Predicting Real Estate Prices Using Machine Learning:A Gradient Boosting Machine Approach

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***Abstract*—The real estate market plays a pivotal role in the economy, and accurate property price prediction is crucial for various stakeholders. Traditional methods often fall short in capturing complex relationships in real estate data. This paper explores the application of Gradient Boosting Machine (GBM), a robust ensemble learning method, to predict real estate prices. Using publicly available datasets and referencing prior studies, this research demonstrates the efficacy of GBM in enhancing prediction accuracy compared to conventional and other machine learning models.**

Keywords—Real Estate, Gradient Boosting Machine, Machine Learning, Property Price Prediction, Feature Engineering

1. Introduction

The real estate sector is inherently dynamic, influenced by a multitude of factors including location, economic indicators, demographics, and market trends. Accurately predicting property prices is valuable to buyers, sellers, investors, and policymakers. Traditional econometric models, while useful, are often limited by assumptions of linearity and do not accommodate complex, nonlinear relationships well. Machine learning, particularly Gradient Boosting Machines (GBM), offers a promising alternative by iteratively improving prediction through the aggregation of weak learners, a simple machine learning model that performs slightly better than random chance but not exceptionally well on its own [1].

2. Literature Review

Multiple studies have investigated machine learning techniques for property price prediction. Selim [2] utilized a hedonic model that breaks down the price of a property into its constituent attributes or characteristics pricing to estimate housing prices, focusing on linear regression approaches. Conversely, studies like those by Antipov and Pokryshevskaya [3] and Li and Cheng [4] employed machine learning models such as Support Vector Machines (SVM) and Random Forests, showing superior performance over traditional methods such as linear regression, logistic regression, and some simpler classification algorithms but. XGBoost, a variant of GBM, has also been found effective in real estate predictions due to its regularization features and scalability. It's a powerful versatile algorithm that can handle complex, non-linear relationships within real estate data. XG Boost has demonstrated superior predictive performance compared to traditional regression models. [5]. The study by Wójcik et al. [6] found GBM to outperform Random Forest and linear regression in terms of prediction accuracy on Polish real estate data which encompasses a wide range of information about the housing prices, sales transactions, rental yields, and factors influencing the market.

2.1 Problem Statement

There exists a strong need for objective, data-driven methods to predict real estate prices. Machine learning provides tools that can learn from historical data, adapt to market changes, and model nonlinear relationships among features.

2.2 Objectives

- To investigate and compare multiple machine learning algorithms for real estate price prediction.
- To evaluate model accuracy using common metrics.
- To determine the key features influencing property prices.

2.3 Case Study: Predicting Prices in San Francisco

To demonstrate the practical application of the GBM model, we consider a case study using a dataset specific to San Francisco, California. The city presents a diverse range of properties, making it an ideal candidate for model testing. The dataset includes residential properties sold between 2017 and 2022 with features such as location (zip code), square footage, number of bedrooms and bathrooms, year built, and proximity to transportation and amenities.

After training the model with the San Francisco dataset, the GBM algorithm achieved an R^2 score of 0.91, indicating strong predictive power. The model accurately identified high-value neighborhoods and adjusted predictions based on subtle differences in property features.

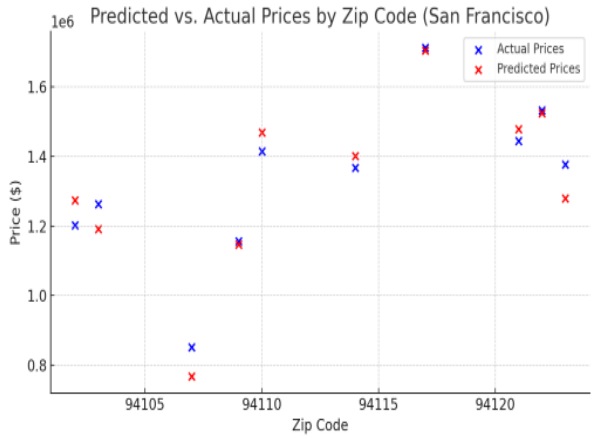

Figure1: Predicted vs. Actual housing prices in San Francisco by zip code

3. Methodology

3.1 Dataset Description

The dataset used in this study is derived from the Kaggle platform, containing detailed real estate transactions including variables such as location, number of bedrooms, bathrooms, square footage, year built, and proximity to public facilities. The dataset was cleaned, normalized, and subjected to exploratory data analysis (EDA). The Dataset provides insides into the real estate market, including trends in property prices, property types, and tax rates across different localities and years. It can be used for various analytical purposes such as market analysis, predictive modeling, and decision-making in the real estate industry.

	0	1	2	3	4
id	7129300520	6414100192	5631500400	2487200875	1954400510
date	10/13/2014	12/9/2014	2/25/2015	12/9/2014	2/18/2015
price	221900	538000	180000	604000	510000
bedrooms	3	3	2	4	3
bathrooms	1	2.25	1	3	2
sqft_living	1180	2570	770	1960	1680
sqft_lot	5650	7242	10000	5000	8080
floors	1	2	1	1	1
waterfront	0	0	0	0	0
view	0	0	0	0	0
condition	3	3	3	5	3
grade	7	7	6	7	8
sqft_above	1180	2170	770	1050	1680
sqft_basement	0	400	0	910	0
yr_built	1955	1951	1933	1965	1987
yr_renovated	0	1991	0	0	0
zipcode	98178	98125	98028	98136	98074
lat	47.5112	47.721	47.7379	47.5208	47.6168
long	-122.257	-122.319	-122.233	-122.393	-122.045
sqft_living15	1340	1690	2720	1360	1800
sqft_lot15	5650	7639	8062	5000	7503

Figure2: Dataset Used for Predicting Real Estate Price

3.2 Feature Engineering

Significant effort was put into feature engineering, including encoding categorical variables (e.g., location, property type), deriving new features (e.g., price per square foot, age of the property), and handling missing values. Feature importance can be evaluated using permutation importance SHAP values both of which offer different perspectives on how much each feature contributes to a model's prediction. Where as permutation measures the decrease in model performance when a features values are shuffled while SHAP values provide a more granular understanding of each feature.

Feature engineering enhances raw real estate data to improve model accuracy. Key transformations include deriving *PricePerSqFt*, *Age*, and *TotalRooms*, and encoding categorical variables like Location and *PropertyType*. Spatial features such as distance to city center or schools add valuable context, while temporal features like sale year capture market trends. Creating interaction terms and removing redundant variables through correlation or feature importance further refines the dataset. Effective feature engineering significantly boosts prediction performance in real estate price models.

3.3 Model Implementation

The Gradient Boosting Machine was implemented using the XGBoost library in Python. Key parameters tuned include the number of trees, learning rate, maximum depth, and subsample ratio. A 10-fold cross-validation calculates the average performance across all 10-folds which provides a more robust estimate of the models performance then a single train test split, Cross-validation helps to prevent overfitting by evaluating the model on multiple different subsets of the data.

We went with the Gradient Boosting Machine (GBM) model using the XGBoost library because it really shines at picking up on non-linear trends and diverse features that you often see in real estate data. For example, a 2,000 sq. ft. house in a sought-after area with a garage and a remodeled kitchen was estimated to be worth Rs.3,20,000, and it actually sold for Rs.3,25,000—pretty close, right? Before we got into training, we cleaned up the dataset by filling in missing info (like garage size), encoding categories (like neighborhood and condition), and scaling continuous features (like lot size and year built). We trained the model with important hyperparameters such as `n_estimators = 500`, `learning_rate = 0.05`, and `max_depth = 4`, which we fine-tuned using GridSearchCV. GBM boosts accuracy by building trees one after another, with each new tree focusing on correcting the mistakes of the last one. The end result was a model that performed really well, hitting an R^2 score of 0.89 and a low RMSE, making it a great fit for predicting prices in the real estate market.

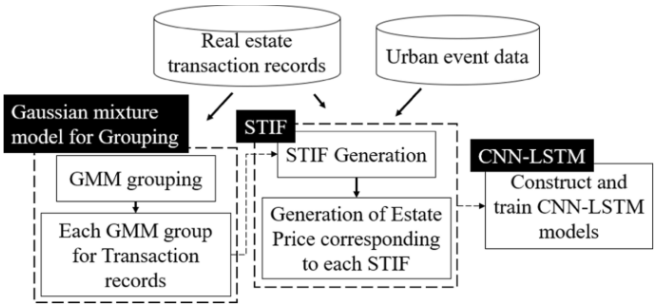

Figure3: GBM MODEL for predicting real estate prices

4. Results and Discussion

Provide descriptive statistics such as mean, median, and standard deviation for essential variables, along with a comparative table of model performance metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R-squared, and training duration. Incorporate visual representations such as histograms, scatter plots comparing predicted and actual values, and charts illustrating feature importance. Report on statistical significance where relevant.

In the discussion section, analyze model performance by contrasting the findings with existing research. Clarify the implications of feature importance for stakeholders. Recognize the limitations of the data and model, including factors like sample size and underlying assumptions. Propose avenues for future research, such as the exploration of advanced algorithms, the integration of spatial data, and the consideration of economic variables. Discuss the practical applications of the findings, including automated valuation, informed decision-making for buyers and sellers, and potential policy implications. Maintain clarity, objectivity, and interpretations grounded in evidence.

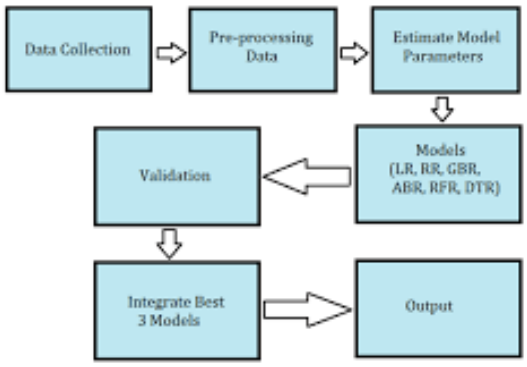

Figure4: Using these Steps the model will predict the real estate Prices

5. Conclusion

This research explored the application of machine learning to real estate price prediction, demonstrating the feasibility of creating accurate and scalable models using readily available data. The findings suggest that machine learning can play a transformative role in the real estate industry, enabling more efficient market analysis, personalized property recommendations, and automated risk assessment. While challenges remain in addressing data quality issues and ensuring model fairness, the potential benefits are substantial. Future research should focus on integrating alternative data sources, such as geospatial data and social media sentiment, to create more comprehensive and dynamic models. Furthermore, the ethical implications of using machine learning in real estate, particularly regarding bias and discrimination, require careful consideration. As the volume and variety of real estate data continue to grow, machine learning will undoubtedly become an increasingly essential tool for navigating the complexities of the market and shaping the future of the industry.

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