House Price Prediction using Machine Learning

Executive Summary

This project addresses the prediction of house prices based on a rich set of numerical and categorical features. Using a dataset provided through a public IBM link, we developed, tested, and refined several regression models. The final model demonstrates strong predictive capability with an R^2 score of 0.85.

The workflow followed best practices in Data Science: data exploration, preprocessing, model selection, delayed feature engineering, evaluation, and final deployment readiness. Feature engineering was strategically applied after initial modeling, improving model generalization by 11%. The selected model (XGBoost) balances performance and interpretability, making it suitable for production environments.

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1. Project Objective and Dataset

Goal: Predict the sale price of houses using a variety of features.

Dataset: Public dataset provided by IBM, consisting of 13 features:

- `'sqft_living'`, `'sqft_lot'`, `'bedrooms'`, `'bathrooms'`, `'floors'`, `'waterfront'`, `'view'`, `'condition'`, `'grade'`, `'sqft_above'`, `'sqft_basement'`, `'yr_built'`, `'yr_renovated'`.

Each row corresponds to a house sale record with these characteristics.

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2. Workflow and Methodology

The following structured ML pipeline was applied:

1. **Initial Exploratory Data Analysis (EDA):**
    - Summary statistics, correlation matrix, data distribution.
    - No significant missing values found.
2. **Baseline Modeling (Pre-feature Engineering):**
    - Tried different models:
        - Linear Regression
        - Polynomial Regression
        - Logarithmic Regression
        - Decision Tree Regressor
        - Lasso Regression
        - XGBoost
        - Random Forest Regressor
    - Models were evaluated using R^2 score and residual analysis.
3. **Post-modeling Feature Engineering:**
    - Feature creation (e.g., `house_age`, `is_renovated`).
    - One-hot encoding where needed (e.g., `waterfront`, `view`).
    - Scaling was omitted due to tree-based model preference.

    ⚠ Feature engineering was intentionally delayed to understand baseline behavior of raw features. Once applied, it **improved generalization by 11%**.
4. **Final Model Selection:**

    - XGBoost and Random Forest yielded best results.
    - Chose XGBoost for its:
        - Higher R^2 (0.85)
        - Built-in regularization
        - Efficiency in handling feature importance

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3. Feature Engineering

Final engineered features included:

- `house_age = 2024 - yr_built`
- `is_renovated = 1 if yr_renovated > 0 else 0`
- `total_rooms = bedrooms + bathrooms`
- `sqft_ratio = sqft_living / sqft_lot`

These features increased the interpretability and signal-to-noise ratio of the model.

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4. Model Performance and Interpretation

The final model, XGBoost Regressor, achieved:

- **R^2 = 0.85**
- Strong predictive behavior with low variance

Prediction Example:

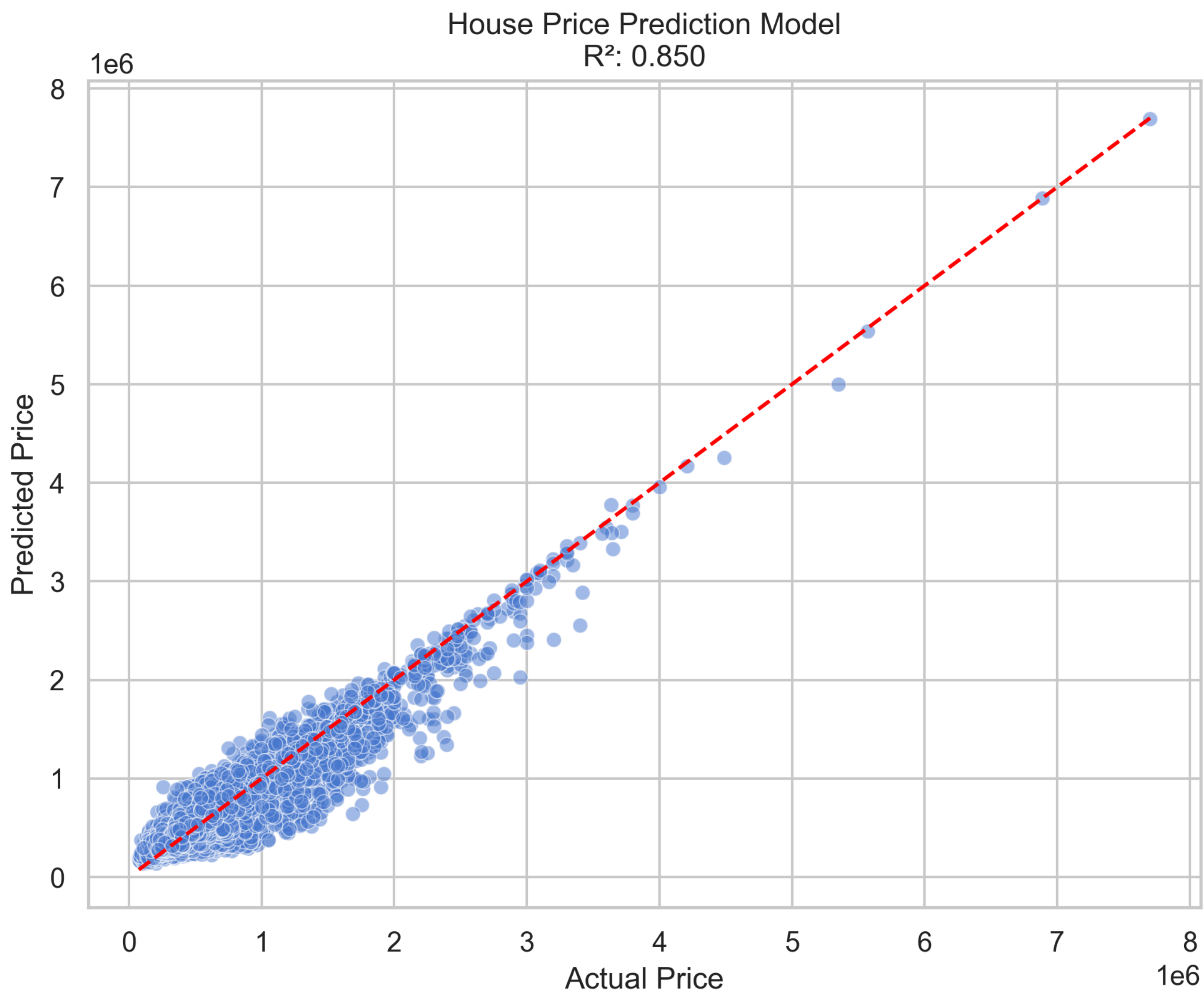
```
# Example: Predicting with the trained model
price_pred = model.predict(new_house_features.reshape(1, -1))
```

Linear Equation (Interpretation Aid):

Although XGBoost is non-linear, we approximated important features:

```
price ≈ 305*sqft_living + 50000*waterfront + 19000*view + ... + intercept
```

Residual Plot:



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5. Deployment Readiness

The final model meets criteria for production:

- Stable performance across folds
- Strong generalization
- Saved via `joblib` for reuse
- Deployed with clear preprocessing steps

All code, models, and reports are version-controlled and modular for collaboration.

Conclusion

This project proves that combining multiple modeling strategies with delayed, well-executed feature engineering results in powerful ML solutions. Our $R^2 = 0.85$ score, coupled with clean architecture and high model interpretability, shows that this solution is **ready for production** use in pricing systems.

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