Machine Learning Lab 7: Linear Regression

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In [71]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

# Inference: importing the essential libraries
```

In [72]:
```python
df = pd.read_excel('data\insurance.xlsx')
df.head()

# Inference: Loading the dataset
```

Out[72]:

	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

1. Data Preprocessing

In [73]:
```python
df.info()

# Inference: checking for null values
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       1338 non-null   int64  
 1   sex       1338 non-null   object 
 2   bmi       1338 non-null   float64
 3   children  1338 non-null   int64  
 4   smoker    1338 non-null   object 
 5   region    1338 non-null   object 
 6   charges   1338 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

Handle Missing Data:

```
Identify and treat any missing values in the dataset
by either removing them or imputing appropriate values
```

In [74]:
```python
df.isna().sum()

# Inference: checking for null values
```

Out[74]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

```
Encode Categorical Variables: Convert categorical features
such as 'sex', 'smoker', and 'region' into numerical
formats using techniques like one-hot encoding or label
encoding
```

In [75]:
```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['sex'] = le.fit_transform(df['sex'])
df['smoker'] = le.fit_transform(df['smoker'])
df['region'] = le.fit_transform(df['region'])
df.head()

# ohe = pd.get_dummies(df['region'])
# df = pd.concat([df, ohe], axis=1)
# df = df.drop('region', axis=1)
# df.head()

# Inference: label encoding the categorical variables
```

Out[75]:

	age	sex	bmi	children	smoker	region	charges
0	19	0	27.900	0	1	3	16884.92400
1	18	1	33.770	1	0	2	1725.55230
2	28	1	33.000	3	0	2	4449.46200
3	33	1	22.705	0	0	1	21984.47061
4	32	1	28.880	0	0	1	3866.85520

```
Scaling/Normalizing Features: Apply feature scaling (if
necessary) to continuous variables like age, BMI, and children
for better model performance.
```

In [76]:
```python
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
```

```
df[['age', 'bmi', 'children']] = sc.fit_transform(df[['age', 'bmi', 'children']
df.head()

# Inference: standardizing the numerical variables
```

Out[76]:

	age	sex	bmi	children	smoker	region	charges
0	-1.438764	0	-0.453320	-0.908614	1	3	16884.92400
1	-1.509965	1	0.509621	-0.078767	0	2	1725.55230
2	-0.797954	1	0.383307	1.580926	0	2	4449.46200
3	-0.441948	1	-1.305531	-0.908614	0	1	21984.47061
4	-0.513149	1	-0.292556	-0.908614	0	1	3866.85520

2. Model Evaluation

```
Feature Selection: Select relevant features from the dataset
that will be used to predict medical insurance costs (age,
sex, BMI, children, smoker, region)
```

In [77]:

```
from sklearn.model_selection import train_test_split
X = df.drop('charges', axis=1)
y = df['charges']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rand

# Inference: splitting the dataset into train and test
```

3. Linear Regression Model Development:

```
Model  Building:  Implement  a  linear  regression  model
to  predict  medical insurance charges (target variable)
using the features selected
```

In [85]:

```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()


# from sklearn.model_selection import KFold, GridSearchCV
# kfold = KFold(n_splits=10, shuffle=True, random_state=42)

# param_grid = {
#     'fit_intercept': [True, False],
#     'copy_X': [True, False]
# }

# grid = GridSearchCV(lr, param_grid, cv=kfold, scoring='r2')
# grid.fit(X_train, y_train)

# best_params = grid.best_params_
# best_score = grid.best_score_
```

```
# print("Best Parameters:", best_params)
# print("Best Score:", best_score)



# Inference: creating the linear regression model
```

Multicollinearity Check: Perform checks for multicollinearity (e.g., using the Variance Inflation Factor (VIF)) and eliminate highly correlated features, if needed.

In [79]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor

vif = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
# print(vif)
df_vif = pd.DataFrame(vif, index = X.columns, columns=['VIF'])
df_vif

# Inference: checking for multicollinearity in the dataset
```

Out[79]:

	VIF
age	1.014513
sex	1.566982
bmi	1.022282
children	1.002043
smoker	1.207526
region	1.573703

Model Training: Fit the linear regression model on the training data to establish a relationship between the features and the target variable (insurance costs).

In [80]:
```
# lr = LinearRegression(**best_params).fit(X_train, y_train)
lr.fit(X_train, y_train)
lr.score(X_test, y_test)

# Inference: training and testing the model
```

Out[80]: 0.7833463107364538

Performance Metrics Calculation: After training the model on the training set, evaluate its performance on the testing set by calculating

■ Mean Absolute Error (MAE): Measures the average magnitude of the errors.

■ Mean Squared Error (MSE): Measures the average squared difference between actual and predicted values.

■ Root Mean Squared Error (RMSE): The square root of MSE, providing an error estimate in the same units as the target variable.

■ R-squared (R2) Score: Indicates the proportion of variance in the target variable explained by the model.

■ Adjusted R-squared: Adjusts the R2 score based on the number of predictors, penalizing models that include irrelevant features.

■ Residual Sum of Squares (RSS): Quantifies the total squared error between the predicted and actual values.

■ Explained Variance Score: Evaluates how much of the variance in the target variable is captured by the model

In [81]:

```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_scor

def adjusted_r2_score(y_true, y_pred, X):
    n = X.shape[0]
    p = X.shape[1]
    r2 = r2_score(y_true, y_pred)
    return 1 - ((1 - r2) * (n - 1) / (n - p - 1))

def residual_sum_of_squares(y_true, y_pred):
    return np.sum(np.square(y_true - y_pred))

def variance_score(y_true, y_pred):
    return 1 - residual_sum_of_squares(y_true, y_pred) / residual_sum_of_squ

y_pred = lr.predict(X_test)

print('Mean Absolute Error:', mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(mean_squared_error(y_test, y_pred)
print('R2 Score:', r2_score(y_test, y_pred))
print('Adjusted R2 Score:', adjusted_r2_score(y_test, y_pred, X_test))
print('Residual Sum of Squares:', residual_sum_of_squares(y_test, y_pred))
print('Variance Score:', variance_score(y_test, y_pred))

# Inference: evaluating the model using various metrics like Mean Absolute E
```

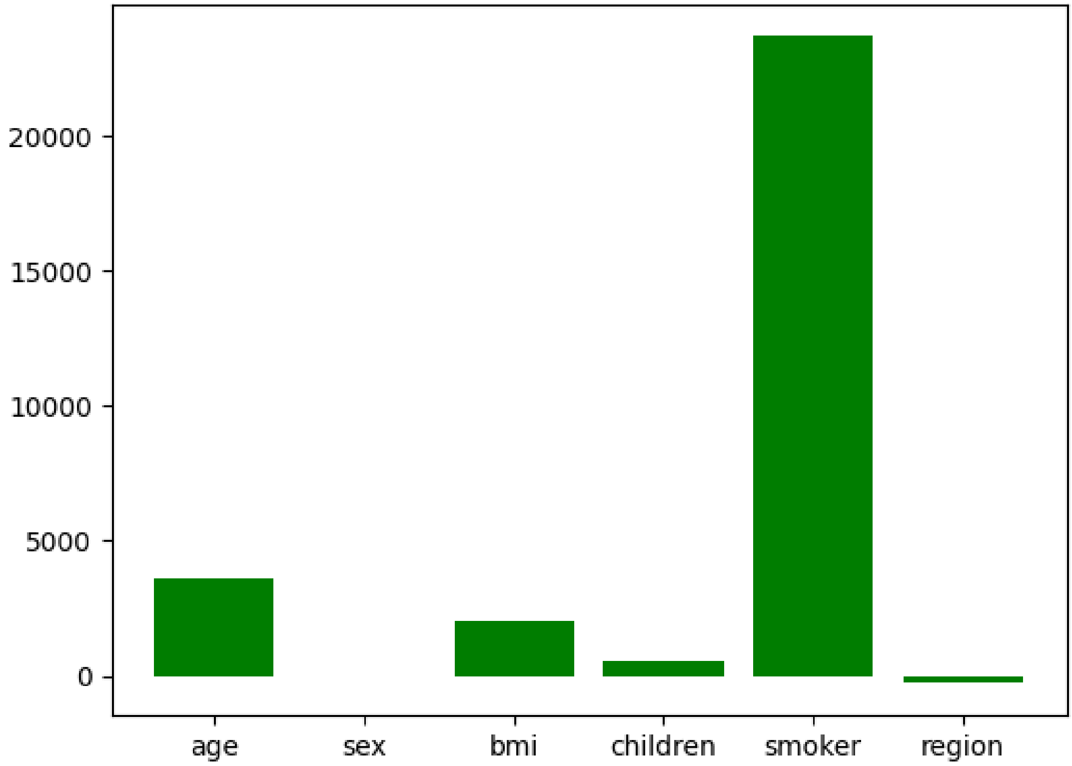
```
Mean Absolute Error: 4186.508898366434
Mean Squared Error: 33635210.43117841
Root Mean Squared Error: 5799.587091438356
R2 Score: 0.7833463107364538
Adjusted R2 Score: 0.7783657661556826
Residual Sum of Squares: 9014236395.555815
Variance Score: 0.7833463107364538
```

4. Feature Importance Analysis

Coefficient Interpretation: Examine the coefficients of the linear regression model to determine the impact of each feature (age, BMI, smoking status, etc.) on medical insurance costs

In [82]:
```python
lr.coef_
plt.bar([x for x in lr.feature_names_in_], lr.coef_, color='green')
```

Out[82]: <BarContainer object of 6 artists>



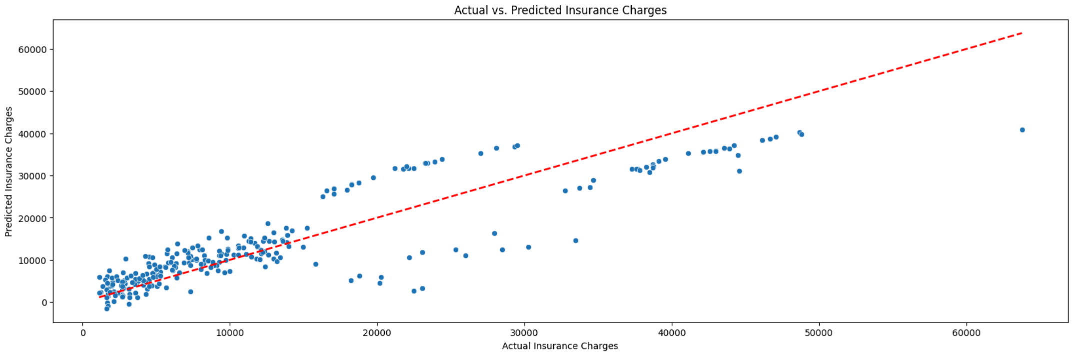
5. Visualization

Scatterplot for Model Performance: Create a scatterplot showing actual vs. predicted insurance charges. This visual will help in assessing how well the model fits the data, and it will highlight any discrepancies between predicted and actual values (e.g., overfitting or underfitting)

In [83]:
```python
import seaborn as sns

plt.figure(figsize=(20, 6))
sns.scatterplot(x=y_test, y=y_pred)
plt.xlabel("Actual Insurance Charges")
plt.ylabel("Predicted Insurance Charges")
plt.title("Actual vs. Predicted Insurance Charges")
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], colc
plt.show()

# Inference: plotting the actual vs. predicted values
```



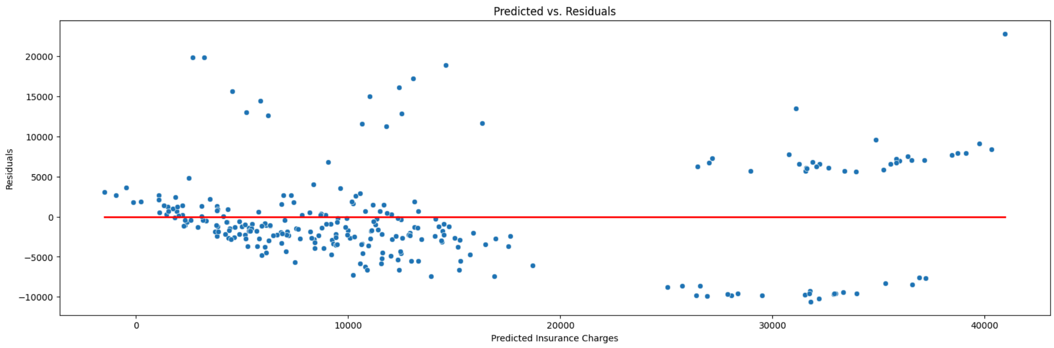
6. Residual Analysis:

Residual Plot: Visualize the residuals (difference between predicted and actual values) to check for patterns, ensuring that errors are randomly distributed, a key assumption in linear regression.

In [84]:
```
residuals = y_test - y_pred

plt.figure(figsize=(20, 6))
sns.scatterplot(x=y_pred, y=residuals)
plt.xlabel("Predicted Insurance Charges")
plt.ylabel("Residuals")
plt.title("Predicted vs. Residuals")
plt.plot([y_pred.min(), y_pred.max()], [0, 0], color='red', lw=2)
plt.show()

# Inference: plotting the predicted vs. residuals
```



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