King County Real Estate Market Analysis: May 2014 - May 2015

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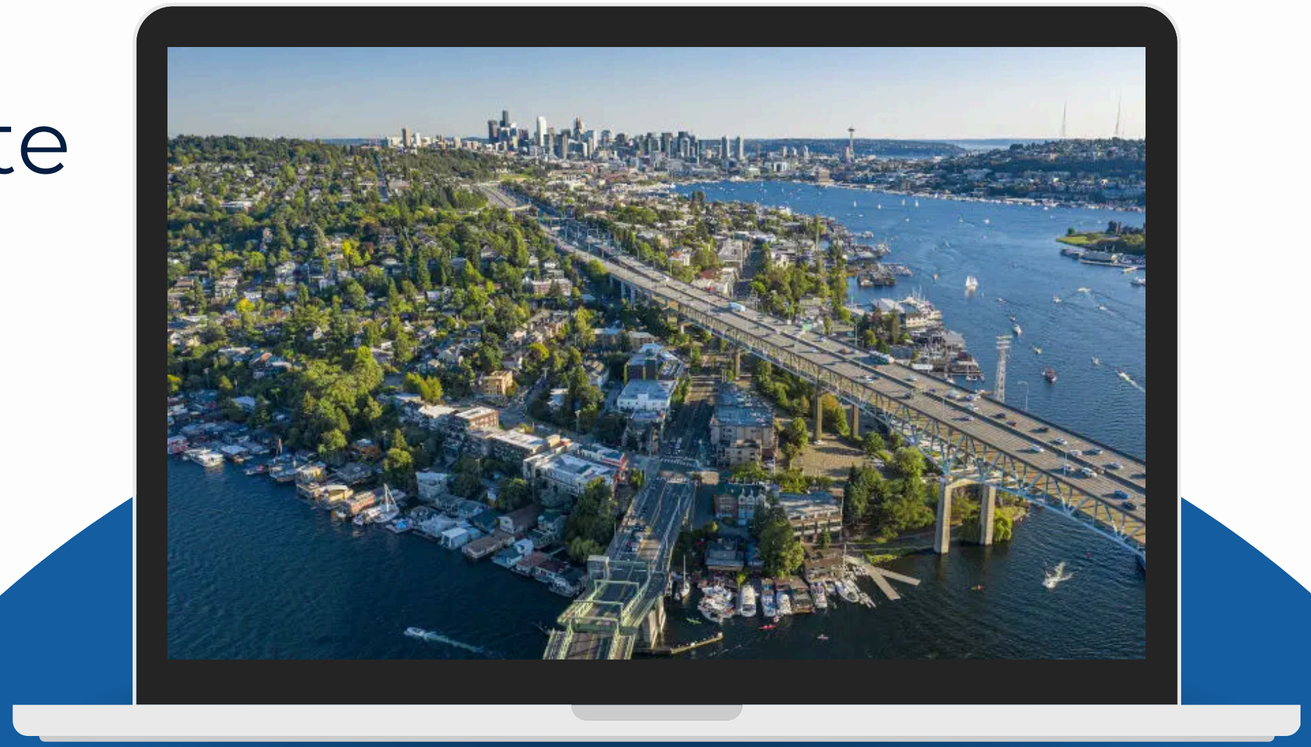

Overview

Project Overview

This project analyzes house sale prices in King County, including Seattle, over one year (May 2014 – May 2015).

The main goal is to predict house prices and identify the most influential factors affecting them. The project involves data exploration and modeling, simulating real-world real estate analysis while applying Python skills and analytical techniques to extract actionable insights from the housing market.

Dataset Description

- House sales in King County (Seattle), May 2014 – May 2015
- 21 features per property: bedrooms, bathrooms, sqft, floors, waterfront, view, condition, grade, year built/renovated, location
- Target variable: price (sale price of the house)

Key Insights

Before moving into modeling, we explored the dataset to detect inconsistencies and patterns. During this exploration, we found some relevant aspects that shaped how we approached the analysis

01

Converted the date column into proper datetime format for accurate analysis.

02

Detected duplicate house IDs, indicating multiple sales of the same property.

03

Decided to follow two approaches:

1. Using the full dataset.
2. Keeping only the most recent transaction per house, since it typically had the highest sale price.

Process

01 **Data Exploration & Cleaning**: overview, handle nulls/duplicates

02 **EDA**: visualize patterns

03 **Prepare Data:** split features/target, encode categoricals

04 **Modeling & Tuning:** train models and improve performance

05 **Feature Importance:** identify key predictors

Models Tested

Linear Regression

ADAboost

XGBoost

Random Forest

Gradient Boost

Cat Boost

Metrics & Evaluation

Linear Regression

All Data

R2 Linear Regression Train: 0.69910
R2 Linear Regression Test: 0.70119

Drop data

R2 Linear Regression Train: 0.69740
R2 Linear Regression Test: 0.70614

ADAboost

R2 ADAregressor Train: 0.70886
R2 ADAregressor Test: 0.65693

R2 ADAregressor Train: 0.70671
R2 ADAregressor Test: 0.68257

XGBoost

R2 XGboost Train: 0.97646
R2 XGboost Test: 0.85513

R2 XGboost Train: 0.97673
R2 XGboost Test: 0.89680

Random Forest

All Data

Mean Squared Error: 2228496940.85
R2 Random Forest Train: 0.98294

Mean Squared Error: 21807588291.06
R2 Random Forest Test: 0.85575

Drop Data

Mean Squared Error: 2391235579.01
R2 Random Forest Train: 0.98208

Mean Squared Error: 15992427088.73
R2 Random Forest Test: 0.88639

Gradient Boost

R2 Gradient Train: 0.98294
R2 Gradient Test: 0.85575

R2 Gradient Train: 0.69062
R2 Gradient Test: 0.69180

Cat Boost

Mean Squared Train Error: 68784.50
R2 Cat Train: 0.96379

Mean Squared Test Error: 125663.72
R2 Cat Test: 0.89554

Mean Squared Train Error: 68536.94
R2 Cat Train: 0.96480

Mean Squared Test Error: 111021.33
R2 Cat Test: 0.91244

Best Models

CatBoost

XGBoost

Random Forest

Improvements made

Before finalizing the model, we added new features and refined the data to help the algorithm capture more patterns and improve predictions.

01

Added month of sale as a new feature to keep both house sale prices for duplicate entries.

02

Removed irrelevant columns and split data into train/test sets (80/20).

03

Trained a CatBoost regressor to improve predictions on house prices.

Results

Cat Boost

```
Mean Squared Train Error: 66879.13
R2 CatBoost Train: 0.96576
```

```
Mean Squared Train Error: 124742.05
R2 CatBoost Test: 0.89707
```

Feature Importance

Lat

Latitude coordinate.

28.2737

Sqft_living

Square footage of the interior living space.

17.9468

Grade

The overall grade given to the house, based on the King County grading system.

13.488

Conclusions and Future Steps

01

Conclusions:

- Data analysis was performed on King County housing dataset (21k+ records).
- After cleaning, key features affecting house prices were identified.
- Latitude, living area (sqft_living), and grade are the strongest predictors of price.
- Features like bedrooms and floors showed little influence on pricing.
- The CatBoost model provided reliable insights into price prediction.
- Results can help homeowners, buyers, and real estate agents make informed decisions.

02

Future Steps:

- Perform hyperparameter tuning on the model to optimize performance.
- Experiment with different train-test splits to evaluate model stability.
- Address overfitting (currently ~10%) by reducing the training set size, which may help improve test accuracy.

THANK YOU!