

# Purwadhika

# JCDS 1202

# Final Project

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Matplotlib Team



# Hello!

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**We are Matplotlib Team**

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

# Table of Contents

- BACKGROUND & PROBLEM IDENTIFICATION
- DATA UNDERSTANDING & DATA EXPLORATION
- MODELING & EVALUATION
- DEPLOYMENT
- FUTURE WORKS

# 1. Background & Problem Identification



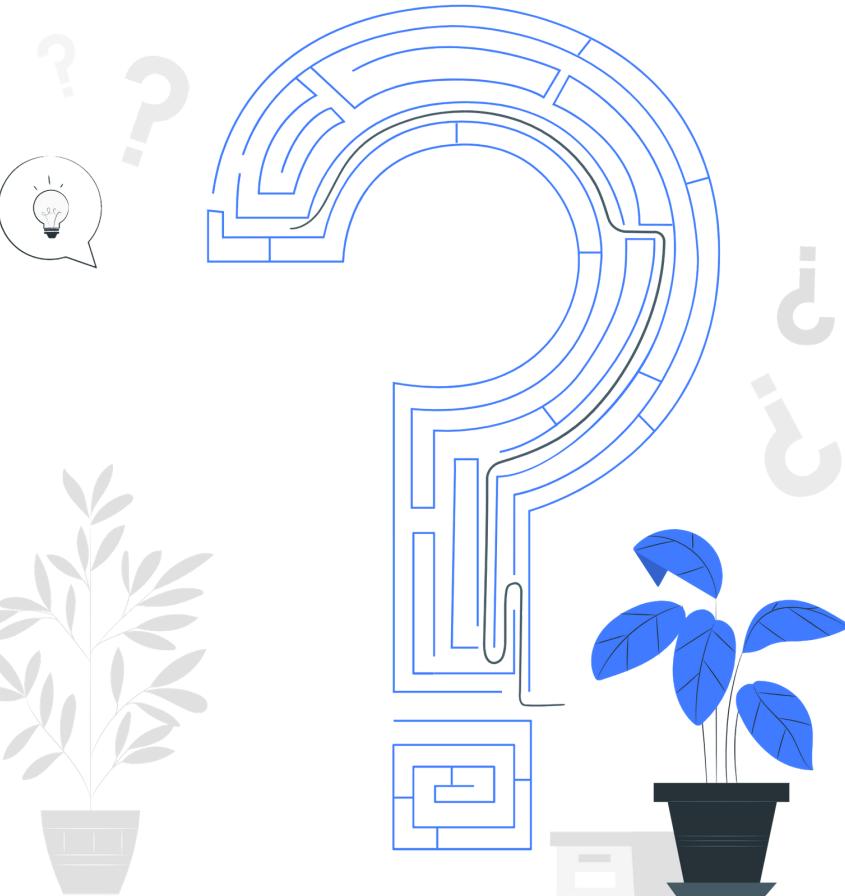
# Background

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

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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 by AMC**

**Difference between the  
Agreed Offer and the Actual  
Property Valuation**

**Improving Accuracy in  
Appraisal Evaluation Process**

# Why?



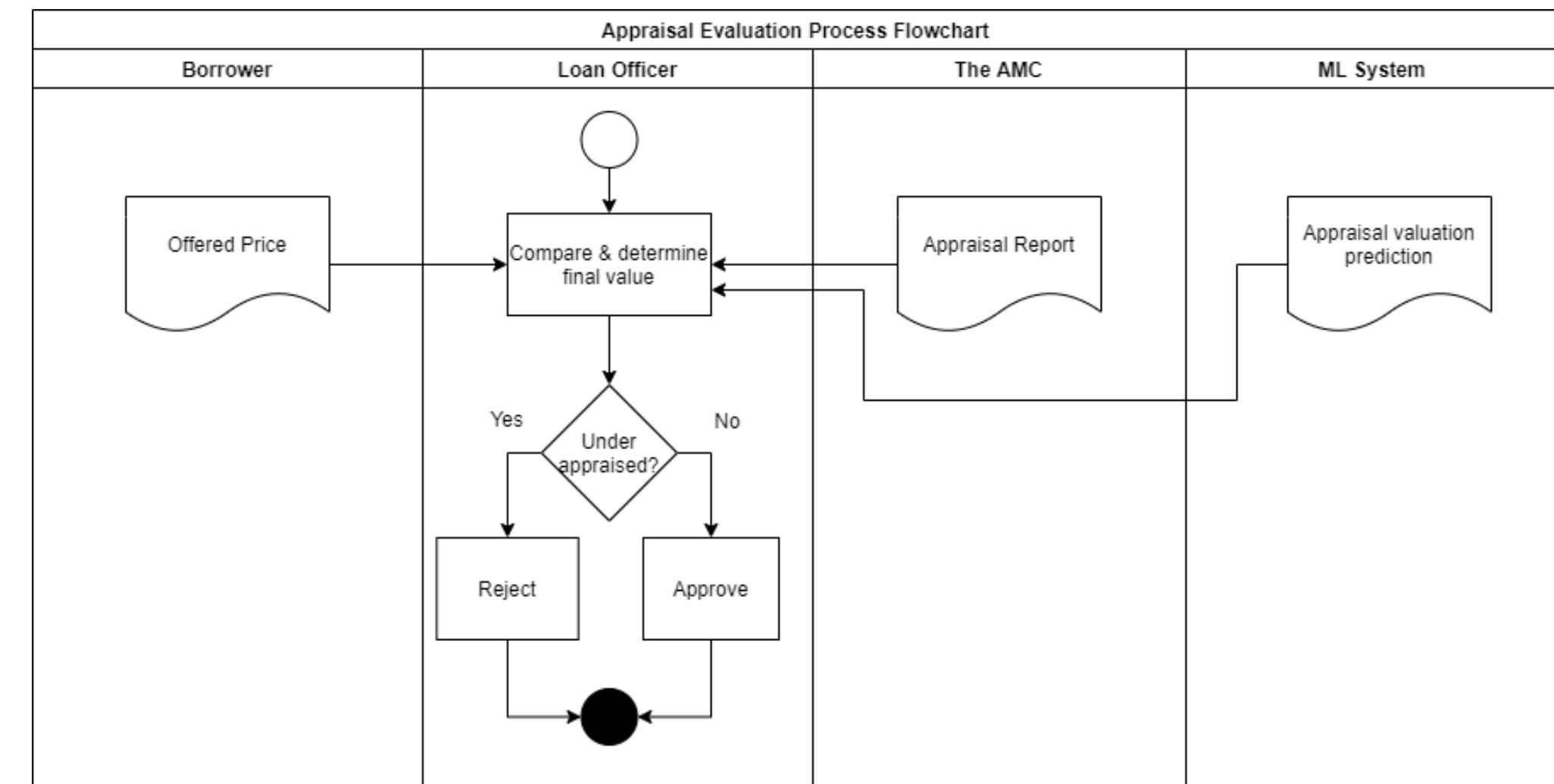
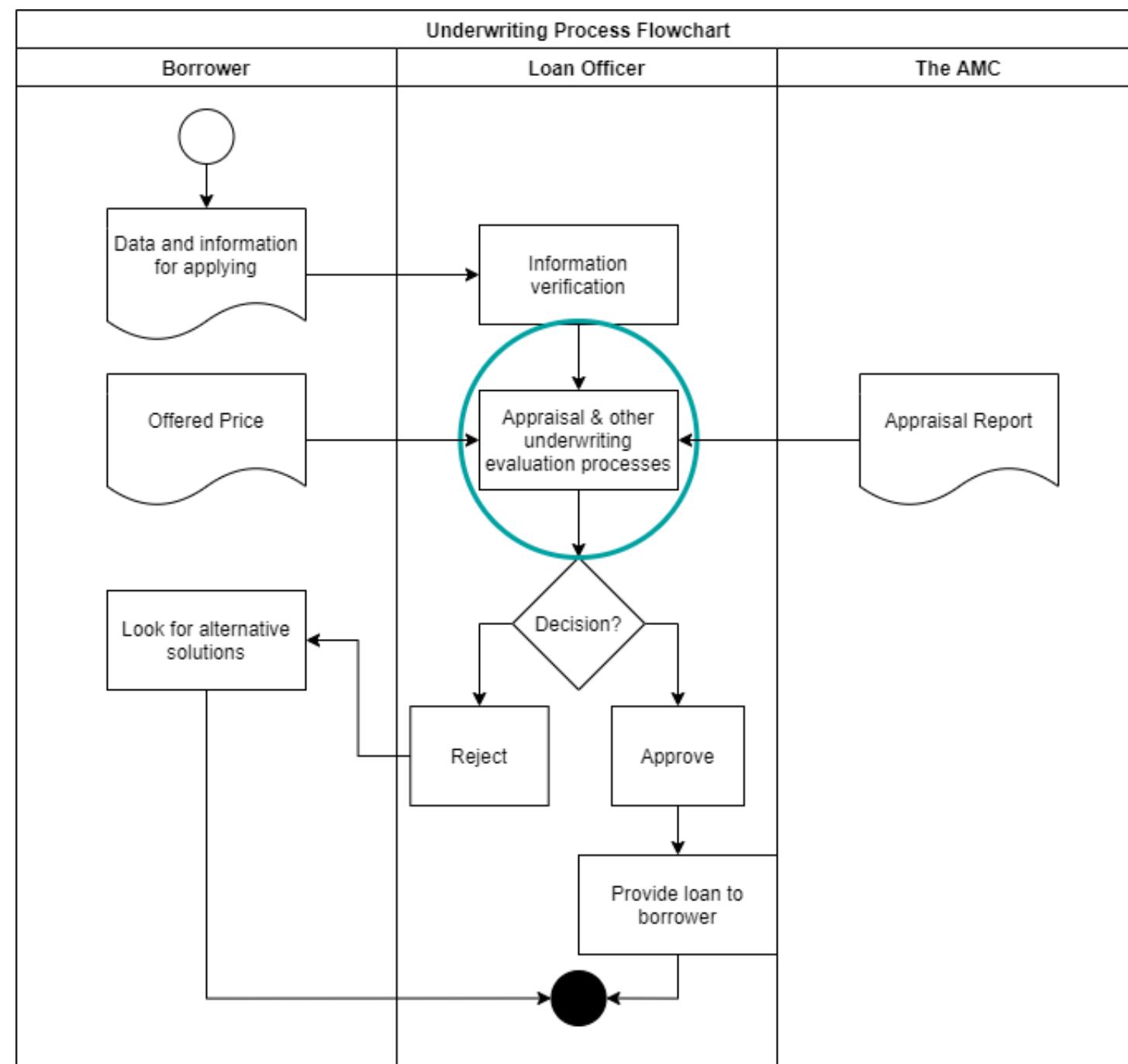
**Appraisal process directly affects company's revenue.**

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.

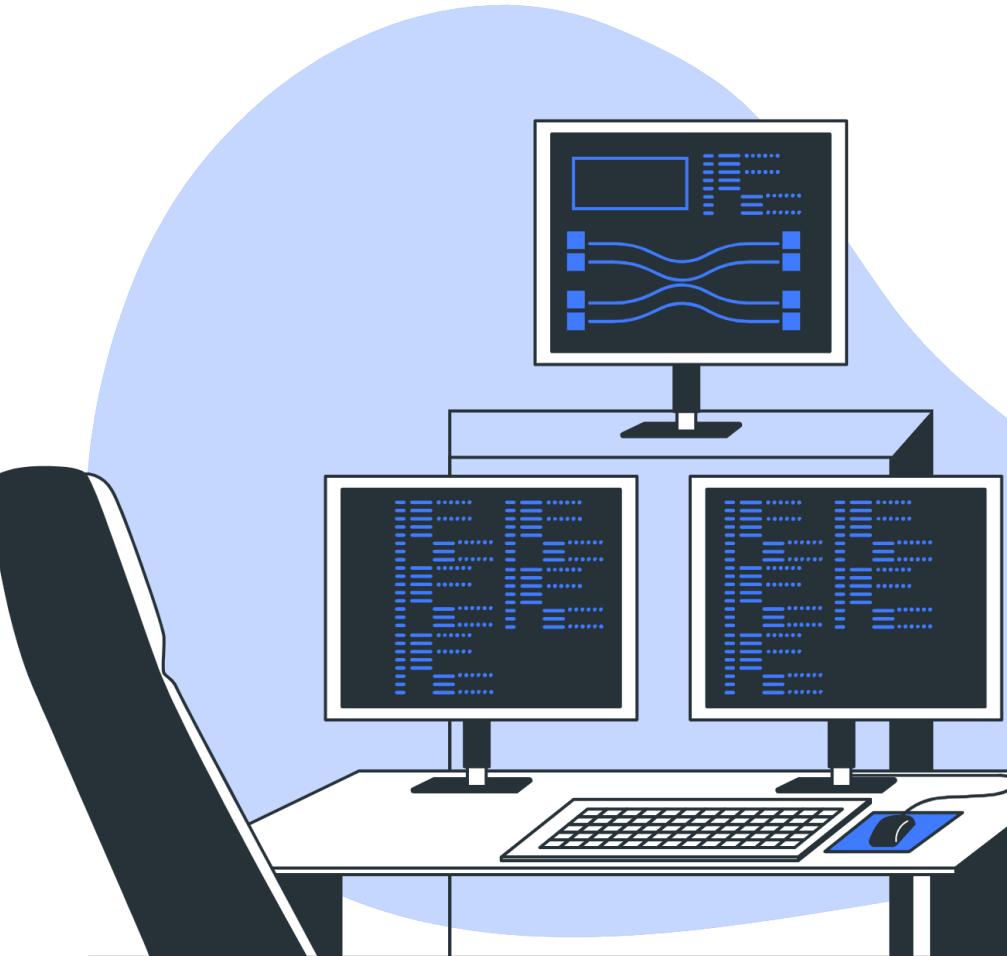
# Appraisal Evaluation Process



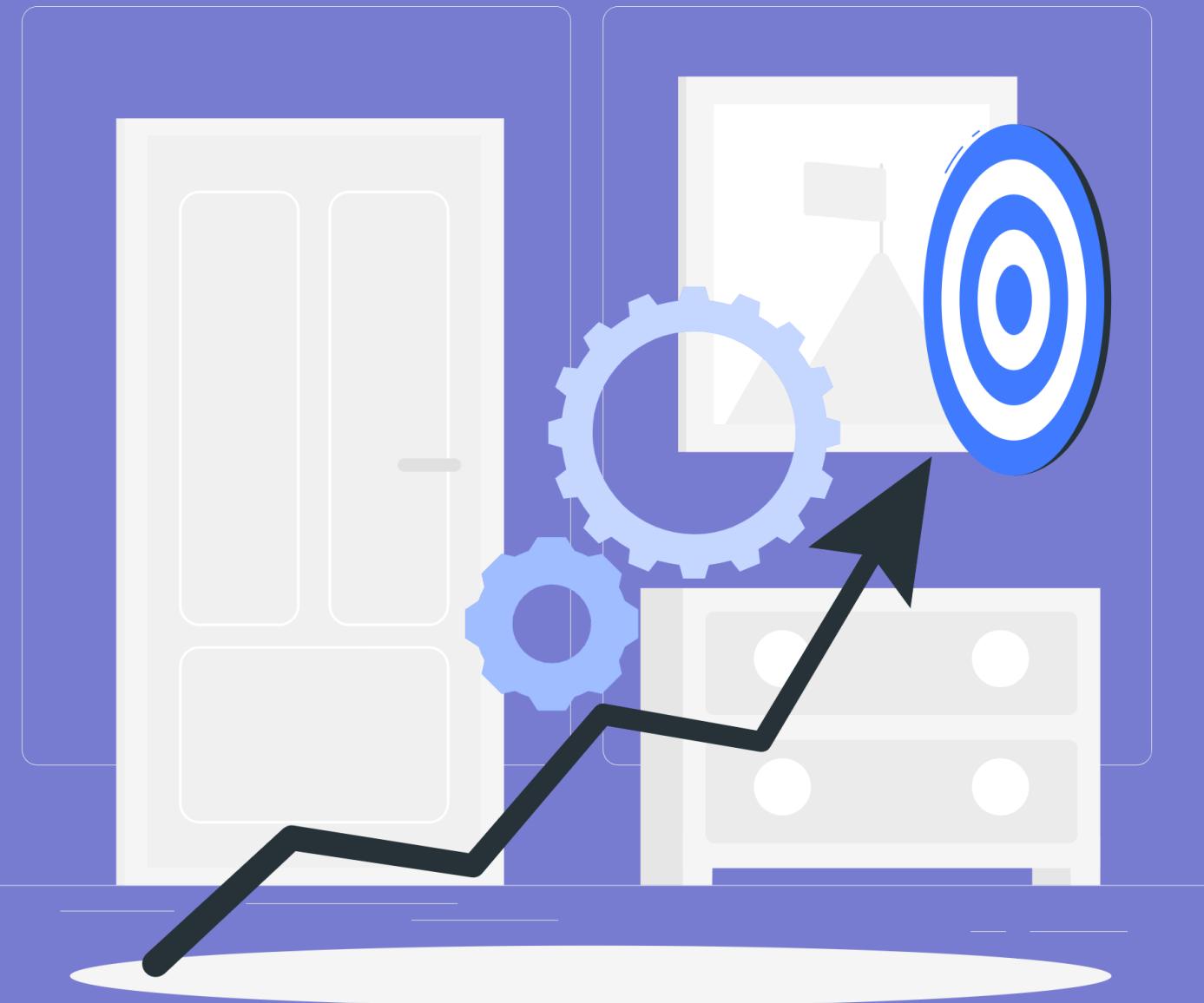
# Expected Output

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 Technique

Target : Continuous Value

Technique : 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

## 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 (in USD)

# 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

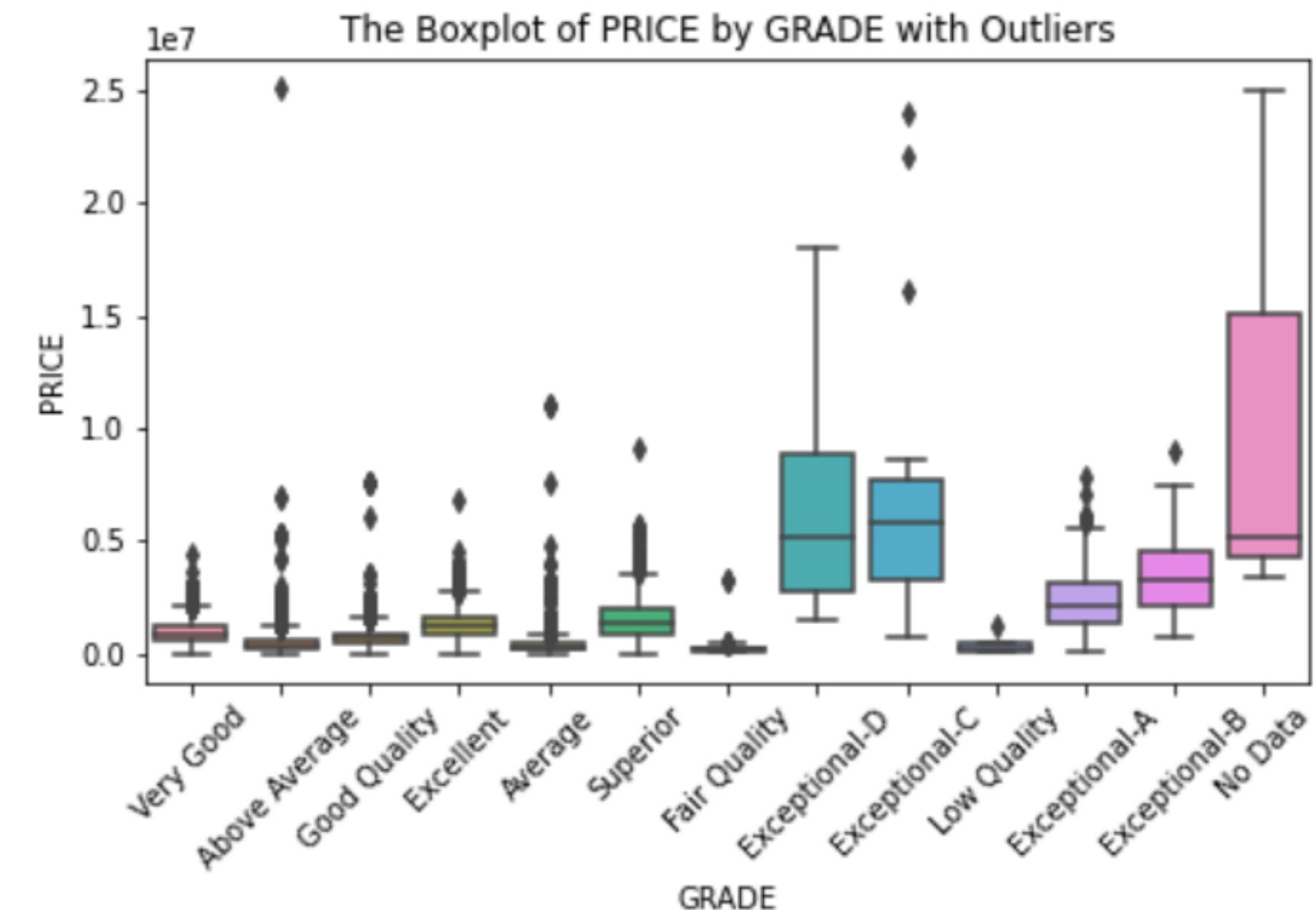
KITCHENS, PRICE, Price based on CNDTN & GRADE

## Re-classify Features

CNDTN, STRUCT, ROOF

# Exceptional Properties Exclusion

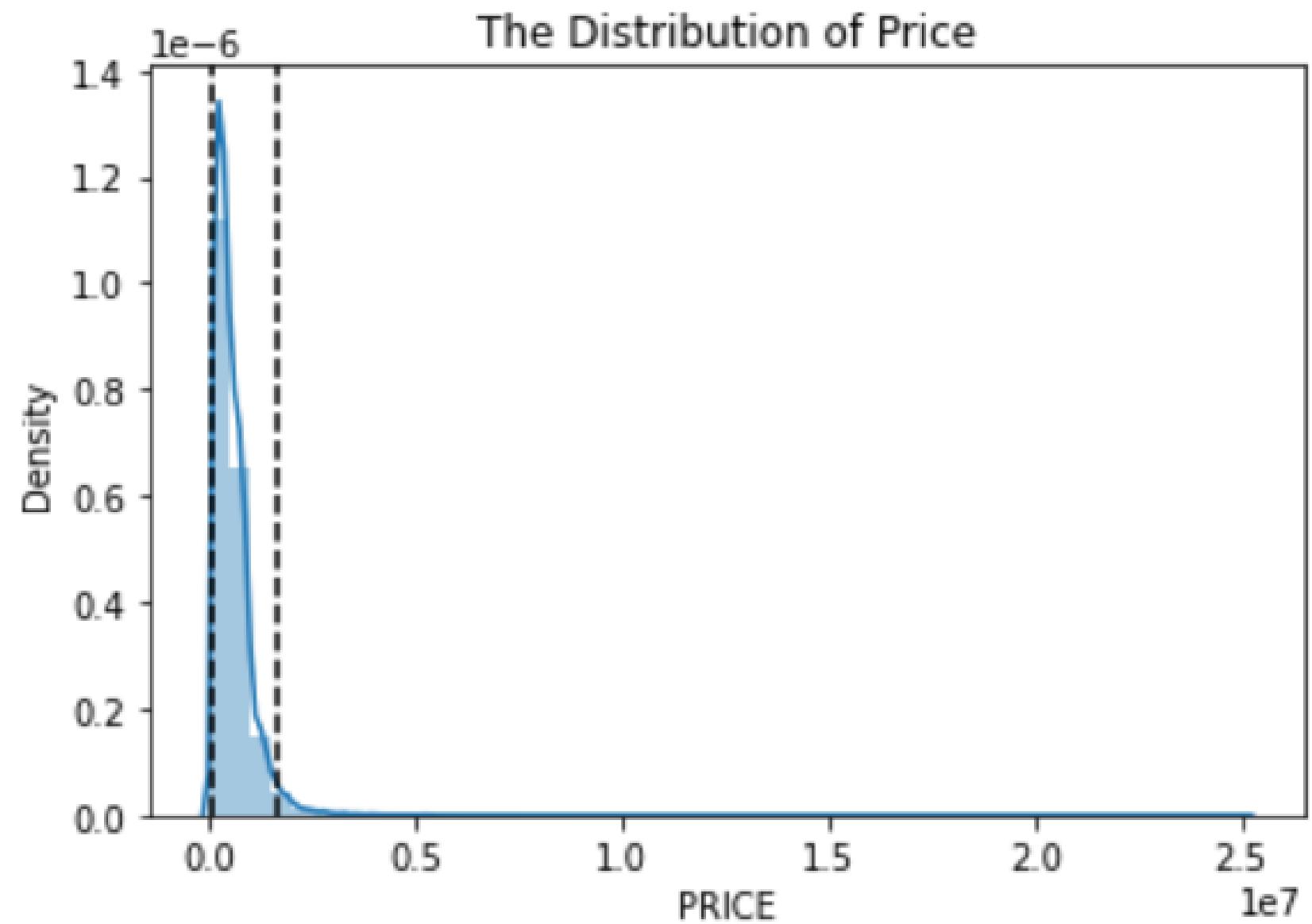
We limit the capability of our model in this project to predict an output only for properties with grade lower than Exceptional since Exceptional properties have a price range that is very different than the rest of other grades and another model needs to be built specifically for them.



# Identifying Outliers in Price

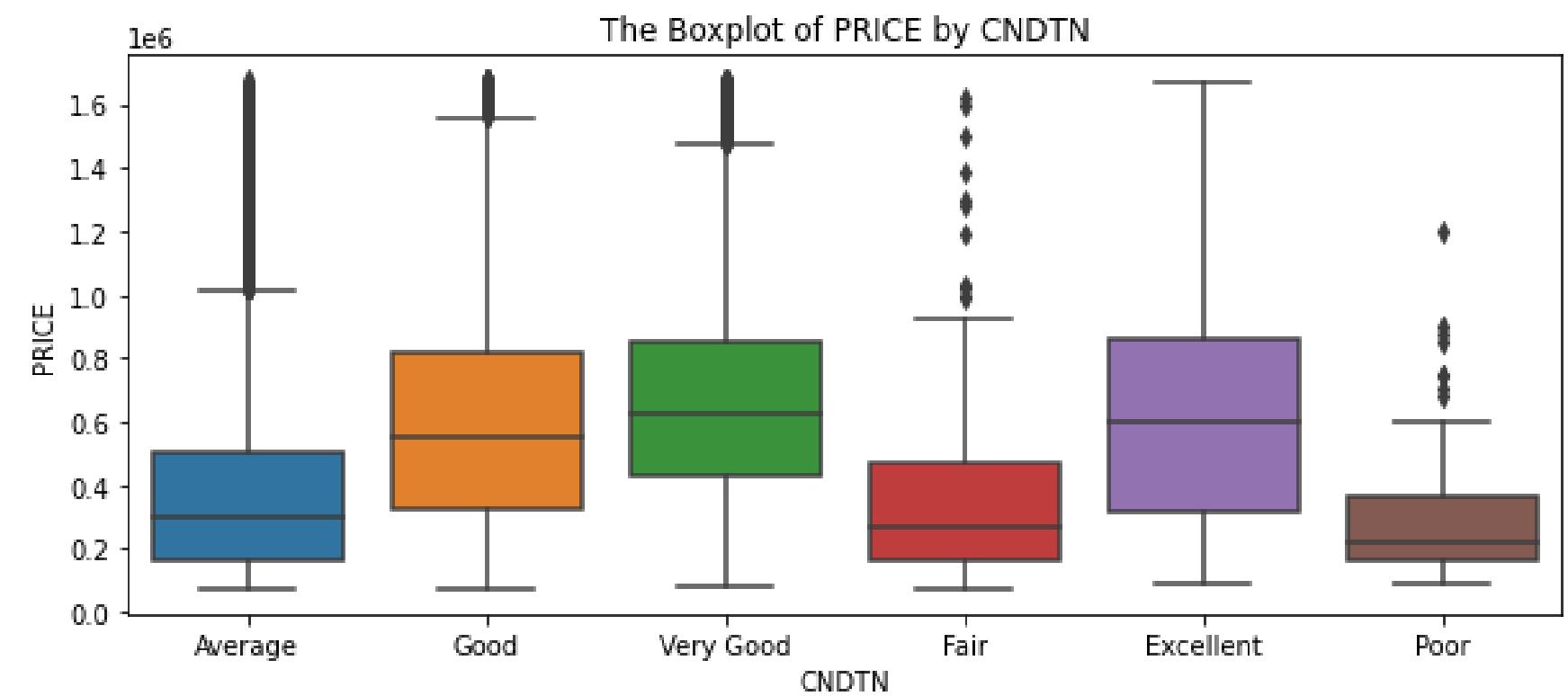
- Erroneous data with very low price (e.g., \$1.0) or extremely expensive price.
- Kaggle : "Property prices are very high in Washington DC, averaging \$647,000 in 2017."
- Drop data with  $\text{PRICE} \leq 25\text{th percentile}$  or  $\geq 97.5\text{th percentile}$  to assume 95% confidence interval.

Please note that we did not perform z-test due to the power of the distribution. Our PRICE distribution is extremely right-skewed 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., \$1.0) 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.



Median Price: \$435,000

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

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

# Re-classify STRUCT & ROOF

Median Price : \$435,000

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

- 0 : Under median
- 1 : Above median

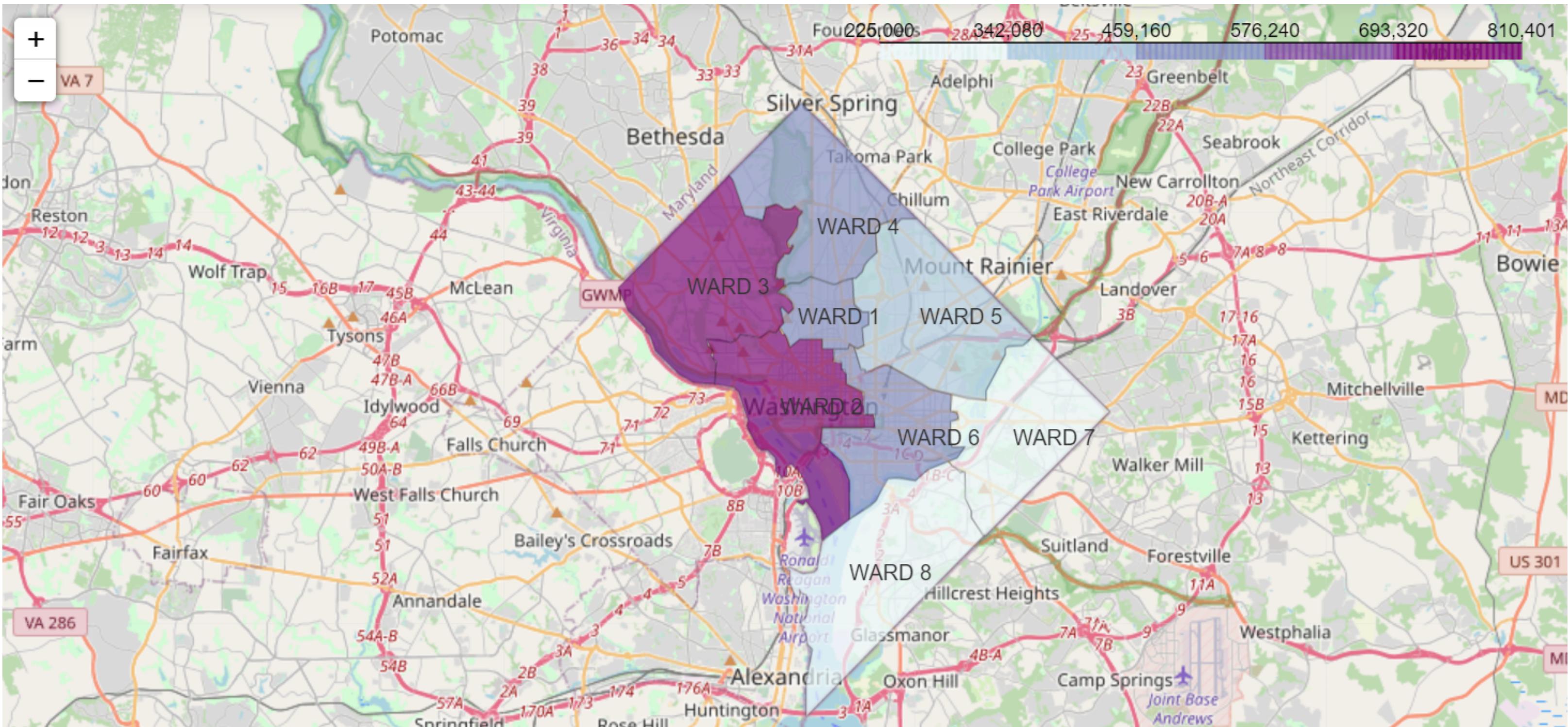
	STRUCT	median_PRICE	total
0	Semi-Detached	275000.0	6107
1	Multi	310500.0	2082
2	Town Inside	349312.5	146
3	Town End	383730.0	61
4	Row End	432090.0	5145
5	Single	489000.0	11266
6	Row Inside	490000.0	17565
7	Default	625000.0	3

	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

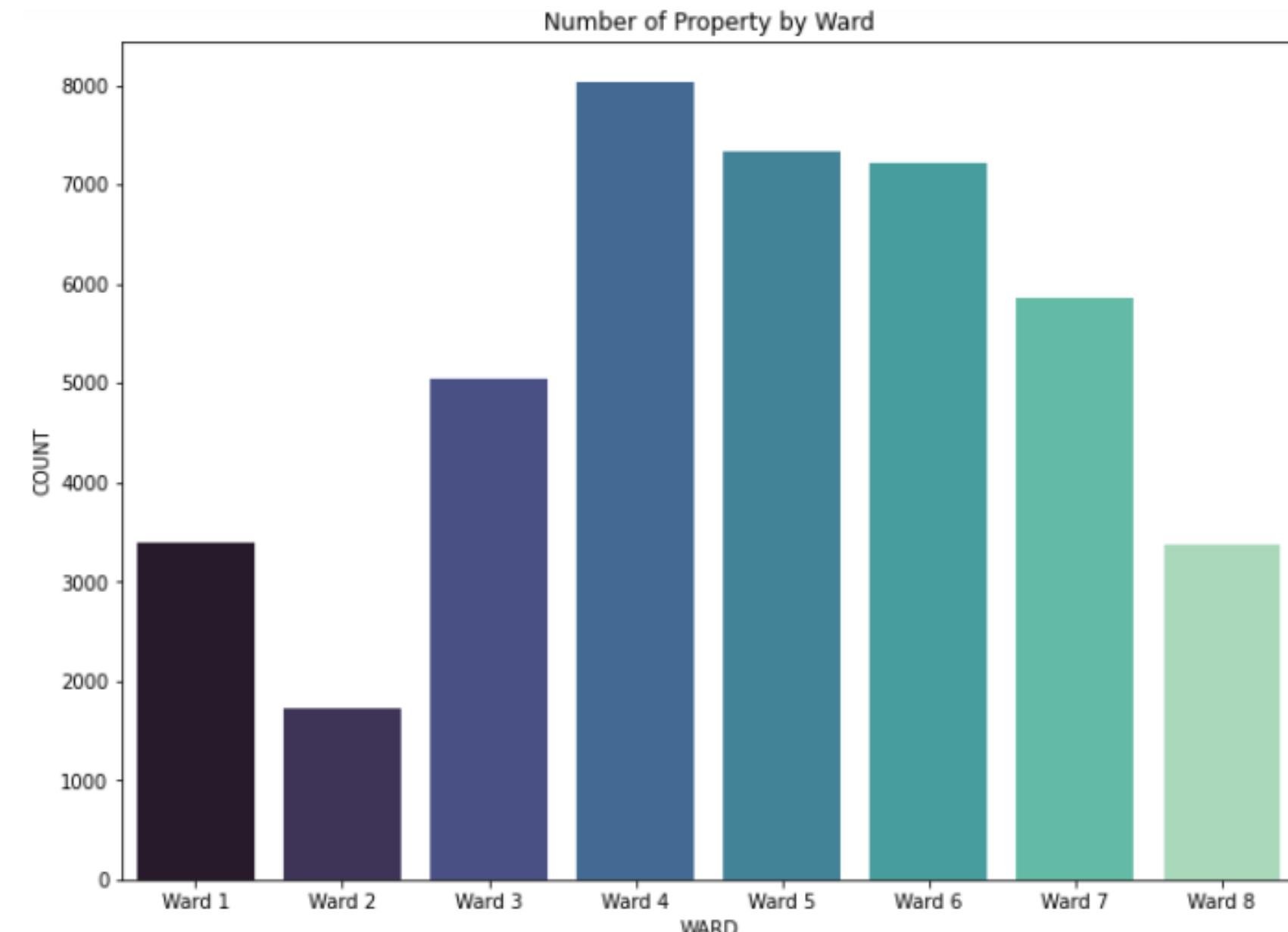
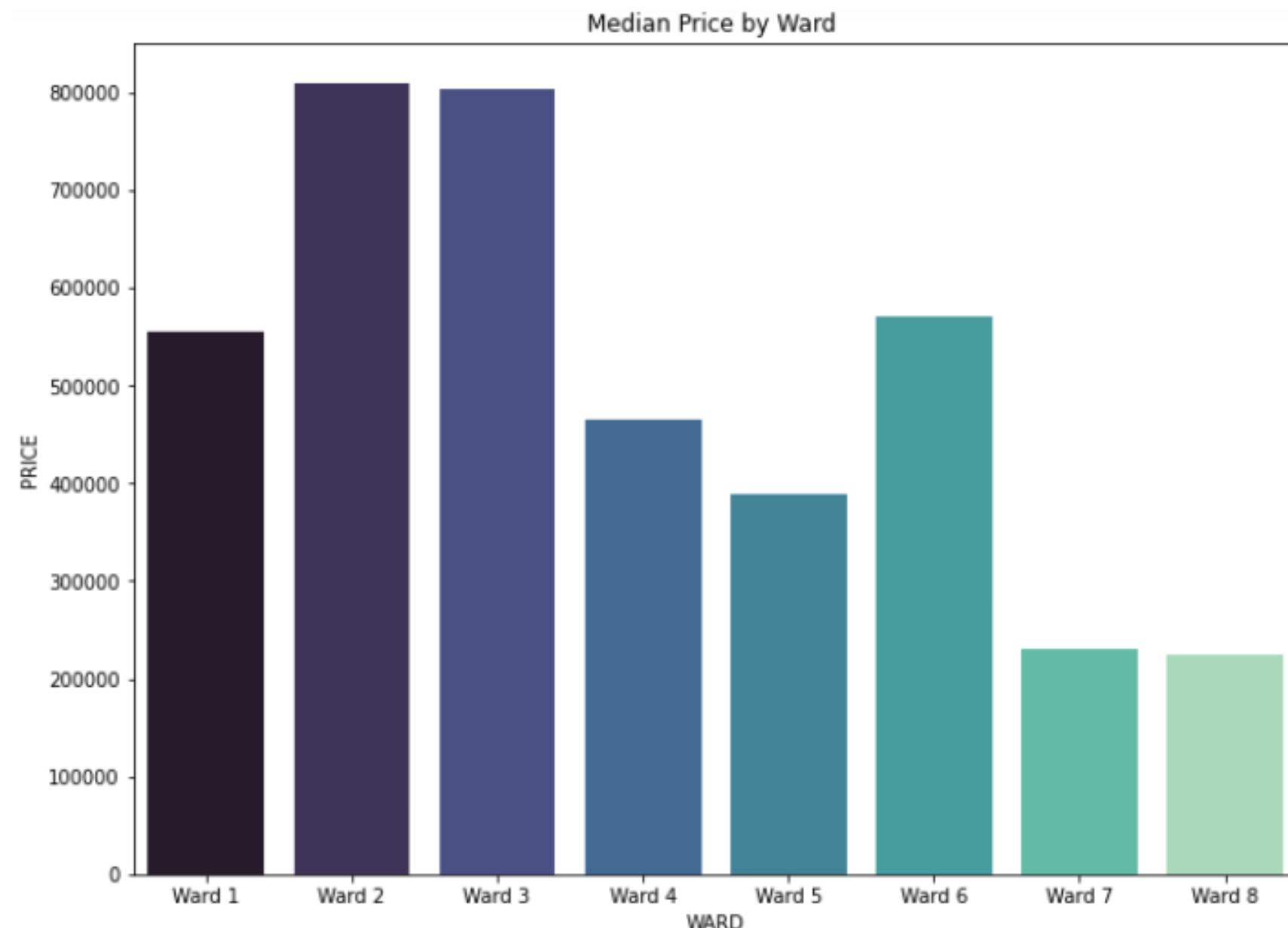
# Insights

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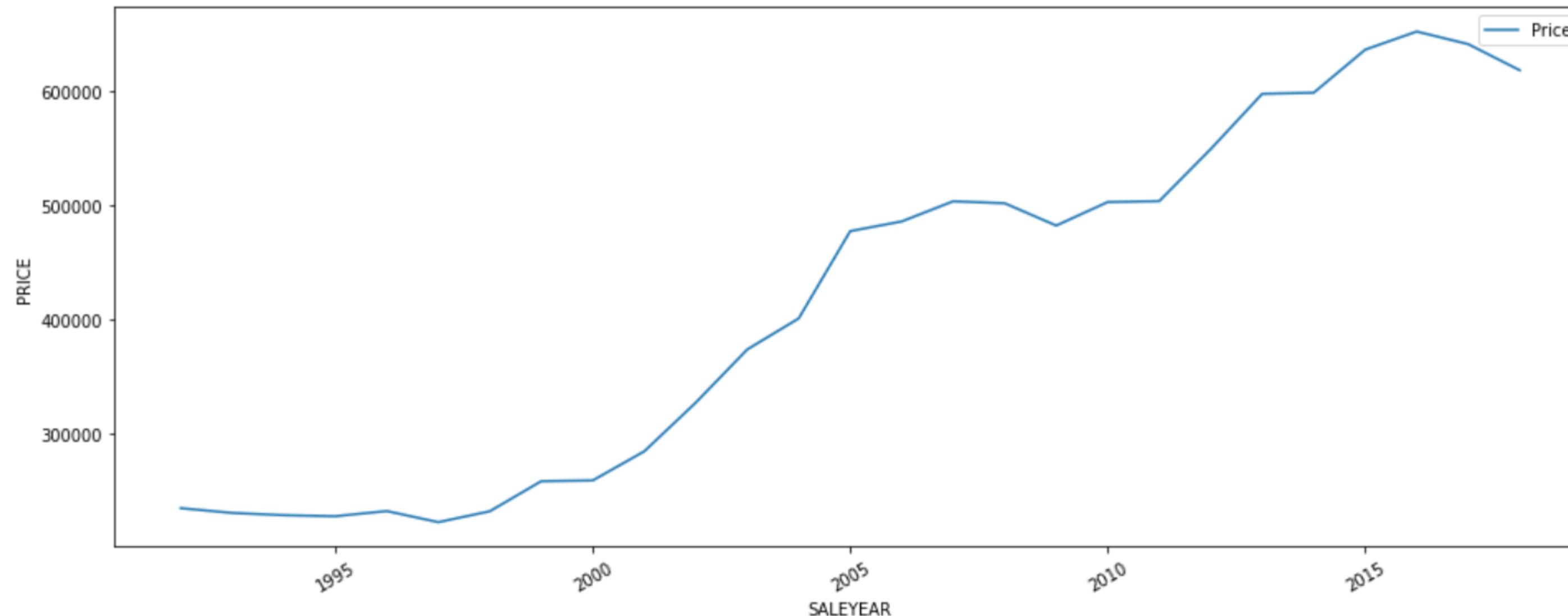
# Map by Ward



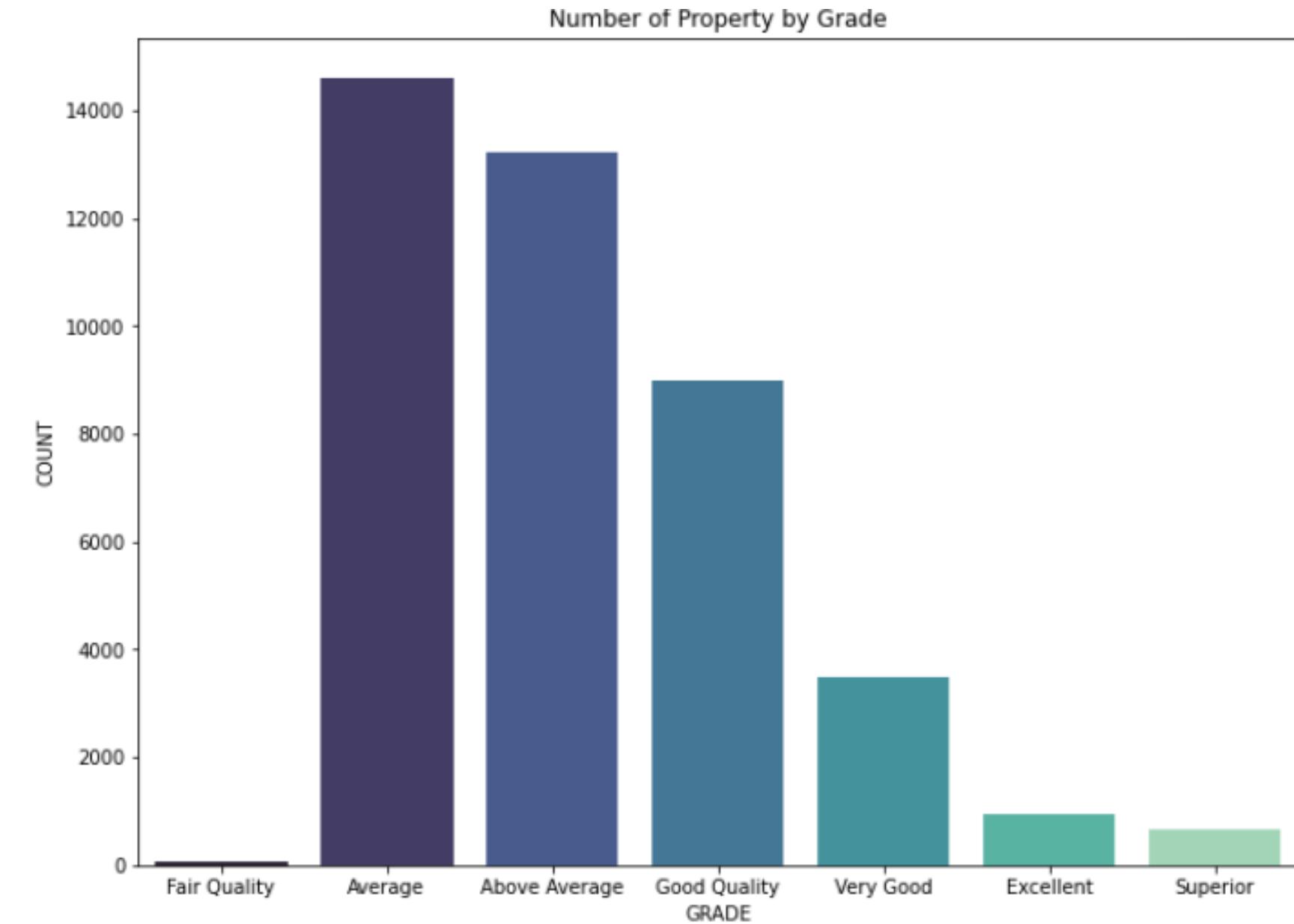
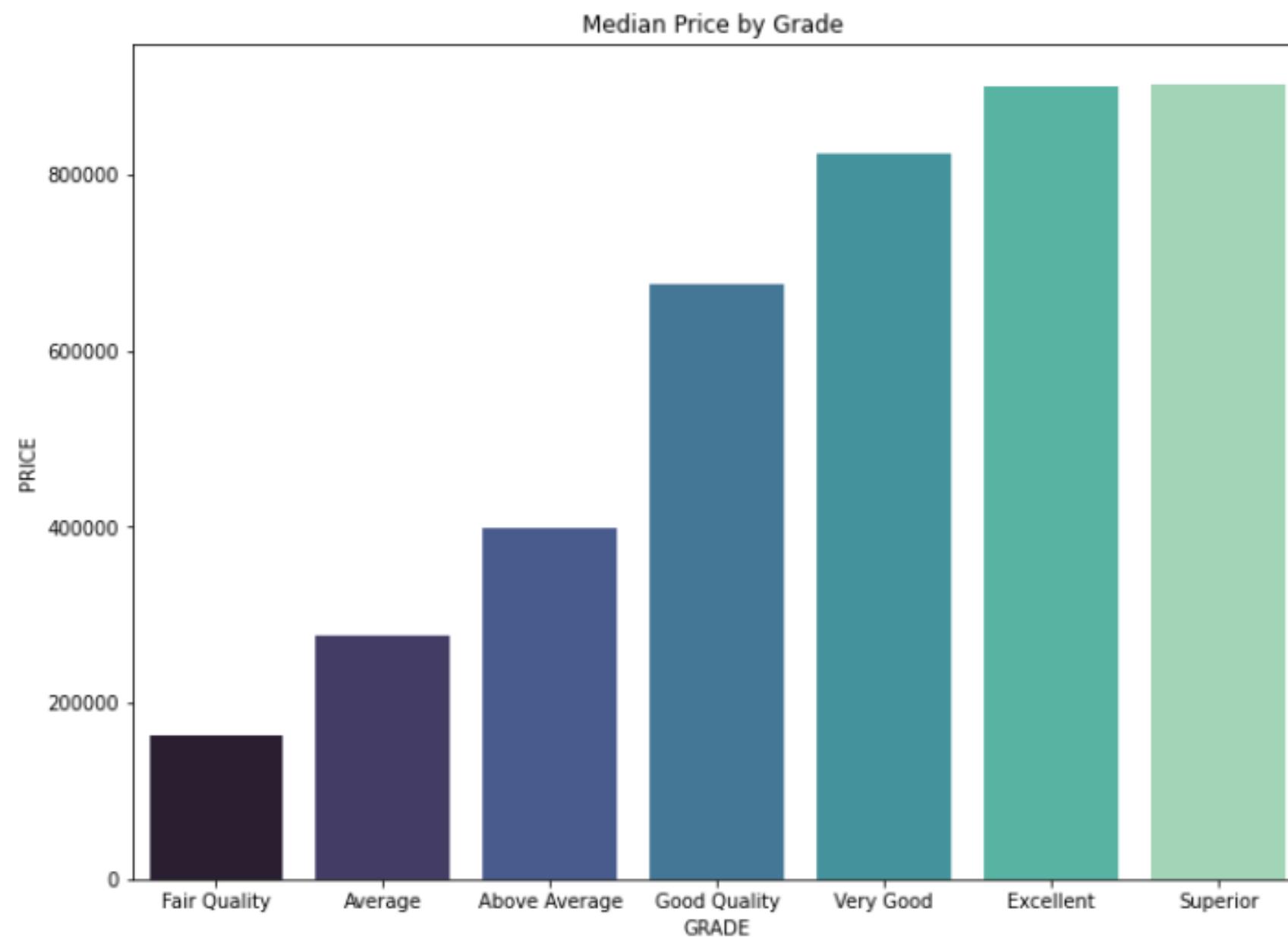
# Median Price & Number of Property by Ward



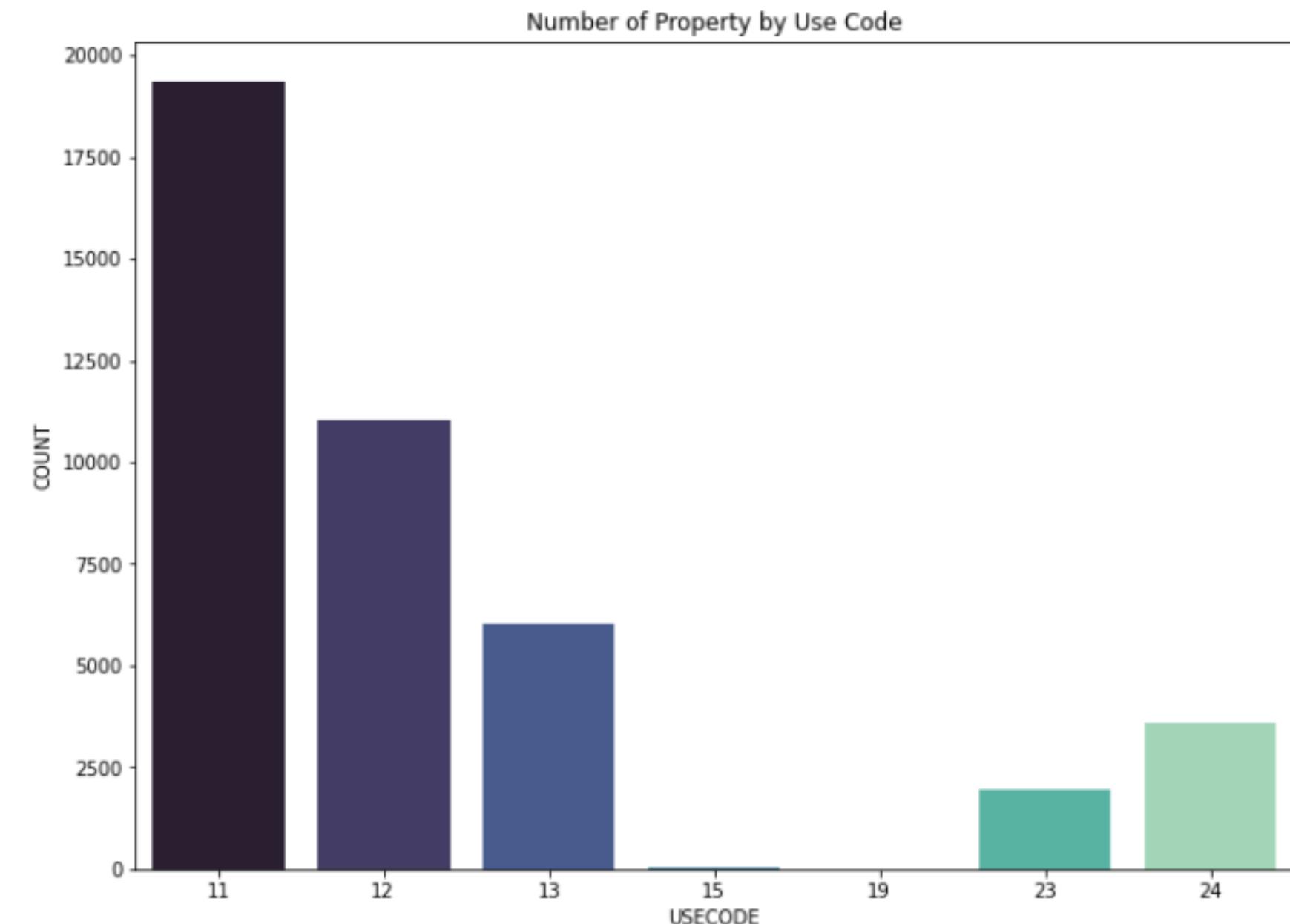
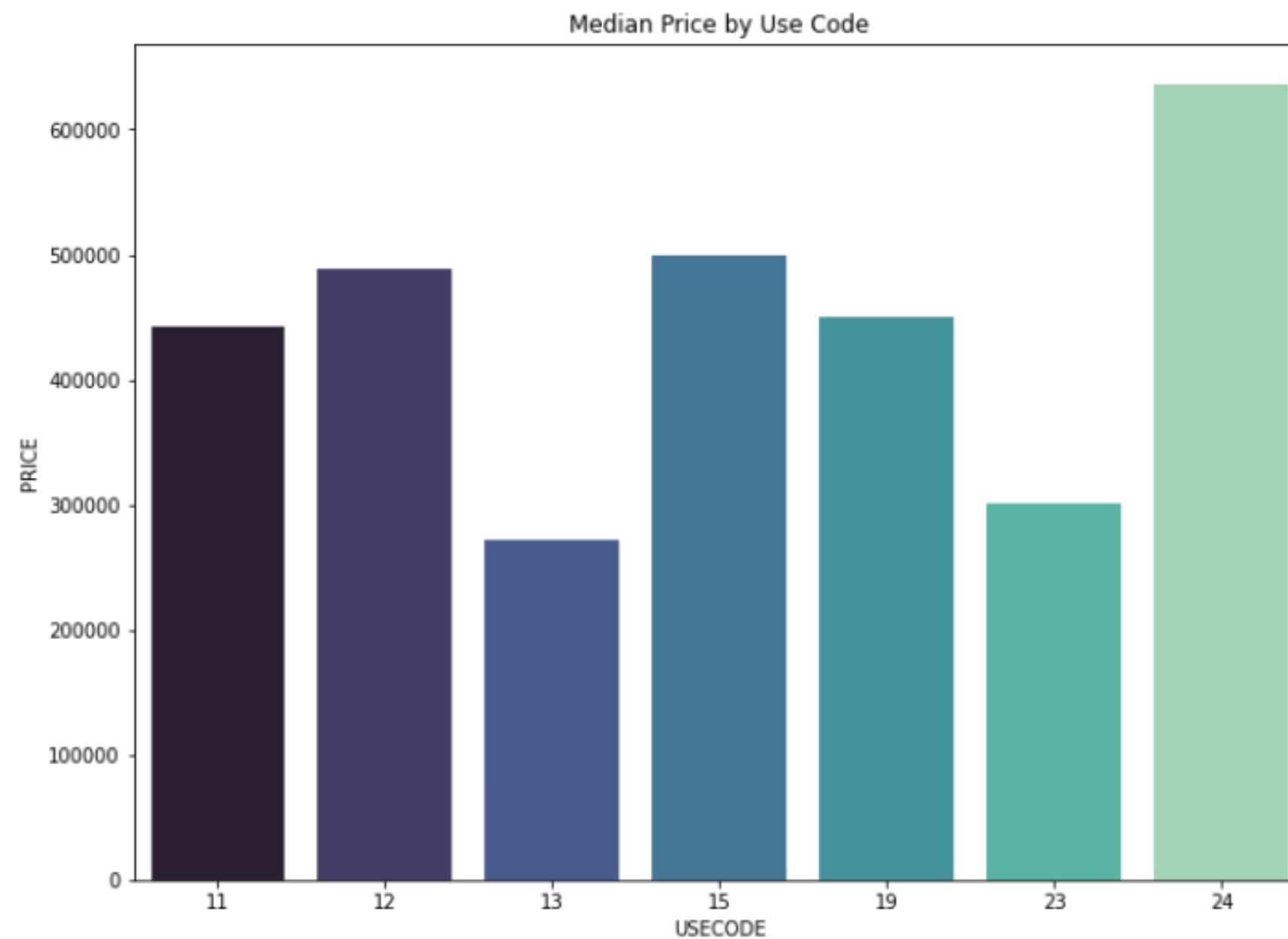
# Median Sale Price per Year



# 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 regression models

- Hyperparameter tuning with GridSearchCV to get best parameters of the best model

We choose the best model based on the  $R^2$  score, Mean Absolute Error (MAE) and resource efficiency.

# Model Assessment

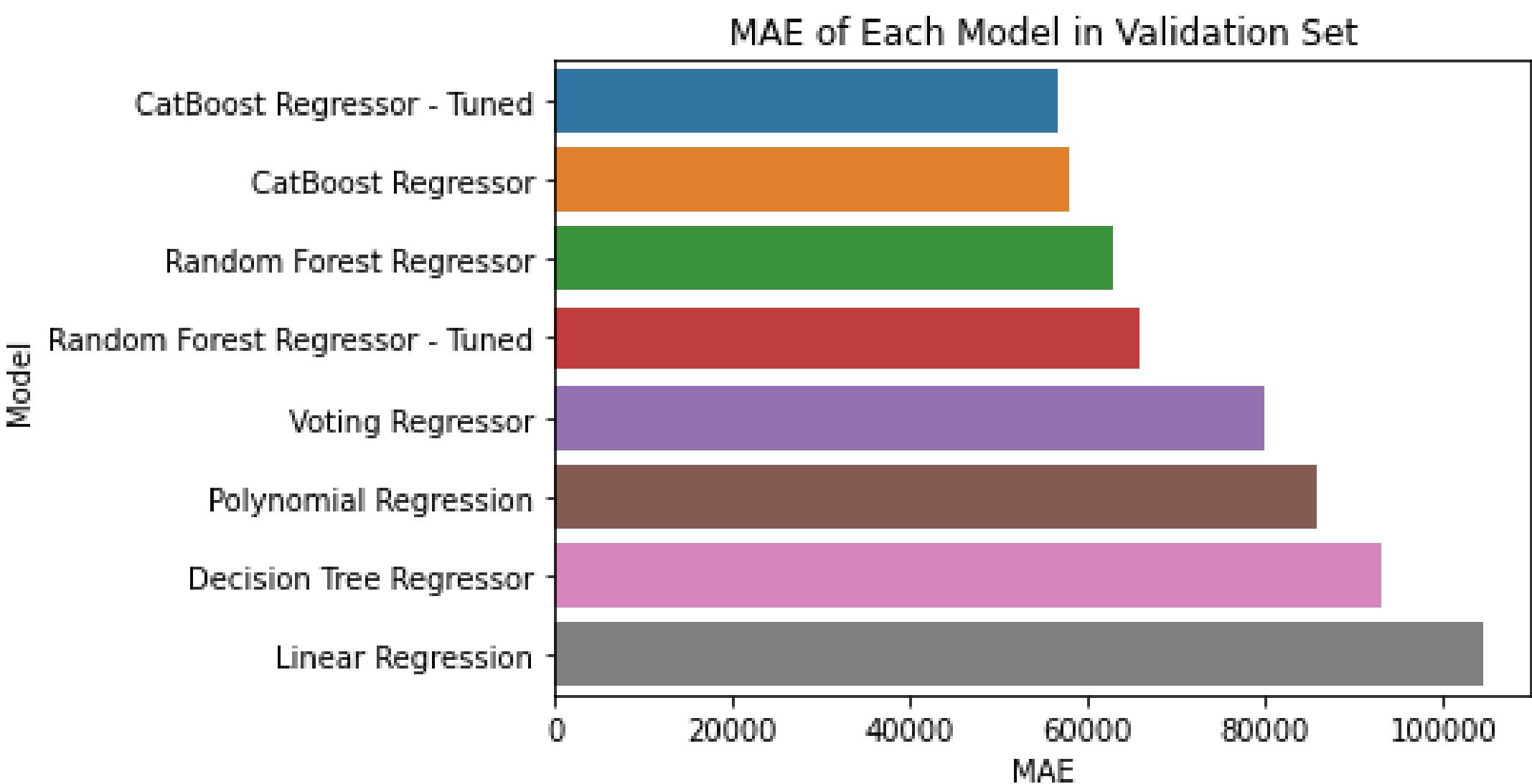
CatBoost Regressor - Tuned has the best R<sup>2</sup> score and the lowest MAE in the validation set.

	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 reducing the MAE by 46% 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

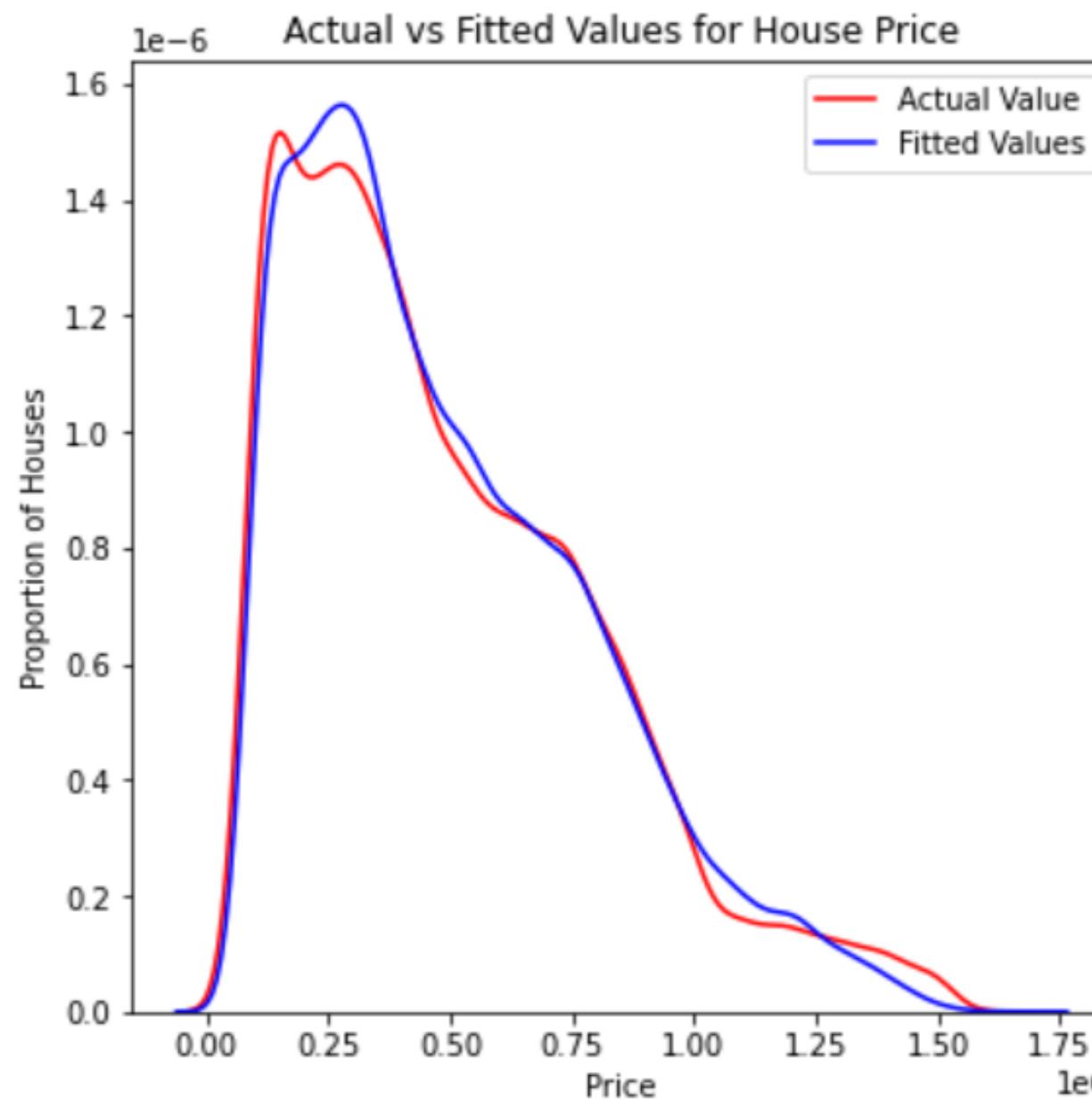
Desired MAE (12% x Median) : 50756.4

Achieved MAE : 46975.76563974304

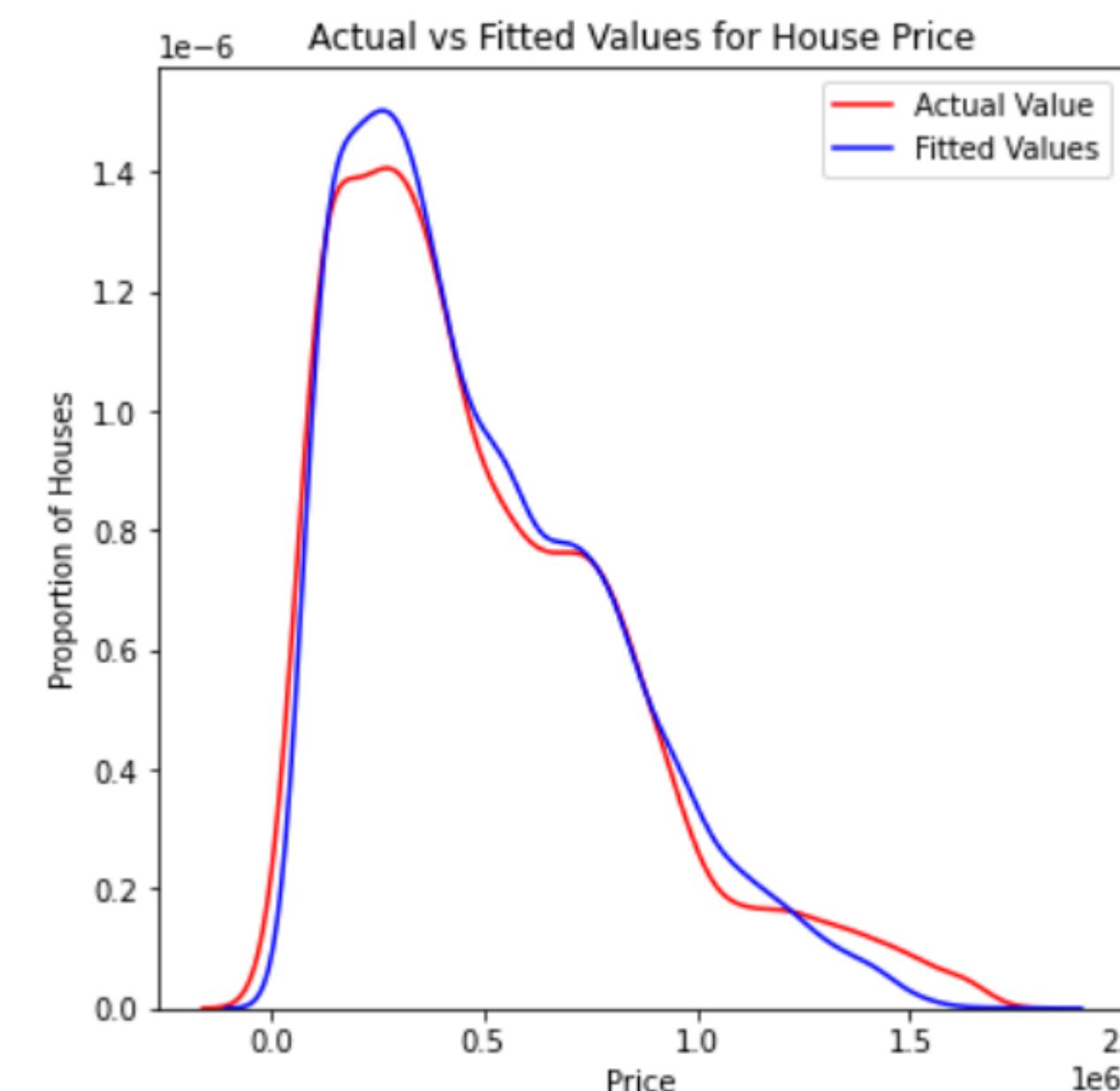
From the result shown above, we have achieved the desired MAE value (under \$50,756.4).

# Distribution Plot of Actual vs Fitted Values

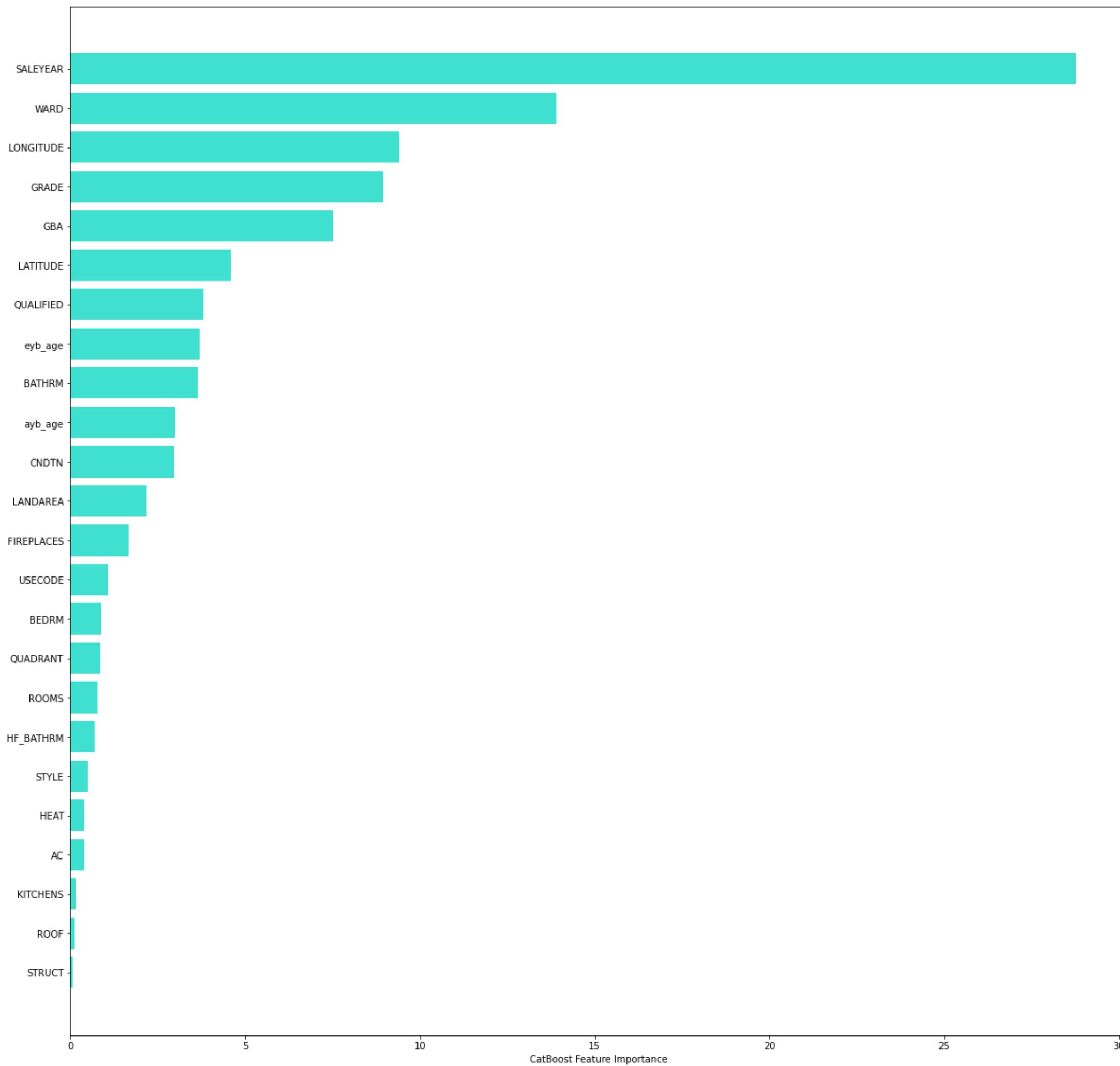
Train Set



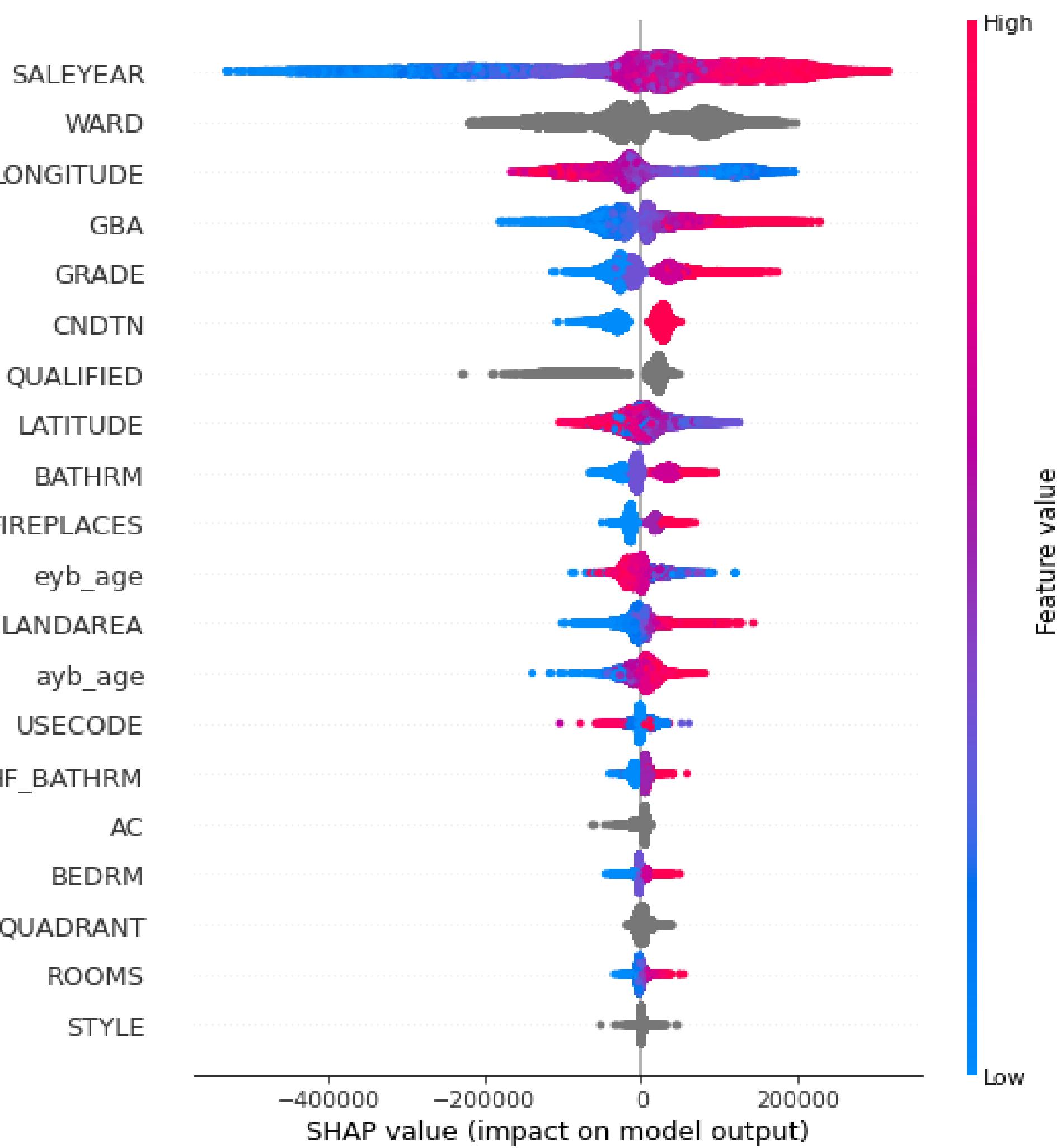
Test Set



# Feature Importances



# Feature Importances with SHAP



# 4. Deployment





# Deployment Page

We deployed the model to a  
webpage using FLASK.

**MPL Bank**

- Home
- About
- Estimator
- Insights
- Bell
- Gear
- Question

## 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 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

- S** To maximize profit by making the right decision to give a loan with an optimal amount.
- To 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 to make a prediction are 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, etc.

### Analytic Approach



ML Technique



Risk



Performance Measure



Action



Value

**MPL Bank**

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- Question

## 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

Estimate

**MPL Bank**

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## Property Value Estimator

Washington DC, USA

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Matplotlib Team

- Lis Cory
- Kemal Isfan
- Rezki Fauziansyah

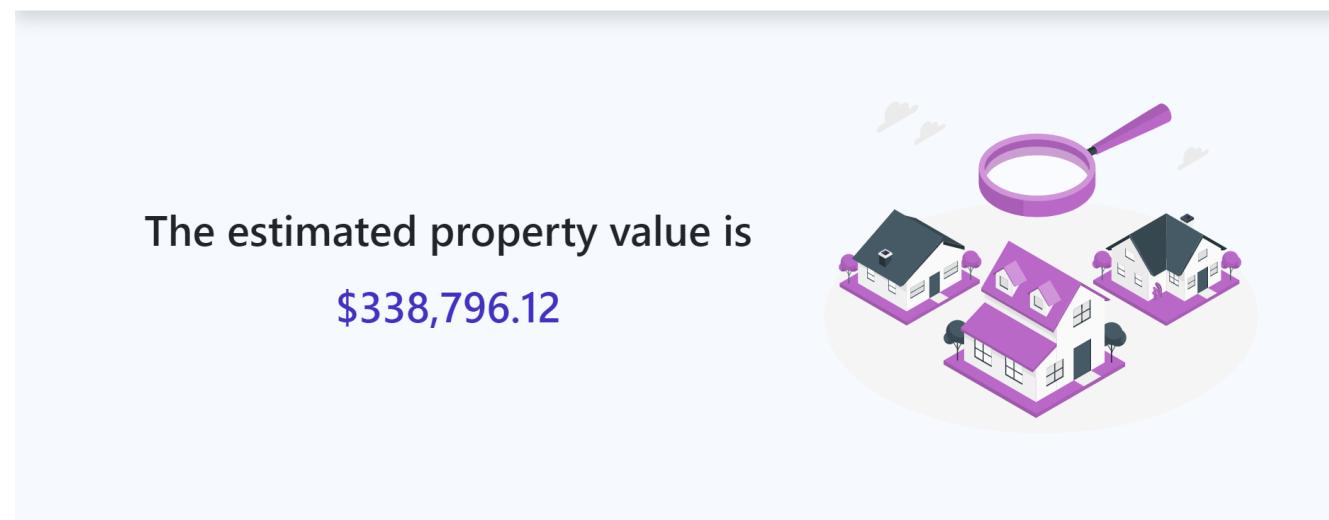
Our Project

- Purwadhika JCDS Final Project

Washington DC, USA.

Designed by TemplateMo

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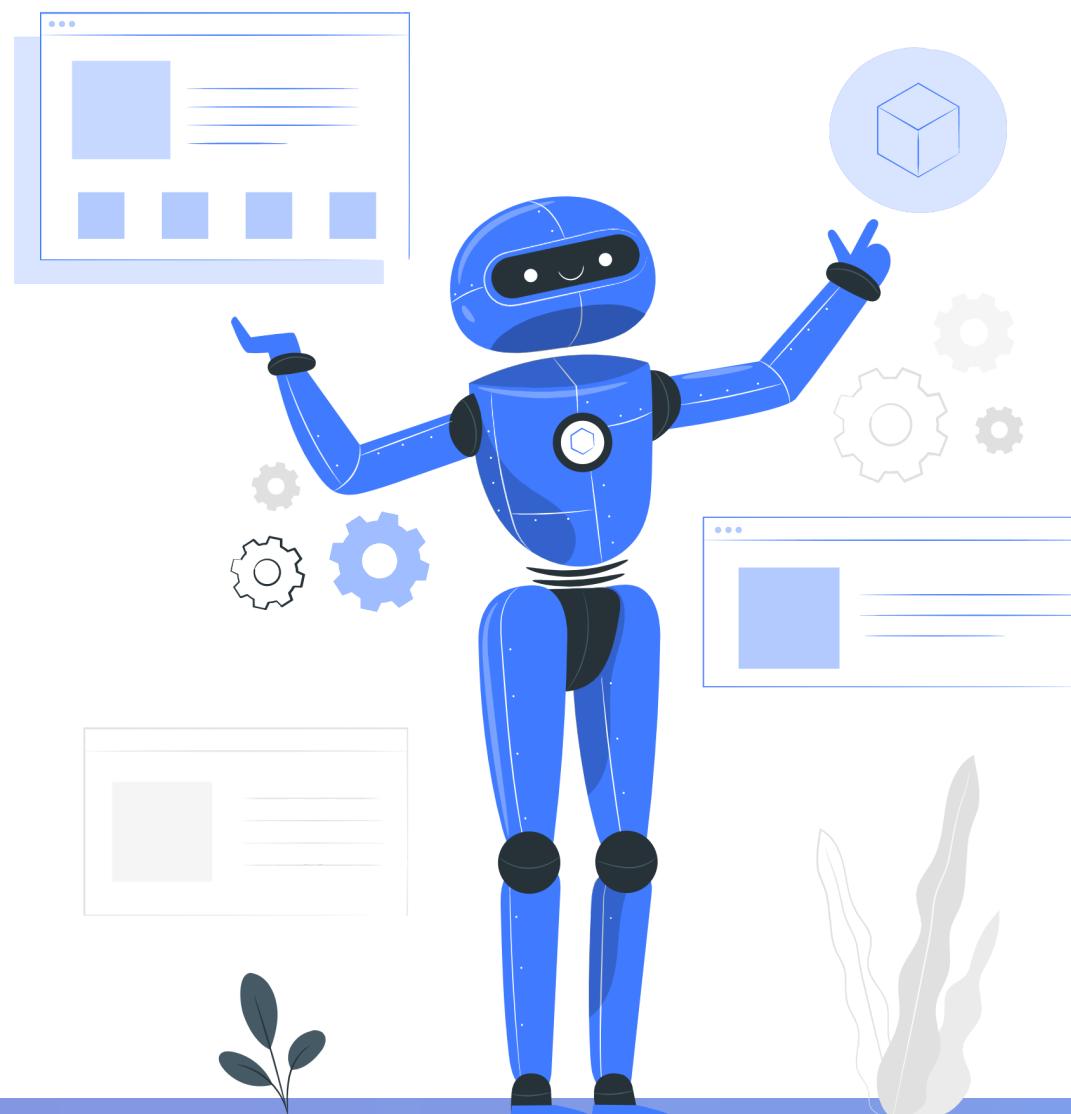


# 5. Future Works



# 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.

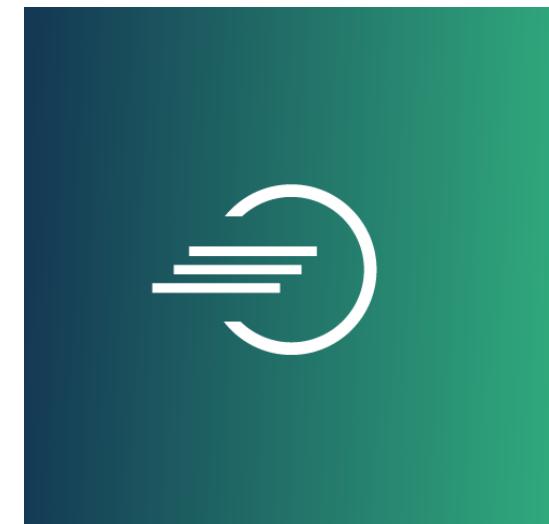
Additionally, for the ease of usage for the business users, we would recommend to add a feature in the application which allows users to input more data instantaneously in a .csv or .xlsx file format.



# Thank You!

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**PURWADHIKA JCDS 1202**  
**MATPLOTLIB TEAM**



Lis Cory

Rezki Fauziansyah

Teuku Muhammad Kemal Isfan

**GITHUB REPOSITORY**

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

[https://github.com/PurwadhikaDev/MatplotlibGroup\\_JC\\_DS\\_12\\_FinalProject](https://github.com/PurwadhikaDev/MatplotlibGroup_JC_DS_12_FinalProject)