Software Impacts 22 (2024) 100718

Contents lists available at ScienceDirect

Software Impacts

journal homepage: www.journals.elsevier.com/software-impacts

Original software publication

LandSin: A differential ML and google API-enabled web server for real-time land insights and beyond

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ARTICLE INFO

Keywords:
Land value estimation
Machine learning
Differential privacy
Urban planning
Property market trends

ABSTRACT

LandSin, a web application with a back-end database, is developed for global land value estimation by combining polynomial regression and differential privacy models. Leveraging local amenities and property details, *LandSin* offers key features, e.g., accurate land value and price predictions, affordability and habitability analysis, and terrain insights using Google Maps. In addition, it facilitates useful infographics, helping stakeholders identify economically deprived but habitable areas for balanced regional development. It also supports real estate agencies and community planners in finding habitable land by making data-driven decisions regarding land investments and regional planning, ensuring informed and strategic choices.

Code metadata

Current code version	*v1.0.0*
Permanent link to code/repository used for this code version	https://github.com/SoftwareImpacts/SIMPAC-2024-260
Permanent link to Reproducible Capsule	https://codeocean.com/capsule/1508359/tree/v3
Legal Code License	*MIT License*
Code versioning system used	*git*
Software code languages, tools, and services used	*Python, Flask*
Compilation requirements, operating environments & dependencies	PostgreSQL, Pandas, Plotly, Dash, Flask and scikit-learn
Link to developer documentation/manual	https://github.com/alauddin-sabari/LandSin/blob/main/README.md
Support email for questions	aladinsabari@gmail.com

1. Introduction

This research introduces *LandSin*, a web-based application with a back-end database, focused on dynamic land and housing value prediction, combining advanced machine learning algorithms and statistical analysis. The platform and database both serve key stakeholders, including real estate agencies, government entities, and community organizations, by providing powerful tools to predict property values, analyze market trends, and support data-driven decision-making [1–3]. Unlike traditional models that rely on static output and predefined

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https://doi.org/10.1016/j.simpa.2024.100718
Received 23 October 2024; Received in revised form 3 November 2024; Accepted 4 November 2024

rules, the *LandSin* dynamically selects the most suitable machine learning model based on the statistical quartile ranges of property values [4,5]. This adaptive approach significantly improves accuracy by tailoring predictions to the unique characteristics of each land parcel or housing lot. By incorporating a range of features, such as affordability analysis, habitability assessments, and geospatial insights through Google Maps and other plots *LandSin* provides users visualization graphs with critical information on land suitability for building and investment potential [6,7].

One of the key challenges in land value estimation is ensuring data accuracy and integrity, particularly when drawing from diverse sources like property records, transaction histories, and market trends [8]. Inaccuracies or inconsistencies in this data can lead to skewed valuations, which may hinder decision-making for buyers, sellers, and policymakers. To overcome this, *LandSin* integrates advanced statistical techniques to ensure robust data processing, protecting against potential biases or errors that might impact the final predictions [9]. The inclusion of features such as price predictions and terrain analysis further differentiates the tool by offering a holistic view of land quality, beyond mere pricing. The ability to provide accurate, real-time property value estimates is crucial in the finance and real estate sectors. Government agencies and community planners, for example, can leverage these insights to identify underdeveloped or economically distressed areas that are ripe for revitalization, enabling targeted interventions. Meanwhile, real estate agencies can better assess investment opportunities by understanding market trends and future land potential [10]. Unlike existing dynamics, the data-driven approach promotes more strategic planning, supporting economic growth and reducing disparities across regions [11]. The technical foundation of *LandSin* includes machine learning models implemented using Python's scikit-learn library, supported by advanced regression techniques like polynomial regression to capture complex, non-linear relationships between property characteristics and market factors [7,12]. Geospatial data integration is achieved through JavaScript, React, and the Google Maps API, ensuring seamless access to terrain information and regional attributes. The application is deployed following DevOps practices to ensure high availability across both mobile and desktop platforms. Through novel feature engineering, *LandSin* enhances predictive accuracy by incorporating factors such as local economic indicators, property characteristics, and geospatial data. The system also uses statistical methods, such as interquartile range (IQR), to account for value distribution, providing more nuanced insights into market dynamics. Differential privacy techniques ensure that sensitive data remains protected, adding a layer of security and trust for all users.

The *LandSin* represents a powerful tool for decision-makers in the real estate and financial sectors. By offering precise predictions, comprehensive statistical insights, and secure data handling, this tool is poised to transform land and housing market analysis. Its potential to drive economic revitalization, particularly in economically deprived areas, makes it an essential tool for fostering equitable and sustainable regional development.

2. Impact

LandSin is actively used by LandSpot [a competitor of Zillow [13]], an enhanced price predictor based on Zillow's research data [13], which is a U.S.-based real estate firm to provide land valuations for *landspout*. We have also worked with Zillow's research data, where its *Zestimate* feature uses machine learning models and neural networks to predict real estate values [like LandSin] but lacks user privacy [14]. Thus it motivated us to employ differential privacy model in our landSin land value estimation tool to secure user's sensitive information. This approach helps us to get more granular price comparisons and visual demand representations across varied locations, empowering our stakeholders to make well-informed, data-driven investment decisions. Although, Zillow has set a benchmark in real estate valuation by continuously adjusting for dynamic market trends and delivering high accuracy [15] in that case we also added multi-degree polynomial regression, which effectively captures nuanced price variations and regional demand patterns even in data with outliers. Through this technique, *LandSpot* achieves a 7% increase in valuation accuracy over Zillow's linear regression model [16,17] for nonlinear data points. This capability grants *LandSpot* a unique advantage, providing insights that address both property-specific characteristics and wider regional dynamics, delivering highly localized and real-time market analyses. Moreover, a detailed list of impacts of *LandSin* is discussed below:

2.1. Impact in finance sector

Machine learning-empowered features of *LandSin* may enhance real-time land and housing value predictions, providing valuable financial sector insights for predicting market trends and assessing investment risks. In addition, the differential Privacy features of *LandSin* ensure data security in financial transactions, protecting sensitive financial data while offering accurate predictions for fintech integration. It may improve the accuracy of high-value property investment, helping investors optimize portfolios by providing insight into future property valuations and understanding current market trends.

2.2. Impact on Governmental Policy making

Governments can use *LandSin* for strategic land use planning by identifying economically deprived but habitable areas, prioritizing investments in regions that need revitalization and ensuring balanced regional growth. As *LandSin* may provide critical data insights, including affordability and habitability analyzes, it can potentially enable policymakers to focus on high-potential growth regions, improving urban-rural living standards. In addition, it may facilitate efficient management of land resources by providing real-time data and terrain insights, ensuring sustainable land use.

2.3. Impact on real estate agencies

The impact of *LandSin* in the market of real estate agencies has already been demonstrated as it is currently competing with a major player like Zillow [18] by providing dynamic and accurate land value predictions, particularly in competitive U.S. markets. Moreover, it assesses real estate investments more effectively by analyzing market trends, geographic features, and growth patterns.

2.4. Impact on individual investors and financing

The *LandSin* may offer localized economic indicators, helping investors align land investments with their personal financial goals. Moreover, differential privacy ensures that sensitive personal and financial information is protected, enhancing security in land transactions.

2.5. Impact on community planners

Community planners may utilize the *LandSin* platform to identify areas requiring development, helping bridge urban-rural disparities and fostering balanced regional growth. By World Map integration through Google Maps API inside our application's backend provides terrain analysis and proximity to essential amenities, supporting planners in making informed decisions about residential and commercial developments.

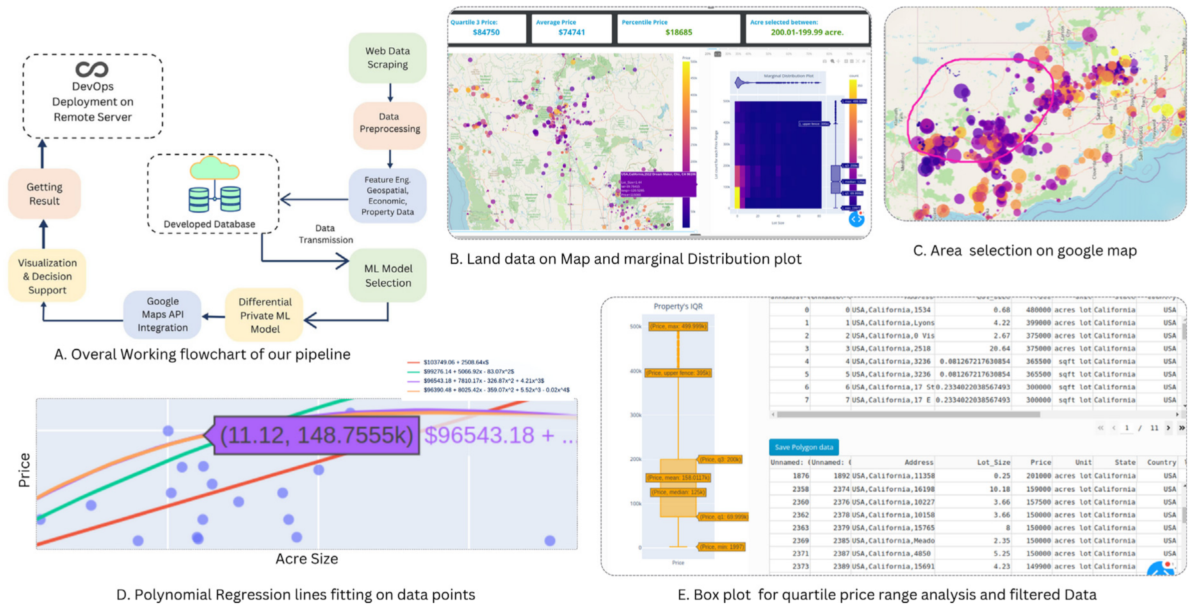

Fig. 1. A: Overall Workflow Chart, illustrating the sequence of operations from data input to analysis and prediction output. B: Interactive Map displaying Land Data points with marginal distribution plot, enabling visualization of location-specific attributes like land count in each price range and their average price and Statistical analysis. C: Google Map Area Selection Tool, allowing users to focus on specific regions for targeted analysis. D: Polynomial Regression Lines Fitted on Data Points, providing trend insights and predictive line fit on data points and interactive regression line choosing options from different regression lines. E: Quartile Price Range analysis through interactive Box Plot, offering a detailed breakdown of price distribution across different land parcels from polygon selection in data distribution world map and filtered data downloadable options for further analysis or specific purposes for the users.

2.6. Broader societal benefits

The features of *LandSin* [see Table 1] may support governments, businesses, and communities in prioritizing development in underserved regions, reducing socioeconomic disparities. It may also identify undervalued but habitable land, driving economic growth in neglected regions, and leading to equitable land distribution and increased investments. Furthermore, the data-driven approach enables inclusive growth, improving living conditions and access to resources in underserved communities.

3. Implementation

LandSin, has two major components: back-end database and front-end Dashboard. In this platform, we explore creative feature engineering techniques, examine various regression methods, and analyze value range quartiles with results from multiple polynomial regressions. We also introduce differential privacy prior to any analysis [7] to securely manage geospatial, economic, and property data, and thus prevent tampering and ensure data integrity, thereby reinforcing model accuracy and preserving the privacy of sensitive information.

3.1. Database development

After scraping data through our developed python selenium web automation and web scraping pipeline [Fig. 1A], we did feature engineering and also obtained latitude and longitude values through the Google map API and then stored in our relational database to plot on the world map. Database development is done by following the steps.

3.1.1. Creative feature extraction

Effective feature engineering enhances the performance of the model, especially for machine learning models that assume a normal distribution of features. However, real-world data often deviates from this assumption. Securely storing geospatial, economic, and property data ensures transparency and prevents manipulation. This approach enables reliable data preprocessing and secure feature engineering, preserving essential features like proximity to amenities or economic indicators:

1. **Normalization and Scaling:** Transforming features to ensure that they follow a normal distribution when possible by removing outliers.
2. **Geospatial Features:** Integrating data from Google Maps on Zillow [18] and other real estate sources and securely storing using Postgresql database to ensure the integrity of features such as user's property owner's information.
3. **Economic Indicators:** Incorporating local economic data, such as average income and employment rates, with differential privacy for manipulation and ensuring transparent preprocessing to secure users' data through differential privacy.
4. **Property Characteristics:** Including attributes like property size, number of bedrooms, and building age, all stored securely using differential privacy technology to store in our Database.

3.2. Regression algorithms

Regression algorithms are vital for real estate value prediction. When training these models we have done feature engineering, and after that, The polynomial regression model used in this study is formulated as:

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_n x^n + \epsilon \quad (1)$$

where y represents the dependent variable (land value), x denotes the independent variables (population density, economic status, school rating, etc., $\beta_0, \beta_1, \ldots, \beta_n$ are the model coefficients, and ϵ is the error term. The coefficients are estimated using least squares minimization.

3.3. Statistical interquartile value range

The interquartile range (IQR) is used to measure the spread of housing values within the middle 50% of the distribution.

3.4. Differential privacy

To ensure privacy in our dataset, we apply differential privacy with the Laplace mechanism. This approach protects individual data

Table 1
System Features and Descriptions.

System Feature	Description
Polygon Drawing on Google Maps	Allows users to draw polygons on Google Maps to select specific regions for getting price prediction and statistical quartile price analysis for that region.
Acre Size Selection	Users can predict values for lots up to 20 acres for finding habitable land, with preset options and adjustable margins based on local standards. Acre sizes are converted from square-foot lots during preprocessing for uniform model input.
Statistical Quartile Prices	Displays quartile price values to inform buying and selling decisions, highlighting market opportunities by showing the distribution of property values for specific regions.
Average Value	Provides the average property value comes from previous sold properties database collected from Zillow [18] within a selected polygon inside our dashboard.
Percentile Value	Displays property values between the first and third quartiles, helping users adjust acre margins for flexible decision-making based on market trends.
Marginal Distribution Plot	Visualizes the distribution of acre sizes and demand, while incorporating violin plot side by side to provide deeper insights. These plots display the lot count for specific acre sizes within various price ranges, helping users identify common and in-demand lot sizes and refine their pricing strategies based on the acre size-price interactive relationship.
Machine Learning Model Performance Comparison Graph	Compares machine learning models in different degree of x of polynomial Regressions) using performance metrics like MSE, RMSE, and R^2 to guide property valuation predictions.
Exporting Filtered Data	Enables users to download filtered data from selected Google Map regions by drawing polygons, facilitating efficient data management and land offering processes.

points by adding noise to the function output, ensuring that adding or removing a single data point minimally impacts the results.

$$\mathscr{A}(D) = f(D) + \text{Laplace}\left(\frac{\Delta f}{\epsilon}\right) \tag{2}$$

where $\mathscr{A}(D)$ is the differentially private algorithm applied to dataset D, $f(D)$ is the original polynomial regression function, Δf is the global sensitivity of f, representing the maximum change in f due to a single data point, and ϵ is the privacy parameter.

3.5. Model evaluation

The performance of the polynomial regression models is assessed using the following metrics Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) Score.

3.6. Visualization of lands' data point

Our application integrates with Google Maps to visualize results using heat maps, value distribution graphs, and predictive analytics on a single dashboard. This tool provides easy access to statistical data, making it accessible to governments, real estate agencies, and communities without the need for data science expertise.

3.7. System development

The *LandSin* platform development involves a combination of Python-based machine learning and data science libraries to create an accurate, scalable, and user-friendly application to dynamically predict the values of land and housing [Fig. 1A]. The core of our system employs Python's ML scikit-learn and other data science libraries to handle data preprocessing, feature engineering, and model training, including *PostgreSQL* (v16.4) *pandas* (v2.2.3), *plotly* (v5.24.1), *Flask* (v3.0.3) and *Dash* (v2.18.1). These libraries allow advanced machine learning techniques, including polynomial regression, to capture non-linear relationships between property characteristics and market factors. For user data storage and retrieval, PostgreSQL serves as the back-end database, ensuring efficient handling of structured data such as property records, transaction histories, and geospatial attributes. Data integrity and security are key components of the system and differential privacy techniques are integrated to protect sensitive data while maintaining robust model performance. The front end of the system is built using Python Dash, which provides an interactive and responsive web interface. This interface is backed by Flask, a lightweight Python web framework, ensuring reliable Database connectivity and efficient processing of user requests. Dash integrates smoothly with Plotly, which is used to render interactive visualizations, allowing users to dynamically analyze predicted values and trends. Users can explore multiple data points in real-time, view interactive maps, and customize their insights based on user-specified parameters.

The *LandSin* application enables seamless interactions between the data visualizations and back-end models, allowing real-time updates based on user inputs. This feature is crucial for stakeholders who rely on dynamic data to make timely, informed decisions. By combining scalable database architecture, secure data handling practices, and interactive visualizations, *LandSin* delivers a comprehensive system for analyzing and predicting property values, tailored to the needs of real estate agencies, government entities, and community planners.

3.8. System usage notes

LandSin is a web-based tool for real estate value prediction, supporting agencies, government planners, and community organizations. Users can interactively explore land values, market trends, and property details. The system enables data-driven decision-making by allowing model selection for precise predictions and ensuring data security through differential privacy. Interactive visualizations let users hover over graphs to delve into specific data points are done by following steps.

3.8.1. Polygon drawing on google maps

The *LandSin* application supports data point selection with Google Maps polygon drawing, enabling users to specify a region-of-interest in obtaining statistics for gathering additional data to enhance model training [Fig. 1C]. By integrating US real estate data via the Google Maps API, the system tailors insights for specific regions and can be adapted for international use by connecting to local databases. This approach aids governments and agencies in obtaining region-specific property analytics and supporting strategic planning.

3.8.2. Acre size selection

Users can predict land values up to 20 acres for building homes with preset options like 0.125, 0.25, 0.5, and 1.25 acres, adjustable based on local standards. Acre margins can also be defined (e.g., a 0.05 margin for 1.25 acres includes lots from 1.2 to 1.3 acres). Square-foot lots are converted to acres during preprocessing for uniform input into the machine-learning model.

3.8.3. Statistical quartile prices

Quartile values are essential for informed buying and selling decisions, linking percentiles to predicted values. The first quartile (25th percentile) [Fig. 1E] suggests that 25% of properties in a given location are at or below this value, indicating potential buying opportunities, as real prices are often higher. The third quartile (75th percentile) shows that most lots are valued here, suggesting familiarity and demand at this price range among buyers.

3.8.4. Average value

This view displays our land's average values within selected data points in our selected area polygon but may be less reliable if numerous outliers or extreme values are present. Hence, an option to set a price range is provided in our application to pre-filter data. Moreover, the outliers are visualized by hovering over interactivity on each data point.

3.8.5. Percentile value

Since the real estate market fluctuates with economic conditions, buying at values between the first and third quartiles can be advantageous as conditions evolve. The acre selection feature shows the chosen range and allows users to adjust acre margins before finalizing a specific lot size, aiding flexible decision-making based on market trends.

3.9. Marginal distribution plot

Analyzing acre size values is essential for identifying which sizes are more common and in popular demand. This insight informs pricing strategies when approaching landowners. The red box plot [Fig. 1E] emphasizes this information, showcasing lot sizes, values, and counts within each color-coded category. This detailed visualization enhances understanding of the distribution and popularity of various acre sizes, supporting informed decision-making in the real estate market.

3.10. Machine learning model performance comparison graph

Fine-tuning machine learning models is crucial for enhancing prediction accuracy in real estate valuations. Mean Squared Error (MSE) measures the average squared difference between predicted and actual values, with lower values indicating better performance. The Root Mean Squared Error (RMSE) provides a more interpretable metric in the original unit of measurement. The orange line demonstrates strong performance for acre sizes between 45 and 50 acres [Fig. 1D], effectively minimizing prediction gaps. However, its reliability diminishes for sizes exceeding 50 acres. Users can access additional insights by hovering over or clicking the equation, visualizing predictions for various acre sizes.

Supporting visual tools, such as the Marginal Distribution Plot and Interquartile Range (IQR) Plot, further aid decision-makers in identifying appropriate pricing strategies [Fig. 1E]. Table 2 provides a detailed comparison of model performance metrics, including MSE, RMSE, and R^2 scores, while highlighting the role of differential privacy in safeguarding sensitive data. Together, these elements establish *LandSin* as a vital tool for informed decision-making in the real estate market.

This summary allows for a quick comparison of each model's effectiveness in predicting land prices, particularly in the $500,000 to 1,000,000$ range. Polynomial regression up to degree 5 demonstrates the best performance, with an MSE of 34,000, RMSE of 184.39, and an R^2 score of 0.87, though degree 5 shows signs of overfitting. Polynomial regression of degree 4 strikes a balance with an MSE of 37,000, RMSE of 192.35, and an R^2 of 0.86, effectively capturing complex data patterns. In contrast, Linear Regression yields higher errors, with an MSE of 50,000, RMSE of 223.61, and an R^2 score of 0.82, making it less reliable for high-value property predictions.

Table 2
Machine learning model performance on predicting property above 500K USD.

Model	MSE	RMSE	R^2
Linear regression	50,000	223.61	0.82
Polynomial regression (Degree 2)	45,000	212.13	0.83
Polynomial regression (Degree 3)	40,000	200.00	0.84
Polynomial regression (Degree 4)	37,000	192.35	0.86
Polynomial regression (Degree 5)	34,000	184.39	0.87(overfitting)

In addition, the integration of differential privacy in these models ensures data security and integrity, enabling automated real-time validation, accuracy checks, model selection, and secure data storage. This enhances the system's reliability and builds trust among stakeholders, including real estate agencies and government organizations.

The impact of this research is significant, as it provides a framework for using advanced machine learning techniques in the real estate sector, leading to more accurate predictions of property values, especially for high-value properties in the $500,000 to $1,000,000 range. The insights derived from this table can guide future studies and applications, emphasizing the need for robust methodologies that balance predictive accuracy with data privacy, ultimately contributing to informed decision-making in property valuation and investment. By leveraging these models, stakeholders can make more informed investment decisions and mitigate risks associated with property transactions.

3.11. Exporting filtered data and their values

We have implemented features that allow users to download data, including email addresses, also filter specific regions on Google Maps by drawing polygons to download relevant data [Fig. 1E], streamlining the process of offering land to multiple owners and enhancing data management efficiency.

4. Notes, limitations and future work

This research presents a robust land value prediction model that significantly enhances decision-making for individuals, communities, and government entities in the finance sector. While the model demonstrates a notable improvement in prediction accuracy over traditional methods, several limitations remain, which offers scopes for future work. Moreover, the reliance of current models on historical data may lead to biases, particularly in areas with limited or uneven value distributions exist. Additionally, the lack of integration with real-time economic indicators could impact the model's adaptability to a surge in market fluctuations. Again, in the future, incorporating differential privacy technology will focus on validating and securing data in future iterations of the model. By ensuring data integrity and enhancing trustworthiness, blockchain technology may be utilized, which may further empower stakeholders — whether individual investors, community planners, or government officials — in making informed financial decisions about land acquisition. Furthermore, the model can be expanded to integrate diverse datasets, including economic indicators and demographic data, enhancing its predictive capabilities. Upgrading the user interface and experience will also be prioritized, making the tool accessible to non-technical users and ensuring that it effectively supports financial decision-making. Ultimately, the goal is to provide a comprehensive and adaptable platform that assists users in identifying habitable properties within their budget, facilitating better financial investments, and contributing to community development and economic stability.

CRediT authorship contribution statement

Alauddin Sabari: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Imran Hasan:** Software, Resources. **Salem A. Alyami:** Writing – review & editing, Funding acquisition. **Pietro Liò:** Writing – review & editing, Funding acquisition. **Md. Sadek Ali:** Writing – original draft, Methodology. **Mohammad Ali Moni:** Writing – review & editing, Validation, Conceptualization. **AKM Azad:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration.

Funding

This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (grant number IMSIU-RP23004).

Declaration of competing interest

None.

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