
A fuzzy logic system for visual evaluation

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Abstract. Research has shown that views are an important factor in the overall satisfaction of building occupants, but, because they are qualitative and subjective, views are difficult to assess. This paper presents a new approach to analyzing views using a fuzzy logic methodology, with the aim of assessing the amenity of views. It illustrates the process of constructing a system from data collection and fuzzy rules design, to inference and defuzzification procedures. With the verification of the prediction outcomes, it is shown that the evaluation model can successfully mimic a human's subjective preferences for scenic views. The methodologies and the underlying principles of the evaluation model are explained.

1 Introduction

Property prices are affected by many factors, including floor area, age, construction materials, views, and accessibility to work, shopping arcades, transport, car parks, and recreation facilities (Do and Sirmans, 1994; Lange and Schaeffer, 2001; Oh and Lee, 2002; Paterson and Boyle, 2002; Pollard, 1982; Rodriguez and Sirmans, 1994; Tse and Love, 2000). A property price does not only represent how much someone is willing to pay for a property, it also reflects attitudes toward living environments. Among the factors affecting property prices, views are qualitative and difficult to measure.

Views reflect the occupants' amenity inside the building enclosure and are an important factor in architectural design. They are passively determined by the surrounding context and actively governed by design parameters, such as window sizes, window locations, position of internal partitions, and overall orientation of the building. Traditionally, architects rely on their own experience and imagination to predict views. Predicting views from the interior of nonexistent buildings in high-rise and high-density environments is difficult. Wrong predictions are easily made, leading to wrong design decisions and the setting of wrong prices for the properties. Even though views can be approximated, it is difficult to judge the potential monetary value of a view. Furthermore, experts and nonexperts may perceive views differently (Daniel and Boster, 1976; Stamps, 1999; Zube, 1974) and the opinions of occupants may not coincide with those of architects (Michelson, 1966). It would be helpful, therefore, if a tool could be created to help designers assess interior views from the perspective of general users. In this paper we present an attempt to automate visual performance evaluation.

2 Literature review

A number of studies on view preference have been carried out. The results are commonly presented in a number of ways: a descriptive format that can be interpreted by experts who aim to design a better environment for their occupants, in the form of regression equations used in evaluating property prices, and in comparative form by psychologists. Gobster and Chenoweth (1989) reviewed fifty studies of visual quality assessment and found 1194 different terms used to refer to attributes hypothesized to be relevant to aesthetic quality. When categorized by meaning, there were still 114 distinguishable attributes common to three or more studies.

From the late 1960s to the early 1970s, Markus carried out extensive research on the influence of views from an architectural perspective. Factors affecting preference were identified separately. He found that, in the context of low-rise, high-density housing, open space and green areas were what most people prefer (Markus et al, 1972). The overall satisfaction was, to a great extent, a function of the amount of grass around the house, the distance between houses, garden size, and open space. The amount of sky that could be seen was also highly correlated with general satisfaction, as was the number of neighboring buildings in view—the more buildings in view the lower the overall satisfaction (Markus and Gray, 1972).

Another type of study is to correlate amenity levels with property prices. Views are typically modeled by using dummy variables in regression equations. Benson et al (1998) used dummy variables to indicate three qualities of view: ocean, lake, and mountain; Paterson and Boyle (2002) used dummy variables for developed area, agriculture, forests, and water; and Fraser and Spencer (1998) used dummy variables for slopes, road, parks, etc. This approach is commonly adopted in property valuation research. Instead of correlating views with property prices, Bishop et al (2004) carried out a survey with the help of a geographic information system (GIS) to investigate people's willingness to pay for views in a high-rise building environment. They concluded that people are willing to pay more for water and green space, whereas buildings and industry have a negative impact on people's willingness to pay. Some researchers realized that these regression models are simplistic and imprecise, as only the existence of a view, rather than the exact quality of a view, is considered. Wolverson (1997) attempted a quantification by interpreting the quality of a view as the angle of vision to the city. Although a correlation between the angle of view and the property price can be found, the real composition of a view is not taken into account.

With an understanding of the physical dimensions of landscapes which affect visual amenity, it is envisaged that these dimensions can be manipulated by managers to increase aesthetic quality (Gobster and Chenoweth, 1989). Dearden (1980) considered thirty landscape elements, including farmland, coastline, residential land, and fresh water, and obtained a regression equation that accounted for 81% of the variance in scenic quality judgments for a rural area in British Columbia. Hull et al (1987) developed scenic beauty models using a psychophysical modeling approach for roadside views of pine forests in the southeastern United States. They found that scenic beauty can be increased by increasing stand age and that there is an optimal stand density for scenic beauty depending on tree age. Much other research on the physical composition of a landscape has centered on forest environments (Gobster and Chenoweth, 1989).

Another approach to studying perception of the environment is the comparative study, commonly employed by environmental psychologists, who have found that people prefer natural over built environments (Van den Berg et al, 2003) and rural over urban areas (Blankson and Green, 1991; Zube, 1973). Also, the presence of water is a factor in preferences on views (Hull and Revell, 1989). Age, gender, education, and culture are other factors affecting landscape preference (Bernáldez et al, 1987; Carp and Carp, 1982; Kaplan and Herbert, 1987; Stamps, 1999; Zube et al, 1983).

3 Methodology

Fuzzy set theory (Zadeh, 1965) is commonly used to formulate knowledge: for complex processes when there is no simple mathematical model and when the processing of linguistically formulated knowledge is to be performed. Knowledge can be broadly classified into two categories: conscious and subconscious. Conscious knowledge can be explicitly expressed, whereas subconscious knowledge is difficult to express.

Knowledge about perception of the environment is subconscious. Although research shows that there are preferences for views, there is no definitive answer as to which view is the best. Knowledge about preferences does exist, but is hard to specify in detail. Conscious knowledge can usually be converted into if–then rules. However, for subconscious knowledge, input–output data have to be collected from typical situations.

3.1 Data collection

Most expert systems rely on input from experts who have certain knowledge in their fields. Nevertheless, we have seen that the preferences of experts (for example, architects and designers) may not coincide with the preferences of general occupants who have not received training in aesthetics. The goal of this study is to evaluate visual amenities from a general occupant's point of view; therefore, opinions from a group of general users towards visual assessment were collected instead of asking a few 'experts'.

According to findings in environmental psychology, some components have little effect on landscape quality assessment: the landscape representation media, whether slides, digital slides, prints, or on-site views (Coeterier, 1983; Daniel and Boster, 1976; Kellomaki and Savolainen, 1984; Stamps, 1990; Vining and Orland, 1989); the observers' response format, whether paired comparisons, rankings, or ratings (Buhyoff et al, 1982; Schroeder, 1984; Shuttleworth, 1980; Stamps, 2000); and the time respondents took to view the scenes (Wade, 1982). Therefore, an interview was designed to collect data for the construction of the fuzzy model.

A total of 105 pictures of common scenes around Hong Kong were given to twenty local citizens of various backgrounds, including university students, computer professionals, accountants, and housewives, with ages ranging from about 20 to 45 years. The photographs were taken in a full range of locations around Hong Kong by one of the authors without any photographic manipulation. They show the commonest types of views in the region. They were printed in color on 3R photographic paper, with labels stuck on the back. Interviewees were asked to take the randomly organized pile and lay the photographs on the table in order of preference. The ranking of each photograph was then taken. After the interview, an average ranking of each picture was computed and mapped onto the scale of 1 to 100: 100 represents the most preferred scene whereas 1 represents the least preferred. The average ranking of the pictures is treated as a relative index, called the visual aspect performance index (VAPI), which is treated as the dependent variable in the analysis.

These 105 pictures were divided randomly into two groups: the creation set and the validation set. The creation set, consisting of eighty-five pictures, was used to construct the rule base of the evaluation model. The validation set, consisting of the other twenty pictures, was used to verify the accuracy of the evaluation model.

3.2 Fuzzy reasoning

In order to develop a fuzzy logic system, major factors affecting preferences about views must first be identified. According to the research findings discussed in section 2, the distance between observers and surrounding buildings (AVDIST), and the proportions of built area (BUILDING), green area (PLANT), sea (SEA), and sky (SKY) are factors which are highly correlated with general satisfaction. A check of the Pearson correlation coefficients between these variables measured in these 105 pictures and the corresponding VAPI confirms that there is significant correlation between the factors and VAPI at the 0.01 level (table 1, over).

As a result, the five factors are taken as fuzzy variables for the fuzzy logic system. Three values are defined for variable AVDIST and four values for each of the other variables. The dependent variable VAPI is further divided into seven values as shown in table 2 (over).

Table 1. Bivariate correlations between five key factors and the visual aspect performance index (VAPI).

	AVDIST	BUILDING	SKY	PLANT	SEA
Pearson correlation	0.476	-0.845	0.684	0.550	0.390
Significance (2-tailed)	0.000	0.000	0.000	0.000	0.000
<i>N</i>	105	105	105	105	105

Table 2. Fuzzy variables and their fuzzy values.

Fuzzy variable	Definition	Fuzzy values
AVDIST	average distance between observer and surrounding buildings	near (N) medium (M) far (F)
BUILDING	percentage of construction in the scene	none (N) low (L) average (A) high (H)
SKY	percentage of sky in the scene	none (N) low (L) average (A) high (H)
PLANT	percentage of green landscape in the scene, including mountains, trees, grass, and artificial planting	non (N) low (L) average (A) high (H)
SEA	percentage of sea or water in the scene	none (N) low (L) average (A) high (H)
VAPI	the dependent variable	excellent (A) very good (B) good (C) average (D) bad (E) very bad (F) poor (G)

3.2.1 Fuzzification

Fuzzification is the process of converting real-world data into the fuzzy values of fuzzy variables. Mapping functions, called membership functions, are used for the conversion. For simplicity of calculation, trapezoidal and triangular functions are used in this research. The membership functions are designed so that each value category contains a similar number of cases.

For example, figure 1(a) shows the membership function of the variable AVDIST. From the dotted lines we can read that an average distance of 150 m belongs to 'medium' with a confidence 0.75 and belongs to 'far' with a confidence 0.26. Figure 1(b)–1(f) show the membership functions for other variables.

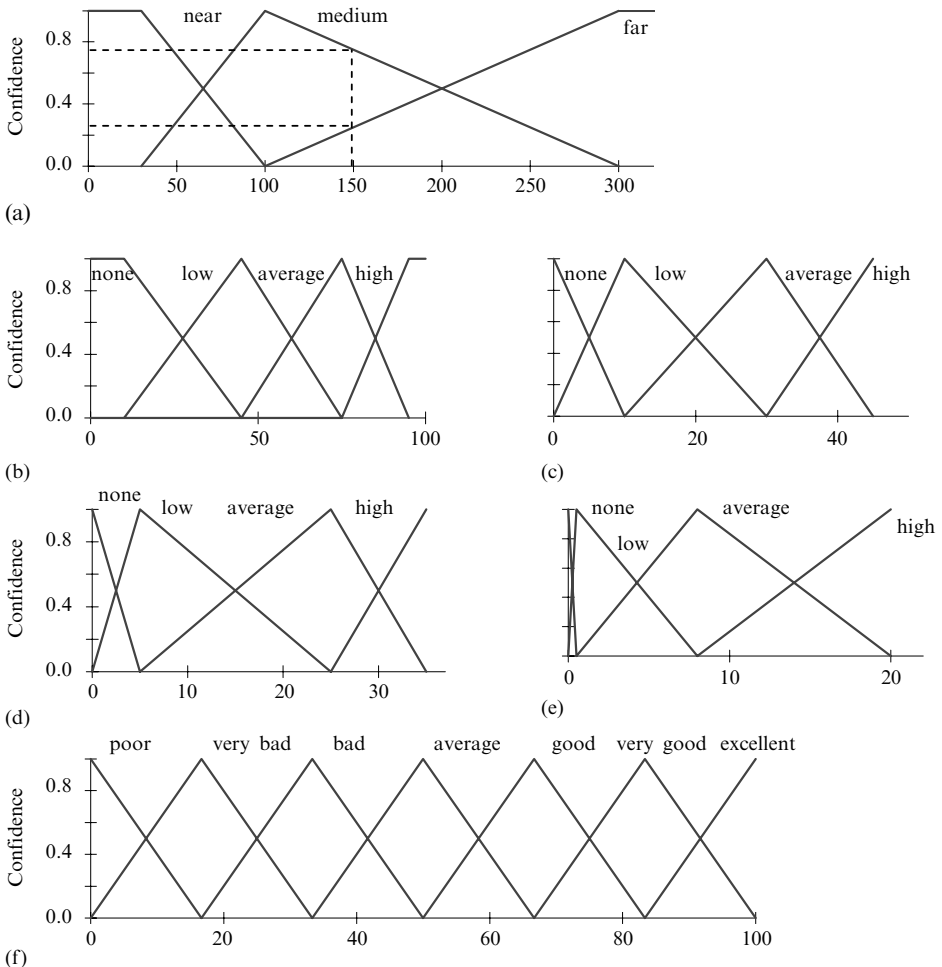


Figure 1. Membership functions for (a) AVDIST, (b) BUILDING, (c) SKY, (d) PLANT, (e) SEA, (f) VAPI.

3.2.2 Fuzzy rules

After the fuzzy variables and their membership functions had been defined, fuzzy rules were created from the creation set (a group of eighty-five pictures). The physical distance between the observation point and the surrounding buildings, and the areas of the four major elements—built area, water, sky, and green area—were measured and fed into the membership functions as described above. Each picture may generate one or more rules.

Figure 2 (over) shows one of the pictures in the creation set. The parameters of the five variables for figure 2 are listed in table 3 (over). After these parameters have been fed into the membership functions, the values and their confidence factors for each fuzzy variable are found (table 3).

From this table, it can be seen that the variable AVDIST has value M with confidence 0.83 and value F with confidence 0.17. Theoretically, any combination of fuzzy values with nonzero confidence can form a rule. But, in order to reduce conflicts and promote higher confidence about the rules, only combinations of the five variables with a product of confidence factors greater than 0.15 are taken into the rule base. In figure 2, for instance, one combination of fuzzy values satisfies this requirement. When AVDIST = H, BUILDING = L, SKY = L, PLANT = H, and

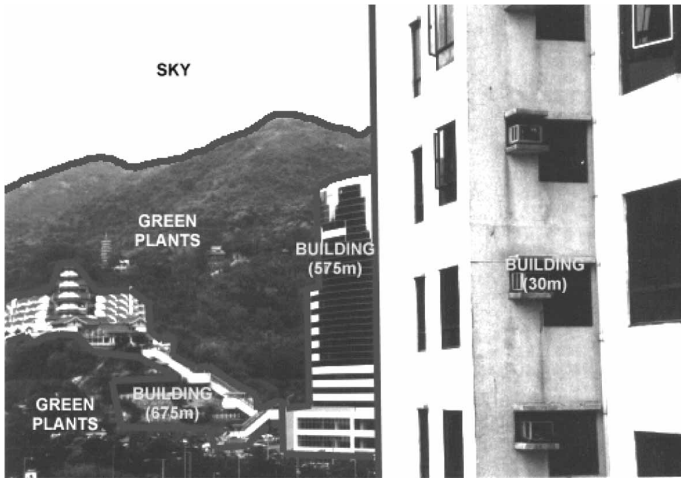


Figure 2. A typical scene taken in Hong Kong (one of the pictures in the creation set).

Table 3. Actual values of the parameters for figure 2.

Variable	Actual value	Fuzzy value	Confidence
AVDIST (m)	134	N	0.00
		M	0.83
		F	0.17
BUILDING (%)	53	N	0.00
		L	0.73
		A	0.27
		H	0.00
SKY (%)		N	0.00
		L	0.75
		A	0.25
		H	0.00
PLANT (%)	32	N	0.00
		L	0.00
		A	0.30
		H	0.70
SEA (%)	53	N	1.00
		L	0.00
		A	0.00
		H	0.00
VAPI	58.7	A	0.00
		B	0.00
		C	0.46
		D	0.54
		E	0.00
		F	0.00
		G	0.00

SEA = N (notated as MLLHN for short), the product of the confidence factors is $0.83 \times 0.73 \times 0.75 \times 0.70 \times 1.00 = 0.32$. Therefore the following rule was created from this picture:

if MLLHN, then VAPI = D.

The conclusion of this rule is $VAPI = D$ because D has the highest confidence in table 3. Similar to the fuzzy variables, each rule has an associated degree of confidence. The confidence of a rule is defined as the product of the confidence values of all variables in the rule. Therefore, the degree of confidence of the above rules equals $0.32 \times 0.54 = 0.17$.

The above process was carried out for all pictures in the creation set and 176 rules were generated from these 85 pictures. Because the rules were not consciously set by experts, conflicting rules might arise. One type of conflict happens when two or more rules have the same parameters but different confidence values. For these cases, the rule with the highest confidence value is kept and the others are discarded. After this elimination process, the number of rules was reduced to 129 which formed the rule base of the fuzzy model.

3.2.3 Inference and defuzzification

After the rules have been constructed, the last step of setting up a fuzzy logic system is to choose an appropriate inference procedure and defuzzifier. The inference procedure is the algorithm to produce a meaningful result from the fuzzy rules. As a rule of thumb, if the rules are independent of each other, they should be combined by union, and therefore the 'minimum' inference engine is used for this evaluation model.

Given a new picture, after the five parameters have been measured and the values fed into the membership functions in section 3.2.1, values of each fuzzy variable and their corresponding confidence values can be determined. All rules matching any combination of these fuzzy values are 'fired'. For each fired rule, a degree of belonging to the rule is obtained and this is assigned as the minimum confidence factor of the five variables.

For example, table 4 lists all the fuzzy values with nonzero confidence for figure 3 (over). Seven rules are fired in this case. When the following rule is fired, the degree of belonging of figure 3 to this rule equals $\min(1.00, 0.21, 0.94, 0.58, 1.00) = 0.21$.

if NLNHN, then $VAPI = C$ (confidence factor = 0.2717).

An intermediate conclusion can be drawn from this rule: $VAPI = C$. The confidence of this conclusion equals the product of the degree of belonging and the confidence of the rule: $0.21 \times 0.2717 = 0.057057$ for this case.

In rare situations when no rule in the rule base matches any combination of values, all rules close to the situation are fired. For instance, there is no matching rule for the condition FAALL. Rules with conditions close to this condition are fired, that is, FAALN, FAANL, and FLALL. The confidence value of the mismatching part in each rule is neglected in the calculation. With this approach, the system can still provide a reasonable estimation for uncommon situations.

Table 4. Values of the five variables for figure 3.

Variable	Value	Confidence factor
AVDIST	N	1.00
BUILDING	L	0.21
	A	0.79
SKY	N	0.94
	L	0.06
PLANT	A	0.42
	H	0.58
SEA	N	1.00



Figure 3. Another typical scene in Hong Kong (one of the pictures in the validation set).

For figure 3, seven rules are fired and thus seven intermediate conclusions can be drawn. Some rules may produce the same result, but some may have different conclusions. In fuzzy logic, it is reasonable for the system to have different values for the same variable, but different confidence values for the same value must be resolved. As the same conclusion is derived via two or more different rules, it should have higher confidence in this conclusion. And hence the resulting confidence must be greater than any original confidence values, but still not greater than 1.0. One way of deriving such a resulting confidence is to use the following formula:

$$\text{resulting confidence} = \sum_i C_i - \sum_{i \neq j} C_i C_j + \sum_{i \neq j \neq k} C_i C_j C_k - \dots + (-1)^{n-1} \prod_i C_i,$$

where C_i ($i = 1, \dots, n$) are the confidence values of the same conclusion, and $0 < C_i < 1$.

Table 5 shows seven intermediate conclusions directly generated from seven rules. After confidence values of same conclusions have been combined, it is simplified to three different conclusions in table 6.

The last step in obtaining a final meaningful conclusion is to convert fuzzy values into a single crisp value. This step is called defuzzification. The commonly used center of gravity method is employed in this research. The expected VAPI of figure 3 is thus found to be 38.3. Compared with the actual VAPI value of 40.2 collected in the interview, the fuzzy model produces a good prediction (figure 4).

Table 5. Intermediate conclusions.

VAPI	Degree of confidence
C	0.057
C	0.013
E	0.330
F	0.224
C	0.091
F	0.024
C	0.008

Table 6. Intermediate conclusions.

VAPI	Degree of confidence
C (good)	0.162
E (bad)	0.330
F (very bad)	0.242

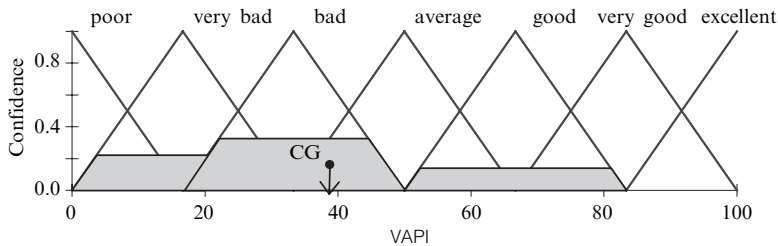


Figure 4. Center of gravity method.

3.3 Verification of the fuzzy model

In order to verify the accuracy of the evaluation model, a validation set of twenty pictures, selected randomly from the 105 pictures used in the interview, was retained. As the data from these twenty pictures were not used in the construction of the fuzzy model, they can serve as a fair test for the accuracy of the prediction.

The results of the expected values produced by the fuzzy model are plotted against the observed values in figure 5. Should the expected VAPI values (E) match the observed values (O) perfectly, the plot of the data will fall onto the line ‘E = O’. A Pearson coefficient of $r(18) = 0.947$ ($p < 0.001$) indicates that the predicted values are highly correlated with the observed values in a positive relationship, although it is not perfect.

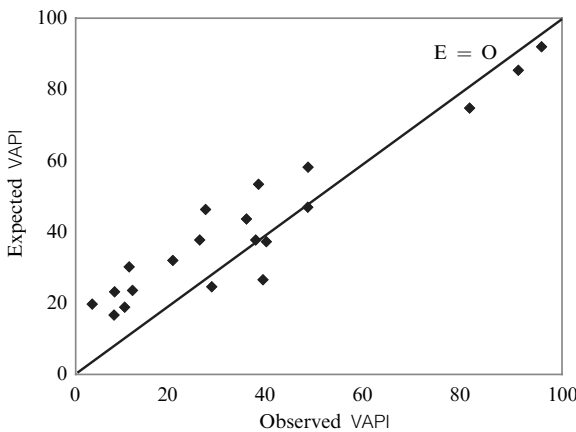


Figure 5. Expected visual aspect performance index (VAPI) against observed (VAPI).

4 Comparison of the fuzzy model with a regression model

To compare further the outcome of this fuzzy logic approach with the simpler regression approach, a linear regression model is constructed with the same set of data used in the fuzzy rule construction. A regression model for the visual amenity index is found as follows:

$$VAPI = 0.005 AVDIST + 0.176 BUILDING + 1.132 SKY + 0.955 PLANT + 0.918 SEA.$$

Table 7. Comparisons of the fuzzy model and a regression model.

	Linear regression model	Fuzzy model
Pearson coefficient	0.878 ($p < 0.001$)	0.947 ($p < 0.001$)
Mean absolute residual	11.72	9.64
Adjusted mean square error	5117.49	2943.84
Percentage of variance accounted for	77.09	89.68

From the four accuracy indicators in table 7, it can be seen that the fuzzy logic model is more effective than the linear regression model. Although the improvement in the correlation coefficient and the variance accounted for is not significantly large, this improvement is still important where the absolute error is concerned. A 2.08 difference between the mean absolute residuals is logically important in a 100-point scale.

5 Conclusions

Traditionally, designers can predict the visual amenity of their design only by drawing from their own experiences, knowledge, and personal preferences. By creating a digital three-dimensional model and using the fuzzy model introduced in this paper, the visual performance of a preliminary design can be predicted with an automated computer program. By placing a virtual camera at appropriate positions to mimic the observer's viewpoint, attributes of the scene can be accurately determined using simple ray-tracing techniques. After the parameters have been fed into the fuzzy model, the visual amenity inside the intended buildings can be calculated. The visual amenity inside the building can be monitored on the fly while a design is evolving. Immediate feedback can be provided to the designer and thus alternative design solutions can be evaluated objectively.

Because the model introduced in this paper was developed in the context of Hong Kong's high-rise and high-density environment and data were collected from local subjects, it may not be directly applicable to other places in the world. In spite of this, this paper demonstrates that the fuzzy reasoning technique can efficiently mimic qualitative and subjective opinion. It illustrates the process of constructing a fuzzy logic system for visual amenity assessment. It also shows that a fuzzy logic model can produce better predictions than a simple regression model. The process of constructing a similar fuzzy model can be repeated elsewhere to produce tailor-made evaluation models for other places.

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