NCAI2011, 13-14 May 2011, Jaipur, India

International Journal of Soft Computing and Engineering (IJSCE)
ISSN: 2231-2307, Volume-1, Issue-NCAI2011, June 2011

Knowledge Representation

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***Abstract*— Artificial intelligence research has foundered on the issue of representation. When intelligence is approached in an incremental manner, with Strict reliance on interfacing to the real world through perception and action, reliance on representation disappears. In this paper we outline our approach to incrementally building complete intelligent Creatures. The fundamental decomposition of the intelligent system is not into independent information processing units which must interface with each other via representations. Instead, the intelligent system is decomposed into independent and parallel activity producers which all interface directly to the world through perception and action, rather than interface to each other particularly much. The notions of central and peripheral systems evaporate very thing is both central and peripheral. Based on these principles we have built a very successful series of mobile robots which operate without supervision as Creatures in standard office environments.**

In this paper, we develop a knowledge representation model for the innovative intelligent retrieval of legal cases, which provides effective legal case management. In our representation model, an issue may need to be further decomposed into sub-issues; factors are categorized into pro-claimant and pro-respondent factors; and contextual features are also introduced to help retrieval. These extensions can effectively reveal the factual relevance between legal cases. Based on the knowledge representation model, we propose the IPF scheme for intelligent legal case retrieval. Experiment and statistical analysis have been conducted to demonstrate the effectiveness of the proposed representation model and retrieval scheme.

***Index Terms*—Genetic Algorithm (GA),Knowledge Management (KM)**

INTRODUCTION

Knowledge is a general term.
Knowledge is a progression that starts with data which is of limited utility.

 By organizing or analyzing the data, we understand what the data means, and this becomes *information*.
 The interpretation or evaluation of information yield knowledge.
 An understanding of the principles embodied within the knowledge is wisdom.

Manuscript received May 27, 2011.

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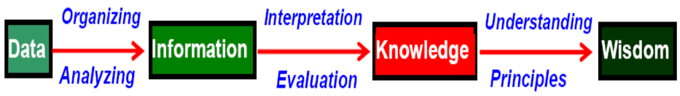
KNOWLEDGE PROGRESSION



■ **Data** is viewed as collection of disconnected facts.
Example: It is raining.

■ **Information** emerges when relationships among facts are established and understood; "who", "what", "where", and "when".
Example: The temperature dropped 15 degrees and then it started raining.

■ **Knowledge** emerges when relationships among patterns are identified and understood; "how".
Example: If the humidity is very high and the temperature drops substantially, then atmospheres are unlikely to hold the moisture, so it rains.

■ **Wisdom** is the pinnacle of understanding, uncovers the principles of relationships that describe patterns. "why".
Example : Encompasses understanding of all the interactions that happen between raining, evaporation, air currents, temperature gradients, changes, and raining.

KNOWLEDGE MODEL

The model tells, that as the degree of "connectedness" and "understanding" increase, we progress from *data* through information and knowledge to wisdom.

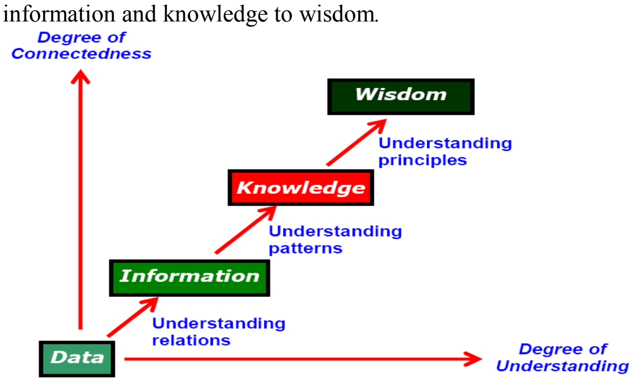


Fig. Knowledge Model

The model represents transitions and understanding.

 The transitions are from data, to information, to knowledge, and finally to wisdom;

 the understanding support the transitions from one stage to the next stage. The distinctions between data, information, knowledge, and wisdom are not very discrete.

 Data and information deal with the past; they are based on the gathering of facts and adding context.

 Knowledge deals with the present that enable us to perform.

 Wisdom deals with the future, acquire vision for what will be, rather than for what is or was.

KNOWLEDGE TYPE

Knowledge is categorized into two major types: *Tacit* and *Explicit*.

 Term *"Tacit"* corresponds to *informal or implicit* type of knowledge,

 Term *"Explicit"* corresponds to *formal* type of knowledge.

Tacit knowledge	**Explicit knowledge**
Exists within a human being; it is embodied.	Exists outside a human being; it is embedded.
Difficult to articulate formally	Can be articulated formally.
Difficult to share/communicate	Can be shared, copied, processed and stored.
Hard to steal or copy	Easy to steal or copy
Drawn from experience, action, subjective insight.	Drawn from artifact of some type as principle, procedure, process, concepts.

KNOWLEDGE TYPE

Cognitive psychologists sort knowledge into *Declarative* and Procedural category and some researchers added strategic as a third category.

Procedural knowledge	**Declarative knowledge**
Knowledge about "how to do Something"; *e.g.,* to determine if Peter or Robert is older, first find their ages.	Knowledge about "that something is true or false". e.g., A car has Four tyres; Peter is older than Robert;.
focuses on tasks that must be performed to reach a particular objective or goal.	refers to representations of objects and events; knowledge about facts and relationships;
examples : procedures, rules, strategies, agendas, models.	*Example:* concepts, objects, facts, propositions, assertions, semantic nets, logic and descriptive models.

FRAMEWORK OF KNOWLEDGE REPRESENTATION

Computer requires a well-defined problem description to process and also provide well-defined acceptable solution. To collect fragments of knowledge we need: first to formulate description in our spoken language and then represent it in formal language so that computer can understand. The computer can then use an algorithm to compute an answer. This process is illustrated below.

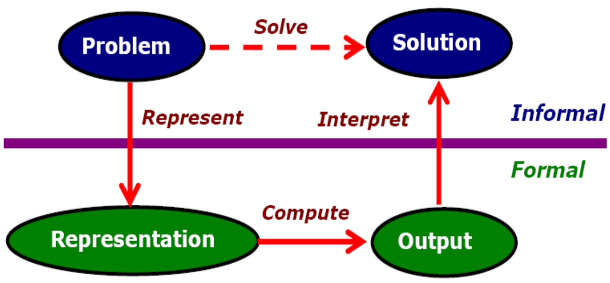
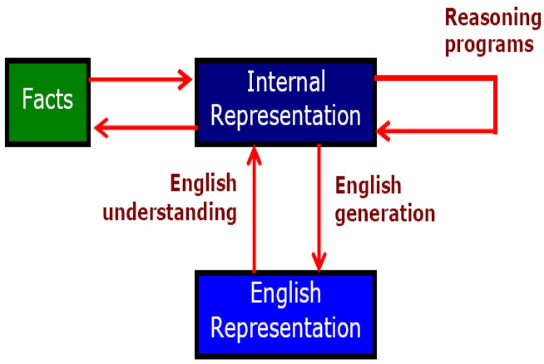


Fig. Knowledge Representation Framework

The steps are :
− The informal formalism of the problem takes place first.
− It is then represented formally and the computer produces an output.
− This output can then be represented in a informally described solution

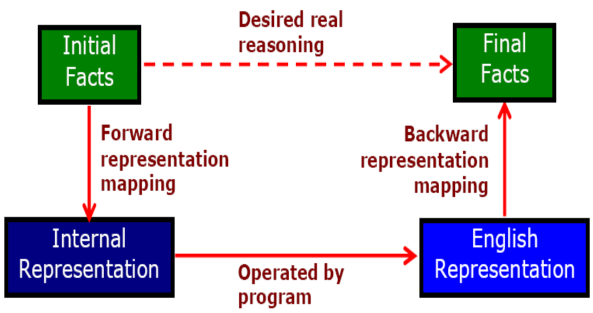
MAPPING BETWEEN FACTS AND REPRESENTATION

Knowledge is a collection of "facts" from some domain. We need a representation of facts that can be manipulated by a program. Normal English is insufficient, too hard currently for a computer program to draw inferences in natural languages. Thus some ***symbolic representation is necessary***. Therefore, we must be able to map "facts to symbols" and "symbols to facts" using forward and backward representation mapping.



FORWARD AND BACKWARD REPRESENTATION

The forward and backward representations are elaborated below :



-The dotted line on top indicates the abstract reasoning process that a program is intended to model.
-The solid lines on bottom indicates the concrete reasoning process that the program performs.

KNOWLEDGE REPRESENTATION SYSTEM REQUIREMENTS

A good knowledge representation enables fast and accurate access to knowledge and understanding of the content. A knowledge representation system should have following properties.

◊ **Representational Adequacy:**
The ability to represent all kinds of knowledge that are needed in that domain.

◊ **Inferential Adequacy:**
The ability to manipulate the representational structures to derive new structure corresponding to new knowledge inferred from old .

◊ **Inferential Efficiency:**
The ability to incorporate additional information into the knowledge structure that can be used to focus the attention of the inference mechanisms in the most promising direction.

◊ **Acquisition Efficiency:**
The ability to acquire new knowledge using automatic methods wherever possible rather than reliance on human intervention.

KNOWLEDGE REPRESENTATION SCHEMES

There are four types of Knowledge representation - *Relational, Inheritable, Inferential, and Declarative/Procedural.*

◊ **Relational Knowledge :**
− provides a framework to compare two objects based on equivalent attributes.
− any instance in which two different objects are compared is a relational type of knowledge.

◊ **Inheritable Knowledge**
− is obtained from associated objects.
− it prescribes a structure in which new objects are created which may inherit all or a subset of attributes from existing objects.

◊ **Inferential Knowledge**
− is inferred from objects through relations among objects.
− e.g., a word alone is a simple syntax, but with the help of other words in phrase the reader may infer more from a word; this inference within linguistic is called semantics.

◊ **Declarative Knowledge**
− a statement in which knowledge is specified, but the use to which that knowledge is to be put is not given.
− e.g. laws, people's name; these are facts which can stand alone, not dependent on other knowledge;

◊ **Procedural Knowledge**
− a representation in which the control information, to use the knowledge, is embedded in the knowledge itself.
− e.g. computer programs, directions, and recipes; these indicate specific use or implementation;

ISSUES IN_ KNOWLEDGE REPRESENTATION

The fundamental goal of Knowledge Representation is to facilitate inference (conclusions) from knowledge. The issues that arise while using KR techniques are many. Some of these are explained below.

◊ ***Important Attributes:***
Any attribute of objects so basic that they occur in almost every problem domain?

◊ ***Relationship among attributes*****:**
Any important relationship that exists among object attributes?

◊ ***Choosing Granularity*** **:**
At what level of detail should the knowledge be represented?

◊ **Set of objects:**
How sets of objects be represented?

◊ ***Finding Right structure:***
Given a large amount of knowledge stored, how can relevant parts are accessed?

GENETIC ALGORITHM CONCEPT

Genetic algorithms were proposed by Holland to solve search and optimisation problems. Strong theoretical foundations which depend on a binary string representation of the possible solutions based on the schema theorem had been developed by Holland. According to , **GAs** are stochastic algorithms whose search methods model some natural phenomena: genetic inheritance and Darwinian strife for survival.

The power of GAs comes from their robustness in representing and solving problems. They can solve a wide range of problems. However, they are not guaranteed to find the optimal solution to a problem. They provide near optimal solution to the problem. In this paper, we apply the **GA** technique to help us solve the knowledge refinement problem. What we find is that GA technique gives us more optimal solution than the gradient descent method used in the traditional **NN.** The differences between the GA and the gradient method are briefly mentioned in the following sections.

4.1 The Genetic Algorithm Technique

GAs belongs to a class of probabilistic algorithms. They are different from the traditional random search algorithm because they possess the elements of directed and stochastic search. During their problem solving process they maintain a population of potential solution. They achieve a balance between the exploitation and exploration of the search space.

The Gradient Search Methods

This methods use the gradient information of a function to guide them perform the searching. It is well known that in **NN** if the activation function is no differentiable, these gradient methods are doomed to fail.
Furthermore, these methods work well under the condition that the function (e.g., the error function) used in **NN** has only one optimal solution. In many real applications which applying **NN** technique what we found is that the error functions are multi-modal. So the traditional back propagation learning algorithm which adopted the gradient descent method can easily get stuck in a local minimum. Furthermore, these methods only exploit the best solution and ignore the exploration of the search space.

REPRESENTATION OF KNOWLEDGE PARAMETERS USING A GENETIC ALGORITHM

In order to solve a problem using genetic algorithm, we have to consider the following five components in a **GA:**

- a way to represent potential solutions to the problem using a GA.
- A way to create an initial population of potential solutions,
- A function which evaluates the fitness of each of the potential solution,
- Genetic operators such as crossover and mutation that change the composition of children of old generation, and
- Values for various parameters that is required in the genetic algorithm. This parameter includes population size, probabilities of crossover and mutation.

Potential Solution Representation

We want to refine or tune is a real value within the range [0,1]. It **is** necessary to consider how to represent these parameters in a genetic algorithm. Representation of problem by a genetic algorithm is the first and most important step. In our proposed approach, a binary vector chromosome is used to represent these real value parameters. The required precision of these parameters determines the length of the vector. Here we assume that a precision of four places after the decimal point.

Since all our parameters are within the range [0,1], we have a length of 1 for the domain of variable x. The range [0,1] in our case should therefore be divided into at least 1*10000 equal size ranges. This requires 14 bits for the binary vector.

$$0 < 10000 <= 2^{14} = 16384$$

The mapping from a binary string say $<a_{13}, a_{12}, \ldots, a_0>$ into a real value x in the range [0.,1] involves two steps:

- change the binary string $<a_{13}, a_{12}, \ldots, a_0>$ from the base 2 to base 10

  $$(<a_{13}, a_{12}, \ldots, a_0>)_2 = (\Sigma^{13}_{i=0}\, a_i * 2^i)_{10} = x'$$

- compute a corresponding real value x:

  $$x = 0.0000 + x' * 1/(2^{14} - 1)$$

where 0.0000 represents the lower limit of the domain and 1 in the numerator represents the length of the domain.

where 0.0000 represents the lower limit of the domain and 1 in the numerator represents the length of the domain. To get a clear picture of this equation, we present an example as follows: say we have a vector (1 100001 101 11 10) which represents a real number 0.7636 which could be computed by the following steps,

x'=(11000011011110),= 12510
$x = 0.0000 + 12510 * 1/(2^{14} - 1) = 0.7636$

when the chromosomes are (00000000000000) and (1 11 11 11 11 11 11 1), they represent the boundary of the parameters we intend to refine, i.e., 0 and 1 respectively.

Creation Of Initial Population

Since our parameters are real number values, it is easy to create the initial population by generating each chromosomes as a binary vector of 14 bits. All the initial population can be generated randomly by using some random number generation functions in a programming language such as C++.

Fitness Function Representation

One may notice in section ***2*** that every knowledge representation parameter has its own role in fuzzy production rule. It is a good start to firstly present a fuzzy reasoning method which makes use of these parameters. In order to draw a conclusion from a give factor, we have to compare the degree of similarity by using degree of subsethood [4] as follows:

$$S_{DS}(A'_i, A_i) = M(A'_i \cap A_i) / M(A'_i)$$

where $M(A'_i)$ is the sigma-count of A'_i, i.e., the size or cardinality of A'_i, and $M(A'_i \cap A_i)$ is the sigma-count of the intersection of A'_i and A_i. It is observed that $S_{DS}(A'_i, A_i)$, which is the degree of subsethood of A'_i in A_i, differs from $S_{DS}(A_i, A'_i)$ which is the degree of subsethood of A_i in A'_i and $0 \le S_{DS}(A'_i, A_i) \le 1$. For instance, if A'_i is a subset of A_i or $A'_i = A_i$, then $S_{DS}(A'_i, A_i) = 1$. If A_i has all its fuzzy membership values equal to zero, then $S_{DS}(A'_i, A_i) = 0$ [10].

According to Yeung [11], the rule will be executed if the computed value of the degree of subsethood $S_{DS}(A'_i, A_i)$ is greater than or equal to its threshold value λ_{Ai} for all A_i. We first define the overall degree of subsethood function S_o as follow:

$$S_o = \Sigma^n_{i=1}\, S_{DS}(A'_i, A_i) * LW_i / (\Sigma^n_{j=1} LW_j) \quad (2)$$

B′ is given by:

$$B' = \mathrm{Min}\,[1, B/S_o].$$

For a conjunctive FPR, B′ can be drawn as:

If $S_{DS}(A'_i, A_i) \ge \lambda_{Ai}$, for all $1 \le i \le n$, then $B' = \min[1, B/S_o]$.

The certainty factor of the drawn consequent B′ is given by:

$$CF_{B'} = CF_R * \min[CF_{F1}, CF_{F2}, \ldots, CF_{Fn}].$$

Backpropagation (backprop) is a well accepted and well known learning algorithm in NNs. One of its drawbacks is that it is easy to get stuck to a local minimum. It is due to the fact that the backpropagation makes use of the gradient descent method. To overcome this problem, we replace the gradient descent method by a GA. The fitness function of our proposed approach is to minimise the error rate in the backprop, i.e., minimise the function F(n). The function can be presented as:

$$\min F(n) = \Sigma^n_{i=1}\, \mathrm{Delta}(i) / n \quad (3)$$

where n is the number of training sample used in NN and Delta(i) is the error of the training sample i when presented to a NN for training.

KNOWLEDGE MANAGEMENT PROBLEMS

The problems identified cover the four KM processes of creation, storage/retrieval, transfer and application. As junior knowledge workers, most respondents expressed the importance of KM and KM problems in their organizations from a knowledge receiver perspective. As knowledge receivers, they desire standardized procedures and specific guidance from supervisors or the organization. In general, explicit knowledge is helpful but usually missing in their work, so the KM problems identified through this viewpoint are more related to explicit knowledge creation, storage, transfer and application.

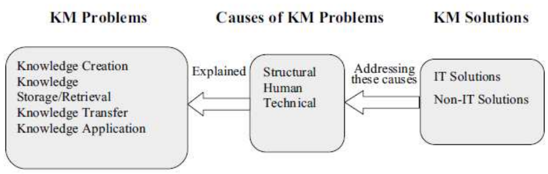


Figure 1: The KM Problems-Causes-Solutions Framework

Knowledge creation:

"Work procedures of work are not standardized"; "Staff seldom share knowledge"; "The information in the system is not enough"; "The skill of selling various products can only be learned by new employees when they face the clients".

Knowledge storage/retrieval

"Staff always repeat the same mistake in issuing credit letter; this kind of mistake should be stored in the system or as a working guideline. However, we did not have such practice"; "General staff cannot access Internet for work purposes. Only senior colleagues have Internet or email functions"; "The company loses knowledge after retirement of staff"; "The special selling skills cannot be learned from colleagues because of the high turnover rate".

Knowledge transfer
"Mentees can't get enough information from mentors in coaching"; "There is a wide communication gap between the senior and junior staff. They (senior staff) do not provide us (junior staff) sufficient knowledge"; "There is no training provided in the work, which leads a long time for new employees to catch up the job"; "Employees in different divisions have different work practices, so there is a lack of inter-division communication"; "Most of our colleagues are very dependent on me. I always spend a lot of time to communicate with them or answer their questions several times. They feel convenient and have developed the habit of asking me questions by phone again and again"; "The company lacks a well organized computer system for checking or updating information".

Knowledge application
"There are different departments in my law firm. Staff cannot identify the major activities performed by each lawyer. For example, in a commercial department, there are different cases like trademark & patent, mortgage, listing, etc. Different lawyers are responsible for different practices although all these practices are classified into commercial cases. It is difficult for us (legal secretaries) to locate experts and apply different kinds of expertise in different contexts". "Each officer possesses unique and specialist knowledge, but it is difficult for junior employees to understand and apply them to their work".

CAUSES OF KM PROBLEM

Though most organizations have recognized the existence of KM problems, the causes of problems need careful analysis if organizations are to conduct corrective actions. Our findings indicate that the causes attributed to the KM problems identified can be classified into three dimensions as below.

Structural (organizational) related causes
Many respondents mentioned that "lack of training", "limited resources" and "lack of dedicated time for discussion" contribute to knowledge creation, storage and transfer problems.

The lack of organizational incentive to create and transfer knowledge appears to be the major explanation for KM problems. One respondent pointed out that "The management does not apply the encouragement/punishment system properly".

The organizational structure is another root cause of KM problems. One respondent indicated "The hierarchy of my company is too flat and is not well managed. Such a structure makes knowledge transfer difficult". Similarly, "the bureaucratic way of work" is also considered as evidence for the establishment of barriers to knowledge creation and transfer.

The inherent organizational culture is a critical factor contributing to KM problems. Some respondents indicated that "there is no good communication atmosphere in the company, so there is not enough sharing among colleagues". "Inter-departmental conflicts hinder knowledge retrieval and transfer, especially for the knowledge transfer among different departments".

Human related causes
The respondents recognize that, in KM systems (KMS), the facilitator plays an important role. When this role is missing, the KMS is doomed to fail: "no specific person is responsible for the knowledge updating work. The information in the system is outdated and no longer applicable to current work practice".

According to the survey findings, individuals may not be willing to contribute documents to the KMS because they are "afraid to share their knowledge given the possibility of losing their power and position". Similarly, "each staff would like to keep their knowledge in their own place", which leads to a lack of standardized practice in knowledge storage and transfer.

Another significant concern related to the knowledge conversion problems lies in the knowledge externalization processes. The respondents thought that "staff feel too difficult to express their experiences, although they know their experiences are very useful for junior staff. Knowledge is too difficult to be translated to text". In China, guanxi or personal relationships, is a determining influence in most areas of human activity, including KM (Fu et al. 2006). Respondents pointed out that "inter-personal conflicts", competition among staff", "lack of trust & relationships" and "intra-departmental conflicts" complicate knowledge transfer.

Technical related causes
The respondents agree that IT is useful in managing knowledge and consider it as an enabler for KM. However, it appears that from the junior knowledge workers' perspective, IT-based KMS have not yet been adopted in Hong Kong organizations, at least for low-level or operational-level work, as illustrated by the following quotations. "The system is outdated and some work has to be done manually" which contributes to KM storage problems. "The current IT system cannot facilitate the changes of KM concepts in the company". "Organizational IT systems do not support knowledge management".

Although some organizations have used information systems (usually intranets), the poor ease of use the non-usefulness of the KMS contribute to the lagging KM practice, as indicated by the quotations: "The capacity of the hardware and software support is not enough". "The system is slow and always busy; sometimes it hangs". "Security of the KMS is a big concern". "The flow of using the KMS is not convenient". "The KMS is too complex to use".

POTENTIAL SOLUTIONS OF THE KM PROBLEMS IDENTIFIED

According to the survey findings, the respondents suggest various corrective actions that can be taken to resolve the identified KM problems, encompassing both IT and non-IT solutions.

We discuss these solutions below. With regard to IT solutions, for instance "organizational fragmentation", which is related to the problem of knowledge storage/retrieval and transfer, respondents suggest "systems to allow coordination/cooperation". The establishment of a knowledge expert list and corporate libraries is a starting point to solve the KM problems: "set up the expert system or knowledge database as so the junior employees can find a way to look for knowledge".

Regarding the difficulties in knowledge creation and codification, they recommended "the use of multimedia to briefly describe what is the basic background knowledge". With respect to the lack of standardized work procedures, most junior knowledge workers suggested "uploading the memo in the e-portal systems, so everyone can retrieve and follow the guidelines", as well as "set up an electronic library to store the training materials or such training manuals". A customized KMS would also be appreciated: "the IT department can provide a user manual and appropriate systems fit for departmental requirements so that the company can better manage their knowledge". The identification shown in the KMS is also a critical concern in the IT solution as several respondents pointed out that "the company should provide a platform for staff to submit knowledge anonymously" and "the knowledge contributors should have the right to choose a real name or a pseudonym".

With regard to non-IT solutions, the encouragement of communication and involvement from the organization is most frequently mentioned by respondents. For example, they suggest "reward staff who are willing to share knowledge", "set up a compensation scheme for the time involved in contributing knowledge", "arrange more seminars and upload all these seminar materials online", and "schedule a time to share/contribute/read knowledge in the KMS". Some respondents also suggest ways to standardize work practices such as "all staff need to write a guideline of their work on paper and then file it", "the company should tell staff to put their knowledge and information in the same place before they start work", "managers can assign suitable staff to write down knowledge such as good working examples and store it properly".

CONCLUSION

In conclusion, I would like to underline again the necessity of a strongly inter disciplinary perspective within the KR community. I hope to have shown that disciplines like philosophy and linguistic can offer a concrete contribution to the everyday practice of knowledge engineering, as they seem to shed some new light to a crucial AI problem like the representation of commonsense reality. We argued that a knowledge representation plays five distinct roles, each important to the nature of representation and its basic tasks.

These roles create multiple, sometimes competing demands, requiring selective and intelligent trade-offs among the desired characteristics. These five roles also aid in clearly characterizing the spirit of the representations and the representation technologies that have been developed. For the practice of knowledge representation work, the view suggests that combining representations is a task that should be driven by insights about how to combine their theories of intelligent reasoning, not their implementation mechanisms. The view also urges the understanding of an indulgence of the fundamental spirit of representations. We suggest that representation technologies should not be considered as opponents to be overcome, forced to behave in a particular way, but instead, they should be understood on their own terms and used in ways that rely on the insights that were their original inspiration and source of power.

The perspective of junior knowledge workers is different from the general understanding of the management of knowledge development processes. Our findings indicate that this perspective focuses more on knowledge storage/retrieval and transfer than knowledge creation and application. As knowledge receivers, junior knowledge workers expect to follow standardized work practices or have some explicit knowledge to learn. Such KM should be done in the process of knowledge storage/retrieval and transfer.

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