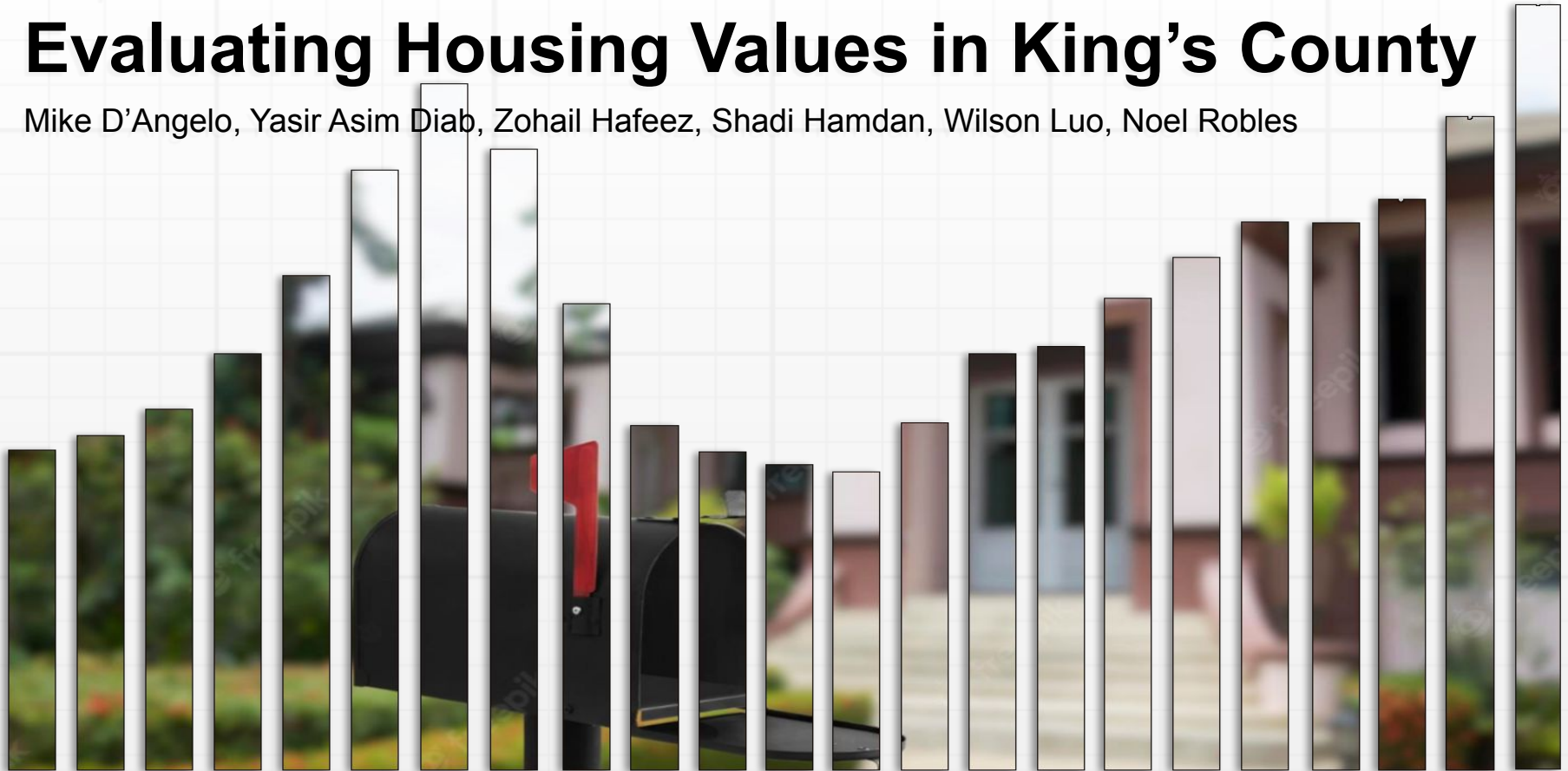


Group 22

Evaluating Housing Values in King's County

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Introduction:

- The average American has **70%** of their net worth tied into a primary residence.
- In the last decade, the U.S. housing market has doubled to over **\$43 trillion**.
- Buying a home is important, so there should be **adequate transparency** when evaluating real estate.
- We **hypothesize** that **square foot** and **location** affect home value the **strongest**.
- What affects the value of a house?
 - Number of Bedrooms & Bathrooms
 - Year Built
 - Location
 - Size
 - And Many More!



Introduction:

Problem:

- **Lack of transparency** in the evaluation of real estate, especially for **buyers**.
- Lenders will often **not move forward** with a transaction if the **appraisal is less than the selling price**. Therefore, it is important that buyers receive accurate pricing on their properties.
- Current solutions, like **Zillow's "Zestimate"** generally do not factor in the current condition of the property, and can accept inaccurate seller data which may lead to **inflated prices**.



Introduction:

Solution:

- We aim to provide a **model that allows users to input features associated with a specific property and receive a reasonable evaluation** based on similar homes in the area. This should help **provide transparency** to potential homebuyers.



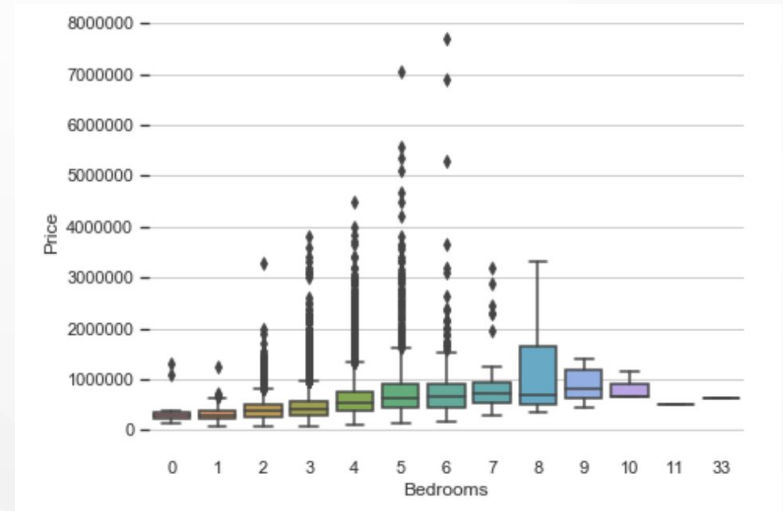
Methods: Dataset Selection

- Looking at dataset of housing prices in King's County, Washington
- 21,600 Samples
- 19 Features
- No missing feature data



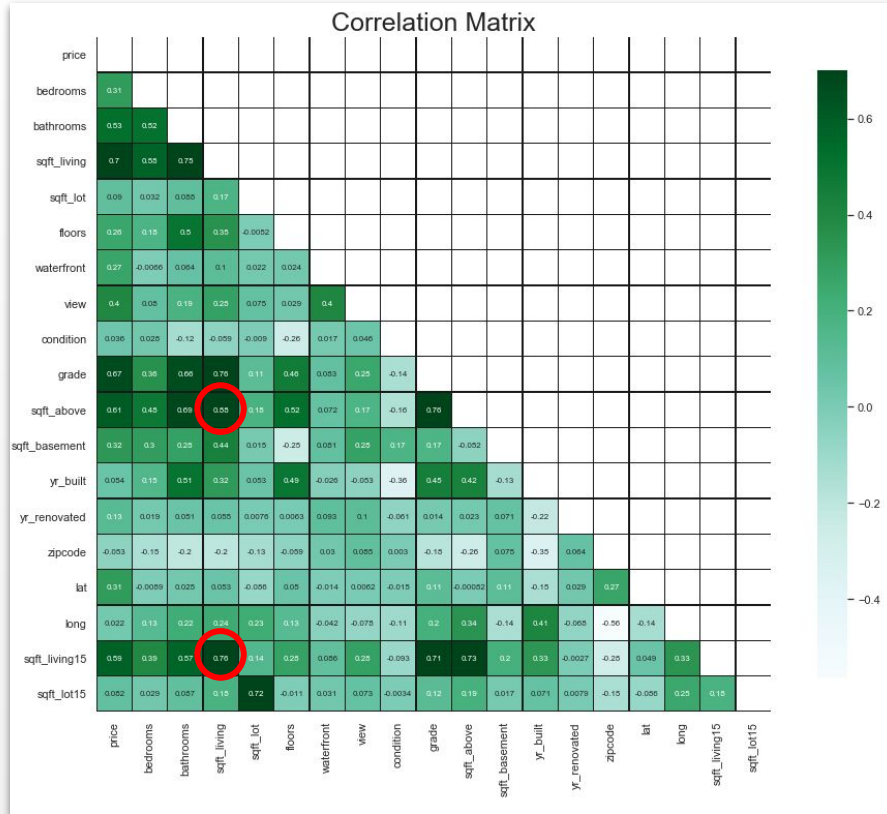
	Total Null	% of Total	Data Type
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date	0	0.00	object
age_rnv_binned_26-50	0	0.00	uint8
age_rnv_binned_1-25	0	0.00	uint8
age_rnv_binned_less_than_1	0	0.00	uint8
age_binned_51_plus	0	0.00	uint8
age_binned_26-50	0	0.00	uint8
age_binned_1-25	0	0.00	uint8
age_binned_less_than_1	0	0.00	uint8
age_rnv	0	0.00	float64
age	0	0.00	int64
sales_yr	0	0.00	object
sqft_lot15	0	0.00	int64
sqft_living15	0	0.00	int64
long	0	0.00	float64
lat	0	0.00	float64
zipcode	0	0.00	int64
yr_renovated	0	0.00	int64
yr_built	0	0.00	int64
sqft_basement	0	0.00	int64
sqft_above	0	0.00	int64
grade	0	0.00	int64
condition	0	0.00	int64
view	0	0.00	int64
waterfront	0	0.00	int64
floors	0	0.00	float64

Methods: Analysis & Feature Engineering



Skewing to the right with an outlier of \$770,000, which we expect from a good housing dataset since there are luxury houses included.

Methods: Analysis & Feature Engineering



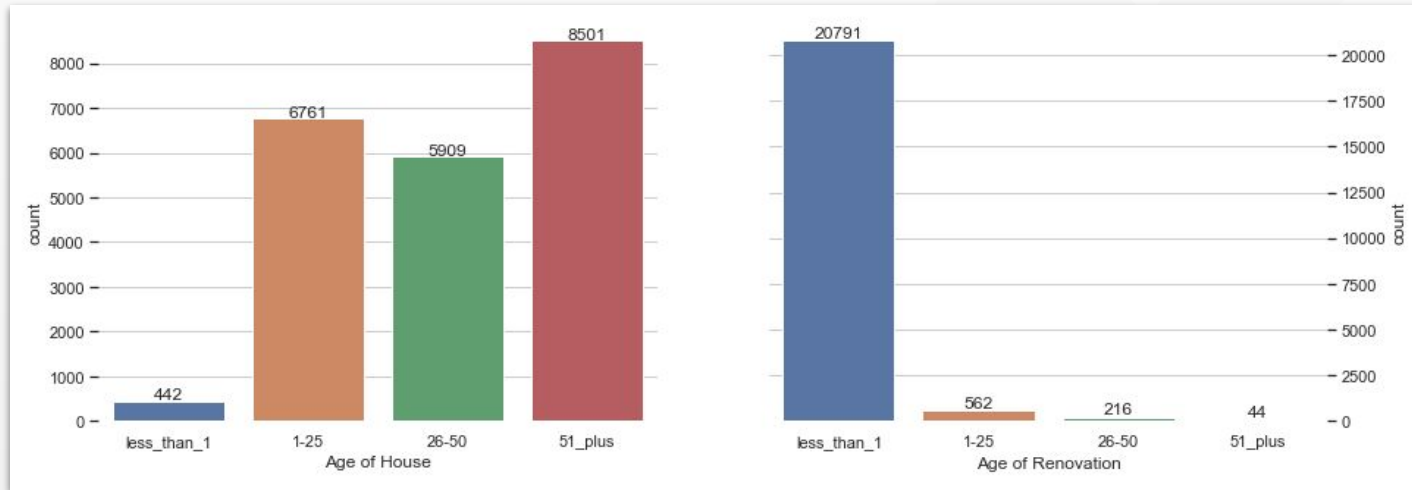
For high correlation to sqft_living, following features removed:

1- Sqft_above

2 - Sqft_living_15

Methods: Analysis & Feature Engineering - Binning

- Creating two new features and binned them:
 1. **Age of house** which is based off of year built.
 2. **Renovation Age** based on renovation year.
 3. Determined **quartile partitions** to be best.

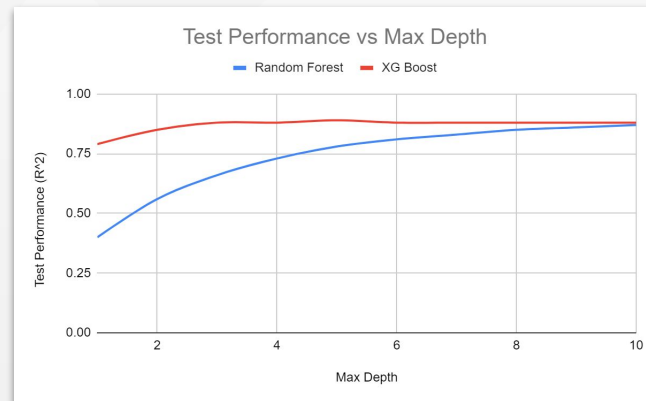
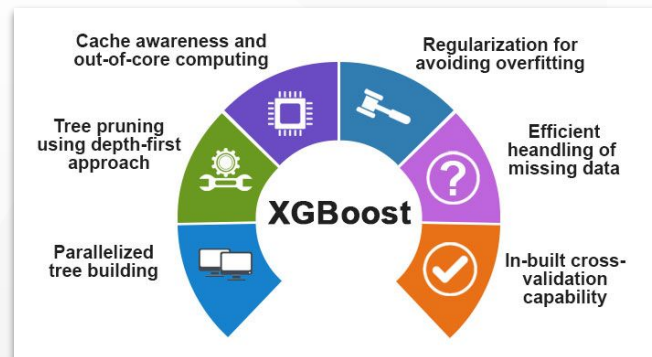


Methods: Model Comparisons - Tuning

Random Forest vs XG Boost - Model Selection Rationale

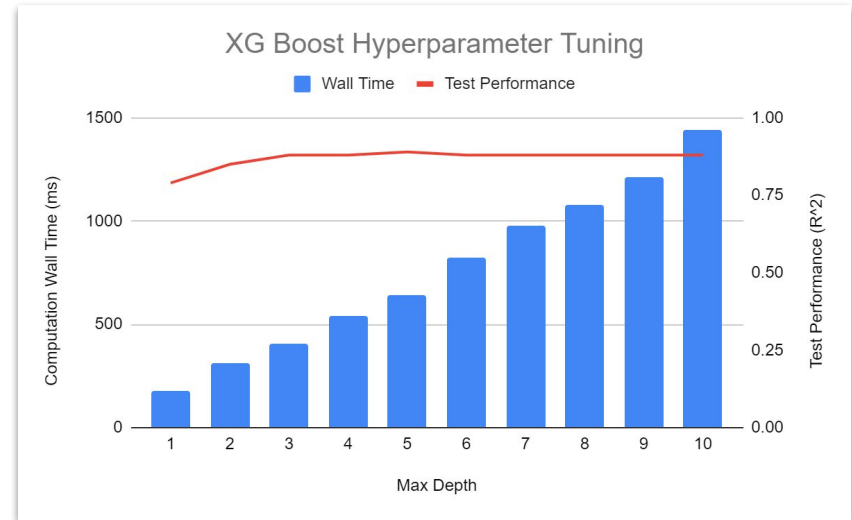
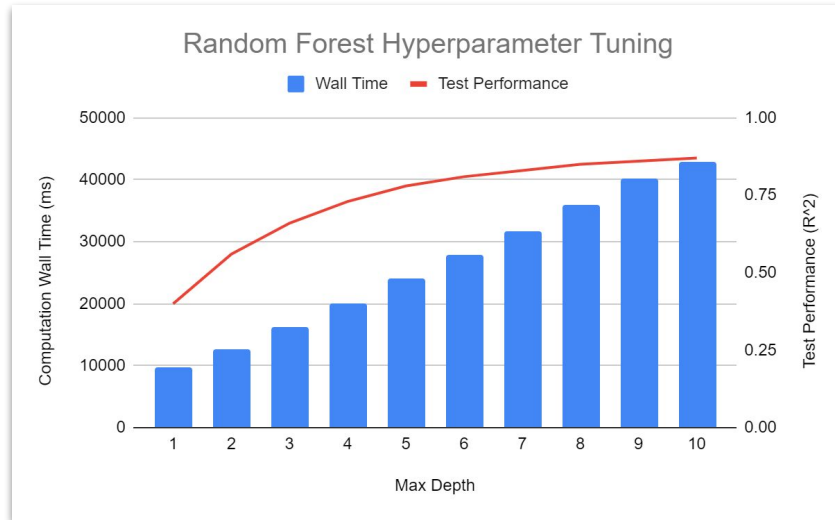
Max Depth
Hyperparameter tuned to
prevent overfitting

- Random Forest Regression
 - Randomly generates decision trees
 - Output is average of predictions
- XG Boost - Implementation of Gradient Boost
 - Evaluates results of each decision tree as they are generated
 - Unlike Random Forest, each new tree generated minimizes the gradient of the loss function



Methods: Model Comparisons

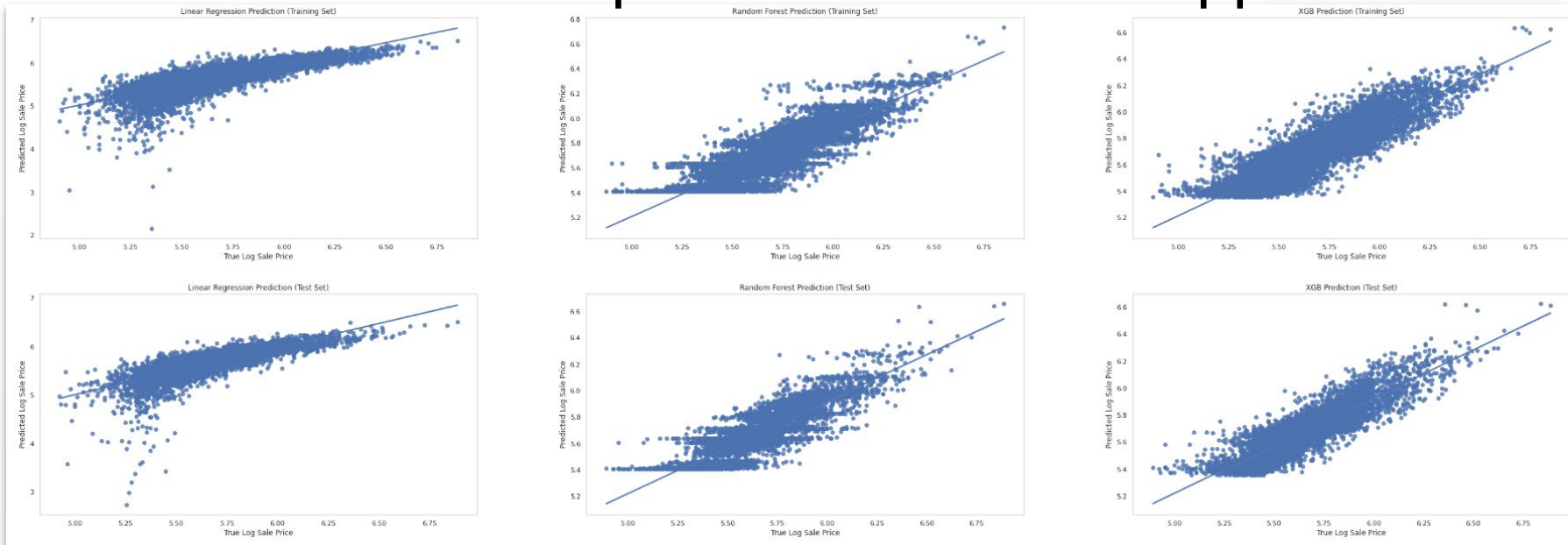
Random Forest vs XG Boost - Model Selection Rationale



****NOTE VERTICAL SCALE****

XG Boost reduces wall time by greater than an order of magnitude

Results: Model Comparisons/Alternate Approaches



Model 1: Linear Regression
Performance on train set: 0.71
Performance on test set: 0.70
Speed: 18.5 ms

Model 2: Random Forest
Performance on train set: 0.76
Performance on test set: 0.73
Speed: 20.9 s

Model 3: XGBoost
Performance on train set: 0.89
Performance on test set: 0.86
Speed 337 ms

Results: Model Comparisons/Alternate Approaches

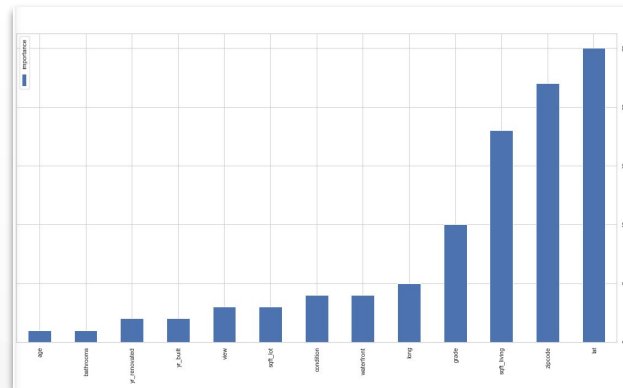
- Accuracy (Training/Test)
 - Linear Regression: 0.71/0.7
 - Random Forest: 0.76/0.73
 - XGBoost: 0.89/0.86
- Speed
 - Linear Regression: 18.5 ms
 - Random Forest: 20.9 s
 - XGBoost: 337 ms
- Data Partition
 - Train Set: 70%
 - Test Set: 30%
- All three models provide accurate results ($R^2 > 0.7$)
- Training and Test Accuracy results are similar - models are not overfitted
- Linear Regression has the fastest computation time but least accurate
- XGBoost is the most accurate model - slower than linear regression but much faster than random forest

Potential Problems:

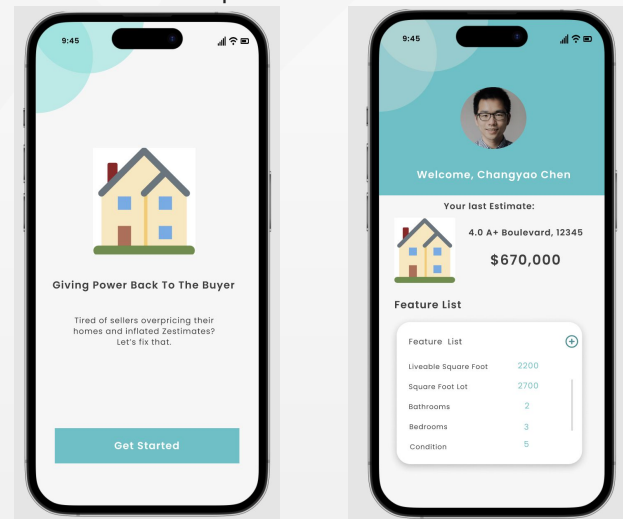
- Dataset does **not** include **supply** and **interest rates**.
- Data has sale prices from 2015, would need more recent data to be applicable to 2022, as just applying average 7.7% appreciation to 2015 price, would not account for rapid appreciation and the migration into rural suburbs seen post-covid.

Future Extensions, Actionable Results & New/Alternate Approaches:

- **Latitude/zip code** is shown to be the strongest feature impacting price. We intend to create a emerging neighborhood feature that tracks number of businesses nearby and median income, as neighborhoods are rapidly changing, a once undesirable zip code can be “up and coming” (I.E Williamsburg/Bushwick).
- Expand dataset to include more locations, as the dataset is specific to King County.
- Factor in features such as supply & interest rates.
- Build out user friendly application (FIGMA prototype shown).



Feature Importance from XGBoost





Any Questions?

Sources:

- <https://yourorlando.com/buying-a-home-in-the-orlando-florida-area>
- <https://www.nerdwallet.com/article/mortgages/fed-mortgage-rates>
- <https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.cut.html>
- <https://towardsdatascience.com/data-preprocessing-with-python-pandas-part-5-binning-c5bd5fd1b950>
- <https://www.creditkarma.com/home-loans/i/average-home-value-increase-per-year#:~:text=Since%201991%2C%20the%20ave rage%20annual.significantly%20from%20state%20to%20state.>
- <https://xgboost.readthedocs.io/en/stable/tutorials/model.html>