

Purwadhika

JCDS 1202

Final Project

Matplotlib Team



Hello!

We are Matplotlib Team

In this final project, we were assigned to make a regression machine learning model using DC Properties dataset.

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- DATA UNDERSTANDING & DATA EXPLORATION
- MODELING & EVALUATION
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- FUTURE WORKS

1. Background & Problem Identification

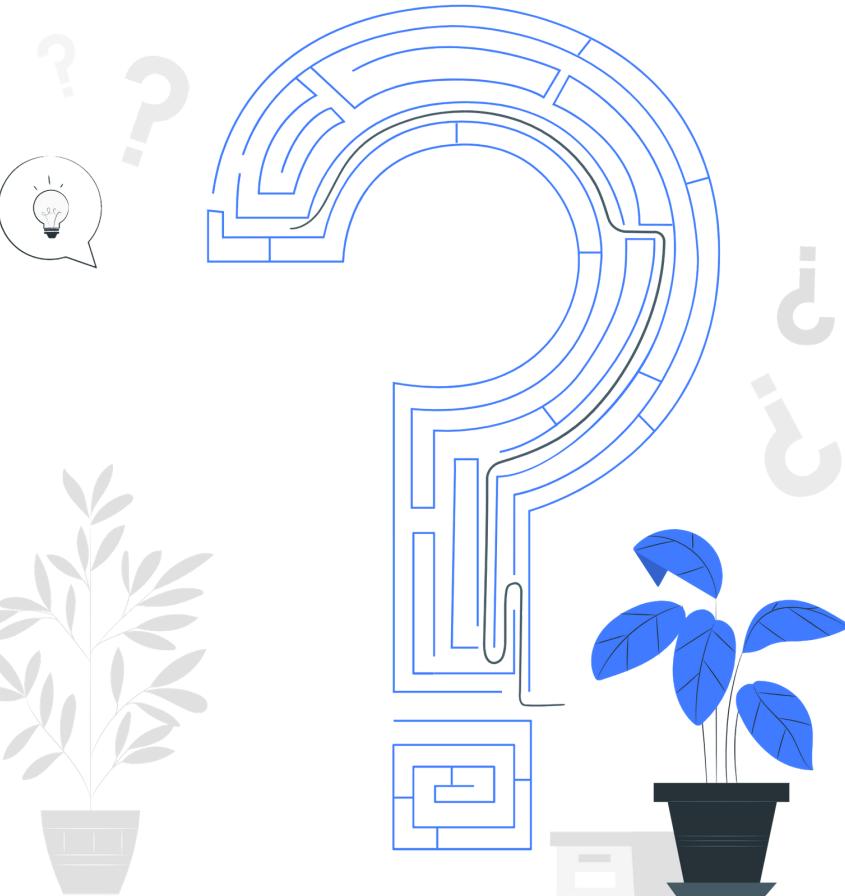


Background

We position ourselves as a Data Scientist Team working at MPL Bank located in Washington DC, USA.

We were assigned to work on a project to develop a Machine Learning (ML) solution for Underwriter Team of MPL Bank. We will help the Underwriter Team to make an improvement in their process of underwriting, specifically in the process of property appraisal and valuation.

Problem Identification



Problem
Definition

Business
Objective

Data
Requirements

Analytic
Approach

Action

Value

Problem Definition



Risk of Fraud & Erroneous Appraisal

Difference between the Agreed Offer and the Actual Property Valuation

Improving Accuracy in Appraisal Evaluation Process

Why?



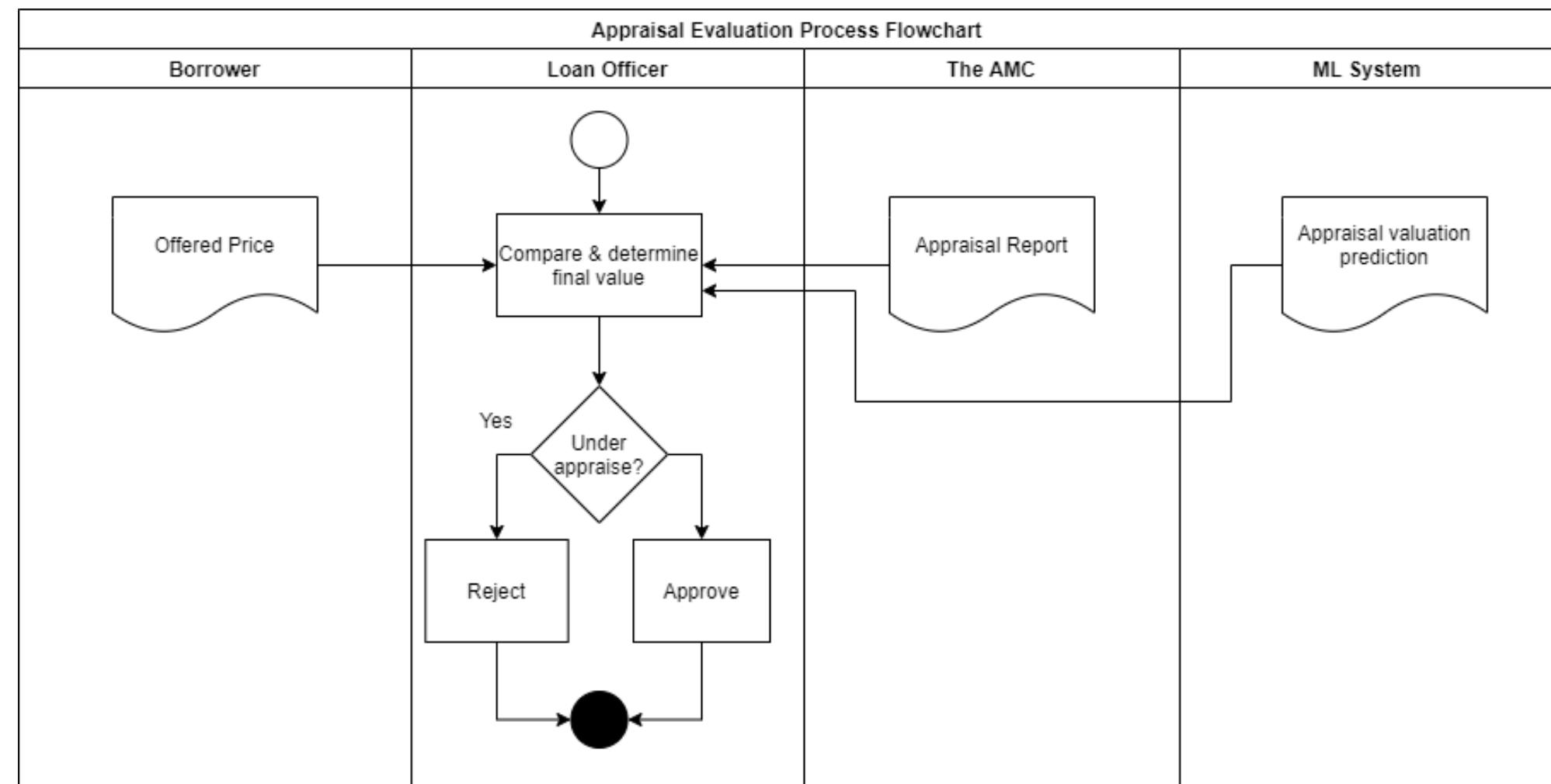
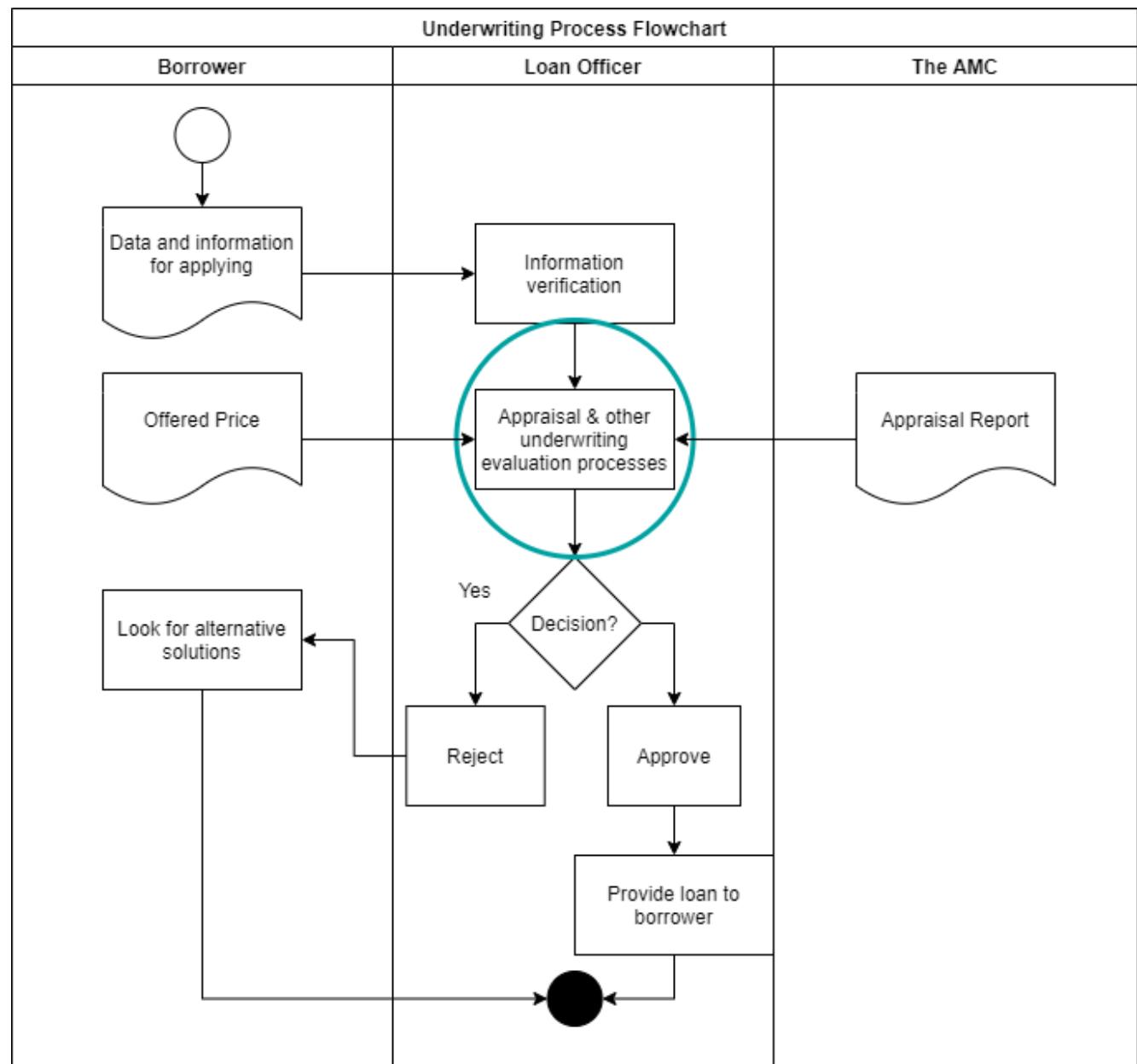
Appraisal process directly affects company's revenue.

The result would determine whether to give loan to a borrower.

A property's value is appraised by AMC and checked by MPL Bank's internal appraisal team.

This is where we come in to help improving the process of property appraisal evaluation.

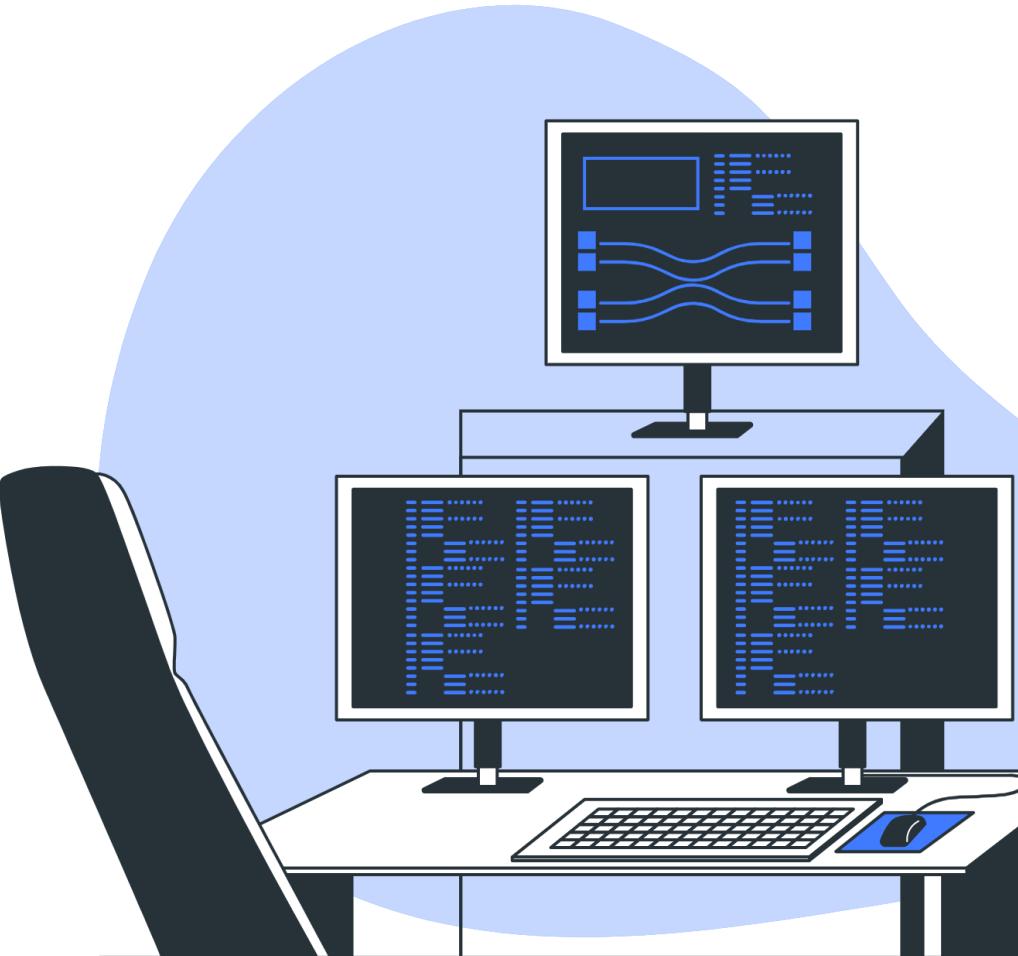
Appraisal Evaluation Process



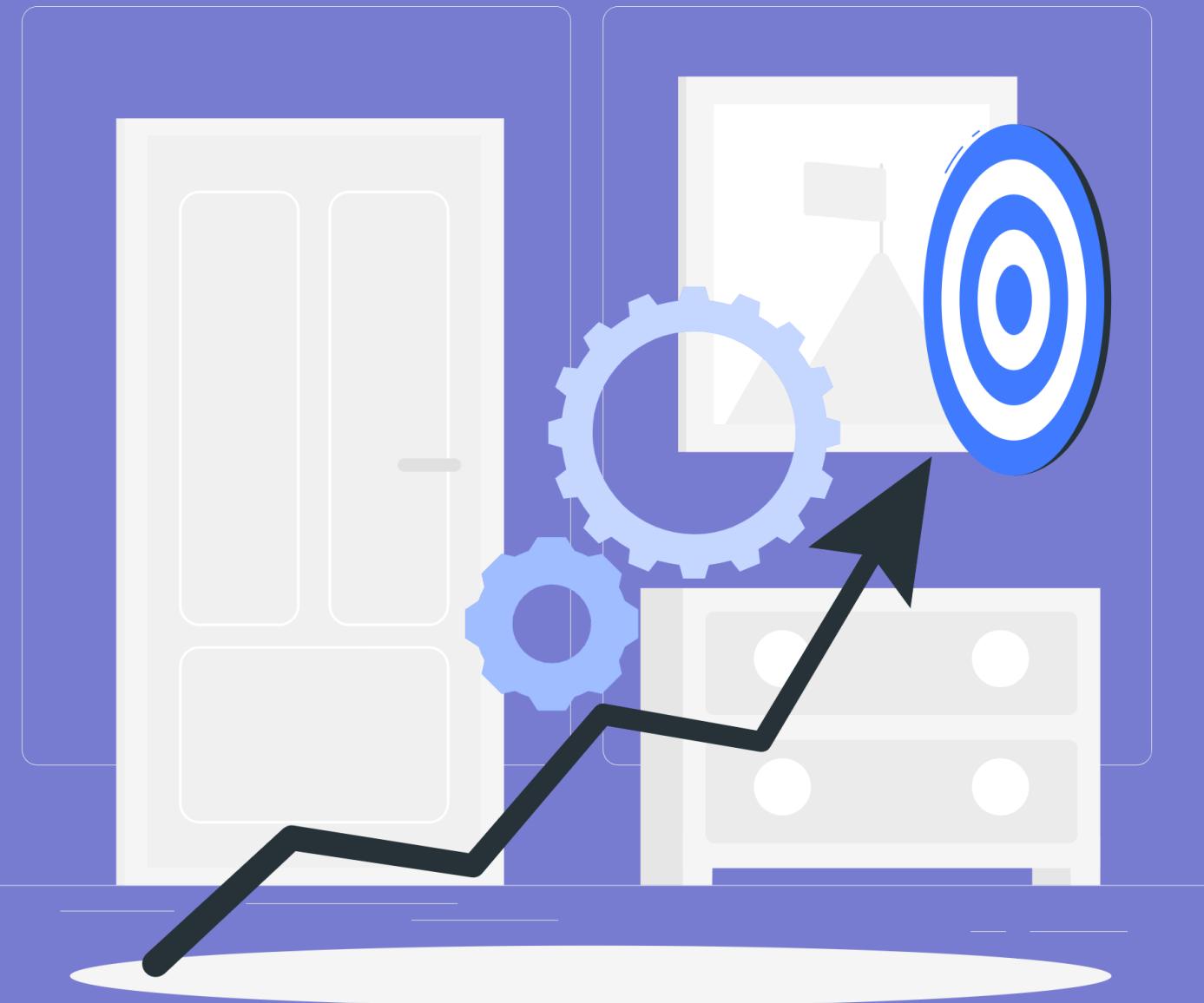
Expected Output

A system that can make an estimation of an accurate and reasonable value (price) for a property based on the aspects of the property by using Machine Learning.

Notes : Due to the limitation of our time budget, we limit the capability of our model in this project to predict an output only for properties with grade lower than Exceptional, since Exceptional properties have a price range that is very different than the rest of properties with other grades.



Business Objectives



Maximize Profit

by helping underwriter team to make the right decision whether to give a loan or not, with an optimal amount.

Minimize Loss

originated from fraud and erroneous valuation.

Notes: In this project we were asked to reach the Mean Absolute Error (MAE) metrics at most 13% to the median of property price.

Data Requirements

- The features of the property (e.g., gross building area, the number of rooms, the number of bedrooms, etc)
- The condition of the property
- The location of the property



Analytic Approach



Machine Learning Techniques

Target : Continuous Value

Machine Learning : Supervised Learning - Regression

Type : Model-based Learning

Risk

- The actual value of the property > prediction value
→ Reject giving loan and resulting in loss of potential borrower.
- The actual value of the property < prediction value (the model gives an under appraised value)
→ Suffer loss when the borrower is unable to pay back.

Performance Measures

- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)
- The Coefficient of Determination (R^2)
- With MAE as the vital metrics as agreed with Underwriter Team.

ACTION

The business user can utilize the prediction result by comparing it with the appraisal value given by the AMC to determine a reasonable property value.

VALUE

To improve the underwriting process by providing a good appraisal prediction model and thus helps business user to make the right business decision, resulting in maximized profit and minimized loss.

2. Data Understanding & Data Exploration



DATA ACCESS & PRIVACY

The data was downloaded from [Kaggle](#).

All data is available at [Open Data D.C.](#).

The residential and address point data is managed by the [Office of the Chief Technology Officer](#).

Distribution Liability: [Data Terms and Conditions](#).

RESIDENTIAL DATA SHAPE

- 106,696 Rows
- 49 Columns

Data
Collection

Data Description

BATHRM Number of Full Bathroom	HF_BATHRM Number of Half Bathroom	HEAT Heating System	AC AC Availability
NUM_UNITS Number of Units	ROOMS Number of Rooms	BEDRM Number of Bedrooms	AYB The earliest time the main portion of the building was built
EYB The year an improvement was built more recent than actual year built	QUALIFIED Government's Criteria on whether the sale is representative of market value	GBA Gross Building Area (in sqft)	STYLE Style

Data Description

STRUCT Structure	GRADE Drade	CNDTN Condition	EXTWALL Exterior Wall
ROOF Roof Type	INTWALL Interior Wall	KITCHENS Number of Kitchens	FIREPLACES Number of Fireplaces
LANDAREA Land Area (in sqft)	LATITUDE Latitude	LONGITUDE Longitude	ASSESSMENT_NBHD Neighborhood ID

Data Description

WARD	QUADRANT	SALEDATE	PRICE
Ward	City Quadrant (NE, SE, SW, NW)	Date of Most Recent Sale	Price

Data Pre-Processing

Drop Unused Columns

Unnamed: 0, SALE_NUM, CMPLX_NUM, LIVING_GBA, X, Y, ASSESSMENT_SUBNBHD, SOURCE, CITY, STATE, NATIONALGRID, GIS_LAST_MOD_DTTM, CENSUS_BLOCK, YR_RMDL, STORIES, FULL_ADDRESS

Fill Missing Values

AYB,
QUADRANT, AC,
NUM_UNITS

Create New Columns

- ayb_age = Present Year - AYB
- eyb_age = Present Year - EYB

Drop Unusual/ Erroneous Data

- BEDRM > ROOMS
- SALEYEAR <= 1991
- EYB < AYB

Drop Rows with Missing Values

SALEDATE, KITCHENS, ROOMS, GRADE, HEAT, BATHRM

Merging Values with Very Few Occurrence

- CNDTN (Default → Good)
- GRADE (Low Quality → Fair Quality)

Excluding Outliers

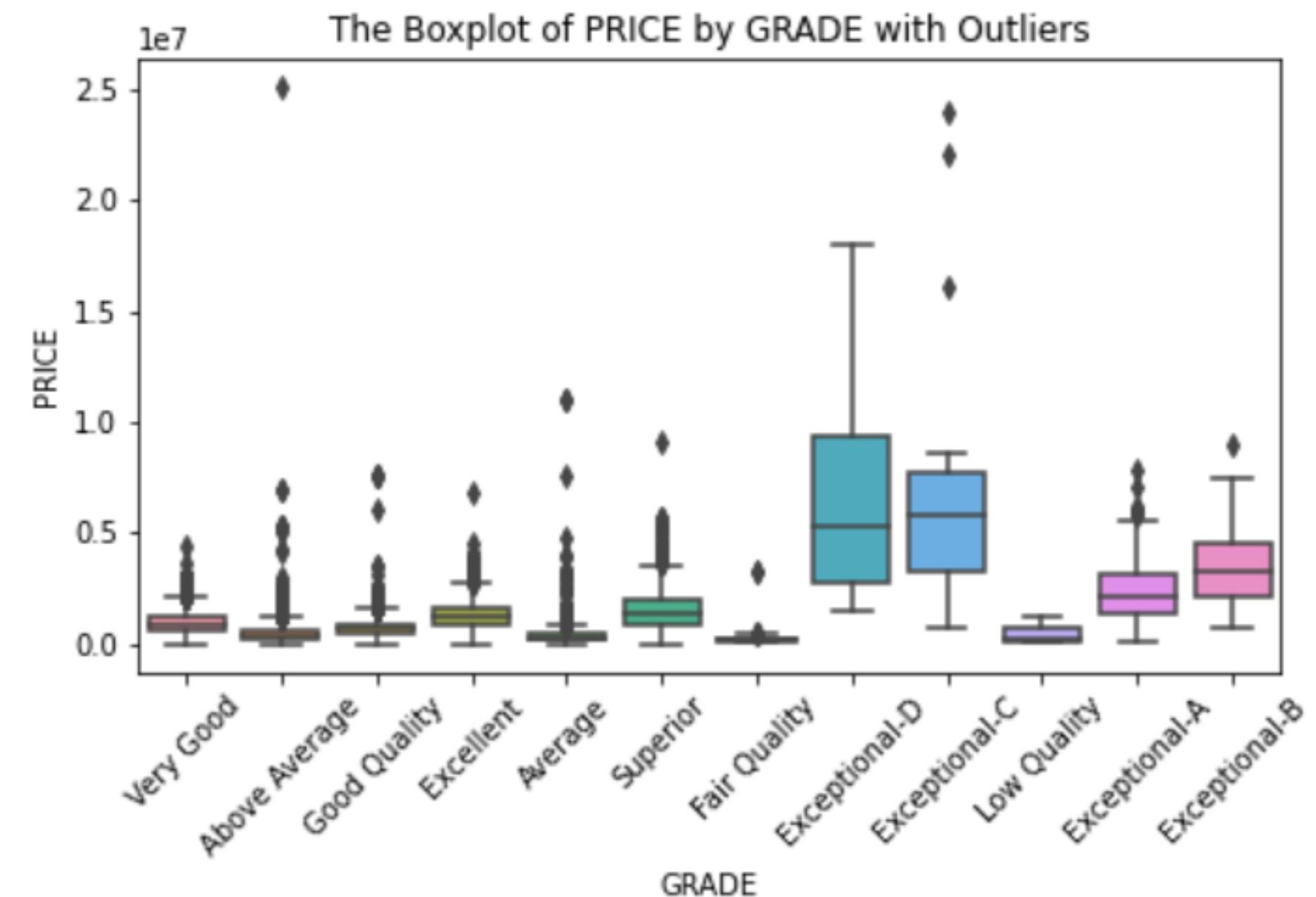
KITCHENS, PRICE, Price based on CNDTN

Re-classify Columns

CNDTN, STRUCT, ROOF

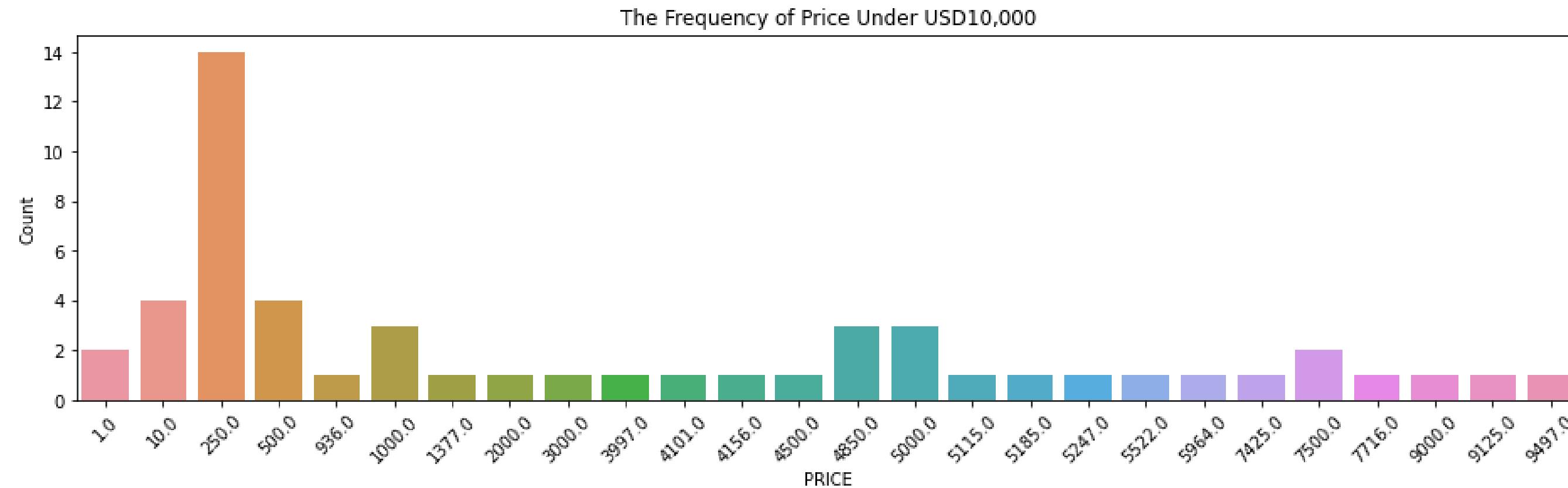
Identifying Outliers in PRICE

We limit the capability of our model in this project to predict an output only for properties with grade lower than Exceptional since Exceptional properties have a price range that is very different than the rest of other grades and another model needs to be built specifically for them.



Erroneous PRICE

We found few suspicious data where properties were being sold for a very low price. We obtain the information that the median of the whole USA residential price is around \pm USD50,000. Thus based on this information, we drop data points with an assumption that there are very few cheap properties with values as low as one-fifth to the median price, which is USD10,000.



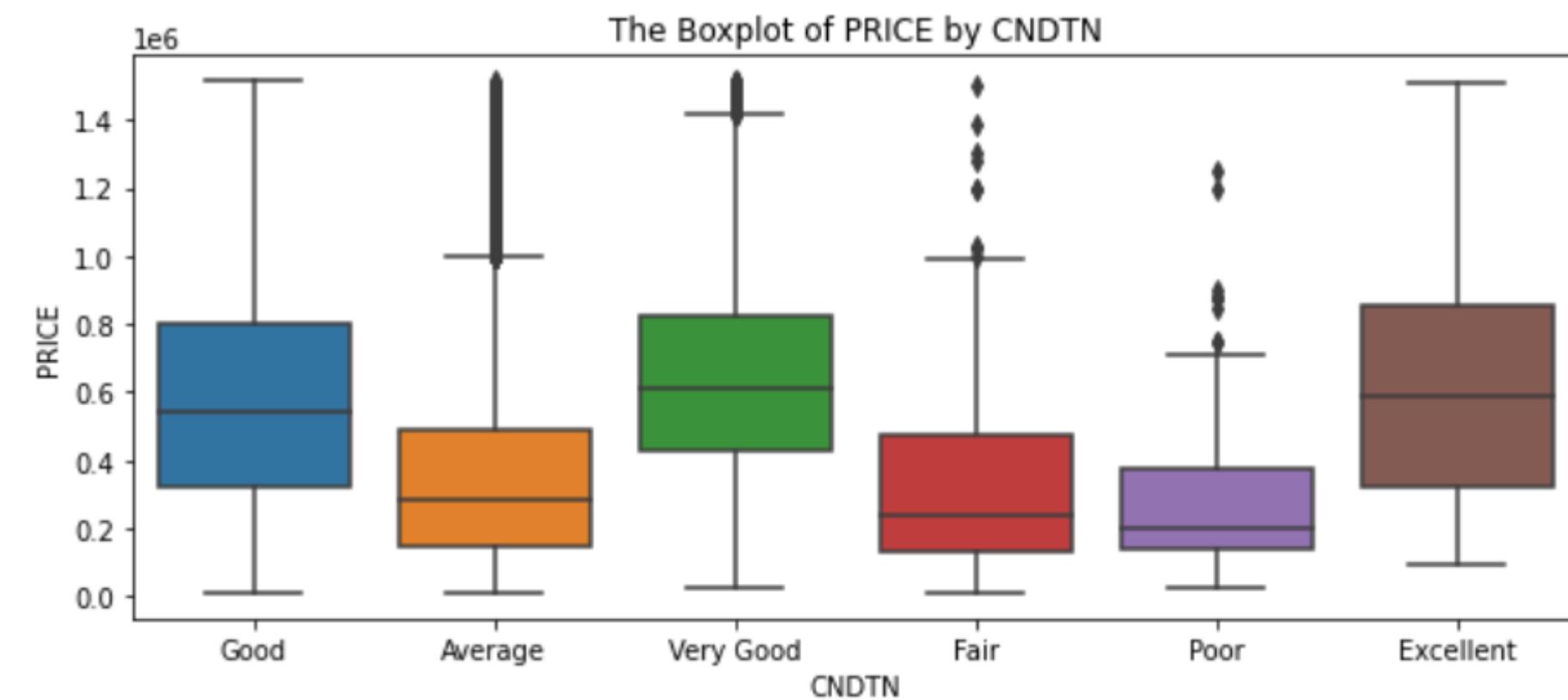
Re-classify CNDTN

There are some overlap between categories, but between 'Fair, Poor, Average' vs 'Good, Very Good, Excellent' they differ quite significantly; as such CNDTN still could potentially be a good predictor of price.

Price Median : USD420,000

We re-classify the categories in CNDTN into 2 groups :

- 0 : Poor (Under median)
- 1 : Good (Above median)



Re-classify STRUCT & ROOF

Price Median : USD420,000

We re-classify the categories
in STRUCT and ROOF into 2
groups :

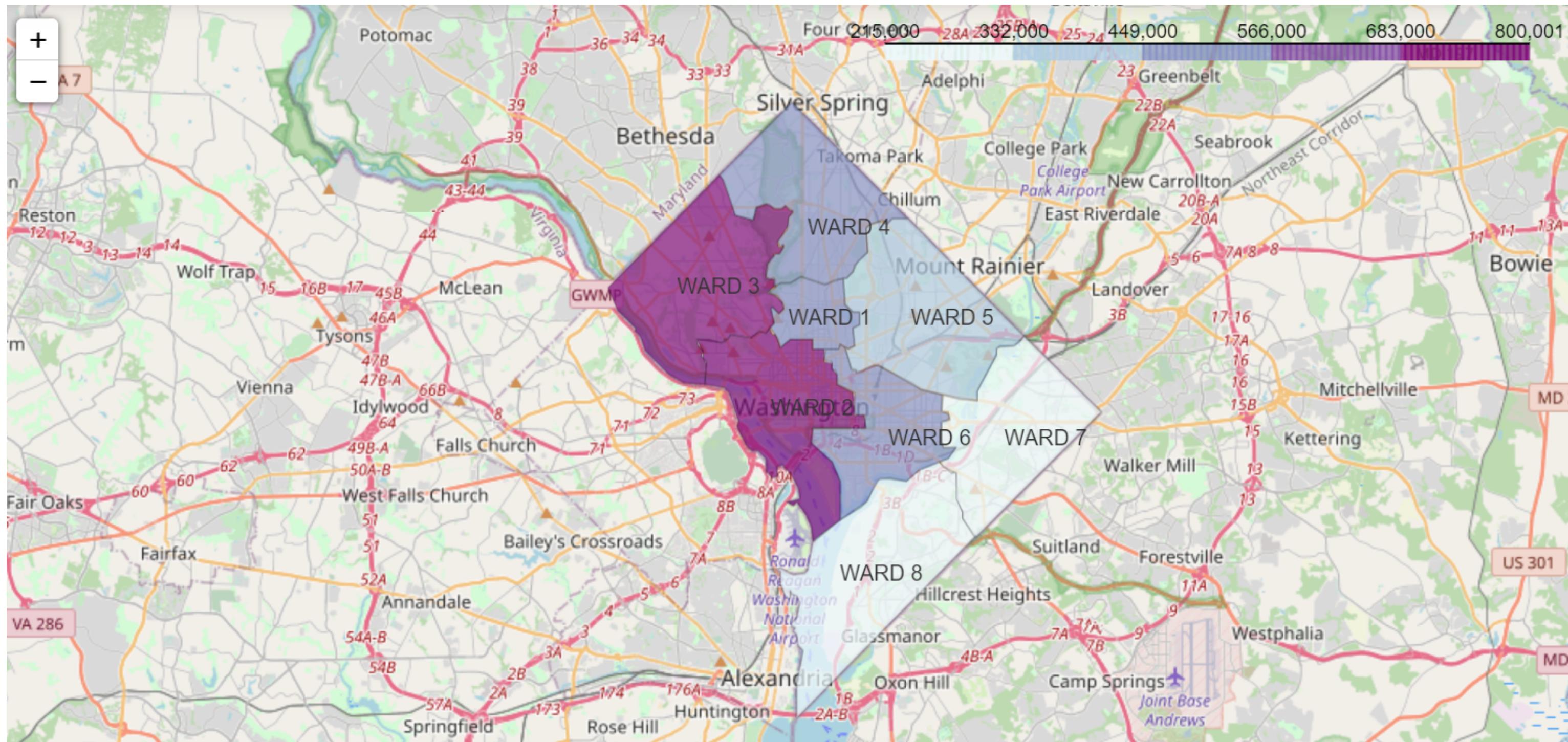
- 0 : Under median
- 1 : Above median

	STRUCT	median_PRICE	total
0	Semi-Detached	267000.0	7961
1	Multi	295000.0	2748
2	Town Inside	349500.0	185
3	Town End	388478.5	76
4	Row End	425000.0	6530
5	Single	471000.0	14267
6	Row Inside	475000.0	22444
7	Default	560000.0	2

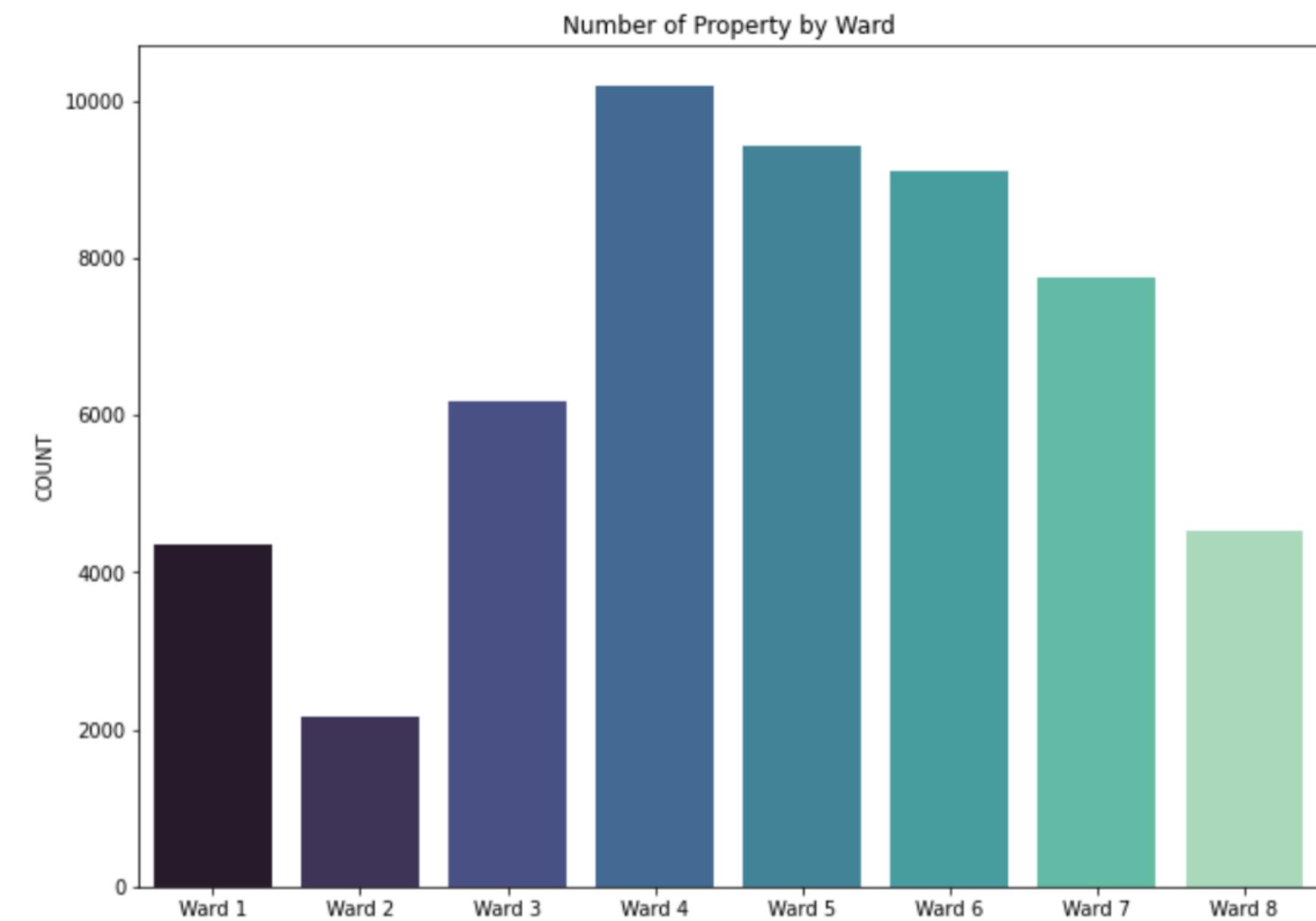
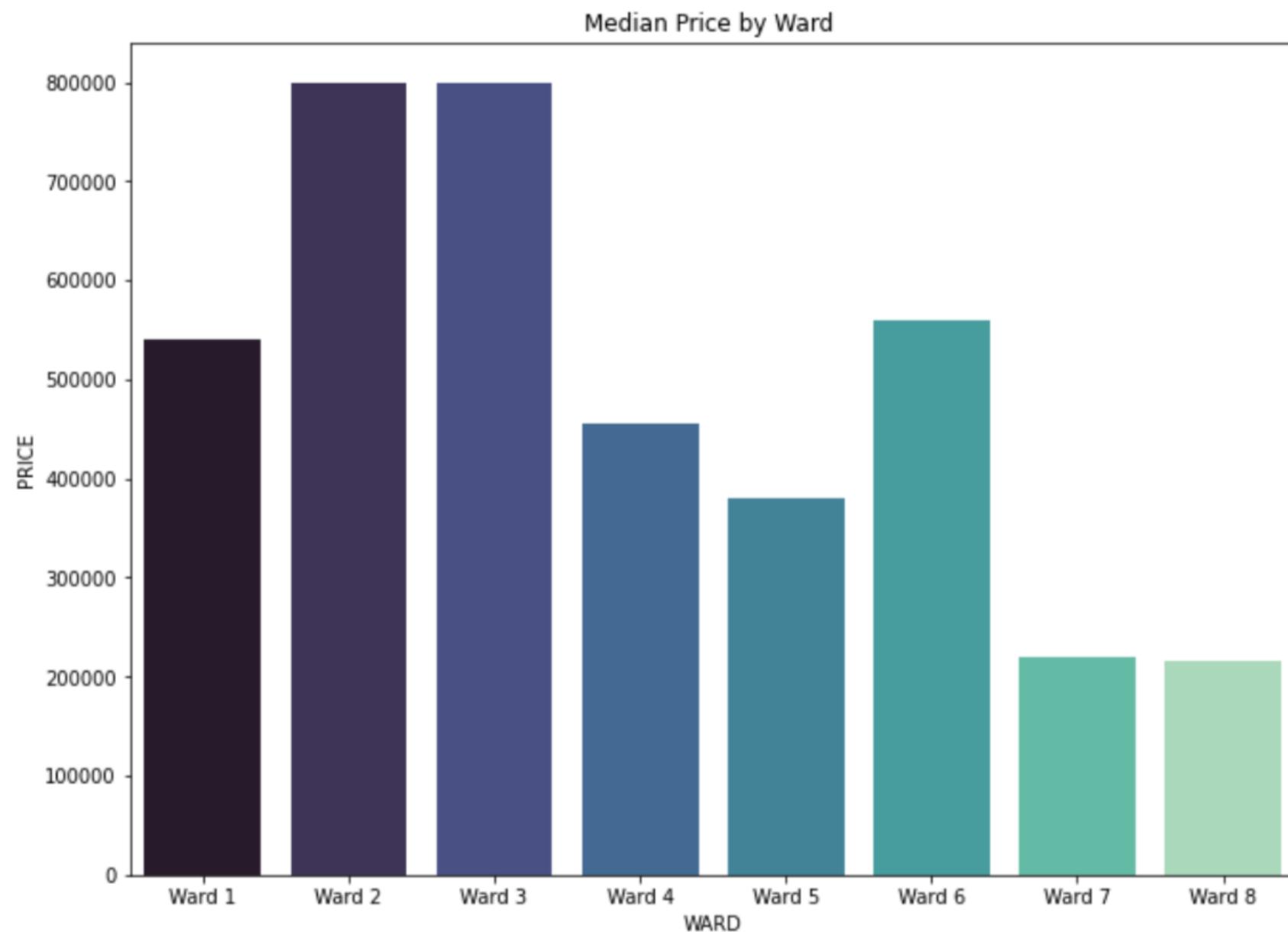
ROOF	median_PRICE	total	
0	Concrete	299900.0	1
1	Comp Shingle	350000.0	15368
2	Built Up	362500.0	16971
3	Metal- Pre	366500.0	133
4	Typical	370000.0	84
5	Composition Ro	410150.0	61
6	Shake	455000.0	334
7	Metal- Sms	484000.0	15369
8	Shingle	493506.0	215
9	Concrete Tile	512500.0	2
10	Water Proof	594000.0	4
11	Clay Tile	650000.0	237
12	Slate	685000.0	4568
13	Neopren	711500.0	849
14	Wood- FS	847500.0	4
15	Metal- Cpr	853500.0	13

Insights

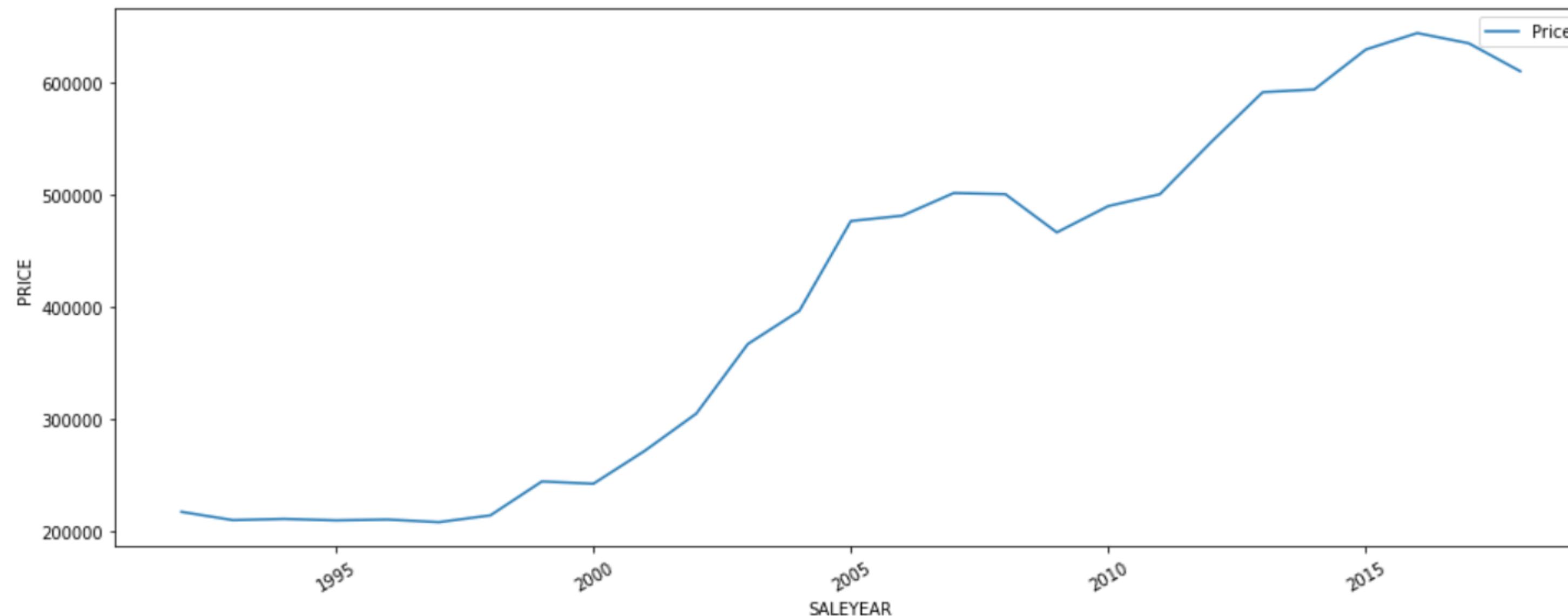
Map by Ward



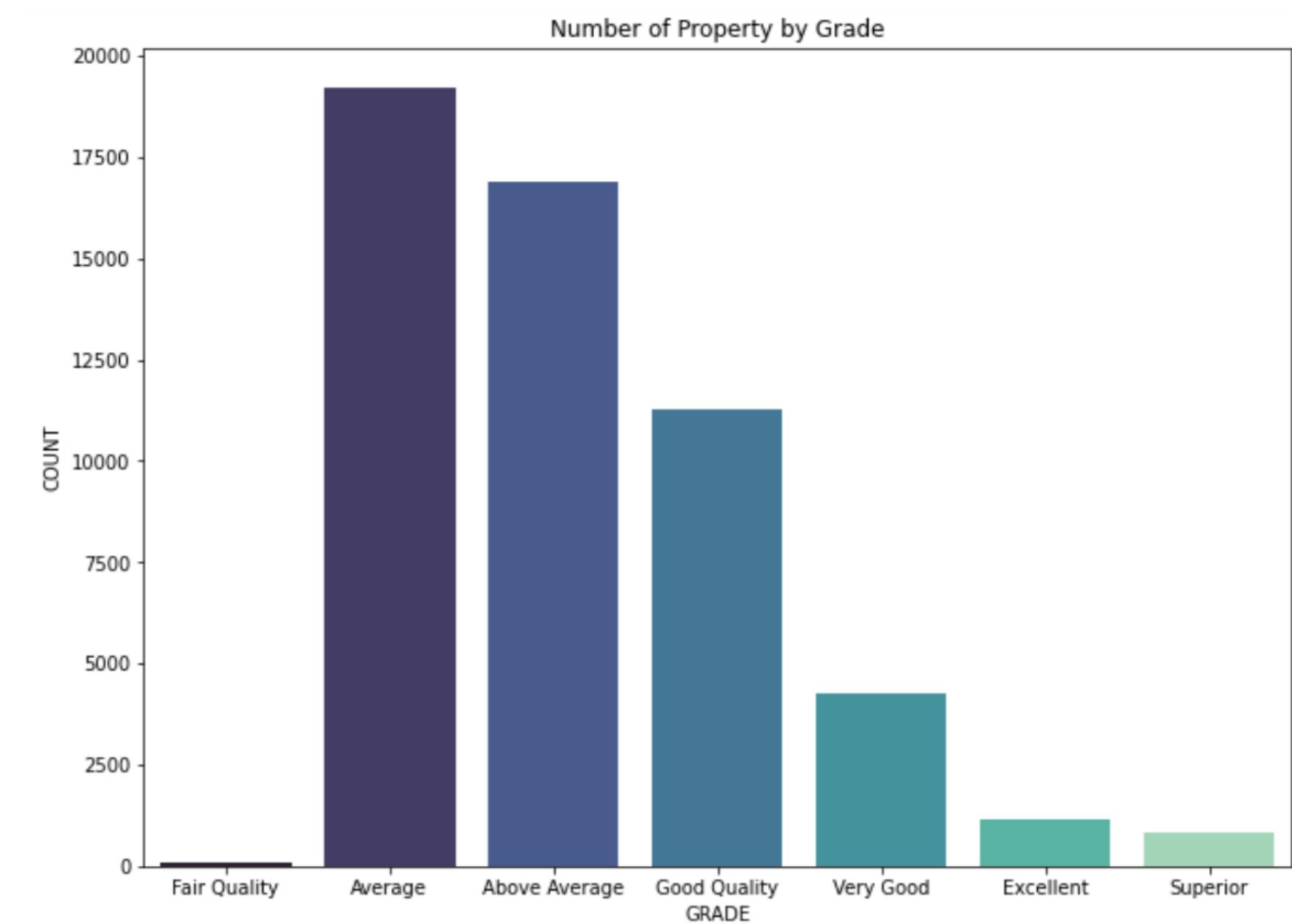
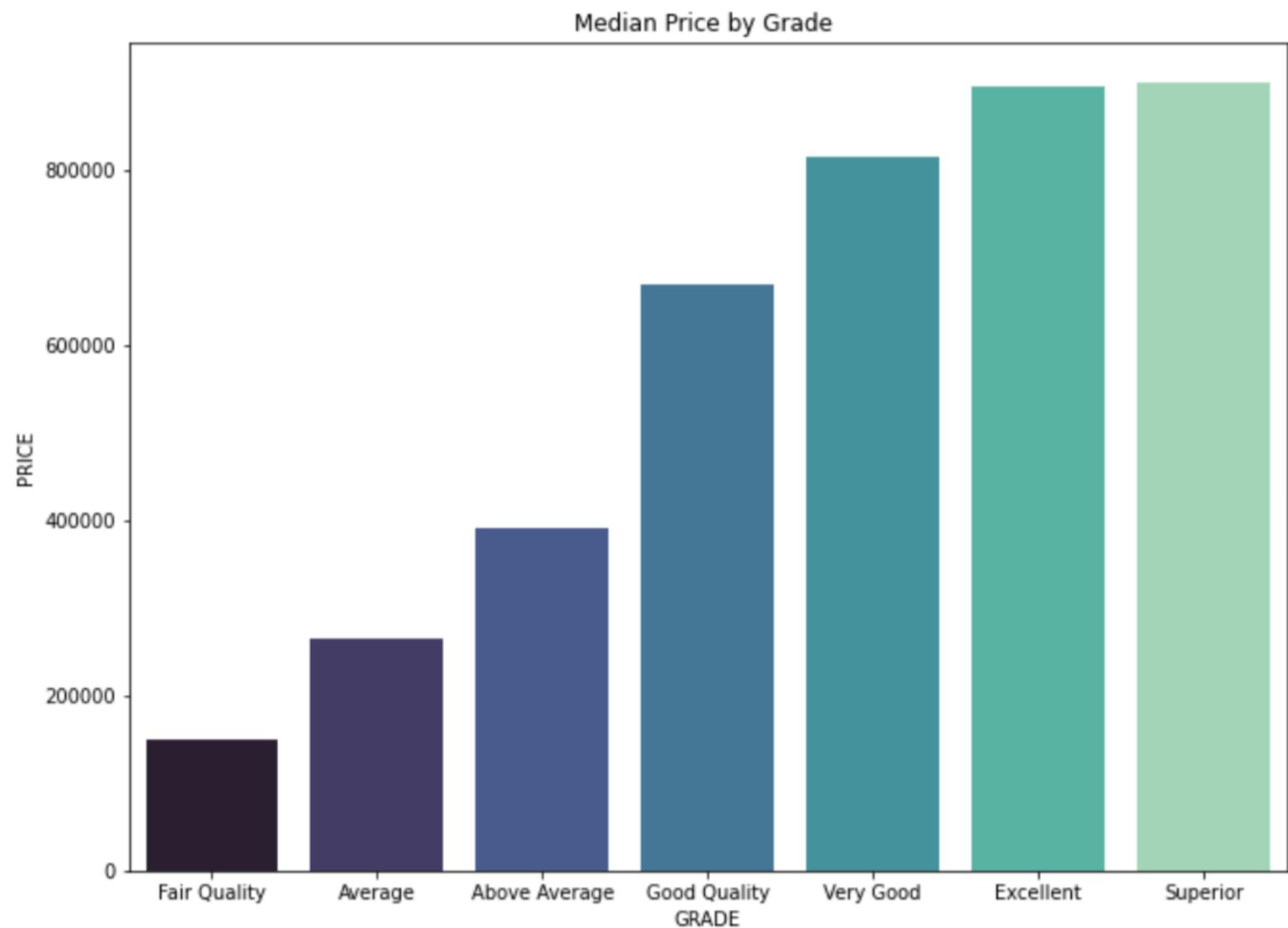
Median Price & Number of Property by Ward



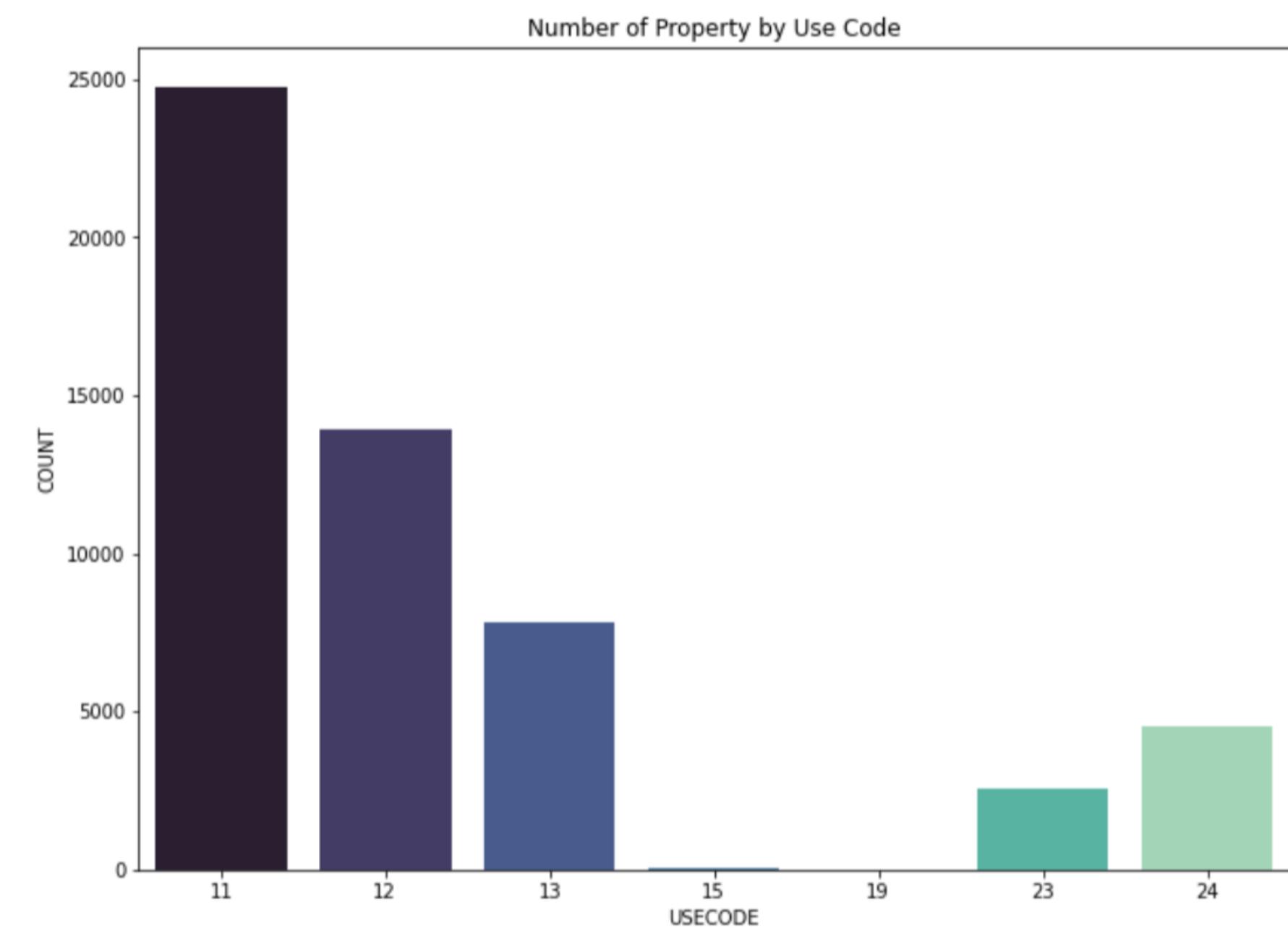
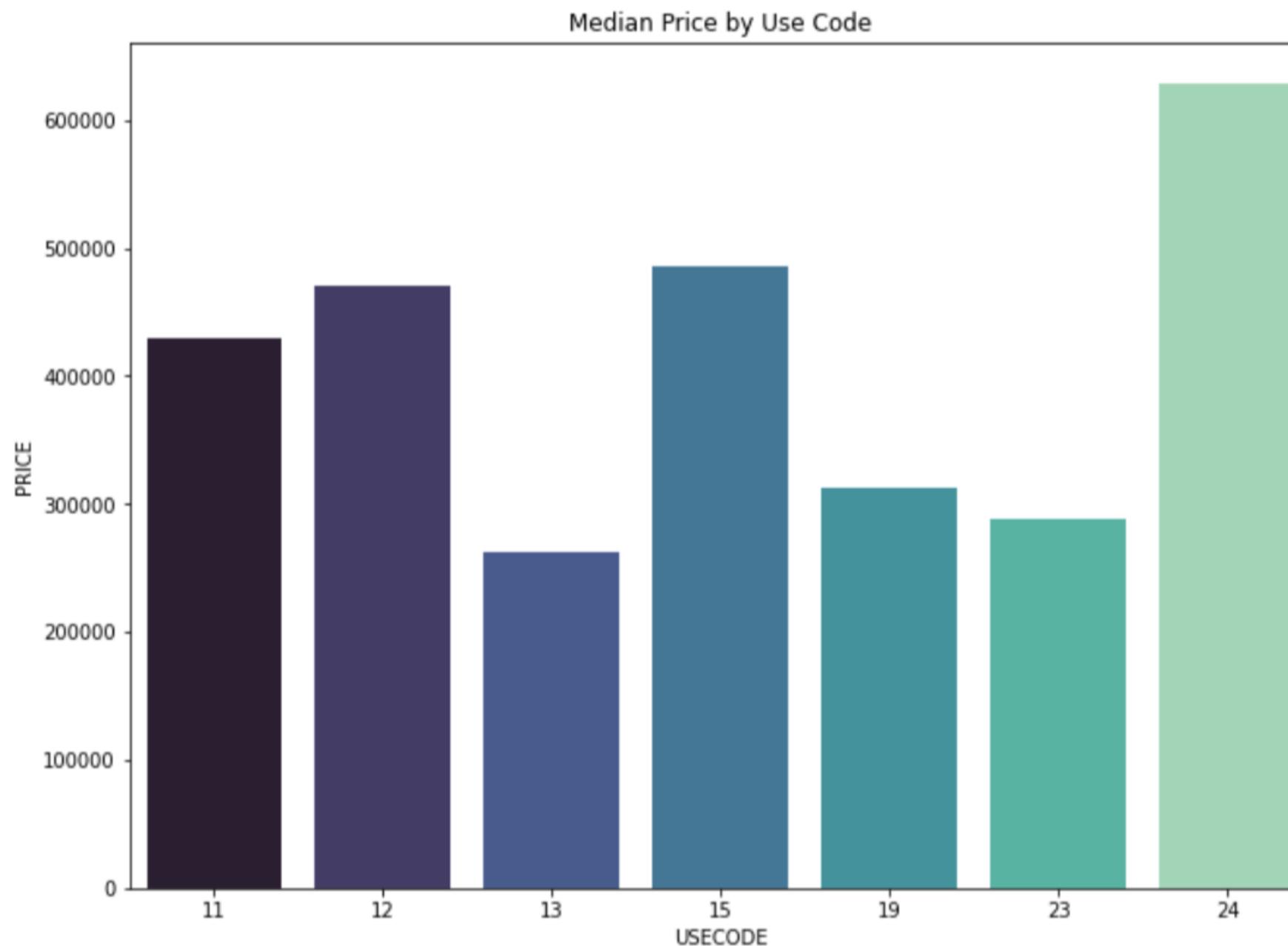
Median Sale Price per Year



Median Price & Number of Property by Grade



Median Price & Number of Property by Use Code



3. Modeling & Evaluation



Modeling Steps

- Encoding categorical features and scaling numerical features
- Training & evaluating different baseline models of regression model
- Hyperparameter tuning with GridSearchCV to get best parameters of the best baseline-model

We choose the best model based on the R² score, Mean Absolute Error (MAE) and resource efficiency.

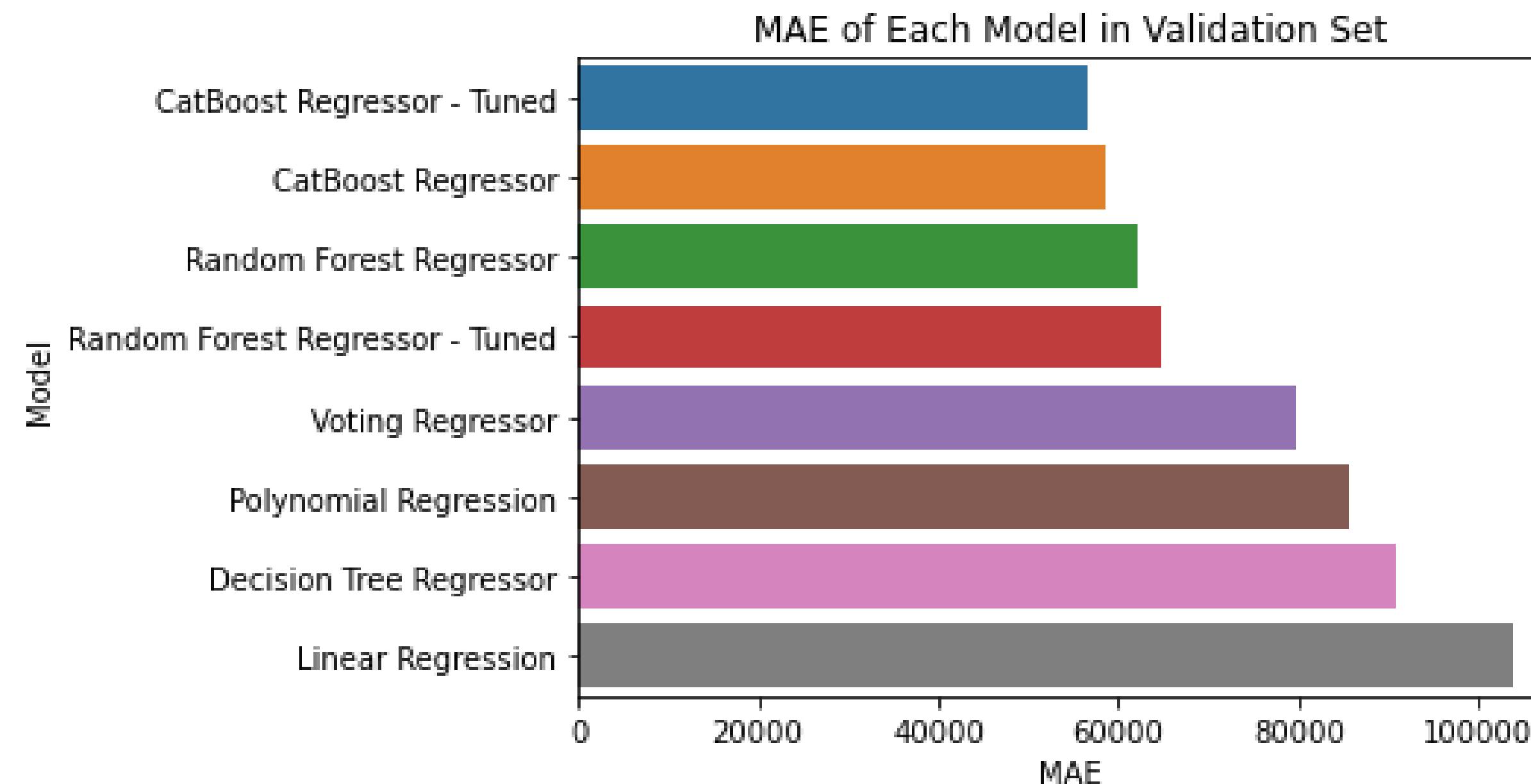
Model Assessment

CatBoost Regressor - Tuned has the best R² score and the lowest MAE in the validation set.

	Model	Set	MSE	RMSE	MAE	R2
1	Linear Regression	Validation	1.903111e+10	137953.273042	103854.302812	0.805568
3	Polynomial Regression	Validation	1.385206e+10	117694.756695	85578.223564	0.858480
5	Decision Tree Regressor	Validation	1.946054e+10	139501.048949	90685.029856	0.801180
7	Random Forest Regressor	Validation	9.184056e+09	95833.478785	62224.824740	0.906171
9	Random Forest Regressor - Tuned	Validation	9.609771e+09	98029.440223	64903.556443	0.901821
11	Voting Regressor	Validation	1.237256e+10	111231.996331	79811.893996	0.873595
13	CatBoost Regressor	Validation	7.999273e+09	89438.655723	58547.042234	0.918275
15	CatBoost Regressor - Tuned	Validation	7.897812e+09	88869.633101	56658.213149	0.919312

Model Assessment

CatBoost Regressor - Tuned has the lowest MAE compared to other models.



Final Model Evaluation

We chose CatBoost Regressor with tuned parameters as our prediction model.

Train Set

MSE: 6079714453.015866
RMSE: 77972.52370557122
MAE: 47183.05421572207
R-squared: 0.9380661353784469

Test Set

MSE: 7307725567.58184
RMSE: 85485.23596260257
MAE: 55157.87421335401
R-squared: 0.9249561938597425

Cross validation test for our best model to check how consistent the model and results are when measurement is repeated.

Training Cross Validation Scores
Mean : 0.9157272844086888
Std : 0.003736664180184315

From the cross validation test, we still get a good result.

Final Model Evaluation

We were asked to reach the Mean Absolute Error (MAE) value below 13% of the median property price.

Price median : 410000.0

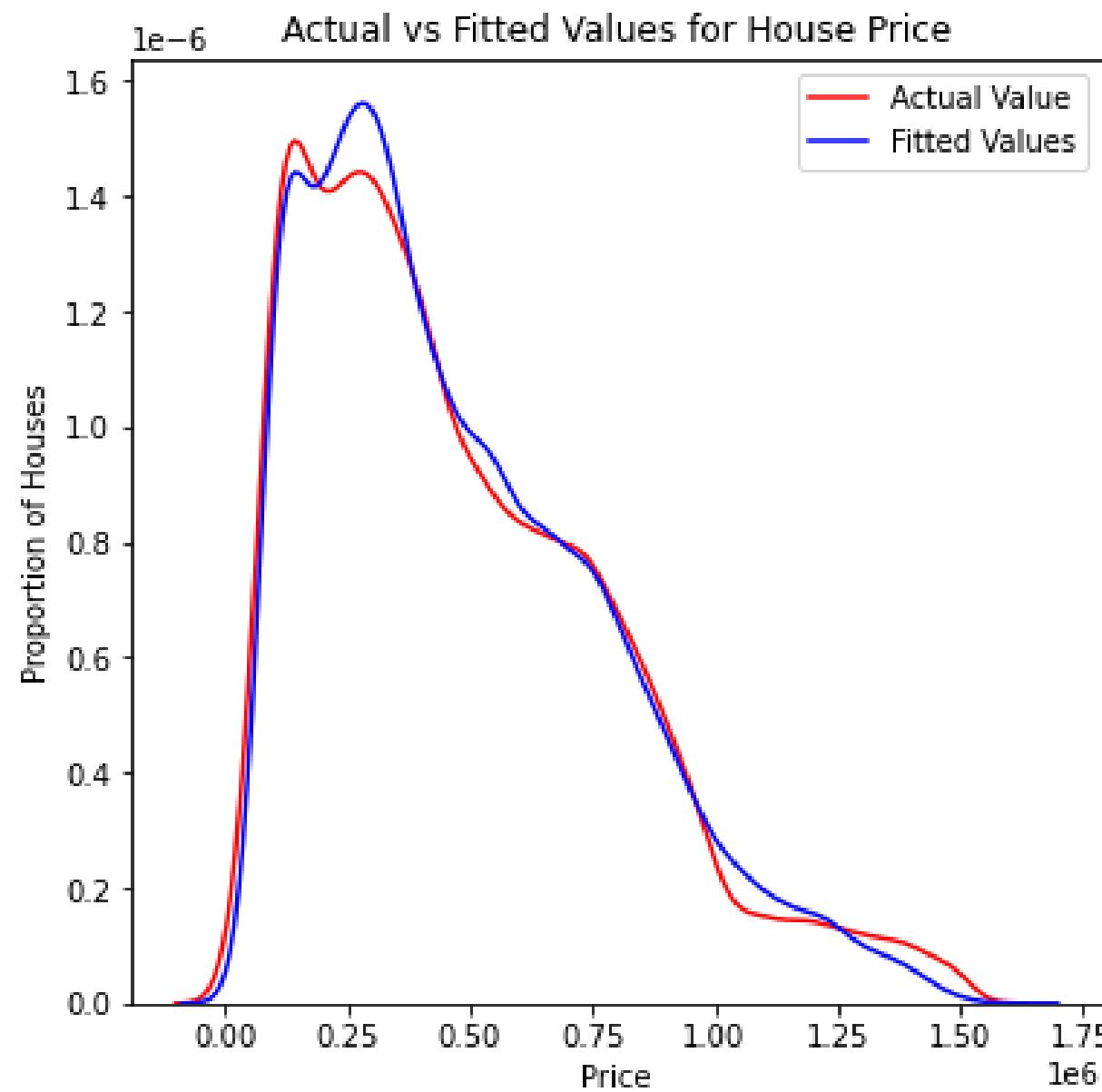
Desired MAE (13% * median) : 53300.0

Achieved MAE : 47183.05421572207

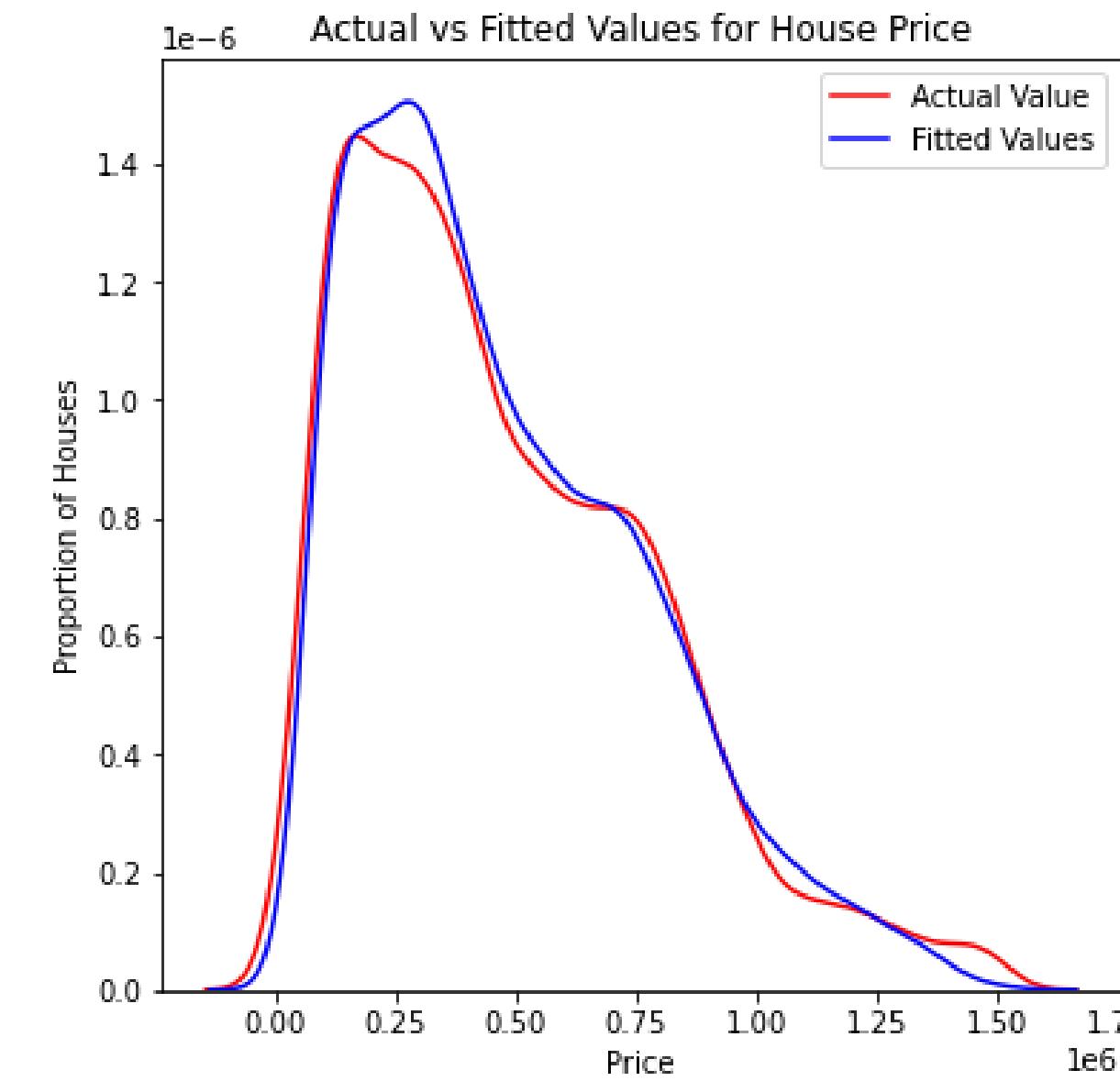
From the result shown above, we have achieved the desired MAE value (under USD53,300).

Distribution Plot of Actual vs Fitted Values

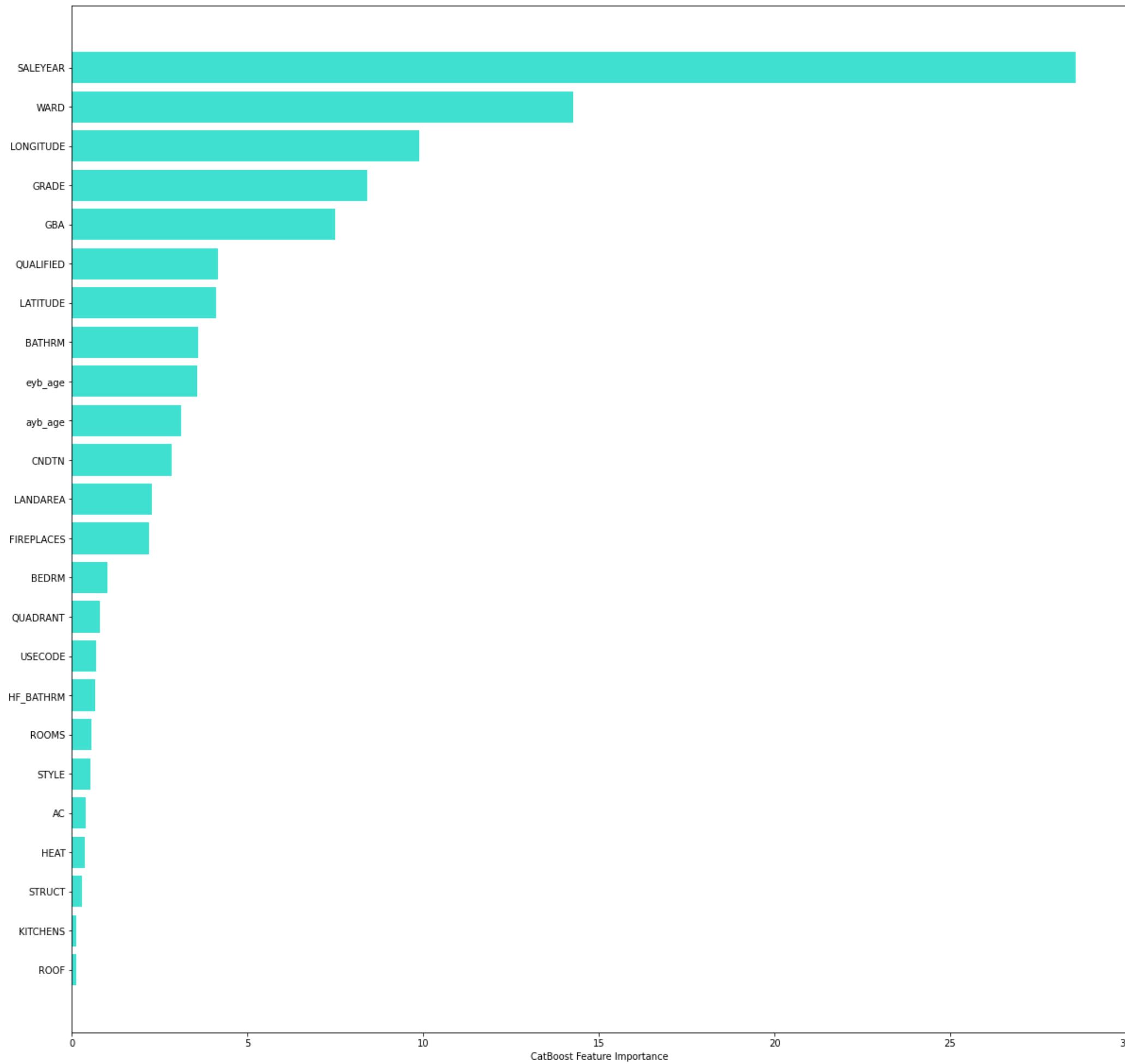
Train Set



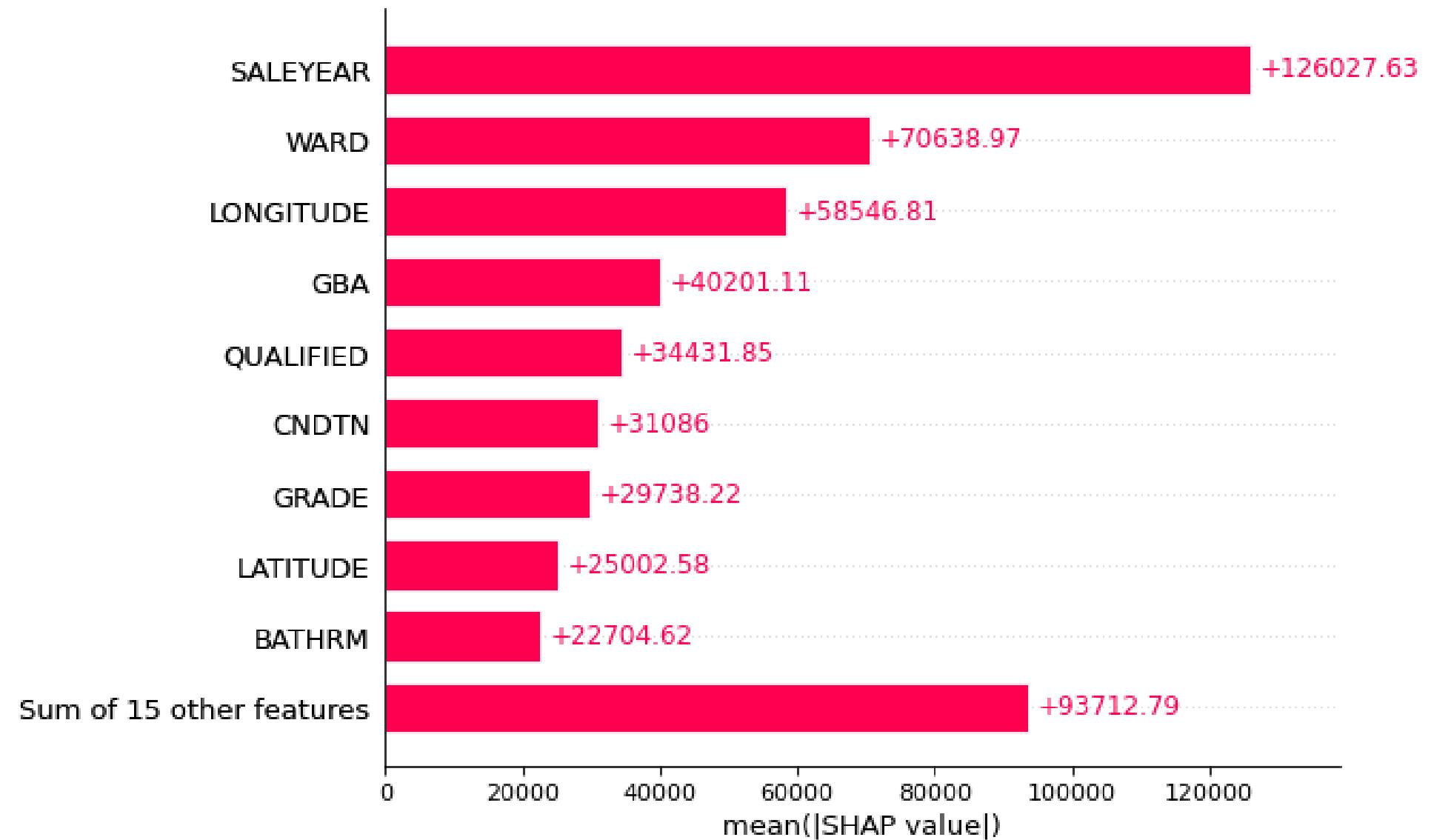
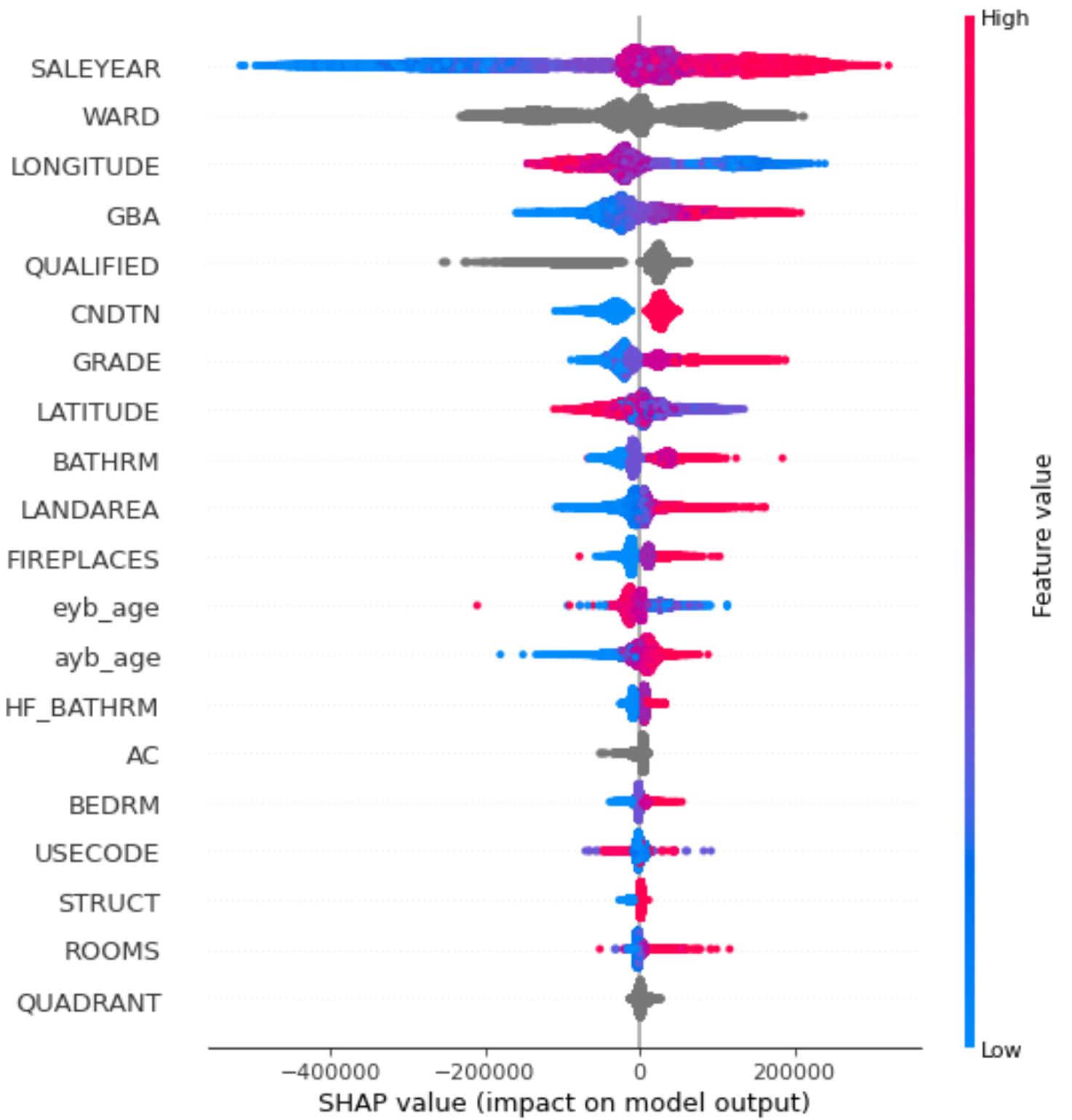
Test Set



Feature Importances



Feature Importances with SHAP



4. Deployment





Deployment Page

We deployed the model to a
webpage using FLASK.

MPL Bank

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Purwadhika JCDS Final Project - Matplotlib Team

In this project, we position ourselves as a part of the Data Scientist Team in a Financial Institution, MPL Bank, in Washington DC, USA. We are assigned to work on a project to develop a Machine Learning (ML) solution. The project owner is the Underwriter Team of MPL Bank. We will help the Underwriter Team to make an improvement in their process of underwriting and valuation.

MPL orders the appraisal through a third party, an appraisal management company (AMC). In order to comply with the federal appraiser independence requirements. However, the appraisal process performed by an external party has a risk of fraud or producing erroneous results. Thus, the project owner wants to address these issues.

Problem Definition

Based on the elicitation process with the project owner, we found that they want to improve the accuracy of their underwriting process, specifically in the process of evaluating the appraisal. In the process of evaluating appraisals, there are some risks that the project owner wants to minimize, such as fraud and erroneous appraisal results given by the AMC. In addition, there is also a problem that often happens regarding the difference between the agreed offer made by a borrower and the property seller and the actual property valuation. Since lenders can't lend out money more than a property is worth, all of these risks may cause the project owner to determine wrong appraisal value and to make a wrong decision whether to give the loan to a borrower.

To address these risks and improve their business process, the project owner needs a reliable autonomous system that can provide an estimation value that can be used to compare the value given by the AMC.

The expected output of this project is a system that can make an estimation of an accurate and reasonable value (price) for a property based on the aspects of the property by using ML. However, due to the limitation of our time budget, we limit the capability of our model in this project to predict an output only for properties with grade lower than Exceptional, since Exceptional properties have a price range that is very different than the rest of properties with other grades.

Business Objectives

- Maximize profit** by making the right decision to give a loan with an optimal amount.
- Minimize loss and risks of fraud and erroneous valuation.**

Data Requirements

The value that we want to predict is the value (price) of a property. The required information needed to make a prediction are the features of the house (e.g., gross building area, the number of rooms, the number of bedrooms, etc), the condition of the house, the location, etc.

Analytic Approach

- ML Techniques**: Since the value (price) that we want to predict is a continuous value, this problem can be addressed with Supervised Learning, more specifically with Regression.
- Risk**: The risk that may be caused by wrong prediction from the ML model is profit loss especially when the model gives underappraised value (price).
- Performance Measure**: The performance measures to evaluate the ML model are Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2).
- Action**: The business user can utilize the prediction result by comparing it with the appraisal value given by the AMC.
- Value**: The values created from the project are the improvement in the underwriting process and the maximized profit from giving the right appraisal and making the right decision in providing loan.

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Matplotlib Team

- Lis Cory
- Kemal Isfan
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Our Project

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Property Value Estimator

Washington DC, USA

The required data to estimate the value of a property are the location, the condition and the specification of the property.

Fill the form to estimate property value!

Location	Condition	Specification
Ward Select Ward	Building Age (in years) Select Building Age	Gross Building Area (in sqft) 1088
Quadrant Select Quadrant	Renovation Years (in years) 67	Land Area (in sqft) 2838
Longitude	Last Sale Year Select Last Sale Year	Style 2 Story
Latitude	Condition Select Condition	Rooms 6
	Grade Select Grade	Bathrooms 1
	Qualified? Qualified?	Bedrooms 3
		Half Bathrooms 1
		Kitchens 1
		Fireplaces 0
		AC Yes
		Heating System Warm Cool
		Roof Concrete / Comp Shingle / Built Up / Metal-Pre / Typical / Co
		Structure Semi-Detached / Multi / Town Inside / Town End
Estimate		

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Property Value Estimator

Washington DC, USA

The required data to estimate the value of a property are the location, the condition and the specification of the property.

Fill the form to estimate property value!

Location	Condition	Specification
Ward Ward 5	Building Age (in years) 67	Gross Building Area (in sqft) 1088
Quadrant NE	Renovation Years (in years) 48	Land Area (in sqft) 2838
Longitude -76.994888	Last Sale Year 2014	Style 2 Story
Latitude 38.95709777	Condition Good	Rooms 6
	Grade Average	Bathrooms 1
	Qualified? Qualified	Bedrooms 3
		Half Bathrooms 1
		Kitchens 1
		Fireplaces 0
		AC Yes
		Heating System Warm Cool
		Roof Concrete / Comp Shingle / Built Up / Metal-Pre / Typical / Co
		Structure Semi-Detached / Multi / Town Inside / Town End
Estimate		

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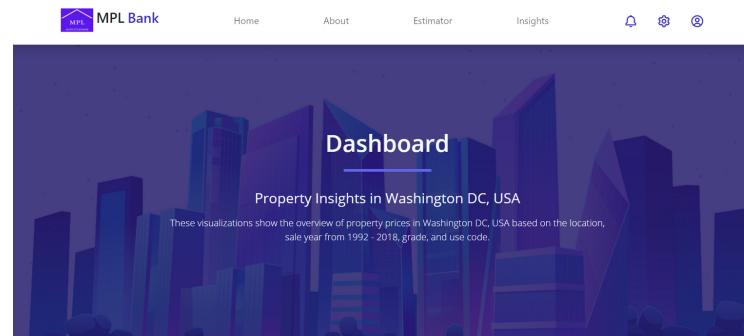
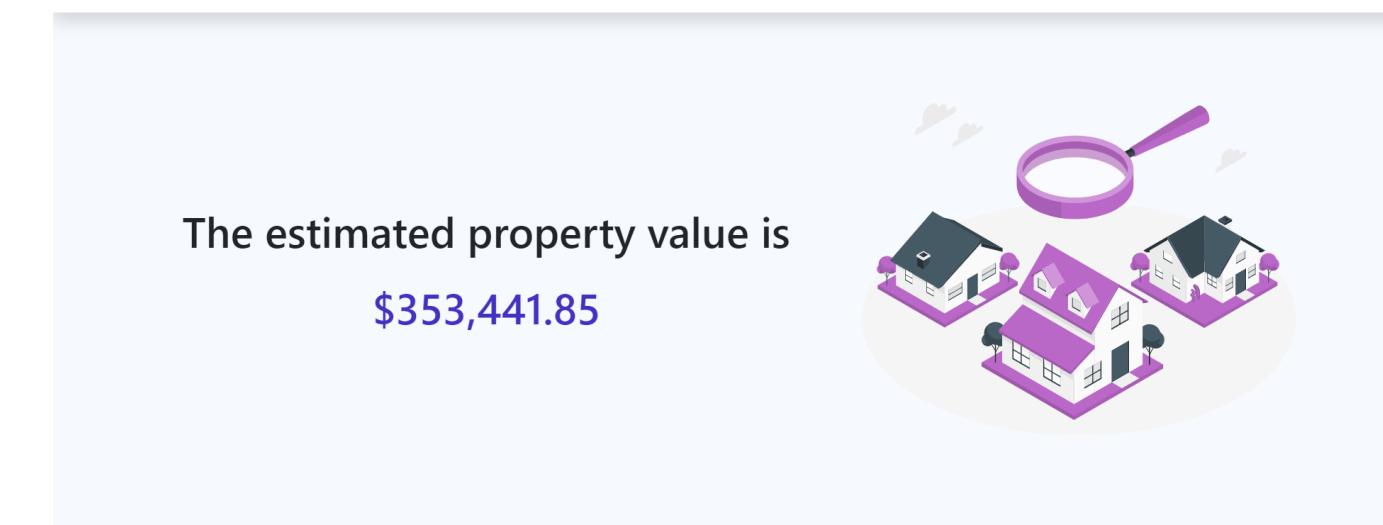
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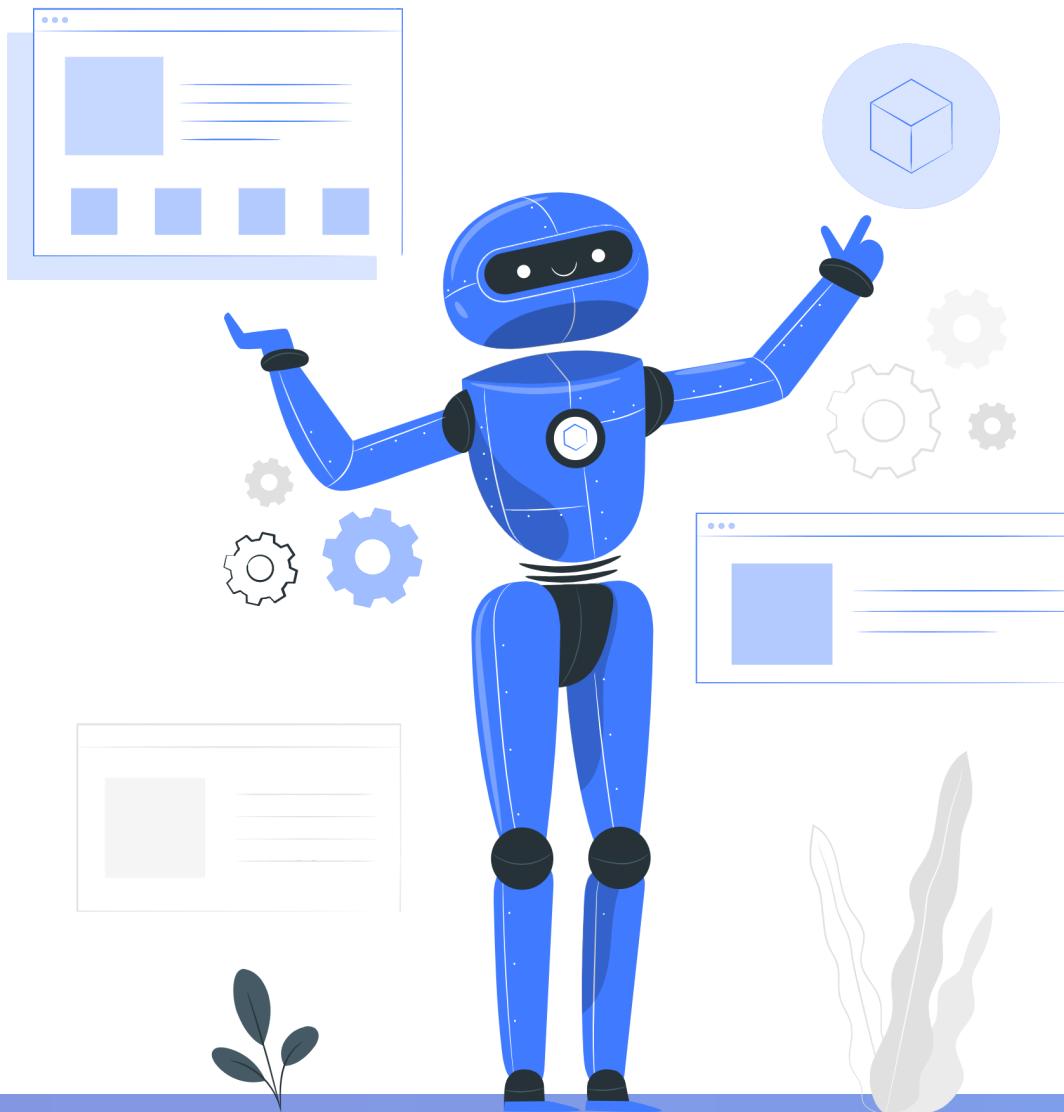


5. Future Works



Future Works

We acknowledge that the result achieved is not perfect as there are more factors that could affect a property's price such as proximity to public services and facilities, tourism spots, purchasing power, area development prospect, etc.

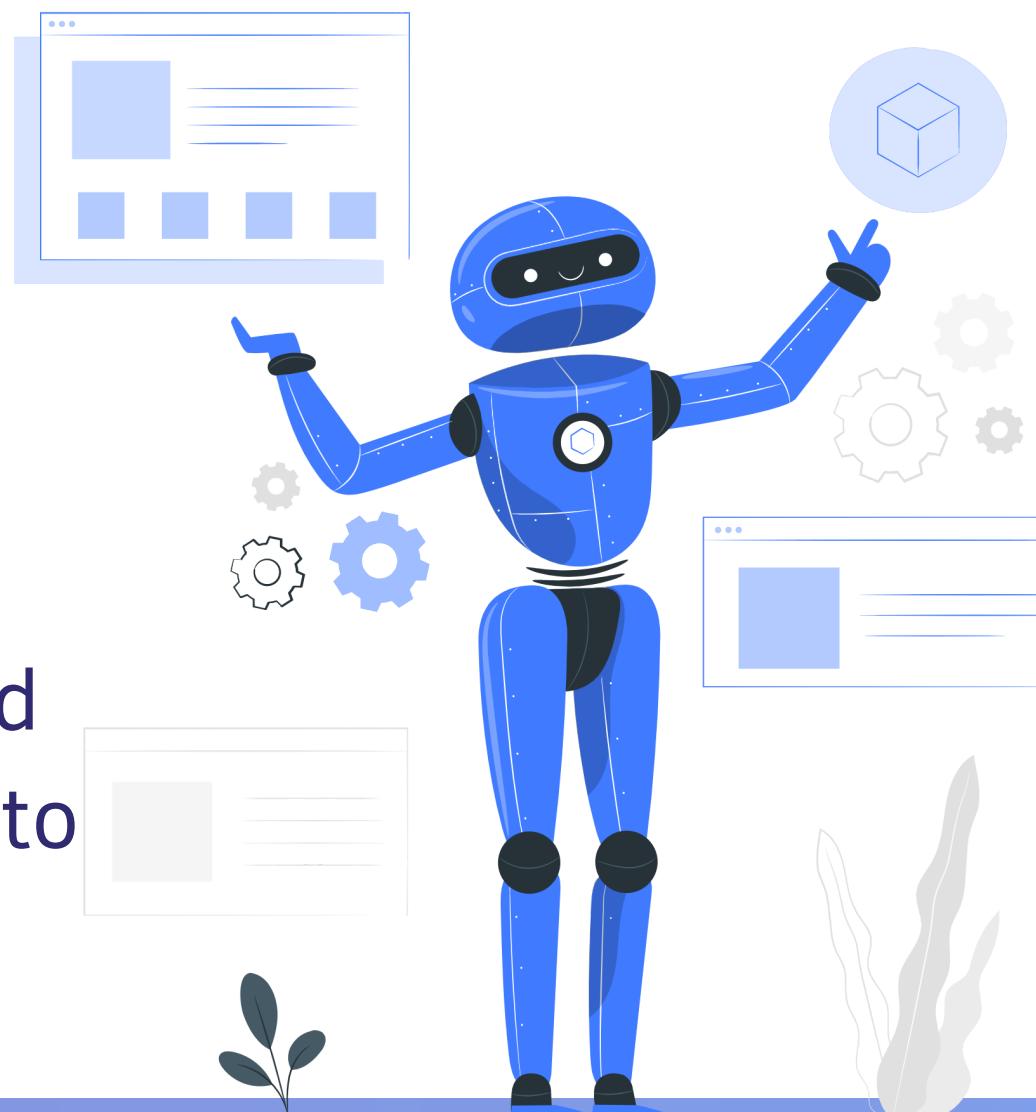


Future Works

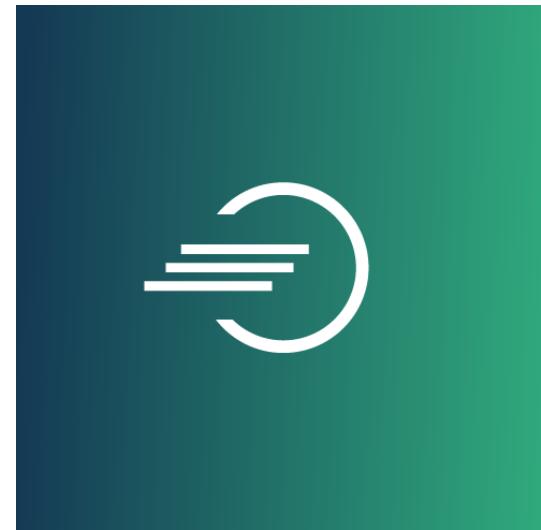
These are a few things that might help to improve model prediction result further :

- Collect more property data in Washington DC.
- Get another relevant dataset such as DC Residents Demographic, Public Services and Facilities, etc.
- Try to experiment with more features.
- Use more parameters in grid search cv.

Additionally, for the ease of usage for the business users, we would recommend to add a feature in the application which allows users to input more data instantaneously in a .csv or .xlsxfile format.



Thank You!



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Teuku Muhammad Kemal Isfan

GITHUB REPOSITORY

<https://github.com/ls-cy/Purwadhika-JCDS-Final-Project>