

```
In [40]: import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
import numpy as np
from sklearn.linear_model import LassoCV
from scipy import stats
import seaborn as sns

In [41]: df = pd.read_csv("C:/Users/gundr/Downloads/Civil_Engineering_Regression_Dataset.csv")

In [44]: X = df.drop(columns=["Project_ID", "Construction_Cost"]) # Exclude ID and target variable
Y = df["Construction_Cost"]

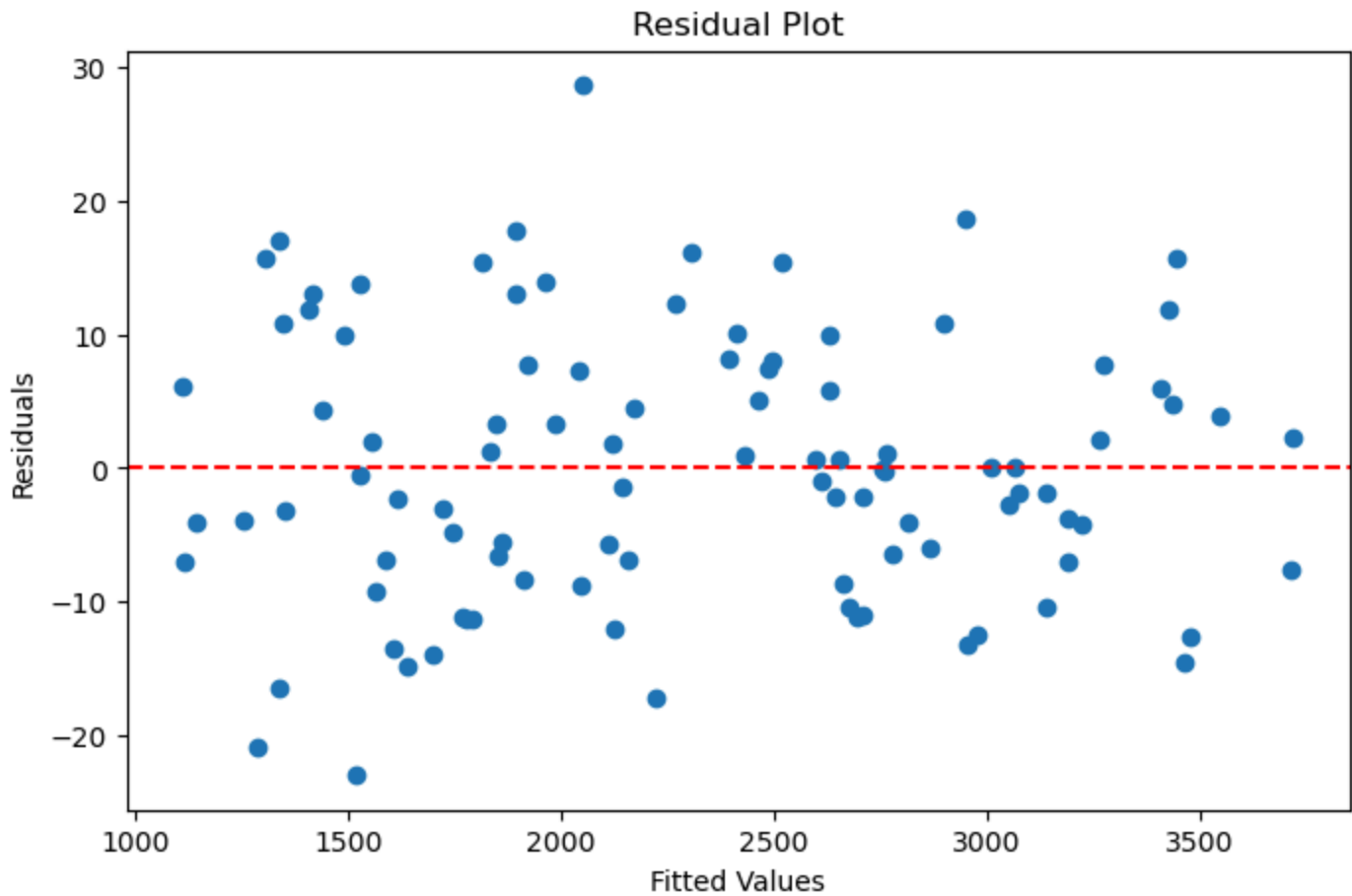
In [46]: lasso = LassoCV(cv=5).fit(X, Y)
selected_features = X.columns[lasso.coef_ != 0]
X_selected = X[selected_features]
X_selected = sm.add_constant(X_selected)

In [48]: model = sm.OLS(Y, X_selected).fit()

In [50]: print(model.summary())
```

| OLS Regression Results | | | | | | |
|---|-------------------|---------------------|---------|-----------|---------|--------|
| ===== | | | | | | |
| Dep. Variable: | Construction_Cost | R-squared: | | 1.000 | | |
| Model: | OLS | Adj. R-squared: | | 1.000 | | |
| Method: | Least Squares | F-statistic: | | 9.153e+04 | | |
| Date: | Wed, 12 Feb 2025 | Prob (F-statistic): | | 1.23e-171 | | |
| Time: | 22:42:03 | Log-Likelihood: | | -372.31 | | |
| No. Observations: | 100 | AIC: | | 756.6 | | |
| Df Residuals: | 94 | BIC: | | 772.3 | | |
| Df Model: | 5 | | | | | |
| Covariance Type: | nonrobust | | | | | |
| ===== | | | | | | |
| | coef | std err | t | P> t | [0.025 | 0.975] |
| ----- | | | | | | |
| const | -15.2800 | 6.217 | -2.458 | 0.016 | -27.624 | -2.935 |
| Building_Height | 49.8898 | 0.079 | 628.588 | 0.000 | 49.732 | 50.047 |
| Material_Quality_Index | 10.6560 | 0.519 | 20.541 | 0.000 | 9.626 | 11.686 |
| Labor_Cost | 0.5191 | 0.015 | 33.818 | 0.000 | 0.489 | 0.550 |
| Concrete_Strength | 20.3084 | 0.115 | 177.325 | 0.000 | 20.081 | 20.536 |
| Foundation_Depth | 30.0042 | 0.432 | 69.423 | 0.000 | 29.146 | 30.862 |
| ===== | | | | | | |
| Omnibus: | 1.217 | Durbin-Watson: | | 1.762 | | |
| Prob(Omnibus): | 0.544 | Jarque-Bera (JB): | | 1.258 | | |
| Skew: | 0.186 | Prob(JB): | | 0.533 | | |
| Kurtosis: | 2.596 | Cond. No. | | 1.23e+03 | | |
| ===== | | | | | | |
| Notes: | | | | | | |
| [1] Standard Errors assume that the covariance matrix of the errors is correctly specified | | | | | | |
| [2] The condition number is large, 1.23e+03. This might indicate that there are strong multicollinearity or other numerical problems. | | | | | | |

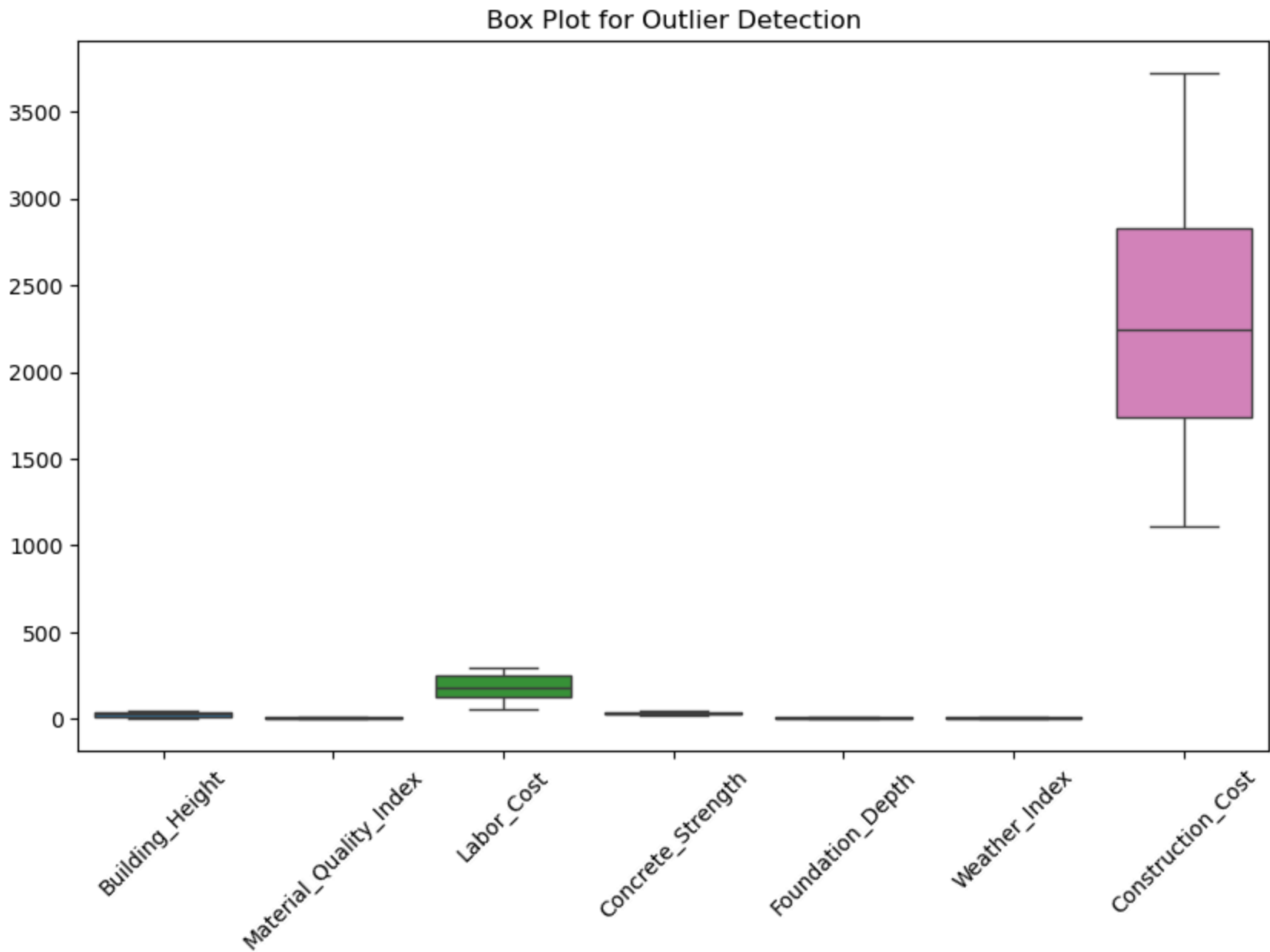
```
In [52]: plt.figure(figsize=(8,5))
plt.scatter(model.fittedvalues, model.resid)
plt.axhline(y=0, color='r', linestyle='--')
plt.xlabel("Fitted Values")
plt.ylabel("Residuals")
plt.title("Residual Plot")
plt.show()
```



```
In [54]: z_scores = np.abs(stats.zscore(df.drop(columns=["Project_ID"])))
outliers = (z_scores > 3).any(axis=1)
print(f"Number of outliers detected: {outliers.sum()}")
```

Number of outliers detected: 0

```
In [56]: plt.figure(figsize=(10,6))
sns.boxplot(data=df.drop(columns=["Project_ID"]))
plt.xticks(rotation=45)
plt.title("Box Plot for Outlier Detection")
plt.show()
```



```
In [58]: print("\nModel Deployment Considerations:")
print("- Integrate real-time material and labor cost updates.")
print("- Incorporate location-based economic factors.")
print("- Utilize cloud-based APIs for dynamic cost estimation.")
```

Model Deployment Considerations:

- Integrate real-time material and labor cost updates.
- Incorporate location-based economic factors.
- Utilize cloud-based APIs for dynamic cost estimation.

```
In [60]: print("\nEthical Considerations & Decision Making:")
print("- Overestimating costs may deter project investments.")
print("- Underestimating costs can lead to financial losses and project delays.")
print("- Accurate cost models enhance project safety by ensuring proper resource allocation.")
```

Ethical Considerations & Decision Making:

- Overestimating costs may deter project investments.
- Underestimating costs can lead to financial losses and project delays.
- Accurate cost models enhance project safety by ensuring proper resource allocation.

