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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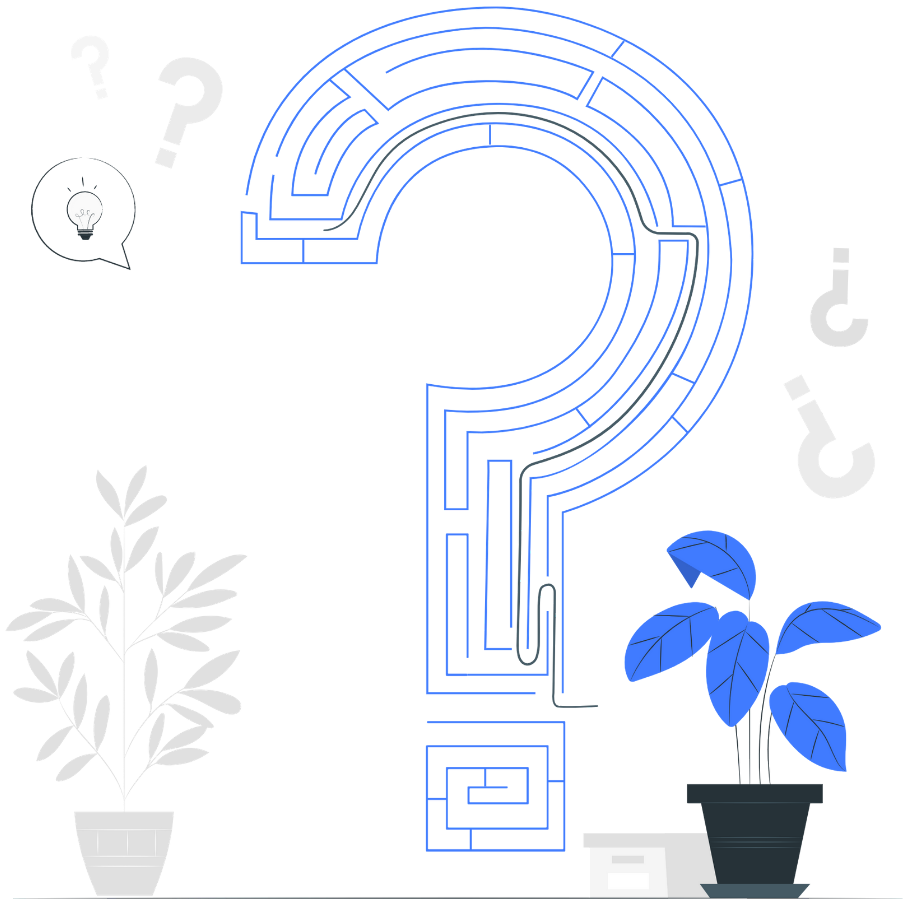
1. Background & Problem Identification

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 <u>Underwriter Team</u> of MPL Bank. We will help the Underwriter Team to make an improvement in their process of underwriting, specifically in the process of property <u>appraisal</u> and <u>valuation</u>.

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?

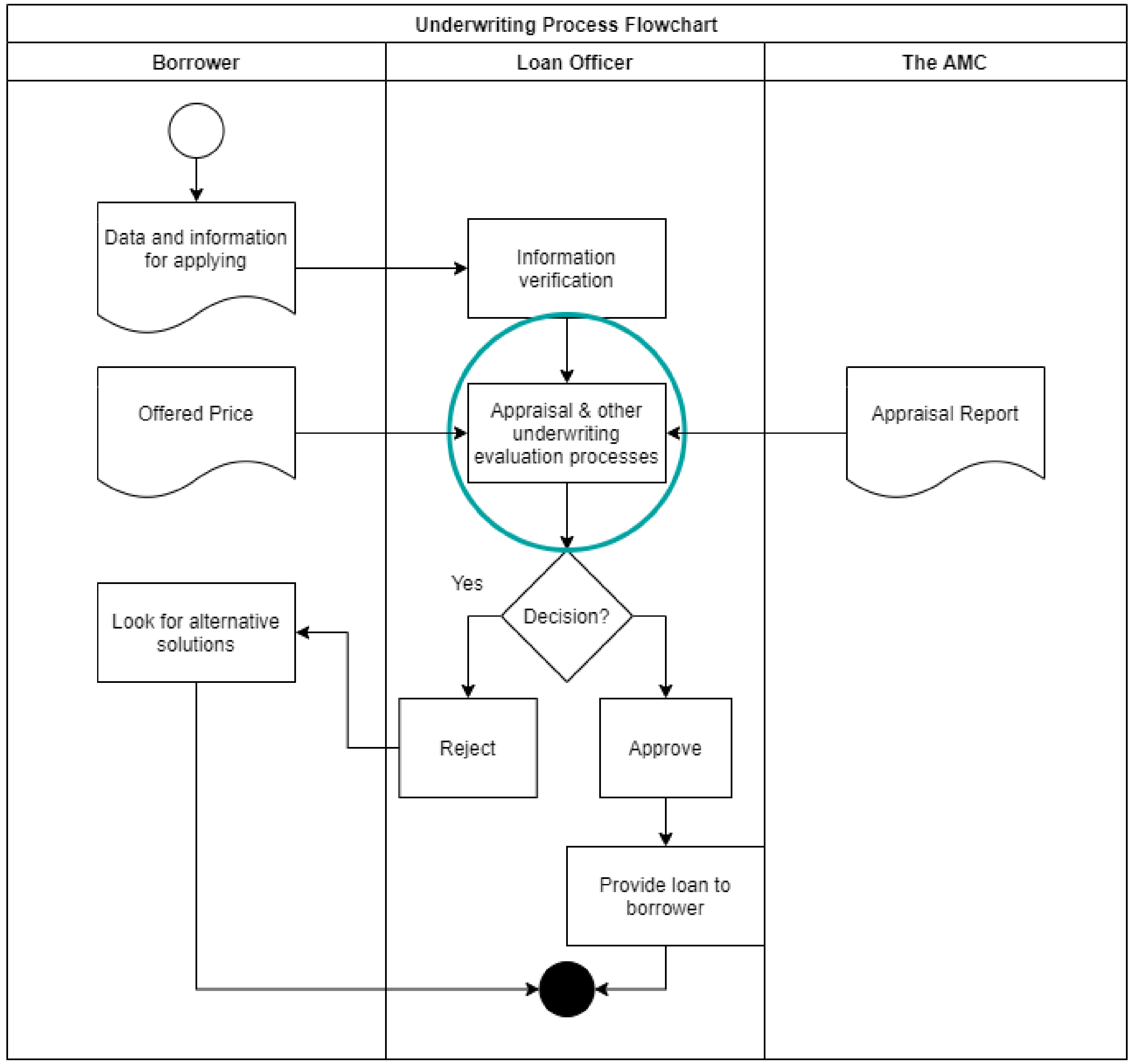
Appraisal process directly affects company's revenue

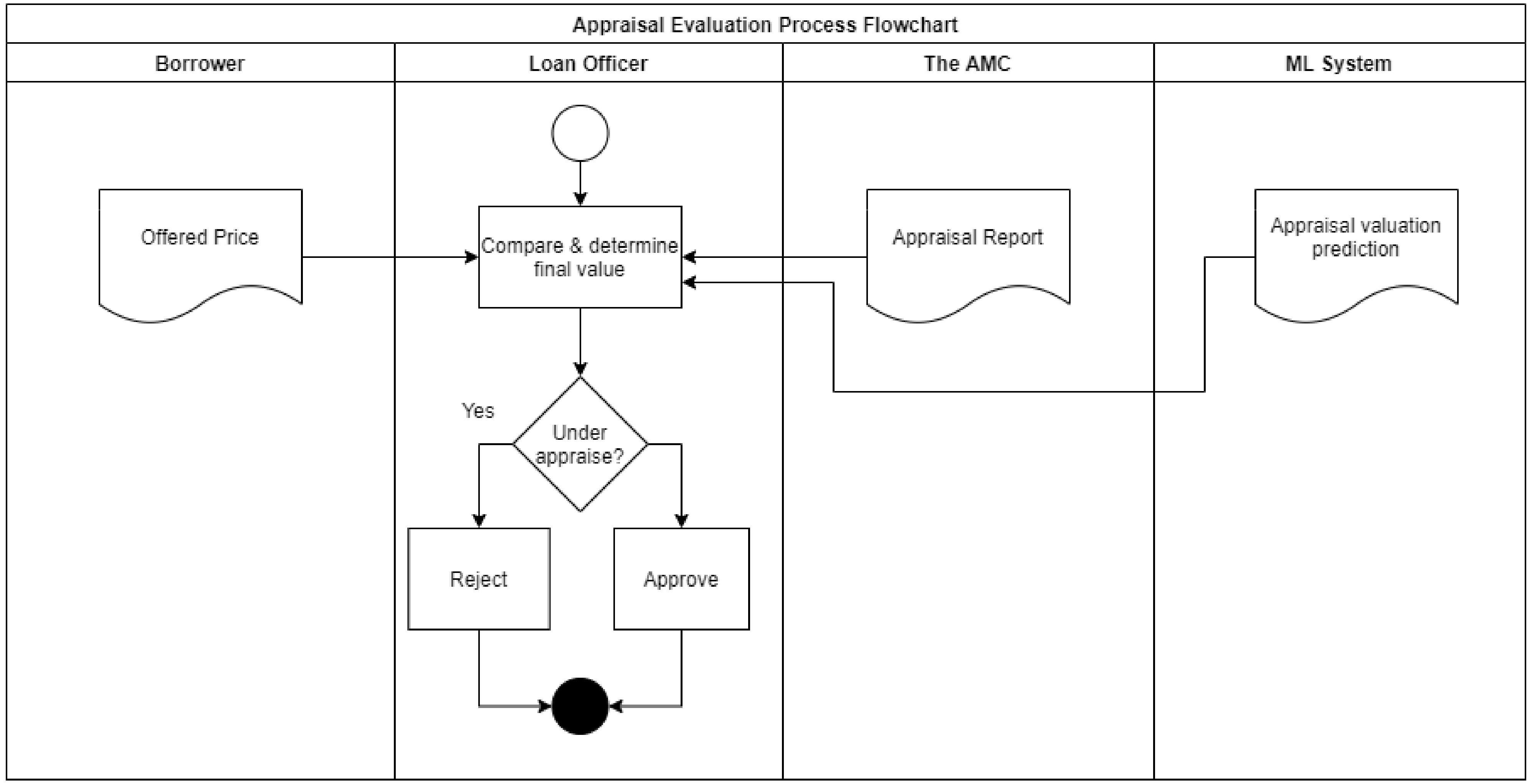
The result would determine whether to give loan to a borrower.

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 Process



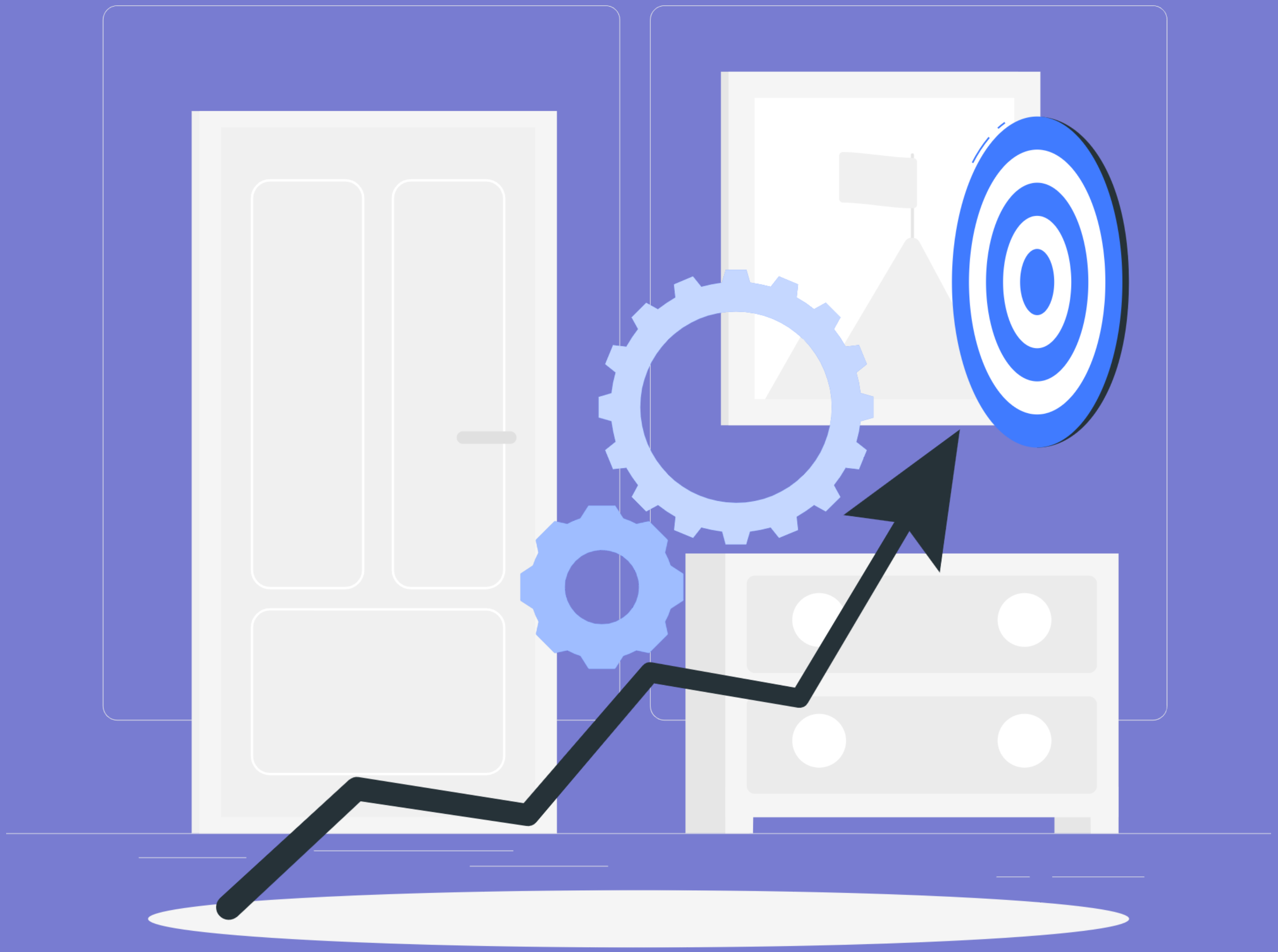


Expected Output

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

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

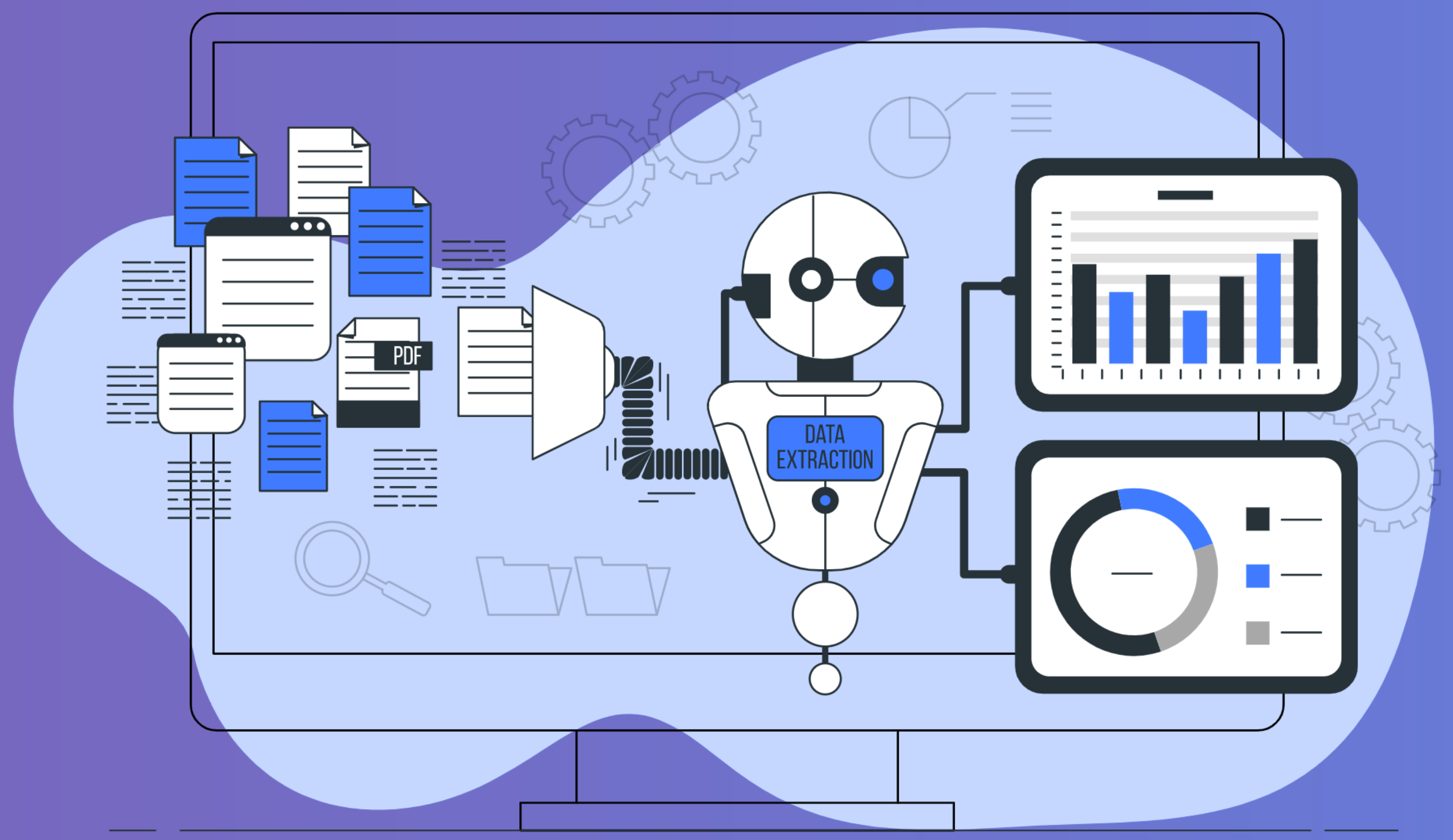
Minimize Loss

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 Learing

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 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.

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

Ward

QUADRANT

City Quadrant
(NE, SE, SW, NW)

SALEDATE

Date of Most Recent Sale

PRICE

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

Drop Rows with Missing Values

SALEDATE, KITCHENS, ROOMS, GRADE, HEAT, BATHRM

Create New Columns

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

Drop Unusual/ Erroneous Data

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

Merging Values with Very Few Occurrence

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

Excluding Outliers

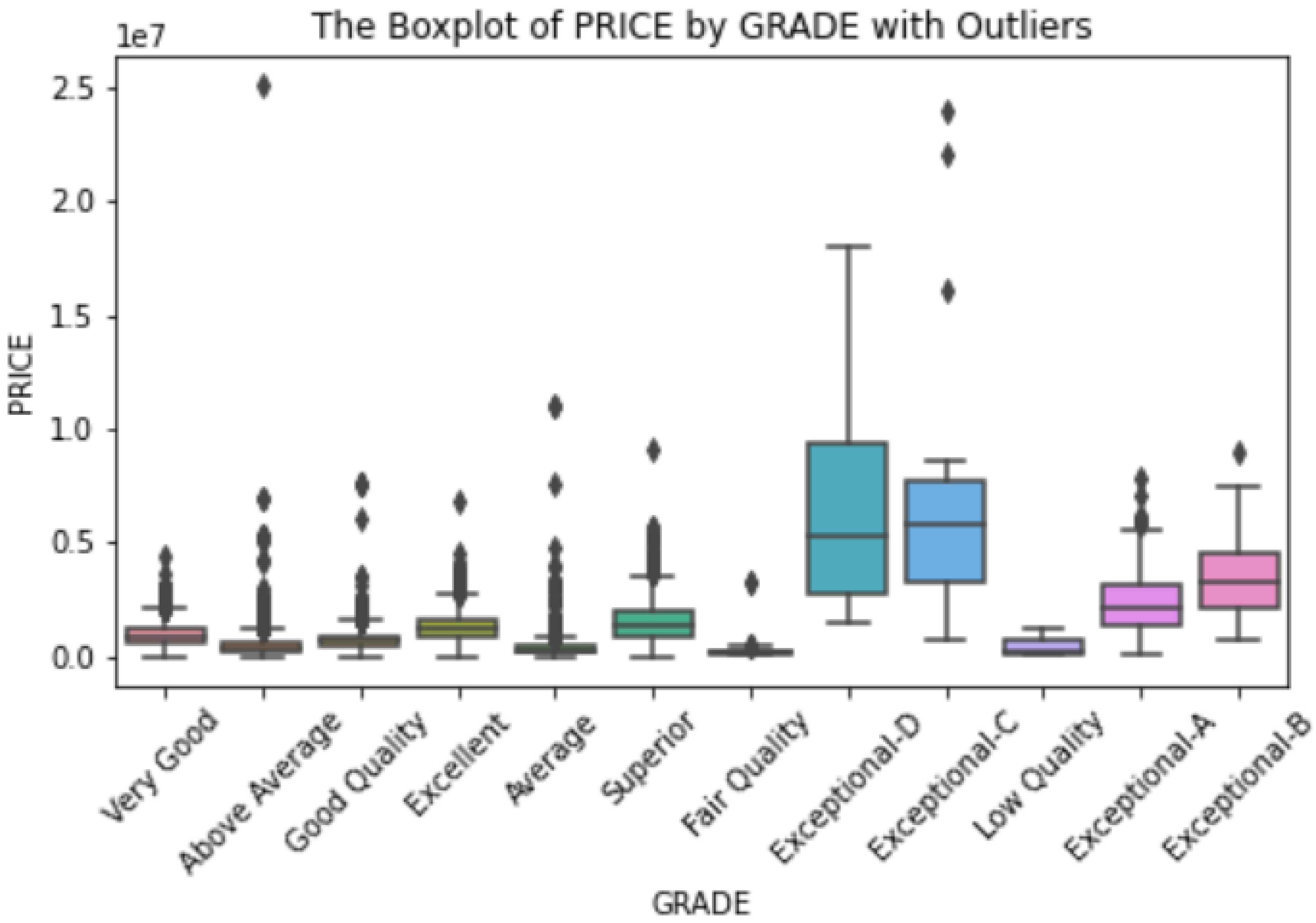
KITCHENS, PRICE, Price based on CNDTN

Re-classify Columns

CNDTN, STRUCT, ROOF

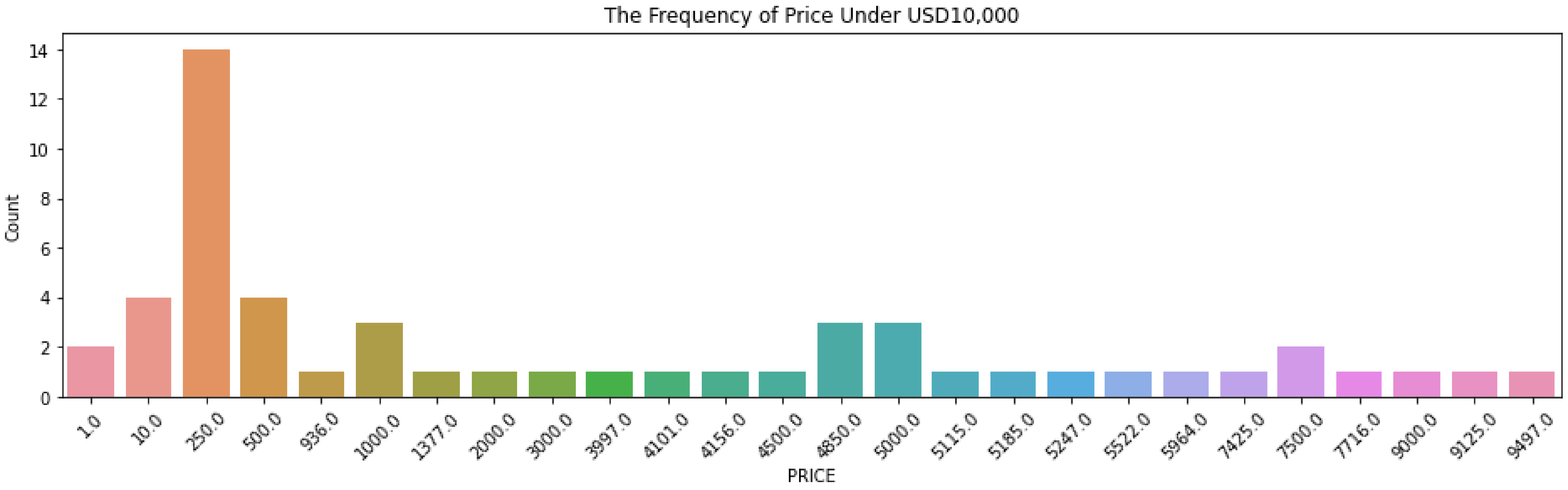
Identifying Outliers in PRICE

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 ±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.



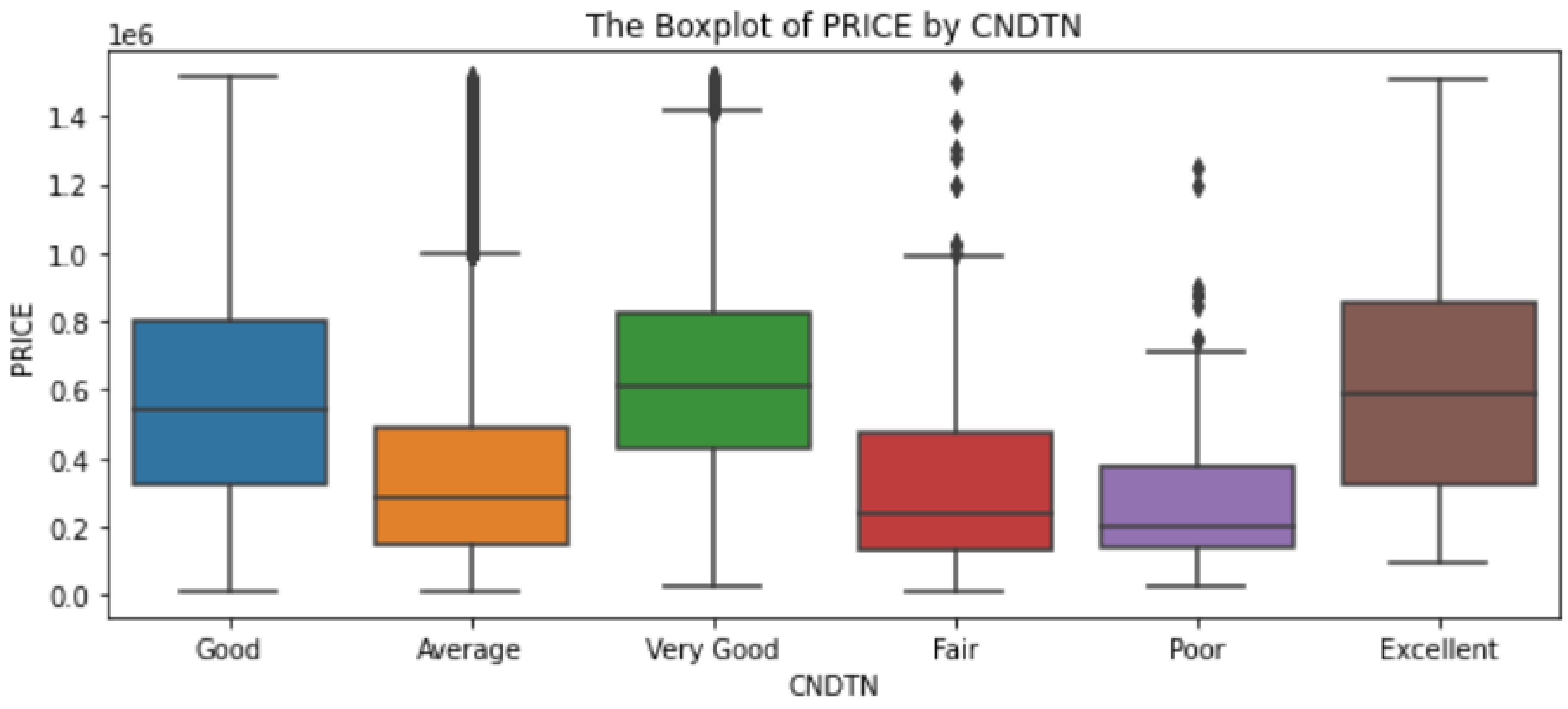
Re-classify CNDTN

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 :

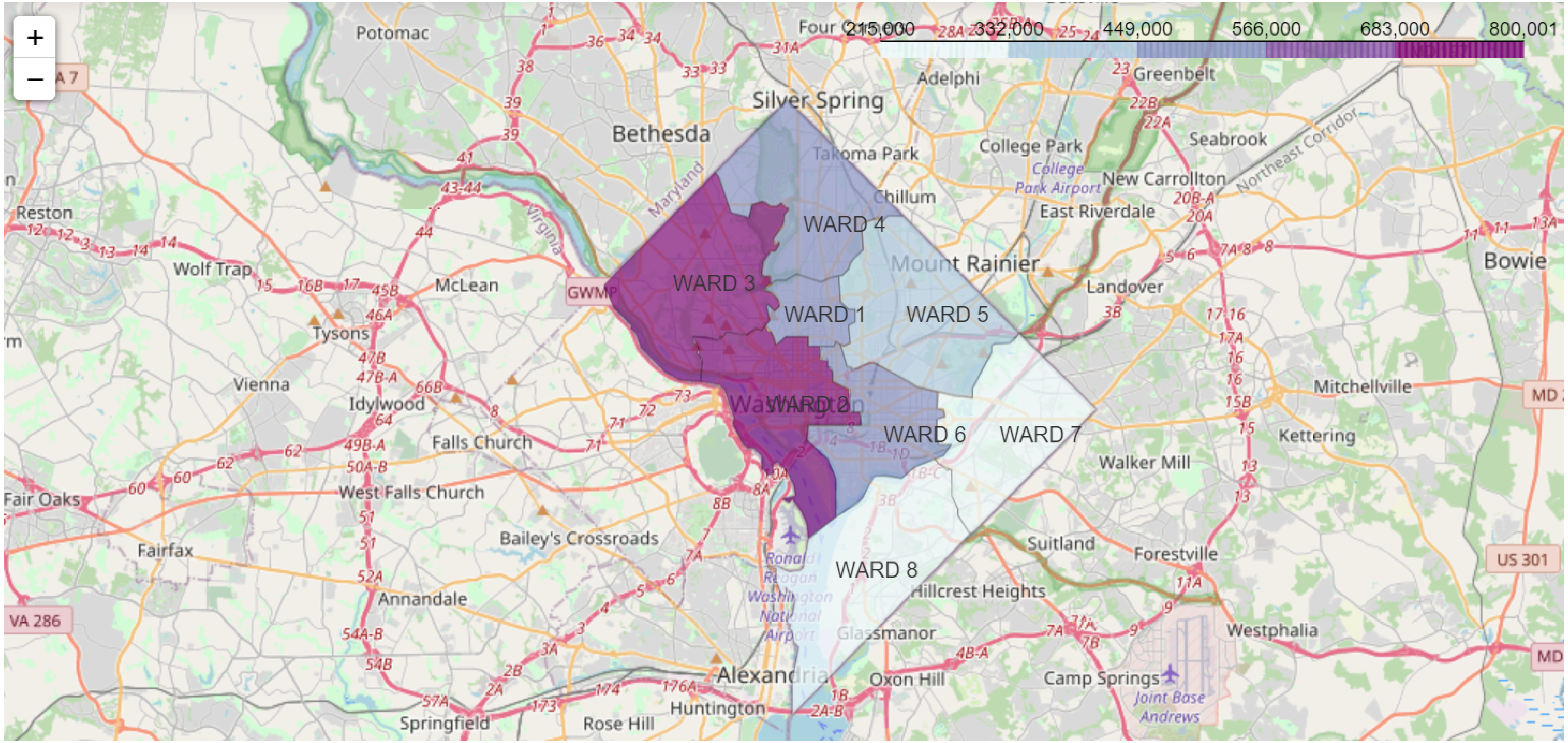
- 0 : Under median
- 1 : Above median

	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

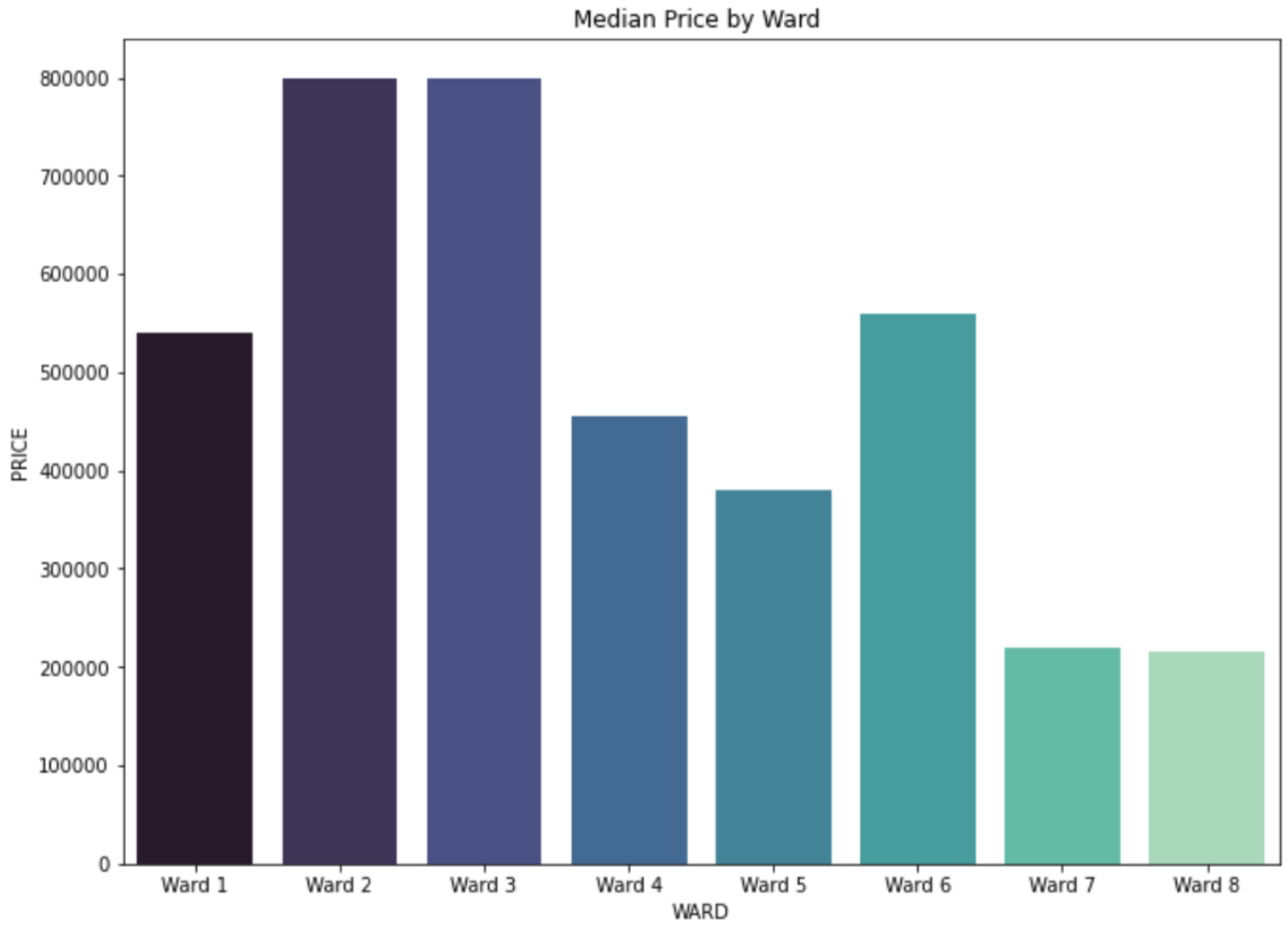
Insights

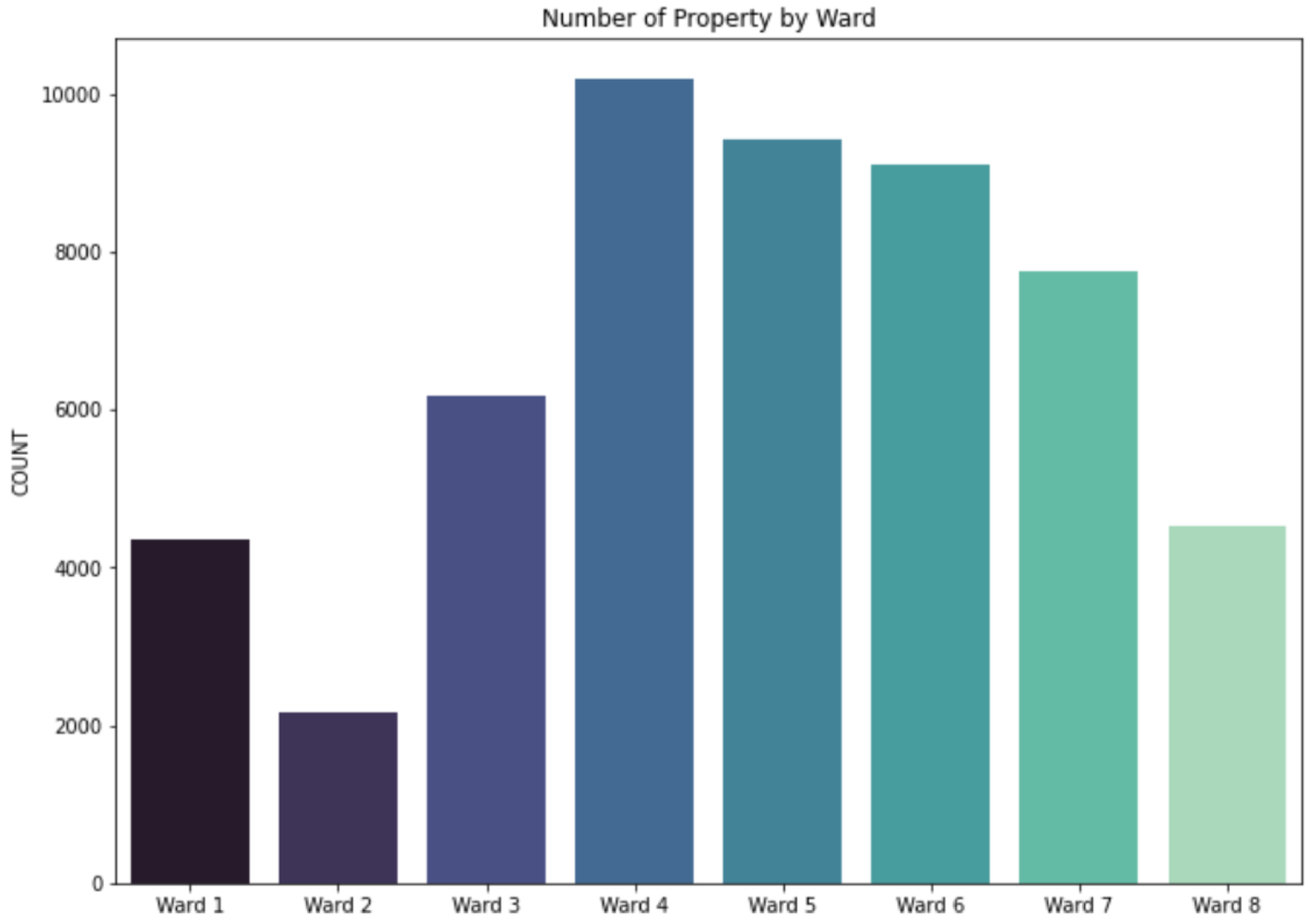
Map by Ward



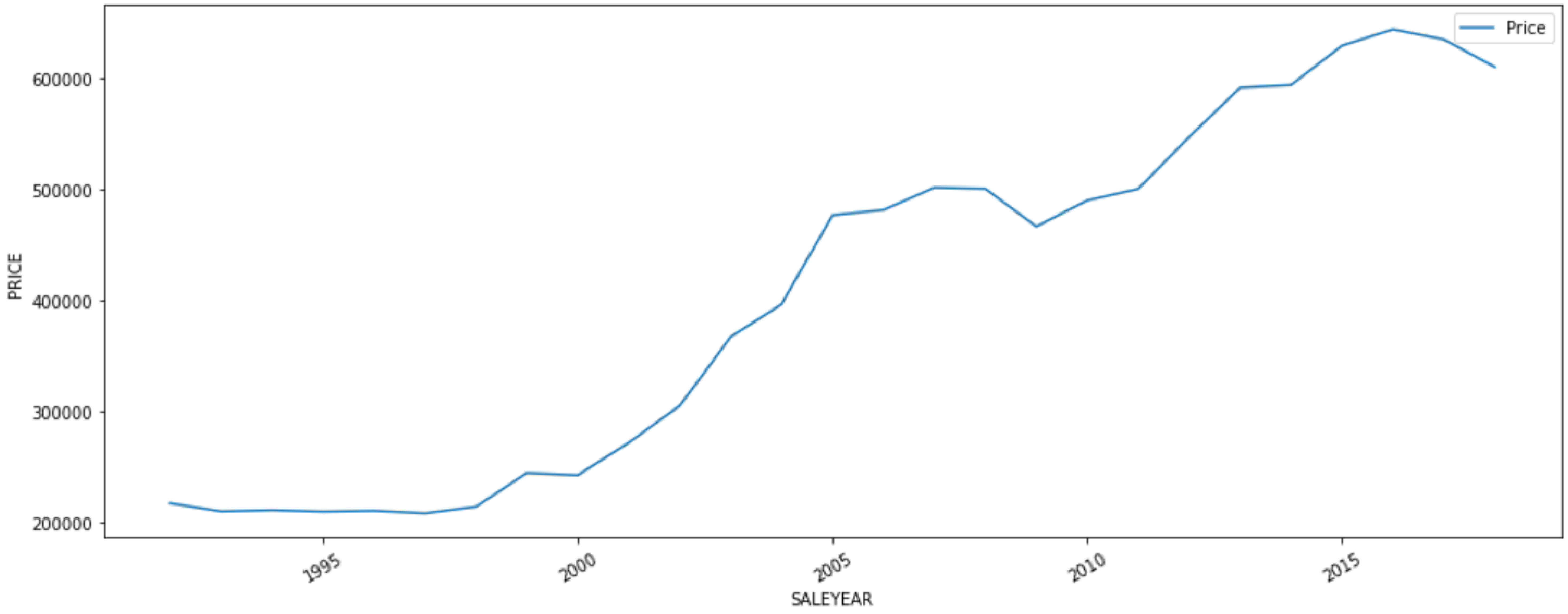
215,000
332,000
449,000
566,000
683,000
800,001
WARD 1
WARD 2
WARD 3
WARD 4
WARD 5
WARD 6
WARD 7
WARD 8
Silver Spring
Bethesda
Takoma Park
College Park
Potomac
Reston
McLean
Tysons
Vienna
Falls Church
Fairfax
Annandale
Alexandria
Springfield
Bowie
Greenbelt
Mount Rainier
Landover
Suitland
Oxon Hill
Camp Springs

Median Price & Number of Property by Ward

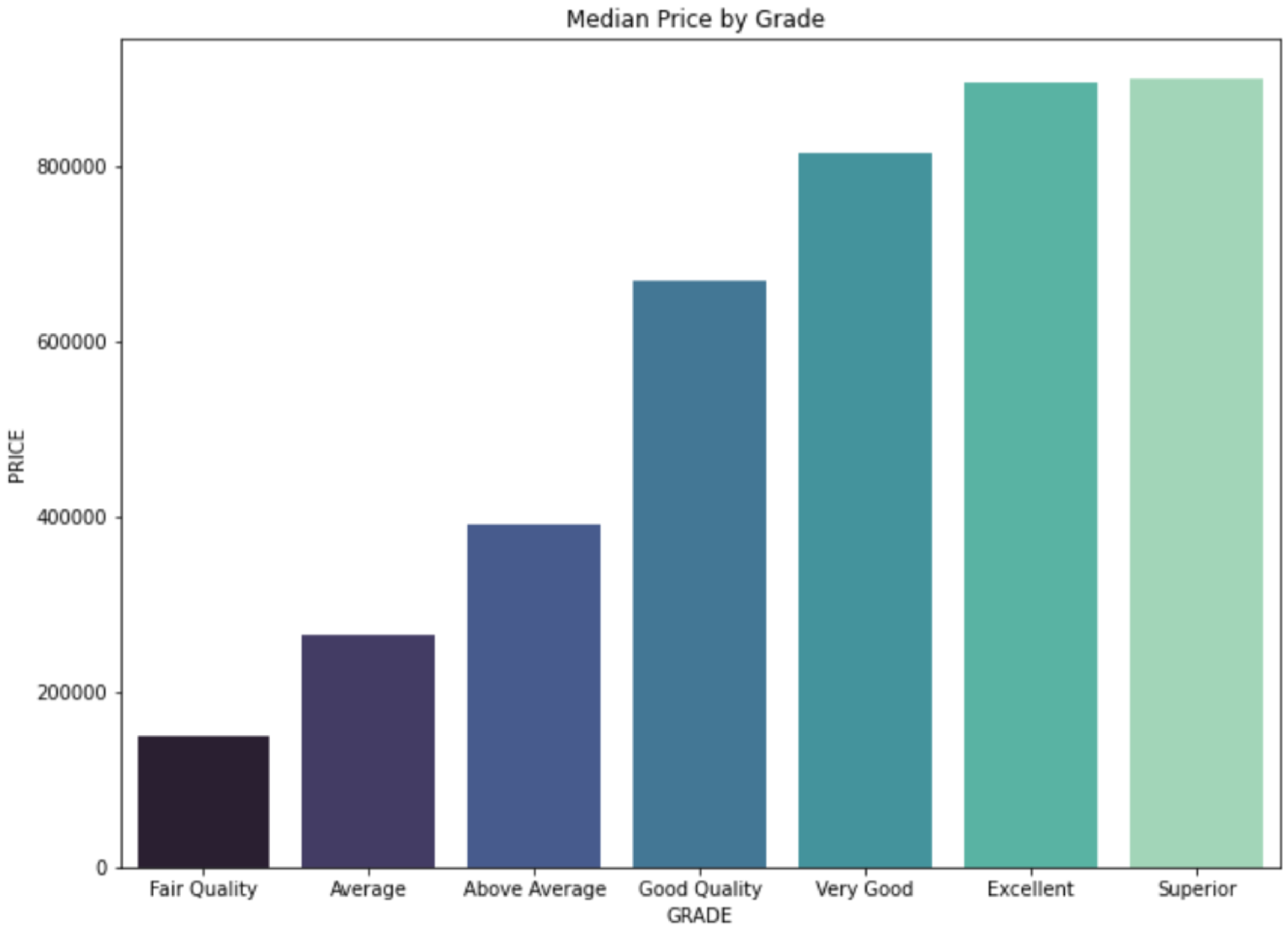


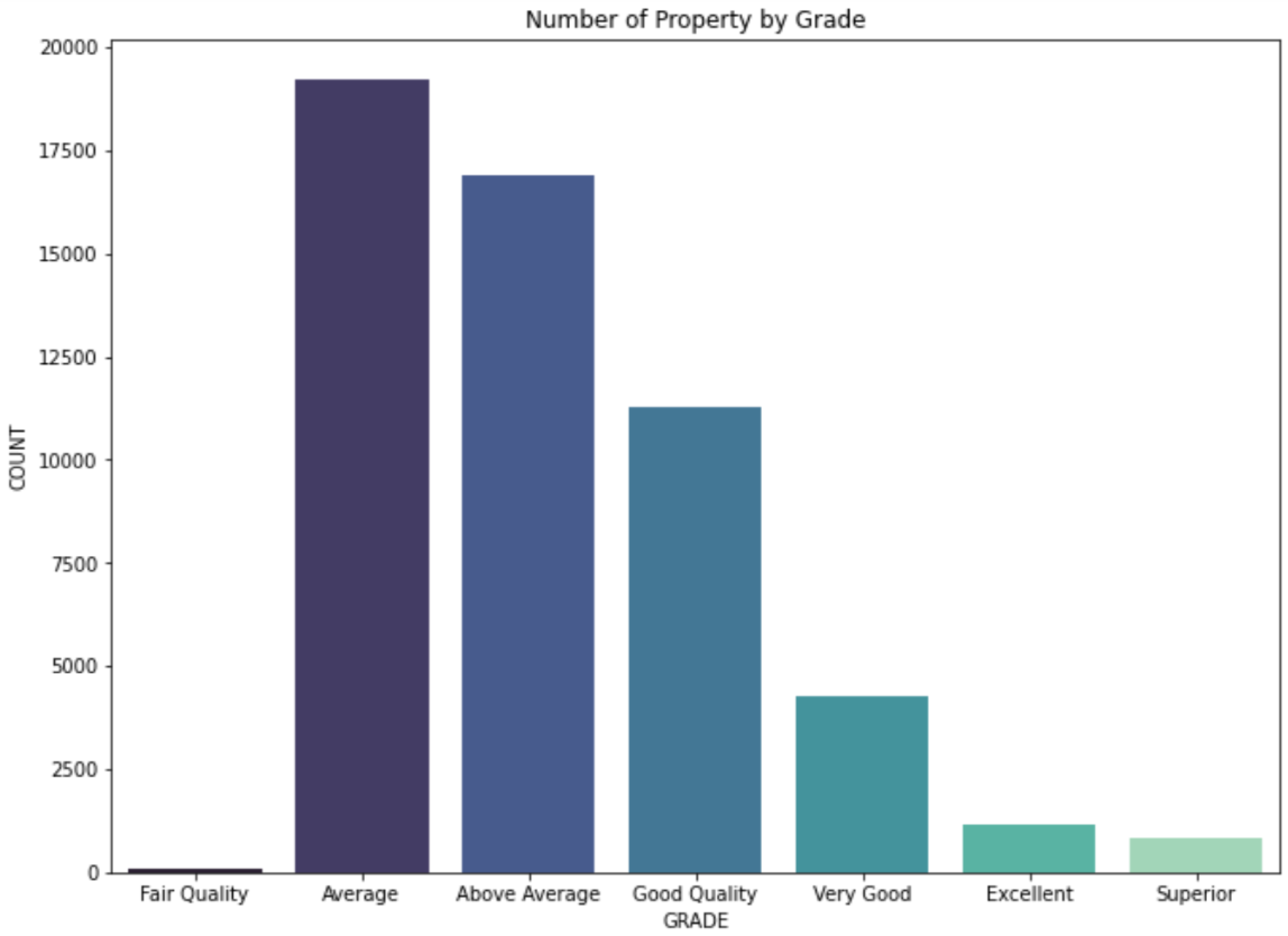


Median Sale Price per Year

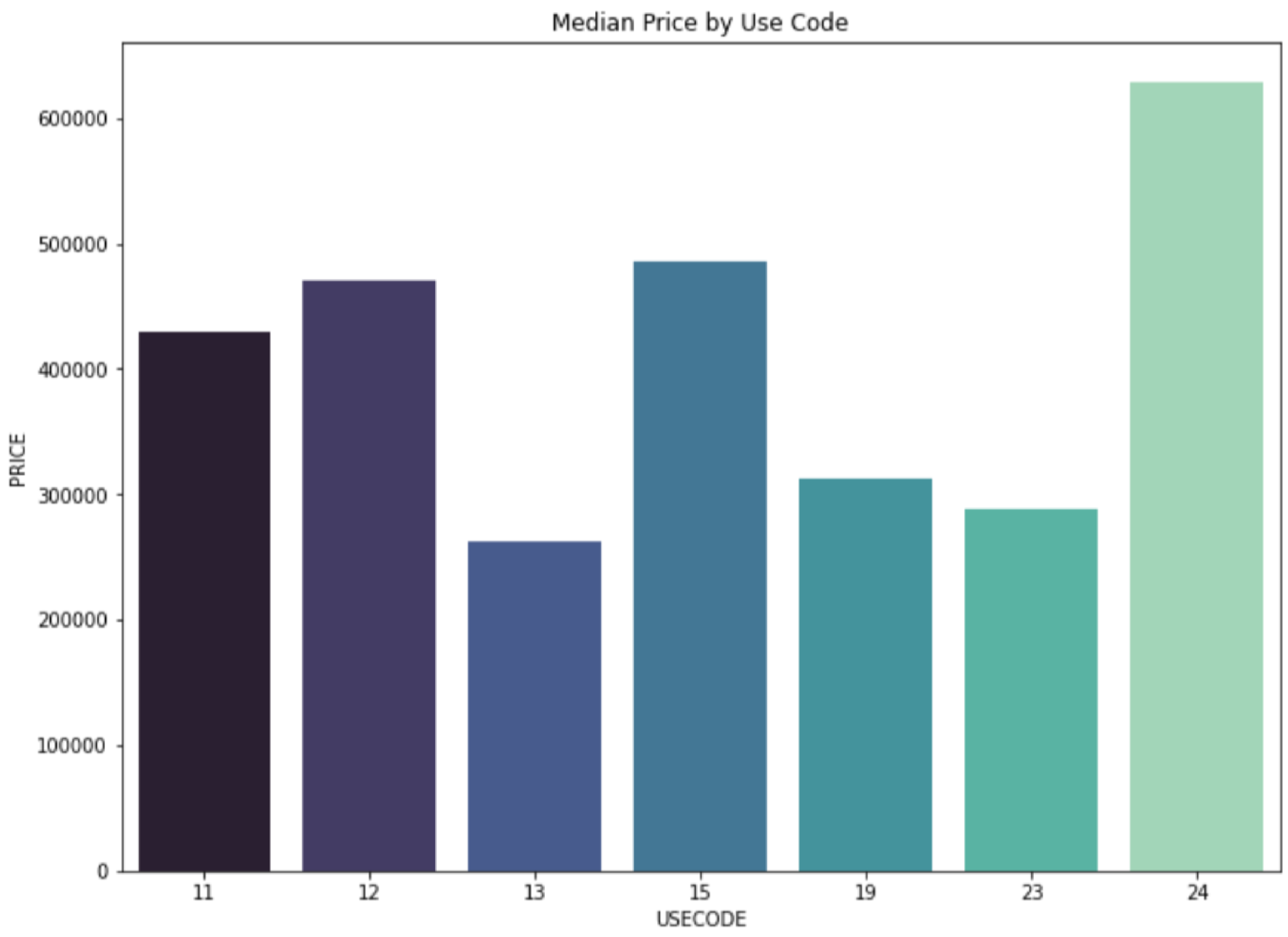


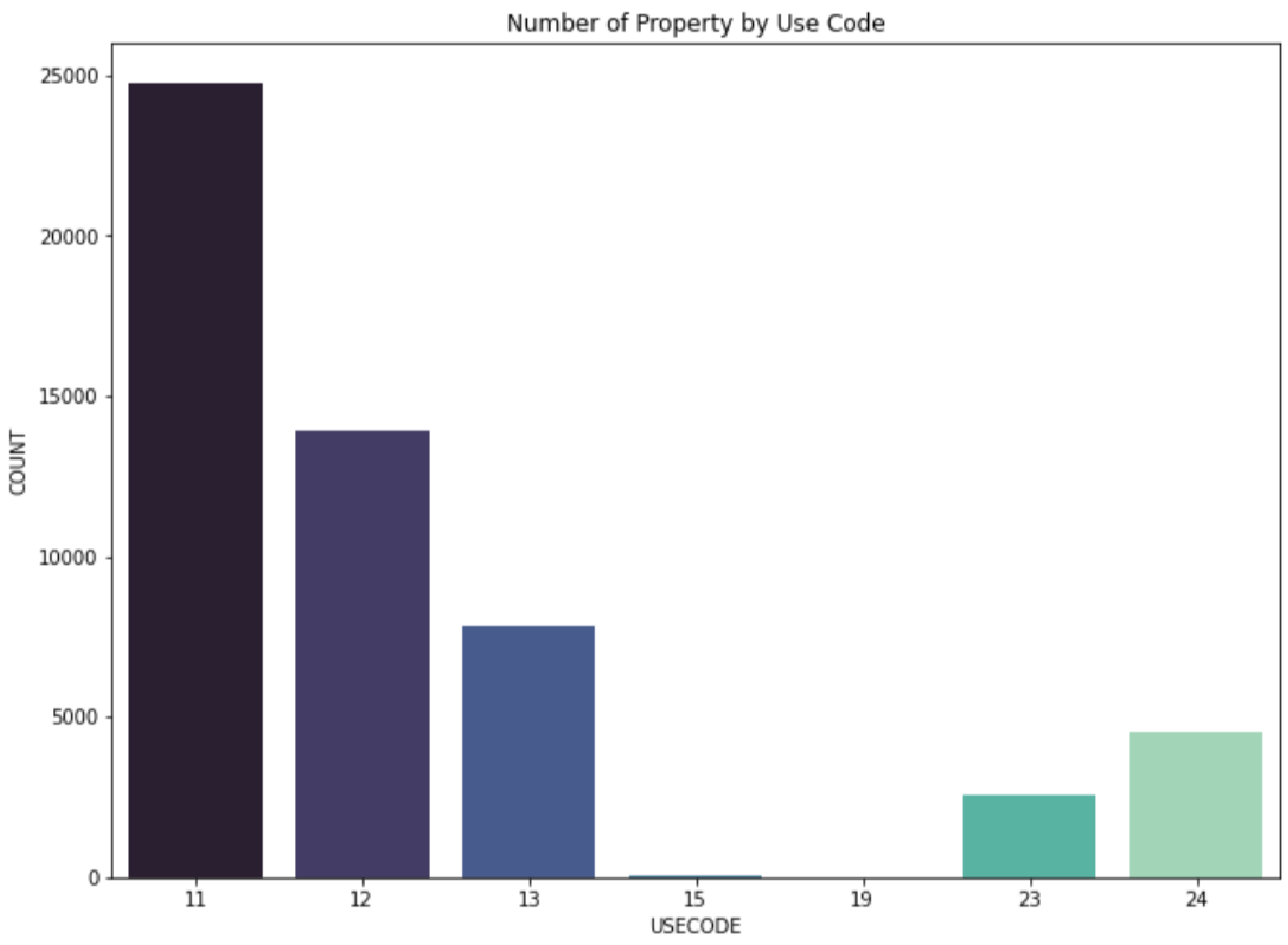
Median Price & Number of Property by Grade





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
- Hyperparaeter tuning with Grid-Search to get best parameters of the best baseline-model

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

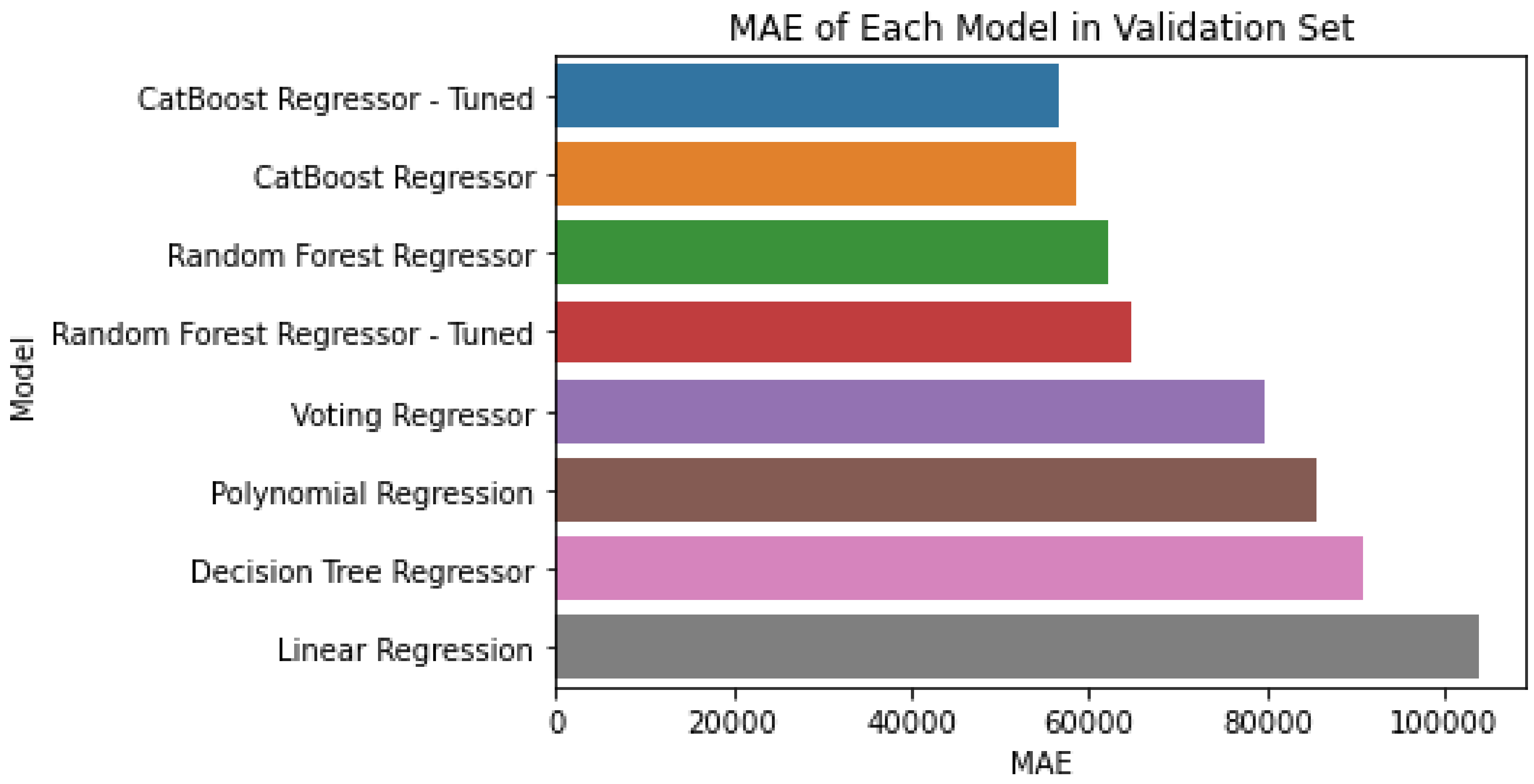
Model Assessment

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 : 0.00373664180184315
```

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

Final Model Evaluation

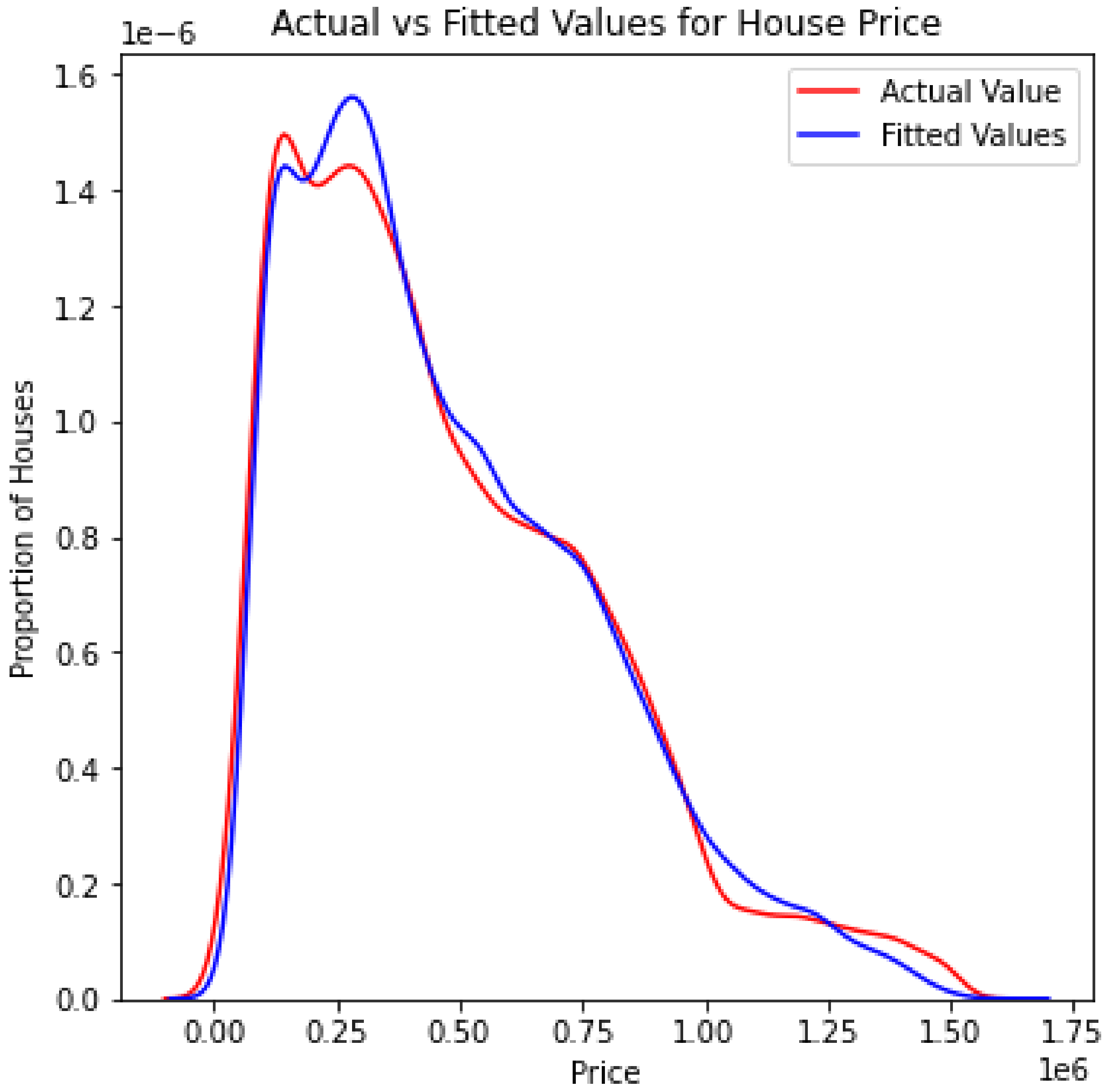
We were asked to reach the Mean Absolute Error (MAE) value below 13% of the median property price.

```
Price median : 410000.0
Desired MAE (13% * median) : 53300.0
Achieved MAE : 47183.05421572207
```

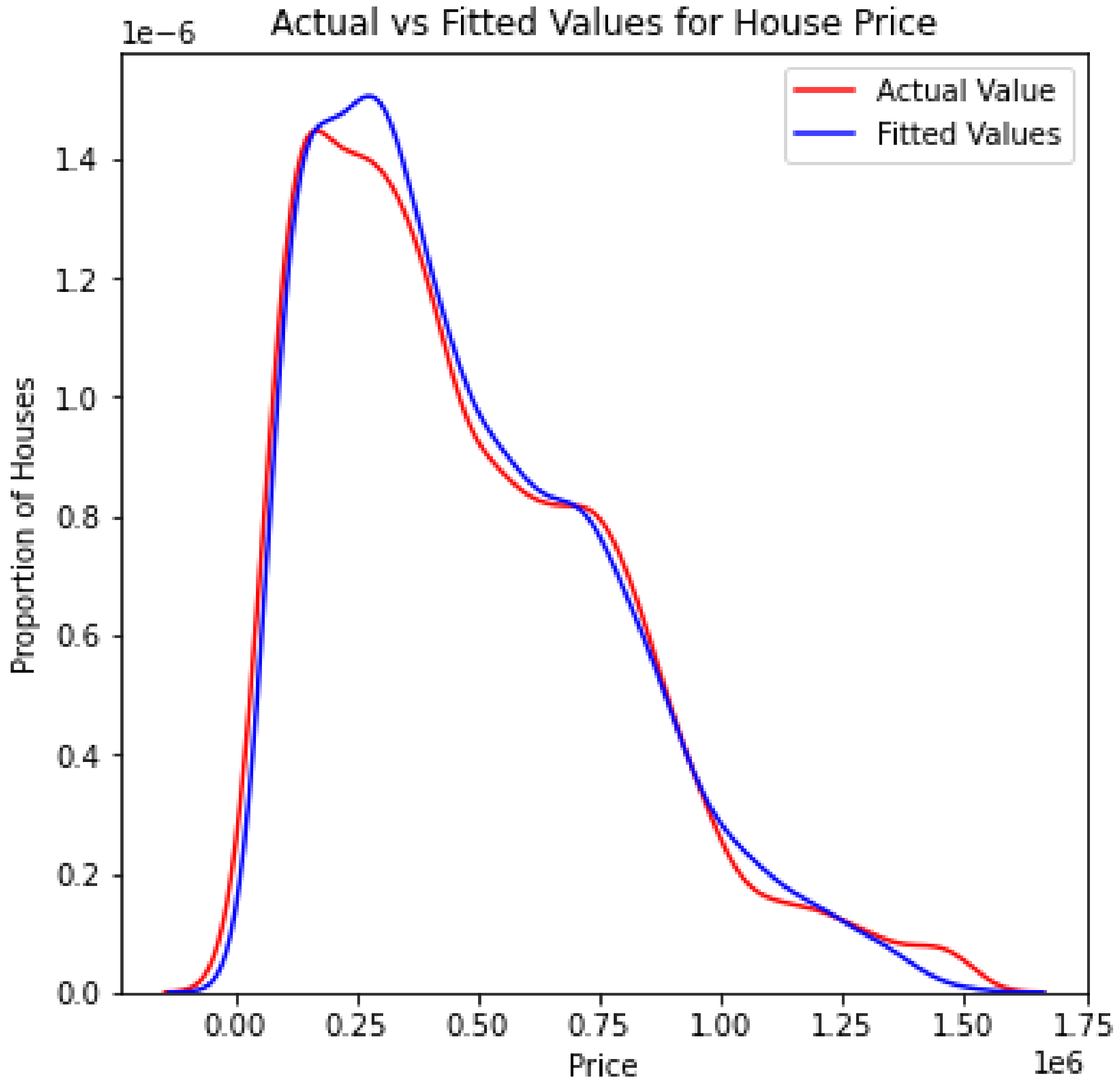
From the result shown above, we have achieved the desired MAE value (under USD53,300).

Distribution Plot of Actual vs Fitted Values

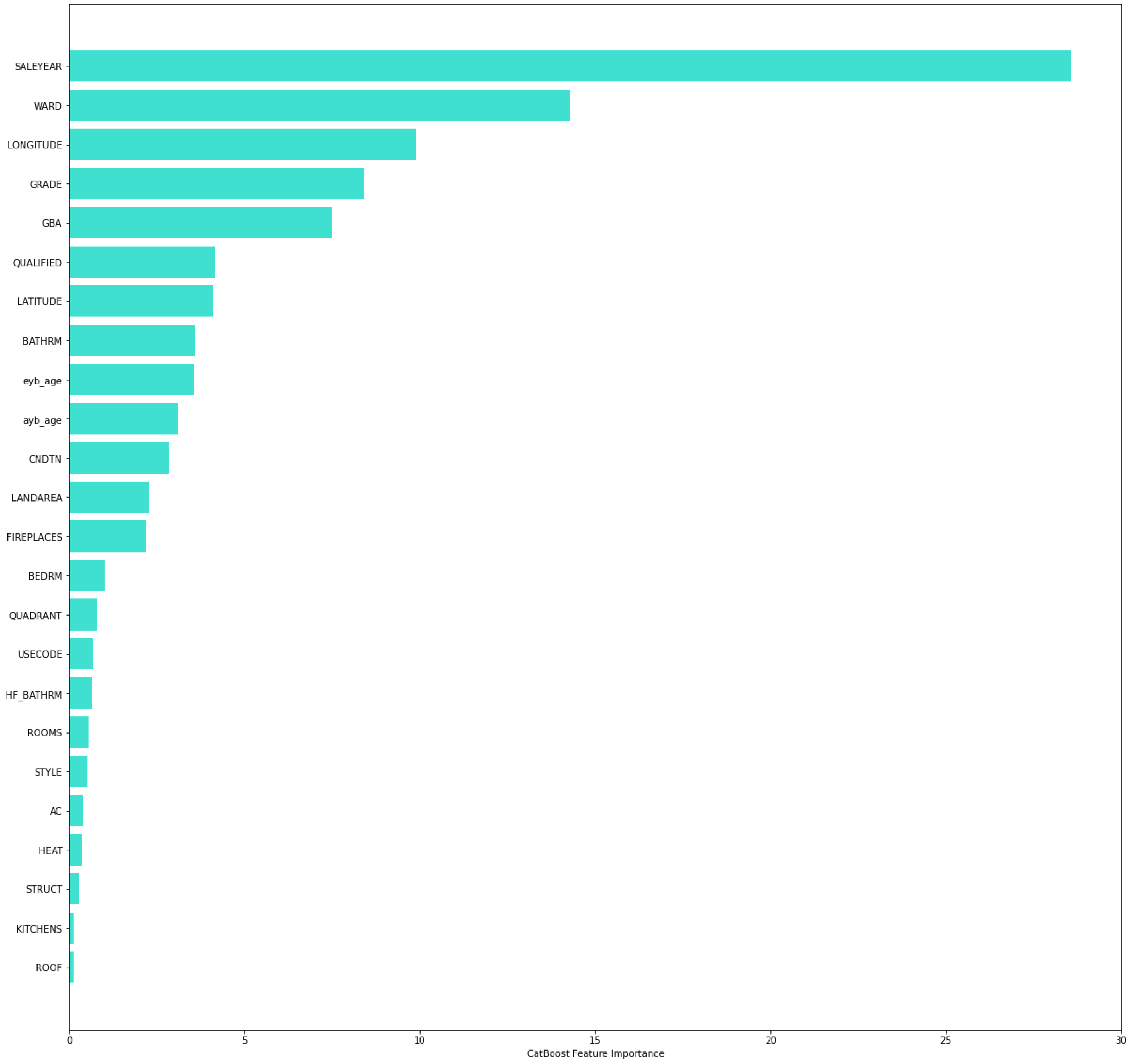
Train Set



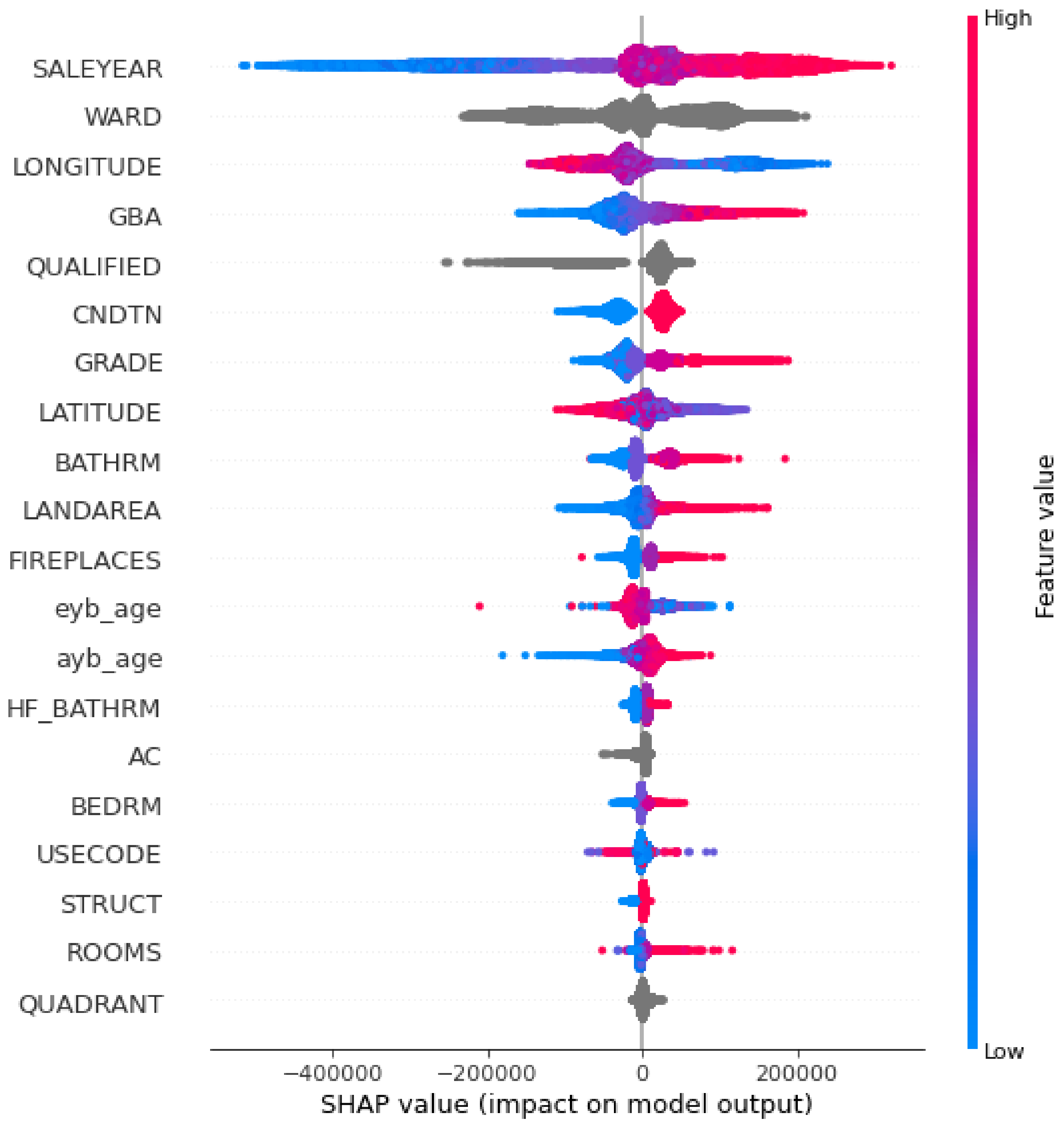
Test Set

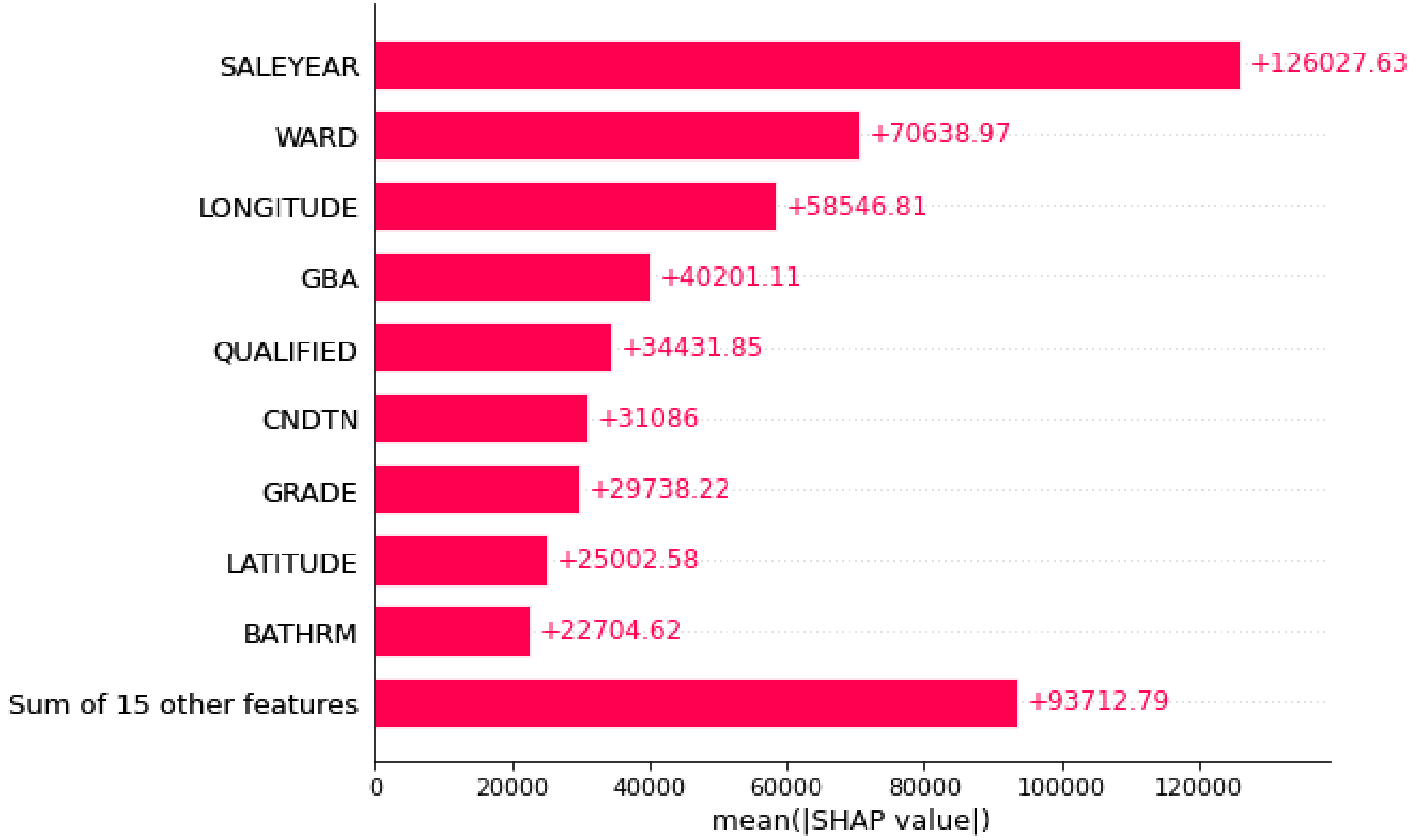


Feature Importances

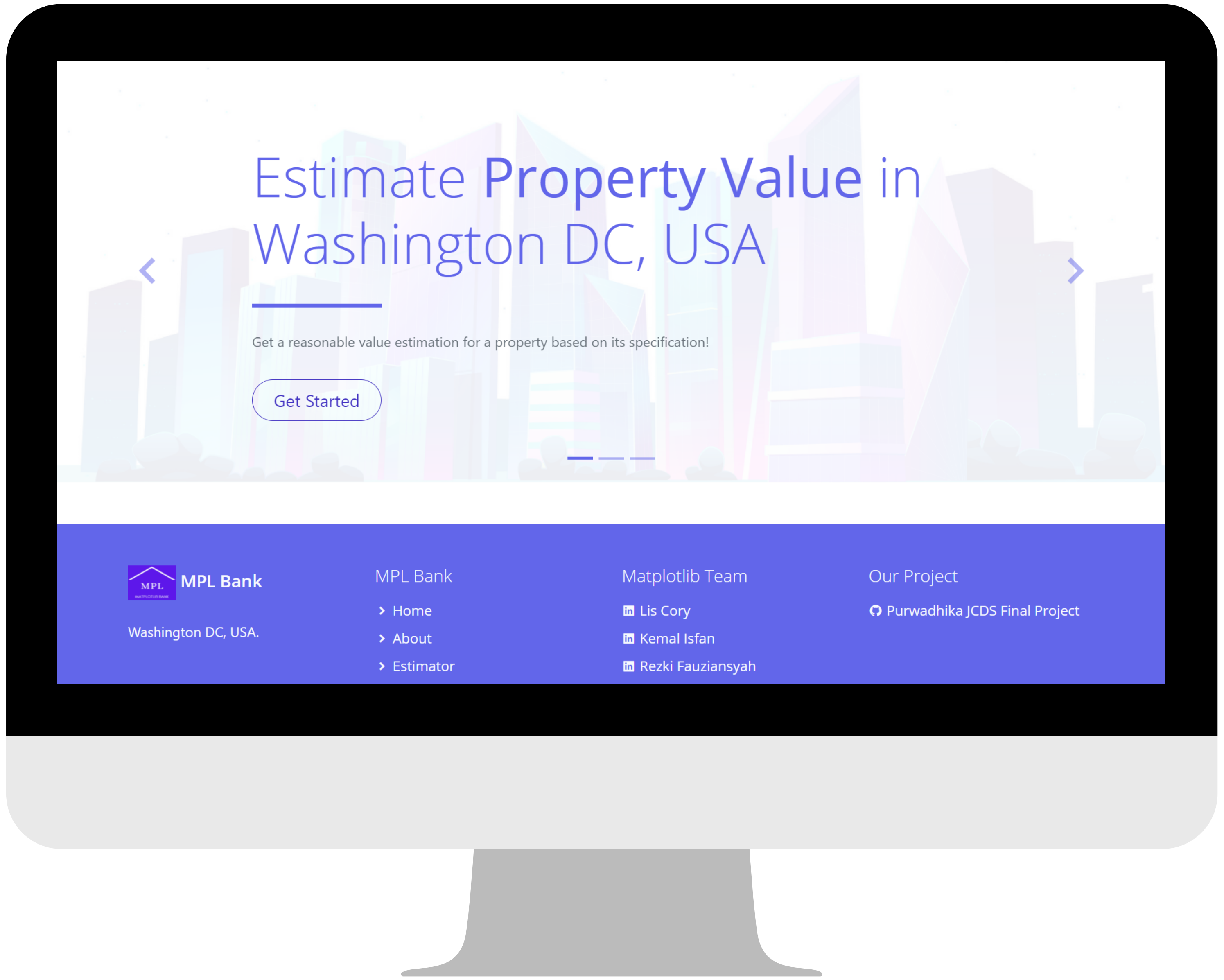


Feature Importances with SHAP





4. Deployment



Deployment Page

We deployed the model to a webpage using FLASK.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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, specifically in the process of property appraisal and valuation.
MPL Bank 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 under appraised 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 (R²).
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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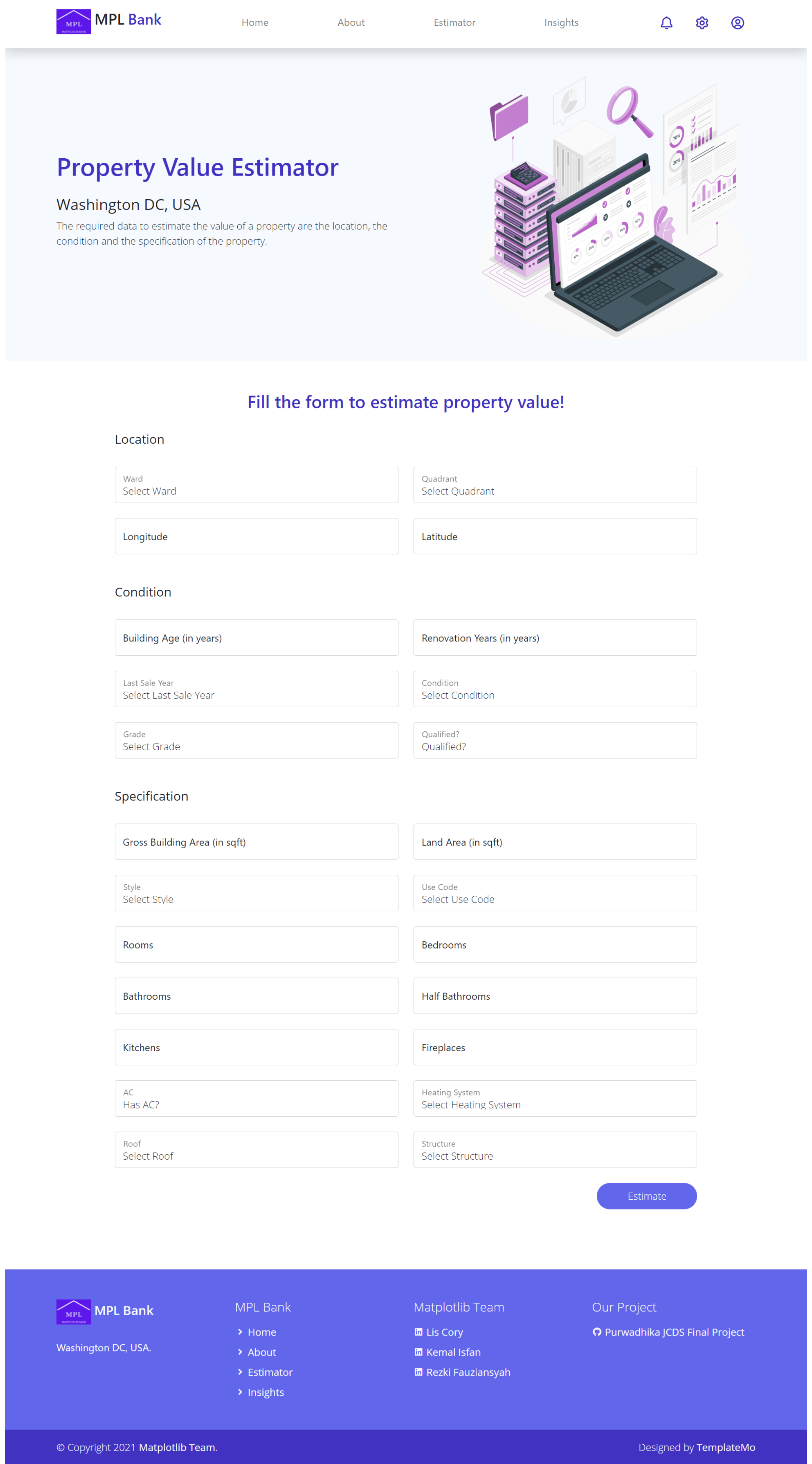
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Property Value Estimator
Washington DC, USA
The required data to estimate the value of a property are the location, the condition and the specification of the property.
Fill the form to estimate property value!
Location
Ward
Select Ward
Quadrant
Select Quadrant
Longitude
Latitude
Condition
Building Age (in years)
Renovation Years (in years)
Last Sale Year
Select Last Sale Year
Condition
Select Condition
Grade
Select Grade
Qualified?
Qualified?
Specification
Gross Building Area (in sqft)
Land Area (in sqft)
Style
Select Style
Use Code
Select Use Code
Rooms
Bedrooms
Bathrooms
Half Bathrooms
Kitchens
Fireplaces
AC
Has AC?
Heating System
Select Heating System
Roof
Select Roof
Structure
Select Structure
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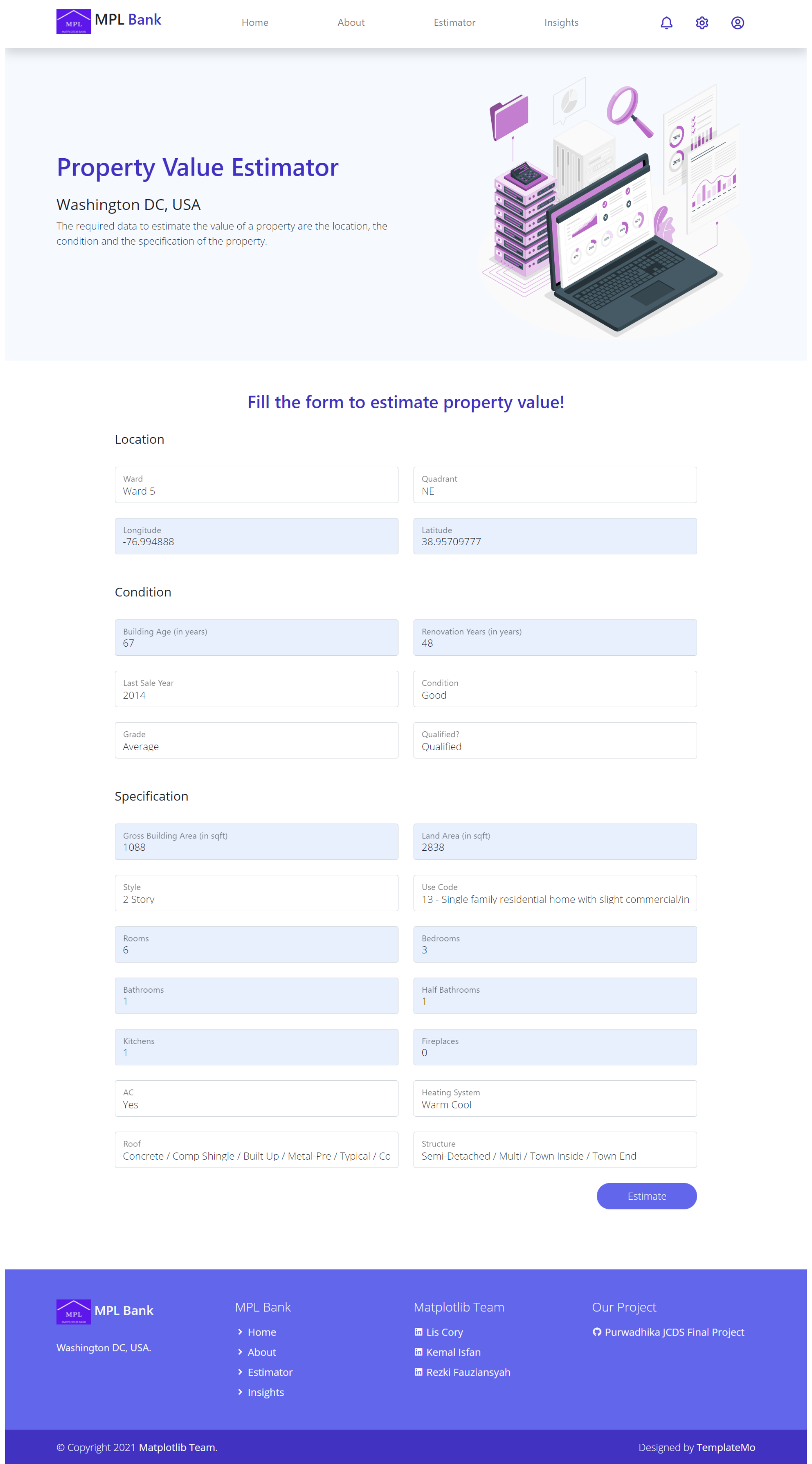
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Property Value Estimator
Washington DC, USA
The required data to estimate the value of a property are the location, the condition and the specification of the property.
Fill the form to estimate property value!
Location
Ward
Ward 5
Quadrant
NE
Longitude
-76.994888
Latitude
38.95709777
Condition
Building Age (in years)
67
Renovation Years (in years)
48
Last Sale Year
2014
Condition
Good
Grade
Average
Qualified?
Qualified
Specification
Gross Building Area (in sqft)
1088
Land Area (in sqft)
2838
Style
2 Story
Use Code
13 - Single family residential home with slight commercial/in
Rooms
6
Bedrooms
3
Bathrooms
1
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
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The estimated property value is

$347,579.00

Property Information

Value Estimation

- Estimated Price : $ 347,579.00
- Estimated Error (Mean Absolute Error) : ± $ 52,397.91

Location

- Area : Ward 5
- Quadrant : NE
- Longitude : -76.994888°
- Latitude : 38.95709777°

Condition

- Building Age : 67 years old
- Renovation Years : 48 years since last renovation
- Last Sold in : 2014
- Condition : Good
- Grade : Average
- Qualified : Yes

Specification

- Gross Building Area : 1088 ft²
- Land Area : 2838 ft²
- Style : 2 Story
- Use Code: 13 - Single family residential home with slight commercial/ind
- Number of Rooms : 6
- Number of Bedrooms : 3
- Number of Bathrooms : 1
- Number of Half Bathrooms : 1
- Number of Kitchens : 1
- Number of Fireplaces : 0
- Air Conditioner : Yes
- Heating System : Warm Cool
- Roof : Concrete / Comp Shingle / Built Up / Metal-Pre / Typical / Composition Ro
- Structure : Semi-Detached / Multi / Town Inside / Town End

MPL Bank
Home About Estimator Insights

Dashboard

Property Insights in Washington DC, USA

These visualizations show the overview of property prices in Washington DC, USA based on the location, sale year from 1992 - 2018, grade, and use code.

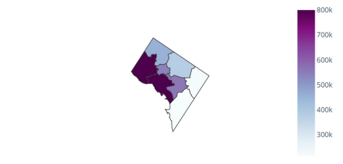
Insight

Below is a Choropleth map of the Washington DC, USA depicting the median property price by Ward (Ward 1-8). Ward 2 & 3 have the highest median price, while Ward 7 & 8 have the lowest median price.

Insight

The median property selling price in Washington DC, USA has an overall upward trend since 1992 until 2018. However, in 2008 - 2009 the price went down due to the global financial crisis and the housing crash.

Washington DC Ward Map



Median Property Price Each Year

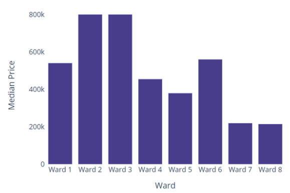
Insight

Properties located in Ward 2 & 3 have the highest median price of around USD800,000. Whereas properties located in Ward 7 & 8 have the lowest median price of around USD220,000.

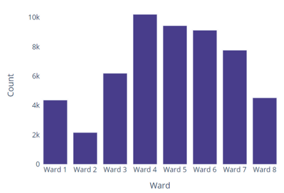
Insight

Ward 4, 5, and 6 are possibly the most densely populated area based on the number of properties located in those wards. Whereas Ward 2 is possibly considered as an elite residential area considering the high median price and the low number of properties.

Median Property Price by Ward



Number of Properties by Ward



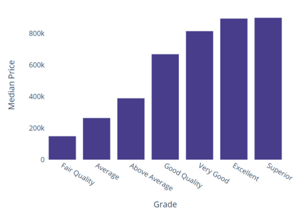
Insight

The grade of a property shows a correlation with the median price. The better the grade of a property is, the higher the price.

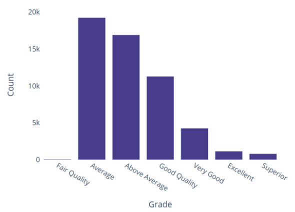
Insight

Most of properties in Washington DC, USA are classified as 'Average' and 'Above Average' by appraisers. There are also very few properties that are classified as 'Fair Quality'.

Median Property Price by Grade



Number of Properties by Grade



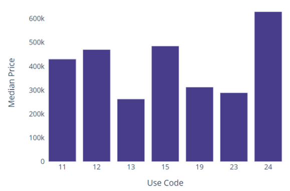
Insight

Based on the property use code, Four Living Units have the highest median price followed by Town House and Single Family Residential.

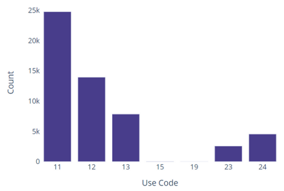
Insight

Most properties in Washington DC, USA are Single Family Residential. There are very few Townhouse and SFR properties.

Median Property Price by Use Code



Number of Properties by Use Code



Remarks

- 11 : Single family residential home used as such
- 12 : Single family residential home with non-economic 2nd unit
- 13 : Single family residential home with slight commercial/ind
- 15 : Townhouse - Planned Development
- 19 : SFR - Manufactured Home (MH on permanent foundation)
- 23 : Triplex; double or duplex with single family home
- 24 : Four living units; e.g. fourplex or triplex w/SFR

MPL Bank
Washington DC, USA.

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- Insights

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Our Project
- Purwadhika JCDS Final Project

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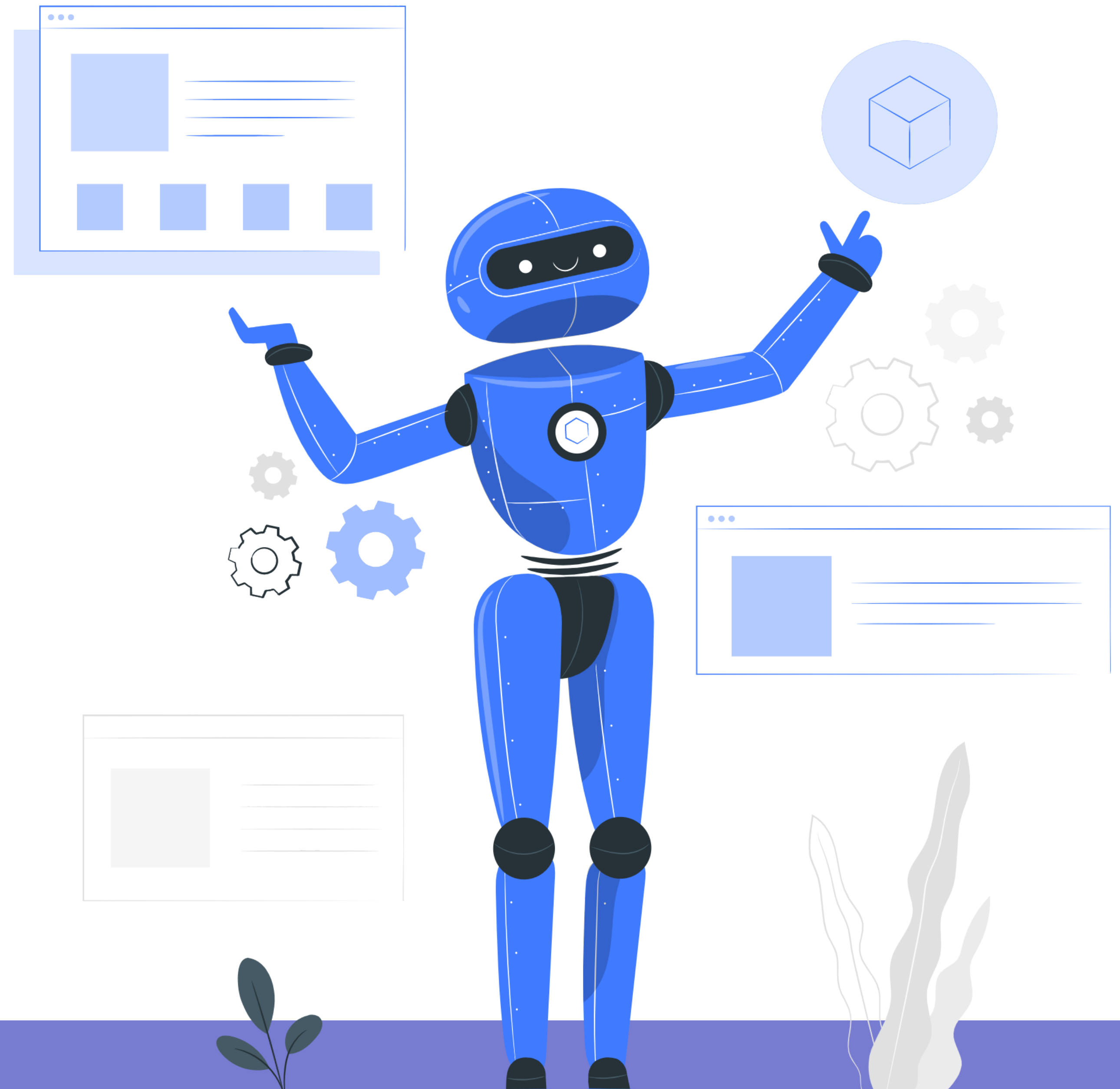
5. Future Works

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.

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 parameter in grid search cv.



Thank You!

PURWADHIKA JCDS 1202
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GITHUB REPOSITORY

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