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.

Table of Contents

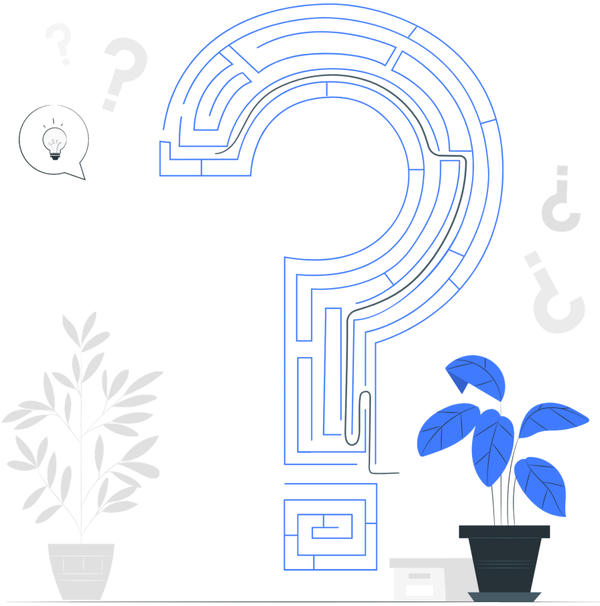
1. Background & Problem Identification

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 by AMC

Difference between the Agreed Offer and the Actual Property Valuation

Improving Accuracy in Appraisal Evaluation Process

Why?

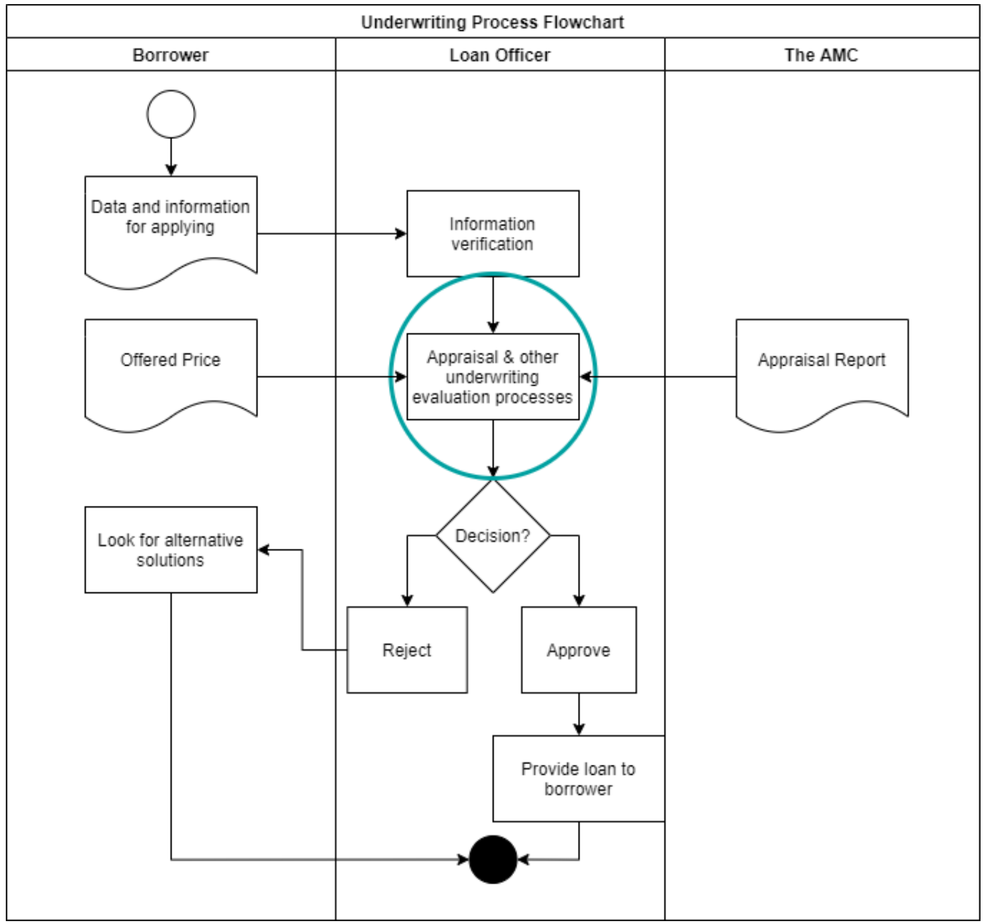
Appraisal process directly affects company’s revenue.

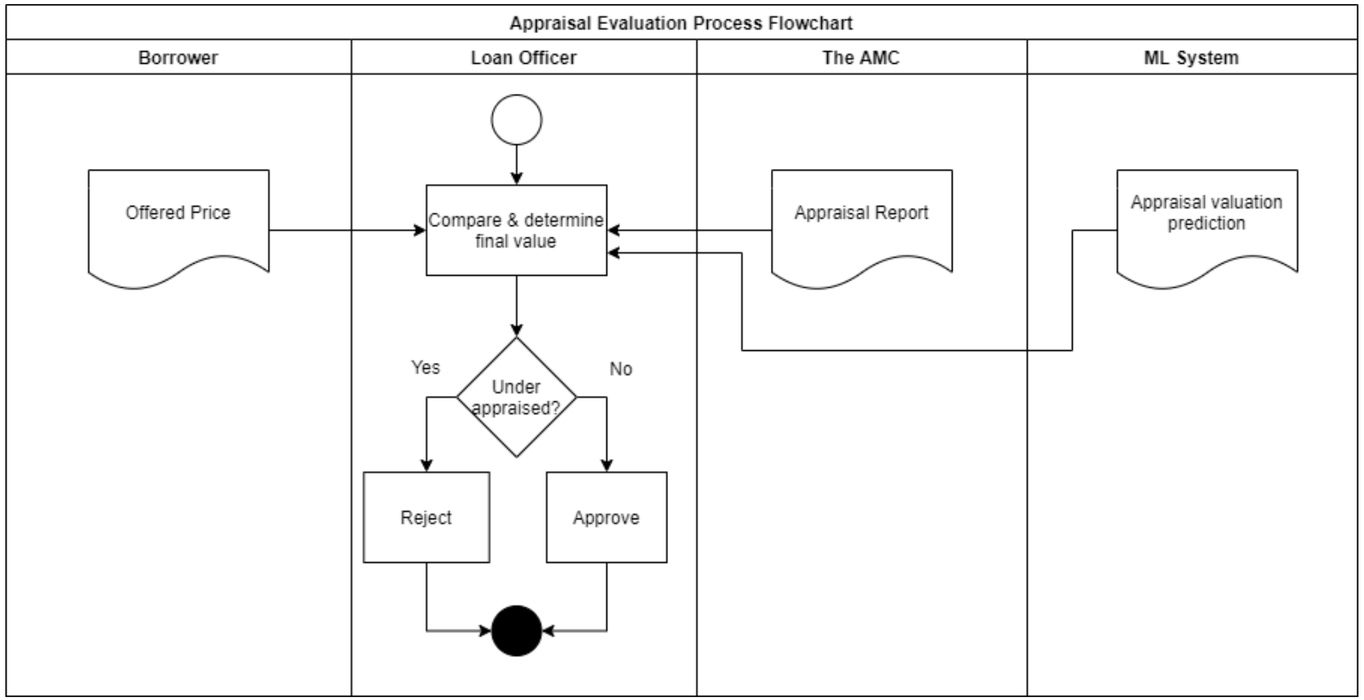
The result would determine whether to give loan to a borrower.

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



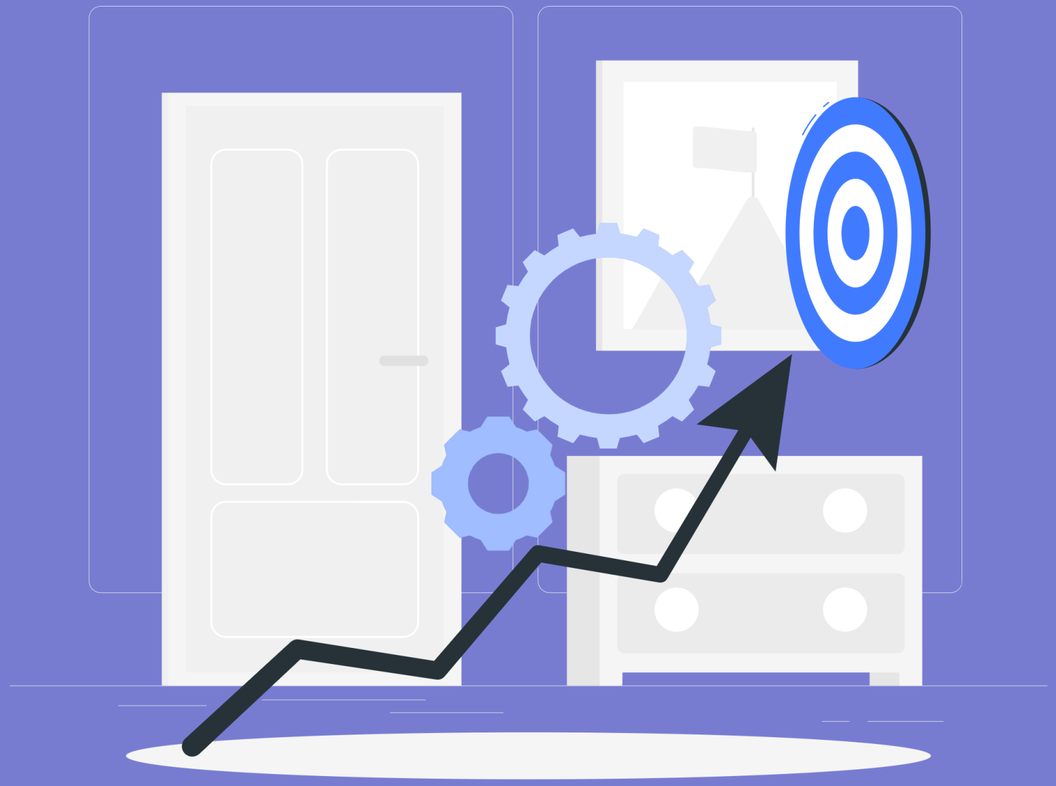


Expected Output

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.

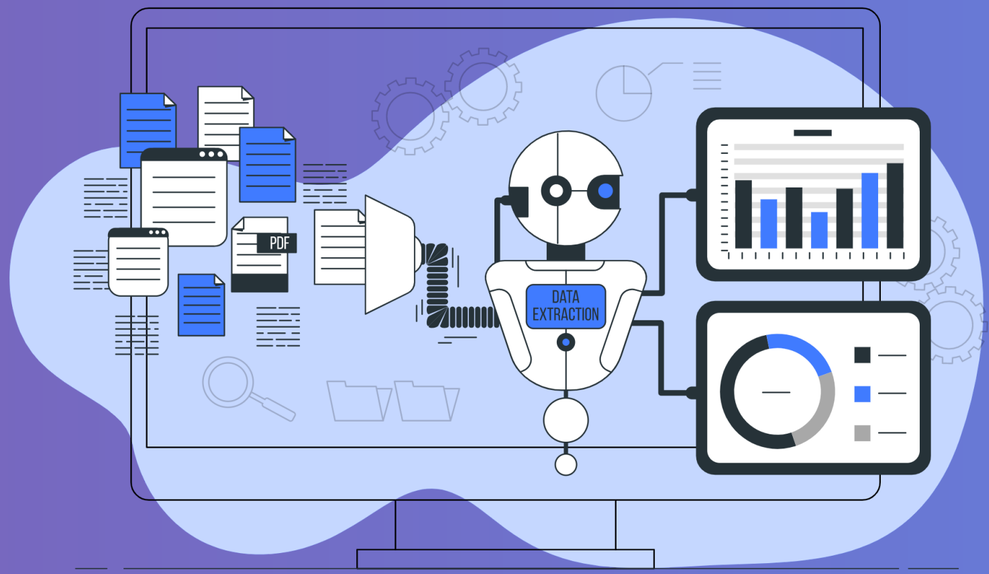
Minimize Loss

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

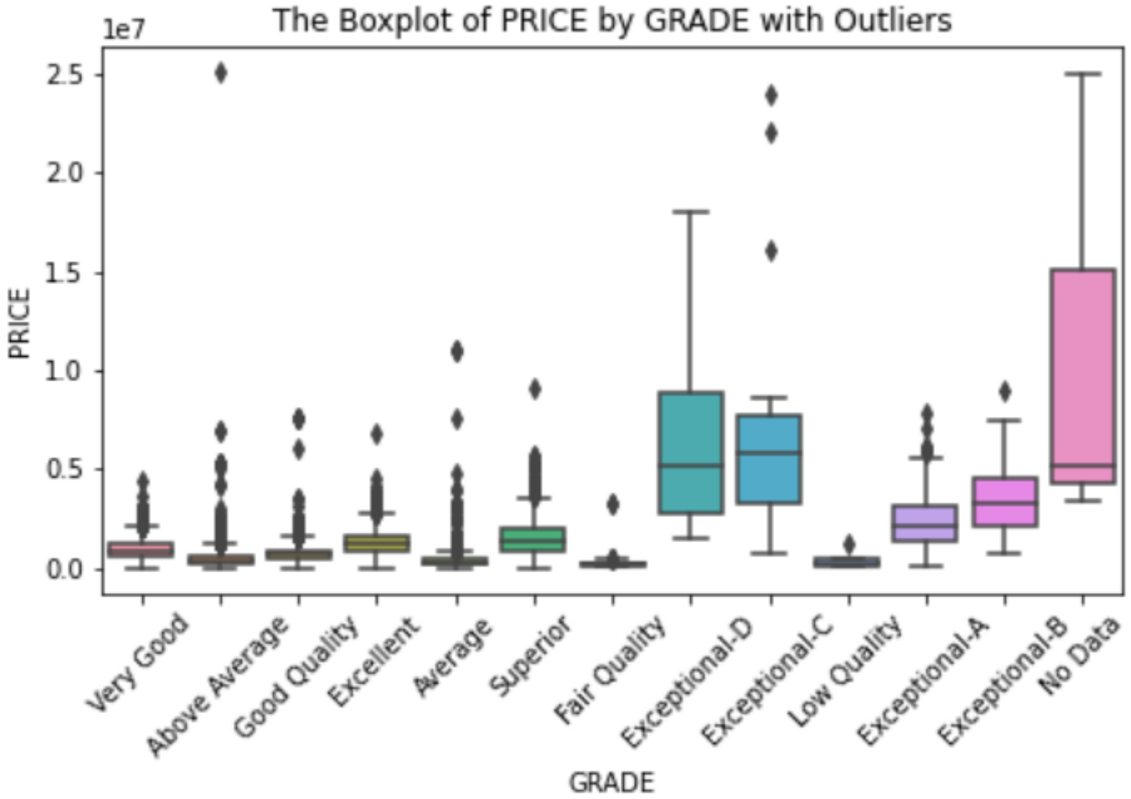
KITCHENS, PRICE, Price based on CNDTN & GRADE

Re-classify Features

CNDTN, STRUCT, ROOF

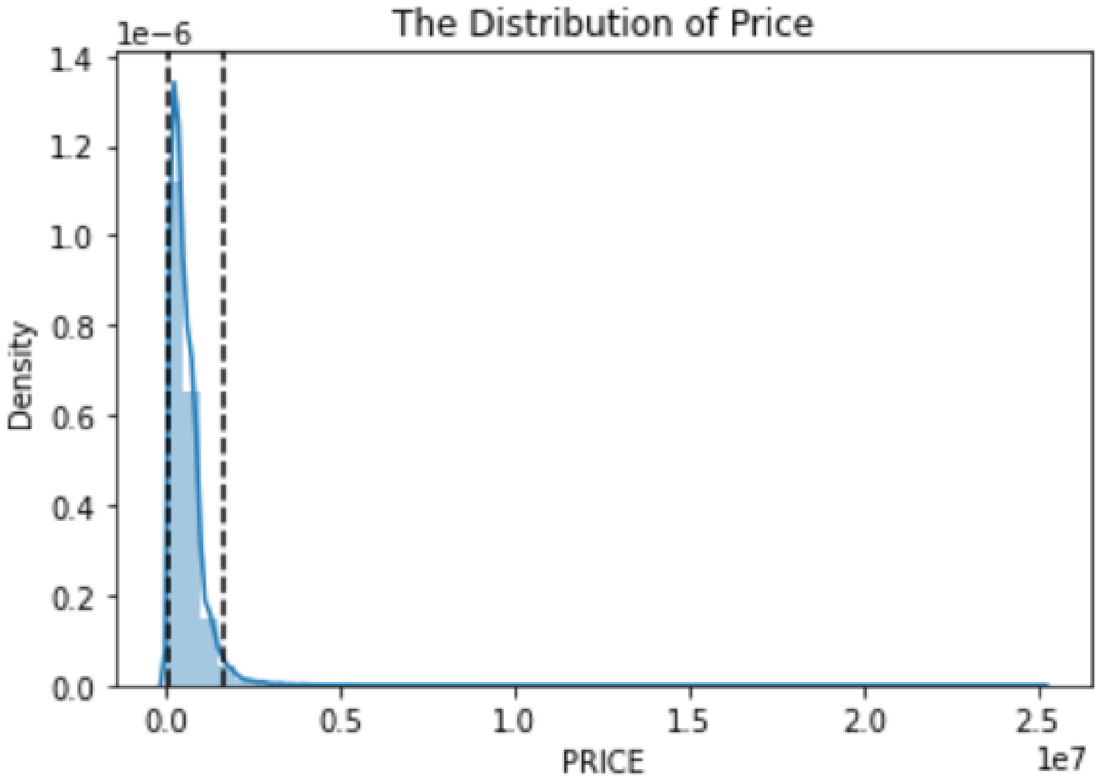
Exceptional Properties Exclusion

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

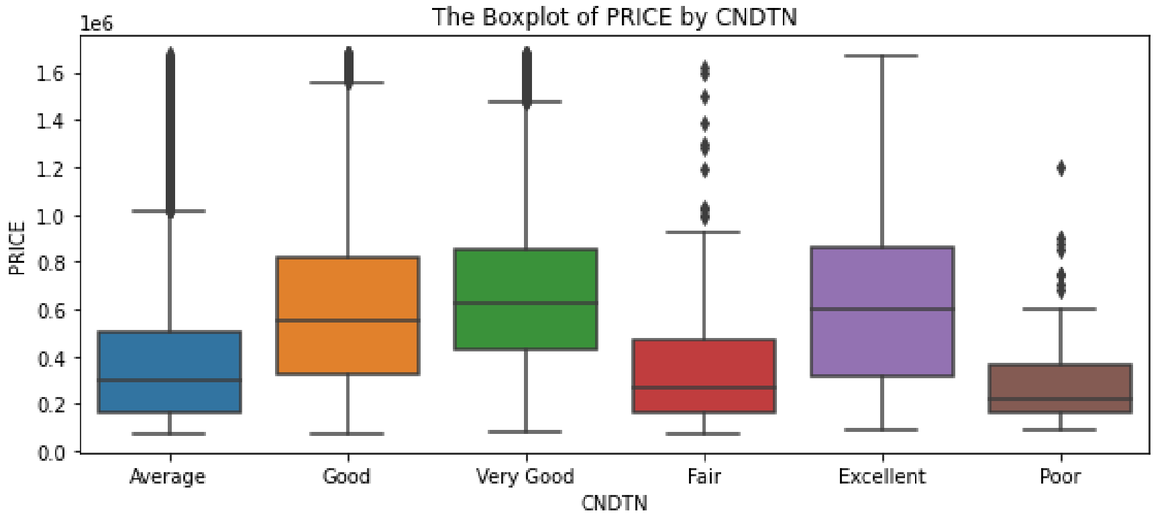
- Erroneous data with very low price (e.g., $1.0) or extremely expensive price.
- Kaggle : "Property prices are very high in Washington DC, averaging $647,000 in 2017."
- Drop data with PRICE <= 2.5th percentile or >= 97.5th percentile to assume 95% confidence interval.



Please note that we did not perform z-test due to the power of the distribution. Our PRICE distribution is 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

* More on deployment demonstration.

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

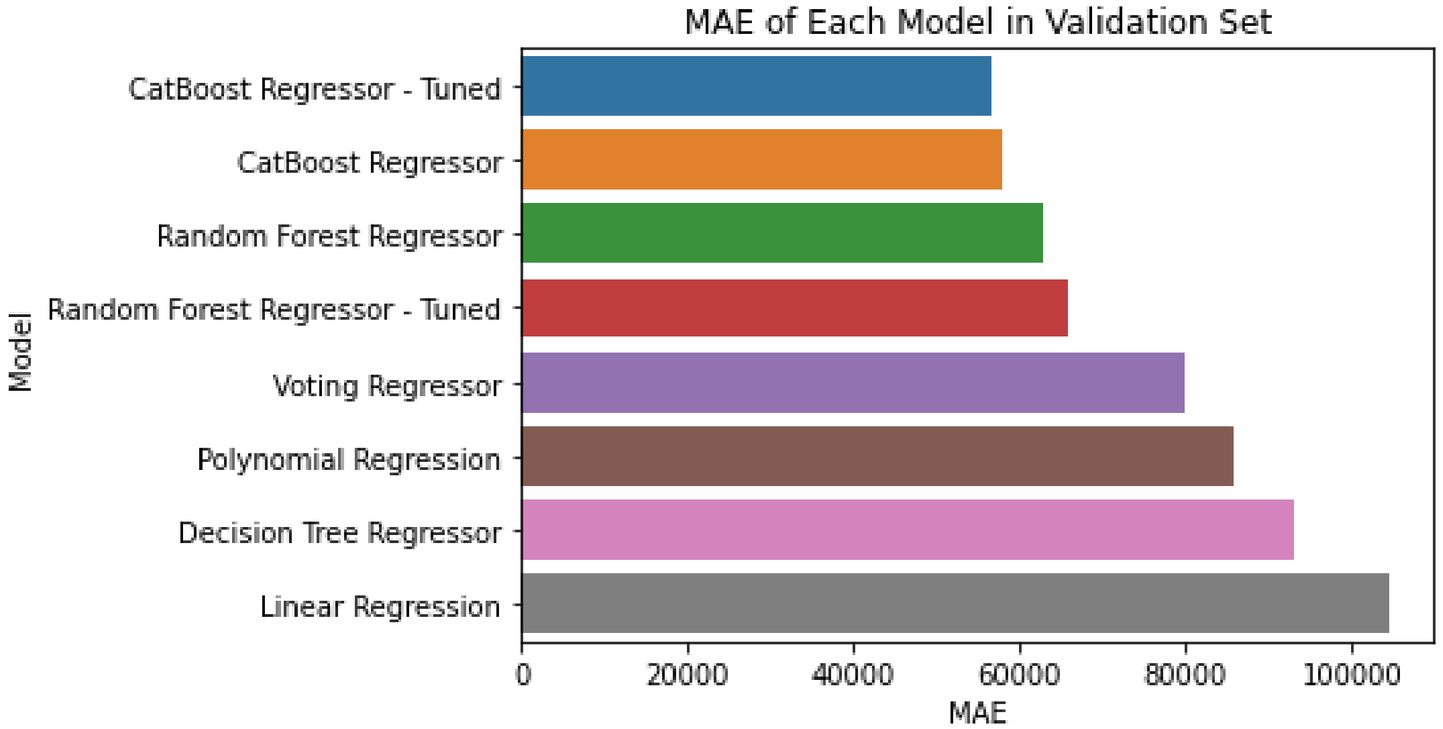
CatBoost Regressor - Tuned has the best R^2 score and the lowest MAE in the validation set.

	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 **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: 0.939295031098159 7

Test Set

MSE: 10815149410.215195
RMSE: 103995.91054563249
MAE: 63782.41628337468
R-squared: 0.907311904382937 7

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

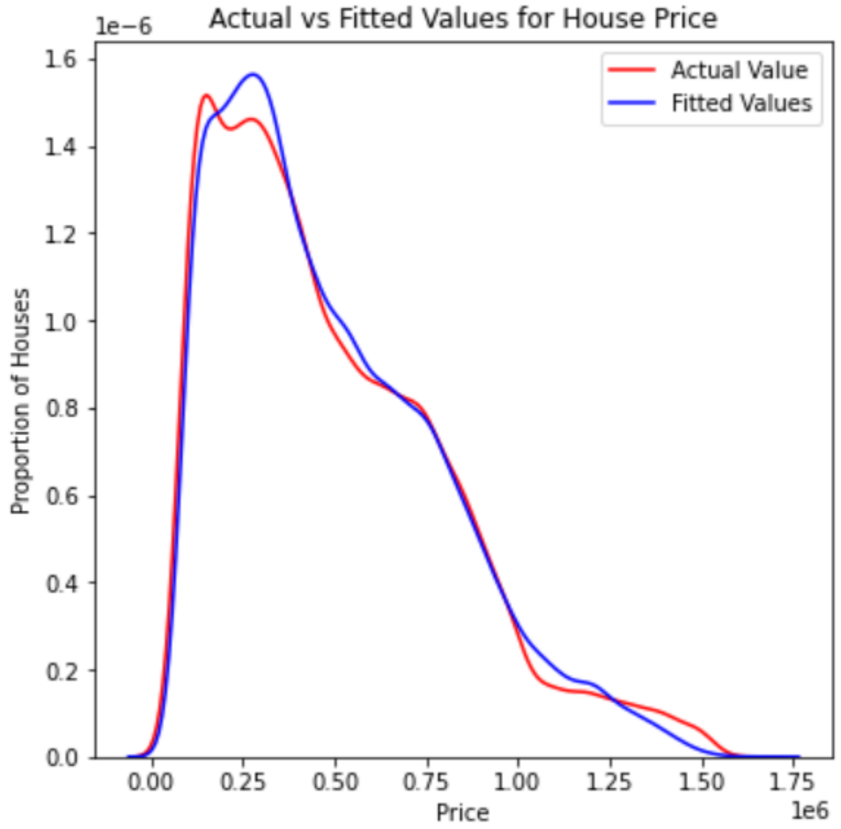
We were asked to reach the Mean Absolute Error (MAE) value below 12% of the median property price.

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

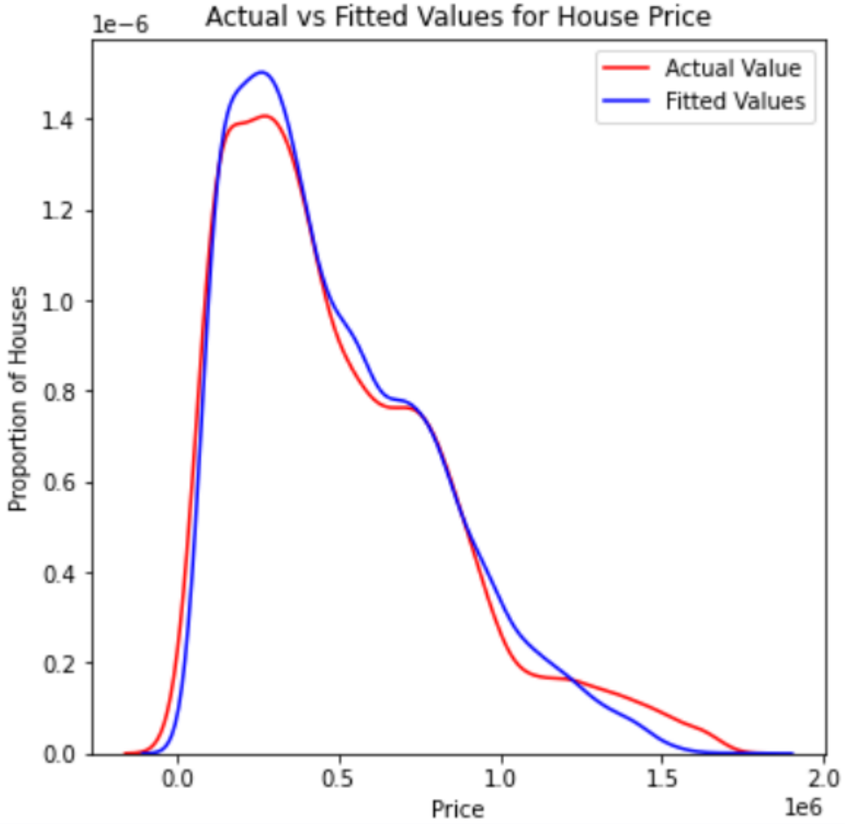
From the result shown above, we have achieved the desired MAE value (under $50,756.4).

Distribution Plot of Actual vs Fitted Values

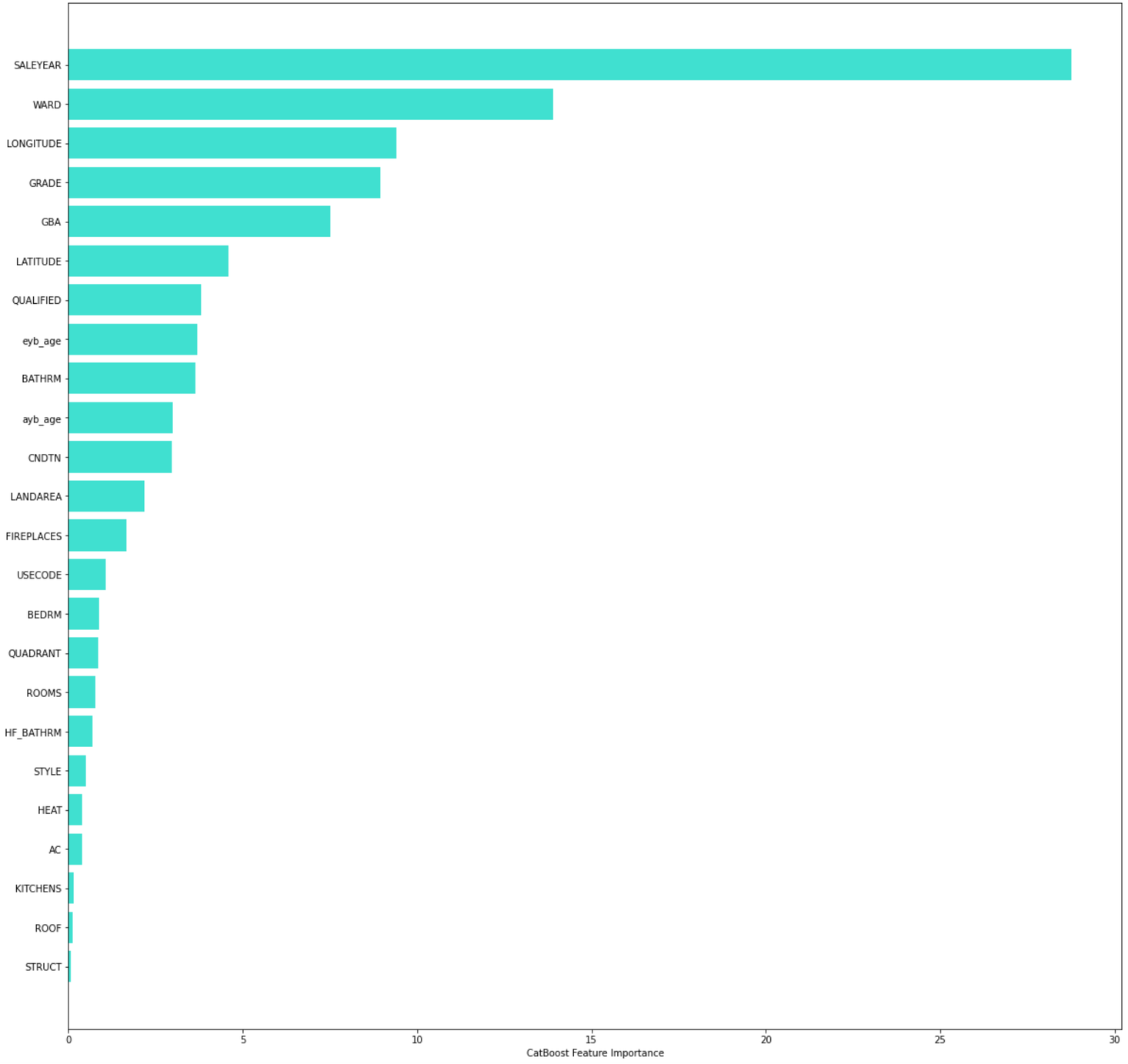
Train Set



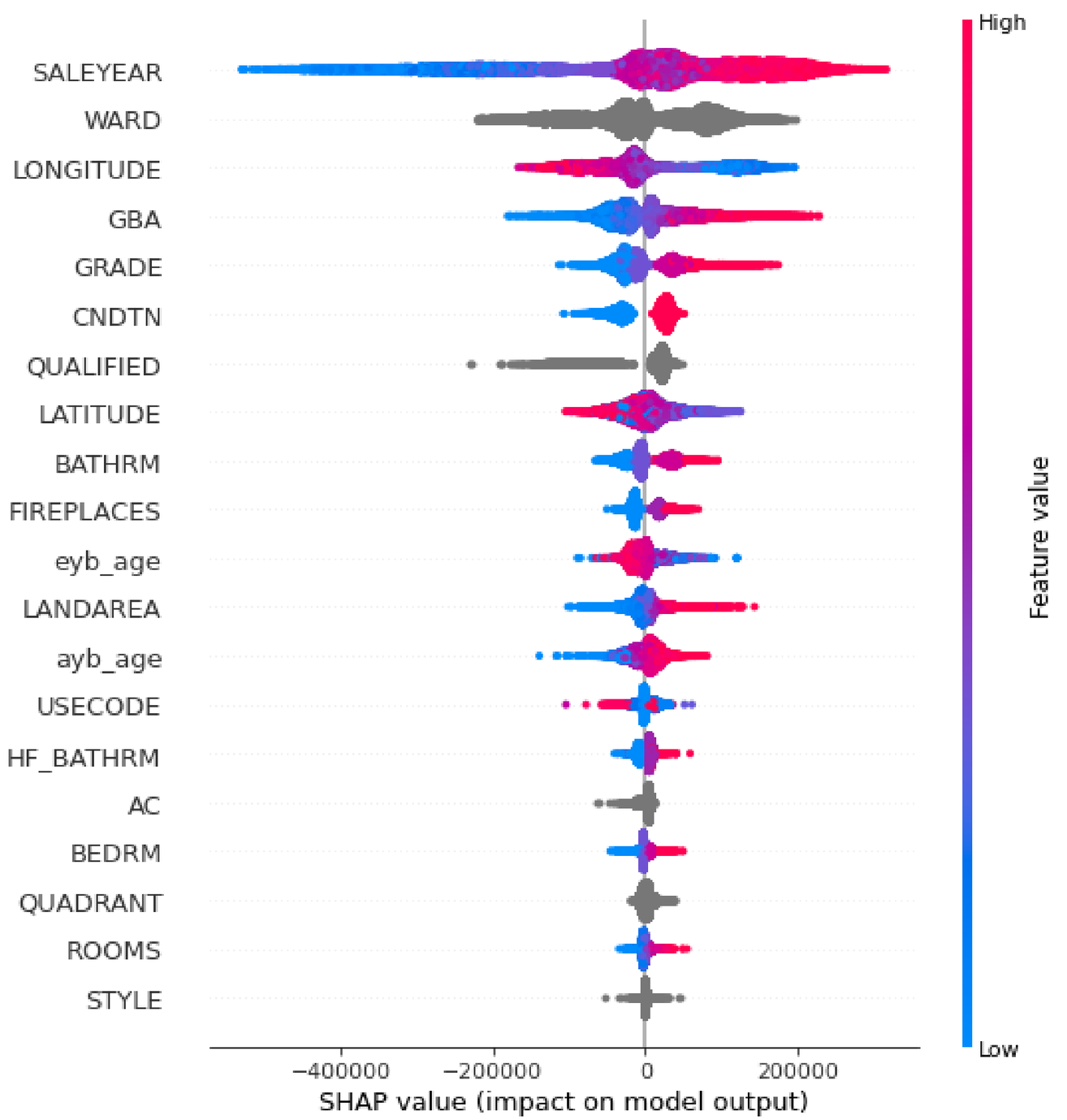
Test Set



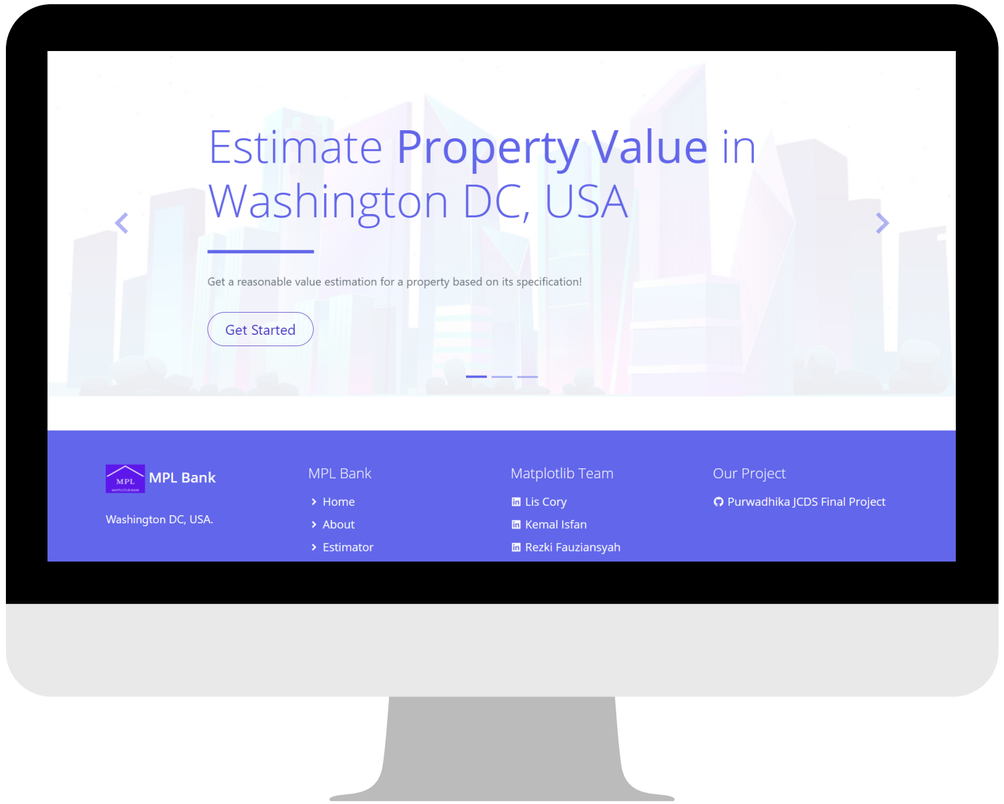
Feature Importances



Feature Importances with SHAP



4. Deployment



Deployment Page

We deployed the model to a webpage using FLASK.

Please go to : http://localhost:5000/

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

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

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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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

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

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

Estimate

MPL Bank
Washington DC, USA.

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Matplotlib Team
- Lis Cory
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Our Project
- Purwadhika JCDS Final Project

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Designed by **TemplateMo**

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 / Row 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

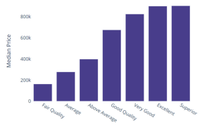
Insight

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

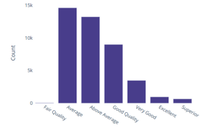
Insight

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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Matplotlib Team
- Lis Cory
- Kemal Isfan
- Rezki Fauziansyah

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!

PURWADHIKA JCDS 1202 MATPLOTLIB TEAM

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GITHUB REPOSITORY

https://github.com/ls-cy/Purwadhika-JCDS-Final-Project
https://github.com/PurwadhikaDev/MatplotlibGroup_JC_DS_12_FinalProject