PREDICTING HOUSE PRICES USING MACHINE LEARNING

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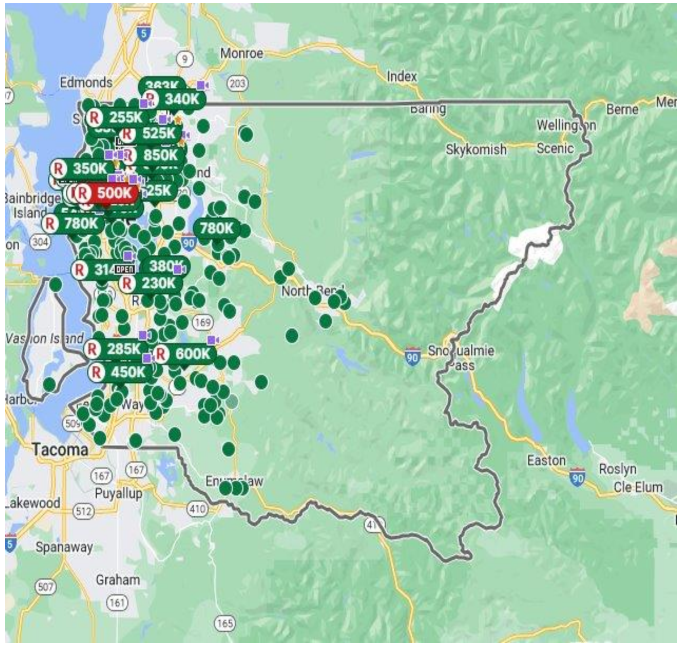
OBJECTIVES

- Predict house prices incorporating traditional and non-traditional features using machine learning
- Build a web application to predict the house price for user input feature values



Why King County ?

Land area: 2126 sq. mi.
Water area: 180.5 sq. mi.

Population density: 1066 people per square mile (very high).

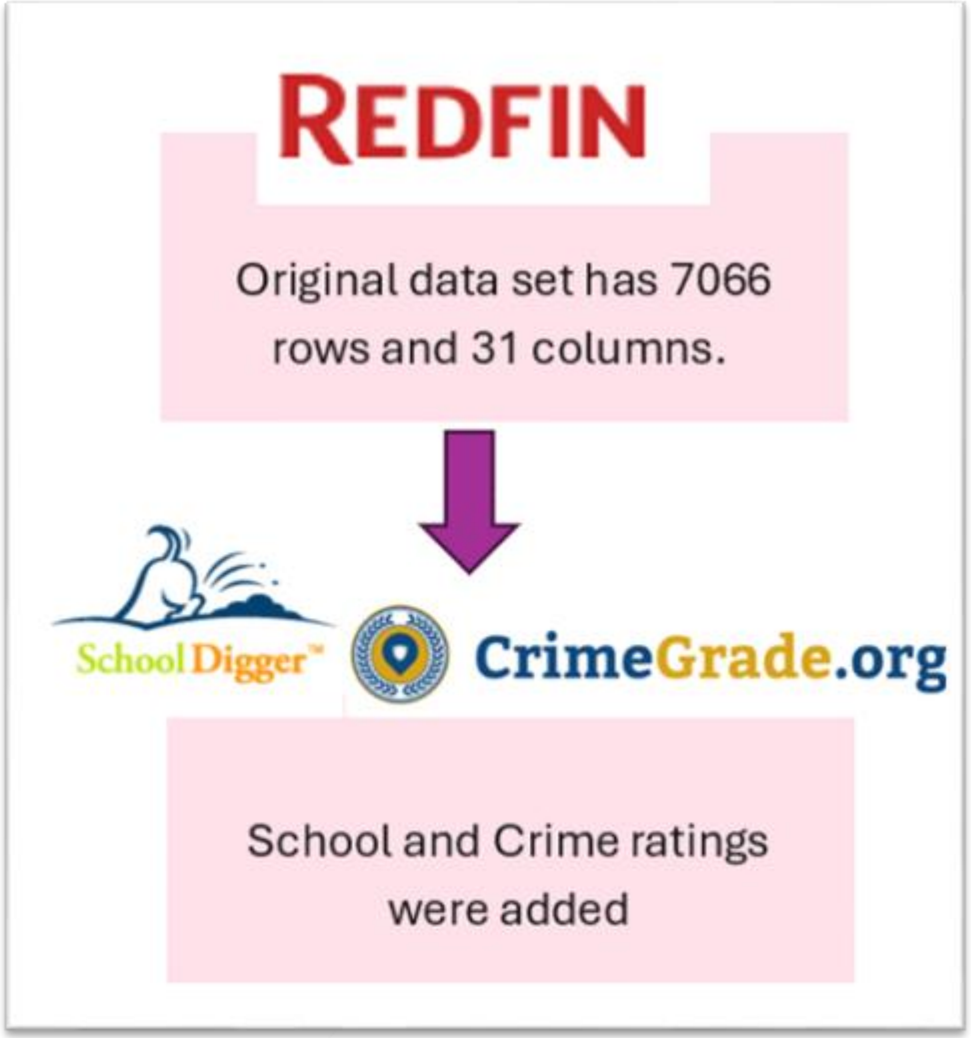
Cost of living index: 111.7 (more than average, U.S. average is 100)

Stakeholders

- Families looking to settle down in King County, WA
- Real estate agents trying to give estimates to housing prices
- Local government agencies

- Presence of many companies such as Boeing, Amazon, Google, Microsoft, etc.
- Scenic parks, Golden Garden Beach
- Historic places such as Pike Place Market, Space-needle

DATA SET



DATA CLEANING

- Removed unnecessary columns and rows with missing values.
- Add new columns
  - Age, Log_price

Age = 2024 – YEAR_BUILT
Log_price = Log(PRICE)

- Cleaned data set has 4700 rows and 19 columns (5 categorical and 14 numerical)

EXPLORATORY DATA ANALYSIS
PRICE DISTRIBUTION

Minimum: 49000

Mean: 1505699

Median: 998975

Maximum: 70000000

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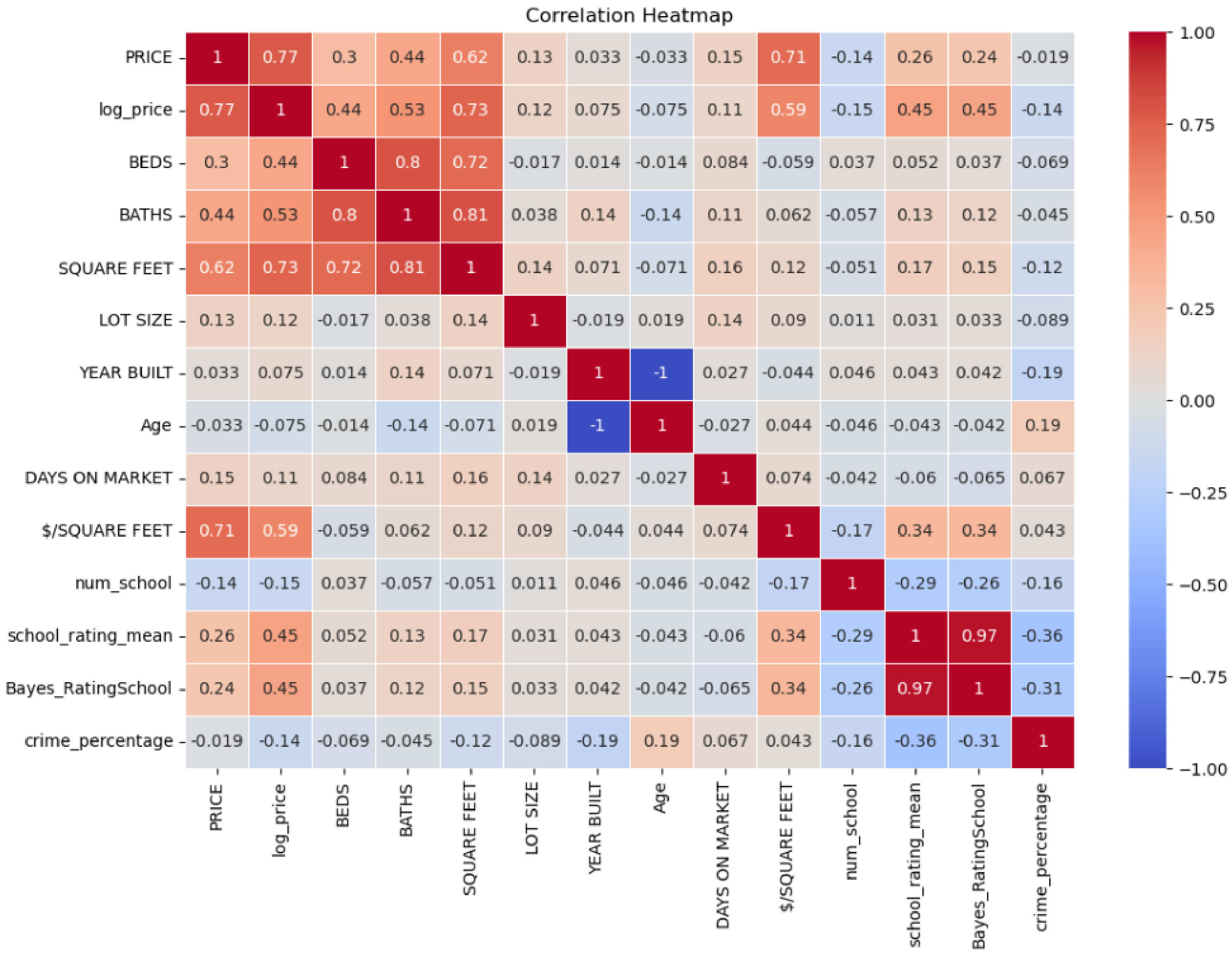
CORRELATION ANALYSIS OF HOUSING MARKET VARIABLES



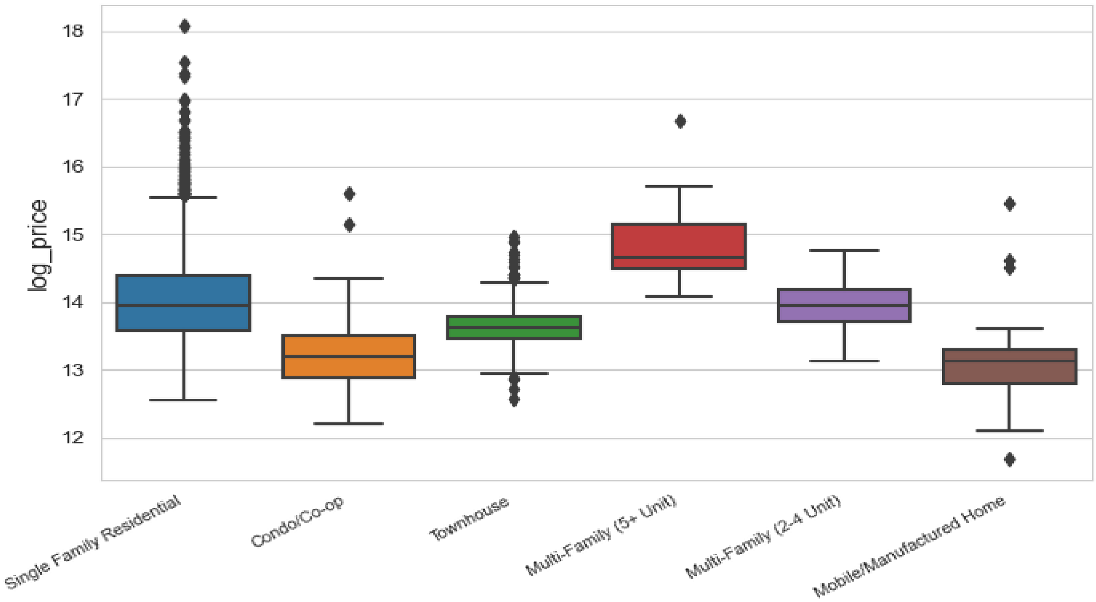
Primary tool: ***seaborn***

Effect of Location on Log_Price colored by Property Type

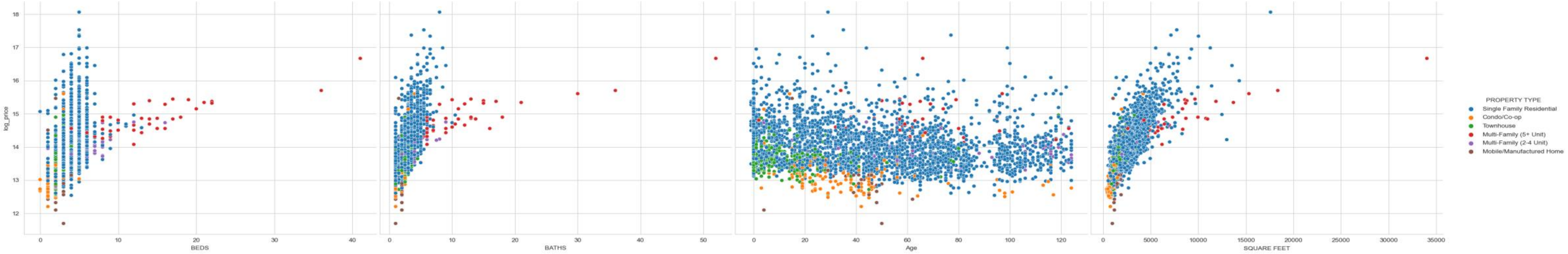
MORE PLOTS

Primary tool: seaborn

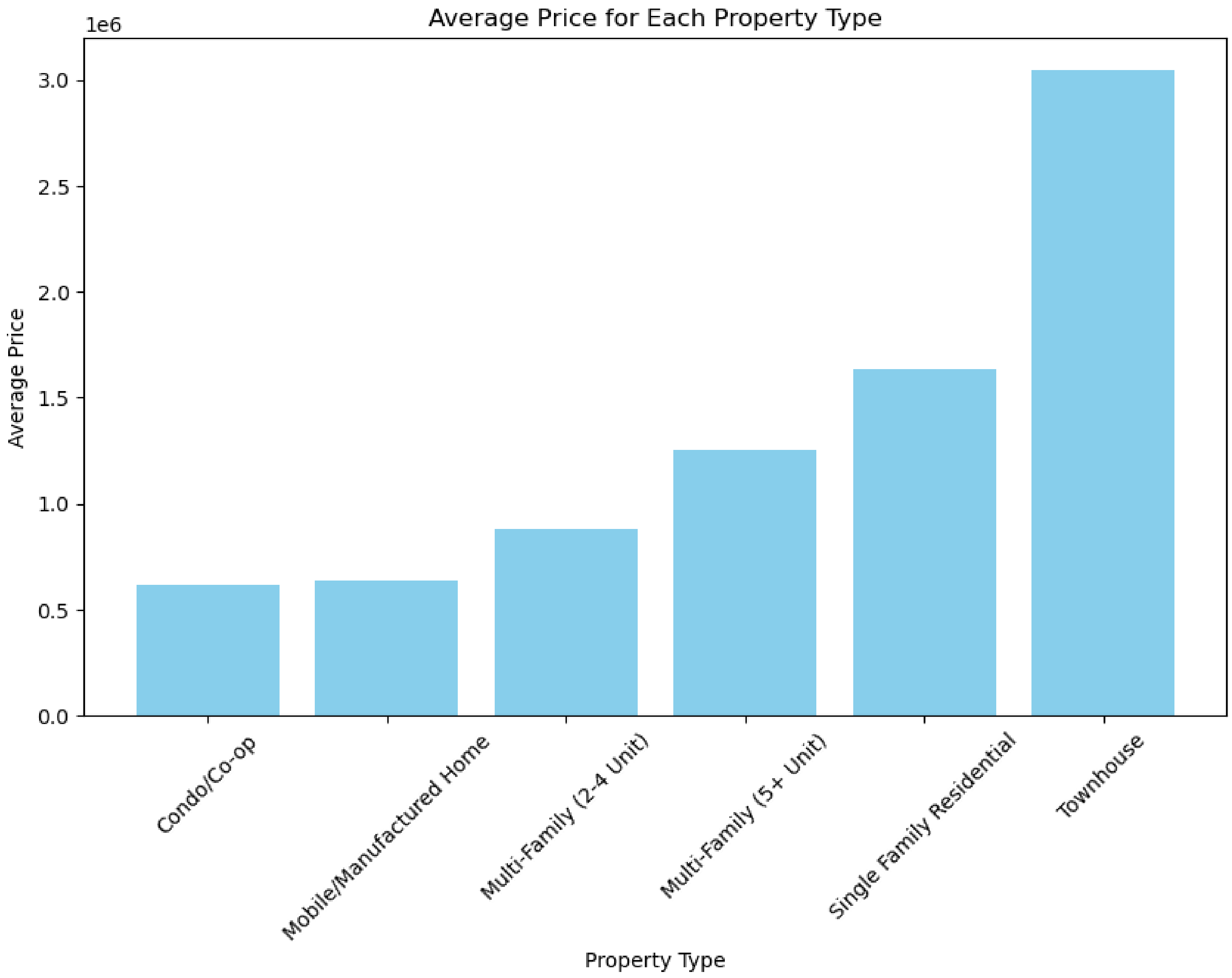
Boxplot on the right shows the distribution of *log_price for the categorical variable property type.*



Property Type



MORE PLOTS



Average Price for Each Property Type
1e6
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Average Price
Condo/Co-op
Mobile/Manufactured Home
Multi-Family (2-4 Unit)
Multi-Family (5+ Unit)
Single Family Residential
Townhouse
Property Type

FEATURE ENGINEERING

- Delete outliers based on price.
- One hot encoding on PROPERTY TYPE column

PROPERTY TYPE

Single Family Residential	3030
Townhouse	430
Condo/Co-op	160
Multi-Family (2-4 Unit)	63
Multi-Family (5+ Unit)	45
Mobile/Manufactured Home	32

FINAL DATA SET

```
Data columns (total 16 columns):
 #   Column               Non-Null Count
---  ------               --------------
 0   BEDS                 3759 non-null
 1   BATHS                3759 non-null
 2   SQUARE FEET          3759 non-null
 3   LOT SIZE             3759 non-null
 4   zipcode              3759 non-null
 5   LATITUDE             3759 non-null
 6   LONGITUDE            3759 non-null
 7   Bayes_RatingSchool   3759 non-null
 8   crime_percentage     3759 non-null
 9   Age                  3759 non-null
 10  Single Family        3759 non-null
 11  Townhouse            3759 non-null
 12  Condo                3759 non-null
 13  Multi_Family4        3759 non-null
 14  Multi_Family5        3759 non-null
 15  log_price            3759 non-null
```

15 features to predict House Price (in log scale)

MODELING

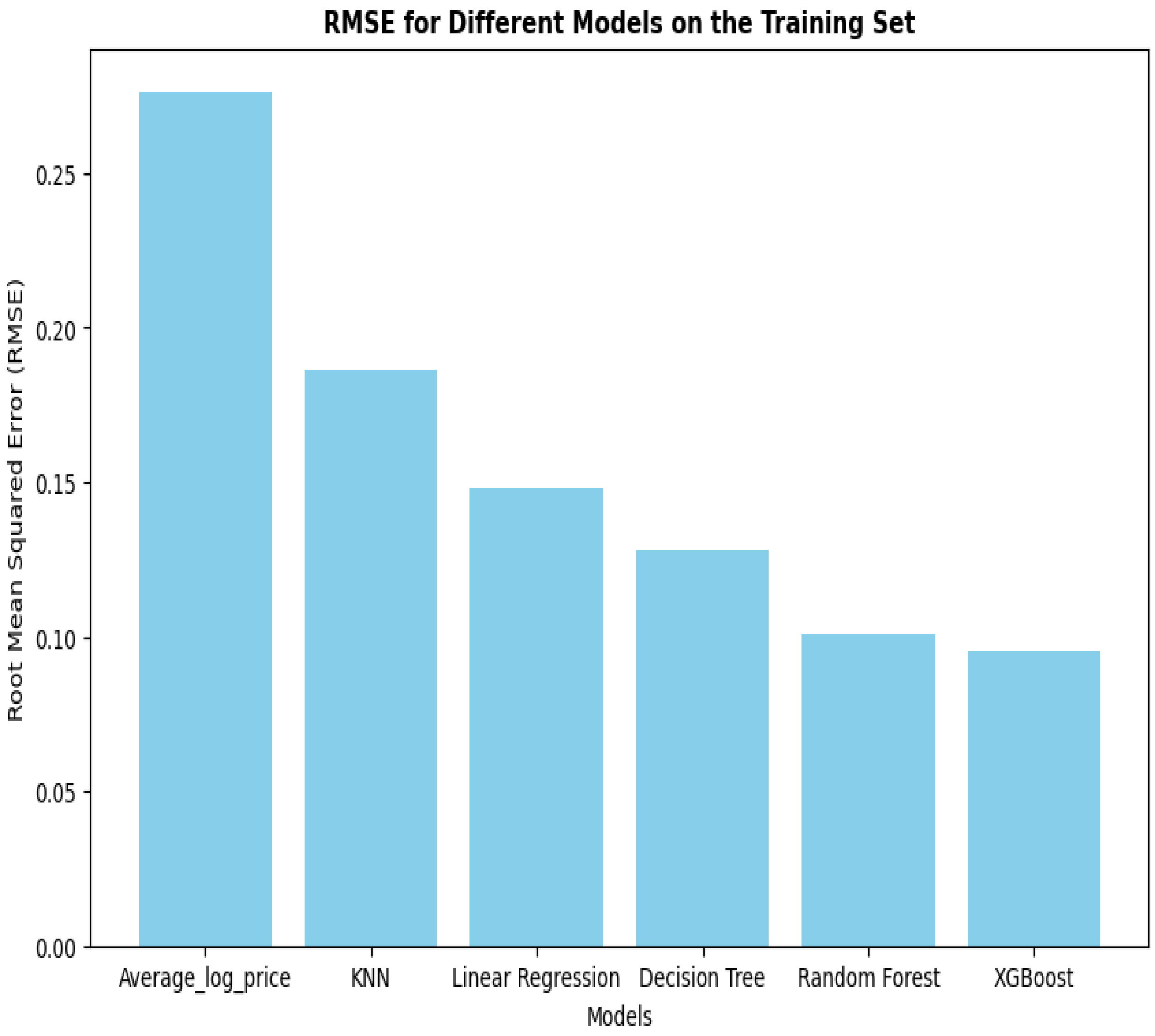
1. The baseline model – Average of the House Prices (log scale)
2. K – Nearest Neighbors
3. Multiple Linear Regression
4. Decision Tree
5. Random Forest
6. XGBoost

Used 5 – fold cross validation on the training set and RMSEs were computed for the predicted price in log scale.

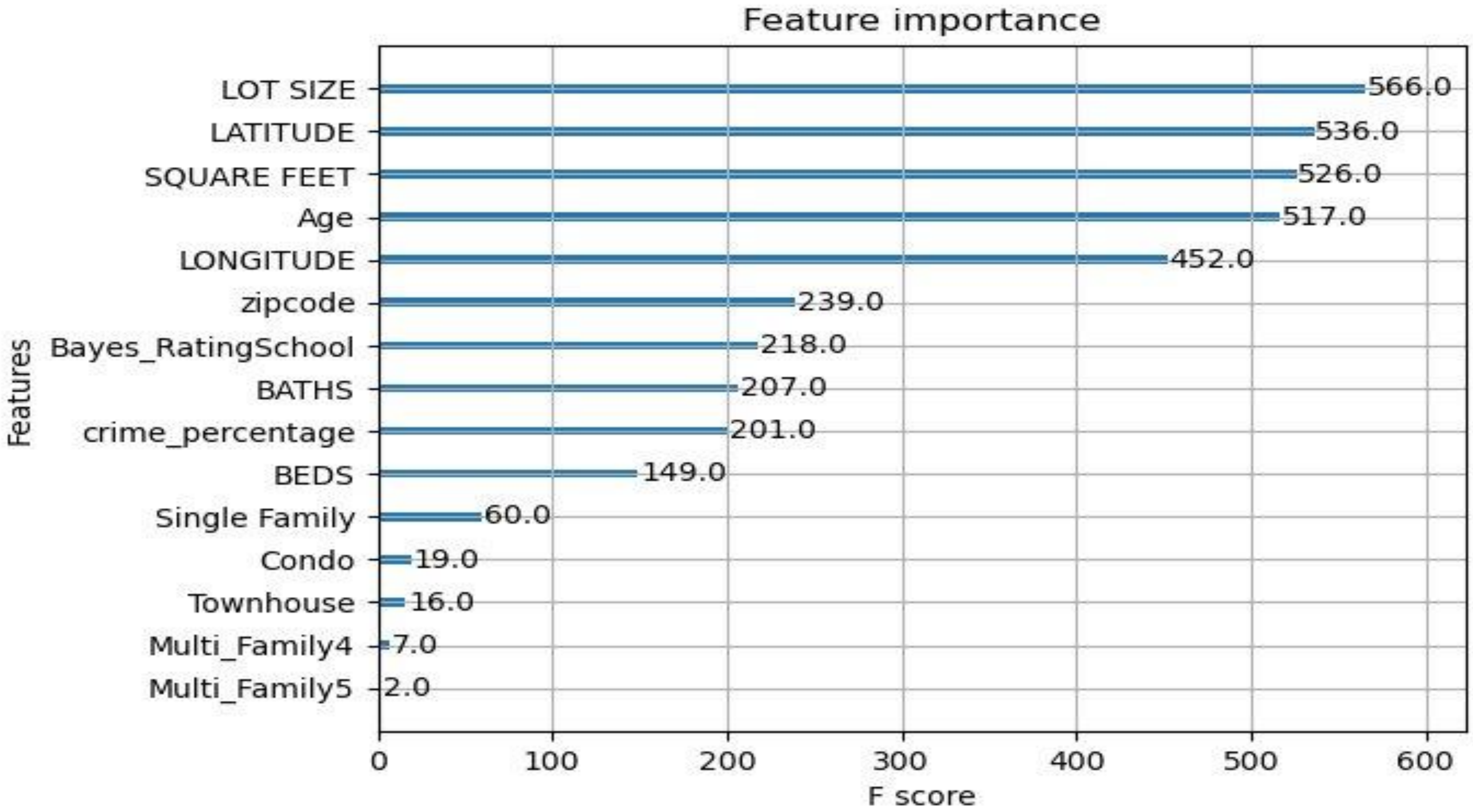
MODEL TUNING

- Used a grid search-based approach to find the best set of parameters for KNN, Decision Tree, Random Forest, and XGBoost.

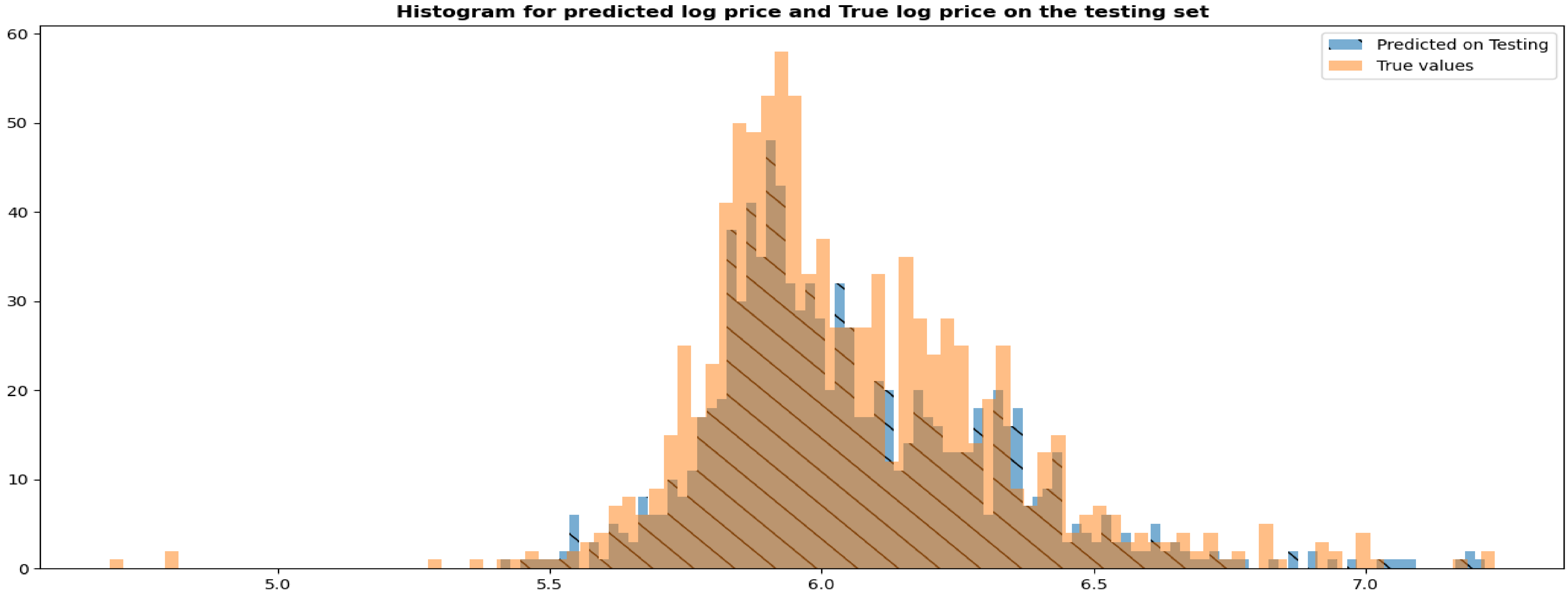
- Best model, XGBoost gives RMSEs,
  - **0.0954 on training set**
  - **0.1003 on testing set**



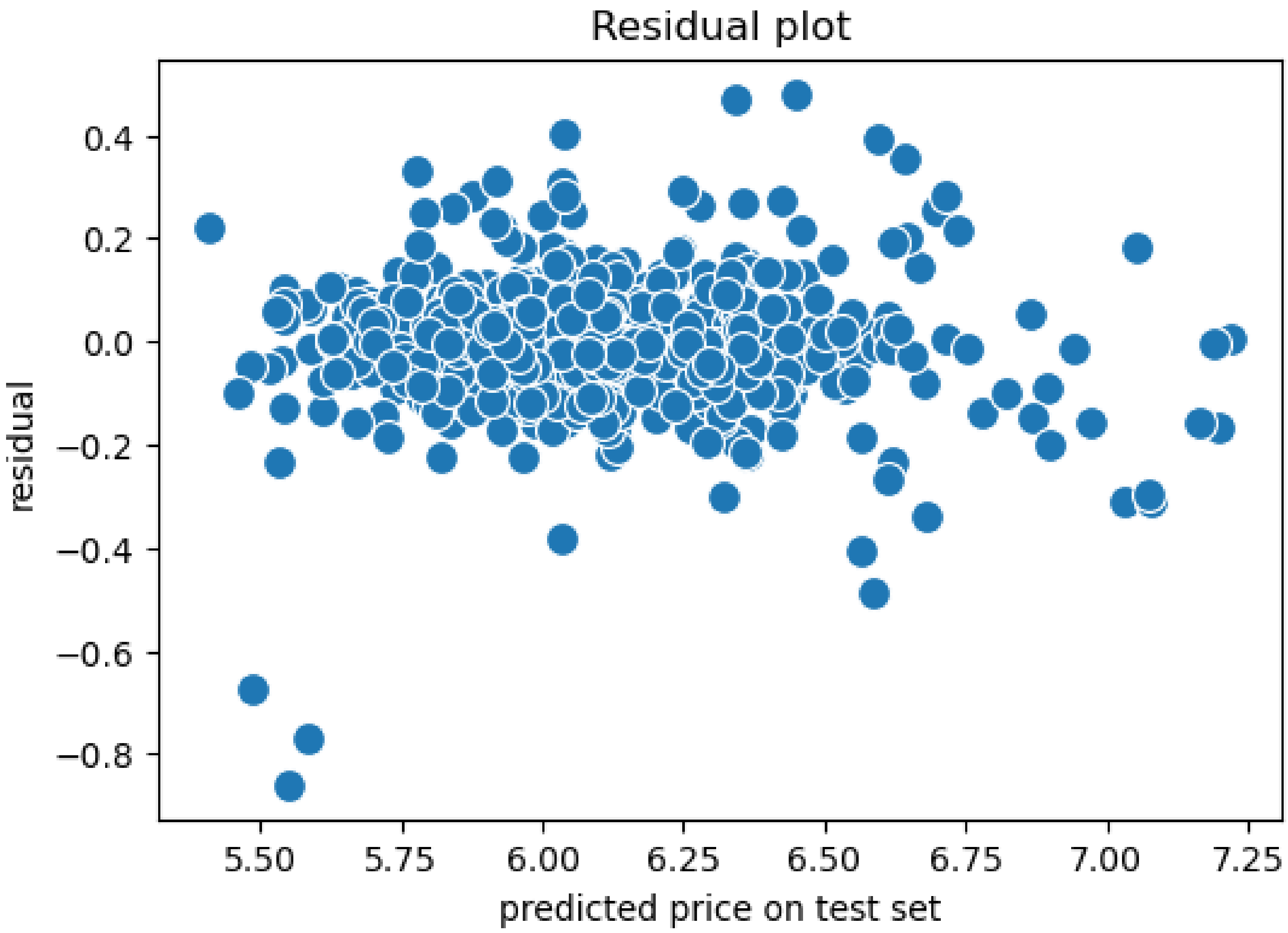
IMPORTANT FEATURES OF XGBOOST



HISTOGRAMS FOR PREDICTED VS TRUE LOG PRICE



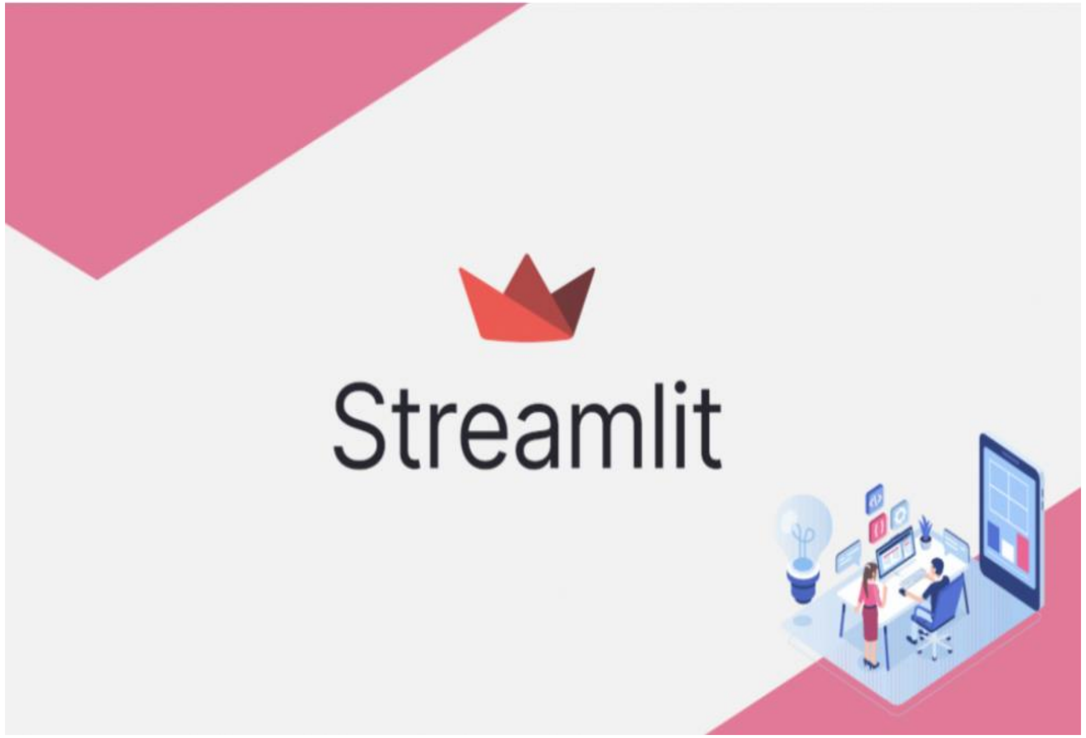
RESIDUAL PLOT



WEB APPLICATION

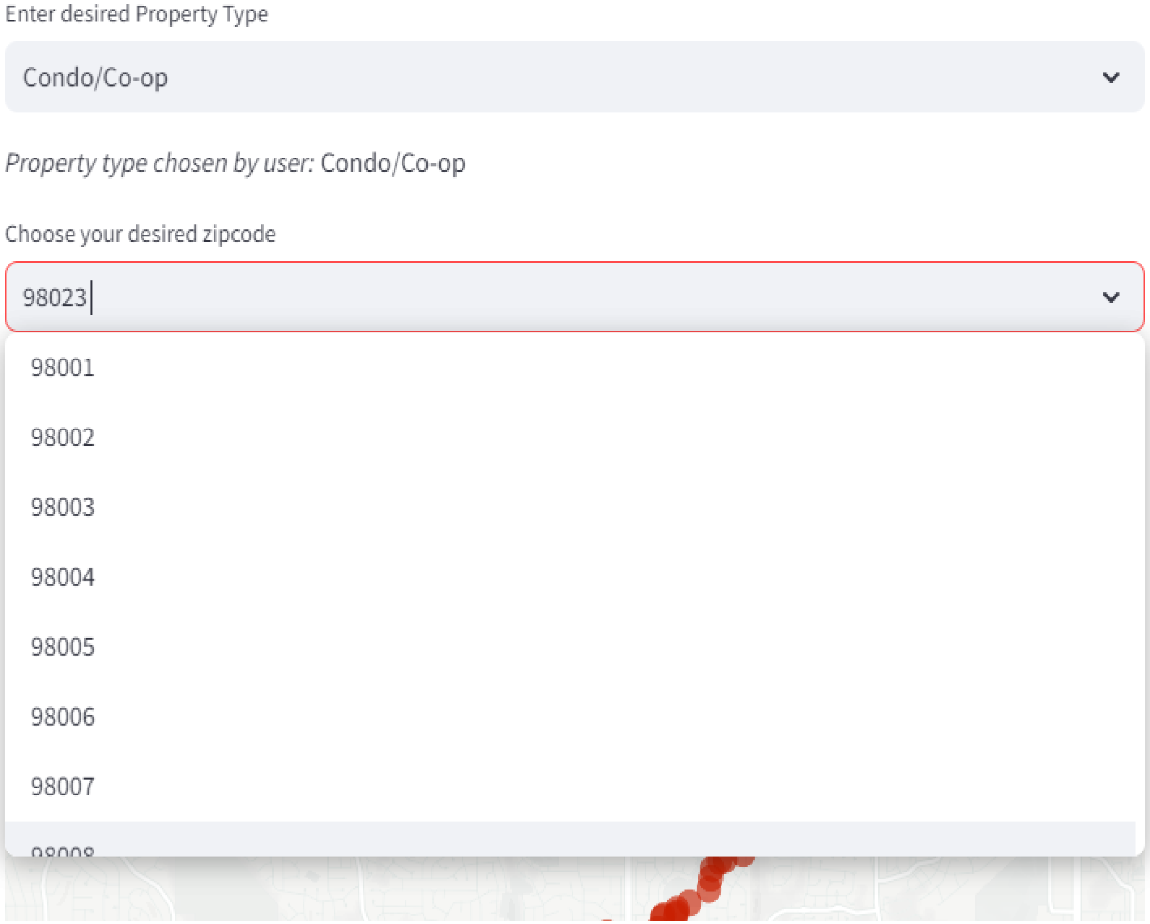
- Using our final model, we built a simple web application on Streamlit that takes in user inputs (relevant to our model) and predicts the house price.

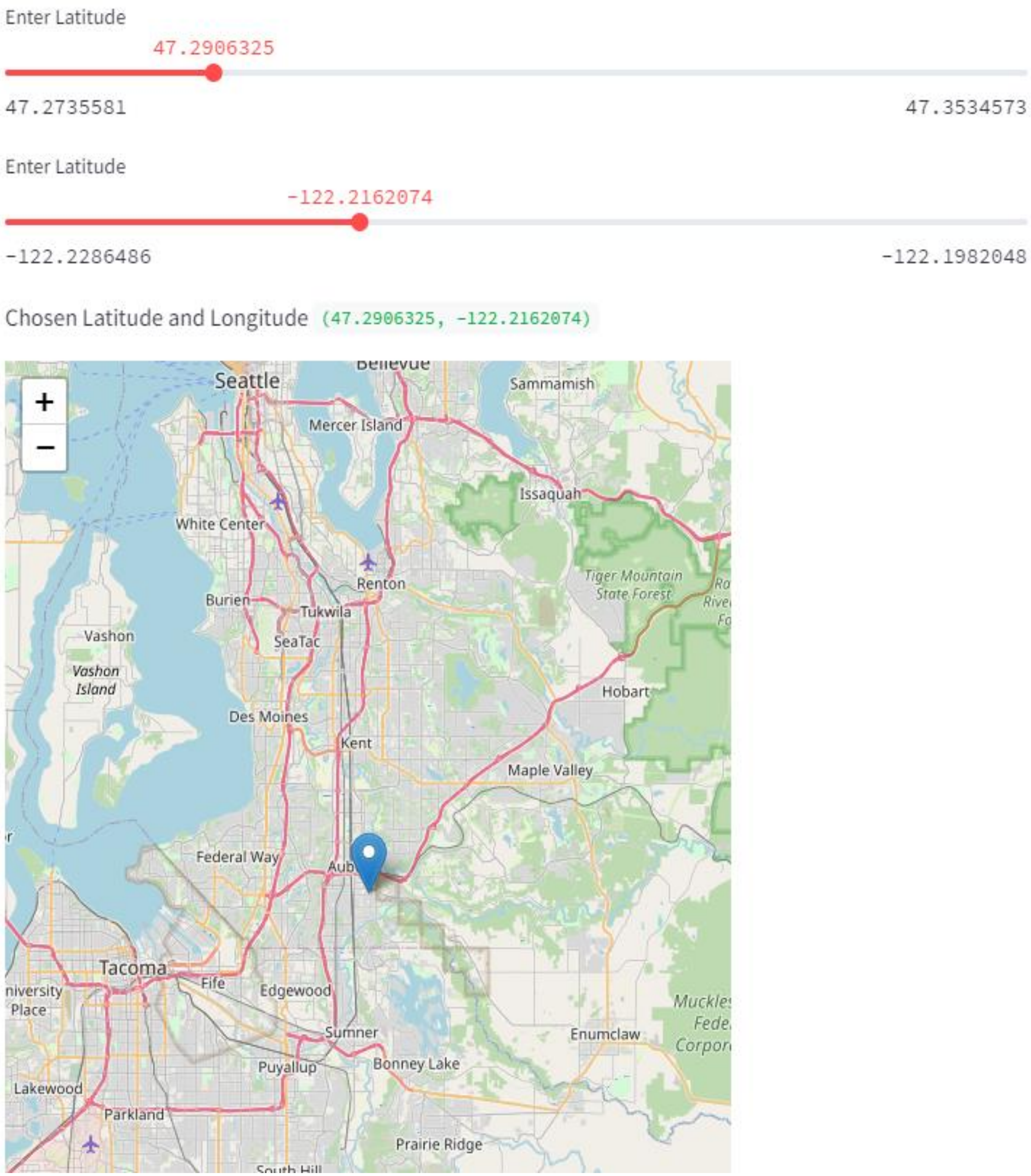
- The app is publicly available at https://erdos-datascience-may2024-realestate-project-nevrbzjn2sh2zgsrc.streamlit.app/



- Visualizations using streamlit_folium

- clearer view of the surrounding big cities, airports, etc. , to make informed choices





CONCLUSIONS

- Overall, all models did improve from the baseline model and did well on predicting the price.
- Contribution of non-traditional features are similar to some of the traditional features.

FUTURE WORK

- Extend the study for other states.
- Incorporate more relevant features such as
  - whether the house has experienced flooding,
  - has mold issues,
  - the quality of construction materials,
  - the floor plan, and
  - whether fixtures and appliances have been recently updated.

ACKNOWLEDGEMENTS

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