saumit-aiml-assessment

May 12, 2024

1 Saumit-AIML-Assessment

1.1 Saumit Kunder

1.2 21070126078

1.3 AIML -B1

2 Libraries

[58]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
```

3 DATASET

[26]:
```
train_df = pd.read_excel("./traindataset.xlsx")
```

[27]:
```
train_df
```

[27]:
```
       ProductType Manufacturer Area Code Sourcing Channel Product Size  \
0             NTM3           X1       A28        WHOLESALE        Large
1             NTM2           X1        A9           DIRECT        Large
2             NTM3           X2       A20           DIRECT        Large
3             NTM3           X1       A18        WHOLESALE        Small
4             NTM2           X1       A28           DIRECT        Large
…                …            …         …                …            …
550171        NTM2           X1        A5           DIRECT        Large
550172        NTM3           X1       A14           DIRECT        Large
550173        NTM2           X1        A5           DIRECT        Small
550174        NTM2           X1        A7           DIRECT        Small
```

```
550175         NTM1           X1        A3           DIRECT         Small

       Product Type Month of Sourcing  Sourcing Cost
0            Powder        2021-05-01         10.158
1            Powder        2020-10-01        134.281
2            Powder        2020-12-01         12.456
3            Powder        2021-02-01        107.220
4            Liquid        2020-11-01        197.763
…             …              …            …
550171       Powder        2020-07-01        136.469
550172       Liquid        2020-10-01         72.559
550173       Powder        2021-03-01        147.639
550174       Powder        2021-02-01        150.044
550175       Powder        2020-11-01        139.421

[550176 rows x 8 columns]
```

[28]:
```
train_df.isnull().sum()
```

[28]:
```
ProductType          0
Manufacturer         0
Area Code            0
Sourcing Channel     0
Product Size         0
Product Type         0
Month of Sourcing    0
Sourcing Cost        0
dtype: int64
```

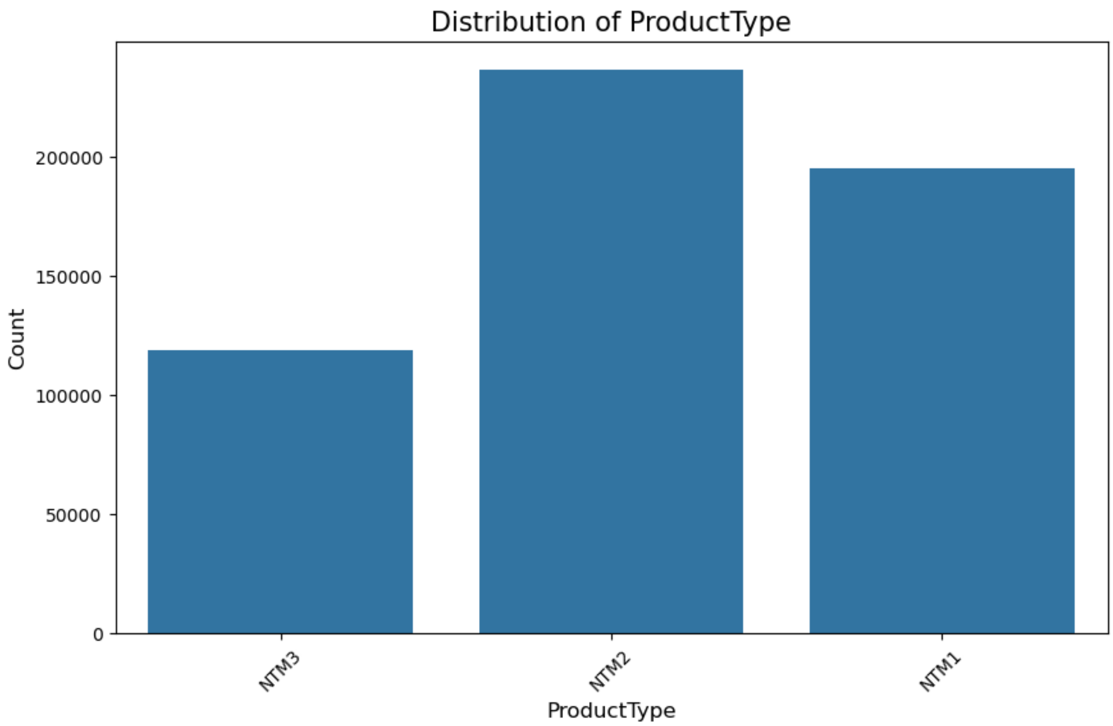
[29]:
```
train_df.dtypes
```

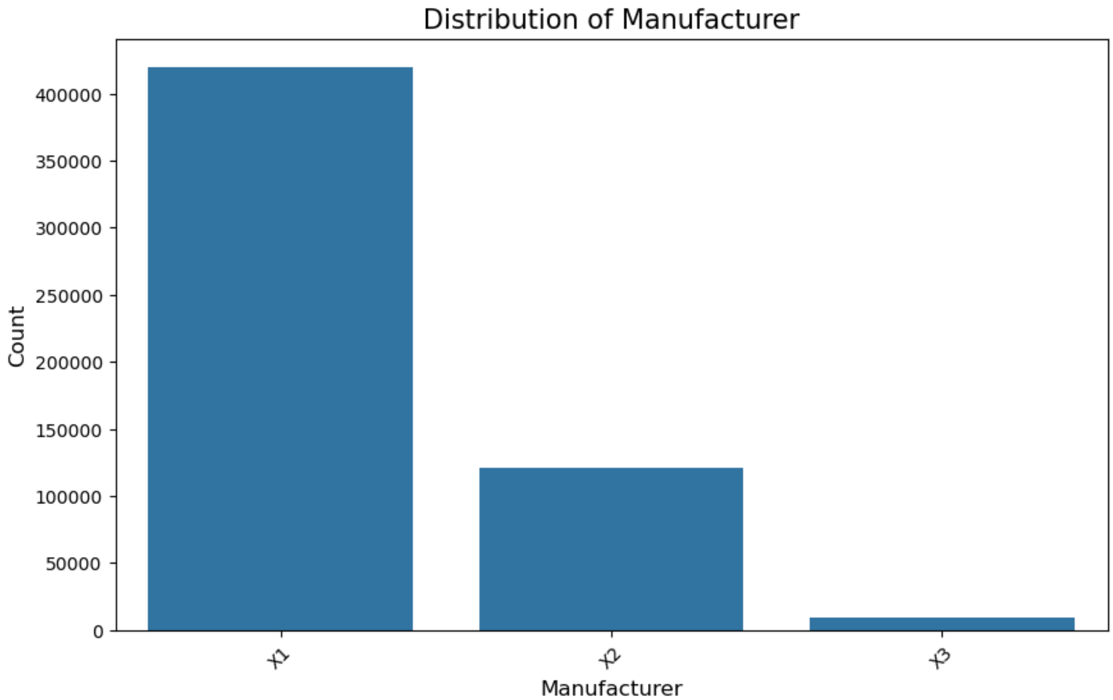
[29]:
```
ProductType                  object
Manufacturer                 object
Area Code                    object
Sourcing Channel             object
Product Size                 object
Product Type                 object
Month of Sourcing    datetime64[ns]
Sourcing Cost               float64
dtype: object
```

[30]:
```
test_df=pd.read_excel("./testdata.xlsx")
```

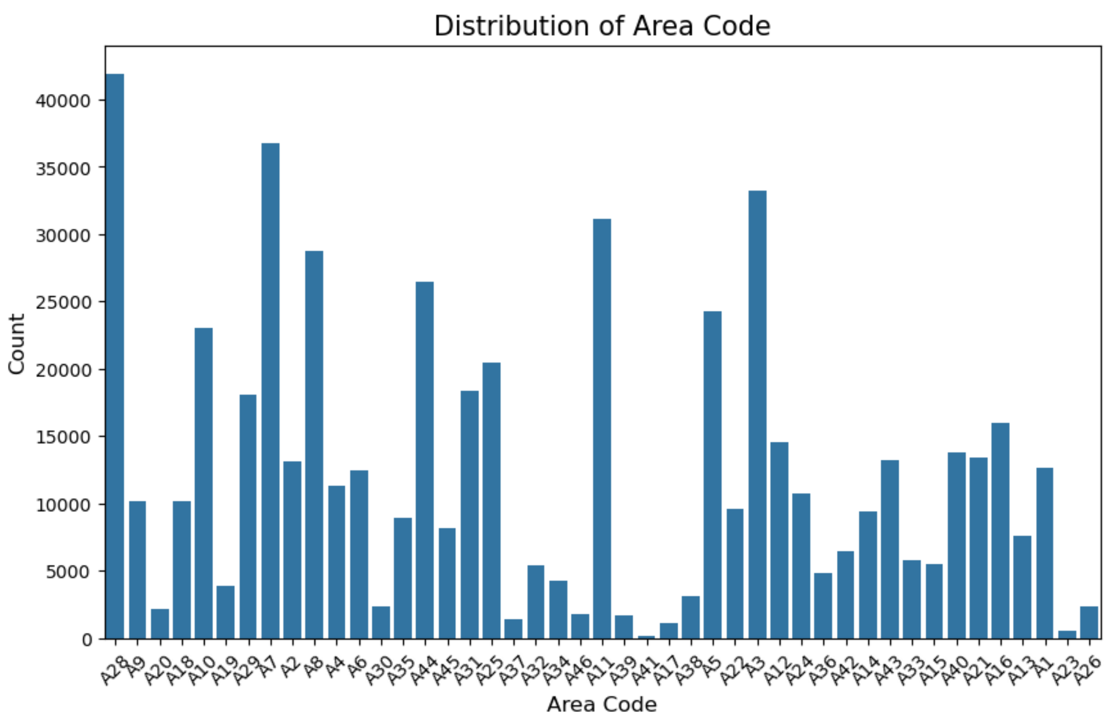
4 EDA

[39]:
```
# List of categorical columns
categorical_columns = ['ProductType', 'Manufacturer', 'Area Code', 'Sourcing␣
↪Channel', 'Product Size']

# Plot count plots for each categorical feature
for feature in categorical_columns:
    plt.figure(figsize=(10, 6))
    sns.countplot(x=feature, data=train_df)
    plt.title(f'Distribution of {feature}', fontsize=15)
    plt.xlabel(feature, fontsize=12)
    plt.ylabel('Count', fontsize=12)
    plt.xticks(rotation=45)
    plt.show()
```

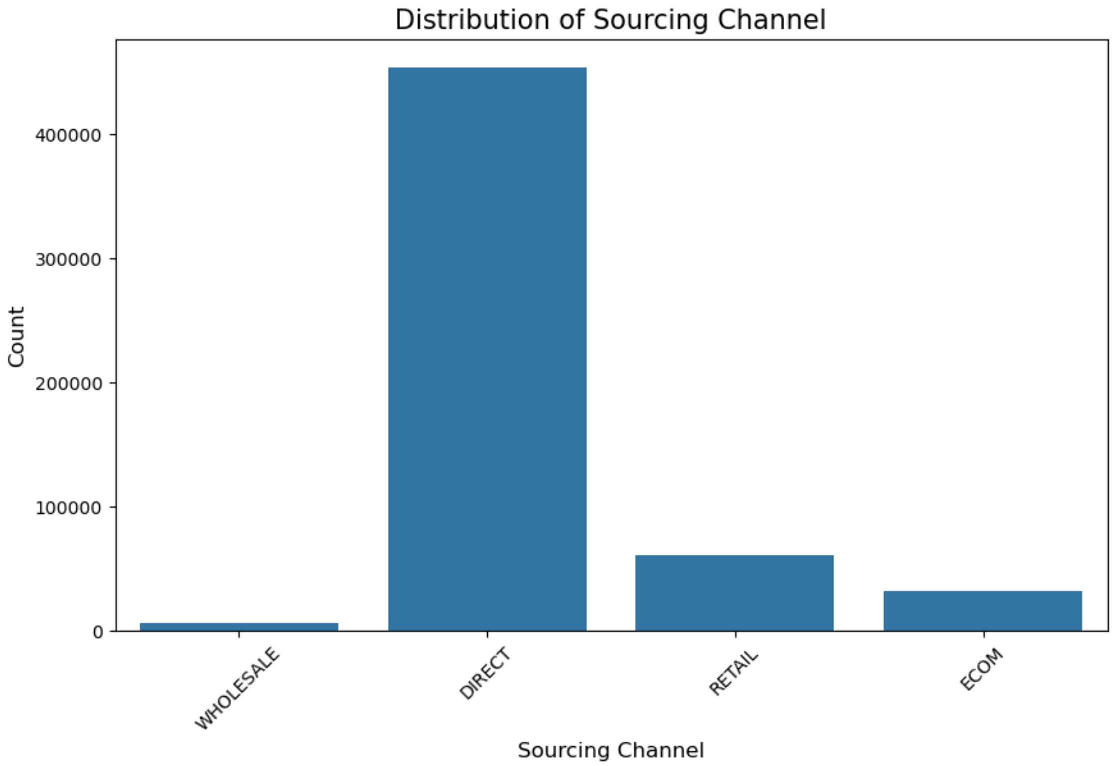


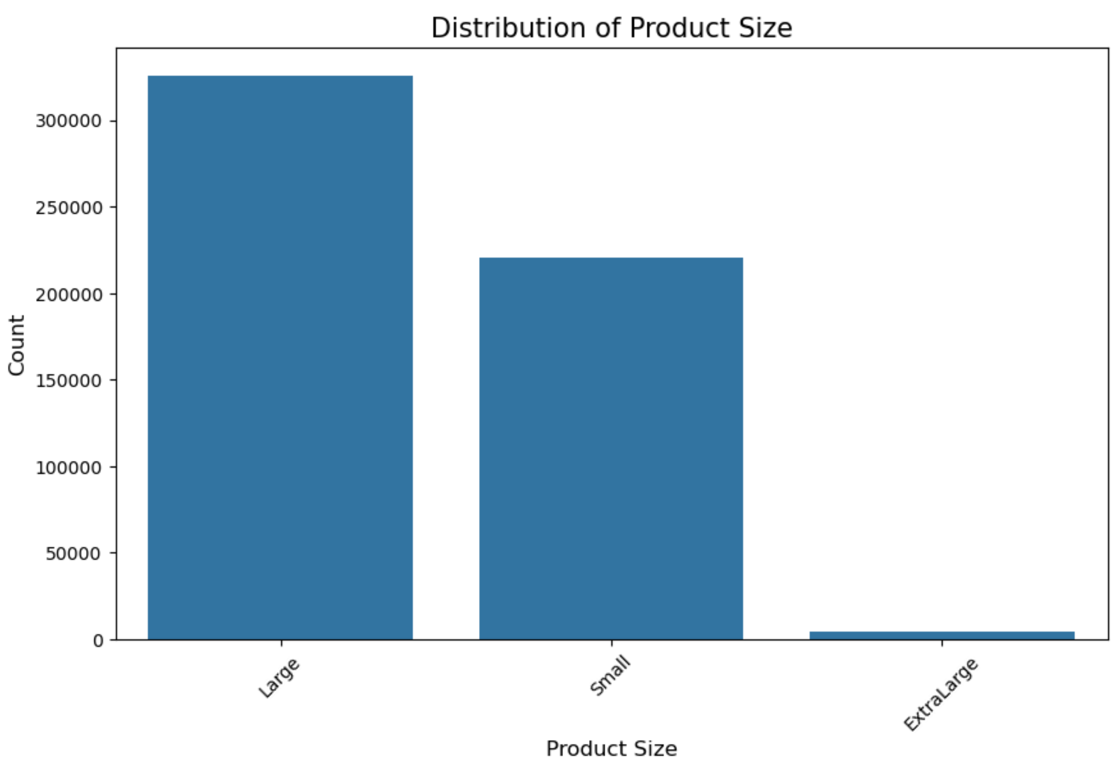


Distribution of Manufacturer
Count
0
50000
100000
150000
200000
250000
300000
350000
400000
X1
X2
X3
Manufacturer

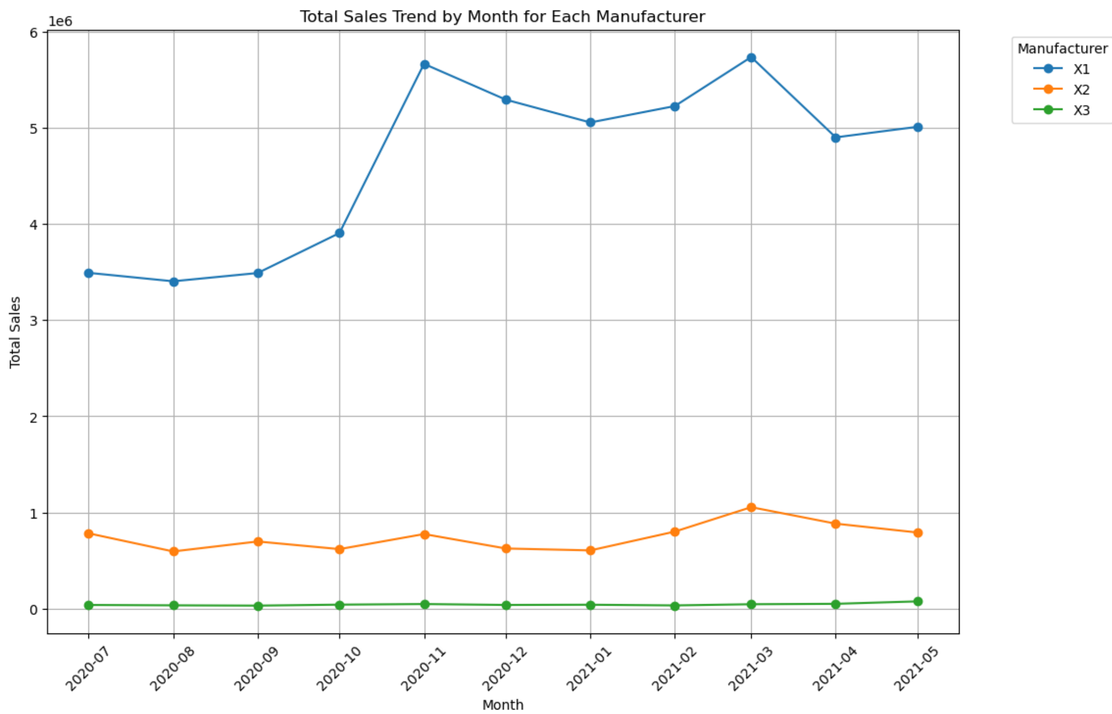


Distribution of Area Code
Count
0
5000
10000
15000
20000
25000
30000
35000
40000
A28 A9 A20 A18 A10 A19 A29 A7 A2 A8 A4 A6 A30 A35 A44 A45 A31 A25 A37 A32 A34 A46 A11 A39 A41 A17 A38 A5 A22 A3 A12 A24 A36 A42 A14 A43 A33 A15 A40 A21 A16 A13 A1 A23 A26
Area Code


Distribution of Sourcing Channel
Count
400000
300000
200000
100000
0
WHOLESALE
DIRECT
RETAIL
ECOM
Sourcing Channel

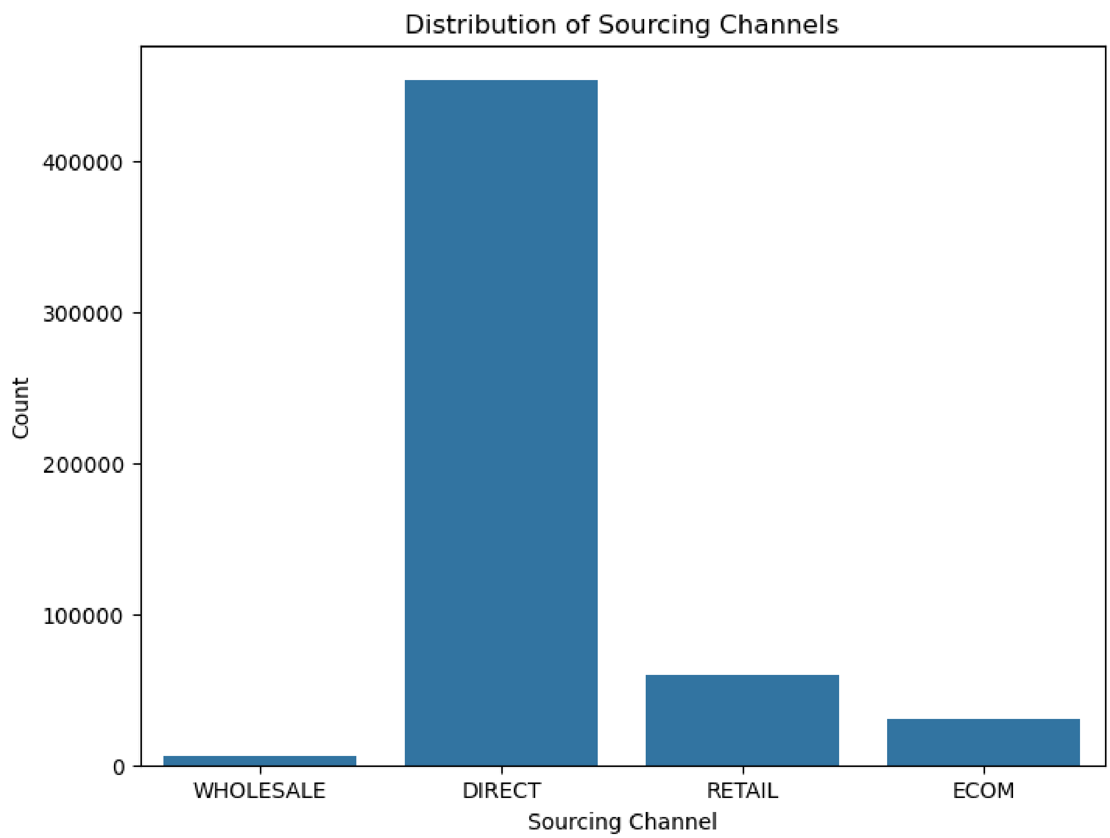

Distribution of Product Size
Count
300000
250000
200000
150000
100000
50000
0
Large
Small
ExtraLarge
Product Size

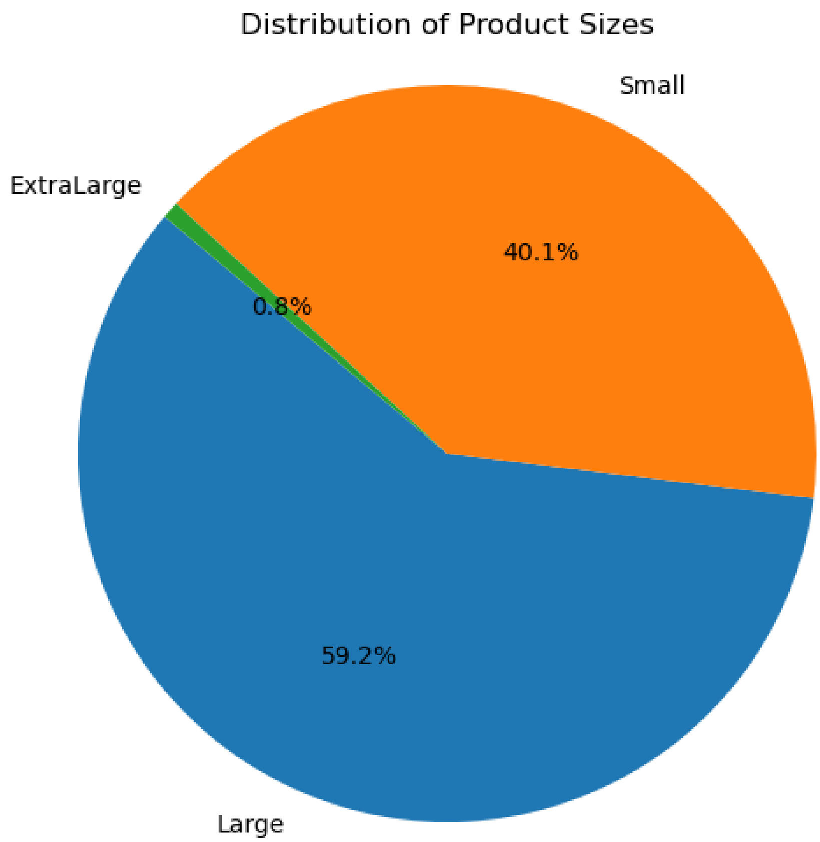
[31]:
```python
# Convert 'Month of Sourcing' column to datetime
train_df['Month of Sourcing'] = pd.to_datetime(train_df['Month of Sourcing'])

# Group data by both manufacturer and month and calculate total sales
monthly_sales_by_manufacturer = train_df.groupby(['Manufacturer',␣
↪train_df['Month of Sourcing'].dt.to_period('M')])['Sourcing Cost'].sum()

# Plotting
plt.figure(figsize=(12, 8))

# Iterate through each manufacturer
for manufacturer, sales in monthly_sales_by_manufacturer.groupby(level=0):
    plt.plot(sales.index.get_level_values('Month of Sourcing').to_timestamp(),␣
↪sales.values, marker='o', linestyle='-', label=manufacturer)

plt.title('Total Sales Trend by Month for Each Manufacturer')
plt.xlabel('Month')
plt.ylabel('Total Sales')
plt.legend(title='Manufacturer', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



[32]:

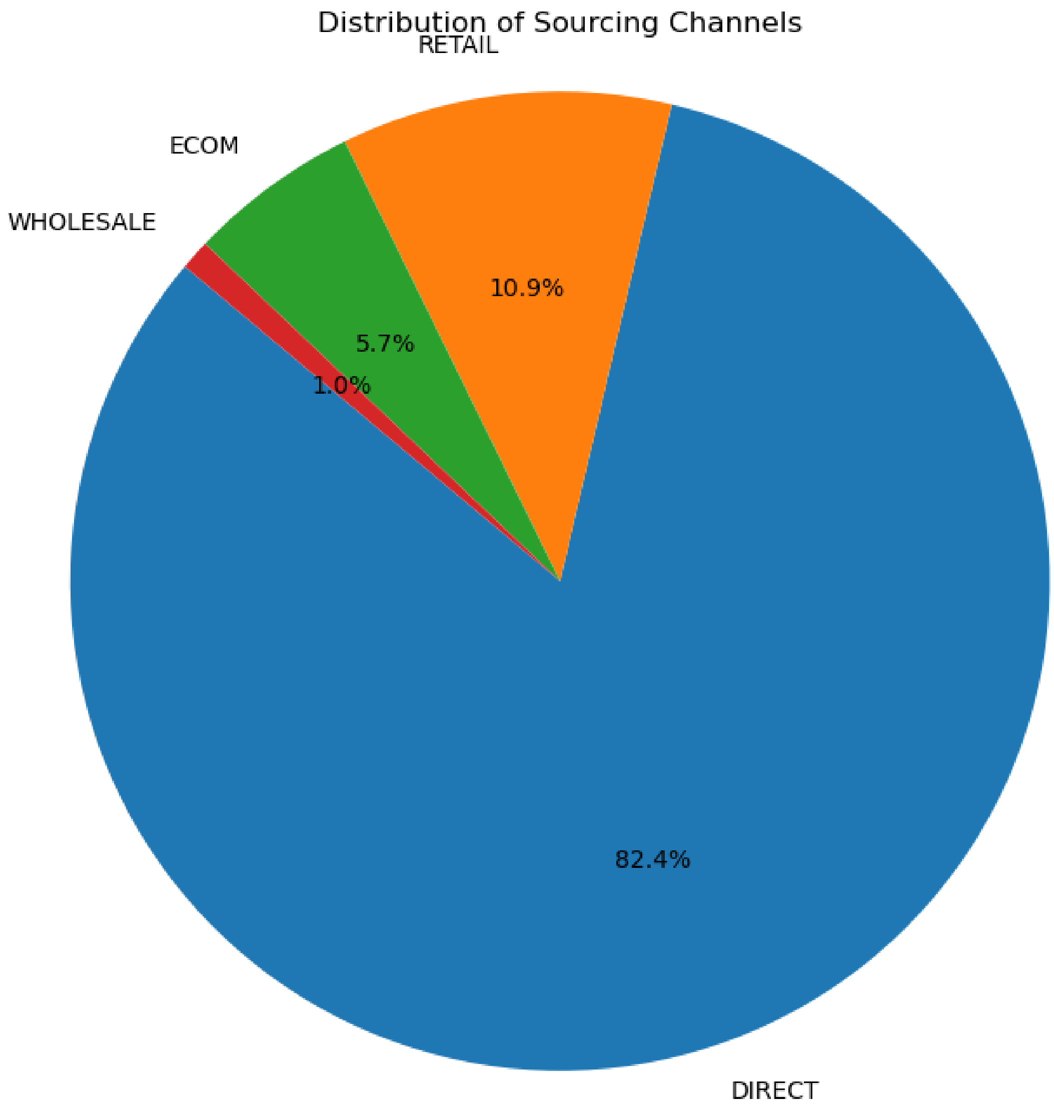
```
# Distribution of Sourcing Channels
plt.figure(figsize=(8, 6))
sns.countplot(data=train_df, x='Sourcing Channel')
plt.title('Distribution of Sourcing Channels')
plt.xlabel('Sourcing Channel')
plt.ylabel('Count')
plt.show()

# Distribution of Product Sizes
plt.figure(figsize=(8, 6))
sizes = train_df['Product Size'].value_counts()
plt.pie(sizes, labels=sizes.index, autopct='%1.1f%%', startangle=140)
plt.title('Distribution of Product Sizes')
plt.axis('equal')
plt.show()
```





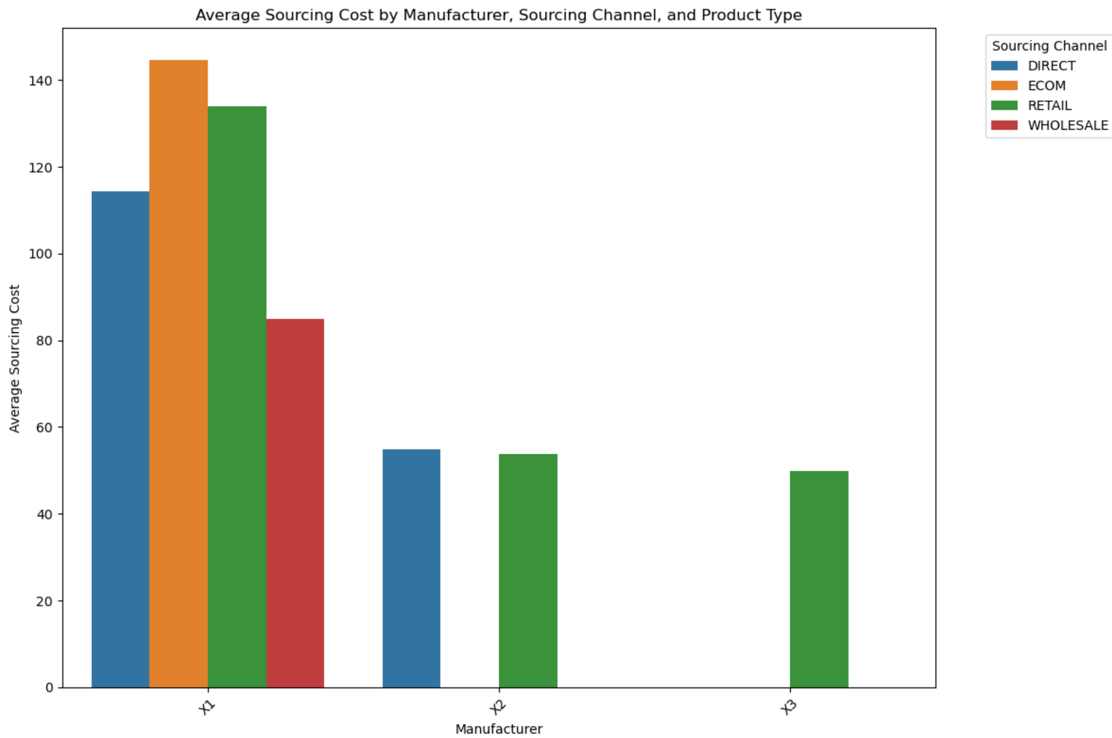
[33]:
```
# Calculate the frequency of each sourcing channel
channel_counts = train_df['Sourcing Channel'].value_counts()

# Plotting
plt.figure(figsize=(8, 8))
plt.pie(channel_counts, labels=channel_counts.index, autopct='%1.1f%%',␣
↪startangle=140)
plt.title('Distribution of Sourcing Channels')
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle
plt.show()


# Group data by Manufacturer, Sourcing Channel, and Product Type and calculate␣
↪average sourcing cost
grouped_data = train_df.groupby(['Manufacturer', 'Sourcing Channel', 'Product␣
↪Type'])['Sourcing Cost'].mean().reset_index()

# Plotting
plt.figure(figsize=(12, 8))
```

```python
sns.barplot(data=grouped_data, x='Manufacturer', y='Sourcing Cost',␣
 ↪hue='Sourcing Channel', ci=None)
plt.title('Average Sourcing Cost by Manufacturer, Sourcing Channel, and Product␣
 ↪Type')
plt.xlabel('Manufacturer')
plt.ylabel('Average Sourcing Cost')
plt.xticks(rotation=45)
plt.legend(title='Sourcing Channel', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



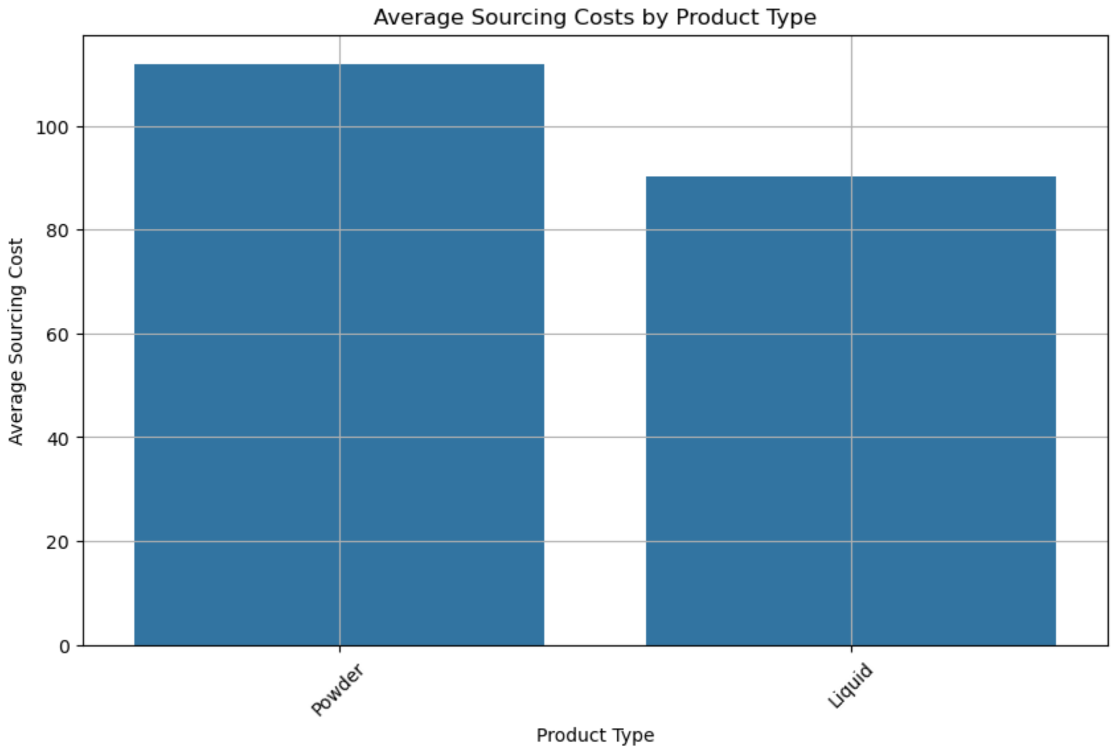

```
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/2719704464.py:17
: FutureWarning:
```

```
The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(data=grouped_data, x='Manufacturer', y='Sourcing Cost',
hue='Sourcing Channel', ci=None)
```

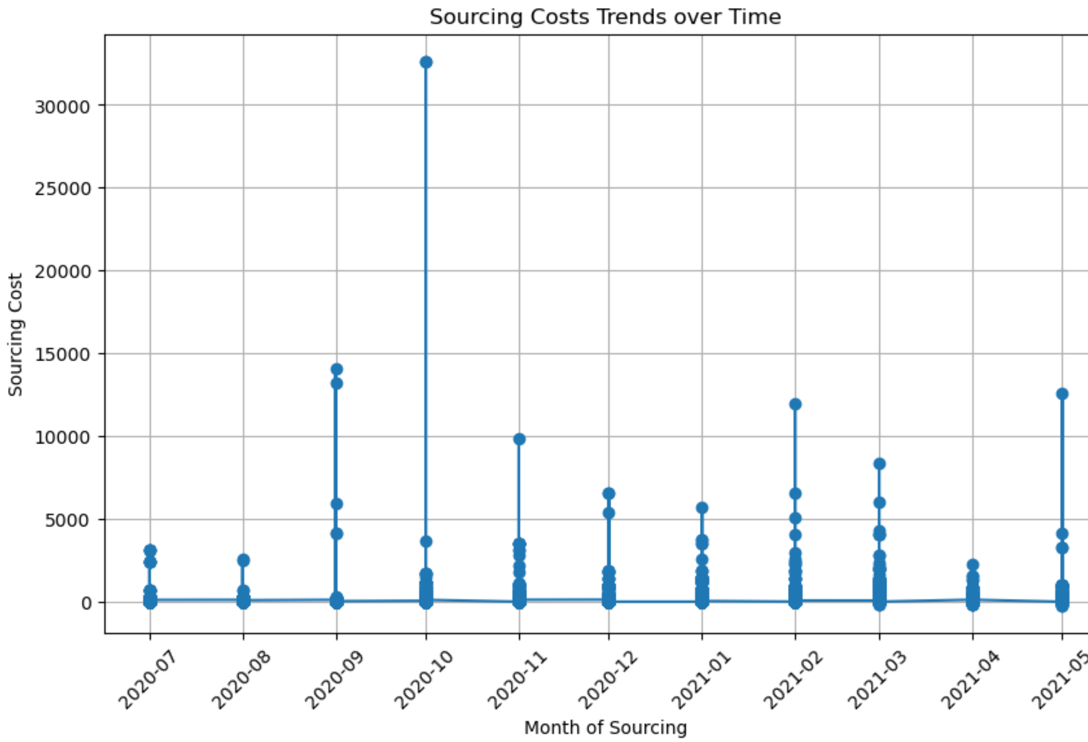


[34]:
```
# Plotting
plt.figure(figsize=(10, 6))
sns.barplot(data=train_df, x='Product Type', y='Sourcing Cost', ci=None)
plt.title('Average Sourcing Costs by Product Type')
plt.xlabel('Product Type')
plt.ylabel('Average Sourcing Cost')
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```

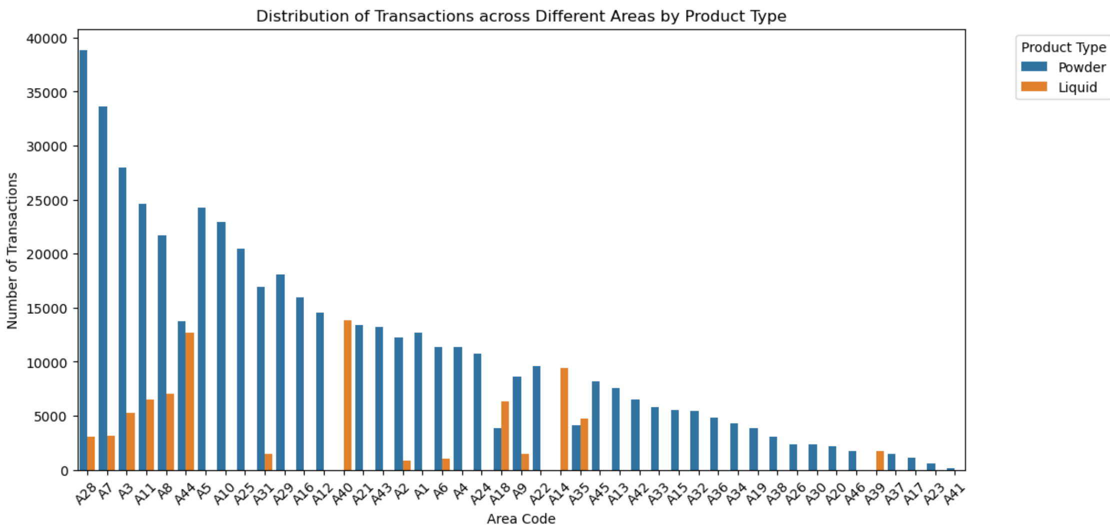
```
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/3878640288.py:3:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(data=train_df, x='Product Type', y='Sourcing Cost', ci=None)
```



[35]:
```
# Convert 'Month of Sourcing' column to datetime
train_df['Month of Sourcing'] = pd.to_datetime(train_df['Month of Sourcing'])

# Sort the DataFrame by 'Month of Sourcing' for plotting
df = train_df.sort_values('Month of Sourcing')

# Plotting
plt.figure(figsize=(10, 6))
plt.plot(df['Month of Sourcing'], df['Sourcing Cost'], marker='o',␣
 ↪linestyle='-')
plt.title('Sourcing Costs Trends over Time')
plt.xlabel('Month of Sourcing')
plt.ylabel('Sourcing Cost')
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



[36]:
```
# Plotting
plt.figure(figsize=(12, 6))
sns.countplot(data=df, x='Area Code', hue='Product Type', order=df['Area Code'].
  ↪value_counts().index)
plt.title('Distribution of Transactions across Different Areas by Product Type')
plt.xlabel('Area Code')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=45)
plt.legend(title='Product Type', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```




```
[ ]:
```

4.1 Outlier Detection

```
[40]: from scipy import stats

# Calculate z-scores
z_scores = stats.zscore(df['Sourcing Cost'])

# Define threshold for outlier detection
threshold = 3

# Identify outliers
outliers = df['Sourcing Cost'][abs(z_scores) > threshold]

# Print outliers
print("Outliers identified using z-score method:")
print(outliers)
# Count outliers identified using z-score method
outliers_count_zscore = len(outliers)
print("Number of outliers identified using z-score method:",␣
↪outliers_count_zscore)
```

```
Outliers identified using z-score method:
332368    3125.792
358951    3125.792
30326      720.000
147317    2412.380
138809    2412.380
```

```
              …
430963      948.896
431023      536.562
431121      948.896
72238       444.600
73142       450.047
Name: Sourcing Cost, Length: 1364, dtype: float64
Number of outliers identified using z-score method: 1364
```

[41]:

```python
# Calculate IQR
Q1 = df['Sourcing Cost'].quantile(0.25)
Q3 = df['Sourcing Cost'].quantile(0.75)
IQR = Q3 - Q1

# Define thresholds for outlier detection
lower_threshold = Q1 - 1.5 * IQR
upper_threshold = Q3 + 1.5 * IQR

# Identify outliers
outliers_iqr = df[(df['Sourcing Cost'] < lower_threshold) | (df['Sourcing␣
 ↪Cost'] > upper_threshold)]['Sourcing Cost']

# Print outliers
print("Outliers identified using IQR method:")
print(outliers_iqr)
# Count outliers identified using IQR method
outliers_count_iqr = len(outliers_iqr)
print("Number of outliers identified using IQR method:", outliers_count_iqr)
```

```
Outliers identified using IQR method:
342015     288.119
481412     288.119
41555      336.522
486424     288.119
327259     288.119
             …
430963     948.896
431023     536.562
431121     948.896
72238      444.600
73142      450.047
Name: Sourcing Cost, Length: 2666, dtype: float64
Number of outliers identified using IQR method: 2666
```

5 Model Training

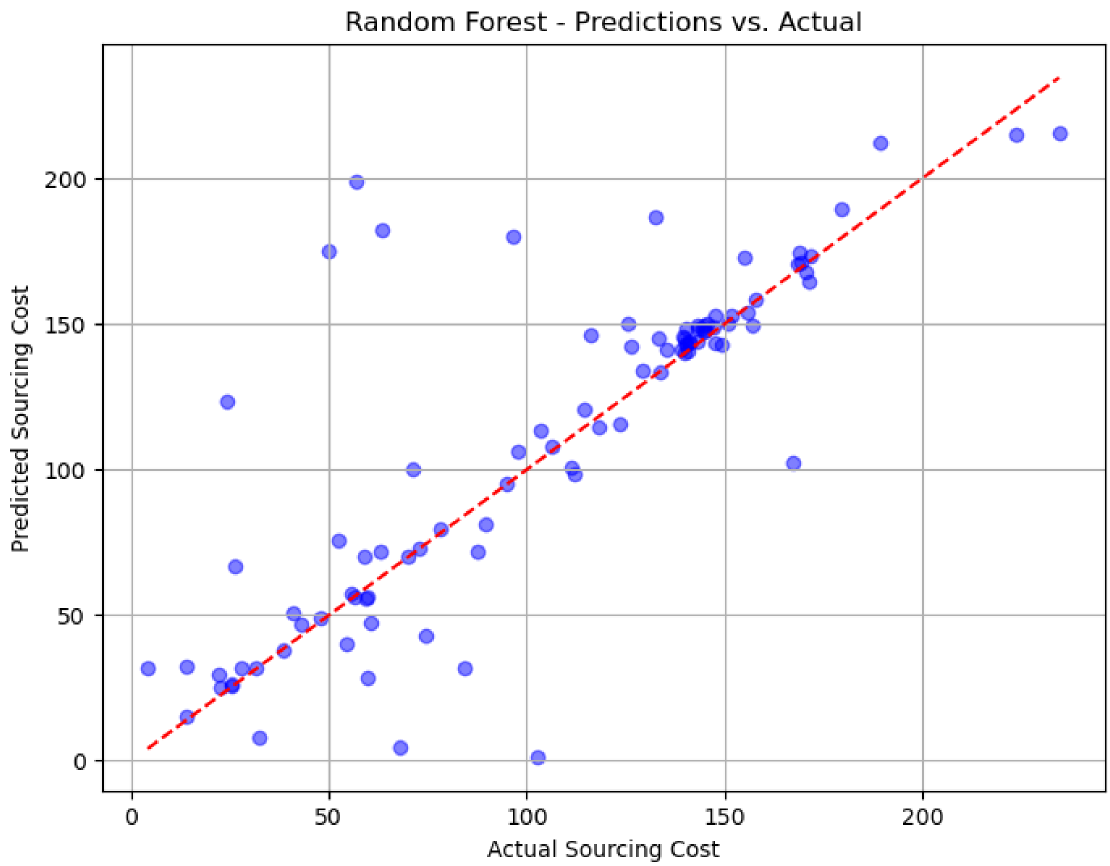
Random Forest

[66]:
```
# Convert 'Month of Sourcing' to datetime
train_df['Month of Sourcing'] = pd.to_datetime(train_df['Month of Sourcing'])
test_df['Month of Sourcing'] = pd.to_datetime(test_df['Month of Sourcing'])

# Extract features from datetime column
train_df['Year'] = train_df['Month of Sourcing'].dt.year
train_df['Month'] = train_df['Month of Sourcing'].dt.month
# Add more features as needed

test_df['Year'] = test_df['Month of Sourcing'].dt.year
test_df['Month'] = test_df['Month of Sourcing'].dt.month
# Add more features as needed

# Separate features (X) and target variable (y) for train and test datasets
X_train = train_df.drop(columns=['Sourcing Cost'])
y_train = train_df['Sourcing Cost']
X_test = test_df.drop(columns=['Sourcing Cost'])
y_test = test_df['Sourcing Cost']

# Encode categorical variables
encoder = OneHotEncoder(drop='first', sparse=False)
X_train_encoded = encoder.fit_transform(X_train[categorical_columns])
X_test_encoded = encoder.transform(X_test[categorical_columns])

# Convert encoded arrays to DataFrame
X_train_encoded = pd.DataFrame(X_train_encoded, columns=encoder.
 ↪get_feature_names_out(input_features=categorical_columns))
X_test_encoded = pd.DataFrame(X_test_encoded, columns=encoder.
 ↪get_feature_names_out(input_features=categorical_columns))

# Combine encoded categorical columns and extracted features
X_train_final = pd.concat([X_train_encoded.reset_index(drop=True),␣
 ↪train_df[['Year', 'Month']].reset_index(drop=True)], axis=1)
X_test_final = pd.concat([X_test_encoded.reset_index(drop=True),␣
 ↪test_df[['Year', 'Month']].reset_index(drop=True)], axis=1)


# Train the Random Forest model
random_forest_model = RandomForestRegressor()
random_forest_model.fit(X_train_final, y_train)

# Evaluate the model
y_pred_rf = random_forest_model.predict(X_test_final)
mse_rf = mean_squared_error(y_test, y_pred_rf)
mae_rf = mean_absolute_error(y_test, y_pred_rf)
r2_rf = r2_score(y_test, y_pred_rf)
rmse_rf = np.sqrt(mse_rf)
```

```python
print("Random Forest - Mean Squared Error:", mse_rf)
print("Random Forest - Mean Absolute Error:", mae_rf)
print("Random Forest - R-squared:", r2_rf)
print("Random Forest - Root Mean Squared Error:", rmse_rf)

# Plot predictions vs. actual values
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred_rf, color='blue', alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',
 ↪linestyle='--')
plt.xlabel('Actual Sourcing Cost')
plt.ylabel('Predicted Sourcing Cost')
plt.title('Random Forest - Predictions vs. Actual')
plt.grid(True)
plt.show()
```

```
/Users/saumit/anaconda3/lib/python3.11/site-
packages/sklearn/preprocessing/_encoders.py:975: FutureWarning: `sparse` was
renamed to `sparse_output` in version 1.2 and will be removed in 1.4.
`sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

```
Random Forest - Mean Squared Error: 1074.392396515443
Random Forest - Mean Absolute Error: 16.569576087977335
Random Forest - R-squared: 0.6039775180717608
Random Forest - Root Mean Squared Error: 32.77792544557149
```



Random forest model using z-score for outlier/anomaly detecion : Here the outliers are filtered out using z-score and then the model is trained.

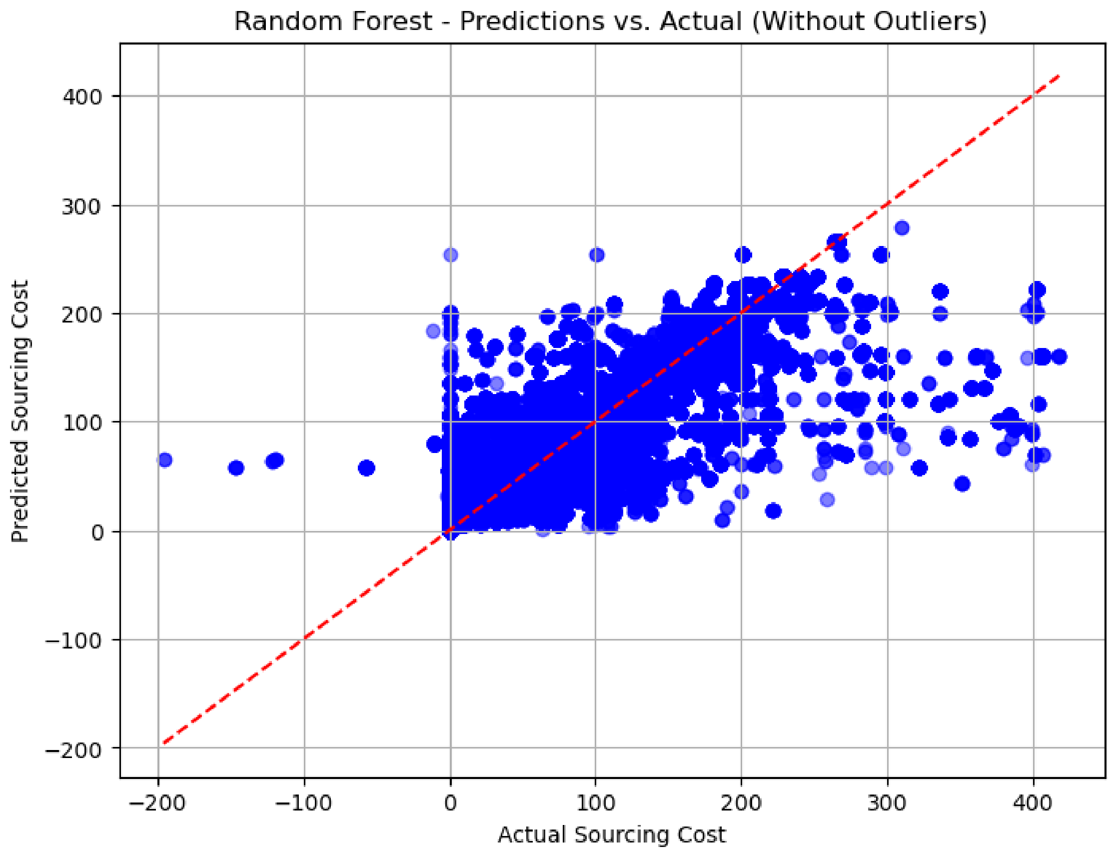
[67]:
```
# Filter out outliers from the original dataset
df_no_outliers = df[abs(z_scores) <= threshold]

# Identify categorical columns
categorical_columns = df_no_outliers.select_dtypes(include=['object']).columns.
 ↪tolist()

# Convert 'Month of Sourcing' to datetime
df_no_outliers['Month of Sourcing'] = pd.to_datetime(df_no_outliers['Month of␣
 ↪Sourcing'])

# Extract features from datetime column
df_no_outliers['Year'] = df_no_outliers['Month of Sourcing'].dt.year
df_no_outliers['Month'] = df_no_outliers['Month of Sourcing'].dt.month

# Separate features (X) and target variable (y)
X = df_no_outliers.drop(columns=['Sourcing Cost'])
```

```
y = df_no_outliers['Sourcing Cost']

# Encode categorical variables
encoder = OneHotEncoder(drop='first', sparse=False)
X_encoded = encoder.fit_transform(X[categorical_columns])

# Convert encoded arrays to DataFrame
X_encoded_df = pd.DataFrame(X_encoded, columns=encoder.
 ↪get_feature_names_out(input_features=categorical_columns))

# Combine encoded categorical columns and extracted features
X_final = pd.concat([X_encoded_df.reset_index(drop=True),␣
 ↪df_no_outliers[['Year', 'Month']].reset_index(drop=True)], axis=1)

# Train the random forest model
model = RandomForestRegressor()
model.fit(X_final, y)

# Predict using the trained model
y_pred = model.predict(X_final)

# Evaluate the model
mse_rf_zscore = mean_squared_error(y, y_pred)
mae_rf_zscore = mean_absolute_error(y, y_pred)
r2_rf_zscore= r2_score(y, y_pred)
rmse_rf_zscore = np.sqrt(mse_rf_zscore)

print("Mean Squared Error:", mse_rf_zscore)
print("Mean Absolute Error:", mae_rf_zscore)
print("R-squared:", r2_rf_zscore)
print("Root Mean Squared Error:", rmse_rf_zscore)

# Plot predictions vs. actual values
plt.figure(figsize=(8, 6))
plt.scatter(y, y_pred, color='blue', alpha=0.5)
plt.plot([min(y), max(y)], [min(y), max(y)], color='red', linestyle='--')
plt.xlabel('Actual Sourcing Cost')
plt.ylabel('Predicted Sourcing Cost')
plt.title('Random Forest - Predictions vs. Actual (Without Outliers)')
plt.grid(True)
plt.show()
```

```
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/413946491.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers['Month of Sourcing'] = pd.to_datetime(df_no_outliers['Month of
Sourcing'])
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/413946491.py:11:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers['Year'] = df_no_outliers['Month of Sourcing'].dt.year
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/413946491.py:12:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers['Month'] = df_no_outliers['Month of Sourcing'].dt.month
/Users/saumit/anaconda3/lib/python3.11/site-
packages/sklearn/preprocessing/_encoders.py:975: FutureWarning: `sparse` was
renamed to `sparse_output` in version 1.2 and will be removed in 1.4.
`sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

```
Mean Squared Error: 483.1666160749332
Mean Absolute Error: 9.808285055001443
R-squared: 0.8515149784801571
Root Mean Squared Error: 21.98105129594427
```



Random forest model using IRQ for outlier/anomaly detecion : Here the outliers are filtered out using IQR(interquartile range) and then the model is trained.

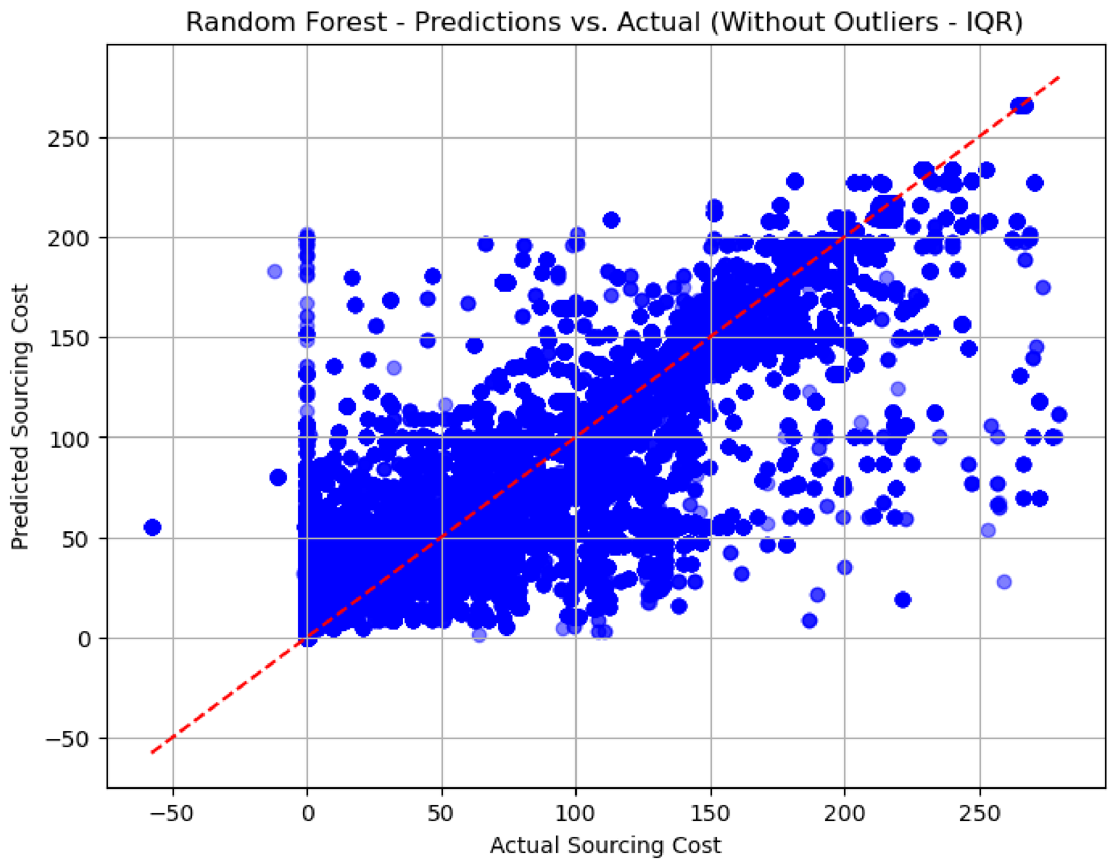
[68]:
```
# Filter out outliers
df_no_outliers_iqr = df[(df['Sourcing Cost'] >= lower_threshold) &␣
↪(df['Sourcing Cost'] <= upper_threshold)]

# Identify categorical columns
categorical_columns = df_no_outliers_iqr.select_dtypes(include=['object']).
↪columns.tolist()

# Convert 'Month of Sourcing' to datetime
df_no_outliers_iqr['Month of Sourcing'] = pd.
↪to_datetime(df_no_outliers_iqr['Month of Sourcing'])

# Extract features from datetime column
df_no_outliers_iqr['Year'] = df_no_outliers_iqr['Month of Sourcing'].dt.year
df_no_outliers_iqr['Month'] = df_no_outliers_iqr['Month of Sourcing'].dt.month

# Separate features (X) and target variable (y)
```

```
X = df_no_outliers_iqr.drop(columns=['Sourcing Cost'])
y = df_no_outliers_iqr['Sourcing Cost']

# Encode categorical variables
encoder = OneHotEncoder(drop='first', sparse=False)
X_encoded = encoder.fit_transform(X[categorical_columns])

# Convert encoded arrays to DataFrame
X_encoded_df = pd.DataFrame(X_encoded, columns=encoder.
 ↪get_feature_names_out(input_features=categorical_columns))

# Combine encoded categorical columns and extracted features
X_final = pd.concat([X_encoded_df.reset_index(drop=True),␣
 ↪df_no_outliers_iqr[['Year', 'Month']].reset_index(drop=True)], axis=1)

# Train the random forest model
model = RandomForestRegressor()
model.fit(X_final, y)

# Predict using the trained model
y_pred = model.predict(X_final)

# Evaluate the model
mse_rf_iqr = mean_squared_error(y, y_pred)
mae_rf_iqr = mean_absolute_error(y, y_pred)
r2_rf_iqr = r2_score(y, y_pred)
rmse_rf_iqr = np.sqrt(mse_rf_iqr)

print("Mean Squared Error:", mse_rf_iqr)
print("Mean Absolute Error:", mae_rf_iqr)
print("R-squared:", r2_rf_iqr)
print("Root Mean Squared Error:", rmse_rf_iqr)

# Plot predictions vs. actual values
plt.figure(figsize=(8, 6))
plt.scatter(y, y_pred, color='blue', alpha=0.5)
plt.plot([min(y), max(y)], [min(y), max(y)], color='red', linestyle='--')
plt.xlabel('Actual Sourcing Cost')
plt.ylabel('Predicted Sourcing Cost')
plt.title('Random Forest - Predictions vs. Actual (Without Outliers - IQR)')
plt.grid(True)
plt.show()
```

```
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/2682994781.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_iqr['Month of Sourcing'] =
pd.to_datetime(df_no_outliers_iqr['Month of Sourcing'])
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/2682994781.py:11
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_iqr['Year'] = df_no_outliers_iqr['Month of Sourcing'].dt.year
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/2682994781.py:12
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_iqr['Month'] = df_no_outliers_iqr['Month of Sourcing'].dt.month
/Users/saumit/anaconda3/lib/python3.11/site-
packages/sklearn/preprocessing/_encoders.py:975: FutureWarning: `sparse` was
renamed to `sparse_output` in version 1.2 and will be removed in 1.4.
`sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

```
Mean Squared Error: 364.87292187978994
Mean Absolute Error: 9.07735567447201
R-squared: 0.8829117663377689
Root Mean Squared Error: 19.101647098608797
```

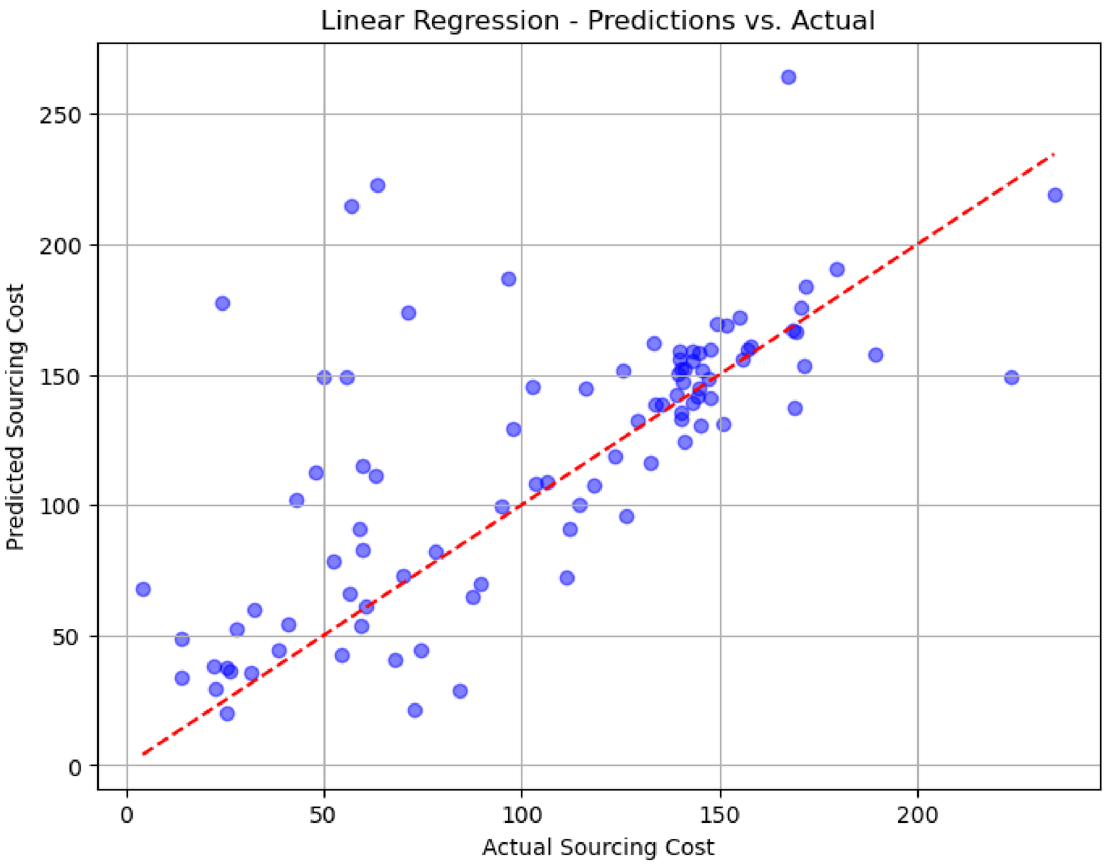


5.1 Linear Regression

[46]:
```
# Train a Linear Regression model
linear_model = LinearRegression()
linear_model.fit(X_train_final, y_train)

# Evaluate the Linear Regression model
y_pred_linear = linear_model.predict(X_test_final)
mse_linear = mean_squared_error(y_test, y_pred_linear)
mae_linear = mean_absolute_error(y_test, y_pred_linear)
r2_linear = r2_score(y_test, y_pred_linear)
rmse_linear = np.sqrt(mse_linear)

print("Linear Regression - Mean Squared Error:", mse_linear)
print("Linear Regression - Mean Absolute Error:", mae_linear)
print("Linear Regression - R-squared:", r2_linear)
print("Linear Regression - Root Mean Squared Error:", rmse_linear)

# Plot predictions vs. actual values for Linear Regression
```

```python
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred_linear, color='blue', alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
↪linestyle='--')
plt.xlabel('Actual Sourcing Cost')
plt.ylabel('Predicted Sourcing Cost')
plt.title('Linear Regression - Predictions vs. Actual')
plt.grid(True)
plt.show()
```

```
Linear Regression - Mean Squared Error: 1804.6054056927085
Linear Regression - Mean Absolute Error: 26.501600052194362
Linear Regression - R-squared: 0.3348200210822406
Linear Regression - Root Mean Squared Error: 42.48064742553612
```



linear regression model using IRQ for outlier/anomaly detecion : Here the outliers are filtered out using IQR(interquartile range) and then the model is trained.

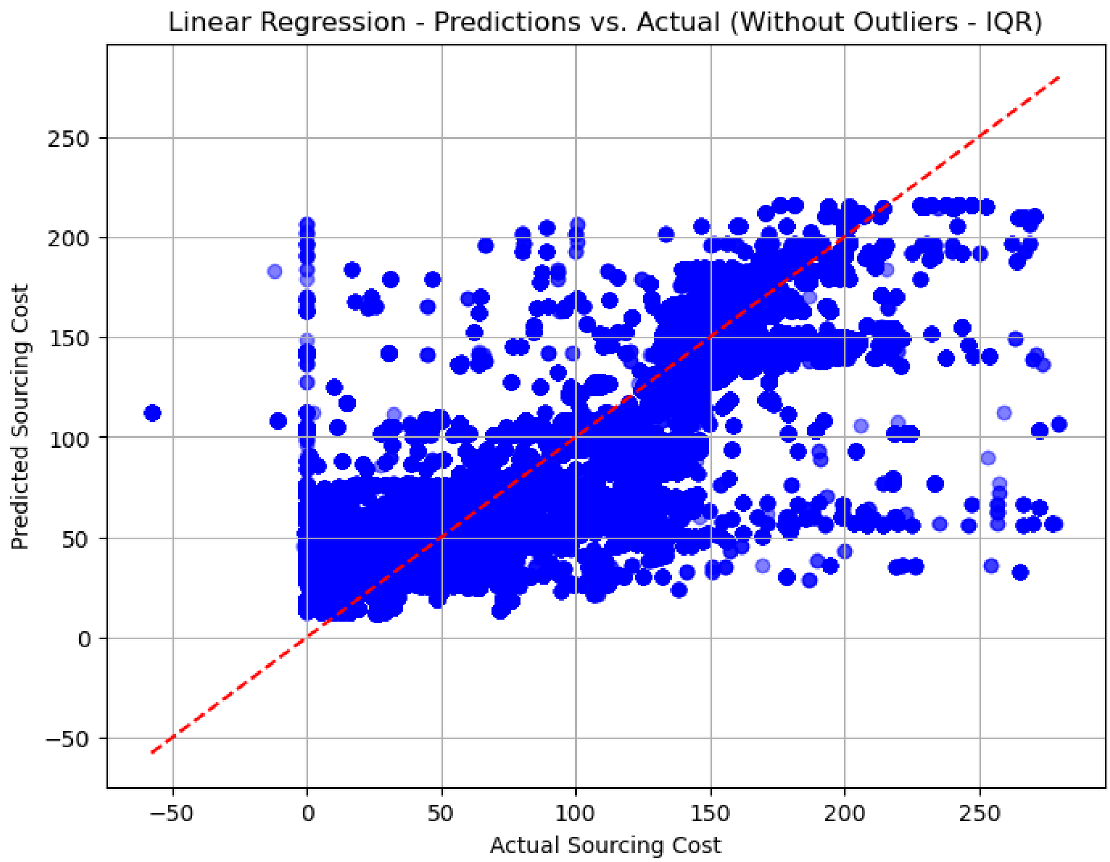
[69]:
```python
#Filter out outliers using IQR method
```

```
df_no_outliers_iqr = df[(df['Sourcing Cost'] >= lower_threshold) & (df['Sourcing Cost'] <= upper_threshold)]

# Identify categorical columns
categorical_columns = df_no_outliers_iqr.select_dtypes(include=['object']).columns.tolist()

# Convert 'Month of Sourcing' to datetime
df_no_outliers_iqr['Month of Sourcing'] = pd.to_datetime(df_no_outliers_iqr['Month of Sourcing'])

# Extract features from datetime column
df_no_outliers_iqr['Year'] = df_no_outliers_iqr['Month of Sourcing'].dt.year
df_no_outliers_iqr['Month'] = df_no_outliers_iqr['Month of Sourcing'].dt.month

# Separate features (X) and target variable (y)
X = df_no_outliers_iqr.drop(columns=['Sourcing Cost'])
y = df_no_outliers_iqr['Sourcing Cost']

# Encode categorical variables
encoder = OneHotEncoder(drop='first', sparse=False)
X_encoded = encoder.fit_transform(X[categorical_columns])

# Convert encoded arrays to DataFrame
X_encoded_df = pd.DataFrame(X_encoded, columns=encoder.get_feature_names_out(input_features=categorical_columns))

# Combine encoded categorical columns and extracted features
X_final = pd.concat([X_encoded_df.reset_index(drop=True), df_no_outliers_iqr[['Year', 'Month']].reset_index(drop=True)], axis=1)

# Train the Linear Regression model
linear_model_iqr = LinearRegression()
linear_model_iqr.fit(X_final, y)

# Predict using the trained model
y_pred_linear_iqr = linear_model_iqr.predict(X_final)

# Evaluate the model
mse_linear_iqr = mean_squared_error(y, y_pred_linear_iqr)
mae_linear_iqr = mean_absolute_error(y, y_pred_linear_iqr)
r2_linear_iqr = r2_score(y, y_pred_linear_iqr)
rmse_linear_iqr = np.sqrt(mse_linear_iqr)

print("Linear Regression - Mean Squared Error (IQR):", mse_linear_iqr)
print("Linear Regression - Mean Absolute Error (IQR):", mae_linear_iqr)
print("Linear Regression - R-squared (IQR):", r2_linear_iqr)
```

```python
print("Linear Regression - Root Mean Squared Error (IQR):", rmse_linear_iqr)

# Plot predictions vs. actual values for Linear Regression
plt.figure(figsize=(8, 6))
plt.scatter(y, y_pred_linear_iqr, color='blue', alpha=0.5)
plt.plot([min(y), max(y)], [min(y), max(y)], color='red', linestyle='--')
plt.xlabel('Actual Sourcing Cost')
plt.ylabel('Predicted Sourcing Cost')
plt.title('Linear Regression - Predictions vs. Actual (Without Outliers - IQR)')
plt.grid(True)
plt.show()
```

```
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/1106546368.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_iqr['Month of Sourcing'] =
pd.to_datetime(df_no_outliers_iqr['Month of Sourcing'])
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/1106546368.py:11
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_iqr['Year'] = df_no_outliers_iqr['Month of Sourcing'].dt.year
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/1106546368.py:12
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_iqr['Month'] = df_no_outliers_iqr['Month of Sourcing'].dt.month
/Users/saumit/anaconda3/lib/python3.11/site-
packages/sklearn/preprocessing/_encoders.py:975: FutureWarning: `sparse` was
renamed to `sparse_output` in version 1.2 and will be removed in 1.4.
`sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

```
Linear Regression - Mean Squared Error (IQR): 700.6212281881392
Linear Regression - Mean Absolute Error (IQR): 17.021741911005222
Linear Regression - R-squared (IQR): 0.7751696627631934
Linear Regression - Root Mean Squared Error (IQR): 26.469250616293223
```



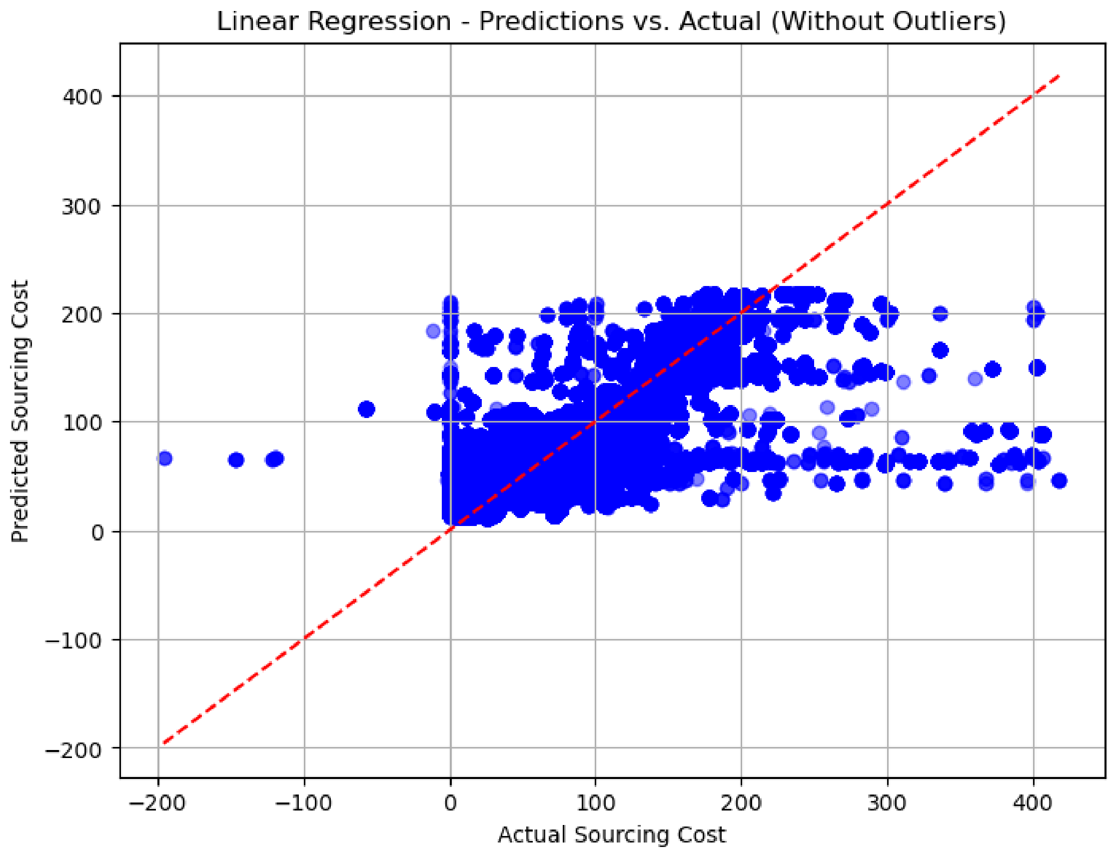
linear regression model using z-score for outlier/anomaly detecion : Here the outliers are filtered out using z-score and then the model is trained.

[70]:
```
# Filter out outliers from the original dataset
df_no_outliers = df[abs(z_scores) <= threshold]

# Identify categorical columns
categorical_columns = df_no_outliers.select_dtypes(include=['object']).columns.
 ↪tolist()

# Convert 'Month of Sourcing' to datetime
df_no_outliers['Month of Sourcing'] = pd.to_datetime(df_no_outliers['Month of␣
 ↪Sourcing'])

# Extract features from datetime column
df_no_outliers['Year'] = df_no_outliers['Month of Sourcing'].dt.year
df_no_outliers['Month'] = df_no_outliers['Month of Sourcing'].dt.month

# Separate features (X) and target variable (y)
X = df_no_outliers.drop(columns=['Sourcing Cost'])
```

```
y = df_no_outliers['Sourcing Cost']

# Encode categorical variables
encoder = OneHotEncoder(drop='first', sparse=False)
X_encoded = encoder.fit_transform(X[categorical_columns])

# Convert encoded arrays to DataFrame
X_encoded_df = pd.DataFrame(X_encoded, columns=encoder.
 ↪get_feature_names_out(input_features=categorical_columns))

# Combine encoded categorical columns and extracted features
X_final = pd.concat([X_encoded_df.reset_index(drop=True),␣
 ↪df_no_outliers[['Year', 'Month']].reset_index(drop=True)], axis=1)

# Train the Linear Regression model
linear_model = LinearRegression()
linear_model.fit(X_final, y)

# Predict using the trained model
y_pred = linear_model.predict(X_final)

# Evaluate the model
mse_lr_zscore = mean_squared_error(y, y_pred)
mae_lr_zscore = mean_absolute_error(y, y_pred)
r2_lr_zscore = r2_score(y, y_pred)
rmse_lr_zscore = np.sqrt(mse_lr_zscore)

print("Mean Squared Error:", mse_lr_zscore)
print("Mean Absolute Error:", mae_lr_zscore)
print("R-squared:", r2_lr_zscore)
print("Root Mean Squared Error:", rmse_lr_zscore)

# Plot predictions vs. actual values
plt.figure(figsize=(8, 6))
plt.scatter(y, y_pred, color='blue', alpha=0.5)
plt.plot([min(y), max(y)], [min(y), max(y)], color='red', linestyle='--')
plt.xlabel('Actual Sourcing Cost')
plt.ylabel('Predicted Sourcing Cost')
plt.title('Linear Regression - Predictions vs. Actual (Without Outliers)')
plt.grid(True)
plt.show()
```

```
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/3890826653.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers['Month of Sourcing'] = pd.to_datetime(df_no_outliers['Month of
Sourcing'])
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/3890826653.py:11
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers['Year'] = df_no_outliers['Month of Sourcing'].dt.year
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/3890826653.py:12
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers['Month'] = df_no_outliers['Month of Sourcing'].dt.month
/Users/saumit/anaconda3/lib/python3.11/site-
packages/sklearn/preprocessing/_encoders.py:975: FutureWarning: `sparse` was
renamed to `sparse_output` in version 1.2 and will be removed in 1.4.
`sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(

Mean Squared Error: 851.7890583295565
Mean Absolute Error: 17.775925477507883
R-squared: 0.7382312592623003
Root Mean Squared Error: 29.18542544369632
```

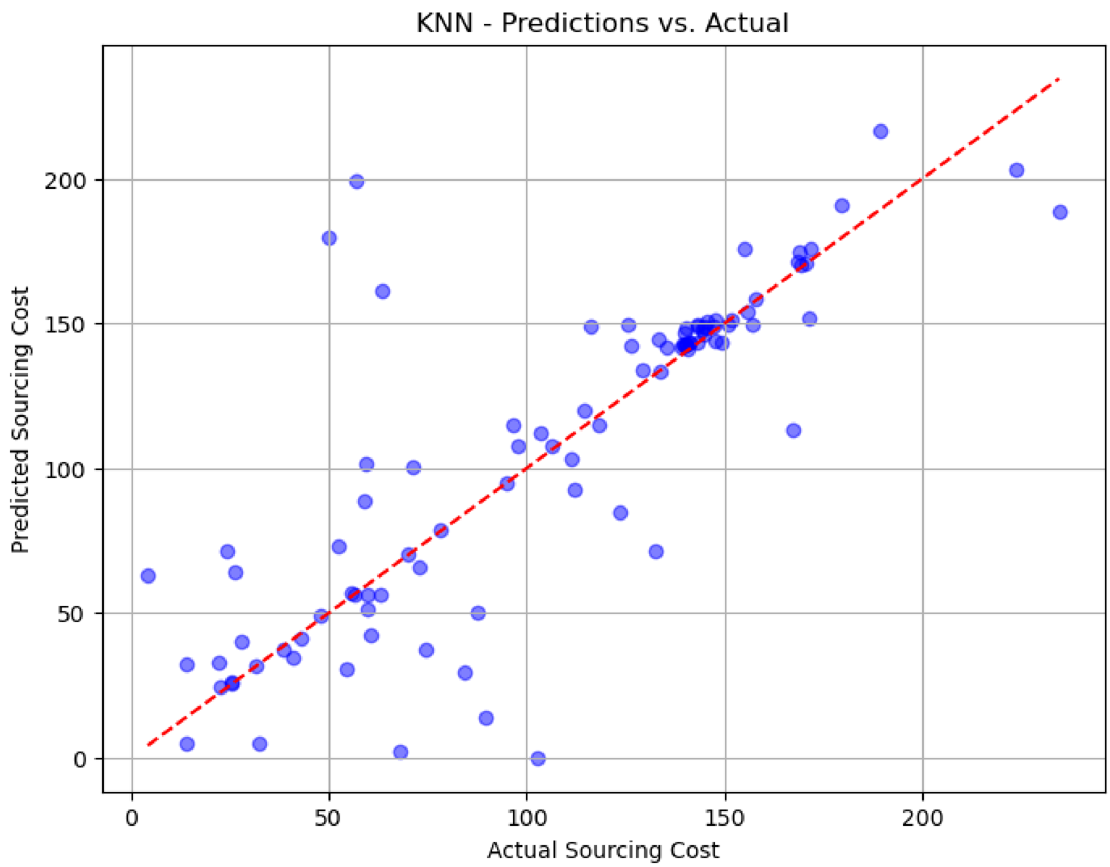


5.2 KNN

[59]:
```python
# Train the KNN model
knn_model = KNeighborsRegressor()
knn_model.fit(X_train_final, y_train)

# Evaluate the KNN model
y_pred_knn = knn_model.predict(X_test_final)
mse_knn = mean_squared_error(y_test, y_pred_knn)
mae_knn = mean_absolute_error(y_test, y_pred_knn)
r2_knn = r2_score(y_test, y_pred_knn)
rmse_knn = np.sqrt(mse_knn)

print("KNN - Mean Squared Error:", mse_knn)
print("KNN - Mean Absolute Error:", mae_knn)
print("KNN - R-squared:", r2_knn)
print("KNN - Root Mean Squared Error:", rmse_knn)

# Plot predictions vs. actual values for KNN
plt.figure(figsize=(8, 6))
```

```
plt.scatter(y_test, y_pred_knn, color='blue', alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
↪linestyle='--')
plt.xlabel('Actual Sourcing Cost')
plt.ylabel('Predicted Sourcing Cost')
plt.title('KNN - Predictions vs. Actual')
plt.grid(True)
plt.show()
```

```
KNN - Mean Squared Error: 1069.2524501025
KNN - Mean Absolute Error: 18.1434875
KNN - R-squared: 0.6058721092304786
KNN - Root Mean Squared Error: 32.69942583750516
```



KNN model using IRQ for outlier/anomaly detecion : Here the outliers are filtered out using IQR(interquartile range) and then the model is trained.

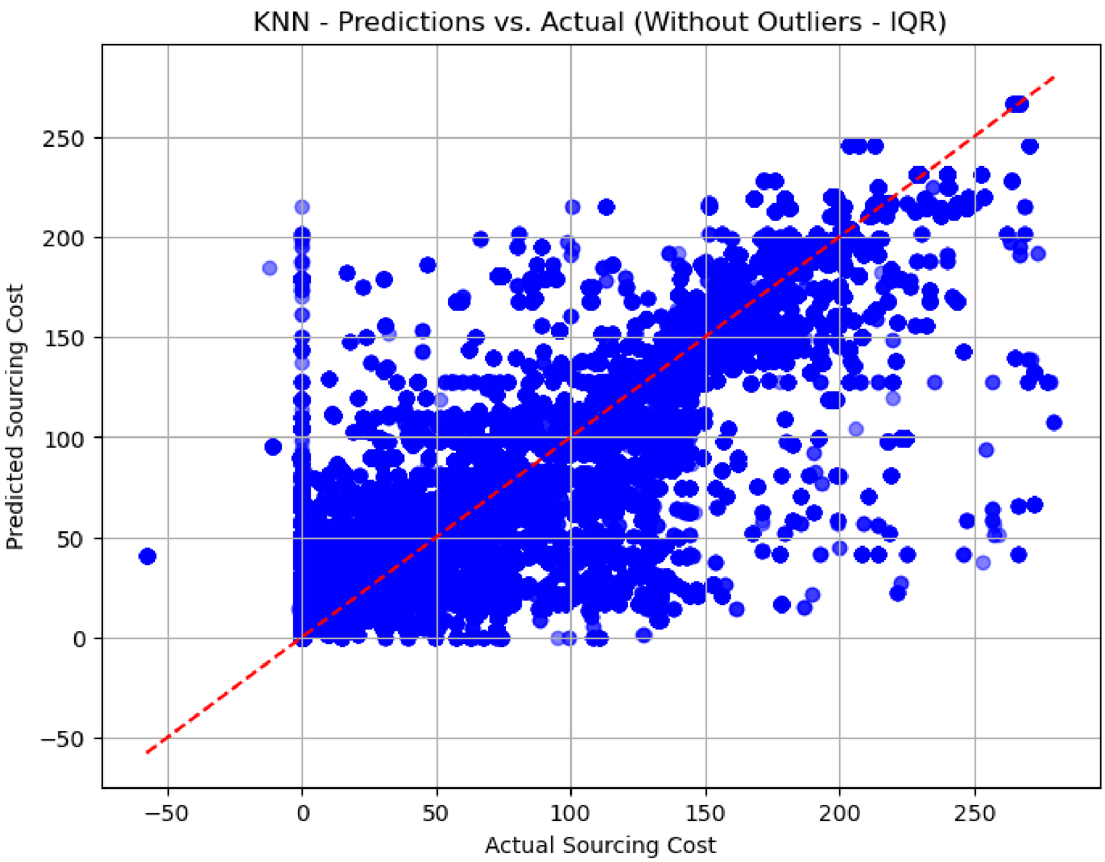
[60]:
```
# Filter out outliers using IQR method
df_no_outliers_iqr = df[(df['Sourcing Cost'] >= lower_threshold) &␣
↪(df['Sourcing Cost'] <= upper_threshold)]
```

```
# Identify categorical columns
categorical_columns = df_no_outliers_iqr.select_dtypes(include=['object']).
 ↪columns.tolist()

# Convert 'Month of Sourcing' to datetime
df_no_outliers_iqr['Month of Sourcing'] = pd.
 ↪to_datetime(df_no_outliers_iqr['Month of Sourcing'])

# Extract features from datetime column
df_no_outliers_iqr['Year'] = df_no_outliers_iqr['Month of Sourcing'].dt.year
df_no_outliers_iqr['Month'] = df_no_outliers_iqr['Month of Sourcing'].dt.month

# Separate features (X) and target variable (y)
X = df_no_outliers_iqr.drop(columns=['Sourcing Cost'])
y = df_no_outliers_iqr['Sourcing Cost']

# Encode categorical variables
encoder = OneHotEncoder(drop='first', sparse=False)
X_encoded = encoder.fit_transform(X[categorical_columns])

# Convert encoded arrays to DataFrame
X_encoded_df = pd.DataFrame(X_encoded, columns=encoder.
 ↪get_feature_names_out(input_features=categorical_columns))

# Combine encoded categorical columns and extracted features
X_final = pd.concat([X_encoded_df.reset_index(drop=True),␣
 ↪df_no_outliers_iqr[['Year', 'Month']].reset_index(drop=True)], axis=1)

# Train the KNN model
knn_model_iqr = KNeighborsRegressor()
knn_model_iqr.fit(X_final, y)

# Predict using the trained model
y_pred_knn_iqr = knn_model_iqr.predict(X_final)

# Evaluate the model
mse_knn_iqr = mean_squared_error(y, y_pred_knn_iqr)
mae_knn_iqr = mean_absolute_error(y, y_pred_knn_iqr)
r2_knn_iqr = r2_score(y, y_pred_knn_iqr)
rmse_knn_iqr = np.sqrt(mse_knn_iqr)

print("KNN - Mean Squared Error (IQR):", mse_knn_iqr)
print("KNN - Mean Absolute Error (IQR):", mae_knn_iqr)
print("KNN - R-squared (IQR):", r2_knn_iqr)
print("KNN - Root Mean Squared Error (IQR):", rmse_knn_iqr)
```

```python
# Plot predictions vs. actual values for KNN
plt.figure(figsize=(8, 6))
plt.scatter(y, y_pred_knn_iqr, color='blue', alpha=0.5)
plt.plot([min(y), max(y)], [min(y), max(y)], color='red', linestyle='--')
plt.xlabel('Actual Sourcing Cost')
plt.ylabel('Predicted Sourcing Cost')
plt.title('KNN - Predictions vs. Actual (Without Outliers - IQR)')
plt.grid(True)
plt.show()
```

```
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/3406452655.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_iqr['Month of Sourcing'] =
pd.to_datetime(df_no_outliers_iqr['Month of Sourcing'])
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/3406452655.py:11
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_iqr['Year'] = df_no_outliers_iqr['Month of Sourcing'].dt.year
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/3406452655.py:12
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_iqr['Month'] = df_no_outliers_iqr['Month of Sourcing'].dt.month
/Users/saumit/anaconda3/lib/python3.11/site-
packages/sklearn/preprocessing/_encoders.py:975: FutureWarning: `sparse` was
renamed to `sparse_output` in version 1.2 and will be removed in 1.4.
`sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

```
KNN - Mean Squared Error (IQR): 448.9442999700203
KNN - Mean Absolute Error (IQR): 9.914246489744482
KNN - R-squared (IQR): 0.8559331428997223
KNN - Root Mean Squared Error (IQR): 21.188305736184297
```



KNN model using z-score for outlier/anomaly detecion : Here the outliers are filtered out using z-score and then the model is trained.

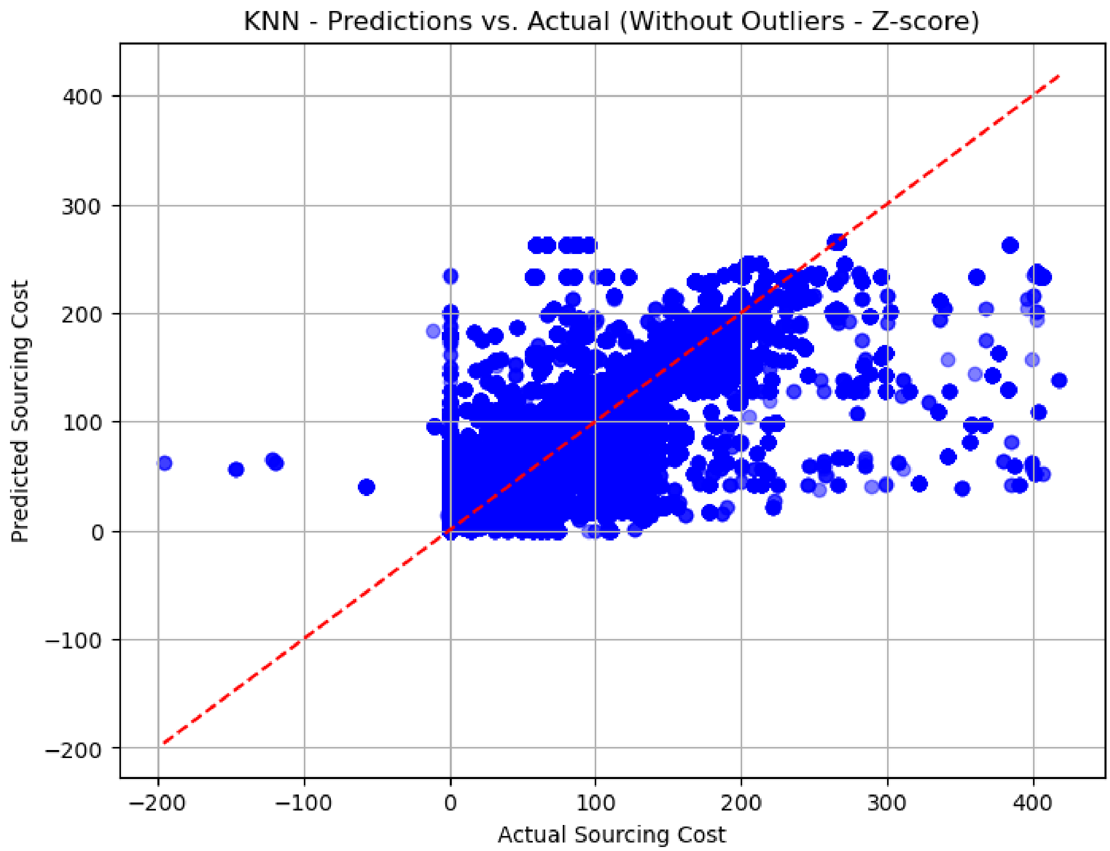
[62]:
```
# Filter out outliers using Z-score method
df_no_outliers_zscore = df[np.abs(stats.zscore(df['Sourcing Cost'])) <␣
↪threshold]

# Identify categorical columns
categorical_columns = df_no_outliers_zscore.select_dtypes(include=['object']).
↪columns.tolist()

# Convert 'Month of Sourcing' to datetime
df_no_outliers_zscore['Month of Sourcing'] = pd.
↪to_datetime(df_no_outliers_zscore['Month of Sourcing'])

# Extract features from datetime column
df_no_outliers_zscore['Year'] = df_no_outliers_zscore['Month of Sourcing'].dt.
↪year
df_no_outliers_zscore['Month'] = df_no_outliers_zscore['Month of Sourcing'].dt.
↪month
```

```
# Separate features (X) and target variable (y)
X = df_no_outliers_zscore.drop(columns=['Sourcing Cost'])
y = df_no_outliers_zscore['Sourcing Cost']

# Encode categorical variables
encoder = OneHotEncoder(drop='first', sparse=False)
X_encoded = encoder.fit_transform(X[categorical_columns])

# Convert encoded arrays to DataFrame
X_encoded_df = pd.DataFrame(X_encoded, columns=encoder.
 ↪get_feature_names_out(input_features=categorical_columns))

# Combine encoded categorical columns and extracted features
X_final = pd.concat([X_encoded_df.reset_index(drop=True),␣
 ↪df_no_outliers_zscore[['Year', 'Month']].reset_index(drop=True)], axis=1)

# Train the KNN model
knn_model_zscore = KNeighborsRegressor()
knn_model_zscore.fit(X_final, y)

# Predict using the trained model
y_pred_knn_zscore = knn_model_zscore.predict(X_final)

# Evaluate the model
mse_knn_zscore = mean_squared_error(y, y_pred_knn_zscore)
mae_knn_zscore = mean_absolute_error(y, y_pred_knn_zscore)
r2_knn_zscore = r2_score(y, y_pred_knn_zscore)
rmse_knn_zscore = np.sqrt(mse_knn_zscore)

print("KNN - Mean Squared Error (Z-score):", mse_knn_zscore)
print("KNN - Mean Absolute Error (Z-score):", mae_knn_zscore)
print("KNN - R-squared (Z-score):", r2_knn_zscore)
print("KNN - Root Mean Squared Error (Z-score):", rmse_knn_zscore)

# Plot predictions vs. actual values for KNN
plt.figure(figsize=(8, 6))
plt.scatter(y, y_pred_knn_zscore, color='blue', alpha=0.5)
plt.plot([min(y), max(y)], [min(y), max(y)], color='red', linestyle='--')
plt.xlabel('Actual Sourcing Cost')
plt.ylabel('Predicted Sourcing Cost')
plt.title('KNN - Predictions vs. Actual (Without Outliers - Z-score)')
plt.grid(True)
plt.show()
```

```
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/1179194688.py:8:
SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_zscore['Month of Sourcing'] =
pd.to_datetime(df_no_outliers_zscore['Month of Sourcing'])
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/1179194688.py:11
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_zscore['Year'] = df_no_outliers_zscore['Month of
Sourcing'].dt.year
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/1179194688.py:12
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_zscore['Month'] = df_no_outliers_zscore['Month of
Sourcing'].dt.month
/Users/saumit/anaconda3/lib/python3.11/site-
packages/sklearn/preprocessing/_encoders.py:975: FutureWarning: `sparse` was
renamed to `sparse_output` in version 1.2 and will be removed in 1.4.
`sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

```
KNN - Mean Squared Error (Z-score): 622.3578191839425
KNN - Mean Absolute Error (Z-score): 10.854056863916968
KNN - R-squared (Z-score): 0.8087392400466707
KNN - Root Mean Squared Error (Z-score): 24.947100416359863
```



[ ]:

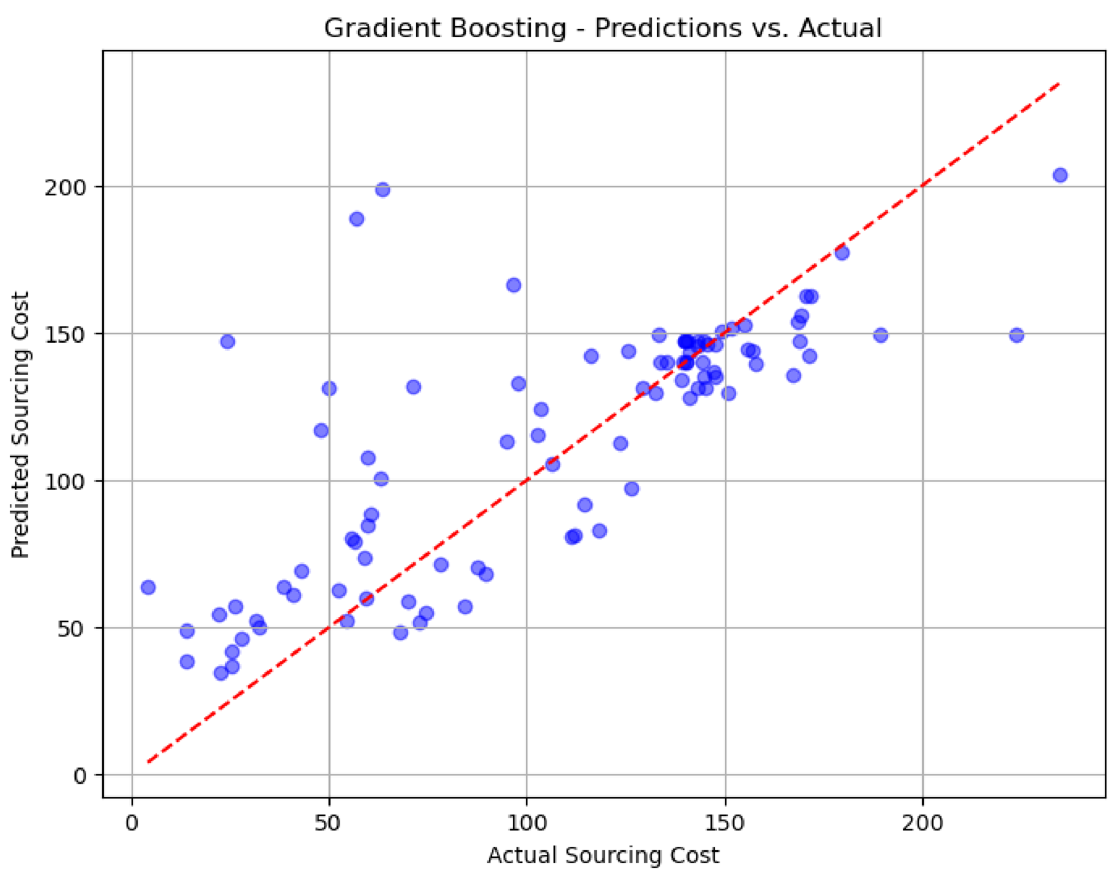
5.3 Gradient Boosting

[63]:

```
# Train the Gradient Boosting model
gradient_boosting_model = GradientBoostingRegressor()
gradient_boosting_model.fit(X_train_final, y_train)

# Evaluate the Gradient Boosting model
y_pred_gradient_boosting = gradient_boosting_model.predict(X_test_final)
mse_gradient_boosting = mean_squared_error(y_test, y_pred_gradient_boosting)
mae_gradient_boosting = mean_absolute_error(y_test, y_pred_gradient_boosting)
r2_gradient_boosting = r2_score(y_test, y_pred_gradient_boosting)
rmse_gradient_boosting = np.sqrt(mse_gradient_boosting)

print("Gradient Boosting - Mean Squared Error:", mse_gradient_boosting)
print("Gradient Boosting - Mean Absolute Error:", mae_gradient_boosting)
print("Gradient Boosting - R-squared:", r2_gradient_boosting)
print("Gradient Boosting - Root Mean Squared Error:", rmse_gradient_boosting)
```

```python
# Plot predictions vs. actual values for Gradient Boosting
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred_gradient_boosting, color='blue', alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
 ↪linestyle='--')
plt.xlabel('Actual Sourcing Cost')
plt.ylabel('Predicted Sourcing Cost')
plt.title('Gradient Boosting - Predictions vs. Actual')
plt.grid(True)
plt.show()
```

```
Gradient Boosting - Mean Squared Error: 1171.4508163724956
Gradient Boosting - Mean Absolute Error: 22.597907613350674
Gradient Boosting - R-squared: 0.568201654012702
Gradient Boosting - Root Mean Squared Error: 34.22646368488126
```



Gradient boosting model using z-score for outlier/anomaly detecion : Here the outliers are filtered out using z-score and then the model is trained.

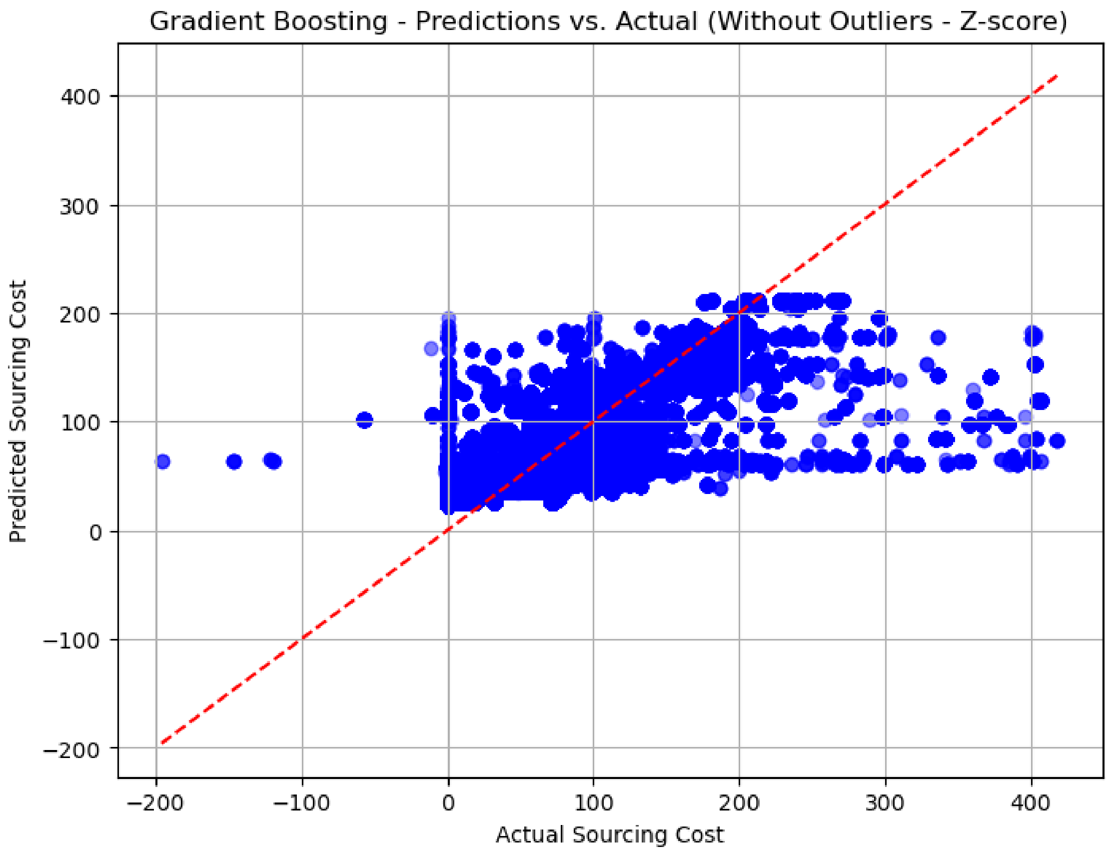
[64]:
```
# Filter out outliers using Z-score method
df_no_outliers_zscore = df[np.abs(stats.zscore(df['Sourcing Cost'])) <␣
 ↪threshold]

# Identify categorical columns
categorical_columns = df_no_outliers_zscore.select_dtypes(include=['object']).
 ↪columns.tolist()

# Convert 'Month of Sourcing' to datetime
df_no_outliers_zscore['Month of Sourcing'] = pd.
 ↪to_datetime(df_no_outliers_zscore['Month of Sourcing'])

# Extract features from datetime column
df_no_outliers_zscore['Year'] = df_no_outliers_zscore['Month of Sourcing'].dt.
 ↪year
df_no_outliers_zscore['Month'] = df_no_outliers_zscore['Month of Sourcing'].dt.
 ↪month

# Separate features (X) and target variable (y)
X = df_no_outliers_zscore.drop(columns=['Sourcing Cost'])
y = df_no_outliers_zscore['Sourcing Cost']

# Encode categorical variables
encoder = OneHotEncoder(drop='first', sparse=False)
X_encoded = encoder.fit_transform(X[categorical_columns])

# Convert encoded arrays to DataFrame
X_encoded_df = pd.DataFrame(X_encoded, columns=encoder.
 ↪get_feature_names_out(input_features=categorical_columns))

# Combine encoded categorical columns and extracted features
X_final = pd.concat([X_encoded_df.reset_index(drop=True),␣
 ↪df_no_outliers_zscore[['Year', 'Month']].reset_index(drop=True)], axis=1)

# Train the Gradient Boosting model
gradient_boosting_model_zscore = GradientBoostingRegressor()
gradient_boosting_model_zscore.fit(X_final, y)

# Predict using the trained model
y_pred_gradient_boosting_zscore = gradient_boosting_model_zscore.
 ↪predict(X_final)

# Evaluate the model
mse_gradient_boosting_zscore = mean_squared_error(y,␣
 ↪y_pred_gradient_boosting_zscore)
```

```
mae_gradient_boosting_zscore = mean_absolute_error(y,␣
  ↪y_pred_gradient_boosting_zscore)
r2_gradient_boosting_zscore = r2_score(y, y_pred_gradient_boosting_zscore)
rmse_gradient_boosting_zscore = np.sqrt(mse_gradient_boosting_zscore)

print("Gradient Boosting - Mean Squared Error (Z-score):",␣
  ↪mse_gradient_boosting_zscore)
print("Gradient Boosting - Mean Absolute Error (Z-score):",␣
  ↪mae_gradient_boosting_zscore)
print("Gradient Boosting - R-squared (Z-score):", r2_gradient_boosting_zscore)
print("Gradient Boosting - Root Mean Squared Error (Z-score):",␣
  ↪rmse_gradient_boosting_zscore)

# Plot predictions vs. actual values for Gradient Boosting
plt.figure(figsize=(8, 6))
plt.scatter(y, y_pred_gradient_boosting_zscore, color='blue', alpha=0.5)
plt.plot([min(y), max(y)], [min(y), max(y)], color='red', linestyle='--')
plt.xlabel('Actual Sourcing Cost')
plt.ylabel('Predicted Sourcing Cost')
plt.title('Gradient Boosting - Predictions vs. Actual (Without Outliers -␣
  ↪Z-score)')
plt.grid(True)
plt.show()
```

```
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/2667107576.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_zscore['Month of Sourcing'] =
pd.to_datetime(df_no_outliers_zscore['Month of Sourcing'])
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/2667107576.py:11
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_zscore['Year'] = df_no_outliers_zscore['Month of
Sourcing'].dt.year
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/2667107576.py:12
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_zscore['Month'] = df_no_outliers_zscore['Month of
Sourcing'].dt.month
/Users/saumit/anaconda3/lib/python3.11/site-
packages/sklearn/preprocessing/_encoders.py:975: FutureWarning: `sparse` was
renamed to `sparse_output` in version 1.2 and will be removed in 1.4.
`sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

```
Gradient Boosting - Mean Squared Error (Z-score): 842.8886407385451
Gradient Boosting - Mean Absolute Error (Z-score): 18.707636144120055
Gradient Boosting - R-squared (Z-score): 0.7409665034897945
Gradient Boosting - Root Mean Squared Error (Z-score): 29.032544510231016
```



Gradient Boosting model using IRQ for outlier/anomaly detecion : Here the outliers are filtered out using IQR(interquartile range) and then the model is trained.

[65]:
```
# Filter out outliers using IQR method
df_no_outliers_iqr = df[(df['Sourcing Cost'] >= lower_threshold) &␣
↪(df['Sourcing Cost'] <= upper_threshold)]
```

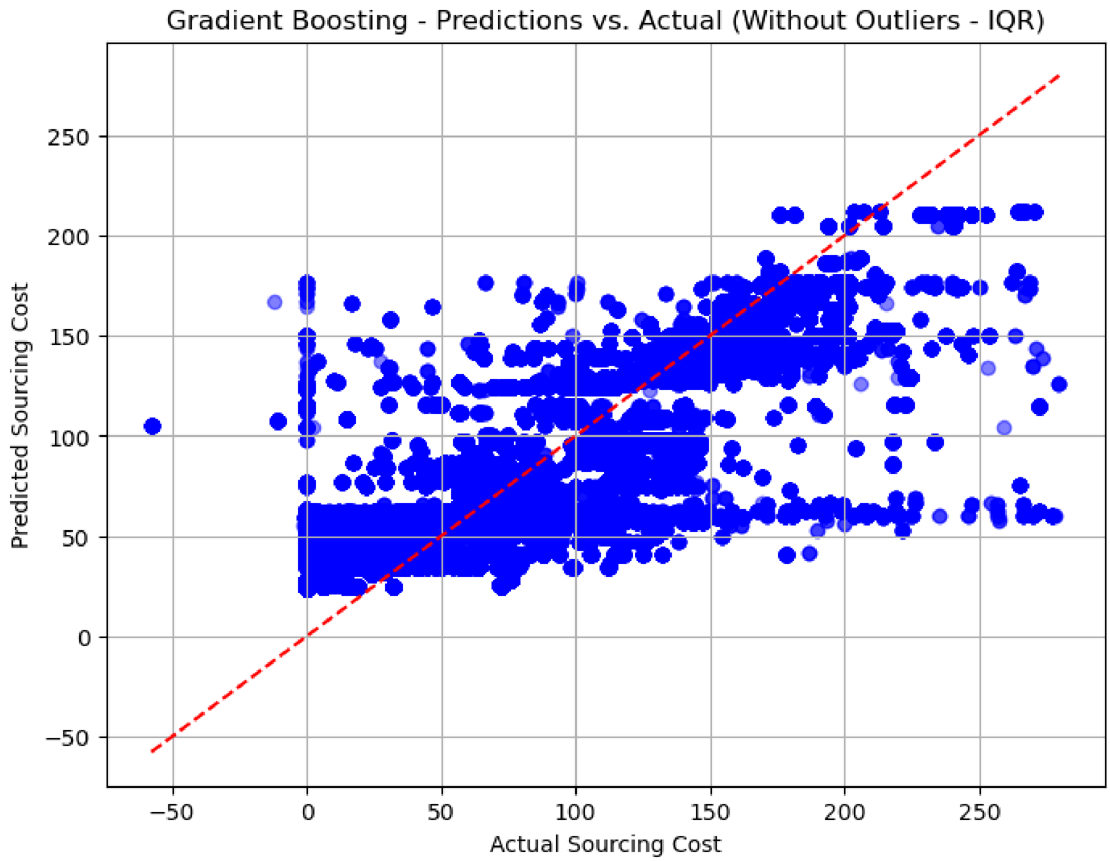
```python
# Identify categorical columns
categorical_columns = df_no_outliers_iqr.select_dtypes(include=['object']).
    ↪columns.tolist()

# Convert 'Month of Sourcing' to datetime
df_no_outliers_iqr['Month of Sourcing'] = pd.
    ↪to_datetime(df_no_outliers_iqr['Month of Sourcing'])

# Extract features from datetime column
df_no_outliers_iqr['Year'] = df_no_outliers_iqr['Month of Sourcing'].dt.year
df_no_outliers_iqr['Month'] = df_no_outliers_iqr['Month of Sourcing'].dt.month

# Separate features (X) and target variable (y)
X = df_no_outliers_iqr.drop(columns=['Sourcing Cost'])
y = df_no_outliers_iqr['Sourcing Cost']

# Encode categorical variables
encoder = OneHotEncoder(drop='first', sparse=False)
X_encoded = encoder.fit_transform(X[categorical_columns])

# Convert encoded arrays to DataFrame
X_encoded_df = pd.DataFrame(X_encoded, columns=encoder.
    ↪get_feature_names_out(input_features=categorical_columns))

# Combine encoded categorical columns and extracted features
X_final = pd.concat([X_encoded_df.reset_index(drop=True),␣
    ↪df_no_outliers_iqr[['Year', 'Month']].reset_index(drop=True)], axis=1)

# Train the Gradient Boosting model
gradient_boosting_model_iqr = GradientBoostingRegressor()
gradient_boosting_model_iqr.fit(X_final, y)

# Predict using the trained model
y_pred_gradient_boosting_iqr = gradient_boosting_model_iqr.predict(X_final)

# Evaluate the model
mse_gradient_boosting_iqr = mean_squared_error(y, y_pred_gradient_boosting_iqr)
mae_gradient_boosting_iqr = mean_absolute_error(y, y_pred_gradient_boosting_iqr)
r2_gradient_boosting_iqr = r2_score(y, y_pred_gradient_boosting_iqr)
rmse_gradient_boosting_iqr = np.sqrt(mse_gradient_boosting_iqr)

print("Gradient Boosting - Mean Squared Error (IQR):",␣
    ↪mse_gradient_boosting_iqr)
print("Gradient Boosting - Mean Absolute Error (IQR):",␣
    ↪mae_gradient_boosting_iqr)
```

```python
print("Gradient Boosting - R-squared (IQR):", r2_gradient_boosting_iqr)
print("Gradient Boosting - Root Mean Squared Error (IQR):",␣
↪rmse_gradient_boosting_iqr)

# Plot predictions vs. actual values for Gradient Boosting
plt.figure(figsize=(8, 6))
plt.scatter(y, y_pred_gradient_boosting_iqr, color='blue', alpha=0.5)
plt.plot([min(y), max(y)], [min(y), max(y)], color='red', linestyle='--')
plt.xlabel('Actual Sourcing Cost')
plt.ylabel('Predicted Sourcing Cost')
plt.title('Gradient Boosting - Predictions vs. Actual (Without Outliers - IQR)')
plt.grid(True)
plt.show()
```

```
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/1483575717.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_iqr['Month of Sourcing'] =
pd.to_datetime(df_no_outliers_iqr['Month of Sourcing'])
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/1483575717.py:11
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_iqr['Year'] = df_no_outliers_iqr['Month of Sourcing'].dt.year
/var/folders/jw/xdjgvbw534x94g51k1ltxy640000gn/T/ipykernel_6328/1483575717.py:12
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_outliers_iqr['Month'] = df_no_outliers_iqr['Month of Sourcing'].dt.month
/Users/saumit/anaconda3/lib/python3.11/site-
packages/sklearn/preprocessing/_encoders.py:975: FutureWarning: `sparse` was
renamed to `sparse_output` in version 1.2 and will be removed in 1.4.
`sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

```
Gradient Boosting - Mean Squared Error (IQR): 723.8604950081095
Gradient Boosting - Mean Absolute Error (IQR): 18.285919315944867
Gradient Boosting - R-squared (IQR): 0.7677121493650024
```

```
Gradient Boosting - Root Mean Squared Error (IQR): 26.904655638162506
```



5.4 Evaluation Table

[71]:
```
#Define evaluation scores for each model and outlier removal method
evaluation_data = {
    'Model': ['Random Forest (IQR)', 'Random Forest (Z-score)', 'KNN (IQR)',␣
 ↪'KNN (Z-score)',
              'Linear Regression (IQR)', 'Linear Regression (Z-score)',
              'Gradient Boosting (IQR)', 'Gradient Boosting (Z-score)'],
    'Mean Squared Error': [mse_rf_iqr, mse_rf_zscore, mse_knn_iqr,␣
 ↪mse_knn_zscore,
                           mse_linear_iqr, mse_lr_zscore,␣
 ↪mse_gradient_boosting_iqr, mse_gradient_boosting_zscore],
    'Mean Absolute Error': [mae_rf_iqr, mae_rf_zscore, mae_knn_iqr,␣
 ↪mae_knn_zscore,
                            mae_linear_iqr, mae_lr_zscore,␣
 ↪mae_gradient_boosting_iqr, mae_gradient_boosting_zscore],
    'R-squared': [r2_rf_iqr, r2_rf_zscore, r2_knn_iqr, r2_knn_zscore,
```

```
                 r2_linear_iqr, r2_lr_zscore, r2_gradient_boosting_iqr,␣
↪r2_gradient_boosting_zscore],
    'Root Mean Squared Error': [rmse_rf_iqr, rmse_rf_zscore, rmse_knn_iqr,␣
↪rmse_knn_zscore,
                                rmse_linear_iqr, rmse_lr_zscore,␣
↪rmse_gradient_boosting_iqr, rmse_gradient_boosting_zscore]
}

# Create DataFrame to store evaluation scores
evaluation_table = pd.DataFrame(evaluation_data)

# Display the table
print("Evaluation Scores for Different Models with Outliers Removed (IQR and␣
↪Z-score):")
print(evaluation_table)
```

```
Evaluation Scores for Different Models with Outliers Removed (IQR and Z-score):
                        Model  Mean Squared Error  Mean Absolute Error  \
0         Random Forest (IQR)          364.872922             9.077356
1     Random Forest (Z-score)          483.166616             9.808285
2                   KNN (IQR)          448.944300             9.914246
3               KNN (Z-score)          622.357819            10.854057
4     Linear Regression (IQR)          700.621228            17.021742
5 Linear Regression (Z-score)          851.789058            17.775925
6     Gradient Boosting (IQR)          723.860495            18.285919
7 Gradient Boosting (Z-score)          842.888641            18.707636

   R-squared  Root Mean Squared Error
0   0.882912                19.101647
1   0.851515                21.981051
2   0.855933                21.188306
3   0.808739                24.947100
4   0.775170                26.469251
5   0.738231                29.185425
6   0.767712                26.904656
7   0.740967                29.032545
```

[72]:

```
from tabulate import tabulate

# Display the table using tabulate
print(tabulate(evaluation_table, headers='keys', tablefmt='grid'))
```

```
+----+-----------------------------+----------------------+---------------------
--+-------------+--------------------------+
|    | Model                       |   Mean Squared Error |    Mean Absolute
Error |   R-squared |   Root Mean Squared Error |
+====+=============================+======================+=====================
```

0	Random Forest (IQR)	364.873	9.07736	0.882912	19.1016
1	Random Forest (Z-score)	483.167	9.80829	0.851515	21.9811
2	KNN (IQR)	448.944	9.91425	0.855933	21.1883
3	KNN (Z-score)	622.358	10.8541	0.808739	24.9471
4	Linear Regression (IQR)	700.621	17.0217	0.77517	26.4693
5	Linear Regression (Z-score)	851.789	17.7759	0.738231	29.1854
6	Gradient Boosting (IQR)	723.86	18.2859	0.767712	26.9047
7	Gradient Boosting (Z-score)	842.889	18.7076	0.740967	29.0325

In conclusion, Random Forest with Interquartile Range (IQR) outlier removal emerges as the top-performing model among those tested.

Robustness to Outliers: The IQR method effectively filters out outliers, ensuring that the Random Forest model is trained on a more representative and less biased dataset. This robustness to outliers enhances the model's ability to generalize well to unseen data.

Ensemble Learning: Random Forest leverages ensemble learning, combining multiple decision trees trained on random subsets of the data. This ensemble approach mitigates overfitting and improves predictive accuracy by capturing diverse patterns in the data.

Non-linear Relationships: Random Forest can model complex, non-linear relationships between features and the target variable. This flexibility allows the model to capture intricate patterns that may exist in the data, leading to superior predictive performance.

Feature Importance: Random Forest provides insights into feature importance, enabling us to identify the most influential predictors. This feature analysis aids in understanding the underlying factors driving the predicted outcomes and can inform decision-making in real-world applications.

[ ]:

```

```