The Heuristic Classification of Functional Land Use: A Knowledge-based Approach

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Abstract: Urban areas present an intense mixture of economic activities and extend over a vast territory. Conventionaly, land uses were classified according to a set of criteria in a dichotomous belong or does not belong perspective. However, the association of a spatial entity to a type of land use is not absolute, but to be expressed as a possibility, notably if we are investigating a spatial system at macro resolutions. The paper has two methodological parts. First, it addresses issues in the representation of knowledge on functional land use. We advocate that land use can be conceived as declarative geographical knowledge about an urban system, and we use a simple semantic network to encode it. Second, it develops an heuristic procedure of classification where a spatial entity has membership values to land uses. The assignment of a membership value applies elements of fuzzy logic through fuzzy numbers in classification rules. The procedure helps the semantic network "learn" (knowledge acquisition) about a spatial system by finding possible associations between spatial entities and land uses. Shanghai, as a complex intra-urban system, is used as a case study to test this methodology in the representation and analysis of geographical systems.

Key Words: Land Use Planning, Spatial Representation, Fuzzy Logic, Heuristics, Semantic Networks, Knowledge-based Systems.

The Problem

One of the main difficulties in planning spatial entities rests on the lack of information about a specific problem. Complete and accurate representations are never faced within geographical systems. Urban areas are notable spatial entities where inaccurate representations can lead to

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mistaken planning decisions. Several methods to assess the state of urban systems in a more or less efficient manner have been used over time. One such method of representation would consist of splitting an urban system in several spatial entities, to undertake a comprehensive gathering and the update of statistical data. Land use / planning zones are thus created. As the spatial resolution changes, the representation of land uses tends to vary in accuracy. At some resolutions, it even becomes "blurred". The level of spatial aggregation creates a problem of land use classification because at different levels there is no clear association of a spatial entity with a type of land use. To reinforce this fact, the majority of urban areas are an intense mixture of diversified economic activities, and also extend over a vast territory.

Land use is a qualitative characteristic of space and the result of a dynamic process involving the spatial accumulation of economic activities. It illustrates the state of urban systems at a given point in time and has been used in planning tools such as Geographic / Land Information Systems (GIS/LIS) for spatial representation and modelling. Through modelling, planners have a good idea of the socioeconomic consequences of their decision-making, but the spatial consequences are often disregarded. By considering a variable as a functional land use, an error is usually made. Neither population density can be considered as residential land use, nor industrial output as industrial land use. Those variables do not display characteristics that relate to urban land use form, pattern and density. We must though be cautious to appraise land uses with regard to any type of information. How can land uses be assessed with available information?

In fact, it is possible to depict predominant types of land use for a spatial entity by creating and updating land use maps. However, the classification used does not necessarily represent the desired information nor the desired resolution. It may well fit a problem, while being incompatible with another problem. Criteria for classification vary over time and source □ land uses of different urban areas cannot be easily compared and analyzed. For instance, high density residential areas may address different structures over different areas, notably if we compare North American, European and Asian cities. From another point of view, land use maps are not always available and agencies often lack the resources to periodically update available information systems. The compilation of land use information requires expensive field surveys using census data, areal photographs, remote sensing images and/or questionnaires. Spatial representation and resolution of land use information are the general problems we bring forward.

In order to address this problem, we suggest the use of a set of variables to express *membership values* of land uses to spatial entities. In other words, some quantitative information indicates a possibility, or degree of existence of a spatial structure of accumulation. The better the knowledge about the relationships between spatial accumulation and land use, the more accurately one or several variables can be associated with the presence of specific land uses. However, it is important to stress the fact that functional land use classification is not useful at micro resolutions because at those resolutions, land uses are easily seperable (see Figure 1). Furthermore, multi-storied buildings with multiple functions (commercial, administrative and residential) challenge the classification of land use at micro resolutions. Generally, classification relates to macro resolutions where land uses are mixed and less spatially separable. For instance, if we look at an administrative division a macro resolution geographical construct is "mostly" residential, "somewhat" commercial and has "some" industrial functions.

The objectives of this paper are twofold.The first one is to explore the possibility of representing geographical systems as a structured information pattern, where functional land use is a fundamental attribute. Knowledge-based computing offers methodologies to express the available knowledge in a comprehensive framework (e.g. Brackman and Levesque, 1985). This is relevant to any resolution for the representation of geographical information. The second consists of defining a classification methodology of land use. This could complement existing transportation / land use models (e.g. Blunden and Black, 1984). The methodology brought forward enables to assess functional land use at macro resolutions from a set of variables representing spatial accumulation.

Definition of a Knowledge-based Approach to Land Use

Land use can be conceptualized as knowledge about a geographical system. If we know the land use of an urban system, our knowledge of that system is increased. If we encode it, we have created a knowledge domain, which is simply the type of information relevant to a problem. A suggestion would be to build a relational structure of the information relevant to land use with the purpose of organizing it in a knowledge domain. Knowledge acquisition procedures can be used with the formalization of available information (Boose and Gaines, 1990). The method of representation used is an adaptation of the *conceptual dependency theory* developed in knowledge-based computing, better known as *semantic networks* (Schank, 1975; Quillian, 1968). This "classic" approach served as the base of multiple issues in knowledge representation, notably in linguistics and natural language processing (Allen, 1987; Winograd, 1983).

In spatially-related disciplines such as geography, the issue of structured knowledge representation is more recent (Couclelis, 1986; Smith 1984; Tikunov, 1990). Early applications involved spatial cognition and decision-making behaviour (Kuipers, 1978; Smith, Clark and Cotton, 1984; Smith, Pellegrino and Colledge, 1982). By their nature, spatial information systems (GIS/LIS) implicitly work with spatial knowledge and are in consequences strong candidates for such an approach (Leung and Leung, 1993a; Peuquet, 1987; Smith and Park, 1992; Smith and Yiang, 1991; Smith *et al*, 1987). In any regards of the domain, spatial knowledge can be declarative and procedural. Both require specific knowledge-based methods. Declarative knowledge is made of concepts, and the relationships between them, independent of any manipulating procedures. Procedural knowledge is about how to perform various tasks, usually represented by procedures related to those tasks (Chabris, 1989). At first, we deal with the representation of declarative knowledge on land use with semantic networks.

Declarative Knowledge

A semantic network is a knowledge representation formalism that presents each object as a node in a graph and the relations between objects as labelled arcs between nodes — the meaning of an object is derived from its relationships to all other objects in the network (Chabris, 1989). We define a semantic network *S*, a directed acyclic graph, by ($N(\Omega)$, $L(\Omega)$), where Ω is the knowledge domain, *N* a set of nodes and *L* a set of links between nodes (see Figure 2). The logical links between nodes are topological or attributive, depending on the nature of the knowledge. We limit ourselves for the problem herein with the application of three types of logical links: instance, element and property.

(1) *Instance*. An instance link, symbolized by ⇒, shows that one node is a unique case of elements in another node, like *{node_a}* ⇒ *{node_b}*. This type of link is often referred as an ISA link. {Socrates} is an instance (unique case) of the set {Human}.

(2) *Element*. An element link, symbolized by ⊂, is used when a node is a part of another, like *{node_a}* ⊂ *{node_b}*. *{node_a}* is a subset of *{node_b}*, where *{node_a}* can be a set or not. The set {Human} is an element of the set {Mortals}. In this article, element links will be mainly used to apply to a geographical membership. For instance {Athenes} has a geographical membership to {Greece}.

(3) *Property*. A property link, symbolized by ⊨, represents a node with an appraisable characteristic of another, like *{node_a}* ⊨ *{node_b}*. A property of {Socrates} could be his {_Age}, {_Height} or {_Gender}.

A problematic of using semantic networks as they grow in complexity is when they tend to become ill-structured, or at least difficult to manipulate. To overcome this problem, we use an elaborate semantic structure where nodes are structured in *frames*. A frame is a data structure, similar to a record in a relational database, which represents a parcel of information with a name and various properties (Rich and Knight, 1991). We may see a frame as a construct of nodes in a semantic network; a knowledge sub-domain. The links between frames (and their nodes) are defined following a value inheritance process. Using this process, a frame takes all the properties and the values of the previous frames which are linked to and therefore allowing to deduce implicit information that is not explicitly represented in this network:

Frame: {Human}
Name: *{node}* (Socrates) ⇒ Profession: *Frame: {Profession}* ⊂ _Birth_Date: *{node}* (470 BC) ⊨ _Height: *{node}* (Unknown) ⊨ _Gender: *{node}* (Male) ⊨

In this example the frame {Human} contains a set of slots, where one refers to the frame {Profession}. Consequently it inherits the properties of the frame {Profession}.

Procedural Knowledge

Now that the declarative knowledge structure is established, lets define procedural knowledge as we intend to use it. Figure 2 describes procedural knowledge manipulation with a semantic network that is composed of a set of nodes *N* (in brackets) and links *L* (arrows). Starting from a semantic network based on limited knowledge (*N-1,L-1*), a knowledge acquisition procedure can be performed. It finds links between existing nodes, adds new nodes and structures them within frames. It represents a process of cognition that can be very complex depending on the knowledge domain (see Morik, 1987 for some issues). The result is an updated semantic network (*N,L*) that has more information than the previous one, and also where information can be queried. We can perform two basic procedural tasks with semantic networks: inferences and procedures.

(1) *Inference*. Knowledge inference associates a set of known nodes and frames to find implicit relations in a set of known linkages. A classic exemple of logical inference is: if {Socrates} is {Human} and all {Human} are {Mortals}, we can conclude that {Socrates} is an element of {Mortals}.

(2) *Procedures*. Procedural knowledge uses available information (nodes, frames and their linkages) into the semantic network to produce new information. For instance to know if {Socrates} is {Dead} we would have to compare, through a procedure, his {_Birth_Date} with the {_Actual_Date}. If the difference is around 80, we can conclude that {Socrates} is an instance of the set {Dead}.

A knowledge-based approach to land use emphasizes the problem of geographical knowledge acquisition, representation and how to formaly encode expertise (Ericsson and Smith, 1991; Lundberg, 1989). Semantic networks enable the representation of land use and give the opportunity to insert new knowledge in them through procedures.

Procedure of Heuristic Classification of Land Use

We have stressed the fact that land use is strictly qualitative information about the state of spatial accumulation in a geographical system. Even so, it is possible to represent land use by discrete values such as economic output and population. With a proposal on the land use of type

$$L_i^n \in \left(E_i^k \ \forall\, k \right)$$

n for a spatial entity i ($L^n{}_i$), it can be represented by a set of quantitative variables k (E_i^k):

$$L_i \in \left(L_i^n \ \forall\, n \in i \right)$$

A spatial entity often contains in diverse proportions several types of land uses:
The functional land use of a zone i (L_i) is the set of all land uses which are elements of that spatial entity. It represents the overall level of spatial accumulation where i reflects the resolution. Equations 1 and 2 do not show the existing associations between variables and land use. In consequences, how can we classify land uses from a set of known variables?

Conventionally, classification is based on one or several criteria, qualitative and/or quantitative. Those criteria assign some membership of an element to a set. Could criteria of classification be heuristic? Heuristics involve experiential, judgmental knowledge; the knowledge underlying "expertise"; rules of the thumb, rules of good guessing, that usually achieve desired results without guaranteeing them (Feigenbaum and McCorduck, 1984). This approach seems quite unorthodox when compared with the rigorous tradition of quantitative geography that has intensively used classification methods like cluster, factorial and discriminant analysis. Without denying the relevance of those statistical methods, we explore the venues of a knowledge-based approach to classification. From this view, heuristic rules offer a formal way to encode procedural expertise on classification.

Rules are a premise-action association used to illustrate both declarative and procedural knowledge needed to solve problems by deduction over known facts. They may thus establish empirical associations, such as classification, developed through experience. There are two main types of reasoning with rules: forward and backward chaining (Pederson, 1989). Forward chaining is a search strategy where the conclusions are inferred from known information. On the other hand, backward chaining starts with an assumption to be proved and finds all the information that would satisfies this assumption. For instance, a forward chaining approach to land use classification would try to infer land uses from a set of known variables, while backward chaining would try to infer some spatial properties if we assume the presence of a type of land use.

The used classification procedure involves forward chaining and also requires the development of rules. From an heuristic point of view, a rule is what we *believe* the association between a variable (an element) and land uses (a set) is bounded by. Since we are talking about a belief, we need to assess a level of certainty to our classification. Fuzzy logic (Zadeth, 1965) considers the problem of variable membership of an element to a set. Although the methodology was initially controversial, applications in numerous disciplines are emerging (McNeill and Freiberger, 1994). In geography, fuzzy logic was mainly used to express approximate spatial linguistic terms and to define boundaries or regions, which are often non-discrete entities (Altman, 1994; Leung, 1982, 1987; Rolland-May, 1987). By the nature of the knowledge they address, geographers are at ease with fuzziness, notably with the fuzziness of space. Spatial representation is one of the major application domain of fuzzy logic related to geography.

Land use classification at macro resolutions requires a similar approach of variable — fuzzy — membership. Over this, Leung and Leung (1993b) have experimented with the classification of formal land use using remote sensing images at a fixed micro resolution (pixels). They acknowledge that most classification problems are domain-specific and suggest a fuzzy expert system shell as a framework for spatial classification. For our classification problem, which involves functional land use at macro resolutions, the classification procedure has yet to be defined. To classify the land uses of a spatial entity using fuzzy logic — as a support for inference within a semantic network — four steps are necessary. The estimation of membership fields, membership functions, membership thresholds and land use adjustment factors.

(1) *Membership fields*

A membership field is a bounded space that includes all the values of a set. For instance, [2,4] is a membership field where values like 2.13, 3, 3.5, 3.99 and 4 are all included. Fuzzy numbers offer a comprehensive prospect to establish membership fields (Kaufmann and Gupta, 1985; Negoita and Ralescu, 1987). A fuzzy number $N^k(L^n)$ that defines a membership field of a

$$N^k(L^n) \rightarrow \left[\ X^k(L^n)\ ,\ a^k(L^n)\ ,\ Y^k(L^n)\ \right] \forall\ k$$

variable k to a type of land use L^n is expressed by:

where: $a^k(L^n)$ = point where for a variable k, the membership value equals 1.0.

$X^k(L^n)$ = lower limit relatively to $a^k(L^n)$ where the membership value equals 0.

$Y^k(L^n)$ = upper limit relatively to $a^k(L^n)$ where the membership value equals 0.

For instance, a fuzzy number $N^k(L^n) \rightarrow [2,3,3]$ indicates that a variable k must have a value between 1 (3-2) and 6 (3+3) for the land use L^n to be a property of a spatial entity. Therefore, the

$$R^n \ \rightarrow\ \{L^n\} \ \mapsto\ \{i\} \ \_ \ \left(E_i^k \ \in\ N^k(L^n)\right) \forall\ k$$
$$\neg R^n \ \rightarrow\ \{L^n\} \neg\mapsto\ \{i\}$$

land use of a spatial entity can be classified by this heuristic rule R^n and rule failure $\neg R^n$:

A type of land use L^n is a property of a spatial entity i ($\{L^n\} \models \{i\}$: there is an attributive semantic association between both) if and only if all the variables E_i^k of that spatial entity are inside boundaries defined by fuzzy numbers. It is important to note that we put brackets between L^n and i to identify them as nodes in a semantic network (see previous section). If the rule fails ($\neg R^n$), then the spatial entity i does not contain the type of land use L^n and a semantic association of non-membership is established ($\{L^n\} \neg\models \{i\}$). How sure can we be about the membership to a

$$R^n \ \rightarrow\ \exists\ P_i(L^n) \ \rightarrow\ [0,1] \ \_ \ \{L^n\} \ \mapsto\ \{i\} \ \_ \ \left(E_i^k \ \in\ N^k(L^n)\right) \forall\ k$$
$$\neg R^n \ \rightarrow\ \{L^n\} \neg\mapsto\ \{i\}$$

set? To incorporate this, equation 4 can be developed to become:

There exists a membership value □ expressing a degree of membership □ of land use L^n to a spatial entity i ($P_i(L^n)$) if and only if all the variables of that spatial entity are inside membership fields. This membership value is the result of a membership function that gives values between 0 and 1.

(2) *Membership functions*

A membership function $u_i(L^n)$ defines how the membership value varies over the

$$u_i(L^n) \rightarrow [0,1]$$

membership field:

where a land use L^n has a membership value to a spatial entity i bounded by 0 and 1. 0 is a total exclusion while values between 0 and 1 represent a growing degree of inclusion. At macro resolutions, it is not very probable that a type of land use will have a membership of 1 to a spatial entity. To illustrate this, if we take an administrative division within a specific urban area, we are virtually certain that this division will contain more than one type of land use (see figure 1). At least there is a possibility of existence of several land uses, L_i^1, L_i^2, ... , L_i^n, each having their own membership values, $P_i(L^1)$, $P_i(L^2)$, ... , $P_i(L^n)$, that illustrate our belief. Equation 5 can

$$
\begin{gathered}
R^n \rightarrow \exists \; P_i(L^n) \,\_\, \{L^n\} \mapsto \{i\} \,\_\, \left(E_i^k \in N^k(L^n)\right) \forall \; k \\
P_i(L^n) = \sum_{\forall \, k} \left(N^k(L^n) \mid u_i^k(L^n) \rightarrow [0,1]\right) w^k(L^n) \\
\sum_{\forall \, k} w^k\left(L^n\right) = 1 \\
\neg R^n \rightarrow \left\{L^n\right\} \neg\!\mapsto \{i\}
\end{gathered}
$$

be extended with equation 6 to become our heuristic rule of land use classification:

where $w^k(L^n)$ is the weight of variable k on the classification of the land use L^n. $P_i(L^n)$ is a weighted summation of membership values; a weighted sum of beliefs. This set of rules works like a fuzzy expert system where there is *fuzzification*, *inference* and *composition* (Cox, 1994). Membership functions give a fuzzification of input variables by assigning a degree of membership to a membership field. An inference is then performed to see if the degree of membership does not equal zero for all relevant variables. Last, composition ponder the degree of membership of sucessfull inferences in one membership value.

Figure 3 presents an hypothetical heuristic classification procedure with four variables (E_i^1, E_i^2, E_i^3 and E_i^4) and linear membership functions. If the value of the four variables are within boundaries defined by fuzzy numbers, then the land use L^n is a property of the spatial entity i (inference). The example of figure 3 gives one membership value for each variable (fuzzification). All those membership values are subject to a weighted sum that computes the possibility of existence of a land use (composition).

(3) *Membership thresholds*

Membership values provided by equation 7 do not explicitly indicate how successful are the associations represented. To do so, a membership threshold, which we define as a bounded certainty of association, is required. For instance $P_i(L^1)$ = 0.2 and $P_j(L^1)$ = 0.8 both exhibit a membership to the land use L^1, but our inference would be more accurate with the latter than the former. Membership thresholds, which we use in a linguistic manner (Leung, 1982), take the

$$\begin{aligned} Strong &\rightarrow [0.6,1] \mid P_i(L^n) \geq 0.6 \\ Average &\rightarrow [0.3,0.7] \mid 0.3 \geq P_i(L^n) \geq 0.7 \\ Weak &\rightarrow [0,0.4] \mid P_i(L^n) \leq 0.4 \\ None &\rightarrow [0,0.1] \mid P_i(L^n) \leq 0.1 \end{aligned}$$

form of:

$P_i(L^1)$ = 0.2 would fit within the *Weak* threshold, while $P_j(L^1)$ = 0.8 is a *Strong* association. We restrain ourselves, for simplicity, to four linguistic membership thresholds. Hedges, like *Very* and *Somewhat* can also be used to alter the range of inclusion (Lakoff, 1973). *Very* would affect the *Strong* membership threshold such that *Very Strong* would be bounded by [0.8, 1] instead of [0.6, 1]. Associations can therefore be discriminated by linguistic thresholds of membership.

(4) *Land use adjustment factors*

Our procedure does not indicate the surface occupied by each type of land use by spatial entity, but only a possibility of existence. It sounds to advance, depending on the available information, that when the membership value of a land use tends towards 1, it is more predominant in a spatial entity. To what extent a possibility of existence can be associated to an actual form, pattern and density? We propose that the surface occupied by each type of land use

$$S_i(L^n) = \left(\frac{P_i(L^n)}{\sum_{\forall n} P_i\left(L^n\right)} \right) \Gamma_i(Lsupn)$$

($S_i(L^n)$) is defined by:

where $\Gamma_i(L^n)$ is an adjusment factor related with the surface of i and the density of land use L^n. The higher the membership value to a spatial entity is, the higher the surface occupied by a land use will be. However, the density of land use is often difficult to assess. A way to bypass that problem is to classify land uses according to density. For instance, residential land use can be divided in categories like high density residential, low density residential etc... Rules have to be designed in order for each category to overlap others.

Procedure of heuristic classification of land use

The accuracy of the developed rule is based upon the knowledge on the relationship between variables of spatial accumulation and land uses. To express those relationships, we have proposed fuzzy numbers that define the membership fields where a variable has a possibility to represent a type of land use. Fuzzy numbers are used in a set of heuristic rules to classify land uses of spatial entities. However, rules are not laws and the results will be reliable as much as the rules can be. Consequently. this will put an emphasis on the realibility of theoretical and empirical knowledge on land use but also on the expertise of those designing rules.

The procedure is organized as follows: Sections 1 (membership fields), 2 (membership functions) and 3 (membership thresholds) form a classification rule with linguistic thresholds of association while section 4 (land use adjustment factors) defines a function to assess a surface by land use:

Procedure: Land_Use_Classification({i}) in semantic network S where Ω = Land_Use_Shanghai
(1) Apply_Rule: $R^n \; \forall \; n$. (2) Apply_Function: $S_i(L^n) \; \forall \; n$.

Knowledge acquisition in the semantic network is performed by first finding links between land uses and spatial entities (sub-procedure Apply_Rule: $R^n \; \forall \; n$, equation 7). Secondly, the procedure sees how well a membership value express a land use surface and density (sub-procedure Apply_Function: $S_i(L^n) \; \forall \; n$, equation 9). The next stage is to implement this procedure into a classification of the land use of Shanghai.

Application

As a municipality accounting for a population of over 13 millions in 1991 (7.5 millions for the city proper), Shanghai is a complex example of a mixture of land uses. This is even more the case with the restructuration of economic functions that induces several transportation / land use changes (Rodrigue, 1994). In regards of our approach, the scope of the concerned geographical system, and the important redefinition of urban land uses, a representation of functionnal land use at a micro resolution is unapplicable. However, the macro resolution of urban districts considers land uses as spatially non discrete entities where it is possible to have a general overview on the state of the system. Figure 4 represents a simple frame-based semantic network applied to Shanghai where an association of various frames (sub-domains) forms a limited knowledge domain (Ω = Land_Use_Shanghai). An example of knowledge inference within that network could be:

Query: {Zhabei} in semantic network S where Ω = Land_Use_Shanghai
{Zhabei} ⇒ **{District},** ⇒ **{Administrative_Division}.** ⊂ **{Shanghai},** ⊂ **{China}** ⇒ **{Country}** ⇒ **{Administrative_Division}.** ⇒ **{City}.**

The highly adaptable knowledge structure of semantic networks is an advantage in the representation of land use. The nature of frames, nodes, and their relationships are not previously fixed. On figure 4, {Land_Use} has only two instance nodes: {Industrial} and {Residential}, and there are five types of variables: {_Input}, {_Output}, {_Heavy}, {_Light} and {_Population}. For clarity, several associations in the Frame: {Geographic_Attributes} are not recorded. The geographical definition of spatial attributes like polygons (administrative divisions), vectors (rivers), georeferencing and the scale is outside the scope of this paper (see for instance Peuquet, 1990). We simply state that all those geographical attributes are within a frame. If needed, more nodes could be added to provide a more complex knowledge domain. Within this semantic network, our procedure will find associations between land uses and urban districts.

In order to acquire knowledge on an urban system by classifying its land uses, we have stressed the requirement of fuzzy numbers (see equation 7). Considering the available information on the urban districts of Shanghai, table 1 presents variables such as fuzzy numbers ($N^k(L^n)$) and weights ($w^k(L^n)$) in our classification problem (rules R^1 to R^5). For simplicity and comparability, all variables are standardized on a scale from 1 to 10.

Table 1: Rules of Classification for Ω = Land_Use_Shanghai

Land Use \ Variable	{_Input}	{_Output}	{_Heavy}	{_Light}	{_Population}
R^1→ {Heavy_Industrial} ⊨ {*i*} →	[8,8,4], 0.60[a]		[10,10,0], 0.40		
R^2→ {Light_Industrial} ⊨ {*i*} →	[8,8,4], 0.60			[10,10,0], 0.40	
R^3→ {HD_Residential} ⊨ {*i*} →		[5,5,10], 0.25			[5,10,0], 0.75
R^4→ {MD_Residential} ⊨ {*i*} →		[4,4,6], 0.25			[4,4,8], 0.75
R^5→ {LD_Residential} ⊨ {*i*} →		[2,2,9], 0.25			[1,2,9], 0.75

HD, MD and LD stand for high, medium and low densities.
{_Input} is the number of persons arriving in a district by transit.
{_Output} is the number of persons departing from a district by transit.
{_Heavy} is the production in Yuan of the heavy industrial sector.
{_Light} is the production in Yuan of the light industrial sector.
{_Population} is the density of persons per square kilometre.
a Weight of the variable in the classification of that type of land use.

Sources for variables: Shanghai tongji nianjian (1986) (Statistical Yearbook of Shanghai). Shanghai O-D matrix survey, 1982.

Fuzzy numbers are defined according to some basic assumptions. Industrial land uses have a high concentration of industrial production and are the destination of important transit movements of labour. The membership value $P_i(\{Heavy\_Industrial\})$ grows as the standardized values of

{_Input} and {_Heavy} reach towards 10. Our assertion would be most certain if {_Input} equals 8 and {_Heavy} equals 10. Residential land uses have a number of persons departing ({_Output}) and a density of population per square kilometres ({_Population}) proportional to its density. It is important to underline that fuzzy numbers of table 1 are heuristic estimations based upon the limited information available. They express a level of expertise in regards of land use classification in Shanghai. The procedure is applicable in other urban contexts, although classification rules would have to be redesigned accordingly. Table 2 presents results from the sub-procedure Apply_Rule: R^n $\forall$ n for specific types of land use and for each urban district of Shanghai.

Table 2: Membership Values of Land Uses to Urban Districts of Shanghai

District \ Land use	{Heavy_Industrial}	{Light_Industrial}	{HD_Residential}	{MD_Residential}	{LD_Residential}
{Changning}	0.3153	0.3417	0.3560	0.6915	0.9149
{Hongkou}	0.7145	0.7979	0.5548	0.7910	0.6857
{Huangpu}	0.1877	0.2196	0.5141	0.7224	0.6921
{Jingan}	0.2553	0.3350	0.8784	0.3481	0.3175
{Luwan}	0.2668	0.2966	0.8618	0.3732	0.3370
{Nanshi}	0.3872	0.3557	0.5872	0.8931	0.6828
{Putuo}	0.5525	0.6609	0.5066	0.7041	0.6593
{Wusong}	0.3919	0.1889	0.0796	0.1483	0.2966
{Xuhui}	0.6449	0.7742	0.3169	0.6122	0.9502
{Yangpu}	0.7000	0.7000	0.3241	0.6679	0.9254
{Zhabei}	0.6881	0.6656	0.4085	0.8536	0.8429

We can now update our initial semantic network where Ω = Land_Use_Shanghai. Figure 5 illustrates a part of the semantic network of figure 4 with *Strong* inferences between land use nodes (part of the land use attributes frame) and urban districts nodes (part of the geographical attributes frame). Depending on the linguistic membership threshold, a scale of consideration can be addressed, like the one related to main land uses (*Strong* property links) or minor ones (*Weak* property links). We have then acquired more knowledge about land uses of Shanghai with the addition of new property links. Evidently, the knowledge domain is highly specific with limited inferences. For instance:

Query: {Land_Use}, {Nanshi} in semantic network S where Ω = Land_Use_Shanghai
{Heavy_Industrial} ⊨ (0.3872: Weak, Average) {Nanshi}. ⇒ {Land_Use}. {Light_Industrial} ⊨ (0.3557: Weak, Average) {Nanshi}. ⇒ {Land_Use}. {HD_Residential} ⊨ (0.5872: Average) {Nanshi}. ⇒ {Land_Use}. {MD_Residential} ⊨ (0.8931: Strong) {Nanshi}. ⇒ {Land_Use}. {LD_Residential} ⊨ (0.6828: Average, Strong) {Nanshi}. ⇒ {Land_Use}.

A comparison of inital results given by the sub-procedure Apply_Function: $S_i(L^n)\ \forall\ n$ with the observed land use ($Obs_i(L^n)$) of Shanghai, with no land use adjustment factors, revealed an average estimation error of 15.98%. Considering this, an optimization (min: $|S_i(L^n) - Obs_i(L^n)|$) was performed to find which adjustment factor for industrial land uses minimizes the average error. Results (table 3) underline that a $\Gamma(Industrial)$ of 0.3853 gives an average error of 7.47%.

Table 3: Semantic Definition of Land Use in Shanghai

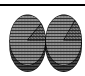
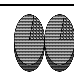
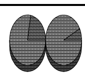
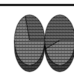
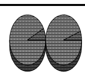
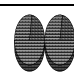
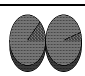
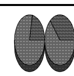
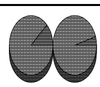
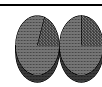
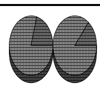
Urban District (error)	Estimation ($S_i(L^n)$) versus Observation	Semantic Definition $\{L^n\} \vDash (P_i(L^n))\ \{i\}$	Urban District (error)	Estimation ($S_i(L^n)$) versus Observation	Semantic Definition $\{L^n\} \vDash (P_i(L^n))\ \{i\}$
{Changning} (2.85%)		{Heavy_Industrial} ⊨ (0.3153) {Changning}. {Light_Industrial} ⊨ (0.3417) {Changning}. {HD_Residential} ⊨ (0.3560) {Changning}. {MD_Residential} ⊨ (0.6915) {Changning}. {LD_Residential} ⊨ (0.9149) {Changning}.	{Putuo} (0.00%)		{Heavy_Industrial} ⊨ (0.5525) {Putuo}. {Light_Industrial} ⊨ (0.6609) {Putuo}. {HD_Residential} ⊨ (0.5066) {Putuo}. {MD_Residential} ⊨ (0.7041) {Putuo}. {LD_Residential} ⊨ (0.6593) {Putuo}.
{Hongkou} (14.60%)		{Heavy_Industrial} ⊨ (0.7145) {Hongkou}. {Light_Industrial} ⊨ (0.7979) {Hongkou}. {HD_Residential} ⊨ (0.5548) {Hongkou}. {MD_Residential} ⊨ (0.7910) {Hongkou}. {LD_Residential} ⊨ (0.6857) {Hongkou}.	{Wusong} (26.64%)		{Heavy_Industrial} ⊨ (0.3919) {Wusong}. {Light_Industrial} ⊨ (0.1889) {Wusong}. {HD_Residential} ⊨ (0.0796) {Wusong}. {MD_Residential} ⊨ (0.1483) {Wusong}. {LD_Residential} ⊨ (0.2966) {Wusong}.
{Huangpu} (1.86%)		{Heavy_Industrial} ⊨ (0.1877) {Huangpu}. {Light_Industrial} ⊨ (0.2196) {Huangpu}. {HD_Residential} ⊨ (0.5141) {Huangpu}. {MD_Residential} ⊨ (0.7224) {Huangpu}. {LD_Residential} ⊨ (0.6921) {Huangpu}.	{Xuhui} (0.32%)		{Heavy_Industrial} ⊨ (0.6449) {Xuhui}. {Light_Industrial} ⊨ (0.7742) {Xuhui}. {HD_Residential} ⊨ (0.3169) {Xuhui}. {MD_Residential} ⊨ (0.6122) {Xuhui}. {LD_Residential} ⊨ (0.9502) {Xuhui}.
{Jingan} (7.58%)		{Heavy_Industrial} ⊨ (0.2553) {Jingan}. {Light_Industrial} ⊨ (0.3350) {Jingan}. {HD_Residential} ⊨ (0.8784) {Jingan}. {MD_Residential} ⊨ (0.3481) {Jingan}. {LD_Residential} ⊨ (0.3175) {Jingan}.	{Yangpu} (14.40%)		{Heavy_Industrial} ⊨ (0.7000) {Yangpu}. {Light_Industrial} ⊨ (0.7000) {Yangpu}. {HD_Residential} ⊨ (0.3241) {Yangpu}. {MD_Residential} ⊨ (0.6679) {Yangpu}. {LD_Residential} ⊨ (0.9254) {Yangpu}.
{Luwan} (7.18%)		{Heavy_Industrial} ⊨ (0.2668) {Luwan}. {Light_Industrial} ⊨ (0.2966) {Luwan}. {HD_Residential} ⊨ (0.8618) {Luwan}. {MD_Residential} ⊨ (0.3732) {Luwan}. {LD_Residential} ⊨ (0.3370) {Luwan}.	{Zhabei} (5.14%)		{Heavy_Industrial} ⊨ (0.6881) {Zhabei}. {Light_Industrial} ⊨ (0.6656) {Zhabei}. {HD_Residential} ⊨ (0.4085) {Zhabei}. {MD_Residential} ⊨ (0.8536) {Zhabei}. {LD_Residential} ⊨ (0.8429) {Zhabei}.
{Nanshi} (2.59%)		{Heavy_Industrial} ⊨ (0.3872) {Nanshi}. {Light_Industrial} ⊨ (0.3557) {Nanshi}. {HD_Residential} ⊨ (0.5872) {Nanshi}. {MD_Residential} ⊨ (0.8931) {Nanshi}. {LD_Residential} ⊨ (0.6828) {Nanshi}.	Residential and industrial land uses. Average error = 7.47% $\Gamma(Industrial)$ = 0.3853		

Table 3 presents a comparison between the surface supplied by the classification procedure and observed ones along with a semantic definition. Since the available information has permitted the calculation of membership values for only industrial and residential land uses, the comparison is henceforth restricted to them. Most of the results are similar, underlining the accuracy of the rules. However, results do not concord in the cases of the districts {Hongkou} (14.60% error), {Yangpu} (14.40%) and {Wusong} (26.64%). The main explanation behind this is the data on the industrial output that says nothing about the geographical variation, in regards of the industrial land use density in Shanghai. We can make a similar assumption for other cities. For instance, the difference between the calculated surface and the real one for central districts ({Hongkou}, {Jingan}, {Luwan} and {Nanshi}) could be attributed to the fact that those districts have an important part of their industrial output in the light industrial sector. This sector is mostly characterized by a high density and relatively productive multi-storeys industrial infrastructures. Therefore, the classification procedure attributes them more space than they are entitled to. {Wusong} shows opposite results (under estimation of industrial land use). This peripheral district is characterized by space consuming heavy industrial infrastructures, notably steel plants. {Yangpu} presents, to a lesser extent, a similar situation.

Discussion

The association of a set of variables with the actual land use structure, pattern and density they represent is not obvious. We discuss here of two general problems related to our approach. First, problems behind the calibration of the classification procedure and second, the usage of semantic networks in the representation of geographical systems.

Calibration

As seen, the calibration of the procedure through backward chaining implies membership fields, membership functions, membership thresholds and land use adjustment factors:

(1) *Membership fields*. What are the variables and weights to use for classification, and to what extent a variable can be associated with land uses? Heuristics play a fundamental role for that

purpose and we have used fuzzy numbers to assess an expertise about the classification procedure, but more importantly an expertise about the spatial system under investigation. The difficulty to overcome limited information is always present, although heuristics offer a way to employ what is available in a relatively successful manner for domain specific problems.

(2) *Membership functions*. How do our belief change over a membership field? We used a linear membership function to express the variation of the existant possibility of a land use in a membership field. As we go towards the center of the membership field, our belief grows. On the other hand, our belief is low near boundaries. Several other membership functions are possible like normal, logistical, exponential and square root. Furthermore, the choice of a membership function can be an objective evaluation and elicitation, an *ad-hoc* form, converted frequencies or probabilities, a physical measurement and from learning and adaptation (Kantrowitz *et al*, 1994). Over the last point, neural networks have been succesfully employed for calibration (Kosko, 1991). Would different membership functions affect the results, and which function better fits specific classification problems? An experiment with square root membership functions, keeping the same membership fields, revealed similar results. Available evidence thus underlines the limited importance of membership functions in land use classification problems.

(3) *Membership thresholds*. What can be considered as a sound association between elements of a semantic network? Linguistic membership thresholds, like *Strong* and *Weak*, provide a way to categorize membership values by degree of belief. Hedges are used, if necessary, to further discriminate associations. Spatial entities may thus be characterized, in addition to their membership, by how well an inference can be performed with the available information. For land uses, it underlines their prominance in spatial entities.

(4) *Land use adjustment factors*. Once a land use is classified, how can a possibility of existence express a land use form, pattern and density? In our case, industrial land use has required an adjustment factor to represent its higher density in regards of residential land uses. Rules for the classification of land use should disagregate it by density. Also, land use density is obviously not similar over an urban area. This may explain part of observed errors in our

application to Shanghai. As pointed out earlier, much theoretical and empirical work remains to be undertaken on the relationships between spatial information and the actual structures (systems) it represents.

Semantic Networks and Spatial Representation

The semantic network developed here is rather simple. However, this network fits the purpose of our demonstration (see figures 4 and 5). *Instance*, *Element* and *Property* links are suitable to assess the state (static view) of a geographical system composed of spatially disjoint and discrete entities ($i \cap j = \varnothing$ at all time). It may be all the links we need to encode associations behind most spatial classification procedures, since they are characterized by a similar resolution. Fuzzy logic can effectively be used to assess attributive links in a semantic network, but what about topological links? If we are to work with spatially non-disjoint and furthermore non-discrete entities, *Element* links are getting fairly more complex to express, as well as inferences to be performed. Smith and Park (1992) bring forward several spatial relations like *disjoint*, *meets*, *overlaps*, *equals*, *covers* and *inside* in order to provide a set of primitives for spatial inference and analysis. More complex and spatially sound semantic networks may be constructed by separating the above spatial relations from the topological *Element* link (see example on figure 6-A). Spatial classification procedures can eventually be refined further and would address a more complete set of situations. For instance, when a roughly defined land use zone overlaps several administrative divisions, the problem related to the attribution of spatial membership adds itself to the one of classification. In situations where the spatial entities are themselves fuzzy, a degree of membership can also be attributed to topological links in a semantic network (figure 6-B). This implies that when a geographical definition of spatial entities is uncertain, inferences to be performed with them must also be uncertain. A semantic network would therefore be a set of fuzzy nodes and links. We have brought forward a preliminary study where the spatial representation of land uses within a spatial entity is ambiguous — an application of fuzzy associations.

Conclusion

Urban areas present an intense mixture of several types of economic activities and are extending over a vast territory. At macro resolutions of representation, where most spatial information is collected, a geographical system must be viewed as an overlapment of diverse economic activities where functional land uses are not separable. Conventionnaly, the land use of a spatial entity was arbitrary classified following a set of criteria in a dichotomous belongs or does not belong perspective. However, even if membership of a spatial entity to a land use type is not absolute, it may be expressed as a possibility. Considering this fact, a methodology was developed to estimate variable memberships of elements to a set. Assignation of membership values was done with an heuristic classification procedure using elements of fuzzy logic to handle uncertainty of attributive associations. Land use can be conceived as knowledge about an urban system, and we have constructed a simple semantic network that represents a knowledge domain. The classification procedure helps the semantic network to "learn" (knowledge acquisition) about an urban system by finding associations between land uses and spatial entities.

Additional research could cover several dimensions like issues in knowledge representation of geographical systems, fuzzy logic in handling spatial information, and inductive approaches to classification problems. Those dimensions include a wide range of topics that may consider expert / decision support systems (deductive) and neural networks (inductive) as decision-making / modelling constructs. Knowledge representation and acquisition are parts of the available knowledge-based computing methodologies that deserve some considerations, and are indeed being increasingly focused upon. They offer a method to formally express spatial information in several geographical domains where knowledge is often ill-structured and inaccurate. Geographic information systems provide a framework as tools for declarative and procedural knowledge manipulation, and several researchers have also started to explore that venue over the last decade. The approach of geographical knowledge engineering is challenging in the way that we must reconsider the way we think about a problem and what we believe is relevant for its representation as well as its analysis. As always in geography and in all other fields were expertise, judgment and experience — if not intuition — play a fundamental role, rules are not laws and knowledge (spatial or aspatial) is not always entirely indubitable. In regards, this paper was an attempt to capture declarative and procedural knowledge on land use classification.

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