

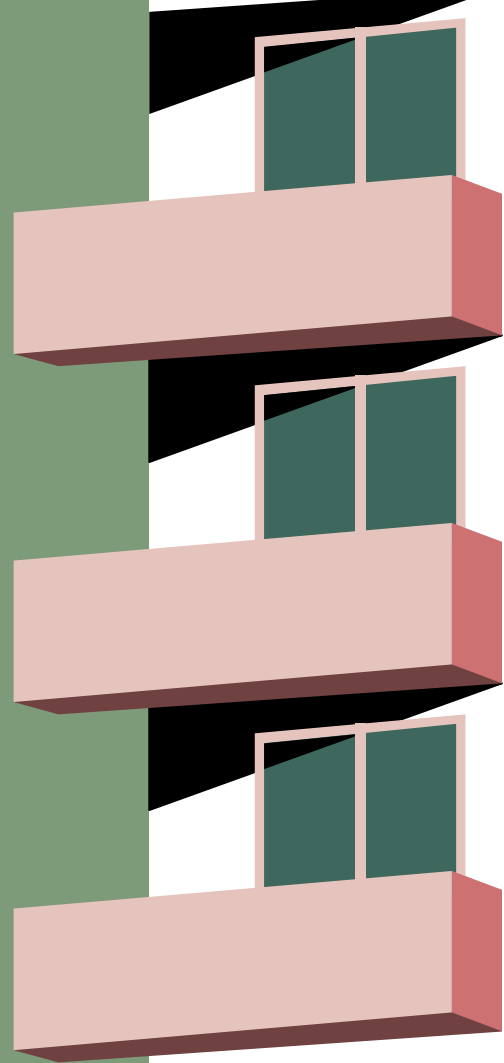
AIRBNB PRICE PREDICTION

Team 1: Jack Wang, Leo Yuan, Kenney
Tran, Ryan Wu, Tanishka Gilara



01

PROBLEM & IMPORTANCE

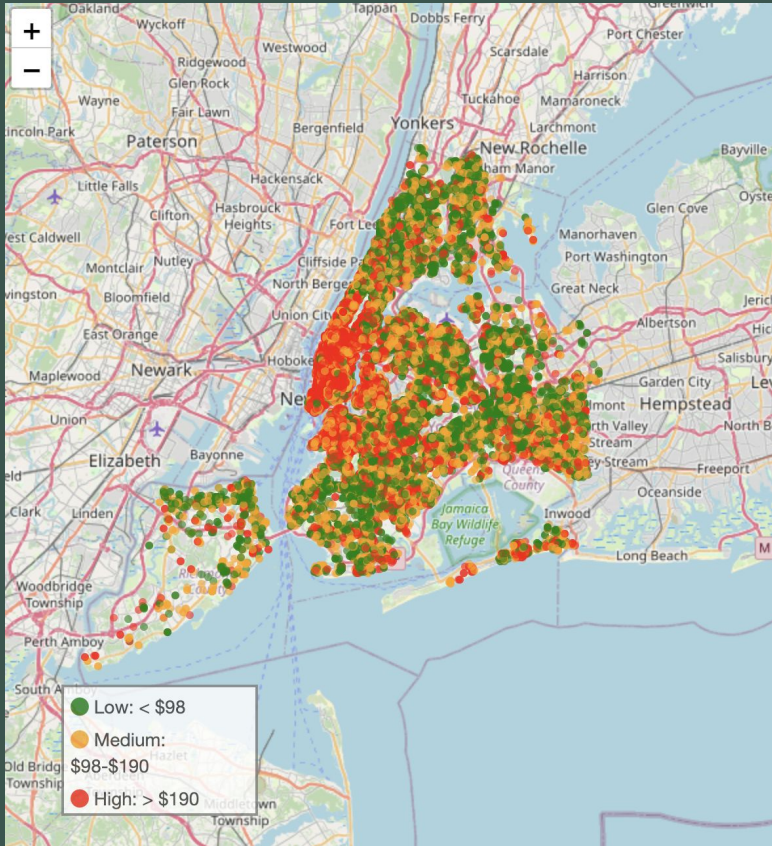


OUR QUESTION AS A TEAM

“WHAT FACTORS CONTRIBUTE TO THE PRICE OF AN AIRBNB IN NEW YORK?”

PROPERTY A :
LOCATED IN BROOKLYN
ACCOMMODATES 2 PEOPLE,
1 BATHROOM,
1 BEDROOM,
1 BED,
4.14 AVERAGE REVIEW SCORE

TAKE YOUR GUESS!



EXPLORING OUR REASONING



Why:

Providing customers with a clearer understanding of factors influencing Airbnb prices



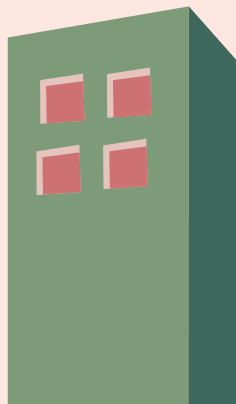
How:

Building models to predict the most impactful factors on price



Target:

Customers looking for better booking deals & fair value in New York (Initial)

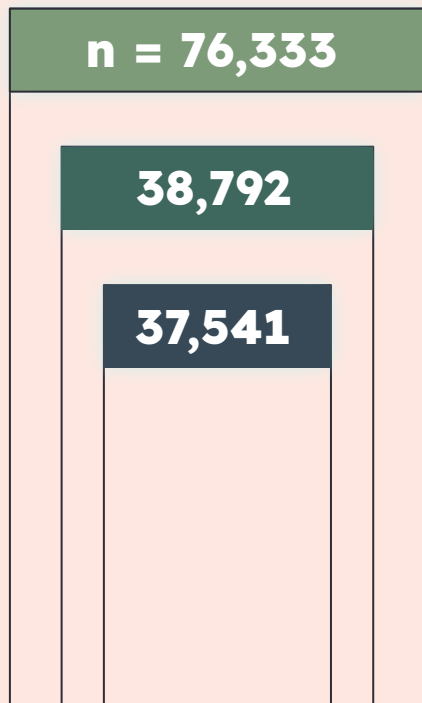




02

DATA SUMMARY

DATASET OVERVIEW



ENTIRE DATASET

Comprises two New York datasets, with 2 categorical features and 17 numerical



MISSING VALUES

11 variables had missing values, ranging from 14k (18% of data) to 22k (30% of data)



IMPORTANT FEATURES

Data spanned 5 neighborhoods, and 5 metrics represented reviews of listing, 26 features post feature engineering



03

PRE-PROCESSING

DATA PRE-PROCESSING METHODOLOGIES



Feature Engineering

has_essentials: essentials, heating, air conditioner, dryer, washer etc

has_kitchen: refrigerator, coffee maker, dishwasher etc

has_entertainment: TV, workspace etc

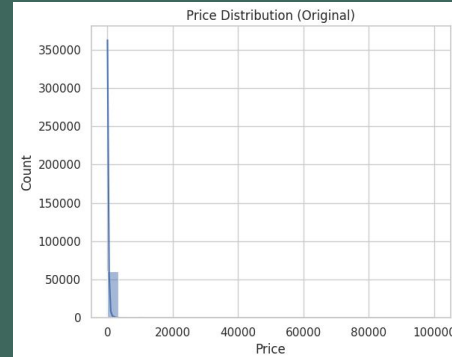
has_safety: smoke, carbon mono etc

has_outdoor_space: backyard, patio

price (label): log transformation to reduce skewness, and to force normal distribution

high_price = price > median

low_price = price < median



Intuition:

Regression:

High p values

$$R^2 = 0.053$$

Regression (Log):

Low p values

$$R^2 = 0.458$$

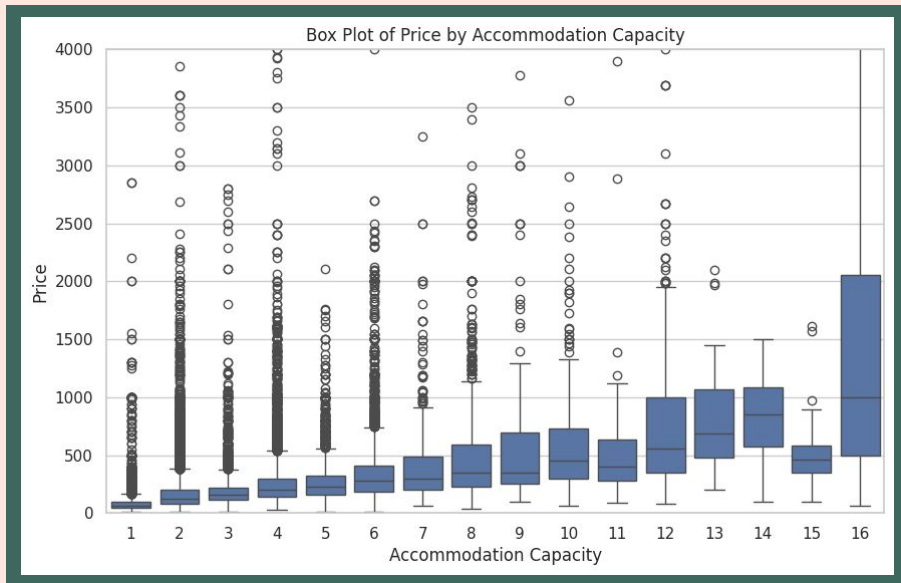
Regression (IQR):

Medium p values

$$R^2 = 0.371$$



DATA PRE-PROCESSING METHODOLOGIES



Intuition: Manhattan Airbnb prices were almost double that of Queens, Bronx, Brooklyn, and Staten Island



Data Imputation

review metrics: cleanliness, location, value, accuracy, communication, checkin, and rating

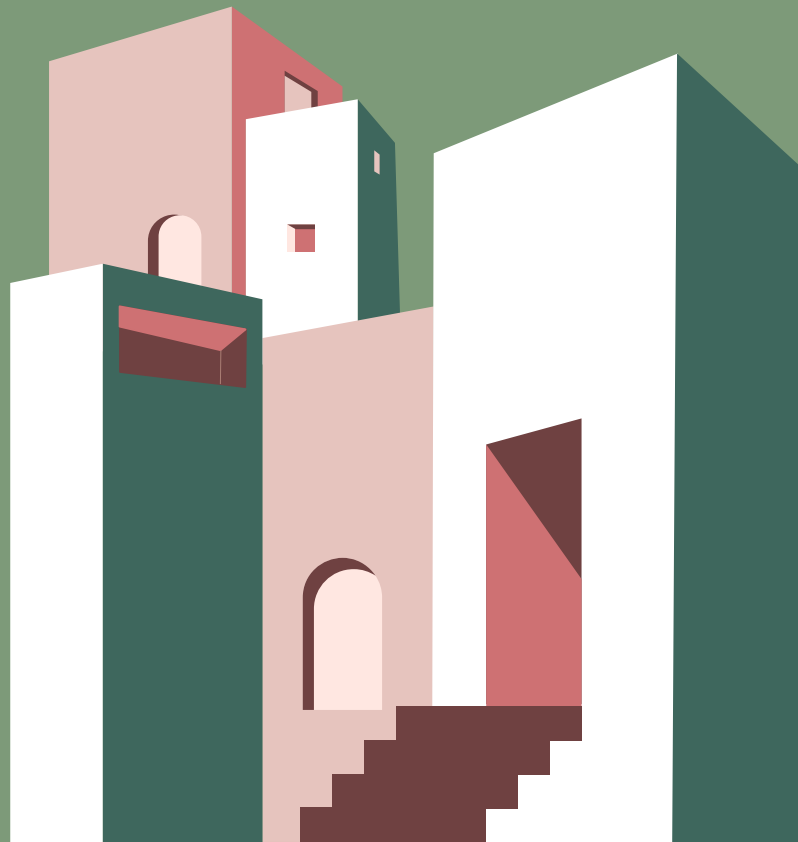
- Imputed grouping by neighborhood means

descriptive metrics: bedrooms, beds, bathrooms

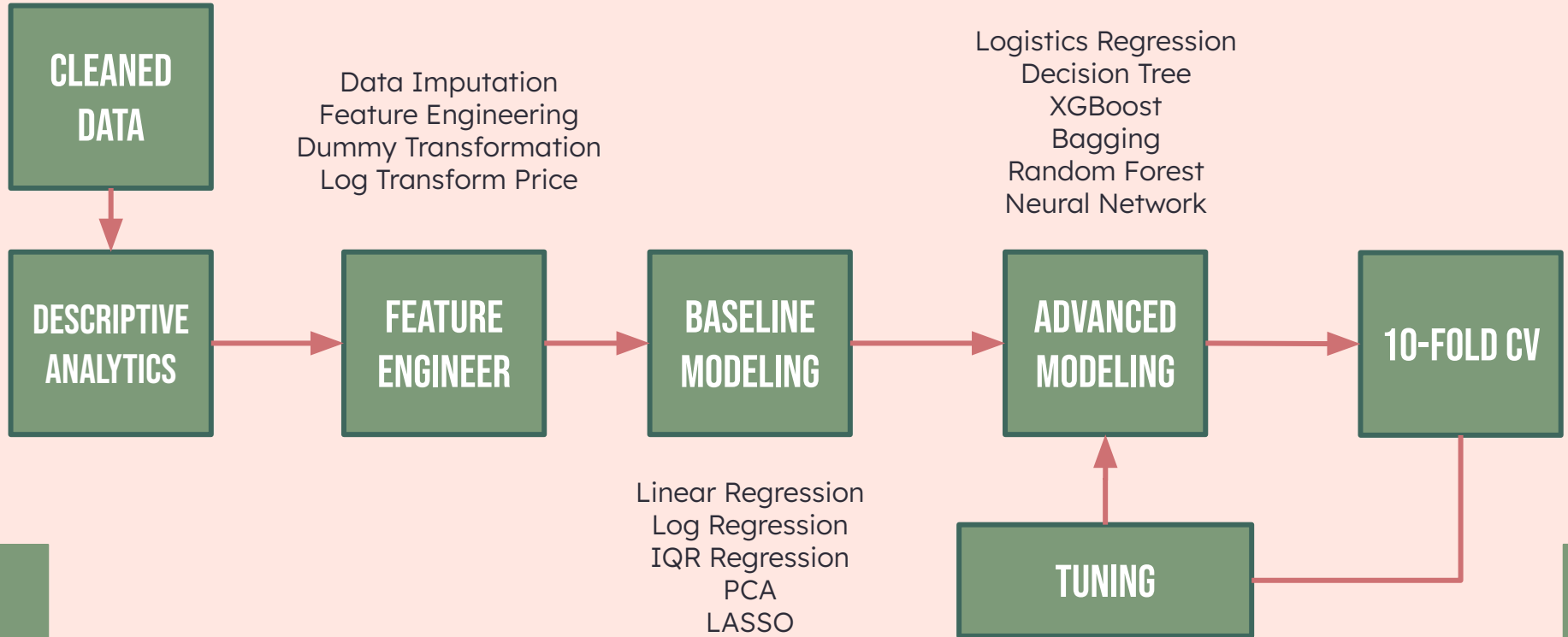
- Imputed grouping by 'accommodates' median to avoid outliers

04

MODELING APPROACH

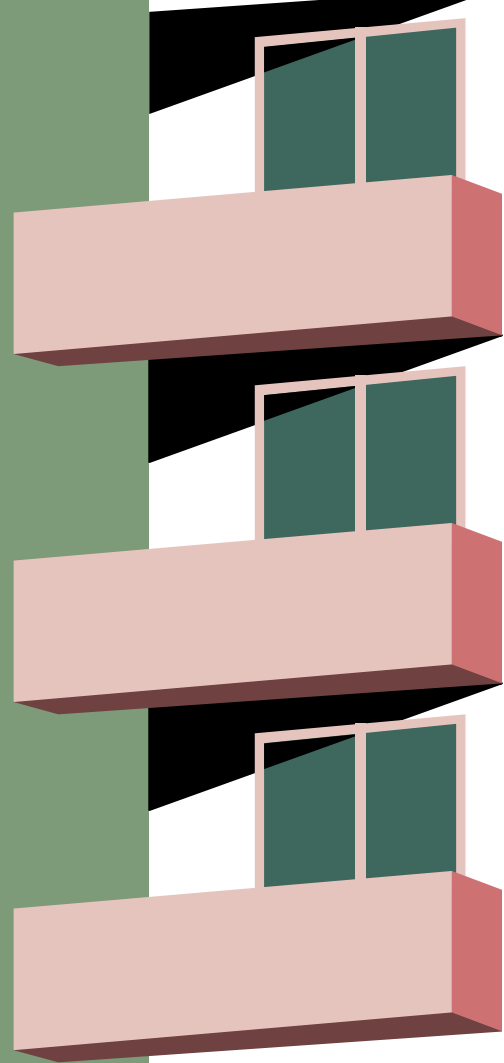


DATAFLOW



05

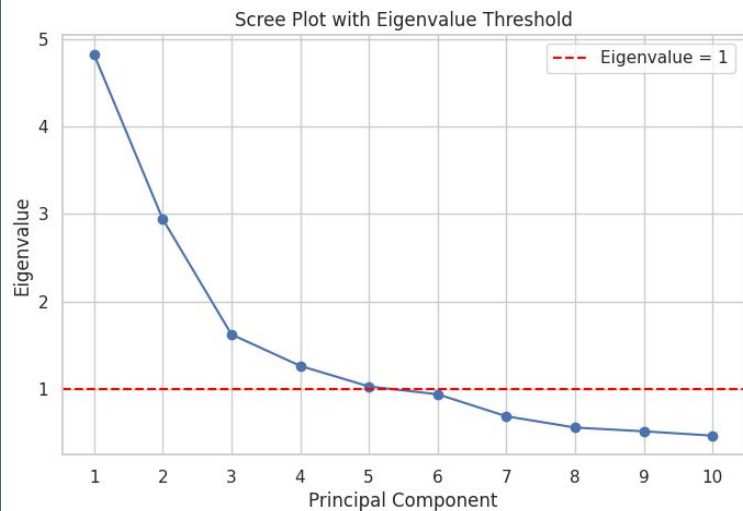
TUNING & MODEL EVALUATION



	LASSO	Bagging	Principal Components	Neural Network
Weakness	Review variables heavily co-linear, LASSO incorrectly drops	Difficult to visualize, black box	No need for dimension reduction	Non-interpretable for general use
Tuning	Lowest α yielded best outcomes	Only reduces variance, did not help in bias reduction	Eigenvalue > 1 at 6 predictors	32,64 hidden layers, 0.1 learning rate
Overall Evaluation	Weak model, Ridge > Lasso	Great model performance, but weak interpretability	Unnecessary as we want interpretability , and the models are parsimonious	Without tuning, it performs similar to the ensemble methods , not many complex relationships to capture

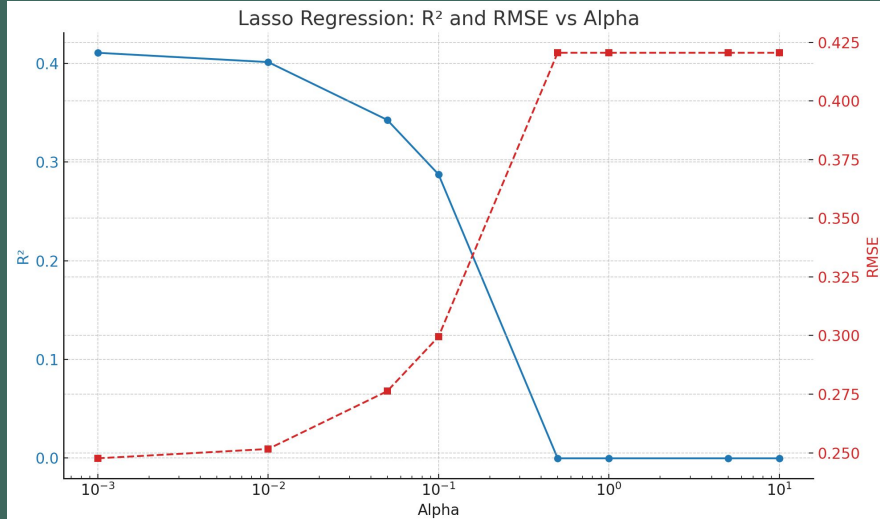
HYPERPARAMETERS TUNING

PCA



Principal components reduce **predictors to 6**, and misses out on **predictive power**

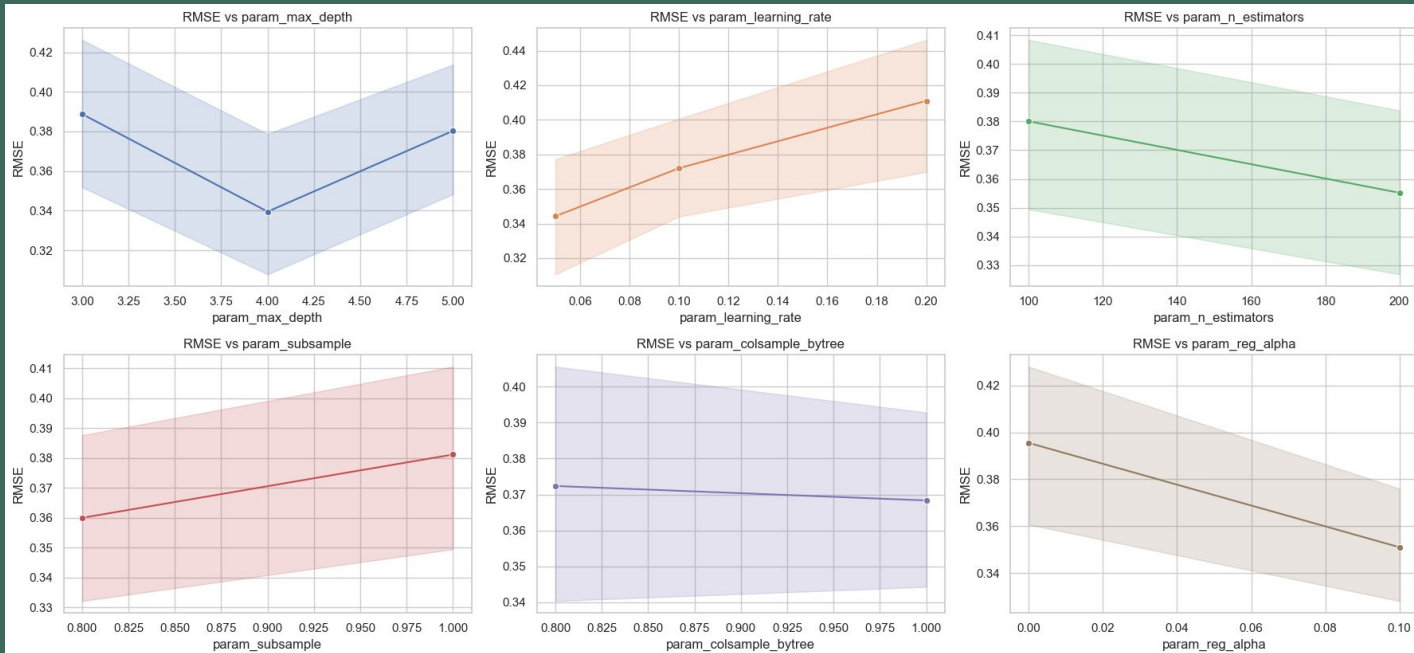
Lasso Regression Tuning



Lowest α performs worse than base log transformed regression, indicating no need to **underfit our model**

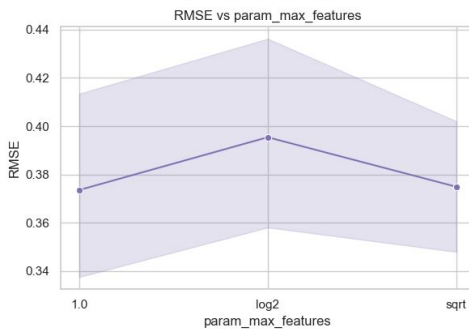
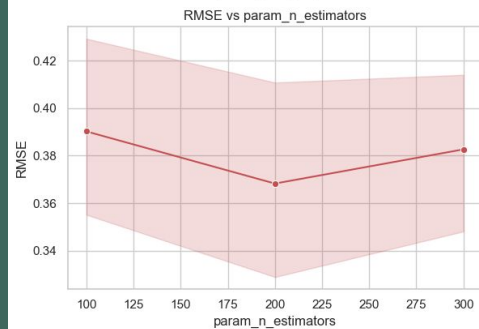
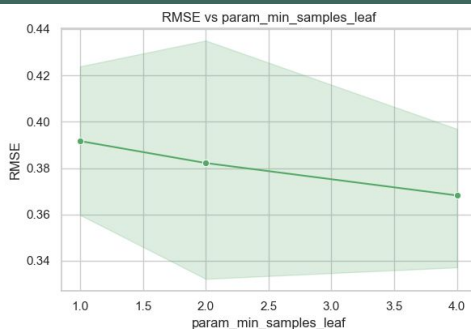
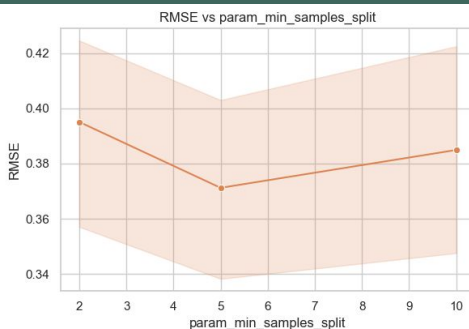
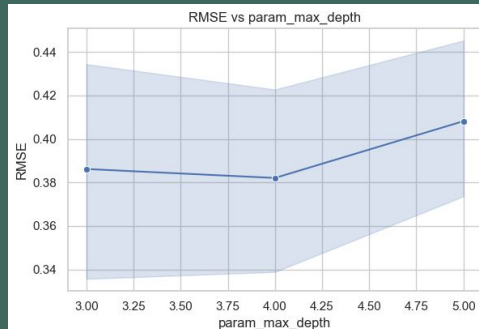
HYPERPARAMETERS TUNING CONT.

XGBoost Decision Tree



HYPERPARAMETERS TUNING CONT.

Random Forest





06

MODEL PERFORMANCE

Weak / Punching Bag Models

Linear Regression

$R^2 = 0.053$

(Log) Linear Regression

$R^2 = 0.458$

Lasso Regression

$R^2 = 0.411$

$\alpha = 0.001$

Decision Tree

$R^2 = 0.465$

RMSE: 0.225

Algorithm Performance (Cross Validated)

Logistics Regression

L2 Penalty
10-Fold CV
CS = 10

ROC AUC = 0.86
Accuracy: 79%

F1 Score: 80%

XGBoost Decision Tree

n = 200
Rate = 0.2
Depth = 5
 $\lambda = 1$

$R^2 = 0.6625$
RMSE = 0.1418

Random Forest

n = 300
Depth = none
Features = 1.0

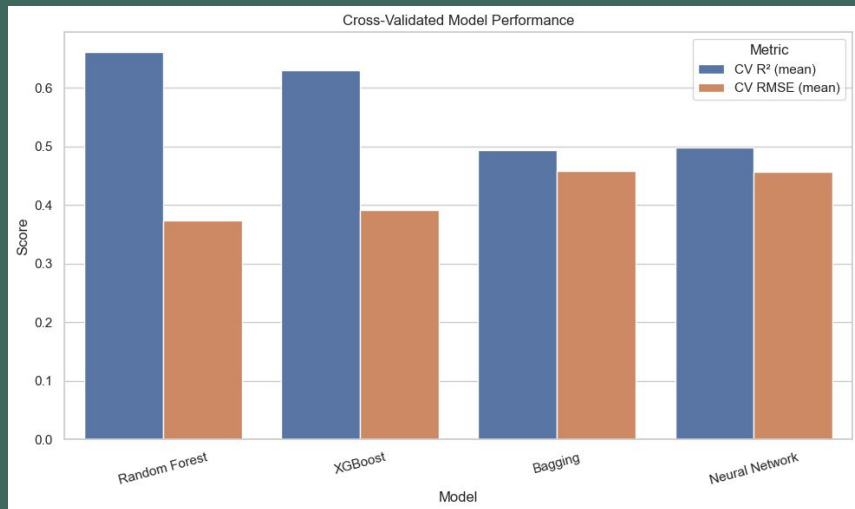
$R^2 = 0.7084$
RMSE = 0.1226

Neural Network

Hidden = (32, 64)
Logistic activation

$R^2 = 0.6137$
RMSE = 0.1624

STRONGEST MODEL?



Model strength should not be the only parameter when deciding on the ultimate algorithm as interpretability and generalizability is crucial

XGBoost - Robust to missing values and non-linearities

Logistics Regression - Interpretable and strong for predicting if price > median

Random Forest - Most powerful model, but not ideal for general use

Log Transformed Regression - Ideal for interpretation, but weak model predictive power



07

CHALLENGES & NEXT STEPS

CHALLENGES

Challenges

Finding a powerful but interpretable model

Interpreting locational data beyond neighborhood splitting

Lack of dimensions and features for predictions

What happened?

Models used have are less interpretable due to the black box models being the most powerful

We interpreted latitude and longitude as is, which isn't robust enough to capture interactions

We lacked features such as age of property, condition, as well as attractions near each listing

How would we address?

Model Stacking
(utilizing Random Forest coefficients in a Neural Network)
Finely tuned Decision Trees

Geography remains a key predictor, and kriging can enhance accuracy

Merge dining / attractions datasets to add additional dimensionality and improve predictive power

Predicted

Actual

Model

Predicted Price

Random Forest

\$90.65

XGBoost

\$76.77

Bagging

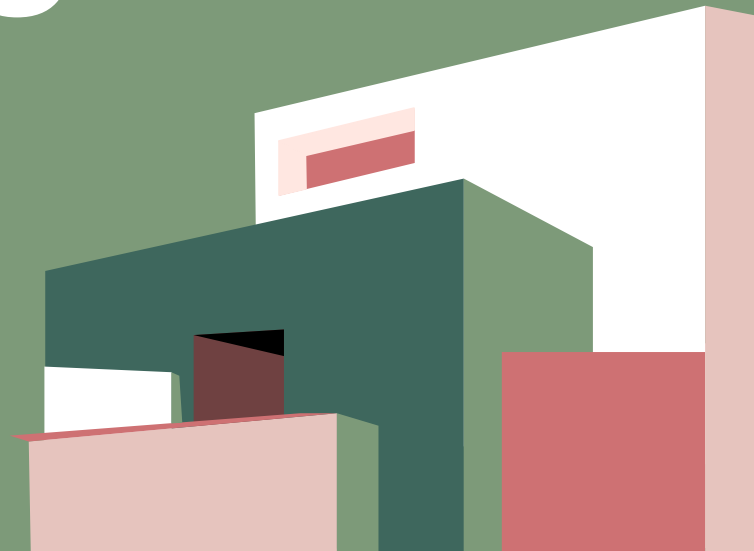
\$85.18

Neural Network

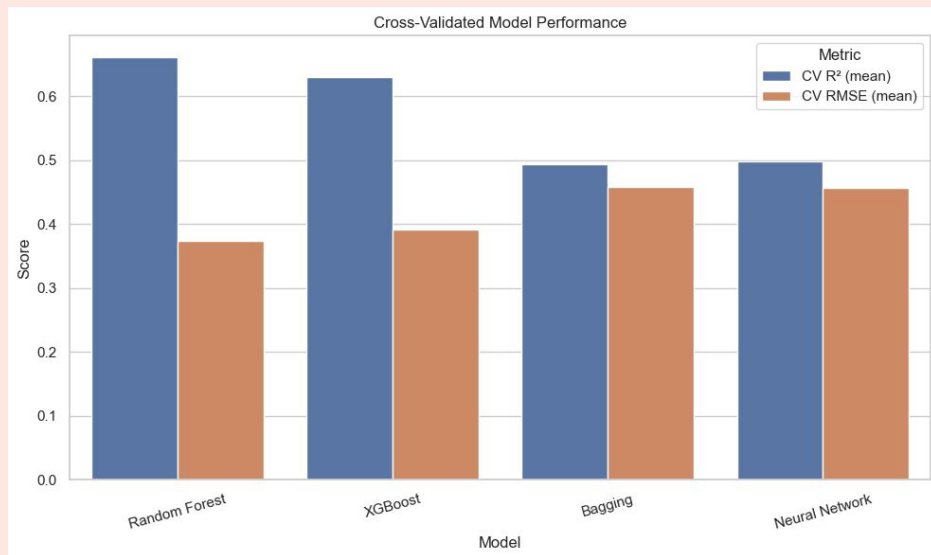
\$166.93

\$95

THANK YOU

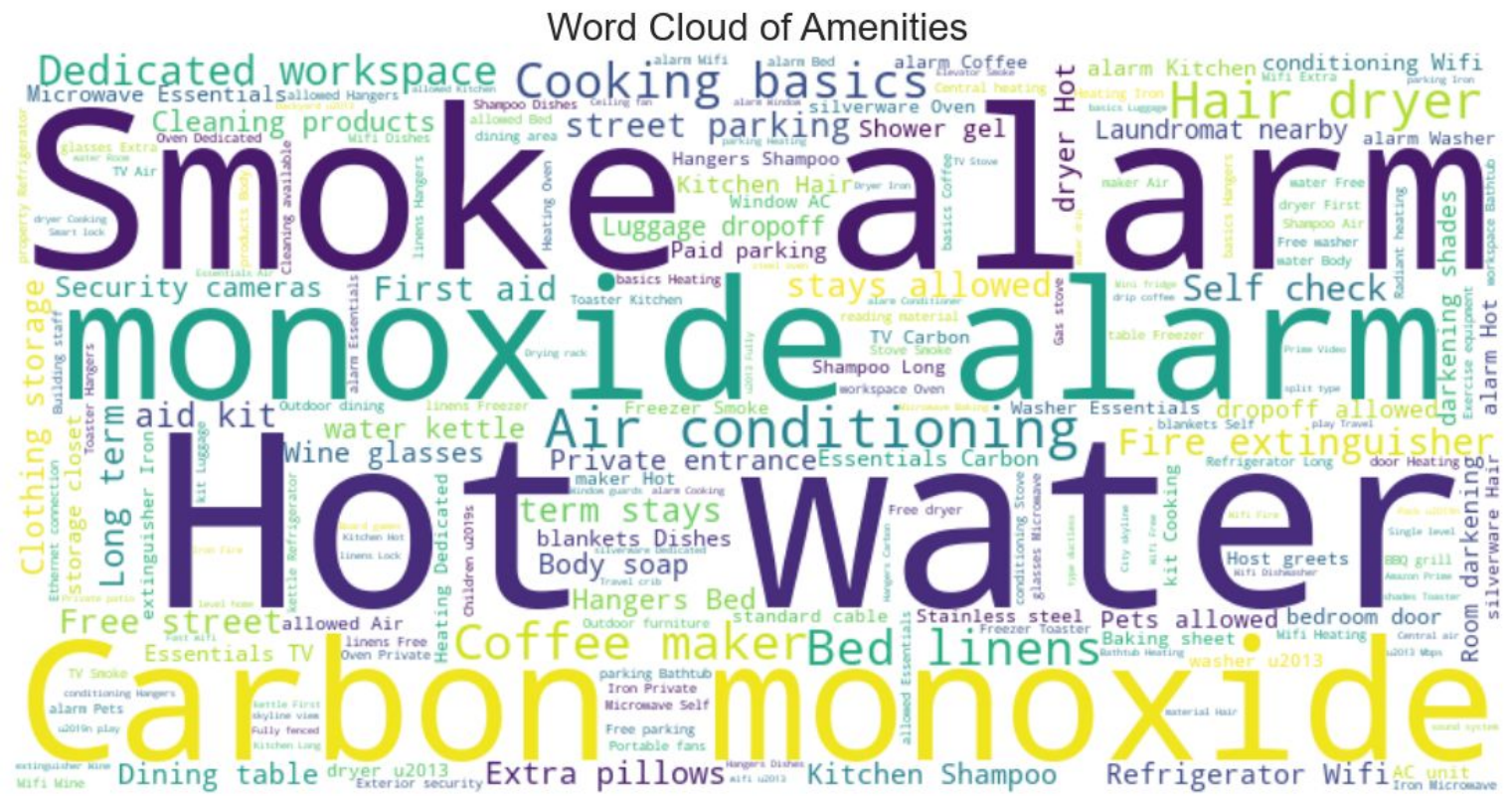


APPENDIX A



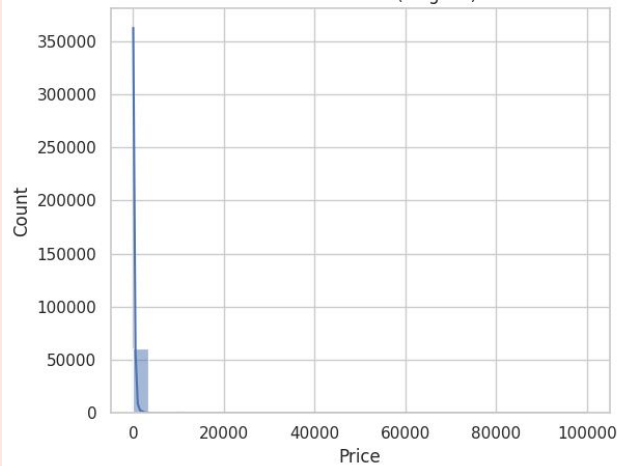
Model		CV R ² (mean)	CV R ² (std)	CV RMSE (mean)	CV RMSE (std)
0	Random Forest	0.661764	0.056405	0.373892	0.019373
1	Bagging	0.494240	0.048128	0.458728	0.007174
2	Boosting	0.629595	0.045716	0.392085	0.010915
3	Neural Network	0.498783	0.039881	0.456948	0.004293

APPENDIX B

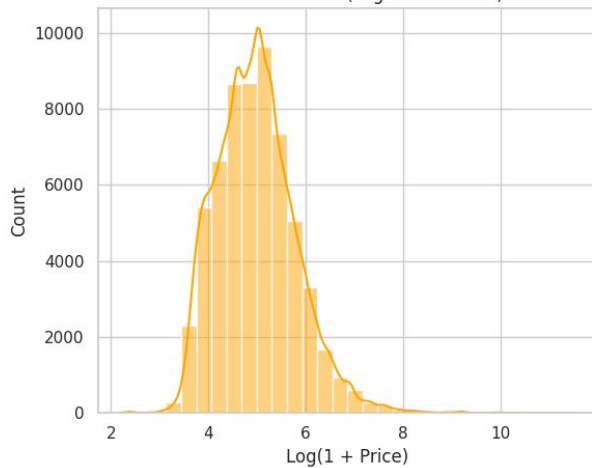


APPENDIX C

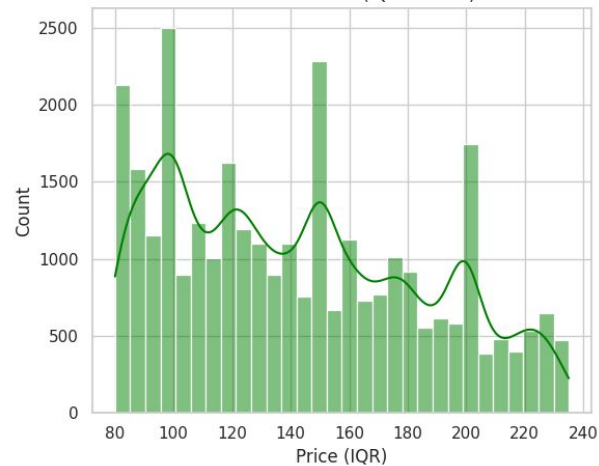
Price Distribution (Original)



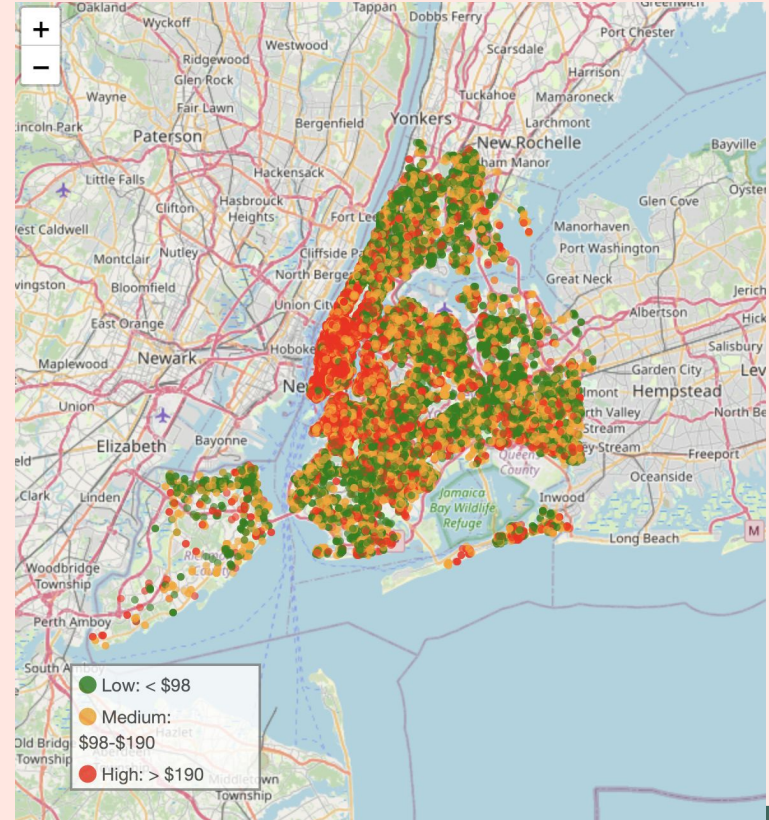
Price Distribution (Log Transformed)



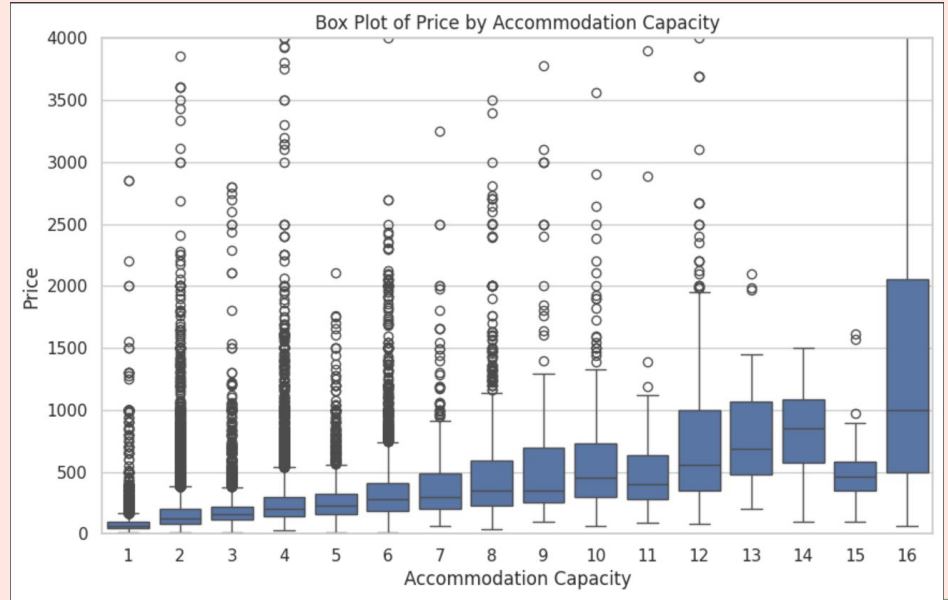
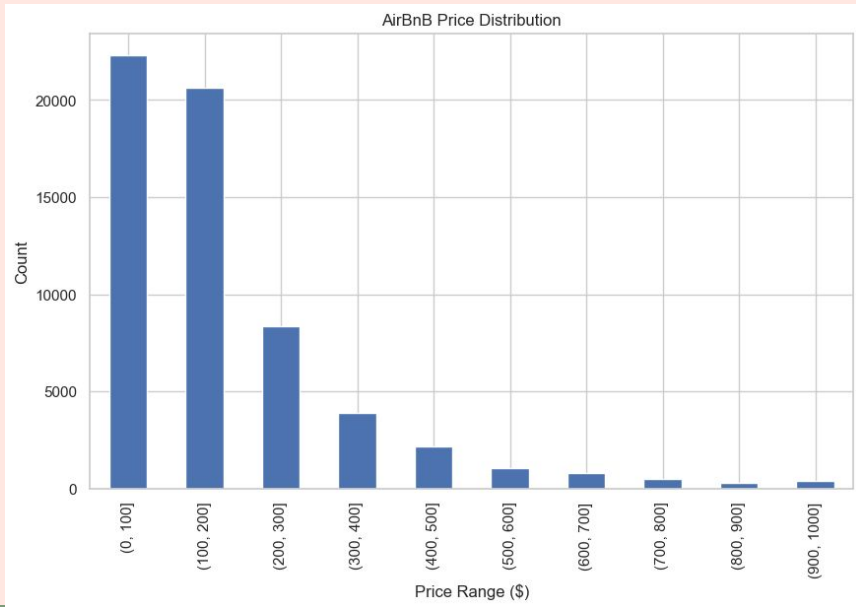
Price Distribution (IQR Filtered)



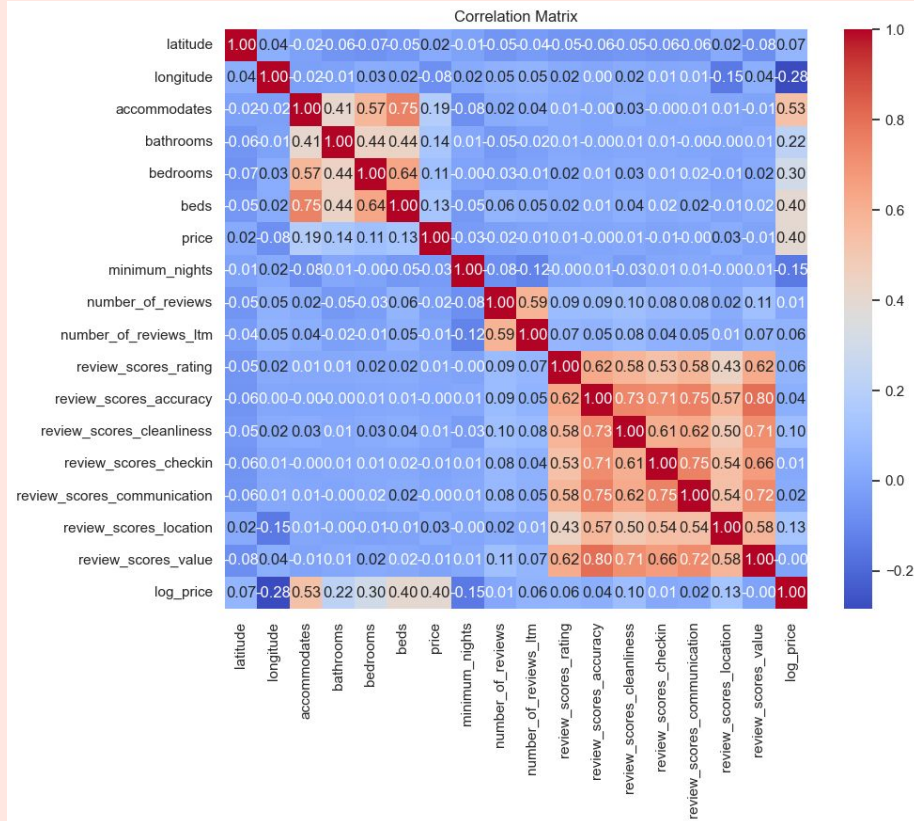
APPENDIX D



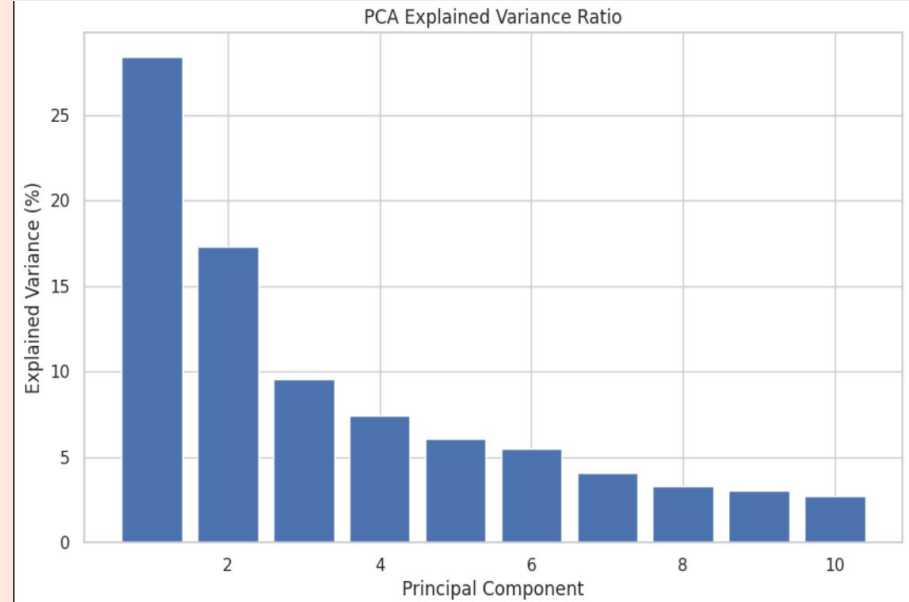
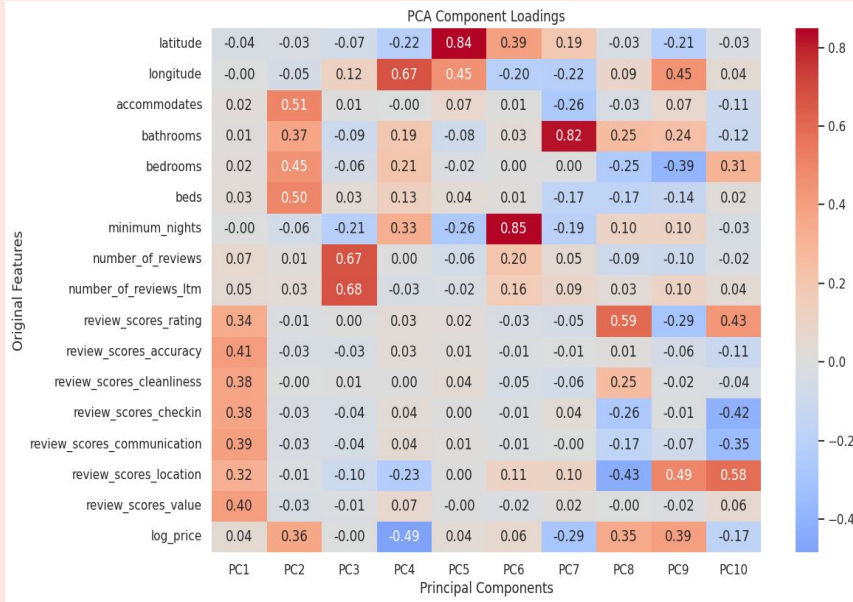
APPENDIX E

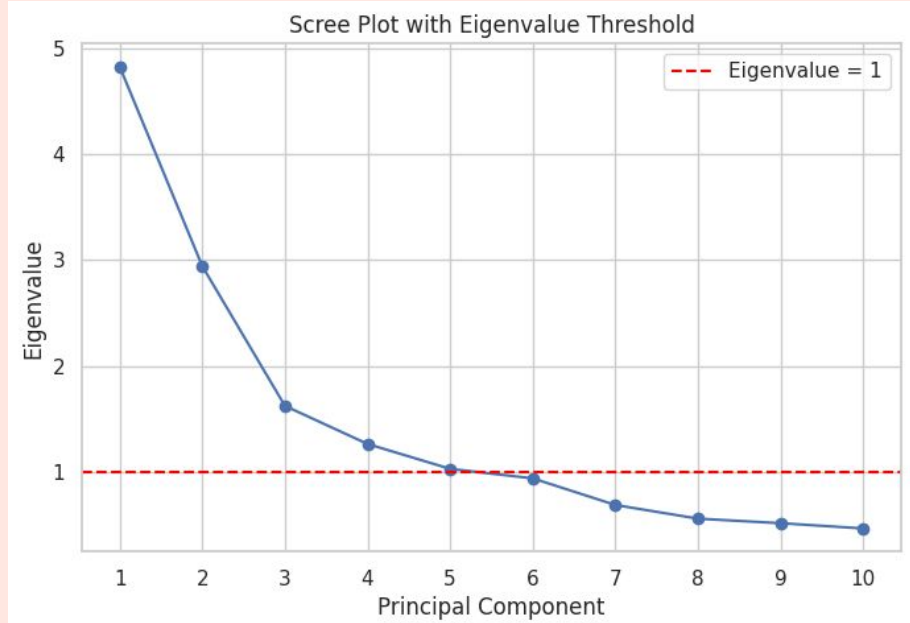
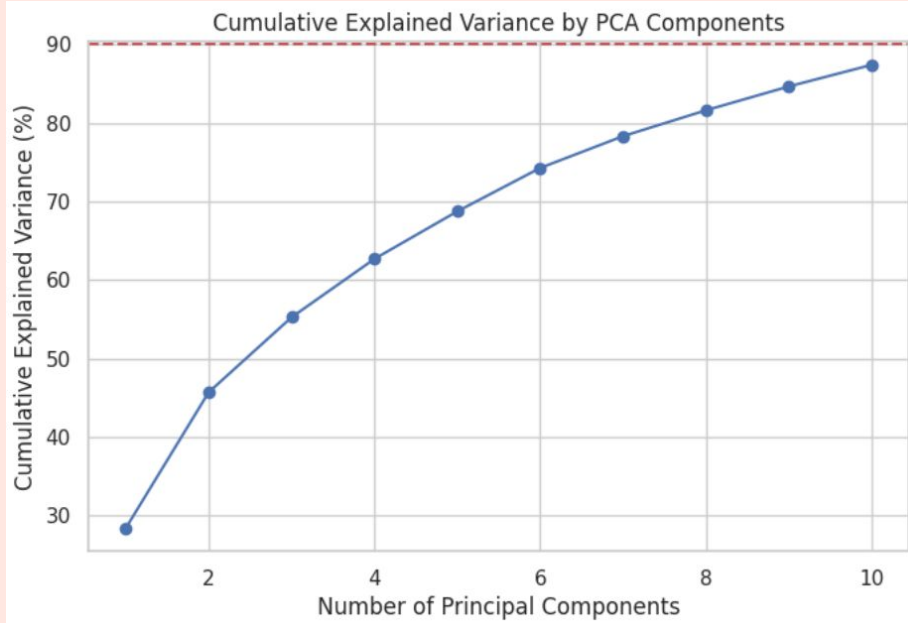


APPENDIX F



APPENDIX G



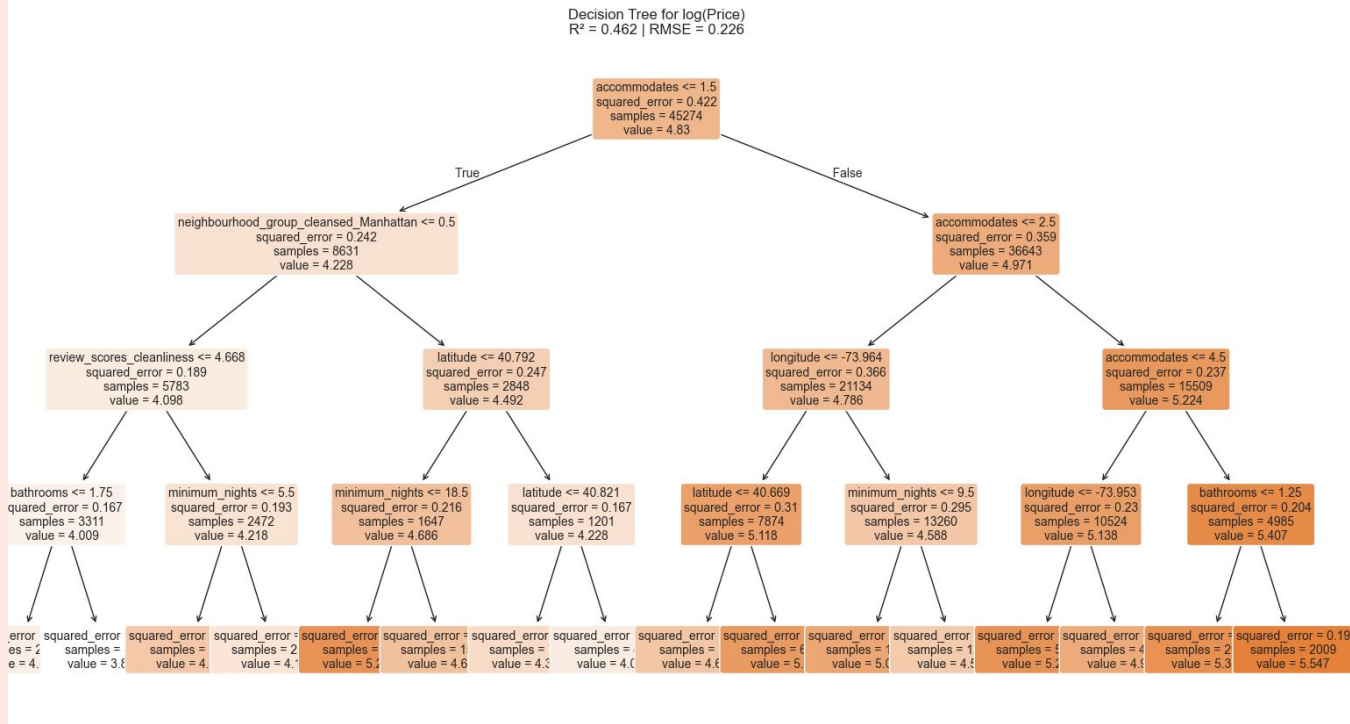


APPENDIX H

OLS Regression Results						
=====						
Dep. Variable:	price	R-squared:	0.053			
Model:	OLS	Adj. R-squared:	0.053			
Method:	Least Squares	F-statistic:	137.1			
Date:	Wed, 02 Apr 2025	Prob (F-statistic):	0.00			
Time:	14:06:00	Log-Likelihood:	-4.9022e+05			
No. Observations:	61333	AIC:	9.805e+05			
Df Residuals:	61307	BIC:	9.807e+05			
Df Model:	25					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	221.8306	2.892	76.696	0.000	216.162	227.500
latitude	-29.2233	4.845	-6.031	0.000	-38.720	-19.726
longitude	-41.7832	4.970	-8.407	0.000	-51.524	-32.042
accommodates	116.3429	4.511	25.792	0.000	107.502	125.184
bathrooms	61.9079	3.361	18.418	0.000	55.320	68.496
bedrooms	2.3224	3.943	0.589	0.556	-5.406	10.051
beds	-15.6121	4.781	-3.265	0.001	-24.983	-6.241
minimum_nights	-11.3286	2.952	-3.838	0.000	-17.114	-5.543
number_of_reviews	-8.0826	3.620	-2.233	0.026	-15.177	-0.988
number_of_reviews_ltm	1.1835	3.596	0.329	0.742	-5.865	8.232
review_scores_rating	6.6948	3.928	1.704	0.088	-1.005	14.394
review_scores_accuracy	-1.5352	5.821	-0.264	0.792	-12.945	9.874
review_scores_cleanliness	9.5353	4.594	2.076	0.038	0.531	18.540
review_scores_checkin	-13.1672	4.752	-2.771	0.006	-22.481	-3.854
review_scores_communication	3.1500	5.116	0.616	0.538	-6.877	13.177
review_scores_location	9.8628	3.916	2.519	0.012	2.187	17.538
review_scores_value	-3.2963	5.514	-0.598	0.550	-14.105	7.512
has_essentials	-0.5742	3.060	-0.188	0.851	-6.571	5.423
has_kitchen	-22.5669	3.002	-7.518	0.000	-28.450	-16.683
has_entertainment	2.6956	3.055	0.882	0.378	-3.293	8.684
has_safety	-5.9358	2.982	-1.990	0.047	-11.781	-0.091
has_outdoor_space	10.7167	2.929	3.659	0.000	4.976	16.457
neighbourhood_group_cleansed_Brooklyn	-48.9820	10.492	-4.668	0.000	-69.547	-28.417
neighbourhood_group_cleansed_Manhattan	19.5861	9.392	2.085	0.037	1.178	37.994
neighbourhood_group_cleansed_Queens	-15.8019	7.310	-2.162	0.031	-30.129	-1.475
neighbourhood_group_cleansed_Staten Island	-32.6685	4.355	-7.502	0.000	-41.203	-24.134

APPENDIX I



APPENDIX J

	precision	recall	f1-score	support
0	0.79	0.82	0.80	6021
1	0.78	0.75	0.77	5298
accuracy			0.79	11319
macro avg	0.79	0.78	0.78	11319
weighted avg	0.79	0.79	0.79	11319
ROC AUC: 0.8605				

Neural Net R^2 : 0.6137

Neural Net RMSE (log): 0.1624

APPENDIX K

=== Best Parameters XGBoost===

```
{'colsample_bytree': 0.8, 'learning_rate': 0.2, 'max_depth': 5, 'n_estimators': 200, 'reg_alpha': 0, 'reg_lambda': 1.5, 'subsample': 1.0}
```

=== Test Performance ===

R²: 0.6609

RMSE (log scale): 0.1425

	feature	# importance
2	accommodates	0.2961251
5	beds	0.10844432
4	bedrooms	0.10109886
6	minimum_nights	0.07528877
22	neighbourhood_group_cleansed_Ma	0.07158521
1	longitude	0.06391023
3	bathrooms	0.033237386
0	latitude	0.032904126
8	number_of_reviews_ltm	0.025478369
11	review_scores_cleanliness	0.023847632

APPENDIX L

=== Best Parameters Random Forest===

```
{'max_depth': None, 'max_features': 1.0, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 300}
```

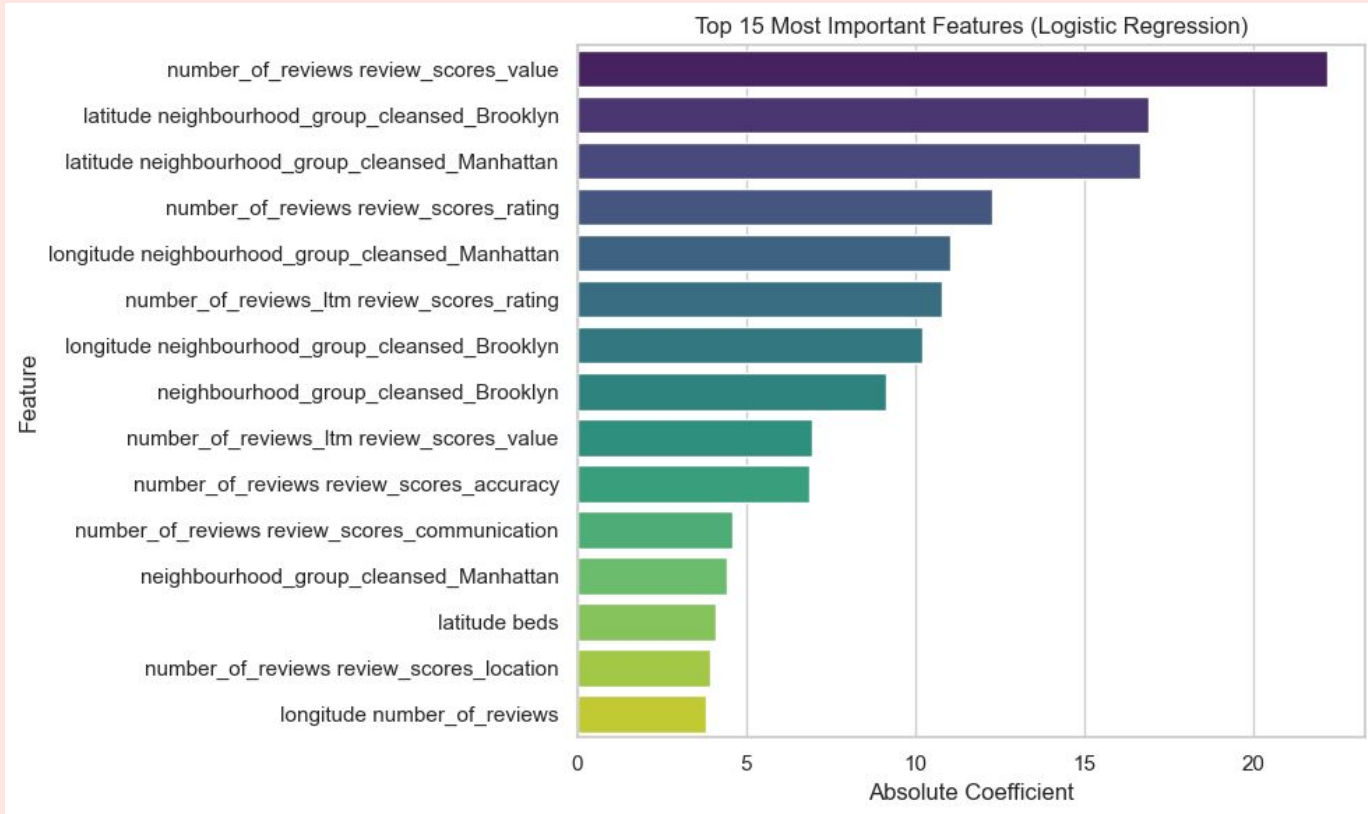
=== Test Performance ===

R^2 : 0.7084

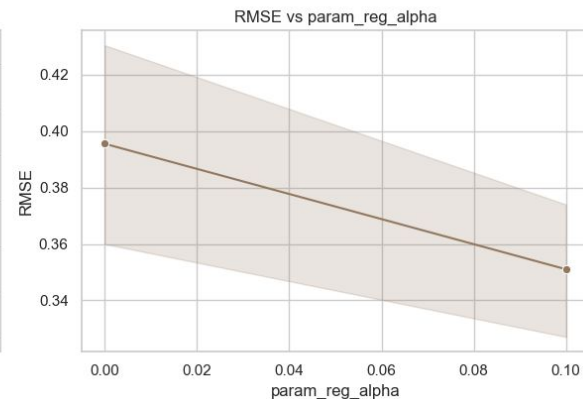
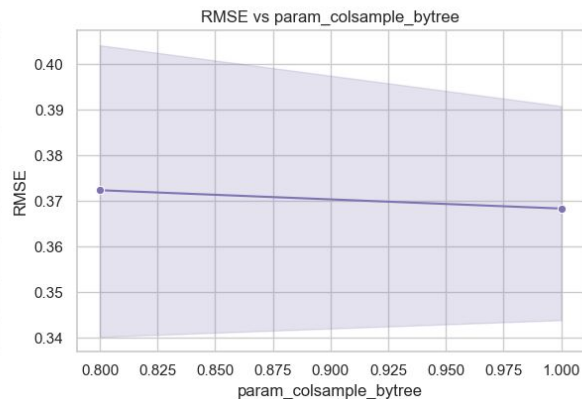
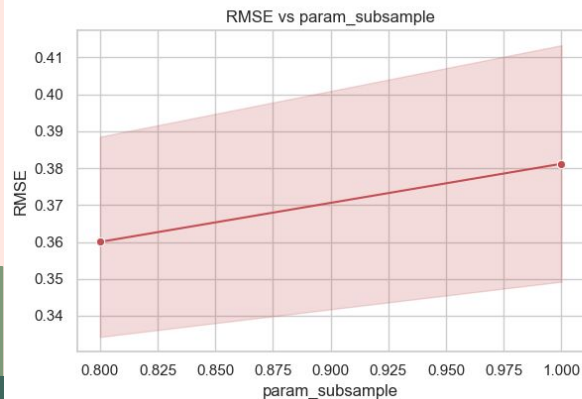
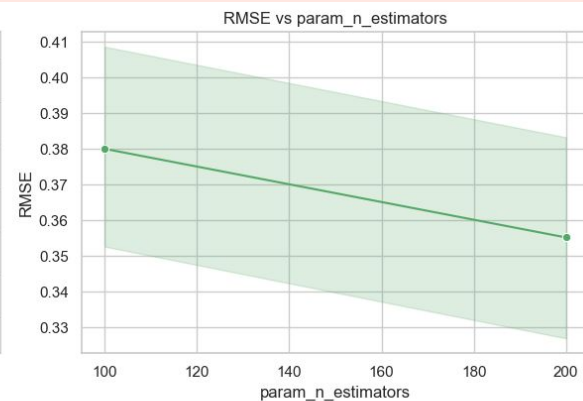
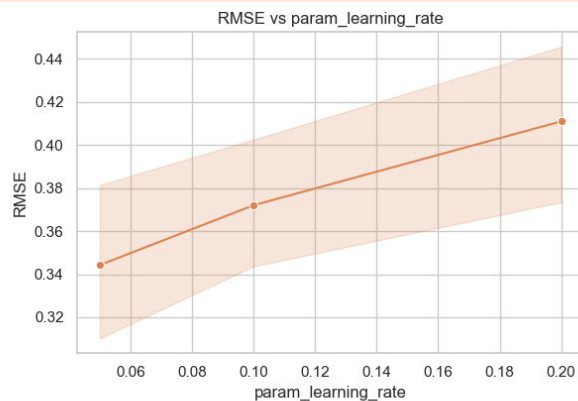
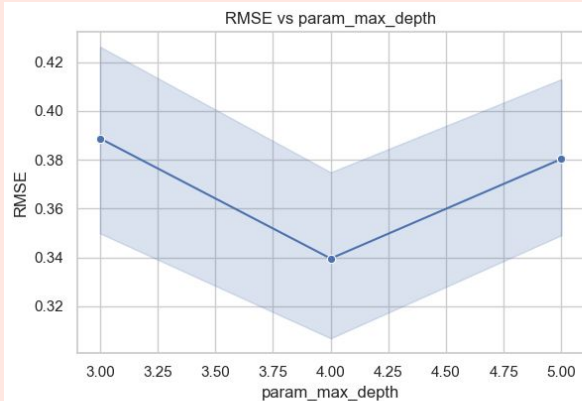
RMSE (log scale): 0.1226

	feature	# importance
2	accommodates	0.30297005215806017
1	longitude	0.20557052975783094
0	latitude	0.14281440184570726
6	minimum_nights	0.052459237961821066
11	review_scores_cleanliness	0.033958953842321185
7	number_of_reviews	0.02975290881249307
8	number_of_reviews_ltm	0.026047732685952518
4	bedrooms	0.02370654450463369
3	bathrooms	0.02343301151045217
15	review_scores_value	0.021154202745674564

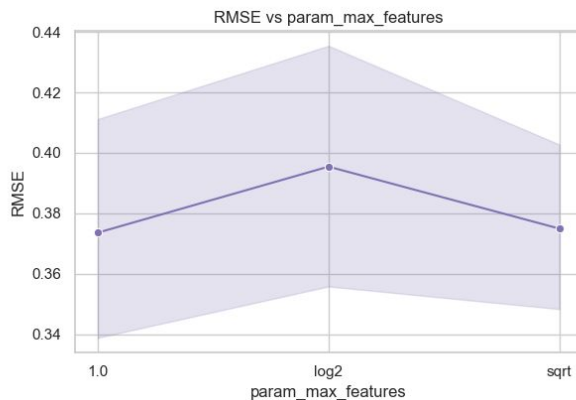
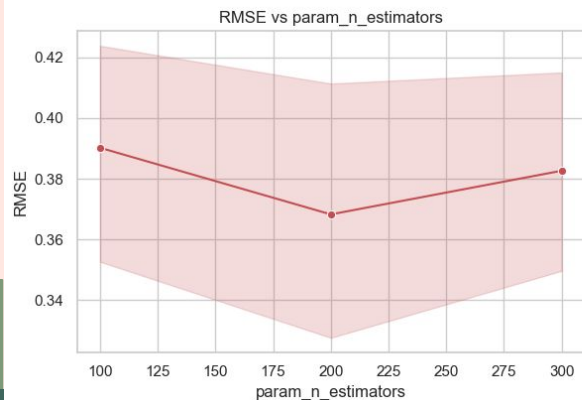
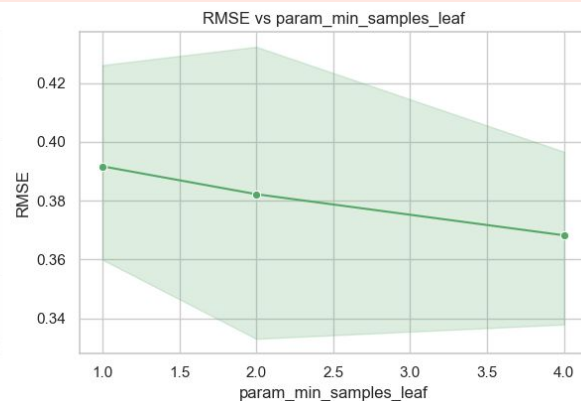
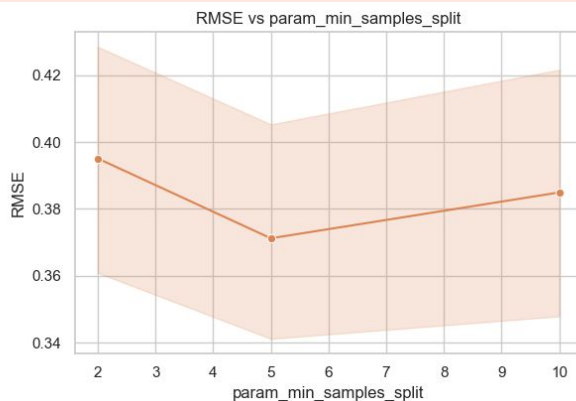
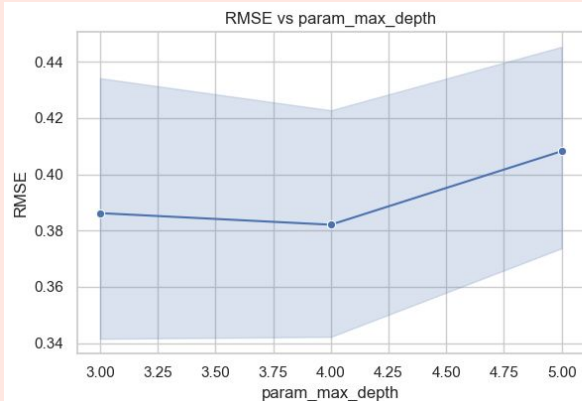
APPENDIX M



APPENDIX N



APPENDIX 0



APPENDIX P

	Model	# Actual Price	# Predicted Price
0	Random Forest	95.0	90.65
1	XGBoost	95.0	76.7699966430664
2	Bagging	95.0	85.18
3	Neural Network	95.0	166.93

APPENDIX 0

