

PEAK PERFORMANCE: PREDICTIVE MODELING FOR VACATION RENTAL REVENUE



CONTENT

01

BUSINESS PARTNER

02

BUSINESS OBJECTIVES

03

DATA ANALYSIS AND METHODS

04

MODELING

05

CONCLUSION

06

NEXT STEPS

07

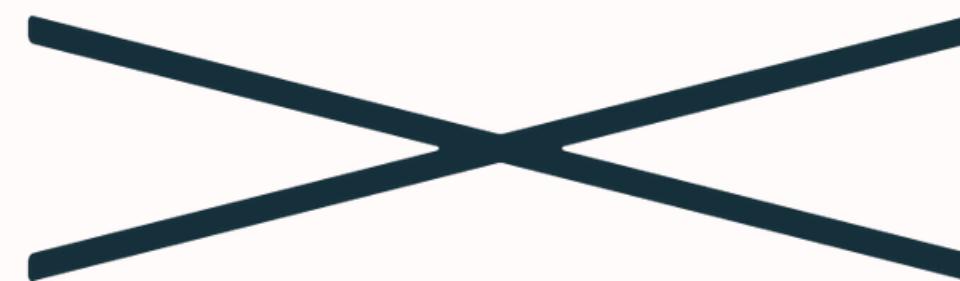
CONTACTS



BUSINESS PARTNER

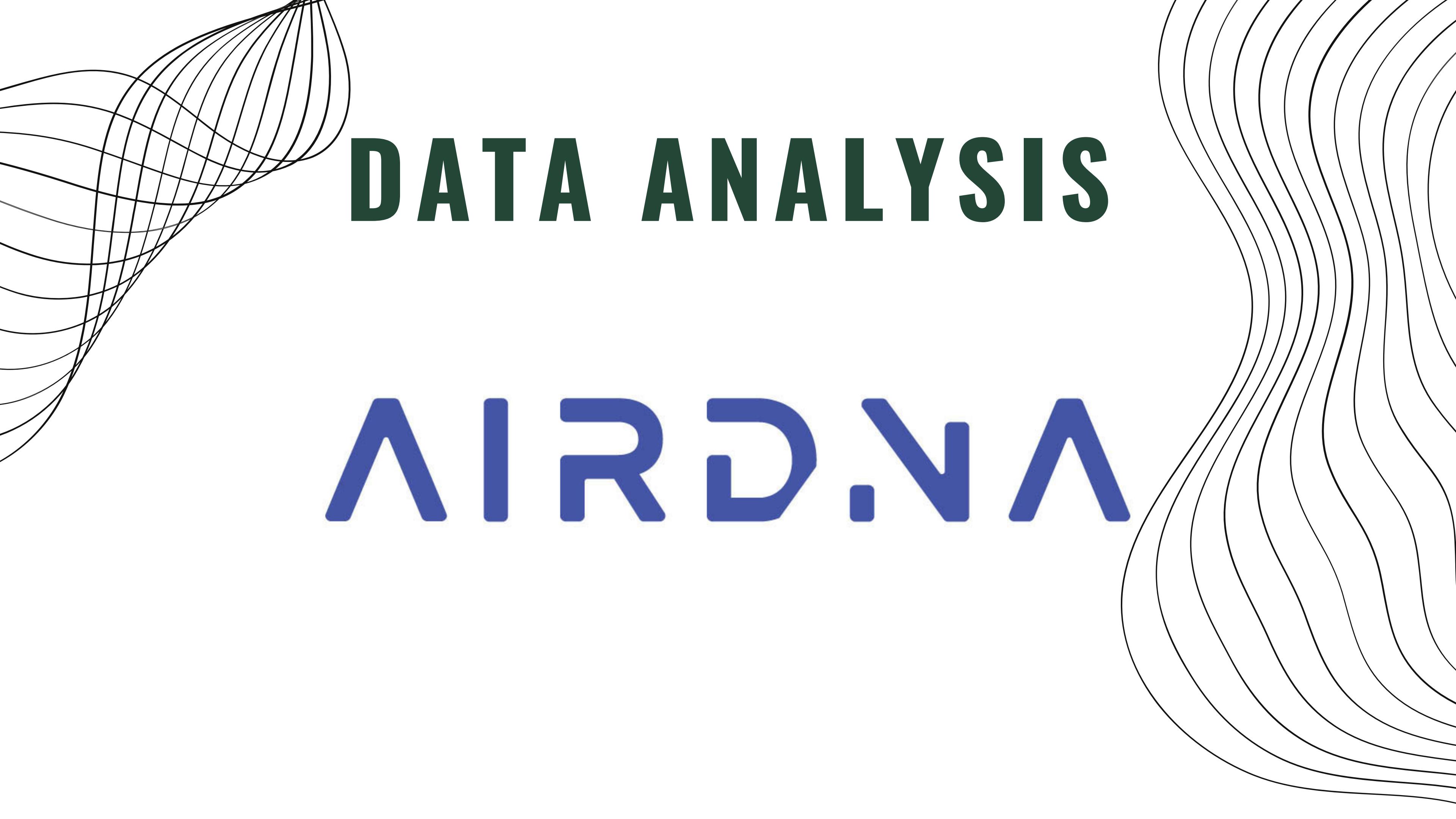


CLOUD 9 CABINS SMOKY MOUNTAINS



BUSINESS PROBLEM/OBJECTIVE

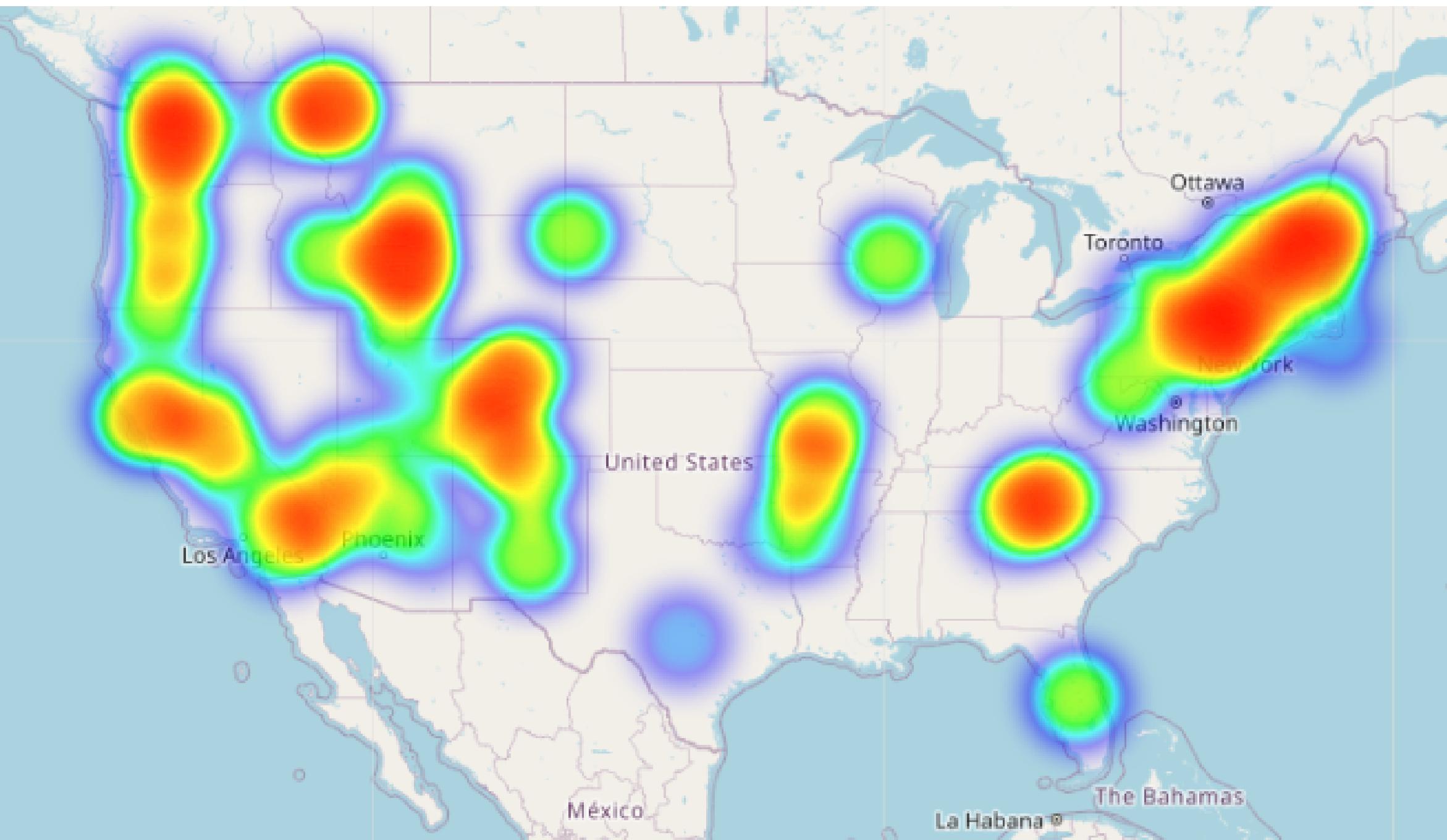
The business problem we aim to address is determining the profitability of potential new properties before committing significant resources to their development.



DATA ANALYSIS

AIRDNA

The Data

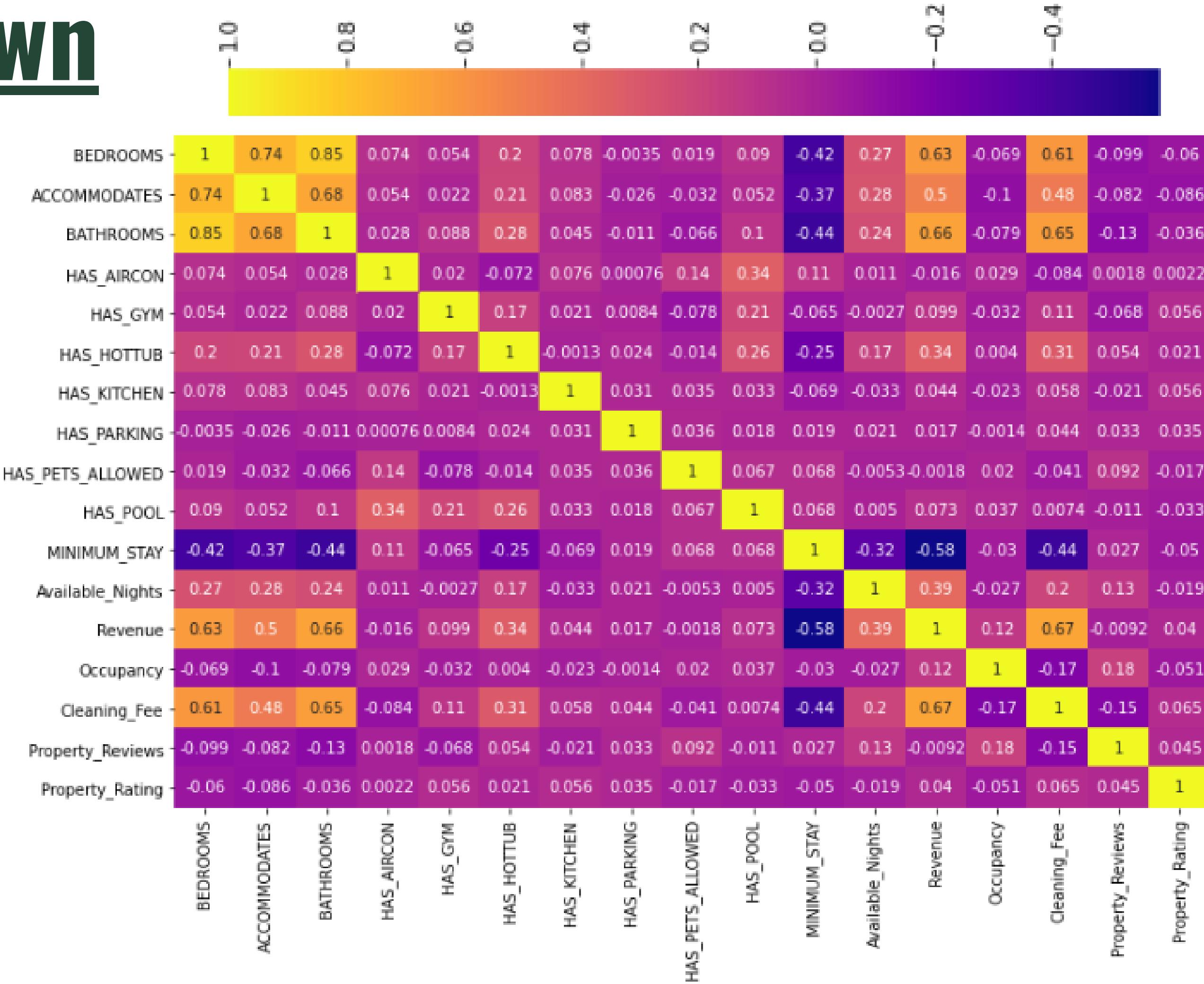


```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9039 entries, 0 to 9038
Data columns (total 33 columns):
 #   Column           Non-Null Count Dtype  
--- 
 0   Property ID      9039 non-null   object  
 1   TITLE            9039 non-null   object  
 2   Property Manager/ Host ID 9039 non-null   object  
 3   BEDROOMS          9029 non-null   float64 
 4   ACCOMMODATES     9031 non-null   float64 
 5   Airbnb Host URL 6397 non-null   object  
 6   Airbnb Listing URL 6397 non-null   object  
 7   BATHROOMS         9035 non-null   float64 
 8   CITY_NAME         9038 non-null   object  
 9   HAS_AIRCON        9039 non-null   bool    
 10  HAS_GYM           9039 non-null   bool    
 11  HAS_HOTTUB        9039 non-null   bool    
 12  HAS_KITCHEN       9039 non-null   bool    
 13  HAS_PARKING        9039 non-null   bool    
 14  HAS_PETS_ALLOWED  9039 non-null   bool    
 15  HAS_POOL           9039 non-null   bool    
 16  INSTANT_BOOK       9022 non-null   object  
 17  LATITUDE          9039 non-null   float64 
 18  LONGITUDE          9039 non-null   float64 
 19  PRICE_TIER         9039 non-null   object  
 20  STATE_NAME         9039 non-null   object  
 21  SUPERHOST          6064 non-null   object  
 22  Vrbo Listing URL  6104 non-null   object  
 23  ZIPCODE            9039 non-null   int64   
 24  MINIMUM_STAY       8539 non-null   float64 
 25  Available Nights  9039 non-null   int64   
 26  Revenue             9039 non-null   int64   
 27  Revenue Potential  9039 non-null   float64 
 28  ADR                9018 non-null   float64 
 29  Occupancy           9039 non-null   float64 
 30  Cleaning Fee        8269 non-null   float64 
 31  Property Reviews    8334 non-null   float64 
 32  Property Rating     7104 non-null   float64 
dtypes: bool(7), float64(12), int64(3), object(11)
memory usage: 1.9+ MB
```

Narrowing Down the Data

Property Filtering Criteria

- Available Nights
 - Fewer than 200 nights: Likely not true short-term rentals.
- Minimum Stay
 - Over 100 days: Indicates long-term rentals.
- Property Reviews
 - Fewer than 10 reviews: Possibly unsuccessful or lack full data.
- Revenue
 - Less than \$10,000: Potentially unsuccessful or temporary listings.
 - Over \$700,000: Outliers.
- Occupancy
 - Below 25%: May indicate unsuccessful rentals or cost subsidization.

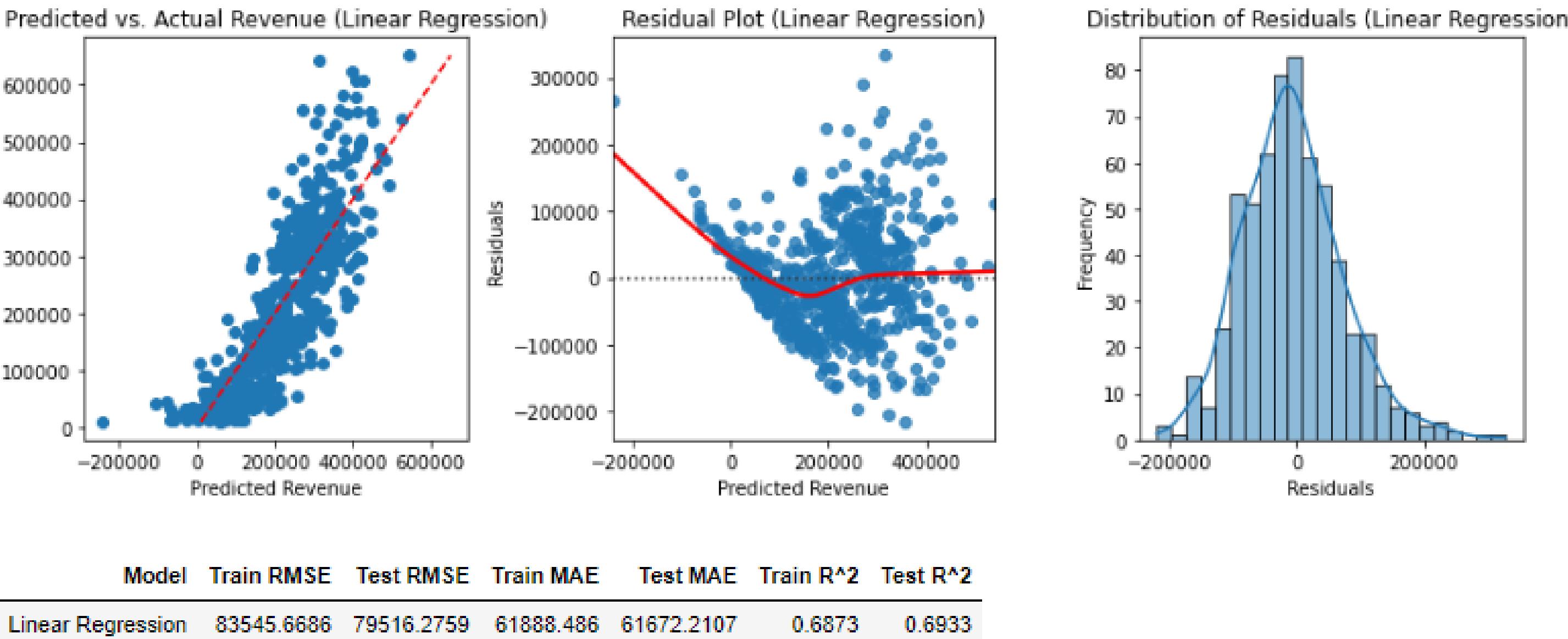


Final Data Set

```
import pandas as pd
df = pd.read_csv('airbnb.csv')
print(df.info())
df.describe()
df['PRICE_TIER'].value_counts()
```

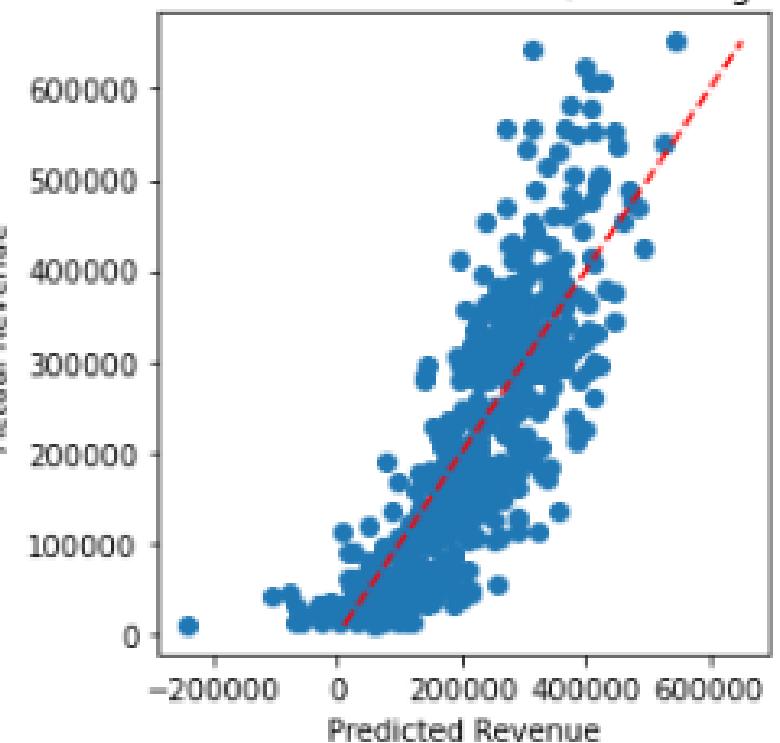
```
class 'pandas.core.frame.DataFrame'
Int64Index: 3070 entries, 0 to 9035
Data columns (total 13 columns):
 #   Column          Non-Null Count  Dtype  
--- 
 0   BEDROOMS        3070 non-null    float64
 1   ACCOMMODATES   3070 non-null    float64
 2   HAS_GYM         3070 non-null    int64  
 3   HAS_HOTTUB      3070 non-null    int64  
 4   HAS_KITCHEN     3070 non-null    int64  
 5   HAS_PARKING     3070 non-null    int64  
 6   HAS_PETS_ALLOWED 3070 non-null    int64  
 7   HAS_POOL         3070 non-null    int64  
 8   PRICE_TIER       3070 non-null    int64  
 9   STATE_NAME       3070 non-null    object 
 10  MINIMUM_STAY    3070 non-null    float64
 11  Available_Nights 3070 non-null    int64  
 12  Cleaning_Fee    2902 non-null    float64
 13  Review_Score    2902 non-null    float64
dtypes: float64(7), int64(5), object(1)
memory usage: 1.0+ MB
```

Baseline Model

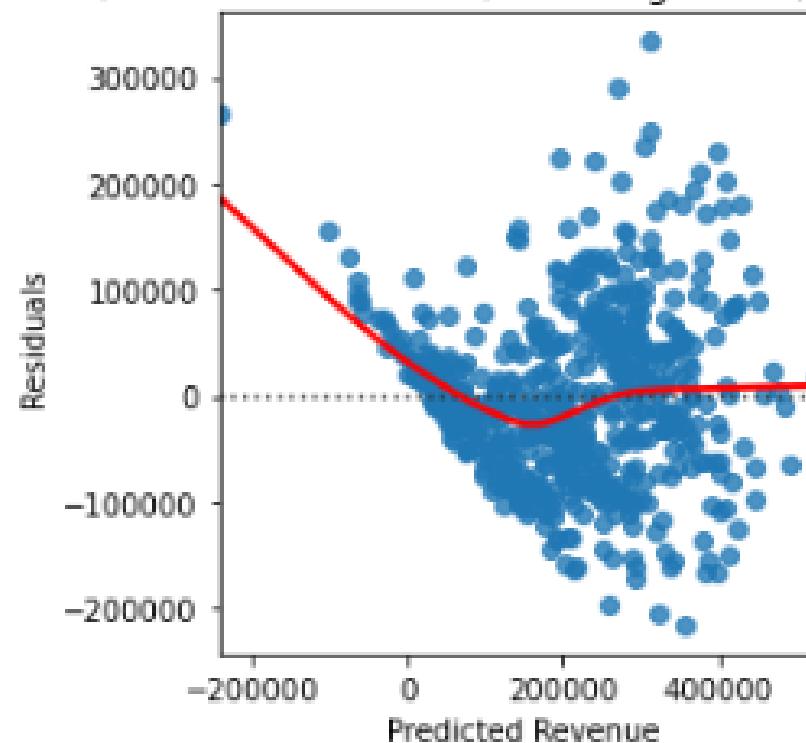


LASSO

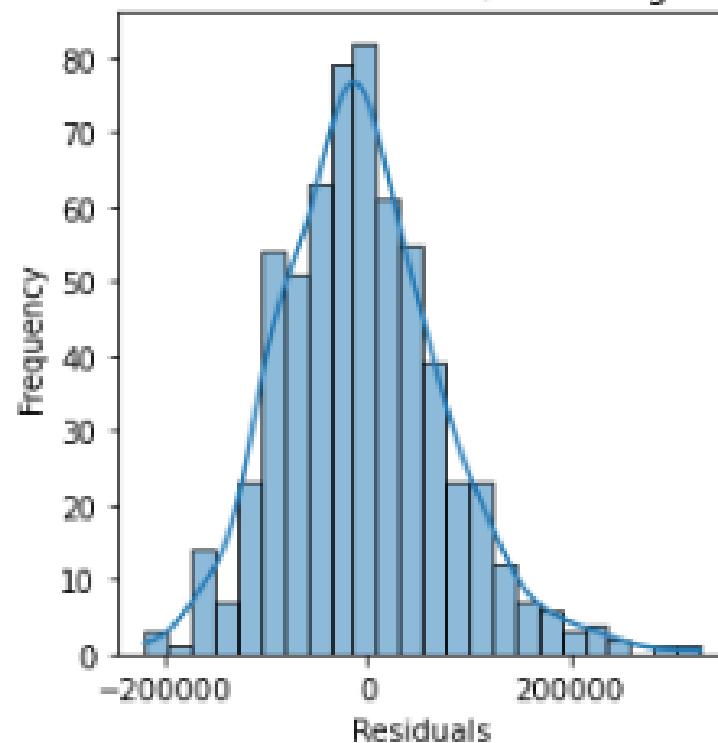
Predicted vs. Actual Revenue (Lasso Regression)



Residual Plot (Lasso Regression)



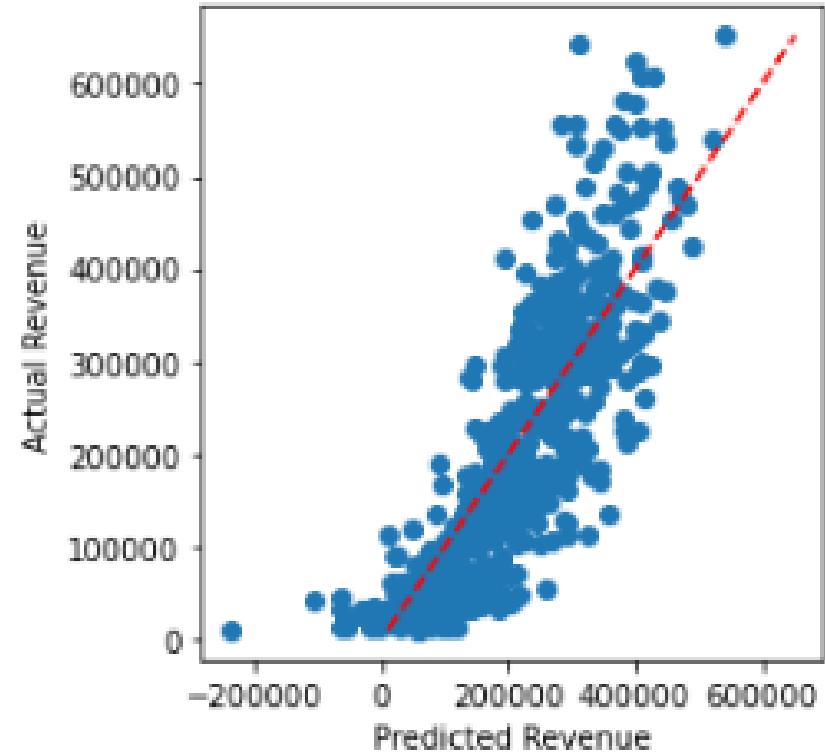
Distribution of Residuals (Lasso Regression)



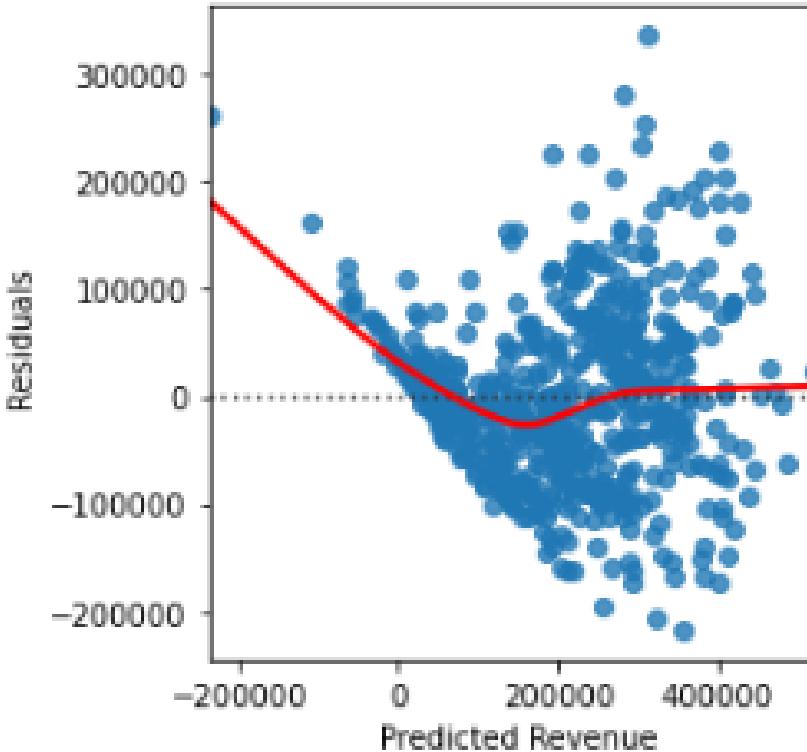
Model	Train RMSE	Test RMSE	Train MAE	Test MAE	Train R^2	Test R^2
-------	------------	-----------	-----------	----------	-----------	----------

0 Lasso Regression	83545.8857	79513.7191	61891.9644	61667.7066	0.6873	0.6934
--------------------	------------	------------	------------	------------	--------	--------

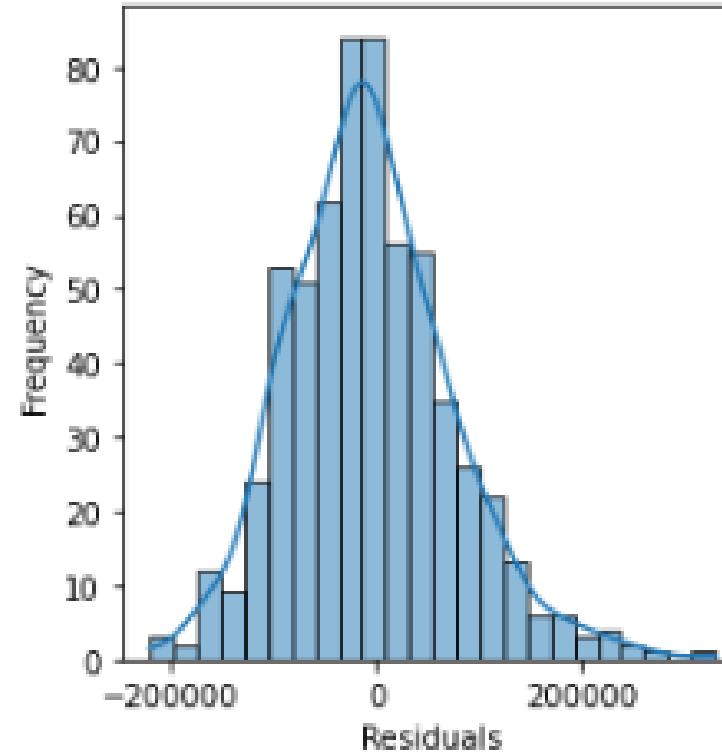
Predicted vs. Actual Revenue (Ridge Regression)



Residual Plot (Ridge Regression)



Distribution of Residuals (Ridge Regression)

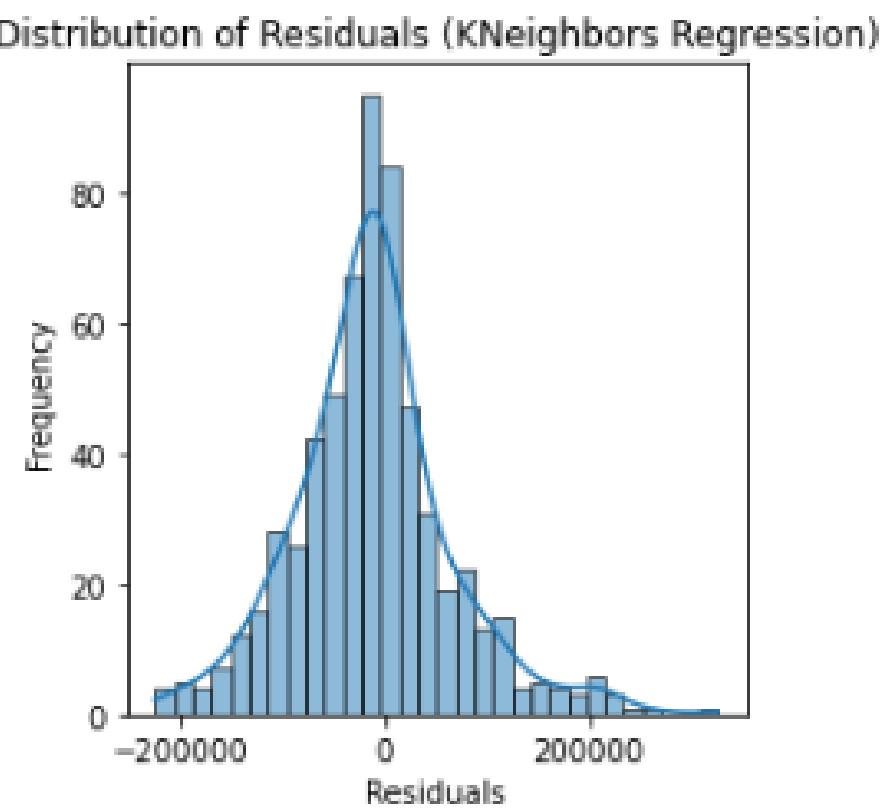
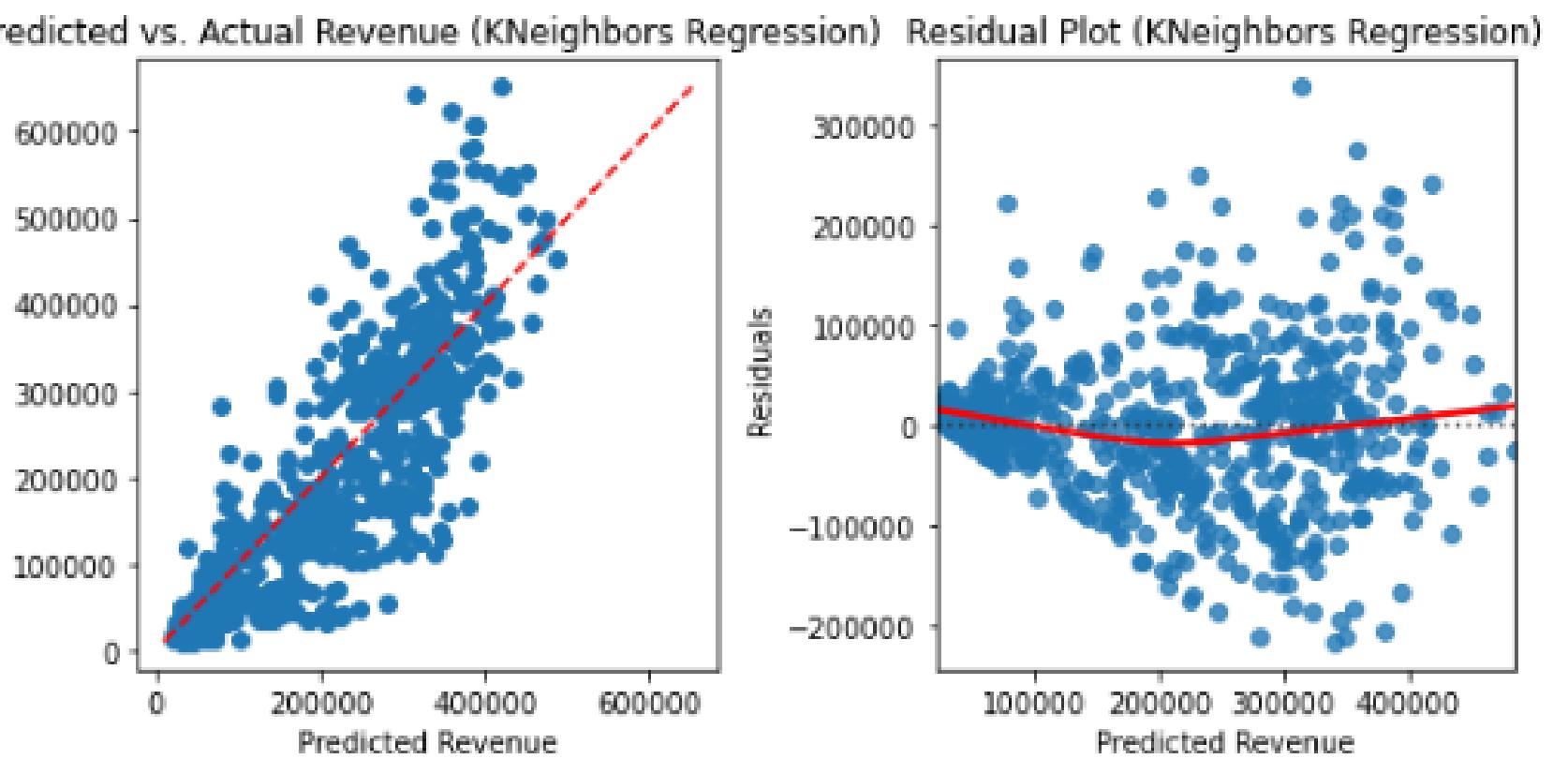


RIDGE

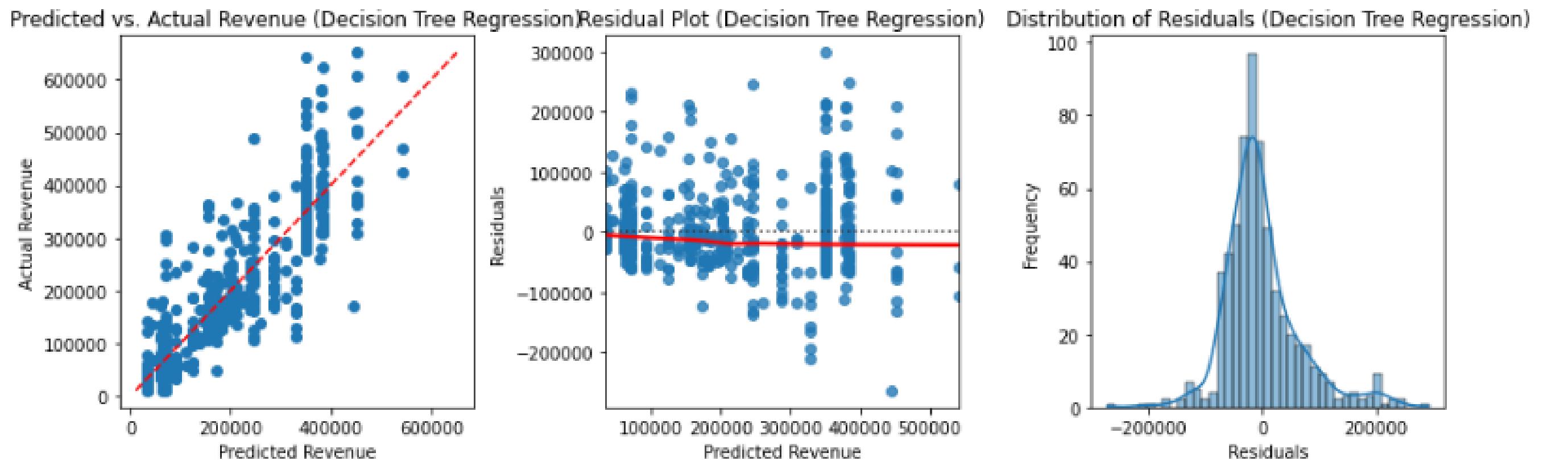
Model	Train RMSE	Test RMSE	Train MAE	Test MAE	Train R^2	Test R^2
-------	------------	-----------	-----------	----------	-----------	----------

0 Ridge Regression	83686.9855	79608.6407	62062.8609	61602.7549	0.6863	0.6926
--------------------	------------	------------	------------	------------	--------	--------

KNN



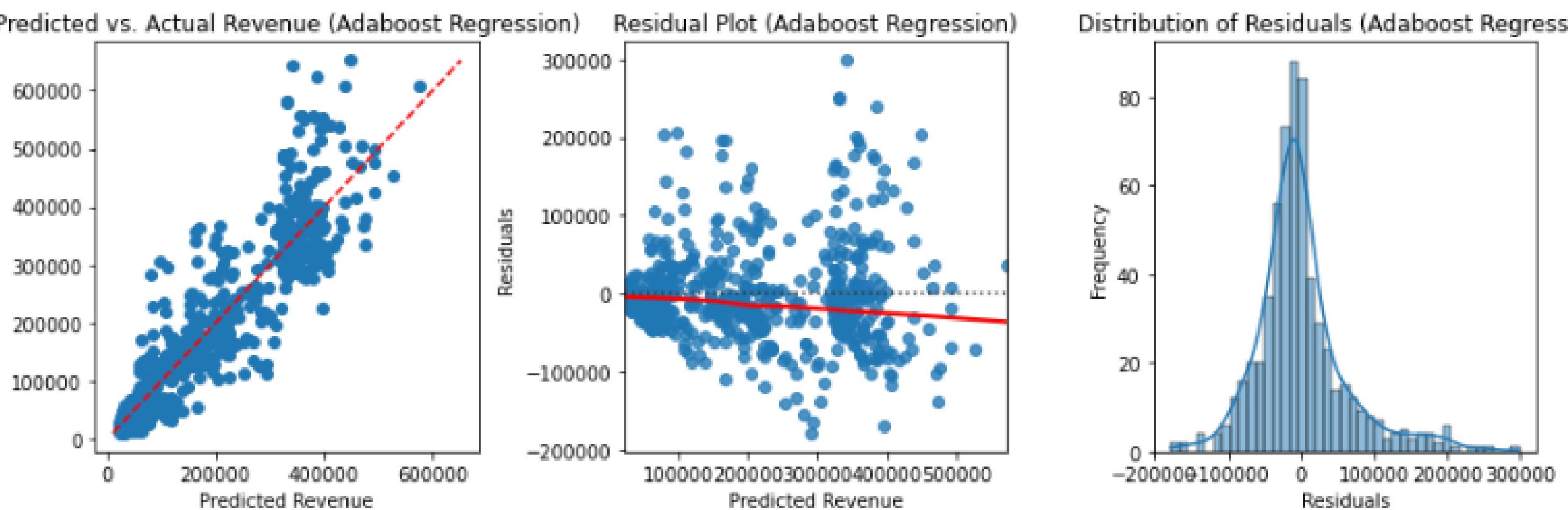
Model	Train RMSE	Test RMSE	Train MAE	Test MAE	Train R^2	Test R^2
0 KNeighbors Regression	474.8732	78556.6315	21.9353	57644.6915	1.0	0.7007



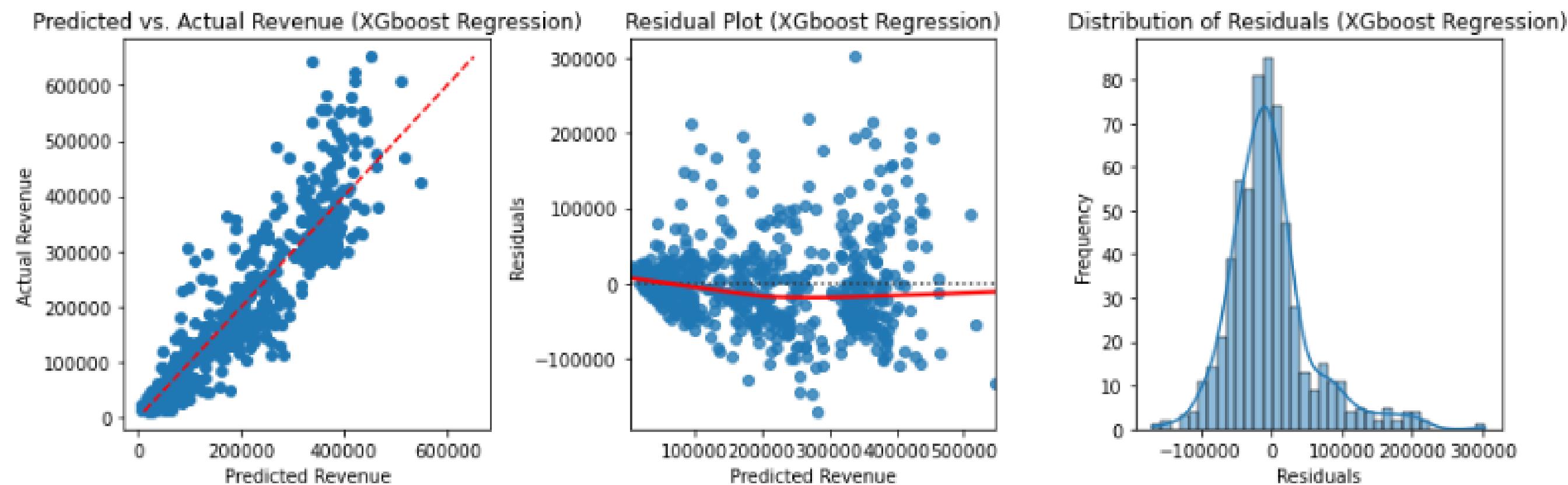
Decision Tree

Model	Train RMSE	Test RMSE	Train MAE	Test MAE	Train R^2	Test R^2
0 Decision Tree Regression	67132.2759	66327.0158	46220.7472	47110.5129	0.7981	0.7866

AdaBoost



Model	Train RMSE	Test RMSE	Train MAE	Test MAE	Train R^2	Test R^2
0 Adaboost Regression	28331.4369	62258.2139	19592.183	42463.9576	0.964	0.812

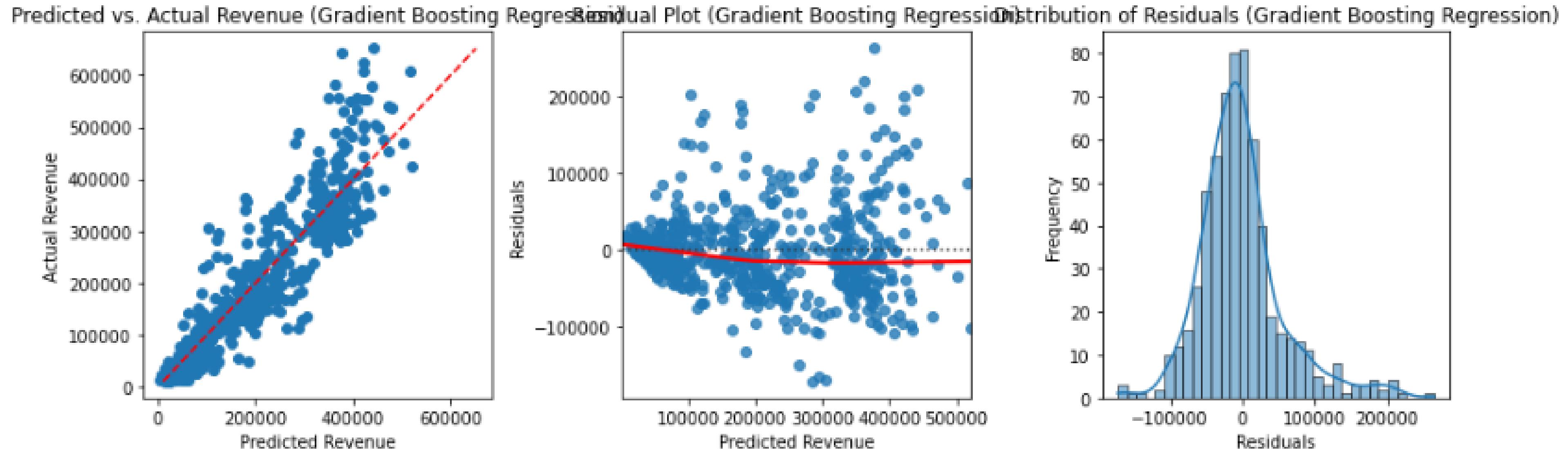


XGBoost

Model	Train RMSE	Test RMSE	Train MAE	Test MAE	Train R^2	Test R^2
0 XGboost Regression	58242.4314	58894.794	39217.4357	41648.1486	0.848	0.8318

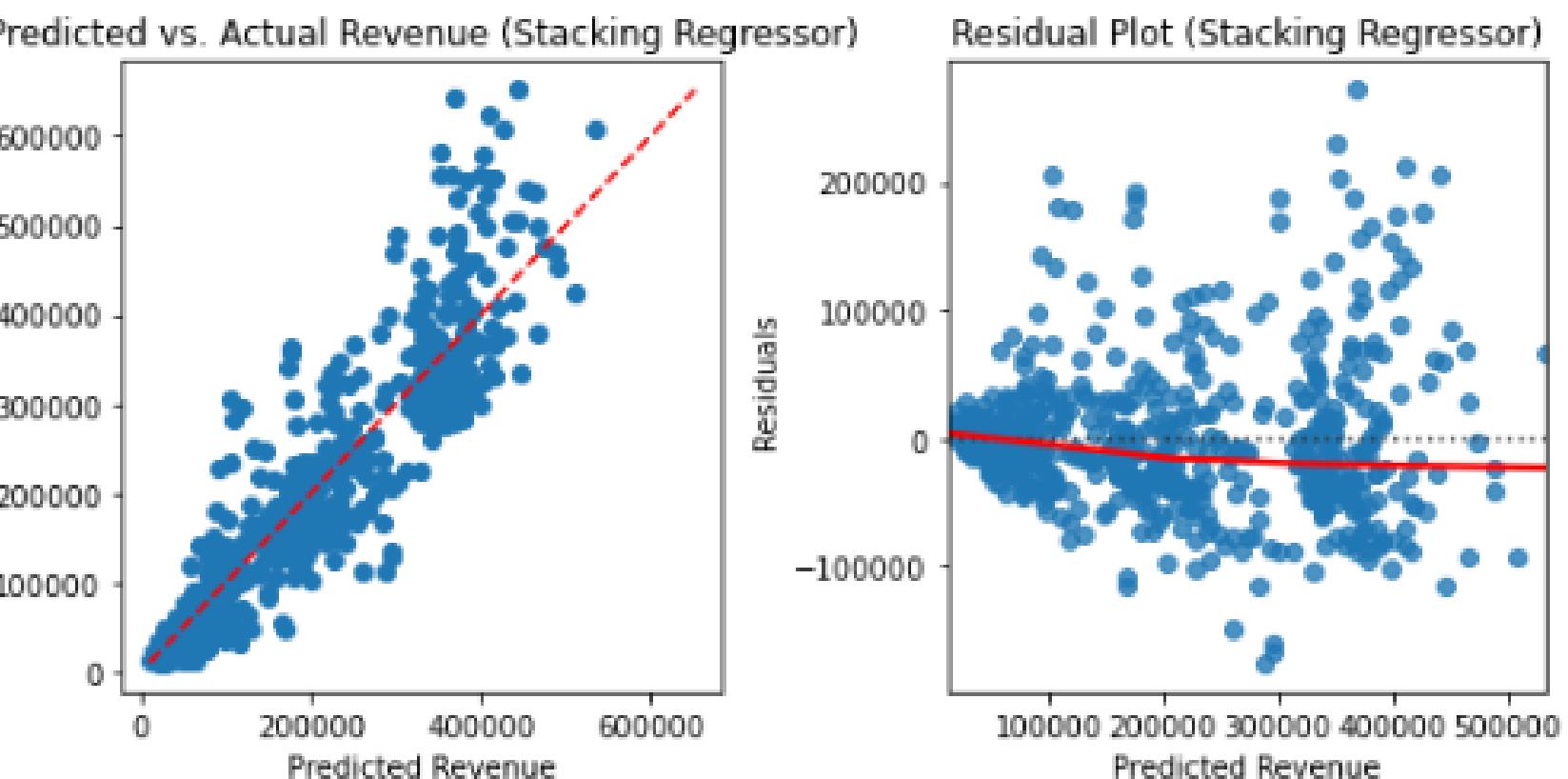
Gradient Boosting

Regressor

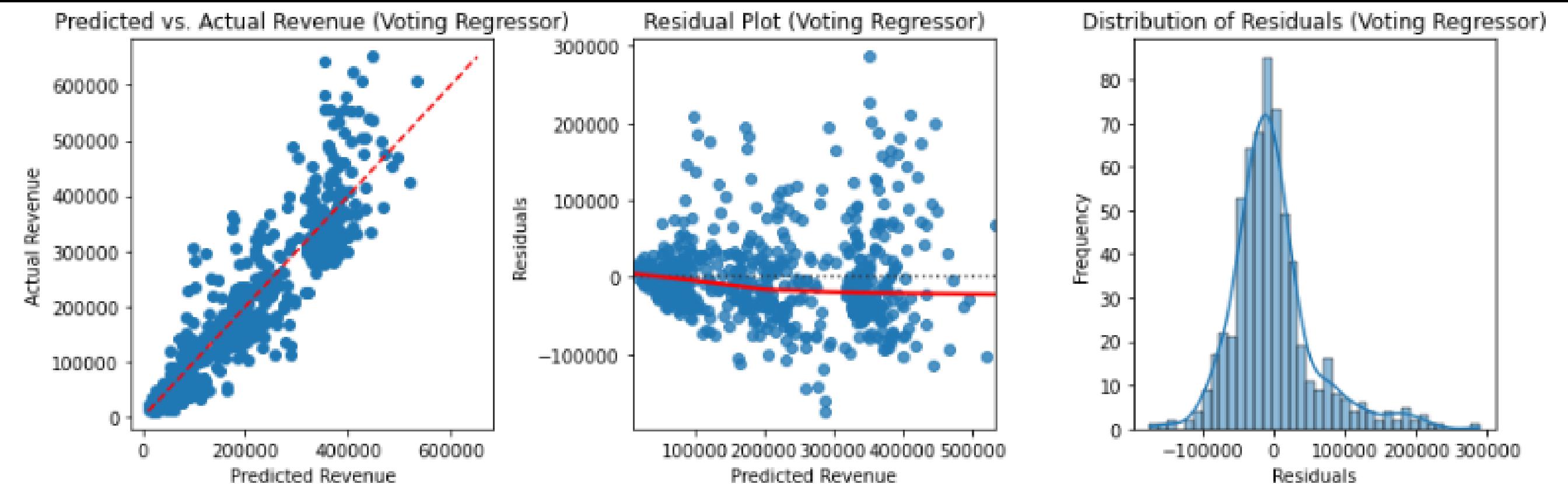


Model	Train RMSE	Test RMSE	Train MAE	Test MAE	Train R^2	Test R^2
0 Gradient Boosting Regression	55043.5355	57729.7362	36787.496	40975.2036	0.8643	0.8384

Stacking



Model	Train RMSE	Test RMSE	Train MAE	Test MAE	Train R^2	Test R^2
0 Stacking Regressor	43716.6124	58025.8784	30743.3438	40870.4684	0.9144	0.8367



Voting

Model	Train RMSE	Test RMSE	Train MAE	Test MAE	Train R^2	Test R^2
0 Voting Regressor	44715.1882	58243.1908	31333.5127	40769.5361	0.9104	0.8355

Summary.

	Model	Train RMSE	Test RMSE	Train MAE	Test MAE	Train R^2	Test R^2
7	Gradient Boosting Regression	55043.5355	57729.7362	36787.4960	40975.2036	0.8643	0.8384
10	Stacking Regressor	43716.6124	58025.8784	30743.3438	40870.4684	0.9144	0.8367
11	Voting Regressor	44715.1882	58243.1908	31333.5127	40769.5361	0.9104	0.8355
6	XGboost Regression	58242.4314	58894.7940	39217.4357	41648.1486	0.8480	0.8318
5	Adaboost Regression	28331.4369	62258.2139	19592.1830	42463.9576	0.9640	0.8120
4	Decision Tree Regression	67132.2759	66327.0158	46220.7472	47110.5129	0.7981	0.7866
3	KNeighbors Regression	474.8732	78556.6315	21.9353	57644.6915	1.0000	0.7007
2	Lasso Regression	83545.8857	79513.7191	61891.9644	61667.7066	0.6873	0.6934
0	Linear Regression	83545.6686	79516.2759	61888.4860	61672.2107	0.6873	0.6933
1	Ridge Regression	83686.9855	79608.6407	62062.8609	61602.7549	0.6863	0.6926
8	Elastic Net Regression	84571.7867	80862.9172	62955.5235	62401.8211	0.6796	0.6829
9	Support Vector Regression	119957.2090	112391.2238	91694.3911	88257.2258	0.3554	0.3873

CONCLUSION / NEXT STEPS

- Summary:
 - the Gradient Boosting Regression stands out as the top performer with the highest test R² value (0.8384) and the lowest test RMSE and MAE values among all models.
- Next Steps:
 - Feature Engineering
 - Time-Series Analysis
 - Customer Segmentation

Contact

- David Johnson : Johnsondavidbjr@gmail.com