Real Estate Price Prediction Using Machine Learning

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EXECUTIVE SUMMARY

Predicting house prices is essential for buyers, sellers, and investors.

This project builds machine learning models to estimate house prices based on historical housing data.

Goal: Provide accurate, data-driven property valuations.

PROBLEM STATEMENT

- Pricing homes is complex due to market variability.
- Stakeholders seek reliable estimates based on tangible features.
- Objective: Build regression models that predict house prices using features like size, location, and amenities.

OBJECTIVES

- Provide accurate, data-driven property price estimates to support better decision-making for agents, developers, buyers, and sellers.
- Analyze and identify key drivers of house prices, such as square footage, location, and amenities.
- Automate the valuation process to reduce manual effort and pricing subjectivity.
- Detect market trends and pricing anomalies for investment insights.
- Simulate how property improvements (like renovations) affect value.
- Build a predictive tool that can be integrated into real estate platforms.

DATASET OVERVIEW

- Source: Kaggle — House Price Prediction Dataset.
- 21,000+ property listings.
- Features include bedrooms, bathrooms, sqft, city, ZIP, etc.
- Region: King County, WA.

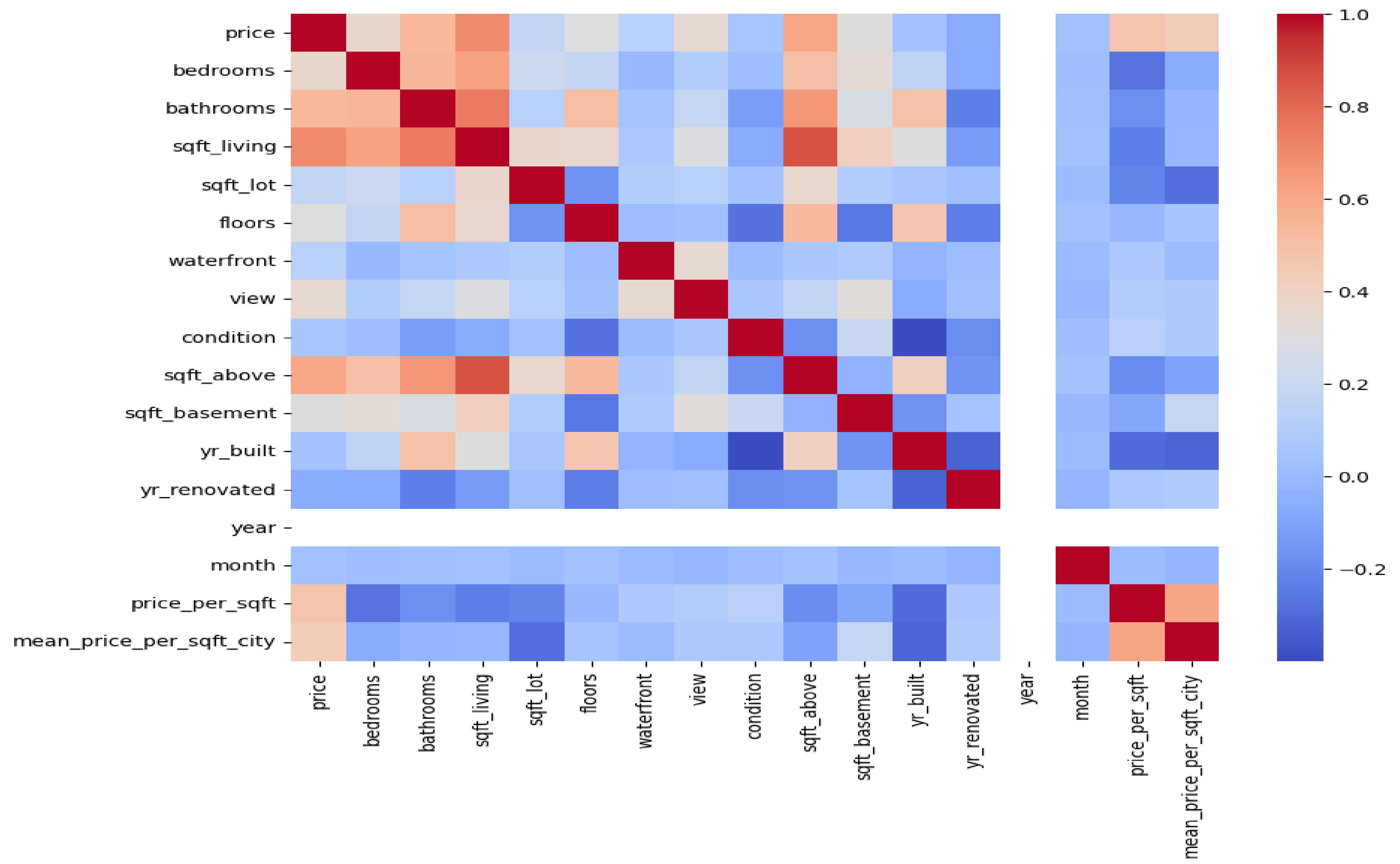
DATA PREPROCESSING

- Removed nulls, irrelevant fields (IDs, exact dates).
- Categorical encoding (e.g., city, ZIP code).
- Feature engineering: year built, year renovated.
- Outlier analysis — excluded 0-price entries only.

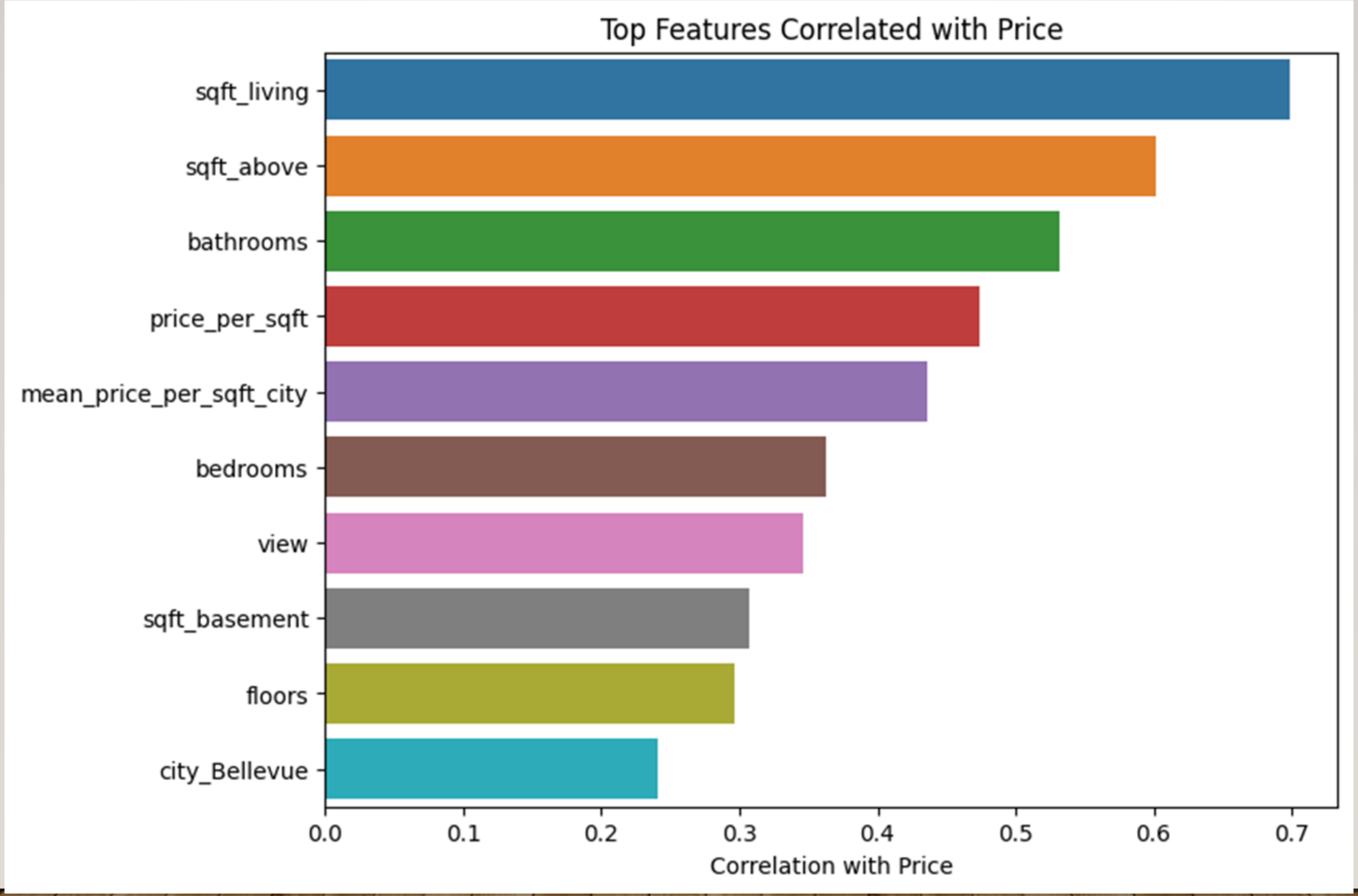
EXPLORATORY DATA ANALYSIS

- Correlation heatmap revealed strong price correlations with:
  - Square footage
  - Bathrooms
  - Location (city, ZIP)
- Visualizations: scatter plots, box plots

CORRELATION HEATMAP



TOP 10 FEATURES CORRELATED WITH PRICE



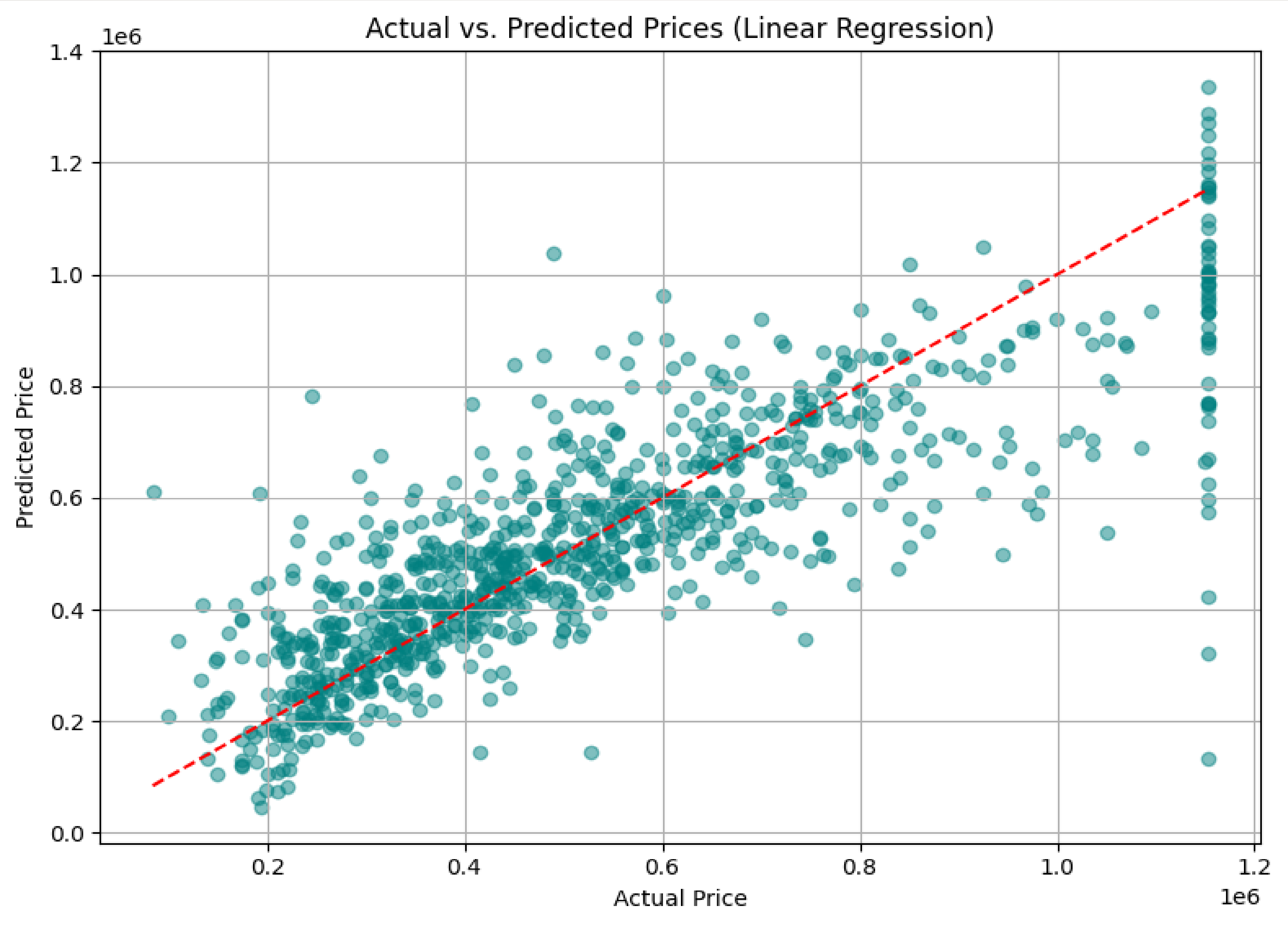
MODELING APPROACH

- Regression Models Used:
  - Linear Regression
  - OLS Regression
  - Decision Tree Regressor
  - Random Forest
  - Gradient Boosting
- Used GridSearchCV for hyperparameter tuning.

EVALUATION METRICS

- R^2 Score — model fit
- MAE — average error in dollars
- RMSE — penalizes large errors
- Baseline model: Linear Regression

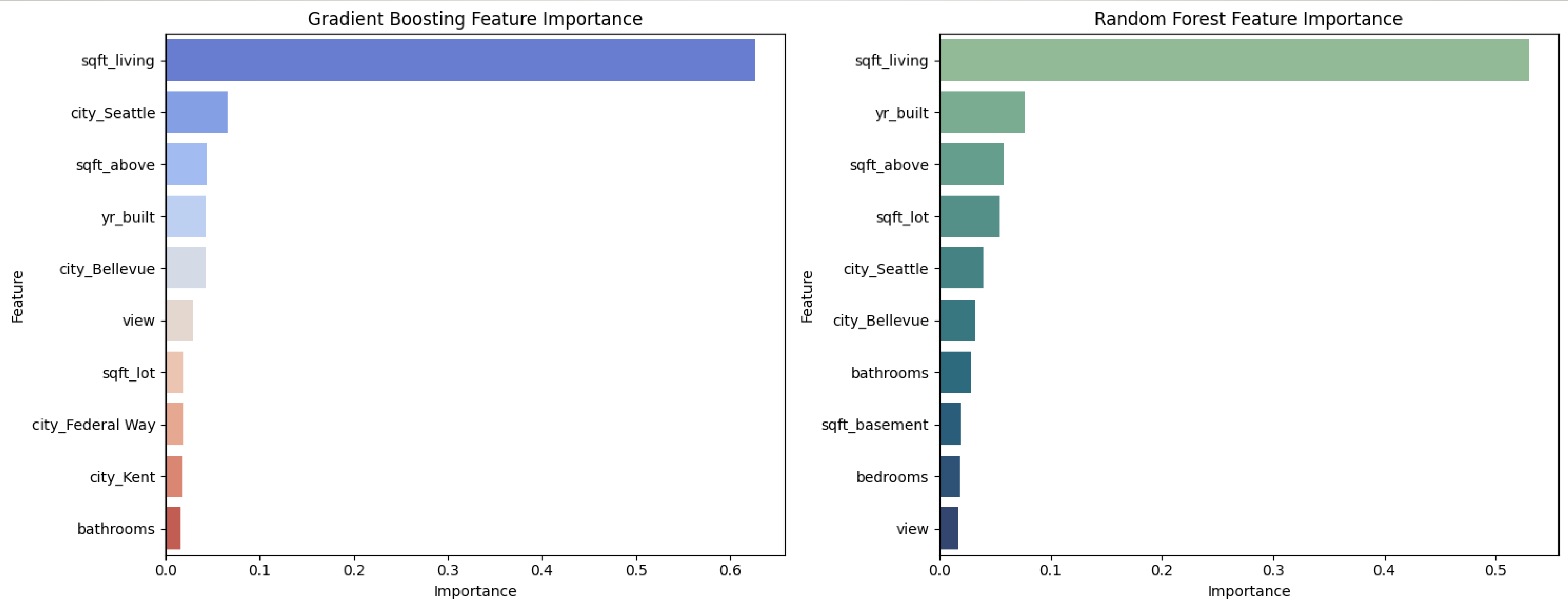
LINEAR REGRESSION RESULTS



MODEL COMPARISON

Model	R^2	MAE	RMSE
Linear Regression	0.6763	$101K	$146K
OLS Regression	0.712	~$99K	~$146K
Decision Tree	0.5670	~	$169K
Random Forest	0.6415	$105K	$153K
Gradient Boosting (Tuned)	**0.6799**	**$99K**	**$145K**

Top 10 Feature Importances



Both models agree that square footage (sqft_living) is the most important feature. Location-based features like city_Seattle and city_Bellevue also rank highly, affirming the significance of geography in real estate pricing.

INSIGHTS & FINDINGS

- Best model: Optimized Gradient Boosting Regressor.
- Linear & Gradient models outperformed tree-based models.
- Square footage and location were the strongest predictors.
- Outlier filtering did not significantly improve performance.

RECOMMENDATIONS

- Use ML-based tools in real estate platforms for price estimation.
- Regularly retrain models with updated market data.
- Use model insights to guide renovation investments.
- Deploy as a web tool or API for user access.

LIMITATIONS & FUTURE WORK

- **Limitations:**
- Geographic bias: limited to King County, WA.
- Sensitive to missing or inaccurate features.
- **Future Work:**
- Add economic indicators (e.g., interest rates).
- Test deep learning models.
- Incorporate maps/geospatial data.
- Build full-stack web app.

CONCLUSIONS

- The project aimed to build a predictive model for house prices using various regression models.
- Among all the models tested, **Optimized Gradient Boosting Regressor** performed best, with:
  - **R^2 Score: 0.6799**
  - **MAE: $99,444.53**
  - **RMSE: $145,521.95**
- However, performance across all models remained below an R^2 of 0.70, suggesting:
  - There is **still unexplained variance**, possibly due to omitted features (e.g. interior design, crime rate, school district).
  - The dataset may benefit from **more granular or external data**.
- **Linear models (OLS, Linear Regression)** performed surprisingly well, indicating that the relationship between features and price is mostly linear with minor non-linearity

RECOMMENDATIONS

- **Feature Engineering**: Add more relevant features (e.g. proximity to amenities, schools, crime rates) to improve model performance.
- **Outlier Handling**: Consider early-stage outlier analysis to improve data quality.
- **Ensemble Methods**: Continue using tree-based models like Gradient Boosting with tuning—they consistently outperform others.
- **Regular Validation**: Ensure you revalidate performance using data from different time periods or locations for generalizability.
- **Deployment Readiness**: While model performance is reasonable, it is not production-grade. A/B testing with real users could provide insights before full deployment.

Thank you!