# Urban Big Data: An Experimental Approach to Building-Value Estimation Using Web-Based Data

Sun-Young Jang, Sung-Ah Kim, Dongyoun Shin

***Abstract*—**Current real-estate value estimation, difficult for laymen, usually is performed by specialists. This paper presents an automated estimation process based on big data and machine-learning technology that calculates influences of building conditions on real-estate price measurement. The present study analyzed actual building sales sample data for Nonhyeon-dong, Gangnam-gu, Seoul, Korea, measuring the major influencing factors among the various building conditions. Further to that analysis, a prediction model was established and applied using RapidMiner Studio, a graphical user interface (GUI)-based tool for derivation of machine-learning prototypes. The prediction model is formulated by reference to previous examples. When new examples are applied, it analyses and predicts accordingly. The analysis process discerns the crucial factors effecting price increases by calculation of weighted values. The model was verified, and its accuracy determined, by comparing its predicted values with actual price increases.

***Keywords*—**Big data, building-value analysis, machine learning, price prediction.

## I. Introduction

EMPIRICAL real-estate value estimation proceeds via the cost approach, the sales comparison approach, or the income approach. In the case of commercial-building lease and/or investment, valuation is calculated by the sales comparison approach, which is grounded in marketability [1]. This method calculates values by collecting a number of trading cases, selecting the appropriate ones and comparing the relevant and related factors (specifically correction of circumstances, modification time, as well as regional and individual factors) [2]. The most important thing is to know which factors have an effect, and to what extent, on the values calculated. This sales comparison method relies especially on experts' opinions on valuations of the relative factors, which opinions are based on considerable experience.

The problem is that most people, which are to say non-experts lacking in the necessary experience, have difficulty understanding the relations among the diverse building-price elements. As an alternative to and substitute for experience, this paper presents an automated solution based on big data and machine-learning technology [3], [4]. By this process, the relations between building-price variations and the various condition factors are determined through repetitive learning based on much data.

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## II. Research Questions

The sales comparison approach considers diverse trading factors along with individual or specific factors in estimating market value. This process currently requires a certified public appraiser. Since this method requires considerable knowledge of many and various relevant conditions, a novice or ordinary person, who typically lacks such experience, cannot immediately know, or easily determine, the factors crucial to price. The important factors could take effect complexly and change according to the features of buildings, uses, locations, circumstances and other conditions. Thus, the necessary judgment that is brought to bear on such issues is and must be based on sophisticated analysis and significant accumulated data.

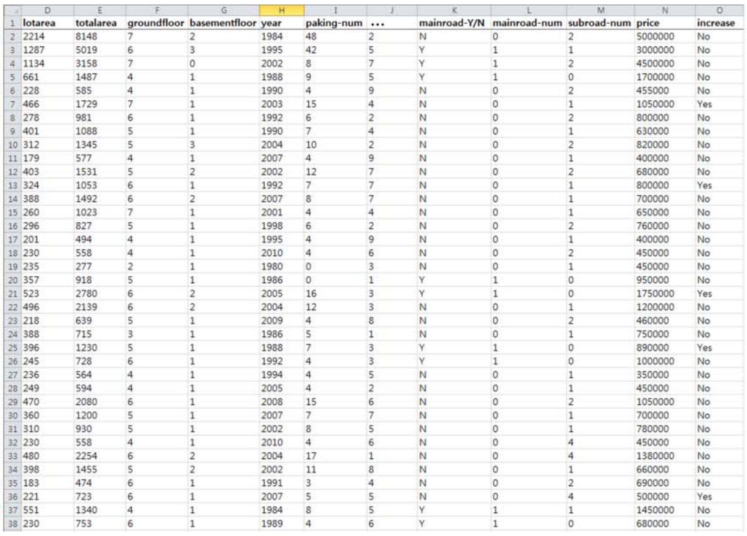
## III. Objectives

The present study is set out to analyze real examples of building sales in Nonhyeon-dong, Gangnam-gu, Seoul, Korea and to measure the major influencing factors among various building conditions. The data utilized for each example were 15 factor types extracted from a publicly accessible real-estate portal site [8]. The employed prediction model was built and applied using RapidMiner Studio [6], a tool for creation of a GUI-type machine-learning prototype [7]. This prediction model is created by reference to previous examples. When new examples to know the value are applied, it analyzes and predicts accordingly. The analysis process identifies the crucial factors affecting prices by calculation of weighted values. As a result, the model is verified by comparing predictive values and actual increase prices and deducing the accuracy.

## IV. Composition and Application of Prediction Model of Building-Price Increase

### *A. Data Gathering and Extraction of Building-Sales Examples*

The utilized data on building sales were obtained at a publicly accessible real-estate portal site [8] for registered building data on the City of Seoul [9] (Fig. 1). A total of 65 examples and actual building-sales information from October 2016 to February 2017 was collected. Each example contained information on the following 15 factors relating to building conditions: Lot number, building use, use district, lot area, total area, ground floor, basement floor, construction year, number of parking lots, subway, status of main road (for cars), number of main roads, number of small streets (for pedestrians), price, and price increase (Fig. 1).

| | D | E | F | G | H | I | J | K | L | M | N | O |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | lotarea | totalarea | groundfloor | basementfloor | year | paking-num | ... | mainroad-Y/N | mainroad-num | subroad-num | price | increase |
| 2 | 2214 | 8148 | 7 | 2 | 1984 | 48 | 2 | N | 0 | 2 | 5000000 | No |
| 3 | 1287 | 5019 | 6 | 3 | 1995 | 42 | 5 | Y | 1 | 1 | 3000000 | No |
| 4 | 1134 | 3158 | 7 | 0 | 2002 | 8 | 7 | Y | 1 | 2 | 4500000 | No |
| 5 | 661 | 1487 | 4 | 1 | 1988 | 9 | 5 | Y | 1 | 0 | 1700000 | No |
| 6 | 228 | 585 | 4 | 1 | 1990 | 4 | 9 | N | 0 | 2 | 455000 | No |
| 7 | 466 | 1729 | 7 | 1 | 2003 | 15 | 4 | N | 0 | 1 | 1050000 | Yes |
| 8 | 278 | 981 | 6 | 1 | 1992 | 6 | 2 | N | 0 | 2 | 800000 | No |
| 9 | 401 | 1088 | 5 | 1 | 1990 | 7 | 4 | N | 0 | 1 | 630000 | No |
| 10 | 312 | 1345 | 5 | 3 | 2004 | 10 | 2 | N | 0 | 2 | 820000 | No |
| 11 | 179 | 577 | 4 | 1 | 2007 | 4 | 9 | N | 0 | 1 | 400000 | No |
| 12 | 403 | 1531 | 5 | 2 | 2002 | 12 | 7 | N | 0 | 2 | 680000 | No |
| 13 | 324 | 1053 | 6 | 1 | 1992 | 7 | 7 | N | 0 | 1 | 800000 | Yes |
| 14 | 388 | 1492 | 6 | 2 | 2007 | 8 | 7 | N | 0 | 1 | 700000 | No |
| 15 | 260 | 1023 | 7 | 1 | 2001 | 4 | 4 | N | 0 | 1 | 650000 | No |
| 16 | 296 | 827 | 5 | 1 | 1998 | 6 | 2 | N | 0 | 2 | 760000 | No |
| 17 | 201 | 494 | 4 | 1 | 1995 | 4 | 9 | N | 0 | 1 | 400000 | No |
| 18 | 230 | 558 | 4 | 1 | 2010 | 4 | 6 | N | 0 | 2 | 450000 | No |
| 19 | 235 | 277 | 2 | 1 | 1980 | 0 | 3 | N | 0 | 1 | 450000 | No |
| 20 | 357 | 918 | 5 | 1 | 1986 | 0 | 1 | Y | 1 | 0 | 950000 | No |
| 21 | 523 | 2780 | 6 | 2 | 2005 | 16 | 3 | Y | 1 | 0 | 1750000 | Yes |
| 22 | 496 | 2139 | 6 | 2 | 2004 | 12 | 3 | N | 0 | 1 | 1200000 | No |
| 23 | 218 | 639 | 5 | 1 | 2009 | 4 | 8 | N | 0 | 2 | 460000 | No |
| 24 | 388 | 715 | 3 | 1 | 1986 | 5 | 1 | N | 0 | 1 | 750000 | No |
| 25 | 396 | 1230 | 5 | 1 | 1988 | 7 | 3 | Y | 1 | 0 | 890000 | Yes |
| 26 | 245 | 728 | 6 | 1 | 1992 | 4 | 3 | Y | 1 | 0 | 1000000 | No |
| 27 | 236 | 564 | 4 | 1 | 1994 | 4 | 5 | N | 0 | 1 | 350000 | No |
| 28 | 249 | 594 | 4 | 1 | 2005 | 4 | 2 | N | 0 | 1 | 450000 | No |
| 29 | 470 | 2080 | 6 | 1 | 2008 | 15 | 6 | N | 0 | 2 | 1050000 | No |
| 30 | 360 | 1200 | 5 | 1 | 2007 | 7 | 7 | N | 0 | 1 | 700000 | No |
| 31 | 310 | 930 | 5 | 1 | 2002 | 8 | 5 | N | 0 | 1 | 780000 | No |
| 32 | 230 | 558 | 4 | 1 | 2010 | 4 | 6 | N | 0 | 4 | 450000 | No |
| 33 | 480 | 2254 | 6 | 2 | 2004 | 17 | 1 | N | 0 | 4 | 1380000 | No |
| 34 | 398 | 1455 | 5 | 2 | 2002 | 11 | 8 | N | 0 | 1 | 660000 | No |
| 35 | 183 | 474 | 6 | 1 | 1991 | 3 | 4 | N | 0 | 2 | 690000 | No |
| 36 | 221 | 723 | 6 | 1 | 2007 | 5 | 5 | N | 0 | 4 | 500000 | Yes |
| 37 | 551 | 1340 | 4 | 1 | 1984 | 8 | 5 | Y | 1 | 1 | 1450000 | No |
| 38 | 230 | 753 | 6 | 1 | 1989 | 4 | 6 | Y | 1 | 0 | 680000 | No |

Fig. 1 Location of Nonhyeon-dong, Gangnam-gu, Seoul (google map) and collected data [8], [9]

The collected data on building sales were defined in their attributes for the composite a prediction model (Table I). The 'Lot Number' of a building was set as 'ID,' and the 'Increase' category was set as 'label'. The price fluctuations were classified as increasing, decreasing, not changing, and unknown. However, this research is simply tested by dividing the label into 'increase (Yes)' and 'not increase (No)' to select only 'increase' examples. The 'No' label includes decreasing, not changing, and unknown.

### *B. Composition of Price-Increase Prediction Model*

The price-increase prediction model was built using the RapidMiner Studio tool. This model judges the probability of future price increase based on the available price-change data and basic building-condition factors. Also, the model determines the important influencing factors by calculating the weighted values of the basic factors influencing price increase. The model components and process are schematized in Fig. 2.

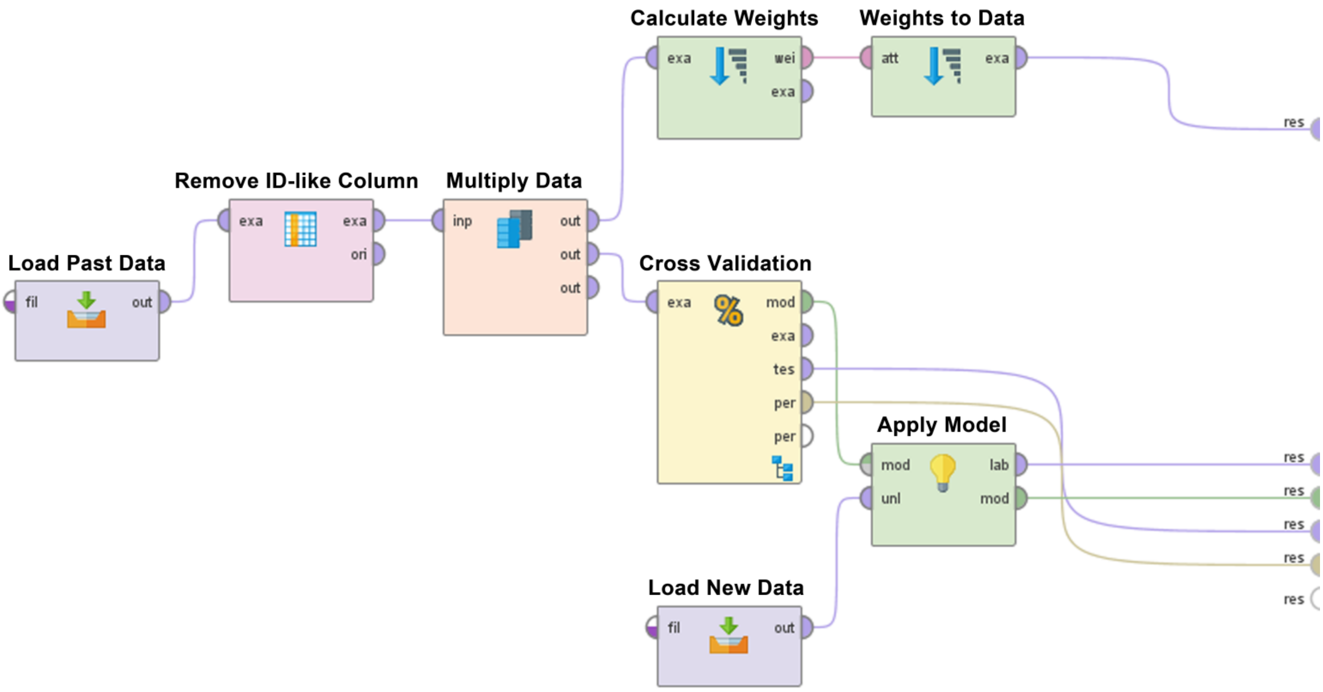



Fig. 2 Process of price-increase prediction model in RapidMiner Studio

TABLE I
REAL-ESTATE DATASET META DATA

| Feature | Value type | Role | Description | Value |
|---|---|---|---|---|
| LotNumber | polynominal | ID | lot number | numeric value |
| BuildingUse | polynominal | attribute | building use | commercial facilities, business, residential facilities |
| UseDistrict | polynominal | attribute | use district | general commercial area, general residential area, 2nd class residential area , 3rd class residential area , semi-residential area |
| LotArea | integer | attribute | lot area ($m^2$) | numeric value |
| TotalArea | integer | attribute | total area ($m^2$) | numeric value |
| GroundFloor | integer | attribute | number of ground floors | numeric value |
| BasementFloor | integer | attribute | number of basement floors | numeric value |
| Year | integer | attribute | year of completion | numeric value |
| Parking-num | integer | attribute | number of parking lots | numeric value |
| Subway | integer | attribute | Subway by walking (min.) | numeric value |
| MainRoad-Y/N | binominal | attribute | statue of roadway | Yes, No |
| MainRoad-num | integer | attribute | number of roadways | numeric value |
| SubRoad-num | integer | attribute | number of streets (mixed use: pedestrians and vehicles) | numeric value |
| Price | integer | attribute | sales price (10,000 KRW) | numeric value |
| Increase | polynominal | label | increasing, decreasing, not changing, unknown | Yes, No |

Process 1 – Building-sales sample data (Excel file) from October 2016 to February 2017 is loaded using the Read Excel operator. This Excel file is past data on price changes for February 2017 relative to October 2016. This data table has 65 actual examples including meta data on the 15 feature types described in Table I. Using the Multiply Data operator, the weight calculation (Process 2) and probability calculation (Process 3) for price increase proceed simultaneously.

Process 2 - Factors affecting price increase are calculated to improve prediction. The Calculate Weights operator computes the relevance among attributes based on information gain.

Process 3 - Training of price-increase model utilizes the Naïve Bayes operator. This operator creates a probability-based Naïve Bayes classification model, which predicts results to the higher side according to probabilities of classifying examples as positive or negative [5]. The Apply Model operator and the Performance operator are applied to this Naïve Bayes operator and tested to predict price increase (Fig. 3).

Process 4 - The trained model is tested using the new sample data set. As a result, the predicted value and confidence of the Yes or No label are determined. The predicted results constitute a performance indicator of the accuracy relative to actual sales prices for March.

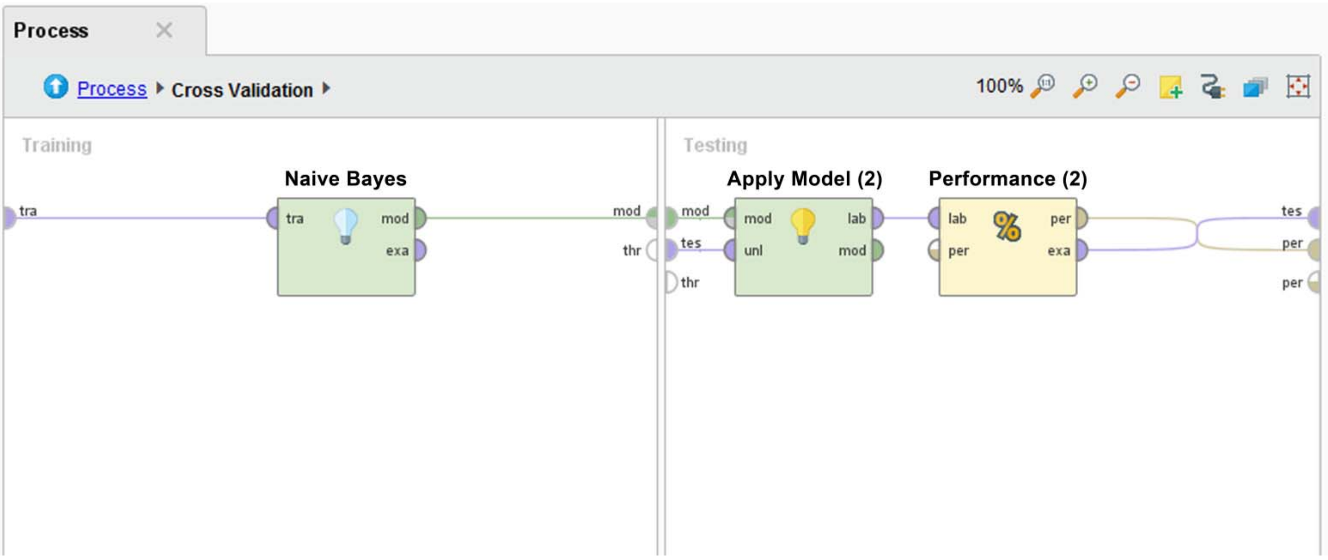



Fig. 3 Process of training and testing of Cross-Validation component

*C. Application of Prediction Model to Nonhyeon-Dong Case*

The prediction model was applied to the 65 Nonhyeon-dong examples. These examples were divided into a training data set for generation of the label-value-prediction model and a test data set for model-performance measurement. The ratio of training data to test data was set as 90/10. The examples were collected as an independent dataset by stratified sampling. Also, the training and test datasets were adjusted for equal proportions of positive and negative labels.

The price-prediction results of the test dataset are shown in Fig. 4. 'Prediction (increase)' represents the model's prediction result. This is shown with each Yes or No confidence class. The confidence value is a basis for judgement (Yes or No). The 'Increase' label is the actual data on the six-months-later increase of each example. In the comparison of 'Increase' with 'Prediction (increase)', there are 5 'correct' examples and 2 'wrong' examples (correct: 71.43%).

| Row No. | lotnumber | increase | prediction(increase) | confidence(No) | confidence(Yes) |
|---|---|---|---|---|---|
| 1 | 126_2 | No | No | 0.996 | 0.004 |
| 2 | 37_3 | No | No | 0.982 | 0.018 |
| 3 | 242_23 | No | No | 0.612 | 0.388 |
| 4 | 87_7 | No | No | 0.810 | 0.190 |
| 5 | 268_14 | Yes | Yes | 0.058 | 0.942 |
| 6 | 42_10 | No | Yes | 0.137 | 0.863 |
| 7 | 240_16 | No | Yes | 0.432 | 0.568 |

Fig. 4 Price-prediction results for test data set

ExampleSet (58 examples, 5 special attributes, 13 regular attributes) Filter (58 / 58 examples): all

| Row No. | lotnumber | increase | prediction(increase) | confidence(No) | confidence(Yes) | buildinguse | usedistrict | lotarea | totalarea | groundfloor | basementfloor | year | paking-num | subway | mainroad-Y/N | mainroad-nu... | subroad-num | price |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 37_16 | No | Yes | 0.214 | 0.786 | residential | general residential | 278 | 981 | 6 | 1 | 1992 | 6 | 2 | N | 0 | 2 | 800000 |
| 2 | 81_9 | No | Yes | 0.312 | 0.688 | commercial | general residential | 401 | 1088 | 5 | 1 | 1990 | 7 | 4 | N | 0 | 1 | 630000 |
| 3 | 116_2 | No | No | 0.678 | 0.322 | commercial | general residential | 236 | 564 | 4 | 1 | 1994 | 4 | 5 | N | 0 | 1 | 350000 |
| 4 | 210 | No | No | 1.000 | 0.000 | commercial | general residential | 791 | 4058 | 6 | 3 | 1993 | 23 | 3 | Y | 1 | 1 | 2300000 |
| 5 | 110-25 | Yes | No | 0.913 | 0.087 | commercial | 2nd class residential | 235 | 277 | 2 | 1 | 1980 | 0 | 3 | N | 0 | 1 | 420000 |
| 6 | 141-10 | Yes | Yes | 0.283 | 0.717 | commercial | general residential | 466 | 1729 | 7 | 1 | 2003 | 15 | 4 | N | 0 | 1 | 1080000 |
| 7 | 66_34 | No | Yes | 0.340 | 0.660 | commercial | general residential | 228 | 585 | 4 | 1 | 1990 | 4 | 9 | N | 0 | 2 | 455000 |
| 8 | 67_24 | No | Yes | 0.200 | 0.800 | commercial | 2nd class residential | 179 | 577 | 4 | 1 | 2007 | 4 | 9 | N | 0 | 1 | 400000 |
| 9 | 74_3 | No | Yes | 0.358 | 0.642 | commercial | general residential | 218 | 639 | 5 | 1 | 2009 | 4 | 8 | N | 0 | 2 | 460000 |
| 10 | 141_10 | No | Yes | 0.271 | 0.729 | commercial | general residential | 466 | 1729 | 7 | 1 | 2003 | 15 | 4 | N | 0 | 1 | 1250000 |
| 11 | 51_8 | Yes | No | 0.948 | 0.052 | commercial | general residential | 496 | 2139 | 6 | 2 | 2004 | 12 | 3 | N | 0 | 1 | 1050000 |
| 12 | 51_6 | No | No | 0.997 | 0.003 | commercial | 3rd class residential | 500 | 2300 | 6 | 2 | 2004 | 28 | 3 | Y | 1 | 1 | 1200000 |
| 13 | 181_10 | Yes | No | 0.934 | 0.066 | residential | general residential | 324 | 1053 | 6 | 1 | 1992 | 7 | 7 | N | 0 | 1 | 800000 |
| 14 | 111_26 | No | Yes | 0.028 | 0.972 | commercial | 3rd class residential | 245 | 728 | 6 | 1 | 1992 | 4 | 3 | Y | 1 | 0 | 1000000 |
| 15 | 57_9 | No | No | 0.947 | 0.053 | residential | general residential | 310 | 930 | 5 | 1 | 2002 | 8 | 5 | N | 0 | 1 | 780000 |
| 16 | 238_11 | No | Yes | 0.047 | 0.953 | commercial | general residential | 230 | 753 | 6 | 1 | 1989 | 4 | 6 | Y | 1 | 0 | 680000 |
| 17 | 213_16 | No | Yes | 0.138 | 0.862 | commercial | 3rd class residential | 426 | 1302 | 6 | 1 | 2010 | 8 | 3 | N | 0 | 1 | 1000000 |
| 18 | 95_7 | No | No | 0.985 | 0.015 | residential | general residential | 193 | 607 | 5 | 1 | 1992 | 4 | 10 | N | 0 | 1 | 520000 |
| 19 | 64_20 | No | No | 0.501 | 0.499 | commercial | general residential | 201 | 494 | 4 | 1 | 1995 | 4 | 9 | N | 0 | 1 | 400000 |
| 20 | 127_9 | No | No | 0.548 | 0.452 | commercial | 3rd class residential | 470 | 2080 | 6 | 1 | 2008 | 15 | 6 | N | 0 | 2 | 1050000 |
| 21 | 268_14 | No | Yes | 0.019 | 0.981 | commercial | general residential | 396 | 1230 | 5 | 1 | 1988 | 7 | 3 | Y | 1 | 0 | 980000 |
| 22 | 268_11 | No | No | 0.841 | 0.159 | commercial | general residential | 523 | 2780 | 6 | 2 | 2005 | 16 | 3 | Y | 1 | 0 | 1800000 |
| 23 | 25_2 | No | No | 0.862 | 0.138 | commercial | general residential | 661 | 1483 | 4 | 1 | 1984 | 20 | 7 | Y | 1 | 0 | 1650000 |
| 24 | 216_18 | No | No | 1 | 0 | commercial | general residential | 1287 | 5019 | 6 | 3 | 1995 | 42 | 5 | Y | 1 | 1 | 3000000 |
| 25 | 268_11 | Yes | No | 1.000 | 0.000 | commercial | general residential | 523 | 2780 | 6 | 2 | 2005 | 16 | 3 | Y | 1 | 0 | 1750000 |
| 26 | 63_4 | No | No | 0.725 | 0.275 | commercial | 3rd class residential | 214 | 602 | 6 | 0 | 1987 | 4 | 14 | N | 0 | 1 | 480000 |
| 27 | 218_7 | No | Yes | 0.424 | 0.576 | commercial | general residential | 201 | 477 | 4 | 1 | 1983 | 2 | 8 | N | 0 | 1 | 230000 |
| 28 | 158 | No | No | 1 | 0 | business | general residential | 1249 | 4318 | 5 | 2 | 1990 | 34 | 10 | N | 0 | 4 | 2000000 |
| 31 | 141_10 | Yes | Yes | 0.384 | 0.616 | commercial | general residential | 466 | 1729 | 7 | 1 | 2003 | 15 | 4 | N | 0 | 1 | 1050000 |
| 32 | 107_45 | No | Yes | 0.238 | 0.762 | commercial | 2nd class residential | 230 | 558 | 4 | 1 | 2010 | 4 | 6 | N | 0 | 2 | 450000 |
| 33 | 51_8 | No | No | 0.799 | 0.201 | commercial | general residential | 496 | 2139 | 6 | 2 | 2004 | 12 | 3 | N | 0 | 1 | 1200000 |
| 34 | 57_5 | No | Yes | 0.314 | 0.686 | commercial | general residential | 494 | 1397 | 3 | 1 | 2007 | 8 | 5 | N | 0 | 2 | 1100000 |
| 35 | 139_24 | No | Yes | 0.450 | 0.550 | commercial | general residential | 266 | 784 | 5 | 1 | 1989 | 5 | 7 | N | 0 | 4 | 400000 |
| 36 | 125_9 | No | Yes | 0.208 | 0.792 | commercial | 3rd class residential | 388 | 1492 | 6 | 2 | 2007 | 8 | 7 | N | 0 | 1 | 700000 |
| 37 | 131_15 | No | No | 0.902 | 0.098 | business | general residential | 296 | 827 | 5 | 1 | 1998 | 6 | 2 | N | 0 | 2 | 760000 |
| 38 | 110_25 | No | Yes | 0.121 | 0.879 | commercial | 2nd class residential | 235 | 277 | 2 | 1 | 1980 | 0 | 3 | N | 0 | 1 | 450000 |
| 39 | 143_5 | Yes | Yes | 0.440 | 0.560 | commercial | general residential | 343 | 675 | 3 | 1 | 1982 | 3 | 3 | Y | 1 | 1 | 1450000 |
| 40 | 266_16 | No | Yes | 0.139 | 0.861 | commercial | general residential | 441 | 957 | 4 | 1 | 2015 | 9 | 6 | N | 0 | 1 | 750000 |
| 41 | 88_5 | No | No | 0.989 | 0.011 | commercial | semi-class residential | 480 | 2254 | 6 | 2 | 2004 | 17 | 1 | N | 0 | 4 | 1350000 |
| 42 | 278_3 | No | No | 1 | 0 | business | general commercial | 2214 | 8148 | 7 | 2 | 1984 | 48 | 2 | N | 0 | 2 | 5000000 |
| 43 | 88_5 | No | No | 0.993 | 0.007 | commercial | semi-class residential | 480 | 2254 | 6 | 2 | 2004 | 17 | 1 | N | 0 | 4 | 1380000 |
| 44 | 125_12 | No | No | 0.703 | 0.297 | residential | general residential | 398 | 1455 | 5 | 2 | 2002 | 11 | 8 | N | 0 | 1 | 660000 |
| 45 | 87_7 | No | No | 0.938 | 0.062 | commercial | semi-class residential | 357 | 918 | 5 | 1 | 1986 | 0 | 1 | Y | 1 | 0 | 945000 |
| 46 | 111_26 | Yes | No | 0.978 | 0.022 | commercial | 3rd class residential | 245 | 728 | 6 | 1 | 1992 | 4 | 3 | Y | 1 | 0 | 780000 |
| 47 | 66_8 | No | No | 0.580 | 0.420 | commercial | general residential | 216 | 529 | 5 | 1 | 1992 | 4 | 15 | N | 0 | 1 | 400000 |
| 48 | 125_25 | No | No | 0.959 | 0.041 | commercial | general residential | 403 | 1531 | 5 | 2 | 2002 | 12 | 7 | N | 0 | 2 | 680000 |
| 49 | 108_6 | Yes | No | 1.000 | 0.000 | commercial | 2nd class residential | 221 | 723 | 6 | 1 | 2007 | 5 | 5 | N | 0 | 4 | 500000 |
| 50 | 238_2 | No | Yes | 0.095 | 0.905 | commercial | general residential | 551 | 1340 | 4 | 1 | 1984 | 8 | 5 | Y | 1 | 1 | 1450000 |
| 51 | 224_17 | No | Yes | 0.137 | 0.863 | residential | general residential | 273 | 500 | 3 | 1 | 1989 | 3 | 6 | N | 0 | 1 | 410000 |
| 52 | 275_4 | No | Yes | 0.032 | 0.968 | residential | general residential | 282 | 694 | 5 | 1 | 1988 | 4 | 18 | N | 0 | 1 | 550000 |
| 53 | 87_4 | No | No | 0.882 | 0.118 | commercial | semi-class residential | 388 | 715 | 3 | 1 | 1986 | 5 | 1 | N | 0 | 1 | 750000 |
| 54 | 125_5 | No | Yes | 0.121 | 0.879 | commercial | 2nd class residential | 249 | 594 | 4 | 1 | 2005 | 4 | 2 | N | 0 | 1 | 450000 |
| 55 | 107_42 | No | Yes | 0.243 | 0.757 | commercial | 2nd class residential | 230 | 558 | 4 | 1 | 2010 | 4 | 6 | N | 0 | 4 | 450000 |
| 56 | 16_1 | No | Yes | 0.324 | 0.676 | commercial | general residential | 352 | 1107 | 5 | 2 | 1989 | 7 | 2 | N | 0 | 3 | 950000 |
| 57 | 66_8 | Yes | No | 1.000 | 0.000 | commercial | general residential | 216 | 529 | 5 | 1 | 1992 | 4 | 15 | N | 0 | 1 | 500000 |
| 58 | 920_8 | No | No | 0.959 | 0.041 | commercial | general residential | 366 | 1971 | 5 | 1 | 1988 | 0 | 8 | N | 0 | 2 | 900000 |

Fig. 5 Cross-Validation results

Fig. 5 provides the cross-validation results for the training data set in the X-Fold Validation framework. The method split the dataset into a data X subset as the test dataset and another, X-1 subset as the training dataset. The test repeated X. And then the average performance was used as the performance indicator. Among the 58 examples, 27 were 'correct' and 31 were 'wrong' (correct: 46.55%).

Table II shows the results of the classification performance indicator according to the cross-validation performance vector. For the case of the 'not increase' class (label=No), the precision is 77.42% and the recall is 50.00%. For the case of the 'increase' class (label= Yes), the precision is 11.11% and the recall is 30.00%.

TABLE II
CLASSIFICATION PERFORMANCE INDICATOR RESULTS OF CROSS-VALIDATION

| | true No | true Yes | class precision |
|---|---|---|---|
| pred. No | 24 | 7 | 77.42% |
| pred. Yes | 24 | 3 | 11.11% |
| Class recall | 50.00% | 30.00% | |

TABLE III
WEIGHTED VALUES OF ATTRIBUTES

| Row No. | Attribute | Weight |
|---|---|---|
| 1 | Year | 1 |
| 2 | Subway | 0.960 |
| 3 | GroundFloor | 0.915 |
| 4 | SubRoad-num | 0.855 |
| 5 | Parking-num | 0.836 |
| 6 | LotArea | 0.716 |
| 7 | Price | 0.716 |
| 8 | UseDistrict | 0.622 |
| 9 | TotalArea | 0.483 |
| 10 | BuildingUse | 0.398 |
| 11 | BasementFloor | 0.151 |
| 12 | MainRoad-Y/N | 0 |
| 13 | MainRoad-num | 0 |

Table III shows the quantified degrees of the attribute effects on the 'increase' label. The role of data as ID, label was excluded. The weighted values were referenced in order to determine the influential factors on price by user. However, these weighted values are not absolute values; rather, they are limited to the outcomes of the used dataset. In these results, Year, Subway, GroundFloor and SubRoad-num are derived relatively high. In case of Year, weight 1 is to be interpreted as a relative rather than an absolute value, because building value reflects depreciation. A new building sets a high price because the cost for maintenance is cheaper. Therefore, this result value can be interpreted in the light of the understanding that the construction year of a building has a significant effect on its price. Subway and SubRoad-num have high weighted values. Also, in general, these factors are highly influential on the price of commercial buildings, in that commercial buildings boasting high-sales shops with many customers are evaluated highly. In these ways, Subway and SubRoad-num are strongly correlated with building value.

## V. PRICE-INCREASE ESTIMATION

The data used for this research, though relatively small in quantity, had many distinguishing attributes to consider. In order to overcome the limitations of such data, the accuracy of the overall model and the estimated results were analyzed in many aspects. First, a consistency issue might arise when data are divided into training data and test data. Therefore, an X-Fold Validation test was performed on the overall data used. The accuracy of the estimation was 74.93%+/-10.02% (mikro: 75.00%). In this test, the accuracy was measured by taking the average value of 10 trials and calculating the error range. The overall accuracy was not low, but the error range was large, because for each case, there were many attributes, most of them expressed in numerical values.

Second, alternative results were derived by changing the ratio of the test data relative to the training data (Table IV). These results showed the highest estimation accuracy when the ratio of the test data was set to 15%. However, an opposite trend was shown when compared with the cross-validation results. The chance to obtain a correct answer became more significant when the test data ratio was smaller. The resultant estimation accuracy was not an absolute value, though. After performing additional tests for cross-changed cases, the error ratio became similar to that of the overall estimation, though similar results were shown for the 10 and 15% ratios.

TABLE IV
RESULTS AFTER CHANGING RATIO OF TEST DATA TO TRAINING DATA

| Case | Ratio of test data | Prediction (increase) | | Cross-Validation | |
|---|---|---|---|---|---|
| | | Correct (%) | Wrong (%) | Correct (%) | Wrong (%) |
| 1 | 10% | 71.43 | 28.57 | 46.55 | 53.45 |
| 2 | 15% | 80.00 | 20.00 | 40.00 | 60.00 |
| 3 | 20% | 53.85 | 46.15 | 65.38 | 34.62 |

## VI. DISCUSSION

This study tested the possibility of making estimations of building-price increases using the machine-learning method based on existing data. We attempted to perform a quantitative and scientific analysis on the effects of building-related city data on price formation. In that way, the users of city information can easily understand the attributes and characteristics of price formation before making a comprehensive judgment.

The process of this study and the estimation result may be used as a price-increase reference when the user is interested in a certain case. However, the following information needs to be considered if the model is to be used as a basis for decision making.

First, there are limitations regarding dataset formation. Although actual data were extracted and practical numbers were used, the actual number of examples is small. Nonhyeon-dong, the target area of this study, has a relatively large number of cases when compared with the adjacent business districts. Although the number of cases is, relatively, large, it is insufficient for machine-learning use. Therefore, in order to obtain a sufficient amount of data, we need to expand the area to include adjacent regions. Still, we also need to consider that the number of cases cannot be expanded unlimitedly, and that, once expanded, there are also other things to consider. The Nonhyeon-dong cases used in this study are of a scale large enough that each example has similar environmental conditions. Thus, if the area is expanded, the items that are unique to each region should be used as attributes.

Second, according to data [8], [9], building price can be classified into four categories: increasing, decreasing, not changing, and unknown. However, the model created in this study can only be applied to estimate prices that are in the increasing category. Thus, using this method, the ratio of 'No' labels is high, and it is difficult to obtain detailed information. It would be more helpful to the user's decision-making process if future models include subclassified information based on sufficient data sources for consideration of the margins of change.

Third, this study lacks information on specific building conditions (e.g., floating population, foregift, claim-obligation relationship, etc.) or practical conditions that are difficult to digitize, such as political aspects. In the Korean market, high foregift is applied to a business building when the floating population is high. However, the amount of this money is not revealed in the portal websites, but depends on the individuals who engage in the deal; thus, there is no absolute value. Having a large floating population is an important factor in evaluating a business building. Since this study had limitations in its capacity to count the floating population, we assumed that it is related to the building's proximity to roads, and so SubRoad information was included. However, SubRoad information is only an external condition, which cannot show the individual circumstances of each landlord and tenant. Also, real estate in Korea is sensitively related to governmental-administrative aspects. And it is difficult to digitize either administrative factors or market expectations. Thus, the user should also consider, additionally to the results calculated by machine learning, practical circumstances as additional attributes.

In sum, the results on building-price increase did not show a significantly higher accuracy. The reason was that building prices cannot be analyzed only by the statistical factors, and that more detailed and case-specific factors must be considered. However, if estimation and data composition can be enhanced by supplementation to overcome the above-noted limitations, the model will have higher accuracy and reliability, and therefore also greater utility.

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