Artificial Intelligence and Expert Systems

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Glossary

Artificial intelligence The study of how to make machines perform tasks requiring human intelligence.
Deep learning Machine learning methods using multiple layers of nonlinear processing units for supervised or unsupervised classification or recognition of features and patterns as well as other decision-making tasks.
Evolutionary computation Computational methods that mimic the mechanisms of biological evolutions in order to solve complex problems.
Expert system Computer system that solves domain-specific problems much like human experts with high level of performance.
Expert system shell General purpose tool that provides complete environments for efficient development of knowledge-based domain-specific expert systems.
Fuzzy logic Nonstandard logic for approximate reasoning with imprecise premises.
Knowledge acquisition The process of acquiring knowledge from domain-specific experts or by machine learning.
Knowledge representation Formalisms for the representation of facts, truth, and knowledge entities in a machine understandable form.
Neural network Simple brain-like computational system made up of interconnected processing elements called neurons that process information, compute, and infer by its dynamic response to system inputs.
Spatial data mining Discovery of useful and nontrivial spatial structures and processes from data.
Spatial decision support system Computer system that supports spatial decision-making by coupling human intelligence with the capabilities of the computer.
Supervised learning A machine learning method which learns from labeled input–output training pairs/examples a function that maps an input to a designated output in such a way that it can be generalized to new situations.
Unsupervised learning A learning method which acquires knowledge or unknown patterns from data without a priori knowledge about the information.

With the ability to amass information from various sources, geographers are encountering information explosion in their analyses. Facing an almost unabated growth of information, it is absolutely necessary to apply geographical knowledge and expertise to streamline, analyze, manage, digest, visualize, and integrate information in an efficient and effective manner. Without knowledge, information becomes static and perhaps useless in our analysis of human behaviors or physical processes in space and time. Geographic information system (GIS) renders an efficient way to manage our data. Geographical analysis, however, goes beyond what GIS has to offer. Geographical analysis is not just the mechanical storage, retrieval, visualization, and simple analysis of information. It often involves deep-level reasoning that integrates information and geographical knowledge to solve structured, semistructured, or unstructured problems with varying degrees of complexity.

Information is the collection, representation, storage, retrieval, processing, and display of data. In general, it involves handling, processing, and organizing data suitable for calculating and measuring, as well as for reasoning with and updating knowledge. *Knowledge* comprises the acquisition, representation, and storage of knowledge, as well as the use of knowledge in inference and analysis. In general, knowledge deals with the handling of the body of truth and principles acquired through experience or association. It serves as a basis for inference and analysis. Furthermore, knowledge can be used to guide researchers to monitor, visualize, explore, integrate, and create information. The interplay of knowledge and information greatly expands the role of information technology in geographical analysis. Artificial intelligence, which comprises both information and knowledge in general and geographical knowledge in particular, is thus a way for achieving such goal.

Spatial Knowledge Representation and Inference

Geographical knowledge may be structured or unstructured. We may organize our knowledge in a highly structured form so that problems can be solved by systematic and procedural form. Mathematical models, statistical methods, and heuristic procedures are knowledge in procedural form. This type of knowledge follows a rigid framework for the representation and analysis of structures and processes in space and time. Procedural knowledge is effective in system specification, calibration, analysis,

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scenario generation, and forecasting of well-specified and structured problems. Through research, we have accumulated, over the years, a wealth of procedural knowledge which can be effectively utilized for geographical analysis in spatial information systems.

A majority of knowledge, however, is loosely structured. Subjective experience, valuation, intuition, and loosely structured expertise often cannot be appropriately captured by rigid procedures. They are declarative in nature and can only be represented by more flexible frameworks. Making inferences from such knowledge structures cannot be done procedurally. Problem-solving by if–then arguments is a typical example of using declarative knowledge for decision-making. This type of knowledge is effective in solving unstructured or semistructured problems. It is suitable for inference with concepts, ideas, and values. Similar to the use of procedural knowledge, declarative knowledge can be utilized in spatial decision-making, especially with spatial information systems. Declarative knowledge is, however, ineffective to solve highly structured problems. Consequently, procedural and declarative knowledge have to be used in synchrony throughout a decision-making process.

Once a spatial structure or process is understood and can be specified in a formal and structured manner, we can always capture it by a mathematical model or procedure. The representation of loosely structured knowledge is, nevertheless, not as straightforward. Declarative knowledge representation and inference have thus become a main concern in building spatial reasoning systems with artificial intelligence. To be able to understand and to reason, an intelligent machine needs prior knowledge about the problem domain. To understand sentences used to describe geographical phenomena, for example, natural language understanding systems have to be equipped with prior knowledge about topics of those phenomena. To be able to see and interpret scenes, spatial vision systems need to have in store prior information about objects to be seen. This also applies to the deep learning paradigm intensively studied in recent years. Therefore, any intelligent system should possess a knowledge or training database containing facts and concepts related to a problem domain and their relationships. There should also be an inference mechanism which can process symbols in the knowledge base and derive implicit knowledge from explicitly expressed knowledge.

Knowledge representation formalism consists of a structure to express domain knowledge, a knowledge representation language, and an inference mechanism. Conventionally, its duty is to select an appropriate symbolic structure to represent knowledge in the most explicit and formal manner, and an appropriate mechanism for reasoning.

Natural language is complex. Humans can name and describe facts by natural language sentences, and are able to reason and infer with facts and beliefs. This mechanism of representing facts and inferring with knowledge may be captured by logic. Though logic is not a theory on knowledge representation, it provides formalism for reasoning about beliefs. It consists of a syntax, a semantic, and a proof theory which can be utilized for knowledge representation and inference. Propositional logic and predicate logic are typical paradigms.

However, human knowledge is usually imprecise and our inferences often consist of a certain level of uncertainty. While uncertainty has various sources, the one that stems from imprecision is rampant in human systems. To represent and infer with such knowledge, we need a logical system which can handle imprecision. Among existing paradigms, fuzzy logic appears to be instrumental in processing imprecision. Fuzzy logic is a nonstandard logic for approximate reasoning. It is a formalism for drawing possibly imprecise conclusions from a set of imprecise premises. A premise is fuzzy if it has imprecise predicates. In the narrow sense, fuzzy logic is a formalism of approximate reasoning. In the broad sense, fuzzy logic is the theory of fuzzy sets.

Though first-order predicate logic gives a powerful mathematical tool to represent knowledge, its theorem-proving mechanism is not efficient and flexible enough to handle spatial reasoning consisting of a large decision tree or a long chain of inference involving a large set of if–then statements. A system containing an ordered set of if–then rules is called a production system. It can be employed to perform tasks involving deep knowledge reasoning.

Unlike logic and production rules which store knowledge independent of each other and with no interconnections between them, a semantic network is a highly interconnected hierarchical representation of knowledge consisting of a set of nodes connected to each other by a set of directed labeled links. Mathematically speaking, it is a labeled, directed graph. The nodes represent objects which can be facts, events, situations, actions, concepts, sets, individuals, propositions, predicates, terms, descriptions, and procedures. The links represent relationships between the objects. A semantic network provides a structure with which knowledge can be formally represented and efficiently retrieved. Retrieval and inference thus become a search for paths between nodes or a match of patterns in the network. Though semantic networks were developed for the purpose of representing the English language, it turns out to be a rather pictorial and effective tool for representing binary spatial relationships and perhaps human associative memories.

Similar to semantic networks, frames are hierarchical representations of knowledge. They in a way can be interpreted as complex semantic networks with internal structures. Frames are generally used to represent prototypical knowledge or knowledge with well-known characteristics. Differing from logic and production rules which store knowledge in small independent trunks, frames store knowledge in larger interconnected chunks (conceptual entities). A knowledge base is then a collection of frames.

A weakness common to semantic networks and frames is that knowledge representation lacks a well-defined structure. Knowledge abstraction, encapsulation, and modularity which are considered as salient features of knowledge representation are not effectively realized in semantic networks and frames. These characteristics, however, can be captured by the object-oriented approach. Under the object-oriented framework, the real world is represented as a hierarchical set of objects linked by some protocols of communication among them. An object is an independent entity consisting of its own attributes (variables) and methods (operations, procedures, actions) that work on them. The attributes depict the state of an object and the methods are used for intraobject controls and interobject communications. The object-oriented approach possesses the advantages of knowledge encapsulation and inheritance. It can make spatial knowledge compact and facilitate inference.

In addition to the major formalisms discussed above, other paradigms such as conceptual dependency, script, logical programming, case-based reasoning, and natural language processing are also potentially useful frameworks for spatial knowledge representation and inference. Though each of the formalisms has its unique structure, they are in some ways related and can be made complementary to each other. It is possible to develop hybrid knowledge representation languages which can take advantages of the salient features of individual languages.

Expert Systems for Domain-Specific Problems

The major challenge in the design of intelligent spatial reasoning systems lies on our ability to build into a system mechanisms to memorize and use knowledge extracted from domain-specific experts, and to automatically acquire knowledge from voluminous but incomplete information through learning by examples. Such system can facilitate machine reasoning in a commonly encountered environment where knowledge (in terms of explicitly specified rules) and information (in the form of raw data, digitized maps, remotely sensed images, etc.) are mixed together. The situation is equivalent to human reasoning with previously taught or acquired knowledge that sits in our memories, and knowledge to be acquired by self-learning from our everyday experience.

In the recognition and classification of remotely sensed images, for instance, instead of statistical methods, there may be a set of rules obtained from remote-sensing experts that can be used to accomplish the task. Thus, reasoning with a mixture of rules and data is a general phenomenon rather than an exception. The advancement of artificial intelligence attempts to design various means for the achievement of such purpose. Expert systems are perhaps a long-standing artificial intelligence product of such undertaking.

Building expert systems from scratch is time-consuming. The general approach is to develop a generic expert system development tool, called a shell, with which expert systems for various problems can be effectively constructed. The shell can assist domain experts to build expert systems to solve specific spatial problems. Using a fuzzy-logic-based expert system shell (FLESS) as an example, it not only can manage rule-based inference under certainty and uncertainty, but can also utilize procedural knowledge, GIS, and remote-sensing operations in an interactive and integrative manner.

Specifically, the shell facilitates the construction of rule-based spatial expert systems with intelligence and decision-making capabilities. Any mix of fuzzy and nonfuzzy terms and uncertainties in rules and facts are allowed in the system. It can employ fuzzy logic to handle approximate reasoning and fuzzy numbers to handle imprecision and certainty factors in rules.

The key features of the shell are knowledge-base development, tracing, dynamic link library (DLL) technology, and operations. Knowledge-base development is the part of the shell which handles the construction of domain-specific knowledge bases necessary for securing knowledge of a specific problem. Knowledge base is built by the knowledge acquisition subsystem of the shell. It is responsible for storing knowledge entities such as objects, rules, and fuzzy terms acquired through the knowledge acquisition subsystem. Knowledge can be hard encoded from domain-specific experts. The acquired knowledge entities, representing expertise, provide knowledge for the inference engine to perform consultations. The knowledge-base development part of the tool consists of management modules for objects, fuzzy terms, rules, and inference options.

Tracing is the part which provides inferential strategies and review management facilities. After defining a knowledge base, consultation can be performed. The system will trace the rule base according to the goal and the tracing method set by users. There are three basic components in the consultation driver. They are the inference engine, the linguistic approximation routine, and the review management module. The inference engine of the shell supports both forward (data-driven) and backward (goal-directed) reasoning. Linguistic approximation is a process that maps the set of fuzzy subsets onto a set of linguistic values or expressions used in decision-making. The review management module monitors and traces relevant rules and facts (objects with inferred values) at any time during consultation. It is also responsible for tracing the reasoning chain when explanations are required. The system provides two types of explanations. Users can ask why a fact is required by the system and how a fact is established. This module can also handle what-if reviews which find out what conclusions will be deduced if certain facts are changed. The feature is especially useful for decision-makers to evaluate different spatial options or scenarios. The ability to provide consultations is an important part of an intelligent system and FLESS is equipped with such capability.

DLL technology is the part which manages communications with the outside environment such as external libraries and databases. In FLESS, function calls in rules are implemented by the methods of DLL, and it provides a mechanism so that data can be exchanged between an application (e.g., a GIS application involving the use of mathematical models; automatic knowledge acquisition by neural networks; or genetic algorithms) and the shell. The application can pass the data required for rule-based inference to the shell. The shell will implement the inference based on the predefined knowledge base and the given data. After making an inference, the shell will display the result or pass it back to the applications for further analysis.

Operations is the part that manages systems operations and file manipulations. There is an assortment of operations in the shell. Pull-down menu and toolbox are major operations for the manipulation of knowledge bases and inference. Under pull-down menu, file operations of the knowledge base include the building of a new knowledge base, retrieving an existing knowledge base, editing a knowledge base, saving a knowledge base, and setting system preferences for external editors. Furthermore, operations for consulting a knowledge base throughout an inferential process are implemented. Help menus for objects, rules, fuzzy terms, and helps are also provided.

Acquisition of Spatial Knowledge

Symbolic approaches to spatial knowledge representation and inference are discussed and applied to construct expert systems in the previous section. Logic (standard and nonstandard), production systems, semantic networks, frames, object-oriented programming, and their hybrids all belong to symbolic systems in which knowledge is modeled by symbols. Intelligence is realized by a symbolic structure in which symbols can be manipulated and reasoning can be made. The advantages of the symbolic approaches are that they provide a structured representation of knowledge so that processing elements corresponding to meaningful concepts and inference can be traced and explained. The approach is thus a top-down approach which gives consensus knowledge to a system by instructing it what to feel and respond without having to gain knowledge through experience. It corresponds to our learning of spatial knowledge from a domain-specific expert.

The symbolic approaches are, however, insufficient or inappropriate to construct intelligent spatial decision support system (SDSS) in general. Symbolic systems are usually intolerant to faults and inefficient in automatic knowledge acquisition and learning via sensation and experience. Intelligence is not attained through evolution, like human race, of these systems. Modeled after the human brain, the neural network approach, on the other hand, provides a mechanism for knowledge acquisition. A neural network is a massively parallel structure in which a large number of processing units (called neurons), each performing simple computational tasks, are connected together to represent and acquire knowledge, and to make inference. Geographical information is distributed to the neurons, and knowledge is encoded by connection strengths and acquired through a learning process. It is, more or less, a bottom-up approach and is regarded by some as an efficient model for recognition, content addressable memory, and associative reasoning. Differing from the symbolic systems, neural network models appear to have stronger learning capability and higher tolerance to faults. Their dynamic behaviors and reasoning processes are, however, difficult to explain. Attainment of intelligence generally takes a longer time and tends to fail in complex situations. This, however, is partially solved by the recent developments in deep learning, particularly in image recognition and object tracking. Convolutional neural networks and their hybrids are perhaps the most successful advance in deep learning.

Parallel to neural networks, evolutionary computation which imitates biological evolution can also be used for automatic spatial knowledge acquisition through learning by examples via a parallel multipoint stochastic search mechanism involving generally the selection, crossover, and mutation operations. We can, for example, learn rules by evolutionary computational models. It can also be employed to evolve the topological structures and to optimize the parameters of deep neural networks.

One may wonder why we need neural networks or evolutionary paradigms for geographical analysis. The answer to the question is mainly twofold. First, as discussed above, the neural network or evolutionary paradigm provides an alternative framework for spatial knowledge representation and inference. Problems such as spatial feature extraction and pattern recognition which cannot be appropriately modeled by the symbolic approaches may be effectively captured by these distributive models. Second, they may serve as a means to acquire spatial knowledge (which may be in symbolic form) through automatic learning.

Taking information, structured and unstructured knowledge as a whole in geographical analysis, their coordination may take on the format depicted in Fig. 1. Sitting on top of the hierarchy is the deep knowledge which captures complicated spatial reasoning and relationships that are still, at the present moment, not easy to be automatically acquired through experience or learned by examples as advocated by neural networks, evolutionary computations, and other machine learning models. This is the type of domain-specific knowledge which can be effectively instilled by experts as symbolic or highly structured knowledge. With the advancement

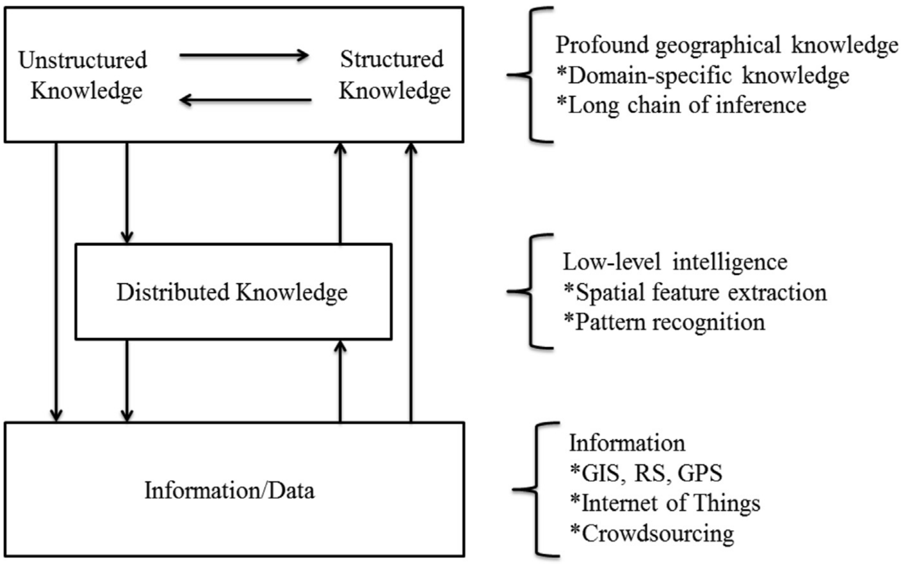

Figure 1 Coordination of knowledge and information. *GIS*, geographic information system; *GPS*, global positioning system; *RS*, remote sensing.

of deep learning in the future, there might be a chance to learn such knowledge to a certain extent. Knowledge in the second level down the hierarchy is of lower level of intelligence. It is responsible for tasks which do not require deep thinking but fast extraction or recognition of spatial features or images. It belongs to the perceptual and cognitive functions of our audio and visual faculties which efficiently detect structures and motions from data. It provides fundamental information for our in-depth thought processes. Such level of intelligence can be rather effectively imitated by neural or evolutionary computations, particularly machine learning models.

The bottom-up process is similar to our unsupervised learning process which acquires knowledge or unknown patterns without a priori knowledge about the information. Cluster analysis is a typical method. The top-down process, on the other hand, is our learning process which uses accumulated and instilled knowledge to orient our faculties to look for useful things contained in information or our everyday experience so that new knowledge can be formed.

To recapitulate, humans often reason with intuitions, values, experiences, and judgments. We tend to organize our knowledge with loosely defined concepts and structures. Reasoning may not require highly structured mathematical models but loosely structured commonsense that has been extensively studied in artificial intelligence. Nevertheless, we generally need both to solve complicated problems in complex geographical systems.

Intelligent Decision Support System—An Integration

In geographical analysis, the demand on domain-specific knowledge, technical know-hows, and accessibility to data is tremendous. It is difficult to make good decisions without powerful systems to provide, in an integrative way, supports in various phases of the decision-making process. Taking the three-phase process as an example, the system needs to support, for instance, problem diagnosis, access and scanning of databases, interpretation and monitoring of information in the intelligence phase; generation of alternatives and prediction in the design phase; and analysis of scenarios (e.g., what-ifs), explanation, and justification in the choice phase. It is almost useless if such a decision support system has no intelligence to handle information efficiently and to apply the right kind of knowledge to assist the decision-making process in a user-friendly manner.

For a system to be able to support decision-making, it has to possess a certain level of intelligence. Therefore, an SDSS should be able to reason with structured and loosely structured knowledge. They should be able to manage data and user communication efficiently and effectively. Their development calls for the utilization of artificial intelligence and knowledge engineering methods to represent and infer with spatial knowledge; software engineering techniques to manage systems development, information and control flows of models and data; and spatial information system technologies to process and display data. All these have to be integrated in a seamless manner.

To be generic and economical, instead of building an SDSS for a specific problem from scratch, we need to develop an SDSS development environment (shell or generator) so that experts can use it to build effectively and efficiently a variety of domain-specific SDSSs. That is, we should have a general development tool which decision-makers can use to customize, modify, adapt, and evolve SDSS for solving specific spatial problems.

A general architecture of such SDSS shell is depicted in Fig. 2. The core of the system, maybe an expert system shell, directs control flows and information flows of the integrated system. It provides facilities to represent and store domain-specific knowledge

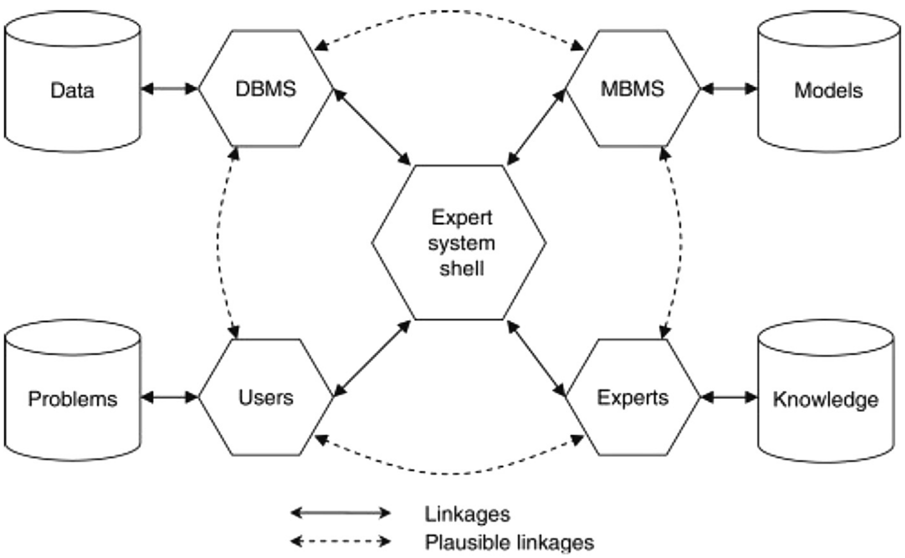

Figure 2 General architecture of an intelligent spatial decision support system. *DBMS*, database management system; *MBMS*, model base management system.

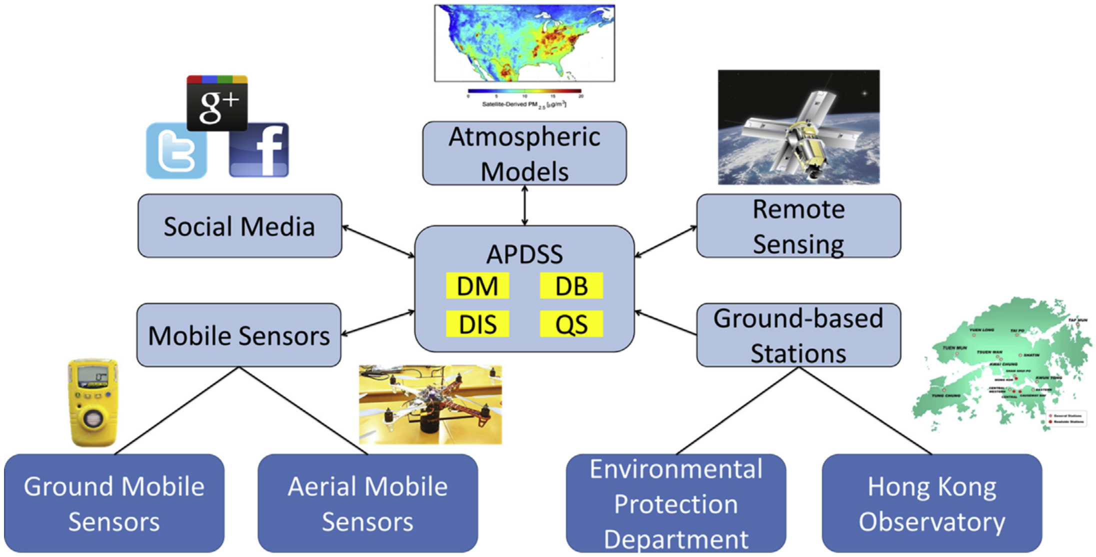

Figure 3 System architecture of the air pollution spatial decision support system. APDSS, air pollution decision support system; DB, database; DIS, display; DM, data mining; QS, query system. Adapted from Fig. 1 of Leung et al., 2018.

acquired from experts or learning examples. It can also contain meta-knowledge for inference control, systems and user interface, and external communication. The shell has in its possession inference mechanisms for reasoning with loosely structured spatial knowledge. It is the brain of the SDSS.

To utilize spatial and nonspatial data, the shell has an interface with external database management system (DBMS) such as GIS, remote sensing systems, Internet of Things (IoT), and crowdsourcing. The communication between the shell and the DBMS can be carried out by intelligent database communication methods, such as application programming interface (API).

To facilitate the utilization of externally stored procedural knowledge such as deep learning algorithms, statistical procedures, and other mathematical models an interface with a model base management system (MBMS) should be incorporated into the shell. Parallel to DBMS, MBMS organizes procedural models into an easy-to-use structure. Calls to MBMS can be invoked by meta-knowledge in the shell.

In addition to linkages to DBMS and MBMS, user-friendly interface and knowledge acquisition modules are essential parts of the shell for human–machine interaction. Web and app interface can be provided to the users and expert to ease knowledge acquisition and decision-making. Communication between DBMS and MBMS, users and experts should also be considered.

Over the years, a number of SDSSs have been developed for solving practical problems. Typical examples are fuzzy-logic-based experts systems; decision support systems for environmental management, landfill design and management, hazard monitoring; classification systems for remotely sensed images based on fuzzy logic; and systems for flood simulation and damage assessment. All of these systems are built fully or partly by the generic SDSS shell discussed above, and they all integrate spatial and nonspatial data, as well as structured and/or unstructured geographical knowledge. Though the applications are problem and site specific, the knowledge and technology are transportable and can be made useful to other places of the world.

With the advancement of information and communication technologies, through the electronic super highway, information is ubiquitous and will take on a highly distributed, instantaneous, and dynamic form. Our SDSS needs to take advantage of such multitype, multisource, and multiscale information in near real time or real time. Taking air pollution monitoring and analysis as an example, a SDSS may take on the structure depicted in Fig. 3. The system integrates remote sensing, station-based air pollution and weather measurements (including land use GIS), mobile sensors (ground or aerial), IoT, air pollution simulation models, and social media to derive a complete profiling of air pollution with hard scientific data and social opinions. Such a framework should be suitable to the analysis and monitoring of other geographical structures and processes.

Conclusion

In the future, geographical analysis will increasingly rely on information and communication technology. We will have to find spatial structures and processes from very large databases which are multisource, multiscale, heterogeneous, imperfect, dynamic, and ubiquitous. Creating spatial data mining and knowledge discovery capability for big and open data is thus a necessity in the development of intelligent SDSS. In addition to the conventional information, IoT, social media, and crowdsourcing will play a dominant role in decision-making in space and time. The globalization of information and decision-making is rapidly taking place. How to discover useful and nontrivial knowledge in such information environment is thus crucial in this knowledge age. Effective utilization and integration of information from various sources with geographical knowledge acquired through our in-depth analysis of the human and physical processes in space and time will greatly enhance our understanding of the ever changing environment and chart out courses of action for the sustainable development of human race. Artificial intelligence, in cooperation with geographical knowledge and big data, will continue to play a major role in the development of intelligent systems to support our spatial decision-making process.

See Also: Evolutionary Algorithms; Fuzzy Set and Fuzzy Logic; Geospatial Intelligence.

Further Reading

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