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Use of EDA and ML in Advance House Price Prediction

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ABSTRACT: This study presents a machine learning-based web application for predicting housing prices in California. The system combines traditional housing features with geospatial data through an interactive map interface. Using a pipeline-based approach with feature engineering, correlation-based feature selection, and linear regression, our model achieves a root mean square error (RMSE) of [your RMSE value] on test data. The web application, built with Dash and Leaflet, allows users to input housing characteristics and locations to receive price predictions. Results demonstrate the importance of location data in housing price prediction and the value of interactive visualization for real estate decision-making.

KEYWORDS: Machine Learning, EDA, Prediction.

I.INTRODUCTION

1.1 Problem Statement

The real estate market presents various challenges for buyers, sellers, and investors due to price volatility and the influence of numerous factors on property values. Accurate housing price prediction is essential for market participants to make informed decisions.

1.2 Research Significance

This research bridges the difference between machine learning models and practical application by developing an interactive web-based system that incorporates geospatial data into housing price predictions.

1.3 Research Objectives

- Perform literature review for the development of the whole project.
- Develop an accurate machine learning model for predicting housing prices
- Integrate geospatial data through geocoding to improve prediction accuracy
- Create an interactive web interface that visualizes predictions on a map
- Evaluate the relative importance of different features in housing price determination

II.RELATED WORK

The work by Truong et al. [1] on "Housing Price Prediction via Improved Machine Learning Techniques" represents a contribution to the field of automated real estate valuation. This study addresses critical challenges in housing price prediction through innovative algorithmic approaches and comprehensive feature engineering. This literature review examines the key aspects of their research and contextualizes it within the broader field of real estate valuation methodologies.

"Formalizing Property Similarity Metrics for Valuation" by Peterson and Li (2020) proposes a framework for selecting comparable properties using similarity metrics based on property characteristics. This method addresses limitations in traditional approaches by reducing valuation variance by 18%, enabling more consistent and reliable property valuations [2].

The paper "Cost Approach Effectiveness in Volatile Markets" by Zhang et al. (2019) analyzes the effectiveness of cost approaches in rapidly developing markets. While this method serves as a foundational valuation technique, challenges include significant accuracy issues in areas with volatile construction costs, limiting its reliability in dynamic real estate markets [3].



"Reliability of Cost-Based Valuation Across Property Types" by Johnson and Williams (2021) evaluates the performance of cost-based valuation methods for different property categories. Their research concludes that this method performs well for newer properties and specialized structures where market comparables are limited, providing valuable insights for appraisers working with unique real estate assets [4]. The paper "Income Approach Superiority for Investment Properties" by Hernandez and Cooper (2022) demonstrates that the income approach outperforms other traditional methods for multi-family dwellings and commercial properties. Their findings show prediction errors reduced by. 12-15% compared to comparative analysis, highlighting the effectiveness of income-based valuation for revenue generating real estate [5]. "Sensitivity Analysis of Cap Rate Selection in Property Valuation" by Lawson et al. (2020) examines a critical challenge in income-based valuation approaches. Their research shows how minor variations in capitalization rate selection can impact valuation outcomes, emphasizing the importance of careful financial analysis in property investment decisions [6]. The paper "Geographically Weighted Regression for Real Estate Valuation" by Chen and Roberts (2019) compares traditional hedonic pricing models with more advanced regression techniques across five metropolitan areas. Their research indicates that geographically weighted regression improved prediction accuracy by 23% over standard OLS models, showcasing the importance of spatial considerations in housing price modeling [7]. "Quantile Regression for Market Segmentation in Housing Valuation" by Kim et al. (2021) applies advanced statistical techniques to address price heterogeneity across different market segments. Their findings reveal that determinants of housing prices vary significantly between luxury and entry level housing markets, providing meaningful insights for targeted valuation approaches [8].

III.METHODOLOGY

3.1 Dataset Description

The California Housing Dataset contains information on housing blocks across California, including median house values, household demographics, and geographical coordinates. The dataset includes [number of samples] observations with the following features:

- Median income in block group Housing median age
- Total rooms and bedrooms
- Population and households
- Geographical coordinates (latitude and longitude)
- Ocean proximity (categorical)
- Median house value (target variable)

-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY
	-122.23 -122.22 -122.24 -122.25	-122.23 37.88 -122.22 37.86 -122.24 37.85 -122.25 37.85	.122.23 37.88 41.0 .122.22 37.86 21.0 .122.24 37.85 52.0 .122.25 37.85 52.0 .122.25 37.85 52.0	-122.23 37.88 41.0 880.0 -122.22 37.86 21.0 7099.0 -122.24 37.85 52.0 1467.0 -122.25 37.85 52.0 1274.0 -122.25 37.85 52.0 1627.0	-122.2337.8841.0880.0129.0-122.2237.8621.07099.01106.0-122.2437.8552.01467.0190.0-122.2537.8552.01274.0235.0-122.2537.8552.01627.0280.0	-122.2337.8841.0880.0129.0322.0-122.2237.8621.07099.01106.02401.0-122.2437.8552.01467.0190.0496.0-122.2537.8552.01274.0235.0558.0-122.2537.8552.01627.0280.0565.0	-122.2337.8841.0880.0129.0322.0126.0-122.2237.8621.07099.01106.02401.01138.0-122.2437.8552.01467.0190.0496.0177.0-122.2537.8552.01274.0235.0558.0219.0-122.2537.8552.01627.0280.0565.0259.0	-122.2337.8841.0880.0129.0322.0126.08.3252-122.2237.8621.07099.01106.02401.01138.08.3014-122.2437.8552.01467.0190.0496.0177.07.2574-122.2537.8552.01274.0235.0558.0219.05.6431-122.2537.8552.01627.0280.0565.0259.03.8462	-122.2337.8841.0880.0129.0322.0126.08.325245260.0-122.2237.8621.07099.01106.02401.01138.08.3014358500.0-122.2437.8552.01467.0190.0496.0177.07.2574352100.0-122.2537.8552.01274.0235.0558.0219.05.6431341300.0-122.2537.8552.01627.0280.0565.0259.03.8462342200.0

longitude latitude housing median age total rooms total bedrooms population households median income median house value ocean proximity

3.2 Data Preprocessing

The dataset undergoes missing value detection, and imputation is performed using the median strategy to maintain data consistency without introducing biases. Outlier analysis is conducted, particularly for properties valued above \$500,000, to identify and handle anomalies that could impact model performance. Feature scaling is applied using StandardScaler to standardize numerical variables, ensuring that different properties/features contribute in equal proportion to the model. Additionally, categorical encoding is implemented using OneHotEncoder to transform categorical variables like ocean proximity into a numerical format suitable for machine learning algorithms.

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3.3 Feature Engineering

- Implementation of a custom transformer (Combined Attributes Adder) to create:
 - o Rooms per household
 - o Bedrooms per room
 - o Population per household
- Smart correlation selection to remove highly correlated features (threshold = 0.9)

Prices of the 30 Most Expensive Properties and Their Nearest City



3.4 Model Development

The implementation utilizes a pipeline-based architecture to ensure reproducible preprocessing and training workflows, enabling consistent data transformation and model development across iterations. Linear regression serves as the primary modeling technique due to its interpretability and established effectiveness in capturing relationships between housing features and prices. The model's performance is rigorously evaluated through 10-fold cross-validation, which provides a robust assessment by testing on overall data subsets while mitigating overfitting concerns. Root Mean Square Error (RMSE) is employed as the key performance metric, quantifying the average magnitude of prediction errors in the same units as the target variable, allowing for intuitive interpretation of the model's accuracy in property valuation scenarios.

3.5 Web Application Architecture

The application leverages the Dash framework for comprehensive web development, providing an interactive and responsive user interface for housing price prediction. Seamless integration with Leaflet enables dynamic mapping capabilities, allowing users to visualize property locations and relevant geographic data that influence valuation. Address geocoding functionality is implemented through the Nominatim service, accurately converting street addresses into precise geographic coordinates essential for location based price predictions. The system incorporates robust user input validation and preprocessing mechanisms that ensure data quality and consistency, handling various input formats and automatically flagging potentially problematic values before they enter the prediction pipeline.



IV. IMPLEMENTATION

4.1 Model Training and Selection

The dataset is split into 75% training and 25% testing to ensure the model generalizes well to unseen data. A pipeline is configured for preprocessing and modeling, streamlining feature engineering, transformations, and regression model application. Feature importance analysis is performed to understand which attributes most significantly impact housing prices. Finally, model persistence is achieved using pickle serialization, allowing the trained model to be saved and loaded for future predictions without retraining.

4.2 Geocoding Integration

Address lookup is performed using the Nominatim geocoder to convert textual addresses into geographical coordinates (latitude and longitude). The system handles potential geocoding errors and failed lookups by verifying whether the provided address can be resolved to valid coordinates. If the lookup is successful, the extracted latitude and longitude are used for mapping and further analysis, such as predicting housing prices based on location. This process ensures that location-based predictions remain accurate and reliable.

4.3 Web Interface Development

Your Dash application includes input components for housing characteristics, allowing users to specify details like the number of rooms, bedrooms, and households, along with median income and ocean proximity. An interactive map dynamically displays the property's location based on the provided address, using geolocation services. The system then processes user inputs, fetches geographical coordinates if an address is given, and predicts housing prices based on the trained model, providing real-time feedback to users.

4.4 System Architecture

Your Dash application follows a client-server model with a Python backend, where user inputs are processed on the server, and predictions are dynamically generated using a trained machine learning model. It features real-time prediction capabilities, allowing users to receive instant feedback based on the provided housing characteristics and location. Additionally, the application is designed with a responsive layout, ensuring accessibility and usability across various devices, smartphones.

V. RESULT & EVALUATION

5.1 Model Performance Metrics

- Cross-validation RMSE: 47254.45
- Test set RMSE: 47290.1467
- Prediction error visualization

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- Relative contribution of each feature to price prediction
- Geographic feature significance
- Engineered feature effectiveness



5.2 Feature Importance Analysis

- Relative contribution of each feature to price prediction
- Geographic feature significance
- Engineered feature effectiveness

5.3 System Usability Evaluation

The application undergoes response time analysis to ensure quick and efficient processing of user inputs, minimizing delays in predictions and map updates. Geocoding accuracy assessment is performed to evaluate the precision of address to-coordinate conversions, ensuring that property locations are correctly mapped. Additionally, an interface usability assessment is conducted to enhance user experience, focusing on intuitive design, ease of navigation, and accessibility across different devices

VI. CONCLUSION & FUTURE SCOPE

Conclusion

In this project, we've created a tool that helps predict housing prices in California by combining data about houses with their locations on a map. Our system uses machine learning to analyze features like number of rooms, income levels, and ocean proximity along with the exact location to estimate property values. The interactive web application we built makes it easy for anyone to enter housing details and an address to get a price prediction visualized on a map. Our analysis shows that location plays a crucial role in housing prices, alongside other factors like income and housing density. This system helps bridge the gap between complex data analysis and practical tools that real people can use when making housing decisions.

Future Scope

In future, there are several methods to improve this project. We could use more advanced machine learning methods that might make even better predictions, especially for unusual properties. Adding historical data would allow us to show price trends over time, which would be valuable for investment planning. We could also expand the system to work in other states or countries to see how well our approach works in different housing markets. Creating a mobile app version would make it convenient for people to check prices while visiting properties. In the real world, this tool could help home buyers find fairly priced houses, assist sellers in setting competitive prices, and support real estate agents in providing data-backed advice to clients. The system could potentially be connected to existing real estate websites or mortgage calculators to create more comprehensive tools for property evaluation.

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