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APPLIED RESEARCH

Graph Convolutional Network-Based Model for Megacity Real Estate Valuation

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ABSTRACT It is challenging to make precise assessments of real estate prices due to its elevated individual prices, complicated influencing factors, and ambiguous attribute selection. As a result of the high demand for owner-occupied and investment properties, real estate is also a substantial concern for society. A hot topic for research by major institutions has been how to accurately estimate its price. Real-world applications of real estate valuation impose stringent requirements on the acquisition of datasets and the generalizability of models. On the basis of SRGCNN, a spatial regression model with excellent generalizability, this paper introduces an external attention mechanism to construct the A-SRGCNN model and compares it to the benchmark model utilizing data from Shanghai, Melbourne, and San Diego. For spatial regression, A-SRGCNN employs graph convolutional neural networks, and the external attention mechanism implicitly considers the relationship between property data. Experiments indicate that the A-SRGCNN model outperforms the benchmark model and has improved real estate price estimation accuracy. In the meantime, this paper employs the A-SRGCNN model to conduct zonal experiments and time-division experiments on the secondary real estate market in Shanghai to analyze the real estate price linkages between different zones and the real estate price linkages at different times. It is revealed that Shanghai real estate prices exhibit spatial aggregation and price aggregation, with comparable prices within the same zones, and that the A-SRGCNN model is effective at predicting house prices.

INDEX TERMS Graph convolutional network, deep learning, real estate valuation, spatial analysis.

I. INTRODUCTION

Appraising real estate prices is of paramount importance for banks to review loan mortgages and national real estate policy formulation. The timely and efficient valuation and forecasting of real estate prices not only brings significant economic benefits directly, but also has tremendous political implications, and major banks, insurance companies, and think tanks are searching for a precise, speedy, and cost-effective mechanism for real estate valuation. Qualitative analysis and quantitative analysis are the two most common categories used to objectively assess real estate prices. The qualitative study concentrates on the economics of macro policies, market trends, and other factors, whereas the quantitative analysis models the characteristics of house prices, such as real estate floor area, number of floors, historical sales prices, etc. Since qualitative analysis is influenced by subjective factors and is difficult to measure precisely and thoroughly, quantitative analysis is highly accurate and credible.The two predominant research directions in the quantitative analysis are the hedonic model and the machine learning model.

Hedonic models are the most frequently used models for valuating real estate prices. The hedonic model assumes that real estate consists of various functionalities that provide different utility to individuals, such as the size of the property, its location, its surroundings, its potential for appreciation, and so on. The variations in the number of features and the manner in which they are combined ascertain the disparities in home prices. By decomposing the factors that influence real estate prices and calculating the prices implied by each factor, it is possible to valuate the prices of real estate based on the differences between properties.The hedonic framework was

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originally employed by S. Rosen to examine the relationship between real estate prices and the living environment [1]. R. Meese et al. utilized hedonic regression models to valuate the dynamic impact of market fundamentals on real estate prices [2]. After many years of development, the hedonic model has become an established method of real estate price valuation, utilized in a large number of appraisal models and serving as a crucial foundation for bank loan approvals and government monetary policies. However, the hedonic method also has some drawbacks, such as the fact that the results of the hedonic model can vary depending on the estimation formula or process selected, which enhances the subjectivity of the appraisal, and necessitates a high demand for analysts with specialized knowledge, and necessitates a large quantity of property price data.

The field of machine learning is another area of research. Earlier stage machine learning models for estimating house values were relatively homogenous and relied on straightforward statistical and mathematical techniques like regression analysis.In multiple regression analysis, R. Dubin et al. used spatial regression techniques to estimate home prices [3]. However, this method ignores the impact of time variation. Real estate price changes can be thought of as a time series because real estate prices are affected by time characteristics as well. To forecast the growth of home prices in four US regions, R. Gupta et al. used a time series model with dynamic factor analysis and Bayesian shrinkage estimation [4]. Time series can also be incorporated into spatial regression models. In order to account for spatial and temporal heterogeneity, B. Huang et al. incorporate time effects into GWR models to assess house prices [5].Although these methods' performance in making forecasts is acceptable, their use in determining actual house prices is very limited. Although these methods' valuation performance is acceptable, there is very little use for them to determine real estate prices. The variables influencing real estate prices are intricate, making it challenging to monitor price changes. It is incredibly difficult for standard mathematical models to accurately model estate prices. Hedonic models have gained in popularity over the past few decades due to their affordability, accuracy, and complexity. Due to deep learning's strong computational capabilities and its many benefits in interdisciplinary fields, complex fitting is now possible. Real estate price valuation is beginning to use deep learning. A lot of people use artificial neural networks (ANN). H. Selim used an artificial neural network model to predict Turkey's real estate prices and noticed that it performed much better than the characteristic price model [6]. When compared to the hedonic model [7], S. Peterson et al. use of ANN on a sizable sample of 46,467 residential data revealed that it performs better when there are a lot of dummy variables because parameter estimation for ANN does not depend on the rank of the regression matrix. Because semi-supervised learning better takes advantage of the nonlinear relationships between the factors involved, Y. Guo et al. discovered that applying a semi-supervised learning strategy to ANN estate prediction can achieve similar or even superior performance compared to a fully supervised ANN method [8]. To estimate house prices in London, UK, S. Law et al. combined housing character traits with a deep neural network model [9].

ANN does have some restrictions. While processing serial data, such as modifications in estate prices over time, ANN often faces challenges with the input order information that is necessary. A deeper level of information from estate attributes, such as the effect of the property's exterior appearance on the estate price, is difficult for ANN to extract. Convolutional neural networks (CNN) and recurrent neural networks can both be used to get around ANN's drawbacks (RNN). When J. Bin et al. used RNN in their estate value estimation model and contrasted it with non-machine learning models, they discovered that RNN performed better [10]. Architectural images are a significant factor in real estate prices as well. O. Poursaeed used CNN to examine the impact of the appearance of the estate on the price of the estate [11]. However, there are concerns as to the applicability of architectural images, and Stephen Law points out that different regions may have different aesthetics, which can have a varying impact on the price assessment of properties [9]. Further investigation revealed that the performance of the CNN and RNN models varied significantly depending on the type of dataset used. Long short-term memory (LSTM) and CNN were both used by L. Yu et al. to predict the price of used homes in Beijing [12]. They discovered that the LSTM model outperformed when time-series data were used, while CNN performed much better when a dataset with deeply crawled feature factors was used. It is simple to see that while CNN can access more in-depth real estate data, LSTM is better suited to handle time series like estate price changes. A new trend involves combining spatial analysis and deep learning. With the use of AI techniques for geographic knowledge discovery, researchers started to look into bridging the gap between deep learning and spatial analysis methodologies, which expands the potential applications for estate price valuation methodologies. X. Xing et al. added the neighbor effect to a raster-based CNN to employ remotely sensed images for estimating the amount of human activity [13]. D. Zhu et al. theoretically demonstrated the possibility of utilizing graph convolutional neural networks (GCNN) to implement spatial regression and proposed Spatial regression graph convolutional neural networks [14].

Real estate appraisals have also implemented the decision tree algorithm. Notably, Kok *et al.* [15] developed a decision tree valuation model, which is superior to HPM in valuing multi-family dwellings. On the basis of decision tree algorithm, random forest algorithm can be constructed. The random forest algorithm comprises multiple regression trees, and each decision tree in the forest is unrelated to the others, and the final output of the model is generated by each decision tree in the forest together. Likewise, the random forest algorithm is a type of ensemble algorithm. Because the random forest algorithm's samples and features are random, it is less highly probable to overfit than traditional decision tree algorithms and is also more precise when the sample size is large [16]. This is clearly more suitable for real estate valuation where a large number of samples and characteristics exist, and therefore, the random forest approach has become a common algorithm for real estate valuation. M. Ceh et al. [17] employed random forest machine learning techniques to predict sales on real estate sales data in the Slovenian capital from 2008 to 2013 and compared them with traditional HPM. It was revealed that the prediction of the random forest method was higher on all the effectiveness indicators. T. Dimopoulos *et al.* [18]compared the effectiveness of random forest and linear multiple regression throughout predicting apartment prices on real estate data in the Nicosia area of Cyprus. It was demonstrated that the random forest approach exhibited higher prediction accuracy, especially for models that included a sufficient number of independent variables. There is another type of ensemble algorithm in which there is a strong dependency between individual weak learners that must be generated serially, which is represented by the Boosting algorithm. In their simulation of the Spanish real estate market, Alfaro-Navarro *et al.* [19] unearthed that the boosting algorithm outperformed the individual tree approach, though overall the random forest approach had moderately superior performance. In addition, J.-L. Alfaro-Navarro pointed out that ensemble learning methods tend to be applied in a limited way to specific geographic areas, while the best models tend to differ from city to city. The combination of decision trees and boosting ideas gave birth to the GBDT algorithm, which inherits the advantages and improves the disadvantages of decision trees and boosting, and, in turn, solves the problem of overfitting well by integrating multiple decision trees through the gradient boosting method.Meanwhile, the dilemma of sequential training and the difficulty of parallelism common to boosting algorithms has been effectively resolved with the advancement of XGBoost and LightGBM (a framework for implementing the GDBT algorithm). Z. Peng *et al.* [20]utilized the XGBoost algorithm to construct a second-hand house price prediction model for Chengdu, China, and observed that the XGBoost algorithm outperformed multiple linear regression and decision tree algorithms, and also had improved generalization and robustness.

When observing objects, individuals are more likely to concentrate their efforts on what is of greater interest. As research advances, some researchers have suggested that the Attention mechanism, which can be considered as a mechanism for reallocating resources based on the importance of activation, be added to machine learning to improve its accuracy. Attention analyzes the input content to determine the correlation between the elements, captures and amplifies the less notable but more important features to increase their influence weight in the training, and allocates more computational resources to the more significant computational units. Almost instantaneously, the Attention mechanism demonstrated significant benefits in areas such as computer vision (CV) and natural language processing (NLP). For instance, J. Liu et al. discovered that although LSTM has an excellent performance in recognizing 3D human actions, not all action joints have a positive effect on training, and some action joints produce a great deal of interference with training, and they added an attention mechanism to the original LSTM model in order to selectively focus on useful action sequences with the aid of global contextual information joints [21]. The Attention mechanism can also be applied to real estate appraisal, as demonstrated by J. Bin *et al.* [22], who conducted a multimodal fusion appraisal of Los Angeles real estate based on attention and discovered that the appraisal model performed well after the introduction of the Attention mechanism. A. Vaswani *et al.* [23] proposed a self-attentive mechanism that can enhance the performance of the model, parallelize the computation, and significantly reduce the training time. This self-aware mechanism does not, however, account for the potential correlation between different samples. M.-H. Guo proposed external attention [24], which captures the global connections between data via external shared units and implicitly considers correlations between all sample data.

Taking full consideration of the previous section, the need for realistic real estate valuation is taken into account. We presume that the A-SRGCNN model is appropriate for real estate valuation since real estate price appraisal is indeed a very typical spatial regression scenario, and the SRGCNN appraisal model performs well in this scenario in comparison to older models [14]. What's more, the external attention mechanism can delve deeper into the linkage between sample data, which corresponds to the close connection among real estate data, so the model would further work on improving the valuation consistent manner on the SRGCNN valuation model's impressive performance. Real estate appraisal models have high requirements in terms of their ability to generalize over validation sets and different data sets. The acquisition of certain attributes for real estate data samples regularly presents some challenges. Consequently, the A-SRGCNN real estate appraisal model is constructed in this paper. The model is based on the spatial regression model SRGCNN, and the spatial regression algorithm shows good generalization ability and stable performance when it comes to different datasets. The most important parameter of the SRGCNN model is the spatial location of real estate, and the spatial information of real estate is often easier to obtain in reality. The A-SRGCNN approach incorporates an attention mechanism by adding an external attention layer before the final output, which is based on the use of the SRGCNN model. There are tight connections between real estate samples, and the external attention layer enhances the algorithm's truthfulness by capturing the global connections between property samples via shared memory units. Accordingly, compared with popular regression valuation models, the A-SRGCNN proposed in this paper is more generalizable, performs stably on different samples, and the attributes of the required samples are easily available, which is more in line with the realistic needs of real estate valuation, while taking into account the accuracy of the valuation.

The remaining sections of this paper are as follows. In Section II, a spatial regression graph convolution model (A-SRGCNN) for real estate price valuation is constructed based on an external attention mechanism. In Section III, the experimental dataset and parameter settings are proffered. In Section IV, the experimental results are presented and analyzed. Section V concludes.

II. SPATIAL REGRESSION GRAPH CONVOLUTION NEURAL NETWORK REAL ESTATE PRICE VALUATION MODEL BASED ON EXTERNAL ATTENTION MECHANISM (A-SRGCNN)

A. SPATIAL REGRESSION GRAPH CONVOLUTION NEURAL NETWORK (SRGCNN)

The structure of our model is introduced with the setting of Shanghai data set as an example. The interpretation of spatial statistical relationships between dependent variables and variables can be modeled using traditional spatial regression. Traditional spatial regression, on the other hand, relies on the assumption that attribute observations are complete when constructing the spatial weight matrix, which leads inevitably to missing data in practical applications. For instance, it is demanding to collect all attribute data for a property so that it can be valuated completely in real estate appraisal, which restricts the use of scenarios for spatial regression models. It is also daunting to capture nonlinear relationships among geographic attributes, and many such nonlinear relationships exist in real estate attributes [25], which will unavoidably affect the assessment's accuracy. Furthermore, spatial regression models' predetermined linear econometric regression models reinforce the assumption that spatial relationships to be studied are linear. Traditional spatial regression, on the other hand, disregards the heterogeneity between sample locations and instead learns the overall spatial relationship by sharing weights.

D. Zhu *et al.* [14] made the SRGCNN proposal and argued that spatial regression could theoretically be implemented using graph convolution. The Spatial Dubin Model (SDM) is shown in the following matrix.

$$y = \rho W y + x\beta + WX\delta + \epsilon \tag{1}$$

Transformation is as follows.

$$\begin{aligned} y &= (I - \rho W)^{-1} (X\Theta + \epsilon) \\ &= \left(I + \rho W + \rho^2 W + \cdots\right)\left(\widetilde{X}\Theta + \epsilon\right) \\ &= \sum_{k=0}^{\infty} (\rho W)^k \widetilde{X}\Theta + \widetilde{\epsilon} \end{aligned} \tag{2}$$

And according to the forward propagation mechanism of the graph convolutional network, the dependent variable is expressed as follows.

$$y = \sigma\left(w_L X\Theta\right) \tag{3}$$

In the back propagation process, the root mean square error is used as the loss function L for parameter updating, so the gradient of the lth level of descent is represented as follows.

$$\begin{aligned} J^{(l)} &= \frac{\partial L}{\partial Z^l} \\ &= \frac{\partial L}{\partial X^l}\frac{\partial X^l}{\partial Z^l} \\ &= \frac{\partial L}{\partial Z^{l+1}}\frac{\partial Z^{l+1}}{\partial X^l}\frac{\partial X^l}{\partial Z^l} \\ &= J^{(l+1)} W_L^T \Theta^l \sigma^l \end{aligned} \tag{4}$$

The response of graph convolutional neural networks' forward and backward propagation to spatial lag illustrates that these networks are capable of modeling dependent and independent variables in a manner similar to spatial regression. This makes it possible to perform spatial regression using graph convolutional neural networks, or SRGCNN, by swapping out the conventional spatial weight matrix for a spatial graph structure that characterizes the structural connections between spatial units.

The real estate samples are intricately connected, particularly the implicit connection between the spatial locations of the real estate samples. Conversely, the majority of linear spatial models rely on a supervised approach, in which only the locations of the observed labels can be incorporated into the trained model. As a result, these models are not directly applicable for valuation or exhibit poor performance when real estate sample data are missing or under-sampled [26]. To solve this issue, SRGCNN employs semi-supervised learning, in which all spatial units are observed and the Label is only partially sampled-a situation that is typical in accurate real estate appraisals-to optimize the parameters. In order to fully capture the spatial dependence and better reflect it in real estate data, semi-supervised learning allows the weights of all spatial units to be taken into account.

The model developed in this paper's SRGCNN layer is depicted in Fig. 1. The location data of the real estate samples is first extracted by the SRGCNN layer, and a spatial graph with a 6000×6000 structure is built using the location data. This spatial graph encodes the spatial weight matrix and cross-sectional data of the real estate samples. The SRGCNN layer then uses additional attribute data from the training set to update all of the nodes. The values are then matrix linearly operated with the memory units WEIGHT and BIAS, which are activated by the activation function Relu and input to the subsequent attention layer. The memory unit BIAS' structure is set to 1×56, and the memory unit WEIGHT's structure is 7×56. Forward propagation is used to update the memory unit's parameters. By training the model using the spatial unit weights of all property samples, including those in the training and validation sets, even if the sample does not appear in the training set, SRGCNN employs a semi-supervised learning strategy to optimize the parameters. The semi-supervised learning strategy makes the SRGCNN model more

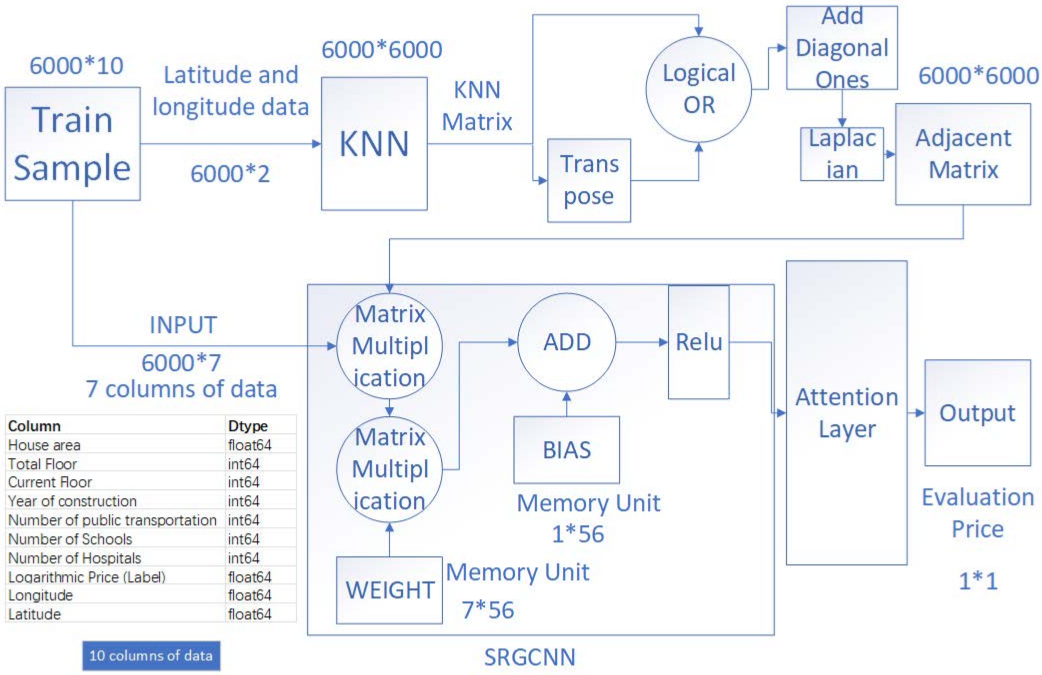


FIGURE 1. Structure of SRGCNN layer.

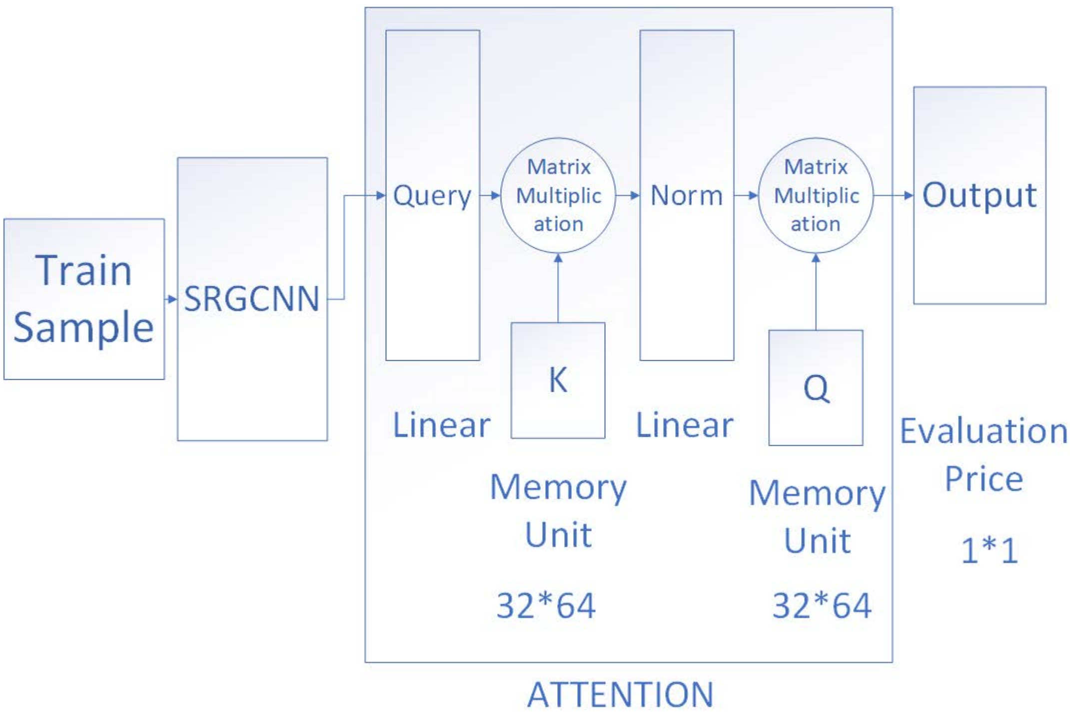


FIGURE 2. Structure of external attention layer.

appropriate for these valuation scenarios because in practice there are regularly cases of missing or under-sampled real estate sample data.

In order to capture long-range dependencies in a single sample, the prevalent self-attention mechanism works on the principle of modifying the features of each location by computing a weighted sum of the pair-wise affinities of all locations. Self-focus, however, excludes potential correlations between various samples and has secondary complexity. The potential correlation between various samples in the valuation of real estate is also very high. As a result, we take into account using external attention in the A-SRGCNN model in this paper. By calculating the similarity between the self-questions and the self-keys, the self-attention mechanism generates an attention map. The A-SRGCNN model's external attention layer implements the attention mechanism by determining the relationship between sub-queries and the more compact learnable Key memory units that catch the broad connections between real estate data.

B. EXTERNAL ATTENTION

In order to capture long-range dependencies in a single sample, the prevalent self-attention mechanism works on the principle of modifying the features of each location by computing a weighted sum of the pair-wise affinities of all locations. Self-focus, however, excludes potential correlations between various samples and has secondary complexity. The potential correlation between various samples in the valuation of real estate is also very high. As a result, we take into account using external attention in the A-SRGCNN model in this paper. By calculating the similarity between the self-questions and the self-keys, the self-attention mechanism generates an attention map. The A-SRGCNN model's external attention layer implements the attention mechanism by determining the relationship between sub-queries and the more compact learnable Key memory units that catch the broad connections between real estate data.

Fig. 2 depicts the A-external SRGCNN's attention layer's organizational structure. Two linear layers are used to implement the model. First, two-dimensional data from the upper SRGCNN layer, which is the data obtained after the SRGCNN layer applies spatial regression using graph convolution on real estate samples, is accepted by the model. The memory cells K and V in the layer of external attention each have a 32×64 structure. The memory units keep track of the attention weight parameters and implicitly take potential correlations between real estate data into account. In order to increase the potential relevance and important features in the real estate data and lessen or even eliminate the weights of the unimportant features in the real estate data, the incoming two-dimensional data from the SRGCNN layer is multiplied along with the weight parameters in the memory cell. The appraised value of the property is output as a 1×1 result by the attention layer in the end. The structure of the memory units of the external attention layer can be modified or bias terms can be added to further improve the optimization of external attention. The appraised price will be compared with the actual price to calculate the error and start a back propagation algorithm to update the parameters in the memory units.

III. DATA AND EXPERIMENT SETUP

The experiments are implemented using Pytroch, a deep learning framework with GPU acceleration. The computing environment is a Linux server with an Nvidia RTX 3070 GPU, a 2.10Ghz Intel i7-12700 CPU and 64GB RAM.

Three datasets are used in this paper, namely the Shanghai transactional real estate transaction dataset provided by a partner real estate company, the San Diego, California, USA real estate dataset on airhnb,and Melbourne, Australia real estate transaction data on kaggle. The following links can be utilized to access the data. https://github.com/n0away/Data-ASRGCNN/ Data on real estate transactions in Shanghai is among those that cannot be released to the public because it is provided by commercial real estate appraisers and involves trade secrets.

Table 1, Table 2, and Table 3 show the structure of the dataset with 31605 entries in the Shanghai dataset, 8887 entries in the Melbourne dataset and 6110 entries in the San Diego dataset. The attributes of each feature have been

TABLE 1. Attributes of the Shanghai dataset.

Column	Dtype
House area	float64
Total Floor	int64
Current Floor	int64
Year of construction	int64
Number of public transportation	int64
Number of Schools	int64
Number of Hospitals	int64
Logarithmic Price (Label)	float64
Longitude	float64
Latitude	float64

TABLE 2. Attributes of the Melbourne dataset.

Column	Dtype
Distance	float64
Rooms	int64
Bedroom	int64
Bathroom	int64
Car	int64
Landsize	int64
BuildingArea	float64
Logarithmic Price (Label)	float64
YearBuilt	int64
Longitude	float64
Latitude	float64

TABLE 3. Attributes of the San Diego dataset.

Column	Dtype
coastal	int64
accommodates	int64
Bedroom	int64
bathroom	int64
beds	int64
pool	int64
Logarithmic Price (Label)	float64
Longitude	float64
Latitude	float64

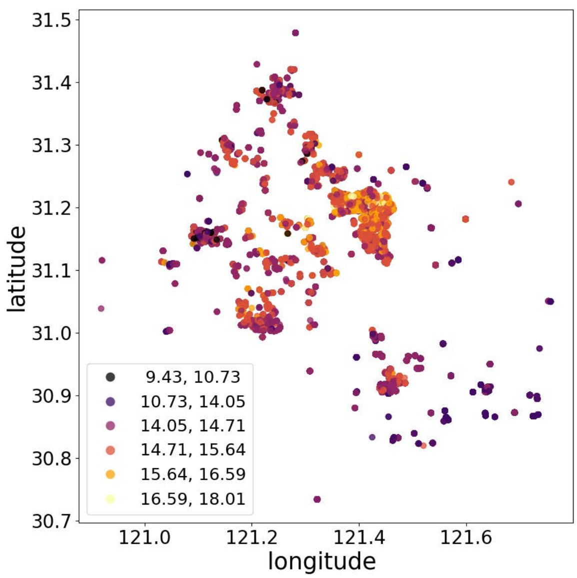


FIGURE 3. Distribution of Shanghai dataset.

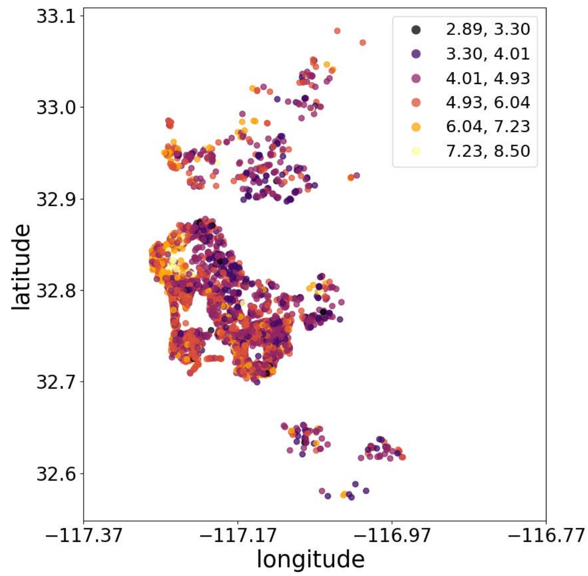


FIGURE 5. Distribution of San Diego dataset.

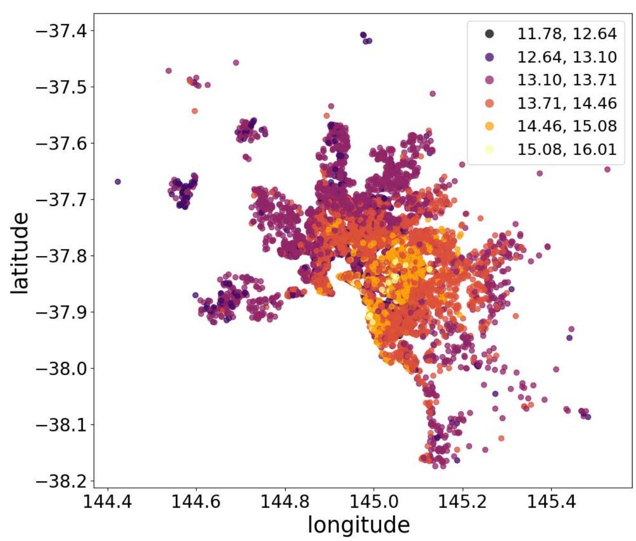


FIGURE 4. Distribution of Melbourne dataset.

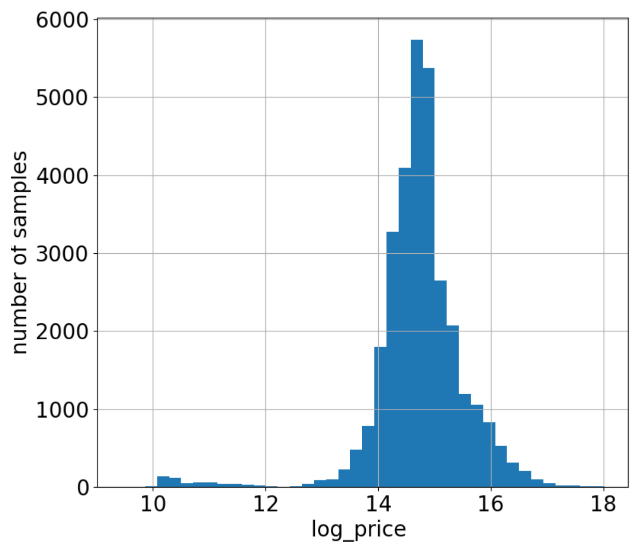


FIGURE 6. Price histogram for the Shanghai dataset.

given in table. The experiments use the logarithmic price of the property as the dependent variable and the latitude and longitude location of the property to generate the adjacency graph.

Fig. 3, Fig. 4, and Fig. 5 show the real estate price distribution. The horizontal and vertical coordinates are the latitude and longitude of the real estate, and the shades of the scatter colors represent the high and low logarithmic prices of the real estate. What can be seen is that there are both high and low house price clusters in the dataset.

Fig. 6, Fig. 7, and Fig. 8 depict a bar chart of house prices, where the horizontal coordinate represents the log price of the property and the vertical coordinate represents the number of corresponding log prices. The log prices of the data set to exhibit a normal distribution, as shown by the horizontal and vertical coordinates.

It is worth mentioning that the shanghai dataset's prices used in the experimental data are the final real estate transaction data, which have higher accuracy compared with the data obtained by web crawlers. In general, due to commercial practices or policy pressure, there is a discrepancy between the listed price and the final real transaction price as published on real estate agent websites. [27].

Seven models, LR, BP, RF, XGBoost, LightGBM, and SRGCNN, were used as the benchmark models. The latitude and longitude of the property location were employed as the variable input to the model because some of the models could not embrace the graph parameters.

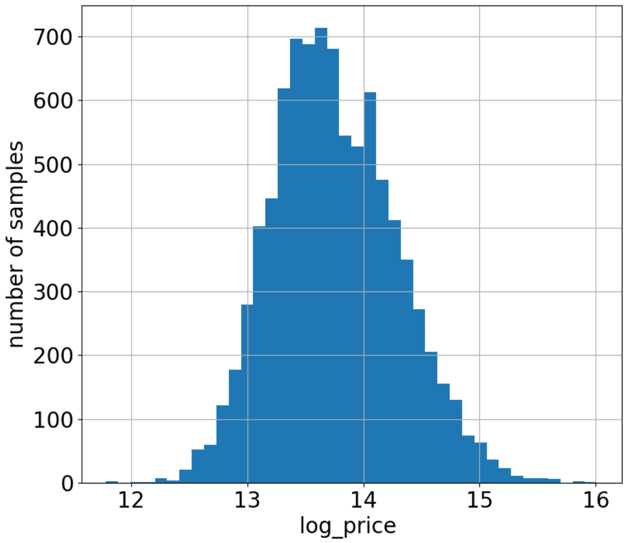


FIGURE 7. Price histogram for the Melbourne dataset.

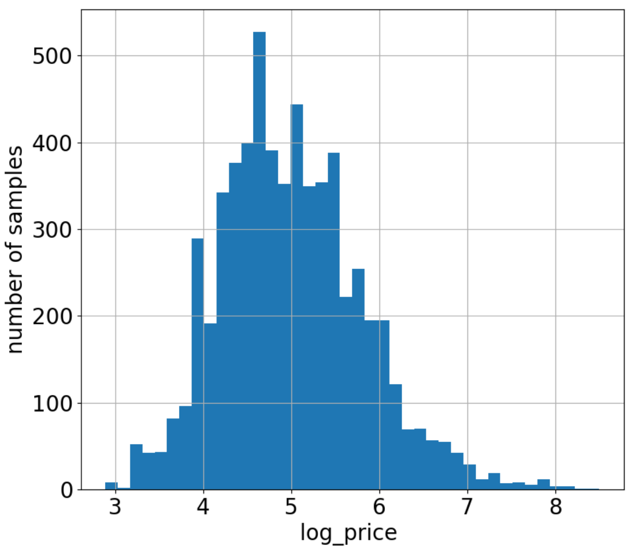


FIGURE 8. Price histogram for the San Diego dataset.

In this paper, the following models are chosen as the benchmark models.

1) LINEAR REGRESSION (LR)

A simple and easy to implement model, the data is modeled using a linear prediction function.

2) BACK PROPAGATION (BP)

A multilayer feedforward network trained by error back propagation, with the basic idea of gradient descent.

3) GRAPH CONVOLUTIONAL NETWORK(GCN)

A powerful graph neural network with a wide range of applications in several fields such as computer vision and natural language processing.

4) RANDOM FOREST(RF)

Random forest regression consists of multiple regression trees, each decision tree in the forest is uncorrelated with one another, and the model output is ascertained cooperatively by each decision tree in the forest.

5) SPATIAL REGRESSION GRAPH CONVOLUTIONAL NEURAL NETWORK(SRGCNN)

The model uses spatial regression implemented with graph convolution and has good performance on multivariate prediction.

6) EXTREME GRADIENT BOOSTING(XGBOOST)

XGBoost implements and engineers many improvements to machine learning algorithms in the Gradient Boosting framework and is widely used in algorithm competitions.

7) LIGHT GRADIENT BOOSTING MACHINE(LIGHTGBM)

Microsoft's framework for the GBDT algorithm, which facilitates efficient parallel training. Specifically, it has the benefits of rapid training speed, low memory consumption, and distributed support.

Real estate has attributes such as high unit price, low liquidity, and long transaction time, which cannot achieve high frequency trading similar to that of stocks. It is challenging to represent the time-series changes of real estate transactions and model them using the time-series data because the real estate transaction data used in this experiment has a more discrete time distribution. Therefore, the more popular LSTM model is not used as the benchmark model in this paper.

We employ the A-SRGCNN model for zonal and time-division experiments following the model comparison experiments. 6000 property data are randomly chosen in Shanghai dataset as experimental data for the model comparison experiment, of which 5000 serve as the training set and 1000 serve as the validation set. The influence of time attributes on property prices can be disregarded because they were chosen at random. 6000 data points from various regions are chosen for the zonal experiments, of which 5000 serve as the training set and 1000 serve as the validation set. The training set for the time-division experiments consists of 5000 real estate prices from 2020 to the first half of 2021, and the validation set consists of 1000 real estate prices from the second half of 2021. When the valuation metrics are stable or the training set has been trained to overfitting, all models stop learning.

IV. RESULT

A. MODEL COMPARISON EXPERIMENTS

Table 4 summarizes the performance results of all benchmark models, and the experiments use mean absolute percentage error (MAPE) to valuate how well the models fit on the training set and how well they valuate on the validation set.

Table 4's model performance findings indicate that the A-SRGCNN model performs impressive. Although the

TABLE 4. Performance in model comparison experiments.

MAPE	LR	BP	GCN	RF	lightGBM	XGBoost	SRGCNN	A-SRGCNN
Shanghai(training set)	2.62%	2.82%	2.29%	3.00%	2.02%	1.11%	2.10%	1.93%
Shanghai(validation set)	2.55%	2.87%	2.34%	3.05%	4.21%	2.92%	2.16%	1.87%
San Diego(training set)	7.83%	8.84%	10.98%	6.45%	5.62%	3.55%	4.29%	3.58%
San Diego(validation set)	7.97%	8.95%	10.54%	6.96%	6.95%	7.06%	4.63%	4.12%
Melbourne(training set)	32.63%	39.54%	12.75%	17.15%	10.40%	3.29%	9.09%	4.57%
Melbourne(validation set)	38.58%	45.27%	12.66%	21.05%	15.44%	15.14%	14.19%	12.80%

TABLE 5. Friedman's test.

Model	Sample size	Median value	Standard deviation	Statistical quantities	p value (two tailed)	Cohen's f value
LR	6	7.9	15.97	24.056	0.001***	0.495
BP	6	8.895	19.148			
lightGBM	6	6.284	4.819			
XGBoost	6	3.422	5.096			
A-SRGCNN	6	3.85	4.071			
SRGCNN	6	4.46	4.72			
RF	6	6.704	7.633			
GCN	6	10.758	4.942			
Note: ***, **, * represent 1%, 5%, 10% significance levels, respectively						

TABLE 6. Wilcoxon signed rank test.

Paired variables	Median ± standard deviation			Z value	Degree of freedom	P value	Cohen's d
	Pair1	Pair2	Pairing Difference (Pair1-Pair2)				
A-SRGCNN pairing SRGCNN	1±0.665	2±0.418	-1±0.408	2.236	5	0.025**	1.501
Note: ***, **, * represent 1%, 5%, 10% significance levels, respectively.							

A-SRGCNN model does not perform optimally on every dataset compared to the benchmark model, the A-SRGCNN model performs worse than the XGBoost model on the validation set of the Shanghai and Melbourne data. Nevertheless, the A-SRGCNN model has superior generalizability and high stability. In the validation set, the A-SRGCNN model has the highest accuracy among the eight models. This signifies that the A-SGRCNN model is more stable and applicable to real-world applications than the benchmark model. The LightGBM algorithm has an error rate of 4.21 percent on the validation set in Shanghai, which is inferior to the RF algorithm's error rate of 3.05 percent and XGBoost's error rate of 2.81 percent. On the San Diego validation set, the errors of RF, lightGBM, and XGBoost are, respectively, 6.96 percent, 6.95 percent, and 7.06 percent, which are comparable.On the Melbourne validation set, the error rate of the LightGBM algorithm is 15.44 percent, which is significant compared to the error rate of XGBoost (15.14 percent) and dramatically decreases the error rate of the RF algorithm (21.05 percent).This suggests that the achievement of these interconnected algorithms is not stable and varies hugely when valuated on various datasets.Especially in contrast to the other comparison algorithms, the A-SRGCNN algorithm outperforms them with errors of 1.87 percent, 4.12 percent, and 12.80 percent on the three datasets, denoting that the A-SRGCNN algorithm has the advantage of stable performance throughout datasets.

Friedman's test was performed on the results, and according to the results in Table 5, the significant p-value is 0.000***<0.05. Therefore, the statistical results are significant, indicating that there are tremendous differences between LR, BP, GCN, RF, light GBM, XGBoost, SRGCNN, and A-SRGCNN. Their difference magnitude Cohen's f value is 1.3. Undoubtedly, the magnitude disparity is enormous. It can also be seen from the box line plot that the A-SRGCNN model has the most stable performance among the eight models.

Further wilcoxon signed rank test was performed on the resultant results and according to the results in Table 6, the significance p-value is 0.025**, which presents significance at the level, so there is a significant difference between the A-SRGCNN model and the SRGCNN model. The significance of the contrast The d-value of Cohen is 1.501, which represents a really massive variation. And thereby,

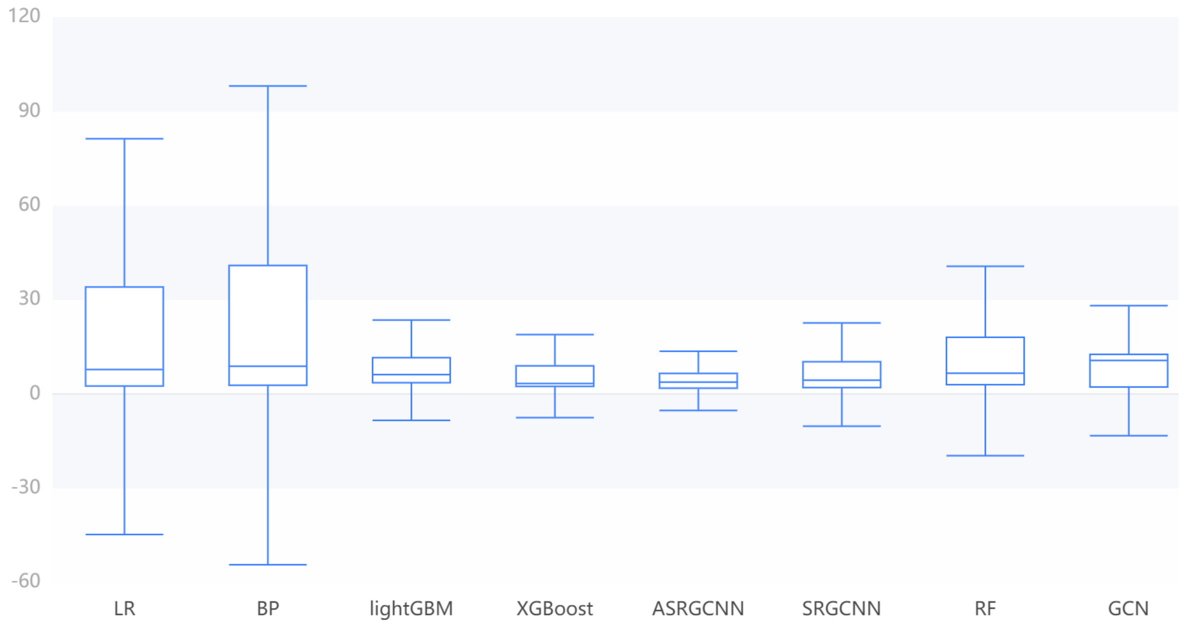
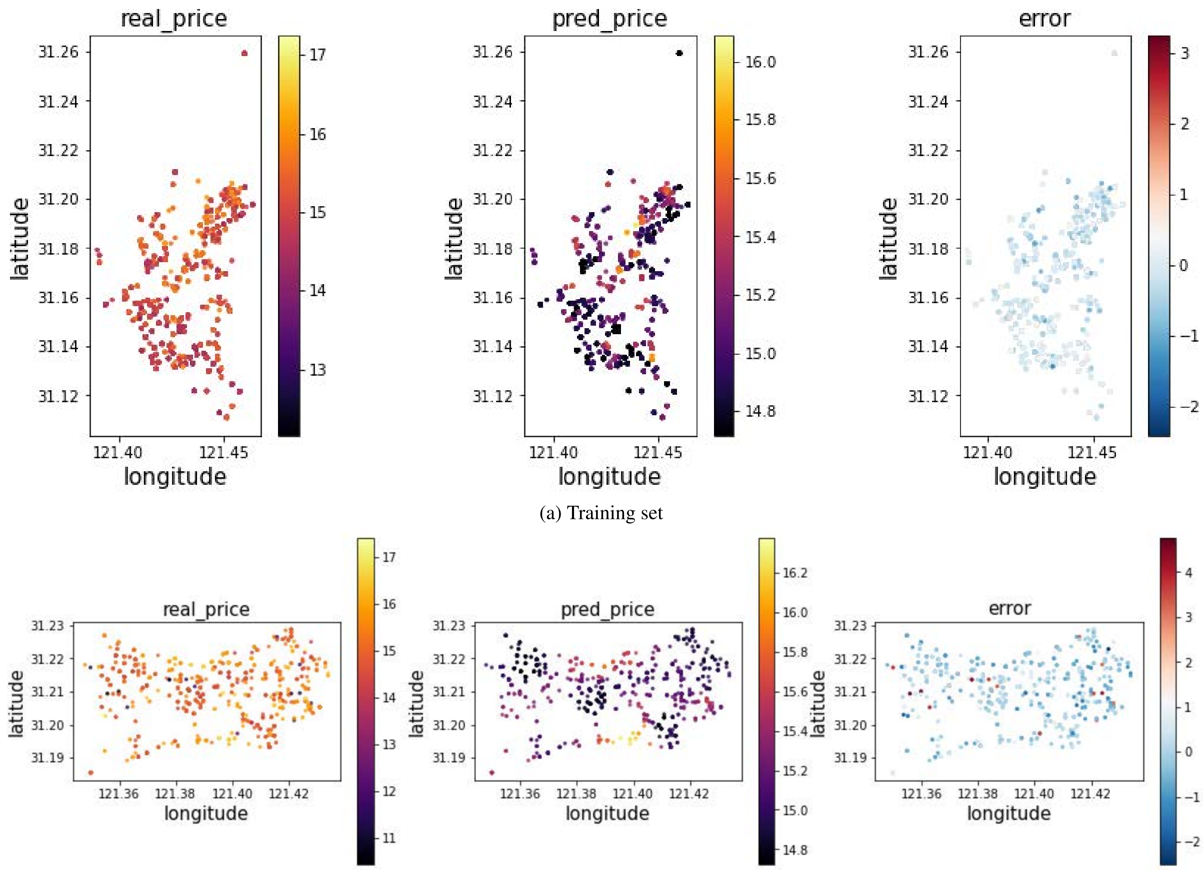


FIGURE 9. Comparison of box line graphs.



(a) Training set

(b) Validation set

FIGURE 10. Heat map of group 1 in the zonal experiments.

we conclude that the A-SRGCNN model demonstrates a statistically meaningful performance advantage over the SRGCNN model without the attention mechanism.

B. ZONAL EXPERIMENTS

Using the A-SRGCNN model, this section conducts zonal experiments. Experiments were conducted in various admin-

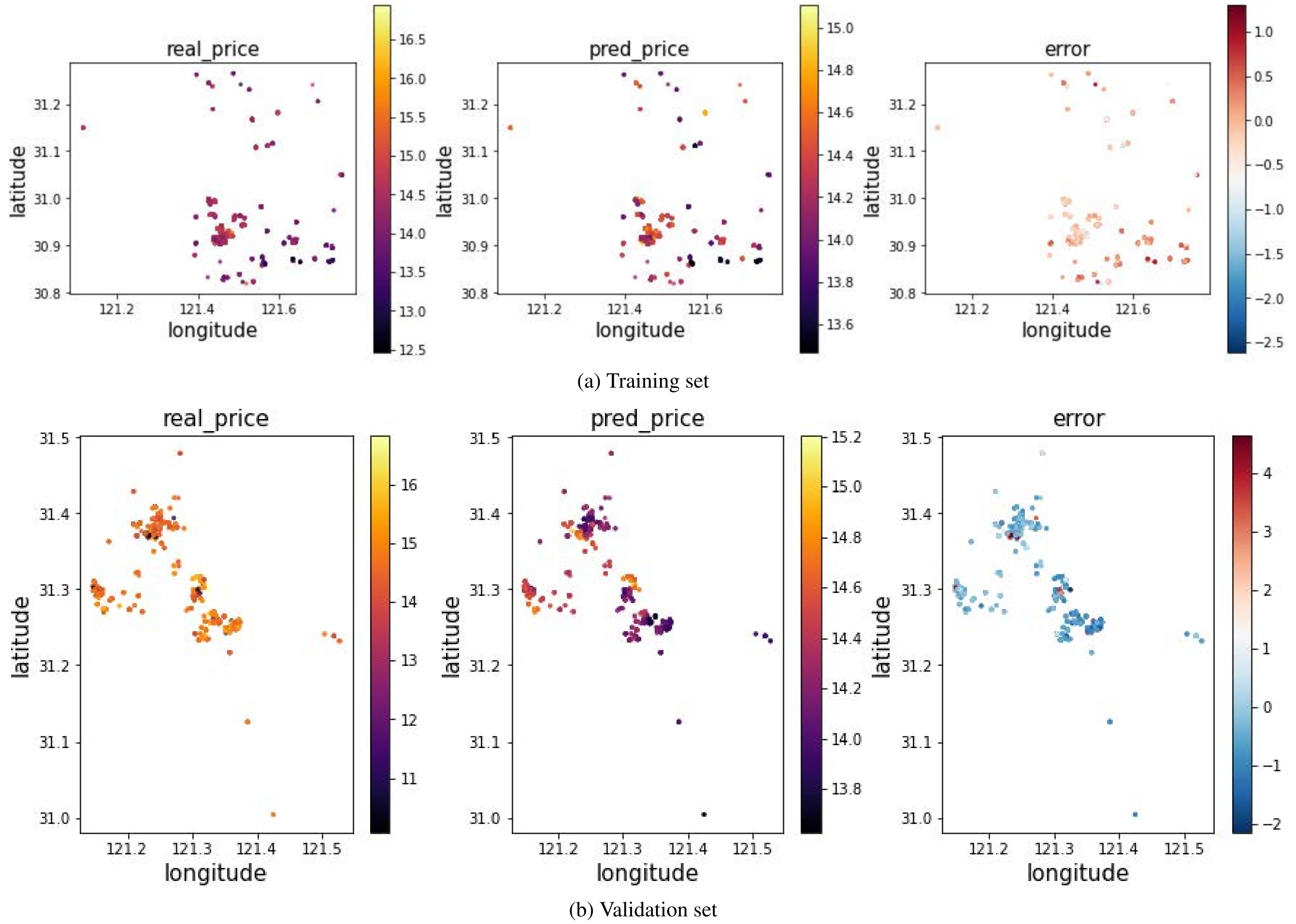


FIGURE 11. Heat map of group 2 in the zonal experiments.

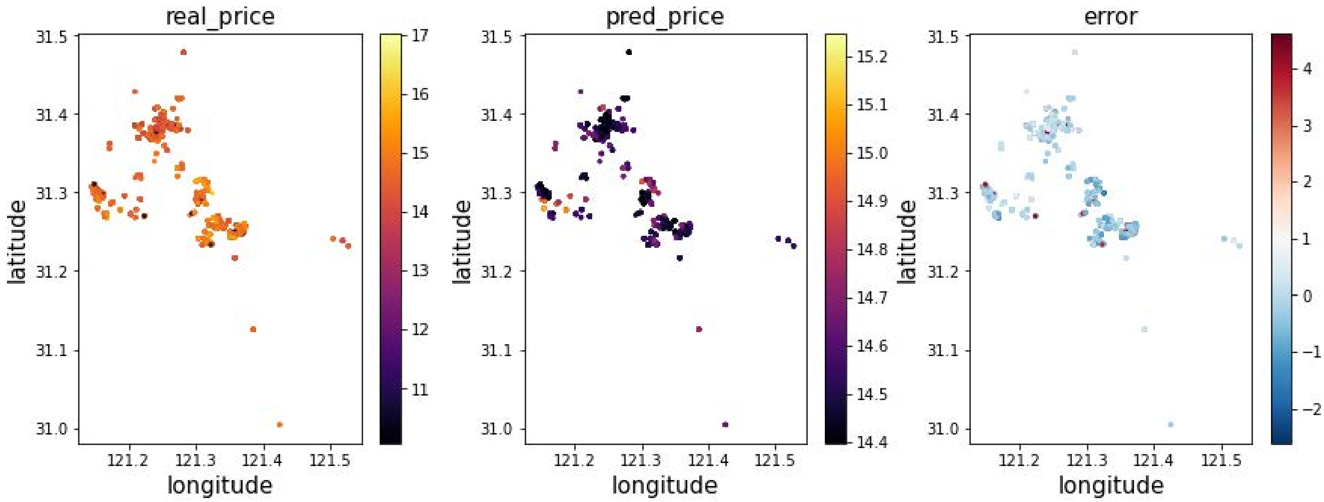
istrative districts to examine the training effect of the model in various districts, the performance of the valuation in other districts, and the relationship between the two. Comparison group 1 used data from the district of Xuhui for its training set and data from the district of Changning for its validation set. Consult Table 7 for a listing of the training and validation sets utilized by other comparison groups.

According to the experimental findings, the validation set error is substantially greater than the model comparison experiments while the training set error is comparatively lesser when using the A-SRGCNN model in the zonal experiments. This implies that while the A-SRGCNN model performs worse than the model-comparison experiment on the validation set, it performs better on the training set in the zonal experiment. It is not difficult to understand, as the data for the zonal experiments were restricted to one district in Shanghai while the data for the model comparison experiment were chosen at random from six regions. In contrast, the zonal experiments' data show more geographical proximity between properties, which means there are more potential connections between properties, leading to better training results on the training set. Though the validation set is also restricted to a single district, it is not surprising that the performance on the validation set is subpar given that the correlation between distinct districts is obviously lower than that of the same district.

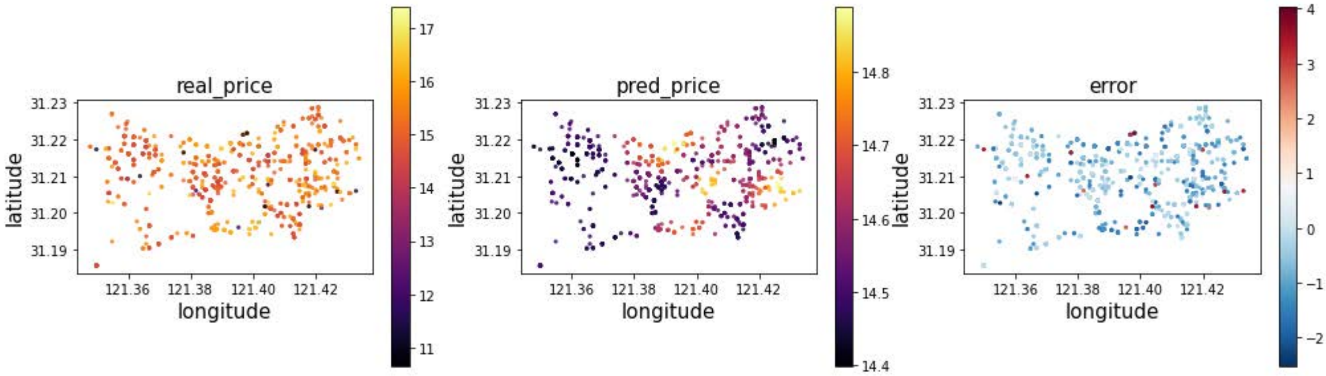
TABLE 7. Performance in zonal experiments.

	Group 1	Group 2	Group 3	Group 4
Training set	Xuhui	Fengxian	Jiading	Changning
Validation set	Changning	Jiading	Changning	Songjiang
MAPE (training set)	1.43%	1.36%	1.80%	1.69%
MAPE (validation set)	1.93%	2.69%	3.29%	2.42%

After analyzing the experimental data, we encountered that, on the one hand, the relative distance between different zones and, on the other, the magnitude of the difference in house prices between zones, determine how effective the assessment is. In comparison group 1, the districts of Xuhui and Changning are very close to one another and are both among Shanghai's more expensive areas. As a result, comparison group 1 has the best prediction results, even coming close to the model comparison experiment's performance. While it is completely obvious that the assessment effect is influenced



(a) Training set



(b) Validation set

FIGURE 12. Heat map of group 3 in the zonal experiments.

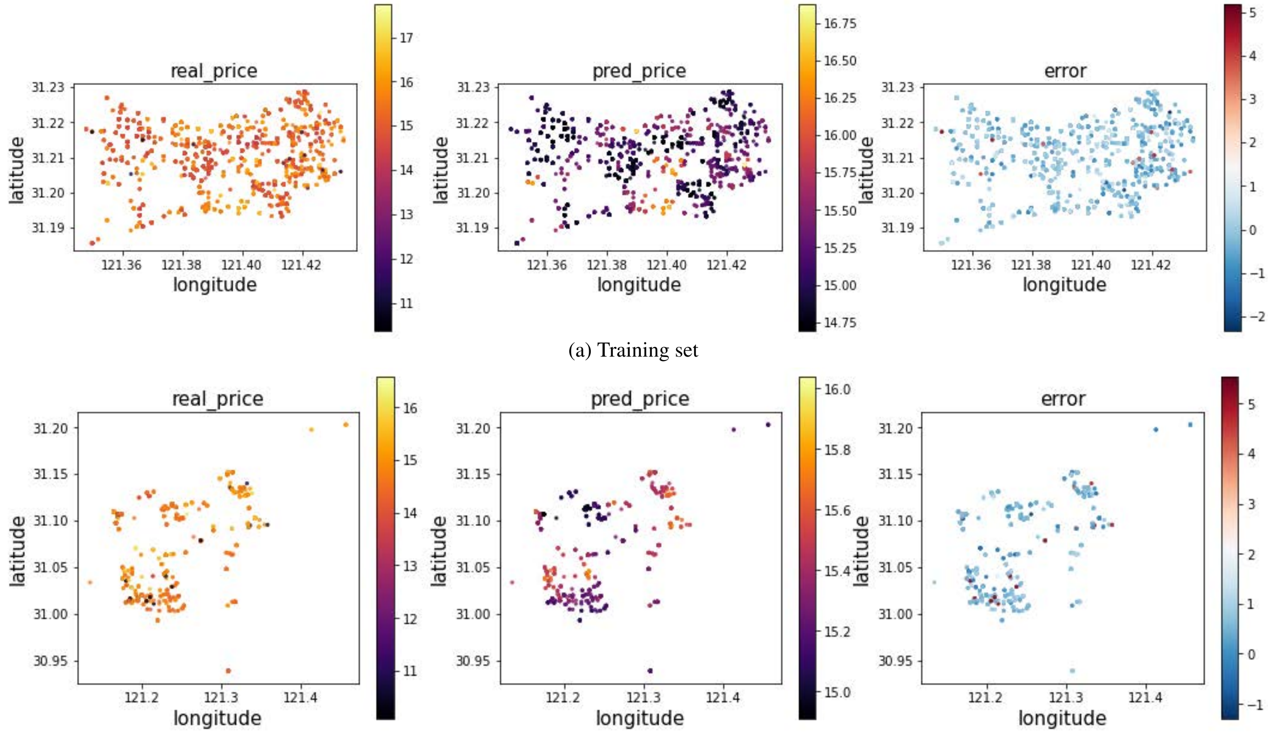
by the zoning distance from the comparison group 1 of the assessment heat map in Fig. 10, that the predicted prices are more accurate in the area of Changning District close to Xuhui District. The same is true for comparison group 2, which also has low property prices in Fengxian and Jiading. However, due to the great physical distance between these two zoning districts, comparison group 2's valuation effect of its validation sets is considerably worse than comparison group 1. This paper, therefore, considers that the district location's distance has an impact on the prediction effect.

Despite their close proximity, Jiading and Changning districts in comparison group 3 belong to the low house price zone while Changning district belongs to the high house price zone. As a result, they perform very poorly in the validation set, which is the worst assessment result in the zonal experiments. Therefore, we think that the difference in house prices between districts has an impact on the assessment effect as well and that the magnitude of the difference in house prices has a greater influence on prediction than the distance between districts. This is further supported by comparison group 4, where the house price level of Songjiang district is situated between Jiading district and Changning district. Despite the fact that there is a distance between these two districts, the A-SRGCNN model used in this comparison group 4 performs a better valuation of the house price than the model used in comparison group 3.

What reveals from the experiment is that administrative clustering and price aggregation are present at a higher level in Shanghai's housing prices. For example, although the model takes into account the number of schools in the vicinity of the property in the experiment, the quality of schools can be high or low between districts, which is evidenced not only in the stage of education but also in the fact that schools with a high level of education have good fitness facilities and a supportive environment that is available to the neighborhood, which can have a more beneficial effect on house prices [28].

C. TIME-DIVISION EXPERIMENTS

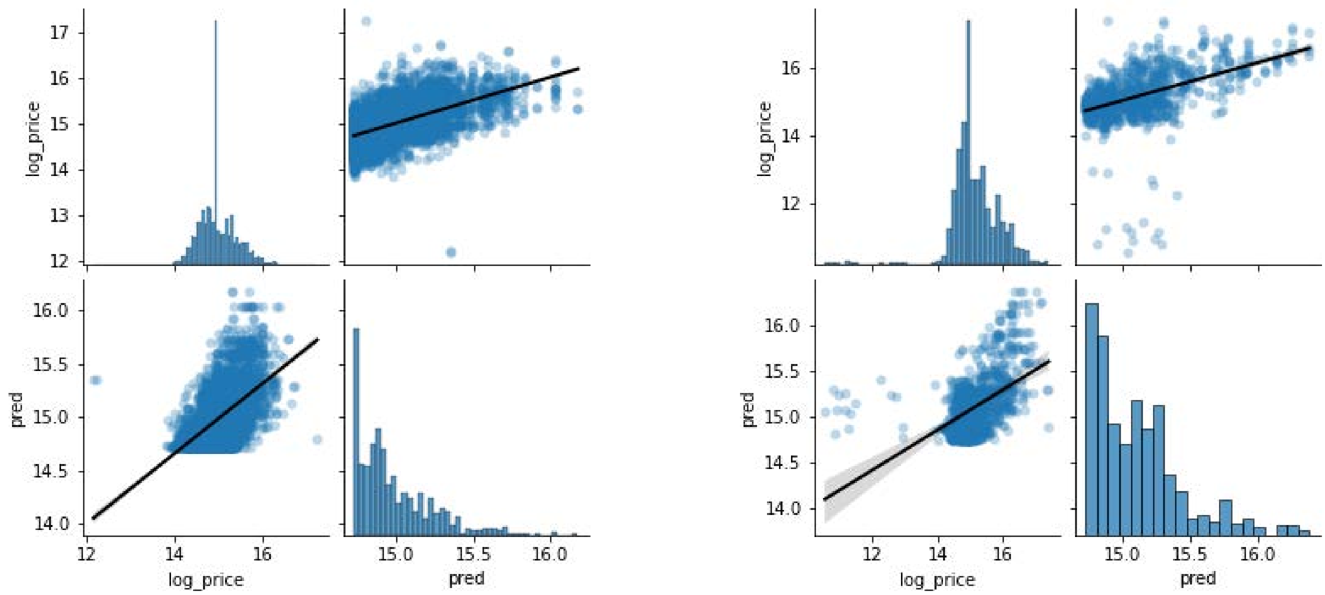
This part of the experiment randomly selected property prices from 2020 to the first half of 2021 as the training set and the second half of 2021 as the validation set to analyze the performance of the A-SRGCNN model in predicting future house prices.



(a) Training set

(b) Validation set

FIGURE 13. Heat map of group 4 in the zonal experiments.

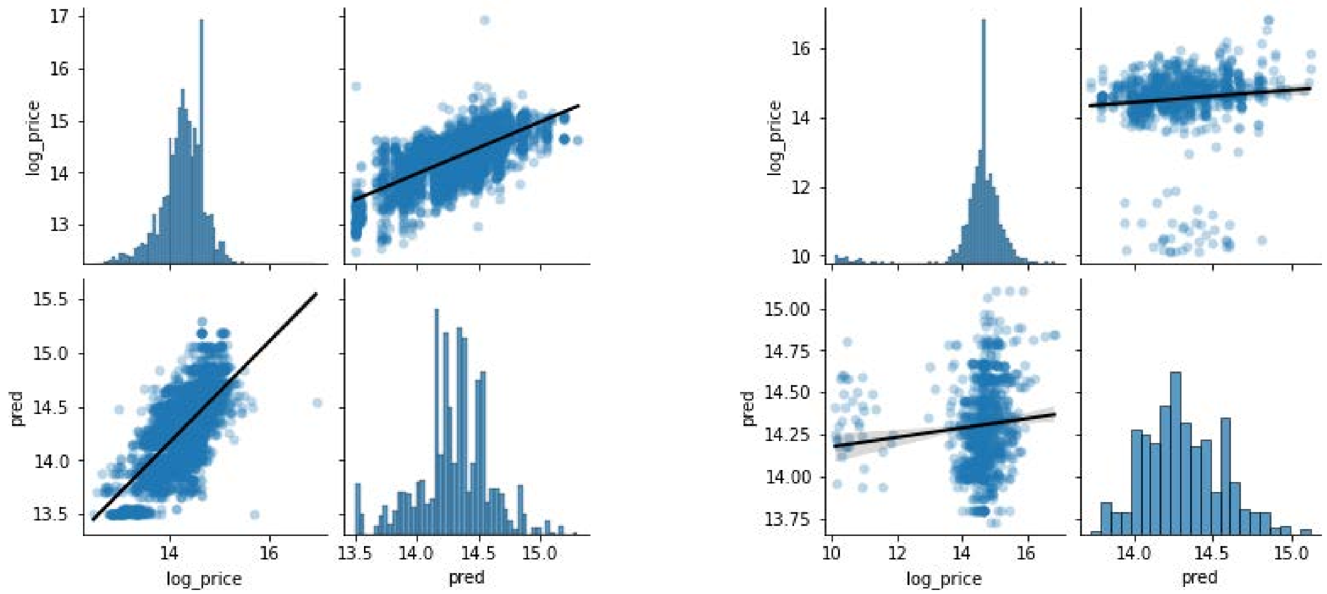


(a) Training set

(b) Validation set

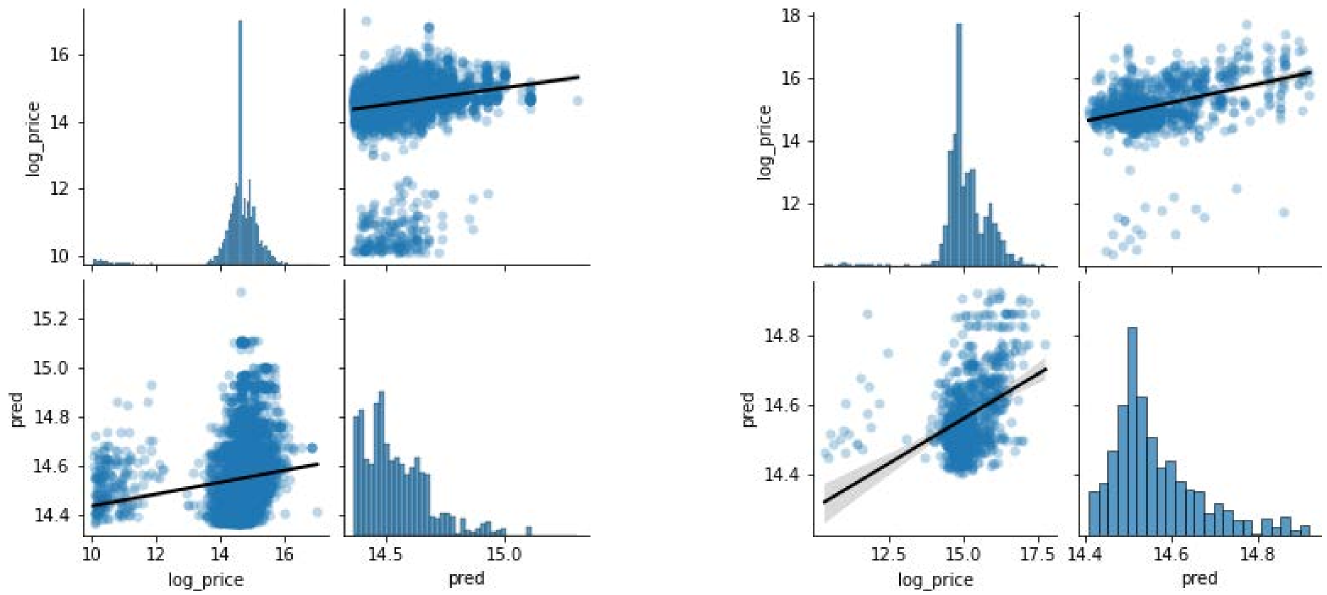
FIGURE 14. Distribution of group 1 in the zonal experiment.

The experimental results indicate that the number of epochs trained by the A-SRGCNN model in the time-division experiments is directly analogous to that of the comparison experiment, and the error of the time division experiment on the validation set is 2.20%. Considering the complexity of appropriately predicting future property prices in the real world, A-SRGCNN of future property prices is not terrible. In model comparison experiments, its error rate of 1.87% is



(a) Training set (b) Validation set

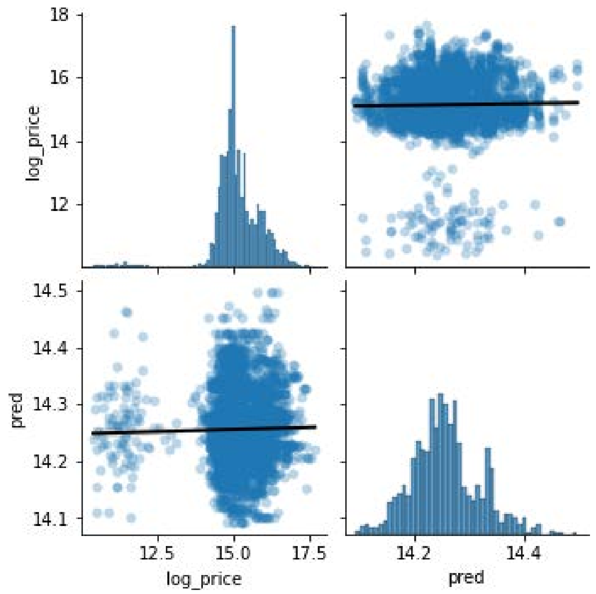
FIGURE 15. Distribution of group 2 in the zonal experiment.



(a) Training set (b) Validation set

FIGURE 16. Distribution of group 3 in the zonal experiment.

inferior to that of the A-SRGCNN model. We believe that the specificity of the data set explains this portion of the difference. China's real estate has been in a bull market prior to 2020 and for the past decades. In contrast, the outbreak of COVID-19 in China at the start of 2020 led to a stagnation of the Chinese economy, which had a dramatic impact on the real estate market, particularly a significant dampening effect on Shanghai real estate prices [29]. And as a result of the rapid containment of COVID-19 in China and the introduction of relatively accommodating economic policies by the Chinese government, Shanghai's real estate prices began to recover quickly [30]. The prediction error of the model in the time-division experiment increased as a result of such a massive shock and upheaval, which caused the dataset to be severely impacted and to no longer accurately reflect the real trend of real estate prices.


(a) Training set

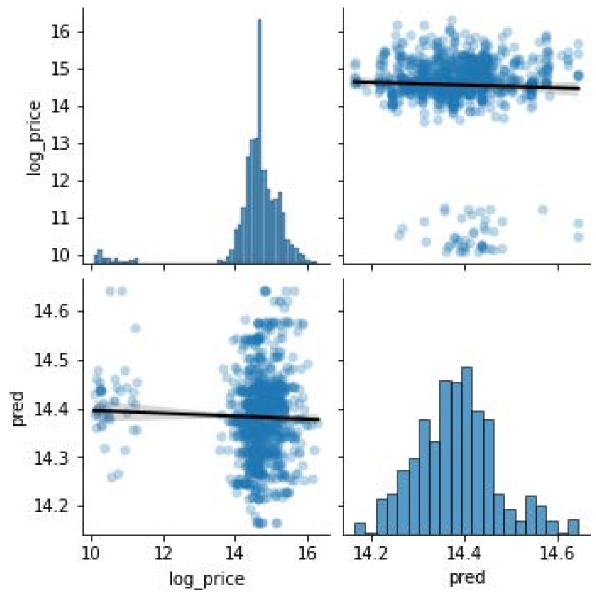

(b) Validation set

FIGURE 17. Distribution of group 4 in the zonal experiment.

TABLE 8. Performance in time-division experiments.

	Time-division experiments
Training set period	January 2020 to June 2021
Validation set period	July 2021 to December 2021
MAPE(training set)	2.01%
MAPE(validation set)	2.20%

TABLE 9. Regional time-division experiments.

	Xuhui	Changning	Fengxian
MAPE(training set)	1.71%	1.75%	1.74%
MAPE(validation set)	1.99%	1.99%	2.09%
Training set period	January 2020 to June		
Validation set period	July 2021 to December 2021		

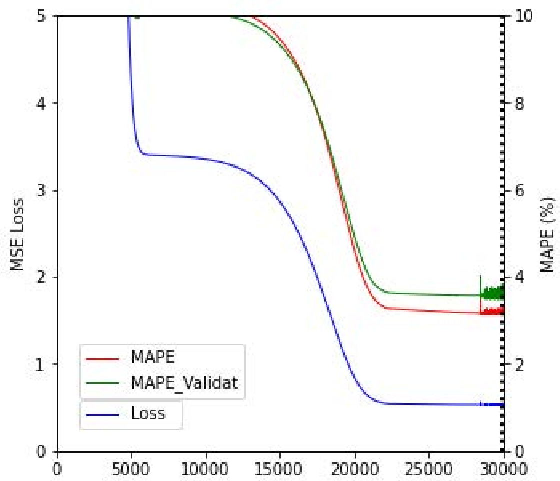
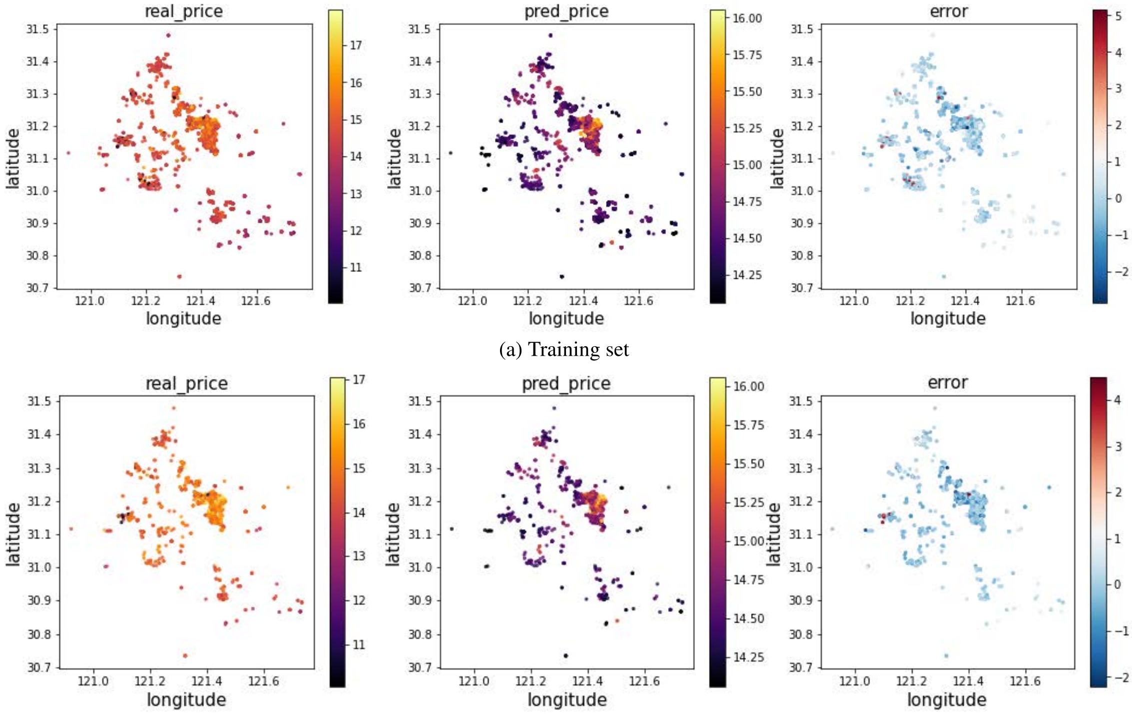


FIGURE 18. Fitted curve of time-division experiments.

Fig. 19 and 20 highlight additional distinctions between the valuation effects of the A-SRGCNN model in time-division experiments and model comparison experiments. From the valuation heat map in Fig. 19, it can be seen that there are more large error points in time-division experiments, and large error points even appear sporadically in the Jiading region. The valuation of the A-SRGCNN model in the time-division experiments is inferior to that of the A-SRGCNN model in the comparison experiment, as shown by the scatter distribution plot in Fig.20, which contains more deviation points.

Additionally, a time-division experiment was also conducted on individual administrative divisions in the dataset. We selected data from Changning, Fengxian and Xuhui districts with a larger number of samples. Notably, the results are portrayed in the Table 9.

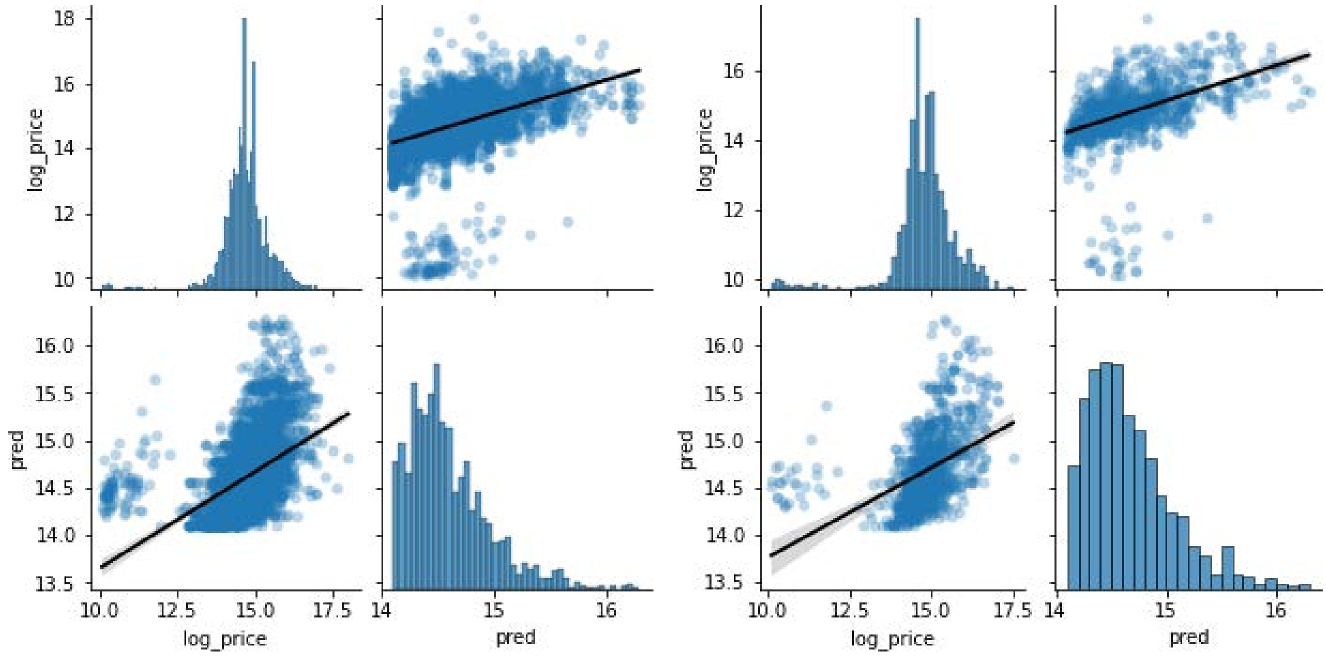
The results illustrated that there was a more favorable performance using data from a single borough to conduct time-sharing experiments. The error of the Changning and Xuhui Districts data in the experiment is only 1.99%, which is better than the 2.2% error of the randomly selected data in the six regions. The error in Fengxian District is 2.09%, which lies in between, which further verifies the conclusions in the previous experiments. The administrative size of Changning and Xuhui Districts is smaller than that of Jiading District, and the distribution of samples is more clustered. The more



(a) Training set

(b) Validation set

FIGURE 19. Heat map of time-division experiments.



(a) training set

(b) validation set

FIGURE 20. Scattered distribution of time-division experiments.

geographically clustered samples usually have more potential connections, and tend to have better valuation effect.

V. CONCLUSION

Addressing the instability of appraisals and difficulties in data acquisition that tend to exist in real estate appraisals, an A-SRGCNN real estate valuation model based on an external attention mechanism is proposed in this paper. The spatial regression model SRGCNN has good generalization, while the geographic information of the properties required by the model is easier to obtain in reality. It is practical and feasible in realistic real estate appraisal. In order to model dependent and independent variables correspondingly to spatial regression, the SRGCNN model employs a graph convolutional neural network. The semi-supervised learning approach accounts for nonlinear relationships between data, and the addition of an attention mechanism enables the model to recognize and remember potential relationships between property data in order to enhance model performance. According to the experiments, SRGCNN has a better ability to estimate house prices than the benchmark model, and the SRGCNN model maintains a very high accuracy with a stable play on different datasets. The valuation's accuracy has also increased with the addition of the attention mechanism; on the validation set, the A-SRGCNN model's error is only 1.87%. Due to the limited data currently available from the cooperating real estate appraisal firms, future research is therefore needed before this method can be applied to increasing complexity data sets. After further analysis of Shanghai second-hand property data using the A-SRGCNN model, we discovered that real estate prices in Shanghai exhibit regional aggregation and price aggregation, with similar prices for properties in the same region and significant differences in prices in different regions even though they are geographically adjacent. The A-SRGCNN model also performs well when comparing prices in similar areas. The A-SRGCNN predicts the future house prices in the time-division experiment and achieves good prediction results with a prediction error of about 2.20%. Nevertheless, it performs less accurately than the A-SRGCNN model, which has an error of 1.87% in the model comparison experiment. In this paper, we argue that this is the rationale behind how major variables like public crises and policy changes can affect trends in real estate prices. Real estate prices are influenced by a variety of factors, so more thorough investigation and study are required to forecast real estate prices with greater accuracy.

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