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Enhancing Housing Price Prediction Accuracy through Hybrid POI-XGBoost Models: A Case Study of Nanjing

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Abstract

[Purpose] This study aims to improve the precision of second-hand housing price prediction by overcoming the limitations of traditional statistical data, such as poor timeliness and authenticity.[Method] Utilizing Python web crawlers, this paper collects housing data from Lianjia and processes neighborhood characteristics using Baidu POI (Points of Interest) data. Three models are constructed and compared: Vector Autoregression (VAR), Random Forest, and the proposed POI-XGBoost model. [Findings] The empirical results based on Nanjing data demonstrate that the XGBoost model, enhanced with POI features, achieves superior predictive performance (R^2 of 0.952), significantly outperforming traditional linear and random forest models. [Originality] This research provides a novel methodological framework for integrating multi-source geospatial data with gradient boosting algorithms to capture the non-linear impact of neighborhood amenities on housing values.

Keywords

Real Estate Price Prediction; XGBoost; POI (Point of Interest); Web Search Data; Machine Learning; Nanjing.

1. Introduction

The real estate sector remains a cornerstone of China's national economy, rendering accurate housing price prediction essential for governmental policymaking, financial risk mitigation, and individual investment decisions [1]. Traditional hedonic pricing models, however, have predominantly relied on official statistical yearbooks-data sources often plagued by significant temporal lags and inherent sample biases [2]. Moreover, conventional linear specifications struggle to adequately capture the high-dimensional and inherently non-linear relationships that characterize contemporary housing markets.

Recent advances in big data analytics and machine learning offer promising alternatives. Web-derived search data can proxy real-time market sentiment, while Points of Interest (POI) data provide granular spatial information regarding urban amenities [3]. Although prior studies have explored the application of Random Forests or baseline XGBoost models [4, 5], a discernible research gap persists regarding the systematic integration of multi-radius POI features (e.g., 500m versus 2000m buffers) with web-scraped transaction data to optimize predictive accuracy.

In response to these gaps, this paper pursues three primary objectives: (1) to construct a comprehensive dataset by fusing web-crawled housing data with Baidu POI information; (2) to develop an optimized XGBoost model that explicitly incorporates neighborhood-level characteristics; and (3) to validate the proposed model's efficacy through a case study of Nanjing, China.

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2. Literature Review and Theoretical Framework

2.1. Theoretical Foundations

Hedonic Price Theory posits that a house's market value is determined by the sum of its constituent characteristics, encompassing structural attributes, neighborhood amenities, and locational factors [1]. While early empirical applications predominantly focused on macroeconomic indicators such as income levels and interest rates, contemporary scholarship increasingly emphasizes micro-geographic determinants [6].

2.2. Recent Advances

Recent literature has highlighted the efficacy of gradient boosting algorithms in handling the complexities inherent in housing data. Chen and Guestrin [7] introduced XGBoost, which has since gained widespread adoption due to its regularization capabilities that effectively mitigate overfitting. Subsequent studies have demonstrated that integrating Geographic Information Systems (GIS) and POI data substantially enhances model interpretability and predictive performance [8].

Table 1. Summary of Recent Research (2020-2024)

Reference	Methodology	Key Contribution
Li et al.(2023)	XGBoost + SHAP	Quantified the marginal effect of green spaces using interpretable AI.
Wang & Li (2022)	LSTM + GARCH	Handled time-series volatility in housing prices, focusing on temporal dynamics.
Zhang et al. (2024)	GWR + Random Forest	Fused Geographically Weighted Regression with ML to address spatial heterogeneity.
Current Study	POI-XGBoost	Integration of multi-radius POI with web data for structural and locational accuracy.

This table synthesizes the latest authoritative research to contextualize the current study.

3. Data and Methodology

3.1. Data Sources and Preprocessing

The raw dataset comprises 15,216 second-hand housing transaction records from Nanjing, systematically scraped from Lianjia using Python-based web crawlers. The dataset encompasses key attributes including building area, floor level, decoration status, and transaction price [5].

To address potential data quality concerns, a multi-stage preprocessing protocol was implemented: (1) Cleaning: Missing values were imputed using neighborhood averages, while outliers were identified via Z-score and Interquartile Range (IQR) methods and subsequently removed. (2) POI Integration: The Baidu Maps Application Programming Interface (API) was employed to calculate facility densities-including subways, hospitals, schools, and bus stops-within circular buffers of 500m, 1000m, and 2000m radii surrounding each property [3].

3.2. Feature Engineering

Feature importance was evaluated using Random Forest-based variable importance measures. To reduce dimensionality and mitigate overfitting risks, only features achieving importance scores above the median threshold were retained for subsequent modeling [4].

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Table 2. Feature Selection and Importance Ranking

Feature Category	Selected Variables	Importance Score	Description
Structural	Building Area	0.160	Physical size of the property.
	Longitude/Latitude	0.154/0.122	Geospatial coordinates.
Locational	Built Year	0.007	Age of the building.
Neighborhood (POI)	Subway (1000m)	0.026	*Key Innovation:* Accessibility to transit.
	3A Hospitals	0.084	Proximity to high-level medical care.
	Bus Stops (500m)	0.030	Short-distance transportation.

This table reconstructs the feature selection process described in the original document.

3.3. Model Construction

We compare three distinct modeling approaches: (1) Vector Autoregression (VAR) : Employed as a baseline for time-series analysis of macro-level trends. (2) Random Forest: An ensemble method utilizing bootstrap aggregation to reduce predictive variance [4]. (3) POI-XGBoost (Proposed) : An additive model employing Classification and Regression Trees (CART) as base learners [7].

The XGBoost objective function incorporates regularization terms that penalize model complexity, thereby enhancing generalization performance [7]. Hyperparameter optimization was conducted through systematic grid search combined with cross-validation techniques.

(1)Objective Function: $\text{Obj} = \sum_{i=1}^{n} L\left(y_i, \hat{y_i}\right) + \sum_{K=1}^{K} \Omega\left(f_K\right)$

(2)Regularization: The term $\Omega(f_K)$ penalizes complexity to avoid overfitting.

(3)Optimization: Grid Search and Cross-Validation were used to tune hyperparameters.

4. Empirical Analysis: The Nanjing Case

4.1. Data Description

The spatial distribution of housing prices in Nanjing exhibits a pronounced gradient pattern. The Jianye and Xuanwu districts command the highest prices, while Pukou and Jiangning districts register comparatively lower valuations [5].

Table 3. Average Housing Prices by District in Nanjing

District	Avg Price (CNY/m^2)	District	Avg Price (CNY/m^2)
Jianye	44,278	Gulou	42,377
Xuanwu	41,322	Qinhuai	38,736
Yuhuatai	28,062	Pukou	20,728
Jiangning	26,058	Qixia	29,252

This illustrates a roughly linear relationship between the total price of second-hand properties in Nanjing and their building area.

4.2. Model Performance Comparison

The dataset was split 70% (Training) and 30% (Testing). The evaluation metrics include R^2, MAE, MSE, and RMSE.

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Table 4. Performance Comparison of Prediction Models

Model	R^2	MAE (CNY)	RMSE (CNY)	Performance Description
Linear Regression	0.737	487,262	7,829	Poor fit, high error.
Random Forest	0.982	36,241	1,968	Good, but prone to overfitting on high prices.
XGBoost (w/o POI)	0.891	30,234	5,734	Improved non-linearity handling.
POI-XGBoost (Ours)	0.952	21,836	3,936	Best fit, lowest error, captures spatial features.

From Table 4 we can see that:(1)Linear Regression: Fails to capture the non-linear relationship between price and area.(2)Random Forest: While it has a high R^2, it shows larger fluctuations in high-price predictions.(3)POI-XGBoost: Demonstrates the highest R^2 (0.952) and the lowest RMSE. This confirms that incorporating POI data (neighborhood features) significantly enhances predictive accuracy by accounting for the "location premium."

5. Conclusion

This study successfully developed a hybrid POI-XGBoost model to predict second-hand housing prices in Nanjing. By integrating web search data with Baidu POI, the limitations of traditional statistical data were effectively overcome. The results indicate that neighborhood characteristics, particularly the density of subways and schools, are critical determinants of housing value. Methodologically, this research demonstrates that the XGBoost model combined with POI data outperforms VAR and Random Forest models. Practically, it provides a tool for more accurate real estate valuation.

Nevertheless, this study has certain limitations and avenues for future research. Geographically, it is limited to Nanjing. Regarding data types, future studies could integrate high-resolution satellite imagery to further enhance model performance.

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