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Decision Support Systems for Creative City Design: Rethinking Urban Competitiveness

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***Abstract*— Competitiveness has become one of the important strategies of government and industry in every nation. The concept of the Creative City, proposed by Charles Landry is driving the imagination of city redevelopers. It is essential for researchers to pay more attention to the issue of Creative City design for rethinking urban competitiveness.**

However, Creative City design must be supported with a wide range of knowledge and a diverse database. Concurrent city development requires to empower efficiency with appropriate evaluation and decision tools. Building a decision support system of Creative City development can help decision-makers to solve semi-structured problems by analyzing data interactively.

The decision support system is based on a new proposed rough set analysis that plays a pivotal role and is employed dynamically. The approach realizes a competent sampling method in rough set analysis that distinguishes whether each subset can be classified in the focal set or not. The algorithm of the rough set model will be used to analyze obtained samples.

In this paper we will first examine the design rules of Creative City development. Second, we will apply rough set theory to select the decision rules and measure the current status of Japanese cities. Finally, we will initiate a prototype decision support system for Creative City design based on the results obtained from the rough set analysis.

***Keywords*—Decision Support Systems, Rough Set, Classification, Sampling method, Urban Design**

I. INTRODUCTION

Competitiveness has become one of the important strategies of government and industry in every nation. Essentially, developing a competitive strategy is to develop a formula for how an organization is going to compete, what its goals should be, and what policies will be needed to carry out those goals [1]. Undoubtedly, repeating past experiences does not work for many cities in the world. City renaissance has played an increasingly important role in urban regeneration. The concept of the Creative City, proposed by Charles Landry is driving the imagination of professionals involved in city redevelopment [2].

Recently, arts-oriented approaches to urban design, involving cultural experiments and activities to bring social, economic and environmental regeneration outcomes, are increasing with various applications to many cities [3]. How do we make sense of a city when walking along the streets? How do we interpret street furniture and public art in urban spaces? In order to enhance the identity of a city, many explorations of urban design have been developed. A method of automatically and quickly describing whether a city is creative would enhance the efficiency of problem-solving in urban planning and development. This is the starting-point of this paper.

The objective of this paper is to create a simple classification method in a rough set approach that distinguishes whether a subset can be classified in the focal set or not.

However, in certain situations, it is difficult for researchers to obtain precise data while applying rough set theory. For example, identifying whether a city is a Creative City requires a very wide range of databases to classify sample cities. Therefore, the intent of this paper is to propose a means to competently define whether a subset can be classified in the focal set or not.

Rough set theory is a new mathematical approach to imperfect knowledge [4]. Currently, those interests in existing methods have been focused on the use of data analysis to find hidden patterns, generate sets of decision rules and so on. One of the important notions underlying rough set theory is approximation. The rough set analysis employs upper and lower approximation. The key advantage of this survey is providing a new method to force discrimination between the upper approximation and the outside. In this paper, using a competent sampling method based on a statistical test, we apply the algorithms of rough set theory to decide whether a city should be classified in the creative city group by evaluating the quantity of public art. Also, in order to minimize the cost and maximize the efficiency, we chose the alternative of utilizing artificial data in this paper.

The remainder of this paper is organized as follows: in Section Ⅱ, the concept of the Creative City and the definition of public art will be briefly explained. Section Ⅲ provides an overview of research in rough set theory and the basic and fundamental concepts of rough sets and rough set analysis. In Section Ⅳ, an adequate sampling method is illustrated on the basis of a statistical test, which economizes and simplifies the evaluation of decision and condition attributes, making it more

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qualified. A simulation example will be demonstrated to show the mechanism of the sampling method for the rough set model in Section Ⅴ. Finally, a prototype of a decision support system will be described in section Ⅵ. Section Ⅶ will conclude this paper with several remarks.

II. The Creative City

A. The Concept of the Creative City

We begin to realize how important creativity and culture are for the life of a society and the well-being of a modern economy. Chris Smith (2005), Former Minster of the Department of Culture, Media and Sport in the United Kingdom stated creativity is the ability that enables people to think afresh, to initial new ideas, to invent new possibilities of doing things, to generate imagination, and so on. It is also the most important component in our own sense of identity, as an individual, a local community, a city or a nation [5]. Increasingly, creative industries are becoming crucial for the economic prosperity and public welfare of the world's great cities.

The concept of the Creative City was initially aimed by Charles Landry to think of a city as a living work of art, where citizens can involve and engage themselves in the creation of a transformed place. This will require different creativities such as those of engineers, sociologists, urban planners, architects, environmentalists, anthropologists, artists and certainly ordinary people living their lives as citizens [2]. An emphasis on creativity in cities has grown as people have realized that cities compete again each other on several perspectives.

A building, a public art installation, a piece of street furniture and any urban space in a city, can foster a creative atmosphere and inspire the citizens. What makes an environment creative is that it gives the residents the sense that they can shape, create and make the city in which they live. The residents are active participants rather than passive consumers. The idea of the Creative City is an ongoing process. It is dynamic, not static. To make a Creative City requires infrastructures beyond rigidly shaped hardware. The creative infrastructure is a combination of the hard and the soft. It will involve mental infrastructure. Indeed, very few places are comprehensively creative, but every city can be more creative than it is [5].

B. Talent, Technology and Tolerance - The Creativity Index

The Creativity Index developed by Florida in 2002 [5], provides a new instrument to measure the creative economy. The proposed equally weighted factors based on Florida's methodology are as follows: (1) Talent - the Creative Class's share of the workforce; (2) Technology- innovation, measured as patents per capita and high-tech industry, using the Milken Institute's widely accepted Tech Pole Index (High-Tech Index); (3) Tolerance, measured by the Gay Index, Bohemian Index and Melting Pot Index.

However, Florida's research is not without its weaknesses. Creative City development is a complex process. The noted factors of Talent, Technology and Tolerance are insufficient to analyze the concept of the creative city. There are still various indicators that need to be considered in order to examine urban redevelopment. Therefore, we will explore another Creativity Index after carefully reviewing our research findings.

C. Creativity Ranking in U.S. Large Cities

Table 1 and Table 2 present the creative index ranking for the top 10 and bottom 10 metropolitan areas among 49 U.S regions with populations over one million [5]. According to Florida's research, Austin, Texas, has now jumped ahead of San Francisco to take first place. Seattle, Boston and Raleigh-Durham are in the list of top five. However, cities like Buffalo, New Orleans, and Louisville are examples of those that have unsuccessfully tried to attract the Creative Class. Again, this Creativity Index ranking has not been examined much because of its limitations. Due to the lack of strong support for evidence of the relationship between the 3T's and successful Creative Cities, further research on appropriate factors for creative city development is required.

Table 1: Top 10 Creative Cities in U.S.

Rank	City with the Highest Creative Index Scores	Technology Rank	Talent Rank	Tolerance Rank
1	Austin-TX	1	3	7
2	San Francisco-CA	3	5	6
3	Seattle-WA	6	6	1
4	Boston-MA	12	4	3
5	Raleigh-Durham-NC	2	2	20
6	Portland-OR	4	19	2
7	Minneapolis-MN	16	9	4
8	Washington-Baltimore	15	1	16
9	Sacramento-CA	5	11	17
10	Denver-CO	22	8	8

Table 2: Bottom 10 Creative Cities in U.S

Rank	City with the Lowest Creative Index Scores	Technology Rank	Talent Rank	Tolerance Rank
39	Detroit-MI	48	22	37
39	Norfolk-VA	37	30	46
41	Cleveland-OH	40	32	43
42	Milwaukee-WI	43	40	41
43	Grand Rapids-MI	33	48	32
44	Memphis-TN	27	43	48
45	Jacksonville-FL	49	39	33
46	Greensboro-NC	41	46	39
47	New Orleans-LA	47	35	39
48	Buffalo-NY	41	37	47

D. The Definition of Public Art

In this paper, we analyze the quantity of public art in a city. The term "public art" refers to works of art in any medium that has been planned and executed with the specific intention of being sited or staged in the public domain, usually outside and accessible to all.

III. Rough Set Theory

Rough set theory is especially useful for domains where collected data are imprecise and/or incomplete. It provides powerful tools for data analysis and data-mining from imprecise and ambiguous data. A reduction is the minimal set of attributes that preserves the indispensability relation, that is, the classification power of the original dataset [6]. The rough set theory has many advantages: It provides competent algorithms for finding hidden patterns in data, finds minimal sets of data (data reduction), evaluates the significance of data, and generates minimal sets of decision rules from data. It is easy to understand and offers a straightforward interpretation of results [7]. These advantages can make its analysis easily, so many applications use a rough set approach as their research method. Rough set theory is of fundamental importance in artificial intelligence and cognitive science, especially in the areas of machine learning, knowledge acquisition, decision analysis, knowledge discovery from databases, expert systems, decision support systems, inductive reasoning, and pattern recognition [8, 9, 10].

The rough set theory has been developed by Pawlak [15] and applied to the management of many issues, including medical diagnosis, engineering reliability, expert systems, empirical study of materials data [11], machine diagnosis [12], travel demand analysis [13], business failure prediction, solving linear programs, data-mining [14] and α -RST [15]. Other papers discuss the preference-order of attribute criteria needed to extend the original rough set theory, such as sorting, choice and ranking problems [16], the insurance market [17], and the unification of rough set theory and fuzzy theory [18]. The rough set theory is a useful method to analyze data and reduct information in a simple way.

A. Overview of the Concepts of Rough Set Theory

In the ordinary set theory, crisp sets are used. A set is then defined by its elements. On the other hand, dealing with uncertain problems in the rough set theory, membership is not the primary concept. The significance of applying rough set analysis is the ability of classification. The results of the rough set approach are examined in the sort of classification or decision rules analyzed from a set of examples [14].Both the fuzzy set and rough set theories deal with the indescribable and perception knowledge. The most substantial difference between them is that the rough set theory does not need to have a membership function, so it can avoid pre-assumption and subjective information upon analysis. The rough set theory provides a new different mathematical approach to analyze the uncertain, and with rough set, we can classify imperfect data or information easily. The results are presented in the form of decision rules. In this research, we use the rough set theory to analyze the urban design problem.

B. Information System

Generally, an information system denoted IS is defined by $IS = (U, A)$, where U consists of finite objects and is named a universe and A is a finite set of attributes $\{a_1, a_2, \cdots, a_n\}$. Each attribute $a \in A$ (attribute a belonging to the considered set of attributes A) defines an information function $f_a : U \to V_a$, where V_a is the set of values of a , called the domain of attribute a . . . .

C. Lower and Upper Approximation

A method to analyze rough set is based on two basic concepts, namely the lower and upper approximations of a focal set. Without doubt, these may be a set. The circle of a focal set is represented by some squares. The squares included completely in the circle are called a lower approximation. The squares both partly and completely included in the circle are called an upper approximation. Let X be a subset of elements in universe U , that is, $X \subset U$. Let us consider a subset in V_a , $P \subseteq V$. The low approximation of P , denoted as $\underline{PX}$, can be defined by the union of all elementary sets X_i contained in X as follows: $\underline{PX} = \{X_i \in U[X_i]_{ind(P)} \subset X\}$ where X_i is an elementary set contained in X_i, $i = 1, 2, \cdots, n$. The upper approximation of P , denoted as $\overline{PX}$, can be denoted by a non-empty intersection of all elementary sets X_i contained in X as follows: $\overline{PX} = \{X_i \in U[X_i]_{ind(P)} \cap X \neq \phi\}$. The boundary of X in U is defined in the following: $PNX = \overline{PX} - \underline{PX}$.

D. Core and Reduct of Attributes

Continuing from the discussion in previous section, core and reduct attribute sets, $COR(B)$ and $RED(P)$, are two fundamental concepts of a rough set. The reduct can be a minimal subset of attributes that provides the same object classification as the full set of attributes. The core is common to all reducts [18]. Reduct attributes can remove the superfluous and redundant attributes and give decision-makers simple and easy information. There may be more than one reduct of attributes. If the set of attributes is dependent, we are interested in finding all possible minimal subsets of attributes that have the same number of elementary sets; these are called the reducts [18]. The reduct attribute set does not affect the process of decision-making, and the core attribute are the most important attribute in decision-making. If the set of attributes is indispensable, the set is called the core [18].

$$RED(P) \subseteq A, \ COR(B) = \bigcap RED(P)$$

E. Decision Rules

Decision rules can also be regarded as a set of decision (classification) rules of the form: $a_k \Rightarrow d_j$. Where a_k means that attribute a_k has value 1 , d_j represents the decision attributes and the symbol ‘ $\Rightarrow$ ’ denotes propositional implication. In the decision rule $\theta \Rightarrow \varphi$, formulae θ and φ are called condition and decision, respectively [19]. With the decision rules we can minimize the set of attributes, reduct the superfluous attributes and group elements into different groups. In this way we can have many decision rules: each rule has meaningful features. The stronger rule will cover more objects and the strength of each decision rule can be calculated in order to determine the appropriate rules.

IV. Efficient Sampling Based on a Statistical Test

According to the algorithms of the rough set method, we have built a qualified sampling model based on a statistical test that can classify data relating to each attribute automatically.

The model increases the efficiency of data classification. That is to say, if we have a large quantity of data or intend to randomly obtain samples, we can save our time and expenses by classifying these data into specific groups according to their attributes. The model will help us solve this problem. We just select the minimal number of samples, say 25 samples, classify them automatically depending on the result of the statistical test and created an approximation for rough set analysis. When these samples are not sufficient to reach a decision, then we take other samples, say 25 samples more. Through this adequate sampling method, we can easily determine whether data are included in the specific group or not, rather automatically.

From Fig. 1 we can identify that the portion with light-colored squares is the positive region of the focal set and the portion with dark-colored squares, such as set1-set17, is the boundary region of the focal set. Obviously the positive region is included in the focal set, but we can also notice that some sets, such as set16 and set17, are almost included in the focal set, while other sets, such as set1 and set2, are much less included in the focal set. So, how to decide whether the boundary region, such as set1 to set17, is included in the focal set? Can we say that set1 to set17 are all included in the focal set? We have set a threshold for each set: if the number of elements inside the set is more than the threshold, then we can include the set into the focal set, and vice versa. This resolves the two concepts of upper and lower approximations.

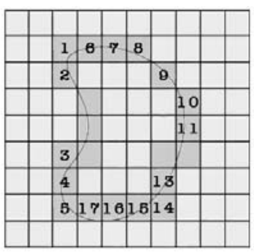

Figure 1. Image of Rough Set

According to the explanation above, we designed the algorithms of our efficient sampling model based on a statistical test. Suppose that there are 30 subsets included in one whole set and each subset has 25 sample values. There is also a discrimination ratio for the whole set, meaning that when the classification result of each subset is bigger than the discrimination ratio, we can include this subset into the focal set. In our artificial situation, this means that some cities can be extracted as Creative Cities. If the statistical test does not assure us that a set considered is classified in the focal set or not, then we obtain further samples, in the example 25 samples more, in order to reach some decision of classification. When we use this model, we can obtain the results of classification problems easily and quickly.

The Statistical Sampling Method

After finishing the sampling step, we should apply Student's t-test to verify the result of each subset because we do not know whether the result of samples accords with the result of the whole subset.

In our test, a both-sided t-test is applied. The equation used is written as following:

$$T = \frac{\bar{x} - \mu_0}{\frac{S_n^*}{\sqrt{n}}}$$

where $\bar{x}$ is the average of each subset. μ_0 is the threshold that we have set for each subset. S_n^* is the modified sample variance of each subset, and n is the number of samples employed. The significance level is α % depending on the problem. Let us take 5 % here. Then the testing step can be concluded as follows:

First, we calculate the average number of each subset. Next we calculate the modified sample variance and the value T . The number of λ can be found in Excel Function "TINV". According to the principle of the t-test, if $T \geq \lambda$ or $T \leq -\lambda$, then we accept the result of sampling if the mean is greater or less than the minus threshold, respectively. Otherwise, we reject the result, which means that we have to continue sampling until the t-test result accepts the sampling result.

V. SIMULATION

In this section, we will apply our rough set model to an artificial creative city classification situation. First we choose 30 cities from the world. Then we sample 25 towns in each city at first, which means that we collect the artificial quantity of public art numbers in each town and apply these numbers to our rough set model. After we input the data into our model, the model will begin its estimation on data classifying, and a city that is significantly bigger than the threshold will be counted. On the other hand, a city that is significantly smaller than the minus threshold will be counted. Finally we can discover which cities can be included in the Creative City group, and which cannot be included.

For example, in city1, we have artificial public art numbers from 25 sample towns. We set the threshold to 55 public art installations to evaluate a city as a Creative City, and we take the confidence ratio of the t-test as 5%. The number of public art installations in each town or each ward that is bigger than 55 will be listed. For example, the ratio of the towns' numbers with a large arts number of whole city1 will also be listed. Then we apply our model to the analysis of the public art values: first we pick the values that are bigger than 55. In city1, there are 16 samples bigger than 55. Then we calculate the ratio of goodness which is 0.64 (=16/25), but we have to test whether the value obtained is really greater than the threshold statistically. Then we apply the t-test of both-sided confidence ratio 5% to the null hypothesis that the value obtained is equal to the threshold. The result told us that the t-test rejected the null hypothesis. Then, considering that the value obtained is greater than the threshold, we concluded statistically that the ratio of goodness in city1 is 0.64, whose number is bigger than the threshold. Then we can say that city1 has been developed into a Creative City according to the results of these samples.

From city2 to city30, we can repeat the algorithm above to analyze the public art data and obtain similar results as we did for city1. Finally we can determine all the results for the 30 cities.

VI. Prototype Decision Support System

In our proposed experimental project, we plan to develop a decision support system for urban design. The prototype model is called *Urban Innovators System.* The system will empower the application of Creative City development for urban planners.

Basically, the *Urban Innovators System* plays a role as an urban planning consultant for the city government. It will consist of three major functions in our prototype *Urban Innovators System* as follows:

A. Creative City Assessment-Creativity Quotient (CQ)

In the *Urban Innovators System*, we will develop a Creativity Quotient (CQ) Score to measure the creativity level for the city, as shown in Figures 2, 3 and 4. After finishing the test, the city will get a score on its Creativity Quotient of 8 indicators: art, culture, talent, technology, economic effects, public space, management, civil society. Also, the Urban Innovators System will provide an evaluation report for the city by the SWOT strategic planning method. SWOT is an acronym for Strengths, Weaknesses, Opportunities and Threats. The analysis will be supported with 3D simulation, text, voice and visual graphics.

Figure 2. Example of Home Page for the Creative City Design System

Figure 3. Example of Creative City Assessment

Figure 4. Examples of Assessment

B. Urban Innovators Consultant

Another function of our prototype *Urban Innovators System* is to provide the candidate city with a suggested Sim-Architecture plan for future urban design and planning. The plan will include the four dimensions of art, industry, space and organization. Also, a GIS application will be employed in the system for displaying the graphics and Sim-Architecture. The city could acquire the design principle from the prototype support system as illustrated in Figures 5 and 6. The examples show the suggestion for designing the street furniture for the users.

Figure 5. Examples of Street Furniture Design Toolkits

Figure 6. Examples of Street Furniture Design Toolkits

C. Best Creative City Practices

In addition, the prototype *Urban Innovators System* will provide a database of the successful examples of Creative Cities including international and local applications. Urban planners who are interested in the case studies can search the database to review those best practices to have better understanding of the Creative City development.

VII. Conclusions

With a large scale system, traditional knowledge acquisition models become inefficient or out of date. We cannot solve 21st-century problems with 19th-century mindset. Today, with the rapid development of technologies, the capability of collecting data has been greatly advanced. Making good decisions requires a decision-maker to understand the current and future state of the world and the way to formulate an appropriate response [20]. Creative City design is a complex adventure. It will integrate with a wide range of knowledge and diverse databases. Building decision support systems for Creative City design can help decision-makers to leverage resources with information technology.

This research explores new possibilities for the application of decision support systems. A prototype *Urban Innovators System* has been developed to support this collaborative model of public participation. This newly initiated System will play a crucial role in designing Creative Cities. It provides an interactive problem-solving platform to urban designers by implementing the proposed three major functions: Creative City assessment, Sim-Architecture and a best practice database in the prototype *Urban Innovators System*.

This study also aims to provide an efficient and accurate classification method based on statistical tests by applying the rough set theory to various practical problems. One of the contributions of our proposed model is enhancing the application of rough set analysis, but there are also many difficulties in applying our proposed model to some practical problems. For example, in some practical situations, collecting the data will be a very huge and complex task even though the proposed sampling method can simplify the procedure. Thus, in order to overcome such difficulties, a further study concerning the application of rough set analysis will be required: we believe that the optimal algorithms of the classification model will be designed using rough set theory and applied to solve some practical problems in a future work. In addition, the suggested procedure can be applicable not only to decision attributes but also to all condition attributes [21].

In conclusion, the city government must fundamentally rethink its strategy to competition and redefine its role because the dynamics of cities and the world urban system have changed dramatically. There are greater incentives for cities to enhance local characteristics. The Creative City is a call to action because the 21st century is the century of cities [2].

A good decision support system for Creative City design can help decision-makers comprehend dynamic changes in the complicated assumptions needed to improve the quality of decisions. The success of an intelligent decision support system depends significantly on its capability to process large quantities of data and extract useful knowledge [22]. Further research efforts are needed to evaluate the effectiveness of the prototype Urban Innovators System and knowledge sharing through simulation.

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