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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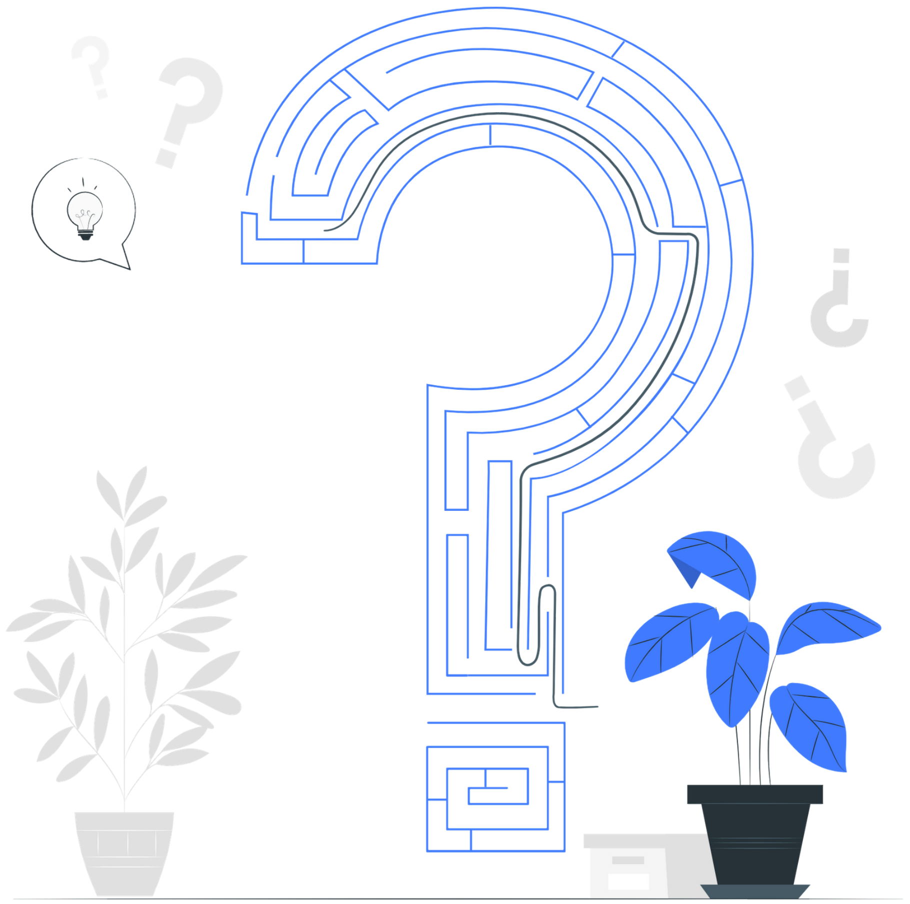
1. Background & Problem Identification

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?

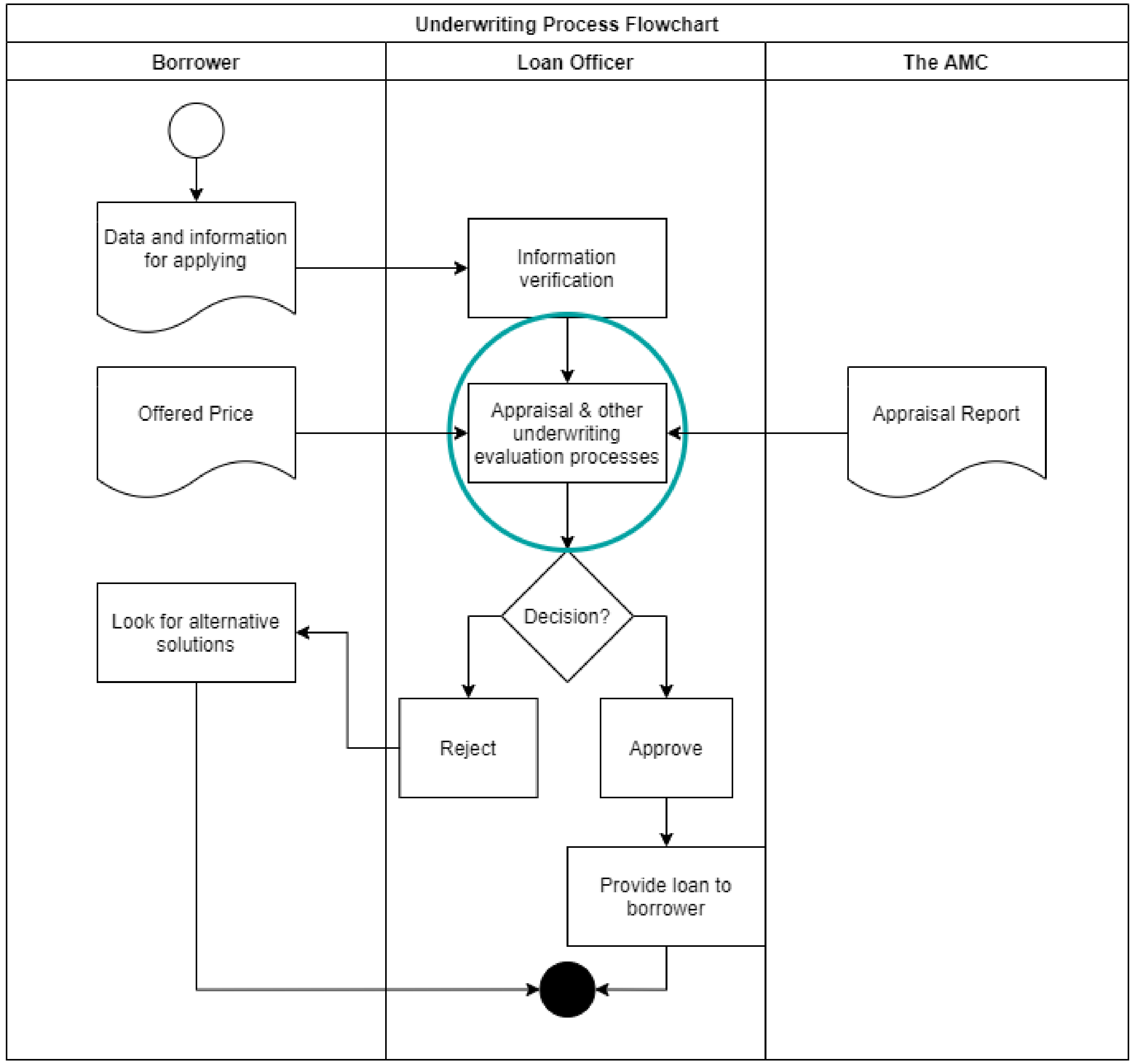
Appraisal process directly affects company’s revenue.

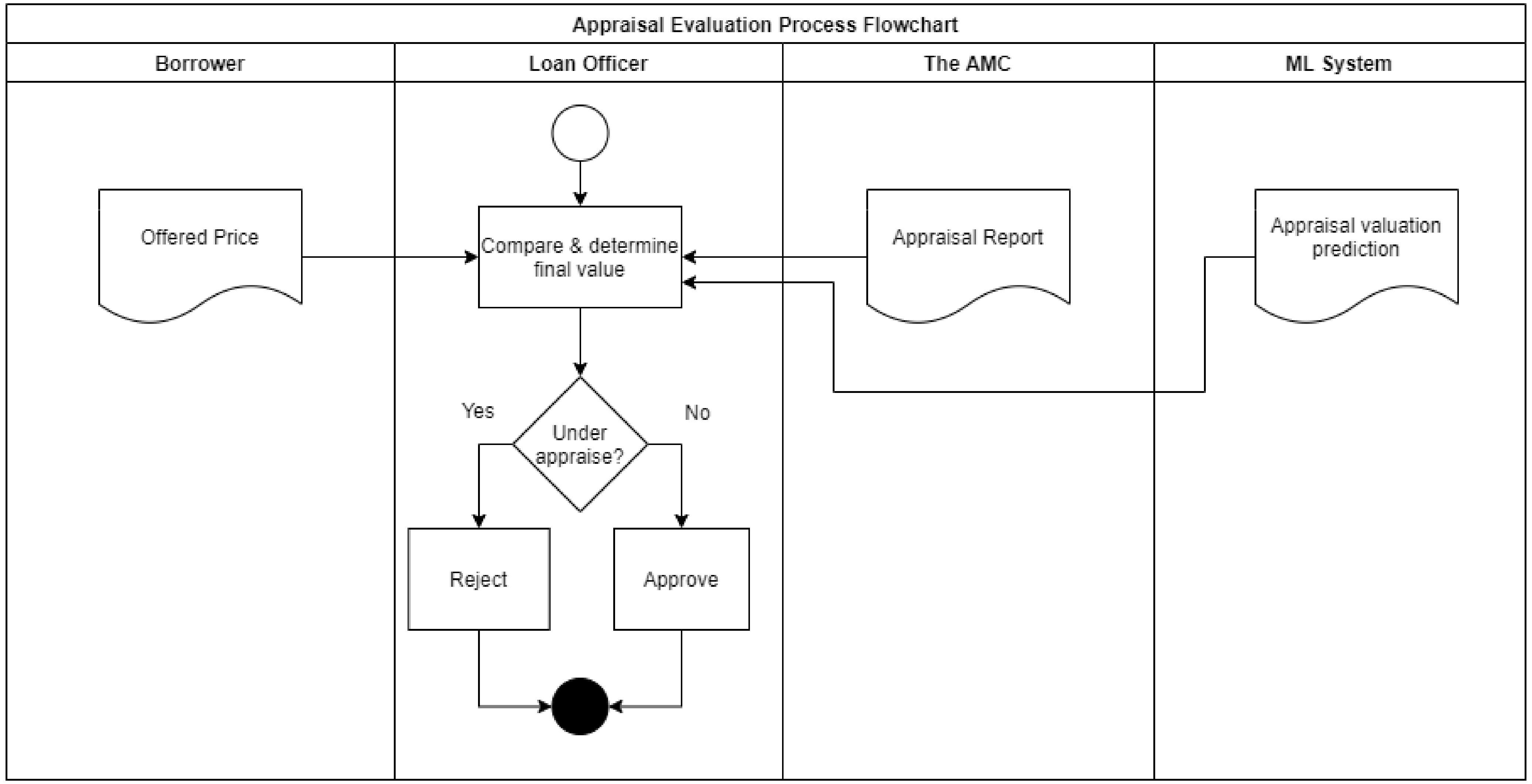
The result would determine whether to give loan to a borrower.

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 Evaluation Process



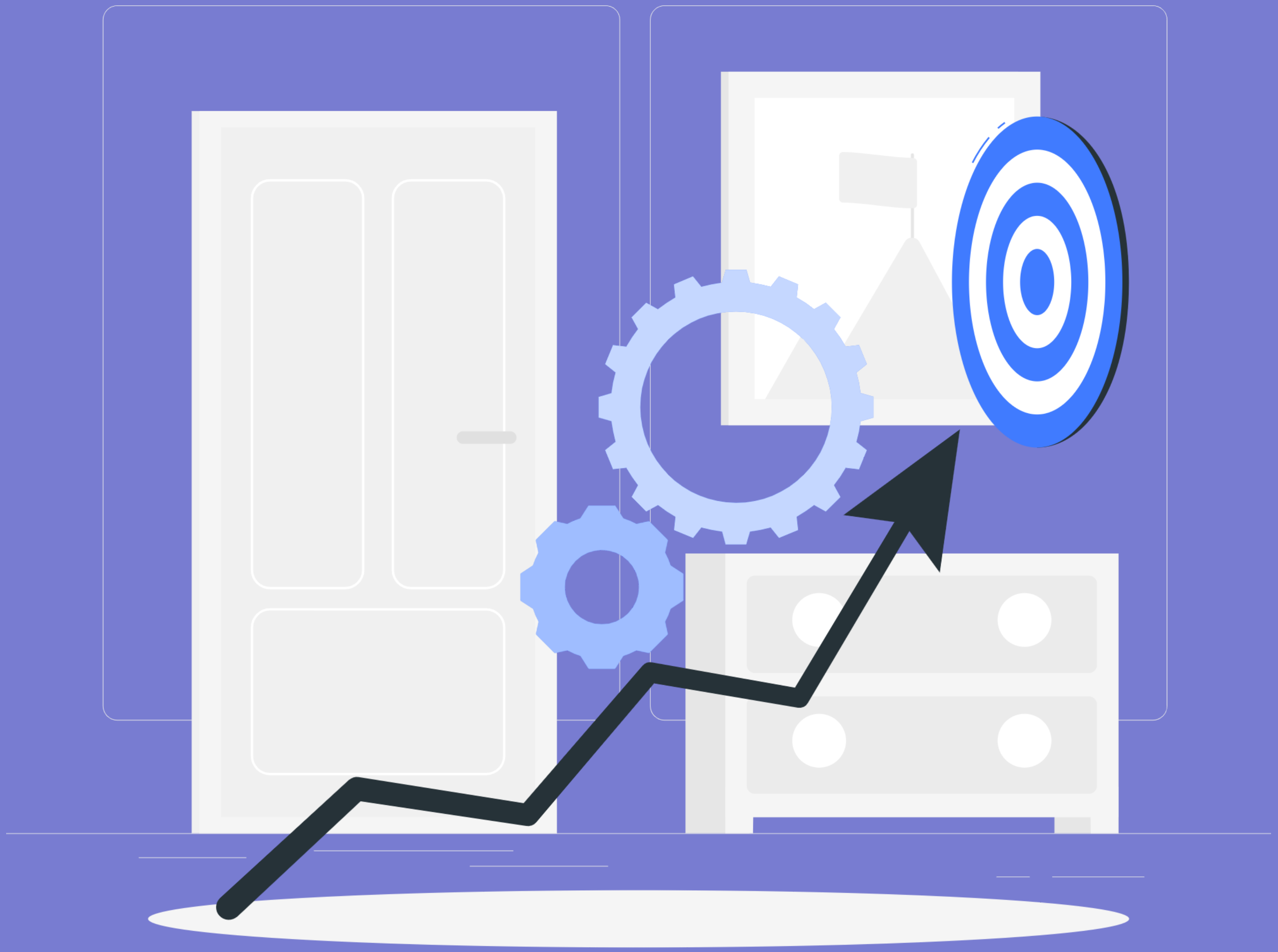


Expected Output

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.

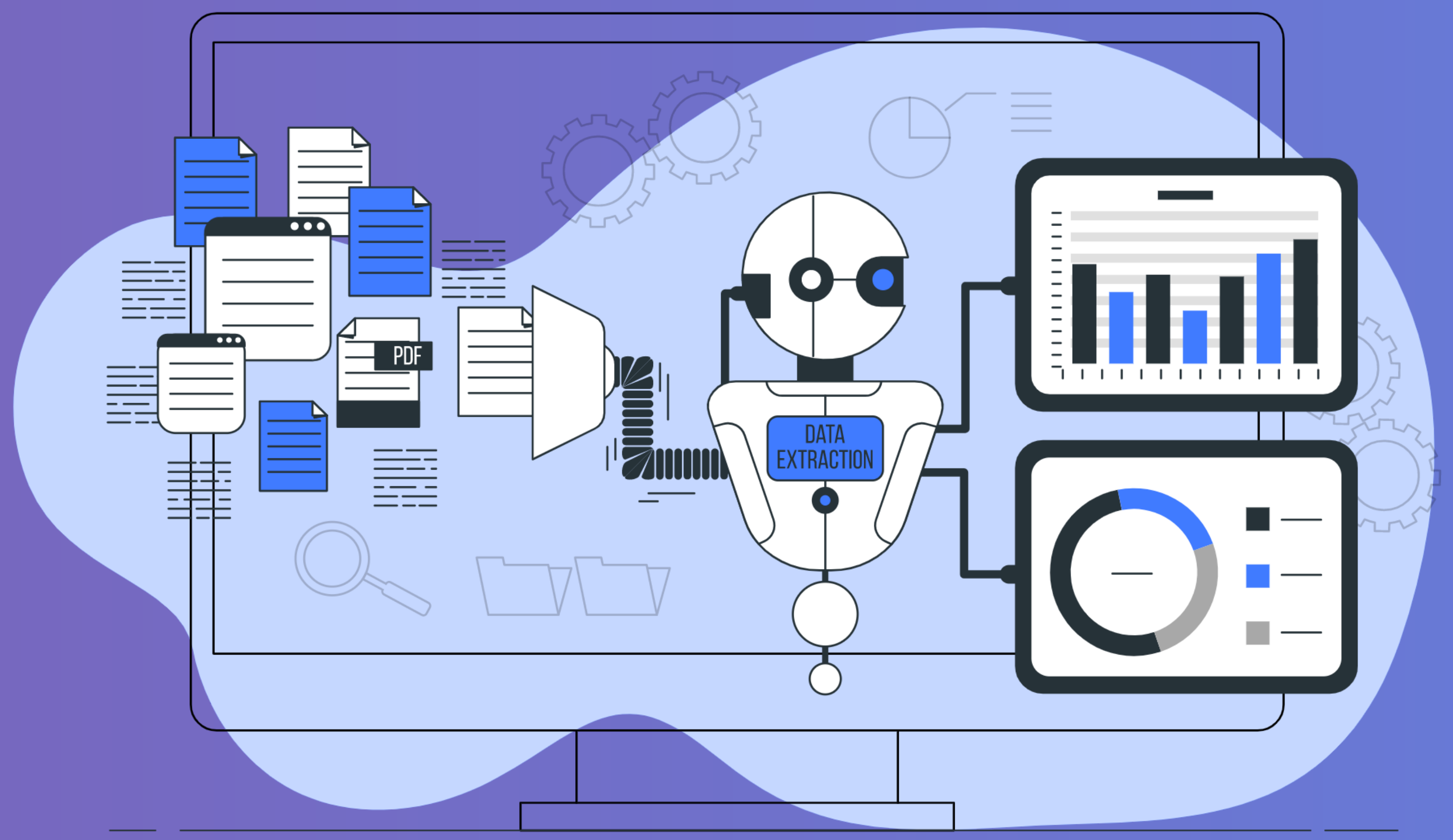
Minimize Loss

originated from fraud and erroneous valuation.

Notes: In this project we were asked to reach the Mean Absolute Error (MAE) metrics at most 12% 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 Collection

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 Description

NUMERICAL

- BATHRM : Number of full bathroom
- HF_BATHRM : Number of half bathroom
- NUM_UNITS : Number of units
- ROOMS : Number of rooms
- BEDRM : Number of bedrooms
- GBA : Gross building area (in sqft)
- KITCHENS : Number of kitchens
- FIREPLACES : Number of fireplaces
- LANDAREA : Land area (in sqft)
- LATITUDE : Latitude
- LONGITUDE : Longitude
- AYB (ayb_age) : The earliest time the main portion of the building was built
- EYB (eyb_age) : The year an improvement was built more recent than actual year built
- PRICE : Price

Data Description

CATEGORICAL - NOMINAL

- HEAT : Heating system
- AC : AC availability
- QUALIFIED : Government's criteria on whether the sale is representative of market value
- USECODE : Use code
- STYLE : Style
- ASSESSMENT_NBHD : Neighborhood ID
- WARD : Ward
- EXTWALL : Exterior wall
- INTWALL : Interior wall
- QUADRANT : City quadrant (NE, SE, SW, NW)

CATEGORICAL - ORDINAL

- GRADE : Grade
- CNDTN : Condition
- STRUCT : Structure
- ROOF : Roof type
- SALEDATE : Date of most recent sale

Data Pre-Processing

Drop Unused Features

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 Features

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

Data Pre-Processing

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

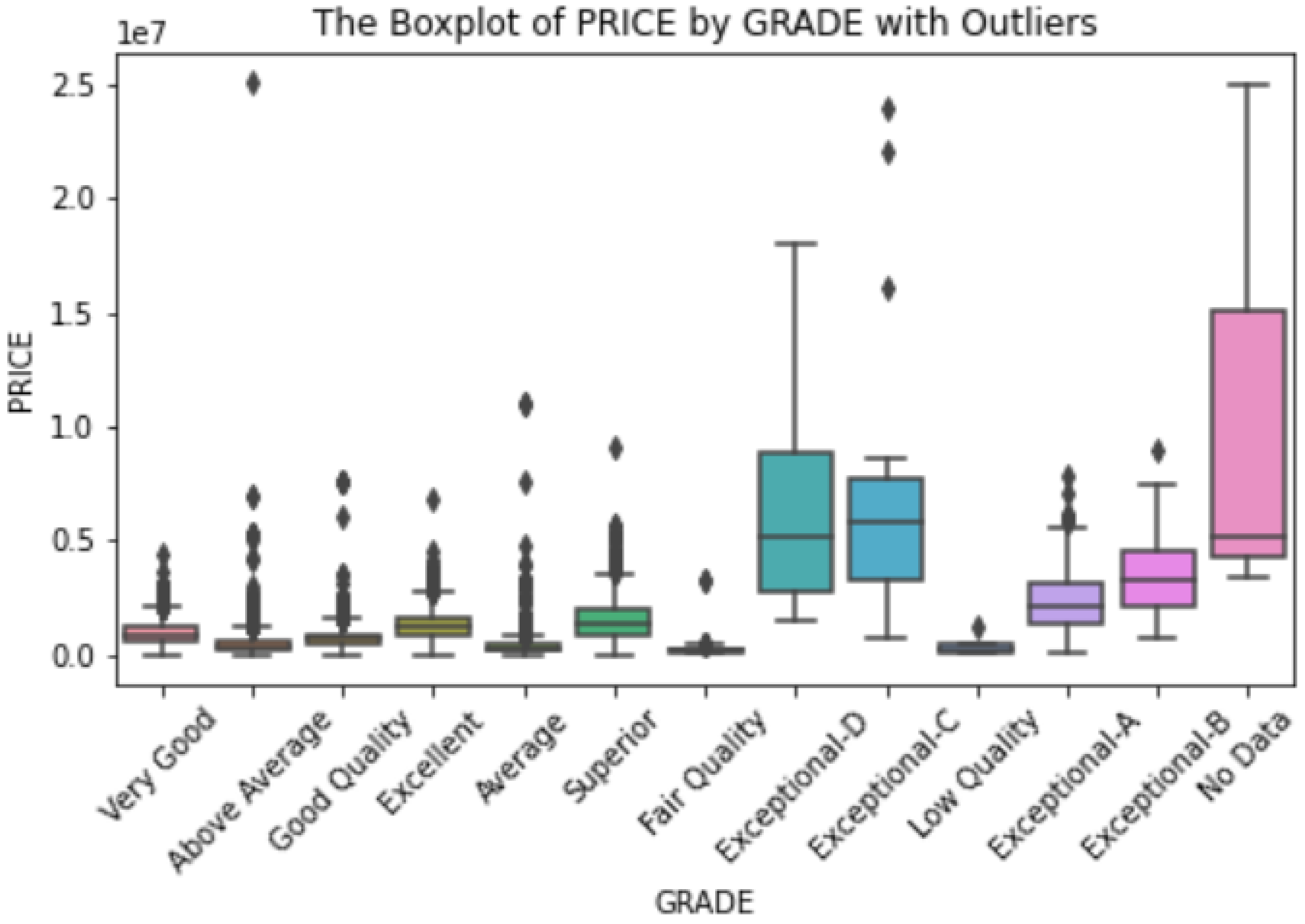
KITCHENS, PRICE, Price based on CNDTN

Re-classify Features

CNDTN, STRUCT, ROOF

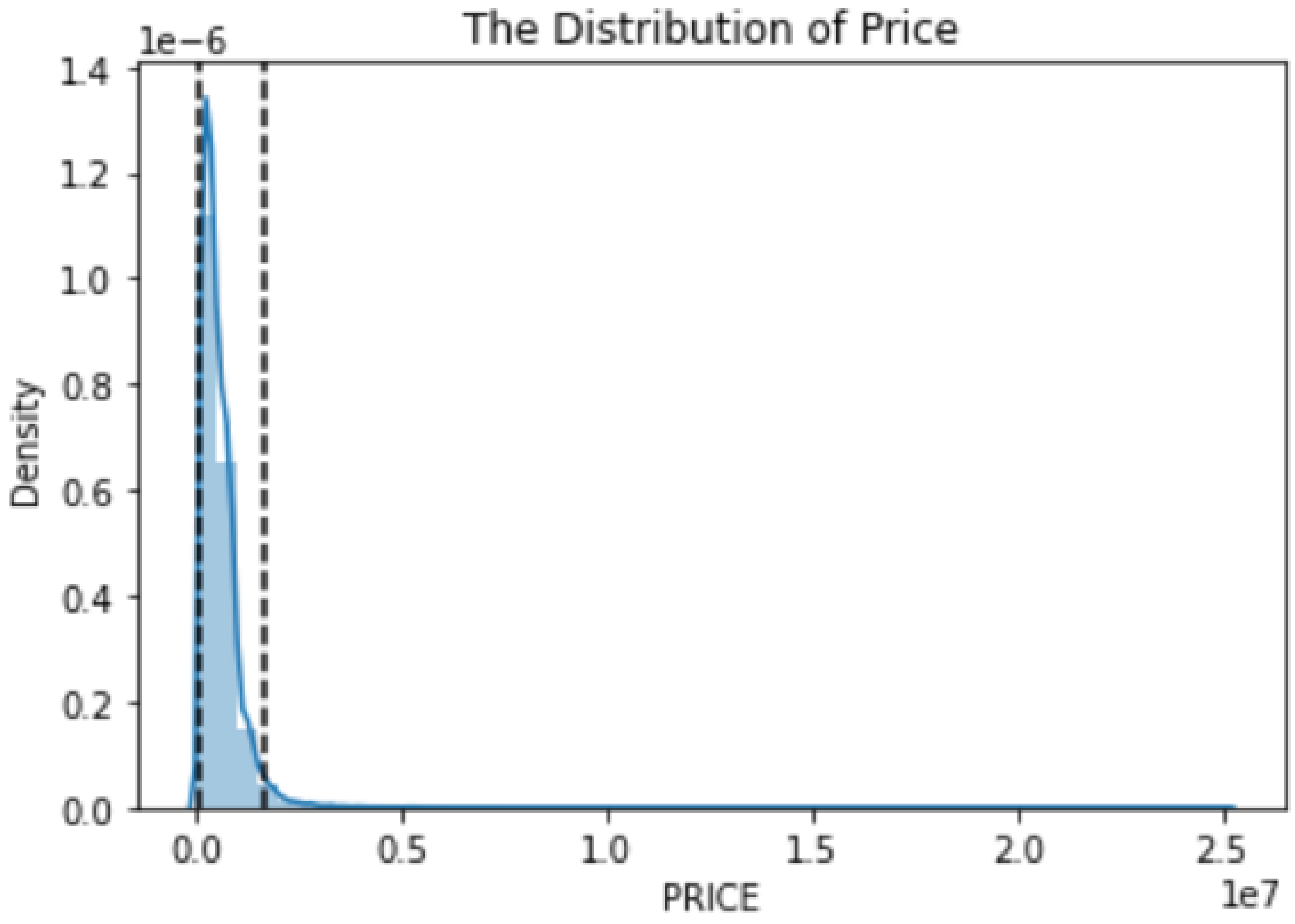
Exceptional Properties Exclusion

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.



Identifying Outliers in Price

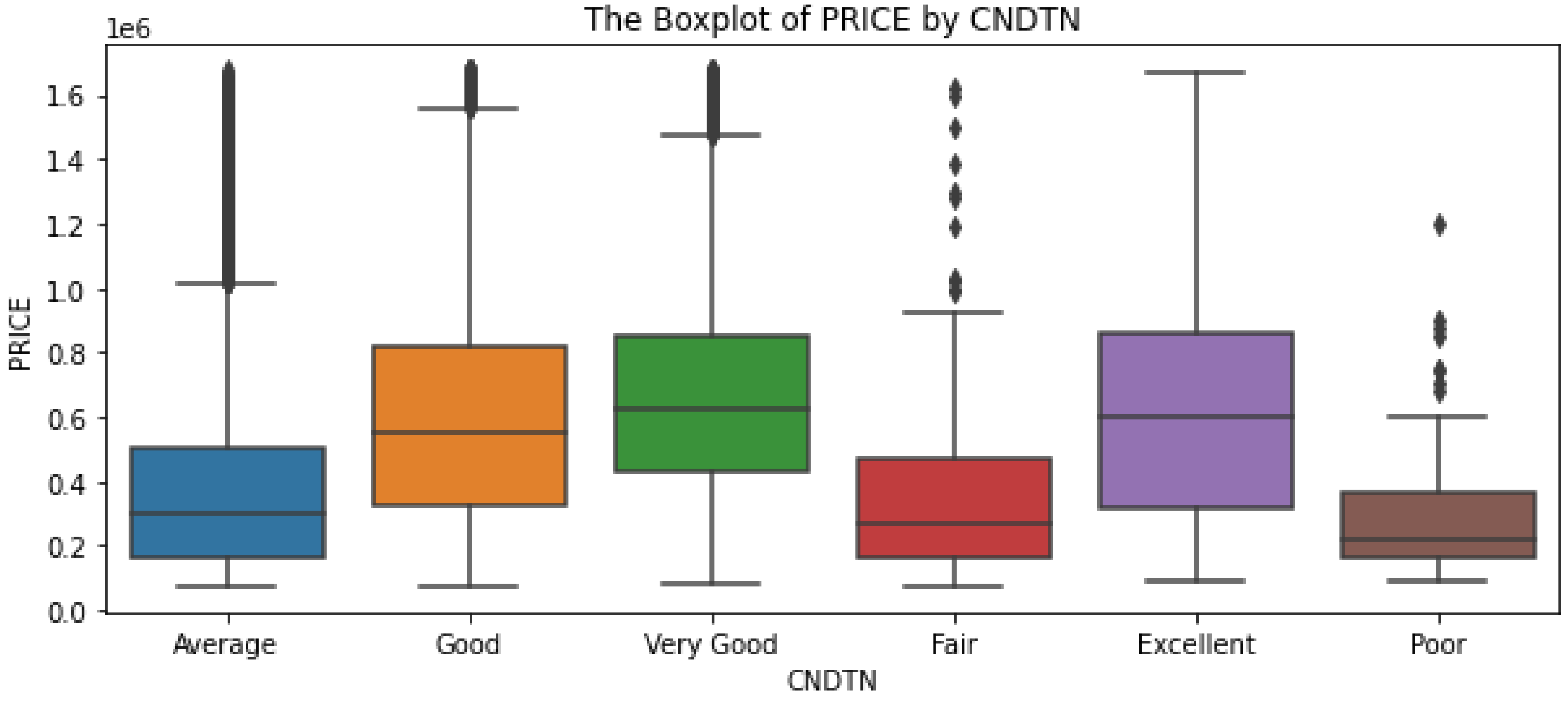
- Erroneous data with very low price (e.g., USD1.0) or extremely expensive price.
- Kaggle : "Property prices are very high in Washington DC, averaging USD647,000 in 2017."
- Drop data with PRICE <= 25th percentile or >= 97.5th percentile to assume 95% confidence interval.



Please note that we did not perform z-test due to the power of the distribution. Our PRICE distribution is <u>extremely right-skewed</u> as such if we use z-test, data that will be considered as outliers are only those with high price while data with very low price (e.g., USD1.0) will still be considered as non-outliers.

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 :

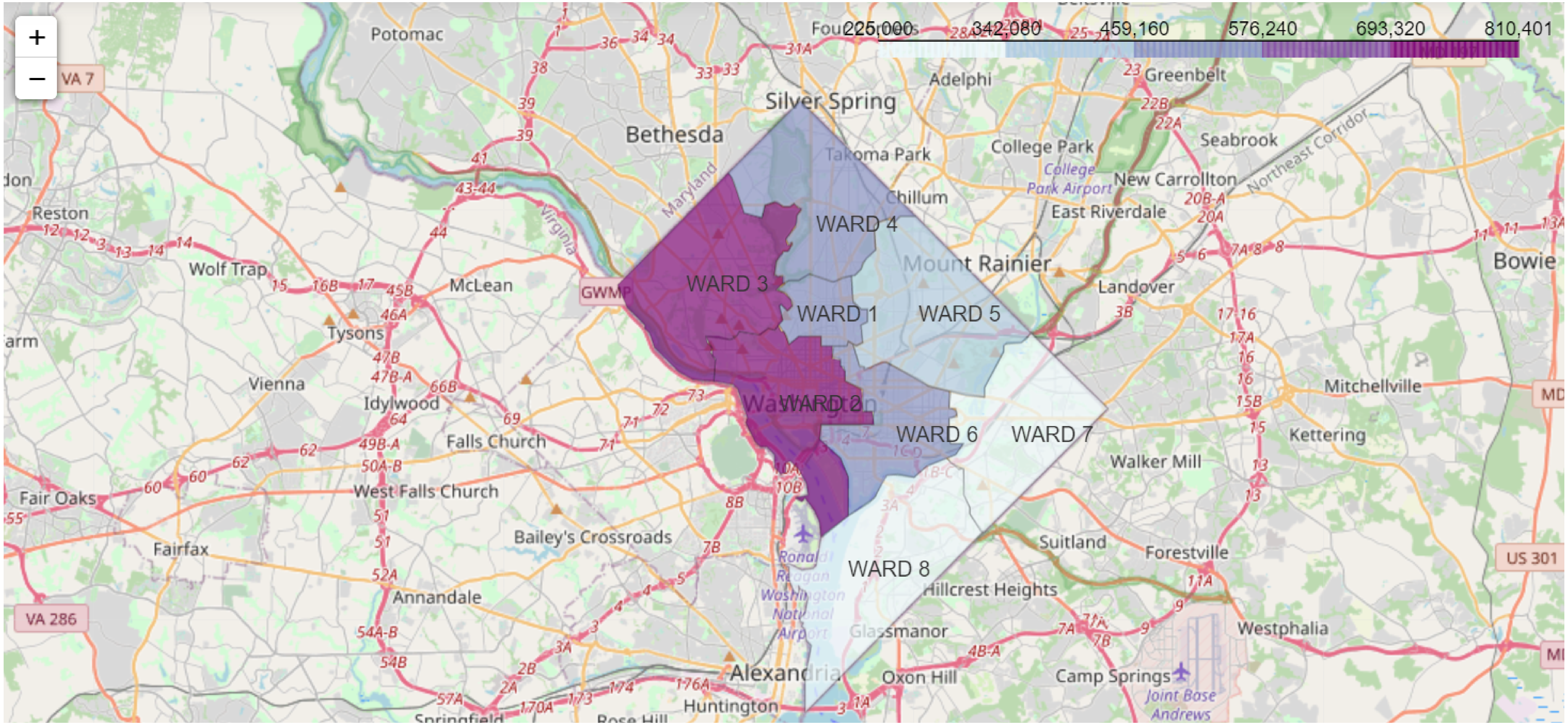
- 0 : Under median
- 1 : Above median

	STRUCT	median_PRICE	total
0	Semi-Detached	275000.0	6107
1	Multi	310500.0	2082
2	Town Inside	349312.5	146
3	Town End	383730.0	61
4	Row End	432090.0	5145
5	Single	489000.0	11266
6	Row Inside	490000.0	17565
7	Default	625000.0	3

	ROOF	median_PRICE	total
0	Concrete	299900.0	1
1	Comp Shingle	359000.0	12051
2	Typical	373750.0	66
3	Built Up	376000.0	13117
4	Composition Ro	410075.0	48
5	Metal- Pre	410749.5	96
6	Shake	480000.0	257
7	Metal- Sms	500000.0	12016
8	Concrete Tile	512500.0	2
9	Water Proof	594000.0	4
10	Shingle	649435.5	168
11	Clay Tile	649900.0	191
12	Slate	700000.0	3649
13	Neopren	724110.0	699
14	Wood- FS	762500.0	2
15	Metal- Cpr	764250.0	8

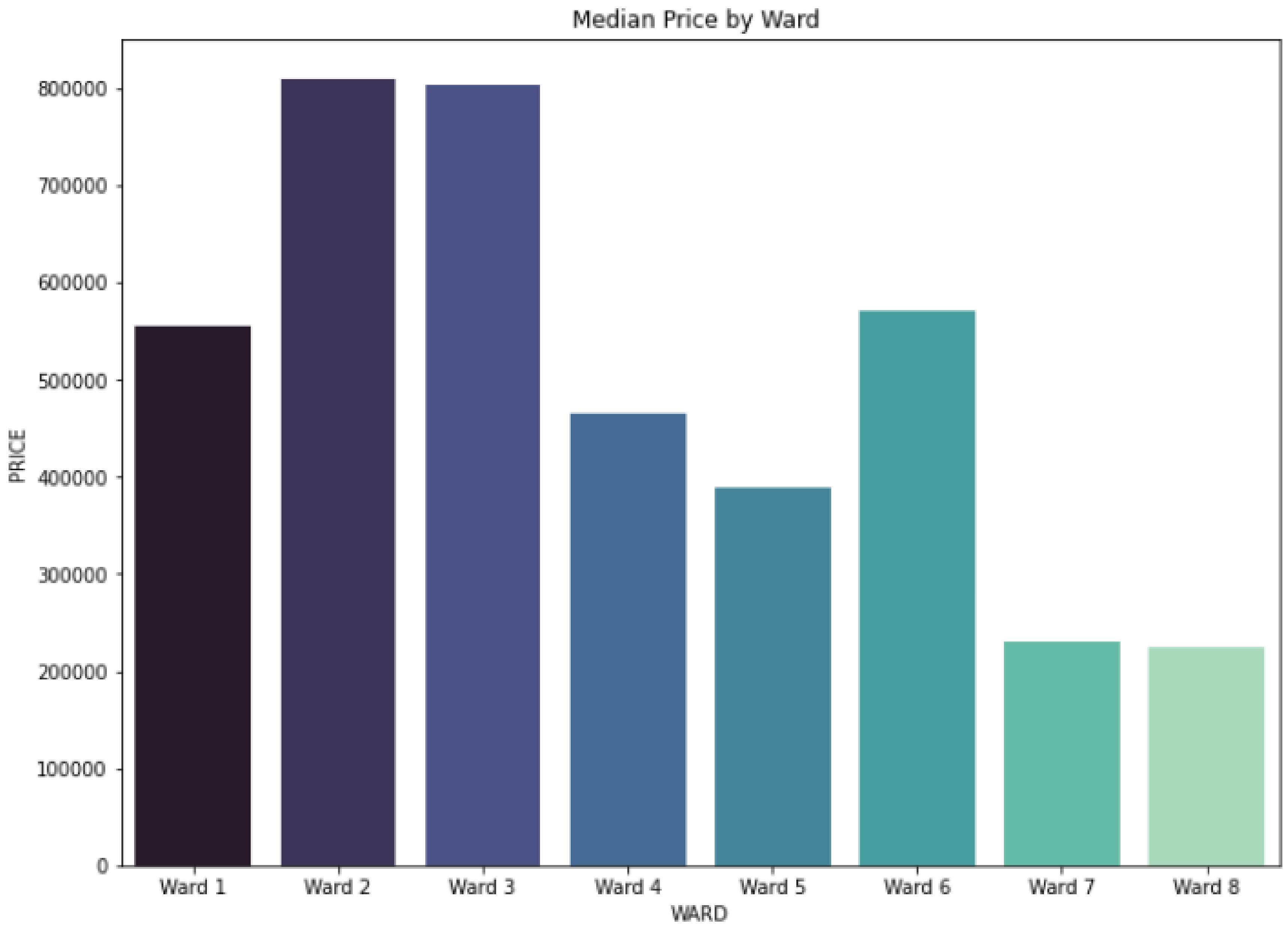
Insights

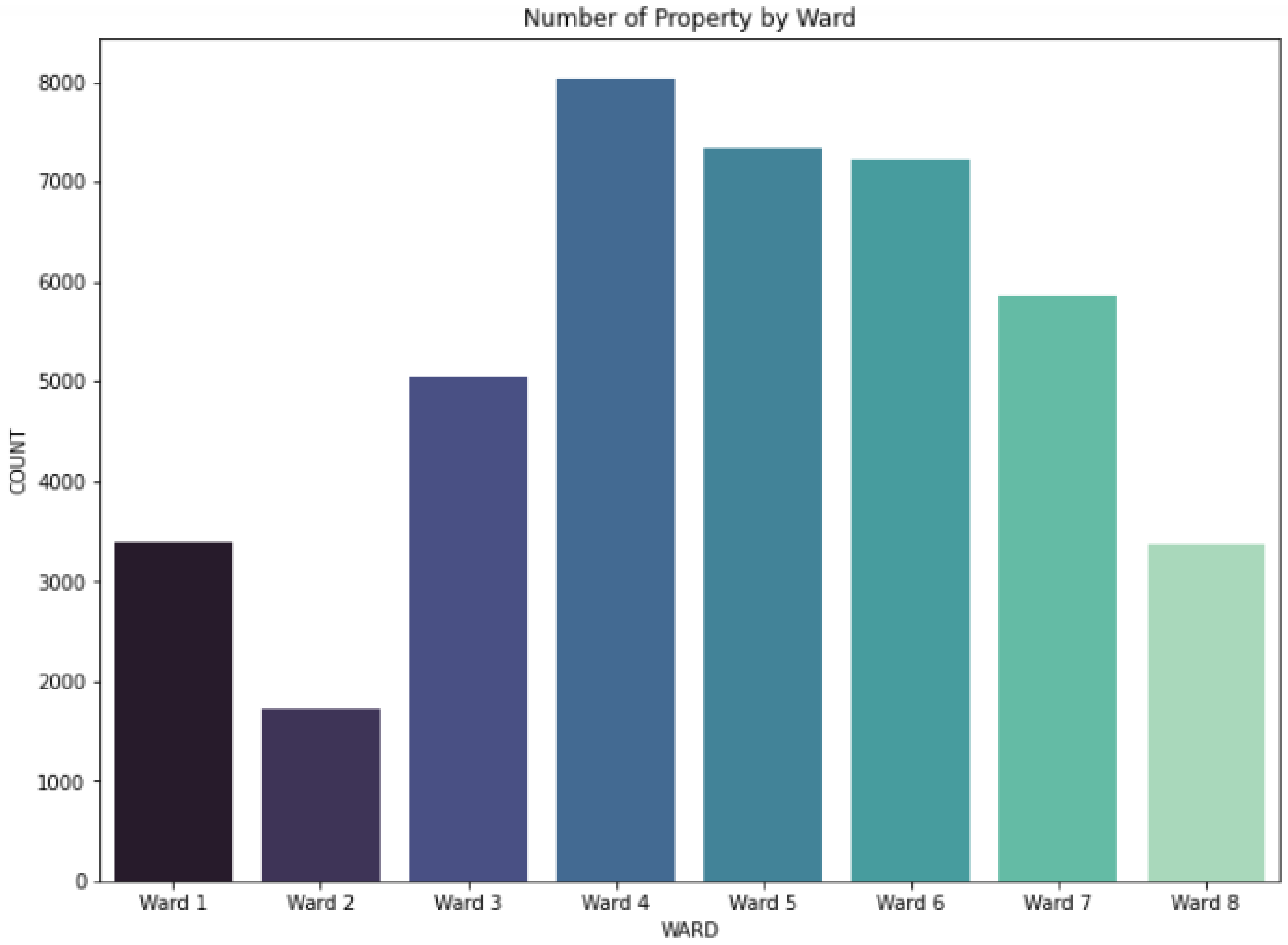
Map by Ward



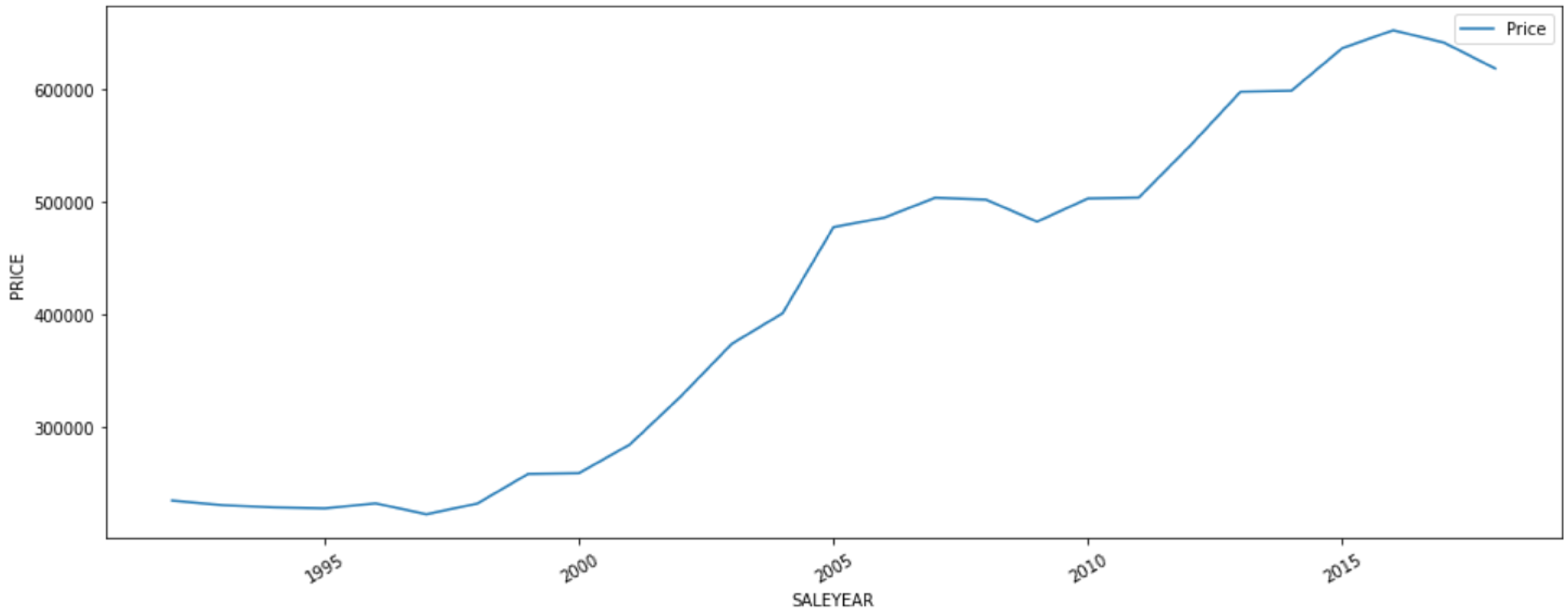
225,000
342,080
459,160
576,240
693,320
810,401
WARD 4
WARD 3
WARD 1
WARD 5
WARD 2
WARD 6
WARD 7
WARD 8

Median Price & Number of Property by Ward

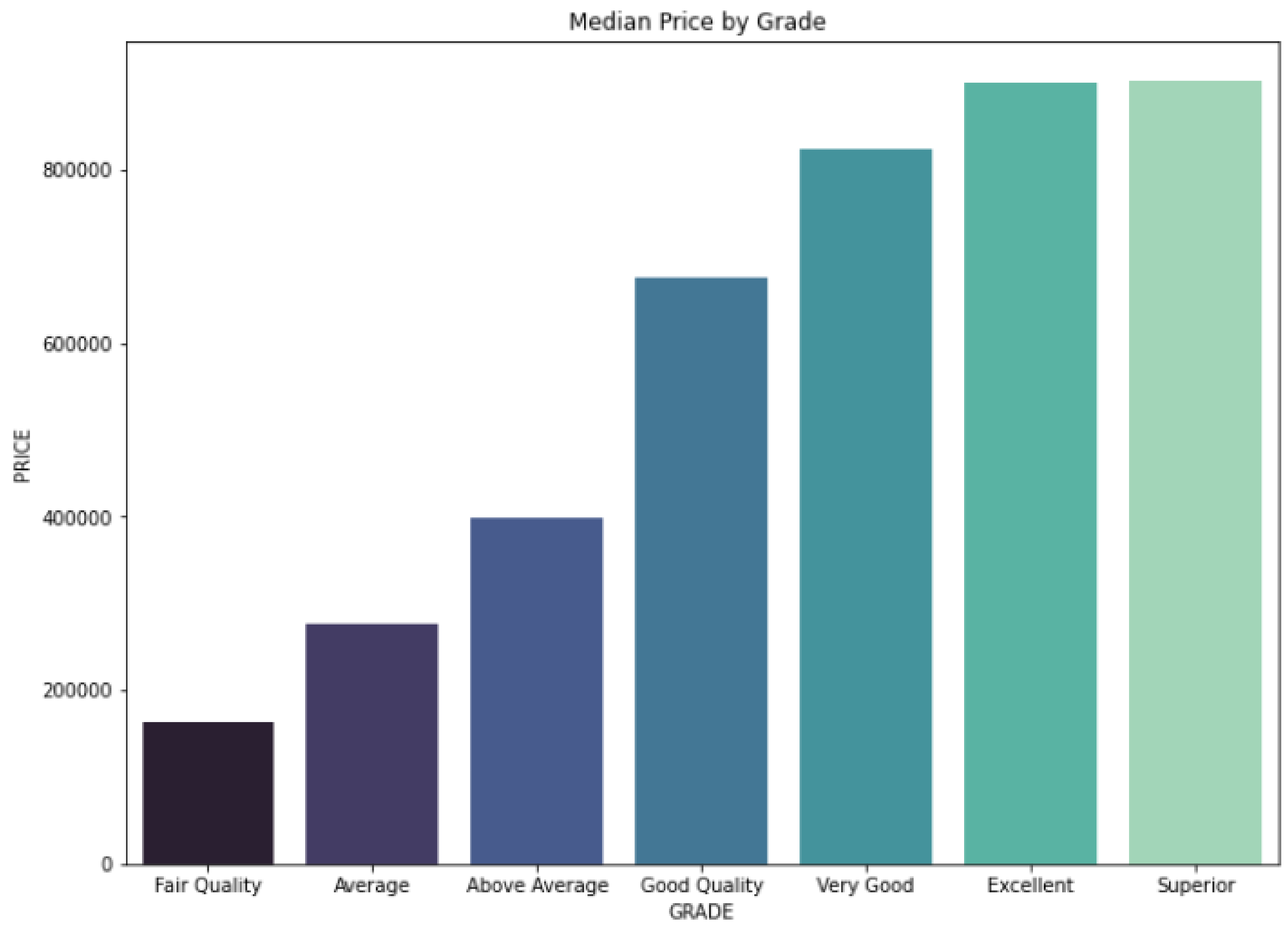


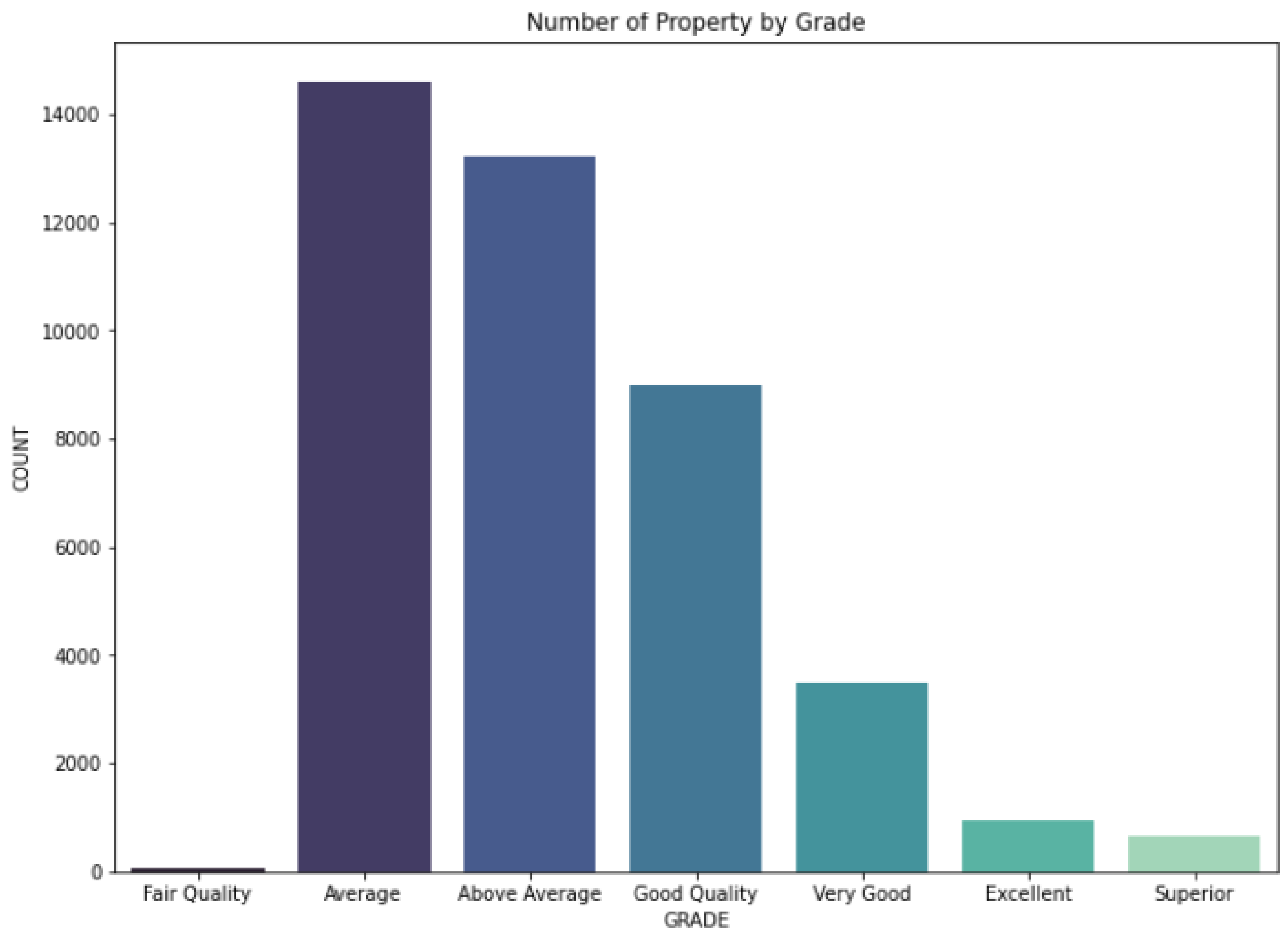


Median Sale Price per Year

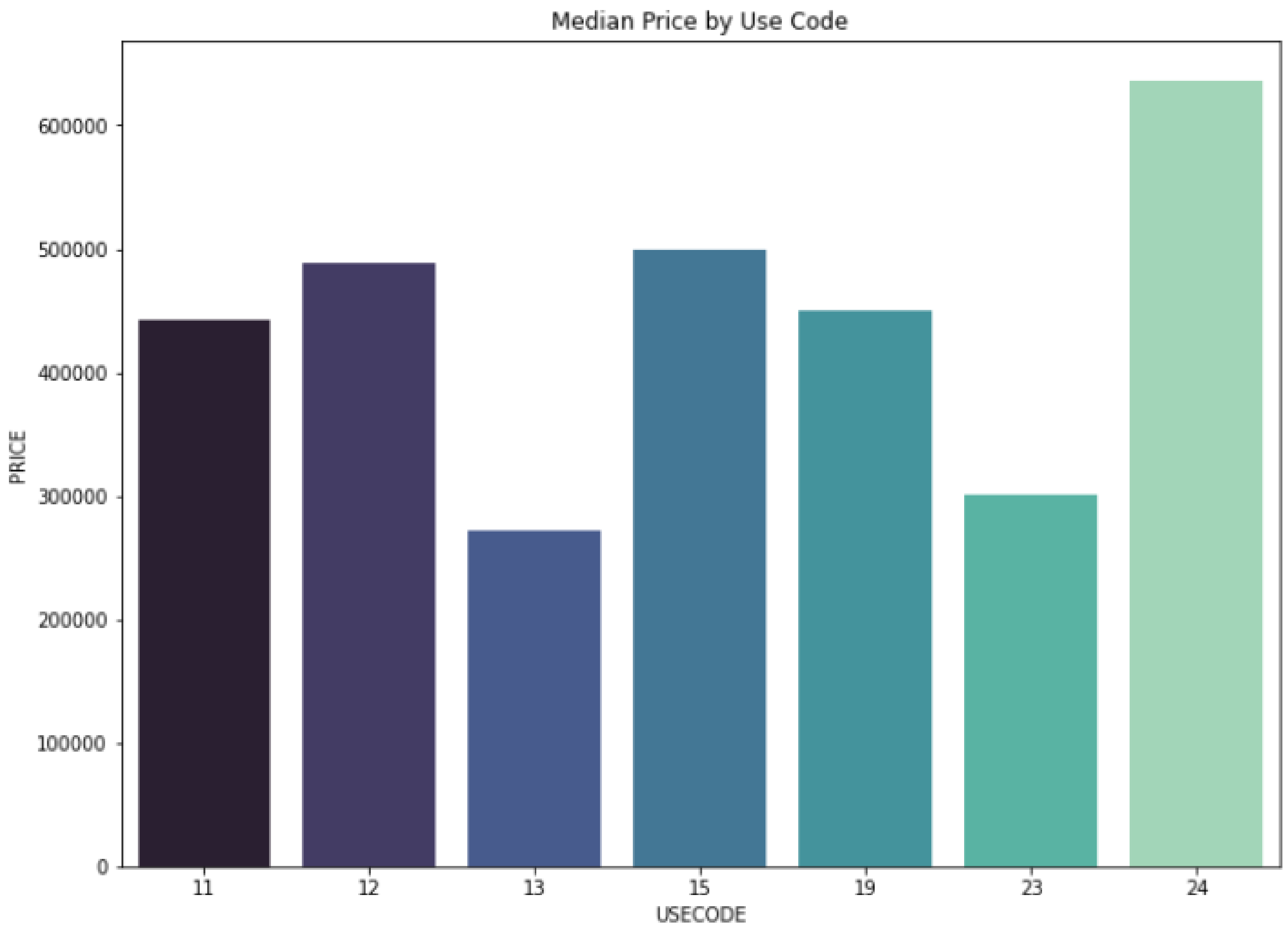


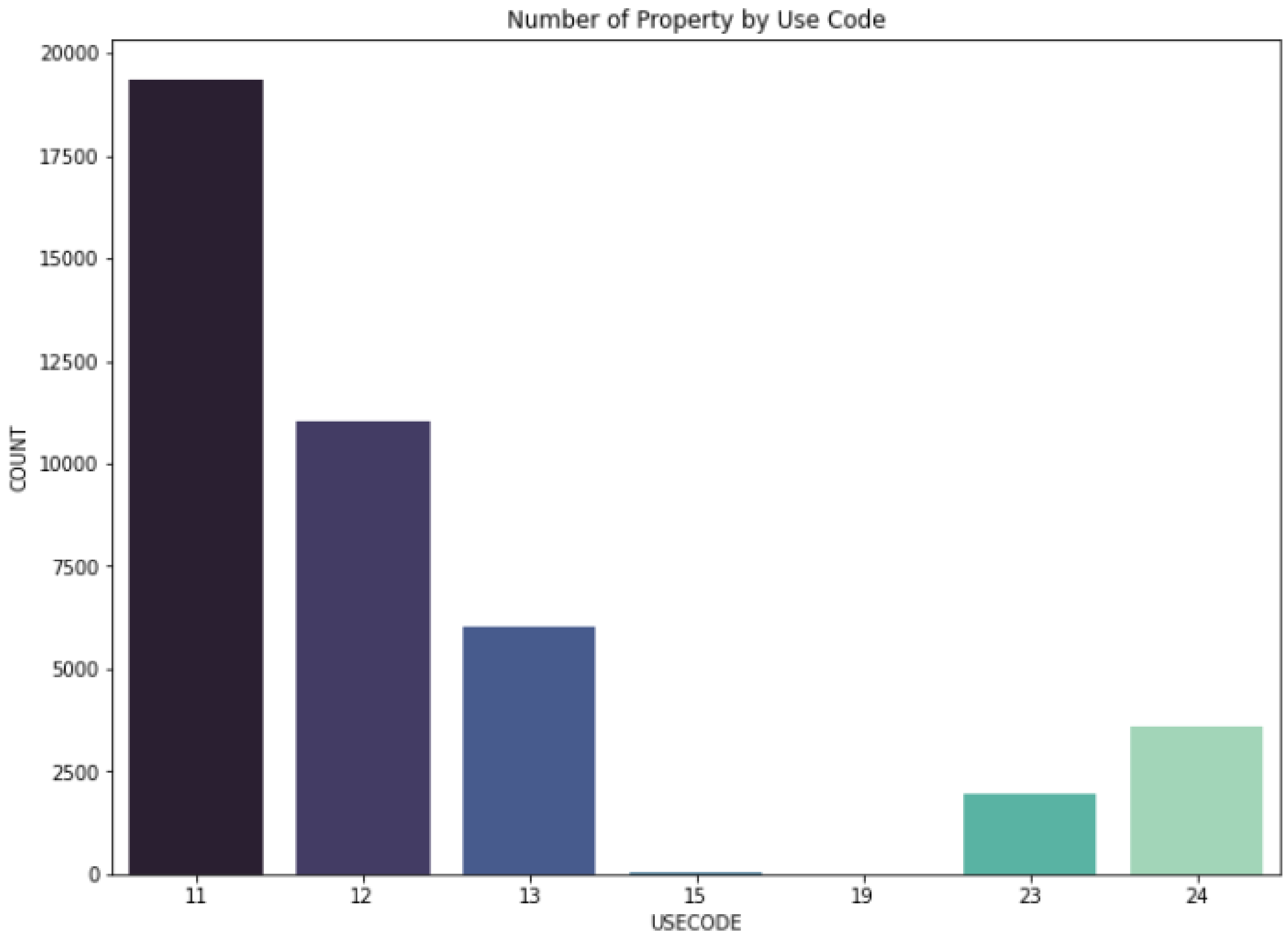
Median Price & Number of Property by Grade





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 R^2 score, Mean Absolute Error (MAE) and resource efficiency.

Model Assessment

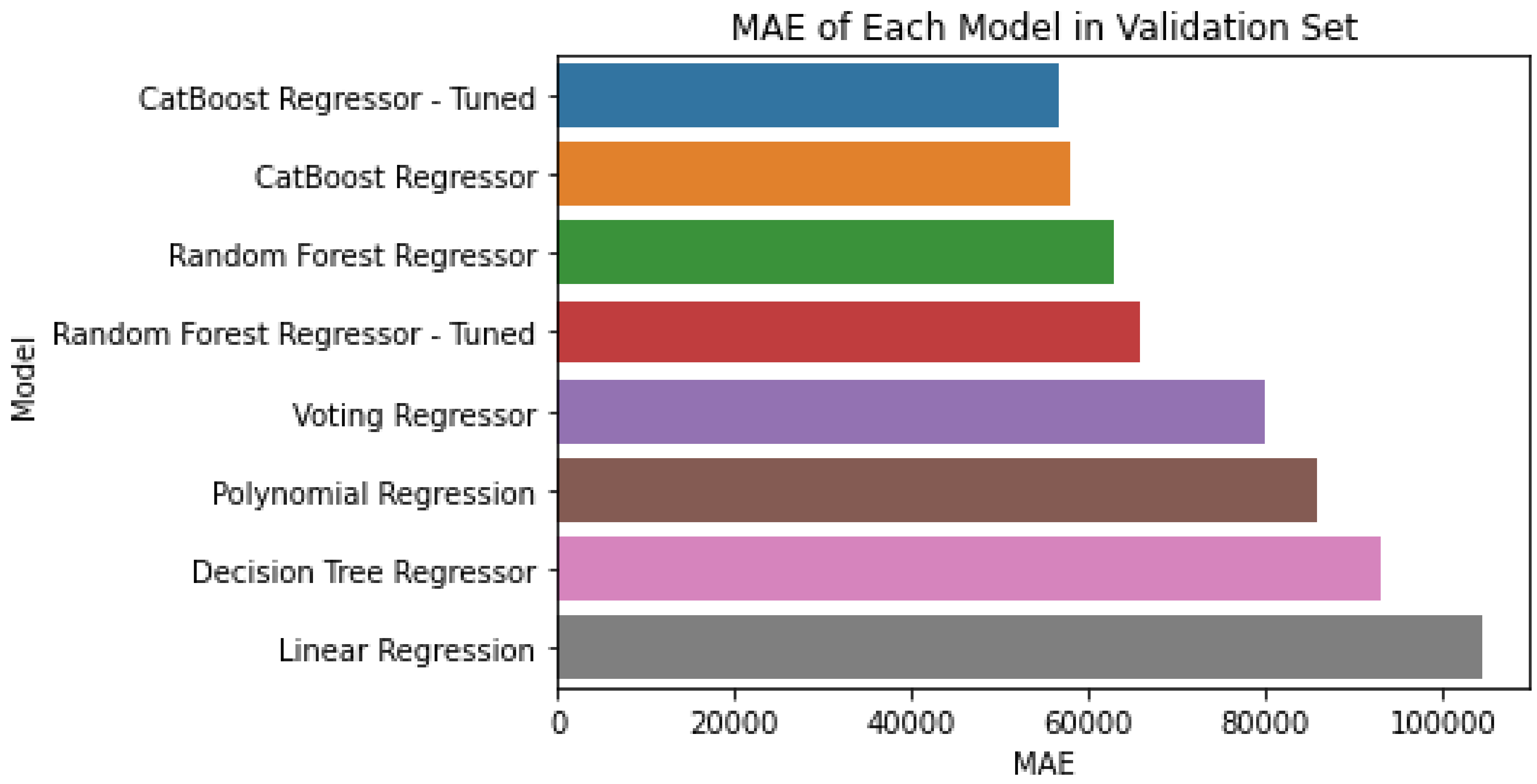
CatBoost Regressor - Tuned has the best R^2 score and the lowest MAE in the validation set.

	Model	Set	MSE	RMSE	MAE	R2
1	Linear Regression	Validation	1.902704e+10	137938.554633	104536.593792	0.803719
3	Polynomial Regression	Validation	1.397333e+10	118208.844948	85763.947553	0.855853
5	Decision Tree Regressor	Validation	2.010742e+10	141800.627564	92944.701611	0.792574
7	Random Forest Regressor	Validation	9.229200e+09	96068.722950	62796.015937	0.904793
9	Random Forest Regressor - Tuned	Validation	9.932636e+09	99662.611843	65918.276415	0.897536
11	Voting Regressor	Validation	1.242826e+10	111482.094846	79979.099662	0.871792
13	CatBoost Regressor	Validation	7.854494e+09	88625.585972	58064.522230	0.918974
15	CatBoost Regressor - Tuned	Validation	7.863497e+09	88676.363136	56813.042752	0.918881

Model Assessment

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

We managed to improve the model performance by <u>reducing the MAE by 54%</u> from the first base model, Linear Regression ($104,536.59), relative to the final model CatBoost Regressor - Tuned ($56,813.04).



Final Model Evaluation

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

Train Set

```
MSE: 5902490242.367122
RMSE: 76827.66586567057
MAE: 46975.76563974304
R-squared: 0.9392950310981597
```

Test Set

```
MSE: 10815149410.215195
RMSE: 103995.91054563249
MAE: 63782.41628337468
R-squared: 0.9073119043829377
```

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 : 0.9174836341473466
Std : 0.0011462151706577988
```

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

Final Model Evaluation

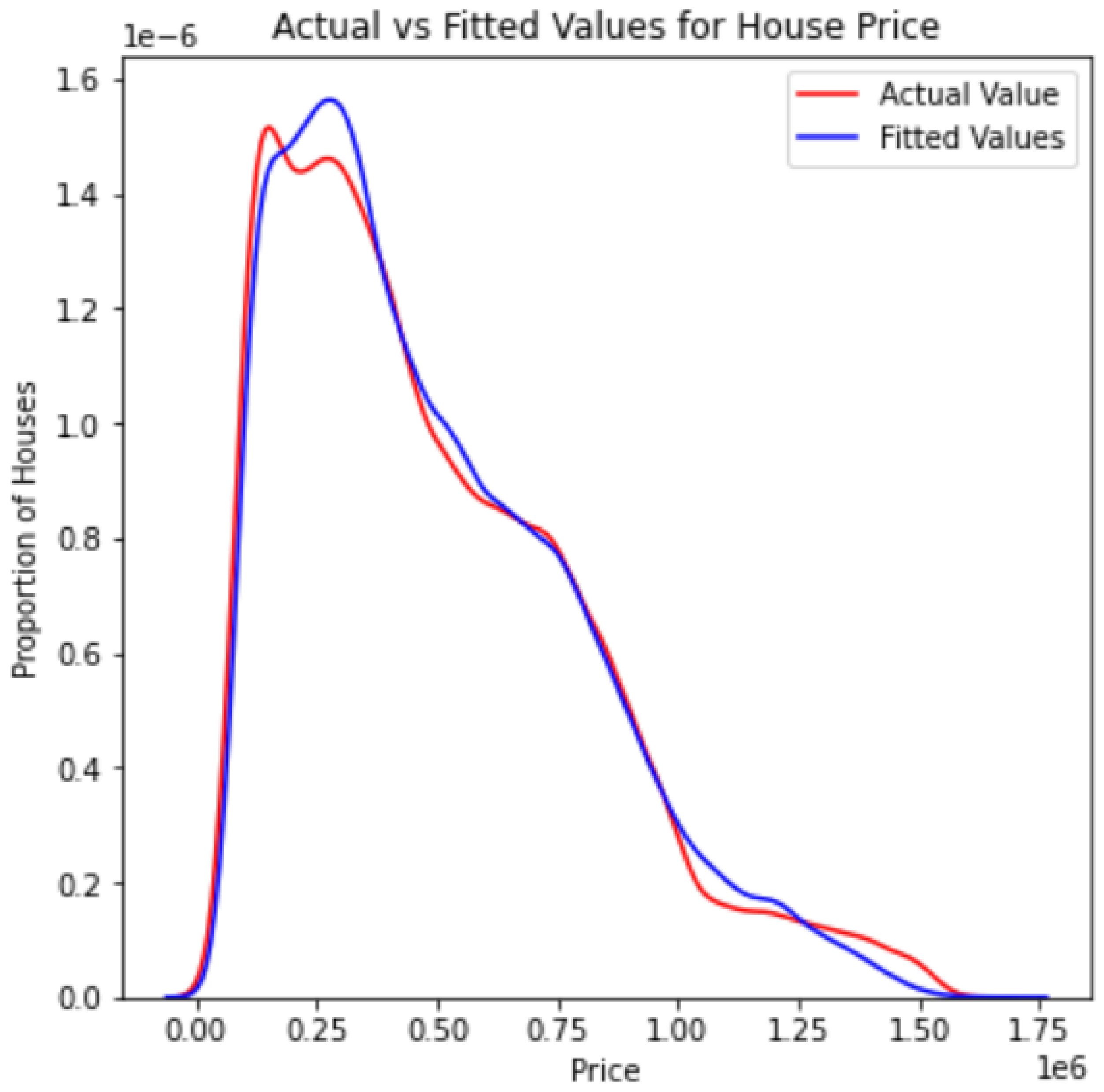
We were asked to reach the Mean Absolute Error (MAE) value below 12% of the median property price.

```
Price Median : 422970.0
Desired MAE (12% x Median) : 50756.4
Achieved MAE : 46975.76563974304
```

From the result shown above, we have achieved the desired MAE value (under USD50,756.4).

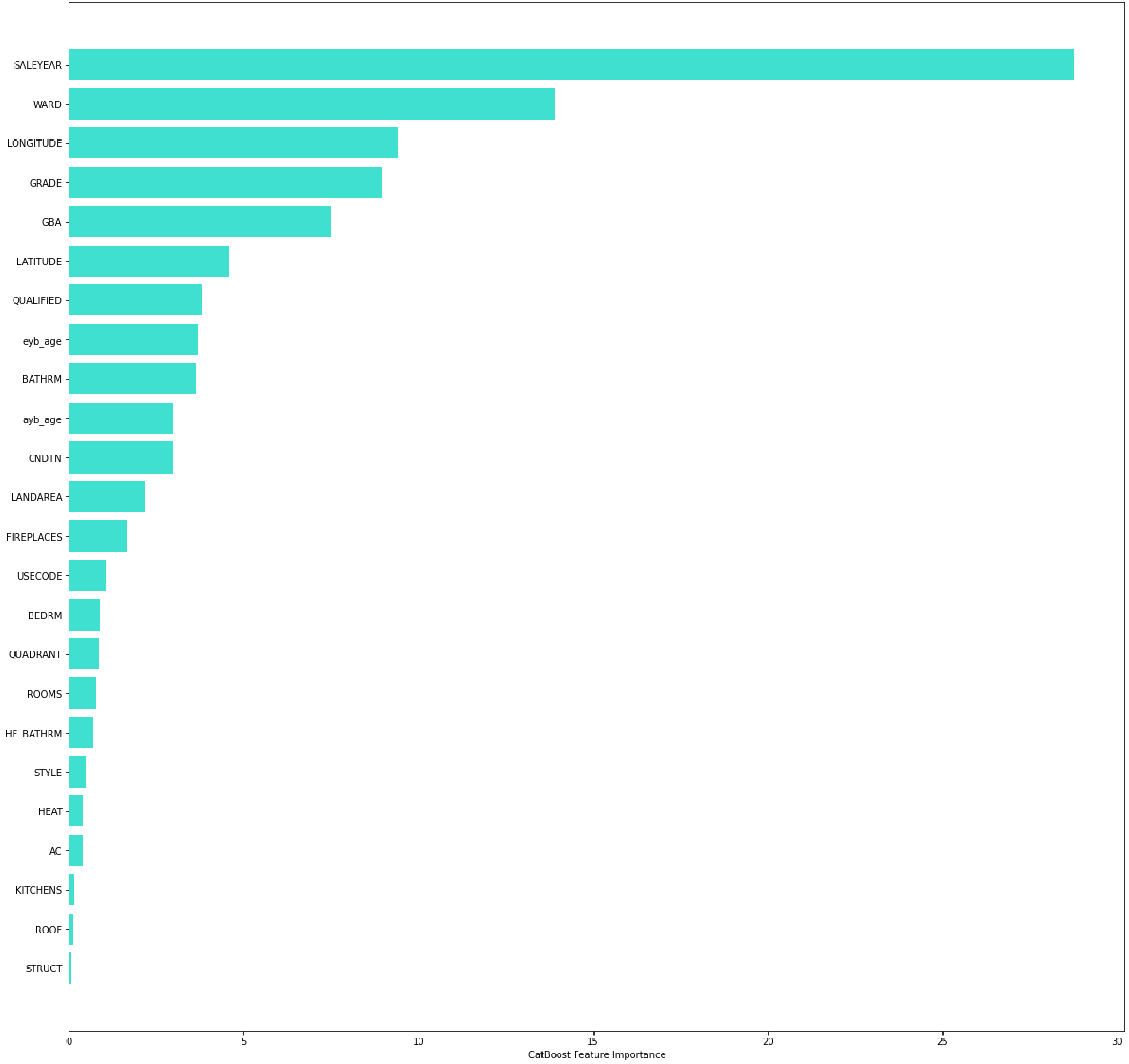
Distribution Plot of Actual vs Fitted Values

Train Set

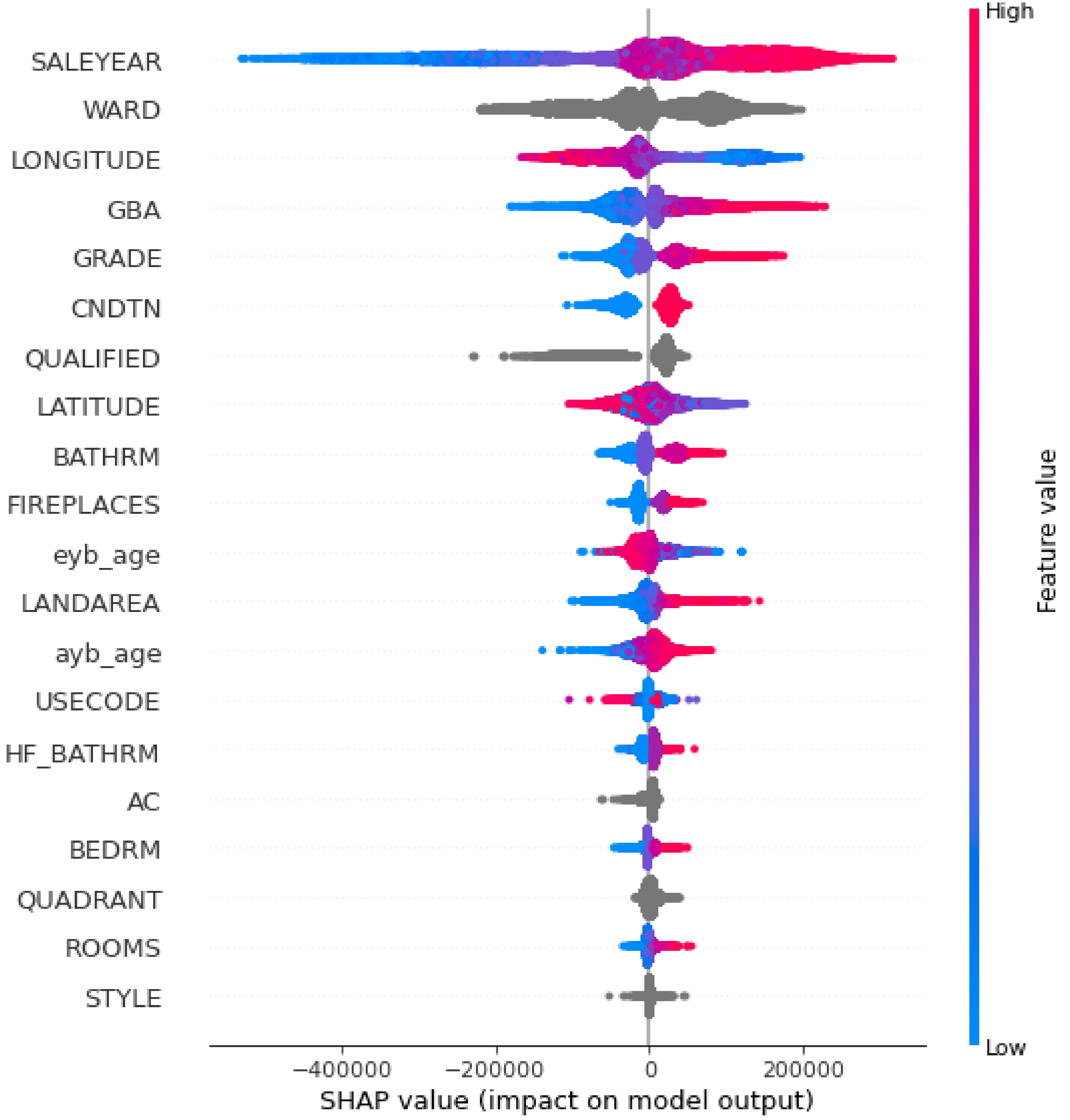


Test Set

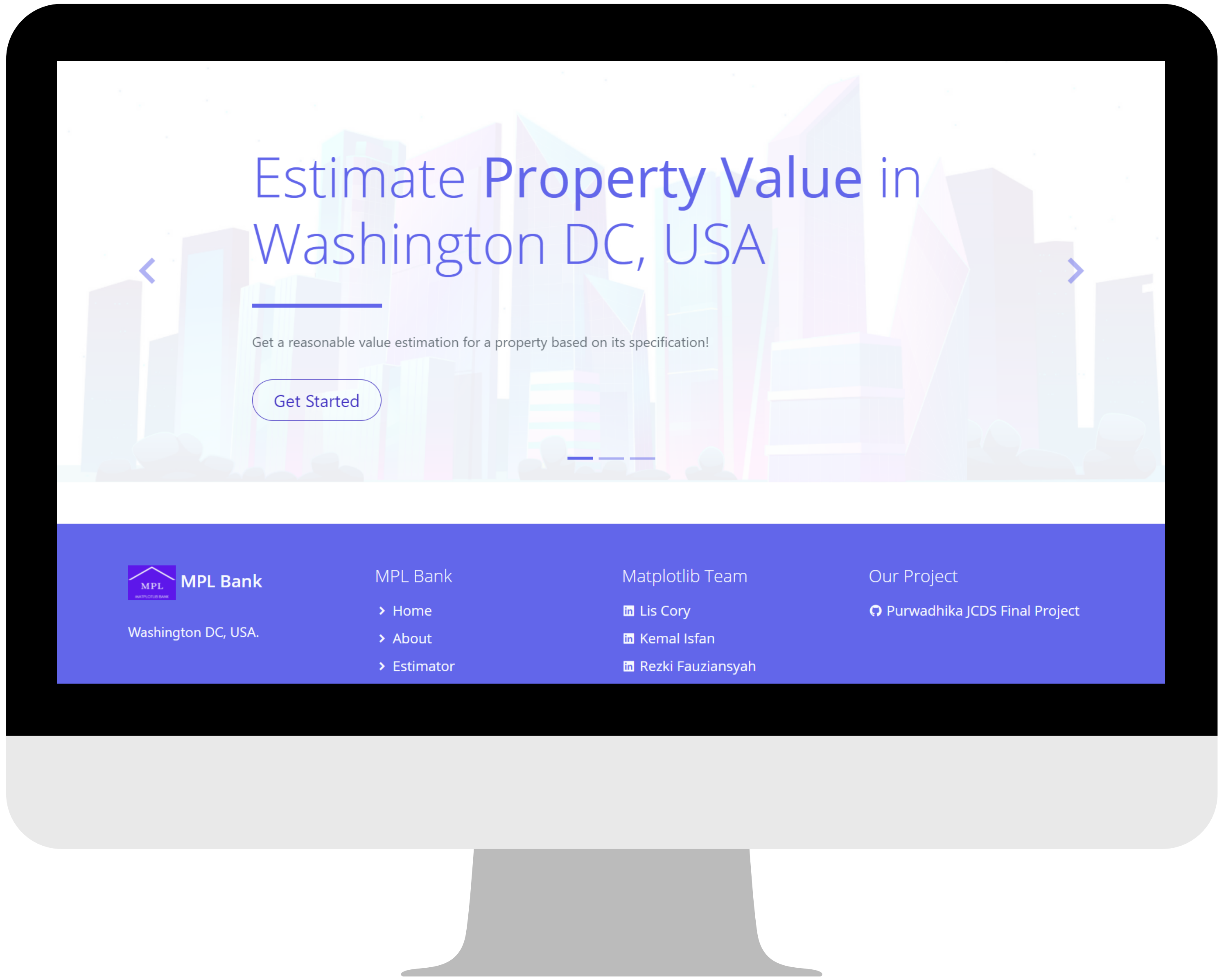
Feature Importances



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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Our Project
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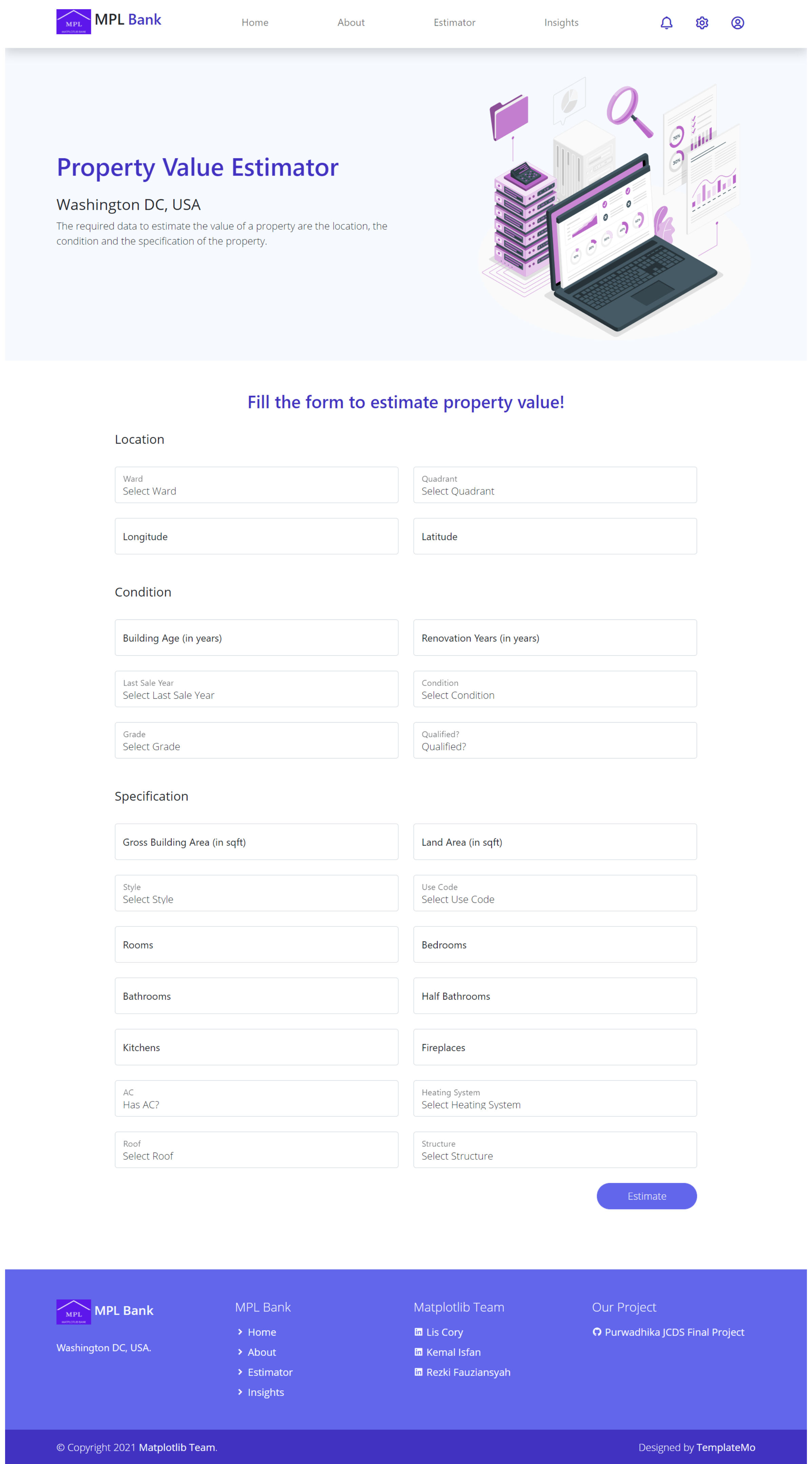

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Property Value Estimator
Washington DC, USA
The required data to estimate the value of a property are the location, the condition and the specification of the property.
Fill the form to estimate property value!
Location
Ward
Select Ward
Quadrant
Select 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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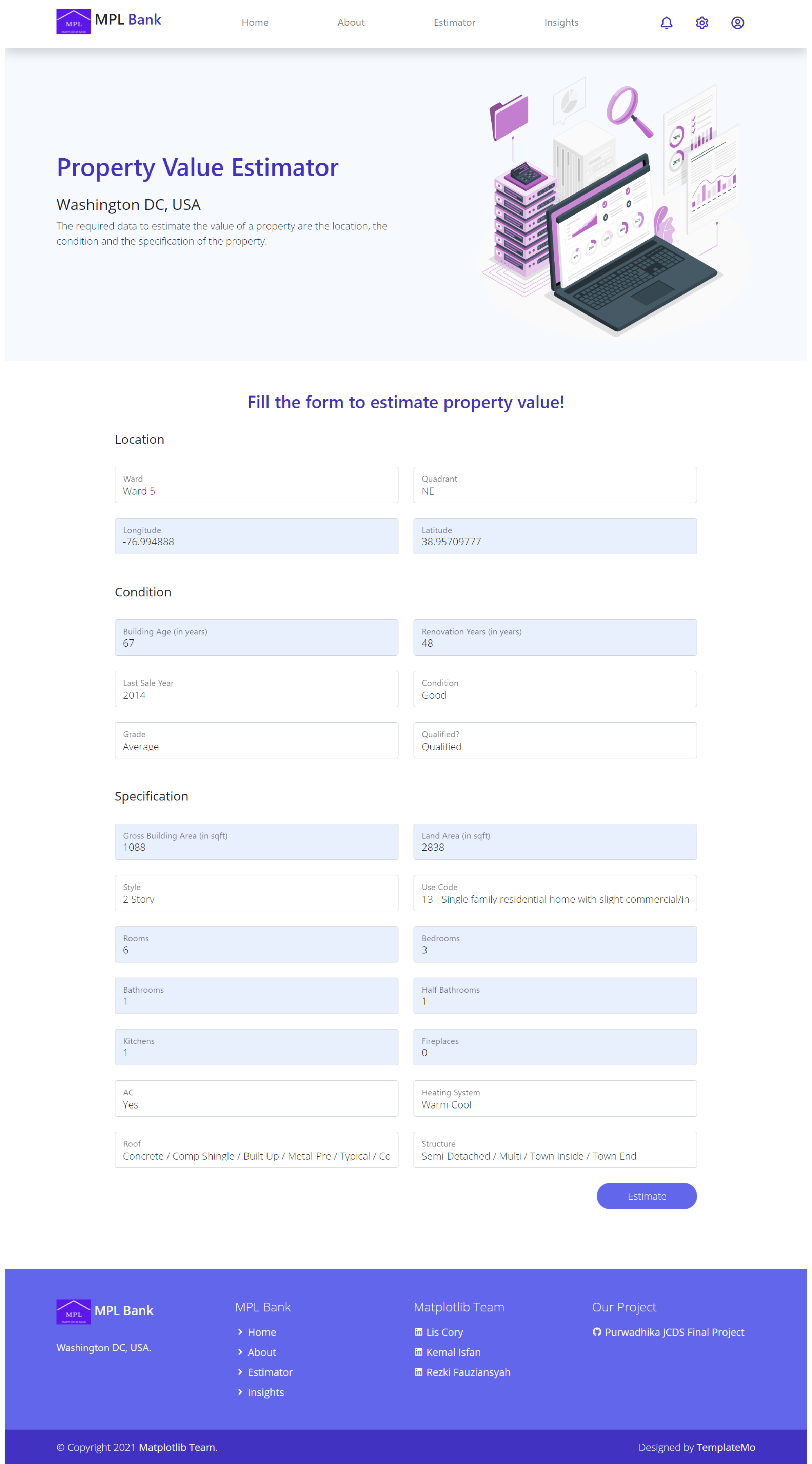

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Property Value Estimator
Washington DC, USA
The required data to estimate the value of a property are the location, the condition and the specification of the property.
Fill the form to estimate property value!
Location
Ward
Ward 5
Quadrant
NE
Longitude
-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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Home
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The estimated property value is
$338,796.12
Property Information
Value Estimation
Estimated Price : $338,796.12
Estimated Error (Mean Absolute Error) : ± $46,975.77
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
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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
Median Price
Sale 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
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
Fair Quality
Average
Above Average
Good Quality
Very Good
Excellent
Superior
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
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.
Matplotlib Team
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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.

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 .xlsx file format.

Thank You!

MPL

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GITHUB REPOSITORY

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