# Project: Linear Regression

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In [82]:
```
#Example of supress warnings for Numpy version out of range (optional)
import warnings
warnings.filterwarnings("ignore", category=Warning)
warnings.simplefilter(action='ignore', category=FutureWarning)

#Some recommended libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_scor
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import learning_curve
from sklearn.pipeline import make_pipeline
import matplotlib.pyplot as plt
import seaborn as sns
import zipfile
import requests
from io import BytesIO
from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import cross_val_score
```

# The Dataset

In [83]:
```
# URL of the Bike Sharing Dataset zip file
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/00275/Bike-

# Fetch the zip file from the URL
response = requests.get(url)
zip_file = zipfile.ZipFile(BytesIO(response.content))

# List files in the zip
print(zip_file.namelist())

# Load the day.csv file into a DataFrame
with zip_file.open('day.csv') as file:
    df = pd.read_csv(file)
    print(df.head())
```

```
['Readme.txt', 'day.csv', 'hour.csv']
   instant      dteday  season  yr  mnth  holiday  weekday  workingday  \
0        1  2011-01-01       1   0     1        0        6           0
1        2  2011-01-02       1   0     1        0        0           0
2        3  2011-01-03       1   0     1        0        1           1
3        4  2011-01-04       1   0     1        0        2           1
4        5  2011-01-05       1   0     1        0        3           1

   weathersit      temp     atemp       hum  windspeed  casual  registered
\
0           2  0.344167  0.363625  0.805833   0.160446     331         654
1           2  0.363478  0.353739  0.696087   0.248539     131         670
2           1  0.196364  0.189405  0.437273   0.248309     120        1229
3           1  0.200000  0.212122  0.590435   0.160296     108        1454
4           1  0.226957  0.229270  0.436957   0.186900      82        1518

    cnt
0   985
1   801
2  1349
3  1562
4  1600
```

# Data Preprocessing

Loading Data: Load the Bike Sharing dataset using Pandas.

Data Exploration and Visualization: Produce some visualizations, statistics, etc. to gain an understanding for the dataset and what it contains.

Handling Missing Values: Check for and handle any missing values in the dataset (if any).

Encoding Categorical Variables: Convert categorical variables to numerical values using techniques like one-hot encoding (if any you see that need this).

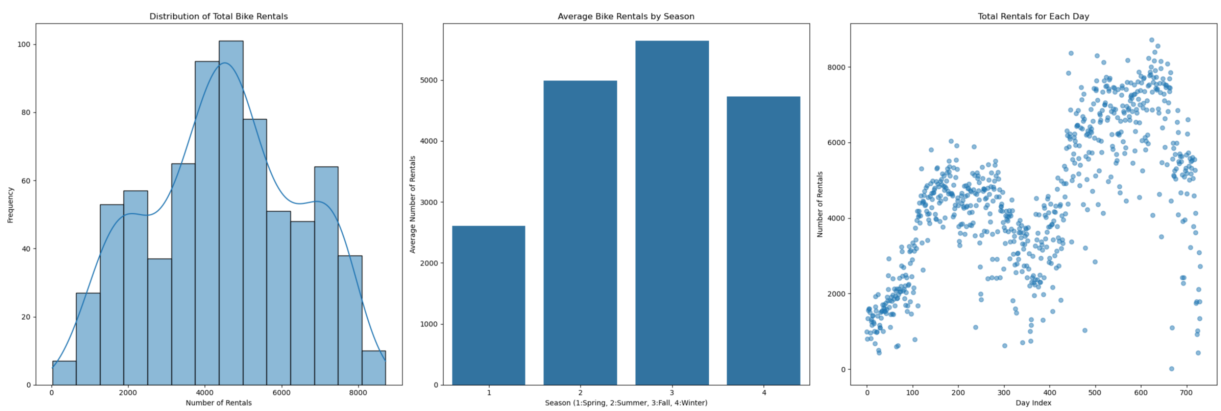
Feature Engineering: Create new features from the date column (e.g., day of the week, month, hour) to capture temporal patterns.

Standardization: Standardize the features to have a mean of 0 and a standard deviation of 1 for consistent training. This step helps ensure that the model is not biased towards features with larger scales.

Train-Test Split: Split the dataset into training and testing sets to evaluate the model's performance on unseen data.

In [92]:
```
df = pd.read_csv('day.csv')


# Data Preprocessing
fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(24, 8))
```

```python
sns.histplot(df['cnt'], kde=True, ax=ax1)
ax1.set_title('Distribution of Total Bike Rentals')
ax1.set_xlabel('Number of Rentals')
ax1.set_ylabel('Frequency')

season_avg = df.groupby('season')['cnt'].mean().reset_index()
sns.barplot(x='season', y='cnt', data=season_avg, ax=ax2)
ax2.set_title('Average Bike Rentals by Season')
ax2.set_xlabel('Season (1:Spring, 2:Summer, 3:Fall, 4:Winter)')
ax2.set_ylabel('Average Number of Rentals')

ax3.scatter(df.index, df['cnt'], alpha=0.5)
ax3.set_title('Total Rentals for Each Day')
ax3.set_xlabel('Day Index')
ax3.set_ylabel('Number of Rentals')

plt.tight_layout()
plt.show()


df.describe(), df.info()
```



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 731 entries, 0 to 730
Data columns (total 16 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   instant     731 non-null    int64  
 1   dteday      731 non-null    object 
 2   season      731 non-null    int64  
 3   yr          731 non-null    int64  
 4   mnth        731 non-null    int64  
 5   holiday     731 non-null    int64  
 6   weekday     731 non-null    int64  
 7   workingday  731 non-null    int64  
 8   weathersit  731 non-null    int64  
 9   temp        731 non-null    float64
 10  atemp       731 non-null    float64
 11  hum         731 non-null    float64
 12  windspeed   731 non-null    float64
 13  casual      731 non-null    int64  
 14  registered  731 non-null    int64  
 15  cnt         731 non-null    int64  
dtypes: float64(4), int64(11), object(1)
memory usage: 91.5+ KB
```

Out[92]:
```
(          instant      season          yr        mnth     holiday     week
day  \
 count  731.000000  731.000000  731.000000  731.000000  731.000000  731.000
000
 mean   366.000000    2.496580    0.500684    6.519836    0.028728    2.997
264
 std    211.165812    1.110807    0.500342    3.451913    0.167155    2.004
787
 min      1.000000    1.000000    0.000000    1.000000    0.000000    0.000
000
 25%    183.500000    2.000000    0.000000    4.000000    0.000000    1.000
000
 50%    366.000000    3.000000    1.000000    7.000000    0.000000    3.000
000
 75%    548.500000    3.000000    1.000000   10.000000    0.000000    5.000
000
 max    731.000000    4.000000    1.000000   12.000000    1.000000    6.000
000

        workingday  weathersit        temp       atemp         hum   windsp
eed  \
 count  731.000000  731.000000  731.000000  731.000000  731.000000  731.000
000
 mean     0.683995    1.395349    0.495385    0.474354    0.627894    0.190
486
 std      0.465233    0.544894    0.183051    0.162961    0.142429    0.077
498
 min      0.000000    1.000000    0.059130    0.079070    0.000000    0.022
392
 25%      0.000000    1.000000    0.337083    0.337842    0.520000    0.134
950
 50%      1.000000    1.000000    0.498333    0.486733    0.626667    0.180
975
 75%      1.000000    2.000000    0.655417    0.608602    0.730209    0.233
214
 max      1.000000    3.000000    0.861667    0.840896    0.972500    0.507
463

             casual   registered          cnt
 count   731.000000   731.000000   731.000000
 mean    848.176471  3656.172367  4504.348837
 std     686.622488  1560.256377  1937.211452
 min       2.000000    20.000000    22.000000
 25%     315.500000  2497.000000  3152.000000
 50%     713.000000  3662.000000  4548.000000
 75%    1096.000000  4776.500000  5956.000000
 max    3410.000000  6946.000000  8714.000000  ,
 None)
```

In [93]:
```
# Checking for missing values
df.isnull().sum()
# no missing values

y = df[['cnt']]
df = df[['season','yr','mnth','holiday','weekday','workingday','weathersit',
```

```python
# Encoding
encoding_cols = ['season', 'mnth','weekday','weathersit']
df[encoding_cols] = df[encoding_cols].astype('category')
df_encoded = pd.get_dummies(df, columns=encoding_cols)

# Feature Engineering
df_processed = df_encoded.copy()
#df_processed['dteday'] = pd.to_datetime(df_processed['dteday'])


#df_processed['day_of_week'] = df_processed['dteday'].dt.dayofweek
#df_processed['day_of_month'] = df_processed['dteday'].dt.day

# Drop the original 'dteday' column
#df_processed = df_processed.drop('dteday', axis=1)

# Display the first few rows to verify the changes
print(df_processed.head())
print(df_processed.info())
```

```
   yr  holiday  workingday      temp     atemp       hum  windspeed  season_
1  \
0   0        0           0  0.344167  0.363625  0.805833   0.160446      Tru
e
1   0        0           0  0.363478  0.353739  0.696087   0.248539      Tru
e
2   0        0           1  0.196364  0.189405  0.437273   0.248309      Tru
e
3   0        0           1  0.200000  0.212122  0.590435   0.160296      Tru
e
4   0        0           1  0.226957  0.229270  0.436957   0.186900      Tru
e

   season_2  season_3  ...  weekday_0  weekday_1  weekday_2  weekday_3  \
0     False     False  ...      False      False      False      False
1     False     False  ...       True      False      False      False
2     False     False  ...      False       True      False      False
3     False     False  ...      False      False       True      False
4     False     False  ...      False      False      False       True

   weekday_4  weekday_5  weekday_6  weathersit_1  weathersit_2  weathersit_3
0      False      False       True         False          True         False
1      False      False      False         False          True         False
2      False      False      False          True         False         False
3      False      False      False          True         False         False
4      False      False      False          True         False         False

[5 rows x 33 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 731 entries, 0 to 730
Data columns (total 33 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   yr            731 non-null    int64
 1   holiday       731 non-null    int64
 2   workingday    731 non-null    int64
 3   temp          731 non-null    float64
 4   atemp         731 non-null    float64
 5   hum           731 non-null    float64
 6   windspeed     731 non-null    float64
 7   season_1      731 non-null    bool
 8   season_2      731 non-null    bool
 9   season_3      731 non-null    bool
 10  season_4      731 non-null    bool
 11  mnth_1        731 non-null    bool
 12  mnth_2        731 non-null    bool
 13  mnth_3        731 non-null    bool
 14  mnth_4        731 non-null    bool
 15  mnth_5        731 non-null    bool
 16  mnth_6        731 non-null    bool
 17  mnth_7        731 non-null    bool
 18  mnth_8        731 non-null    bool
 19  mnth_9        731 non-null    bool
 20  mnth_10       731 non-null    bool
 21  mnth_11       731 non-null    bool
 22  mnth_12       731 non-null    bool
```

```
 23  weekday_0     731 non-null    bool
 24  weekday_1     731 non-null    bool
 25  weekday_2     731 non-null    bool
 26  weekday_3     731 non-null    bool
 27  weekday_4     731 non-null    bool
 28  weekday_5     731 non-null    bool
 29  weekday_6     731 non-null    bool
 30  weathersit_1  731 non-null    bool
 31  weathersit_2  731 non-null    bool
 32  weathersit_3  731 non-null    bool
dtypes: bool(26), float64(4), int64(3)
memory usage: 58.7 KB
None
```

In [99]:

```
df_standardized = df_processed.copy()

scaler = StandardScaler()

X = scaler.fit_transform(df_standardized)

#print(df_standardized.head())
#print(df_standardized.info())
#print(df_standardized[['cnt_standardized']].describe())

#Train-Test Split: Split the dataset into training and testing sets to evalu
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
```

# Building the Linear Regression Model

Model Initialization:

Choosing Hyperparameters: Explain key hyperparameters such as the fit_intercept and normalize.

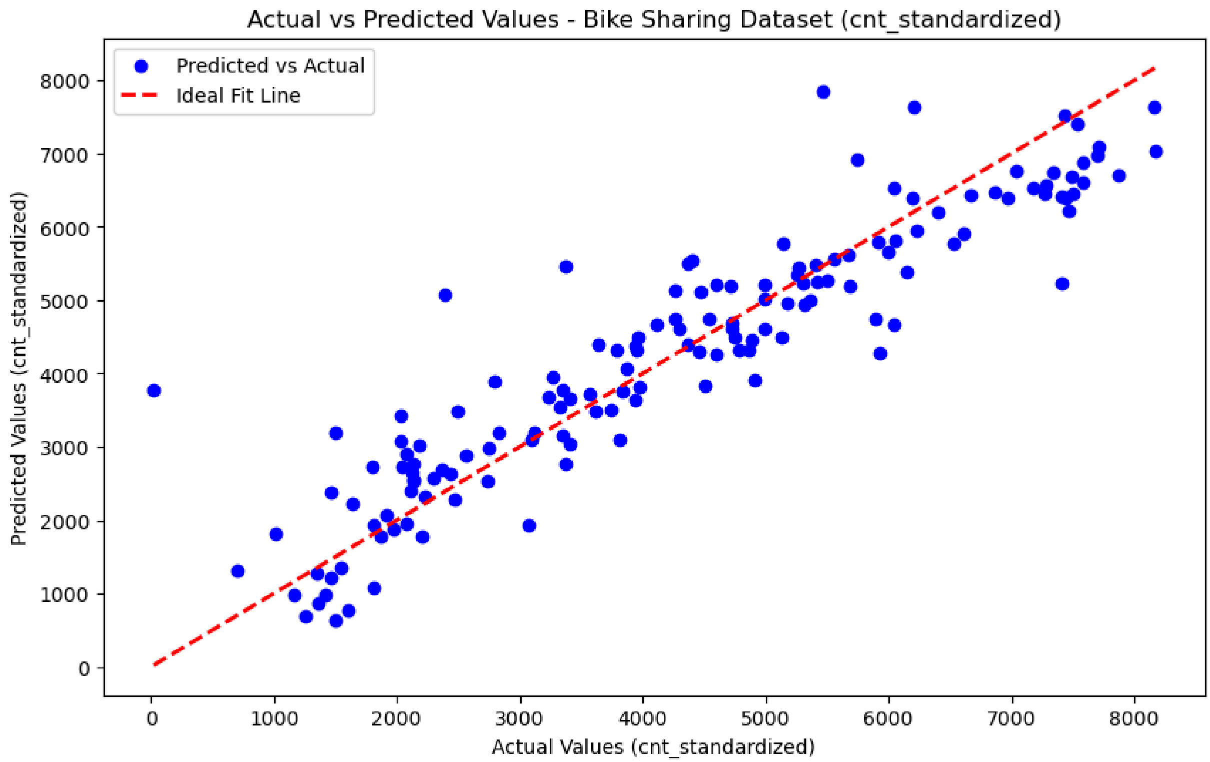
Linear Regression Initialization: Use the LinearRegression class from Scikit-learn, specifying the chosen hyperparameters.

Model Fitting: Fit the Linear Regression model to the standardized Bike Sharing dataset.

In [100…

```
model = LinearRegression(fit_intercept=True)
model.fit(X_train, y_train)

#Make predictions on the testing set
y_hat = model.predict(X_test)

# Plotting actual vs. predicted values
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_hat, color='blue', label='Predicted vs Actual')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--',
plt.xlabel('Actual Values (cnt_standardized)')
plt.ylabel('Predicted Values (cnt_standardized)')
plt.title('Actual vs Predicted Values - Bike Sharing Dataset (cnt_standardiz
```

```
plt.legend()
plt.show()
```




- `fit_intercept` determines where the intercept of the model is.
    - `fit_intercept=True` (default): allows the model to calculate the intercept
    - `fit_intercept=False` : forces the intercept to be zero
- `normalize` controls whether the input features were normalized before fitting the model.
    - `normalize=True` : scales each feature to have mean 0 and variance/std. dev. 1.
        - useful if data wasn't preprocessed and ensures model isn't biased by certain features
    - `normalize=False` (default): the features remain unchanged, so the regression can be affected by features with vastly different scale and biased.

# Evaluating the Model

Performance Metrics: Calculate metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R2) to evaluate the model. These metrics provide insights into the model’s predictive performance and its ability to generalize.

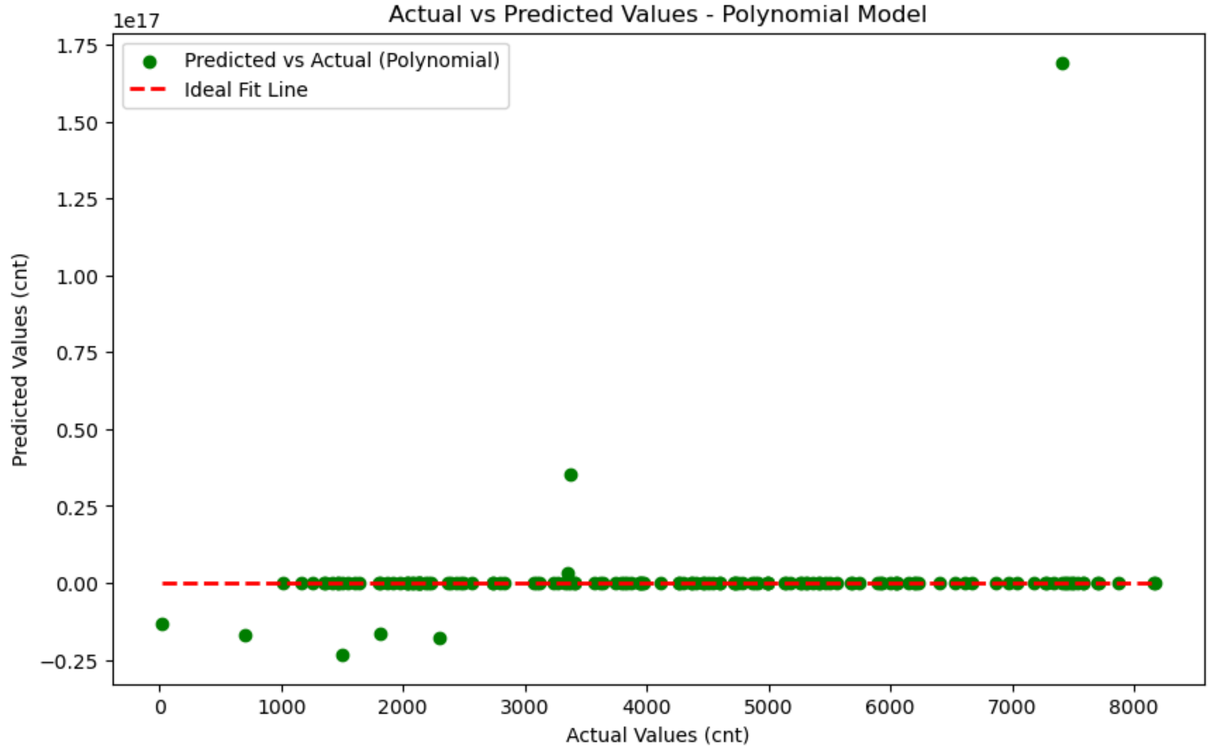
In [103…
```
mae = mean_absolute_error(y_test, y_hat)
mse = mean_squared_error(y_test, y_hat)
r2 = r2_score(y_test, y_hat)

print(f"Mean Absolute Error: {mae}")
print(f"Mean Squared Error: {mse}")
print(f"Root Mean Squared Error: {np.sqrt(mse)}")
print(f"R-squared: {r2}")
```

```
Mean Absolute Error: 581.9830117326251
Mean Squared Error: 632069.226018419
Root Mean Squared Error: 795.0278146193497
R-squared: 0.8423721245339336
```

Residual Analysis: Plot the residuals to understand the difference between the observed and predicted values.

## Polynomial Model

In [107…
```
poly_model = make_pipeline(PolynomialFeatures(degree=2), LinearRegression())
poly_model.fit(X_train, y_train)
y_train_pred_poly = poly_model.predict(X_train)
y_hat_poly = poly_model.predict(X_test)

plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_hat_poly, color='pink', label='Predicted vs Actual (Po
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--',
plt.xlabel('Actual Values (cnt)')
plt.ylabel('Predicted Values (cnt)')
plt.title('Actual vs Predicted Values - Polynomial Model')
plt.legend()
plt.show()
```




# Tuning Model Parameters (Completed in Unit 4)

- Parameter Tuning:
- Polynomial Features and Cross-Validation: Instead of *tuning fit_intercept* and *normalize* parameters, we will use polynomial features to improve our Linear Regression model. We will systematically explore different polynomial degrees to identify the degree that results in the best performance. Additionally, we will employ cross-validation to ensure that the tuning process is robust and the results are not biased by a single train-test split.
- Specific Tuning Steps:
  - Define polynomial degrees to try: `degrees = [1, 2, 3]`
  - For each degree:
    - Use PolynomialFeatures from Scikit-learn to create polynomial features.
    - Transform the training and testing data using the polynomial features.
    - Initialize and fit a LinearRegression model.
    - Perform cross-validation using cross_val_score to evaluate the model's performance.
    - Identify the degree with the best cross-validation score.
    - Refit the model with the best degree using the entire training set.

In [113…

```
# Define polynomial degrees to try
degrees = [1, 2, 3, 4]
```

```
best_score = float('-inf')
best_degree = 0
best_model = None

for degree in degrees:
    # Use PolynomialFeatures from Scikit-learn to create polynomial features
    poly_features = PolynomialFeatures(degree=degree)
    X_poly_train = poly_features.fit_transform(X_train)
    X_poly_test = poly_features.transform(X_test)

    # Initialize and fit a LinearRegression model
    model = LinearRegression()
    model.fit(X_poly_train, y_train)

    # Perform cross-validation using cross_val_score to evaluate the model's
    scores = cross_val_score(model, X_poly_train, y_train, cv=5, scoring='ne
    mean_score = scores.mean()

    # Identify the degree with the best cross-validation score
    if mean_score > best_score:
        best_score = mean_score
        best_degree = degree
        best_model = model

# Refit the model with the best degree using the entire training set
poly_features = PolynomialFeatures(degree=best_degree)
X_poly_train = poly_features.fit_transform(X_train)
best_model.fit(X_poly_train, y_train)

# Make predictions on the test set
X_poly_test = poly_features.transform(X_test)
y_hat_best = best_model.predict(X_poly_test)
```

# Evaluating the Tuned Model (Completed in Unit 4)

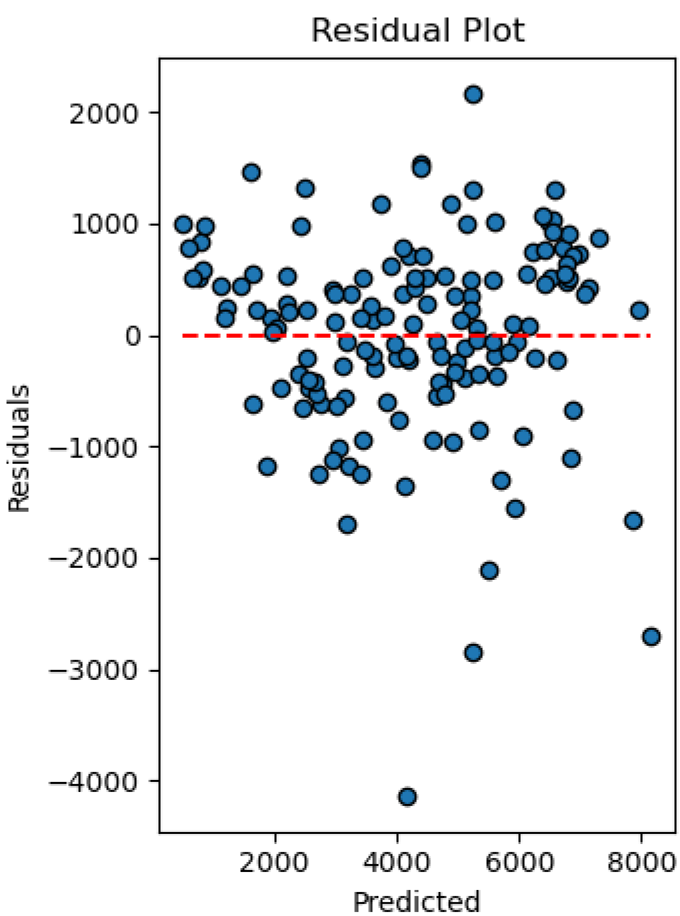
- Model Evaluation:
  - Performance Metrics: Calculate metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R2) to evaluate the model. These metrics provide insights into the model's predictive performance and its ability to generalize.
- Residual Analysis: Plot the residuals to understand the difference between the observed and predicted values.

In [114…

```
# Calculate performance metrics
mae = mean_absolute_error(y_test, y_hat_best)  # Use y_pred from the best mo
mse = mean_squared_error(y_test, y_hat_best)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_hat_best)

# Print the performance metrics
```

```
print(f"Mean Absolute Error: {mae}")
print(f"Mean Squared Error: {mse}")
print(f"Root Mean Squared Error: {rmse}")
print(f"R-squared: {r2}")

plt.subplot(1, 2, 2)
residuals = y_test - y_hat_best
plt.scatter(y_hat_best, residuals, edgecolors=(0, 0, 0))
plt.hlines(0, y_hat_best.min(), y_hat_best.max(), colors='r', linestyles='da
plt.xlabel('Predicted')
plt.ylabel('Residuals')
plt.title('Residual Plot')

plt.tight_layout()
plt.show()
```

```
Mean Absolute Error: 655.648741845371
Mean Squared Error: 765250.7633467517
Root Mean Squared Error: 874.7861243451176
R-squared: 0.8091587961258868
```




## Visualizing Results (Completed in Units 4 and 6)

In [ ]:
```
#Insert Code Here
```