```
# Install necessary packages
!pip install statsmodels openpyxl scipy matplotlib seaborn

# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_percentage_error, r2_score
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from statsmodels.stats.stattools import durbin_watson
from statsmodels.stats.diagnostic import het_goldfeldquandt
from scipy.stats import bartlett
```

```
Requirement already satisfied: statsmodels in /usr/local/lib/python3.11/dist-packages (0.14.4)
Requirement already satisfied: openpyxl in /usr/local/lib/python3.11/dist-packages (3.1.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (1.15.3)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (3.10.0)
Requirement already satisfied: seaborn in /usr/local/lib/python3.11/dist-packages (0.13.2)
Requirement already satisfied: numpy<3,>=1.22.3 in /usr/local/lib/python3.11/dist-packages (from statsmodels) (2.0.2)
Requirement already satisfied: pandas!=2.1.0,>=1.4 in /usr/local/lib/python3.11/dist-packages (from statsmodels) (2.2.2)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.11/dist-packages (from statsmodels) (1.0.1)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.11/dist-packages (from statsmodels) (24.2)
Requirement already satisfied: et-xmlfile in /usr/local/lib/python3.11/dist-packages (from openpyxl) (2.0.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (4.58.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (1.4.8)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (11.2.1)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas!=2.1.0,>=1.4->statsmodels) (2025
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas!=2.1.0,>=1.4->statsmodels) (20
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matplotlib) (1.17.0)
```

```
from google.colab import files
uploaded = files.upload()
```

Choose files Data for Case Study.xlsx

- **Data for Case Study.xlsx**(application/vnd.openxmlformats-officedocument.spreadsheetml.sheet) - 980507 bytes, last modified: 12/05/2025 - 100% done

```
# Load data
file_path = '/content/Data for Case Study.xlsx'  # Update this path in Colab
df = pd.read_excel(file_path)
```

```
df.head()
```

	Order ID	Name	Category	Sub Category	City	Order Date	Region	State	Sales	Discount	Profit
0	OD1	James	Frozen Foods	Ice Cream	Houston	2019-08-11 00:00:00	North	Texas	44882.684644	0.344161	10816.370636
1	OD2	John	Personal Care	Shampoo	Dallas	2019-08-11 00:00:00	South	Texas	39178.119470	0.307477	8306.974288
2	OD3	William	Baby Care	Baby Formula	Austin	2019-12-06 00:00:00	West	Texas	60843.752663	0.351436	14129.644123

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
# Basic Info
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Order ID      9994 non-null   object
 1   Name          9994 non-null   object
 2   Category      9994 non-null   object
 3   Sub Category  9994 non-null   object
 4   City          9994 non-null   object
 5   Order Date    9994 non-null   object
 6   Region        9994 non-null   object
 7   State         9994 non-null   object
 8   Sales         9994 non-null   float64
 9   Discount      9994 non-null   float64
 10  Profit        9994 non-null   float64
dtypes: float64(3), object(8)
memory usage: 859.0+ KB
```

	Sales	Discount	Profit
count	9994.000000	9994.000000	9994.000000
mean	50730.359420	0.273465	10270.835211
std	10945.859065	0.067854	2593.158935
min	10000.000000	0.010000	1000.000000
25%	43405.590005	0.228057	8539.296680
50%	50767.571421	0.273506	10287.824893
75%	58060.835275	0.319310	12014.393055
max	100000.000000	0.500000	20000.000000

```
# Check for missing values
df.isnull().sum()
```

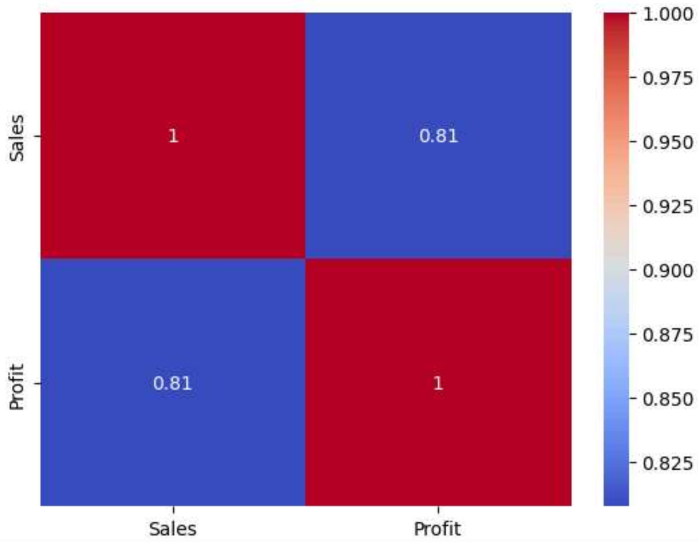
	0
Order ID	0
Name	0
Category	0
Sub Category	0
City	0
Order Date	0
Region	0
State	0
Sales	0
Discount	0
Profit	0

dtype: int64

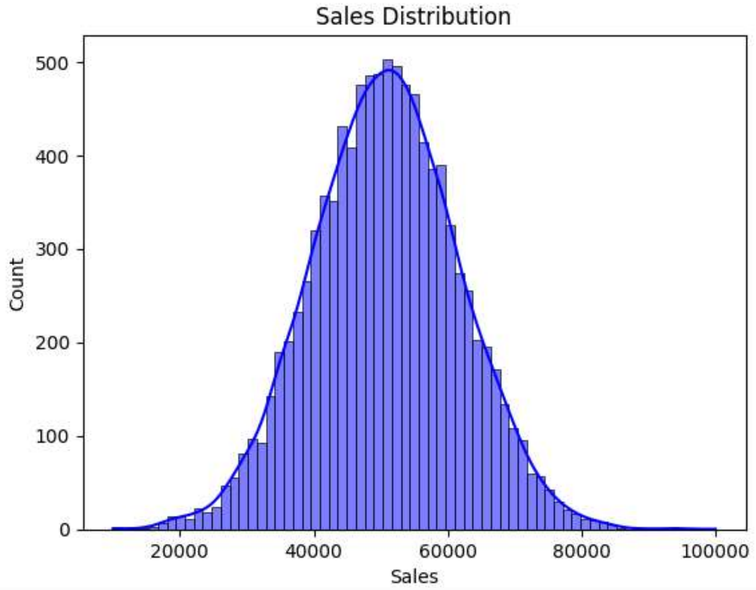
```
# Plot Sales vs Profit
plt.figure(figsize=(8, 6))
sns.scatterplot(data=df, x='Sales', y='Profit',color='green', alpha=0.7, marker='o')
plt.title("Sales vs Profit")
plt.xlabel("Sales")
plt.ylabel("Profit")
plt.grid(True)
plt.show()
```


```
# Correlation
print("Correlation between Sales and Profit:", df['Sales'].corr(df['Profit']))
sns.heatmap(df[['Sales', 'Profit']].corr(), annot=True, cmap='coolwarm')
plt.show()
```

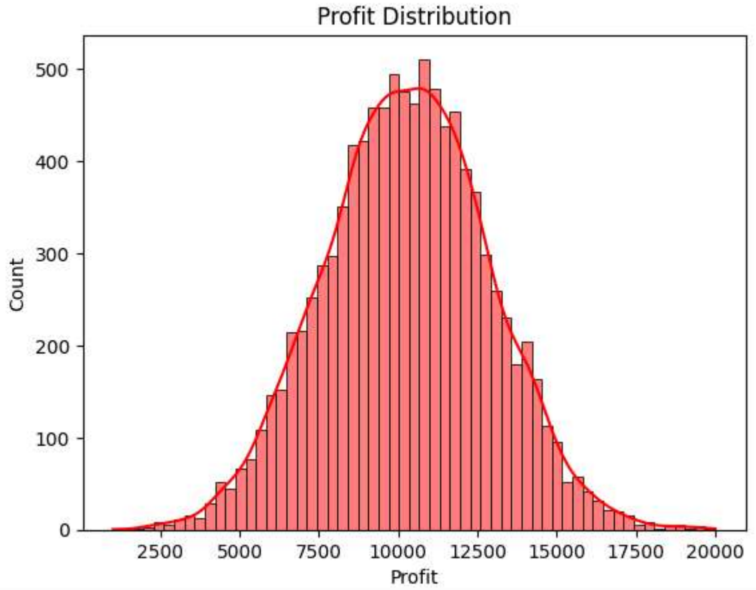
```
Correlation between Sales and Profit: 0.8075448975628339
```




```
# Distribution plots of Sales
sns.histplot(df['Sales'], kde=True, color='blue', edgecolor='black')
plt.title("Sales Distribution")
plt.show()
```




```
# Distribution plots of Profit
sns.histplot(df['Profit'], kde=True, color='red', edgecolor='black')
plt.title("Profit Distribution")
plt.show()
```




```
# Removing Outlier
from scipy.stats import zscore

df_filtered = df[(np.abs(zscore(df[['Sales', 'Profit']])) < 3).all(axis=1)]


print("Original dataset size:", df.shape)
print("Filtered dataset size:", df_filtered.shape)
```

```
Original dataset size: (9994, 11)
Filtered dataset size: (9948, 11)
```

```
# Define X and y
X = df_filtered[['Sales']]
y = df_filtered['Profit']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Fit model
lr = LinearRegression()
lr.fit(X_train, y_train)

# Predict
y_pred = lr.predict(X_test)
```

```
# Evaluate
r2_simple = r2_score(y_test, y_pred)
mape_simple = mean_absolute_percentage_error(y_test, y_pred)

print(f"Filtered Linear Regression R²: {r2_simple:.4f}")
print(f"Filtered Linear Regression MAPE: {mape_simple:.4f}")
```

```
Filtered Linear Regression R²: 0.6543
Filtered Linear Regression MAPE: 0.1296
```

```
#Durbin-Watson Test
X_const = sm.add_constant(X_train)
model = sm.OLS(y_train, X_const).fit()
residuals = model.resid

dw = durbin_watson(residuals)
print(f"Durbin-Watson Statistic: {dw:.4f}")
```

```
Durbin-Watson Statistic: 1.9618
```

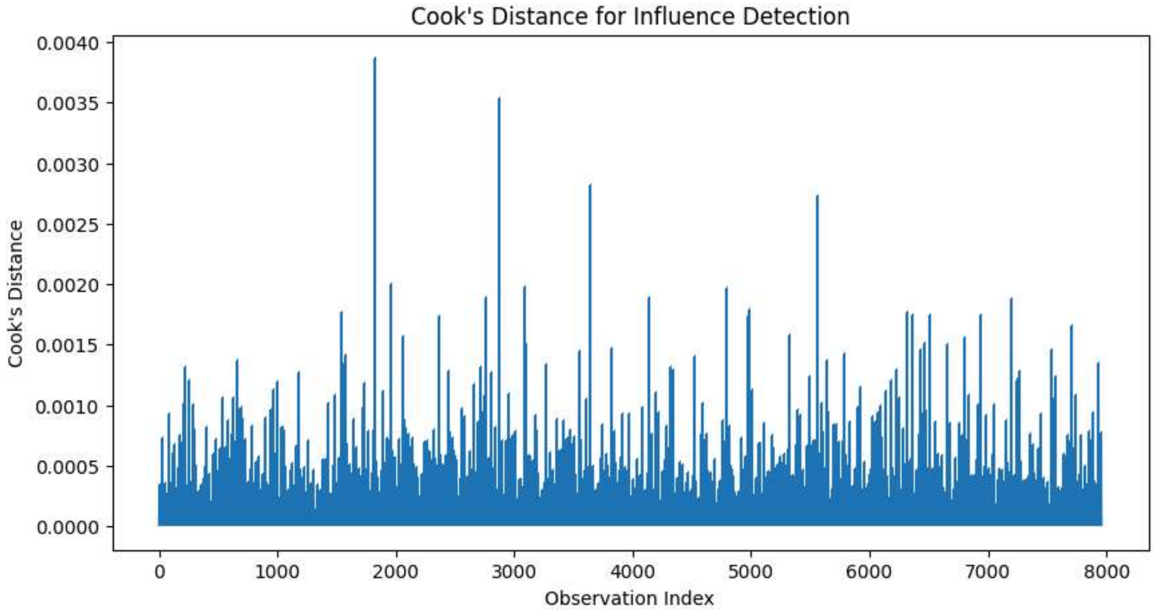
```
# Goldfeld-Quandt Test
gq_test = het_goldfeldquandt(y_train, X_const)
print("\nGoldfeld-Quandt p-value:", gq_test[1])

# Interpretation
if gq_test[1] < 0.05:
    print("→ Heteroscedasticity detected (reject null hypothesis of equal variance)")
else:
    print("→ No evidence of heteroscedasticity (fail to reject null hypothesis)")
```

```

Goldfeld-Quandt p-value: 0.5399972378108977
→ No evidence of heteroscedasticity (fail to reject null hypothesis)
```

```
# Divide residuals into two groups: low and high sales
median_sales = X_train['Sales'].median()
group1 = residuals[X_train['Sales'] <= median_sales]
group2 = residuals[X_train['Sales'] > median_sales]

bartlett_test = bartlett(group1, group2)
print(f"Bartlett Test Statistic: {bartlett_test.statistic:.4f}, p-value: {bartlett_test.pvalue:.4f}")
```

```
Bartlett Test Statistic: 0.0291, p-value: 0.8646
```

```
influence = model.get_influence()
cooks = influence.cooks_distance[0]

# Plot Cook's Distance
plt.figure(figsize=(10, 5))
plt.stem(np.arange(len(cooks)), cooks, markerfmt=",", basefmt=" ")
plt.title("Cook's Distance for Influence Detection")
plt.xlabel("Observation Index")
plt.ylabel("Cook's Distance")
plt.show()

# Show influential points
influential_points = np.where(cooks > 4 / len(X_train))[0]
print("Influential Point Indexes:", influential_points)
```




```
Influential Point Indexes: [  29   84  120  124  125  174  183  206  209  216  220  248  251  288
  301  393  403  457  475  508  538  556  582  597  607  617  621  625
  643  650  653  667  689  700  727  783  816  840  891  894  940  945
  967  982  995  996 1034 1037 1047 1050 1125 1152 1172 1178 1251 1257
 1380 1406 1428 1429 1476 1485 1519 1541 1556 1571 1572 1577 1583 1584
 1602 1642 1658 1662 1721 1734 1735 1736 1770 1807 1812 1816 1836 1884
 1888 1901 1921 1933 1954 1969 1978 1984 1988 2024 2047 2055 2058 2069
 2072 2084 2102 2118 2120 2132 2141 2153 2239 2250 2266 2267 2273 2282
 2304 2316 2317 2330 2350 2362 2368 2369 2389 2413 2414 2439 2443 2448
 2471 2474 2476 2485 2500 2514 2560 2577 2578 2621 2622 2627 2657 2693
 2717 2720 2727 2750 2755 2777 2809 2835 2870 2889 2926 2945 2951 2971
 2972 2983 2984 3003 3086 3095 3103 3123 3128 3151 3173 3179 3192 3269
 3271 3306 3362 3373 3384 3397 3417 3419 3434 3448 3475 3476 3483 3507
 3544 3546 3553 3564 3607 3635 3728 3742 3744 3779 3819 3836 3839 3859
 3904 3905 3963 4030 4081 4136 4162 4193 4207 4215 4271 4280 4311 4318
 4335 4344 4398 4413 4515 4516 4580 4591 4592 4610 4621 4687 4762 4782
 4786 4809 4817 4913 4917 4946 4971 4979 4982 5002 5066 5069 5072 5109
 5175 5186 5221 5248 5258 5270 5272 5300 5314 5316 5321 5376 5377 5392
 5412 5413 5471 5487 5495 5510 5531 5547 5551 5558 5561 5585 5591 5601
 5634 5647 5693 5699 5705 5713 5740 5772 5789 5794 5831 5833 5836 5895
 5898 5899 5906 5911 5912 5916 5954 6020 6041 6067 6089 6105 6138 6175
 6178 6222 6227 6235 6244 6277 6295 6316 6336 6346 6362 6365 6423 6426
 6438 6440 6448 6466 6471 6505 6556 6569 6581 6607 6658 6672 6674 6725
 6757 6777 6788 6798 6810 6829 6831 6837 6908 6913 6919 6932 6979 7038
 7045 7046 7149 7159 7196 7199 7246 7252 7261 7266 7279 7350 7372 7377
 7419 7431 7449 7538 7546 7556 7569 7635 7637 7649 7673 7695 7698 7702
```

```python
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline

# Remove outliers using Cook's Distance
threshold = 4 / len(X_train)
mask = cooks < threshold
X_train_filtered = X_train[mask]
y_train_filtered = y_train[mask]

# Create a pipeline with Polynomial Features (degree 2) + Linear Regression
poly_model = make_pipeline(PolynomialFeatures(degree=2), LinearRegression())

# Fit on filtered data
poly_model.fit(X_train_filtered, y_train_filtered)

# Predict on test set
y_pred_poly = poly_model.predict(X_test)

# Evaluation
r2_poly = r2_score(y_test, y_pred_poly)
mape_poly = mean_absolute_percentage_error(y_test, y_pred_poly)

print(f"Polynomial Regression (degree=2) R²: {r2_poly:.4f}")
print(f"Polynomial Regression (degree=2) MAPE: {mape_poly:.4f}")
```

```
Polynomial Regression (degree=2) R²: 0.6543
Polynomial Regression (degree=2) MAPE: 0.1296
```

```
# Add small constant to avoid log(0)
df['log_Sales'] = np.log1p(df['Sales'])
df['log_Profit'] = np.log1p(df['Profit'])

# Redefine X and y
X_log = df[['log_Sales']]
y_log = df['log_Profit']

# Split
X_train_log, X_test_log, y_train_log, y_test_log = train_test_split(X_log, y_log, test_size=0.2, random_state=42)

# Fit model
log_model = LinearRegression()
log_model.fit(X_train_log, y_train_log)

# Predict
y_pred_log = log_model.predict(X_test_log)

# Back-transform predictions
y_pred_actual = np.expm1(y_pred_log)
y_test_actual = np.expm1(y_test_log)

# Evaluate
r2_log = r2_score(y_test_actual, y_pred_actual)
mape_log = mean_absolute_percentage_error(y_test_actual, y_pred_actual)

print(f"Log-Transformed Model R²: {r2_log:.4f}")
print(f"Log-Transformed Model MAPE: {mape_log:.4f}")
```

```
Log-Transformed Model R²: 0.6424
Log-Transformed Model MAPE: 0.1348
```

```
# First, check for actual column names
print(df_filtered.columns)

# Strip trailing spaces from all column names
df_filtered.columns = df_filtered.columns.str.strip()
```

```
Index(['Order ID', 'Name', 'Category', 'Sub Category ', 'City', 'Order Date',
       'Region', 'State', 'Sales', 'Discount ', 'Profit'],
      dtype='object')
```

```
# Feature columns
feature_cols = ['Sales', 'Discount'] + \
               [col for col in df_filtered.columns if col.startswith('Category_') or col.startswith('Region_')]

X = df_filtered[feature_cols]
y = df_filtered['Profit']

# Train-test split
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_absolute_percentage_error

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Fit model
model = LinearRegression()
model.fit(X_train, y_train)

# Predict and evaluate
y_pred = model.predict(X_test)
r2_multi = r2_score(y_test, y_pred)
mape_multi = mean_absolute_percentage_error(y_test, y_pred)

print(f"Multiple Linear Regression R²: {r2_multi:.4f}")
print(f"Multiple Linear Regression MAPE: {mape_multi:.4f}")
```

```
Multiple Linear Regression R²: 0.9853
Multiple Linear Regression MAPE: 0.0260
```

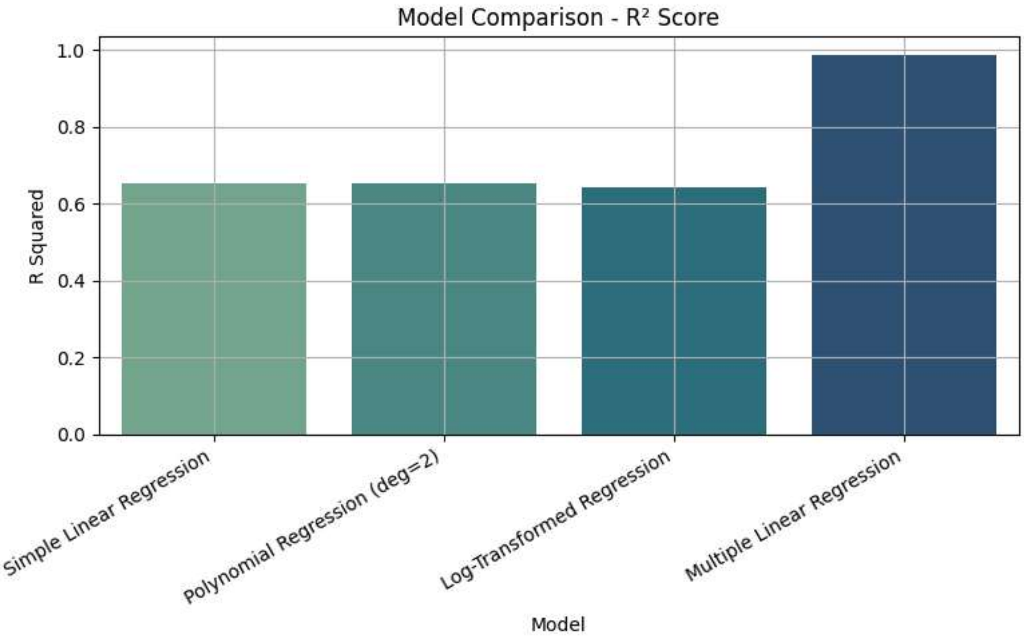
```
# Create summary dataframe
results = pd.DataFrame({
    'Model': [
        'Simple Linear Regression',
        'Polynomial Regression (deg=2)',
```

```
        'Log-Transformed Regression',
        'Multiple Linear Regression'
    ],
    'R²': [r2_simple, r2_poly, r2_log, r2_multi],
    'MAPE': [mape_simple, mape_poly, mape_log, mape_multi]
})

# Display
print(results)
```

```
                          Model        R²      MAPE
0       Simple Linear Regression  0.654349  0.129587
1  Polynomial Regression (deg=2)  0.654295  0.129578
2     Log-Transformed Regression  0.642439  0.134841
3     Multiple Linear Regression  0.985282  0.025964
```

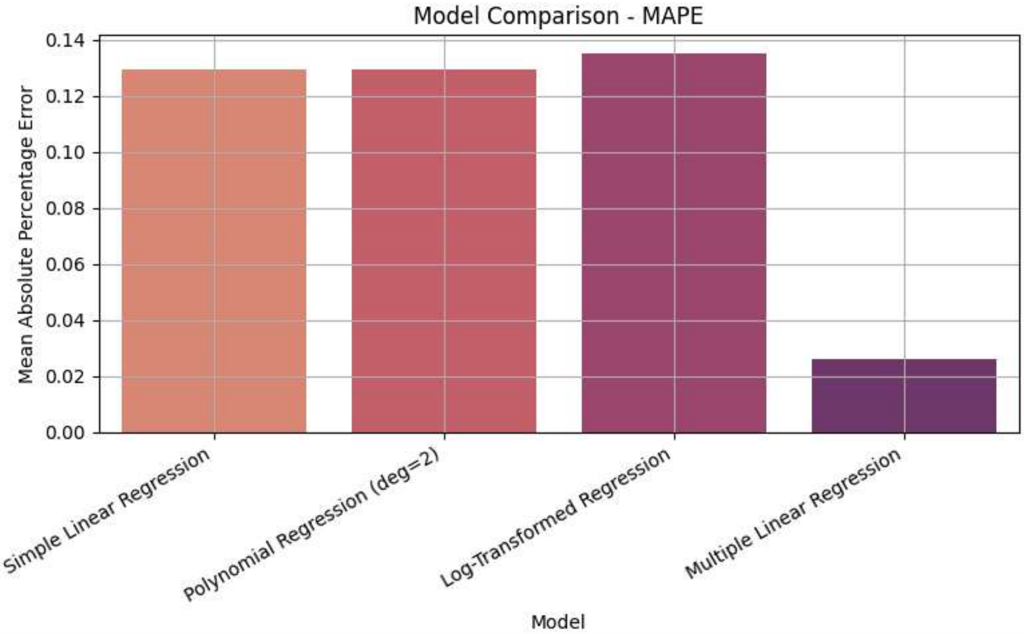
```
plt.figure(figsize=(8, 5))
sns.barplot(data=results, x='Model', y='R²', palette='crest')
plt.title('Model Comparison - R² Score')
plt.xticks(rotation=30, ha='right')
plt.ylabel('R Squared')
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
<ipython-input-48-c2e98864e2db>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `le

  sns.barplot(data=results, x='Model', y='R²', palette='crest')
```




```
plt.figure(figsize=(8, 5))
sns.barplot(data=results, x='Model', y='MAPE', palette='flare')
plt.title('Model Comparison - MAPE')
plt.xticks(rotation=30, ha='right')
plt.ylabel('Mean Absolute Percentage Error')
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
<ipython-input-49-caca8a3fa184>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `le

  sns.barplot(data=results, x='Model', y='MAPE', palette='flare')
```




```
# Get feature names and their coefficients
feature_importance = pd.DataFrame({
    'Feature': X.columns,
    'Coefficient': model.coef_
})

# Sort by absolute value
feature_importance['Abs_Coeff'] = feature_importance['Coefficient'].abs()
feature_importance = feature_importance.sort_values(by='Abs_Coeff', ascending=False)

# Plot
plt.figure(figsize=(10, 6))
sns.barplot(data=feature_importance, x='Abs_Coeff', y='Feature', palette='viridis')
plt.title("Feature Importance (Based on Coefficients)")
plt.xlabel("Absolute Coefficient Value")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```

```
<ipython-input-50-9c68a6bb4d15>:13: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `le

  sns.barplot(data=feature_importance, x='Abs_Coeff', y='Feature', palette='viridis')
```

Feature Importance (Based on Coefficients)

```
# Calculate residuals
residuals = y_test - y_pred

# Histogram of residuals
plt.figure(figsize=(8, 4))
sns.histplot(residuals, bins=30, kde=True, color='red')
plt.title("Residual Distribution")
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.grid(True)
plt.show()

# Residuals vs. Predicted
plt.figure(figsize=(8, 5))
sns.scatterplot(x=y_pred, y=residuals)
plt.axhline(0, color='red', linestyle='--')
plt.title("Residuals vs. Predicted Values")
plt.xlabel("Predicted Profit")
plt.ylabel("Residuals")
plt.grid(True)
plt.show()
```