SHORT-PAPER

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LINKin-PARK: Land Valuation Information and Knowledge in Predictive Analysis and Reporting Kit via Dual Attention-DCCNN

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ABSTRACT

We present LINKin-PARK, an innovative system that seamlessly merges geographic visualization with an advanced Dual Attention Double Channel Convolutional Neural Network with Multilayer Perceptron (Dual Attention-DCCNN+MLP) to facilitate the efficient analysis of land valuation. LINKin-PARK provides robust visualization capabilities for intuitive comprehension. Our model outperforms traditional methods, e.g., linear regression, multilayer perceptron (MLP), Extreme Gradient Boosting (XGBoost), and the combination of CNN (Convolutional Neural Network) with MLP. An ablation study further evaluates the influence of specific components within the model, revealing that spatial and channel-wise attention mechanisms and the integration of DCCNN and skip connections are crucial for capturing spatial details and improving prediction accuracy. Users have the flexibility to explore and predict developable land valuation based on their specific requirements and provide their feedback to minimize errors in model prediction. For instance, this system can forecast future development potential and market demand for everywhere in an urban space, enabling users to make informed decisions before purchasing a property. Similarly, retailers can anticipate future revenues to aid in strategic decisions, such as selecting optimal locations for establishing new retail outlets. In summary, LINKin-PARK effectively combines geographic visualization and Dual Attention-DCCNN+MLP to assist users in analyzing and predicting land valuation and other scenarios.

CCS CONCEPTS

• **Computing methodologies → Artificial intelligence**; • **Information systems → Data management systems**.

KEYWORDS

dual-attention, spatial data mining, model interpretation, geographic visualization interface

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1 INTRODUCTION

Understanding and analyzing land value data are crucial across various fields, from urban planning to real estate management [1, 9, 10]. Estimating the value of developable land is crucial for urban development. As land value estimation is needed for commercial activities or real estate transactions, we are exploring developable land valuation. Land value data encompasses location, distance, and distribution, providing deep insights into spatial patterns, trends, and relationships [7]. However, merely visualizing land value data may not uncover critical insights, especially for those unfamiliar with land valuation and geographic analysis. For example, in engaging

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the public for real estate market analysis, a limited understanding of geographic analysis among citizens impedes insightful conclusions. Similarly, stakeholders and decision-makers face challenges in interpreting nuanced implications of land value data, affecting effective decision-making [5]. To overcome this challenge, we have integrated deep learning with geographic visualization to extract meaningful patterns and trends.

We introduce LINKin-PARK, an innovative system that combines 2D and 3D visualization with an advanced Dual Attention Double Channel Convolutional Neural Network with Multilayer Perceptron (Dual Attention-DCCNN+MLP) to enhance land value data analysis in various cities. The interface caters to non-experts in machine and deep learning, such as urban planners, real estate agents, and the general public, facilitating effective land value data analysis. For general users, the interface offers: 1) A rich set of visualization features to intuitively understand land value data. 2) Fast and effective calculations between layers, along with simultaneous display of statistical results and spatial value distribution. For professionals, the tool additionally provides: 1) Integration of various modules of machine learning to shape Dual Attention-DCCNN+MLP for rapid prediction generation and interpretation.; 2) In-depth analysis of specified areas, aiding understanding of area characteristics and advantages.

LINKin-PARK is applicable to various scenarios. For example, homebuyers can use historical data and LINKin-PARK's models to predict future property values. Government staff can predict the prosperity of different regions for land valuation. Shop owners can import past data to forecast revenue for new store locations.

2 METHODOLOGIES

Fig. 1 shows the architecture of the proposed system, which consists of three main components: **grid-based information generation**, **prediction models**, and **visualization system**. After obtaining points of interest (POIs), and land use data, the system undergoes several preprocessing and feature extraction steps and stores all features that are correlated with land value data into divided urban spaces. Then, depending on data characteristics, different models are applied. Finally, the predicted result is presented visually through the visualization system.

2.1 Input Data and Grid-based Information

In this study, the urban space is divided into square grids with side lengths of 100m, and the land value data of each road segment[1] should be estimated. The input data includes POIs, building attributes, and land use ratio, as shown in our demonstration. The POI data was collected from various sources, including Google Map API, web crawlers, and government open data. They encompass transportation points, dining venues, shopping places, public facilities, educational institutions, medical facilities, undesirable amenities, financial institutions, temples, churches, and more. There are a total of 28 categories of POIs in the dataset. This type of data contains a variety of common POIs in urban areas, sufficient to represent the heterogeneity between different areas in one city. The building attributes data contain the development-related characteristics of a single grid, such as the average floor area ratio, average building coverage ratio, and average age of the building. These features offer valuable insights into the land conditions within the respective grid. To standardize the processing of linear roads, points of interest (POIs), and polygon-shaped housing data, they are mapped onto a grid to facilitate the estimation of developable land value.

[1]A road section consisting of a series of grids.

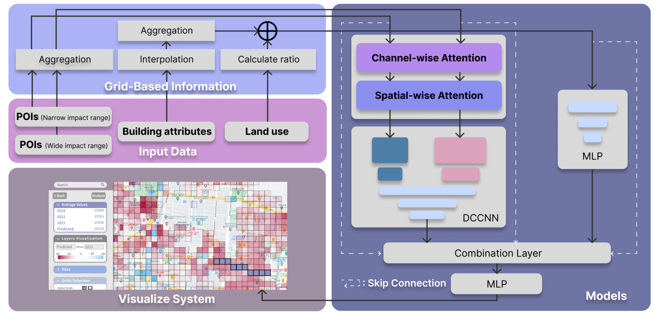
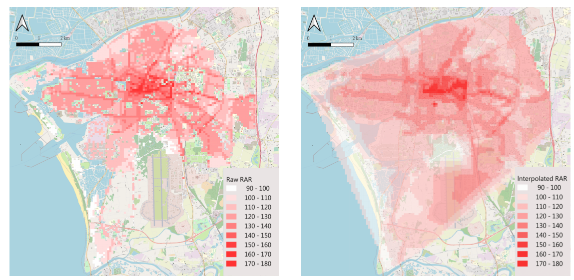


Figure 1: The architecture of LINKin-PARK. The dashed line indicates skip connections.



(a) The distribution of origin land values, with a total of 4,311 grids.

(b) The distribution of interpolated land values, with a total of 9,484 grids.

Figure 2: The demonstration is part of the interpolation result in total area, with redder shades indicating larger values.

In certain non-residential areas such as schools and parks, the developable land valuation may not be applicable, leading to a scarcity of readily available land value data. To address this limitation and provide insights for future land changes and rezoning, we utilized the Inverse Distance Weighting (IDW) Interpolation [6]. This method allowed us to estimate missing land value data by leveraging information from neighboring locations. We present Fig. 2 to visualize the impact of the interpolation process. The land use ratio was obtained by capturing the land use status within the map provided by the National Land Surveying and Mapping Center [12], which was consolidated into 18 different land use types (i.e., residential, transportation, and commercial), and the proportion of each type within a grid was calculated. These ratios enable the model to capture spatial differences in land use situations.

2.2 Prediction Models

CNN models have demonstrated remarkable benefits in extracting spatial features, leading to their widespread adoption for geospatial

Table 1: Prediction performance comparison: the metrics are MAE in land valuation task and MSE in housing valuation task.

Tasks	Land Valuation (*MAE*)					Housing Valuation (*MSE*)				
γ	0.9	0.7	0.5	0.3	0.1	0.9	0.7	0.5	0.3	0.1
LR	0.298	0.299	0.385	0.375	0.475	94.346	145.572	128.759	159.166	226.854
MLP	0.308	0.352	0.280	0.400	0.405	66.019	67.226	83.897	125.447	136.11
XGBoost	0.379	0.380	0.381	0.385	0.387	50.943	52.947	53.13	57.207	67.316
CNN+MLP	0.269	0.279	0.286	0.284	0.291	29.601	40.632	50.092	73.376	95.912
Dual Attention-DCCNN+MLP	**0.171**	**0.181**	**0.189**	**0.206**	**0.221**	**20.944**	**29.581**	**37.452**	**41.727**	**61.126**

Table 2: Prediction performance of four ablation study scenarios.

Tasks	Land Valuation (*MAE*)					Housing Valuation (*MSE*)				
γ	0.9	0.7	0.5	0.3	0.1	0.9	0.7	0.5	0.3	0.1
Dual Attention-DCCNN+MLP	**0.171**	**0.181**	**0.189**	**0.206**	**0.221**	**20.944**	**29.581**	37.452	**41.727**	**61.126**
w/o ATT	0.197	0.203	0.212	0.232	0.235	24.216	34.826	43.636	59.59	90.851
w/o DCCNN	0.217	0.224	0.237	0.261	0.253	27.218	26.929	**36.618**	63.979	99.698
w/o SKIP	0.219	0.189	0.200	0.213	0.231	21.471	31.126	38.46	46.002	66.187

information processing [4]. Among these models, the Double Channel Convolutional Neural Network (DCCNN) [11] stands out in urban planning scenarios by leveraging two different CNN kernel sizes to multi-scale information of POIs. According to the experiments in [11], DCCNN has been proven effective in assessing market demand potential scenarios, and outperformed existing models, achieving better RMSE scores than Single-Channel CNN 22.61% and Extreme Gradient Boosting (XGBoost) [3] 19.29%. Furthermore, spatial-wise attention and channel-wise attention mechanisms (Dual Attention) have been demonstrated to be sufficient in extracting critical spatial information and learning important features, respectively [2] [8]. These attention mechanisms effectively assist the model in extracting essential information from a vast number of features.

Our model (Dual Attention-DCCNN+MLP) leverages DCCNN's performance by incorporating spatial-wise and channel-wise attention mechanisms. We also use MLP to extract the embeddings of numerical data on each grid cell. The extracted embeddings from DCCNN and MLP are subsequently combined by concatenation. Meanwhile, skip connections were also used to prevent overfitting. After concatenation, a separate MLP module is employed to predict the land value data. Our visualization system allows users to observe the land value data of every grid in a city.

3 EXPERIMENT

3.1 Model Comparisons

We compare our proposed model with commonly used machine learning methods, including linear regression (LR), multilayer perceptron (MLP), Extreme Gradient Boosting (XGBoost) [3], and CNN+MLP, which could better extract spatial information. Due to the sparsity and discontinuity of developable land, we simulate various proportions relative to the total area to validate that our model maintains advantages across different ratios through the hyperparameter γ. It represents the percentage of training data; for example, $\gamma = 0.1$ means that 10% of the total area was used as training data and the rest as testing data. We investigate the performance of all models in different scenarios by varying this hyperparameter. Table 1 displays the average of five experiments' results in terms of Mean Absolute Error (MAE) and Mean Squared Error (MSE), which are commonly used metrics in regression tasks. Our proposed model outperforms all baselines in all cases.

3.2 Ablation Study

In Table 2, we evaluate the impact of different components in our model, using the average MAE and MSE from five experiments. We compare our model with three scenarios, each removing a specific component: **w/o ATT**: We remove the spatial-wise attention and channel-wise attention mechanisms from the model. **w/o DCCNN**: We replace the DCCNN module with a regular, Single-Channel CNN module. **w/o SKIP**: Removing skip connections. The ablation study results show that the Single-Channel CNN module alone fails to capture intricate spatial features effectively. However, incorporating spatial-wise and channel-wise attention mechanisms significantly enhances information extraction and overall performance. Additionally, skip connections were found to improve performance.

3.3 Transferability

Our model accurately predicts land value in urban regions and can be transferred to other cities for housing tasks like predicting housing prices valuation, commercial potential, and housing loans (see Table 1 and 2). It can serve as a tool for spatial information management, including development potential, market demand, land zoning, geological conditions, and infrastructure analysis.

4 IMPLEMENTATIONS

LINKin-PARK is a web platform that enhances land and housing value data processing and modeling efficiency and provides clearer spatial characteristic explanations via various features (Fig. 3, 4).

4.1 System Features

The system, developed with Flask, utilizes GeoPandas for managing land value data, providing robust analysis capabilities. On the frontend, we leverage Google Map API and JavaScript for intuitive visualization, enabling easy exploration via 3D Google Street View and satellite imagery layers (Fig. 4 (b)). For prediction tasks, we build models by packages like PyTorch, XGBoost, and scikit-learn.

Layer Selection and Visualization. LINKin-PARK provides several land value and POI data visualization layers such as the "prediction," "historical," and "POI." Users can switch between the above layers or observe the differences between any two layers. Through these functionalities, users will be able to (a) compare land value data changes over time, (b) observe the distribution and

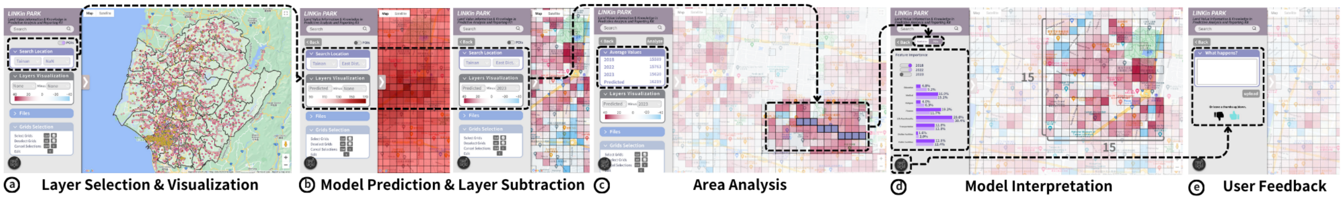


Figure 3: The workflows of LINKin-PARK. It merges spatial visualization and Dual Attention-DCCNN+MLP, offering key features: (a) layer visualization, (b) model prediction and layer subtraction, (c) area analysis, (d) model interpretation, and (e) user feedback.

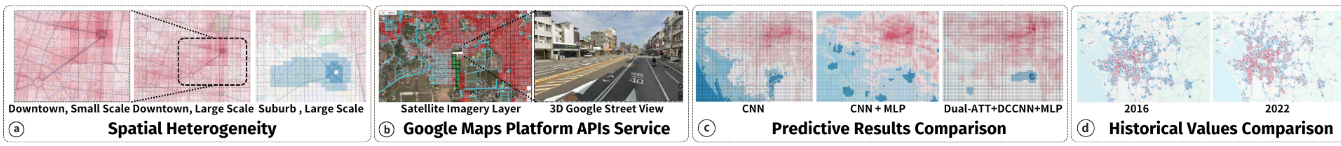


Figure 4: Examples of using LINKin-PARK in various studies. Redder to bluer shades mean the values from higher to lower.

reasonableness of land value data with POI, and (c) intuitively identify the disparities between various layers. An example interface is given in Fig. 3 (a). The system defines different features of each data as separate layers and visualizes them with detailed grid-based information to highlight the spatial heterogeneity in land valuation between multi-scale and downtown-suburb disparities (Fig. 4 (a)).

Model Prediction and Layer Subtraction. To automate the comparison between model performance in predictions and historical data by subtracting layers, users select two arbitrary layers from the dropdown menu, designate land value as the prediction target, and specify the grid's side length. Users can flexibly switch between layers or compare any two of them. These functions allow users to (a) review model-predicted values, (b) assess data distributions and explore reasonability, and (c) intuitively visualize layer differences (Fig. 3 (b)). The system will map input data into square grids using GeoPandas to ensure effective feature extraction and provide prediction values for each grid. Once predictions are generated, a new "Prediction Values" layer is added to the interface for users to review. After comparing different models on spatial numerical distribution patterns and regional feature contour capture, we ensured that our Dual Attention-DCCNN+MLP can accurately predict the rational distribution of land valuation both globally and locally (Fig. 4 (c)). Furthermore, the model's validity was verified by 12 experts in land valuation, geographic information systems, and urban planning from industry, government, and academia.

Area Analysis and Model Interpretation. Users can freely select grids for detailed investigation, with the system automatically calculating their average values and displaying them in the left-hand menu. This function assists in analyzing variously shaped geographical areas in depth (Fig. 3 (c)). Upon grid selection, the interface visualizes feature importance percentage of POI in the surrounding area using a histogram (Fig. 3 (d)). We leverage channel-wise attention weight to predict the target attribute based on the surrounding 15*15 grids, generating interpretation results. This aids users in comprehending prediction rationale and assessing area characteristics swiftly. The system also auto-saves selected grid information in GeoJSON format for future reference. It is noteworthy that this system is adaptable to various land value data formats, making it applicable to diverse usage scenarios, such as site selection for businesses. Also, historical data can be incorporated into the system to clearly illustrate historical changes (Fig. 4 (d)).

4.2 Users Application and Effectiveness

LINKin-PARK integrates spatial visualization techniques with our model to offer rich, flexible analytical tools. It presents land value data intuitively, conducts swift predictions, and provides interpretations, enhancing the understanding of geographical spaces for both professionals and ordinary users. Feedback is used to improve model predictions and result analysis (Fig. 3 (e)). For instance, professional evaluations compared the time spent on traditional systems to the time spent on each stage of LINKin-PARK's implementation. Results show that LINKin-PARK saves 95.8% of time and labor costs compared to existing systems with unstructured data pipelines.

5 CONCLUSION

LINKin-PARK provides rich visualization features and our model prediction to aid in analysis of land value data. It applies grid-based data and incorporates DCCNN, MLP, and attention mechanisms, using POIs and land use ratios. Our model outperforms baselines regarding MSE and MAE. LINKin-PARK empowers users, even those without expertise to generate and observe predictions intuitively using a visualization platform for such spatial information.

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