

MONOPOLY: Learning to Price Public Facilities for Revaluing Private Properties with Large-Scale Urban Data

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Motivation

- M1: Have you ever wondered about the true value of your **private property**?
- M2: How much do these public facilities contribute to the price of your house?
- M3: If you are a tycoon, how much will you pay to acquire these **public facilities**?



Algorithm



Figure 4: The distributed learning algorithm of "Monopoly" under the framework of MapReduce .

Assessment

Figure 1: A screenshot of the housing prices of the Haidian District in Beijing. We can see that there are three kinds of dash circles colored by red, blue, and orange. Red circle: the average price of the properties near the *Xibeiwang Station of No.16 Metro* is 79,772 CNY/m². Blue circle: the average price of the properties near the *Zhongguancun No. 2 Primary School (Baiwang Campus)* is 82,216 CNY/m². Orange circle: however, the average price of the properties without those public facilities nearby is 70,744 CNY/m², noticeably lower than the two other areas.

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Generally speaking, the "Monopoly" project aims to assign virtual prices to public facilities based on the values of existing private properties, and in turn, the virtual prices of public facilities can help estimate the worth of a newly-established realty.



Real-world Datasets

City	#(Res. Blocks) #(F	Pub. Facilities)	#(Other Res.	Blocks) per Re	s. Block	#(Pub. Facilities) per Res. Block
Beijing	7,573	843,426	1.5 (within 0.	5 km) 5.9 (with	n 1.0 km)	115.6 (within 0.5 km) 296.3 (within 1.0 km)
Shanghai	11,604	970,566	3.6 (within 0.5	km) 12.3 (with	n 1.0 km)	147.4 (within 0.5 km) 313.9 (within 1.0 km)
Guangzhou	6,508	810,465	4.1 (within 0.5	km) 14.4 (with	n 1.0 km)	213.0 (within 0.5 km) 364.7 (within 1.0 km)
Shenzhen	3,849	724,320	2.9 (within 0.5	km) 10.4 (with	n 1.0 km)	197.0 (within 0.5 km) 371.9 (within 1.0 km)
AVERAGE	7,384	837,194	3.0 (within 0.5	km) 10.8 (with	n 1.0 km)	168.3 (within 0.5 km) 336.7 (within 1.0 km)
TOTAL	29,534	3,348,777			-	-

Table 1: The statistics of the urban data we used to conduct experiments. The datasets are collected from four metropolises (i.e., Beijing, Shanghai, Guangzhou, and Shenzhen) in China. For the other columns, #(Res. Blocks): the number of residential blocks; #(Pub. Facilities): the number of public facilities; #(Other Res. Blocks) per Res. Block: the average number of surrounding residential blocks per residential block; #(Pub. Facilities) per Res. Block: the average number of surrounding residential blocks per residential block.

Experimental Results

Method	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE) R ² Score (R ²)
Avg. Prices (citywide)	$18,631 \pm 4,517 \text{ CNY/m}^2$	$25,151 \pm 6,260 \text{ CNY/m}^2 0.0001 \pm 0.0001$
Macro Avg. Prices (within 0.5 km)	$15,110\pm3,928~{ m CNY/m^2}$	$21,593 \pm 5,826 \text{ CNY/m}^2 \ 0.2668 \pm 0.1580$
Macro Avg. Prices (within 1.0 km)	$14,963 \pm 3,771 \; \text{CNY}/\text{m}^2$	$20,745 \pm 5,492 \text{ CNY/m}^2 \ 0.3251 \pm 0.1349$
Micro Avg. Prices (within 0.5 km)	$15,089 \pm 3,889 \; \mathrm{CNY/m^2}$	$21,589 \pm 5,793 \text{ CNY/m}^2 \ 0.2690 \pm 0.1572$
Micro Avg. Prices (within 1.0 km)	$14,172 \pm 3,650 \; \text{CNY}/\text{m}^2$	$20,575\pm5,508~{ m CNY/m^2}~0.3361\pm0.1342$
Linear Regression (within 0.5 km)	$12,764 \pm 3,250 \text{ CNY/m}^2$	$18,897 \pm 5,086 \text{ CNY/m}^2 \ 0.4400 \pm 0.0414$
Linear Regression (within 1.0 km)	$10,717 \pm 2,150 \text{ CNY/m}^2$	$16,303 \pm 4,027 \text{ CNY/m}^2 \ 0.5769 \pm 0.0512$
Boosting Trees (within 0.5 km)	$11,515 \pm 2,847 \; \text{CNY}/\text{m}^2$	$18,650 \pm 4,617 \; { m CNY/m^2} \; 0.5082 \pm 0.0681$
Boosting Trees (within 1.0 km)	$10,594\pm2,085~\text{CNY}/\text{m}^2$	$16,125\pm4,018~{ m CNY/m^2}~0.5846\pm0.0670$
DNN (within 0.5 km)	$11,280 \pm 2,425 \text{ CNY/m}^2$	$17,144 \pm 4,359 \text{ CNY/m}^2 \ 0.5351 \pm 0.0484$
DNN (within 1.0 km)	$9,947\pm1,845~\mathrm{CNY/m^2}$	$15,440 \pm 3,580 \; \mathrm{CNY/m^2} \; 0.6161 \pm 0.0566$
Monopoly (within 0.5 km)	$9,531 \pm 1,745 \; \text{CNY}/\text{m}^2$	$15,352 \pm 3,764 \text{ CNY/m}^2 0.6192 \pm 0.0746$
Monopoly (within 1.0 km)	$9,544 \pm 1,728 \; \mathrm{CNY}/\mathrm{m}^2$	$15,234 \pm 3,640 \text{ CNY/m}^2 0.6231 \pm 0.0773$

Table 2: The comparison results between our method on "Monopoly" and other baselines evaluated by the metrics of MAE, RMSE, and R^2 score. All the numbers (i.e., mean \pm standard

Figure 2: An illustration of the organization of urban data employed by the "Monopoly" project. To be specific, our approach regards many points of interest (POIs) as nodes in an undirected weighted graph based on their geographic information. Then we formulate the factors, including the variables that indicate the values of surrounding public facilities, to parallelly regress to the housing prices we know. As a result, the estimated values of both public facilities and private properties can be updated iteratively until convergence.

Significance

Besides deploying the "Monopoly" project in our web mapping service (i.e., Baidu Maps), we plan to directly establish an independent platform where multiple business intelligent agents could automatically give more suggestions on investments, urban planning, and taxation powered by our large-scale urban data.



deviation) in this table are obtained by averaging the results of the four cities in Table 1.

Discoveries

Tune of Dublic Escility	Average Virtual Price						
	Beijing	Shanghai	Guangzhou	Shenzhen			
Governmental Agency	$(66, 125) + 6,082 \text{ CNY/m}^2$	$(55,670) + 3,833 \text{ CNY/m}^2$	$(31, 209) + 1,328 \text{ CNY/m}^2$	$(59,478) + 183 \text{ CNY/m}^2$			
Educational Institution	$(66, 125) + 4,441 \text{ CNY/m}^2$	$(55,670) + 4,379 \text{ CNY}/\text{m}^2$	$(31, 209) + 2,501 \text{ CNY}/\text{m}^2$	$(59, 478) + 3,099 \text{ CNY}/\text{m}^2$			
Financial Institution	$(66, 125) + 5,238 \text{ CNY/m}^2$	$(55, 670) + 4,918 \text{ CNY}/\text{m}^2$	$(31, 209) + 3,616 \text{ CNY}/\text{m}^2$	$(59, 478) + 1,603 \text{ CNY}/\text{m}^2$			
Recreational Facility	$(66, 125) + 2,361 \text{ CNY/m}^2$	$(55, 670) + 3,222 \text{ CNY}/\text{m}^2$	$(31, 209) + 554 \text{ CNY/m}^2$	$(59, 478) + 2,863 \text{ CNY/m}^2$			
Medical Treatment	$(66, 125) + 4,225 \text{ CNY/m}^2$	$(55, 670) + 3,440 \text{ CNY}/\text{m}^2$	$(31, 209) + 867 \text{ CNY/m}^2$	$(59, 478) + 112 \text{ CNY/m}^2$			
Commercial Office	$(66, 125) + 1,313 \text{ CNY/m}^2$	$(55,670) + 1,161 \text{ CNY}/\text{m}^2$	$(31, 209) - 146 \text{ CNY/m}^2$	$(59, 478) - 636 \text{ CNY/m}^2$			
Transportation	$(66, 125) + 4,393 \text{ CNY/m}^2$	$(55, 670) + 2,750 \text{ CNY/m}^2$	$(31, 209) + 2,007 \text{ CNY}/\text{m}^2$	$(59, 478) + 3,278 \text{ CNY}/\text{m}^2$			
Scenic Spot	$(66, 125) + 6,425 \text{ CNY/m}^2$	$(55, 670) + 5,415 \text{ CNY}/\text{m}^2$	$(31, 209) + 1,055 \text{ CNY}/\text{m}^2$	$(59, 478) + 3,855 \text{ CNY/m}^2$			
Wasteyard	$(66, 125) - 7, 647 \text{ CNY/m}^2$	$(55, 670) - 6,221 \text{ CNY}/\text{m}^2$	$(31, 209) - 1,873 \text{ CNY}/\text{m}^2$	$(59, 478) - 1,043 \text{ CNY}/\text{m}^2$			
Cemetery	$(66, 125) - 4, 129 \text{ CNY}/\text{m}^2$	$(55,670) - 8,276 \text{ CNY}/\text{m}^2$	$(31, 209) - 569 \text{ CNY/m}^2$	$(59, 478) - 2,607 \text{ CNY}/\text{m}^2$			

Table 3: The virtual prices of the public facilities acquired by "Monopoly" in the four metropolises of China.



Figure 3: Creative applications serving customers (2C), business (2B), and governments (2G).

Solution

Model Overall, the formulation we propose to assess the value of a private property is:

$$\widehat{\mathbf{h}} = S(\mathbf{x}; \Theta) \times (\mathbf{w} \cdot F(\mathbf{D}; \Phi)).$$
(1)

Suppose that we have n instances of private properties in a training set Δ , the learning objective can be defined as:

minimize
$$\mathcal{L} = \sum_{i=1}^{n} \left(h^{(i)} - \hat{h}^{(i)} \right)^2$$
, (2)

where i is the index of the i-th instance in the training set, and $h^{(i)}$ stands for the ground-truth price of that instance.

Figure 5: An illustration on the average performance (i.e., mean \pm standard deviation) of "Monopoly" measured by MAE and RMSE, along with different values (i.e., 0.5 km, 1.0 km, 3.0 km, and 5.0 km) of influencing radius.



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