```python
plt.scatter(X_train['bmi'], y_train, color='blue', label ='Training data')
plt.scatter(X_test['bmi'], y_test, color = 'red', label ='Test data')
plt.xlabel('X-bmi')
plt.ylabel('y-Charge')
plt.title('Training and Testing Data split of bmi and charges')
plt.legend()
plt.show()
```



In [25]:
```python
plt.scatter(X_train['children'], y_train, color='blue', label ='Training data')
plt.scatter(X_test['children'], y_test, color = 'red', label ='Test data')
plt.xlabel('X-Children')
plt.ylabel('y-Charge')
plt.title('Training and Testing Data split of Children and charges')
plt.legend()
plt.show()
```

In [26]:
```python
plt.scatter(X_train['smoker'], y_train, color='blue', label ='Training data')
plt.scatter(X_test['smoker'], y_test, color = 'red', label ='Test data')
plt.xlabel('X-smoker')
plt.ylabel('y-Charge')
plt.title('Training and Testing Data split of smoker and charges')
plt.legend()
plt.show()
```



9. Create and train the regression model

In [27]:
```python
model= LinearRegression()
model.fit(X_train,y_train)
```

Out[27]:
```
▸ LinearRegression
LinearRegression()
```

10. Make predictions

In [28]:
```python
y_pred= model.predict(X_test)
```

11. Evaluate the model

In [29]:
```python
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

In [30]:
```python
mse
```

Out[30]:
```
35493102.61165053
```

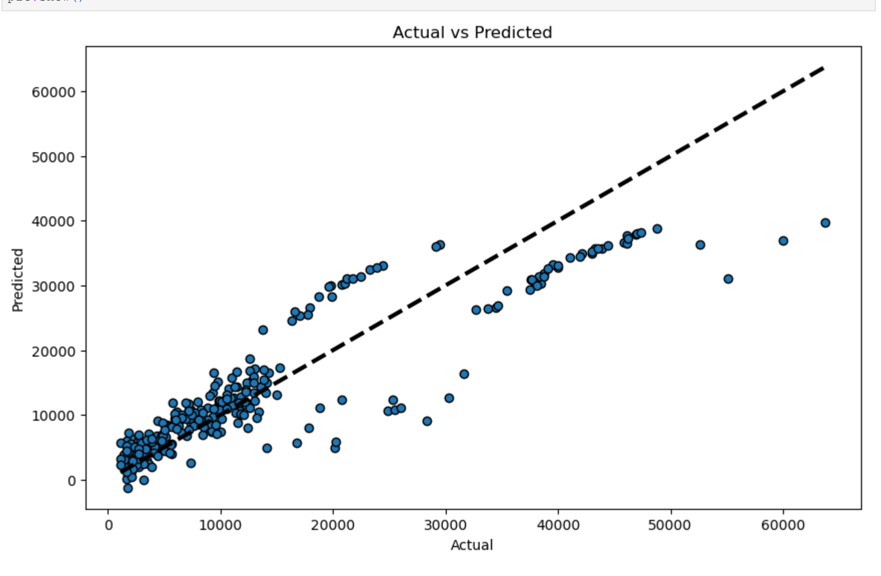
In [31]:
```python
r2
```

Out[31]:
```
0.8068466322629111
```

In [32]:
```python
## To visualize the results of a multiple regression, we often focus on plotting predicted vs actual values,
## plotting the residuals (the differences between the observed and predicted values),plotting partial regressi
##  to check the assumptions of linear regression.
## Since we have multiple independent variables, a simple 2D plot of the regression line like in simple linear
## regression isn't possible.
```

12. Plotting Predicted vs Actual Values:

In [33]:
```python
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, edgecolors=(0, 0, 0))
plt.plot([y.min(), y.max()], [y.min(), y.max()], 'k--', lw=3)
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs Predicted')
plt.show()
```

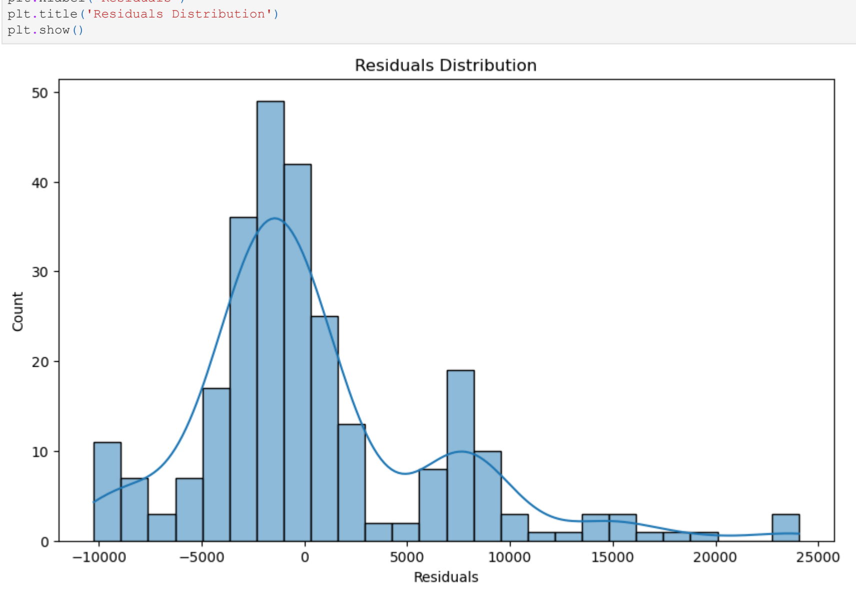


Interpretation from the plot

R2 score of 0.80 suggests that there is a strong correlation between the actual insurance charges (y_test) and the predicted insurance charges (y_pred). This means that the model has captured a significant portion of the relationship between the independent variables (e.g., age, BMI, smoking status) and the dependent variable (insurance charges).

13. Plotting Residuals

In [34]:
```python
# This helps to check the distribution of residuals to ensure they are normally distributed.
plt.figure(figsize=(10, 6))
residuals = y_test - y_pred
sns.histplot(residuals, kde=True)
plt.xlabel('Residuals')
plt.title('Residuals Distribution')
plt.show()
```

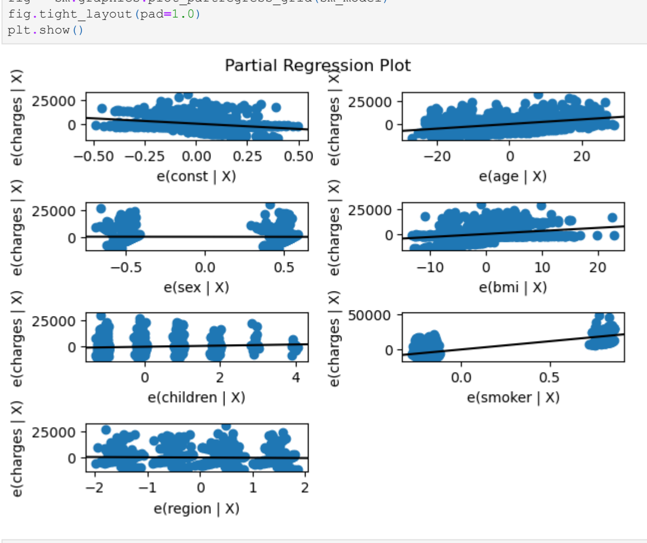


Interpretation from the histogram of residual

Peak at Zero Residual signifies most of the predictions are close to the actual values, indicating a generally good model fit. Ideally, residuals should be randomly scattered around zero without any discernible pattern. Patterns could indicate issues like non-linearity or heteroscedasticity.

14. Partial Regression Plots:

In [35]:
```python
# This helps to visualize the relationship between each independent variable and
# the dependent variable while holding the other variables constant.
import statsmodels.api as sm
X_train_with_const = sm.add_constant(X_train)
sm_model = sm.OLS(y_train, X_train_with_const).fit()
fig = sm.graphics.plot_partregress_grid(sm_model)
fig.tight_layout(pad=1.0)
plt.show()
```



In [36]:
```python
#### The pair plot will help visualize how each feature relates to the charges.
sns.pairplot(data)
plt.show()
```

15.R2 computation for each independent variable with the dependent variable

In [37]:
```python
X.shape
```

Out[37]:
```
(1337, 6)
```

In [38]:
```python
X
```

Out[38]:

	age	sex	bmi	children	smoker	region
0	19	0	27.900	0	1	3
1	18	1	33.770	1	0	2
2	28	1	33.000	3	0	2
3	33	1	22.705	0	0	1
4	32	1	28.880	0	0	1
...	...	...	...	...	...	...
1333	50	1	30.970	3	0	1
1334	18	0	31.920	0	0	0
1335	18	0	36.850	0	0	2
1336	21	0	25.800	0	0	3
1337	61	0	29.070	0	1	1

1337 rows × 6 columns

In [39]:
```python
independent_variables= X
r2_scores = {}
```

In [40]:
```python
for var in independent_variables:
    X = data[[var]].values.reshape(-1, 1) # to extract specific column values (ie.independent variable) as a da
    # and reshaped to 2D array
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    model = LinearRegression()
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    r2 = r2_score(y_test, y_pred)
    r2_scores[var] = r2

# Display the R^2 scores
for var, score in r2_scores.items():
    print(f'R-squared for {var} with charges: {score}')
```

```
R-squared for age with charges: 0.09513000782072023
R-squared for sex with charges: -0.0059343865026528775
R-squared for bmi with charges: 0.05172261154295266
R-squared for children with charges: -0.013367948483225867
R-squared for smoker with charges: 0.6732662703492573
R-squared for region with charges: -0.008374849983498578
```

In [41]:
```python
r2_scores
```

Out[41]:
```
{'age': 0.09513000782072023,
 'sex': -0.0059343865026528775,
 'bmi': 0.05172261154295266,
 'children': -0.013367948483225867,
 'smoker': 0.6732662703492573,
 'region': -0.008374849983498578}
```

In [42]:
```python
data.corr()
```

Out[42]:

	age	sex	bmi	children	smoker	region	charges
age	1.000000	-0.019814	0.109344	0.041536	-0.025587	0.001626	0.298308
sex	-0.019814	1.000000	0.046397	0.017848	0.076596	0.004936	0.058044
bmi	0.109344	0.046397	1.000000	0.012755	0.003746	0.157574	0.198401
children	0.041536	0.017848	0.012755	1.000000	0.007331	0.016258	0.067389
smoker	-0.025587	0.076596	0.003746	0.007331	1.000000	-0.002358	0.787234
region	0.001626	0.004936	0.157574	0.016258	-0.002358	1.000000	-0.006547
charges	0.298308	0.058044	0.198401	0.067389	0.787234	-0.006547	1.000000

Interpretation from the correlation matrix

Value: The correlation coefficient of 0.78 between smoker and charges. Interpretation: This indicates a strong positive correlation. Being a smoker is strongly associated with higher insurance charges. As the value is relatively close to 1, it suggests that smoking status is a significant factor in determining insurance charges. In practical terms, smokers are likely to have higher insurance charges compared to non-smokers.

Value: The correlation coefficient of 0.29 between age and charges. Interpretation: This indicates a weak positive correlation. Age has a relatively small positive association with insurance charges. While there is a slight tendency for insurance charges to increase with age, the relationship is not very strong. This means that other factors besides age might be playing a more significant role in determining insurance charges.

Insights and Practical Implications:

Smoking Status: As the strongest predictor, smoking status has a profound impact on insurance charges. Insurers often charge higher premiums to smokers due to the elevated health risks.

Age: While age shows a weaker correlation, it still contributes to the model. Older individuals might face slightly higher charges, but other factors play a more significant role.

BMI: Although BMI has a weaker correlation with insurance charges, it remains an important factor due to the health risks associated with higher BMI values.

Number of Children: Family size has a minor impact, suggesting slight cost adjustments for larger families.

Sex and Region: These variables have varying effects, often less influential individually but important when combined with other factors.

Conclusion:

Understanding the behavior of these independent variables helps in creating accurate predictive models for insurance charges. By leveraging Multiple Linear Regression, we can identify key factors that influence costs and make data-driven decisions to optimize pricing strategies. This approach not only improves accuracy but also provides valuable insights into the factors driving insurance costs, ultimately benefiting both insurers and policyholders.

In [ ]: