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Intelligent Agents

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Abstract: ***Computer systems are becoming commonplace; indeed, they are almost ubiquitous. We find them central to the functioning of most business, governmental, military, environmental, and health-care organizations. They are also a part of many educational and training programs. But these computer systems, while increasingly affecting our lives are rigid, complex and incapable of rapid change. To help us and our organizations cope with the unpredictable eventualities of an ever-more volatile world, these systems need capabilities that will enable them to adapt readily to change. They need to be intelligent. Our national competitiveness depends increasingly on capacities for accessing, processing, and analyzing information. The computer systems used for such purposes must also be intelligent. Health-care providers require easy access to information systems so they can track health- care delivery and identify the most recent and effective medical treatments for their patients' conditions. Crisis management teams must be able to explore alternative courses of action and support decision making. Educators need systems that adapt to a student's individual needs and abilities. Businesses require flexible manufacturing and software design aids to maintain their leadership position in information technology, and to regain it in manufacturing.***

Keywords: artificial intelligence, knowledge, earth centric model.

I. INTRODUCTION (ARTIFICIAL INTELLIGENCE)

(AI) is a field of study based on the premise that intelligent thought can be regarded as a form of computation - one that can be formalized and ultimately mechanized. To achieve this, however, two major issues need to be addressed. The first issue is knowledge representation, and the second is knowledge manipulation. Within the intersection of these two issues lies mechanized intelligence Section 2 describes these issues. Section 3 includes risks of artificial intelligence. And in section 4 we concluded the whole paper.

II. ISSUES OF ARTIFICIAL INTELLIGENCE

A. KNOWLEDGE REPRESENTATION

It has long been recognized that the language and models used to represent reality profoundly impact one's understanding of reality itself. When humans think about a particular system, they form a mental model of that system and then proceed to discover truths about the system. These truths lead to the ability to make predictions or general statements about the system [1]. However, when a model does not sufficiently match the actual problem, the discovery of truths and the ability to make predictions becomes exceedingly difficult.

A classic example of this is the pre-Copernican model in which the Sun and planets revolved around the Earth. In such a model, it was prohibitively difficult to predict the position of planets. However, in the Copernican revolution this Earth-centric model was replaced with a model where the Earth and other planets revolved around the Sun. This new model dramatically increased the ability of astronomers to predict celestial events. Arithmetic with Roman numerals provides a second example of how knowledge representation can severely limit the ability to manipulate that knowledge. Both of these examples stress the important relationship between

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knowledge representation and thought. Through artificial intelligence, engineers and computer scientists are capable of creating machines that perform dangerous tasks in place of humans. Here, a police robot handles a live bomb. In AI, a significant effort has gone into the development of languages that can be used to represent knowledge appropriately. Languages such as LISP, which is based on the lambda calculus, and Prolog, which is based on formal logic, are widely used for knowledge representation. Variations of predicate calculus are also common languages used by automated reasoning systems. These languages have well-defined semantics and provide a very general framework for representing and manipulating knowledge

B. KNOWLEDGE MANIPULATION

Many problems that humans are confronted with are not fully understood. This partial understanding is reflected in the fact that a rigid algorithmic solution—a routine and predetermined number of computational steps— cannot be applied. Rather, the concept of search is used to solve such problems. When search is used to explore the entire solution space, it is said to be exhaustive. Exhaustive search is not typically a successful approach to problem solving because most interesting problems have search spaces that are simply too large to be dealt with in this manner, even by the fastest computers. Therefore, if one hopes to find a solution (or a reasonably good approximation of a solution) to such a problem, one must selectively explore the problem's search space

The difficulty here is that if part of the search space is not explored, one runs the risk that the solution one seeks will be missed. Thus, in order to ignore a portion of a search space, some guiding knowledge or insight must exist so that the solution will not be overlooked. Heuristics is a major area of AI that concerns itself with how to limit effectively the exploration of a search space. Chess is a classic example where humans routinely employ sophisticated heuristics in a search space. A chess player will typically search through a small number of possible moves before selecting a move to play. Not every possible move and countermove sequence is explored. Only reasonable sequences are examined. A large part of the intelligence of chess players resides in the heuristics they employ

A heuristic-based search results from the application of domain or problem-specific knowledge to a universal search function. The success of heuristics has led to focusing the application of general AI techniques to specific problem domains. This has led to the development of expert systems capable of sophisticated reasoning in narrowly defined domains within fields such as medicine, mathematics, chemistry, robotics, and aviation[2].

Another area that is profoundly dependent on domain-specific knowledge is natural language processing. The ability to understand a natural language such as English is one of the most fundamental aspects of human intelligence, and present s one of the core challenges for the AI community. Small children routinely engage in natural language processing, yet it appears to be almost beyond the reach of mechanized computation. Over the years, significant progress has been made in the ability to parse text to discover its syntactic structure. However, much of the meaning in natural language is context-dependent as well as culture-dependent, and capturing such dependencies has proved highly resistant to automation.

III. RISKS IN ARTIFICIAL INTELLIGENCE

A. GLOBAL RISK

Providing insights to support informed decision making is the primary objective of Risk Management. In practice, Risk Management concentrates on performing bottom-up, detailed, continuous assessment of risk and opportunity. It focuses on addressing the day-to-day operational risks that a program faces. Risk Management follows a two-stage, repeatable and iterative process of assessment (i.e., the identification, estimation and evaluation of the risks confronting a program) and management (i.e., the planning for, monitoring of, and controlling of the means to eliminate or reduce the likelihood or consequences of the risks discovered). It is performed continually over the life of a program, from initiation to retirement.

There are a variety of risks that confront the global software industry, as illustrated in Figure 1 [McManus, 2004], which will be discussed in more detail. The characteristics of the legal, social, economic and competitive environments impose constraints and opportunities that help to define the nature of the risks (and their exposure levels) for suppliers, buyers, and other stakeholders in the software acquisition and development process.

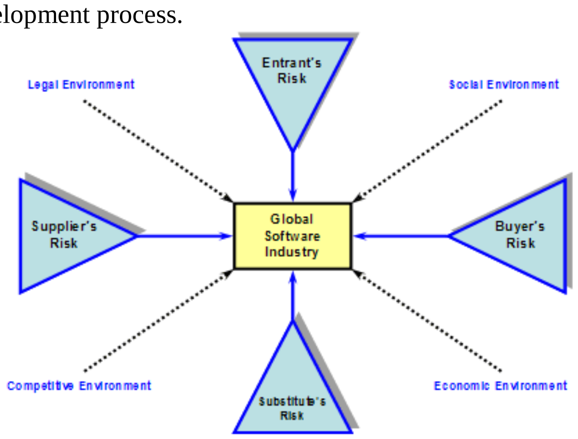

Figure 1: Risk and the Global Software Industry [McManus, 2004]

B. POSITIVE RISK

Positive risk refers to risk that we initiate ourselves because we see a potential opportunity along with a potential for failure (the negative risk associated with ―loss‖ of the opportunity). There are several kinds of opportunities that can be leveraged in projects if responses to them are well-timed and prompt action is initiated [Kahkonen, 2001]. These include:

- ✓ Business opportunities, e.g., product development, customer care during the project life cycle, and focused attention on high profit margin activities.

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- ✓ Operational opportunities, e.g., value-added, do what is important, minimize rework.
- ✓ Systemic opportunities, which typically mean long- term savings resulting from improved safety, insurance, etc.

C. SOFTWARE RISKS

There are numerous reasons as to why formal risk management is difficult to implement effectively. These include the sheer number of risk factors that have been identified in the literature. For example, Capers Jones assessed several hundred organizations and observed over 100 risk factors (of which 60 he discusses in detail in [Jones, 1994]). He observed, however, that few projects have more than 15 active risk factors at any one time, but many projects have approximately six simultaneous risk factors[3].

Another reason for the relatively low implementation of formal risk management methods in practice are, according to [Kontio, 1998], the fact that risk is an abstract or fuzzy concept for which users lack the necessary tools to more accurately define risk for a deeper analysis. In addition, many risk management methods may be based on risk quantification. Users may not have the ability to provide accurate estimates for probability and loss/opportunity projections required for a reliable risk analysis. Table-based approaches can sometimes be too biased or too coarse for proper risk prioritization. Risks may also have different implications for different stakeholders (or, conversely, be perceived differently by different stakeholders). Existing risk management methods may not provide support for dealing with these differences. Risks may also affect a project in more than one way. For example, most risk management approaches focus on cost, schedule or quality risks, but there may be combinations of risks or other characteristics such as future required maintenance, company reputation, or potential liability/litigation that should be considered important in influencing the decision-making process. Finally, many current risk management techniques may be perceived as too costly or too complex to use. Simple, straightforward risk management techniques that require an acceptable amount of time to produce results might be the answer.

The Risk Management Map contains five evolutionary stages of risk management capability, defined as:

- ✓ Problem Stage: Describes circumstances when risk identification is not seen as positive. Characterized by lack of communication which causes a subsequent lack of coordination. Crisis management is used to address existing problems. Risks ignored or tracked in ad-hoc fashion.
- ✓ Mitigation Stage: Details a shift from crisis management to risk management. People become aware of risks but do not systematically confront them. There is uncertainty as to how to communicate risks. Risks are usually recorded, tracked and handled as discovered.
- ✓ Prevention Stage: Discusses the shift of risk management as solely a manager's activity to risk management as a team activity. This is a transitional stage from avoidance of risk symptoms to identification and elimination of root cause of risk, characterized by team, and sometimes customer, involvement. For risk management to succeed it must occur at each level within an organization. This stage represents a turning point from a reactive to a more proactive approach to risk management. Risks systematically… analyzed, planned, tracked and resolved.
- ✓ Anticipation Stage: Describes the shift from subjective to quantitative risk management, through the use of measures to anticipate predictable risks, that is characterized by the use of metrics to anticipate failures and predict future events. This stage involves the ability to learn from, adapt to, and anticipate change, representing a completely proactive approach to risk management. Quantified analysis used to determine resolution cost/benefit for the project.
- ✓ Opportunity Stage: This represents a positive vision of risk management that is used to innovate and shape the future. Risks are perceived as an opportunity to save money and do better than planned.

Risk, like quality, is everyone's responsibility. A continuous process of identifying, communicating and resolving risks in an open and non-threatening environment is used. Admissions that some things are not known are acceptable and allowances are made for their existence using a best-case, worst-case scenario. Risk statistics are used to make organizational/process improvements. On a detailed plan that evolves over time.

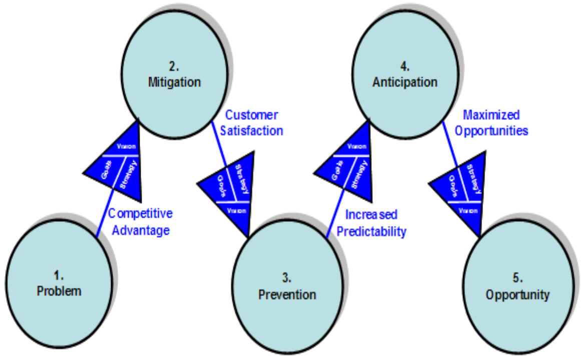

Figure 2: Risk Management Map

IV. CONCLUSION

AI is a young field and faces many complexities. Nonetheless, the Spring 1998 issue of AI Magazine contained articles on the following innovative applications of AI: This is suggestive of the broad potential of AI in the future.

- ✓ "Case- and Constraint-Based Project Planning for Apartment Construction"
- ✓ "CREWS–NS: Scheduling Train Crews in The Netherlands"
- ✓ "An Intelligent System for Case Review and Risk Assessment in Social Services"
- ✓ "CHEMREG: Using Case-Based Reasoning to Support Health and Safety Compliance in the Chemical Industry"
- ✓ "MITA: An Information-Extraction Approach to the Analysis of Free-Form Text in Life Insurance Applications"

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REFERENCES

[1] Luger, George F., and William A. Stubblefield. Artificial Intelligence: Structures and Strategies for Complex Problem Solving. Redwood City, CA: Benjamin/ Cummings Publishing Company, 1993.

[2] Mueller, Robert A., and Rex L. Page. Symbolic Computing with LISP and Prolog. New York: Wiley and Sons, 1988.

[3] Russel, Stuart J., and Peter Norvig. Artificial Intelligence: A Modern Approach. Englewood Cliffs, NJ: Prentice Hall, 1994