Capturing Social Value using Ordinal Data, Gower Distance & Quality Point

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Abstract

Social value refers to an actionable concept and something that will positively impact stakeholders and broader society for better living. Capturing the social value of a building in a sales or rental price is very important but challenging because its definition could be interpreted widely due to the subjectivity and nature of social value for each case building, which produces ambiguity for the different auditors and the stakeholders. To give a reasonable estimate for the value (either for sales and/or rental price), we propose and illustrate how to use ordinal (and nominal) rating data to capture social value together with other common building characteristics. We propose a novel, simple, and practical approach using Gower Distance, i.e., Gower (Dis)similarity index(es) among comparable buildings & clustering technique as the basis. Hence, it is more flexible in selecting comparable buildings & can be easily adapted to measure Social Value. Together with the classic grid adjustment method (Quality Point/Quality Rating adjustment), they can be used to provide a fair market estimate for the rental (or sale) price of buildings capturing the social value. Calculation using numerical examples from a client in Jakarta is provided to illustrate how the proposal works.

Introduction & Problem Description

Generally, an investor considers building design based on the conventional business driver to gain the best profit, fulfill government technical policy, and provide environmental imperatives (Vischer, 2008). Mainly, the measurement of the building value will be based on the internal element (physical condition) and the external element related to the building (accessibility, facility, etc.). At the same time, rare of them pay attention to the functional value of the building for the user. In the last decade, there has been a need to measure and communicate the social impact of building in several countries, called the social value (Raiden et al., 2019). Social value refers to an actionable concept and something that will positively impact stakeholders and broader society for better living (Kuratko et al., 2017 and Watson et al., 2016). However, the definition of social value could be interpreted very widely due to the subjectivity and nature of social value for each case building, which produces ambiguity for the different auditors and the stakeholders (Watts et al., 2018). For example, the previous researchers evaluated the social value of enterprise hiring homeless people, local businesses employing apprentices, and multinational organizations raising money for a charity partner (Cabinet Office, 2015). Watson et al. (2016) and Bridgeman et al. (2015) proposed the Social Return on Investment (SROI) method, which involved the value of money as a measurement of social value. Gjolberg (2009) claimed that the other measurement tools, such as the social value portal and Local Multiplier 3 that converse the social value as a monetary metric, have low consistency in the calculation and are short of comparable output. Refutations of using quantitative monetary metrics to measure social value considered as largely qualitative phenomena should not be simply measured since it is difficult to measure social and ecological factors (Korhonen, 2003). Therefore, this study proposes a simple and practical approach using Gower Distance, i.e., Gower (Dis)similarity index(es) among comparable buildings & clustering technique as the qualitative data to measure social value qualitatively. The building attributes as the variable considering the aspects of social value to communicate them in a general way that can be understood by numerous stakeholders simultaneously.

The most common methodology used by a public appraiser to determine a fair rental rate for a proposed office building is using the Market Approach by comparing some attributes of the subject asset with identical or similar assets for which price information is available. In this study, we propose a practical methodology to assess the market value consisting of commercial and social value. Here is an example of the proposed office building utilized as a data center, compared with the other existing buildings located within the competitiveness area, to simulate this new concept in appraisal. The result of the analysis is a typical Rental Rate & Service Charge measured in unit value, e.g., Rp/m^2.

Within these comparable buildings, one of the methods to determine a fair rental price (or sale price) that public appraiser commonly uses is a linear regression with scoring. This analysis aims to compare the object with its competitor using the weights of these attributes (characteristics) as the independent variable(s) and to estimate the object's fair rental price when compared to its competitors. To illustrate this process, consider Table 1 from some comparable buildings in Jakarta, Indonesia.

Table 1. 17 buildings & subject of study with 7 ordinal attributes

Weight	20%	15%	15%	15%	15%	10%	10%	100%	
Building	Attribute #1	Attribute #2	Attribute #3	Attribute #4	Attribute #5	Attribute #6	Attribute #7	Total Index	Rental Price (IDR/m^2)
Building 01	4,0	4,5	3,0	4,0	4,0	3,5	1,0	3,58	180.000
Building 02	5,0	4,0	4,0	4,5	5,0	4,0	3,0	4,33	250.000
Building 03	5,0	5,0	3,0	4,0	4,0	3,5	1,0	3,85	185.000
Building 04	3,0	3,0	3,0	1,0	3,0	2,0	2,0	2,50	130.000
Building 05	5,0	4,0	4,0	4,0	4,0	4,0	2,0	4,00	250.000
Building 06	3,0	3,0	3,0	3,0	2,0	2,0	4,0	2,85	140.000
Building 07	5,0	5,0	3,0	3,0	5,0	3,5	1,0	3,85	165.000
Building 08	5,0	4,0	4,0	4,5	5,0	4,0	2,0	4,23	250.000
Building 09	4,0	5,0	3,0	3,0	4,0	4,0	3,0	3,75	225.000
Building 10	5,0	4,0	3,0	2,0	3,0	3,0	1,0	3,20	130.000
Building 11	5,0	4,0	4,0	4,0	5,0	3,5	1,0	4,00	250.000
Building 12	5,0	5,0	4,0	4,5	5,0	4,0	3,0	4,48	200.000
Building 13	4,5	4,0	4,0	4,0	5,0	4,0	2,0	4,05	220.000
Building 14	4,5	4,0	3,0	3,5	5,0	4,0	2,0	3,83	180.000
Building 15	4,0	5,0	3,0	3,0	5,0	3,5	1,0	3,65	190.000
Building 16	5,0	5,0	4,0	4,5	5,0	4,0	4,0	4,58	275.000
Building 17	4,5	4,0	4,0	4,0	5,0	4,0	3,0	4,15	225.000
Object of Study	3,0	3,0	3,0	3,0	3,0	3,0	5,0	3,20	

The object of our study with specific scores of characteristics/attributes (the last row) is compared with 17 other comparable buildings according to 7 ordinal attributes (commercial and social attributes). Several attributes are usually proposed to assess the commercial value relate to the location accessibility (Lari et al., 2009) (Kemp et al., 2013), the developed infrastructure, the facility, employment opportunities (Hojs et al., 2012), and so on. Based on the social value definition declared by International Valuation

Standards Council (IVSC), the social value provides the benefit to asset users and non-asset users, such as the well-being delivered to the community (health benefits, job opportunities, economics rising, infrastructure improvement to the society, and so on. Nowadays, global warming is one of the issues considered to provide a better life for the world. MacNaughton et al. (2018) stated that buildings consume nearly 40% of primary energy production globally, negatively impacting environmental quality. Toledo and Gupta (2010) believe that good energy consumption management will reduce the emissions of greenhouse gases. The movement toward the green building concept is one solution to deal with this problem. The idea of “green” is that mechanical, electrical, and computer systems are designed simultaneously to achieve maximum energy efficiency and minimum environmental impact (Gowri, 2005). Therefore, the green building concept could be considered one of the variables representing social values impacting society.

Given that all 7 Attributes are ordinal values from 17 comparable buildings, the use of multiple linear regression is often questionable. First, multiple linear regression quickly will only have 17 – 7 = 10 degrees of freedom. Second, the ordinal nature of these attributes will be questioned by purists (of Statisticians) – see Williams (2020) for further discussion about ordinal independent variables. Furthermore, these Attributes usually need to be given some weight to account for the usage of the building (e.g., the office will have a different weight than the data center). These weights are subjective to the appraiser.

One practice that is commonly being used in Indonesia is to obtain the Total Index by using weights assigned to each attribute score (Sudibyanung & Dewi, 2019). Once the Total Index is obtained, we can then run a straightforward Linear Regression using the first 17 data points with the following equation to obtain the parameters (for rental price):

$$Rental\ Price = b_0 + b_1 \times Total\ Index \quad [1]$$

Once the value of b_0 and b_1 are obtained, they can be used to predict the fair rental price and service charge of the object of study (for a given total index). Running simple linear regression using the Rental Price in Table 1 as the dependent variable and Total Index

(3.20) as the explanatory variable, we obtain the following prediction of IDR's fair market rental price of 160K/m^2 per month (with R^2 = 69.03%, note that the intercept is not significant).

$$Rental\ Price = -59{,}586 + 68{,}738 \times Total\ Index \quad [1a]$$

Furthermore, if we force the intercept to be 0 since the intercept is not significant, we obtain the following result (with R^2 = 98.45%), predicting IDR's fair market rental price of 171 K/m^2 per month (for the same Total Index = 3.20):

$$Rental\ Price = 53{,}420 \times Total\ Index \quad [1b]$$

Our immediate research question here is very straightforward, is there any alternative approach to estimating a reasonable rental price given the input type (ordinal scoring)? Furthermore, we are looking for a more general approach that can also work with different input data scales (since Social Value attributes can also be nominal/binary while Commercial Value can be ratio/interval) and a situation with small sample sizes. The fact that the most common methodology is using the market rental price of other comparable (office) buildings by comparing some attributes leads us immediately to think about the Similarity (Dissimilarity) index(es) in the Clustering Algorithm. Hence, our first attempt is to find literature on such a possibility and justify the current practice of using the Total Index in linear regression.

Literature Review

The use of the Total Index above seems to have its starting point from Ratcliff (1972) – in Indonesia; it seems to have been called: Quality Rating (or Quality Rating Value Estimation). However, the popularization of this technique in Indonesia seems to be due to Hartoyo (2013). At the international level, the Real Estate division within the University of British Columbia (UBC) Sauder School of Business in British Columbia, Canada, also covers the same concept of Quality Point (QP). The web page for course BUSI 344 defined it as follows: "Quality Point is an extension of the qualitative adjustment techniques for the direct comparison approach. QP is also a useful option for situations where there is insufficient data to justify quantitative adjustments accurately." A commentary from Zaric (2003) pointed out the use of the Optimization technique to find out the best set of weights to minimize the coefficient of variation.

To the best of our research, Colwell et al. (1983) is perhaps the first paper that gives a complete statistical (mathematical) foundation in explaining the sales comparison & grid adjustment technique in appraisal methodology. They pointed out that the estimated fair market price of the subject property (a vector of constant value, i.e., the same estimated fair market price) can be represented in the following mathematical form:

$$\boldsymbol{P}_s = \boldsymbol{P}_o + \boldsymbol{B}(\boldsymbol{X}_s - \boldsymbol{X}_o) + \boldsymbol{\varepsilon} \quad [2]$$

Where: $\boldsymbol{P}_o$ = a vector of $n \times 1$ observed price of a comparable properties, $\boldsymbol{B}$ = a $1 \times k$ vector of coefficients, $\boldsymbol{X}_s$ and $\boldsymbol{X}_o$ are an $n \times k$ matrices of comparable properties data & their characteristics/attributes (*n* properties and *k* attributes/characteristics). Of course, ideally the error term $n \times 1$ vector $\boldsymbol{\varepsilon}$ should be normally distributed. It should be clear that in relationship with our data in Table 1, we have $n = 17$ and $k = 7$.

Wang et al. (2019) gave a systematic review of recent development. They cover over 100 papers from various countries (Australia, China, Nigeria, Poland, USA, etc.) between 2000 – 2018 and highlight 31 trends. However, most of these techniques are unsuitable since most assume a large amount of available data. Moreover, they are usually applied to residential sale prices, and the explanatory variables are usually numeric of type interval (ratio). The problem we presented in Table 1 deals with ordinal scoring data (in a Likert-like scale), and we often have a minimal number of comparable buildings.

One important concept that has been known for a long time in Clustering is the (Dis)similarity index. One such index that is commonly used (in particular with mixed types of variables) is the one that was introduced by Gower many years ago (Gower, 1971) and later extended to cover ordinal data by Podani (1999) as well as by Kauffmann & Rousseeuw (1990, 2005). Recently D'Orazio (2021) has provided some modifications using Inter-Quartile Range in calculating the distance on the interval, and ratio scaled variables.

Recently, Rahim & Razali (2018) studied using 3 similarity indexes (Euclidian, Minskowsky, & Cosine) to decide the Sale Price of 4 most recent two-story houses in Bandar Baru Bangi, Selangor, Malaysia. The study subjects compared with 17 other two-story houses sold earlier from 2017 data. It is worth pointing out that their explanatory variables are of type ratio/interval scale (land area in m^2, build-up area in m^2, age of the house, & time difference in days). They used these Similarity indexes to select the top 5 houses (out of 17) and used the regression coefficients to adjust the value of the 4 subject houses. They found that Cosine similarity seems to produce the closest to the actual price (8.7%), while Euclidian ranges from 8.7% to 13.7%, and Minskowsky could vary from 8.7% to 23.9%. Our idea is similar to theirs, except that we deal with ordinal data, and we also propose the use of Partition Around Medoids (PAM) Clustering to select the number of comparable.

Proposed Methodology and Data

Knowing the history & encouraged by the above literature review, we construct the following proposal.

Step 1 – Gower Distance & Its Extensions

In Clustering, one of the most common measures/indexes is known as Gower distance. Gower first proposed this method in 1971, and it was proven to satisfy the following (Mathematical) distance properties:

Non-negative: $d(P_1, P_2) \geq 0$ (with $d(P_i, P_i) = 0 \ \forall i$)

Symmetry: $d(P_1, P_2) = d(P_2, P_1)$

Triangle Inequality: $d(P_1, P_2) \leq d(P_1, P_3) + d(P_3, P_2)$

Dissimilarity is a more flexible way to measure unlikeliness between objects. It is worth noting that the original proposal by Gower (1971) does not consider ordinal data, such as in Table 1. Podani (1999) and Kaufmann & Russeauw (1990, 2005) are the ones who proposed some modifications to cover the ordinal scale as well. We use the modification proposed by Podani in this article. Within the context of appraisal of a building, for a characteristic (attribute) t, the Gower Distance (Dissimilarity index) with Podani's extension (equation 4) for building i and building j is defined as follows:

For data with Interval/Ratio scale:

$$d_t(i,j) = \frac{|x_{i,t} - x_{j,t}|}{\max_k\{x_{k,t}\} - \min_k\{x_{k,t}\}} \quad [3]$$

For data with Ordinal scale:

$$d_t(i,j) = \frac{|\text{Rank}(x_{i,t}) - \text{Rank}(x_{j,t})| - \left(\frac{T_{i,t}-1}{2}\right) - \left(\frac{T_{j,t}-1}{2}\right)}{\max_k\{\text{Rank}(x_{k,t})\} - \min_k\{\text{Rank}(x_{k,t})\} - \left(\frac{T_{max,t}-1}{2}\right) - \left(\frac{T_{min,t}-1}{2}\right)} \quad [4]$$

where: $T_{i,t}$ = the number of buildings that have the same rank as building i for attribute t, and $T_{min,t}$ (& $T_{max,t}$) are the number of buildings that have the minimum rank (& maximum rank respectively).

For data with Binary/Nominal scale: $d_t(i,j) = \begin{cases} 1 & \text{if } x_{i,t} = x_{j,t} \\ 0 & \text{if } x_{i,t} \neq x_{j,t} \end{cases}$ [5]

Equations [3] – [5] can be used to construct dissimilarity index between an object of study (e.g., Building 00) with its comparable buildings (*e.g.*, Building 01 – Building 17) depending on the characteristics that are available to the appraisal. Notice that all values of dissimilarity index $d_t(i,j)$ are between 0 and 1, *i.e.*, $0 \leq d_t(i,j) \leq 1$.

Obviously, the similarity index between 2 objects (i,j) for an attribute t is then defined as:

$$s_t(i,j) = 1 - d_t(i,j) \quad [6]$$

Also, if we have weights for every characteristic t (*i.e.*, w_t) – as in the top of Table 1, we can easily multiply the (dis)similarity index(es) for each characteristic by the corresponding weight to obtain a singular value that represents (dis)similarity between 2 objects. More importantly, the equation [6] still holds, namely: $s(i,j) + d(i,j) = 1 \; \forall i,j$. Given that we are interested to find out the fair rental price of Building 0, we can simply calculate $s(0,j) \; \forall j = 1, \dots, n$. This is our first step, and we can choose a reasonable cut-off point for $s(0,j)$, for example: 0.50 or 0.75 to select those comparable buildings, or better yet, using more scientific Clustering technique such as Partition Around Medoids (PAM) to select some buildings to be used in comparison.

To accomplish step 1, we use R package "FD" (Laliberte & Legendre, 2010) to calculate the Gower Distance with Podani's extension. Furthermore, for PAM method, we simply use R package "cluster" (Maechler *et.al.*, 2021). Lastly, we could choose the number of clusters that maximize Silhouette width as normally used in Clustering analysis. It is worth pointing out that previous studies, such as Epley (1997) or Kummerow & Galfalvy (2002) proposed some optimization techniques to minimize variance or coefficient of variation in order to decide the number of comparable buildings. Nonetheless, some comparable buildings need to be chosen.

Step 2 – Construction of Fair Rental Price

To construct an estimate fair rental (market) price ($\hat{P}_{0j}$) of our object of study, *i.e.*, Building 00, using the rental price of comparable building j (P_j) we can start from the following equation (which is essentially equation [2] – for the general case):

$$\hat{P}_{0j} = P_j + b_1\left(I_{00} - I_j\right) \; \forall j \text{ from Step 1} \quad [7]$$

where: I_{00} and I_j are the Total Index of building 00 and comparable building j being selected as comparison.

Finally, the estimated fair rental (market) price can be easily calculated as $\hat{P}_0 = \frac{\sum_{j=1}^{m} \hat{P}_{0j}}{m}$. If one would like to incorporate some weighting to the comparable buildings being used, we can easily modify take the similarity measure as the weight. Hence, the final fair rental price can be represented as:

$$\hat{P}_0 = \frac{\sum_{\boldsymbol{j}} \boldsymbol{s}(\boldsymbol{0},\boldsymbol{j})\left(P_j + b_1\left(I_{00} - I_j\right)\right)}{\sum_{\boldsymbol{j}} \boldsymbol{s}(\boldsymbol{0},\boldsymbol{j})} \quad [8]$$

One will notice that we still need to run (multiple) linear regression to account for adjustment. When we have a limited number of comparable buildings, we found out that

Rank Transformation Regression as proposed by Iman et al. (1979) and popularized in real estate by Cronan et al. (1986). Unfortunately, Rank Transformation Regression has its limitations. Namely, it does not do extrapolation. Data in Table 1 for Attribute #7 shows that Building 00 needs extrapolation.

Step 3 – Separation of Commercial & Social Values

If one wishes to separate the Commercial & Social Values, we can easily separate out the predicted values from [8] by using their weight and scales. The following equations give the values attributed to Commercial and Social attributes:

$$V_{CV} = \frac{\sum_{i \in CV} w_i s_i}{\sum_{j \in SV \cup CV} w_j s_j} \quad [9a]$$

$$V_{SV} = \frac{\sum_{i \in SV} w_i s_i}{\sum_{j \in SV \cup CV} w_j s_j} \quad [9b]$$

Data

We use the data in Table 1 (from KJPP Susan Widjojo & Rekan) to try out our proposed methodology. Data in Table 1 is based on a project to estimate the fair market rental price of an office building in Jakarta that will be used for the Data Center. The ordinal data of comparable buildings around Jakarta (as in Table 1) are collected between January – June 2022. All values are in IDR/m^2 per month (rounded to thousands).

Discussion & Numerical Experiments

On the Weights in Total Index – to make it as linear as possible

First, it is imperative to discuss a little bit about the weights used in Table 1 to get the Total Index. The best weights, mathematically, to best linearize the relationship between Rental Price vs. Total Index should be given by the result of multiple linear regression using all 7 attributes as explanatory variables for Rental Price. For example, running multiple linear regression gives us the following (with R^2 = 0.8153, and the estimated rental price of Building 00 = Rp. 170K/m^2 per month instead of Rp. 171K/m^2 per month as previously obtained):

Rental Price = –79,995 – 12,954 A1 + 9,624 A2 + 52,613 A3 + 6,686 A4 – 2,618 A5 + 29,163 A6 + 526 A7

Therefore, the best weight (mathematically – allowing negative value) is actually to set $w_i = \frac{b_i}{\sum b_i}\ \forall i = 1, \ldots, 7$. Using the example in Table 1, the new Total Index that can be used is given in Table 2. We refer to Karina *et.al.* (2022 to appear) for further discussion of this topic.

Table 2. new Total Index with $w_i = \frac{b_i}{\sum b_i}\ \forall i = 1, \ldots, 7$

Building	Build 01	Build 02	Build 03	Build 04	Build 05	Build 06	Build 07	Build 08	Build 09	Build 10	Build 11	Build 12	Build 13	Build 14	Build 15	Build 16	Build 17	Build 00
new Total Index	3.23	3.85	3.13	2.48	3.83	2.69	3.02	3.84	3.40	2.71	3.62	3.96	3.88	3.20	3.18	3.97	3.88	3.01

However, we leave the weight's decision based on the appraiser's decision, who knows the importance of those characteristics in the context of the usage of the building. For example, suppose the building usage is for the data center. In that case, security could be given more weight. On the other hand, location or transportation access could be more critical if the usage is for offices.

Study Case

We are ready to illustrate the proposed methodology with a numerical example. Using equation [4] and data in Table 1, we can obtain the following Table 3, which is the result of the computation of the Gower (Dis)similarity index using the Podani extension. The result is obtained using the gowdist function in R package “FD” with parameter ord = c(“Podani”) and weight w = c(0.2, 0.15, 0.15, 0.15, 0.15, 0.1, 0.1).

Step 1: Table 3 contains the Gower Distance (Dissimilarity) as in equation [4] as well as Similarity index for building 00 to all 17 buildings. We can see that Buildings 06, 04, 09, 10, and 01 are the most similar to building 00 with similarity index $s(0, j) =$ 0.9497, 0.8832, 0.6430, 0.6099, and 0.6060 respectively. This is equivalent to assigning a cut-off value for similarity index $s(0, j) \geq 0.60$.

Table 3. Gower (Dis)similarity between 17 buildings to Building B00 using *gowdist* function

00	Building	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17
3	PAM Cluster	1	2	1	3	2	3	1	2	1	1	2	2	2	1	1	2	2
0.0000	GD with Weight	0.3940	0.7634	0.5829	0.1168	0.6621	0.0503	0.6040	0.7945	0.3570	0.3901	0.7280	0.8523	0.6461	0.4622	0.4540	0.8316	0.6150
1.0000	Similarity = 1 - GD	0.6060	0.2366	0.4171	0.8832	0.3379	0.9497	0.3960	0.2055	0.6430	0.6099	0.2720	0.1477	0.3539	0.5378	0.5460	0.1684	0.3850
3.20	Total Index	3.58	4.33	3.85	2.50	4.00	2.85	3.85	4.23	3.75	3.20	4.00	4.48	4.05	3.83	3.65	4.58	4.15

Furthermore, using a more scientific approach of PAM and Silhouette width, we obtain the best cluster of $k = 3$ and building 06 as well as building 04 are together with building 00 in the same cluster (*i.e.*, Cluster #3).

Step 2: Using the grid adjustment for the 5 comparable buildings (assuming $s(0, j) \geq 0.60$) using equation [1b] as grid adjustment, we can estimate:

$$\hat{P}_{0,6} = P_6 + b_1(I_0 - I_j) = 140{,}000 + 53{,}420 \times (3.20 - 2.85) = \text{IDR } 158{,}697$$

$$\hat{P}_{0,4} = P_4 + b_1(I_0 - I_j) = 130{,}000 + 53{,}420 \times (3.20 - 2.50) = \text{IDR } 167{,}394$$

$$\hat{P}_{0,9} = P_9 + b_1(I_0 - I_j) = 225{,}000 + 53{,}420 \times (3.20 - 3.75) = \text{IDR } 195{,}619$$

$$\hat{P}_{0,10} = P_{10} + b_1(I_0 - I_j) = 130{,}000 + 53{,}420 \times (3.20 - 3.20) = \text{IDR } 130{,}000$$

$$\hat{P}_{0,1} = P_1 + b_1(I_0 - I_j) = 180{,}000 + 53{,}420 \times (3.58 - 3.20) = \text{IDR } 159{,}967$$

Lastly, we can obtain the estimated fair rental (market) price for our subject as IDR 162,336 (simple average of the above 5 values) or IDR 162,676 (using the Gower similarity index as the weighting factor). If we use the PAM clustering, the estimated fair rental (market) price for building 00 is IDR 163,046 for simple average or IDR 162,888 for weighted average using Gower similarity.

Figure 4. Buildings 6, 4, 9, 10, and 1 are adjusted to the Total Index of Building 00

The whole process of this calculation can be displayed in Figure 4. Four comparable buildings with the closest similarity index (*i.e.*, Building 6, 4, 10, & 9 – in blue solid dot) are grid adjusted to Total Index = 3.2 (to the subject of study, *i.e.*, Building 00 – as the red circle), and then they can be averaged or weighted averaged (using $s(0, j)$ – similarity index) to produce the estimated fair market rental price.

Step3: If we assume Attribute 6 is a green building concept and since the weight of the social value parameter (Attribute 6) is 10%, we can calculate the social value contribution that is accommodated in the total index as:

$$\frac{(s_{SV_1}\ x\ w_{SV_1})+(s_{SV_2}\ x\ w_{SV_2})+......+(s_{SV_n}\ x\ w_{SV_n})}{Total\ Index} \times \text{fair market price} \quad [10]$$

$$\frac{3\ x\ 0.1}{3.2} \times Rp\ 162{,}336 = Rp\ 15{,}219$$

With S is the attribute score and W is the attribute weight, the green building concept as the social value attribute for the proposed building has a value of Rp 15,219/m^2. If we assume Attributes 6 and 7 are the social value parameters, The green building concept as the social value attribute for the proposed building has a value of Rp 40.584/m^2.

Conclusion & Further Recommendation

We propose a novel yet simple approach to calculating a fair market rental price for an office building using Gower (Dis)similarity index with grid adjustment when the input characteristics are ordinal data. Furthermore, the Gower Distance can be replaced, modified, and improved. Hence, render this method flexible. In this paper, we rely on previous well-accepted approaches such as linear regression for the grid adjustment. However, this can also be substituted with other acceptable adjustment techniques. This method is simple and flexible, yet it produces an excellent fair market value estimate. Some appraisers can use this methodology to practice how to do their ordinal scoring or how to put weights across attributes to get a reasonable, fair market rental price (value) of offices (buildings) from a set of comparable ones. We believe the more experienced appraisers will be able to produce an ordinal scoring closer to the real-life market value/sales/rental price. In other words, this technique can be used as a training method for junior appraisers.

Furthermore, it will also be interesting to research and extend other regression techniques, e.g., Rank Transformation Regression proposed by Iman & Connover (1979) and popularized by Epley (1997), to deal with grid adjustment, in particular when the input characteristics are ordinal. Some authors claim that Rank Transformation Regression can work with much fewer data and is more robust in dealing with outliers – see Cronan et al. (1986), for example. Along with similar Statistical concepts, the use of Principal Component Analysis and Factor Analysis can also yield interesting findings.

Lastly, numerous research in the area of Clustering deals with ordinal input. This will be a good direction to pursue. Recent research such as Shi et al. (2016) can also be tried to replace Podani's or Kaufmann & Rousseeuw's approach for ordinal scale input. Similarly, Walesiak's proposal for Ordinal measure can also be used. It is also interesting to compare how the PAM cluster behaves for all distance measures.

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