Coffee Shop Revenue Prediction Prediction using Scikit-learn

This presentation explores how to utilize Scikit-learn for predicting coffee shop revenue based on various factors.

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Data Import and Library Setup

Import necessary libraries:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Load data from a CSV file:

```
df =
pd.read_csv(r'C:\Downloads\coffee_shop_revenue.
csv')
```

	Number_of_Customers_Per_Day	Average_Order_Value	Operating_Hours_Per_Day	Number_of_Employees	Marketing_Spend_Per_Day	Location_Foot_Traffic	Daily_Revenue
0	152	6.74	14	4	106.62	97	1547.81
1	485	4.50	12	8	57.83	744	2084.68
2	398	9.09	6	6	91.76	636	3118.39
3	320	8.48	17	4	462.63	770	2912.20
4	156	7.44	17	2	412.52	232	1663.42

Handling Missing and Duplicate Data

Identify missing values:

```
data.isnull().sum()
```

Impute missing values:

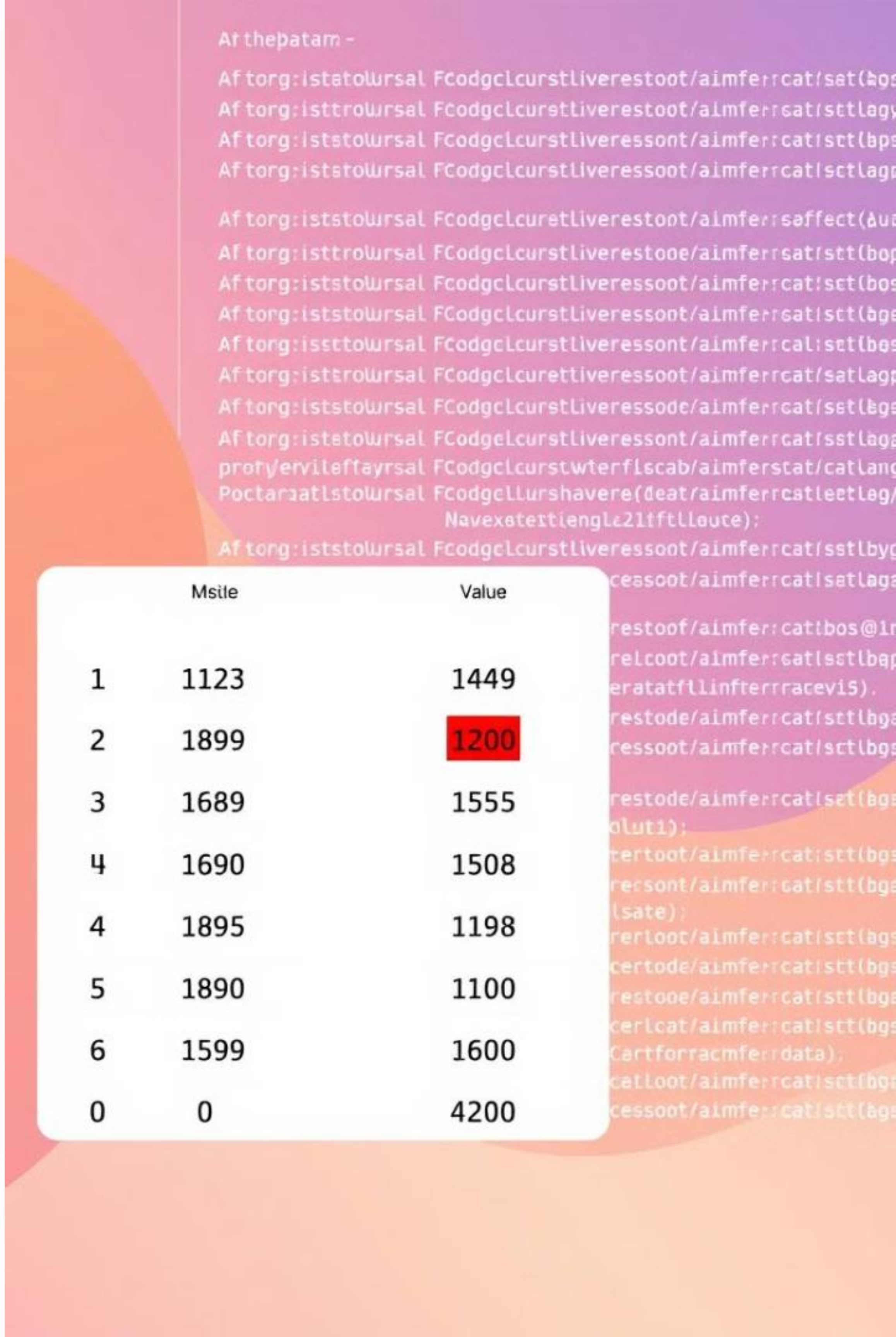
```
data['column'].fillna(data['column'].mean(), inplace=True)
```

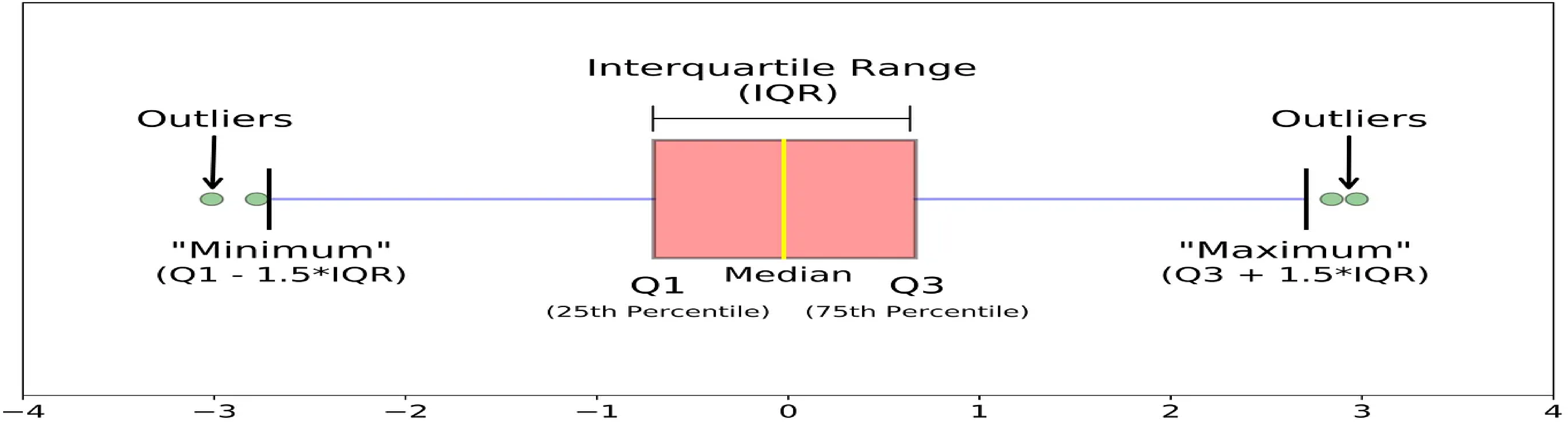
Identify duplicates:

```
data.duplicated().sum()
```

Remove duplicates:

```
data.drop_duplicates(inplace=True)
```





Outlier Detection and Treatment Strategies

Box plots can visually identify outliers.

Remove outliers using IQR method or other suitable techniques.

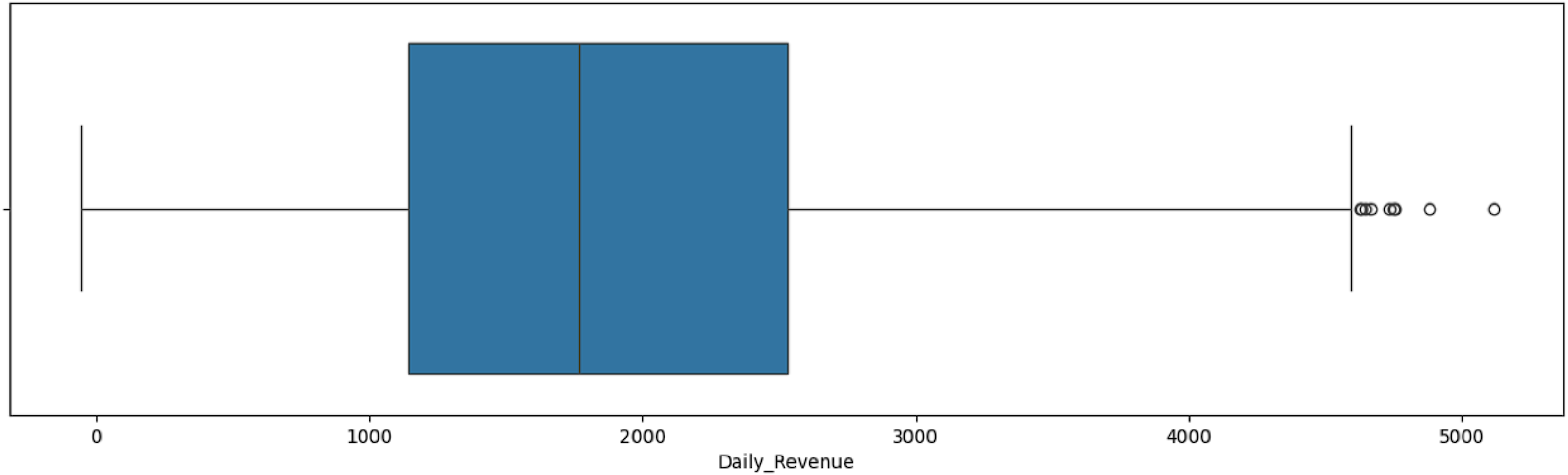
HOW TO FIND OUTLIER PRESENT OR NOT

```
df.describe()
```

	Number_of_Customers_Per_Day	Average_Order_Value	Operating_Hours_Per_Day	Marketing_Spend_Per_Day	Location_Foot_Traffic	Daily_Revenue
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	274.296000	6.261215	11.667000	252.614160	534.893500	1917.325940
std	129.441933	2.175832	3.438608	141.136004	271.662295	976.202746
min	50.000000	2.500000	6.000000	10.120000	50.000000	-58.950000
25%	164.000000	4.410000	9.000000	130.125000	302.000000	1140.085000
50%	275.000000	6.300000	12.000000	250.995000	540.000000	1770.775000
75%	386.000000	8.120000	15.000000	375.352500	767.000000	2530.455000
max	499.000000	10.000000	17.000000	499.740000	999.000000	5114.600000

In the dataset the large difference between the minimum (-58.95), mean (1917.33), and maximum (5114.60) values in the **Daily_Revenue** column suggests potential outliers.

```python
# checking for outlier
plt.figure(figsize=(15,4))
sns.boxplot(x="Daily_Revenue",data=df)
plt.show()
plt.savefig("outlier.jpg")
```



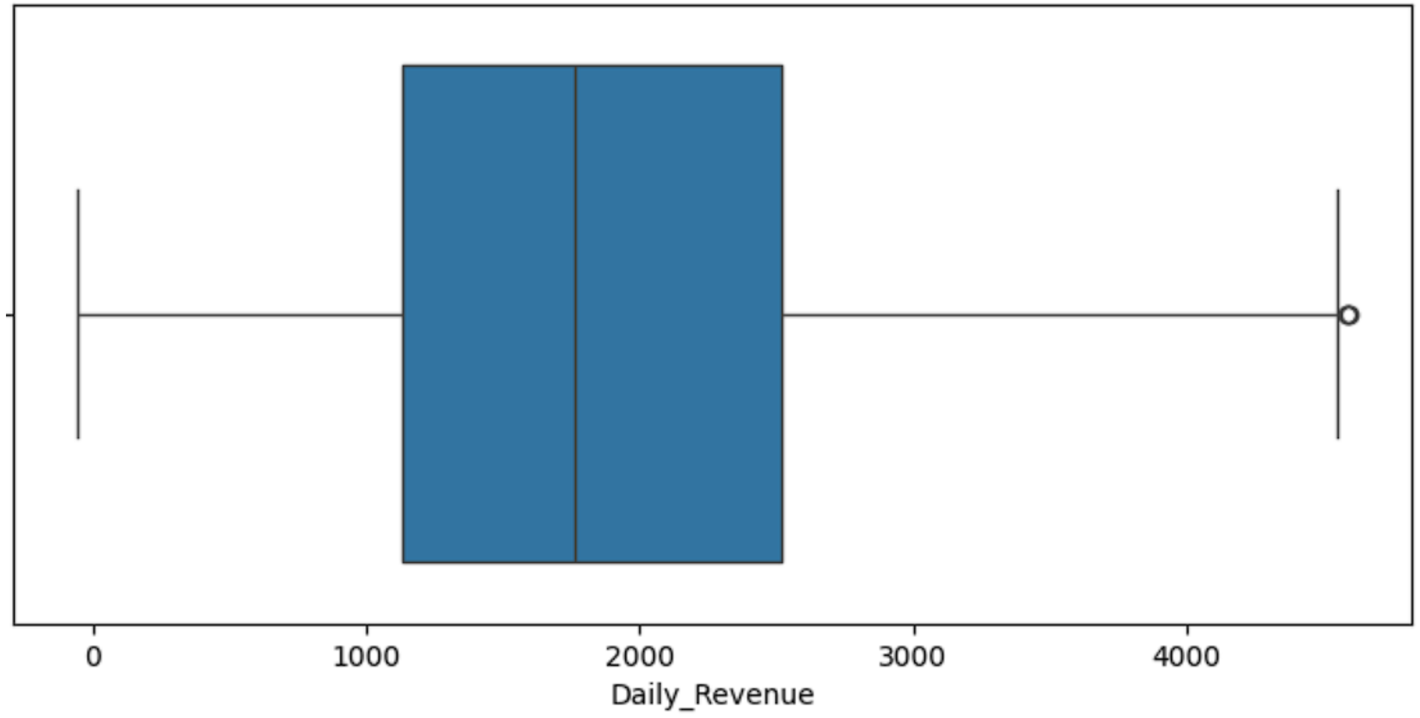
Remove the outlier by the INTER QUARTILE RANGE (IQR) method

```
# remove the outlier
q1 = df["Daily_Revenue"].quantile(0.25)
q3 = df ["Daily_Revenue"].quantile(0.75)
IQR= (q3 - q1)
```

```
min_range= q1 -(1.5*IQR)
max_range=q3 +(1.5*IQR)
df1=df[df["Daily_Revenue"]<= max_range]
```

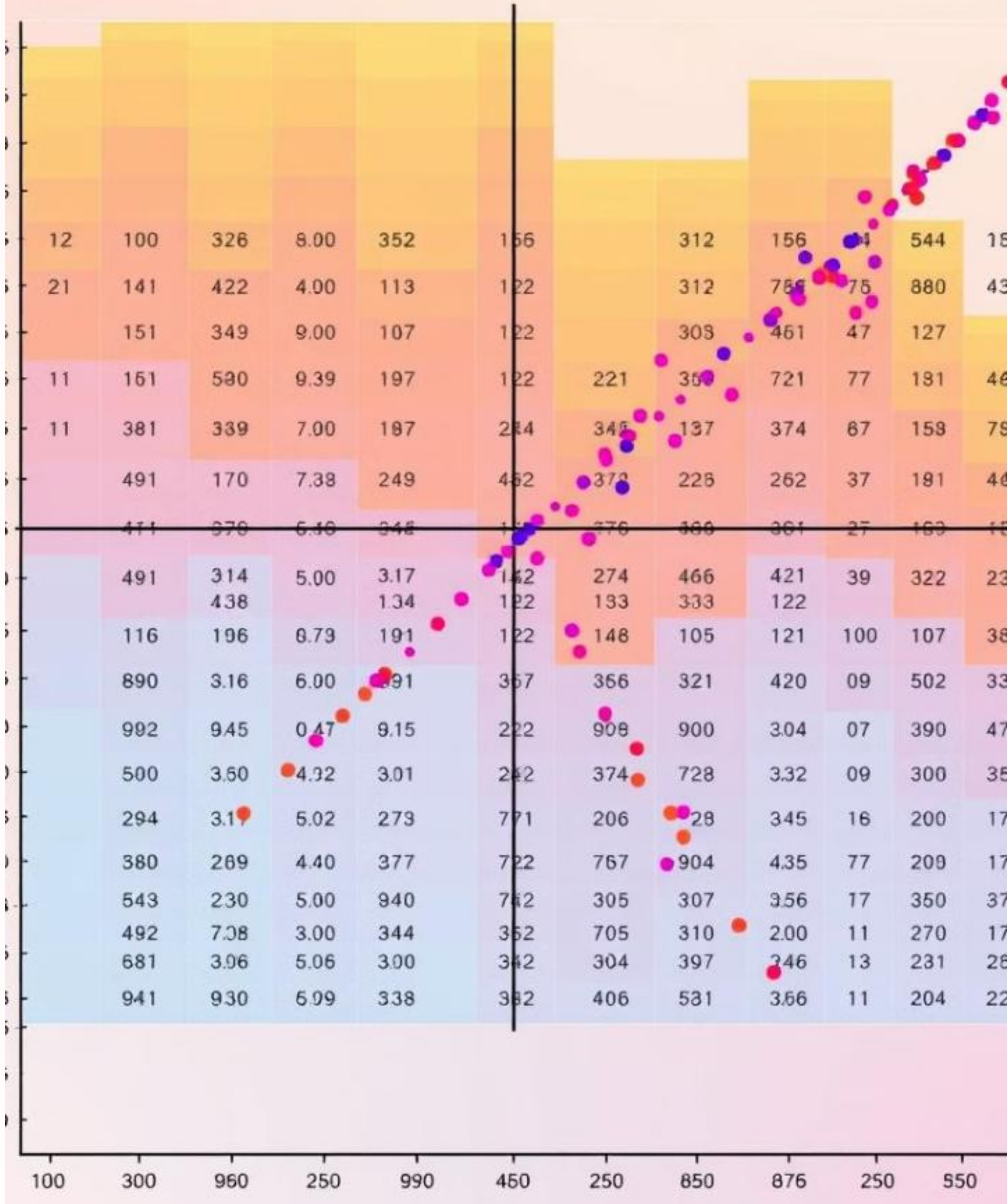
Checking the outlier present or not

```
# checking for outlier
plt.figure(figsize=(9,4))
sns.boxplot(x="Daily_Revenue",data=df1)
plt.show()
```



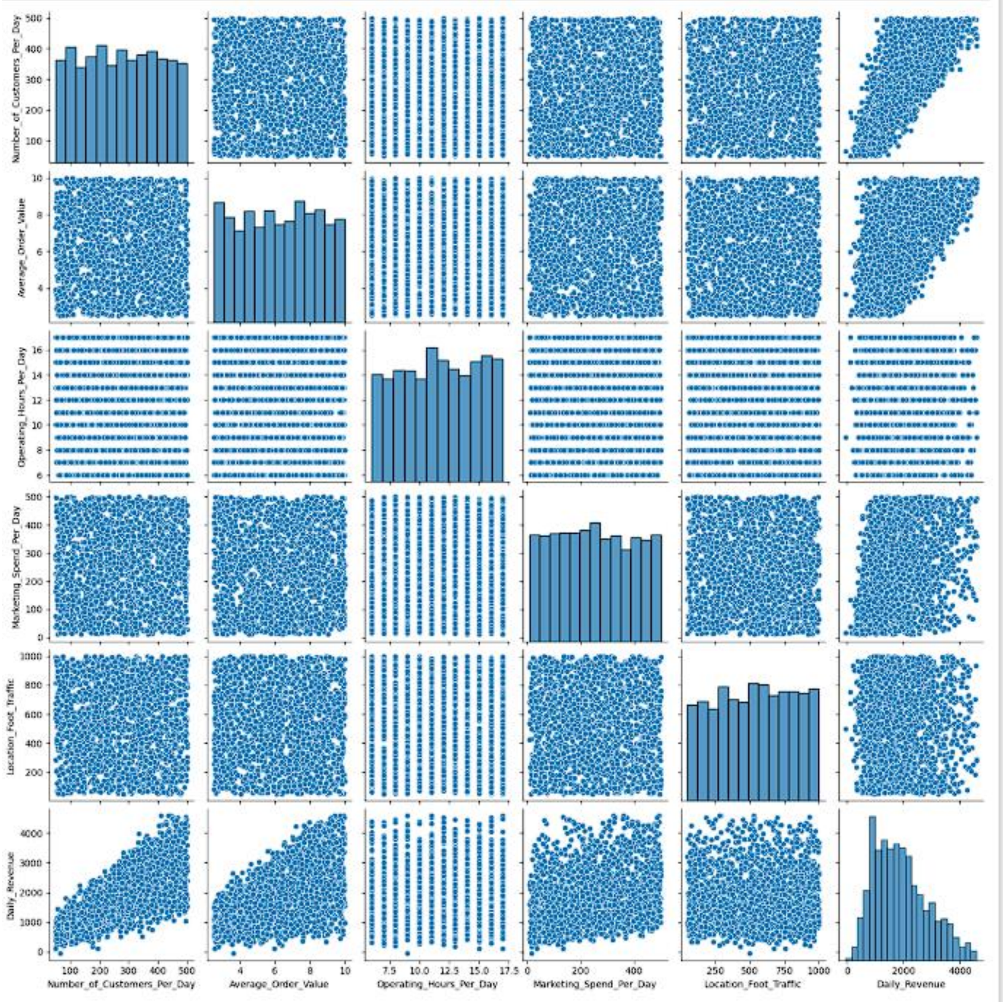
Feature Selection: Analyzing Input-Output Relationships

1. Examine correlation between features and target variable.
2. Use feature selection methods such as SelectKBest or recursive feature elimination.
3. Remove irrelevant features to improve model accuracy.

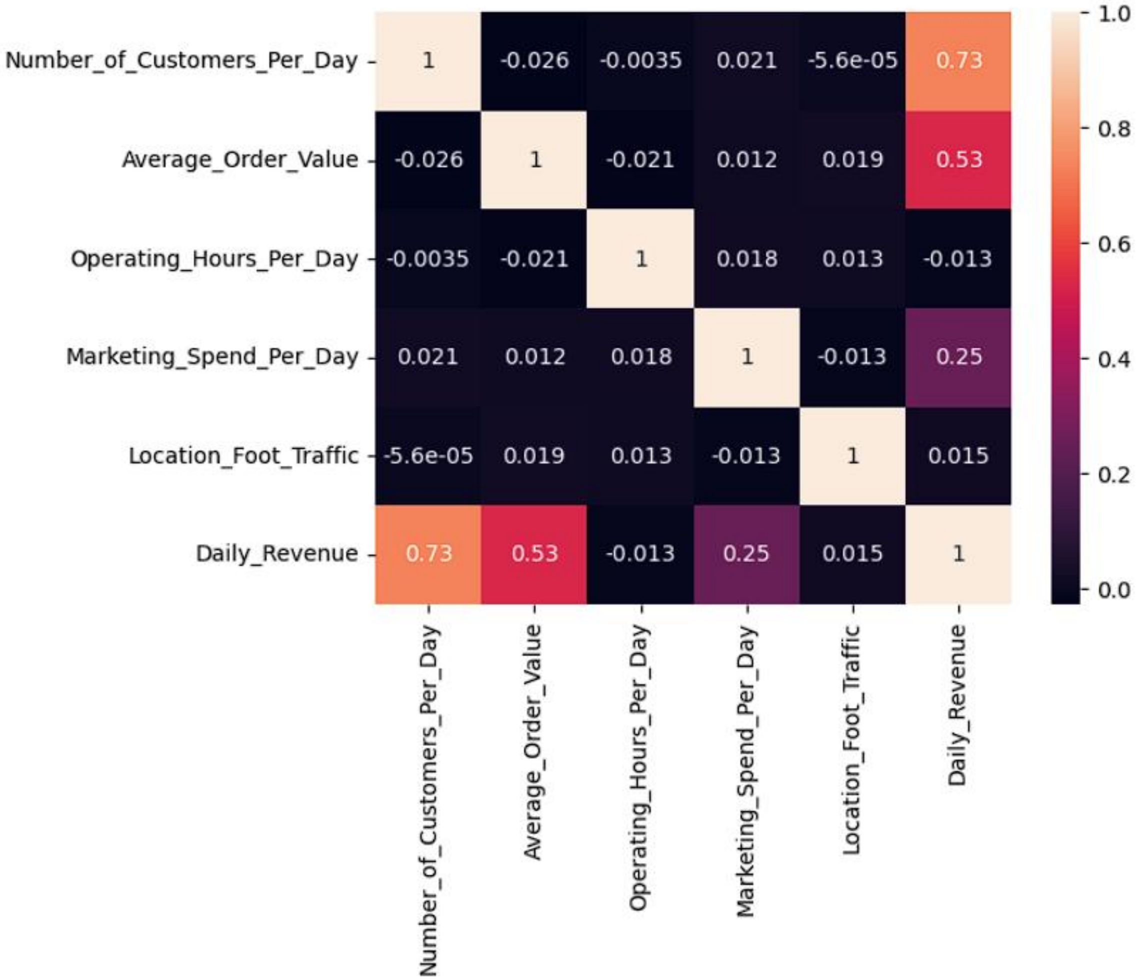


Find relationship between output and input features

```python
sns.pairplot(data=df1)
plt.show()
```

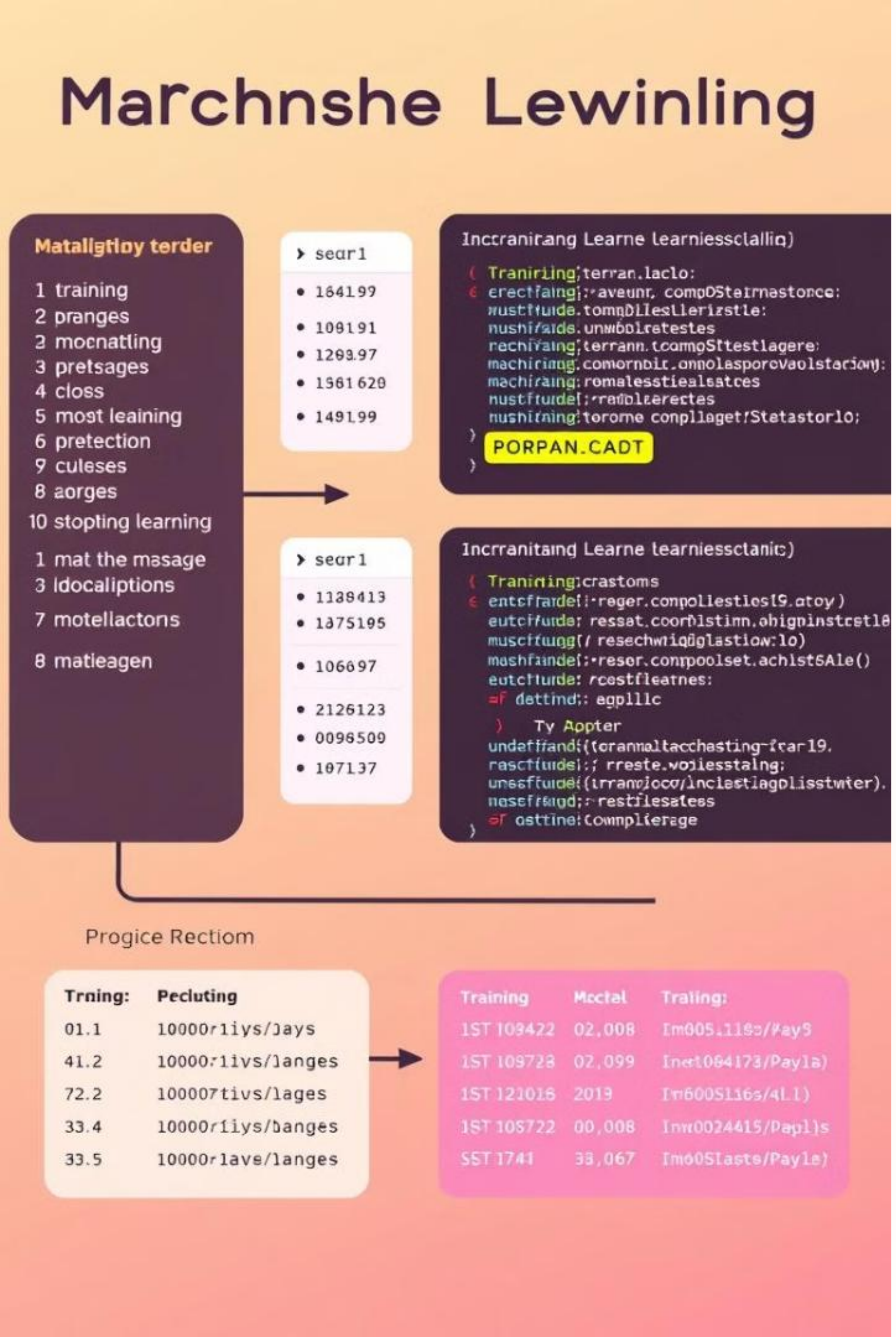


```python
sns.heatmap(data=df1.corr(),annot=True)
plt.show()
plt.savefig("heatmap.jpg")
```



, from the pair plot, we can see that:

- **Number_of_Customers_Per_Day vs. Daily_Revenue** shows a strong positive linear relationship.
- **Average_Order_Value vs. Daily_Revenue** also exhibits a linear trend.
- **Marketing_Spend_Per_Day vs. Daily_Revenue** has a somewhat positive linear correlation.



Machine Learning Model Deployment and Prediction

1. Split data into training and testing sets.
2. Train a linear regression model on the training data.
3. Make predictions on the testing data.

Separate the all-input features and output

```python
x= df1.iloc[:, :3]
y=df1["Daily_Revenue"]
```

```python
x
```

	Number_of_Customers_Per_Day	Average_Order_Value	Marketing_Spend_Per_Day
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1	485	4.50	57.83
2	398	9.09	91.76
3	320	8.48	462.63
4	156	7.44	412.52
...	...	...	...
1995	372	6.41	466.11
1996	105	3.01	12.62

Split the the data into two parts and Deployment Machine Learning Model Model

```
# split the data into 2 parts
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.25,random_state=35)
```

```
import numpy as np
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(x_train,y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
# testing data
y_pred=lr.predict(x_test)
```

```
lr.score(x_test,y_test)*100
```

```
90.14407476562933
```

```
lr.coef_
```

```
array([  5.46355433, 238.07113104,   1.53244795])
```

```
lr.intercept_
```

```
-1466.7042318707547
```

Model Evaluation: Accuracy, Coefficients, and Intercept Intercept

90.144

Accuracy

Evaluate model performance using metrics like R-squared or mean squared error.

5.463, 238.071, 1.532

Coefficients

Interpret coefficients to understand the impact of each feature on revenue.

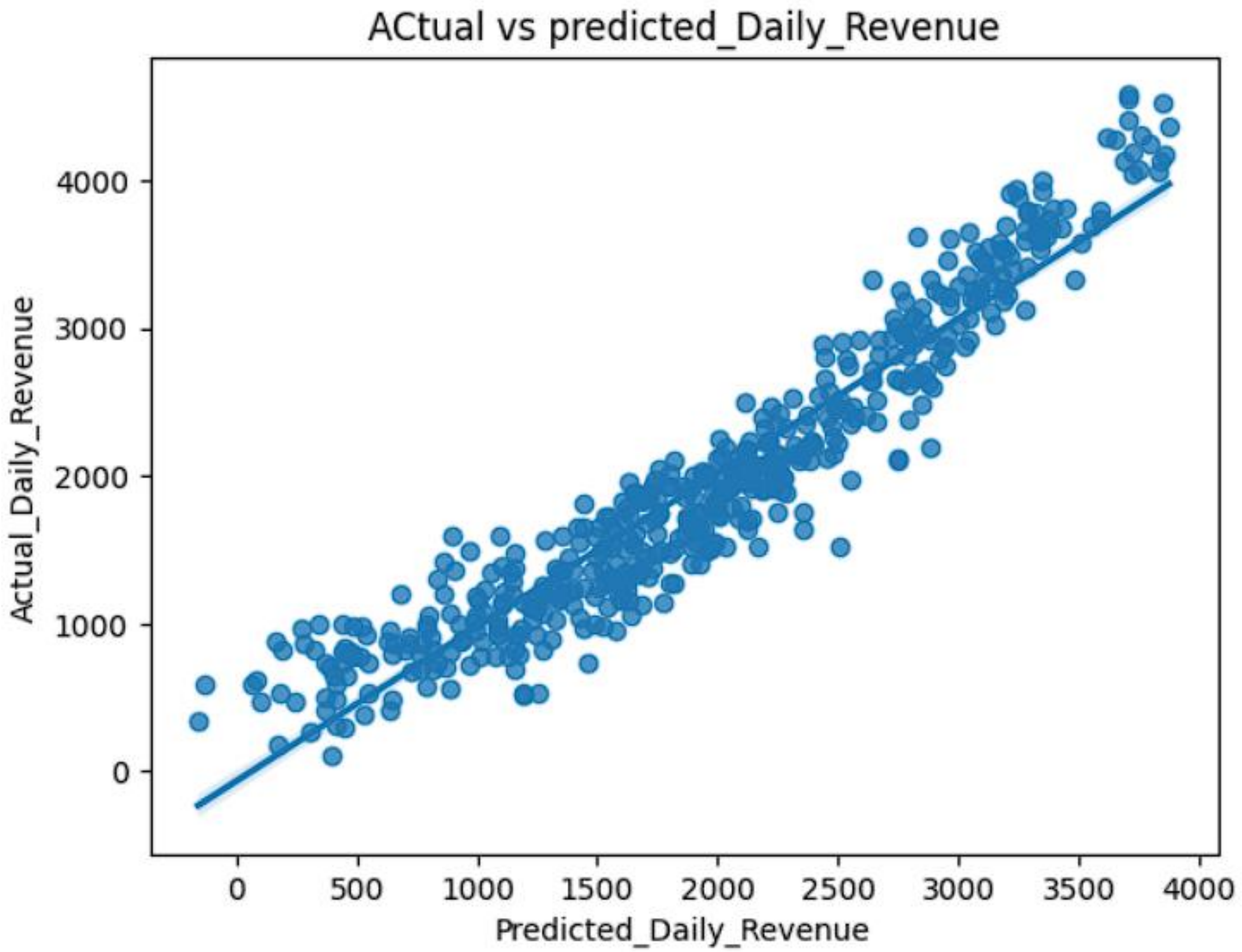
-1466.704

Intercept

The intercept represents the baseline revenue when all features are zero.

Actual vs predicted_Daily_Revenue

```
sns.regplot(x=y_pred, y=y_test)
plt.xlabel("Predicted_Daily_Revenue")
plt.ylabel('Actual_Daily_Revenue')
plt.title("Actual vs predicted_Daily_Revenue")
plt.show()
plt.savefig("Daily_Revenue_prediction.jpg")
```



Conclusion: Key Findings and Future Improvements

The model provides a valuable tool for predicting coffee shop revenue, helping to inform decision-making and optimize operations. Future improvements include exploring more advanced models, incorporating seasonal trends, and expanding the dataset for better accuracy.

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